```python
# Importing the libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
sns.set()
import warnings
warnings.filterwarnings('ignore')

# Loading the dataset
df = pd.read_csv('Salary_Data_Based_country_and_race.csv')
df.head()
```

```
   Unnamed: 0   Age  Gender Education Level          Job Title  \
0           0  32.0    Male      Bachelor's  Software Engineer
1           1  28.0  Female        Master's       Data Analyst
2           2  45.0    Male             PhD     Senior Manager
3           3  36.0  Female      Bachelor's    Sales Associate
4           4  52.0    Male        Master's           Director

   Years of Experience    Salary Country      Race
0                  5.0   90000.0      UK     White
1                  3.0   65000.0     USA  Hispanic
2                 15.0  150000.0  Canada     White
3                  7.0   60000.0     USA  Hispanic
4                 20.0  200000.0     USA     Asian
```

Some Numerical Information about the Data

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6704 entries, 0 to 6703
Data columns (total 9 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Unnamed: 0           6704 non-null   int64
 1   Age                  6702 non-null   float64
 2   Gender               6702 non-null   object
 3   Education Level      6701 non-null   object
 4   Job Title            6702 non-null   object
 5   Years of Experience  6701 non-null   float64
 6   Salary               6699 non-null   float64
 7   Country              6704 non-null   object
 8   Race                 6704 non-null   object
dtypes: float64(3), int64(1), object(5)
memory usage: 471.5+ KB
```

```python
df.nunique()
```

```
Unnamed: 0             6704
Age                      41
Gender                    3
Education Level           7
Job Title               193
Years of Experience      37
Salary                  444
Country                   5
Race                     10
dtype: int64
```

Data Cleaning

```python
# Drop NaN Values
df.dropna(how='any', axis=0, inplace=True)

# Reduce unique values of Gender
df = df[df['Gender'] != 'Other']
df['Gender'].value_counts()
```

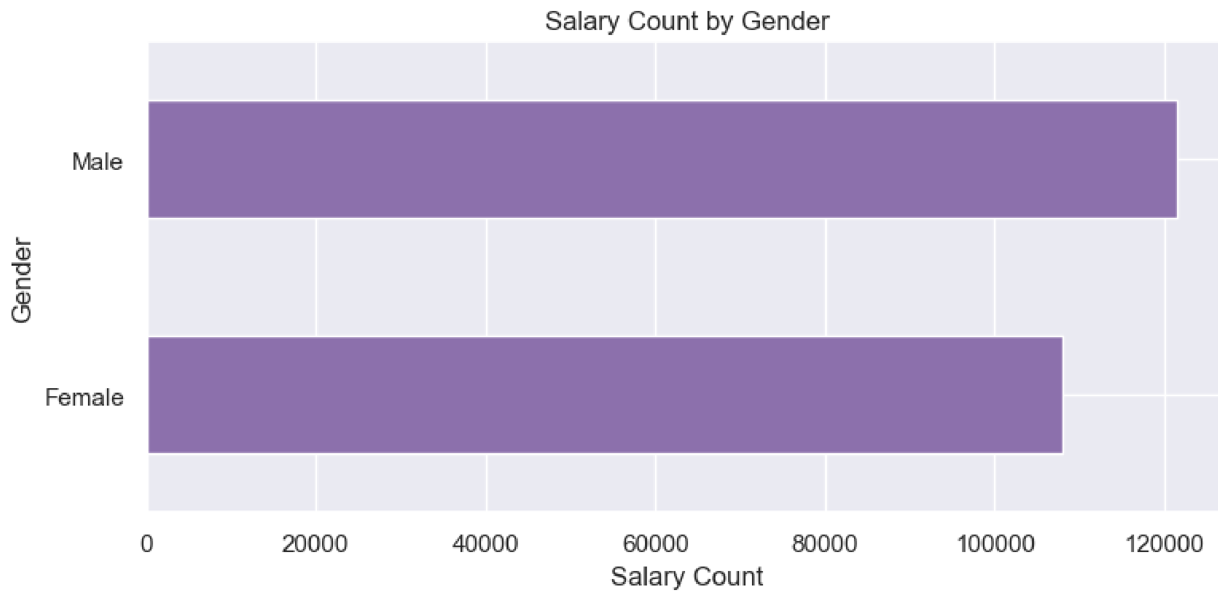
```
Gender
Male      3671
Female    3013
Name: count, dtype: int64
```

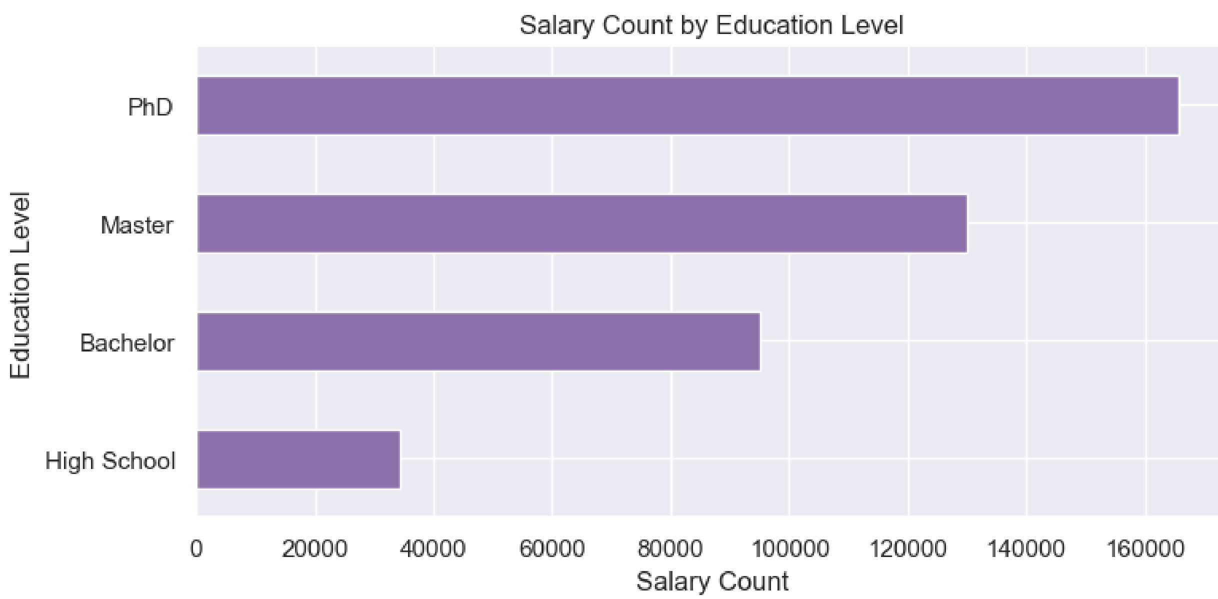
```python
# Reduce unique values of Education Level
def edu_group(x):
    if x in ['Bachelor\'s Degree', 'Bachelor\'s']:
        return 'Bachelor'
    elif x in ['Master\'s Degree', 'Master\'s']:
        return 'Master'
    elif x in ['PhD', 'phD']:
        return 'PhD'
    elif x == 'High School':
        return 'High School'

