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ICAD-MI: Interdisciplinary concept association discovery from the perspective of metaphor interpretation ☆

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ABSTRACT

Interdisciplinary concept association discovery is a fundamental task in interdisciplinary knowledge organization. Unlike general concept association, interdisciplinary concept association mainly manifests in the correlation between fine-grained concept properties, which requires that interdisciplinary concept association discovery be explored through a fine-grained semantic association discovery tool. Existing concept association discovery methods are limited in their ability to identify interdisciplinary concept associations at fine-grained conceptual properties because they can only identify which two concepts are associated at the coarse level. To bridge this gap, we propose a method we called interdisciplinary concept association discovery based on metaphor interpretation (ICAD-MI). First, we explored the mechanism of interdisciplinary conceptual metaphor on both the cognitive and language layers, which provides a solid foundation for our method. Second, we introduced the four-step ICAD-MI method, which integrates deep learning techniques with word semantics and multidimensional contexts. We tested the ICAD-MI framework using a dataset comprising a total of 1,915 data points of interdisciplinary metaphorical expressions (IMEs) on a typical interdisciplinary conceptual metaphor *Computer is a brain*. Our model achieved a precision of 94.4%, a recall of 73.9%, and an F1 score of 82.9%, which outperforms the four baseline methods. Additionally, we conducted parameter analysis to further validate the effectiveness of our proposed method. The code and datasets are publicly available at: https://github.com/haihua0913/ICADMI.

1. Introduction

Interdisciplinarity is a common phenomenon within the research community in multiple disciplines because of its significant advantages in addressing contemporary problems [1]. However, a well-known barrier that plagues interdisciplinary research is the disciplinary boundary [2], which forces different disciplines to organize themselves internally and makes knowledge exchange associated with interdisciplinary research frameworks difficult. In this context, developing an interdisciplinary knowledge organization system can promote interdisciplinary research [3]. To the best of our knowledge, the key to successfully developing knowledge organization systems, such as thesauri, ontology, semantic web, and others, is accurately explaining concept associations [4]. Therefore, interdisciplinary concept association discovery becomes a crucial task in developing interdisciplinary research. A disciplinary concept, as a general notion of corresponding disciplinary entities, consists of the entities' essential features selected to describe these entities by researchers from their own disciplinary perspectives. However, different disciplines have unique research objects, fundamental problems, and research methods, leading to different disciplinary perspectives. Therefore, two disciplinary concepts across disciplines are not equivalent in most cases [5], but they are associated through partial connotative properties. Therefore, fine-grained interdisciplinary concept association discovery at the property level is necessary and urgent.

Existing approaches to concept association discovery can be summarized into two categories: general concept association discovery methods and interdisciplinary concept association discovery methods. General concept association discovery methods are mainly based on the co-word analysis method and similarity calculation methods [6]. However, these methods can only discover

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general concept associations but fail in interdisciplinary concept association discovery. The main reason for failure is the lack of disclosure of concepts' interdisciplinary characteristics. To bridge this gap, interdisciplinary concept association discovery methods, such as the Literature-Related Discovery approaches [7–9], are proposed to connect disciplines by linking two or more concepts from different disciplines. Nevertheless, this type of approach can only discover interdisciplinary concept associations from the perspective of literature and fail to capture the semantic characteristics of the concepts. Moreover, these approaches only present the relationship between two concepts at a coarse-grained level, leaving the correlation at the fine-grained level unknown.

Conceptual metaphor, as a fundamental technique of human cognition [10], provides us with a mechanism for discovering interdisciplinary concept associations at the fine-grained level. The conceptual metaphor theory [11] argued that metaphor is an effective way for people to understand one conceptual domain, or a concept's semantics, in terms of another conceptual domain. The conceptual domain from which we draw metaphors to understand another conceptual domain is called the source domain, while the conceptual domain that is understood this way is the target domain. Conceptual metaphor allows us to export the conceptual structure of the source domain to the target domain. For example, in the case *life is journey*, we talk and think about the concept "life" (target domain) in terms of the concept "journey" (source domain) [12]. Conceptualizing "life" as a "journey" allows us to map the various properties comprising a "journey" onto properties of "life". These correspondences, called mappings, are the primary function of conceptual metaphors. Conceptual metaphors also play a crucial role in generating interdisciplinary conceptual systems [13], because concepts from one discipline are often understood and experienced in terms of concepts from another discipline by property mapping. This paper regards this phenomenon as interdisciplinary conceptual metaphor. Since interdisciplinary conceptual metaphor interpretation can link concepts from two different disciplines at the semantic level and explore the properties that make the two concepts associated [14], it provides a feasible approach to discovering interdisciplinary concept associations in a fine-grained manner. To this end, this study aims to develop a new interdisciplinary concept association discovery method from the novel perspective of metaphor interpretation (ICAD-MI) to detect the semantic associations between disciplinary concepts at the fine-grained level. To achieve this research goal, several core issues need to be addressed and our study will make the following contributions:

- **What is the mechanism of interdisciplinary conceptual metaphor?** To effectively discover interdisciplinary concept associations from the perspective of metaphor interpretation, we should know the essence of interdisciplinary conceptual metaphor first. Therefore, based on the conceptual metaphor theory, we analyzed the mechanism of interdisciplinary conceptual metaphor from the cognitive and language layers and have found that interdisciplinary conceptual metaphor is governed by disciplinary and topical contexts at the cognitive level and by sentential context at the language level.
- **How to extract properties of the source and target domains?** Each interdisciplinary conceptual metaphor has lots of interdisciplinary metaphorical expressions (IMEs). Each IME typically relates to a property of a particular interdisciplinary concept, which is usually implicit in particular contexts. This poses a big challenge to property extraction. To solve this issue, we have trained a deep-learning-based concept property extraction model to capture semantic and contextual information of IME, which was found to be more effective than existing rule-based methods and machine learning-based methods. This model achieves state-of-the-art performance in property extraction with a precision of 84.4%, a recall of 87.3%, and an F1 score of 85.8%.
- **How to filter properties of the source and target domains in an interdisciplinary conceptual metaphor based on contexts?** Properties cannot be selected in an interdisciplinary conceptual metaphor without considering the context. This is because, given suitable contexts, coherence considerations can lead to a precise interpretation of an interdisciplinary conceptual metaphor. Previous work on property filtering, which mostly focused on verbal metaphors and ignored the influence of contextual information, has some limitations (e.g., ignoring the polysemy of metaphor). In this paper, we present a novel property filtering method that takes into account the relevance of topical and sentential contexts.
- **How to detect the most accurate interdisciplinary concept association between the source and target domains?** Existing studies on concept association discovery based on metaphor interpretation can be divided into two categories: word-based methods and context-driven methods. Word-based methods heavily rely on the semantic information of words to select the most relevant property pair, while ignoring the contextual information [15]. In contrast, context-driven methods that combine word semantics and contextual information typically achieve better performance [16]. However, previous context-driven methods mainly used contextual information from a single dimension, which prevented them from achieving deep and accurate mining of contexts. To improve the performance of interdisciplinary concept association discovery, this paper first obtains interdisciplinary associated property pairs through semantic matching. Then to obtain the most accurate interdisciplinary concept association, we rank the property pairs based on the topical and sentential contexts. Through experiments, we have found that the topical context is of more importance than the sentential context in ICAD-MI and that ICAD-MI performs the best when the weight of the topical context is set at 0.3 and the weight of the sentential context at 0.7. Furthermore, our experiments on the well-known interdisciplinary conceptual metaphor *Computer is a brain* in Computer Science show that our method has a higher performance than the four baseline methods.

The rest of the paper is organized as follows: Section 2 reviews the related work in concept association discovery and metaphor interpretation. Section 3 introduces the mechanism of interdisciplinary conceptual metaphor. Section 4 discusses the method of ICAD-MI. Section 5 presents the experimental settings and results. Section 6 summarizes the paper and presents limitations and future work.

2. Related work

This research mainly focuses on discovering interdisciplinary concept associations between disciplinary concepts at a fine-grained level through metaphor interpretation. Therefore, we review existing studies from two aspects: (a) concept association discovery and (b) metaphor interpretation.

2.1. Concept association discovery

Concept association discovery plays a crucial role in knowledge organization. Table 1 presents a compilation of existing concept association discovery methods, which can be divided into two main categories: general concept association discovery methods and interdisciplinary concept association discovery methods.

Table 1
Categories of the existing concept association discovery methods.

Categories	Methods	Limitations in interdisciplinary concept association discovery
General concept association discovery methods	Co-word analysis method [17,18]	(1) Discover coarse-grained concept associations. (2) Lack of consideration for interdisciplinary characteristics of concepts. (3) Fail to explore the deep semantics of disciplinary concepts.
	Name similarity calculation methods [19–22]	(1) Discover coarse-grained concept associations. (2) Lack of consideration for interdisciplinary characteristics of concepts. (3) Fail to explore the deep semantics of disciplinary concepts.
	Semantic similarity calculation methods [23–29]	(1) Discover coarse-grained concept associations. (2) Lack of consideration for the interdisciplinary characteristics of concepts.
Interdisciplinary concept association discovery methods	Literature-Related Discovery approaches [7–9]	(1) Discover coarse-grained concept associations. (2) Fail to explore the deep semantics of disciplinary concepts.
	Literature-Related Discovery and Innovation approaches [30]	(1) Discover coarse-grained concept associations. (2) Fail to explore the deep semantics of disciplinary concepts.

2.1.1. General concept association discovery methods

Most of the existing concept association discovery methods fall under the category of general concept association discovery methods. These methods rarely consider the interdisciplinary characteristics of concepts and are not suitable for interdisciplinary concept association discovery. The most popular method in this category is developed based on co-word analysis [31], which measures the relevance of concepts based on their co-occurrence in literature. For example, Callon et al. [17] used co-word analysis to build the knowledge structure in the field of iMetrics proposed by Milojević and Leydesdorff [32], which can reveal associations between keywords. Rohani and Makkizadeh [18] uncovered the essential associations between keywords in medical sociology research areas based on co-word analysis. However, the co-word analysis method can only discover two associated concepts from the perspective of literature without considering the interdisciplinary semantic information of the concepts. Hence, it is not appropriate for interdisciplinary concept association discovery.

Other researchers have also tried to discover concept associations by calculating the similarity between concepts. In its early stage, concept association discovery relied on the calculation of name similarity, using classical algorithms, such as Levenshtein Distance [19], Knuth–Morris–Pratt [20], Boyer–Moore [21], and Jaccard Distance [22]. Given those concepts with similar names are not necessarily similar in semantics and that concepts with similar semantics are not necessarily similar in name, many semantic-based methods have since been put forward [33]. In general, the semantic-based methods can be further broken down into three categories: corpus-based concept association discovery methods [23–25], knowledge-based concept association discovery methods [26–28], and hybrid concept association discovery methods that use both knowledge-based and corpus-based techniques [29]. These methods are limited in interdisciplinary concept association discovery because the interdisciplinary characteristics of concepts are not considered and the discovered concept associations are coarse-grained.

