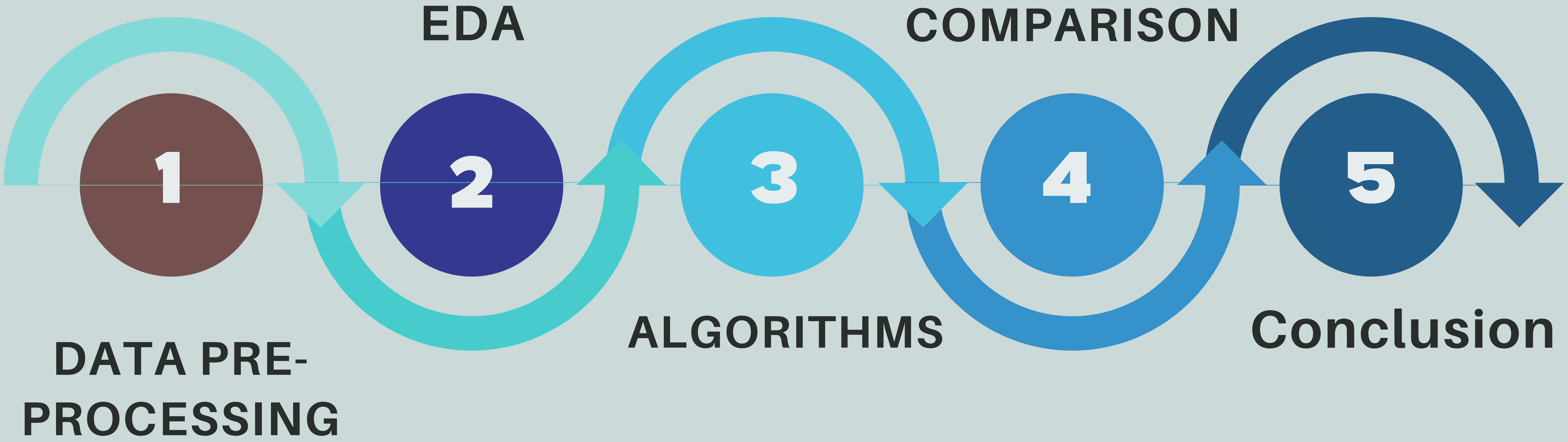
## MACHINE LEARNING CLASSIFICATION PROJECT

# CREDIT RISK PREDICTION


TEAM-2
G. MADHU KIRAN
CHIRAMJEEVI
P SHRAVANI
SATHVIKA REDDY

BHAVAN'S VIVEKANANDA COLLEGE | BSC HONS DATA SCIENCE

# MACHINE LEARNING PROJECT STAGES



## ABOUT THE DATA:

The task here is to build a classification model to predict **"TARGET_credit_risk"**.

## OBJECTIVE:

The original dataset contains 1000 entries with 20 categorial/symbolic attributes. Each person is classified as good or bad credit risks according to the set of attributes. We have to predict the credit risk of a person.

## THE PATH:

Implementing different classification models to fit the best one to the dataset. We followed a traditional approach with dummy variable encoding

# DATA AND DATA QUALITY CHECK:

**INTRODUCTION**

Brief about the instances and attributes

**VARIABLES**

Detailed description about variables

**DATA PRE PROCESSING**

Data Cleaning, Data Transformation etc

## INTRODUCTION:

| | |
|---|---|
| Number of instances | 1000 |
| Number of Attributes | 21 |
| Attribute breakdown | 20 quantitative input variables, and 1 quantitative output variable |
| Missing Attribute Values | None |