df['Education Level'] = df['Education Level'].apply(lambda x :
edu_group(x))

# Reduce unique values of Job Title
def categorize_job_title(job_title):
    job_title = str(job_title).lower()
    if 'software' in job_title or 'developer' in job_title:
        return 'Software/Developer'
    elif 'data' in job_title or 'analyst' in job_title or 'scientist'
in job_title:
        return 'Data Analyst/Scientist'
    elif 'manager' in job_title or 'director' in job_title or 'vp' in
job_title:
        return 'Manager/Director/VP'
```

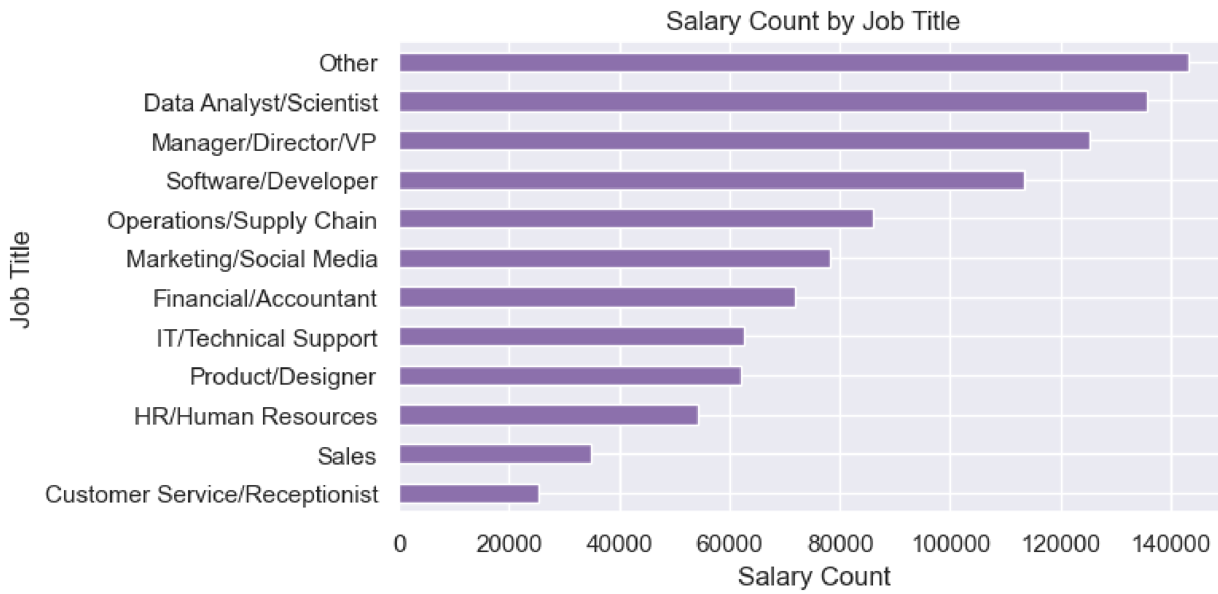
```python
    elif 'sales' in job_title or 'representative' in job_title:
        return 'Sales'
    elif 'marketing' in job_title or 'social media' in job_title:
        return 'Marketing/Social Media'
    elif 'product' in job_title or 'designer' in job_title:
        return 'Product/Designer'
    elif 'hr' in job_title or 'human resources' in job_title:
        return 'HR/Human Resources'
    elif 'financial' in job_title or 'accountant' in job_title:
        return 'Financial/Accountant'
    elif 'project manager' in job_title:
        return 'Project Manager'
    elif 'it' in job_title or 'support' in job_title:
        return 'IT/Technical Support'
    elif 'operations' in job_title or 'supply chain' in job_title:
        return 'Operations/Supply Chain'
    elif 'customer service' in job_title or 'receptionist' in
job_title:
        return 'Customer Service/Receptionist'
    else:
        return 'Other'

df['Job Title'] = df['Job Title'].apply(categorize_job_title)

