# Customer Segmentation Analysis with **STARBUCKS**°



## Outline

The Problem

Data Cleaning & Wrangling

Clustering & Analysis

Conclusion & Recommendations



16,000,000

active members

**40%** 

of total sales from rewards program

Available on a mobile app to market products, send out offers, collect payments, and give rewards for freebies.



## The Problem

### **Problem statement**



Given the **diversity** in customer behavior, how can we identify and create experiences for **effective acquisition and retention**?

### **Problem statement**



**Customer Segmentation:** 

process of dividing customers into groups based on common characteristics

### **Problem statement**

How can we use unsupervised machine learning to segment our customers?



#### Marketing

- What offers should be sent to each customer?

#### Sales

- Which customers we should focus for retention?
- Who are our most profitable customers?
- Which customers to nurture or focus for potential growth?

## Data Cleaning & Wrangling

### **Dataset**

#### Raw Dataset

#### promotion.json:

10 promotional offers metadata:

BOGO, discount, informational

#### profile.json:

17,000 customer demographics:

age, income, gender, date as member

#### event-log.json:

306,534 timed customer activity

logs: transactions, offers

received, viewed, completed

### **Dataset**

#### Raw Dataset

#### promotion.json:

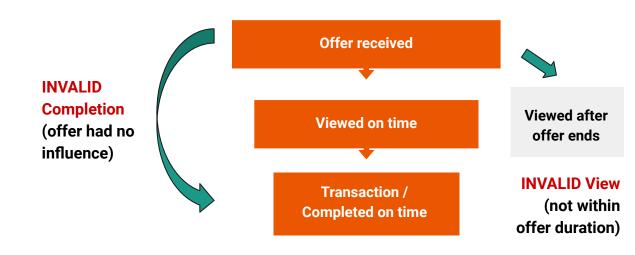
10 promotional offers metadata: **BOGO, discount, informational** 

#### profile.json:

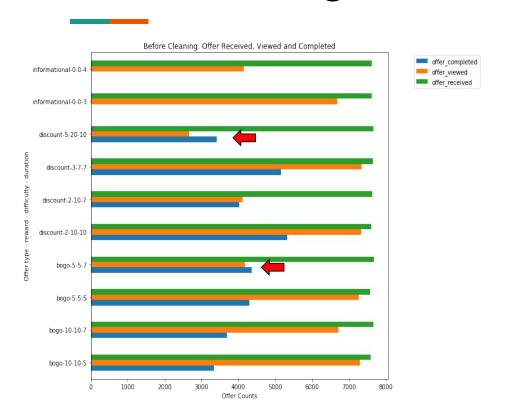
17,000 customer demographics: age, income, gender, date as member

#### event-log.json:

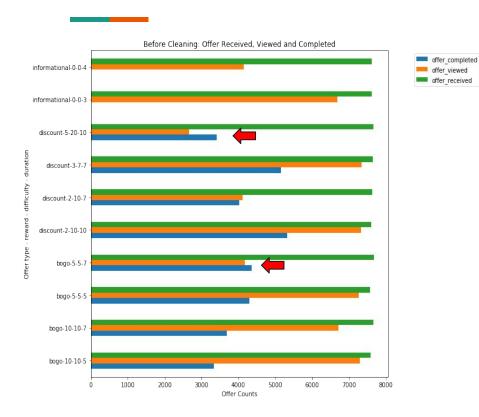
306,534 customer timed activity logs: transactions, offers received, viewed, completed

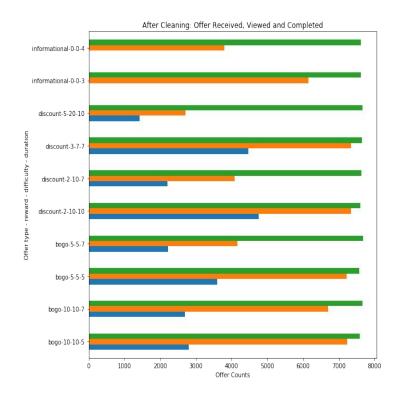


## **Data Cleaning**

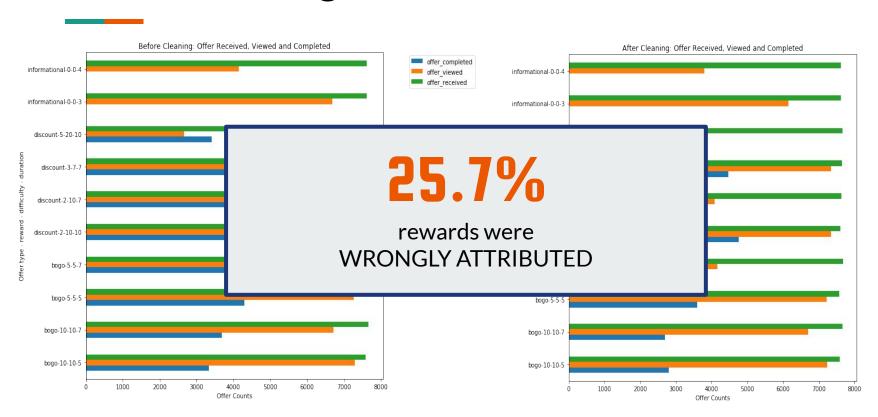


## **Data Cleaning**





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### **Dataset**

#### Raw Dataset

#### Cleaning & Preprocessing

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306,534 customer timed activity logs: transactions, offers received, viewed, completed

