In [5]:
```
# for numerical computing
import numpy as np

# for dataframes
import pandas as pd

# for easier visualization
import seaborn as sns

# for visualization and to display plots
from matplotlib import pyplot as plt
%matplotlib inline

# import color maps
from matplotlib.colors import ListedColormap

# Ignore Warnings
import warnings
warnings.filterwarnings("ignore")

from math import sqrt

# to split train and test set
from sklearn.model_selection import train_test_split

# to perform hyperparameter tuning
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV

from sklearn.linear_model import Ridge  # Linear Regression + L2 regularization
from sklearn.linear_model import Lasso  # Linear Regression + L1 regularization
from sklearn.svm import SVR # Support Vector Regressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor

# Evaluation Metrics
from sklearn.metrics import mean_squared_error as mse
from sklearn.metrics import r2_score as rs
from sklearn.metrics import mean_absolute_error as mae
```

```
#import xgboost
import os
mingw_path = 'C:\\Program Files\\mingw-w64\\x86_64-7.2.0-posix-seh-rt_v5-rev0\\mingw64\\bin'
os.environ['PATH'] = mingw_path + ';' + os.environ['PATH']
from xgboost import XGBRegressor
from xgboost import plot_importance  # to plot feature importance

# to save the final model on disk
from sklearn.externals import joblib
```

In [6]:
```
doc = pd.read_csv('BlackFriday 2.csv')
```

In [7]:
```
np.set_printoptions(precision=2, suppress=True) #for printing floating point numbers upto  precision 2
```

Loaded Black Friday from CSV

In [8]:
```
doc.shape
```

Out[8]:
```
(537577, 12)
```

Columns of the dataset

In [9]:
```
doc.columns
```

Out[9]:
```
Index(['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'],
      dtype='object')
```

Display the first 5 rows to see hows the data set

In [10]:

```
pd.set_option('display.max_columns', 12) ## display max 12 columns
doc.head(5)
```

Out[10]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	P
0	1000001	P00069042	F	0-17	10	A	2	0	3	
1	1000001	P00248942	F	0-17	10	A	2	0	1	
2	1000001	P00087842	F	0-17	10	A	2	0	12	
3	1000001	P00085442	F	0-17	10	A	2	0	12	
4	1000002	P00285442	M	55+	16	C	4+	0	8	

Some are numerical data and some are categorical

Filtering the categorical Data:

In [11]:

```
doc.dtypes[doc.dtypes=='object']
```

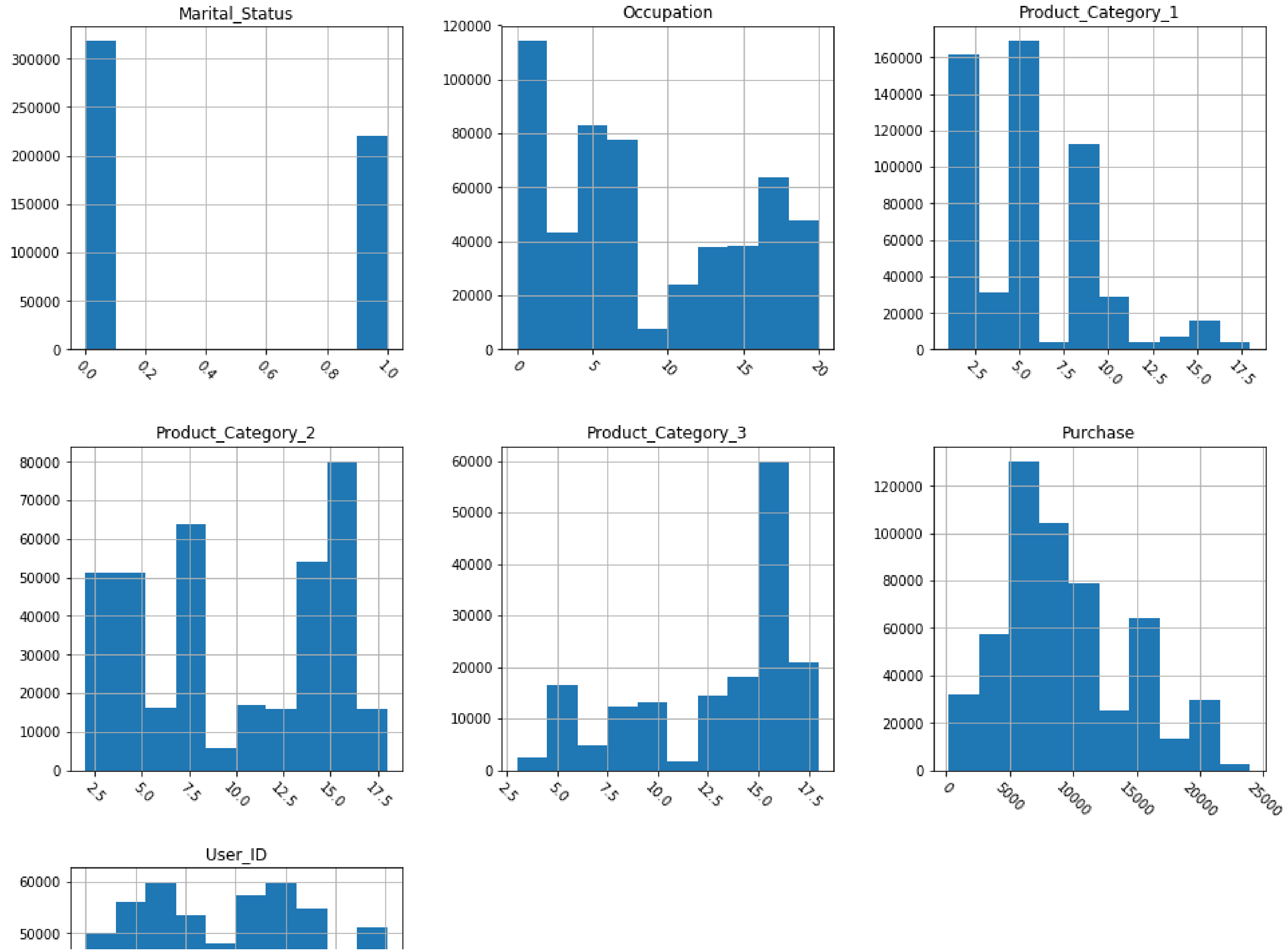
Out[11]:

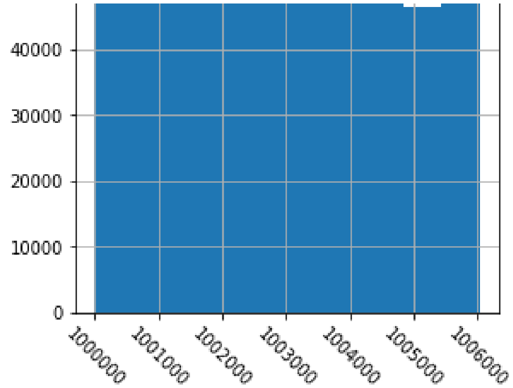
```
Product_ID                    object
Gender                        object
Age                           object
City_Category                 object
Stay_In_Current_City_Years    object
dtype: object
```

Distributions of numeric features

In [49]:
```
# ploted histogram grid
doc.hist(figsize=(16,16), xrot=-45) ## Display the labels rotated by 45 degress

# Clear the text "residue"
plt.show()
```





Observations:We can make out quite a few observations:

For example, We can see That the histogram that maritarial satus descibes more than 300000 people are married and more than 200000 are unmarried by showing 0's and 1's.

