fevo-ds-challenge

July 23, 2022

1 Introduction

FEVO interview data scientist challenge

1.0.1 Imports

Import libraries and write settings here.

[268]:
```
# Data manipulation
import pandas as pd
import numpy as np
import json
from datetime import date
from collections import Counter

# Options for pandas
pd.options.display.max_columns = 50
pd.options.display.max_rows = 30
pd.set_option('display.float_format', lambda x: '%.5f' % x)

# Display all cell outputs
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = 'all'

from IPython import get_ipython
ipython = get_ipython()

# autoreload extension
if 'autoreload' not in ipython.extension_manager.loaded:
    %load_ext autoreload

%autoreload 2

# Visualizations
import matplotlib.pyplot as plt
plt.style.use('ggplot')
import plotly as py
from plotly.offline import iplot, init_notebook_mode
```

```
init_notebook_mode(connected=True)
import seaborn as sns
import warnings # current version of seaborn generates a bunch of warnings that␣
 ↪we'll ignore
warnings.filterwarnings("ignore")

# # mlxtend library for market basket analysis
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules

# liftimes module for CLV models
import lifetimes

# scikit learn imports
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score, precision_score, f1_score,␣
 ↪recall_score, roc_curve, accuracy_score, silhouette_score,␣
 ↪adjusted_rand_score
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.pipeline import Pipeline

from warnings import simplefilter
from sklearn.exceptions import ConvergenceWarning
simplefilter("ignore", category=ConvergenceWarning)
```

1.0.2 Import data

[143]:
```
# Order data
order_data_ = pd.read_csv("../data/raw/order_data.csv")
print(order_data_.shape)
order_data_.head()
```

```
(100, 24)
```

[143]:

	id	order_number	order_revision	\
0	0227fb74-6fef-4705-93d3-267ea8c223ac	3J5VKYMIKZ	1	
1	08383211-31c7-41e8-af62-040ab57bef91	MVZKEXZSDU	1	
2	09cec2ef-f47d-4529-9efc-4eb566f7fb50	A747ETYTIC	1	
3	0c0278ee-9754-47ff-a898-3d56e140f82b	HZ7KBD2	1	
4	0e3fafb7-cd99-4052-8315-056f1446301d	9HZUUSGPFZ	1	

```
          order_created_at_utc  sub_total_amount  tax_total_amount  \
0   2021-05-14 00:11:47.42191+00               100           4.38000
1  2021-05-28 00:07:40.913547+00               500           0.00000
2  2021-05-04 10:18:26.465221+00               110           0.00000
3  2021-04-16 00:05:23.058775+00               110           9.76000
4   2021-04-27 20:56:05.03676+00               110           0.00000

   shipping_total_amount  fee_total_amount  order_total_amount  \
0                4.68000                 0           109.06000
1                9.52000                 0           509.52000
2               54.63000                 0           164.63000
3                5.98000                 0           125.74000
4                2.46000                 0           113.46000

   requires_payment  charged_amount  charge_refunded  refunded_amount  \
0              True           10906            False              NaN
1              True           50952            False              NaN
2              True           16463            False              NaN
3              True           12574            False              NaN
4              True           11346            False              NaN

  refunded_at_utc                              customer_id  age  gender  \
0             NaN  20210514001013249-Q175Xwh9gpaGskvABkJwxq   40  female
1             NaN  20210528000605652-Un6WDdXuj76sDYpMzbkawK   45  female
2             NaN  20210504101656950-RfopULDB5fK7G8AWXuTnKd   40    male
3             NaN  20210415235313985-JW3kmgjjyyFd3sPh8aQC7j   34  female
4             NaN  20210401153734568-5uMfDDzFxZs6imnFWABG4o   41  female

   income                                           group_id      group_name  \
0   29000  grp-b8c2e546-9a03-4897-afa2-81a73b8975ee--good…    Lynch's Team
1  107000  grp-b8c2e546-9a03-4897-afa2-81a73b8975ee--good…  Psycho's Group
2   45000  grp-09b1da02-2347-4e94-a085-a2abbcfeeb9c--good…  Scar's Familia
3  119000  grp-2c9721c6-26bb-46cc-b666-5b038df57b84--good…  Colt's Winners
4  117000  grp-24f6a18e-8bb9-43af-9137-9b0e82cc0c98--good…    Rigs's Group

  customer_state customer_country device_type  \
0             NY               US     Desktop
1             NY               US     Desktop
2             SK               MK     Desktop
3             NY               US      Mobile
4             CA               US     Desktop

                             orderlineitems_jsonb
0  [{"id": "oli-BkGazB3VRPkDA7Tb3vGf43", "price":…
1  [{"id": "oli-VJKa2uJG8CXEJW8MxNYjG8", "price":…
2  [{"id": "oli-XuWxxvdru5i4nN89vvdKht", "price":…
```

```
3  [{"id": "oli-RFy1mAqazJVNdgQ842EiHe", "price":…
4  [{"id": "oli-Gr1QeqP7RFzbKpzGX3KyVB", "price":…
```

[3]:
```python
# Order with product sold denormalized data
order_with_product_ = pd.read_csv("../data/raw/order_with_product_sold.csv")
print(order_with_product_.shape)
order_with_product_.head()
```

```
(186, 29)
```

[3]:
```
                                     id order_number  order_revision  \
0  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
1  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
2  10ef2c45-cb42-41ec-82ea-6e241a205021   RF5LR2UURJ               2
3  3c6a5fd9-5e57-4cf1-9ed1-332a2117dfcb   2EWVBFAYGR               1
4  cafdecc9-f3bf-4274-93d8-4f7cda91c842   JCTR6OHJBK               1

             order_created_at_utc  sub_total_amount  tax_total_amount  \
0  2021-04-26 10:27:48.058595+00               220          15.40000
1  2021-04-26 10:27:48.058595+00               220          15.40000
2   2021-04-27 13:04:26.70683+00               100           0.00000
3  2021-04-28 13:21:45.829622+00               100           4.88000
4  2021-04-27 17:29:40.519036+00               220           0.00000

   shipping_total_amount  fee_total_amount  order_total_amount  \
0                9.52000                 0           244.92000
1                9.52000                 0           244.92000
2                4.68000                 0             0.00000
3                4.68000                 0           109.56000
4               51.49000                 0           271.49000

   requires_payment  charged_amount  charge_refunded  refunded_amount  \
0              True           24492            False              NaN
1              True           24492            False              NaN
2              True           10468            False      10468.00000
3              True           10956            False              NaN
4              True           27149            False              NaN

                 refunded_at_utc                              customer_id  \
0                            NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ
1                            NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ
2  2021-04-27 13:09:35.607894+00  20210427130320635-Xo7MTkGzMZHKu6APFBHuja
3                            NaN  20210428123305906-K5rxcBo3Q2uMwjD6H4mwq5
4                            NaN  20210406163142240-MEpprnTNETHBEnusY3r6pN

   age  gender  income                                          group_id  \
0   51  female   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
```

```
1  51  female   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
2  27    male   42000  grp-b8c2e546-9a03-4897-afa2-81a73b8975ee--good…
3  45    male   79000  grp-b8c2e546-9a03-4897-afa2-81a73b8975ee--good…
4  36  female   98000  grp-edadeef5-6800-4929-8f6b-bae579c7faac--good…

        group_name customer_state customer_country device_type  \
0    Cobra's Group             NY               US     Desktop
1    Cobra's Group             NY               US     Desktop
2    Ranger's Team             NY               US     Desktop
3  Mad Dog's Group             NY               US     Desktop
4              pdf            NaN               RS     Desktop

                                orderlineitems_jsonb  price  \
0  [{"id": "oli-E8hTJtpoz2uW5v75Bnm7Rd", "price":…    110
1  [{"id": "oli-E8hTJtpoz2uW5v75Bnm7Rd", "price":…    110
2  [{"id": "oli-CLXZp7xNbgpjcSKU4WKXwe", "price":…    100
3  [{"id": "oli-MLSxCZcLySaMWHPmtLkDDJ", "price":…    100
4  [{"id": "oli-QMmcEsvprhMARgGDkdsfFC", "price":…    110

                    product_id      product_title  \
0  product-gsbrightbluehoodie   Beam Blue Hoodie
1  product-gsbrightbluehoodie   Beam Blue Hoodie
2  product-gsbrightbluesweats   Beam Blue Sweats
3  product-gsbrightbluesweats   Beam Blue Sweats
4  product-gsbrightbluehoodie   Beam Blue Hoodie

                    product_variant_id product_variant_title
0  pvariant-gsbrightbluehoodiemedium                 Medium
1  pvariant-gsbrightbluehoodiemedium                 Medium
2  pvariant-gsbrightbluesweatsmedium                 Medium
3  pvariant-gsbrightbluesweatsmedium                 Medium
4  pvariant-gsbrightbluehoodiemedium                 Medium
```

[4]:
```python
# product sold data
product_sold_ = pd.read_csv("../data/raw/product_sold.csv")
print(product_sold_.shape)
product_sold_.head()
```

```
(185, 7)
```

[4]:
```
                                     id order_number  price  \
0  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ    110
1  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ    110
2  f2fb6009-3cf4-4795-b5b8-2f66721b243f   RF5LR2UURJ    100
3  10ef2c45-cb42-41ec-82ea-6e241a205021   RF5LR2UURJ    100
4  3c6a5fd9-5e57-4cf1-9ed1-332a2117dfcb   2EWVBFAYGR    100
```

```
                      product_id     product_title  \
0  product-gsbrightbluehoodie  Beam Blue Hoodie
1  product-gsbrightbluehoodie  Beam Blue Hoodie
2  product-gsbrightbluesweats  Beam Blue Sweats
3  product-gsbrightbluesweats  Beam Blue Sweats
4  product-gsbrightbluesweats  Beam Blue Sweats

                     product_variant_id product_variant_title
0  pvariant-gsbrightbluehoodiemedium                Medium
1  pvariant-gsbrightbluehoodiemedium                Medium
2  pvariant-gsbrightbluesweatsmedium                Medium
3  pvariant-gsbrightbluesweatsmedium                Medium
4  pvariant-gsbrightbluesweatsmedium                Medium
```

2 EDA, data prep

Spot-checking distributions - Checking for extreme values - Checking for negative values

2.1 order_data

[144]:
```
order_data = order_data_.copy()
```

[145]:
```
# Describe data
order_data.describe()
```

[145]:
```
       order_revision  sub_total_amount  tax_total_amount  \
count       100.00000         100.00000         100.00000
mean          1.06000         192.55000           6.74510
std           0.23868         204.79541          18.06084
min           1.00000          30.00000           0.00000
25%           1.00000         100.00000           0.00000
50%           1.00000         110.00000           0.00000
75%           1.00000         220.00000           9.76000
max           2.00000        1700.00000         150.90000

       shipping_total_amount  fee_total_amount  order_total_amount  \
count              100.00000         100.00000           100.00000
mean                10.12290           0.00000           198.39580
std                 13.52626           0.00000           224.92137
min                  0.00000           0.00000             0.00000
25%                  4.68000           0.00000           104.68000
50%                  5.98000           0.00000           113.68000
75%                  9.52000           0.00000           229.26000
max                 57.52000           0.00000          1860.42000

       charged_amount  refunded_amount        age        income
```

```
count    100.00000        4.00000 100.00000    100.00000
mean   20951.80000    19341.50000  39.25000  76790.00000
std    22231.53015    19885.53923  10.64522  23773.46581
min     3385.00000     5598.00000  10.00000  22000.00000
25%    10468.00000     9250.50000  32.00000  60000.00000
50%    12361.00000    11456.00000  38.00000  77500.00000
75%    24904.00000    21547.00000  45.00000  93750.00000
max   186042.00000    48856.00000  69.00000 126000.00000
```

Spot-checking null values - Ensure that order_number, orderlineitems not missing because this would prohibit building an order basket

[7]:
```python
order_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 24 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     100 non-null    object
 1   order_number           100 non-null    object
 2   order_revision         100 non-null    int64
 3   order_created_at_utc   100 non-null    object
 4   sub_total_amount       100 non-null    int64
 5   tax_total_amount       100 non-null    float64
 6   shipping_total_amount  100 non-null    float64
 7   fee_total_amount       100 non-null    int64
 8   order_total_amount     100 non-null    float64
 9   requires_payment       100 non-null    bool
 10  charged_amount         100 non-null    int64
 11  charge_refunded        100 non-null    bool
 12  refunded_amount        4 non-null      float64
 13  refunded_at_utc        6 non-null      object
 14  customer_id            100 non-null    object
 15  age                    100 non-null    int64
 16  gender                 100 non-null    object
 17  income                 100 non-null    int64
 18  group_id               100 non-null    object
 19  group_name             93 non-null     object
 20  customer_state         92 non-null     object
 21  customer_country       94 non-null     object
 22  device_type            100 non-null    object
 23  orderlineitems_jsonb   100 non-null    object
dtypes: bool(2), float64(4), int64(6), object(12)
memory usage: 17.5+ KB
```

It seems some orders were refunded/returned. Let's exclude these from analysis since there's few of them and they do not really add information to what we need to know.

However, a future analysis (with more data) could be to look at factors associated with returns/refunds.

[146]:
```
order_data = order_data[order_data["refunded_at_utc"].isnull()] # drop refunded␣
↪orders
```

[9]:
```
print(order_data.shape)
order_data.isnull().sum()
```

```
(94, 24)
```

[9]:
```
id                       0
order_number             0
order_revision           0
order_created_at_utc     0
sub_total_amount         0
tax_total_amount         0
shipping_total_amount    0
fee_total_amount         0
order_total_amount       0
requires_payment         0
charged_amount           0
charge_refunded          0
refunded_amount         94
refunded_at_utc         94
customer_id              0
age                      0
gender                   0
income                   0
group_id                 0
group_name               6
customer_state           8
customer_country         6
device_type              0
orderlineitems_jsonb     0
dtype: int64
```

Are there duplicates?

[147]:
```
duplicates = order_data[order_data.duplicated(["id","order_number"])]
print(duplicates.shape)
duplicates.head()
```

```
(1, 24)
```

[147]:
```
                                      id order_number  order_revision  \
96  fd9df330-0b7e-47de-850a-578c1666a4fa   169NPU5TSH               1
```

```
            order_created_at_utc  sub_total_amount  tax_total_amount  \
96  2021-04-27 23:31:19.997899+00               100           0.00000

    shipping_total_amount  fee_total_amount  order_total_amount  \
96                4.68000                 0           104.68000

    requires_payment  charged_amount  charge_refunded  refunded_amount  \
96              True           10468            False              NaN

   refunded_at_utc                              customer_id  age  gender  \
96             NaN  20210427232749440-83MDMhELkrpn6hrWbcJSxM   60  female

    income                                          group_id  \
96   43000  grp-b8c2e546-9a03-4897-afa2-81a73b8975ee--good…

            group_name customer_state customer_country device_type  \
96  Sasquatch's Familia             NY               US     Desktop

                                   orderlineitems_jsonb
96  [{"id": "oli-WdRhhGLe7z4SvgPfbjrDPS", "price":…
```

Drop 1 duplicate record based on ID and order number

[148]:
```python
order_data = order_data.drop_duplicates(subset=["id","order_number"])
print(order_data.shape)
order_data.head()
```

```
(93, 24)
```

[148]:
```
                                     id order_number  order_revision  \
0  0227fb74-6fef-4705-93d3-267ea8c223ac   3J5VKYMIKZ               1
1  08383211-31c7-41e8-af62-040ab57bef91   MVZKEXZSDU               1
2  09cec2ef-f47d-4529-9efc-4eb566f7fb50   A747ETYTIC               1
3  0c0278ee-9754-47ff-a898-3d56e140f82b      HZ7KBD2               1
4  0e3fafb7-cd99-4052-8315-056f1446301d   9HZUUSGPFZ               1

            order_created_at_utc  sub_total_amount  tax_total_amount  \
0   2021-05-14 00:11:47.42191+00               100           4.38000
1  2021-05-28 00:07:40.913547+00               500           0.00000
2  2021-05-04 10:18:26.465221+00               110           0.00000
3  2021-04-16 00:05:23.058775+00               110           9.76000
4   2021-04-27 20:56:05.03676+00               110           0.00000

   shipping_total_amount  fee_total_amount  order_total_amount  \
0                4.68000                 0           109.06000
1                9.52000                 0           509.52000
2               54.63000                 0           164.63000
```

```
3               5.98000                  0           125.74000
4               2.46000                  0           113.46000

   requires_payment  charged_amount  charge_refunded  refunded_amount  \
0              True           10906            False              NaN
1              True           50952            False              NaN
2              True           16463            False              NaN
3              True           12574            False              NaN
4              True           11346            False              NaN

  refunded_at_utc                                customer_id  age  gender  \
0             NaN  20210514001013249-Q175Xwh9gpaGskvABkJwxq   40  female
1             NaN  20210528000605652-Un6WDdXuj76sDYpMzbkawK   45  female
2             NaN  20210504101656950-RfopULDB5fK7G8AWXuTnKd   40    male
3             NaN  20210415235313985-JW3kmgjjyyFd3sPh8aQC7j   34  female
4             NaN  20210401153734568-5uMfDDzFxZs6imnFWABG4o   41  female

   income                                           group_id      group_name  \
0   29000  grp-b8c2e546-9a03-4897-afa2-81a73b8975ee--good…    Lynch's Team
1  107000  grp-b8c2e546-9a03-4897-afa2-81a73b8975ee--good…  Psycho's Group
2   45000  grp-09b1da02-2347-4e94-a085-a2abbcfeeb9c--good…  Scar's Familia
3  119000  grp-2c9721c6-26bb-46cc-b666-5b038df57b84--good…  Colt's Winners
4  117000  grp-24f6a18e-8bb9-43af-9137-9b0e82cc0c98--good…    Rigs's Group

  customer_state customer_country device_type  \
0             NY               US     Desktop
1             NY               US     Desktop
2             SK               MK     Desktop
3             NY               US      Mobile
4             CA               US     Desktop

                               orderlineitems_jsonb
0  [{"id": "oli-BkGazB3VRPkDA7Tb3vGf43", "price":…
1  [{"id": "oli-VJKa2uJG8CXEJW8MxNYjG8", "price":…
2  [{"id": "oli-XuWxxvdru5i4nN89vvdKht", "price":…
3  [{"id": "oli-RFy1mAqazJVNdgQ842EiHe", "price":…
4  [{"id": "oli-Gr1QeqP7RFzbKpzGX3KyVB", "price":…
```

Checking for skew and outliers

[12]:
```
order_data.skew()
```

[12]:
```
order_revision          0.00000
sub_total_amount        4.43992
tax_total_amount        5.83517
shipping_total_amount   2.47342
fee_total_amount        0.00000
```

```
order_total_amount      4.54059
requires_payment        0.00000
charged_amount          4.54059
charge_refunded         0.00000
refunded_amount             NaN
refunded_at_utc             NaN
age                     0.28396
income                  0.00325
dtype: float64
```

Let's look at the distributions of the skewed features to see about outliers

[14]:
```
plt.figure(figsize=(16,20))
plt.subplot(5,2,1)
sns.histplot(order_data['sub_total_amount'])
plt.subplot(5,2,2)
sns.boxplot(order_data['sub_total_amount'])
plt.subplot(5,2,3)
sns.histplot(order_data['tax_total_amount'])
plt.subplot(5,2,4)
sns.boxplot(order_data['tax_total_amount'])
plt.subplot(5,2,5)
sns.histplot(order_data['order_total_amount'])
plt.subplot(5,2,6)
sns.boxplot(order_data['order_total_amount'])
plt.subplot(5,2,7)
sns.histplot(order_data['shipping_total_amount'])
plt.subplot(5,2,8)
sns.boxplot(order_data['shipping_total_amount'])
plt.subplot(5,2,9)
sns.histplot(order_data['charged_amount'])
plt.subplot(5,2,10)
sns.boxplot(order_data['charged_amount'])
plt.savefig('../reports/figures/original_distribution.png')
plt.show()
```

[14]: <Figure size 1152x1440 with 0 Axes>

[14]: <AxesSubplot:>

[14]: <AxesSubplot:xlabel='sub_total_amount', ylabel='Count'>

[14]: <AxesSubplot:>

[14]: <AxesSubplot:xlabel='sub_total_amount'>

[14]: <AxesSubplot:>

[14]: <AxesSubplot:xlabel='tax_total_amount', ylabel='Count'>

[14]: <AxesSubplot:>

[14]: <AxesSubplot:xlabel='tax_total_amount'>

[14]: <AxesSubplot:>

[14]: <AxesSubplot:xlabel='order_total_amount', ylabel='Count'>

[14]: <AxesSubplot:>

[14]: <AxesSubplot:xlabel='order_total_amount'>

[14]: <AxesSubplot:>

[14]: <AxesSubplot:xlabel='shipping_total_amount', ylabel='Count'>

[14]: <AxesSubplot:>

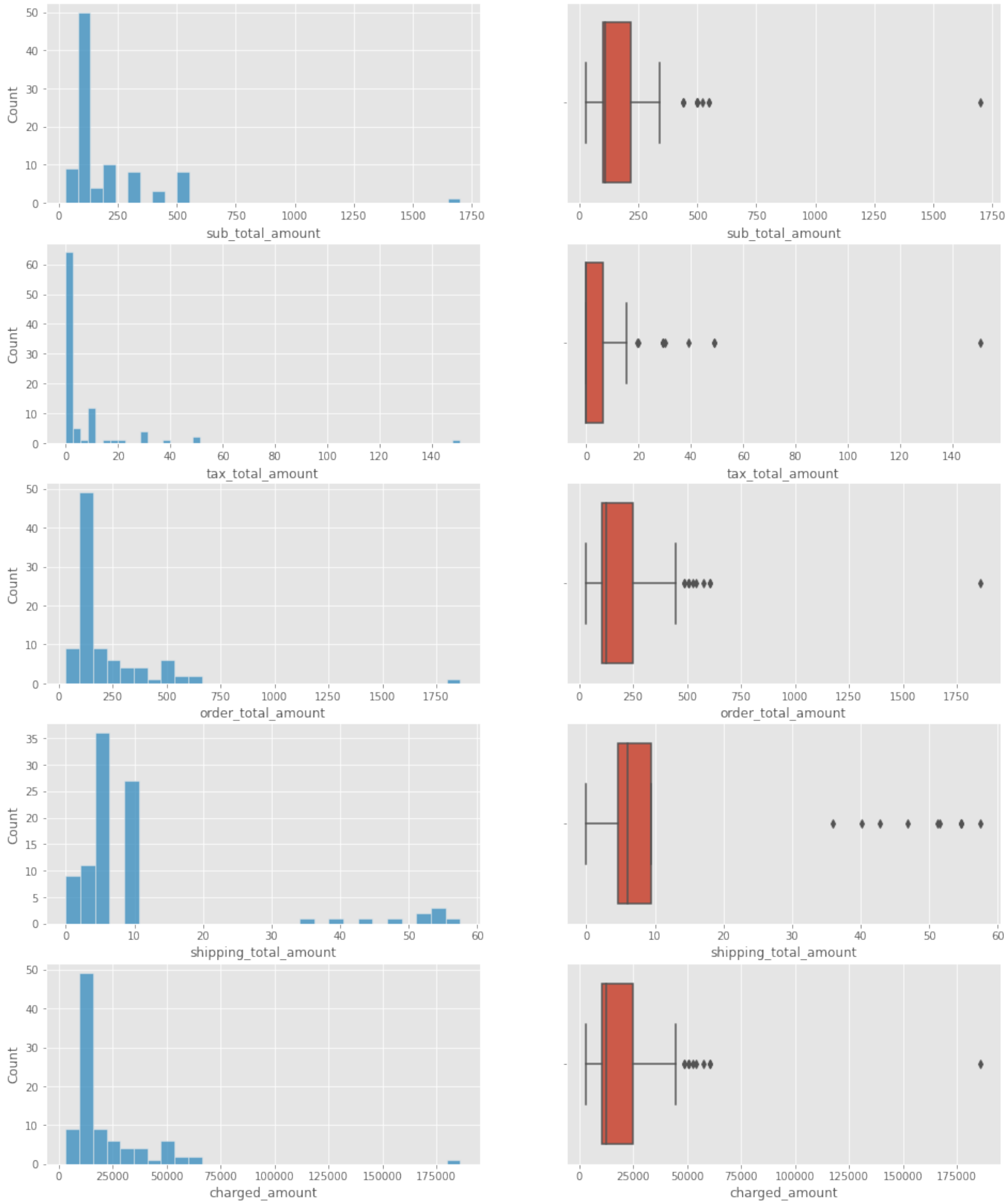
[14]: <AxesSubplot:xlabel='shipping_total_amount'>

[14]: <AxesSubplot:>

[14]: <AxesSubplot:xlabel='charged_amount', ylabel='Count'>

[14]: <AxesSubplot:>

[14]: <AxesSubplot:xlabel='charged_amount'>



Based on skewness and distributions it appears sub total amount, tax total amount, shipping total amount, order total amount, and charged amount have outliers. Will threshold these outliers so they do not unfairly bias future models using these features

[149]:
```
# Since distributions are skewed we will use interquartile range to threshold
 ↪outliers
# setting threshold to be 1.5 above and below IQR
```

```python
def outlier_thresholds(dataframe, variable):
    quartile1 = dataframe[variable].quantile(0.25)
    quartile3 = dataframe[variable].quantile(0.75)
    interquantile_range = quartile3 - quartile1
    up_limit = quartile3 + 1.5 * interquantile_range
    low_limit = quartile1 - 1.5 * interquantile_range
    return low_limit, up_limit
def replace_with_thresholds(dataframe, variable):
    low_limit, up_limit = outlier_thresholds(dataframe, variable)
    dataframe.loc[(dataframe[variable] < low_limit), variable] = low_limit
    dataframe.loc[(dataframe[variable] > up_limit), variable] = up_limit
```

[150]:
```python
col_list = ["sub_total_amount", "tax_total_amount", "order_total_amount",␣
↪"shipping_total_amount", "charged_amount"]
for col in col_list:
    replace_with_thresholds(order_data, col)
```

[17]:
```python
plt.figure(figsize=(16,20))
plt.subplot(5,2,1)
sns.histplot(order_data['sub_total_amount'])
plt.subplot(5,2,2)
sns.boxplot(order_data['sub_total_amount'])
plt.subplot(5,2,3)
sns.histplot(order_data['tax_total_amount'])
plt.subplot(5,2,4)
sns.boxplot(order_data['tax_total_amount'])
plt.subplot(5,2,5)
sns.histplot(order_data['order_total_amount'])
plt.subplot(5,2,6)
sns.boxplot(order_data['order_total_amount'])
plt.subplot(5,2,7)
sns.histplot(order_data['shipping_total_amount'])
plt.subplot(5,2,8)
sns.boxplot(order_data['shipping_total_amount'])
plt.subplot(5,2,9)
sns.histplot(order_data['charged_amount'])
plt.subplot(5,2,10)
sns.boxplot(order_data['charged_amount'])
plt.savefig('../reports/figures/outliers_removed_distributions.png')
plt.show()
```

[17]:
```
<Figure size 1152x1440 with 0 Axes>
```

[17]:
```
<AxesSubplot:>
```

[17]:
```
<AxesSubplot:xlabel='sub_total_amount', ylabel='Count'>
```

[17]: <AxesSubplot:>

[17]: <AxesSubplot:xlabel='sub_total_amount'>

[17]: <AxesSubplot:>

[17]: <AxesSubplot:xlabel='tax_total_amount', ylabel='Count'>

[17]: <AxesSubplot:>

[17]: <AxesSubplot:xlabel='tax_total_amount'>

[17]: <AxesSubplot:>

[17]: <AxesSubplot:xlabel='order_total_amount', ylabel='Count'>

[17]: <AxesSubplot:>

[17]: <AxesSubplot:xlabel='order_total_amount'>

[17]: <AxesSubplot:>

[17]: <AxesSubplot:xlabel='shipping_total_amount', ylabel='Count'>

[17]: <AxesSubplot:>

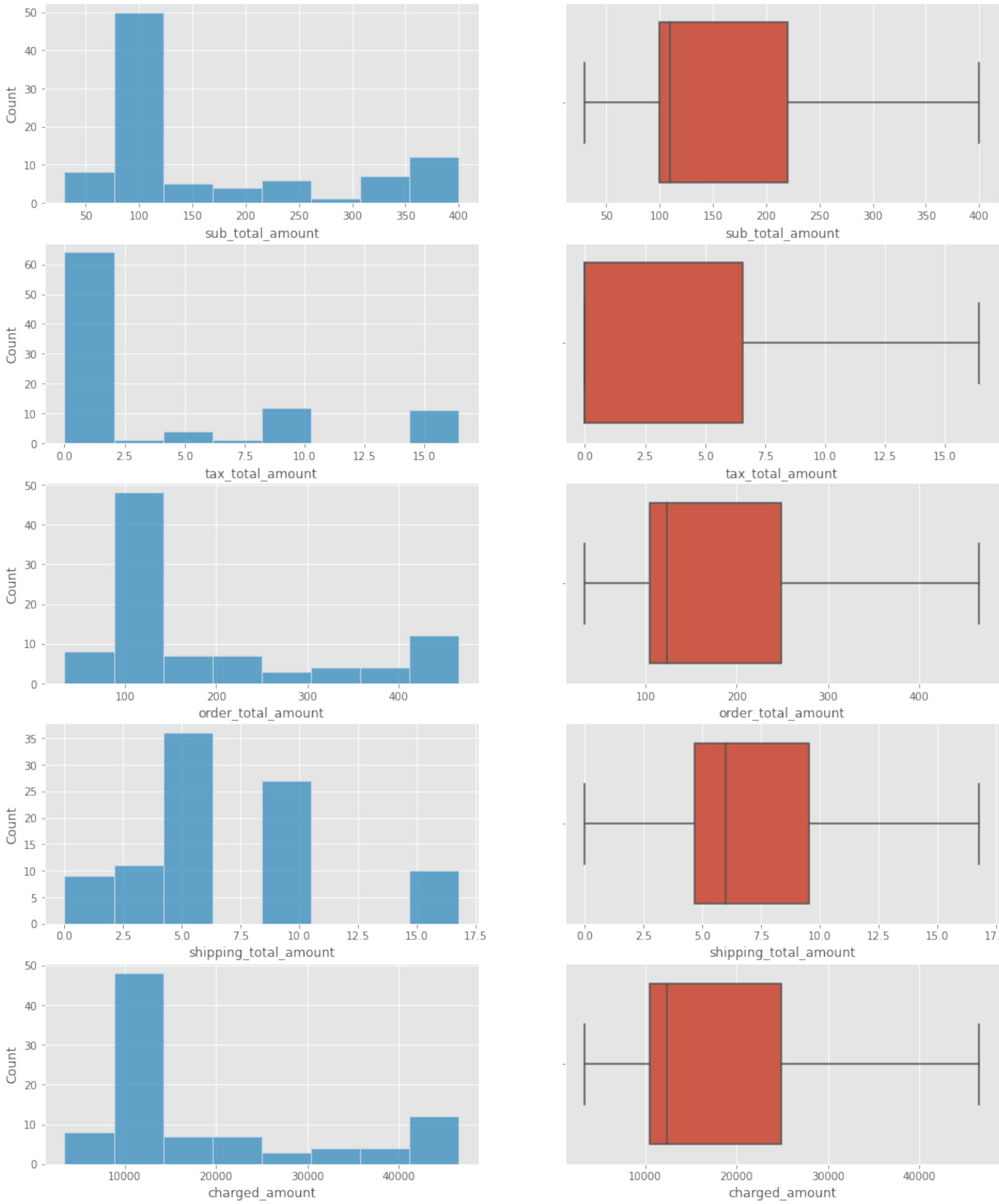
[17]: <AxesSubplot:xlabel='shipping_total_amount'>

[17]: <AxesSubplot:>

[17]: <AxesSubplot:xlabel='charged_amount', ylabel='Count'>

[17]: <AxesSubplot:>

[17]: <AxesSubplot:xlabel='charged_amount'>



We've now truncated our outliers, but these distributions are still non-normal. When we build models later for purchase probability, etc. it's a good idea to standardize these distributions and/or transform into a normal (or some known parametric distribution).

