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)

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

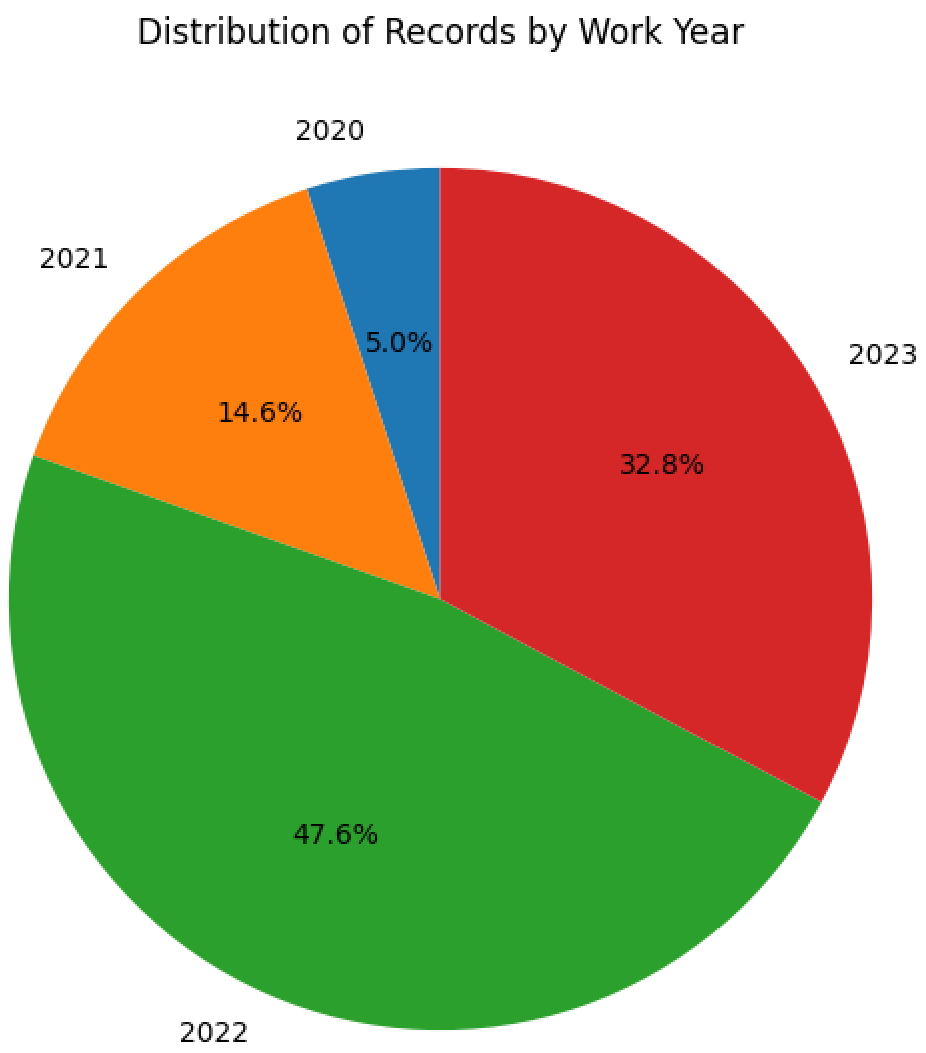
```
(1500, 11)
work_year               int64
experience_level       object
employment_type        object
job_title              object
salary                float64
salary_currency        object
salary_in_usd         float64
employee_residence     object
remote_ratio            int64
company_location       object
company_size           object
dtype: object
```

Work Year

```
import 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)

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

```
# --- 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()
```

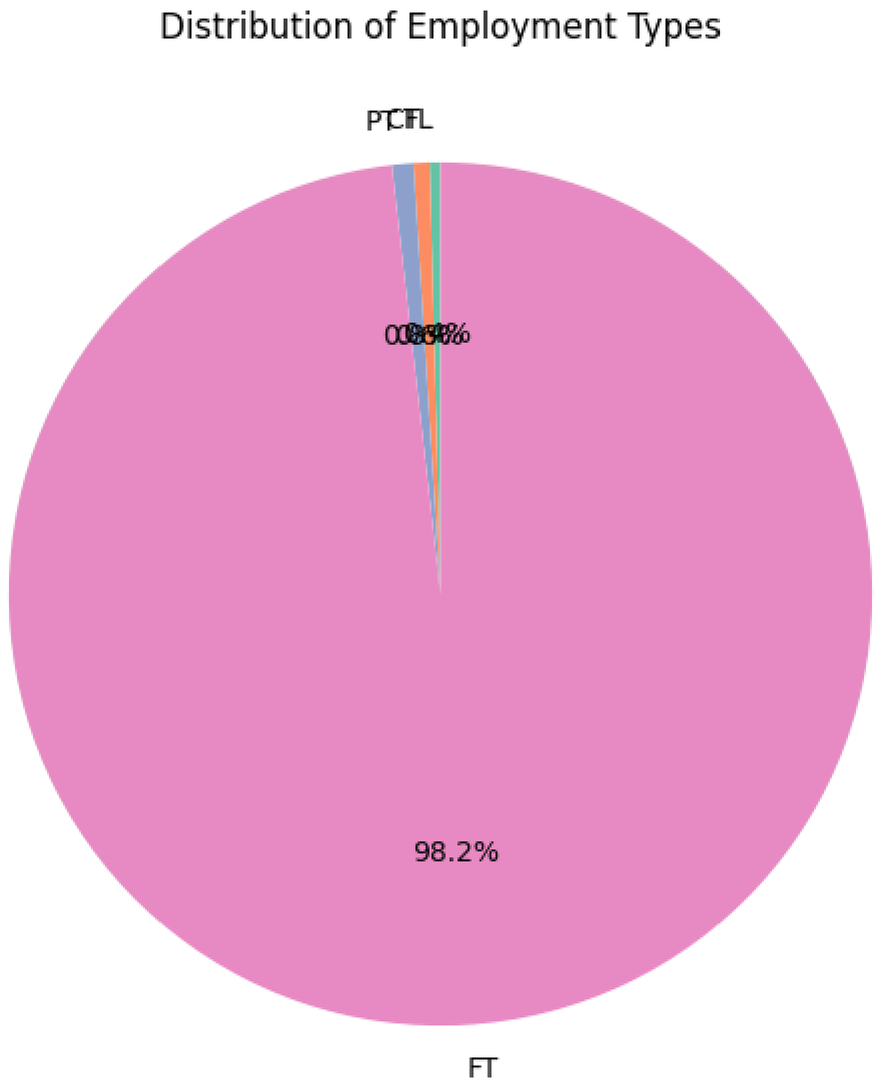
```
           count  percentage
work_year
2020          75         5.0
2021         219        14.6
2022         714        47.6
2023         492        32.8
```



Employment Type

```python
import matplotlib.pyplot as plt

# 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)

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

print(result)

