H. Zhuge, Cyber-Physical-Social Intelligence on Human-Machine-Nature Symbiosis, Springer, 2020.

Chapter 3
Cyber-Physical-Social Semantic Link Network

Is there any cause-effect link between thinking, experiencing and knowledge? This problem has challenged philosophers and scientists for centuries. Understanding and representing reality is a key step toward finding the link. Semantics modelling is an approach to understanding and representing reality.

Computer scientists have studied semantics modelling for about half a century to create better representation systems for developing various application systems through unifying understandings. Traditional methods are mainly based on unary methodology, single abstraction, static representation and single space, which are limited in ability to reflect multi-dimensional, complex, evolutional, physical and social nature of reality.

Reality evolves with co-evolution of cyberspace, physical space and social space and interactions between spaces. Understanding and modelling reality in cyber-physical-social space, and unveiling relevant rules and principles become a new challenge.

This research creates a Cyber-Physical-Social Semantic Link Network model (CPSoSLN) consisting of a base network reflecting generality and basic structure of reality; a superstructure reflecting particularity and regularity in various spaces; persistent mappings between the base network and the superstructure and between the spaces that construct the superstructure; and, operations that evolve the base network, superstructure and the spaces with emerging patterns, categories, social linking rules, relational reasoning rules, principles, properties and dimensions. The model evolves with incorporating new rules, properties, principles, and methods and finally reaches a general form. It links reality to knowledge with an open and evolving cyber-physical-social relational system that helps understand reality, discover relations and rules, interpret and summarize discoveries, and predict and influence the evolution of reality.

3.1 Modelling the Evolving Reality

Recognizing the nature of reality involves such behaviors as: (1) observation of reality directly or through equipment to identify characteristics of things in reality; (2) discovery of relations between things and rules on relations; (3) interpretation of discoveries by using existing relations and rules; (4) summarization of discoveries to form systematic knowledge about reality; and, (5) creation of various spaces including physical spaces, social spaces and cyberspaces, which are emerged, linked, split and merged along coevolution (Zhuge 2011).

Sharing knowledge through society, people establish beliefs on knowledge and use knowledge to interpret what are observed and experienced but most people neglect the big picture of reality. Recognition of reality is a constant process of exploring the nature of reality, during which knowledge can be challenged, confirmed, improved, completed and falsified.

Humans explore the physical space through interacting with the physical objects and with each other, reflecting reality, building and understanding semantic images, and finding rules on the semantic images (Zhuge 2010; 2011). A semantic image consists of concepts reflecting various things in reality, concepts generalized through understanding, and relations between concepts. The semantic images built by an individual can only reflect a small part of the physical space. Therefore, the physical space people built in mind so far does not completely reflect reality.

Science assumes that the natural physical space is independent of human cognition and its regularity can be recognized through observation, experiment and practice. The mismatch between reality and the semantic images in the minds of scientists lead to the inconsistence between theories. This is a cause that leads to the falsifiability of scientific theories (Popper 1959).

What people know about social space is the semantic images generated in minds from observation and various interactions. Social space contains social objects (individuals), motivations, values, resources, relations, rules, policies, processes (productions) and principles. The study of social space concerns such disciplines as philosophy, politics, economics and laws. The semantic image of an individual only reflects a small part of social space. Social space has mapping image in the physical space.

The semantic image of cyberspace consists of services based on various representations, links between representations, operations on representations and links, and computing that transforms one form of representation into another form of representation. An individual usually have a semantic image of a small part of cyberspace. Research and development of cyberspace including computer science and engineering, network science and engineering, data science and artificial intelligence drive the evolution of cyberspace.

What is the link between experience and knowledge? This problem has challenged philosophers and scientists for centuries. Chomsky named this problem a Plato's problem: How can we know so much given so little evidence?

Understanding reality is the first step to link experience to knowledge. Socrates inspired uneducated people to learn Pythagorean theorem by asking them related questions and using diagrams to help them understand the problem.

Semantics modelling is an approach to understanding reality. A framework of transforming various forms of data into knowledge was proposed (Zhuge 2015, 2016). This chapter focuses on exploring the method for semantics modelling.

Gödel's incompleteness theorem and Simon's bounded rationality shape the boundary of recognizing reality from the perspectives of theory and cognition. How to extend the boundary is a challenge of semantics modelling. A strategy is to build an evolving semantic link network of various models developed by different people with different methods of understanding reality. Figure 3.1 depicts a way to link reality to knowledge through semantics modeling with the ground consisting of cyberspace, physical space and social space.

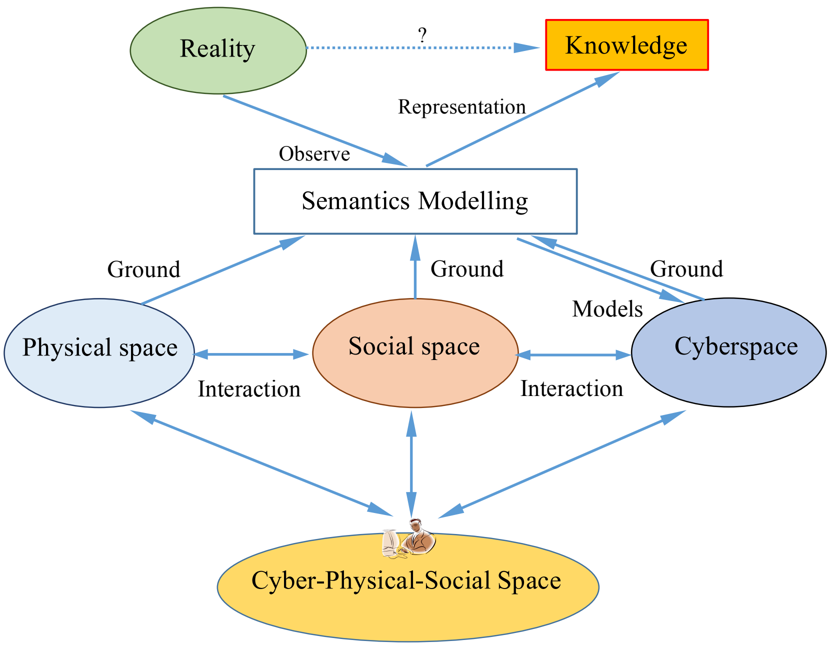


Fig 3.1 Modelling reality in cyber-physical-social space.

3.2 Modelling Society

3.2.1 *Socio-Relational Systems*

Relation is the generalization of regular direct or indirect interactions between things, or the commonality between their features. Recognizing relations is the human nature of knowing the structure of reality, evolution process of reality, and limitation of sensing and thinking the whole and parts of reality at the same time. Relation is a basic dimension of observing and studying reality.

Society consists of complex things like organization, which consists of individuals, rich semantic links between individuals, and social rules and principles that are different from rules and principles in cyberspace. Society evolves with the development of humans and productive forces. The evolution of human society has experienced stone age, bronze age, ion age, steam age, electric age and information age, which has created different levels of productive force and corresponding productive relations.

Viewing from relational dimension, a society can be modelled by a complex relational system consisting of a base relational network and a superstructure that determines the semantics, motivations, strategies, policies, rules and principles of operating and evolving the base network, which influence the evolution of the superstructure.

The base relational network evolves with operations such as adding (i.e., generating) nodes, removing (i.e., dying out) nodes, adding links and removing links, consequently renders and evolves patterns of different scales. One category of relations influences the other to a certain extent. A relational system also evolves with operations on its superstructure that defines and motivates and conducts operations (including reasoning) on the base network, and it also interprets and evaluates operations and reasoning.

Societies at different development stages form different patterns of the base networks and different superstructures.

In primitive society, people created stone tools and hunt cooperatively. Resources and products are equally distributed within clans, which organize people according to kinship. Clans evolve through two stages: matrilineal society and patriarchal society. Society consists of clans distributed in geographically separated places. The socio-relational system within clan consists of a small cooperative base network and the superstructure based on kinship relation (it is usually not completely separated from the base network).

In a capital society, more people work with more efficient tools developed through innovation, reforming productive forces and productive relations of this historic development stage. The productive forces and the relations of production form a pattern of production at a particular development stage. Marx defined the relation of production as the sum total of social relationships that people must involve so as to survive, produce and reproduce their means of life (Marx 1867).

Alongside curiosity that drives the development of science and technology, *competition plays a key role in adopting technical innovations in production*. In western economic society, rational self-interest and competition can make economic prosperity (Smith 1776). In western society, families usually keep a small scale as children will live independently when they are married. This lays the basis for generating free competition society.

Symbiosis is another basic social phenomenon for improving social production. Different development stages of society develop different forms of symbiosis. In agrarian society, production relies on human labor, so families need more family members to take care of more crops, which can save cost for hiring people. Children live together with their parents even after they married. In industrial society, production relies on machines, so people are mainly organized by machinery production. Families no longer play the major role in organizing productions. People with different expertise meet different needs of production. Therefore, families tend to be small.

The above discussion from evolutionism shows that a socio-relational system operates with rich types of nodes including autonomous nodes like various organizations that can actively select input flows and the way to process flows according to motivation, prediction of interest (or profit), technique, knowledge, and rules of competition and policy, which are defined in a space that co-evolves with the base network of the socio-relational system. This requests an autonomous model for modeling society.

3.2.2 *Competition and Symbiosis*

One of the fundamental scientific problems is how living beings are created and developed. An explanation from the evolutionism is that long-term change (including climate change) in the physical space provides the conditions for the nature to select the fittest species from survival competition, i.e., the natural selection in Darwin's theory on the origin of species (Darwin 1859).

Competition is a relation formed from the motivation of occupying limited resources in general. In human society, competition is a relation formed from common motivations (Maslow 1943), such as occupying limited material resources and obtaining social merits. *Competition is a basic force to drive the development of species. It forces species to adjust and enhance themselves to gain competitive advantages*. Evolution was also regarded as a change from an incoherent homogeneity to a coherent heterogeneity, accompanying the dissipation of motion and integration of matter (Spencer 1896).

Symbiosis is also a basic relation that structures the pattern of survival along the evolution of species. *Symbiosis increases the fitness* (or competitive advantage) of individuals or species through various reciprocal interactions (including those in form of material flow, energy flow, data flow, knowledge flow and information flow) with other species along evolution. Interactions provide the condition for establishing symbiotic links and evolving patterns in society, which drives the evolution of species.

Building and maintaining symbiosis is also a force that drives the evolution of society.

Competition carries out with external strategies (e.g., differentiate markets for products, introduce new techniques into the existing products, and develop new products) and internal strategies (e.g., improve efficiency and reduce cost for operating enterprises). Porter's Five Forces model reflects the external factors of competitive intensity of industrial organizations (Porter 1979), but it neglects the internal factors (e.g., optimization of production process) and the effect of symbiosis.

Symbiosis carries out through complementing functions between things (individuals, organizations, or communities) to enhance the benefits of both parties and the capacity of competition. Many instances show that competition and symbiosis carry out through direct interaction, indirect interaction or influence.

Symbiosis is the major mechanism that constructs the primitive society. Mosuo is a matrilineal minority living in Lugu Lake area in Yunnan Province in China. Children live together with mother in their lifetime. Grandmother has the power to distribute material resources and deal with important family affairs. To keep sustainable development, a family tends to be big (usually around 30 people) so that family members can carry out diverse productions that are cooperative to support self-sufficient materials and social life. Families within the same region are organized into a community according to religion, regulation and power of making decision on community affairs. Families and communities construct a socio-relational system of different scales consisting of a base symbiotic network and a superstructure of management.

3.2.3 *Productive Force and Productivity*

Productive force is the combination of human labor (based on individual bodies, mental behaviors and organizational behaviors) with the means of labor (including tools, machinery, land and infrastructure) (Marx 1867).

The development of productive force (e.g., the invention and adoption of mechanization, water power and steam power in production) drives the evolution of productive relation (machines replace more and more human labor), and thus drives the evolution of the structure of the relational system. The change of production relations influences the change of flows (including material flow, human flow, money flow and knowledge flow) locally and globally (especially with the building of more efficient transportation network like express railway network), therefore evolves the relational system in the physical space and the relational system in mental space, which in turn improves productive force through inventions (e.g., mass production and computer) and eventually influences the change of production relations.

The development of productive force greatly enriches material wealth, human demands have gradually developed from material consumption toward information and knowledge services as well as healthy and sustainable development, which requests material flow cycle through productions. The development of knowledge and services in turn drives the development of productive force and thus pushes forward the evolution of productive relation.

Productivity is a measure of the efficiency of production in a space of multiple dimensions, including:

1. *Power dimension*, which measures the productivity of a node in the network of productions from the power of changing status (e.g., steam power, electric power, mechanical power and manpower).
2. *Management dimension*, which measures the productivity of a node from the effectiveness of managing production organization (e.g., mass production promotes productivity through optimizing production management).
3. S*kill dimension*, which measures the efficiency of a node from using and developing skills (the higher the better).
4. *Intelligence dimension*, which measures the productivity of a node from the development of intelligence (the higher the better).

Any point in the space has a projection at every dimension.

The productivity of a socio-relational system is determined by the productivity of its nodes and semantic links between nodes as well as flows through the links. The productivity of a node corresponds to a point in the productivity space.

3.2.4 *Flows*

One individual or organization influences the other through material flow, money flow, data flow, information flow, knowledge flow and human flow, which coordinate each other to organize and evolve society. The influence of flows in social network starts from local and then becomes global in the long run, some influences become prominent through amplification of the nodes while others become subtle through the damping effect of nodes along propagation.

In a closed system, materials can change form but the total mass of the system remains constant (i.e., the law of conservation of mass). Efficient management of material flow is a way to realize sustainable development of society (Shi and Li 2019). The law of conservation of mass indicates the approach to detecting waste emission through analyzing material flow network. Material flow is the original force of forming competition and symbiosis in society with limited resources. The value of material resources increases through production for meeting social requirements. Different types of material resources need different production processes, which usually follow different rules and involve different networks of competition and symbiosis. From the view of resources and meeting social demands, service flow has the same characteristics as material flow.

Money flow usually works with material (or service) flow to organize productions in society according to economic principles. Figure 3.2 shows the evolution of money flow networks of various sectors from 1967 to 2017 in the UK (data are obtained from: www.ons.gov.uk/economy/nationalaccounts/supplyandusetables), where nodes represent sectors and nodes of a larger size represent higher value and lines represent money flow between nodes and a thicker line reflects a higher value. The change of values reflects the change of the absolute importance of nodes and links within the network under the uniform measure. As the figure shows, real estate, science and technology, finance and insurance, information and healthcare sectors grow quickly while retail, textile, warehousing and farm shrink through the development process. The change of connecting a node to other nodes reflects the change of the dependence between the node and the other nodes. Money flow can also work independently to increase its value with knowledge and strategies and amplify competition and symbiosis through more efficient use of money.

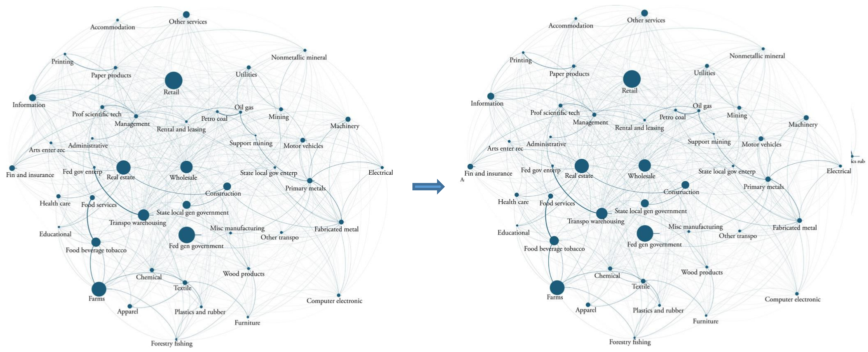


Fig. 3.2 Evolution of money flow networks in the UK from 1967 to 2017.

Data flow and information flow reflect the dynamicity of the observed system that humans are limited in ability to sense directly through organs. Data flow and information flow also provide the mechanisms for optimizing the observed system through modeling and prediction. Knowledge flow passes through human minds through verification based on reasoning, applications in supporting intelligent behaviors, evaluation and linking to existing knowledge. Material flow, data flow, information flow and knowledge flow operate with specific principles and form different levels of competition and symbiosis in society. They are also resources that incur competition and innovation.

Human flows form symbiosis between organizations and evolve the structure of communities in social space. For example, universities input human flows (students) from high schools and then output human flows (graduates) to various organizations (including enterprises and public organizations), which further output human flows with specific knowledge to different organizations. Rules (e.g., non-compete agreement) are needed to maintain the order of flow. Knowledge in minds and organizations evolve as the effect of the flows.

3.2.5 *The Role of Motivation*

The difference of social statuses of human individuals determines different levels of motivations, which introduce different levels of competition and symbiosis. To reflect dimensionality of motivation, motivations can be specified in a multi-dimensional motivation space where different dimensions specify different hierarchies of motivations.

A real social network operates in a complex space that can be viewed from multiple dimensions (Zhuge 2008; Zhuge 2012). Symbiosis and competition involve in the development of society of different scales and along different dimensions. Different dimensions may have different influences on the evolution of social network. Therefore, a social network can be specialized by mapping it onto different dimensions for particular analysis in different applications. On the global scale, countries belong to an international relational system and compete on impacts and interests while benefiting each other through material flow, money flow, information flow and knowledge flow according to economic rules and politic strategies. On the middle scale, competition and symbiosis carry out on a social network of organizations (e.g., social network of enterprises), which involve in different types of flow with different motivations and different strategies. On the small scale, individuals interact for competition and symbiosis within social network of individuals who process different levels of flows with different motivations and strategies.

3.2.6 *Locality and Global Influence*

In the Newton mechanical space, one object influences the other only through direct interaction (e.g., force and gravity), which depends on the distance between objects. This determines the locality of interactions, which widely exists in various spaces consisting of objects and direct interactions between objects. The locality was also studied in language representation, understanding and processing (Zhuge 2016). The locality in the biological world demonstrates a phenomenon of least effort (Zipf 1949). Viewing from a different dimension, the locality may not hold, e.g., in microscopic spaces like the quantum space (quantum entanglement is irrelevant to distance).

A socio-relational system takes some features of the Newton mechanical space. One node influences another node only through a direct link or a chain that can derive out a direct link between two nodes or carry flows through. As an effect of locality, flows usually pass through nodes within a community to efficiently share flows. Viewing from a different dimension, the influence of operation can be global in the long run, e.g., changing the rank of a node could influence the rank of all nodes. Data, information and knowledge flow through nodes can be localized in cyberspace while the nodes are globally distributed in physical space. Enterprises' experiences of adopting work-from-home model during pandemic COVID-19 show advantages in promoting productivity and saving energy.

The above phenomena indicate the necessity of adopting a multi-dimensional methodology to integrate and interpret different theories in a space of methodologies (Zhuge 2012; Zhuge 2016).

3.2.7 *Value of Relational Systems*

In a real social network, a node needs to assess the value of linking itself to another node. The value of linking a node to another node is determined by the following aspects:

1. *The value of satisfying motivation* at a certain level and to a certain extent: 1) basic physiological needs, 2) safety and health, 3) love and friendship, 4) recognition or achievement, and 5) self-actualization or achievement of full potential (Maslow, 1943). The value is proportional to the level and the degree.
2. *The value of network*, which is in proportional to the square of the number of nodes (Metcalfe's law). Linking operation prefers to join a network with a higher value so that the new node can gain a higher value by contributing to and benefiting from the network.
3. *The value of effective time*. A linking operation can establish a more effective symbiosis between nodes if it can coordinate the stages of lifecycles of the nodes so that cooperation can be more stable and effective.
4. *The value of flows*, including material flow, data flow, information flow and knowledge flow.

It is an autonomous node if it can have insight of predicting the change of the above aspects, e.g., the change of motivation and the change of flows at different stages of lifecycle.

In a hyperlink network, linking a node (webpage) *n* to another node *n*' contributes the rise of the rank of *n*' but *n* does not get any rank reward from *n*' because *n*' may not be aware of this link and it does not introduce its readers to *n*. In a citation network, a paper *p* citing another paper *p*' contributes to the rise of the impact of *p*' but *p* does not get any reward of network effect from *p*' but *p* gets knowledge from *p*'. Social media platforms like Twitter provide operations of different intensities for users such as "visit", "impression", "view", "like", "mention" and "follow". Therefore, persons are linked for passing information through different types of operations reflecting different intensities of interest.

Different from the general social networks (Zhuge and Zhang 2010), a social network in a capital society follows economic principles. Any node (individual or organization) in society contributes to others with a certain productivity. The node with processing more flows (including material flow, data flow, information flow and knowledge flow) contributes (or receive) more resources to (or from) more nodes, therefore it works with a higher productivity.

On the other hand, linking an individual (a node) *n* to another *n*' implies that *n* also inputs/outputs flows of various resources (material, data, information and knowledge) from/to *n*'. In a society with limited resources, individuals compete for resources, the individuals with limited resources will gain some potential power of obtaining reward from contributing limited resources to others because an individual can freely select another individual for cooperation in a self-organized social network.

The following proposition can be drawn from the above discussions.

The emerging importance on flows. *For a community with limited resources, an individual (or organization) becomes more important with processing more flows, including material flow, data flow, information flow and knowledge flow.*

3.3 Social Semantic Link Network Model

From rationalism point of view, nothing happens without a reason as Leibniz pointed out. From empiricism point of view, knowledge consists of relations of ideas and matters of facts as Hume pointed out. Understanding the relations between things in society is the basis for knowing reasons behind things.

3.3.1 *Basic Semantic Link Network Model*

A basic question needs to be answered first is why network model is considered to model social semantics? The following are main reasons:

1. Human organs are limited in ability to sense, understand and think the whole complex system. An approach to understanding a bigger picture is to focus on its parts (components) while finding the links between parts. Discovering implicit links is important for understanding the bigger picture.
2. Linking is a basic social motivation and behavior, which organizes and evolves communities.
3. Network is an abstract model of most systems formed through interactions among its parts.

4. Meaningfully linking parts of a complex system is a way to observe the social semantics of the system.

The above consideration coincides with the worldview of rationalism (e.g., Spinoza) and Simon's idea about the structure of the near decomposable systems.

Modeling social semantics is based on the following basic assumptions:

Assumption 3.1. *There exists a common language for the society to understand what are observed and represent what are understood.*

The above assumption is the basis for representing, understanding and using models.

Assumption 3.2. *A lightweight language consisting of a set of basic language units (i.e., words or phrases) and a simple grammar for composing language units to identify nodes (i.e., components of a system or reality) and relations between nodes can be selected from the language (assumed in assumption 3.1).*

Based on the above assumption, a network of things identified by the lightweight language is understandable within the society.

Assumption 3.3. *There is a fundamental existence — the ability of judgment, which forms concepts through experience or reason. Some concepts are abstractions of perceptual things and others are abstract concepts.*

Concepts form a concept hierarchy (or concept network), where nodes are concepts and links are abstraction relation. A concept x is called an abstraction of a set of concepts Y if the attributes of x is inherited by the concepts in Y. *The concepts that have no more abstract concepts are called categories.* Concepts are identified by basic language units.

Assumption 3.4. *Interactions between components of system can be understood according to concepts.*

Based on the above assumptions, we have the following definition.