Many models, notably logistic and linear regression, are mathematically based on the assumption of a bivariate or multivariate normal distributions, although linear is known to still work well as long as the model errors are normally distributed and not necessarily the data itself.

Even though some ML models, such as decision tree and XGBoost, do not have the assumption of normality and still work well on raw data, it's generally a good idea to expore data to understand the underlying distributions to make sure they fit the assumptions of any of the models under consideration. Even more complex neural network type model architectures often still rely out logistic or linear output activation functions that would be more mathematically performant under the assumption of gaussian data structures.

Moral of the story: know your data because garbage in = garbage out. :-)

[19]:
```
#Check distributions after transformation
order_data.describe().T
```

[19]:
```
                       count        mean         std         min  \
order_revision      93.00000     1.00000     0.00000     1.00000
sub_total_amount    93.00000   170.05376   114.73622    30.00000
tax_total_amount    93.00000     3.49849     5.78634     0.00000
shipping_total_amount 93.00000   6.89817     4.54089     0.00000
fee_total_amount    93.00000     0.00000     0.00000     0.00000
order_total_amount  93.00000   189.51903   132.41415    33.85000
charged_amount      93.00000 18951.90323 13241.41516  3385.00000
refunded_amount      0.00000         NaN         NaN         NaN
age                 93.00000    38.81720    10.35872    10.00000
income              93.00000 77204.30108 23737.49517 22000.00000

                            25%         50%         75%          max
order_revision          1.00000     1.00000     1.00000      1.00000
sub_total_amount      100.00000   110.00000   220.00000    400.00000
tax_total_amount        0.00000     0.00000     6.57000     16.42500
shipping_total_amount   4.68000     5.98000     9.52000     16.78000
fee_total_amount        0.00000     0.00000     0.00000      0.00000
order_total_amount    104.68000   123.61000   249.04000    465.58000
charged_amount      10468.00000 12361.00000 24904.00000  46558.00000
refunded_amount             NaN         NaN         NaN          NaN
age                    32.00000    37.00000    45.00000     69.00000
income              61000.00000 78000.00000 96000.00000 126000.00000
```

2.2 denormalized data

[20]:
```
order_denorm = order_with_product_.copy()
```

[21]:
```
# Describe data
order_denorm.describe()
```

[21]:
```
       order_revision  sub_total_amount  tax_total_amount  \
count       186.00000         186.00000         186.00000
mean          1.06452         294.38172          11.46022
std           0.24633         289.23154          26.95656
min           1.00000          30.00000           0.00000
```

```
25%           1.00000        110.00000          0.00000
50%           1.00000        210.00000          0.00000
75%           1.00000        440.00000          9.76000
max           2.00000       1700.00000        150.90000

       shipping_total_amount  fee_total_amount  order_total_amount  \
count              186.00000         186.00000           186.00000
mean                13.29935           0.00000           303.22495
std                 15.22884           0.00000           320.20000
min                  0.00000           0.00000             0.00000
25%                  4.68000           0.00000           109.17500
50%                  9.52000           0.00000           209.52000
75%                  9.52000           0.00000           486.94000
max                 57.52000           0.00000          1860.42000

       charged_amount  refunded_amount        age        income      price
count       186.00000          8.00000 186.00000     186.00000 186.00000
mean      31920.58065      28691.50000  39.46774   77344.08602 104.38172
std       31404.15938      21676.60007   9.89794   23464.74970  52.58732
min        3385.00000       5598.00000  10.00000   22000.00000  25.00000
25%       11000.00000       9250.50000  34.00000   63250.00000 100.00000
50%       21678.00000      30650.00000  37.00000   78000.00000 100.00000
75%       48856.00000      48856.00000  45.00000   96000.00000 110.00000
max      186042.00000      48856.00000  69.00000  126000.00000 340.00000
```

Spot-checking null values - Ensure that order_number, orderlineitems not missing because this would prohibit building an order basket

[22]:
```
order_denorm.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 186 entries, 0 to 185
Data columns (total 29 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     186 non-null    object
 1   order_number           186 non-null    object
 2   order_revision         186 non-null    int64
 3   order_created_at_utc   186 non-null    object
 4   sub_total_amount       186 non-null    int64
 5   tax_total_amount       186 non-null    float64
 6   shipping_total_amount  186 non-null    float64
 7   fee_total_amount       186 non-null    int64
 8   order_total_amount     186 non-null    float64
 9   requires_payment       186 non-null    bool
 10  charged_amount         186 non-null    int64
 11  charge_refunded        186 non-null    bool
 12  refunded_amount        8 non-null      float64
```

```
 13  refunded_at_utc        12 non-null     object
 14  customer_id            186 non-null    object
 15  age                    186 non-null    int64
 16  gender                 186 non-null    object
 17  income                 186 non-null    int64
 18  group_id               186 non-null    object
 19  group_name             177 non-null    object
 20  customer_state         175 non-null    object
 21  customer_country       179 non-null    object
 22  device_type            186 non-null    object
 23  orderlineitems_jsonb   186 non-null    object
 24  price                  186 non-null    int64
 25  product_id             186 non-null    object
 26  product_title          186 non-null    object
 27  product_variant_id     186 non-null    object
 28  product_variant_title  186 non-null    object
dtypes: bool(2), float64(4), int64(7), object(16)
memory usage: 39.7+ KB
```

It seems some orders were refunded/returned. Let's exclude these from analysis

[23]:
```
order_denorm = order_denorm[order_denorm["refunded_at_utc"].isnull()] # drop␣
↪refunded orders
```

[24]:
```
print(order_denorm.shape)
order_denorm.isnull().sum()
```

```
(174, 29)
```

[24]:
```
id                         0
order_number               0
order_revision             0
order_created_at_utc       0
sub_total_amount           0
tax_total_amount           0
shipping_total_amount      0
fee_total_amount           0
order_total_amount         0
requires_payment           0
charged_amount             0
charge_refunded            0
refunded_amount          174
refunded_at_utc          174
customer_id                0
age                        0
gender                     0
income                     0
group_id                   0
```

```
group_name                 7
customer_state            11
customer_country           7
device_type                0
orderlineitems_jsonb       0
price                      0
product_id                 0
product_title              0
product_variant_id         0
product_variant_title      0
dtype: int64
```

Checking for skew and outliers

[25]:
```
order_denorm.skew()
```

[25]:
```
order_revision           0.00000
sub_total_amount         3.07214
tax_total_amount         3.98043
shipping_total_amount    1.84245
fee_total_amount         0.00000
order_total_amount       3.16862
requires_payment         0.00000
charged_amount           3.16862
charge_refunded          0.00000
refunded_amount              NaN
refunded_at_utc              NaN
age                      0.39601
income                  -0.11053
price                    3.21599
dtype: float64
```

[26]:
```
df = order_denorm.copy()
plt.figure(figsize=(16,25))
plt.subplot(6,2,1)
sns.histplot(df['sub_total_amount'])
plt.subplot(6,2,2)
sns.boxplot(df['sub_total_amount'])
plt.subplot(6,2,3)
sns.histplot(df['tax_total_amount'])
plt.subplot(6,2,4)
sns.boxplot(df['tax_total_amount'])
plt.subplot(6,2,5)
sns.histplot(df['order_total_amount'])
plt.subplot(6,2,6)
sns.boxplot(df['order_total_amount'])
plt.subplot(6,2,7)
```

```
sns.histplot(df['shipping_total_amount'])
plt.subplot(6,2,8)
sns.boxplot(df['shipping_total_amount'])
plt.subplot(6,2,9)
sns.histplot(df['charged_amount'])
plt.subplot(6,2,10)
sns.boxplot(df['charged_amount'])
plt.subplot(6,2,11)
sns.histplot(df['price'])
plt.subplot(6,2,12)
sns.boxplot(df['price'])
plt.savefig('../reports/figures/original_distribution_denorm.png')
plt.show()
```

```
[26]: <Figure size 1152x1800 with 0 Axes>

[26]: <AxesSubplot:>

[26]: <AxesSubplot:xlabel='sub_total_amount', ylabel='Count'>

[26]: <AxesSubplot:>

[26]: <AxesSubplot:xlabel='sub_total_amount'>

[26]: <AxesSubplot:>

[26]: <AxesSubplot:xlabel='tax_total_amount', ylabel='Count'>

[26]: <AxesSubplot:>

[26]: <AxesSubplot:xlabel='tax_total_amount'>

[26]: <AxesSubplot:>

[26]: <AxesSubplot:xlabel='order_total_amount', ylabel='Count'>

[26]: <AxesSubplot:>

[26]: <AxesSubplot:xlabel='order_total_amount'>

[26]: <AxesSubplot:>

[26]: <AxesSubplot:xlabel='shipping_total_amount', ylabel='Count'>

[26]: <AxesSubplot:>

[26]: <AxesSubplot:xlabel='shipping_total_amount'>
```

[26]: <AxesSubplot:>

[26]: <AxesSubplot:xlabel='charged_amount', ylabel='Count'>

[26]: <AxesSubplot:>

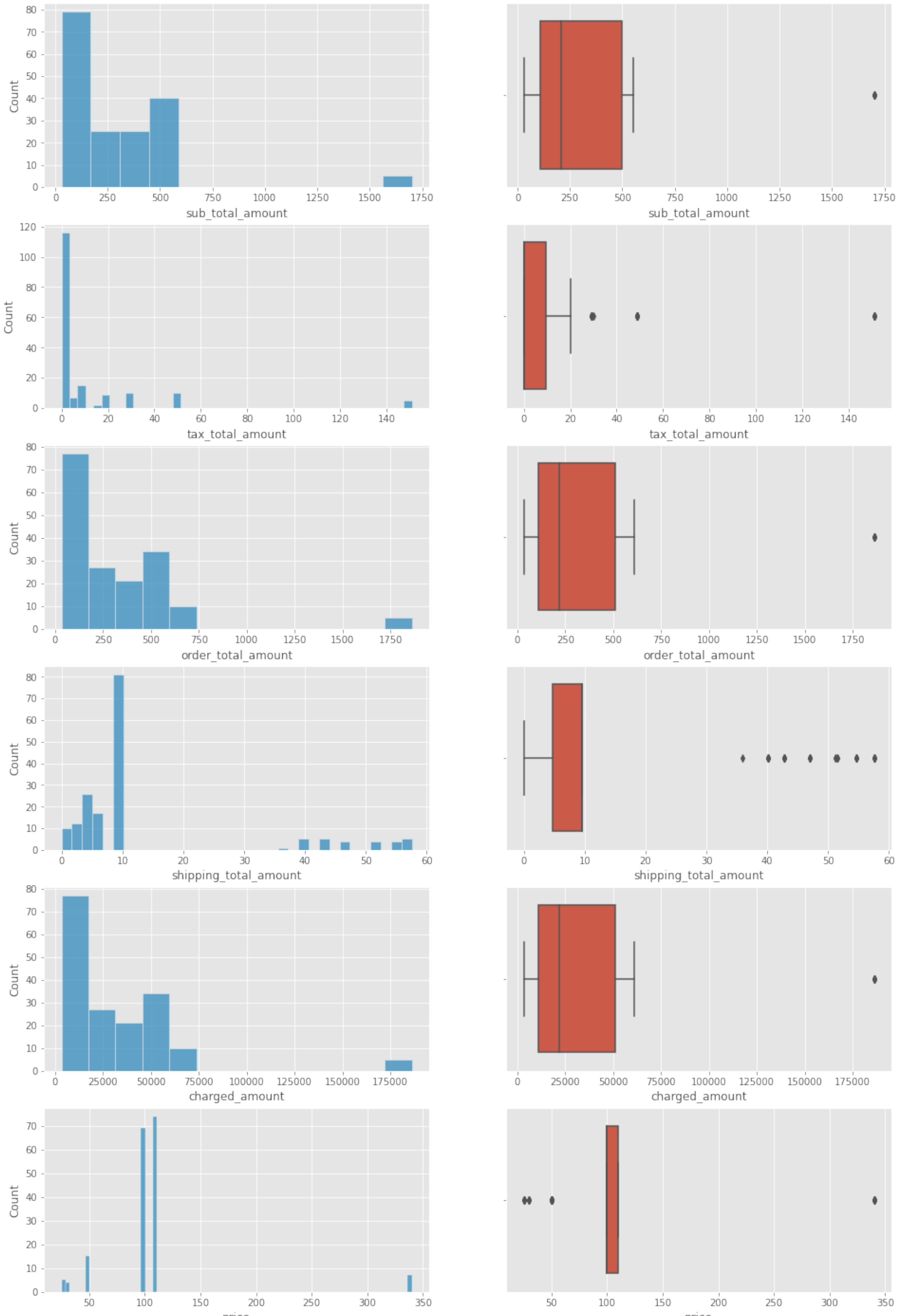
[26]: <AxesSubplot:xlabel='charged_amount'>

[26]: <AxesSubplot:>

[26]: <AxesSubplot:xlabel='price', ylabel='Count'>

[26]: <AxesSubplot:>

[26]: <AxesSubplot:xlabel='price'>


Count
sub_total_amount
sub_total_amount
Count
tax_total_amount
tax_total_amount
Count
order_total_amount
order_total_amount
Count
shipping_total_amount
shipping_total_amount
Count
charged_amount
charged_amount
Count
price
price

Based on skewness and distributions it appears sub total amount, tax total, price, shipping total amount, order total amount, and charged amount have outliers. Will threshold these outliers so they do not unfairly bias future models using these features

[671]:
```
col_list = ["sub_total_amount", "tax_total_amount", "order_total_amount",␣
↪"shipping_total_amount", "charged_amount", "price"]
for col in col_list:
    replace_with_thresholds(order_denorm, col)
```

[377]:
```
df = order_denorm.copy()
plt.figure(figsize=(16,25))
plt.subplot(6,2,1)
sns.histplot(df['sub_total_amount'])
plt.subplot(6,2,2)
sns.boxplot(df['sub_total_amount'])
plt.subplot(6,2,3)
sns.histplot(df['tax_total_amount'])
plt.subplot(6,2,4)
sns.boxplot(df['tax_total_amount'])
plt.subplot(6,2,5)
sns.histplot(df['order_total_amount'])
plt.subplot(6,2,6)
sns.boxplot(df['order_total_amount'])
plt.subplot(6,2,7)
sns.histplot(df['shipping_total_amount'])
plt.subplot(6,2,8)
sns.boxplot(df['shipping_total_amount'])
plt.subplot(6,2,9)
sns.histplot(df['charged_amount'])
plt.subplot(6,2,10)
sns.boxplot(df['charged_amount'])
plt.subplot(6,2,11)
sns.histplot(df['price'])
plt.subplot(6,2,12)
sns.boxplot(df['price'])
plt.savefig('../reports/figures/outliers_removed_distribution_denorm.png')
plt.show()
```

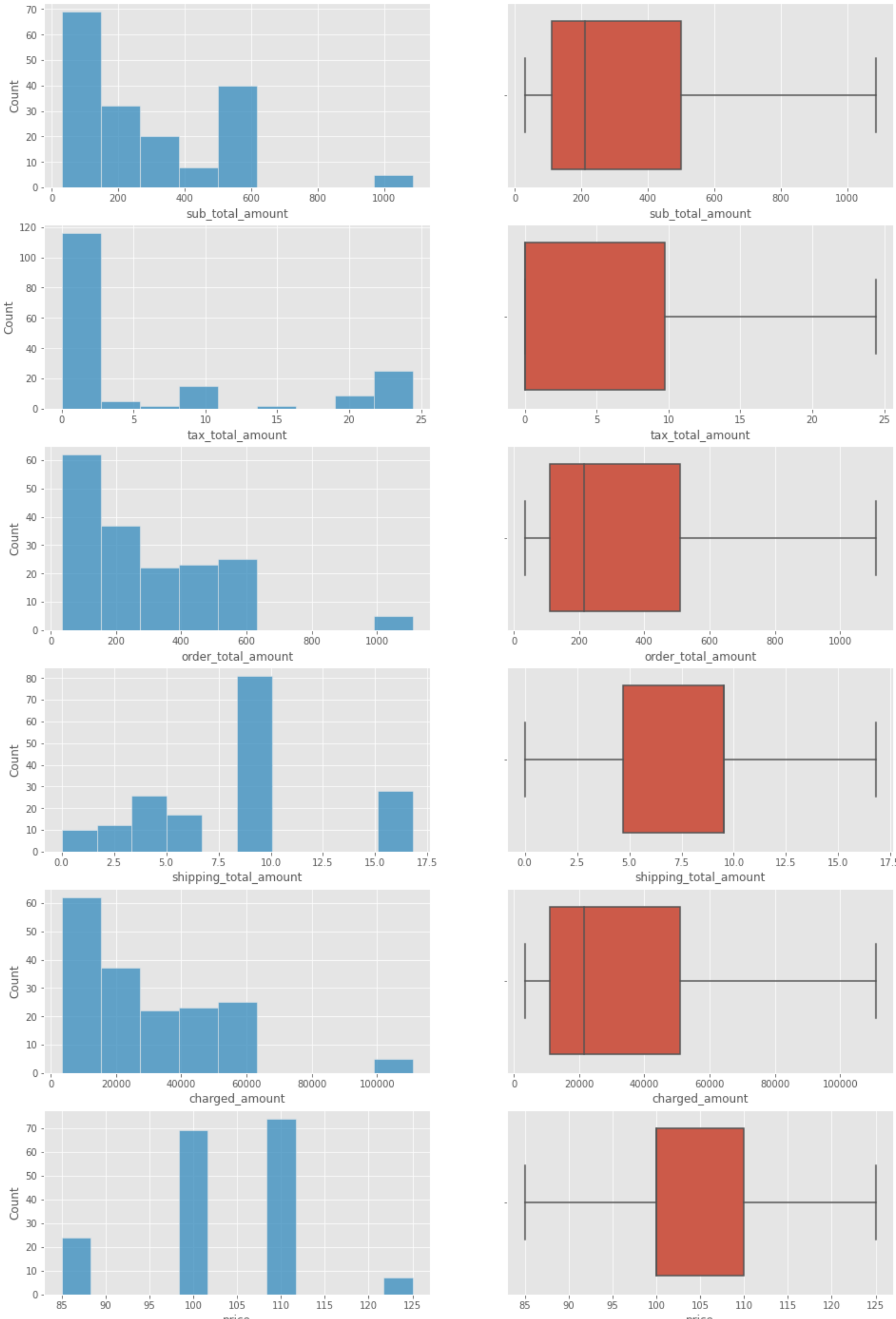
[377]: <Figure size 1152x1800 with 0 Axes>

[377]: <AxesSubplot:>

[377]: <AxesSubplot:xlabel='sub_total_amount', ylabel='Count'>

[377]: <AxesSubplot:>

```
[377]: <AxesSubplot:xlabel='sub_total_amount'>

[377]: <AxesSubplot:>

[377]: <AxesSubplot:xlabel='tax_total_amount', ylabel='Count'>

[377]: <AxesSubplot:>

[377]: <AxesSubplot:xlabel='tax_total_amount'>

[377]: <AxesSubplot:>

[377]: <AxesSubplot:xlabel='order_total_amount', ylabel='Count'>

[377]: <AxesSubplot:>

[377]: <AxesSubplot:xlabel='order_total_amount'>

[377]: <AxesSubplot:>

[377]: <AxesSubplot:xlabel='shipping_total_amount', ylabel='Count'>

[377]: <AxesSubplot:>

[377]: <AxesSubplot:xlabel='shipping_total_amount'>

[377]: <AxesSubplot:>

[377]: <AxesSubplot:xlabel='charged_amount', ylabel='Count'>

[377]: <AxesSubplot:>

[377]: <AxesSubplot:xlabel='charged_amount'>

[377]: <AxesSubplot:>

[377]: <AxesSubplot:xlabel='price', ylabel='Count'>

[377]: <AxesSubplot:>

[377]: <AxesSubplot:xlabel='price'>
```


Count
sub_total_amount
sub_total_amount
Count
tax_total_amount
tax_total_amount
Count
order_total_amount
order_total_amount
Count
shipping_total_amount
shipping_total_amount
Count
charged_amount
charged_amount
Count
price
price

[27]:
```python
#Check distributions after transformation
order_denorm.describe().T
```

[27]:
```
                         count        mean         std         min  \
order_revision       174.00000     1.00000     0.00000     1.00000
sub_total_amount     174.00000   299.33908   295.36740    30.00000
tax_total_amount     174.00000    11.07264    27.47286     0.00000
shipping_total_amount 174.00000    13.65632    15.67601     0.00000
fee_total_amount     174.00000     0.00000     0.00000     0.00000
order_total_amount   174.00000   324.13701   320.65909    33.85000
charged_amount       174.00000 32413.70115 32065.90926  3385.00000
refunded_amount        0.00000         NaN         NaN         NaN
age                  174.00000    38.92529     9.36542    10.00000
income               174.00000 76925.28736 23717.51246 22000.00000
price                174.00000   105.83333    53.21481    25.00000

                             25%         50%         75%          max
order_revision           1.00000     1.00000     1.00000      1.00000
sub_total_amount       110.00000   210.00000   500.00000   1700.00000
tax_total_amount         0.00000     0.00000     9.76000    150.90000
shipping_total_amount    4.68000     9.52000     9.52000     57.52000
fee_total_amount         0.00000     0.00000     0.00000      0.00000
order_total_amount     110.00000   216.78000   509.52000   1860.42000
charged_amount       11000.00000 21678.00000 50952.00000 186042.00000
refunded_amount              NaN         NaN         NaN          NaN
age                     33.00000    37.00000    44.75000     69.00000
income               63000.00000 76500.00000 96750.00000 126000.00000
price                  100.00000   100.00000   110.00000    340.00000
```

[28]:
```python
# convert order date to datetime type
order_denorm["order_created_at_utc"] = pd.
 ↪to_datetime(order_denorm["order_created_at_utc"])
```

[29]:
```python
order_denorm.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 174 entries, 0 to 185
Data columns (total 29 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     174 non-null    object
 1   order_number           174 non-null    object
 2   order_revision         174 non-null    int64
 3   order_created_at_utc   174 non-null    datetime64[ns, UTC]
 4   sub_total_amount       174 non-null    int64
 5   tax_total_amount       174 non-null    float64
```

```
 6   shipping_total_amount  174 non-null    float64
 7   fee_total_amount       174 non-null    int64
 8   order_total_amount     174 non-null    float64
 9   requires_payment       174 non-null    bool
 10  charged_amount         174 non-null    int64
 11  charge_refunded        174 non-null    bool
 12  refunded_amount        0 non-null      float64
 13  refunded_at_utc        0 non-null      object
 14  customer_id            174 non-null    object
 15  age                    174 non-null    int64
 16  gender                 174 non-null    object
 17  income                 174 non-null    int64
 18  group_id               174 non-null    object
 19  group_name             167 non-null    object
 20  customer_state         163 non-null    object
 21  customer_country       167 non-null    object
 22  device_type            174 non-null    object
 23  orderlineitems_jsonb   174 non-null    object
 24  price                  174 non-null    int64
 25  product_id             174 non-null    object
 26  product_title          174 non-null    object
 27  product_variant_id     174 non-null    object
 28  product_variant_title  174 non-null    object
dtypes: bool(2), datetime64[ns, UTC](1), float64(4), int64(7), object(15)
memory usage: 38.4+ KB
```

2.3 Feature engineering

2.3.1 Sequential rank column

Create a new column to sequentially rank the order within each customer by chronological order.

[151]:
```python
print(order_data.groupby('customer_id')['order_number'].count())
order_data.groupby('customer_id')['order_total_amount'].sum()
# 73 distinct customers
# It seems like not many repeat customers
```

```
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ    2
20210316112735216-9KTsUNszerowF4A1X1NBhg    1
20210317171023585-M2tZ3kjFMaTVmE4shqXxua    1
20210317172029708-JQryUiA4jZKCdwq1p8voq     1
20210317223206213-NfzPJbS9UTFStXosGMDBZV    1
                                           ..
20210514161709553-H4qBL986VFoNUKnNoaUPYd    1
20210526011612546-nTTW3Ch8Bx7UMtHK5ekea     1
20210527154659858-Jd4dGGxNjzXU9EMQhEbRgV    1
20210528000605652-Un6WDdXuj76sDYpMzbkawK    1
20210528225016277-RRBDhn7MLryxsibC7jUVoU    1
```

```
Name: order_number, Length: 73, dtype: int64
```

[151]:
```
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   369.36000
20210316112735216-9KTsUNszerowF4A1X1NBhg   113.51000
20210317171023585-M2tZ3kjFMaTVmE4shqXxua    55.98000
20210317172029708-JQryUiA4jZKCdwq1p8voq    110.00000
20210317223206213-NfzPJbS9UTFStXosGMDBZV   465.58000
                                              …
20210514161709553-H4qBL986VFoNUKnNoaUPYd    33.85000
20210526011612546-nTTW3Ch8Bx7UMtHK5ekea    123.61000
20210527154659858-Jd4dGGxNjzXU9EMQhEbRgV   339.52000
20210528000605652-Un6WDdXuj76sDYpMzbkawK   465.58000
20210528225016277-RRBDhn7MLryxsibC7jUVoU   465.58000
Name: order_total_amount, Length: 73, dtype: float64
```

[152]:
```
# This is the same as the SQL row number function
# row number() over(partition by customer_id order_data by order_created_at_utc)
#1. ROW NUMBER() --> .RANK(method='first')
# Ranks orders over time by Customer ID
order_data['row_num'] = order_data.
 ↪groupby(['customer_id'])['order_created_at_utc'].rank(method='first')

# Sorts values by Customer ID and Order Date in ascending order
order_data.sort_values(by= ['customer_id','order_created_at_utc'], inplace =␣
 ↪True)
order_data = order_data.reset_index(drop = True)
order_data['row_num'] = order_data['row_num'].astype("int")
order_data.head()
```

[152]:
```
                                     id order_number  order_revision  \
0  efd688aa-c021-4766-9721-83dd92710c63      2PBDJLI               1
1  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
2  4ac870d3-fe19-4203-ad28-6313793103b8      L3MSP59               1
3  aeaa4c4d-12e1-4016-bc47-30d08f00041c   CAHWWSMWOD               1
4  42dd34c1-f1ed-4f90-b7af-9261f423ebc9      FXPF4J2               1

             order_created_at_utc  sub_total_amount  tax_total_amount  \
0  2021-04-20 15:38:33.133957+00               110           9.76000
1  2021-04-26 10:27:48.058595+00               220          15.40000
2  2021-04-16 09:36:34.040838+00               110           0.00000
3  2021-04-26 18:05:00.426515+00                50           0.00000
4   2021-04-22 15:08:34.07912+00               110           0.00000

   shipping_total_amount  fee_total_amount  order_total_amount  \
0                4.68000                 0           124.44000
1                9.52000                 0           244.92000
```

```
2               2.51000                 0           113.51000
3               5.98000                 0            55.98000
4               0.00000                 0           110.00000

   requires_payment  charged_amount  charge_refunded  refunded_amount  \
0              True           12444            False              NaN
1              True           24492            False              NaN
2              True           11351            False              NaN
3              True            5598            False              NaN
4              True           11000            False              NaN

  refunded_at_utc                               customer_id  age  gender  \
0             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
1             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
2             NaN  20210316112735216-9KTsUNszerowF4A1X1NBhg   24  female
3             NaN  20210317171023585-M2tZ3kjFMaTVmE4shqXxua   35    male
4             NaN   20210317172029708-JQryUiA4jZKCdwq1p8voq   53  female

   income                                           group_id  \
0   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
1   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
2   39000  grp-49abab43-13d6-439c-80de-3e98b4083758--good…
3   75000  grp-e49d32ee-df44-4e9e-a3ab-d6ab4b6988d9--good…
4   97000  grp-5228870e-24ec-4e97-a41c-db62394ed4f1--good…

          group_name customer_state customer_country device_type  \
0  Sasquatch's Group             NY               US     Desktop
1      Cobra's Group             NY               US     Desktop
2                NaN            NaN              NaN     Desktop
3    Diablo's Winners             PA               US     Desktop
4        Rigs's Group             NY               US     Desktop

                              orderlineitems_jsonb  row_num
0  [{"id": "oli-NHz5q5rPAh4oj3QtZDfgQ3", "price":…        1
1  [{"id": "oli-E8hTJtpoz2uW5v75Bnm7Rd", "price":…        2
2  [{"id": "oli-MAucg88ir2tsPhjF9a98Np", "price":…        1
3  [{"id": "oli-VJoPK9Jcao9objad3qxYMY", "price":…        1
4  [{"id": "oli-DxrhtnugrvEVqBsXgPwHtJ", "price":…        1
```

2.3.2 Parse orderLineItem_json object

Parse and extract 'product_variant_id' and 'price' from the orderLineItem_jsonb object. https://towardsdatascience.com/cleaning-and-extracting-json-from-pandas-dataframes-f0c15f93cb38

[32]:
```
order_sample = json.loads(order_data["orderlineitems_jsonb"][3])
print(order_sample)
```

[{'id': 'oli-VJoPK9Jcao9objad3qxYMY', 'price': {'amount': 2500, 'currency':
'USD', 'iso4217Decimal': 2}, 'createdAt': {'epoch': 1619460290470, 'iso8601':
'2021-04-26T18:04:50.470202Z'}, 'productId': 'product-socksbundle',
'dateCreated': {'epoch': 1619460290470, 'iso8601':
'2021-04-26T18:04:50.470201Z'}, 'productVariantId': 'pvariant-socksbundle-
size'}, {'id': 'oli-Hmr9fASQtAQVJAS7U1AcH', 'price': {'amount': 2500,
'currency': 'USD', 'iso4217Decimal': 2}, 'createdAt': {'epoch': 1619460290470,
'iso8601': '2021-04-26T18:04:50.470208Z'}, 'productId': 'product-socksbundle',
'dateCreated': {'epoch': 1619460290470, 'iso8601':
'2021-04-26T18:04:50.470208Z'}, 'productVariantId': 'pvariant-socksbundle-
size'}]

