Constructing a New-Style Conceptual Model of Brain Data for Systematic Brain Informatics

Ning Zhong, *Senior Member*, *IEEE*, and Jianhui Chen

Abstract—The development of brain science has led to a vast increase of brain data. To meet requirements of a systematic methodology of Brain Informatics (BI), this paper proposes a new conceptual model of brain data, namely Data-Brain, which explicitly represents various relationships among multiple human brain data sources, with respect to all major aspects and capabilities of human information processing systems (HIPS). A multidimension framework and a BI methodology-based ontological modeling approach have been developed to implement a Data-Brain. The Data-Brain, Data-Brain-based BI provenances, and heterogeneous brain data can be used to construct a Data-Brain-based brain data center which provides a global framework to integrate data, information, and knowledge coming from the whole research process for systematic BI study. Such a Data-Brain modeling approach represents a radically new way for domain-driven conceptual modeling of brain data, which models a whole process of systematically investigating human information processing mechanisms.

Index Terms—Data-brain, brain informatics, domain-driven conceptual modeling, ontologies, provenance

1 Introduction

The capabilities of human intelligence can be broadly divided into two main aspects: perception and thinking. The latter is involved with multiple "higher" cognitive functions, such as reasoning, problem-solving, decision-making, learning, and so on. In order to understand "intelligence" of human information processing systems (HIPS) in depth, Brain Informatics (BI) focuses on thinking centric cognitive functions [55], [56]. Aiming at the characteristics of thinking centric investigations, BI emphasizes on a *systematic* approach to investigate human information processing mechanisms guided by a systematic BI methodology.

However, such a systematic BI study cannot be realized only depending on the traditional expert-driven approach. A powerful brain data center needs to be developed on the wisdom web and knowledge grids as the global research platform to support the whole systematic BI research process [51], [52], [54]. This brain data center is not only a brain database. In fact, it should be a data cycle system which integrates various information systems to transform the systematic research process of BI, i.e., BI "data, information, knowledge" cycle (BI data cycle for short), from the expert-driven and state-of-the-art process to the normative and propagable one [58]. For constructing such a data cycle system, the core issue is to develop an effective mechanism to integrate valuable data, information and knowledge for various data requests which are coming from different aspects of a systematic BI study.

In this paper, we propose a new conceptual model of brain data called Data-Brain as a global mechanism for the integration of data, information and knowledge in the whole process of systematic BI study. A multidimension framework and a BI methodology-based ontological modeling approach are developed to implement the Data-Brain. Such a Data-Brain modeling methodology represents a radically new way for domain-driven conceptual modeling of brain data, which models a whole process of systematically investigating human information processing mechanisms in BI. The remainder of this paper is organized as follows: Section 2 discusses background and related work. Section 3 gives the definition of Data-Brain and describes how to construct a Data-Brain. Based on the preparations, Section 4 presents the Brain Informatics methodology-based modeling approach, and Section 5 provides two realistic examples to evaluate the modeling approach and reports the experimental results. Finally, Section 6 concludes the paper.

2 Background and Related Work

2.1 Brain Informatics and Its Methodology

Brain Informatics is a new interdisciplinary field to study human information processing mechanism systematically from both macro and micro points of view by cooperatively using experimental/computational cognitive neuroscience and web intelligence (WI) centric advanced information technologies [49], [50]. It can be regarded as brain sciences in the WI centric IT age [53].

As stated above, the capabilities of human intelligence can be broadly divided into two main aspects: perception and thinking. Our BI studies focus on thinking centric investigations. Comparing with the perception-oriented investigations, thinking centric ones are more complex and involved in multiple interrelated cognitive functions with respect to activated brain areas and their neurobiological processes of spatiotemporal features for a given task. The complexity of

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thinking centric investigations decides that Brain Informatics is "systematic," i.e., BI adopts a systematic methodology to investigate human information processing mechanisms, which includes four core issues: systematic investigation of human thinking centric mechanisms, systematic design of cognitive experiments, systematic human brain data management, and systematic human brain data analysis and simulation [57].

Guided by such a BI methodology, the whole research process of BI can be regarded as a BI data cycle which is implemented by measuring, collecting, modeling, transforming, managing, mining, interpreting, and explaining multiple forms of brain data obtained from various cognitive experiments by using powerful equipments, such as functional magnetic resonance imaging (fMRI) and electroencephalogram (EEG). Such a systematic BI study needs the supporting of various information technologies. Furthermore, in order to make sure the consistency and persistence of "data, information, knowledge" cycle, these information technologies need to be realized as various information systems and integrated into a brain data center as the global BI data cycle system of BI community. Regarding the data centric BI study, this integration should be based on the different forms of data in the BI data cycle, including raw brain data, data-related information, extracted data features, found domain knowledge related to human intelligence, etc. Thus, the core issue of BI data cycle system is how to integrate valuable data, information, and knowledge in the whole research process of BI for various data requests coming from information systems which provide different types of research supporting functions for different aspects of a systematic BI study.

2.2 Conceptual Modeling of Brain Data for Systematic Brain Informatics

Conceptual modeling of data "transforms" things from real world into "data" world. It is a key issue in the developing of information systems.[1] In the database design, conceptual data modeling represents data entities and relationships among them for the data organization, storage, and query. In the metadata developing, conceptual schema design of metadata represents data knowledge for the collection, organization, and query of data information. In data-related ontology modeling, domain ontologies model and integrate the domain knowledge about data for knowledge driven data utilizations. In general, conceptual modeling of data is an effective mechanism to integrate data, information, and knowledge for various data utilizations coming from information systems. It provides a practical approach to resolve the above core issue of BI data cycle system.

However, as a core of BI data cycle system, the conceptual model of brain data should be a new-style conceptual model of data which is oriented to not a or several special data applications in BI study but various data requests coming from information systems. In order to realize systematic BI study, all of information systems in BI study should be oriented to the implementation of systematic BI methodology. Thus, the corresponding data requests are coming from different aspects of a systematic BI study and can be generalized based on the above four core issues of BI methodology. This means that, for systematic Brain Informatics, the conceptual model of brain data should be able to integrate the valuable data, information, and knowledge in the whole research process of BI for various data requests which are coming from different aspects of a systematic BI study:

- **Systematic investigation of human thinking centric mechanisms**. For understanding the principles and mechanisms of HIPS in depth, human thinking centric cognitive functions, such as reasoning, problem-solving, decision-making and learning, and their relationships need to be investigated systematically. In order to support such a systematic investigation, various data requests, such as "*get all of activations of sentential induction tasks, as well as the corresponding experimental groups and experimental tasks, which are located in the frontal lobe and whose sizes are larger than 100 voxels*" and "*get all of similar data features which are extracted from the data of both induction and computation*," are often given for studying not only a specific cognitive function but also multiple kinds of cognitive functions systematically.
- **Systematic design of cognitive experiments**. Because of the complexity of human thinking centric cognitive functions, each investigation of cognitive functions requires not only single data source obtained from a single measuring method and cognitive task, but also multiple data sources from various practical measuring methods, such as combining fMRI and EEG/ERP, and a series of cognitive experiments/tasks. In order to support such systematic experimental designs, various data requests, such as "*get all of experiment disposals about the reversed triangle inductive task*" and "*get all of experiment disposals about human induction*," are often requested for designing not only a specific experimental disposal but also a set of experimental disposals systematically.
- **Systematic human brain data management**. Aiming at the systematic investigation and experimental design, the distributed and heterogeneous brain data need to be effectively stored, organized, maintained, and updated for realizing a radically new ways of sharing data/knowledge and high speed, distributed, large-scale, multiaspect analysis and computation on the wisdom web and knowledge grids. In order to support such a systematic data management, various data requests, such as "*get all of experimental data with the Object-Attribute-Value Mode*" and "*get all of data resources coming from the ERP experiments of reversed triangle inductive task*," are often given for managing not only a specific kind of brain data but also multiple kinds of brain data coming from a group of experiments or data processing systematically.
- **Systematic human brain data analysis and simulation**. The agent-enriched, multiaspect brain data analysis is implemented to combine various human brain data and data analysis/simulation methods for understanding complex brain data in depth, in order

1. In our studies, the conceptual modeling of data does not limit to conceptual data modeling in the database domain. Conceptual schema design of metadata and data-related ontology modeling are also regarded as the conceptual modeling of data.

to uncover the information processing courses of thinking centric cognitive functions with respect to their neural structures and mechanisms. In order to support such a systematic human brain data analysis and simulation, various data requests, such as "*get the analytical process and related instances of SPM based brain activation finding*" and "*get all of analytical methods which can find activations from fMRI data*," are often requested for utilizing not only a specific analytical method but also multiple kinds of analytical methods.

