MINI PROJECT

Title

Forecasting Software Developer Salaries: A Machine Learning Approach.

Objectives

- Collecting relevant data on software developer salaries.
- Identifying key features that influence software developer salaries.
- Building a predictive model using machine learning algorithms.
- Evaluating the performance of the model and refining it for better accuracy..

Outcomes

- A predictive model capable of estimating the salary of software developers with a high degree of accuracy.
- Insights into the factors that most significantly impact software developer salaries.
- Potential applications in HR and recruitment processes for salary negotiations and budget planning.

Software

- Programming Language: Python
- Libraries: Scikit-learn, Pandas, NumPy, Matplotlib/Seaborn, Streamlit.
- Tools: Jupyter Notebook, Anaconda

Theory

Machine Learning Approach:

➢ Supervised Learning: In supervised learning, the model learns from labeled data, where each example is paired with a corresponding target variable. In the context of your project, the target variable would be the salary of software developers, and the model learns to predict this variable based on input features.

Feature Selection:

➢ Identifying Relevant Features: The success of your salary prediction model depends on selecting the right features that have a significant impact on software developer salaries. These features may include programming languages, years of experience, education level, location, industry, and company size, among others.

Feature Engineering:

➢ This involves transforming raw data into meaningful features that better represent the underlying problem and improve the performance of the model. Techniques such as one-hot encoding for categorical variables, scaling numerical features, and creating new features through mathematical transformations or domain knowledge can be employed.

Model Selection:

- Regression Algorithms: Since your project involves predicting a continuous variable (salary), regression algorithms are suitable for the task. Common regression algorithms include Linear Regression, Ridge Regression, Lasso Regression, Random Forest Regression, Gradient Boosting Regression, and Support Vector Regression, among others.

Hyperparameter Tuning:

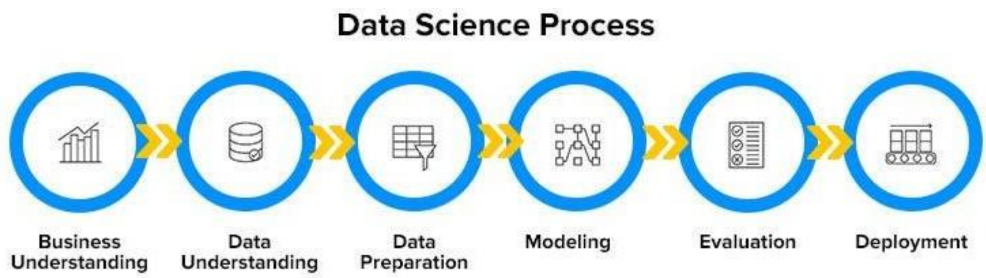
- Each regression algorithm comes with its set of hyperparameters that control the behavior of the model. Hyperparameter tuning involves selecting the optimal combination of hyperparameters to maximize the model's performance. Techniques such as grid search or randomized search can be used for this purpose.

Evaluation Metrics:

- Mean Absolute Error (MAE): MAE measures the average absolute difference between the predicted salaries and the actual salaries. It provides a straightforward interpretation of prediction error in the same units as the target variable (salary).
- Mean Squared Error (MSE): MSE measures the average squared difference between the predicted salaries and the actual salaries. It penalizes larger errors more heavily than MAE, making it sensitive to outliers.
- R-squared (R2): R-squared represents the proportion of variance in the target variable (salary) that is explained by the independent variables (features) in the model. It ranges from 0 to 1, where higher values indicate a better fit of the model to the data.

Data Preprocessing:

- Handling Missing Values: Missing values in the dataset need to be addressed before training the model. Techniques such as imputation (replacing missing values with a calculated estimate) or deletion of missing values can be employed.
- Scaling and Normalization: Scaling numerical features ensures that all features contribute equally to the model fitting process and prevents features with larger scales from dominating the model.
- Encoding Categorical Variables: Categorical variables need to be encoded into numerical format for model training. Techniques such as one-hot encoding or label encoding can be used depending on the nature of the categorical variables**.**



Algorithm:

1. Data Collection:
   - Gather data on software developer salaries from reliable sources such as job boards, company websites, salary surveys, or APIs.
   - Include relevant features such as years of experience, education level, programming languages, location, industry, company size, etc.
2. Data Preprocessing:
   - Handle missing values by imputation or deletion.
   - Encode categorical variables using techniques like one-hot encoding.
   - Scale numerical features to ensure they have similar magnitudes.
   - Split the data into training and testing sets to evaluate the model's performance.
3. Feature Engineering:
   - Explore feature relationships and engineer new features if necessary.
   - Consider transformations or combinations of features to better represent the underlying patterns in the data.
4. Model Selection:
   - Choose Gradient Boosting Regression as the algorithm for predicting software developer salaries due to its ability to handle non-linear relationships and robustness to outliers.
   - Implement the Gradient Boosting Regression model using Scikit-learn or other suitable libraries in Python.
5. Model Training:
   - Train the Gradient Boosting Regression model on the training data.
   - Experiment with different hyperparameters and settings to optimize the model's performance.
   - Use techniques like cross-validation to assess the model's generalization ability and prevent overfitting.
6. Model Evaluation:
   - Evaluate the trained model's performance on the testing data using appropriate valuation metrics such as Mean Absolute Error (MAE).
   - Compare the model's performance against baseline models or other algorithms to assess its effectiveness.
7. Model Interpretation:
   - Analyse the feature importance scores provided by the Gradient Boosting Regression model to understand which factors have the most significant impact on software developer salaries.
8. Deployment:
   - Integrate the trained model into a user-friendly application using Streamlit.
   - Develop an intuitive interface where users can input their information (e.g., years of experience, location, etc.) and receive salary predictions in real-time.
   - Ensure the application is well-documented and easy to use for both technical and non-technical users.
9. Testing and Validation:
   - Conduct thorough testing of the deployed application to ensure its functionality and accuracy.

