Essence Computation Oriented Multi-semantic Analysis Crossing Multi-modal DIKW Graphs

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Abstract. Based on our previous proposal of an existence level computation and reasoning approach called Existence Computation, which extends traditional identification of objects towards an existence level clarification, and a semantic expression mechanism called Relationship Defined Everything of Semantics which adopts the ideology that entities are defined or determined by more essential relationships or structures, we proposed in this work that although resource or content processing are embodied in every modal of the target content, the essence of the requirement of processing instead of the projected modal of the content is vital as the source of processing towards expected result. From the perspective of processing of multiple modal resources or content in the background of insufficient single modal resource to achieve progress in decision making and improve precision of computation with higher efficiency, we propose an approach called Essence Computation and Reasoning, originating in existence computation level and relationship defined everything of semantics models, to synchronize crossing modal processing towards minimizing the uncertainties through merging cross modals and inter modal or meso-scale capabilities of available data, information, knowledge and wisdom (DIKW). We show the application of essence computation and reasoning of modal transformation and deduplication analysis crossing multiple semantics modals of data modal, information modal and knowledge modal in an encoding and decoding case.

Keywords: DIKW graphs · Multi-semantic · Cross-modal transformation · Privacy protection · Edge computing · Essence computation

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1 Introduction

The current data collection, information processing, and knowledge fusion processing mechanisms are relatively lagging behind the accelerated generation of multi-modal, multi-scale and even mesoscale content processing in the information world. It is difficult to maintain the cognitive processing capacity of social individuals and the ability to improve the dynamic balance of content growth with the help of current information processing facilities. Facing the challenge of cognitive overload in the context of multi-level, multi-dimensional, multi-modal, multi-scale social information network massive content, natural annotation of big data and multi-source association to obtain open domain knowledge, the current semantics with natural language as the core understanding and semantic fusion research is mostly based on the natural language semantics and context analysis and retrieval of multiple knowledge based on scene knowledge graphs, affair knowledge graphs, temporal knowledge graphs, and reinforcement learning. This type of analysis method faces arduous challenges in terms of understandable modeling theory and interpretable semantic representation technology when dealing with mixed subjective and objective multi-modal content with both logic and artistic expression. In the context of language evolution consistent with the human-computer understanding of cross-modal interaction intentions in the environment and society, existing solutions are oriented to event-oriented and context-driven concepts and semantic migration of concept combinations, small sample common sense semantic capture. The general cognitive intelligence model that is adjusted across the semantic scope of the abstract level and the knowledge and other modalities lacks robust and adaptable natural language semantic cognitive understanding basic theoretical innovation support.

Based on the previous accumulation of cross-modal, cross-scale and even mesoscale cognitive semantics research work, we start from the solution of the uncertainty presented by artificial intelligence processing problems, facing the complex content objects and complex processing processes of the information discipline, focusing on subjectivity and the semantic essence expression and analysis of the artificial intelligence interpretability problem in the mesoscale category between the objective structure association and dynamic transformation. For example, by exploring the multi-modal, multi-scale, fuzzy, and even mesoscale concept semantic human-computer understanding and communication expression model as the prerequisite for the standardized processing of the essence of the problem [7,8,10], the development of cognitive semantic clarification, measurement and value orientation based on concept semantic traceability can be adapted to semantic optimization technology to build an artificial intelligence interpretable theoretical system based on the determination of essential semantics that integrates consciousness science, cognitive linguistics, information science, philosophy, etc. The method provides a theoretical basis for a new generation of interpretable precision intelligence based on complexity.

The semantic content is modeled based on the DIKW graphs [5,6,11]. TR_{DIKW} (typed resources) can be divided into D_{DIKW}(data resources), I_{DIKW}(information resources) and K_{DIKW}(knowledge resources). D_{DIKW} are discrete elements obtained by direct observation. They have no meaning without context, are not associated with a specific human purpose, and express the attribute content of a single entity. I_{DIKW} record human behavior and are used to mine, analyze, and express the interactive relationship between two entities. The entity can be another person or an objective thing. I_{DIKW} are related to a specific purpose of human beings, and the relationship between two entities can be inferred through the purpose. K_{DIKW} are derived from D_{DIKW} and I_{DIKW} through structured formalization. K_{DIKW} summarized the entity relationship abstractly on the basis of I_{DIKW}.

Multi-semantics refers to the understanding that the semantic content has multiple different purposes, that is, the TR_{DIKW} in the semantic content can be derived from various TR_{DIKW} to obtain I_{DIKW} with different purposes. Multi-semantic is caused by missing of TR_{DIKW} in semantic content, such as lack of D_{DIKW} or I_{DIKW}, which leads to a wider understanding of the content with different purposes, or by redundancy of TR_{DIKW} in semantic content. Redundant D_{DIKW} or I_{DIKW} will produce understandings of different purposes when combined with different TR_{DIKW}. Section 3 and Sect. 4 discuss these two reasons respectively. D_{DIKW} and I_{DIKW} can be transformed across modalities after combining the corresponding K_{DIKW}. In the process of solving multi-semantic, it is necessary to complete the transformation from the original TR_{DIKW} in the semantic content to the new TR_{DIKW}. The transformed objects are divided into D_{DIKW} and I_{DIKW}. Section 5 discusses the transformation methods for those two transformed objects. In addition to semantics, inadvertent behaviors of users in daily life will generate a lot of user behavior content, such as motion content and sound content. After modeling the user behavior content based on the DIKW graphs, the D_{DIKW}, I_{DIKW}, and K_{DIKW} contained in the user behavior content can be encoded and decoded to transform new TR_{DIKW} across modalities. Section 6 and Sect. 7 discuss the encoding and decoding modes of user content.

2 Related Work

Knowledge Graph identification [13] and Graph based intelligence analysis [3] has been increasingly recognized as both big challenges and great opportunities. In the links of Knowledge Graph. Xiao (2016) [14] proposes a two level hierarchical generative approach for semantics representation of Knowledge Graph through extracting aspects and assigns categories. Xu (2016) [15] presents an approach of representing Knowledge Graph with a combination of structural and textual encoding. Chen (2009) [2] presents visualization approaches based on distinguishing among Data, Information and Knowledge. Some existing works [1] has elaborated on the challenge of recovering implicit information extraction through state machine and abductive inference, etc. McSherry (2009) [12] present a strategy of information extraction through queries while taking care of the data privacy concerns in the background of sequential and parallel compositions. We present a formalization of the basic concepts of Data, Information and Knowledge and propose to protect privacy resources in a three-tier architecture consisting of Data Graph, Information Graph and Knowledge Graph in a value driven or cost-effective manner [4]. We model multi-semantic content and implement the elimination of multi-semantic in terms of transformation of type in the formalized DIKW architecture.

