# @ NYC Data Science Academy(15th September 2017)

# Sito Mobile Big Data Analysis

#### by

#### **Team Entropy**

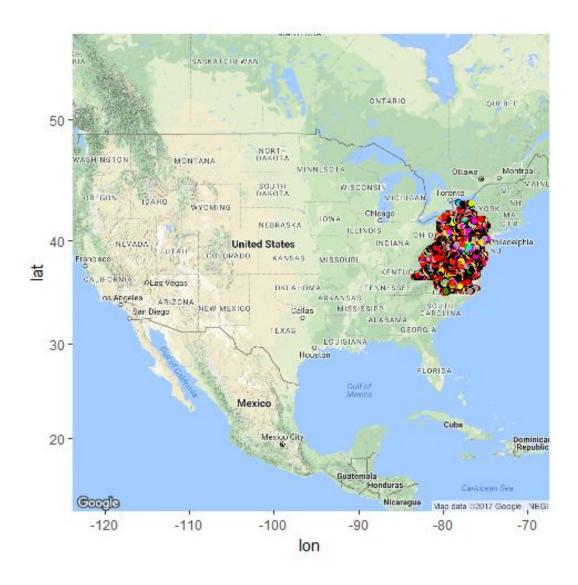
Yadi Li, Kumar Nathan, Wei Liu, Janet Hu and Andre Toujas

- I Overview
- **II** Exploratory Data Analysis
- **III Unsupervised Learning**
- **IV Supervised Learning**
- **V** Conclusions and Future Work

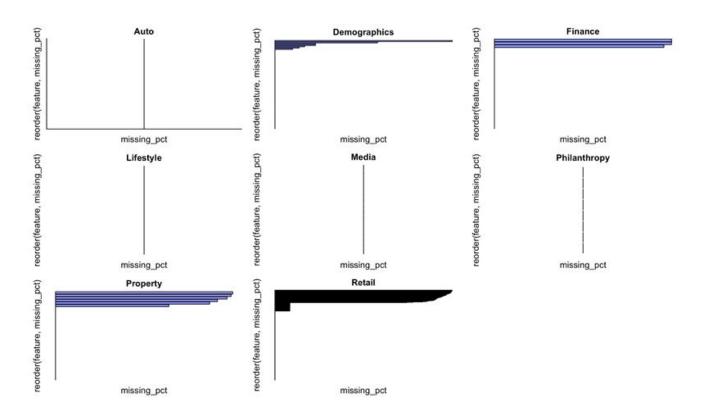
#### I Overview

- **Goal:** Customer Segmentation to provide business insights
- **Data:** ~150MM observations in 500+ Parquets
- **Parquet:** ~250K observations & 962 features (551 numerical)
- Strategy/Workflow:
  - a) Performed EDA on data set
  - b) Assigned verticals to features
  - c) Analyzed aggregate results in several parquets
  - d) Performed dimension reduction and clustering on entire parquets
  - e) Performed dimension reduction and clustering on each vertical category
  - f) Performed supervised learning to answer specific business-related questions

• Geospatial location of observations in Parquet 222 [similar pattern for other Parquets]

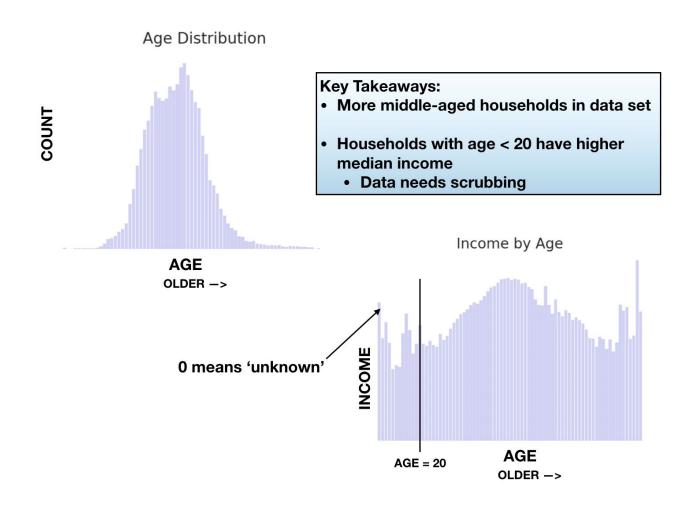


Missingness in the Dataset [Parquet 222]