# Drop Outlayers
df = df[df['Salary']>1000]
```

Data Visualization

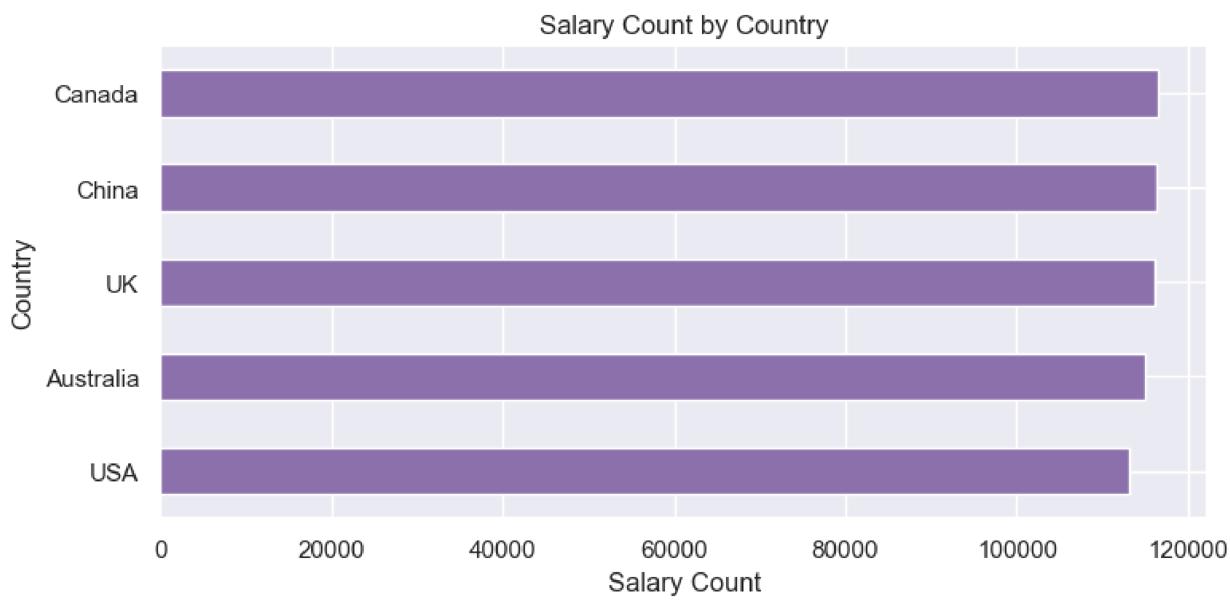
```python
# Define a Function for Barh Plot
def bar_plot(x, y, df):
    barh = df.groupby([x])[y].mean()
    barh.sort_values(ascending=True, inplace=True)
    barh.plot(kind='barh',  color = '#8c70ac', figsize=(8,4))
    plt.title(f'{y} Count by {x}')
    plt.xlabel(f'{y} Count')
    plt.ylabel(x)

    plt.tight_layout()
    plt.show()