Occupation in 0 has the most number of occupation near about 118000.

In puschase most puchases were between 5k to 10k more than 100000 to more than 125000.

Displaing summary statistics for the numerical features.

In [13]:
```
doc.describe()
```

Out[13]:

	User_ID	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
count	5.375770e+05	537577.00000	537577.000000	537577.000000	370591.000000	164278.000000	537577.000000
mean	1.002992e+06	8.08271	0.408797	5.295546	9.842144	12.669840	9333.859853
std	1.714393e+03	6.52412	0.491612	3.750701	5.087259	4.124341	4981.022133
min	1.000001e+06	0.00000	0.000000	1.000000	2.000000	3.000000	185.000000
25%	1.001495e+06	2.00000	0.000000	1.000000	5.000000	9.000000	5866.000000
50%	1.003031e+06	7.00000	0.000000	5.000000	9.000000	14.000000	8062.000000
75%	1.004417e+06	14.00000	1.000000	8.000000	15.000000	16.000000	12073.000000
max	1.006040e+06	20.00000	1.000000	18.000000	18.000000	18.000000	23961.000000

Obeservation:

Look at the 'year_built' column, we can see that its max value is 2015. The 'basement' feature has some missing values, also its standard deviation is 0.0, while its min and max are both 1.0. Maybe this is a feature that should be binary consisting values 0 and 1.

In [14]:
```
doc.describe(include=['object'])
```

Out[14]:

	Product_ID	Gender	Age	City_Category	Stay_In_Current_City_Years
count	537577	537577	537577	537577	537577
unique	3623	2	7	3	5
top	P00265242	M	26-35	B	1
freq	1858	405380	214690	226493	189192

Observation:

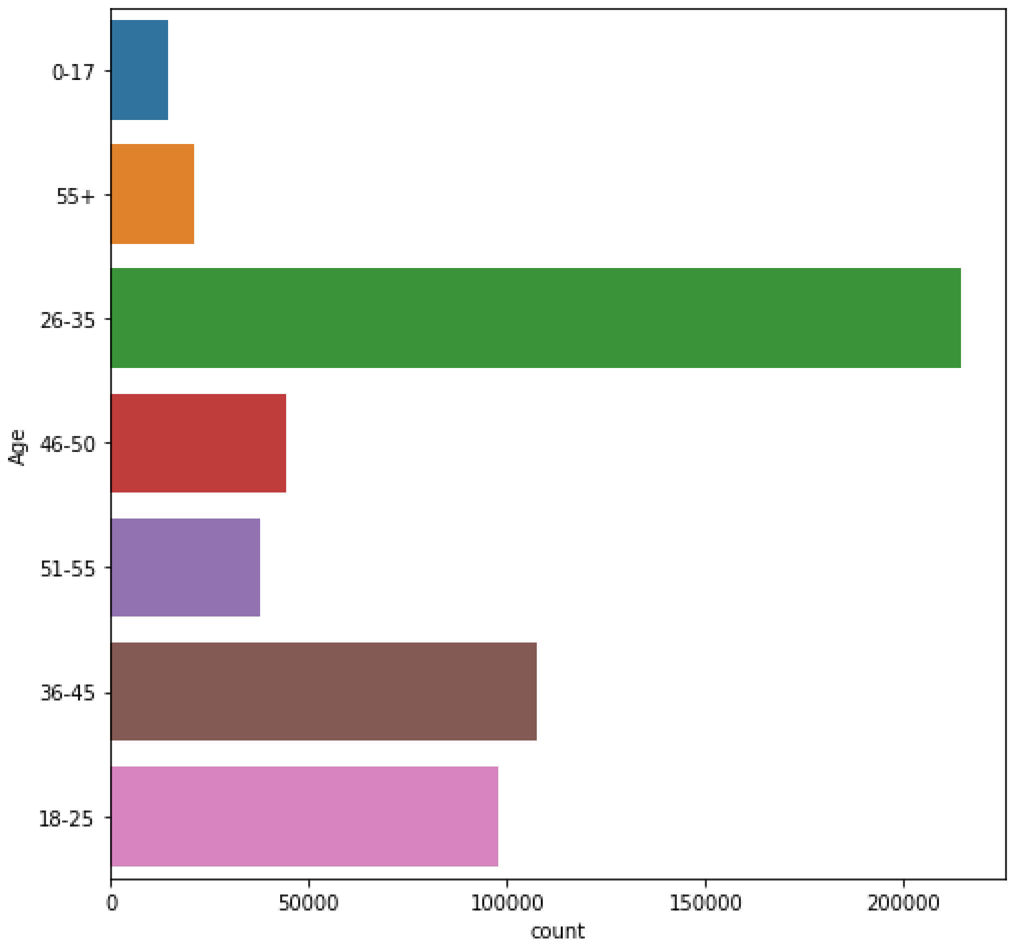
'Age' and 'Stay_In_Current_City_Year' have missing values There are 16 unique classes for 'exterior_walls' and ' ' The most frequent element for exterior_walls is 'Brick'and it has come 687 times.

Bar plots for categorical Features

Plot bar plot for the 'Age' Data.

