

CEBD 1260 - Big Data Analytics

Black Friday

A study of sales trough consumer behaviours

Team Project

Ricardo Luis da Costa Rocha

Frank So

Black Friday Study

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Black Friday Study

Problem statement

“A retail company “ABC Private Limited” wants to understand the customer purchase behaviour (specifically, purchase amount) against various products of different categories. 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.

Now, they want 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.”

<https://datahack.analyticsvidhya.com/contest/black-friday/>

Black Friday Study

Problem definition

“The dataset here is a sample of the transactions made in a retail store. The store wants to know better the customer purchase behaviour 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.

Classification problem can also be settled in this dataset since several variables are categorical, and some other approaches could be "Predicting the age of the consumer" or even "Predict the category of goods bought". This dataset is also particularly convenient for clustering and maybe find different clusters of consumers within it.”

<https://www.kaggle.com/mehdidag/black-friday>

Dataset description

“Dataset of 550 000 observations about the black Friday in a retail store, it contains different kinds of variables either numerical or categorical. It contains missing values”

[illegible]

Data

| 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) |

Your model performance will be evaluated on the basis of your prediction of the purchase amount for the test data (test.csv), which contains similar data-points as train except for their purchase amount. Your submission needs to be in the format as shown in "SampleSubmission.csv". We at our end, have the actual purchase amount for the test dataset, against which your predictions will be evaluated. Submissions are scored on the root mean squared error (RMSE). RMSE is very common and is a suitable general-purpose error metric. Compared to the Mean Absolute Error, RMSE punishes large errors:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2},$$



Black Friday Study

Approach

Data Wrangling & Cleaning

Removing not relevant columns

All the columns appears to be relevant. Even User_ID and Product_ID can be used depending on the type of involving Product_Category_2 & Product_Category_3 in our calculations due to its obscurity. Nonetheless said categories as complimentary products due to its association with Product_Category_1 and product ID.

Removing duplicates

```
In [7]: # There are no duplicates to be removed
duplicateRowsDF = df[df.duplicated()]
print("Duplicate Rows except first occurrence based on all columns are :")
print(duplicateRowsDF)
```

Duplicate Rows except first occurrence based on all columns are :
Empty DataFrame

Columns: [User_ID, Product_ID, Gender, Age, Occupation, City_Category, Stay_In_Current_City_Years, Marital_Status, Product_Category_1, Product_Category_2, Product_Category_3, Purchase]
Index: []

Dealing with missing values ¶

```
In [8]: # Checking for missing values by columns
print(df.isnull().sum())
```

| | |
|----------------------------|--------|
| 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 | 166986 |
| Product_Category_3 | 373299 |
| Purchase | 0 |
| dtype: | int64 |

```
In [9]: ## Assigning value zero for the NaN cases
df.fillna(value=0,inplace=True)
```

Black Friday Study

Approach

Exploratory Data Analysis

Jupyter exploratory_data_analysis_final (autosaved)

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Run Stop Restart Clear All Run and Stop All

Data Perspective

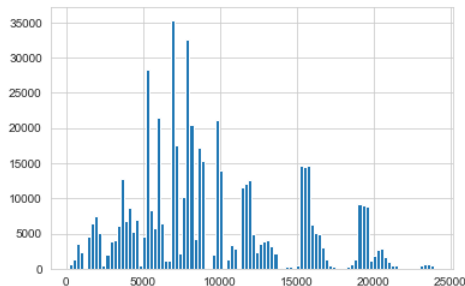
One Variable (numeric)

```
In [32]: # Analyze purchase distribution

# Histogram
print(df['Purchase'].describe().round())
plt.hist(df['Purchase'], bins=100)
plt.show()

# Box plot
plt.boxplot(df['Purchase'])
plt.xticks([1], ['Purchase'], rotation='horizontal')
plt.show()
```

```
count    537577.00
mean       9334.00
std       4981.00
min        185.00
25%       5866.00
50%       8062.00
75%      12073.00
max      23961.00
Name: Purchase, dtype: float64
```



25000

Black Friday Study - Approach EDA

Jupyter exploratory_data_analysis_final (autosaved)