Definition (Semantic Link Network). *Semantic Link Network (in short SLN) is a model for representing social semantics with a four tuple or a mapping represented as follows*:

$$<N, L, \Im, f>, \text{ or in form of } <f: \{N, L\} \rightarrow \Im>, \text{ where}:$$

1. *N is an open set of nodes (called semantic nodes), each node represents a concept or a semantic link network of concepts.*
2. *L is an open set of links (called semantic links) between nodes. The semantics of a link is specified by its attributes and possible interactions between nodes. A semantic link is identified by a language unit to represent reference, definition (e.g., subtype or is-a), structure (e.g., is-part-of, similar, etc.), reasoning (e.g., cause-effect, implication, equal, etc.), competition and symbiosis.*

3. *$\Im$ =< $\wp$, $\Re$> is a semantic space consisting of a network of concepts $\wp$ shared in society, an open set of rules $\Re$ consisting of rules for reasoning on L and social linking rules for guiding the connection of nodes. Each rule takes the form $\alpha\cdot\beta\Rightarrow\gamma$ representing that the connection of link α and link β implies link γ marked by the lightweight language. A society can have multiple sets of basic concepts representing differences of communities.*
4. *f is a mapping from {N, L} into $\Im$ such that any node in N has a corresponding concept in $\wp$ and any link in L has a corresponding concept or structure in $\wp$ and can have a corresponding rule in $\Re$, and applying $\Re$ to L generates new links $\Re$ (L) $\supseteq$ L, and operation L=$\Re$(L) updates L. The function f reflects the beliefs of the autonomous nodes formed through interactions that evolve the base network and the superstructure.*

The basic SLN is an algebra structure that reflects the semantics of social system, especially the evolving systems self-organized through interactions among components. It is also a framework system for developing socio-relational systems by defining the base network and the semantic space according to application requirements. A socio-relational system can carry out relational reasoning and provide intelligent information services such as question answering and summarization based on semantic links and linking rules. For example, a question-answering system can answer questions about what and why with the help of definition relation and cause-effect relation. Therefore, Semantic Link Network can be an autonomous semantic data model (Zhuge 2012).

Intelligence emerges with interactions among multiple relational systems, including SLNs in minds, SLNs of local reality and SLN of global reality where humans and machines behave and influence their evolution. Interactions form flows through links including data flow, information flow and knowledge flow (introduced in chapter 5).

Establishing and maintaining competition and symbiosis push forward the evolution of social network with specific rules in addition to the operations on general social network, for example, a new node tends to link to the nodes that can enhance its competitive power.

For a social network with competition link and symbiotic link, a new node and the existing communities need to consider competition situation and strategies to enhance their competitive advantages. It has to consider joining which community can best enhance its competitive advantages and which node should be linked to establish symbiotic link. A community needs to consider accepting which node can best enhance its advantages in competing with other communities. Therefore, social linking rules that influence the formation and evolution of social network should be incorporated into social network modelling.

3.3.2 *Social Semantics*

Semantics concerns mapping between representations in different languages. Different communities may have different worldviews and different beliefs, which lead to different dimensions of representation and mapping.

Traditional study of semantics concerns language, programming languages, formal logics and semiotics. Social semantics was distinguished from traditional study of semantics with emphasis on interaction (interactive semantics) and evolution (Zhuge 2010).

An evolving SLN represents social semantics. Human individuals can be nodes of the network or the operators of the network or a part of the network. For a large-scale network, individuals are limited in ability to have a global view. Therefore, different mappings are possible, different semantic links can be derived from the same network and contradict semantic links can even reasonably co-exist.

The category network in Wikipedia reflects a kind of social semantics extracted from the framed natural language representation where the contents are defined by people in communities with different beliefs. Therefore, we cannot simply say that contradict links are wrong or one of the two contradict links is wrong. This is one of the features of the SLN distinguished from the logic-based systems.

Adding a semantic link that contradicts to an existing semantic link may incur a reasoning that can derive out a new link probably useful for the person who adds the link according to a different worldview. As shown in Figure 3.3, adding a *cause-effect* link C—ce→A (in red arrow) to the existing semantic link network incurs a derivation: C—ce→A, A—ce→B ⇒ C—ce→B (in red dotted arrow), which cannot be derived from the existing network. Another person can add B—ce→F (in blue arrow) to the network, leading to F—ce→A to be derived (in blue dotted arrow) from the changed SLN.

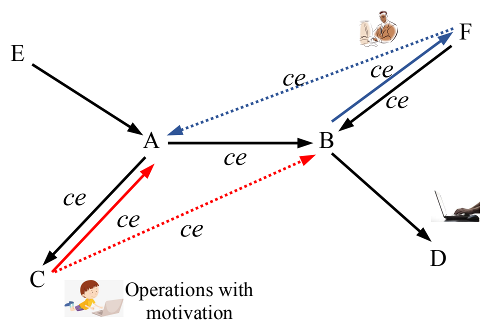


Fig. 3.3 People can operate the same SLN by adding various semantic links with different beliefs.

More semantic links may be further derived from the derived links, which influence the evolution of the whole network. The derived links are probably useful from the view of the persons who add the links. It is significant to the system for providing personalized knowledge services for users.

A large-scale SLN should contain different beliefs of users and reflect temporal relations (Zhuge 2016). To reflect diverse constraints, semantic links can take the following forms:

1. *Common semantic links*, which are agreed by all people in the community sharing the SLN, and can join other semantic links for reasoning, represented as $X \text{——} \alpha \rightarrow Y$, where α denotes a relation.
2. *Uncertain semantic link*, which reflects a relation that probably holds. It can be represented as $X \text{——} < \alpha,\ \mathit{cd}\text{: } \mathit{value} > \rightarrow Y$, where α denotes the relation, and *cd* represents the certainty degree. For example, as $X \text{——} < \mathit{similar},\ \mathit{cd}\text{: } 0.6 > \rightarrow Y$ represents that X is similar to Y with certainty degree 0.6.
3. *Belief semantic link*, which reflects a relation subjective to a user or a community. It can be represented as $X \text{——} < \alpha,\ \mathit{belief\text{-}of}\text{: } \mathit{user} > \rightarrow Y$, where α denotes the relation, and *belief* represents the *belief* of the *user* (or a community) who adds the semantic link to the SLN. For example, $X \text{——} < \mathit{ce},\ \mathit{belief\text{-}of}\text{: } \mathit{Hai} > \rightarrow Y$ represents the *cause-effect* link between X and Y with belief of *Hai*.
4. *Temporal semantic link,* which is effect or believed during a period of time. On one hand, relation may change with time because some relations hold during a period of time, e.g., supervisor relation between a professor and a research student holds only during the studying period of the student (reflecting the constraints on both parties). This type of semantic link will be discussed further in section 3.7.
5. *Evidence-based semantic link*, which can be represented as $X \text{——} < \alpha,\ \mathit{evidence}\text{: } e > \rightarrow Y$, where α denotes the relation and e represents the evidence of α. Different people can provide different evidences for a semantic link. For example, some people can provide evidence for supporting that the emission of more CO_2 is the cause of global warming but some people can provide evidences for supporting that global warming is the cause of emitting more CO_2.

Multiple reasoning processes on a large-scale SLN can carry out with diverse beliefs of people who operate the network as operators or influence the network as nodes.

3.3.3 Semantics of Semantic Link Network

Semantics of SLN is specified by the structure of its base network and the semantic space above the structure. The basic semantic space includes a network of categories representing concepts, relations between concepts, linking rules and relational reasoning rules.

The basic semantics of a node is indicated by:

1. its concept and category;
2. the concepts and categories of the links it has;
3. the concepts and categories of its neighbor nodes; and,
4. the links between the above concepts.

The basic semantics of a link is indicated by:

1. its concept and category;
2. the concepts and categories of two nodes that the link connects;
3. the concepts and categories of the neighbor links;
4. the links between the above concepts; and,
5. relevant linking rules on the links that can derive new links.

A significance of introducing category is that it can uniquely determine the semantics of a node or a link because there may have multiple ways of abstraction. With different categories, different concepts are linked from experiencing the same reality. For example, an observation of a street demonstration can be linked to different concepts such as "democracy", "riot" and "fun", which belong to different categories. A language representation can be linked to different concepts, for example, a word "apple" can be linked to different concepts with category "machine" and category "food" respectively. So, a category can uniquely determine the semantics of a word. In applications, a concept at a higher level concept hierarchy can also determine the semantics of a concept, for example, concept "computer" and concept "fruit" can determine the semantics of the word "apple".

In addition to concept hierarchy, the structure of the base network especially the neighbor node and link also render the semantics of a node or a link. For example, different neighbor words such as "eat" and "phone" of the word "apple" rendered different concepts.

An active concept can be represented in the following SLN-based form: where the *structure* represents its internal structure in form of an instance of SLN, the *attributes* reflect its external attributes, the *links* reflect the relations it connects to other concepts (links between concepts form a concept network), the *services* is a set of functions with parameters, the *rules* is a set of rules for linking and providing services, and the *experience* consists of *definitions* with *citation*, *instances* of using the category and *pattern* of using the concept in instances.

ConceptID {
Structure: *internal structure*;
Attributes: {$attribute_1$: $value_1$, …, $attribute_k$: $value_k$}

Links: *semantic links to other concepts*;
Services: [*service*$_1$(*parameters*), …, *service*$_n$(*parameters*)];
Rules: *a set of liking rules*;
Experience: [*definition(cite)*, *instances*, *pattern*]}.

A pattern can be a simple SLN. For example, the pattern of a text can take the following form: $<[(w_1, f_1), \ldots, (w_n, f_n)], L>$, where w_1, …, and w_n are words appeared in texts, f_1, …, and f_n are frequencies of the words appeared within the text, and L are a set of semantic links between words. The semantics of the basic components is defined by the Interactive Semantic Base ISB proposed in (Zhuge 2010).

For example, the concept of "university" can be represented as follows:

University {
Structure: <{*College of Science*, *College of Engineering*,
College of Business, *College of Social Science*},
<*is-part-of*}>;
Attributes: [*type*: public;
location: UK;
number of teachers: 2000;
number of students: 10000;
time of establishment: 1960]
Links: [*category*: organization,
student-from: high-school,
graduate-orientation: (enterprise, university)];
Service: [*Bachelor-program*, *Master-program*, *PhD-program, Research*];
Rules: Regulations;
Experience: [*definition*: A university is an institution of higher education and research which awards academic degrees in various academic disciplines (link: *Wikipedia page*),
instances: (Oxford, Cambridge, Stanford),
pattern: [(*university*, 0.7), (*college*, 0.2), (*school*, 0.1)]}.

The above SLN-based representation has the advantages of ontology, frame and semantic net. Further, the semantic space enriches the semantics of the base network of the SLN. Its complex structure enables it to reflect more semantics of things than string-based representations or vector-based representations.

As depicted in Figure 3.4, the semantics of node A is indicated by:

1. Its concept and category in the concept hierarchy.
2. Semantics of its neighbor nodes B, C and E.
3. Semantic links x, α and γ.

The semantics of link x is indicated by:

1. Its concept and category.

2. Semantics of node A, semantics of node B and its neighbor semantic links γ, δ, τ, α and β.
3. Reasoning rules on the neighbor semantic links, e.g., $\alpha \cdot \beta \Rightarrow x$.

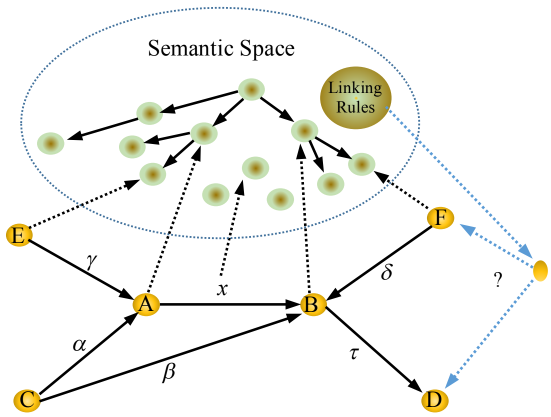


Fig. 3.4 The basic semantic space of Semantic Link Network.

If there are more than one semantic link between nodes, a semantic link may exist between two semantic links, for example, link y is *girl-friend* and link x is *friend*, $y \Rightarrow x$ holds. Generally, the following property holds:

Property of relation implication. *If the concept of link x is more general than (i.e., a super-concept of) y on an abstraction chain of concepts, $y \Rightarrow x$ holds.*

Different from traditional social network, a node with richer types of links takes the priority to emerge than the node with single type of links (Zhuge 2011). Combining the diversity of semantic links and the ranks of structure leads to the following proposition:

Diversity of emerging semantic links. *The rank of a node emerges in proportion to the diversity of its semantic links and link structure (i.e., the number of its link and the rank of its neighbors).*

3.3.4 *Modelling Ability*

SLN opens to operations on the base network and superstructure, e.g., incorporating more types of semantic links and richer semantic space. The modelling ability of an SLN relies on the semantic richness of its base network and completeness of its superstructure for domain applications. More diverse semantic links an SLN contains, the richer semantics it has. The completeness of the semantic space means that it contains enough semantic definitions including the concept hierarchy and rules on semantic links so that all semantic nodes and semantic links within the base network can have semantic images and implicit semantic links can be derived.

Comparing with other semantic models like Semantic Net and Linked Data, the modelling ability of SLN is mainly empowered by the following two aspects:

1. Diversity of semantic links; and,
2. Its superstructure with such abilities as abstraction, linking rules and relational reasoning abilities.

Property of semantic modelling ability. *A Semantic Link Network with richer semantic links has a stronger semantic modelling ability*.

The following are two reasons of this property from empirical observations and previous experiments:

1. *From the expressiveness dimension*, an SLN with two types of semantic link has a stronger modeling ability than an SLN with only one of the two types of semantic link. Evidences can be found in modeling text:
   - An SLN with only one reference link reduces to a hyperlink network, a citation network or a probabilistic graph, which cannot represent richer relations (such as *similar-to*, *cause-effect* and *subtype*) between components of a complex system.
   - Combination of *similar-to* link and *is-part-of* link as well as combination of *cause-effect* link and *similar-to* link can better represent the content of text than just one type of semantic link according to the study of text summarization through representing text by SLN (Zhuge 2016).
   - More semantic links reflect richer semantics of the observed system and provide more conditions for deriving implicit links — reflecting the nature of the system.
2. *From question-answering ability dimension*, an SLN with richer semantic links can answer more questions. An evidence is that an SLN-based text representation without *cause-effect* link and definition (*is-a*) link is hard to reasonably answer the question about why and what.

For a base network, incorporating more linking properties and rules into the superstructure can enhance the ability to model a complex system because more implicit links can be derived from more reasoning rules.

3.3.5 *Property of Linking*

In a Cyber-Physical-Social Space, a node can be mapped onto different dimensions (subspaces), a semantic link can be in one space or cross spaces, and therefore reasoning can carry out in one space or cross spaces.

Material, money, data, information and knowledge flows through links are processed by nodes to support their activities.

The following axiom can be derived from the basic assumption of science.

Axiom. *There exists a cause that two nodes are linked, and the cause can be observed, interpreted, or derived from existing superstructure.*

The basic causes of a semantic link between two nodes are relations between the features of two nodes and the basic interactions between the two nodes.

Property of Linking. *A semantic link between two nodes has the following reasons of existence:* 1) *the concepts of two nodes share a set of attributes*; 2) *there is a relation between their attributes*; 3) *there is a common or conflict goal between two nodes*; *and,* 4) *there is a common motivation between two nodes*.

The following observations support the above property:

1. A citation link between two papers is indicated by: (1) their common features, e.g., the features of the citing paper match the features of the cited paper including author name, title, journal/conference name, and publication time appeared on the papers, (2) the similarity between the citing content, which is mainly reflected by the paragraph with the citation mark, and (3) the cited content, i.e., the main contribution of the cited work reflected by the problem and solution stated in the abstract and conclusion (Zhuge, 2016).
2. Collaboration link between researchers is indicated by their common features in their publications (e.g. they were collaborators on some papers, they commonly cite or are cited by one paper or more papers, and they work for the same institution), links between their attributes (e.g. one is the colleague or the supervisor of the other), and common motivation of research and common goal of publication.
3. Correlation between the performance of two stocks in stock market indicates: (1) some common attributes, e.g., companies of the same sector often perform similarly; (2) the cause-effect link between the attributes of the two stocks; (3) a material flow from one company to the other, which indicates that one company is the supplier of the other; (4) they have the same product or provide the same service for customers; and, (5) they share the same group of customers.

This property is the basis for discovering explicit and implicit semantic links and carrying out reasoning on semantic links for supporting prediction of potential links based on existing commonalities.

A semantic link can also indicate the relevancy between the structures of two nodes belonging to different spaces. For example, a semantic link between an individual (denoted as *A*) in social space (denoted as *S*) and a text (denoted as *B*) in cyberspace (denoted as *C*), *A* in *S –authorOf– B* in *C*, indicates that: (1) the individual's mind contains a structure similar to the structure of the text, (2) there is an information flow between two nodes, and (3) there is a cause-effect link between the change of the structure in *A*'s mind and the formation process of the text.

The following is a representation of reasoning on semantic links across spaces.

$$A \text{ in } X -\alpha- B \text{ in } X,\ B \text{ in } X -\beta- C \text{ in } Y \Rightarrow A \text{ in } X -\gamma- C \text{ in } Y,$$

where *X* and *Y* represent two spaces, α, β and γ are semantic links and there exists an operation such that $\alpha \cdot \beta = \gamma$.

The following is an instance of reasoning on semantic links with explicit spaces:

Researcher X in S –authorOf– paper Y in C, paper Y in C –cite– paper Z in C ⇒

Researcher X in S –readerOf– paper Z in C,

where the rule *readerOf* = *authorOf* · *cite* indicates the relevancy between author's mind, reader's mind and their papers.

A semantic link *Researcher X'* in *S –authorOf– paper Y in C* implies a semantic link *Researcher X' in S –co-author– Researcher X in S*.

Explicitly representing the spaces where nodes belong to can help distinguish nodes in different spaces and apply rules on nodes and links in different spaces. The space can be omitted when the current application concerns only one space.

3.3.6 *Social Linking Rules*

In addition to the general reasoning rules on the basic set of semantic links, the semantic space of SLN needs to incorporate linking rules specific to the observed system to reflect its particularity (Zhuge 2004; Zhuge 2009; Zhuge 2010; Zhuge 20012). Knowing social linking rules and the effect of linking can enhance the ability to modeling the social nature of the observed system (Zhuge 2011).

Social linking rules are empirical rules obtained from observing limited experience with insight. They show the following patterns, where arrow $-x\rightarrow$ represents a semantic linking operation with a certain or uncertain relation *x* and ⇒ represents the possible result of the operation:

1. $n -\alpha\rightarrow n' \Rightarrow n -x\rightarrow n'/p$, which means that linking node *n* to node *n*' with a semantic link α leads to adding a semantic link *x* between them with probability *p*.

2. $n\ -\alpha\rightarrow\ n' \Rightarrow n\ -x\rightarrow\ n''/p$, which means that linking node *n* to node *n*' with a semantic link α leads to adding a semantic link *x* between node *n* and another node *n*'' with probability *p*.
3. $n\ -\alpha\rightarrow\ n' \Rightarrow n'\ -x\rightarrow\ n''/p'$, which means that linking node *n* to node *n*' with a semantic link α leads to adding a link *x* between node *n'* and another node *n*'' with probability *p'*.
4. $n\ -\alpha\rightarrow\ n' \Rightarrow n\ -x\rightarrow\ n''/p,\ n'\ -y\rightarrow\ n''/p'$, which means that linking node *n* to node *n*' with a certain link α leads to adding a semantic link *x* between node *n* and another node *n*'', and adding a semantic link *y* between node *n*' and another node *n*'' with a probability *p'*.
5. $n\ -\alpha\rightarrow\ n',\ n'\ -\beta\rightarrow\ n'' \Rightarrow n{-}x{\rightarrow}n''/p$, which means that linking node *n* to node *n*' with a semantic link α, and linking *n*' to *n*'' with semantic link β leads to adding a link *x* between node *n* and another node *n*'' with probability *p*, and α and β imply *x,* i.e., $\alpha \cdot \beta \Rightarrow x$.

Ordinary semantic links reflect a certain or uncertain existence of relations between things, and reasoning rules on semantic links reflect certain or uncertain relational reasoning (implication) on two neighbor semantic links. In contrast, a social linking rule concerns the motivation of linking and influence of linking: leading to adding another semantic link. It is important for governor, enterprise manager or individual to have this insight before making a decision. For example, it can help a company to know the effect of establishing a symbiotic relation with another company before making a decision.

These social linking rules can include successful and unsuccessful instances of application to provide interpretations for the current application:

Linking Rule: <*rule*>;
With Successful Instances: <*instances*>; and,
Unsuccessful Instances: <*instances*>.

These rules can be incorporated into existing information systems (e.g. personal assistant systems, enterprise information systems and decision support systems) to provide intelligent assistant to decisions.

As symbiosis and competition are basic forces to evolve society, the following part of this section investigates some principles about symbiosis and competition for setting empirical social linking rules.

Principle for Social Linking Rule 1. *If one node is linked to another node as a symbiotic partner, they tend to make a common friend for symbiosis (i.e. the probability of making a common friend is high).*

The following is the pattern of this rule: $n\ -symbiosis\rightarrow\ n' \Rightarrow n\ -symbiosis\rightarrow\ n''/p,\ n'\ -symbiosis\rightarrow\ n''/p'$, where *p* and $p' \in (0.6, 1)$.

In a society, individuals or organizations have a higher probability to join the same events (e.g. conference and research project) or community (e.g. academic community or business community) where they can know common friends.

The essential reason is that a symbiotic link is established on some flows including data flow, information flow, knowledge flow and material flow. If node A links to node B for symbiosis, they should have common interest and benefit from each other through at least one flow. If B has a friend C, the flow from A to B can easily reach C (guided by the friend link between B and C) and the flow from C to B can easily reach A (guided by the symbiotic link between A and B) than other nodes that have no symbiotic link to B, therefore it is easier for A to make friend with C for symbiosis. This can be represented as the following pattern where p is the probability of the link:

1. n –*symbiosis*→ n', n' –*friend*– n'' ⇒ n–*friend*→n''/p.
2. n –*friend*→n', n' –*symbiosis*– n'' ⇒ n–*friend*→n''/p.

This principle also indicates the importance of flows through symbiotic links. *If a semantic link does not carry any flow, it will become less important than other links that guide flow within a community*. For example, a kinship link between two persons becomes less important if there is no flow (material, data, information and knowledge flows) between them although kinship itself is important in reflecting the evolution pattern of species from biological dimension.

There can be more types of semantic links between two nodes. Different semantic links play different roles in guiding flows, for example, the *supervisor-of* link mainly guides knowledge flow and the *supplier* link mainly guides material flow. Incorporating the correlation between types of semantic link and types of flow into SLN can better reflect the observed system. The correlation can be established through mapping between the semantic image of the link and the semantic image of the flow. For example, the semantic image of a supervisor link concerns knowledge levels: PhD supervisor, master supervisor, and undergraduate supervisor. The semantic image of knowledge flow concerns knowledge fields, which can be defined by a multi-dimensional classification space.

A semantic link incorporating flow can be represented as follows:

n–(α, *flow*)→n', where (α, *flow*) represents a relation α and the corresponding *flow* from node n to node n', where *flow*=<*name*, *type*: *representation*>, *type*∈{*material*, *data*, *information*, *knowledge*}, and *representation* refers to material representation, data representation, information representation and knowledge representation that are understandable in the semantic space.

Relational reasoning on semantic link and flow can be represented as:

n–(α, *flow*)→n', n' –(α, *flow*)–n''⇒n—(α, *flow*)→n''/p.

n–(α, *flow*)→n', n' –(β, *flow*)–n''⇒n—(γ, *flow*)→n''/p, where $\gamma=\alpha\cdot\beta$ is determined according to relational reasoning rule (Zhuge 2012).

The following implications can be drawn from this principle:

1. It provides an evidence (driving force) for evolving an SLN.

2. It provides a reason for ranking semantic links for the management of an SLN.
3. It suggests a strategy for maintaining semantic links: transmitting flows through semantic links to build symbiosis.
4. It provides a way to detect possible behaviors.

