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
```

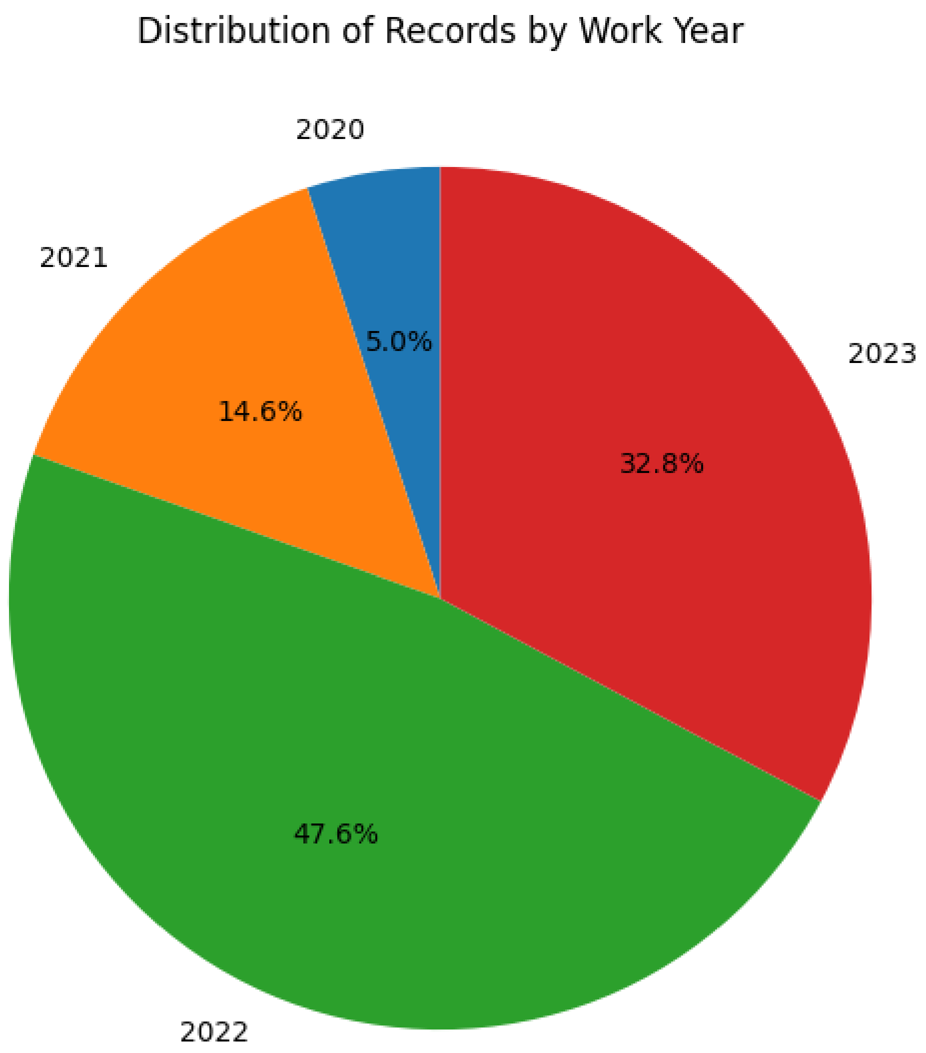
Work Year

```
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()
```



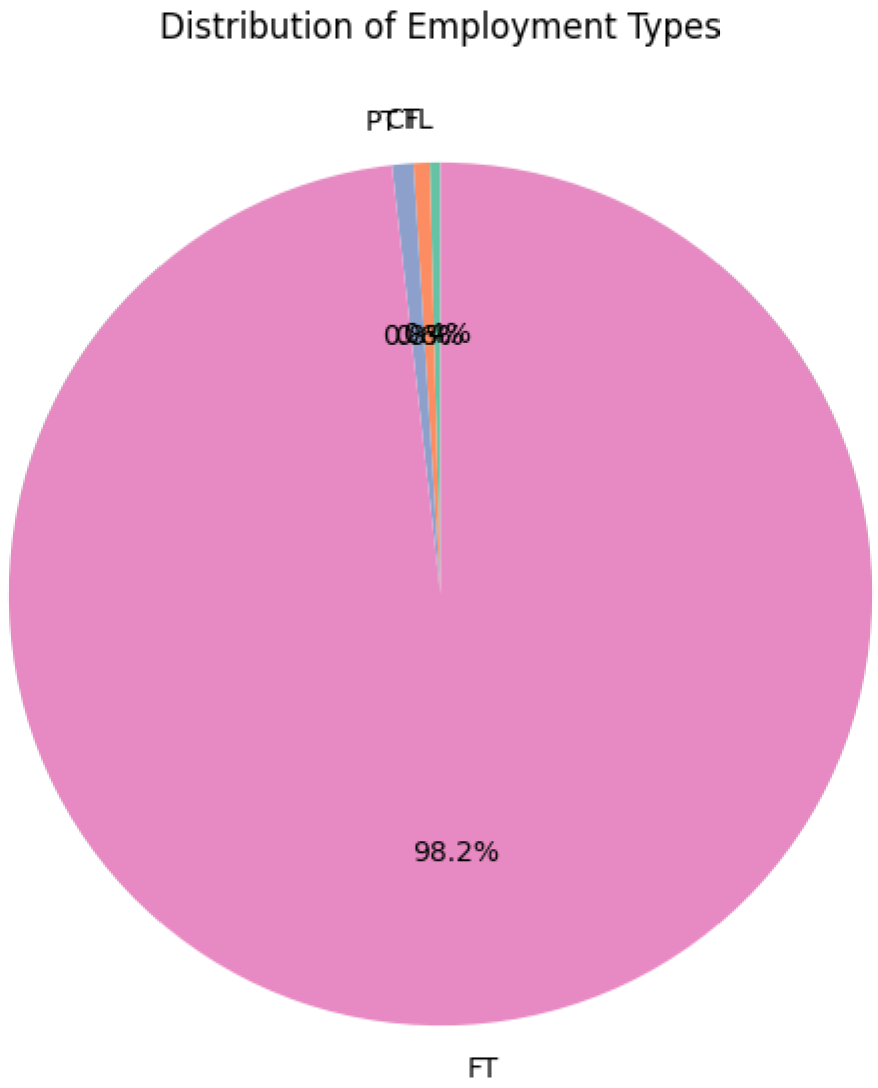
Employment Type

