Employee Salary Prediction System

Meet The Query Troop

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Background

- Salary prediction is essential for fair compensation and workforce planning.
- Analyzing data on factors such as age and education allows us to predict salary outcomes.
- Accurate predictions enable effective compensation strategies and inform employee expectations.
- Data-driven insights support informed decisions for both employers and employees in the evolving job market.

Technologies

Python

Sci-kit Learn

NumPy

Matplotlib

Pandas

Flask

HTML

Bootstrap

Target & Business Goal

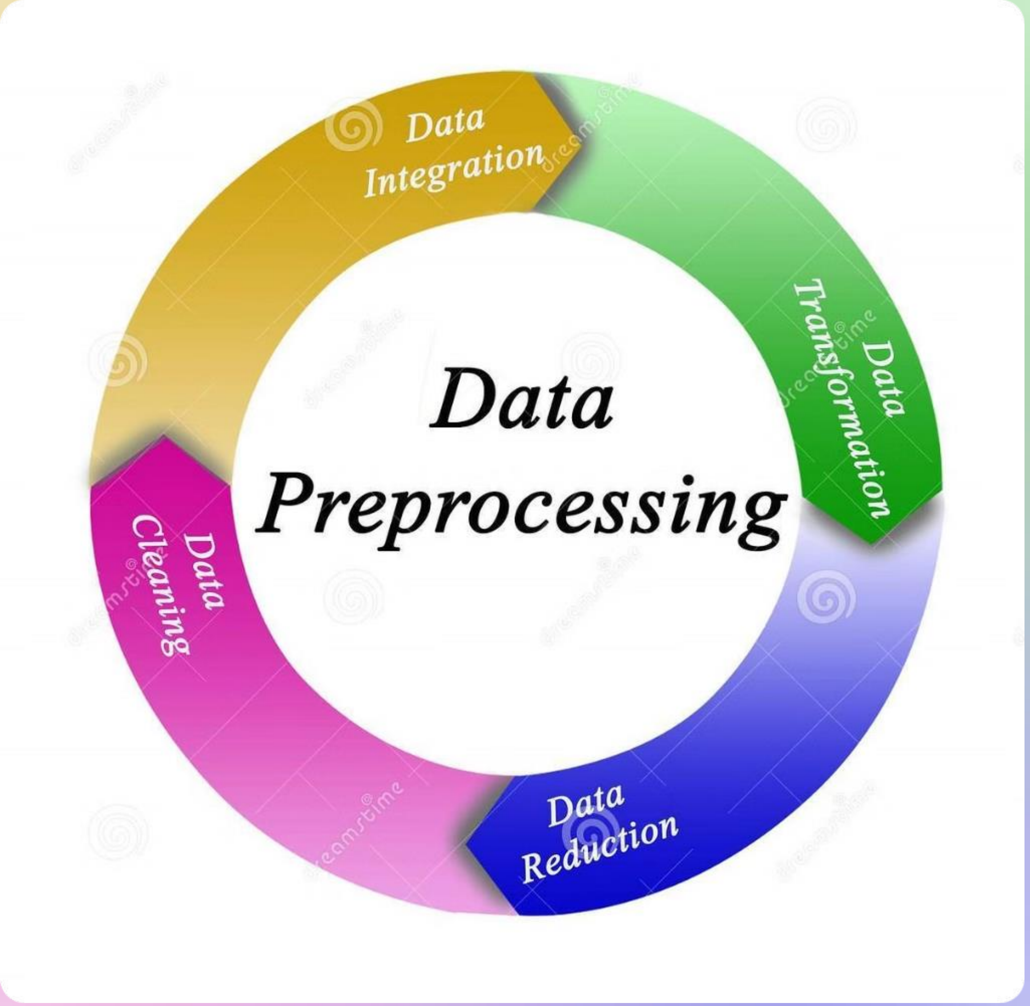
Target

- To create a precise predictive analytics model for forecasting salary outcomes based on employee attributes.

Business Goal

- To enhance compensation strategies and improve employee satisfaction, contributing to talent retention and overall business growth.

