# Customer Segmentation Analysis with **STARBUCKS**°



# Outline

The Problem

Data Cleaning and Wrangling

K-Means Clustering

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**

The 'average customer' is a concept of the past.

Hitting the average does not mean hitting the majority, and this one-size-fits-all strategy **does not work** anymore.

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

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### **Customer Segmentation:**

process of dividing customers into groups based on common characteristics

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**

#### **Initial 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**

#### **Initial Dataset**

#### promotion.json:

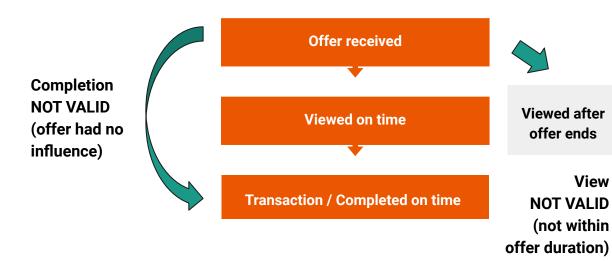
10 promotional offers metadata: **BOGO, discount, informational** 

#### profile.json:

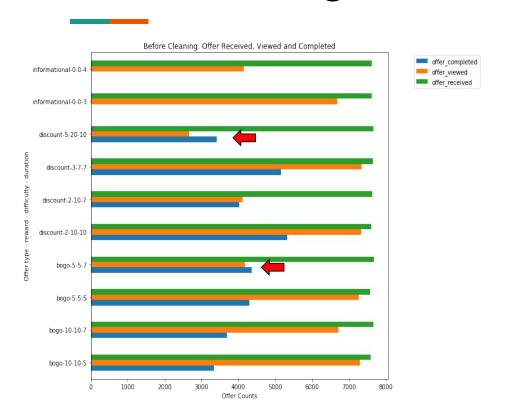
17,000 customer demographics: age, income, gender, date as member

#### event-log.json:

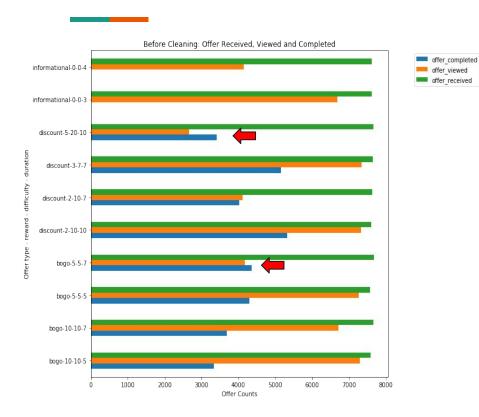
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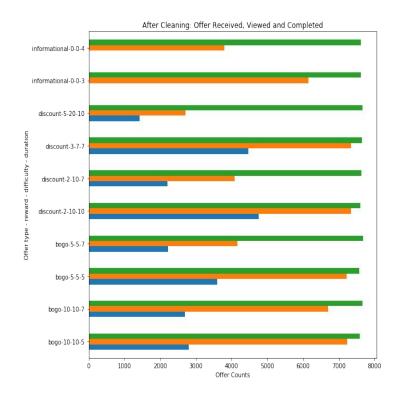


# **Data Cleaning**

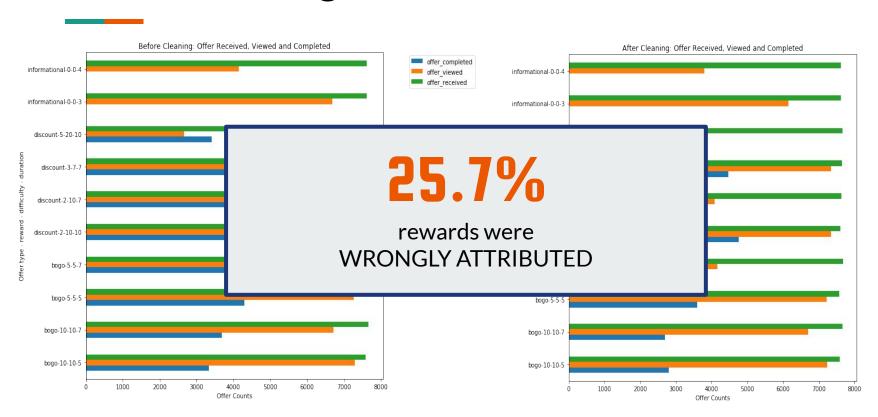


# **Data Cleaning**





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### **Dataset**

#### **Initial Dataset**

#### Cleaning & Preprocessing

#### promotion.json:

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#### event-log.json:

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

- Valid views (viewed within offer duration)
- Valid completions
   (completed after viewing)
- 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**

