Factors Influencing Salaries of Data Science Roles

Data Exploration

Dataset Overview

```
import pandas as pd

salaries_data_frame = pd.read_csv("data/jobs_salaries_2023.csv")
print(salaries_data_frame.shape)
```

```
(1500, 11)
```

```
column_types = salaries_data_frame.dtypes
print(column_types)
```

```
work_year               int64
experience_level       object
employment_type        object
job_title              object
salary                float64
salary_currency        object
salary_in_usd         float64
employee_residence     object
remote_ratio            int64
company_location       object
company_size           object
dtype: object
```

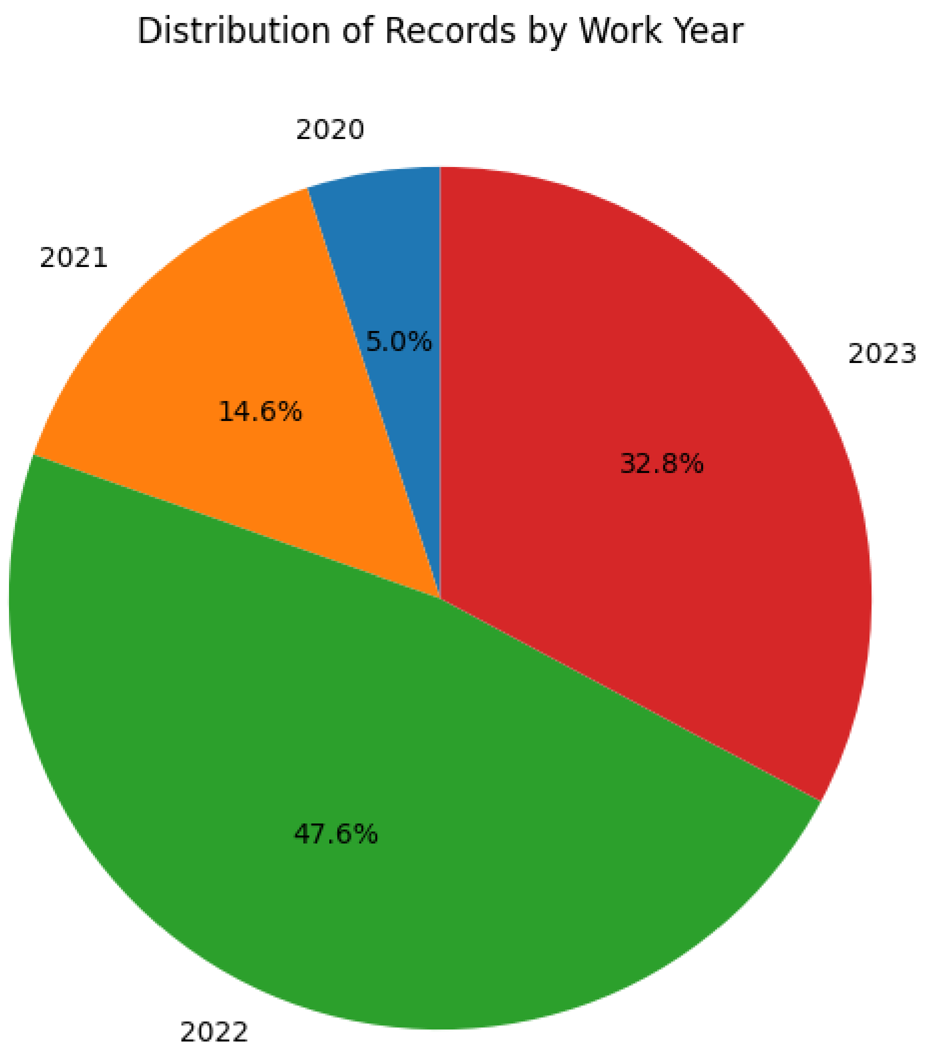
Work Year

```
import pandas as pd
import matplotlib.pyplot as plt

# Count occurrences of each work_year and sort by year
work_year_counts =
salaries_data_frame["work_year"].value_counts().sort_index()

# Calculate percentages
work_year_percent = (work_year_counts / work_year_counts.sum() *
```

```
100).round(2)

# Calculate mean and median salary per year
mean_salary = salaries_data_frame.groupby("work_year")
["salary_in_usd"].mean().round(2)
median_salary = (
    salaries_data_frame.groupby("work_year")
["salary_in_usd"].median().round(2)
)

# Combine into one DataFrame for display
result = pd.DataFrame(
    {
        "count": work_year_counts,
        "percentage": work_year_percent,
        "mean_salary": mean_salary,
        "median_salary": median_salary,
    }
)

print(result)
```

```
           count  percentage  mean_salary  median_salary
work_year
2020          75         5.0     92266.67        72000.0
2021         219        14.6     95977.39        82500.0
2022         714        47.6    129573.32       130000.0
2023         492        32.8    154600.18       148500.0
```

```
# --- Pie Chart ---
plt.figure(figsize=(7, 7))
plt.pie(
    work_year_counts, labels=work_year_counts.index, autopct="%1.1f%%",
startangle=90
)
plt.title("Distribution of Records by Work Year")
plt.show()
```



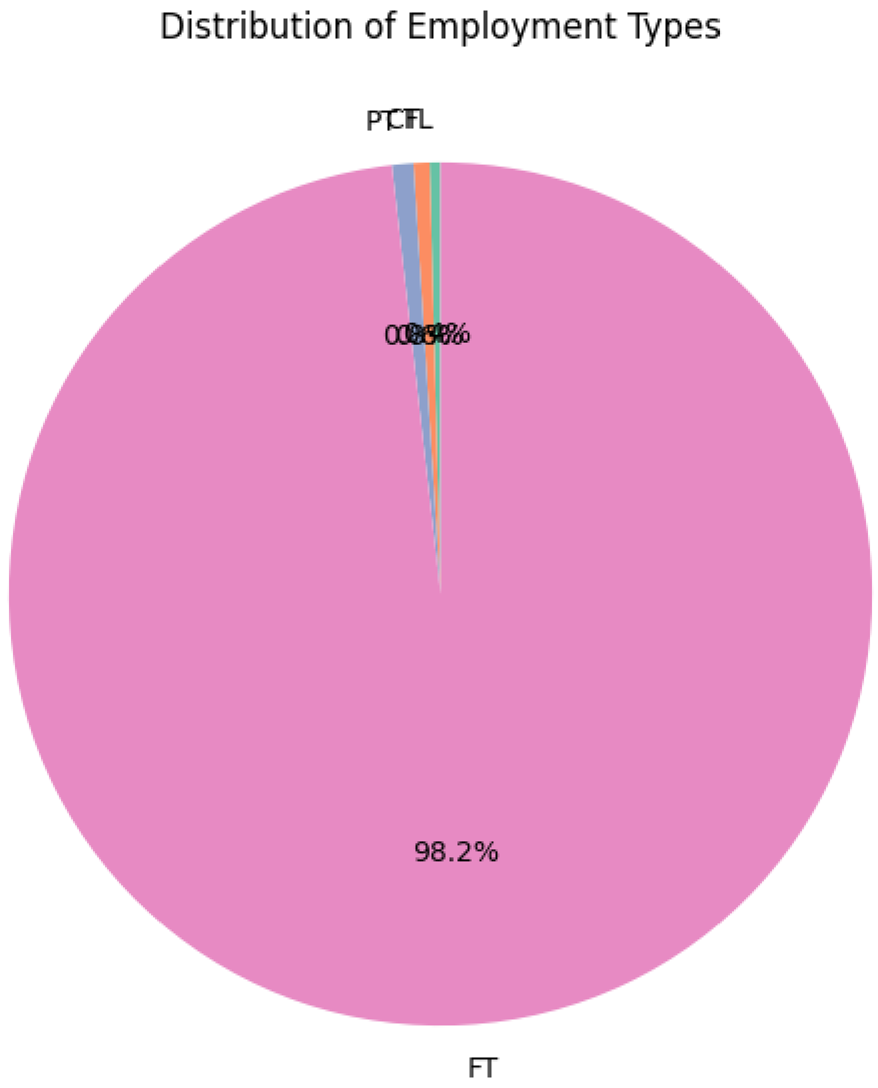
Employment Type

```
import pandas as pd

# Define custom order
order = ["FL", "CT", "PT", "FT"]

# Count occurrences of each employment_type
employment_type_counts =
salaries_data_frame["employment_type"].value_counts()

# Reorder according to the custom order
employment_type_counts = employment_type_counts.reindex(order)

# Calculate percentages
employment_type_percent = (
    employment_type_counts / employment_type_counts.sum() * 100
).round(2)

# Calculate mean and median salary per employment_type
mean_salary = (
```

```
    salaries_data_frame.groupby("employment_type")["salary_in_usd"]
    .mean()
    .round(2)
    .reindex(order)
)
median_salary = (
    salaries_data_frame.groupby("employment_type")["salary_in_usd"]
    .median()
    .round(2)
    .reindex(order)
)

# Combine into one DataFrame
result = pd.DataFrame(
    {
        "count": employment_type_counts,
        "percentage": employment_type_percent,
        "mean_salary": mean_salary,
        "median_salary": median_salary,
    }
)

print(result)
```

```
                 count  percentage  mean_salary  median_salary
employment_type
FL                   6         0.4     45420.50        40261.5
CT                   9         0.6    116052.11        60000.0
PT                  12         0.8     38112.83        20371.0
FT                1473        98.2    132134.13       130000.0
```

```
# --- Pie Chart ---
import matplotlib.pyplot as plt

plt.figure(figsize=(7, 7))
plt.pie(
    employment_type_counts,
    labels=employment_type_counts.index,
    autopct="%1.1f%%",
    startangle=90,
    colors=["#66c2a5", "#fc8d62", "#8da0cb", "#e78ac3"],
)
plt.title("Distribution of Employment Types")
plt.show()
```



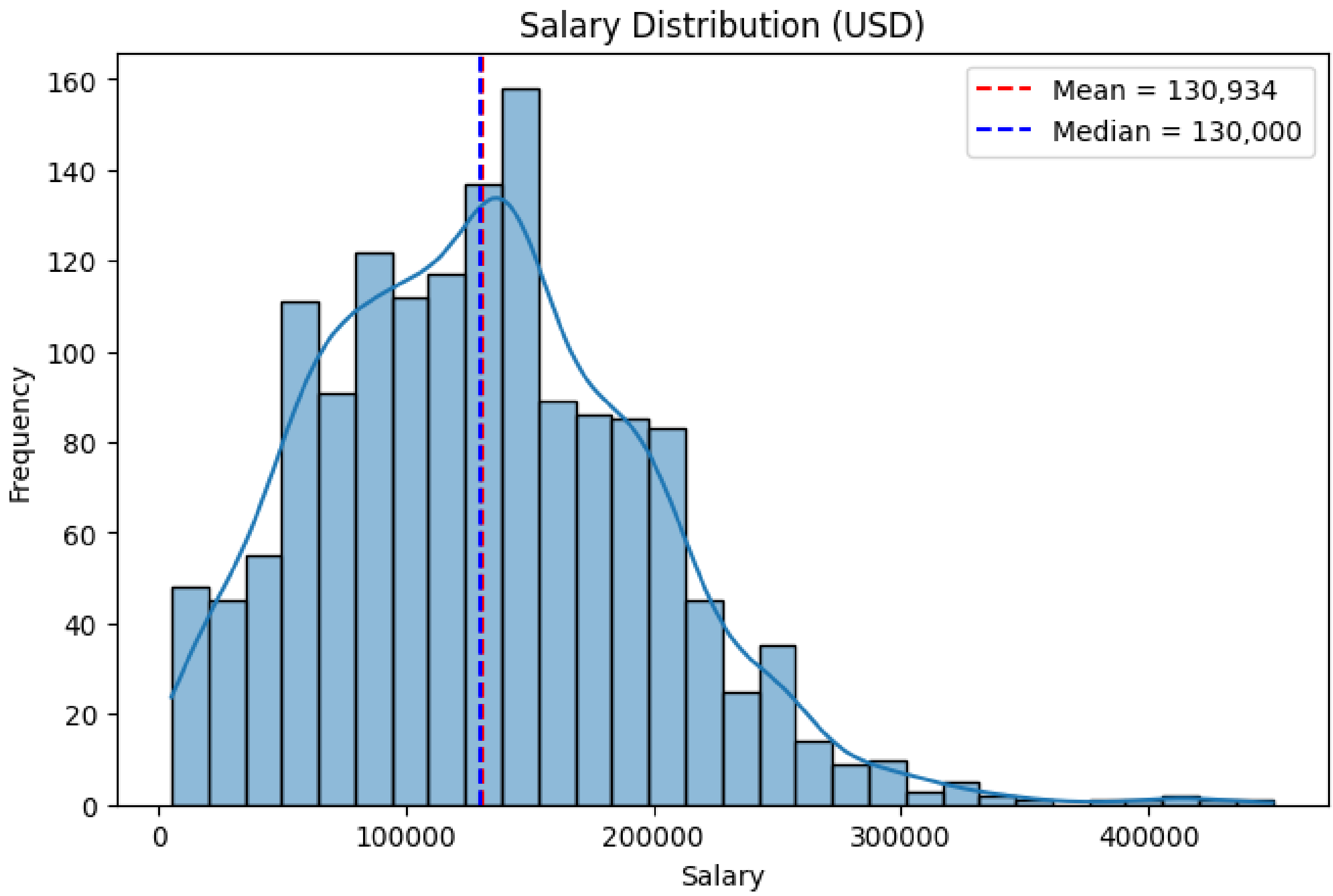
Salary

```python
import matplotlib.pyplot as plt
import seaborn as sns


salary_in_usd_series = salaries_data_frame["salary_in_usd"]


# --- 1. Descriptive statistics ---
mean_salary = salary_in_usd_series.mean()
median_salary = salary_in_usd_series.median()
min_salary = salary_in_usd_series.min()
max_salary = salary_in_usd_series.max()


print(f"Salary ranges from ${min_salary:,.0f} to ${max_salary:,.0f}")
print(f"Mean salary: ${mean_salary:,.0f}")
print(f"Median salary: ${median_salary:,.0f}")
```

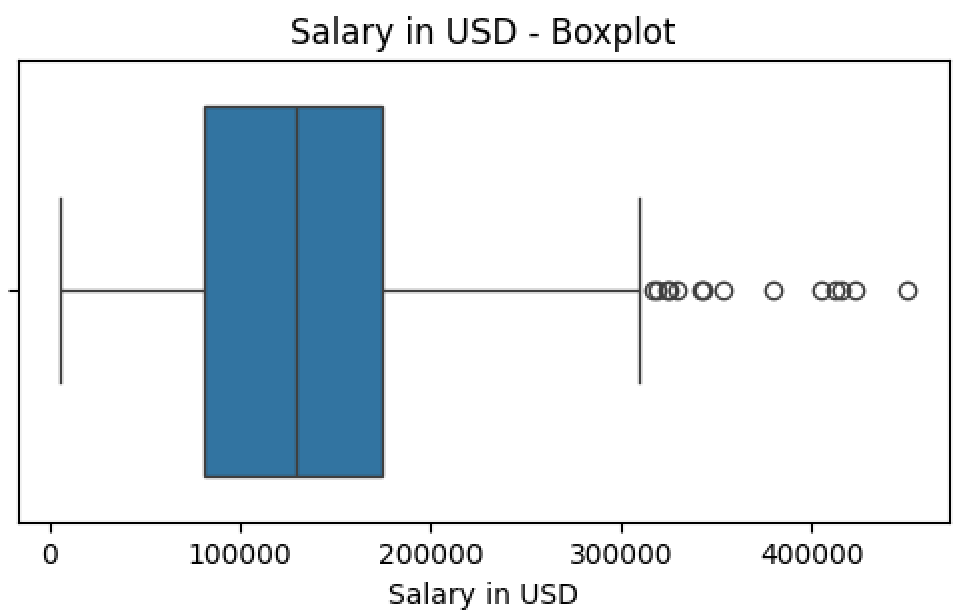
```
# Skew check
skewness = salary_in_usd_series.skew()
print(f"Skewness: {skewness:.2f}")
```

```
Salary ranges from $5,409 to $450,000
Mean salary: $130,934
Median salary: $130,000
Skewness: 0.59
```

```
# --- 2. Histogram ---
plt.figure(figsize=(8, 5))
sns.histplot(salary_in_usd_series, bins=30, kde=True)
plt.axvline(
    mean_salary, color="red", linestyle="--", label=f"Mean =
{mean_salary:,.0f}"
)
plt.axvline(
    median_salary, color="blue", linestyle="--", label=f"Median =
{median_salary:,.0f}"
)
plt.title("Salary Distribution (USD)")
plt.xlabel("Salary")
plt.ylabel("Frequency")
plt.legend()
plt.show()
```




```
# --- 3. Boxplot (to reveal outliers) ---
plt.figure(figsize=(6, 3))
sns.boxplot(x=salary_in_usd_series)
plt.title("Salary in USD - Boxplot")
plt.xlabel("Salary in USD")
plt.show()
```