2.1.2. Interdisciplinary concept association discovery methods

To detect interdisciplinary concept associations, interdisciplinary concept association discovery methods have emerged, which are mainly embodied in the Literature-Related Discovery approaches [7–9]. The Literature-Related Discovery approaches use the linking of two or more literature concepts that have not been linked before to generate potential discovery. Two major Literature-Related Discovery approaches to extrapolate knowledge from one discipline to another include the Literature-Based Discovery approach and the Literature-Assisted Discovery approach. The Literature-Based Discovery approach originated from Swanson [34], in which he assumed that two kinds of disjoint disciplinary literature could be generated, so concept A is related to concept B in the first disciplinary literature and literature concept B is related to concept C in the second disciplinary literature. He further assumed that the linkages between A and C can be identified through concept B connecting them, and this connection has not been recorded in any literature before. In this way, the Literature-Based Discovery approach produces a potential discovery through the analysis of the scientific literature alone. Unlike the Literature-Based Discovery approach, the Literature-Assisted Discovery approach generates potential discovery through both literature analysis and interactions among selected literature authors. Later on, Kostoff [30] proposed the Literature-Related Discovery and Innovation approaches, the most recent incarnation of the Literature-Related Discovery approaches, to solve problems of interest by integrating discovery with innovation. The Literature-Related Discovery and Innovation approaches have two components: the Literature-Based Discovery and Innovation approach and the Literature-Assisted Discovery and Innovation approach. The above methods can only discover which two disciplinary concepts are interdisciplinarily associated based on knowledge links in the literature, which cannot fully reveal the interdisciplinary semantic associations between disciplinary concepts at the fine-grained level.

In summary, the concept association discovery methods discussed above can identify equivalence, hierarchical, and other relations between concepts, based on which generic knowledge organization systems are constructed [35]. A significant constraint on these methods in interdisciplinary concept association discovery is that they discover coarse-grained concept associations (discover which two concepts are associated) without revealing more tangibly the semantic associations between concepts. However, the interdisciplinary concept association is an associative relation that manifests as several connotative property associations. Thus interdisciplinary concept association discovery should be fine-grained (discover which properties are associated in interdisciplinary concept pairs). Furthermore, general concept association discovery methods lack the disclosure of interdisciplinary characteristics of disciplinary concepts, while interdisciplinary concept association discovery methods are limited to exploring the deep semantics of concepts. Neither of them is capable of achieving accurate interdisciplinary concept association discovery. Therefore, this paper proposes an interdisciplinary concept association discovery method from a new perspective of metaphor interpretation, which can effectively discover interdisciplinary concept association at the fine-grained level.

2.2. Metaphor interpretation

Metaphor is a fundamental way of human thinking and a widespread phenomenon in natural language [36]. How humans

Table 2
Methods of the existing property extraction and property association discovery in metaphor interpretation.

Topics	Methods	Limitations in interdisciplinary conceptual metaphor interpretation
Property extraction of concepts	Property database-based methods [38,39]	No available database of properties for disciplinary concepts.
	Rule-based methods [40,41]	Require a lot of manual work.
	Machine learning-based methods [42,43]	Heavily rely on manual feature extraction and large training datasets.
	Deep learning-based methods [44–46]	High cost of training and deploying deep learning models.
Property association discovery between concepts	Word-based methods [38,39]	Lack consideration for contextual information in metaphor interpretation.
	Context-driven methods [15,37,47,48]	Lack consideration for multidimensional contexts in metaphor interpretation.

interpret metaphors has received significant attention. The objective of metaphor interpretation is to identify the highly related property pair between the source and target domains [37], and the whole process can be divided into two parts: property extraction of concepts and property association discovery between concepts. Table 2 presents the existing methods of both of them.

2.2.1. Property extraction of concepts

Property extraction is the prerequisite for metaphor interpretation. The existing metaphor interpretation studies usually obtain properties from the existing property database. Su et al. [38] extracted properties of the source and target domains from Sardonicus, an adjective taxonomy that provides the exemplary properties of objects in the real world. Su et al. [39] used the Property Database developed by Xiamen University and the Sardonicus database for property extraction. This method, however, is not applicable to interdisciplinary concept association discovery because there is no readily available database for disciplinary concepts.

In the field of natural language processing, property extraction is a prominent area of exploration. There are three main methods of property extraction: rule-based methods [40,41], machine learning-based methods [42,43], and deep learning-based methods [44–46]. For the rule-based methods, the accuracy of property extraction depends heavily on the quality of the rules. It requires a lot of manual work and migration is poor because they are usually oriented to a specific domain. The machine learning-based methods are more flexible, but need the support of artificial features and large-scale training datasets. In addition, the properties of the source and target domains are usually implicit within particular contexts, which also imposes a big challenge to rule-based methods and machine learning-based methods. In contrast, deep learning-based methods can effectively learn the complex contextual information of an IME, which can perform property extraction more effectively than existing rule-based methods and machine learning-based methods. Therefore, we adopt the deep learning technique to extract properties in ICAD-MI.

However, deep learning-based property extraction methods require substantial amounts of data and computing resources. In this context, Baidu [49] has developed the Easy DL platform [50] which offers a comprehensive AI development capability for data collection, annotation, cleaning, model training, and deployment, with great advantages of a zero threshold, high accuracy, low cost, and wide adaptability. Its underlying framework is built from Baidu's self-developed Flying Paddle deep learning framework, with built-in mature pre-trained models based on Baidu's ERINE model [51] and self-developed AutoDL technology. The framework can help users obtain models with excellent performance based on a small number of data. Easy DL is gradually being adopted by researchers to assist with scientific research due to its ease of use and high performance [52,53]. Therefore, we use the Easy DL platform to achieve property extraction of disciplinary concepts.

2.2.2. Property association discovery between concepts

In general, the methods of property association discovery between concepts in metaphor interpretation can be divided into two categories: word-based methods and context-driven methods.

Previous research on property association discovery in metaphor interpretation mainly focused on word semantic information while ignoring contextual information, which we call word-based methods. For example, Su et al. [38] explored a nominal and verbal metaphor interpretation algorithm based on latent semantic similarity. They used WordNet to extend the perceptual features of both source and target domains and then tried to find an extension path between the features from one to the other. Su et al. [39] chose the property of the source domain that matched the target domain for interpretation after obtaining the semantic relatedness between the source domain's property and the target domain. However, metaphor interpretation should be viewed as a complex issue in discourse processing, and the context should be attributed with high values in the interpretation of metaphors [54,55]. Therefore, word-based methods lack accuracy as they do not account for the context.

Considering the great importance of context to metaphor interpretation, some researchers have tried to take context into account from different perspectives. Su et al. [47] explored a context-sensitive nominal metaphor interpretation algorithm. Later, Su et al. [15] described a metaphor interpretation method based on semantic relatedness for context-dependent nominal metaphors. Contending that context can eliminate the uncertainty of metaphor interpretation, the authors calculated the relatedness between the target domain and the property of the source domain based on sentential context and word semantic relatedness. Rai et al. [37] argued that a metaphor embeds emotion. Therefore, they addressed the metaphor interpretation issue from the perspective of emotion. Su et al. [48] developed a culture-related hierarchical semantic model of metaphor interpretation under the idea that metaphor usually contains cultural connotations. They considered sentiment information and the topic of both words and discourse to better present contextual information. Previous studies of context-driven methods offer some insights into property association discovery in interdisciplinary conceptual metaphor interpretation, but they still have two limitations.

On the one hand, existing studies analyzed the context of the metaphor from a single dimension, such as emotion, culture, or topic. In modern pragmatics, the context is considered to be an environmental system that produces discourse and consists of multiple elements [56]. In many cases, we can only get an accurate metaphor interpretation result through the combined analysis of numerous contextual factors. On the other hand, interdisciplinary conceptual metaphor is a special type of conceptual metaphor, so previous contexts analyzed in conceptual metaphor interpretation may not be applicable to interdisciplinary conceptual metaphor interpretation.

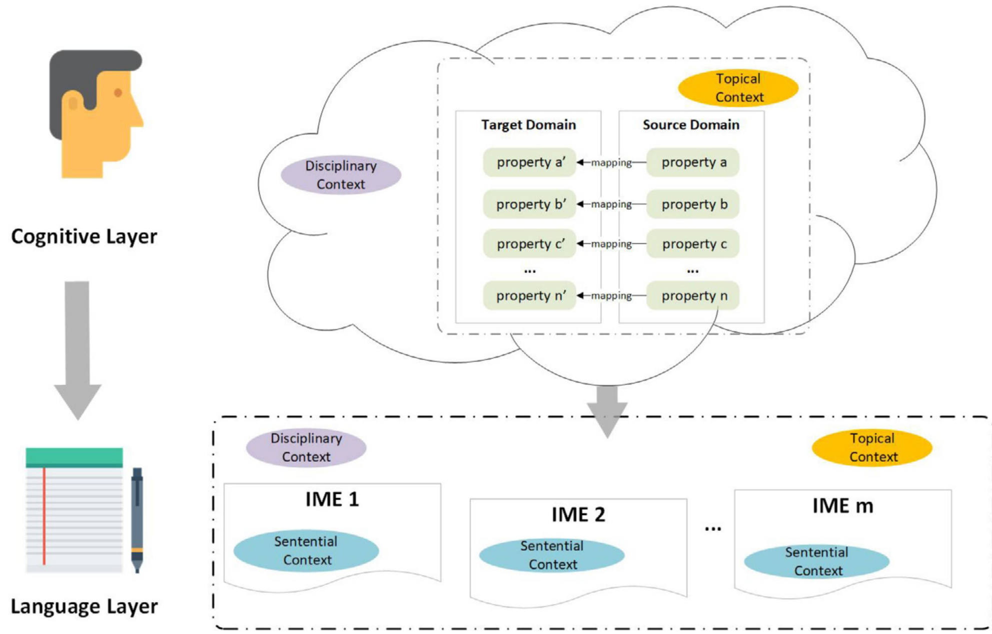

Fig. 1. The mechanism of interdisciplinary conceptual metaphor.

From the above review, it is evident that the existing property association discovery methods, which rely on metaphor interpretation, are not suitable for interdisciplinary property association discovery due to insufficient or inadequate consideration of context. Although multiple contexts in interdisciplinary conceptual metaphor need to be considered in interdisciplinary concept association discovery, there is currently a lack of research analyzing the contexts in interdisciplinary conceptual metaphor. To bridge this gap, this paper explores the interdisciplinary conceptual metaphor mechanism to summarize the multidimensional contexts in interdisciplinary conceptual metaphor interpretation, which supports the ICAD-MI method we have proposed.

3. Mechanism of interdisciplinary conceptual metaphor

In this section that lays down the foundation for ICAD-MI, we analyze the mechanism of interdisciplinary conceptual metaphor. The conceptual metaphor theory [11] argues that metaphor, as a matter of thought and action, is reflected in our daily language by a wide range of metaphorical expressions. Consequently, we can use metaphorical expressions in language to gain an understanding of conceptual metaphors in cognition. Moreover, a range of IMEs exists under an interdisciplinary conceptual metaphor. With that, we systematically analyze the mechanism of interdisciplinary conceptual metaphor, shown in Fig. 1, which comprises two layers, the cognitive layer, and the language layer. A detailed analysis of each layer is presented below.

