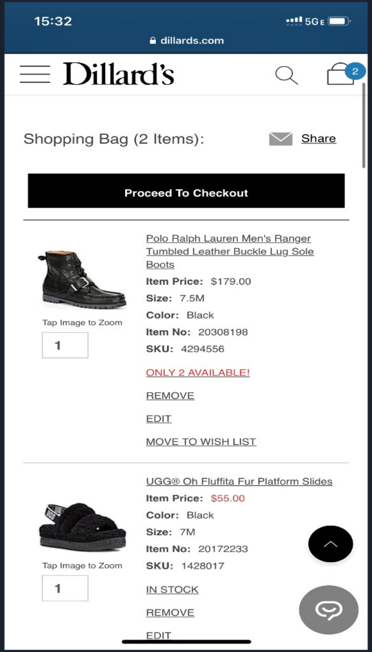
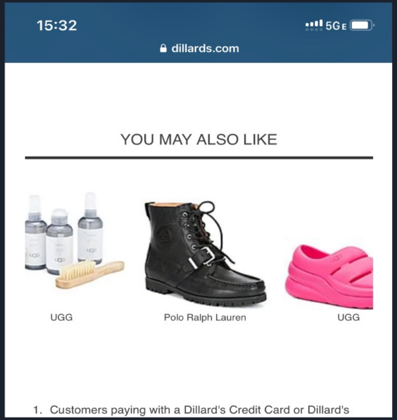
MSiA 400 Group 1

Product (SKU) Clustering for Dillard’s

Motivations: Dillards.com Today





- Completely **rule-based** recommendation system
- Only products from **same brands** as items in cart are recommended
- Very **similar** type of products
- Barely a personalized experience

Challenges: Why is making recommendations difficult for Dillard’s?

- **<u>Large data sets</u>**
  - Too much transactional data from various system databases

- **<u>Primarily offline stores</u>**
  - Limited access to customer data comparing to other ecommerce platforms
  - Difficult to track revealed preferences at customer level

Solutions

- **<u>Utilize POS data and master data on product (SKU)</u>**
  - Leverage relational database to join and perform analysis
  - Use SKU features to place products into clusters
  - Without customer-level purchase history data, recommend similar items to current transaction (at checkout or fitting stage)

Features of Choice

- **<u>Brand</u>**:

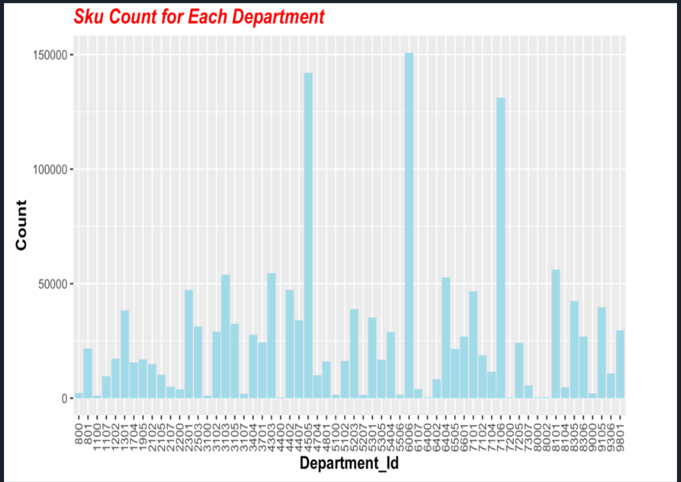
  - Good predictor as consumers tend to stick with certain brands.

