Starbucks Capstone Challenge

Introduction

This data set contains simulated data that mimics customer behavior on the Starbucks rewards mobile app. Once every few days, Starbucks sends out an offer to users of the mobile app. An offer can be merely an advertisement for a drink or an actual offer such as a discount or BOGO (buy one get one free). Some users might not receive any offer during certain weeks.

Not all users receive the same offer, and that is the challenge to solve with this data set.

Your task is to combine transaction, demographic and offer data to determine which demographic groups respond best to which offer type. This data set is a simplified version of the real Starbucks app because the underlying simulator only has one product whereas Starbucks actually sells dozens of products.

Every offer has a validity period before the offer expires. As an example, a BOGO offer might be valid for only 5 days. You'll see in the data set that informational offers have a validity period even though these ads are merely providing information about a product; for example, if an informational offer has 7 days of validity, you can assume the customer is feeling the influence of the offer for 7 days after receiving the advertisement.

You'll be given transactional data showing user purchases made on the app including the timestamp of purchase and the amount of money spent on a purchase. This transactional data also has a record for each offer that a user receives as well as a record for when a user actually views the offer. There are also records for when a user completes an offer.

Keep in mind as well that someone using the app might make a purchase through the app without having received an offer or seen an offer.

Example

To give an example, a user could receive a discount offer buy 10 dollars get 2 off on Monday. The offer is valid for 10 days from receipt. If the customer accumulates at least 10 dollars in purchases during the validity period, the customer completes the offer.

However, there are a few things to watch out for in this data set. Customers do not opt into the offers that they receive; in other words, a user can receive an offer, never actually view the offer, and still complete the offer. For example, a user might receive the "buy 10 dollars get 2 dollars off offer", but the user never opens the offer during the 10 day validity period. The customer spends 15 dollars during those ten days. There will be an offer completion record in the data set; however, the customer was not influenced by the offer because the customer never viewed the offer.

Cleaning

This makes data cleaning especially important and tricky.

You'll also want to take into account that some demographic groups will make purchases even if they don't receive an offer. From a business perspective, if a customer is going to make a 10 dollar purchase without an offer anyway, you wouldn't want to send a buy 10 dollars get 2 dollars off offer. You'll want to try to assess what a certain demographic group will buy when not receiving any offers.

Final Advice

Because this is a capstone project, you are free to analyze the data any way you see fit. For example, you could build a machine learning model that predicts how much someone will spend based on demographics and offer type. Or you could build a model that predicts whether or not someone will respond to an offer. Or, you don't need to build a machine learning model at all. You could develop a set of heuristics that determine what offer you should send to each customer (i.e., 75 percent of women customers who were 35 years old responded to offer A vs 40 percent from the same demographic to offer B, so send offer A).

Data Sets

The data is contained in three files:

- portfolio.json - containing offer ids and meta data about each offer (duration, type, etc.)
- profile.json - demographic data for each customer
- transcript.json - records for transactions, offers received, offers viewed, and offers completed

Here is the schema and explanation of each variable in the files:

portfolio.json

- id (string) - offer id
- offer_type (string) - type of offer ie BOGO, discount, informational
- difficulty (int) - minimum required spend to complete an offer
- reward (int) - reward given for completing an offer
- duration (int) - time for offer to be open, in days
- channels (list of strings)

profile.json

- age (int) - age of the customer
- became_member_on (int) - date when customer created an app account
- gender (str) - gender of the customer (note some entries contain 'O' for other rather than M or F)
- id (str) - customer id
- income (float) - customer's income

transcript.json

- event (str) - record description (ie transaction, offer received, offer viewed, etc.)
- person (str) - customer id
- time (int) - time in hours since start of test. The data begins at time t=0
- value - (dict of strings) - either an offer id or transaction amount depending on the record

In [ ]:
```
import pandas as pd
import numpy as np
import math
import json
%matplotlib inline


import seaborn as sns
import scipy.stats as stats
import matplotlib.pyplot as plt
from scipy.linalg import svd
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score


# read in the json files
portfolio = pd.read_json('data/portfolio.json', orient='records', lines=True)
profile = pd.read_json('data/profile.json', orient='records', lines=True)
transcript = pd.read_json('data/transcript.json', orient='records', lines=True)
```

In [ ]:
```
portfolio.head()
```

Out[ ]:

	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

In [ ]:

```
profile.head()
```

Out[ ]:

	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

In [ ]:

```
transcript.head()
```

Out[ ]:

	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

In [ ]:

```
# Check basic statistics
print(profile.describe())
print(portfolio.describe())
print(transcript.describe())
```

```
                age  became_member_on         income
count  17000.000000      1.700000e+04   14825.000000
mean      62.531412      2.016703e+07   65404.991568
std       26.738580      1.167750e+04   21598.299410
min       18.000000      2.013073e+07   30000.000000
25%       45.000000      2.016053e+07   49000.000000
50%       58.000000      2.017080e+07   64000.000000
75%       73.000000      2.017123e+07   80000.000000
max      118.000000      2.018073e+07  120000.000000
          reward  difficulty   duration
count  10.000000   10.000000  10.000000
mean    4.200000    7.700000   6.500000
std     3.583915    5.831905   2.321398
min     0.000000    0.000000   3.000000
25%     2.000000    5.000000   5.000000
50%     4.000000    8.500000   7.000000
75%     5.000000   10.000000   7.000000
max    10.000000   20.000000  10.000000
                time
count  306534.000000
mean      366.382940
std       200.326314
min         0.000000
25%       186.000000
50%       408.000000
75%       528.000000
max       714.000000
```