The following are more observations of this linking rule:

1. When recruiting a new faculty member, a candidate who has cooperated with or has potential to cooperate with the existing faculty members (i.e., there is a friend or a potential friend link that guides information flow and knowledge flow) usually gets higher probability to be recruited because they tend to consider whether the new faculty member can enhance the strength of the existing team or not.
2. A researcher is likely to introduce his collaborators (e.g. research students) to participate in conferences and workshops of the research community and therefore the collaborators can get chance to know and cooperate with more researchers within the community.

Principle for Social Linking Rule 2. *If there is a competition link between two nodes, one tends to join a symbiotic community without the other.*

This is because one node tends to exclude the other from communicating with the members of its community (to avoid sharing knowledge with the competitor), and the community without one tends to accept the other to gain competitive advantage. For example, this is hold in business when competition between two companies is for getting more customers within the same region. In research community, a researcher *A* tends to join a research group (or university department) without another researcher *B* who aims at solving the same problem, otherwise the research group has a high probability to be damaged because of competition between *A* and *B* on obtaining the priority of publication and research resources.

Experiment. Publications (3542 papers) in Artificial Intelligence journal from 1970 to 2018 show that 66% collaborators have apparent difference in citation (≥ 4, the number of authors with less than 4 citations is about 85% of total authors). Publications (4613 papers) in Future Generation Computer Systems from 1995 to 2019 show that about 71.2% collaborators also have apparent difference in citation. The data also show that about half cooperation links take place between different institutions. An explanation is that cooperation is built with tendency of avoiding existing competition.

The principle for social linking rule 2 can be represented as the following pattern, where n'' is a member of a community C, and p is the probability of this rule.

$$n \text{ –}competition\rightarrow n' \Rightarrow n\text{–}symbiosis\rightarrow n'',\ n'' \in C \text{ and } n' \notin C \text{ with } p.$$

Based on this social linking rule, the following social linking rule can be drawn.

Principle for Social Linking Rule 3. *If two nodes compete for the same set of resources, they tend to select different symbiotic partners.*

This is because if *B* and *C* compete for the same set of resources and *A* links to both *B* and *C* for symbiosis, *B* and *C* will tend to prevent *A* from linking to their communities, and they will be prudent in sending flows to A. For scientific research, researchers avoid cooperating with the two research groups that compete for solving the same problem as only one of them can publish the solution and only the published one can be confirmed by scientific community (cited by peers).

This principle can be represented as the following pattern:

n –compete⟶ *n*' ⇒ *n*''*–symbiosis*⟶ either *n* or *n*' / *p*.

If *A* is linked to both *B* and *C* for competition, the competition situation changes: node *A* becomes the third competitor, therefore competition strategies of each party need to consider three parties. An organization should avoid internal tense competition. If *A* is linked to both *B* and *C* for symbiosis, *A* has to meet the needs of both *B* and *C*.

Principle for Social Linking Rule 4. *If node A and node B compete for a set of resources R, and B and C compete for another set of resources R', then node A tends to link to node C for symbiosis.*

This is because node *B* competes with both node *A* and node *C* for common resources *R* and *R*' (e.g., customers, materials, data and knowledge), and there is no conflict between *A* and *C*, so establishing symbiosis between *A* and *C* is easier and enables both *A* and *C* to gain competitive power with regard to *B*. This is in line with the old proverb: The enemy of enemy is friend.

This principle can be represented as the following pattern:

n –<compete for R>⟶ *n*', *n' –<compete for R'>*⟶ *n*''⇒
n–symbiosis⟶*n*'' / *p*, where *R* and *R*' denote resources.

Principle for Social Linking Rule 5. *If node A competes with node B on a set of resources R, and node B competes with node C on R, then there is a competition link between node A and node C on R.*

This transitivity of competition is due to the conflict on getting common resources *R*. This rule can be extended to multiple nodes competing on the same limited set of resources. This principle can be represented as the following pattern:

n –<compete for R>⟶ *n*', *n' –<compete for R>*⟶ *n*''⇒
n–<compete for R>⟶*n*'' / *p*.

The social linking rule 1 can be extended to the following rule.

Principle for Social Linking Rule 6. *New symbiotic links tend to be added within a symbiotic community for strengthening competitive advantages.*

This is because the existing symbiotic community provides a local symbiotic environment (more links and flows) for nodes to find more potential symbiotic links easily and efficiently. Higher connectivity leads to more intensive locality. For a community of sharing resources, a higher connectivity provides a higher probability for sharing resources more efficiently.

Continually adding new links to a network evolves its structure. The pattern of the structure is significantly influenced by the preference of linking. Communities emerge when links between nodes within community are denser than the links between nodes of different communities. Discovering communities within graph-based social networks and semantic communities within semantic link network were studied (Newman 2004; Zhuge 2009).

A community tends to be prudent in accepting a member from another community with a lower weight unless the existing nodes of the community can gain weight from the new comer and its community. The weight here can be understood as a rank like the page rank on hyperlink network. An extended definition will be introduced later. The following principle describes the tendency of a community in deciding whether a node should be accepted or not.

Principle for Social Linking Rule 7. *A new node tends to be accepted by a community if* 1) *its weight is higher than the edge nodes of the community*; and, 2) *it can establish symbiosis with the existing members through introducing flows that one (or more) existing member(s) requires (require) with ease and low cost.*

Accepting a new member can bring some advantages to a community (e.g., bring new cooperation and resources) but it may face a risk: new members may introduce friends (i.e. neighbours with different ranks and resources from the existing community) more easily into the community without obeying the rules (or making use of the existing rules), therefore changing the structure of the existing communities. More and more diverse nodes can be easily accepted by a newly formed community as less resistance comes from the existing members. A mature community tends to be more prudent in accepting new members as the distribution of weights and knowledge structure has reached a stable state, and members have to spend more time to know the knowledge structure of the new member. The following principle is inspired from this observation.

Principle for Social Linking Rule 8. *A community with stable symbiotic relation tends to be prudent when accepting a new member.*

The following are some more observations about this principle:

1. Universities with a long history tend to be more prudent than new universities in recruiting faculty members (some universities such as Oxford and Cambridge even do not recruit faculty members every year) and students (some

universities such as Oxford and Cambridge recruit almost fix number of student each year).

2. Members of a mature community often show less interest in establishing cooperation with the new comer without any real cooperation for realizing motivation or socioeconomic benefits due to such aspects as: 1) common knowledge, which significantly influences the efficiency and efficacy of cooperation; 2) similar view of value; and, 3) stable social status.
3. When recruiting a new faculty member, the existing faculty members are prudent in making decisions because they will consider whether the new faculty member can enhance their strength or not, including ranks and resources (e.g. bring more funding and research students).
4. A mature enterprise often shows prudent in transforming the existing business, especially when the existing business is running well, i.e., in a comfort zone. The following chapters on applications will analyse the evolution of information system.
5. A mature research group is prudent in recruiting a new researcher because existing members have built complement knowledge structure (e.g. some researchers have insights to propose original ideas, some are specializing in building models, and some are specializing in experiments) and have been working on a long-term research direction. They usually need to spend time to train a new member. This is why enterprises tend to recruit graduates who have placement experience in enterprises.

Society linking rules concerns fundamental socioeconomic factors including motivation, humanity and value, which determine other factors. Some rules can be inducted from data on behaviors. For example, rules on citation behaviors can be got from discovering the frequently occurred patterns on citation network. Incorporating social linking rules into the Semantic Link Network enhances its capacity for analysis and prediction.

The social linking rules also provide a relational dimension for studying real social networks. In a social network with competition link, more links connected to a node may not be a positive contribution to its rank as involving in more competitive links puts a heavier cap on the productivity of a node, i.e. the damping effect on the growth of network (Zhuge 2005). However, *an appropriate number of competition links can stimulate nodes to improve the intrinsic productivity of the nodes through optimizing their internal organization to raise the efficiency of production, improving technology, and creating new products*.

Ancient Chinese thinker and militarist Sun Tzu created a set of basic rules for gaining competitive advantage in competition situation (Sun Tzu on the Art of War, 475BC—221BC). His fundamental idea is that the world is objective, things in the world are changing, and strategies should be made to actively create conditions for transforming negative factors toward positive factors. The deterministic factors of gaining competitive advantage involve politics, economic status, foreign affair, competitive strength (military), and natural condition rather than belief. His "Thirty-Six Stratagems" includes a set of strategies for gaining competitive advantage in making military decision, for example:

1. "*Attacking the enemy by passing through a common neighbor*", which suggests that borrowing the resources of ally to attack common enemy. This is similar to "*killing someone with a borrowed knife*", which suggests that making use of all possible strengths including enemy's own strength to against the enemy. This is in line with the discussed social linking rule 4.
2. "*Decamping being the best, running away as the best choice*", which suggests that retreating and regrouping your strength when your current course of action will lead to defeat obviously. As long as you are not defeated, you still have a chance.
3. "*Giving the enemy something to induce him to lose more valuable things*", which suggests that baiting someone by making him believe he gains something or just make him react to it and obtain something valuable from him in return.
4. "*Befriending the distant enemy while attacking a nearby enemy*", which indicates that nations that border each other often become enemies (because of easy envision, undetermined border, psychological pressure from economic and military unbalance, etc.) while nations separated by distance and obstacles make better allies. This is also in line with the discussed principle for social linking rule 4.

The above strategies emphasize competition while neglecting symbiosis, which plays a harmonious role in developing society.

Traditional studies of physics and computer science are mainly for solving scientific problems and computable problems respectively based on logic reasoning on facts, but social rules are discovered through non-logic reasoning such as inductive reasoning and analogical reasoning on experience (small data), which results in interpretations that may not be derived from logic reasoning. Humans usually solve social problems by applying social rules according to their judgements on current situation with bounded rationality. In some fields such as military applications and social system design, data are too small to support statistics-based decision and verification. A cyber-physical-socio-relational system operates with the integration of social rules discovered through relational reasoning on bounded realty reflected by small data (facts, relations and situation), statistics-based rules and light logic rules. Traditional logics-based systems, knowledge engineering and statistics-based approaches focus on one aspect respectively.

Linking and reaction of linking evolve an SLN. Incorporating the principles of social linking rules into an SLN enables its operators (or nodes) to know the reactions of a linking operation so as to make foreseeable decision.

3.4 General Model and Effect of Symbiosis and Competition

Forming appropriate competition and symbiosis is a fundamental force to drive the evolution of society. Symbiosis and competition enable individuals (or organizations) to interact with each other through various flows and co-evolve according to different strategies, constraints and rules in various spaces. Symbiosis is built with mutual benefit strategies while competition is built with selfish strategies. Symbiotic network provides a mutual benefit context for individuals and communities, and competition forces them to adopt more efficient strategies.

Introducing symbiosis and competition into the Semantic Link Network as two special types of semantic link leads to specific emerging effect (Zhuge 2011):

> *The node with richer types of link takes a higher priority to emerge in the competition of gaining rank and keeps a stable state in competition and symbiosis during the evolution of social network.*

Richer type of link provides more ways to make use of resources. This effect provides more semantics for studying social network, e.g., different ranking approaches can be created. It has been verified in text processing applications like text summarization (Zhuge, 2016).

The World Wide Web emerges webpages with the change of the number of hyperlinks and the ranks of neighbors as hyperlink does not pass through any negative impact. However, a social network with competition link and symbiotic link emerge nodes with positive influence of symbiosis and possible negative influence of competition.

Competition leads to the division of resources and people therefore divides material flow, money flow, information flow, and knowledge flow within the network into balanced branches, which enable different communities of society to develop harmoniously.

Competition can also form a certain positive influence on the evolution of organization, e.g., in forcing enterprises to optimize the structure of organization, upgrade technology, and transform products to enhance competitive advantages. Therefore, calculating the impact of symbiotic link and competition link needs to consider not only the external links but also the internal characteristics of nodes. Modelling the functions of complex organizations is necessary for interpreting why a node links to another node.

Motivation space, strategy and policy space as well as value space significantly influence the behaviors of autonomous nodes, especially for human individuals or organizations. Considering these spaces, Cyber-Physical-Social SLN (in short CPSoSLN) model can be represented as the following complex form based on the representation of SLN:

$$<f\colon \{N, L\} \rightarrow \{\Im=<\wp, \Re>, M, V, S, P\}, O>, \text{ where}$$

1. *M* is a motivation space that specifies the motivation from multiple dimensions and the rules that guide decisions toward the fulfilment of motivation. Any node in *N* representing a human individual or organization has a mapping image in *M*, which motivates behaviors including decisions of linking and processing flows.
2. *V* is a value space that reflects the values of nodes calculated according to the motivation of differentiating the priority of linking and processing flows. The value of an SLN is greater than the sum of the values of its nodes.
3. *S* is a space of strategies and policies, represented as an SLN: <*Strategy*, *L*, *Policy*>, where *Strategy* is a set of high-level plans (each plan can be represented as an SLN of decisions), *L* is a set of semantic links between strategies, and *Policy* is a set of rules for guiding decisions on linking or processing flows such that different strategies made under the same policy can be compared in the value space.
4. *P* represents the space of evaluating productivities of nodes defined according to the principles such that nodes can be distinguished according to the efficiency of producing products or providing services for meeting the needs defined in the motivation space.
5. *f* is a function that maps $\{N, L\}$ into $\Im$, *M*, *V, S* and *P* such that any node in *N* and any link in *L* has a mapping image in these spaces respectively.

The SLN can model self-organized cyber-physical-social systems as its nodes can be anything (including cyber objects, physical objects, human individuals and organizations) and semantic links can be various relations including *is-part-of* relation, *similar* relation, *subtype* relation, *instance* relation, *cause-effect* relation, *implication* relation, *reference* relation and *sequential* relation (Zhuge 2012). Competition and symbiosis are two special types of semantic links that drive the evolution of CPSoSLN.

Motivation has been studied by many psychologists, among which Maslow argued that people are motivated by unsatisfied needs of hierarchical structure from the most basic to the most complex: 1) *physiology*, including hunger, thirst, sleep, etc.; 2) *safety*, including security, shelter and health; 3) *social*, including love, friendship, self-esteem, recognition and achievement and 4) *self-actualization* (Maslow 1943), which can be regarded as *four dimensions of the motivation space*.

Chinese ancient philosopher Xi Zhu (1130—1200) early regulated social motivation from eight levels: 1) study things; 2) reach toward the greatest knowledge and understanding; 3) sincerity; 4) righteous; 5) cultivate one's morality; 6) keep a family in order; 7) manage state affairs and 8) order the land under heaven.

Autonomous nodes will decide linking behaviors according to motivation, strategy and policy, reflecting values and productivities of nodes. For modeling particular application systems, some of these spaces can be omitted and some spaces can be considered. Value and productivity will be discussed in chapter 6 in detail.

Symbiosis and competition are two dimensions of the motivation space as shown in Figure 3.5. The motivation space, the policy space, the semantic space and the network structure jointly determine the behaviors of nodes.

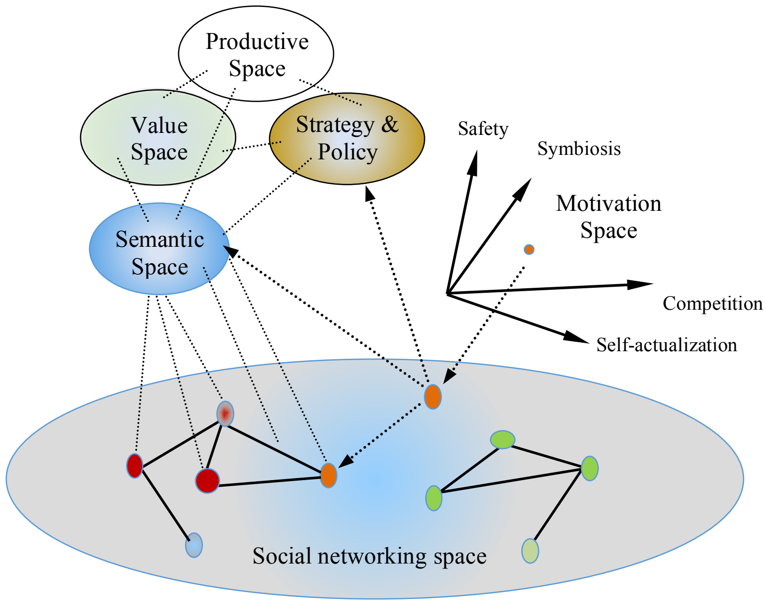


Fig. 3.5 The social networking space evolves with a superstructure consisting of semantic space, motivation space, value space and productivity space as well as strategy and policy space, which can be centralized or decentralized.

The social networking space can answer how the nodes are linked so that a node knows the external situation when making decisions according to internal knowledge. The semantic space interprets what are the nodes, links, linking rules and relational reasoning rules on links, and how implicit links could be derived from the existing links, in a light-weight language. The motivation space interprets why a node links to another node. In practice, the motivation of a node can be measured by mapping its cyber image (e.g., profile) into a point in the motivation space and comparing it with the mapping image of other nodes within its community.

3.5 Probabilistic Semantic Link Network

An SLN can be uncertain due to the following causes:

1. *Changing weights of nodes*, which influences their probability of attracting new links.
2. *Uncertainty on node*. Nodes (e.g., representing event and emotion) in some applications are uncertain. This requests SLN to reflect and process uncertainty of the existence of nodes.
3. *Uncertainty of belief on semantic link*. Semantic links can be set with uncertainty either by the operators (users) of the socio-relational system or by the autonomous nodes of the system.
4. *Uncertainty of reasoning on uncertain semantic link*. Implicit semantic links could be predicted with uncertainty through reasoning on uncertain semantic links or derived by statistical or analogical reasoning.
5. *Uncertainty of generalization*. There are different ways to generalize various semantic relations between two nodes, i.e., there may exist multiple corresponding super concepts or categories in the semantic space. Therefore, a general semantic link can belong to different concepts or categories with different probabilities.
6. *Uncertainty of operations*. The operations on nodes and links are uncertain for large-scale semantic link network (e.g., adding what kind of node to the network or adding what kind of link between two nodes is uncertain).

Therefore, the evolution of a large-scale network is uncertain due to the above causes. As the consequence, the probabilities of nodes and links change. If nodes can be explicitly represented (e.g. in form of a vector or a multi-dimensional space), the probabilities of semantic links can be calculated.

A semantic community emerges a common semantics through evolution. The following is an empirical property.

Property of Uncertain Semantic Linking. *A semantic link chain between two nodes renders a direct semantic link between them with a probability. The more semantic chains exist between them the higher the probability.*

This property can be informally proved as follows.

Proof. Assume that the given SLN has a set of semantic link chains between node *A* and node *B* and a set of linking rules that can derive new semantic links from the existing semantic links but no direct semantic link between node *A* and node *B* as shown in Figure 3.6.

1. Adding more semantic chains between *A* and *B* increases the ranks of *A* and *B* (in terms of the degree of connection), therefore *A* has a higher probability to link to *B* and *B* also has a higher probability to link to *A* according to the preference principle of self-organized network.
2. Adding more semantic chains between *A* and *B* increases the richness of semantic links to *A* and *B*, which increases the two nodes' probability of partic-

ipating in reasoning with other semantic links within the semantic community of A and B. This results in a high probability of deriving a direct semantic link between A and B.

3. Adding more semantic chains increases the probability of deriving out new links between some semantic links of these semantic chains, e.g. deriving new links between nodes E, D and C from some semantic links of the semantic chains according to the linking rules of the SLN. These new links increase the probability of deriving a direct link between A and B.
4. Adding more semantic chains between A and B increases the probability of introducing more flows (material flow, data flow, information flow or knowledge flow) through the chain. A flow between A and B indicates a semantic link between A and B because material, data, information and knowledge cannot flow between completely isolated nodes. More flows between A and B increase the probability of emerging a semantic link between A and B.

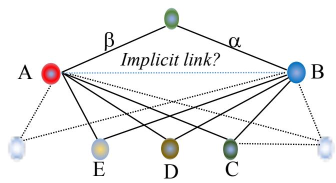


Fig. 3.6 Derive an implicit semantic link with a probability from semantic chains.

A Semantic Link Network carrying flow has some specific properties.

Property of Flow and Semantic Link. *In a probabilistic SLN, a valuable flow tends to pass through a semantic link with a higher probability than through an unknown link*.

This is because any node sends a valuable flow with a motivation and expects an effect (especially obtaining rewards in a certain form, e.g. material, data, information and knowledge as well as socioeconomic benefits from the receiver or the network) otherwise the social system cannot sustainably operate according to socioeconomic principles.

The following lemma can be drawn from the Principle of Social Linking Rule 3 in a probability space.

Lemma 3.1. *If there is a semantic link x between node A and node B, and the two nodes share some attributes and share the same set of limited resources, x implies a competition link between the two nodes with a certain probability*.

The initial framework of Probabilistic Semantic Link Network P-SLN was proposed to represent uncertain semantic link, uncertain reasoning rules, uncertain classification of nodes (resources) and attribute-to-resource rules (Zhuge 2012). The idea was applied to some information service applications (Zhuge 2006, 2007).

Related work on Probabilistic Semantic Link Network concerns Bayes network and Markov network (Pearl 1985). As an abstract model, Bayes network represents cause-effect relation between variants and cause-effect reasoning. Markov Network represents a general dependence relation on a set of random variants with Markov property, i.e. memoryless property of stochastic process (the conditional probability distribution of future states of the process depends only on the present state). It is able to represent dependence loop but typically limited in ability to represent cause-effect relation and reasoning. Markov logic network was proposed by combing first-order logic and Markov Network in a single representation (Richardson and Domingos 2006). The Bayes network and Markov Network are limited in ability to model the probabilistic systems with diverse semantic links and reasoning on semantic links.

3.6 Autonomous Semantic Link Network

A distinguished characteristic of an autonomous SLN is that it contains autonomous nodes, which can act with motivations, including: 1) actively processing data, information, knowledge and materials; 2) establishing semantic links with appropriate nodes for symbiosis or competition; and, 3) transmitting data, information, knowledge and materials. The ability of modelling autonomous nodes enhances the ability of SLN in modelling autonomous socio-relational systems. Autonomous nodes can transmit various flows through semantic links in sequential (as depicted in the left-hand side of Figure 3.7) or in parallel (as depicted in the right-hand side of Figure 3.7).

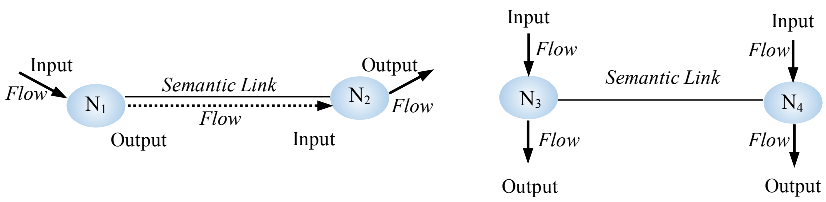


Fig. 3.7 An autonomous node can actively link to other nodes for cooperation through transforming input flows into output flows.

Autonomous nodes can actively influence SLN through linking to other nodes, which evolve communities with basic operations on the network structure, including operations on nodes, links and flows.

Both nodes and links change weights through evolution. Different from the calculation of page rank, the weight of a node depends on the following factors:

1. the number of its semantic links;
2. the richness of the semantic links;
3. the weights of its neighbour nodes;
4. the weights of the semantic links and
5. the weights of the flows it processes.

The weight of a semantic link depends on the weights of the two connected nodes and the weight of passing flows.