Data preprocessing



Handling Null Values

1)find null values

```
df.isnull().sum()
```

```
age                  0
workclass         1836
fnlwgt               0
education            0
education_num        0
marital_status       0
occupation        1843
relationship         0
race                 0
sex                  0
capital_gain         0
capital_loss         0
hours_per_week       0
native_country     584
income               0
dtype: int64
```

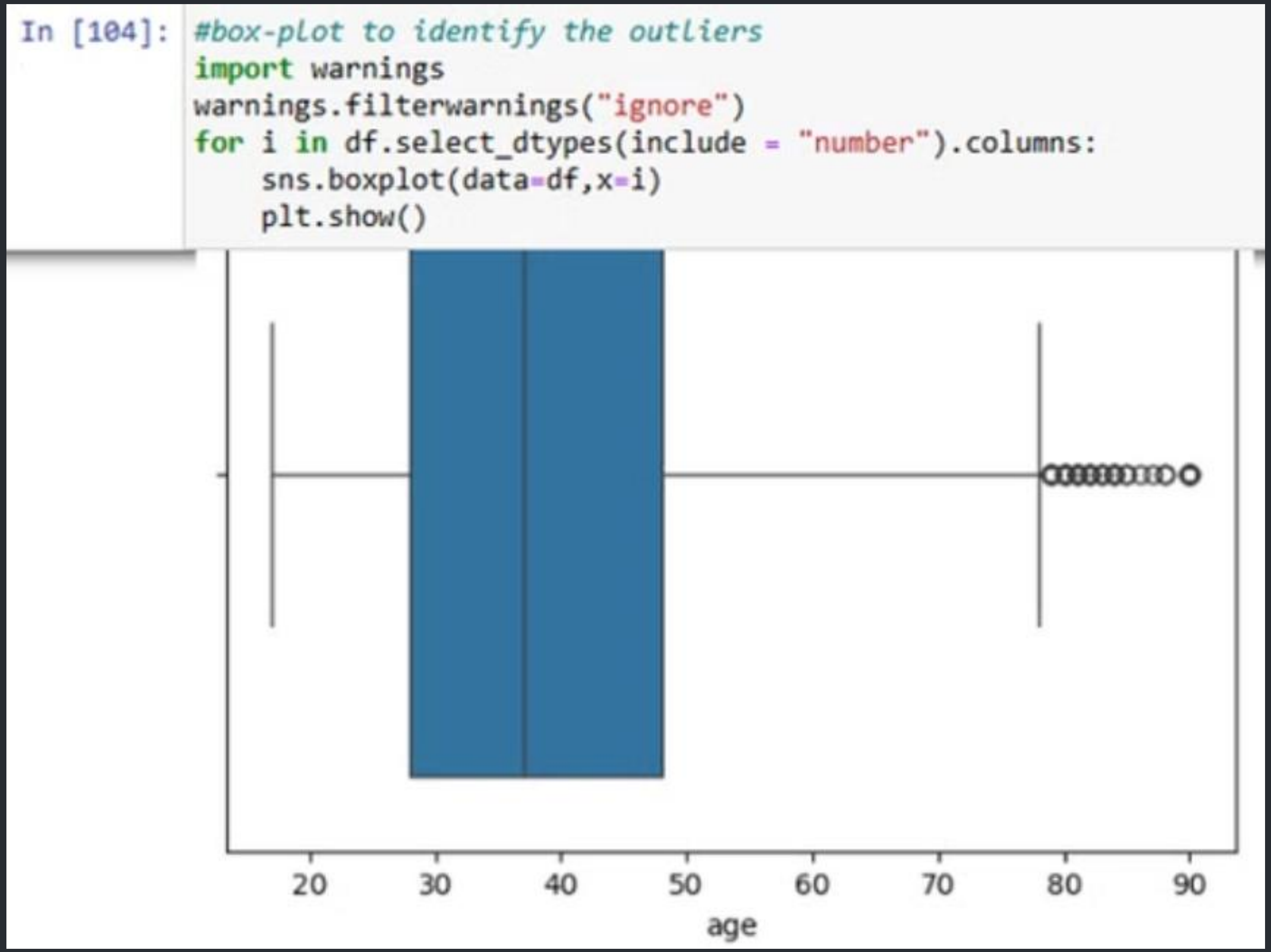
2)Filing missed values with mode

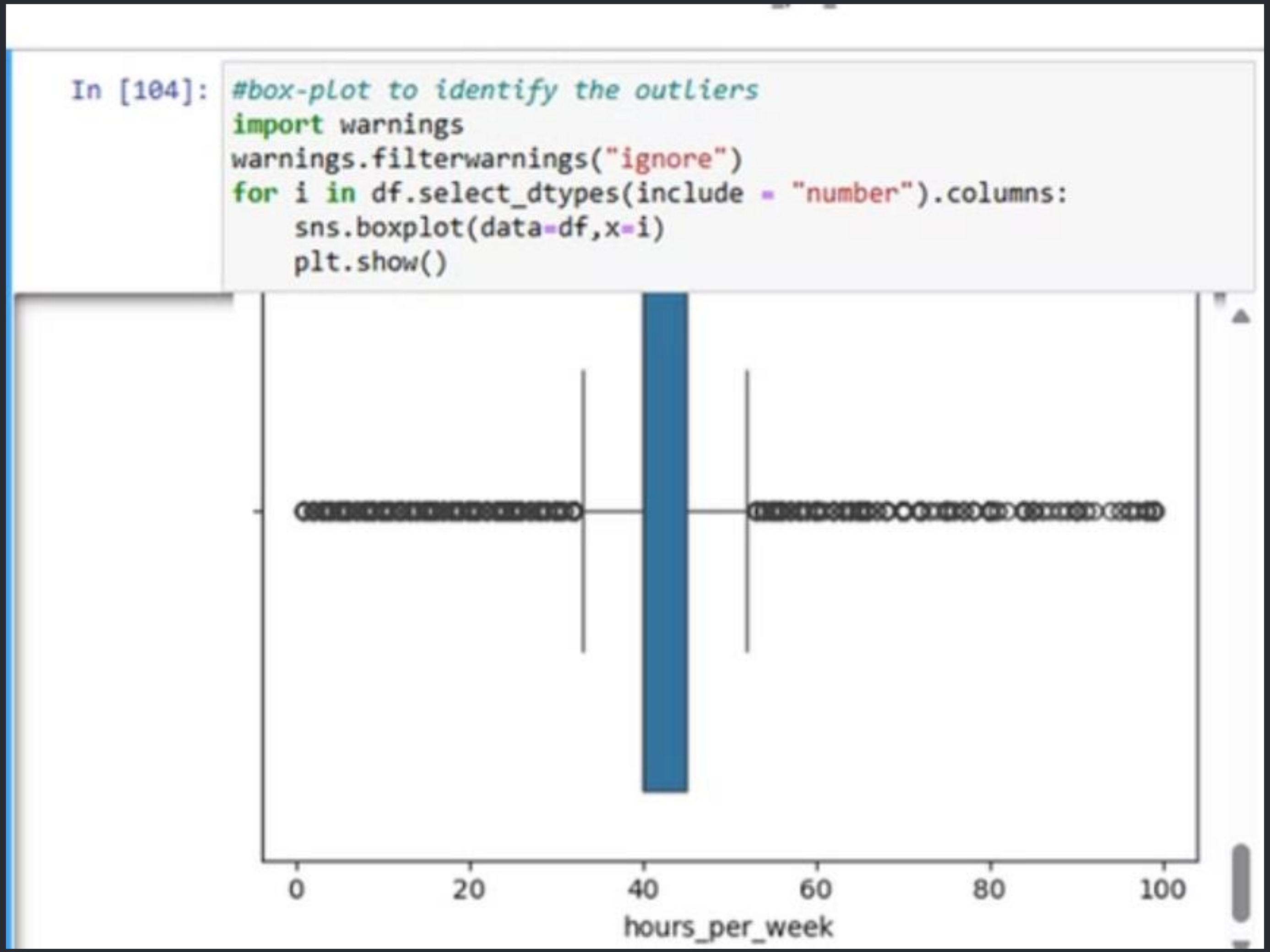
```
111]: for i in ["workclass", "occupation", "native_country"]:
          df[i].fillna(df[i].mode()[0], inplace=True)
```

```
113]: df.isnull().sum()
```

```
113]: age               0
      workclass         0
      fnlwgt            0
      education         0
      education_num     0
      marital_status    0
      occupation        0
      relationship      0
      race              0
      sex               0
      capital_gain      0
      capital_loss      0
      hours_per_week    0
      native_country    0
      income            0
      dtype: int64
```