3.1. The cognitive layer

According to the conceptual metaphor theory, when cognitive subjects try to understand and conceptualize something abstract, unfamiliar, or new, they mostly choose those physically or psychologically similar concepts to the target domain, attributed mainly to their experiences and the contexts of the target and source domains [11]. Accordingly, interdisciplinary conceptual metaphor, as the fundamental tool of human cognition, is to use the cognitive model of the source domain in a discipline to activate and re-conceptualize the target domain in another discipline. Therefore, through interdisciplinary conceptual metaphor, interdisciplinary concept associations are created based on property mapping (or metaphorical structuring) at the fine-grained level. In most cases, due to the differences in contexts between the source and target domains in different disciplines, the metaphorical structure involved in the process of interdisciplinary conceptual metaphor is often partial rather than complete. Under these premises, the primary concern lies in examining how contexts affect metaphorical structuring during the process of interdisciplinary conceptual metaphor.

As we know, interdisciplinary conceptual metaphor is different from the general conceptual metaphor since the source and target domains of interdisciplinary conceptual metaphor belong to different disciplines. Therefore, interdisciplinary conceptual metaphor is firstly influenced by the disciplinary context when perceiving the target domain with the cognitive model of the source discipline. In this situation, disciplinary context can be applied to filter the source domain and clarify its connotative properties for understanding the target domain. Moreover, similar cognitive pathways and outcomes may also arise under a similar topic across disciplines [57]. Therefore, interdisciplinary conceptual metaphor is also influenced by topical context, which can help identify the source domain for the target domain and realize subsequent one-to-one property mapping between the target and source domains within a similar topic, as only the properties under a similar topic may have the potential to be mapped.

Based on the above analysis, we conclude that interdisciplinary conceptual metaphor is governed by both disciplinary context and topical context at the cognitive level, as shown in Fig. 1. The disciplinary context helps to clarify the connotations of the source domain. The topical context further helps to find the source domain with similarities and determine the mapped properties.

3.2. The language layer

At the language layer, based on the interdisciplinary conceptual metaphor and its mapped properties in the cognitive layer, multiple IMEs are generated in language by people to deliver

Table 3
The role of contexts in ICAD-MI.

Context type	Their role in ICAD-MI
Disciplinary context	(1) Identify the disciplines to which the source and target domains belong. (2) Determine the properties of the source and target domains.
Topical context	(1) Find properties related to the topic. (2) Select the property pair most relevant to the contextual information. (3) Integrate the interdisciplinary concept association discovery results for multiple IMEs according to the topic.
Sentential context	(1) Find properties related to the IME. (2) Select the property pair most relevant to the contextual information.

ideas efficiently. Sentential context, as the basis for the semantic formation of language [58], plays a crucial role in IMEs. Therefore, it is necessary to consider sentential contextual information when analyzing the interdisciplinary conceptual metaphor mechanism at the language layer.

The fact is that the mapped properties involved at the cognitive level are reflected by their immediate sentential contexts in IMEs. For example, in the IME *The firm is a ship sailing in a rough sea*, the lexical form for the target domain "firm", is embedded in sentential contexts: "sailing", "rough", and "sea", which describes the cognitive model of an angry sea. With the above sentential contexts, we are thus able to discover the properties of "ship" that correspond to "firm", which helps us arrive at the construal of the "firm" as a "ship" during the process of comprehension. From the above discussion, we can see that sentential contexts in IME reveal pieces of information that embed the target domain. These pieces of information are organized according to the cognitive models. Therefore, the selected properties in interdisciplinary conceptual metaphor are reflected in the sentential context of each IME [15,59]. People use the mapped properties between the source and target domains of an interdisciplinary conceptual metaphor to express their thoughts about the target domain in IMEs. In summary, IMEs are closely related to the disciplinary context, topical context, and sentential context, as shown in Fig. 1.

The above analysis demonstrates that interdisciplinary conceptual metaphor can help people perceive the target domain in several aspects at the cognitive level and express specific ideas about the target domain at the language layer. In terms of interdisciplinary concept association discovery, we can discover the semantic associations between concepts from different disciplines through the IME interpretation at the language level. Moreover, the interdisciplinary conceptual metaphor mechanism can shed light on the ICAD-MI method by choosing the most related property pair of the source and target domains within the disciplinary context, topical context, and sentential context of each IME. We summarize the role of the three contexts in ICAD-MI in Table 3.

4. Methodology

Interdisciplinary conceptual metaphor interpretation is useful to manifest the fine-grained interdisciplinary concept association in an IME. According to the interdisciplinary conceptual metaphor mechanism discussed above, the results of metaphor interpretation for all IMEs are integrated to uncover the diverse interdisciplinary concept associations between the two concepts of an interdisciplinary conceptual metaphor. This paper proposes an ICAD-MI method combining word semantics and multidimensional contexts to detect the semantic associations between disciplinary concepts at a fine-grained level, as shown in Fig. 2.

The ICAD-MI method includes four steps: (a) property extraction, in which the properties of the source and target domains are extracted from the scientific literature using the Easy DL platform within the disciplinary context; (b) property filtering, in which the properties of the target and source domains are filtered according to the topical context and sentential context; (c) property matching, in which the candidate properties from the filtering step are matched based on word semantics; and (d) property ranking, in which the properties are ranked by topic relevance and expression relevance. We discuss the four steps in detail in the following sections.

4.1. Property extraction

In this step, a textual entity relationship extraction model is constructed using Easy DL to extract the properties of disciplinary concepts. Entity-relationship extraction refers to the extraction of predefined entity types and relationship types between entities from text, which we can use to extract properties of concepts and obtain relationships between concepts and properties. The result of property extraction can be represented as a triplet: concept, relationship, and property. The specific processes are:

1. Define the type of relationship between concepts and properties. Three types of concept-property relationships are defined to explore the properties of disciplinary concepts: feature, function, and structure relationships. These three relationships are described in Table 4.
2. Collect and annotate data. Considering that disciplinary concepts are discipline-specific, to ensure all possible properties are extracted, the top information provider in China, China National Knowledge Infrastructure (CNKI) [60], is used, which is the world's leading digital library providing public knowledge services. We use CNKI's Conceptual Knowledge Element Search function to retrieve the concepts in the scientific literature and annotate the search results by selecting sentences that describe properties.
3. Train model and evaluate effects. In this phase, we create a text entity relationship extraction model and import the annotated property extraction dataset to train the model using Easy DL.
4. Extract properties. Taking disciplinary context into account, we first retrieve the relevant sentences from the scientific literature in the corresponding disciplines of the source and target domains based on CNKI and then input them into the model we trained. In this phase, the properties of the disciplinary concepts can be fully extracted.

4.2. Property filtering

After property extraction, we filter out two types of properties: (a) properties that are not consistent with the topic to which the IME belongs and (b) properties that are not consistent with the contextual cues of the IME. Two different types of context are used: topical context and sentential context.

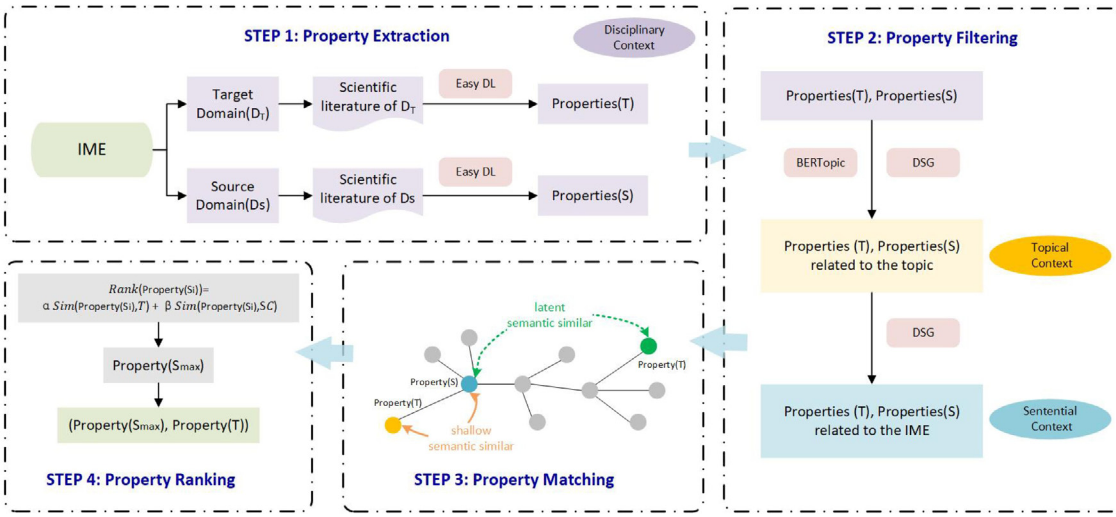

Fig. 2. The framework of the ICAD-MI method.

Table 4
Description of three concept-property relationships. Bold text in the examples represents the concept and the underlying texts indicate the properties described in the sentence.

Relationship type	Explanation	Examples
Feature	Describe the characteristics of the concept	The **brain** is characterized by high blood flow, high metabolic rate, and high oxygen consumption.
Function	Describe the role or use of the concept	The **brain** is capable of regenerative repair and functional reorganization.
Structure	Describe the composition of the concept	The **brain** consists of the cerebrum, cerebellum, pons, midbrain, and medulla oblongata.

4.2.1. Property filtering based on topical context

From the previous analysis, we know that the topical context creates a cognitive space for the interdisciplinary conceptual metaphor to achieve one-to-one property mapping within a particular topic. Therefore, when filtering out properties based on topical context, we remove the properties that are irrelevant to the topic of the IME. Fig. 3 describes the process of property filtering based on topical context, which can be divided into three steps:

1. Discovering topics of IMEs based on BERTopic. Topic modeling is an essential task in many fields, such as natural language processing and information retrieval. We apply BERTopic [61], the state-of-the-art topic modeling method, for discovering topics in this paper. More specifically, we first carry out data pre-processing of a given dataset of IMEs, including text segmentation and removal of stop words. Then we perform BERTopic modeling to obtain a document-topic distribution matrix and a topic-word distribution matrix, according to which the first topic of each IME is extracted to serve as the topic and the first n words of the first topic are extracted to represent it. In this way, the topic T of an IME is represented by a series of words $(t_1, t_2, \ldots, t_n)$.
2. Vector representation of topics and properties based on Directional Skip-Gram (DSG). Word embedding has been shown to be effective for natural language processing, and DSG [62] is a simple but effective enhancement of the skip-gram model by explicitly distinguishing left and right context in word prediction. In this step, the DSG model is used to obtain the vector $\vec{T}$ for each IME's T first. Specifically, the vector $\vec{t_i}$ for each word of T is first obtained using DSG. Secondly, the word probabilities acquired from the topic-word distribution matrix generated by BERTopic are normalized to gain the weight w_i for each word of T. Lastly, multiply w_i with $\vec{t_i}$ and sum the results to calculate $\vec{T}$. $\vec{T}$ is calculated using Eq. (1) and represented as $(c_1, c_2, \ldots, c_q)$. Then, we utilize the DSG model to obtain the vector of properties, with the vector $\vec{p}$ for property p being represented as $(r_1, r_2, \ldots, r_q)$.

$$\vec{T} = \sum_{i=1}^{n} w_i \vec{t_i} \tag{1}$$

3. Property filtering based on cosine similarity calculation. In this step, we compute the cosine similarity between $\vec{T}$ and $\vec{p}$ to identify the topic-related properties of the source and target domains through Eq. (2).

$$Sim\,(p, T) = dis_{cos}\left(\vec{p}, \vec{T}\right) = \frac{\sum_{j=1}^{q} r_j c_j}{\sqrt{\sum_{j=1}^{q} r_j^{2}}\sqrt{\sum_{j=1}^{q} c_j^{2}}} \tag{2}$$

4.2.2. Property filtering based on sentential context

The information about associated properties is either explicitly or implicitly implied in IMEs. Therefore, properties are filtered based on the sentential context in this step. Firstly, the sentential context SC is expressed as a set of words $(s_1, s_2, \ldots, s_n)$ that come from the IME, excluding the stop words and the marked source and target domains. Then, the DSG model is used to generate vector $\vec{s_i}$ for the word s_i in the sentential context, which is represented as $(e_{i1}, e_{i2}, \ldots, e_{iq})$. Lastly, we calculate the cosine similarity between each $\vec{s_i}$ for the word in the sentential context and $\vec{p}$ separately and average all similarities to obtain the similarity between the sentential context and the property, based on which we identify the expression-related properties of the source and target domains. The specific calculation is as shown in Eq. (3).

