

## TARGET AUDIENCE FOR DIRECT MARKETING IN STARBUCKS REWARDS MOBILE APP

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# PROBLEM STATEMENT





Target Audience For A Marketing Campaign



#### **QUESTIONS:**

- Which Customers Love Coupons?
- Which Don't?
- What Types of Offers Send to Whom?



#### **SOLUTION:**

Customer
Segmentation
Using PCA & Kmeans Clustering



#### **METRICS:**

Response Rate (RR)
Conversion Rate (CVR)

## DATASET OVERVIEW



portfolio.json (10 offers x 6 fields)

- offer types sent during 30-day test period (bogo, discounts, informational offers)

profile.json (17000 users x 5 fields)

- demographic profile of app users (age, income, gender, membership duration)

transcript.json (306648 events x 4 fields)

- event log on transactions, tracking of offers received, viewed, completed

# DATA CLEANING

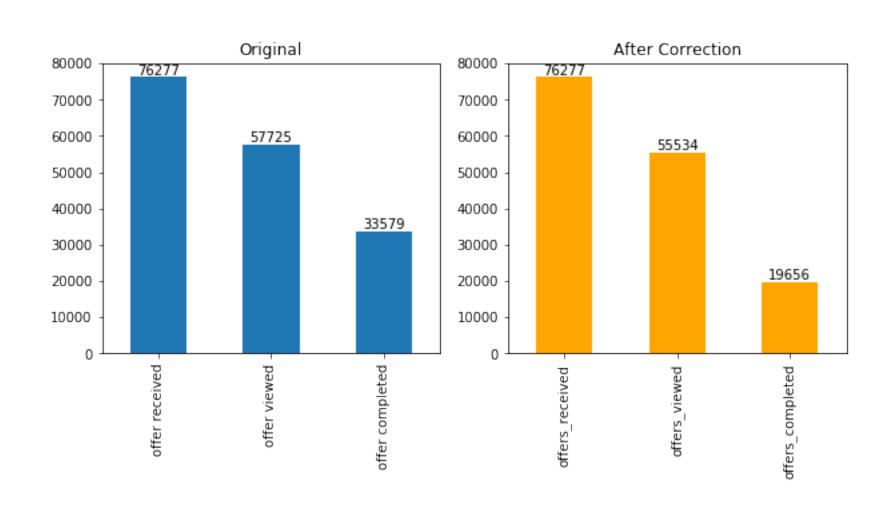




Challenge: improper tracking of offers viewed & offers completed

Impact: correct tracking could save \$70,000 per month

# DATA CLEANING RESULTS



# FEATURE ENGINEERING

Calculated 27 new Features for Each Customer

total\_amount

offers\_received

offers\_viewed

offers\_completed

transactions\_num

bogo\_received

bogo\_viewed

bogo\_completed

avg\_order\_size

discount\_received

discount\_viewed

discount\_completed

avg\_reward\_size

informational\_received

informational viewed

avg\_bogo\_size

avg\_discount\_size

total\_rewarded

total\_bogo

total\_discount

offers\_rr offers\_cvr bogo\_rr

discount\_rr

informational\_rr

fers\_cvr bogo\_cvr

discount\_cvr

# EXPLORATIVE DATA ANALYSIS

#### Average Starbucks Rewards App Customer:

- o middle-aged (median 55 years)
- \$64000 income
- spent \$104.44 in total
- o got \$5.6 rewarded
- o made 8 transactions spending \$13.34 per order
- o received 4-5 offers, viewed 3 offers, completed 1 offer

#### Metrics:

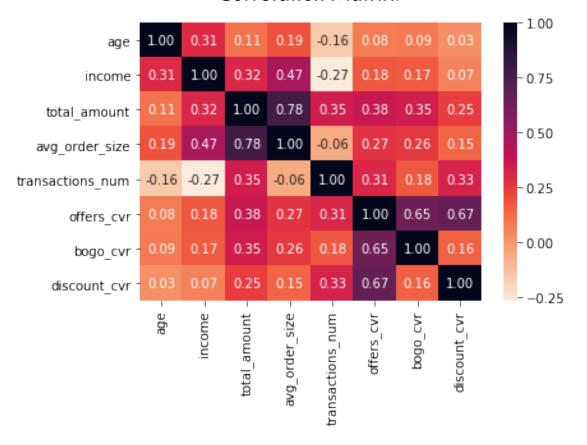
Response Rate (RR) - 73% of offers received

Conversion Rate (CVR) - 34% of offers viewed



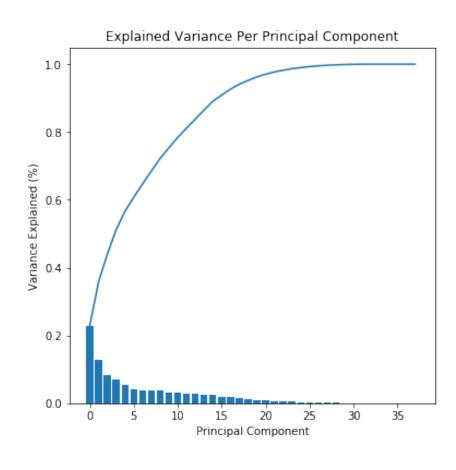
# **EXPLORATIVE DATA ANALYSIS**

#### **Correlation Matrix:**



Not demographics, but spending habits correlate more with Conversion Rates.