An autonomous SLN takes the general framework of SLN with some features brought by autonomous nodes: An autonomous node connects other nodes with semantic links and transforms input flow into output flow with motivation and its mapping image, where the *input* and the *output* can be data, information, knowledge and materials, t is a function that transforms the *input* into the *output*, $m \in M$, $v \in V$, $s \in S$ and $p \in P$ defined in the SLN model.

$$f(n)=\langle rank, output=t(input), m, v, s, p\rangle.$$

The semantic image of a semantic link can be represented as $f(l)=\langle link(n, n'), rank\rangle$, where *link* corresponds to a concept in the concept hierarchy $\wp$ and regulated by the rules in the semantic space $\Re$ defined in the SLN.

An autonomous SLN has the following distinguished characteristics:

1. *It models autonomous relational systems. A node can actively find and cooperate with appropriate nodes to evolve the structure and function of the network, i.e. nodes with different functions can be connected to render a complex function.*
2. *An autonomous SLN evolves with emerging semantic communities, which renders the semantics of the network and complex function through semantic linking and transforming various flows.*
3. *An SLN not only interprets the relation between nodes but also provides a context for interpreting why a node links to another node.*
4. *Operations of nodes such as join or leave will not only influence the semantics of the network but also the operation of the whole network.*
5. *Human individuals, cyber objects and physical objects as nodes can play different roles to form and evolve a human-machine-nature symbiotic network.*

As shown in Figure 3.8, a semantic link connects various nodes in different spaces to form a human-machine-nature symbiotic network. A semantic link not only connects nodes but also narrows the space of transferring flows (Zhuge and Li 2007), which in turn empower the nodes to fulfil social values.

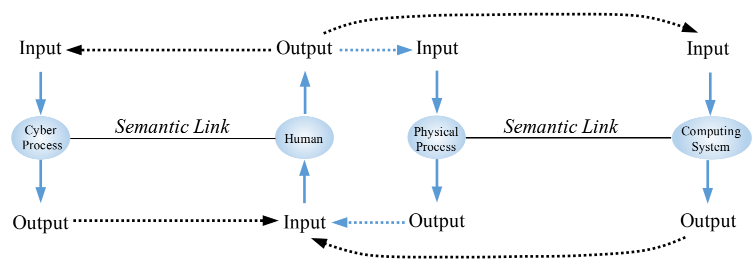


Fig. 3.8 Semantic link and flows through autonomous nodes coordinate nodes in different spaces to form a human-machine-nature symbiotic network.

The following property can be drawn from the assumption that nodes process flows with a certain motivation.

Property of Flow. *If there is a flow between two nodes of a Semantic Link Network, there exists a semantic link between the two nodes or there exists a concept in the semantic space that indicates a semantic relation between the two nodes.*

Operations on Semantic Link Network emerge communities that render semantics (Zhuge 2009). A community with richer semantic links reflects more diverse motivation for processing flows. The following phenomena can be observed:

1. Knowledge mainly flows and develops within communities with priority. Different communities operate different knowledge systems.
2. Information flows specific to communities, and different communities (like online chat groups) pass through information they are interested in.
3. Various flows (data flow, information flow, knowledge flow and material flow) are dense within community (e.g. city), and a bigger community has more and denser flows as the operation and sustainable development of community requires more and more diverse resources including data, information, knowledge and materials.

Therefore, we have the following property:

Property of Semantic Community. *A flow operates within a semantic community with a higher probability.*

To a certain extent, competition and symbiosis are for attracting flows and managing flows through links rather than just attracting links as did in general graph-based social networks. Autonomous nodes can play different roles in socio-relational systems. Figure 3.9 shows some basic patterns with two types of flow: one can be material flow (black arrows) and the other can be money flow (yellow arrows). A complex socio-relational system consists of basic patterns, which will be discussed in the application part of this book.

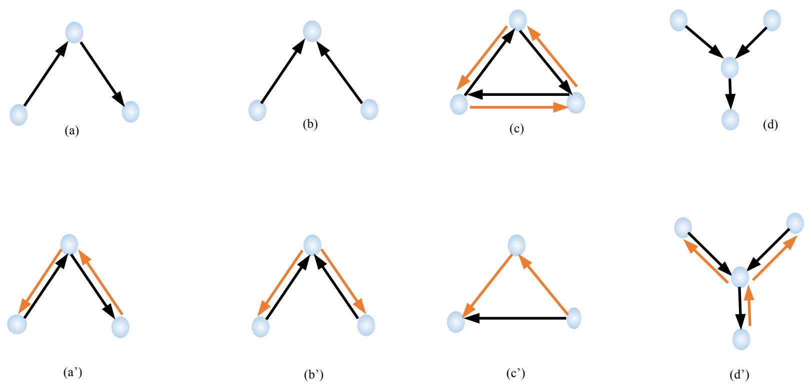


Fig. 3.9 Roles of autonomous nodes in the basic patterns of socio-relational system.

For a closed system, mass does not disappear according to the principle of mass conservation, but the system's entropy never decreases. A sustainable social system should be open and keep a certain difference between nodes so that flows can efficiently operate within society.

When a social system develops towards an advanced stage, material consumption will reach a stable state, but the system will continually increase data, information and knowledge to fulfil motivation, otherwise the social system is unable to sustainably develop with the limitation of materials. Therefore, we have the following principle.

Principle of Flow Differentiation. *Total amount of materials processed by a sustainable social system will reach a constant while total data, information and knowledge as well as services based on them will increase constantly.*

The following lemma can be drawn from the above principle.

Lemma 3.2. *Within a sustainable social system, (1) for any node that processes materials, the total amount of its input material flows equals to the total amount of output material flows pluses the possible storage of the materials within the node and (2) the total amount of input material flow of the whole system equals to its total amount of output material flow pluses the possible storage of the materials within the system.*

The input flows come from the environment. For enterprises, the output flow mainly consists of two parts: products used by the system and wastes that return to the environment. This lemma assumes that a sustainable social system generates no waste materials. The storage of materials can be transformed into other forms of material or energy for the operations of some nodes such as human individuals and power plants.

According to the property of flowing, we have the following lemma.

Lemma 3.3. *If there is a semantic link between node A and node B, a semantic link between node B and node C, and a flow f passing through A, B and C indicates a semantic link between A and C.*

The semantic link between A and C is determined by the relation between flow f and the type of semantic link. The weakest semantic link is just the relation of supplying flow f.

The following property can be drawn in a probabilistic space according to the definition of symbiosis.

Property of symbiosis. *If a semantic link between two nodes introduces a flow (including material flow, data flow, information flow and knowledge flow) between the two nodes, the semantic link implies a symbiotic link between the nodes with a certain probability*.

Traditional semantics modelling approaches including the semantic net, the semantic data models and the linked data focus on static relations between static concepts. With the ability of processing data, information, knowledge and material flows, an autonomous SLN can better model Cyber-Physical-Social Systems.

3.7 Spatial-Temporal Semantic Link Network

Things have mapping images linked one another and evolve in mental space, some images reflect cyber objects in cyberspace, some reflect productive force, productive relations and values in social space, and some reflect physical objects in the physical space. The images evolve with various interactions within or between spaces.

Abstraction of things such as concepts, categories, relations and rules are stable before they are updated with a transformational evolution of objects. A specific relation between two things depends on the statuses of their features during a certain phase, and it changes with the change of status, e.g. different stages of the lifecycle of an enterprise.

Specific things like events evolve with time, place and involved people, so relations between events can change prominently with the change of time, place and people. Human individuals change their personal characteristics and social features in lifetime so relations on humans also change. Compared to physical entities, artificial systems like information systems need to be updated with the development of business and techniques (including the development of chips according to Moore's Law), and therefore relations between systems and humans also change.

Things in different spaces evolve with different rules, for example, Newton laws of motion in the physical space and the Moore's law and Metcalfe's Law in cyberspace.

Time and space are two dimensions for specifying, distinguishing and managing changing things. They play an important role in modelling workflow processes (Zhuge 2001) and spatial information retrieval (Zhuge 2004). They are also important for applications in prominently changing environments, e.g. the evolution of social events, battle field and traffic of city.

Spatial-temporal SLN is a specialization of SLN by adding spatial dimension and time dimension to the model so as to make the model suitable for modelling the evolving reality where nodes move in the physical space and evolve with different life spans, some are long like universities while some are short like events, and semantics of a semantic links between nodes changes with the change of the states of nodes.

The abstract relations such as *cause-effect*, *farther* and *son* are persistent while the relations between specific nodes can be temporal. For example, semantics of the *supervisor-of* relation between a supervisor and a student changes (in terms of the responsibility of supervision) after the student graduates, therefore an effect time should be set on the relation between two nodes.

The base structure of the temporal SLN changes with the change of the effect nodes and links, so a historical repository is needed to record historical information so as to provide information services related to history. For example, historical semantic link network of news (with classification of fake news, distorted news, incomplete news and authorized news) plays an important role in detecting fake news.

A spatial-temporal SLN specializes SLN from two parts: representation and reasoning. Representation concerns the following two components:

1. The base network is specialized by representing nodes with an effect duration represented as n(*space*, *time*=[t, t']), where *space* defines the location of node n. It can take a range (*longitude*=[x, x'], *latitude*=[y, y']) for a surface object. Some nodes like papers that have no or unknown end time and location is unconcerned can be represented as n(*, *time*=[$time_{begin}$, *]). If only spatial dimension or time dimension is concerned, a node can be represented as n(*location*) or n(*time*: [t, t']) respectively. The effect space and temporal duration of a specific semantic link depends on the effect space and temporal duration of the two nodes it links, represented as α(*space, time*).
2. The superstructure is specialized by adding spatial range and temporal duration. The semantic space consisting of a network of concepts with effect spatial range and temporal duration as well as rules with effect space and temporal duration, e.g., rules are represented as $\alpha\cdot\beta\Rightarrow\gamma$ (*space, time*). Other spaces also include elements with effect space and temporal duration.
3. A historical repository that records historically prominent statuses of nodes, links, categories and rules, which are useful in predicting and interpreting things based on reasoning and summarizing history.

The spatial-temporal semantic link $X(S,\ T)$—$\alpha\rightarrow Y(S,\ T)$ represents that node X and node Y take effect at S during T, and the semantic link α is an abstract relation that takes effect at S during T. $X(S,\ T)$—$\alpha\rightarrow Y(S,\ T) = X(S)$—$\alpha\rightarrow Y(S) \wedge X(T)$—$\alpha\rightarrow Y(T)$.

As a special case, the temporal semantic link $X[\tau_1,\tau_2]$—$\alpha[\tau_3,\tau_4]\rightarrow Y[\tau_5,\ \tau_6]$ represents that node $X(t)$ and node $Y(t)$ work or take place during time intervals $t\in[\tau_1,\ \tau_2]$ and $t\in[\tau_5,\ \tau_6]$ respectively, and semantic link α takes effect during $[\tau_3,\ \tau_4]$ when $max(\tau_1,\tau_5) \leq\tau_3\leq\tau_4\leq min(\tau_2,\tau_6)$. When $\tau_4<t$ (the current time), the semantic link represents a past relation, and a new relation could be established between X and Y during their effect time periods. More specifically, when the link happens at a particular time, a temporal semantic link can be represented as $X(t)$—$\alpha(t)\rightarrow Y(t)$.

There can be different semantic links within different time intervals, some of which can be overlapped while some can be in sequential: $X[\tau_1,\ \tau_2]$—$(\alpha[\tau_3,\ \tau_4],\ \beta[\tau_7,\ \tau_8])\rightarrow Y[\tau_1,\ \tau_2]$, where $\tau_1\leq\tau_4\leq\tau_8\leq\tau_2$. A sequential link and a co-occurrence link can be easily established between two events in an event space with time dimension.

A spatial-temporal SLN supports spatial-temporal services, for example, it can answer the following question about time: "Who is Dr Shi's closest friend from 1990 to 2000?" (Similar questions can be asked about the best business partnership between companies) and "Where did Dr Shi work from 1990 to 2000?". It is difficult for an information system to answer this question without spatial-temporal information on people because friend relation changes at different stages of life and work place may also change. Different from spatial or temporal databases, the spatial-temporal SLN provides the possibility for deriving implicit spatial-temporal link from the current spatial-temporal semantic links and linking rules specified in the superstructure.

A distinguished characteristic of a temporal SLN is that a phase-out node does not process any flow, and a phase-out semantic link does not motivate any flow. A transitive semantic link will no longer be transitive once it phases out. For example, a disappeared symptom should not be the cause of an illness, and a living node is unable to build a new friendship link with a phase-out node. So, reasoning rules of an SLN need to be checked to ensure whether they are applied to a particular time interval of applications.

Temporal reasoning mainly takes the following forms:

1. *Reasoning on semantic links with a common effect time on semantic nodes*, concerning relational reasoning, inductive reasoning and analogical reasoning, where reasoning depends on not only reasoning rules on relations but also relations among time intervals (Zhuge 2012). Relational reasoning takes the following form: $X[T_1]$—$\alpha\rightarrow Y[T_2]$, $Y[T_2]$—$\beta\rightarrow Z[T_3] \Rightarrow X[T_1]$—$\gamma\rightarrow Z[T_3]$, where γ depends on not only α and β based on relational semantics but also relations among T_1, T_2 and T_3 based on interval semantics. The relations can be one after another or overlap. The following is a cause-effect reasoning on temporal semantic links: $X[\tau_1,\ \tau_2]$—$ce\rightarrow Y[\tau_3,\ \tau_4]$, $Y[\tau_3,\ \tau_4]$—$ce\rightarrow Z[\tau_5,\ \tau_6] \Rightarrow X[\tau_1,$

$\tau_2]$—ce→$Z[\tau_5, \tau_6]$, where $\tau_2 \le \tau_3 \le \tau_4 \le \tau_5$. It can be used for cause-effect reasoning on events.

2. *Predict a future link based on existing links and past links* (e.g., using previous cooperation links to predict a future cooperation link). The following are some patterns for link predictions:
   (1) *Induction*: $X(t_1)$—$\alpha(t_1)$→$Y(t_1)$, …, $X(t_k)$—$\alpha(t_k)$→$Y(t_k)$ ⇒ $X(t_{k+1})$—$\alpha(t_{k+1})$→$Y(t_{k+1})$.
   (2) *Transitivity*: $\{X(t_i)$—$\alpha(t_i)$→$Y(t_i)$, $Y(t_i)$—$\alpha(t_i)$→$Z(t_i)$ | $i \in [1, k]\}$ ⇒ $X(t_{k+1})$—$\alpha(t_{k+1})$→$Z(t_{k+1})$.
   (3) *Consistency on time*: $X(t_k)$—$\alpha(t_k)$→$Y(t_k)$ ⇒ $X(t_{k+1})$—$\alpha(t_{k+1})$→$Y(t_{k+1})$, where t_{k+1} is the immediate next time after time t_k. It assumes that a relation between things is consistent and stable during a period of time. But, a relation especially social relation often changes after a longer period of time, therefore it becomes a historical relation.

Historical relations interpret the evolution of relations and support reasoning on new relations. For example, a supervise relation between a professor and a research student becomes a past relation after the student graduates. The supervise relation becomes a peer relation if the student becomes a researcher. A probable cooperation relation can be derived if they continue to work on the same research direction or related research directions.

The patterns on rule consistency on time can be derived from the consistency on time.

(1) "$X(t_k)$—$\alpha(t_k)$→$Y(t_k)$, $Y(t_k)$—$\alpha(t_k)$→$Z(t_k)$ ⇒ $X(t_k)$—$\alpha(t_k)$→$Z(t_k)$" ⇒ "$X(t_{k+1})$—$\alpha(t_{k+1})$→$Y(t_{k+1})$, $Y(t_{k+1})$—$\alpha(t_{k+1})$→$Z(t_{k+1})$ ⇒ $X(t_{k+1})$—$\alpha(t_{k+1})$→$Z(t_{k+1})$".

(2) "$X(t_k)$—$\alpha(t_k)$→$Y(t_k)$, $Y(t_k)$—$\alpha(t_k)$→$Z(t_k)$ ⇒ $X(t_k)$—$\alpha(t_k)$→$Z(t_k)$" ⇒ "$X(t_k)$—$\alpha(t_k)$→$Y(t_k)$, $Y(t_{k+1})$—$\alpha(t_{k+1})$→$Z(t_{k+1})$ ⇒ $X(t_{k+1})$—$\alpha(t_{k+1})$→$Z(t_{k+1})$".

Figure 3.10 depicts a spatial-temporal SLN in a space with a time dimension and a spatial dimension. A spatial SLN, SLN(S), is the projection of a spatial-temporal SLN (S, T) onto the spatial dimension to get spatial relations and reasoning rules. A set of spatial relations and reasoning rules were proposed for semantic image retrieval (Zhuge 2012). A temporal SLN, SLN(T), is the projection of a spatial-temporal SLN(S, T) onto the time dimension to get the temporal relations and temporal reasoning rules. A set of relations between intervals such as *before*, *meet*, *overlap*, *start*, *during*, *end* and *equal* was used for temporal reasoning (Vilain and Kautz 1986).

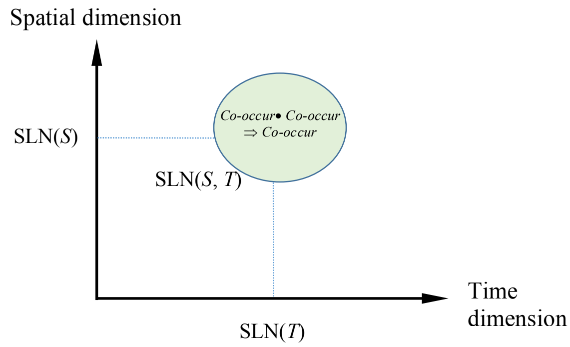


Fig. 3.10 Spatial-temporal SLN(S, T) in a space of spatial dimension and time dimension.

Space and time provide additional conditions for relational reasoning. Some relational reasoning rules do not hold in logic but hold in a spatial-temporal space. For example, the following relational reasoning rule A —*co-occur*— B, B —*co-occur*— $C \Rightarrow A$ —*co-occur*— C does not hold in logic because A —*co-occur*— B, B —*co-occur*— C may not take place in the same spatial-temporal space, an instance is that person A and person B co-occur in an event and person B and person C co-occur in another event. But, a relational reasoning rule holds when the co-occur relations hold in the same spatial-temporal space, full representation of the reasoning rule takes the following pattern: *A in S* —*co-occur*— *B in S*, *B in S*—*co-occur*— *C in S* $\Rightarrow$ *A in S* —*co-occur*— *C in S*, where S is a spatial-temporal space. If all relations and rules of an application are in the same space, the space representation can be omitted. For relations in different spaces, some reasoning rules still hold, for example, the following reasoning rules hold:

Spatial-Temporal Reasoning Rule 1: *A in S_1 —co-occur— B in S_1, B in S_2—co-occur— C in S_2, $S_1 \subseteq S_2 \Rightarrow A$ in S_1 —co-occur— C in S_2, where $S_1 \subseteq S_2$ means that S_1 is a subspace of S_2.*

This is because $S_1 \subseteq S_2 \Rightarrow$ *B in S_1* implies *B in S_2*. It is about co-occurrence links so time is omitted. Similarly, we have the following rule.

Spatial-Temporal Reasoning Rule 2: *A in S_1 —co-occur— B in S_1, B in S_2—co-occur— C in S_2, $S_1 \subseteq S$, $S_2 \subseteq S \Rightarrow A$ in S—co-occur— C in S.*

The significance of rule 2 depends on the scale of S. For some applications, the smaller the better. Whether spatial-temporal reasoning is useful or not in real applications is relevant to space and time such as security, law and military.

Conditions can be added to specific semantic links and semantic linking rules to reflect the condition of applying semantic links and semantic linking rules. This is a reason for having contradict links with different conditions. In uncertain applications, a temporal semantic link needs to include a certainty degree *cd* represented as $X([S_1, T_1], cd_1)$—$(\alpha[S_2, T_2], cd_2)\rightarrow Y([S_3, T_3], cd_3)$ to reflect the uncertainty of nodes and links. Integrating spatial-temporal SLN and probabilistic SLN enables SLN to model reality with spatial, temporal and probabilistic characteristics.

From the symbiosis point of view, a friend relation is determined by symbiotic link between people (or between organizations). The more flows a semantic link carries the closer the friendship. A close friendship may not be close anymore if material flow, data flow, information flow and knowledge flow between friends stop. Therefore, it is necessary to incorporate time duration into the representation of flows: $flow(type(S, T))$, where S represents the space of the flow from the source to the destination and T represents the time duration of running the flow.

3.8 Cyber-Physical-Social Semantic Link Network

There are two views of observing the SLN in Cyber-Physical-Social Space.

3.8.1 *A Multi-Space View*

The multi-space view concerns relations between things in the same space (such as *similar*, *cause-effect*, *sub-type* and *is-part-of*) and relations between things in different spaces (such as *co-occurrence*, *mapping* and *influence*).

Figure 3.11 depicts the multi-space view of SLN on enjoying music in Cyber-Physical Society. The black lines denote the semantic links between things in the same space. The blue lines denote the semantic links between things in different spaces. The arrows denote mapping from things in cyberspace, physical space and social space into their semantic images in mental space. A music work (e.g. $music_1$) is linked to some other music works (e.g. $music_2$ and $music_3$) and the texts that introduce its background in cyberspace. It is often used to render some natural phenomena (e.g. sounds of wind, thunderstorm, train and airplane) in physical space and events (e.g. various ceremonies, military march and sports) in social space as a musical work is created with a certain motivation.

When an experienced people hearing a music work, the semantic images of similar music pieces in cyberspace, the semantic images of natural phenomena in the physical space that are often commonly recalled, and the semantic images of events in social space that often use the similar music works can co-emerge to render a complex feeling.

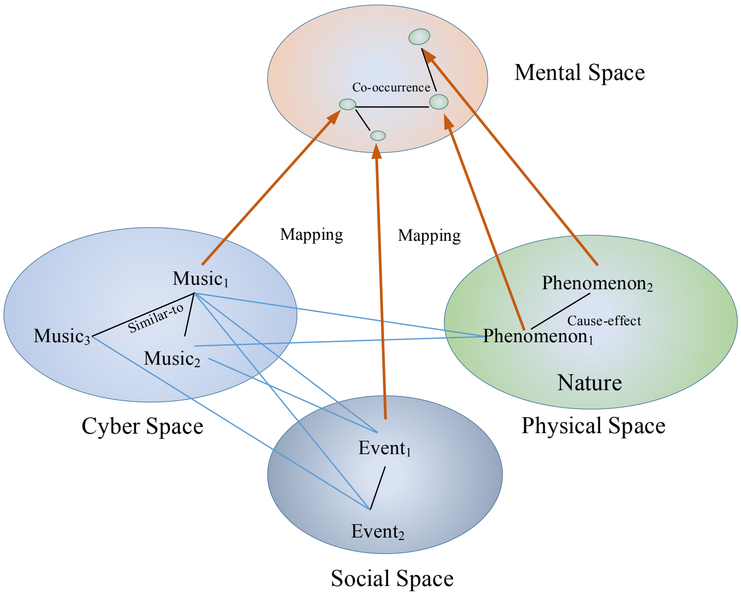


Fig. 3.11. A multi-space view of Cyber-Physical-Social SLN on enjoying music.

