employee-salary-insights

October 30, 2024

[ ]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
```

[ ]:
```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[ ]:
```python
data = '/content/drive/MyDrive/ds_salaries.csv'
df = pd.read_csv(data)
```

[ ]:
```python
# First few rows

print("First few rows of the dataset:")
df.head()
```

```
First few rows of the dataset:
```

[ ]:
```
   Unnamed: 0  work_year experience_level employment_type  \
0           0       2020               MI              FT
1           1       2020               SE              FT
2           2       2020               SE              FT
3           3       2020               MI              FT
4           4       2020               SE              FT

                    job_title  salary salary_currency  salary_in_usd  \
0              Data Scientist   70000             EUR          79833
1  Machine Learning Scientist  260000             USD         260000
2           Big Data Engineer   85000             GBP         109024
3        Product Data Analyst   20000             USD          20000
4   Machine Learning Engineer  150000             USD         150000
```

```
  employee_residence  remote_ratio company_location company_size
0                 DE             0               DE            L
1                 JP             0               JP            S
2                 GB            50               GB            M
3                 HN             0               HN            S
4                 US            50               US            L
```

[ ]:
```
# Check for missing values in each column

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

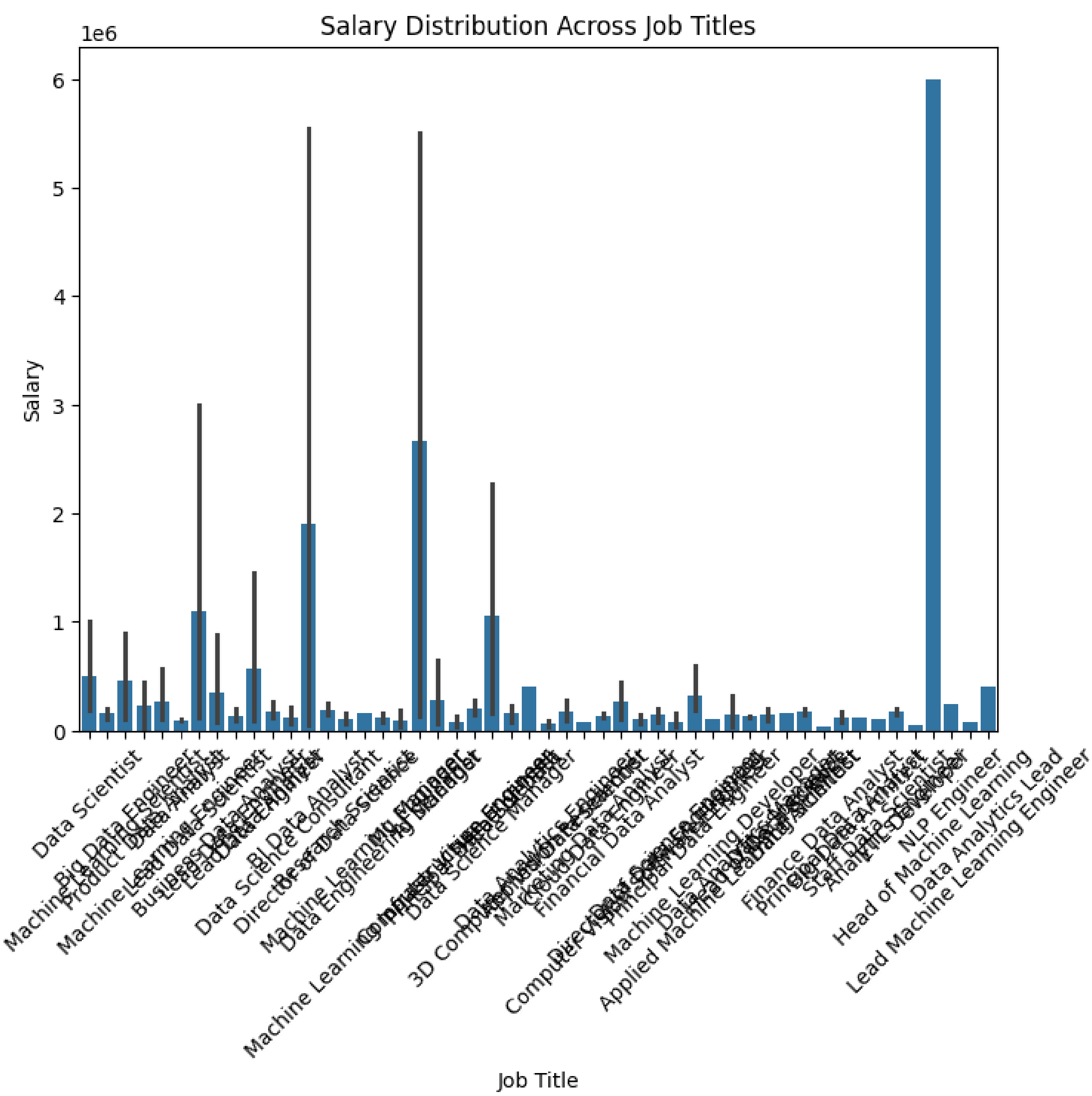
[ ]:
```
Unnamed: 0            0
work_year             0
experience_level      0
employment_type       0
job_title             0
salary                0
salary_currency       0
salary_in_usd         0
employee_residence    0
remote_ratio          0
company_location      0
company_size          0
dtype: int64
```

[ ]:
```
# Get summary statistics for numerical columns

