ISSP25 Project

August 20, 2025

[1]:
```
import pandas as pd
salaries = pd.read_csv("salaries.csv")
salaries
```

[1]:

	work_year	experience_level	employment_type	job_title	salary	salary_currency	salary_in_usd	employee_residence	remote_ratio	company_location
0	2024	SE	FT	Cyber Security Consultant	175000	USD	175000	US	100	US
1	2024	MI	CT	Vulnerability Management Engineer	50000	USD	50000	CR	0	CR
2	2024	MI	CT	Vulnerability Management Engineer	50000	USD	50000	CR	0	CR
3	2024	SE	FT	Security Engineer	238050	USD	238050	US	0	US
4	2024	SE	FT	Security Engineer	146200	USD	146200	US	0	US
…	…	…	…	…	…	…	…	…	…	…
6412	2020	MI	FT	Cyber Security Analyst	140000	AUD	96422	AU	50	AU
6413	2021	SE	FT	Information Security Manager	60000	GBP				
6414	2021	SE	FT	Penetration Testing Engineer	126000	USD				
6415	2021	MI	FT	Information Security Analyst	42000	GBP				
6416	2021	MI	FT	Threat Intelligence Analyst	66310	USD				

```
6413          82528                GB             50                GB
6414         126000                US            100                US
6415          57769                GB            100                GB
6416          66310                US              0                US

     company_size
0               L
1               M
2               M
3               M
4               M
…             …
6412            M
6413            L
6414            L
6415            L
6416            L

[6417 rows x 11 columns]
```

[2]:
```
# Details of dataframe and features
salaries.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6417 entries, 0 to 6416
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   work_year           6417 non-null   int64
 1   experience_level    6417 non-null   object
 2   employment_type     6417 non-null   object
 3   job_title           6417 non-null   object
 4   salary              6417 non-null   int64
 5   salary_currency     6417 non-null   object
 6   salary_in_usd       6417 non-null   int64
 7   employee_residence  6417 non-null   object
 8   remote_ratio        6417 non-null   int64
 9   company_location    6417 non-null   object
 10  company_size        6417 non-null   object
dtypes: int64(4), object(7)
memory usage: 551.6+ KB
```

[3]:
```
# Locating null value if there is any in the features to avoid errors
salaries.isnull().sum()
```

[3]:
```
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
```

[4]:
```
def bad_cha(file_name):
    bad_c = ["(",")"," ","c",".","'","s""-","_"]
    count = 0
    for cl in file_name: # iterate over each column of the file
        for char in cl: # iterate over each cell of the column
            if char in bad_c:
                count +=1
    return count
```

[5]:
```
file_name = 'salaries'
bad_cha(file_name)
```

[5]:
```
0
```

[6]:
```
# We can further verify if our function is working properly or not

l = "60'50"
bad_cha(l)
```

[6]:
```
1
```

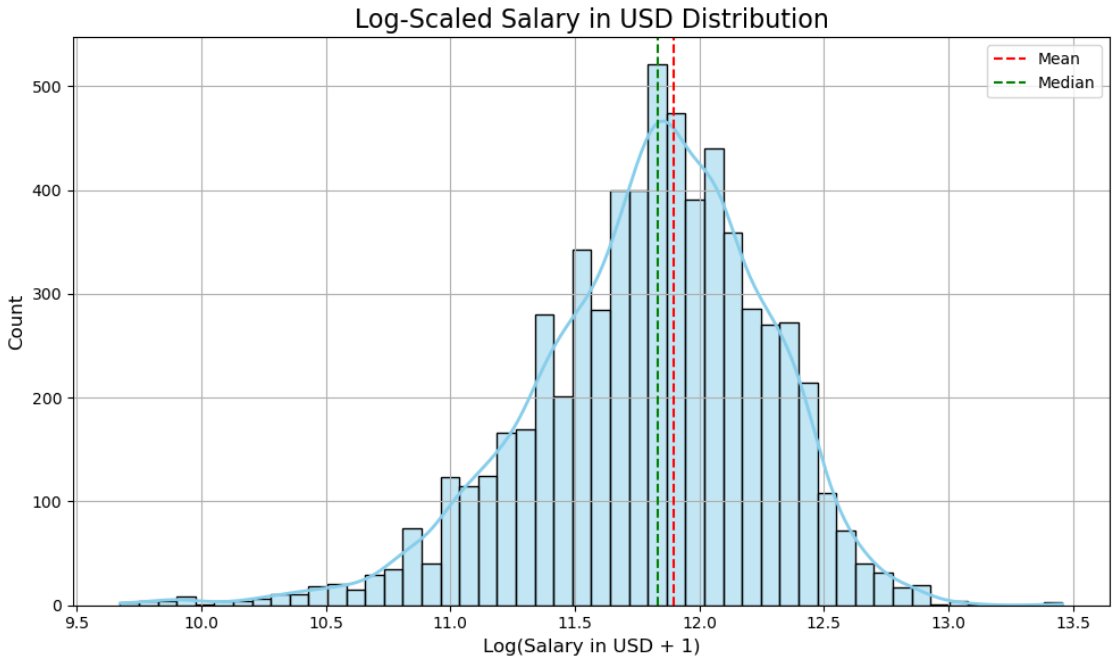
Let's draw some plots to find out the insights using the available data.