Flow Chart:

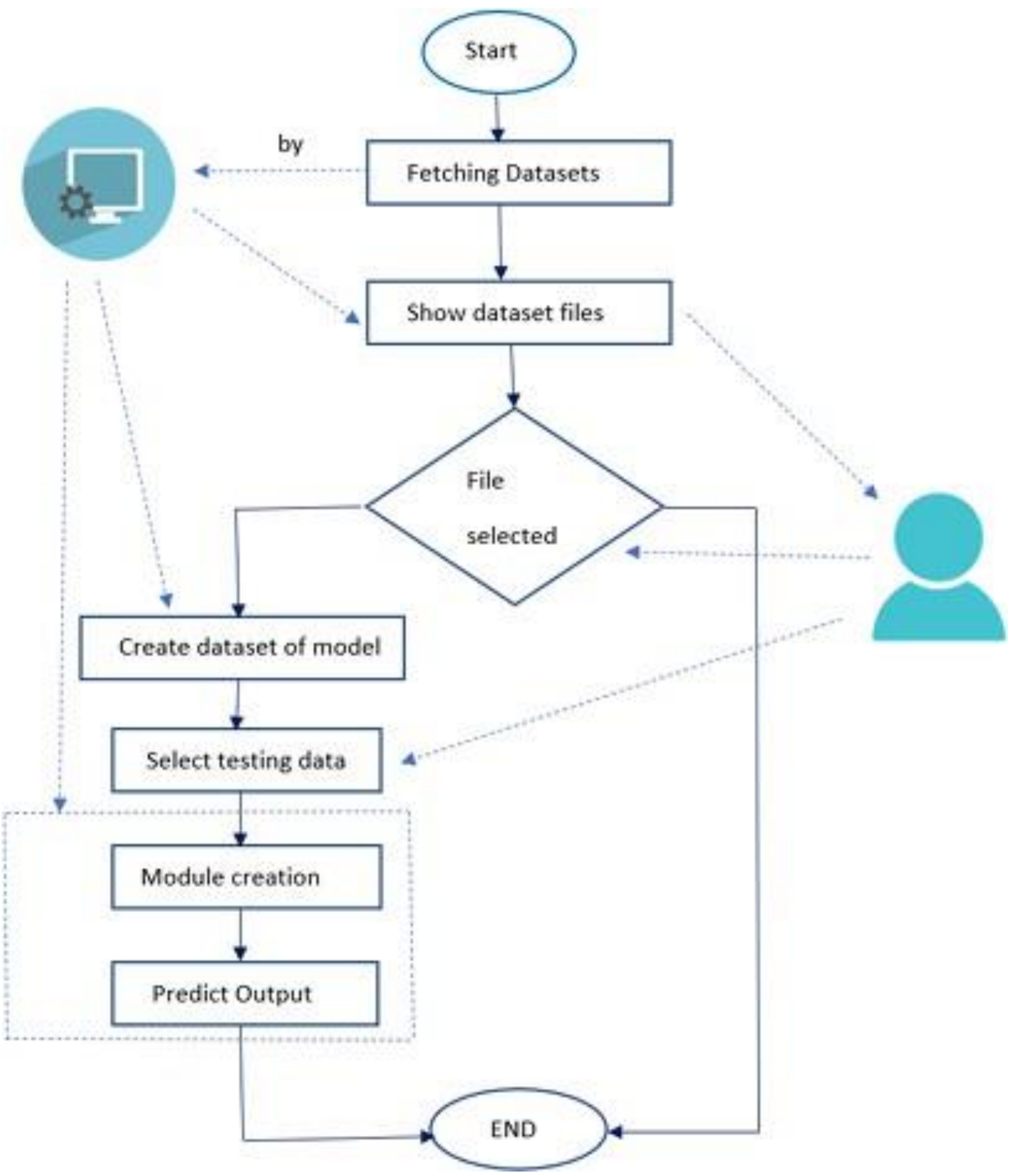


Fig no. 1. Flow Chart for Project

Conclusion

In conclusion, the project " Predicting Software Developer Salaries" offers a comprehensive solution to the challenge of accurately forecasting the salaries of software developers. Through meticulous data collection, preprocessing, feature engineering, and model training, we have developed a robust predictive model using Gradient Boosting Regression.

salaryprediction

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt

df = pd.read_csv("survey_results_public.csv")
```

0.0.1 DATA CLEANING

[2]:
```
df.head()
```

[2]:
```
   Respondent                                         MainBranch  Hobbyist  \
0           1                     I am a developer by profession       Yes
1           2                     I am a developer by profession        No
2           3                        I code primarily as a hobby       Yes
3           4                     I am a developer by profession       Yes
4           5  I used to be a developer by profession, but no...       Yes

    Age  Age1stCode CompFreq  CompTotal  ConvertedComp             Country  \
0   NaN          13  Monthly        NaN            NaN             Germany
1   NaN          19      NaN        NaN            NaN      United Kingdom
2   NaN          15      NaN        NaN            NaN  Russian Federation
3  25.0          18      NaN        NaN            NaN             Albania
4  31.0          16      NaN        NaN            NaN       United States

     CurrencyDesc  ...                  SurveyEase           SurveyLength  \
0   European Euro  ...  Neither easy nor difficult  Appropriate in length
1  Pound sterling  ...                         NaN                    NaN
2             NaN  ...  Neither easy nor difficult  Appropriate in length
3    Albanian lek  ...                         NaN                    NaN
4             NaN  ...                        Easy              Too short

  Trans                                      UndergradMajor  \
0    No  Computer science, computer engineering, or sof...
1   NaN  Computer science, computer engineering, or sof...
2   NaN                                                NaN
3    No  Computer science, computer engineering, or sof...
4    No  Computer science, computer engineering, or sof...
```