In [15]:
```
plt.figure(figsize=(8,8))
sns.countplot(y='Age', data=doc)
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x18f73da73c8>



Observations: More than 200000 are '26-35' shows count of more than 200k which are most frequent

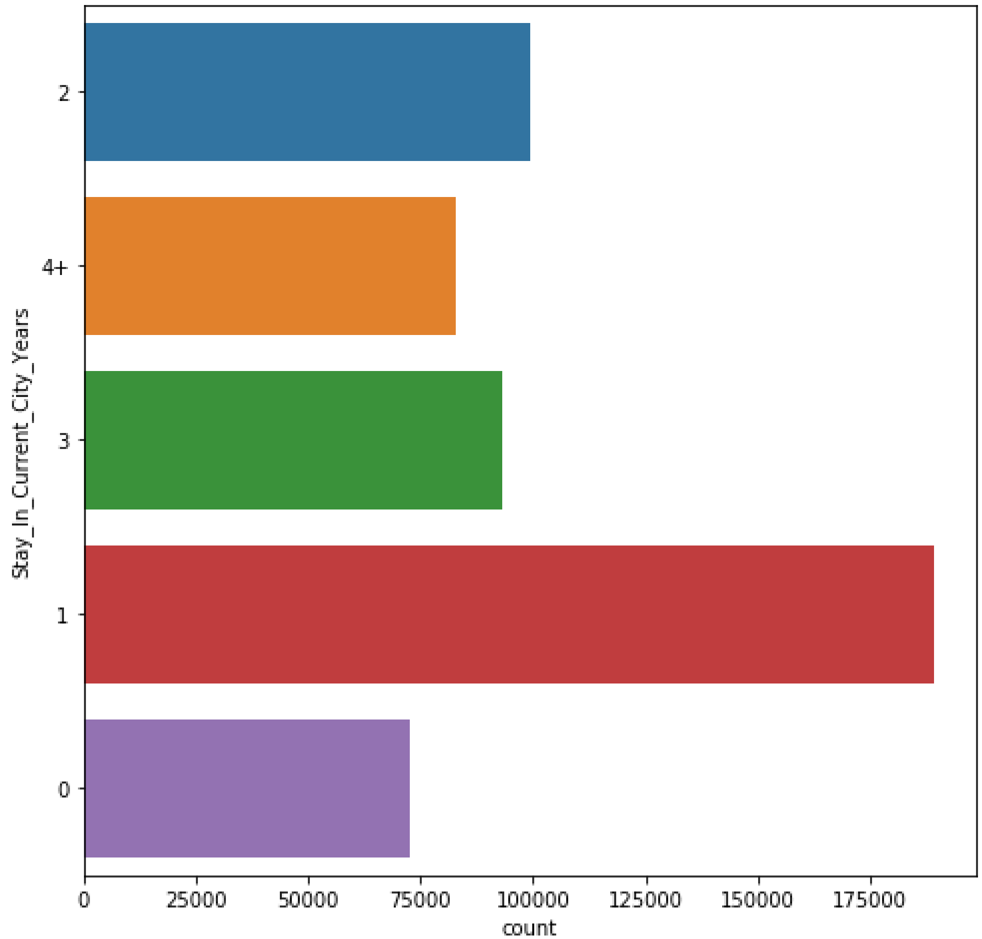
'36-45' Is the 2nd most with more than 100k '18-25' is the 3rd most with almost 100k

There are no sparse classes as all categories have a significant number of observations.

Similarly Plot bar plot for the '' feature.

In [53]:
```
plt.figure(figsize=(8,8))
sns.countplot(y='Stay_In_Current_City_Years', data=doc)
```

Out[53]: <matplotlib.axes._subplots.AxesSubplot at 0x262aa530b00>



Observations:

The class which has a lasrgest count is '1' Following are the rest of the classes with a larger amount of years. with similiar distribution between them.

'0', '2', '3' & '4+'.

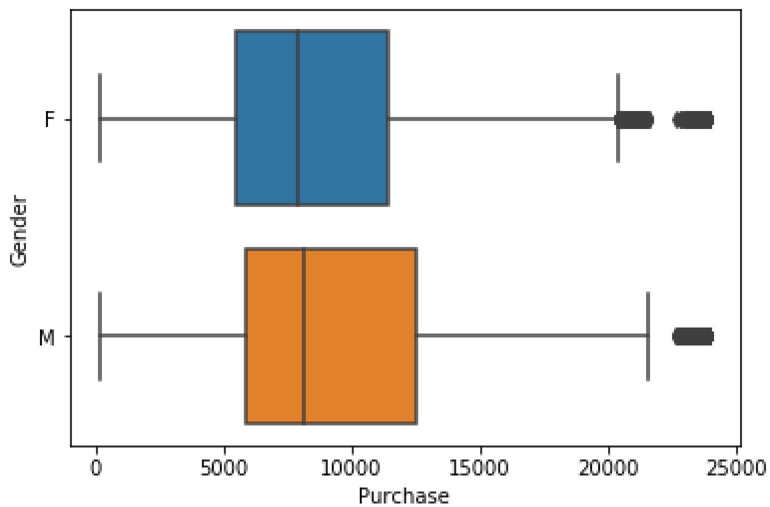
Segmentations

Segmentations are powerful ways to cut the data to observe the relationship between categorical features and numeric features.

Segmenting the target variable by key categorical features.

In [16]:
```
sns.boxplot(y='Gender', x='Purchase', data=doc)
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x18f75281b38>



In [55]:
```
# Observation: In general, it looks like Males were making more purchases in this black friday Observations
# Let's compare the two Gender categories across other features as well
```

In [17]:
```
doc.groupby('Gender').mean()
```

Out[17]:

	User_ID	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
Gender							
F	1.003088e+06	6.742672	0.417733	5.595445	10.007969	12.452318	8809.761349
M	1.002961e+06	8.519705	0.405883	5.197748	9.789072	12.732924	9504.771713

Observations :

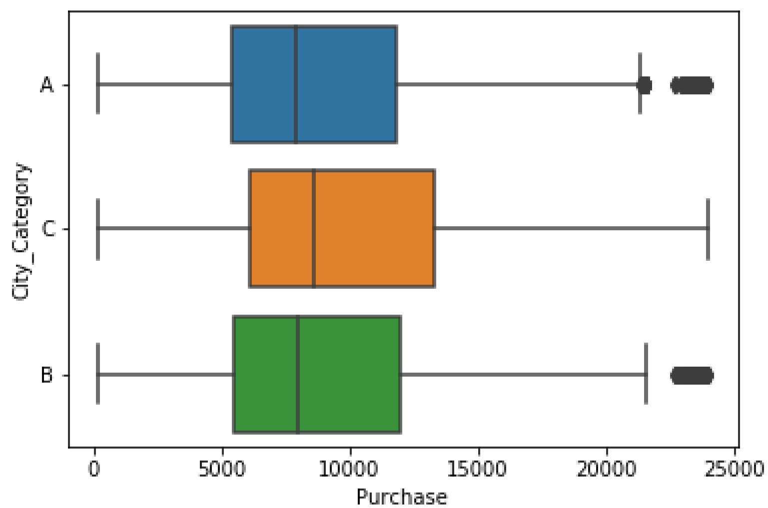
There is nearly the same 40% marital status of zero both for males and females.

The product categories columns dont show significant change between the genders. excepet for a slight higher numbers in category 1 and 3 towards female.

As observed before - there were more purchaes made by males The mean of male purchaes is 9504 while female's is 8809.

In [57]:
```
sns.boxplot(y='City_Category', x='Purchase', data=doc)
```

Out[57]: <matplotlib.axes._subplots.AxesSubplot at 0x262aa734e10>



Observation:

For City_Category 1 and 3 ther are less observations foe people purchasing in more then 225k tan there are from 0-225k.

Segment by property_type and display the means and standard deviations within each class

In [58]:
```
doc.groupby('Age').agg([np.mean, np.std])
```

Out[58]:

	User_ID		Occupation		Marital_Status		...	Product_Category_2		Product_Category_3		Purchase
	mean	std	mean	std	mean	std	...	mean	std	mean	std	mean
Age												
0-17	1.002676e+06	1755.525095	8.790236	4.491994	0.000000	0.000000	...	9.023027	5.176184	11.850282	4.383450	9020.126878
18-25	1.002766e+06	1716.270135	6.737141	5.949072	0.211412	0.408312	...	9.474317	5.140842	12.395286	4.243974	9235.197575
26-35	1.003075e+06	1719.986312	7.902343	6.698011	0.392035	0.488206	...	9.810403	5.075915	12.648689	4.123401	9314.588970
36-45	1.003030e+06	1677.032766	8.847152	6.588780	0.395418	0.488942	...	9.954321	5.082563	12.750717	4.078818	9401.478758
46-50	1.003152e+06	1768.300690	8.526367	6.682162	0.723038	0.447502	...	10.177195	5.016661	12.937952	3.993584	9284.872277
51-55	1.002950e+06	1667.161146	8.809506	6.664605	0.717183	0.450374	...	10.280446	5.028167	13.108187	3.941584	9620.616620
55+	1.002951e+06	1644.942652	9.537961	6.358962	0.634981	0.481447	...	10.462992	4.941885	13.154686	3.938299	9453.898579