[153]:
```
df = order_data.copy()
json_cols = ["orderlineitems_jsonb"]
def clean_json(x):
    "Create apply function for decoding JSON"
    return json.loads(x)

# Apply the function column wise to each column of interest
for x in json_cols:
    df[x] = df[x].apply(clean_json)
```

[154]:
```
# Look at first row of items
df["orderlineitems_jsonb"][0]
```

[154]:
[{'id': 'oli-NHz5q5rPAh4oj3QtZDfgQ3',
  'price': {'amount': 11000, 'currency': 'USD', 'iso4217Decimal': 2},
  'createdAt': {'epoch': 1618933104976,
   'iso8601': '2021-04-20T15:38:24.976030Z'},
  'productId': 'product-gsbrightbluehoodie',
  'dateCreated': {'epoch': 1618933104976,
   'iso8601': '2021-04-20T15:38:24.976029Z'},
  'productVariantId': 'pvariant-gsbrightbluehoodiemedium'}]

[155]:
```
# Testing
result = []
# test_list = json.loads(order_data["orderlineitems_jsonb"][3])
test_list = df["orderlineitems_jsonb"][0]
# print(test_list)
# type(test_list)
for i in range(len(test_list)):
    current = test_list[i]
    # print(current)
    for key, value in current.items():
        if key == "price":
            price = "{:.2f}".format(round(value["amount"]/
↪10**value["iso4217Decimal"], 2))
```

```
            print(price)
            result.append(price)
print(result)
```

```
110.00
['110.00']
```

[156]:

```
## Create function for pandas apply
def get_price(row):
    test_list = row["orderlineitems_jsonb"]
    result = []
    for i in range(len(test_list)):
        current = test_list[i]
        for key, value in current.items():
            if key == "price":
                price = "{:.2f}".format(round(value["amount"]/
 ↪10**value["iso4217Decimal"], 2))
                result.append(price)

    return result
```

[157]:

```
# Loop over all columns and clean json and create new columns
df["price"] = df.apply(get_price, axis=1)
```

[158]:

```
df.head()
```

[158]:

```
                                     id order_number  order_revision  \
0  efd688aa-c021-4766-9721-83dd92710c63      2PBDJLI               1
1  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
2  4ac870d3-fe19-4203-ad28-6313793103b8      L3MSP59               1
3  aeaa4c4d-12e1-4016-bc47-30d08f00041c   CAHWWSMWOD               1
4  42dd34c1-f1ed-4f90-b7af-9261f423ebc9      FXPF4J2               1

             order_created_at_utc  sub_total_amount  tax_total_amount  \
0  2021-04-20 15:38:33.133957+00               110           9.76000
1  2021-04-26 10:27:48.058595+00               220          15.40000
2  2021-04-16 09:36:34.040838+00               110           0.00000
3  2021-04-26 18:05:00.426515+00                50           0.00000
4   2021-04-22 15:08:34.07912+00               110           0.00000

   shipping_total_amount  fee_total_amount  order_total_amount  \
0                4.68000                 0           124.44000
1                9.52000                 0           244.92000
2                2.51000                 0           113.51000
3                5.98000                 0            55.98000
4                0.00000                 0           110.00000
```

```
  requires_payment  charged_amount  charge_refunded  refunded_amount  \
0             True           12444            False              NaN
1             True           24492            False              NaN
2             True           11351            False              NaN
3             True            5598            False              NaN
4             True           11000            False              NaN

 refunded_at_utc                             customer_id  age  gender  \
0            NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
1            NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
2            NaN  20210316112735216-9KTsUNszerowF4A1X1NBhg   24  female
3            NaN  20210317171023585-M2tZ3kjFMaTVmE4shqXxua   35    male
4            NaN   20210317172029708-JQryUiA4jZKCdwq1p8voq   53  female

  income                                          group_id  \
0  73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
1  73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
2  39000  grp-49abab43-13d6-439c-80de-3e98b4083758--good…
3  75000  grp-e49d32ee-df44-4e9e-a3ab-d6ab4b6988d9--good…
4  97000  grp-5228870e-24ec-4e97-a41c-db62394ed4f1--good…

         group_name customer_state customer_country device_type  \
0  Sasquatch's Group             NY               US     Desktop
1      Cobra's Group             NY               US     Desktop
2                NaN            NaN              NaN     Desktop
3   Diablo's Winners             PA               US     Desktop
4       Rigs's Group             NY               US     Desktop

                             orderlineitems_jsonb  row_num  \
0  [{'id': 'oli-NHz5q5rPAh4oj3QtZDfgQ3', 'price':…        1
1  [{'id': 'oli-E8hTJtpoz2uW5v75Bnm7Rd', 'price':…        2
2  [{'id': 'oli-MAucg88ir2tsPhjF9a98Np', 'price':…        1
3  [{'id': 'oli-VJoPK9Jcao9objad3qxYMY', 'price':…        1
4  [{'id': 'oli-DxrhtnugrvEVqBsXgPwHtJ', 'price':…        1

             price
0         [110.00]
1  [110.00, 110.00]
2         [110.00]
3    [25.00, 25.00]
4         [110.00]
```

[159]:

```
df["price"].describe()
```

[159]:

```
count           93
unique          21
top       [100.00]
```

```
freq             27
Name: price, dtype: object
```

One hot encode the json data - this will help us build the basket for each order too

[160]:
```python
def product_basket(x):

    # store values
    ls = []

    # loop through the list f dictionaries
    for y in range(len(x[0])):
        # Access each key and value in each dictionary
        for k, v in x[0][y].items():
            if k == "productVariantId":
                # append column names to ls
                #ls.append(str(k)+ "_" +str(v))
                ls.append(str(v))
                print(ls)

    # create a new column or change 0 to 1 if keyword exists
    for z in range(len(ls)):
        print(z)

        # If column not in the df columns then make a new column and assign␣
 ↪zero values while changing the current row to 1
        if ls[z] not in df.columns:
            df[ls[z]] = 0
            df[ls[z]].iloc[x.name] = 1
        else:
            df[ls[z]].iloc[x.name] = 1
    return

print("Original Shape",df.shape)

# Loop over all columns and clean json and create new columns
for x in ["orderlineitems_jsonb"]:
    df[[x]].apply(product_basket, axis=1)

print("New Shape", df.shape)
```

```
Original Shape (93, 26)
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
0
1
```

```
['pvariant-gsbrightbluehoodieextrasmall']
0
['pvariant-socksbundle-size']
['pvariant-socksbundle-size', 'pvariant-socksbundle-size']
0
1
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
0
1
2
3
['pvariant-gsbrightbluehoodieextrasmall']
0
['pvariant-truckerhatone-size']
0
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium']
0
1
2
['pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium']
0
1
2
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
0
1
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
0
1
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
```

```
0
1
['pvariant-wegoodgreyteemedium']
0
['pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
0
1
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-wegoodgreyteemedium']
0
1
['pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium']
0
1
2
3
4
['pvariant-socksbundle-size']
['pvariant-socksbundle-size', 'pvariant-socksbundle-size']
['pvariant-socksbundle-size', 'pvariant-socksbundle-size', 'pvariant-
socksbundle-size']
['pvariant-socksbundle-size', 'pvariant-socksbundle-size', 'pvariant-
socksbundle-size', 'pvariant-socksbundle-size']
['pvariant-socksbundle-size', 'pvariant-socksbundle-size', 'pvariant-
socksbundle-size', 'pvariant-socksbundle-size', 'pvariant-socksbundle-size']
0
1
2
3
4
['pvariant-gsbrightbluesweatsextrasmall']
0
['pvariant-gsbrightbluehoodieextrasmall']
0
['pvariant-basicwhiteteemedium']
0
['pvariant-basicwhiteteemedium']
```

```
['pvariant-basicwhiteteemedium', 'pvariant-basicwhiteteemedium']
0
1
['pvariant-wegoodgreyteemedium']
['pvariant-wegoodgreyteemedium', 'pvariant-truckerhatone-size']
0
1
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium']
0
1
2
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
0
1
2
3
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-wegoodgreyteemedium']
['pvariant-wegoodgreyteemedium', 'pvariant-wegoodgreyteemedium']
['pvariant-wegoodgreyteemedium', 'pvariant-wegoodgreyteemedium', 'pvariant-
wegoodgreyteemedium']
0
1
2
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium']
0
1
2
['pvariant-gsbrightbluesweatsmedium']
0
```

```
['pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
0
1
['pvariant-basicwhiteteemedium']
['pvariant-basicwhiteteemedium', 'pvariant-basicwhiteteemedium']
['pvariant-basicwhiteteemedium', 'pvariant-basicwhiteteemedium', 'pvariant-
basicwhiteteemedium']
0
1
2
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
0
1
2
3
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
0
1
['pvariant-wegoodgreyteemedium']
0
['pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium']
0
1
2
3
4
['pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
```

```
'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium']
0
1
2
3
4
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
0
1
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-basicwhiteteemedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-truckerhatone-size']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
0
1
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium']
```

```
0
1
2
3
4
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluebundlemedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium']
0
1
2
['pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium']
0
1
2
3
4
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium']
0
```

```
1
2
3
4
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
0
1
['pvariant-gsbrightbluebundlemedium']
['pvariant-gsbrightbluebundlemedium', 'pvariant-gsbrightbluebundlemedium']
['pvariant-gsbrightbluebundlemedium', 'pvariant-gsbrightbluebundlemedium',
'pvariant-gsbrightbluebundlemedium']
['pvariant-gsbrightbluebundlemedium', 'pvariant-gsbrightbluebundlemedium',
'pvariant-gsbrightbluebundlemedium', 'pvariant-gsbrightbluebundlemedium']
['pvariant-gsbrightbluebundlemedium', 'pvariant-gsbrightbluebundlemedium',
'pvariant-gsbrightbluebundlemedium', 'pvariant-gsbrightbluebundlemedium',
'pvariant-gsbrightbluebundlemedium']
0
1
2
```

```
3
4
['pvariant-gsbrightbluebundlemedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-wegoodgreyteemedium']
0
1
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-gsbrightbluesweatsmedium']
0
['pvariant-truckerhatone-size']
0
['pvariant-gsbrightbluehoodiemedium']
0
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium']
0
1
2
['pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium']
['pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium', 'pvariant-gsbrightbluesweatsmedium',
'pvariant-gsbrightbluesweatsmedium']
0
1
2
3
4
['pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
```

```
'pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium']
['pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium', 'pvariant-gsbrightbluehoodiemedium',
'pvariant-gsbrightbluehoodiemedium']
0
1
2
3
4
```

[160]:

```
0     None
1     None
2     None
3     None
4     None
      …
88    None
89    None
90    None
91    None
92    None
Length: 93, dtype: object

New Shape (93, 35)
```

[161]:

```
df.head()
```

[161]:

```
                                     id order_number  order_revision  \
0  efd688aa-c021-4766-9721-83dd92710c63      2PBDJLI               1
1  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
2  4ac870d3-fe19-4203-ad28-6313793103b8      L3MSP59               1
3  aeaa4c4d-12e1-4016-bc47-30d08f00041c   CAHWWSMWOD               1
4  42dd34c1-f1ed-4f90-b7af-9261f423ebc9      FXPF4J2               1

             order_created_at_utc  sub_total_amount  tax_total_amount  \
0  2021-04-20 15:38:33.133957+00               110           9.76000
1  2021-04-26 10:27:48.058595+00               220          15.40000
2  2021-04-16 09:36:34.040838+00               110           0.00000
3  2021-04-26 18:05:00.426515+00                50           0.00000
4   2021-04-22 15:08:34.07912+00               110           0.00000

   shipping_total_amount  fee_total_amount  order_total_amount  \
0                4.68000                 0           124.44000
1                9.52000                 0           244.92000
2                2.51000                 0           113.51000
3                5.98000                 0            55.98000
4                0.00000                 0           110.00000
```

```
  requires_payment  charged_amount  charge_refunded  refunded_amount  \
0             True           12444            False              NaN
1             True           24492            False              NaN
2             True           11351            False              NaN
3             True            5598            False              NaN
4             True           11000            False              NaN

  refunded_at_utc                               customer_id  age  gender  \
0             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
1             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
2             NaN  20210316112735216-9KTsUNszerowF4A1X1NBhg   24  female
3             NaN  20210317171023585-M2tZ3kjFMaTVmE4shqXxua   35    male
4             NaN   20210317172029708-JQryUiA4jZKCdwq1p8voq   53  female

   income                                           group_id  \
0   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
1   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
2   39000  grp-49abab43-13d6-439c-80de-3e98b4083758--good…
3   75000  grp-e49d32ee-df44-4e9e-a3ab-d6ab4b6988d9--good…
4   97000  grp-5228870e-24ec-4e97-a41c-db62394ed4f1--good…

         group_name customer_state customer_country device_type  \
0  Sasquatch's Group             NY               US     Desktop
1      Cobra's Group             NY               US     Desktop
2                NaN            NaN              NaN     Desktop
3   Diablo's Winners             PA               US     Desktop
4       Rigs's Group             NY               US     Desktop

                              orderlineitems_jsonb  row_num  \
0  [{'id': 'oli-NHz5q5rPAh4oj3QtZDfgQ3', 'price':…        1
1  [{'id': 'oli-E8hTJtpoz2uW5v75Bnm7Rd', 'price':…        2
2  [{'id': 'oli-MAucg88ir2tsPhjF9a98Np', 'price':…        1
3  [{'id': 'oli-VJoPK9Jcao9objad3qxYMY', 'price':…        1
4  [{'id': 'oli-DxrhtnugrvEVqBsXgPwHtJ', 'price':…        1

              price  pvariant-gsbrightbluehoodiemedium  \
0          [110.00]                                  1
1  [110.00, 110.00]                                  1
2          [110.00]                                  0
3    [25.00, 25.00]                                  0
4          [110.00]                                  1

  pvariant-gsbrightbluehoodieextrasmall  pvariant-socksbundle-size  \
0                                     0                          0
1                                     0                          0
2                                     1                          0
3                                     0                          1
```

```
4                                          0                            0

   pvariant-truckerhatone-size  pvariant-gsbrightbluesweatsmedium  \
0                            0                                  0
1                            0                                  0
2                            0                                  0
3                            0                                  0
4                            0                                  0

   pvariant-wegoodgreyteemedium  pvariant-gsbrightbluesweatsextrasmall  \
0                             0                                      0
1                             0                                      0
2                             0                                      0
3                             0                                      0
4                             0                                      0

   pvariant-basicwhiteteemedium  pvariant-gsbrightbluebundlemedium
0                             0                                  0
1                             0                                  0
2                             0                                  0
3                             0                                  0
4                             0                                  0
```

3 Analysis/Modeling

3.1 Market Basket Analysis

It helps retailers with:

- Increases customer engagement
- Boosting sales and increasing RoI
- Improving customer experience
- Optimize marketing strategies and campaigns
- Help to understand customers better
- Identifies customer behavior and pattern

The steps of working of the **apriori algorithm** can be given as:-

- First, define the minimum support and confidence for the association rule.
- Find out all the subsets in the transactions with higher support(sup) than the minimum support.
- Find all the rules for these subsets with higher confidence than minimum confidence.
- Sort these association rules in decreasing order.
- Analyze the rules along with their confidence and support.

3.1.1 order_data

[42]:
```python
basket_cols = df.columns.str.contains("pvariant")
baskets = df[df.columns[basket_cols]]
print(baskets.shape)
baskets.head()
```

```
(93, 9)
```

[42]:
```
   pvariant-gsbrightbluehoodiemedium  pvariant-gsbrightbluehoodieextrasmall  \
0                                  1                                      0
1                                  1                                      0
2                                  0                                      1
3                                  0                                      0
4                                  1                                      0

   pvariant-socksbundle-size  pvariant-truckerhatone-size  \
0                          0                            0
1                          0                            0
2                          0                            0
3                          1                            0
4                          0                            0

   pvariant-gsbrightbluesweatsmedium  pvariant-wegoodgreyteemedium  \
0                                  0                             0
1                                  0                             0
2                                  0                             0
3                                  0                             0
4                                  0                             0

   pvariant-gsbrightbluesweatsextrasmall  pvariant-basicwhiteteemedium  \
0                                      0                             0
1                                      0                             0
2                                      0                             0
3                                      0                             0
4                                      0                             0

   pvariant-gsbrightbluebundlemedium
0                                  0
1                                  0
2                                  0
3                                  0
4                                  0
```

[43]:
```python
#Generate frequent itemsets
frequent_itemsets = apriori(baskets, min_support = 0.005, use_colnames=True)
```

```
/Users/jrudd/opt/anaconda3/lib/python3.8/site-
```

```
packages/mlxtend/frequent_patterns/fpcommon.py:111: DeprecationWarning:

DataFrames with non-bool types result in worse computationalperformance and
their support might be discontinued in the future.Please use a DataFrame with
bool type
```

[44]:
```python
print(frequent_itemsets)
```

```
    support                                         itemsets
0   0.38710             (pvariant-gsbrightbluehoodiemedium)
1   0.03226         (pvariant-gsbrightbluehoodieextrasmall)
2   0.02151                     (pvariant-socksbundle-size)
3   0.04301                   (pvariant-truckerhatone-size)
4   0.40860             (pvariant-gsbrightbluesweatsmedium)
5   0.06452                  (pvariant-wegoodgreyteemedium)
6   0.01075         (pvariant-gsbrightbluesweatsextrasmall)
7   0.04301                  (pvariant-basicwhiteteemedium)
8   0.03226             (pvariant-gsbrightbluebundlemedium)
9   0.01075  (pvariant-gsbrightbluesweatsmedium, pvariant-g…
10  0.01075  (pvariant-wegoodgreyteemedium, pvariant-gsbrig…
11  0.01075  (pvariant-truckerhatone-size, pvariant-wegoodg…
12  0.01075  (pvariant-wegoodgreyteemedium, pvariant-gsbrig…
```

[45]:
```python
#Generating the rules
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1)
rules.head()
```

[45]:
```
                    antecedents                     consequents  \
0   (pvariant-truckerhatone-size)  (pvariant-wegoodgreyteemedium)
1  (pvariant-wegoodgreyteemedium)   (pvariant-truckerhatone-size)

   antecedent support  consequent support  support  confidence    lift  \
0             0.04301             0.06452  0.01075     0.25000 3.87500
1             0.06452             0.04301  0.01075     0.16667 3.87500

   leverage  conviction
0   0.00798     1.24731
1   0.00798     1.14839
```

This is really small data for this so findings not super interesting; most folks only bought 1 item. The most popular item was the medium bright blue hoodie, with 38% of transactions including that item.

For association rules, we're limited to looking at transactions with more than 1 item. The highest confidence itemset includes the trucker hat with the we good grey tee size medium, with 25% of transactions containing the trucker hat also containing the tee.

Controlling for the general transaction popularity of the medium sized tee, the lift indicates that

that the tee is likely to be purchased with the trucker hat.

3.1.2 denormalized data

[46]:
```
order_denorm.head()
```

[46]:
```
                                     id order_number  order_revision  \
0  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
1  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
3  3c6a5fd9-5e57-4cf1-9ed1-332a2117dfcb    2EWVBFAYGR              1
4  cafdecc9-f3bf-4274-93d8-4f7cda91c842    JCTR6OHJBK              1
5  cafdecc9-f3bf-4274-93d8-4f7cda91c842    JCTR6OHJBK              1

              order_created_at_utc  sub_total_amount  tax_total_amount  \
0 2021-04-26 10:27:48.058595+00:00               220          15.40000
1 2021-04-26 10:27:48.058595+00:00               220          15.40000
3 2021-04-28 13:21:45.829622+00:00               100           4.88000
4 2021-04-27 17:29:40.519036+00:00               220           0.00000
5 2021-04-27 17:29:40.519036+00:00               220           0.00000

   shipping_total_amount  fee_total_amount  order_total_amount  \
0                9.52000                 0           244.92000
1                9.52000                 0           244.92000
3                4.68000                 0           109.56000
4               51.49000                 0           271.49000
5               51.49000                 0           271.49000

   requires_payment  charged_amount  charge_refunded  refunded_amount  \
0              True           24492            False              NaN
1              True           24492            False              NaN
3              True           10956            False              NaN
4              True           27149            False              NaN
5              True           27149            False              NaN

  refunded_at_utc                              customer_id  age  gender  \
0             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
1             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
3             NaN  20210428123305906-K5rxcBo3Q2uMwjD6H4mwq5   45    male
4             NaN  20210406163142240-MEpprnTNETHBEnusY3r6pN   36  female
5             NaN  20210406163142240-MEpprnTNETHBEnusY3r6pN   36  female

   income                                          group_id       group_name  \
0   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…    Cobra's Group
1   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…    Cobra's Group
3   79000  grp-b8c2e546-9a03-4897-afa2-81a73b8975ee--good…  Mad Dog's Group
4   98000  grp-edadeef5-6800-4929-8f6b-bae579c7faac--good…              pdf
5   98000  grp-edadeef5-6800-4929-8f6b-bae579c7faac--good…              pdf
```

```
  customer_state customer_country device_type  \
0             NY               US     Desktop
1             NY               US     Desktop
3             NY               US     Desktop
4            NaN               RS     Desktop
5            NaN               RS     Desktop

                              orderlineitems_jsonb  price  \
0  [{"id": "oli-E8hTJtpoz2uW5v75Bnm7Rd", "price":…    110
1  [{"id": "oli-E8hTJtpoz2uW5v75Bnm7Rd", "price":…    110
3  [{"id": "oli-MLSxCZcLySaMWHPmtLkDDJ", "price":…    100
4  [{"id": "oli-QMmcEsvprhMARgGDkdsfFC", "price":…    110
5  [{"id": "oli-QMmcEsvprhMARgGDkdsfFC", "price":…    110

                 product_id     product_title  \
0  product-gsbrightbluehoodie  Beam Blue Hoodie
1  product-gsbrightbluehoodie  Beam Blue Hoodie
3  product-gsbrightbluesweats  Beam Blue Sweats
4  product-gsbrightbluehoodie  Beam Blue Hoodie
5  product-gsbrightbluehoodie  Beam Blue Hoodie

                 product_variant_id product_variant_title
0  pvariant-gsbrightbluehoodiemedium                Medium
1  pvariant-gsbrightbluehoodiemedium                Medium
3  pvariant-gsbrightbluesweatsmedium                Medium
4  pvariant-gsbrightbluehoodiemedium                Medium
5  pvariant-gsbrightbluehoodiemedium                Medium
```

[47]:
```
order_denorm["price"].describe()
```

[47]:
```
count    174.00000
mean     105.83333
std       53.21481
min       25.00000
25%      100.00000
50%      100.00000
75%      110.00000
max      340.00000
Name: price, dtype: float64
```

[48]:
```
basket_denorm = order_denorm.
 ↪groupby(["order_number","product_variant_id"])["product_id"].count().
 ↪unstack().reset_index().fillna(0).set_index("order_number")
print(basket_denorm.shape)
basket_denorm.head()
```

```
(88, 9)
```

[48]:
```
product_variant_id  pvariant-basicwhiteteemedium  \
order_number
169NPU5TSH                               0.00000
2EWVBFAYGR                               0.00000
2GGEEHZ                                  0.00000
2GTMKPQ                                  0.00000
2PBDJLI                                  0.00000

product_variant_id  pvariant-gsbrightbluebundlemedium  \
order_number
169NPU5TSH                                    0.00000
2EWVBFAYGR                                    0.00000
2GGEEHZ                                       0.00000
2GTMKPQ                                       0.00000
2PBDJLI                                       0.00000

product_variant_id  pvariant-gsbrightbluehoodieextrasmall  \
order_number
169NPU5TSH                                        0.00000
2EWVBFAYGR                                        0.00000
2GGEEHZ                                           0.00000
2GTMKPQ                                           0.00000
2PBDJLI                                           0.00000

product_variant_id  pvariant-gsbrightbluehoodiemedium  \
order_number
169NPU5TSH                                    0.00000
2EWVBFAYGR                                    0.00000
2GGEEHZ                                       4.00000
2GTMKPQ                                       0.00000
2PBDJLI                                       1.00000

product_variant_id  pvariant-gsbrightbluesweatsextrasmall  \
order_number
169NPU5TSH                                        0.00000
2EWVBFAYGR                                        0.00000
2GGEEHZ                                           0.00000
2GTMKPQ                                           0.00000
2PBDJLI                                           0.00000

product_variant_id  pvariant-gsbrightbluesweatsmedium  \
order_number
169NPU5TSH                                    1.00000
2EWVBFAYGR                                    1.00000
2GGEEHZ                                       0.00000
```

```
2GTMKPQ                                         5.00000
2PBDJLI                                         0.00000

product_variant_id  pvariant-socksbundle-size  pvariant-truckerhatone-size  \
order_number
169NPU5TSH                            0.00000                      0.00000
2EWVBFAYGR                            0.00000                      0.00000
2GGEEHZ                               0.00000                      0.00000
2GTMKPQ                               0.00000                      0.00000
2PBDJLI                               0.00000                      0.00000

product_variant_id  pvariant-wegoodgreyteemedium
order_number
169NPU5TSH                               0.00000
2EWVBFAYGR                               0.00000
2GGEEHZ                                  0.00000
2GTMKPQ                                  0.00000
2PBDJLI                                  0.00000
```

[49]:
```python
# Encoding to boolean
def encode_units(x):
    if x <= 0:
        return 0
    if x >= 1:
        return 1
basket_sets = basket_denorm.applymap(encode_units)
basket_sets.head()
```

[49]:
```
product_variant_id  pvariant-basicwhiteteemedium  \
order_number
169NPU5TSH                                     0
2EWVBFAYGR                                     0
2GGEEHZ                                        0
2GTMKPQ                                        0
2PBDJLI                                        0

product_variant_id  pvariant-gsbrightbluebundlemedium  \
order_number
169NPU5TSH                                          0
2EWVBFAYGR                                          0
2GGEEHZ                                             0
2GTMKPQ                                             0
2PBDJLI                                             0

product_variant_id  pvariant-gsbrightbluehoodieextrasmall  \
order_number
169NPU5TSH                                              0
```

```
2EWVBFAYGR                                            0
2GGEEHZ                                               0
2GTMKPQ                                               0
2PBDJLI                                               0

product_variant_id  pvariant-gsbrightbluehoodiemedium  \
order_number
169NPU5TSH                                        0
2EWVBFAYGR                                        0
2GGEEHZ                                           1
2GTMKPQ                                           0
2PBDJLI                                           1

product_variant_id  pvariant-gsbrightbluesweatsextrasmall  \
order_number
169NPU5TSH                                            0
2EWVBFAYGR                                            0
2GGEEHZ                                               0
2GTMKPQ                                               0
2PBDJLI                                               0

product_variant_id  pvariant-gsbrightbluesweatsmedium  \
order_number
169NPU5TSH                                        1
2EWVBFAYGR                                        1
2GGEEHZ                                           0
2GTMKPQ                                           1
2PBDJLI                                           0

product_variant_id  pvariant-socksbundle-size  pvariant-truckerhatone-size  \
order_number
169NPU5TSH                                0                            0
2EWVBFAYGR                                0                            0
2GGEEHZ                                   0                            0
2GTMKPQ                                   0                            0
2PBDJLI                                   0                            0

product_variant_id  pvariant-wegoodgreyteemedium
order_number
169NPU5TSH                                     0
2EWVBFAYGR                                     0
2GGEEHZ                                        0
2GTMKPQ                                        0
2PBDJLI                                        0
```

[50]:
```
#Generate frequent itemsets
```

```
frequent_itemsets_denorm = apriori(basket_sets, min_support = 0.01,␣
↪use_colnames=True)
print(frequent_itemsets_denorm)
```

```
    support                                        itemsets
0   0.04545              (pvariant-basicwhiteteemedium)
1   0.03409           (pvariant-gsbrightbluebundlemedium)
2   0.03409         (pvariant-gsbrightbluehoodieextrasmall)
3   0.38636           (pvariant-gsbrightbluehoodiemedium)
4   0.01136         (pvariant-gsbrightbluesweatsextrasmall)
5   0.42045           (pvariant-gsbrightbluesweatsmedium)
6   0.01136                  (pvariant-socksbundle-size)
7   0.03409               (pvariant-truckerhatone-size)
8   0.05682              (pvariant-wegoodgreyteemedium)
9   0.01136  (pvariant-gsbrightbluesweatsmedium, pvariant-g…
10  0.01136  (pvariant-wegoodgreyteemedium, pvariant-gsbrig…
11  0.01136  (pvariant-wegoodgreyteemedium, pvariant-gsbrig…
```

```
/Users/jrudd/opt/anaconda3/lib/python3.8/site-
packages/mlxtend/frequent_patterns/fpcommon.py:111: DeprecationWarning:

DataFrames with non-bool types result in worse computationalperformance and
their support might be discontinued in the future.Please use a DataFrame with
bool type
```

[51]:
```
#Generating the rules
rules = association_rules(frequent_itemsets_denorm, metric="support",␣
↪min_threshold=0.01)

rules.head()
```

[51]:
```
                         antecedents                         consequents  \
0  (pvariant-gsbrightbluesweatsmedium)  (pvariant-gsbrightbluehoodiemedium)
1  (pvariant-gsbrightbluehoodiemedium)  (pvariant-gsbrightbluesweatsmedium)
2       (pvariant-wegoodgreyteemedium)  (pvariant-gsbrightbluehoodiemedium)
3  (pvariant-gsbrightbluehoodiemedium)       (pvariant-wegoodgreyteemedium)
4       (pvariant-wegoodgreyteemedium)  (pvariant-gsbrightbluesweatsmedium)

   antecedent support  consequent support  support  confidence    lift  \
0             0.42045             0.38636  0.01136     0.02703 0.06995
1             0.38636             0.42045  0.01136     0.02941 0.06995
2             0.05682             0.38636  0.01136     0.20000 0.51765
3             0.38636             0.05682  0.01136     0.02941 0.51765
4             0.05682             0.42045  0.01136     0.20000 0.47568

   leverage  conviction
```

```
0  -0.15108      0.63068
1  -0.15108      0.59711
2  -0.01059      0.76705
3  -0.01059      0.97176
4  -0.01253      0.72443
```

3.2 Customer lifetime value

- total revenue a business can expect from a single customer account
- increase revenue
- target best customers
- reduce customer aquisition costs
- Using this basic implementation due to small size of data, not many repeat customers