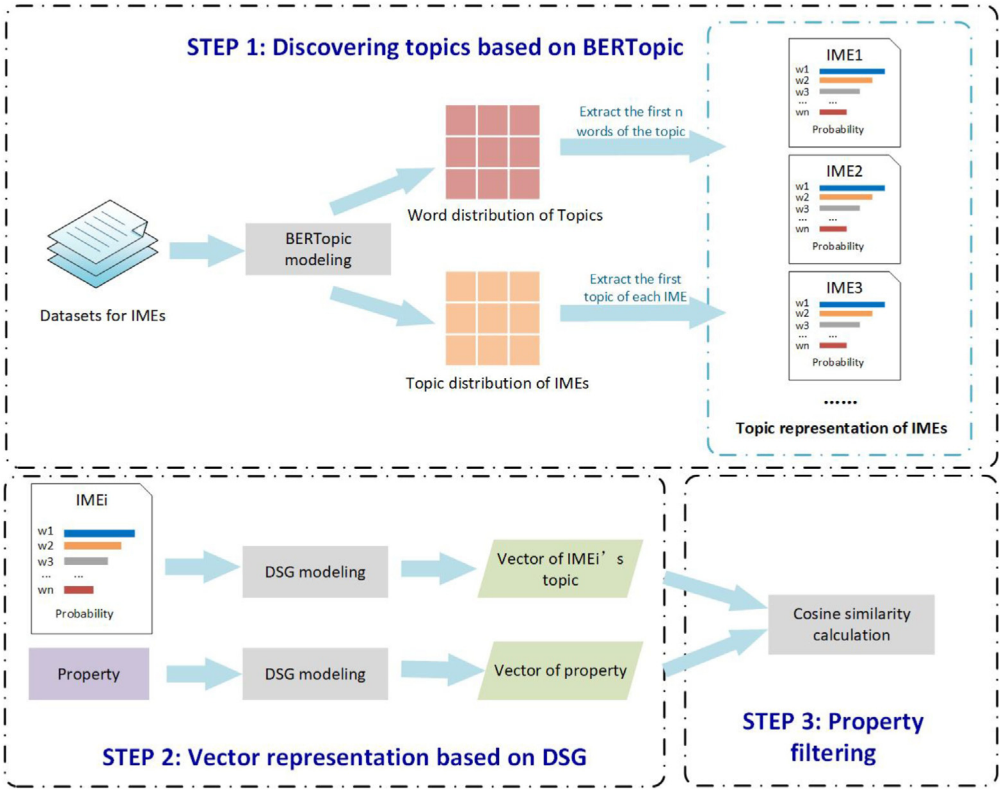

Fig. 3. The process of property filtering based on topical context.

$$Sim\left(p,SC\right)=\frac{\sum_{i=1}^{n}dis_{cos}\left(\vec{p},\vec{s_i}\right)}{n}=\frac{\sum_{i=1}^{n}\left(\frac{\sum_{j=1}^{q}r_je_{ij}}{\sqrt{\sum_{j=1}^{q}{r_j}^2}\sqrt{\sum_{j=1}^{q}{e_{ij}}^2}}\right)}{n} \tag{3}$$

4.3. Property matching

After the properties are extracted and filtered out, the properties of the source and target domains are matched based on word semantics to get the interdisciplinary associated property pairs. There are two kinds of correspondence between the associated properties of the source and target domains in metaphor interpretation [38]: shallow semantic similarity, where the source and target domains share common properties, and latent semantic similarity, where the properties of both domains are not identical but similar. In this paper, shallow semantic similarity and latent semantic similarity are defined as follows:

Definition 1 (*The Shallow Semantic Similarity*)**.** Given two properties, A and B, if B is a synonym of A in WordNet [63], then A and B have a shallow semantic similarity, represented as $Shallow(A,B)$.

Definition 2 (*The Latent Semantic Similarity*)**.** Given two properties A and B, if B is not a synonym of A in WordNet but there is an intermediate node C connecting A and B, then A and B have a latent semantic similarity, represented as $Latent(A,B)$. Fig. 4 shows the four situations of latent semantic similarities between A and B: (a) if $Shallow(A,C)\wedge Shallow(C,B)$, then $Latent(A,B)$; (b) if $Shallow(A,C)\wedge Latent(C,B)$, then $Latent(A,B)$; (c) if $Latent(A,C)\wedge Shallow(C,B)$, then $Latent(A,B)$; (d) if $Latent(A,C)\wedge Latent(C,B)$, then $Latent(A,B)$.

Based on the above definitions, the property matching method is proposed:

1. Generate property pairs. In the property extraction section, three relationship types between concepts and properties are defined as feature, function, and structure. Consequently, properties of the source and target domains sharing the same property relationship type constitute the property pairs to be matched.
2. Determine shallow semantic similarity. For a property pair, we first find the synonyms of the source domain's property using WordNet. The two properties are regarded to have a shallow semantic similarity if the target domain's property is found in the synonyms of the source domain.
3. Determine latent semantic similarity. If the property pair is not shallow semantic similar, we further determine whether it is latent semantic similar. We first discover all the synonyms of the source domain's property, then we randomly select one of the synonyms and discover all of its synonyms. This process is repeated until the target domain's property is found in the set of synonyms. According to Six Degrees of Separation [64], everyone and everything is six steps or less away, so we limit the number of iterations to six. Hence, if we find the target domain's property in no more than six iterations, the two properties have a latent semantic similarity.

4.4. Property ranking

With the above steps, several interdisciplinary associated property pairs of an IME are obtained based on multidimensional contexts and word semantics. Interdisciplinary associated property pairs are ranked to find the most accurate interdisciplinary concept association for an IME. According to relevance theory, the best metaphor interpretation results should have the most

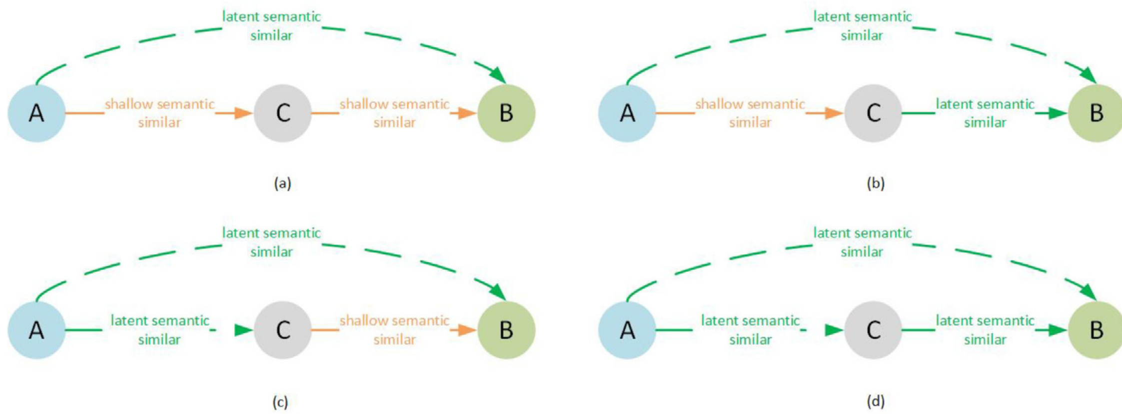

Fig. 4. The four situations of latent semantic similarity between A and B. Node C is the intermediary node that makes A and B latent semantic similar. The solid yellow line represents two nodes that are shallow semantic similar, and the dashed green line represents two nodes that are latent semantic similar.

significant relevance to the context [65], so we rank the property pairs based on the topical and sentential contexts analyzed above. Firstly, considering that people tend to use the source domain's properties to express their thoughts about the target domain, we rank the property pairs based on the similarity between the source domain's properties and both the topical and expressive contexts [15]. The calculation is shown in Eq. (4), where α and β are the weights of the topical context and sentential context, respectively, and $\alpha+\beta=1$. If the most relevant source domain's property is found in more than one of the interdisciplinary associated property pairs, we select the property pair with which the target domain's property is also most relevant to the topical and sentential contexts through Eq. (4).

$$Sim(p, context) = \alpha Sim\,(p, T) + \ \beta Sim\,(p, SC) \tag{4}$$

5. Experiment and results

In this study, we conducted a group of experiments to validate the effectiveness of the proposed ICAD-MI method on interdisciplinary concept association discovery. The programming language used in the experiments was Python. In addition, in terms of the tools used in the experiments, we used the Easy DL platform with a Tesla P40 24G GPU for property extraction, BERTopic topic model, and Tencent AI Lab Embedding Corpus [66] for property filtering and property ranking, and WordNet for property matching.

5.1. Datasets

In the experiments, we constructed two datasets:

1. The IME dataset. The proposed ICAD-MI method was applied to a dataset of IMEs under the interdisciplinary conceptual metaphor *Computer is a brain* in Computer Science. The reason we selected this interdisciplinary conceptual metaphor is that a computer and the nervous system of the human brain overlap in several topics, such as information processing [67], which provides the basis for using the concept "brain" in Biology to understand and develop the concept "computer" in Computer Science. Especially with the recent widespread interest in artificial intelligence, *Computer is a brain* is being used more and more widely [68]. Moreover, since this metaphor is widely used and well-known, it is easier for domain experts to interpret, validate, and evaluate our experimental results. To collect all possible relevant IMEs, IMEs of *Computer is a brain* in Computer Science were extracted from CNKI and, finally, a total of 1,915 IMEs in the published scientific literature on CNKI were retrieved. In our experiments, we grouped the 1,915 IMEs into two sets: a reference set and a test set to evaluate the proposed method in this paper. The reference set consists of 1,723 IMEs, and the test set consists of 192 IMEs randomly selected from the dataset.
2. The property extraction dataset. To train the property extraction model based on Easy DL, terms in Library and Information Science were chosen as the source of disciplinary concepts. We used CNKI's Conceptual Knowledge Element Search function to obtain 4,491 relevant sentences describing the properties of the above concepts. To construct the property extraction dataset, we annotated these sentences with concepts, properties, and relationship types. The details of the property extraction dataset are given in Table 5.

Table 5
The detailed description of the property extraction dataset.