```
  WebframeDesireNextYear   WebframeWorkedWith \
0          ASP.NET Core  ASP.NET;ASP.NET Core
1                   NaN                   NaN
2                   NaN                   NaN
3                   NaN                   NaN
4  Django;Ruby on Rails         Ruby on Rails

                              WelcomeChange WorkWeekHrs YearsCode YearsCodePro
0   Just as welcome now as I felt last year        50.0        36           27
1  Somewhat more welcome now than last year         NaN         7            4
2  Somewhat more welcome now than last year         NaN         4          NaN
3  Somewhat less welcome now than last year        40.0         7            4
4   Just as welcome now as I felt last year         NaN        15            8

[5 rows x 61 columns]
```

[3]:

```
df = df[["Country", "EdLevel", "YearsCodePro", "Employment", "ConvertedComp"]] 
 # keep this 4 columns inly
df = df.rename({"ConvertedComp": "Salary"}, axis=1)  #replacing convertedcomp
 to salary
df.head()
```

[3]:

```
              Country                                         EdLevel  \
0             Germany  Master's degree (M.A., M.S., M.Eng., MBA, etc.)
1      United Kingdom     Bachelor's degree (B.A., B.S., B.Eng., etc.)
2  Russian Federation                                              NaN
3             Albania  Master's degree (M.A., M.S., M.Eng., MBA, etc.)
4       United States     Bachelor's degree (B.A., B.S., B.Eng., etc.)

  YearsCodePro                                        Employment Salary
0           27  Independent contractor, freelancer, or self-em...    NaN
1            4                                 Employed full-time    NaN
2          NaN                                               NaN    NaN
3            4                                               NaN    NaN
4            8                                 Employed full-time    NaN
```

[4]:

```
df = df[df["Salary"].notnull()]  #removing null values
df.head()
```

[4]:

```
           Country                                            EdLevel  \
7    United States       Bachelor's degree (B.A., B.S., B.Eng., etc.)
9   United Kingdom    Master's degree (M.A., M.S., M.Eng., MBA, etc.)
10  United Kingdom       Bachelor's degree (B.A., B.S., B.Eng., etc.)
11           Spain  Some college/university study without earning ...
12     Netherlands  Secondary school (e.g. American high school, G...

   YearsCodePro        Employment   Salary
```

```
7              13  Employed full-time   116000.0
9               4  Employed full-time    32315.0
10              2  Employed full-time    40070.0
11              7  Employed full-time    14268.0
12             20  Employed full-time    38916.0
```

[5] :
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 34756 entries, 7 to 64154
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Country       34756 non-null  object
 1   EdLevel       34188 non-null  object
 2   YearsCodePro  34621 non-null  object
 3   Employment    34717 non-null  object
 4   Salary        34756 non-null  float64
dtypes: float64(1), object(4)
memory usage: 1.6+ MB
```

[6] :
```
df = df.dropna() #drop all the rows not a number
df.isnull().sum() #counting null values
```

[6] :
```
Country         0
EdLevel         0
YearsCodePro    0
Employment      0
Salary          0
dtype: int64
```

[7] :
```
df = df[df["Employment"] == "Employed full-time"]    #only where the user was␣
↪employed full time
df = df.drop("Employment", axis=1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 30019 entries, 7 to 64154
Data columns (total 4 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Country       30019 non-null  object
 1   EdLevel       30019 non-null  object
 2   YearsCodePro  30019 non-null  object
 3   Salary        30019 non-null  float64
dtypes: float64(1), object(3)
memory usage: 1.1+ MB
```

[8] :
```python
df['Country'].value_counts() #cleaning the country data
```

[8] :
```
Country
United States      7569
India              2425
United Kingdom     2287
Germany            1903
Canada             1178
                   ...
Benin                 1
Fiji                  1
San Marino            1
Guinea                1
Andorra               1
Name: count, Length: 154, dtype: int64
```

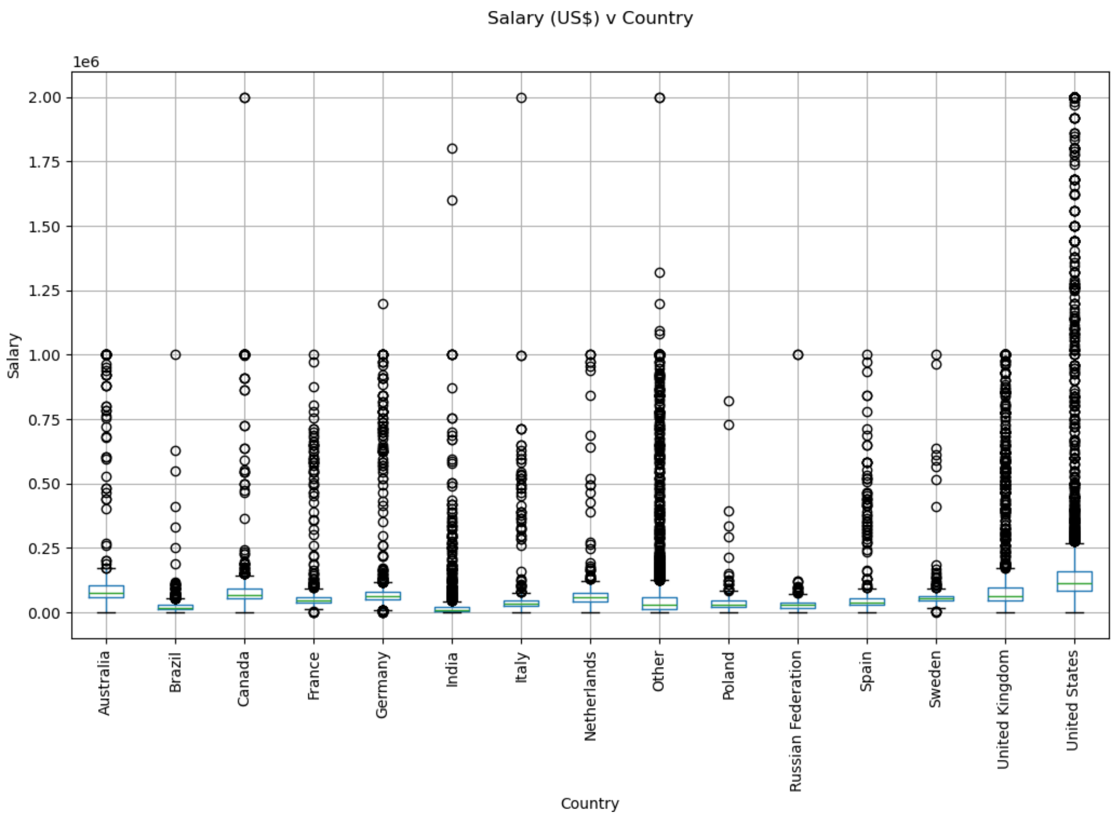
[9] :
```python
def shorten_categories(categories, cutoff):
    categorical_map = {}
    for i in range(len(categories)):
        if categories.values[i] >= cutoff:
            categorical_map[categories.index[i]] = categories.index[i]
        else:
            categorical_map[categories.index[i]] = 'Other'
    return categorical_map

#converting the countries less than 400 employess into one grp
```