# --- Pie Chart ---
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()
```

```
                 count  percentage
employment_type
FL                   6         0.4
CT                   9         0.6
PT                  12         0.8
FT                1473        98.2
```

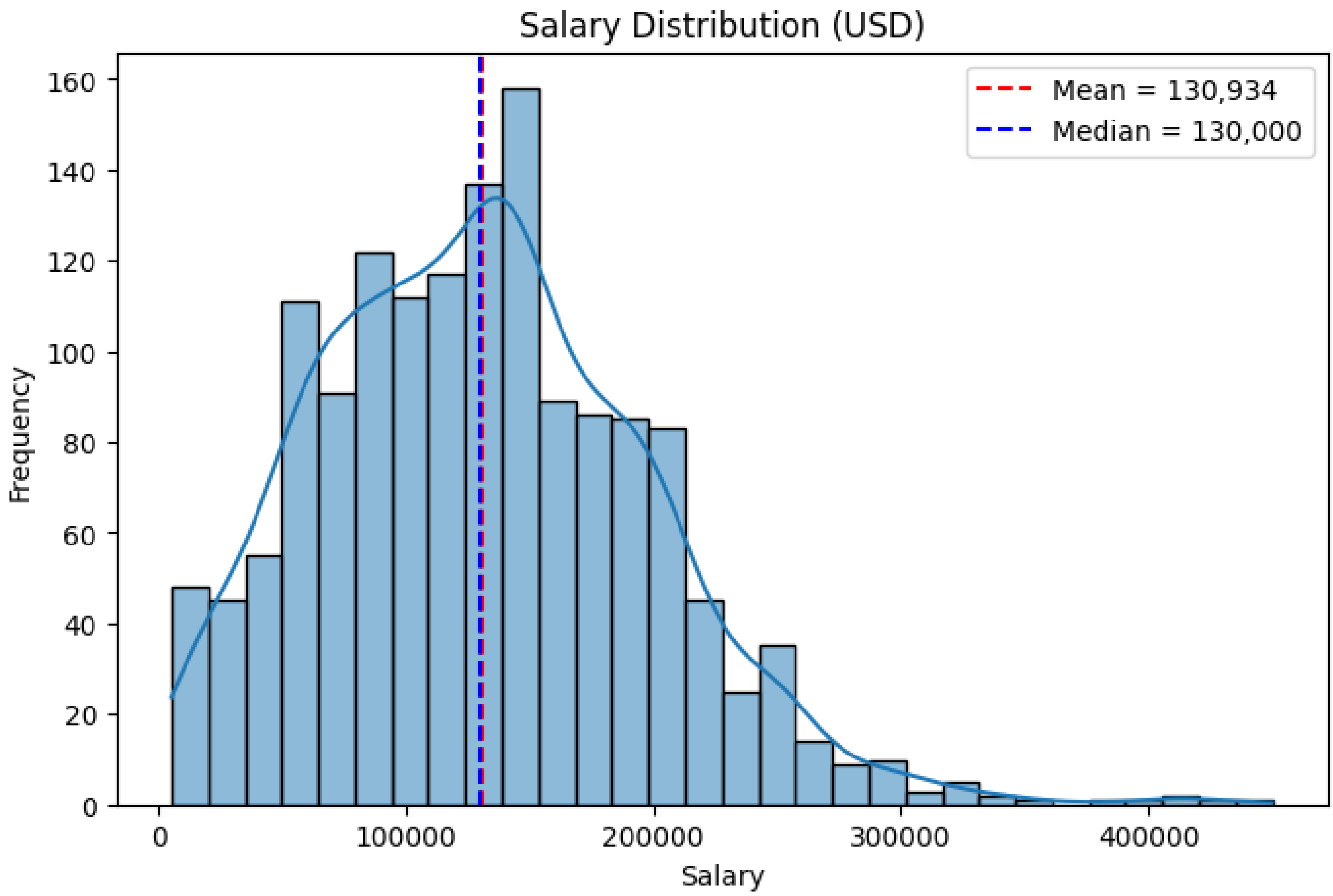


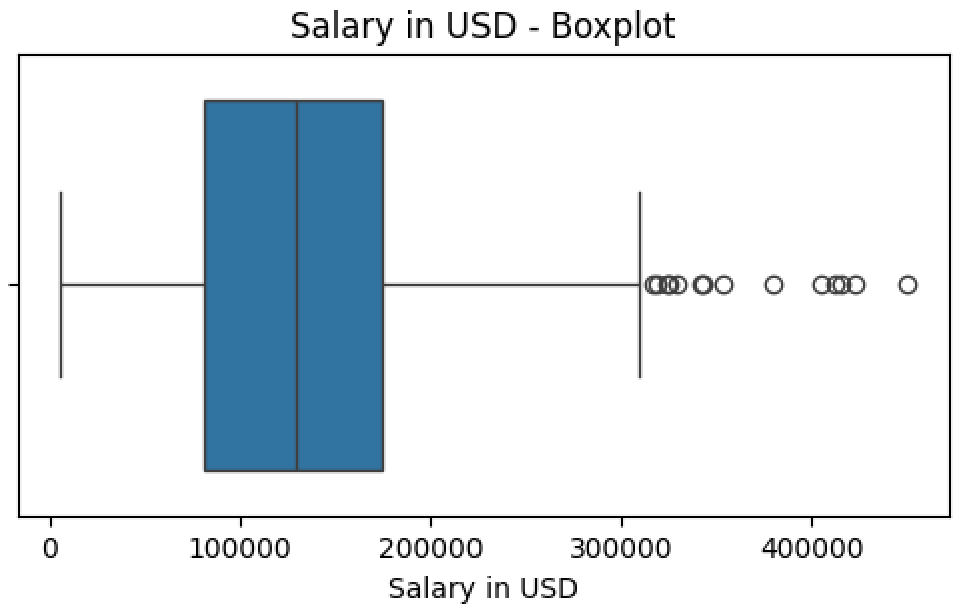
Salary

```
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}")


