Constructing a Scene-Based Knowledge System for E-Commerce Industries: Business Analysis and Challenges (Postprint)

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Abstract

Online marketers make efforts to sell more products to their customers to increase turnover. One way to sell more products is to ensure that products belonging to the same scene are offered together. As such, it is beneficial to categorize products into different groups and tag them to particular, defined scenes. The mechanism of building relationships between products and scenes is called "scene-based knowledge system construction". The construction of a scene-based knowledge system is usually based on business operators' expert knowledge and past experiences, which often causes product categorization to be inaccurate. Hence, in this paper, we discuss the importance and necessity of constructing a scene-based knowledge system, analyze it from a business perspective, and discuss its challenges.

Full Text

Preamble

Constructing a Scene-Based Knowledge System for E-Commerce Industries: Business Analysis and Challenges

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Abstract

Online marketers continually strive to increase turnover by selling more products to their customers. One effective strategy is to ensure that products belonging to the same usage scenario are offered together. This necessitates categorizing products into distinct groups and tagging them with specific, well-defined scenes—a process we term "scene-based knowledge system construction."Currently, this construction process relies heavily on business operators' expert knowledge and past experiences, often resulting in inaccurate product categorization. In this paper, we discuss the importance and necessity of constructing such a system, analyze it from a business perspective, and examine its inherent challenges.

1. Introduction

In the global e-commerce landscape, businesses compete across multiple dimensions—including markets, products, customers, platforms, sellers, and operational technologies—to maximize profits and overall turnover [1]. Every e-commerce enterprise, particularly large-scale operators such as Alibaba [2], invests considerable effort in encouraging consumers to purchase more products from their online platforms. One key strategy involves displaying multiple products that belong to the same scenario—or "scene" —to customers, thereby increasing the likelihood of multi-item purchases. This approach is commonly known as "item-binding sales" [3]. In practice, when a customer searches for a specific product, the system also displays other products sharing the same scene, prompting the customer to select and purchase additional items. To implement this mechanism successfully, retailers must first determine the appropriate scenes for their products, which requires categorizing products into groups, each tagged with a particular scene. We refer to this entire process as "constructing a scene-based knowledge system."

The construction of a scene-based knowledge system is important for three primary reasons. First, it provides detailed information about the relationships between products and scenes. Second, it enables personalized recommendations to buyers, helping them discover relevant products without initiating new searches. Third, it assists online shop owners in binding related items together for display, ultimately leading to increased sales and higher profits.

Existing approaches to constructing scene-based knowledge systems typically depend on the expert knowledge and past experiences of business operators to group products into functional categories [4,5,6]. However, these methods lack consistency and accuracy because they are not generalizable. Moreover, the relationships between products and scenes are highly dependent on the specific business scopes and requirements of individual e-commerce companies, making standardized categorization difficult. Consequently, more fine-grained methods are needed for constructing scene-based knowledge systems in e-commerce. To develop such methods, we must first understand the business rationale behind these systems, clarify their requirements, goals, and value, and then examine their challenges [7] while proposing potential solutions.

This paper makes four key contributions. First, we formulate an official definition of a scene-based knowledge system for e-commerce that can be adopted by any corporation worldwide. Second, we conduct a detailed business analysis of the construction process, examining its rationale, requirements, goals, and value. Third, we provide a comprehensive list of challenges faced in creating such systems for e-commerce, with detailed explanations and analysis for each. Fourth, we propose a series of potential solutions to address these challenges, which can be widely applied across the e-commerce industry.

The remainder of this paper is organized as follows. Section 2 discusses the background, Section 3 covers related work, and Section 4 presents a motivating example. Section 5 conducts a business analysis of scene-based knowledge system construction, while Section 6 lists the associated challenges and Section 7 proposes potential solutions. Section 8 provides a discussion, and Section 9 concludes the paper and outlines future work.

2. Background

This section covers two aspects: the definition of a scene-based knowledge system in e-commerce and its current usage across the industry.