**Initial Dataset** 

#### Cleaning & Preprocessing

**Final 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** 

- Valid views (viewed within offer duration)
- Valid completions (completed after viewing)
- Identifying repeat exposures to same offers by assigning unique offer ids

#### **Features engineered:**

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

Aggregate all into a final customer-centric dataset

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

Total 37 features

# **K-Means Clustering**

### 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

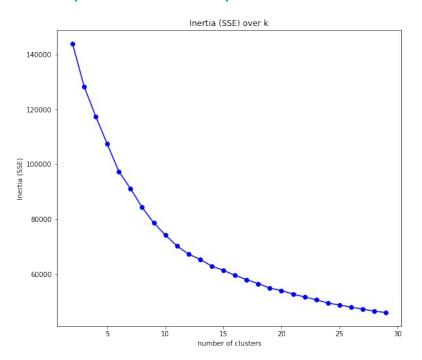


#### Recency / last visit:

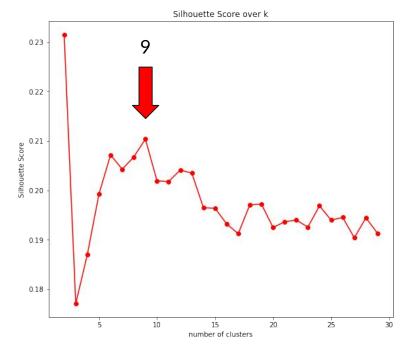
recency

### Clustering: Searching for optimal number of clusters

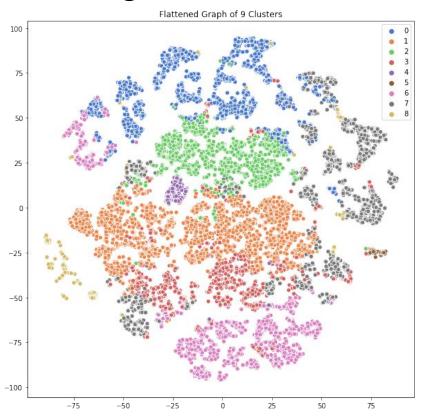
#### **Inertia (Intracluster distance)**



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



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



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



View rates, conversion rates, offer-related transactions and spent, rewards

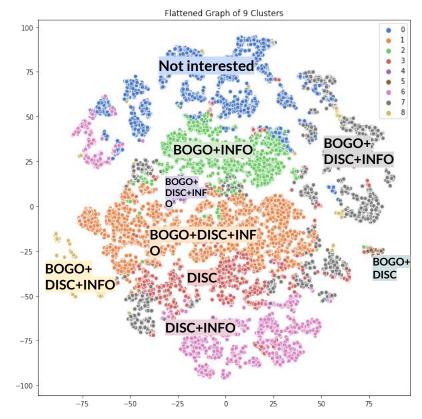
**BOGO & DISCOUNT**: Cluster 1, 4, 5, 7, 8

**BOGO only**: Cluster 2

**DISCOUNT only**: Cluster 3, 6

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

**NOT INTERESTED**: Cluster 0



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



#### Total spent



**Cluster 1, 4, 5** 

- Common: older age, high income, long-time members.
- Other than the usual offers, it is important to make them feel exclusive and special such as tiered benefits.



#### **Cluster 2, 3, 6**

- Common: **long-time** members
- We want to continue engaging them and making sure of a positive experience.



#### Cluster 0, 7, 8

- Common: newer members.
- Reengage and drive subsequent purchases in these segments. Retention is important.

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



# Similar attributes to clusters in higher profitability levels

#### Cluster 0 & 7 (in low-profitability)

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

#### Cluster 2 (in mid-profitability)

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

#### Interested, frequent but no spending power yet

#### **Cluster 3 (in mid-profitability)**

- 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:
- 117k non-offer transactions = avg \$11.46 spent per transaction 22k offer-related transactions = avg \$19.73 spent per transaction
- **Improve marketing focus**: Push offers only to segments that resonate better with specific offers, optimizing our costs.
- Most and least profitable customers: who to focus for retention, for maintaining the relationship / keeping them happy while increasing their purchases.
- **Pockets of potential growth**: Shifting customers from 4 segments into more profitable segments.

### Limitations

- Missing demographics in 12.8% of our customers.
- **Identifying misattributions:** confirming offer completions using separate redemption mechanisms (rather than auto) in the app or implement a tracking system.
- Dataset across 30-day test period only: unable to identify the spending patterns prior to this.
- No information on how the data was collected

## **Next Steps**

- Explore other clustering algorithm: hierarchical clustering
- Identify the influence of channels: tracking source of each activity
- Explore influence of informational offers
- Explore the impact of offer attributes (duration, rewards, difficulty)
- Building prediction models: predicting customer response to offers, customer lifetime value prediction, churn prediction, next purchase day

# Thank you.