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Python 3

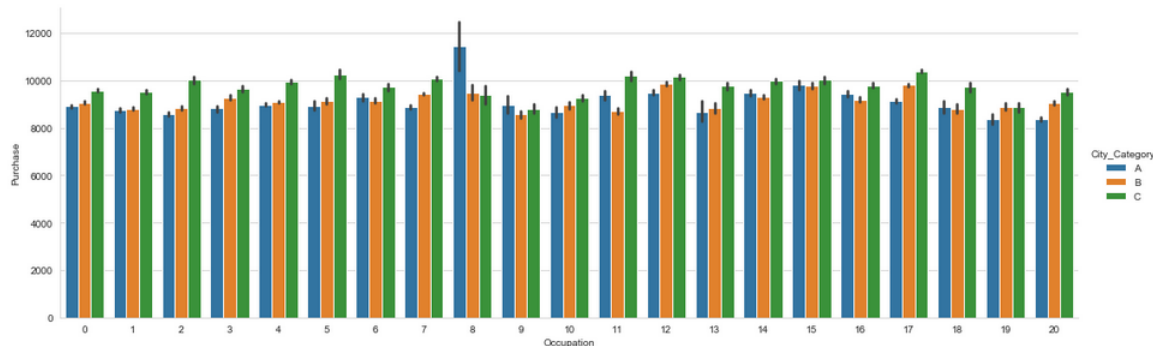
Run Code

Business Perspective

"An approximate answer to the right question is worth a great deal more than a precise answer to the wrong question." John Tukey

```
In [43]: # Cat plot to show the distribution between Occupation x Purchase
sns.catplot(x = "Occupation",
            y = "Purchase",
            hue = "City_Category",
            hue_order = ["A", "B", "C"],
            aspect = 3,
            kind = "bar",
            data = df)
```

Out[43]: <seaborn.axisgrid.FacetGrid at 0x7f4032344668>



This figure accounts for the occupation of our customers across different cities in terms of purchase. Let's first address the spike for Occupation 8 in City

Black Friday Study - Approach ML Model

jupyter machine_learning_model Last Checkpoint: 2019-05-28 (autosaved)



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Run Code

Feature Engineering

```
In [4]: # TODO: create a loop to transform the categorical columns to numerical
for col in ['Gender', 'Age', 'Occupation', 'City_Category', 'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category_1', 'Product_Category_2', 'Product_Category_3']:
    df_dummies = pd.get_dummies(df[col], prefix=col)
    df = pd.concat([df, df_dummies], axis=1)
    # Remove the original columns
    del df[col]
df.head()
```

```
Out[4]:
```


| | User_ID | Product_ID | Purchase | Gender_F | Gender_M | Age_0-17 | Age_18-25 | Age_26-35 | Age_36-45 | Age_46-50 | ... | Product_Category_3_9 | Product_Category_1 |
|---|---------|------------|----------|----------|----------|----------|-----------|-----------|-----------|-----------|-----|----------------------|--------------------|
| 0 | 1000001 | P00069042 | 8370 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | ... | 0 | 0 |
| 1 | 1000001 | P00248942 | 15200 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | ... | 0 | 0 |
| 2 | 1000001 | P00087842 | 1422 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | ... | 0 | 0 |
| 3 | 1000001 | P00085442 | 1057 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | ... | 0 | 0 |
| 4 | 1000002 | P00285442 | 7969 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 |

5 rows x 95 columns

```
In [5]: df.dtypes
```

```
Out[5]: User_ID          int64
Product_ID        object
Purchase          int64
Gender_F          uint8
Gender_M          uint8
Age_0-17          uint8
Age_18-25         uint8
```

Black Friday Study - Approach ML Model

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Run Code

Model Training

```
In [7]: threshold = 0.8
X = df[X_columns]
y = df[y_column]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=1.0-threshold, shuffle=True)

print('X_train', X_train.shape)
print('y_train', y_train.shape)
print('X_test', X_test.shape)
print('y_test', y_test.shape)

X_train (430061, 93)
y_train (430061, 1)
X_test (107516, 93)
y_test (107516, 1)
```

Model Evaluation

Linear Regression

```
In [8]: from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