2.1 Definition of a Scene-Based Knowledge System

To understand the term "scene-based knowledge system," we must first examine its core components: "scene"and "knowledge system." A scene refers to a scenario in which a particular customer makes a purchase for a specific purpose, while a knowledge system represents the type of knowledge embodied by relationship information between two entities—such as the relationship between products and scenes. For example, a pair of basketball training shoes belongs to the scene of playing basketball.

We first define "scene" formally. While other works [8,9,10] define shopping scenes as scenarios where people purchase products to meet various needs (e.g., living or educational needs), we adopt the 4-W principle, which comprises four aspects: (1) when, (2) who, (3) where, and (4) what. This means that a certain person (who) does something (what) in a certain location (where) at a certain time (when). Not all four Ws must be present in every scene; however, the "what" is essential. The other three Ws (when, who, and where) can combine with "what" either separately or jointly. For instance, a scene can be expressed as "who does what,""when it is done,""where it is done,"or "who does what where and when." A shopping scene is equivalent to the shopping purpose because the scene reflects the reason why a customer wants to buy a particular product. For example, purchasing basketball training shoes belongs to the scene of playing basketball and is used for that purpose. According to our definition, a scene is formulated as:

$$Scene = Tuple(What) \cup \{Sw | Sw \in Tuple(When, Who, Where)\}.$$

Next, we formally define "knowledge system." Based on existing knowledge graph research, a knowledge system refers to a knowledge infrastructure that represents complete relationships among multiple knowledge nodes [7,11,12]. In the e-commerce context, we define a knowledge system as information that depicts relationships between two knowledge entities, such as products and scenes, and use it to describe the knowledge architecture within the industry.

Finally, we define the complete term "scene-based knowledge system" as a data-oriented knowledge architecture containing all mapping relationships between products and scenes. While a knowledge system typically depicts entities and their relationships at a high abstraction level, our scene-based knowledge system serves all business services and activities within e-commerce industries (such as Alibaba Group). We therefore use "knowledge system" to imply deep functionalities and insights derived from product-scene relationships. We denote the scene-based knowledge system as SBKS, defined as:

$$SBKS = \{Tuple(Product, Scene) | Product \text{ is used in } Scene \,\&\, Scene \text{ includes } Product\}.$$

2.2 Current Usage of Scene-Based Knowledge System in E-Commerce Businesses

Several major Chinese e-commerce corporations, including Alibaba Group and JD.com, have constructed scene-based knowledge systems [2,13] and applied them to areas such as shopping guidance, product recommendations, and item-binding sales [2,13]. This strategy has yielded substantial profit increases, significant turnover growth, and improved customer satisfaction.

JD.com' s "Tiny Eastern Courtyard" product illustrates this approach well [13]. Developed to increase user visits, page clicks, and purchase rates on its mobile app, the product encompasses over 1,300 shopping scenes, with 200 actively used on the app' s front end [13]. JD.com combined intelligent algorithms with business operators' strategies to review and manually build relationships between products and scenes. Applying this constructed system to product recommendations and shopping guidance substantially increased user visits and purchase rates, earning strong positive reputation within JD.com Group [13].

Alibaba' s online shops provide another example. With numerous products of various functionalities displayed on main pages and detail pages, customers often struggle to find all products belonging to the same scene, wasting time and effort. To address this, Alibaba Group developed two applications by constructing a scene-based knowledge system: "Have Good Things" and "Must-Buy List" [2].

The former recommends products within the same shopping scene, while the latter provides guidance to uncertain customers [2]. These applications have increased user visits, page clicks, and purchase rates across Alibaba’ s online shops [14].

3. Related Work

Since we intend to employ machine learning techniques to address challenges in constructing scene-based knowledge systems for e-commerce, we first discuss relevant applications of machine learning to financial and commercial problems. These include using machine learning to predict share market prices, forecast financial time series, and predict crude oil prices [15]. These works relate to our research through their use of machine learning to determine product scenes, analyze product properties and scene characteristics, and mine relationships between them.