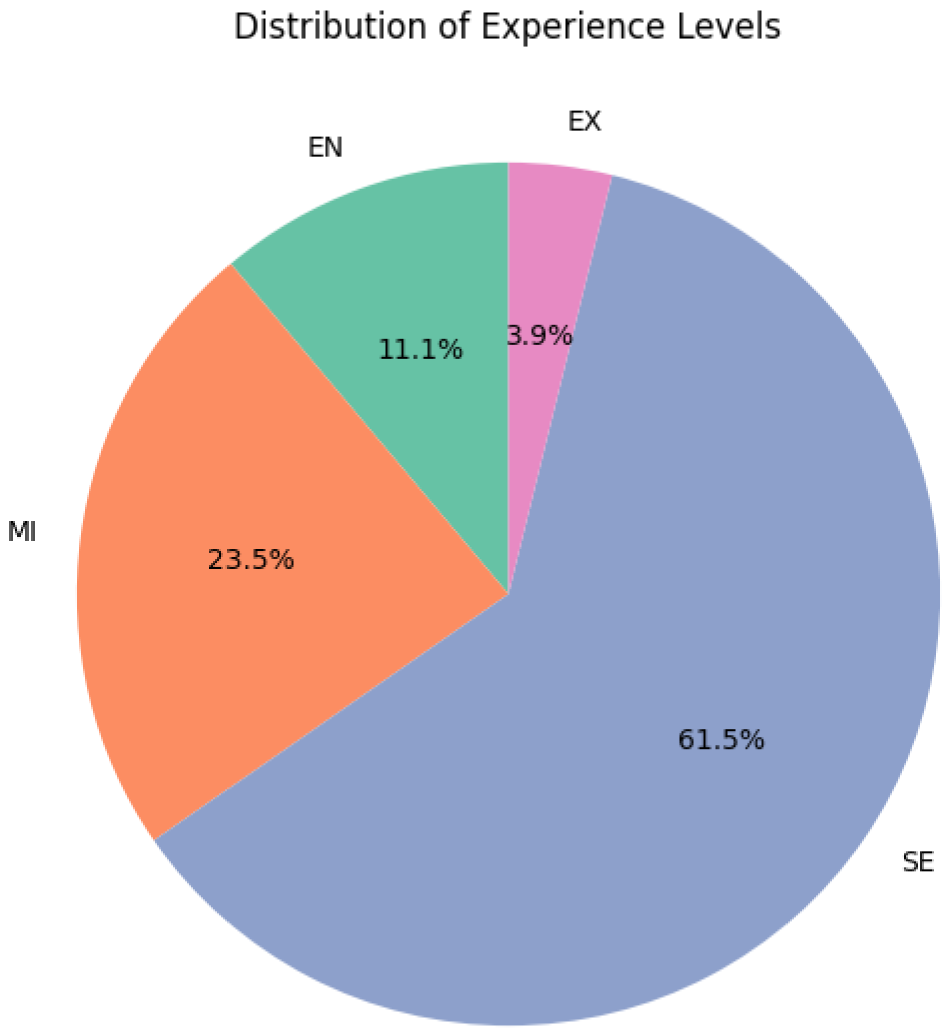
Experience Level (with Salary)

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# ========================
# Preprocessing
# ========================
experience_level_order = ["EN", "MI", "SE", "EX"]
salaries_data_frame["experience_level"] = pd.Categorical(
    salaries_data_frame["experience_level"],
    categories=experience_level_order,
    ordered=True,
)

# ========================
# Counts and Percentages
# ========================
experience_level_counts = (
    salaries_data_frame["experience_level"].value_counts().sort_index()
)
experience_level_percent = (
    experience_level_counts / experience_level_counts.sum() * 100
).round(1)

result = pd.DataFrame(
    {"count": experience_level_counts, "percentage":
experience_level_percent}
)

# ========================
# Mean and Median Salaries
# ========================
summary_table = (
    salaries_data_frame.groupby("experience_level")["salary_in_usd"]
    .agg(Mean="mean", Median="median")
    .round(0)
)

# ========================
# Combine Tables
# ========================
combined_table = result.join(summary_table)
print("Experience Level Summary:")
print(combined_table)
```

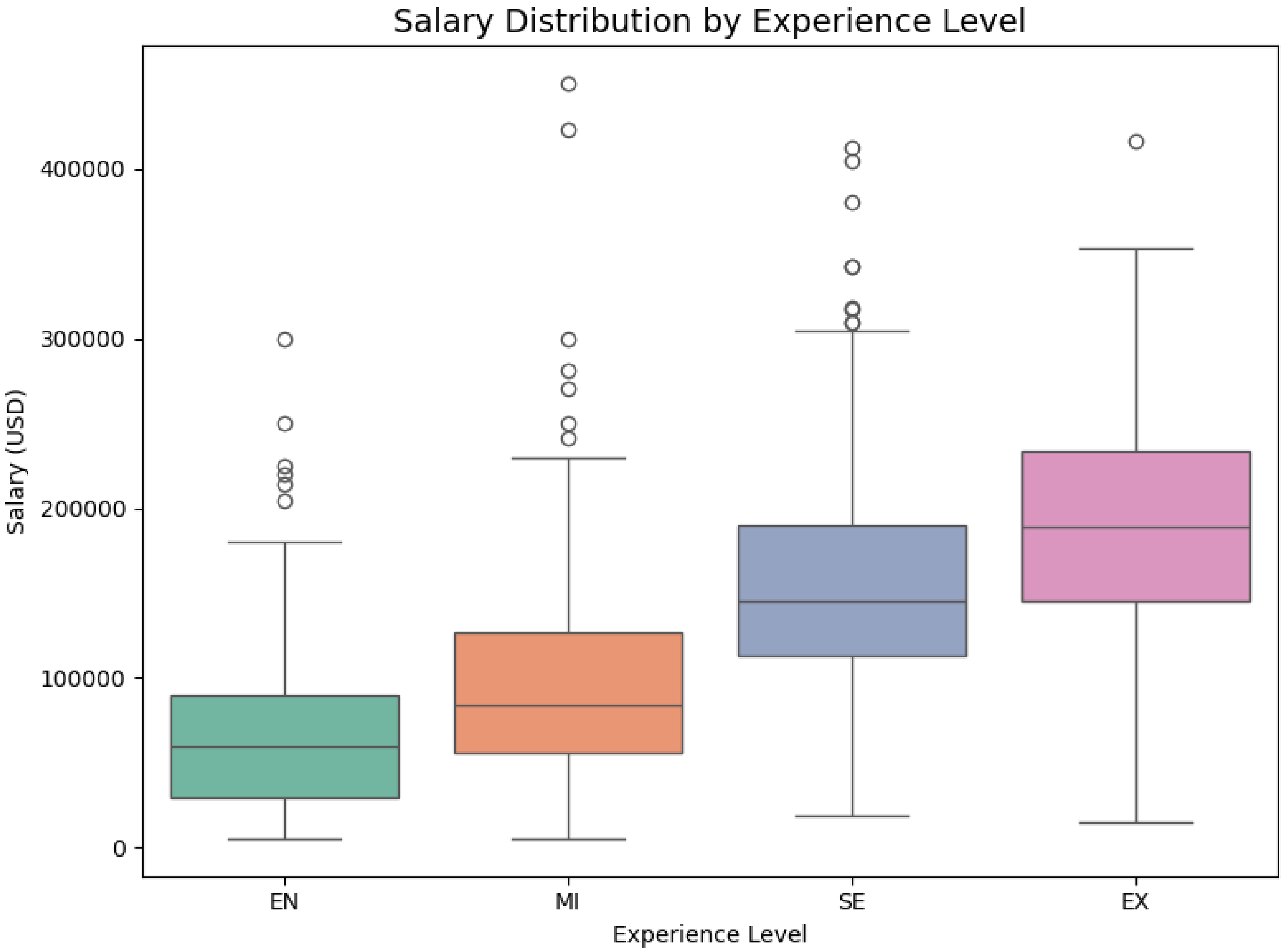
```
Experience Level Summary:
                  count  percentage     Mean   Median
experience_level
EN                  167        11.1  69627.0  60000.0
MI                  353        23.5  95473.0  84053.0
```

```
SE                        922          61.5  151640.0  145000.0
EX                         58           3.9  192463.0  188518.0


/var/folders/jh/z981c7zj0vz0gmyfc8mhdxdr0000gn/T/ipykernel_6856/674642401.
py:33: FutureWarning: The default of observed=False is deprecated and will
be changed to True in a future version of pandas. Pass observed=False to
retain current behavior or observed=True to adopt the future default and
silence this warning.
  salaries_data_frame.groupby("experience_level")["salary_in_usd"]
```

```
# ========================
# Pie Chart
# ========================
plt.figure(figsize=(7, 7))
plt.pie(
    experience_level_counts,
    labels=experience_level_counts.index,
    autopct="%1.1f%%",
    startangle=90,
    colors=["#66c2a5", "#fc8d62", "#8da0cb", "#e78ac3"],
)
plt.title("Distribution of Experience Levels")
plt.show()
```




```python
# ========================
# Boxplot
# ========================
plt.figure(figsize=(8, 6))
sns.boxplot(
    data=salaries_data_frame,
    x="experience_level",
    y="salary_in_usd",
    order=experience_level_order,
    palette="Set2",
    hue="experience_level",
    legend=False,
)
plt.title("Salary Distribution by Experience Level", fontsize=14)
plt.ylabel("Salary (USD)")
plt.xlabel("Experience Level")
plt.tight_layout()
plt.show()
```



Job Title (with Salary)

```
import pandas as pd

# ========================
# Job title counts & percentages
# ========================
job_counts = salaries_data_frame["job_title"].value_counts()
total_jobs = job_counts.sum()

# DataFrame with count and percentage
all_job_titles = job_counts.to_frame("count").reset_index()
all_job_titles.columns = ["job_title", "count"]
all_job_titles["percentage"] = (all_job_titles["count"] / total_jobs * 
100).round(2)

# Add accumulated count and percentage
all_job_titles["accumulated_count"] = all_job_titles["count"].cumsum()
all_job_titles["accumulated_percentage"] = (
    all_job_titles["accumulated_count"] / total_jobs * 100
).round(2)

# ========================
# Mean and median salary
```

```
# ========================
salary_summary = (
    salaries_data_frame.groupby("job_title")["salary_in_usd"]
    .agg(Mean="mean", Median="median")
    .round(0)
    .reset_index()
)

# ========================
# Combine tables
# ========================
all_job_titles = all_job_titles.merge(salary_summary, on="job_title",
how="left")

# Print summary
print(f"Number of unique job titles: {len(all_job_titles)}")
print("\nAll job titles with accumulation, mean & median salary:")
print(all_job_titles.to_string(index=False, line_width=10000))
```

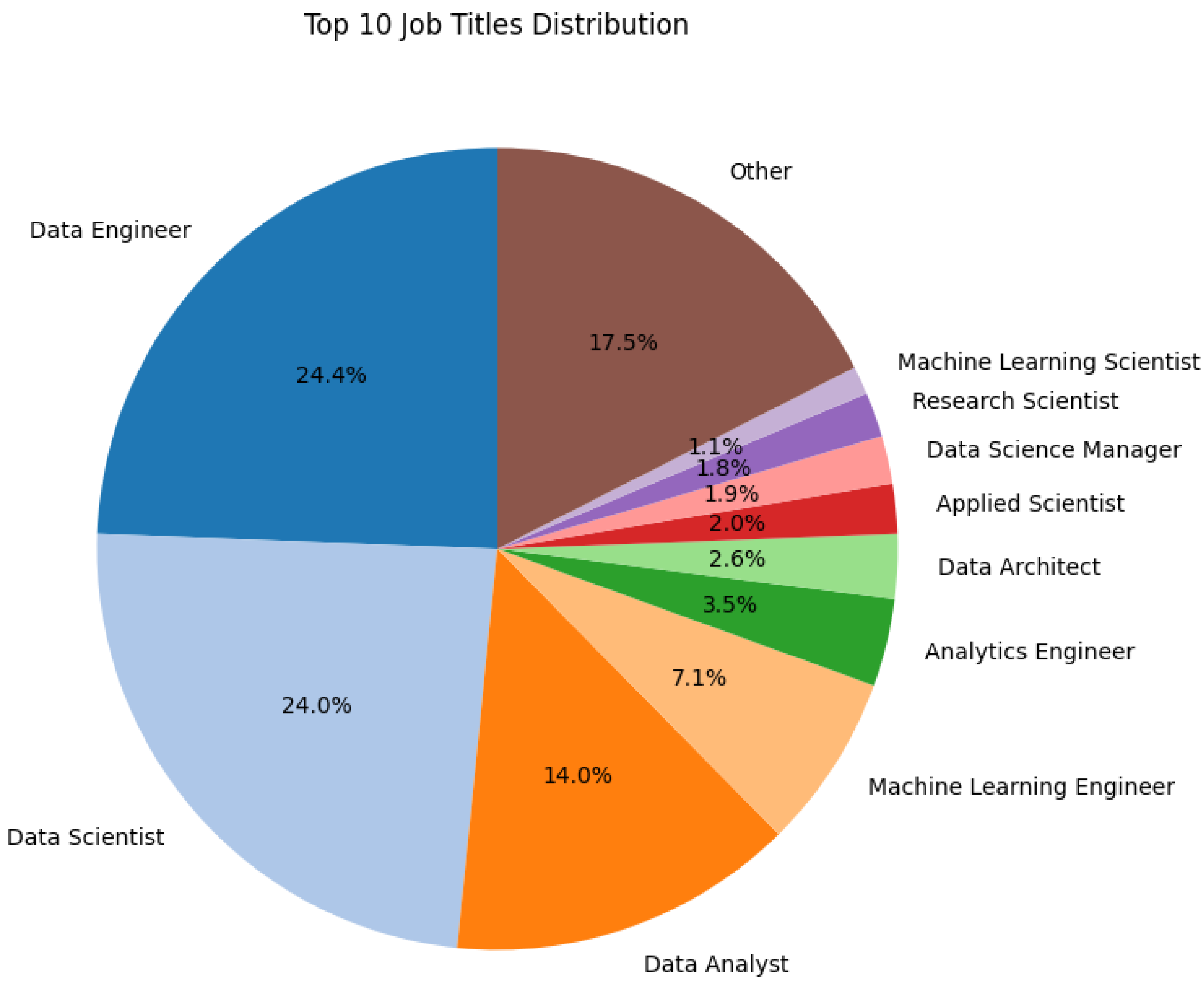
```
Number of unique job titles: 69