# VARIABLES:

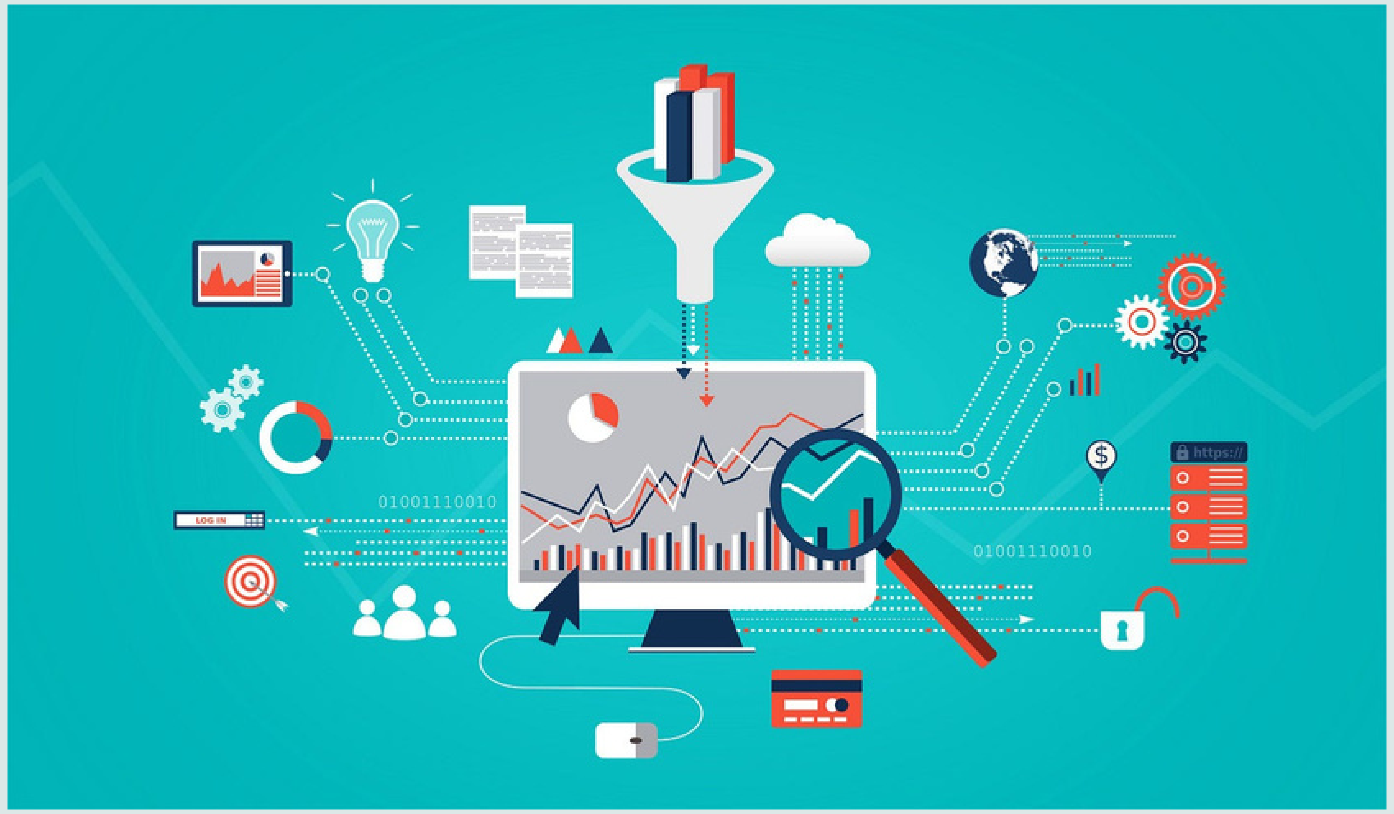
| | |
|---|---|
| **TARGET_creditrisk** | Has the credit contract been complied with (good) or not (bad) |
| **status** | status of the debtor's checking account with the bank |
| **duration** | duration in months |
| **credit_history** | history of compliance with previous or concurrent credit contracts |
| **purpose** | purpose for which the credit is needed |
| **saving** | debtor's savings |
| **employment_duration** | duration of debtor's employment with current employer |

