Contrast Pattern Mining: A Survey

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ABSTRACT

Contrast pattern mining (CPM) is an important and popular subfield of data mining. Traditional sequential patterns cannot describe the contrast information between different classes of data, while contrast patterns involving the concept of contrast can describe the significant differences between datasets under different contrast conditions. Based on the number of papers published in this field, we find that researchers' interest in CPM is still active. Since CPM has many research questions and research methods, it is difficult for new researchers in the field to understand the general situation of the field in a short period of time. Therefore, the purpose of this article is to provide an up-to-date comprehensive and structured overview of the research direction of contrast pattern mining. First, we present an in-depth understanding of CPM, including basic concepts, types, mining strategies, and metrics for assessing discriminative ability. Then we classify CPM methods according to their characteristics into boundary-based algorithms, tree-based algorithms, evolutionary fuzzy system-based algorithms, decision tree-based algorithms, and other algorithms. In addition, we list the classical algorithms of these methods and discuss their advantages and disadvantages. Advanced topics in CPM are presented. Finally, we conclude our survey with a discussion of the challenges and opportunities in this field.

1. Introduction

With the rapid development of technologies such as the Internet of Things and artificial intelligence, the volume of data has explosive growth, with data types ranging from single structured data to diverse unstructured data and semi-structured data. According to a Cisco report, people, machines, and things will generate about 850 zettabytes (ZB) of data by 2021 [1]. The amount of information generated but not stored is two orders of magnitude higher than the amount of information that ends up being stored, and there is also the possibility of data graves (data being stored but never analyzed). This means that while the raw data is rich, valuable knowledge or information is scarce. In order to discover the valuable knowledge and information behind the data, data mining and data analysis technology have rapidly developed and a mature theoretical knowledge and technical system has been formed [2, 3]. Data mining, also known as knowledge discovery, combines concepts and techniques from different fields and focuses on extracting knowledge or information from large amounts of application data [4, 5]. Data analysis can be divided into two categories: prediction task and description task [6]. Predictive tasks, which aim to predict interesting information and trends, are studied by the machine learning community. While descriptive tasks, which aim at finding understandable patterns, are the research tasks of the data mining community [7, 8]. Contrast pattern mining (CPM) [9] discussed in this article is a typical descriptive task. Contrast patterns describe significant differences between datasets with different contrast conditions.

CPM aims to find interesting contrast patterns in the data. This data can be classified into three categories: structured data, unstructured data, and semi-structured data. Structured data includes sequence data, graph data, web data, etc. Semi-structured data includes XML, JSON, etc. Unstructured data includes text data, music data, image data, etc. Since structured data management is basically in the form of a database and structured data is easy to process and statistically analyze. The type of data analyzed in this article is structured data. The core idea of CPM analysis data is contrast. Contrast is one of the most important means of analysis. The contrast analysis approach has the advantage of evaluating different options, helping to understand the problem, avoid potential risks, and choose the best solution. The advantage of using contrast to analyze problems is that the best solution can be found. In addition, contrast can

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be used to find connections between datasets and to help understand and solve problems. Comparisons involving two or more datasets are referred to as comparisons under statically defined conditions. Such datasets can be different subsets of a particular dataset or from different categories or time periods. On the contrary, comparisons where only one dataset is required for the comparison are referred to as comparisons under dynamically defined conditions. Contrast patterns describe the similarities and differences between datasets. CPM allows users to obtain interesting trends over different time, space, and classification or other contrast conditions. Building interpretable and accurate classifiers is also a classical application of CPM. CPM has become an important subfield of data mining that is effective in solving real-world problems, and researchers have used CPM to solve many practical problems with a wide range of CPM applications [9]. For example, in the field of network traffic analysis, CPM can detect anomalous activities and identify changes in the system [10].

![Figure 1: Statistics of papers retrieved on DBLP for contrast pattern mining.](image-url)

We used the DBLP website to count the number of papers published in the field of CPM for each year. The starting year of the search is 2001. The search phrase is "contrast|emerging|discriminative pattern". Figure 1 shows the results of the statistics. According to Figure 1, it is clear that the research interest in CPM remains active. Since CPM has many research questions and research methods. It is difficult for new researchers in the field to understand the general situation of the field in a short period of time. This article aims to help new researchers to have a general understanding of the basics of this research direction, current methods, advanced topics, and research opportunities. Therefore, the purpose of this article is to provide a detailed review and summary of the current state of CPM, attempting to provide an in-depth overview of the latest technologies, advanced topics, and challenges in this field.

- We provide an up-to-date comprehensive description of CPM in detail, including types of contrast pattern, mining strategies, methods of assessment of discriminative power, and applications.
- We summarize the methods of CPM, including border-based, tree-based, evolutionary fuzzy systems-based, decision tree-based, and other algorithms. Use tables to help readers understand its development.
- We review advanced topics in CPM in recent years, including class imbalance problems, fuzzy comparison models, CPM in big data environments, and data visualization.
- Finally, there are still many interesting research questions in this research area, so we discuss several important issues and research opportunities in CPM.

The rest of this article is organized as follows. The following section introduces some basic concepts. In Section 3, the classification of CPM algorithms is introduced. In Section 4, we discuss the advanced topics of CPM. In Section 5, we describe the future directions and challenges of CPM. Finally, our conclusions are given in Section 6.

2. Basic Concept: Contrast Pattern Mining

2.1. Preliminary and Types of Contrast Patterns

Table 1 describes some of the basic concepts. Because of the diversity of contrast patterns. We made a family tree of contrast patterns to introduce the common types of contrast patterns, as shown in Figure 2. The purpose of this
section is to introduce the patterns mentioned in Figure 2.

![Contrast Pattern Family Tree](image)

**Figure 2:** Contrast pattern family tree

**Definition 1 (Contrast Sequential Patterns, CSP [11, 12, 13]).** CSP is defined as a pattern that occurs frequently in one sequence dataset but not in the others. Before judging the pattern as CSP, we need to understand the concept of growth rate in advance. Given two sequence datasets: $D_1$ belongs to class $c_1$ and $D_2$ belongs to class $c_2$. The growth rate from $D_2$ to $D_1$ of a sequential pattern $X$ is denoted as:

$$GR_{c_1}(X) = \begin{cases} \infty, & \text{if } sup(X, c_1) = 0 \text{ or } sup(X, c_2) \neq 0 \\ \frac{sup(X, c_2)/|D_2|}{sup(X, c_1)/|D_1|}, & \text{otherwise} \end{cases}$$

(1)

Similarly, the growth rate from $D_1$ to $D_2$ of a sequential pattern $X$ is denoted as:

$$GR_{c_2}(X) = \begin{cases} \infty, & \text{if } sup(X, c_2) = 0 \text{ or } sup(X, c_1) \neq 0 \\ \frac{sup(X, c_1)/|D_1|}{sup(X, c_2)/|D_2|}, & \text{otherwise} \end{cases}$$

(2)

The contrast rate of $X$ is denoted as:

$$CR(X) = \begin{cases} \infty, & \text{if } GR_{c_1}(X) = 0 \text{ or } GR_{c_2}(X) = 0 \\ \max\{GR_{c_1}(X), GR_{c_2}(X)\}, & \text{otherwise} \end{cases}$$

(3)

A sequence $s$ in a sequential database is said to be a CSP [13] if its contrast rate is no less than the given CR threshold $mincr$: CSP $\leftarrow \{s \mid cr(s) \geq mincr\}$. Unlike frequent sequential pattern mining [12], contrast sequential pattern mining (CSPM) [11] can discover the characteristics of different classes in sequence datasets, which has been widely used in sequential data analysis, such as protein/DNA dataset analysis, anomaly detection, and customer behavior analysis.