All job titles with accumulation, mean & median salary:
                               job_title  count  percentage
accumulated_count  accumulated_percentage     Mean    Median
                           Data Engineer    366       24.40
366                      24.40 131523.0 130000.0
                          Data Scientist    360       24.00
726                      48.40 135659.0 141300.0
                            Data Analyst    210       14.00
936                      62.40 100195.0 100000.0
               Machine Learning Engineer    106        7.07
1042                      69.47 145421.0 141942.0
                      Analytics Engineer     53        3.53
1095                      73.00 159451.0 152700.0
                          Data Architect     39        2.60
1134                      75.60 165886.0 167500.0
                       Applied Scientist     30        2.00
1164                      77.60 189030.0 184000.0
                    Data Science Manager     29        1.93
1193                      79.53 177154.0 175100.0
                      Research Scientist     27        1.80
1220                      81.33 127143.0 102772.0
              Machine Learning Scientist     17        1.13
1237                      82.47 164900.0 180000.0
                       Research Engineer     14        0.93
1251                      83.40 184365.0 179500.0
                Computer Vision Engineer     12        0.80
1263                      84.20 139076.0 147500.0
                             ML Engineer     12        0.80
1275                      85.00 114463.0  80682.0
```

```
                  Data Analytics Manager     11         0.73
1286                       85.73 133176.0 140000.0
                         BI Data Analyst     10         0.67
1296                       86.40  56665.0  51900.0
                            AI Scientist     10         0.67
1306                       87.07  89447.0  50448.0
                Director of Data Science     10         0.67
1316                       87.73 202086.0 180018.0
                   Business Data Analyst     10         0.67
1326                       88.40  80750.0  84566.0
      Applied Machine Learning Scientist      9         0.60
1335                       89.00 114501.0  75000.0
                       Big Data Engineer      9         0.60
1344                       89.60  51565.0  48289.0
                           ETL Developer      8         0.53
1352                       90.13 125192.0  93635.0
                            Data Manager      8         0.53
1360                       90.67 124000.0 117500.0
                Principal Data Scientist      8         0.53
1368                       91.20 198171.0 164630.0
                  Applied Data Scientist      8         0.53
1376                       91.73 127158.0  89178.0
                            Head of Data      7         0.47
1383                       92.20 199780.0 230000.0
                 Data Science Consultant      7         0.47
1390                       92.67  69421.0  76833.0
                         Data Specialist      7         0.47
1397                       93.13 130000.0 130000.0
                Data Operations Engineer      6         0.40
1403                       93.53  80000.0  80000.0
                            AI Developer      6         0.40
1409                       93.93 169670.0 154000.0
                      Lead Data Engineer      6         0.40
1415                       94.33 139230.0 120111.0
                     Lead Data Scientist      5         0.33
1420                       94.67  87416.0  61566.0
Machine Learning Infrastructure Engineer      5         0.33
1425                       95.00 127133.0 148800.0
              Machine Learning Developer      5         0.33
1430                       95.33  89726.0  76814.0
                    Data Quality Analyst      5         0.33
1435                       95.67  92000.0 100000.0
          Business Intelligence Engineer      4         0.27
1439                       95.93 174150.0 171150.0
       Computer Vision Software Engineer      4         0.27
1443                       96.20  83705.0  82873.0
                    Head of Data Science      4         0.27
1447                       96.47 146719.0 138938.0
                 Data Analytics Engineer      4         0.27
1451                       96.73  64799.0  64598.0
                       Lead Data Analyst      4         0.27
```

```
1455                     97.00  86152.0  77500.0
                        Product Data Analyst      3         0.20
1458                     97.20  55357.0  20000.0
                       Data Science Engineer      3         0.20
1461                     97.40  75803.0  60000.0
                     Principal Data Engineer      2         0.13
1463                     97.53 192500.0 192500.0
              Lead Machine Learning Engineer      2         0.13
1465                     97.67  89720.0  89720.0
                         Cloud Data Engineer      2         0.13
1467                     97.80 124647.0 124647.0
                      Principal Data Analyst      2         0.13
1469                     97.93 122500.0 122500.0
                                ETL Engineer      2         0.13
1471                     98.07  71394.0  71394.0
                     Data Operations Analyst      2         0.13
1473                     98.20  73500.0  73500.0
                      Financial Data Analyst      2         0.13
1475                     98.33  87500.0  87500.0
                                Data Modeler      2         0.13
1477                     98.47 118900.0 118900.0
          Machine Learning Research Engineer      2         0.13
1479                     98.60  16086.0  16086.0
                             Data Strategist      2         0.13
1481                     98.73  81000.0  81000.0
                              MLOps Engineer      2         0.13
1483                     98.87 129000.0 129000.0
                        Data DevOps Engineer      1         0.07
1484                     98.93  53654.0  53654.0
                            BI Data Engineer      1         0.07
1485                     99.00  60000.0  60000.0
                        Staff Data Scientist      1         0.07
1486                     99.07 105000.0 105000.0
                          Big Data Architect      1         0.07
1487                     99.13  99703.0  99703.0
                          Staff Data Analyst      1         0.07
1488                     99.20  15000.0  15000.0
                      Marketing Data Analyst      1         0.07
1489                     99.27  88654.0  88654.0
               3D Computer Vision Researcher      1         0.07
1490                     99.33   5409.0   5409.0
                 Machine Learning Researcher      1         0.07
1491                     99.40  50000.0  50000.0
                    Machine Learning Manager      1         0.07
1492                     99.47 117104.0 117104.0
           Applied Machine Learning Engineer      1         0.07
1493                     99.53  69751.0  69751.0
                         Data Analytics Lead      1         0.07
1494                     99.60 405000.0 405000.0
                     Compliance Data Analyst      1         0.07
1495                     99.67  30000.0  30000.0
```

```
                  Data Analytics Consultant      1         0.07
1496                       99.73 113000.0 113000.0
                   Head of Machine Learning      1         0.07
1497                       99.80  76309.0  76309.0
                               NLP Engineer      1         0.07
1498                       99.87  60000.0  60000.0
                       Cloud Data Architect      1         0.07
1499                       99.93 250000.0 250000.0
                       Finance Data Analyst      1         0.07
1500                      100.00  61896.0  61896.0
```

```
import matplotlib.pyplot as plt
import pandas as pd

# Count all job titles and calculate percentages
job_counts = salaries_data_frame["job_title"].value_counts()
total_jobs = job_counts.sum()

# Keep top 10 job titles and group the rest as 'Other'
top_n = 10
top_jobs = job_counts.head(top_n)
other_count = total_jobs - top_jobs.sum()

# Use pd.concat to combine top jobs and 'Other'
job_counts_for_pie = pd.concat([top_jobs, pd.Series({"Other":
other_count})])

# Pie Chart
plt.figure(figsize=(8, 8))
plt.pie(
    job_counts_for_pie,
    labels=job_counts_for_pie.index,
    autopct="%1.1f%%",
    startangle=90,
    colors=plt.cm.tab20.colors  # color map for slices
)
plt.title(f"Top {top_n} Job Titles Distribution")
plt.show()
```



Company Location

```
import pandas as pd
import matplotlib.pyplot as plt

# ========================
# Count company locations
# ========================
location_counts = salaries_data_frame["company_location"].value_counts()
total_locations = location_counts.sum()

# Create DataFrame with count and percentage
all_locations = location_counts.to_frame("count").reset_index()
all_locations.columns = ["company_location", "count"]
all_locations["percentage"] = (all_locations["count"] / total_locations *
100).round(2)

# Add accumulated count and percentage
all_locations["accumulated_count"] = all_locations["count"].cumsum()
all_locations["accumulated_percentage"] = (
```

```
    all_locations["accumulated_count"] / total_locations * 100
).round(2)

# ========================
# Mean and Median Salaries
# ========================
salary_summary = (
    salaries_data_frame.groupby("company_location")["salary_in_usd"]
    .agg(Mean="mean", Median="median")
    .round(0)
    .reset_index()
)

# Merge with main table
all_locations = all_locations.merge(salary_summary, on="company_location",
how="left")

# ========================
# Print summary
# ========================
print(f"Number of unique company locations: {len(all_locations)}")
```

```
Number of unique company locations: 58
```

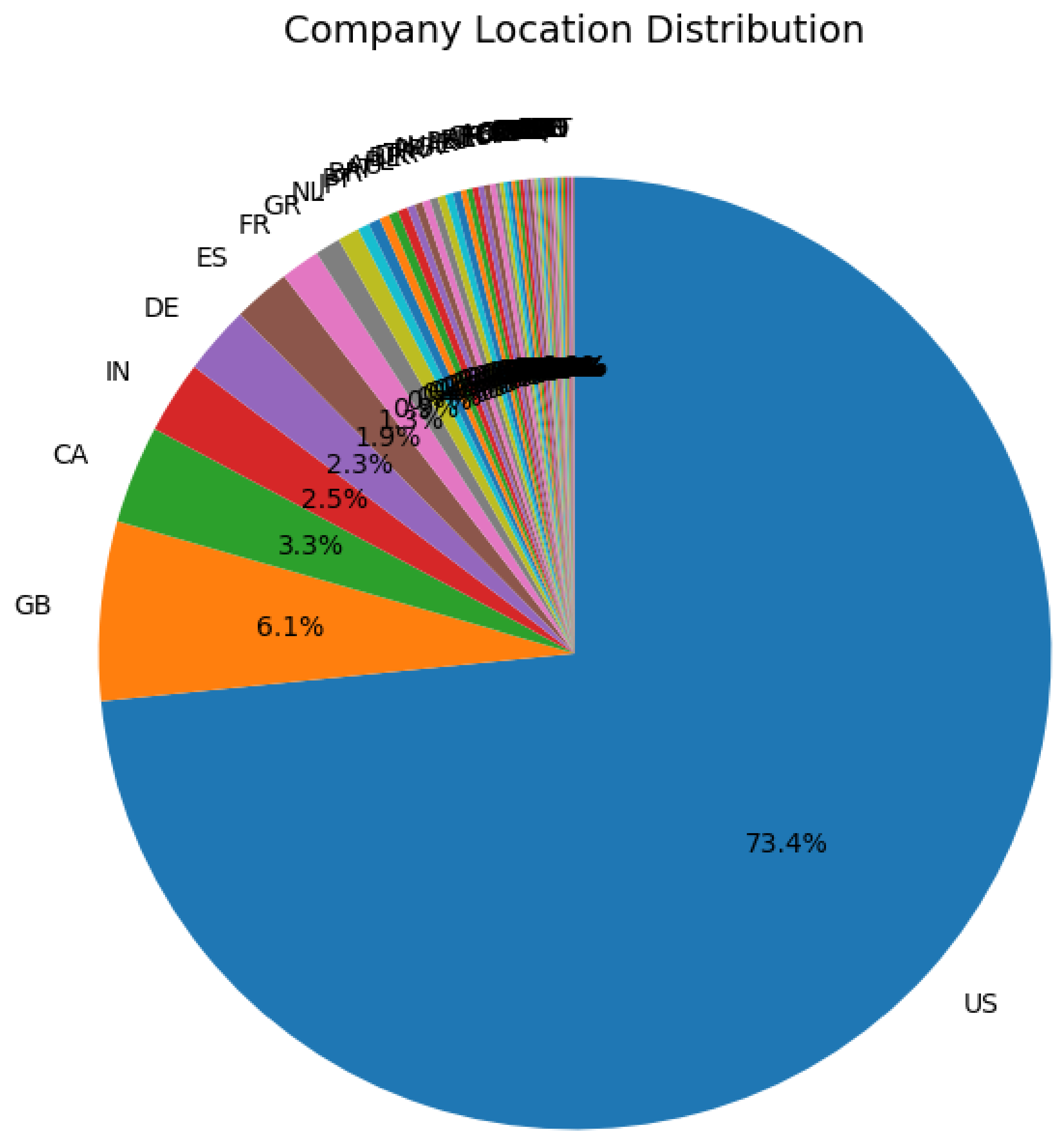
```
pd.set_option("display.max_rows", None)  # Show all rows in output
print("\nAll company locations with salary stats:")
print(all_locations.to_string(index=False, line_width=10000))
```

```
All company locations with salary stats:
company_location  count  percentage  accumulated_count
accumulated_percentage     Mean   Median
              US   1101       73.40               1101
73.40 152070.0 145000.0
              GB     91        6.07               1192
79.47  83555.0  80036.0
              CA     50        3.33               1242
82.80 117373.0  97908.0
              IN     37        2.47               1279
85.27  33720.0  20670.0
              DE     35        2.33               1314
87.60  86249.0  76833.0
              ES     29        1.93               1343
89.53  50044.0  47282.0
              FR     20        1.33               1363
90.87  61112.0  55196.0
              GR     13        0.87               1376
```

```
91.73  54786.0  52533.0
              NL     11         0.73                 1387
92.47  71873.0  69741.0
              JP      6         0.40                 1393
92.87 114127.0  75682.0
              PT      6         0.40                 1399
93.27  40065.0  40062.0
              BR      5         0.33                 1404
93.60  13975.0  12901.0
              AT      5         0.33                 1409
93.93  67765.0  61989.0
              AU      5         0.33                 1414
94.27 100834.0  83864.0
              PL      4         0.27                 1418
94.53  65587.0  40103.0
              BE      4         0.27                 1422
94.80  76865.0  83398.0
              DK      4         0.27                 1426
95.07  45558.0  37252.0
              TR      4         0.27                 1430
95.33  21322.0  22586.0
              PR      4         0.27                 1434
95.60 167500.0 167500.0
              NG      4         0.27                 1438
95.87  47500.0  40000.0
              UA      4         0.27                 1442
96.13  57850.0  55000.0
              IE      3         0.20                 1445
96.33 117764.0 113750.0
              PK      3         0.20                 1448
96.53  13333.0  12000.0
              FI      3         0.20                 1451
96.73  68793.0  68318.0
              LU      3         0.20                 1454
96.93  43943.0  59102.0
              AE      3         0.20                 1457
97.13 100000.0 115000.0
              CH      3         0.20                 1460
97.33  60940.0  56536.0
              IT      2         0.13                 1462
97.47  36366.0  36366.0
              RU      2         0.13                 1464
97.60 157500.0 157500.0
              SI      2         0.13                 1466
97.73  63831.0  63831.0
              MX      2         0.13                 1468
97.87  46756.0  46756.0
              CF      2         0.13                 1470
98.00  48609.0  48609.0
              CZ      2         0.13                 1472
98.13  50234.0  50234.0
```

```
              SG      2         0.13                 1474
98.27  77276.0  77276.0
              ID      2         0.13                 1476
98.40  34208.0  34208.0
              AS      2         0.13                 1478
98.53  34026.0  34026.0
              CO      1         0.07                 1479
98.60  21844.0  21844.0
              HU      1         0.07                 1480
98.67  35735.0  35735.0
              KE      1         0.07                 1481
98.73   9272.0   9272.0
              TH      1         0.07                 1482
98.80  15000.0  15000.0
              NZ      1         0.07                 1483
98.87 125000.0 125000.0
              CL      1         0.07                 1484
98.93  40038.0  40038.0
              MD      1         0.07                 1485
99.00  18000.0  18000.0
              HR      1         0.07                 1486
99.07  45618.0  45618.0
              IL      1         0.07                 1487
99.13 119059.0 119059.0
              CN      1         0.07                 1488
99.20 100000.0 100000.0
              EE      1         0.07                 1489
99.27  31520.0  31520.0
              IQ      1         0.07                 1490
99.33 100000.0 100000.0
              RO      1         0.07                 1491
99.40  60000.0  60000.0
              DZ      1         0.07                 1492
99.47 100000.0 100000.0
              HN      1         0.07                 1493
99.53  20000.0  20000.0
              HK      1         0.07                 1494
99.60  65062.0  65062.0
              MY      1         0.07                 1495
99.67  40000.0  40000.0
              EG      1         0.07                 1496
99.73  22800.0  22800.0
              AR      1         0.07                 1497
99.80  50000.0  50000.0
              PH      1         0.07                 1498
99.87  50000.0  50000.0
              BO      1         0.07                 1499
99.93   7500.0   7500.0
              MT      1         0.07                 1500
100.00  28369.0  28369.0
```