# --- 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()
```

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





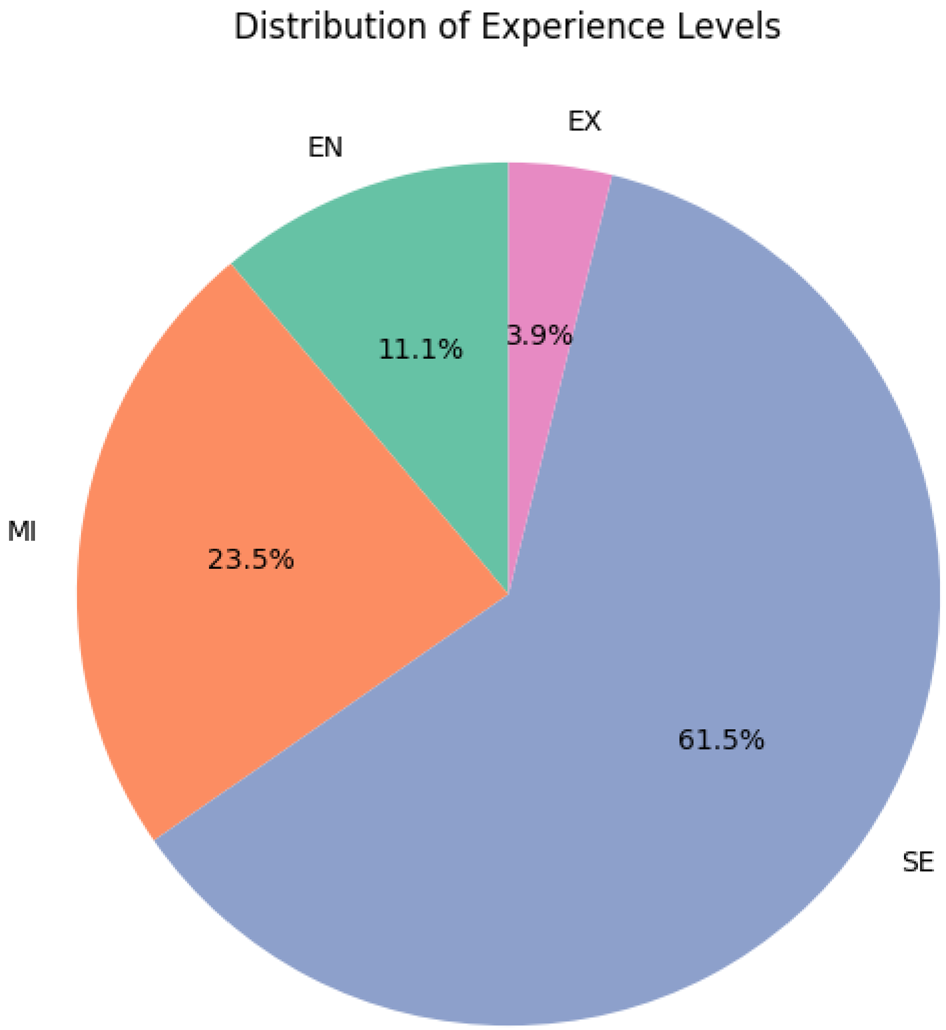
Experience Level (with Salary)

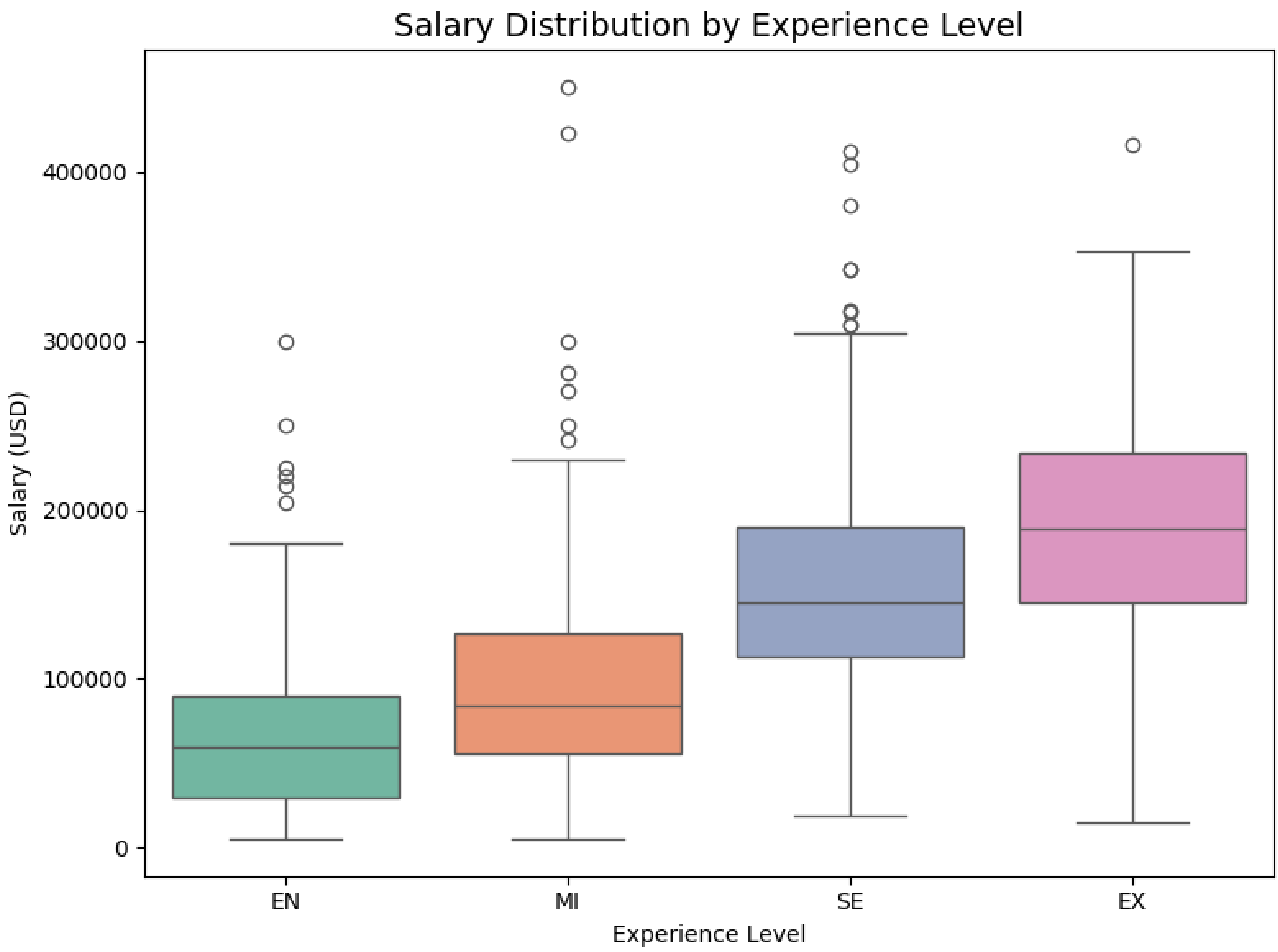
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# ========================
# 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)

# ==========================
# 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()

# ==========================
# 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()
```

```
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_11047/312431798
9.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"]
```


Distribution of Experience Levels
EX
EN
3.9%
11.1%
MI
23.5%
61.5%
SE



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))
```

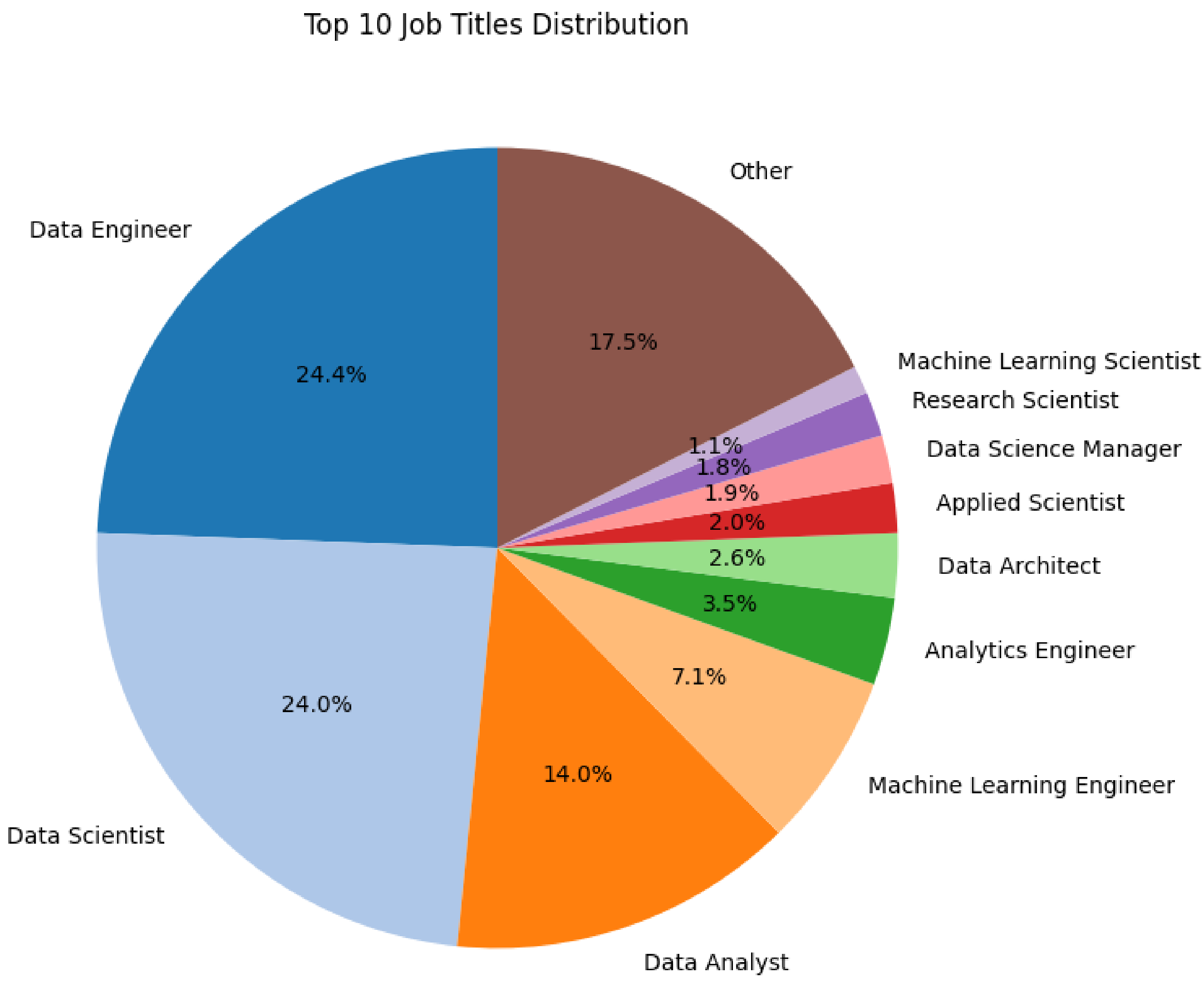
```
Number of unique job titles: 69

