Starbucks_Capstone_notebook

June 11, 2022

1 Starbucks Capstone Challenge

1.0.1 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.

1.0.2 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.

1.0.3 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.

1.0.4 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).

2 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

Note: If you are using the workspace, you will need to go to the terminal and run the command `conda update pandas` before reading in the files. This is because the version of pandas in the workspace cannot read in the transcript.json file correctly, but the newest version of pandas can. You can access the terminal from the orange icon in the top left of this notebook.

You can see how to access the terminal and how the install works using the two images below. First you need to access the terminal:

Then you will want to run the above command:

Finally, when you enter back into the notebook (use the jupyter icon again), you should be able to run the below cell without any errors.

2.1 Project Definition

2.2 Additional Background

Marketing new products and offers is a difficult and critical aspect to any business endeavor. Well established companies such as Starbucks regularly require new marketing strategies in order to maintain their customer loyalty and maintain an advantage ahead of their competition.

Targeting customers with new offers and promotions can have mixed results depending on the customer's preferences and interests. While some promotions may encourage increased attendance, other promotions to the same customer base may not elicit strong responses, or perhaps elicit negative responses. Building advertising models that are careful to consider customer pervious habits and demographic information can produce tailored recommendations to deliver the most effective promotion strategy in an effort to maximize customer loyalty.

The business case for building effective marketing models are clear, additional technological implications about time-phased recommendations presents an interesting challenge to build effective models where a recommendation may differ depending on timing in addition to a customer's profile.

2.3 Problem Statement

The analysis for this final report has developed predictive models that can predict if a BOGO offer will be effective provided BOGO offer details as well as customer profile data.

2.4 Metrics

The models generated will be evaluated using accuracy and against a DummyClassifier that will serve as a baseline accuracy. The DummyClassifier will select the most frequent class regardless of inputs. This will provide insight to any applied bias to the datasets.

2.5 Analysis

2.5.1 Data Exploration

[1]:
```
!python -m pip install black isort scikit-learn
```

```
Requirement already satisfied: black in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (22.3.0)
Requirement already satisfied: isort in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (5.10.1)
Requirement already satisfied: scikit-learn in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (1.1.1)
Requirement already satisfied: platformdirs>=2 in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (from black) (2.5.2)
Requirement already satisfied: pathspec>=0.9.0 in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (from black) (0.9.0)
Requirement already satisfied: tomli>=1.1.0 in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (from black) (2.0.1)
```

```
Requirement already satisfied: mypy-extensions>=0.4.3 in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (from black) (0.4.3)
Requirement already satisfied: typing-extensions>=3.10.0.0 in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (from black) (4.2.0)
Requirement already satisfied: click>=8.0.0 in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (from black) (8.1.3)
Requirement already satisfied: threadpoolctl>=2.0.0 in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (from scikit-learn)
(3.1.0)
Requirement already satisfied: numpy>=1.17.3 in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (from scikit-learn)
(1.21.3)
Requirement already satisfied: scipy>=1.3.2 in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (from scikit-learn)
(1.8.1)
Requirement already satisfied: joblib>=1.0.0 in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (from scikit-learn)
(1.1.0)
Requirement already satisfied: colorama in
d:\programdata\miniconda3\envs\pytorch\lib\site-packages (from
click>=8.0.0->black) (0.4.4)
```

[2]:
```
import sys
sys.version
```

[2]:
```
'3.9.0 | packaged by conda-forge | (default, Nov 26 2020, 07:53:15) [MSC v.1916
64 bit (AMD64)]'
```

[3]:
```
%load_ext autoreload

import pathlib
import pandas as pd
import numpy as np

from IPython.display import display

%matplotlib inline

# read in the json files
data_dir = pathlib.Path('data')
files = {stem: data_dir / f"{stem}.json"
         for stem in ('portfolio','profile', 'transcript')}
dataframes = {key: pd.read_json(file, orient='records', lines=True)
              for key, file in files.items()}
portfolio = dataframes.get("portfolio")
profile = dataframes.get("profile")
transcript = dataframes.get("transcript")
```

[4]:
```
portfolio.head()
```

[4]:
```
   reward                      channels  difficulty  duration  offer_type  \
0      10        [email, mobile, social]          10         7           bogo
1      10  [web, email, mobile, social]          10         5           bogo
2       0          [web, email, mobile]           0         4  informational
3       5          [web, email, mobile]           5         7           bogo
4       5                  [web, email]          20        10       discount

                                 id
0  ae264e3637204a6fb9bb56bc8210ddfd
1  4d5c57ea9a6940dd891ad53e9dbe8da0
2  3f207df678b143eea3cee63160fa8bed
3  9b98b8c7a33c4b65b9aebfe6a799e6d9
4  0b1e1539f2cc45b7b9fa7c272da2e1d7
```

[5]:
```
transcript.head()
```

[5]:
```
                             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
```

[6]:
```
profile.head()
```

[6]:
```
  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
```

2.6 Data Preprocessing

The following cell will write a file into a local module and be loaded to clean the dataframes before feature engineering will be performed. This will add values to null that were coded as another value, expand nested data types into columns; such as lists; categorize columns where appropriate, and convert date columns into DateTime values.

[7]:
```
%autoreload 2
from capstone_tools.data_cleaners import clean
```

[8]:
```
clean_dataframes = {key: clean(df, key) for key, df in dataframes.items()}
portfolio = clean_dataframes['portfolio']
profile = clean_dataframes['profile']
transcript = clean_dataframes['transcript']
```

[9]:
```
print('Portfolio:')
display(portfolio.head())
print('Profile:')
display(profile.head())
print('Transcript:')
display(transcript.head())
```

```
Portfolio:

   offer_reward  offer_difficulty     offer_type  \
0            10                10           bogo
1            10                10           bogo
2             0                 0  informational
3             5                 5           bogo
4             5                20       discount

                                 id  web  email  mobile  social  \
0  ae264e3637204a6fb9bb56bc8210ddfd    0      1       1       1
1  4d5c57ea9a6940dd891ad53e9dbe8da0    1      1       1       1
2  3f207df678b143eea3cee63160fa8bed    1      1       1       0
3  9b98b8c7a33c4b65b9aebfe6a799e6d9    1      1       1       0
4  0b1e1539f2cc45b7b9fa7c272da2e1d7    1      1       0       0

   offer_duration
0           168.0
1           120.0
2            96.0
3           168.0
4           240.0
Profile:

  gender   age                                id became_member_on    income
0    NaN   NaN  68be06ca386d4c31939f3a4f0e3dd783       2017-02-12       NaN
1      F  55.0  0610b486422d4921ae7d2bf64640c50b       2017-07-15  112000.0
2    NaN   NaN  38fe809add3b4fcf9315a9694bb96ff5       2018-07-12       NaN
3      F  75.0  78afa995795e4d85b5d9ceeca43f5fef       2017-05-09  100000.0
4    NaN   NaN  a03223e636434f42ac4c3df47e8bac43       2017-08-04       NaN
Transcript:

                             person           event  time  \
```

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

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

2.7 Merge Data to Events

[10]:
```
def merge_data(df_map):
    transcript = df_map['transcript']
    profile = df_map['profile']
    portfolio = df_map['portfolio']
    return (
        transcript
        .merge(profile, left_on='person', right_on='id', how='left')
        .drop(['id'], axis=1)
        .merge(portfolio, left_on='offer_id', right_on='id', how='left')
        .drop(['id'], axis=1)
    )

events = merge_data(clean_dataframes)
events.head()
```

[10]:
```
                             person           event  time  \
0  78afa995795e4d85b5d9ceeca43f5fef  offer received     0
1  a03223e636434f42ac4c3df47e8bac43  offer received     0
2  e2127556f4f64592b11af22de27a7932  offer received     0
3  8ec6ce2a7e7949b1bf142def7d0e0586  offer received     0
4  68617ca6246f4fbc85e91a2a49552598  offer received     0

                           offer_id  reward  amount gender   age  \
0  9b98b8c7a33c4b65b9aebfe6a799e6d9     NaN     NaN      F  75.0
1  0b1e1539f2cc45b7b9fa7c272da2e1d7     NaN     NaN    NaN   NaN
2  2906b810c7d4411798c6938adc9daaa5     NaN     NaN      M  68.0
3  fafdcd668e3743c1bb461111dcafc2a4     NaN     NaN    NaN   NaN
4  4d5c57ea9a6940dd891ad53e9dbe8da0     NaN     NaN    NaN   NaN

  became_member_on    income  offer_reward  offer_difficulty offer_type  web  \
0       2017-05-09  100000.0           5.0               5.0       bogo  1.0
1       2017-08-04       NaN           5.0              20.0   discount  1.0
```

```
2       2018-04-26   70000.0            2.0              10.0    discount   1.0
3       2017-09-25       NaN            2.0              10.0    discount   1.0
4       2017-10-02       NaN           10.0              10.0        bogo   1.0

   email  mobile  social  offer_duration
0    1.0     1.0     0.0           168.0
1    1.0     0.0     0.0           240.0
2    1.0     1.0     0.0           168.0
3    1.0     1.0     1.0           240.0
4    1.0     1.0     1.0           120.0
```

2.8 Data Visualization

[11]:
```
%autoreload 2
from capstone_tools.enums import Event
```

Comparing Advertising types - there appears to be even distribution of web, email, mobile, and social types and more BOGO and discount types over informational

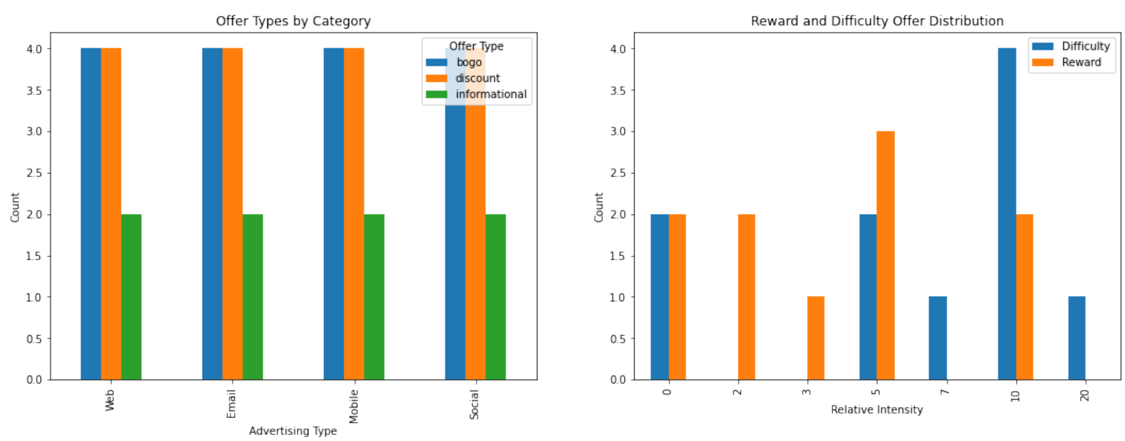
2.8.1 Portfolio Data

Comparing offers to difficulty and reward intensities, there is not an even distribution, but does not appear to be skewed, the log data will need to be compared to evaluate if this is true.