```python
# ========================
# Pie Chart
# ========================
plt.figure(figsize=(8, 8))
plt.pie(
    all_locations["count"],
    labels=all_locations["company_location"],  # now from column
    autopct="%1.1f%%",
    startangle=90,
    counterclock=False,
)
plt.title("Company Location Distribution", fontsize=14)
plt.show()
```



Employee Residence

```python
import pandas as pd
import matplotlib.pyplot as plt

# ========================
# Count company locations
# ========================
location_counts = salaries_data_frame["employee_residence"].value_counts()
total_locations = location_counts.sum()

# Create DataFrame with count and percentage
all_locations = location_counts.to_frame("count").reset_index()
all_locations.columns = ["employee_residence", "count"]
all_locations["percentage"] = (all_locations["count"] / total_locations * 
100).round(2)

# Add accumulated count and percentage
all_locations["accumulated_count"] = all_locations["count"].cumsum()
all_locations["accumulated_percentage"] = (
    all_locations["accumulated_count"] / total_locations * 100
).round(2)

# ========================
# Mean and Median Salaries
# ========================
salary_summary = (
    salaries_data_frame.groupby("employee_residence")["salary_in_usd"]
    .agg(Mean="mean", Median="median")
    .round(0)
    .reset_index()
)

# Merge with main table
all_locations = all_locations.merge(salary_summary, 
on="employee_residence", how="left")

# ========================
# Print summary
# ========================
print(f"Number of unique company locations: {len(all_locations)}")
```

```
Number of unique company locations: 61
```

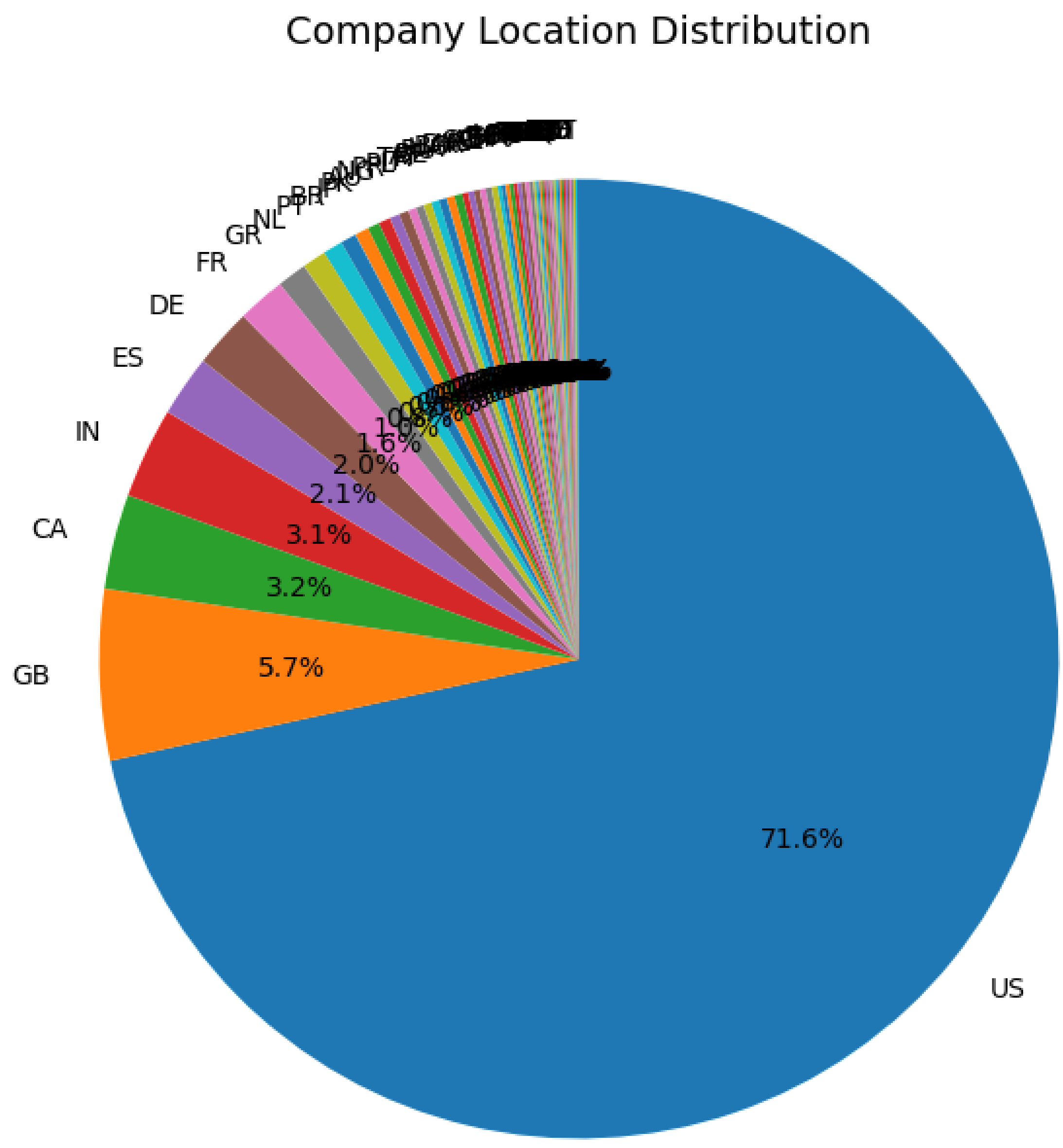
```python
pd.set_option("display.max_rows", None)  # Show all rows in output
print("\nAll company locations with salary stats:")
print(all_locations.to_string(index=False, line_width=10000))
```

```
All company locations with salary stats:
employee_residence  count  percentage  accumulated_count
accumulated_percentage     Mean   Median
                US   1074       71.60               1074
71.60 153964.0 145000.0
                GB     86        5.73               1160
77.33  83552.0  80036.0
                CA     48        3.20               1208
80.53 118217.0  99852.0
                IN     46        3.07               1254
83.60  41481.0  22124.0
                ES     31        2.07               1285
85.67  58777.0  48289.0
                DE     30        2.00               1315
87.67  91712.0  78015.0
                FR     24        1.60               1339
89.27  54593.0  55196.0
                GR     15        1.00               1354
90.27  57953.0  52533.0
                NL     12        0.80               1366
91.07  72966.0  71644.0
                PT     10        0.67               1376
91.73  48791.0  40850.0
                BR      8        0.53               1384
92.27  42735.0  15904.0
                JP      7        0.47               1391
92.73 103538.0  74000.0
                PK      6        0.40               1397
93.13  27036.0  16000.0
                AU      6        0.40               1403
93.53  95414.0  83518.0
                NG      5        0.33               1408
93.87  41000.0  30000.0
                PR      5        0.33               1413
94.20 166000.0 160000.0
                PL      4        0.27               1417
94.47  55682.0  40103.0
                IT      4        0.27               1421
94.73  61600.0  36366.0
                TR      4        0.27               1425
95.00  21322.0  22586.0
                AT      4        0.27               1429
95.27  69339.0  68060.0
                BE      4        0.27               1433
95.53  76865.0  83398.0
                RU      4        0.27               1437
95.80 105750.0  72500.0
                UA      4        0.27               1441
96.07  57850.0  55000.0
                BO      3        0.20               1444
```

```
96.27  52500.0  75000.0
                DK      3        0.20               1447
96.47  31193.0  28609.0
                AR      3        0.20               1450
96.67  52667.0  50000.0
                IE      3        0.20               1453
96.87 117764.0 113750.0
                SG      3        0.20               1456
97.07  91203.0  89294.0
                AE      3        0.20               1459
97.27 100000.0 115000.0
                SI      2        0.13               1461
97.40  63831.0  63831.0
                CH      2        0.13               1463
97.53  88469.0  88469.0
                CF      2        0.13               1465
97.67  48609.0  48609.0
                RO      2        0.13               1467
97.80  51419.0  51419.0
                HK      2        0.13               1469
97.93  65542.0  65542.0
                VN      2        0.13               1471
98.07  44200.0  44200.0
                FI      2        0.13               1473
98.20  69030.0  69030.0
                PH      2        0.13               1475
98.33  47880.0  47880.0
                HU      2        0.13               1477
98.47  35997.0  35997.0
                RS      1        0.07               1478
98.53  25532.0  25532.0
                JE      1        0.07               1479
98.60 100000.0 100000.0
                KE      1        0.07               1480
98.67   9272.0   9272.0
                LU      1        0.07               1481
98.73  59102.0  59102.0
                CO      1        0.07               1482
98.80  21844.0  21844.0
                NZ      1        0.07               1483
98.87 125000.0 125000.0
                CL      1        0.07               1484
98.93  40038.0  40038.0
                MD      1        0.07               1485
99.00  18000.0  18000.0
                HR      1        0.07               1486
99.07  45618.0  45618.0
                MX      1        0.07               1487
99.13  33511.0  33511.0
                EG      1        0.07               1488
99.20  22800.0  22800.0
```

```
                BG      1        0.07                  1489
99.27  80000.0  80000.0
                IQ      1        0.07                  1490
99.33 100000.0 100000.0
                DZ      1        0.07                  1491
99.40 100000.0 100000.0
                CZ      1        0.07                  1492
99.47  69999.0  69999.0
                TN      1        0.07                  1493
99.53  30469.0  30469.0
                HN      1        0.07                  1494
99.60  20000.0  20000.0
                EE      1        0.07                  1495
99.67  31520.0  31520.0
                MY      1        0.07                  1496
99.73 200000.0 200000.0
                ID      1        0.07                  1497
99.80  15000.0  15000.0
                DO      1        0.07                  1498
99.87 110000.0 110000.0
                TH      1        0.07                  1499
99.93  15000.0  15000.0
                MT      1        0.07                  1500
100.00  28369.0  28369.0
```

```
# ========================
# Pie Chart
# ========================
plt.figure(figsize=(8, 8))
plt.pie(
    all_locations["count"],
    labels=all_locations["employee_residence"],  # now from column
    autopct="%1.1f%%",
    startangle=90,
    counterclock=False,
)
plt.title("Company Location Distribution", fontsize=14)
plt.show()
```



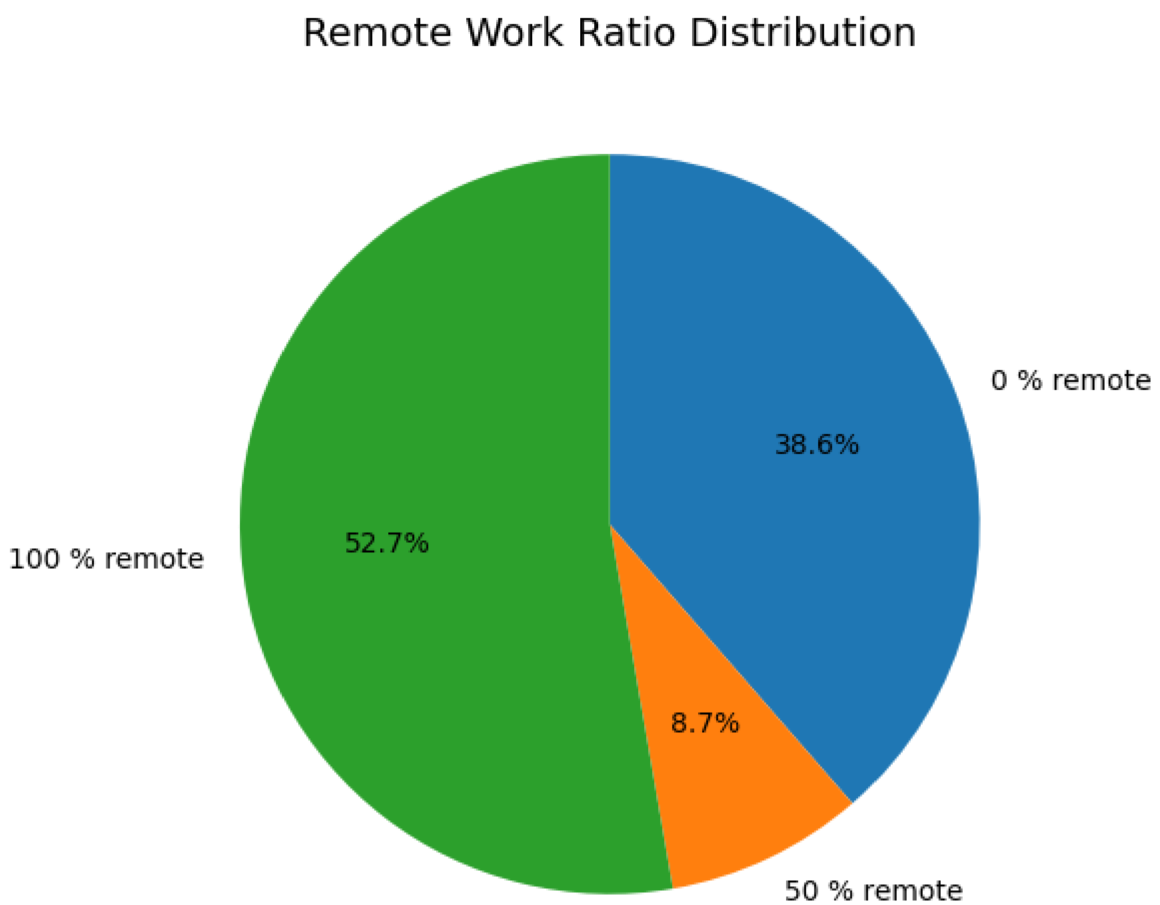
Remote Ratio (with Salary)

```
import pandas as pd
import matplotlib.pyplot as plt

# ========================
# Define custom order
# ========================
order = [0, 50, 100]

# Count occurrences of each remote_ratio
remote_ratio_counts = salaries_data_frame["remote_ratio"].value_counts()

# Reorder according to the custom order
remote_ratio_counts = remote_ratio_counts.reindex(order)
```

```
# Calculate percentages
remote_ratio_percent = (remote_ratio_counts / remote_ratio_counts.sum() *
100).round(2)

# ========================
# Mean and Median Salaries
# ========================
salary_summary = (
    salaries_data_frame.groupby("remote_ratio")["salary_in_usd"]
    .agg(Mean="mean", Median="median")
    .round(0)
    .reindex(order)
)

# ========================
# Combine into one DataFrame
# ========================
result = pd.DataFrame(
    {
        "count": remote_ratio_counts,
        "percentage": remote_ratio_percent,
        "Mean": salary_summary["Mean"],
        "Median": salary_summary["Median"],
    }
)

print("Remote Work Ratio Summary:")
print(result)
```

```
Remote Work Ratio Summary:
              count  percentage      Mean    Median
remote_ratio
0               579       38.60  143867.0  139430.0
50              130        8.67   81360.0   65135.0
100             791       52.73  129658.0  131050.0
```