3.1 Share Market Price Prediction with Artificial Neural Networks

In 2011, researchers from Shahjalal University of Science and Technology proposed a stock market price prediction mechanism based on artificial neural networks [15,16]. This work addressed the challenge of insignificant relationships between variables in the share market chaos system and share prices [15,16]. They applied a traditional multi-layer perceptron (MLP) model with backpropagation (BP) to compute and update weight values for intermediate inputs and outputs [15,16]. However, the approach had several drawbacks: (1) the network used only two hidden layers without justification or performance comparison with deeper architectures; (2) the input variables considered only company financial information, neglecting other important features such as customer size or launch timing [15,16]. Moreover, the method was evaluated on only one company with two input datasets, leaving its validity insufficiently proven [15,16].

3.2 Financial Time Series Forecasting with ANNs

Researchers from Bond University, Australia identified artificial neural networks (ANNs) as the most powerful technique for predicting financial time series in stock markets [15,17]. While alternative methods primarily relied on evolutionary and optimization technologies, researchers preferred to enhance established ANN models with new training algorithms or combine them with emerging technologies into hybrid systems [15,17]. However, it remains unclear how real-world constraints impact forecasting accuracy and stock index prediction, and whether investors’ risk-return tradeoffs can be improved [15,17].

3.3 Crude Oil Price Prediction with ANN-Q

In 2010, researchers from the University of Manchester proposed an artificial neural network quantitative (ANN-Q) model for crude oil price prediction [15,18].

This framework addressed the challenge that crude oil prices are linked to numerous factors whose changes can significantly impact price volatility [15,18]. By analyzing 22 key factors affecting crude oil prices, researchers developed an ANN-Q model [15,18]. To improve the model, they categorized these factors by impact level (large, medium, small) and utilized a Back Propagation Neural Network (BPNN) for training input variables [15,18]. Simulation experiments monitored accuracy progressively, demonstrating that parameter tuning could improve model performance [15,18].

4. A Motivating Example

This section presents a motivating example that demonstrates the benefits of constructing a scene-based knowledge system for e-commerce businesses. With such a system, companies can fulfill various business requirements and strategic goals through applications like product recommendations and item-binding sales. The example is illustrated in Figure 1 [Figure 1: see original paper].

Figure 1. A motivating example. A customer is associated with several life scenes, one of which could be the birth of a baby. This primary scene consists of multiple subsidiary scenes, requiring the customer to recognize and navigate the main scene. After analyzing these sub-scenes, the customer identifies several child scenes: selecting a hospital, getting pregnancy scans, prenatal education, preparing for birth, post-delivery care, buying newborn insurance, and ensuring vaccinations. Based on these sub-scenes, the customer generates numerous shopping requirements that break down into child-related needs.

This process involves various online applications such as Baidu, Zhihu, WeChat, vertical sites, e-commerce platforms, and the Taobao App. From these sub-requirements, the customer determines the need to purchase over 70 baby products, including milk powder, diapers, and bottles. Next, they must select appropriate shopping channels from options like Taobao App, JD.com, NetEase, and Baobao Tree. The customer then makes purchasing decisions by analyzing product features, comparing prices, and reviewing feedback before placing orders. This scenario reveals that many products belong to the same scene or sub-scene. By grouping these products into categories tagged with specific scenes, customers can more easily and conveniently purchase items belonging to the same scene. Thus, constructing a scene-based knowledge system is essential for e-commerce sales in scenarios like welcoming a new baby.

5. Business Analysis for Scene-Based Knowledge System Construction

This section provides a detailed business analysis of scene-based knowledge system construction, covering the business reasons supporting its development, its requirements, goals, and value.