Data Cleaning

In [ ]:
```
# Extract offer id from value column where applicable
transcript['offer_id'] = transcript['value'].apply(lambda x: x.get('offer id'))
transcript['amount'] = transcript['value'].apply(lambda x: x.get('amount', 0))

print(transcript.head())
```

```
                             person           event  \
0  78afa995795e4d85b5d9ceeca43f5fef  offer received
1  a03223e636434f42ac4c3df47e8bac43  offer received
2  e2127556f4f64592b11af22de27a7932  offer received
3  8ec6ce2a7e7949b1bf142def7d0e0586  offer received
4  68617ca6246f4fbc85e91a2a49552598  offer received

                                              value  time  \
0  {'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}     0
1  {'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}     0
2  {'offer id': '2906b810c7d4411798c6938adc9daaa5'}     0
3  {'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}     0
4  {'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}     0

                           offer_id  amount
0  9b98b8c7a33c4b65b9aebfe6a799e6d9     0.0
1  0b1e1539f2cc45b7b9fa7c272da2e1d7     0.0
2  2906b810c7d4411798c6938adc9daaa5     0.0
3  fafdcd668e3743c1bb461111dcafc2a4     0.0
4  4d5c57ea9a6940dd891ad53e9dbe8da0     0.0
```

In [ ]:
```
# Assuming 'offer_id' is None for transactions without associated offers
transactions_without_offers = transcript[(transcript['event'] == 'transaction') & (

# Calculate spending without offers for each user
# Ensure that 'person' is the correct identifier in the transactions DataFrame
user_spending_without_offers = transactions_without_offers.groupby('person')['amoun
user_spending_without_offers.rename(columns={'amount': 'spending_without_offers', '

# Merge this data back into the profile DataFrame using 'id' as the key
profile = profile.merge(user_spending_without_offers, on='id', how='left')
profile['spending_without_offers'].fillna(0, inplace=True)
```

```
C:\Users\kilgo\AppData\Local\Temp\ipykernel_37644\3287058969.py:11: FutureWarning: A
value is trying to be set on a copy of a DataFrame or Series through chained assignm
ent using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because
the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method
({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform
the operation inplace on the original object.


  profile['spending_without_offers'].fillna(0, inplace=True)
```

In [ ]:
```
# Clean profile data
profile['became_member_on'] = pd.to_datetime(profile['became_member_on'], format='%
profile['age'] = profile['age'].replace(118, np.nan)  # Assuming '118' means missin
profile.dropna(inplace=True)  # Dropping rows with any missing values
```

In [ ]:
```
def create_user_offer_matrix(transcript):

    # Filter only 'offer received' and 'offer completed' events
    offer_received = transcript[transcript['event'] == 'offer received']
    offer_completed = transcript[transcript['event'] == 'offer completed']

    # Create a matrix of users and offers using the correct key 'offer_id'
    user_offer_matrix = offer_received.pivot_table(index='person', columns='offer_i
    user_offer_matrix = (user_offer_matrix > 0).astype(int)  # Convert to binary

    # Incorporate information from offer completed
    completed_matrix = offer_completed.pivot_table(index='person', columns='offer_i
    completed_matrix = (completed_matrix > 0).astype(int)  # Convert to binary

    # Update the received offers with completed offers information
    user_offer_matrix.update(completed_matrix)

    return user_offer_matrix

# Now call the function
user_offer_matrix = create_user_offer_matrix(transcript)
```

In [ ]:
```
def funk_svd(matrix, latent_features=12, learning_rate=0.0001, iterations=100):
    # Initialize user and offer matrices with random values
    n_users, n_offers = matrix.shape
    user_mat = np.random.normal(scale=1./latent_features, size=(n_users, latent_fea
    offer_mat = np.random.normal(scale=1./latent_features, size=(n_offers, latent_f

    # Perform gradient descent
    for iteration in range(iterations):
        for i in range(n_users):
            for j in range(n_offers):
                if matrix[i, j] > 0:  # only update if interaction is known
                    error = matrix[i, j] - np.dot(user_mat[i, :], offer_mat[j, :])
                    for k in range(latent_features):
                        user_mat[i, k] += learning_rate * (2 * error * offer_mat[j,
                        offer_mat[j, k] += learning_rate * (2 * error * user_mat[i,

        # Print loss every 10 iterations
        if (iteration % 10 == 0):
            mse = mean_squared_error(matrix, np.dot(user_mat, offer_mat.T))
            print('Iteration %d: MSE %.4f' % (iteration, mse))

    return user_mat, offer_mat

# Convert DataFrame to numpy array for faster operations
```

```
user_offer_np = user_offer_matrix.to_numpy()
user_features, offer_features = funk_svd(user_offer_np)
```

```
Iteration 0: MSE 0.3729
Iteration 10: MSE 0.3726
Iteration 20: MSE 0.3724
Iteration 30: MSE 0.3722
Iteration 40: MSE 0.3719
Iteration 50: MSE 0.3716
Iteration 60: MSE 0.3710
Iteration 70: MSE 0.3700
Iteration 80: MSE 0.3684
Iteration 90: MSE 0.3658
```