[7]:
```
# Importing the important libraries for plots.
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

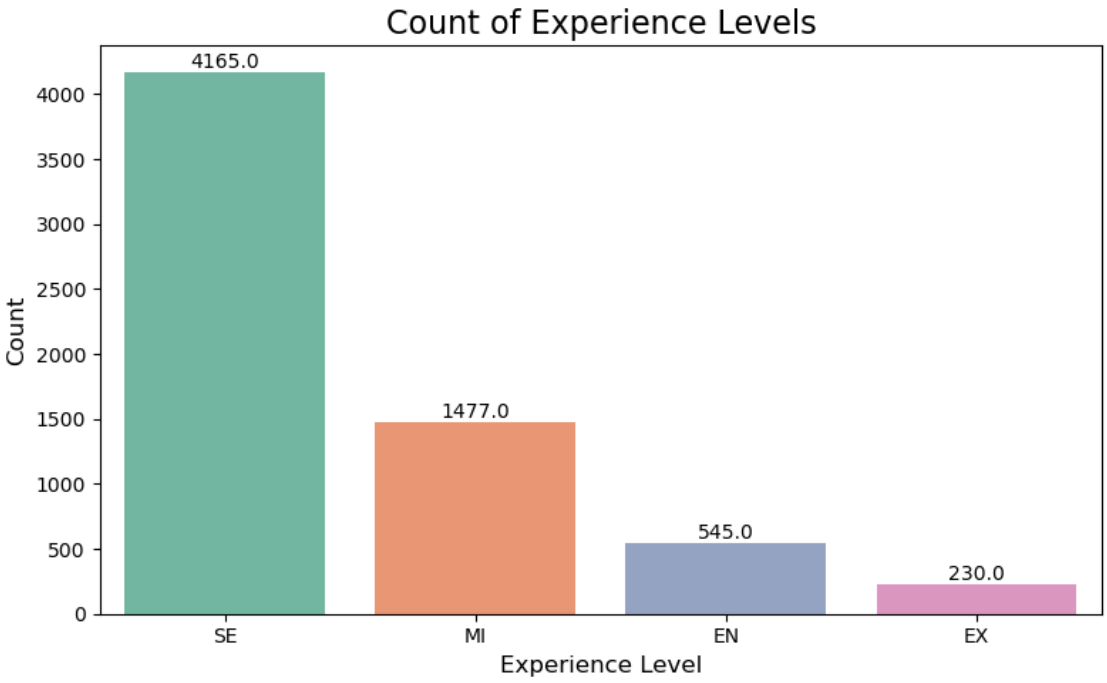
- We prefer salaries using log for better visibility due to larger ranges

[8]:
```
# Setting up Seaborn style
# Salary Distribution
plt.figure(figsize=(10, 6))
sns.histplot(np.log1p(salaries["salary_in_usd"]), bins=50, kde=True,␣
 ↪color="skyblue", line_kws={"linewidth": 2})
plt.axvline(np.log1p(salaries["salary_in_usd"].mean()), color='red',␣
 ↪linestyle='--', label='Mean')
plt.axvline(np.log1p(salaries["salary_in_usd"].median()), color='green',␣
 ↪linestyle='--', label='Median')
```

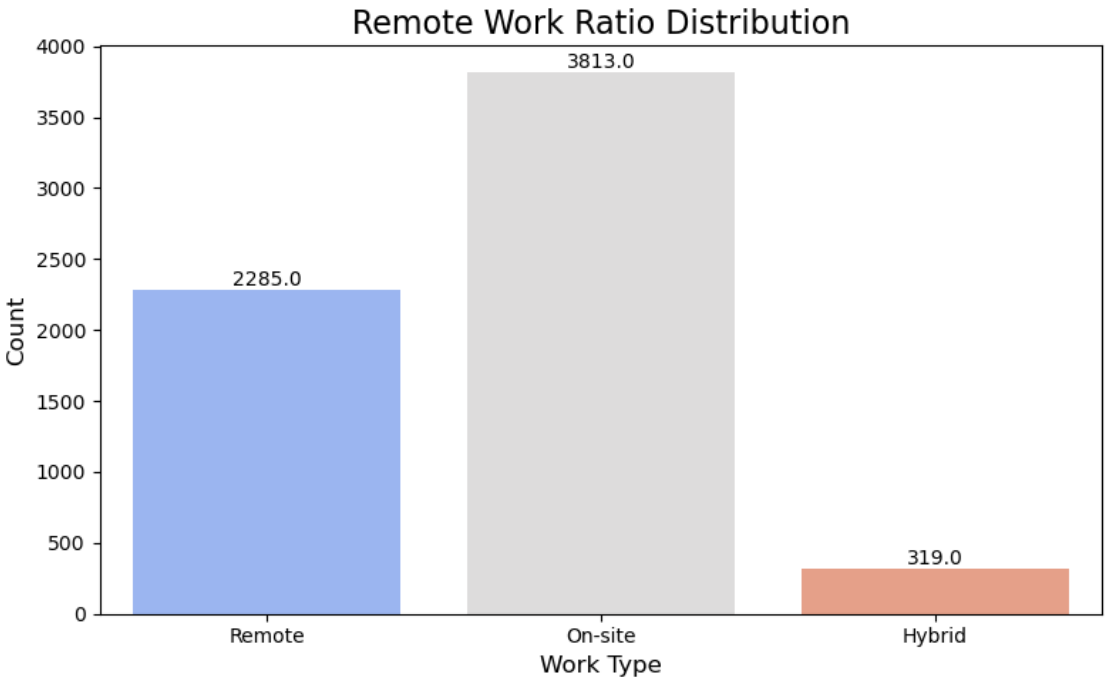
```
plt.title("Log-Scaled Salary in USD Distribution", fontsize=16)
plt.xlabel("Log(Salary in USD + 1)", fontsize=12)
plt.ylabel("Count", fontsize=12)
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