# DATA PRE-PROCESSING:

1. There are few columns in the dataset which are categorical but they're coded as 0's and 1's.

2. There are no null values in the data set.

3. There are No duplicate values in the dataset.



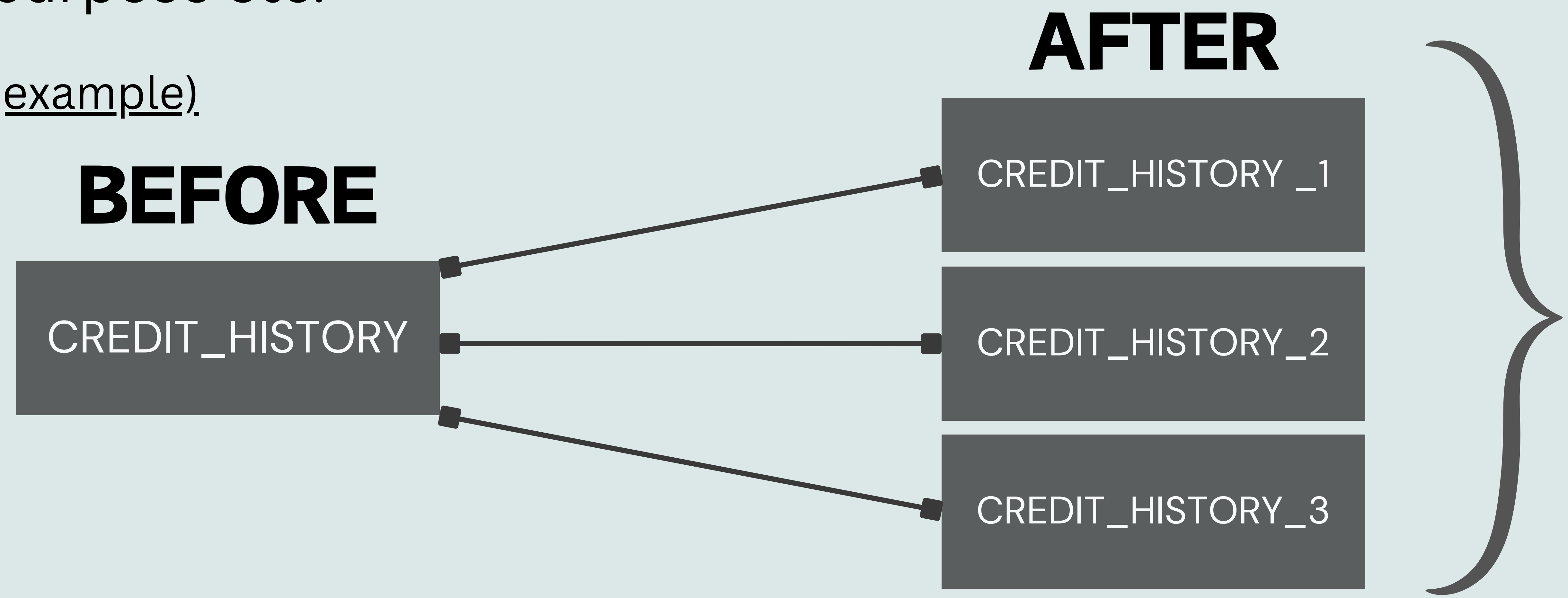
<u>**DUMMY VARIABLE ENCODING:**</u>

1. Before dummy variable encoding, there were 21 columns

2. After dummy variable encoding, resultant obtained to 35 columns

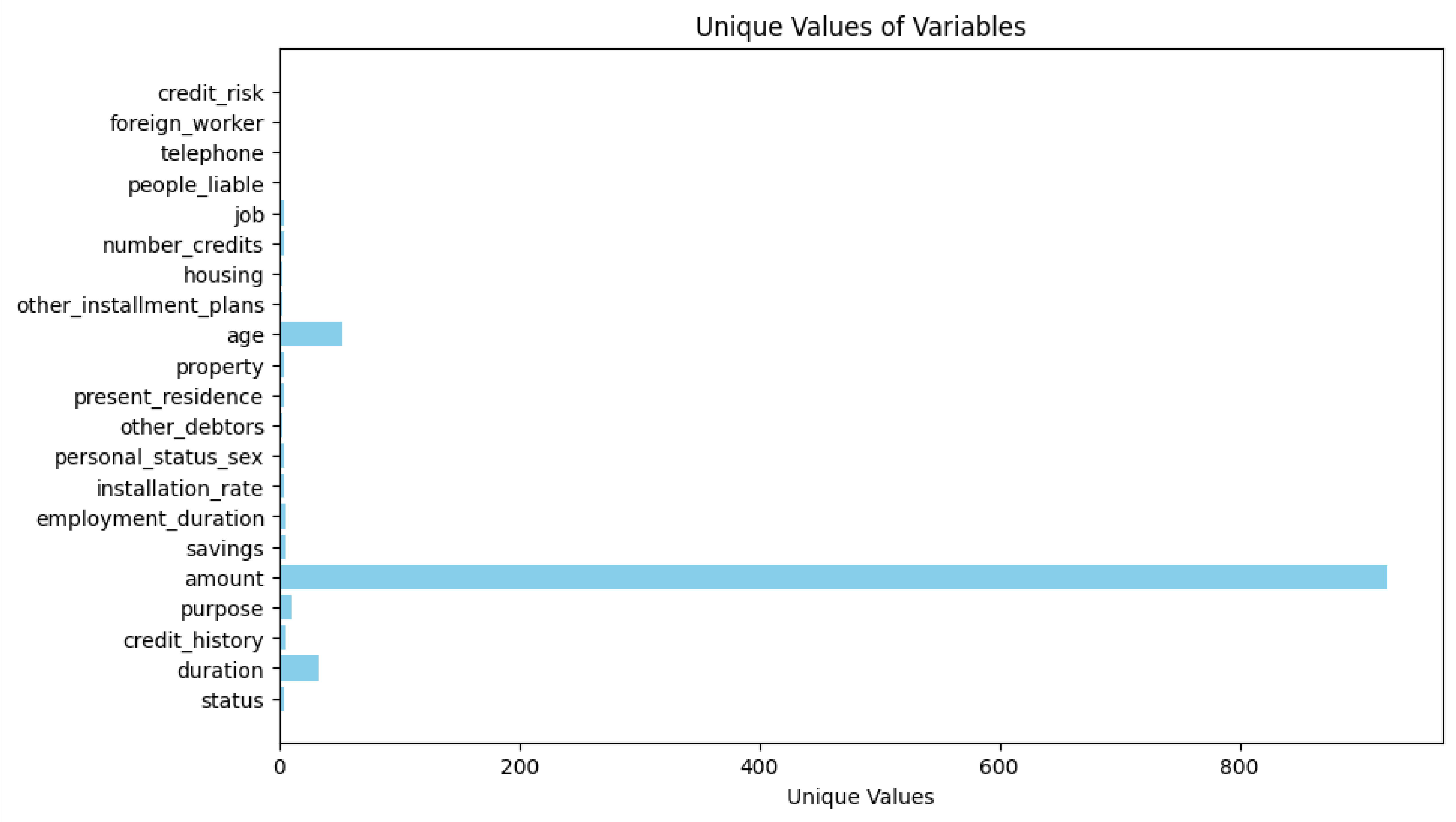
3. Categorical columns are status, credit history, personal status sex, other debtors, purpose etc.

