Salary_Analysis_and_Prediction

August 7, 2025

1 Data Science Salary Analysis and Prediction

1.1 1. Import Libraries

[1]:
```
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.preprocessing import LabelEncoder, StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
import warnings

warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', None)
sns.set_style('whitegrid')
```

1.2 2. Load and Explore Data

[3]:
```
df = pd.read_csv('salaries.csv')
print("Dataset shape:", df.shape)
print("First 5 rows:")
display(df.head())
print("Data types and missing values:")
df.info()
print("Summary statistics:")
display(df.describe(include='all'))
```

```
Dataset shape: (151445, 11)
First 5 rows:

   work_year experience_level employment_type       job_title  salary  \
0       2025               EX              FT    Head of Data  348516
1       2025               EX              FT    Head of Data  232344
2       2025               SE              FT  Data Scientist  145400
```

```
3      2025              SE              FT  Data Scientist   81600
4      2025              MI              FT        Engineer  160000

  salary_currency  salary_in_usd employee_residence  remote_ratio  \
0             USD         348516                 US             0
1             USD         232344                 US             0
2             USD         145400                 US             0
3             USD          81600                 US             0
4             USD         160000                 US           100

  company_location company_size
0               US            M
1               US            M
2               US            M
3               US            M
4               US            M

Data types and missing values:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 151445 entries, 0 to 151444
Data columns (total 11 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   work_year           151445 non-null  int64
 1   experience_level    151445 non-null  object
 2   employment_type     151445 non-null  object
 3   job_title           151445 non-null  object
 4   salary              151445 non-null  int64
 5   salary_currency     151445 non-null  object
 6   salary_in_usd       151445 non-null  int64
 7   employee_residence  151445 non-null  object
 8   remote_ratio        151445 non-null  int64
 9   company_location    151445 non-null  object
 10  company_size        151445 non-null  object
dtypes: int64(4), object(7)
memory usage: 12.7+ MB
Summary statistics:

            work_year experience_level employment_type       job_title  \
count   151445.000000           151445          151445          151445
unique            NaN                4               4             422
top               NaN               SE              FT  Data Scientist
freq              NaN            87491          150541           18751
mean      2024.435313              NaN             NaN             NaN
std          0.671842              NaN             NaN             NaN
min       2020.000000              NaN             NaN             NaN
25%       2024.000000              NaN             NaN             NaN
50%       2025.000000              NaN             NaN             NaN
75%       2025.000000              NaN             NaN             NaN
```

```
max       2025.000000              NaN              NaN              NaN

                salary salary_currency  salary_in_usd employee_residence  \
count   1.514450e+05          151445  151445.000000             151445
unique           NaN              26            NaN                104
top              NaN             USD            NaN                 US
freq             NaN          143173            NaN             135506
mean    1.628380e+05             NaN  157527.458411                NaN
std     2.080124e+05             NaN   74150.772377                NaN
min     1.400000e+04             NaN   15000.000000                NaN
25%     1.060000e+05             NaN  105800.000000                NaN
50%     1.470000e+05             NaN  146100.000000                NaN
75%     1.990000e+05             NaN  198000.000000                NaN
max     3.040000e+07             NaN  800000.000000                NaN

          remote_ratio company_location company_size
count    151445.000000           151445       151445
unique             NaN               97            3
top                NaN               US            M
freq               NaN           135569       147302
mean         20.938625              NaN          NaN
std          40.620393              NaN          NaN
min           0.000000              NaN          NaN
25%           0.000000              NaN          NaN
50%           0.000000              NaN          NaN
75%           0.000000              NaN          NaN
max         100.000000              NaN          NaN
```