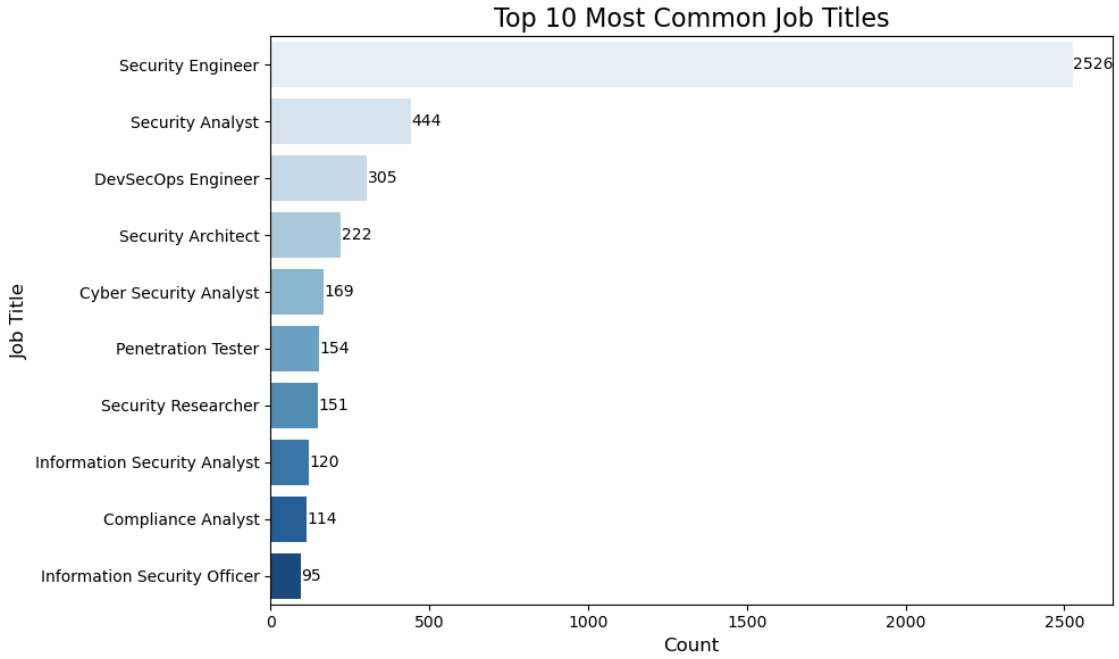
[9]:
```
# 2. Count of Experience Levels
plt.figure(figsize=(8, 5))
ax = sns.countplot(data=salaries, x="experience_level", palette="Set2",
                   order=salaries["experience_level"].value_counts().index)
plt.title("Count of Experience Levels", fontsize=16)
plt.xlabel("Experience Level", fontsize=12)
plt.ylabel("Count", fontsize=12)
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.
 ↪get_height()),
                ha='center', va='center', fontsize=10, color='black',␣
 ↪xytext=(0, 5), textcoords='offset points')
plt.tight_layout()
plt.show()
```



