Capstone 1 Report

Objective

The store wants to know better the customer purchase behavior against different products. Specifically, here the problem is a regression problem where we are trying to predict the dependent variable (the amount of purchase) with the help of the information contained in the other variables. Line of questioning:

1. What are the characteristics of my top revenue generators?
2. Who buys the top products?
3. To what accuracy can we predict purchase amount?

Step 1: Data Wrangling

Data acquisition:

Data has been provided and is taken from Kaggle competition at the below location: https://www.kaggle.com/mehdidag/black-friday. There is a file 'BlackFriday' of size ~25 Mb containing shopping patterns of a store on black Friday with 537,577 records which is made available for the task at hand.

Data type and null values:

From the total of 12 columns, 2 columns have null values 'Product_Category_2' and 'Product_Category_3'. These product categories have float64 as type compared to int64 of 'Product_Category_1' column.

```
# Lets see the data types and null values
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 537577 entries, 0 to 537576
Data columns (total 12 columns):
User_ID                     537577 non-null int64
Product_ID                  537577 non-null object
Gender                      537577 non-null object
Age                         537577 non-null object
Occupation                  537577 non-null int64
City_Category               537577 non-null object
Stay_In_Current_City_Years  537577 non-null object
Marital_Status              537577 non-null int64
Product_Category_1          537577 non-null int64
Product_Category_2          370591 non-null float64
Product_Category_3          164278 non-null float64
Purchase                    537577 non-null int64
dtypes: float64(2), int64(5), object(5)
memory usage: 49.2+ MB
```

Before

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 537577 entries, 0 to 537576
Data columns (total 13 columns):
User_ID                     537577 non-null int64
Product_ID                  537577 non-null object
Gender                      537577 non-null object
Age                         537577 non-null object
Occupation                  537577 non-null int64
City_Category               537577 non-null object
Stay_In_Current_City_Years  537577 non-null object
Marital_Status              537577 non-null int64
Purchase                    537577 non-null int64
ProdCat1                    537577 non-null int64
ProdCat2                    537577 non-null int32
ProdCat3                    537577 non-null int32
ProdCombo                   537577 non-null object
dtypes: int32(2), int64(5), object(6)
memory usage: 49.2+ MB
```

After

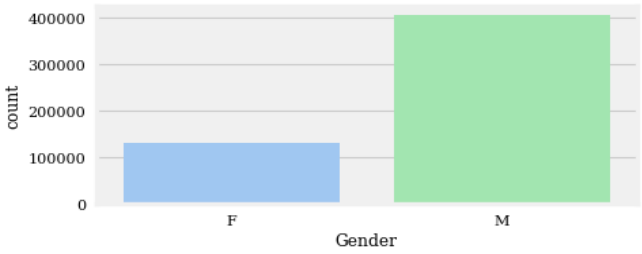
1. First, let's handle the null values. Upon checking the null columns, it is found that none of them have the value 0 as product category. So, a decision to replace the null values to 0 is taken.
2. Next, the columns of Product_Category_* are renamed for ease of understanding to ProdCat* and during the process, Product_Category_2 and Product_Category_3 are converted from float64 to int64 type. The original Product_Category_* columns are dropped.
3. We checked if column User_ID represents a unique person by grouping by User_ID and Gender. The count of the unique User_ID was compared to the group by count and it matched. It can therefore be concluded that User_ID is associated with a unique person.
4. We can now check if the Product_ID – User_ID is a unique combination by same means. It can be seen that group by count also matches with the total number or records. It can therefore be concluded that Product_ID – User_ID is a unique key for the dataset.
5. We can now investigate if the product combination is related to a unique product ID. We do a group by of the ProdCat* columns and compare the counts to that of Product_ID. They do not match. Therefore, Product_ID does not seem to be directly related to the combination of categories.

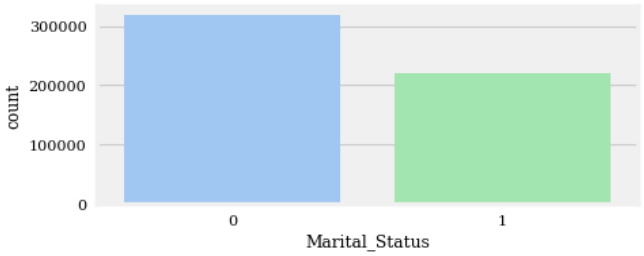
6. The above point can be expanded to the ordering of ProdCat* columns can be permanently captured in a separate called 'ProdCombo'. This order is compared to that of the Product_ID and again there doesn't seem to be any specific relation. It can also be said that the same combo of records could exist with a different Product_ID.
7. Let's check out some rows and confirm this. It can be seen that for User_ID 1001015, the same ProdCombo has 3 different Product_IDs.

Step 2: Exploratory Data Analysis - Inferential Statistics

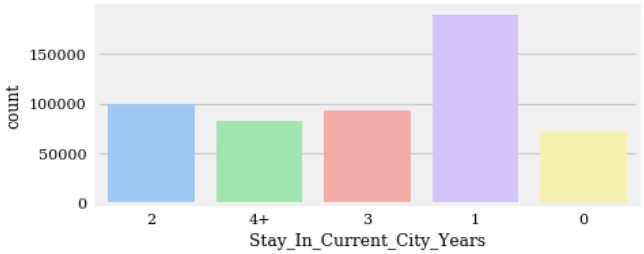
Data Visualization:

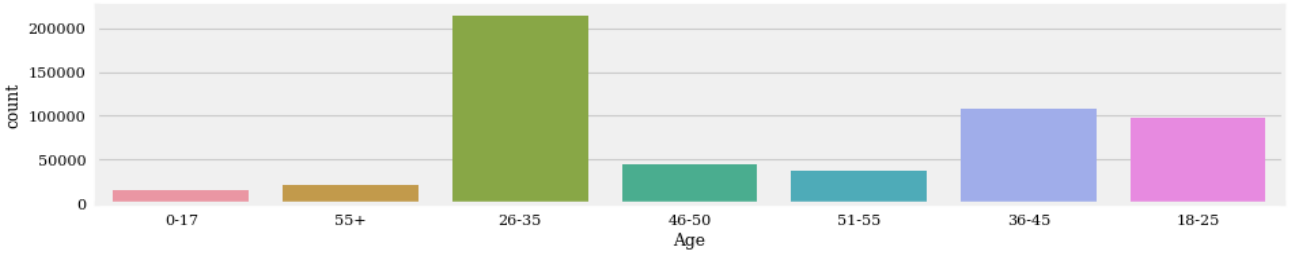
- Looking at the spread of the data by doing a Histogram, it can be inferred that most of the purchases are between $3,000 and $12,000 and around $16,000 mark.