```
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 = (
```

```python
    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
```

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



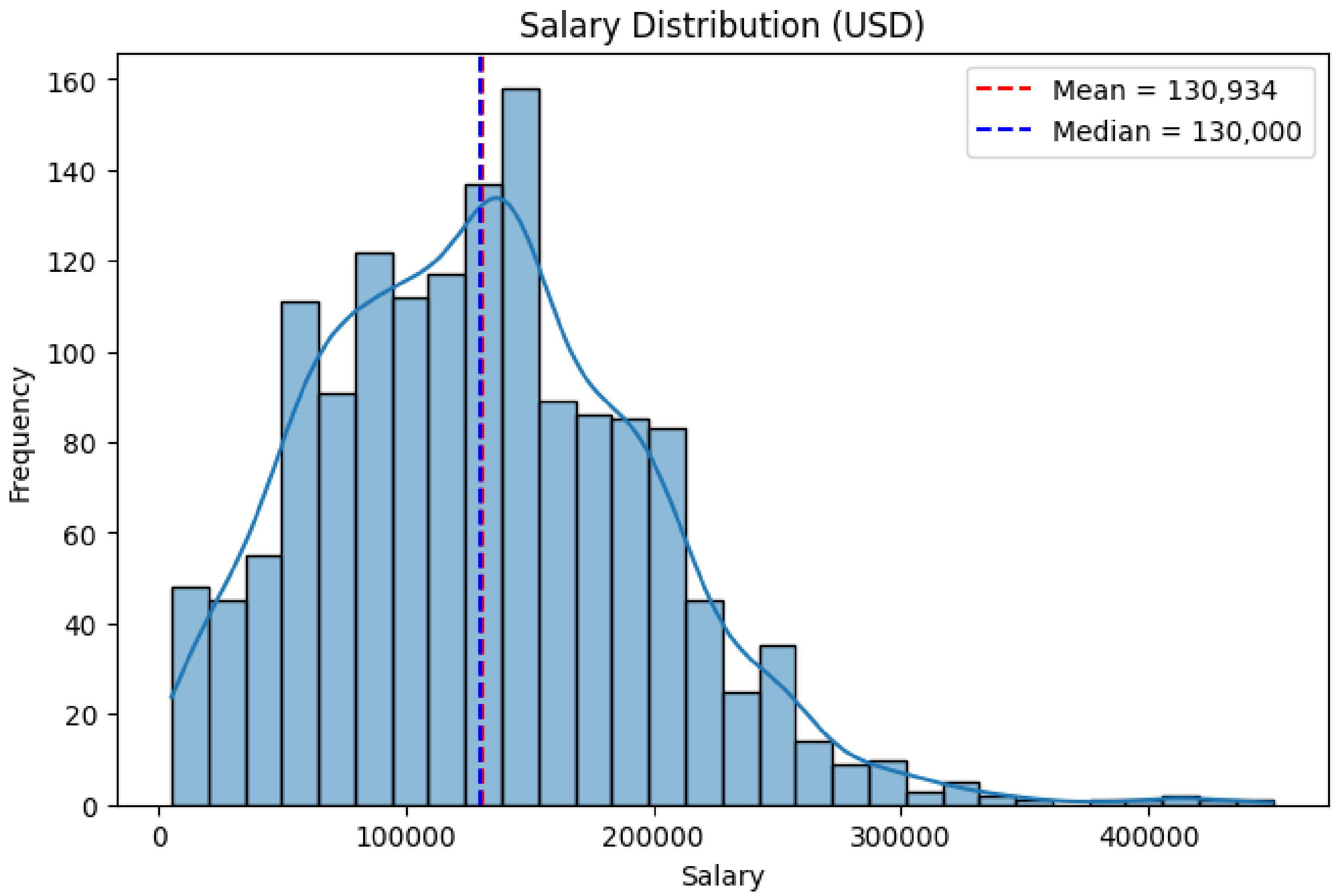
Salary

```
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}")
```

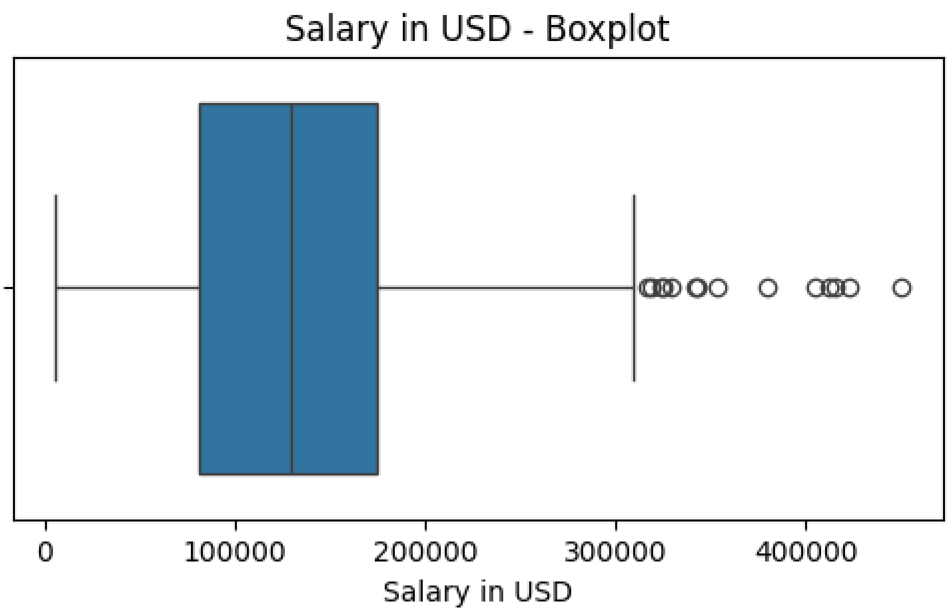
```python
# Skew check
skewness = salary_in_usd_series.skew()
print(f"Skewness: {skewness:.2f}")
```

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

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



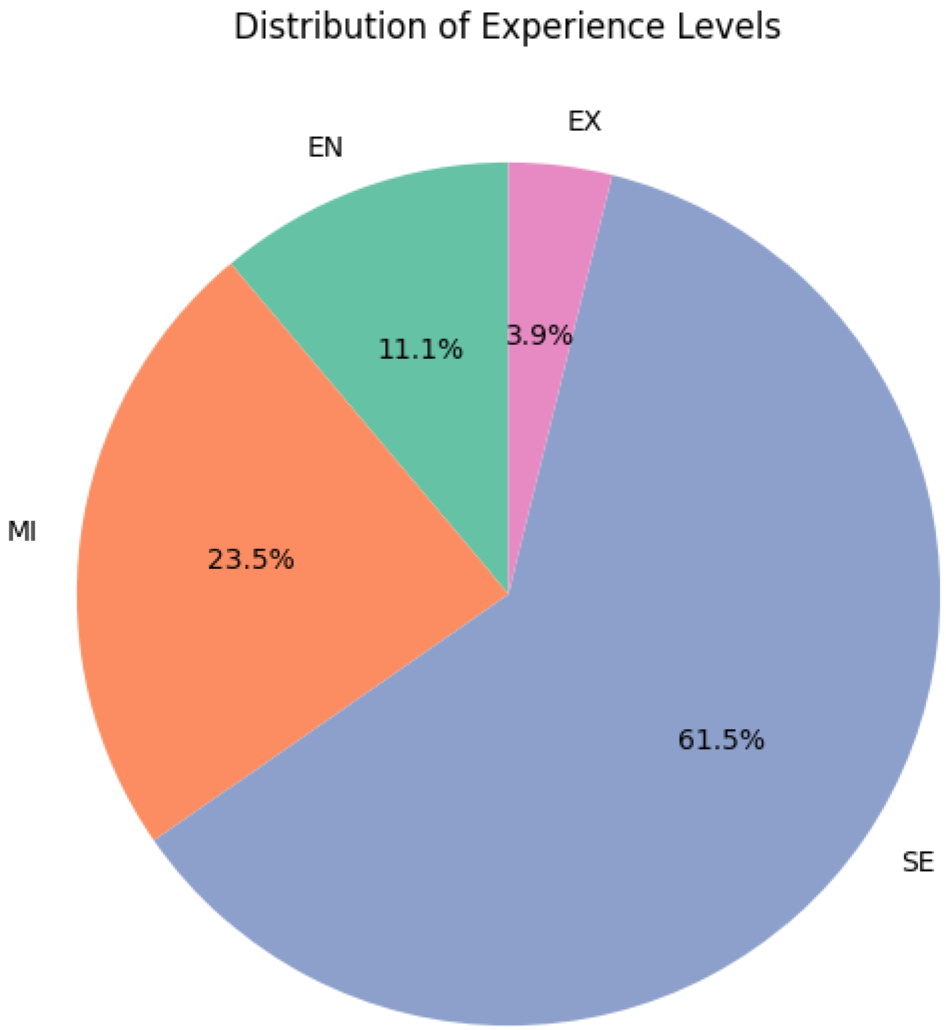
Experience Level (with Salary)