1.3 3. Data Cleaning and Feature Engineering

[4]:
```python
print(f"Shape before dropping duplicates: {df.shape}")
df = df.drop_duplicates()
print(f"Shape after dropping duplicates: {df.shape}")

# Feature Engineering
df['is_remote'] = df['remote_ratio'].apply(lambda x: 1 if x > 50 else 0)
df['is_us'] = df['company_location'].apply(lambda x: 1 if x == 'US' else 0)

def categorize_job(title):
    title = title.lower()
    if 'data scientist' in title:
        return 'Data Scientist'
    elif 'data engineer' in title:
        return 'Data Engineer'
    elif 'machine learning' in title or 'ml' in title:
        return 'Machine Learning'
    elif 'ai' in title:
```

```python
        return 'AI'
    elif 'analyst' in title:
        return 'Analyst'
    elif 'manager' in title:
        return 'Manager'
    elif 'engineer' in title:
        return 'Engineer'
    elif 'software' in title:
        return 'Software Engineer'
    elif 'research' in title:
        return 'Research'
    else:
        return 'Other'

df['job_family'] = df['job_title'].apply(categorize_job)

print("Cleaned dataframe sample with new features:")
display(df.head())
```

```
Shape before dropping duplicates: (151445, 11)
Shape after dropping duplicates: (71913, 11)
Cleaned dataframe sample with new features:
```

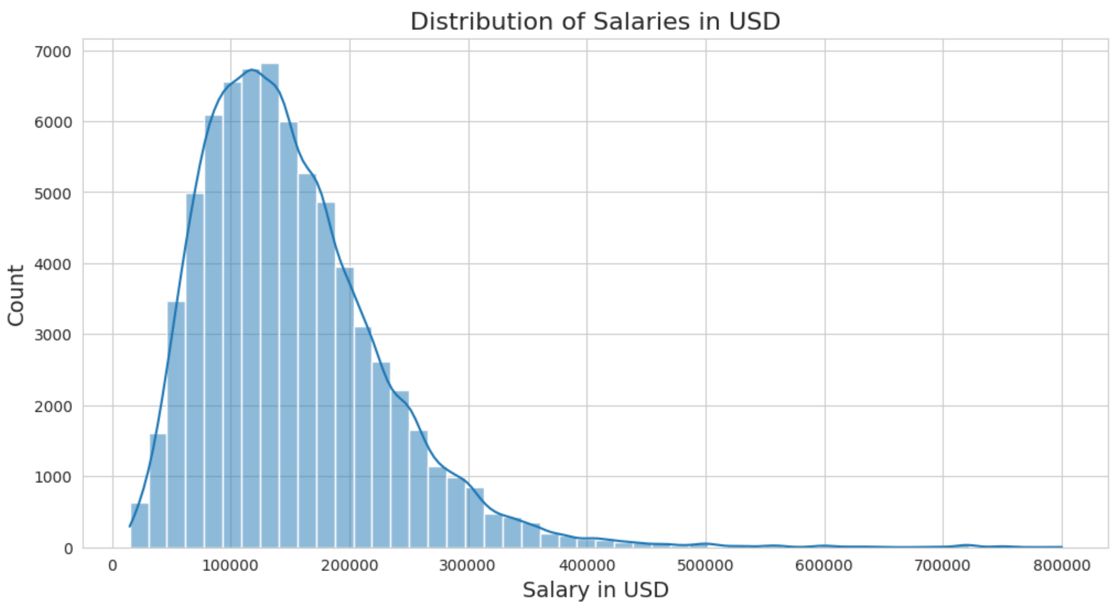
```
   work_year experience_level employment_type       job_title  salary  \
0       2025               EX              FT    Head of Data  348516
1       2025               EX              FT    Head of Data  232344
2       2025               SE              FT  Data Scientist  145400
3       2025               SE              FT  Data Scientist   81600
4       2025               MI              FT        Engineer  160000

  salary_currency  salary_in_usd employee_residence  remote_ratio  \
0             USD         348516                 US             0
1             USD         232344                 US             0
2             USD         145400                 US             0
3             USD          81600                 US             0
4             USD         160000                 US           100

  company_location company_size  is_remote  is_us      job_family
0               US            M          0      1           Other
1               US            M          0      1           Other
2               US            M          0      1  Data Scientist
3               US            M          0      1  Data Scientist
4               US            M          1      1        Engineer
```