summary_stats = df.describe()
print("\nSummary statistics for numerical columns:")
print(summary_stats)
```

```
Summary statistics for numerical columns:
       Unnamed: 0    work_year        salary  salary_in_usd  remote_ratio
count  607.000000   607.000000  6.070000e+02     607.000000     607.00000
mean   303.000000  2021.405272  3.240001e+05  112297.869852      70.92257
std    175.370085     0.692133  1.544357e+06   70957.259411      40.70913
min      0.000000  2020.000000  4.000000e+03    2859.000000       0.00000
25%    151.500000  2021.000000  7.000000e+04   62726.000000      50.00000
50%    303.000000  2022.000000  1.150000e+05  101570.000000     100.00000
75%    454.500000  2022.000000  1.650000e+05  150000.000000     100.00000
max    606.000000  2022.000000  3.040000e+07  600000.000000     100.00000
```

[ ]:
```
'''EDA and Data Vizualization'''

# Salary Distribution Across Job Titles
```

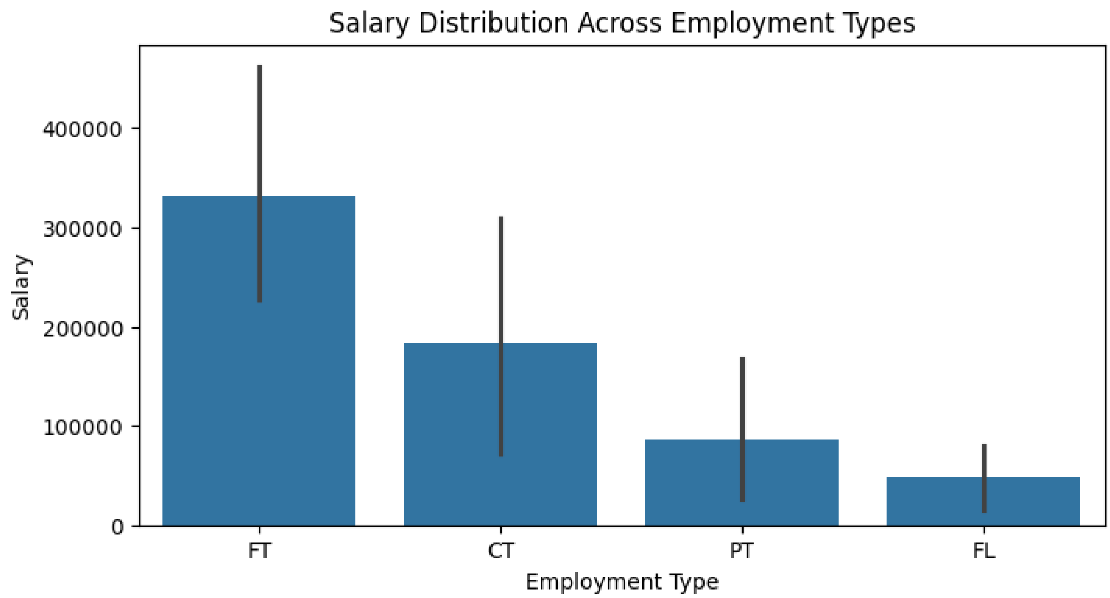
```python
plt.figure(figsize=(8, 6))
sns.barplot(x='job_title', y='salary', data=df)
plt.xticks(rotation=45)
plt.title('Salary Distribution Across Job Titles')
plt.xlabel('Job Title')
plt.ylabel('Salary')
plt.show()
```



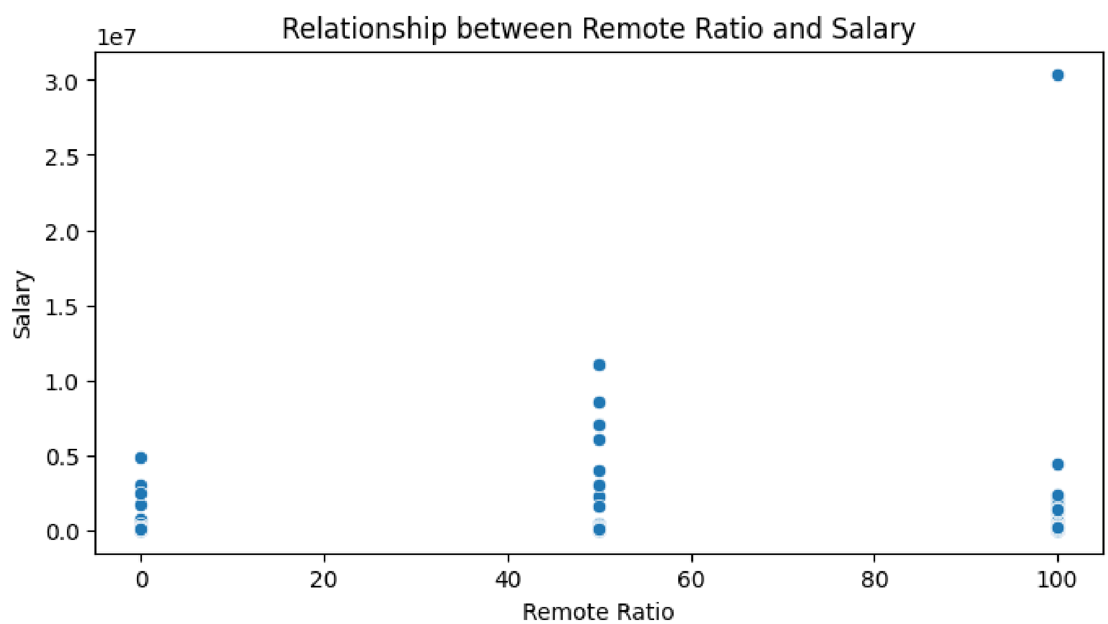
[ ]:
```python
# Salary Distribution Across Experience Levels

plt.figure(figsize=(8, 4))
sns.barplot(x='experience_level', y='salary', data=df)
plt.title('Salary Distribution Across Experience Levels')
```

