

CSCI 4022 Spring 2021

nb0708 day. Announcements:

HW 3 Due Monday! Some **hints**:

Load nb0708

"kmeans" &amp; "EM"

Check out: companion notebooks with consolidated "solutions" to k-means and 1-Dim EM. This should make your "by-hand" implementations easier.

- 2a Sample covariance is almost the same calculation as sample variance! But you should do this by hand, since np.var/np.cov won't do probability-weighted calculations.  $mean: \frac{1}{n} \sum x_i \cdot p_i$
- 2b To compute distance-from-point-to-component, you can either choose **the most likely component** for a single distance, or do **probability weighted distance** to *all* components. The latter will perform better as  $k$  increases, since there will be more "uncertain" points. Or come up with your own distance measure!
- 3 It should not surprise you if plotting *mpg* versus *disp* makes unnormalized clusters **look** better than normalized clusters. You should already know why based on your answer in 3B! But consider other plots to demonstrate this, at least to yourself.

# Market Basket Analysis

**Definition:** The *support* for itemset  $I$  is the number of baskets that contain all items in  $I$ . Often, support is expressed as a fraction of the total number of baskets. Given a *support threshold*  $s$ , the sets of items that appear in at least  $s$  baskets are called *frequent itemsets*.

**Definition:** The *confidence* of the association rule  $I \rightarrow J$  is the ratio of the support for  $I \cup \{j\}$  to the support for  $I$ .

$$\text{conf}(I \rightarrow J) = \frac{\text{support}(I \cup \{j\})}{\text{support}(I)}$$

**Definition:** The *interest* of the association rule  $I \rightarrow J$  is the difference between its confidence and the fraction of baskets that contain  $j$  :

$$\text{interest}(I \rightarrow J) = \text{conf}(I \rightarrow J) - P(j)$$

## Association Rules: Top down

Suppose we have an assoc. rule  $I \rightarrow j$  with support  $s$ , and high confidence  $c$ . Then  $I \cup j$  has support of at least  $cs$  because

$$\text{conf}(I \rightarrow j) = \frac{\text{support}(I \cup \{j\})}{\text{support}(I)} \Leftrightarrow c = \frac{\text{support}(I \cup \{j\})}{s}$$

This suggests a top-down mining algorithm to list off rules given set frequencies.

1. Find all itemsets with support at least  $cs$  (Set 1)
2. Find all itemsets with support at least  $s$  (Set 2, which will be a subset of Set 1 since  $s \geq cs$ )
3. Loop: For each itemset  $J$  of Set 1...
  - 3.1 Consider the  $\text{support}(J) = s_2$  (we would have previously computed this)
  - 3.2 For each element  $j \in J$ , remove  $j$  and compute  $\text{support}(J - \{j\}) = s_1$
  - 3.3 If  $s_1/s_2 \geq c$  then  $J - \{j\} \rightarrow j$  is an acceptable association rule.

## Market Basket: Storing Counts

May be a preliminary step of data processing to encode names of items as numbers (e.g., through a bar code, or hash table). Then we store counts!

- The function:

$$a[k] = (i) \left( n - \frac{i+1}{2} \right) + j - i - 1$$

will (0-indexed) store item counts for the pair  $i, j$ , where  $1 \leq i < j \leq n$ . This is a **triangular array**, because it saves exactly the information of the upper triangle (column  $j >$  row  $i$ ) of a matrix where  $i, j$  is the support of  $\{i, j\}$ .

- Alternatively, store counts as a list of triples  $[i, j, c]$  where  $c$  is the count of  $\{i, j\}$ ,  $j > i$ .  
Upside here: no saving "0" when  $i$  and  $j$  don't ever overlap.

Usually we'll have to preface this with a hash table to translate items as they appear in a file to integers.

We deal with these concepts today in notebooks 7 and 8.