- A count-plot is used to see how the data is spread amongst each of the individual variables of Gender, Marital_Status, City_Category, Stay_In_Current_City_Years, Age and Occupation. Following inferences can be made:
  1. Men shopped 3 times as much as women. This could be due to the fact that men paid for the purchases too.
  2. Singles shopped more times than married ones. May be they have more disposable income.
  3. Maximum number of purchases were made by people from City B, and people from cities A and C shop approximately the same number of times.
  4. People who have been in the city for a year shop most frequently.
  5. People between the age group of 26-35 shop the most followed by 36-45 and 18-25 groups
  6. People in occupations 0, 4, 7 shop the most and 8 shop the least.
- Looking at the count plots of Product categories, these observations can be made:
  1. It can be seen that products 1, 5 and 8 from Category 1 dominate the sales numbers by far and seem to be the favorites.
  2. There are a large number of products in Categories 2 and 3 that are either missing or not shopped for. Products in category 3 have very low numbers.
  3. Although Category 2 is not all that popular, there are some products that seems to be popular. Such as 2,8,14 and 16.


count
400000
300000
200000
100000
0
F
M
Gender

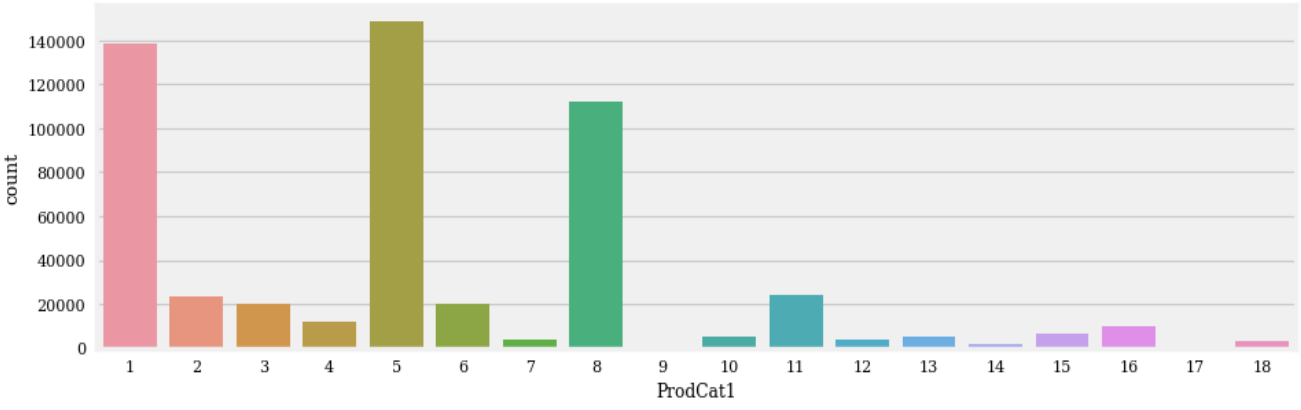

count
300000
200000
100000
0
0
1
Marital_Status

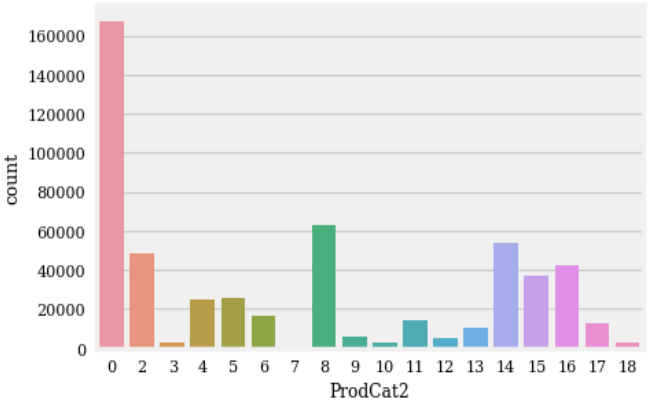