[52]:
```python
# Each row is an item in the order
order_denorm.head()
```

[52]:
```
                                     id order_number  order_revision  \
0  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
1  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
3  3c6a5fd9-5e57-4cf1-9ed1-332a2117dfcb    2EWVBFAYGR               1
4  cafdecc9-f3bf-4274-93d8-4f7cda91c842    JCTR6OHJBK               1
5  cafdecc9-f3bf-4274-93d8-4f7cda91c842    JCTR6OHJBK               1

              order_created_at_utc  sub_total_amount  tax_total_amount  \
0 2021-04-26 10:27:48.058595+00:00               220          15.40000
1 2021-04-26 10:27:48.058595+00:00               220          15.40000
3 2021-04-28 13:21:45.829622+00:00               100           4.88000
4 2021-04-27 17:29:40.519036+00:00               220           0.00000
5 2021-04-27 17:29:40.519036+00:00               220           0.00000

   shipping_total_amount  fee_total_amount  order_total_amount  \
0                9.52000                 0           244.92000
1                9.52000                 0           244.92000
3                4.68000                 0           109.56000
4               51.49000                 0           271.49000
5               51.49000                 0           271.49000

   requires_payment  charged_amount  charge_refunded  refunded_amount  \
0              True           24492            False              NaN
1              True           24492            False              NaN
3              True           10956            False              NaN
4              True           27149            False              NaN
5              True           27149            False              NaN

  refunded_at_utc                              customer_id  age  gender  \
0             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
```

```
1             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
3             NaN  20210428123305906-K5rxcBo3Q2uMwjD6H4mwq5   45    male
4             NaN  20210406163142240-MEpprnTNETHBEnusY3r6pN   36  female
5             NaN  20210406163142240-MEpprnTNETHBEnusY3r6pN   36  female

   income                                           group_id       group_name  \
0   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…    Cobra's Group
1   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…    Cobra's Group
3   79000  grp-b8c2e546-9a03-4897-afa2-81a73b8975ee--good…  Mad Dog's Group
4   98000  grp-edadeef5-6800-4929-8f6b-bae579c7faac--good…              pdf
5   98000  grp-edadeef5-6800-4929-8f6b-bae579c7faac--good…              pdf

  customer_state customer_country device_type  \
0             NY               US     Desktop
1             NY               US     Desktop
3             NY               US     Desktop
4            NaN               RS     Desktop
5            NaN               RS     Desktop

                                orderlineitems_jsonb  price  \
0  [{"id": "oli-E8hTJtpoz2uW5v75Bnm7Rd", "price":…    110
1  [{"id": "oli-E8hTJtpoz2uW5v75Bnm7Rd", "price":…    110
3  [{"id": "oli-MLSxCZcLySaMWHPmtLkDDJ", "price":…    100
4  [{"id": "oli-QMmcEsvprhMARgGDkdsfFC", "price":…    110
5  [{"id": "oli-QMmcEsvprhMARgGDkdsfFC", "price":…    110

                  product_id     product_title  \
0  product-gsbrightbluehoodie  Beam Blue Hoodie
1  product-gsbrightbluehoodie  Beam Blue Hoodie
3  product-gsbrightbluesweats  Beam Blue Sweats
4  product-gsbrightbluehoodie  Beam Blue Hoodie
5  product-gsbrightbluehoodie  Beam Blue Hoodie

                  product_variant_id product_variant_title
0  pvariant-gsbrightbluehoodiemedium                Medium
1  pvariant-gsbrightbluehoodiemedium                Medium
3  pvariant-gsbrightbluesweatsmedium                Medium
4  pvariant-gsbrightbluehoodiemedium                Medium
5  pvariant-gsbrightbluehoodiemedium                Medium
```

[54]:
```
# Aggregate customer orders
# Using order revision as a count of rows (items) purchased by that customer
cltv = order_denorm.groupby("customer_id").agg({"order_number": lambda x: x.
↪nunique(), "order_revision": lambda x: x.count(), "price": lambda x: x.
↪sum()})
cltv.head()
```

[54]:

```
                                         order_number  order_revision  price
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ             2               3    330
20210316112735216-9KTsUNszerowF4A1X1NBhg             1               1    110
20210317172029708-JQryUiA4jZKCdwq1p8voq              1               2    220
20210317223206213-NfzPJbS9UTFStXosGMDBZV             1               4    440
20210318001813104-KWTskbtB4bs7j5uqbboSrk             1               1    110
```

[55]:

```
cltv.columns = ["total_transactions", "total_units", "total_price"]
cltv.head()
```

[55]:

```
                                          total_transactions  total_units  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ                   2            3
20210316112735216-9KTsUNszerowF4A1X1NBhg                   1            1
20210317172029708-JQryUiA4jZKCdwq1p8voq                    1            2
20210317223206213-NfzPJbS9UTFStXosGMDBZV                   1            4
20210318001813104-KWTskbtB4bs7j5uqbboSrk                   1            1

                                          total_price
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ          330
20210316112735216-9KTsUNszerowF4A1X1NBhg          110
20210317172029708-JQryUiA4jZKCdwq1p8voq           220
20210317223206213-NfzPJbS9UTFStXosGMDBZV          440
20210318001813104-KWTskbtB4bs7j5uqbboSrk          110
```

[56]:

```
# Calculate average order value
cltv['avg_order_value'] = cltv['total_price']/cltv['total_transactions']
cltv.head()
```

[56]:

```
                                          total_transactions  total_units  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ                   2            3
20210316112735216-9KTsUNszerowF4A1X1NBhg                   1            1
20210317172029708-JQryUiA4jZKCdwq1p8voq                    1            2
20210317223206213-NfzPJbS9UTFStXosGMDBZV                   1            4
20210318001813104-KWTskbtB4bs7j5uqbboSrk                   1            1

                                          total_price  avg_order_value
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ          330        165.00000
20210316112735216-9KTsUNszerowF4A1X1NBhg          110        110.00000
20210317172029708-JQryUiA4jZKCdwq1p8voq           220        220.00000
20210317223206213-NfzPJbS9UTFStXosGMDBZV          440        440.00000
20210318001813104-KWTskbtB4bs7j5uqbboSrk          110        110.00000
```

[57]:
```python
# Calculate purchase frequency
print(cltv.shape)

cltv["purchase_frequency"] = cltv['total_transactions']/cltv.shape[0]
```

```
(69, 4)
```

[58]:
```python
cltv.head()
```

[58]:
```
                                            total_transactions  total_units  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ                     2            3
20210316112735216-9KTsUNszerowF4A1X1NBhg                     1            1
20210317172029708-JQryUiA4jZKCdwq1p8voq                      1            2
20210317223206213-NfzPJbS9UTFStXosGMDBZV                     1            4
20210318001813104-KWTskbtB4bs7j5uqbboSrk                     1            1

                                            total_price  avg_order_value  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ            330        165.00000
20210316112735216-9KTsUNszerowF4A1X1NBhg            110        110.00000
20210317172029708-JQryUiA4jZKCdwq1p8voq             220        220.00000
20210317223206213-NfzPJbS9UTFStXosGMDBZV            440        440.00000
20210318001813104-KWTskbtB4bs7j5uqbboSrk            110        110.00000

                                            purchase_frequency
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ               0.02899
20210316112735216-9KTsUNszerowF4A1X1NBhg               0.01449
20210317172029708-JQryUiA4jZKCdwq1p8voq                0.01449
20210317223206213-NfzPJbS9UTFStXosGMDBZV               0.01449
20210318001813104-KWTskbtB4bs7j5uqbboSrk               0.01449
```

[59]:
```python
# Calculate repeat rate and churn
repeat_rate = cltv[cltv.total_transactions > 1].shape[0] / cltv.shape[0]
print(f"Repeat purchase rate: {repeat_rate}")
print(f"There are {cltv[cltv.total_transactions > 1].shape[0]} customers with␣
 ↪repeat purchases")
#If there is more than  'one' transaction choose it.
churn_rate = 1 - repeat_rate
print(f"Customer churn rate: {churn_rate}")
```

```
Repeat purchase rate: 0.2753623188405797
There are 19 customers with repeat purchases
Customer churn rate: 0.7246376811594203
```

Profit margin (assuming 10%). This link says avg net profit is around 10%, and this link says profit margins are generally between 4 to 13%

[60]:
```
# Profit margin (assuming 10%).
cltv['profit_margin'] = cltv['total_price'] * 0.10
cltv.head()
```

[60]:
```
                                          total_transactions  total_units  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ                   2            3
20210316112735216-9KTsUNszerowF4A1X1NBhg                   1            1
20210317172029708-JQryUiA4jZKCdwq1p8voq                    1            2
20210317223206213-NfzPJbS9UTFStXosGMDBZV                   1            4
20210318001813104-KWTskbtB4bs7j5uqbboSrk                   1            1

                                          total_price  avg_order_value  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ          330        165.00000
20210316112735216-9KTsUNszerowF4A1X1NBhg          110        110.00000
20210317172029708-JQryUiA4jZKCdwq1p8voq           220        220.00000
20210317223206213-NfzPJbS9UTFStXosGMDBZV          440        440.00000
20210318001813104-KWTskbtB4bs7j5uqbboSrk          110        110.00000

                                          purchase_frequency  profit_margin
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ             0.02899       33.00000
20210316112735216-9KTsUNszerowF4A1X1NBhg             0.01449       11.00000
20210317172029708-JQryUiA4jZKCdwq1p8voq              0.01449       22.00000
20210317223206213-NfzPJbS9UTFStXosGMDBZV             0.01449       44.00000
20210318001813104-KWTskbtB4bs7j5uqbboSrk             0.01449       11.00000
```

[61]:
```
# Customer value - avg order value * purchase frequency
cltv['customer_value'] = (cltv['avg_order_value'] * cltv["purchase_frequency"])␣
↪/ churn_rate
cltv.head()
```

[61]:
```
                                          total_transactions  total_units  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ                   2            3
20210316112735216-9KTsUNszerowF4A1X1NBhg                   1            1
20210317172029708-JQryUiA4jZKCdwq1p8voq                    1            2
20210317223206213-NfzPJbS9UTFStXosGMDBZV                   1            4
20210318001813104-KWTskbtB4bs7j5uqbboSrk                   1            1

                                          total_price  avg_order_value  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ          330        165.00000
20210316112735216-9KTsUNszerowF4A1X1NBhg          110        110.00000
20210317172029708-JQryUiA4jZKCdwq1p8voq           220        220.00000
20210317223206213-NfzPJbS9UTFStXosGMDBZV          440        440.00000
```

```
20210318001813104-KWTskbtB4bs7j5uqbboSrk        110       110.00000

                                          purchase_frequency  profit_margin  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ             0.02899       33.00000
20210316112735216-9KTsUNszerowF4A1X1NBhg             0.01449       11.00000
20210317172029708-JQryUiA4jZKCdwq1p8voq              0.01449       22.00000
20210317223206213-NfzPJbS9UTFStXosGMDBZV             0.01449       44.00000
20210318001813104-KWTskbtB4bs7j5uqbboSrk             0.01449       11.00000

                                          customer_value
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ         6.60000
20210316112735216-9KTsUNszerowF4A1X1NBhg         2.20000
20210317172029708-JQryUiA4jZKCdwq1p8voq          4.40000
20210317223206213-NfzPJbS9UTFStXosGMDBZV         8.80000
20210318001813104-KWTskbtB4bs7j5uqbboSrk         2.20000
```

[62]:

```python
# CLTV - (customer_value/churn_rate) * profit margin
cltv['cltv'] = cltv['customer_value'] * cltv['profit_margin']
cltv.head()
```

[62]:

```
                                          total_transactions  total_units  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ                   2            3
20210316112735216-9KTsUNszerowF4A1X1NBhg                   1            1
20210317172029708-JQryUiA4jZKCdwq1p8voq                    1            2
20210317223206213-NfzPJbS9UTFStXosGMDBZV                   1            4
20210318001813104-KWTskbtB4bs7j5uqbboSrk                   1            1

                                          total_price  avg_order_value  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ        330       165.00000
20210316112735216-9KTsUNszerowF4A1X1NBhg        110       110.00000
20210317172029708-JQryUiA4jZKCdwq1p8voq         220       220.00000
20210317223206213-NfzPJbS9UTFStXosGMDBZV        440       440.00000
20210318001813104-KWTskbtB4bs7j5uqbboSrk        110       110.00000

                                          purchase_frequency  profit_margin  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ             0.02899       33.00000
20210316112735216-9KTsUNszerowF4A1X1NBhg             0.01449       11.00000
20210317172029708-JQryUiA4jZKCdwq1p8voq              0.01449       22.00000
20210317223206213-NfzPJbS9UTFStXosGMDBZV             0.01449       44.00000
20210318001813104-KWTskbtB4bs7j5uqbboSrk             0.01449       11.00000

                                          customer_value      cltv
```

```
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ        6.60000 217.80000
20210316112735216-9KTsUNszerowF4A1X1NBhg        2.20000  24.20000
20210317172029708-JQryUiA4jZKCdwq1p8voq         4.40000  96.80000
20210317223206213-NfzPJbS9UTFStXosGMDBZV        8.80000 387.20000
20210318001813104-KWTskbtB4bs7j5uqbboSrk        2.20000  24.20000
```

[63]:
```python
# Scaling CLTV between 0 and 1 to compare and rank customers
scaler = MinMaxScaler(feature_range=(0, 1))
scaler.fit(cltv[["cltv"]])
cltv["scaled_cltv"] = scaler.transform(cltv[["cltv"]])
cltv.sort_values(by="scaled_cltv", ascending=False).head()
```

[63]: MinMaxScaler()

[63]:
```
                                             total_transactions  total_units  \
customer_id
20210504130925953-GJsTQgjYTZde9smEgwhWPk                      2            6
20210414185957231-DmKCxnbm1FRsdPnC6MuZYL                      2            7
20210427085254181-2kM2V2DLFrMGA9irexvxb8                      2            7
20210326204748930-FWcnyAzHQ97DtAfgRtstFP                      2            6
20210412175134872-5g5bWEW1PQYFXePRXiTATu                      2           10

                                             total_price  avg_order_value  \
customer_id
20210504130925953-GJsTQgjYTZde9smEgwhWPk            2040       1020.00000
20210414185957231-DmKCxnbm1FRsdPnC6MuZYL             770        385.00000
20210427085254181-2kM2V2DLFrMGA9irexvxb8             740        370.00000
20210326204748930-FWcnyAzHQ97DtAfgRtstFP             630        315.00000
20210412175134872-5g5bWEW1PQYFXePRXiTATu             625        312.50000

                                             purchase_frequency  profit_margin  \
customer_id
20210504130925953-GJsTQgjYTZde9smEgwhWPk                0.02899      204.00000
20210414185957231-DmKCxnbm1FRsdPnC6MuZYL                0.02899       77.00000
20210427085254181-2kM2V2DLFrMGA9irexvxb8                0.02899       74.00000
20210326204748930-FWcnyAzHQ97DtAfgRtstFP                0.02899       63.00000
20210412175134872-5g5bWEW1PQYFXePRXiTATu                0.02899       62.50000

                                             customer_value       cltv  \
customer_id
20210504130925953-GJsTQgjYTZde9smEgwhWPk           40.80000 8323.20000
20210414185957231-DmKCxnbm1FRsdPnC6MuZYL           15.40000 1185.80000
20210427085254181-2kM2V2DLFrMGA9irexvxb8           14.80000 1095.20000
20210326204748930-FWcnyAzHQ97DtAfgRtstFP           12.60000  793.80000
20210412175134872-5g5bWEW1PQYFXePRXiTATu           12.50000  781.25000
```

```
                                          scaled_cltv
customer_id
20210504130925953-GJsTQgjYTZde9smEgwhWPk      1.00000
20210414185957231-DmKCxnbm1FRsdPnC6MuZYL      0.14228
20210427085254181-2kM2V2DLFrMGA9irexvxb8      0.13140
20210326204748930-FWcnyAzHQ97DtAfgRtstFP      0.09518
20210412175134872-5g5bWEW1PQYFXePRXiTATu      0.09367
```

[64]:

```python
# Divide customers into 4 groups
cltv["segment"] = pd.qcut(cltv["scaled_cltv"], 4, labels=["D", "C", "B", "A"])
cltv.head()
```

[64]:

```
                                          total_transactions  total_units  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ                   2            3
20210316112735216-9KTsUNszerowF4A1X1NBhg                   1            1
20210317172029708-JQryUiA4jZKCdwq1p8voq                    1            2
20210317223206213-NfzPJbS9UTFStXosGMDBZV                   1            4
20210318001813104-KWTskbtB4bs7j5uqbboSrk                   1            1

                                          total_price  avg_order_value  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ          330        165.00000
20210316112735216-9KTsUNszerowF4A1X1NBhg          110        110.00000
20210317172029708-JQryUiA4jZKCdwq1p8voq           220        220.00000
20210317223206213-NfzPJbS9UTFStXosGMDBZV          440        440.00000
20210318001813104-KWTskbtB4bs7j5uqbboSrk          110        110.00000

                                          purchase_frequency  profit_margin  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ             0.02899       33.00000
20210316112735216-9KTsUNszerowF4A1X1NBhg             0.01449       11.00000
20210317172029708-JQryUiA4jZKCdwq1p8voq              0.01449       22.00000
20210317223206213-NfzPJbS9UTFStXosGMDBZV             0.01449       44.00000
20210318001813104-KWTskbtB4bs7j5uqbboSrk             0.01449       11.00000

                                          customer_value      cltv  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ         6.60000 217.80000
20210316112735216-9KTsUNszerowF4A1X1NBhg         2.20000  24.20000
20210317172029708-JQryUiA4jZKCdwq1p8voq          4.40000  96.80000
20210317223206213-NfzPJbS9UTFStXosGMDBZV         8.80000 387.20000
20210318001813104-KWTskbtB4bs7j5uqbboSrk         2.20000  24.20000

                                          scaled_cltv segment
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ      0.02596       B
```

```
20210316112735216-9KTsUNszerowF4A1X1NBhg      0.00269       C
20210317172029708-JQryUiA4jZKCdwq1p8voq       0.01142       B
20210317223206213-NfzPJbS9UTFStXosGMDBZV      0.04631       A
20210318001813104-KWTskbtB4bs7j5uqbboSrk      0.00269       C
```

[65]:
```
#Sort [most valuable to least valuable]
cltv[["total_transactions", "total_units", "total_price", "cltv",␣
↪"scaled_cltv"]].sort_values(by="scaled_cltv",ascending=False).head()
```

[65]:
```
                                          total_transactions  total_units  \
customer_id
20210504130925953-GJsTQgjYTZde9smEgwhWPk                   2            6
20210414185957231-DmKCxnbm1FRsdPnC6MuZYL                   2            7
20210427085254181-2kM2V2DLFrMGA9irexvxb8                   2            7
20210326204748930-FWcnyAzHQ97DtAfgRtstFP                   2            6
20210412175134872-5g5bWEW1PQYFXePRXiTATu                   2           10

                                          total_price       cltv  scaled_cltv
customer_id
20210504130925953-GJsTQgjYTZde9smEgwhWPk         2040 8323.20000      1.00000
20210414185957231-DmKCxnbm1FRsdPnC6MuZYL          770 1185.80000      0.14228
20210427085254181-2kM2V2DLFrMGA9irexvxb8          740 1095.20000      0.13140
20210326204748930-FWcnyAzHQ97DtAfgRtstFP          630  793.80000      0.09518
20210412175134872-5g5bWEW1PQYFXePRXiTATu          625  781.25000      0.09367
```

[66]:
```
# Group customers into the segments
cltv.
↪groupby('segment')[['total_transactions','total_units','total_price','cltv','scaled_cltv']]
↪agg({'count','mean','sum'})
```

[66]:
```
        total_transactions                 total_units                 \
                       sum count    mean         sum count    mean
segment
D                       19    19 1.00000          19    19 1.00000
C                       23    20 1.15000          36    20 1.80000
B                       25    15 1.66667          40    15 2.66667
A                       21    15 1.40000          79    15 5.26667

        total_price                         cltv                   scaled_cltv  \
                sum count      mean          sum count       mean          sum
segment
D              1660    19  87.36842    313.60000    19   16.50526      0.03358
C              3130    20 156.50000   1040.60000    20   52.03000      0.12072
B              4060    15 270.66667   2282.40000    15  152.16000      0.27104
A              9565    15 637.66667  16782.05000    15 1118.80333      2.01349
```

```
         count    mean
segment
D           19 0.00177
C           20 0.00604
B           15 0.01807
A           15 0.13423
```

Segment A is our highest value customer segment with the most units purchased on average and higher spending per customer compared to the other segments.

3.3 Purchase probability

[94]:
```
order_denorm.head()
```

[94]:
```
                                     id order_number  order_revision  \
0  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
1  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
3  3c6a5fd9-5e57-4cf1-9ed1-332a2117dfcb    2EWVBFAYGR               1
4  cafdecc9-f3bf-4274-93d8-4f7cda91c842    JCTR6OHJBK               1
5  cafdecc9-f3bf-4274-93d8-4f7cda91c842    JCTR6OHJBK               1

                order_created_at_utc  sub_total_amount  tax_total_amount  \
0 2021-04-26 10:27:48.058595+00:00               220          15.40000
1 2021-04-26 10:27:48.058595+00:00               220          15.40000
3 2021-04-28 13:21:45.829622+00:00               100           4.88000
4 2021-04-27 17:29:40.519036+00:00               220           0.00000
5 2021-04-27 17:29:40.519036+00:00               220           0.00000

   shipping_total_amount  fee_total_amount  order_total_amount  \
0                9.52000                 0           244.92000
1                9.52000                 0           244.92000
3                4.68000                 0           109.56000
4               51.49000                 0           271.49000
5               51.49000                 0           271.49000

   requires_payment  charged_amount  charge_refunded  refunded_amount  \
0              True           24492            False              NaN
1              True           24492            False              NaN
3              True           10956            False              NaN
4              True           27149            False              NaN
5              True           27149            False              NaN

  refunded_at_utc                              customer_id  age  gender  \
0             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
1             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
3             NaN  20210428123305906-K5rxcBo3Q2uMwjD6H4mwq5   45    male
4             NaN  20210406163142240-MEpprnTNETHBEnusY3r6pN   36  female
```

```
5             NaN  20210406163142240-MEpprnTNETHBEnusY3r6pN   36  female

   income                                              group_id       group_name  \
0   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…    Cobra's Group
1   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…    Cobra's Group
3   79000  grp-b8c2e546-9a03-4897-afa2-81a73b8975ee--good…  Mad Dog's Group
4   98000  grp-edadeef5-6800-4929-8f6b-bae579c7faac--good…              pdf
5   98000  grp-edadeef5-6800-4929-8f6b-bae579c7faac--good…              pdf

  customer_state customer_country device_type  \
0             NY               US     Desktop
1             NY               US     Desktop
3             NY               US     Desktop
4            NaN               RS     Desktop
5            NaN               RS     Desktop

                                orderlineitems_jsonb  price  \
0  [{"id": "oli-E8hTJtpoz2uW5v75Bnm7Rd", "price":…    110
1  [{"id": "oli-E8hTJtpoz2uW5v75Bnm7Rd", "price":…    110
3  [{"id": "oli-MLSxCZcLySaMWHPmtLkDDJ", "price":…    100
4  [{"id": "oli-QMmcEsvprhMARgGDkdsfFC", "price":…    110
5  [{"id": "oli-QMmcEsvprhMARgGDkdsfFC", "price":…    110

                    product_id     product_title  \
0  product-gsbrightbluehoodie  Beam Blue Hoodie
1  product-gsbrightbluehoodie  Beam Blue Hoodie
3  product-gsbrightbluesweats  Beam Blue Sweats
4  product-gsbrightbluehoodie  Beam Blue Hoodie
5  product-gsbrightbluehoodie  Beam Blue Hoodie

                  product_variant_id product_variant_title
0  pvariant-gsbrightbluehoodiemedium                Medium
1  pvariant-gsbrightbluehoodiemedium                Medium
3  pvariant-gsbrightbluesweatsmedium                Medium
4  pvariant-gsbrightbluehoodiemedium                Medium
5  pvariant-gsbrightbluehoodiemedium                Medium
```

[95]:

```python
# Keep columns for prediction of purchase - drop columns that could leak info,
↪i.e. cost of item, etc
order_denorm_predict = order_denorm[["order_created_at_utc", "age", "gender",
↪"income", "group_name", "customer_state", "customer_country", "device_type",
↪"product_title"]]
order_denorm_predict.head()
```

[95]:

```
               order_created_at_utc  age  gender  income       group_name  \
0 2021-04-26 10:27:48.058595+00:00   51  female   73000    Cobra's Group
1 2021-04-26 10:27:48.058595+00:00   51  female   73000    Cobra's Group
```

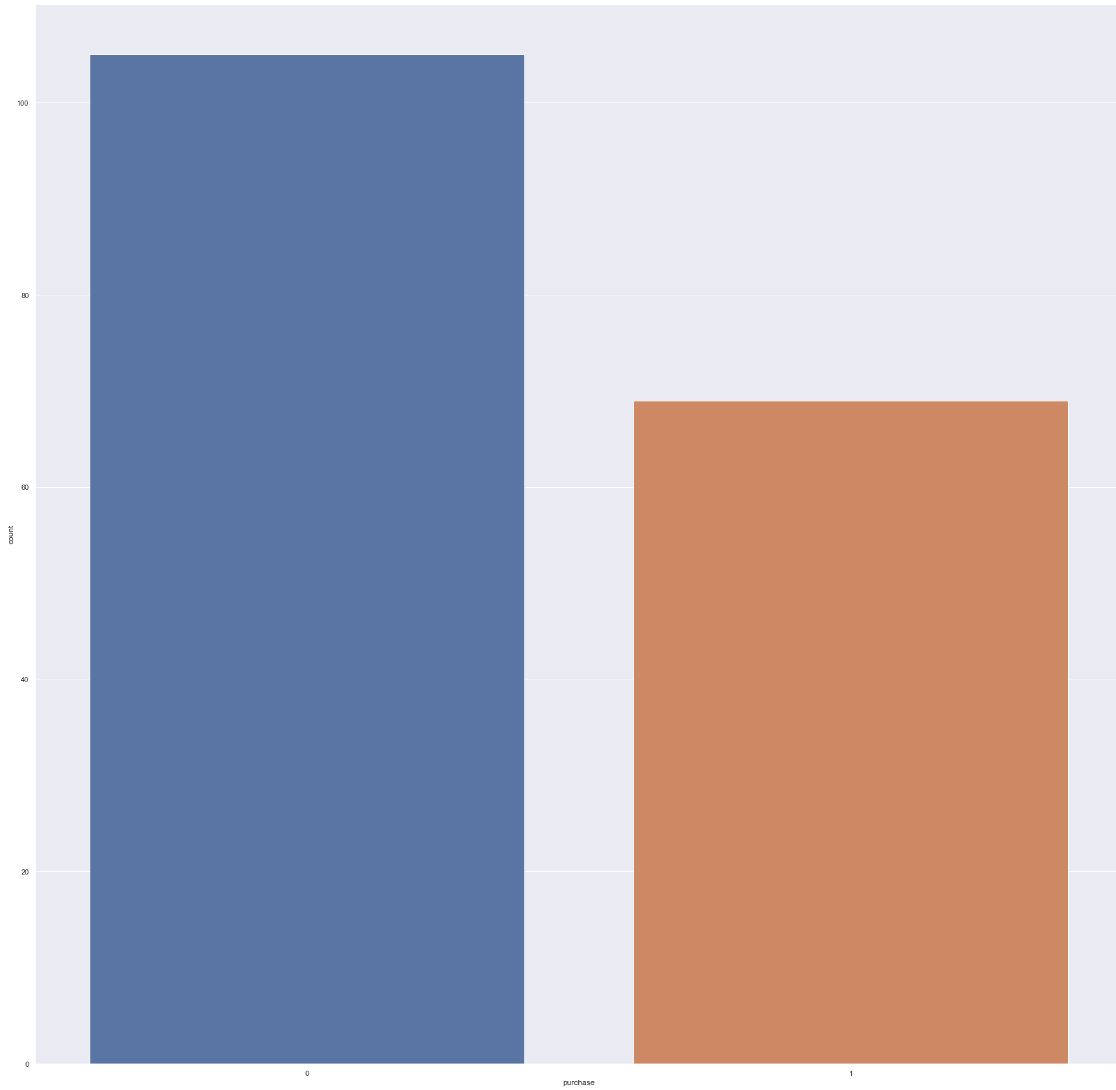
```
3 2021-04-28 13:21:45.829622+00:00   45    male   79000  Mad Dog's Group
4 2021-04-27 17:29:40.519036+00:00   36  female   98000              pdf
5 2021-04-27 17:29:40.519036+00:00   36  female   98000              pdf

  customer_state customer_country device_type     product_title
0             NY               US     Desktop  Beam Blue Hoodie
1             NY               US     Desktop  Beam Blue Hoodie
3             NY               US     Desktop  Beam Blue Sweats
4            NaN               RS     Desktop  Beam Blue Hoodie
5            NaN               RS     Desktop  Beam Blue Hoodie
```

[96]:
```python
# Create label
order_denorm_predict["purchase"] = np.
↪where(order_denorm_predict["product_title"] == "Beam Blue Sweats", 1, 0)
```

[98]:
```python
print(Counter(order_denorm_predict['purchase']))
sns.countplot(order_denorm_predict['purchase'])
plt.savefig('../reports/figures/purchase_distribution.png')
```

```
Counter({0: 105, 1: 69})
```

[98]: `<AxesSubplot:xlabel='purchase', ylabel='count'>`



[99]:
```
# Create weekday indicator
order_denorm_predict["day_of_week"] =␣
↪order_denorm_predict["order_created_at_utc"].dt.weekday
```

[100]:
```
order_denorm_predict["day_of_week"].value_counts()
```

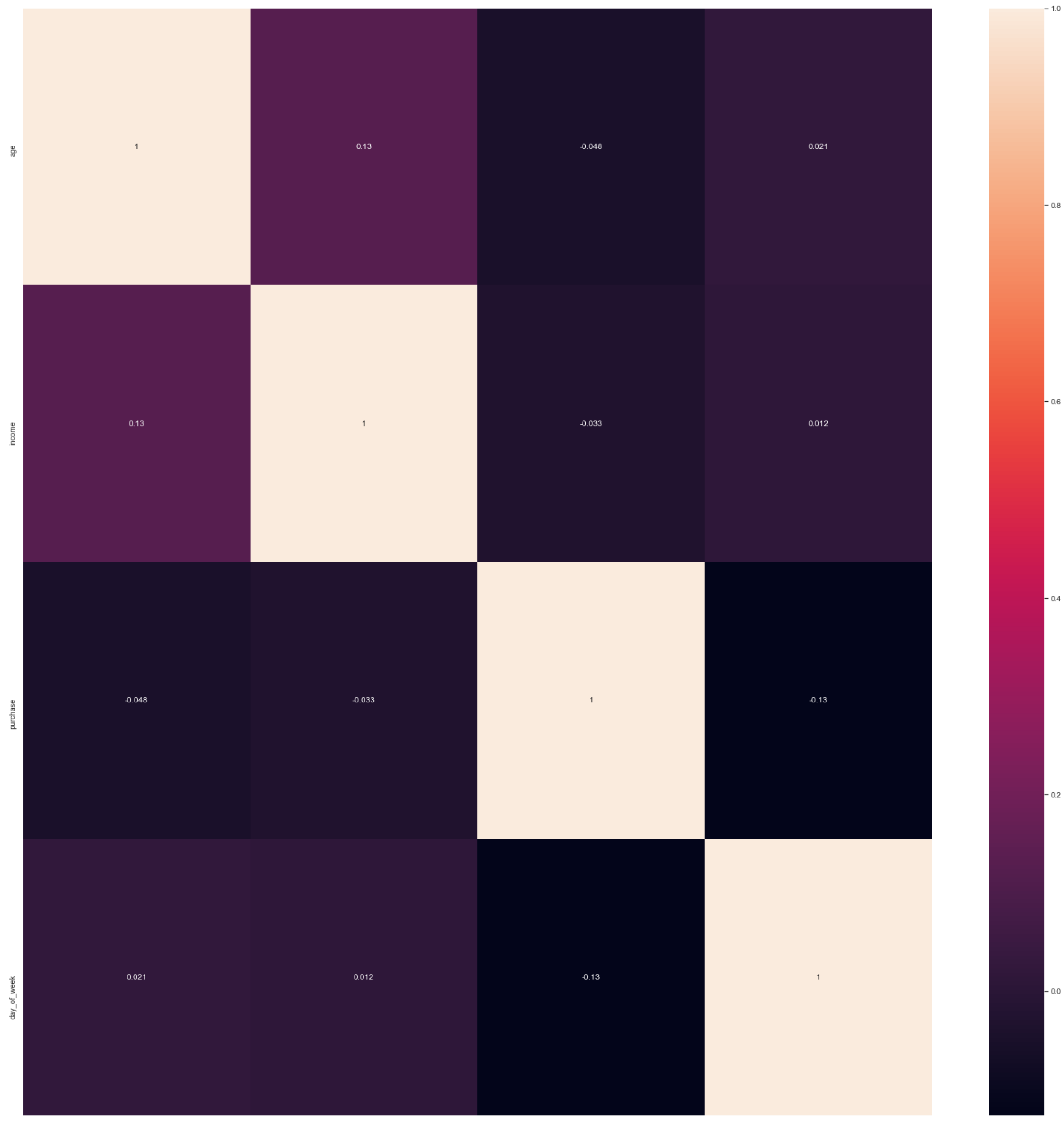
[100]:
```
4    46
2    39
0    33
1    30
3    26
Name: day_of_week, dtype: int64
```

Interestingly, no weekend purchases, so this store is not open on weekends?

