EMPLOYER PROJECT

Bank Of England Project Report

Background/context of the business

Project Aim

The project aimed to analyse the influence of Bank of England (BoE) speeches on UK economic trends over the past three decades. The initial objective was to provide a toolkit for the Bank of England (BoE) to optimise the soft power capabilities of their speeches. However, after the first consultation, the team moved towards a more exploratory and descriptive analysis. The final problem statement was, 'Does speech sentiment effectively limit shock?' To answer this, the goals driving the project were identified as follows:

- Evaluating potential relationships between speech sentiment and the economy.
- Determining the effectiveness of the bank's communications in mitigating the impact of crises.

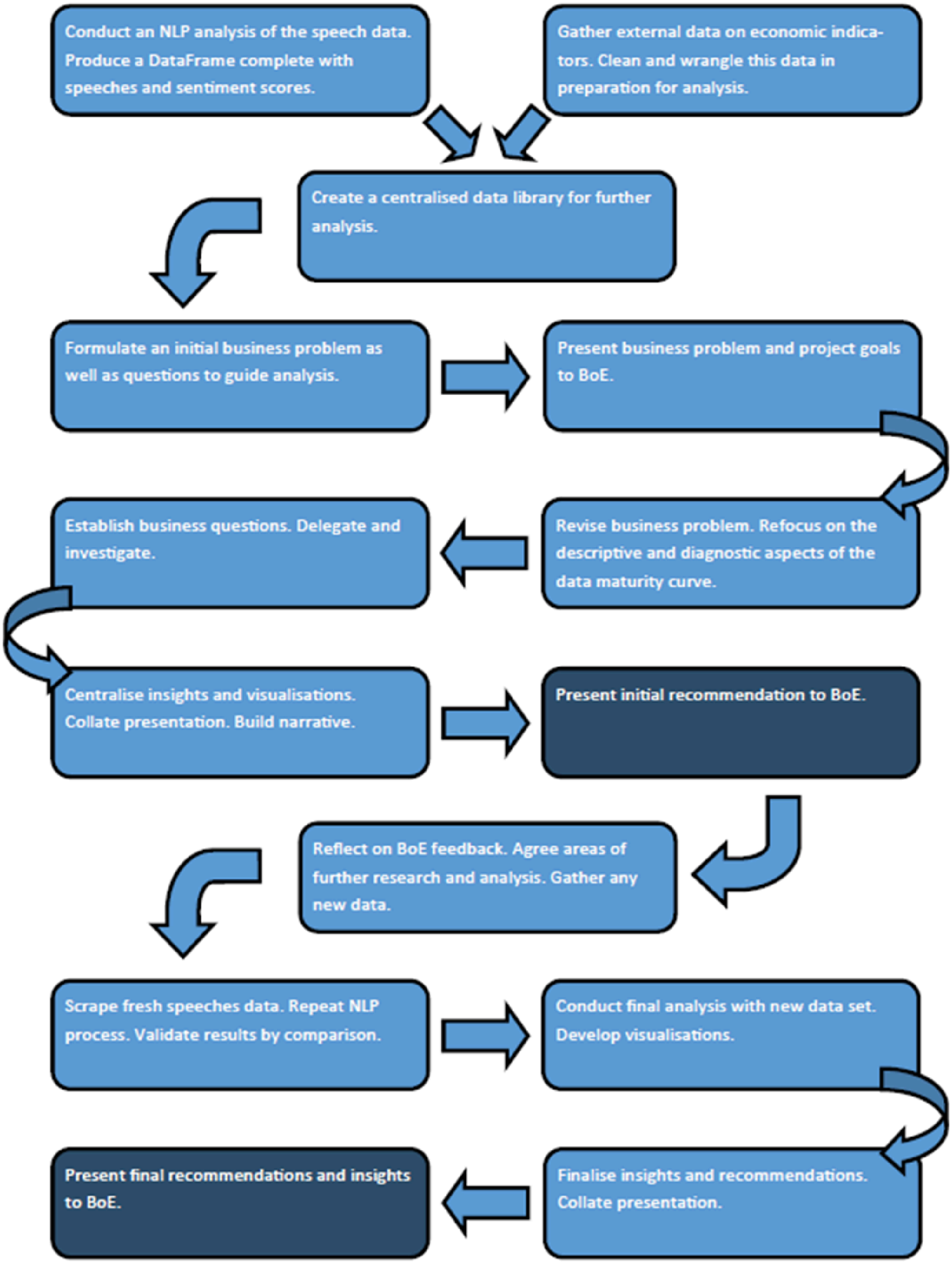
The presentation assumed a technically literate audience, blending technical jargon with narrative elements. Subsequent report sections will detail the project's process and coding specifics.