count
200000
150000
100000
50000
0
A
C
B
City_Category


count
150000
100000
50000
0
2
4+
3
1
0
Stay_In_Current_City_Years


count
200000
150000
100000
50000
0
0-17
55+
26-35
46-50
51-55
36-45
18-25
Age


count
60000
40000
20000
0
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
Occupation


count
140000
120000
100000
80000
60000
40000
20000
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
ProdCat1


count
160000
140000
120000
100000
80000
60000
40000
20000
0
0
2
3
4
5
6
7
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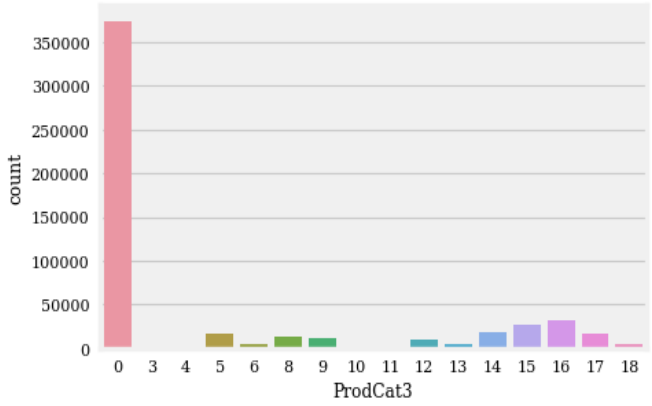
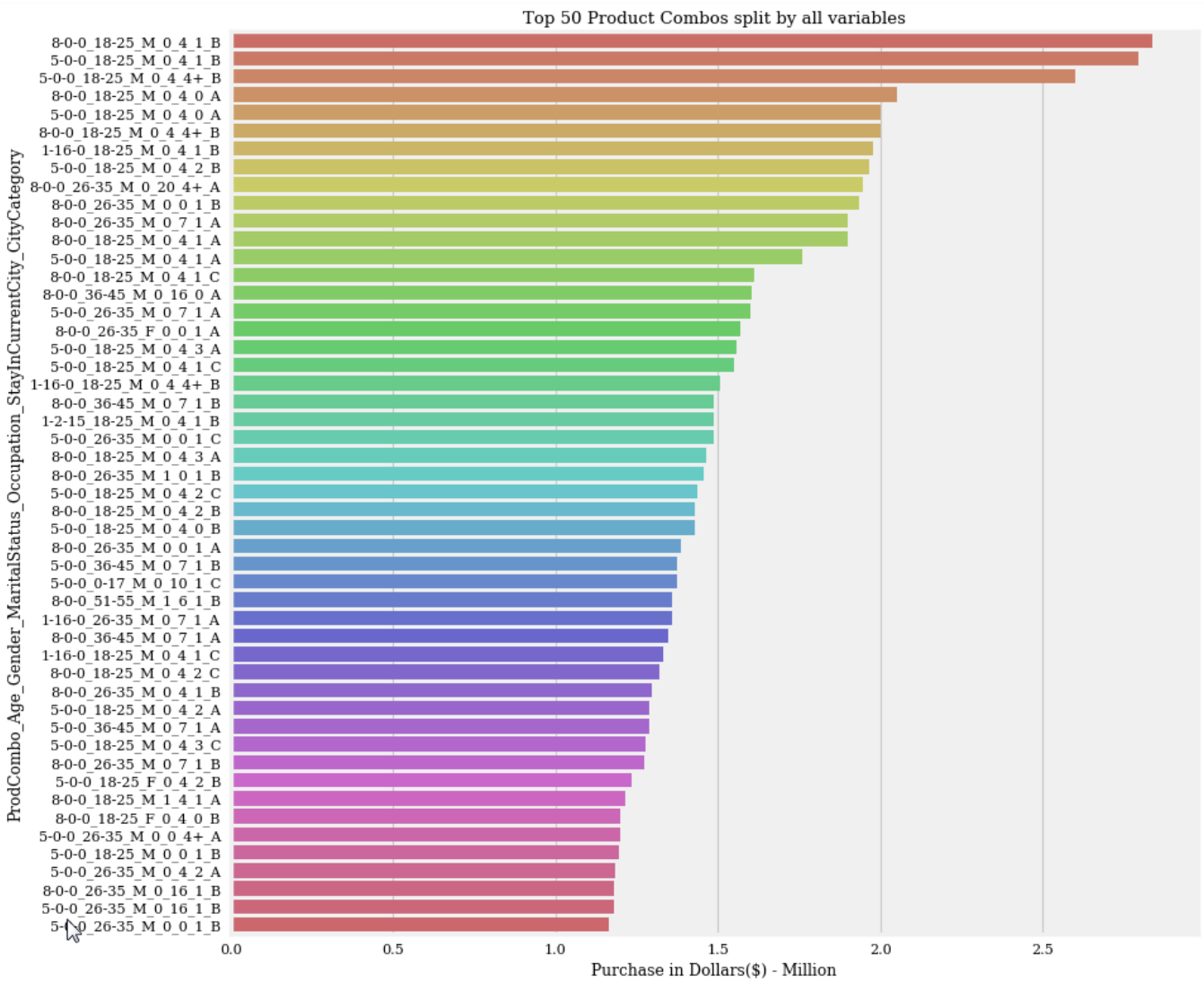
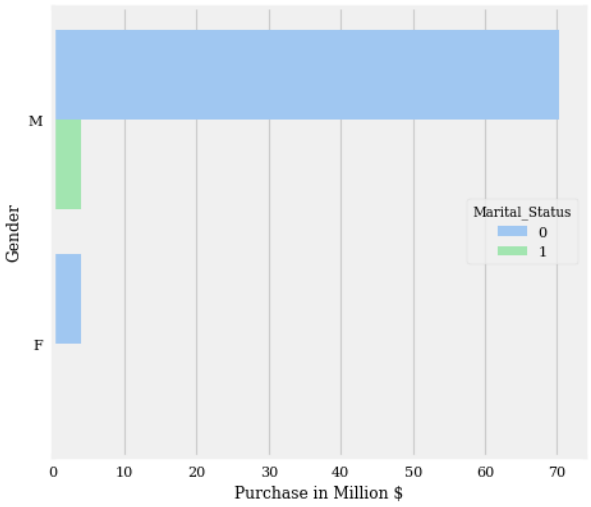
11
12
13
14
15
16
17
18
ProdCat2

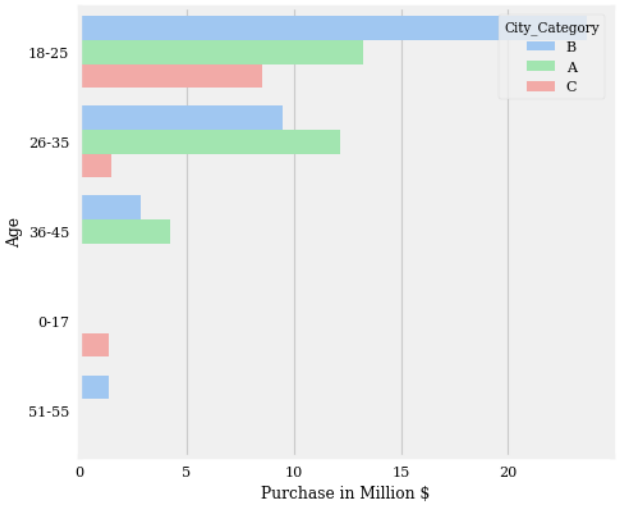

count
350000
300000
250000
200000
150000
100000
50000
0
0
3
4
5
6
8
9
10
11
12
13
14
15
16
17
18
ProdCat3

- Next we look at the influence of the same variables on total purchase value to see how it compares. Comparing this to the counts plots, it is now clear that the distribution in amounts is sort of similar to the distribution in counts. This means that we cannot see any variable disproportionately affecting the purchase. For example, it could have been possible that women bought all the expensive products and even though they shopped less number of times, they could have generated the most revenue. The two plots seems somewhat similar and we can conclude that no variable/distribution needs special attention.