In [ ]:

```
def recommend_offers(user_features, offer_features, user_id, user_offer_matrix):
    # Calculate the dot product of user features and offer features
    predictions = np.dot(user_features, offer_features.T)

    # Convert predictions to a DataFrame for easier handling
    predictions_df = pd.DataFrame(predictions, index=user_offer_matrix.index, colum

    # Get the offers for the user
    user_row = predictions_df.loc[user_id]
    # Sort the offers by predicted value
    recommended_offers = user_row.sort_values(ascending=False)

    return recommended_offers

# Example usage:
user_id = profile.iloc[0]['id']
recommended_offers = recommend_offers(user_features, offer_features, user_id, user_
print(recommended_offers.head())
```

```
offer_id
0b1e1539f2cc45b7b9fa7c272da2e1d7    0.067946
9b98b8c7a33c4b65b9aebfe6a799e6d9    0.066744
fafdcd668e3743c1bb461111dcafc2a4    0.062280
4d5c57ea9a6940dd891ad53e9dbe8da0    0.059823
2298d6c36e964ae4a3e7e9706d1fb8c2    0.032511
Name: 0610b486422d4921ae7d2bf64640c50b, dtype: float64
```

In [ ]:

```
# Assuming user_features and offer_features have been obtained from funk_svd functi
predictions_matrix = np.dot(user_features, offer_features.T)

# Assuming user_offer_matrix is indexed by 'person' and columns labeled by 'offer_i
user_ids = user_offer_matrix.index
offer_ids = user_offer_matrix.columns

# Create DataFrame from the predictions matrix
predictions_df = pd.DataFrame(predictions_matrix, index=user_ids, columns=offer_ids

# Melt the DataFrame
predictions_df = predictions_df.reset_index().melt(id_vars=['person'], value_vars=p

# Merge demographic data
predictions_df = predictions_df.merge(profile, left_on='person', right_on='id', how
```

```
# Merge offer data
predictions_df = predictions_df.merge(portfolio, left_on='offer_id', right_on='id',

# Drop extra columns if necessary (e.g., repeated 'id' columns)
predictions_df.drop(columns=['id_x', 'id_y'], inplace=True)

# Example of what predictions_df will look like:
print(predictions_df.head())
```

```
                             person                          offer_id  \
0  0009655768c64bdeb2e877511632db8f  0b1e1539f2cc45b7b9fa7c272da2e1d7
1  00116118485d4dfda04fdbaba9a87b5c  0b1e1539f2cc45b7b9fa7c272da2e1d7
2  0011e0d4e6b944f998e987f904e8c1e5  0b1e1539f2cc45b7b9fa7c272da2e1d7
3  0020c2b971eb4e9188eac86d93036a77  0b1e1539f2cc45b7b9fa7c272da2e1d7
4  0020ccbbb6d84e358d3414a3ff76cffd  0b1e1539f2cc45b7b9fa7c272da2e1d7

      score gender   age became_member_on   income  spending_without_offers  \
0 -0.021337      M  33.0       2017-04-21  72000.0                   127.60
1  0.103134    NaN   NaN              NaT      NaN                      NaN
2 -0.130167      O  40.0       2018-01-09  57000.0                    79.46
3 -0.000645      F  59.0       2016-03-04  90000.0                   196.86
4 -0.091938      F  24.0       2016-11-11  60000.0                   154.05

   reward      channels  difficulty  duration offer_type
0       5  [web, email]          20        10   discount
1       5  [web, email]          20        10   discount
2       5  [web, email]          20        10   discount
3       5  [web, email]          20        10   discount
4       5  [web, email]          20        10   discount
```

In [ ]:

```
# Group by demographics and offer type to see response rates
demographic_response = predictions_df.groupby(['age_group', 'gender', 'offer_type']
print(demographic_response)
```

In [ ]:

```
# Convert 'score' to float if it's not, handle conversion errors silently
predictions_df['score'] = pd.to_numeric(predictions_df['score'], errors='coerce')



print(predictions_df.dtypes)

# Now check for any NaN values in 'score' which might indicate conversion issues
print(predictions_df['score'].isna().sum())

# Calculate mean scores by offer type
offer_performance = predictions_df.groupby('offer_type')['score'].mean()

# Print the performance metrics
print("Average Scores by Offer Type:")
print(offer_performance)

# Example to check unique values in 'score' if suspected to be non-numeric
print(predictions_df['score'].unique())
```

```
person                            object
offer_id                          object
score                            float64
gender                            object
age                              float64
became_member_on          datetime64[ns]
income                           float64
spending_without_offers          float64
reward                             int64
channels                          object
difficulty                         int64
duration                           int64
offer_type                        object
dtype: object
0
Average Scores by Offer Type:
offer_type
bogo             0.018404
discount         0.018894
informational    0.020895
Name: score, dtype: float64
[-0.0213369   0.10313353 -0.13016704 ...  0.09931643 -0.03688065
 -0.02749344]
```