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"] = (
```

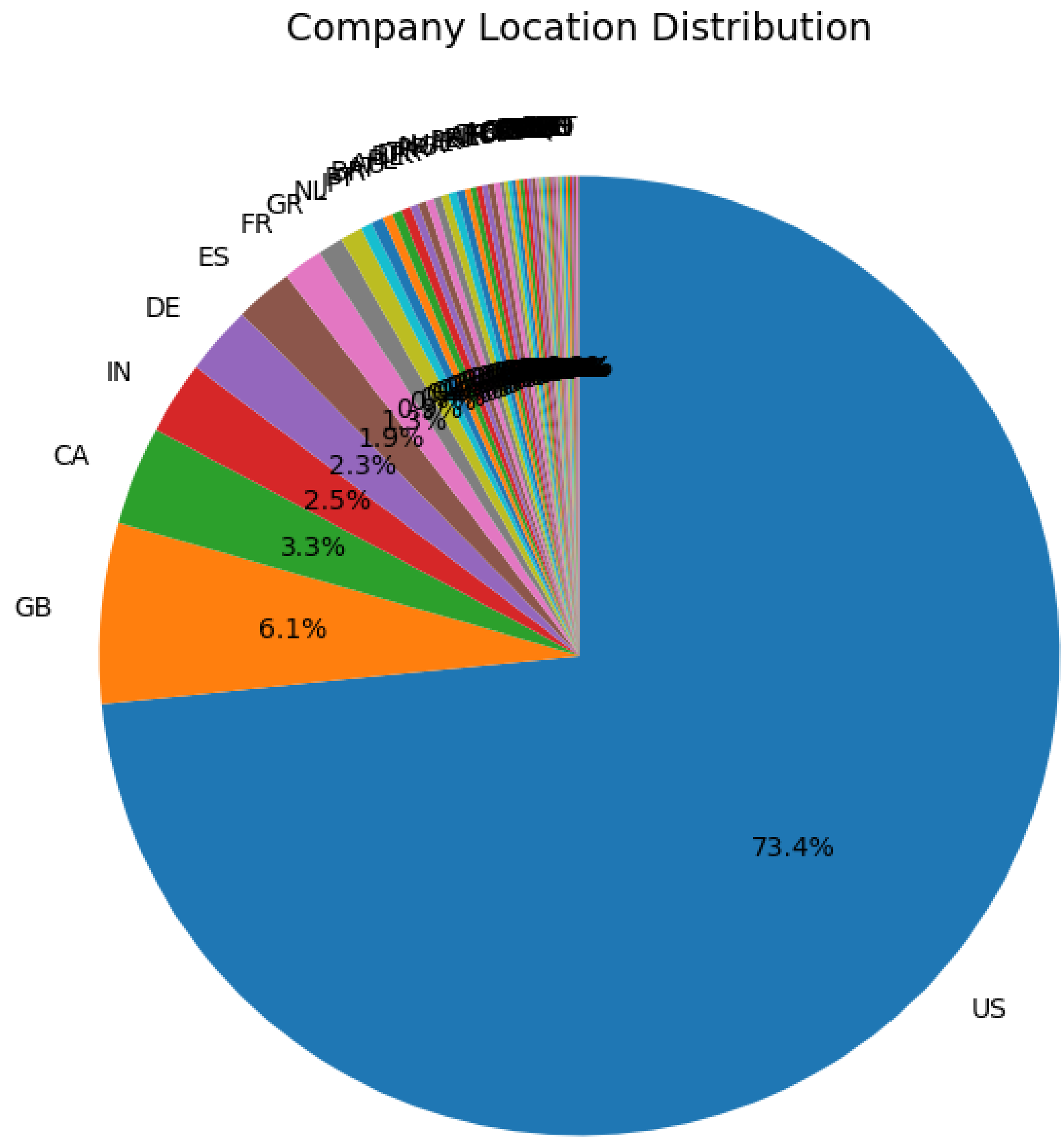
```
    all_locations["accumulated_count"] / total_locations * 100
).round(2)

# ========================
# 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)}")

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))

# ========================
# 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()
```

```
Number of unique company locations: 58

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
```



Employee Residence

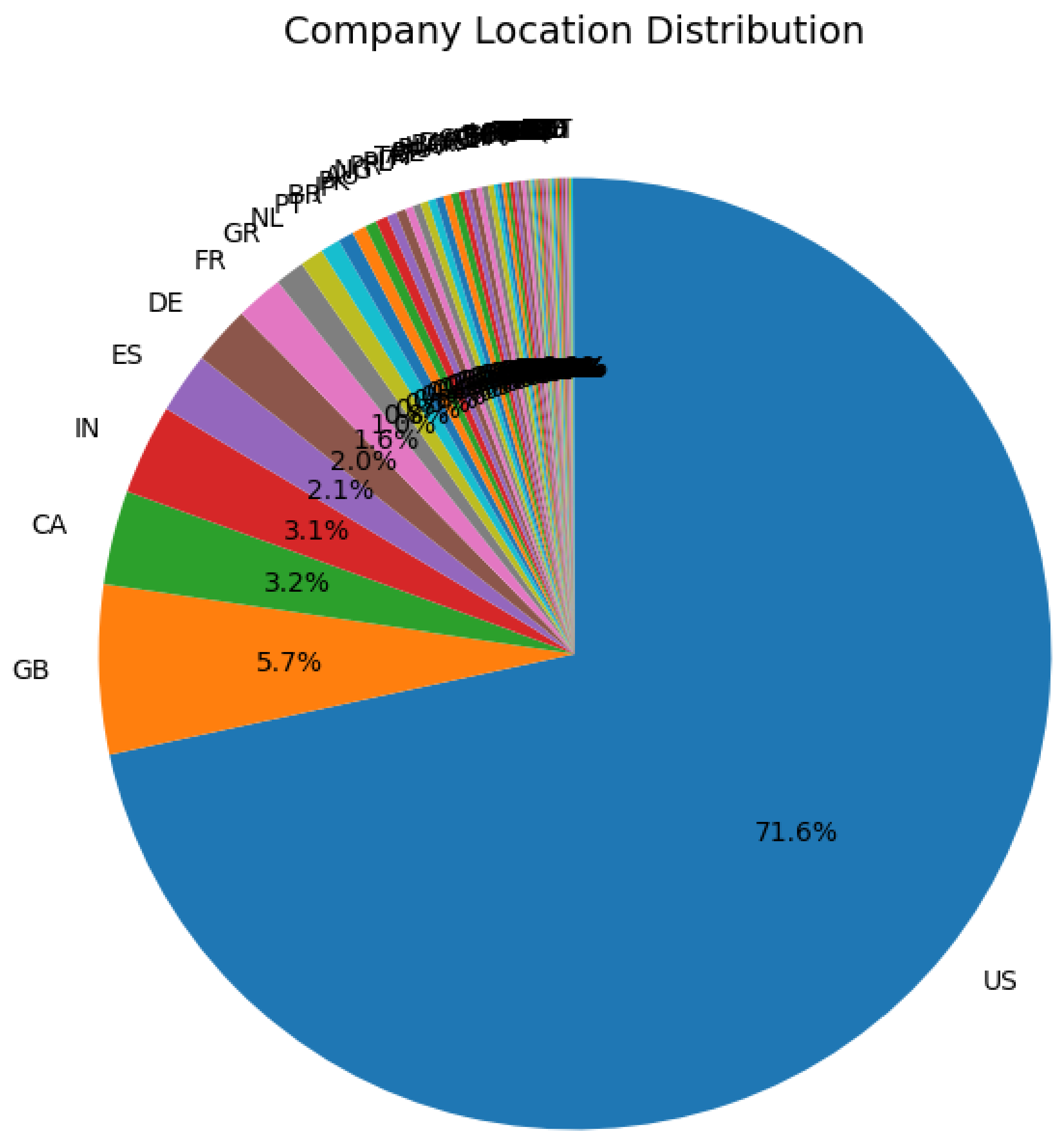
```python
import pandas as pd
import matplotlib.pyplot as plt