```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)
```

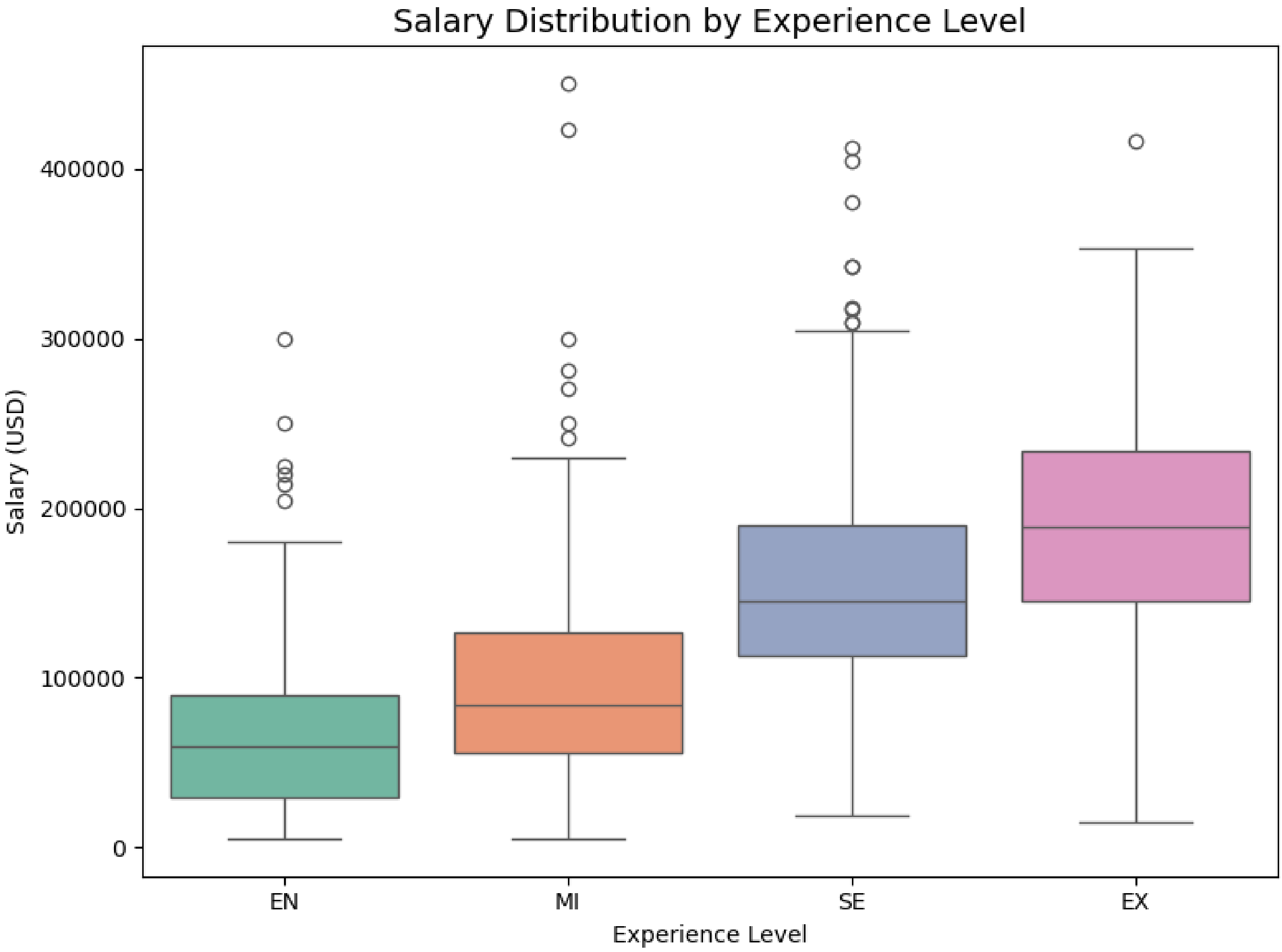
```
Experience Level Summary:
                  count  percentage     Mean   Median
experience_level
EN                  167        11.1  69627.0  60000.0
MI                  353        23.5  95473.0  84053.0
```

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


/var/folders/jh/z981c7zj0vz0gmyfc8mhdxdr0000gn/T/ipykernel_67267/674642401
.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()
```