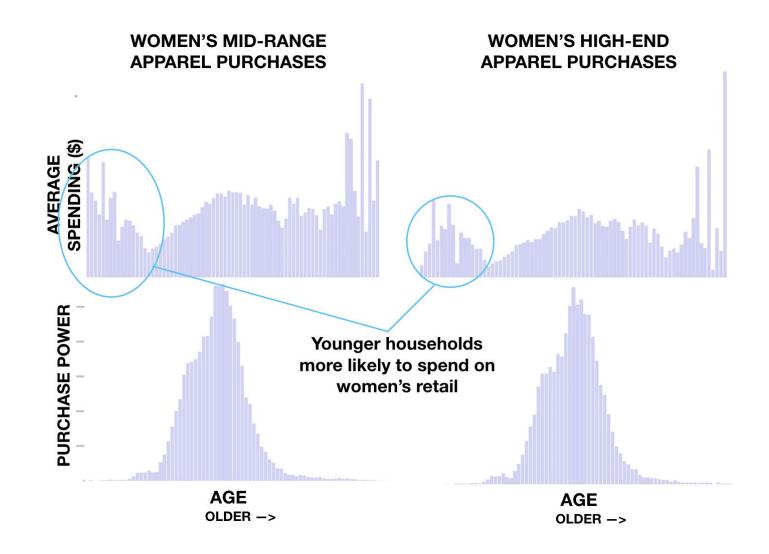


551 Numeric columns categorized into 8 verticals

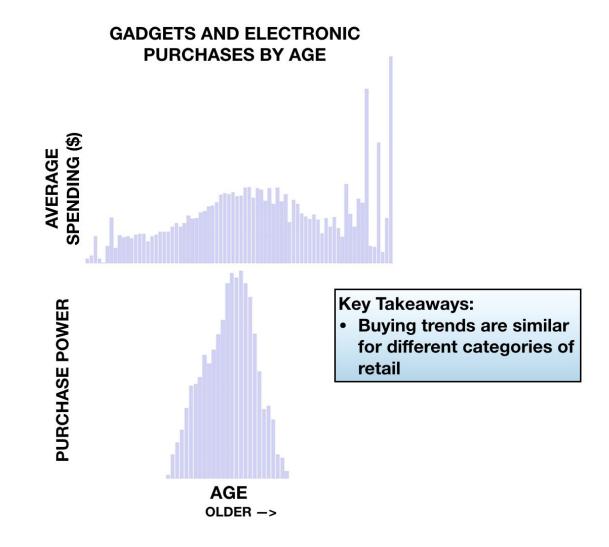
- Used grouping by household median age for example
- Example answers business-related questions
- Plotting functions created in Databricks for quick visualizations for future analysis



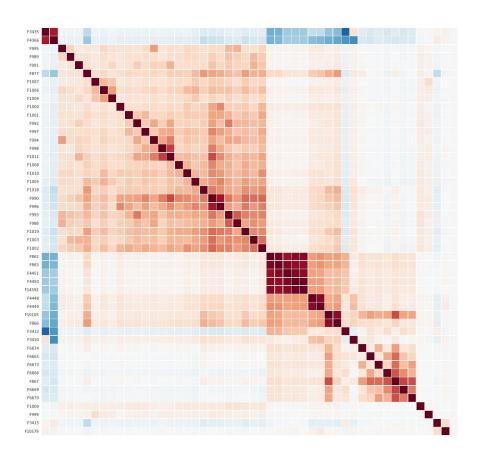
Women's Retail



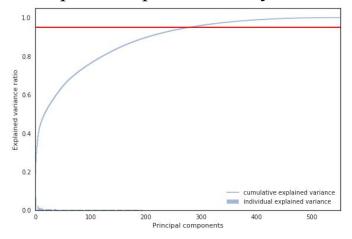
Electronics



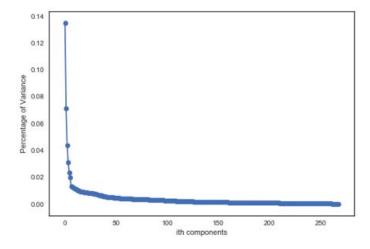
Correlation Analysis [Parquet 222]: Only the first 50 columns displayed



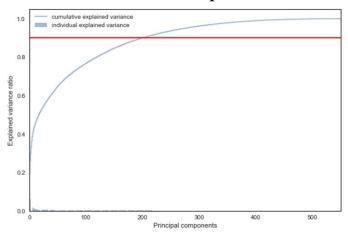
Principal Component Analysis on all the numerical features in the Parquet



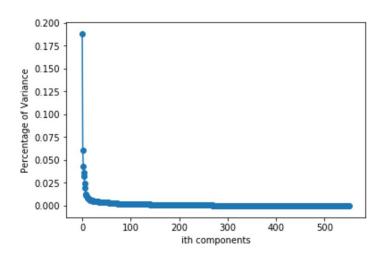
Parquet 11 204 out of the original 551



Parquet 20 204 out of the original 562

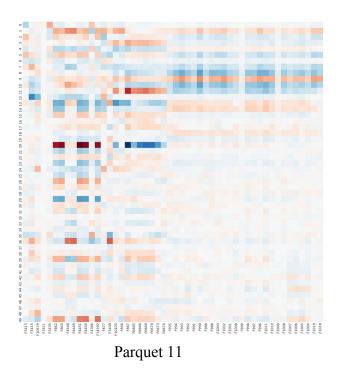


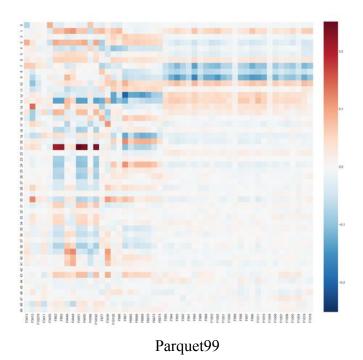
Parquet 99
201 Principal Components out of 551



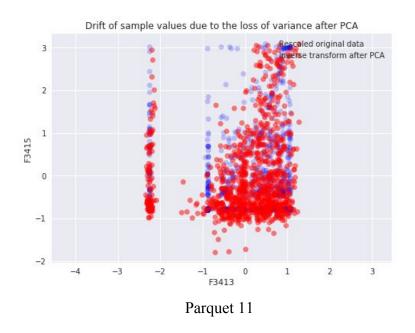
Parquet 490 194 out of the original 562

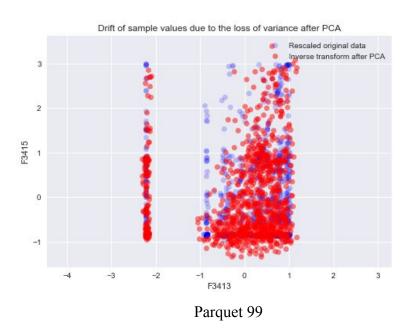
Principal Component Analysis on all the numerical features in the Parquet





