Salary Prediction Machine Learning Project by Furqan Alam

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0.1 DATA ANALYSIS AND MACHINE LEARNING PROJECT

0.2 SALARY PREDICTION

0.3 IMPORTING LIBRARIES

[46]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn.datasets
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn import metrics
from datetime import datetime
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
import joblib
```

0.4 IMPORTING THE DATASET

[3]:
```python
HR_Dataset = pd.read_csv("HR Dataset.csv")
```

0.5 VIEWING THE DATAFRAME

[4]:
```python
HR_Dataset.head()
```

[4]:
```
              NAME  SALARY             HIRE_DATE DEPARTMENT_NAME   JOB_ID  \
0     Steven King   24000  2013-06-17T00:00:00Z       Executive  AD_PRES
1      Neena Yang   17000  2015-09-21T00:00:00Z       Executive    AD_VP
2      Lex Garcia   17000  2011-01-13T00:00:00Z       Executive    AD_VP
3  Alexander James    9000  2016-01-03T00:00:00Z              IT  IT_PROG
4     Bruce Miller    6000  2017-05-21T00:00:00Z              IT  IT_PROG

                      JOB_TITLE  LOCATION_ID       CITY  \
0                     President         1700    Seattle
```

```
1  Administration Vice President          1700     Seattle
2  Administration Vice President          1700     Seattle
3                       Programmer          1400   Southlake
4                       Programmer          1400   Southlake

              COUNTRY_NAME
0  United States of America
1  United States of America
2  United States of America
3  United States of America
4  United States of America
```

0.6 HANDLE MISSING VALUES

[5]:
```
print(HR_Dataset.isnull().sum())
```

```
NAME               0
SALARY             0
HIRE_DATE          0
DEPARTMENT_NAME    0
JOB_ID             0
JOB_TITLE          0
LOCATION_ID        0
CITY               0
COUNTRY_NAME       0
dtype: int64
```

There is no missing values in my DataFrame.

0.7 FEATURE ENGINEERING

[6]:
```
HR_Dataset['HIRE_DATE'] = pd.to_datetime(HR_Dataset['HIRE_DATE']).dt.
 ↪tz_localize(None)
```

Initially, the HIRE_DATE column in the dataset included timezone details. I removed the timezone information to enable accurate calculation of tenure in years from the hire date.

[7]:
```
HR_Dataset['HIRE_DATE'] = pd.to_datetime(HR_Dataset['HIRE_DATE'])
HR_Dataset['TENURE_YEARS'] = (datetime.today() - HR_Dataset['HIRE_DATE']).dt.
 ↪days // 365
```

Calculate TENURE_YEARS and add it as a new column in the DataFrame.

[8]:
```
HR_Dataset.head()
```

[8]:
```
            NAME  SALARY  HIRE_DATE DEPARTMENT_NAME   JOB_ID  \
0    Steven King   24000 2013-06-17       Executive  AD_PRES
1     Neena Yang   17000 2015-09-21       Executive    AD_VP
2     Lex Garcia   17000 2011-01-13       Executive    AD_VP
```

```
3  Alexander James    9000 2016-01-03            IT  IT_PROG
4     Bruce Miller    6000 2017-05-21            IT  IT_PROG

                       JOB_TITLE  LOCATION_ID       CITY  \
0                      President         1700    Seattle
1  Administration Vice President         1700    Seattle
2  Administration Vice President         1700    Seattle
3                     Programmer         1400  Southlake
4                     Programmer         1400  Southlake

               COUNTRY_NAME  TENURE_YEARS
0  United States of America            12
1  United States of America             9
2  United States of America            14
3  United States of America             9
4  United States of America             8
```

[9]:
```python
HR_Dataset1 = HR_Dataset.copy()
dept_sizes = HR_Dataset['DEPARTMENT_NAME'].value_counts().to_dict()
HR_Dataset1['DEPARTMENT_SIZE'] = HR_Dataset['DEPARTMENT_NAME'].map(dept_sizes)
```

[10]:
```python
HR_Dataset1.head()
```

[10]:
```
              NAME  SALARY  HIRE_DATE DEPARTMENT_NAME   JOB_ID  \
0      Steven King   24000 2013-06-17       Executive  AD_PRES
1       Neena Yang   17000 2015-09-21       Executive    AD_VP
2       Lex Garcia   17000 2011-01-13       Executive    AD_VP
3  Alexander James    9000 2016-01-03              IT  IT_PROG
4     Bruce Miller    6000 2017-05-21              IT  IT_PROG

                       JOB_TITLE  LOCATION_ID       CITY  \
0                      President         1700    Seattle
1  Administration Vice President         1700    Seattle
2  Administration Vice President         1700    Seattle
3                     Programmer         1400  Southlake
4                     Programmer         1400  Southlake