Handling Outliers





Data Transform

- We grouped the following features into unique categories to reduce the number of unique entries in the dataset: education, work class, marital status, occupation, race, relationship, and native country.

```
In [77]: # Strip leading/trailing spaces from the 'education' column
         df['education'] = df['education'].str.strip()

         # Apply the function to group certain education levels under 'Othe
         def add_education(inpt):
             if inpt in ['10th', '7th-8th', 'Prof-school', '9th', '12th', '
                 return 'Other'
             else:
                 return inpt

         # Apply the function
         df['education'] = df['education'].apply(add_education)

         # Check the value counts
         print(df['education'].value_counts())

         education
         HS-grad         10501
         Some-college     7291
         Bachelors        5355
         Other            4067
         Masters          1723
         Assoc-voc        1382
         11th             1175
         Assoc-acdm       1067
         Name: count, dtype: int64
```

```
In [79]: df['workclass'].value_counts()

Out[79]: workclass
         Private             22696
         Self-emp-not-inc     2541
         Local-gov            2093
         State-gov            1298
         Self-emp-inc         1116
         Federal-gov           960
         Without-pay            14
         Never-worked            7
         Name: count, dtype: int64
```

Encoding Categorical Features

```
In [119]: df = pd.get_dummies(df)
```

```
In [121]: df.head()
```

Out[121]:

	age	hours_per_week	workclass_Government	workclass_Other	workclass_Private	workclass_Self Employeed	education_11th	education_Assoc-acdm	education_Assoc-voc	edu
0	39	40	True	False	False	False	False	False	False	
1	50	13	False	False	False	True	False	False	False	
2	38	40	False	False	True	False	False	False	False	
3	53	40	False	False	True	False	True	False	False	
4	28	40	False	False	True	False	False	False	False	