# ========================
```

```
# 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)}")

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))

# ========================
# 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()
```

```
Number of unique company locations: 61

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
```

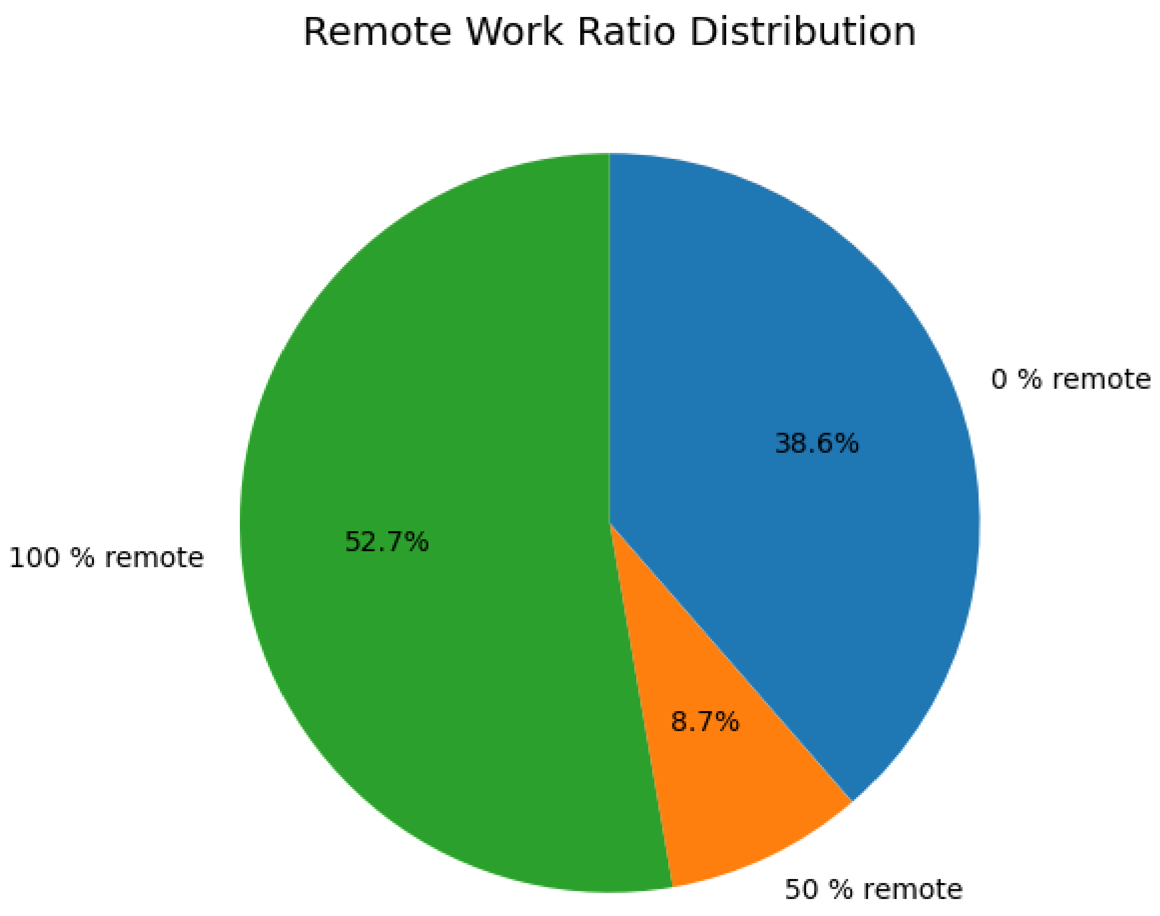


Remote Ratio (with Salary)

```
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)
```

```python
# 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)

# ========================
# 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()
```

```
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
```

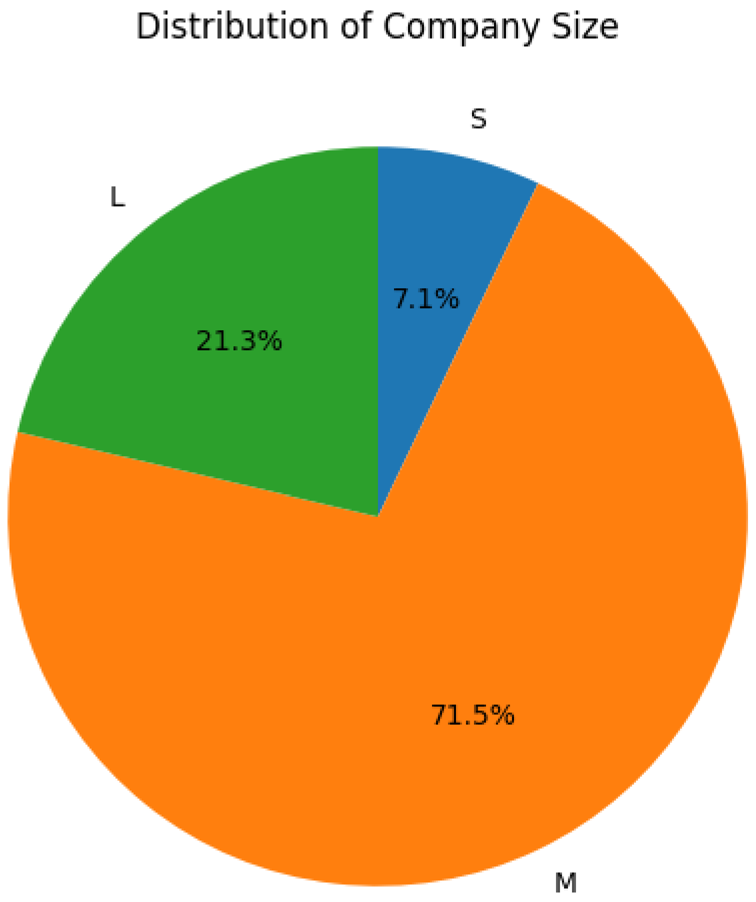


Company Size (with Salary)