[10] :
```python
country_map = shorten_categories(df.Country.value_counts(), 400)
df['Country'] = df['Country'].map(country_map)
df.Country.value_counts()
```

[10]:
```
Country
Other                 8549
United States         7569
India                 2425
United Kingdom        2287
Germany               1903
Canada                1178
Brazil                 991
France                 972
Spain                  670
Australia              659
Netherlands            654
Poland                 566
Italy                  560
Russian Federation     522
Sweden                 514
```

Name: count, dtype: int64

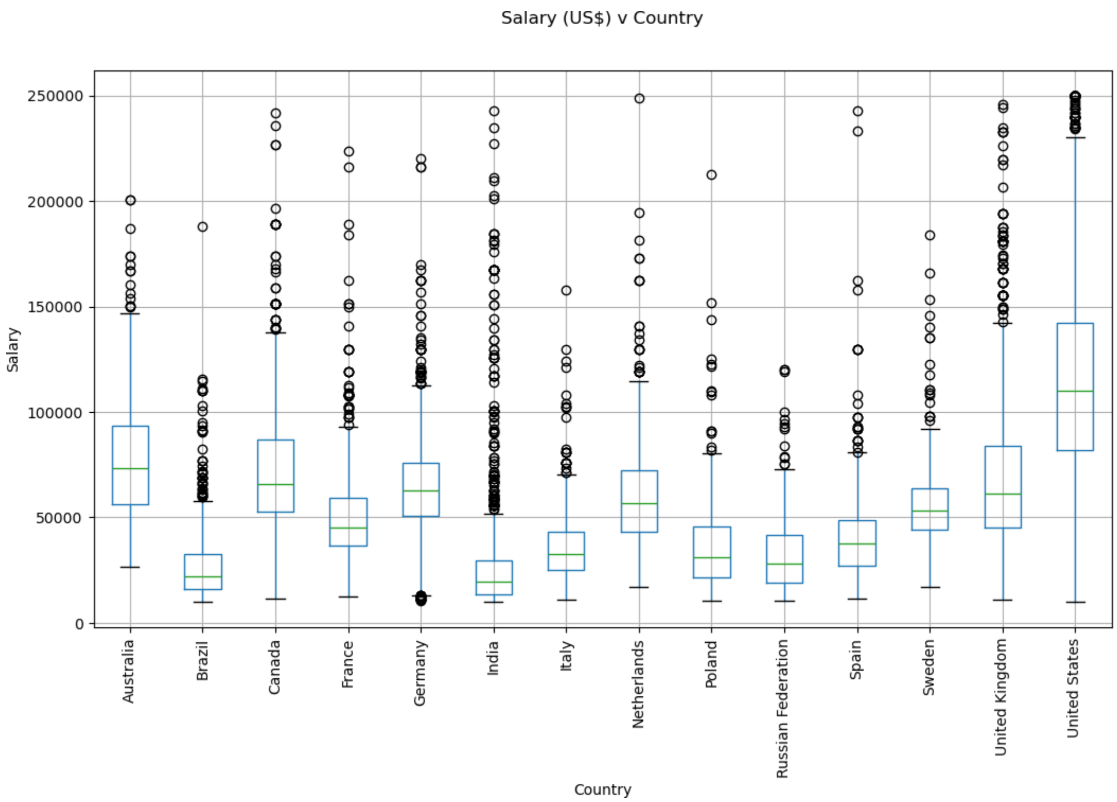
[11] :
```
fig, ax = plt.subplots(1,1, figsize=(12, 7))
df.boxplot('Salary', 'Country', ax=ax)
plt.suptitle('Salary (US$) v Country')
plt.title('')
plt.ylabel('Salary')
plt.xticks(rotation=90)
plt.show()

#box plot for salary  vs countries
```



[12] :
```
df = df[df["Salary"] <= 250000]
df = df[df["Salary"] >= 10000]
df = df[df['Country'] != 'Other']
#all the salaries near to the median only taken
```

[13] :
```
fig, ax = plt.subplots(1,1, figsize=(12, 7))
df.boxplot('Salary', 'Country', ax=ax)
plt.suptitle('Salary (US$) v Country')
plt.title('')
```

```
plt.ylabel('Salary')
plt.xticks(rotation=90)
plt.show()
```



