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A Summary of Research on Commodity Knowledge Graph

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Abstract

Business knowledge graph technology can build a knowledge base with semantic processing capabilities and open interconnection capabilities can effectively organize and manage massive commodity information and can generate application value in intelligent information services such as intelligent search, intelligent question answering, and personalized recommendations. Based on the comprehensive description of the definition and architecture of the commodity knowledge graph, this article summarizes the information extraction in the knowledge graph, the research progress of knowledge integration technology, and some typical applications.

Keywords

Knowledge graph, Information extraction, Knowledge integration.

1. Introduction

With the development of the Internet economy, the number of commodities on e-commerce platforms has reached a huge order of magnitude. How to effectively manage and tap the commodity information of the e-commerce platform is a difficult problem. The knowledge graph describes the concepts, entities, and relationships in the objective world in a structured way, which improves the ability to better organize, manage, and understand Internet nautical information[1]. To this end, using knowledge graphs can effectively organize, store, and mine the accumulated product and user data resources of the platform[2]. And based on knowledge, develop intelligent search, personalized recommendation, intelligent question answering, and other applications to improve users' shopping experience.

This article takes the commodity knowledge graph as an object to deeply analyze the definition and architecture of the commodity knowledge graph; the second part will focus on the key technologies in the knowledge graph, elaborate on the information extraction, related research in the knowledge fusion technology and some technical details; The three parts will briefly introduce some of the applications based on the commodity knowledge graph, mainly introducing the typical application of the knowledge graph in intelligent search and in-depth question and answer; the fourth part will summarize the content of the full text.

2. Commodity Knowledge Graph

2.1 Definition of Commodity Knowledge Graph

Knowledge Graph is a knowledge base used by Google to enhance its search engine functions in 12 years[3]. A knowledge graph is essentially a semantic network that reveals the relationship between entities. That is, the knowledge graph is composed of some connected entities and their attributes, and its expression is mainly in the form of triples, namely <entity>, <relationship>, <entity> or <entity>, <attribute>, < Attribute value> and other structural forms[4]. The entity is the most basic element in the knowledge graph. The entity has different relationships among different entities; concepts mainly refer to collections, categories, object types, and types of things; attributes mainly

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refer to the attributes and characteristics that objects may have. Features, characteristics, and parameters; attribute values mainly refer to values of specified attributes of objects. Through the collection, knowledge extraction, knowledge fusion, knowledge storage, knowledge editing, knowledge annotation, and other data processing processes of massive unstructured data, a structured triplet set is obtained for storage, and a computer-readable knowledge base is completed. The construction of knowledge graph[5]. At present, there are three mainstream knowledge expression forms: Resource Description Framework (RDF) and Web Ontology Language (OWL) and attribute graph model developed by W3C[6].

The commodity knowledge graph is a large-scale semantic network centered on user needs, connecting products, users, shopping needs, and various types of open-domain knowledge and common sense. Not only includes the knowledge graph centered on commodities, but also the knowledge graph centered on the explicit node concept of user needs

2.2 Commodity Knowledge Graph Architecture

The commodity knowledge graph is logically divided into the data layer and the model layer [7]. In the data layer, knowledge is stored in units of facts. The facts are usually stored in the graph database in the form of triples, such as the open-source Neo4j [8], Twitter FlockDB [9], and Sones GraphDB [10] are the current mainstream graph database. The schema layer defines the limiting rules that the data layer should follow [11]. The ontology library is usually used to manage the pattern layer of the knowledge graph, and the ontology library's ability to support axioms, rules, and constraints is used to regulate the relationships between entities, relationships, and the types and attributes of entities. Due to the wide variety of products and brands, bottom-up construction is suitable. Bottom-up refers to extracting entities from some open-link data, selecting the ones with higher confidence to join the knowledge base, and then building the top-level pattern layer [12].