               COUNTRY_NAME  TENURE_YEARS  DEPARTMENT_SIZE
0  United States of America            12                3
1  United States of America             9                3
2  United States of America            14                3
3  United States of America             9                5
4  United States of America             8                5
```

I calculated the department size based on the number of employees within each department and included it as a new column in the DataFrame.

[11]:
```
HR_Dataset2 = HR_Dataset1.copy()
country_avg = HR_Dataset2.groupby('COUNTRY_NAME')['SALARY'].transform('mean')
HR_Dataset2['COUNTRY_AVG_SALARY'] = country_avg
```

[12]:
```
HR_Dataset2.head()
```

[12]:
```
              NAME  SALARY  HIRE_DATE DEPARTMENT_NAME   JOB_ID  \
0      Steven King   24000 2013-06-17       Executive  AD_PRES
1       Neena Yang   17000 2015-09-21       Executive    AD_VP
2       Lex Garcia   17000 2011-01-13       Executive    AD_VP
3  Alexander James    9000 2016-01-03              IT  IT_PROG
4     Bruce Miller    6000 2017-05-21              IT  IT_PROG

                     JOB_TITLE  LOCATION_ID       CITY  \
0                    President         1700    Seattle
1  Administration Vice President         1700    Seattle
2  Administration Vice President         1700    Seattle
3                   Programmer         1400  Southlake
4                   Programmer         1400  Southlake

               COUNTRY_NAME  TENURE_YEARS  DEPARTMENT_SIZE  COUNTRY_AVG_SALARY
0  United States of America            12                3         5064.941176
1  United States of America             9                3         5064.941176
2  United States of America            14                3         5064.941176
3  United States of America             9                5         5064.941176
4  United States of America             8                5         5064.941176
```

Calculate average salary per country and assign it to each employee row.

[13]:
```
HR_Dataset3 = HR_Dataset2.copy()
le = LabelEncoder()
HR_Dataset3['JOB_TITLE_ENCODED'] = le.fit_transform(HR_Dataset3['JOB_TITLE'])
HR_Dataset3['DEPARTMENT_NAME_ENCODED'] = le.
 ↪fit_transform(HR_Dataset3['DEPARTMENT_NAME'])
HR_Dataset3['COUNTRY_NAME_ENCODED'] = le.
 ↪fit_transform(HR_Dataset3['COUNTRY_NAME'])
```

[14]:
```
HR_Dataset3.head()
```

[14]:
```
              NAME  SALARY  HIRE_DATE DEPARTMENT_NAME   JOB_ID  \
0      Steven King   24000 2013-06-17       Executive  AD_PRES
1       Neena Yang   17000 2015-09-21       Executive    AD_VP
2       Lex Garcia   17000 2011-01-13       Executive    AD_VP
3  Alexander James    9000 2016-01-03              IT  IT_PROG
4     Bruce Miller    6000 2017-05-21              IT  IT_PROG

                     JOB_TITLE  LOCATION_ID       CITY  \
0                    President         1700    Seattle
```

```
1  Administration Vice President         1700    Seattle
2  Administration Vice President         1700    Seattle
3                     Programmer         1400  Southlake
4                     Programmer         1400  Southlake

               COUNTRY_NAME  TENURE_YEARS  DEPARTMENT_SIZE  \
0  United States of America            12                3
1  United States of America             9                3
2  United States of America            14                3
3  United States of America             9                5
4  United States of America             8                5

   COUNTRY_AVG_SALARY  JOB_TITLE_ENCODED  DEPARTMENT_NAME_ENCODED  \
0         5064.941176                  8                        2
1         5064.941176                  3                        2
2         5064.941176                  3                        2
3         5064.941176                  9                        5
4         5064.941176                  9                        5

   COUNTRY_NAME_ENCODED
0                     3
1                     3
2                     3
3                     3
4                     3
```

Convert categories to numeric labels (e.g. Analyst = 0, Manager = 1)

[15]:
```python
HR_Dataset4 = HR_Dataset3.copy()
HR_Dataset4= pd.get_dummies(HR_Dataset4, columns=['JOB_TITLE',␣
 ↪'DEPARTMENT_NAME', 'COUNTRY_NAME'], drop_first=True)
```

[16]:
```python
HR_Dataset4.head()
```

[16]:
```
             NAME  SALARY  HIRE_DATE   JOB_ID  LOCATION_ID       CITY  \
0     Steven King   24000 2013-06-17  AD_PRES         1700    Seattle
1      Neena Yang   17000 2015-09-21    AD_VP         1700    Seattle
2      Lex Garcia   17000 2011-01-13    AD_VP         1700    Seattle
3  Alexander James   9000 2016-01-03  IT_PROG         1400  Southlake
4     Bruce Miller   6000 2017-05-21  IT_PROG         1400  Southlake

   TENURE_YEARS  DEPARTMENT_SIZE  COUNTRY_AVG_SALARY  JOB_TITLE_ENCODED  …  \
0            12                3         5064.941176                  8  …
1             9                3         5064.941176                  3  …
2            14                3         5064.941176                  3  …
3             9                5         5064.941176                  9  …
4             8                5         5064.941176                  9  …
```

```
   DEPARTMENT_NAME_Human Resources  DEPARTMENT_NAME_IT  \
0                            False               False
1                            False               False
2                            False               False
3                            False                True
4                            False                True

   DEPARTMENT_NAME_Marketing  DEPARTMENT_NAME_Public Relations  \
0                      False                             False
1                      False                             False
2                      False                             False
3                      False                             False
4                      False                             False

   DEPARTMENT_NAME_Purchasing  DEPARTMENT_NAME_Sales  \
0                       False                  False
1                       False                  False
2                       False                  False
3                       False                  False
4                       False                  False