2.3 Existing Studies on Conceptual Modeling of Brain Data

In brain science, the existing studies on conceptual modeling of brain data can be divided into the following three types:

- *The conceptual schema design of brain database*. When the main functions of brain database centric systems are to support transaction operations, such as simple query, addition, deletion, brain databases are oriented to the storage of brain data and data-related information. The corresponding conceptual modeling of brain data focuses on intuitional descriptions of data entities and a certain aspect of relationships among them, in order to effectively store brain data and related information for those transaction operations. The created conceptual models of brain data are just conceptual schemata of brain databases, such as the conceptual schema of neuroimage database [44] and the conceptual schema of EEG database [23]. The main modeling tools are some graphical conceptual data modeling languages, such as Entity-Relationship (ER) model [5].
- *The conceptual schema design of metadata*. When the main functions of systems are to publish brain data on the web, brain databases are oriented to the storage of origins about brain data. The corresponding conceptual modeling of brain data focuses on intuitional descriptions about origins of brain data, involving with various experiments and data processing, in order to integrate related information for describing the published data. The created conceptual models are just conceptual schemata of metadata or provenances [40], [26], such as the ontological metadata schemata of neuroimages [18], [45]. The main modeling tools are some graphical languages or signs.
- *The domain ontology modeling*. When the main functions of systems are to share data on the web, brain databases need to include various formal domain knowledge for data/metadata annotations. The corresponding conceptual modeling of brain data focuses on formal descriptions of data-related domain knowledge. The created conceptual models of brain data are just various brain data-related domain ontologies, such as NeuroElectroMagnetic Ontologies (NEMO) [11] and OntoNeuroBase [41]. The main modeling tools are the formal ontological languages, such as OWL (web ontology language) [29].

These existing studies show that aiming at different functions of information systems, the conceptual modeling of brain data often adopts different modeling approaches and tools to describe brain data from different aspects and granularities.

Although the above database schemata, metadata schemata, and ontologies provide various conceptual models of brain data, which can model a kind of data as an entity, a concept or a class, respectively, all of them only describe various brain data and their relationships from a specific aspect and granularity at the conceptual level. Obviously, these existing conceptual models of brain data cannot integrate the valuable data, information, and knowledge in the whole research process of BI to effectively respond the above four types of data requests. Thus, for constructing the data cycle system, BI needs a domain-driven conceptual model of brain data, i.e., the Data-Brain, which models the whole life cycle of brain data in the BI "data, information, knowledge" cycle.

3 Data-Brain and Its Modeling

3.1 What is a Data-Brain?

The Data-Brain is a domain-driven conceptual model of brain data, which represents multiaspect relationships among multiple human brain data sources, with respect to all major aspects and capabilities of HIPS, for systematic investigation and understanding of human intelligence [6], [7]. It is neither a digital brain which models brain structures by digital and visual technologies nor a logical brain which models brain functions for the simulation and the development of new IT technologies. For supporting the systematic investigation and understanding of human intelligence in BI, the Data-Brain models heterogeneous brain data and multiaspect relationships among them at the conceptual level to integrate key data, information, and knowledge for the constructions of various research supporting systems which can form a BI data cycle system to carry out the systematic BI methodology and support the whole BI research processes.

Constructing such a Data-Brain is attributed to the characteristics of BI. In order to develop a BI data cycle for systematic BI study, BI needs a Data-Brain to integrate key data, information, and knowledge for various data requests of a systematic BI study. Based on this way, it provides a long-term, holistic vision to uncover the principles and mechanisms of underlying HIPS. On the other hand, BI methodology supports such a Data-Brain construction. As a BI-oriented conceptual model of brain data, the Data-Brain can adopt a BI methodology-based modeling approach. In other words, the Data-Brain goes beyond specificity of a certain application and straightly models the four aspects of systematic BI methodology as stated in Section 2. This is just so-called "domain-driven."

Based on the systematic BI methodology, we design a multiview and multidimension framework for the Data-Brain. For supporting systematic investigation and understanding of human intelligence, the Data-Brain includes multiple conceptual views which represent systematic BI investigations and their interrelationships from different viewpoints based on functional relationships among related human cognitive functions. These conceptual views provide a series of long-term and holistic visions of BI thinking centric investigation. They can be regarded as cognitive/brain

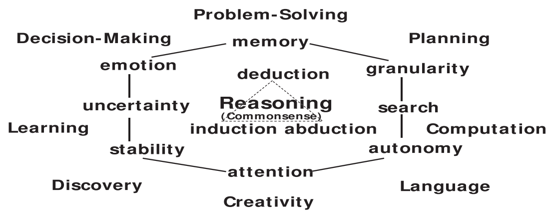

Fig. 1. A "Reasoning" centric conceptual view of the Data-Brain.

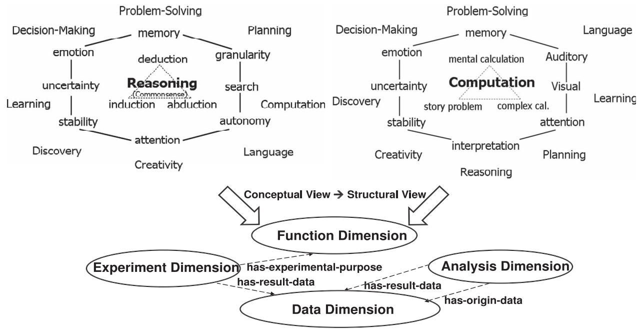

Fig. 2. A multidimension framework of the Data-Brain.

scientists' interfaces to facilitate their own research activities and cooperation with different focusing and research issues. Fig. 1 gives an abstract representation of the conceptual view, which illustrates reasoning centric BI investigations and their interrelationships based on functional relationships among related human cognitive functions. The core issue is to investigate human deduction, induction, and abduction-related reasoning mechanisms, as well as including commonsense reasoning, as shown in the central of Fig. 1. Heuristic search, attention, emotion, and memory are some component functions to implement human reasoning, as well as granularity, autonomy, stability, and uncertainty are some interesting characteristics, which need to be investigated with respect to human thinking-related cognitive functions, as illustrated in the middle circle of this figure. Furthermore, decision-making, problem-solving, planning, computation, language, learning, discovery, and creativity are the major human thinking-related cognitive functions, which will be studied systematically, as illustrated outside the middle circle of this figure.

As stated in previous sections, the thinking centric investigations of BI are implemented by a systematic BI methodology including four core issues. Accordingly, the conceptual view of Data-Brain, which represents various thinking centric investigation of BI, is also transformed into its own structural view with four dimensions, namely function dimension, data dimension, experiment dimension, and analysis dimension, which are connected to each other and corresponding to the four issue of BI methodology, respectively. Fig. 2 illustrates such a transformation, in which we only give two conceptual views, the reasoning centric view and the computation centric view, because of the limitation of space. We will describe an ontological modeling approach for dimension constructions in the next section, and present the technical details for constructing the four dimensions of Data-Brain and their relationships, as well as for extracting a conceptual view from the function dimension in Section 4.

3.2 How to Construct a Data-Brain

Generally speaking, conceptual modeling approaches can be divided into two types: conceptual data modeling and ontology modeling. Although both ontologies and data models are partial accounts of conceptualizations [43] and share many common features [21], they do have some differences. Fonseca et al. defined two criteria to differentiate ontologies from conceptual data models: the objectives of modeling and objects to model [16].

As stated in the previous section, the Data-Brain includes four dimensions with respect to the four aspects of systematic BI methodology, which can be regarded as a machine-readable embodiment of BI methodology. Its objective of modeling is not a specific implementation and its objects represent generic things in a domain. Obviously, it is a good way to use an ontological modeling approach for constructing the Data-Brain.

At present, researches on ontology construction have acquired a large amount of productions, which are involved with many ontology engineering methodologies [42], [14] and ontology learning technologies [1], [2], [47]. The former focuses on developing a standard knowledge acquisition process to guide the manual process of ontology modeling. The latter applies itself to change the ontology modeling from the manual process to the semiautomatic process by various technologies, including machine learning, statistics, etc. Because the existing technologies on ontology learning cannot realize an absolutely automatic process to construct ontologies, the practical approach for Data-Brain modeling is a manual knowledge acquisition process guided by special ontology engineering methodologies, in which some ontology learning technologies can be adopted for special subprocesses of knowledge acquisition.