[12]:
```
import matplotlib.pyplot as plt

def plot_offers_metrics_basic(portfolio: pd.DataFrame):
    fig, axs = plt.subplots(1, 2, figsize=(18,6))
    (
        portfolio
        .rename(columns=lambda x: x.title().replace('_', ' '))
        .groupby('Offer Type')
        .count()
        [['Web', 'Email','Mobile', 'Social']]
        .T
        .plot(
            kind='bar',
            xlabel='Advertising Type',
            ylabel='Count',
            ax=axs[0],
            title='Offer Types by Category',
        )
    )
    (
        pd.concat(objs=(
            portfolio.groupby('offer_difficulty').count()[['offer_reward']].
 ↪rename(columns=lambda _: 'Difficulty'),
```

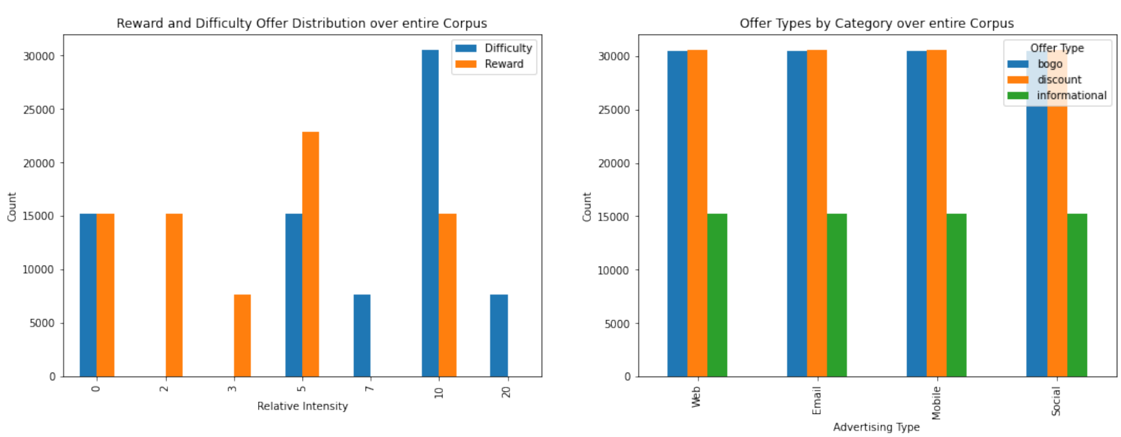
```
            portfolio.groupby('offer_reward').count()[['offer_difficulty']].
↪rename(columns=lambda _: 'Reward')
        ), axis=1).plot(
            kind='bar',
            ax=axs[1],
            xlabel='Relative Intensity',
            ylabel='Count',
            title='Reward and Difficulty Offer Distribution')
    )
    return fig, axs

plot_offers_metrics_basic(portfolio)
```

[12]:
```
(<Figure size 1296x432 with 2 Axes>,
 array([<AxesSubplot:title={'center':'Offer Types by Category'},
xlabel='Advertising Type', ylabel='Count'>,
        <AxesSubplot:title={'center':'Reward and Difficulty Offer
Distribution'}, xlabel='Relative Intensity', ylabel='Count'>],
       dtype=object))
```



[13]:
```
def plot_offers_metrics(transcript: pd.DataFrame, portfolio: pd.DataFrame):
    offers_sent = (
        pd.merge(
            transcript,
            portfolio,
            left_on='offer_id',
            right_on='id'
        )
        .query(f'event == "{Event.received}"')
    )

    fig, axs = plt.subplots(1, 2, figsize=(18,6))
```

```
    (
        pd.concat(objs=(
            offers_sent.groupby('offer_difficulty').count()[['offer_reward']].
↪rename(columns=lambda _: 'Difficulty'),
            offers_sent.groupby('offer_reward').count()[['offer_difficulty']].
↪rename(columns=lambda _: 'Reward')
        ), axis=1).plot(
            kind='bar',
            ax=axs[0],
            xlabel='Relative Intensity',
            ylabel='Count',
            title='Reward and Difficulty Offer Distribution over entire Corpus')
    )

    (
        offers_sent
        .rename(columns=lambda x: x.title().replace('_', ' '))
        .groupby('Offer Type')
        .count()
        [['Web', 'Email','Mobile', 'Social']]
        .T
        .plot(
            kind='bar',
            xlabel='Advertising Type',
            ylabel='Count',
            ax=axs[1],
            title='Offer Types by Category over entire Corpus',
        )
    );
    return fig, axs

plot_offers_metrics(transcript, portfolio);
```



Reviewing the entire corpus, the distribution appears to be the same.

2.8.2 Profile Data

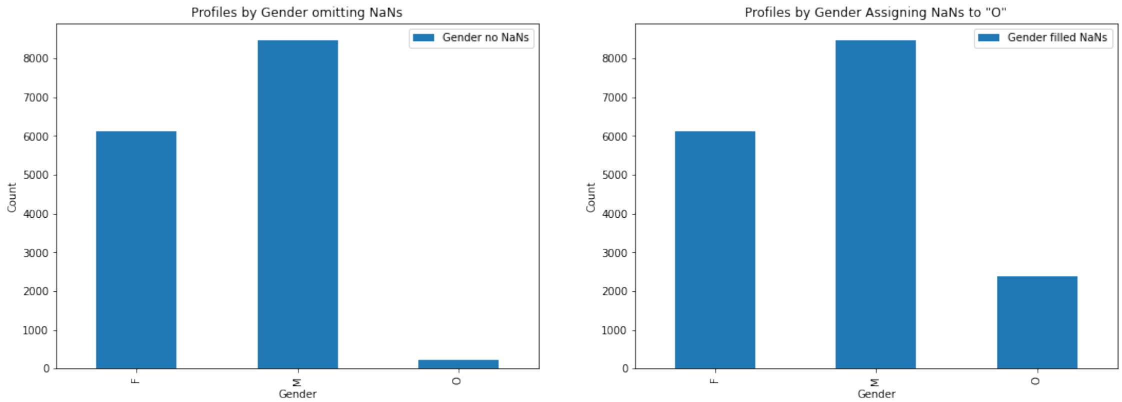
The profile data is a bit more tricky, nans exist within this dataset and some information will have to be provided as an additional category. Looking at Gender and age distributions there is a significant portion of nan values. As well as a significant skew in gender category:

[14]:
```
print(f"Number of Profiles: {len(profile)}")
print(f"Number of Complete Profiles: {len(profile.dropna())}")
```

```
Number of Profiles: 17000
Number of Complete Profiles: 14825
```

[15]:
```
def plot_gender(profile: pd.DataFrame):
    fig, axs = plt.subplots(1, 2, figsize=(18,6))

    (
        profile
        # .assign(gender=lambda df: df['gender'].fillna('O'))
        .groupby('gender')
        .count()
        [['id']]
        .rename(columns=lambda _: 'Gender no NaNs')
        .plot(
            kind='bar',
            xlabel='Gender',
            ylabel='Count',
            ax=axs[0],
            title='Profiles by Gender omitting NaNs',
        )
    );
    (
        profile
        .assign(gender=lambda df: df['gender'].fillna('O'))
        .groupby('gender')
        .count()
        [['id']]
        .rename(columns=lambda _: 'Gender filled NaNs')
        .plot(
            kind='bar',
            xlabel='Gender',
            ylabel='Count',
            ax=axs[1],
            title='Profiles by Gender Assigning NaNs to "O"',
        )
    )
```

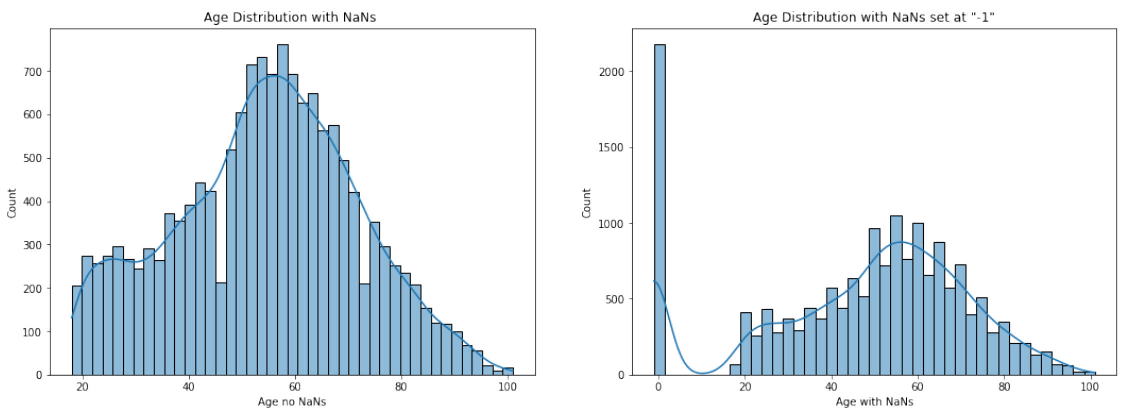
```
    return fig, axs

plot_gender(profile);
```



There is significant skew in gender where Male is the most common followed by female and other is a significant minor population - much lower than the profiles omitting gender all together.

[16]:
```
import seaborn as sns



def plot_age(profile):
    fig, axs = plt.subplots(1, 2, figsize=(18,6))
    age_profile_no_nans = (
        profile
        # .assign(gender=lambda df: df['age'].fillna(99))
        # .groupby('age')
        # .count()
        [['age']]
        .rename(columns=lambda _: 'Age no NaNs')
        .dropna()
    )
    age_profile_with_nan = (
        profile
        .assign(age=lambda df: df['age'].fillna(-1))
        # .groupby('age')
        # .count()
        [['age']]
        .rename(columns=lambda _: 'Age with NaNs')
    )
    splots = []
    splots.append(sns.histplot(
        data=age_profile_no_nans,
        x = 'Age no NaNs',
```