<u>(example)</u>

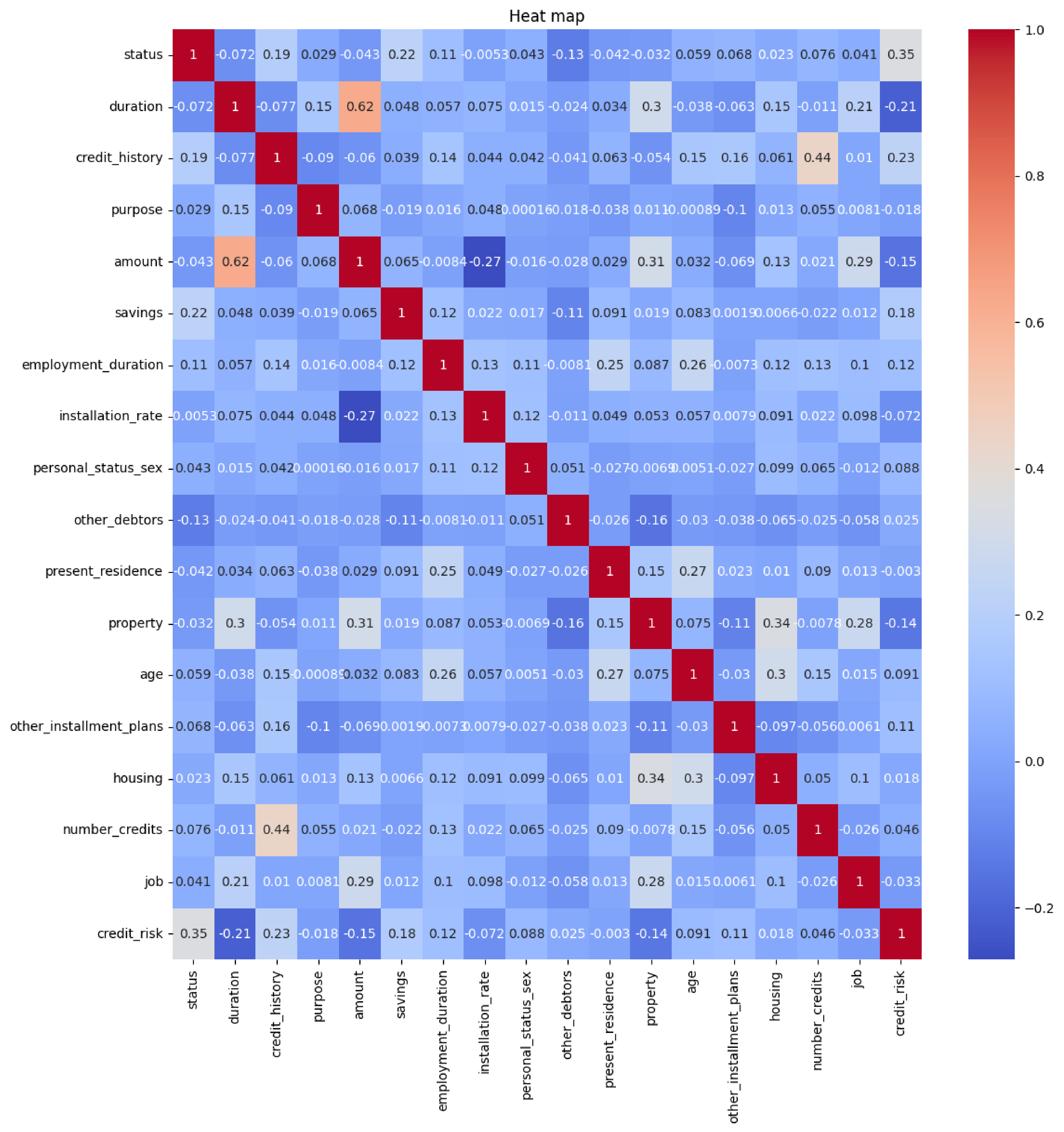



categorical columns like these have been dummified, which