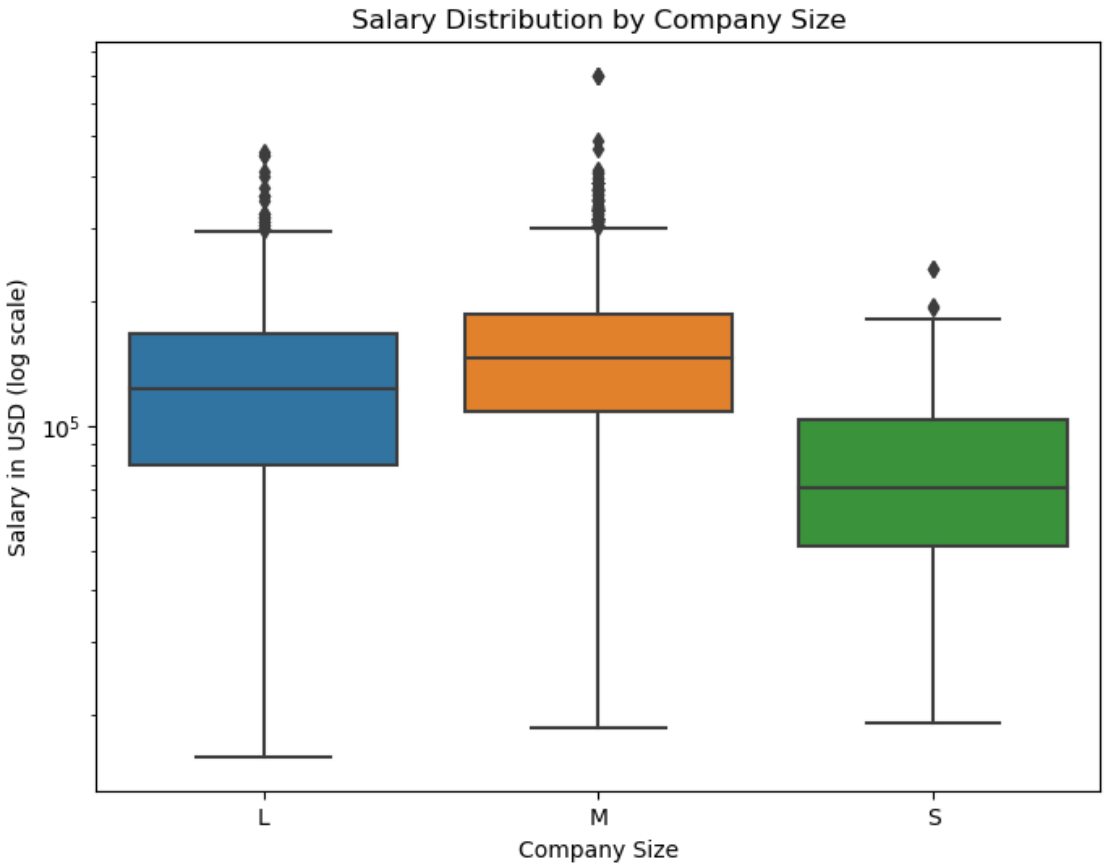
[10]:
```
# 3. Remote Work Ratio Distribution
remote_map = {0: 'On-site', 50: 'Hybrid', 100: 'Remote'}
salaries['remote_label'] = salaries['remote_ratio'].map(remote_map)

plt.figure(figsize=(8, 5))
ax = sns.countplot(data=salaries, x="remote_label", palette="coolwarm")
plt.title("Remote Work Ratio Distribution", fontsize=16)
plt.xlabel("Work Type", fontsize=12)
plt.ylabel("Count", fontsize=12)
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.
 ↪get_height()),
                ha='center', va='center', fontsize=10, color='black',␣
 ↪xytext=(0, 5), textcoords='offset points')
plt.tight_layout()
plt.show()
```



