A Survey of Utility-Oriented Pattern Mining

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Abstract—The main purpose of data mining and analytics is to find novel, potentially useful patterns that can be utilized in real-world applications to derive beneficial knowledge. For identifying and evaluating the usefulness of different kinds of patterns, many techniques/constraints have been proposed, such as support, confidence, sequence order, and utility parameters (e.g., weight, price, profit, quantity, etc.). In recent years, there has been an increasing demand for utility-oriented pattern mining (UPM). UPM is a vital task, with numerous high-impact applications, including cross-marketing, e-commerce, finance, medical, and biomedical applications. This survey aims to provide a general, comprehensive, and structured overview of the state-of-the-art methods of UPM. First, we introduce an in-depth understanding of UPM, including concepts, examples, and comparisons with related concepts. A taxonomy of the most common and state-of-the-art approaches for mining different kinds of high-utility patterns is presented, including Apriori-based, tree-based, projection-based, vertical-horizontal-data-format-based, and other hybrid approaches. A comprehensive review of advanced topics of existing high-utility pattern mining techniques is offered, with a discussion of their pros and cons. Finally, we present several well-known open-source software packages for UPM. We conclude our survey with a discussion on open and practical challenges in this field.

Index Terms—Data mining, economics, utility theory, utility-oriented, high-utility pattern, application.

1 INTRODUCTION

Data mining [1], [2] focuses on extraction of information from a large set of data and transforms it into an easily interpretable structure for further use. It is an interdisciplinary field focused on scientific methods, processes, and systems to extract knowledge or insights from data in various forms, either structured or unstructured. Mining interesting patterns from different types of data is quite important in many real-life applications [1], [3], [4], [5], [6]. In recent decades, the task of interesting pattern mining [e.g., frequent pattern mining (FPM) [7], [8], association rule mining (ARM) [9], [10], frequent episode mining (FEM) [11], [12], [13], [14], and sequential pattern mining (SPM) [5], [15], [16]] has been extensively studied. These are important and fundamental data-mining techniques [1] that satisfy the requirements of real-world applications in numerous domains. Furthermore, most of them aim at extracting the desired patterns using frequency or co-occurrence [7], [8], [9], [10], as well as other properties and interestingness measures [3], [17], [18], [19], [20].

Despite the wide use of data-mining techniques in client-segmentation and market-analysis applications, so far there have been no algorithms that allow for the discovery of utility-oriented patterns, i.e., those that contribute the most to a predefined utility threshold, an objective function, or a performance metric. In general, some implicit factors, such as the utility, interestingness, or risk of objects/patterns, are commonly seen in real-world situations. The knowledge that is actually important to the user may not be found by traditional data-mining algorithms. Therefore, a novel utility-oriented mining framework, called high-utility pattern mining (HUPM) [21], [22], [23], [24], which considers the relative importance of items (utility-oriented [25]), has become an emerging research topic in recent years. In HUPM, the utility (i.e., importance, interest, or risk) of each item can be predefined based on a user’s background knowledge or preferences.

According to Wikipedia¹, in economics, utility is a measure of preferences over some set of goods (including services, i.e., something that satisfies human wants); it represents satisfaction experienced by the consumer of a good. Hence, utility is a subjective measure. This definition indicates that a subjective value is associated with a specific value in a domain to express user preference. In practice, the value of utility is assigned by the user according to his interpretation of domain-specific knowledge measured by a specific value, such as cost, profit, or aesthetic value. According to the studies of Li et al. [17], interestingness measures can be classified as objective measures, subjective measures, and semantic measures [17], [19], [20]. Objective measures [20], [26], such as support or confidence for pattern mining, are based only on data itself, whereas subjective measures [27], [28], such as unexpectedness or novelty, take into account the user’s domain knowledge. For the semantic measures [23], such as utility, they consider the data itself, as well as the user’s expectation. Hence, utility is a quantitative representation of user preference, and the usefulness of an itemset is quantified in terms of its utility value. Utility can be defined as “A measure of how ‘useful’ (i.e., profitable) an itemset is.” [23], [29] Formally, a pattern is said to be useful to a user if it satisfies a specific utility constraint. In practice, the utility value of a pattern can be measured in...
terms of cost, profit, aesthetic value, or other measures of user preference.

To address these issues, utility-oriented pattern mining (hereinafter called UPM or utility mining) becomes a useful task and emerges as an important topic in data mining. In utility mining, each object/item has an unit utility (e.g., unit profit) and can appear more than once in each transaction or event (e.g., purchase quantity). The utility of a pattern represents its importance or satisfaction, which can be measured in terms of risk, profit, cost, quantity, or other information depending on user preference. In general, the utility of a pattern is based on local transaction utility (also called internal utility) and external utility [23], [29]. The internal utility of an object/item is defined according to the information stored in a transaction/event, such as the quantity of the object/item occurred or sold. The external utility can be a measure for describing user preferences. Therefore, the utility of a pattern depends on the utility function specified by the user, which can be the Sum, Average, or Multiplication of quantity and profit of this pattern in databases. More specifically, the utility-based method for pattern mining can find various types of patterns that could not be identified using previous theories and techniques. According to previous studies, utility mining has a wide range of applications, including website click-stream analysis [30], [31], [32], cross-marketing in retail stores [33], [34], [35], mobile commerce environment [36], [37], gene regulation [38], and biomedical applications [39]. Through 15 years of study and development, many techniques and approaches have been extensively proposed for UPM in various applications. As shown in Fig. 1, there has been a rapid surge of interest in UPM in recent years in terms of the number of academic papers published in several sub-fields, including high-utility itemsets [29], high-utility rules [40], [41], high-utility sequential patterns [42], [43], and high-utility episodes [44], [45].

![Number of Publications](image)

**Fig. 1.** Number of published papers that use “High Utility Pattern Mining” in sub-areas of data mining and analytics. These publication statistics are obtained from Google Scholar. Notice that the search phrase is defined as the sub-field named with the exact phrase “utility pattern,” and at least one of utility or itemset/rule/episode/sequential pattern appearing, e.g., “utility itemset,” “utility pattern,” “utility sequential pattern.”

In spite of the fact that there are a considerable number of existing published studies and surveys about data mining, especially for pattern mining, none of them discuss HUPM. Yet, after more than 15 years of theoretical development, a significant number of new technologies and applications have appeared in the UPM field. Unfortunately, there is no comprehensive survey of utility-oriented pattern mining methods and no study that systematically compares the state-of-the-art algorithms. We believe that now is a good time to summarize the new technologies and address the gap between theory and application. Here, we attempt to find a clearer way to present the concepts and practical aspects of UPM for the data-mining research community. In this paper, we provide a systematic and comprehensive survey of the significant advances in HUPM. The methods discussed in this article are not only important for high-utility pattern (i.e., itemset [23], [29], rule [40], [41], sequence, episode, etc.) mining but can also serve as inspiration for other data-mining tasks [1], [2], including episode mining [11], [12], [13], [14], distributed data mining [46], and incremental/dynamic data mining [47], [48]. The major contributions are listed as follows:

1) This paper first presents a comprehensive survey of UPM. This survey investigates more than 100 papers published in the last 15 years and summarizes them in a systematic fashion.

2) This survey deeply and comprehensively summarizes the developments of this field, comparing state-of-the-art work to earlier work. This survey introduces an in-depth understanding of UPM, including concepts, examples, and comparisons with related concepts.

3) A taxonomy of the most common and the state-of-the-art approaches for mining high-utility patterns is presented, including Apriori-based, tree-based, projection-based, vertical/horizontal-data-format-based, and other hybrid approaches. We further analyze the pros and cons of each type of approach.

4) A comprehensive review of advanced topics of existing high-utility pattern mining techniques is offered, with a discussion of their pros and cons. Not only the representative algorithms but also the advances and latest progress are reviewed.

5) We further review some well-known open-source software in the fields of UPM and hope that these resources may reduce barriers for future research. Finally, we identify several important issues and research opportunities for UPM.

The remainder of this article is organized as follows. In Section II, we introduce the necessary background information, the basic concepts and examples, and the motivations in this field. In Section III, we give a high-level overview of emerging UPM problems and survey several popular methods, as well as recent developments. In Section IV, we discuss advanced topics and techniques of UPM. In addition, in Section V, we describe some open challenges and opportunities in this area. Several future directions are described in Section VI.

### 2 Basic Concept: Utility-Oriented Pattern Mining Problem

Here, we first present the notations, as summarized in Table I. Then, we briefly introduce the conceptual paradigm of utility-oriented pattern mining. Finally, we present some background information on UPM methods, including several kinds of utility patterns, comparisons with related
techniques, example applications, and the introduction of some common utility evaluation measures.

2.1 Notations

| Symbol | Definition |
|--------|------------|
| D      | An unordered set of m distinct items, \( I = \{i_1, i_2, \ldots, i_m\} \) |
| QSD    | A quantitative sequential database = \( \{t_1, t_2, \ldots, t_k\} \) |
| T(D)   | Each \( t_i \in D \) has a unique transaction identifier. |
| X \( k \)-itemset | consisting of \( k \) distinct items \( \{i_1, i_2, \ldots, i_k\} \). |
| sup(X) | \( X \) is support of \( X \) in database \( D \) or QSD. |
| \( q(i_j, t_q) \) | The utility of an item \( i_j \) in transaction \( t_q \). |
| \( u(t_q) \) | The total utility of transaction \( t_q \). |
| \( u(X, t_q) \) | The utility of a pattern \( X \) in transaction \( t_q \). |
| pr(i_j) | The predefined profit of an item \( i_j \). |
| \( \text{minconf} \) | A predefined minimum confidence threshold. |
| \( \text{minsup} \) | A predefined minimum support threshold. |
| \( \text{minutil} \) | A predefined minimum utility (high-utility) threshold. |
| \( \text{HTWUI} \) | The transaction-weighted utility of a pattern. |
| \( \text{minutilf} \) | A predefined minimum confidence threshold. |


2.2 Preliminary and Types of Utility-Oriented Patterns

Here, we introduce related preliminaries of HUPM and then define the problem of HUPM. Based on pattern diversity, utility-oriented pattern mining can be classified using the following basic criteria and extended patterns.