# DATA PRE-PROCESSING



Imputed Missing Values (12.8% of data in the profile dataset)

One Hot Encoded Categorical Features

Scaled Features with Standard Scaler

Reduced Dimensionality with PCA:

kept the first 10 components that in total captured almost 80% of the variance in the data.

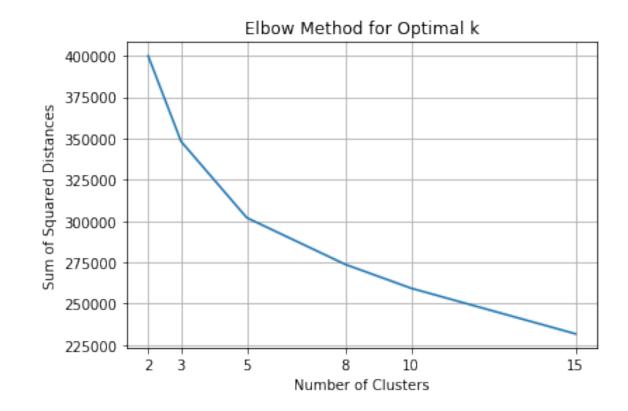
# MODELLING

Run K-Means Clustering on Pre-Processed Data

Decided upon Optimal Cluster Number:

- Elbow Method 3 or 5 clusters
- Silhouette Score for 3 higher than for 5
- Visual Validation 3 better than 5

Decision: 3 clusters



# MODELLING RESULTS

#### Cluster 1 - "Disinterested":

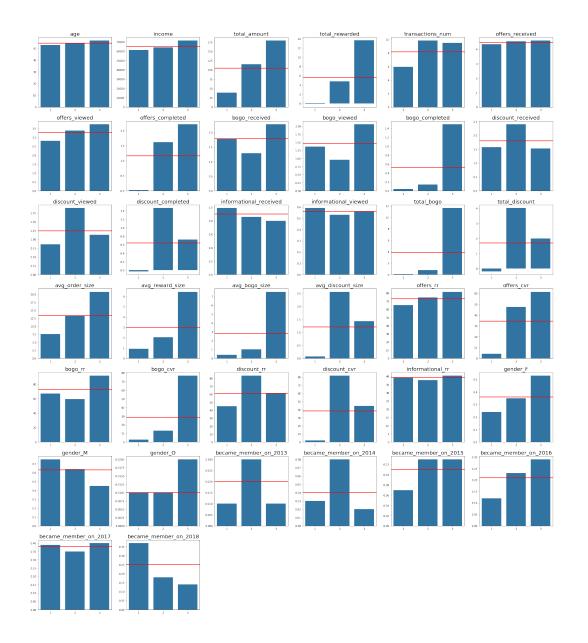
This group of customers are predominantly male that just recently became members. They tend to spend not much with below average number of transactions and small average order size. Although slightly more than 60% in this group view offers, they don't complete them.

#### Cluster 2 - "Discount-Type":

This group of customers are also mostly male but with the longest membership status (since 2013/2014). They tend to receive more discounts, which they love and actively complete. Their spending habits are slightly above average - they make small orders but buy frequently.

#### Cluster 3 - "Bogo-Type":

This is the only segment where female dominate over male. The customers in this group tend to be older and have higher income. They are loyal customers for few years already. They spend a lot - make huge orders and buy frequently. With such spending habits, no wonder that they are interested in bogo and get rewarded the most. They complete bogo offers way beyond average, but also react to discounts from time to time.



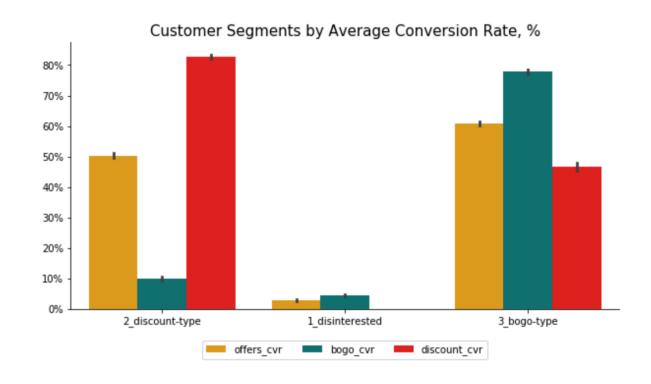
# BUSINESS CASE CONCLUSION

#### 3 Customer Segments:

- Disinterested (~40%)
- Discount-Type (~31%)
- Bogo-Type (~29%)

#### Next Step:

A/B testing with push notifications



# TECHNICAL CONCLUSION

#### Performed full Analysis Cycle

- o cleaning & preprocessing the data
- dealing with missing values
- feature engineering
- feature scaling
- one hot encoding
- dimensionality reduction
- clustering

**Automated Reporting by refactoring & writing functions** 