**Definition 2 (Contrast Subgraph [14, 15, 16, 17, 18]).** Suppose there are two graph datasets $G_a = \{G_{a1}, G_{a2}, \ldots, G_{ax}\}$ and $G_b = \{G_{b1}, G_{b2}, \ldots, G_{by}\}$. Subgraph $C$ is considered as a contrast subgraph if it satisfies the following two conditions: (1) $C$ is not subgraph isomorphic to subgraphs of any element in $G_a$. (2) One or more elements of $G_b$ are subgraph isomorphic to $C$ [9]. In addition, Ting et al. [16] proposed the concept of a minimal contrast subgraph to reduce the number of contrast patterns to be mined. When all subgraphs of the contrast subgraph $C$ are not contrast subgraphs, $C$ is the minimum contrast subgraph.

Contrast subgraphs can distinguish between different graph datasets by revealing structural differences between them. Ting et al. [16] proposed a method to find the minimal contrast subgraph, which is a graph pattern that appears in one graph but not in the other graph, and all of its proper subgraphs are either shared by or not contained in the two graphs. Wang et al. [17] and Gionis et al. [14] studied how to find the anomalous subgraphs that contrast others in one graph. Yang et al. [18] adopted subgraph density as the measure for mining contrast subgraphs. Jiao et al. [15] proposed a scalable self-supervised graph representation via subgraph contrast, SUBG-CON.
Calculating the support of subsequences; and removing subsequences by Ji conditions, then the itemset \( p \) fulfills the \( g \)-gap constraint if \( i \) to appear consecutively, which means that gaps can exist between items. Suppose there are two sequences: \( s \), \( t \) are sequences of indices \( \{i_1, i_2, i_3, \ldots, i_m\} \) if \( 1 \leq i_j \leq n \), \( 1 \leq t \leq m \), \( e'^t \), \( s' \) is a subsequence of \( s \). The occurrence \( o_s \) of \( s' \) in \( s \) is a sequence of indices \( \{i_1, i_2, i_3, \ldots, i_m\} \) if \( 1 \leq i \leq n \), \( 1 \leq i < i + 1 \). The gap constraint is denoted by \( g \). The occurrence \( o_s \) fulfills the \( g \)-gap constraint if \( i_{k+1} - i_k \leq g + 1 \) for each \( 1 \leq k \leq m - 1 \). Subsequence \( s' \) satisfies the \( g \)-gap constraint when at least one occurrence of \( s' \) satisfies the \( g \)-gap constraint.

Suppose there are two sequences \( s_1 \) which belongs to class \( c_1 \) and \( s_2 \) which belongs to class \( c_2 \). Then \( \text{sup}(p, g, s) \) and \( \text{sup}(p, g, s) \) denote the supports of itemset \( p \) in \( s_1 \) and \( s_2 \), respectively, where \( g \) is a maximum gap. If an itemset \( X \) satisfies the following conditions: \( \text{sup}(p, g, s) \geq \delta \) and \( \text{sup}(p, g, s) \leq \alpha \). If no subsequence of \( p \) satisfies both conditions, then the itemset \( X \) is said to be MCP with \( g \)-gap constraint. MDS is a type of contrast pattern proposed by Ji et al. [23]. The algorithm for mining MDS can be divided into three steps: generating candidate subsequences; calculating the support of subsequences; and removing subsequences [22].
Definition 6 (Emerging Patterns, EPs). EP is a subset of CP. Table 2 summarizes the common types of emerging patterns. Figure 3 [24, 25] illustrates the relationships between these patterns. Emerging patterns were proposed by Dong et al. in 1999 [26] and are defined as itemsets with significantly increased support from one dataset to another. Trends that appear in the timestamp database can be captured by EPs. EPs can also find useful contrasts between data classes.

### Types of emerging patterns

| Abbreviation | Name                              | Description                                                                                                                                 |
|--------------|-----------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------|
| EP           | Emerging pattern                  | A pattern \( p \) is an emerging pattern if its support ratio in dataset \( D^+ \) and \( D^- \) is not less than a given threshold value \( \rho \), which can be expressed as \( EP = \{ p | GR(p) = \frac{\sup(p, D^+)}{\sup(p, D^-)} \geq \rho \} \) [26]. |
| FEP          | Fuzzy emerging pattern            | FEP alleviates the disadvantage that general EP depends on clear numerical characteristic boundaries. FEPs are patterns generated by fuzzy selectors [Attribute \( \in \) FuzzySet] [27]. |
| JEP          | Jumping emerging pattern          | Suppose a pattern \( p \) satisfies the following conditions: \( sup(p, D^+) = 0 \), \( GR(p) = \frac{\sup(p, D^+)}{\sup(p, D^-)} = \infty \), then \( p \) is said to be the JEP [28]. In short, JEPs are EPs that contain only the items in dataset \( D^+ \). |
| Minimal EP   | Minimal emerging pattern          | An emerging pattern \( p \) is a minimal EP if none of its sub-patterns is an EP [6].                                                                 |
| Maximal EP   | Maximal emerging pattern          | If none of the sup-patterns of the emerging pattern \( p \) is an EP, then \( p \) is a maximal EP [29].                                           |
| SJEP         | Strong jumping emerging pattern   | SJEP is also called Essential jumping emerging pattern (EJEP) in [30]. For a JEP \( p \), if there is no sup-pattern of \( p \) that is a JEP, then \( p \) is a SJEP [31]. |
| NEP          | Noise-tolerant emerging pattern   | NEP is also called constrained emerging pattern (CEP). Suppose there are two threshold \( \lambda_1 \) and \( \lambda_2 \). An emerging pattern \( p \) satisfies the following conditions: \( \lambda_2 \geq \lambda_1 \), \( sup(p, D^+) \leq \lambda_1 \) and \( sup(p, D^-) \geq \lambda_2 \), then \( p \) is said to be a NEP [31]. |
| Chi-EP       | Chi emerging pattern              | Chi-EP is similar in concept to NEP, with the difference that Chi-EP use a \( \chi^2 \) test to measure differences in distributional significance [32]. |
| BEP          | Balanced emerging pattern         | Suppose a pattern \( p \) satisfies the following conditions: \( a^{k \cdot supp(D^+)} \geq \delta \) and \( sup(p, D^+) > \theta \), where \( a \) is the correlative correction parameter, \( \delta \) is the actual degree of growth of \( p \), \( k \) is the balance factor, \( \delta \) is the minimum support threshold, \( \theta \) is the minimum contrast coefficient, then \( p \) is said to be the BEP [33]. |
| JEPN         | Jumping emerging patterns with negation | A negated item indicates that the item is not included in the transaction. A negated value indicates that the value does not exist in the example. JEPNs allow JEPs to contain negated items [34]. JEPNs can be defined as: \( JEPNs = \{ p | GR(p) = \frac{\sup(p, D^+)}{\sup(p, D^-)} = \infty \} \), where \( p = \{ x_1, x_2, ..., x_n \ | \supp(p) \in P \} \), \( P = \{ x \subseteq I \cup \overline{I} \forall i \in x \rightarrow i \notin x \} \), \( I \) is the collection of existing selectors, \( \overline{I} \) is the collection of selectors with negated values, \( \mathcal{I} \) is an item space [24, 34]. |

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Figure 3: Relationships between different types of emerging patterns.