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

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

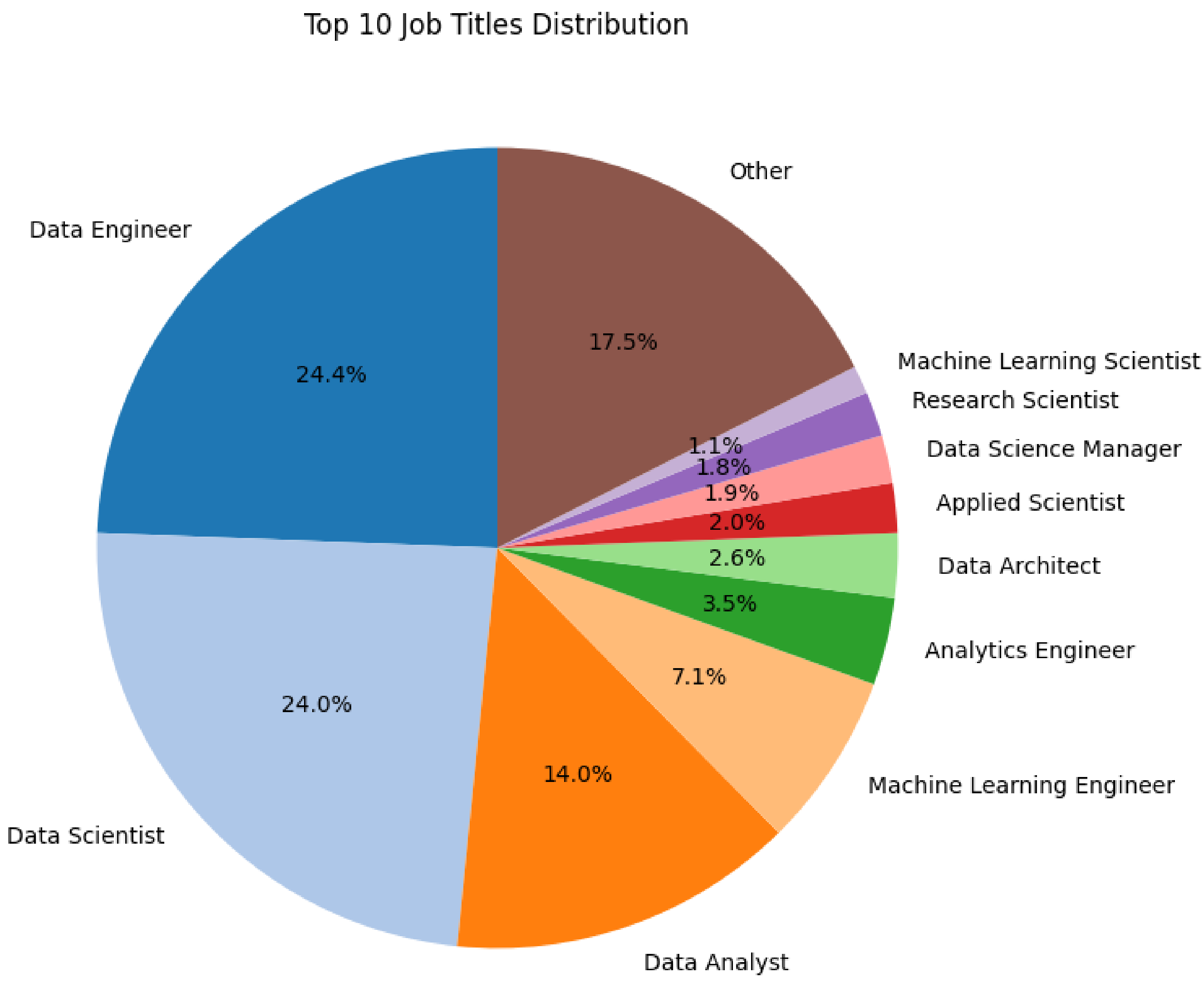
```
Number of unique job titles: 69

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
```

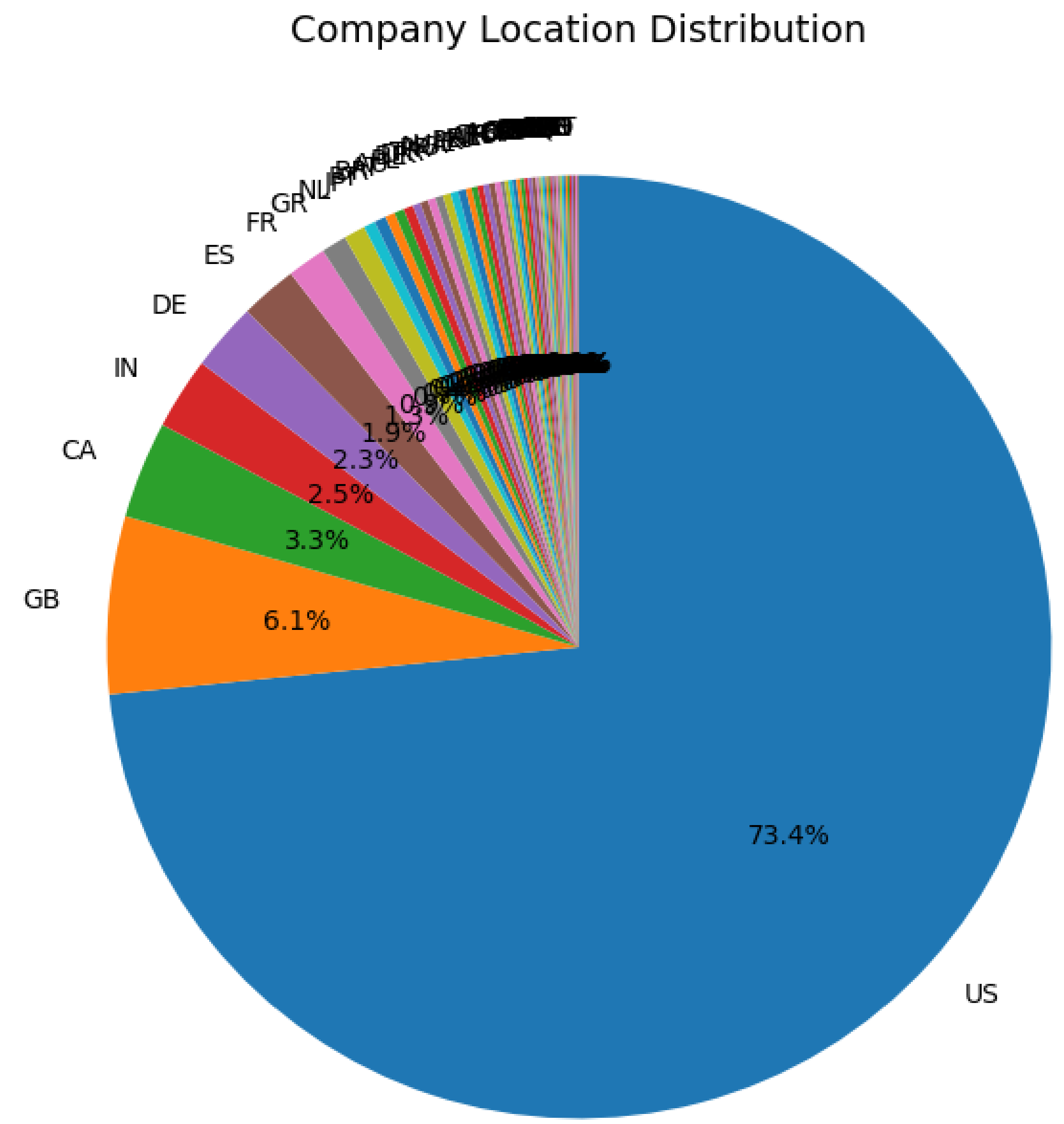
```
pd.set_option("display.max_rows", None)  # Show all rows in output
print("\nAll company locations with salary stats:")
print(all_locations.to_string(index=False, line_width=10000))
```

```
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
```