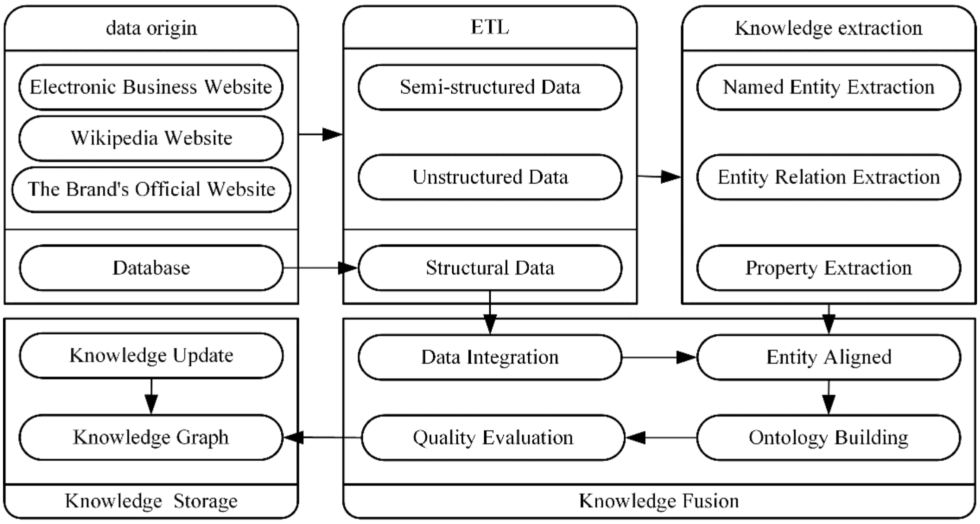

Figure 1 Commodity Knowledge Graph Architecture

The process of product knowledge graph construction is the process of knowledge extraction and knowledge fusion of product information data. After obtaining the product data of the e-commerce platform, the knowledge graph construction platform builds the product knowledge graph as the basic data and stores the integrated knowledge And application. In the process of obtaining data, ETL technology is used to synchronize metadata, and technical means such as mode conversion, mode mapping, and attribute extraction are used to ensure data consistency. When the commodity data of the e-commerce platform changes, the data in the knowledge library database To be updated simultaneously. When a knowledge graph database is created, database tables, table-type fields, and the relationship between tables are constructed in strict accordance with the logic of indexing, the

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fields are divided, and users, commodities, commodity classifications, merchants, and order data are modeled. The architecture of the commodity knowledge graph is shown in Figure 1:

3. Commodity Knowledge Graph Key Technology

Commodity knowledge graphs require a variety of intelligent information processing technologies in the construction and application, mainly including natural language processing technologies such as information extraction, knowledge fusion, and knowledge reasoning. Information extraction technology can extract entities, relationships, attributes, and other elements from semi-structured and unstructured data to enrich the knowledge set. Knowledge fusion can eliminate the ambiguity of knowledge elements, combine different expressions of the same knowledge, and form a high-quality, low-redundancy knowledge base. Knowledge reasoning is to further mine the hidden knowledge based on the existing knowledge base, to expand and enrich the knowledge base.

3.1 Information Extraction

Information extraction is mainly to extract effective knowledge elements through natural language processing technology in the face of semi-structured and unstructured text data. Therefore, according to the category of knowledge elements, information extraction can be divided into named entity recognition, relationship extraction, and attribute extraction, and constitute the fact expressed in the form of triples, which lays the foundation for the construction of the pattern layer.

3.1.1 Named Entity Recognition

Named entity recognition (NER) refers to the automatic recognition of named entities from the original corpus. Since the entity is the most basic element in the knowledge graph, the completeness, accuracy, and recall rate of its extraction have a greater impact on the quality of the knowledge base. Therefore, NER is the most important step in knowledge extraction.

Through the statistical analysis of the real corpus, the characteristics of Chinese product named entities are mainly reflected in the following aspects:

1). Characteristics of the performance form. According to statistical findings, the number of product naming entities that use "brand name + product model" and product model alone appearing in real corpus account for more than 97% of the total number of product naming entities[13]. Therefore, product naming entity identification is mainly to identify these two forms of expression.

2). Vocabulary features. Product series and product models are usually represented by character strings composed of letters, numbers, and some special symbols such as ‘-’, ‘/’, etc. For example Haier refrigerator model “BCD-268WBCS”.

3). Lexical features. The part-of-speech of each component of the product named entity is relatively fixed. Among them, the brand name is a proper noun, the product series and product model are generally strings containing numbers, and the product category is a noun.

4). Grammatical features. In nominal phrases describing product named entities, proper nouns are used to indicate the brand name of a product.

Reference[14] comprehensively analyzes the previous research methods and defines 7-dimensional features: ①the character of the word itself; ②the part-of-speech feature POS; ③contains the capital letter feature if it is marked with PABB, otherwise NONPABB; ④abbreviated feature, If it is an abbreviation, it is marked as ABB, otherwise NONABB; ⑤whether it is a pure number, it is marked as NUM, otherwise it is NONMK.