  - But over 2000 factors, tough for one hot encoding

  - "**<u>Department</u>**" (60 columns) used instead to capture the features of "Brand"

Top Three:

	id [PK] bigint	dept_name character varying	count bigint
1	4505	POLOMEN	142108
2	6006	INVEST	150815
3	7106	BRIOSO	131106



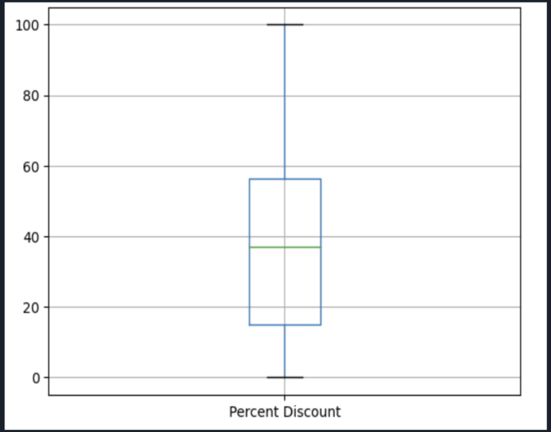
Features of Choice

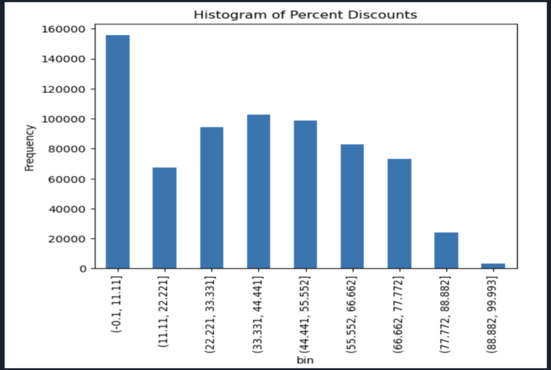
➢ When it comes to any form of business, money related topic never goes away:

- **Avg Price** : average price of each sku

- **Percent Discount**: the average discount percent of an item

- **Percent Return**: the average rate of return of an item





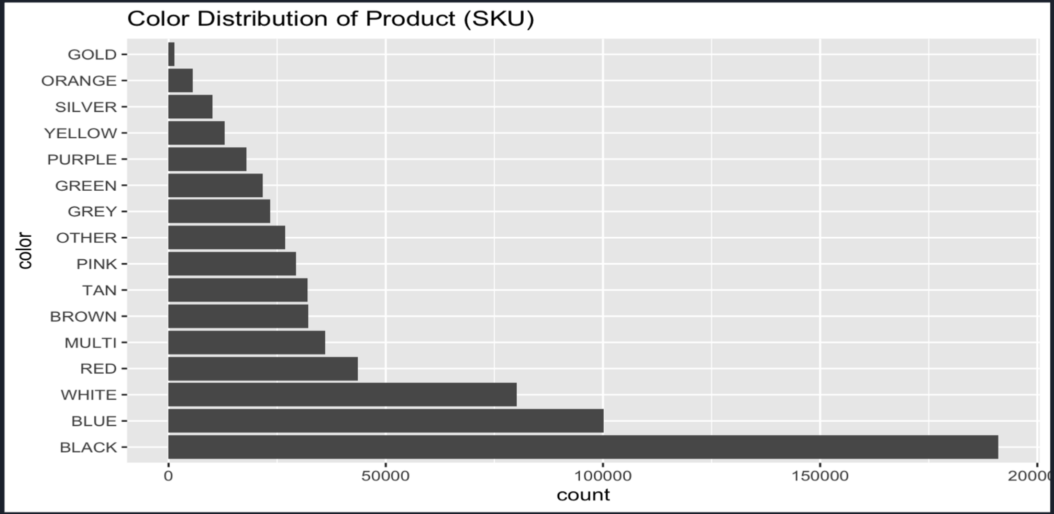
Features of Choice

➢ **<u>Color</u>**:

- Over 200 used colors in SKU, after one hot encoding too computationally intensive