resulted in increasing to 35 columns

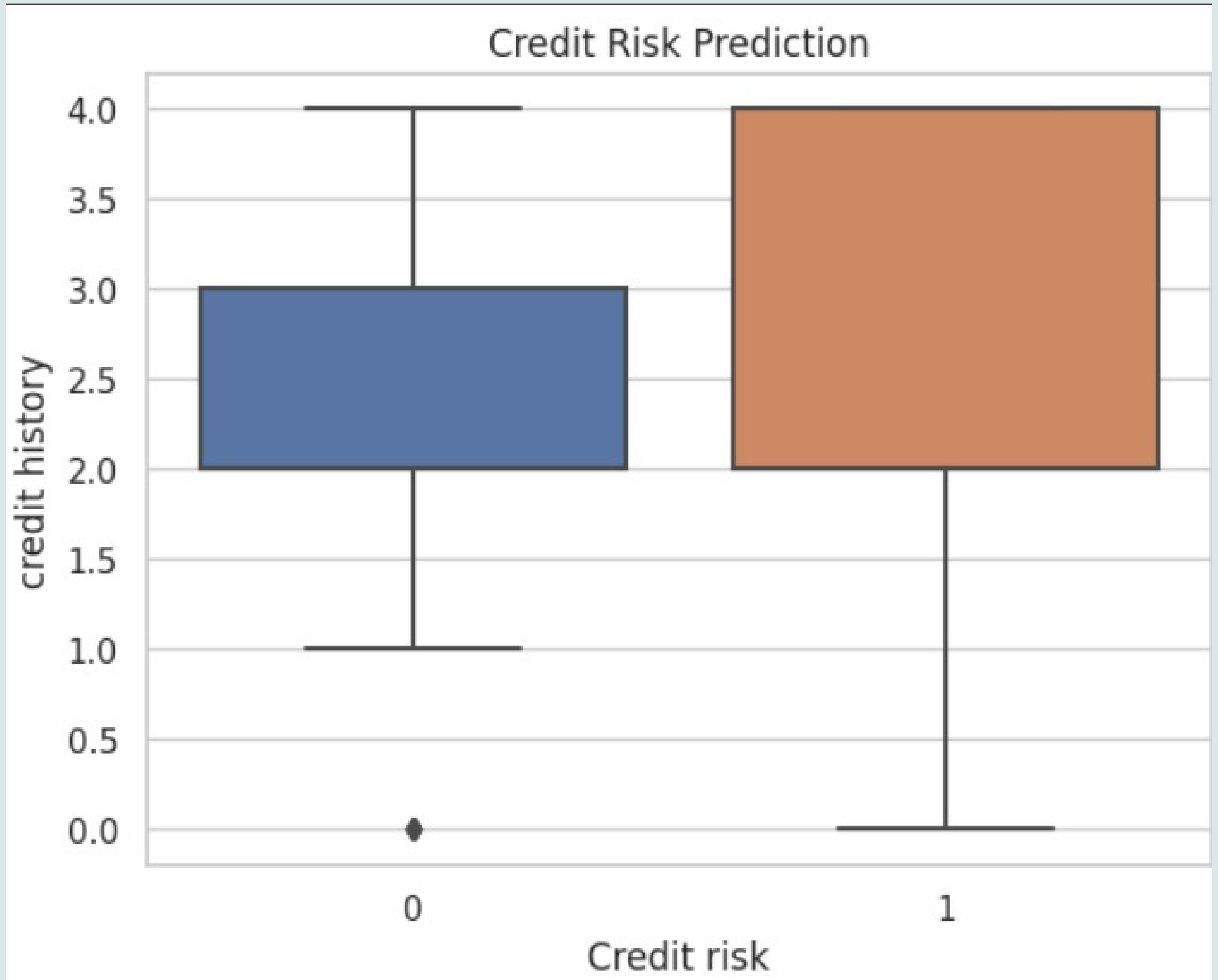
# EXPLORATORY DATA ANALYSIS:




Graph represents the unique values of each variable

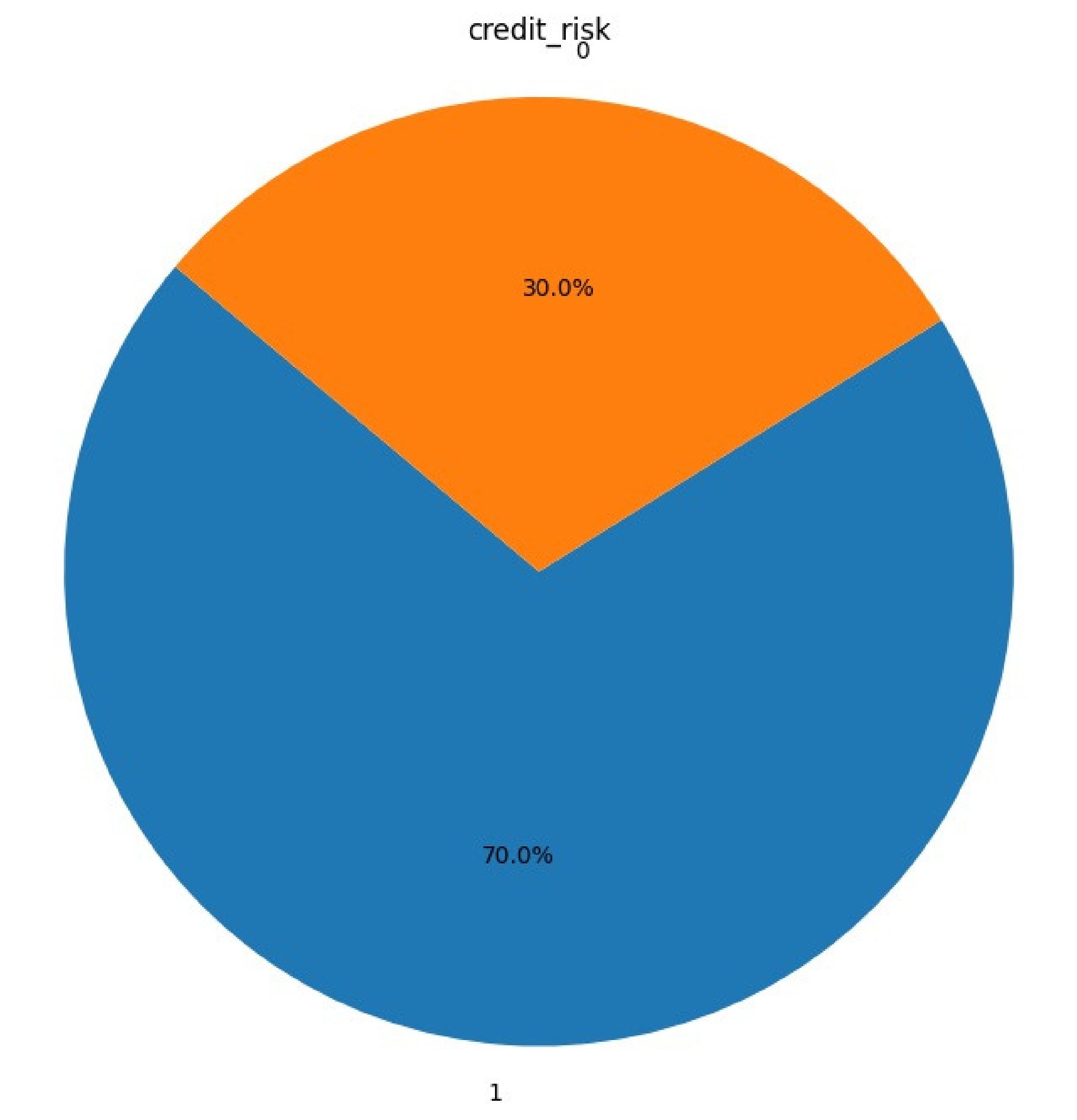



- Heatmap represents the correlation between different variables.
- There is a positive correlation between duration and amount
- Red indicates positive correlation




- **Box Plot** to represent outliers.

- **Pie Chart** representing the 700 good and 300 bad credits with 20 predictor variables.



# VARIANCE INFLATION FACTOR MULTICOLINEARITY ANALYSIS

Variables with Low VIF:

- purpose_1 to purpose_10, telephone, other_debtors_2, other_debtors_3, other_installment_plans_2, other_installment_plans_3, housing_3, etc. (VIF values less than 5)

| **VARIABLES** | VIF |
|---|---|
| duration | 8.121870 |
| amount | 5.747600 |
| savings | 3.163318 |
| employment_duration | 11.026173 |
| installation_rate | 11.056842 |
| present_residence | 9.727082 |
| property | 9.850866 |
| age | 13.796849 |
| number_credits | 10.236151 |

# MODEL BUILDING:

## 1. DECISION TREE CLASSIFIER:

| TRAIN_TEST RATIO | ACCURACY |
|---|---|
| 65-35 | 69% |
| 70-30 | 68% |
| 75-25 | 71.2% |
| **80-20** | **71.5%** |

## 2. K NEIGHBORS CLASSIFIER:

| TRAIN_TEST RATIO | ACCURACY |
|---|---|
| 65-35 | 88% |
| 70-30 | 86% |
| 75-25 | 87% |
| 80-20 | 85% |

# 3. SUPPORT VECTOR CLASSIFIER:

| TRAIN_TEST RATIO | ACCURACY |
|---|---|
| 65-35 | 94% |