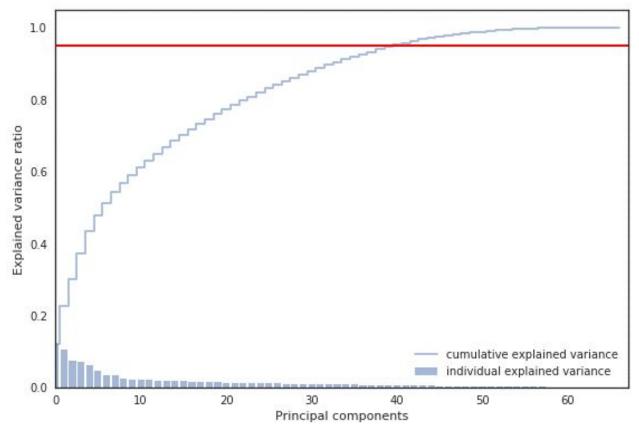
## Principal Component Analysis





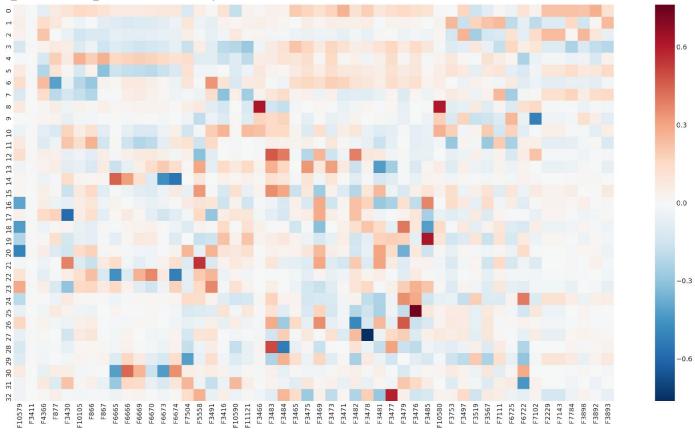
# III Unsupervised Learning [Vertical--Demographics, Paquet 222]

Principal Component Analysis [Partition 222]



## III Unsupervised Learning [Vertical--Demographics, Paquet 222]

Principal Component Analysis



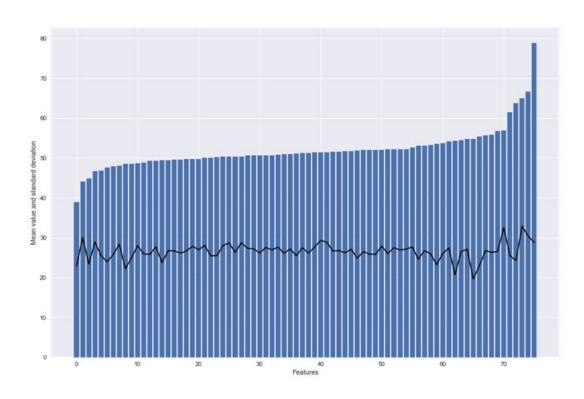
#### 1st pc:

- Number of Bathrooms
- Percentage of Households that are Married Couple Family Households with Presence of Persons Under 18

# Lifestyle Features

- Model predicted likelihood of households interests/activities
  - 63 columns
  - Numeric features, 0-99
  - 1: highest likelihood, 99: lowest likelihood
  - 0: unknown, replaced with 50
- Real data of household interests/activities
  - 202 columns
  - · Apparently from two different sources: self reported and survey data
  - Categorical features
  - Y: Yes(6.5%), U: unknown(66.6%), NA(26.9%)

#### **EDA** on numeric features



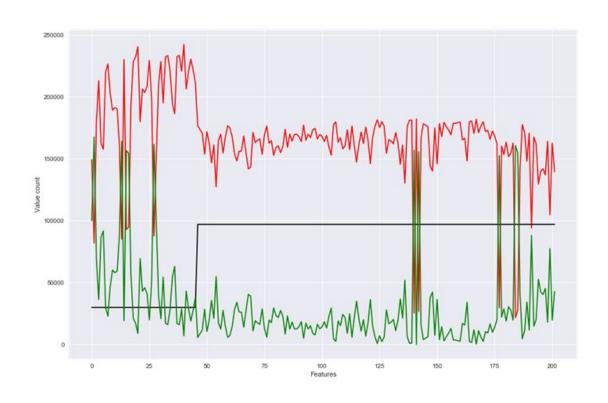
#### On average more likely:

- Hunting Enthusiasts
- Sweepstakes/Lottery
- Do-it-yourselfers

#### On average Less likely:

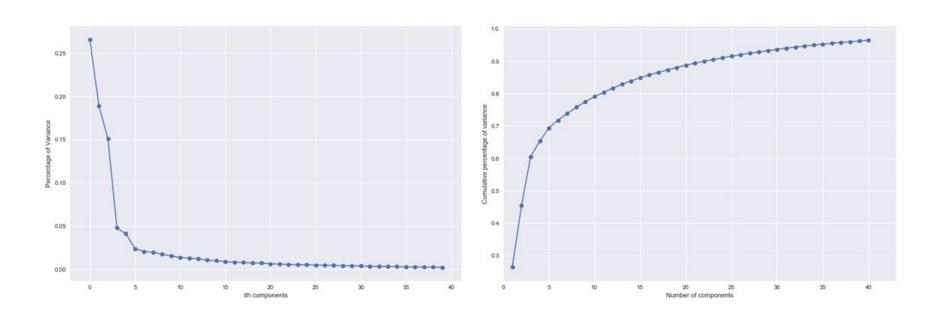
- Medicare Policy Holders
- High Frequency Business Traveler
- · Have Grandchildren
- Military Active
- Military Inactive