Most contrast pattern mining algorithms based on user-specified thresholds can be divided into two steps: first generating candidate patterns and then checking whether the contrast of the candidate patterns is greater than the threshold. The ConSGapMiner algorithm uses two support thresholds to discover the contrast patterns, meaning that all subsequences that satisfy the threshold and minimization conditions are put into the contrast pattern result set [23]. Most threshold-based contrast pattern mining algorithms set thresholds based on the contrast rate and support of the pattern. Different algorithms calculate the contrast rate in different ways. For example, the eCSP algorithm calculates the contrast rate of a pattern using the growth rate, and then uses the minimum contrast \( \min_{cr} \) and minimum support \( \min_{sup} \) thresholds to discover useful patterns [13].

Top-\( k \)-based contrast pattern mining algorithms have the advantage over the first type of algorithm. It can avoid the need for the user to set inappropriate thresholds, and the user only needs to set the number of patterns that they want to discover. The method is widely used in the fields of sequence patterns, association rules, sequence rules, and so on. In 2007, Osmar et al. proposed the definition of top-\( n \) emerging sequence and the TopES algorithm, which mines the contrast patterns that occur most frequently in two datasets [35]. Although the patterns mined by TopES are only the significant sequences in the datasets and not the difference patterns, TopES is still important as an early top-\( k \)-mining algorithm. The kDSP-Miner algorithm, which was proposed in 2015, uses the top-\( k \)-method instead of support thresholds to discover contrasting sequence patterns [36]. The paper used top-\( k \) to discover the \( k \) most contrasting sequence patterns and build a classifier to achieve an effective method for diagnostic gene discovery [37].

Previous studies have not considered the problem of mining distinguished sequential patterns in event sequences. Based on this problem, Duan et al. proposed the concept of distinguishing temporal event patterns (DTEP), and introduced an algorithm to discover the top-\( k \) contrasting significant DTEPs [38]. The previously mentioned algorithm does not consider the gap constraint well. Adaptively adjusting the gap constraint is one of the advantages of the SCP-Miner algorithm [12]. SCP-Miner can find top-\( k \) adaptive contrast patterns from positive and negative sequences. Top-\( k \)-mining strategy can also be applied to itemsets. For example, the paper addresses the proposed problem of how to use sampling methods to discover itemsets for discriminative sequences that are independent of the selected quality measure, and introduces two algorithms, called SeqScout and MCTSExtent, to extract the top-\( k \) best non-redundant discriminative patterns and discover relevant subgroups in itemset-based sequences [39].

Discussion: The first type of algorithm is suitable for users who want to filter out all contrast patterns that satisfy the conditions, and the second type of algorithm is suitable for users who want a given number of contrast patterns with high statistical significance. Most of the current mining algorithms based on top-\( k \) sorting strategies are focused on sequential contrast patterns, while other types of contrast patterns are less studied, such as episodes, subgraphs, events, and streams. In addition, most mining algorithms do not consider constraints, such as density constraints, length constraints, minimization pattern constraints, etc. Constraints can reduce the number of found patterns and lead
Table 3
A table of the number of pattern $p$

|       | $D^+$ | $D^-$ | Sum |
|-------|-------|-------|------|
| $p$   | $n_{11}$ | $n_{12}$ | $n_1$ |
| $\bar{p}$ | $n_{21}$ | $n_{22}$ | $n_2$ |
| Sum   | $|D^+|$ | $|D^-|$ | $|D|$ |

to more interesting patterns.

2.3. Statistical Measures of Discriminative Ability Assessment

When using contrast patterns, an important task is to assess their discriminative ability [40]. Discriminative ability can be used as a way to assess the feature recognition ability of contrast patterns, or as a way to determine whether a pattern is a contrasting pattern. In this section, we summarize a series of common evaluation metrics used to assess the discriminative ability of individual patterns or groups of patterns. The common methods used to assess the discriminative ability of contrast patterns in two datasets can be generalized to multiple datasets. To facilitate the illustration of comparative assessment metrics, this section only describes how to apply the assessment metrics in the two datasets [41].

First, we describe some terms that will be used to explain the comparative assessment indicators. Suppose there is a database $D$ with a set of $n$ transactions, $D = \{(x_i, y_i)\}_{i=1}^{n}$, where $(x_i, y_i)$ is a transaction, $I = \{i_1, i_2, ..., i_I\}$, $x_i \subseteq I$ is an itemset, and $y_i \in \{+, -\}$ is the class label for $x_i$. We denote the dataset with all instances of class label $+$ as $D^+$ and the dataset with all instances of class label $-$ as $D^−$, where $D^+ \cup D^- = D$. A pattern $p = \{i_1, i_2, ..., i_k\} \subseteq I$. Table 3 [41] shows the number of pattern $p$ in databases $D^+$ and $D^-$, where $n_{11}$ denotes the number of patterns $p$ in $D^+$ and $|D|$ denotes the number of transactions for $D$. The support of $p$ in $D$, $D^+$, $D^-$ respectively is denoted as:

\[
sup(p, D) = \frac{n_1}{|D|}, \quad sup(p, D^+) = \frac{n_{11}}{|D^+|}, \quad sup(p, D^-) = \frac{n_{12}}{|D^-|}.
\] (4)

Table 4 [24, 42, 41, 43] shows the popular comparative assessment indicators. These evaluation indicators are important for eliminating unimportant patterns and obtaining accurate knowledge. In contrast pattern mining, how to choose assessment metrics is a question worth thinking about. It is not reasonable to talk about the merits of these metrics in isolation from the problem itself, so before selecting evaluation indicators, researchers need not only clarity about the problem needs but also likely insight into the domain knowledge. The evaluation metrics in Table 4 are described as follows:

- **Growth Rate (GR)**. GR is based on the calculation of support, which calculates the ratio of support between two different classes. Dong et al. [26] first use GR as a metric to evaluate contrast. If GR of pattern $p$ not less than the user-given threshold (gr), then $p$ is considered to be a contrast pattern.

- **Support Different (DiffSup)**. DiffSup is support difference between positive class and negative [44].

- **Unusualness (WRAcc)**. WRAcc is also known as Weighted Relative Accuracy. WRAcc measures the balance between pattern generality and confidence. a high value of WRAcc indicates a high balance between generality and confidence [24].

- **Generalization quotient ($q_g$)**. WRAcc and $q_g$ are two popular methods to evaluate the comparative ability of subgroups. The $g$ in the formula for $q_g$ is a user-defined parameter [41, 45].

- **OddsRatio**. OddsRatio is a biometric measure that are typically used to assess simple risk factors. Linking OddsRatio to pattern mining algorithms was first proposed by Li et al. [46], making it possible to discover compound risk factors in large-scale datasets. However, OR alone cannot infer whether the probability of occurrence or relative probability of occurrence of pattern $p$ in two categories is high or low [46].