| 70-30 | 94.3% |
| 75-25 | 94.8% |
| **80-20** | **95%** |

# 4. GRADIENT BOOSTING:

| TRAIN_TEST RATIO | ACCURACY |
|---|---|
| 65-35 | 89% |
| 70-30 | 87% |
| 75-25 | 90% |
| **80-20** | **91%** |

# 5. NAIVE BAYES CLASSIFIER:

| TRAIN_TEST RATIO | ACCURACY |
|---|---|
| 65-35 | 94% |
| 70-30 | 95% |
| 75-25 | 96.4% |
| 80-20 | 96% |

# 6. RANDOM FOREST CLASSIFIER:

| TRAIN_TEST RATIO | N_ESTIMATORS | ACCURACY |
|---|---|---|
| 65-35 | 100 | 97.4% |
| 70-30 | 100 | 98.6% |
| **75-25** | **100** | **98.8%** |
| 80-20 | 100 | 97.5% |

# 7. NEURAL NETWORK:

| TRAIN_TEST RATIO | ARCHITECTURE | OPTIMIZER | ACCURACY | EPOCHS |
|---|---|---|---|---|
| **65-35** | **128-64-1** | **Adam** | **98.2%** | **100** |
| 70-30 | 128-64-1 | Adam | 97% | 100 |
| 75-25 | 128-64-1 | Adam | 96% | 100 |
| 80-20 | 128-64-1 | Adam | 96.2% | 100 |

# COMPARISON OF MODELS:

| MODEL | ACCURACY(Test Size 75-25) |
|---|---|
| Decision Tree Classifier | 71.2% |
| K Neighbors Classifier | 87% |
| Support Vector Classifier | 94.8% |
| Gradient Boosting | 90% |
| Naive Bayes | 96.4% |
| **Random Forest Classifier** | **98.8%** |
| Neural Network | 96% |

# CONCLUSION:

1. For this Credit dataset, we applied 7 algorithms. Decision Tree, K Neighbors, Support Vector, Gradient Boosting, Random Forest, Naive Bayes, Neural Network.

