SPENDING INSIGHTS- PREDICTING CUSTOMER PURCHASES.

Spending Insights- Predicting Customer Purchases

Import the Data.

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# Let's Load the datasets
client_info = pd.read_csv('ClientInfo.csv')
client_transactions = pd.read_csv('ClientTransactions.csv')
financial_forecast = pd.read_csv('FinancialForecast.csv')

# Merge datasets into one
final_data = pd.DataFrame(client_info.merge(client_transactions,
on='Client_ID').merge(financial_forecast, on='Client_ID'))
final_data
```

```
C:\Users\HP\anaconda3\Lib\site-packages\pandas\core\arrays\
masked.py:60: UserWarning: Pandas requires version '1.3.6' or newer of
'bottleneck' (version '1.3.5' currently installed).
  from pandas.core import (
```

```
     Client_ID Account_Category     Sex  Years_of_Age
Earnings  \
0            1         standard  Female            66  Above_Average

1            2          premium  Female            31        Average

2            3          premium    Male            35  Below_Average

3            4         standard  Female            43  Above_Average

4            5         standard  Female            38        Average

..         ...              ...     ...           ...            ...

495        496         standard    Male            41  Below_Average

496        497         standard  Female            58        Average

497        498         standard    Male            21  Below_Average

498        499          premium  Female            57  Above_Average
```

```
499        500          premium    Male            58  Below_Average


     Job_Tenure_Years  Years_with_Bank  Residence_Zone
Uses_OnlineBanking  \
0                  23                4               2
0
1                   8               22               2
1
2                  13               12               3
1
3                   8               13               1
0
4                  23                3               4
0
..                ...              ...             ...
...
495                20               18               5
1
496                29               12               5
0
497                 4               23               2
1
498                 7               14               2
0
499                28                2               6
0

     Average_Transaction_Gap  ...  Credit_Txn_May  Max_Credit_May  \
0                         14  ...               9    32671.801454
1                         24  ...              42    25309.303627
2                         18  ...              10    47099.381368
3                         17  ...              13    29528.547478
4                          4  ...              20    36523.946704
..                       ...  ...             ...             ...
495                       16  ...              28    31174.060875
496                        1  ...              20    11715.284357
497                       22  ...               6    42989.986379
498                        2  ...               8    40626.226050
499                        3  ...              32    34884.697331

      Debits_June  Credits_June  Debit_Txn_June  Credit_Txn_June  \
0    19448.354899  28090.150684              19                7
1    38631.681829  21468.278030              20               20
2    35342.730917  35453.403105               3               18
3    26310.574000  20294.708303               4               43
4    15814.338412   8616.107687              26               41
..            ...           ...             ...              ...
495   1547.872396  23481.179379              35               17
496  30976.111435  32485.931275               8               12
```

```
497  29982.107217  11411.345170                8              22
498   1874.641966  34721.863275               42              14
499  15729.765458  33001.078351               37              34

     Max_Credit_June  Loan_Inquiry_Recent  Active_EMI_Payment
Future_CC_Spend
0       44188.089797                   No          636.212632
14307.040795
1       35651.535666                  Yes         2867.378244
NaN
2       35225.590780                  Yes         4198.467197
4048.850382
3       32298.013633                  Yes         2081.295468
4635.880423
4       14928.738971                   No         5950.858966
14863.424705
..               ...                  ...                 ...
...
495     17979.191813                   No         2340.215257
13005.083195
496     25987.780701                   No         3255.507698
14277.454235
497     41513.844463                   No         1588.075803
10957.849285
498     26077.184239                   No         6076.135273
5162.068125
499     43255.917987                   No         4144.437237
7001.126198

[500 rows x 49 columns]
```

Display the Data

```
# Display the first few rows of the merged dataset
print(final_data.head())

   Client_ID Account_Category     Sex  Years_of_Age       Earnings  \
0          1         standard  Female            66  Above_Average
1          2          premium  Female            31        Average
2          3          premium    Male            35  Below_Average
3          4         standard  Female            43  Above_Average
4          5         standard  Female            38        Average

   Job_Tenure_Years  Years_with_Bank  Residence_Zone
Uses_OnlineBanking  \
0                23                4               2
0
1                 8               22               2
1
2                13               12               3
```

```
1
3                8                13                1
0
4               23                 3                4
0

   Average_Transaction_Gap  ...  Credit_Txn_May  Max_Credit_May
Debits_June  \
0                       14  ...               9    32671.801454
19448.354899
1                       24  ...              42    25309.303627
38631.681829
2                       18  ...              10    47099.381368
35342.730917
3                       17  ...              13    29528.547478
26310.574000
4                        4  ...              20    36523.946704
15814.338412

   Credits_June  Debit_Txn_June  Credit_Txn_June  Max_Credit_June  \
0  28090.150684              19                7     44188.089797
1  21468.278030              20               20     35651.535666
2  35453.403105               3               18     35225.590780
3  20294.708303               4               43     32298.013633
4   8616.107687              26               41     14928.738971

   Loan_Inquiry_Recent  Active_EMI_Payment  Future_CC_Spend
0                   No          636.212632     14307.040795
1                  Yes         2867.378244              NaN
2                  Yes         4198.467197      4048.850382
3                  Yes         2081.295468      4635.880423
4                   No         5950.858966     14863.424705

[5 rows x 49 columns]
```

Data Preprocessing

DATA CHECKING

```
# Check data types
print(final_data.info())

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 49 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Client_ID                500 non-null    int64
 1   Account_Category         500 non-null    object
 2   Sex                      500 non-null    object
```