Definition 1 (Frequent pattern and association rule [9]). An association rule is an implication of the form, \( X \rightarrow Y \), where \( X \subseteq I \), \( Y \subseteq I \), and \( X \cap Y = \emptyset \). \( X \) and \( Y \) are disjoint, and \( X \) is non-empty, meaning that if a transaction includes \( X \), then it also has \( Y \). An association rule consists of frequent itemsets, and its confidence is no less than the minimum confidence sometimes called strong rules. It was first proposed by Agrawal et al. [9] in the context of frequent itemset and association-rule mining. For example, \( \{\text{Cheese, Milk}\} \rightarrow \text{Bread} \) \( \subseteq \{\text{Cheese}, 5\% , \text{conf} = 80\%\} \); this association rule means that 80% of customers who buy cheese and milk also buy bread, and 5% of customers buy all these products together.

Definition 2 (High-utility itemset, HUI [29]). The utility of an item \( i_j \) appearing in a transaction \( t_q \) is denoted as \( u(i_j, t_q) \) and defined as \( u(i_j, t_q) = q(i_j, t_q) \times pr(i_j) \). The utility of an itemset \( X \) in \( D \) is defined as \( u(X, D) = \sum_{i_j \in X \setminus \bigcup_{t_p \in T_q} u(i_j, t_p)} \). The total utility of \( X \) in a database \( D \) is denoted as \( u(X, D) = \sum_{t_p \in D} u(X, t_p) \). An itemset is said to be a high-utility itemset (HUI) if its total utility in a database is no less than the user-specified minimum utility threshold \( \text{minutil} \); otherwise, it is called a low-utility itemset.

Definition 3 (High-utility association rule, HUAR [40], [41]). Since the usefulness of association rules can be defined as a utility function based on the business objective, the utility and confidence can be used to extend the concepts of high-utility itemsets and association rules. An association rule is considered to have high utility if it meets the \( \text{minutil} \) constraint. Thus, a high-utility association rule (HUAR) consists of high-utility itemsets, and its confidence is no less than the minimum confidence. Generally speaking, discovery of HUIs started as the first phase in the discovery of HUARs, but it has been generalized by formulating a new pattern-mining framework.

Definition 4 (High-utility sequential pattern, HUSP [42], [43]). The utility of an item \( i_j \) in a \( q \)-itemset \( v \) is denoted as \( u(i_j, v) \), and defined as \( u(i_j, v) = q(i_j, v) \times pr(i_j) \), where \( q(i_j, v) \) is the quantity of \( i_j \) in \( v \) and \( pr(i_j) \) is the profit of \( i_j \). The utility of a \( q \)-itemset \( v \) is denoted as \( u(v) \) and defined as \( u(v) = \sum_{i_j \in v} u(i_j, v) \). The utility of a \( q \)-sequence \( s = v_1, v_2, \ldots, v_q \geq \) is denoted as \( u(s) \) and defined as \( u(s) = \sum_{v_i \in s} u(v) \). A sequence \( s \) in a quantitative sequential database \( QSD \) is said to be a high-utility sequential pattern (HUSP) if its utility is no less than the minimum threshold of \( s \) as \( HUSP \subseteq \{s | u(s) \geq \text{minutil}\} \). Considering the ordered sequences, high-utility sequential pattern mining (HUSPM) [42], [43] can discover more informative sequential patterns. This process is more complicated than the traditional HUI or SPM since the order and the utilities of itemsets should be considered together.

Definition 5 (High-utility mobile sequential pattern, HUMSP [37]). Given a mobile sequential database, the utility of a moving pattern \( P \) in this database is denoted as \( u(P) \). It is similar to the utility of a sequence [43], and the details can be referred to [37]. Given a minimum support threshold \( \text{minsup} \) and a minimum utility threshold \( \text{minutil} \), a moving pattern \( P \) is called a mobile sequential pattern if \( sup(P) \geq \text{minsup} \), and \( P \) is called a high-utility mobile sequential pattern (abbreviated as HUMSP) if \( sup(P) \geq \text{minsup} \) and \( u(P) \geq \text{minutil} \). Hence, the concept of HUMSP is an extension of HUSP.

Definition 6 (High-utility sequential rule, HUSR [49]). A sequential rule \( R: X \rightarrow Y \) [50] is a relationship between two unordered itemsets \( X, Y \subseteq I \) such that \( X \cap Y = \emptyset \) and \( X, Y \neq \emptyset \). The interpretation of a rule \( R: X \rightarrow Y \) is that if items of \( X \) occur in a sequence, then items of \( Y \) will occur afterward in the same sequence. Let \( \text{minsup}, \text{minconf} \in [0, 1] \) and \( \text{minutil} \) be thresholds set by the user and SDB be a sequence database. A sequential rule \( R \) is said to be a high-utility sequential rule (HUSR) [49] iff \( u(R) \geq \text{minutil} \) and \( R \) is a valid rule, in which \( u(R) \) is the total utility of \( R \) in SDB. Otherwise, it is said to be a low-utility sequential rule. The problem of mining high-utility sequential rules from a sequence database is the discovery of all high-utility sequential rules.

Definition 7 (High-utility episode, HUE [44], [45]). An episode \( \alpha \) is a non-empty totally ordered set of simultaneous events of the form \( \langle SE_1, SE_2, \ldots, SE_k \rangle \), where \( SE_i \) appears before \( SE_j \) for all \( 1 \leq i < j \leq k \). For example, \( \langle (AB), (C) \rangle \) is an episode containing
Frequent pattern mining (FPM) [7, 8, 9, 10] is a common and fundamental topic in data mining. FPM is a key phase of association-rule mining (ARM), but it has been generalized to many kinds of patterns, such as frequent sequential patterns [16], frequent episodes [11], and frequent subgraphs [51]. The goal of FPM is to discover all the desired patterns having support no lower than a given minimum support threshold. If a pattern has higher support than this threshold, it is called a frequent pattern; otherwise, it is called an infrequent pattern. Unlike HUPM, studies of FPM seldom consider the database having purchased quantities of items, and none of them considers the utility feature. Under the “economic view” of consumer rational choices, utility theory can be used to maximize the estimated profit. Utility mining considers both statistical significance and profit significance, whereas FPM aims at discovering the interesting patterns that frequently co-occur in databases. In other words, any frequent pattern is treated as a significant one in FPM. However, in practice, these frequent patterns do not show the business value and impact. In contrast, the goal of HUPM is to identify the useful patterns that appear together and also bring high profits to the merchants [52]. In UPM, managers can investigate the historical databases and extract the set of patterns having high combined utilities. Such problems cannot be tackled by the support/frequency-based FPM framework.

- **UPM vs. FPM.** In a related area, the relative importance of each object/item is not considered in the concept of FPM. To address this problem, weighted frequent-pattern mining (WFPM) was proposed [53, 54, 55, 56, 57, 58, 59, 60]. In the framework of WFPM, the weights of items, such as unit profits of items in transaction databases, are considered. Therefore, even if some patterns are infrequent, they might still be discovered if they have high weighted support [53, 54, 55]. However, the quantities of objects/items are not considered in WFPM. Thus, the requirements of users who are interested in discovering the desired patterns with high risks or profits cannot be satisfied. The reason is that the profits are composed of unit profits (i.e., weights) and purchased quantities.

In view of this, utility-oriented pattern mining has emerged as an important topic. It refers to discovering the patterns with high profits. As mentioned previously, the meaning of a pattern’s utility is the interestingness, importance, or profitability of the pattern to users. The utility theory is applied to data mining by considering both unit utility (i.e., profit, risk, and weight) and purchased quantities. This has led to the concept of high-utility pattern mining [52], which selects interesting patterns based on minimum utility rather than minimum support.

- **UPM vs. SPM.** Different from FIM, sequential pattern mining (SPM) [5, 15, 16], which discovers frequent sub-sequences as patterns in a sequence database that contains the embedded timestamp information of an event, is more complex and challenging. In 1995, Agrawal and Srikant first extended the concept of the frequent itemset mining model to handle sequences [15]. Consider the sequence \(<\{a, e\}, \{b\}, \{c, d\}, \{g\}, \{e\}>\), which represents five events made by a customer at a retail store. Each single letter represents an item (i.e., \{a\}, \{e\}, \{g\}, etc.), and items between curly braces represent an itemset (i.e., \{a, e\} and \{c, d\}). Simply speaking, a sequence is a list of temporally ordered itemsets (also called events). Owing to the absence of time constraints in FPM not present in SPM, SPM has a potentially huge set of candidate sequences [16]. In a related area, through 20 years’ study and development, many techniques and approaches have been proposed for mining sequential patterns in a wide range of real-world applications [5]. In general, SPM mainly focuses on the co-occurrence of derived patterns; it does not consider the unit profit and purchase quantities of each product/item.

So far, we have reviewed a wide range of pattern-mining frameworks that aim to discover various types of patterns, such as itemsets [9, 53], sequences [15, 16], and graphs [51]. These frameworks, however, only select high-frequency/support patterns. Patterns below the minimum threshold are considered useless and are discarded. Frequency is the main interestingness measurement, and all objects/items and transactions are treated equally in such a framework. Clearly, this assumption contradicts the truth of many real-world applications because the importance of different items/itemsets/sequences might be significantly different. In these circumstances, the frequency-/support-based framework is inadequate for pattern mining and selection. Based on the above concerns, researchers proposed the concept of UPM.

### 2.4 Why Utility-Oriented Pattern Mining and Analysis

With the rapid advancement of research on UPM, numerous applications in different domains have been proposed in recent years. We next describe several important applications.

- **Market basket analysis.** In market basket analysis, each transaction recorded with a customer contains several products/items, annotated with their purchase time, purchase quantities and the selling price. An important technique is based on the theory that if customers buy a certain set of items, customers are more (or less) likely...
to buy another set of items. For the problem of mining-characterized association rules from market basket data, the goal is to not only discover the buying patterns of customers but also the highly profitable patterns and customers. In some existing frameworks [33], [34], [35], [61], [62], the utility (i.e., importance, interest, or risk) of each product can be predefined based on users’ background knowledge or preferences. As a result, HUPM is able to offer richly detailed information about users’ purchasing behaviors.

- **Web mining.** There is much rich information in web data. For example, users’ click-stream and purchase behaviors are recorded in web logs. In such data, a user’s click operation (there are one or many clicks in one session) and browsing time on a web page can be expressed as the internal utility of the web page. Obviously, each web page has different importance depending on users’ different preferences (i.e., external utility). Thus, utility mining technology can be used to discover utility-oriented patterns from web logs, such as high-utility access patterns [63] and high-utility traversal patterns [64]. The derived results are quite useful for electronic commerce for such things as improving website services, providing some navigation suggestions for web browsing, and improving the design of web pages.