7 rows × 14 columns

Correlations

In [59]:
```
# Finally, let's take a look at the relationships between numeric features and other numeric features.
# Correlation is a value between -1 and 1 that represents how closely values for two separate features.
# Positive correlation means that as one feature increases, the other increases.
# Negative correlation means that as one feature increases, the other decreases.
# Correlations near -1 or 1 indicate a strong relationship.
# Those closer to 0 indicate a weak relationship.
# 0 indicates no relationship.
```

In [18]:

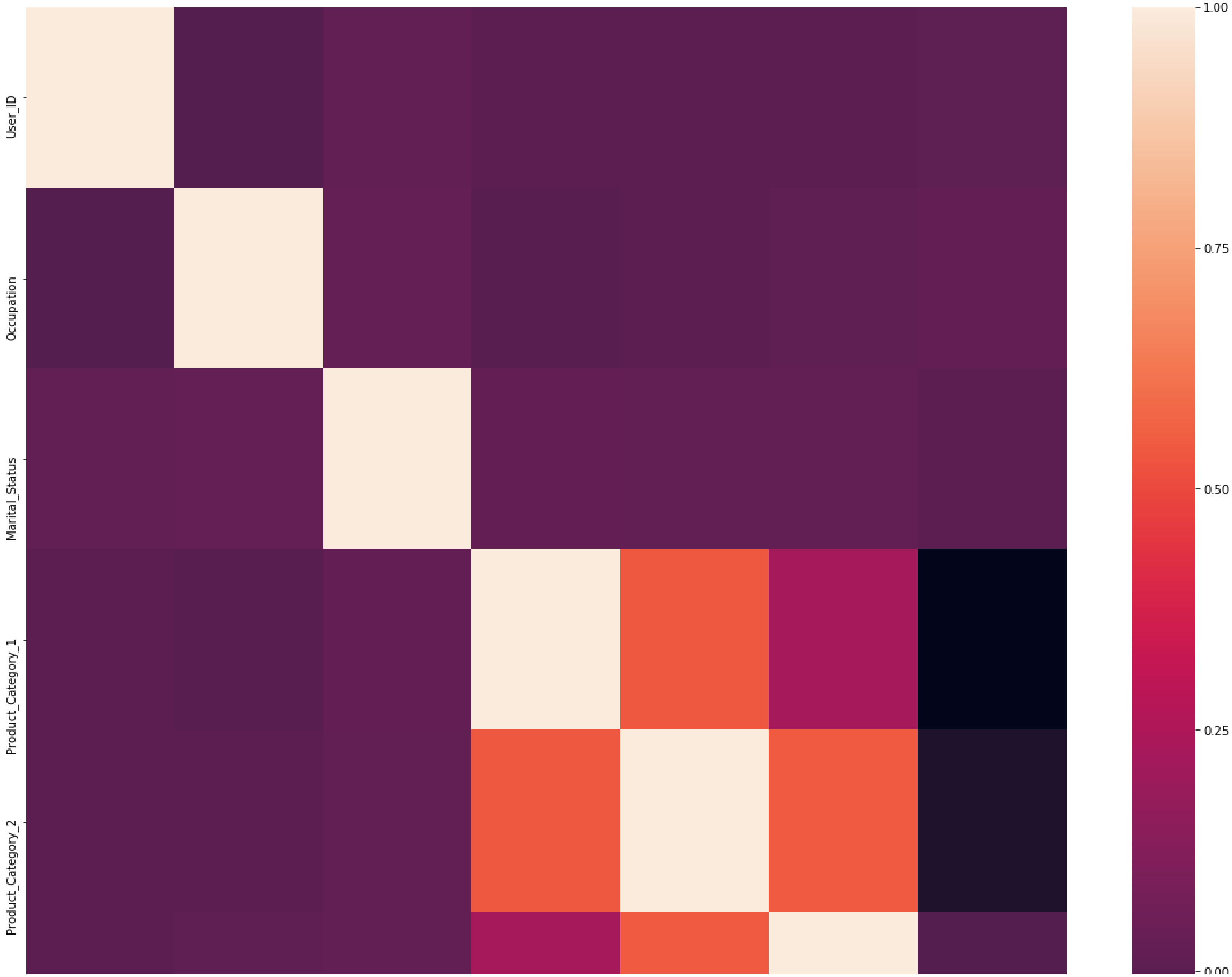
```
doc.corr()
```

Out[18]:

	User_ID	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
User_ID	1.000000	-0.023024	0.018732	0.003687	0.001471	0.004045	0.005389
Occupation	-0.023024	1.000000	0.024691	-0.008114	-0.000031	0.013452	0.021104
Marital_Status	0.018732	0.024691	1.000000	0.020546	0.015116	0.019452	0.000129
Product_Category_1	0.003687	-0.008114	0.020546	1.000000	0.540423	0.229490	-0.314125
Product_Category_2	0.001471	-0.000031	0.015116	0.540423	1.000000	0.543544	-0.209973
Product_Category_3	0.004045	0.013452	0.019452	0.229490	0.543544	1.000000	-0.022257
Purchase	0.005389	0.021104	0.000129	-0.314125	-0.209973	-0.022257	1.000000

In [61]:
```
plt.figure(figsize=(20,20))
sns.heatmap(doc.corr())
```

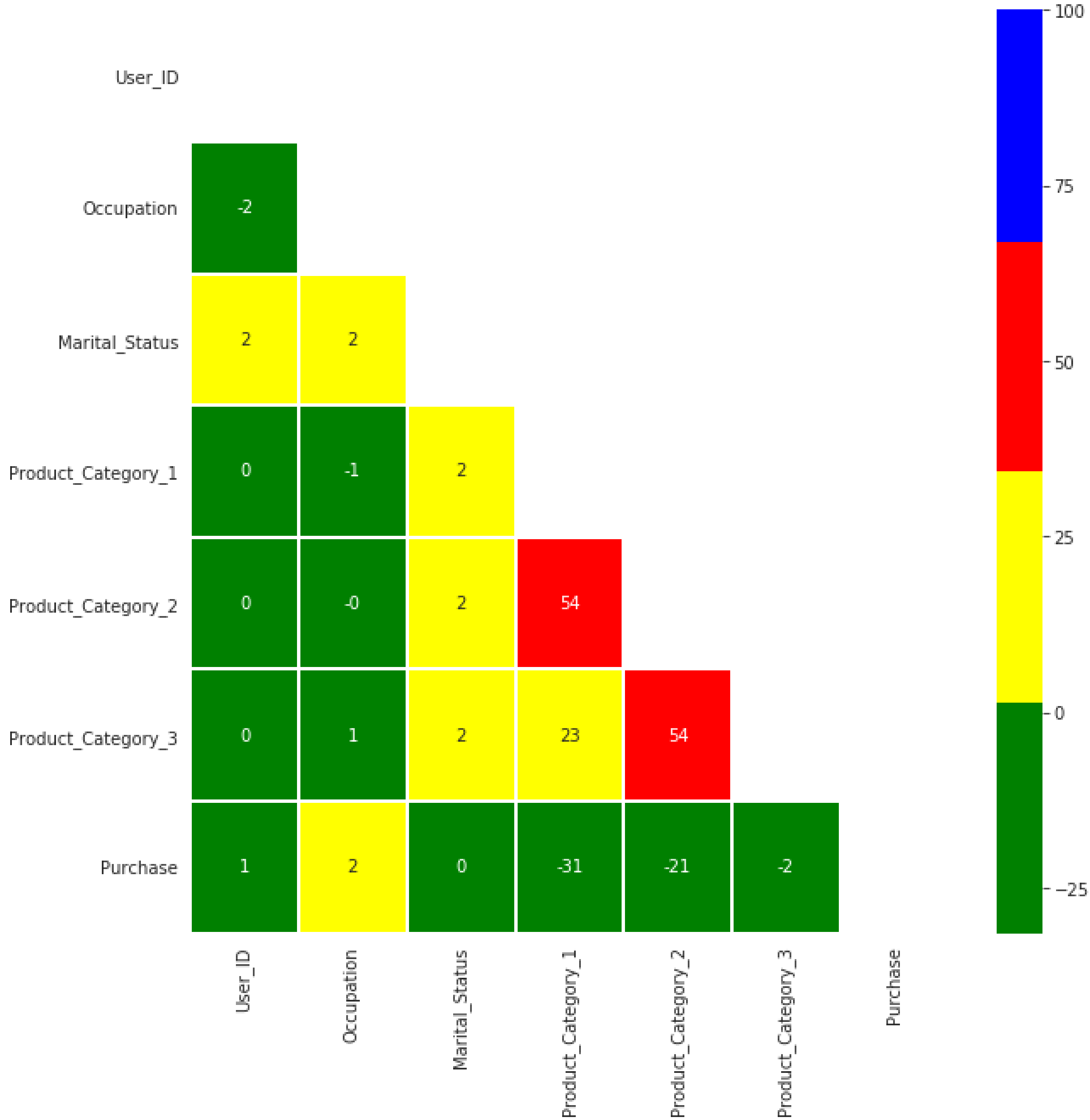
Out[61]: <matplotlib.axes._subplots.AxesSubplot at 0x262aa7825c0>