```
 3   Years_of_Age              500 non-null    int64
 4   Earnings                  500 non-null    object
 5   Job_Tenure_Years          500 non-null    int64
 6   Years_with_Bank           500 non-null    int64
 7   Residence_Zone            500 non-null    int64
 8   Uses_OnlineBanking        500 non-null    int64
 9   Average_Transaction_Gap   500 non-null    int64
 10  CC_spend_April            500 non-null    float64
 11  DC_spend_April            500 non-null    float64
 12  CC_spend_May              500 non-null    float64
 13  DC_spend_May              500 non-null    float64
 14  CC_spend_June             500 non-null    float64
 15  DC_spend_June             500 non-null    float64
 16  CC_txn_count_April        500 non-null    int64
 17  CC_txn_count_May          500 non-null    int64
 18  CC_txn_count_June         500 non-null    int64
 19  DC_txn_count_April        500 non-null    int64
 20  DC_txn_count_May          500 non-null    int64
 21  DC_txn_count_June         500 non-null    int64
 22  Max_Card_Limit            500 non-null    float64
 23  Has_Personal_Loan         500 non-null    int64
 24  Has_Vehicle_Loan          500 non-null    int64
 25  Personal_Loan_Closed      500 non-null    int64
 26  Vehicle_Loan_Closed       500 non-null    int64
 27  Investment_A              500 non-null    float64
 28  Investment_B              500 non-null    float64
 29  Investment_C              500 non-null    float64
 30  Investment_D              500 non-null    float64
 31  Debits_April              500 non-null    float64
 32  Credits_April             500 non-null    float64
 33  Debit_Txn_April           500 non-null    int64
 34  Credit_Txn_April          500 non-null    int64
 35  Max_Credit_April          500 non-null    float64
 36  Debits_May                500 non-null    float64
 37  Credits_May               500 non-null    float64
 38  Debit_Txn_May             500 non-null    int64
 39  Credit_Txn_May            500 non-null    int64
 40  Max_Credit_May            500 non-null    float64
 41  Debits_June               500 non-null    float64
 42  Credits_June              500 non-null    float64
 43  Debit_Txn_June            500 non-null    int64
 44  Credit_Txn_June           500 non-null    int64
 45  Max_Credit_June           500 non-null    float64
 46  Loan_Inquiry_Recent       500 non-null    object
 47  Active_EMI_Payment        500 non-null    float64
 48  Future_CC_Spend           425 non-null    float64
dtypes: float64(22), int64(23), object(4)
memory usage: 191.5+ KB
None
```

```python
# check for missing values
print(final_data.isnull().sum())
```

```
Client_ID                   0
Account_Category            0
Sex                         0
Years_of_Age                0
Earnings                    0
Job_Tenure_Years            0
Years_with_Bank             0
Residence_Zone              0
Uses_OnlineBanking          0
Average_Transaction_Gap     0
CC_spend_April              0
DC_spend_April              0
CC_spend_May                0
DC_spend_May                0
CC_spend_June               0
DC_spend_June               0
CC_txn_count_April          0
CC_txn_count_May            0
CC_txn_count_June           0
DC_txn_count_April          0
DC_txn_count_May            0
DC_txn_count_June           0
Max_Card_Limit              0
Has_Personal_Loan           0
Has_Vehicle_Loan            0
Personal_Loan_Closed        0
Vehicle_Loan_Closed         0
Investment_A                0
Investment_B                0
Investment_C                0
Investment_D                0
Debits_April                0
Credits_April               0
Debit_Txn_April             0
Credit_Txn_April            0
Max_Credit_April            0
Debits_May                  0
Credits_May                 0
Debit_Txn_May               0
Credit_Txn_May              0
Max_Credit_May              0
Debits_June                 0
Credits_June                0
Debit_Txn_June              0
Credit_Txn_June             0
Max_Credit_June             0
Loan_Inquiry_Recent         0
```

```
Active_EMI_Payment          0
Future_CC_Spend            75
dtype: int64
```

Conversion of Categorical Values-One Hot Encoding

Generally,we try to avoid using categorical variables directly; instead we convert them into numeric formats using techniques like one-hot encoding or label encoding.

We have four columns that are categorical.

```
import pandas as pd

# We assume the final_data is our DataFrame
final_data_encoded = pd.get_dummies(final_data,
columns=['Account_Category', 'Sex', 'Earnings',
'Loan_Inquiry_Recent'], drop_first=True)

# Now our final_data_encoded is ready for modeling
final_data_encoded
```

```
     Client_ID  Years_of_Age  Job_Tenure_Years  Years_with_Bank  \
0            1            66                23                4
1            2            31                 8               22
2            3            35                13               12
3            4            43                 8               13
4            5            38                23                3
..         ...           ...               ...              ...
495        496            41                20               18
496        497            58                29               12
497        498            21                 4               23
498        499            57                 7               14
499        500            58                28                2

     Residence_Zone  Uses_OnlineBanking  Average_Transaction_Gap  \
0                 2                   0                       14
1                 2                   1                       24
2                 3                   1                       18
3                 1                   0                       17
4                 4                   0                        4
..              ...                 ...                      ...
495               5                   1                       16
496               5                   0                        1
497               2                   1                       22
498               2                   0                        2
499               6                   0                        3

     CC_spend_April  DC_spend_April  CC_spend_May  ...  Debit_Txn_June
\
```

```
0      4434.237640    4681.872917   8691.681587  ...              19
1      5444.512627    3740.867000   5391.629443  ...              20
2     10055.915467    4186.830418  10883.941630  ...               3
3      1878.747575    1416.917930   5625.613589  ...               4
4      8951.647245    8867.753934  10863.717832  ...              26
..             ...            ...           ...  ...             ...
495    4402.010574    6853.191704   7850.529045  ...              35
496    6318.214025    5236.272480   1465.519889  ...               8
497    2362.114576    8656.023154   9574.780082  ...               8
498    8068.175508    8700.546048   5597.823385  ...              42
499   11974.117974     396.133746   1315.040627  ...              37

     Credit_Txn_June  Max_Credit_June  Active_EMI_Payment
Future_CC_Spend  \
0                  7     44188.089797          636.212632
14307.040795
1                 20     35651.535666         2867.378244
NaN
2                 18     35225.590780         4198.467197
4048.850382
3                 43     32298.013633         2081.295468
4635.880423
4                 41     14928.738971         5950.858966
14863.424705
..               ...              ...                 ...
...
495               17     17979.191813         2340.215257
13005.083195
496               12     25987.780701         3255.507698
14277.454235
497               22     41513.844463         1588.075803
10957.849285
498               14     26077.184239         6076.135273
5162.068125
499               34     43255.917987         4144.437237
7001.126198

     Account_Category_standard  Sex_Male  Earnings_Average  \
0                         True     False             False
```

```
1                               False     False                True
2                               False      True               False
3                                True     False               False
4                                True     False                True
..                                ...       ...                 ...
495                              True      True               False
496                              True     False                True
497                              True      True               False
498                             False     False               False
499                             False      True               False

     Earnings_Below_Average  Loan_Inquiry_Recent_Yes
0                     False                    False
1                     False                     True
2                      True                     True
3                     False                     True
4                     False                    False
..                      ...                      ...
495                    True                    False
496                   False                    False
497                    True                    False
498                   False                    False
499                    True                    False