```
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
# ========================
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)

# ========================
# 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()
```

```
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
```



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
```

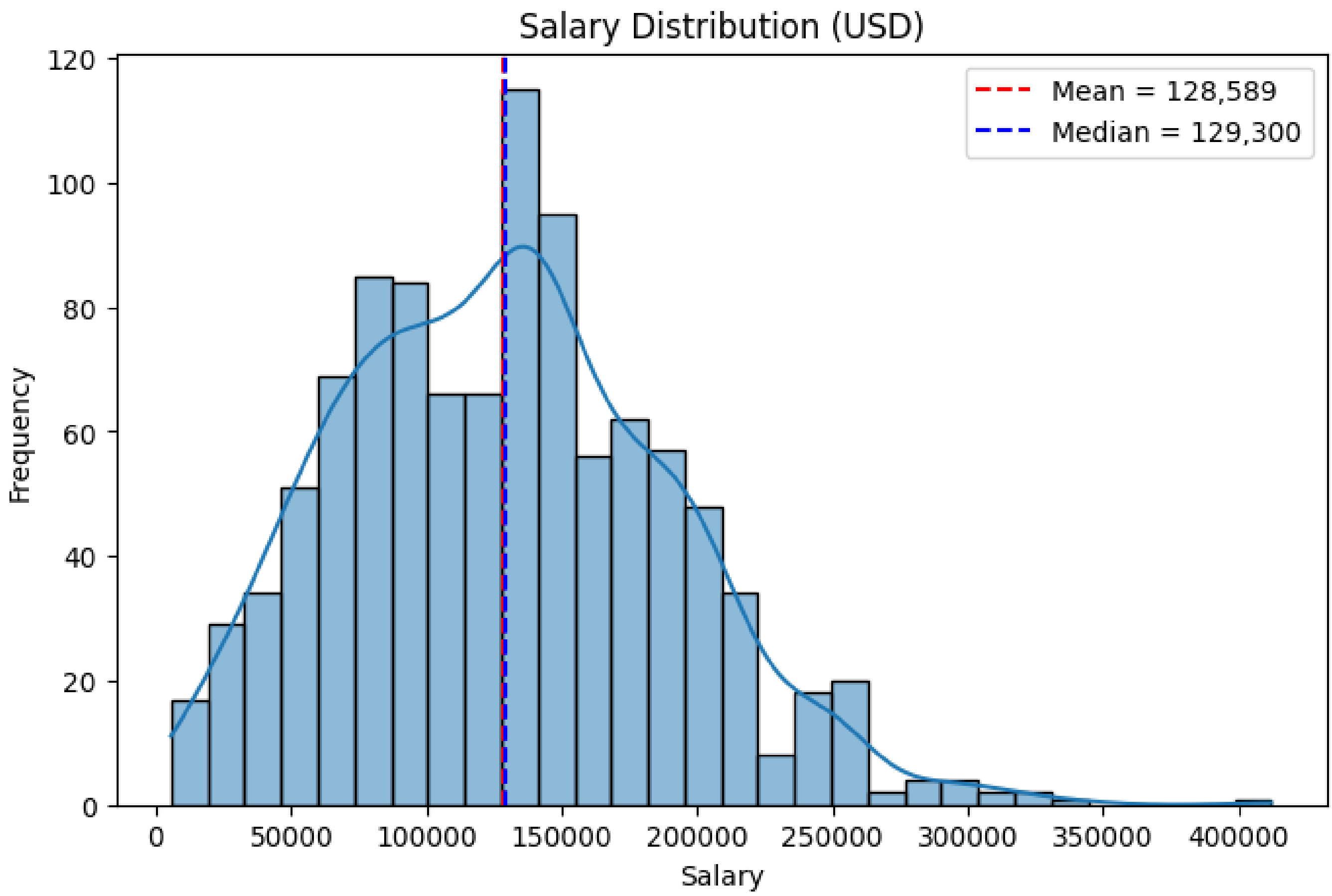
```
(1030, 11)
```

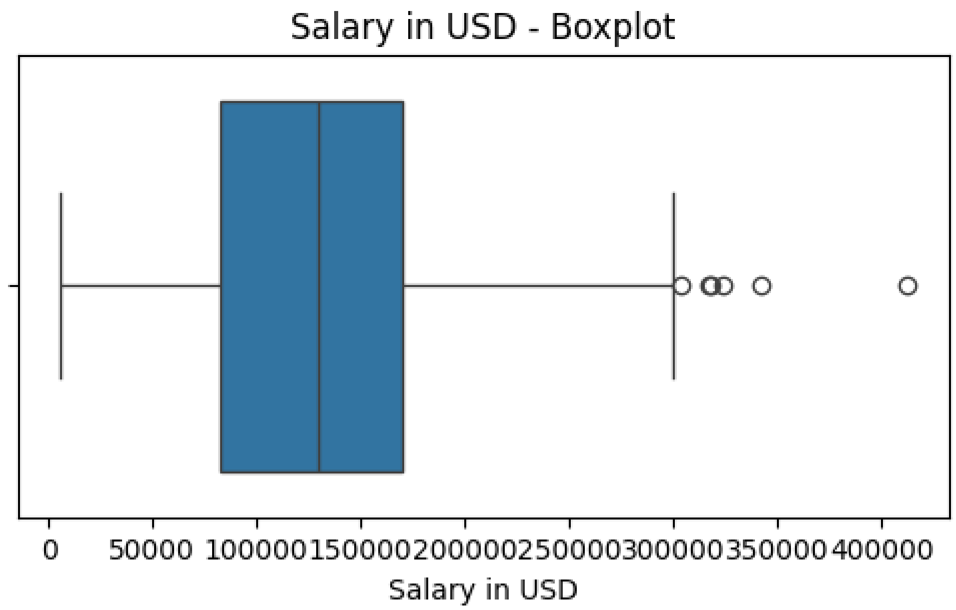
Salary Distribution after Filter

```
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}")


# --- 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))


# --- 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}")
```

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






```
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

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 = [
    "experience_level",
    "job_title",
    "employee_residence",
```

```
    "company_location",
    "company_size",
]
numeric_cols = ["remote_ratio"]
features = categorical_cols + numeric_cols

X = salaries_data_frame[features]
X.shape

y = salaries_data_frame["salary_in_usd"]
y.shape

# ========================
# 3. Split dataset
# ========================
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

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

X_train_processed = preprocessor_1.fit_transform(X_train)
X_test_processed = preprocessor_1.transform(X_test)

# ========================
# 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 = {}
true_avg_salary = y_test.mean()  # True average salary

for name, model in models_1.items():
    model.fit(X_train_processed, y_train)
    y_pred = model.predict(X_test_processed)

    rmse = root_mean_squared_error(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    pred_avg_salary = y_pred.mean()  # Predicted average salary

    results[name] = {
        "RMSE": rmse,
        "RMSE % of Avg": (rmse / true_avg_salary) * 100,
        "MAE": mae,
        "MAE % of Avg": (mae / true_avg_salary) * 100,
        "R²": r2,
        "True Avg Salary": true_avg_salary,
        "Predicted Avg Salary": pred_avg_salary,
    }

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

print(results_df.round(2).to_string(line_width=10000))
print("\nBest model based on R²:", results_df.index[0])
```

```
(1024, 11)
                      RMSE  RMSE % of Avg       MAE  MAE % of Avg    R²
```

