AI Job Market Visulization

- Explore salaries, skills, remote work, and trends in the global AI job market.
- **Dataset Time Period:** January 2024 - May 2025

```python
# Step 0: Import libraries and load data
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
import numpy as np
import warnings
warnings.filterwarnings('ignore')
# For better plots
sns.set(style="whitegrid")
plt.rcParams["figure.figsize"] = (10,6)
# Load dataset
df = pd.read_csv('aijob.csv')
# Quick peek
print(df.head())
print(f"Dataset shape: {df.shape}")
```

```
    job_id              job_title  salary_usd salary_currency  \
0  AI00001  AI Research Scientist       90376             USD
1  AI00002   AI Software Engineer       61895             USD
2  AI00003          AI Specialist      152626             USD
3  AI00004           NLP Engineer       80215             USD
4  AI00005          AI Consultant       54624             EUR

  experience_level employment_type company_location company_size  \
0               SE              CT            China            M
1               EN              CT           Canada            M
2               MI              FL      Switzerland            L
3               SE              FL            India            M
4               EN              PT           France            S

  employee_residence  remote_ratio  \
0              China            50
1            Ireland           100
2        South Korea             0
3              India            50
4          Singapore           100

                                   required_skills education_required
\
0         Tableau, PyTorch, Kubernetes, Linux, NLP           Bachelor

1  Deep Learning, AWS, Mathematics, Python, Docker             Master
```

```
2     Kubernetes, Deep Learning, Java, Hadoop, NLP         Associate

3                        Scala, SQL, Linux, Python               PhD

4                      MLOps, Java, Tableau, Python           Master


   years_experience    industry posting_date application_deadline  \
0                 9  Automotive   2024-10-18           2024-11-07
1                 1       Media   2024-11-20           2025-01-11
2                 2   Education   2025-03-18           2025-04-07
3                 7  Consulting   2024-12-23           2025-02-24
4                 0       Media   2025-04-15           2025-06-23

   job_description_length  benefits_score       company_name
0                    1076             5.9    Smart Analytics
1                    1268             5.2       TechCorp Inc
2                    1974             9.4    Autonomous Tech
3                    1345             8.6     Future Systems
4                    1989             6.6  Advanced Robotics
Dataset shape: (15000, 19)
```

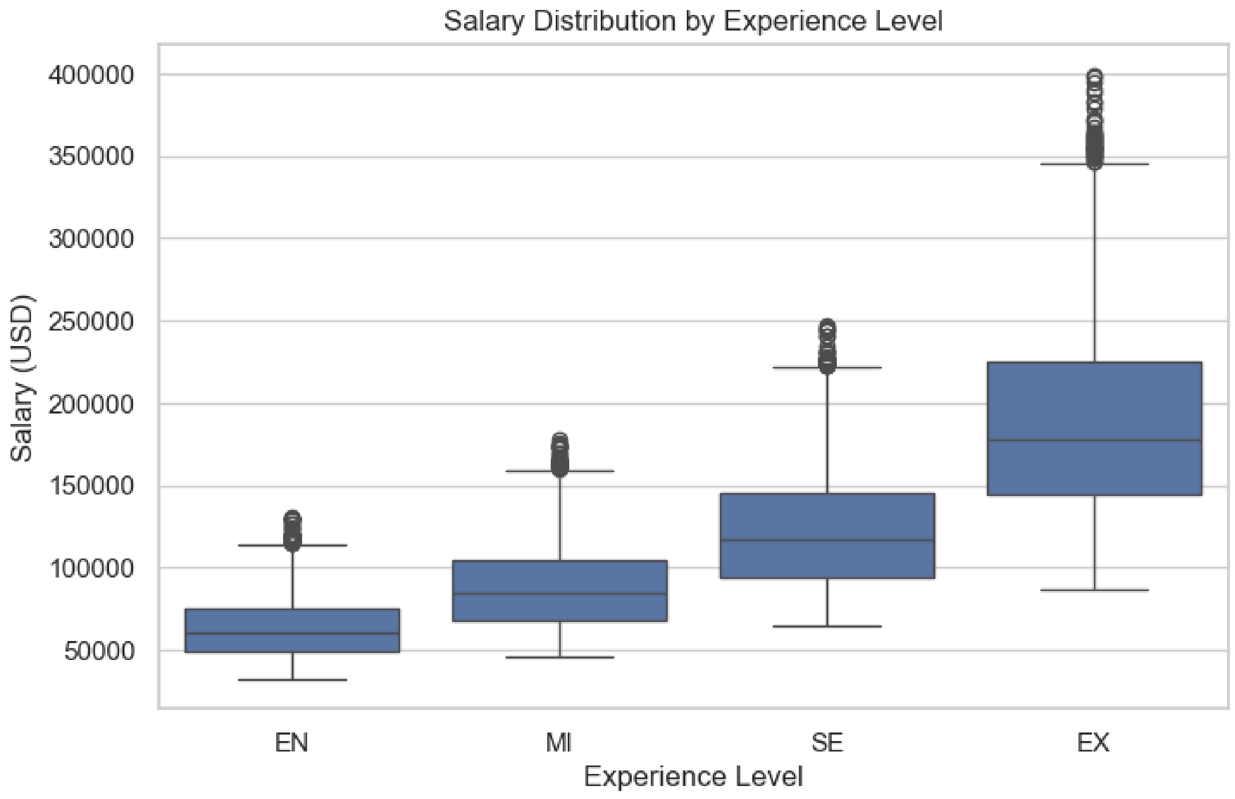
```python
# Step 1: Basic info & cleaning
print(df.info())
print(df.isnull().sum())
# Drop columns if you want, or fill missing values for key cols
# For example, fill missing salary with median or drop rows with
missing salary
df = df.dropna(subset=['salary_usd', 'experience_level', 'industry'])
# Convert posting_date to datetime
df['posting_date'] = pd.to_datetime(df['posting_date'],
errors='coerce')
# Clean remote_ratio to numeric if needed
df['remote_ratio'] = pd.to_numeric(df['remote_ratio'],
errors='coerce')
# Quick check
print(df.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15000 entries, 0 to 14999
Data columns (total 19 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   job_id                  15000 non-null  object
 1   job_title               15000 non-null  object
 2   salary_usd              15000 non-null  int64
 3   salary_currency         15000 non-null  object
 4   experience_level        15000 non-null  object
 5   employment_type         15000 non-null  object
 6   company_location        15000 non-null  object
 7   company_size            15000 non-null  object
 8   employee_residence      15000 non-null  object
 9   remote_ratio            15000 non-null  int64
 10  required_skills         15000 non-null  object
 11  education_required      15000 non-null  object
 12  years_experience        15000 non-null  int64
 13  industry                15000 non-null  object
 14  posting_date            15000 non-null  object
 15  application_deadline    15000 non-null  object
 16  job_description_length  15000 non-null  int64
 17  benefits_score          15000 non-null  float64
 18  company_name            15000 non-null  object
dtypes: float64(1), int64(4), object(14)
memory usage: 2.2+ MB
None
job_id                    0
job_title                 0
salary_usd                0
salary_currency           0
experience_level          0
employment_type           0
company_location          0
company_size              0
employee_residence        0
remote_ratio              0
required_skills           0
education_required        0
years_experience          0
industry                  0
posting_date              0
application_deadline      0
job_description_length    0
benefits_score            0
company_name              0
dtype: int64
          salary_usd  remote_ratio  years_experience  \
count   15000.000000  15000.000000      15000.000000
mean   115348.965133     49.483333          6.253200
min     32519.000000      0.000000          0.000000
25%     70179.750000      0.000000          2.000000
50%     99705.000000     50.000000          5.000000
75%    146408.500000    100.000000         10.000000
max    399095.000000    100.000000         19.000000
std     60260.940438     40.812712          5.545768

                     posting_date  job_description_length
benefits_score
count                       15000            15000.000000
15000.000000
```

```
mean   2024-08-29 08:48:51.840000            1503.314733
7.504273
min           2024-01-01 00:00:00             500.000000
5.000000
25%           2024-04-29 00:00:00            1003.750000
6.200000
50%           2024-08-28 00:00:00            1512.000000
7.500000
75%           2024-12-29 00:00:00            2000.000000
8.800000
max           2025-04-30 00:00:00            2499.000000
10.000000
std                           NaN             576.127083
1.450870
```

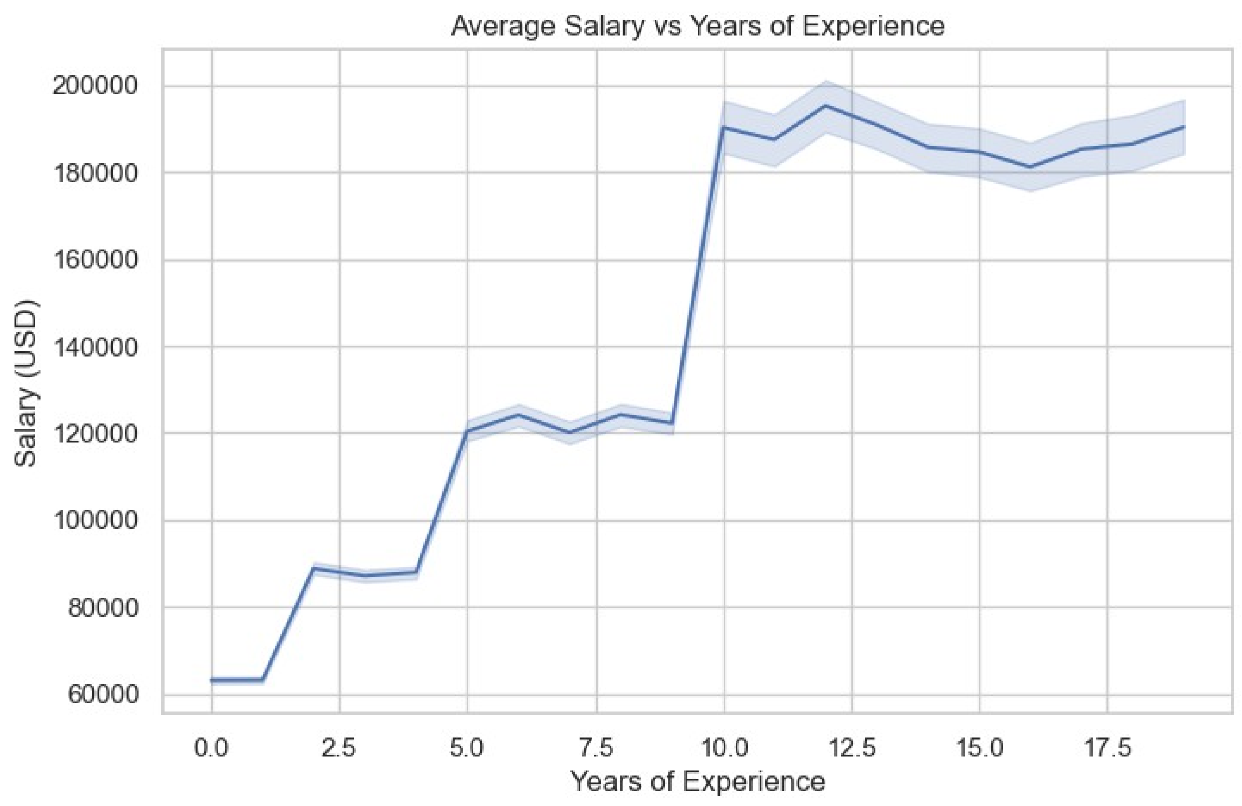
Salary Distribution by Experience Level

```python
# Step 2: Salary vs Experience Level
plt.figure(figsize=(8,5))
sns.boxplot(data=df, x='experience_level', y='salary_usd',
order=['EN', 'MI', 'SE', 'EX'])
plt.title("Salary Distribution by Experience Level")
plt.ylabel("Salary (USD)")
plt.xlabel("Experience Level")
plt.show()
```



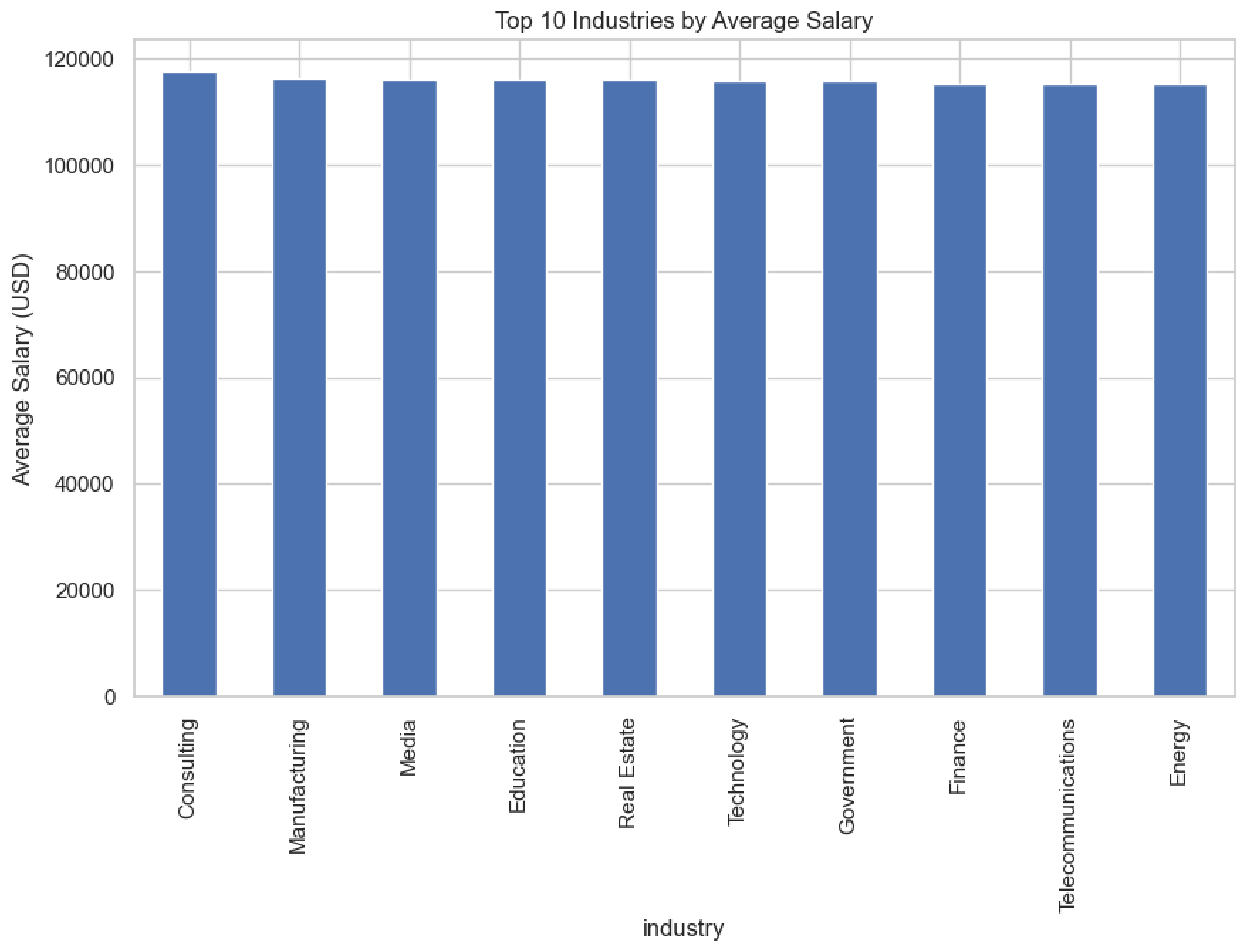
Average Salary vs Years of Experience

```
# Step 3: Scatter plot salary vs years_experience
plt.figure(figsize=(8,5))
sns.lineplot(data=df, x='years_experience', y='salary_usd',
estimator='mean')
plt.title("Average Salary vs Years of Experience")
plt.xlabel("Years of Experience")
plt.ylabel("Salary (USD)")
plt.show()
```



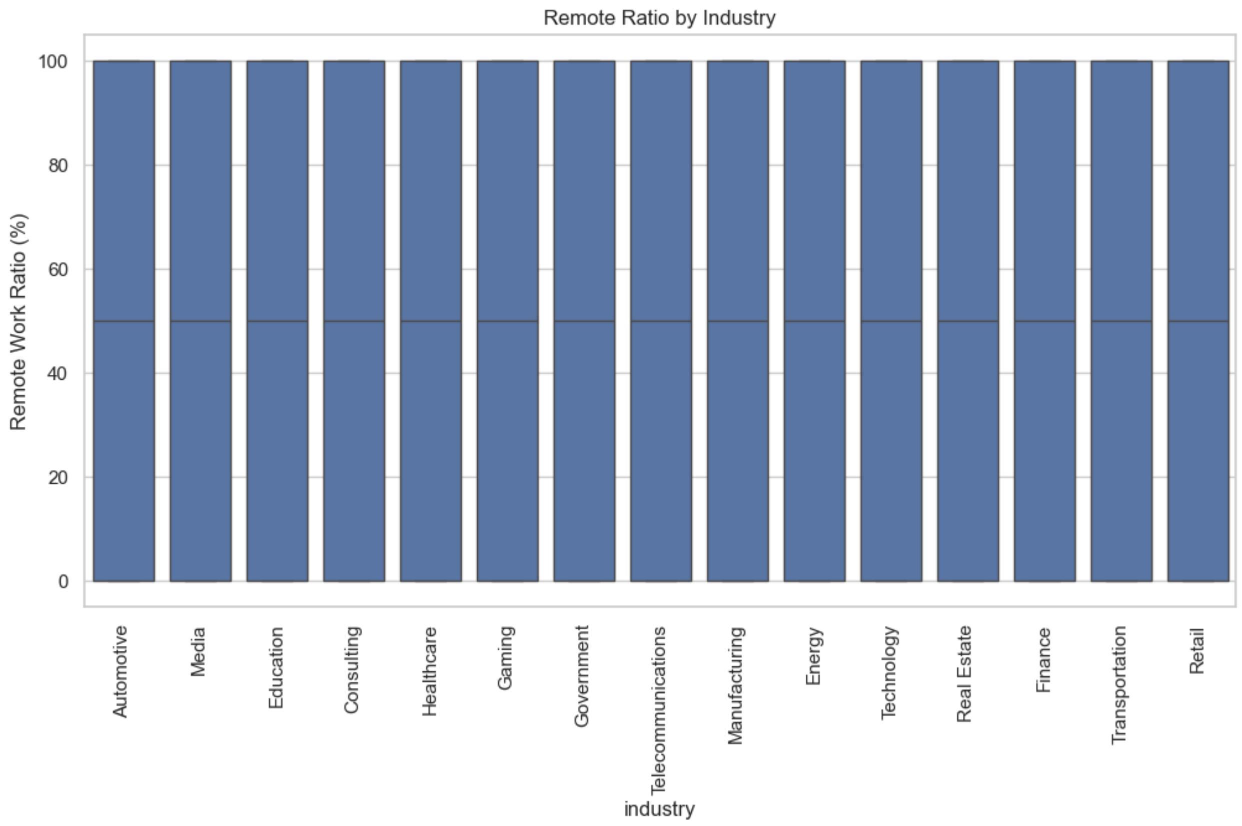
Top 10 Industries by Average Salary

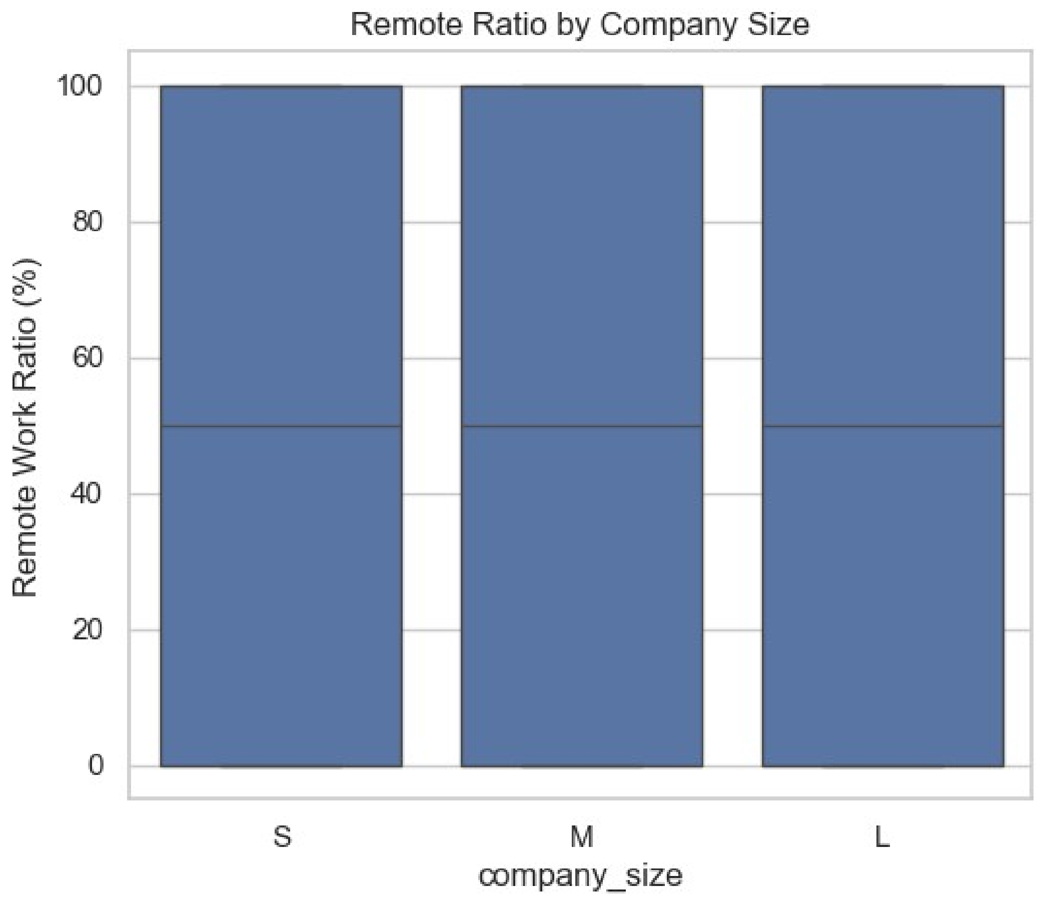
```
# Step 4: Top 10 industries by average salary
industry_salary = df.groupby('industry')
['salary_usd'].mean().sort_values(ascending=False).head(10)
industry_salary.plot(kind='bar')
plt.title("Top 10 Industries by Average Salary")
plt.ylabel("Average Salary (USD)")
plt.show()
```



Remote Work Ratio by Industry and Remote Work by Company Size

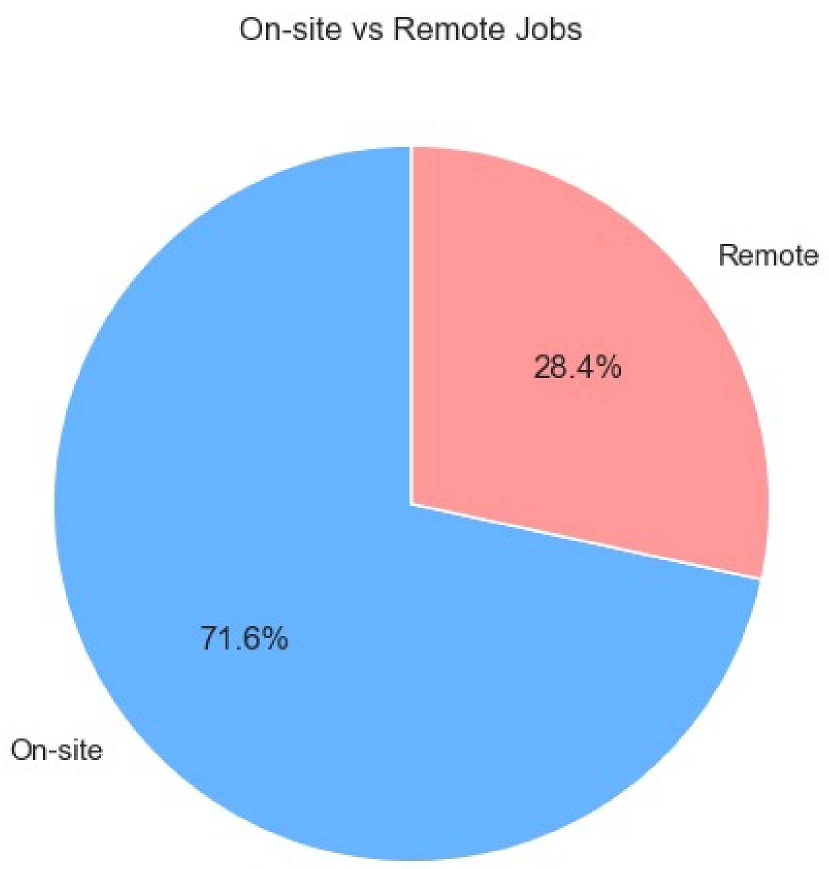
```
# Step 5: Remote ratio distribution by industry
plt.figure(figsize=(12,6))
sns.boxplot(data=df, x='industry', y='remote_ratio')
plt.xticks(rotation=90)
plt.title("Remote Ratio by Industry")
plt.ylabel("Remote Work Ratio (%)")
plt.show()

# Remote ratio by company size
plt.figure(figsize=(6,5))
sns.boxplot(data=df, x='company_size', y='remote_ratio', order=['S',
'M', 'L'])
plt.title("Remote Ratio by Company Size")
plt.ylabel("Remote Work Ratio (%)")
plt.show()
```


Remote Ratio by Industry
Remote Work Ratio (%)
100
80
60
40
20
0
Automotive
Media
Education
Consulting
Healthcare
Gaming
Government
Telecommunications
Manufacturing
Energy
Technology
Real Estate
Finance
Transportation
Retail
industry



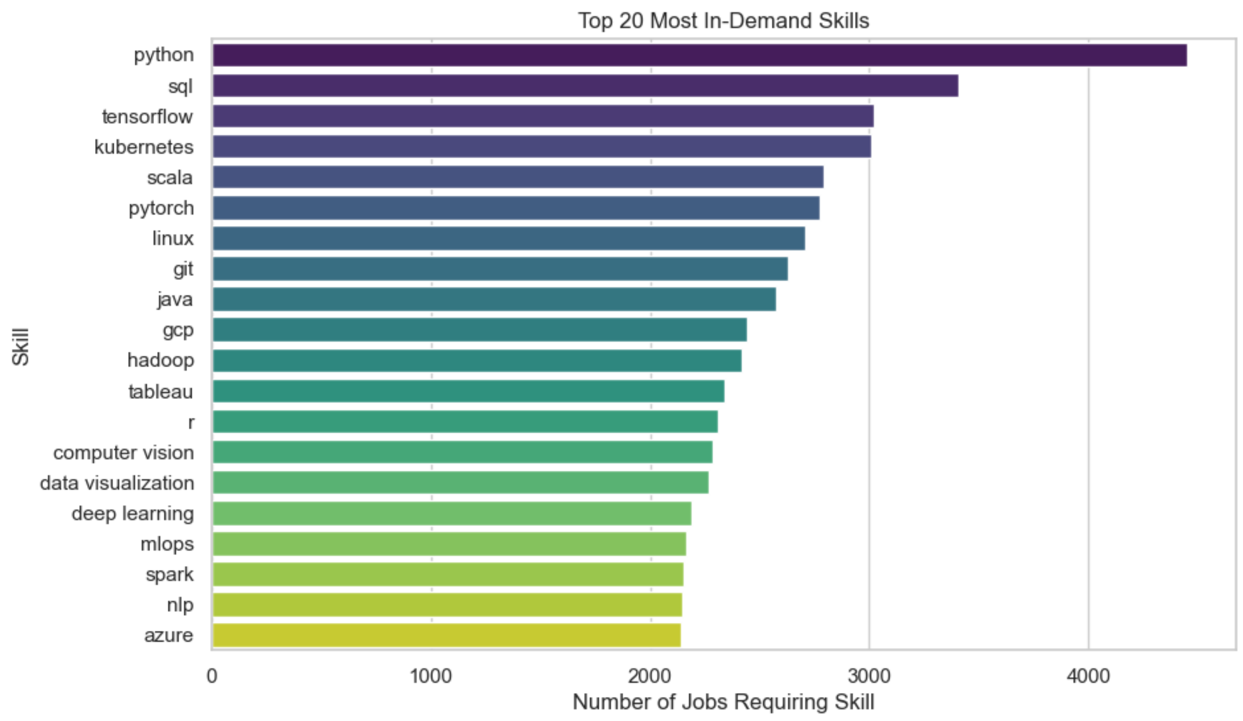
On-site vs Remote Jobs

```
# Step 6: Count jobs where employee_residence == company_location (on-
site) vs remote
df['is_remote'] = np.where(df['employee_residence'] ==
df['company_location'], 'On-site', 'Remote')
remote_counts = df['is_remote'].value_counts()
remote_counts.plot(kind='pie', autopct='%1.1f%%', startangle=90,
colors=['#66b3ff','#ff9999'])
plt.title("On-site vs Remote Jobs")
plt.ylabel('')
plt.show()
```



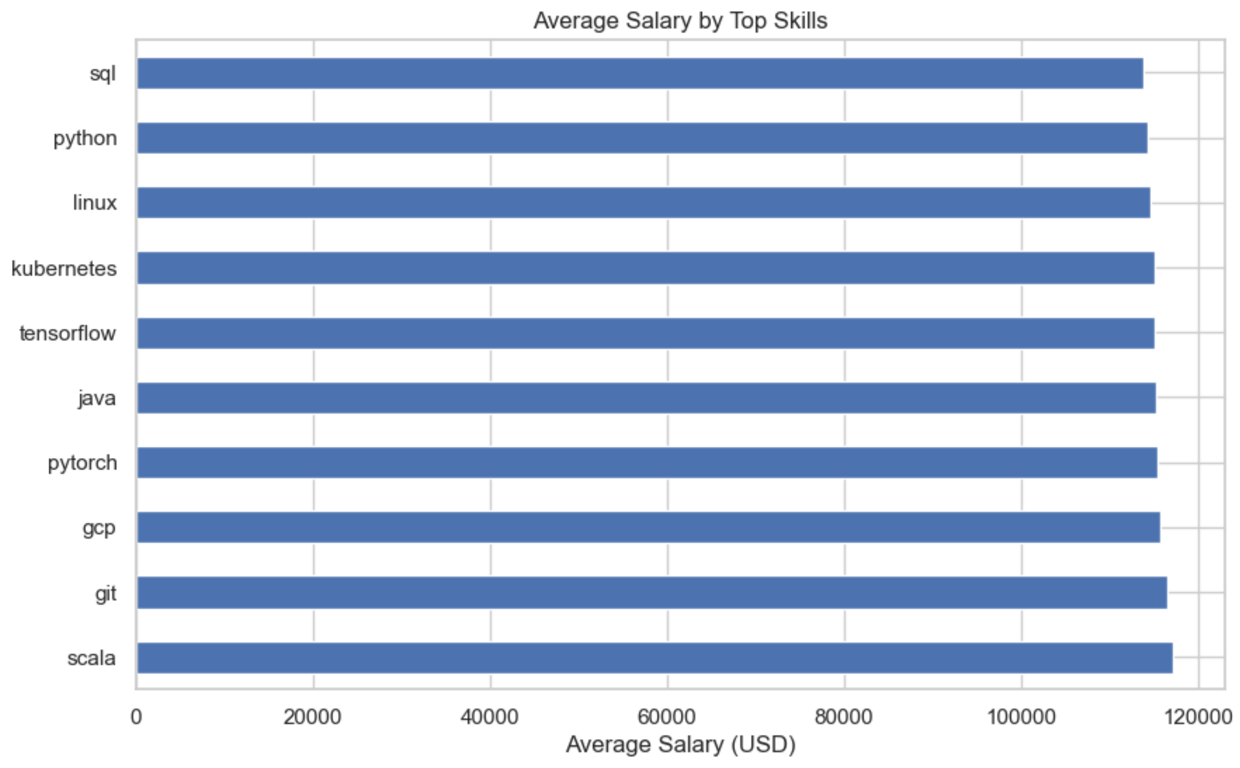
Top 20 Most In-Demand Skills

```python
# Step 7: Extract and count required skills
# Assuming skills are comma separated strings
all_skills = 
df['required_skills'].dropna().str.split(',').explode().str.strip().st
r.lower()
skill_counts = Counter(all_skills)
# Top 20 skills
top_skills = pd.DataFrame(skill_counts.most_common(20), 
columns=['Skill', 'Count'])
sns.barplot(data=top_skills, x='Count', y='Skill', palette='viridis')
plt.title("Top 20 Most In-Demand Skills")
plt.xlabel("Number of Jobs Requiring Skill")
plt.show()
```



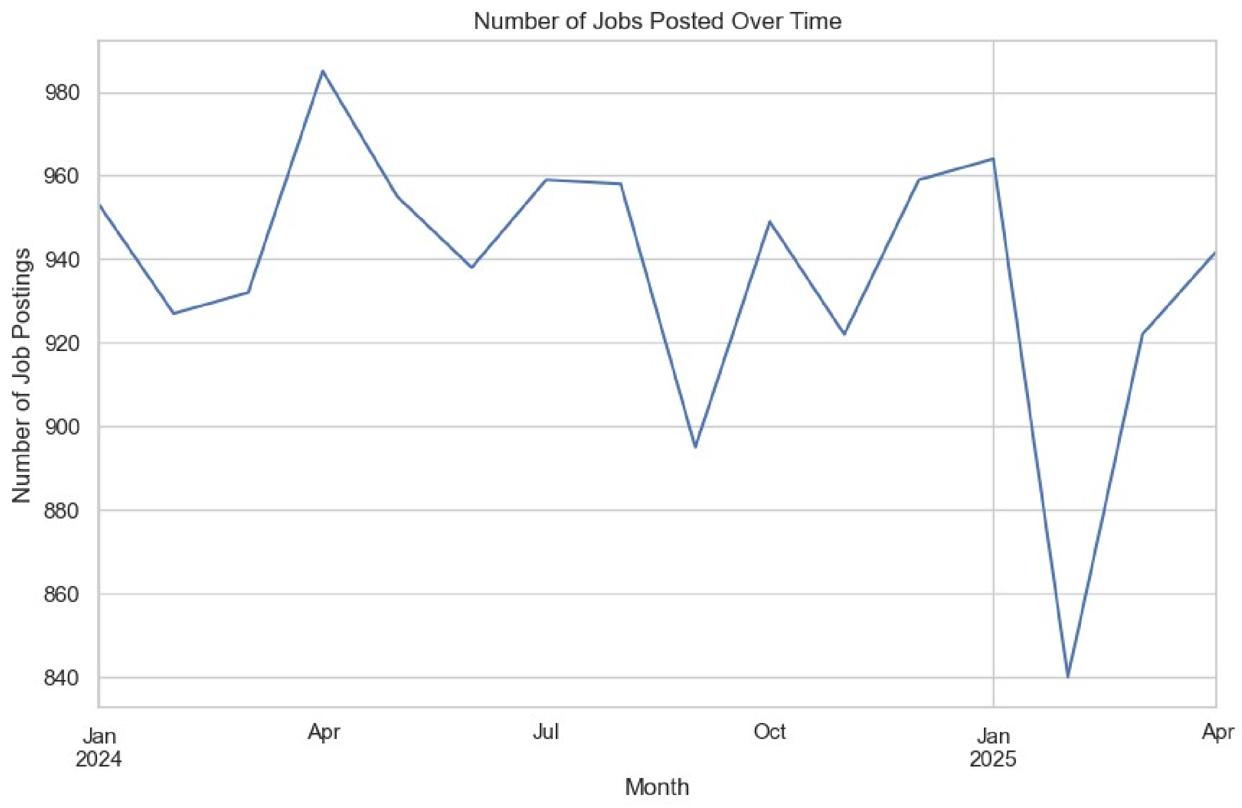
Average Salary for Top 10 Skills

```
# Step 8: Average salary for top 10 skills

# Filter dataset to rows that contain each top skill and calculate
average salary
avg_salary_skills = {}
for skill in top_skills['Skill'][:10]:
    mask = df['required_skills'].str.lower().str.contains(skill,
na=False)
    avg_salary_skills[skill] = df.loc[mask, 'salary_usd'].mean()
avg_salary_df = pd.DataFrame.from_dict(avg_salary_skills,
orient='index', columns=['Average_Salary'])
avg_salary_df = avg_salary_df.sort_values(by='Average_Salary',
ascending=False)
avg_salary_df.plot(kind='barh', legend=False)
plt.title("Average Salary by Top Skills")
plt.xlabel("Average Salary (USD)")
plt.show()
```



Jobs Posted Over Time

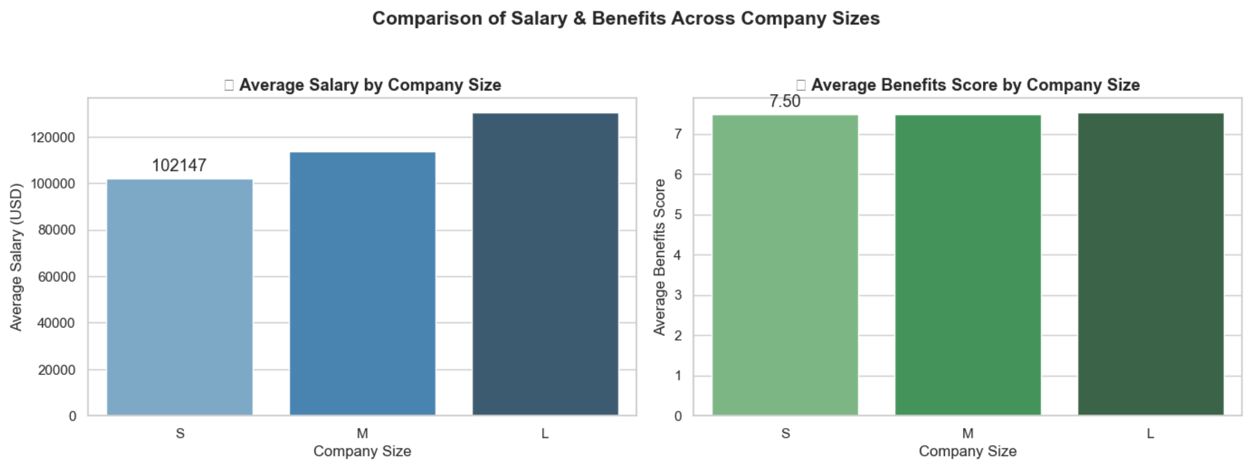
```
# Step 9: Number of jobs posted monthly
df['posting_month'] = df['posting_date'].dt.to_period('M')
jobs_per_month = df.groupby('posting_month').size()
jobs_per_month.plot()
plt.title("Number of Jobs Posted Over Time")
plt.ylabel("Number of Job Postings")
plt.xlabel("Month")
plt.show()
```



Salary & Benefits by Company Size

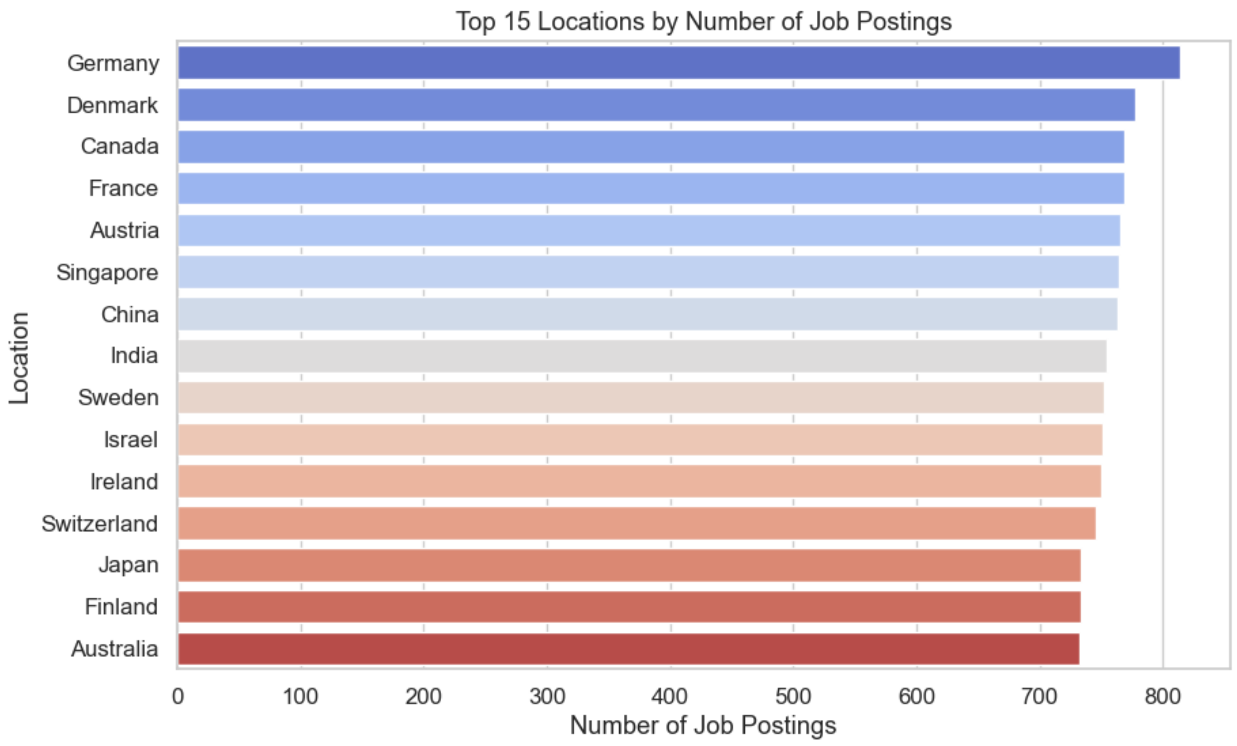
```
salary_by_size = df.groupby('company_size')
['salary_usd'].mean().reindex(['S', 'M', 'L'])
benefits_by_size = df.groupby('company_size')
['benefits_score'].mean().reindex(['S', 'M', 'L'])

# Plot
fig, ax = plt.subplots(1, 2, figsize=(14, 5))
sns.set_theme(style="whitegrid", font_scale=1.1)

# Bar plot: Salary
sns.barplot(x=salary_by_size.index, y=salary_by_size.values,
palette='Blues_d', ax=ax[0])
ax[0].set_title("□ Average Salary by Company Size", fontweight='bold')
ax[0].set_xlabel("Company Size")
ax[0].set_ylabel("Average Salary (USD)")
ax[0].bar_label(ax[0].containers[0], fmt='%.0f', padding=3)

# Bar plot: Benefits Score
sns.barplot(x=benefits_by_size.index, y=benefits_by_size.values,
palette='Greens_d', ax=ax[1])
ax[1].set_title("□ Average Benefits Score by Company Size",
fontweight='bold')
```

```
ax[1].set_xlabel("Company Size")
ax[1].set_ylabel("Average Benefits Score")
ax[1].bar_label(ax[1].containers[0], fmt='%.2f', padding=3)

plt.suptitle("Comparison of Salary & Benefits Across Company Sizes",
fontsize=15, fontweight='bold', y=1.03)
plt.tight_layout()
plt.show()
```



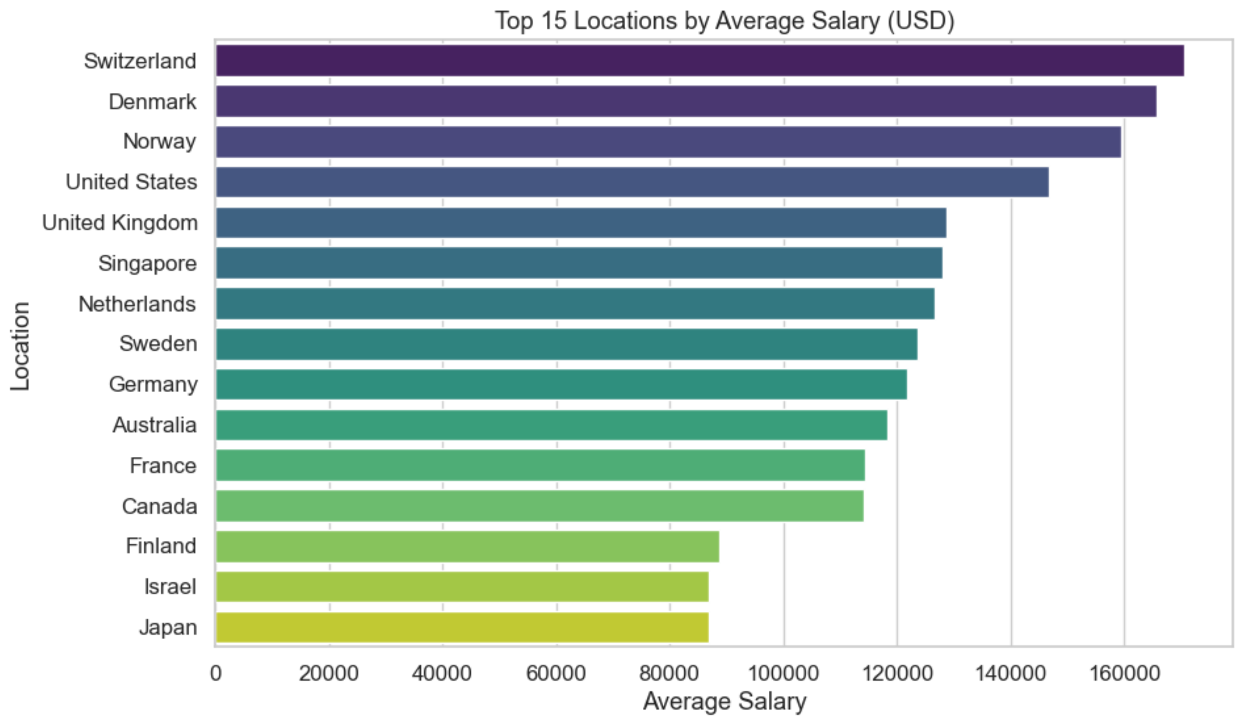
Top 15 Job Locations

```
top_locations = df['company_location'].value_counts().head(15)
plt.figure(figsize=(10,6))
sns.barplot(x=top_locations.values, y=top_locations.index,
palette='coolwarm')
plt.title('Top 15 Locations by Number of Job Postings')
plt.xlabel('Number of Job Postings')
plt.ylabel('Location')
plt.show()
```



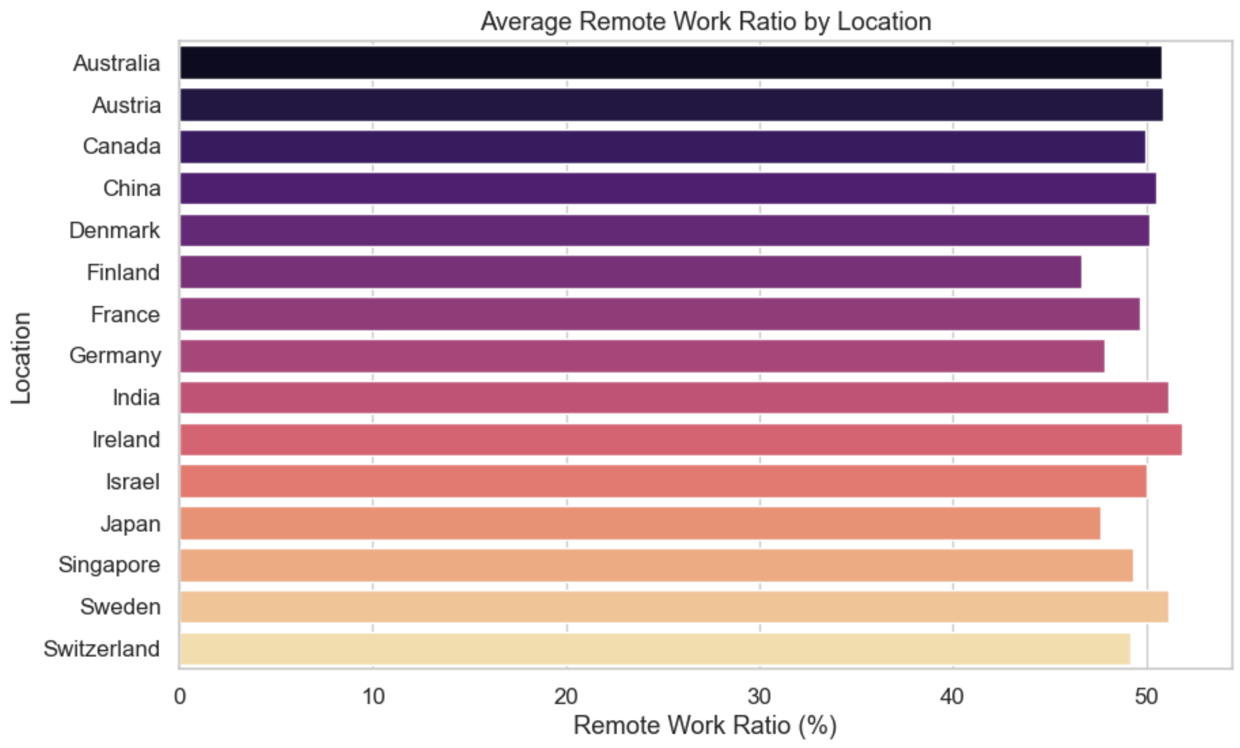
Top 15 Locations by Salary

```
avg_salary_loc = df.groupby('company_location')
['salary_usd'].mean().sort_values(ascending=False).head(15)

plt.figure(figsize=(10,6))
sns.barplot(x=avg_salary_loc.values, y=avg_salary_loc.index,
palette='viridis')
plt.title('Top 15 Locations by Average Salary (USD)')
plt.xlabel('Average Salary')
plt.ylabel('Location')
plt.show()
```



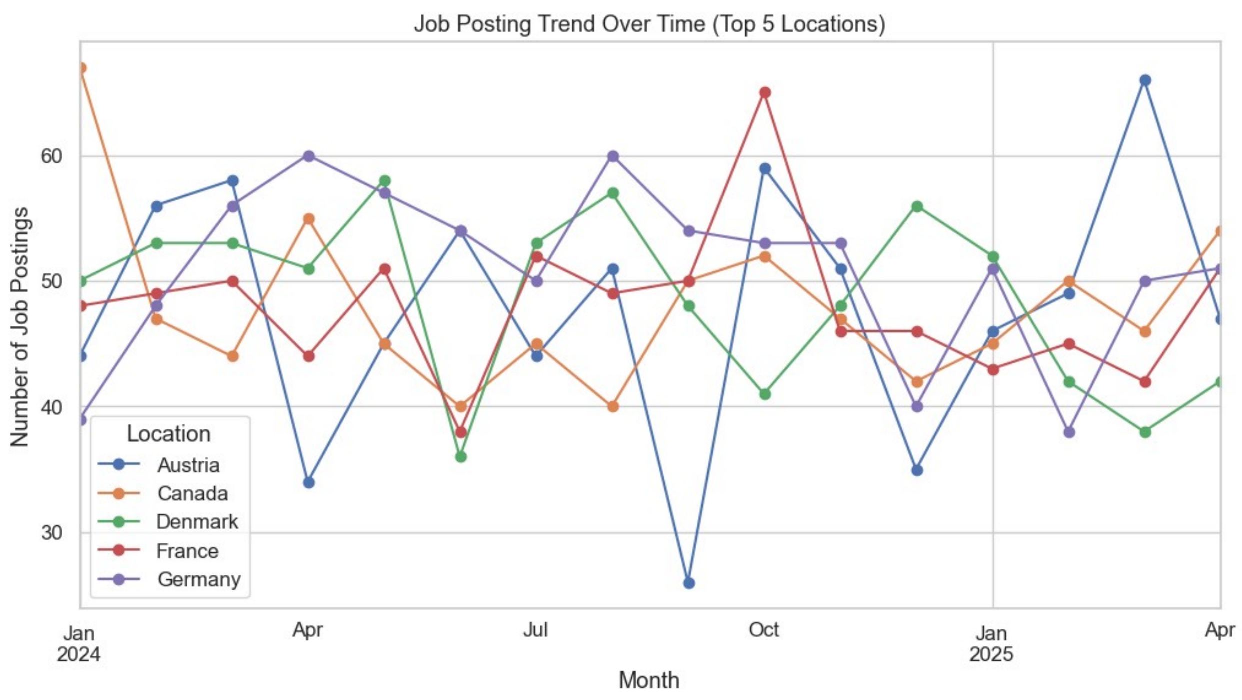
Percentage of Remote Work Done by Employees in Various Countries

```
# Calculate average remote_ratio per location (only locations with
enough data)
remote_loc = df.groupby('company_location')['remote_ratio'].mean()
remote_loc = remote_loc[remote_loc.index.isin(top_locations.index)]

plt.figure(figsize=(10,6))
sns.barplot(x=remote_loc.values, y=remote_loc.index, palette='magma')
plt.title('Average Remote Work Ratio by Location')
plt.xlabel('Remote Work Ratio (%)')
plt.ylabel('Location')
plt.show()
```



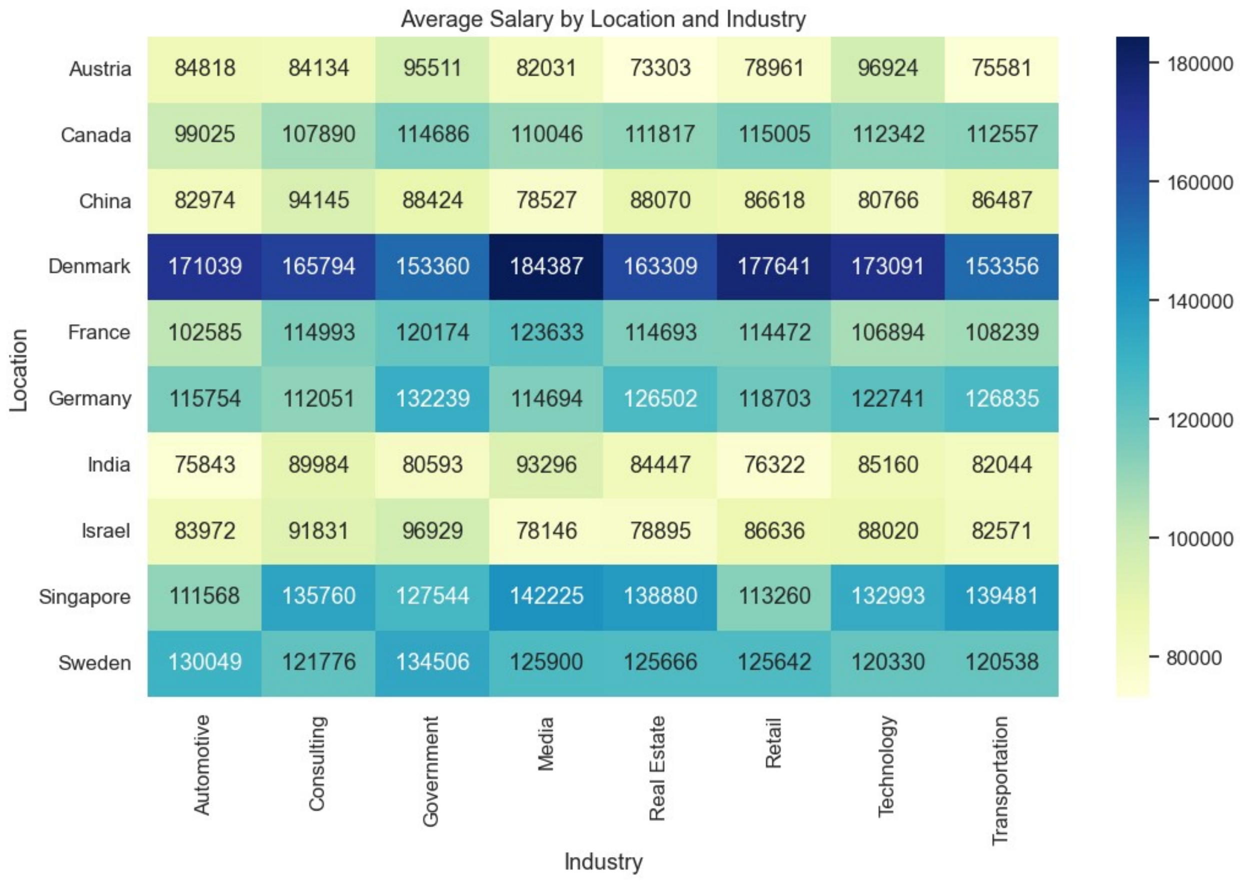
Job Posting Trend Over Time (Top 5 Locations)

```
# Filter for top 5 locations for clarity
top5_locations = top_locations.index[:5]

df['posting_month'] = df['posting_date'].dt.to_period('M')

jobs_time_loc =
df[df['company_location'].isin(top5_locations)].groupby(['posting_mont
h', 'company_location']).size().unstack(fill_value=0)

jobs_time_loc.plot(figsize=(12,6), marker='o')
plt.title('Job Posting Trend Over Time (Top 5 Locations)')
plt.xlabel('Month')
plt.ylabel('Number of Job Postings')
plt.legend(title='Location')
plt.show()
```



Salary Heatmap (Top 10 Locations × Top 8 Industries)

```
# Top 10 locations and top 8 industries
top10_locations = df['company_location'].value_counts().head(10).index
top8_industries = df['industry'].value_counts().head(8).index

pivot_salary = df[(df['company_location'].isin(top10_locations)) &
(df['industry'].isin(top8_industries))]\
    .pivot_table(values='salary_usd', index='company_location',
columns='industry', aggfunc='mean')

plt.figure(figsize=(12,7))
sns.heatmap(pivot_salary, annot=True, fmt=".0f", cmap='YlGnBu')
plt.title('Average Salary by Location and Industry')
plt.xlabel('Industry')
plt.ylabel('Location')
plt.show()
```



Location	Automotive	Consulting	Government	Media	Real Estate	Retail	Technology	Transportation
Austria	84818	84134	95511	82031	73303	78961	96924	75581
Canada	99025	107890	114686	110046	111817	115005	112342	112557
China	82974	94145	88424	78527	88070	86618	80766	86487
Denmark	171039	165794	153360	184387	163309	177641	173091	153356
France	102585	114993	120174	123633	114693	114472	106894	108239
Germany	115754	112051	132239	114694	126502	118703	122741	126835
India	75843	89984	80593	93296	84447	76322	85160	82044
Israel	83972	91831	96929	78146	78895	86636	88020	82571
Singapore	111568	135760	127544	142225	138880	113260	132993	139481
Sweden	130049	121776	134506	125900	125666	125642	120330	120538