❖ By looking at the total purchase value breakdown by product category, it is clear that there could be lot of hidden information from various combination of the categories. So we ask 2 questions and create a master plot of top 50 product combinations to uncover more info. But this needs to be looked in conjunction with the how other variables influence these 50 combos.



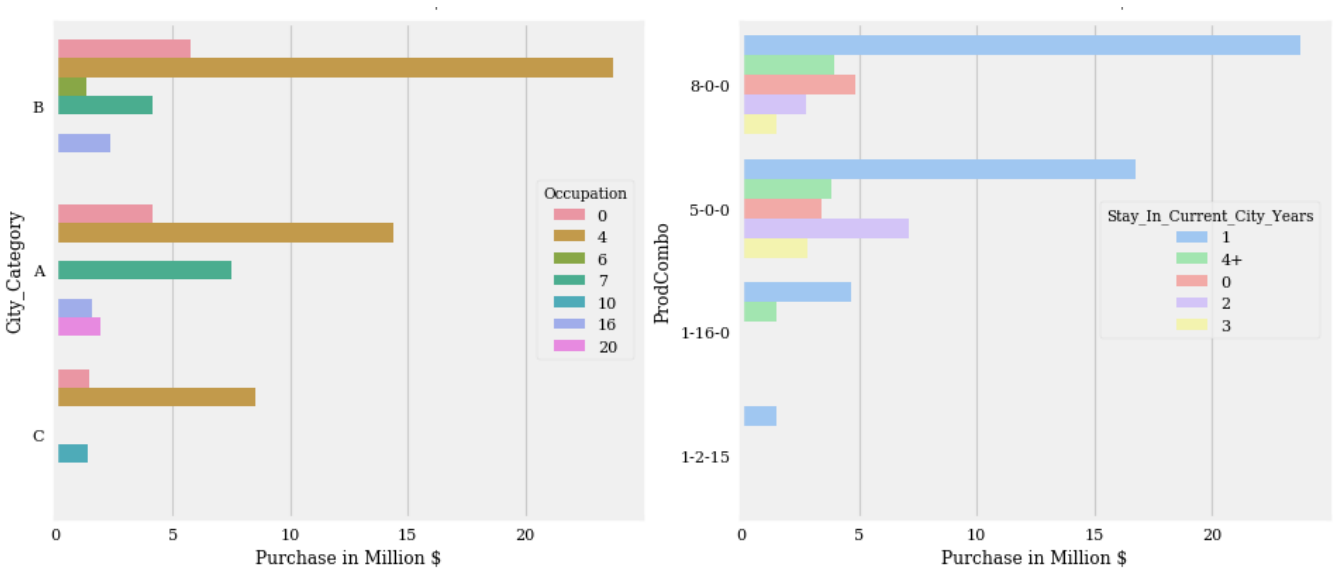




1. **What are the characteristics of my top revenue generators or who is my target audience?**
   Driven by data of top 50 combos, it can be inferred that:

a) Single males buy the most

b) These single males are mainly from city B, in age group of 18-35. They are followed by city A in age groups of 18-25 and 25-36.