Due to the characteristics of product named entities, which are different from conventionally named entity recognition such as person names and place names, there are mainly the following difficulties in the following aspects[15]:

1). The manifestation of product named entities is flexible and changeable. For example: "Hisense TV LED32K580X3D", "Hisense LED32K-580X3D TV", "Hisense LED32K580X3D" all mean the same product.

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2). The context of product naming entities lacks specific clue words. For example, clue words such as "Mr.", "Ms.", and "Say" that often appear in the context of a person's name not only have a good indication effect on the name recognition but can also be used to help determine the boundary of the person's name.

Reference[16] further modified the labeling specifications, integrated word segmentation, part-of-speech labeling, and named entities for integrated labeling, to avoid errors caused by the delay of pre-order errors. For example, "BenQ BenQ M770GT mobile phone" is marked as "[BenQ BenQ/**BRA** M770GT/**TYPE** mobile phone]/**PRO**". Among them, **BRA** stands for the brand name, **TYPE** stands for model, n stands for the part of speech of the word is a noun, and **PRO** stands for the product name. The labeling method hierarchically labels phrases, but the labeling method is more complicated, and it takes a lot of time to label a large amount of data. Reference[17] used conditional random fields(CRF) for the first time to identify named entities of English products. The method is marked at the word level, and a characteristic template is designed for the collected brand vocabulary, and finally, a high recognition accuracy rate is obtained. The article also proposes a new **PROD-O** labeling method, that is, the product entity is labeled **PROD**, otherwise the label is **O**. Besides, there is the **BIO** annotation method[18], that is, **B-begin** marks the beginning of the entity, **I-in** is inside the entity, and **O** is the non-entity.

Early NER products mainly focused on rule-based and statistical methods. For example, document[19] defines commodity NER as consisting of brand name, model, category words and some other product attribute information, and proposes a commodity NER method based on hierarchical hidden Markov model. This method integrates the linguistic features of different levels through the integration of statistical models, organically integrates with the knowledge base and heuristic rules into a unified framework, and achieves better performance.

Reference[20] comprehensively uses the rule dictionary and statistical methods, establishes a three-layer semi-supervised learning framework, and uses hidden conditional random fields for sequence recognition, fully uses bootstrapping to obtain the hidden state of the data, and finally realizes product name recognition.

Literature[21] proposed a product NER method based on the maximum entropy model of the knowledge base. After introducing the characteristics of the brand library, the accuracy of brand recognition was improved, but the method can only be effective in certain product categories. As a result, literature[22] integrated domain ontology into the statistical model, combined with part-of-speech feature and context feature to form a multi-feature model to conduct product naming entity recognition experiment, which proved the effectiveness of domain ontology feature to NER. It can be seen from the above literature that the ontology knowledge embedding can improve the performance of NER in a certain field, but the construction of ontology has certain difficulties, especially for modeling massive commodities. From the current point of view, the deep learning framework embedded with knowledge will be one of the NER's follow-up research focuses.

3.1.2 Relationship Extraction

From the perspective of product functions and product market circulation from the perspective of e-commerce, the relationship in the product knowledge graph model layer is subdivided into four categories: synonymous relationship, IsA relationship, whole-part relationship, an attribute relationship. Different types of relationships have different characteristics and different extraction methods.

1). Synonymous relationship: refers to the same or similar language expression at the conceptual level, existing between concepts, entities or attributes, such as "screen" and "display", "grip" and "hand feeling" in the field of mobile phones. The goal of synonymous relationship extraction is to find terms that are different but represent the same concept, entity, or attribute. The extraction of synonymous relations in the model layer of the product knowledge graph will use the synonyms and the "alias" entry of the encyclopedia website. Specifically, input the concepts in the product field into the thesaurus and return the corresponding synonyms to obtain the synonymous relationship. Enter the

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concepts in the product field into the encyclopedia system, and use the "alias" entry of the encyclopedia page to extract synonyms of the concepts to further supplement the synonymous relationship.