bar_plot('Gender', 'Salary', df)
bar_plot('Education Level', 'Salary', df)
bar_plot('Job Title', 'Salary', df)
bar_plot('Country', 'Salary', df)
bar_plot('Race', 'Salary', df)
```


Salary Count by Gender
Gender
Male
Female
0
20000
40000
60000
80000
100000
120000
Salary Count

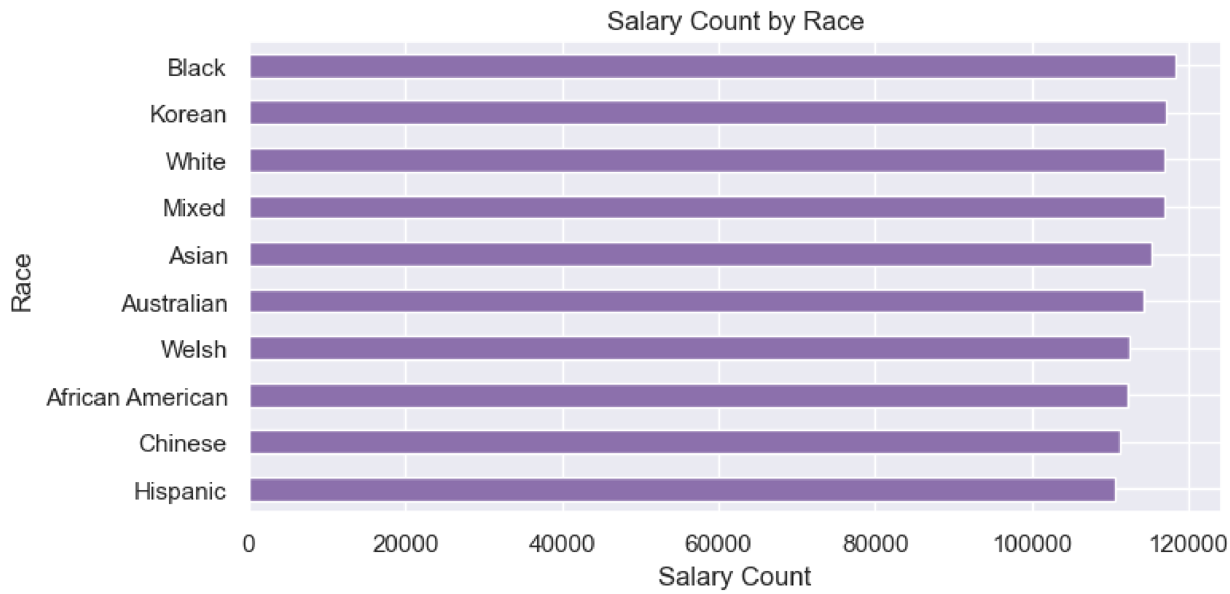

Salary Count by Education Level