- **Gain**. Gain can be used to assess the discriminatory ability of a pattern and to measure information about pos classes and other classes including that pattern [41].
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Table 4
Summary of discriminative ability assessment approaches

| Name                  | Measures                                                                 |
|-----------------------|---------------------------------------------------------------------------|
| Growth Rate           | $\text{GR}(p, D^+, D^-) = \sup(p, D^+) / \sup(p, D^-)$                   |
| Support Different     | $\text{DiffSup}(p, D^+, D^-) = [\sup(p, D^+) - \sup(p, D^-)]$           |
| Unusualness           | $\text{WRAcc}(p, D^+, D^-) = |D| \left( \frac{n_{11}}{n_i} - \frac{|D^+|}{|D|} \right)$               |
| Generalization Quotient | $q_s(p, D^+, D^-) = \frac{n_{11}}{n_{12} + g}$                           |
| OddsRatio             | $\text{OddsRatio}(p, D^+, D^-) = \frac{\sup(p, D^+)/\sup(p, D^-)}{1 - \sup(p, D^-)} / \sup(p, D^+)$ |
| Gain                  | $\text{Gain}(p, D^+, D^-) = \sup(p, D^+) \times \log \frac{\sup(p, D^+)}{\sup(p, D^-) \cup |D^+|} - \log |D^-| \cup |D^+|)$ |
| SupMaxK               | $\text{SupMaxK}(p, D^+, D^-) = \sup(p, D^+) \times \max_{\subseteq p, D^-}$ |
| MutualInformation     | $\text{MI}(p, D^+, D^-) = \sum_{i=1}^{n_{12}} \sum_{j=1}^{n_{22}} \frac{n_{ij}}{|D|} \log \frac{n_{ij}}{|D|}$ |
| Chi-squared           | $\chi^2 = \sum_{i=1}^{n_{12}} \sum_{j=1}^{n_{22}} \frac{(n_{ij} - E_{ij})^2}{E_{ij}}$ |
| p - value             | $p - value = \sum_{i=1}^{\min(n_{12}, n_{21})} \frac{t_1, t_2, |D^+|, |D^-|!}{|D|!(n_{11} + i)!(n_{12} - i)!(n_{21} - i)!(n_{22} + i)!}$ |
| True Positive Rate    | $\text{TPR} = \frac{n_{11}}{n_{12}}$                                 |
| False Positive Rate   | $\text{FPR} = \frac{n_{21}}{n_{22}}$                                  |
| Strength              | $\text{Strength}(p) = \frac{\sup(p, D^+)^2}{\sup(p, D^+) + \sup(p, D^-)}$ |

- SupMaxK. SupMaxK can not only find very low-frequency contrast patterns from high density and high dimensional datasets but also be used to prune the search space [41]. In addition, according to the calculation formula of SupMaxK and DiffSup, the lower bound of DiffSup is SupMaxK.

- Mutual information (MI). MI is based on information theory [47]. MI can be used to evaluate the correlation between pattern distribution and expected pattern frequency of each type [48].

- Chi-squared ($\chi^2$). The chi-square test is used to test the independence of the variables in the column table [49]. $E_{ij}$ is the expected frequency count of cell ij in cell ij given independence of the row and column variables in the table [50, 41].

- p-value. The p-value can be used to measure the inconsistency between the original hypothesis and the sample. A smaller p-value means a stronger inconsistency. If the p-value is less than a predetermined threshold (significance level), the original hypothesis is considered to be rejected [51, 52].

- True positive rate (TPR). TPR shows the percentage of pattern p in the positive dataset. It unites the precision and generality of the class [53, 24].

- False positive rate (FPR). FPR describes the proportion of pattern $\overline{p}$ in the neg dataset. FPR can be used to measure generality and precision. Normally, we minimize the FPR value of pattern [53, 24].

- Strength. Strength is expressed by calculating the support of pattern p in each of the two classes or by calculating $\text{GR}(p)$ and $\sup(p, D^+)$ [54]. The strength satisfies the following formula: $\text{Strength}(p) = \frac{\sup(p, D^+)^2}{\sup(p, D^+) + \sup(p, D^-)}$

$$\text{Strength}(p) = \frac{\text{GR}(p, D^+, D^-)}{\text{GR}(p, D^+, D^-) + 1} \times \sup(p, D^+) [54].$$

From the formula, we can see that $\text{Strength}(p) = \sup(p, D^+)$ when $\text{GR}(p, D^+, D^-) = \infty$. 

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2.4. Applications of CPM

A major research theme in CPM in recent years has been the application of CPM to real-life situations. Many relevant papers have been presented to solve real-world problems. Interesting knowledge can be gained by applying CPM algorithms to real-world datasets. The CPM algorithm has been applied to solve problems in several areas, as follows:

- **Medical domains.** CPM is widely used in the medical field. Ríos-Méndez *et al.* [55] applied the EPM algorithm to a dataset of medical opinions about the decreasing number of autopsies in hospitals, with the aim of discovering medical experience in terms of doctors’ choice or refusal of autopsies. In addition, EPM can be used to predict myocardial ischemia, diagnose coronary artery disease [56] and discover toxicological knowledge [57, 58, 59].

- **Education domain.** Researchers are increasingly employing data mining techniques to solve difficulties in the field of education. CPM is one of the data mining techniques that can be used to investigate the differences and similarities in learning patterns of different groups of students [60] and to explore the relationships between learning attitudes [61]. In addition, contrast mining can be used in conjunction with association rule mining in education, for example, to obtain a contrast-based rule mining model [62].

- **Other applications.** CPM is also used in other fields. In the security domain, CPM can be used to build one-class of anomaly detection [63] and malware detection [64]. CPM can also be applied to bioinformatics to predict gene expression patterns [65]. In the field of cheminformatics, EP is used as an emerging chemical pattern (ECP), such as using ECP to predict the activity of compounds [66]. CPM can also be utilized to solve actual photovoltaic-related issues [67]. As a final example, CPM is applied to commodity applications, such as using EP to identify product sales trends [68] for smart retail.

3. Methods of Contrast Pattern Mining

During the past decades, a significant number of contrast pattern mining algorithms have been proposed. According to the mining principles and available data structures, we classify these algorithms into the following categories: 1) border-based algorithms; 2) tree-based algorithms; 3) evolutionary fuzzy system-based algorithms; 4) decision tree-based algorithms; and 5) others.

3.1. Border-based Algorithms

Dong *et al.* [26] proposed emerging patterns (EPs) for the first time and used border-based method to discover emerging patterns. Itemsets with significant increases in support from one dataset to another are emerging patterns. Borders are used to describe large collections of itemsets or other types of collections. The concept of border and the typical algorithms are described below:

**Definition 7 (Border [26, 69, 6]).** \( \mathcal{L} \) is a set of minimal emerging patterns. \( \mathcal{R} \) is a set of maximal emerging patterns. An ordered pair \( \langle \mathcal{L}, \mathcal{R} \rangle \) is a border, when the following conditions are satisfied:

- Each element of \( \mathcal{L} \) and \( \mathcal{R} \) is an anti-chain collection of sets. An anti-chain is a collection whose elements are subsets, and no element contains another, that is, for an anti-chain \( S, \forall M, N \in S: M \nsubseteq N, N \nsubseteq M \).