Relationship type	Amount
Feature	2379
Function	2184
Structure	865

5.2. Gold standard construction

To create a gold standard for our experiments, we invited five domain experts with backgrounds in metaphorical knowledge and artificial intelligence research to annotate the interdisciplinary associated property pair in the test set. Before the annotation, the properties of the source domain "brain" and the target domain "computer" were provided to the experts. The annotation process is as follows:

1. Each expert gave the most relevant property of the source domain for each IME based on their experience.
2. The property of the target domain mapping to that property of the source domain was found based on WordNet. If not found, the property of the source domain was reselected for property matching. If more than one property of the target domain was found, the most relevant property of the target domain was given according to their own experience. An associated property pair for each IME was given by each expert. If the interdisciplinary conceptual metaphor interpretation results of IMEs differed between

experts, further discussions were held among the experts to obtain consistent results.

3. The gold standard of interdisciplinary conceptual metaphor interpretation was generated for each IME in the test set. The standard of interdisciplinary concept associations between the source and target domains was generated by integrating the results of interdisciplinary conceptual metaphor interpretation for the test set.

5.3. Evaluation metrics

This paper integrates the interdisciplinary conceptual metaphor interpretation results for all IMEs of an interdisciplinary conceptual metaphor to discover multiple fine-grained property associations of the interdisciplinary concept pair. Therefore, we evaluated the performance of the proposed ICAD-MI method from interdisciplinary conceptual metaphor interpretation and interdisciplinary concept association discovery, respectively.

5.3.1. Evaluation metrics for interdisciplinary conceptual metaphor interpretation

Interdisciplinary conceptual metaphor interpretation can identify the associated property pair of an IME. In our experiments, the rank-n accuracy and Cumulative Match Characteristic (CMC) curve were selected to evaluate the accuracy of interdisciplinary conceptual metaphor interpretation using the proposed ICAD-MI method. Rank-n accuracy measures how often a predicted class is in the top n results. We rank the interdisciplinary associated property pairs for each IME. The prediction is regarded as correct if the predicted result falls into the first n results. The rank-n accuracy is calculated using Eq. (5), where $Correct_{IMEs}$ is the number of predicted correct IMEs, $Total_{IMEs}$ is the total number of all IMEs.

$$Rank - n\ accuracy = \frac{Correct_{IMEs}}{Total_{IMEs}} \tag{5}$$

Moreover, the CMC curve is a curve on the rank score and rank-n accuracy to measure the performance of identification algorithms based on the accuracy for each rank. The starting point of the CMC curve (rank-1 accuracy) and its slope can give a good indication of performance evaluation for interdisciplinary conceptual metaphor interpretation.

5.3.2. Evaluation metrics for interdisciplinary concept association discovery

Fine-grained interdisciplinary associated property pairs for disciplinary concepts can be found by integrating the interdisciplinary conceptual metaphor interpretation results of all IMEs for an interdisciplinary conceptual metaphor. In this experiment, precision, recall, and F1 score were computed with Eq. (6), Eq. (7), and Eq. (8) to measure the performance of the proposed ICAD-MI method on interdisciplinary concept association discovery.

$$Precision = \frac{Correct_{ICA}}{Total_{ICA}} \tag{6}$$

$$Recall = \frac{Correct_{ICA}}{Annotation_{ICA}} \tag{7}$$

$$F1\ score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{8}$$

Where $Correct_{ICA}$ represents the number of correct interdisciplinary concept associations discovered, $Total_{ICA}$ represents the total number of interdisciplinary concept associations discovered, $Annotation_{ICA}$ represents the number of annotated interdisciplinary concept associations.

Table 6
Evaluation results of the property extraction model.

Evaluation indicators	Performance
Precision	84.4%
Recall	87.3%
F1 score	85.8%

5.4. Baseline methods

To evaluate the performance of our method, we implemented four state-of-the-art baseline methods for comparison. Our proposed method is first compared to the LSS [38] to validate context's critical role in interdisciplinary concept association discovery based on metaphor interpretation; then to the CDMI [15] to verify the performance of our method in taking multiple contexts into consideration; furthermore, to TCMI, which ignores the sentential context in contrast to our method, to demonstrate the need to consider the sentential context in ICAD-MI; and, finally, to ECMI, which does not consider topical context, to verify the advantage of our method that accounts for both contexts. Moreover, it is helpful to compare the performance of TCMI and ECMI in determining the parameters of α and β.

5.5. Results

In this subsection, we first show the interdisciplinary concept association discovery results for the selected interdisciplinary conceptual metaphor *Computer is a brain*. We then compare the performance of our proposed ICAD-MI method with four state-of-the-art baselines on interdisciplinary conceptual metaphor interpretation and interdisciplinary concept association discovery to validate the effectiveness of our method.

5.5.1. Results of interdisciplinary concept association discovery

The proposed ICAD-MI method was used to discover fine-grained interdisciplinary associated property pairs of "brain" and "computer" in the test set. The experimental results are as follows:

1. Property extraction of the "computer" and "brain". We trained the property extraction model using the labeled property extraction dataset. The performance is presented in Table 6, demonstrating the effectiveness of the model. Figs. 5 and 6 display the results of property extraction using the trained property extraction model introduced earlier.
2. Property filtering of the "computer" and "brain" based on topical context. We used BERTopic to get the topic-word distribution and the document-topic distribution of 1,915 IMEs. Six topics were generated, and their topic-word distribution is shown in Fig. 7. We chose the first topic of each IME as the IME's topic, and the distribution of IMEs under each topic is shown in Fig. 8. It can be seen that the interdisciplinary conceptual metaphor *Computer is a brain* is mainly used in artificial neural network and computer vision. After that, the Tencent AI Lab Embedding Corpus, trained with the DSG model and providing pre-trained word embedding of over 8 million words, was used to obtain the vector of each IME's topic and vector of properties. Then we filtered out properties that are not relevant to the topic through Eq. (2). Table 7 and Table 8 show the top 20 properties of "computer" and "brain" most relevant to each topic, respectively. For multiple IMEs under the same topic in the test set, their property filtering results in this step are the same.

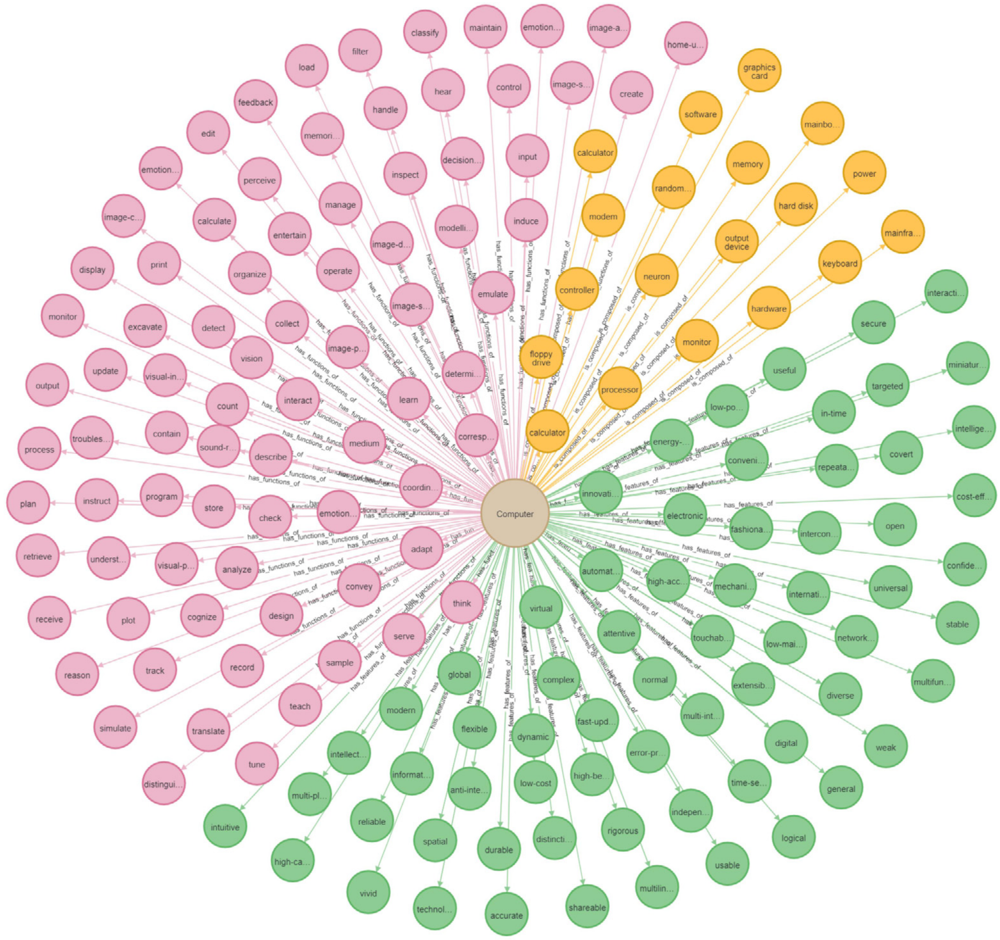

Fig. 5. Results for "computer" property extraction. The green nodes, the pink nodes, and the yellow nodes are the feature properties, function properties, and structure properties of the "computer", respectively.

3. Property filtering of "computer" and "brain" based on sentential context. Following the property filtering results based on topical context, we further filtered the properties of "computer" and "brain" based on sentential context via Eq. (3). Table 9 shows the property filtering results based on the sentential context of an example in the test set. The example IME is *The creation of artificial neural networks was inspired by biological neural networks in an attempt to give computers the ability to think like a brain*. It belongs to the topic of artificial neural network.
4. Property matching of "computer" and "brain". After property filtering, properties were matched based on shallow semantic similarity and latent semantic similarity. Fig. 9 presents the property matching results for the example IME from the test set.
5. Parameter analysis. Comparing the performance of TCMI and ECMI on the rank-1 accuracy and F1 score in Table 10, we conclude that sentential context is more important than topical context. Therefore, we set the values of parameters α and β to (0.1, 0.9), (0.2, 0.8), (0.3, 0.7), and (0.4, 0.6), respectively. The objective is to determine the optimal set of values that yield the best performance for ICAD-M. The performance evaluation results of ICAD-MI with different parameter values are given in Fig. 10, in which the ICAD-MI method has the best rank-1 accuracy, precision, recall, and F1 score when α is 0.3 and β is 0.7. Therefore, in our experiments, we set the parameters α to 0.3 and β to 0.7.
6. Interdisciplinary associated property pairs ranking. Interdisciplinary associated property pairs of each IME were ranked by Eq. (4). Table 11 shows the ranking results for the example IME from the test set.
7. Integration of interdisciplinary conceptual metaphor interpretation results. The interdisciplinary concept association of each IME in the test set was identified based on the previous steps. After integrating the results, fine-grained interdisciplinary concept associations between "computer" and "brain" under different topics for the test set are shown in Fig. 11.