5 rows × 37 columns

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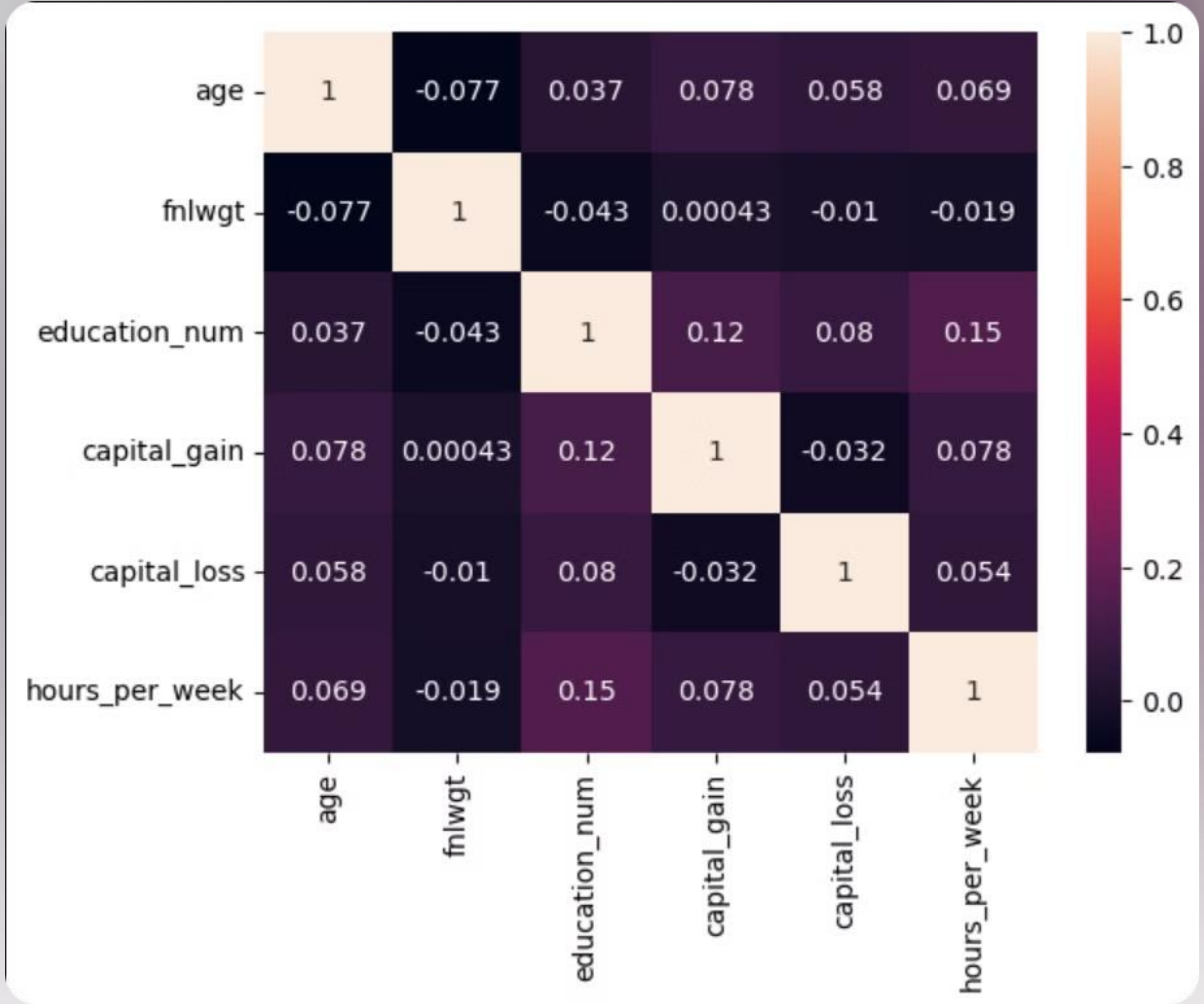
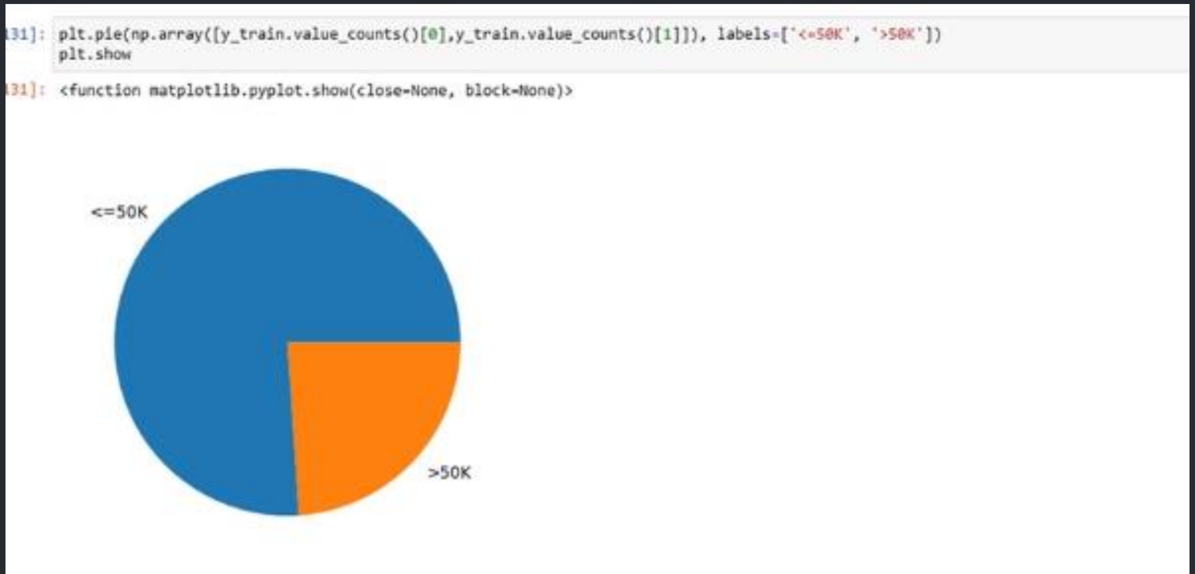