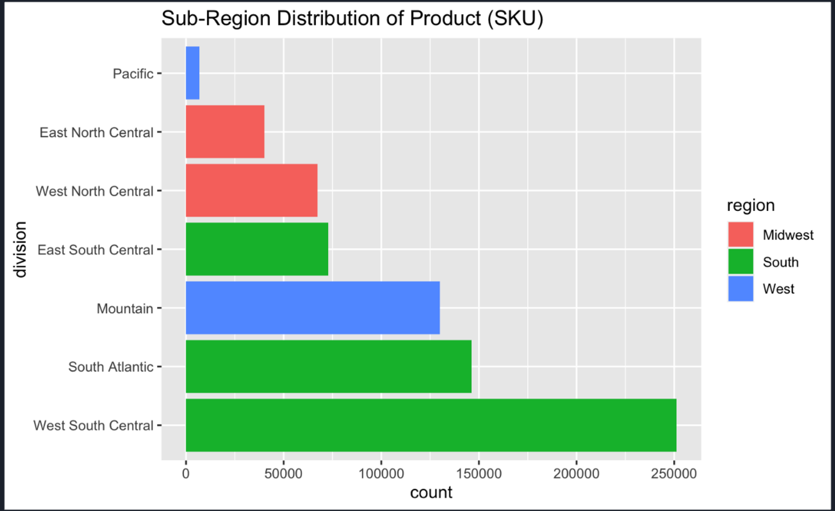
- Reduced to 17 most-common color groups

- Each sku assigned to a color



Features of Choice

- **Location**:
  - People in different regions might have entirely different preferences
  - For each product, find the state that the item was sold the most
  - Used a mapping table from US census to get the "Region"



Clustering Techniques - 1

Principal Component Analysis

- Breaks the features down into principal components such that each component is linearly independent of the other component
- Can explore it if more computational resources were available

K-Means Clustering

- Select the number of 7 groups with corresponding randomly initialized center points
- Classify each data point by computing its distance and repeat the steps till it converges or we reach the maximum number of iterations

Clustering Techniques - 2

Gaussian Mixture Modeling

- ❑ Assumes each data point from a gaussian distribution. There is a latent variable γ for each data point that determines which type of gaussian distribution was used.
- ❑ Similar to k-means, we assumed 7 clusters.

Hierarchical Clustering

- ❑ Computationally expensive. Cannot handle 680,000 rows. We ran it on 10000 rows and it gave 2 clusters
- ❑ We stop when the inertia by clusters elbows. We used 7 clusters in our analysis

Results - Illustrated

- Randomly select 25 skus and perform two clustering methods (K-means and GMM)

- The colored ones are the pairs that both algorithms put into the same cluster

sku	K-means Cluster	Gmm Labels
5157585	3	6
4786297	3	6
3558696	7	2
3829286	7	2
2528788	5	0
4192124	7	1
754438	2	6
6876630	1	1
5711256	1	1
9007336	6	2
7664037	4	6
8411572	4	6
2444420	5	1
5044109	3	1
4198166	7	6
2948120	7	6
3181271	7	5
3613505	7	5
5243871	3	2
9890968	6	4
5736285	1	2
50316	2	0
2474743	5	6
6988824	1	0