5.5.2. Model comparison for interdisciplinary conceptual metaphor interpretation

Interdisciplinary conceptual metaphor interpretation is performed for each IME, through which we can identify the associated property pair implied by each IME, as the foundation for interdisciplinary concept association discovery. The ICAD-MI method proposed in this paper discovers interdisciplinary concept associations by integrating the results of interdisciplinary conceptual metaphor interpretation for each IME under the interdisciplinary conceptual metaphor. Therefore, evaluating the results of the interdisciplinary conceptual metaphor interpretation is an important aspect of the method evaluation. Fig. 12 shows the rank-1 accuracy and CMC curve of interdisciplinary conceptual metaphor interpretation regarding our method and the four baseline methods, from which we have the following observations:

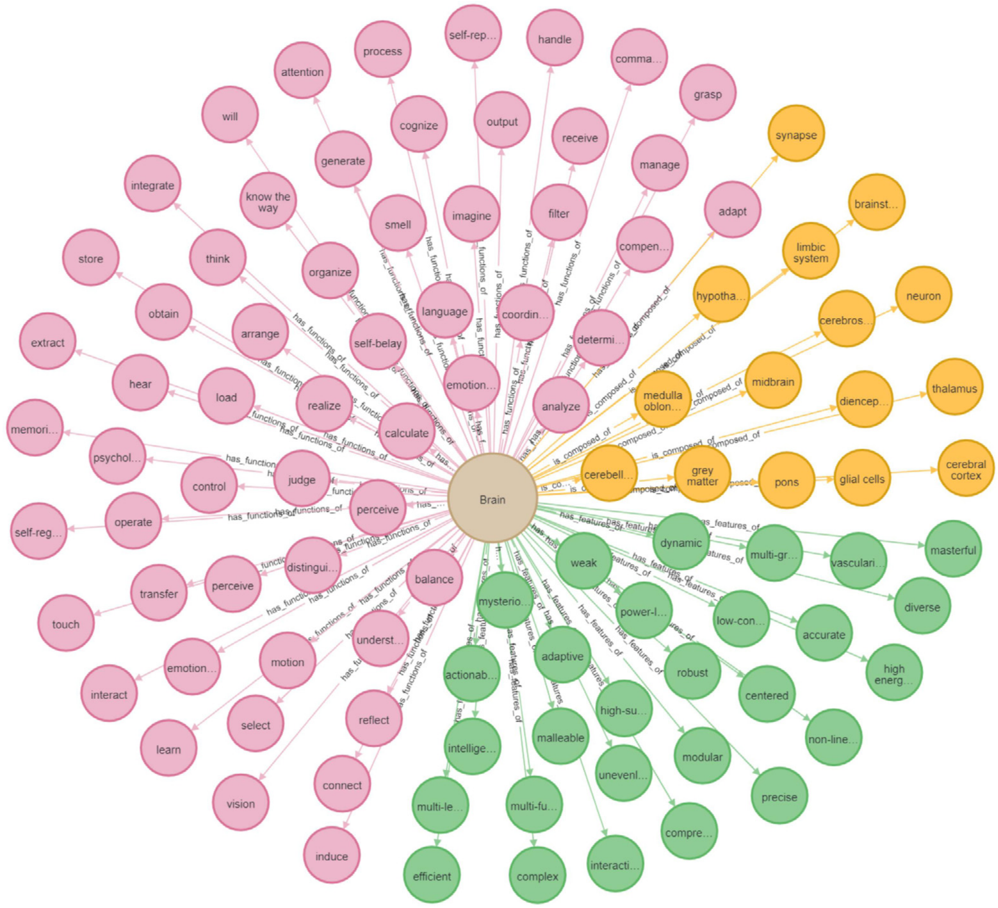

Fig. 6. Results for "brain" property extraction. The green nodes, the pink nodes, and the yellow nodes are the feature properties, function properties, and structure properties of the "brain", respectively.

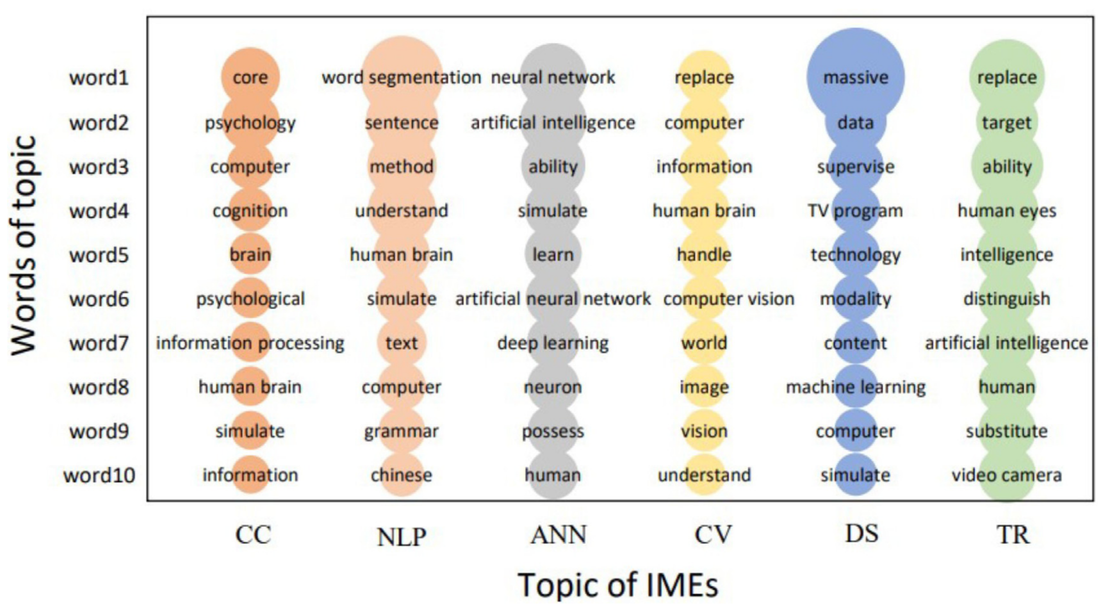

Fig. 7. The top 10 words in each topic category. CC: cognitive computing, NLP: natural language processing, ANN: artificial neural network, CV: computer vision, DS: data supervision, TR: target recognition. Different colored bubbles represent topic words under different topics and the size of the bubble indicates the probability of each word being related to the topic.

Table 7
The top 20 most relevant properties of "computer" under each topic. CC: cognitive computing, NLP: natural language processing, ANN: artificial neural network, CV: computer vision, DS: data supervision, TR: target recognition. The number in the bracket following each property is the similarity of the property to the topic.

Index	CC	NLP	ANN	CV	DS	TR
1	think (0.8518)	translate (0.7667)	neuron (0.7679)	correspond (0.7337)	image-process (0.7699)	distinguish (0.7344)
2	memorize (0.7449)	program (0.7567)	image-analysis (0.7466)	simulate (0.7316)	program (0.7694)	input device (0.6857)
3	simulate (0.7201)	understand (0.7531)	image-distinguish (0.7394)	image-process (0.7256)	simulate (0.7622)	control (0.6857)
4	cognize (0.7160)	simulate (0.7211)	emotion-distinguish (0.7290)	program (0.7215)	software (0.7622)	perceive (0.6817)
5	perceive (0.6991)	memorize (0.7051)	image-process (0.7255)	think (0.7123)	correspond (0.7460)	output device (0.6817)
6	understand (0.6986)	software (0.7023)	think (0.7242)	software (0.7092)	image-analysis (0.7267)	correspond (0.6772)
7	program (0.6887)	think (0.6937)	visual-perceive (0.7080)	output device (0.7047)	image-distinguish (0.7097)	monitor (0.6742)
8	learn (0.6652)	induce (0.6814)	program (0.7047)	memorize (0.7000)	virtual (0.7001)	simulate (0.6710)
9	correspond (0.6631)	sound-record (0.6661)	vision (0.6969)	store (0.6966)	emulate (0.6951)	receive (0.6616)
10	neuron (0.6403)	learn (0.6613)	virtual (0.6956)	input device (0.6937)	retrieve (0.6935)	store (0.6596)
11	medium (0.6340)	teach (0.6597)	calculator (0.6784)	understand (0.6855)	input device (0.6933)	software (0.6584)
12	hear (0.6333)	determine (0.6577)	simulate (0.6771)	plot (0.6839)	monitor (0.6919)	medium (0.6578)
13	reason (0.6324)	classify (0.6541)	interact (0.6619)	distinguish (0.6827)	output device (0.6847)	memorize (0.6551)
14	determine (0.6308)	plot (0.6532)	input device (0.6553)	image-analysis (0.6718)	store (0.6837)	think (0.6533)
15	hardware (0.6288)	distinguish (0.6510)	modeling (0.6464)	monitor 0.6702)	hardware (0.6825)	image-process (0.6362)
16	input device (0.6255)	edit (0.6509)	perceive (0.6461)	describe (0.6690)	calculator (0.6806)	understand (0.6190)
17	teach (0.6231)	calculator (0.6504)	miniaturized (0.6428)	hardware (0.6674)	automatic (0.6777)	output (0.6186)
18	software (0.6214)	input device (0.6492)	emulate (0.6328)	memory (0.6638)	memory (0.6767)	collect (0.6160)
19	analyze (0.6207)	output device (0.6454)	digital (0.6295)	receive (0.6625)	distinguish (0.6665)	plot (0.6139)
20	image-process (0.6198)	input (0.6435)	memorize (0.6291)	calculator (0.6617)	count (0.6644)	program (0.6125)

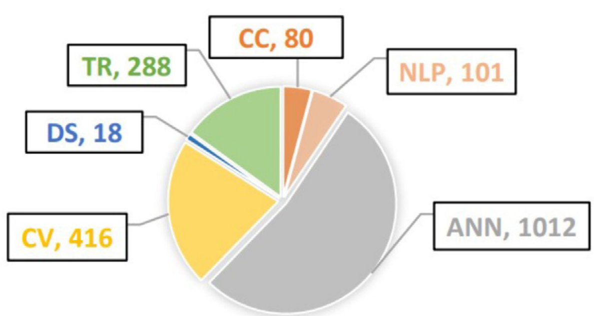

Fig. 8. The IME distribution under each topic. CC: cognitive computing, NLP: natural language processing, ANN: artificial neural network, CV: computer vision, DS: data supervision, TR: target recognition.