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

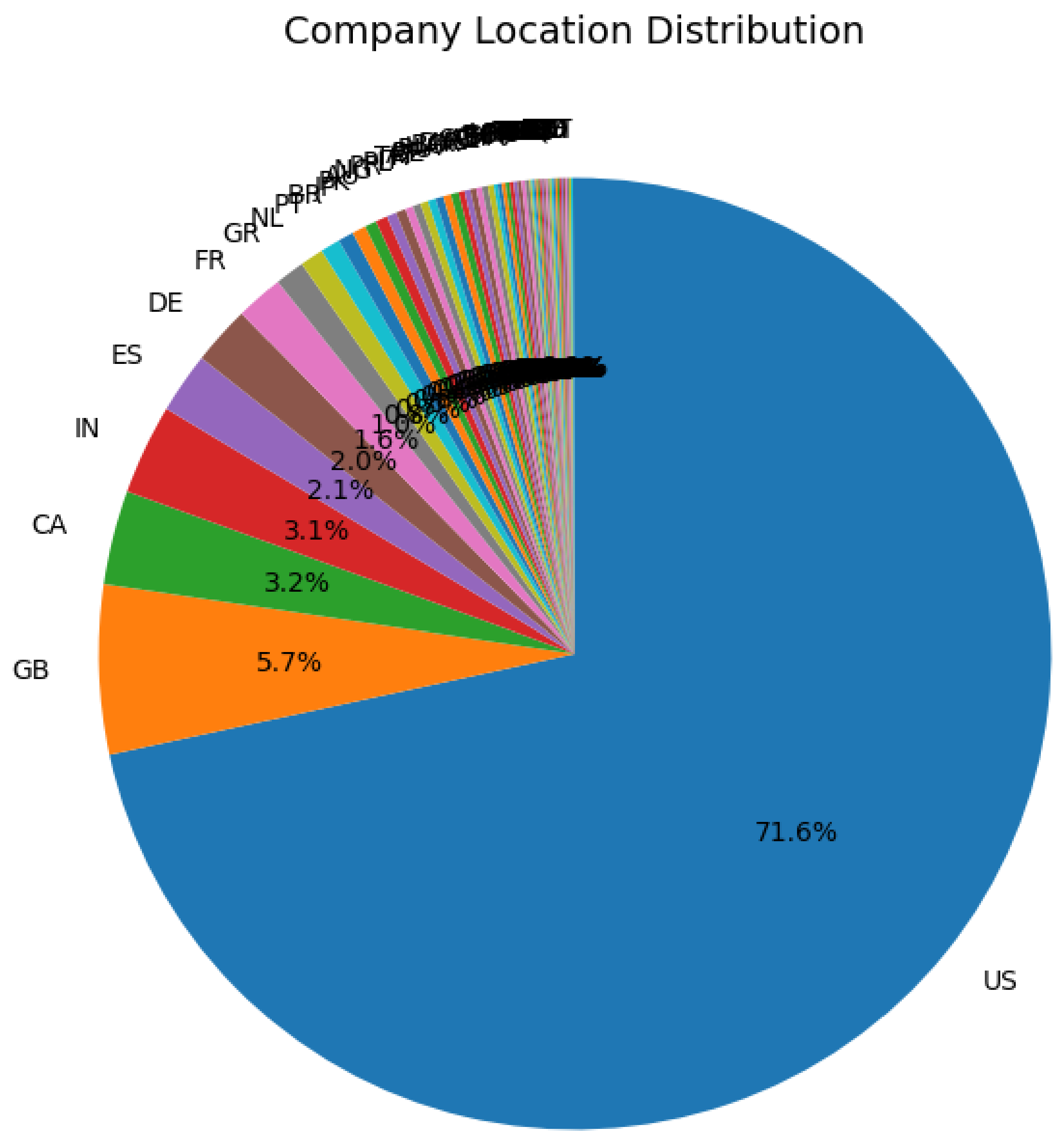
```python
pd.set_option("display.max_rows", None)  # Show all rows in output
print("\nAll company locations with salary stats:")
print(all_locations.to_string(index=False, line_width=10000))
```

```
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()
```