However, though there are many mature ontology engineering methodologies, the Data-Brain modeling still needs to be studied in depth. On the one hand, the multidimension Data-Brain is involved with multidomain knowledge. The main purpose of Data-Brain modeling is not to develop a multidomain ontology about brain data but to construct a conceptual model of brain data to integrate data, information, and knowledge for systematic BI study. Thus, the Data-Brain modeling cannot be realized only by adopting the existing ontology engineering methodologies to collect related domain knowledge from other domains of brain science. The further studies are needed to design the knowledge acquisition process of Data-Brain modeling more detailed based on the rules and restrictions which are coming from the systematic BI methodology. On the other hand, based on a large amount of previous studies, the systematic BI methodology has formed and is being perfected constantly. The study on Data-Brain modeling provides a chance to embody the BI methodology and develop a BI data cycle system for the system driven systematic BI study.

Based on the existing ontology engineering methodologies and ontology learning technologies, we propose a Brain Informatics methodology-based approach for Data-Brain modeling, including the following eight steps:

- terms gathering,
- constructing the function dimension based on systematic investigation,

- constructing the experiment dimension based on systematic experimental design,
- constructing the data dimension based on systematic data management,
- constructing the analysis dimension based on systematic data analysis and simulation,
- extracting conceptual views from the function dimension,
- constructing relations among dimensions for BI provenances, and
- the evaluation of Data-Brain and its evolution.

In our recent studies, OWL is used as the modeling language.

In the above steps, the core one is the dimension construction, involved with steps 2, 3, 4, and 5. Each dimension can be regarded as a subontology and is corresponding to the four issues of BI methodology stated above, respectively, which can be constructed by the following four steps:

- defining the domain and scope,
- identifying key concepts and properties,
- defining the concept hierarchy by taxonomic relations, and
- constructing axioms.

Different from the existing ontology engineering methodologies which only define the purpose of each step, this BI methodology-based approach is domain driven, i.e., the implementation rules in each step of dimension constructions are explicitly represented according to different aspects of BI methodology. The more descriptions will be given in the next sections.

4 A Brain Informatics Methodology-Based Approach for Data-Brain Modeling

4.1 Terms Gathering

Terms are some important words in domains. They are candidate concepts or relationships for the ontology construction. In ontology engineering methodologies, terms are often acquired by "Brainstorming" [43]. In order to simplify the Data-Brain modeling and the information system integration, our studies adopt ontology learning technologies to gather terms from our existing research supporting systems, including a brain database and an analytical record system. The former stores the experimental information about brain data and the latter records the analytical information about brain data. The gathering process includes the following two steps:

- ontology learning based on conceptual schemata of databases,
- instance construction based on tuples.

The method stated in [47] is adopted to implement ontology learning.

In fact, as shown in Fig. 3, simple ontologies can be constructed by the above steps. However, because conceptual schemata of databases lack enough semantic information, the obtained ontologies are too simple and can only be regarded as the term sets for the following dimension constructions.

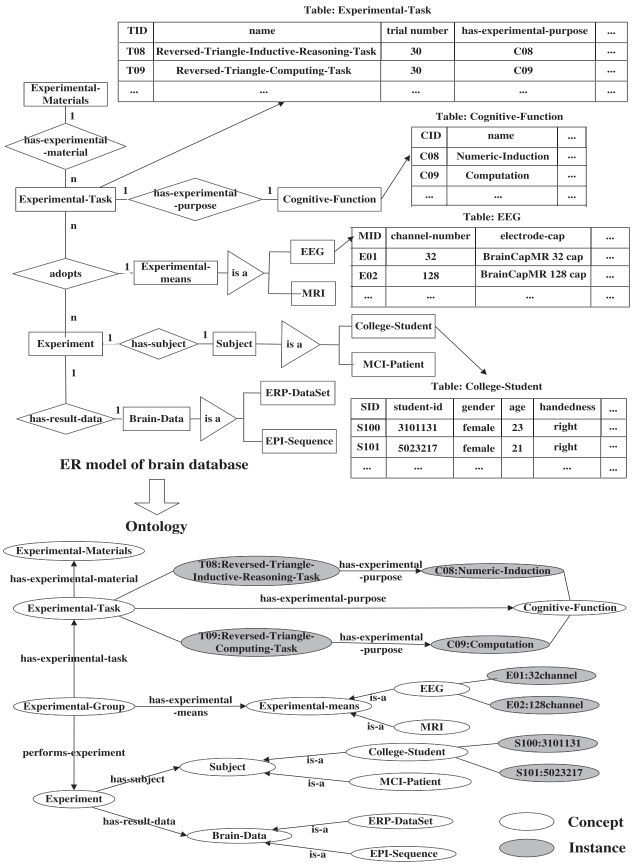

Fig. 3. A fragment of conceptual schemata of brain database and the corresponding simple ontology. In this transformation, the triple relation "adopts" in the ER model is replaced by a new concept "Experimental-Group" and three binary relations "has-experimental-task," "has-experimental-means," and "performs-experiment" in the simple ontology.

4.2 Constructing the Function Dimension Based on Systematic Investigation

The function dimension models the systematic investigation of BI methodology. It describes information processing courses of human thinking centric cognitive functions and functional relationships among them at the conceptual level. As stated above, the thinking centric cognitive functions are complex and closely related to each other. Thus, the Data-Brain needs to include a function dimension for guiding the systematic investigation.

According to the four steps of dimension constructions stated in Section 3.2, the process of constructing a function dimension can be described as follows:

- **Defining the domain and scope of the function dimension**. Because the function dimension models the systematic investigation, the objects of investigation decide the domain and scope of a function dimension. Its domain is human cognitive functions and its scope covers human thinking centric cognitive functions and other related cognitive functions, on which systematic BI investigation focuses.
- **Identifying key concepts and properties**. The key concepts in the function dimension for systematic investigation are with respect to human thinking centric cognitive functions, such as "Reasoning" and "Problem-Solving," and their subfunction concepts,

such as "Deduction" and "Induction." These key concepts are described by properties, including data properties and object properties. Data properties are used to describe concepts themselves and object properties are used to describe relations among concepts. In systematic BI investigation, each concept with respect to a cognitive function represents a series of study activities. For providing a holistic BI study view and a comprehensive functional model of human brain, the function dimension needs to focus on functional relationships among cognitive functions. Thus, there is no key data property in the function dimension. Only the key object property "has-functional-relationship-with," which describes functional relationships among cognitive functions, is included in the function dimension. It includes various subproperties, such as "includes-in-function" and "related-to-in-function," which are used to describe different types of functional relationships.

- **Defining the concept hierarchy**. Since no standard taxonomy of human cognitive functions, researchers often classify cognitive functions according to their own study viewpoints, such as LRMB model [46]. Because the systematic investigation of BI methodology is a thinking centric one, we define the concept hierarchy of a function dimension as follows: first, the concepts with respect to human cognitive functions can be classified into two classes, "Perception-Centric-Cognitive-Functions" and "Thinking-Centric-Cognitive-Functions." The former includes the concepts with respect to perception-oriented cognitive functions, such as "Vision" and "Hearing." The latter includes the concepts with respect to thinking centric cognitive functions on which BI focuses, such as "Reasoning." Second, all of cognitive functions are specialized into more characterized subclasses. For example, the concept "Reasoning" can be specialized into multiple subconcepts, such as "Induction" and "Deduction."
- **Constructing axioms**. Axioms are formal assertions that model sentences that are always true. They provide a way of representing more information about concepts, such as constraining on their own internal structure and mutual relationships. The primary axioms in the Data-Brain are restriction axioms, including value constraints and cardinality constraints. Thus, constructing axioms in the Data-Brain can be specialized as that related concepts are described by data properties and object properties with constraints. Because of lacking data properties, constructing axioms in the function dimension is just to use the key object property "has-functional-relationship-with" and its subproperties to describe concepts with respect to cognitive functions in a function dimension with constraints. For example, the object property "includes-in-function" can be used to describe the concept "Induction" as follow:

$$\textit{Induction} \subseteq \textit{Restriction}(\exists\ \textit{includes-in-function}\ \textit{Attention}).$$

This means that "Induction" includes "Attention" as a subcomponent, but not only includes "Attention."

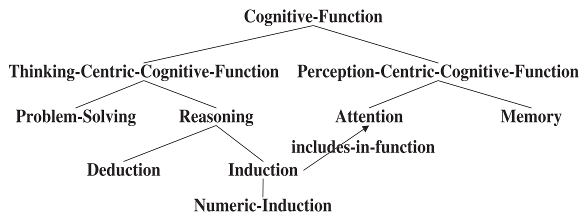

Fig. 4. A fragment of the function dimension. A solid line between two concepts represents a direct specialization relation. An arrow line between two concepts represents a nontaxonomic relation.