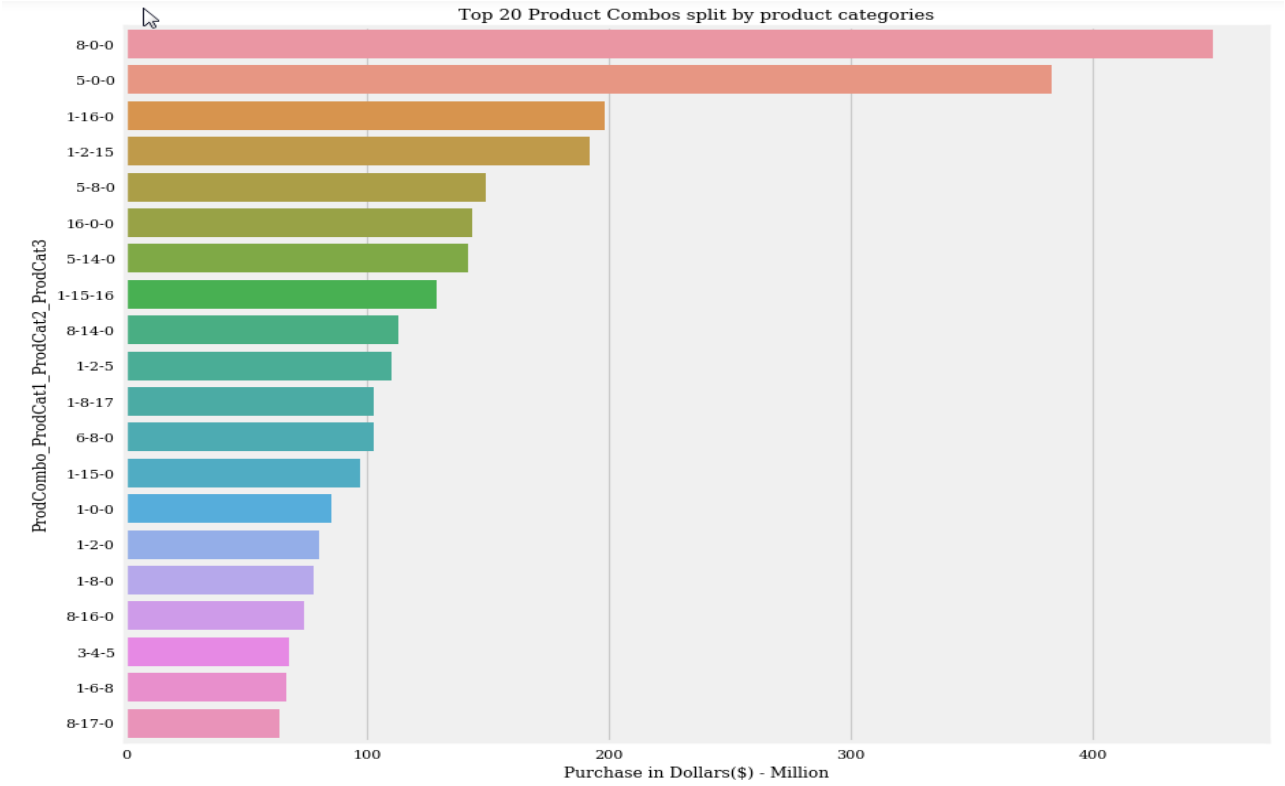
c) A disproportionate number of these people are in Occupation 4, mainly buying from city B and A.

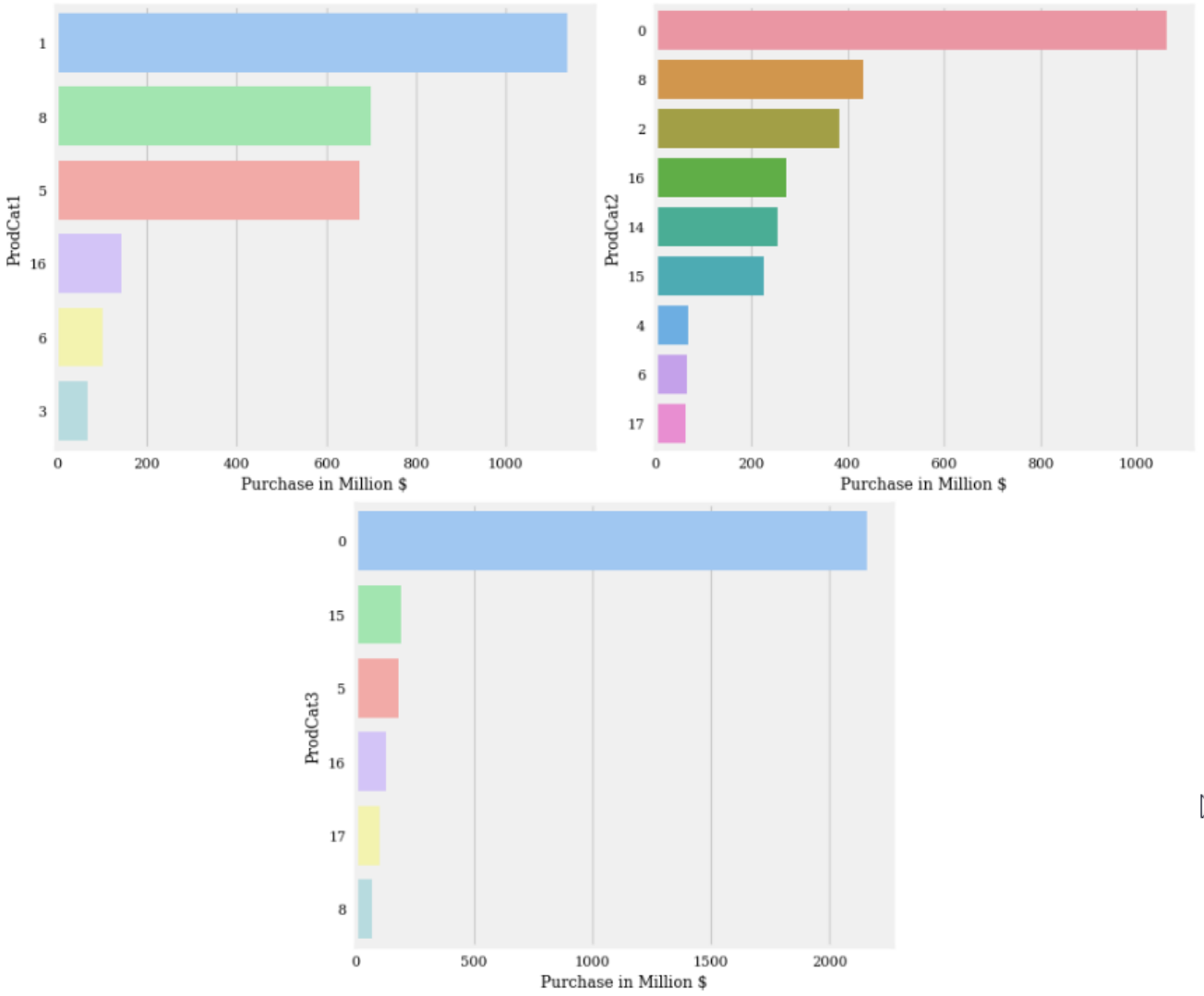
d) People who mainly buy ProdCombos 8-0-0 and 5-0-0 have been living in the city around 1 year.