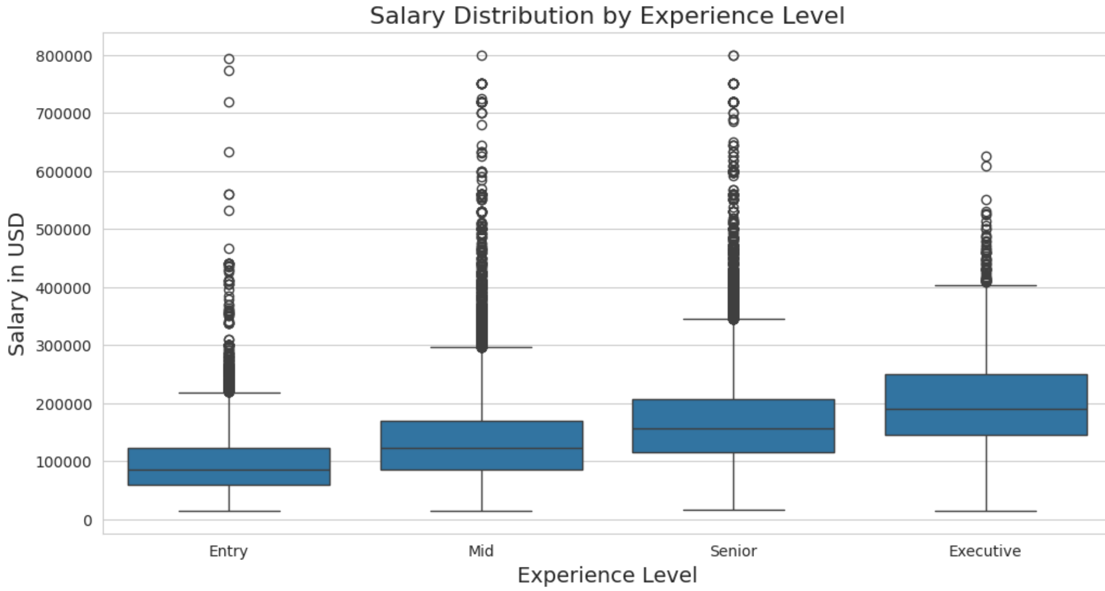
1.4 4. Exploratory Data Analysis (EDA)

[5]:
```
plt.figure(figsize=(12, 6))
sns.histplot(df['salary_in_usd'], bins=50, kde=True)
plt.title('Distribution of Salaries in USD', fontsize=16)
plt.xlabel('Salary in USD', fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.show()
```