- **Mobile commerce.** With the explosive growth of the Internet of Things (IoT) [65] technologies in the Big Data era, such as smart-phones, wireless networks, and GPS devices, information about users’ mobile behavior (e.g., locations and payment records) can be acquired and integrated in data analytics. In this scenario, utility-oriented mining technologies can be used to discover valuable user behaviors. Shie et al. first proposed a new framework named high-utility mobile sequential-pattern mining [36], [37] in mobile environments. It can successfully extract associations between customers’ purchase behaviors and location trajectories. The discovered high-utility patterns can be utilized for many applications essential to mobile commerce, such as location-based advertisement or recommendations, navigational services, and utility-based recommendation systems.

- **Stream processing.** The majority of data is born as continuous streams [66], [67]: sensor events, user activity on a website, financial trades, and others; all these data are created as a series of events over time. In general, some stream data contain rich and important features that are similar to the general static data. In contrast to the support-based pattern-mining technologies, the utility-oriented pattern-mining technologies can be applied to extract useful patterns and knowledge from website click-streams [68]. Some preliminary studies have been carried out on this issue, such as [30], [31], [32].

- **Biomedicine.** In gene expression data, each row represents a set of genes and their expression levels (i.e., internal utility) under an experimental condition. In addition, each gene has a degree of importance for biological processes (i.e., external utility). In bioinformatics, utility mining technology can discover useful relationships between genes. For example, Liu et al. [69] applied a utility mining method to successfully discover interesting gene regulation patterns from a time-course of comparative gene expression data. By analyzing the discovered results, medical researchers can find new drugs for the treatment of diseases. Recently, Zihayat et al. proposed a utility model by considering both the gene-disease association scores and their degrees of expression levels in a biological investigation [38].

  - **Other applications.** Since the “utility” of a pattern measures the importance of the pattern to the user (i.e., risk, weight, cost, and profit), utility mining has broad real-life applications; several examples follow. In risk prediction, the risk that events may occur is indicated by occurrence probabilities and risk. For example, the event \(<\{A, I, 80\}; (D, 5, 15); (E, 3, 125)\> 90\%> indicates that this event consists of three sub-events \(\{A, D, E\}\) with occurrence frequencies \(\{1, 5, 3\}\), while their risk \(80, 15, 125\), respectively, has a 90\% probability of occurring. In e-commerce business, this manifests as identifying customers who visit web pages a number of times by taking pages visited as a utility parameter. In online banking fraud detection, the transfer of a large amount of money to an unauthorized overseas account may appear once or many times in several million transactions, yet it has a substantial business impact.

### Table 2

| Measure                  | Description                                                                                     |
|--------------------------|-----------------------------------------------------------------------------------------------|
| Utility                  | The commonly used utility measure in many UPM models and algorithms and its definition has been given from Definitions 2 to 7, and details can be referred to [45], [52]. |
| Average utility          | Considers the length of itemset as a major factor, and the average utility of X in \(T_q\) is defined as \(au(X, T_q) = \sum_{i,j \in X, C \subseteq T_q} p(i, T_q) \times pr(i, j) / |X| \) [70], where \(k\) is the number of items in X. |
| Expected/potential utility | Measures both probability and utility of a pattern in uncertain databases [71]; the expected support [72] is measured as \(expSup(X) = \sum_{i \in |I|} (\prod_{X \in X, \in p(X, T_q)})\). |
| Affinitive utility       | The affinitive utility [73] of a pattern \(X\) in \(T_q\) is defined as \(af(X, T_q) = \sum_{i,j \in X} pr(i, j)\) and \(af(X, T_q)\) denote the affinitive frequency of a pattern \(X\) in \(T_q\) that is \(af(X, T_q) = \prod_{X \in X, \in p(X, T_q)} pr(i, j)\) \(\forall X \in |X| \). |
| Utility occupancy        | Depends on the contribution of unit item. The utility occupancy [74] of an itemset \(X\) in \(T_q\) and \(D\) are defined as \(uo(X, T_q) = au(X, T_q) / tu(X)\) and \(uo(X) = \sum_{X \subseteq T_q} tu(T_q) / D\) \(uo(X, T_q) / |X| \), respectively. |

### 2.5 Evaluation Measures of Utility

Here, we briefly describe several key measures that have been used in the literature to determine utility-oriented relationships in UPM. In Section 2.2, the theoretical foundations of utility mining frameworks were analyzed. Based on the utility theory [25], many evaluation measures of utility have been proposed. Some commonly used evaluation measures of the utility of a pattern in the UPM field are summarized in Table 2.

### 3 Basic Approaches for High-Utility Itemset Mining

#### 3.1 Overview of Proposed Categorization

Utility-oriented algorithm development has always been an important issue in data-mining research. During the past decade, a significant number of utility-oriented algorithms have been proposed to mine utility-patterns from various types of data (i.e., transaction data [9], sequential data [15], episode data [11], stream data [66], [67], etc). Considering that it is infeasible to go through all existing
algorithms within a limited space, in this review we select some representative high-utility pattern-mining algorithms. According to the different mining principles and data structures, Fig. 2.5 presents a rough overview of techniques to address the utility-oriented pattern-mining problem. Specifically, to facilitate our discussion, we classify these efforts into the following categories: 1) Apriori-based approaches; 2) tree-based approaches; 3) projection-based approaches; and 4) vertical-/horizontal-data-based approaches.

3.2 Apriori-based Approaches

In 1994, Agrawal and Srikant proposed the well-known downward closure property, also known as the Apriori property [9], which states that all non-empty subsets of a frequent itemset must also be frequent, and any superset of an infrequent itemset cannot be frequent. For example, assuming \( \{a, b, c\} \) is frequent, all of its sub-itemsets, such as \( \{a, c\} \), are also frequent. If \( \{d, e\} \) is infrequent, its supersets, such as \( \{a, d, e\} \), are not frequent. Some Apriori-based approaches for HUI-M have been further developed.

- OOA Apriori & top-\(k\) closed utility mining [21], [22]. In 2002, Shen and Yang proposed an objective-oriented association (OOA) mining approach [21]. They integrated the utility constraint into OOA Apriori (a variant of Apriori [9]) to prune candidates for deriving the OOA rules. The interestingness of OOA rules are measured in terms of probabilities and utilities in supporting the user’s objective. The utility constraint for OOA rules is neither monotone nor anti-monotone. In 2003, Chan et al. first defined the concept of utility mining and proposed an objective-directed mining algorithm to mine the top-\(k\) closed-utility patterns [22]. This was the first time the term “utility mining” was presented and used to identify both frequent and high-utility itemsets based on business objectives. In this utility-based mining framework, a pruning strategy based on a weak but anti-monotonic condition was developed to reduce search space.

- MEU (Mining with Expected Utility) [52]. In 2005, Yao et al. proposed a utility mining model, called mining with expected utility (MEU) [52], which considers both the purchase quantities (called internal utility) and unit profits (called external utility) of items to mine high-utility itemsets. Note that the term “mining high-utility itemsets” first appeared in [22], but their concept and definitions were quite different from the definitions of high-utility itemset mining today. It is widely believed that utility-based itemset mining, sequence mining, and web mining originated in [52]. Researchers in the field of HUPM consider the MEU model as the first theoretical model and strict definition of high-utility itemset mining. MEU uses a heuristic to determine candidates and usually overestimates. However, it cannot maintain the downward closure property of Apriori [9], and the derived results are incomplete.

- UMining and UMining-H [29]. Yao et al. then proposed UMining and heuristic UMining-H [29] for finding HUIs based on several mathematical properties of the utility measure. The utility constraint is characterized by a property giving the upper bound of the utility value of an itemset. In UMining, the property of utility upper bound is used as a pruning strategy. UMining-H utilizes another pruning strategy based on a heuristic method [29]. However, some high-utility itemsets may be erroneously pruned by this heuristic method. Furthermore, neither of them have the downward closure property of Apriori [9], and they overestimate too many patterns. Therefore, they suffer from excessive candidate generation and poor scalability.

- Two-Phase [75]. Note that the downward closure property (w.r.t. the Apriori property [9]) of the support measure does not hold for the utility. To address the challenge that the utility measure is neither monotone nor anti-monotone, Liu et al. proposed the well-known Two-Phase algorithm [75]. Two-Phase introduces a novel concept named the Transaction-Weighted Downward Closure (TWDC) property (for any itemset \( X \), if \( X \) is not a HTWUI, any superset of \( X \) is not an HUI) and used it to discover HUIs in two phases. Phase 1: it finds each itemset \( X \) such that \( TWU(X) \geq minutil \) using the TWU upper bound to prune the search space. Initially, it scans a database
once to get all 1-itemset $HTWUI_1$; then generates $(k+1)$-level candidate itemsets (with length $k+1$) from length-$k$ candidates $HTWUI_k$ (where $k > 0$). In each iteration, it needs to test the TWU values of candidates by scanning the database once. Finally, it is terminated when no candidate can be generated. 

Phase 2: it scans the database again to calculate the exact utility of each candidate in the set of $HTWUI_k$ and then outputs the desired HUs.

- **IIDS, FUM and DCG+** [35]. It has been shown that algorithms for the itemset share-mining problem, such as ShFSM [34] and DCG [34], can be directly converted to the utility mining problem by replacing the frequency value of each item in every transaction by its total profit (i.e., multiplying the frequency value by its unit profit). The isolated items discarding strategy (IIDS) [35] was proposed to reduce the number of candidates in every database scan. By discarding isolated items to reduce the number of candidates and to shrink the database scan in each pass, IIDS can improve the level-wise, multi-pass candidate-generation process. Applying IIDS to ShFSM and DCG, Fast Utility Mining (FUM) [35] and Direct Candidates Generation (DCG+) [35] were further developed. The results showed that FUM and DCG+ [34] are better than MEU, UMining, UMining_H and Two-Phase. However, both still suffer the problem of generating and testing candidates in a level-wise way and require multiple database scans.