[102]:

```python
corrMatrix = order_denorm_predict.corr()
sns.set(rc={'figure.figsize':(30, 30)})
sns.heatmap(corrMatrix, annot=True)
plt.savefig('../reports/figures/orders_correlation_matrix.png')
```

[102]: <AxesSubplot:>



[104]:

```python
# Encode categorical features
order_denorm_predict = pd.get_dummies(order_denorm_predict, columns =
 ['day_of_week','gender','group_name', 'customer_state', 'customer_country',
 'device_type'])
```

[105]:
```
order_denorm_predict.head()
```

[105]:
```
                order_created_at_utc  age  income     product_title  purchase  \
0 2021-04-26 10:27:48.058595+00:00   51   73000  Beam Blue Hoodie         0
1 2021-04-26 10:27:48.058595+00:00   51   73000  Beam Blue Hoodie         0
3 2021-04-28 13:21:45.829622+00:00   45   79000  Beam Blue Sweats         1
4 2021-04-27 17:29:40.519036+00:00   36   98000  Beam Blue Hoodie         0
5 2021-04-27 17:29:40.519036+00:00   36   98000  Beam Blue Hoodie         0

   day_of_week_0  day_of_week_1  day_of_week_2  day_of_week_3  day_of_week_4  \
0              1              0              0              0              0
1              1              0              0              0              0
3              0              0              1              0              0
4              0              1              0              0              0
5              0              1              0              0              0

   gender_female  gender_male  group_name_AB_2021-04-20_1  \
0              1            0                           0
1              1            0                           0
3              0            1                           0
4              1            0                           0
5              1            0                           0

   group_name_Aspect's Team  group_name_Bender's Team  \
0                        0                         0
1                        0                         0
3                        0                         0
4                        0                         0
5                        0                         0

   group_name_Big Papa's Familia  group_name_Big Papa's Winners  \
0                             0                              0
1                             0                              0
3                             0                              0
4                             0                              0
5                             0                              0

   group_name_Bowser's Familia  group_name_Bowser's Team  \
0                           0                         0
1                           0                         0
3                           0                         0
4                           0                         0
5                           0                         0

   group_name_Bowser's Winners  group_name_Bruise's Group  \
0                           0                          0
1                           0                          0
```

```
3                            0                          0
4                            0                          0
5                            0                          0

   group_name_Bruise's Team  group_name_Bruise's Winners  \
0                         0                            0
1                         0                            0
3                         0                            0
4                         0                            0
5                         0                            0

   group_name_Cannon's Familia  group_name_Cannon's Group  …  \
0                            0                          0  …
1                            0                          0  …
3                            0                          0  …
4                            0                          0  …
5                            0                          0  …

   customer_state_AL  customer_state_BC  customer_state_BY  customer_state_CA  \
0                  0                  0                  0                  0
1                  0                  0                  0                  0
3                  0                  0                  0                  0
4                  0                  0                  0                  0
5                  0                  0                  0                  0

   customer_state_CT  customer_state_Kharkivs'ka oblast  customer_state_MA  \
0                  0                                  0                  0
1                  0                                  0                  0
3                  0                                  0                  0
4                  0                                  0                  0
5                  0                                  0                  0

   customer_state_MN  customer_state_NJ  customer_state_NY  customer_state_PA  \
0                  0                  0                  1                  0
1                  0                  0                  1                  0
3                  0                  0                  1                  0
4                  0                  0                  0                  0
5                  0                  0                  0                  0

   customer_state_PR  customer_state_Qro.  customer_state_SK  \
0                  0                    0                  0
1                  0                    0                  0
3                  0                    0                  0
4                  0                    0                  0
5                  0                    0                  0

   customer_state_UP  customer_country_CA  customer_country_DE  \
```

```
0                    0                     0                     0
1                    0                     0                     0
3                    0                     0                     0
4                    0                     0                     0
5                    0                     0                     0

   customer_country_IN  customer_country_MK  customer_country_MX  \
0                    0                    0                    0
1                    0                    0                    0
3                    0                    0                    0
4                    0                    0                    0
5                    0                    0                    0

   customer_country_RS  customer_country_UA  customer_country_US  \
0                    0                    0                    1
1                    0                    0                    1
3                    0                    0                    1
4                    1                    0                    0
5                    1                    0                    0

   device_type_Desktop  device_type_Mobile
0                    1                   0
1                    1                   0
3                    1                   0
4                    1                   0
5                    1                   0

[5 rows x 100 columns]
```

Encoded dates as days of week indicators, and blue beam purchase as binary indicator so will drop date and product title to avoid redundancies.

[106]:
```
order_denorm_predict = order_denorm_predict.
 ↪drop(["order_created_at_utc","product_title"], axis=1)
```

[107]:
```
order_denorm_predict[order_denorm_predict.columns[1:]].corr()['purchase'][:].
 ↪sort_values(ascending=False).to_frame()
```

[107]:

	purchase
purchase	1.00000
gender_male	0.35524
device_type_Desktop	0.27386
group_name_Decay's Familia	0.25256
customer_state_CT	0.21218
…	…
customer_state_NJ	-0.16597
group_name_Mad Dog's Winners	-0.16597

```
day_of_week_4                 -0.16627
device_type_Mobile            -0.27386
gender_female                 -0.35524

[97 rows x 1 columns]
```

Models and feature selection

Illustrating a broad selection of model types

[139]:
```
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score, precision_score, f1_score,␣
 ↪recall_score, roc_curve, accuracy_score
```

[209]:
```
result_dict = {}

def summarize_classification(y_test,y_pred):

    acc = accuracy_score(y_test,y_pred,normalize=True)
    num_acc = accuracy_score(y_test,y_pred,normalize=False)

    prec = precision_score(y_test,y_pred)
    recall = recall_score(y_test,y_pred)
    F1_score =  f1_score(y_test,y_pred)
    auc_score = roc_auc_score(y_test,y_pred)


    return{'Accuracy:': acc,
           'Accuracy_count:': num_acc,
           'Precision:': prec,
           'Recall:': recall,
           'F1_score:':F1_score,
           'AUC_ROC:':auc_score}
```

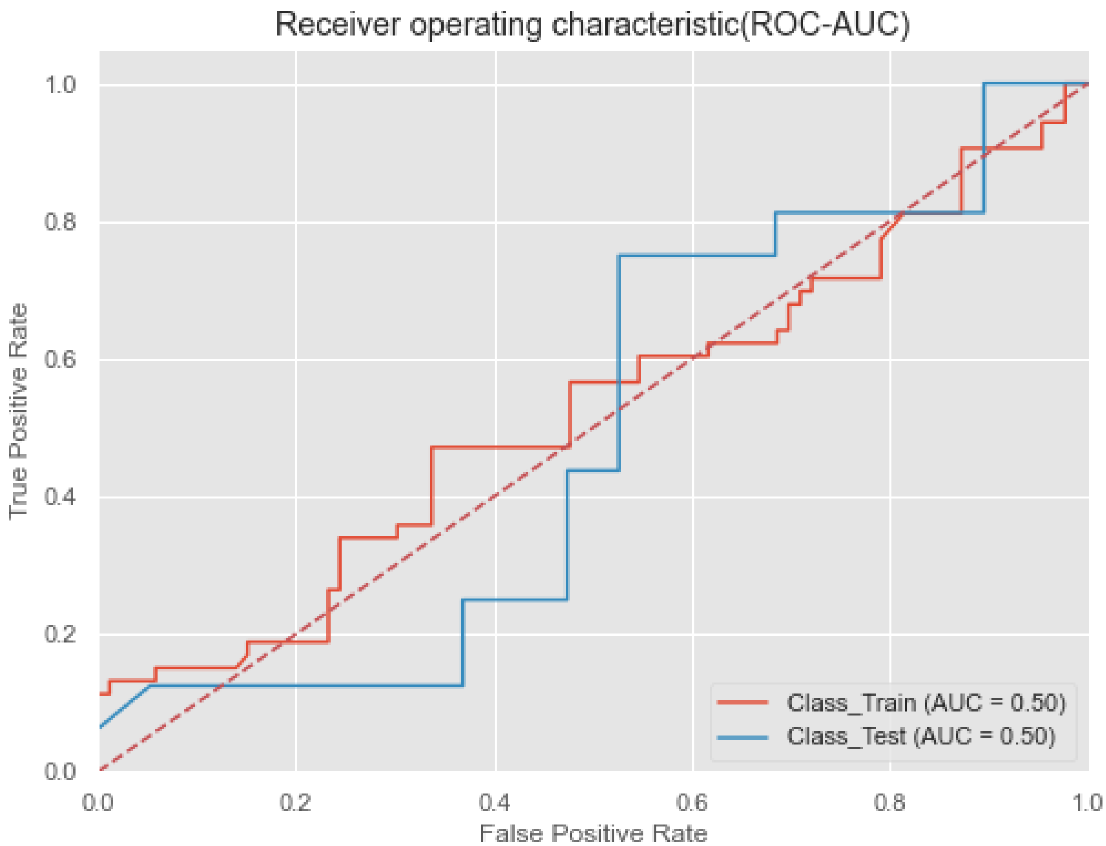
[210]:
```
# Helper function to Build Model
def build_model(classifier_fn,
                name_of_y_col,
                df,test_frac=0.2,
                show_plot_auc=None):

    # Separating the  input features (X) and target variable (y)
    X = df.drop(name_of_y_col, axis=1)
    Y = df[name_of_y_col]
```

```
    # feature Scaling
    scale_x = StandardScaler()
    x = scale_x.fit_transform(X)

    x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size=0.
↪2,random_state=0)

    model = classifier_fn(x_train,y_train)

    y_pred = model.predict(x_test)

    y_pred_train = model.predict(x_train)

    train_summary = summarize_classification(y_train,y_pred_train)
    test_summary = summarize_classification(y_test,y_pred)

    pred_result = pd.DataFrame({'y_test':y_test,'y_pred':y_pred})

    model_crosstab = pd.crosstab(pred_result.y_pred,pred_result.y_test)

    if show_plot_auc==True:
        plt.figure(figsize=(8,6))

        logit_roc_auc1 = roc_auc_score(y_train, model.predict(x_train))
        fpr1, tpr1, thresholds1 = roc_curve(y_train, model.
↪predict_proba(x_train)[:,1])
        plt.plot(fpr1, tpr1, label='Class_Train (AUC = %0.2f)' % logit_roc_auc1)

        logit_roc_auc2 = roc_auc_score(y_test, model.predict(x_test))
        fpr2, tpr2, thresholds2 = roc_curve(y_test, model.
↪predict_proba(x_test)[:,1])
        plt.plot(fpr2, tpr2,label='Class_Test (AUC = %0.2f)' % logit_roc_auc2)
        plt.plot([0, 1], [0, 1],'r--')
        plt.xlim([0.0, 1.0])
        plt.ylim([0.0, 1.05])
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.title('Receiver operating characteristic(ROC-AUC)')
        plt.legend(loc="lower right")
        plt.show()


    return{'training':train_summary,
          'test':test_summary,
          'confusion_matrix':model_crosstab
          }
```

```python
# Helper function to compare the score of different Model.
def compare_result():
    for key in result_dict:
        print('Classification: ',key)

        print()
        print('Training data:-')
        for score in result_dict[key]['training']:
            print(score,result_dict[key]['training'][score])

        print()
        print('Test Data:-')
        for score in result_dict[key]['test']:
            print(score,result_dict[key]['test'][score])

        print()
```

Logistic regression

[127]:
```python
def logistic_fn(x_train,y_train):
    model = LogisticRegression(solver='liblinear',random_state=12)
    model.fit(x_train,y_train)

    return model

result_dict['Purchase ~ Logistic'] = \
    build_model(logistic_fn,'purchase',order_denorm_predict,show_plot_auc=True)
print(result_dict)
```



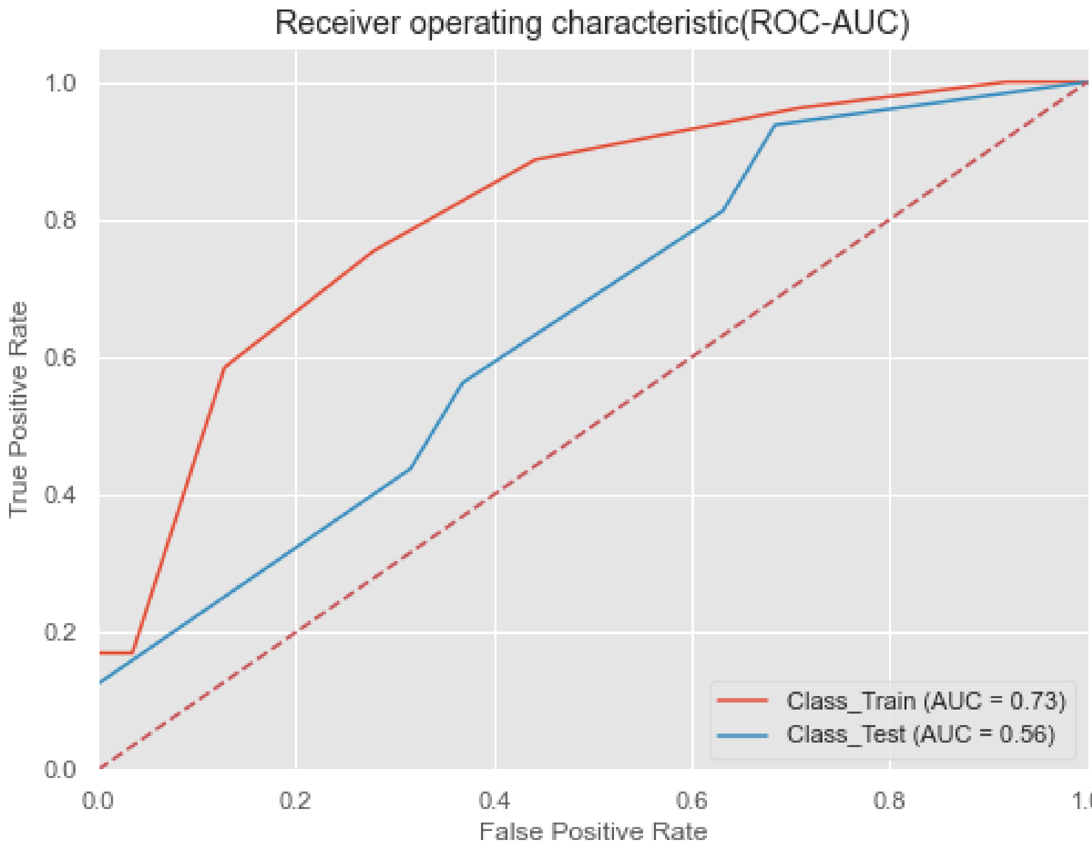

```
{'Purchase ~ Logistic': {'training': {'Accuracy:': 0.6187050359712231,
'Accuracy_count:': 86, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0,
'AUC_ROC:': 0.5}, 'test': {'Accuracy:': 0.5428571428571428, 'Accuracy_count:':
19, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.5},
'confusion_matrix': y_test   0   1
y_pred
0        19  16}}
```

This baseline model can pretty much not determine the difference between transactions that purchase the sweats ant those that do not - it's effectively a coin toss using this model

KNN

[128]:
```
def knn_fn(x_train,y_train,n_neighbors=9,random_state=12):

    model = KNeighborsClassifier(n_neighbors=n_neighbors)
    model.fit(x_train,y_train)

    return model

result_dict['Purchase ~ KNN'] = \
```

```
build_model(knn_fn,'purchase',order_denorm_predict,show_plot_auc=True)
```



KNN performs better than logistic in training but poorly on holdout data, indicating model overfit.

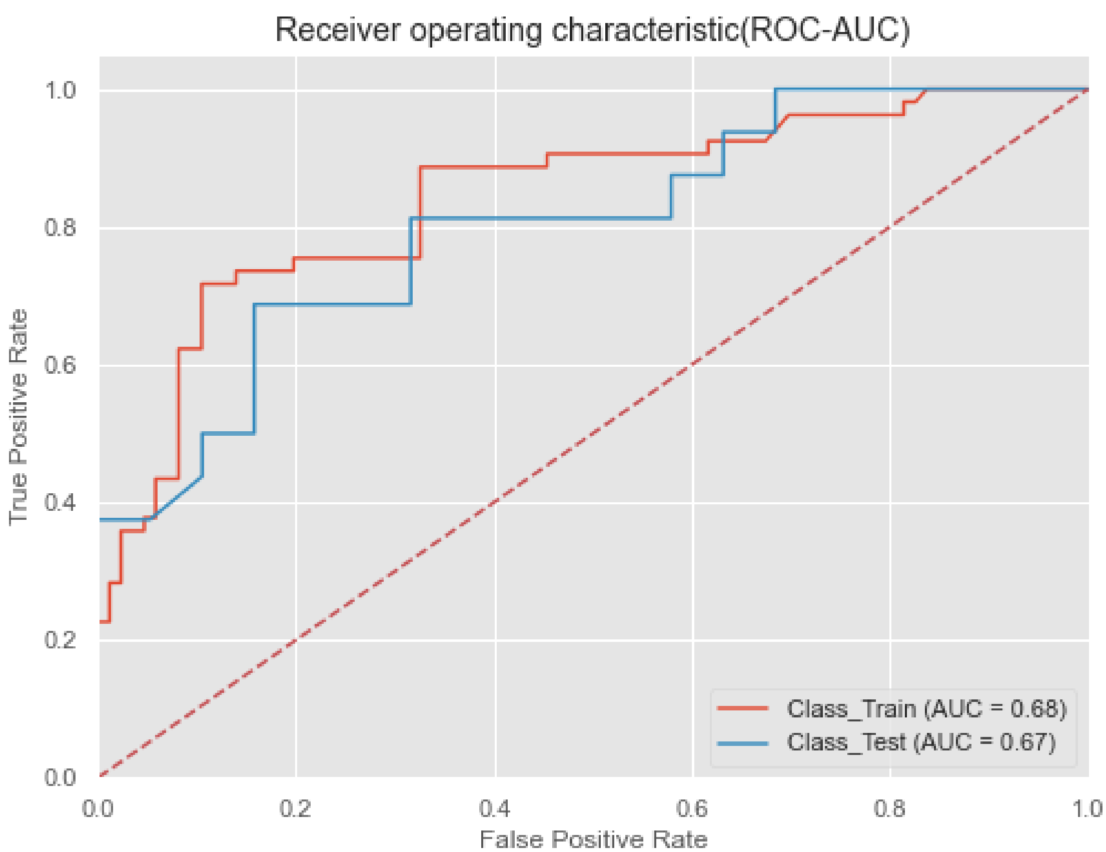
[129]:
```
print(result_dict)
```

```
{'Purchase ~ Logistic': {'training': {'Accuracy:': 0.6187050359712231,
'Accuracy_count:': 86, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0,
'AUC_ROC:': 0.5}, 'test': {'Accuracy:': 0.5428571428571428, 'Accuracy_count:':
19, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.5},
'confusion_matrix': y_test   0   1
y_pred
0       19  16}, 'Purchase ~ KNN': {'training': {'Accuracy:': 0.762589928057554,
'Accuracy_count:': 106, 'Precision:': 0.7380952380952381, 'Recall:':
0.5849056603773585, 'F1_score:': 0.6526315789473685, 'AUC_ROC:':
0.7284993418165863}, 'test': {'Accuracy:': 0.5714285714285714,
'Accuracy_count:': 20, 'Precision:': 0.5384615384615384, 'Recall:': 0.4375,
'F1_score:': 0.4827586206896552, 'AUC_ROC:': 0.5608552631578947},
'confusion_matrix': y_test   0  1
y_pred
0       13  9
```

1   6   7}}

Naive Bayes

[130]:
```
def naive_bayes_fn(x_train,y_train,priors=None):

    model = GaussianNB(priors=priors)
    model.fit(x_train,y_train)

    return model

result_dict['Purchase ~ Naive_Bayes'] = \
    ␣
  ↪build_model(naive_bayes_fn,'purchase',order_denorm_predict,show_plot_auc=True)
print(result_dict)
```




```
{'Purchase ~ Logistic': {'training': {'Accuracy:': 0.6187050359712231,
'Accuracy_count:': 86, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0,
'AUC_ROC:': 0.5}, 'test': {'Accuracy:': 0.5428571428571428, 'Accuracy_count:':
19, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.5},
'confusion_matrix': y_test   0   1
```

```
y_pred
0       19  16}, 'Purchase ~ KNN': {'training': {'Accuracy:': 0.762589928057554,
'Accuracy_count:': 106, 'Precision:': 0.7380952380952381, 'Recall:':
0.5849056603773585, 'F1_score:': 0.6526315789473685, 'AUC_ROC:':
0.7284993418165863}, 'test': {'Accuracy:': 0.5714285714285714,
'Accuracy_count:': 20, 'Precision:': 0.5384615384615384, 'Recall:': 0.4375,
'F1_score:': 0.4827586206896552, 'AUC_ROC:': 0.5608552631578947},
'confusion_matrix': y_test   0  1
y_pred
0       13   9
1        6   7}, 'Purchase ~ Naive_Bayes': {'training': {'Accuracy:':
0.7410071942446043, 'Accuracy_count:': 103, 'Precision:': 0.7931034482758621,
'Recall:': 0.4339622641509434, 'F1_score:': 0.5609756097560975, 'AUC_ROC:':
0.6820974111452391}, 'test': {'Accuracy:': 0.6857142857142857,
'Accuracy_count:': 24, 'Precision:': 0.7777777777777778, 'Recall:': 0.4375,
'F1_score:': 0.56, 'AUC_ROC:': 0.6661184210526315}, 'confusion_matrix': y_test
0  1
y_pred
0       17   9
1        2   7}}
```

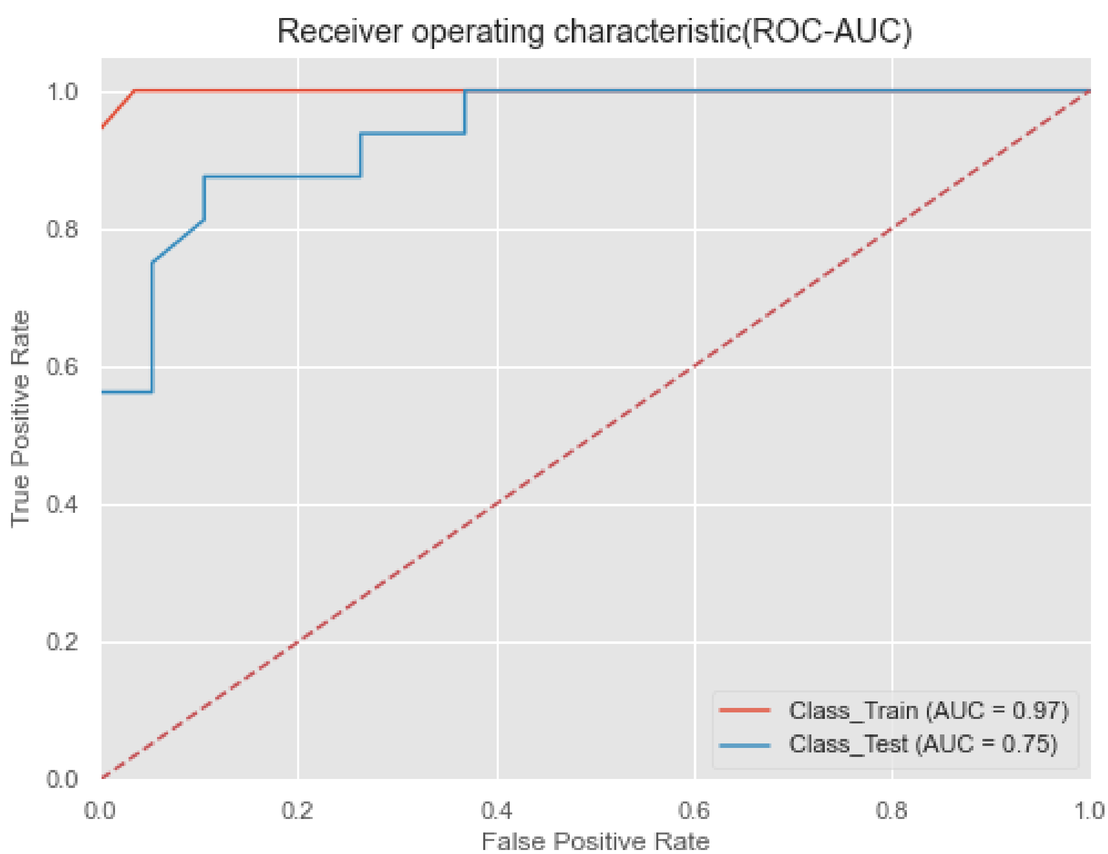
Better than logistic and better than KNN on test set

[131]:
```
pd.DataFrame.from_dict(result_dict)
```

[131]:
```
                                                       Purchase ~ Logistic  \
training          {'Accuracy:': 0.6187050359712231, 'Accuracy_co…
test              {'Accuracy:': 0.5428571428571428, 'Accuracy_co…
confusion_matrix       y_test   0   1
y_pred
0        19  16

                                                            Purchase ~ KNN  \
training          {'Accuracy:': 0.762589928057554, 'Accuracy_cou…
test              {'Accuracy:': 0.5714285714285714, 'Accuracy_co…
confusion_matrix  y_test   0  1
y_pred
0        13  9
1   …

                                                    Purchase ~ Naive_Bayes
training          {'Accuracy:': 0.7410071942446043, 'Accuracy_co…
test              {'Accuracy:': 0.6857142857142857, 'Accuracy_co…
confusion_matrix  y_test   0  1
y_pred
0        17  9
1   …
```

Random Forest

[132]:
```
def random_forest_fn(x_train,y_train):
    model = RandomForestClassifier(n_estimators= 50, max_depth =␣
 ↪15,random_state=12 )
    model.fit(x_train,y_train)

    return model

result_dict['Purchase ~ Random_Forest'] = \
   ␣
 ↪build_model(random_forest_fn,'purchase',order_denorm_predict,show_plot_auc=True)
print(result_dict)
```




```
{'Purchase ~ Logistic': {'training': {'Accuracy:': 0.6187050359712231,
'Accuracy_count:': 86, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0,
'AUC_ROC:': 0.5}, 'test': {'Accuracy:': 0.5428571428571428, 'Accuracy_count:':
19, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.5},
'confusion_matrix': y_test   0   1
y_pred
0       19  16}, 'Purchase ~ KNN': {'training': {'Accuracy:': 0.762589928057554,
```

```
'Accuracy_count:': 106, 'Precision:': 0.7380952380952381, 'Recall:':
0.5849056603773585, 'F1_score:': 0.6526315789473685, 'AUC_ROC:':
0.7284993418165863}, 'test': {'Accuracy:': 0.5714285714285714,
'Accuracy_count:': 20, 'Precision:': 0.5384615384615384, 'Recall:': 0.4375,
'F1_score:': 0.4827586206896552, 'AUC_ROC:': 0.5608552631578947},
'confusion_matrix': y_test   0  1
y_pred
0       13  9
1        6  7}, 'Purchase ~ Naive_Bayes': {'training': {'Accuracy:':
0.7410071942446043, 'Accuracy_count:': 103, 'Precision:': 0.7931034482758621,
'Recall:': 0.4339622641509434, 'F1_score:': 0.5609756097560975, 'AUC_ROC:':
0.6820974111452391}, 'test': {'Accuracy:': 0.6857142857142857,
'Accuracy_count:': 24, 'Precision:': 0.7777777777777778, 'Recall:': 0.4375,
'F1_score:': 0.56, 'AUC_ROC:': 0.6661184210526315}, 'confusion_matrix': y_test
0  1
y_pred
0       17  9
1        2  7}, 'Purchase ~ Random_Forest': {'training': {'Accuracy:':
0.9784172661870504, 'Accuracy_count:': 136, 'Precision:': 1.0, 'Recall:':
0.9433962264150944, 'F1_score:': 0.970873786407767, 'AUC_ROC:':
0.9716981132075472}, 'test': {'Accuracy:': 0.7714285714285715,
'Accuracy_count:': 27, 'Precision:': 0.9, 'Recall:': 0.5625, 'F1_score:':
0.6923076923076923, 'AUC_ROC:': 0.7549342105263158}, 'confusion_matrix': y_test
0  1
y_pred
0       18  7
1        1  9}}
```

Random Forest performs the best of our considered models but indicates some overfitting due to decreased performance on the holdout data. Would consider training on larger dataset, training using cross-validation, and/or some regularization method such as L1 or L2 regularization. L1 (Lasso) regularization also acts as a feature selection method.