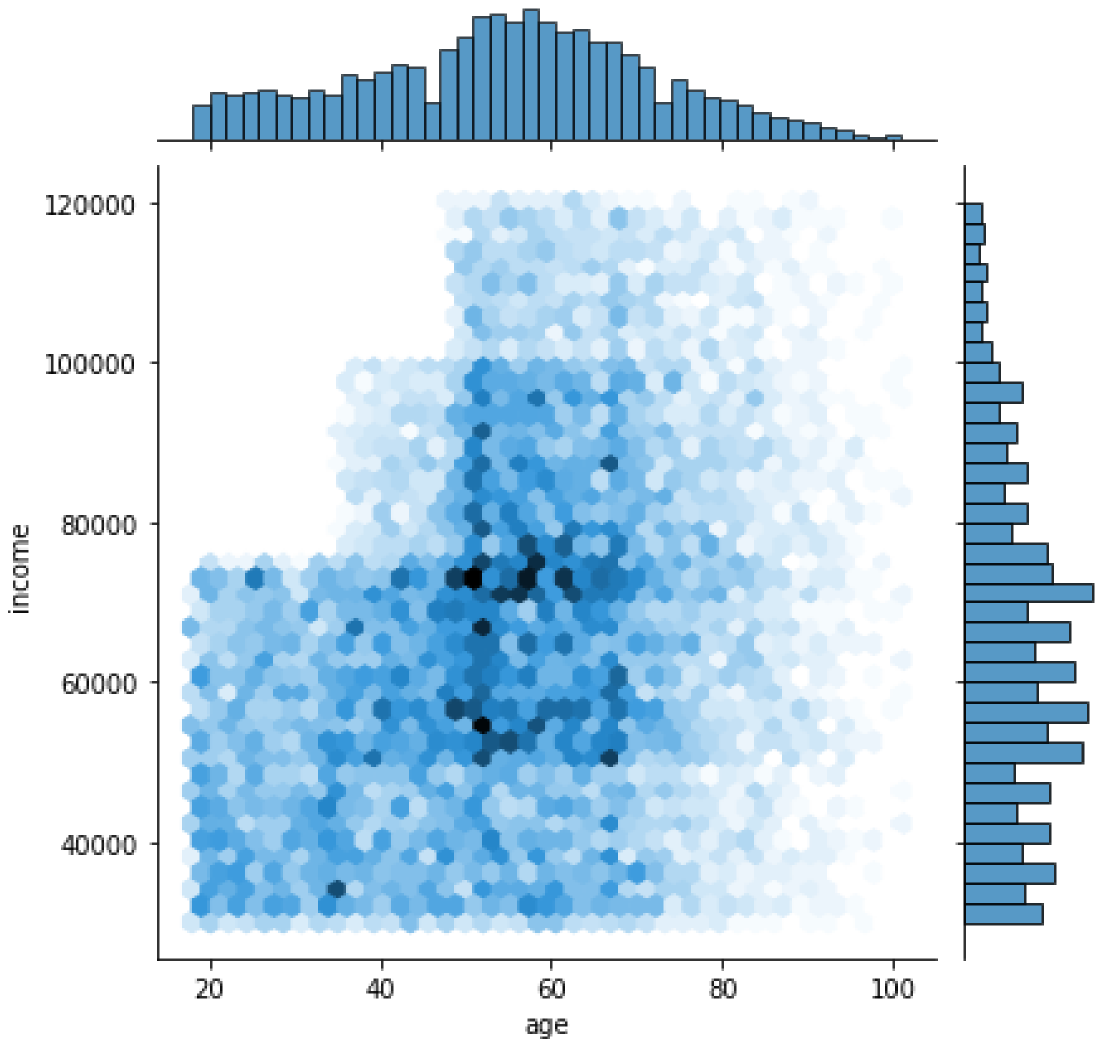
```
        kde=True,
        ax=axs[0]
    ))
    splots.append(sns.histplot(
        data=age_profile_with_nan,
        x = 'Age with NaNs',
        kde=True,
        ax=axs[1],
    ))
    splots[0].set_title('Age Distribution with NaNs ')
    splots[1].set_title('Age Distribution with NaNs set at "-1"')
    return splots

plot_age(profile);
```



Moreover - there appears to be use skewness with income and membership length for income, age, and gender:

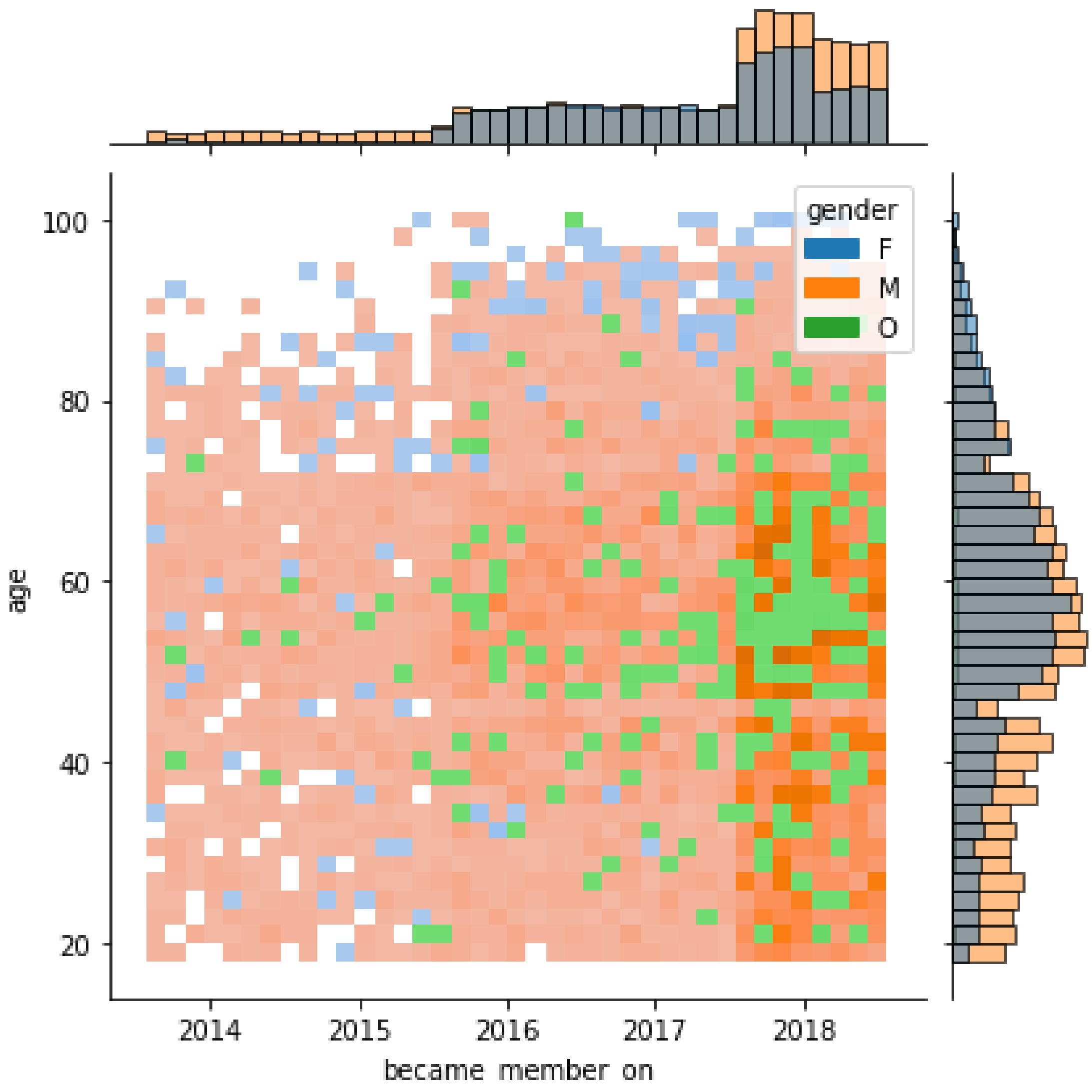
[17]:
```
sns.jointplot(data=profile, x='age', y='income', kind='hex')
```

[17]: <seaborn.axisgrid.JointGrid at 0x1efdeaec790>




```
[18]: sns.jointplot(
          data=profile,
          x='became_member_on',
          y='age',
          kind='hist',
          hue='gender'
      )
```

```
[18]: <seaborn.axisgrid.JointGrid at 0x1efde6bf880>
```



There appears to be significantly more newer members that select the non-binary gender and there appears to be much more members added between 2015 and 2016

2.9 Feature Generation

Feature generation will transform the cleaned data to derived values. The following list describes each field and the intended use:

1. `event_id`: This is a unique id generated for each unique offer period started by an "Offer Received" event
2. `sales`: This is the amount of sales generated for each `event_id`
3. `cost`: This is the cost incurred by the `event_id` (i.e. if a discount was applied to a sale - the amount of the discount was captured here - a.k.a the reward of the offer)
4. `profit`: This is sales - cost for each `event_id`

5. `offer_viewed`: This is marked true for each item after the "Offer Viewed" event
6. `offer_valid`: This is marked true for each event less than the offer duration (defined by `elapsed_time` column)
7. `offer_redeemed`: This is marked true only at events labeled as "Offer Completed" - intended to be used to generate `offer_success` column
8. `offer_success`: This is marked true if and only if `offer_viewed`, `offer_valid`, and `offer_redeemed` are all true
9. `gender`: This column has been assigned a numerical category where -1 is nan, 0 is male, 1 is female, 2 is other
10. `became_member_on`: This column has been converted to a numerical category where each enumeration represents an equal distribution cut of 5 separate categories where 1 are the most loyal customers and 5 are the newest customers. 0 is NaN
11. `age`: This column has been converted to a numerical category where each enumeration represents an equal distribution cut of 5 separate categories where 1 are the youngest customers and 5 are the oldest customers. 0 is NaN
12. `income`: This column has been converted to a numerical category where each enumeration represents an equal distribution cut of 5 separate categories where 1 are the lowest income customers and 5 are the most affluent customers. 0 is NaN
13. `offer_start`: this column is filled with the value of when the offer was started for all offers within the `event_id`
14. `elapsed_time`: this column is the time elapsed after the start of the event_id defined by `offer_start`

`profit` was originally used as my target value to generate a `best_offer` category, but was ultimately scrapped. `offer_success` is ultimately used to evaluate given portfolio and profile information if an offer will be successful to the individual.

[19]:
```
%autoreload 2
from capstone_tools.feature_generation import transform
```

[42]:
```
from capstone_tools.enums import Offer
from capstone_tools.feature_generation import transform
tx_events = transform(events, 'events')
outcomes = {}
for offer in Offer.to_list():
    outcomes[offer] = transform(tx_events, 'outcomes', offer=offer)
outcomes['All'] = transform(tx_events, 'outcomes', offer=None)
```

[43]:
```
print("Event Data - Transformed:")
display(tx_events.head())
print("Outcome Data - Transformed:")
display(outcomes[Offer.discount].head())
```

```
Event Data - Transformed:

                                  person           event  time  \
index
155351  129d54616fba45cda310d24179b0643d  offer received   408
168993  129d54616fba45cda310d24179b0643d     transaction   414
```

```
172394  129d54616fba45cda310d24179b0643d    offer viewed   420
6399    5db2207d5a194b81b986f37107ef63f7  offer received     0
14124   5db2207d5a194b81b986f37107ef63f7    offer viewed     0

                                offer_id  reward  amount  gender  age  \
index
155351  4d5c57ea9a6940dd891ad53e9dbe8da0     NaN     NaN       1    4
168993  4d5c57ea9a6940dd891ad53e9dbe8da0     NaN    1.13       1    4
172394  4d5c57ea9a6940dd891ad53e9dbe8da0     NaN     NaN       1    4
6399    5a8bc65990b245e5a138643cd4eb9837     NaN     NaN      -1  NaN
14124   5a8bc65990b245e5a138643cd4eb9837     NaN     NaN      -1  NaN

       became_member_on income  …                          event_id  \
index                           …
155351                4      1  …  000220b2730c49459da9fe32129dc3f6
168993                4      1  …  000220b2730c49459da9fe32129dc3f6
172394                4      1  …  000220b2730c49459da9fe32129dc3f6
6399                  3    NaN  …  000229b97f63420e8799a38773c7a18f
14124                 3    NaN  …  000229b97f63420e8799a38773c7a18f

        offer_start elapsed_time  offer_valid  offer_viewed  offer_redeemed  \
index
155351        408.0          0.0            1             0               0
168993        408.0          6.0            1             0               0
172394        408.0         12.0            1             1               0
6399            0.0          0.0            1             0               0
14124           0.0          0.0            1             1               0

        offer_success  sales costs  profit
index
155351              0   0.00   0.0    0.00
168993              0   1.13   0.0    1.13
172394              0   1.13   0.0    1.13
6399                0   0.00   0.0    0.00
14124               0   0.00   0.0    0.00

[5 rows x 28 columns]
```

```
Outcome Data - Transformed:
```