2. Here, we conclude that Random Forest Classifer is the best model for Credit Dataset with 98.8% accuracy, test size of 75-25 ratio

3. Among all the important variables, Credit_History is the most impactful to the target variable Credit_Risk. (Based on the past credit history, we can predict potential risks which may occur in near future by deploying different classification models)


# THANK YOU

TEAM-2
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P. SHRAVANI
SATHVIKA REDDY

# APPENDIX

## TRAINING AND TESTING :

```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.3)
```

## CHECKING ACCURACY :

```
print("accuracy",metrics.accuracy_score(y_test,y_pred))
```

# DUMMY VARIABLE ENCODING :

```
] categorical_columns = ["status","credit_history","purpose","personal_status_sex","other_debtors","other_insta
  # Renameing the column 'saving' to avoid keyword conflict
  df.rename(columns={'saving': 'savings'}, inplace=True)
  # Perform dummy variable encoding for each categorical column
  for column in categorical_columns:
      dummy_df = pd.get_dummies(df[column], prefix=column,drop_first=True)
      df = pd.concat([df, dummy_df], axis=1)
  # Drop the original categorical columns
  df = df.drop(categorical_columns, axis=1)
  print("\nDataFrame after encoding:")
  print(df)
```

# DECISION TREE CLASSIFIER :

```
model=DecisionTreeClassifier()
model.fit(X_train,y_train)
y_pred=model.predict(X_test)
y_pred
```

# K NEIGHBORS CLASSIFIER :

```
clf=KNeighborsClassifier(n_neighbors=5)
clf.fit(X_train,y_train)
```

```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

# SUPPORT VECTOR CLASSIFIER :

```
cls=SVC(kernel='linear')
```

```
cls.fit(X_train,y_train)
```

```
▾ SVC
SVC(kernel='linear')
```

# GRADIENT BOOSTING :

```
clf=GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, max_depth=3, random_state=42)
clf.fit(X_train,y_train)
```

```
▾ GradientBoostingClassifier
GradientBoostingClassifier(random_state=42)
```

# NAIVE BAYES :

```
# Initialize the Gaussian Naive Bayes classifier
naive_bayes_classifier = GaussianNB()
naive_bayes_classifier.fit(X_train,y_train)
```

```
▾ GaussianNB
GaussianNB()
```

# RANDOM FOREST CLASSIFIER:

```
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
rf_classifier.fit(X_train,y_train)
```

```
▾ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

# NEURAL NETWORK:

```
# Define the ANN model
model = Sequential()
model.add(Dense(128, activation='relu', input_dim=X_train.shape[1]))
model.add(Dropout(0.2))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(1, activation='sigmoid'))
```

```
# Compile the model
model.compile(loss='binary_crossentropy', optimizer=Adam(), metrics=['accuracy'])
```

```
# Train the model
model.fit(X_train, y_train, epochs=100, batch_size=32)
```

```
# Evaluate the model on the test set
score = model.evaluate(X_test, y_test, verbose=0)
print('Test loss:',score[0])
print('Test accuracy:',score[1])
```

# VARIANCE INFLATION FACTOR:

```
# Import library for VIF
from statsmodels.stats.outliers_influence import variance_inflation_factor

def calc_vif(df):
  vif = pd.DataFrame()
  vif["variables"] = df.columns
  vif["VIF"] = [variance_inflation_factor(df.values,i) for i in range((df).shape[1])]
  return(vif)
calc_vif(df)
```

| | | |
|---|---|---|
| 28 | purpose_9 | 1.609290 |
| 29 | purpose_10 | 1.169066 |
| 30 | personal_status_sex_2 | 6.417080 |
| 31 | personal_status_sex_3 | 11.066844 |
| 32 | personal_status_sex_4 | 2.647124 |
| 33 | other_debtors_2 | 1.121344 |
| 34 | other_debtors_3 | 1.180528 |
| 35 | other_installment_plans_2 | 1.390659 |
| 36 | other_installment_plans_3 | 7.620601 |
| 37 | housing_2 | 5.969744 |
| 38 | housing_3 | 2.305738 |