In [ ]:

```
# Calculate average scores by demographic segments
# Ensure 'age' and 'income' from profile are included in predictions_df before this
predictions_df['age_group'] = pd.cut(predictions_df['age'], bins=[18, 30, 45, 60, 7
predictions_df['income_group'] = pd.cut(predictions_df['income'], bins=[30000, 5000

avg_scores_by_age = predictions_df.groupby('age_group')['score'].mean()
avg_scores_by_income = predictions_df.groupby('income_group')['score'].mean()

# Print the results
print("Average Scores by Age Group:")
print(avg_scores_by_age)
print("Average Scores by Income Group:")
print(avg_scores_by_income)
```

```
Average Scores by Age Group:
age_group
(18, 30]     0.021116
(30, 45]     0.018017
(45, 60]     0.019346
(60, 75]     0.017749
(75, 90]     0.018166
(90, 120]    0.022362
Name: score, dtype: float64
Average Scores by Income Group:
income_group
(30000, 50000]      0.018028
(50000, 70000]      0.019997
(70000, 90000]      0.016869
(90000, 110000]     0.021791
(110000, 130000]    0.017717
Name: score, dtype: float64
```

```
C:\Users\kilgo\AppData\Local\Temp\ipykernel_37644\3624836523.py:6: FutureWarning: Th
e default of observed=False is deprecated and will be changed to True in a future ve
rsion of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  avg_scores_by_age = predictions_df.groupby('age_group')['score'].mean()
C:\Users\kilgo\AppData\Local\Temp\ipykernel_37644\3624836523.py:7: FutureWarning: Th
e default of observed=False is deprecated and will be changed to True in a future ve
rsion of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  avg_scores_by_income = predictions_df.groupby('income_group')['score'].mean()
```

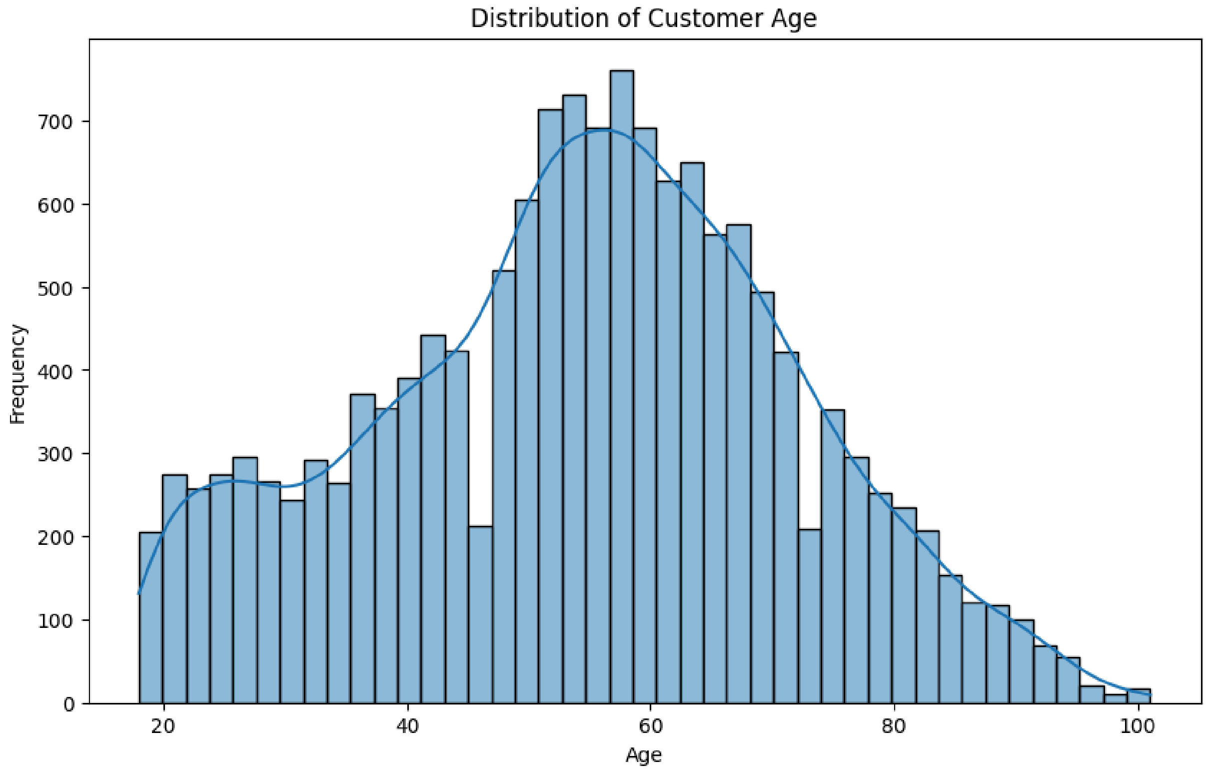
In [ ]:

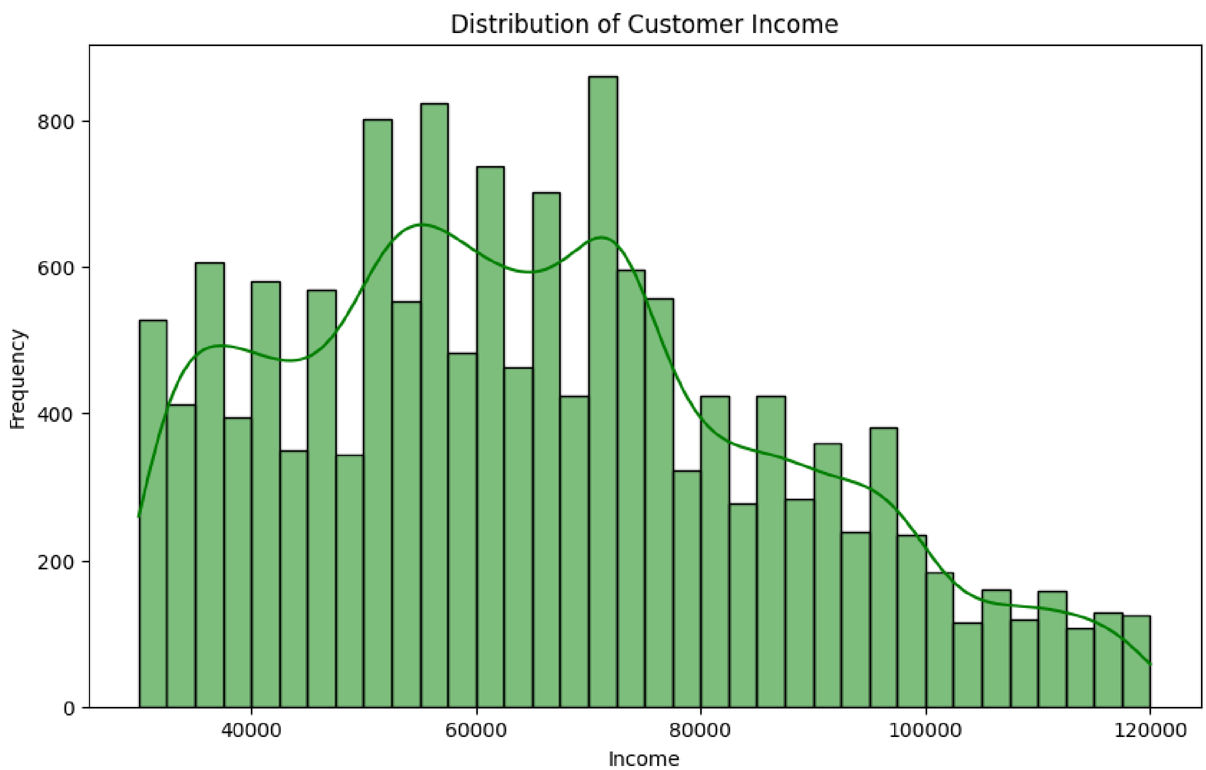
```
```

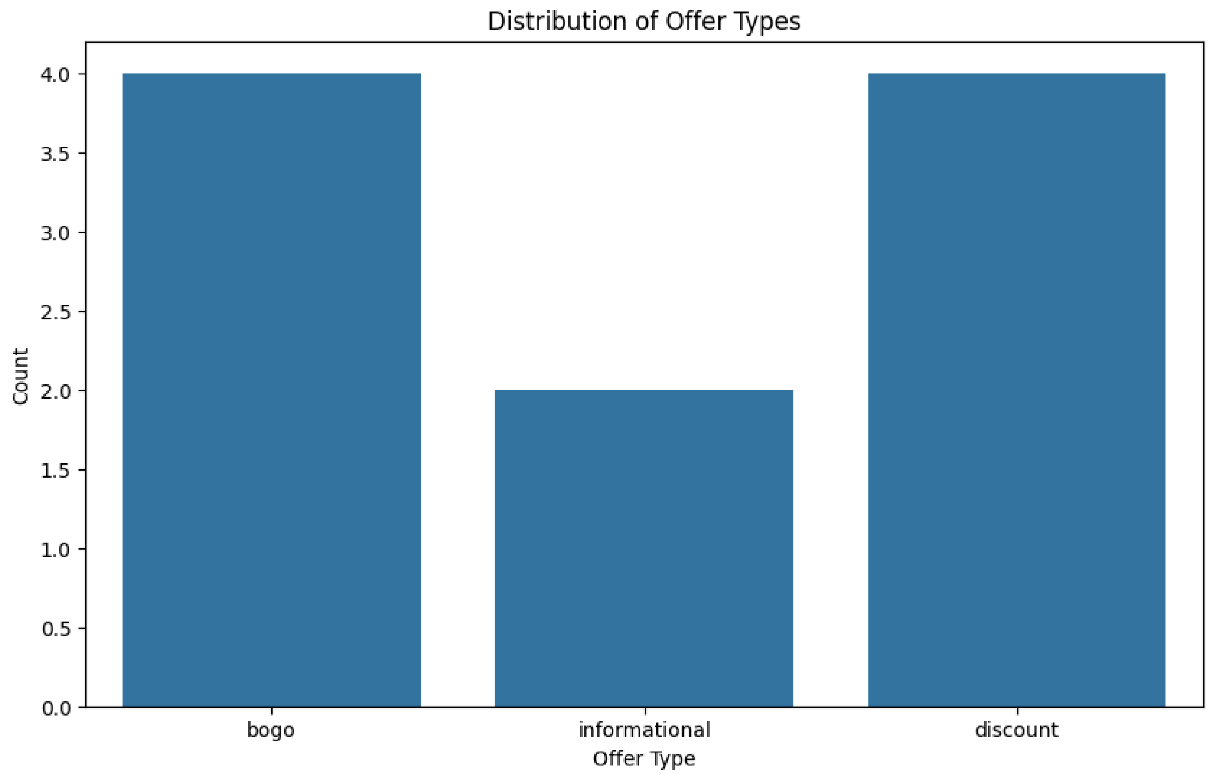
Visualizations

In [ ]:

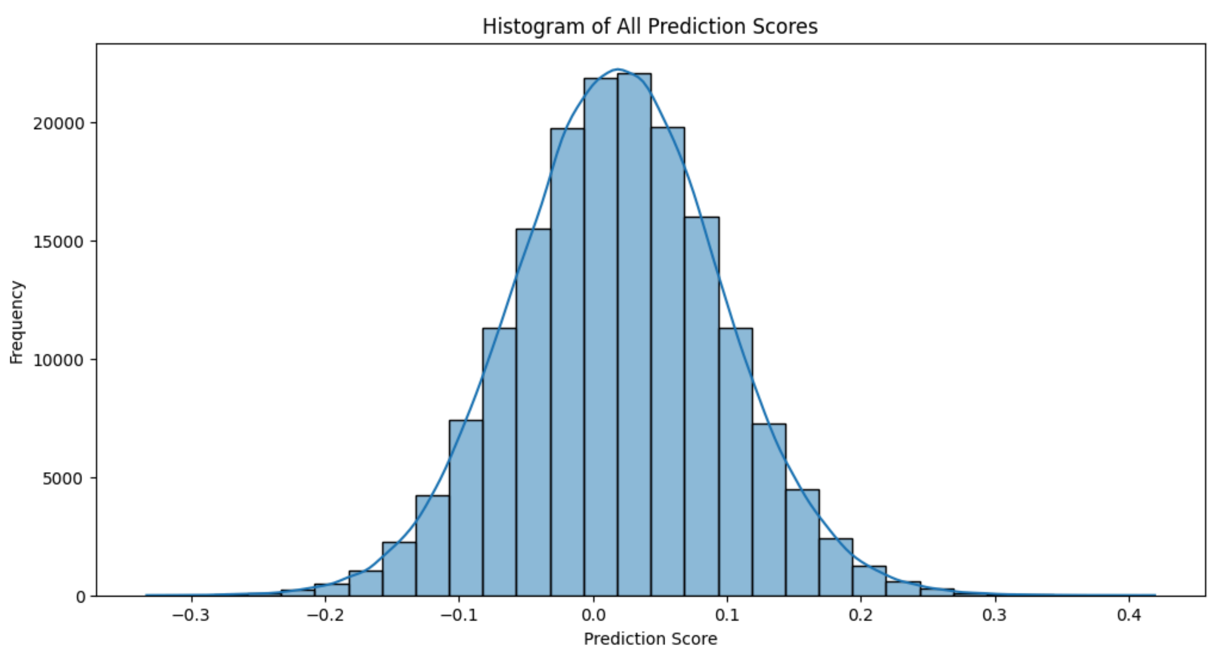
```python
# Distribution of Age
plt.figure(figsize=(10, 6))
sns.histplot(profile['age'].dropna(), kde=True)
plt.title('Distribution of Customer Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()

# Distribution of Income
plt.figure(figsize=(10, 6))
sns.histplot(profile['income'], kde=True, color='green')
plt.title('Distribution of Customer Income')
plt.xlabel('Income')
plt.ylabel('Frequency')
plt.show()

# Offer Type Distribution
plt.figure(figsize=(10, 6))
sns.countplot(data=portfolio, x='offer_type')
plt.title('Distribution of Offer Types')
plt.xlabel('Offer Type')
plt.ylabel('Count')
plt.show()
```


Distribution of Customer Age
Frequency
0
100
200
300
400
500
600
700
20
40
60
80
100
Age


Distribution of Customer Income
Frequency
0
200
400
600
800
40000
60000
80000
100000
120000
Income



In [ ]:
```
# Histogram of all scores to see overall distribution
plt.figure(figsize=(12, 6))
sns.histplot(predictions_df['score'], kde=True, bins=30)
plt.title('Histogram of All Prediction Scores')
plt.xlabel('Prediction Score')
plt.ylabel('Frequency')
plt.show()
```



In [ ]:
```
# Perform ANOVA test to see if there are statistically significant differences amon
fvalue, pvalue = stats.f_oneway(predictions_df[predictions_df['offer_type'] == 'bog
                                predictions_df[predictions_df['offer_type'] == 'dis
```

```
                                predictions_df[predictions_df['offer_type'] == 'inf
print('ANOVA test results: F-value =', fvalue, ', P-value =', pvalue)
```

```
ANOVA test results: F-value = 12.171066957893709 , P-value = 5.182643330848802e-06
```