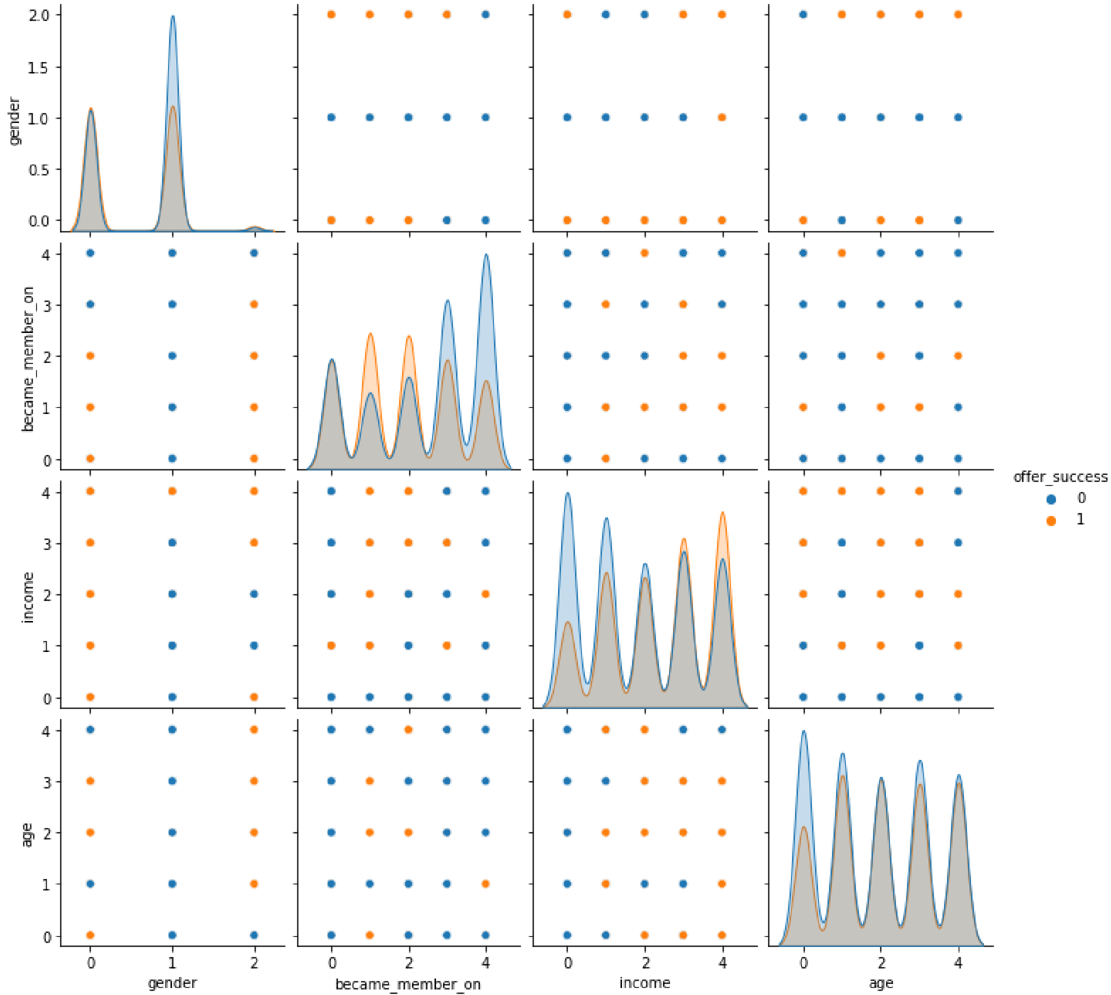
```
                           event_id  time  offer_viewed  offer_redeemed  \
0  0007813652d94bda8509e4956b9335d6   540             1               1
1  00082957ac6b4cc59439b6b27bc0bb3e   210             1               1
2  000a0ba2f60749bebfcf8e91d56b6d7a   282             1               1
3  000be0436698410fb00af359d00a63f0   336             1               0
4  000e70c0183c4ab48d9a80656fadb3f1   504             0               0

   offer_success  sales  costs  profit                            person  \
0              1  27.87    3.0   24.87  df3da7cfcf614b3481b65c89657994ed
```

```
1               1   7.86    3.0    4.86  70743262fadd4895adf8e5907da3c654
2               1  14.71    3.0   11.71  793913a9f33c4ae596cfa55ef3bfd901
3               0   0.00    0.0    0.00  b64fdf87a8424569ab616686c1c48641
4               0   0.00    0.0    0.00  42fd8e1e7c4548c9b4c151a1c3af134b

                           offer_id  offer_reward  offer_difficulty  gender  \
0  2298d6c36e964ae4a3e7e9706d1fb8c2           3.0               7.0       0
1  2298d6c36e964ae4a3e7e9706d1fb8c2           3.0               7.0       1
2  2298d6c36e964ae4a3e7e9706d1fb8c2           3.0               7.0       0
3  fafdcd668e3743c1bb461111dcafc2a4           2.0              10.0      -1
4  0b1e1539f2cc45b7b9fa7c272da2e1d7           5.0              20.0       1

   age became_member_on income offer_type
0    2                0      4   discount
1    0                1      0   discount
2    4                3      3   discount
3  NaN                3    NaN   discount
4    2                3      0   discount
```

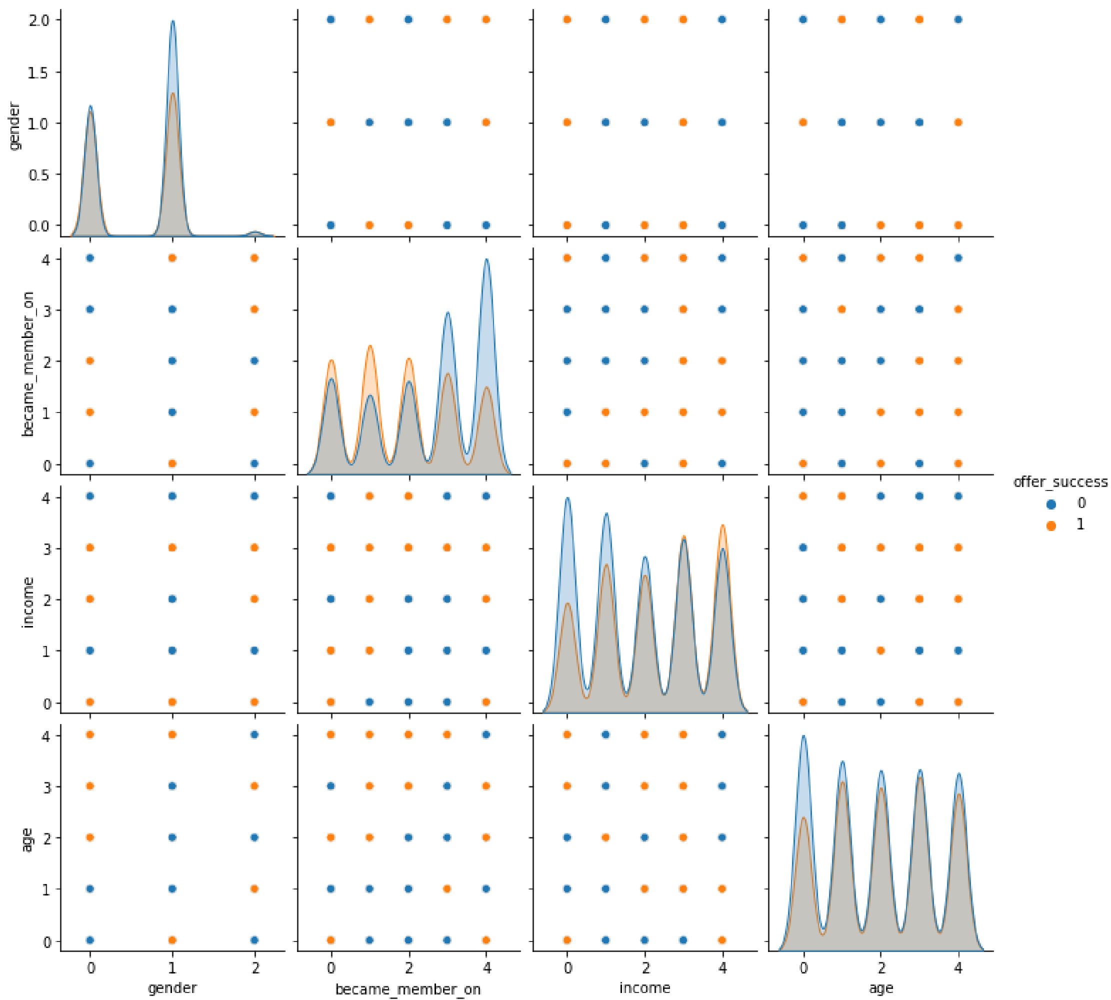
2.10 Data Refinement

[44]:
```python
drop_cols = ['person', 'offer_id', 'event_id', 'offer_type', 'offer_viewed',␣
↪'offer_redeemed', 'costs', 'profit']
keep_cols = ['gender', 'became_member_on', 'income', 'age', 'offer_success']

# sns.pairplot(outcomes.drop(drop_cols, axis=1), hue='offer_success')
for key, outcome_df in outcomes.items():
    print(f"Evaluation by Offer={key}")
    sns.pairplot(
        outcome_df[keep_cols].dropna().astype(int),
        hue='offer_success',
    )
    plt.show()
```

