Deliverables

1. **Using a dataset from Project Milestone 2, select one (1) use case:**

    a. CEO Strategy Themes:

    i. Objective: Identify unique linguistic or thematic signatures of individual CEOs or companies.

    ii. Possible Techniques: Use topic modeling (e.g., BERTopic) and visualizations to explore different themes by company or industry (this would require you to map company to industries).

2. **Jupyter notebook (ideally Colab) or GitHub repo/folder of initial POC: Provide a clear, concise, and working example of five different inputs and corresponding outputs of the model. This section should demonstrate the model's practical application and allow others to easily understand and replicate the process. For instance, in an NER project, show an input text string and its annotated output; for a search/retrieval task, provide a query and the corresponding returned output.**

    a. Include all dependencies required to run the project in the notebook or an accompanying requirements.txt file.

    b. Ensure there are no dependency conflicts that prevent the notebook from running.

    c. Well organized notebook; e.g., use of Markdown headers and sections to organize the notebook clearly.

    d. Logical flow of the code with clear, concise, and relevant comments explaining the purpose of each code block.

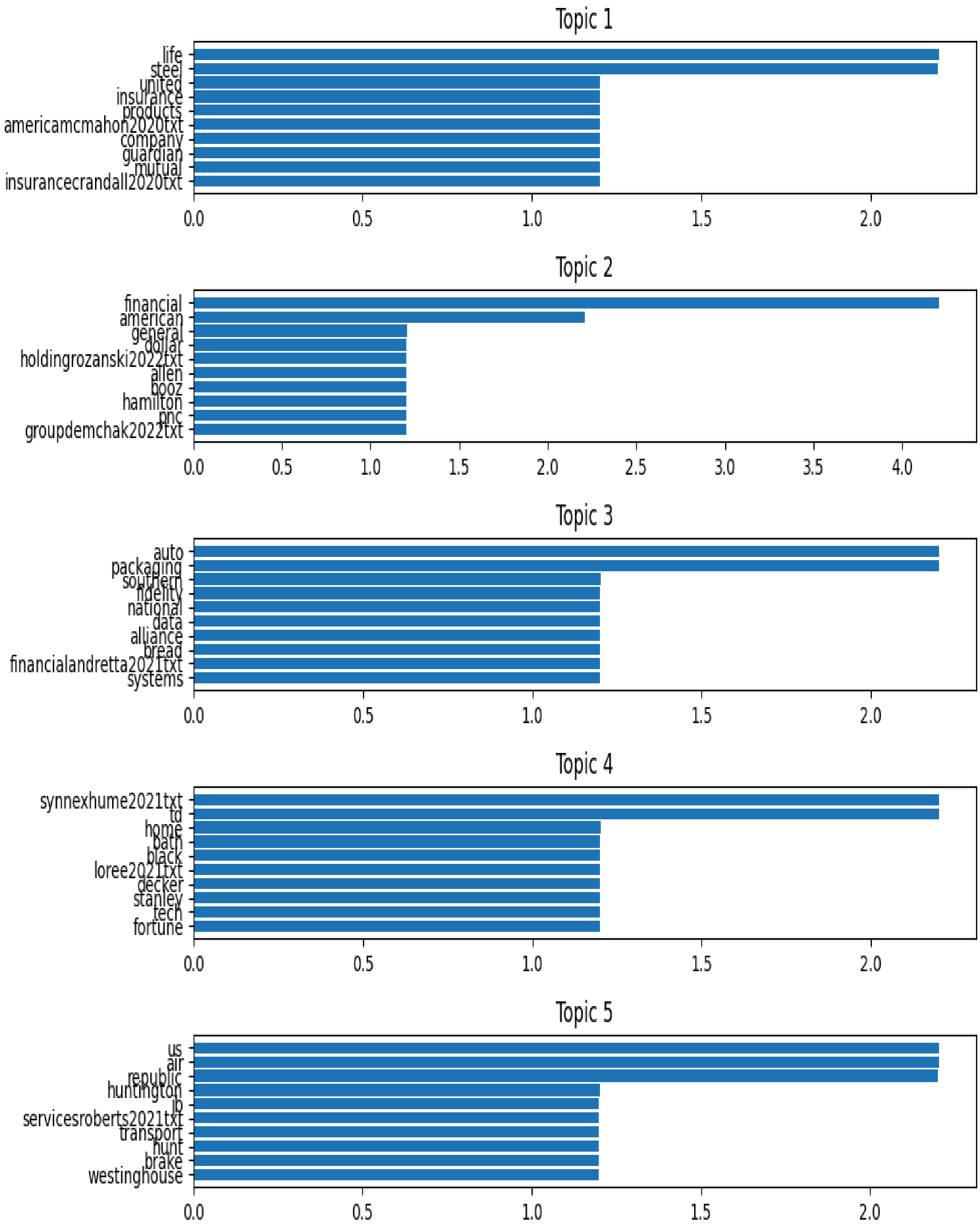
    e. Avoidance of excessive details that do not contribute to understanding or running the code (e.g., printing the full dataset).