```
In [9]: mae = mean_absolute_error(y_test, y_pred)
print('MAE', round(mae, 2))
```

Black Friday Study - Results Experiments

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Python 3

Run Code

Experiments

```
In [9]: def model_training(model_name, model, X_train, y_train):
        model.fit(X_train, y_train)
        return model

def model_prediction(model, X_test):
    y_pred = model.predict(X_test)
    return y_pred

def model_evaluation(model_name, y_test, y_pred):
    print(model_name)
    print('MAE', mean_absolute_error(y_test, y_pred))
    print('RMSE', np.sqrt(mean_squared_error(y_test, y_pred)))
    plt.scatter(y_test, y_pred, alpha=0.3)
    # plt.plot(range(0, 5000000, 100), range(0, 5000000, 100), '--r', alpha=0.3, label='Line1')
    plt.plot(range(0, 10), range(0, 10), '--r', alpha=0.3, label='Line1')
    plt.title(model_name)
    plt.xlabel('True Value')
    plt.ylabel('Predict Value')
    # plt.xlim([0, 5000000])
    # plt.ylim([0, 5000000])
    plt.show()
    print('')

def run_experiment(model_name, model, X_train, y_train, X_test):
    train_model = model_training(model_name, model, X_train, y_train)
    predictions = model_prediction(train_model, X_test)
    model_evaluation(model_name, y_test, predictions)

run_experiment('Linear Regression', LinearRegression(), X_train, y_train, X_test)
run_experiment('KNN 5', KNeighborsRegressor(5), X_train, y_train, X_test)
run_experiment('KNN 2', KNeighborsRegressor(2), X_train, y_train, X_test)
run_experiment('Decision Tree', DecisionTreeRegressor(), X_train, y_train, X_test)
run_experiment('Random Forest 10', RandomForestRegressor(10), X_train, y_train, X_test)
```

Black Friday Study - Results Error Analysis

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Python 3

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Error Analysis

```
In [11]: model = RandomForestRegressor(100)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

/home/coastrock/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:2: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().

```
In [12]: #for i in range(len(X_test.columns)):
fi = []
for i, col in enumerate(X_test.columns):
    fi.append([col, model.feature_importances_[i]])
pd.DataFrame(fi).sort_values(1, ascending=False)
```

| | | |
|----|-----------------|----------|
| 4 | Gender_M | 0.008624 |
| 34 | City_Category_B | 0.008042 |
| 33 | City_Category_A | 0.007579 |
| 12 | Occupation_0 | 0.007434 |
| 19 | Occupation_7 | 0.006780 |
| 13 | Occupation_1 | 0.006691 |
| 16 | Occupation_4 | 0.006637 |
| 29 | Occupation_17 | 0.006328 |
| 35 | City_Category_C | 0.006142 |
| 9 | Age_46-50 | 0.006123 |
| 32 | Occupation_20 | 0.006023 |