Based on the above four steps, an ontological function dimension can be constructed as shown in Fig. 4. The function dimension provides a holistic, conceptual functional model of human brain for systematic investigation. It also provides a machine-readable knowledge base for constructing various conceptual views.

4.3 Constructing the Experiment Dimension Based on Systematic Experimental Design

The experiment dimension models the systematic experimental design of BI methodology. It describes characteristics of various experimentation plans, their classification and inter-relationships at the conceptual level. Systematic experimental design is an important issue of BI methodology. For uncovering the principles and mechanisms of HIPS, BI researchers need to design a series of cognitive experiments for obtaining high quality of experimental data, which represent different aspects of various thinking centric cognitive functions, based on a systematic methodology of cognitive experimental design. Thus, the Data-Brain needs to include an experiment dimension for guiding such a systematic experimental design.

The process of constructing an experiment dimension can be described as follows:

- **Defining the domain and scope of the experiment dimension**. Because the experiment dimension models the systematic experimental design, the methodology of systematic experimental design decides the domain and scope of an experiment dimension. Its domain is cognitive experiments about human brain and its scope covers different aspects of experiments including experimental tasks, measuring instruments, etc.
- **Identifying key concepts and properties**. The systematic experimental design of BI methodology needs to synthetically use various experimental tasks, measuring instruments, and subjects. Thus, besides the concept "Experiment-Group," the key concepts in the experiment dimension are various experiment-related concepts, including experiment concepts, such as "ERP-Experiment" and "fMRI-Experiment," experimental task concepts, such as "Reversed-Triangle-Inductive-Task" and "Sentential-Inductive-Strength-Judgment-Task," measuring instrument concepts, such as "EEG" and "MRI," and subject concepts, such as "MCI-Patient" and "College-Student." For describing systematic BI cognitive experiments in detail, the properties describing the above experiment-related concepts are the key data properties in the experiment dimension, including the properties describing subjects, such as

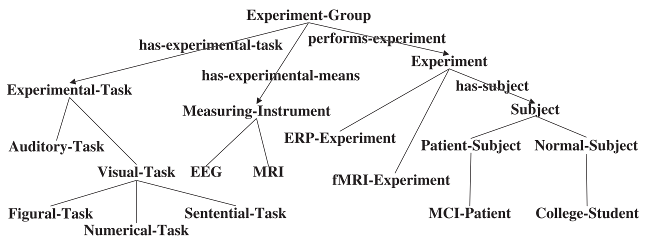

Fig. 5. A fragment of the experiment dimension.

"age" and "name," the properties describing experimental parameters, such as "TR" and "TE," etc. For describing systematic BI cognitive experiment in the round, the key object properties in the experiment dimension are the properties which describe the relations between the concept "Experiment-Group" and other experiment-related concepts, such as the object property "has-experimental-task."

- **Defining the concept hierarchy**. The experiment dimension mainly includes four types of concepts, namely, experiment concepts, experimental task concepts, measuring instrument concepts, and subject concepts, which have the concept hierarchies of themselves. These four types of concepts form four subdimensions in the experiment dimension. For example, the concept "Experimental-Task" can be specialized into more characterized subclasses, "Auditory-Task" and "Visual-Task," based on the receiving mode of information first. Second, based on the appearance format of tasks, these two subclasses can be further specialized into subclasses, such as "Figural-Task" and "Numerical-Task."
- **Constructing axioms**. Constructing axioms in an experiment dimension is just to describe the concept "Experiment-Group" and other experiment-related concepts by data properties and object properties with constraints. For example, the object property "has-experimental-task" can be used to describe the concept "Experiment-Group" as follows:

$$\begin{aligned} &\textit{Experiment-Group}\\ &\quad\subseteq \textit{Restriction}(\forall \textit{has-experimental-task}\\ &\qquad\qquad \textit{Experimental-Task})\\ &\quad\subseteq \textit{Restriction}(\textit{has-experimental-task} \geq 1). \end{aligned}$$

  This means that each "Experiment-Group" has one or more "Experimental-Task"s.

Based on the above four steps, an ontological experiment dimension can be constructed as shown in Fig. 5. The experiment dimension provides a holistic knowledge framework to integrate multiaspect experiment-related knowledge for describing the systematic experimental design of BI methodology. By relations with the function and data dimensions, it explicitly describes various relationships among various data sources. Using the experiment dimension, cognitive experiments-related information can be stamped on each data set for supporting the systematic data analysis and simulation.

4.4 Constructing the Data Dimension Based on Systematic Data Management

The data dimension models the systematic brain data management of BI methodology. It describes multiple views, schemata, and organizations of human brain data with multiple data sources, multiple data forms, multiple levels of data granularity at the conceptual level. Conceptual modeling heterogeneous brain data using the data dimension is the key to realize systematic human brain data management of BI methodology.

The process of constructing a data dimension can be described as follows:

- **Defining the domain and scope of the data dimension**. Because the data dimension models the systematic brain data management, the objects of systematic data management decide the domain and scope of a data dimension. Its domain is brain data and its scope covers various original data, deriving data and data features (analyzed results), which need to be stored into the brain database.
- **Identifying key concepts and properties**. The systematic data management needs to store various brain data, including original data, deriving data, and data features. Thus, the key concepts in the data dimension are various BI-related experimental data concepts, such as "BOLD-Image-Sequence," deriving data concepts, such as "Smoothed-ERP-Data-with-Channel-Time-Amplitude-Mode," and data feature concepts, such as "ERP-Component" and "Activation." In the systematic data management, these data concepts are used to represent different kinds of data which need to be stored into a brain data center as database records or data files. Thus, the key data properties in the data dimension are the storage fields of structured data, such as "electrode-site" and "latent-period," and description fields of unstructured data, such as "file-size" and "postfix-name." The key object properties in the data dimension are the properties which are used to describe structural relationships among data, such as the object property "has-bold-data."
- **Defining the concept hierarchy**. At present, there is not a standard taxonomy of brain data. Thus, we classify these data concepts based on our requirements. The data dimension is oriented to the systematic data management whose purposes are to effectively store heterogeneous brain data and support systematic data analysis. Based on these purposes, we define the concept hierarchy of a data dimension as follows: first, according to different storage modes, data concepts are classified into two classes, "Unstructured-Data" and "Structured-Data;" Second, according to different functions in systematic data analysis, each of the above two classes is specialized into three subclasses, "Original-Data," "Deriving-Data," and "Data-Feature," respectively, which include different specific data concepts.
- **Constructing axioms**. Similar to the function dimension, constructing axiom in a data dimension can be specialized as that related concepts are described by data properties and object properties with constraints. For example, the object property "has-bold-data" can be used to describe the concept "fMRI-DataSet" as follows:

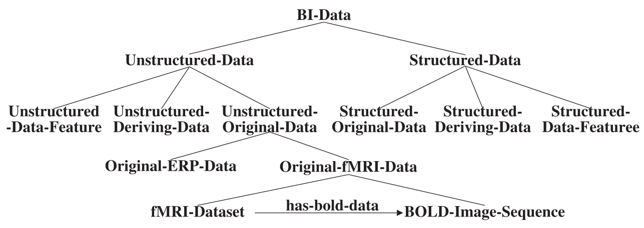

Fig. 6. A fragment of the data dimension.

$$fMRI\text{-}DataSet \subseteq Restriction(\forall has\text{-}bold\text{-}data\ BOLD\text{-}Image\text{-}Sequence).$$

This means that "BOLD-Image-Sequence" is the only bold data type in "fMRI-DataSet."

Based on the above four steps, an ontological data dimension can be constructed as shown in Fig. 6. The data dimension provides a multilevel data representation by modeling, abstracting, and transforming for systematic data management. It supports the realization of a grid-based, analysis and simulation-oriented, dynamic, spatial, and multimedia database for storing and managing the heterogeneous brain data efficiently and effectively.

4.5 Constructing the Analysis Dimension Based on Systematic Data Analysis and Simulation

The analysis dimension models the systematic data analysis and simulation of BI methodology. It describes characteristics of various analysis and simulation methods, as well as their relationships with multiple human brain data for multiaspect analysis and simulation. Agent-enriched data mining for multiaspect data analysis is an important issue of BI methodology because the brain is too complex for a single data mining algorithm to analyze all the available data. Thus, the Data-Brain needs to include an analysis dimension for guiding the agent-enriched computing.