- Each element of \( \mathcal{L} \) is a subset of some element in \( \mathcal{R} \) and each element of \( \mathcal{R} \) is a superset of some element in \( \mathcal{L} \), which defined as \( \forall M \in \mathcal{L}, \exists N \in \mathcal{R} \) such that \( M \subseteq N, \forall N \in \mathcal{R}, \exists M \in \mathcal{L} \) such that \( N \supseteq M \).

- MBD-LLBORDER [26]. This algorithm can efficiently discover all EPs that satisfy the constraint, where borders are defined as the interval-closed collections represented by the borders’ element. Large borders are discovered using Max Miner or HORIZON Miner, and the discovered borders are used as input to the MBD-LLBORDER algorithm which uses the borders to find the EPs that can be used to build the classifier. Besides, this algorithm introduces a multiborder-differential method to eliminate the need to check too many candidates.

- JEPProducer [70]. The concept of JEP space consists of all JEPs about a given positive and negative dataset. An algorithm is proposed and the property of JEP space satisfies convexity. That is, the JEP space is bounded and can be
expressed concisely by boundary elements. This algorithm can be used to maintain the JEP space incrementally when extensive changes are made to previously processed data.

- DeEPs [69]. It is a lazy classifier, based on instances, where an instance is defined as a set of attribute-value pairs. The method uses bounds to concisely represent the EPs, which has the advantage of avoiding the need to enumerate the entire set of instance subsets during the discovery process and all patterns during the enumeration output. The found boundary EPs have many uses, such as: providing differentiation knowledge for our understanding of the instance $T$, utilizing the frequency of the boundary EPs to predict the class label of the test instance, and classifying $T$ if it is a test instance.

3.2. Tree-based Algorithms

Algorithms based on tree structure usually scan the dataset only once, and the data information is stored in the tree. Trees that mine contrast patterns usually have nodes that need to store information from both datasets. Patterns are formed by the path from the root to the node. The mining results are obtained based on the tree traversal. Mining of contrast patterns using tree structure has the following advantages: (1) Advantage in data storage. Since the tree can compress the representation of the dataset by sharing common prefixes [67], it takes less time to scan the database and allows more data to be stored in the main memory. (2) Advantages in mining patterns and high mining efficiency. The items can be sorted according to certain values (e.g., growth rate) when building the tree. This makes the items with high comparative power closer to the root and allows them to be mined faster [24]. In addition, such algorithms can employ pruning strategies to discard uninteresting patterns.

Algorithms based on tree structures face the following challenges: (1) Constructing a suitable tree. Table 5 summarizes the common tree structures for mining the comparison patterns. These tree structures have different characteristics. Depending on the problem requirements, choose the appropriate tree structure or construct a new tree structure. (2) Choosing pruning strategies. Algorithms based on tree structures can easily face the problem that the search space is too large, resulting in high computational cost. Based on this problem, many pruning strategies have been proposed, such as: pruning non-minimal patterns [71], generating only promising branches [72], and pruning strategies based on a priori principles [73]. One of the deciding factors for choosing a pruning strategy is the structure of the tree. (3) Redundancy in mining results. Detecting the redundancy of pattern sets is an important problem in contrast pattern mining that has not yet been solved.

3.3. Evolutionary Fuzzy Systems-based Algorithms

The evolutionary fuzzy system-based algorithms is a rule extraction algorithm with better descriptive power than the previous classes of algorithms [86]. It combines the concepts of fuzzy logic systems and natural evolution. The concept of a fuzzy logic system is relative to a traditional logic system. Traditional logic systems have values of either 0 or 1, whereas in fuzzy logic, a value between 0 and 1 can exist. Fuzzy rules are closer to the knowledge representation of human reasoning. Fuzzy logic can improve the quality of mining patterns and the interpretability of results. The principle of natural evolution is that organisms with access to resources tend to have offspring in the future. Evolutionary algorithms allow us to find a good solution in a large search space. A big data approach for extracting fuzzy emerging patterns has a reasonable amount of time [86]. In an evolutionary algorithm, starting from an initial set of randomly generated individuals, the next generation of individuals is derived, following the genetic pattern of living organisms. Individuals are then selected according to their fitness to improve the quality of the next generation population, and after several iterations, the optimal solution is gradually approached. The evolutionary algorithm is essentially a search and find method of optimization.

- EvAEP [67]. It is an evolutionary fuzzy system algorithm for the extraction of emerging patterns, applied to the problem of concentrated photovoltaic technology. EvAEP uses an evolutionary algorithm. It considers the solution as an individual, represented as a connection of pairs of variable values defined in a discrete domain. When the variables are defined in the continuous domain, EvAEP uses a fuzzy logic where the fuzzy set consists of linguistic labels. These labels are defined by uniform triangular forms. The algorithm uses an iterative rule learning model to find high quality solutions. In each iteration of the evolutionary process, the current best solution is passed on to the next generation, which acquires new individuals by applying genetic operators to the previous generation.

- EvAEFP-Spark [87]. This algorithm is an optimization of the EvAEP algorithm. It applies the MapReduce paradigm, allowing the EvAEFP Spark algorithm to quickly discover EPs with highly descriptive features on large datasets. The main idea of EvAEFP Spark is to apply the MapReduce framework to modify the way in which individuals are evaluated during evolution, thus reducing the complexity when evaluating groups or sets of individuals [6].
Map and reduce are the two phases of MapReduce. In the map phase, the dataset is decomposed and each subset is analyzed in a different mapper for all the individuals in the population and an obfuscation matrix is obtained for each population [88]. In the reduce phase, all the obfuscation matrices are accumulated into a generic matrix and the fitness of each individual is calculated.

- MOEA-EFEP [86]. It is a multi-objective evolutionary algorithm for the extraction of fuzzy emerging patterns. MOEA-EFEP has some commonalities with the EvAEP algorithm, for example, the encoding method is “chromosome = rule” [25]. The main difference between them is that EvAEP is a multi-objective evolutionary algorithm. The main difference is that EvAEP is a single-objective based evolutionary algorithm, whereas MOEA-EFEP is multi-objective. The algorithm uses a cooperative-competitive model for elite groups, allowing simultaneous optimization of multiple quality measures, where individuals cooperate by maximising the average unusualness of the group and compete to obtain the optimal solution to the problem following a token competition procedure.

- E2PAMEA [89]. It is a cooperative competition multi-objective evolutionary fuzzy system, which adopts cooperative competition schema and token competition program to improve the reliability of results. The algorithm uses an evaluation process called Bit-LUT to improve the effectiveness of the method. Bit-LUT is a MapReduce method based on precise methods. Bit-LUT is faster and requires less physical memory than previous evaluation methods. E2PAMEA algorithm can be used in big data environment to efficiently extract high-quality EPs. Compared with the EPM evolutionary algorithm of big data proposed in the past, E2PAMEA algorithm has higher applicability and the results of mining are more reliable and universal.

- CE3P-MDS [42]. It is used to extract EPs in massive data streams from various sources through Apache Kafka streaming media platform and Apache Spark streaming media library. This algorithm combines the ideas of fuzzy logic and cell-based multi-objective evolutionary algorithm, and proposes a coverage-ratio-based approach, which is used to reduce the redundancy of patterns and is also used as a reinitialization process. The algorithm uses an informed strategy, which is used to process data, and a reinitialization and filtering mechanism, which is used to reduce redundancy and low reliability patterns. Experiments showed that the algorithm is very fast in data processing, and it takes about 4 seconds to process more than 750,000 instances. In addition, massive, heterogeneous and high-speed data streams can be processed by the algorithm.

