

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler, LabelEncoder, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV
from sklearn.svm import SVC
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.metrics import accuracy_score
import joblib
import time
from scipy.stats import uniform
```

```
from google.colab import drive
drive.mount('/content/drive')
```

↗ Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive")

```
# Loading dataset
credit = pd.read_csv("/content/drive/MyDrive/final_proyect/credit_scores.csv", low_memory=False)
df = credit.copy()
```

## ✓ Dropping Columns

```
delete_columns = ["Name", "SSN", "ID", "Customer_ID"]
df.drop(delete_columns, axis=1, inplace=True)
df.head()
```



Month	Age	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Inte:
-------	-----	------------	---------------	-----------------------	-------------------	-----------------	-------

0	July	23.0	Scientist	19114.12	1824.843333	3.0	4.0
1	February	28.0	Teacher	34847.84	3037.986667	2.0	4.0
2	May	28.0	Teacher	34847.84	3037.986667	2.0	4.0
3	June	28.0	Teacher	34847.84	3037.986667	2.0	4.0
4	August	28.0	Teacher	34847.84	3037.986667	2.0	4.0

5 rows × 31 columns

## ✓ Selecting Numerical and Categorical Data

```
numerical_format=['float64','int']
numerical_data = df.select_dtypes(include=numerical_format).columns
categorical_data = df.select_dtypes(include='object').columns
```

```
print("Numerical Data")
print(numerical_data)
print("")
print("Categorical Data")
print("")
print(categorical_data)
```

```

Numerical Data
Index(['Age', 'Annual_Income', 'Monthly_Inhand_Salary', 'Num_Bank_Accounts',
      'Num_Credit_Card', 'Interest_Rate', 'Delay_from_due_date',
      'Num_of_Delayed_Payment', 'Changed_Credit_Limit',
      'Num_Credit_Inquiries', 'Outstanding_Debt', 'Credit_Utilization_Ratio',
      'Credit_History_Age', 'Total_EMI_per_month', 'Amount_invested_monthly',
      'Monthly_Balance', 'Count_Auto Loan', 'Count_Credit-Builder Loan',
      'Count_Personal Loan', 'Count_Home Equity Loan', 'Count_Not Specified',
      'Count_Mortgage Loan', 'Count_Student Loan',
      'Count_Debt_Consolidation Loan', 'Count_Business Loan'])

```

```
Count_Debt Consolidation Loan , Count_Payday Loan ],
dtype='object')
```

### Categorical Data

```
Index(['Month', 'Occupation', 'Credit_Mix', 'Payment_of_Min_Amount',
      'Payment_Behaviour', 'Credit_Score'],
      dtype='object')
```

```
# Checking the min, max and mean values for each Numerical category
```

```
for col in numerical_data:
```

```
    print(f"{col} : Min {df[col].min()} - Max {df[col].max()} - {df[col].mean()}")
```

```
Age : Min 14.0 - Max 95.0 - 32.963502994011975
```

```
Annual_Income : Min 7005.93 - Max 24198062.0 - 180449.1165729597
```

```
Monthly_Inhand_Salary : Min 303.64541666666666 - Max 15204.633333333331 - 4011.3346753538767
```

```
Num_Bank_Accounts : Min -1.0 - Max 1798.0 - 17.670518846741114
```

```
Num_Credit_Card : Min 0.0 - Max 1499.0 - 22.108409927846473
```

```
Interest_Rate : Min 1.0 - Max 5797.0 - 77.57309661387383
```

```
Delay_from_due_date : Min -5.0 - Max 67.0 - 22.085661247342735
```

```
Num_of_Delayed_Payment : Min 0 - Max 4397 - 32.5789773067481
```

```
Changed_Credit_Limit : Min -6.44 - Max 36.29 - 10.788655728870394
```

```
Num_Credit_Inquiries : Min 0.0 - Max 2597.0 - 28.006347495433996
```

```
Outstanding_Debt : Min 0.23 - Max 4998.07 - 1510.6508349799412
```

```
Credit_Utilization_Ratio : Min 20.88125003902868 - Max 49.56451934738699 - 32.22058395632018
```