   DEPARTMENT_NAME_Shipping  COUNTRY_NAME_Germany  \
0                     False                 False
1                     False                 False
2                     False                 False
3                     False                 False
4                     False                 False

   COUNTRY_NAME_United Kingdom of Great Britain and Northern Ireland  \
0                                              False
1                                              False
2                                              False
3                                              False
4                                              False

   COUNTRY_NAME_United States of America
0                                   True
1                                   True
2                                   True
3                                   True
4                                   True

[5 rows x 43 columns]
```

Create binary columns for each category to avoid order bias.

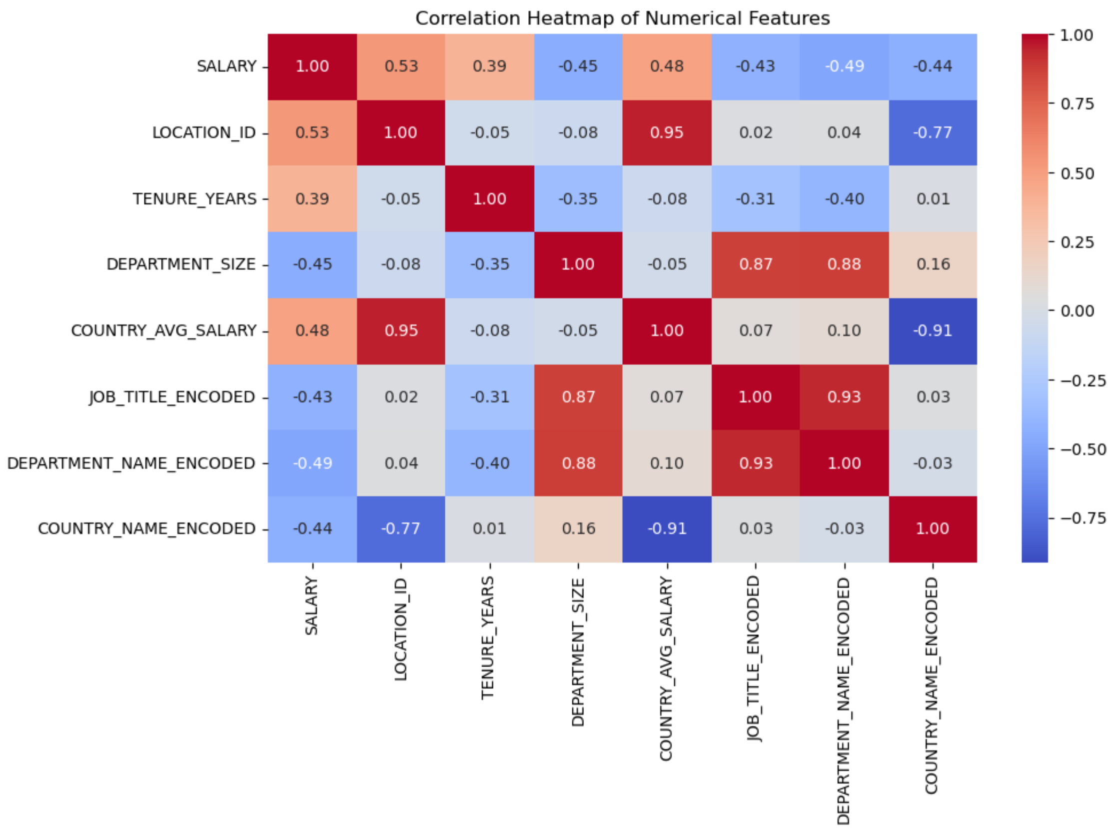
0.8 EXPLORATORY DATA ANALYSIS (EDA)

[17]:
```
HR_Dataset5 = HR_Dataset4.copy()
numerical_cols = HR_Dataset5.select_dtypes(include=np.number).columns
```

[18]:
```
correlation_matrix = HR_Dataset5[numerical_cols].corr()
```

Calculate correlation matrix

[19]:
```
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Heatmap of Numerical Features")
plt.show()
```



I generated a correlation heatmap to analyze the relationships between numerical variables within the dataset. This visualization helps identify features that are strongly correlated, either positively or negatively. Highly correlated features can impact model performance and are useful for feature selection, multicollinearity checks, and gaining deeper insights into the data.

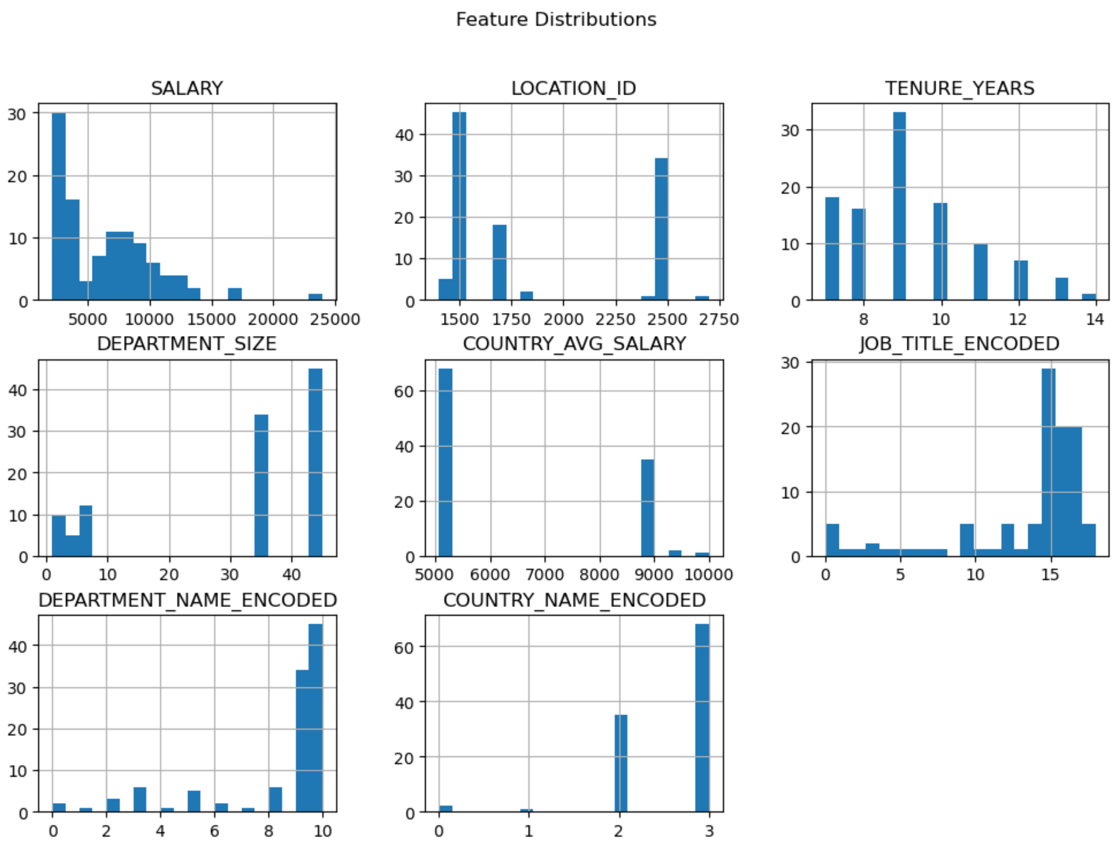
[20]:
```
HR_Dataset5.head()
```

[20]:

```
              NAME  SALARY  HIRE_DATE   JOB_ID  LOCATION_ID       CITY  \
0      Steven King   24000 2013-06-17  AD_PRES         1700    Seattle
1       Neena Yang   17000 2015-09-21    AD_VP         1700    Seattle
2       Lex Garcia   17000 2011-01-13    AD_VP         1700    Seattle
3  Alexander James    9000 2016-01-03  IT_PROG         1400  Southlake
4     Bruce Miller    6000 2017-05-21  IT_PROG         1400  Southlake

   TENURE_YEARS  DEPARTMENT_SIZE  COUNTRY_AVG_SALARY  JOB_TITLE_ENCODED  …  \
0            12                3         5064.941176                  8  …
1             9                3         5064.941176                  3  …
2            14                3         5064.941176                  3  …
3             9                5         5064.941176                  9  …
4             8                5         5064.941176                  9  …

   DEPARTMENT_NAME_Human Resources  DEPARTMENT_NAME_IT  \
0                            False               False
1                            False               False
2                            False               False
3                            False                True
4                            False                True

   DEPARTMENT_NAME_Marketing  DEPARTMENT_NAME_Public Relations  \
0                      False                             False
1                      False                             False
2                      False                             False
3                      False                             False
4                      False                             False

   DEPARTMENT_NAME_Purchasing  DEPARTMENT_NAME_Sales  \
0                       False                  False
1                       False                  False
2                       False                  False
3                       False                  False
4                       False                  False

   DEPARTMENT_NAME_Shipping  COUNTRY_NAME_Germany  \
0                     False                 False
1                     False                 False
2                     False                 False
3                     False                 False
4                     False                 False

   COUNTRY_NAME_United Kingdom of Great Britain and Northern Ireland  \
0                                              False
1                                              False
2                                              False
3                                              False
```

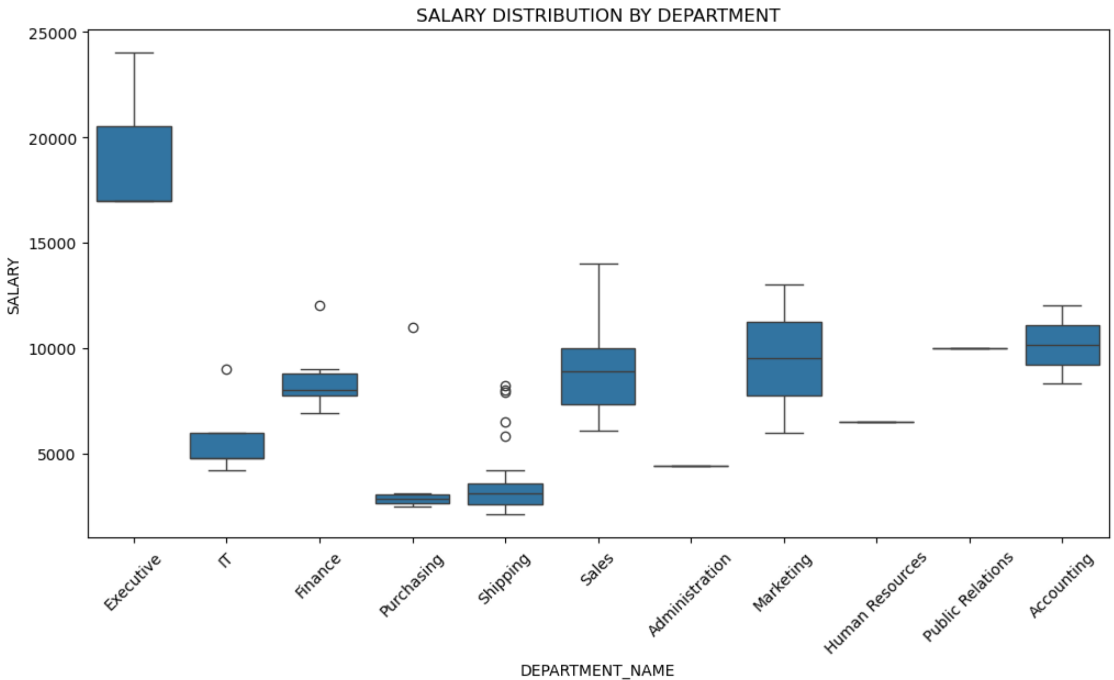
```
4                                              False