5.1 Business Reasons for Constructing a Scene-Based Knowledge System

Based on our experience and insights from business professionals at other e-commerce organizations, we identify eight key reasons for constructing a scene-based knowledge system. First, information about shopping scene categories helps e-commerce businesses better understand complete scenes (e.g., the baby care scene includes purchasing infant food, planning wellness, and buying clothing). Second, analyzing online product features in a scene-oriented manner helps stakeholders identify which scenes products belong to (e.g., basketball shoes' features include weight, materials, durability, and color). Third, online shopping systems need to understand how to group products and sell categorized items together in a single round (e.g., binding basketball shoes with basketball shorts). Fourth, user visits, page clicks, and purchase rates are highly correlated with scene-based product categorization mechanisms (e.g., binding shoes with shorts increases overall click rates and sales for both items). Fifth, product categorization by scene and purpose directly improves customer shopping experiences (e.g., customers view sites as convenient when basketball shoes are bundled with related gear). Sixth, e-commerce businesses can increase total profits and turnover through strategies like product recommendations and item-binding sales that rely on scene-based knowledge systems (e.g., selling both shoes and shorts generates more profit than selling shoes alone). Seventh, there is no standardized mechanism for defining relationships between online products and shopping scenes across global e-commerce businesses, hindering unified product categorization by scene. Eighth, the current definition of scene-based knowledge systems is not formalized, and their usage is not standardized among e-commerce businesses worldwide.

5.2 Business Requirements for Constructing a Scene-Based Knowledge System

We formulate six business requirements for constructing a scene-based knowledge system in e-commerce. First, all customer scenes and shopping purposes on online platforms must be completely enumerated daily to identify important scenes for decision-making. Second, scenes and their interrelationships must be defined clearly and accurately. Third, mapping relationships between each online product and each scene must be precisely determined and easily understandable. Fourth, the multitude of products belonging to an identical scene must be properly defined. Fifth, if a product can belong to multiple scenes, all such scenes must be identified. Sixth, the constructed scene-based knowledge system must be stored in an accessible format at a reasonable location.

5.3 Business Goals for Constructing a Scene-Based Knowledge System

The business goals of constructing a scene-based knowledge system are fourfold. First, the system should be generalizable for use by all e-commerce businesses as a standardized decision-making tool. Second, it should enable worldwide e-commerce businesses to develop sophisticated online shopping application functionalities. Third, it should substantially increase user visits and page clicks through improved product recommendations and item-binding sales. Finally, it should significantly increase purchase conversion rates, overall profits, and total turnover.

5.4 Business Value of Constructing a Scene-Based Knowledge System

The business value of constructing a scene-based knowledge system is threefold. First, it provides a global standard for organizing and managing products, scenes, and their relationships across all e-commerce businesses. Second, it helps achieve key business metrics including total user visits, page click rates, purchase rates, profits, and turnover. Third, it sets a valuable precedent for e-commerce businesses and companies in other domains for building knowledge systems closely aligned with business strategy.

6. Challenges

This section identifies eight major challenges in constructing a scene-based knowledge system for e-commerce.

1. **Scene determination is non-trivial** because there is no standardized definition of what constitutes "a scene" and no prior work to reference for understanding scene properties. We must therefore develop definitions based on our own e-commerce corporation' s contextual information and business strategies.

2. **No existing methodology** exists for systematically defining and formulating a scene-based knowledge system, leaving us without references to describe and structure the system. We must rely on our own context and business scope to systematically formulate definitions and construct product-scene relationships.

3. **The core aspect of a scene is "a thing,"** but "thing" is ambiguous, with different interpretations among people. Moreover, relationships between a thing and other scene aspects are not always straightforward.

4. **Modeling individual customer shopping requirements is difficult** because customers may not fully understand their own purchase motivations. Shopping requirements can be complex, complicating the modeling process.

5. **Scene definitions depend on operational rules,** but these rules are challenging to define because different business operators maintain different standards, and rules often appear in various forms. Creating a generic definition is therefore difficult.

6. **Determining product-scene relationships is demanding** because it requires comprehensive understanding of all products, their features,

all scenes, and their properties. This process is time-consuming, labor-intensive, and difficult to automate.

7. **Verifying relationship accuracy is problematic** because it requires substantial manpower and human effort. Accuracy depends heavily on business scope and requirements, and even automated mechanisms cannot guarantee sufficient precision.