Feature selection

[133]:
```
# Separating the  input features (X) and target variable (y)
X = order_denorm_predict.drop('purchase', axis=1)
Y = order_denorm_predict['purchase']
```

[134]:
```
## Finding Important Features using ChiSq
from sklearn import svm
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2

list_one =[]
feature_ranking = SelectKBest(chi2, k=5)
fit = feature_ranking.fit(X, Y)
```

```python
for i, (score, feature) in enumerate(zip(feature_ranking.scores_, X.columns)):
    list_one.append((score, feature))

dfObj = pd.DataFrame(list_one)
dfObj.sort_values(by=[0], ascending = False)

dfObj[0].describe()
```

[134]:
```
             0                           1
1   1395.01008                      income
8     17.54069                 gender_male
96    11.10005          device_type_Mobile
34    10.65217  group_name_Decay's Familia
76     7.60870           customer_state_CT
..         …                           …
54     0.08944    group_name_Reaper's Team
24     0.08944  group_name_Clink's Familia
10     0.05010    group_name_Aspect's Team
90     0.01553         customer_country_MK
85     0.01553           customer_state_SK

[97 rows x 2 columns]
```

[134]:
```
count      97.00000
mean       16.69285
std       141.43045
min         0.01553
25%         0.65714
50%         1.52174
75%         3.04348
max      1395.01008
Name: 0, dtype: float64
```

[135]:
```python
drop_cols = dfObj[dfObj[0] < 5]
```

[136]:
```python
drop_cols = drop_cols[1].to_list()
print(drop_cols)
```

```
['age', 'day_of_week_0', 'day_of_week_1', 'day_of_week_2', 'day_of_week_3',
'day_of_week_4', 'gender_female', 'group_name_AB_2021-04-20_1',
"group_name_Aspect's Team", "group_name_Bender's Team", "group_name_Big Papa's
Familia", "group_name_Big Papa's Winners", "group_name_Bowser's Familia",
"group_name_Bowser's Team", "group_name_Bowser's Winners", "group_name_Bruise's
Group", "group_name_Bruise's Team", "group_name_Bruise's Winners",
"group_name_Cannon's Familia", "group_name_Cannon's Group", "group_name_Cannon's
Squad", "group_name_Cannon's Team", "group_name_Clink's Familia",
"group_name_Clink's Group", "group_name_Cobra's Familia", "group_name_Cobra's
```

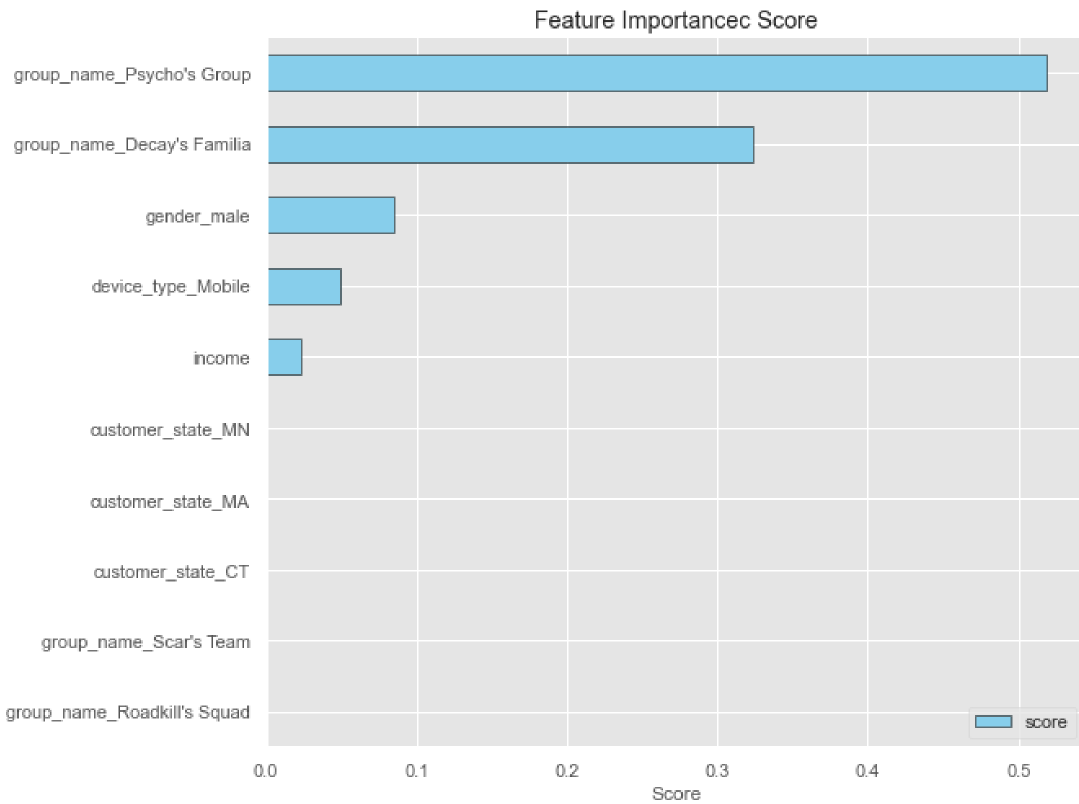
```
Group", "group_name_Cobra's Team", "group_name_Colt's Winners",
"group_name_Creep's Group", "group_name_Creep's Team", "group_name_Daemon's
Winners", "group_name_Danny's Group", "group_name_Decay's Group",
"group_name_Decay's Team", "group_name_Doom's Squad", "group_name_Doom's
Winners", "group_name_Dracula's Group", "group_name_Dracula's Team",
"group_name_Kraken's Squad", "group_name_Kraken's Winners", "group_name_Lynch's
Familia", "group_name_Lynch's Squad", "group_name_Lynch's Team", "group_name_Mad
Dog's Group", "group_name_Mad Dog's Winners", "group_name_Magda's Peoples",
"group_name_Psycho's Winners", "group_name_Ranger's Team", "group_name_Ratchet's
Squad", "group_name_Ratchet's Winners", "group_name_Reaper's Team",
"group_name_Rigs's Group", "group_name_Rigs's Squad", "group_name_Roadkill's
Familia", "group_name_Roadkill's Team", "group_name_Roadkill's Winners",
"group_name_Ronin's Familia", "group_name_Ronin's Group", "group_name_Rubble's
Winners", "group_name_Sasquatch's Familia", "group_name_Sasquatch's Group",
"group_name_Sasquatch's Squad", "group_name_Sasquatch's Team",
"group_name_Scar's Familia", "group_name_Scar's Squad", 'group_name_pdf',
'customer_state_AL', 'customer_state_BC', 'customer_state_BY',
'customer_state_CA', "customer_state_Kharkivs'ka oblast", 'customer_state_NJ',
'customer_state_NY', 'customer_state_PA', 'customer_state_PR',
'customer_state_Qro.', 'customer_state_SK', 'customer_state_UP',
'customer_country_CA', 'customer_country_DE', 'customer_country_IN',
'customer_country_MK', 'customer_country_MX', 'customer_country_RS',
'customer_country_UA', 'customer_country_US', 'device_type_Desktop']
```

[137]:
```
X.drop(drop_cols, axis=1, inplace=True)
```

[140]:
```
# Feature seelction using XGBoost
# feature Scaling
scale_x = StandardScaler()
x = scale_x.fit_transform(X)

x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size=0.
↪2,random_state=0)
model = XGBClassifier()
model.fit(x_train,y_train)

XGBoost_eval_metric_y_pred = model.predict(x_test)

print(summarize_classification(y_test,XGBoost_eval_metric_y_pred))

# Horizontal bar chart for feature Importance
feature_imp = pd.DataFrame({'feature':list(X.columns),'score':model.
↪feature_importances_})
feature_imp.sort_values('score').
↪plot(x='feature',y='score',kind='barh',color='skyblue',edgecolor='black',figsize=(9,8))

#plot formatting
```

```python
plt.xlabel('Score')
plt.xticks()
plt.yticks()
plt.ylabel(' ')
plt.title('Feature Importancec Score')
plt.legend(loc="lower right")
plt.show();
```

```
[12:51:07] WARNING: ../src/learner.cc:1061: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
{'Accuracy:': 0.7714285714285715, 'Accuracy_count:': 27, 'Precision:':
0.8333333333333334, 'Recall:': 0.625, 'F1_score:': 0.7142857142857143,
'AUC_ROC:': 0.7598684210526316}
```



Psycho's Group, Decay's Familia, male gender, mobile device transaction, and income are the top features for predicting purchase of the Blue Beam Sweats

3.4 Repeat purchase

[162]:
```
df.head()
```

[162]:
```
                                     id order_number  order_revision  \
0  efd688aa-c021-4766-9721-83dd92710c63      2PBDJLI               1
1  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
2  4ac870d3-fe19-4203-ad28-6313793103b8      L3MSP59               1
3  aeaa4c4d-12e1-4016-bc47-30d08f00041c   CAHWWSMWOD               1
4  42dd34c1-f1ed-4f90-b7af-9261f423ebc9      FXPF4J2               1

             order_created_at_utc  sub_total_amount  tax_total_amount  \
0  2021-04-20 15:38:33.133957+00               110           9.76000
1  2021-04-26 10:27:48.058595+00               220          15.40000
2  2021-04-16 09:36:34.040838+00               110           0.00000
3  2021-04-26 18:05:00.426515+00                50           0.00000
4   2021-04-22 15:08:34.07912+00               110           0.00000

   shipping_total_amount  fee_total_amount  order_total_amount  \
0                4.68000                 0           124.44000
1                9.52000                 0           244.92000
2                2.51000                 0           113.51000
3                5.98000                 0            55.98000
4                0.00000                 0           110.00000

   requires_payment  charged_amount  charge_refunded  refunded_amount  \
0              True           12444            False              NaN
1              True           24492            False              NaN
2              True           11351            False              NaN
3              True            5598            False              NaN
4              True           11000            False              NaN

  refunded_at_utc                                customer_id  age  gender  \
0             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
1             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
2             NaN  20210316112735216-9KTsUNszerowF4A1X1NBhg   24  female
3             NaN  20210317171023585-M2tZ3kjFMaTVmE4shqXxua   35    male
4             NaN   20210317172029708-JQryUiA4jZKCdwq1p8voq   53  female

   income                                       group_id  \
0   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
1   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
2   39000  grp-49abab43-13d6-439c-80de-3e98b4083758--good…
3   75000  grp-e49d32ee-df44-4e9e-a3ab-d6ab4b6988d9--good…
4   97000  grp-5228870e-24ec-4e97-a41c-db62394ed4f1--good…

         group_name customer_state customer_country device_type  \
```

```
0  Sasquatch's Group             NY                US     Desktop
1      Cobra's Group             NY                US     Desktop
2                NaN            NaN               NaN     Desktop
3   Diablo's Winners             PA                US     Desktop
4       Rigs's Group             NY                US     Desktop

                              orderlineitems_jsonb  row_num  \
0  [{'id': 'oli-NHz5q5rPAh4oj3QtZDfgQ3', 'price':…        1
1  [{'id': 'oli-E8hTJtpoz2uW5v75Bnm7Rd', 'price':…        2
2  [{'id': 'oli-MAucg88ir2tsPhjF9a98Np', 'price':…        1
3  [{'id': 'oli-VJoPK9Jcao9objad3qxYMY', 'price':…        1
4  [{'id': 'oli-DxrhtnugrvEVqBsXgPwHtJ', 'price':…        1

             price  pvariant-gsbrightbluehoodiemedium  \
0         [110.00]                                  1
1  [110.00, 110.00]                                 1
2         [110.00]                                  0
3    [25.00, 25.00]                                 0
4         [110.00]                                  1

   pvariant-gsbrightbluehoodieextrasmall  pvariant-socksbundle-size  \
0                                      0                          0
1                                      0                          0
2                                      1                          0
3                                      0                          1
4                                      0                          0

   pvariant-truckerhatone-size  pvariant-gsbrightbluesweatsmedium  \
0                            0                                  0
1                            0                                  0
2                            0                                  0
3                            0                                  0
4                            0                                  0

   pvariant-wegoodgreyteemedium  pvariant-gsbrightbluesweatsextrasmall  \
0                             0                                      0
1                             0                                      0
2                             0                                      0
3                             0                                      0
4                             0                                      0

   pvariant-basicwhiteteemedium  pvariant-gsbrightbluebundlemedium
0                             0                                  0
1                             0                                  0
2                             0                                  0
3                             0                                  0
4                             0                                  0
```

Make indicator for whether an order is a repeat customer purchase or not

[167]:
```
df["repeat_purchase"] = np.where(df["row_num"] > 1, 1, 0)
df.head()
```

[167]:
```
                                     id order_number  order_revision  \
0  efd688aa-c021-4766-9721-83dd92710c63      2PBDJLI               1
1  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
2  4ac870d3-fe19-4203-ad28-6313793103b8      L3MSP59               1
3  aeaa4c4d-12e1-4016-bc47-30d08f00041c   CAHWWSMWOD               1
4  42dd34c1-f1ed-4f90-b7af-9261f423ebc9      FXPF4J2               1

             order_created_at_utc  sub_total_amount  tax_total_amount  \
0  2021-04-20 15:38:33.133957+00               110           9.76000
1  2021-04-26 10:27:48.058595+00               220          15.40000
2  2021-04-16 09:36:34.040838+00               110           0.00000
3  2021-04-26 18:05:00.426515+00                50           0.00000
4   2021-04-22 15:08:34.07912+00               110           0.00000

   shipping_total_amount  fee_total_amount  order_total_amount  \
0                4.68000                 0           124.44000
1                9.52000                 0           244.92000
2                2.51000                 0           113.51000
3                5.98000                 0            55.98000
4                0.00000                 0           110.00000

   requires_payment  charged_amount  charge_refunded  refunded_amount  \
0              True           12444            False              NaN
1              True           24492            False              NaN
2              True           11351            False              NaN
3              True            5598            False              NaN
4              True           11000            False              NaN

  refunded_at_utc                              customer_id  age  gender  \
0             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
1             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
2             NaN  20210316112735216-9KTsUNszerowF4A1X1NBhg   24  female
3             NaN  20210317171023585-M2tZ3kjFMaTVmE4shqXxua   35    male
4             NaN   20210317172029708-JQryUiA4jZKCdwq1p8voq   53  female

   income                                           group_id  \
0   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
1   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
2   39000  grp-49abab43-13d6-439c-80de-3e98b4083758--good…
3   75000  grp-e49d32ee-df44-4e9e-a3ab-d6ab4b6988d9--good…
4   97000  grp-5228870e-24ec-4e97-a41c-db62394ed4f1--good…
```

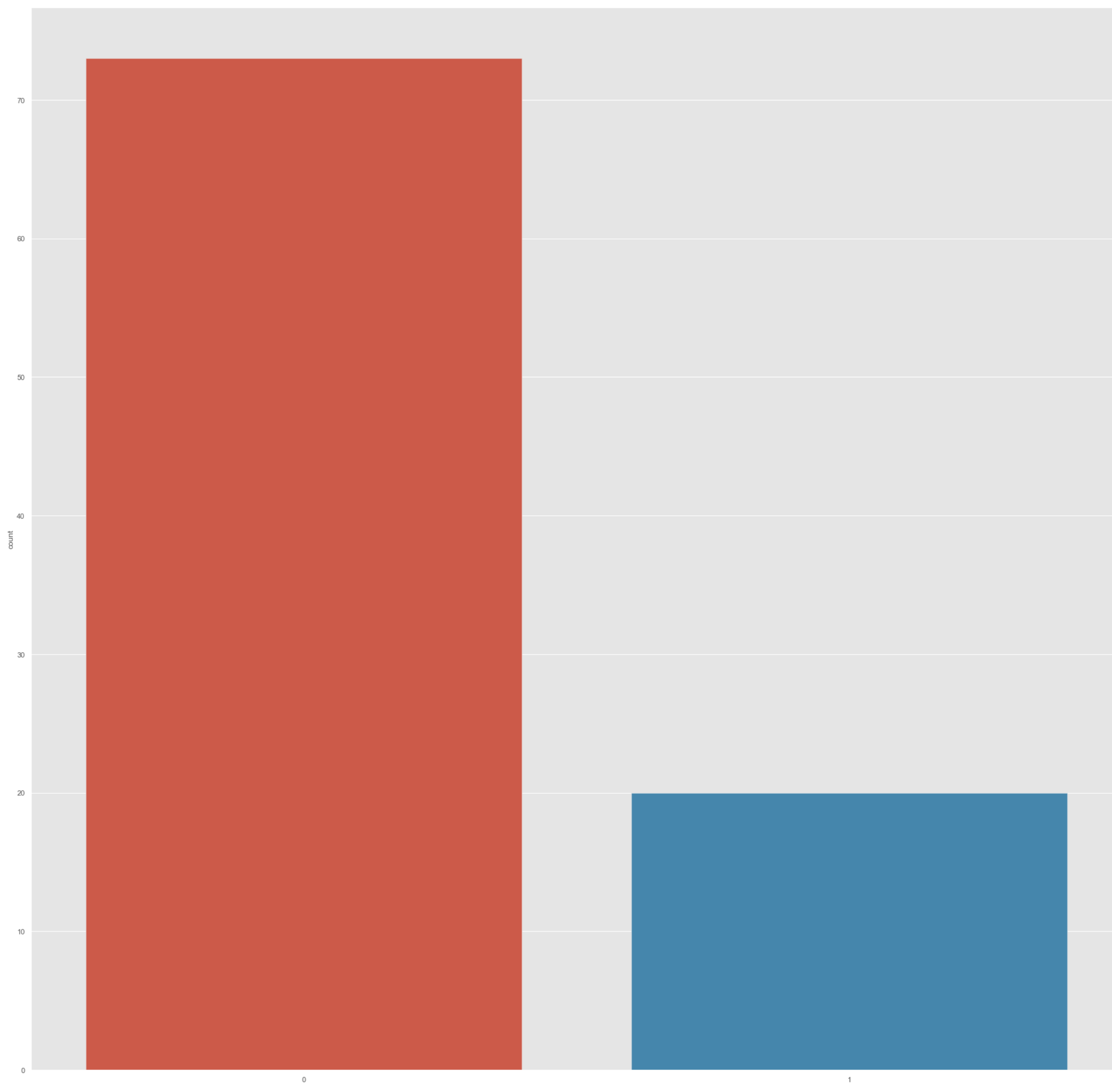
```
          group_name customer_state customer_country device_type  \
0  Sasquatch's Group             NY               US     Desktop
1      Cobra's Group             NY               US     Desktop
2                NaN            NaN              NaN     Desktop
3   Diablo's Winners             PA               US     Desktop
4       Rigs's Group             NY               US     Desktop

                               orderlineitems_jsonb  row_num  \
0  [{'id': 'oli-NHz5q5rPAh4oj3QtZDfgQ3', 'price':…        1
1  [{'id': 'oli-E8hTJtpoz2uW5v75Bnm7Rd', 'price':…        2
2  [{'id': 'oli-MAucg88ir2tsPhjF9a98Np', 'price':…        1
3  [{'id': 'oli-VJoPK9Jcao9objad3qxYMY', 'price':…        1
4  [{'id': 'oli-DxrhtnugrvEVqBsXgPwHtJ', 'price':…        1

              price  pvariant-gsbrightbluehoodiemedium  \
0          [110.00]                                  1
1  [110.00, 110.00]                                  1
2          [110.00]                                  0
3    [25.00, 25.00]                                  0
4          [110.00]                                  1

   pvariant-gsbrightbluehoodieextrasmall  pvariant-socksbundle-size  \
0                                      0                          0
1                                      0                          0
2                                      1                          0
3                                      0                          1
4                                      0                          0

   pvariant-truckerhatone-size  pvariant-gsbrightbluesweatsmedium  \
0                            0                                  0
1                            0                                  0
2                            0                                  0
3                            0                                  0
4                            0                                  0

   pvariant-wegoodgreyteemedium  pvariant-gsbrightbluesweatsextrasmall  \
0                             0                                      0
1                             0                                      0
2                             0                                      0
3                             0                                      0
4                             0                                      0

   pvariant-basicwhiteteemedium  pvariant-gsbrightbluebundlemedium  \
0                             0                                  0
1                             0                                  0
2                             0                                  0
3                             0                                  0
```

```
4                              0                                   0

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

[170]:
```
print(Counter(df['repeat_purchase']))
sns.countplot(df['repeat_purchase'])
plt.savefig('../reports/figures/repeat_purchase_distribution.png')
```

```
Counter({0: 73, 1: 20})
```

[170]:
```
<AxesSubplot:xlabel='repeat_purchase', ylabel='count'>
```



[198]:
```
# # Keep columns for prediction of repeat purchase - keep order_total and drop␣
↪other payment features since redundant, etc
# drop_cols = ["id", "order_number", "order_revision", "sub_total_amount",␣
↪"tax_total_amount","shipping_total_amount","fee_total_amount",␣
↪"charged_amount", "charge_refunded", "refunded_amount", "refunded_at_utc",␣
↪"customer_id","group_id", "orderlineitems_jsonb", "price"]
# df_predict = df.drop(drop_cols, axis=1)
# df_predict.head()
```

[199]:
```
# Keep columns for prediction of purchase - drop columns that could leak info,␣
↪i.e. cost of item, etc
df_predict = df[["order_created_at_utc", "age", "gender", "income",␣
↪"group_name", "customer_state", "customer_country", "device_type",␣
↪"order_total_amount", "repeat_purchase"]]
df_predict.head()
```

[199]:
```
            order_created_at_utc  age  gender  income          group_name  \
0  2021-04-20 15:38:33.133957+00   51  female   73000  Sasquatch's Group
1  2021-04-26 10:27:48.058595+00   51  female   73000      Cobra's Group
2  2021-04-16 09:36:34.040838+00   24  female   39000                NaN
3  2021-04-26 18:05:00.426515+00   35    male   75000   Diablo's Winners
4   2021-04-22 15:08:34.07912+00   53  female   97000       Rigs's Group

  customer_state customer_country device_type  order_total_amount  \
0             NY               US     Desktop           124.44000
1             NY               US     Desktop           244.92000
2            NaN              NaN     Desktop           113.51000
3             PA               US     Desktop            55.98000
4             NY               US     Desktop           110.00000

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

[200]:
```
# convert order date to datetime type
df_predict["order_created_at_utc"] = pd.
↪to_datetime(df_predict["order_created_at_utc"])
```

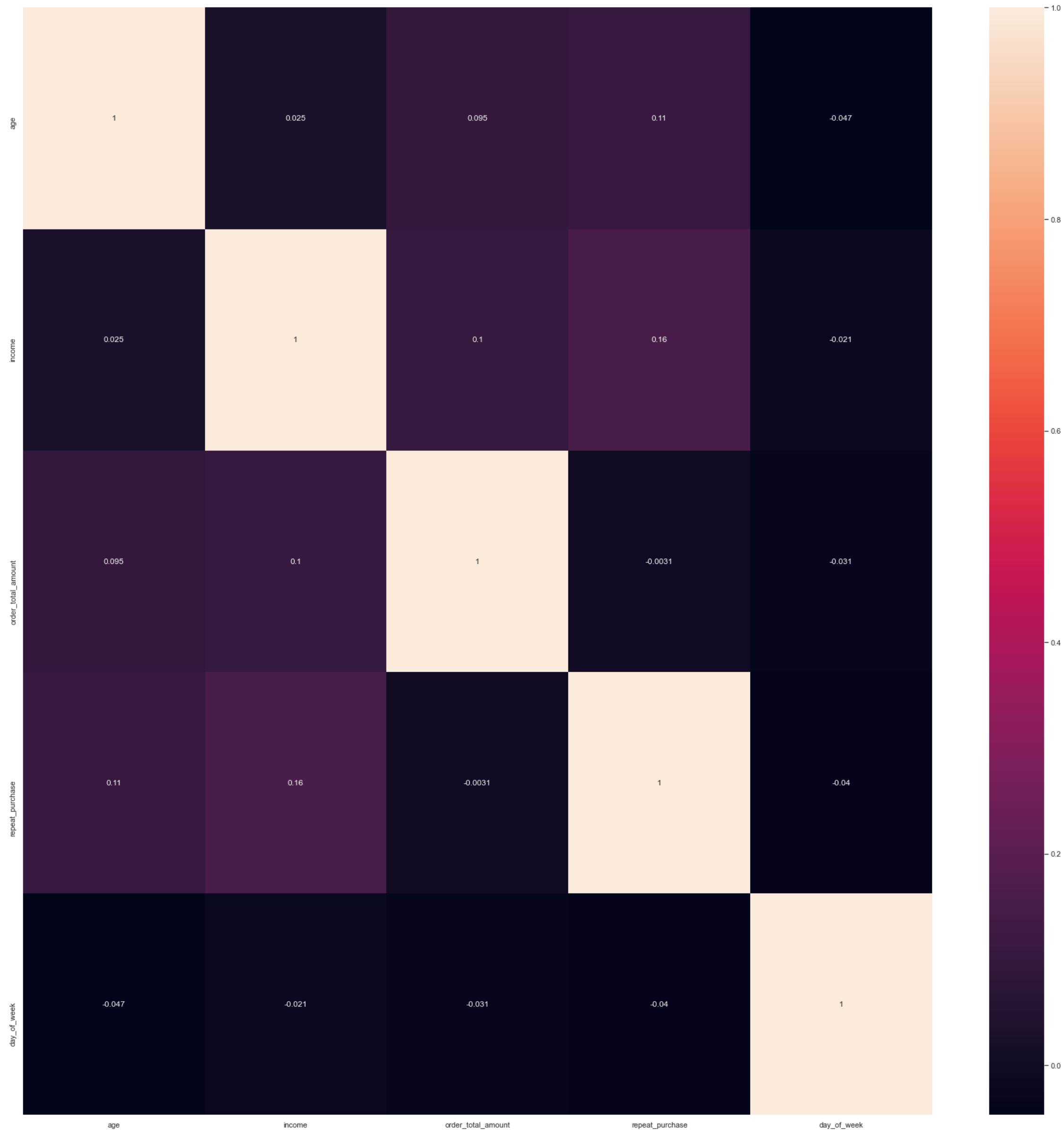
[201]:
```
# Create weekday indicator
df_predict["day_of_week"] = df_predict["order_created_at_utc"].dt.weekday
```

[202]:
```
df_predict["day_of_week"].value_counts()
```

[202]:
```
0    23
4    23
1    18
3    15
2    14
Name: day_of_week, dtype: int64
```

[203]:
```
corrMatrix = df_predict.corr()
sns.set(rc={'figure.figsize':(30, 30)})
sns.heatmap(corrMatrix, annot=True)
plt.savefig('../reports/figures/repeat_purchase_correlation_matrix.png')
```

[203]:
```
<AxesSubplot:>
```



[204]:
```
# Encode categorical features
df_predict = pd.get_dummies(df_predict, columns =␣
↪['day_of_week','gender','group_name', 'customer_state', 'customer_country',␣
↪'device_type'])
```

[205]:
```
df_predict.head()
```

[205]:
```
                  order_created_at_utc  age  income  order_total_amount  \
0 2021-04-20 15:38:33.133957+00:00   51   73000           124.44000
1 2021-04-26 10:27:48.058595+00:00   51   73000           244.92000
2 2021-04-16 09:36:34.040838+00:00   24   39000           113.51000
```

```
3 2021-04-26 18:05:00.426515+00:00   35   75000            55.98000
4 2021-04-22 15:08:34.079120+00:00   53   97000           110.00000

   repeat_purchase  day_of_week_0  day_of_week_1  day_of_week_2  \
0                0              0              1              0
1                1              1              0              0
2                0              0              0              0
3                0              1              0              0
4                0              0              0              0

   day_of_week_3  day_of_week_4  gender_female  gender_male  \
0              0              0              1            0
1              0              0              1            0
2              0              1              1            0
3              0              0              0            1
4              1              0              1            0

   group_name_AB_2021-04-20_1  group_name_Aspect's Team  \
0                           0                         0
1                           0                         0
2                           0                         0
3                           0                         0
4                           0                         0

   group_name_Bender's Team  group_name_Big Papa's Familia  \
0                         0                              0
1                         0                              0
2                         0                              0
3                         0                              0
4                         0                              0

   group_name_Big Papa's Winners  group_name_Bowser's Familia  \
0                              0                            0
1                              0                            0
2                              0                            0
3                              0                            0
4                              0                            0

   group_name_Bowser's Team  group_name_Bowser's Winners  \
0                         0                            0
1                         0                            0
2                         0                            0
3                         0                            0
4                         0                            0

   group_name_Bruise's Group  group_name_Bruise's Team  \
0                          0                         0
```

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

   group_name_Bruise's Winners  group_name_Cannon's Familia  \
0                            0                            0
1                            0                            0
2                            0                            0
3                            0                            0
4                            0                            0

   group_name_Cannon's Group  …  customer_state_AL  customer_state_BC  \
0                          0  …                  0                  0
1                          0  …                  0                  0
2                          0  …                  0                  0
3                          0  …                  0                  0
4                          0  …                  0                  0

   customer_state_BY  customer_state_CA  customer_state_CT  \
0                  0                  0                  0
1                  0                  0                  0
2                  0                  0                  0
3                  0                  0                  0
4                  0                  0                  0

   customer_state_Kharkivs'ka oblast  customer_state_MA  customer_state_MN  \
0                                  0                  0                  0
1                                  0                  0                  0
2                                  0                  0                  0
3                                  0                  0                  0
4                                  0                  0                  0

   customer_state_NJ  customer_state_NY  customer_state_PA  customer_state_PR  \
0                  0                  1                  0                  0
1                  0                  1                  0                  0
2                  0                  0                  0                  0
3                  0                  0                  1                  0
4                  0                  1                  0                  0

   customer_state_Qro.  customer_state_SK  customer_state_UP  \
0                    0                  0                  0
1                    0                  0                  0
2                    0                  0                  0
3                    0                  0                  0
4                    0                  0                  0
```

```
   customer_country_CA  customer_country_DE  customer_country_IN  \
0                    0                    0                    0
1                    0                    0                    0
2                    0                    0                    0
3                    0                    0                    0
4                    0                    0                    0

   customer_country_MK  customer_country_MX  customer_country_RS  \
0                    0                    0                    0
1                    0                    0                    0
2                    0                    0                    0
3                    0                    0                    0
4                    0                    0                    0

   customer_country_UA  customer_country_US  device_type_Desktop  \
0                    0                    1                    1
1                    0                    1                    1
2                    0                    0                    1
3                    0                    1                    1
4                    0                    1                    1

   device_type_Mobile
0                   0
1                   0
2                   0
3                   0
4                   0

