# Credit Score Analysis

Group 7

# Category

- Data Exploration Analysis
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# Data Exploration Analysis

- Data Overview
- Interest Rate vs Credit Score
- Average Interest Rate vs Occupation
- Number of Delayed Payments vs Salary

# Dataset Overview

| | Month | Annual_Income | Monthly_Inhand_Salary | Num_Bank_Accounts | Num_Credit_Card | Interest_Rate | Num_of_Loan | Delay_from_due_date |
|---|---|---|---|---|---|---|---|---|
| count | 48553.000000 | 4.855300e+04 | 48553.000000 | 48553.000000 | 48553.000000 | 48553.000000 | 48553.000000 | 48553.000000 |
| mean | 4.488785 | 1.798519e+05 | 4155.531542 | 16.574609 | 22.687249 | 74.505654 | 2.893395 | 20.970403 |
| std | 2.293813 | 1.462779e+06 | 3173.526932 | 114.427362 | 128.814423 | 476.489303 | 61.174505 | 14.770478 |
| min | 1.000000 | 7.005930e+03 | 319.556250 | -1.000000 | 0.000000 | 1.000000 | -100.000000 | -5.000000 |
| 25% | 2.000000 | 1.935837e+04 | 1617.160833 | 3.000000 | 4.000000 | 8.000000 | 1.000000 | 10.000000 |
| 50% | 4.000000 | 3.677934e+04 | 3044.806667 | 6.000000 | 6.000000 | 13.000000 | 3.000000 | 18.000000 |
| 75% | 6.000000 | 7.220752e+04 | 5913.505000 | 7.000000 | 7.000000 | 20.000000 | 5.000000 | 28.000000 |
| max | 8.000000 | 2.419806e+07 | 15167.180000 | 1794.000000 | 1499.000000 | 5797.000000 | 1485.000000 | 67.000000 |

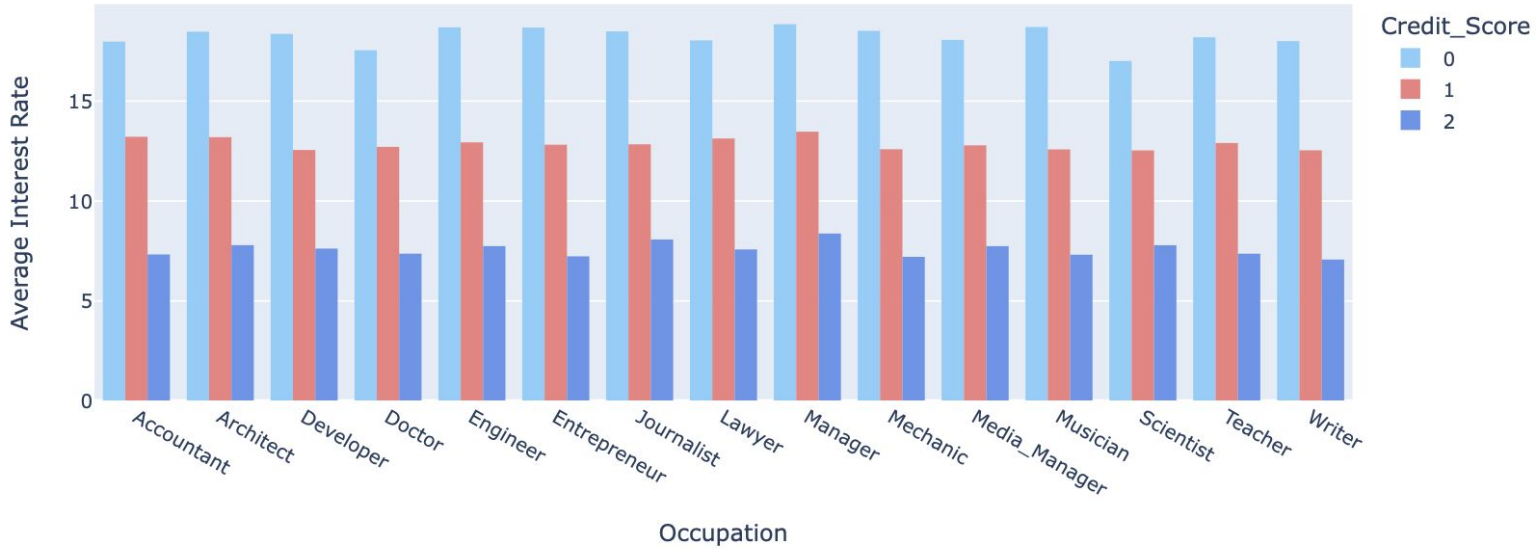
Tool: Python

Size: 48553

Target: Credit Score

# Interest Rate vs Credit Score

# Average Interest Rate vs Occupation



# Number of Delayed Payments vs Salary

# Database

Tool: Python & SQLAlchemy
Process:

- Import datasets (Customer Info & Credit Change)
- Combine two tables
- Export csv file

```
Customer_Info = db.Table('Customer_Info', metadata,
              db.Column('Customer_ID', db.String, primary_key=True),
              db.Column('Name', db.String),
              db.Column('Age', db.Integer),
              db.Column('Occupation', db.String)
              )

Credit_Change = db.Table('Credit_Change', metadata,
              db.Column('ID', db.String, primary_key=True),
              db.Column('Customer_ID', db.String),
              db.Column('Month', db.Integer),
              db.Column('Annual_Income', db.Float),
              db.Column('Monthly_Inhand_Salary', db.Float),
              db.Column('Num_Bank_Accounts', db.Integer),
              db.Column('Num_Credit_Card', db.Integer),
              db.Column('Interest_Rate', db.Integer),
              db.Column('Num_of_Loan', db.Float),
              db.Column('Type_of_Loan', db.String),
              db.Column('Delay_from_due_date', db.Integer),
              db.Column('Num_of_Delayed_Payment', db.Float),
              db.Column('Num_Credit_Inquiries', db.Float),
              db.Column('Outstanding_Debt', db.Float),
              db.Column('Credit_Utilization_Ratio', db.Float),
              db.Column('Credit_History_Age', db.Float),
              db.Column('Payment_of_Min_Amount', db.String),
              db.Column('Total_EMI_per_month', db.Float),
              db.Column('Amount_invested_monthly', db.Float),
              db.Column('Payment_Behaviour', db.String),
              db.Column('Monthly_Balance', db.Float),
              db.Column('Credit_Score', db.String)
                        )
metadata.create_all(engine)
```

```
query_new = (
    db.select([
Credit_Change.c.ID,
Credit_Change.c.Customer_ID,
Credit_Change.c.Month,
Credit_Change.c.Annual_Income,
Credit_Change.c.Monthly_Inhand_Salary,
Credit_Change.c.Num_Bank_Accounts,
Credit_Change.c.Num_Credit_Card,
Credit_Change.c.Interest_Rate,
Credit_Change.c.Num_of_Loan,
Credit_Change.c.Type_of_Loan,
Credit_Change.c.Delay_from_due_date,
Credit_Change.c.Num_of_Delayed_Payment,
Credit_Change.c.Num_Credit_Inquiries,
Credit_Change.c.Outstanding_Debt,
Credit_Change.c.Credit_Utilization_Ratio,
Credit_Change.c.Credit_History_Age,
Credit_Change.c.Payment_of_Min_Amount,
Credit_Change.c.Total_EMI_per_month,
Credit_Change.c.Amount_invested_monthly,
Credit_Change.c.Payment_Behaviour,
Credit_Change.c.Monthly_Balance,
Credit_Change.c.Credit_Score,
Customer_Info.c.Name,
Customer_Info.c.Age,
Customer_Info.c.Occupation
]).
    select_from(Credit_Change.join(Customer_Info, Customer_Info.c.Customer_ID == Credit_Change.c.Customer_ID))
)
```

# Model Building

- Supervised Machine Learning
- Deep Machine Learning

# Supervised Machine Learning

Labeled Data >> Supervised Learning Model

Predict Outcome >> Classification

Algorithms : BalancedRandomForestClassifier

```
BalancedRandomForestClassifier(random_state=1)
```

```
# Calculated the balanced accuracy score
predictions = clf.predict(X_test)
from sklearn.metrics import confusion_matrix, balanced_accuracy_score, classification_report
balanced_accuracy_score(y_test, predictions)
```

```
0.7556544705127921
```

```
# Display the confusion matrix
confusion_matrix(y_test, predictions)
```

```
array([[1863,   39,  215],
       [ 342, 2959,  293],
       [1411, 1394, 3623]])
```

```
# Print the imbalanced classification report
print(classification_report_imbalanced(y_test, predictions))
```

| | pre | rec | spe | f1 | geo | iba | sup |
|---|---|---|---|---|---|---|---|
| Good | 0.52 | 0.88 | 0.83 | 0.65 | 0.85 | 0.73 | 2117 |
| Poor | 0.67 | 0.82 | 0.83 | 0.74 | 0.83 | 0.68 | 3594 |
| Standard | 0.88 | 0.56 | 0.91 | 0.69 | 0.72 | 0.50 | 6428 |
| avg / total | 0.75 | 0.70 | 0.87 | 0.70 | 0.77 | 0.59 | 12139 |

# Deep Machine Learning

3 hidden layers

Neurons : 100, 80, 60

Epochs: 50

```
# Define the model - deep neural net, i.e., the number of input features and h
number_input_features = len(X_train[0])
hidden_nodes_layer1 = 100
hidden_nodes_layer2 = 80
hidden_nodes_layer3 = 60


nn = tf.keras.models.Sequential()

# First hidden layer
nn.add(
    tf.keras.layers.Dense(units=hidden_nodes_layer1, input_dim=number_input_fe
)


# Second hidden layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer2, activation="sigmoid"))

# Third hidden layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer3, activation="sigmoid"))

# Output layer
nn.add(tf.keras.layers.Dense(units=1, activation="sigmoid"))

# Check the structure of the model
nn.summary()
```

```
# Evaluate the model using the test data
model_loss, model_accuracy = nn.evaluate(X_test_scaled,y_test,verbose=2)
print(f"Loss: {model_loss}, Accuracy: {model_accuracy}")
```

```
12139/1 - 1s - loss: -1.5519e+02 - accuracy: 0.6093
Loss: -169.74806474889067, Accuracy: 0.6092758774757385
```

# Model Evaluation - Ensemble Learning

- Are robust against overfitting
- be used to rank the importance of input variables
- Can handle thousands of input variables without variable deletion
- Are robust to outliers and nonlinear data
- Run efficiently on large datasets

# References


- https://machinelearningmastery.com/why-use-ensemble-learning/
- https://www.kaggle.com/datasets/parisrohan/credit-score-classification