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Association rule mining in data mining pdf

Part of a series reMachine learning anddata mining Problems Classification Clustering Regression Anomaly Detection AutoML Association rules Strengthening learning Structured prediction Feature engineering Feature learning Online learning Semi-supervised learning Unsupervised learning Learning to rank Grammar induction Monitored learning (classification • regression) Decision trees Ensembles Sacks Boosting Random forest k-NN Linear Regression Naive Bayes Artificial Neural Network Logistic Regression Perceptron Relevance Vector Machine (RVM) Support Vector Machine (SVM) Clustering BIRCH CURE Hierarchical k-means Expectation-maximization (EM) DBSCAN OPTIK Mean-shift Dimensionality Reduction Factor analysis CCA ICA LDA NMF PCA PA PGD t-SNE Structured prediction Graphic models Bayes net Conditional random field Hidden Markov Anomaly detection k-NN Local outlier factor Artificial neural network Autoencoder Deep learning Deepdream Multilayer perceptron RNN LSTM GRU ESN Restricted Boltzmann machine GAN SOM Convolutional neural network U-Net Transformer Reinforcement learning Q-learning SARSA Temporal difference (TD) Theory Bias-variance dilemma Computational learning theory Empirical risk minimizing Occam learning PAC learning Statistical learning VC theory Machine-learning venues NeurIPS ICML ML JMLR ArXiv : cs. LG Glossary of Artificial Intelligence Glossary of Artificial Intelligence Related Articles List of Data Sets for Machine Learning Research Sketch of Machine Learning VTE Association Rule Learning is a rule-based machine learning method for discovering interesting relationships between variables in large databases. It is intended to identify strong rules discovered in databases using some targets of interestingness. [1] On the basis of the concept of strong rules, Rakesh Agrawal, Tomasz Imieliński and Arun Swami[2] introduced association rules to detect regularity between products in large transaction data recorded by pos systems (pos) in supermarkets. For example, the rule { o n i o n s , p o t a t o e s } ⇒ { b you are g e r } {\displaystyle \{\mathrm {onions, potatoes} \}\Rightarrow \{\mathrm {burger} \}} found in the sales data of a supermarket would indicate that if a customer buys onions and potatoes together, they are likely to also buy hamburger meat. Such information may be used as a basis for decisions on marketing activities, such as marketing activities. In addition to the above example from the market basket analysis association rules are employed today in many applications, including web mining, intrusion detection, continuous production, and bioinformatics. Unlike sequence mining, association rule learning typically does not take into account the order of items either in a transaction or across transactions. Definition Sample database of 5 transactions and 5 goods transaction ID milk bread butter beer diapers 1 1 1 0 0 0 2 0 0 1 0 0 0 0 0 1 1 1 1 1 1 1 1 0 0 5 0 1 0 0 the original definition of Agrawal, Imieliński, Swami[2] the problem of association rule mining is defined as: Let I = { in 1 , in 2 , ... , in n } {\displaystyle I=\{i_{1},i_{2},\ldots , i_{n}\}} be a set of n {\displaystyle n} binary attributes called elements. Let D = { t 1 , t 2 , ... , t m } {\displaystyle D=\{t_{1},t_{2},\ldots ,t_{m}\}} be a set of transactions called the database. Each transaction in D {\displaystyle D} has a unique transaction ID and contains a subset of the items in I {\displaystyle I} . A rule is defined as a consequence of the form: X ⇒ Y {\displaystyle X\Rightarrow Y}, where X , Y ⊆ In {\displaystyle X,Y\subeteq I} . In Agrawal, Imieliński, Swami[2], a rule is defined only between one set and a single element, X ⇒ in j {\displaystyle X\Rightarrow i_{j}} for i j ∈ In {\displaystyle i_{j}\in I} . Each rule consists of two different sets of elements, also called itemsets, X {\displaystyle X} and Y {\displaystyle Y}, where X {\displaystyle X} is called the prior or left side (LHS) and Y {\displaystyle Y} as a follower or right side (RHS). To illustrate the concepts, we use a small example from the supermarket domain. The set of the items is I = { m i l k , b r e a d , b u t t e r , b e e r , d i a p e r s } {\displaystyle I=\{\mathrm {milk,bread,butter,beer,diapers} \}} and the table displays a small database, that contains the items where the value 1 in each entry means the presence of the item in the corresponding transaction, and the value 0 represents the absence of an item in that transaction. A supermarket sample rule could be { b u t e r , b r e a d } ⇒ { m i l } {\displaystyle \{\mathrm {butter,bread} \}\Rightarrow \{\mathrm {milk} \}} means that customers also buy milk if butter and bread are purchased. Note: This example is extremely small. In practical applications, a rule requires support from several hundred transactions before it can be considered statistically significant [recvisation required], and data sets often