Education Level
PhD
Master
Bachelor
High School
0
20000
40000
60000
80000
100000
120000
140000
160000
Salary Count



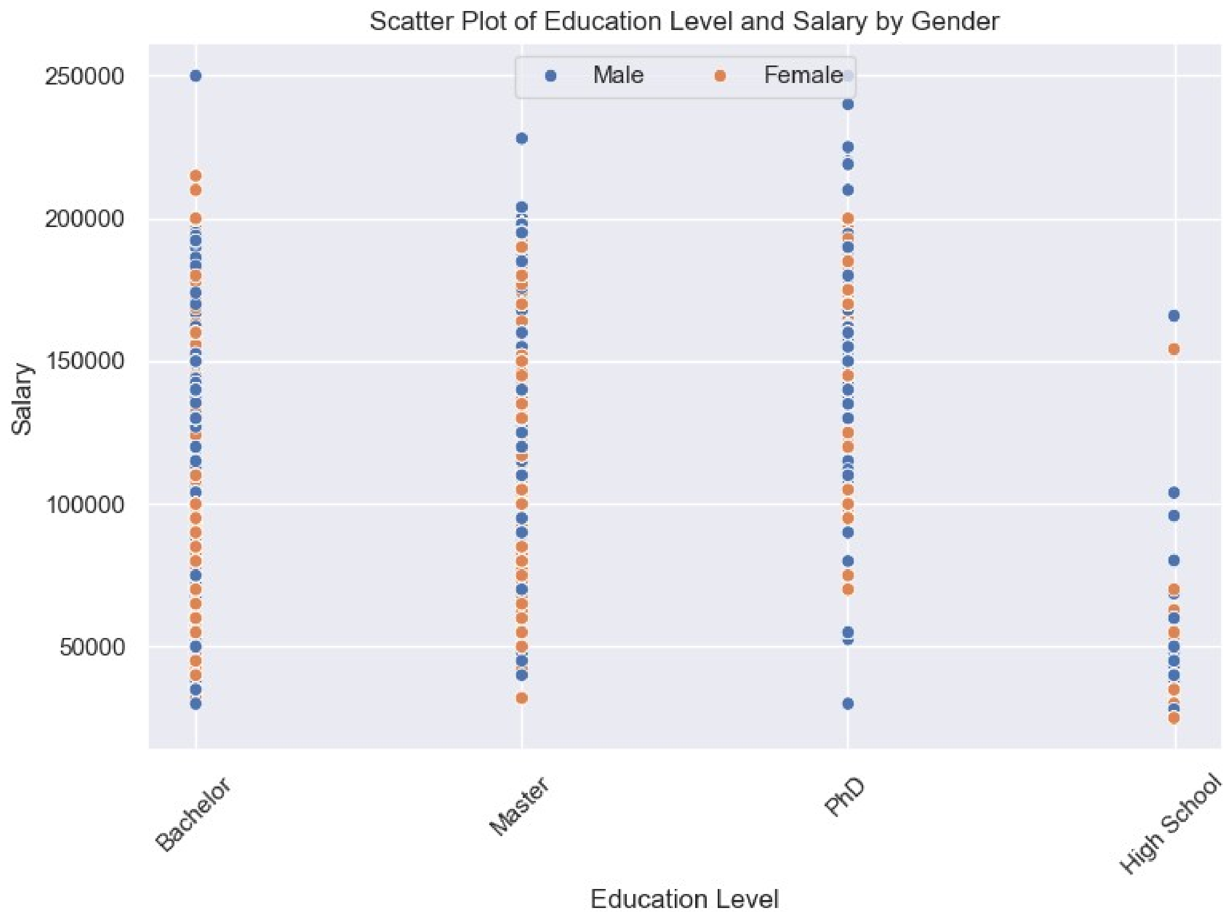
Salary Count by Job Title
Other
Data Analyst/Scientist
Manager/Director/VP
Software/Developer
Operations/Supply Chain
Marketing/Social Media
Financial/Accountant
IT/Technical Support