    f. Clear and concise Markdown text descriptions (or comments) explaining the objectives, methodology, and conclusions of each section.

    g. Efficient use of code, avoiding redundant or unnecessarily complex functions or loops.

    h. Appropriate error handling to ensure the notebook runs smoothly from start to finish without crashing.

    i. Test notebooks in a clean environment (e.g., using a new kernel) to ensure that notebooks are fully reproducible with the provided dependencies.



3. 2-Page Write Up

Progress since the last milestone

Following the completion of our initial data preprocessing, we have made significant progress in identifying common themes/topics within the CEO letters to shareholders dataset. We employed BERTopic, a recently developed neural-based topic modeling technique, to automatically discover latent topics within the letters. We optimized our output by eliminating stopwords, punctuation, and numerical values- likely signifying years. This resulted in the identification of seven distinctive topics within our dataset. We analyzed the top keywords associated with each identified topic to gain a thematic understanding. Topics include financial growth and performance, employee health, company capital, etc.

Failed Ideas/Experiments

Initially, we tried to identify common themes and topics in the dataset without the elimination of stopwords, punctuation, and numerical values. This returned less than desirable results as it primarily returned words such as “and, for, or” etc.

For one of our experiments, we wanted to see if we could build a topic model for our consolidated dataset using a pre-trained model but filtering only financial terms into different topics. The objective of this experiment was to construct a model capable of generating word representations that encompass semantic similarities. This, in turn, would give us a better analysis of financial text data from our CEO Letter.

We started by defining some “seed” words that would be used for filtering financial text (words like: ['financial', 'bank', 'economy', 'market', 'investment', 'revenue', 'profit', 'capital', 'asset', 'income', 'equity', 'debt', 'loan', 'stock', 'bond', 'dividend']). We then loaded a pre-trained model (word2vec-google-news-300) through the gensim API. Instead of training a Word2Vec model from scratch on our own dataset, we wanted to try a pre-trained model, which has already learned rich representations of financial words based on the patterns present in the training data.

The utilization of the pre-trained Word2Vec model in our study involves computing the cosine similarity between tokens extracted from the text data and a predefined set of financial terms.

Our findings yielded favorable outcomes, as we successfully derived five distinct topics related to financial concepts. These topics exhibit slight variations from one another, showcasing an understanding of financial terms. Moving forward, our intention is to further refine our model through experimentation with a more specialized dataset focused on a single industry. By doing so, we aim to enhance the quality of our results and achieve greater differentiation among topics, thereby enriching our understanding of the underlying financial narratives.

Blockers

During this process of experimenting with the parameters of our BERTopic models, we found that the modeling process could be particularly tedious, as some cells would take 2 minutes to run. This resulted in a lot of time we spent just waiting on our code to finish running since we frequently needed to adjust the parameters of the model to best fit the contents of each individual industry.

Beyond this, we did not run into any other consistent technical issues that were significant to the success of our project.

Preliminary Results

The preliminary results of our modeling efforts were promising and continued to improve as we found ways to make the model better, like by excluding certain stopwords, years and any other unnecessary content. In some instances, we also made use of BERTopics ability to specify the number of topics so we could ensure that we were capturing all of the relevant trends within a particular corpus. Although our final results for each model were well-polished and for the most part, generally relevant to each industry that they pertained to, we still believe there is room for improvement and plan to continue development of these models or others like them to achieve more optimal results.

Next Steps:

1. Refine Topic Interpretation: Continue refining our code to conduct a deeper analysis of keywords and potential subtopics within each identified theme.
2. Sentiment Analysis: Explore the sentiment associated with each topic across different years/industries with the code from our initial discovery.
3. External Events: Consider the possibility of correlating the content of our topics with external events or general trends of the years they originated from.