3.8.2 *A Two-Level View*

A Cyber-Physical-Social System can be modelled by a CPSoSLN consisting of a base structure and a superstructure as depicted in Figure 3.12. The base network consists of a set of nodes *N* that can input, process, and then output various flows, and a set of semantic links *L* between nodes. Some nodes are passive like various physical objects, some are machines that provide various services based on data, information, knowledge and materials, and some are humans (including individuals and organizations). The superstructure consists of a semantic space $\mathfrak{I}$ that consists of a concept hierarchy $\wp$, a set of rules $\mathfrak{R}$, a set of theories *T*, a motivation space *M*, a value space *V*, a strategy and policy space *S*, and a productivity space *P*. A function *f* maps the base structure into the superstructure to get the semantics of nodes and links and gets theory for processing flows and evaluating the quality and value of nodes and links. A set of operations *O* for operating and maintaining the base structure and the superstructure such as linking nodes, reasoning, and processing flows according to the rules. All components of the model open to accept new elements. A CPSoSLN takes the following form:

$$<f: \{N, L\} \rightarrow \{\mathfrak{I}=<\wp, \mathfrak{R}, T>, M, V, S, P\}, O>.$$

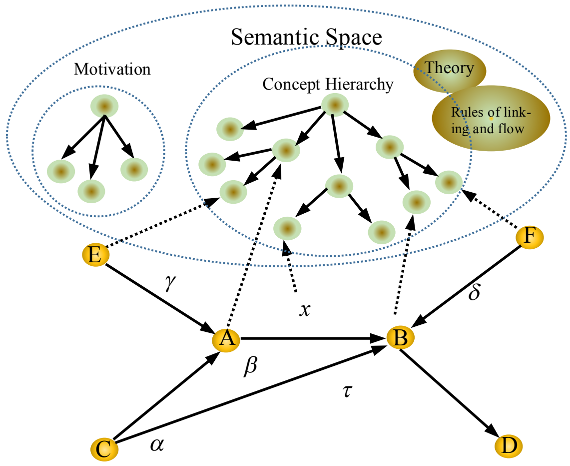


Fig. 3.12 The base network and superstructure of Cyber-Physical-Social SLN.

In addition to previous definitions, the semantic space $\Im$ includes a set of theories T for modeling complex nodes in Cyber-Physical-Social Space and the relations between link and flow, and between link and superstructure. Simple nodes can be defined by $\wp$ and $\Re$ as in SLN while complex nodes need to be modelled by a theory in T. Theories in T can be incomplete or incompatible.

The semantic link in L integrated with flow ζ takes the following form: n—(α, ζ)→n'—(α', ζ')→n'', where node n' inputs flow ζ from node n through semantic link α and then outputs flow ζ' to node n'' through semantic link α' after processing according to a theory in T, ζ and ζ' can be material flow, data flow, information flow and knowledge flow when the theory is for processing materials, data, information and knowledge, respectively.

The theory on CPSoSLN concerns the relationship between the base network and the superstructure, which influence each other. The evolution of the base network provides the environment for those autonomous nodes to form an initial superstructure including semantic space and motivation space. The initial superstructure then develops with interactions and influences the development of the base structure. The motivation space in the superstructure determines the behaviours of adding a node and linking it (or itself) to another node according to the reasoning rules in the semantic space and social linking rules, which support the formation of the strategy and policy space. It is the basis for generating demands on data flow, information flow, knowledge flow and material flow between nodes.

For natural systems, there are different views on the original driving force, including evolutionism, idealism and theism. For societies, there are also different views on the original driving forces, including enlightenment and evolution. For artificial systems (e.g., World Wide Web), motivation is the original driving force to create the initial structure of the base structure (e.g., hyperlink network and browser), which evolves and influences the development of the superstructure consisting of various standards, ontologies, policies and applications on the Web.

Establishing symbiosis between autonomous nodes can increase the density of links and flows within a community as well as the quantity and diversity of flows, which can further increase the productivity of the autonomous nodes. The increased productivity leaves more time for the autonomous nodes (humans) to think, study and interact with each other, which evolve the superstructure.

3.9 Mass and Weight in Value Space

Linking nodes and processing flows are two basic behaviours for meeting the motivations of social beings. A socio-relational system evolves with the co-evolution of the base network and the superstructure. Autonomous nodes include human individuals, organizations and machines. Passive nodes include objects in physical space and artefacts in social space such as houses and industrial products.

Previous research on network analysis mainly concerns structure such as connectivity, centrality identification and community discovery (Newman 2004; Barabási and Albert 1999; Zhuge 2009; Zhuge and Zhang 2010; Zhuge 2012).

CPSoSLN concerns not only the semantics of links and nodes but also the flows that empower the productivity of individuals and organizations in an evolving socio-relational system. The value space in the superstructure evaluates the socio-economic values of nodes and links so that operations on links and flows can fulfil motivation.

Within a self-organized network, nodes compete for gaining rank. One strategy for a node to gain rank is to link it to high-rank nodes just as the preferential attachment property that drives the evolution of the World Wide Web. Nodes within a community of a higher mass take higher competitive advantage than the individuals within a community of a lower mass. The above phenomena coincide a social common sense: *Your friends define you*.

It is a social characteristic of humans to compete for meeting socioeconomic motivations at various levels (Maslow 1943). The value of an individual in a society concerns multiple dimensions, including social dimension and economic dimension. The rank of being linked in the base network reflects the difference of a node at one dimension.

For a society with limited resources, owning resources forms a resource dimension to a node. Therefore, the mass of a node can be defined to measure the value of its existence, which depends on the rank and the resources it owns as follows, where $Rank(n_i)$ denotes the rank of node n_i in structure and $R(n_i)$ denotes the resources (in various spaces) occupied by node n_i and v is a function for evaluating the value of the node according to two dimensions: the rank of the node and the resources that the node owns such that the mass of a node is proportional to the value of its rank and the value of the resources it owns, $Mass_n(n_i)=v(Rank(n_i))$ if $R(n_i)=0$, and $Mass_n(n_i)=v(R(n_i))$ if $Rank(n_i)=0$:

$$Mass_n(n_i) = v(Rank(n_i), R(n_i)).$$

When we use a number within [0, 1] to represent the value of resources and the rank of a node, a way to calculate the mass of a node is as follows: $Mass_n(n_i)= \alpha \times Rank(n_i) + \beta \times R(n_i)$, where α, $\beta \in [0, 1]$, representing the emphasis on rank and resource respectively.

When resources are regarded as nodes of the network, one node owning a set of resources can be regarded as an ownership link between the node and the resources, therefore the resources contribute their ranks of connection to the rank of the node.

Some communities obtain more resources than others, for example, prosperous research areas like big data and artificial intelligence are attracting more resources (including researchers, funding and students) alongside the growth of the network of scientific papers. Consequently, new thoughts in these areas can be more widely propagated in society. Therefore, individuals in prosperous areas take the advantage of obtaining resources on the whole scientific networks within the life spans of the research areas.

An autonomous node processes flows with certain resources. The weight of an autonomous node is proportional to its capacity of processing flow (mass) and the actual flow it processes, measured as follows, where *FlowSet*={*material flow*, *data flow*, *information flow*, *knowledge flow*, *human flow*}, and $v(node(flow))-v(flow)$ represents the difference between the value of the flow processed by the *node* and the value of the flow inputting into the node respectively.

$$Weight(node) = Mass(node) \times \sum_{flow \in FlowSet} v\big(node(flow)\big) - v(flow)$$

Autonomous nodes such as enterprises and schools influence their neighbours through links and more significantly through flows. A node with heavier weight has a greater influence on its neighbours. To gain weight, an autonomous node can actively select a more appropriate node as neighbour (for symbiosis). For the passive nodes that do not process any flow, the weight of a node is only determined by its mass, that is $Weight(node_i) = Mass(node_i)$.

The weight of a network is determined by the weights of its nodes, the number of links (denoted as $|L|$) and the number of nodes (denoted as $|N|$) as follows.

$$Weight(network) = \frac{|L|}{|N| \times |N|} \times \sum_{node \in N} Weight(node)$$

The weight of nodes and the weight of network provide the means for measuring change within an evolving CPSoSLN.

3.10 Relativity of Importance

In a free competition society, the importance and advantage of individuals or organization are measured by a uniform matrix, therefore it is rational to assume that the importance based on advantage are absolute (Smith 1776).

Traditional approaches to ranking a social network assign absolute values to all nodes of the network like the approaches to ranking Web pages within hyperlink network (i.e., Page Rank). Absolute ranking provides a dimension for observers to know the states through the evolution of social network. However, the absolute approaches are unable to reflect the locality and relativity of importance, rendered by the structure of society.

3.10.1 *Locality of Importance*

A real social network evolves communities owing different resources. In many cases, ranking nodes within community is more significant than ranking nodes globally. Globally unimportant nodes can be important nodes within the communities they belong to. The following are some instances: (1) The head of a village usually has a higher impact on the people of the village than other persons with higher ranks in the country; (2) The leader of the student union of a university can usually influence the students of the university than staffs of the university; (3) For a researcher, knowing top-k highly cited papers on the research topic he/she is investigating is more significant than knowing the top-cited papers in the field or the whole science. (4) The key words of a sentence (or a paragraph) are more important to rendering its meaning than the top-ranked words within the whole text. Similarly, the key sentences of a section are more important to rendering its meaning than the top-ranked sentences within the whole text. The local importance renders a pattern for representation and understanding (Zhuge 2016).

On the other hand, the ranking approach to measuring the global importance can be easily abused if it becomes a social criterion. A node can increase its rank by adopting some strategies for increasing the number of links and the links to high-rank nodes if linking is cheap enough. For example, the impact factor of a journal can be easily increased if its editors or reviewers request authors to cite its previously published papers. The key is that listing a paper in the reference section of a paper is free and easy. In fact, the impact factor based on citation number has been abused in some practices of assessing journals and researchers.

As an empirical social law, the Goodhart's law suggests that any observed statistical regularity will tend to collapse once pressure is placed on it for control purposes (Goodhard 1984). In other words, a measure ceases to be a good measure when it becomes a target. Similarly, Campbell suggested that the more a quantitative social indicator is used for social decision-making, the more subject it will be to corruption pressures and the more apt it will be to distort and corrupt the social processes it is intended to monitor (Campbell 1979).

Measuring local importance is a way to avoid abusing an absolute measure to a certain extent because the ranks are localized within communities with different characteristics and rules. The smaller a community the less opportunity to abuse a local importance because members are more easily to know the semantics of nodes and links, for example, interactions within a small research group and a team of software development rely on the contents of work, inspiration and contributions to realize group/team goal. A simple way to calculate the local importance of nodes is to discover the communities within a social network and then rank the nodes within each community.

Semantic link can help remove irrelevant links. Taking citation for example, the impact factor of a journal can be more appropriate if calculation can differentiate various semantics involved in citation, including: 1) self-citation, some self-citations are necessary as closely related works can help trace the thought of research while some are unnecessary; 2) citation from authors/journals of different ranks, the higher and more diverse the better; 3) citation from different countries, the more and more diverse the better; 4) citation from different research areas, the more and more diverse the better; 5) citation from journals of different themes, the more and more diverse the better; and, 6) content of citation, the more contribution to the citing work the better.

Discovering semantic communities is different from discovering communities on general graph because implicit semantic links could be derived from the existing semantic links according to relational reasoning rules and different semantic links may take different priorities. The diversity of semantic links helps emerge the ranks of semantics-rich communities and individuals (i.e. nodes) in real social network (Zhuge 2009, 2011).

The following are some observations on the locality of importance.

1. Images and words are often organized into an integrated representation (as in advertisement and poster) so that people can understand it at a glimpse (due to the locality of human sensory organ). Different components of a representation play different roles in rendering the semantics of the representation, but they are less important in the environment of using many representations.
2. The meaning of subtitles of a movie are localized to scenes. The interval between subtitles can be used to cut clips according to scenes. The sequential one-time-play characteristic of movie determines that the memories of movie watchers will be shifted quickly from one scene to the next one. People will recall a scene when they read the corresponding subtitle. Therefore, the importance of words within subtitle is local to scenes.
3. Words render semantics of the sentences, paragraphs, sections and papers that contain them. The words within a sentence are more important to the sentence that contains them than to other sentences.

4. Different relations (e.g. sequential relation) between words form different representations. The order of words is restricted by grammar for rendering semantics. Changing the orders of words influences the semantics of representation. The following are examples: (1) “the policeman arrests the thief” and “the thief arrests the policeman” render different semantics; (2) “Mark met Mary” and “Mary met Mark” render the same semantics; (3) different orders of clauses can render different semantics, e.g. “X because of Y” and “Y because of X”, and “X is part of Y” and “Y is part of X”; and, (4) different orders of sentences can render different semantics if the concept of one sentence is the basis of understanding the concept of the next sentence.
5. A sentence contributes to the semantics of the paragraph that contains it together with other sentences with a certain relation within the paragraph although it also contributes to the semantics of other paragraphs. The sentence is more important to the paragraph than the sentences that belong to other paragraphs.
6. Explicit semantic links like cause-effect usually connect sequential semantic units (e.g., neighbour clauses or sentences) to render a complete semantics. Implicit long semantic links may exist but they connect contents in nearby locations in mind for better rendering semantics of the whole representation, e.g. authors often arrange similar sentences at the beginning and the end of text to emphasize the main idea.

The following properties can be drawn from the above observations:

Property (on the structure of representation) *A set of semantic components organized by different semantic links renders different semantics that significantly influence understanding*.

This property indicates that *using different orders of words can significantly influence the results of retrieving contents from text*. These observations show that the bag-of-words model disregarding word order is suitable for distinguishing a text from other texts but it is limited in ability to retrieve a language unit (e.g. sentence) that renders a certain semantics.

Property (on direct contribution) *A representation mainly contributes to the formation (semantics or importance) of the minimum unit that contains it*.

The semantics of a sentence is rendered by its words and the relations between words restricted by grammar. The semantics of a paragraph is rendered by its sentences and the semantic links between the sentences. Some semantic links like cause-effect link request order between sentences while some semantic links like similar-to link do not request order (i.e. the change of order does not significantly influence semantics). The semantics of a larger component like section is rendered by the semantics of its paragraphs and the semantic links between the paragraphs. Therefore, words need stronger constraints than sentences to render semantics, and sentences need stronger constraints than paragraphs to render semantics. This indicates the following proposition.

Property *A basic representation needs more constraints than a complex representation to render semantics*.

This is because a complex representation renders its semantics through its internal structure, components and external structure while a basic representation like word has no internal structure that renders semantics. The above observations indicate that *the approach to measuring the global importance of a node is proportional to the importance of a thing within its minimum organization* and *the importance of the organization*.

A measure of importance is reasonable only when it can uniformly measure the components of different scales, which jointly contribute to emerging the structure of a complex system (Zhuge 2016).

3.10.2 *Relativity of Ranking*

For an individual in a self-organized society, it is more significant to know which one is more important than others when making a decision on linking itself to others. Linking to an appropriate node that can bring more valuable flows or chances to fulfil motivation is more significant than linking to a top-linked node that has to share time and resources through many links. So, it is necessary to study the relativity of ranking nodes.

Relative rank. *Within a network, if there is a direct link between node A and node B, the relative rank of node B to node A denoted as Rank(B to A) is determined by the absolute ranks of the two nodes, distribution of the ranks through links, and the influence of common friends through the link chain as following*:

$$Rank(B \text{ to } A) = (1+Com(A, B)) \times (Rank(B)/L(B))/L(A), \text{ where}$$

1. *Rank(B) denotes the absolute rank of node B, which is determined by the ranks of its neighbours, and the number and diversity of its links.* It can be calculated with reference to the Page Rank of the hyperlink network.
2. *L(B) denotes the number of links that B owns.*
3. *L(A) denotes the number of links that A owns.*
4. *Com(A, B) represents the influence from common friends defined as*: $2\times (1/Length(Path_1(A, B)) + \ldots +1/Length(Path_n(A, B)))$, *where n is an integer and* $Length(Path_i(A, B))$ *denotes the number of links on the ith path from node B to node A (i=1, 2, …, n). If there is no common friend, C(A, B)=0.*

If links have ranks, $1/L(B)$ and $1/L(A)$ will be replaced by the rank of the link from *B*'s view and the rank of the link from *A*'s view.

According to the above definition, the following lemma can be drawn:

Lemma 3.4. *If there is a direct link between A and B and a direct link between B and C but there is no direct link between A and C, then the relative importance of*

C to A, *Rank*(*C* to *A*) < *Rank*(*B* to *A*), and *Rank*(*C* to *A*) = *Rank*(*C* to *B*) × *Rank*(*B* to *A*) / *Rank*(*B*).

Proof. The given condition indicates that the influence from common friends *C*(*C*, *B*)=0 and *C*(*B*, *A*)=0. According to the definition of relative rank, we have the following derivation:

$$\begin{aligned} Rank(C \text{ to } A) &= (Rank(C)/L(C))/L(A) \\ &= ((Rank(C)/L(C))/L(B)) \times (Rank(B)/L(B)/ L(A))/Rank(B) \\ &= Rank(C \text{ to } B) \times Rank(B \text{ to } A)/Rank(B). \end{aligned}$$

The following lemma can be further drawn from the above lemma:

Lemma 3.5. *If there is a direct link between A and B, a direct link between B and C, and a direct link between C and D, but there is no direct link between A and D, between A and C, and between B and D, then Rank*(*D* to *A*) < *Rank*(*C* to *A*) < *Rank*(*B* to *A*).

Taking Fig. 3.13 for example, node *C* is the top-linked node in the network, but node *B* is more important to node *A* than node *C* because *A* and *B* have more direct common friends than *A* and *C* do, and *B* has less links than *C* to share the capacity to contribute the rank of *A*.

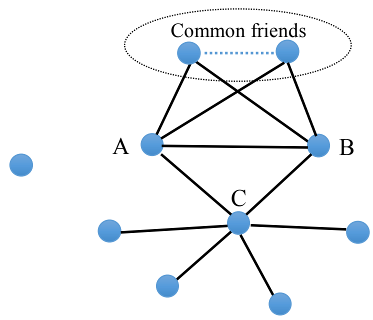


Fig. 3.13 Relative importance of nodes.

If the common friends of node *A* and node *B* make friends (i.e. building a direct symbiotic link between common friends as the dotted link in the figure), node *B* will become more important to node *A* because one more symbiotic chain is increased, and therefore the rank of node *B* and the rank of node *A* will be increased. This can be represented as the following social rule of linking.

Social rule of linking through common friend. *The probability of emerging a link between two nodes that have a common friend is higher than that between those having no common friend. The probability increases with making more* *common friends between the two nodes and adding links between their commonly linked nodes* (i.e. common friends).

Proof. This rule can be informally proved from the following aspects:

1. It is reasonable to assume that a node prefers to link to a node that is important to it with a higher probability. Two nodes (denoted as A and B) having a common friend have a higher relative importance to each other than those having no common friend according to the definition of relative importance of nodes.
2. Making more common friends between A and B increases the probability of emerging a link between A and B because $C(A, B)$ and $C(B, A)$ in the definition of relative rank becomes higher, which consequently increases the relative rank of one to the other.
3. Adding a new link between two common friends of two nodes (denoted as A and B in Fig. 3.13) increases the ranks of the common friends, which contributes to the increase of the ranks of both A and B. The increasing ranks of A and B increases the probability of attracting new links to enhance the link between A and B according to the assumption of preferential attachment assumption, i.e. the Matthew effect, which interprets the distribution of ranks during the evolution process of self-organized systems such as the World Wide Web and citation network.

The discussed link refers to a kind of friend (or cooperation) relation, which can be generalized as a symbiotic relation that brings mutual benefit defined in society. Traditional research on the growth of the World Wide Web concerns one type of link — hyperlink, which can be regarded as a symbiotic link that brings mutual benefit on introducing the flow of clicking webpages. A community for sharing resources (e.g. materials and knowledge) evolves mainly with incorporating symbiotic link. A symbiotic community tends to exclude a competitive link according to the principles of social linking rules introduced in section 3.3.6.

Further, a friend link is likely to emerge between two nodes that have been linked directly or indirectly, i.e. the following rule of emerging link.

Social rule of emerging link. *The probability of emerging a new link between a pair of nodes that have been linked directly or indirectly is higher than any pair of nodes that have not been linked directly or indirectly*.

Proof. This social rule can be proved from the following two cases. Case 1: Two nodes are isolated or belong to two communities if they have not been linked directly or indirectly. A new link has a higher probability to emerge within a community because of sharing resources (usually in form of various flows) and it has a higher probability to be requested between two nodes within the same community (e.g. the probability of emerging a new citation link within the same research area is higher than that between areas). Case 2: Two nodes that have been linked directly or indirectly have higher ranks than other nodes that have not been linked directly or indirectly (e.g. they are isolated). The nodes with higher ranks have a higher probability to attract new links according to the preferential attachment assumption of the growth of self-organized social network.

Lemma 3.6. *The probability of emerging a new link between two nodes that have been linked directly or indirectly with more links is higher than that of those with less links*.

Proof. More links between the two nodes increase their ranks, which in turn increases the probability of attracting a new link according to the preferential attachment assumption of the growth of self-organized social network.

Then, the following lemma can be drawn.

Lemma 3.7. *In a growing self-organized network, the probability of emerging a new link between two nodes with a common friend (node) is higher than those without a common friend*.

Experiment. The coauthor network of scientific papers is a growing self-organized network. A coauthor network on 1812 papers with 2895 authors published in the Artificial Intelligence journal was constructed. Observing its evolution from 1991 to 2011 and from 2012 to 2018 reaches the following results that support the above rules:

1. There are 3912 pair of authors who satisfy *A* —*coauthor*—*B*, *B*—*coauthor*—*C* and there is no cooperation link between *A* and *C* during the period [1996, 2011], that is, *B* is the common friend of *A* and *C*. There are 19 coauthor links *A*—*coauthor*—*C* during [2012, 2018], the probability is about 0.49%.
2. There are 2134 pair of authors who satisfy *A* —*coauthor*—*B*, *B*—*coauthor*—*C* and *A*—*coauthor*—*C* during [1996, 2011]. There are 71 coauthor links *A*—*coauthor*—*C* established during [2012, 2018]. The probability is about 3.3%, which is 6.7 times higher than case 1. *This shows that new links tend to be established between nodes with existing links, and direct link plays much more important role than indirect link in attracting new link*.
3. There are 1544 pair of authors who satisfy *A* —*coauthor*—*B*, *B*—*coauthor*—*C*, *C*—*coauthor*—*D, and A*—*coauthor*—*D* during [1996, 2011]. There are 48 coauthor links *A*—*coauthor*—*D* established during [2012, 2018], the probability is about 3.1%, which is similar to case 2 and much higher than case 1. *This further confirms the result of case 2, and that a shorter link chain plays more important role than a long link chain in attracting new link*.
4. There are 2044868 pairs of authors who have no coauthor link and there is no indirect coauthor link between them during [1996, 2011]. There are 83 coauthor links established during [2012, 2018], the probability is 0.004%. Case 1 is about 128 times higher than case 4, which shows that *common friends of two nodes can help attract direct link*.

The above observation also shows the following propositions:

Probabilistic rule for reasoning on semantic links. The probability of reasoning "A —*coauthor*→B, B—*coauthor*→C, C—*coauthor*→D ⇒ A—*coauthor*→D" is lower than the probability of reasoning "A —*coauthor*→B, B—*coauthor*→C ⇒ A—*coauthor*→C".

Proposition of cooperation. *Cooperation mainly carries out within a connected semantic link network*.

A connected semantic link network is called the third normal form of SLN (Zhuge 2012).

Interactions in cyberspace, physical space and social space are the basis of establishing semantic links, which form semantic communities. They carry material flow, data flow, information flow and knowledge flow with motivations from high level to low level at the motivation hierarchy: *motivation for knowledge* > *motivation for information* > *motivation for data* > *motivation for materials*. Different from material flow, data flow and information flow, knowledge flow has a community characteristic: knowledge is mainly shared and developed within a community. Coauthor links on publications and citation links between publications form and evolve scientific knowledge flows within scientific communities. Teacher-student relation also carries knowledge flows about learning subjects. Different motivations and knowledge flows evolve different communities. The following proposition reflects the relation between knowledge and semantic link:

Proposition of knowledge flow through semantic link. *Knowledge tends to flow within a semantic community*.