[14]:
```
df["YearsCodePro"].unique()
```

[14]:
```
array(['13', '4', '2', '7', '20', '1', '3', '10', '12', '29', '6', '28',
       '8', '23', '15', '25', '9', '11', 'Less than 1 year', '5', '21',
       '16', '18', '14', '32', '19', '22', '38', '30', '26', '27', '17',
       '24', '34', '35', '33', '36', '40', '39', 'More than 50 years',
       '31', '37', '41', '45', '42', '44', '43', '50', '49'], dtype=object)
```

[15]:
```
def clean_experience(x):
    if x == 'More than 50 years':
        return 50
    if x == 'Less than 1 year':
        return 0.5
    return float(x)

df['YearsCodePro'] = df['YearsCodePro'].apply(clean_experience)

#converting experience less than 1 year to 0.5 and more than 50 years to 50
```

[16] :
```
df["EdLevel"].unique() #same with the education level
```

[16] :
```
array(['Bachelor’s degree (B.A., B.S., B.Eng., etc.)',
       'Master’s degree (M.A., M.S., M.Eng., MBA, etc.)',
       'Some college/university study without earning a degree',
       'Secondary school (e.g. American high school, German Realschule or
Gymnasium, etc.)',
       'Associate degree (A.A., A.S., etc.)',
       'Professional degree (JD, MD, etc.)',
       'Other doctoral degree (Ph.D., Ed.D., etc.)',
       'I never completed any formal education',
       'Primary/elementary school'], dtype=object)
```

[17] :
```
def clean_education(x):
    if 'Bachelor’s degree' in x:
        return 'Bachelor’s degree'
    if 'Master’s degree' in x:
        return 'Master’s degree'
    if 'Professional degree' in x or 'Other doctoral' in x:
        return 'Post grad'
    return 'Less than a Bachelors'

df['EdLevel'] = df['EdLevel'].apply(clean_education)
```

[18] :
```
df["EdLevel"].unique()
```

[18] :
```
array(['Bachelor’s degree', 'Master’s degree', 'Less than a Bachelors',
       'Post grad'], dtype=object)
```

[19] :
```
from sklearn.preprocessing import LabelEncoder
le_education = LabelEncoder()
df['EdLevel'] = le_education.fit_transform(df['EdLevel'])
df["EdLevel"].unique()
#le.classes_
#converting edulevel from string to number
```

[19] :
```
array([0, 2, 1, 3])
```

[20] :
```
le_country = LabelEncoder()
df['Country'] = le_country.fit_transform(df['Country'])
df["Country"].unique()

#each country to a unique number
```

[20] :
```
array([13, 12, 10,  7,  4,  2,  6,  1,  3,  5, 11,  8,  0,  9])
```

0.0.2 MODEL TRAINING

[21] :
```
X = df.drop("Salary", axis=1) #spliting  the  data
y = df["Salary"]
```

[22] :
```
from sklearn.linear_model import LinearRegression
linear_reg = LinearRegression()
linear_reg.fit(X,  y.values)
#model from sklearn using linear regression
#training
```

[22] :
```
LinearRegression()
```

[23] :
```
y_pred = linear_reg.predict(X) #to predict new values #testing
```

[24] :
```
from sklearn.metrics import mean_squared_error, mean_absolute_error
import numpy as np
error = np.sqrt(mean_squared_error(y, y_pred))
#calculating mse in y and y_prediction
```

[25] :
```
error # error rate is high so we use another model
```

[25]:
```
39274.75368318509
```

[26] :
```
from sklearn.tree import DecisionTreeRegressor
dec_tree_reg = DecisionTreeRegressor(random_state=0)
dec_tree_reg.fit(X,  y.values)
```

[26] :
```
DecisionTreeRegressor(random_state=0)
```

[27] :
```
y_pred = dec_tree_reg.predict(X)
```

[28] :
```
error = np.sqrt(mean_squared_error(y, y_pred))
print("${:,.02f}".format(error))
```

```
$29,414.94
```

[29] :
```
from sklearn.ensemble import RandomForestRegressor
random_forest_reg = RandomForestRegressor(random_state=0)
random_forest_reg.fit(X,  y.values)
#one more
```

[29] :
```
RandomForestRegressor(random_state=0)
```

[30] :
```
y_pred = random_forest_reg.predict(X)
```

[31] :
```
error = np.sqrt(mean_squared_error(y, y_pred))
print("${:,.02f}".format(error))
```

$29,487.31

[32] :
```
from sklearn.model_selection import GridSearchCV

max_depth = [None, 2,4,6,8,10,12]
parameters = {"max_depth": max_depth}

regressor = DecisionTreeRegressor(random_state=0)
gs = GridSearchCV(regressor, parameters, scoring='neg_mean_squared_error')
gs.fit(X, y.values)

#each time evaluates the error using the max value and find the min value
```

[32] :
```
GridSearchCV(estimator=DecisionTreeRegressor(random_state=0),
             param_grid={'max_depth': [None, 2, 4, 6, 8, 10, 12]},
             scoring='neg_mean_squared_error')
```

[33] :
```
regressor = gs.best_estimator_

regressor.fit(X, y.values)
y_pred = regressor.predict(X)
error = np.sqrt(mean_squared_error(y, y_pred))
print("${:,.02f}".format(error))
```

$30,428.51

[34] :
```
X
```

[34]:

	Country	EdLevel	YearsCodePro
7	13	0	13.0
9	12	2	4.0
10	12	0	2.0
11	10	1	7.0
12	7	1	20.0
...	...	...	...
64113	13	1	15.0
64116	13	0	6.0
64122	13	1	4.0
64127	13	3	12.0
64129	13	2	4.0

[18491 rows x 3 columns]

[35] :
```
X = np.array([["United States", 'Master's degree', 15 ]])
X
#the output will act as a x
```

[35]:
```
array([['United States', 'Master's degree', '15']], dtype='<U15')
```

[36]:
```
#label encoder 0 for country , degree for 1
X[:, 0] = le_country.transform(X[:,0])
X[:, 1] = le_education.transform(X[:,1])
X = X.astype(float)
X
```