2). IsA relationship: also called hierarchical relationship, that is, the concept and sub-concepts are determined according to the scope. For example, the subordinate words of "country" include "China" and "United States". Given the limited number of such relationships in the domain, from the perspective of extraction cost and efficiency, we rely on the classification system of the Encyclopedia website to obtain the subordinate relationship between the domain concepts. Specifically, using the classification system of the encyclopedia website, the concepts and sub-concepts are extracted and matched to obtain the concept pairs with an IsA relationship.

3). Whole-part relationship: It mainly appears in the composition of products. There is a whole-part relationship between product components and the whole product, such as "computer" and "CPU" in the digital field. Similar to the subordinate relationship, the whole-part relationship extraction in the product field also depends on the encyclopedia website. Specifically, using the category to which the concept belongs in the encyclopedia website, the concept and its parent concept are obtained and matched as a concept pair with a whole-part relationship.

4). Attribute relationship: generally represented by the triple of <entity, attribute, value range>, involving the features and feature values of products or product parts, etc., obtained from open-link databases and semi-structured web pages (eg: electricity Business website).

The goal of relationship extraction is to solve the problem of semantic links between entities. Early relationship extraction was mainly to identify entity relationships by artificially constructing semantic rules and templates. Subsequently, the relationship model between entities gradually replaced artificially predefined grammar and rules. However, it is still necessary to define the type of relationship between entities in advance. Wendi[23] has presented an open domain-oriented information extraction framework (OIE), which is a huge improvement in the extraction model. However, the OIE method has poor performance in the extraction of implicit relationships between entities, so some researchers have proposed a deeply hidden relationship extraction method based on Markov logic network (MLN)[24] and ontology reasoning[25].

The attribute extraction of entities in the product knowledge graph can be divided into two cases: one is that the concept corresponding to the entity contains attributes, and only the attribute value needs to be extracted; the other is that the concept to which the entity belongs has no attributes, and its attributes and attribute values need to be extracted. For the first case, the relationship extraction in the schema layer includes the extraction of attribute relationships between concepts, and the extraction result is <object, attribute, value range>, that is, it contains information such as attributes and attributes value ranges. Therefore, when constructing the data layer, part of the data (concept and value range, etc.) of the pattern layer can be reused. The second case relies entirely on entity attribute extraction. The more effective way of attribute extraction is to use structured and semi-structured information resources. There are many high-quality product-related websites in the e-commerce field, such as product official websites, industry evaluation websites, etc., attribute extraction can use the semi-structured information on these websites to directly obtain the attributes and attribute values of entities.

3.2 Knowledge Integration

Due to the wide range of knowledge sources in the knowledge graph, the quality of knowledge is uneven, the knowledge from different data sources is duplicated, and the relationship between knowledge is not clear enough. Therefore, knowledge fusion must be carried out. Knowledge fusion is a high-level knowledge organization[26], which enables knowledge from different knowledge sources to perform heterogeneous data integration, disambiguation, processing, reasoning verification, and update steps under the same framework specification to achieve data, information, methods, and experience And the fusion of human thoughts to form a high-quality knowledge base.

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3.2.1 Entity Alignment

Entity alignment is mainly used to eliminate inconsistencies such as entity conflicts and unknown directions in multi-source heterogeneous data. There are several difficulties in entity alignment[27]: ①computational complexity. The computational complexity of the matching algorithm increases with the growth of the knowledge base, and the resources consumed in the large knowledge base are huge; ②Data quality. The knowledge base itself may have problems such as similar repeated data, isolated data, and inconsistent time granularity of data; ③prior training data. Usually, it is necessary to construct a priori training data manually, and it is more difficult. The literature defines the main process of entity alignment as[28]:

1). Partition the data to be aligned to reduce the calculation complexity;

2). Use similarity function or similarity algorithm to find matching examples;

3). Use entity alignment algorithm for instance fusion;

4). Combine the results of step 2) and step 3) to form the final alignment result.

Alignment algorithms can be divided into two categories: paired entity alignment and collective entity alignment, and collective entity alignment can be divided into local collective entity alignment and global collective entity alignment.

3.2.2 Ontology Construction

The basic unit of knowledge is obtained through information extraction and entity alignment, and knowledge processing is also required to form a large-scale knowledge system from the level.

Ontology is the semantic basis for communication and connection between different subjects in the same field[29]. It mainly presents a tree-like structure, and there is a strict "IsA" relationship between adjacent hierarchical nodes or concepts, which is conducive to constraint and reasoning. However, it is not conducive to express the diversity of concepts. The status of ontology in the knowledge graph is equivalent to that of the knowledge base. The knowledge base formed by the ontology database not only has a strong hierarchical structure but also has a low degree of redundancy[30].

