# Udacity

Project: Capstone Project Starbucks

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# Contents

## Introduction:

This project uses a Starbucks dataset to create personalized suggestions based on how well various offers work in an effort to increase sales. Businesses can optimize revenue production by effectively allocating resources and customizing promotions by identifying which offers provide the biggest gains. This is an important effort that will increase profitability and improve customer happiness by using targeted marketing strategies.

## Description of Input Data:

The portfolio.json file contains metadata about each offer, including offer IDs, offer types (e.g., BOGO, discount), minimum required spend (difficulty), reward, duration of the offer, and channels through which the offer is distributed. The profile.json file provides demographic data for each customer, such as age, gender, customer ID, income, and the date when the customer created an app account. The transcript.json file records various events, including transactions, offers received, offers viewed, and offers completed. Each record includes details such as event type, customer ID, time of the event, and value (either an offer ID or transaction amount).

### Portfolio

| | reward | channels | difficulty | duration | offer_type | id |
|---|---|---|---|---|---|---|
| 0 | 10 | [email, mobile, social] | 10 | 7 | bogo | ae264e3637204a6fb9bb56bc8210ddfd |
| 1 | 10 | [web, email, mobile, social] | 10 | 5 | bogo | 4d5c57ea9a6940dd891ad53e9dbe8da0 |
| 2 | 0 | [web, email, mobile] | 0 | 4 | informational | 3f207df678b143eea3cee63160fa8bed |
| 3 | 5 | [web, email, mobile] | 5 | 7 | bogo | 9b98b8c7a33c4b65b9aebfe6a799e6d9 |
| 4 | 5 | [web, email] | 20 | 10 | discount | 0b1e1539f2cc45b7b9fa7c272da2e1d7 |

### Profile

| | gender | age | id | became_member_on | income |
|---|---|---|---|---|---|
| 0 | None | 118 | 68be06ca386d4c31939f3a4f0e3dd783 | 20170212 | NaN |
| 1 | F | 55 | 0610b486422d4921ae7d2bf64640c50b | 20170715 | 112000.0 |
| 2 | None | 118 | 38fe809add3b4fcf9315a9694bb96ff5 | 20180712 | NaN |
| 3 | F | 75 | 78afa995795e4d85b5d9ceeca43f5fef | 20170509 | 100000.0 |
| 4 | None | 118 | a03223e636434f42ac4c3df47e8bac43 | 20170804 | NaN |

### Transcript

| | person | event | value | time |
|---|---|---|---|---|
| 0 | 78afa995795e4d85b5d9ceeca43f5fef | offer received | {'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'} | 0 |
| 1 | a03223e636434f42ac4c3df47e8bac43 | offer received | {'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'} | 0 |
| 2 | e2127556f4f64592b11af22de27a7932 | offer received | {'offer id': '2906b810c7d4411798c6938adc9daaa5'} | 0 |
| 3 | 8ec6ce2a7e7949b1bf142def7d0e0586 | offer received | {'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'} | 0 |
| 4 | 68617ca6246f4fbc85e91a2a49552598 | offer received | {'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'} | 0 |

## Strategy for solving the problem:

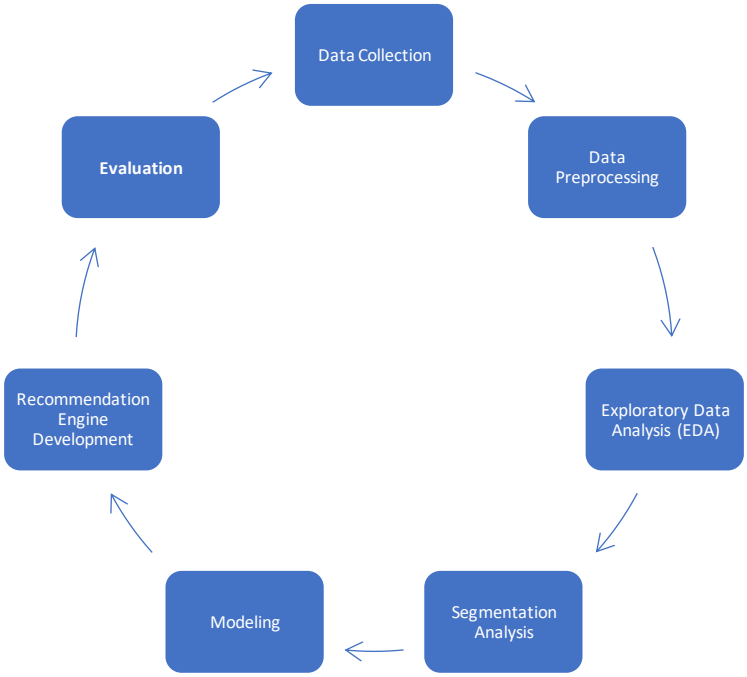
Leverage the dataset to determine the most effective offers to send to individual customers by addressing two key questions:

1. Which offer prompts increased purchasing from a specific customer?
2. Which demographic segments are most responsive to offer types?

Through advanced analytics techniques, including segmentation analysis and predictive modeling, we will tailor recommendations based on customer purchasing history, demographics, and offer preferences. This engine seeks to optimize Starbucks' promotional efforts, driving sales and enhancing customer engagement.

## Expected solution.

Below figure shows steps to achieve results




## Exploratory Data Analysis (EDA):

During EDA, we will visualize and analyze the dataset to uncover patterns, trends, and insights that can inform the development of the recommendation engine. Key findings may include:

## Data cleaning

Clean and preprocess the portfolio DataFrame. Args:portfolio: DataFrame containing portfolio data to be cleaned. Returns: portfolio: DataFrame with cleaned portfolio data.

- Create a copy of the DataFrame
- Convert duration from days to hours
- Apply one-hot encoding to the channels column
- Apply one-hot encoding to the offer_type column
- Drop the channels and offer_type columns
- Merge the DataFrame with one-hot encoded offer types

| | reward | difficulty | duration | id | duration_hours | web | email | mobile | social | bogo | discount | informational |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 10 | 10 | 7 | ae264e3637204a6fb9bb56bc8210ddfd | 168 | 0 | 1 | 1 | 1 | True | False | False |
| 1 | 10 | 10 | 5 | 4d5c57ea9a6940dd891ad53e9dbe8da0 | 120 | 1 | 1 | 1 | 1 | True | False | False |
| 2 | 0 | 0 | 4 | 3f207df678b143eea3cee63160fa8bed | 96 | 1 | 1 | 1 | 0 | False | False | True |
| 3 | 5 | 5 | 7 | 9b98b8c7a33c4b65b9aebfe6a799e6d9 | 168 | 1 | 1 | 1 | 0 | True | False | False |
| 4 | 5 | 20 | 10 | 0b1e1539f2cc45b7b9fa7c272da2e1d7 | 240 | 1 | 1 | 0 | 0 | False | True | False |

Cleanse the profile DataFrame. Args:profile: DataFrame to be cleansed.Returns:cleaned_profile: The sanitized DataFrame.