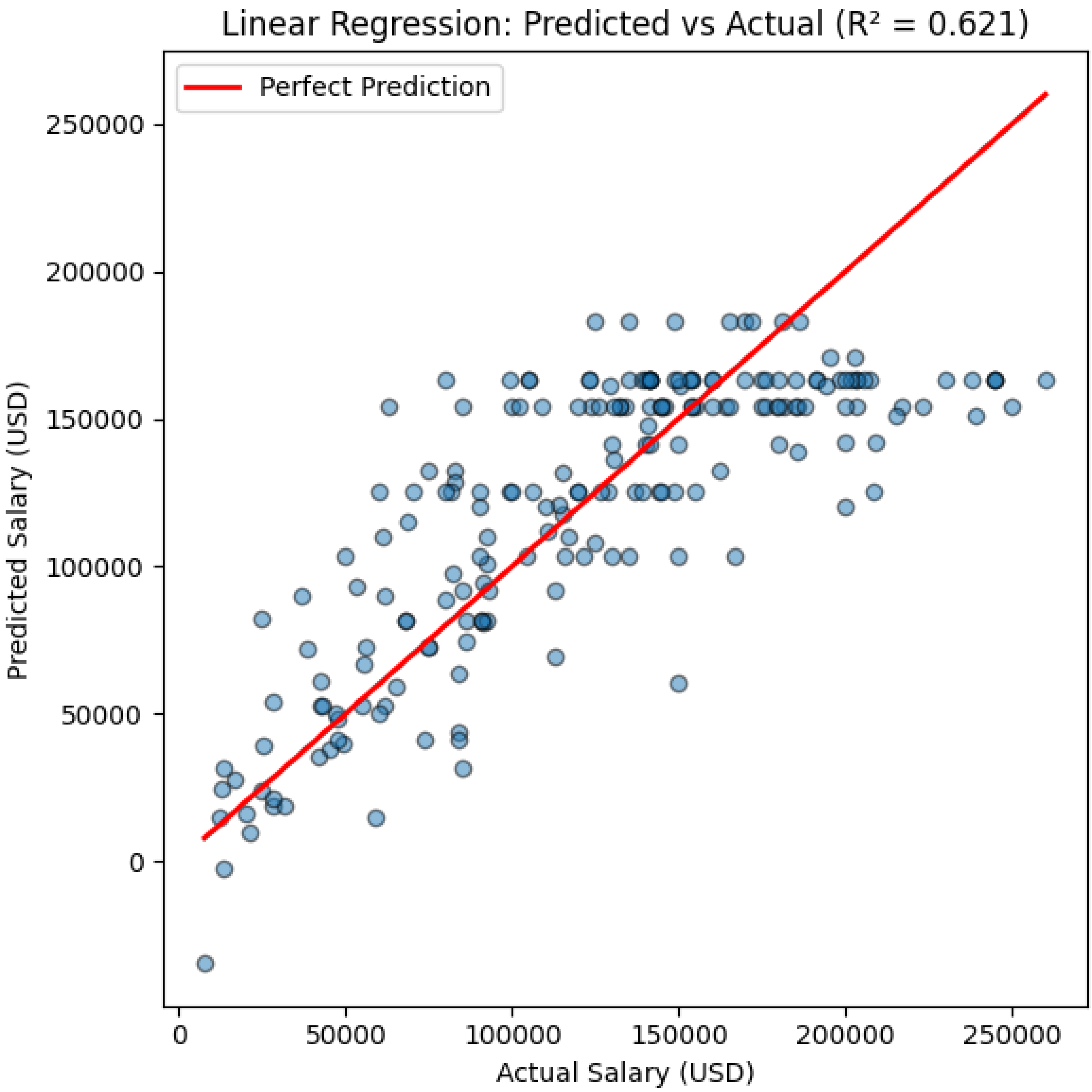
```
True Avg Salary  Predicted Avg Salary
LinearRegression  35762.74         29.00  27385.69         22.21  0.62
123309.06            120824.26
RandomForest      36751.52         29.80  29248.37         23.72  0.60
123309.06            124106.12
CatBoost          36966.07         29.98  28581.21         23.18  0.59
123309.06            124048.19
LightGBM          37853.95         30.70  30307.25         24.58  0.58
123309.06            124148.50
GradientBoosting  37888.40         30.73  28769.98         23.33  0.57
123309.06            124405.32
XGBoost           39276.33         31.85  29720.77         24.10  0.54
123309.06            125220.46

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(
```

Linear Regression

```python
import matplotlib.pyplot as plt

# Fit Linear Regression only
lin_model = LinearRegression()
lin_model.fit(X_train_processed, y_train)

# Predictions
y_pred_lin = lin_model.predict(X_test_processed)

# Evaluation
rmse = root_mean_squared_error(y_test, y_pred_lin)
r2 = r2_score(y_test, y_pred_lin)

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

# ======== Plot Predicted vs Actual ========
plt.figure(figsize=(6,6))
plt.scatter(y_test, y_pred_lin, alpha=0.5, edgecolor="k")
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.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: 35762.74, R²: 0.621
```

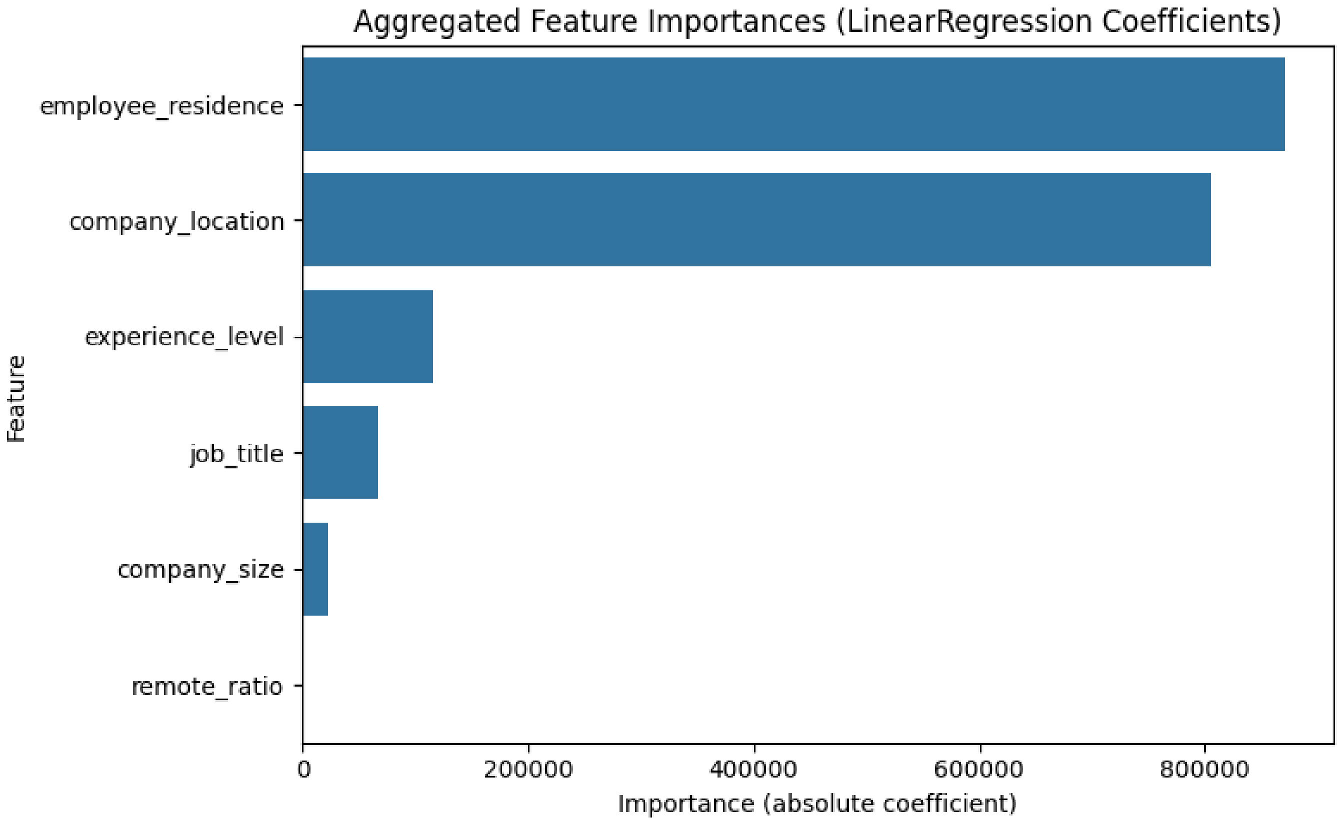


Features Importance

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

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

# Use same OHE feature names as before
ohe = preprocessor_1.named_transformers_["cat"]
ohe_features = ohe.get_feature_names_out(categorical_cols)
```