#### **EDA** on categorical features



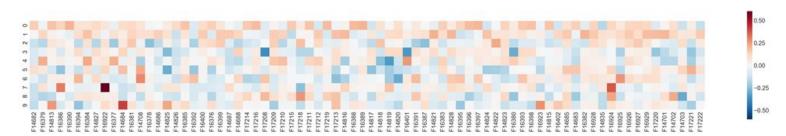
- Data clearly from two sources
- · Features that have more "Yes":
  - Computers/peripherals
  - Purchased through the mail
  - Internet/online subscriber
  - · Purchase via online
  - Hi-tech owner
  - PC & Internet:Own Computer
  - PC & Internet:Use Internet Servi
  - Info/Buying:Purc By Internet
  - Buying:By Catalog
  - Buying:By Internet

#### **PCA** on numeric features



The first 5 principal components seem to capture significant amount of variance

#### **Interpretation of principal components**



PC1: pop music, sports, education, young people

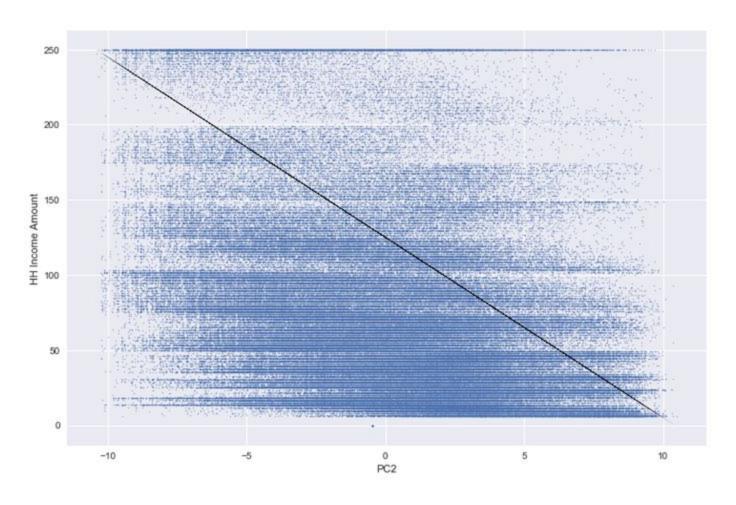
Attend/Order Educational Programs(F14813), Avid Runners(F16390), E-Book Reader(F16385), Listens to Alternative Music(F17216), Listens to Music(F17211), Listens to Pop Music(F17219), Music Download(F16388), Music Streaming(F16389), Plays Soccer(F16396), Plays Tennis(F16397), Snow Sports (F16393), Sports Enthusiast(F16398), Video Gamer(F14815), - Have Grandchildren (F14835)

· PC2: travel, golf, rock music, middle age rich

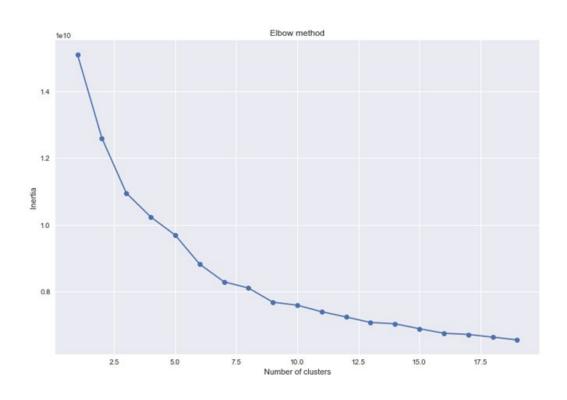
Book Reader(F16384), Healthy Living(F16399), Listens to Rock Music(F17213), MLB Enthusiast(F14816), PGA Tour Enthusiast(F14821), Play Golf(F14828), Political Viewing on TV - Conservative(F14824), Gardening(F16382), Hotel Guest Loyalty Program(F16929), Interest in Religion(F17220), Life Insurance Policy Holders (F14701)

- PC3: pet, outdoor, country music vs travel around the world
- PC4: religion, Christian music
- PC5: man vs woman