```
plt.xlabel('Experience Level')
plt.ylabel('Salary')
plt.show()
```

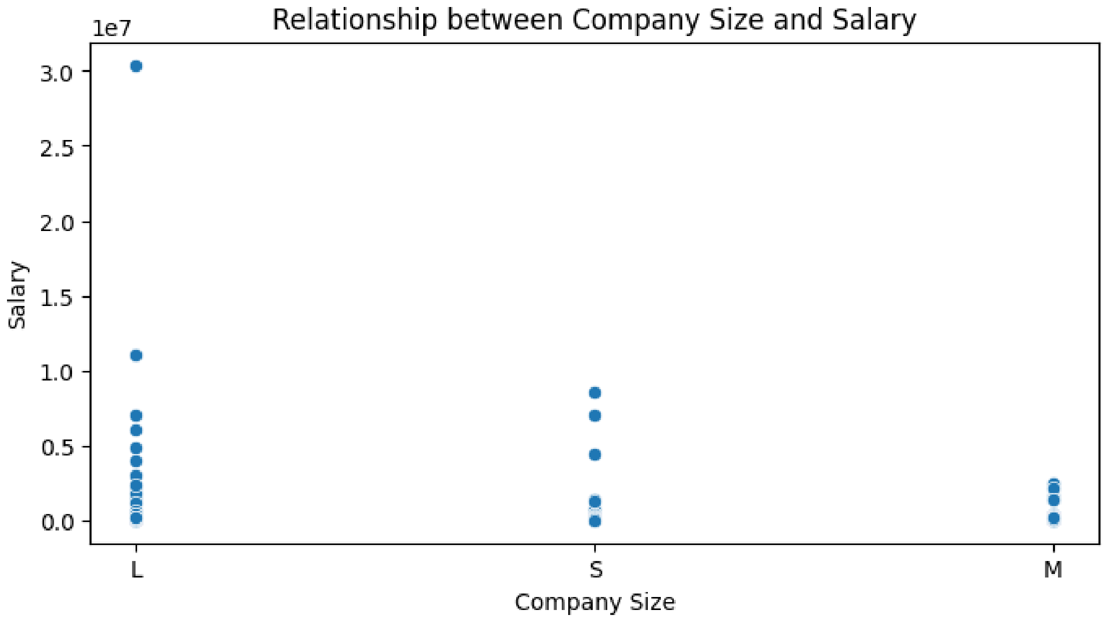

```
[ ]: # Salary Distribution Across Employment Types

plt.figure(figsize=(8, 4))
sns.barplot(x='employment_type', y='salary', data=df)
plt.title('Salary Distribution Across Employment Types')
plt.xlabel('Employment Type')
plt.ylabel('Salary')
plt.show()
```



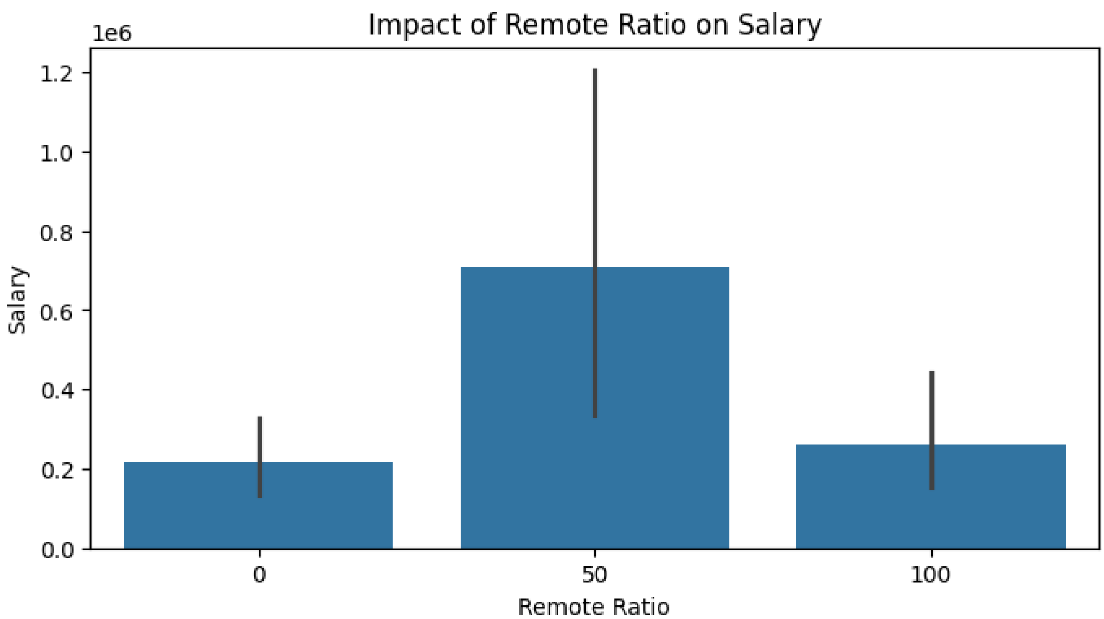
[ ]:
```
# Visualize relationships using scatter plots and histograms