contain thousands or millions of transactions. Useful concepts To choose interesting rules from the set of all possible rules, restrictions are applied to different goals of importance and interest. The best-known restrictions are minimum thresholds for support and trust. Let X , Y {\displaystyle X,Y} be itemsets, X ⇒ Y {\displaystyle X\Rightarrow Y} an association rule and T {\displaystyle T} a set of transactions for a given database. Support support is an indication of how often the items appear in the dataset. Support for X {\displaystyle X} for T {\displaystyle T} is defined as the percentage of transactions t {\displaystyle t} in the dataset that contains the itemset X {\displaystyle X} . s u p p (X) = | { t ∈ T ; X ⊆ t } | | T | {\displaystyle \mathrm {supp} (X)={\frac {|\{t\in T; X\subseteq t\}|} {| T|}}} In the sample dataset, itemset X = { b e e r , d i a p e r s } {\displaystyle X=\{\mathrm {beer,diapers} \}} has a support of 1 / 5 = 0.2 1/5=0.2} because it occurs in 20% of all transactions (1 out of 5 transactions). The argument for s u p p ( ) {\displaystyle \mathrm {supp} ()} is a set of prerequisites and thus becomes more restrictive as it grows (instead of more inclusive). [3] Trust trust is an indication of how often the rule has turned out to be true. The confidence value of a rule, X ⇒ Y {\displaystyle X\Rightarrow Y} for a set of transactions T {\displaystyle T} is the part of the transactions that contains X {\displaystyle X} that also contains Y {\displaystyle Y} . Trust is defined as: c o n f (X ⇒ Y) = s u p (X ∪ Y) / s u p p (X) {\displaystyle \mathrm {conf} (X\Rightarrow Y)=\mathrm {supp} (X\cup Y)/\mathrm {supp} (X)} rule {b u t e r , b r e a d ⇒ } <1> <6> { m i l } {\displaystyle \{\mathrm {butter,bread} \}\Rightarrow \{\mathrm {milk} \}} has a trust of 0.2 / 0.2 = 1.0 {\displaystyle 0.2/0.2=1.0} in the database which means that for 100% of the transactions containing the butter and bread rule is correct (100% of the times a customer buys butter and bread, milk is bought as well). Note that s u p (X ∪ Y) {\displaystyle \mathrm {supp} (X\cup Y)} means support for the association of the elements in X and Y. This is somewhat confusing as we usually think in terms of probabilities for events and not sets of records. We can rewrite s u p p (X ∪ Y) {\displaystyle \mathrm {supp} (X\cup Y)} as probability P (E X ∩ E Y) {\displaystyle P(E_ X}\cap E_ {Y})} where E X {\displaystyle E_{X}} and E Y {\displaystyle E_{Y}} are the events that a transaction contains, respectively contains the items X {\displaystyle X} and Y {\displaystyle Y}. [4] Confidence can thus be interpreted as an estimate of the conditional probability P (E Y | E X) {\displaystyle P(E_{Y}| E_{X})} is the probability of finding the RHS for the rule in transactions, provided that these transactions also contain LHS. [3] [5] Lift the lift of a rule is defined as: l i f t (X ⇒ Y) = s u p p (X ∪ Y) s u p p (X) × s u p p (Y) {\displaystyle \mathrm {lift} (X\Rightarrow Y)={\frac {\mathrm {supp} (X\cup Y)}{\mathrm {supp} (X)\times \mathrm {supp} (Y)}}} or the relationship between the observed support and the expected if X and Y were independent. For example, if you're a 100-year rule { m i l k , b r e a d } ⇒ { b u t t t e r } {\displaystyle \{\mathrm {milk,bread} \}\Rightarrow \{\mathrm {butter} \}} has a lift of 0 0.2 0.4 × 0.4 = 1.25 {\displaystyle {\frac {0.2}{0.4\times 0.4}}=1.25} . If the rule had a lift of 1, it would imply that the probability of the occurrence of the prior and the resulting is independent of each other. When two events are independent of each other, no rule involving these two events can be drawn. If the elevator is > 1, it tells us the extent to which these two events depend on each other, and makes these rules potentially useful for predicting the resulting in future data sets. If is < 1, we saw by elements are in replacement for each other. This means that the presence of an item has a negative impact on the presence of other products and vice versa. The value of the lift is that it considers both the support of the rule and the overall data set. [3] Conviction Conviction The conviction of a rule is defined as c o n v (X ⇒ Y) = 1 − s u p p (Y) 1 − c o n f (X ⇒ Y) {\displaystyle \mathrm {conv} (X\Rightarrow Y)={\frac {1-\mathrm {supp} (Y)}{1-\mathrm {conf} (X\Rightarrow Y)}}} . [6] For example, the rule { m i l k , b r e a d } ⇒ { b u t t e r } {\displaystyle \{\mathrm {milk,bread} \}\Rightarrow \{\mathrm {butter} \}} has a conviction of 1 − 0.4 1 − 1 − 00.5 = 1.2 {\displaystyle {\frac {1-0.4}{1-0.5}}=1.2} and can be interpreted as the ratio of the expected frequency, x occurs without Y (i.e., the frequency , as the rule gives an incorrect prediction) if X and Y were independent, divided by the observed frequency of incorrect predictions. In this example, the sentencing value of 1.2 shows that the rule { m i l k , b r e a d } ⇒ { b u t t r } {\displaystyle \{\mathrm {milk,bread} \}\Rightarrow \{\mathrm {butter} \}} would be incorrect 20% more often (1.2 times as often) if the association between X and Y was purely random. Alternative measures of interestingness In addition to trust, other measures of interest for the rules have been proposed. Some popular measures are: All-confidence[7] Collective Strength[8] Leverage[9] Several more measures are presented and compared by Tan et al.