```
# ========================
# Draw Pie Chart
# ========================
plt.figure(figsize=(6, 6))
plt.pie(
    result["count"],
    labels=result.index.astype(str) + " % remote",
    autopct="%1.1f%%",
    startangle=90,
    counterclock=False,
)
plt.title("Remote Work Ratio Distribution", fontsize=14)
plt.show()
```



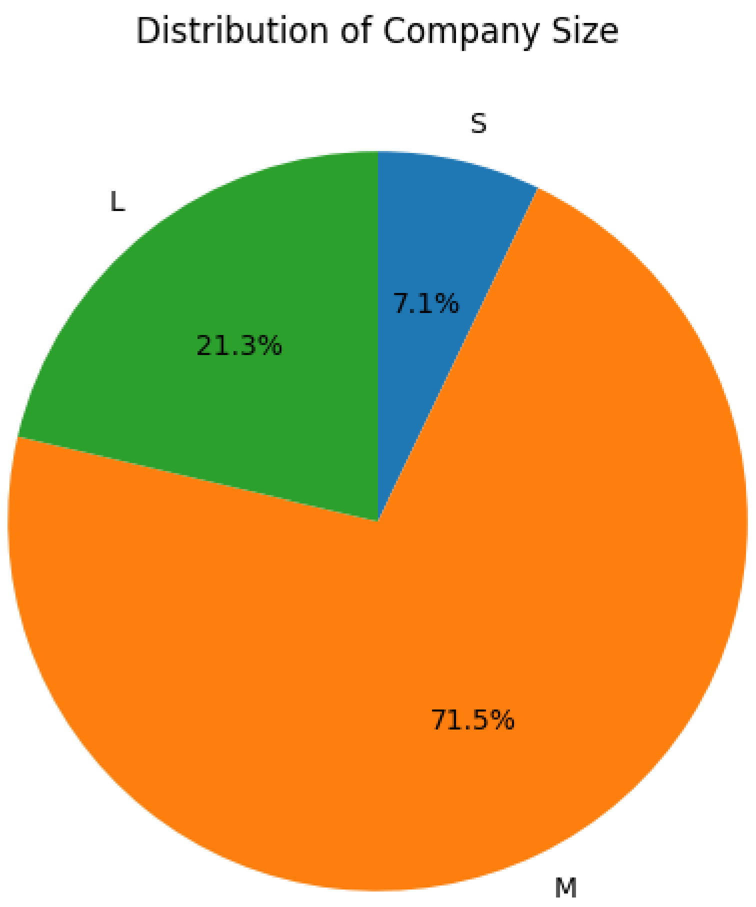
Company Size (with Salary)

```
import pandas as pd
import matplotlib.pyplot as plt

# ========================
# Define custom order
# ========================
order = ["S", "M", "L"]

# Count occurrences of each company_size
company_size_counts = salaries_data_frame["company_size"].value_counts()

# Reorder according to the custom order
company_size_counts = company_size_counts.reindex(order)

# Calculate percentages
company_size_percent = (company_size_counts / company_size_counts.sum() *
100).round(2)

# ========================
# Mean and Median Salaries
# ========================
```

```python
salary_summary = (
    salaries_data_frame.groupby("company_size")["salary_in_usd"]
    .agg(Mean="mean", Median="median")
    .round(0)
    .reindex(order)
)

# ========================
# Combine into one DataFrame
# ========================
result = pd.DataFrame(
    {
        "count": company_size_counts,
        "percentage": company_size_percent,
        "Mean": salary_summary["Mean"],
        "Median": salary_summary["Median"],
    }
)

print("Company Size Summary:")
print(result)
```

```
Company Size Summary:
              count  percentage      Mean    Median
company_size
S               107        7.13   77723.0   61566.0
M              1073       71.53  139114.0  137270.0
L               320       21.33  121396.0  112300.0
```

```python
# ========================
# Pie chart visualization
# ========================
plt.figure(figsize=(6, 6))
plt.pie(
    company_size_counts,
    labels=order,
    autopct="%1.1f%%",
    startangle=90,
    counterclock=False,
)
plt.title("Distribution of Company Size")
plt.show()
```



Data Preparation and Model Training

Handling Data Issues

Missing Values Issues

```
# Drop rows with any missing values
salaries_data_frame = salaries_data_frame.dropna()
salaries_data_frame.shape
```

```
(1494, 11)
```

Employment Type Filter

```
# Keep only full-time employees
salaries_data_frame =
salaries_data_frame[salaries_data_frame["employment_type"] == "FT"]  #
assuming "FT" is the code for full-time
salaries_data_frame.shape
```

```
(1467, 11)
```

Job Titles Filter

```
# ===== FILTER OUT JOB TITLES WITH FEWER THAN 100 RECORDS =====
threshold = 100
job_counts = salaries_data_frame["job_title"].value_counts()
salaries_data_frame =
salaries_data_frame[salaries_data_frame["job_title"].isin(job_counts[job_c
ounts >= threshold].index)]
salaries_data_frame.shape
```

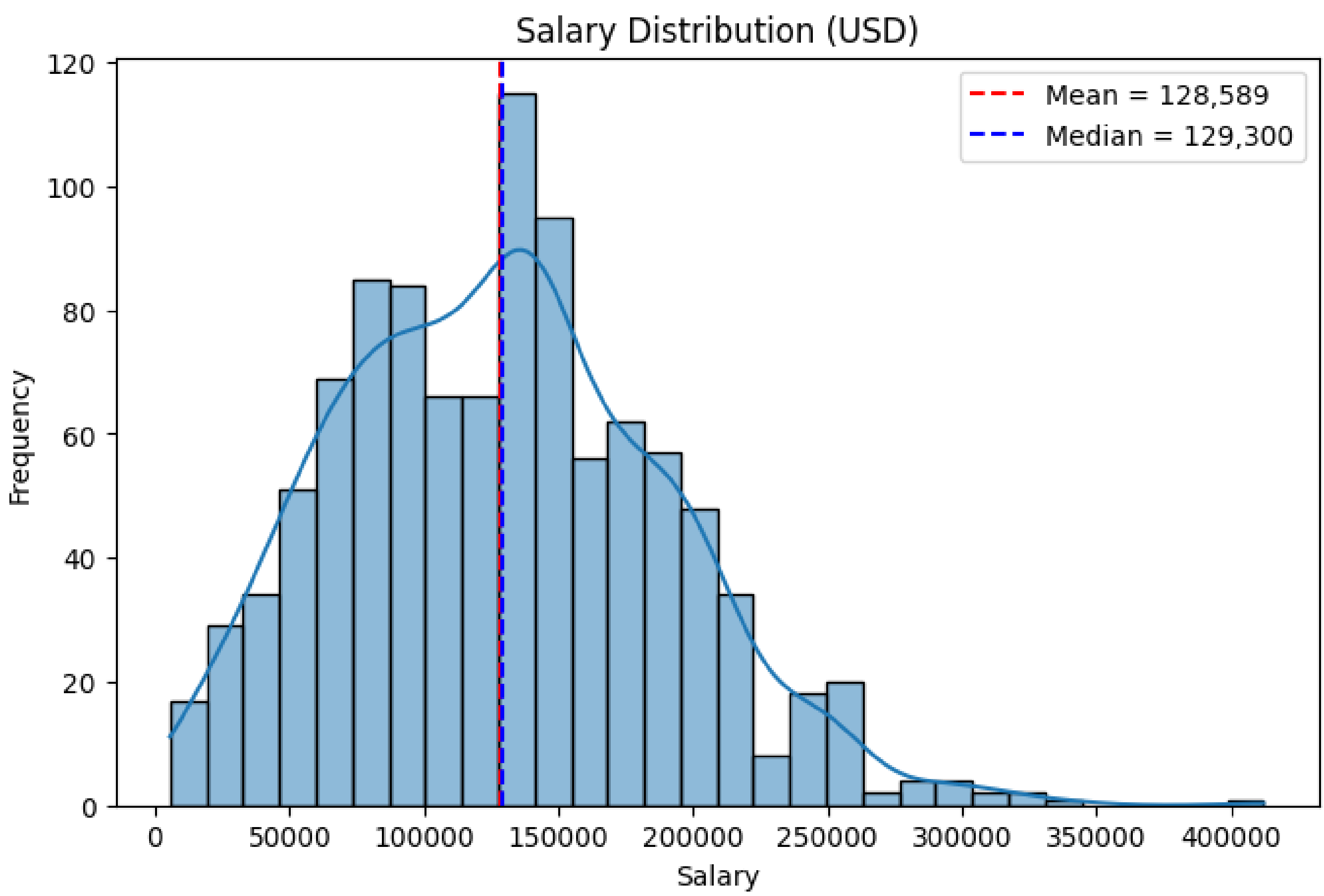
```
(1030, 11)
```

Salary Distribution after Filter

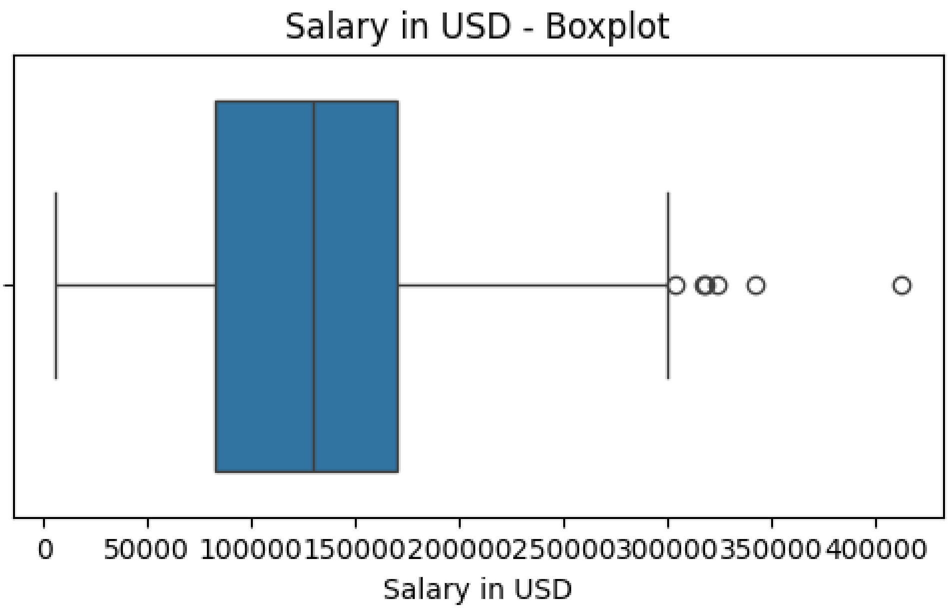
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# --- 1. Descriptive statistics ---
salary_in_usd_series = salaries_data_frame["salary_in_usd"]

mean_salary = salary_in_usd_series.mean()
median_salary = salary_in_usd_series.median()
min_salary = salary_in_usd_series.min()
max_salary = salary_in_usd_series.max()

print(f"Salary ranges from ${min_salary:,.0f} to ${max_salary:,.0f}")
print(f"Mean salary: ${mean_salary:,.0f}")
print(f"Median salary: ${median_salary:,.0f}")

# Skew check
skewness = salary_in_usd_series.skew()
print(f"Skewness: {skewness:.2f}")
```

```
Salary ranges from $5,679 to $412,000
Mean salary: $128,589
Median salary: $129,300
Skewness: 0.43
```

```
# --- 2. Histogram ---
plt.figure(figsize=(8, 5))
sns.histplot(salary_in_usd_series, bins=30, kde=True)
plt.axvline(
    mean_salary, color="red", linestyle="--", label=f"Mean =
{mean_salary:,.0f}"
)
plt.axvline(
    median_salary, color="blue", linestyle="--", label=f"Median =
{median_salary:,.0f}"
)
plt.title("Salary Distribution (USD)")
plt.xlabel("Salary")
plt.ylabel("Frequency")
plt.legend()
plt.show()
```




```
# --- 3. Boxplot (to reveal outliers) ---
plt.figure(figsize=(6, 3))
sns.boxplot(x=salary_in_usd_series)
plt.title("Salary in USD - Boxplot")
plt.xlabel("Salary in USD")
plt.show()
```




```
# --- 4. Identify outliers using IQR rule ---
Q1 = salary_in_usd_series.quantile(0.25)
Q3 = salary_in_usd_series.quantile(0.75)
IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

outliers = salaries_data_frame[
    (salaries_data_frame["salary_in_usd"] < lower_bound)
    | (salaries_data_frame["salary_in_usd"] > upper_bound)
]

print(f"\nNumber of outliers: {len(outliers)}")
print("Outlier rows:")
print(outliers.sort_values("salary_in_usd").to_string(index=False,
line_width=10000))
```

```
Number of outliers: 6
Outlier rows:
 work_year experience_level employment_type                 job_title
salary salary_currency  salary_in_usd employee_residence  remote_ratio
company_location company_size
      2023               SE              FT Machine Learning Engineer
304000.0            USD       304000.0                 US          100
US             M
      2023               SE              FT            Data Scientist
317070.0            USD       317070.0                 US            0
US             M
      2023               SE              FT Machine Learning Engineer
318300.0            USD       318300.0                 US          100
US             M
```

```
      2022                EX                FT              Data Engineer
324000.0             USD       324000.0                      US           100
US             M
      2023                SE                FT Machine Learning Engineer
342300.0             USD       342300.0                      US             0
US             L
      2020                SE                FT             Data Scientist
412000.0             USD       412000.0                      US           100
US             L
```

```
# --- 5. Remove outliers ---
print(f"\nData shape before removing outliers:
{salaries_data_frame.shape}")

salaries_data_frame = salaries_data_frame[
    (salaries_data_frame["salary_in_usd"] >= lower_bound)
    & (salaries_data_frame["salary_in_usd"] <= upper_bound)
].copy()

print(f"Data shape after removing outliers: {salaries_data_frame.shape}")
```

```
Data shape before removing outliers: (1030, 11)
Data shape after removing outliers: (1024, 11)
```

Model Training and Performance (Supervised Learning)

First Try

```
# ========================
# 1. Import libraries
# ========================
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
import matplotlib.pyplot as plt
import seaborn as sns
from xgboost import XGBRegressor
from lightgbm import LGBMRegressor
from catboost import CatBoostRegressor
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
from sklearn.metrics import root_mean_squared_error, r2_score,
mean_absolute_error
from sklearn.preprocessing import StandardScaler, OneHotEncoder
```

```
print(salaries_data_frame.shape)

# ========================
# 2. Define features & target
# ========================
categorical_cols_1 = [
    "experience_level",
    "job_title",
    "employee_residence",
    "company_location",
    "company_size",
]
numeric_cols_1 = ["work_year", "remote_ratio"]
features = categorical_cols_1 + numeric_cols_1

X_1 = salaries_data_frame[features]
X_1.shape

y_1 = salaries_data_frame["salary_in_usd"]
y_1.shape

# ========================
# 3. Split dataset
# ========================
X_train_1, X_test_1, y_train_1, y_test_1 = train_test_split(
    X_1, y_1, test_size=0.2, random_state=42
)

# ========================
# 4. Preprocess features
# ========================
preprocessor_1 = ColumnTransformer(
    transformers=[
        ("cat", OneHotEncoder(handle_unknown="ignore"),
categorical_cols_1),
        ("num", StandardScaler(), numeric_cols_1),
    ]
)

X_train_processed_1 = preprocessor_1.fit_transform(X_train_1)
X_test_processed_1 = preprocessor_1.transform(X_test_1)

# ========================
# 5. Define models_1
# ========================
models_1 = {
    "LinearRegression": LinearRegression(),
    "RandomForest": RandomForestRegressor(
        n_estimators=500,
        max_depth=10,
        min_samples_leaf=2,
        max_features="sqrt",
        random_state=42,
        n_jobs=-1,
```

```
    ),
    "GradientBoosting": GradientBoostingRegressor(
        n_estimators=500, learning_rate=0.05, max_depth=5, random_state=42
    ),
    "XGBoost": XGBRegressor(
        n_estimators=500,
        learning_rate=0.05,
        max_depth=6,
        subsample=0.8,
        colsample_bytree=0.8,
        random_state=42,
    ),
    "LightGBM": LGBMRegressor(
        n_estimators=500,
        learning_rate=0.05,
        max_depth=-1,
        num_leaves=31,
        subsample=0.8,
        colsample_bytree=0.8,
        random_state=42,
        verbose=-1,
    ),
    "CatBoost": CatBoostRegressor(
        iterations=500, learning_rate=0.05, depth=6, random_state=42,
verbose=0
    ),
}
# ========================
# 6. Train & evaluate
# ========================
results_1 = {}
true_avg_salary_1 = y_test_1.mean()  # True average salary

for name, model in models_1.items():
    model.fit(X_train_processed_1, y_train_1)
    y_pred_1 = model.predict(X_test_processed_1)

    r2_1 = r2_score(y_test_1, y_pred_1)
    mae_1 = mean_absolute_error(y_test_1, y_pred_1)
    rmse_1 = root_mean_squared_error(y_test_1, y_pred_1)
    pred_avg_salary_1 = y_pred_1.mean()  # Predicted average salary

    results_1[name] = {
        "R²": r2_1,
        "MAE": mae_1,
        "RMSE": rmse_1,
        "Predicted Avg Salary": pred_avg_salary_1,
        "True Avg Salary": true_avg_salary_1,
        "MAE % of Avg": (mae_1 / true_avg_salary_1) * 100,
        "RMSE % of Avg": (rmse_1 / true_avg_salary_1) * 100,
    }

# Convert to DataFrame for easy comparison
results_1_df = pd.DataFrame(results_1).T
```

```
results_1_df = results_1_df.sort_values(by="R²", ascending=False)

print(results_1_df.to_string(line_width=10000))
print("\nBest model based on R² (first try):", results_1_df.index[0])
```