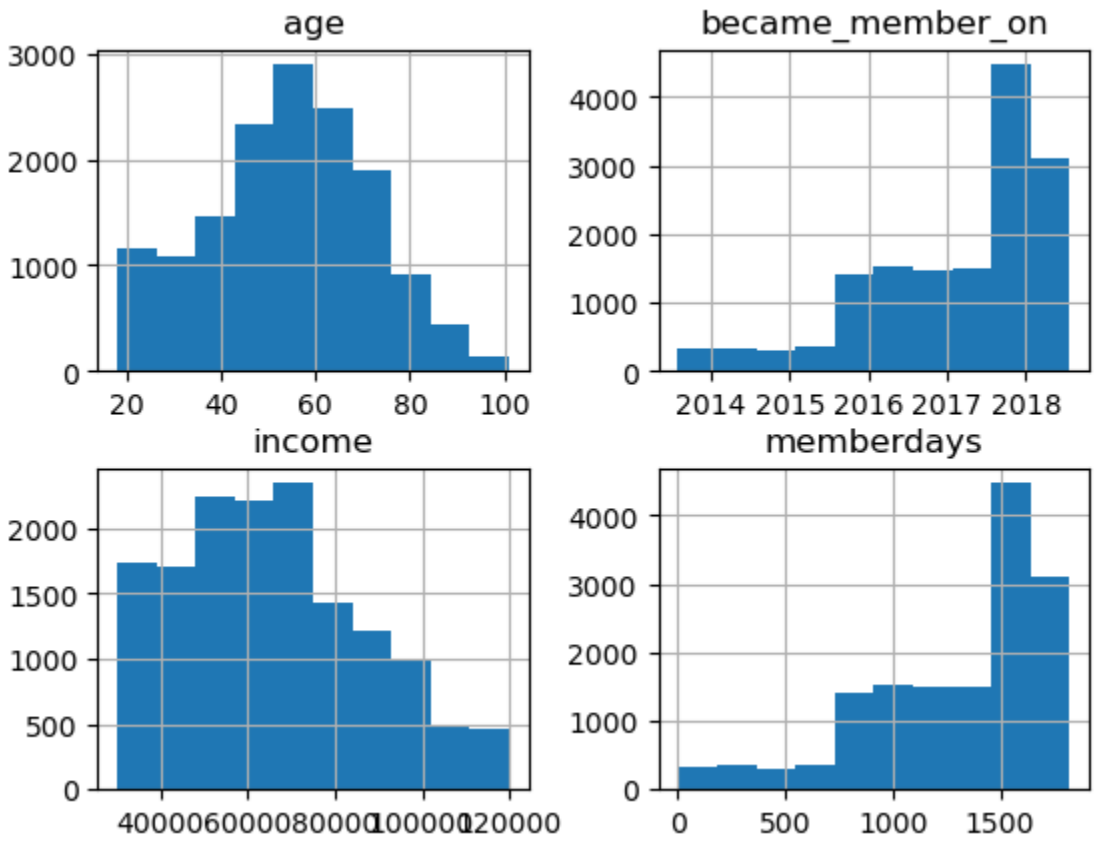
- Replace missing values encoded as 118 with NaN
- Drop rows with missing values
- Convert 'became_member_on' column to datetime format
- Calculate the number of days since the user became a member of Starbucks

| | gender | age | id | became_member_on | income | memberdays |
|---|---|---|---|---|---|---|
| 1 | F | 55.0 | 0610b486422d4921ae7d2bf64640c50b | 2017-07-15 | 112000.0 | 1447 |
| 3 | F | 75.0 | 78afa995795e4d85b5d9ceeca43f5fef | 2017-05-09 | 100000.0 | 1380 |
| 5 | M | 68.0 | e2127556f4f64592b11af22de27a7932 | 2018-04-26 | 70000.0 | 1732 |
| 8 | M | 65.0 | 389bc3fa690240e798340f5a15918d5c | 2018-02-09 | 53000.0 | 1656 |
| 12 | M | 58.0 | 2eeac8d8feae4a8cad5a6af0499a211d | 2017-11-11 | 51000.0 | 1566 |

## Visualization

During EDA, we will visualize and analyze the dataset to uncover patterns, trends, and insights that can inform the development of the recommendation engine. Key findings may include:

- Distribution of customer demographics (age, gender, income) and their impact on purchasing behavior.
- Frequency and effectiveness of different offer types (BOGO, discount, informational).
- Correlation between offer difficulty, reward, and customer responsiveness.
- Time trends in offer usage and customer engagement.
- Interaction patterns between offers received, viewed, and completed.