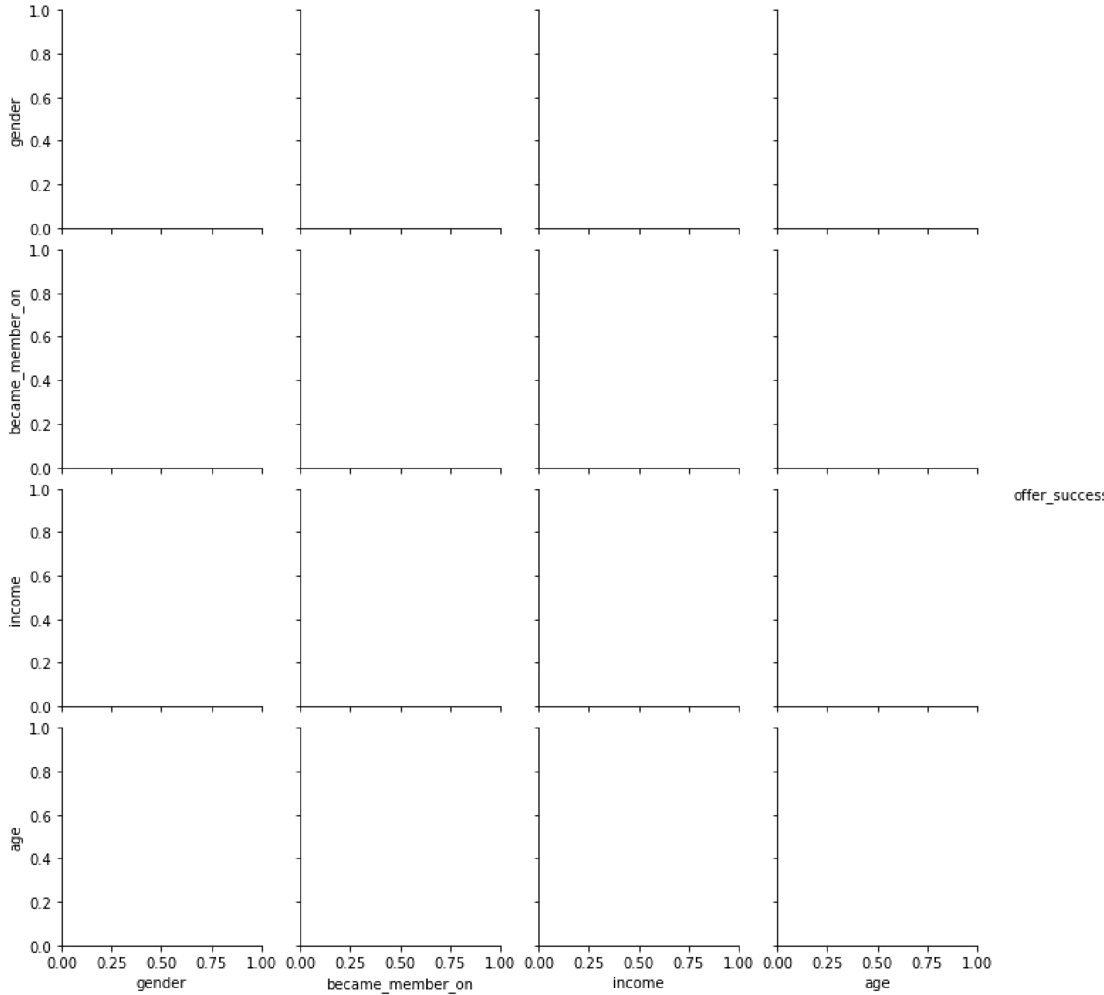
```
Evaluation by Offer=bogo
```



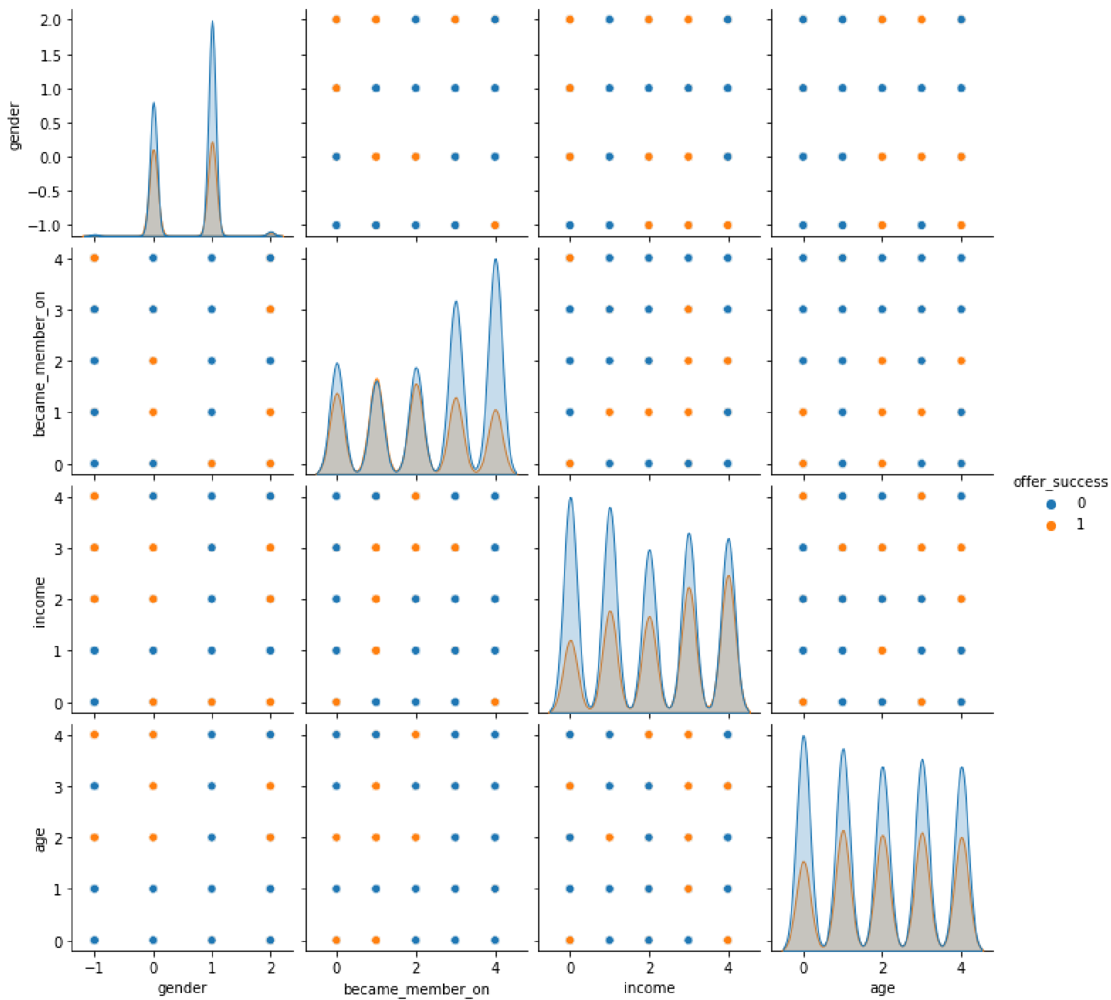
Evaluation by Offer=discount



Evaluation by Offer=info



Evaluation by Offer=All



Engineering Decision: It appears that BOGO offers provide the most variation between offer success and failure. I will select this subset of data to evaluate my models against.

Engineering Decision: I have also made the decision to include NAN categories as '0' categories for `['gender', 'became_member_on', 'income', 'age']`. This decision was made since I already have converted numerical values into categories the inclusion of NANs are much easier to keep.

[46]:
```
from capstone_tools.feature_generation import EventTransformer

def one_hot_cat_cols(df, cols):
    for col in cols:
        df = EventTransformer.merge_cats_to_one_hots(df, col)
    return df

cat_cols = ['became_member_on', 'gender', 'age', 'income']
model_data = one_hot_cat_cols(outcomes[Offer.bogo], cat_cols)
```

```
[48]: print("Model Data - BOGO offers with one-hot values for category cols:")
      display(model_data)
```

```
Model Data - BOGO offers with one-hot values for category cols:

                               event_id  time  offer_viewed  offer_redeemed  \
0      000220b2730c49459da9fe32129dc3f6   420             1               0
1      0002b54031f44094b18a426774737129   360             1               1
2      0003098c6ab6419bb8a44103da55f9cf   504             0               0
3      00050b1e361648e4a80390bad36135f3   600             0               1
4      000b1b3be86d407a8ea15ba3f5496910   522             1               1
…                                   …   …           …             …
31458  fff76f197ede4da8a8b58cc4392b3cb3   246             1               1
31459  fff8445bf2fb470d890ca3202e821244   462             1               1
31460  fff8da4cd1274bc59db580b38332ef49   414             0               1
31461  fffcac3900e64e51aba3c02ff6f1d6d6   606             1               0
31462  fffff41fb51b480a9c8ea14163cefd7a   228             1               0

       offer_success  sales  costs  profit                            person  \
0                  0   1.13    0.0    1.13  129d54616fba45cda310d24179b0643d
1                  1  11.81    5.0    6.81  1f9b6e1cebeb48dcb6cd5965b408c989
2                  0   0.00    0.0    0.00  0df14ab3f3274a0bbc4c76acef224f02
3                  0  21.79   10.0   11.79  be85e0f528c24ae9acae162d6a2bc832
4                  1  24.39    5.0   19.39  4f519b617c554988b17714a0a4ac767e
…                …     …     …      …                               …
31458              1  26.66    5.0   21.66  be63245084964ff0a3e154202123e222
31459              1  85.61   10.0   75.61  aeea18cf2e8d455c98453c546292a9f6
31460              0  15.59    5.0   10.59  304183fd053441f0a13bc4d648b7cff1
31461              0   2.76    0.0    2.76  7b864e6e295f4b4b8da46f9f43ef673e
31462              0   7.02    0.0    7.02  4d5618b1bd0c4d1693b860e5b4daac40

                               offer_id  …  age_0  age_1 age_2  age_3  \
0      4d5c57ea9a6940dd891ad53e9dbe8da0  …      0      0     0      0
1      f19421c1d4aa40978ebb69ca19b0e20d  …      1      0     0      0
2      9b98b8c7a33c4b65b9aebfe6a799e6d9  …      1      0     0      0
3      4d5c57ea9a6940dd891ad53e9dbe8da0  …      1      0     0      0
4      9b98b8c7a33c4b65b9aebfe6a799e6d9  …      0      0     1      0
…                                   …   …    …    …    …    …
31458  9b98b8c7a33c4b65b9aebfe6a799e6d9  …      0      0     1      0
31459  4d5c57ea9a6940dd891ad53e9dbe8da0  …      0      0     0      1
31460  9b98b8c7a33c4b65b9aebfe6a799e6d9  …      0      0     0      0
31461  4d5c57ea9a6940dd891ad53e9dbe8da0  …      1      0     0      0
31462  ae264e3637204a6fb9bb56bc8210ddfd  …      1      0     0      0

       age_4  income_0  income_1  income_2  income_3  income_4
0          1         0         1         0         0         0
1          0         1         0         0         0         0
2          0         0         1         0         0         0
```

```
3          0        0        0        0        1        0
4          0        0        0        0        0        1
…      …       …       …       …       …       …
31458      0        0        0        0        1        0
31459      0        0        0        0        1        0
31460      1        1        0        0        0        0
31461      0        1        0        0        0        0
31462      0        0        1        0        0        0

[31463 rows x 32 columns]
```

2.11 Model Implementation

2.11.1 Standard Scaling

If nans still exist within the data the models will break, in order to prevent an accident - I will apply a median imputer to impute any nan data - though my data cleaning should have accounted for this already.