[36]:
```
array([[13.,  2., 15.]])
```

[37]:
```
y_pred = regressor.predict(X)
y_pred
```

```
C:\Users\neelk\anaconda3\envs\ml\lib\site-packages\sklearn\base.py:464:
UserWarning: X does not have valid feature names, but DecisionTreeRegressor was
fitted with feature names
  warnings.warn(
```

[37]:
```
array([139427.26315789])
```

[42]:
```
import pickle #to save the model
```

[43]:
```
data = {"model": regressor, "le_country": le_country, "le_education":␣
↪le_education}
with open('saved_steps.pkl', 'wb') as file:
    pickle.dump(data, file)

#we create a dictionary open in write binary mode
```

[46]:
```
with open('saved_steps.pkl', 'rb') as file:
    data = pickle.load(file)

regressor_loaded = data["model"]
le_country = data["le_country"]
le_education = data["le_education"]
#we can check it
```

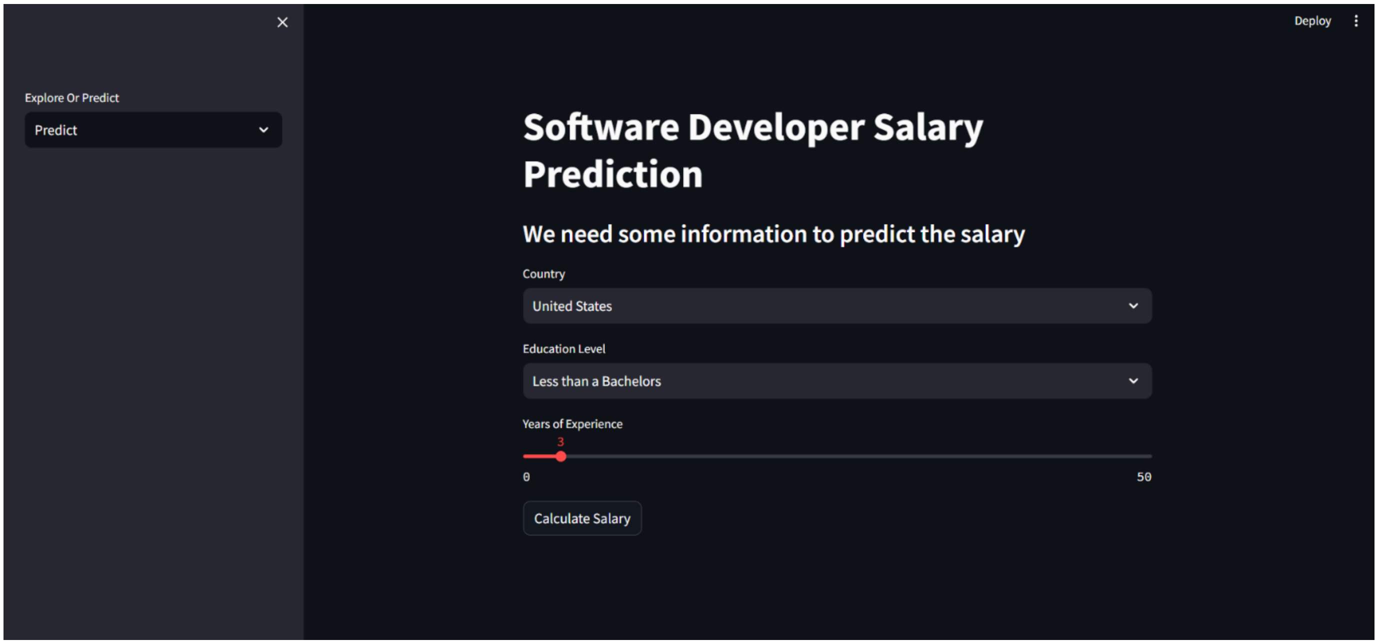
[47]:
```
y_pred = regressor_loaded.predict(X)
y_pred
```

```
C:\Users\neelk\anaconda3\envs\ml\lib\site-packages\sklearn\base.py:464:
UserWarning: X does not have valid feature names, but DecisionTreeRegressor was
fitted with feature names
  warnings.warn(
```