   COUNTRY_NAME_United States of America
0                                    True
1                                    True
2                                    True
3                                    True
4                                    True

[5 rows x 43 columns]
```

[21]:
```
HR_Dataset5[numerical_cols].hist(figsize=(12, 8), bins=20)
plt.suptitle("Feature Distributions")
plt.show()
```



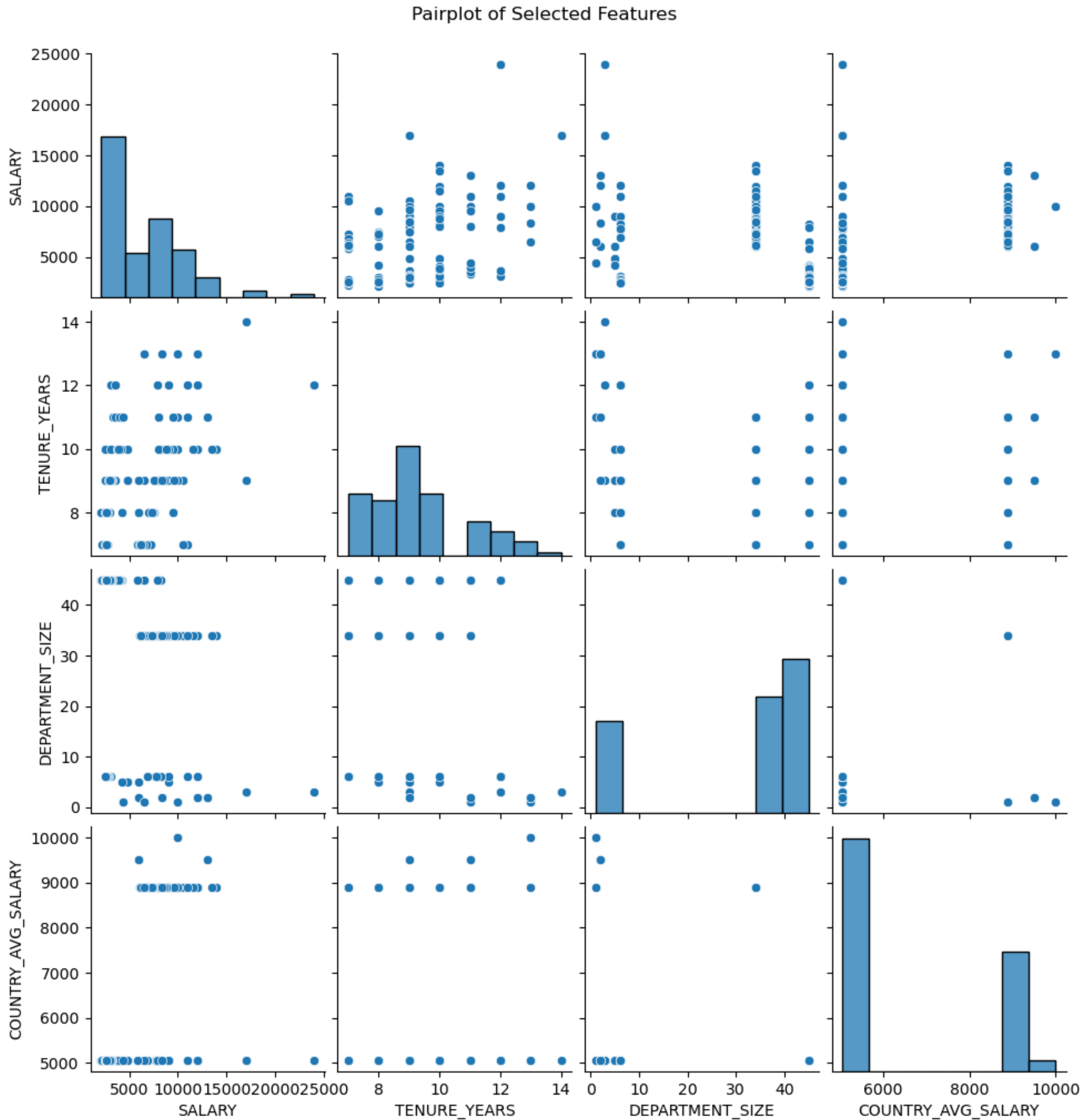
I visualized the distribution of all numerical features using histograms. Since the dataset contains 8 numerical columns, the output generated 8 individual histograms to help analyze the spread and shape of each feature's data.