[500 rows x 50 columns]
```

Data Correlation Check

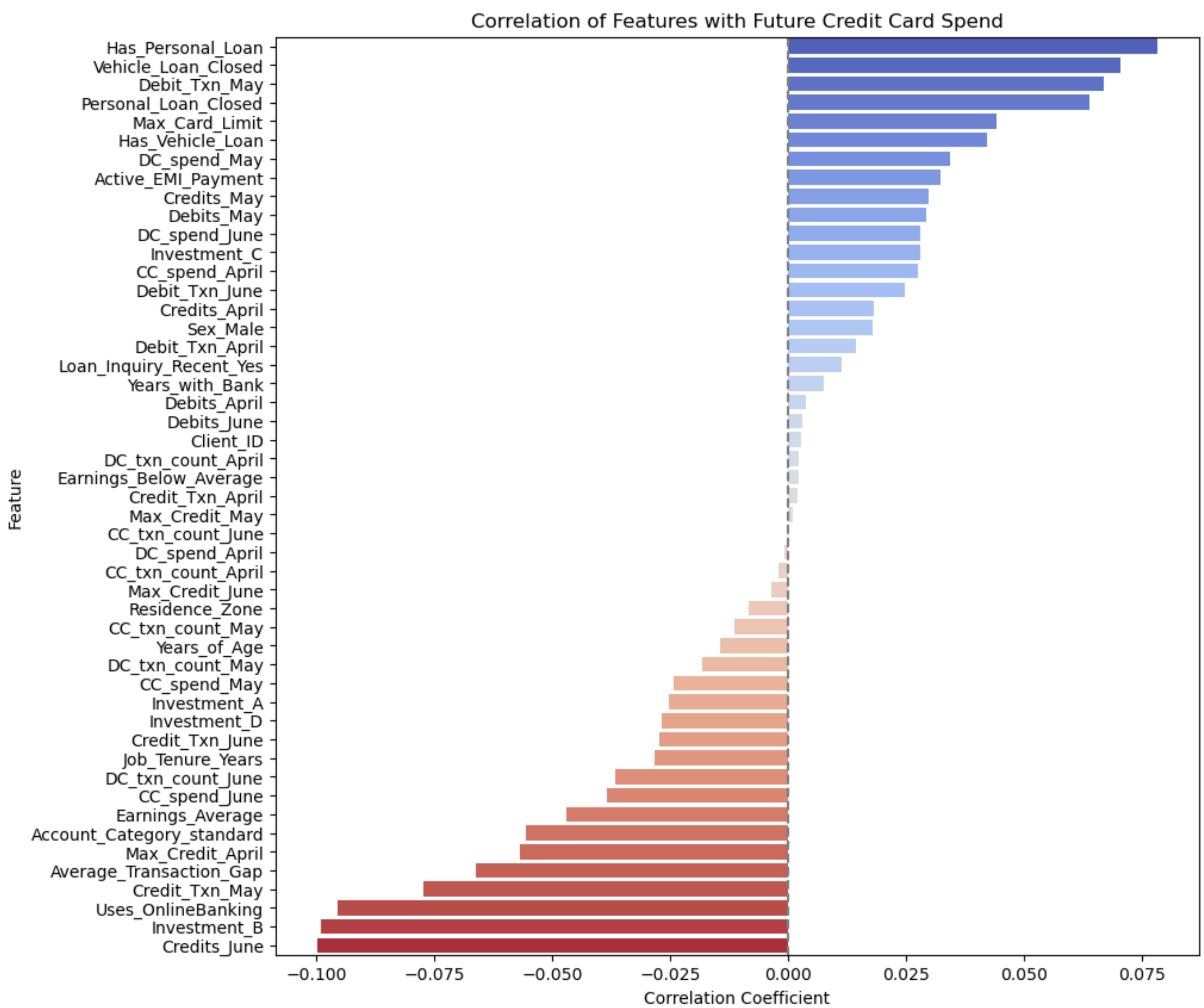
```
# Our data should be a pandas dataframe.
import pandas
corr_data = final_data_encoded
corr_matrix = corr_data.corr()
print(corr_matrix["Future_CC_Spend"].sort_values(ascending=False))
```

```
Future_CC_Spend             1.000000
Has_Personal_Loan           0.078201
Vehicle_Loan_Closed         0.070341
Debit_Txn_May               0.067026
Personal_Loan_Closed        0.063929
Max_Card_Limit              0.044157
Has_Vehicle_Loan            0.042194
DC_spend_May                0.034234
Active_EMI_Payment          0.032210
Credits_May                 0.029650
Debits_May                  0.029373
DC_spend_June               0.027990
Investment_C                0.027954
CC_spend_April              0.027487
Debit_Txn_June              0.024731
```

```
Credits_April                  0.018089
Sex_Male                       0.018026
Debit_Txn_April                0.014264
Loan_Inquiry_Recent_Yes        0.011216
Years_with_Bank                0.007528
Debits_April                   0.003813
Debits_June                    0.002942
Client_ID                      0.002832
DC_txn_count_April             0.002356
Earnings_Below_Average         0.002212
Credit_Txn_April               0.001860
Max_Credit_May                 0.001087
CC_txn_count_June             -0.000402
DC_spend_April                -0.000874
CC_txn_count_April            -0.002005
Max_Credit_June               -0.003671
Residence_Zone                -0.008440
CC_txn_count_May              -0.011402
Years_of_Age                  -0.014376
DC_txn_count_May              -0.018127
CC_spend_May                  -0.024371
Investment_A                  -0.025413
Investment_D                  -0.026698
Credit_Txn_June               -0.027233
Job_Tenure_Years              -0.028432
DC_txn_count_June             -0.036739
CC_spend_June                 -0.038498
Earnings_Average              -0.047051
Account_Category_standard     -0.055700
Max_Credit_April              -0.056819
Average_Transaction_Gap       -0.066218
Credit_Txn_May                -0.077464
Uses_OnlineBanking            -0.095422
Investment_B                  -0.099137
Credits_June                  -0.099795
Name: Future_CC_Spend, dtype: float64
```

```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Here we are assuming final_data is your DataFrame
correlation_matrix = final_data_encoded.corr()

# Getting the correlation values with the target feature
'Future_CC_Spend'
target_correlation =
correlation_matrix['Future_CC_Spend'].sort_values(ascending=False)

# Converting to DataFrame for visualization
```

```
target_correlation_df = target_correlation.reset_index()
target_correlation_df.columns = ['Feature', 'Correlation']

# Filtering out the target feature itself
target_correlation_df =
target_correlation_df[target_correlation_df['Feature'] !=
'Future_CC_Spend']