Product/Designer
HR/Human Resources
Sales
Customer Service/Receptionist
Job Title
0
20000
40000
60000
80000
100000
120000
140000
Salary Count



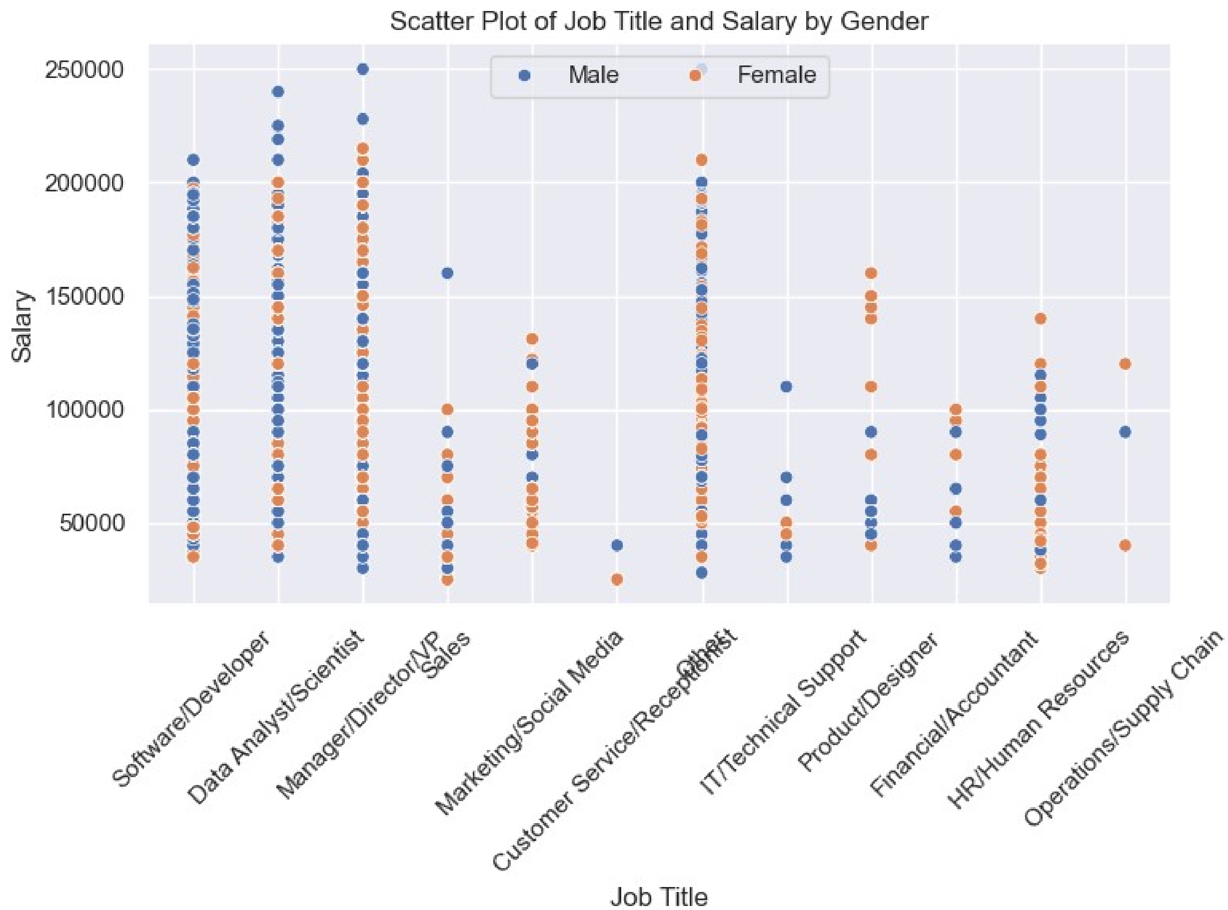
Salary Count by Country
Canada
China
UK
Australia
USA
Country
0
20000
40000
60000
80000
100000
120000
Salary Count



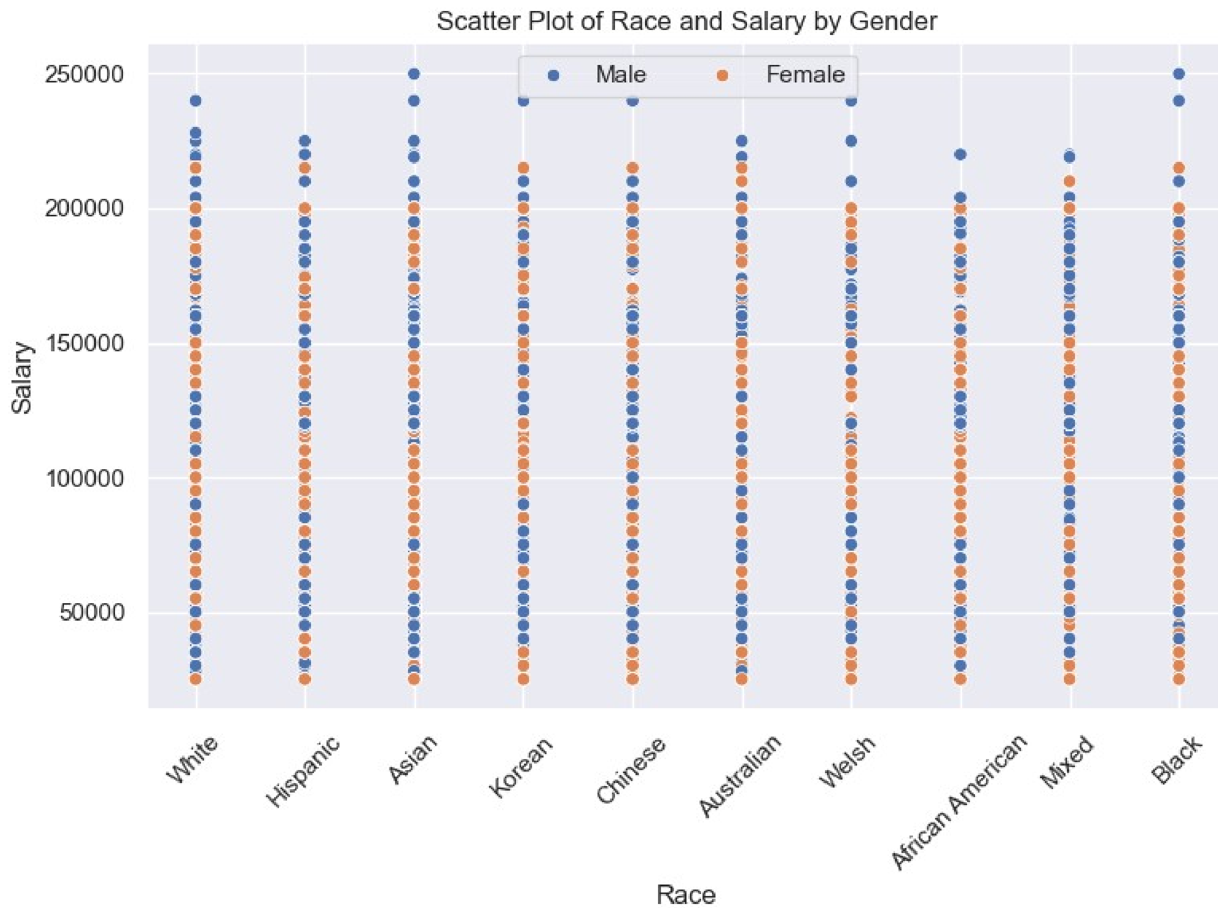