[5 rows x 104 columns]
```

Encoded dates as days of week indicators so will drop date to avoid redundancies.

[206]:
```
df_predict = df_predict.drop(["order_created_at_utc"], axis=1, errors="ignore")
```

[207]:
```
df_predict[df_predict.columns[1:]].corr()['repeat_purchase'][:].
↪sort_values(ascending=False).to_frame()
```

[207]:
```
                            repeat_purchase
repeat_purchase                     1.00000
group_name_Decay's Team             0.19918
group_name_pdf                      0.19918
group_name_Cobra's Group            0.19918
group_name_Creep's Squad            0.19918
…                                       …
group_name_Reaper's Team           -0.07760
customer_state_NY                  -0.09174
group_name_Decay's Familia         -0.09556
```

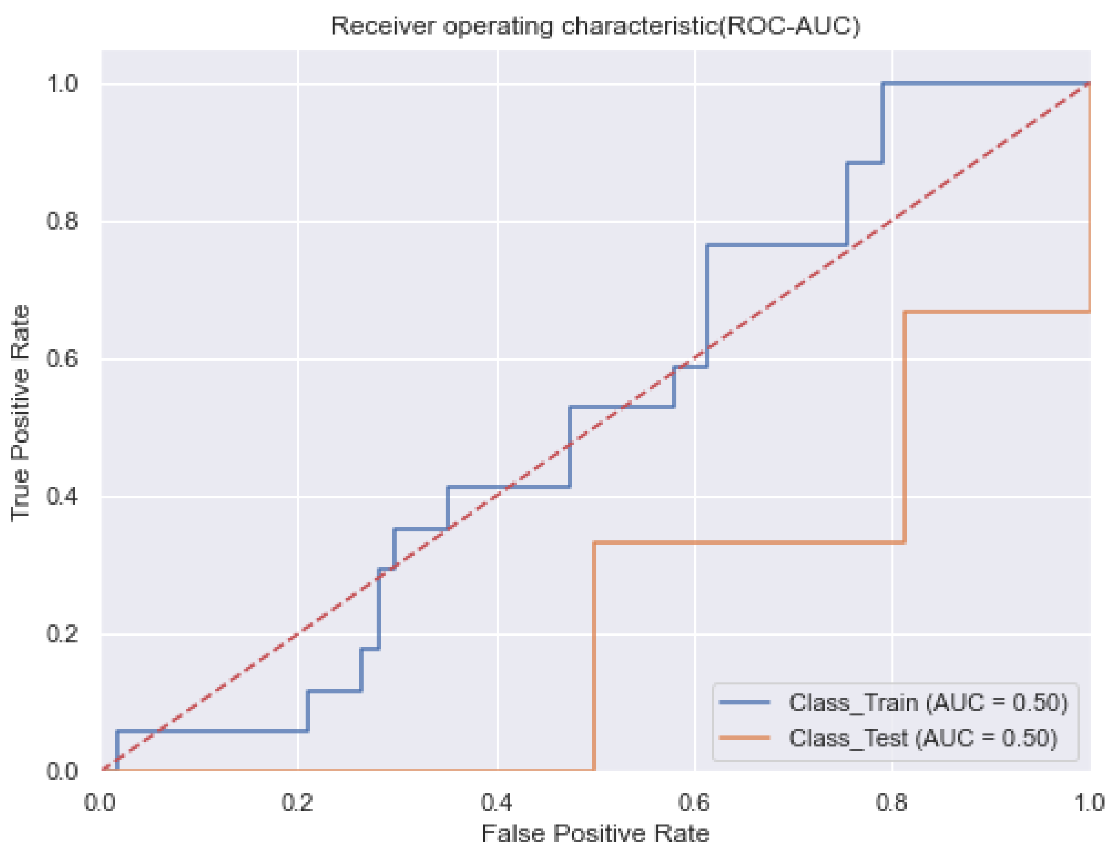
```
customer_country_US                   -0.13972
gender_male                           -0.17872

[102 rows x 1 columns]
```

Let's use same prediction models we tested above in Models and feature selection

3.4.1 Models and feature selection

Logistic regression

[211]:
```
def logistic_fn(x_train,y_train):
    model = LogisticRegression(solver='liblinear',random_state=12)
    model.fit(x_train,y_train)

    return model

result_dict['Repeat Purchase ~ Logistic'] = \
    build_model(logistic_fn,'repeat_purchase',df_predict,show_plot_auc=True)
print(result_dict)
```



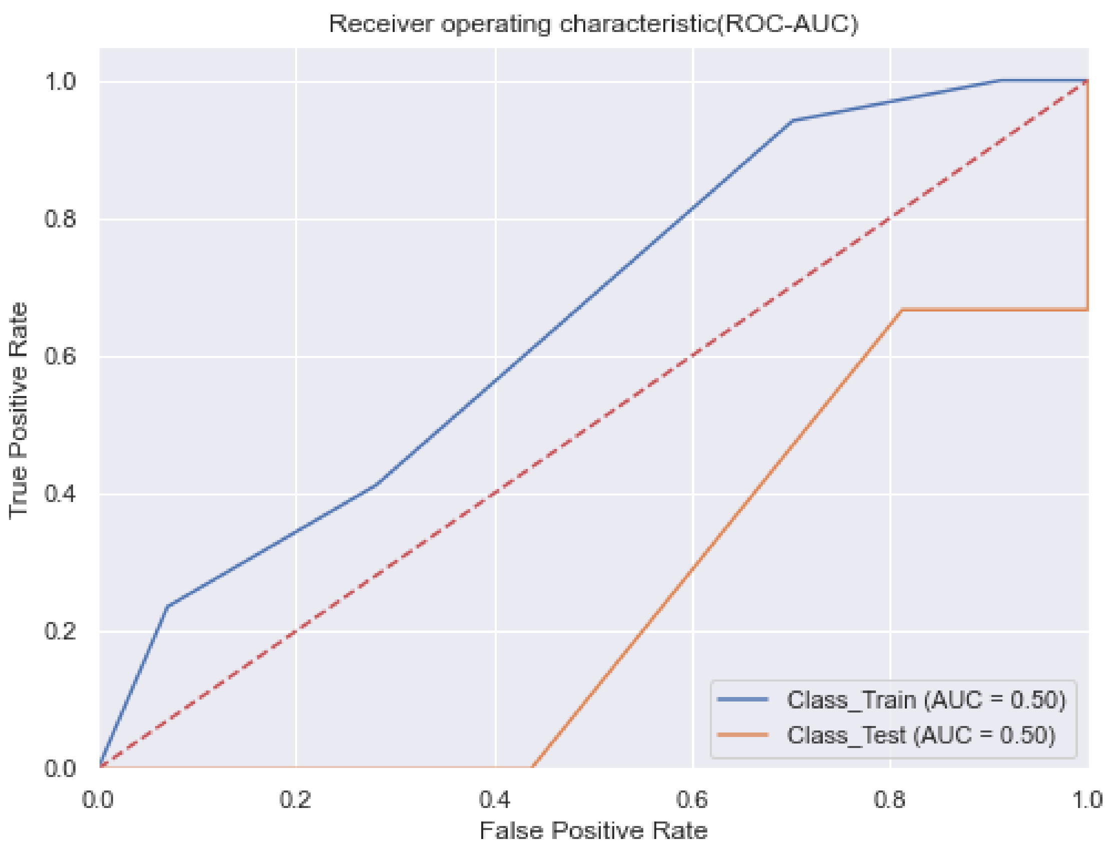

```
{'Repeat Purchase ~ Logistic': {'training': {'Accuracy:': 0.7702702702702703,
```

```
'Accuracy_count:': 57, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0,
'AUC_ROC:': 0.5}, 'test': {'Accuracy:': 0.8421052631578947, 'Accuracy_count:':
16, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.5},
'confusion_matrix': y_test   0  1
y_pred
0       16  3}}
```

This baseline model can pretty much not determine the difference between transactions that are repeat purchases and not

KNN

[212]:
```python
def knn_fn(x_train,y_train,n_neighbors=9,random_state=12):

    model = KNeighborsClassifier(n_neighbors=n_neighbors)
    model.fit(x_train,y_train)

    return model

result_dict['Repeat Purchase ~ KNN'] = \
    build_model(knn_fn,'repeat_purchase',df_predict,show_plot_auc=True)
```

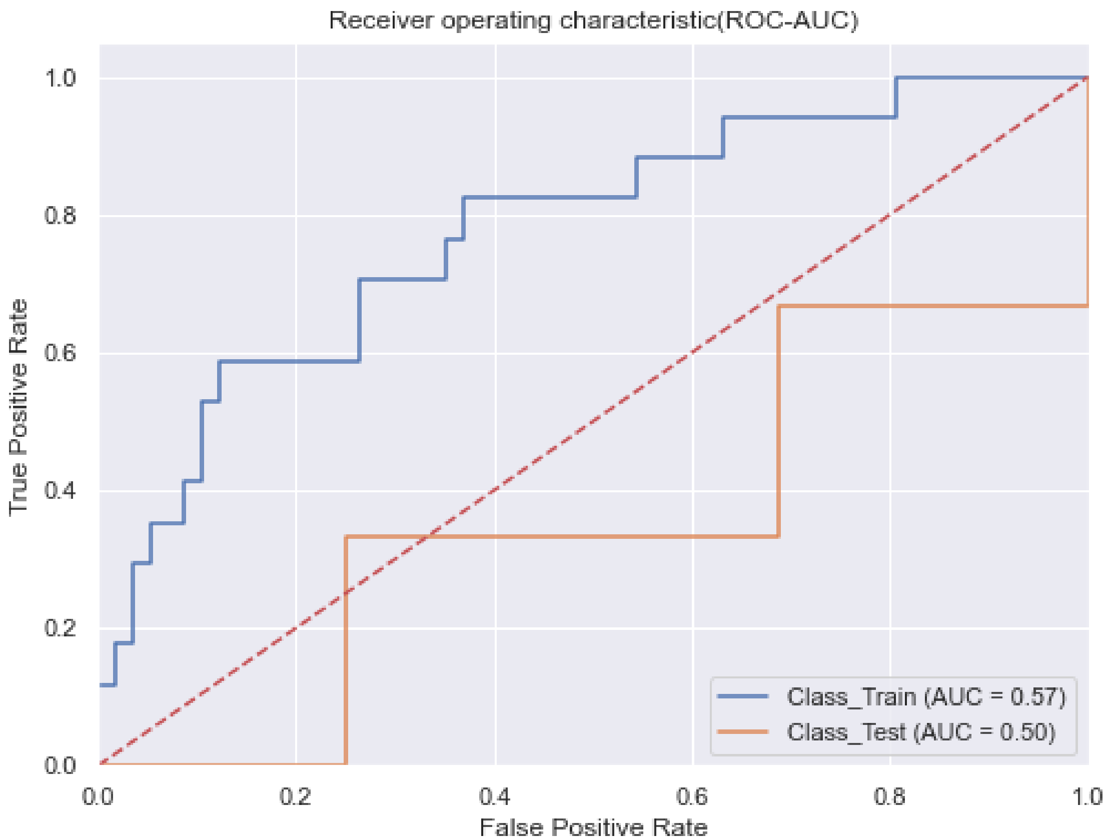


[213]:
```python
print(result_dict)
```

```
{'Repeat Purchase ~ Logistic': {'training': {'Accuracy:': 0.7702702702702703,
'Accuracy_count:': 57, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0,
'AUC_ROC:': 0.5}, 'test': {'Accuracy:': 0.8421052631578947, 'Accuracy_count:':
16, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.5},
'confusion_matrix': y_test   0  1
y_pred
0       16  3}, 'Repeat Purchase ~ KNN': {'training': {'Accuracy:':
0.7702702702702703, 'Accuracy_count:': 57, 'Precision:': 0.0, 'Recall:': 0.0,
'F1_score:': 0.0, 'AUC_ROC:': 0.5}, 'test': {'Accuracy:': 0.8421052631578947,
'Accuracy_count:': 16, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0,
'AUC_ROC:': 0.5}, 'confusion_matrix': y_test   0  1
y_pred
0       16  3}}
```

Naive Bayes

[214]:
```python
def naive_bayes_fn(x_train,y_train,priors=None):

    model = GaussianNB(priors=priors)
    model.fit(x_train,y_train)

    return model

result_dict['Repeat Purchase ~ Naive_Bayes'] = \
    build_model(naive_bayes_fn,'repeat_purchase',df_predict,show_plot_auc=True)
print(result_dict)
```



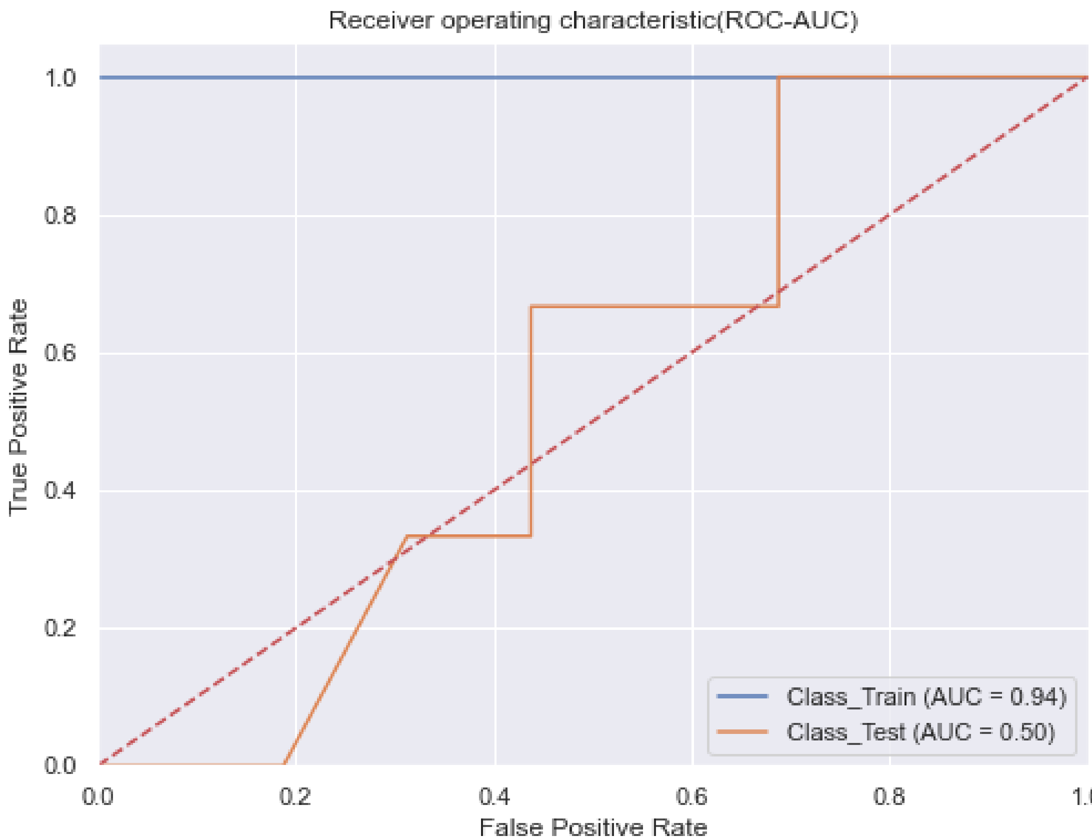

```
{'Repeat Purchase ~ Logistic': {'training': {'Accuracy:': 0.7702702702702703,
'Accuracy_count:': 57, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0,
'AUC_ROC:': 0.5}, 'test': {'Accuracy:': 0.8421052631578947, 'Accuracy_count:':
16, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.5},
'confusion_matrix': y_test   0  1
y_pred
0       16  3}, 'Repeat Purchase ~ KNN': {'training': {'Accuracy:':
0.7702702702702703, 'Accuracy_count:': 57, 'Precision:': 0.0, 'Recall:': 0.0,
'F1_score:': 0.0, 'AUC_ROC:': 0.5}, 'test': {'Accuracy:': 0.8421052631578947,
'Accuracy_count:': 16, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0,
'AUC_ROC:': 0.5}, 'confusion_matrix': y_test   0  1
y_pred
0       16  3}, 'Repeat Purchase ~ Naive_Bayes': {'training': {'Accuracy:':
0.7837837837837838, 'Accuracy_count:': 58, 'Precision:': 0.6, 'Recall:':
0.17647058823529413, 'F1_score:': 0.2727272727272727, 'AUC_ROC:':
0.5706914344685243}, 'test': {'Accuracy:': 0.8421052631578947,
'Accuracy_count:': 16, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0,
'AUC_ROC:': 0.5}, 'confusion_matrix': y_test   0  1
y_pred
0       16  3}}
```

[215]:
```python
pd.DataFrame.from_dict(result_dict)
```

[215]:
```
                                              Repeat Purchase ~ Logistic  \
training          {'Accuracy:': 0.7702702702702703, 'Accuracy_co…
test              {'Accuracy:': 0.8421052631578947, 'Accuracy_co…
confusion_matrix          y_test   0  1
y_pred
0        16  3

                                                   Repeat Purchase ~ KNN  \
training          {'Accuracy:': 0.7702702702702703, 'Accuracy_co…
test              {'Accuracy:': 0.8421052631578947, 'Accuracy_co…
confusion_matrix          y_test   0  1
y_pred
0        16  3

                                           Repeat Purchase ~ Naive_Bayes
training          {'Accuracy:': 0.7837837837837838, 'Accuracy_co…
test              {'Accuracy:': 0.8421052631578947, 'Accuracy_co…
confusion_matrix          y_test   0  1
y_pred
0        16  3
```

Random Forest

[222]:
```python
def random_forest_fn(x_train,y_train):
    model = RandomForestClassifier(n_estimators= 10, max_depth =␣
↪15,random_state=12 , max_features="auto")
    model.fit(x_train,y_train)

    return model

result_dict['Repeat Purchase ~ Random_Forest'] = \
   ␣
↪build_model(random_forest_fn,'repeat_purchase',df_predict,show_plot_auc=True)
print(result_dict)
```



{'Repeat Purchase ~ Logistic': {'training': {'Accuracy:': 0.7702702702702703, 'Accuracy_count:': 57, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.5}, 'test': {'Accuracy:': 0.8421052631578947, 'Accuracy_count:': 16, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.5}, 'confusion_matrix': y_test   0 1
y_pred
0   16 3}, 'Repeat Purchase ~ KNN': {'training': {'Accuracy:': 0.7702702702702703, 'Accuracy_count:': 57, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.5}, 'test': {'Accuracy:': 0.8421052631578947, 'Accuracy_count:': 16, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.5}, 'confusion_matrix': y_test   0 1
y_pred
0   16 3}, 'Repeat Purchase ~ Naive_Bayes': {'training': {'Accuracy:': 0.7837837837837838, 'Accuracy_count:': 58, 'Precision:': 0.6, 'Recall:': 0.17647058823529413, 'F1_score:': 0.2727272727272727, 'AUC_ROC:': 0.5706914344685243}, 'test': {'Accuracy:': 0.8421052631578947, 'Accuracy_count:': 16, 'Precision:': 0.0, 'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.5}, 'confusion_matrix': y_test   0 1
y_pred
0   16 3}, 'Repeat Purchase ~ Random_Forest': {'training': {'Accuracy:': 0.972972972972973, 'Accuracy_count:': 72, 'Precision:': 1.0, 'Recall:':

```
0.8823529411764706, 'F1_score:': 0.9375, 'AUC_ROC:': 0.9411764705882353},
'test': {'Accuracy:': 0.8421052631578947, 'Accuracy_count:': 16, 'Precision:':
0.0, 'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.5}, 'confusion_matrix':
y_test   0  1
y_pred
0       16  3}}
```

Random Forest performs the best of our considered models but it's very much overfitting due to decreased performance on the holdout data. Would consider training on larger dataset, training using cross-validation, and/or some regularization method such as L1 or L2 regularization. L1 (Lasso) regularization also acts as a feature selection method.

Feature selection

[223]:
```python
# Separating the  input features (X) and target variable (y)
X = df_predict.drop('repeat_purchase', axis=1)
Y = df_predict['repeat_purchase']
```

[224]:
```python
## Finding Important Features using ChiSq
from sklearn import svm
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2

list_one =[]
feature_ranking = SelectKBest(chi2, k=5)
fit = feature_ranking.fit(X, Y)

for i, (score, feature) in enumerate(zip(feature_ranking.scores_, X.columns)):
    list_one.append((score, feature))

dfObj = pd.DataFrame(list_one)
dfObj.sort_values(by=[0], ascending = False)

dfObj[0].describe()
```

[224]:
```
                0                          1
1    16151.42367                      income
56       3.65000    group_name_Ratchet's Squad
72       3.65000  group_name_Sasquatch's Team
24       3.65000     group_name_Cannon's Team
31       3.65000     group_name_Creep's Group
..           …                           …
7        0.23061                day_of_week_4
101      0.08682           device_type_Mobile
2        0.08402           order_total_amount
100      0.01286          device_type_Desktop
5        0.00005                day_of_week_2

[102 rows x 2 columns]
```

[224]:
```
count      102.00000
mean       159.19112
std       1599.14525
min          0.00005
25%          0.27397
50%          0.27397
75%          0.96199
max      16151.42367
Name: 0, dtype: float64
```

[225]:
```
drop_cols = dfObj[dfObj[0] < 1]
```

[226]:
```
drop_cols = drop_cols[1].to_list()
print(drop_cols)
```

```
['order_total_amount', 'day_of_week_0', 'day_of_week_1', 'day_of_week_2',
'day_of_week_3', 'day_of_week_4', 'gender_female', 'group_name_AB_2021-04-20_1',
"group_name_Aspect's Team", "group_name_Bender's Team", "group_name_Big Papa's
Familia", "group_name_Big Papa's Winners", "group_name_Bowser's Familia",
"group_name_Bowser's Team", "group_name_Bowser's Winners", "group_name_Bruise's
Group", "group_name_Bruise's Team", "group_name_Cannon's Familia",
"group_name_Cannon's Group", "group_name_Cannon's Squad", "group_name_Clink's
Familia", "group_name_Clink's Group", "group_name_Cobra's Familia",
"group_name_Cobra's Team", "group_name_Colt's Winners", "group_name_Daemon's
Winners", "group_name_Decay's Familia", "group_name_Decay's Group",
"group_name_Diablo's Winners", "group_name_Doom's Squad", "group_name_Doom's
Winners", "group_name_Dracula's Group", "group_name_Dracula's Team",
"group_name_Kraken's Squad", "group_name_Kraken's Winners", "group_name_Lynch's
Familia", "group_name_Lynch's Squad", "group_name_Lynch's Team",
"group_name_Lynch's Winners", "group_name_Mad Dog's Group", "group_name_Mad
Dog's Winners", "group_name_Magda's Peoples", "group_name_Psycho's Group",
"group_name_Psycho's Winners", "group_name_Ranger's Team", "group_name_Ratchet's
Winners", "group_name_Reaper's Team", "group_name_Rigs's Group",
"group_name_Rigs's Squad", "group_name_Ripley's Winners", "group_name_Roadkill's
Familia", "group_name_Roadkill's Squad", "group_name_Roadkill's Team",
"group_name_Roadkill's Winners", "group_name_Ronin's Familia",
"group_name_Ronin's Group", "group_name_Rubble's Winners",
"group_name_Sasquatch's Familia", "group_name_Sasquatch's Group",
"group_name_Sasquatch's Squad", "group_name_Scar's Familia", "group_name_Scar's
Squad", "group_name_Scar's Team", 'customer_state_AL', 'customer_state_BC',
'customer_state_BY', 'customer_state_CA', 'customer_state_CT',
"customer_state_Kharkivs'ka oblast", 'customer_state_MA', 'customer_state_MN',
'customer_state_NJ', 'customer_state_NY', 'customer_state_PA',
'customer_state_PR', 'customer_state_Qro.', 'customer_state_SK',
'customer_country_CA', 'customer_country_DE', 'customer_country_MK',
'customer_country_MX', 'customer_country_RS', 'customer_country_UA',
'customer_country_US', 'device_type_Desktop', 'device_type_Mobile']
```

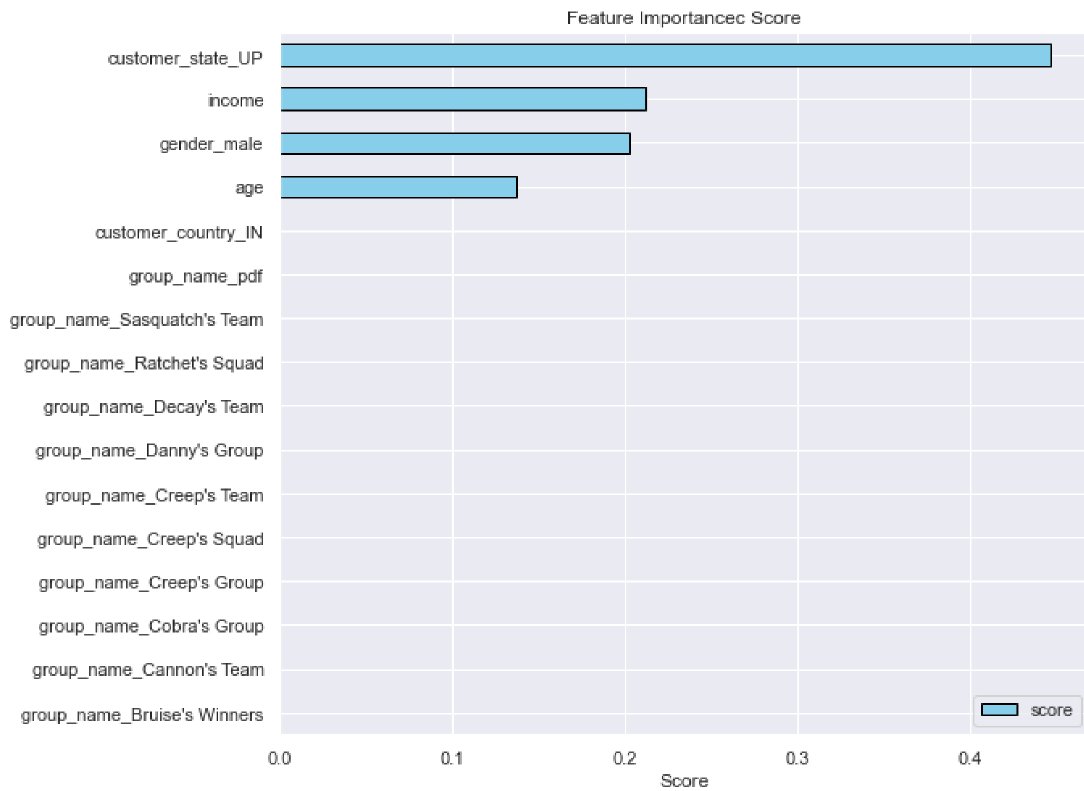
[227]:

```
X.drop(drop_cols, axis=1, inplace=True)
```

[228]:

```
# Feature seelction using XGBoost
# feature Scaling
scale_x = StandardScaler()
x = scale_x.fit_transform(X)

x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size=0.
↪2,random_state=0)
model = XGBClassifier()
model.fit(x_train,y_train)

XGBoost_eval_metric_y_pred = model.predict(x_test)

print(summarize_classification(y_test,XGBoost_eval_metric_y_pred))

# Horizontal bar chart for feature Importance
feature_imp = pd.DataFrame({'feature':list(X.columns),'score':model.
↪feature_importances_})
feature_imp.sort_values('score').
↪plot(x='feature',y='score',kind='barh',color='skyblue',edgecolor='black',figsize=(9,8))

#plot formatting
plt.xlabel('Score')
plt.xticks()
plt.yticks()
plt.ylabel(' ')
plt.title('Feature Importancec Score')
plt.legend(loc="lower right")
plt.show();
```

```
[14:53:13] WARNING: ../src/learner.cc:1061: Starting in XGBoost 1.3.0, the
default evaluation metric used with the objective 'binary:logistic' was changed
from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
{'Accuracy:': 0.631578947368421, 'Accuracy_count:': 12, 'Precision:': 0.0,
'Recall:': 0.0, 'F1_score:': 0.0, 'AUC_ROC:': 0.375}
```



Customer_state_UP, income, gender_male, and age are the drivers of whether a transaction is a repeat purchase or not.

3.5 Sales forecast

[ ]:

```

```

[866]:

```
order_data.head()
```

[866]:

```
                                     id order_number  order_revision  \
0  efd688aa-c021-4766-9721-83dd92710c63      2PBDJLI               1
1  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
2  4ac870d3-fe19-4203-ad28-6313793103b8      L3MSP59               1
3  aeaa4c4d-12e1-4016-bc47-30d08f00041c   CAHWWSMWOD               1
4  42dd34c1-f1ed-4f90-b7af-9261f423ebc9      FXPF4J2               1

             order_created_at_utc  sub_total_amount  tax_total_amount  \
0 2021-04-20 15:38:33.133957+00:00               110           9.76000
1 2021-04-26 10:27:48.058595+00:00               220          15.40000
2 2021-04-16 09:36:34.040838+00:00               110           0.00000
3 2021-04-26 18:05:00.426515+00:00                50           0.00000
4 2021-04-22 15:08:34.079120+00:00               110           0.00000
```

```
   shipping_total_amount  fee_total_amount  order_total_amount  \
0                4.68000                 0           124.44000
1                9.52000                 0           244.92000
2                2.51000                 0           113.51000
3                5.98000                 0            55.98000
4                0.00000                 0           110.00000

   requires_payment  charged_amount  charge_refunded  refunded_amount  \
0              True           12444            False              NaN
1              True           24492            False              NaN
2              True           11351            False              NaN
3              True            5598            False              NaN
4              True           11000            False              NaN

  refunded_at_utc                               customer_id  age  gender  \
0             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
1             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
2             NaN  20210316112735216-9KTsUNszerowF4A1X1NBhg   24  female
3             NaN  20210317171023585-M2tZ3kjFMaTVmE4shqXxua   35    male
4             NaN   20210317172029708-JQryUiA4jZKCdwq1p8voq   53  female

   income                                          group_id  \
0   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
1   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
2   39000  grp-49abab43-13d6-439c-80de-3e98b4083758--good…
3   75000  grp-e49d32ee-df44-4e9e-a3ab-d6ab4b6988d9--good…
4   97000  grp-5228870e-24ec-4e97-a41c-db62394ed4f1--good…

          group_name customer_state customer_country device_type  \
0  Sasquatch's Group             NY               US     Desktop
1      Cobra's Group             NY               US     Desktop
2                NaN            NaN              NaN     Desktop
3   Diablo's Winners             PA               US     Desktop
4       Rigs's Group             NY               US     Desktop

                              orderlineitems_jsonb  row_num  day_of_week  \
0  [{"id": "oli-NHz5q5rPAh4oj3QtZDfgQ3", "price":…        1            1
1  [{"id": "oli-E8hTJtpoz2uW5v75Bnm7Rd", "price":…        2            0
2  [{"id": "oli-MAucg88ir2tsPhjF9a98Np", "price":…        1            4
3  [{"id": "oli-VJoPK9Jcao9objad3qxYMY", "price":…        1            0
4  [{"id": "oli-DxrhtnugrvEVqBsXgPwHtJ", "price":…        1            3

   day_of_month  month
0            20      4
1            26      4
2            16      4
```