The bottom-up construction process of ontology is mainly divided into the following three stages[31]: ①Calculation of the parallel relationship between vertical concepts. By calculating the similarity between two entities, it is judged whether they belong to a unified concept; Subordinate relationship extraction is to mine the "IsA" relationship between entities; ③ontology generation. Cluster all levels of concepts and assign common superordinates to each type of entity. ④Quality evaluation. Quality assessment is usually carried out in conjunction with physical alignment tasks. Its purpose is to quantify the credibility of knowledge, retain knowledge with high confidence, and ensure the quality of knowledge.

3.2.3 Knowledge Update

To ensure the effectiveness of knowledge, the content of the knowledge graph also needs to keep pace with the times, constantly iteratively update, expand and revise existing knowledge, and add new knowledge.

Knowledge update is divided into the data layer update and model layer update. The update of the data layer refers to the update of entity elements, including the addition, modification, and deletion of entities, as well as the basic information and attribute values of entities. Because the update of the data layer generally has less impact, it is usually done in an automated manner. The pattern layer update refers to the concept update in the ontology, so it will affect all direct and indirect entities and sub-concepts. Therefore, the pattern layer is usually completed under strict manual review.

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4. Commodity Knowledge Graph Application

At present, the product knowledge graph has been applied in intelligent search, personalized recommendation, in-depth questions, and answers, etc., which improves the user's shopping experience.

4.1 Intelligent Search

Based on knowledge graph-based intelligent search, the user's search request is no longer a simple keyword matching fuzzy search, but inference based on the user's query context intent combined with the knowledge base to achieve semantic search. The returned search results are also hierarchical and structured to help users organize the content they need. For example, when searching for a product, the engine will infer the product that matches the user's intention based on the user's historical browsing situation, shopping habits, and product information, and provide important information about the product. It can be seen that the knowledge graph enables the computer to understand natural language, and more intelligently feedback the answers required by users[32].

4.2 Personalized Recommendation

The introduction of the knowledge graph effectively solves the cold start problem and data sparsity problem in the previous recommendation algorithm [33]. The knowledge graph connects project entities through different types of relationships to capture semantic information between projects, thereby alleviating the sparsity of user behavior records and cold start problems [34][35]. Explore the user's potential preference items along with the relationship in the knowledge graph, which improves the accuracy, diversity, and interpretability of the recommendation results. In the e-commerce platform, the personalized recommendation is not only the recommendation of the homepage content but also often connected with the search. Reference [36] proposes a collocation recommendation method that is different from the product similarity recommendation. This recommendation method combines knowledge graphs with collocation recommendation technology to solve the feature extraction problem of multi-source heterogeneous data in the current collocation recommendation technology. In this way, collocation recommendation technology can more accurately calculate the correlation between commodities and commodities, users and commodities, and users and users, and enhance the semantic information of the data to further improve the accuracy of recommendations and thereby improve the user experience.

4.3 In-depth Questions

Question answering system is an advanced form of information retrieval system, which can provide users with answers to questions in accurate and concise natural language. The reason why Q&A is an advanced form of retrieval is that there are also two important processes of query understanding and knowledge retrieval in the Q&A system, and they are completely consistent with the relevant details in the corresponding process of intelligent search. Most question answering systems prefer to decompose a given question into multiple small questions, then go to the knowledge base to extract matching answers one by one, and automatically detect their coincidence in time and space, etc., and finally merge the answers, Present to users in an intuitive way.

Under the e-commerce platform, intelligent customer service can efficiently complete basic communication with customers, while reducing the workload of manual customer service and providing customers with personalized shopping guidance.

5. Conclusion

Based on the definition and structure of the commodity knowledge graph, this article studies some key technologies in the commodity knowledge graph. Especially for the particularity of named entities of commodities, the method of identifying named entities applicable to commodities was studied. It also briefly describes the current product knowledge graph in terms of intelligent search, personalized recommendation, and in-depth questions and answers. The importance of the

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commodity knowledge graph lies in its powerful semantic processing capabilities and the interconnection capabilities of development, which can effectively manage and organize massive commodity information, and bring more intelligent applications in the form of knowledge embedding, bringing to the e-commerce platform. New vitality.

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