Product_Category_3
Purchase
User_ID
Occupation
Marital_Status
Product_Category_1
Product_Category_2
Product_Category_3
Purchase
−0.25

In [19]:

```
mask=np.zeros_like(doc.corr())
mask[np.triu_indices_from(mask)] = True
plt.figure(figsize=(10,10))
with sns.axes_style("white"):
    ax = sns.heatmap(doc.corr()*100, mask=mask, fmt='.0f', annot=True, lw=1, cmap=ListedColormap(['green', '
```



Data Cleaning

In [20]:
```
doc = doc.drop_duplicates()  # Dropping the duplicates
print( doc.shape )
```

```
(537577, 12)
```

In [21]:
```
doc = doc.drop_duplicates()
print( doc.shape )
```

```
(537577, 12)
```

In [65]:
```
# It looks like we didn't have any duplicates in our original dataset. (Same case for black friday data)
# Even so, it's a good idea to check this as an easy first step for cleaning your dataset
```

Fix structural errors

Could not find similiar structural errors

Typos and capitalization

Could not find similiar typos or capitalization errors

Mislabeled classes

Could not find the errors indicated

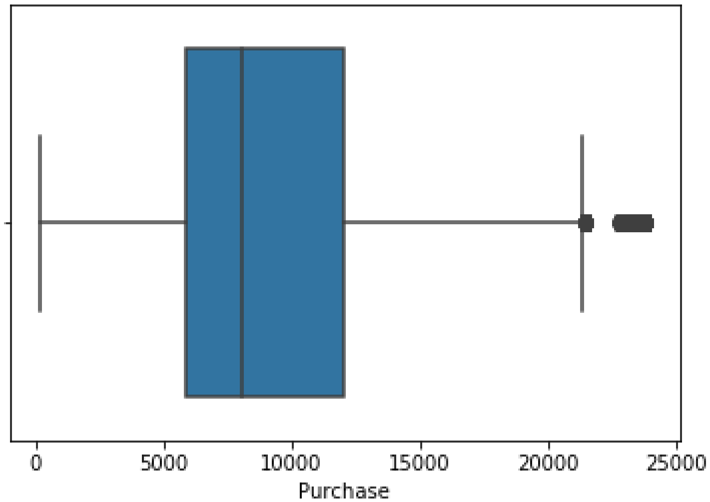
Outliers can cause problems with certain types of models.

Boxplots are a nice way to detect outliers

Let's start with a box plot of your target variable, since that's what you're actually trying to predict