```
3             26      4
4             22      4
```

[862]:
```
order_data["order_created_at_utc"].min()
```

[862]:
```
Timestamp('2021-04-16 00:05:23.058775+0000', tz='UTC')
```

[863]:
```
order_data["order_created_at_utc"].max()
```

[863]:
```
Timestamp('2021-05-28 22:51:49.713931+0000', tz='UTC')
```

[867]:
```
# convert order date to datetime type
order_data["order_created_at_utc"] = pd.
↪to_datetime(order_data["order_created_at_utc"])
```

[868]:
```
order_data.head()
```

[868]:
```
                                     id order_number  order_revision  \
0  efd688aa-c021-4766-9721-83dd92710c63      2PBDJLI               1
1  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
2  4ac870d3-fe19-4203-ad28-6313793103b8      L3MSP59               1
3  aeaa4c4d-12e1-4016-bc47-30d08f00041c   CAHWWSMWOD               1
4  42dd34c1-f1ed-4f90-b7af-9261f423ebc9      FXPF4J2               1

              order_created_at_utc  sub_total_amount  tax_total_amount  \
0 2021-04-20 15:38:33.133957+00:00               110           9.76000
1 2021-04-26 10:27:48.058595+00:00               220          15.40000
2 2021-04-16 09:36:34.040838+00:00               110           0.00000
3 2021-04-26 18:05:00.426515+00:00                50           0.00000
4 2021-04-22 15:08:34.079120+00:00               110           0.00000

   shipping_total_amount  fee_total_amount  order_total_amount  \
0                4.68000                 0           124.44000
1                9.52000                 0           244.92000
2                2.51000                 0           113.51000
3                5.98000                 0            55.98000
4                0.00000                 0           110.00000

   requires_payment  charged_amount  charge_refunded  refunded_amount  \
0              True           12444            False              NaN
1              True           24492            False              NaN
2              True           11351            False              NaN
3              True            5598            False              NaN
4              True           11000            False              NaN

  refunded_at_utc                              customer_id  age  gender  \
0             NaN   20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
```

```
1             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
2             NaN  20210316112735216-9KTsUNszerowF4A1X1NBhg   24  female
3             NaN  20210317171023585-M2tZ3kjFMaTVmE4shqXxua   35    male
4             NaN   20210317172029708-JQryUiA4jZKCdwq1p8voq   53  female

   income                                           group_id  \
0   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
1   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
2   39000  grp-49abab43-13d6-439c-80de-3e98b4083758--good…
3   75000  grp-e49d32ee-df44-4e9e-a3ab-d6ab4b6988d9--good…
4   97000  grp-5228870e-24ec-4e97-a41c-db62394ed4f1--good…

         group_name customer_state customer_country device_type  \
0  Sasquatch's Group             NY               US     Desktop
1      Cobra's Group             NY               US     Desktop
2                NaN            NaN              NaN     Desktop
3   Diablo's Winners             PA               US     Desktop
4       Rigs's Group             NY               US     Desktop

                              orderlineitems_jsonb  row_num  day_of_week  \
0  [{"id": "oli-NHz5q5rPAh4oj3QtZDfgQ3", "price":…        1            1
1  [{"id": "oli-E8hTJtpoz2uW5v75Bnm7Rd", "price":…        2            0
2  [{"id": "oli-MAucg88ir2tsPhjF9a98Np", "price":…        1            4
3  [{"id": "oli-VJoPK9Jcao9objad3qxYMY", "price":…        1            0
4  [{"id": "oli-DxrhtnugrvEVqBsXgPwHtJ", "price":…        1            3

   day_of_month  month
0            20      4
1            26      4
2            16      4
3            26      4
4            22      4
```

[875]:
```
df = order_data.drop(["age","income","row_num"], axis=1)
```

[884]:
```
df = order_data.groupby([order_data["order_created_at_utc"].dt.date]).sum()
df.reset_index(inplace=True)
df.head()
```

[884]:
```
  order_created_at_utc  order_revision  sub_total_amount  tax_total_amount  \
0           2021-04-16              14              2340          65.22500
1           2021-04-19              10              2020          42.61000
2           2021-04-20               3               410           9.76000
3           2021-04-21               4               950          20.42500
4           2021-04-22               5               590          26.18500

   shipping_total_amount  fee_total_amount  order_total_amount  \
```

```
0              108.45000                 0         2626.55000
1               84.40000                 0         2248.30000
2               20.18000                 0          439.94000
3               34.54000                 0         1100.66000
4               23.03000                 0          643.31000

   requires_payment  charged_amount  charge_refunded  refunded_amount  age  \
0                14          262655                0          0.00000  502
1                10          224830                0          0.00000  390
2                 3           43994                0          0.00000  113
3                 4          110066                0          0.00000  130
4                 5           64331                0          0.00000  177

    income  row_num  day_of_week  day_of_month  month
0  1155000       17           56           224     56
1   857000       11            0           190     40
2   234000        3            3            60     12
3   240000        4            8            84     16
4   366000        6           15           110     20
```

[886]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19 entries, 0 to 18
Data columns (total 17 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   order_created_at_utc   19 non-null     object
 1   order_revision         19 non-null     int64
 2   sub_total_amount       19 non-null     int64
 3   tax_total_amount       19 non-null     float64
 4   shipping_total_amount  19 non-null     float64
 5   fee_total_amount       19 non-null     int64
 6   order_total_amount     19 non-null     float64
 7   requires_payment       19 non-null     int64
 8   charged_amount         19 non-null     int64
 9   charge_refunded        19 non-null     int64
 10  refunded_amount        19 non-null     float64
 11  age                    19 non-null     int64
 12  income                 19 non-null     int64
 13  row_num                19 non-null     int64
 14  day_of_week            19 non-null     int64
 15  day_of_month           19 non-null     int64
 16  month                  19 non-null     int64
dtypes: float64(4), int64(12), object(1)
memory usage: 2.6+ KB
```

[887]:
```python
# convert order date to datetime type
df["order_created_at_utc"] = pd.to_datetime(df["order_created_at_utc"])
```

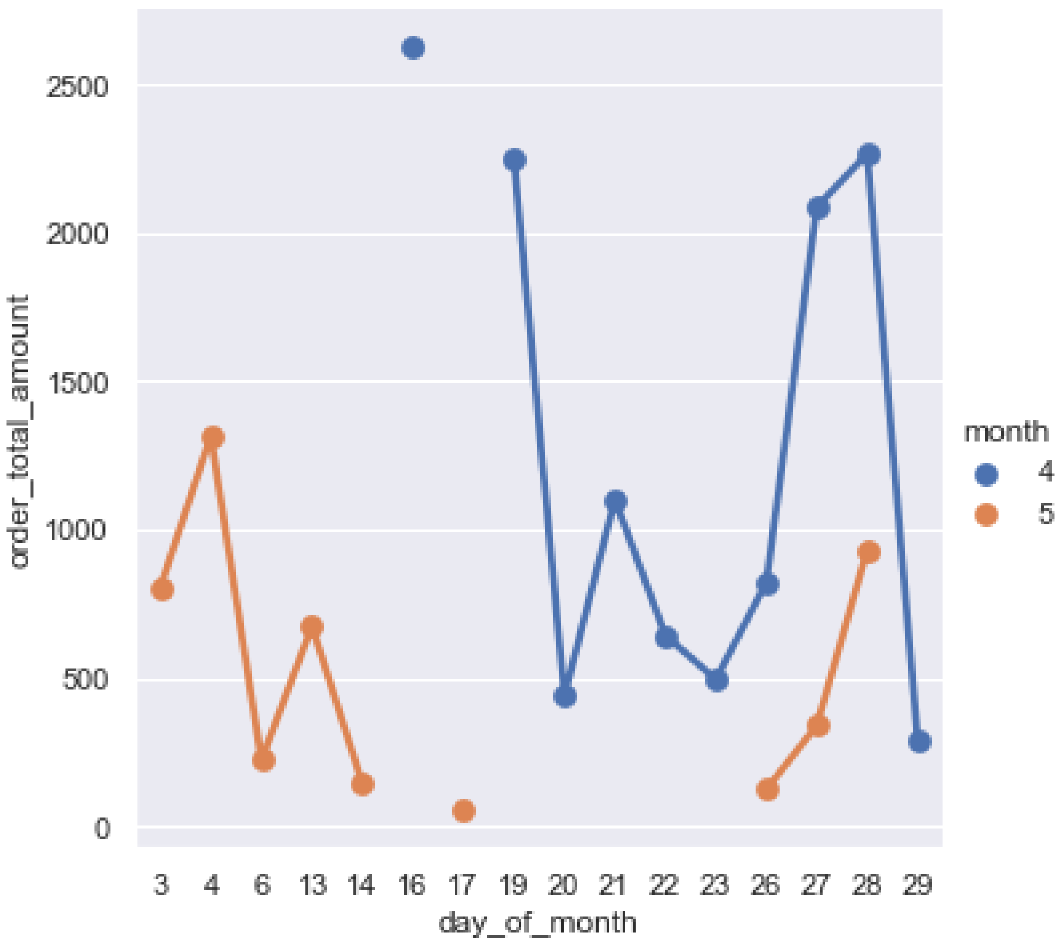
[888]:
```python
# Create weekend indicator
df["day_of_week"] = df["order_created_at_utc"].dt.dayofweek
df["day_of_month"] = df["order_created_at_utc"].dt.day
df["month"] = df["order_created_at_utc"].dt.month
```

[889]:
```python
df.head()
```

[889]:
```
  order_created_at_utc  order_revision  sub_total_amount  tax_total_amount  \
0           2021-04-16              14              2340          65.22500
1           2021-04-19              10              2020          42.61000
2           2021-04-20               3               410           9.76000
3           2021-04-21               4               950          20.42500
4           2021-04-22               5               590          26.18500

   shipping_total_amount  fee_total_amount  order_total_amount  \
0              108.45000                 0          2626.55000
1               84.40000                 0          2248.30000
2               20.18000                 0           439.94000
3               34.54000                 0          1100.66000
4               23.03000                 0           643.31000

   requires_payment  charged_amount  charge_refunded  refunded_amount  age  \
0                14          262655                0          0.00000  502
1                10          224830                0          0.00000  390
2                 3           43994                0          0.00000  113
3                 4          110066                0          0.00000  130
4                 5           64331                0          0.00000  177

    income  row_num  day_of_week  day_of_month  month
0  1155000       17            4            16      4
1   857000       11            0            19      4
2   234000        3            1            20      4
3   240000        4            2            21      4
4   366000        6            3            22      4
```

[891]:
```python
# Sales trend over the months and year
sns.factorplot(data = df, x ="day_of_month", y = "order_total_amount", hue =␣
↪'month')
```

[891]: <seaborn.axisgrid.FacetGrid at 0x7fa16c23d820>



3.6 Customer social cluster

[230]:
```
df.head()
```

[230]:
```
                                     id order_number  order_revision  \
0  efd688aa-c021-4766-9721-83dd92710c63      2PBDJLI               1
1  ded54adc-adb0-4559-8d05-7c5440edd606      FCZXSMZ               1
2  4ac870d3-fe19-4203-ad28-6313793103b8      L3MSP59               1
3  aeaa4c4d-12e1-4016-bc47-30d08f00041c   CAHWWSMWOD               1
4  42dd34c1-f1ed-4f90-b7af-9261f423ebc9      FXPF4J2               1

             order_created_at_utc  sub_total_amount  tax_total_amount  \
0  2021-04-20 15:38:33.133957+00               110           9.76000
1  2021-04-26 10:27:48.058595+00               220          15.40000
2  2021-04-16 09:36:34.040838+00               110           0.00000
3  2021-04-26 18:05:00.426515+00                50           0.00000
4   2021-04-22 15:08:34.07912+00               110           0.00000
```

```
   shipping_total_amount  fee_total_amount  order_total_amount  \
0                4.68000                 0           124.44000
1                9.52000                 0           244.92000
2                2.51000                 0           113.51000
3                5.98000                 0            55.98000
4                0.00000                 0           110.00000

   requires_payment  charged_amount  charge_refunded  refunded_amount  \
0              True           12444            False              NaN
1              True           24492            False              NaN
2              True           11351            False              NaN
3              True            5598            False              NaN
4              True           11000            False              NaN

  refunded_at_utc                               customer_id  age  gender  \
0             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
1             NaN  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   51  female
2             NaN  20210316112735216-9KTsUNszerowF4A1X1NBhg   24  female
3             NaN  20210317171023585-M2tZ3kjFMaTVmE4shqXxua   35    male
4             NaN   20210317172029708-JQryUiA4jZKCdwq1p8voq   53  female

   income                                           group_id  \
0   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
1   73000  grp-ecae9171-f81d-4c25-9ab8-24b68702f4b9--good…
2   39000  grp-49abab43-13d6-439c-80de-3e98b4083758--good…
3   75000  grp-e49d32ee-df44-4e9e-a3ab-d6ab4b6988d9--good…
4   97000  grp-5228870e-24ec-4e97-a41c-db62394ed4f1--good…

         group_name customer_state customer_country device_type  \
0  Sasquatch's Group             NY               US     Desktop
1      Cobra's Group             NY               US     Desktop
2                NaN            NaN              NaN     Desktop
3   Diablo's Winners             PA               US     Desktop
4       Rigs's Group             NY               US     Desktop

                              orderlineitems_jsonb  row_num  \
0  [{'id': 'oli-NHz5q5rPAh4oj3QtZDfgQ3', 'price':…        1
1  [{'id': 'oli-E8hTJtpoz2uW5v75Bnm7Rd', 'price':…        2
2  [{'id': 'oli-MAucg88ir2tsPhjF9a98Np', 'price':…        1
3  [{'id': 'oli-VJoPK9Jcao9objad3qxYMY', 'price':…        1
4  [{'id': 'oli-DxrhtnugrvEVqBsXgPwHtJ', 'price':…        1

              price  pvariant-gsbrightbluehoodiemedium  \
0          [110.00]                                  1
1  [110.00, 110.00]                                  1
2          [110.00]                                  0
```

```
3    [25.00, 25.00]                                  0
4          [110.00]                                  1

   pvariant-gsbrightbluehoodieextrasmall  pvariant-socksbundle-size  \
0                                      0                          0
1                                      0                          0
2                                      1                          0
3                                      0                          1
4                                      0                          0

   pvariant-truckerhatone-size  pvariant-gsbrightbluesweatsmedium  \
0                            0                                  0
1                            0                                  0
2                            0                                  0
3                            0                                  0
4                            0                                  0

   pvariant-wegoodgreyteemedium  pvariant-gsbrightbluesweatsextrasmall  \
0                             0                                      0
1                             0                                      0
2                             0                                      0
3                             0                                      0
4                             0                                      0

   pvariant-basicwhiteteemedium  pvariant-gsbrightbluebundlemedium  \
0                             0                                  0
1                             0                                  0
2                             0                                  0
3                             0                                  0
4                             0                                  0

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

[231]:

```
# Aggregate customer orders
# Using order revision as a count of rows (items) purchased by that customer
grouped_customers = df.groupby("customer_id").agg({"order_number": lambda x: x.
 ↪nunique(), "order_revision": lambda x: x.count(), "order_total_amount":␣
 ↪lambda x: x.sum(), "age":"first","gender":"first","income":
 ↪"first","customer_state":"first","customer_country":"first"})
grouped_customers.head()
```

[231]:
```
                                          order_number  order_revision  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ             2               2
20210316112735216-9KTsUNszerowF4A1X1NBhg             1               1
20210317171023585-M2tZ3kjFMaTVmE4shqXxua             1               1
20210317172029708-JQryUiA4jZKCdwq1p8voq              1               1
20210317223206213-NfzPJbS9UTFStXosGMDBZV             1               1

                                          order_total_amount  age  gender  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ           369.36000   51  female
20210316112735216-9KTsUNszerowF4A1X1NBhg           113.51000   24  female
20210317171023585-M2tZ3kjFMaTVmE4shqXxua            55.98000   35    male
20210317172029708-JQryUiA4jZKCdwq1p8voq            110.00000   53  female
20210317223206213-NfzPJbS9UTFStXosGMDBZV           465.58000   37  female

                                          income customer_state  \
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ   73000             NY
20210316112735216-9KTsUNszerowF4A1X1NBhg   39000           None
20210317171023585-M2tZ3kjFMaTVmE4shqXxua   75000             PA
20210317172029708-JQryUiA4jZKCdwq1p8voq    97000             NY
20210317223206213-NfzPJbS9UTFStXosGMDBZV   96000           Qro.

                                         customer_country
customer_id
20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ               US
20210316112735216-9KTsUNszerowF4A1X1NBhg             None
20210317171023585-M2tZ3kjFMaTVmE4shqXxua               US
20210317172029708-JQryUiA4jZKCdwq1p8voq                US
20210317223206213-NfzPJbS9UTFStXosGMDBZV               MX
```

[232]:
```python
# Encode categorical features
grouped_customers = pd.get_dummies(grouped_customers, columns =␣
 ↪['gender','customer_state', 'customer_country'])
```

[238]:
```python
grouped_customers.reset_index(inplace=True)
grouped_customers.head()
```

[238]:
```
                                customer_id  order_number  order_revision  \
0  20210316012807791-Xc2t5uiAkLzvTPxjhtJJHQ             2               2
1  20210316112735216-9KTsUNszerowF4A1X1NBhg             1               1
2  20210317171023585-M2tZ3kjFMaTVmE4shqXxua             1               1
3   20210317172029708-JQryUiA4jZKCdwq1p8voq             1               1
4  20210317223206213-NfzPJbS9UTFStXosGMDBZV             1               1

   order_total_amount  age  income  gender_female  gender_male  \
```

```
0         369.36000  51  73000              1           0
1         113.51000  24  39000              1           0
2          55.98000  35  75000              0           1
3         110.00000  53  97000              1           0
4         465.58000  37  96000              1           0

   customer_state_AL  customer_state_BC  customer_state_BY  customer_state_CA  \
0                  0                  0                  0                  0
1                  0                  0                  0                  0
2                  0                  0                  0                  0
3                  0                  0                  0                  0
4                  0                  0                  0                  0

   customer_state_CT  customer_state_Kharkivs'ka oblast  customer_state_MA  \
0                  0                                  0                  0
1                  0                                  0                  0
2                  0                                  0                  0
3                  0                                  0                  0
4                  0                                  0                  0

   customer_state_MN  customer_state_NJ  customer_state_NY  customer_state_PA  \
0                  0                  0                  1                  0
1                  0                  0                  0                  0
2                  0                  0                  0                  1
3                  0                  0                  1                  0
4                  0                  0                  0                  0

   customer_state_PR  customer_state_Qro.  customer_state_SK  \
0                  0                    0                  0
1                  0                    0                  0
2                  0                    0                  0
3                  0                    0                  0
4                  0                    1                  0

   customer_state_UP  customer_country_CA  customer_country_DE  \
0                  0                    0                    0
1                  0                    0                    0
2                  0                    0                    0
3                  0                    0                    0
4                  0                    0                    0

   customer_country_IN  customer_country_MK  customer_country_MX  \
0                    0                    0                    0
1                    0                    0                    0
2                    0                    0                    0
3                    0                    0                    0
4                    0                    0                    1
```

	customer_country_RS	customer_country_UA	customer_country_US
0	0	0	1
1	0	0	0
2	0	0	1
3	0	0	1
4	0	0	0

Since k-means is a distance-based metric, it's important to scale features so that one feature with a very large scale (income) does not drive the algorithm

[257]:
```
scaler = MinMaxScaler()
features = grouped_customers.drop("customer_id", axis=1)
scaled_features = scaler.fit_transform(features)
```

We'll use elbow method and within-cluster-sum-of-squares (sum of distances of observations from their cluster centroids) to determine best number of clusters

[258]:
```
wcss=[]

# fit kmeans and compute wcss for a range of cluster values
for i in range(1,16):
    kmeans = KMeans(n_clusters=i, init ='k-means++', max_iter=300, ␣
 ↪n_init=10,random_state=0 )

    kmeans.fit(scaled_features)

    wcss.append(kmeans.inertia_)
```

[258]: KMeans(n_clusters=1, random_state=0)

[258]: KMeans(n_clusters=2, random_state=0)

[258]: KMeans(n_clusters=3, random_state=0)

[258]: KMeans(n_clusters=4, random_state=0)

[258]: KMeans(n_clusters=5, random_state=0)

[258]: KMeans(n_clusters=6, random_state=0)

[258]: KMeans(n_clusters=7, random_state=0)

[258]: KMeans(random_state=0)

[258]: KMeans(n_clusters=9, random_state=0)

[258]: KMeans(n_clusters=10, random_state=0)

[258]: KMeans(n_clusters=11, random_state=0)

[258]: KMeans(n_clusters=12, random_state=0)

[258]: KMeans(n_clusters=13, random_state=0)

[258]: KMeans(n_clusters=14, random_state=0)

[258]: KMeans(n_clusters=15, random_state=0)

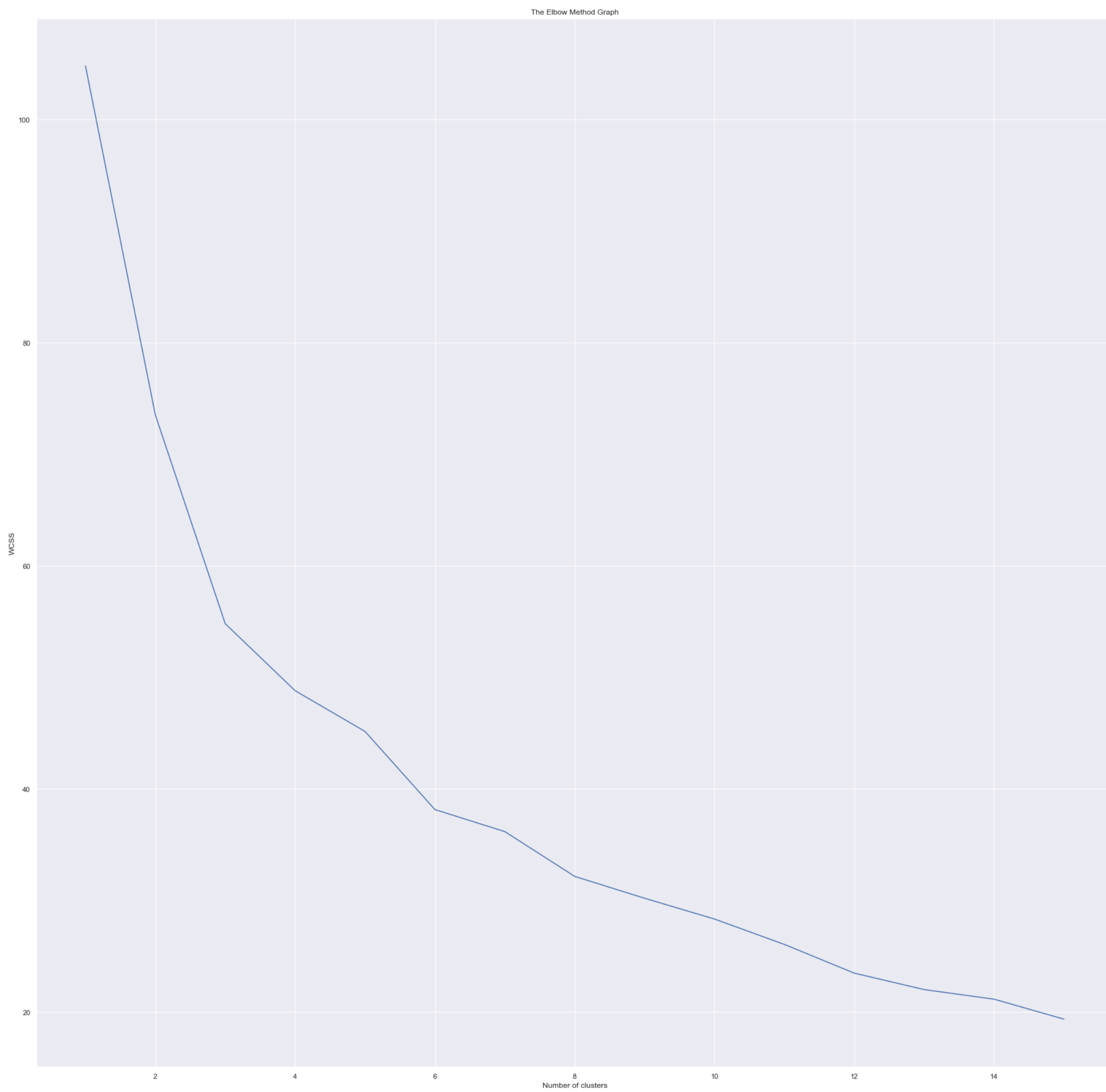
[259]:
```
# Plot the elbow graph
plt.plot(range(1,16),wcss)
plt.title('The Elbow Method Graph')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```

[259]: [<matplotlib.lines.Line2D at 0x7f85b9893670>]

[259]: Text(0.5, 1.0, 'The Elbow Method Graph')

[259]: Text(0.5, 0, 'Number of clusters')

[259]: Text(0, 0.5, 'WCSS')



Seems like elbow around 6 clusters.

[260]:
```
preprocessor = Pipeline(
    [
        ("scaler", MinMaxScaler()),
        ("pca", PCA(n_components=2, random_state=42)),
    ]
)
```

[261]:
```
n_clusters = 6
clusterer = Pipeline(
   [
       (
           "kmeans",
```

```
            KMeans(
                n_clusters=n_clusters,
                init="k-means++",
                n_init=50,
                max_iter=500,
                random_state=42,
            ),
        ),
    ]
)
```

[262]:
```
pipe = Pipeline(
    [
        ("preprocessor", preprocessor),
        ("clusterer", clusterer)
    ]
)
```

[264]:
```
pipe.fit(features)
```

[264]:
```
Pipeline(steps=[('preprocessor',
                 Pipeline(steps=[('scaler', MinMaxScaler()),
                                 ('pca',
                                  PCA(n_components=2, random_state=42))])),
                ('clusterer',
                 Pipeline(steps=[('kmeans',
                                  KMeans(max_iter=500, n_clusters=6, n_init=50,
                                         random_state=42))]))])
```

[265]:
```
preprocessed_data = pipe["preprocessor"].transform(features)

predicted_labels = pipe["clusterer"]["kmeans"].labels_

silhouette_score(preprocessed_data, predicted_labels)
```

[265]:
```
0.8403284558572204
```

This silhouette score indicates that observations are closer to the centroids in their assigned clusters than to other clusters

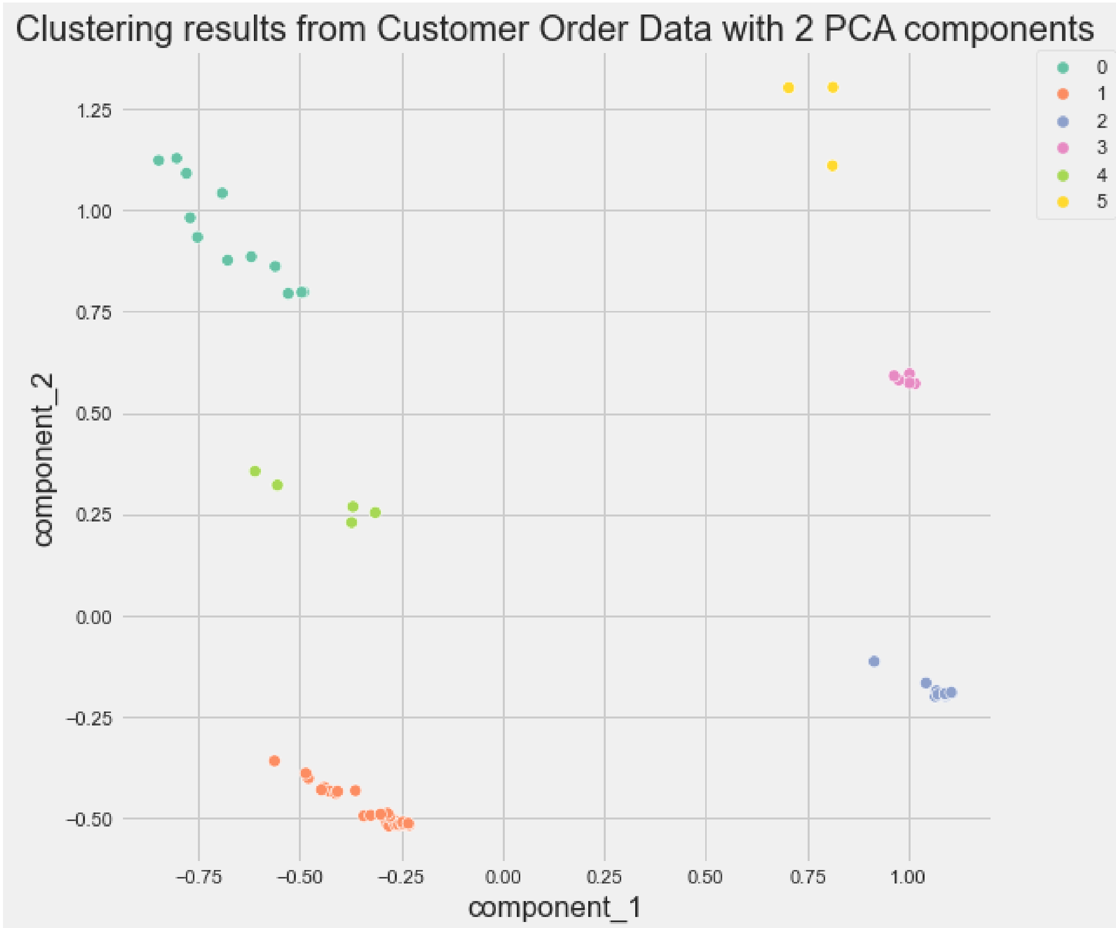
[267]:
```
pcadf = pd.DataFrame(
    pipe["preprocessor"].transform(features),
    columns=["component_1", "component_2"],
)

pcadf["predicted_cluster"] = pipe["clusterer"]["kmeans"].labels_
# pcadf["true_label"] = label_encoder.inverse_transform(true_labels)
```

```
plt.style.use("fivethirtyeight")
plt.figure(figsize=(8, 8))

scat = sns.scatterplot(
    "component_1",
    "component_2",
    s=50,
    data=pcadf,
    hue="predicted_cluster",
    # style="true_label",
    palette="Set2",
)

scat.set_title(
    "Clustering results from Customer Order Data with 2 PCA components"
)
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.0)
plt.savefig('../reports/figures/customer_segmentation.png')
plt.show()
```

[267]: <Figure size 576x576 with 0 Axes>

[267]: Text(0.5, 1.0, 'Clustering results from Customer Order Data with 2 PCA components')

[267]: <matplotlib.legend.Legend at 0x7f859ab03b80>



4 Discussion/Next Steps

- I created this challenge in a full project to illustrate my work flow process and how I start most data science projects.
- This project is started from a custom Cookiecutter template I created based off of my repeated experience building DS pipelines, and is pre-loaded with structure, tools, requirements, makefile, etc. that I feel lead to a consistent and efficient MVP. This template can be found here: Jessica Rudd's cookiecutter data science template
- This template also includes a Data Science Project Checklist for quickly starting a DS project.
- After building experimental code in a Jupyter Notebook (as in this challenge), I would then start modularizing the relevant pieces of this code into a package within the structure under 'src' folder as well as building out a test suite with pytest.
- Package code could be pushed to an internal pypi server for sharing among colleagues and/or packaged into a Docker container for easy portabilty among systems.
- I believe starting projects with this structure lends itself to good code and experiment habits and, hopefully, leads to smoother handoffs between data scientists and engineers, i.e. preventing models from dying in PowerPoint hell without ever being productionalized. :-)

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```