#### PC2 vs household income

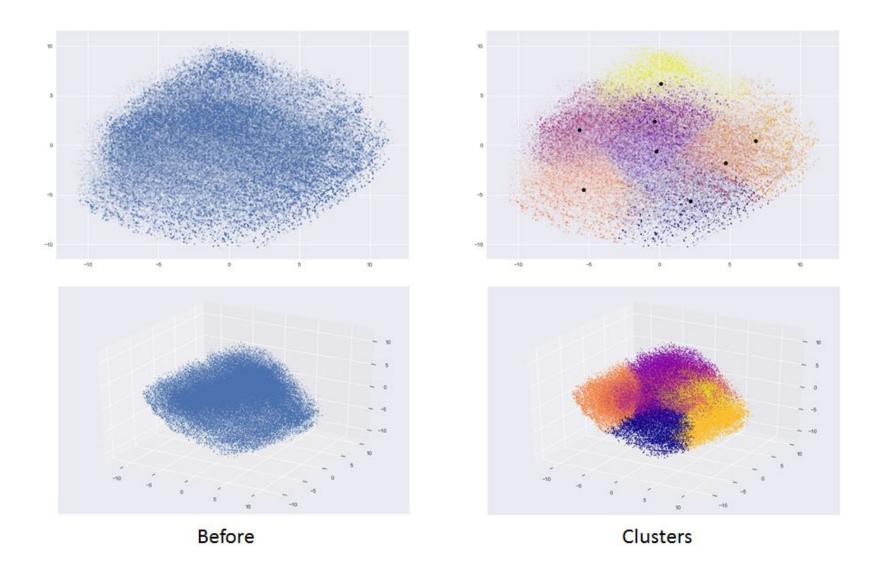


#### K-means Clustering using MiniBatchKMeans

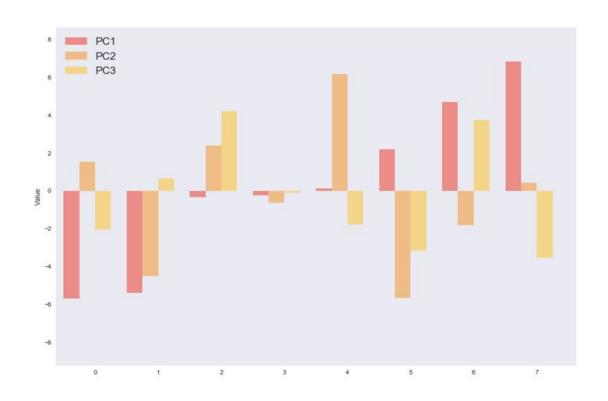


- MiniBatchKmeans is a variant of Kmeans
- uses mini-batches to reduce the computation time while still attempting to optimise the same objective function
- the quality of the results is reduced.
   In practice this difference in quality can be quite small

## Clusters (K = 8)



#### Visualization of clusters

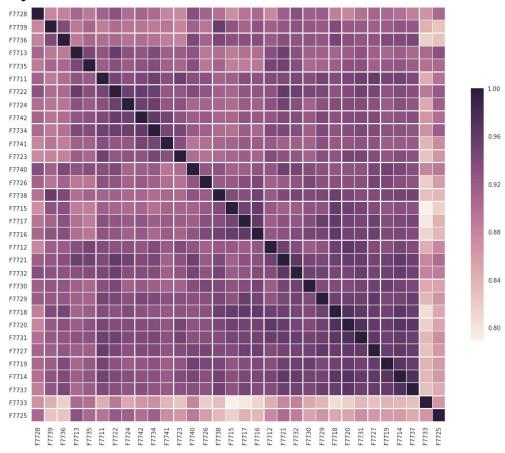


- Households in cluster 1 and 2 have young people who lives In parents house or has moved out
- Cluster 3,4,5 are households of people finished education and just started working
- Cluster 6,7,8 are households of parents and grandparents

#### **Checking the clusters**

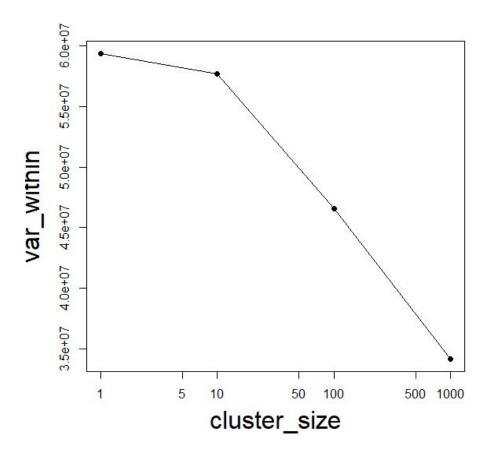
	F4810	F4850	F4855	F4871	F4874	F8975	F8977	F9253	F9269	F9273	pc1	pc2	рс3
clusters													
5	0.866611	0.895821	0.862190	0.855124	0.851912	0.896501	0.894234	0.888641	0.893213	0.898201	-5.816368	-4.656116	0.561528
0	0.508644	0.529893	0.513614	0.497599	0.494694	0.702783	0.699974	0.695460	0.700766	0.705712	-5.605243	1.524159	-1.607674
1	0.560203	0.571352	0.555362	0.546069	0.541811	0.612880	0.610512	0.603604	0.608463	0.618799	-0.264535	-0.088037	0.030486
3	0.452824	0.473940	0.453136	0.420885	0.412682	0.645442	0.639734	0.627632	0.638673	0.661317	0.339158	6.311155	-1.778416
7	0.578416	0.601865	0.577011	0.557001	0.546512	0.726357	0.721778	0.704288	0.718023	0.729288	0.444676	1.731120	5.011385
6	0.886030	0.898659	0.865793	0.854616	0.848419	0.892854	0.888579	0.878539	0.884618	0.909130	1.226509	-5.884211	-2.491926
2	0.832396	0.832759	0.811532	0.784789	0.768860	0.850484	0.841776	0.817464	0.830056	0.867611	5.536839	-2.086107	2.810786
4	0.690555	0.659001	0.643330	0.612164	0.603324	0.738026	0.731018	0.718481	0.726194	0.797788	6.664705	-0.054646	-3.993693

Correlation Analysis

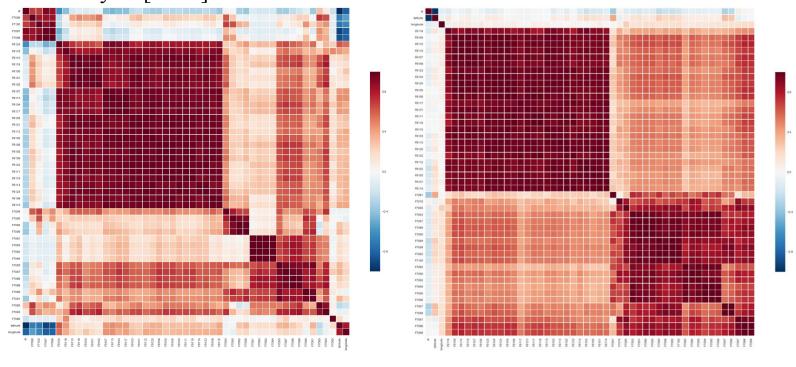


# **III Unsupervised Learning [Parquet 11]**

Cluster Analysis



• Cluster Analysis [k=14]



