Aegis School of Data Science, Mumbai

Project Report II

Black Friday Sales Prediction (Regression)

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Abstract

In this project, we experiment with real world dataset for classification. We explore few machine learning classification algorithms to fit the data. We were expected to gain experience using scikit ML library and how different algorithms works over a specific data. We have to explore the dataset using EDA processes then fit multiple models and tune the hyper parameters to get the maximum accuracy. A retail company wants to understand the customer purchase behaviour (specifically, purchase amount) against various products of different categories. After performing required tasks, herein lies our final project report.

1.Introduction:

We have selected regression challenge that is hosted on www.analyticsvidhya.com. In this challenge, we have to predict the purchase amount of customer against various products which will help to create personalized offer for customers against different products. In order to do this, complete information about They have shared purchase summary of various customers for selected high volume products from last month. The data set also contains customer demographics (age, gender, marital status, city_type, stay_in_current_city), product details (product_id and product category) and Total purchase_amount from last month

2. Problem Definition

The task is to predict the purchase amount of customer against various products for black Friday sale. In order to do this, complete information about the data set contains customer demographics (age, gender, marital status, city_type, stay_in_current_city), product details (product_id and product category) and Total purchase_amount from last month is given.

Now, we have to build a model to predict the purchase amount of customer against various products which will help them to create personalized offer for customers against different products. The output of a prediction is a continuous variable.

Official website: https://datahack.analyticsvidhya.com/contest/black-friday/

3. Exploratory Data Analysis

3.1 Descriptive Analysis:

Dataset csv files : train.csv

We have 550068 data points consisting 12 features.

Data Description :

| Variable | Definition | |
|----------------------------|---|--|
| User_ID | User ID | |
| Product_ID | Product ID | |
| Gender | Sex of User | |
| Age | Age in bins | |
| Occupation | Occupation (Masked) | |
| City_Category | Category of the City (A,B,C) | |
| Stay_In_Current_City_Years | Number of years stay in current city | |
| Marital_Status | Marital Status | |
| Product_Category_1 | Product Category (Masked) | |
| Product_Category_2 | Product may belongs to other category also (Masked) | |
| Product_Category_3 | Product may belongs to other category also (Masked) | |
| Purchase | Purchase Amount (Target Variable) | |

train.csv contain columns as follows:

| # | Column | Non-Null | L Count | Dtype |
|----|----------------------------|----------|----------|---------|
| | | | | |
| 0 | User_ID | 550068 | non-null | int64 |
| 1 | Product_ID | 550068 | non-null | object |
| 2 | Gender | 550068 | non-null | object |
| 3 | Age | 550068 | non-null | object |
| 4 | Occupation | 550068 | non-null | int64 |
| 5 | City_Category | 550068 | non-null | object |
| 6 | Stay_In_Current_City_Years | 550068 | non-null | object |
| 7 | Marital_Status | 550068 | non-null | int64 |
| 8 | Product_Category_1 | 550068 | non-null | int64 |
| 9 | Product_Category_2 | 376430 | non-null | float64 |
| 10 | Product_Category_3 | 166821 | non-null | float64 |
| 11 | Purchase | 550068 | non-null | int64 |

Missing Values:

| In [7]: | df.isnull().sum() | | | |
|---------|----------------------------|--------|--|--|
| Out[7]: | User ID | 0 | | |
| | Product ID | 0 | | |
| | Gender | 0 | | |
| | Age | 0 | | |
| | Occupation | 0 | | |
| | City Category | 0 | | |
| | Stay In Current City Years | 0 | | |
| | Marital_Status | 0 | | |
| | Product Category 1 | 0 | | |
| | Product_Category_2 | 173638 | | |
| | Product Category 3 | 383247 | | |
| | Purchase | 0 | | |
| | dtype: int64 | | | |

Here, we can see that, Product_Category_2, Product_Category_3 has many missing values i.e. 173638, 383247 respectively. We impute it using a constant.