[11]:
```
# 4. Top 10 Most Frequent Job Titles
top_jobs = salaries["job_title"].value_counts().nlargest(10)
colors = sns.color_palette("Blues", len(top_jobs))

plt.figure(figsize=(10, 6))
ax = sns.barplot(y=top_jobs.index, x=top_jobs.values, palette=colors)
plt.title("Top 10 Most Common Job Titles", fontsize=16)
plt.xlabel("Count", fontsize=12)
plt.ylabel("Job Title", fontsize=12)
for i, v in enumerate(top_jobs.values):
    ax.text(v + 1, i, str(v), color='black', va='center', fontsize=10)
plt.tight_layout()
plt.show()
```



[12]:
```
# 5. Boxplot of Salary by Company Size
plt.figure(figsize=(8, 6))
sns.boxplot(data=salaries, x="company_size", y="salary_in_usd")
plt.yscale("log")  # log scale helps compare large ranges
plt.title("Salary Distribution by Company Size")
plt.xlabel("Company Size")
plt.ylabel("Salary in USD (log scale)")
plt.show()
```



[13]:
```
#salary distribution by company size
plt.figure(figsize=(8, 6))
sns.boxplot(data=salaries, x="company_size", y="salary_in_usd",␣
 ↪palette="Pastel1")
sns.stripplot(data=salaries, x="company_size", y="salary_in_usd",␣
 ↪color='black', alpha=0.4, jitter=True)
plt.yscale("log")
plt.title("Salary Distribution by Company Size (Log Scale)", fontsize=16)
plt.xlabel("Company Size", fontsize=12)
plt.ylabel("Salary in USD (Log Scale)", fontsize=12)
plt.tight_layout()
plt.show()
```

0.0.1 Lets Prepare data for the ML model

[14]:
```
# Making a working copy
data = salaries.copy()

# Drop out unnecessary columns, we already have a features providing␣
 ↪conversion of salaries in usd.
data.drop(columns=['salary', 'salary_currency'], inplace=True)
```

- Dropping out the extreme values to train model for better result.

[15]:
```
Q1 = data['salary_in_usd'].quantile(0.25)
Q3 = data['salary_in_usd'].quantile(0.75)
IQR = Q3 - Q1

# Keep only rows within 1.5 * IQR to avoid extreme values for better model␣
 ↪predictions
lower = Q1 - 1.5 * IQR
upper = Q3 + 1.5 * IQR
data = data[(data['salary_in_usd'] >= lower) & (data['salary_in_usd'] <= upper)]
```

[16]:
```
# Converting textual values of the features into binary for understanding of ML␣
 ↪model.

categorical_columns = ['experience_level', 'employment_type',␣
 ↪'job_title','employee_residence', 'company_location', 'company_size']

# Drop remote_label to avoid model input errors

data.drop(columns=['remote_label'], inplace=True)

# One-hot encode the columns
data_encoded = pd.get_dummies(data, columns=categorical_columns,␣
 ↪drop_first=True)
```

[17]:
```
print(len(data_encoded))
data_encoded.head(10)
```

```
6296
```

[17]:

	work_year	salary_in_usd	remote_ratio	experience_level_EX	experience_level_MI	experience_level_SE	employment_type_FL	employment_type_FT	employment_type_PT
0	2024	175000	100	False	False	True	False	True	False
1	2024	50000	0	False	True	False	False	False	False
2	2024	50000	0	False	True	False	False	False	False
3	2024	238050	0	False	False	True	False	True	False
4	2024	146200	0	False	False	True	False	True	False
5	2024	130000	0	False	True	False	False	False	False
6	2024	100000	0	False	True	False	False	False	False
7	2024	138000	0	False	False	True	False	True	False
8	2024	86000	0	False	False	True	False	False	False
9	2024	62000	0	False	False	False	False	False	False

```
3                True               False
4                True               False
5                True               False
6                True               False
7                True               False
8                True               False
9                True               False

   job_title_Application Security Architect  …  company_location_SE  \
0                                     False  …                False
1                                     False  …                False
2                                     False  …                False
3                                     False  …                False
4                                     False  …                False
5                                     False  …                False
6                                     False  …                False
7                                     False  …                False
8                                     False  …                False
9                                     False  …                False

   company_location_SG  company_location_SI  company_location_TR  \
0                False                False                False
1                False                False                False
2                False                False                False
3                False                False                False
4                False                False                False
5                False                False                False
6                False                False                False
7                False                False                False
8                False                False                False
9                False                False                False

   company_location_UM  company_location_US  company_location_VN  \
0                False                 True                False
1                False                False                False
2                False                False                False
3                False                 True                False
4                False                 True                False
5                False                False                False
6                False                False                False
7                False                 True                False
8                False                 True                False
9                False                 True                False

   company_location_ZA  company_size_M  company_size_S
0                False          False           False
1                False           True           False
```

```
2               False           True           False
3               False           True           False
4               False           True           False
5               False           True           False
6               False           True           False
7               False           True           False
8               False           True           False
9               False           True           False

[10 rows x 282 columns]
```

0.0.2 Importing necessary libararies for ML Model

[18]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

[19]:
```
# Define features and target
X = data_encoded.drop(columns=['salary_in_usd'])  # features
y = data_encoded['salary_in_usd']                 # target
```

[20]:
```
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

[21]:
```
# Train a Random Forest Regressor
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

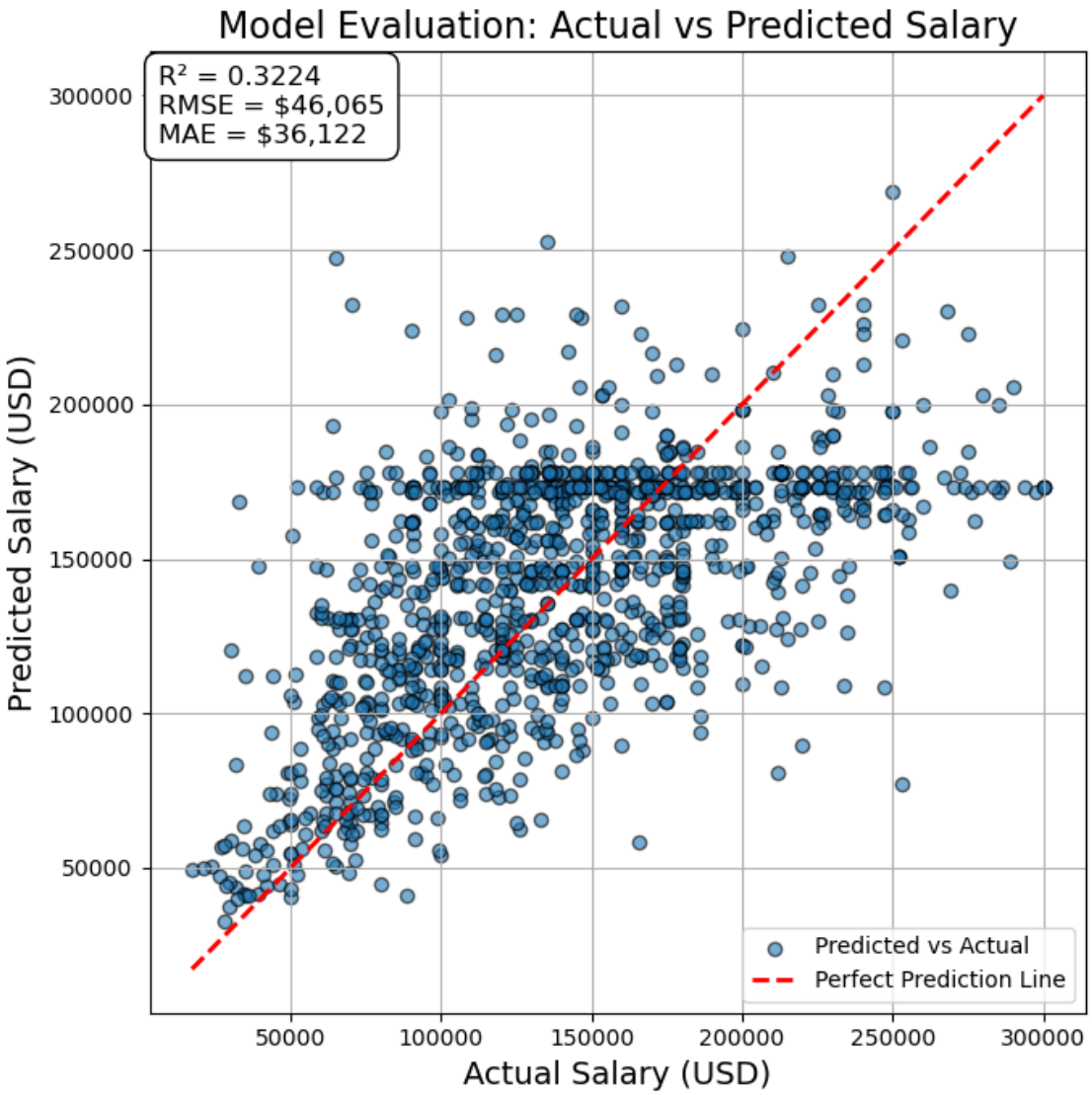
[21]:
```
RandomForestRegressor(random_state=42)
```