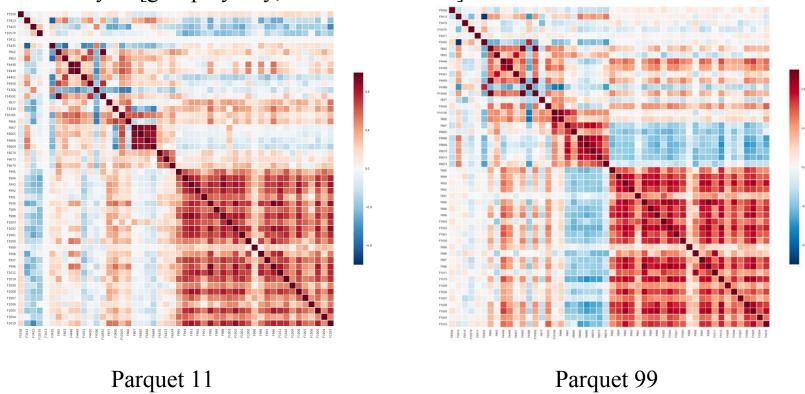
Parquet 11

Parquet 99

F9100 - F9124 Probability of purchase (clothes, furniture, pet supply, electronics)

F7079 - F7093 Total amount spent/ purchase frequency

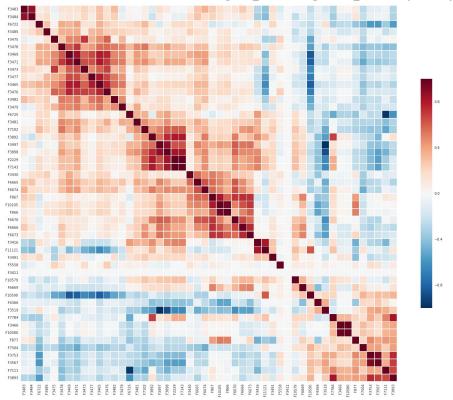
Cluster Analysis [group by city, 102 distinct cities]



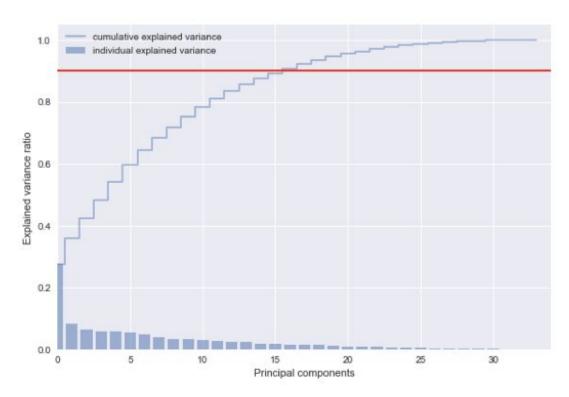
F995 - F1019: Number of times different categories are purchased

- Different cities have different income level (NYC-Upscale merchandise)
- Can be expanded in more detailed geospatial segmentation(zip code, communities)

Cluster Analysis [correlation of mean demographics grouped by city ]

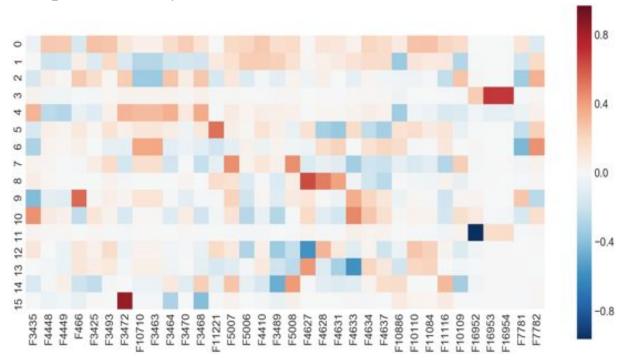


Principal Component Analysis [Partition 222]



16 out of 34 explain 90% of variance

Principal Component Analysis

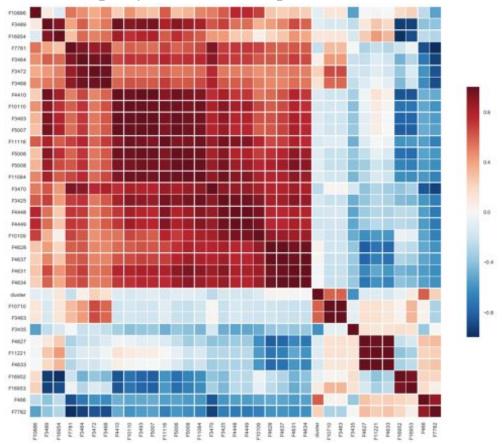


1st pc: monthly spending(mortgage, payment)

2nd pc: percentage(percentage of loan, percentage of total value)

## III Unsupervised Learning[Vertical--Property, Paquet 222]

Cluster Analysis [k=4, Property vertical, Parquet 222]

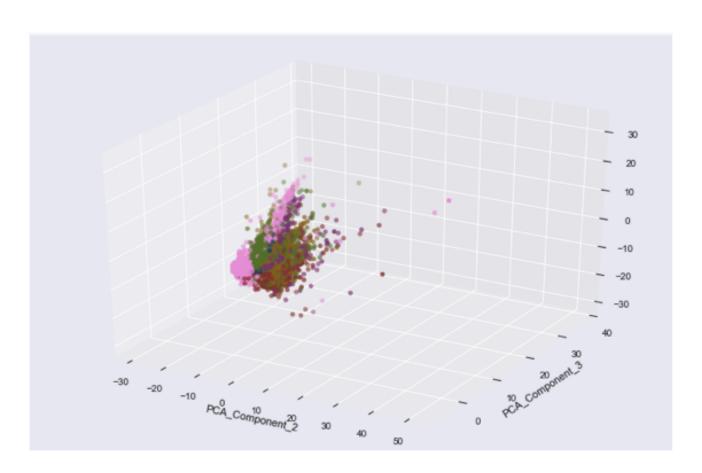


Positive: values(home value, mortgage amount)