[10] and by Hahsler. [4] Looking for techniques that can model what the user has known (and use these models as interestingness measures) is currently an active research trend under the name Subjective Interesting. Beting Frequently Itemet grid, where the color of the field indicates how many transactions contain the combination of items. Note that lower levels of the grid may contain no more than the minimum number of their parents' records; for example, {ac} can have no more than m in n (a , c) {\displaystyle min(a,c)} items. This is called the downward closing property. [2] Association rules are usually required to meet a user-specified minimum support and a user-specified minimum confidence at the same time. Association rule generation is usually divided into two separate steps: a minimum support limit is applied to find all frequent elements of a database. A minimum trust restriction is applied to these frequent elements to form rules. While the second step is straightforward, the first step requires more attention. It's hard to find all frequent item sets in a database because it involves searching all sorts of item sets (element combinations). The set of possible elements sets is powered over I {\displaystyle I} and has size 2 n − 1 {\displaystyle 2^{n}-1} (except for the empty set, which is not a valid itemet). Although the size of the power set is growing exponentially in the number of It is possible to use the down-to-the-counter property[2][11] (also known as anti-monotonicity[12]), which guarantees that all its subsets for a frequently itemset are also frequent and that there can therefore be no rare set of a frequently itemset. Effective use of this property can find effective algorithms (e.g. History The concept of association rules became popular especially because of the article in Agrawal et al.,[2] from 1993, which has acquired more than 18,000 citations according to Google Scholar from August 2015 and thus is one of the most quoted papers in the Data Mining area. However, what is now called association rules is already introduced in the 1966 document[15] on GUHA, a general data mining method developed by Petr Hájek et al.[16] An early (approx. 1989) the use of minimal support and confidence to find all association rules are function-based modeling frameworks, which found all rules with s u p p (X) {\displaystyle \mathrm {supp} (X)} and c o n f (X ⇒ Y) {\displaystyle \mathrm {conf} (X\Rightarrow Y)} greater than custom limits. [17] Statistically sound associations A limitation of the standard approach to discovering associations is that, by seeking a massive number of possible associations searching for collections of objects that appear to be connected, there is a high risk of finding many false associations. These are collections of items that simultaneously occur with unexpected frequency in the data, but only do so by chance. For example, suppose we're considering a collection of 10,000 items and looking for rules that contain two left-hand elements and 1 item on the right side. There are about 1,000,000,000,000 such rules. If we use a statistical test for independence with a significance level of 0.05, this means that there is only a 5% chance of accepting a rule if there is no association. If we assume that there are no associations, we should still expect to find 50 000 000 000 rules. Statistically sound association registration[18][19] controls this risk, which in most cases reduces the risk of finding false associations to a user-specified significance level. Algorithms Many algorithms for generating mapping rules have been suggested. Some well-known algorithms are Apriori, Eclat and FP-Growth, but they do only half the job as they are algorithms for mining frequent itemsets. A second step must be taken to generate rules from frequent items that exist in a database. Apriori algorithm Main article: Apriori algorithm Apriori[13] uses a width-first search strategy to count support of itemsets and uses a graduate generation feature that utilizes the downward closure property support. Eclat algorithm Eclat[14] (alt. ECLAT, stands for Equivalence Class Transformation) is a depth-first search algorithm based on set ticks. It is suitable for both sequential as well as parallel execution with location-enhancing properties. [20] [21] algorithm FP stands for frequent pattern. [22] In the first throughput, the algorithm counts the instances of items (attribute value pairs) in the dataset for transactions and stores those counts in a 'header table'. In the second throughput, the FP tree structure is built by inserting transactions into a trie. Items in each transaction