- The proposed ICAD-MI method outperforms other baseline methods from rank-1 to rank-10 accuracy, proving its effectiveness in interdisciplinary conceptual metaphor interpretation. Moreover, the slope of the CMC curve for our method is smaller than that of the baseline methods, revealing that the current performance of our method on interdisciplinary conceptual metaphor interpretation is excellent. Therefore, the potential for improvement is limited. The best performance of ICAD-MI is due to the fact that it takes into account multidimensional relevant contexts in interdisciplinary conceptual metaphor interpretation.
- LSS has the lowest accuracy for each rank score in the CMC curve, suggesting that LSS performs worst in interdisciplinary conceptual metaphor interpretation. The reason might be that LSS only considers word semantics while ignoring contexts. This result highlights the importance of context in interdisciplinary conceptual metaphor interpretation.
- Regarding rank-1 accuracy and the CMC curve results, CDMI outperforms the LSS but is inferior to ICAD-MI, mainly because this method only considers the single contextual dimension of sentential context. The result reveals the significance of considering multidimensional contexts in interdisciplinary conceptual metaphor interpretation. Furthermore, compared to ECMI, which also considers sentential context only, CDMI has the worse performance. The main reason is that CDMI sums contextual and word semantic similarity to rank properties, which tends to make the results less accurate by allowing properties with high word semantic similarity and low contextual similarity to be selected in interdisciplinary conceptual metaphor interpretation. In contrast, ECMI ranks properties according to contextual similarity based on the associated property pairs, which is proven to be more scientific and effective.
- The performance of both TCMI and ECMI on rank-1 accuracy and CMC curve is worse than that of ICAD-MI, reflecting the importance of integrating multidimensional contexts – i.e., topical context and sentential context – into the interdisciplinary conceptual metaphor interpretation. In addition, ECMI outperforms TCMI in both rank-1 accuracy

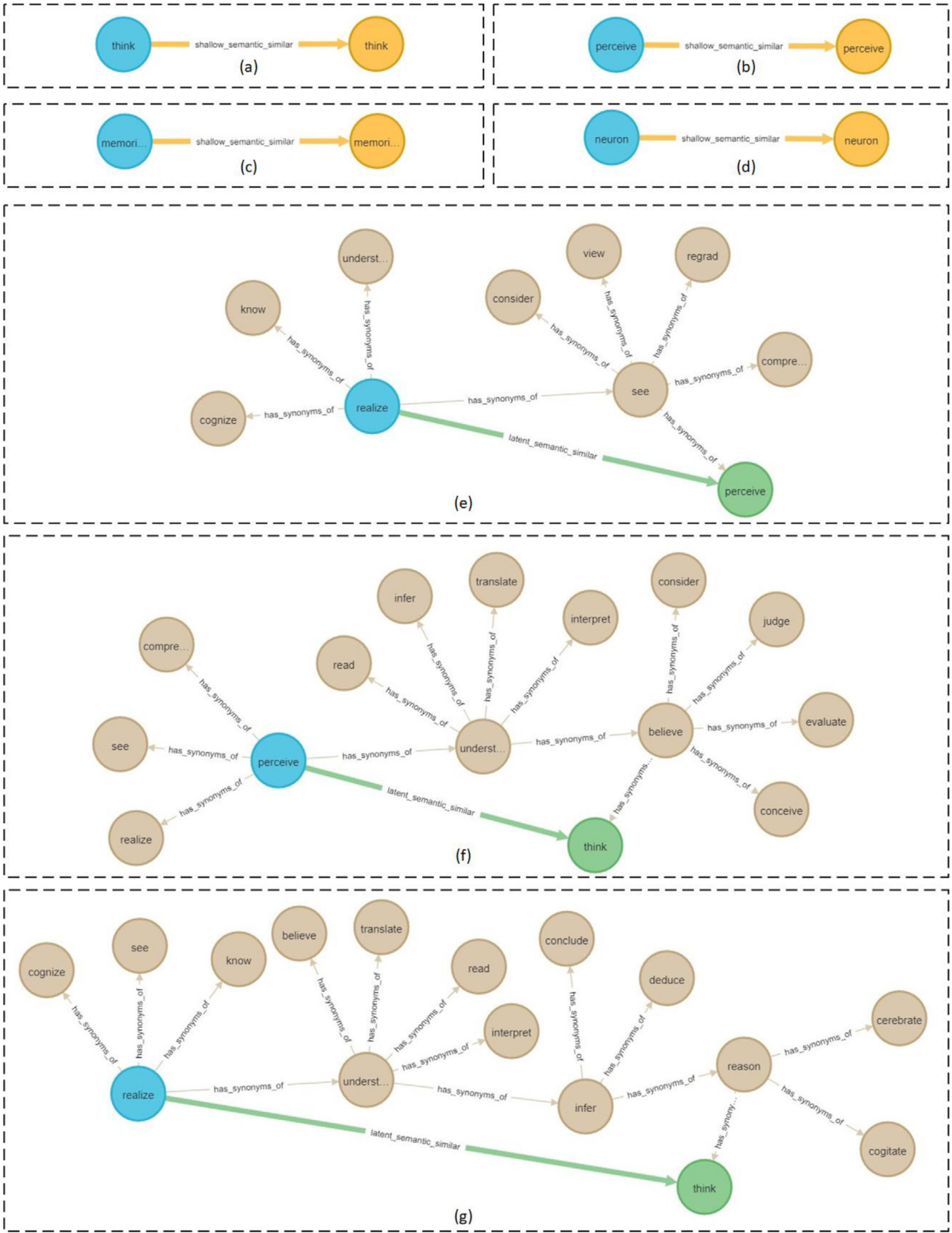

Fig. 9. An example of property matching. (a) *Shallow*(*think*, *think*), (b) *Shallow*(*perceive*, *perceive*), (c) *Shallow*(*memorize*, *memorize*), (d) *Shallow*(*neuron*, *neuron*), (e) *Latent*(*realize*, *perceive*), (f) *Latent*(*perceive*, *think*), (g) *Latent*(*realize*, *think*). The blue nodes represent the properties of the "brain", the brown nodes are synonyms found in WordNet, and the yellow and green nodes are the properties of the "computer". The yellow line indicates that the two nodes are shallow semantic similar and the green line means that the two nodes are latent semantic similar.

Table 8
The top 20 most relevant properties of "brain" under each topic. CC: cognitive computing, NLP: natural language processing, ANN: artificial neural network, CV: computer vision, DS: data supervision, TR: target recognition. The number in the bracket following each property is the similarity of the property to the topic.

Index	CC	NLP	ANN	CV	DS	TR
1	think (0.8518)	language (0.8212)	neuron (0.7679)	transfer (0.7394)	transfer (0.7284)	intelligent (0.7409)
2	realize (0.7567)	understand (0.7531)	psychological-represent (0.7504)	language (0.7224)	language (0.7095)	distinguish (0.7344)
3	memorize (0.7449)	operate (0.7085)	synapse (0.7352)	think (0.7123)	operate (0.7009)	transfer (0.7071)
4	cognize (0.7160)	memorize (0.7051)	robust (0.7352)	memorize (0.7000)	store (0.6837)	control (0.6857)
5	language (0.7082)	think (0.6937)	think (0.7242)	store (0.6966)	distinguish (0.6665)	perceive (0.6817)
6	perceive (0.6991)	induce (0.6814)	non-linear (0.7077)	operate (0.6949)	interact (0.6610)	receive (0.6616)
7	psychological-represent (0.6987)	learn (0.6613)	glial cells (0.6982)	understand (0.6855)	intelligent (0.6552)	judge (0.6612)
8	understand (0.6986)	distinguish (0.6510)	operate (0.6945)	distinguish (0.6827)	generate (0.6547)	store (0.6596)
9	cerebral cortex (0.6921)	transfer (0.6352)	limbic system (0.6868)	intelligent (0.6819)	think (0.6530)	load (0.6581)
10	reflect (0.6824)	psychological-represent (0.6328)	interact (0.6619)	judge (0.6782)	manage (0.6523)	memorize (0.6551)
11	learn (0.6652)	store (0.6169)	cerebral cortex (0.6544)	receive (0.6625)	robust (0.6498)	think (0.6533)
12	limbic system (0.6631)	judge (0.6027)	perceive (0.6461)	vision (0.6572)	non-linear (0.6491)	realize (0.6425)
13	transfer (0.6521)	intelligent (0.6007)	emotion-distinguish (0.6378)	control (0.6507)	integrate (0.6391)	accurate (0.6379)
14	cerebellum (0.6412)	reflect (0.5960)	adaptive (0.6349)	obtain (0.6474)	obtain (0.6338)	obtain (0.6206)
15	neuron (0.6403)	output (0.5926)	memorize (0.6291)	perceive (0.6459)	receive (0.6313)	understand (0.6190)
16	will (0.6338)	analyze (0.5902)	transfer (0.6290)	realize (0.6399)	memorize (0.6153)	output (0.6186)
17	hear (0.6333)	generate (0.5878)	language (0.6265)	interact (0.6387)	psychological-represent (0.6133)	language (0.6109)
18	synapse (0.6301)	realize (0.5847)	cerebellum (0.6259)	generate (0.6385)	accurate (0.6129)	operate (0.6063)
19	analyze (0.6207)	manage (0.5710)	realize (0.6096)	manage (0.6366)	control (0.6094)	vision (0.6005)
20	operate (0.6206)	accurate (0.5697)	interactive (0.6071)	accurate (0.6363)	learn (0.6029)	imagine (0.6002)

Table 9
An example of property filtering based on sentential context. The number in the bracket following each property is the similarity of the property to the sentential context.

Index	Brain property	Computer property
1	think (0.5045)	think (0.5045)
2	perceive (0.4951)	perceive (0.4951)
3	memorize (0.4810)	memorize (0.4810)
4	realize (0.4717)	neuron (0.4675)
5	synapse (0.4678)	simulate (0.4266)
6	neuron (0.4675)	image-process (0.3428)
7	psychological-represent (0.4614)	interact (0.3878)
8	limbic system (0.4434)	program (0.3824)
9	glial cells (0.4398)	calculator (0.3780)
10	non-linear (0.4320)	visual-perceive (0.3748)

Table 10
Comparison of TCMI and ECMI performance.

Method	Rank-1 accuracy	F1 score
TCMI	0.422	0.345
ECMI	**0.656**	**0.700**

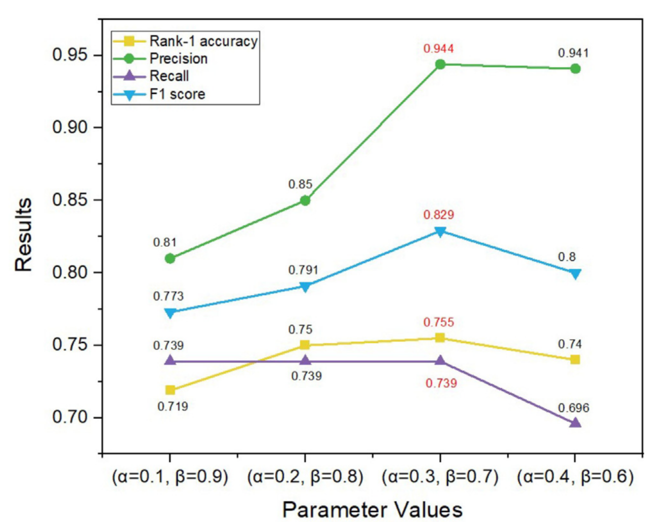

Fig. 10. The ICAD-MI performance evaluation results with different parameters.