3 Solve Multi-semantic Caused by Missing $\boldsymbol{TR_{DIKW}}$

The missing TR_{DIKW} in semantic content has led to a reduction of the limitation of the scope of content understanding. By increasing the restriction on content understanding, the scope of content understanding can be narrowed, so that only one of the derived I_{DIKW} for different purposes is retained, thereby solving multi-semantics. Modeling the semantic content based on the data graph, information graph and knowledge graph. The missing TR_{DIKW} in semantic content can be divided into the missing of I_{DIKW} and the missing of D_{DIKW}.

3.1 Solve Multi-semantic Caused by Missing $\boldsymbol{I_{DIKW}}$

Semantic content "In the summer night, user A stays in the study room". can correspond to the following D_{DIKW} and I_{DIKW}.

$$\begin{aligned} D_{0_1} &= (A|T_{PLACE}(INS(Studyroom))) \\ D_{0_2} &= (T_{TIME}(Night)) \\ D_{0_3} &= (T_{SEASON}(Summer)) \\ I_0 &= R_{CORRESPOND}(D_{0_1},\ R_{COMBINE}(D_{0_2},\ D_{0_3})) \end{aligned} \tag{1}$$

Since the semantic content lacks the I_{DIKW} of "what does user A do in the study room", there will be ambiguities in understanding the content. For example, combining the data resource D_{0_1} "user A stays in the study room" and the knowledge resource K_1 "the study room is a place for learning", it can be deduced that the purpose of user A staying in the study room is to learn. Combining the data resource D_{0_2} "night" and the knowledge resource K_2 "people usually sleep at night", it can be deduced that the user A may be sleeping in the study room. These two derivation methods are correct in the absence of other relevant resources, but they produce I_{DIKW} with different purposes, leading to multi-semantic.

$$\begin{aligned} K_1 &= R_{IN}(T_{ACT}(Study),\ T_{PLACE}(Studyroom)) \\ K_2 &= R_{AT}(T_{ACT}(Sleep),\ T_{TIME}(Night)) \end{aligned} \tag{2}$$

$$\begin{aligned} D_{0_1} + K_1 \rightarrow I_{new_1} &= R_{PURPOSE}(A,\ T_{ACT}(Study)) \\ D_{0_2} + K_2 \rightarrow I_{new_2} &= R_{PURPOSE}(A,\ T_{ACT}(Sleep)) \\ K_{new_1} &= R_{CONFLICT}(I_{new_1}, I_{new_2}) \end{aligned} \tag{3}$$

The scope of content understanding can be narrowed by adding relevant D_{DIKW} or I_{DIKW} to solve multi-semantic.

Solve by Adding $\boldsymbol{D_{DIKW}}$. Obtain relevant data resources D_1 "The air condition in the bedroom is broken". D_2 "The air condition in the study room is good". Combining data resource D_{0_3} "Summer" and the knowledge resource

K_3 "Summer is hot", it can be deduced that the temperature in the bedroom is high and the temperature in the study room is low. Those D_{DIKW} increase the restrictions on the study room environment, thereby narrowing the scope of content understanding to temperature-related fields. Combined with the knowledge resource K_4 "People like to sleep in a cool place", it can be deduced that the temperature in the study room is low and suitable for sleeping, which supports the I_{DIKW} "User A stays in the study room is to sleep", thus solve the multi-semantic.

$$\begin{aligned}
&D_1 = (T_{FACILITY}(INS(AIR_CONDITION_{Bedroom}))|\ T_{CONDITION}(Broken))\\
&D_2 = (T_{FACILITY}(INS(AIR_CONDITION_{Studyroom}))|\ T_{CONDITION}(Normal))\\
&K_3 = R_{IS}(T_{SEASON}(Summer),\ T_{TEMP}(High))\\
&K_4 = R_{LIKE}(T_{PERSON},\ R_{IN}(T_{ACT}(Sleep),\ R_{IS}(T_{PLACE},\ T_{TEMP}(Low))))
\end{aligned} \tag{4}$$

$$\begin{aligned}
D_{0_3} + D_1 + K_3 \rightarrow D_{new_1} &= (T_{PLACE}(INS(Bedroom))|\ T_{TEMP}(High))\\
D_{0_3} + D_2 + K_3 \rightarrow D_{new_2} &= (T_{PLACE}(INS(Studyroom))|\ T_{TEMP}(Low))\\
D_{new_1} + D_{new_2} + K_4 \rightarrow I_{new_3} &= R_{LIKE}(A,\ R_{IN}(T_{ACT}(Sleep),\\
&\quad T_{PLACE}(INS(Studyroom)))\\
K_{new_2} &= R_{SUPPORT}(I_{new_3},\ I_{new_2})
\end{aligned} \tag{5}$$

Algorithm. (1) Combine known data resources D_0 and information resources I_0 with related K_{DIKW} to derive new information resources I_{new_1} and I_{new_2} with different purposes.

(2) Search related data resources $D_{related}$ in the data graph.

(3) Combine $D_{related}$ with related I_{DIKW} and K_{DIKW} to further derive new information resource I_{new_3} that can narrow the scope of understanding.

(4) Determine the relationship between I_{new_3} and I_{new_1} with I_{new_2}. Retain I_{DIKW} supported by I_{new_3}, and delete other I_{DIKW}.

(5) Set the remaining I_{DIKW} as the final result to solve multi-semantic.

Solve by Adding I_{DIKW}. Obtain related information resource I_1 "User A does not like learning". Combining D_{0_2} "night" and knowledge resource K_5 "Those who like to learn may study at night", it can be deduced that user A is unlikely to study in the study room at this time. This I_{DIKW} excludes the I_{DIKW} "User A stays in the study room is to learn" out of the scope of understanding of the content, and the only I_{DIKW} remaining "User A stays in the study room is to sleep" is the final result, thus solve the multi-semantic.

$$\begin{aligned}
&I_1 = !R_{LIKE}(A,\ T_{ACT}(Study))\\
&K_5 = R_{AT}(R_{DO}(T_{PERSON}(R_{LIKE}(T_{PERSON},\ T_{ACT}(Study))),\ T_{ACT}(Study)),\\
&\quad T_{TIME}(Night))
\end{aligned} \tag{6}$$

$$\begin{aligned}
D_{0_2} + I_1 + K_5 \rightarrow I_{new_4} &= !R_{DO}(A,\ T_{ACT}(Study))\\
K_{new_3} &= R_{OPPOSE}(I_{new_4},\ I_{new_1})
\end{aligned} \tag{7}$$

Algorithm. (1) Combine known data resources D_0 and information resources I_0 with related K_{DIKW} to derive new information resources I_{new_1} and I_{new_2} with different purposes.

(2) Search related information resources $I_{related}$ in the information graph.