Project Development Process

Introduction to Project Workflow

The project embarked on an initial phase of Natural Language Processing (NLP) analysis and collection of economic indicators data, laying the groundwork for addressing the business problem and goals. Refinement of the problem, formulation of guiding questions, and data analysis lead to the presentation of preliminary recommendations. After BoE feedback, further analysis ensued, incorporating the scraping of additional speech data for NLP validation. Final analysis, visualisation creation, and recommendation refinement lead to the ultimate presentation of insights to the BoE. An overview of the workflow can be seen in the following diagram.

Workflow Diagram



<u>Data Cleaning and Preprocessing</u>

Starting with Natural Language Processing (NLP), the team endeavoured data cleaning and wrangling to ensure the data's readiness for subsequent analysis. We chose the provided BoE wordlist for NLP analysis due to its status as an academic standard, mindful of its previous use in examining discourse within the finance sector **(Bodnaruk, Loughran, McDonald,2015**). While VADER and FinBERT were considered, VADER's social media orientation and FinBERT's technical limitations made them less suitable for analysis. In Python, the initial steps involved purging missing values and standardising the date column for consistency across the board. The cleaning phase addressed null types and length disparities, with duplicates scrutinised and handled to avoid any potential biases downstream. The dataset was separated into UK and foreign speeches, with the analysis primarily homing in on the former, owing to its direct relevance to the UK economy and to enhance processing speed. Sentiments were systematically interrogated, scored, and added as new columns in a fresh dataset, where they were normalised by speech length to facilitate fair comparisons. We chose the concept of average sentiment for its contextual relevance. Using rolling average conveyed the intended message better, as totals simply reflect noise from all speeches. The analysis found speeches often had consistent proportions of sentiments, making total values less insightful compared to the mean.

<u>Integration of Economic Indicators:</u>

Following data cleaning, the team gathered economic indicator data from reliable databases *(Appendix Table 1).* While initially suggested in the brief, the team independently concluded that these indicators accurately depict the fundamental image of economic stability. They were plotted alongside sentiment data to uncover correlations and interplay.

<u>Analysis after the first presentation.</u>

Feedback prompted deeper exploration into the potential correlation between speech sentiment and voting unity of the Monetary Policy Committee (MPC), achieved through statistical analysis. During the project's timeline, considerations arose for integrating additional indicators across a wide range of metrics, which were investigated for having a relationship with speech sentiments through exploratory visualisations and calculating correlations. Some yielded intriguing results, in particular those related to income inequality, while others did not. The analysis was dealt with in detail for the second presentation. While the Monetary Policy Report (MPR) and Financial Stability Report (FSR) provided avenues for exploration, initial exploration showed little evidence of a correlation with sentiment. The investigation was postponed to continue with other facets of the existing analysis.

Web Scraping and Descriptive Analysis

Concurrently, a parallel endeavour was undertaken, involving the scraping of the BoE website for up-to-date speech data. This initiative proved instrumental in enriching the analysis, given the limitations discovered in the initial dataset, including, "32 null authors", "32 null titles", "14 duplicate texts", and inconsistent governor status. The newly acquired data underwent NLP processing to ensure analytical consistency and the results were validated against the old dataset. A sub-team embarked on a descriptive analysis of the newly scraped speech data.The analysis helped form a picture of the overall tone of sentiments through different speakers' output and explain the dataset in its entirety.