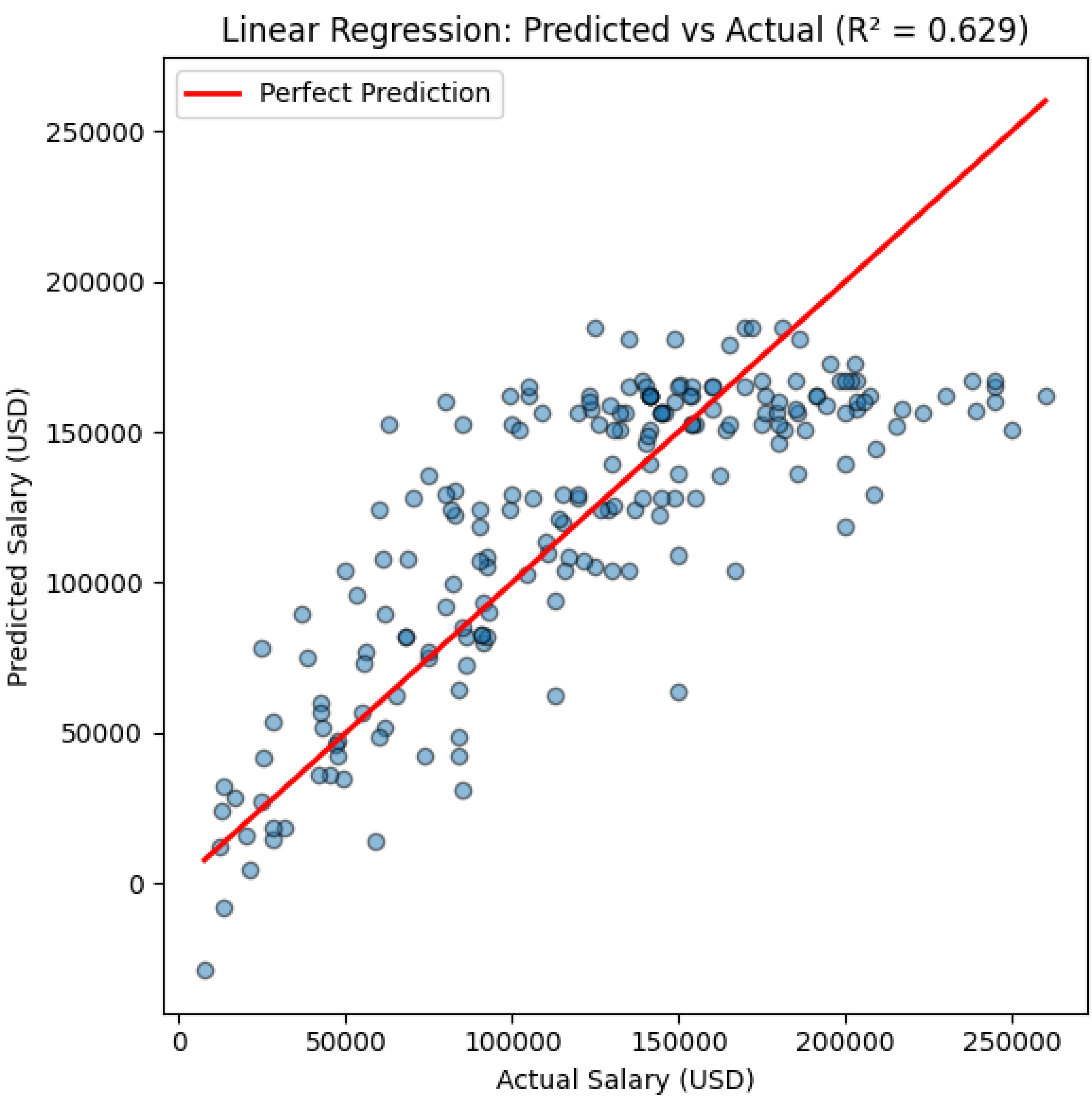
```
(1024, 11)
                        R²            MAE          RMSE  Predicted Avg
Salary  True Avg Salary  MAE % of Avg  RMSE % of Avg
LinearRegression  0.629053  27303.373122  35368.517685
120906.412330    123309.063415     22.142227      28.682821
CatBoost          0.616604  28005.258412  35957.105376
122872.555382    123309.063415     22.711436      29.160148
RandomForest      0.606062  29080.926635  36448.131228
124015.973678    123309.063415     23.583771      29.558355
LightGBM          0.592627  29326.523212  37064.429899
122512.490878    123309.063415     23.782942      30.058155
GradientBoosting  0.588988  28621.231316  37229.615673
123475.372894    123309.063415     23.210971      30.192116
XGBoost           0.568748  29118.501412  38135.275702
123119.304688    123309.063415     23.614243      30.926580

Best model based on R² (first try): LinearRegression


/opt/homebrew/lib/python3.13/site-
packages/sklearn/utils/validation.py:2739: UserWarning: X does not have
valid feature names, but LGBMRegressor was fitted with feature names
  warnings.warn(
```

Linear Regression

```
import matplotlib.pyplot as plt

# Fit Linear Regression only
lin_model = LinearRegression()
lin_model.fit(X_train_processed_1, y_train_1)

# Predictions
y_pred_lin_1 = lin_model.predict(X_test_processed_1)

# Evaluation
rmse = root_mean_squared_error(y_test_1, y_pred_lin_1)
r2 = r2_score(y_test_1, y_pred_lin_1)

print(f"Linear Regression → RMSE: {rmse:.2f}, R²: {r2:.3f}")

# ======== Plot Predicted vs Actual ========
plt.figure(figsize=(6,6))
```

```
plt.scatter(y_test_1, y_pred_lin_1, alpha=0.5, edgecolor="k")
plt.plot(
    [y_test_1.min(), y_test_1.max()],
    [y_test_1.min(), y_test_1.max()],
    color="red",
    linewidth=2,
    label="Perfect Prediction",
)

plt.xlabel("Actual Salary (USD)")
plt.ylabel("Predicted Salary (USD)")
plt.title(f"Linear Regression: Predicted vs Actual (R² = {r2:.3f})")
plt.legend()
plt.tight_layout()
plt.show()
```

```
Linear Regression → RMSE: 35368.52, R²: 0.629
```

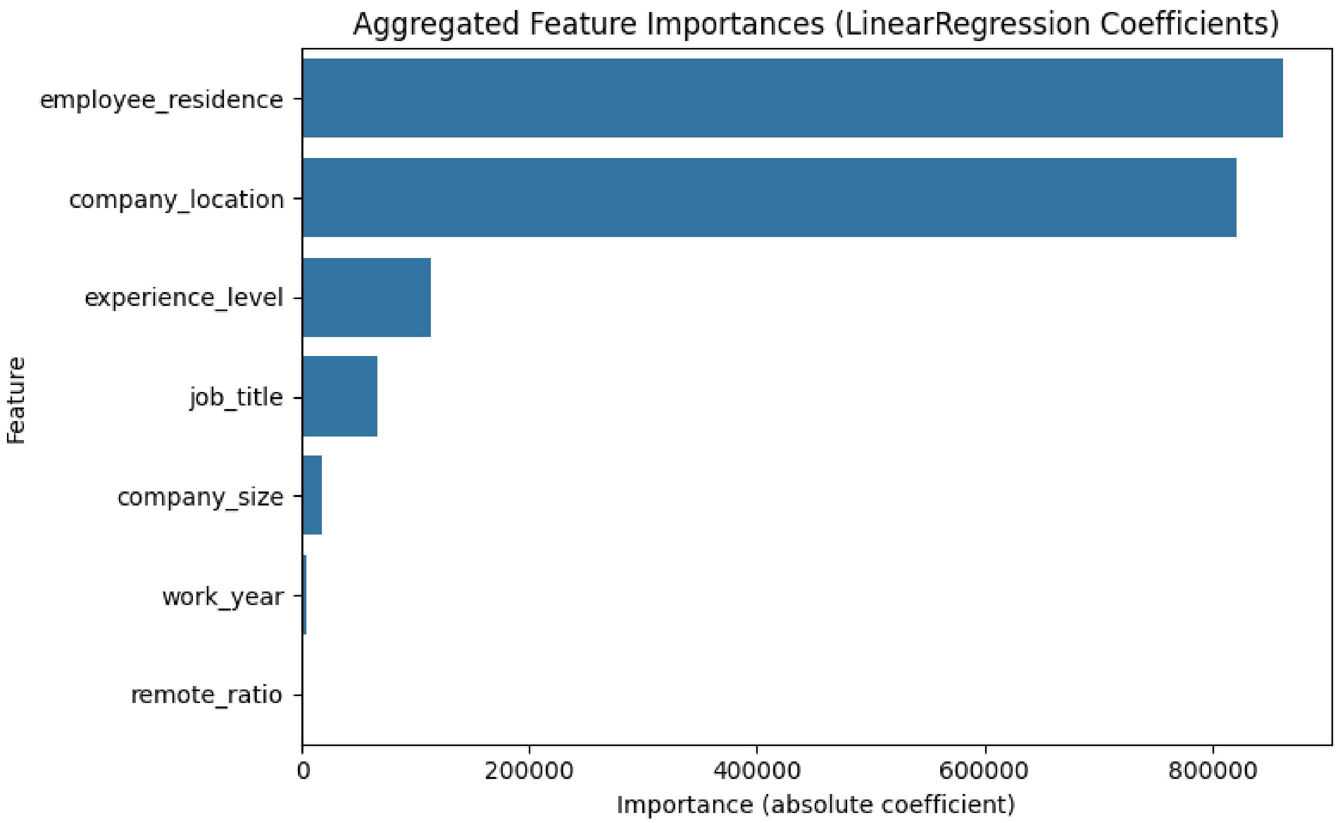


Features Importance

```
# ========================
# 7. Aggregate feature importances by original feature (LinearRegression)
# ========================

# Get coefficients from LinearRegression
linreg_coefs_1 = models_1["LinearRegression"].coef_

# Use same OHE feature names as before
ohe_1 = preprocessor_1.named_transformers_["cat"]
ohe_features_1 = ohe_1.get_feature_names_out(categorical_cols_1)
all_features_1 = list(ohe_features_1) + numeric_cols_1


# Map back to original columns
def map_to_original(feature_name_1):
    for col_1 in categorical_cols_1:
        if feature_name_1.startswith(col_1 + "_"):
            return col_1
    if feature_name_1 in numeric_cols_1:
        return feature_name_1
    return feature_name_1


original_features = [map_to_original(f) for f in all_features_1]

# Aggregate absolute coefficients as importance
feature_importance_salaries_data_frame_1 = (
    pd.DataFrame({"feature": original_features, "importance":
abs(linreg_coefs_1)})
    .groupby("feature")
    .sum()
    .sort_values(by="importance", ascending=False)
    .reset_index()
)

print("\n=== Aggregated Feature Importances (LinearRegression
coefficients) ===")
print(feature_importance_salaries_data_frame_1)
```

```
=== Aggregated Feature Importances (LinearRegression coefficients) ===
              feature     importance
0  employee_residence  861523.318181
1    company_location  821887.349490
2    experience_level  113766.160440
3           job_title   65834.525101
4        company_size   18510.995165
5           work_year    4035.817322
6        remote_ratio     871.710623
```

```python
# ========================
# 8. Visualize aggregated feature importances
# ========================
plt.figure(figsize=(8, 5))
sns.barplot(x="importance", y="feature",
data=feature_importance_salaries_data_frame_1)
plt.title("Aggregated Feature Importances (LinearRegression
Coefficients)")
plt.xlabel("Importance (absolute coefficient)")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```



Second Training (Removing Work Year, Company Size and Remote Ratio)

```python
# ========================
# 1. Import libraries
# ========================
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from xgboost import XGBRegressor
from lightgbm import LGBMRegressor
from catboost import CatBoostRegressor
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor,
```

```
GradientBoostingRegressor
from sklearn.metrics import root_mean_squared_error, r2_score,
mean_absolute_error
from sklearn.preprocessing import OneHotEncoder


print(salaries_data_frame.shape)

# ========================
# 2. Define features & target
# ========================
features_2 = ["experience_level", "job_title", "employee_residence",
"company_location"]

X = salaries_data_frame[features_2]
X.shape

y = salaries_data_frame["salary_in_usd"]
y.shape

# ========================
# 3. Split dataset
# ========================
X_train_2, X_test_2, y_train_2, y_test_2 = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# ========================
# 4. Preprocess features
# ========================
preprocessor_2 = ColumnTransformer(
    transformers=[("cat", OneHotEncoder(handle_unknown="ignore"),
features_2)]
)

X_train_processed_2 = preprocessor_2.fit_transform(X_train_2)
X_test_processed_2 = preprocessor_2.transform(X_test_2)

# ========================
# 5. Define models_2
# ========================
models_2 = {
    "LinearRegression": LinearRegression(),
    "RandomForest": RandomForestRegressor(
        n_estimators=500,
        max_depth=10,
        min_samples_leaf=2,
        max_features="sqrt",
        random_state=42,
        n_jobs=-1,
    ),
    "GradientBoosting": GradientBoostingRegressor(
        n_estimators=500, learning_rate=0.05, max_depth=5, random_state=42
    ),
```

```
    "XGBoost": XGBRegressor(
        n_estimators=500,
        learning_rate=0.05,
        max_depth=6,
        subsample=0.8,
        colsample_bytree=0.8,
        random_state=42,
    ),
    "LightGBM": LGBMRegressor(
        n_estimators=500,
        learning_rate=0.05,
        max_depth=-1,
        num_leaves=31,
        subsample=0.8,
        colsample_bytree=0.8,
        random_state=42,
        verbose=-1,
    ),
    "CatBoost": CatBoostRegressor(
        iterations=500, learning_rate=0.05, depth=6, random_state=42,
verbose=0
    ),
}

# ========================
# 6. Train & evaluate
# ========================
results_2 = {}
true_avg_salary = y_test_2.mean()  # True average salary

for name, model in models_2.items():
    model.fit(X_train_processed_2, y_train_2)
    y_pred_2 = model.predict(X_test_processed_2)

    rmse_2 = root_mean_squared_error(y_test_2, y_pred_2)
    mae_2 = mean_absolute_error(y_test_2, y_pred_2)
    r2_2 = r2_score(y_test_2, y_pred_2)
    pred_avg_salary_2 = y_pred_2.mean()  # Predicted average salary

    results_2[name] = {
        "R²": r2_2,
        "MAE": mae_2,
        "RMSE": rmse_2,
        "Predicted Avg Salary": pred_avg_salary_2,
    }

# Convert to DataFrame for easy comparison
results_df_2 = pd.DataFrame(results_2).T
results_df_2 = results_df_2.sort_values(by="R²", ascending=False)

print(results_df_2)
print("\nBest model based on R²:", results_df_2.index[0])
```

```
(1024, 11)
                        R²          MAE          RMSE  Predicted Avg
Salary
LinearRegression  0.627127  27612.691817  35460.262713
120270.467793
CatBoost          0.615005  28061.036067  36032.043269
122543.885647
GradientBoosting  0.609749  27990.598879  36277.145824
123513.312532
XGBoost           0.601621  28507.822847  36652.996185
123548.078125
RandomForest      0.599430  29243.640004  36753.630485
123197.168178
LightGBM          0.588351  29757.696103  37258.456403
122402.832104