```
Credit_History_Age : Min 0.0 - Max 404.0 - 193.59627533758496
```

```
Total_EMI_per_month : Min 4.4628374669131645 - Max 82204.0 - 1403.5067912154855
```

```
Amount_invested_monthly : Min 0.0 - Max 10000.0 - 614.0763433835015
```

```
Monthly_Balance : Min 0.4534564914083034 - Max 1552.9460937445635 - 381.59373833367243
```

```
Count_Auto Loan : Min 0.0 - Max 4.0 - 0.42262207718331785
```

```
Count_Credit-Builder Loan : Min 0.0 - Max 4.0 - 0.4532934131736527
```

```
Count_Personal Loan : Min 0.0 - Max 4.0 - 0.4406287425149701
```

```
Count_Home Equity Loan : Min 0.0 - Max 5.0 - 0.44211251160144904
```

```
Count_Not Specified : Min 0.0 - Max 4.0 - 0.44275106293790045
```

```
Count_Mortgage Loan : Min 0 - Max 5 - 0.43859649122807015
```

```
Count_Student Loan : Min 0 - Max 5 - 0.4400335309262918
```

```
Count_Debt Consolidation Loan : Min 0 - Max 5 - 0.43359679061134065
```

```
Count_Payday Loan : Min 0 - Max 5 - 0.4569187473803964
```

```
# Dropping values
```

```
..
```

```

# Age
df.drop(df[df.Age < 0].index, inplace=True)

# Num_Bank_Accounts
df.drop(df[df["Num_Bank_Accounts"] < 0].index, inplace=True)

# Reseting index values
df.reset_index(drop=True, inplace=True)

# Checking Null Values
#features_null_values = []
#for col in numerical_data:
#    if df[col].isnull().sum() !=0:
#        features_null_values.append(col)

#####
#print(features_null_values)

df.isna().sum()

```

Month	2
Age	2
Occupation	2
Annual_Income	0
Monthly_Inhand_Salary	0
Num_Bank_Accounts	1
Num_Credit_Card	1
Interest_Rate	1
Delay_from_due_date	3
Num_of_Delayed_Payment	0
Changed_Credit_Limit	1
Num_Credit_Inquiries	3
Credit_Mix	0
Outstanding_Debt	0
Credit_Utilization_Ratio	0
Credit_History_Age	3
Payment_of_Min_Amount	0
Total_EMI_per_month	4
Amount_invested_monthly	0
Payment_Behaviour	1
Monthly_Balance	1

```

Monthly_Balance      1
Credit_Score         0
Count_Auto Loan      1
Count_Credit-Builder Loan  2
Count_Personal Loan  2
Count_Home Equity Loan  1
Count_Not Specified  4
Count_Mortgage Loan  0
Count_Student Loan   0
Count_Debt Consolidation Loan  0
Count_Payday Loan    0
dtype: int64

```

## ✓ Splitting the data

```

X = df.drop('Credit_Score', axis=1)
y = df['Credit_Score']

```

```
X.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 33397 entries, 0 to 33396
Data columns (total 30 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Month                                33395 non-null  object
1   Age                                  33395 non-null  float64
2   Occupation                           33395 non-null  object
3   Annual_Income                        33397 non-null  float64
4   Monthly_Inhand_Salary                33397 non-null  float64
5   Num_Bank_Accounts                    33396 non-null  float64
6   Num_Credit_Card                      33396 non-null  float64
7   Interest_Rate                       33396 non-null  float64
8   Delay_from_due_date                  33394 non-null  float64
9   Num_of_Delayed_Payment                33397 non-null  int64
10  Changed_Credit_Limit                  33396 non-null  float64
11  Num_Credit_Inquiries                  33394 non-null  float64
12  Credit_Mix                           33397 non-null  object

```