8. **System generalization is challenging** because different e-commerce businesses have distinct characteristics, products, and categories, making it difficult to create a mechanism applicable to all businesses worldwide.

7. Potential Solutions

To address these challenges, we propose the following potential solutions:

1. **For scene definition challenges**, we propose conducting a business study of all customer purchase purposes, modeling these drivers, and mining shopping scene information from them. Specifically, we should identify all scene aspects and clarify which are core versus secondary.

2. **For knowledge system definition challenges**, we propose reviewing our e-commerce corporation' s business and operational requirements to understand the necessary knowledge system type and identify all features needed for formulation.

3. **For "thing" definition challenges**, we propose summarizing all objective entities within online shopping purposes across customer types and identifying patterns to model each entity, where "things" become patterns in proper form.

4. **For shopping requirement modeling challenges**, we propose gathering historical shopping requirements from all customers (manually or automatically) and applying data analytics, mining, and statistical learning to discover correct modeling approaches. These models should be stored for external reuse.

5. **For operational rule definition challenges**, we propose determining a formal expression method for operational rules. To express rules properly, we must identify included factors and organize them into a scientific, model-oriented paradigm for recording operational rules.

6. **For product-scene relationship determination challenges**, we propose a two-mechanism approach: (1) using machine learning to generate and classify scenes, and (2) having humans verify operational rule conformance. First, generate a scene for each product; second, validate whether the generated scene properly fits the product.

7. **For relationship accuracy challenges**, we propose applying cross-validation to the determined product-scene relationships. Specifically,

we can use 10-fold cross-validation: divide the dataset into ten sections, train on nine sections, predict on the remaining section, and calculate accuracy. Repeating this process ten times and averaging the accuracy values allows us to verify if the result is sufficiently high.

8. **For system generalization challenges**, we propose summarizing all products and scenes for each global e-commerce business, building product-scene relationships for each to create small scene-based knowledge systems, then unifying them into a larger centralized system. Different e-commerce businesses can then use this centralized system to develop their own strategic solutions and fulfill their business goals.

8. Discussion

In practice, constructing a scene-based knowledge system is one of many strategies for fulfilling e-commerce business goals and requirements. Alternative strategies include marketing solutions such as intelligent red packets [9], intelligent coupons, intelligent price determinations [6], or price discounting mechanisms. We argue that scene-based knowledge systems are more viable than these alternatives because customer purchase purposes are fundamental to successful e-purchasing.

While scene-based knowledge systems can achieve business goals like increasing user visits, page views, purchase rates, profits, and turnover, they also offer additional benefits: strengthening business reputations and supporting expansion efforts. Therefore, it is vital for global e-commerce businesses to allocate resources for constructing scene-based knowledge systems.

9. Conclusion and Future Work

Every online shop owner aims to sell more products and increase total turnover. One effective method is ensuring that products belonging to the same scene are grouped together, requiring firms to categorize products into scene-tagged groups. We call this process "scene-based knowledge system construction." Existing methods rely on business operators' expert knowledge and past experience, often producing inaccurate categorizations. This paper provides a detailed business analysis of this construction process, discusses its challenges, and proposes potential solutions.

Our future work includes two main tasks. First, we will propose a formal method for constructing a scene-based knowledge system, implementing and evaluating it using real-world scenarios. This method will combine the potential solutions from Section 7, refined and generalized for different business requirements across multiple e-commerce industries. Second, we will identify additional business requirements that the system should support and verify whether our methodology can fulfill them.

Author Contributions

This work was a collaborative effort among all authors. M. Fu (hanhao.fm@alibaba-inc.com) is the main writer for the research project. Q. Chen (lapu.cq@alibaba-inc.com), W. Lin (weijiang.lw@alibaba-inc.com), P. Wang (wp146049@alibaba-inc.com), and W. Zhang (lantu.zw@alibaba-inc.com) provided insights and information for the business analysis, challenges, and methodology sections. All authors contributed meaningfully to revising and proofreading the manuscript.

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Note: Figure translations are in progress. See original paper for figures.

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