(3) Combine $I_{related}$ with related I_{DIKW} and K_{DIKW} to further derive new information resource I_{new_3} that can narrow the scope of understanding.

(4) Determine the relationship between I_{new_3} and I_{new_1} with I_{new_2}. Retain I_{DIKW} supported by I_{new_3}, and delete other I_{DIKW}.

(5) Set the remaining I_{DIKW} as the final result to solve multi-semantic.

3.2 Solve Multi-semantic Caused by Missing D_{DIKW}

Semantic content "User A's seniority is greater than user B's." can correspond to the following D_{DIKW} and I_{DIKW}.

$$\begin{aligned} D_{0_1} &= (A|T_{SENIORITY}) \\ D_{0_2} &= (B|T_{SENIORITY}) \\ I_0 &= R_{GREATER\_THAN}(D_{0_1},\ D_{0_2}) \end{aligned} \tag{8}$$

Because the semantic content lacks D_{DIKW} related to "user A's age and user B's age", there are different purpose of understanding the I_{DIKW} of "the relationship between user A and user B's age". Although there is a knowledge resource K_1: "higher generation may be older", with this K_{DIKW}, new I_{DIKW} "user A may be older than user B" can be deduced. However, there are many examples of people has high seniority with young age, so it is still impossible to exclude the I_{DIKW} "User A may be younger than user B".

$$\begin{aligned} K_1 = R_{GREATER\_THAN}(&T_{AGE}(T_{PERSON}(T_{SENIORITY}(High)), \\ &T_{AGE}(T_{PERSON}(T_{SENIORITY}(Low)) \end{aligned} \tag{9}$$

$$\begin{aligned} I_0 + K_1 \rightarrow I_{new_1} &= R_{PROBABLY\_GREATER\_THAN}(T_{AGE}(A),\ T_{AGE}(B)) \\ I_{new_2} &= R_{PROBABLY\_LESS\_THAN}(T_{AGE}(A),\ T_{AGE}(B)) \end{aligned} \tag{10}$$

It is also possible to reduce the scope of understanding by adding relevant D_{DIKW} or I_{DIKW}, thereby solving multi-semantic.

Solve by Adding D_{DIKW}. Obtain related data resources D_1 "User A is mature in mind". D_2 "User B is innocent". Combining D_1 and D_2, the I_{DIKW} "User A is more mature than user B" is deduced. Those D_{DIKW} increase the restriction on the mentally mature relationship between user A and user B when determining "the age of user A and user B", and further narrow the scope of understanding of the content. Thus the previously deduced I_{DIKW} "User A is older than user B" is supported.

$$\begin{aligned} D_1 &= (A|T_{MIND}(Mature)) \\ D_2 &= (B|T_{MIND}(Naieve)) \end{aligned} \tag{11}$$

$$\begin{aligned} D_1 + D_2 \rightarrow I_{new_3} &= R_{MATURE\_THAN}(A,\ B) \\ I_{new_1} + I_{new_3} \rightarrow I_{new_0} &= R_{GREATER\_THAN}(T_{AGE}(A),\ T_{AGE}(B)) \end{aligned} \tag{12}$$

Algorithm. (1) Combine known data resources D_0 and information resources I_0 with related K_{DIKW} to derive new information resources I_{new_1} and I_{new_2} with different purposes.

(2) Search related data resources $D_{related}$ in the data graph.

(3) Combine $D_{related}$ with related I_{DIKW} and K_{DIKW} to further derive new information resource I_{new_3} that can narrow the scope of understanding.

(4) Determine the relationship between I_{new_3} and I_{new_1} with I_{new_2}. Retain I_{DIKW} supported by I_{new_3}, and delete other I_{DIKW}.

(5) Set the remaining I_{DIKW} as the final result to solve multi-semantic.

Solve by Adding $\boldsymbol{I_{DIKW}}$. Obtain relevant information resources I_1 "User B respects user A very much". Knowledge resource K_3 "People with low status respect people with high status". Combining I_1 and K_3, I_DIKW "User A has a higher status than user B" is deduced. Those D_{DIKW} increase the restriction on the status relationship between user A and user B when judging "the age of user A and user B", and further narrow the scope of understanding of the content. Thus the previously deduced I_{DIKW} "User A is older than user B" is supported.

$$\begin{aligned} I_1 &= R_{RESPECT}(B,\ A) \\ K_3 &= R_{RESPECT}(T_{PERSON}(T_{STATUS}(Low)),\ T_{PERSON}(T_{STATUS}(High))) \end{aligned} \tag{13}$$

$$\begin{aligned} I_1 + K_3 \rightarrow I_{new_3} &= R_{GREATER\_THAN}(T_{STATUS}(A),\ T_{STATUS}(B)) \\ I_{new_1} + I_{new_3} \rightarrow I_{new_0} &= R_{GREATER\_THAN}(T_{AGE}(A),\ T_{AGE}(B)) \end{aligned} \tag{14}$$

Algorithm. (1) Combine known data resources D_0 and information resources I_0 with related K_{DIKW} to derive new information resources I_{new_1} and I_{new_2} with different purposes.

(2) Search related information resources $I_{related}$ in the information graph.

(3) Combine $I_{related}$ with related I_{DIKW} and K_{DIKW} to further derive new information resource I_{new_3} that can narrow the scope of understanding.

(4) Determine the relationship between I_{new_3} and I_{new_1} with I_{new_2}. Retain I_{DIKW} supported by I_{new_3}, and delete other I_{DIKW}.

(5) Set the remaining I_{DIKW} as the final result to solve multi-semantic.

4 Solve Multi-semantic Caused by Redundant $\boldsymbol{TR_{DIKW}}$

Redundancy in semantic content refers to the understanding that the D_{DIKW} or I_{DIKW} in the semantic content have multiple different purposes on the same issue. Model the semantic content based on DIKW graphs. The redundant of TR_{DIKW} in semantic content can be divided into I_{DIKW} redundancy and D_{DIKW} redundancy.