# Plotting
plt.figure(figsize=(10, 10))
sns.barplot(x='Correlation', y='Feature', data=target_correlation_df,
palette='coolwarm')
plt.title('Correlation of Features with Future Credit Card Spend')
plt.xlabel('Correlation Coefficient')
plt.ylabel('Feature')
plt.axvline(0, color='grey', linestyle='--')  # Add a vertical line at
0 for reference
plt.show()
```



Featutre selection & Engineering

Now from the bar chart it is pretty evident which are the features we should drop

```python
# List of features to drop
features_to_drop = [
    'Debits_April',
    'Debits_June',
    'DC_txn_count_April',
    'Earnings_Below_Average',
    'Credit_Txn_April',
    'Max_Credit_May',
    'CC_txn_count_June',
    'DC_spend_April',
    'CC_txn_count_April',
    'Max_Credit_June',
    'Residence_Zone',
    'CC_txn_count_May',
    'Years_of_Age',
    'DC_txn_count_May',
    'Investment_D'
]

# Dropping the features
final_data_dropped = final_data_encoded.drop(columns=features_to_drop)

# Displaying the new DataFrame shape
print(final_data_dropped.shape)

# Displaying the first few rows of the updated DataFrame
print(final_data_dropped.head())
```

```
(500, 35)
   Client_ID  Job_Tenure_Years  Years_with_Bank  Uses_OnlineBanking  \
0          1                23                4                   0
1          2                 8               22                   1
2          3                13               12                   1
3          4                 8               13                   0
4          5                23                3                   0

   Average_Transaction_Gap  CC_spend_April  CC_spend_May  DC_spend_May
\
0                       14     4434.237640   8691.681587   5402.427022

1                       24     5444.512627   5391.629443   4196.194939

2                       18    10055.915467  10883.941630   8387.519584

3                       17     1878.747575   5625.613589   2256.350893
```

```
4                         4     8951.647245  10863.717832   7920.827946


   CC_spend_June  DC_spend_June  ...  Credit_Txn_May  Credits_June  \
0    5260.062916    7084.427003  ...               9  28090.150684
1    5343.527352    8838.356828  ...              42  21468.278030
2    3948.561236    2536.948509  ...              10  35453.403105
3    8895.319344    1572.890498  ...              13  20294.708303
4   10801.133378    8993.102295  ...              20   8616.107687

   Debit_Txn_June  Credit_Txn_June  Active_EMI_Payment
Future_CC_Spend  \
0              19                7          636.212632
14307.040795
1              20               20         2867.378244
NaN
2               3               18         4198.467197
4048.850382
3               4               43         2081.295468
4635.880423
4              26               41         5950.858966
14863.424705

   Account_Category_standard  Sex_Male  Earnings_Average  \
0                       True     False             False
1                      False     False              True
2                      False      True             False
3                       True     False             False
4                       True     False              True

   Loan_Inquiry_Recent_Yes
0                    False
1                     True
2                     True
3                     True
4                    False

[5 rows x 35 columns]

# Now we will Select features and target variable
X = final_data_dropped.drop(columns=['Future_CC_Spend'])
y = final_data_dropped['Future_CC_Spend']

# And Encode categorical variables(if necessary,again)
X = pd.get_dummies(X, drop_first=True)
```

Exploratory Data Analysis(EDA)

```
# Summary statistics
print(final_data_dropped.describe())
```

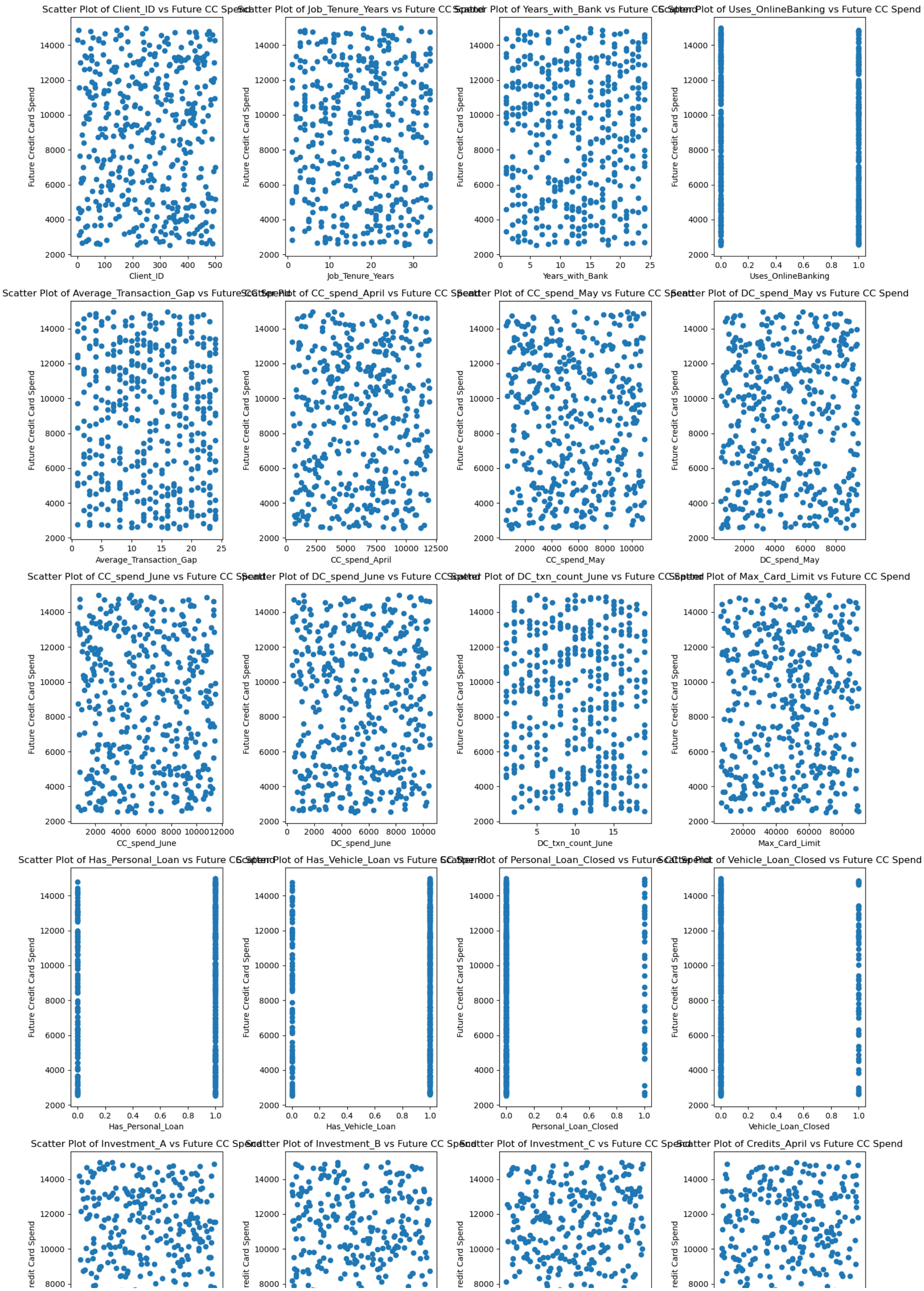
```
        Client_ID  Job_Tenure_Years  Years_with_Bank  
Uses_OnlineBanking  \
count  500.000000        500.000000       500.000000  
500.000000   
mean   250.500000         17.818000        12.488000  
0.514000   
std    144.481833          9.529034         6.975326  
0.500305   
min      1.000000          1.000000         1.000000  
0.000000   
25%    125.750000          9.000000         6.000000  
0.000000   
50%    250.500000         19.000000        13.000000  
1.000000   
75%    375.250000         25.250000        19.000000  
1.000000   
max    500.000000         34.000000        24.000000  
1.000000   