Answer: The target/valuable audience for Black Friday sale are single males from cities A and B in the age group of 18-35 in occupation 4 who have been living in their cities for around 1 year.

2. Who buys the top product combinations?

For this analysis, we restrict the top 50 to further of top 20 product combinations to get some meaningful conclusion. In the top 20 combos, you can now confirm that product 1 in Category 1 still has the most number of combos and generates the highest revenue, followed by 8 and 5. In terms of combos across all three categories, 1-2-15, 1-15-16 and 1-2-5 are frequently bought together.





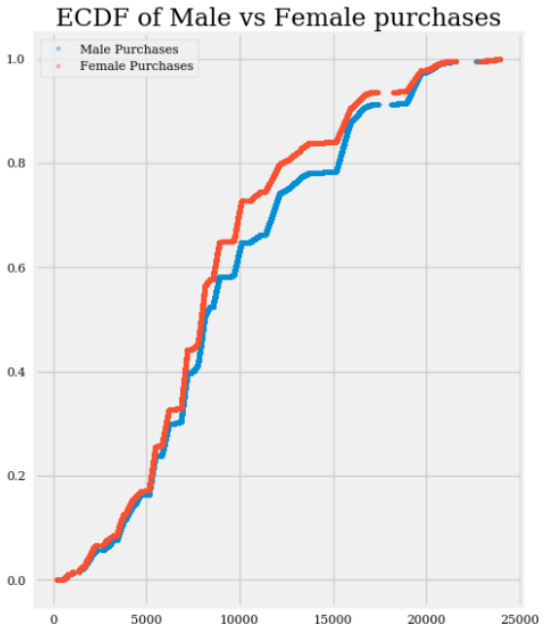
Overall, assuming that these 3 categories have independent products, the top products are:

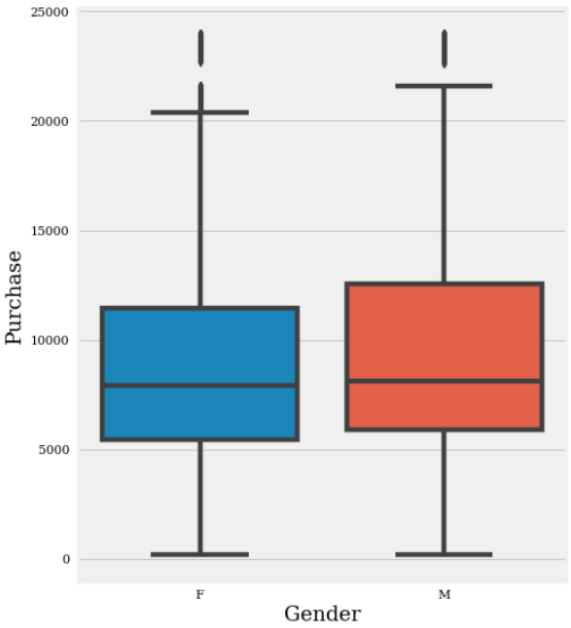
a) Category 1: 1,8,5
b) Category 2: 8,2,16
c) Category 3: 15,5,16

Step 3 Inferential Statistics: To find out hidden relationship, we ask some interesting questions.

Question 1: Do men buy more expensive things than women?

To find out this, we plot ECDF of Male vs Female Purchases and compliment that with a box plot.





It seems like men tend to make more expensive purchases by looking at ECDF. Expensive purchase = $10,000.

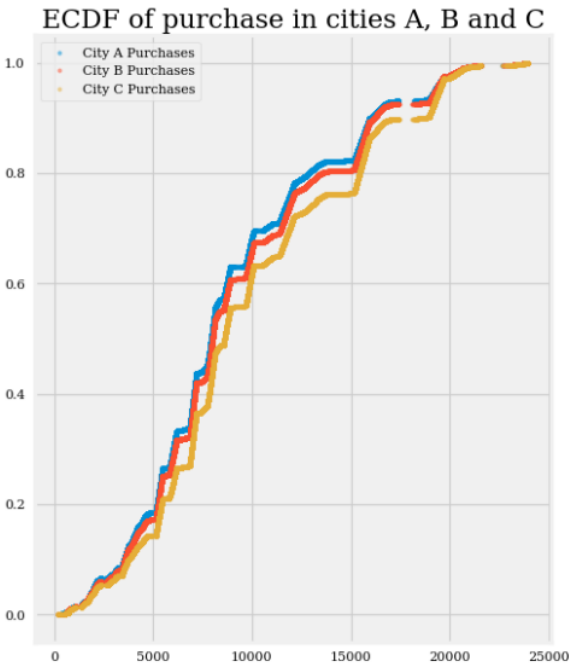
- **H0**: The average purchase price by men is the same as women for expensive items.
- **H1**: The average purchase price by men is more than women for expensive items.

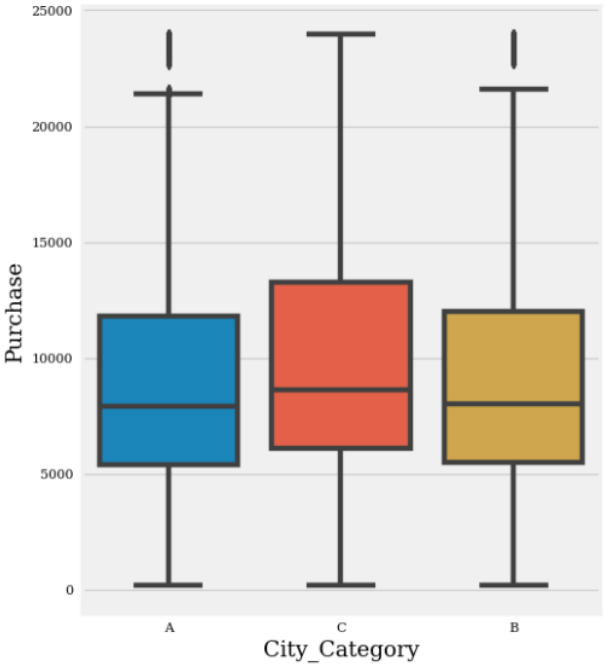
Findings:

- Mean of men's purchase is: 15068.7163
- Mean of women's purchase is: 14931.9739
- Mean of total purchase is: 15082.73146804466
- The probability that average purchases by men is equal to that of women is 0.002
- This negates the null hypothesis. Meaning the average purchase price by men is more than women for expensive items.