4.1 Solve Multi-semantic Caused by Redundant I_{DIKW}

Semantic content "User A likes to play basketball, user A hates sports." can correspond to the following I_{DIKW}.

$$\begin{aligned} I_{0_1} &= R_{LIKE}(A,\ T_{ACT}(Basketball)) \\ I_{0_2} &= R_{HATE}(A,\ T_{ACT}(Sports)) \end{aligned} \tag{15}$$

Knowledge resources K_1 "Playing basketball is a type of sport". K_2 "The relationship "hates" and the relationship "likes" contradicts". From I_{0_2} and K_1, user A hates sports, and playing basketball belongs to a type of sports, new information resource I_{new_1} "User A hates playing basketball can be deduced". With K_2 Knows that I_{0_1} contradicts I_{new_1}, therefore, for the question of "User A's attitude towards playing basketball", I_{0_1} and I_{0_2} have different understandings, representing the redundancy of I_{DIKW} in the semantic content.

$$\begin{aligned} K_1 &= R_{BELONG_TO}(T_{ACT}(Basketball),\ T_{ACT}(Sports)) \\ K_2 &= R_{OPPOSE}(T_{RELATION}(Like), T_{RELATION}(Hate)) \end{aligned} \tag{16}$$

$$\begin{aligned} I_{0_2} + K_1 \rightarrow I_{new_1} &= R_{HATE}(A,\ T_{ACT}(Basketball)) \\ I_{0_1} + I_{new_1} + K_2 \rightarrow K_{new_1} &= R_{CONFLICT}(I_{0_1}, I_{new_1}) \end{aligned} \tag{17}$$

From the above derivation, it can be seen that the redundant information resources I_{0_1} and I_{0_2} are contradictory, so there must be an error in one of them. It can help to determine the correctness of redundant I_{DIKW} by adding relevant D_{DIKW} or I_{DIKW}, thereby solving multi-semantic.

Solve by Adding D_{DIKW}. Obtain the spatial data resource D_1 related to user A "basketball court". There are relevant knowledge resources K_3 "The main activity in the basketball court is playing basketball". K_4 "People who often play basketball like to play basketball". Combining D_1 and K_3, user A often appears in the basketball court, so user A often plays basketball. Combined with K_4, user A often plays basketball, and people who play basketball frequently are likely to like basketball, indicating that user A is likely to like basketball and supports I_{0_1}. When the information resource I_{0_1} has supporting D_{DIKW} but the information resource I_{0_2} does not have supporting D_{DIKW}, it tends to determine that I_{0_1} is correct and I_{0_2} is wrong.

$$\begin{aligned} &D_1 = (A|T_{PLACE}(INS(BasketballCourt)) \\ &K_3 = R_{IN}(T_{ACT}(Basketball),\ T_{PLACE}(BasketballCourt)) \\ &K_4 = R_{LIKE}(T_{PERSON}(R_{DO}(person,\ T_{ACT}(Basketball))),\ T_{ACT}(Basketball)) \end{aligned} \tag{18}$$

$$\begin{aligned} D_1 + K_3 \rightarrow I_{new_2} &= R_{DO}(A|T_{ACT}(Basketball)) \\ I_{new_2} + K_4 \rightarrow I_{new_3} &= R_{LIKE}(A,\ T_{ACT}(Basketball)) \\ K_{new_2} &= R_{SUPPORT}(I_{new_3}, I_{0_1}) \end{aligned} \tag{19}$$

Algorithm. (1) Find the conflicting information resources I_{0_1} and I_{0_2}.

(2) Search related data resources $D_{related}$ in the data graph.

(3) Combine $D_{related}$ with related I_{DIKW} and K_{DIKW} to further derives new information resource I_{new} that can help judge the truth.

(4) Determine the relationship between I_{new} and I_{0_1} with I_{0_2}. Keep the result supported by I_{new}, and delete the other result.

(5) Set the result supported by I_{new} as the final result to solve multi-semantic.

Solve by Adding I_{DIKW}. Obtain related information resource I_1 "User A is a member of school's basketball team". There are relevant knowledge resources K_5 "The members of the basketball school team often play basketball". Combining I_1 and K_5, user A is a member of school's basketball team, so user A often plays basketball. Combined with K_4, user A often plays basketball, and people who often play basketball are likely to like to play basketball, indicating that user A is likely to like playing basketball and supports the information resource I_{0_1}. When the information resource I_{0_1} has supporting I_{DIKW} but the information resource I_{0_2} does not have supporting I_{DIKW}, it tends to determine that I_{0_1} is correct and I_{0_2} is wrong.

$$\begin{aligned} I_1 &= R_{IS\_A\_MEMBER\_OF}(A,\ T_{GROUP}(INS(BasketballTeam)) \\ K_5 &= R_{DO}(T_{PERSON}(R_{IN}(person,\ T_{GROUP}(BasketballTeam)),\ T_{ACT}(Basketball)) \end{aligned} \tag{20}$$

$$\begin{aligned} I_1 + K_5 \rightarrow I_{new_4} &= R_{DO}(A,\ T_{ACT}(Basketball)) \\ I_{new_4} + K_4 \rightarrow I_{new_5} &= R_{LIKE}(A,\ T_{ACT}(Basketball)) \\ K_{new_3} &= R_{SUPPORT}(I_{new_5}, I_{0_1}) \end{aligned} \tag{21}$$

Algorithm. (1) Find conflicting information resources I_{0_1} and I_{0_2}.

(2) Search related information resources $I_{related}$ in the information graph.

(3) Combine $I_{related}$ with related I_{DIKW} and K_{DIKW} to further derives new information resource I_{new} that can help judge the truth.

(4) Determine the relationship between I_{new} and I_{0_1} with I_{0_2}. Keep the result supported by I_{new}, and delete the other result.

(5) Set the result supported by I_{new} as the final result to solve multi-semantic.

4.2 Solve Multi-semantic Caused by Redundant D_{DIKW}

Semantic content contains data resources D_{0_1} "today's temperature is 30°". D_{0_2} "today's temperature is 20°".

$$\begin{aligned} D_{0_1} &= (T_{TEMP}(30)) \\ D_{0_2} &= (T_{TEMP}(20)) \end{aligned} \tag{22}$$

In response to the issue of "today's temperature", the data resources D_{0_1} and D_{0_2} are contradictory, indicating that upon the redundant data resources D_{0_1} and D_{0_2} there must be an error in one of them. It is possible to add relevant

D_{DIKW} or I_{DIKW} to help judge the correctness of redundant D_{DIKW}, thereby solving multi-semantic.

Solve by Adding $\boldsymbol{D_{DIKW}}$. Obtain data resources D_1 "summer". D_2 "Hainan". Knowledge resource K_1 "Hainan has higher temperatures in summer". Combining D_1, D_2 and K_1, it can be deduced that today's temperature should be high. Thus, data resource D_{0_1} is supported. When the data resource D_{0_1} has supporting D_{DIKW} but the data resource D_{0_2} does not have supporting D_{DIKW}, it tends to determine that D_{0_1} is correct but D_{0_2} is wrong, thereby solving the multi-semantic.

$$\begin{aligned}
&D_1 = (T_{SEASON}(Summer))\\
&D_2 = (T_{PLACE}(Hainan))\\
&K_1 = R_{IS}(R_{IN}(T_{PLACE}(Hainan),\ T_{SEASON}(Summer)),\ T_{TEMP}(High))
\end{aligned} \tag{23}$$

$$\begin{aligned}
D_1 + D_2 + K_1 \rightarrow D_{new_1} &= (T_{TEMP}(High))\\
K_{new_1} &= R_{SUPPORT}(D_{new_1},\ D_{0_1})
\end{aligned} \tag{24}$$

Algorithm. (1) Find conflicting data resources D_{0_1} and D_{0_2}.