Data Visualisation

Data visualisation played a pivotal role, emerging as a powerful tool for unravelling the descriptive nuances of the speech dataset and conceptualising its essence. The dashboards generated (through Looker Studio) served as vital components, offering insights into speaker sentiments and highlighting similarities or differences among them (*Appendix Fig 1*). Additionally, a correlation matrix visually depicted the relationships and interactions between various indicators, serving as a foundational reference point for subsequent independent analyses (*Appendix Fig 2*). To enhance the effectiveness of our visualisations, we focused on several key strategies and they are listed below:

No.	Visualisation Configuration Decisions
1	Selected colour-sentiment combinations to avoid stereotypical associations, ensuring that our visualizations were accurate.
2	Consistent colour usage across all visualizations ,allowing the audience to develop familiarity and easily interpret the data presented
3	Employed rolling values in numerous instances to maintain granularity and ensured that the graphs remained digestible.
4	Incorporated historical events in a subdued grey or BoE blue, utilizing an alpha grading for transparency.
5	Placed historical events behind the lines on the graph rather than in front helped maintain the focus on sentiment analysis
6	To distinguish between different types of events, we utilized various dashed line styles, including '--', '-:', and ':'.
7	The dual y-axis were consistent throughout where Y2 was always the sentiment and Y1 was the rate, indicator etc.

The following section will provide a technical overview of the analysis.

Technical overview of the code.

The analysis started with the NLP for the speech data and interrogated against the sentiment wordlist. A matrix has been provided (*Appendix Table 2*) detailing all the libraries used in Python. The process of the analysis can be explained as follows.

- After converting words to lowercase, we created a dictionary associating each word with sentiment scores. Using a custom function, each speech was scored for sentiments. These scores were added as new columns to the dataset. Later, we normalised sentiment scores by dividing them by speech length. These adjusted scores were merged back into the dataset. This approach provided comprehensive insights into speech sentiment while accounting for variations in speech lengths and providing more accurate insights into sentiment trends. The decision not to stem or lemmatise the wordlist in the NLP analysis was intentional, preserving the unique characteristics of the categorised words. The wordlist covered various forms of the same word (*Appendix Table 3*) and stemming or lemmatisation could potentially strip away essential context from the sentiment attached to these words, compromising analysis accuracy.
- The web scrape utilised various tools for accessing web pages, processing HTML content, handling PDF files, and organising data. It initialised a headless browser session, defined base URLs, and configured a session for making HTTP requests. Functions were created to extract speech metadata and content from both HTML and PDF formats. The scraping process began by navigating to the BoE sitemap page where individual speech page links were stored, handling any pop-up messages, and ensuring the availability of speeches for collection. It iterated through each speech URL, extracting data and text.
- Following the creation of the NLP dataset using the new speech data, the team overlayed economic indicators onto sentiment data over periods, generating line plots for analysis. The sentiments were rolled on a 30-day average in most instances to enhance the trend observation. During the overlay process, the team highlighted three major financial events spanning the past three decades. To enhance the narrative, more financial events were plotted later on, emphasising BoE's soft influence. These included UK-specific events for detail. Line plots illustrated the time-series aspect, with dual y-axes ensuring sentiment and indicators consistency. Integrating economic data enabled trend visualisation and correlation identification.
- Feedback prompted analysis of the Monetary Policy Committee (MPC) voting unity against speech sentiments. The analysis covered a specific time period, employing entropy as a proxy for voting unity and a 30-day rolling average for sentiment. The goal was to uncover any correlations or discrepancies between MPC unity and the sentiment conveyed in public speeches, with notable events marked for reference. Overall, these analyses aimed to provide insights into the interplay between MPC actions and public sentiment within the specified time frames.