Description of data:

In [5]: df.describe()

Out[5]:

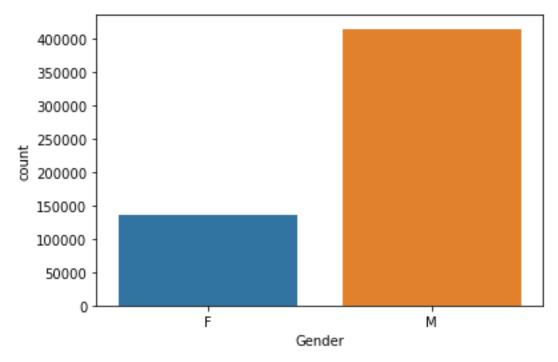
| | User_ID | Occupation | Marital_Status | Product_Category_1 | Product_Category_2 | Product_Category_3 | Purchase |
|-------|--------------|---------------|----------------|--------------------|--------------------|--------------------|---------------|
| count | 5.500680e+05 | 550068.000000 | 550068.000000 | 550068.000000 | 376430.000000 | 166821.000000 | 550068.000000 |
| mean | 1.003029e+06 | 8.076707 | 0.409653 | 5.404270 | 9.842329 | 12.668243 | 9263.968713 |
| std | 1.727592e+03 | 6.522660 | 0.491770 | 3.936211 | 5.086590 | 4.125338 | 5023.065394 |
| min | 1.000001e+06 | 0.000000 | 0.000000 | 1.000000 | 2.000000 | 3.000000 | 12.000000 |
| 25% | 1.001516e+06 | 2.000000 | 0.000000 | 1.000000 | 5.000000 | 9.000000 | 5823.000000 |
| 50% | 1.003077e+06 | 7.000000 | 0.000000 | 5.000000 | 9.000000 | 14.000000 | 8047.000000 |
| 75% | 1.004478e+06 | 14.000000 | 1.000000 | 8.000000 | 15.000000 | 16.000000 | 12054.000000 |
| max | 1.006040e+06 | 20.000000 | 1.000000 | 20.000000 | 18.000000 | 18.000000 | 23961.000000 |

Skewness in data:

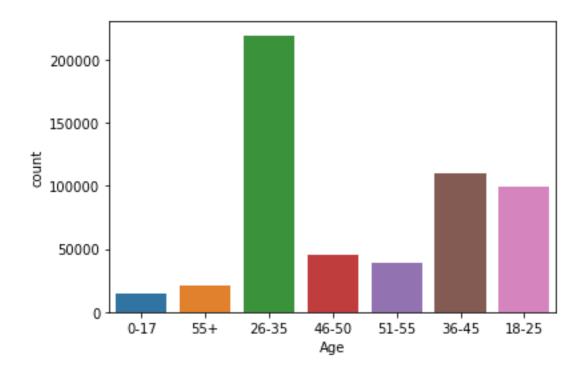
| User ID | 0.003066 |
|--------------------|-----------|
| Occupation | 0.400140 |
| Marital_Status | 0.367437 |
| Product Category 1 | 1.025735 |
| Product Category 2 | -0.162758 |
| Product Category 3 | -0.765446 |
| Purchase | 0.600140 |

 $\label{lem:product_Category_1} \ \text{has the positive skewness. All other columns are not so skewed.}$

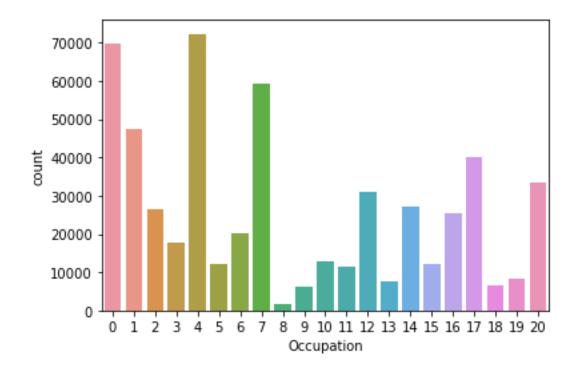
3.2 Data Visualizations:



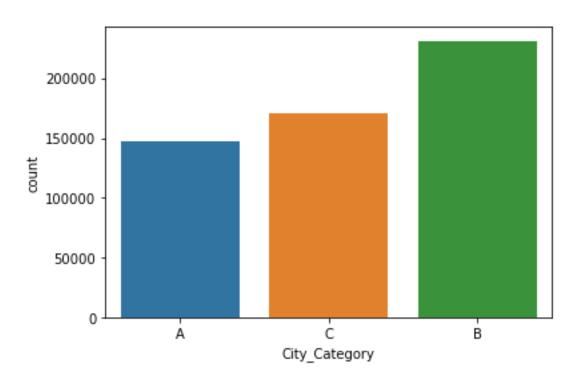
Male customer are more in our dataset compare to female.



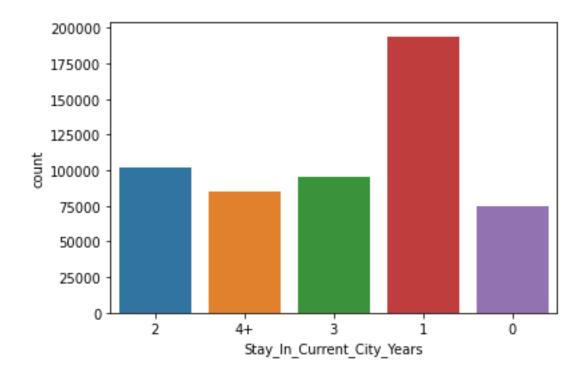
More people aged 26-35 years are purchasing more.



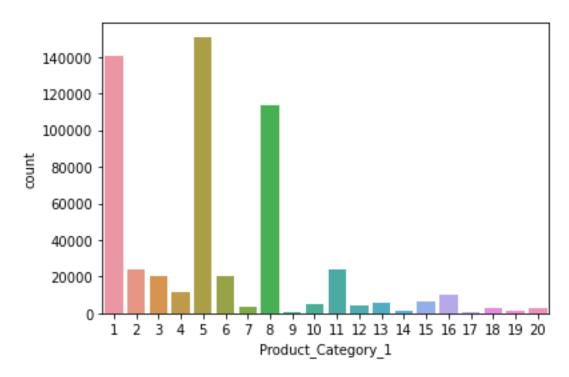
People having occupation masked [0,4,7,1] are usually purchase more during sales.



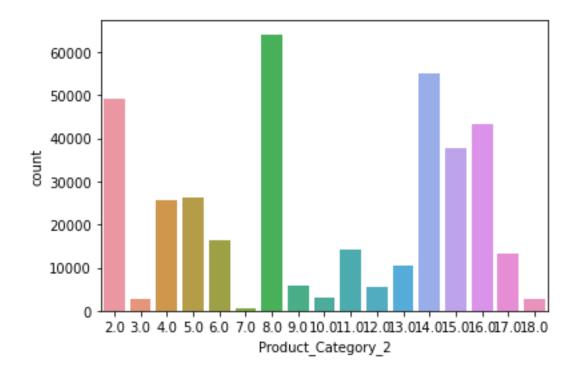
We have more people from city B who has max numbers in dataset.



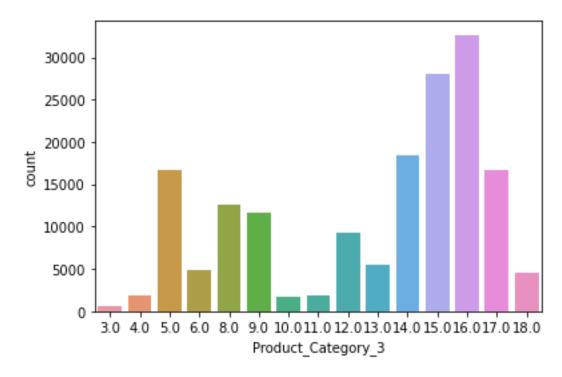
People who are residency in city for 1 year are tent to purchase more.



Product category_1's products are more often purchased. List of these type of products are 1,5,8 (masked).