The process of constructing an analysis dimension can be described as follows:

- **Defining the domain and scope of the analysis dimension**. Because the analysis dimension models the systematic data analysis and simulation, the methodology of systematic data analysis and simulation decides the domain and scope of an analysis dimension. Its domain is brain data analysis and its scope covers different aspects of brain data analysis including analytic task, software, etc.
- **Identifying key concepts and properties**. The multiaspect data analysis is a practical approach for realizing the systematic data analysis and simulation of BI methodology. It adopts various analysis and simulation methods on multiple human brain data for understanding data in depth. Thus, the key concepts in the analysis dimension are various brain data analysis-related concepts, including analytic process concepts, such as "Finding-Peculiarities-in-Amplitude-by-Peculiarity-Oriented Mining (POM)," analytic task concepts, such as "Data-Preprocessing" and "Feature-Extraction," software concepts, such as "Brain-Vision-Analyzer" and "C-Program-of-POM," and algorithm concepts, such as "POM" and "PVOM" (Peculiarity Vector-Oriented Mining). An agent-enriched mining process is necessary for implementing the large-scale multiaspect data analysis. Thus, for guiding the agent computing, the key data properties in the analysis dimension are various parameters of analysis methods, such as "threshold-value-of-POM." Furthermore, for describing systematic BI data analysis in the round, the key object properties in the analysis dimension are the properties which describe the relations between the concept "Analytic-Process" and other brain data analysis-related concepts, such as the object property "performs-task."
- **Defining the concept hierarchy**. The analysis dimension mainly includes four types of concepts, namely, analytic process concepts, analytic task concepts, software concepts, and algorithm concepts, which have the concept hierarchies of themselves. These four types of concepts form four subdimensions in the analysis dimension. For example, the concept "Software" can be specialized into more characterized subclasses, "Algorithm-Tool" and "Multifunction Software," based on their functions.
- **Constructing axioms**. Similar to the experiment dimension, constructing axioms in an analysis dimension is just to describe brain data analysis-related concepts by data properties and object properties with constraints. For example, the object property "uses" can be used to describe the concept "Finding-Peculiarities-in-Amplitude-by-POM" as follows:

$$Finding\text{-}Peculiarities\text{-}in\text{-}Amplitude\text{-}by\text{-}POM \subseteq Restriction(\exists\ uses\ C\text{-}Program\text{-}of\text{-}POM).$$

This means that the software "C-Program-of-POM" is used in the analytic process "Finding-Peculiarities-in-Amplitude-by-POM."

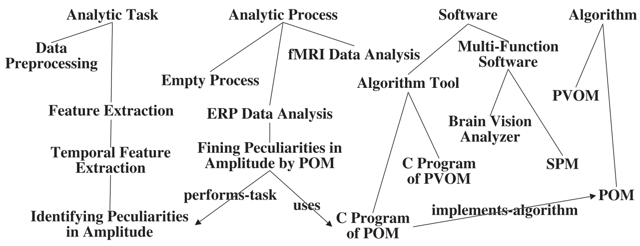

Fig. 7. A fragment of the analysis dimension.

Based on the above four steps, an ontological analysis dimension can be constructed as shown in Fig. 7. The analysis dimension provides a holistic knowledge framework to integrate the knowledge about multiaspect brain data analysis for describing the systematic data analysis and simulation of BI methodology. Based on the analysis dimension corresponding to the data and experiment dimensions, various methods for data processing, mining, reasoning, and simulation can be deployed as agents on a multiphase process for performing multiaspect analysis as well as multilevel conceptual abstraction and learning, which aims at discovering useful knowledge to understand human intelligence in depth [53].

4.6 Extracting Conceptual Views from the Function Dimension

In this section, we present a traversal view-based method for conceptual view extraction of a Data-Brain. As described in previous sections, the Data-Brain includes various conceptual views which can be extracted from the function dimension of a Data-Brain. Since we use ontologies to model the Data-Brain, its conceptual views are just the traversal views [35] of the function dimension and can be defined based on the definition of a traversal view. First, we give some related definitions:

Definition 1. *A* view core, *denoted by* Core, *is a thinking centric cognitive function concept in the function dimension. As the core of a conceptual view, it is corresponding to a BI study issue and represents all the study activities of this issue.*

For example, in the reasoning centric conceptual view shown in Fig. 1, the view core is the "Reasoning," i.e., $Core = Reasoning$.

Definition 2. *A* traversal directive *for the source ontology O, denoted by TD, is a pair*

$$<C_{st}, RT>, \tag{1}$$

where C_{st} is a concept in the source ontology O from which a view is extracted, and represents the starter concept of the traversal; $RT = <R, n>$ is a relation directive, where R is a relation in O and n is a nonnegative integer or infinity which specifies the depth of the traversal along the relationship R. If $n = \infty$, then the traversal includes a transitive closure for R starting with C_{st}.

Definition 3. *A* traversal directive result *(the result of applying directive TD to O), denoted by $TD(O)$, is a set of concepts from the source ontology O such that*

1. *$TD = <C_{st}, RT>$;*
2. *$RT = <R, n>$, $n > 0$. If C_{st} is a concept in the starts of the relation R, and a concept $C \in O$ is the corresponding end of the relation R, then C is in $TD(O)$;*
3. *$RT_{next} = <R, n-1>$ is a relation directive. If $n = \infty$, then $n - 1 = \infty$. For each concept F that was added to $TD(O)$ in step 2, the traversal directive result $TD_F(O)$ for a traversal directive $TD_F = <F, RT_{next}>$ is in $TD(O)$.*

No other concepts are in $TD(O)$.

For example, if the source ontology O is the function dimension FD shown in Fig. 4, the *traversal directive* $TD = <C_{st}, <R, n\gg = <Induction, <includes\text{-}in\text{-}function, 1\gg$ is a path from the concept "Induction" to the concept "Attention" in the FD, where the $C_{st} = Induction$ is the start point of path; $R = includes\text{-}in\text{-}function$ is the edge type of path; $n = 1$ is the length of path. The corresponding *traversal directive result* $TD(O) = <Induction, <includes\text{-}in\text{-}function, 1\gg(FD) = \{Induction, Attention\}$ is a concept set which includes all of concepts in the path represented by the TD.

Based on the above definitions, a conceptual view of the Data-Brain can be defined as follows:

Definition 4. *A* conceptual view, *denoted by CV, is a five-tuple:*

$$(Core, CF, CFIC, RF, R), \tag{2}$$

where

- $CF = <\text{Core}, <\text{parentClassOf}, \infty\gg(FD)$ *is a specialization of $TD(O)$ and represents the concept set of core cognitive functions in a conceptual view, where "*parentClassOf*" is the inverse relation of the relation "subClassOf," and FD is the function dimension of a Data-Brain;*
- $$CFIC = < \text{Core}, < \text{includes-in-function}, \infty \gg (FD)$$ *is a specialization of $TD(O)$ and represents the concept set of component cognitive functions and interesting characteristics in a conceptual view, where "*includes-in-function*" is a relation in the function dimension and used to describe the functional part-whole relationship among cognitive functions;*
- $RF = < \text{Core}, < \text{related-to-in-function}, \infty \gg (FD)$ *is a specialization of $TD(O)$ and represents the concept set of related cognitive functions in a conceptual view, where "*related-to-in-function*" is a relation in the function dimension, which describes the functional pertinence among cognitive functions;*
- $$R = \{\text{parentClassOf}, \text{includes-in-function}, \\ \text{related-to-in-function}\}$$ *is a set of relations which are used to construct the conceptual view.*

For example, the reasoning centric conceptual view as shown in Fig. 1 can be defined as $CV = (Core, CF, CFIC, RF, R)$, where

$$\begin{aligned}
&Core = Reasoning,\\
&CF = <Core, <parentClassOf, \infty\gg(FD)\\
&\quad = \{deduction, induction, abduction\},\\
&CFIC = <Core, <includes\text{-}in\text{-}function, \infty\gg(FD)\\
&\quad = \{emotion, memory, granularity, search, autonomy,\\
&\qquad attention, stability, uncertainty\},\\
&RF = <Core, <related\text{-}to\text{-}in\text{-}function, \infty\gg(FD)\\
&\quad = \{Problem-Solving, Planning, Computation,\\
&\qquad Language, Creativity, Discovery, Learning,\\
&\qquad Decision-Making\},\\
&R = \{parentClassOf, includes\text{-}in\text{-}function,\\
&\qquad related\text{-}to\text{-}in\text{-}function\}.
\end{aligned}$$

According to the above definitions, the algorithm for extracting a conceptual view from an OWL-DL-based Data-Brain is shown in Algorithm 1. In Algorithm 1, the input parameters are the view core $Core$ and the function dimension FD; the output is the $Core$ centric conceptual view CV; the function TDR shown in Algorithm 2 is used to get the traversal directive result. Furthermore, in Algorithm 2, the input parameters are C_{st}, R, n, and O, which are corresponding to the starter concept, the name of relation, the depth of the traversal, and the source ontology in the definition of traversal directive result, respectively.