       Average_Transaction_Gap  CC_spend_April  CC_spend_May  
DC_spend_May  \
count                500.000000      500.000000    500.000000  
500.000000   
mean                  13.402000     6111.240720   5750.299794  
4912.181201   
std                    6.828004     3277.933535   3004.696204  
2638.348384   
min                    1.000000      500.353267    606.218564  
456.272786   
25%                    8.000000     3398.302015   3156.416710  
2646.676213   
50%                   14.000000     6055.377861   5605.401859  
4841.938494   
75%                   19.000000     8719.365609   8398.782231  
7098.133246   
max                   24.000000    11974.117974  10918.210651  
9489.015716   

       CC_spend_June  DC_spend_June  ...  Max_Credit_April  
Debits_May  \
count     500.000000     500.000000  ...        500.000000  
500.000000   
mean     5929.983408    5430.170521  ...      28618.180831  
20437.079960   
std      3201.028528    2912.154108  ...      12671.250756  
11410.982325   
min       592.906206     364.497682  ...       6024.384122  
1511.924679   
25%      3121.659409    2995.316317  ...      17728.341515  
10821.417620   
```

```
50%      5898.259891    5458.002098  ...      29535.267153
19895.436818
75%      8833.283910    7976.240661  ...      39616.036085
30669.173977
max     11494.094458   10485.392187  ...      49996.692381
39929.727409

        Credits_May  Debit_Txn_May  Credit_Txn_May  Credits_June  \
count    500.000000     500.000000       500.00000    500.000000
mean   23522.626904      23.522000        22.29000  24792.616201
std    12101.238292      12.372375        12.91726  12177.146347
min     2010.855543       2.000000         1.00000   2168.820451
25%    13632.539050      13.000000        11.00000  14765.784036
50%    23815.697927      24.000000        22.00000  24920.841872
75%    33333.382531      35.000000        34.00000  35309.559300
max    44963.431371      44.000000        44.00000  44994.471846

       Debit_Txn_June  Credit_Txn_June  Active_EMI_Payment
Future_CC_Spend
count      500.000000       500.000000          500.000000
425.000000
mean        23.502000        22.038000         3667.897217
8728.339886
std         12.202943        12.858898         2019.195640
3733.671314
min          2.000000         1.000000          118.981869
2531.193170
25%         13.000000        10.000000         1966.092703
5142.662697
50%         24.000000        22.500000         3713.009235
9041.594921
75%         34.000000        33.000000         5413.820199
11884.852206
max         44.000000        44.000000         6999.316741
14975.890670

[8 rows x 31 columns]
```

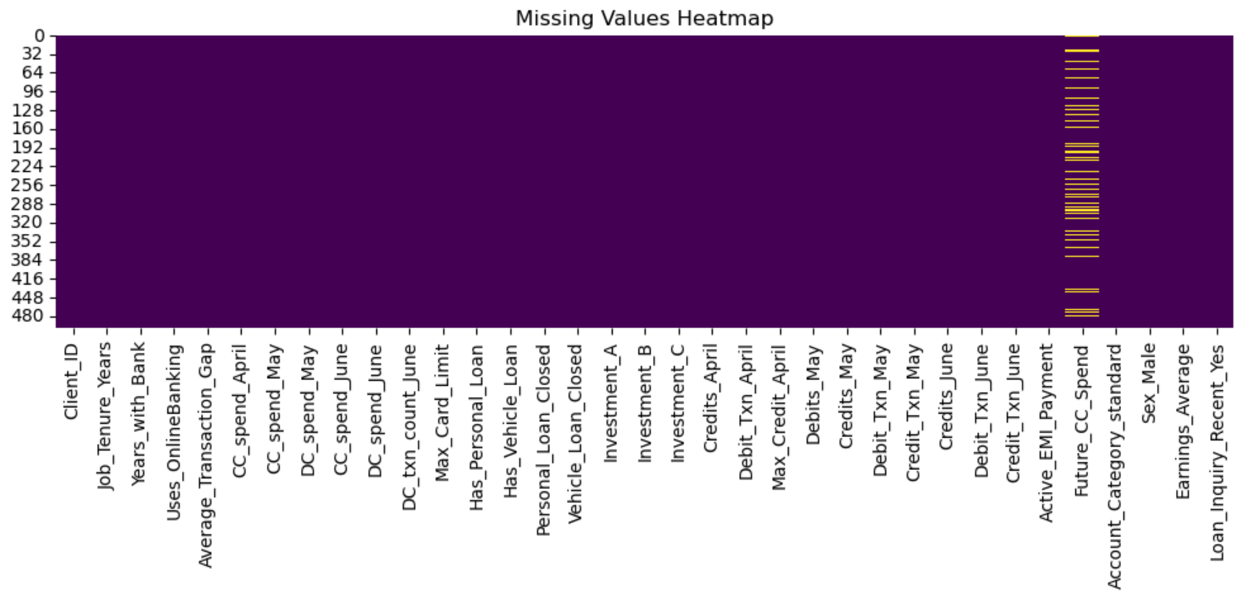
LET'S PLOT THE SCATTER PLOTS OF EACH FEATURE WITH THE TARGET