Use Case 1

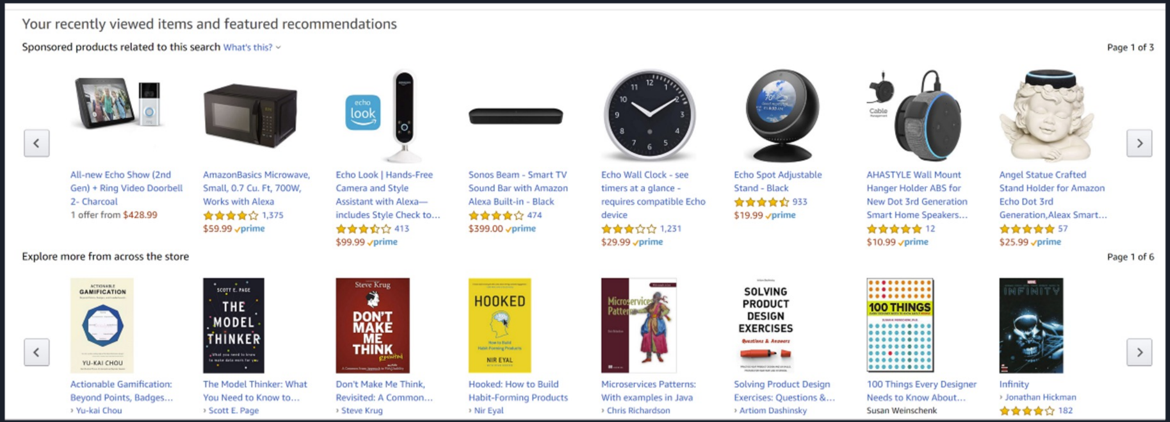
Physical Department Stores

- Sales reps scan QR code to get sku when customer takes an item to fitting room or checkout line
- System automatically recommends items from corresponding cluster
- Sales reps select items from clusters to recommend based on knowledge
- Record customer's decision for further data collection

Use Case 2

Dillards.com Online Store

- Replace current recommendation system with clustering-based system so that products in the same cluster as the items in the cart are recommended to the user
- Half of the results will use filter by the same brand to achieve at least similar success as the current baseline

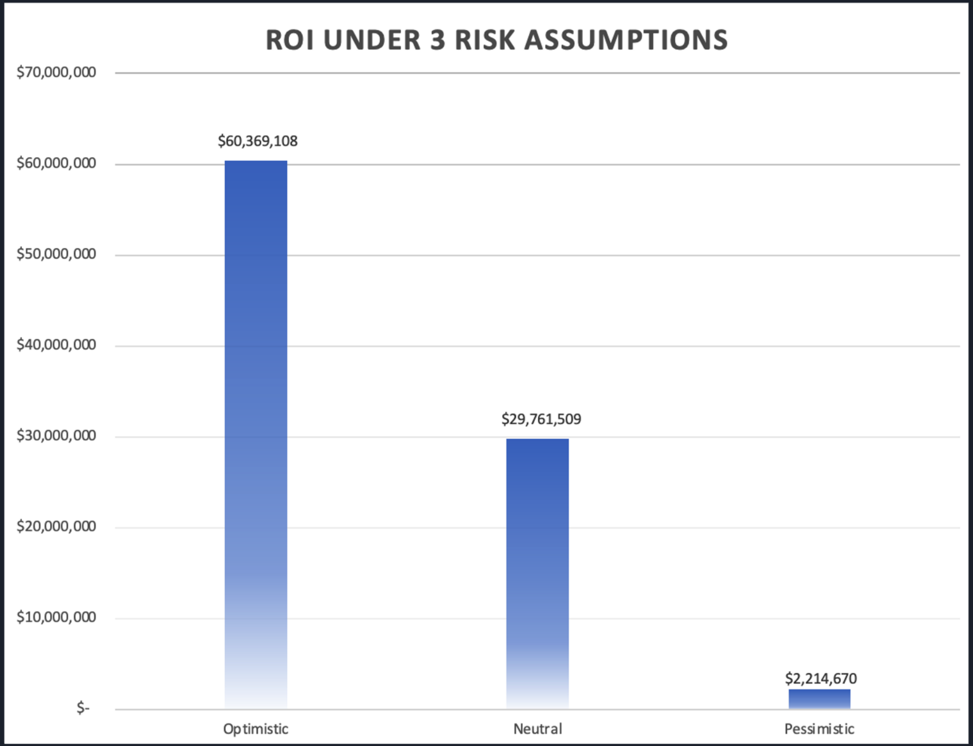


ROI

- Without A/B Testing results, we can only assume the lift percentage of implementing our model

- ROI Analysis constructed under 3 sets of assumptions:
  - ✓ Bull case: lift = 20%
  - ✓ Neutral case: lift = 10%
  - ✓ Bear case: lift = 1%

- Even under the bear case, the ROI amount is $2.2million dollars; ROI rate is 362%



Given More Time/Resources/Data....

If more time & resources are given:

- Use brand as feature.

  - More accurate cluster based on over 2000 brands

- Try hierarchical clustering on entire dataset

  - Obtain the optimal number of clusters, human intervention not required

  - Clear visualization from dendrograms, practical and easy to understand

- Get more and more recent data for training

  - Never a bad thing to have more data