- Misattributions: identify valid views, valid completions
- Repeat exposures to same offers by assigning unique offer ids

#### **Features engineered:**

- Days as member
- Viewed rates, conversion rates for each offer type
- Total spent and number of transactions (offer and non-offer related)
- Recency

### **Dataset**

Raw Dataset Cleaning & Preprocessing

Final Dataset

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#### Features engineered:

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Aggregate all into a final customer-centric dataset

**Each unique customer:** demographics, spendings, behaviours

**Total 37 features** 

## **Clustering & Analysis**

## Clustering: Feature Selection & Scaling



#### **View Rates:**

bogo\_viewed\_rate, discount\_viewed\_rate, info\_viewed\_rate



#### **Conversion Rates:**

bogo\_conversion\_rate,
discount conversion rate



#### **Rewards:**

total\_rewarded



#### **Frequency / number of transactions:**

offer\_num\_transactions, actual\_num\_transactions



#### Monetary / amount spent:

offer\_spent, actual\_spent

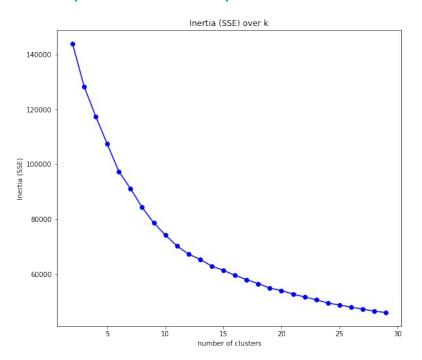


#### Recency / last visit:

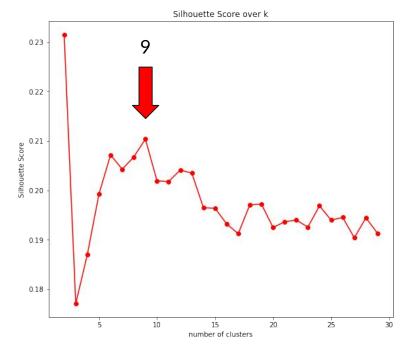
recency

### Clustering: Searching for optimal number of clusters

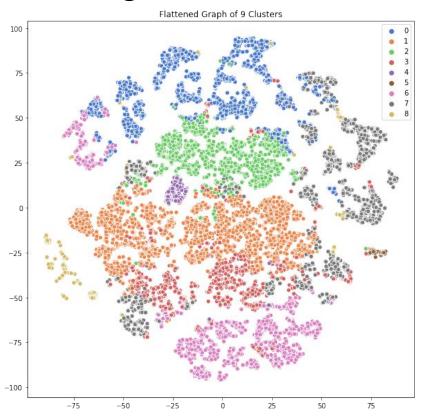
#### **Inertia (Intracluster distance)**



#### **Silhouette (Intercluster distance)**



## **Clustering:** Running K-Means & Visualizing Clusters



### Cluster Analysis: What offers to send to our customers?





**BOGO & DISCOUNT**: Cluster 1, 4, 5, 7, 8



BOGO only: Cluster 2



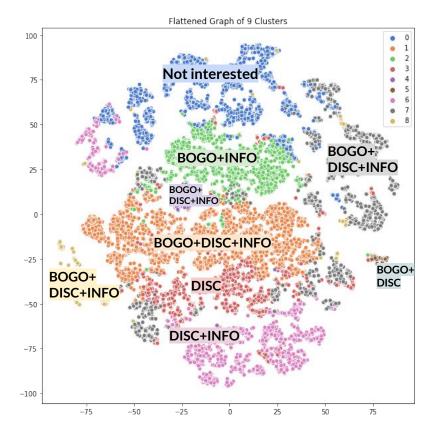
**DISCOUNT only**: Cluster 3, 6



**INFORMATIONAL**: All clusters except 3 and 5



**NOT INTERESTED (YET)**: Cluster 0



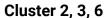
### Cluster Analysis: Who are our most profitable customers?



**Cluster 1, 4, 5** 

- Common: older age, high income, long-time members.
- Usual offers + make them feel exclusive





- Common: **long-time** members
- Continue **engaging**, ensure positive experience.



#### Cluster 0, 7, 8

- Common: newer members.
- Reengage, drive subsequent purchases, **retention** is important.

### Cluster Analysis: Which customers to focus for potential growth?



## Similar attributes to clusters in higher profitability levels

#### Cluster 0 & 7

- Key difference: **very new members.**
- Already have the interest / desire in our offers, we want to develop and nurture them into the mid-profitability range with time.

#### Cluster 2

- Key difference: not receiving as much offers
- Send more offers to engage better



## Interested, frequent but no spending power yet

#### Cluster 3

- Younger and lowest income.
- Assuming the natural trend: incomes increases as they gain work experience, this cluster would potentially develop into the high-profitability section.

## **Conclusion & Recommendations**

## **Key Findings:**

- Using offers to quickly generate additional revenue when needed

Non-offer transactions = ~\$12 spent per transaction

Offer-related transactions = ~\$20 spent per transaction

- Improve marketing focus
- Most and least profitable customers segments
- 4 pockets of potential growth

### Limitations

- Missing demographics in 12.8% of our customers.
- Identifying misattributions
- Dataset across 30-day test period only
- No information on how the data was collected

## **Next Steps**

- Explore other clustering algorithm
- Identify the influence of channels
- Explore influence of informational offers
- Explore the impact of offer attributes
- Building prediction models: predicting customer response to offers, customer lifetime value prediction, churn prediction, next purchase day

## Thank you.