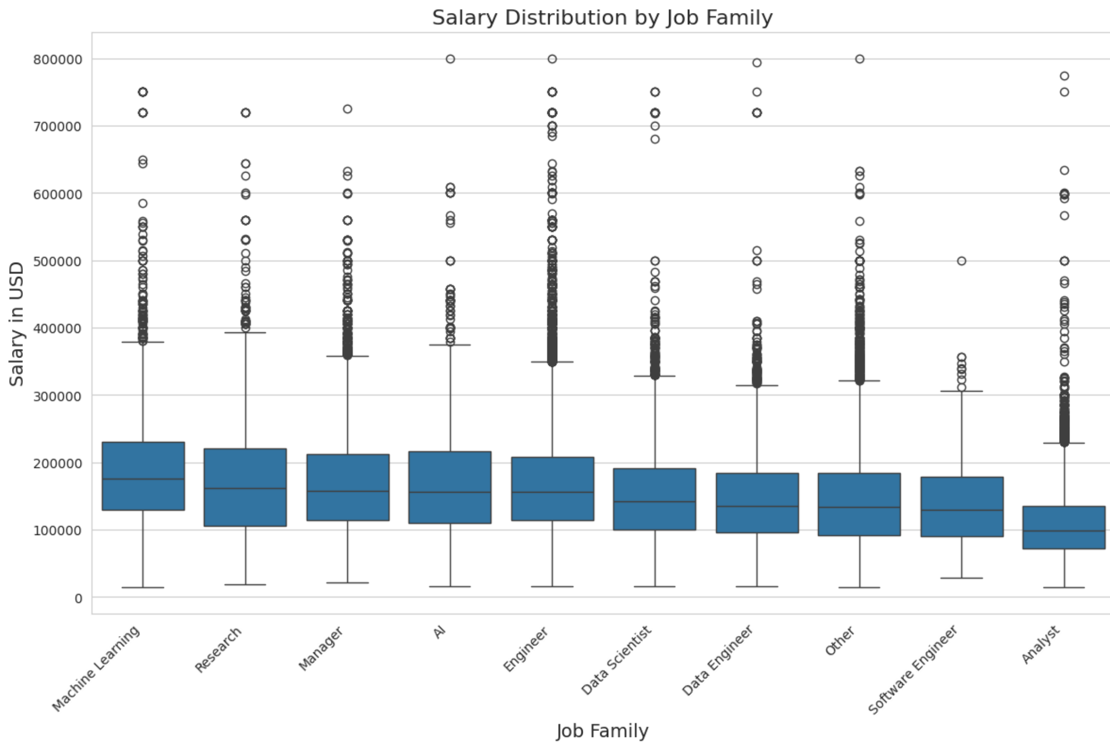
1.4.1 Salary by Experience Level

[6]:
```
plt.figure(figsize=(12, 6))
order = ['EN', 'MI', 'SE', 'EX']
sns.boxplot(x='experience_level', y='salary_in_usd', data=df, order=order)
plt.title('Salary Distribution by Experience Level', fontsize=16)
plt.xlabel('Experience Level', fontsize=14)
plt.ylabel('Salary in USD', fontsize=14)
plt.xticks([0, 1, 2, 3], ['Entry', 'Mid', 'Senior', 'Executive'])
plt.show()
```



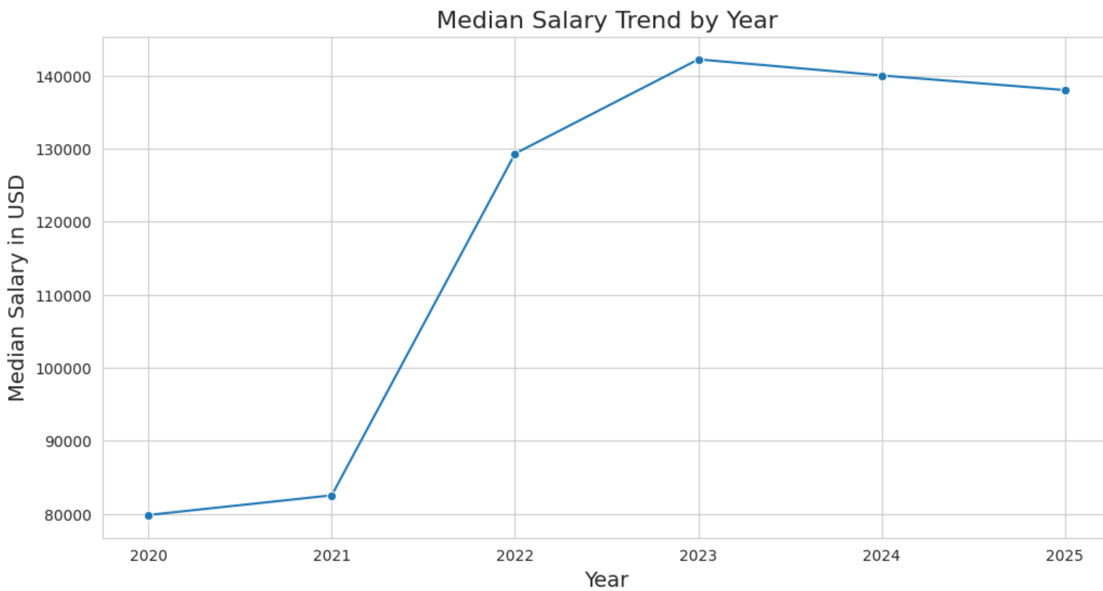
1.4.2 Salary by Job Family

[7]:
```
plt.figure(figsize=(14, 8))
order = df.groupby('job_family')['salary_in_usd'].median().
↪sort_values(ascending=False).index
sns.boxplot(x='job_family', y='salary_in_usd', data=df, order=order)
plt.title('Salary Distribution by Job Family', fontsize=16)
plt.xlabel('Job Family', fontsize=14)
plt.ylabel('Salary in USD', fontsize=14)
plt.xticks(rotation=45, ha='right')
plt.show()
```