In [22]:
```
sns.boxplot(doc.Purchase)
```

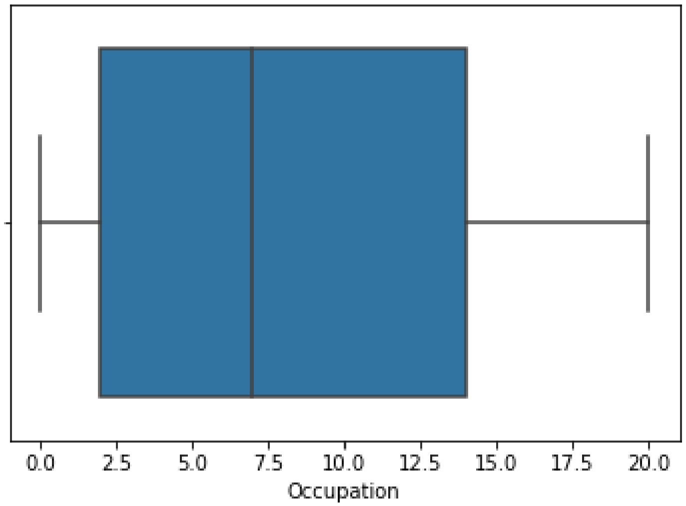
Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x18f75607080>
```



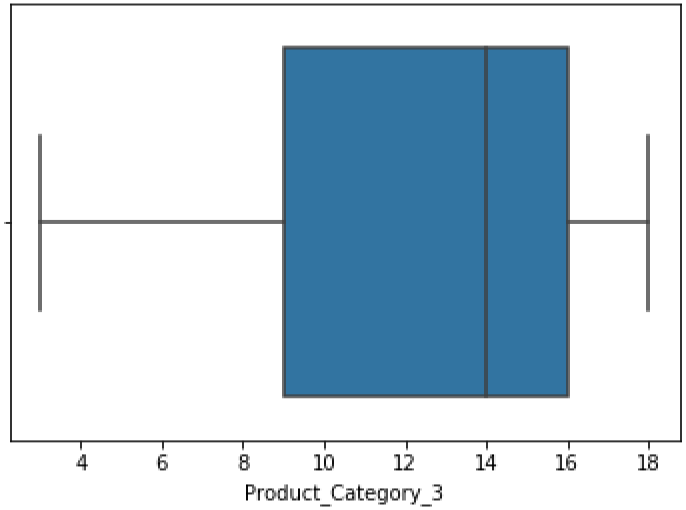
Interpretation

The two vertical bars on the ends are the min and max values. All purchases were between $0 and$25,000 The box in the middle is the interquartile range (25th percentile to 75th percentile). Half of all observations fall in that box. Finally, the vertical bar in the middle of the box is the median.

In [23]:
```
sns.boxplot(doc.Occupation) # Checking outliers in Occupation
```
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x18f00119630>



In [24]:
```
# Checking outliers in Product_Category_3
sns.boxplot(doc.Product_Category_3)
```
Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x18f00175630>



Label missing categorical data

In [69]:
```
# You cannot simply ignore missing values in your dataset.
# You must handle them in some way for the very practical reason that Scikit-Learn algorithms
# do not accept missing values.
```

In [25]:
```
# Display number of missing values by categorical feature
doc.select_dtypes(include=['object']).isnull().sum()
```

Out[25]:
```
Product_ID                    0
Gender                        0
Age                           0
City_Category                 0
Stay_In_Current_City_Years    0
dtype: int64
```

In [71]:
```
# Observation: There are no missing values in the categorical columns
```

Flag and fill missing numeric data

In [26]:
```
# Display number of missing values by numeric feature
doc.select_dtypes(exclude=['object']).isnull().sum()
```

Out[26]:
```
User_ID                    0
Occupation                 0
Marital_Status             0
Product_Category_1         0
Product_Category_2    166986
Product_Category_3    373299
Purchase                   0
dtype: int64
```

In [73]:
```
# I tried runnin this code to fill the nan values but it caused a problem
#instead Im running it afer Loading the new analyticaldf and it works fine
```

Feature Engineering

Indicator variables

In [74]:
```
# Since there is no evident correlation that indicates a strong connection between some variables rather the
# there is no need to do this step.
```

Interaction features

In [75]:
```
# Since there is no evident correlation that indicates a strong connection between some variables rather the
# there is no need to do this step.
```

Handling Sparse Classes

In [76]:
```
# I did not identify Sparse classes in the data base.
```

Encode dummy variables (One Hot Encoding)

In [77]:
```
# Machine learning algorithms cannot directly handle categorical features. Specifically, they cannot handle
# Therefore, we need to create dummy variables for our categorical features.
# Dummy variables are a set of binary (0 or 1) features that each represent a single class from a categorica
```

In [27]:
```
doc.head()
```

Out[27]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	P
0	1000001	P00069042	F	0-17	10	A	2	0	3	
1	1000001	P00248942	F	0-17	10	A	2	0	1	
2	1000001	P00087842	F	0-17	10	A	2	0	12	
3	1000001	P00085442	F	0-17	10	A	2	0	12	
4	1000002	P00285442	M	55+	16	C	4+	0	8	

In [28]:
```
# Create a new dataframe with dummy variables for for our categorical features.
doc = pd.get_dummies(doc, columns=['Gender', 'Age', 'City_Category', 'Stay_In_Current_City_Years'])
```

In [29]:
```
# Note: There are many ways to perform one-hot encoding,
# you can also use LabelEncoder and OneHotEncoder classes in SKLEARN or use the above pandas function.
```

In [30]:
```
doc.head()
```

Out[30]:

	User_ID	Product_ID	Occupation	Marital_Status	Product_Category_1	Product_Category_2	...	City_Category_C	Stay_In_Current_(
0	1000001	P00069042	10	0	3	NaN	...	0	
1	1000001	P00248942	10	0	1	6.0	...	0	
2	1000001	P00087842	10	0	12	NaN	...	0	
3	1000001	P00085442	10	0	12	14.0	...	0	
4	1000002	P00285442	16	0	8	NaN	...	1	

5 rows × 25 columns

Remove unused or redundant features

In [31]:
```
doc = doc.drop(['User_ID'], axis=1)
doc= doc.drop(['Product_ID'], axis=1)
```

In [32]:
```
# looking at the columns of the dataset

doc.head(2)
```

Out[32]:

	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase	...	City_Category_C	Stay_In
0	10	0	3	NaN	NaN	8370	...	0	
1	10	0	1	6.0	14.0	15200	...	0	

2 rows × 23 columns

In [39]:
```
doc.to_csv(r'C:\Users\Owner\Desktop\270work\B.csv', index=None)
```

Machine Learning Models

Data Preparation

In [40]:
```
doc = pd.read_csv('B.csv')
```

In [45]:
```
doc.head()
```

Out[45]:

	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase	...	City_Category_C	Stay_In
0	10	0	3	0.0	0.0	8370	...	0	
1	10	0	1	6.0	14.0	15200	...	0	
2	10	0	12	0.0	0.0	1422	...	0	
3	10	0	12	14.0	0.0	1057	...	0	
4	16	0	8	0.0	0.0	7969	...	1	

5 rows × 23 columns

In [46]:
```
doc = doc.fillna(0)
```

In [47]:
```
doc.head()
```

Out[47]:

	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase	...	City_Category_C	Stay_In
0	10	0	3	0.0	0.0	8370	...	0	
1	10	0	1	6.0	14.0	15200	...	0	
2	10	0	12	0.0	0.0	1422	...	0	
3	10	0	12	14.0	0.0	1057	...	0	
4	16	0	8	0.0	0.0	7969	...	1	

5 rows × 23 columns

Train and Test Splits

In [48]:
```
# Separate your dataframe into separate objects for the target variable (y)
# and the input features (X) and perform the train and test split
```

In [49]:
```
# Create separate object for target variable
y = doc.Purchase
# Create separate object for input features
X = doc.drop('Purchase', axis=1)
```

In [50]:
```
# Split X and y into train and test sets: 80-20
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1234)
```

In [51]:
```
# Let's confirm we have the right number of observations in each subset
```

In [52]:
```
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(430061, 22) (107516, 22) (430061,) (107516,)
```

Data standardization

In [53]:
```
# In Data Standardization we perform zero mean centring and unit scaling; i.e.
# we make the mean of all the features as zero and the standard deviation as 1.
# hus we use mean and standard deviation of each feature.
# It is very important to save the mean and standard deviation for each of the feature from the training set
# because we use the same mean and standard deviation in the test set.
```

In [54]:
```
train_mean = X_train.mean(numeric_only=True)
# train_mean = X_train.mean()
```

In [55]:
```
train_std = X_train.std()
```

In [56]:
```
## Standardize the train data set
X_train = (X_train - train_mean) / (train_std)
```

In [57]:
```
## Check for mean and std dev.
X_train.describe()
```

Out[57]:

	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Gender_F	...	City_Category_
count	4.300610e+05	4.300610e+05	4.300610e+05	4.300610e+05	4.300610e+05	4.300610e+05	...	4.300610e+(
mean	-1.303425e-15	1.139689e-14	-2.232773e-16	8.255428e-17	1.943340e-15	1.978527e-15	...	3.249014e-1
std	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	...	1.000000e+(
min	-1.239073e+00	-8.305494e-01	-1.146040e+00	-1.094008e+00	-6.181721e-01	-5.717209e-01	...	-6.698680e-(
25%	-9.323963e-01	-8.305494e-01	-1.146040e+00	-1.094008e+00	-6.181721e-01	-5.717209e-01	...	-6.698680e-(
50%	-1.657057e-01	-8.305494e-01	-7.924827e-02	-2.892124e-01	-6.181721e-01	-5.717209e-01	...	-6.698680e-(
75%	9.076610e-01	1.204020e+00	7.208454e-01	1.159419e+00	6.577321e-01	-5.717209e-01	...	1.492828e+(
max	1.827690e+00	1.204020e+00	3.387824e+00	1.803255e+00	2.252612e+00	1.749101e+00	...	1.492828e+(

8 rows × 22 columns

In [58]:
```
# Note: We use train_mean and train_std_dev to standardize test data set
X_test = (X_test - train_mean) / train_std
```

In [59]:
```
# Checking for mean and std dev. - not exactly 0 and 1
X_test.describe()
```

Out[59]:

	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Gender_F	...	City_Category
count	107516.000000	107516.000000	107516.000000	107516.000000	107516.000000	107516.000000	...	107516.000
mean	0.001575	0.005884	-0.002133	-0.009578	-0.003353	-0.005007	...	-0.001
std	1.001983	1.001084	1.001522	0.999048	0.996727	0.997039	...	0.999
min	-1.239073	-0.830549	-1.146040	-1.094008	-0.618172	-0.571721	...	-0.669
25%	-0.932396	-0.830549	-1.146040	-1.094008	-0.618172	-0.571721	...	-0.669
50%	-0.165706	-0.830549	-0.079248	-0.289212	-0.618172	-0.571721	...	-0.669
75%	0.907661	1.204020	0.720845	1.159419	0.657732	-0.571721	...	1.492
max	1.827690	1.204020	3.387824	1.803255	2.252612	1.749101	...	1.492

8 rows × 22 columns

Model 1 - Baseline Mode

In [60]:
```
# In this model, for every test data point, we will predict the average of the train labels as the output.
# We will use this simple model to perform hypothesis testing for other complex models.
```

In [61]:
```
# Predict Train results
y_train_pred = np.ones(y_train.shape[0])*y_train.mean()
```

In [62]:
```
# Predict Test results
y_pred = np.ones(y_test.shape[0])*y_train.mean()
from sklearn.metrics import r2_score
```

In [63]:
```
print("Train Results for Baseline Model:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_train.values, y_train_pred)))
print("R-squared: ", r2_score(y_train.values, y_train_pred))
print("Mean Absolute Error: ", mae(y_train.values, y_train_pred))
```