[49]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
```

[51]:
```
def get_labels(model_data, label_cols):
    """Get label columns from model_data"""
    return model_data[label_cols]

def get_data(model_data, drop_cols):
    """Get data columns from model_data"""
    return model_data.drop(drop_cols, axis=1)

def make_pipeline(pca=None):
    """
    Make a data processing pipeline appends a trained PCA model if provided
    """
    pre_proc = Pipeline([
            ('imputer', SimpleImputer(strategy='median')),
            ('scaler', StandardScaler()),
        ])
    if pca:
        return Pipeline([
            ("preprocessor", pre_proc),
            ('pca', pca),
        ])
    return pre_proc
```

[58]:
```
label_cols  = [
    "event_id",
```

```python
    "person",
    "offer_id",
    # "viewed_and_redeemed",
    "offer_success"
]
drop_cols = [
    "offer_viewed",
    "offer_redeemed",
    "sales",
    "costs",
    "profit",
    "time",
    "offer_type",
]
drop_cols.extend(label_cols)
labels = get_labels(model_data, label_cols)
data = get_data(model_data, drop_cols)
print("Data Input:")
display(data.head())
print("Data Labels:")
display(labels.head())
```

```
Data Input:

   offer_reward  offer_difficulty  became_member_on_0  became_member_on_1  \
0          10.0              10.0                   0                   0
1           5.0               5.0                   0                   0
2           5.0               5.0                   0                   0
3          10.0              10.0                   0                   1
4           5.0               5.0                   0                   0

   became_member_on_2  became_member_on_3  became_member_on_4  gender_-1  \
0                   0                   0                   1          0
1                   0                   1                   0          0
2                   0                   1                   0          0
3                   0                   0                   0          0
4                   0                   0                   1          0

   gender_0  gender_1  …  age_0  age_1  age_2  age_3  age_4  income_0  \
0         0         1  …      0      0      0      0      1         0
1         1         0  …      1      0      0      0      0         1
2         0         1  …      1      0      0      0      0         0
3         1         0  …      1      0      0      0      0         0
4         0         1  …      0      0      1      0      0         0

   income_1  income_2  income_3  income_4
0         1         0         0         0
1         0         0         0         0
```

```
2          1          0          0          0
3          0          0          1          0
4          0          0          0          1

[5 rows x 21 columns]
```

```
Data Labels:
```

```
                           event_id                            person  \
0  000220b2730c49459da9fe32129dc3f6  129d54616fba45cda310d24179b0643d
1  0002b54031f44094b18a426774737129  1f9b6e1cebeb48dcb6cd5965b408c989
2  0003098c6ab6419bb8a44103da55f9cf  0df14ab3f3274a0bbc4c76acef224f02
3  00050b1e361648e4a80390bad36135f3  be85e0f528c24ae9acae162d6a2bc832
4  000b1b3be86d407a8ea15ba3f5496910  4f519b617c554988b17714a0a4ac767e

                           offer_id  offer_success
0  4d5c57ea9a6940dd891ad53e9dbe8da0              0
1  f19421c1d4aa40978ebb69ca19b0e20d              1
2  9b98b8c7a33c4b65b9aebfe6a799e6d9              0
3  4d5c57ea9a6940dd891ad53e9dbe8da0              0
4  9b98b8c7a33c4b65b9aebfe6a799e6d9              1
```

[76]:

```python
def scale_data(data, preprocessor):
    data_scaled = preprocessor.fit_transform(data)
    _, n_cols = data_scaled.shape
    if n_cols == len(data.columns):
        return pd.DataFrame(
            data=data_scaled, columns=data.columns, index=data.index
        )
    return pd.DataFrame(data=data_scaled, index=data.index)

preprocessor = make_pipeline()
data_scaled = scale_data(data, preprocessor)
display(data_scaled)
```

```
       offer_reward  offer_difficulty  became_member_on_0  became_member_on_1  \
22696      1.017368          1.017368            2.191157            -0.45443
9343      -0.982929         -0.982929           -0.456380            -0.45443
4357      -0.982929         -0.982929           -0.456380            -0.45443
23657      1.017368          1.017368           -0.456380             2.20056
25381      1.017368          1.017368           -0.456380            -0.45443
…               …               …                 …                  …
15999      1.017368          1.017368           -0.456380            -0.45443
7626       1.017368          1.017368           -0.456380            -0.45443
3472       1.017368          1.017368           -0.456380            -0.45443
21727     -0.982929         -0.982929           -0.456380            -0.45443
25454     -0.982929         -0.982929           -0.456380            -0.45443

       became_member_on_2  became_member_on_3  became_member_on_4  gender_-1  \
```

```
22696          -0.474576           -0.539853           -0.572681   2.621446
9343            2.107144           -0.539853           -0.572681  -0.381469
4357           -0.474576            1.852355           -0.572681  -0.381469
23657          -0.474576           -0.539853           -0.572681  -0.381469
25381           2.107144           -0.539853           -0.572681  -0.381469
…                    …                   …                   …         …
15999          -0.474576            1.852355           -0.572681  -0.381469
7626            2.107144           -0.539853           -0.572681  -0.381469
3472           -0.474576           -0.539853            1.746173  -0.381469
21727          -0.474576            1.852355           -0.572681  -0.381469
25454          -0.474576           -0.539853            1.746173  -0.381469

       gender_0  gender_1  …     age_0     age_1     age_2     age_3  \
22696 -0.758755 -0.991822  … -0.455363 -0.477088 -0.452392 -0.465672
9343   1.317948 -0.991822  … -0.455363 -0.477088  2.210472 -0.465672
4357   1.317948 -0.991822  … -0.455363 -0.477088  2.210472 -0.465672
23657 -0.758755  1.008245  … -0.455363 -0.477088 -0.452392  2.147434
25381 -0.758755  1.008245  … -0.455363  2.096051 -0.452392 -0.465672
…           …         …  …       …         …         …         …
15999  1.317948 -0.991822  … -0.455363  2.096051 -0.452392 -0.465672
7626   1.317948 -0.991822  … -0.455363 -0.477088 -0.452392 -0.465672
3472   1.317948 -0.991822  …  2.196051 -0.477088 -0.452392 -0.465672
21727 -0.758755  1.008245  …  2.196051 -0.477088 -0.452392 -0.465672
25454 -0.758755  1.008245  … -0.455363  2.096051 -0.452392 -0.465672

          age_4  income_0  income_1  income_2  income_3  income_4
22696 -0.448904 -0.447796 -0.468533 -0.428815 -0.468785 -0.485020
9343  -0.448904 -0.447796 -0.468533 -0.428815 -0.468785  2.061772
4357  -0.448904 -0.447796 -0.468533  2.332009 -0.468785 -0.485020
23657 -0.448904 -0.447796 -0.468533 -0.428815 -0.468785  2.061772
25381 -0.448904 -0.447796 -0.468533  2.332009 -0.468785 -0.485020
…           …         …         …         …         …         …
15999 -0.448904 -0.447796  2.134321 -0.428815 -0.468785 -0.485020
7626   2.227647 -0.447796  2.134321 -0.428815 -0.468785 -0.485020
3472  -0.448904 -0.447796 -0.468533  2.332009 -0.468785 -0.485020
21727 -0.448904  2.233158 -0.468533 -0.428815 -0.468785 -0.485020
25454 -0.448904 -0.447796 -0.468533 -0.428815  2.133173 -0.485020

[18877 rows x 21 columns]
```

2.11.2 Train, Test, Validation Sets

[60]:
```
import pickle

def write_col_names(location: pathlib.Path, data: pd.DataFrame):
    """Write column names to location"""
    file = location.joinpath('col_names.pkl')
```

```
    with open(file, 'wb') as fh:
        pickle.dump(data.columns, fh)

root = pathlib.Path('data/processed')
root.mkdir(exist_ok=True, parents=True)
write_col_names(root, data)
```

[61]:
```
import pathlib
import pickle
import numpy as np

from capstone_tools.data_splitting import PreSplitData, process_scaled_data

val_splits = 0.2
test_splits = 0.2
data_cargo = PreSplitData(data_scaled, labels, test_splits, val_splits)
root = pathlib.Path('.')
location = root / "data/processed"

process_scaled_data(data_cargo, location)
```

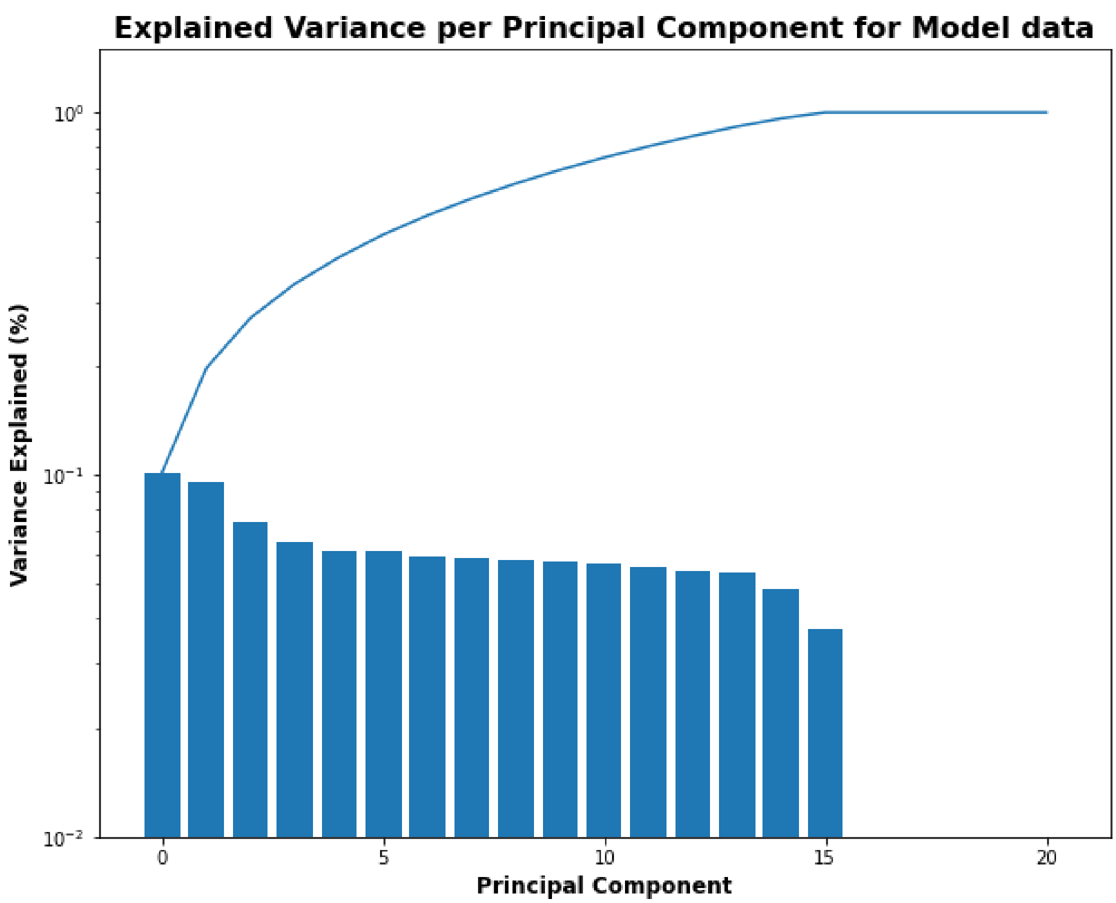
2.12 PCA

Can start from here if you have saved your data

[62]:
```
import pathlib
import numpy as np
import pandas as pd

from capstone_tools.data_loaders import load_dataset

root = pathlib.Path('data/processed')
train_loc = root.joinpath('train')
train_data, train_labels = load_dataset(train_loc)
```

[69]:
```
from sklearn.decomposition import PCA

pcas = (PCA() for _ in range(1))

fig, ax = plt.subplots(1, 1, figsize=(10, 8))
dataset = (train_data,)
names = ("Model",)
axs = (ax,)
for ax, pca, data, name in zip(axs, pcas, dataset, names):
    results = pca.fit_transform(data)
    vars = pca.explained_variance_ratio_
    n = len(vars)
```