Algorithm 1. Conceptual View Extraction
Input: $Core$ and FD.
Output: CV.
1. Initialize empty concept sets $CV.CF$, $CV.CFIC$ and $CV.RF$;

2. Set $CV.Core = Core$;
3. Set $CV.R = \{$"$parentClassOf$", "$includes\text{-}in\text{-}function$", "$related\text{-}to\text{-}in\text{-}function$"$\}$;
4. $CV.CF = TDR(Core,$ "$parentClassOf$"$, \infty, FD)$;
5. $CV.CFIC = TDR(Core,$ "$includes\text{-}in\text{-}function$"$, \infty, FD)$;
6. $CV.RF = TDR(Core,$ "$related\text{-}to\text{-}in\text{-}function$"$, \infty, FD)$;
7. return CV

Algorithm 2. Getting Traversal Directive Result: TDR
Input: C_{st}, R, n, and O.
Output: $Concepts$.

1. Initialize an empty set of result concepts, $Concepts$;
2. Initialize the depth of the traversal, $depth = n$;
3. If ($depth == 0$) then
4.   return $Concepts$;
5. $depth_{next} = depth$;
6. If ($depth_{next} <> \infty$) then
7. $depth_{next} = depth_{next} - 1$;
8. If ($R ==$ "$parentClassOf$") then
9.   For each class c_i in O
10.   If (c_i $subClassOf$ C_{st}) then
11.   Add c_i into $Concepts$;
12.   Add $TDR(c_i, R, depth_{next}, O)$ into $Concepts$;
13.   End If
14.   End For
15. Else
16.   For each $Restriction$ in C_{st}
17.   If ($Restriction$ is a value constraint and its property name $= R$) then
18. $c_i =$ Range of $Restriction$;
19.   Add c_i into $Concepts$;
20.   Add $TDR(c_i, R, depth_{next}, O)$ into $Concepts$;
21.   End If
22.   End For
23. End If
24. return $Concepts$

Using the above algorithms, we can choose different cognitive function concepts as view cores to construct various conceptual views based on various viewpoints of BI investigation.

4.7 Constructing Relations among Dimensions for BI Provenances

Systematic BI study produces various original data, deriving data and data features, which include a large number of unstructured data, especially multimedia data. For effectively managing, sharing, and utilizing these data, various metadata are needed. Aiming at different purposes of data sharing and data utilization, the metadata need to include different contents. The metadata describing the origin and subsequent processing of biological images are often referred to as "provenance" [40]. Similarly, we call "BI Provenance," including *data provenances* and *analysis provenances*, which is the metadata describing the origin and subsequent processing of various human brain data in systematic BI study.

The above four ontological dimensions of a Data-Brain provide a holistic, data-related knowledge framework for different aspects of a systematic BI study. The four ontological dimensions and their own domain ontologies form a knowledge base for constructing BI provenances. Thus, these four dimensions can be connected by the relations among dimensions to provide a holistic conceptual schemata for various BI provenances.

A BI *data provenance* is a metadata set that describes the BI data origin by multiaspect experiment information, including subjects information, how experimental data of subjects were collected, what instrument was used, etc. For providing a general conceptual schemata for BI data provenances, the function, experiment, and data dimensions are connected by the following two relations:

- *has-experimental-purpose*. It is between experimental task concepts in an experiment dimension and the corresponding cognitive function concepts in a function dimension, which describes an experimental purpose.
- *has-result-data*. It is between experiment concepts in an experiment dimension and the corresponding original data concepts in a data dimension, which describes results of an experiment.

By using the above two relations, cognitive function-related concepts and experiment design-related concepts are connected to the corresponding original data concepts. They form a general conceptual schema for describing the BI data origin. By extracting specific cognitive function concepts, such as "Numerical-Induction," specific experiment-related concepts, such as "EEG," "College-Student," and specific data concepts, such as "BOLD-Image-Sequence," as well as the corresponding relations among concepts, various conceptual schemata of BI data provenances can be obtained from the ontological Data-Brain. We can create instances of concepts and relations by collecting related information, for constructing various BI data provenances.

Furthermore, a BI *analysis provenance* is a metadata set that describes what processing in a brain data set has been carried out, including what analytic tasks were performed, what experimental data were used, what data features were extracted, and so on. For providing a general conceptual schema for BI analysis provenances, the experiment, data and analysis dimensions are connected by the following two relations:

- *has-origin-data*. It is between analytic process concepts in an analysis dimension and the corresponding data concepts in a data dimension, which describes input data of analytic processes.
- *has-result-data*. It is between analytic process concepts in an analysis dimension and the corresponding data concepts in a data dimension, which describes results of analytic processes.

By using the above two relations, data analysis-related concepts are connected to the corresponding data concepts. They form a general conceptual schema for describing what processing in a brain data set has been carried out. We can also extract specific analysis-related concepts and data concepts, as well as the corresponding relations among

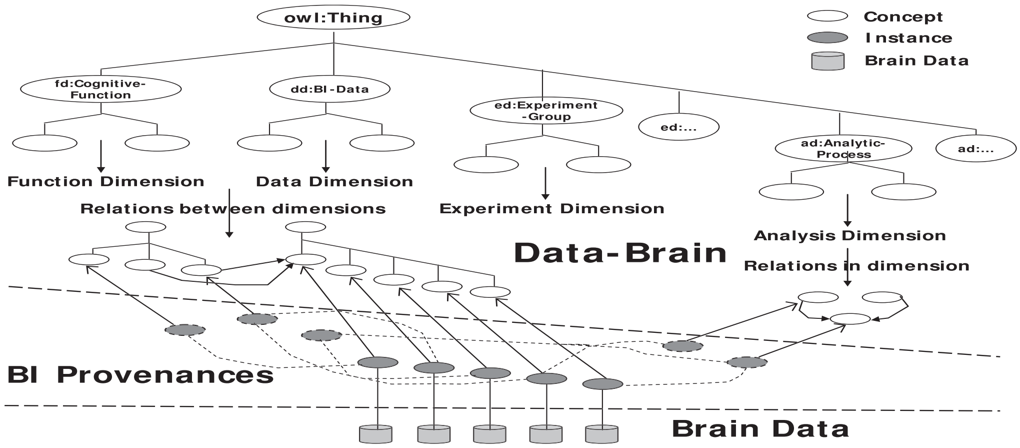

Fig. 8. Data-Brain, BI provenances, and brain data are integrated to construct a brain data center.

them, to obtain various conceptual schemata of BI analysis provenances. Various BI analysis provenances can also be constructed by creating and integrating instances of corresponding concepts and relations.

By using BI provenances as a bridge, the Data-Brain and various brain data can be integrated to construct a brain data center, as shown in Fig. 8. Such a brain data center is a brain data and knowledge base and stores original data, derived data and data features, as well as multiaspect and multilevel of data-related information and knowledge, for meeting various data requests of a systematic BI study.

4.8 The Evaluation of Data-Brain and Its Evolution

The evaluation of Data-Brain is an important issue of Data-Brain modeling. The existing approaches of ontology evaluation can be divided into four categories: golden standard, application based, data driven, and assessment by humans [4]. However, as stated above, the main purpose of Data-Brain modeling is not to develop a multidomain ontology about brain data but to construct a conceptual model of brain data to integrate data, information, and knowledge for various data requests of a systematic BI study. Thus, the evaluation of Data-Brain can only depend on the domain experts and an application-based approach. We evaluate the Data-Brain based on the responding levels of various data requests which are coming from different aspects of a systematic BI study and sent by researchers or research supporting systems.

The evolution of Data-Brain is another important issue of Data-Brain modeling. In order to enrich and update the Data-Brain constantly, we need to popularize the above BI methodology-based modeling approach in the global BI research community. A graphical modeling language and the corresponding modeling tools need to be developed to simplify and guide the whole modeling process. Similar work has been done in Geoinformatics [39] and Bioinformatics [12]. We also completed some primary work [6].

However, it is impossible to develop a powerful Data-Brain which can drive the systematic BI research approach, only depending on the manual and small-scale modeling work in the BI community. Existing resources and experiments should be included in the Data-Brain by some artful semiautomatic approaches. Related work is involved with the following two issues:

- how experiments encoded in existing databases or ontological resources can be reused, and
- how experiments and the knowledge described in scientific papers can be uploaded/absorbed in the Data-Brain.