The above was the last analysis that was done using Python and thus brought the coding process of the project to a finish line. The final section highlights the insights of the project.

Patterns, trends, and insights.

The analysis revealed significant insights into the relationship between sentiments expressed in (BoE) speeches and economic indicators. In line with the goals that were defined at the start of the report, the insights can be grouped and revealed as follows:

Insights of Project Goal 1: Evaluating potential relationships between speech sentiment and the economy.

- Prevailing negative sentiment characterised these speeches, persisting even when sentiments were averaged out.
- Soft influence, notably through bank rate and 'uncertainty' sentiment, was evident pre and post-financial crash (*Appendix Fig 3*). Further exploration revealed consistent use of 'litigious' and 'constraining' sentiments by the BoE, indicating a strategic approach during economic instability. Constraining sentiment persisted even during rising GDP, suggesting the BoE's proactive stance against inflationary pressures (*Appendix Fig 4*).

Insights of Project Goal 2: Determining the effectiveness of the bank's communications in mitigating the impact of crises.

- Limited evidence showed the deployment of litigious sentiments alongside hard controls like during the Kwarteng mini budget announcement. This deployment was aimed at stabilising the FTSE 250 reaction.

Additional Insights

- Additionally, the latest analysis showed that sustained, and high levels of, disunity among the MPC had not 'leaked' into the sentiments broadcast in bank speeches.
- The project highlighted an established eco-system governing BoE communications with the economy. It emphasised the need for caution in making changes within this eco-system, underscoring the intricate dynamics at play in central bank communication.

Further Areas of Exploration and Conclusion.

The report would like to highlight unexplored areas due to scope limitations, such as the desire to scrape(MPR)/(FSR) data for additional sentiment analysis, which would serve as a better comparison against speech sentiment than only the periodicity of releasing these reports. We developed a sentiment database which can serve as a foundation for future research, confirming or challenging intuitions encountered during analysis. In conclusion, while the analysis provided valuable insights, further research with additional resources can deepen our understanding of the relationship between speech sentiment and the economy.

Appendix

References:

1) Bodnaruk, A., Loughran, T. and McDonald, B., 2015. Using 10-K text to gauge financial constraints. Journal of Financial and Quantitative Analysis, 50(4), pp.623-646.

Table 1: Databases for Economic Indicators.

No.	Indicator	Database.
1	GDP	https://www.ons.gov.uk/economy/grossdomesticproductgdp/datasets/quarterlynationalaccounts
2	GDP per capita	https://data.worldbank.org/indicator/ny.gdp.pcap.cd?most_recent_value_desc=false
3	GDP per capita change	Calculated in excel using annual GDP per capita
4	CPI	https://www.ons.gov.uk/economy/inflationandpriceindices/timeseries/l55o/mm23
5	Unemployment	https://data.worldbank.org/indicator/SL.UEM.TOTL.NE.ZS?locations=GB
6	GINI Index	https://data.worldbank.org/indicator/SI.POV.GINI?most_recent_value_desc=true
7	Bank Rate	https://www.bankofengland.co.uk/monetary-policy/the-interest-rate-bank-rate
8	Gov Debt	https://data.worldbank.org/indicator/GC.DOD.TOTL.GD.ZS
9	20% Income share	https://data.worldbank.org/indicator/SI.DST.FRST.20?locations=xn
10	R&D Spending	https://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS?name_desc=false
11	Net FDR	https://data.worldbank.org/indicator/BX.KLT.DINV.WD.GD.ZS?quantity=1
12	Tax Revenue	https://data.worldbank.org/indicator/GC.TAX.TOTL.GD.ZS?name_desc=true
13	Final Consumption expenditure	https://data.worldbank.org/indicator/NE.CON.TOTL.ZS?name_desc=true
14	Imports	https://data.worldbank.org/indicator/NE.IMP.GNFS.CD
15	Gross Savings	https://data.worldbank.org/indicator/NY.GDS.TOTL.CD
16	FTSE 250	https://www.londonstockexchange.com/reports?tab=ftse-index-values

Table 2: Custom Python Library Matrix highlighting those used specifically for this project by team members.