Question 2: Do people shop equally in all three cities?

To find out this, we plot ECDF of Purchases in cities A, B and C along with a box plot.





From the ECDF and box plots, we can see that in general people from city C generate more revenue. Whereas people from city A and B seems to have similar buying patterns. But does is mean people from city C also spend more? We will take the "Average Purchase value" as the measure for this. Let's see the statistical significance of this happening.

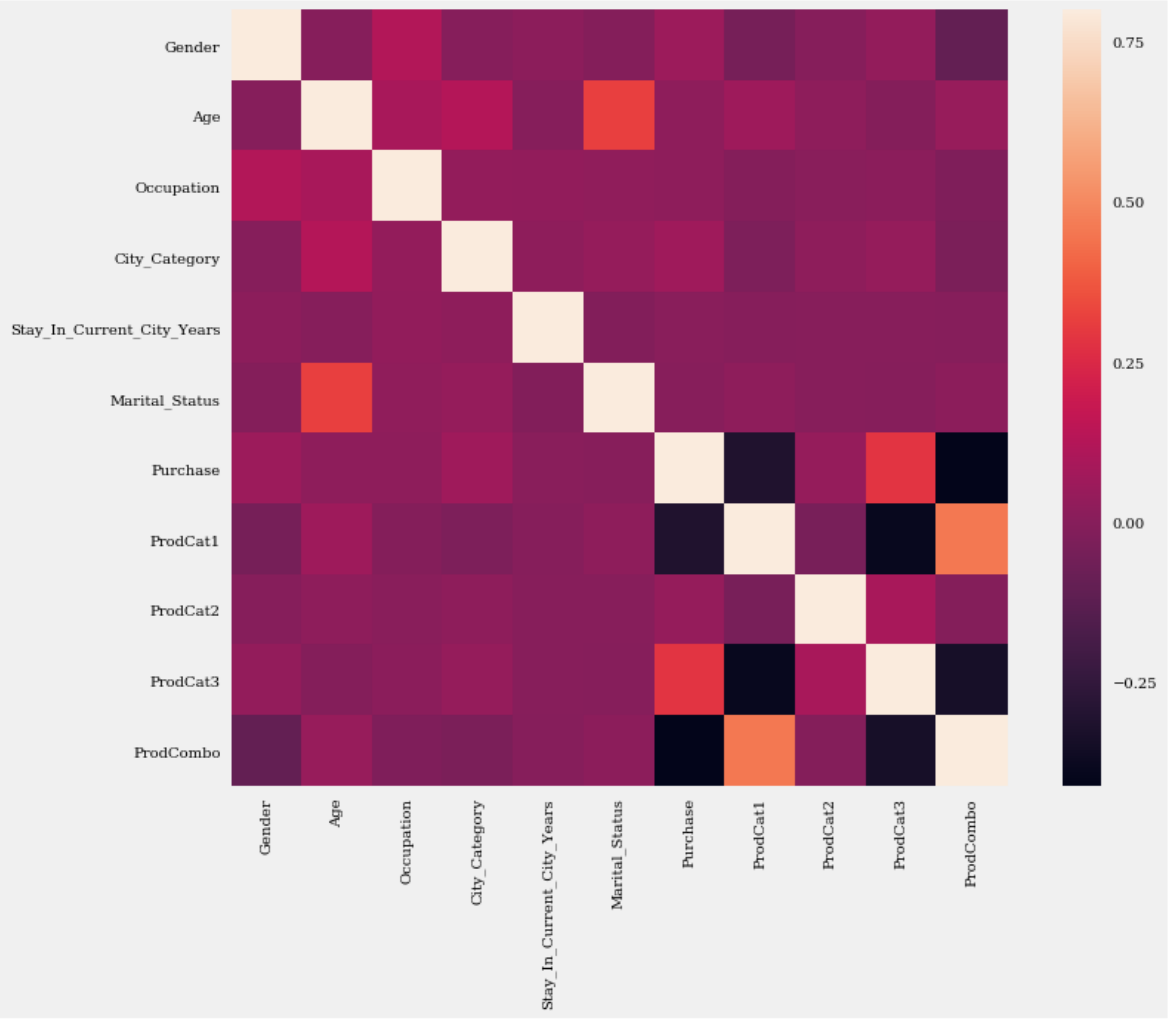
- **H0**: The average purchase price by people in cities A, B and C is the same.
- **H1**: The average purchase price by people in cities A, B and C is NOT the same.

Findings:

- The mean purchase value by people from city A is: 9131.392
- The mean purchase value by people from city B is: 9366.509
- The mean purchase value by people from city C is: 9792.204
- The probability that average purchases from City A are equal to City C are: 0.001
- The probability that average purchases from City A are equal to City B are: 0.141
- The probability that average purchases from City B are equal to City C are: 0.028
- This negates the null hypothesis. Meaning, the average purchase price by people in cities A, B and C is NOT the same.

Correlations

Let's see if there are any correlations in the variables. In order to do that, let's plot them in a heat map.