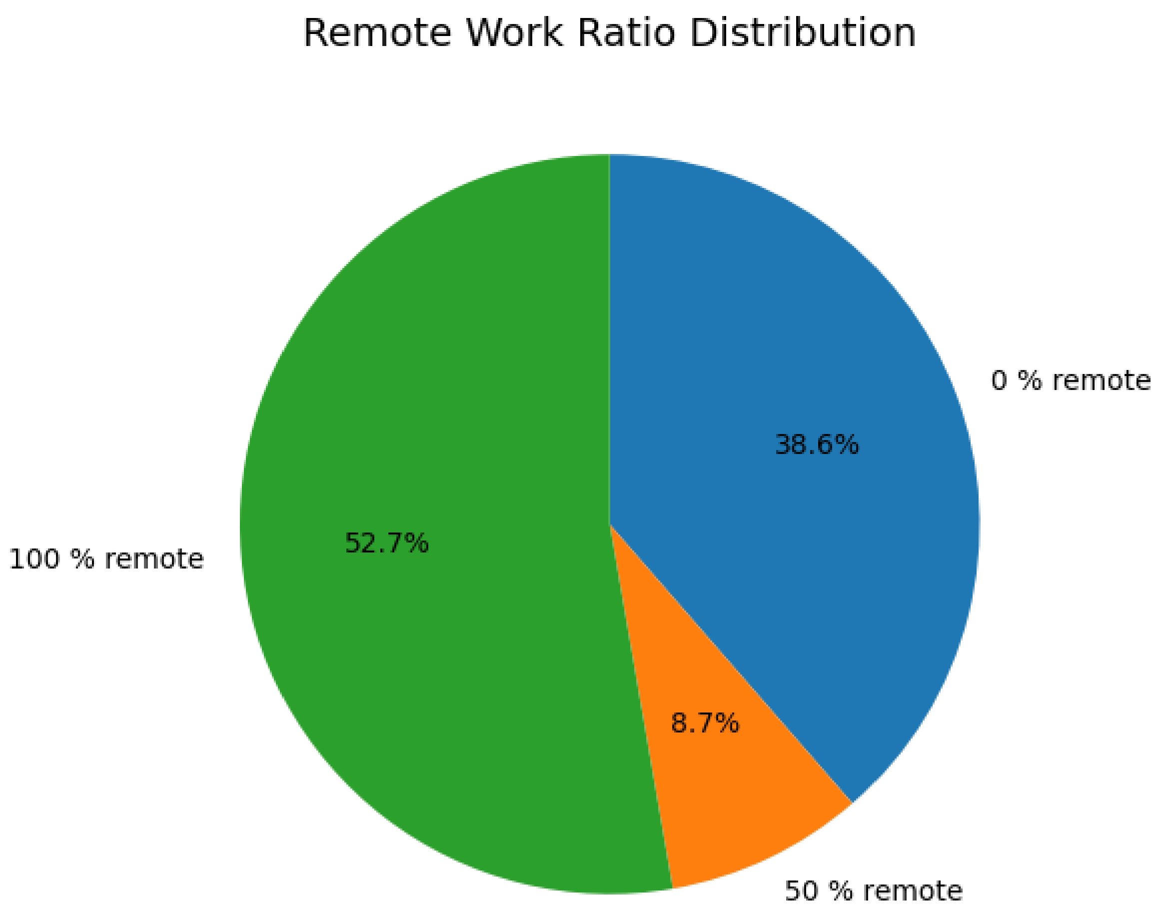
Remote Ratio (with Salary)

```python
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)
```

```
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
```

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



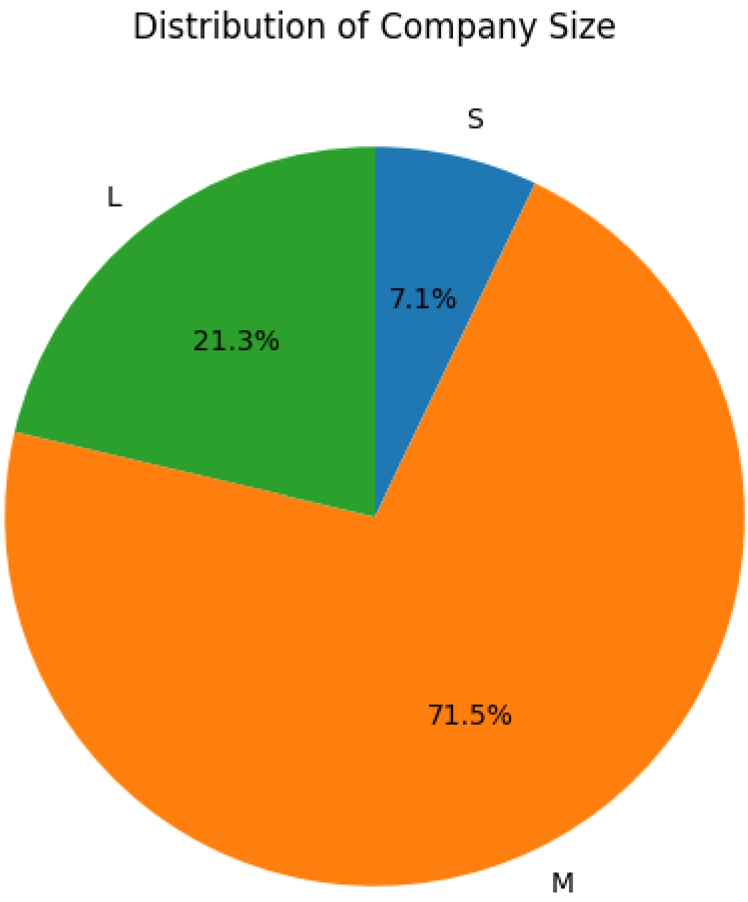
Company Size (with Salary)

```
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
```