Libraries	Project Tasks			Description
	Webscrape	NLP	EDA	
pandas	✓	✓	✓	Provides data manipulation and analysis tools using data structures like DataFrames.
numpy			✓	Offers support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions.
scipy		✓	✓	Extends numpy with additional modules for optimization, linear algebra, integration, and statistics.
datetime	✓	✓	✓	Enables manipulation and formatting of dates and times.

Table 3: Rationale behind not lemmatising and Stemming.

Figure 1: Mean Sentiment Score Governor Speeches (Descriptive Speech Analysis)

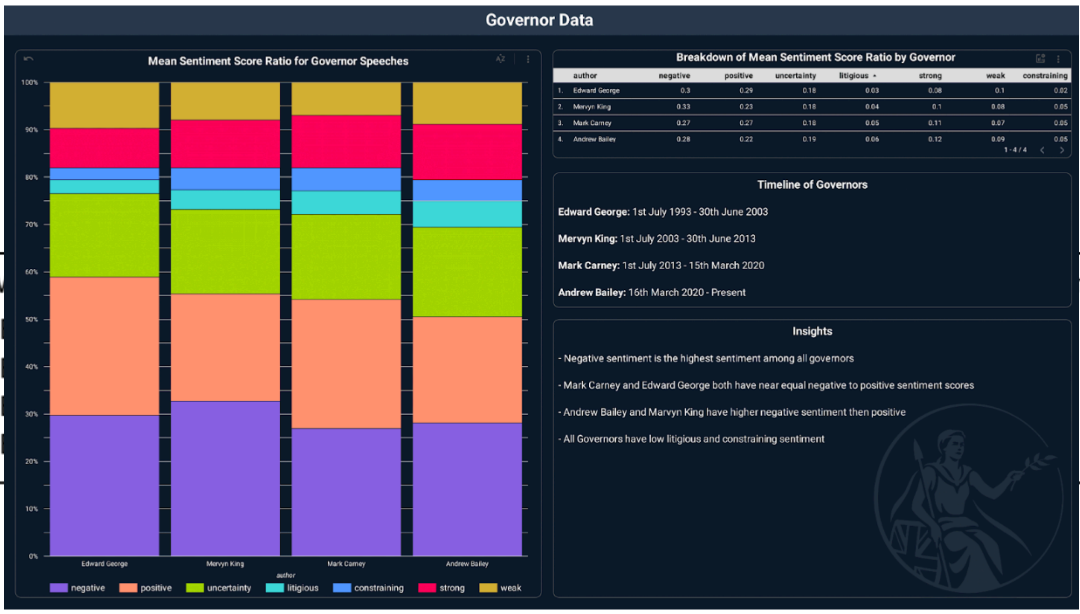


Figure 2: Correlation Matrix

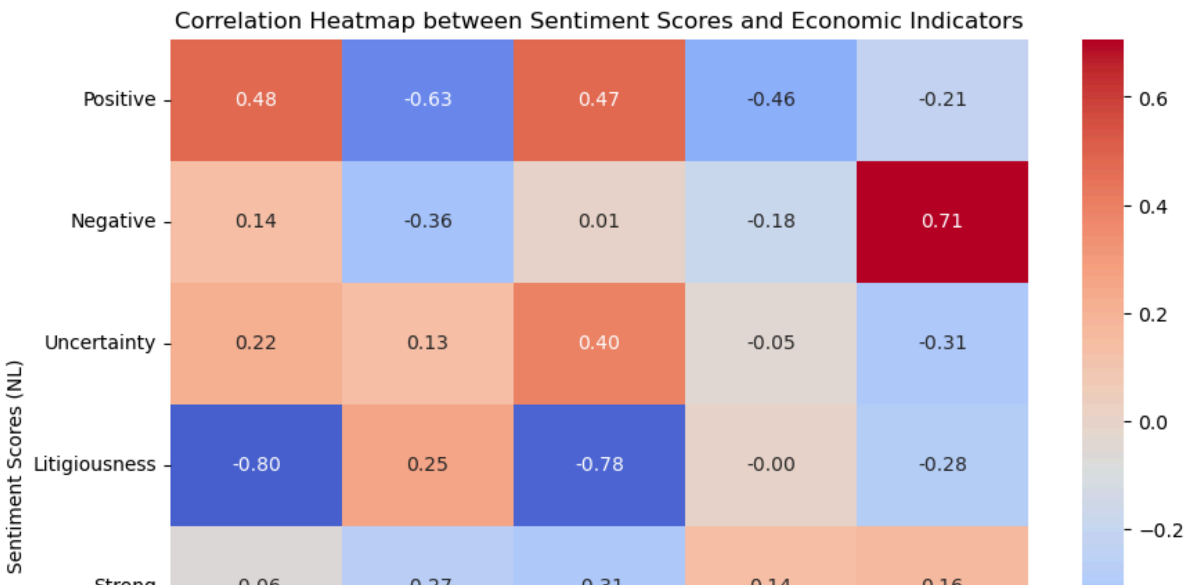


Fig 3 : Bank Rate and Uncertain Sentiment

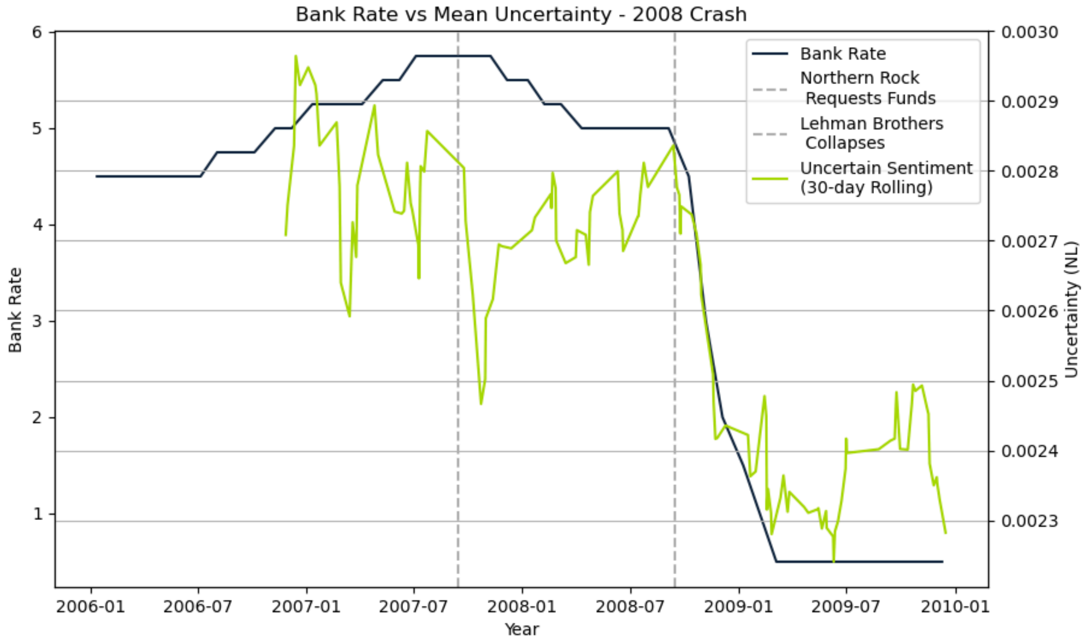


Figure 4: GDP and Counterintuitive Positive Sentiment