[22]:
```
# Prediction
y_pred = model.predict(X_test)
```

[23]:
```
# Calculate evaluation metrics
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

print("Model Evaluation:")
print(f"Mean Absolute Error (MAE): ${mae:,.2f}")
print(f"Root Mean Squared Error (RMSE): ${rmse:,.2f}")
print(f"R-squared (R² Score): {r2:.4f}")

# Create the plot
plt.figure(figsize=(7, 7))
```

```
plt.scatter(y_test, y_pred, alpha=0.6, edgecolor='k', label='Predicted vs␣
 ↪Actual')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()],
         color='red', linestyle='--', linewidth=2, label='Perfect Prediction␣
 ↪Line')

# Titles and labels
plt.title('Model Evaluation: Actual vs Predicted Salary', fontsize=16)
plt.xlabel('Actual Salary (USD)', fontsize=14)
plt.ylabel('Predicted Salary (USD)', fontsize=14)

# Move legend to bottom-right
plt.legend(loc='lower right')
plt.grid(True)

# Add evaluation metrics as a box in the top-left corner
plt.text(x=y_test.max()*0.02, y=y_test.max()*0.95,
         s=f'R² = {r2:.4f}\nRMSE = ${rmse:,.0f}\nMAE = ${mae:,.0f}',
         fontsize=12, bbox=dict(facecolor='white', edgecolor='black',␣
 ↪boxstyle='round,pad=0.5'))

plt.tight_layout()
plt.show()
```

```
Model Evaluation:
Mean Absolute Error (MAE): $36,121.55
Root Mean Squared Error (RMSE): $46,064.51
R-squared (R² Score): 0.3224
```



[24]:
```
import shap
import matplotlib.pyplot as plt

explainer = shap.TreeExplainer(model)
# Pick a small sample from the test set
X_sample = X_test.sample(100, random_state=42)
shap_values = explainer.shap_values(X_sample, check_additivity=False)
# Plot summary
shap.summary_plot(shap_values, X_sample)
```