**Discussions.** In summary, all of the early HUPM approaches improved on the Apriori work [9]. An important drawback is that all of them need to generate a huge amount of candidates since they rely on a loose upper bound on the utilities of candidates. As a result, these approaches may suffer from long execution times and consume a huge amount of memory. Moreover, all these algorithms suffer from the same limitations as Apriori-based ARM algorithms, which are to generate candidates not appearing in the database and to perform multiple database scans to mine the desired information. The computational complexity of these Apriori-based HUPM techniques depends on the level-wise manner that generates a huge number of candidates. These techniques may have quadratic complexity if the processed data containing long transactions or a low minimum threshold value is used.

### 3.3 Tree-Based Pattern-Growth Approaches

Many early HUIM approaches perform a level-wise exploration of the search space to find HUs. To avoid the drawback of an Apriori-based level-wise search, several tree-based HUIM algorithms were then proposed to efficiently mine HUs based on the TWDC property and the pattern-growth-mining approach. Generally speaking, the tree-based HUPM algorithms are inspired by the traditional tree-based FPM algorithms, i.e., FP-Growth [7].

- **HYP tree (High-Yield Partition tree)** [76]. In 2007, Hu et al. proposed an approximation method that identifies the contribution of the predefined utility, objective function, and performance metric, and can take advantage of item attributes [76]. It identifies high-utility item combinations and then finds high-utility patterns through a specialized high-yield partition (HYP) tree. In contrast to the traditional FPM and ARM techniques, its goal is to find segments of data and combinations of items/rules that satisfy certain conditions and maximize a predefined objective function. Different from the former UPM approaches, it conducts “rule-discovery” with respect to individual attributes and the overall criterion for the discovered results. It aims at mining groups of patterns that when combined, contribute the most to an objective function [76].

- **HUC-Prune (High-Utility Candidates Prune)** [77]. Since the existing Apriori-like HUIM algorithms suffer from the candidate generation-and-test problem, Ahmed et al. proposed a novel tree-based algorithm named High-Utility Candidates Prune (HUC-Prune) to extract high-utility patterns. The proposed HUC-tree structure is a prefix tree storing the candidate items in descending order of TWU values. Each node in the HUC-tree consists of the item’s name and its TWU value. Similar to IHUP [31], HUC-Prune replaces the level-wise candidate generation process by a pattern-growth-mining approach. It needs at least three database scans for mining the HUs, thus outperforming Apriori-based algorithms, which perform multiple database scans.

- **IHUP (Incremental High-Utility Pattern mining)** [31]. The tree-based algorithm named IHUP with three tree structures (IHUP$_{PL}$-tree, IHUP$_{FT}$-tree and IHUP$_{TWU}$-tree) was proposed for incremental and interactive high-utility pattern mining [31]. Each node in the IHUP-tree represents an itemset and consists of the itemset’s name, a TWU value, and a support count. The IHUP algorithm has three steps: 1) construction of IHUP-tree, 2) generation of HTWUIs [75], and 3) identification of high-utility itemsets. Figure 3 shows the constructed IHUP-tree for the example database given in [78]. In step 2, all HTWUIs are generated from the constructed IHUP-tree using the FP-Growth [7] approach.

#### Table 3: Apriori-based algorithms for high-utility pattern mining.

| Name | Description | Pros. | Cons. | Year |
|------|-------------|-------|-------|------|
| MEU [32] | The first theoretical model and strict definitions of high-utility itemset mining. | MEU uses a heuristic to determine candidates and usually overestimates. | It cannot maintain the downward closure property of Apriori [9], and the derived results are incomplete. | 2004 |
| UMining [29] & UMining_H [29] | The general HUIM model with several mathematical properties of the utility measure. UMining uses the utility upper bound and UMining_H utilizes a heuristic pruning strategy. | It generates a large amount of candidate patterns and suffers from excessive candidate generations and poor scalability. | | 2006 |
| Two-Phase [79] | The TWDC property was proposed to discover HUs in two phases. | It can greatly prune a large amount of candidate patterns. | If suffers from the problem of candidates level-wisely generation-and-test [9], and requires multiple database scans. | 2005 |
| IIDS [33], FUM [35], DCG+ [35] | By applying IIDS to ShFSM and DCG, two methods - FUM and DCG+ were implemented. | For any existing level-wise utility mining method, it can reduce the number of candidates and improve performance. | It has the same performance issues as Apriori [9]. | 2008 |
Therefore, HTWUIs can be discovered without generating any candidates. In step 3, all HUIs and their utilities can be identified from the set of HTWUIs by scanning the database once. Thus, IHUP can avoid generating candidates in a level-wise way. Although IHUP significantly outperforms IIDS [35] and Two-Phase [75], it still produces too many HTWUIs in phase 1. Note that both IHUP and Two-Phase use the TWU framework to overestimate the utilities of itemsets. Thus, they produce the same huge number of HTWUIs in phase 1. Such a large number of HTWUIs will substantially degrade the mining performance in terms of execution time and memory consumption. Moreover, the performance of phase 2 is affected by the number of HTWUIs. The reason is that the more HTWUIs the algorithm generates in phase 1, the longer the execution time required for mining HUIs in phase 2.

- **UP-Growth [79]** and **UP-Growth+ [78]**. Tseng et al. designed a more compressed utility-pattern tree (UP-tree) and proposed the well-known utility pattern-growth algorithm (UP-Growth) [79] to efficiently mine HUIs. UP-Growth is inspired by the frequency-based FP-Growth method. It integrates four novel strategies, named DLU (Discarding Local Unpromising items), DGN (Decreasing Global Node utilities), DLU and DLN (Decreasing Local Node utilities during the construction of a global UP-tree), and DGN (Decreasing Global Node utilities during the construction of a global UP-tree). After two scans of the original database, the UP-tree can be constructed. In the first scan, the utility of each transaction and TWU of each single item are calculated. Discarding global unpromising items, those unpromising items that are not HTWUIs are removed from each transaction, and utilities are eliminated again. Then, the remaining promising items in each transaction are sorted in the descending order of TWU. In the second scan, transactions are inserted into UP-tree by using DGU and DGN strategies. After building the complete UP-tree, as shown in Fig. 4, the potential HUIs (PHUIs) are generated from the global UP-tree with DLU and DLN strategies. In summary, the framework of UP-Growth consists of three steps: 1) scan the database twice to construct a global UP-tree with the DLU and DLN strategies; 2) recursively generate PHUIs from global UP-tree and local UP-trees by UP-Growth with the DGU and DGN strategies; and 3) identify final HTUIs from the set of PHUIs. As an improvement of UP-Growth, UP-Growth+ [78] was then developed by utilizing the minimal utilities of each node in each path in the UP-tree. Compared with UP-Growth, the enhanced UP-Growth+ can decrease the overestimated utilities of PHUIs and greatly reduce the number of candidates.

- **SIQ-tree (Sum of Item Quantities-tree) [81]**. Tree construction with a single database scan is significant since a database scan is a time-consuming task. In utility mining, an additional database scan is necessary to identify actual high-utility patterns from candidates. A novel tree structure, namely SIQ-tree (Sum of Item Quantities tree) [81], was developed recently to capture database information through a single pass. Moreover, a restructuring method is proposed with strategies for reducing overestimated utilities. It can construct the SIQ-tree with only a single scan and decrease the number of candidate patterns effectively with the reduced overestimation utilities, through which mining performance is improved.

**Discussions**. Characteristics and differences of these tree structures are presented in Table 4. In addition, there are various other utility-based mining methods based on tree structures [82], [83]. These tree-based algorithms comprise three steps: 1) construction of trees, 2) generation of candidate HUIs from the trees using the designed pattern-growth approach, and 3) identification of HUIs from the set of candidates. Although these trees are often compact, they may not be minimal and still occupy a large memory space. The mining performance of these methods is closely related to the number of conditional trees constructed during the entire mining process and the construction/traversal cost of each conditional tree. When using these algorithms on a large database with a low-utility threshold, the storage and traversal costs of numerous conditional trees are high. Thus, one of the performance bottlenecks of these algorithms is the generation of a huge number of conditional trees, which has high time and space costs.

In summary, to address the disadvantages of the Apriori-
like HUPM algorithm, and to improve efficiency, the advantages of pattern-growth tree-based techniques are as follows: 1) only need two or three passes over dataset; 2) “compresses” datasets into the tree structure; 3) no candidate generation; and 4) much faster than Apriori-like approaches. However, they still have some disadvantages: 1) the constructed tree may not fit in memory; 2) the designed tree is expensive to build; 3) it is time-consuming to recursively process all conditional prefix trees to generate candidates; and 4) the constructed tree is sensitive to the parameters of the minutil.

### 3.4 Projection-Based Pattern-Growth Approaches

In the past, some of projection-based techniques have been commonly used in data mining, i.e., FP-Growth [3] for FPM and PrefixSpan [16] for SPM. The general idea of projection-pattern mining is to use target items to recursively project the processed database into some smaller projected sub-databases, and then grow the itemset or subsequence fragments in each projected sub-database. To overcome the disadvantages of the tree-based HUIM approaches, some projection-based techniques have been developed for HUPM.

- **CTU-PRO and CTU-PROL [33].** In 2007, Erwin et al. first proposed a projection-based CTU-PRO algorithm for HUIM. It mines HUls by bottom-up traversal of a compressed utility pattern tree (CUP-tree) [33], which is a variant of CTU-tree [82]. The mining of a subdivision from CUP-tree consists of three steps: 1) Construction of ProTemTable, 2) construction of ProCUP-tree, and 3) mining by ProCup-tree traversal. CTU-PRO creates a GlobalCUP-tree from the transaction database after identifying the individual HTWUIs [75] with the concept of TWU. For each HTWUI, a smaller projection tree called the LocalCUP-tree is extracted from the GlobalCUP-tree for returning all high-utility itemsets with that item as prefix. CTU-PRO constructs parallel sub-divisions on disk that can be mined independently. The performance of CTU-PRO is better than Two-Phase [75] and CTU-Mine [82]. CTU-PROL introduces two new concepts, compressed transaction utility-prol and CUP-tree, which are used for parallel projection of the transaction database. Note that the anti-monotone property of TWU is used to prune the search space of sub-divisions in CTU-PROL. However, unlike Two-Phase, it avoids a rescan of the database to calculate the actual utilities of HTWUIs. The results show that CTU-PROL outperforms Two-Phase [75] and CTU-Mine [82].

