Question 2b, Part iii Suppose we wanted to investigate trends in how often the word "AI" is mentioned in NYT articles since the 1980s.

Is news\_df a suitable dataset for this investigation? Explain your reasoning.

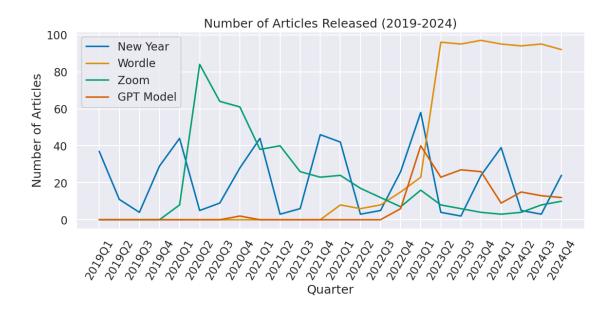
No, news\_df is not suitable for investigating trends in how often the word "AI" is mentioned in NYT articles since the 1980s. According to the assignment, news\_df only contains filtered NYT articles from 2019 to 2024, meaning it does not include data from the 1980s. Since trend analysis requires a dataset covering multiple decades, a more comprehensive dataset from the NYT Archive API with articles from the 1980s onward would be needed.

Additionally, news\_df appears to contain only a subset of articles rather than a complete collection of all NYT articles, which may introduce selection bias. A more comprehensive dataset, such as one covering full NYT archives, would be more appropriate for this investigation.

## 0.0.1 Question 2f

Let's visualize the article counts for each topic by quarter from 2019 to 2024.

Question 2f, Part i Using sns.lineplot (documentation) and topic\_mentions, visualize the topic trends across quarters. Your plot should look like this:



Question 2f, Part ii For each of the four topics, identify one interesting pattern in the visualization and provide a tentative explanation of why you think the pattern exists.

New Year: The mentions of "New Year" show a recurring spike in the first quarter of each year, which makes sense given that news coverage around New Year's Eve, celebrations, and resolutions tends to peak in January. After that, mentions drop off as other topics become more relevant.

Wordle: There is a sharp increase in early 2022, which corresponds with when Wordle became widely popular. The game went viral on social media, and major news outlets covered it extensively, leading to a surge in mentions. After that, the mentions stabilize at a lower level, likely as its novelty wore off.

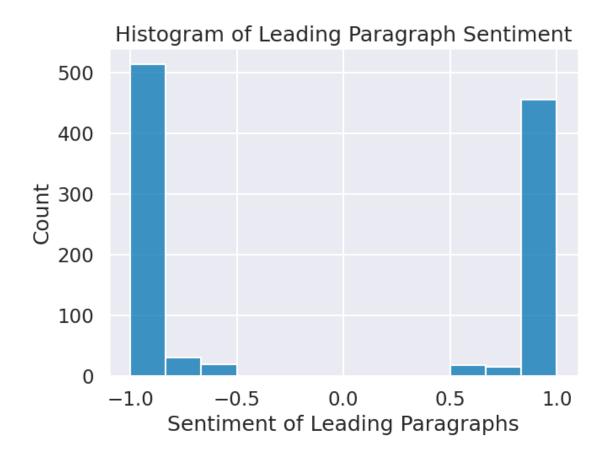
Zoom: The mentions of "Zoom" peak dramatically around 2020Q2, which aligns with the onset of the COVID-19 pandemic. As workplaces, schools, and events transitioned to remote settings, discussions around Zoom skyrocketed. After the initial surge, the mentions gradually declined, likely due to hybrid work becoming more common and the initial novelty of video conferencing wearing off.

GPT Model: There's a clear increase in mentions starting around 2023, which likely reflects the rise of AI models like ChatGPT and other advancements in generative AI. The steady level of mentions after the spike suggests that AI remained a major topic in tech and business discussions.

## 0.0.2 Question 3c

Let's now visualize the distribution of article sentiment.

Using seaborn, we created a histogram to visualize the distribution of article\_sentiment. Run the cell below to display the plot.



Are you at all surprised by the distribution of sentiment in the graph above? Describe what you notice

about the graph and how it relates to what you learned in part 3a.

The distribution of sentiment in the histogram is not surprising. The graph shows that most articles have sentiment scores near -1 or 1, with fewer articles around 0. This suggests that the model tends to classify articles as either strongly positive or strongly negative, rather than neutral. This pattern aligns with Part 3a, where we examined how sentiment is derived from the text. Since the sentiment scores are based on a model that assigns polarity, the presence of strong sentiment peaks is expected

Question 3d, Part ii Do you agree with the current sentiment-based ordering of news articles, or would you rearrange the ordering? Do you feel that the DistilBERT model is a good model for our task of analyzing sentiment in news articles?

The sentiment-based ordering largely makes sense, with positive articles featuring celebratory language and negative ones discussing layoffs and market declines. However, DistilBERT may overstate sentiment in news writing, which often aims for neutrality. For example, factual reports on stock declines might be classified as highly negative due to word associations. While the model performs well at a broad level, fine-tuning on journalistic data or incorporating context-aware scoring could improve accuracy.

## 0.0.3 Question 3e

Let's visualize our data more effectively. We will still use sns.lineplot, but instead of plotting every observation, we will first aggregate our data, and then plot the aggregated values.

We will also compare sentiment scores across three topics: New Year, Zoom, and GPT.

We will use the DataFrame news\_df\_sentiment in this question.

- 1. For each topic, generate a DataFrame that shows the average article sentiment for each quarter. In each DataFrame, be sure to include a column called Topic that has the same string value in every row (either New Year, Zoom or GPT).
- 2. Concatenate the DataFrames obtained from step (1) using pd.concat (documentation). Assign this to all\_topic\_qtr\_avg\_sentiments.
- 3. Finally, we have provided the code to plot each topic's average article sentiment in each quarter using all\_topic\_qrt\_avg\_sentiments.

Your graph should have a similar title, axis labels, markers, and x-axis tick label ordering as the one below.

```
In [580]: fig, ax = plt.subplots(figsize=(15, 5))
 dfs_per_topic = []
 for topic in topics:
     df_of_current_topic = (
         news_df_sentiment[news_df_sentiment[topic] > 0]
         .groupby("Quarter")["article_sentiment"]
         .mean()
         .reset index())
     df_of_current_topic["Topic"] = topic
     dfs_per_topic.append(df_of_current_topic)
 all_topic_qtr_avg_sentiments = pd.concat(dfs_per_topic)
 sns.lineplot(data=all_topic_qtr_avg_sentiments, x="Quarter",y="article_sentiment", hue="Topic
 plt.title('Avg. Sentiment per Topic Across Quarters')
 plt.xlabel('Time')
plt.ylabel('Lead Paragraph Sentiment')
 # If the above are implemented correctly, running this cell should produce the graph shown ab
 plt.axhline(0, color='black')
plt.xticks(rotation=65);
```