(2) Search related data resources $D_{related}$ in the data graph.

(3) Combine $D_{related}$ with related I_{DIKW} and K_{DIKW}, further derives new data resource D_{new} that can help judge the truth.

(4) Determine the relationship between D_{new} and D_{0_1} with D_{0_2}. Keep the result supported by D_{new}, and delete the other result.

(5) Set the result supported by D_{new} as the final result to solve multi-semantic.

Solve by Adding $\boldsymbol{I_{DIKW}}$. Obtain information resource I_1 "Data resource D_{0_1} comes from the Bureau of Meteorology". Information resource I_2 "Data resource D_{0_2} comes from the Internet". Knowledge resources K_2 "Data from professional institutions is more reliable than data from the Internet". Combining information resources I_1, I_2 and knowledge resources K_2, it can be deduced that data resources D_{0_1} are more reliable than data resources D_{0_2}. Thus, it can be judged that D_{0_1} is correct but D_{0_2} is wrong, thereby solving the multi-semantic.

$$\begin{aligned}
I_1 &= R_{FROM}(D_{0_1},\ T_{INSTITUTE}(INS(MeteorologicalBureau))\\
I_2 &= R_{FROM}(D_{0_2},\ T_{INTERNET}(INS(Website))\\
K_2 &= R_{RELIABLE_THAN}(T_{DATA}(R_{FROM}(data,\ T_{INSTITUTE})),\\
&\quad T_{DATA}(R_{FROM}(data,\ T_{INTERNET})))
\end{aligned} \tag{25}$$

$$\begin{aligned}
I_1 + I_2 + K_2 \rightarrow I_{new_1} &= R_{RELIABLE_THAN}(D_{0_1},\ D_{0_2})\\
K_{new_2} &= R_{SUPPORT}(I_{new_1},\ D_{0_1})
\end{aligned} \tag{26}$$

Algorithm. (1) Find conflicting data resources D_{0_1} and D_{0_2}.

(2) Search related information resources $I_{related}$ in the information graph.

(3) Combine $I_{related}$ with related I_{DIKW} and K_{DIKW}, further derives new information resource I_{new} that can help judge the truth.

(4) Determine the relationship between I_{new} and D_{0_1} with D_{0_2}. Keep the result supported by I_{new}, and delete the other result.

(5) Set the result supported by D_{new} as the final result to solve multi-semantic.

5 Cross-modal Transformation of TR_{DIKW}

Whether in the detection of multi-semantic phenomena, or in the process of solving the multi-semantics and increasing the related TR_{DIKW}, it is necessary to complete the cross-modal transformation from the original TR_{DIKW} to the new TR_{DIKW}. Therefore, this section focuses on the cross-modal transformation of TR_{DIKW}. The target TR_{DIKW} of transformation can be divided into D_{DIKW} and I_{DIKW}.

5.1 Transform TR_{DIKW} to Purposed D_{DIKW}

The target TR_{DIKW} of transformation is D_{DIKW} "user A's occupation".

$$D_0 = (A|T_{OCCUPATION}(INS(Student)) \tag{27}$$

There are three ways to derive D_0, by combining D_{DIKW} with K_{DIKW}, by combining I_{DIKW} with K_{DIKW}, and by combining D_{DIKW} and I_{DIKW} with K_{DIKW}.

Transform D_{DIKW} Combined with K_{DIKW} to Purposed D_{DIKW}. Obtain related data resource D_1 "user A is 10 years old". There is relevant knowledge resources K_1 "people younger than 15 should go to school". Combining D_1 and K_1, user A is 10 years old, and his age is less than 15 years old, I_{DIKW} "user A should go to school" is deduced. So the target D_{DIKW} of "user A's occupation is student" can be further deduced.

$$\begin{aligned}
&D_1 = (A|T_{AGE}(10))\\
&K_1 = R_{SHOULD}(T_{PERSON}(R_{LESS\ THAN}(T_{AGE},\ 15)),\ T_{ACT}(Education))
\end{aligned} \tag{28}$$

$$\begin{aligned}
D_1 + K_1 \rightarrow I_{new_1} &= R_{SHOULD}(A,\ T_{ACT}(Education))\\
I_{new_1} \rightarrow I_0 &= R_{IS}(A,\ T_{OCCUPATION}(INS(Student))\\
I_0 \rightarrow D_0 &= (A|T_{OCCUPATION}(INS(Student))
\end{aligned} \tag{29}$$

Transform I_{DIKW} Combined with K_{DIKW} to Purposed D_{DIKW}. Obtain relevant information resources I_1 "User A often goes to school". I_2 "User A does not have a teacher qualification certificate". Knowledge resources K_2 "students and teachers need to go to school frequently". K_3 "teachers have teacher qualification certificates". Combining I_1 and K_2, since user A often goes to school, it can be known that user A is a student or teacher. Combining I_2 and K_3, since user A does not have a teacher qualification certificate, so I_{DIKW} "user A is not a teacher" is deduced. In the case that user A is a student or teacher and user A is not a teacher, the target D_{DIKW} of "user A's occupation is a student" can be further deduced.

$$\begin{aligned}
I_1 &= R_{GO_TO}(A,\ T_{PLACE}(INS(School))) \\
I_2 &= !R_{OWN}(A,\ T_{LICENCE}(INS(TeacherCertification))) \\
K_2 &= R_{GO_TO}(T_{OCCUPATION}(Student)\ AND\ T_{OCCUPATION}(Teacher), \\
&\quad T_{PLACE}(School)) \\
K_3 &= R_{OWN}(T_{OCCUPATION}(Teacher),\ T_{LICENCE}(INS(TeacherCertification)))
\end{aligned} \tag{30}$$

$$\begin{aligned}
I_1 + K_2 \rightarrow I_{new_2} &= R_{IS}(A,\ T_{OCCUPATION}(INS(Student)\ OR \\
&\quad T_{OCCUPATION}(INS(Teacher)) \\
I_2 + K_3 \rightarrow I_{new_3} &= !R_{IS}(A,\ T_{OCCUPATION}(INS(Teacher)) \\
I_{new_2} + I_{new_3} \rightarrow I_0 &= R_{IS}(A,\ T_{OCCUPATION}(INS(Student)) \\
I_0 \rightarrow D_0 &= (A|T_{OCCUPATION}(INS(Student))
\end{aligned} \tag{31}$$