## Explore More

example user: 'a03223e636434f42ac4c3df47e8bac43

- Check unique events in the 'event' column
- Check how many times the offer was sent (offer received)
- Filter transcript records for a specific user (example user: 'a03223e636434f42ac4c3df47e8bac43')
- Print the filtered transcript records for the user

```
Unique events: ['offer received' 'offer viewed' 'offer completed']
Number of times offer was received: 6
Transcript records for user a03223e636434f42ac4c3df47e8bac43 :
                                  person           event  \
1       a03223e636434f42ac4c3df47e8bac43  offer received
15562   a03223e636434f42ac4c3df47e8bac43    offer viewed
110829  a03223e636434f42ac4c3df47e8bac43  offer received
123539  a03223e636434f42ac4c3df47e8bac43    offer viewed
150599  a03223e636434f42ac4c3df47e8bac43  offer received
201573  a03223e636434f42ac4c3df47e8bac43  offer received
245125  a03223e636434f42ac4c3df47e8bac43  offer received
281785  a03223e636434f42ac4c3df47e8bac43    offer viewed

                                                   value  time  \
1       {'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}     0
15562   {'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}     6
110829  {'offer id': '3f207df678b143eea3cee63160fa8bed'}   336
123539  {'offer id': '3f207df678b143eea3cee63160fa8bed'}   336
150599  {'offer id': '5a8bc65990b245e5a138643cd4eb9837'}   408
201573  {'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}   504
245125  {'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}   576
281785  {'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}   624
```

## Data Processing

Return the user-item matrix indicating the number of offer completions by each user.

This function creates a user-item matrix based on the offer dataframe, where:

- Rows represent users.
- Columns represent offers.
- Values represent the number of offer completions by the user (1 if completed, 0 otherwise).

INPUT:

offer (DataFrame): A cleaned transcript dataframe.

filename (str): The filename to save the user-item matrix as a pickle file.

OUTPUT:

Creation of training datasets as ‘train_df.p’, Testing datasery as ‘train_df.p’ and full dataset as user_item_matrix.p

## Modeling:

```
This function performs matrix factorization using a basic form of FunkSVD with no
regularization
    INPUT:
    complete_mat - (numpy array) a matrix with users as rows, offers as columns,
and offer completed as values
    latent_features - (int) the number of latent features used
    learning_rate - (float) the learning rate
    iters - (int) the number of iterations
    OUTPUT:
    user_mat - (numpy array) a user by latent feature matrix
    offer_mat - (numpy array) a latent feature by offer matrix
```

Steps

- Set up useful values to be used through the rest of the function.
- initialize the user and matrices with random values.
- initialize sse at 0 for first iteration.
- keep track of iteration and MSE
- for each iteration update our sse
- For each user-offer pair
- if the rating exists
- compute the error as the actual minus the dot product of the user and offer latent features.
- Keep track of the sum of squared errors for the matrix
- update the values in each matrix in the direction of the gradient.
- Create user-by-item matrix - nothing to do here
- Fit FunkSVD with the specified hyper parameters to the training data
- Test for the best number of latent feature. (with latent features 10)
- Test for the best number of latent feature. (with latent features 5)

```
Optimizaiton Statistics
Iterations | Mean Squared Error
1                0.176739
2                0.164066
3                0.164005
4                0.163943
5                0.163881
6                0.163818
7                0.163755
8                0.163691
9                0.163626
10               0.163561
Optimizaiton Statistics
Iterations | Mean Squared Error
1                0.172455
2                0.162875
3                0.162799
4                0.162723
5                0.162646
6                0.162569
7                0.162491
8                0.162413
9                0.162335
10               0.162256
Optimizaiton Statistics
```

