Complete guide to Association Rules (1/2)

Algorithms that help you shop faster and smarter

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Looking back at the multitude of concepts that have been introduced to me in the statistics boot camp, there is a lot to write and share. I choose to start with Association Rules because of two reasons. First, this was one of the concepts which I enjoyed learning the most and second, there are a limited resources available online to get a good grasp.

In Part 1 of the blog, I will be introducing some key terms and metrics aimed at giving a sense of what "association" in a rule means and some ways to quantify the strength of this association. Part 2 will be focused on discussing the mining of these rules from a list of thousands of items using *Apriori Algorithm*.

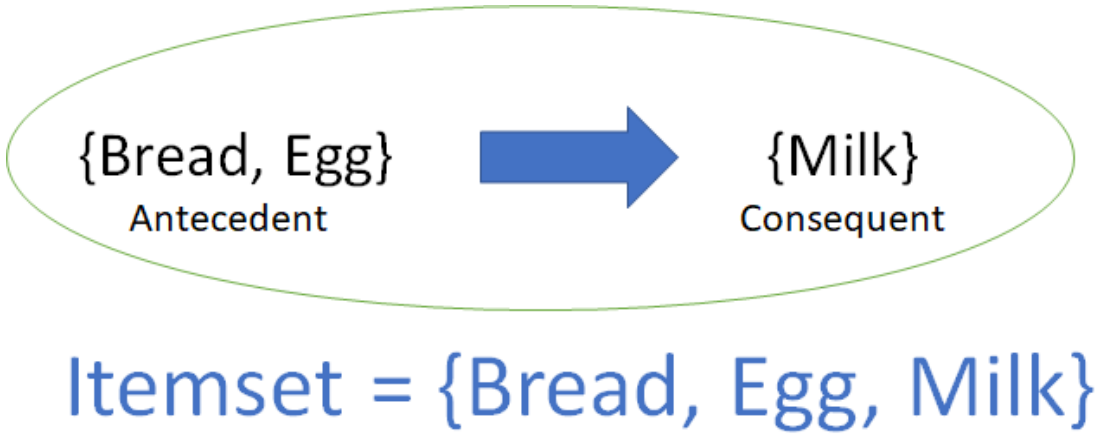
Association Rules is one of the very important concepts of machine learning being used in market basket analysis. In a store, all vegetables are placed in the same aisle, all dairy items are placed together and cosmetics form another set of such groups. Investing time and resources on deliberate product placements like this not only reduces a customer's shopping time, but also reminds the customer of what relevant

items (s)he might be interested in buying, thus helping stores cross-sell in the process. Association rules help uncover all such relationships between items from huge databases. One important thing to note is-

> *Rules do not extract an individual's preference, rather find relationships between set of elements of every distinct transaction. This is what makes them different from collaborative filtering.*

To elaborate on this idea — Rules do not tie back a users' different transactions over time to identify relationships. List of items with unique transaction IDs (from all users) are studied as one group. *This is helpful in placement of products on aisles.* On the other hand, collaborative filtering ties back all transactions corresponding to a user ID to identify similarity between users' preferences. *This is helpful in recommending items on e-commerce websites, recommending songs on spotify, etc.*

Lets now see what an association rule exactly looks like. It consists of an antecedent and a consequent, both of which are a list of items. Note that implication here is co-occurrence and not causality. For a given rule, ***itemset*** is the list of all the items in the antecedent and the consequent.



Various metrics are in place to help us understand the strength of association between these two. Let us go through them all.

1. Support

This measure gives an idea of how frequent an *itemset* is in all the transactions. Consider *itemset1* = {bread} and *itemset2* = {shampoo}. There will be far more transactions containing bread than those containing

shampoo. So as you rightly guessed, *itemset1* will generally have a higher support than *itemset2*. Now consider *itemset1* = {bread, butter} and *itemset2* = {bread, shampoo}. Many transactions will have both bread and butter on the cart but bread and shampoo? Not so much. So in this case, *itemset1* will generally have a higher support than *itemset2*. Mathematically, support is the fraction of the total number of transactions in which the itemset occurs.

$$Support(\{X\} \rightarrow \{Y\}) = \frac{Transactions\ containing\ both\ X\ and\ Y}{Total\ number\ of\ transactions}$$

Value of support helps us identify the rules worth considering for further analysis. For example, one might want to consider only the itemsets which occur at least 50 times out of a total of 10,000 transactions i.e. support = 0.005. If an *itemset* happens to have a very low support, we do not have enough information on the relationship between its items and hence no conclusions can be drawn from such a rule.