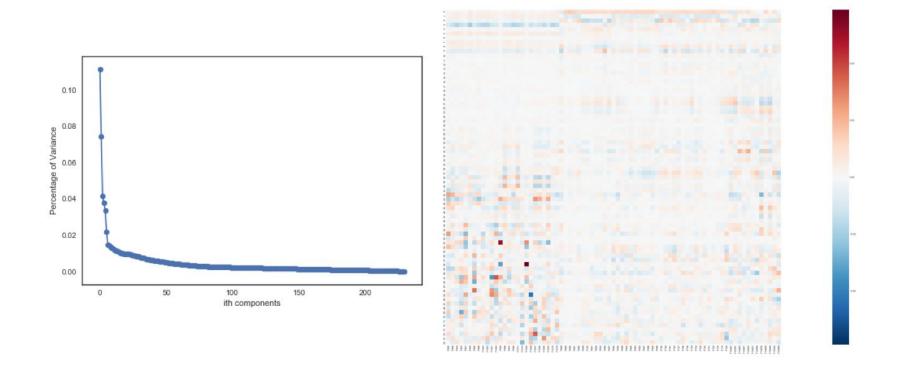
Negative: owner vs. renter(percentage owner occupied vs. percentage renter occupied)

# III Unsupervised Learning[Vertical--Property, Paquet 222]

Cluster Analysis [k=4, Property vertical, Parquet 222]
 Par222 Property Vertical Clustering Results



Principal Component Analysis [variance\_ratio=.80,n\_components=77]

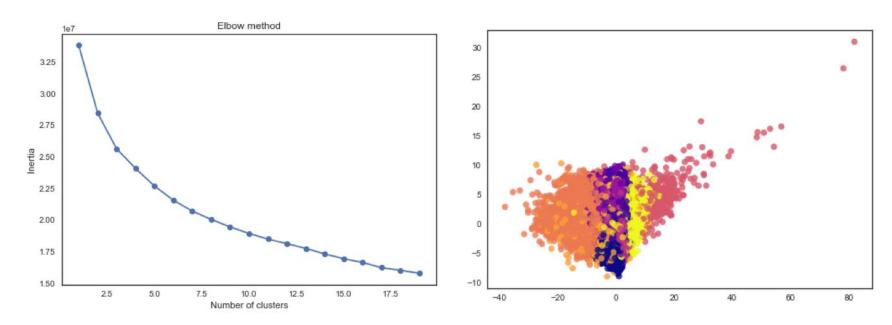


- Used PCA to do dimension reduction, contained 80% of information and picked 77 principal components.
- The heatmap of 77 principal components:

y axis: principal components--from 0 to 77

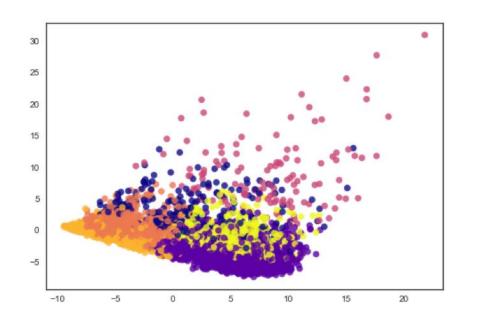
x axis: features of retail columns

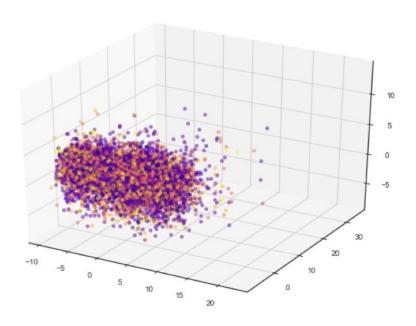
• Cluster Analysis [k:1~20, k=10]



- Cluster analysis based on the entire dataset and use principal component analysis results to visualize different group of clustering.
- Tested different choice of K, the right one is choosing 10 groups

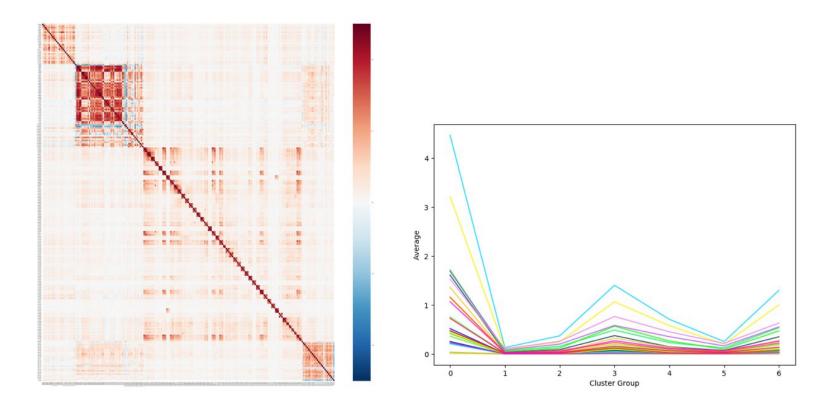
• Cluster Analysis [k=7, n\_components=77 (PCA)]





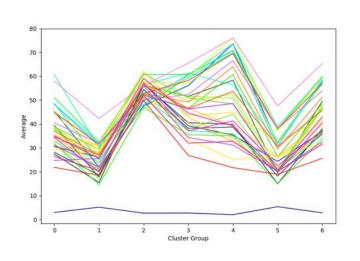
- Choosed 7 groups, and the left one is clustering distribution using the first principal component and the second principal component.
- 3D image of clustering distribution using the first, second and third principal component.