Within a community, one semantic link can play more important role than the other. For example, kinship relation plays a more important role than marriage relation in family (especially in some eastern countries). Figure 3.14 shows a basic community: a family of three persons. When node C is young, C is more important to node A than node B, and C is also more important to B than A because C has a kinship link to both A and B and economically depends on them but there is only one marriage link (no kinship link) between A and B. When C has a new family as shown in the dotted links, it becomes less important to A and B because it does not economically depend on A and B anymore and distributes its importance to the new family.

Within the base network of SLN, calculating the relative importance $Rank(B \text{ to } A) = (1+C(A, B)) \times (Rank(B)/L(B))/L(A)$ needs to consider the characteristics of semantic links: Calculating $C(A, B)$, $Rank(B)$, $L(B)$ and $L(A)$ according to the number of semantic links, the strengths of different semantic links, the richness of semantic links between nodes, and the potential links that can be derived from the existing links.

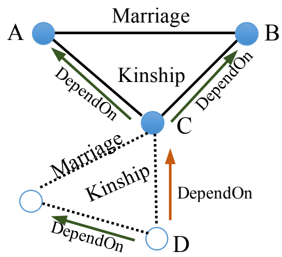


Fig. 3.14 Relative importance within Semantic Link Network.

With regard to Figure 3.14, node A and node B play a more important role in a basic community (family) in term of richness of links (Zhuge, 2011), which is reasonable in terms of economic role, daily life responsibility and role in society.

3.10.3 *Relative Weight*

The importance of a node within a social network also depends on the ability and added value of processing flows in addition to its ranks on links. For example, the value of a manufacturer mainly depends on the way to processing material flow and the value of a university mainly depends on student flow (carrying socioeconomic values) and knowledge flow it involves (contribution to the development of knowledge).

If there are flows from node B to node A of social network, the relative importance of B to A depends on the weight of B and the value gained by A through processing flows from B to A (denoted as $B \rightarrow A$) as follows:

$$Weight\ (B\ to\ A) = Weight\ (B) \times \sum_{flow \in FlowSet} \left(v\left(A\left(flow(B \rightarrow A)\right)\right) - v\left(flow(B \rightarrow A)\right)\right).$$

3.10.4 *Energy of Change*

The evolution of a society accompanies the evolution of communities with growing, static or shrinking number of nodes and links. A current small community (e.g. a promising research community) can grow faster than a big community driven by motivation (e.g. peer esteem). A fast growing community can also attract new links in addition to the weights of nodes and density of connections. The growing rate can be reflected as: (*number of new nodes* + *number of new links*) / (*total number of nodes* + *total number of links*). A fast growing community gives individuals a better expectation than a static community and a shrinking community because growing can attract more interests of individuals. In a self-organized society, a rational investment concerns more long-term benefit rather than the existing benefit, just as investing stock market. The following proposition can be drawn from the above discussion:

Proposition of community growth. *For two communities A and B of the same weight in a self-organized society, if A grows at a faster rate than B, A has a higher probability than B in attracting new nodes and links*.

There are some social interests (including fulfilling a certain level of motivation) behind the phenomenon of growth. A fast growing community can attract more resources brought by new nodes, which support activities of nodes to drive the evolution of the community. However, the growth rate will become flat with the expansion of the size of the community due to some constraints such as the limitation of total resources (e.g. population), the resources (materials) in society and competition with other communities, especially the emerging fast growing communities. The constraints can be regarded as a damping effect (Zhuge 2005). For the same reason, a shrinking community has a lower probability than a growing community in attracting new nodes and links.

A prominently evolving network shows characteristics different from a static network. *A node gains a kind of momentum when changing its weight*. *The momentum is a function in proportional to its weight and the rate of changing weight*.

In a prominently evolving community, *the rank of a node during a time interval is a function in proportional to the following factors*:

1. *Current number of neighbor nodes.*
2. *Current ranks of neighbor nodes.*
3. *Richness of semantic links that connect it to its neighbors.*
4. *Rate of changing the number of the neighbor nodes.*
5. *Rate of changing the ranks of the neighbor nodes*.

In cyberspace, an individual can be well-known within a short period of time if its neighbors grow quickly. The concept of social energy was defined as the number of individuals who have changed their communities and the total number of individuals in a society (Zhuge 2011). An intuitive interpretation is that a society with a higher socio energy has a higher probability to transform it from one state into another state.

The following proposition describes the energy of an evolving community.

Energy of evolving community. *The energy of an evolving community is a function EC(Weight, rate) in proportional to its Weight and the rate of change such that EC(Weight, rate) ≥ EC(Weight', rate') if Weight ≥ Weight' and rate ≥ rate'*.

A community with a higher energy can attract new nodes and links with a higher probability than a community with a lower energy. Therefore, the community with a higher energy gains competitive advantages and influences interactions between communities through co-evolution.

3.11 Evolving Social-Relational System through Establishing Symbiosis among Understanding, Learning, Modeling and Construction

SLN is an open model that reflects the observed cyber-physical-social system based on existing knowledge including theories, models, rules and experience as well as insightful thinking, which is generated through learning, understanding and thinking. It evolves with the evolution of the relations between understanding, learning, modelling and construction.

3.11.1 *General Architecture*

The general architecture for developing a socio-relational system based on the SLN model is depicted in Figure 3.15.

SLN instances are constructed for supporting various socio-relational systems through establishing symbiosis among various behaviours of learning knowledge, contributing knowledge, understanding reality, observing and modelling the observed system, checking consistency between the model and existing knowledge, and interpreting the instances based on the model and existing knowledge. As the consequence, the observed system evolves the cyber-physical-social reality.

The SLN model evolves with incorporating more types of links and enriching the semantic space, the motivation space, the value space, and the strategy and policy space along with the deepening of understanding reality.

There are two approaches to constructing the instances of the SLN for applications: human construction and automatic construction. Human construction relies on the understanding of domain SLN and the experience of constructing SLN. Automatic construction of SLN is based on two approaches: machine learning from data and discovering patterns in various data through generalization with insight, for example, the discovery of cause-effect relation in scientific paper (Cao, et al. 2018).

Deep learning provides a tool for discovering explicit and simple links on data through training. It creates a paradigm for solving problems based on data and training process. However, it has the following limitations: (1) It mainly focuses on minimizing the difference between the result and the target while neglecting the complexity so a deep learning model usually contains a big number of parameters, which requests a powerful computer to operate. (2) It lacks the abilities of interpreting and controlling problem-solving process. That is, deep learning with data can find some explicit and simple links in data but it is limited in ability to interpret various semantic links. A system that requires high reliability faces risk if it is based on a black box algorithm. (3) It is limited in ability to find implicit links and social linking rules, which need knowledge, insight and reasoning to discover. (4) It is unable to create the semantic space, the motivation space, the value space and the policy and policy space for semantic linking without participation of humans as the work needs knowledge, methods and insight beyond data. (5) Deep learning does not follow traditional scientific paradigms, which can help train and promote insight in problem domain, inspire thinking to take a further step toward the understanding of reality, learn knowledge and develop theories to share with others for solving problems in other fields.

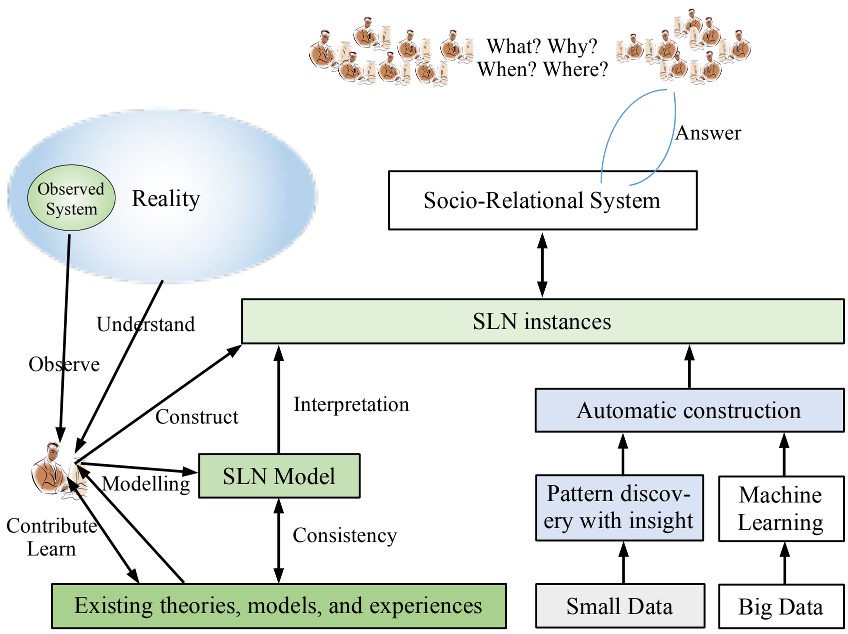


Fig. 3.15 General architecture for creating and evolving a socio-relational system through modelling and automatic construction based on pattern discovery and learning.

It is significant to integrate the pattern-based approach and the deep-learning-based approach for discovering semantic links. A result of deep learning can provide indicators of possible semantic links for social relational systems (or humans) to complete the patterns obtained through reasoning.

Compared with traditional data-based information systems including traditional database systems, information retrieval systems (including search engines), or data-based QA systems, *an advantage of the SLN-based social-relational system is that it can answer users' questions about what, where, when, why and how and interpret answers according to SLN. CPSoSLN can further answer questions and interpret answers according to laws and principles in cyberspace, physical space and social space*.

3.11.2 *Application: Summarization based on Semantic Link Network*

Summarization is to generate a short version from a source, usually in form of text. Solutions include extractive approaches that compose a summary by ranking and selecting sentences within texts and the abstractive approaches that compose a summary by generating and composing new sentences. A multi-dimensional classification space was used to summarize various summarization methods (Zhuge 2016). In general, traditional summarization approaches are closed algorithms that transform a source into a summary.

Summarization research needs to be based on some basic assumptions, which are neglected in previous research.

Assumptions of summarization:

1. *The community of practice where the source is created and shared satisfies with its quality*. This assumption excludes extra jobs such as checking grammar errors and representation weakness.
2. *The author(s) of the source representation and the reader(s) of the summary are at the same cognitive level.* This assumption ensures the consistency between the cognitive level of the author and that of the reader.
3. *The source consists of relatively independent components*, *which are also representations in the same language as the source*. This assumption ensures the consistency between the source and summary.
4. *The meaning of a representation is rendered by its components and relations between them*. This assumption provides a reason for generating a summary by composing components of representation.
5. *The components of a representation have differences in rendering its meaning*. This assumption provides a reason for the summarization approaches based on ranking components and composing components with high ranks.
6. *The source has a core meaning rendered by a set of representations and the semantic links between them.* This assumption provides the feasibility of summarizing the source. If a source has multiple core meanings (e.g., in multi-document summarization), there should have semantic links between them, which render a concept at a higher abstraction level.
7. *Authors spend more time to use more representations to render the core meaning*. This assumption provides a reason for summarizing the source by

ranking and selecting more important representations from author's point of view, and then composing them through semantic links.

The above assumption provides the basis for studying summarization methods. The following property can be derived from the above assumption.

Property of core representation. *The highlighted representation (including titles, keywords, bold front, caption of figures and capital letters), frequently occurred representations and representations highly connected by semantic links indicate the core meaning*.

The basic representations are words, which have different parts of speech. Nouns, verbs and adjectives play a more important role in rendering meaning than other parts of speech because they directly reflect realty: nouns represent objects in cyberspace, physical space and social space, verbs represent actions, and adjectives represent features and extents.

The experience of reading indicates that nouns, verbs and adjectives attract more attentions of readers than other parts of speech.

Experiment. To further know the weights of different parts of speech, a small-scale experiment (ten people read ten one-page essays with an eye tracker) was carried out by tracing the movement of eyes on words. The following is the experiment result:

1. *Total nouns*, *verbs and adjectives* / *total words* = 64.4%; this reflects a characteristic of representation.
2. *Total notice words* / *total words* = 78.9%; this reflects that the commonality between readers and authors is high — readers concern most words presented by authors to understand the presentation.
3. *Nouns*, *verbs and adjectives of total notice words* / *total notice words* =72.2%; and *nouns*, *verbs and adjectives above average notice time* / *noticed words* = 78.2%. This reflects a characteristic of parts of speech from readers — most of the noticed words are nouns, verbs and adjectives.
4. *Total nouns above average notice time* / *notice nouns* = 38.5%; *total verbs above average noticed time* / *notice verbs* = 19.2%, *and total adjectives above average notice time* / *noticed adjectives* = 20.5%. This reflects that nouns attract more notice than verbs and adjectives.

It is rational to assume that the notice time represents reader's interest. Therefore, nouns and verbs represent the core meaning of text and adjectives emphasize the meaning. Although nouns and noun phrases have been used as key words, the above experiment provides an evidence for extracting key words from texts. The following characteristic can be reached from the above discussion.

Characteristic of Part of Speech. *Nouns, adjectives and verbs of a sentence represent its core meaning*.

As a text consists of sentences, the core meaning of a text is rendered by nouns, adjectives and verbs. This characteristic can be further verified by detecting most attended words through tracking eye movements.

A semantic link network of words can be extracted from text to render the core semantics of text by mapping sentences into semantic links (nouns are as nodes, adjectives represent the specialization between concepts indicated by nouns and verbs are as links). A text summarization approach can be developed by ranking words and links on the network, selecting sentences based on the ranks of the contained words, and composing sentences into summary with keeping coherence between sentences (by increasing the rank of the words that have semantic links to the selected sentences).

Further, the semantic link network of different granularities of representations (including phrases, sentences and paragraphs) can be extracted from text to represent the semantics of text through discovering the semantic links between these representations on the basis of finding the patterns of representing various relations between representations, e.g., "*x* is a *y*", "*x* is a kind of *y*" and "*x* is a part of *y*".

One phenomenon is that authors tend to use most important words in the beginning of a text to draw readers' attention and to remind readers of the whole story in the end. Scientific papers begin with abstract and introduction, which state the background, problem, the significance of the problem, the research method, result and related work, and they end with conclusion that emphasises the result and innovation points. News normally begins with summarization of the event including time, place, people and facts within the first paragraph (or within the first sentence in short news). Search engines usually display the first sentences of webpages as introductions. This is in line with the heuristic peak–end rule in psychology (Fredrickson and Kahneman 1993): people judge an experience largely based on the most intense point (i.e. the peak) and at the end point. This rule has been verified in many empirical applications although the cause is unclear. For computing applications, how to define the peak point is the key as different individuals with different knowledge structures have different interests.

The observation of representing and understanding text indicates the following rule.

Beginning-Peak-End Rule. *The core of a representation is mainly rendered by the representation components in the beginning, the peak part where components are highlighted, and the end*.

The cost (time used for understanding a representation) dimension and intensity (in term of connection to other representations) dimension were used to classify representations (e.g., sentences and paragraphs) (Zhuge 2016). Herein, the part-of-speech rule, the beginning-peak-end rule and the intensity (the connectivity of words) dimension provide a three-dimensional space for selecting key words from the words of a set of texts as shown in Figure 3.16.

A phenomenon observed from the experiment is that readers tend to spent more time on reading the beginning but they pay more attention to the ending when writing summaries immediately after reading. An interpretation is that readers need time to build the semantic images about the content in short-term memories through retrieving relevant semantic images in the long-term memory when reading the beginning, and then they can spend less time to extend the semantic images in short-term memories. They write according to the semantic images in short-term memory after finishing reading when the ending is more impressive than the beginning in short-term memory.

Research on summarizing scientific papers has verified that the composition of representation components (especially sentences) through semantic links (such as *is-part-of*, *similar-to* and *cause-effect*) plays an important role in representing and understanding texts (Zhuge 2016; Sun and Zhuge 2018; Cao, et al. 2018). The semantic link networks of representations (i.e., representation components) of different levels provide a near decomposable structure for emerging semantics at a higher level from the semantic link network of representation components at a lower level. For text applications, the semantic link network of words emerges the semantics of sentences, and the semantic link network of sentences emerges the semantics of paragraphs.

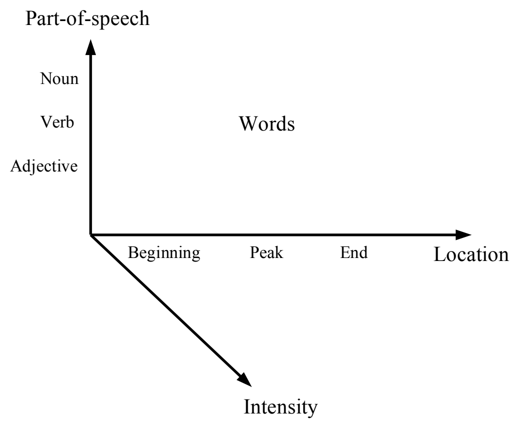


Fig. 3.16 Dimensions for identifying core words.

Summarization can be generalized as a function S that transforms a document D composed by a set of language representations (or called semantic nodes) N, a set of semantic links L and a relational reasoning rule set R into a document d composed by a smaller set of representations N', a smaller set of semantic links L' and a smaller set of relational reasoning rules R', represented as follows:

$$S: D(N, L, R) \rightarrow d(N', L', R'), \text{ such that:}$$

1. $S(N)=N'$ according to a ranking algorithm on N based on L and R, and for any $n' \in N'$: (1) there exists an $n \in N$, $S(n)=n'$ or n and n' correspond to a common concept within the concept hierarchy (e.g., $S(n)$ is the synonym of n), and (2)

$|N'|<|N|$, i.e., the number of language representations in *N*' is less than that in *N*.

2. $S(L)=L'$, $L'\subset L$, and any two representations in *N*' are linked by a semantic link *l* in *L*'.
3. $S(R)=R'$, $R'\subset R$, and all links derived from *R*' are in *L*'.
4. Representations of *N*' correspond to *top*-$|N'|$ ranked representations in *N*.

$S(N)$ selects the important representations connected by $S(L)$ based on $S(R)$ to render the semantics of the summary.

A summarization system carries out with the evolution of the following key elements:

1. *Requirement*, including the scale of summary for a general summarization or a question for a question-based summarization.
2. *Semantic links selected for composing a summary*. Different applications (or users) focus on different semantic links, e.g., cause-effect relation plays an important role in scientific documents and query applications.
3. *Rules*, which are applied to deriving implicit or missing semantic links from the selected semantic links.
4. *Mapping method*, which determines the mapping from *D* into *d* according to the characteristics of *D* (or types of D such as news, scientific papers, books, websites and movies) and the requirements of queries (e.g., texts, slides and posters).

The key of a SLN-based summarization approach is to rank semantic links for selecting the most important semantic links required in summary and ranking appropriate representation components (such as sentences) connected by the semantic links as in traditional extractive summarization approaches.

The criterion for selecting semantic links depends on the following aspects:

1. *Contribution of a semantic link to the content*, measured by:
   a) the frequency of the semantic link occurred in the whole SLN of the source;
   b) the ranks of the neighbour semantic links; and,
   c) the ranks of the representations (nodes) connected by the semantic link.
2. *Connectivity of semantic link network*. A connected semantic link network of representations can better render a core concept than isolated representations do. *Connectivity is a factor that leads to a better coherence and readability of a representation*.
3. *Density of semantic link network*. A connected semantic link network forms semantic communities (Zhuge 2009). A larger semantic community with denser semantic links has a higher weight than a smaller semantic community with sparse semantic links. This is based on the cost assumption that author spends more time on representing more important concepts.

The theory of SLN provides the basis for making a summarization. A set of normal forms of SLN was proposed for regulating different patterns of semantic link network (Zhuge 2012). *Text summarization can be regarded as a task of* *finding the minimum subgraph that contains high-rank nodes and satisfies the 4^{th} Normal Form SLN from the whole SLN on the source.*

The following is a general SLN-based summarization solution, which is suitable for both single source and multiple sources:

1. *Discover semantic links within the given source.*
2. *Construct semantic link network according to the semantic links.*
3. *Derive implicit semantic links from reasoning rules on the semantic links.*
4. *Discover semantic communities within the semantic link network.*
5. *Select the semantic community to represent the source according to the rank of the community, which is proportional to: (a) the ranks of the nodes of the community; (b) the diversity of semantic links; (c) the density of semantic links; and, (d) total contributions of semantic links within the semantic community.*
6. *Use the selected semantic community to compose the summary.*

The traditional summarization approaches (including multi-document summarization approaches and single-document summarization approaches) focus on single theme (core) represented by representation components (especially sentences) rather than relations. Therefore, *traditional summarization approaches are limited in ability to generate a summary that covers multiple related themes, which is often requested by multi-document summarization.*

To enable a summarization approach to generating a summary that coherently covers multiple related themes, semantic links (e.g., citation link) between themes need to be processed by a summarization approach and important semantic links should be selected and retained in the generated summary in addition to representation component such as words and sentences. A summarization with cross-area semantic link is useful in summarizing cross-area research, e.g., research cross "artificial intelligence", "natural language processing" and "software engineering".

For summarizing scientific papers on multiple themes, citation links connect the semantic link network of one paper to the semantic link network of another paper, forming a semantic link network on all papers to be summarized.

From a bigger picture, summarization is to establish symbiosis among learning various relations and rules in cyber-physical-social space, understanding relations (within or between documents) and rules in different spaces, modelling reality represented in the sources, and constructing summaries for humans to read or for applications to further process. Without understanding various relations and rules, it is hard for a summarization algorithm to generate a satisfied summary.

The above discussion indicates a Rule-Based Summarization RBS. Its general architecture is depicted in Figure 3.17.

The Open Link Set contains semantic links discovered from resources (e.g., texts), between resources (or citation links), and defined by humans. Different types of sources hold different types of semantic links, for example, cause-effect link plays a more important role in rendering the contents of scientific papers than the contents of news. Citation links between scientific papers provide a context for a paper to be summarized. The citation of a paper constructs its extension. Pattern-based approaches and machine-learning approaches can be used to discover semantic links. Humans can also define new semantic links according to the characteristics of domain.

The Open Rule Base contains rules and strategies defined through learning from experience and defined by humans (users of the system) who have experience of writing summaries. Different from traditional rule base systems, it opens to incorporating new rules from humans and automatic discovery systems.

User profile can be default (for a general summarization), a set or a semantic link network of representations (for query-based summarization), and a template of representations (for professional summarization). *Professional knowledge significantly influences the focus of core*. For example, reading the same novel, architects concern the contents on buildings, doctors concern the contents on health, and politicians concern the contents on policies. *The relation between the professions of users and language components can guide a general summarizer to generate summaries that suit users*.

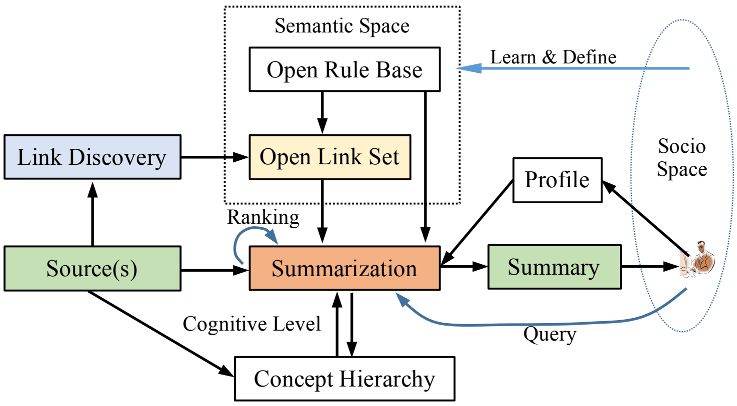


Fig. 3.17 General architecture for SLN-based summarization.

The concept hierarchy of the Semantic Link Network determines the cognitive level of query and the cognitive level of representations. Receiving a query, the query-based summarization mechanism determines the concepts within the query, selects components according to the concepts and then maps representation components into the summary at the cognitive level of the query. As the SLN-based summarization method is based on the semantic links between representations, it is suitable for summarizing multimedia sources.