```

13 Outstanding_Debt          33397 non-null float64
14 Credit_Utilization_Ratio  33397 non-null float64
15 Credit_History_Age        33394 non-null float64
16 Payment_of_Min_Amount     33397 non-null object
17 Total_EMI_per_month       33393 non-null float64
18 Amount_invested_monthly   33397 non-null float64
19 Payment_Behaviour         33396 non-null object
20 Monthly_Balance           33396 non-null float64
21 Count_Auto Loan           33396 non-null float64
22 Count_Credit-Builder Loan 33395 non-null float64
23 Count_Personal Loan       33395 non-null float64
24 Count_Home Equity Loan    33396 non-null float64
25 Count_Not Specified       33393 non-null float64
26 Count_Mortgage Loan       33397 non-null int64
27 Count_Student Loan        33397 non-null int64
28 Count_Debt Consolidation Loan 33397 non-null int64
29 Count_Payday Loan         33397 non-null int64
dtypes: float64(20), int64(5), object(5)
memory usage: 7.6+ MB

```

```

# Split the data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)

# Selecting again the numerical and categorical data but this time from splitted dataset
numerical_format = ['float64', 'int']
numerical_data = X.select_dtypes(include=numerical_format).columns
categorical_data = X.select_dtypes(include='object').columns

```

✓ Replacing NaN Values from Numerical and Categorical Columns with Mean and most frequent words.

```

# Numerical pipeline
mean_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', StandardScaler())
])

```

```

])

# Categorical pipeline
cat_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Combine pipelines using ColumnTransformer
preprocessor = ColumnTransformer([
    ('num', mean_pipeline, numerical_data),
    ('cat', cat_pipeline, categorical_data)
], remainder='passthrough')

```

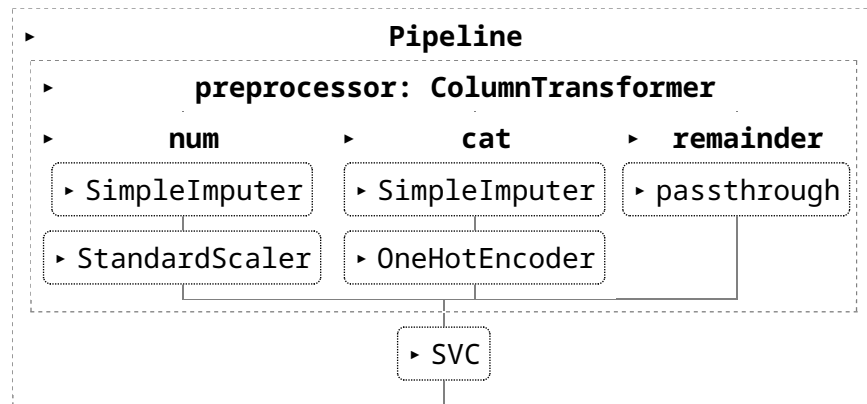
## ✓ Applying pipelines and creating a SVC model

```

# Create a complete pipeline with the preprocessor and the SVM model
svm_pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', SVC(kernel='rbf', C=10))
])

# Fit the SVM model on the training data
svm_pipeline.fit(X_train, y_train)

```



```
# Predict the target values for the test data
y_pred = svm_pipeline.predict(X_test)

# Evaluate and report the accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of the SVM model: {accuracy:.2f}")
```

Accuracy of the SVM model: 0.69

```
import pickle
```

```
with open('svm_model.pkl','wb') as file:
    pickle.dump(svm_pipeline, file)
```

```
# Save the trained model to a file
#model_filename = 'svm_model.joblib'
#model_filename = 'svm_model.pkl'
#joblib.dump(svm_pipeline, model_filename)
#print(f"Model saved to {model_filename}")
```

```
df.iloc[0]
```



