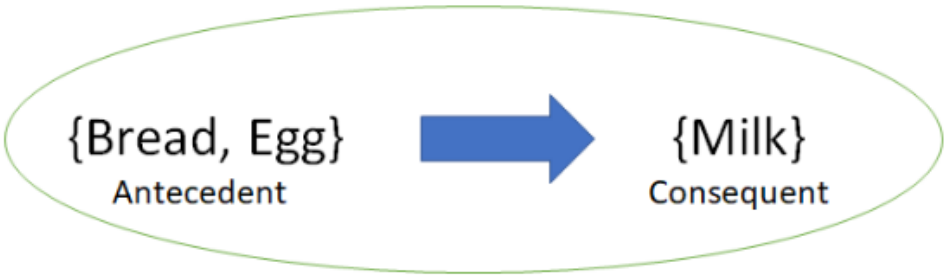
This is helpful in placement of products on aisles. On the other hand, collaborative filtering ties back all transactions corresponding to a user ID to identify similarity between users' preferences. This is helpful in recommending items on e-commerce websites, recommending songs on spotify, etc.

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.



Itemset = {Bread, Egg, Milk}

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.

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.

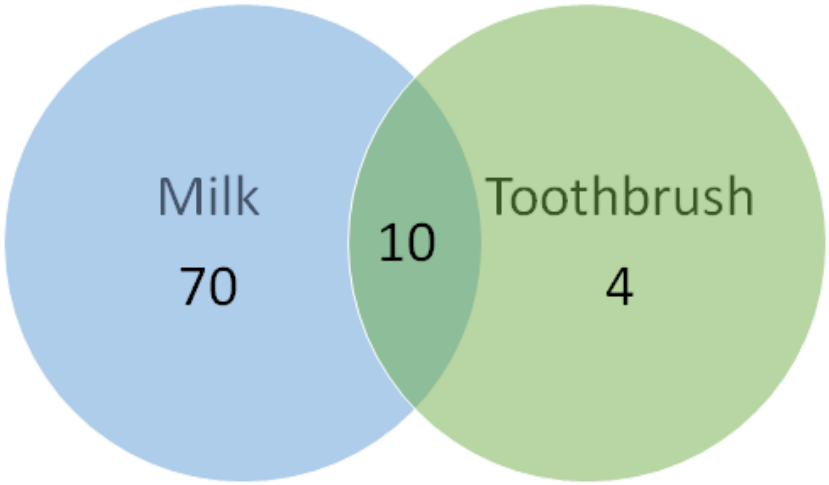
This measure defines the likeliness of occurrence of consequent on the cart given that the cart already has the antecedents. That is to answer the question — of all the transactions containing say, {Captain Crunch}, how many also had {Milk} on them? We can say by common knowledge that {Captain Crunch} → {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.

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.