```
# Define a Function for Scatter Plot
def scatter_plot(data, x, y, hue):
    plt.figure(figsize=(8,6))
    sns.scatterplot(data=data, x=x, y=y, hue=hue)
    plt.title(f'Scatter Plot of {x} and {y} by {hue}')
    plt.legend(title=None, ncol=2, loc='upper center')
    plt.xticks(rotation=45)
    plt.xlabel(x)
    plt.ylabel(y)

    plt.tight_layout()
    plt.show()

scatter_plot(data=df, x="Education Level", y="Salary", hue="Gender")
scatter_plot(data=df, x="Job Title", y="Salary", hue="Gender")
scatter_plot(data=df, x="Race", y="Salary", hue="Gender")
scatter_plot(data=df, x="Age", y="Salary", hue="Gender")
scatter_plot(data=df, x="Years of Experience", y="Salary",
hue="Gender")
```



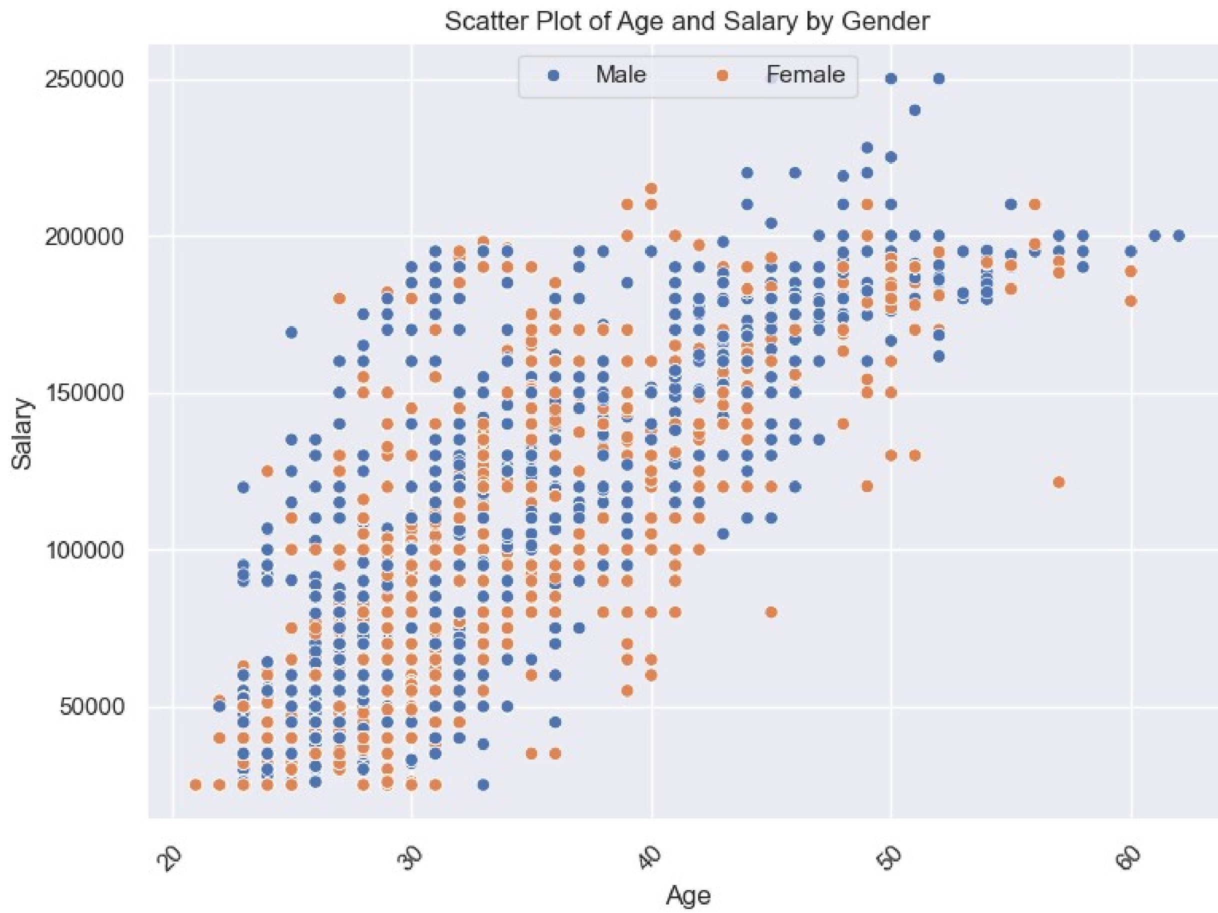
Scatter Plot of Education Level and Salary by Gender
Male
Female
250000
200000
150000
100000
50000
Salary
Bachelor
Master
PhD
High School
Education Level



Scatter Plot of Job Title and Salary by Gender
Male
Female
Salary
250000
200000
150000
100000
50000
Software/Developer
Data Analyst/Scientist
Manager/Director/VP
Sales
Marketing/Social Media
Customer Service/Receptionist
Other
IT/Technical Support
Product/Designer
Financial/Accountant
HR/Human Resources
Operations/Supply Chain
Job Title



Scatter Plot of Race and Salary by Gender
Male
Female
250000
200000
150000
100000
50000
Salary
White
Hispanic
Asian
Korean
Chinese
Australian
Welsh
African American
Mixed
Black
Race


Scatter Plot of Age and Salary by Gender
Male
Female
250000
200000
150000
100000
50000
Salary
20
30
40
50
60
Age

Data Preprocessing

```
from sklearn.preprocessing import LabelEncoder, StandardScaler

# Initialize StandardScaler
stc = StandardScaler()
# Initialize LabelEncoder
le = LabelEncoder()

stc_cols = ['Age','Salary', 'Years of Experience']
dum_cols = [ 'Education Level', 'Job Title', 'Country', 'Race']
le_cols = ['Gender']

# Apply Label Encoder to the selected columns
for col in le_cols :
    df[col] = le.fit_transform(df[col])

# Apply Standard Scaler to the selected columns
df[stc_cols] = stc.fit_transform(df[stc_cols])
# Apply Get Dummies to the selected columns
df = pd.get_dummies(df, columns=dum_cols)
```

Training and Evaluating Different Models

```
from sklearn.model_selection import train_test_split

x = df.drop(['Salary', 'Unnamed: 0'], axis=1)
y = df['Salary']    # Target Variable

x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2, random_state=42)

#Importing the Libraries
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import VotingRegressor
from xgboost import XGBRegressor

# List of Mdels to Try
models = [
    ('Gradient Boosting', GradientBoostingRegressor()),
    ('K-Nearest Neighbors', KNeighborsRegressor()),
    ('Decision Tree', DecisionTreeRegressor()),
    ('Random Forest', RandomForestRegressor()),
    ('XGB Regressor', XGBRegressor())
]

# Train and evaluate each model
for name, model in models:
    model.fit(x_train, y_train)
    y_pred = model.predict(x_test)
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    print(f'{name}: Mean Squared Error = {round(mse,3)}, R-squared =
{round(r2, 3)}')
```

```
Gradient Boosting: Mean Squared Error = 0.125, R-squared = 0.876
K-Nearest Neighbors: Mean Squared Error = 0.209, R-squared = 0.791
Decision Tree: Mean Squared Error = 0.064, R-squared = 0.936
Random Forest: Mean Squared Error = 0.049, R-squared = 0.951
XGB Regressor: Mean Squared Error = 0.053, R-squared = 0.947
```

```
from sklearn.model_selection import GridSearchCV

# Define the parameter grid to search
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
}
```

```python
# Initialize the Random Forest Regressor
rf_model_tuned = RandomForestRegressor(random_state=42)