In [ ]:
```
# Adjusting the number of latent features
latent_features_options = [5, 10, 20]
learning_rates = [0.0001, 0.001, 0.01]

for features in latent_features_options:
    for lr in learning_rates:
        user_features, offer_features = funk_svd(user_offer_np, latent_features=fea
        predictions = np.dot(user_features, offer_features.T)
        mse = mean_squared_error(user_offer_np, predictions)
        print(f'Latent features: {features}, Learning rate: {lr}, MSE: {mse}')
```

```
Iteration 0: MSE 0.3789
Iteration 10: MSE 0.3747
Iteration 20: MSE 0.3733
Iteration 30: MSE 0.3728
Iteration 40: MSE 0.3727
Iteration 50: MSE 0.3726
Iteration 60: MSE 0.3726
Iteration 70: MSE 0.3726
Iteration 80: MSE 0.3726
Iteration 90: MSE 0.3726
Latent features: 5, Learning rate: 0.0001, MSE: 0.3726745335519889
Iteration 0: MSE 0.3759
Iteration 10: MSE 0.3727
Iteration 20: MSE 0.3752
Iteration 30: MSE 0.4405
Iteration 40: MSE 0.5707
Iteration 50: MSE 0.6076
Iteration 60: MSE 0.6189
Iteration 70: MSE 0.6233
Iteration 80: MSE 0.6253
Iteration 90: MSE 0.6263
Latent features: 5, Learning rate: 0.001, MSE: 0.6267438743558673
Iteration 0: MSE 0.3787
Iteration 10: MSE 0.6275
Iteration 20: MSE 0.6276
Iteration 30: MSE 0.6276
Iteration 40: MSE 0.6276
Iteration 50: MSE 0.6276
Iteration 60: MSE 0.6276
Iteration 70: MSE 0.6276
Iteration 80: MSE 0.6276
Iteration 90: MSE 0.6276
Latent features: 5, Learning rate: 0.01, MSE: 0.6275862068965516
Iteration 0: MSE 0.3734
Iteration 10: MSE 0.3729
Iteration 20: MSE 0.3726
Iteration 30: MSE 0.3724
Iteration 40: MSE 0.3721
Iteration 50: MSE 0.3718
Iteration 60: MSE 0.3714
Iteration 70: MSE 0.3708
Iteration 80: MSE 0.3697
Iteration 90: MSE 0.3680
Latent features: 10, Learning rate: 0.0001, MSE: 0.36562437762676553
Iteration 0: MSE 0.3729
Iteration 10: MSE 0.3405
Iteration 20: MSE 0.5329
Iteration 30: MSE 0.6121
Iteration 40: MSE 0.6227
Iteration 50: MSE 0.6257
Iteration 60: MSE 0.6268
Iteration 70: MSE 0.6272
Iteration 80: MSE 0.6274
Iteration 90: MSE 0.6275
Latent features: 10, Learning rate: 0.001, MSE: 0.6275451124558541
Iteration 0: MSE 0.4693
```

```
Iteration 10: MSE 0.6276
Iteration 20: MSE 0.6276
Iteration 30: MSE 0.6276
Iteration 40: MSE 0.6276
Iteration 50: MSE 0.6276
Iteration 60: MSE 0.6276
Iteration 70: MSE 0.6276
Iteration 80: MSE 0.6276
Iteration 90: MSE 0.6276
Latent features: 10, Learning rate: 0.01, MSE: 0.6275862068965516
Iteration 0: MSE 0.3725
Iteration 10: MSE 0.3724
Iteration 20: MSE 0.3723
Iteration 30: MSE 0.3721
Iteration 40: MSE 0.3719
```

In [ ]:

```python
# Suggesting business actions based on insights
if pvalue < 0.05:
    print("Statistically significant differences found among offer types. Suggestin
    best_type = predictions_df.groupby('offer_type')['score'].mean().idxmax()
    print(f"Focus more on '{best_type}' offers as they have the highest average sco
else:
    print("No significant differences among offer types. Focus on optimizing overal
```

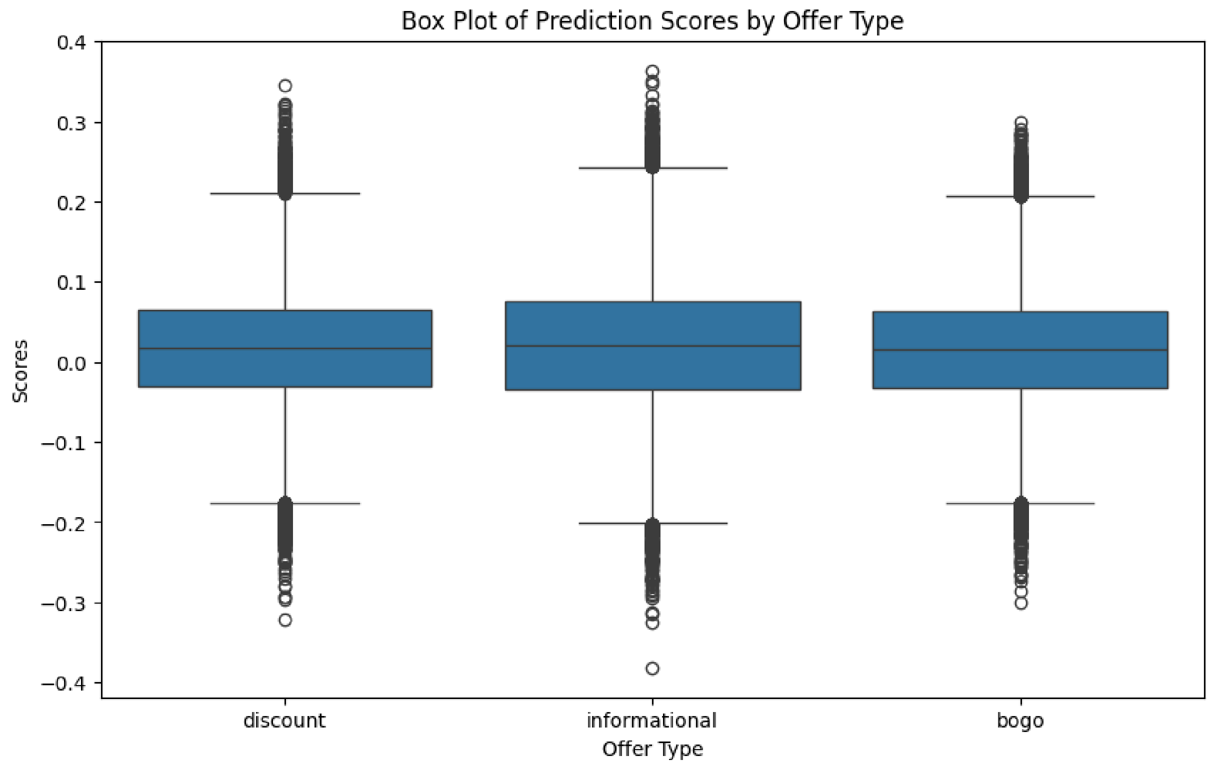
```
Statistically significant differences found among offer types. Suggesting targeted s
trategies.
Focus more on 'informational' offers as they have the highest average score.
```