```python
import matplotlib.pyplot as plt
import numpy as np

# Here we assume that X is our input features DataFrame and Y is your
target variable
features_to_plot = X.columns  # Get feature names from X
num_features = len(features_to_plot)

# Here we are calculating the number of rows and columns for subplots
```

```python
num_cols = 4
num_rows = np.ceil(num_features / num_cols).astype(int)

# And setting up the plotting area
plt.figure(figsize=(15, 5 * num_rows))

# Looping through features to create the scatter plots
for i, feature in enumerate(features_to_plot):
    plt.subplot(num_rows, num_cols, i + 1)
    plt.scatter(X[feature], y)
    plt.xlabel(feature)
    plt.ylabel('Future Credit Card Spend')
    plt.title(f'Scatter Plot of {feature} vs Future CC Spend')

plt.tight_layout()  # Adjust layout
plt.show()
```


Scatter Plot of Client_ID vs Future CC Spend
Client_ID
Scatter Plot of Job_Tenure_Years vs Future CC Spend
Job_Tenure_Years
Scatter Plot of Years_with_Bank vs Future CC Spend
Years_with_Bank
Scatter Plot of Uses_OnlineBanking vs Future CC Spend
Uses_OnlineBanking
Scatter Plot of Average_Transaction_Gap vs Future CC Spend
Average_Transaction_Gap
Scatter Plot of CC_spend_April vs Future CC Spend
CC_spend_April
Scatter Plot of CC_spend_May vs Future CC Spend
CC_spend_May
Scatter Plot of DC_spend_May vs Future CC Spend
DC_spend_May
Scatter Plot of CC_spend_June vs Future CC Spend
CC_spend_June
Scatter Plot of DC_spend_June vs Future CC Spend
DC_spend_June
Scatter Plot of DC_txn_count_June vs Future CC Spend
DC_txn_count_June
Scatter Plot of Max_Card_Limit vs Future CC Spend
Max_Card_Limit
Scatter Plot of Has_Personal_Loan vs Future CC Spend
Has_Personal_Loan
Scatter Plot of Has_Vehicle_Loan vs Future CC Spend
Has_Vehicle_Loan
Scatter Plot of Personal_Loan_Closed vs Future CC Spend
Personal_Loan_Closed
Scatter Plot of Vehicle_Loan_Closed vs Future CC Spend
Vehicle_Loan_Closed
Scatter Plot of Investment_A vs Future CC Spend
Scatter Plot of Investment_B vs Future CC Spend
Scatter Plot of Investment_C vs Future CC Spend
Scatter Plot of Credits_April vs Future CC Spend
Future Credit Card Spend

```python
# Finally we will visualize the missing values.

plt.figure(figsize=(12, 3))
sns.heatmap(final_data_dropped.isnull(), cbar=False, cmap='viridis')
plt.title('Missing Values Heatmap')
plt.show()
```



Model Selection

Now we are tasked with selecting the best model that works well with regression problems.

We can choose between:

1.Linear Regression

2.Decision Tree Regressor

3.Random Forest Regressor

4.XGBoost Regressor

We will use Random Forest Regressor

Q-WHY RANDOM FOREST REGRESSOR?

We chose Random Forest Regressor for this problem because it is effective for regression tasks, can absorb to overfitting, and can handle large datasets with multiple features.

Q-WHY ARE WE USING RANDOM FOREST REGRESSOR AND NOT RANDOM FOREST CLASSIFIER?

Because of the nature of the problem,

Random Forest Regressor is used for regression tasks, where the goal is to predict a continuous numerical value. In this project, we are predicting the average purchase amount for `Future CC Spend`, which is a continuous numeric value (e.g., 1000 dollars, 5000 dollars, etc.).

Random Forest Classifier is used for classification tasks, where the goal is to predict a category or class label (e.g., whether a transaction is fraudulent or not, or predicting if a customer will churn or not). In classification problems, the target variable is discrete (e.g., Yes/No, 0/1, High/Low, etc.).

Here The target variable is `Future CC Spend`, which represents a numeric value (continuous variable). For predicting such continuous outputs, we need a regression model, and Random Forest Regressor is designed to handle regression tasks effectively.

Model Training

Now we will Separate the dataset into two parts:

Training Set: Rows where the `Future_CC_Spend` is not missing (this will be used to train the model).

Test Set: Rows where the `Future_CC_Spend` is missing (this is where we will predict the missing values).

SPLIT THE MODEL

```
# First we will have to separate the dataset into two parts: with and
without missing target values
train_data =
final_data_dropped[final_data_dropped['Future_CC_Spend'].notna()]
test_data =
final_data_dropped[final_data_dropped['Future_CC_Spend'].isna()]

# Then we will separate features and target for training data
X_train = train_data.drop('Future_CC_Spend', axis=1)
Y_train = train_data['Future_CC_Spend']

# And we will also assign Features for the test data (with missing
target values)
X_test = test_data.drop('Future_CC_Spend', axis=1)
```

TRAIN THE MODEL

```
from sklearn.ensemble import RandomForestRegressor

# Training the Random Forest model
model = RandomForestRegressor(random_state=42)
model.fit(X_train, Y_train)

RandomForestRegressor(random_state=42)
```

VALIDATE THE MODEL

```
# Predicting missing values for Future_CC_Spend
predictions = model.predict(X_test)

# Adding the predictions to the test data DataFrame
test_data['Future_CC_Spend'] = predictions
```

```
C:\Users\HP\AppData\Local\Temp\ipykernel_3972\1500729630.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  test_data['Future_CC_Spend'] = predictions
```

COMBINING THE TEST & TRAIN DATA

```
# Combining the original train data and the test data with predictions
final_predictions = pd.concat([train_data, test_data],
ignore_index=True)

# Displaying the final predictions DataFrame
print(final_predictions.head())
```

```
   Client_ID  Job_Tenure_Years  Years_with_Bank  Uses_OnlineBanking  \
0          1                23                4                   0
1          3                13               12                   1
2          4                 8               13                   0
3          5                23                3                   0
4          6                 1               22                   1

   Average_Transaction_Gap  CC_spend_April  CC_spend_May  DC_spend_May
\
0                       14     4434.237640   8691.681587   5402.427022

1                       18    10055.915467  10883.941630   8387.519584

2                       17     1878.747575   5625.613589   2256.350893

3                        4     8951.647245  10863.717832   7920.827946

4                       23     6611.731513   8447.521357   5474.967090


   CC_spend_June  DC_spend_June  ...  Credit_Txn_May  Credits_June  \
0    5260.062916    7084.427003  ...               9  28090.150684
1    3948.561236    2536.948509  ...              10  35453.403105
2    8895.319344    1572.890498  ...              13  20294.708303
3   10801.133378    8993.102295  ...              20   8616.107687
```