# Initialize GridSearchCV
grid_search = GridSearchCV(rf_model_tuned, param_grid, cv=3,
scoring='neg_mean_squared_error', n_jobs=-1, verbose=True)

# Fit the grid search to the data
grid_search.fit(x_train, y_train)

# Get the best parameters
rf_best_params = grid_search.best_params_

# Retrain the model with the best parameters
rf_model_best = RandomForestRegressor(**rf_best_params,
random_state=42)
rf_model_best.fit(x_train, y_train)

# Predict using the updated features
y_pred_best = rf_model_best.predict(x_test)
```

```
Fitting 3 folds for each of 9 candidates, totalling 27 fits
```

```python
# Evaluate the tuned Random Forest model
mse_best = mean_squared_error(y_test, y_pred_best)
r2_best = r2_score(y_test, y_pred_best)

print(f'Best Parameters: {rf_best_params}')
print(f'Mean Squared Error (Tuned Random Forest): {round(mse_best,
3)}')
print(f'R-squared (Tuned Random Forest): {round(r2_best, 3)}')
```

```
Best Parameters: {'max_depth': 20, 'n_estimators': 100}
Mean Squared Error (Tuned Random Forest): 0.05
R-squared (Tuned Random Forest): 0.95
```

```python
from sklearn.model_selection import GridSearchCV

# Define the parameter grid to search
param_grid = {
    'n_estimators': [100, 150, 200],
    'max_depth': [3, 5, 8],
    'learning_rate': [0.01, 0.1, 0.2],
    'subsample': [0.7, 0.8, 0.9],
}

# Initialize the XGB Regressor
xgb_best = XGBRegressor()
# Initialize GridSearchCV
grid_search = GridSearchCV(xgb_best, param_grid, cv=3,
```

```
scoring='neg_mean_squared_error', n_jobs=-1, verbose=True)

# Fit the grid search to the data
grid_search.fit(x_train, y_train)

# Get the best parameters
xgb_best_params = grid_search.best_params_

# Retrain the model with the best parameters
xgb_model_best = XGBRegressor(**xgb_best_params)
xgb_model_best.fit(x_train, y_train)

# Predict using the updated features
y_pred_best = xgb_model_best.predict(x_test)
```

```
Fitting 3 folds for each of 81 candidates, totalling 243 fits
```

```
# Evaluate the tuned Random Forest model
mse_best = mean_squared_error(y_test, y_pred_best)
r2_best = r2_score(y_test, y_pred_best)

print(f'Best Parameters: {xgb_best_params}')
print(f'Mean Squared Error (Tuned XGB): {round(mse_best, 3)}')
print(f'R-squared (Tuned XGB): {round(r2_best, 3)}')
```

```
Best Parameters: {'learning_rate': 0.1, 'max_depth': 8,
'n_estimators': 100, 'subsample': 0.8}
Mean Squared Error (Tuned XGB): 0.047
R-squared (Tuned XGB): 0.953
```

```
model1 = XGBRegressor(**xgb_best_params)
model2 = RandomForestRegressor( **rf_best_params)

# Create Ensemble Model
ensemble_model = VotingRegressor(estimators=[('xgb', model1), ('rf',
model2)])

# Model Training
ensemble_model.fit(x_train, y_train)

# Predict y_test  Values
y_best_pred = ensemble_model.predict(x_test)

# Evaluate Model Accuracy
mse = mean_squared_error(y_test, y_best_pred)
r2 = r2_score(y_test, y_best_pred)
print(f'Ensemble Model : Mean Squared Error = {round(mse,3)}\n R-
squared = {round(r2, 3)}')
```

```
Ensemble Model : Mean Squared Error = 0.046
 R-squared = 0.954
```

```
# Visualize the Predicted Prices Against the Actual Prices
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_test, y=y_best_pred)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()],
linestyle='--', color='black', label='Perfect Prediction')
plt.title('Actual Prices vs. Predicted Prices (Ensemble Model)')
plt.ylabel('Predicted Prices')
plt.xlabel('Actual Prices')
plt.legend()
plt.show()
```

Summary and Conclusion

In this project, I aimed to predict individuals' salaries using various data preprocessing techniques and machine learning models. The steps and methodologies employed are as follows:

1. Data Cleaning and Preprocessing:
   - Handling Missing Values: Given the very few missing values, they were removed as their impact on the final prediction was negligible.

2. Categorical Encoding and Feature Engineering:
   – Gender Simplification: The gender feature, which initially had three categories, was reduced to two categories.
   – Education and Occupation Simplification: Unique values in the education and occupation features were reduced to simplify the model and decrease complexity.
3. Data Visualization:
   – Appropriate visualizations were created to explore and understand the data patterns and relationships.
4. Data Standardization and Labeling:
   – Data standardization was performed to normalize the features, and label encoding was applied to convert categorical variables into numerical format.
5. Model Training and Optimization:
   – The performance of two models, XGBoost (XGB) and Random Forest, was optimized using Grid Search.
   – The optimized models were then combined into an ensemble model, which resulted in a final accuracy of 95.4%.

These steps ensured a comprehensive analysis and model training process, leading to a highly accurate prediction model for individuals' salaries.

Developed by Hosein Mohammadi

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