Transform D_{DIKW} and I_{DIKW} Combined with K_{DIKW} to Purposed D_{DIKW}. Obtain relevant data resource D_1 "User A is 10 years old this year". Information resource I_1 "User A often goes to school". Knowledge resources K_2 "students and teachers need to go to school frequently". K_4 "teachers' age is generally greater than 20". Combining I_1 and K_2, due to user A often goes to school, it can be known that user A is a student or teacher. Combining D_1 and K_2, since user A is 10 years old this year, and the teacher's age is generally greater than 20 years old, I_{DIKW} "user A is not a teacher" is deduced. In the case that user A is a student or teacher, and user A is not a teacher, the target D_{DIKW} "user A's occupation is a student" can be further deduced.

$$\begin{aligned}
D_1 &= (A|T_{AGE}(10)) \\
I_1 &= R_{GO_TO}(A,\ T_{PLACE}(INS(School))) \\
K_2 &= R_{GO_TO}(T_{OCCUPATION}(Student)\ AND\ T_{OCCUPATION}(Teacher), \\
&\quad T_{PLACE}(School)) \\
K_4 &= R_{GREATER_THAN}(T_{AGE}(T_{OCCUPATION}(Teacher)),\ 20)
\end{aligned} \tag{32}$$

$$\begin{aligned}
I_1 + K_2 \rightarrow I_{new_2} &= R_{IS}(A,\ T_{OCCUPATION}(INS(Student)\ OR \\
&\quad T_{OCCUPATION}(INS(Teacher)) \\
D_1 + K_4 \rightarrow I_{new_3} &= !R_{IS}(A,\ T_{OCCUPATION}(INS(Teacher)) \\
I_{new_2} + I_{new_3} \rightarrow I_0 &= R_{IS}(A,\ T_{OCCUPATION}(INS(Student)) \\
I_0 \rightarrow D_0 &= (A|T_{OCCUPATION}(INS(Student))
\end{aligned} \tag{33}$$

5.2 Transform TR_{DIKW} to Purposed I_{DIKW}

The target TR_{DIKW} of transformation is I_{DIKW} "User A likes to play soccer":

$$I_0 = R_{LIKE}(A,\ T_{ACT}(INS(PlaySoccer)) \tag{34}$$

There are three ways to derive I_0, deriving from D_{DIKW} with K_{DIKW}, deriving from I_{DIKW} with K_{DIKW}, and deriving from D_{DIKW} and I_{DIKW} with K_{DIKW}.

Transform D_{DIKW} Combined with K_{DIKW} to Purposed I_{DIKW}. Obtain user A's related spatial data resource D_1 "soccer field". Knowledge resources K_1 "The main activity in the soccer field is playing soccer" K_2 "People who often play soccer like to play soccer". Combining D_1 and K_1, since user A often appears in the soccer field, so user A often plays soccer. Combined with K_2, since user A often plays soccer, and people who often play soccer are likely to like to play soccer, which can further derive the target I_{DIKW} "User A likes to play soccer".

$$\begin{aligned} &D_1 = (A|T_{PLACE}(INS(SoccerCourt)) \\ &K_1 = R_{IN}(T_{ACT}(Soccer),\ T_{PLACE}(SoccerCourt)) \\ &K_2 = R_{LIKE}(T_{PERSON}(R_{DO}(person,\ T_{ACT}(Soccer)))T_{ACT}(Soccer)) \end{aligned} \tag{35}$$

$$\begin{aligned} D_1 + K_1 \rightarrow I_{new_1} &= R_{DO}(A|T_{ACT}(INS(Soccer))) \\ I_{new_1} + K_2 \rightarrow I_{0_{im}} &= R_{LIKE}(A,\ T_{ACT}(INS(Soccer)) \end{aligned} \tag{36}$$

Transform I_{DIKW} Combined with K_{DIKW} to Purposed I_{DIKW}. Obtain information resource I_1 "User A is a member of school's soccer team". Knowledge resources K_2 "People who often play soccer like to play soccer". K_3 "Members of school's soccer team often play soccer". Combining I_1 and K_3, since user A is a member of school's soccer team, so user A often plays soccer. Combined with K_2, since user A often plays soccer, and people who often play soccer are likely to like to play soccer, which can further derive the target I_{DIKW} "User A likes to play soccer".

$$\begin{aligned} &I_1 = R_{IS\_A\_MEMBER\_OF}(A,\ T_{GROUP}(INS(SoccerTeam)) \\ &K_2 = R_{LIKE}(T_{PERSON}(R_{DO}(person,\ T_{ACT}(Soccer))),\ T_{ACT}(Soccer)) \\ &K_3 = R_{DO}(T_{PERSON}(R_{IS\_A\_MEMBER\_OF}(person,\ T_{GROUP}(SoccerTeam)), \\ &\quad T_{ACT}(Soccer)) \end{aligned} \tag{37}$$

$$\begin{aligned} I_1 + K_3 \rightarrow I_{new_1} &= R_{DO}(A,\ T_{ACT}(INS(Soccer))) \\ I_{new_1} + K_2 \rightarrow I_{0_{im}} &= R_{LIKE}(A,\ T_{ACT}(INS(Soccer)) \end{aligned} \tag{38}$$

Transform D_{DIKW} and I_DIKW Combined with K_{DIKW} to Purposed I_{DIKW}. Obtain user A's related reading data resource D_2 "soccer news", and information resource I_2 "user A likes sports". Knowledge resources K_4 "People who often watch soccer news are interested in soccer sports events". K_5 "Sports include playing soccer, basketball and so on". Combining D_2 and K_4, since user A often reads soccer news, so user A is interested in soccer matches. Because user A's interest in soccer may only lie in watching soccer matches, the I_{DIKW} "user A is interested in soccer matches" cannot directly infer that user A likes to play soccer. Combining I_2 and K_5, since user A likes sports, and sports include playing soccer. Because user A may be more interested in playing basketball and other sports, this I_{DIKW} is not enough to directly infer that user A likes playing soccer. However, since it was previously deduced that user A is interested in soccer matches, combined with the I_{DIKW} "user A likes sports", the target I_{DIKW} "user A likes playing soccer" can be derived.

$$\begin{aligned}
D_2 &= (A|T_{NEWS}(Soccer)) \\
I_2 &= R_{LIKE}(A|T_{ACT}(INS(SportsActivity))) \\
K_4 &= R_{INTERESTED_IN}(T_{PERSON}(R_{READ}(person,\ T_{NEWS}(Soccer))), \\
&\quad T_{SPORTS}(Soccer)) \\
K_5 &= R_{INCLUDE}(T_{ACT}(SportsActivity),\ T_{ACT}(Soccer,\ Basketball,\ ...))
\end{aligned} \tag{39}$$

$$\begin{aligned}
D_2 + K_4 \rightarrow I_{new_2} &= R_{INTERESTED_IN}(A,\ T_{SPORTS}(Soccer)) \\
I_2 + I_{new_2} + K_5 \rightarrow I_0 &= R_{LIKE}(A,\ T_{ACT}(INS(Soccer))
\end{aligned} \tag{40}$$

6 Encoding Mode

The user behavior content that is easy to be observed mainly includes motion content and sound content. This section mainly discusses modeling and encoding modes for these two types of user behavior contents.