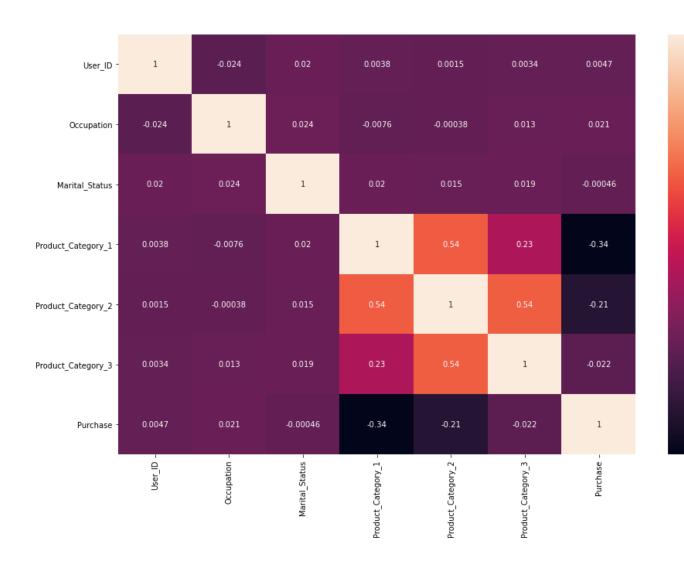


Product category_2's products are more often purchased. List of these type of products are 2, 8, 14, 15, 16(masked).



Product category_3's products are more often purchased. List of these type of products are 5, 14, 15, 16 (masked).

Heatmap:



- 1.0

- 0.8

- 0.6

0.4

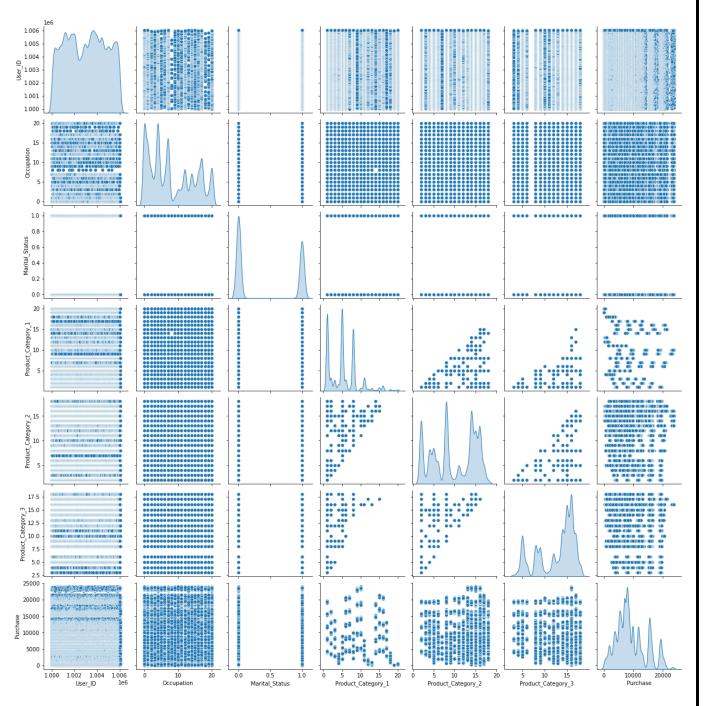
- 0.2

- 0.0

-0.2

There is no clear interpretation of feature that are linearly corelated. But we can infer via lightly shaded area, that there is some collinearity in the dataset.

Pairplot:



Diagonally we can see the distribution of the features.

4. Evaluate Algorithms

4. 1 Linear Regression:

Score:

model_1_LinearRegression.score(X_test, y_test) 0.14497179163973384

4.2 Decision Tree Regressor:

Scores:

model_2_DecisionTreeRegressor.score(X_test,y_test) 0. 5673416953318338

4.3 XGboost:

```
Models parameters:
```

```
{ objective ='reg:linear', n_estimators = 25, seed = 10}
```

Scores:

model_3_XGBRegressor.score(X_test,y_test) 0. 6638326837907499

4.4 Random Forest Regressor:

```
Model's Best paramters : { max_features='sqrt', n_estimators=500, n_jobs=-1, warm_start=True}
```

Scores:

0.6381038302184262