```
4   10851.221909    1939.620071  ...             29  43985.871844

   Debit_Txn_June  Credit_Txn_June  Active_EMI_Payment  
Future_CC_Spend  \
0              19                7          636.212632  
14307.040795  
1               3               18         4198.467197  
4048.850382  
2               4               43         2081.295468  
4635.880423  
3              26               41         5950.858966  
14863.424705  
4              37               14         1142.591098  
11569.564967  

   Account_Category_standard  Sex_Male  Earnings_Average  \
0                       True     False             False   
1                      False      True             False   
2                       True     False             False   
3                       True     False              True   
4                       True      True             False   

   Loan_Inquiry_Recent_Yes  
0                    False  
1                     True  
2                     True  
3                    False  
4                     True  

[5 rows x 35 columns]
```

Why not calculating the errors?

CALCULATE MAE,MSE,RMSE AND RMPSE

```
from sklearn.metrics import mean_absolute_error, mean_squared_error, 
r2_score

# Here we have created a Function to calculate and display metrics

def display_metrics(y_true, y_pred):
    mae = mean_absolute_error(y_true, y_pred)
    mse = mean_squared_error(y_true, y_pred)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_true, y_pred)

    # Calculating an unique metric, RMSPE
    rmspe = np.sqrt(np.mean(((y_true - y_pred) / y_true) ** 2)) * 100
```

```
    print(f"MAE: {mae:.2f}")
    print(f"MSE: {mse:.2f}")
    print(f"RMSE: {rmse:.2f}")
    print(f"R² Score: {r2:.2f}")
    print(f"RMSPE: {rmspe:.2f}%")
    print("\n")


# Making predictions on the training data
y_train_pred = model.predict(X_train)

# Displaying metrics
display_metrics(Y_train, y_train_pred)
```

```
MAE: 1238.98
MSE: 2046891.88
RMSE: 1430.70
R² Score: 0.85
RMSPE: 29.07%
```

As we can see the R-Squared value of our model is 0.85,means

The Explained Variance: 85% of the variance in the target variable is explained by the model. Which means the model’s predictions are very close to the actual values.

The Unexplained Variance: 15% of the variance in the target variable remains unexplained by the model.

Consideration: While the high R^2 indicates the model's predictions are closely aligned with the actual values, it doesn't always mean that our model is perfect. If the data has outliers or is overfitted, R^2 could give a falsely high impression of accuracy.

1.1234.59 is the Mean Absolute Error (MAE).

The average absolute difference between the expected and actual values is represented by the MAE. A lower number corresponds to higher forecasting accuracy. In our instance, the model has a mean error of about 1234.59 units, which can be considered relatively small as our target variables are much higher.

2.2023653.42 is the Mean Squared Error (MSE).

The MSE reflects the average of the squared differences between the predicted and actual values. The high value of MSE suggests that the predictions deviate from the true values, and the large squared differences can point to some larger errors in predictions.

Consideration: The MSE can be heavily influenced by outliers because it squares the error values, so larger errors have a greater impact,and as it seems our dataset has outliers.

3.Root Mean Squared Error (RMSE): 1422.55

The RMSE is the square root of the MSE and is in the same units as the target variable. It gives you a sense of how much error Wwe can expect in predictions. An RMSE of 1422.55 indicates the magnitude of prediction error in the model.

4.Root Means Square Percentage Error(RMSPE):

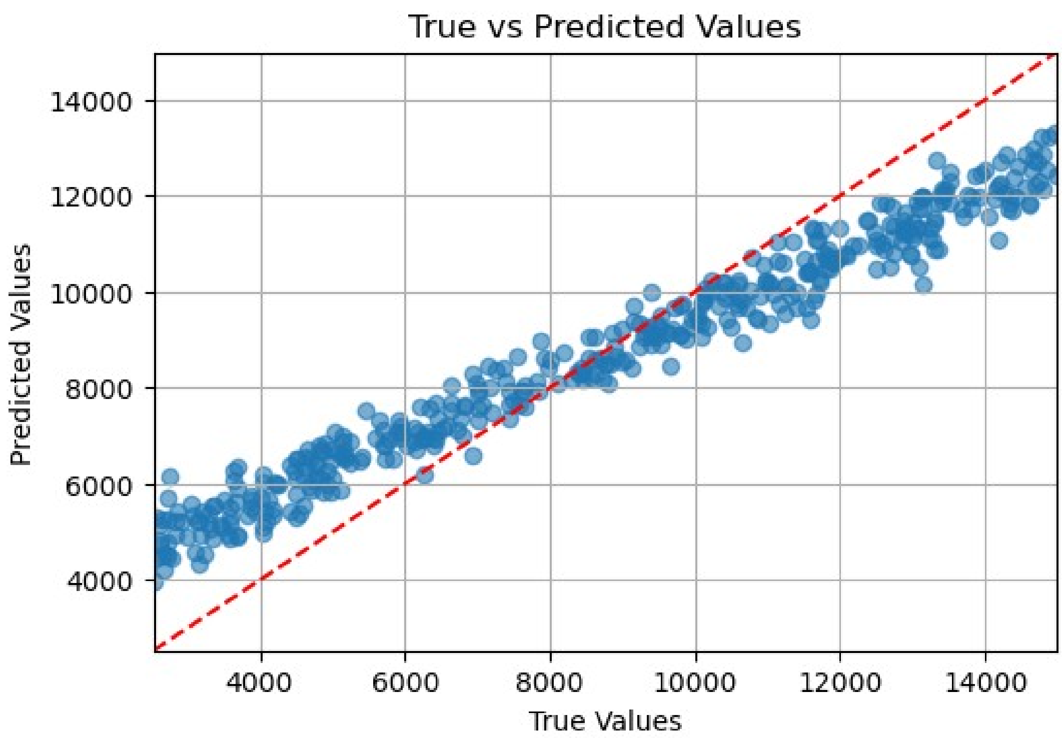
RMSPE (Root Mean Squared Percentage Error) is a metric used to measure the accuracy of a model's predictions. It expresses the error as a percentage of the actual values, making it easier to interpret in terms of relative performance.

Consideration: It can be skewed by very small actual values. If any of the actual values are close to zero, the percentage error can become disproportionately large.

True vs Predicted Values

Now we will be creating a plot that can visualize the True vs Predicted value of out model.