Best model based on R²: LinearRegression


/opt/homebrew/lib/python3.13/site-
packages/sklearn/utils/validation.py:2739: UserWarning: X does not have
valid feature names, but LGBMRegressor was fitted with feature names
  warnings.warn(
```

Third Try (Add Work Year Again)

```
# ========================
# 1. Import libraries
# ========================
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from xgboost import XGBRegressor
from lightgbm import LGBMRegressor
from catboost import CatBoostRegressor
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
from sklearn.metrics import root_mean_squared_error, r2_score,
mean_absolute_error
from sklearn.preprocessing import StandardScaler, OneHotEncoder


print(salaries_data_frame.shape)

# ========================
# 2. Define features & target
# ========================
categorical_cols_3 = [
    "experience_level",
```

```
    "job_title",
    "employee_residence",
    "company_location",
]
numeric_cols_3 = ["work_year"]
features = categorical_cols_3 + numeric_cols_3

X_3 = salaries_data_frame[features]
X_3.shape

y_3 = salaries_data_frame["salary_in_usd"]
y_3.shape

# ========================
# 3. Split dataset
# ========================
X_train_3, X_test_3, y_train_3, y_test_3 = train_test_split(
    X_3, y_3, test_size=0.2, random_state=42
)

# ========================
# 4. Preprocess features
# ========================
preprocessor_3 = ColumnTransformer(
    transformers=[
        ("cat", OneHotEncoder(handle_unknown="ignore"),
categorical_cols_3),
        ("num", StandardScaler(), numeric_cols_3),
    ]
)

X_train_processed_3 = preprocessor_3.fit_transform(X_train_3)
X_test_processed_3 = preprocessor_3.transform(X_test_3)

# ========================
# 5. Define models_1
# ========================
models_3 = {
    "LinearRegression": LinearRegression(),
    "RandomForest": RandomForestRegressor(
        n_estimators=500,
        max_depth=10,
        min_samples_leaf=2,
        max_features="sqrt",
        random_state=42,
        n_jobs=-1,
    ),
    "GradientBoosting": GradientBoostingRegressor(
        n_estimators=500, learning_rate=0.05, max_depth=5, random_state=42
    ),
    "XGBoost": XGBRegressor(
        n_estimators=500,
        learning_rate=0.05,
        max_depth=6,
```

```
            subsample=0.8,
            colsample_bytree=0.8,
            random_state=42,
        ),
        "LightGBM": LGBMRegressor(
            n_estimators=500,
            learning_rate=0.05,
            max_depth=-1,
            num_leaves=31,
            subsample=0.8,
            colsample_bytree=0.8,
            random_state=42,
            verbose=-1,
        ),
        "CatBoost": CatBoostRegressor(
            iterations=500, learning_rate=0.05, depth=6, random_state=42,
verbose=0
        ),
}
# ========================
# 6. Train & evaluate
# ========================
results_3 = {}
true_avg_salary_3 = y_test_3.mean()  # True average salary

for name, model in models_3.items():
    model.fit(X_train_processed_3, y_train_3)
    y_pred_3 = model.predict(X_test_processed_3)

    r2_3 = r2_score(y_test_3, y_pred_3)
    mae_3 = mean_absolute_error(y_test_3, y_pred_3)
    rmse_3 = root_mean_squared_error(y_test_3, y_pred_3)
    pred_avg_salary_3 = y_pred_3.mean()  # Predicted average salary

    results_3[name] = {
        "R²": r2_3,
        "MAE": mae_3,
        "RMSE": rmse_3,
        "Predicted Avg Salary": pred_avg_salary_3,
        "True Avg Salary": true_avg_salary_3,
        "MAE % of Avg": (mae_3 / true_avg_salary_3) * 100,
        "RMSE % of Avg": (rmse_3 / true_avg_salary_3) * 100,
    }

# Convert to DataFrame for easy comparison
results_3_df = pd.DataFrame(results_3).T
results_3_df = results_3_df.sort_values(by="R²", ascending=False)

print(results_3_df.to_string(line_width=10000))
print("\nBest model based on R² (third try):", results_3_df.index[0])
```

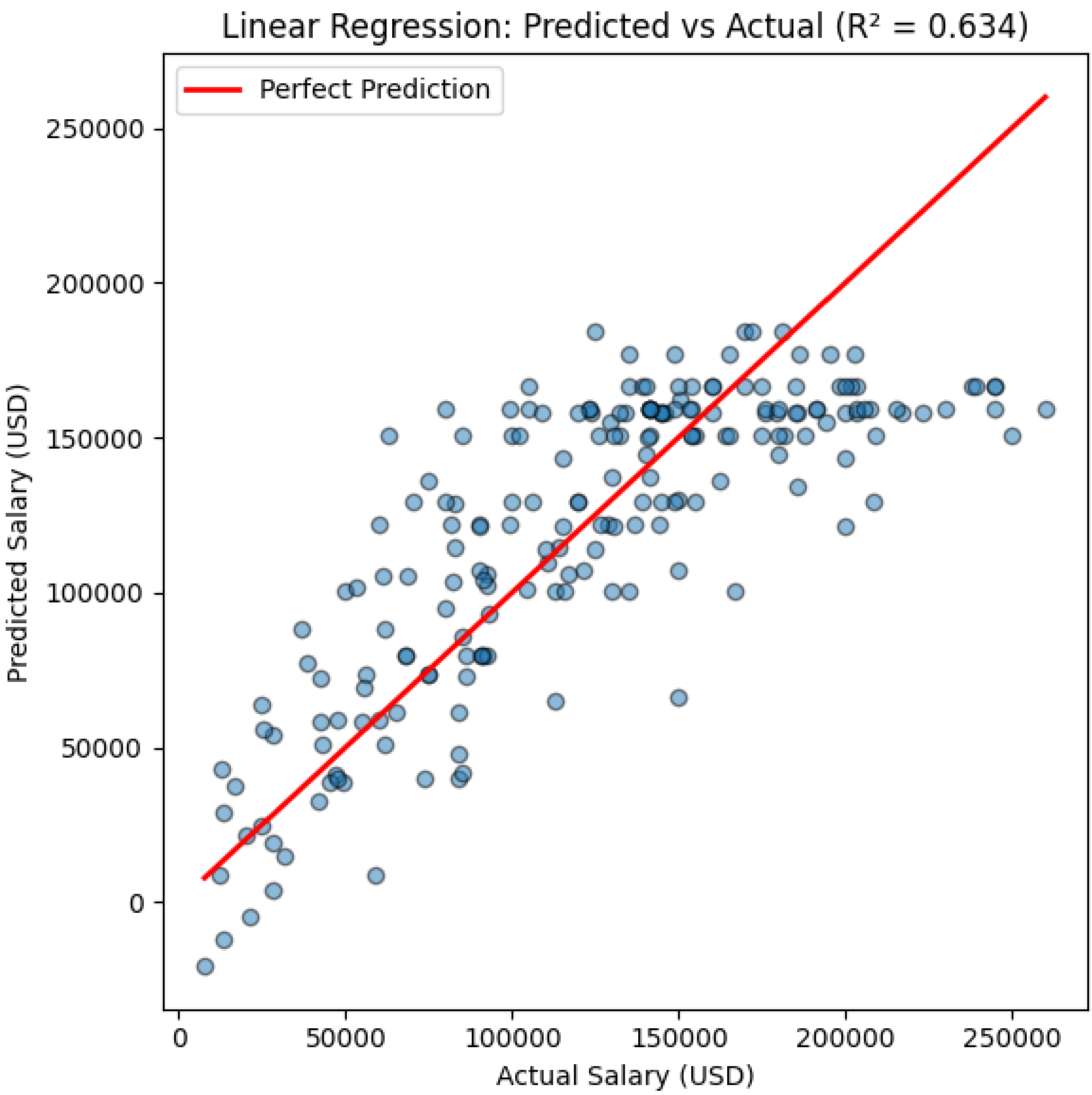
```
(1024, 11)
                        R²           MAE          RMSE  Predicted Avg
Salary  True Avg Salary  MAE % of Avg  RMSE % of Avg
LinearRegression  0.633920  27537.129602  35135.728152
120678.288725    123309.063415     22.331797      28.494035
CatBoost          0.627474  27833.232327  35443.753920
121734.009514    123309.063415     22.571927      28.743835
GradientBoosting  0.612539  28147.782603  36147.263382
122598.011727    123309.063415     22.827018      29.314361
RandomForest      0.606847  28923.872697  36411.778818
123142.905195    123309.063415     23.456404      29.528875
LightGBM          0.591634  29415.146085  37109.596027
121173.885429    123309.063415     23.854813      30.094784
XGBoost           0.581715  29218.391549  37557.537273
121785.054688    123309.063415     23.695251      30.458051

Best model based on R² (third try): LinearRegression


/opt/homebrew/lib/python3.13/site-
packages/sklearn/utils/validation.py:2739: UserWarning: X does not have
valid feature names, but LGBMRegressor was fitted with feature names
  warnings.warn(
```

Linear Regression

```python
import matplotlib.pyplot as plt

# Fit Linear Regression only
lin_model = LinearRegression()
lin_model.fit(X_train_processed_3, y_train_3)

# Predictions
y_pred_lin_3 = lin_model.predict(X_test_processed_3)

# Evaluation
rmse = root_mean_squared_error(y_test_3, y_pred_lin)
r2 = r2_score(y_test_3, y_pred_lin_3)

print(f"Linear Regression → RMSE: {rmse:.2f}, R²: {r2:.3f}")

# ======== Plot Predicted vs Actual ========
plt.figure(figsize=(6, 6))
plt.scatter(y_test_1, y_pred_lin_3, alpha=0.5, edgecolor="k")
plt.plot(
    [y_test_3.min(), y_test_3.max()],
    [y_test_3.min(), y_test_3.max()],
    color="red",
    linewidth=2,
```

```
    label="Perfect Prediction",
)

plt.xlabel("Actual Salary (USD)")
plt.ylabel("Predicted Salary (USD)")
plt.title(f"Linear Regression: Predicted vs Actual (R² = {r2:.3f})")
plt.legend()
plt.tight_layout()
plt.show()
```

```
Linear Regression → RMSE: 35368.52, R²: 0.634
```



Feature Coefficent

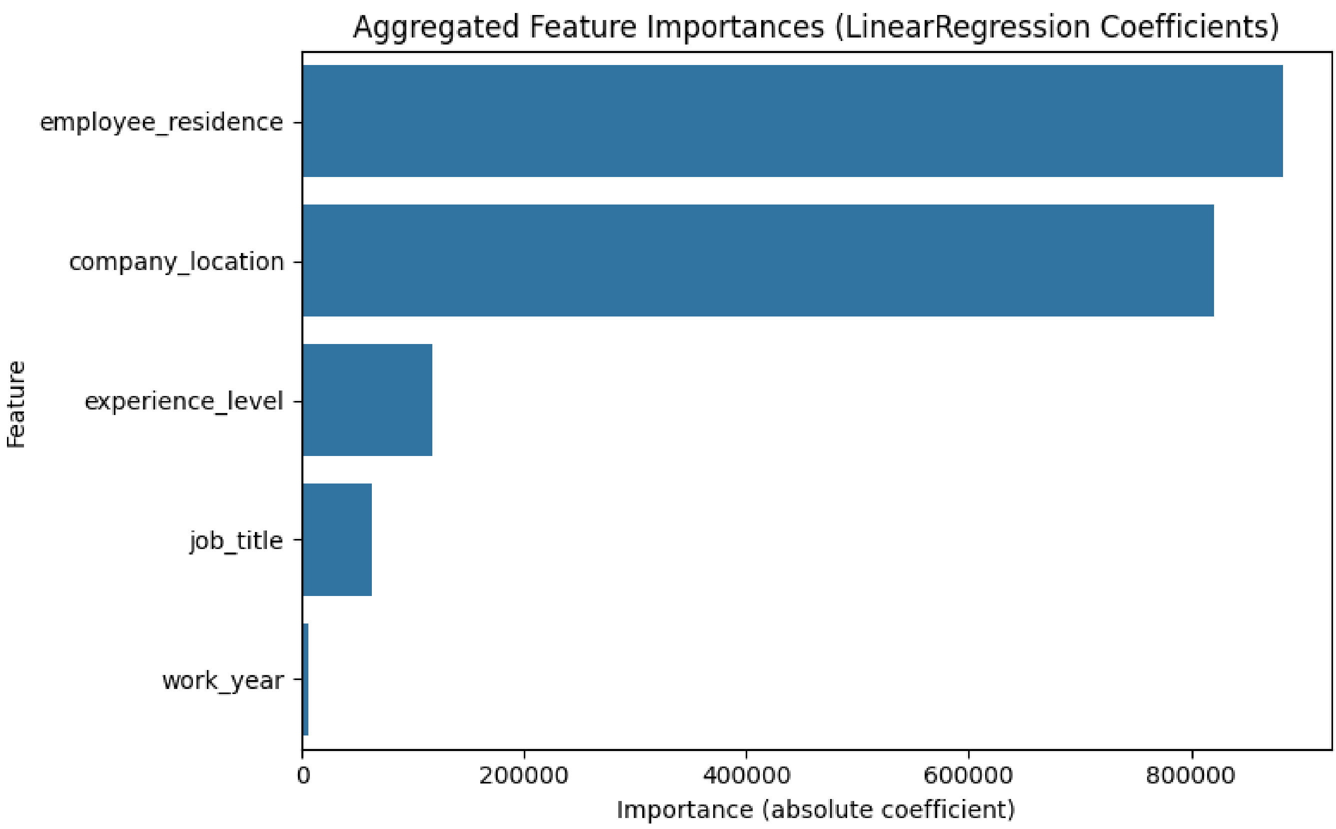
```
# ========================
# 7. Aggregate feature importances by original feature (LinearRegression)
# ========================
```

```
# Get coefficients from LinearRegression
linreg_coefs_3 = models_3["LinearRegression"].coef_

# Use same OHE feature names as before
ohe_3 = preprocessor_3.named_transformers_["cat"]
ohe_features_3 = ohe_3.get_feature_names_out(categorical_cols_3)
all_features_3 = list(ohe_features_3) + numeric_cols_3


# Map back to original columns
def map_to_original(feature_name):
    for col_3 in categorical_cols_3:
        if feature_name.startswith(col_3 + "_"):
            return col_3
    if feature_name in numeric_cols_3:
        return feature_name
    return feature_name


original_features_3 = [map_to_original(f_3) for f_3 in all_features_3]

# Aggregate absolute coefficients as importance
feature_importance_salaries_data_frame_3 = (
    pd.DataFrame({"feature": original_features_3, "importance":
abs(linreg_coefs_3)})
    .groupby("feature")
    .sum()
    .sort_values(by="importance", ascending=False)
    .reset_index()
)

print("\n=== Aggregated Feature Importances (LinearRegression
coefficients) ===")
print(feature_importance_salaries_data_frame_3)
```

```
=== Aggregated Feature Importances (LinearRegression coefficients) ===
              feature     importance
0  employee_residence  881968.462912
1    company_location  820034.549297
2    experience_level  118230.637728
3           job_title   63336.200112
4           work_year    5565.467702
```

```
# ========================
# 8. Visualize aggregated feature importances
# ========================
plt.figure(figsize=(8, 5))
sns.barplot(x="importance", y="feature",
```

```
    data=feature_importance_salaries_data_frame_3)
plt.title("Aggregated Feature Importances (LinearRegression
Coefficients)")
plt.xlabel("Importance (absolute coefficient)")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```