1.4.3 Salary Trend by Year

[8]:
```
plt.figure(figsize=(12, 6))
sns.lineplot(x='work_year', y='salary_in_usd', data=df, estimator='median',
 ↪errorbar=None, marker='o')
plt.title('Median Salary Trend by Year', fontsize=16)
plt.xlabel('Year', fontsize=14)
plt.ylabel('Median Salary in USD', fontsize=14)
plt.xticks(df['work_year'].unique())
plt.show()
```



1.5 5. Machine Learning Model to Predict Salary

[9]:
```
# Define features and target
features = ['experience_level', 'employment_type', 'job_family',␣
 ↪'remote_ratio', 'company_size', 'is_us']
target = 'salary_in_usd'

X = df[features]
y = df[target]

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Define preprocessing steps
categorical_features = ['experience_level', 'employment_type', 'job_family',␣
 ↪'company_size']
numerical_features = ['remote_ratio', 'is_us']

preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_features),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features)
    ])

# Create the pipeline
pipeline = Pipeline(steps=[('preprocessor', preprocessor),
```

```
                            ('regressor',␣
↪RandomForestRegressor(random_state=42))])
```

1.5.1 Hyperparameter Tuning with GridSearchCV

[10]:
```
param_grid = {
    'regressor__n_estimators': [100, 200],
    'regressor__max_depth': [10, 20],
    'regressor__min_samples_leaf': [2, 4]
}

grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='r2', n_jobs=-1,␣
↪verbose=2)
grid_search.fit(X_train, y_train)

print("Best parameters found:", grid_search.best_params_)
best_model = grid_search.best_estimator_
```

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=2,
regressor__n_estimators=100; total time=  14.9s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=2,
regressor__n_estimators=100; total time=  15.0s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=2,
regressor__n_estimators=100; total time=  15.2s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=2,
regressor__n_estimators=100; total time=  16.9s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=2,
regressor__n_estimators=100; total time=  14.6s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=2,
regressor__n_estimators=200; total time=  29.0s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=2,
regressor__n_estimators=200; total time=  30.6s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=2,
regressor__n_estimators=200; total time=  29.5s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=2,
regressor__n_estimators=200; total time=  29.2s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=4,
regressor__n_estimators=100; total time=  13.9s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=4,
regressor__n_estimators=100; total time=  13.6s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=4,
regressor__n_estimators=100; total time=  13.2s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=4,
regressor__n_estimators=100; total time=  13.4s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=4,
regressor__n_estimators=100; total time=  14.6s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=2,
```

```
regressor__n_estimators=200; total time=  30.4s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=4,
regressor__n_estimators=200; total time=  31.9s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=4,
regressor__n_estimators=200; total time=  34.8s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=4,
regressor__n_estimators=200; total time=  34.0s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=4,
regressor__n_estimators=200; total time=  34.0s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=2,
regressor__n_estimators=100; total time=  22.5s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=2,
regressor__n_estimators=100; total time=  25.2s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=2,
regressor__n_estimators=100; total time=  24.3s
[CV] END regressor__max_depth=10, regressor__min_samples_leaf=4,
regressor__n_estimators=200; total time=  32.8s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=2,
regressor__n_estimators=100; total time=  23.2s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=2,
regressor__n_estimators=100; total time=  24.7s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=2,
regressor__n_estimators=200; total time=  44.7s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=2,
regressor__n_estimators=200; total time=  46.1s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=2,
regressor__n_estimators=200; total time=  42.0s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=2,
regressor__n_estimators=200; total time=  47.4s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=4,
regressor__n_estimators=100; total time=  21.5s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=4,
regressor__n_estimators=100; total time=  20.2s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=2,
regressor__n_estimators=200; total time=  45.5s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=4,
regressor__n_estimators=100; total time=  21.6s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=4,
regressor__n_estimators=100; total time=  20.3s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=4,
regressor__n_estimators=100; total time=  21.6s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=4,
regressor__n_estimators=200; total time=  41.7s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=4,
regressor__n_estimators=200; total time=  44.8s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=4,
regressor__n_estimators=200; total time=  45.4s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=4,
```