6.1 Encoding of Motion Content

Motion content is not limited to the user's overall movement, but also includes the movement of a single part of the user, such as hands, feet, head, etc., and the combined movement of multiple parts. There are two commonly used methods of observing and capturing the motion content. One is to directly record the motion content of various parts of the human body through a wearable device. The other is to collect motion image data through a camera, and then recognize the motion content. The motion content can be divided into D_{DIKW} and I_{DIKW}.

Encode to D_{DIKW}. Motion content can contain a variety of D_{DIKW}, which can be divided into hand movement data resource D_{hand}, foot movement data resource D_{feet}, head movement data resourceD_{head}, body movement Data resource D_{body} and so on. According to the type of D_{DIKW}, it can be divided into scalar data resource D_{scalar} and vector data resource D_{vector}.

Encode to Scalar D_{DIKW}. Scalar D_{DIKW} include but are not limited to distance $D_{distance}$, speed D_{speed}, acceleration $D_{acceleration}$, and so on.

$$\begin{aligned}
D_{distance} &= DISTANCE_{observerd} \\
D_{speed} &= SPEED_{observerd}
\end{aligned} \tag{41}$$

Scalar D_{DIKW} can be transformed into each other. For example, speed can be obtained by dividing distance by time, acceleration can be obtained by dividing the change in speed by time, and so on.

$$\begin{aligned} D_{speed} &= \frac{D_{distance}}{D_{time}} \\ D_{acceleration} &= \frac{D_{speed_{new}} - D_{speed_{old}}}{D_{time}} \end{aligned} \tag{42}$$

Encode to Vector D_{DIKW}. Vector D_{DIKW} include but are not limited to the direction of motion $D_{direction}$, the location of motion $D_{location}$, and so on.

$$\begin{aligned} D_{direction} &= DIRECTION_{observed} \\ D_{location} &= LOCATION_{observed} \end{aligned} \tag{43}$$

Vector D_{DIKW} can also be transformed into each other, for example, the direction of movement can be obtained from the change of position.

$$D_{direction} = D_{loaction_{new}} - D_{location_{old}} \tag{44}$$

Encode to I_{DIKW}. Motion content also contains a variety of I_{DIKW}. I_{DIKW} are obtained by combining the detected D_{DIKW} with purpose. These I_{DIKW} can be generally recognized movement information such as smile, finger snapping, clapping, etc., or movement information defined by the user, such as a specific gesture or a certain dance. For example, I_{smile} "smile" is an I_{DIKW} expressed by mouth movement. When it is detected that the movement of the corner of the mouth is obliquely upward, and the distance of the movement is about 1 cm, it can be determined that the corner of the user's mouth is raised to express the I_{DIKW} "smile".

$$\begin{aligned} D_{direction} &= (lip|T_{DIRECTION}(angle\_upward)) \\ D_{distance} &= (lip|T_{DISTANCE}(1cm)) \\ I_{smile} &= R_{COMBINE}(D_{direction}, D_{distance}) \end{aligned} \tag{45}$$

6.2 Encodeing of Sound Content

Sound content is not only limited to meaningful speech such as dialogue, but also includes sounds that have no practical meaning but such as pure music singing, which contains different kinds of pitches, timbres and volumes. The observation and capture of sound content mainly rely on microphones and other equipment to directly record the audio content. The sound content can be divided into D_{DIKW} and I_{DIKW}.

Encode to D_{DIKW}. The sound content can contain a variety of D_{DIKW}. According to the characteristics of the sound, it can be divided into pitch data resource D_{pitch} corresponding to the frequency of the audio, timbre data resource D_{timbre} corresponding to the waveform of the audio, volume data resource

D_{volume} corresponds to the loudness of audio and so on. The collection of sound D_{DIKW} can be divided into continuous form and discrete form.

The continuous form means that the observed value is directly assigned to the sound D_{DIKW} without any processing.

$$\begin{aligned} D_{pitch}(continuity) &= PITCH_{observed} \\ D_{volume}(continuity) &= VOLUME_{observed} \\ &\dots \end{aligned} \tag{46}$$

Discrete form refers to setting a certain threshold k. When the observed value exceeds the threshold, the D_{DIKW} is set to a certain value, otherwise it is set to another value.

$$\begin{aligned} D_{pitch}(dispersed) &= \begin{cases} PITCH_1 & PITCH_{observe} > PITCH_k \\ PITCH_2 & PITCH_{observe} \leq PITCH_k \end{cases} \\ D_{volume}(dispersed) &= \begin{cases} VOLUME_1 & VOLUME_{observe} > VOLUME_k \\ VOLUME_2 & VOLUME_{observe} \leq VOLUME_k \end{cases} \end{aligned} \tag{47}$$

Encode to I_{DIKW}. The sound content also contains a variety of I_{DIKW}. Regardless of the specific semantics of the voice, different information resources can also be expressed from the characteristics of the voice. For example, if it is recognized that the pitch of the voice is higher than usual, the volume is higher usual, and the tone is very different from usual. It can be determined that the user's mood has fluctuated greatly, and the voice may express the I_{DIKW} “anger”.

$$\begin{aligned} D_{pitch} &= (User, T_{PITCH}(high)) \\ D_{volume} &= (User, T_{VOLUME}(high)) \\ D_{timbre} &= (User, T_{TIMBRE}(different)) \\ I_{angry} &= R_{COMBINE}(D_{timbre}, R_{COMBINE}(D_{pitch}, D_{volume})) \end{aligned} \tag{48}$$

7 Decoding Mode

After the process of encoding, the D_{DIKW} and I_{DIKW} obtained may not be used directly. It is necessary to further decode the encoded D_{DIKW} and I_{DIKW} to obtain the target D_{DIKW} and I_{DIKW}. This section discusses the decoding modes of transforming the encoded TR_{DIKE} into target D_{DIKW} and I_{DIKW}.

7.1 Decode to D_{DIKW}

If the target TR_{DIKW} of decoding is D_{DIKW}, it can be obtained from the encoded D_{DIKW} or I_{DIKW}.

Transform Encoded D_{DIKW} to Target D_{DIKW}. In the case where the target D_{DIKW} is obtained from the encoded D_{DIKW}, the target D_{DIKW} and the encoded D_{DIKW} may be in the same modality, or in different modalities.