3.11.3 *Recommending research collaborator*

Recommending an appropriate research collaborator is to select two researchers and establish a collaboration link between them according to existing data for inspiring thinking and promoting the productivity of their research. Scientific, technical and social factors influence a successful research collaboration, e.g. (1) research area (some areas like bioengineering usually need more teamwork than others like mathematics), (2) organizations of researchers (companies usually need more teamwork than universities), (3) distance and communication between researchers (long-distance communication was greatly improved before and after the widely use of the Internet), (4) gender of researchers (male researchers are more in population and more active in collaboration than female researchers in some countries), (5) policy and (6) culture.

This case study is based on data (scientific papers) and analysis of various semantic links and rules on the data.

Scientific papers within a research area contain the following semantic links about semantic nodes including papers, researchers and organizations:

1. *Cite* link between papers. It indicates a relevancy between the contents of papers and knowledge flow between researchers through reading, thinking and writing (Zhuge 2006, 2016). Constant publication of papers constructs an evolving citation network on papers. The link is explicit and fix once the papers are published. A cite link can be represented as $a \xrightarrow{cite(x)} b$, where a and b are papers and x denotes a representation (a sentence or several sentences) of a that cites b, i.e., there exists a semantic link: $x \xrightarrow{is\text{-}part\text{-}of} a$, and b semantically includes x, i.e., x is a summary of b or a part of b about x. Multiple papers can cite one paper on either the same content or different contents.
2. *Author-of* link between author and paper. A researcher can be the author of one paper or many papers, and a paper can have one author or multiple authors (co-authors). The link is explicit and fix once a paper is published.
3. *Work-for* link between researchers and the organization they work for. The link is explicit and fix when papers are published. It can be generally represented as $X \xrightarrow{work\text{-}for} Y$, where X denotes researchers and Y denotes an organization that X is affiliated. As a researcher can work for multiple organizations at different stages, a *work-for* link is bound onto a paper in this application. So, the semantic link can be specialized as $X \xrightarrow{work\text{-}for(p)} Y$, where p denotes a variable that specializes the semantic link for reflecting one paper or a set of papers of X.
4. *Similar-to* link between papers on the same research theme and between research interests of researchers. This link is implicit and has a degree of similarity.
5. *Complement* link between research interests, which is implicit and has a degree of complement.

6. *Co-author* link between authors on a paper, which is explicit and fix once the paper is published. The link can be represented as X—*co-author(p)*→Y, where X and Y represent researchers and p represents a paper of X and Y.

Constant publication of papers evolves a semantic link network consisting of the above semantic links and semantic nodes following not only scientific rules but also social rules. The following reasoning rules enable one semantic link to be derived from other semantic links, where X, Y and Z represent researchers and a, b, c and p represent papers:

Reasoning Rule 1: X —*author-of*→a, Y—*author-of*→a ⇒ X—*co-author(a)* →Y.

Reasoning Rule 2: X —*work-for*(a)→ Y, Z —*work-for*(a)→ Y ⇒ X —*co-author*(a)→ Z.

Reasoning Rule 3: a —*cite(x)*→b, c—*cite(x)*→b ⇒ a—*similar-to*→c. The similarity dues to x.

Reasoning Rule 4: a—*cite(x)*→f, f—*cite(x)*→c ⇒ a—*similar-to*→c. The similarity dues to x.

Reasoning Rule 5: a—*cite*(x)→b, b—*cite*(x)→c ⇒ c—*flow*(x)→a, i.e., a knowledge flow on x from c to a.

Generally, any pair of researchers has a certain probability to cooperate. Constant publication of papers emerges various patterns and characteristics of research, including research theme and research interests. Semantic links, rules, common (or complement interests) and experience of cooperation influence the probability of cooperation between researchers.

Social rules influence the evolution and therefore influence the probability of collaboration, for example, two researchers have a higher probability to cooperate if they have more common research interests because similarity between interests provides common languages and common cognitive level for cooperation. For cross-area research, it also increases the probability of cooperation if researchers have overlapped common interests.

The keywords of all papers written by a researcher can reflect his/her research interest. Therefore, a higher similarity between research interests of two researchers indicates a higher probability of cooperation between them.

The research interest of a researcher can be represented as a mapping from a set of *Researchers* into a set of *Keywords*, *K*: *Researchers*→*Keywords*, such that for any researcher X in *Researchers*, there is a corresponding set of *Words, a subset of Keywords*, extracted from X's papers, denoted as $K(X(t))=Words(X(t))$, where t represents the time period for keeping the research interest. A *similar-to* link can be established between researcher X and researcher Y when $K(X(t))\cap K(Y(t))/K(X(t))\cup K(Y(t)) > 0$ with a certain similarity degree. This rule can be represented as the following probabilistic rule for enforcing recommendation of collaboration on a theme or paper p defined by $K(X(t))\cap K(Y(t))$, where "$\Rightarrow$" denotes the recommendation of collaboration at time t+1 with a positive probability.

Rule of Recommendation 1: $K(X(t)) \xrightarrow{similar\text{-}to} K(Y(t)) \Rightarrow X(t+1) \xrightarrow{cooperate(p)} Y(t+1)$, where p is a task for possible cooperation.

A complement link can be established between research interests when $K(X(t))\cup K(Y(t))=K(Theme(t))$, where $K(Theme(t))$ denotes the set of keywords of a research *Theme*. The following rule represents that the complement of interests of two researchers can increase the probability of collaboration between them on a theme or a paper p defined by $K(Theme(t))$.

Rule of Recommendation 2: $K(X(t)) \xrightarrow{complement} K(Y(t)) \Rightarrow X(t+1) \xrightarrow{co\text{-}author(p)} Y(t+1)$.

Cooperation experience also increases the probability of future cooperation because two researchers who cooperate before should share common interests and a researcher who has cooperation experience is willing to cooperate and has the characteristic of cooperation. The following rule reflects the positive influence of experience on cooperation.

Rule of Recommendation 3: $X(t) \xrightarrow{co\text{-}author(p_1)} Y(t)$, …, $X(t) \xrightarrow{co\text{-}author(p_n)} Y(t) \Rightarrow X(t+1) \xrightarrow{co\text{-}author(p)} Y(t+1)$, where p, p_1, …, and p_n denote paper and $p \supseteq p_1\cup\ldots\cup p_n$, *n is an integer and* $n>1$.

Some cooperation links depend on social roles. If a researcher $X(t)$ is the supervisor of another researcher $Y(t)$ during a time period t, the probability of cooperation between them is high because their common interests are built through education process including meeting and discussion on the same research theme and cooperation is bound by the responsibilities of jobs. The following rule is for the enforcement of recommending collaboration.

Rule of Recommendation 4: $X(t) \xrightarrow{is\text{-}supervisor\text{-}of} Y(t) \Rightarrow X(t+1) \xrightarrow{co\text{-}author(p)} Y(t+1)$, where p is determined according to $K(X(t))\cup K(Y(t))$.

If two researchers $X(t)$ and $Y(t)$ cite the same paper, they have a high probability to cooperate because they should have close research interests. The following rule for recommendation enforcement can be drawn from Rule 1.

Rule of Recommendation 5: $X(t) \xrightarrow{is\text{-}author\text{-}of} a(t)$, $a(t) \xrightarrow{cite} c(t)$, $Y(t) \xrightarrow{is\text{-}author\text{-}of} b(t)$, $b(t) \xrightarrow{cite} c(t) \Rightarrow X(t+1) \xrightarrow{co\text{-}author(p)} Y(t+1)$, where paper $p \supseteq K(X(t))\cup K(Y(t))$.

Although the probability of collaboration within an organization is high (partially due to members of a research team usually belong to the same organization), it will be more significant to recommend collaborators from different organizations given the same condition because researchers in the same organization should already know each other so it is easy for them to collaborate in the future or they are collaborating with each other. The following is a rule for recommending collaboration with positive enforcement:

Rule of Recommendation 6: $X(t)$ —*work-for*→$O(t)$, $Y(t)$ —*work-for*→$O(t)$, $Z(t)$ —*work-for*→$Q(t)$, $X(t)$—*co-author*(p_1)→$Y(t)$, $X(t)$—*co-author*(p_2)→$Z(t)$ $\Rightarrow$ $X(t+1)$—*co-author*(p)→$Z(t+1)$, where O and Q are organizations, and the content of paper p is defined by $K(X(t))\cup K(Z(t))$.

The evolution of the semantic link network on researchers, papers, and organizations emerges some implicit links between semantic links, e.g., between citation link and co-author link. Previously introduced experiment on citation and collaboration indicates the following rule for determining the probability of emerging a collaboration link.

Probability of emerging a collaboration link.

1. *The probability of emerging a new collaboration link between a researcher with a high citation number and a researcher with a low citation number > the probability of emerging a new collaboration between two researchers with high citation numbers*.
2. *The probability of emerging a new collaboration link between two researchers with low citations > the probability of emerging a collaboration link between two researchers with high citations*.

Experiment. Publication data of two journals (AI journal and FGCS journal) indicate the following phenomena:

1. The probability of collaborating with the same researcher(s) constantly is small for a highly cited researcher.
2. About 50% of top-10 highly cited researchers collaborate with top-10 highly cited researchers. About another 50% of those researchers collaborate with low citation researchers.
3. Collaboration between researchers with low citation is about 77% of all citations, and collaboration between researchers with high citation is less than 7%.
4. More than 70% of the cooperation between high-citation researchers and low-citation researchers come from the same organization.

This rule can be interpreted from the following aspects:

1. Researchers with low citation are usually young researchers who have not formed a long-term personal research direction, so they are flexible in collaborating with more researchers on different research themes.
2. Many young researchers are students who often collaborate with their supervisors in the same organization.

3. Researchers with high citation are usually senior researchers who have formed a personal long-term research direction, so they are more difficult to find a collaborator with the same interest or complementary interest.
4. A researcher with high citation usually have multiple research students or research assistants for collaborative research.
5. Researchers with high citation usually own research funding, which supports them to attend conferences and visit universities and companies where they have higher probability to meet young researchers for collaborative research given the population of young researchers.
6. The number of researchers with a low citation number is much more than the number of researchers with a high citation number, therefore the probability of emerging a new collaboration between a researcher with a high citation number and a researcher with a low citation number is much higher than the probability of emerging a new collaboration between two researchers with a high citation number.

The evolution of semantic link network with the above determined rules and the probabilistic rules emerges a probabilistic pattern of potential collaboration. The pattern is the basis of recommending future links as it should not change frequently with short-term operations once formed.

The above set of *Rules* transforms the pattern of semantic link network on two researchers into a co-author link with a *probability* represented as follows:

$Rules(link_1(X(t), Y(t)), \ldots, link_n(X(t), Y(t))) \Rightarrow X(t+1) \text{—} co\text{-}author(p) \rightarrow Y(t+1)$,
where $link_1(t)$, …, and $link_n(t)$ are semantic links on person $X(t)$ and person $Y(t)$, which determine the rules for recommendation.

A more general problem is recommending one semantic link or several semantic links between things to realize a certain goal about the semantic link network. Solutions request the understanding of the evolution of a real semantic link network (e.g., epidemic network) and the recommendation of a set of semantic links between important nodes for predictive operations, for example: finding the key infection link for curbing an epidemic with the minimum cost, and promoting effective interactions for research collaboration on a scientific research network.

Recommending a semantic link needs to consider semantic nodes (with features, states and functions), semantic links (with type, probability and time) and flows (of material, data, information and knowledge) influencing the state of node. The evolution of an SLN emerges patterns, which provide the context for predicting a new link between existing nodes and between a new node and the existing nodes.

Chapter 10 will discuss an application of SLN to manage epidemic networks.

3.12 General Model for Cyber-Physical-Social Semantic Link Network

3.12.1 *General Model*

The general model for CPSoSLN is a complex system consisting of a persistent mapping from a base network into a superstructure to persistently obtain its semantic images through evolution and a set of operations to evolve the base network and the superstructure:

$$(K\text{: } \langle N, L, F\rangle \rightarrow \Omega, O)\text{, where}$$

1. $\langle N, L, F\rangle$ is the base network consisting of (1) an open set of nodes N, each of which can be anything, passively or actively linked to other nodes; (2) an open set of links L, each of which is a relation between nodes indicated by a simple structure with a light-weight grammar, representing the pattern of relation; and, (3) an open set of flows F, each of which carries material, data, information and knowledge processed by autonomous nodes and flows from one node to another node.
2. Ω is an open superstructure consisting of semantic space, cyberspace, physical space, social space, probabilistic space and time, each of which consists of relations, linking rules, relational reasoning rules and theory. A space can be defined by a basic SLN or other spaces (for example, the social space consists of such subspaces as motivation space, value space, productive space as well as strategy and policy space). The superstructure of a basic SLN consists of a semantic space with a concept hierarchy, linking rules and reasoning rules.
3. K is a set of persistent mappings, consisting of:
   (1) a persistent mapping from the base network into the superstructure to get the semantic images of nodes, links and flows as well as relevant rules and principles specific to different spaces;
   (2) persistent mappings between spaces, including
      - persistent mappings from cyberspace, physical space, social space, probabilistic space and time space (or dimension) into semantic space for persistently obtaining the semantic images of things (including nodes, links, rules and theories) in those spaces;
      - persistent mappings from physical space and social space into cyberspace for persistently obtaining the cyber images of things in physical space and social space;
      - persistent mappings from cyberspace into physical space, social space, probabilistic space and time space for persistently obtaining social and physical images of cyber things;
      - persistent mapping from social space into physical space for getting social images of things in the physical space;
      - persistent mapping from physical space into social space for persistently getting the physical image of things in social space; and,
      - persistent mappings from cyberspace, physical space and social space into probabilistic space for persistently obtaining their probabilistic images in probabilistic space.

4. Operations O=<{O_1, O_2, …, O_n}, *Method*> is a set of operations on the base network, the superstructure and the mappings with a set of methods *Method*, including the maintenance operations (such as changing the structure, attributes, links, services, rules and experience) and methods (including classifying things such as nodes, links, rules, operations and methods as well as discovering links between things and rules on semantic links). The base network, superstructure and mappings evolve with operations.

CPSoSLN evolves with the following operations:

1. *Linking*, reflecting self-organization process of organization.
2. *Relational reasoning*, reflecting the intrinsic structure of organization.
3. *Classification*, reflecting generalization and specialization.
4. *Mapping*, reflecting analogy and association; a persistent mapping is a function of the base network, the superstructure and time.
5. *Maintenance*, operations on the base network and the superstructure.
6. *Influencing*, reflecting the change of the state of the base network and the state of the superstructure due to operations.

Classification and categorization drive the evolution of CPSoSLN with emerging concepts and categories. Classifying and categorizing a set of nodes concern classification of its attributes, experience of appearance and services, and link them to the existing categories. Classifying and categorizing the links of a node through comparing common or different attributes between nodes is a way to understanding the situation of the node. Classifying and categorizing all links within the base network emerge the pattern of links to reflect the situation of nodes.

An application scenario of classifying and categorizing links is enterprise situation analysis. An enterprise can build a view of an enterprise symbiotic network, a social-relational network, by finding and analysing various links and flows between relevant enterprises through the following steps:

1. Finding explicit and implicit relations (semantic links) to other enterprises and between enterprises.
2. Classifying and categorizing the links such as supplier, customer, competitor and co-operator by mapping the links into the concept hierarchy in the semantic space.
3. Identifying the flows through the links.
4. Ranking the general links according to the richness of the links and flows through the links.
5. Identifying linking rules according to the links and flows.
6. Recommending a ranking list of the links and flows with values and possible influences (measured according to linking rules, reasoning rules and flows) to the managers of the enterprise to consider before making an enterprise strategy.

Knowing the symbiotic network and the influence of a strategy can help decision makers to make foreseeable decision on business strategies.

CPSoSLN renders the complexity of the evolution process of the observed system with diverse operations, semantic links, linking rules and reasoning rules. It divides a complex system into two subsystems — a base network and a superstructure, which evolve with a simpler complexity and more specific rules and principles.

In contrast, the traditional semantics modelling methods including the Semantic Net, semantic data models, knowledge representation methods and probabilistic graph are single-level network, which limits the ability of modelling complex systems because of lacking social linking rules and relational reasoning rules.

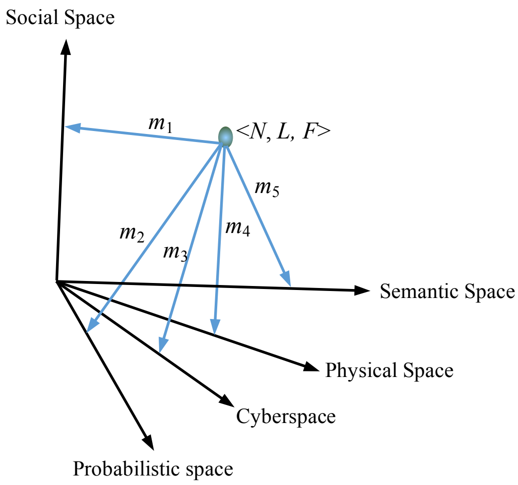
Figure 3.18 (a) depicts a multi-dimensional view of mapping (denoted as m) the model into different dimensions, resulting in different images:

1. Semantic images of nodes, links and flows with concept hierarch (or network), linking rules and relational reasoning rules at the semantic dimension.
2. Social images of nodes, links and flows with social linking rules, motivations, values, productivities, policies and strategies at the social dimension.
3. Physical images of nodes, links and flows as well as rules, principles and theories at the physical dimension.
4. Cyber images of nodes and links with linking rules as well as theories and techniques of computing and communication at the cyber dimension, concerning representation, storage and efficient operations of the network. To support globally distributed massive operations (including storage, management, reasoning and interpretation) on a large-scale SLN is a challenge to cyber-infrastructure.
5. Probabilistic images of nodes, links, flows and rules in the probabilistic space reflecting the uncertainty of representation and understanding.

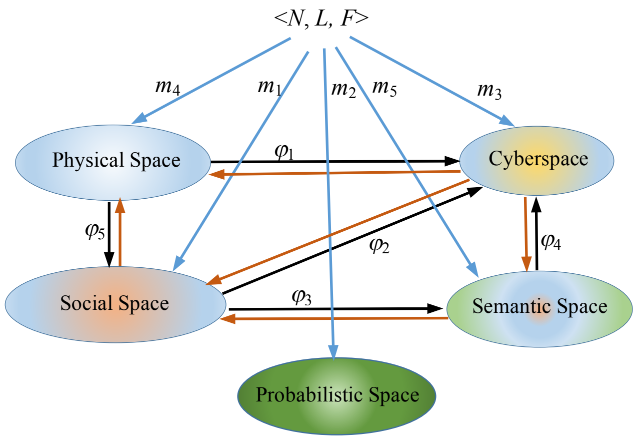
Figure 3.18 (b) depicts a cyber-physical-social view where black arrows denote mappings (φ) between spaces (the yellow arrows denote the corresponding reverse mappings). With the mappings, a physical object can have a cyber image, a social image, a semantic image and a probabilistic image, and a social object like human individual, organization or event can have a cyber image, a semantic image, a physical image and a probabilistic image. The images in various spaces support cyber-physical-social services, e.g., answering a question with cyber image, physical image, social image, semantic image and probabilistic image with interpretation from different spaces.

The reverse of a mapping in the same space exists and follows the same principle, such as light and reflection of light as well as force and reaction force in the physical space. However, a reverse of a mapping in different spaces may not exist. For example, some abstraction concepts such as good and true in the mental space have no corresponding sources in the physical space.

With the expansion of various images in cyberspace (e.g., big data), physical space and social space, computing in cyberspace is developing toward a computing in cyber-physical-social space. Recognizing reality reflected by various images in cyber-physical-social space, understanding the patterns and their evolution hidden in the images, and uncovering the implicit links between the evolutions of patterns become more and more important tasks, which are also the basis of discovering fundamental problems.



(a) A multi-dimensional view of CPSoSLN.



(b) A cyber-physical-social view of CPSoSLN.

Fig. 3.18 Cyber-Physical-Social Semantic Link Network.

CPSoSLN can be regarded as a model for linking cyber-physical-social things and images, carrying out complex relational reasoning, discovering emerging patterns and predicting evolutions according to cyber-physical-social relations, rules and principles.

3.12.2 *Necessity, Assumption and Method*

In general, the necessity of this research lies in meeting the following requirements:

1. *The requirement of exploring the prominently evolving reality and the challenge of shifting scientific paradigm*. The rapid development of technologies changes the ways of interactions between humans and between humans and the nature, therefore the structure of reality and fundamental scientific problems change. Exploring the changing reality requires a new methodology, models, theories and tools.
2. *The requirement of developing Cyber-Physical Society with harmonious coordination and co-evolution of humans, machines and the nature*. The capabilities of intelligent machines have surpassed humans in solving well-defined problems. How to build symbiosis among humans, machines and the nature to ensure the sustainable development of Cyber-Physical Society is a challenge.
3. *The requirement of understanding complex reality from* different dimensions and scales. Research concerns individuals, interactions between individuals, influences of interactions, rules of interactions, rules of influence, patterns of interactions, transformation of patterns, condition of transformation, generality and particularity.

The study of CPSoSLN is based on the following assumptions:

Assumption 3.5 *Various models reflecting different understandings of reality are necessary but insufficient for modelling reality*. This is because knowledge and time of the inventors are limited and may hold different worldviews.

Based on assumption 3.5, this chapter studies and integrates models on different dimensions to model reality.

Assumption 3.6 *Reality evolves through interactions among evolving spaces with different rules and principles, which cannot be completely represented and transformed from one space into another space*.

Based on assumption 3.6, this chapter explores the modelling of reality from evolutionism.

Assumption 3.7. *Symbiosis among human, machine and the nature can be established, and it evolves sustainably based on the development of science and technology*.

Based on assumption 3.7, this chapter studies reality through constructing symbiosis between individuals, between spaces, and between various processes.

It is feasible with the development various sensors, robots and human-machine interfaces.

Gödel's incompleteness theorem shapes the boundaries of formal systems (Gödel 1951). Simon's bounded rationality shapes the general limitations of recognizing reality in terms of cognition, time and information (Simon 1957). The physical symbol system hypothesis: "A physical symbol system has the necessary and sufficient means for general intelligent action" (Newell and Simon 1976), which sets the basis for symbolism of developing Artificial Intelligence. These ideas can be traced to the rationalism of philosophy.

CPSoSLN tries to extend the boundary of semantics modelling by creating an open two-level architecture:

1. *A base network with the following characteristics*:
   - *generality*, it reflects the complex structure of reality, which is modelled by complex network or abstract algebra system;
   - *evolution*, it evolves structure and emerges communities with operations on nodes, links and flows;
   - *self-organization*, a node can determine which node it should link to according to the rules defined in the superstructure;
   - *openness*, it accepts new nodes and links at any time; and,
   - *interactive*, nodes can actively interact with each other or be passively linked.
2. *A superstructure with the following characteristics*:
   - *particularity*, it has different spaces that contain specific rules, principles and strategies;
   - *multiple spaces*, it includes semantic space, cyberspace, physical space and social space, and any space can have sub-spaces with specific rules, principles and strategies, for example, social space can have a subspace on strategy and policy, which can further have a socialism subspace and a capitalism subspace, following different rules and policies in addition to the general rules and policies;
   - *evolution*, its spaces evolve with changing dimensions to reflect evolving reality and learning new categories and rules from the base structure and the external environment; and,
   - *openness*, its spaces can accept new elements and rules, on the other hand, semantics of basic elements is based on the common sense concepts as defined in the Interactive Semantic Base that support understanding of interactions (Zhuge 2011).
3. *Persistent mappings*, it includes the persistent mapping between the base network and the superstructure that holds the images of nodes and links within the evolving base network and the rules of operations in the evolving spaces at any time, and the persistent mappings between the evolving spaces to hold the images of things in different spaces at any time. The persistent mappings enable CPSoSLN to render Cyber-Physical-Social Intelligence.