```
import matplotlib.pyplot as plt

# Creating a function for the plot

def plot_true_vs_predicted(y_true, y_pred, title):
    plt.figure(figsize=(6, 4))
    plt.scatter(y_true, y_pred, alpha=0.6)
    plt.plot([y_true.min(), y_true.max()], [y_true.min(),
y_true.max()], color='red', linestyle='--')  # 45-degree line
    plt.title(title)
    plt.xlabel('True Values')
    plt.ylabel('Predicted Values')
    plt.xlim(y_true.min(), y_true.max())
    plt.ylim(y_true.min(), y_true.max())
    plt.grid()
    plt.show()

# Plot true vs predicted for the training data before tuning
plot_true_vs_predicted(Y_train, y_train_pred, 'True vs Predicted
Values')
```



Prediction of Missing Values

Once we are satisfied with the model's performance on the validation set, we will use the trained model to predict the missing values in the test set.

```
# Creating a DataFrame to show the Client_ID and predicted
Future_CC_Spend for the missing values

predicted_values_df = test_data[['Client_ID']].copy()
predicted_values_df['Predicted_Future_CC_Spend'] = predictions

# Displaying the DataFrame with predicted values

print(predicted_values_df)
```

```
     Client_ID  Predicted_Future_CC_Spend
1            2                7893.381092
7            8                8288.461763
9           10                9348.382233
25          26                7774.013925
27          28                7965.574324
..         ...                        ...
473        474               10465.229556
476        477                7608.172593
479        480                8216.400947
480        481                8427.307146
494        495                7164.344265
```

```
[75 rows x 2 columns]
```

Exporting the Results

```
#The last step,here we will save the results in a csv file and it's done!

predicted_values_df.to_csv('Predicted_Future_CC_Spend.csv',
index=False)
```

Key Concepts

WHAT IS RMSPE?

RMSPE measures the prediction error in terms of percentages, giving an idea of how far off the predictions are in relative terms,this is a metric used to evaluate the accuracy of a model's predictions, especially in regression problems. It measures the percentage difference between the predicted and actual values, making it particularly useful when the scale of the data varies widely.

As we can see the RMSPE(Root Mean Square Percentage Error) is high with a value of 153.80%,this means that the model's predictions are, on average, more than 1.5 times the actual values, indicating a poor fit.

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{\widehat{y_i} - y_i}{y_i} \right|$$

Now there can be several reasons for this,

Missing Data:

Handling missing values poorly can distort model performance. If missing values are not properly imputed or handled, the model may make inaccurate predictions, leading to high errors. If the pattern of missing data is significant (e.g., non-random), this can affect the model's ability to learn from the data.

Data quality:

If the dataset contains noise, outliers, or unbalanced features, the model may struggle to capture meaningful relationships, resulting in large errors.

Feature engineering:

Poorly chosen features or lack of relevant information could cause the model to perform poorly, contributing to a high RMSPE.

Model limitations:

Some algorithms, like Random Forests, may not handle noisy or complex data well without hyperparameter tuning. The default settings of a Random Forest might not generalize well to your validation set, leading to poor prediction accuracy.

HOW TO IMPROVE MODEL PERFORMANCE TO REDUCE RMSPE?

There are several ways to improve the model performance for this,

Let's Handle the missing data:

Imputation: Replace missing values using strategies like mean/median imputation, forward/backward filling, or predictive imputation (e.g., using KNN). Dropping missing rows: If the missing data is random, consider dropping those rows, though this reduces data size.

Also can use more advanced models:

We can Try algorithms like XGBoost, LightGBM, or Gradient Boosting, which may handle missing data better and provide more accurate predictions.

Hyperparameter tuning:

Tuning the hyperparameters of the model (e.g., n_estimators, max_depth, min_samples_split) to help improve performance.

Feature engineering:

We can Create new features or remove irrelevant ones to help the model learn better patterns from the data.

Cross-validation:

We can also Use techniques like k-fold cross-validation to evaluate the model performance on multiple validation sets instead of a single one, giving you a more reliable estimate of its performance.

Final Evaluation

Summary of Metrics:

- **Target Column (`Future_CC_Spend`)**:
  - Maximum Value: 14,950.31
  - Minimum Value: 1,002.59
  - Average Value: 8,314.19

Evaluation of Metrics:

1. **Mean Absolute Error (MAE: 1238.98)**:

- The MAE represents the average absolute error in our predictions. Given that the average value of `Future_CC_Spend` is approximately 8,314.19, the MAE of 1,238.98 constitutes about 14.9% of the average value. This is a reasonable error level, indicating that the model provides reasonably accurate predictions relative to the average value.

2. **Mean Squared Error (MSE: 2,046,891.88)**:
   - The MSE penalizes larger errors more heavily due to squaring the differences. Given the maximum value of 14,950.31, a high MSE may suggest that there are some significant outliers or that the model struggles with certain ranges of predictions. Comparing it to the range of your target, the MSE seems quite high, indicating that there may be room for improvement.
3. **Root Mean Squared Error (RMSE: 1,430.70)**:
   - RMSE is in the same unit as the target variable and provides an interpretable average error magnitude. The RMSE represents approximately 17.2% of the average value of `Future_CC_Spend` (1,430.70 / 8,314.19), which is moderately acceptable but suggests that the model could be improved.
4. **R^2 Score (0.85)**:
   - An R^2 score of 0.85 indicates that the model explains 85% of the variance in `Future_CC_Spend`. This is considered a strong performance, suggesting that the model captures a significant amount of the underlying trend.

Conclusion:

- **Overall Assessment**:
  - **MAE**: This value is Reasonably acceptable, it indicates good average performance relative to the average target value.
  - **MSE**: It's High, suggests potential issues with larger prediction errors; worth investigating further.
  - **RMSE**: It's Moderate, but indicates that there are significant errors that could be reduced.
  - **R^2**: Strong, indicating good explanatory power.

Recommendations:

- **Investigate Outliers**: We can look at the errors into the data for outliers or influential points that might be driving the high MSE and RMSE.
- **Feature Engineering**: We can Consider adding or transforming features to capture more of the variance in `Future_CC_Spend`.
- **Model Improvement**: Also we can further apply hyperparameter tuning and try different algorithms may help reduce errors and improve overall performance,although the overfitting issue can still be probalamatic and in that case after tuning the errors might increase.

In summary, while our metrics show a strong model performance in terms of variance explanation (R^2), there are still areas for improvement regarding the error metrics.