Findings: Marital status seems to have strong positive correlation with Age. And ProdCat1 seems to be strongly correlated with ProdCombo, but this does not mean much. It could be possible that there are a lot of products from Category1 in ProdCombo column. There is slight negative correlation between Purchase and ProdCat3 and ProdCombo,

which means there are a lot fewer items of category 3. Other than that, there doesn't seems to be any strong correlation between the variables.

Step 4: In-Depth Analysis

Traditional Approach

The categorical variables were encoded using one-hot encoding:
Gender as Gender_enc, Age as Age_*, City_Category as City_*, Stay_In_Current_City_Years as stay, Occupation as occu, ProdCombo as pc_*, ProdCat1 as pc1_*, ProdCat2 as pc2_*, ProdCat3 as pc3_*. The continuous variable was chosen as target and various models were tried out.

Linear Regression: There are 122 features that give the below results
R^2 with Prod Categories: 0.6376223400425602
Root Mean Squared Error with Prod Categories: 2989.4402029238413
Cross validation score is with Prod Categories: 0.6389821282926864

Decision Tree: A configuration of (max_depth=15, min_samples_leaf=100) gave the below results.
R^2: 0.635121867047957
Root Mean Squared Error: 2999.736317822526

Elastic CV: A configuration of (cv=5, alphas=np.linspace(0.001,1,50)) gave the below results
R^2: 0.6400716117954796
Root Mean Squared Error: 2993.6060388057804

Random Forest: A configuration of (max_depth=16, n_estimators=90) gave the below result
R^2: 0.6424529101374172
Root Mean Squared Error: 2983.686705716457

In general we are not getting past the 0.65 accuracy mark. Let's try some feature engineering to improve the scores.

Feature Engineering

Four functions were created that return

1. Average Purchase Value per column.
2. Average Count of column
3. Total count of column
4. Median purchase value of column

New columns were created after applying the above functions for each of the categorical variables such as Age, Occupation, Stay_In_Current_City_Years, ProdCat1, ProdCat2, ProdCat3, Gender, City_Category, ProdCombo, User_ID and Product_ID.

After Feature engineering results: The models were again tried to see if there was any improvement.

Linear Regression:
R^2: 0.7176789707438745
Root Mean Squared Error: 2638.6438593275593
Cross validation score with new features is: 0.7191447714961551

Decision Tree: Configuration of **(**max_depth=400, min_samples_leaf=112, min_samples_split=40) gave

R^2 Test: 0.7373382707106608
Root Mean Squared Error Test: 2552.277662635797

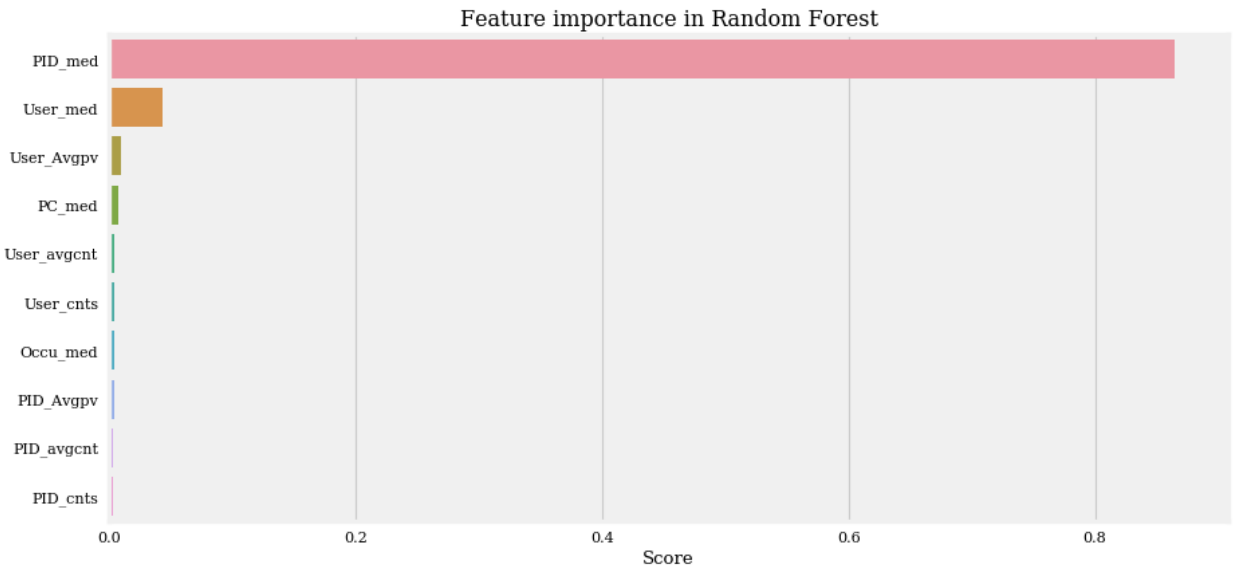
Elastic CV: A configuration of (cv=5, alphas=np.linspace(0.001,1,50)) gave the below results
R^2: 0.7197624634394806
Root Mean Squared Error: 2641.494731114654

Random Forest: A configuration of (max_depth=16, n_estimators=90) gave the below result
R^2: 0.7467830310391308
Root Mean Squared Error: 2510.7525519630262

Conclusion

It can be concluded that feature engineering helped boost the overall accuracy score past 70% to 74.6%. The model of choice would be Random Forest.

Here is the feature importance chart.



As you can see, the engineered feature of median price of Product_ID is the most important one.

Further investigation:

1. Instead of setting the missing values to 0, we can try putting in mean/median values in the product category and checking if the prediction would be any different.
2. Try more parameters to see if Random Forest can be more effective in increasing accuracy.
3. Try Gradient Boosting and XGB to see if it is any better than Random Forest.
4. Try Neural Network Regression – feature engineering is not usually needed with neural networks as they are really good at detecting hidden features. Try to see if gives better accuracy.