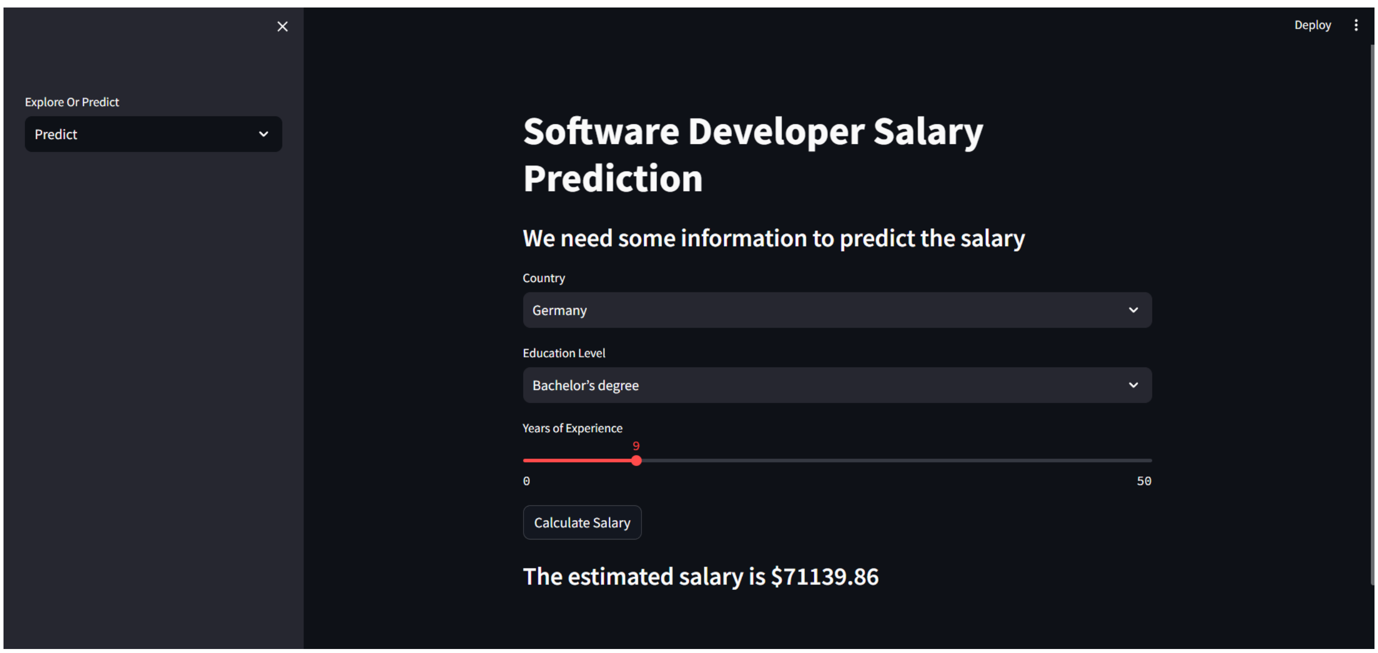
[47]:
```
array([139427.26315789])
```

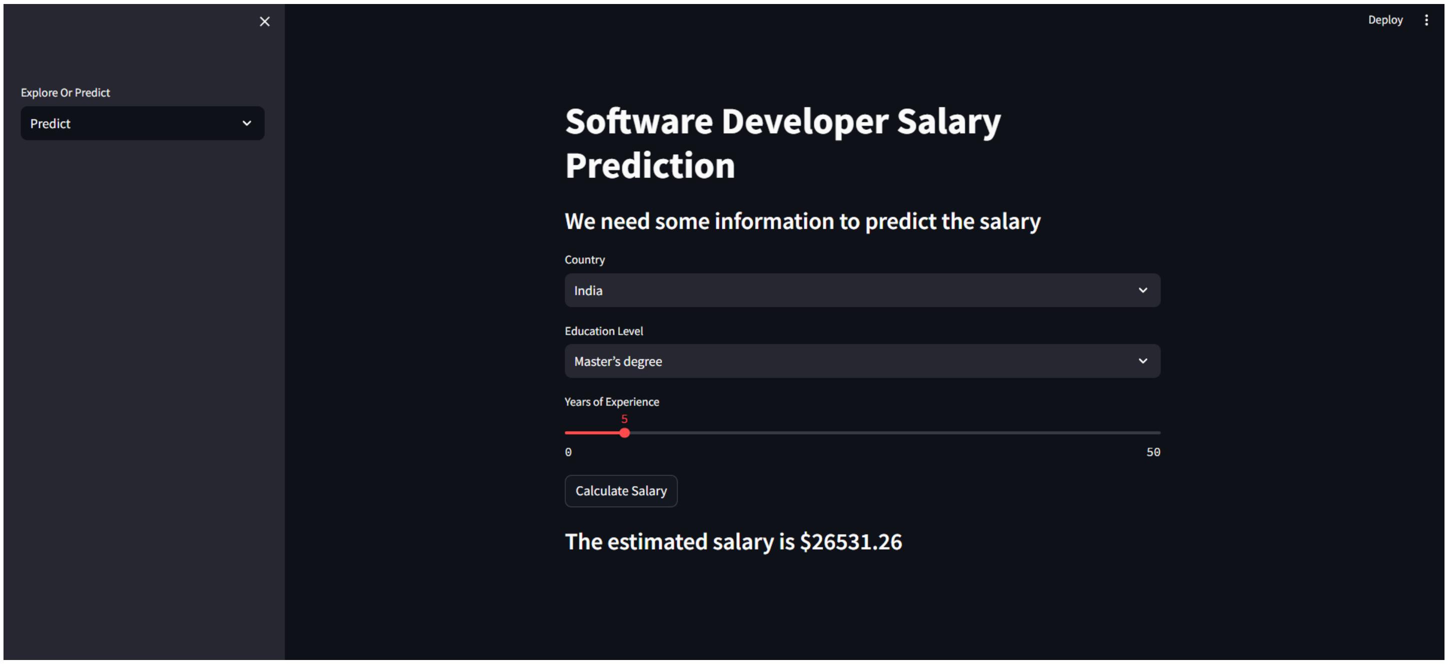
[48]:
```
#we get the some name before and now
```

Home Page:



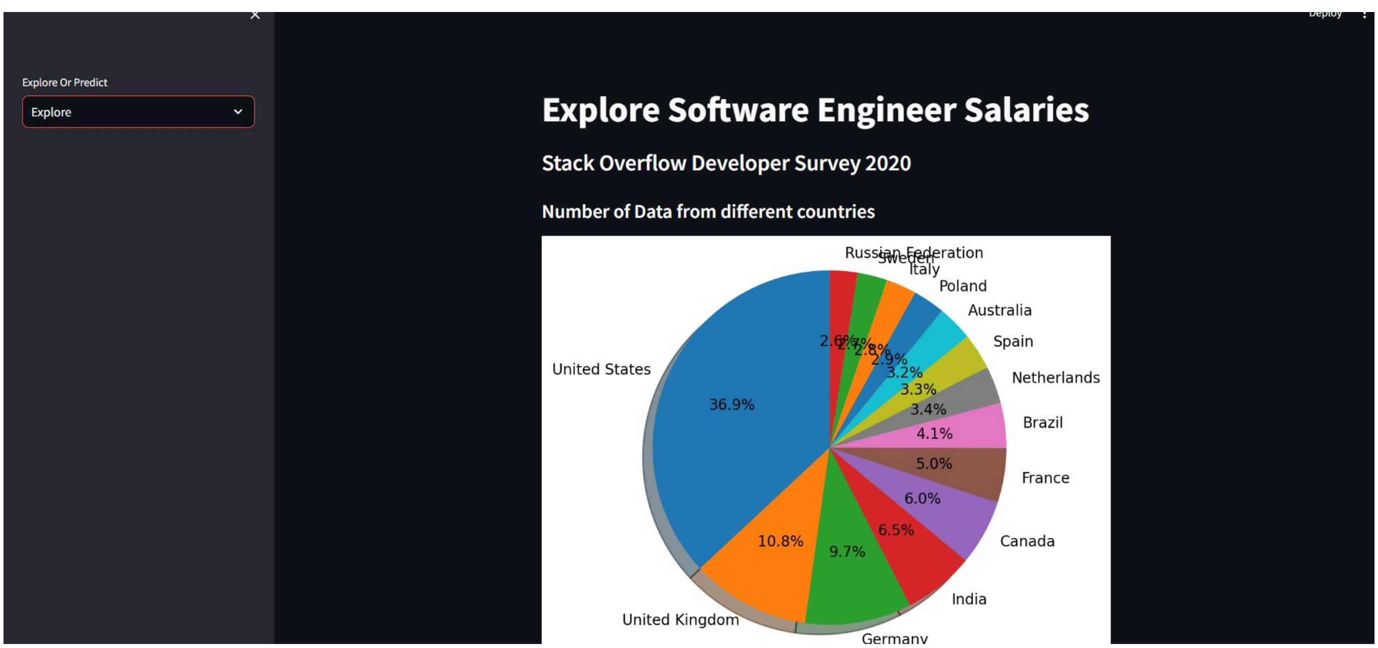
Prediction:



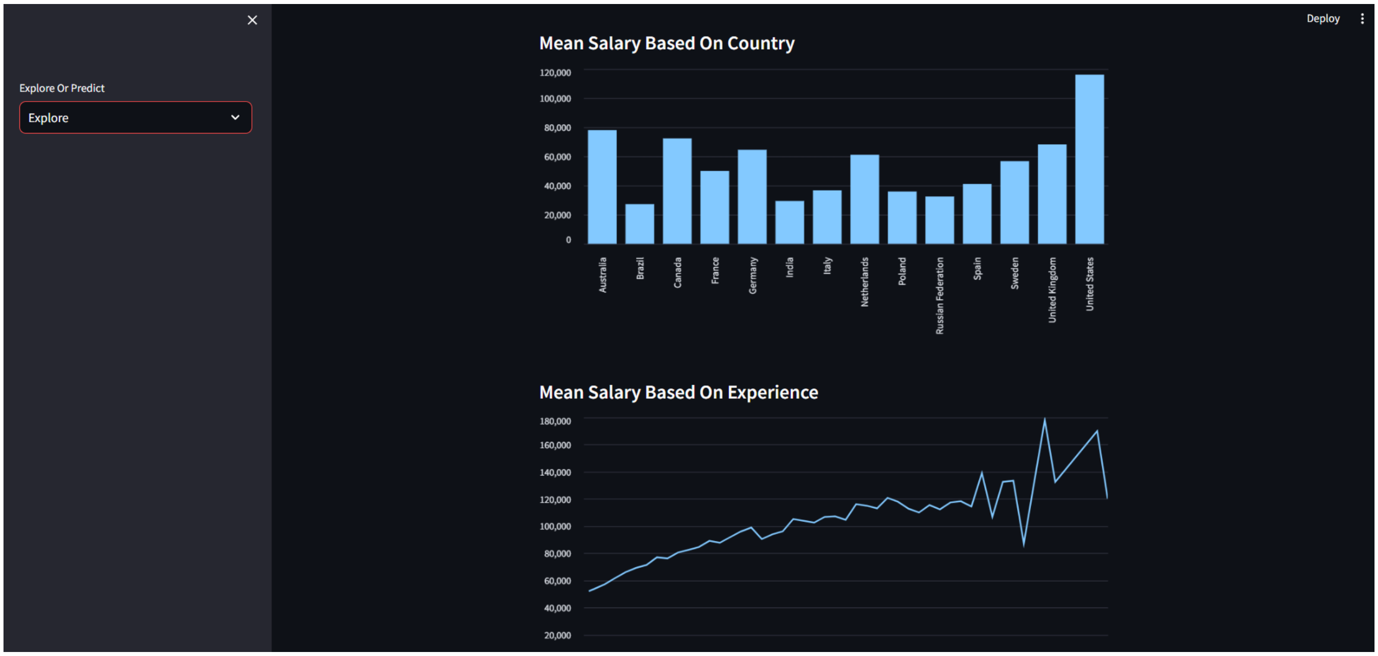


Deploy
Explore Or Predict
Predict
Software Developer Salary Prediction
We need some information to predict the salary
Country
India
Education Level
Master's degree
Years of Experience
5
0
50
Calculate Salary
The estimated salary is $26531.26

EDA:



Explore Or Predict
Explore
Explore Software Engineer Salaries
Stack Overflow Developer Survey 2020
Number of Data from different countries
Russian Federation
Sweden
Italy
Poland
Australia
Spain
Netherlands
Brazil
France
Canada
India
Germany
United Kingdom
United States
36.9%
10.8%
9.7%
6.5%
6.0%
5.0%
4.1%
3.4%
3.3%
3.2%
2.9%
2.6%



Explore Or Predict
Explore
Deploy
Mean Salary Based On Country
120,000
100,000
80,000
60,000
40,000
20,000
0
Australia
Brazil
Canada
France
Germany
India
Italy
Netherlands
Poland
Russian Federation
Spain
Sweden
United Kingdom
United States
Mean Salary Based On Experience
180,000
160,000
140,000
120,000
100,000
80,000
60,000
40,000
20,000