## Results/Conclusion

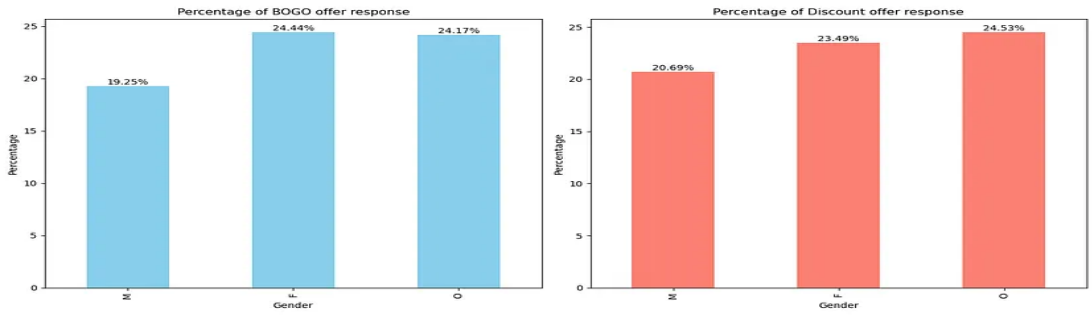
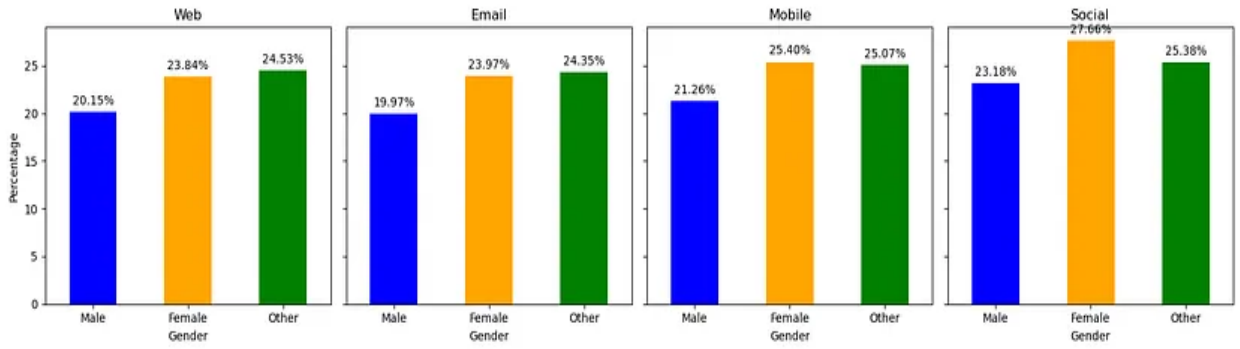



fig1.gender offer

Based on the above fig1.gender offer of offers sent and responses by gender, it's evident that both BOGO (Buy One Get One) and discount offers were more frequently directed towards males, followed by females and individuals of other genders. Despite this distribution, males consistently exhibited higher response rates to both offer types compared to females and individuals of other genders. While females generally displayed slightly lower response rates than males, individuals of other genders consistently had the lowest response rates across both offer types. These findings suggest potential gender-based variations in response behaviors, with males showing greater engagement overall. Further analysis is required to discern the underlying factors driving these disparities and to optimize offer strategies accordingly.




f2.gender offer channel

The analysis of f2.gender offer channel of offers sent and responses by gender across different channels reveals consistent patterns of engagement. Regardless of the channel, males consistently exhibited higher response rates compared to females and individuals of other genders, with females generally displaying slightly lower response rates than males and individuals of other genders having the lowest response rates overall. While the distribution of offers across channels remained relatively consistent, with email being the most popular channel followed by web, mobile, and social media, the response patterns by gender persisted across all channels. These findings highlight the importance of considering

gender-based differences in response behaviors when designing marketing strategies, suggesting potential avenues for further exploration to optimize engagement and enhance overall effectiveness across diverse demographic groups.


fig3.best sale offer

fig3.best sale offer presents offer IDs and their corresponding gains, indicating the financial performance associated with each offer. The offer with the ID “fafdcd668e3743c1bb461111dcafc2a4” yielded the highest gain of $669,455.13, followed by offer ID “2298d6c36e964ae4a3e7e9706d1fb8c2” with a gain of $622,010.36. The offers identified by IDs “f19421c1d4aa40978ebb69ca19b0e20d,” “ae264e3637204a6fb9bb56bc8210ddfd,” and “4d5c57ea9a6940dd891ad53e9dbe8da0” also contributed significantly to gains, amounting to $567,904.42, $534,014.80, and $523,901.10, respectively. The remaining offers, with IDs “2906b810c7d4411798c6938adc9daaa5,” “9b98b8c7a33c4b65b9aebfe6a799e6d9,” and “0b1e1539f2cc45b7b9fa7c272da2e1d7,” generated gains of $414,035.01, $412,546.01, and $310,107.10, respectively. This data provides insights into the relative effectiveness of different offers in generating revenue, which can inform future marketing strategies and investment decisions.

## Acknowledgment

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