2. Confidence

This measure defines the likeliness of occurrence of consequent on the cart given that the cart already has the antecedents. That is to answer the

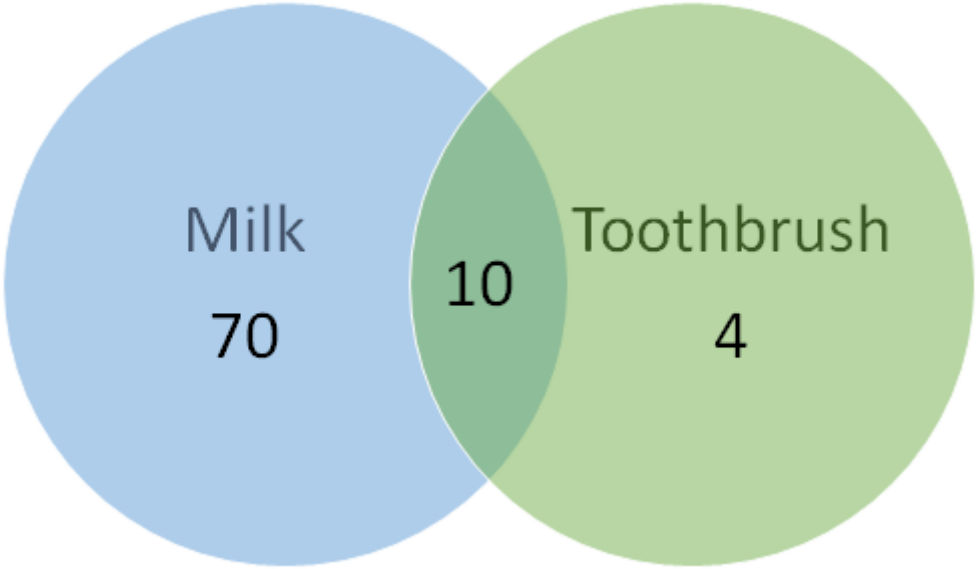
question — of all the transactions containing say, {Captain Crunch}, how many also had {Milk} on them? We can say by common knowledge that {Captain Crunch} → {Milk} should be a high confidence rule. Technically, confidence is the conditional probability of occurrence of consequent given the antecedent.

$$Confidence(\{X\} \rightarrow \{Y\}) = \frac{Transactions\ containing\ both\ X\ and\ Y}{Transactions\ containing\ X}$$

Let us consider few more examples before moving ahead. What do you think would be the confidence for {Butter} → {Bread}? That is, what fraction of transactions having butter also had bread? Very high i.e. a value close to 1? That's right. What about {Yogurt} → {Milk}? High again. {Toothbrush} → {Milk}? Not so sure? Confidence for this rule will also be high since {Milk} is such a frequent itemset and would be present in every other transaction.

> *It does not matter what you have in the antecedent for such a frequent consequent. The confidence for an association rule having a very frequent consequent will always be high.*

I will introduce some numbers here to clarify this further.



Total transactions = 100. 10 of them have both milk and toothbrush, 70 have milk but no toothbrush and 4 have toothbrush but no milk.

Consider the numbers from figure on the left. Confidence for {Toothbrush} → {Milk} will be $10/(10+4) = 0.7$

Looks like a high confidence value. But we know intuitively that these two products have a weak association and there is something misleading about this high confidence value. *Lift* is introduced to overcome this challenge.

> Considering just the value of confidence limits our capability to make any business inference.

3. Lift

Lift controls for the *support* (frequency) of consequent while calculating the conditional probability of occurrence of {Y} given {X}. *Lift* is a very literal term given to this measure. Think of it as the *lift* that {X} provides to our confidence for having {Y} on the cart. To rephrase, *lift* is the rise in probability of having {Y} on the cart with the knowledge of {X} being present over the probability of having {Y} on the cart without any knowledge about presence of {X}. Mathematically,

$$Lift(\{X\} \rightarrow \{Y\}) = \frac{(Transactions\ containing\ both\ X\ and\ Y)/(Transactions\ containing\ X)}{Fraction\ of\ transactions\ containing\ Y}$$

In cases where {X} actually leads to {Y} on the cart, value of lift will be greater than 1. Let us understand this with an example which will be continuation of the {Toothbrush} → {Milk} rule.

Probability of having milk on the cart with the knowledge that toothbrush is present (i.e. *confidence*) : 10/(10+4) = 0.7

Now to put this number in perspective, consider the probability of having milk on the cart without any knowledge about toothbrush: 80/100 = 0.8

These numbers show that having toothbrush on the cart actually reduces the probability of having milk on the cart to 0.7 from 0.8! This will be a lift of 0.7/0.8 = 0.87. Now that's more like the real picture. A value of lift less than 1 shows that having toothbrush on the cart does not increase the chances of occurrence of milk on the cart in spite of the rule showing a high confidence value. A value of lift greater than 1 vouches for high association between {Y} and {X}. More the value of lift, greater are the chances of preference to buy {Y} if the customer has already bought {X}. *Lift* is the measure that will help store managers to decide product placements on aisle.

Association Rule Mining

Now that we understand how to quantify the importance of association of products within an itemset, the next step is to generate rules from the entire

list of items and identify the most important ones. This is not as simple as it might sound. Supermarkets will have thousands of different products in store. After some simple calculations, it can be shown that just 10 products will lead to 57000 rules!! And this number increases exponentially with the increase in number of items. Finding lift values for each of these will get computationally very very expensive. How to deal with this problem? How to come up with a set of most important association rules to be considered? *Apriori algorithm* comes to our rescue for this.

Read more about Apriori algorithm and find answers to all the unanswered questions here in Part 2.

Please let me know of your thoughts/questions on this blog in the comments.

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Machine Learning Data Science Data Analysis Business Rules