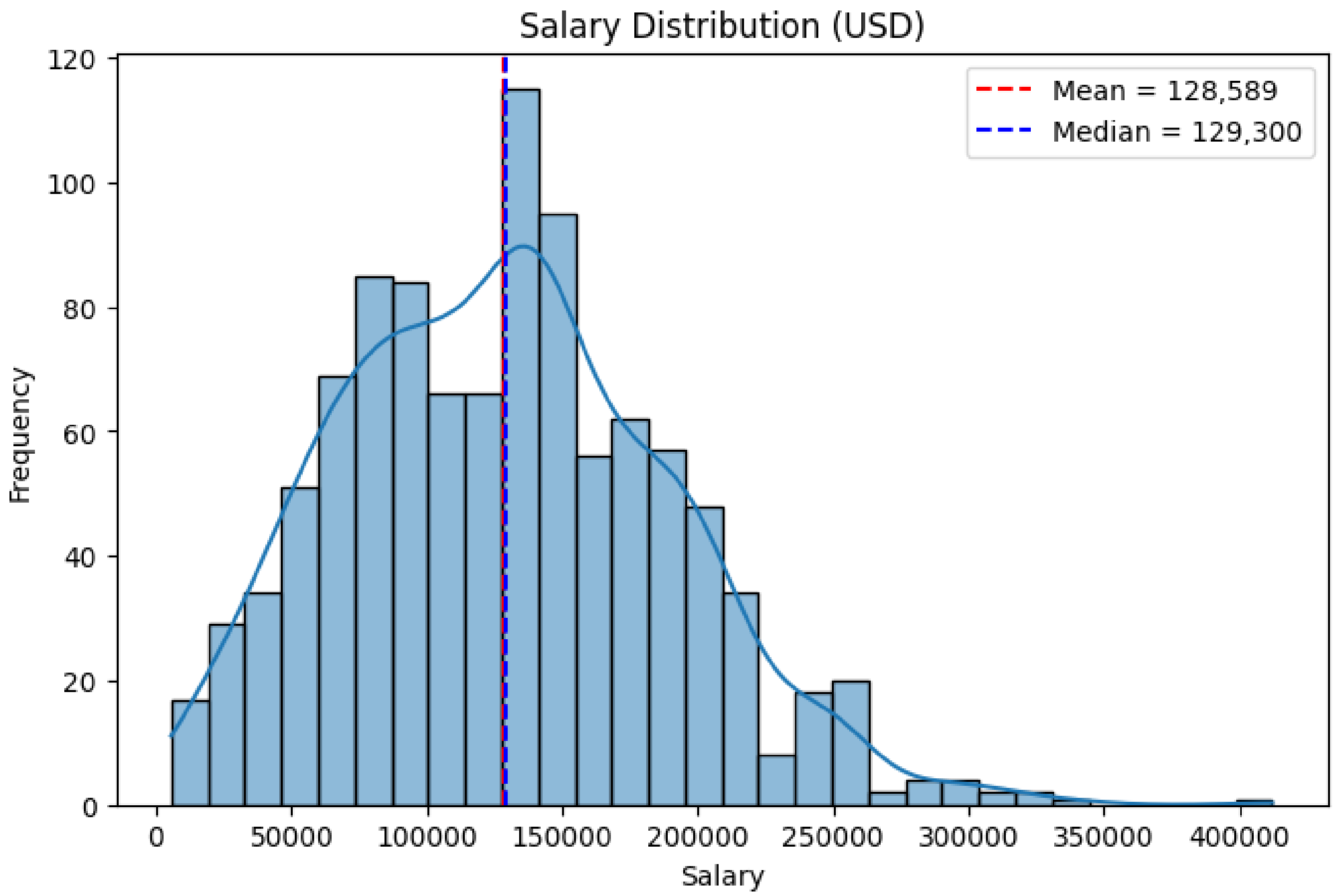
```
(1030, 11)
```

Salary Distribution after Filter

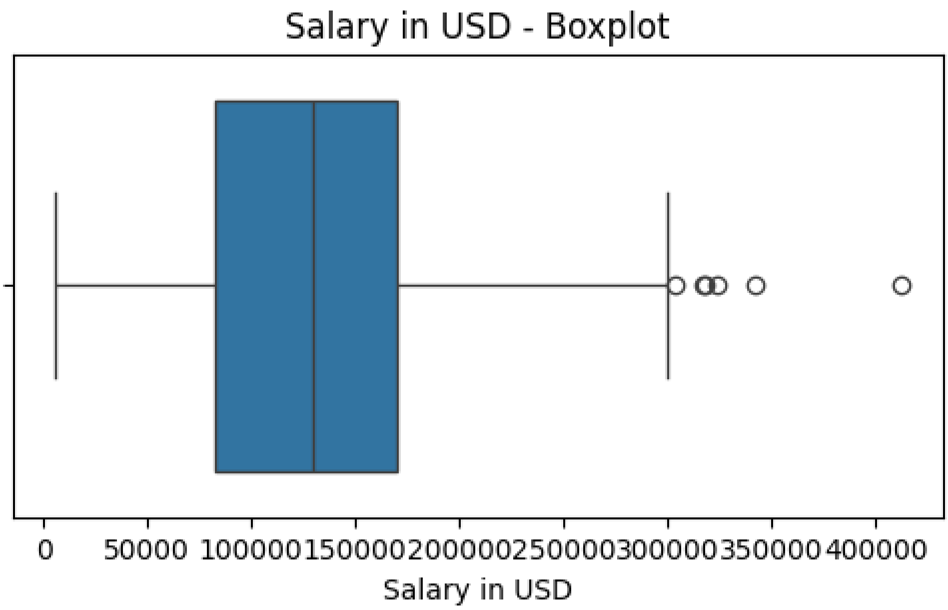
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# --- 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()
```




```python
# --- 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 = preprocessor_1.fit_transform(X_train_1)
X_test_processed = 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, y_train_1)
    y_pred_1 = model.predict(X_test_processed)