plt.figure(figsize=(8, 4))
sns.scatterplot(x='remote_ratio', y='salary', data=df)
plt.title('Relationship between Remote Ratio and Salary')
plt.xlabel('Remote Ratio')
plt.ylabel('Salary')
plt.show()
```



[ ]:
```python
# Relationship between Company Size and Salary

plt.figure(figsize=(8, 4))
sns.scatterplot(x='company_size', y='salary', data=df)
plt.title('Relationship between Company Size and Salary')
plt.xlabel('Company Size')
plt.ylabel('Salary')
plt.show()
```



[ ]:
```python
# Visualize trends in remote work percentages and company sizes.

plt.figure(figsize=(8,4))
sns.barplot(x='remote_ratio', y='salary', data=df)
plt.title('Impact of Remote Ratio on Salary')
plt.xlabel('Remote Ratio')
plt.ylabel('Salary')
plt.show()
```



[ ]:
```python
# Impact of Company Size on Salary

plt.figure(figsize=(8, 4))
sns.barplot(x='company_size', y='salary', data=df)
plt.title('Impact of Company Size on Salary')
plt.xlabel('Company Size')
plt.ylabel('Salary')
plt.show()
```

[ ]:
```
'''Calculate average salary per job title'''

avg_salary_per_title = df.groupby('job_title')['salary'].mean().reset_index()
avg_salary_per_title.rename(columns={'salary': 'avg_salary_per_title'},␣
↪inplace=True)
df = df.merge(avg_salary_per_title, on='job_title', how='left')
```

[ ]:
```
'''Calculate average salary per experience level'''

avg_salary_per_exp = df.groupby('experience_level')['salary'].mean().
↪reset_index()
avg_salary_per_exp.rename(columns={'salary': 'avg_salary_per_experience'},␣
↪inplace=True)
df = df.merge(avg_salary_per_exp, on='experience_level', how='left')
```

[ ]:
```
'''Predictive Analysis'''