- **GPA and PB [84].** Since the tree-based pattern-growth approaches recursively perform tree traversal and generate a series of sub-tree structures, Lan et al. proposed two alternative efficient projection-based utility mining approaches, named GPA (Gradual Pruning Approach) [84] and PB (Projection-Based mining approach) [84]. Compared with the level-wise techniques, the property of a projection-based technique is more suitable for improving the utility upper bound. The general idea is to use the overestimated HTWUIs [75] to recursively project item/sequence databases into some smaller projected databases and grow item/subsequence fragments in each projected sub-database. In addition, PB applies a novel pruning strategy and an indexing mechanism to speed up the runtime and reduce the memory requirement of the mining process. The indexing mechanism imitates traditional projection algorithms (i.e., PrefixSpan [16]) by projecting sub-databases. Using projection, GPA and PB can significantly reduce database size when deriving larger itemsets and outperform Two-Phase [75].

- **PTA [84].** Different from PB [84] and GPA [84], pruning and filtering strategies are proposed to tighten the upper bounds of utility values in the projection-based upper-bound tightening approach (abbreviated as PTA). The framework of PTA includes the following: 1) finds HTWUIs and high-utility 1-itemsets; 2) performs the pruning strategy and the indexing strategy; 3) projects transactions required by the prefix items to be processed; and 4) finds k-HTWUIs and high-utility k-itemsets. An effective

TABLE 4

| Name       | Description                                                                 | Pros.                                                                 | Cons.                                                                 | Year  |
|------------|-----------------------------------------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------|-------|
| HYT tree   | An approximation method identifies the utility contribution.                | It can find segments of data through combinations of few items/rules. | The built HYT tree is huge, and the memory is costly.                | 2007  |
| CTU-Mine   | A pattern growth approach based on a compact data representation named CTU-tree for utility mining. | The pattern growth, which avoids candidate generation-and-test, is suitable for dense data. | The CTU-tree is complex and stores too much information, which may consume much memory. | 2007  |
| HUC-Prune  | High-utility candidate prune without level-wise candidate generation-and-test. | It replaces the level-wise candidate generation process by a pattern-growth mining approach. | The upper bound is high, and the constructed tree is huge.          | 2009  |
| HTWUI      | A tree-based approach for incremental and interactive high-utility pattern mining. | The HTWUI-tree is more compact than previous trees, and HTU is significantly faster than IDS and Two-Phase. | It still uses the TWU and produces too many HTWUIs in phase 1.       | 2009  |
| CTU-Mine   | The utility pattern growth algorithm with more compressed utility pattern tree (UP-tree). | UP-tree is more compact than HUC-Prune-tree, and the strategies are powerful to reduce the number of candidates. | It is time-consuming to recursively process all conditional prefix trees to generate candidates. | 2010  |
| CTU-PROL   | An improved version of CTU-Mine with two pruning strategies.              | Two mechanisms, shared variables and message passing, can make the CHUI-tree more compact. | It is time-consuming to recursively process all conditional prefix trees to generate candidates. | 2013  |
| IUHP       | Concurrent High-Utility Itemset Mine (HUIM) algorithm by dynamically pruning the CHUI-tree. | Recursive processing all conditional prefix trees is time-consuming. | Recursive processing all conditional prefix trees is time-consuming. | 2014  |
| SIQ-tree   | Sum of Item Quantities.                                                    | Constructs the SIQ-tree with only a single scan and decreases the number of candidate patterns. | Recursive processing all conditional prefix trees is time-consuming. | 2016  |
index mechanism is applied to reduce the time cost of searching relevant transactions that need to be projected in sub-databases. Thus, PTA only needs one database scan. Through experiments, the results show that PTA outperforms the other existing approaches (i.e., Two-Phase [75], GPA [84], PB [84], CTU-PRO [33], IHUP [31], IHUP\(_{TWU} [31]\), and IHUP\(_{TF} [31]\)) in terms of pruning unpromising itemsets, memory usage, and runtime, respectively.

**Discussions.** In summary, the above HUPM approaches, which utilize the database projection mechanism, have the following advantages: 1) mine the complete set of high-utility patterns but reduce the effort of candidate generation; 2) prefix-projection reduces the size of the projected sub-database and leads to efficient processing; and 3) bi-level projection and pseudo-projection may improve mining efficiency.

### 3.5 New Data-Format-Based Approach

To achieve more efficiency than the tree-based HUPM approaches, some algorithms that mine high-utility itemsets using a vertical or horizontal data structure with a single phase were proposed recently, such as HUI-Miner [24], FHM [85], d2HUP [86], HUP-Miner [87], and EFIM [88]. Both d2HUP and EFIM use a horizontal database, while others use the vertical data structure. All these algorithms cannot only avoid the disadvantages of Apriori-based approaches but can also avoid the disadvantages of the tree-based HUIIM approaches. Details are shown in Table 6 and described below.

- **HUI-Miner (High-Utility Itemset Miner) [24]**. HUI-Miner is the first one-phase algorithm to discover HUIs. It proposes a vertical data structure named utility list [24] and the concept of *remaining utility* [24], which have been widely extended in many other newly HUPM algorithms. As a compact data structure, utility-list can store utility information for the potential patterns that may have high utility value. The utility-list of an itemset \(X\) in a database \(D\) is a set of tuples corresponding to the transactions in which \(X\) appears. Each tuple is defined as \(<tid, iu, ru>\) for every transaction \(T_\text{d}\) containing \(X\), in which \(tid\) element is the transaction identifier of \(T_\text{d}\), the \(iu\) element is the utility value of \(X\) in \(T_\text{d}\), and \(ru\) element is the remaining utility value of \(X\) in \(T_\text{d}\). The reader is referred to [24] for details about the remaining utility, utility-list structure, and its construction. The construction process of utility-list is quite efficient and consumes little memory. By keeping necessary information from the transaction database in memory, HUI-Miner can directly mine HUIs by scanning the search space w.r.t. a set-enumeration tree [91].

Using the designed utility-list [24], HUI-Miner needs only two database scans to create and maintain a series of utility-lists of 1-itemsets satisfying the TWU value. Then, utility-lists of \((k+1)\)-itemsets can be obtained by performing the join operations of utility-lists of \(k\)-itemsets. The main contributions of HUI-Miner are the developed utility-list and a powerful pruning strategy that utilizes the upper bound of the remaining utility. It thus directly discovers HUIs by keeping utility-list in memory, and outperforms the all previous algorithms. However, the drawback is that it needs to perform costly join operations among a series of utility-lists, which can be time costly.

- **FHM [85]**. As an enhanced version of HUI-Miner [24], FHM (Fast High-Utility Miner) [85] utilizes a novel pruning strategy named EUCP (Estimated Utility Co-occurrence Pruning) to reduce the costly join operations of utility-lists. EUCP is based on the Estimated Utility Co-occurrence Structure (EUCS) [85], which is simultaneously built during the construction of utility-list. The EUCS is defined as a set of triples of the form \(\langle a, b, c \rangle \in |F^*| \times |F^*|\), and a triple means that \(TWU(\langle a, b \rangle) = c\). It can be constructed as a triangular matrix or a hash map in which only tuples of the form \(c \neq \emptyset\) are kept. FHM also utilizes the depth-first search procedure and adopts the *utility-list* structure [24] to explore the search space. Thus, larger itemsets are obtained by performing join operations of utility-lists of the smaller itemsets during the mining process. FHM is more faster than HUI-Miner [24], especially for dense databases, but not efficient for databases that are sparse.

- **d2HUP [86]**. d2HUP is also able to directly discover HUIs without generating candidates. It utilizes another novel data structure, named CAUL (Chain of Accurate Utility Lists) [86] to store the necessary information. In contrast to HUI-Miner, it enumerates an itemset as a prefix extension of its prefix itemset. In fact, the search space of d2HUP is a variant of set-enumeration tree [91]. It can efficiently calculate the utility of each enumerated itemset and the upper bound on utilities of the prefix-extended itemsets. In fact, d2HUP also utilizes the similar concept of *remaining utility* to tighten the utility upper bound, which is much tighter than TWU. This upper bound is tightened by iteratively filtering out irrelevant items when constructing CAUL. More specifically, it requires less memory than different kinds of tree structures used in the above-mentioned algorithms. d2HUP was shown to be more efficient than Two-Phase [75], UP-Growth [79], and HUI-Miner [24], but the performance was not compared with some recent algorithms, such as FHM [85] and HUP-Miner [87].

- **HUP-Miner**. HUP-Miner [87] is an improvement algo-

### Table 5

Projection-based pattern-growth approaches for HUPM.

| Name | Description | Pros. | Cons. | Year |
|------|-------------|-------|-------|------|
| CTU-PRO [33] & CTU-PROL [33] | Two projection-based algorithms with Compressed Utility Pattern-tree (CUP-tree). | They construct parallel sub-divisions on disk that can be mined independently and have good performance. | TWU is adopted as the upper bound, which generates many redundant candidates. | 2008 |
| GPA and PB [84] | Two projection-based mining approaches. GPA (Gradual Pruning Approach) and PB (Projection-Based mining approach). | Using projection, they can speed up the runtime and reduce database size when deriving larger itemsets. | TWU is adopted as the upper bound, which generates many redundant candidates. | 2012 |
| PTA [84] | A projection-based upper-bound tightening approach. | Two effective strategies, named pruning and filtering, are proposed to tighten the upper bounds of utility values. | The projection of sub-databases is sometimes time-consuming. | 2012 |

The construction process of utility-list is quite efficient and consumes little memory. By keeping necessary information from the transaction database in memory, HUI-Miner can directly mine HUIs by scanning the search space w.r.t. a set-enumeration tree [91].
Another algorithm that can directly discover HUIs without maintaining candidates.

Pros.
The first one-phase model to mine high-utility itemsets.

Cons.
The join operations between utility lists of \((k+1)\)-itemsets and \(k\)-itemsets is time-consuming.

HUP-Miner [87]
An improved version of HUI-Miner with two new pruning strategies (PU-Prune and LA-Prune).

Pros.
The two new pruning strategies can reduce the join operations between utility lists.

Cons.
It needs to explicitly set the number of dataset partitions, while these partitions cannot always improve the efficiency.

EFH [88]
Uses projection and transaction-merging techniques for reducing the cost of database scans.

Pros.
It consumes less memory, and its complexity is roughly linear with the number of items in the search space.

Cons.
Sometimes the recursive projection is time-consuming and uses a lot of memory.

IMHUP [89]
A novel utility-list-based algorithm for HUI mining without any candidate generation.

Pros.
It uses the indexed utility list to reduce the join operations between utility lists.