### 3.4. Decision Tree-based Algorithms

A decision tree is an algorithm that can be used to solve classification problems. It is also a kind of supervised learning. This process is called supervised learning, which first builds a model from a bunch of samples of known categories, each with a set of attributes and a classification result, and then uses the model to predict the test sample set. A decision tree is a tree structure summarized from training data, in which each internal node represents a judgment on an attribute, each leaf node represents a classification result, and each branch represents the output of a judgment result. The general steps of the contrast pattern mining algorithm based on decision trees can be divided into the following two points: (1) Summarize different decision trees with training datasets and strategies to create diverse decision trees. (2) Extract contrast patterns from each induced decision tree [90]. The time complexity of mining contrast patterns from all induced decision trees is $O(Tm\log_2(n))$, where $T$ represents the number of established induced decision trees, $m$ is the number of features in the training dataset, and $n$ is the number of objects in the training dataset [25].

Table 6 [90, 24, 25] summarizes the decision tree-based algorithms and lists the differences between them. Compared with other types of algorithms, the advantages of the CPM algorithms based on decision trees are as follows:

- It is easy to understand, extract rules, and explain in a decision tree. And decision trees can be visually analyzed.
- High accuracy: The discovered classification rules have high accuracy and are easy to understand. The decision tree can clearly show which fields are more important; that is, understandable rules can be generated.
- Running speed is relatively fast.

The decision tree algorithms also have some disadvantages, such as:

- Over-fitting is prone to occur. A decision tree model tends to produce an overly complex model, which has poor generalization performance for data, which is called over-fitting. To put it simply, the decision tree describes the characteristics of training samples too accurately, which makes it impossible to analyze the new samples reasonably. The over-fitting phenomenon can be reduced by cutting the branches that affect the prediction accuracy.
There are two common pruning strategies: pre-pruning and post-pruning. The pre-pruning strategies mainly restrict the full growth of decision trees by establishing some rules, while the post-pruning strategies prune after the full growth of decision trees.

• Different feature selection criteria will lead to different feature selection tendencies. For example, the information gain criterion has a preference for attributes with a large number of redeemable values (typically represented by the ID3 algorithm), while the gain rate criterion (CART) has a preference for attributes with a few redeemable values.

3.5. Others

We group the algorithms that do not belong to the previous categories into this section, such as the ZBDDs algorithm, which can handle higher dimensional data, and the GEP algorithm, which is based on the principle of natural selection.

• Zero-suppressed binary decision diagrams-based algorithms [91]. The Zero-suppressed binary decision diagram (ZBDD) is an excellent data structure for handling sparse data and high-dimensional datasets. Previous EP classifiers were incapable of handling datasets with more than 60 dimensions, while ZBDDs can solve this problem. ZBDDs use two reduction rules: the merging rule and the zero-suppression rules. The merge rule implies a shared equivalence subtree, and the zero-suppression rule means that nodes with real edges pointing to the rule allow high compression operations on Boolean formulas. The study [91] uses disjunction and conjunction to generalize EP and names these patterns as disjunctive emerging patterns. Two algorithms are presented: mineEP and mineDEP. The mineEP algorithm takes ZBDD as the input parameter and uses a bottom-up approach to find the smallest EP, while the mineDEP algorithm uses a top-down approach to discover the largest disjunction EPs. According to the experimental results, the advantage of ZBDDs over pattern trees is that ZBDDs can handle higher-dimensional datasets and have shorter running times.

• Gene expression programming [92]. Gene expression programming (GEP) selects individuals based on fitness, which is encoded as a fixed-length linear string and subsequently expressed as an expression tree. GEP can find the optimal solution by iterative evolution [93]. The GepDSP algorithm [92] was designed based on the GEP framework. Two types of sequences are used as input variables for GepDSP. The algorithm first generates a random number of individuals (considered as individuals of the first generation) to form the initial population. An evolutionary process is performed on each generation of individuals (including assessing the fitness of each individual, saving the $k$ individuals with the highest contrast score, selecting individuals, modifying the selected individuals, and then replicating them) until some conditions are met. The experiments validated the effectiveness and efficiency of the GepDSP algorithm on mining kDSPs with flexible gap constraints.
Table 5
Tree-based algorithms for contrast pattern mining