For the first issue, the core is ontology mapping [9], [22] including ontology integration [36] and alignment [19] because the experiments encoded in public brain data repositories, such as fMRI data center [61], can be "translated" as ontological resources by database-based [47] or web-based [1], [2] ontology learning technologies. Aiming at some special ontological resources which describe the small-scale and special domain knowledge, such as NEMO [11] and brain cortex anatomy ontology [20], the Data-Brain can directly import them as sub-models or refer to them as external knowledge sources by ontology alignment. Aiming at some general or temporary ontological resources, especially the ontological resources "translated" from the experiments in databases, some technologies of ontology mapping and integration, such as assessing concept similarity [17], need to be adopted. This is an issue for ontology mapping between an integrated global ontology and local ontologies [9], and can be supported by some existing tools [3], [10].

For the second issue, the core is ontology learning from texts, involved with concept extraction [30], [32], relation discovery (taxonomic relation discovery [15], [31] and nontaxonomic relation discovery [27], [28]), and axiom acquisition [38]. In the Data-Brain modeling, the study on ontology learning from texts mainly focuses on concept extraction and nontaxonomic relation discovery, just like the studies in other life science domains [25], [48]. Though recent technologies on taxonomic relation discovery, such as probabilistic taxonomy learning [13], have been applied in various ontology learning tasks successfully, they can only play a secondary role on defining the concept hierarchy of dimension for the Data-Brain modeling. As stated above, the Data-Brain modeling is not to develop a multidomain ontology about brain data but to construct a conceptual model of brain data for systematic BI study. Thus, the concept hierarchy of dimension should be defined based on

TABLE 1
Experimental Data Stored in the Brain Data Center

ExpGroupID	Description
EG2	30 fMRI experiments for the sentential inductive strength judgment
EG3	22 fMRI experiments for the sentential induction with multi-level preconditions
EG6	14 fMRI experiments for the figural induction
EG7-1	11 ERP experiments for the reversed triangle induction
EG7-2	30 fMRI experiments for the reversed triangle induction
EG8	14 ERP experiments for the simultaneously presented reversed triangle induction
EG9	14 ERP experiments for the sentential inductive strength judgment
EG10	16 ERP supplementary experiments for the sentential inductive strength judgment

TABLE 2
Analytical Results Stored in the Brain Data Center

ID	Name	Data Feature
AP1	The data analysis for the fMRI dataset of EG2	23 Activations
AP2	The data analysis for the fMRI dataset of EG3	15 Activations
AP3	The data analysis for the fMRI dataset of EG6	86 Activations
AP4	The data analysis for the ERP dataset of EG7-1	10 ERP components
AP5	The data analysis for the fMRI dataset of EG7-2	15 Activations
AP6	The data analysis for the ERP dataset of EG8	14 ERP components
AP7	The data analysis for the ERP dataset of EG9	12 ERP components
AP8	The data analysis for the supplementary ERP dataset of EG10	20 ERP components

viewpoints of systematic BI methodology, as stated in the above BI methodology-based modeling approach.

5 Illustrative Examples

In this section, two realistic use cases are used to illustrate the usefulness of the Data-Brain for various data requests of a systematic BI study.

Experiments are based on a prototype system of brain data center which stores the human inductive reasoning centric BI experimental data. As shown in Table 1, these data were obtained from 151 subjects in eight groups of experiments. The corresponding analytical results shown in Table 2 were also stored into this data center. Assisted by domain experts, a Data-Brain prototype was constructed by the BI methodology-based modeling approach as stated in Section 4, which includes 119 concepts and 36 relations.

The function dimension is very simply. It includes the cognitive function concepts with respect to human inductive reasoning and its direct/indirect subclasses. Furthermore, since many same data features are obtained from the numeric induction tasks and the computation tasks [33], we added the relation "related-to-in-function" between the concept "Numeric Induction" and the concept "Computation." Similarly, we also added the relation "includes-in-function" between the concept "Induction" and the concept "Memory." Based on this function dimension, as shown in Fig. 9, a human inductive reasoning centric conceptual view can be extracted by Algorithm 1. Although it is quite simple, this conceptual view provides a comprehensive view of human inductive reasoning centric BI investigations and can be regarded as a user interface to access the brain data center.

The information coming from related experimental studies and data analysis, including subject information, experimental process information, scanning protocol information, analytical parameters, etc., was used to construct various Resource Description Framework [24] (RDF)-based BI provenances by a Data-Brain-based approach [8]. Furthermore, the OWL-based Data-Brain and RDF-based BI provenances were combined as a knowledge base of BI data to respond Simple Protocol and RDF Query Language (SPARQL) [37] queries for various data requests of a systematic BI study as stated in Section 2.2. Because of the limitation of space, we only introduce two typical use cases as follows:

Use case 1. For uncovering the principles and mechanisms of HIPS, BI often focuses on the information about activated brain areas during human information processing courses, including which brain areas are activated, what the size of activated areas are, etc. Thus, during studies of human sentential induction, researchers often need to know what brain areas are activated in the information processing

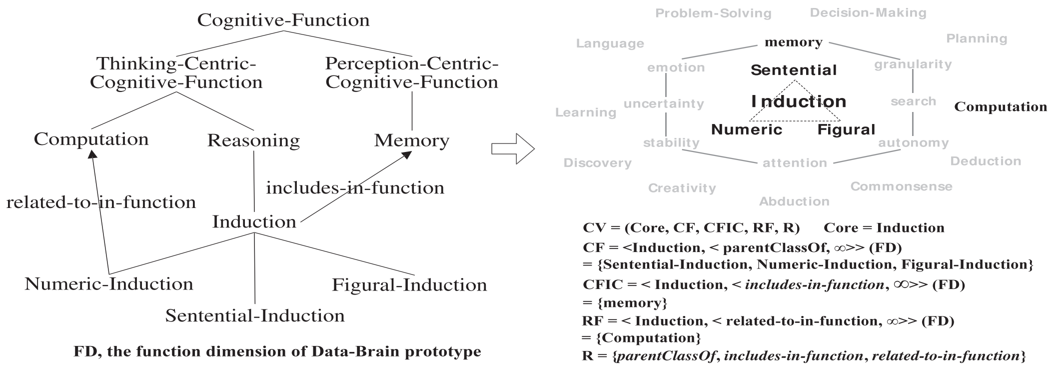

Fig. 9. View extraction for an inductive reasoning centric conceptual view. The light-color words, such as "Problem-Solving" and "emotion," represent some cognitive functions which have potential functional relationships with "Induction," but the relationships cannot be proved by the data and analytical results in the brain data center.

```
Q1: SELECT DISTINCT ?ExpGroupID ?ExpTaskID ?DataFeatureURI
WHERE {
(1) ?ExpGroupURI ed:has-experimental-means ?MeasuringInstrument.
(2) ?MeasuringInstrument rdf:type ed:MRI.
(3) ?ExpGroupURI ed:ID ?ExpGroupID.
(4) ?ExpGroupURI ed:has-experimental-task ?ExpTaskURI.
(5) ?ExpTaskURI ed:ID ?ExpTaskID.
(6) ?ExpTaskURI db:has-experimental-purpose ?CognitiveFunction.
(7) ?CognitiveFunction rdf:type fd:Sentential-Induction.
(8) ?DataFeatureURI db:produced-by ?ExpTaskURI.
(9) ?DataFeatureURI rdf:type dd:Activation.
(10)?DataFeatureURI db:located-in ?BrainAreaURI.
(11)?BrainAreaURI rdf:type rd:Frontal-Lobe.
(12)?DataFeatureURI dd:nox ?Nox.
(13)FILTER ( xsd:integer(?Nox) > 100)
} ORDER BY ASC(?ExpGroupID)
```

Fig. 10. The SPARQL query Q1.

TABLE 3
Results of Query Q1

ExpGroupID	ExpTaskID	DataFeatureURI
EG2	ST02	../Activation/A16
EG2	ST02	../Activation/A17
EG2	ST02	../Activation/A18
EG2	ST02	../Activation/A19
EG2	ST03	../Activation/A27

courses of human sentential induction based on the existing experimental data and analytical results in the current brain data center. The relevant data request can be described as: "get all of activations (8-9) of sentential induction tasks (6-7), as well as the corresponding experimental groups and experimental tasks (1-5), which are located in the frontal lobe (10-11) and whose sizes are larger than 100 voxels (12-13)" (note: the numbers appearing in parenthesis refer to the line numbers within the query Q1). Fig. 10 is the corresponding query expression expressed in SPARQL language.