```
    ax.bar(range(n), vars)
    ax.plot(range(n), vars.cumsum())
    ax.set_ylabel("Variance Explained (%)", fontweight='bold', fontsize=12)
    ax.set_xlabel(
        f"Principal Component",
        fontweight='bold',
        fontsize=12,
    )
    ax.semilogy()
    ax.set_ylim([0.01, 1.5])
    ax.set_title(
        f"Explained Variance per Principal Component for {name.title()} data",
        fontweight='bold',
        fontsize=16,
    )

plt.show()
```



Now that I have increased the number of data columns into categorical data, PCA appears to create more use, where I can reduce the number of components by close around 40% if I were to reduce the number of components down to 15 and still retain 100% of the variance.

2.12.1 New Pipeline with PCA in line

[80]:
```
pipeline_pca = PCA(n_components=15)
pca_preprocessor = make_pipeline(pipeline_pca)
data_scaled = scale_data(data, pca_preprocessor)
print("Scaled data wtih PCA applied:")
display(data_scaled.head())
```

```
Scaled data wtih PCA applied:

              0         1         2         3         4         5         6  \
22696  0.270234  1.428850  2.586098 -1.314301 -0.797313  0.928886 -0.277778
9343   2.549380 -1.644775 -0.857079 -0.432272  0.270677 -0.192223  1.130957
4357   1.038802 -1.562395 -0.448989  1.026756 -1.153379  0.736682  0.435915
23657  0.686365  1.392251 -0.916238 -1.619063 -0.486751 -2.635043 -1.067007
25381 -1.003022  1.479274 -0.606811 -1.226894 -0.349356  2.478883  0.999725

              7         8         9        10        11        12        13  \
22696 -0.338374 -1.100685 -0.396680  0.643909  1.234907  0.156145  1.685199
9343   1.259244 -1.977645  1.057316 -0.273992 -1.473155 -0.719024  0.119113
4357  -1.075901 -1.284727 -1.802280 -0.638362 -1.649991 -1.891620 -0.699108
23657 -0.722911  0.249004  0.799678  1.576467  0.148040  0.524720 -1.192824
25381 -0.495256 -0.084063  1.671452 -0.181624 -0.595570 -0.530871 -2.171459

             14
22696 -0.282567
9343  -0.188534
4357   0.002182
23657  0.015092
25381 -0.076368
```

2.13 Model Predictions - Unsupervised Learning

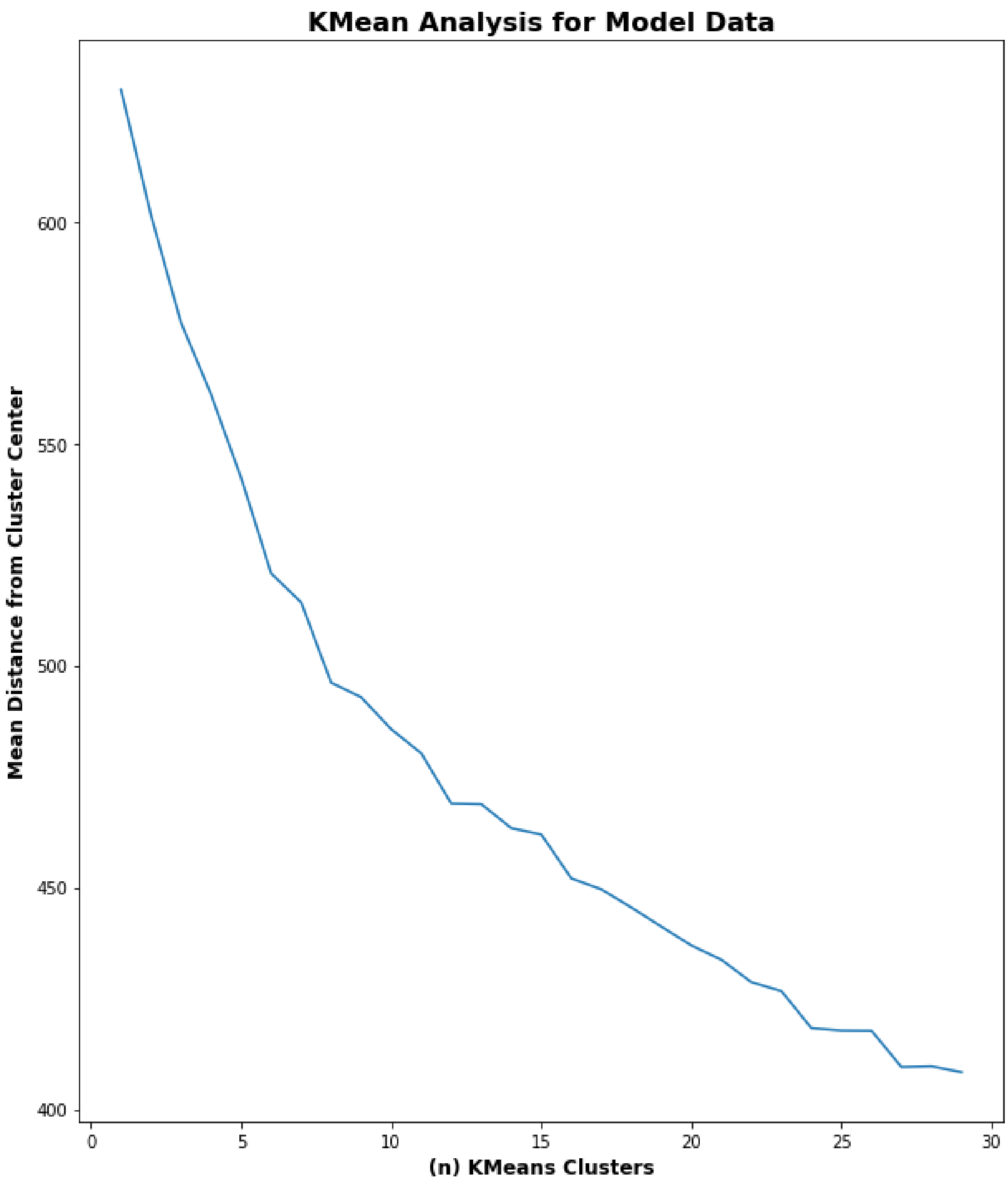
The following segment investigates if the profiles follow similar behaviors and if they can be classified into clusters.

[81]:
```
import pathlib

import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
import numpy as np

from capstone_tools.data_loaders import load_dataset
```

[82]:
```python
root = pathlib.Path('data/processed')

train_loc = root.joinpath('train')
train_data, _ = load_dataset(train_loc)
train_data = train_data.values
```

[83]:
```python
mean_dist = []
total_clusters = 30
for n in range(1, total_clusters):
    clf = KMeans(n_clusters=n)
    clf.fit(train_data)
    d = np.sqrt(-clf.score(train_data))
    mean_dist.append(d)
```

[85]:
```python
fix, ax = plt.subplots(1, 1, figsize=(10, 12))
ax.plot(range(1, total_clusters), mean_dist)
# ax.semilogy()
ax.set_ylabel(
    "Mean Distance from Cluster Center",
    fontweight='bold',
    fontsize=12
)
ax.set_xlabel(
    "(n) KMeans Clusters",
    fontweight='bold',
    fontsize=12,
)
# ax.semilogy()
# ax.set_ylim([0.05, 1.5])
ax.set_title(
    "KMean Analysis for Model Data",
    fontweight='bold',
    fontsize=16,
)
plt.show()
```



There seems to be a two sections where KMeans clustering can be utilized. There seems to be deviations from the mean distance scores at around 8 clusters. Moving forward, if unsupervised learning is applied, election of either 4 or 8 clusters will be used for the final model.

2.14 Recommendation Model

2.14.1 Baseline Model

[86]:
```
%load_ext autoreload
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

[87]:
```
%autoreload 2

import pathlib

import pickle
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import (
    RandomForestClassifier,
    GradientBoostingClassifier,
    AdaBoostClassifier,
)
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.dummy import DummyClassifier

from capstone_tools.data_loaders import load_data_corpus
from capstone_tools.model_trainers import SKLearnModelTrainer


data_loc = pathlib.Path("data/processed")
datasets = load_data_corpus(data_loc)

save_loc = pathlib.Path('models')
```

[88]:
```
baseline_clfs = [
    (DummyClassifier, {}),
    (GaussianNB, {}),
    (RandomForestClassifier, {"n_estimators": 100}),
    (GradientBoostingClassifier, {"n_estimators": 100, "learning_rate": 0.1}),
    (AdaBoostClassifier, {"n_estimators": 100, "learning_rate": 0.1}),
    (DecisionTreeClassifier, {}),#"max_depth": 5, "min_samples_split": 5}),
    (LogisticRegression, {"C": 1}),
]
acc_scores = {}
rel_scores = {}
baseline_score = 0.0
for Clf, kwargs in baseline_clfs:
    datasets = load_data_corpus(data_loc)
    clf = Clf(**kwargs)
```

```
    clf_name = clf.__class__.__name__
    model_file = save_loc.joinpath(f"{clf_name.lower()}-model.pkl")
    sk_trainer = SKLearnModelTrainer(clf)
    scores = sk_trainer.train(datasets, save_path=model_file)
    if isinstance(clf, DummyClassifier):
        baseline_score = scores.get('test', 0.0)
    acc_scores[clf_name] = scores
    rel_scores[clf_name] = scores.get('test') - baseline_score
    acc_file = save_loc.joinpath(f"{clf_name.lower()}-scores.pkl")
    with open(acc_file, 'wb') as fh:
        pickle.dump(acc_scores, fh)
    print(
        f"{clf!r}: trained with training accuracy: "
        f"{scores['train']*100:.2f}%"
        f"  test accuracy: {scores['test']*100:.2f}%"
        f"  rel-score: {rel_scores[clf_name]*100:.2f}%"
    )
```

```
DummyClassifier(): trained with training accuracy: 59.23%  test accuracy: 60.35%
rel-score: 0.00%
GaussianNB(): trained with training accuracy: 65.90%  test accuracy: 66.18%
rel-score: 5.83%
RandomForestClassifier(): trained with training accuracy: 69.90%  test accuracy:
67.84%  rel-score: 7.48%
GradientBoostingClassifier(): trained with training accuracy: 68.58%  test
accuracy: 68.62%  rel-score: 8.26%
AdaBoostClassifier(learning_rate=0.1, n_estimators=100): trained with training
accuracy: 67.89%  test accuracy: 68.19%  rel-score: 7.83%
DecisionTreeClassifier(): trained with training accuracy: 69.90%  test accuracy:
67.74%  rel-score: 7.39%
LogisticRegression(C=1): trained with training accuracy: 67.97%  test accuracy:
68.50%  rel-score: 8.15%
```