In [ ]:

```python
# Calculate and print the mean scores by offer type to understand the magnitude of
mean_scores = predictions_df.groupby('offer_type')['score'].mean()
print("Mean Scores by Offer Type:", mean_scores)

# Visualizing the scores by offer type
plt.figure(figsize=(10, 6))
sns.boxplot(x='offer_type', y='score', data=predictions_df)
plt.title('Box Plot of Prediction Scores by Offer Type')
plt.xlabel('Offer Type')
plt.ylabel('Scores')
plt.show()
```

```
Mean Scores by Offer Type: offer_type
bogo             0.016000
discount         0.017517
informational    0.020729
Name: score, dtype: float64
```

```
c:\Users\kilgo\AppData\Local\Programs\Python\Python311\Lib\site-packages\seaborn\cat
egorical.py:632: FutureWarning: SeriesGroupBy.grouper is deprecated and will be remo
ved in a future version of pandas.
  positions = grouped.grouper.result_index.to_numpy(dtype=float)
```



Objective: Build models that predict customer response to offers and customer spending based on demographics and offer type.

In [ ]:

```
# Assuming 'response' is a binary feature indicating whether an offer was completed
X = predictions_df[['age', 'income', 'gender', 'offer_type_encoded', 'spending_with
y = predictions_df['response']  # This needs to be created based on your criteria

# Encode categorical data and split the dataset
X = pd.get_dummies(X, columns=['gender', 'offer_type'], drop_first=True)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta

# Building a Random Forest model
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Predicting and evaluating the model
predictions = model.predict(X_test)
print("Random Forest Model Accuracy:", accuracy_score(y_test, predictions))
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
Cell In[130], line 2
      1 # Assuming 'response' is a binary feature indicating whether an offer was co
mpleted after being viewed
----> 2 X = predictions_df[['age', 'income', 'gender', 'offer_type_encoded', 'spendi
ng_without_offers']]
      3 y = predictions_df['response']  # This needs to be created based on your cri
teria
      5 # Encoding categorical data

File c:\Users\kilgo\AppData\Local\Programs\Python\Python311\Lib\site-packages\pandas
\core\frame.py:4108, in DataFrame.__getitem__(self, key)
   4106     if is_iterator(key):
   4107         key = list(key)
-> 4108     indexer = self.columns._get_indexer_strict(key, "columns")[1]
   4110 # take() does not accept boolean indexers
   4111 if getattr(indexer, "dtype", None) == bool:

File c:\Users\kilgo\AppData\Local\Programs\Python\Python311\Lib\site-packages\pandas
\core\indexes\base.py:6200, in Index._get_indexer_strict(self, key, axis_name)
   6197 else:
   6198     keyarr, indexer, new_indexer = self._reindex_non_unique(keyarr)
-> 6200 self._raise_if_missing(keyarr, indexer, axis_name)
   6202 keyarr = self.take(indexer)
   6203 if isinstance(key, Index):
   6204     # GH 42790 - Preserve name from an Index

File c:\Users\kilgo\AppData\Local\Programs\Python\Python311\Lib\site-packages\pandas
\core\indexes\base.py:6252, in Index._raise_if_missing(self, key, indexer, axis_nam
e)
   6249     raise KeyError(f"None of [{key}] are in the [{axis_name}]")
   6251 not_found = list(ensure_index(key)[missing_mask.nonzero()[0]].unique())
-> 6252 raise KeyError(f"{not_found} not in index")

KeyError: "['offer_type_encoded', 'spending_without_offers'] not in index"
```

In [ ]:

```
# Predicting how much a user will spend based on demographics and whether they rece
X = profile[['age', 'income', 'spending_without_offers', 'gender_encoded']]
y = profile['total_spending']  # Assume total spending is a column in profile

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta

lr = LinearRegression()
lr.fit(X_train, y_train)
print("R^2 Score:", lr.score(X_test, y_test))
```

In [ ]:

```
# Example heuristic: Send BOGO offers to high spenders, discount offers to frequent
profile['recommended_offer'] = profile.apply(lambda x: 'BOGO' if x['income'] > 7000
```