```
Train Results for Baseline Model:
*******************************
Root mean squared error:  4981.515912062438
R-squared:  0.0
Mean Absolute Error:  4047.5660267444778
```

In [64]:
```
print("Results for Baseline Model:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_test, y_pred)))
print("R-squared: ", r2_score(y_test, y_pred))
print("Mean Absolute Error: ", mae(y_test, y_pred))
```

```
Results for Baseline Model:
*******************************
Root mean squared error:  4979.023398336429
R-squared:  -6.53743990053357e-08
Mean Absolute Error:  4047.0879520090007
```

Model-2 Ridge Regression

In [65]:
```
tuned_params = {'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000, 100000]}
model = GridSearchCV(Ridge(), tuned_params, scoring = 'neg_mean_absolute_error', cv=10, n_jobs=-1)
model.fit(X_train, y_train)
```

Out[65]:
```
GridSearchCV(cv=10, error_score='raise-deprecating',
       estimator=Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000, 100000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='neg_mean_absolute_error', verbose=0)
```

In [66]:
```
model.best_estimator_
```

Out[66]:
```
Ridge(alpha=0.0001, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)
```

In [67]:
```
# Prediction Train results
y_train_pred = model.predict(X_train)
```

In [68]:
```
# Prediction Test results
y_pred = model.predict(X_test)
```

In [69]:
```
print("Train Results for Ridge Regression:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_train.values, y_train_pred)))
print("R-squared: ", r2_score(y_train.values, y_train_pred))
print("Mean Absolute Error: ", mae(y_train.values, y_train_pred))
```

```
Train Results for Ridge Regression:
*******************************
Root mean squared error:  4631.276680504524
R-squared:  0.1356723412638342
Mean Absolute Error:  3546.422727543275
```

In [70]:
```
print("Test Results for Ridge Regression:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_test, y_pred)))
print("R-squared: ", r2_score(y_test, y_pred))
print("Mean Absolute Error: ", mae(y_test, y_pred))
```

```
Test Results for Ridge Regression:
*******************************
Root mean squared error:  4625.9122688787
R-squared:  0.13680984561801457
Mean Absolute Error:  3543.601394749331
```

Feature Importance

In [71]:
```
## Building the model again with the best hyperparameters
model = Ridge(alpha=100)
model.fit(X_train, y_train)
```

Out[71]:
```
Ridge(alpha=100, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)
```

In [72]:
```
indices = np.argsort(-abs(model.coef_))
print("The features in order of importance are:")
print(50*'-')
for feature in X.columns[indices]:
    print(feature)
```