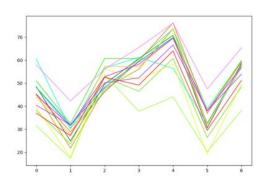
• Cluster Analysis [correlation map, k=7, mean, n\_colnums=26]

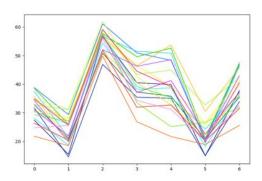


- Correlation analysis of all the retail columns, there are 4 obvious group of columns from the correlation plot.
- Labeled all the observations from clustering analysis, group by clustering label and get the mean value of each features
- The first group of correlation columns: 26 columns; MOR (Mail Order Responders)--the number of times people bought the products.
- Group 0,3,6 people much more frequency buying behavior than group 1,2,4, and 5

• Cluster Analysis [ k=7, mean, n\_colnums=39(17,21)]

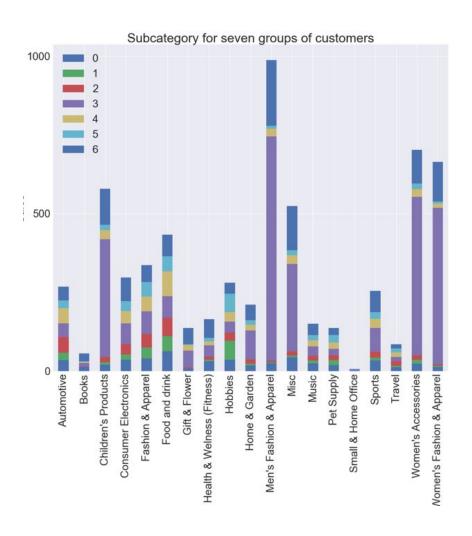






- The second group of correlation columns; subcategory: Auto; 39 columns; Model prediction of the likelihood of buying different types of cars
- The number of clustering group -- the mean value of each columns
- Two different behavior trends: group 2/group 4 shows the most likelihood of buying cars
- Group 2,3,4,6 show more interest and likelihood of buying cars than other groups

• Cluster Analysis Conclusion



- Group 3 customers have high buying power of women's and men's fashion and apparel, women's accessories and children's' products.
- Group 6 customers have high buying power of books, consumer electronics, health & wellness, music and sports.
- Group 5 customers have high buying power of hobbies and pet supply.
- Group 1 overall buying power smaller than other groups.
- Group 3 overall buying power larger than other groups.

- Chose subset of demographic columns
  - Columns selected based on data could be easily collected
  - o Proof of concept: can add more columns easily for better results
- Make predictions to answer business-related questions
  - o Predicted frequency households bought high-end women's retail
  - Classified median household income
  - Used Gradient Boosting Machine in Spark ML for regression
  - Used Random Forest Classifier for classification

#### **GRADIENT BOOSTING MACHINE**

TREE-BASED METHOD THAT BUILDS TREES SEQUENTIALLY

USES RESIDUAL INFO FROM PREVIOUS TREE TO FIT NEW TREE

USED K-FOLD (K=5) CROSS-VALIDATION GRID SEARCH

**USED MEAN AVERAGE ERROR (MAE) EVALUATION METRIC** 

ADVANTAGES	DISADVANTAGES				
Good predictive power	Needs CV to prevent overfitting				
Handles non-scaled data well	Computationally/time expensive				

RESULTS						
GBM	n_trees = 500 shrinkage = .001 Max depth = 15 Min obs in terminal node = 8	MAE = 1.4486				

#### **RANDOM FOREST CLASSIFIER**

TREE-BASED METHOD

RANDOMLY SAMPLES BOTH OBSERVATIONS AND FEATURES

USES ENSEMBLING PHILOSOPHY BY COMBINING WEAK LEARNERS AND AVERAGING RESULTS

#### **SEE CONFUSION MATRIX FOR RESULTS**

ADVANTAGES	DISADVANTAGES				
Good predictive power	Need lots of data				
Handles non-scaled data well	Computationally/time expensive				
Over-fitting not an issue	Results can vary due to random nature				

RESULTS						
RF Classifier	n_trees = 1000 Min obs in terminal node = 4 Feature Subset Strategy = 'auto'	See confusion matrix				

• Random Forest Classifier Confusion Matrix

# PREDICTED MEDIAN INCOME CLASSES

	F14593_index	0	2	3	5	6
	0	58731	2041	18220	2	2
ဂ္ဂ	1	44804	1020	11864	2	0
SSI	2	37297	2215	17029	1	1
CLASSES	3	16471	1358	30783	2	1
	4	30721	1098	10994	0	0
<u> </u>	5	21252	1292	19986	6	3
Z Z	6	21787	1230	17447	3	6
MEDIAN INCOME	7	29587	637	9204	1	1
	8	18607	377	4606	0	1
ACTUAL	9	11893	166	3169	0	0
Ę	10	10645	223	3829	1	0
⋖	11	7421	132	2447	0	0
	12	8115	50	1106	1	0

#### Key Takeaways:

- Add more columns for better results
- Class 0, 2, 3 majority classes predicted

#### V Conclusions

- Dimension reducing and clustering full parquet did not produce very interpretable results
- Clustering specific verticals produced more interpretable results
- Can find interesting patterns through EDA to gain business insight
- Subsetting data set to answer specific questions is a good strategy
- Findings from individual parquets similar and can be generalized to population

# QUESTIONS???