| Structure     | Description                                                                 | Characteristics                                                                                   | Ref.   |
|---------------|----------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------|--------|
| P-tree        | P-tree is an ordered extended prefix tree structure, where order refers to   | Pruning strategies such as Chi-square test, data class superposition, generating only promising   | [30, 74, 72, 21] |
|               | the supports-ratio of items in descending order [30]. Closer to the root are   | branches and anti-monotonicity conditions can be used.                                           |        |
|               | items with higher supports-ratio.                                            |                                                                                                  |        |
| CP-tree       | CP-tree is similar to P-tree in that both are ordered multi-way tree        | CP-trees can be used to discover non-monotonic patterns and mine SJEPs and top-k minimal JEPs. | [31, 71] |
|               | structures, the difference is that CP-tree has no node links [31]. The      | Pruning strategies are based on the anti-monotonicity or apriori principle [73].                  |        |
|               | number of items in each node of the CP-tree is changeable.                  |                                                                                                  |        |
| DGCP-tree     | The DGCP tree is an ordered tree structure that is used to store growth     | The difference between DGCP-tree and CP-tree is that there is no need to scan the dataset to     | [73]   |
|               | patterns and arrays of path codes from bit-string compression trees. Each    | build a DGCP-tree, and there is no need to merge any nodes when accessing the nodes of a         |        |
|               | node registers two arrays of path codes [73].                               | DGCP-tree                                                                                         |        |
| TDCSP-tree    | It is a contrast sequential pattern suffix tree with information on time     | The difference between a TDCSP-tree and a suffix tree that the root is not empty. The root of a   | [11]   |
|               | distribution [11]. This method requires only one scan of the database and   | TDCSP-tree is a node containing a set of items [11].                                               |        |
|               | stores data in a tree.                                                      |                                                                                                  |        |
| CSP-tree      | The nodes of the CSP-tree need to record the prefix frequency of each class. | The CSP tree can be pruned using Apriori-like pruning and some support-based pruning approaches,  | [13]   |
|               | The CSP-tree structure does not require the generation of candidate         | such as heuristic cardinality pruning approaches                                                  |        |
|               | sequences [13].                                                            |                                                                                                  |        |
| Nettree       | Nettree is a tree-like data structure where the number of roots can be      | The same node label might appear several times at different levels in Nettree, which effectively  | [11]   |
|               | greater than one and there may be multiple paths from a node to its         | determines Whether or not a sequence of characters can be reused                                  |        |
|               | ancestors [11].                                                             |                                                                                                  |        |
| SLD-tree      | It is a kind of subsequence position distribution suffix-tree, which can    | In contrast to the null root of a suffix-tree, the root of the SLD-tree is also a node that      | [75]   |
|               | analyze the position distribution difference of different subsequences      | holds a set of objects. Each item has six fields                                                   |        |
|               | adaptively [75].                                                           |                                                                                                  |        |
| Prefix-leaf   | A prefix leaf tree is a type of prefix tree in which each internal node    | All candidate patterns can be organized using the prefix-leaf tree. Depth-first traversal is used  | [76]   |
| tree          | holds the symbols of its leaf node offspring, regardless of whether its     | to find the collection of candidate patterns that match                                         |        |
|               | parent is the root node or has numerous children.                          |                                                                                                  |        |
| T*-tree       | The T*-tree (transaction tree) structure is divided into trunk and branch.  | A T*-tree is an index structure that asks how many transactions match a particular pattern,     | [19]   |
|               | By gain ratio, the attributes are listed in descending order, with the top 10% | where transactions being represented as spatial objects wrapped by Minimal bounding boxes (MBBs)  |        |
|               | attributes as trunk nodes and the rest attributes as branch nodes [19].     |                                                                                                  |        |
| FP-tree, TFP-tree | The node of FP Tree records the project frequency of each class [77, 78].   | FP Tree is an early structure used to discover JEPs [77, 78]. Compared to FP-tree, TFP-tree has   | [77, 78, 79] |
|               | TFP-tree means generating a T-tree from a P-tree using a similar priori     | shorter generation time and is more efficient in memory management                               |        |
|               | approach, where T-tree is a compressed set enumeration tree [79].           |                                                                                                  |        |
| Name       | Description                                                                                       | Pros.                                                                 | Cons.                                                                 | Year  |
|------------|---------------------------------------------------------------------------------------------------|------------------------------------------------------------------------|------------------------------------------------------------------------|-------|
| LCMine [80]| This method induces a series of decision trees and filtering operations to find high-quality discriminative attributes. | Discriminant rules can be efficiently found on training sample sets with incomplete and mixed data. | This method requires post-filtering of the schema, which is time-consuming. | 2010  |
| CEPM [81]  | The improved version of LCMine uses a new weighting scheme to mine various patterns without global discretization. | CEPM is faster and more accurate than LCMINE. CEPM does not require schema filtering post-processing. | The operation of estimating the minimum support threshold is inefficient. | 2010  |
| EPRFm [82] | The algorithm generates decision trees in the same way as random forest and mines decision rules for each data class. | EPRFm can be used for video database and get good classification results. | For small data, the classification result of random forest is not good. | 2010  |
| FEPM [27]  | The algorithm uses a set of fuzzy decision trees to extract fuzzy emerging patterns.               | It first introduces the concept of fuzzy emerging pattern (FEP) and the algorithm of mining FEP. | The same pattern will appear on different trees, resulting in time consuming. | 2010  |
| DBF [83]   | The core idea of DBF is to remove certain attributes that appear in many patterns by removing features in the induced decision tree. | The situation of creating too many repeating patterns has been improved. | Deleting a feature directly causes other relationships for that feature to be deleted along with it, thus losing many of the resulting patterns. | 2015  |
| DBP [83]   | From deleting features to deleting attributes, it does not allow the attributes of root nodes to exist in other induced decision trees. | DBP maintains the integrity of research results to a certain extent. | There may be attributes that have the same properties as the best attributes, making DBP less useful. | 2015  |
| DBPL [83]  | Remove the best attribute by level, allowing a given attribute to appear in a sublevel.            | To a certain extent, it solves the inaccuracy of results caused by DBP’s strict deletion. | Determining attribute levels is tedious and changeable. | 2015  |
| RFM [83]   | Random forest is one of the best methods to discover CP, which is most suitable for classifying data. | The classifier based on random forest has the advantages of low cost and high accuracy. | Due to the complexity of the algorithm, it takes more time to train and costs more than other algorithms. | 2015  |
| Bagging [83]| One of the best ways to discover CP and performs best when used with numerical data.               | For any support threshold, Bagging’s abstinence rate is low and accurate. | The algorithm requires more time to train than other algorithms. | 2015  |
| PBC4cip [84]| A strategy is proposed to solve the class imbalance problem.                                        | In class imbalance problem, PBC4cip can get good classification results. | Due to the limitations of the Hellinger distance, PBC4cip can only solve two kinds of problems. | 2017  |
| MHRFm [85] | MHRFm uses Multivariate decision trees to deal with multiple types of problems.                   | MHRFm removes the restriction that HRFm handles only two types of problems. | MHRFm’s filtering operation takes a long time to run. | 2019  |
4. Advanced Topics of CPM

4.1. Class Imbalance Problem in CPM

In previous studies, CPM was mostly based on the assumption that the dataset distribution is basic and balanced. However, in the real world, it is a common phenomenon that datasets have class imbalance problems. The class imbalance problem refers to the problem of uneven distribution of objects into classes, which is manifested by the fact that the number of objects in some classes is much smaller than that in other classes [94]. In some applications, people tend to be more interested in learning about rare or few classes of data in a dataset. For example, in credit card fraud detection, there are far fewer fraudulent transactions than legitimate transactions, but people are more concerned about fraudulent transactions than information about legitimate transactions. Many problems can arise when a classifier based on the assumption that the distribution of the dataset is balanced is applied to an unbalanced dataset. These classifiers tend to sacrifice the accuracy of the minority class in order to improve overall accuracy, ignoring the reality that in many actual applications, misclassification of the minority class samples is usually more expensive [33]. Many methods have been proposed to solve the class imbalance problem in the dataset. These methods can be classified into the following three categories: 1) data-level methods, 2) algorithm-level methods, and 3) cost-sensitive learning methods [95, 96].

4.2. Fuzzy Contrast Pattern Mining

EP-based classifiers usually contain a prior discretization operation, which is used to discretize individual attributes. This operation has the following two disadvantages: 1) The discretization process can easily result in information loss. 2) Numerical discretization usually defines explicit numerical feature boundaries, and pattern matching relationships lack flexibility. For example, the object (2, 6) may match a pattern while (2.001, 6) may not. To address these drawbacks, FEP was proposed by García-Borroto [27]. FEP is a pattern that combines the concepts of fuzzy logic with emerging patterns to obtain a knowledge representation that is close to human reasoning. The advantage of FEP is to make patterns easier to read and interpret and to avoid information loss in the process of discretization [53]. So far, several research studies have been proposed. The MOEA-EFEP algorithm [86] is based on the NSGA-II algorithm for mining EP. And a multi-objective evolutionary algorithm has been used to discover FEP. Researchers have also studied mining FEPs in different environments, such as data streams [97] and big data [87, 89, 53].

4.3. CPM in The Big Data Environment

In the era of digital economy, Big Data is characterized by large volume, fast generation, diversity, accuracy, and value (the 5V’s model) [42]. Mining contrast patterns in the Big Data environment is a meaningful research direction. Mining CP is a challenge due to the characteristics of the 5V’s model of Big Data. Existing approaches to mining CPs from big data can be divided into the following two categories:

- Designing parallelized CPM algorithms, such as the DCP-Growth algorithm solves the problem by dividing the search space of CPs into small, independent units, where these units can be mined in a parallel manner, providing a scalable solution for mining large datasets [98].

- Developing CPM algorithms based on existing Big Data technologies (such as MapReduce [99] and Spark [100]), such as the EvAEFP Spark algorithm and the BD-EFEP algorithm. The EvAEFP Spark algorithm uses the MapReduce paradigm, developed in Apache Spark, to efficiently analyze huge datasets [87, 6]. BD-EFEP uses the MapReduce method and evolutionary method to process large amounts of data efficiently [53].