Cons.
The upper bound on utilities is not tight enough.

mHUI-Miner [90]
An efficient one-phase algorithm that combines some ideas from HUI-Miner and IHUP.

Pros.
It utilizes utility list and remaining utility and performs well on sparse datasets.

Cons.
It still suffers from some problems similar to those of HUI-Miner and IHUP.

RHUP-Miner [91]
A pruning strategy and search space reduction technique.

Pros.
The tree structure and CAUL consume more memory.

Cons.
The join operations between utility lists of \((k+1)\)-itemsets and \(k\)-itemsets is time-consuming.

Table 6: Utility-list-based algorithms for high-utility pattern mining.

| Name               | Description                                                                 | Pros.                                                                 | Cons.                                                                 | Year |
|--------------------|-----------------------------------------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------|------|
| HUI-Miner [24]     | The first one-phase model to mine high-utility itemsets.                    | It first introduced the concept of the remaining utility and the vertical data structure w.r.t. utility-list. | The join operations between utility lists of \((k+1)\)-itemsets and \(k\)-itemsets is time-consuming. | 2012 |
| d2HUP [86]         | Another algorithm that can directly discover HUIs without maintaining candidates. | It efficiently obtains the utility of each enumerated itemset and the upper bound on utilities using the CAUL. | The tree structure and CAUL consume more memory. | 2012 |
| FHM [85]           | An improved version of HUI-Miner with a pruning strategy named EUCP.        | It not only has the advantages of HUI-Miner but also reduces the join operations between utility lists. | It consumes slightly more memory than HUI-Miner and has poor performance on dense datasets. | 2014 |
| HUP-Miner [87]     | An improved version of HUI-Miner with two new pruning strategies (PU-Prune and LA-Prune). | The two new pruning strategies can reduce the join operations between utility lists. | It needs to explicitly set the number of dataset partitions, while these partitions cannot always improve the efficiency. | 2015 |
| EFH [88]           | Uses projection and transaction-merging techniques for reducing the cost of database scans. | It consumes less memory, and its complexity is roughly linear with the number of items in the search space. | Sometimes the recursive projection is time-consuming and uses a lot of memory. | 2015 |
| IMHUP [89]         | A novel utility-list-based algorithm for HUIs mining without any candidate generation. | It uses the indexed utility list to reduce the join operations between utility lists. | The upper bound on utilities is not tight enough. | 2017 |
| mHUI-Miner [90]    | An efficient one-phase algorithm that combines some ideas from HUI-Miner and IHUP. | It utilizes utility list and remaining utility and performs well on sparse datasets. | It still suffers from some problems similar to those of HUI-Miner and IHUP. | 2017 |

Algorithm based on HUI-Miner [24]. Two new pruning strategies, PU-Prune (based on dataset partition) and LA-Prune (based on the concept of lookahead pruning), are introduced in HUP-Miner to limit the search space for mining HUIs [87]. It needs to set the number of dataset partitions \(K\), which determines how many partitions processed internally. However, the optimal value of \(K\) is hard to find empirically for a given dataset. Based on the concept of remaining utility [24], LA-Prune provides a tighter utility upper bound of any \(k\)-itemset. Thus, a huge number of unpromising \(k\)-itemset \((k \geq 2)\) that have low utility can be pruned. It has been shown that HUP-Miner is significantly faster than HUI-Miner. In fact, the PU-Prune strategy based on dataset partition does not always have an effect on runtime and memory consumption. In addition, a shortcoming is that the number of partitions is required to be set explicitly by users, since it is an additional parameter.

- **IHUI-Mine** (Index High-Utility Itemsets Mine) [92]. As mentioned before, these candidate generation-and-test approaches suffer from the drawbacks of having an immense candidate pool and requiring several database scans. Meanwhile, methods based on pattern growth tend to consume large amounts of memory to store conditional trees. IHUI-Mine uses the subsume index [93], a data structure for efficient frequent itemset mining, to enumerate the desired HUIs and prune the search space. The experimental results show that IHUI-Mine outperforms some popular algorithms, including Two-Phase [75], FUM [35], and HUC-Prune [77], but it has not been compared with all state-of-the-art algorithms.

- **IMHUP** (Indexed list-based Mining of High-Utility Patterns) [89]. In the framework of list-based high-utility pattern mining without any candidate generation, there are a number of comparison and join operations of entries within lists causing enormous execution time costs. Thus, Ryang and Yun proposed an indexed, list-based data structure (named indexed utility-list, or IU-list) [89] to discover high-utility patterns more efficiently through the newly proposed entry joining operations without any TID comparison. Two techniques were developed based on the data structure for reducing utility upper-bounds to the extent that they satisfy the anti-monetone property, and for generating high-utility patterns without any construction of additional local lists when the current lists only contain information of the same revised transactions. IMHUP-RUI and CHI [89] utilize reducing upper-bound utilities in IU-lists to decrease the search space in the proposed data structure.

- **EFIM** [88]. Recently, an efficient one-phase projection-based algorithm named Efficient high-utility Itemset Mining (EFIM) was proposed [88]. It introduces several new ideas, i.e., two new upper bounds named revised sub-tree utility and local utility, and a array-based utility computing technique named fast utility counting. To reduce the cost of database scans, EFIM further proposes the database projection and transaction merging techniques named High-utility Database Projection (HDP) and High-utility Transaction Merging (HTM). As larger itemsets are explored, both projection and merging reduce the size of the database. The main ideas of HDP and HTM are described in [88]. The time and space complexity of EFIM is roughly linear with the number of distinct items in the search space. Results show that EFIM is in general 2 to 3 orders of magnitude faster than the state-of-the-art algorithms (UP-Growth+ [78], HUI-Miner [24], FHM [85], d2HUP [86], and HUP-Miner [87]) on dense databases and performs quite well on sparse datasets.

- **mHUI-Miner** (modified HUI-Miner). mHUI-Miner [90] is an efficient one-phase algorithm for discovering high-utility itemsets from transaction databases. It is a hybrid algorithm that combines some ideas from HUI-Miner [24] and IHUP-tree [31]. It utilizes the utility-list, remaining utility, and IHUP-tree. It also utilizes a tree structure to guide the itemset expansion process, and thus the itemsets that are nonexistent in the database can be avoided. Unlike current techniques, it does not have a complex pruning strategy that requires expensive computational overhead. It was shown to perform well on sparse datasets, and provides the best runtime on sparse datasets, while having a comparable performance than other state-of-the-art algorithms (e.g., HUI-Miner [24], FHM [85], and EFIM [88]) on dense...
Discussions. All the algorithms discussed in this subsection utilize the new data structure to store necessary information about each itemset. By spanning the search space w.r.t. a set-enumeration tree [91], they can easily calculate the total utility of an itemset by performing joins on the utility-lists. Moreover, an upper bound on the overall utilities of itemsets called the remaining utility is calculated using utility-lists. It can be used to determine if each pattern and its extensions are not high-utility itemsets (to reduce the search space). The upper bound with remaining utility is equivalent to the upper bound proposed in d2HUP [86]. Although a pattern-growth approach is used in d2HUP, it can avoid considering itemsets not appearing in the database, the used hyper-structure still consumes a considerable amount of memory [86].

As shown at Table 6, the HUIM algorithms are based on a combination of vertical or horizontal data formats and typical approaches. These hybrid algorithms combine different techniques to mine high-utility patterns in such a way that the strengths of each technique are utilized to maximize their efficiency. The properties of these one-phase algorithms are as follows:

1) Complete result: The completeness is guaranteed as the traversal of the search space w.r.t. set-enumeration tree.
2) Stable result: The result is stable as all exact utility information is stored in a vertical or horizontal data structure. Depth-first searching is also used to quickly calculate the utilities.
3) Efficiency: The algorithm is efficient relative to algorithms that traverse the complete search space. Moreover, the sort order of items in set-enumeration tree affects the mining efficiency, but not the final mining results of patterns.
4) Parameter sensitivity: These algorithms, except for HUP-Miner, only have minutil as the parameter, and are sensitive to it.

4 Advanced Topic of UPM

4.1 Mining High Average Utility Itemsets

A main challenge in HUIM is that the exponential search space for HUIM is extremely large when the number of distinct items or the size of the database is too large. The other challenge is that existing HUIM methods overlook the fact that longer itemsets result in higher utility values. A large itemset may have an unreasonable estimated profit as opposed to its actual value. Therefore, the concept named high average-utility itemset mining (HAUIM) is proposed [70]. HAUIM discovers utility patterns by considering both their utilities and lengths, thus providing a different utility measure than traditional HUIM. HAUIM divides the utility of an itemset by its length (the number of items that the itemset contains). Up to now, some interesting works have been extensively studied, such as Apriori-based algorithms [70], projection-based PAI [94], utility-list-based HAUI-Miner [95], [96], and other hybrid algorithms with different upper-bound models [96], [97].

4.2 HUIM in Dynamic Environments

In a wide range of applications, the processed data may be commonly dynamic but not static. The dynamic data are more complicated and difficult to handle than the static data. Most algorithms process a static database to mine HUls. In real-world applications, records/transactions are dynamically changed (i.e., inserted, deleted, and modified) in the original database. Some preliminary studies have been done on this issue for HUPM.

- Case 1: HUIM with record insertion. Data mining is an iterative process, and incremental data mining [98], [99] provides the ability to continuous analyze and mine the data by using previous data structure and mining results. Up to now, some incremental models have been developed for mining HUls with record insertion, such as IHUP [31], FUP-HUI-INS [100], PRE-HUI-INS [101], HUI-list-INS [102], and EIHI [103]. Among these, the early algorithms, e.g., FUP-HUI-INS and PRE-HUI-INS, utilize the utility-oriented dynamic maintain strategies that are extended by the original FUP [98] and pre-large [99] concepts. Since FUP-HUI-INS and PRE-HUI-INS algorithms are processed by a Two-Phase model, an additional database rescans is still necessary to find the actual HUls. Furthermore, computations are required to find the HTWUs based on the pattern-growth approach. Both HUI-list-INS [102] and EIHI [103] utilize the utility-list [24] and utility property to significantly reduce runtime and memory usage. For a complete review, the reader is referred to [48].