As shown in Table 3, the results of query Q1 can be easily reformatted into a table where the column names are the variables of the SELECT section of the query. We can see that five activations are included in this table. This means that, based on the experimental data and analytical results stored in the brain data center, five activations in frontal lobe whose sizes are larger than 100 voxels are found during the information processing course of human sentential induction.

Table 4 gives the detail information of the activations in Table 3. Note that, in Q1 only the anatomical area *Frontal-Lobe* was initially specified (line 11). However, because we performed the *Q1* on the inference model which is obtained by reasoning on the knowledge base using the commonsense rule "any data feature which is located in a $Brain\text{-}Area_1$, also is located in any *Brain-Area* that *includes* $Brain\text{-}Area_1$," the system can infer that the *A19* located in *Left Middle Frontal Gyrus* and *A27* located in *Right Inferior Frontal Gyrus* are also located in *Frontal-Lobe* and so returns them. Similarly, using the commonsense rule "any data feature which is located in a $Brain\text{-}Area_1$, also is located in any *Brain-Area* that $Brain\text{-}Area_1$ *may-be*," the system returns the activations *A16*, *A17*, and *A18*. These results cannot be obtained by the traditional relational database-based data/metadata bases. This is the reason that the Data-Brain and BI provenances are constructed by using OWL and RDF.

TABLE 4
The Detail Information of Activations Found by Q1

ID	Location	nox	Coordinate	T
A16	Left Superior or Medial Frontal Gyrus (BA8)	823	(-12.0,32.0,48.0)	5.56
A17	Left Superior or Medial Frontal Gyrus (BA9)	823	(-8.0,50.0, 40.0)	4.01
A18	Left ACC or Medial Frontal Gyrus (BA32/9)	128	(-8.0,38.0,22.0)	4.4
A19	Left Middle Frontal Gyrus (BA10/11)	169	(-38.0,50.0,-6.0)	3.97
A27	Right Inferior Frontal Gyrus (BA45/46)	237	(50.0,34.0,8.0)	5.07

```
Q2: SELECT DISTINCT ?ExpTaskName1 ?FeatID1 ?ExpTaskName2
?FeatID2 ?FeatureName WHERE {
(1) ?ExpTaskURI1 db:has-experimental-purpose ?CognitiveFunction1.
(2) ?CognitiveFunction1 rdf:type fd:Induction.
(3) ?ExpTaskURI1 ed:name ?ExpTaskName1.
(4) ?ExpTaskURI2 db:has-experimental-purpose ?CognitiveFunction2.
(5) ?CognitiveFunction2 rdf:type fd:Computation.
(6) ?ExpTaskURI2 ed:name ?ExpTaskName2.
(7) ?ExpTaskURI1 db:produces ?FeatureURI1.
(8) ?ExpTaskURI2 db:produces ?FeatureURI2.
(9) ?FeatureURI1 rdf:type dd:Structured-Data-Feature.
(10)?FeatureURI2 rdf:type dd:Structured-Data-Feature.
(11)?FeatureURI1 dd:ID ?FeatID1.
(12)?FeatureURI2 dd:ID ?FeatID2.
(13)?FeatureURI1 dd:name ?FeatureName.
(14)?FeatureURI2 dd:name ?FeatureName.
} ORDER BY ASC(?ExpTaskName1)
```

Fig. 11. The SPARQL query Q2.

Use case 2. Systematic investigation of human thinking centric cognitive functions is an important issue of BI methodology. For example, a researcher focusing on human induction also needs to take into account the relationships between induction and other related human cognitive functions. The conceptual view shown in Fig. 9 hints that induction is functionally related to computation based on the data and analytical results in the brain data center. Thus, researchers often want to know what relationships exist between induction and computation. The relevant data request can be described as: "get all of similar (13-14) data features (7-12) which are extracted from the data of both induction (1-3) and computation (4-6)" (note: the numbers appearing in parenthesis refer to the line numbers within the query Q2). Fig. 11 shows the corresponding query expression.

The results of query Q2 are shown in Table 5. Table 6 gives the detail information of the found data features. For different objectives, researchers often identify the "similar" data features according to different rules. In Q2, we adopt a kind of qualitative rule (line 13-14), i.e., "all of data features which have a same name are the *similar* data features."[2] The nine results in Table 5 show that the analytical results coming from three types of inductive tasks have some similar ERP components with the results of a reversed

2. It is difficult to quantitatively compare the analytical results coming from different ERP experiments because of the huge differences on experimental designs and subjects. Researchers often adopt some qualitative methods/rules. During the ERP data analysis, researchers need to consider multiple factors, including time, location, amplitude, information processing course, etc., for naming ERP components. Thus, the name of ERP components is a kind of useful feature for qualitatively comparing the analytical results belonging to different experiments, as well as identifying the "similar" ERP components.

TABLE 5
Results of Query Q2

ExpTaskName1	Feat1	ExpTaskName2	Feat2
The reversed triangle inductive task (ERP)	EC15	The reversed triangle computing task (ERP)	EC16
The reversed triangle inductive task (ERP)	EC17	The reversed triangle computing task (ERP)	EC18
The reversed triangle inductive task (ERP)	EC19	The reversed triangle computing task (ERP)	EC20
The reversed triangle inductive task (ERP)	EC21	The reversed triangle computing task (ERP)	EC22
The simultaneously presented reversed triangle inductive task	EC11	The reversed triangle computing task (ERP)	EC22
The simultaneously presented reversed triangle inductive task	EC12	The reversed triangle computing task (ERP)	EC24
The congruent task for sentential inductive strength judgment	EC33	The reversed triangle computing task (ERP)	EC24
...	...	...	...

TABLE 6
The Detail Information of Data Features Found by Q2

ID	Name	Information processing Course
EC15	the posterior P100	number recognition
EC16	the posterior P100	number recognition
EC17	the frontal P300	understanding of tasks in working memory
EC18	the frontal P300	understanding of tasks in working memory
EC19	the posterior P300	understanding of tasks in working memory
EC20	the posterior P300	understanding of tasks in working memory
...	...	...

triangle computing task. These ERP components provide a useful evidence for the relation "related-to-in-function" between the concept "Numeric Induction" and the concept "Computation." They are important information for further studies. Other qualitative and quantitative rules for identifying the similar data features can be realized by queries similar to Q2. We can also use the commonsense rules stated above to get more results based on the part-whole relationships among brain areas.

Furthermore, only the general concept *Induction* (2) was initially indicated in Q2. However, since in the function dimension of the Data-Brain *Sentential Induction*, *Numeric Induction*, and *Figural Induction* are subsumed by *Induction*, the system can infer that the sentential, numeric, and figural inductions are also induction and integrate their data as data sources for finding relevant data features.

In summary, these two use cases illustrate that, the BI methodology-based domain-driven modeling approach makes it possible to integrate the necessary data, information, and knowledge based on a Data-Brain for responding various data requests of a systematic BI study. While a concise data request is requested, the system, thanks to our conceptual model of brain data, i.e., the Data-Brain, and Data-Brain-based BI provenances, automatically broadens the search to find relevant data, information, and knowledge for such a specific requirement. This shows the usefulness of the proposed Data-Brain modeling approach.

6 Conclusions

The Data-Brain modeling is a core issue of BI study. For supporting systematic BI study, we proposed a new conceptual model of brain data, called Data-Brain, which is with multiple conceptual views and its own four dimensions corresponding to the four aspects of systematic BI methodology. Such a Data-Brain can be constructed by a BI methodology-based ontological modeling approach. Two realistic use cases illustrated how the Data-Brain can be used for various data requests which are coming from different aspects of a systematic BI study. This shows the usefulness of the proposed modeling method by an application-based approach. As the core of BI data cycle system, the Data-Brain represents a radically new ways of storing and sharing data and knowledge, as well as enables high speed, distributed, large-scale, multiaspect analysis and computation on the wisdom web and knowledge grids. It plays a central role in BI study by providing the following functions:

- A domain-driven conceptual model of human brain data, which explicitly describes the relationships among multiple human brain data, with respect to all major aspects and capabilities of a domain of HIPS studies, for supporting systematic human brain data management, integration and sharing;
- A knowledge base of systematic BI study, which integrates brain data-related multiaspect domain knowledge to support various knowledge-driven data applications and to provide valuable knowledge sources for solving special domain problems;
- A global view and knowledge framework for constructing a BI data cycle system, on which various brain data sources and research supporting functions are deployed as agents to support the whole BI methodology-based systematic BI study.

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