Separating the base network from the superstructure brings the following advantages:

1. It can coordinate between generality and particularity and between different spaces.
2. It can reflect evolutions at different levels with different rules and principles, emerging different patterns.
3. It can identify relations (or influence) between different components of reality.
4. CPSoSLN can be observed and operated separately by different operators.

Incorporating various spaces into the superstructure brings the following advantages:

1. *Keeping persistent mappings between spaces can keep reflecting the evolution of various spaces* such as physical space and social space, which are characterized by different linking rules, reasoning rules and principles, reflecting different aspects of reality. In contrast, traditional approaches map different spaces into symbol space and then focus on operating symbols separately from the evolution of different spaces through modelling process. The problem is that the modelling process is unable to reflect the change of reality (sometimes change can be prominent, e.g., change of business).
2. *It keeps gaining combined power along co-evolution*. People carry out modelling with bounded rationality. An individual researcher or a team of researchers is limited in ability to learn all knowledge of various spaces. Limited knowledge determines limited ability to recognize reality. The persistent mappings of the proposed model create an environment where physicians keep contributing models and theories about physical space, socialists keep contributing models and theories about social space, computer scientists keep contributing models and theories about cyberspace, and IT professionals keep contributing to evolve the infrastructure of cyberspace.
3. *Support advanced services through mappings between spaces*, such as question answering, summarization and recommendation based on inter-space mapping, linking, complex reasoning and interpretation. Any prominent change in one space will be mapped into the other spaces in real time, influencing the evolution of the superstructure and the base network.

Figure 3.19 depicts the general problem and the research method of CPSoSLN, which provides a cyber-physical-social relational system for linking reality to knowledge. The red rectangular encloses the main work of this chapter.

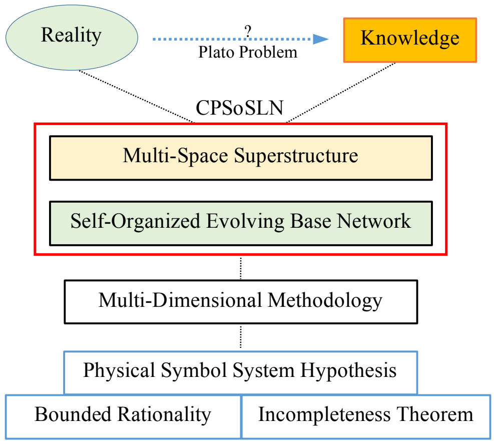


Fig. 3.19 General problem, method and methodology.

3.13 A Brief History of Graphical Semantics Modeling

There is a long history of using graph to represent reality at a high abstraction level, for example, Euler's research on the Königsberg Bridge problem in 1736. Graph theory studies the structure of abstract graph consisting of nodes and edges. The meaning of a graph is described in natural language separated from graph for understanding reality.

3.13.1 *Semantic Net*

Half century ago (1956-1970), a logic-based labeled graph, Semantic Net (i.e., Semantic Network, https://en.wikipedia.org/wiki/Semantic_network) was used by a group of scientists and engineers for processing natural language and developing application systems in the UK, Europe and American (Richens, 1956; Quillian 1967; Quillian 1967; Minsky 1968). It takes such forms as definitional networks, assertion networks, implicational networks, executable networks, learning networks and hybrid networks in various applications (Sowa 1987).

Semantic Net was used as a knowledge representation approach for implementing some knowledge-based systems at the age of knowledge engineering (section 3.13.3 will discuss this further) including expert systems like the Prospector – a computer-based consultation system for mineral exploration (Hart and Duda 1977). Compared with other knowledge representation approaches like production rule, Semantic Net was not so widely applied to the implementation of knowledge-based systems due to the following limitations to a certain extent:

1. *Closed system*. It is hard to communicate between systems developed by different people who may use different symbols to indicate the same semantics or use the same symbol to indicate different semantics. This is a historical limitation due to the early development stage of computing technology. The initiative of Open Knowledge Base Connectivity (OKBC) addressed this issue (http://www.ai.sri.com/~okbc/, 1995). OKBC aimed at a uniform model in form of application programming interface for accessing knowledge bases stored in knowledge representation systems based on common conceptualization of classes, individuals, slots, facets and inheritance.
2. *Static and weak semantics*. It simply uses words to indicate semantics of nodes and edges while neglecting the nature of semantics as discussed in this book, especially the social characteristics of semantics (Zhuge 2010), including diversity, dynamicity, evolution, interactivity and particularity of different semantic relations.
3. *Logic-based*. Some Semantic Nets are based on the first-order logic, which supports logic reasoning but it is limited in ability to reflect the semantics that is not mainly relied on logic.
4. *Subgraph-matching-based reasoning*. It is limited in ability to carry out reasoning on diverse relations and has a high computing complexity.
5. *Labour-intensive construction*. The construction of the Semantic Net relies on humans. Research neglects automated construction due to the early development stage of computing technology. The cost spent on constructing a high-quality large-scale Semantic Net is very high, especially on ensuring the consistency between the parts contributed by different developers.

Semantic Net has the similar limitation as other knowledge representation approaches in developing knowledge-based systems. For example, they have the bottleneck of knowledge acquisition. This is mainly because there is a big gap between knowledge in mind and the "knowledge" represented in the systems. It is hard to create a universal model that can represent all human knowledge.

A relevant event during this period is that Newell and Simon developed the General Problem Solver system in 1959 for solving any formally represented problem based on their physical symbol system hypothesis and theoretical work on logic machines. They received 1975 Turing Award for their "basic contributions to artificial intelligence, the psychology of human cognition, and list processing".

Generality is a pursue of scientific research. However, establishing a universal theory for solving all problems is impossible according to Gödel's incompleteness theorem.

3.13.2 *Data Models*

The network data model adopted graphical data structure as database schema and programmers as navigators (Bachman 1969; Bachman 1973). Bachman created the Integrated Data Store (IDS) based on the model (i.e., the navigational database model). He received the Turing Award in 1973 “for his outstanding contribution to database technology”. Relational data model organizes data according to relations (e.g., functional dependency) on attributes of data and normalizes relations (normal forms) for correct operations in a structured query language (Codd 1970). Codd received the Turing Award in 1981 “for his fundamental and continuing contributions to the theory and practice of database management systems”.

Semantic data models including the Entity-Relation (ER) model was proposed for modelling domain business as the basis for designing data model so that database can provide appropriate functions for domain applications (Abrial 1974; Chen 1975).

Following the network model and the hyperlink network of the World Wide Web, graph databases drew researchers’ attention for efficient operations on graph structures of data (Angles and Gutierrez 2008).

The network data model, the ER-model-like semantic data models, and the graph database can be generalized as a Semantic Net at a certain abstraction level, however different models concerns different particularities of reality.

Social network analysis more concerns the structural characteristics of a large network and applications based on the characteristics (Kossinets and Watts 2006; Liben-Nowell and Kleinberg 2007). From a multi-dimensional view on various resources, research on the Resource Space Model (RSM) adopts a multi-dimensional classification space to manage various data based on a set of normal forms on the space (Zhuge 2008; Zhuge and Xing 2012).

3.13.3 *Knowledge Representation and Reasoning*

As the achievement of exploring reality, humans generate knowledge for sharing, understanding and interpreting reality through necessary reasoning. Studying the theory of knowledge is the core of philosophy.

Feigenbaum classified knowledge into two categories: (1) facts of the domain, i.e., the shared knowledge written in textbooks and journals; and, (2) heuristic knowledge, consisting of the rules of expertise, the rules of good practice, the judgmental rules, the rules of plausible reasoning, which are transmitted through practice and rarely written down.

He pointed out the following characteristics of domain problem-solving: (1) relying on domain knowledge in addition to common knowledge (including mathematics, philosophy and methodologies); (2) heuristic approaches, which are widely used to solve problems, especially those that are hard to be precisely defined in mathematics; (3) inductive reasoning and abstraction reasoning, in addition to deductive reasoning and (4) the ability to process uncertainty and incompleteness, including facts and knowledge. Humans use heuristic knowledge to solve problems, learn knowledge, and then update knowledge during problem-solving process.

He proposed the term Knowledge Engineering in 1977 to model human expertise in solving domain problems, which is usually based on heuristic rules, inductive reasoning, abstraction ability as well as the ability to process uncertainty and incompleteness. It focuses on three scientific problems: knowledge representation, knowledge utilization and knowledge acquisition (Feigenbaum 1980). He received the Turing Award in 1994 together with Raj Reddy for "pioneering the design and construction of large-scale artificial intelligence systems, demonstrating the practical importance and potential commercial impact of artificial intelligence technology".

The approach to modeling expertise tries to break the limit of logic-based approaches to modeling human intelligence but it encounters difficulties in the practice of building expert systems and in solving the scientific problems, especially knowledge acquisition and representation of expertise.

As a kind of knowledge representation method, Probabilistic Graph Models were proposed. One branch of research is Bayesian network, a Directed Acyclic Graph (DAG), is good at reflecting cause-effect relation (Pearl 1985; 1986). Judea Pearl received 2011 Turing Award for "fundamental contributions to artificial intelligence through the development of a calculus for probabilistic and causal reasoning". Another research branch is Markov random field (or Markov network), an undirected graphical model where random variables have Markov property described by an undirected graph (Dobruschin 1968). It is good at reflecting symmetrical relationships such as similarities and affinities. Efforts have been made to enrich semantics, e.g., combining probabilistic graph models and first-order logic (Richardson & Domingos, 2006). In general, they are limited in ability to represent rich relations in reality.

In addition to technical challenges, the methodology of knowledge engineering has the following two shortcomings:

1. Its research object was set as knowledge rather than problem and reality. Traditional computing is to define problem and solve problem through designing algorithm. It is a challenge to process the problems that are hard to be precisely defined. The knowledge engineering methodology neglects the complicated psychological, cognitive and social processes of generating and sharing knowledge, which make the modeling of expertise difficult. Establishing symbiosis between humans and machines is an approach to making use of both advantages of machines and humans.
2. It neglects the nature of knowledge, which involves social, diverse, evolving, semantic and multi-dimensional characteristics. Traditional knowledge acquisition and representation approaches are limited in ability to reflect the characteristics.

Some researchers retarget their research object to data and try to discover knowledge in database (Piateski and Frawley 1991).

Neural network is also a knowledge representation method (connectionism). Deep learning obtains significant progress in obtaining expertise from data (LeCun 2015). The pioneers of deep learning Yoshua Bengio, Geoffrey Hinton and Yann LeCun received the 2018 Turing Award "for conceptual and engineering breakthroughs that have made deep neural networks a critical component of computing". As a black box approach, deep learning is limited in ability to generate explicit knowledge representation, carry out reasoning and interpret reality. Most Artificial Neural Networks can be generalized as a Probabilistic Graph Model.

The problem of how humans bridge the gap between experience and knowledge has puzzled scientists and philosophers for centuries. A related problem is how humans can know so much given limited experience. It was named Plato's problem by Noam Chomsky. It is difficult to solve the problem if we only investigate individual behaviours. A multi-dimensional space view of knowledge was proposed to model knowledge as a space, which evolves with such dimensions as cyberspace, physical space, social space and mental space (Zhuge 2012).

This chapter provides a semantic link view of knowledge: points (or subspace) in a knowledge space are connected by various semantic links in the complex space with such dimensions as cyberspace, physical space, social space and mental space. A point integrates mapping images in physical space, mental space, social space and cyberspace. The knowledge spaces of individuals belonging to the same community can be integrated into the knowledge space of the community. Mapping between knowledge spaces is established through the semantic links and mappings between spaces. Knowledge spaces grow through establishing and maintaining links and mappings.

An individual's experience is limited but a community of practice helps individuals obtain indirect experience and grow knowledge through linking and mappings. The development of interconnection environment (including the Internet and wireless communication network) provides the condition for sharing information and experience world widely. Experience can grow quickly through direct mapping from cyberspace, physical space and social space. A knowledge space evolves when it gains knowledge points through semantic links. A systematic knowledge space forms when all of its points are linked and linked to other spaces with consistency.

3.13.4 *Hyperlink, Linked Data and Knowledge Graph*

The hyperlink network of the World Wide Web is a self-organized network consisting of webpages and hyperlinks without any rule for restricting linking operations (Berners-Lee and Fischetti 1999). The hyperlink network, Web browser, and search engine provide a paradigm for sharing information globally on the Web. Web 2.0 provides an interactive platform for people to communicate with each other, reflecting social behaviors. Tim Berners-Lee received the 2016 Turing Award for “inventing the World Wide Web, the first web browser and the fundamental protocols and algorithms allowing the Web to scale”.

The Web evolves prominently through self-organization. Any person can create any webpage and link it to any other webpage, but people tend to link their webpages to the authority webpages that have many links. Therefore, some webpages attract more links than others through the evolution of the hyperlink network. If webpages are ranked by their links and the ranks of neighbors (Page 1999) and new webpages are constantly linked to the network, the ranks of webpages within the hyperlink network monotonously increase. Another effect of linking one webpage A to another webpage B is that A contributes reading flow to B and increases the rank of B, which in turn influences the neighbors of B.

Tim Berners-Lee proposed an open system initiative — the Linked Data in 2006 for publishing structured data so that data can be interlinked and become more useful in supporting semantic queries (www.w3.org/DesignIssues/LinkedData.html). Linked Data is a technical proposal for solving the problem of linking data of multiple sources on the Web although it can be generalized as a Semantic Net. Research and applications involve in technological problems.

It is worth mentioning that an initiative on open system connectivity Open Database Connectivity (ODBC) were made in 1990s. It is a standard application programming interface, independent of database systems and operating systems, for accessing database management systems.

W3C proposed a framework for defining triple structure (RDF) in 2004 (updated in 2014, https://www.w3.org/RDF) to support structured and semi-structured data to be mixed, exposed and shared across Web applications. It is a directed and labelled graph like the Semantic Net in general. However, it does not define the semantics of nodes and links nor the rules and reasoning on the links. A logic-based Web Ontology Language (OWL) was developed as a Semantic Web language for representing rich and complex knowledge about things and relations between things (https://www.w3.org/OWL/, 2004, updated in 2009 and 2012). RDF, OWL and SPARQL (RDF query language) are parts of the W3C’s Semantic Web technology stack. The initiative is to create standards and tools for building open databases on the World Wide Web.

Linked data initiative attacks the closed world problem of previous semantic models and enables globally distributed data to interact with each other. However, it relies on human construction and its main aim is not semantics modelling.

Google proposed knowledge graph in 2012 for structuring multimedia data from search results and other sources to better reflect relations among entities. The initiative has drawn R&D attentions, especially from search enterprises. Essentially, it adopts the idea of the Semantic Net, Linked Data and SLN for improving search result and user experience. However, there is a big gap between a graph of multi-media data and a graph of knowledge (Zhuge, 2004, 2012).

3.13.5 *Semantic Link Network*

Research on Semantic Link Network (SLN) can be traced to the discovery of the rules of inheritance for efficient retrieval of models in model repository (Zhuge 1998) and the implementation of Active Document Framework through building semantic links between documents respectively (Zhuge 2003). A systematic theory and method was developed for representing the basic semantic structure of complex systems in 2004 (Zhuge 2004) and complemented in 2010 and 2012 (Zhuge 2010, 2012).

SLN was integrated with the Resource Space Model based on the multi-dimensional classification space to effectively organize and operate various resources (Zhuge 2008). The expression ability of the Resource Space Model was studied by comparing with relational data model and OWL (Zhuge and Xing 2012). Its theory and method have been applied to various application areas to improve existing research such as in decentralized semantic networking (Zhuge et al 2004; Zhuge 2006, 2007; Zhuge and Li 2007), e-learning (Zhuge 2009), and text summarization (Zhuge 2016; Cao et al. 2018; Sun and Zhuge 2018). SLN can also enhance question-answering systems with such functions as selecting semantically relevant answer, expanding question and answer, and matching answer and question through various semantic links (Zhuge 2007).

A research challenge is to automatically build the SLN for various applications. Efforts have been made to discover semantic links, e.g., within texts based on explicit patterns (Zhuge et al 2004; Zhuge 2012; Cao et al 2018). Structure information, statistic rules and linguistic rules inspire unsupervised approach to discovering implicit patterns from texts. Deep learning provides a supervised approach to automatically discovering semantic links on data through training with examples. However, it is still a challenge to automatically build the superstructure of SLN including motivation, social linking rules, relational reasoning rules, strategies, policies and theories.

3.13.6 *Mapping Models into Multi-Dimensional Space*

Different models can be mapped into a space with graph dimension, time dimension, semantics dimension and probability dimension for identifying their characteristics on these dimensions as shown in Figure 3.20. Each dimension can be divided into different sub-dimensions, e.g., semantic dimension can be divided into two sub-dimensions: formal semantics dimension and social semantics dimension.

Graph theory has projections at the graph dimension. Semantic Net, ER model, Linked Data and Knowledge Graph have projections at the graph dimension and the semantics dimension. Probabilistic graph model has projections at the graph dimension and the probability dimension. SLN has projections at the graph dimension, semantics dimension and probability dimension.

All models have invention times at the time dimension. The important milestone of the development of semantics modelling is the invention of the World Wide Web, which not only provides a platform for implementing large-scale semantics modelling for globally distributed diverse applications but also requests open system that benefits diverse communities. This also provides the necessity for studying interactive semantics and social semantics (Zhuge 2010, 2011), which were not urgently requested for small, special-purpose and close systems before the invention of the Web.

Models can also be mapped into a multi-dimensional methodology space, which consists of rationalism dimension, empiricism dimension, constructionism dimension and evolutionism dimension. The probabilistic graph model more belongs to rationalism while Semantic Net, ER model, Linked Data and Knowledge Graph more belong to empiricism. SLN has projections at rationalism dimension, empiricism dimension, constructionism dimension and evolutionism dimension.

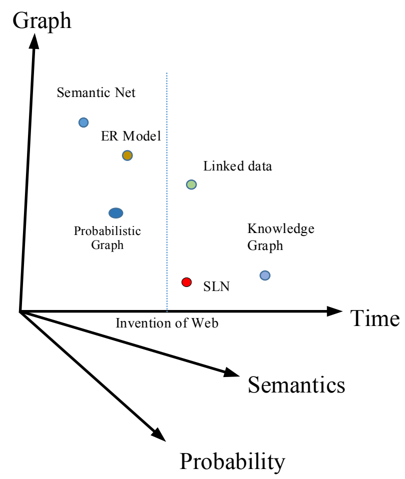


Fig. 3.20 A multi-dimensional space for summarizing various graphical semantic models.

3.13.7 *Cyber-Physical-Social Semantic Link Network*

With the co-evolution of cyberspace, physical space and social space, a cyber-physical-social space emerges. Building human-machine-nature symbiosis becomes a new challenge. SLN was extended to connect things in cyberspace, physical space and social space to support Cyber-Physical-Socio Intelligence with the characteristics of *abstraction*, *dimensionality*, *interactivity*, *evolutionary*, *diversity and sociality* of linking things in different spaces, and reasoning for *human-machine-nature symbiosis* (Zhuge 2011, 2012).

Some characteristics and principles of cyber-physical-socio-mental SLN (SLN 3.0) was proposed in (Zhuge 2012). CPSoSLN extends SLN 3.0 to a complex cyber-physical-social-relational system with a base network and a superstructure that makes the sense of the base network and regulates its evolution with categorizing nodes, links and flows, and incorporating linking rules and relational reasoning rules into the motivation space, value space and productivity space as well as policy and strategy space. The study of CPSoSLN also helps deepen the understanding of the future interconnection environment (Zhuge 2005).

3.14 Summary

Finding the reason or the cause of why a thing happens is a major concern of philosophers and scientists.

Modelling is a paradigm of scientific exploration through observation, experiment, generalization, thinking, formulation, prediction and evaluation with necessary knowledge and representation based on a certain level of language. Humans play the central role in creating various models through observing reality, linking reality to knowledge, and applying knowledge to understanding and modelling reality. Models can be interpreted by existing knowledge, and the modelling processes are testable and interpretable. Through creating and adapting models, humans (including developers and users of models) gain insight, learn and apply knowledge, form theories, obtain inspiration, evolve minds, and develop sciences and techniques. The expressive abilities of different models depend on their abilities to reflect the observed system and the language used to express the model.

Traditional methods for semantics modelling (including the semantic net, the semantic data models and the knowledge representation methods) are mainly based on unary methodology, single abstraction (or single language), and single space (especially cyberspace). *Rationalism focuses on developing representation systems based on logics, graphics, probability or statistics*. *Empiricism focuses on creating various standard languages like linked data and platforms for supporting applications*. However, they are limited in ability to reflect the nature of reality, especially the physical and social characteristics.

Gödel’s incompleteness theorem, Simon’s bounded rationality, and Newell and Simon’s physical symbol system hypothesis shape the sphere of recognizing reality from the perspectives of theory, cognition and language. The ideas are in line with rationalism.

This research is to extend the sphere by creating an evolving two-level semantic model CPSoSLN with a multi-dimensional methodology for organizing, analysing, and integrating methods from different dimensions for modelling reality.

CPSoSLN consists of the following components: (1) a base network that evolves patterns of links and flows with characteristics of generality, evolution, self-organization, openness and interactivity; (2) a superstructure that models categories, relations, rules, principles and strategies with characteristics of particularity, multiple spaces, evolution and openness; (3) persistent mappings between the base network and the superstructure, and between the spaces for supporting advanced services and (4) operations that manage and evolve the base network, the superstructure and the mappings.

The nature of reality is reflected through operations and mappings. Operations on the base network evolve the network with emerging patterns, following linking rules, relational reasoning rules, and properties specified in the motivation space, value space, strategy and policy space and productive space of the superstructure. Semantics emerges and evolves through linking, multi-dimensional classification and categorization, and mappings according to determined or non-determined rules, which is different from logic deduction systems. Its modelling ability is enhanced through the evolution of its base network and superstructure with increasing categories, linking rules, relational reasoning rules, properties and principles reflecting the evolving reality. Reflecting both generality and particularity, coordinating different spaces through persistent mappings, and concerning openness and evolution differentiate CPSoSLN from previous semantic models.

Research adopts the multi-dimensional methodology to observe, understand, and formulate reality from methodologies of multiple dimensions (Zhuge 2012). From evolutionism, semantics evolves with the evolution of the base network and superstructure through categorization, semantic linking, relational reasoning and operations. From rationalism, CPSoSLN integrates algebra system, graphics and probabilistic model with temporal characteristics. From empiricism, CPSoSLN incorporates social linking rules, relational reasoning rules, principles, strategies and policies to support complex reasoning integrating relational reasoning, inductive reasoning and analogical reasoning for advanced services (Zhuge 2012). From constructivism, CPSoSLN concerns both patterns discovered through experience and automatic discovery (e.g., automatic process for discovering semantic links and linking rules) in cyber-physical-social space.

For a particular application, an instance of the model can be generated by establishing or discovering semantic links and incorporating domain categories and rules into the superstructure. In different domains, semantic links have particularities, and different combinations of semantic links can form different roles in rendering semantics, e.g., in representing and understanding documents (Zhuge 2012; Sun and Zhuge 2018).

The proposed social linking rules, properties, principles, lemmas and methods form a theory for linking reality to knowledge as an evolving cyber-physical-social relational system, which emerges, enhances, integrates and evolves semantic images, abstractions, specializations and discoveries of various links. Cyber-physical-social space provides a cyber-physical-social life experience (with mapping images in cyberspace, physical space and social space) for the linking process.

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