- Case 2: HUIM with record deletion. In practical situations, record deletion is also an important issue in databases. Cheung et al. designed the FUP2 concept [104] to discover frequently updated itemsets for record deletion. Hong et al. developed the pre-large concept [99] for handling record deletion to avoid a multiple database scan each time. Two support thresholds are separately set in pre-large [99], and thus the original database is not required to be scanned until the number of accumulative deleted transactions achieves the designed safety bound. Since the FUP2 concept [104] cannot be directly applied to the HUIM, Lin et al. separately designed the FUP-HUI-DEL [105] and PRE-HUI-DEL [106] algorithms for handling record deletion to maintain and update the new HUls based on the Two-Phase model. Recently, an efficient dynamic algorithm named HUI-list-DEL [107] was developed to discover HUls by maintaining the built utility-list [24] structure for record deletion in dynamic databases. The new HUls can be directly produced without candidate generation or numerous database scans.

- Case 3: HUIM with record modification. As one of the three common operations (record insertion, deletion, and modification) in databases, record modification is also commonly seen in real-life situations. For example, some typos or errors may occur when the collected data from periodic transactions is input into a computer using a keyboard. Thus, some information may become invalid or new information may arise. Lin et al. first proposed the FUP-HUP-tree-MOD algorithm [108] to address this issue. It is based on the FUP concept [98] and shows better performance compared to Two-Phase and some tree-based algorithms in batch mode. In addition, a faster PRE-HUI-MOD algorithm [109] extends the pre-large concept [99] to set the effective
upper bound for discovering HTWUIs and HUIs from the dynamic databases.

4.3 Concise Representations of Utility Patterns

In the field of FPM, many techniques have been devised to derive compact representations of frequent patterns that eliminate redundancy but have rich information, such as free sets [110], non-derivable sets [111], maximal itemsets [112], and closed itemsets [113]. These representations significantly reduce the number of extracted frequent patterns, but some lead to loss of information (e.g., maximal itemsets [112]). Although the above UPM methods perform well in some cases, their performance may degrade when the minimum utility threshold is low. A large number of HUIs and candidates lead to long execution times and huge memory consumption. When computing resources are limited, this is a serious problem for the mining task. However, a large amount of HUIs is difficult to comprehend and be analyzed by users. Thus, it is often impractical to generate and return the entire set of HUIs.

- **Maximal high-utility pattern.** To return representative HUIs to users, some concise representations of HUIs were proposed. Chan et al. introduced the concept of a utility frequent closed pattern [22], the definition of which is different from high-utility itemset [52], [78]. Shie et al. then proposed a new representation called maximal high-utility itemset in which a HUI is not a subset of any other HUI [114]. Although maximal HUI reduces the number of extracted HUIs, it is not lossless because the utilities of the subsets of a maximal HUI cannot be known without rescanning the database. Moreover, recovering all HUIs from the set of maximal HUIs is very inefficient since many subsets of a maximal HUI may have low utility.

- **Closed high-utility pattern.** To provide not only compact but also complete information about high-utility itemsets to users, Tseng et al. first addressed the problem of redundancy in high-utility itemset mining [115]. A lossless and compact representation named closed high-utility itemset [115] was introduced. To mine this representation, they proposed three algorithms named AprioriHC (Apriori-based approach for mining High-Utility Closed itemsets), AprioriHC-D (AprioriHC algorithm with Discarding unpromising and isolated items), and CHUID (Closed High-Utility itemset Discovery) [115]. Fournier-Viger et al. then proposed a fast and memory efficient algorithm named EFIM-Closed [116] to discover closed HUIs by extending the EFIM model [88]. It proposes three strategies to mine CHUIs efficiently: closure jumping, forward closure checking, and backward closure checking. EFIM-Closed relies on two new upper bounds, named local utility and sub-tree utility, to prune the search space, and a FUC technique to calculate these upper bounds efficiently. Inspired by utility-list [24], some more efficient one-phase algorithms have been proposed to address this interesting issue, such as CHUI-Miner [117] and CHUM [118].

4.4 Mining High-Utility Quantitative Itemsets/Rules

Although extensive studies have been proposed for high-utility itemset mining, a critical limitation of these studies is that they ignore the quantity attribute of items in discovered HUIs. However, such information can be very useful and valuable in many applications. In view of this, the concept of High-Utility Quantitative Itemset mining (abbreviated as HUQI) [39], [119] has emerged. In the framework of HUQI mining, an item may have different quantities in the database and each item carrying a different quantity is regarded as a quantitative item. HUQI [39] and more efficient vertical utility-list-based VHUQI [119] were thus developed. An example of such a rule is (bread, 3, 4) ⇒ (milk, 2, 3), which means that most customers who purchased three or four breads also purchased two or three milks. We can use this information to package products with quantities that have high utility and estimate the number of items that need to be reserved according to the number of other items.

4.5 High-Utility Sequential Pattern Mining

By integrating the utility factor and sequence data, the problem of high-utility sequential pattern mining (HUSPM) was introduced. For handling the utility of web log sequences, two tree structures, called utility-based WAS tree (UWAS-tree) [63] and incremental UWAS-tree (IUWAS-tree) [63], were developed separately to mine web access sequences (WASs). However, a sequence element with multiple items, such as [((a, 3)|(c, 4))], cannot be supported in these two models. The considered scenarios are rather simple, which limits their applicability for handling complex sequences. Then, some algorithms were proposed to address the HUSPM problem.

- **UL and US** [42]. Since both UWAS-tree and IUWAS-tree algorithms cannot deal with sequences containing multiple items in each sequence element (transaction), Ahmed et al. designed two algorithms (level-wise Utility-Level (UL) [42] and pattern-growth Utility-Span (US) [42]) to mine HUSPs. UL and US extend traditional sequential pattern mining (SPM). The utility of a sequential pattern is calculated in two ways. The utilities of sequences having only distinct occurrences are added together, while the highest occurrences are selected from sequences with multiple occurrences and used to calculate the utilities. However, the problem definition in UL and US [42] is rather specific. No generic framework for transferring from SPM to high-utility sequence analysis has been proposed.

- **USpan** [43]. Yin et al. then formalized the problem of HUSPM, and proposed a generic framework and the USpan algorithm to mine high-utility sequences. [43]. A lexicographic quantitative sequence tree (LQS-tree) is constructed as the search space. Two concatenation mechanisms, I-Concatenation and S-Concatenation, are used to generate newly concatenated utility-based sequences. Based on the LQS-tree structure, USpan [43] adopts the SWU measure and the Sequence Weighted Downward Closure (SWDC) property to prune unpromising sequences and to improve the mining performance. However, a shortcoming of USpan is that the data representation w.r.t. the utility matrix is quite complex and memory-costly.

- **PHUS** [120]. Lan et al. then proposed the projection-based high-utility sequential pattern mining (PHUS) algorithm for mining HUSPs with the maximum utility measure and a sequence-utility upper-bound (SUUB) model [120]. The algorithm extends PrefixSpan [16] and uses a
projection-based pruning strategy to obtain tight upper bounds on sequence utilities. Thus, it can avoid considering too many candidates, and improves the performance of mining HUSPs using the SUUB model.

- **CRoM** [121] and **HUS-Span** [122]. Alkan et al. [121] designed another upper-bound method called Cumulate Rest of Match (CRoM) and developed a PBCG strategy to prune unpromising sequences for mining HUSPs. In view of the previous upper bounds on sequence utilities not being tight enough, the HUS-Span algorithm proposed two tight utility upper bounds, called prefix extension utility and reduced sequence utility, as well as two companion pruning strategies, to identify high-utility sequential patterns. It outperforms the all existing HUSPM algorithms by employing these two pruning strategies.

- **BigHUSP** [123] and **MAHUSP** [124]. Recently, the BigHUSP model was first introduced to address Big Data, and to discover distributed and parallel high-utility sequential patterns [123]. BigHUSP uses multiple steps of MapReduce [125] to process Big Data in parallel. In contrast to the traditional approaches, it can efficiently deal with large-scale sequential data. MAHUSP is a memory-adaptive approximation algorithm to efficiently discover high-utility sequential patterns over data streams [124]. It employs a memory-adaptive mechanism using a bounded portion of memory, and guarantees that all HUSPs are discovered under certain circumstances. Experimental study shows that MAHUSP can not only discover HUSPs over data streams efficiently, but also adapt to memory allocation without sacrificing much of the quality of discovered HUSPs.

    In addition, Shie et al. explored a new problem of mining high-utility mobile sequential patterns (HUMSPs) by integrating mobile data mining with utility mining [36], [37]. This is the first work that combines mobility patterns with utility factor to find high-utility mobile sequential patterns. Two tree-based methods, named UMSP-T and UMSP-L, are proposed to address the HUMSPs, which are mobile sequential patterns with their utilities.

### 4.6 High-Utility Episode Mining

When the sequential data becomes an event sequence, the task of frequent episode mining (FEM) [11] is introduced. FEM reveals a significant amount of useful information hidden in the event sequence with a wide range of applications [11], [12], [13], [14]. However, the discovered frequent episode is still too simple and primitive. In some cases, FEM may lose some rich information, such as utility, important, risk, etc. Wu et al. [44] presented the first attempt to solve the problem of high-utility episode mining (HUEM) in a complex event sequence. However, the proposed UP-Span algorithm suffers from low efficiency in both runtime and memory consumption. Furthermore, the proposed upper-bound named Episode Weighted Utility (EWU) is a loose and basic utility bound for episodes. Guo et al. then proposed the TSpan algorithm with several improvements for UP-Span in a much more efficient manner [126], which can save considerable search space and runtime. Then, Lin et al. separately introduced some models to process complex event sequences and stock investment using high-utility episode mining and a genetic algorithm [45], [127]. In addition, the top-k issue of HUEM has been studied recently [128].

### 4.7 HUPM in Stream Data

A data stream is an infinite sequence of data elements continuously arriving at a rapid rate [66], [67]. Mining useful patterns from data streams has become one of interesting problems of data mining [67], [129], [130]. However, few works on mining data streams consider the utility factor embedded in data streams. Tseng et al. first proposed the THUI-Mine (Temporal High-Utility Itemsets) model to mine temporal HUIs from data streams [131]. THUI-Mine can effectively identify the temporal HUIs by generating fewer temporal 2-itemsets of HTWUIs. Thus, the execution time can be reduced significantly in mining all HUIs from data streams. In this way, the discovery process under all time windows of data streams can be achieved with limited memory space and less candidates. Then, researchers for HUIM proposed several stream mining models, such as MHUI-BIT (Mining High-Utility Itemsets based on BITvector) [30], MHUI-TID (Mining High-Utility Itemsets based on TIDlist) [30], and GUIDE (Generation of maximal high-Utility Itemsets from Data strEams) [114]. GUIDE is a framework that mines the compact maximal HUIs from data streams with different models (i.e., the landmark, sliding, and time fading window models) [114].