Black Friday Study - Results Clustering Kmeans

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Run Code

Model Training

```
In [4]: k = 7
kmeans = KMeans(n_clusters=k).fit(df_norm.values)

print(set(kmeans.labels_))
print(collections.Counter(kmeans.labels_))

df_results = df.copy()
df_norm['cluster'] = kmeans.labels_
df_results['cluster'] = kmeans.labels_

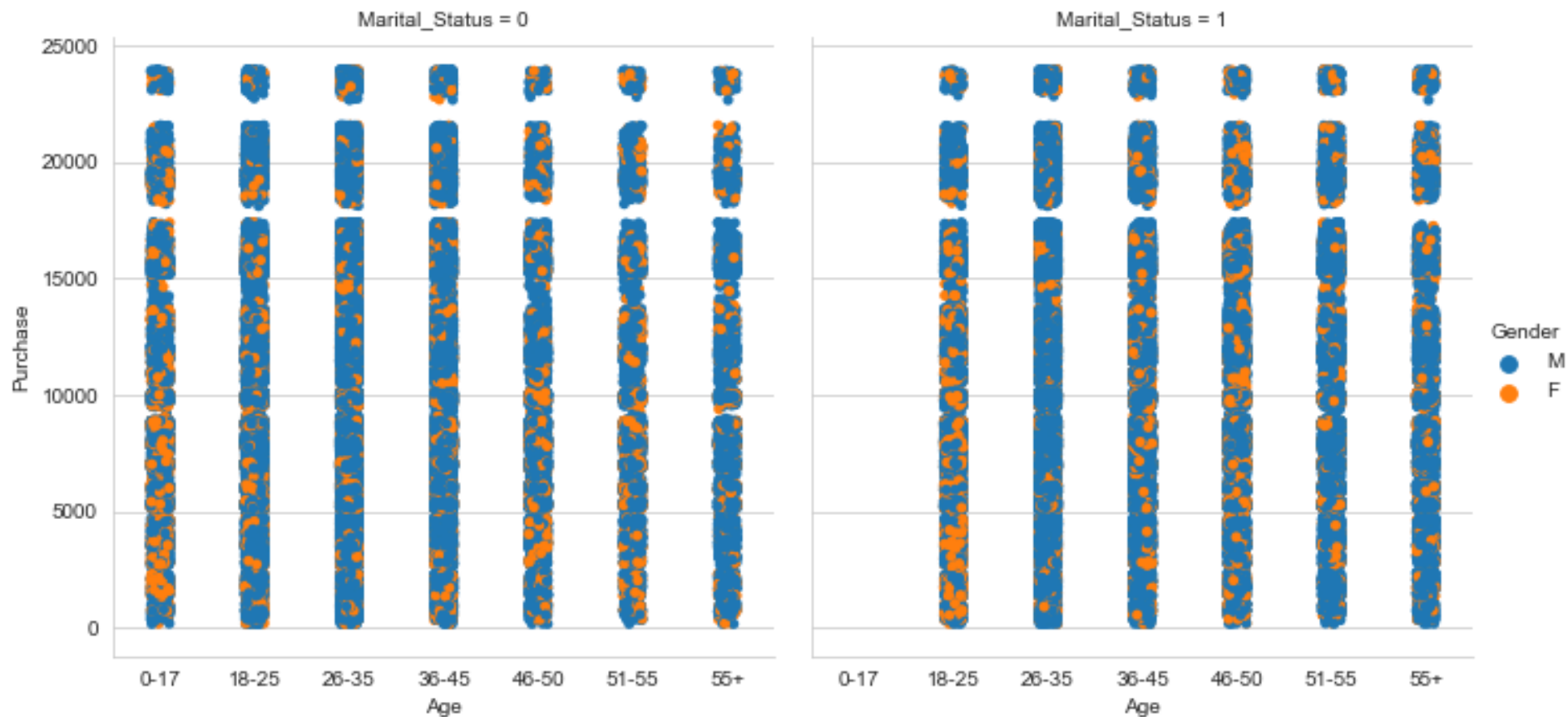
{0, 1, 2, 3, 4, 5, 6}
Counter({2: 47619, 5: 17664, 0: 16651, 4: 12995, 1: 2426, 3: 1490, 6: 1154})
```

```
In [5]: # Analyze the results
df_results = df_results.reset_index()
for cluster in sorted(set(kmeans.labels_)):
    print(collections.Counter(df_results[df_results['cluster']==cluster]['Age']).most_common(5))

n_clusters = len(set(kmeans.labels_))
for col in X_columns:
    print(col)
    i = 1
    plt.figure(figsize=(16,3))
    for cluster in sorted(set(kmeans.labels_)):
        plt.subplot(1, n_clusters, i)
        plt.xlim([0,df_results[col].max()])
        plt.hist(df_results[df_results['cluster']==cluster][col], label=str(cluster), alpha=0.3, bins=20)
        i += 1
    plt.show()
```

```
[('26-35', 7071), ('36-45', 3992), ('18-25', 2966), ('46-50', 1034), ('51-55', 976)]
[('0-17', 2086), ('18-25', 307), ('55+', 20), ('36-45', 10), ('26-35', 3)]
[('26-35', 20239), ('36-45', 9019), ('18-25', 8713), ('46-50', 4251), ('51-55', 3795)]
[('55+', 956), ('51-55', 357), ('46-50', 114), ('36-45', 60), ('0-17', 31)]
```

Black Friday Study - Discussion



Black Friday Study

Thank you!

Questions?