```
[21]: plt.figure(figsize=(12, 6))
sns.boxplot(x='DEPARTMENT_NAME', y='SALARY', data=HR_Dataset3)
plt.xticks(rotation=45)
plt.title("SALARY DISTRIBUTION BY DEPARTMENT")
plt.show()
```



I used a boxplot to visualize salary distribution across different departments. This plot helps to quickly identify differences in salary ranges, medians, and potential outliers within each department.

```
[22]: selected_features = ['SALARY', 'TENURE_YEARS', 'DEPARTMENT_SIZE',␣
    ↪'COUNTRY_AVG_SALARY']
sns.pairplot(HR_Dataset5[selected_features])
plt.suptitle("Pairplot of Selected Features", y=1.02)
plt.show()
```



I used a pairplot to visually examine the relationships and distributions among key numerical features such as salary, tenure in years, department size, and country-wise average salary. This technique helps identify trends, correlations, and potential patterns between variables.

0.9 MODEL BUILDING - REGRESSION MODELS

0.10 LINEAR REGRESSION

[25]:
```
feature_cols = ['TENURE_YEARS', 'DEPARTMENT_SIZE', 'COUNTRY_AVG_SALARY',
                'JOB_TITLE_ENCODED', 'DEPARTMENT_NAME_ENCODED',␣
 ↪'COUNTRY_NAME_ENCODED']
```

```
X = HR_Dataset5[feature_cols]
y = HR_Dataset5['SALARY']
```

I selected key engineered numerical and encoded categorical features as the input variables for my machine learning model. The target variable chosen was salary, with the goal of building a predictive model to estimate employee salary based on tenure, department size, country salary averages, and job-related encodings.

[26]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

I split the dataset into training (80%) and testing (20%) sets to train and evaluate the machine learning model effectively. A fixed random state was used to ensure reproducibility of the results.

[27]:
```
lr_model = LinearRegression()
```

[28]:
```
lr_model.fit(X_train, y_train)
```

[28]:
```
LinearRegression()
```

I used the Linear Regression algorithm from scikit-learn to build a salary prediction model. The model was trained on historical data, learning relationships between factors such as tenure, department size, and country salary averages to accurately estimate employee salary.

[29]:
```
y_pred = lr_model.predict(X_test)
```

I used the trained Linear Regression model to predict employee salaries on the unseen test data. These predictions will be compared to the actual salaries to evaluate the model's performance.

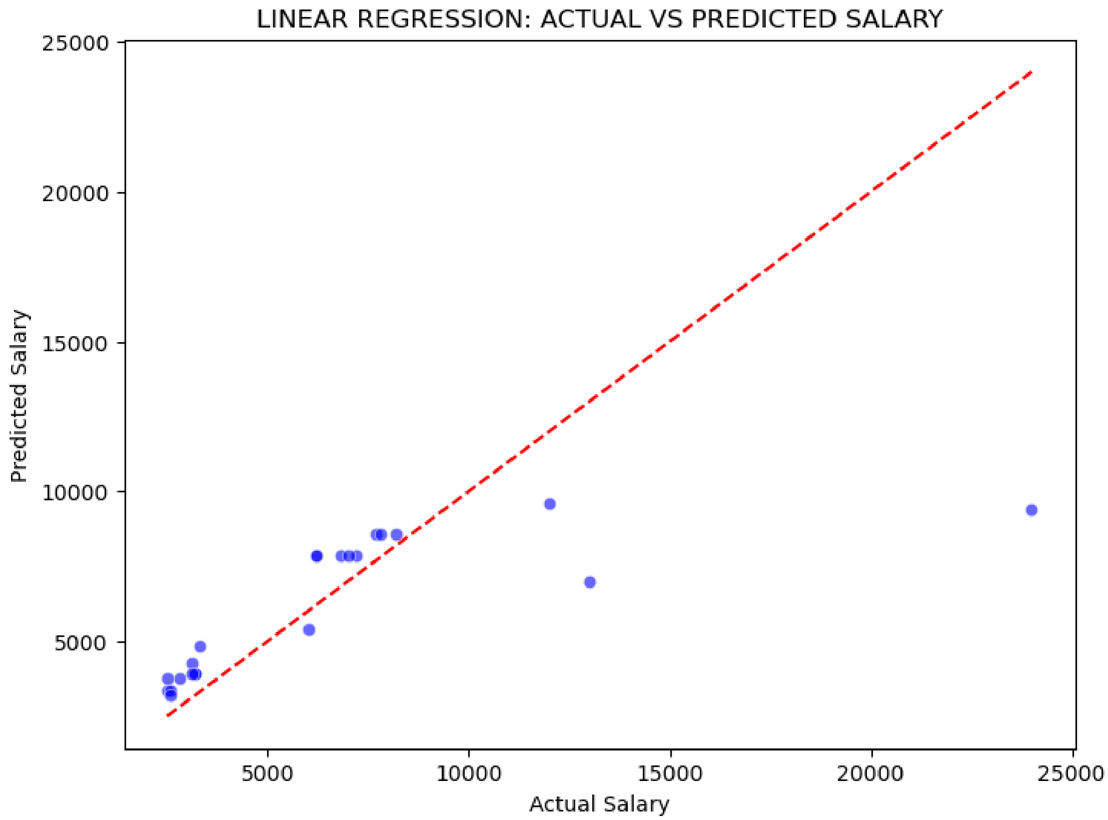
[30]:
```
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Squared Error: {mse:.2f}")
print(f"R² Score: {r2:.2f}")
```