### 4.8 HUPM with Various Interesting Constraints

Up to now, most of the algorithms for HUPM have been developed to improve the efficiency of the mining process,
while effectiveness of the algorithms for HUPM is also very important, because it is related to its usefulness for various data, constraints, and applications. Researchers in the field of utility-oriented pattern mining have proposed many algorithms and models to extend effectiveness. Many constraint-based HUPM algorithms have been extensively developed for various problems, targeting a wide range of applications. For example, mining high-utility itemsets with products’ on-shelf time period [84], [132], HUPM by considering negative profit values [133], mining the up-to-date HUIs that reflect recent trends [134], mining discriminative high-utility patterns [73], [135], mining top-k high-utility itemsets without setting the minimum utility threshold [68], [136], HUPM with multiple minimum utility thresholds [137], utility-based association rule mining [40], [41], HUPM with consideration of various discount strategies [61], mining high-utility itemsets with or without negative utility profits [133], [138], HUPM from uncertain data [138], [139], extracting non-redundant correlated HUIs [62], and HUPM from Big Data [140], [141]. Obviously, HUPM with various interesting constraints is an active research topic.

4.9 Privacy Preserving for UPM

Since more useful information is in the expected utility-based patterns than in that of the frequent itemsets or sequences, privacy preserving for high-utility pattern mining (PPUM) is more realistic and critical than privacy-preserving data mining (PPDM) [142], [143], [144], [145]. Some preliminary studies have been done on this issue. Yeh et al. first designed two models, named Hiding High-Utility Itemset First (HHUIF) and Maximum Sensitive Itemsets Conflict First (MSICF), to hide sensitive HUIs in PPUM [146]. The main task of PPUM is to hide the sensitive high-utility itemsets (SHUIs). Lin et al. first developed a genetic-algorithm-based method to hide the user-specified SHUIs by inserting the dummy transactions into the original databases [147]. Yun et al. then developed a tree-based algorithm called the Fast Perturbation algorithm Using a Tree structure and Tables (FPUTT) for hiding SHUIs [148]. Then, other faster and more efficient algorithms were developed for PPUM, such as [149], [150].

5 OPEN CHALLENGES AND OPPORTUNITIES

5.1 Open-Source Software

Although the problem of UPM has been studied for more than 15 years, and the advanced topic of utility pattern mining also has been extended to many research fields, few implementations or source code of these algorithms have been released. This raises some barriers to other researchers in that they need to re-implement algorithms to use them or compare their performance with that of novel proposed algorithms. To make matters worse, this may introduce unfairness in running experimental comparisons, since the performance of pattern mining algorithms may commonly depend on the compiler and machine architecture used. We now list some open-source software/tools specialized for UPM.

- **UP-Miner.** Tseng et al. proposed a first-of-its-kind utility mining toolbox named Utility Pattern Miner (UP-Miner) [151]. UP-Miner provides various models for utility-oriented pattern mining. The main merits of UP-Miner have three aspects. First, to the best of our knowledge, it is the first-of-its-kind cross-platform utility mining system. Second, it provides complete Java implementations of 13 algorithms for discovering different types of utility-oriented patterns, such as high-utility itemset (HUI), high-utility sequential rule (HUSR), high-utility sequential pattern (HUSP), and high-utility episode (HUE), as well as the concise representations of utility patterns. In addition, it offers four functionalities for processing utility-based databases. Third, the toolbox and relevant materials, including source codes, demo paper, benchmark datasets, and data generators, have been made public on Web² for the benefit of the research community.

- **SPMF.** SPMF [152] is a well-known open-source data-mining library, which offers implementations of many algorithms and has been cited in more than 600 research papers since 2010. SPMF is written in Java, and provides implementations of 150 data-mining algorithms, specializing in pattern mining. SPMF has the largest collection of implementations of various algorithms for pattern mining algorithms (i.e., FPM, ARM, SPM, etc.) and provides a user-friendly graphical interface³. In particular, it also provides the relevant materials, including source codes, documentation, user instruction, benchmark datasets, data generators, and academic papers. SPMF offers up to 30 algorithms for high-utility pattern mining, such as Two-Phase, UP-Growth, UP-Growth+, HUI-Miner, d2HUP, EFIM, USpan, and many other state-of-the-art algorithms. More specifically, SPMF is distributed under the GPL v3 license and is very suitable for both academic and industrial purposes.

5.2 Open Challenges and Opportunities for HUPM

Here, we discuss important open problems that have the potential to become future research areas in utility-oriented pattern mining. Owing to the rapid growth of the volume of data stored in databases, we have entered the era of Big Data. While analyzing utility-oriented patterns, we have identified numerous technical challenges and opportunities for UPM. We next highlight some important research opportunities, which are common to many, and sometimes all, UPM algorithms.

- **Application-driven algorithms.** Up to now, most of the algorithms for HUPM have been developed to improve the efficiency of mining processes. The effectiveness of the algorithms for HUPM is also very important, because it is related to the usefulness on various data, constraints, and applications. In general, the application-driven algorithms with many particular features of utility patterns reflect real-life problems of different applications in various fields. How to propose a specialized UPM model for different applications and experimentally show its effectiveness is necessary and challenging. Moreover, the incorporation of domain knowledge [153] has a higher influence on performance.

1. http://bigdatalab.cs.nctu.edu.tw/software.php
2. http://bigdatalab.cs.nctu.edu.tw/software.php
3. http://www.philippe-fournier-viger.com/spmf/index.php
for some data-mining methods. Utility mining guided by domain knowledge thus provides many opportunities.

- Developing more efficient algorithms. Traditionally, most pattern mining algorithms, especially high-utility pattern mining algorithms, are computationally expensive in terms of execution time and memory cost. This may be a serious problem for dense databases or databases containing numerous items or long transactions, depending on the minimum high-utility threshold chosen by the user. Although current UPM algorithms are much efficient than previous algorithms, there is still room for improvement. For example, more compact data structure (i.e., tree, list, graph, other data structure, etc.), more powerful pruning strategies, and more interactive and adaptive utility mining methods comprise the interesting issues.

- Unified framework for HUPM. Many variations of utility mining have been proposed to deal with various types of data and to solve different problems. The current paradigm used to solve utility-oriented pattern mining problems is to first define the definition of utility-based patterns with interest and their properties, and then develop an algorithm that can exploit the properties of the utility (e.g., upper bound) to efficiently mine them. Hence, this laborious process can be avoided if the following problem is solved: “Is there a paradigm such that existing and new definitions of a utility-based pattern can be solved by a unifying algorithm?” Owing to these challenges, the utility-oriented pattern mining problem, in its most general form, is not easy to solve. In fact, most of the existing utility mining techniques solve a specific formulation of a specific problem. Therefore, how to formalize utility mining tasks in a generic framework is crucial and challenging. Focus on general principles and modeling of UPM rather than specific implementations is more important and challenging.

- Deal with complex data. The amount of complex data has been exploding during the past two decades, while most of the data-mining and analysis approaches are not utility oriented. Many current techniques of UPM are not suited to dealing with various types of complex data, such as “structured data” 4 (i.e., pattern mining), “unstructured data” 5 (including documents, health records, audio, video, images, etc.), and “semi-structured data” 6 (i.e., XML, JSON), and most of these are the heterogeneous data. More specifically, there are commonly seen dynamic data, high-dimensional datasets of moderate size, or very large datasets of moderate complexity in real-life applications. Bridging this gap requires the solution of fundamentally new research problems, which can be grouped into the following broad challenges: 1) How to define the utility function integrating with various rich features on complex data; 2) how to achieve utility maximization for the goal and mining task; and 3) how to develop new frameworks and algorithms to deal with new types of data. A need therefore arises for a better framework that extends the existing data-mining methodologies, techniques, tools, and applications, guided by utility and knowledge.

- Large-scale data. Efficiently mining large-scale databases may result in a high computational cost and memory consumption. Under the batch model, traditional UPM algorithms must be repeatedly applied to obtain updated results when new data are inserted. However, in the Big Data era, incrementally or dynamically processing data and taking into count the results of prior analysis is crucial. There are some challenging research opportunities of UPM for handling large-scale data: how to design a parallelized UPM algorithm and how to develop a UPM algorithm based on the existing technologies of Big Data (i.e., MapReduce [125] and Spark [154]). Some other promising areas of research are the design of distributed, parallel, multi-core, or graphical-processing-unit-based algorithms [46], [155] for UPM. There are some open challenges and opportunities to improve the scalability of utility mining tasks from resource-constraint devices to collaborative and hybrid execution models.

- Scalable real-time pattern mining. One of the most important future challenges is to develop scalable high-utility-pattern online mining approaches for streaming data from electronic commerce. Specifically, research should focus on algorithms that are sub-linear to the input or, at the very least, linear. Other computational challenges, such as the demands of the results being returned in real- or near-real-time, are the open issues in the data-mining community. Pattern sets, i.e., real time mining with optimization, requires a new formalism and solving techniques. As mentioned before, increasing quantity and complexity of data demands scalable solutions. Using the existing computational infrastructures for real-time utility-oriented mining massive datasets may be a feasible way.

6 Conclusions

The term utility is commonly used to mean “the quality of being useful,” and utilities are widely used in data-mining and decision-making processes to extract different useful kinds of knowledge. Utilities are subjective and can be acquired from domain experts/users. Utility-oriented pattern mining (UPM) in data is a vital task, with numerous high-impact applications, including cross-marketing, e-commerce, finance, medical, and biomedical applications. Up to now, many techniques and approaches have been extensively proposed for the task of UPM. In this survey, we have provided a comprehensive review of utility-oriented pattern mining, both in terms of current status and future directions. This survey describes various problems associated with mining utility-based patterns and methods for addressing these problems, including 1) high-utility itemset mining (HUIM), 2) high-utility association-rule mining (HUARM), 3) high-utility sequential-pattern mining (HUSPM), 4) high-utility sequential-rule mining (HUSRM), and 5) high-utility episode mining (HUEM). Overall, we have not only reviewed the most common, as well as the state-of-the-art, approaches for UPM but have also provided a comprehensive review of advanced UPM topics. Finally, we have identified several important issues and research opportunities for UPM.

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