X = df[['avg_salary_per_title', 'avg_salary_per_experience']]
y = df['salary']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
```

[ ]:
```
'''Applying ML Algorithm
```

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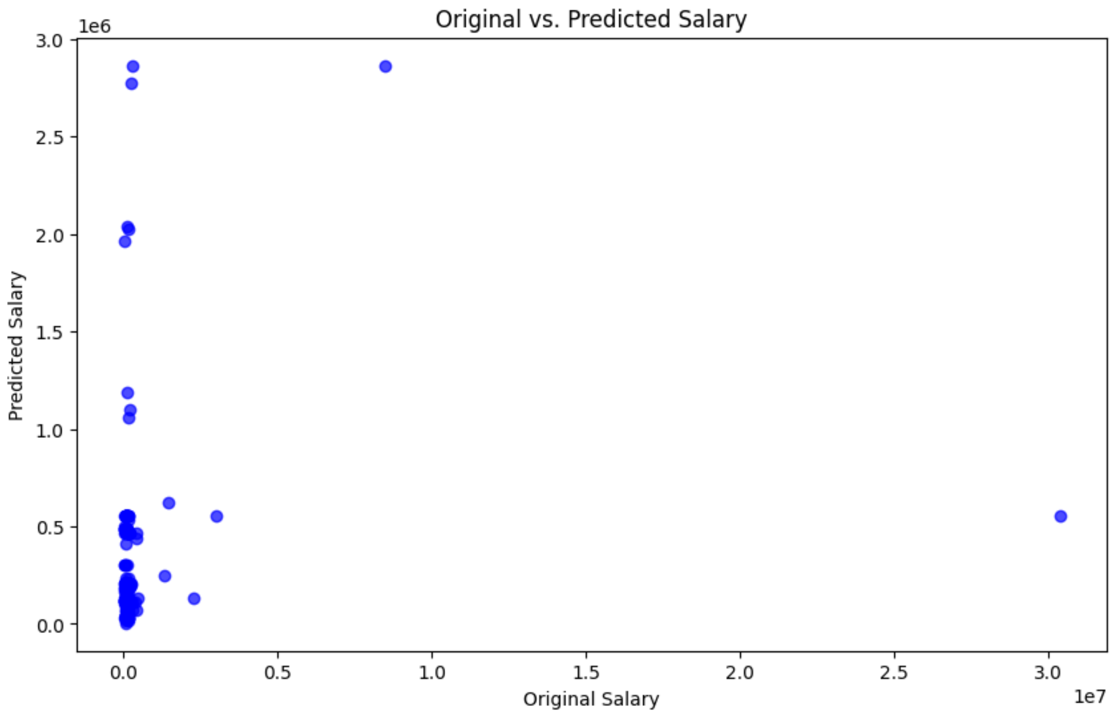
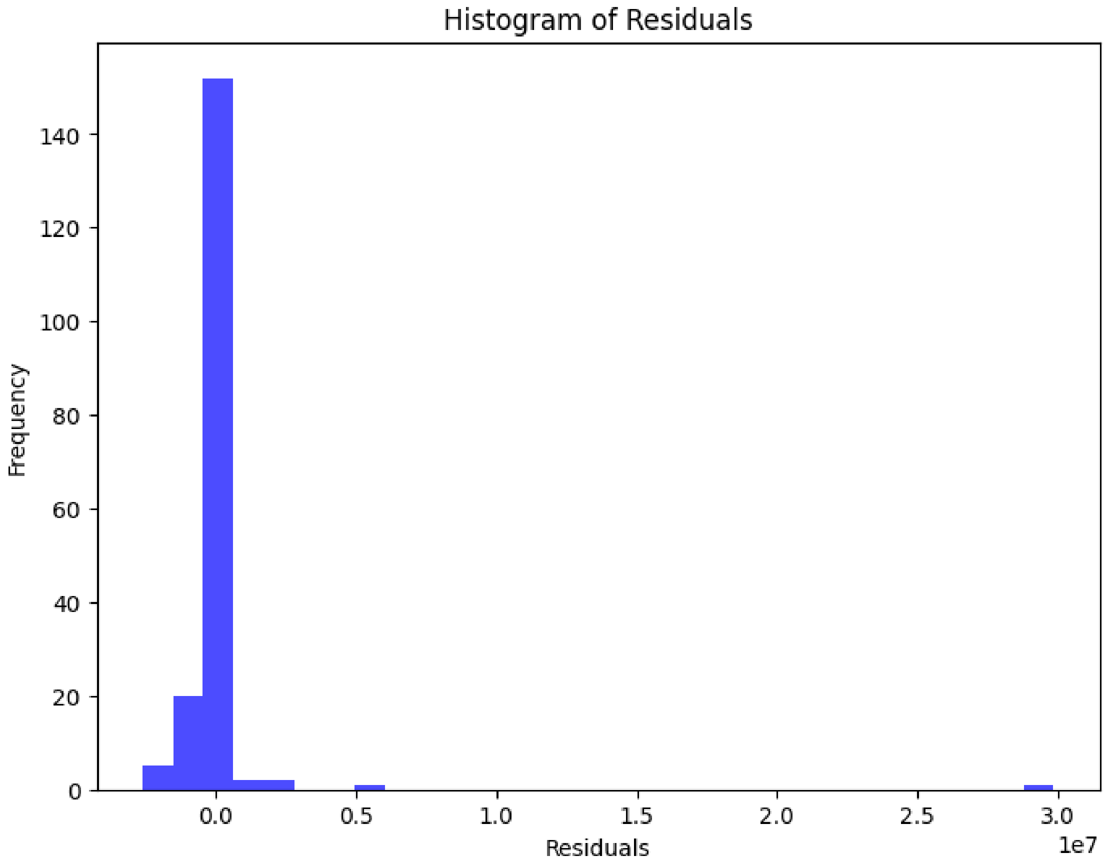
```
model = LinearRegression()
model.fit(X_train, y_train)