    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])
```

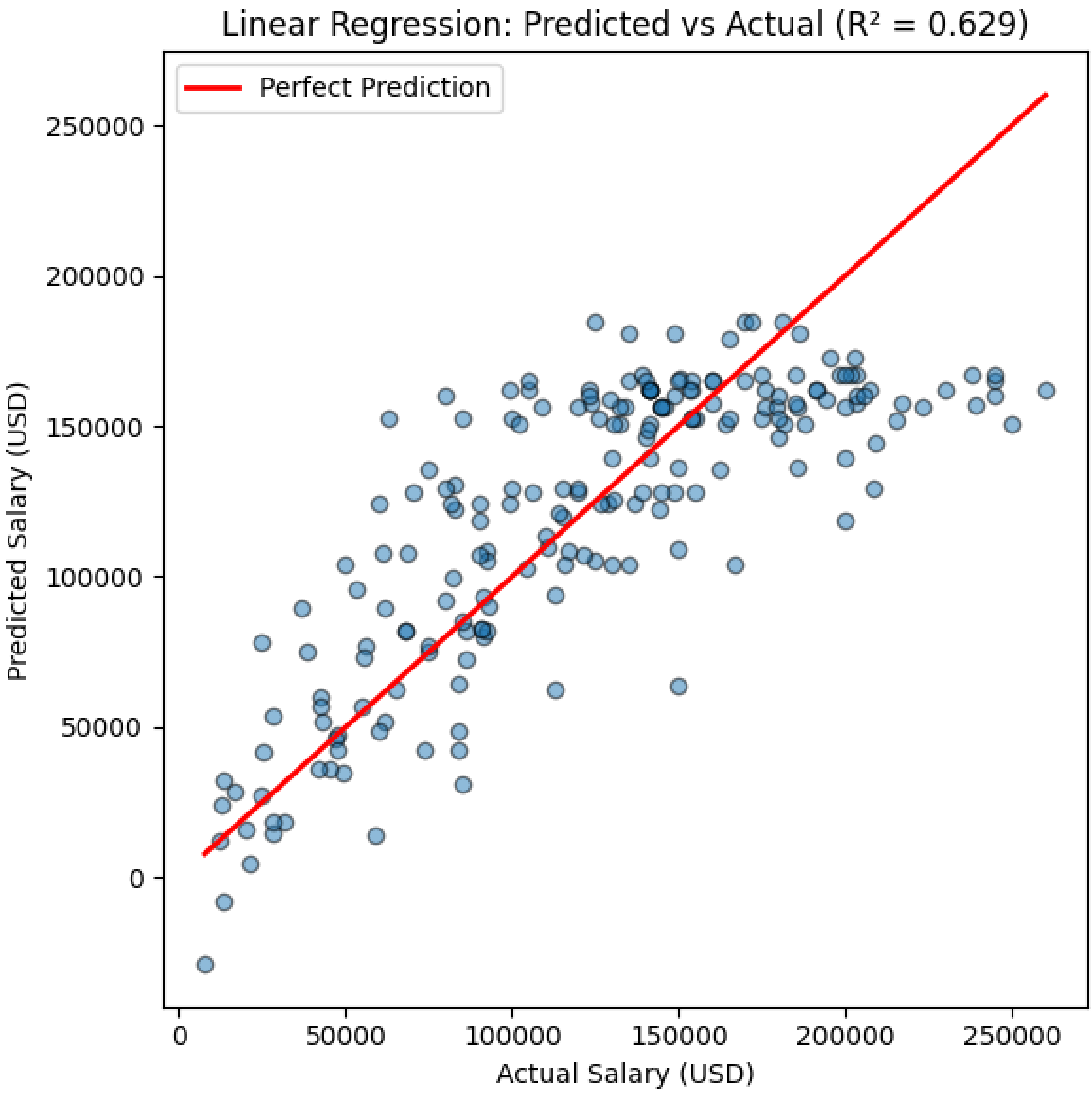
```
(1024, 11)
                        R²            MAE           RMSE  Predicted Avg
Salary  True Avg Salary  MAE % of Avg  RMSE % of Avg
LinearRegression  0.629053  27303.373122  35368.517685
120906.412330    123309.063415     22.142227      28.682821
CatBoost          0.616604  28005.258412  35957.105376
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, 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: 35368.52, R²: 0.629
```

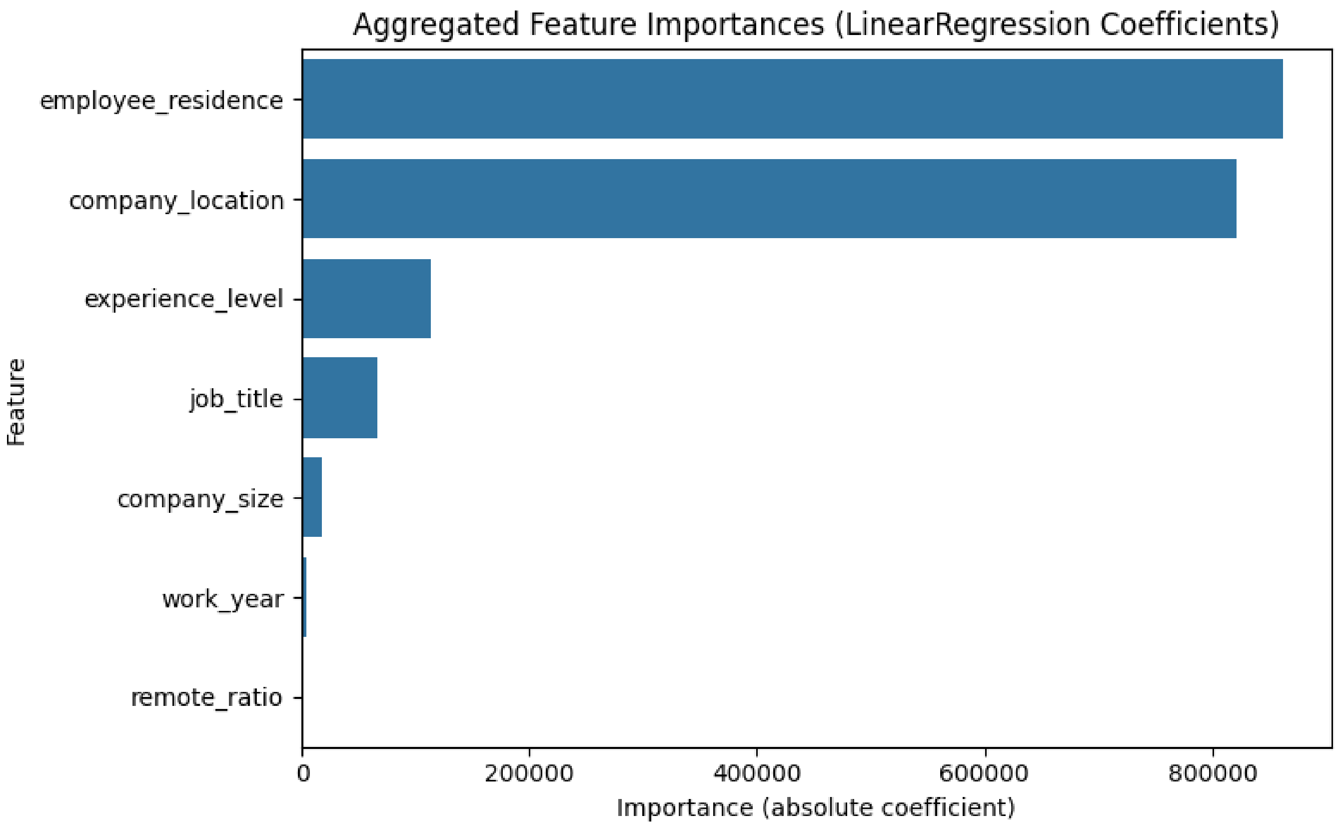


Features Importance

```python
# ========================
# 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_1)
all_features = list(ohe_features) + numeric_cols_1

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

```
=== 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
```

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



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

```
# ========================
# 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 Choice (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", "remote_ratio"]
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 = preprocessor_3.fit_transform(X_train_3)
X_test_processed = 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, y_train_3)
    y_pred_3 = model.predict(X_test_processed)

    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)
```

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

```python
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_67267/346195264
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_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"
)
```

```python
# 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            167389.26              4.62 ✅ Acceptable
      2023               MI              FT  Data Engineer
GB                GB            L              50  82528.0             USD
82528.0             87356.71               5.85 ✅ Acceptable
      2023               EN              FT   Data Analyst
BR                BR            S               0   8000.0             USD
8000.0            -14442.74            -280.53 ⚠ High Error
```