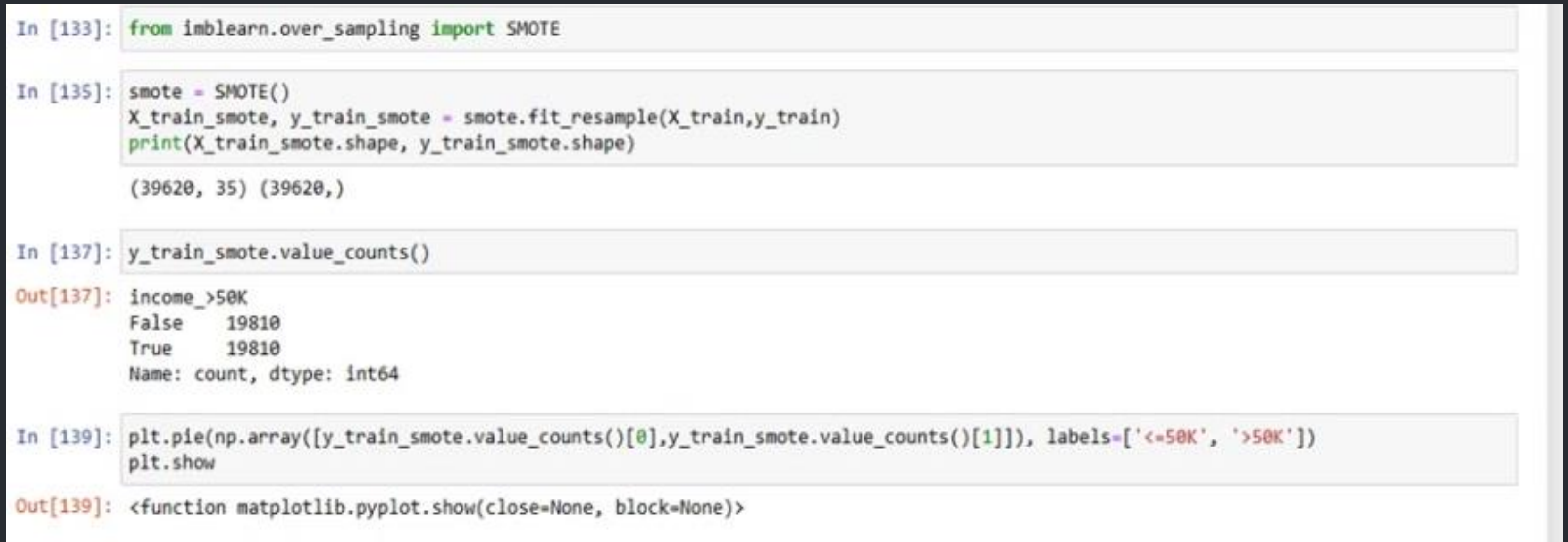
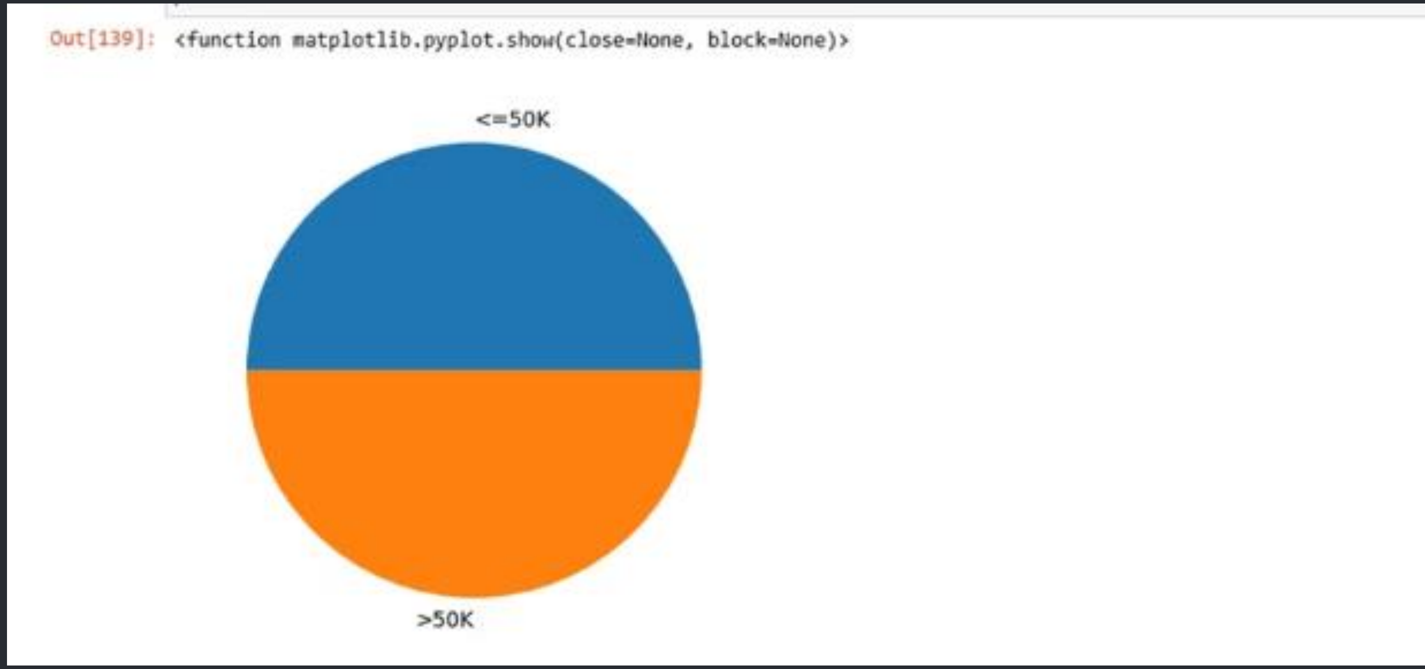
Correlation Matrix