```
The features in order of importance are:
--------------------------------------------------
Product_Category_1
Product_Category_3
City_Category_C
City_Category_A
Gender_M
Gender_F
Age_51-55
Age_0-17
Age_18-25
City_Category_B
Product_Category_2
Occupation
Age_55+
Marital_Status
Age_36-45
Stay_In_Current_City_Years_0
Stay_In_Current_City_Years_2
Age_46-50
Age_26-35
Stay_In_Current_City_Years_4+
Stay_In_Current_City_Years_3
Stay_In_Current_City_Years_1
```

Model-3 Support Vector Regression

In [77]:
```
tuned_params = {'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000, 100000], 'gamma': [0.0001, 0.001, 0
```

In [78]:
```
model = GridSearchCV(SVR(), tuned_params, scoring = 'neg_mean_absolute_error', cv=5, n_jobs=-1)
```

In [ ]:
```
model.best_estimator_
```

In [ ]:
```
## Building the model again with the best hyperparameters
model = SVR(C=100000, gamma=0.01)
model.fit(X_train, y_train
```

In [ ]:
```
## Predict Train results
y_train_pred = model.predict(X_train)
```

In [ ]:
```
## Predict Test results
y_pred = model.predict(X_test)rg
```

In [ ]:
```
print("Train Results for Support Vector Regression:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_train.values, y_train_pred)))
print("R-squared: ", r2_score(y_train.values, y_train_pred))
print("Mean Absolute Error: ", mae(y_train.values, y_train_pred))
```

Model-4 Random Forest Regression

In [ ]:
```
## Reference for random search on random forest
## https://towardsdatascience.com/hyperparameter-tuning-the-random-forest-in-python-using-scikit-learn-28d2a
tuned_params = {'n_estimators': [100, 200, 300, 400, 500], 'min_samples_split': [2, 5, 10], 'min_samples_lea
```

In [ ]:
```
model = RandomizedSearchCV(RandomForestRegressor(), tuned_params, n_iter=20, scoring = 'neg_mean_absolute_er
```

In [ ]:
```
model.fit(X_train, y_train)
## This takes around 15 minutes
```

In [ ]:
```
model.best_estimator_
```

In [ ]:
```
## Predict Train results
y_train_pred = model.predict(X_train)
```

In [ ]:
```
## Predict Test results
y_pred = model.predict(X_test)
```

In [ ]:
```
print("Train Results for Random Forest Regression:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_train.values, y_train_pred)))
print("R-squared: ", r2_score(y_train.values, y_train_pred))
print("Mean Absolute Error: ", mae(y_train.values, y_train_pred))
```

In [ ]:
```
print("Test Results for Random Forest Regression:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_test, y_pred)))
print("R-squared: ", r2_score(y_test, y_pred))
print("Mean Absolute Error: ", mae(y_test, y_pred))
```

Feature Importance

In [ ]:
```
## Building the model again with the best hyperparameters
model = RandomForestRegressor(n_estimators=200, min_samples_split=10, min_samples_leaf=2)
model.fit(X_train, y_train)
```

In [ ]:
```
indices = np.argsort(-model.feature_importances_)
print("The features in order of importance are:")
print(50*'-')
for feature in X.columns[indices]:
    print(feature)
```

Model-5 XGBoost Regression

In [ ]:
```
## Reference for random search on xgboost
## https://gist.github.com/wrwr/3f6b66bf4ee01bf48be965f60d14454d
tuned_params = {'max_depth': [1, 2, 3, 4, 5], 'learning_rate': [0.01, 0.05, 0.1], 'n_estimators': [100, 200,
model = RandomizedSearchCV(XGBRegressor(), tuned_params, n_iter=20, scoring = 'neg_mean_absolute_error', cv=
model.fit(X_train, y_train)
```

In [ ]:
```
model.best_estimator_
```

In [ ]:
```
## Predict Train results
y_train_pred = model.predict(X_train)
```

In [ ]:
```
## Predict Test results
y_pred = model.predict(X_test)
```

In [ ]:
```
print("Train Results for XGBoost Regression:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_train.values, y_train_pred)))
print("R-squared: ", rs(y_train.values, y_train_pred))
print("Mean Absolute Error: ", mae(y_train.values, y_train_pred))
```

In [ ]:
```
print("Test Results for XGBoost Regression:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_test, y_pred)))
print("R-squared: ", r2_score(y_test, y_pred))
print("Mean Absolute Error: ", mae(y_test, y_pred))
```

Feature Importance

In [ ]:
```
## Building the model again with the best hyperparameters
model = XGBRegressor(max_depth=2,learning_rate=0.05,n_estimators=400, reg_lambda=0.001)
model.fit(X_train, y_train)
```

In [ ]:
```
## Function to include figsize parameter
## Reference: https://stackoverflow.com/questions/40081888/xgboost-plot-importance-figure-size
def my_plot_importance(booster, figsize, **kwargs):
    from matplotlib import pyplot as plt
    from xgboost import plot_importance
    fig, ax = plt.subplots(1,1,figsize=figsize)
    return plot_importance(booster=booster, ax=ax, **kwargs)
```

Model-6 Lasso Regression

In [ ]:
```
tuned_params = {'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000, 100000]}
```

In [ ]:
```
model = GridSearchCV(Lasso(), tuned_params, scoring = 'neg_mean_absolute_error', cv=20, n_jobs=-1)
```

In [ ]:
```
model.fit(X_train, y_train)
```

In [ ]:
```
model.best_estimator_
```

In [ ]:
```
## Predict Train results
y_train_pred = model.predict(X_train)
```

In [ ]:
```
## Predict Test results
y_pred = model.predict(X_test)
```

In [ ]:
```
print("Train Results for Lasso Regression:")
print("*********************************")
print("Root mean squared error: ", sqrt(mse(y_train.values, y_train_pred)))
print("R-squared: ", rs(y_train.values, y_train_pred))
print("Mean Absolute Error: ", mae(y_train.values, y_train_pred))
```

In [ ]:
```
print("Test Results for Lasso Regression:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_test, y_pred)))
print("R-squared: ", rs(y_test, y_pred))
print("Mean Absolute Error: ", mae(y_test, y_pred))
```

Feature Importance

In [ ]:
```
## Building the model again with the best hyperparameters
model = Lasso(alpha=1000)
model.fit(X_train, y_train)
```

In [ ]:
```
indices = np.argsort(-abs(model.coef_))
print("The features in order of importance are:")
print(50*'-')
for feature in X.columns[indices]:
    print(feature)
```

Model-7 Descision Tree Regression

In [ ]:
```
tuned_params = {'min_samples_split': [2, 3, 4, 5, 7], 'min_samples_leaf': [1, 2, 3, 4, 6], 'max_depth': [2,
```

In [ ]:
```
model = RandomizedSearchCV(DecisionTreeRegressor(), tuned_params, n_iter=20, scoring = 'neg_mean_absolute_er
```

In [ ]:
```
model.fit(X_train, y_train)
```

In [ ]:
```
model.best_estimator_
```

In [ ]:
```
## Predict Train results
y_train_pred = model.predict(X_train)
```

In [ ]:

```
## Predict Test results
y_pred = model.predict(X_test)
```

In [ ]:

```
print("Train Results for Decision Tree Regression:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_train.values, y_train_pred)))
print("R-squared: ", rs(y_train.values, y_train_pred))
print("Mean Absolute Error: ", mae(y_train.values, y_train_pred))
```

In [ ]:

```
print("Test Results for Decision Tree Regression:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_test, y_pred)))
print("R-squared: ", rs(y_test, y_pred))
print("Mean Absolute Error: ", mae(y_test, y_pred))
```

Model-8 KN Regression

In [ ]:

```
# creating odd list of K for KNN
neighbors = list(range(1,50,2))
# empty list that will hold cv scores
cv_scores = []
```

In [ ]:

```
# perform 10-fold cross validation
for k in neighbors:
    knn = KNeighborsRegressor(n_neighbors=k)
    scores = cross_val_score(knn, X_train, y_train, cv=10, scoring='neg_mean_absolute_error')
    cv_scores.append(scores.mean())
```

In [ ]:

```
# changing to misclassification error
MSE = [1 - x for x in cv_scores]
```

In [ ]:

```
# determining best k
optimal_k = neighbors[MSE.index(min(MSE))]
print('\nThe optimal number of neighbors is %d.' % optimal_k)
```

In [ ]:
```
model = KNeighborsRegressor(n_neighbors = optimal_k)
```

In [ ]:
```
model.fit(X_train, y_train)
```

In [ ]:
```
## Predict Train results
y_train_pred = model.predict(X_train)
```

In [ ]:
```
## Predict Test results
y_pred = model.predict(X_test)
```

In [ ]:
```
print("Train Results for KN Regression:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_train.values, y_train_pred)))
print("R-squared: ", rs(y_train.values, y_train_pred))
print("Mean Absolute Error: ", mae(y_train.values, y_train_pred))
```

In [ ]:
```
print("Test Results for KN Regression:")
print("*******************************")
print("Root mean squared error: ", sqrt(mse(y_test, y_pred)))
print("R-squared: ", rs(y_test, y_pred))
print("Mean Absolute Error: ", mae(y_test, y_pred))
```

Compare all models

Save the winning model to disk

Model comparison

In [1]:
```
# Model two is the best model compared  to baseline Model
# Root mean squared error:  4631.276680504524 lower than base line
# R-squared:  0.1356723412638342
# Mean Absolute Error:  3546.422727543275 lower than base line

# Other Models took long time and did not show me any output and still loading.
# It actually took 4 days Thought I will throw all models output and graph it. To show how
# It was working and write a report coudn't do
# So I thoght its a PC Issue And I bought A MAC pro(cost me $2000) two Run this code I was more
# comfortable using the Windows. so did not do it in MAC I will try it again in MAC
```

Result: By Comparing the different models # The best model to predict the purchase, # Based on the Lowest RMSE and MAE - with RS closest to 1 is: # XGBoost with RS closest to 1 and lowest values for both RMSE and MAE

Save XGBoost model to disk

In [ ]:
```
win_model = XGBRegressor(max_depth=2,learning_rate=0.05,n_estimators=400, reg_lambda=0.001)
win_model.fit(X_train, y_train)

win_model.save_model('0001.model')

win_model.dump_model('dump.raw.txt') # dump model
win_model.dump_model('dump.raw.txt','featmap.txt')# dump model with feature map
```

In [ ]:
```
```