```
regressor__n_estimators=200; total time=  42.2s
[CV] END regressor__max_depth=20, regressor__min_samples_leaf=4,
regressor__n_estimators=200; total time=  35.8s
Best parameters found: {'regressor__max_depth': 20,
'regressor__min_samples_leaf': 4, 'regressor__n_estimators': 200}
```

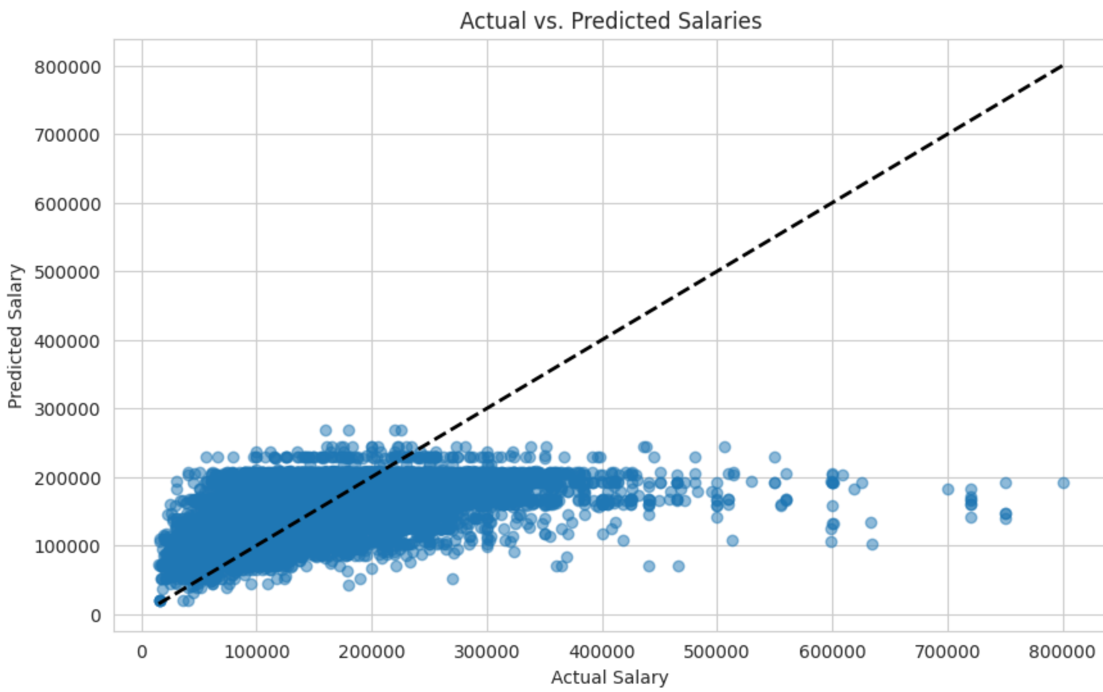
1.5.2 Model Evaluation

[11]:
```python
y_pred = best_model.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

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

plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.plot([y.min(), y.max()], [y.min(), y.max()], 'k--', lw=2)
plt.xlabel('Actual Salary')
plt.ylabel('Predicted Salary')
plt.title('Actual vs. Predicted Salaries')
plt.show()
```

```
Root Mean Squared Error (RMSE): $67,995.63
R-squared (R2) Score: 0.24
```



1.6 6. Conclusion

This analysis provides a comprehensive overview of data science salaries. Key findings include: - Salaries have been steadily increasing from 2020 to 2025. - Experience level is a major factor in determining salary, with Executive-level professionals earning significantly more. - The United States is the highest-paying country for data science roles. - The 'Machine Learning' and 'Data Scientist' job families command the highest salaries.

The machine learning model can predict salaries with a reasonable R-squared value, indicating that the selected features have predictive power. Further improvements could be made by including more features, trying different models like Gradient Boosting, and gathering more data.