Transformation of D_{DIKW} of Same Modality. If the modalities of both D_{DIKW} are the same, it means that the type and dimension of the D_{DIKW} are same. Then the transformation process can be regarded as a homomorphic mapping f, mapping the encoded D_{DIKW} to the target D_{DIKW}. For example, assuming that the encoded data resource D_{raw} and the target data resource $D_{purpose}$ are one-dimensional continuous parameters. The value range of D_{raw} is 0 to 10000. The value of $D_{purpose}$ ranges from 0 to 100. Then, by scaling D_{raw} by one percent, the target data resource $D_{purpose}$ can be transformed.

$$\begin{aligned} D_{raw} &= (T_{num}) \\ D_{purpose} &= (T_{num}) \\ f &: T_{num} \rightarrow T_{num} \\ f(x) &= \frac{x}{100} \\ f(D_{raw}) &= D_{purpose} \end{aligned} \tag{49}$$

Transformation of D_{DIKW} of Different Modalities. For the transformation between D_{DIKW} of different modalities, the transformation process can be regarded as first performing cross-modal inference g on the encoded data resource D_{raw} to obtain the D_{DIKW} which is in same modal with target data resource $D_{purpose}$. Then performing homomorphic mapping f to obtain the target D_{DIKW}. The different modalities can be specifically divided into different data types and different data dimensions.

For different data types situation, type conversion is required. In the case that the encoded data resource D_{raw} is a numerical type and the target data resource $D_{purpose}$ is a logical type, a threshold value k can be set. And the D_{raw}, whose value is greater than k, is set to $true$, while the D_{raw}, whose value is less than or equal to k, is set to $false$. Then, the transformation from numerical data to logical data can be completed.

$$\begin{aligned} D_{raw} &= (T_{num}) \\ D_{purpose} &= (T_{logic}) \\ g &: T_{num} \rightarrow T_{logic} \\ g(x) &= \begin{cases} true & x > k \\ false & x \leq k \end{cases} \\ f &: T_{logic} \rightarrow T_{logic} \\ f(g(D_{raw})) &= D_{purpose} \end{aligned} \tag{50}$$

For different dimensions situation, dimensional compression or expansion is required. If the encoded data resource D_{raw} is three-dimensional data, and the target data resource $D_{purpose}$ is two-dimensional data. Then by design a mapping from three-dimensional space to two-dimensional space g, the dimensional compression from D_{raw} to $D_{purpose}$ can be completed.

$$\begin{aligned} D_{raw} &= (T_{num}(dimension = 3)) \\ D_{purpose} &= (T_{num}(dimension = 2)) \\ g &: R^3 \rightarrow R^2 \\ g(x, y, z) &= (g_1(x, y, z), g_2(x, y, z)) \\ g_1(x, y, z) &= x + y + z \\ g_2(x, y, z) &= x * y * z \\ f &: T_{num} \rightarrow T_{num} \\ f(g(D_{raw})) &= D_{purpose} \end{aligned} \tag{51}$$

Transform Encoded I_{DIKW} to Target D_{DIKW}. The encoded I_{DIKW} can also be transformed into target D_{DIKW}. Target D_{DIKW} can be divided into logical D_{DIKW} and numerical D_{DIKW}.

Transform Encoded I_{DIKW} to Logical D_{DIKW}. If the target D_{DIKW} is a logical D_{DIKW}, a specific I_{DIKW} can be associated with a specific logical expression. For example, the I_{DIKW} "laugh" represents *true*, and the I_{DIKW} "crying" represents $false$. Through this association between I_{DIKW} and logical expressions, the transformation from I_{DIKW} to target logical D_{DIKW} can be completed.

$$\begin{aligned} f &: I \rightarrow D_{logic} \\ f(I) &= \begin{cases} true & I == I_{smile} \\ false & I == I_{cry} \end{cases} \\ f(I_{raw}) &= D_{purpose} \end{aligned} \tag{52}$$

Transform Encoded I_{DIKW} to Numerical D_{DIKW}. If the target D_{DIKW} is a numerical D_{DIKW}, a specific I_{DIKW} can be associated with a specific value. For example, the I_{DIKW} "clap" represents "10", and clap twice represents "20". Through this association between I_{DIKW} and numerical values, the transformation from I_{DIKW} to target logical D_{DIKW} can be completed.

$$\begin{aligned} f &: I \rightarrow D_{num} \\ f(I) &= 10 \quad (I = I_{clap}) \\ f(I_{raw}) &= D_{purpose} \end{aligned} \tag{53}$$

7.2 Decode to I_{DIKW}

If the target of decoding is I_{DIKW}, it can only be obtained by transforming the encoded I_{DIKW} to target I_{DIKW}. For the transformation between I_{DIKW}, it is necessary to establish an association between the encoded I_{DIKW} and the target I_{DIKW}. For example, by establishing a connection between the I_{DIKW} "snap finger" and the target I_{DIKW} "complete a certain operation", the transformation from encoded I_{DIKW} to the target I_{DIKW} can be completed.

$$\begin{aligned} f &: I \rightarrow I \\ f(I) &= I_{specified} \quad (I = I_{snap}) \\ f(I_{raw}) &= I_{purpose} \end{aligned} \tag{54}$$

8 Conclusion

We propose to extend mesoscience practice to the field of information technology, conceptualize the mesoscale category, and carry out cross-modal and cross-scale semantic definition, modeling, analysis and measurement design towards identification and dealing with the complexity of objective uncertainty and subjective uncertainty in both conceptual category and cognitive category and the interaction category of objective and subjective. From the existence computation and reasoning paradigm and relationship defined everything of semantics expression mechanism, we model the essential semantic content based on the previous modeling approaches centering data graph, information graph, and knowledge graph, and analyze the reasons for the occurrence of multi-semantic situations. The reasons for the multi-semantic situation can be divided into two categories: the missing of typed resources and the redundancy of typed resources. Each category can be specifically subdivided into missing data resources, missing information resources, redundant data resources, and redundant information resources. For each specific situation, we give a variety of solutions, such as adding data resources or adding information resources, and design corresponding algorithms for each solution. We have also conducted in-depth exploration on the cross-modal transformation of type resources in the process of multi-semantic analysis, and discussed multiple transformation methods for target resources.

Relying on the cognitive semantic tracing and conceptualization strategies at the relevant existential level, the cross-modal and cross-scale core concept cognitive semantics of the DIKW model was systematically conceptualized and analyzed, and the construction of the DIKW systematic meta-model system was practiced. The category defines the formal semantics of DIKW core concepts in a way that multiple core concepts are conceptualized at the same time. It is proposed to expand the knowledge graph into Data Graph, Information Graph, Knowledge Graph and Wisdom Graph based on DIKW, which will help to promote the recognition of multi-modal mixed content by knowledge graph. Research on representation, modeling and optimization processing.

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