```
Mean Squared Error: 12482035.25
R² Score: 0.47
```

The Linear Regression model achieved an R^2 score of 0.47, indicating it explains approximately 47% of the variance in employee salaries. The Mean Squared Error (MSE) of 12.48 million shows the model's salary predictions deviate significantly on average. While the model captures some salary patterns, further feature engineering or using more advanced models might improve accuracy.

[32]:
```
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_test, y=y_pred, alpha=0.6, color='blue')
plt.xlabel("Actual Salary")
plt.ylabel("Predicted Salary")
plt.title("LINEAR REGRESSION: ACTUAL VS PREDICTED SALARY")
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')  #␣
↪Ideal line
```

```
plt.show()
```



The scatter plot for the Linear Regression model shows a moderate spread of predicted values around the ideal line. While some predictions align well with actual salaries, others show significant deviation, indicating the need for more complex modeling techniques.

0.11 XGBOOST REGRESSION

[33]:
```
xgb_model = XGBRegressor(objective='reg:squarederror', random_state=42)
xgb_model.fit(X_train, y_train)
```

[33]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             feature_weights=None, gamma=None, grow_policy=None,
             importance_type=None, interaction_constraints=None,
             learning_rate=None, max_bin=None, max_cat_threshold=None,
             max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
             max_leaves=None, min_child_weight=None, missing=nan,
             monotone_constraints=None, multi_strategy=None, n_estimators=None,
```

```
              n_jobs=None, num_parallel_tree=None, …)
```

I implemented an XGBoost regression model to predict employee salaries. XGBoost is a robust machine learning algorithm known for high performance on structured data. I used the squared error objective function for regression, and the model was trained on historical HR data to capture patterns in features like tenure, department size, and job role.

[34]:
```python
params = {
    'n_estimators': [100, 200],
    'max_depth': [3, 5, 7],
    'learning_rate': [0.1, 0.01],
    'subsample': [0.8, 1.0]
}
grid_search = GridSearchCV(estimator=xgb_model,
                           param_grid=params,
                           scoring='r2',
                           cv=3,
                           verbose=1,
                           n_jobs=-1)
grid_search.fit(X_train, y_train)
best_xgb = grid_search.best_estimator_
```

```
Fitting 3 folds for each of 24 candidates, totalling 72 fits
```

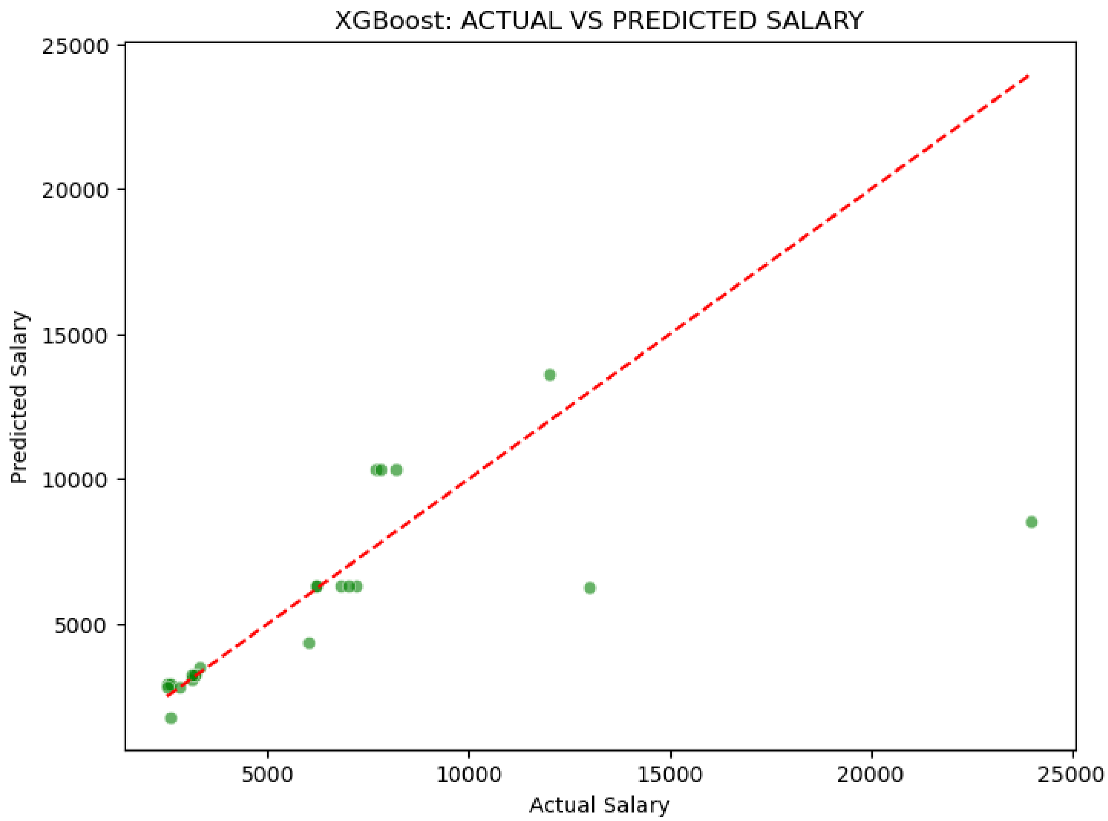
I used GridSearchCV to perform hyperparameter tuning on the XGBoost regression model. The search evaluated combinations of parameters like tree depth, number of estimators, learning rate, and subsampling rate. The model with the best R^2 performance across cross-validation was selected for final evaluation.