Balance the Dataset







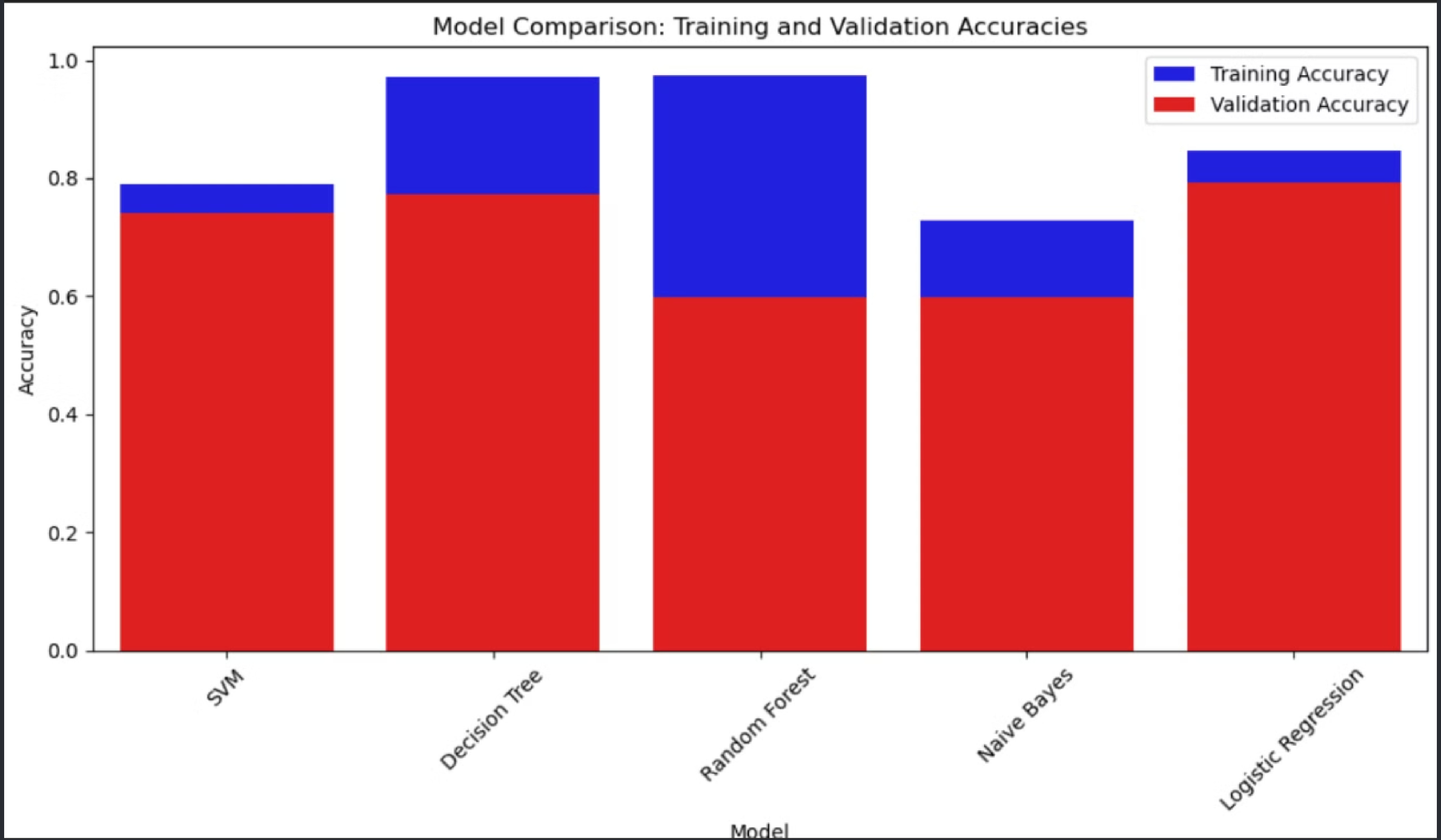
Model Implementation

Model Implementation

1. We used five different models here to predict the customer churn or not.

- Linear Regression
- Random Forest Decision Tree
- Classification
- Naïve Bayes Classification
- Support Vector Classification

2. The Random Forest Model was selected as the most effective in terms of predictive performance.



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Improving the Accuracy

Improving best model by hyperparameter tuning

```
In [155]: from sklearn.model_selection import GridSearchCV

          parameters = {'n_estimators':[10, 50, 100],
                        'criterion':['gini', 'entropy', 'log_loss']}

          grid_obj = GridSearchCV(estimator=rfc, param_grid=parameters)

          grid_fit = grid_obj.fit(X_train_smote, y_train_smote)

          best_model = grid_fit.best_estimator_

          best_model.score(X_test, y_test)

Out[155]: 0.7911868570551205
```

Final Product

Employee Salary Prediction System

Challenges

- Poor data quality can result in inaccurate salary predictions.
- Certain groups may be underrepresented, causing class imbalance.
- Electing the right machine learning model is essential for accurate predictions.

Solutions

- Clean and validate data for accuracy.
- Apply SMOTE to balance classes.
- Experiment with models like logistic regression and random forests.
- Select the model with the best performance.

Further implementations and developing goals

1. Modify the system to position it as a marketable product.
2. Develop a product tailored to the Sri Lankan job market.
3. Ensure the system addresses the unique dynamics of rapid salary fluctuations in various sectors.

THANK YOU!