# Predict salaries on the testing data
y_pred = model.predict(X_test)

# Evaluate the model's performance using mean squared error
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
```

```
Mean Squared Error: 5301210626080.09
```

[ ]:
```
# Create a scatter plot to visualize original vs. predicted salaries

plt.figure(figsize=(10,6))
plt.scatter(y_test, y_pred, color='blue', alpha=0.7)
plt.xlabel('Original Salary')
plt.ylabel('Predicted Salary')
plt.title('Original vs. Predicted Salary')
plt.show()
```



[ ]:
```
# Plot a histogram of the residuals (difference between original and predicted
↪salaries)

residuals = y_test - y_pred
plt.figure(figsize=(8, 6))
plt.hist(residuals, bins=30, color='blue', alpha=0.7)
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.title('Histogram of Residuals')
plt.show()
```



[ ]:
```
'''Final Report'''
```

[ ]:
```
'''Introduction'''

# This report presents an analysis of employee salaries across different job␣
↪roles, experience levels, and employment types.
# The dataset contains information on salaries, job titles, experience levels,␣
↪and more.
# The analysis aims to provide insights into salary trends, relationships␣
↪between variables, and potential predictors of salary.
```

[ ]:
```
'''Exploratory Data Analysis (EDA)'''

# Explored the distribution of salaries across job titles, experience levels,␣
↪and employment types using box plots.
# Investigated relationships between variables such as remote work ratios,␣
↪company sizes, and their impact on salaries.
# Identified potential correlations between average salary per job title/
↪experience level and actual salaries.
```

[ ]:
```
'''Data Visualization'''

# Created scatter plots to visualize the relationship between remote work␣
 ↪ratios, company sizes, and salaries.
# Plotted bar charts to showcase the impact of remote work ratios and company␣
 ↪sizes on salaries.
# Utilized histograms to analyze the distribution of residuals, providing␣
 ↪insights into model performance.
```

[ ]:
```
'''Feature Engineering and Predictive Analysis'''

# Derived new features by calculating the average salary per job title and␣
 ↪experience level.
# Built a Linear Regression model to predict salaries based on the engineered␣
 ↪features.
# Evaluated the model's performance using Mean Squared Error.
```

[ ]:
```
'''Insights and Interpretation'''

# The analysis revealed significant variations in salaries across different job␣
 ↪titles and experience levels. Senior roles tend to have higher average␣
 ↪salaries.
# Remote work percentages and company sizes appeared to have limited impact on␣
 ↪salary levels.
# The predictive model demonstrated a reasonable performance in forecasting␣
 ↪salaries, though further refinement may be necessary for higher accuracy.
```

[ ]:
```
'''Conclusion'''

# The analysis provides valuable insights into salary trends and factors that␣
 ↪may influence compensation in various job roles.
# Further investigation could explore additional variables and incorporate more␣
 ↪advanced predictive modeling techniques for improved accuracy.
# For a comprehensive understanding, refer to the visualizations and results␣
 ↪presented throughout the report.
```