4.4. Data Visualizations

Applying CPM to the data can obtain interesting information, but this information might be difficult to comprehend. Data visualization is used as a tool in data mining to better interpret data. Data visualization can not only help users to make sense of complex problems, but also discover other interesting phenomena by extracting and analyzing information. Combining research results with data visualization has been a popular strategy in recent years because it allows users to view data from a variety of angles. In 2015, a method for visualizing and predicting spatial-temporal events based on contrast patterns was proposed [101]. In the following year, Nishiguchi et al. proposed a visualization method based on path diagrams, called CRPD, which could be used to explain the relationships between CPs [102]. The idea of visualization has been applied to practical problems. For example, Loyola-González et al. present the first scientometrics study of world university rankings based on contrast patterns and a method for visualizing extracted...
patterns, with the aim of helping policy-makers to develop and evaluate strategies for ranking world universities [103]. In 2021, Neto et al. proposed a visual analysis method called VAX [104]. VAX uses the descriptive capabilities of JEPs to analyze information. Matrix-like visual metaphors were used in this method in order to present JEPs.

4.5. CPM with New Technologies
The new generation of information technologies includes the Internet of Things (IoT) [105], 5G [106], cloud computing [107], blockchain [108], and artificial intelligence [109]. Their combination with data mining plays an important role in promoting the development of the digital economy and creates infinite application value together. As a subfield of data mining, the combination of CPM and new technology is an advanced topic. 5G technology is distinguished by its high bandwidth, low latency, and high stability [110]. 5G solves the problem of communication transmission efficiency, and the value will be reflected in data mining. Data mining uses efficient data transmission to analyze data. The combination of data mining and new technology has great application space and research value, such as the combination of data mining and the IoT [111, 112]. In addition, the combination of data mining and various technologies has also been investigated by researchers. For example, a cloud platform based on cloud computing was applied to IoT data mining technology [113, 114]. The combined technology has many advantages, such as reducing the time of data transmission, improving the efficiency of data mining, and avoiding the failure of data storage.

5. Challenges and Opportunities
While research on CPM has been fruitful, there are still some key issues that need to be studied in depth. In this section, we discuss the open challenges and opportunities in this area.

- **Mining multivariate contrast patterns.** A univariate contrast pattern is a contrast pattern in which each term of the pattern involves only one feature. Most of the CPM studies are based on univariate contrast patterns, but they have limitations. In some datasets, the univariate contrast pattern-based classifier does not work well. Therefore, the concept of multivariate contrast patterns (MCP) has emerged, where the items of MCP can be either univariate or multivariate items [85]. MCPs have better classification performance than univariate contrast patterns, but they have the disadvantage of being more difficult to understand. At present, there is little research on MCP, but MCP is an interesting research direction. There are some challenging research opportunities for MCP: how to discover MCPs in different data environments; how to classify using fuzzy multivariate patterns; and how to design unsupervised classifiers based on MCPs.

- **Open-source software.** Although CPM has been studied for more than 20 years, there is no well-known open-source platform that provides source code for studying CPM for researchers to exchange and learn. This is a problem that needs to be looked at. The lack of an open-source platform not only makes the exchange of source code difficult, but also hinders the further development of the field to some extent. This is because researchers often need to re-implement other researchers’ algorithms in order to improve them or to compare the performance of new ones. Therefore, there is an urgent need to develop an open-source platform for contrast pattern mining.

- **Datasets for CPM.** CPM research requires the support of open-source datasets. The lack of open-source datasets makes it difficult for researchers to evaluate the performance of algorithms, as too few experimental datasets are not conducive to discovering algorithm flaws and strengths, and experimental results lack credibility. One of the current research trends is to use algorithms to solve real-world problems directly, and the study of real-world problems often requires the support of relevant datasets, so the issue of whether these datasets are open source is very important. Some common open source datasets are listed below:
  - The UCI repository: https://archive.ics.uci.edu/ml/index.php
  - The FIMD repository: http://fimi.ua.ac.be/data
  - SPMF: http://www.philippe-fournier-viger.com/spmf/index.php

- **Integration with other concepts.** Adding concepts from other fields to CPM is a promising research direction. Researchers can consider combining contrast patterns (CPs) with other types of patterns. Take advantage of their features and strengths to solve practical problems effectively. Some researchers have already combined CPs and utility patterns to come up with the concept of the conditional contrast high-utility itemset. In addition,
researchers can combine CPs with concepts from other fields to obtain new concepts. For example, FEP is the concept obtained by combining fuzzy logic with EP [27]. CPs combined with other concepts can also be used directly to solve certain problems. For example, EP combined with Random Forest is used to identify complex activities in smart homes [115].

- **Dynamic data mining.** With the rapid development of data acquisition, storage, and transmission technologies, data is no longer static and can be updated dynamically. The timeliness of data is getting shorter and the scale of data is getting larger, and the use of traditional static data mining techniques to analyze the constantly generated information can no longer meet the realistic needs. In order to obtain the knowledge of interest in the constantly generated data streams, researchers have proposed many approaches to dynamically process real-time data, and related works include online data mining [116], incremental pattern mining algorithms [117], and streaming data mining [97]. There are still some research opportunities in dynamic data mining: how to develop CPM algorithms based on existing big data technologies such as MapReduce [99], Spark [100], and Storm [118], and how to improve the efficiency of algorithms.

- **Privacy & Security.** Concern about data privacy and security has become a worldwide trend. Using private data to discover patterns will inevitably cause privacy problems, so how to discover patterns on the basis of protecting data privacy becomes an urgent problem to be solved. So far, researchers have proposed some methods to protect the privacy of frequent patterns [119, 120, 121]. However, in the field of CPM, there is no research on the contrast pattern of privacy protection. Some application scenarios have privacy requirements. For example: marketing and healthcare. In these application scenarios, we need to protect the privacy of datasets and the security of mining results while mining contrast patterns. In order to expand the application scenarios of contrast patterns, the research of privacy-preserving contrast pattern mining should be given more attention.

- **Contrastive learning.** Data mining is closely related to machine learning. On the one hand, machine learning provides the underlying technical support for data mining. On the other hand, machine learning needs a large amount of valid data for training. CPM belongs to data mining. Contrastive learning belongs to self-supervised learning in machine learning. In contrastive learning, positive and negative samples are compared in the feature space to learn the features of samples [122]. Contrastive learning focuses on learning the common characteristics between similar instances and distinguishing the differences between non-similar instances [123]. CPM compares positive and negative datasets to discover patterns of contrast. There are ideological similarities between CPM and contrastive learning. Contrastive learning can provide underlying technical support and thought inspiration for the CPM field.

6. Conclusions

Contrast pattern mining can be used to solve many real-world problems effectively, and other types of pattern mining methods actually use the concept of contrast. The combination of contrast pattern mining with other pattern mining methods is a very interesting research direction, and their combination may help discover more efficient solutions to old problems or discover and solve new problems. Therefore, contrast pattern mining is a very important research topic. However, there are few studies that summarize and classify contrastive pattern mining methods. In this study, we introduce the basic concepts of types of CPM, mining strategies, and assessment of comparative power. In addition, classical algorithms of CPM are classified and their advantages and disadvantages are introduced for analysis. Advanced and up-to-date topics related to CPM are also discussed. As an important area of data mining, although CPM research has been fruitful, there are still some key issues that need to be studied in-depth. Thus, open challenges and future directions of contrast pattern mining are presented at the end.

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