```
all_features = list(ohe_features) + numeric_cols

# Map back to original columns
def map_to_original(feature_name):
    for col in categorical_cols:
        if feature_name.startswith(col + "_"):
            return col
    if feature_name in numeric_cols:
        return feature_name
    return feature_name

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

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

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

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

```
=== Aggregated Feature Importances (LinearRegression coefficients) ===
              feature     importance
0  employee_residence  870374.002466
1    company_location  805913.144172
2    experience_level  116335.128606
3           job_title   66494.832056
4        company_size   22893.529989
5        remote_ratio      42.901199
```



Second Training

```
# ========================
# 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
# ========================
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.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] = {
        "RMSE": rmse_2,
        "MAE": mae_2,
        "R²": r2_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)
                          RMSE           MAE        R²  Predicted Avg
Salary
LinearRegression  35460.262713  27612.691817  0.627127
120270.467793
CatBoost          36032.043269  28061.036067  0.615005
122543.885647
GradientBoosting  36277.145824  27990.598879  0.609749
123513.312532
XGBoost           36652.996185  28507.822847  0.601621
123548.078125
RandomForest      36753.630485  29243.640004  0.599430
123197.168178
LightGBM          37258.456403  29757.696103  0.588351
122402.832104
```

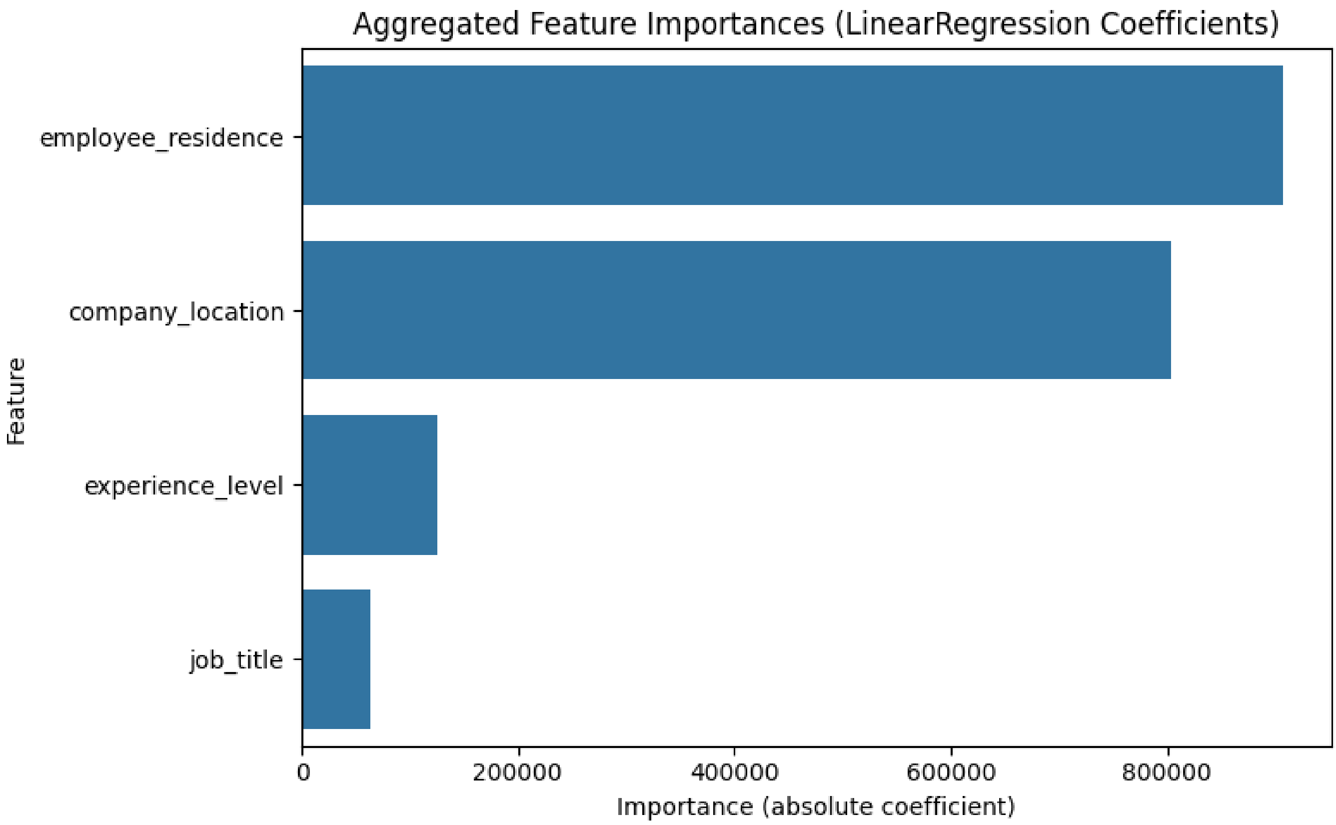
```
Best model based on R²: LinearRegression


/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(
```

Feature Importance

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

# Get coefficients from LinearRegression
linear_regression_coefs = models_2["LinearRegression"].coef_

# Use same OHE feature names as before
ohe_2 = preprocessor_2.named_transformers_["cat"]
ohe_features_2 = ohe_2.get_feature_names_out(features_2)
all_features_2 = list(ohe_features_2)


# Map back to original columns
def map_to_original(feature_name):
    for col in categorical_cols:
        if feature_name.startswith(col + "_"):
            return col
    if feature_name in numeric_cols:
        return feature_name
    return feature_name


original_features_2 = [map_to_original(f) for f in all_features_2]

# Aggregate absolute coefficients as importance
feature_importance_salaries_data_frame = (
    pd.DataFrame(
        {"feature": original_features_2, "importance":
abs(linear_regression_coefs)}
    )
    .groupby("feature")
    .sum()
    .sort_values(by="importance", ascending=False)
    .reset_index()
)

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

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

```
=== Aggregated Feature Importances (LinearRegression coefficients) ===
             feature     importance
0  employee_residence  906657.879079
1    company_location  803909.312904
2    experience_level  125013.224016
3           job_title   62849.875465
```



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_11047/346195264
2.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_2.transform(X_new)

# 4. Predict using the trained model
predictions = models_2["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              161299.83             0.81 ✅  Acceptable
      2023                 MI               FT  Data Engineer
GB                GB             L              50  82528.0             USD
82528.0               78889.00             -4.41 ✅  Acceptable
      2023                 EN               FT   Data Analyst
BR                BR             S               0   8000.0             USD
8000.0              -23555.56           -394.44 ⚠ High Error
```