[36]:
```python
y_pred_xgb = best_xgb.predict(X_test)
mse_xgb = mean_squared_error(y_test, y_pred_xgb)
r2_xgb = r2_score(y_test, y_pred_xgb)
print(f"XGBoost MSE: {mse_xgb:.2f}")
print(f"XGBoost R² Score: {r2_xgb:.2f}")
```

```
XGBoost MSE: 14108815.00
XGBoost R² Score: 0.40
```

The XGBoost Regressor model was optimized using GridSearchCV and evaluated on the test dataset. It achieved a Mean Squared Error (MSE) of 14.11 million and an R^2 score of 0.40, indicating that the model explains around 40% of the variance in the target variable.There is potential for improvement through advanced feature engineering or hyperparameter tuning.

[37]:
```python
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_test, y=y_pred_xgb, alpha=0.6, color='green')
plt.xlabel("Actual Salary")
plt.ylabel("Predicted Salary")
plt.title("XGBoost: ACTUAL VS PREDICTED SALARY")
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.show()
```



The scatter plot for the XGBoost Regressor displays a modest improvement over Linear Regression. While several predictions lie close to the ideal line, there remains noticeable deviation, suggesting that further tuning or additional features may enhance performance.

0.12 RANDOM FOREST REGRESSION

[40]:
```
rf_model = RandomForestRegressor(n_estimators=100, max_depth=7, random_state=42)
rf_model.fit(X_train, y_train)
```

[40]:
```
RandomForestRegressor(max_depth=7, random_state=42)
```

I implemented a Random Forest Regression model to predict employee salaries. Random Forest aggregates multiple decision trees trained on random subsets of the data, which helps reduce overfitting and improve prediction accuracy. I specified 100 trees with a maximum depth of 7 to maintain a balance between model complexity and generalization.

[41]:
```
y_pred_rf = rf_model.predict(X_test)
```

I used the trained Random Forest model to predict employee salaries on the unseen test dataset. The model aggregates the outputs from 100 decision trees to generate robust and accurate salary predictions.

[42]:
```python
mse_rf = mean_squared_error(y_test, y_pred_rf)
r2_rf = r2_score(y_test, y_pred_rf)

print(f"Random Forest MSE: {mse_rf:.2f}")
print(f"Random Forest R² Score: {r2_rf:.2f}")
```

```
Random Forest MSE: 10839776.34
Random Forest R² Score: 0.54
```

The Random Forest model achieved an MSE of approximately 10.9 million and an R^2 score of 0.54. This means the model explains 54% of the variance in employee salaries and predicts with a lower error than the Linear Regression model. Random Forest captures more complex relationships in the data, making it a better fit for this problem compared to simpler linear models.

[43]:
```python
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_test, y=y_pred_rf, alpha=0.6, color='orange')
plt.xlabel("Actual Salary")
plt.ylabel("Predicted Salary")
plt.title("RANDOM FOREST: ACTUAL VS PREDICTED SALARY")
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.show()
```

The Random Forest scatter plot demonstrates higher prediction accuracy compared to other models. Most data points align closely with the ideal prediction line, suggesting the ensemble trees were effective at learning underlying patterns in salary data.

[44]:
```
results = pd.DataFrame({
    'Model': ['Linear Regression', 'XGBoost Regressor', 'Random Forest␣
↪Regressor'],
    'MSE': [mse, mse_xgb, mse_rf],
    'R² Score': [r2, r2_xgb, r2_rf]
})

print(results)
```

```
                    Model           MSE  R² Score
0       Linear Regression  1.248204e+07  0.468950
1       XGBoost Regressor  1.410882e+07  0.399739
2  Random Forest Regressor  1.083978e+07  0.538821
```

Among the three models tested, Random Forest Regressor performed the best, achieving the lowest Mean Squared Error (10.8M) and the highest R^2 score (0.54). This indicates it captured the underlying patterns in the data more effectively than both Linear Regression and XGBoost. While XGBoost showed slight improvement over Linear Regression, Random Forest delivered the most reliable salary predictions overall.

[45]:
```
joblib.dump(rf_model, 'salary_predictor.pkl')
```

[45]:
```
['salary_predictor.pkl']
```

The trained Random Forest Regressor model was saved using joblib for future use. This allows loading the model without retraining it each time.

0.13 MODEL DEPLOYMENT USING STREAMLIT

After training and saving the salary prediction model (salary_predictor.pkl), the model was deployed using Streamlit, a Python library for creating interactive web applications.