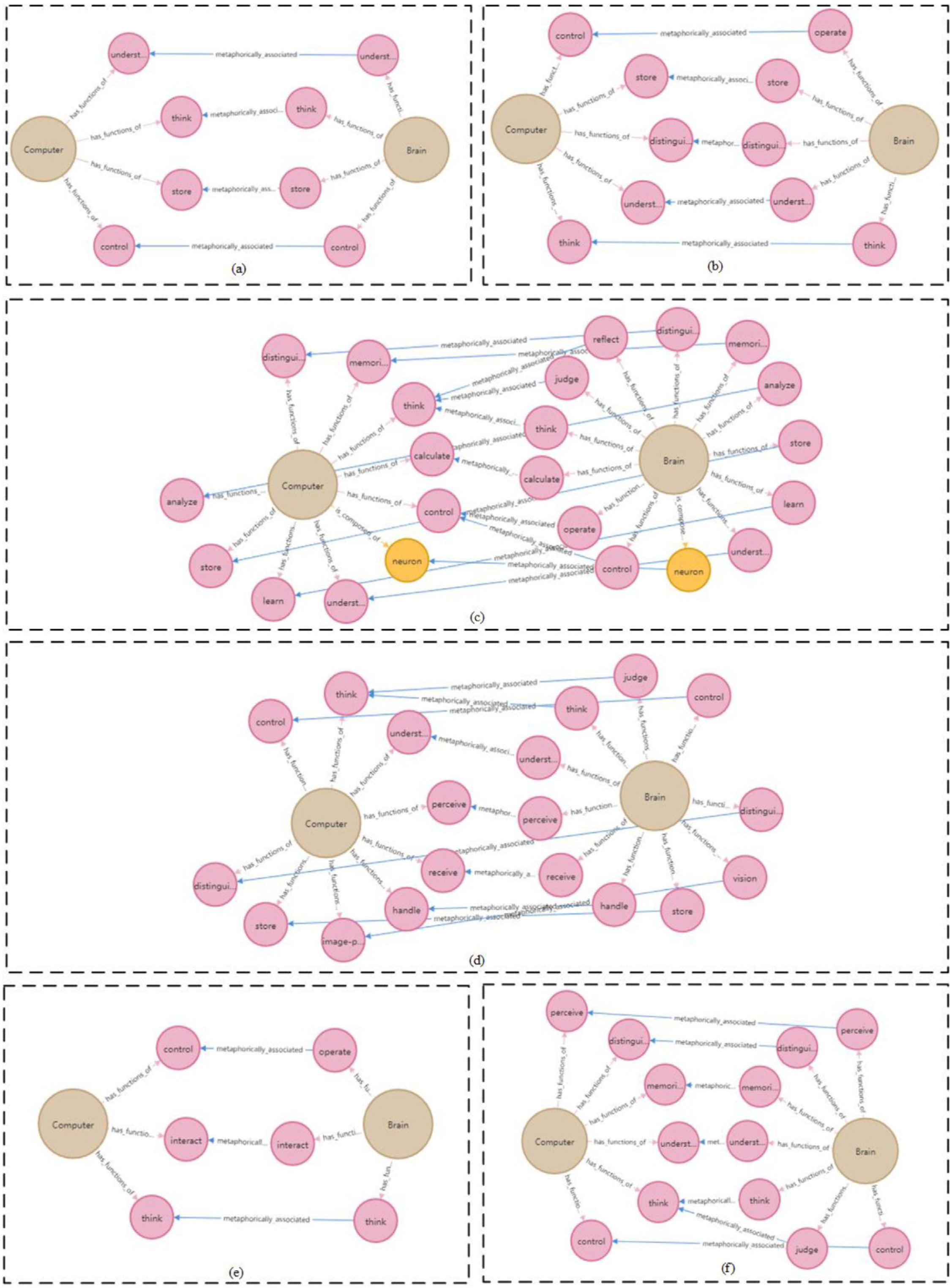

Fig. 11. Interdisciplinary concept associations between "computer" and "brain" under different topics: (a) cognitive computing, (b) natural language processing, (c) artificial neural network, (d) computer vision, (e) data supervision, and (f) target recognition. The pink and yellow nodes are the function properties and structure properties, respectively.

Table 11
An example of property ranking. Sim(Property(B), C): similarity of the properties of "brain" to topical and sentential contexts, Sim(Property(C), C): similarity of the properties of "computer" to topical and sentential contexts.

Rank	Property pairs	Sim(Property(B), C)	Sim(Property(C), C)
1	**(think, think)**	0.5704	0.5704
2	(neuron, neuron)	0.5576	0.5576
3	(perceive, think)	0.5404	0.5704
4	(perceive, perceive)	0.5404	0.5404
5	(memorize, memorize)	0.5254	0.5254
6	(realize, think)	0.5131	0.5704
7	(realize, perceive)	0.5131	0.5404

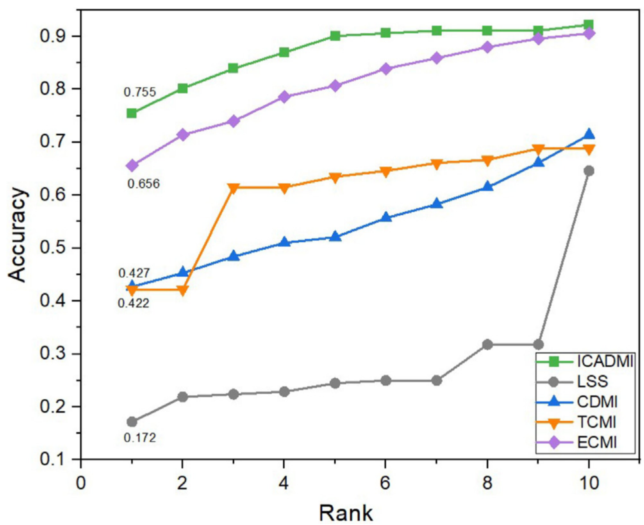

Fig. 12. Evaluation results of interdisciplinary conceptual metaphor interpretation.

and CMC curve results, showing that the sentential context is of greater importance than the topical context in interdisciplinary conceptual metaphor interpretation.

5.5.3. Model comparison for interdisciplinary concept association discovery

An interdisciplinary conceptual metaphor has multiple IMEs at the language level to convey diverse ideas. By conducting interdisciplinary conceptual metaphor interpretation of each IME, we can uncover the interdisciplinary concept association embedded in this IME. Accordingly, multiple fine-grained interdisciplinary concept associations of an interdisciplinary concept pair can be systematically discovered by integrating the results of interdisciplinary conceptual metaphor interpretation of all IMEs under an interdisciplinary conceptual metaphor. In this section, we further evaluate the performance of interdisciplinary concept association discovery based on interdisciplinary conceptual metaphor interpretation. Fig. 13 presents the performance of interdisciplinary concept association discovery based on our method and the four baseline methods in terms of precision, recall, and F1 score. Our findings are:

- ICAD-MI achieves the best performance with the F1 score of 0.829, recall of 0.739, and precision of 0.944 because of its advantages in considering multidimensional contexts.
- LSS performs the worst with the lowest recall and F1 score, confirming the importance of considering contextual information in interdisciplinary concept association discovery based on metaphor interpretation. The lowest recall is due to the fact that this method ignores contextual information, resulting in multiple interdisciplinary concept associations in different contexts not being identified. However, LSS exhibits the highest precision because the interdisciplinary concept association identified based on word semantics are the most semantically relevant properties of the source and target domains, which are highly likely to be present in interdisciplinary conceptual metaphors.
- CDMI performs worse than ICAD-MI, revealing the need to consider multiple contexts in interdisciplinary concept association discovery based on metaphor interpretation. Furthermore, ECMI also performs better than CDMI, demonstrating the validity of property matching based on word semantics and property ranking based on contexts.
- TCMI has a lower recall and F1 score than ICAD-MI, but higher precision, suggesting the importance of considering the sentential context in ICAD-MI. The reason the recall of TCMI is much lower than that of ICAD-MI is that this method only considers the topical context and ignores the sentential context in interdisciplinary conceptual metaphor interpretation. This makes it difficult to identify interdisciplinary concept associations in different sentential contexts, thus making the interdisciplinary concept associations found incomplete. However, the interdisciplinary concept associations found by TCMI have the highest topical relevance, and they are likely to be present in interdisciplinary conceptual metaphor. This leads to TCMI's high precision.
- ECMI performs worse than ICAD-MI but better than TCMI, underscoring the importance of integrating topical and sentential contexts in interdisciplinary concept association discovery based on metaphor interpretation. The result also reveals that sentential context is more important than topical context.

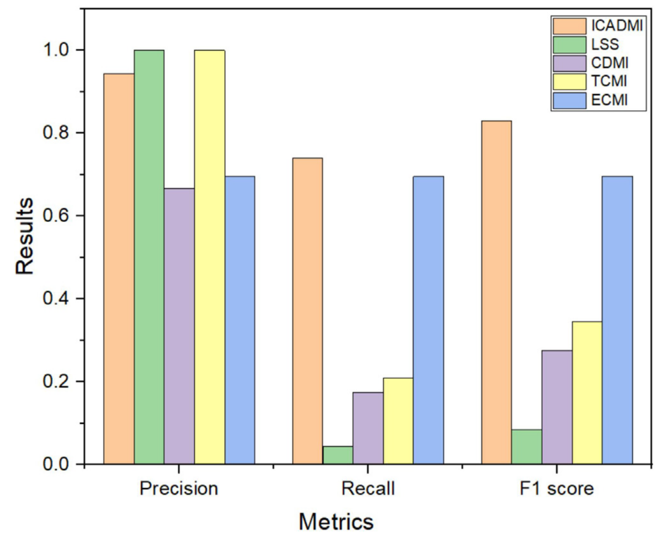

Fig. 13. Evaluation results of interdisciplinary concept association discovery.

6. Conclusion

In this paper, we propose an ICAD-MI method to discover fine-grained interdisciplinary concept associations. Specifically, we first analyze the mechanism of interdisciplinary concept metaphor based on conceptual metaphor theory at the cognitive and language layers, summarizing the multidimensional contexts in interdisciplinary conceptual metaphor. In addition, we propose an ICAD-MI method based on multidimensional contexts and word semantics, which consists of four sequential steps: property extraction based on the disciplinary context, property filtering based on the topical and sentential contexts, property matching based on word semantics, and property ranking based on the topical and sentential contexts. Finally, the analysis on the IME dataset of the interdisciplinary concept metaphor *Computer is a brain* shows that our method outperforms the other four state-of-the-art methods in supporting interdisciplinary concept association discovery.

Several key findings are obtained through this study: (a) ICAD-MI method that considers multidimensional contexts (i.e., disciplinary context, topical context, and sentential context) is more accurate in interdisciplinary concept association discovery based on metaphor interpretation than methods that consider no context or a single dimensional context; (b) sentential context plays a more important role than the topical context in interdisciplinary concept association discovery based on metaphor interpretation; and (c) property ranking should rely on both topical and sentential contexts, which contributes to the accuracy of interdisciplinary concept association discovery based on metaphor interpretation. Overall, our proposed method and findings provide a valuable reference for future interdisciplinary concept association discovery studies and have major implications for promoting interdisciplinary knowledge organization.

There are some limitations in this study. On one hand, there is room for further improvement in the performance of our trained property extraction model. This can be achieved by constructing larger and higher quality datasets and training a more effective property extraction model in future research. On the other hand, the performance of our proposed method ICAD-MI has only been validated on the typical interdisciplinary conceptual metaphor *Computer is a brain*. The generalizability of the method needs to be confirmed on large-scale data. In the future, we will construct larger datasets on interdisciplinary conceptual metaphors and their IMEs to showcase the effectiveness of the developed method.

CRediT authorship contribution statement

Zhongyi Wang: Writing – original draft, Software, Methodology, Conceptualization. **Siyuan Peng:** Writing – original draft, Software, Data curation. **Jiangping Chen:** Writing – review & editing, Writing – original draft. **Xian Zhang:** Writing – review & editing. **Haihua Chen:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Zhongyi Wang reports financial support was provided by National Social Science Foundation of China.

Data availability

Data will be made available on request.

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