must be sorted by descending order by their frequency in the dataset before they are inserted so that the tree can be processed quickly. Items in each transaction that do not meet the minimum support requirement are discarded. If many transactions share the most frequent items, the FP tree provides high compression close to the tree root. Recursive processing of this compressed version of the main dataset grows frequent element sets directly instead of generating candidate elements and testing them against the entire database (as in the apriori algorithm). The growth begins from the bottom of the header table, i.e. the growth of the header table. Call this item In {\displaystyle I} . A new conditional tree is created, which is the original FP tree projected on to I {\displaystyle I} . The supportings of all nodes in the projected tree are counted again with each node that causes the sum of its children to count. Nodes (and thus subtrees) that do not meet the minimum support are cropped. Recursive growth ends when no single item contingent on I {\displaystyle I} meets the minimum support limit. The resulting curves from root to I {\displaystyle I} will be frequent items. After this step, processing continues with the second least supported header element in the original FP tree. [23] Other ASSOC ASSOC procedure[24] is a GUHA method that extracts general association rules through rapid bitstring operations. The association rules obtained by this method are more general than those produced with apriori, for example, OPUS search OPUS is an effective rule-tracking algorithm that, unlike most alternatives, does not require either monotonous or antimontone restrictions such as [25] Originally it was used to find rules for a fixed follow[25][26] it has subsequently been extended to find rules with any object as a result. [27] OPUS search is core technology in it popular Magnum Opus Association Registration System. Lore A famous history of association rule mining is beer and diaper history. An alleged investigation into the behaviour of supermarket shoppers discovered that customers (presumably young men) who buy diapers also tend to buy beer. This anecdote became popular as an example of unexpected mapping rules can be found from daily data. There are different opinions about how much of the story is true. [28] Daniel Powers says:[28] In 1992, Thomas Blischok, head of a retail consulting group at Teradata, and his staff produced an analysis of 1.2 million market baskets from about 25 Osco Drug stores. Database queries were developed to identify affiliations. The analysis found that between 5am and 7pm.m consumers were buying beer and nappies. Osco executives don't exploit the beer and diapers ratio by moving the products closer together on the shelves. Other types of association rule mining Multi-Relation Association Rules: Multi-Relation Association Rules (MRAR) are association rules in which each element can have multiple relationships. These relationships indicate indirect relationships between the objects. Consider the following MRAR, where the first point consists of three relationships living in, nearby and humid: Those who live in a place that is near a city with humid climate type and are also younger than 20-> their health condition is good. Such association rules may be extracted from RDBMS data or semantic web data. [29] Contrast set learning is a form of associative learning. Contrast sets students use rules that differ meaningfully in their distribution across subsets. [30] [31] Weighted class learning is another form of associative learning, with the emphasis on classes to highlight a particular issue of concern to consumers of the results of data mining. High-order pattern discovery facilitate the conquest of high-order (polythetic) patterns or event associations that are inextricably linked to complex real-world data. [32] K-optimal pattern discovery is an alternative to the standard approach to association rule learning, which requires each pattern to be frequently displayed in the data. Approximate Frequent Itemset mining is a casual version of Frequent Itemset mining, that allows some of the elements of some of the rows to be 0. [33] Generalized Association Rules hierarchical taxonomy (concept hierarchy) Quantitative Association Rules rules categorical and quantitative data Interval Data Association Rules, e.g. partitioning the age of 5-year-increase varied Sequential pattern mining detects subquences common to more than minsup [clarification necessary] sequences in a sequence database where minsup is set by the user. A sequence is a sorted list of transactions. [34] Subspace Clustering, a specific type of clustering high-dimensional data, is in many variants also based on the downward closing property for specific clustering models. [35] Warmr is sent as part of the ACE data mining suite. It allows for association rule learning for first order relational rules. 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