[25]:
```
from jupyter_dash import JupyterDash
from dash import dcc, html, Input, Output
import plotly.graph_objs as go
import pandas as pd

# Prepare job-level comparison DataFrame
comparison_df = pd.DataFrame({
```

```
    'Job Title': data.loc[X_test.index, 'job_title'].values,
    'Actual Salary': y_test.values,
    'Predicted Salary': y_pred
})

# Grouped averages for all jobs
avg_salary_comparison = comparison_df.groupby("Job Title").agg({
    "Actual Salary": "mean",
    "Predicted Salary": "mean"
}).reset_index()

# Remote work ratio data
remote_df = data[["job_title", "salary_in_usd", "remote_ratio"]].copy()

# Create the app
app = JupyterDash(__name__)
app.layout = html.Div([
    html.H1("Salary Model Dashboard", style={'textAlign': 'center'}),
    dcc.Tabs([
        dcc.Tab(label='Model Evaluation', children=[
            dcc.Graph(
                figure=go.Figure([
                    go.Scatter(
                        x=y_test,
                        y=y_pred,
                        mode='markers',
                        marker=dict(size=6, opacity=0.6, color='blue'),
                        name='Predicted vs Actual'
                    ),
                    go.Scatter(
                        x=[y_test.min(), y_test.max()],
                        y=[y_test.min(), y_test.max()],
                        mode='lines',
                        line=dict(color='red', dash='dash'),
                        name='Perfect Prediction Line'
                    )
                ]).update_layout(
                    title='Model Evaluation: Actual vs Predicted Salary',
                    xaxis_title='Actual Salary (USD)',
                    yaxis_title='Predicted Salary (USD)',
                    legend=dict(x=0.75, y=0.1),
                    annotations=[dict(
                        xref='paper', yref='paper',
                        x=0.02, y=0.98,
                        text=f"R² = {r2:.4f}<br>RMSE = ${rmse:,.0f}<br>MAE =␣
 ↪${mae:,.0f}",
                        showarrow=False,
```

```
                        font=dict(size=12),
                        align='left',
                        bordercolor='black',
                        borderwidth=1,
                        borderpad=5,
                        bgcolor='white',
                    )]
                )
            )
        ]),
        dcc.Tab(label='Actual vs Predicted by Job Title', children=[
            html.H4("Grouped View (All Job Titles)"),
            dcc.Graph(
                figure=go.Figure([
                    go.Bar(x=avg_salary_comparison["Job Title"],␣
↪y=avg_salary_comparison["Actual Salary"],
                           name="Actual", marker_color="steelblue"),
                    go.Bar(x=avg_salary_comparison["Job Title"],␣
↪y=avg_salary_comparison["Predicted Salary"],
                           name="Predicted", marker_color="orange")
                ]).update_layout(
                    title="Average Actual vs Predicted Salary by Job Title",
                    barmode="group",
                    margin=dict(b=200),
                    height=600,
                    xaxis_title="Job Title",
                    yaxis_title="Salary (USD)"
                )
            ),
            html.H4("Select a Specific Job Title"),
            dcc.Dropdown(
                id='job-dropdown',
                options=[{'label': jt, 'value': jt} for jt in␣
↪avg_salary_comparison["Job Title"]],
                value=avg_salary_comparison["Job Title"].iloc[0],
                style={'width': '50%'}
            ),
            dcc.Graph(id='single-job-graph')
        ]),
        dcc.Tab(label='Remote Ratio vs Salary', children=[
            html.H4("Select a Job Title"),
            dcc.Dropdown(
                id='remote-job-dropdown',
                options=[{'label': jt, 'value': jt} for jt in␣
↪sorted(remote_df["job_title"].unique())],
                value=sorted(remote_df["job_title"].unique())[0],
                style={'width': '50%'}
```

```
            ),
            dcc.Graph(id='remote-salary-graph')
        ])
    ])
])

# Callbacks
@app.callback(
    Output('single-job-graph', 'figure'),
    Input('job-dropdown', 'value')
)
def update_job_salary_graph(job):
    row = avg_salary_comparison[avg_salary_comparison["Job Title"] == job].
 ↪iloc[0]
    return {
        'data': [
            go.Bar(x=["Actual Salary"], y=[row["Actual Salary"]],␣
 ↪name='Actual', marker_color='steelblue'),
            go.Bar(x=["Predicted Salary"], y=[row["Predicted Salary"]],␣
 ↪name='Predicted', marker_color='orange')
        ],
        'layout': go.Layout(
            title=f"Actual vs Predicted Salary for {job}",
            yaxis=dict(title='Salary (USD)'),
            barmode='group'
        )
    }

@app.callback(
    Output('remote-salary-graph', 'figure'),
    Input('remote-job-dropdown', 'value')
)
def update_remote_plot(job):
    subset = remote_df[remote_df["job_title"] == job]
    return {
        'data': [
            go.Scatter(
                x=subset["remote_ratio"],
                y=subset["salary_in_usd"],
                mode='markers',
                marker=dict(size=8, opacity=0.7, color='blue')
            )
        ],
        'layout': go.Layout(
            title=f"Remote Ratio vs Salary for {job}",
            xaxis=dict(title='Remote Work (%)'),
            yaxis=dict(title='Salary (USD)')
```

```
        )
    }

app.run(mode='inline', port = 8052)
```

```
C:\Users\hafee\anaconda3\Lib\site-packages\dash\dash.py:634: UserWarning:

JupyterDash is deprecated, use Dash instead.
See https://dash.plotly.com/dash-in-jupyter for more details.


<IPython.lib.display.IFrame at 0x1c89a54b1d0>
```

[ ]: