733 assignment 1-Analysing the job market trends(year 2021)

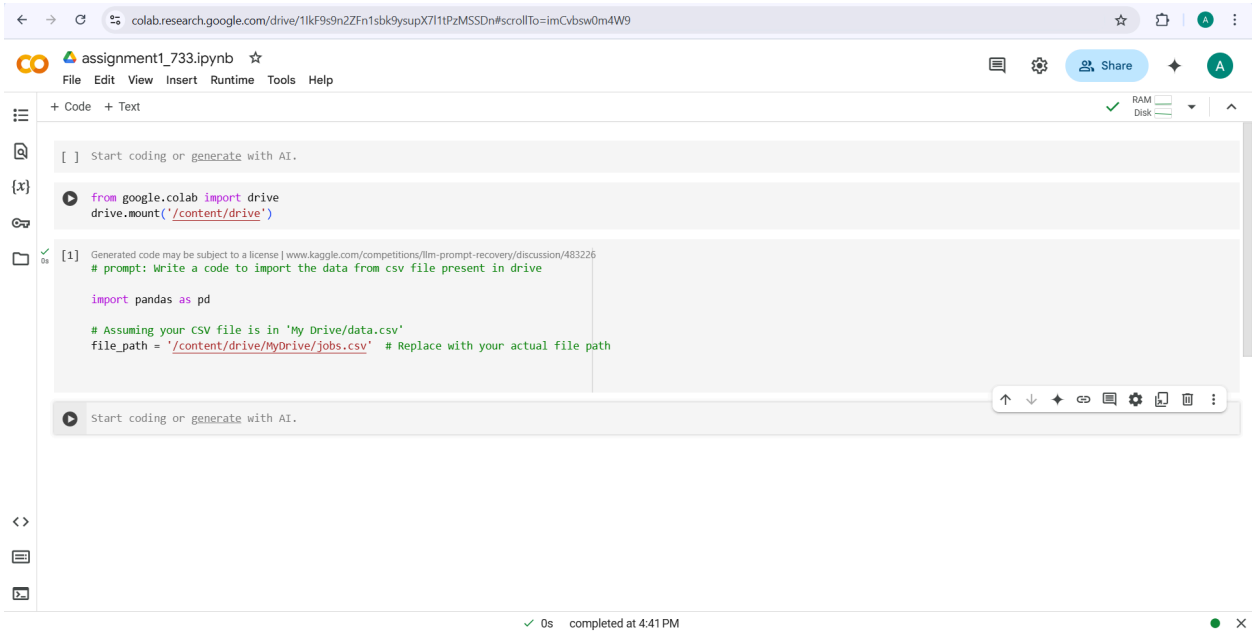
Google collab link- assignment1_733.ipynb

PPT link- 733_assignment1

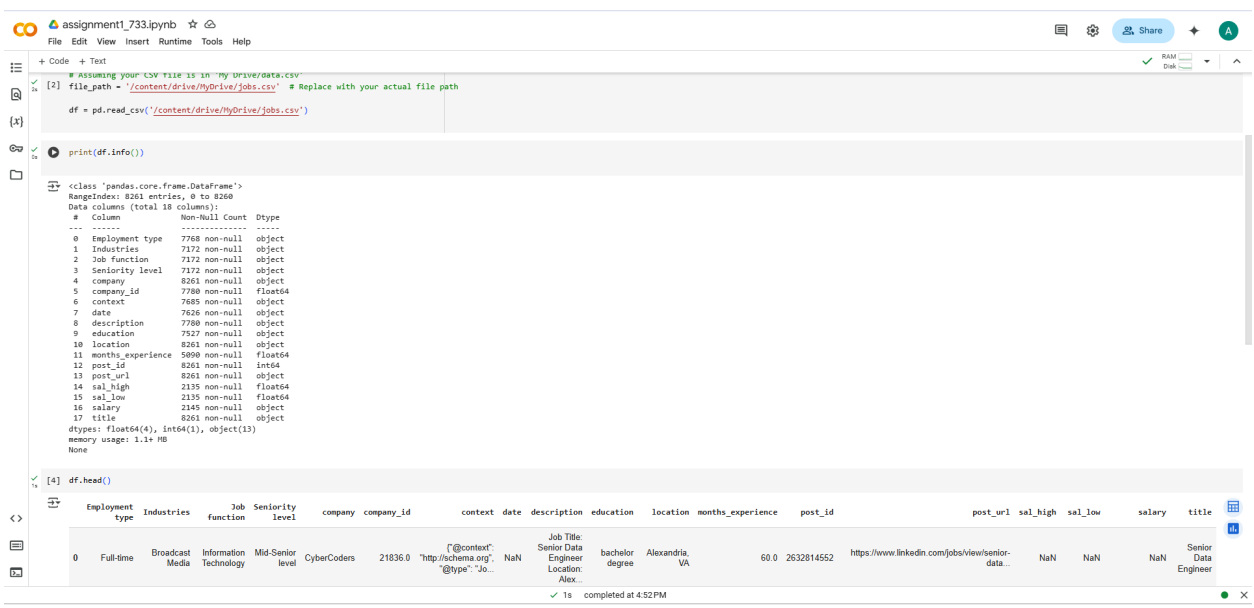
Data set link

https://github.com/Mlawrence95/LinkedIn-Tech-Job-Data/blob/main/jobs.csv

1) Mounting dataset



2) Exploring the Dataset



```python
df.head()
```

	Employment type	Industries	Job function	Seniority level	company	company_id	context	date	description	education	lo
0	Full-time	Broadcast Media	Information Technology	Mid-Senior level	CyberCoders	21836.0	{"@context": "http://schema.org", "@type": "Jo...	NaN	Job Title: Senior Data Engineer Location: Alex...	bachelor degree	Alex
1	Full-time	Hospital & Health Care, Medical Devices, and P...	Engineering and Information Technology	Not Applicable	Johnson & Johnson	1207.0	{"@context": "http://schema.org", "@type": "Jo...	NaN	Ethicon, part of Johnson & Johnson Medical Dev...	bachelor degree	Cla
2	Full-time	Computer Hardware, Computer Software, and Info...	Engineering and Information Technology	Not Applicable	Microsoft	1035.0	{"@context": "http://schema.org", "@type": "Jo...	NaN	Microsoft's WCB health team is looking for a S...	bachelor degree	Wash
3	Full-time	Computer Hardware, Computer Software, and Info...	Engineering and Information Technology	Not Applicable	Microsoft	1035.0	{"@context": "http://schema.org", "@type": "Jo...	NaN	Microsoft's WCB health team is looking for a S...	bachelor degree	Res
4	Full-time	Computer Hardware, Computer Software, and Info...	Engineering and Information Technology	Not Applicable	Microsoft	1035.0	{"@context": "http://schema.org", "@type": "Jo...	NaN	Microsoft's WCB health team is looking for a S...	bachelor degree	Irv

```python
print(df.describe())
```

```
         company_id  months_experience       post_id       sal_high  \
count  7.780000e+03        5090.000000  8.261000e+03    2135.000000
mean   6.680769e+06          50.457171  2.679644e+09  150923.400937
std    1.520843e+07          28.439375  6.876523e+07   44080.915030
min    1.000000e+03           3.000000  1.038733e+08     100.000000
25%    4.787000e+03          36.000000  2.663260e+09  119000.000000
50%    1.624790e+05          48.000000  2.682321e+09  151000.000000
75%    3.334793e+06          60.000000  2.693585e+09  180000.000000
max    8.011415e+07         180.000000  2.764037e+09  416000.000000

             sal_low
count    2135.000000
mean    94313.941920
std     27242.371257
min       120.000000
25%     75450.000000
50%     91300.000000
75%    113000.000000
max    312000.000000
```

```
print(df.isnull().sum())
#check missing value
```

```
Employment type       493
Industries           1089
Job function         1089
Seniority level      1089
company                 0
company_id            481
context               576
date                  635
description           481
education             734
location                0
months_experience    3171
post_id                 0
post_url                0
sal_high             6126
sal_low              6126
salary               6116
title                   0
dtype: int64
```

→ So mostly all column has some missing values.We will fill all the numeric values with the median and categorical values with the mode and will remove all the duplicates

```
[ ] # Fill numeric columns with median
    numeric_columns = df.select_dtypes(include=[np.number]).columns
    df[numeric_columns] = df[numeric_columns].fillna(df[numeric_columns].median())
```

```
[ ] # Fill categorical columns with mode
    categorical_columns = df.select_dtypes(include=['object']).columns
    df[categorical_columns] = df[categorical_columns].fillna(df[categorical_columns].mode().iloc[0])
```

```
[ ] #remove duplicates
    df.drop_duplicates(inplace=True)
```

3) Counting the number of instances in the dataset

There are 8261 rows in the dataset

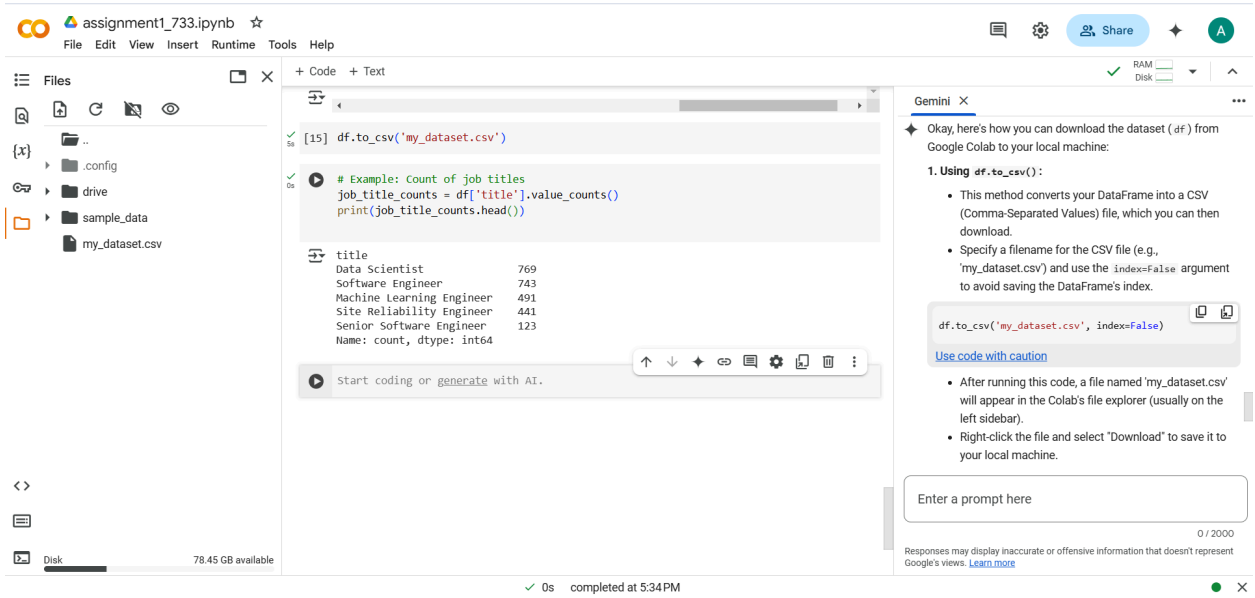
There are 18 columns in the dataset

```
Name: count, dtype: int64

[18] num_rows,num_cols = df.shape
     print("Number of rows:",num_rows)
     print("Number of columns:",num_cols)

Number of rows: 8261
Number of columns: 18

Start coding or generate with AI.
```

Disk 78.45 GB available

4) Finding the most popular job-

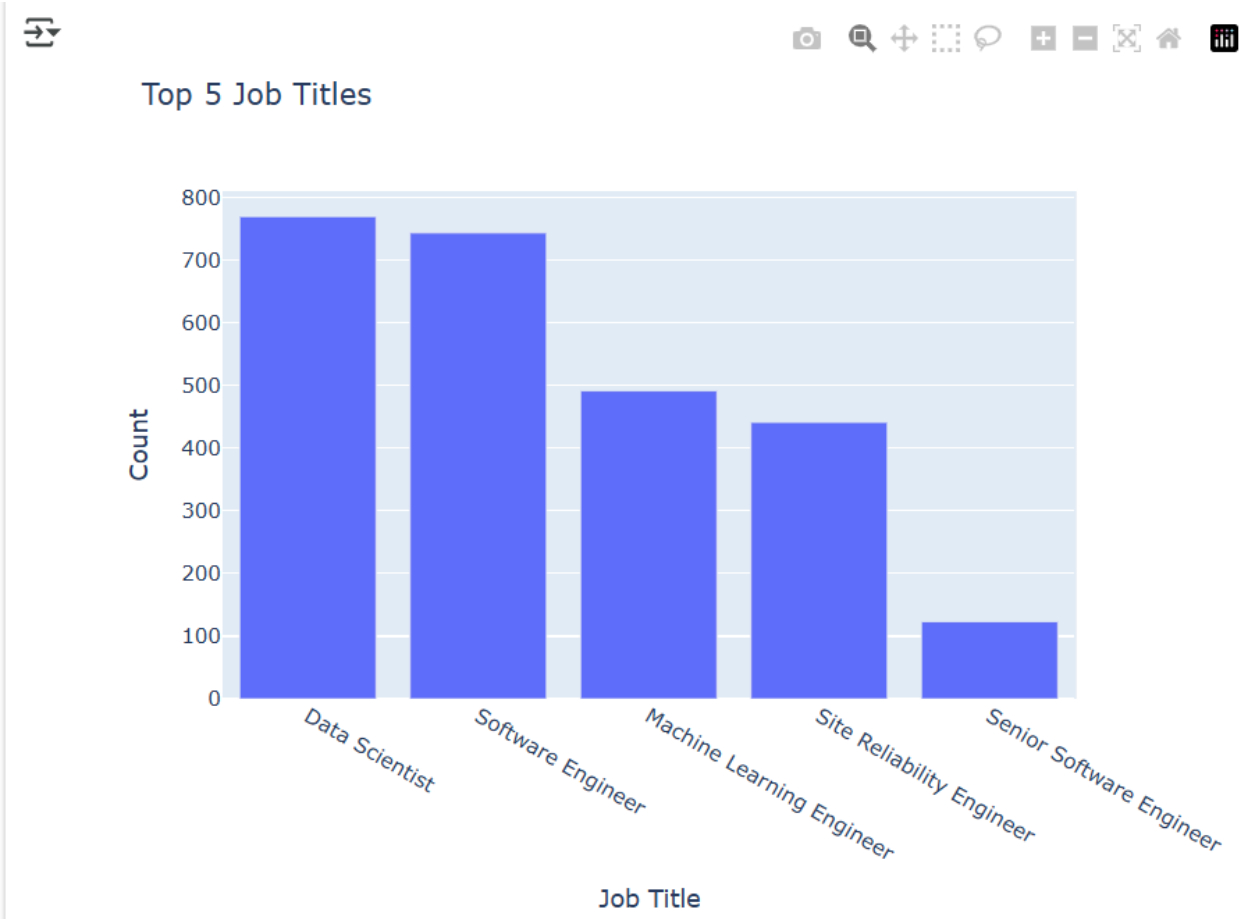
From the visualization, we can see that Data Scientist has the highest number of jobs compared to other fields.



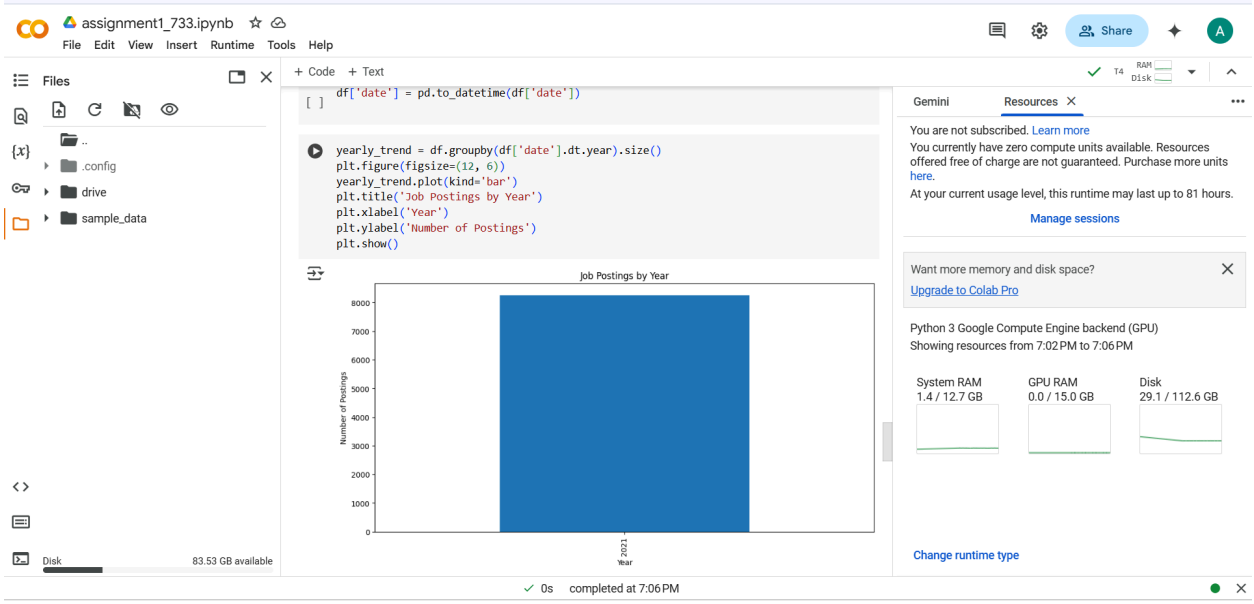

```python
import plotly.express as px

# Get the top 5 job titles
job_title_counts = df['title'].value_counts().reset_index().head(5)
job_title_counts.columns = ['Job Title', 'Count']  # Rename columns

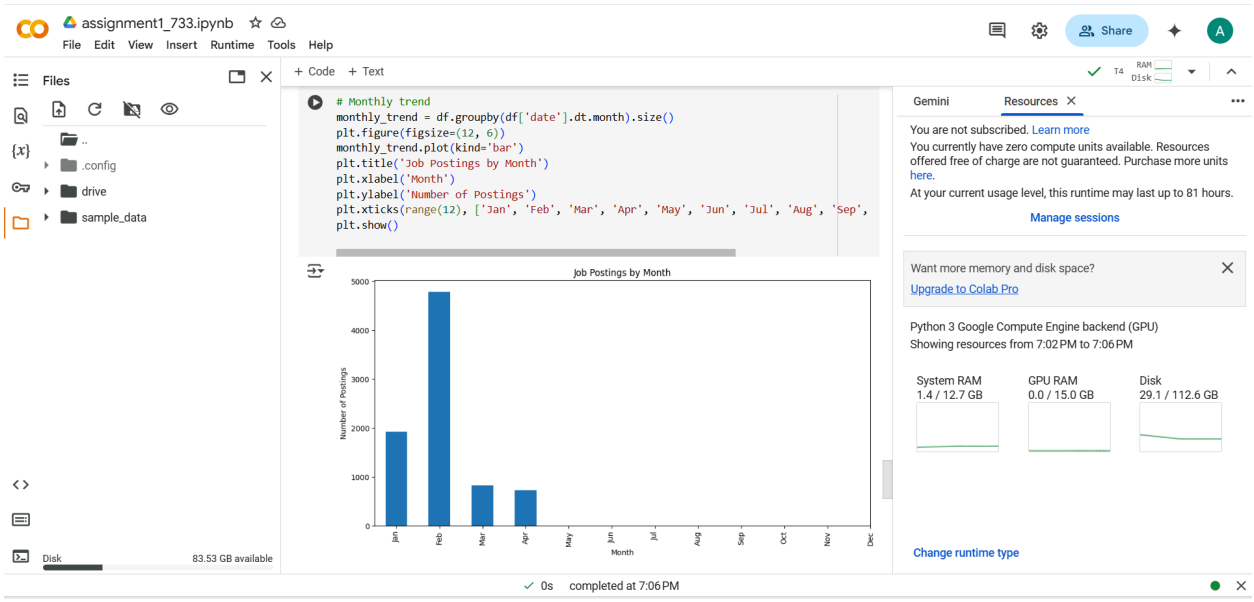
# Create the bar graph for the top 5 titles
fig = px.bar(job_title_counts, x='Job Title', y='Count',
             title='Top 5 Job Titles',
             labels={'Job Title': 'Job Title', 'Count': 'Count'})
fig.show()
```



5) Job Posting trend yearly



6) Job posting trend in distribution of Months



7) Job posting trend in distribution of days of the Week

8) Violin plots to visualize the distribution of sal_high and sal_low for different categories like employment_type, seniority_level

A) High Salary Distribution by Employment Type

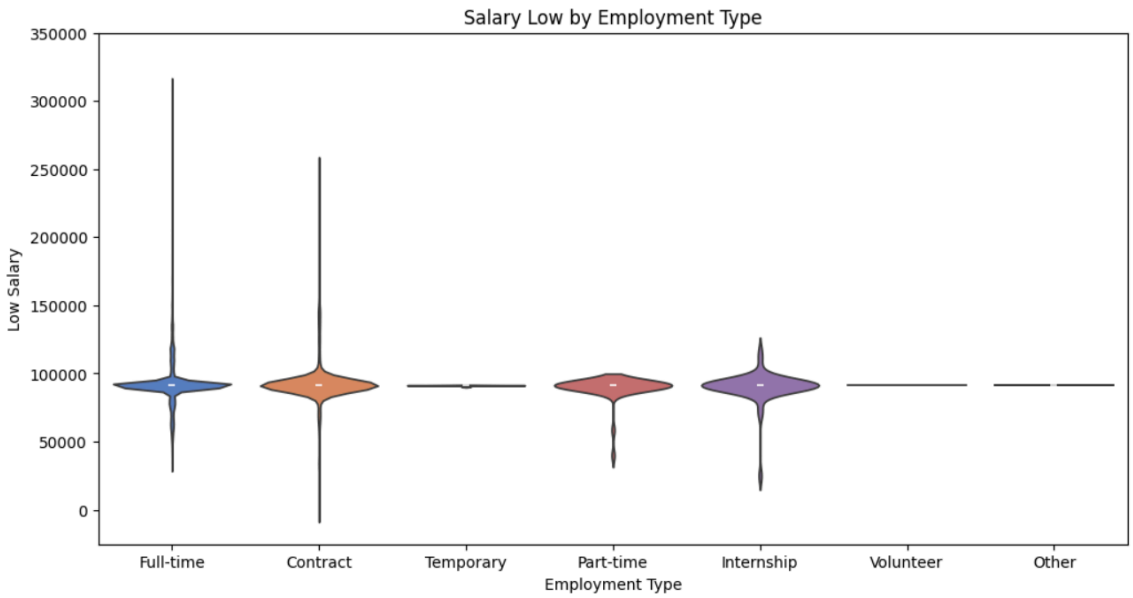
Understanding the Violin Plot Components:

- **Vertical Shape (Width):** Shows the **density** of salary data at different levels.
- **White Dot (Median):** Represents the **median high salary** for each employment type.
- **Thick Bar (IQR):** Displays the **interquartile range (25th–75th percentile)**.
- **Thin Line (Whiskers):** Illustrates the **full range** of data, excluding outliers.

🔍 Key Insights:

- **Full-Time:**
  - **Widest distribution** indicating **diverse salary ranges** depending on industry and role.
  - **Higher median** compared to other employment types, reflecting the stable and lucrative nature of full-time jobs.
- **Internship:**
  - Displays a **long upper tail**, suggesting **some internships offer competitive pay**, potentially in **tech or finance** sectors.
- **Part-Time & Temporary:**
  - More **concentrated salary ranges**, implying **standard hourly wages**.
  - **Lower median salaries**, indicating these positions generally offer less compensation.
- **Volunteer:**
  - **No variability**, suggesting **unpaid roles** across the dataset.

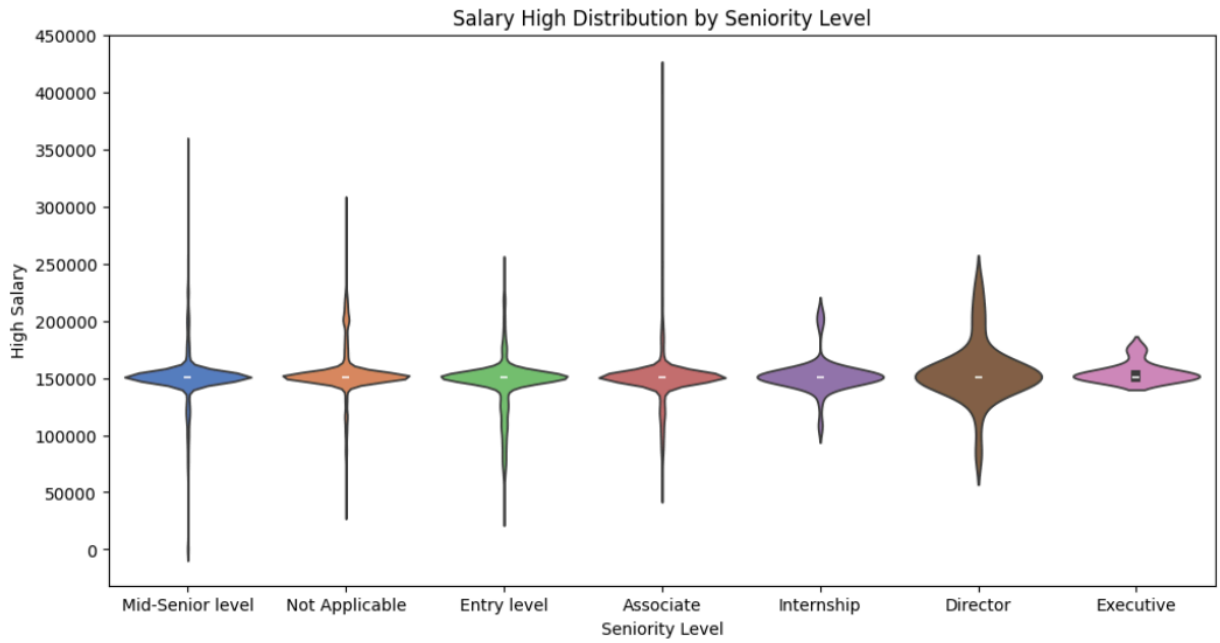
📉 B) Low Salary Distribution by Employment Type



🔍 Insights from the Plot:

- **Full-Time:**
  - **Median low salary:** ~$90,000.
  - Most salaries are **clustered in a narrow range**, showing **consistency** in base pay for full-time roles.
- **Contract:**
  - **Similar median** to full-time positions but with a **wider spread**—some **low salaries approach zero**, reflecting **part-time contracts or unpaid trial periods**.
- **Temporary & Part-Time:**
  - **Compressed distributions** with medians around $90,000, indicating **uniform low salaries**, likely due to **regulated hourly rates**.
- **Internship:**
  - **Greater spread** than part-time roles.
  - Some salaries close to zero, suggesting **stipend-based** or **unpaid internships**.
- **Volunteer & Other:**
  - **Very narrow distributions**, confirming these roles are either **unpaid** or have **fixed compensation structures**.

🏆 C) High Salary Distribution by Seniority Level

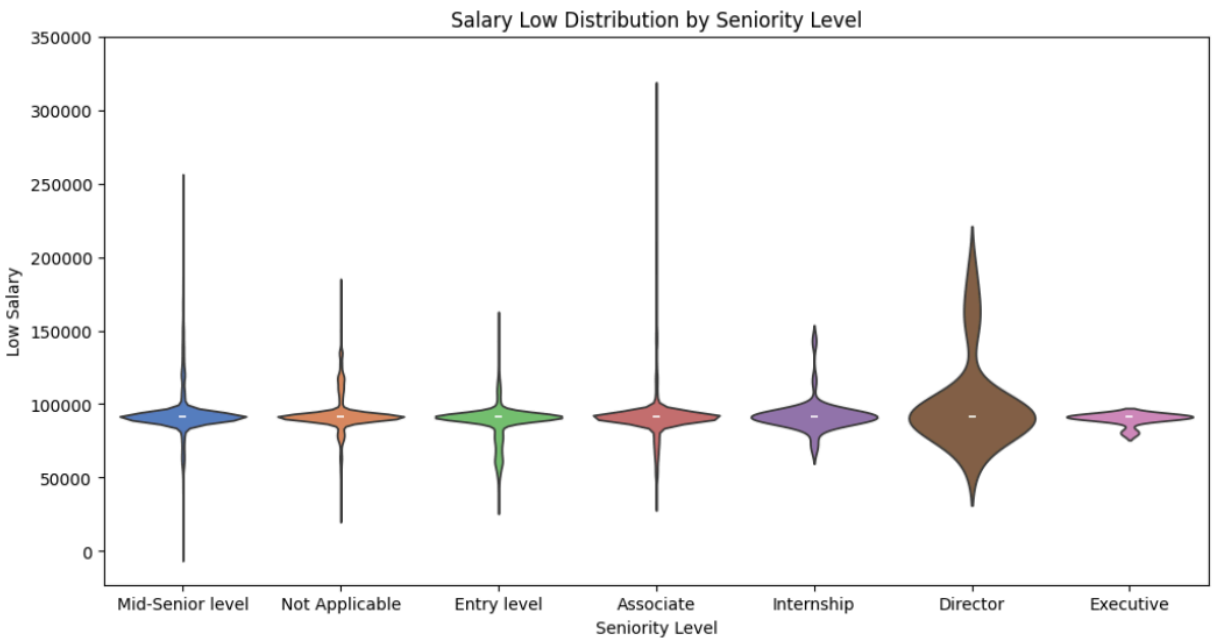



```
<ipython-input-28-50e15070a5cd>:23: FutureWarning:
```

🔍 Insights from the Plot:

- **Executive Level:**
  - **Highest median high salary** among all levels.
  - **Narrow distribution**, indicating **less variation** in top executive pay.
- **Director Level:**
  - **Broad salary range** with **high upper outliers**, indicating some **directors earn salaries comparable to executives**.
- **Mid-Senior & Associate Levels:**
  - **Similar median salaries** but with **wide spreads**, highlighting **overlaps in earnings potential** between these levels.
  - **Greater variability** suggests **industry-specific salary adjustments**.
- **Entry Level:**
  - **Lower median salaries** with a **narrower distribution**, indicating **stable starting pay**.
- **Internship:**
  - **Lowest median high salary** with **occasional outliers**, representing **highly paid internships** in **competitive sectors**.

D) Low Salary Distribution by Seniority Level



🔍 Insights from the Plot:

- **Executive Level:**
  - **Highest median low salary** across all seniority levels.
  - **Narrow spread**, indicating **stable base salaries** at the executive tier.
- **Director Level:**
  - **Widest spread**, showing **high variability** in base pay.
  - **Outliers** suggest some **directors earn salaries equivalent to executives**.
- **Mid-Senior & Associate Levels:**
  - **Similar median low salaries** with **wide spreads**, indicating **salary overlaps** between these levels.
  - **Associates** display a **broad salary range**, reflecting **inconsistencies** possibly based on **role or company**.
- **Entry Level:**
  - **Consistent median low salary** with a **narrow distribution**, implying **stable starting salaries**.
- **Internship:**
  - **Lowest median low salary** with **notable outliers**, indicating that **some internships offer competitive base salaries**.

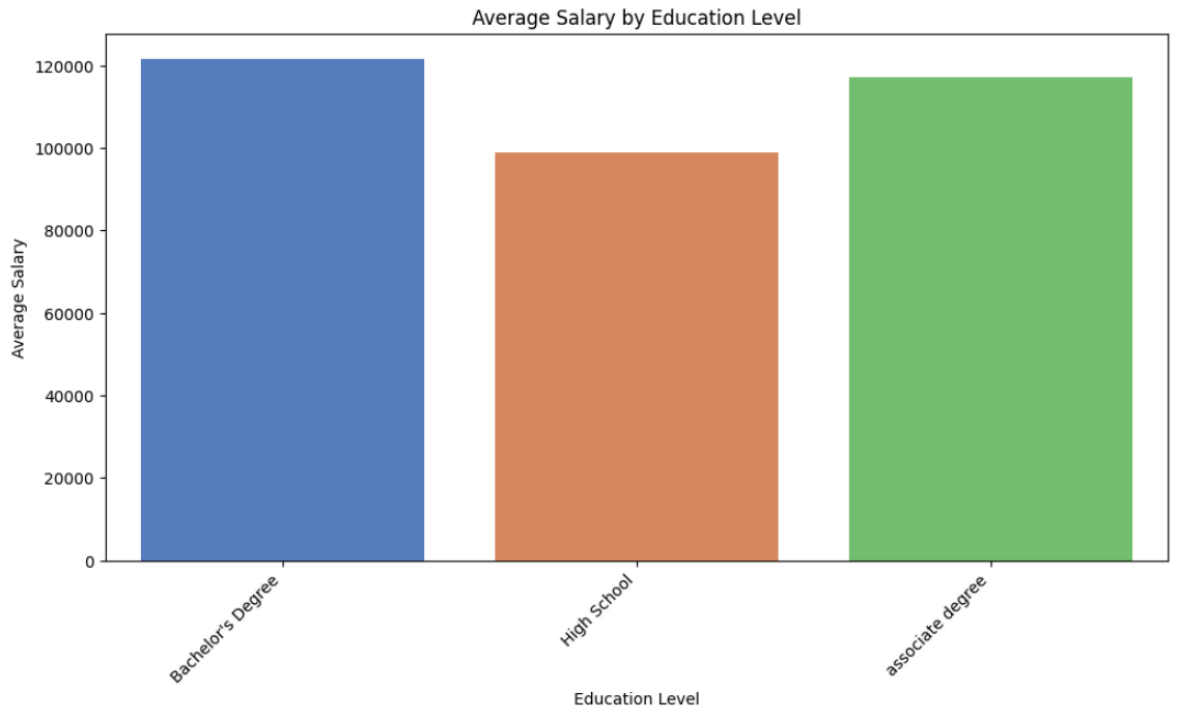
💡 Overall Key Takeaways:

1. **Employment Type Influence:**

- **Full-time roles** dominate in both **high and low salary distributions**, reflecting **stable pay structures**.
- **Contract roles** show **greater variability**, suggesting a **diverse compensation structure** based on role complexity.
- **Internships** can be **highly rewarding** in **specialized industries**, evidenced by **upper outliers** in high salary distributions.

2. **Seniority Level Dynamics:**
   - **Executives** enjoy the **highest and most stable salaries**, indicating **fixed compensation structures** at top levels.
   - **Directors** experience **greater salary variability**, possibly influenced by **performance-based pay** or **industry factors**.
   - **Entry-level positions** are the **most stable** across both **high and low salary distributions**, reflecting **standardized entry pay**.
   - **Mid-Senior and Associate levels** show **overlaps**, indicating **potential for rapid salary growth** within these categories.
3. **Outlier Significance:**
   - **High-salary outliers** in **internship and entry-level positions** suggest **premium roles** in **high-demand industries** like **tech** and **finance**.
   - **Low-salary outliers** in **contract positions** might represent **short-term projects** or **freelance gigs** with **variable compensation**.

9) Average salary by education level:



10) Word clouds from the description column to see the most frequently mentioned skills and requirements.

```
from wordcloud import WordCloud, STOPWORDS

import matplotlib.pyplot as plt

# Combine all descriptions into a single string

text = ' '.join(df['description'].astype(str).tolist())

# Create a WordCloud object

wordcloud = WordCloud(width=800, height=400, background_color='white',

                      stopwords=STOPWORDS,
min_font_size=10).generate(text)

# Plot the WordCloud image

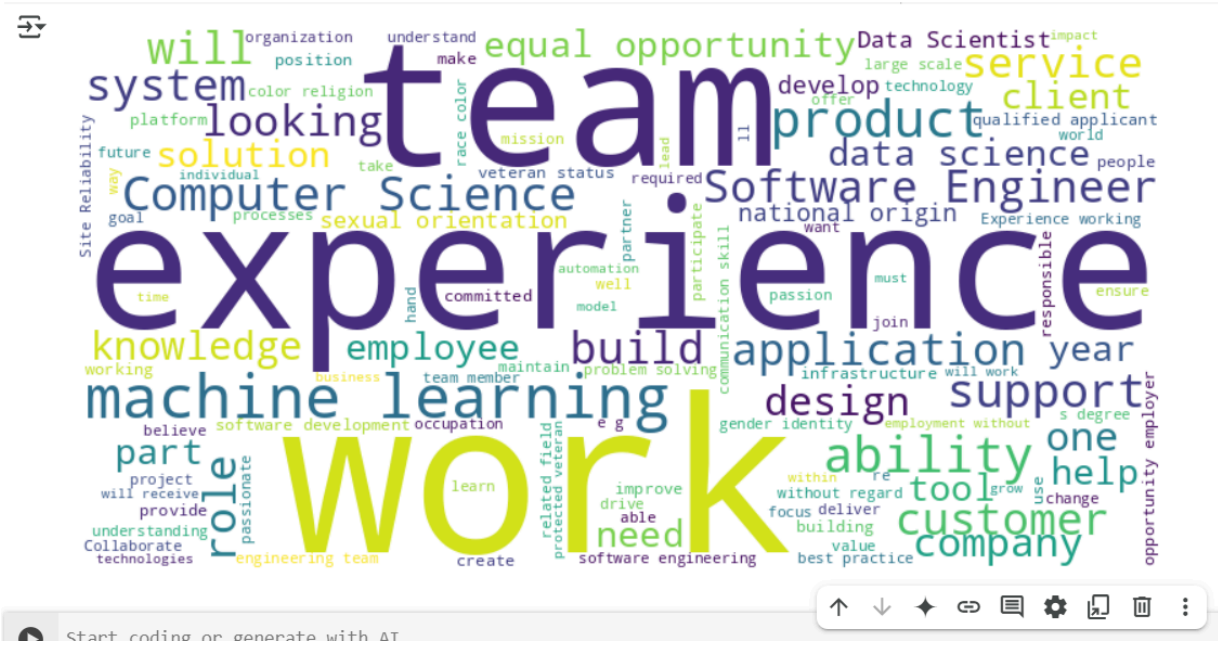
plt.figure(figsize=(8, 8), facecolor=None)

plt.imshow(wordcloud)

plt.axis("off")

plt.tight_layout(pad=0)

plt.show()
```



→ The terms which are most popular in all of the job descriptions are team,experience and work.

11) A word cloud from the `title` column to understand the most common job titles.

```
from wordcloud import WordCloud, STOPWORDS

import matplotlib.pyplot as plt

# Combine all titles into a single string

text = ' '.join(df['title'].astype(str).tolist())

# Create a WordCloud object

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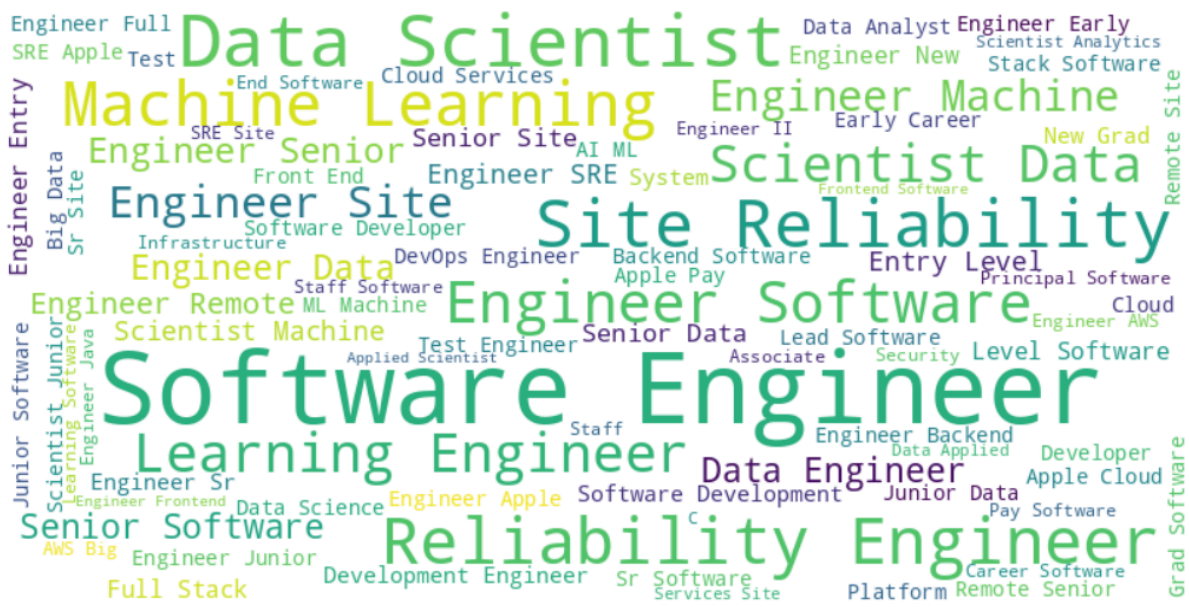
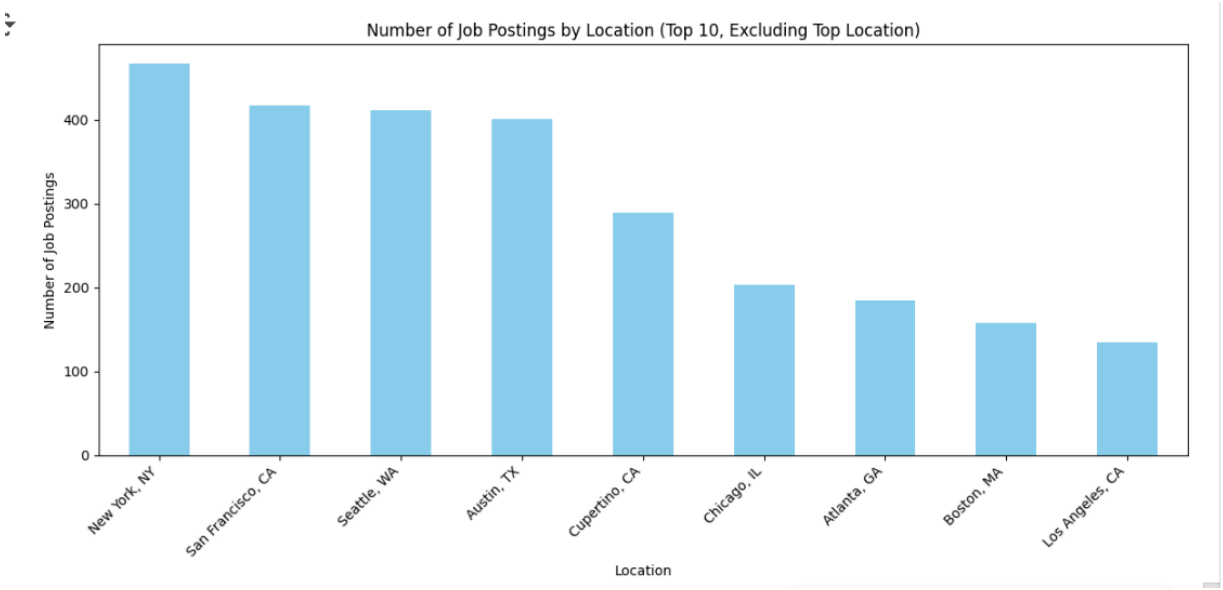
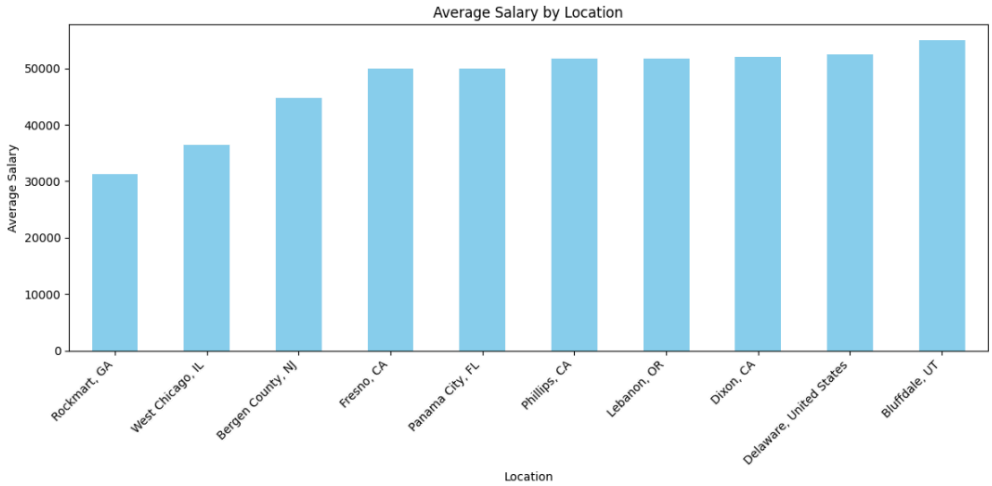


12) Location-Based Analysis:

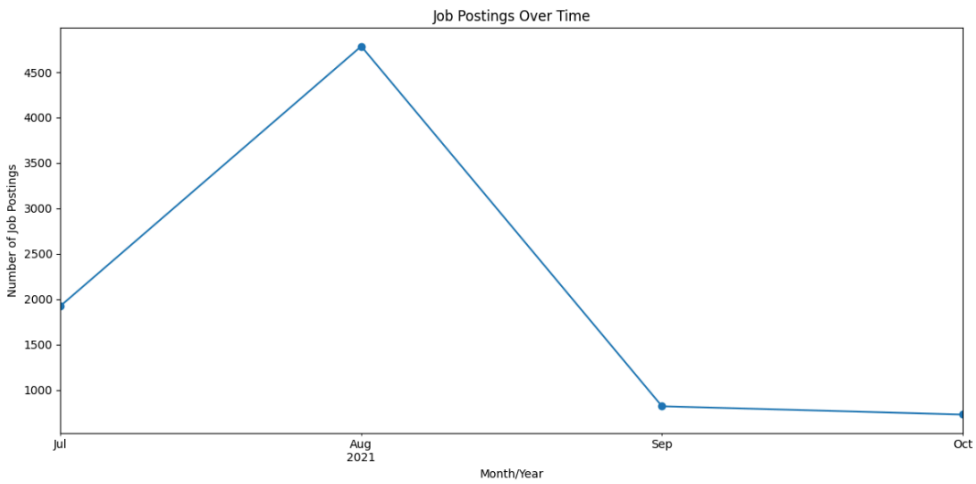
- Bar Chart of Job Postings by Location:
    - Visualize the number of job postings for each location to identify areas with high job demand.



- Location vs. Average Salary:
    - Display this using a bar chart to see which locations offer the highest average salaries.



- Job posting over time



From the graph we can clearly see that the job posting is increased in month of august

13) Visualizations Related to Company and Industry:

- Top Companies Hiring:
  - Visualize the top companies with the most job postings.

```
company_counts = df['company'].value_counts().nlargest(10)



plt.figure(figsize=(12, 6))

company_counts.plot(kind='bar', color='skyblue')

plt.title('Top 10 Companies with the Most Job Postings')

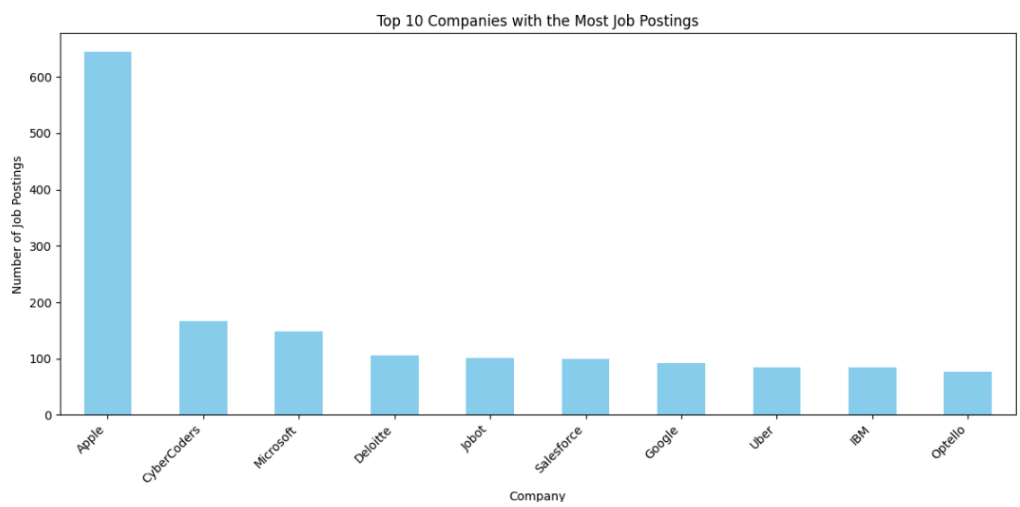
plt.xlabel('Company')
```

```
plt.ylabel('Number of Job Postings')

plt.xticks(rotation=45, ha='right')

plt.tight_layout()

plt.show()
```



- Industries by Seniority Level:
    - Use a grouped bar chart to show the distribution of seniority levels within each industry.

```
industry_seniority.plot(kind='barh', figsize=(12, 6))  # barh
for horizontal

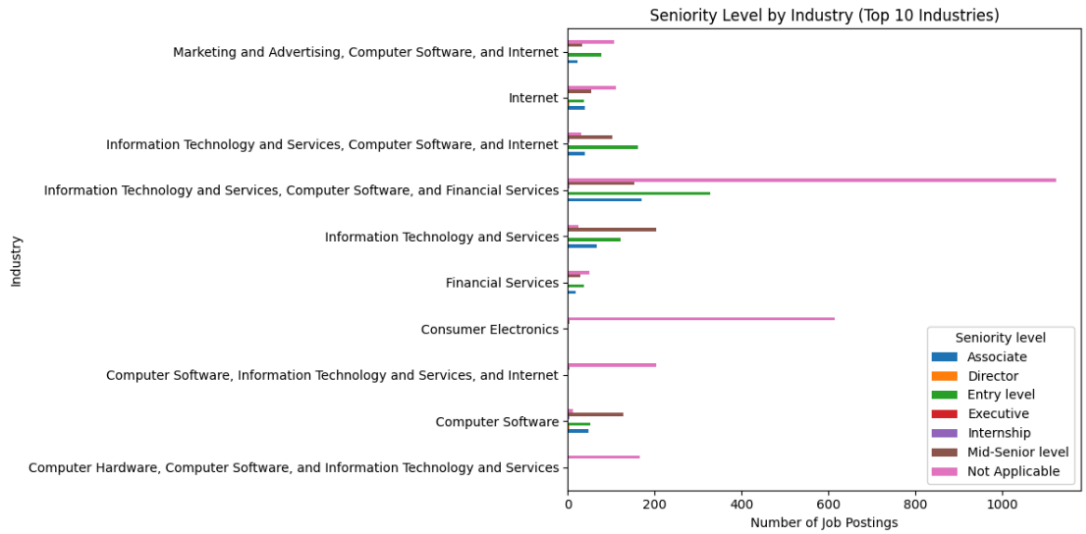
plt.title(f'Seniority Level by Industry (Top {top_n}
Industries)')

plt.ylabel('Industry')  # Switch labels for horizontal chart
```

```
plt.xlabel('Number of Job Postings')

plt.tight_layout()

plt.show()
```



14) Count of unique values in each column

The column `post_id` tells you how many total rows there are, while the rest are indicators of how much variety is in the dataset.