Group Employees by Job Title, Experience Level, Employee Residence, Company Location

```
import pandas as pd

# Group by multiple columns
grouped = (
    salaries_data_frame.groupby(
        ["job_title", "experience_level", "employee_residence",
"company_location"]
    )["salary_in_usd"]
    .agg(count="count", mean_salary="mean", median_salary="median")
    .reset_index()
)

# Round salaries
grouped["mean_salary"] = grouped["mean_salary"].round(0)
grouped["median_salary"] = grouped["median_salary"].round(0)

# Add percentage column
total_count = grouped["count"].sum()
```

```
grouped["percentage"] = (grouped["count"] / total_count * 100).round(2)

# Remove rows with count = 0 (safety check)
grouped = grouped[grouped["count"] > 0]

# Sort by count (descending)
grouped = grouped.sort_values(by="count", ascending=False)

# Reorder columns
grouped = grouped[
    [
        "job_title",
        "experience_level",
        "employee_residence",
        "company_location",
        "count",
        "percentage",
        "mean_salary",
        "median_salary",
    ]
]

# Show result
print(grouped.to_string(index=False, line_width=10000))
```

```
                job_title experience_level employee_residence
company_location  count  percentage  mean_salary  median_salary
            Data Engineer               SE                 US
US    216       21.09     154309.0       150000.0
           Data Scientist               SE                 US
US    212       20.70     165500.0       160000.0
             Data Analyst               SE                 US
US    114       11.13     121276.0       115467.0
Machine Learning Engineer               SE                 US
US     52        5.08     177997.0       183000.0
            Data Engineer               MI                 US
US     35        3.42     117558.0       110000.0
             Data Analyst               MI                 US
US     29        2.83     109606.0       110000.0
           Data Scientist               MI                 US
US     28        2.73     129219.0       130000.0
            Data Engineer               MI                 GB
GB     27        2.64      84430.0        82528.0
            Data Engineer               EN                 US
US     16        1.56      82625.0        82500.0
           Data Scientist               MI                 GB
GB     16        1.56      86411.0        78497.0
             Data Analyst               EN                 US
US     15        1.46      74620.0        72000.0
            Data Engineer               EX                 US
```

```
US      13          1.27    206038.0        207000.0
             Data Scientist                EN                  US
US      11          1.07     89355.0         90000.0
             Data Scientist                SE                  CA
CA      10          0.98    169443.0        175500.0
               Data Analyst                MI                  GB
GB       9          0.88     50965.0         49253.0
Machine Learning Engineer                  EN                  US
US       8          0.78    137635.0        131500.0
Machine Learning Engineer                  MI                  US
US       7          0.68    203479.0        193900.0
               Data Analyst                SE                  CA
CA       7          0.68    109198.0        130000.0
              Data Engineer                MI                  GR
GR       6          0.59     70920.0         73546.0
              Data Engineer                SE                  GB
GB       6          0.59     88682.0         89281.0
              Data Engineer                MI                  ES
ES       6          0.59     70920.0         73546.0
             Data Scientist                SE                  ES
ES       6          0.59     43460.0         43460.0
              Data Engineer                EN                  IN
IN       5          0.49     19215.0         17022.0
             Data Scientist                MI                  IN
IN       5          0.49     26236.0         30523.0
             Data Scientist                MI                  DE
DE       5          0.49     82179.0         88654.0
             Data Scientist                EN                  FR
FR       4          0.39     44382.0         44781.0
             Data Scientist                EX                  US
US       4          0.39    197188.0        192500.0
             Data Scientist                EN                  IN
IN       4          0.39     24712.0         25646.0
             Data Scientist                MI                  NL
NL       4          0.39     83265.0         81426.0
               Data Analyst                EN                  CA
CA       3          0.29     53221.0         52000.0
Machine Learning Engineer                  MI                  GB
GB       3          0.29    112461.0        116976.0
               Data Analyst                MI                  GR
GR       3          0.29     31182.0         31520.0
Machine Learning Engineer                  EN                  GB
GB       3          0.29     40168.0         35093.0
              Data Engineer                EN                  GB
GB       3          0.29     45913.0         45390.0
             Data Scientist                MI                  ES
ES       3          0.29     41137.0         38776.0
              Data Engineer                SE                  PR
PR       2          0.20    167500.0        167500.0
             Data Scientist                MI                  CA
CA       2          0.20     71686.0         71686.0
```

```
               Data Analyst              MI                 ES
ES      2          0.20      36773.0        36773.0
               Data Analyst              MI                 CA
CA      2          0.20      80000.0        80000.0
               Data Analyst              EX                 US
US      2          0.20     120000.0       120000.0
Machine Learning Engineer                SE                 IN
IN      2          0.20      45304.0        45304.0
Machine Learning Engineer                SE                 PR
PR      2          0.20     167500.0       167500.0
             Data Scientist              EN                 BE
BE      2          0.20      68030.0        68030.0
             Data Scientist              EN                 CA
CA      2          0.20      51417.0        51417.0
             Data Scientist              EN                 DE
DE      2          0.20      55997.0        55997.0
               Data Analyst              EN                 FR
FR      2          0.20      43735.0        43735.0
              Data Engineer              SE                 CA
CA      2          0.20     161600.0       161600.0
              Data Engineer              MI                 TR
TR      2          0.20      20060.0        20060.0
              Data Engineer              MI                 DE
DE      2          0.20      62484.0        62484.0
               Data Analyst              SE                 CF
CF      2          0.20      48609.0        48609.0
               Data Analyst              SE                 GB
GB      2          0.20      73880.0        73880.0
               Data Analyst              SE                 ES
ES      2          0.20      43602.0        43602.0
Machine Learning Engineer                SE                 AE
AE      2          0.20      92500.0        92500.0
             Data Scientist              SE                 FR
FR      2          0.20      65438.0        65438.0
             Data Scientist              SE                 IE
IE      2          0.20     142500.0       142500.0
              Data Engineer              EN                 PK
DE      2          0.20      55108.0        55108.0
              Data Engineer              MI                 FR
FR      2          0.20      67640.0        67640.0
Machine Learning Engineer                SE                 CA
CA      2          0.20     105000.0       105000.0
             Data Scientist              SE                 GB
GB      2          0.20     104663.0       104663.0
             Data Scientist              SE                 TR
TR      1          0.10      20171.0        20171.0
             Data Scientist              MI                 TR
TR      1          0.10      25000.0        25000.0
             Data Scientist              SE                 BR
US      1          0.10     100000.0       100000.0
Machine Learning Engineer                EN                 CH
```

```
  CH      1         0.10      56536.0          56536.0
             Data Scientist                  SE                  ES
  GB      1         0.10      88256.0          88256.0
             Data Scientist                  SE                  GR
  US      1         0.10      68428.0          68428.0
             Data Scientist                  SE                  AT
  AT      1         0.10      91237.0          91237.0
  Machine Learning Engineer                  MI                  FR
  DE      1         0.10      84053.0          84053.0
  Machine Learning Engineer                  EN                  CO
  CO      1         0.10      21844.0          21844.0
  Machine Learning Engineer                  EN                  DE
  DE      1         0.10      24823.0          24823.0
  Machine Learning Engineer                  SE                  PT
  US      1         0.10     150000.0         150000.0
  Machine Learning Engineer                  SE                  NL
  NL      1         0.10      59888.0          59888.0
  Machine Learning Engineer                  SE                  IE
  IE      1         0.10      68293.0          68293.0
  Machine Learning Engineer                  SE                  HR
  HR      1         0.10      45618.0          45618.0
  Machine Learning Engineer                  SE                  FI
  FI      1         0.10      63040.0          63040.0
  Machine Learning Engineer                  SE                  DE
  DE      1         0.10      94564.0          94564.0
  Machine Learning Engineer                  SE                  BE
  BE      1         0.10      82744.0          82744.0
  Machine Learning Engineer                  MI                  SI
  SI      1         0.10      24823.0          24823.0
  Machine Learning Engineer                  MI                  PL
  PL      1         0.10      46597.0          46597.0
  Machine Learning Engineer                  MI                  NL
  NL      1         0.10      96578.0          96578.0
  Machine Learning Engineer                  MI                  JP
  JP      1         0.10      74000.0          74000.0
  Machine Learning Engineer                  MI                  IT
  IT      1         0.10      51064.0          51064.0
  Machine Learning Engineer                  MI                  IN
  IN      1         0.10      20984.0          20984.0
             Data Scientist                  MI                  RU
  US      1         0.10      48000.0          48000.0
  Machine Learning Engineer                  MI                  ES
  ES      1         0.10      47282.0          47282.0
  Machine Learning Engineer                  MI                  BE
  BE      1         0.10      88654.0          88654.0
  Machine Learning Engineer                  MI                  AU
  AU      1         0.10      83864.0          83864.0
  Machine Learning Engineer                  EN                  NL
  DE      1         0.10      85000.0          85000.0
  Machine Learning Engineer                  EN                  IN
  IN      1         0.10      20000.0          20000.0
```

```
              Data Scientist                 MI                  SG
  IL       1         0.10     119059.0        119059.0
                Data Analyst                 EN                  AR
  AR       1         0.10      50000.0         50000.0
              Data Scientist                 MI                  RS
  DE       1         0.10      25532.0         25532.0
                Data Analyst                 SE                  DE
  DE       1         0.10      63831.0         63831.0
               Data Engineer                 MI                  NL
  NL       1         0.10      45391.0         45391.0
               Data Engineer                 MI                  MT
  MT       1         0.10      28369.0         28369.0
               Data Engineer                 MI                  HK
  GB       1         0.10      66022.0         66022.0
               Data Engineer                 MI                  ES
  US       1         0.10     130800.0        130800.0
               Data Engineer                 MI                  AT
  AT       1         0.10      74130.0         74130.0
               Data Engineer                 EN                  NL
  NL       1         0.10      59888.0         59888.0
               Data Engineer                 EN                  JP
  JP       1         0.10      41689.0         41689.0
               Data Engineer                 EN                  DE
  DE       1         0.10      65013.0         65013.0
                Data Analyst                 SE                  PH
  PH       1         0.10      50000.0         50000.0
                Data Analyst                 SE                  BG
  US       1         0.10      80000.0         80000.0
               Data Engineer                 MI                  RO
  US       1         0.10      26005.0         26005.0
                Data Analyst                 MI                  SG
  SG       1         0.10      65257.0         65257.0
                Data Analyst                 MI                  PK
  PK       1         0.10       8000.0          8000.0
                Data Analyst                 MI                  IN
  IN       1         0.10       5723.0          5723.0
                Data Analyst                 MI                  FR
  FR       1         0.10      46759.0         46759.0
                Data Analyst                 EN                  PT
  PT       1         0.10      22809.0         22809.0
                Data Analyst                 EN                  NG
  NG       1         0.10      10000.0         10000.0
                Data Analyst                 EN                  IN
  IN       1         0.10       6072.0          6072.0
                Data Analyst                 EN                  ID
  ID       1         0.10      15000.0         15000.0
                Data Analyst                 EN                  FR
  IN       1         0.10       6359.0          6359.0
               Data Engineer                 MI                  PL
  PL       1         0.10      28476.0         28476.0
               Data Engineer                 SE                  ES
```

```
US       1        0.10    193000.0         193000.0
             Data Scientist              MI                 PL
PL       1        0.10     33609.0          33609.0
             Data Scientist              MI                 CL
CL       1        0.10     40038.0          40038.0
             Data Scientist              MI                 PH
US       1        0.10     45760.0          45760.0
             Data Scientist              MI                 NG
NG       1        0.10     50000.0          50000.0
             Data Scientist              MI                 IN
US       1        0.10      5679.0           5679.0
             Data Scientist              MI                 IN
ID       1        0.10     53416.0          53416.0
             Data Scientist              MI                 HU
HU       1        0.10     35735.0          35735.0
             Data Scientist              MI                 HK
HK       1        0.10     65062.0          65062.0
             Data Scientist              MI                 FR
LU       1        0.10     62726.0          62726.0
             Data Scientist              MI                 FR
FR       1        0.10     42197.0          42197.0
             Data Scientist              MI                 DE
AT       1        0.10     61467.0          61467.0
             Data Scientist              MI                 CH
CH       1        0.10    120402.0         120402.0
              Data Engineer              SE                 GR
GR       1        0.10     47899.0          47899.0
             Data Scientist              MI                 BR
BR       1        0.10     12901.0          12901.0
               Data Analyst              EN                 BR
BR       1        0.10      7799.0           7799.0
             Data Scientist              EN                 UA
UA       1        0.10     13400.0          13400.0
             Data Scientist              EN                 JP
MY       1        0.10     40000.0          40000.0
             Data Scientist              EN                 ES
ES       1        0.10     31520.0          31520.0
             Data Scientist              EN                 AU
AU       1        0.10     83171.0          83171.0
              Data Engineer              EX                 ES
ES       1        0.10     79833.0          79833.0
              Data Engineer              SE                 RO
GB       1        0.10     76833.0          76833.0
              Data Engineer              SE                 MX
MX       1        0.10     33511.0          33511.0
             Data Scientist              EN                 US
DE       1        0.10     50000.0          50000.0


/var/folders/jh/z981c7zj0vz0gmyfc8mhdxdr0000gn/T/ipykernel_6856/3461952642
.py:5: FutureWarning: The default of observed=False is deprecated and will
```

```
be changed to True in a future version of pandas. Pass observed=False to
retain current behavior or observed=True to adopt the future default and
silence this warning.
  salaries_data_frame.groupby(
```

```
# 1. Create new samples with STRING values and updated realistic salary
fields
new_samples = pd.DataFrame(
    [
        {
            "work_year": 2023,
            "experience_level": "SE",
            "employment_type": "FT",
            "job_title": "Data Scientist",
            "employee_residence": "US",  ## United States
            "company_location": "US",  ## United States
            "company_size": "M",
            "remote_ratio": 100,
            "salary": 160000,
            "salary_currency": "USD",
            "salary_in_usd": 160000,
        },
        {
            "work_year": 2023,
            "experience_level": "MI",
            "employment_type": "FT",
            "job_title": "Data Engineer",
            "employee_residence": "GB",  ## United Kingdom
            "company_location": "GB",  ## United Kingdom
            "company_size": "L",
            "remote_ratio": 50,
            "salary": 82528.0,
            "salary_currency": "USD",
            "salary_in_usd": 82528.0,
        },
        {
            "work_year": 2023,
            "experience_level": "EN",
            "employment_type": "FT",
            "job_title": "Data Analyst",
            "employee_residence": "BR",  ## Brazil
            "company_location": "BR",  ## Brazil
            "company_size": "S",
            "remote_ratio": 0,
            "salary": 8000,
            "salary_currency": "USD",
            "salary_in_usd": 8000,
        },
    ]
)
```

```
# 2. Drop target columns (keep only features the model expects)
X_new = new_samples.drop(columns=["salary", "salary_currency",
"salary_in_usd"])

# 3. Apply the SAME preprocessing pipeline you used for training
X_new_processed = preprocessor_3.transform(X_new)

# 4. Predict using the trained model
predictions = models_3["LinearRegression"].predict(X_new_processed)

# 5. Attach predictions back
new_samples["predicted_salary_usd"] = predictions.round(2)
import numpy as np

# 6. Compute error percentage
new_samples["error_percentage"] = (
    (new_samples["predicted_salary_usd"] - new_samples["salary_in_usd"])
    / new_samples["salary_in_usd"]
    * 100
).round(2)

# 7. Add comment about acceptability (e.g., <20% is okay in salary
prediction)
new_samples["comment"] = np.where(
    new_samples["error_percentage"].abs() <= 20, "✅ Acceptable", "⚠ High
Error"
)

# 8. Print results clearly
print(new_samples.to_string(index=False, line_width=10000))
```

```
 work_year experience_level employment_type      job_title
employee_residence company_location company_size  remote_ratio   salary
salary_currency  salary_in_usd  predicted_salary_usd  error_percentage
comment
      2023               SE              FT Data Scientist
US                US             M          100 160000.0             USD
160000.0            166271.88                3.92 ✅ Acceptable
      2023               MI              FT  Data Engineer
GB                GB             L           50  82528.0             USD
82528.0             86858.68               5.25 ✅ Acceptable
      2023               EN              FT   Data Analyst
BR                BR             S            0   8000.0             USD
8000.0            -13262.27             -265.78 ⚠ High Error
```