2.14.2 Optimization for best model

[123]:
```
max_depth = [int(x) for x in 10**(np.linspace(6, 20, 10) / 10)]
max_depth
```

[123]:
```
[3, 5, 8, 11, 16, 23, 34, 48, 69, 100]
```

[126]:
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import GradientBoostingClassifier
best_clf = GradientBoostingClassifier()
```

```
learning_rates = [np.round(x, 3) for x in 10**(np.linspace(-30, 0, 10) / 10)]
estimators = [int(x) for x in 10**(np.linspace(0, 26, 10) / 10)]
sample_split = [int(x) for x in 10**(np.linspace(4, 20, 10) / 10)]
max_depth = [int(x) for x in 10**(np.linspace(6, 20, 10) / 10)]

search_grid = {
    "learning_rate": learning_rates,
    "n_estimators": estimators,
    "criterion": ["friedman_mse", "squared_error"],
    "min_samples_split": sample_split,
    "max_depth": max_depth,
}
search_clf = RandomizedSearchCV(
    estimator=best_clf,
    param_distributions=search_grid,
    n_jobs=-1,
)
```

[131]:
```
datasets = load_data_corpus(data_loc)
clf_name = search_clf.__class__.__name__
model_file = save_loc.joinpath(f"{clf_name.lower()}-model.pkl")
sk_trainer = SKLearnModelTrainer(search_clf)
scores = sk_trainer.train(datasets, save_path=model_file)
acc_scores[clf_name] = scores
rel_scores[clf_name] = scores.get('test') - baseline_score
acc_file = save_loc.joinpath(f"{clf_name.lower()}-scores.pkl")
with open(acc_file, 'wb') as fh:
    pickle.dump(acc_scores, fh)
```

[131]: 'RandomizedSearchCV'

[133]:
```
print(
    f"{search_clf!r}: trained with training accuracy: "
    f"{scores['train']*100:.2f}%"
    f"  test accuracy: {scores['test']*100:.2f}%"
    f"  rel-score: {rel_scores[clf_name]*100:.2f}%"
)
```

```
RandomizedSearchCV(estimator=GradientBoostingClassifier(), n_jobs=-1,
                   param_distributions={'criterion': ['friedman_mse',
                                                      'squared_error'],
                                        'learning_rate': [0.001, 0.002, 0.005,
                                                          0.01, 0.022, 0.046,
                                                          0.1, 0.215, 0.464,
                                                          1.0],
                                        'max_depth': [3, 5, 8, 11, 16, 23, 34,
                                                      48, 69, 100],
```

```
                                            'min_samples_split': [2, 3, 5, 8, 12,
                                                                  19, 29, 44, 66,
                                                                  100],
                                            'n_estimators': [1, 1, 3, 7, 14, 27, 54,
                                                             105, 204, 398]}):
trained with training accuracy: 68.43%  test accuracy: 68.57%  rel-score: 8.22%
```

[135]:
```python
search_clf.best_params_
```

[135]:
```
{'n_estimators': 54,
 'min_samples_split': 44,
 'max_depth': 5,
 'learning_rate': 0.046,
 'criterion': 'friedman_mse'}
```

[136]:
```python
best_clf = search_clf.best_estimator_
```

The randomized search provided a similar performing Gradient Boosing Classifier only producing an increase in test accuracy of 8.22% over a random choice.

2.14.3 Advanced Model

[89]:
```python
%load_ext autoreload
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

[90]:
```python
%autoreload 2
import pathlib

import pickle
from torch.optim import Adam
from torch.nn import CrossEntropyLoss

from capstone_tools.model import RecommendationModel, ModelDimensions
from capstone_tools.model_trainers import TorchTrainer, TorchModelData
from capstone_tools.data_loaders import load_data_corpus


data_loc = pathlib.Path("data/processed")
datasets = load_data_corpus(data_loc)
```

[91]:
```python
_, input_dim = datasets['train'].X.shape
output_dim = len(set(datasets['train'].y))
```

[92]:
```python
dims = ModelDimensions(
    input_size=input_dim,
    hidden_layers=(256, 256, 256),
```

```
    output_size=output_dim
)
clf = RecommendationModel(
    dims,
    has_dropout=True,
    p_drop=0.2,
    has_batch_norm=True,
)
```

[93]:
```
clf
```

[93]:
```
RecommendationModel(
  (linear_stack): Sequential(
    (0): Linear(in_features=21, out_features=256, bias=True)
    (1): ReLU()
    (2): Dropout(p=0.2, inplace=False)
    (3): BatchNorm1d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (4): Linear(in_features=256, out_features=256, bias=True)
    (5): ReLU()
    (6): Dropout(p=0.2, inplace=False)
    (7): BatchNorm1d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (8): Linear(in_features=256, out_features=256, bias=True)
    (9): ReLU()
    (10): Linear(in_features=256, out_features=2, bias=True)
  )
)
```

[94]:
```
optimizer = Adam(clf.parameters(), lr=0.01)
critereon = CrossEntropyLoss()
model_data = TorchModelData(
    model=clf, optimizer=optimizer, critereon=critereon
)
trainer = TorchTrainer(model_data)
model_loc = pathlib.Path('models/nn-rec-model.pth')
losses_loc = pathlib.Path('models/nn-rec-losses.pkl')
model_loc.parent.mkdir(parents=True, exist_ok=True)
```

[95]:
```
epochs = 100
losses = trainer.train(
    datasets,
    n_epochs=epochs,
    batch_size=64,
    save_path=model_loc,
    patience=10,
)
```

```python
with open(losses_loc, 'wb') as fh:
    pickle.dump(losses, fh)
```

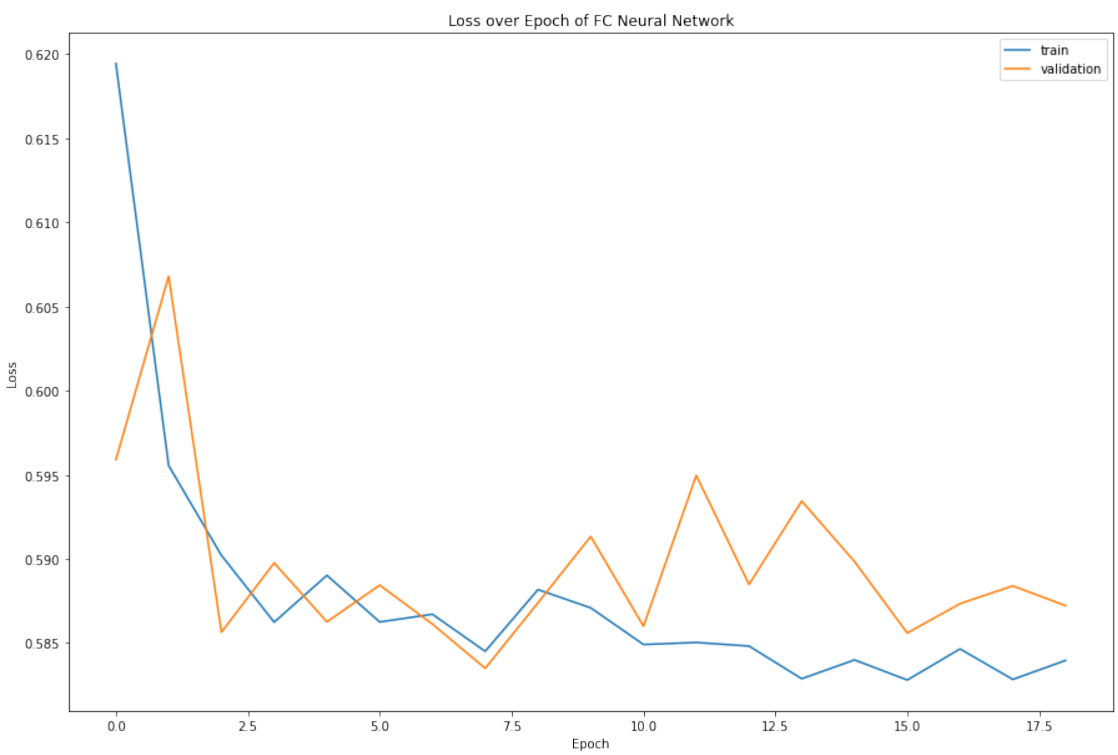
```
Epoch: 1        Training Loss:0.6194    Valid Loss:0.5959
Validation Loss decreased(inf -> 0.5959) Saving Model…
Epoch: 3        Training Loss:0.5902    Valid Loss:0.5856
Validation Loss decreased(0.5959 -> 0.5856) Saving Model…
Epoch: 8        Training Loss:0.5845    Valid Loss:0.5835
Validation Loss decreased(0.5856 -> 0.5835) Saving Model…
Early stopping triggered, stopping…Loss:0.5872
```

[96]:
```python
print(f"Baseline Score: {baseline_score}")
trainer.eval(datasets['test'], batch_size=64)
```

```
Baseline Score: 0.6035277292229462
Test Loss: 0.5843       Accuracy: 68.76 (4327/6293)
```

[97]:
```python
import pandas as pd

pd.DataFrame(losses).plot(
    figsize=(15, 10), xlabel='Epoch', ylabel='Loss',
    title='Loss over Epoch of FC Neural Network'
)
```

[97]: <AxesSubplot:title={'center':'Loss over Epoch of FC Neural Network'}, xlabel='Epoch', ylabel='Loss'>



[140]:
```python
print(f'FC NN performance above baseline: {68.76-60.35:.2f}%')
```

```
FC NN performance above baseline: 8.41%
```

Though the neural network does perform better than the ML models tested above, the performance is only 8.4% better than a random choice.

2.15 Final Model Evaluation

Analyzing the Starbucks customer data is quite challenging. The provided data can be analyzed and manipulated several ways to produce varying degrees of success.

Along with the my original proposal, I first attempted to build models that were capable of predicting the best offer type provided similar data inputs. The best offer was determined by the sum of the sales from the transactions between offer events minus the reward generated by the offer. Unfortunately, this method did not produce any models that performed better than a random choice and the effort was discarded.

A new analysis strategy was adopted after this first failed attempt to analyze offer success. Offer success was defined by an offer that was completed, within the offer validity time, defined by the duration of the offer, and that was viewed by the customer prior to completing the offer. Similar models were tested as before, but upon the entire corpus of data. However, the results of this analysis and model production generated an optimal model able to predict if an offer will be successful with a ~6% accuracy better than a random choice.

Finally, the data was filtered to only BOGO offers (shown in this notebook). Where the two best models, Gradient Boosting and a custom fully connected neural network with batch normalization and dropout, were able to produce similar performance of an 8.2% and 8.4% accuracy better than random choice (test accuracy of 68.57% and 68.76%), respectively.

As a comparison, I reviewed other posts covering similar data analysis of the Starbucks customer dataset and found that others were able to achieve a similar analysis with model performance closer to 71% using XGBoost. This is may be worth considering - though I suspect, I may need to clean my data in by some additional means to achieve such performance.