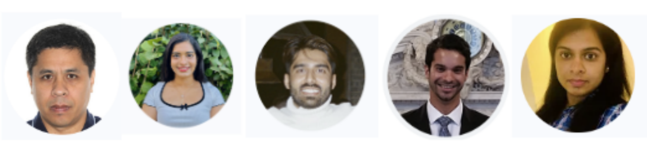
Data Sentients: Bank of England Employer project report



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Background/context of the business:

The Bank of England (BoE) and Prudential Regulation Authority (PRA) face a significant challenge overseeing 1,500 financial institutions effectively. While numerical indicators are well established for risk monitoring, there is a crucial gap in leveraging qualitative data.

Quarterly earnings calls with CEOs and analysts provide a rich, untapped source of data extending beyond traditional financial metrics, offering insights into potential risks through linguistic patterns, sentiment analysis, and topic modelling to uncover underlying themes and behavioural cues.

This project aims to improve the Bank of England's risk assessments of firms by applying advanced language models to analyse quarterly results transcripts, scale qualitative analysis, convert that into a quantitative metric (Financial stability and risk score - FSRS) that detects early signs of distress in a bank and is likely to collapse. Uncovering these insights can help understand a firm's stability and risk profile before they appear in traditional financial metrics.

This project has the potential to significantly enhance the PRA's ability to proactively assess firms, enable efficient resource prioritisation and improving oversight of firms engaging in high-risk behaviour thereby helping prevent future financial crises'.

Project development process:

Approach

The team began by thoroughly understanding the BoEs & PRAs business problem through an initial project briefing and reviewing relevant materials. Leveraging a collaborative online environment through a team Miro board for the full life cycle of the project, we conducted strategic planning sessions for ideation, SMART goal setting, roles and responsibilities allocation, roadmap development incorporating agile project management methodologies.

Feedback loops and weekly review sessions were established early with a product owner/mentor to refine our approach, validate hypotheses, and ensure alignment with the business objectives. The roadmap was iteratively improved along with a detailed project plan balancing the use of familiar tools (e.g., Excel for planning) with new platforms like AzureDevOps.

The aim of the Bank of England was to look beyond conventional financial metrics and explore if qualitative metrics could be used to predict bank distress. The primary source for this explorative analysis was the quarterly earnings calls with executive leadership of the banks and analysts from other banks.

Our development process started with researching, including literature reviews of other approaches to topic modelling and sentiment analysis in the financial domain. Along with understanding of the 2008 & 2023 crisis along with the prior period leading up to the crisis and the recovery period post crisis, to ensure banking cycles are properly captured.

5 fundamental behaviours were identified that could predict bank failure and refined into linguistic markers that could be identified in the call transcripts.

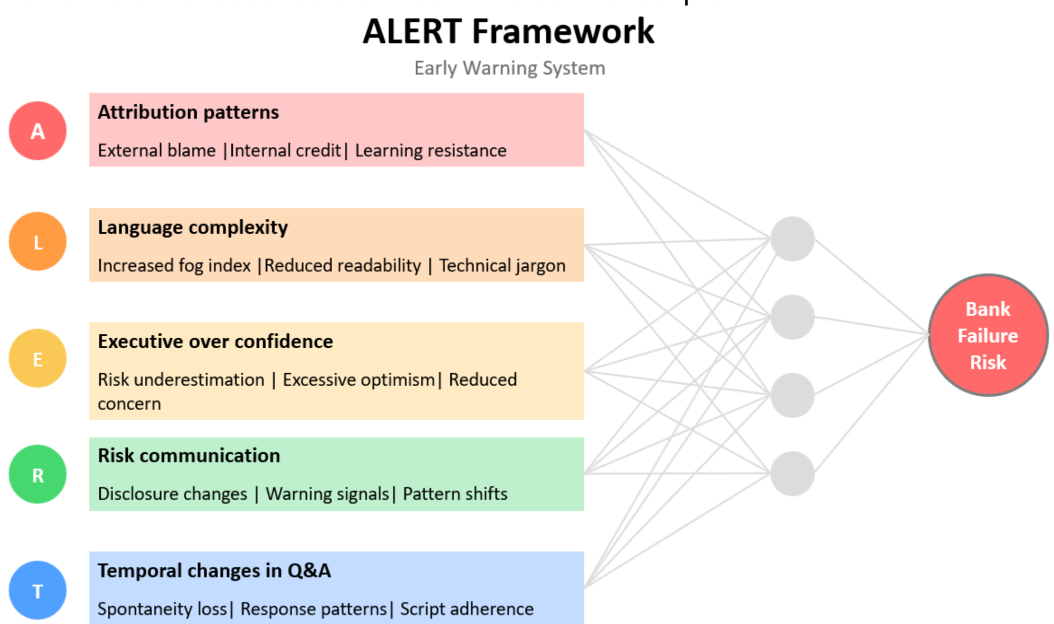


Figure 1: ALERT Framework

A key decision was bank selection was extensive and iterative, involving lengthy research, team discussions, and presentations to the product owner for guidance. Our bank selection strategy aimed to balance market conditions and similarity of operations across global markets. Banks were categorised into 3 broad categories: ‘Distressed’, ‘Stable’ and ‘Volatile’.

SVB and CS collapsed in the same month (March) although for different reasons, with SVB sharply collapsing due to region specific economic issues, while CS had a long history of scandals and loss of confidence over a longer period with a heavy loss due to Archego's collapse. Finally, Fitch believes Nomura has a larger risk appetite than its Japanese peers (Fitch Ratings, 2023), especially in overseas markets which would be of high interest to the BoE and PRA.

Similar to Credit Suisse, Nomura is involved in controversies including a bond scandal and although profits surge to their highest point in 4 years in q1 2024 they were fined by the Japanese banking regulator with the CEO taking a paycut (Keohane, 2024), (Bridge, 2024) and insider trading scandal (Emoto and Layne, 2012).

Nomura provides an interesting contrast to SVB and CS, as it faced its own liquidity and risk management challenges during the Archegos debacle with a $2.3bn loss (Makortoff, 2021). Nomura sentiment shifts and risk signals could be tracked allowing identification of early warning indicators leading up to and during a crisis as well as stability indicators post crisis. It is possible we would be able to see how banks' responses evolve when they move from positive/neutral to distress to recovery to record profit.

These bank choices were strategic considering the aim and short timescale of this project, allowing us to capture the industry trend rather than a region specific trend.

Bank	**SVB (USA)**	**Credit Suisse (Europe)**	**Nomura (Asia)**
Summary	Concentrated tech-sector risk, liquidity crisis, and panic triggered loss of confidence and global instability.	Reputation issues, scandals, losses due to Archegos collapse resulting in loss of confidence and liquidity problems amplified crisis impact.	Geographically diversified, strong risk management, conservative lending, benefited from regional low-rate stability, and recovered from heavy losses during Archegos collapse.

Table 1: Bank selection summary

In order to use qualitative data to predict bank distress, our methodology followed a multi model approach to analyse these quarterly earnings calls. Overall our architecture combined these language models with Retrieval Augmented Generation (RAG), which tackled the problem of hallucinations. Data preparation followed an extract, load and transform (ELT) pipeline that incorporated advanced preprocessing steps

Models & Techniques

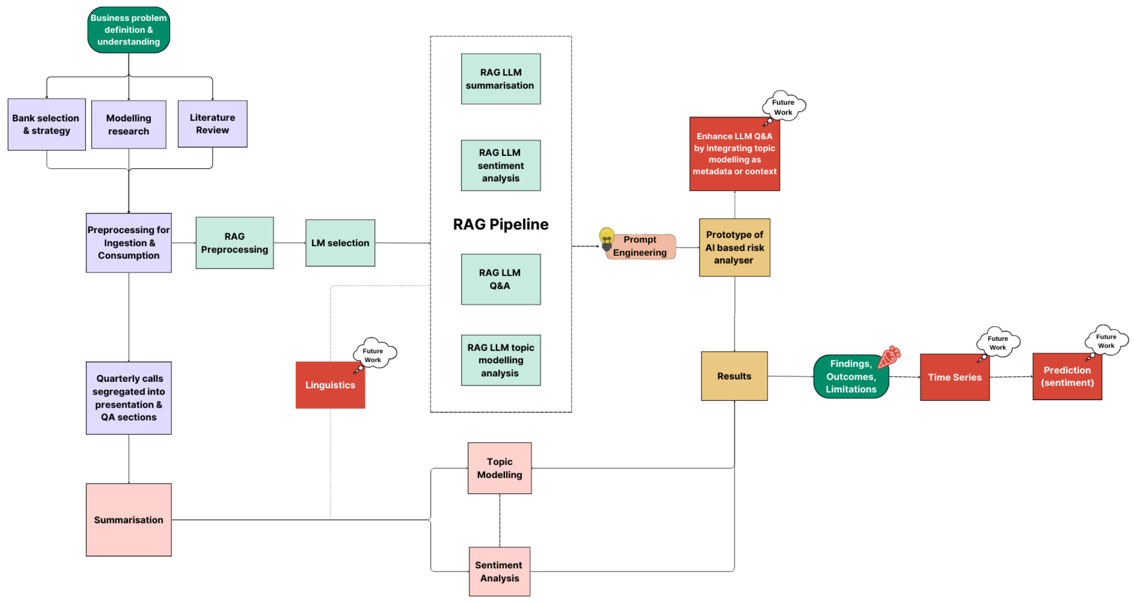


Figure 2: General overview of the project

ELT Pipeline

The ELT pipeline was implemented to efficiently extract, load, and transform earnings call transcripts in PDFs, enabling seamless analysis and model integration.

For the load phase, the raw data was stored in a structured repository for batch or real-time access as required.

In the transform phase, the data was cleaned and refined to normalise it, segmented by speaker/quarter/QA dialogues/presentations, transcripts were summarised using NLTK and prepared as a structured dataset ready for deeper analysis.

Language Model Selection & Evaluation

The BoE & PRA face an enormous task trying to analyse 1500 firms therefore selecting a language model (LM) for the project was a critical task.

A number of key performance metrics were considered including; flexibility, reasoning, cost, context window/token limit, specialisation, resource efficiency, type of model and finally Instruct models were selected as they allow for complex instructions and the ability to capture lengthy conversations in the transcripts.

Aspect	SLM with RAG	LLMs with RAG
Models Identified	microsoft/Phi-3-mini-4k-instruct	Phi-3.5-MoE-128k, Gemini

Purpose	General-purpose, suitable for lightweight setups for answering queries, summarization, and insights	General-purpose (Gemini Flash) / Financial-purpose (MoE)
Resource Requirements	Minimal, fits within free Google Colab limits	Higher GPU memory needed
Metrics	32k tokens, 4k (short context), 4k/128k (long context)	**MoE:** 128k context length **Gemini Flash/Pro:** 1/2M context length
Strengths	Efficient for smaller tasks; accessible	Handles complex tasks and large documents seamlessly
Limitations	Limited context window, lacks financial fine-tuning	High resource needs; Gemini Flash is not domain-tuned, data hungry, MoE lacks multimodal data
Best Fit	MVP testing, quick prototyping	Advanced workflows
Notable Features	Small-scale instruction-tuned	MoE: Financial-specific tuning, performs exceptionally well compared to models of larger size, **see table X**; Gemini: Multimodal support
Cost	Free	Free, Gemini is also free aside for some rate limits and context caching

Table 2: Language model justification (Google Cloud, 2024), (Hugging Face, 2024)

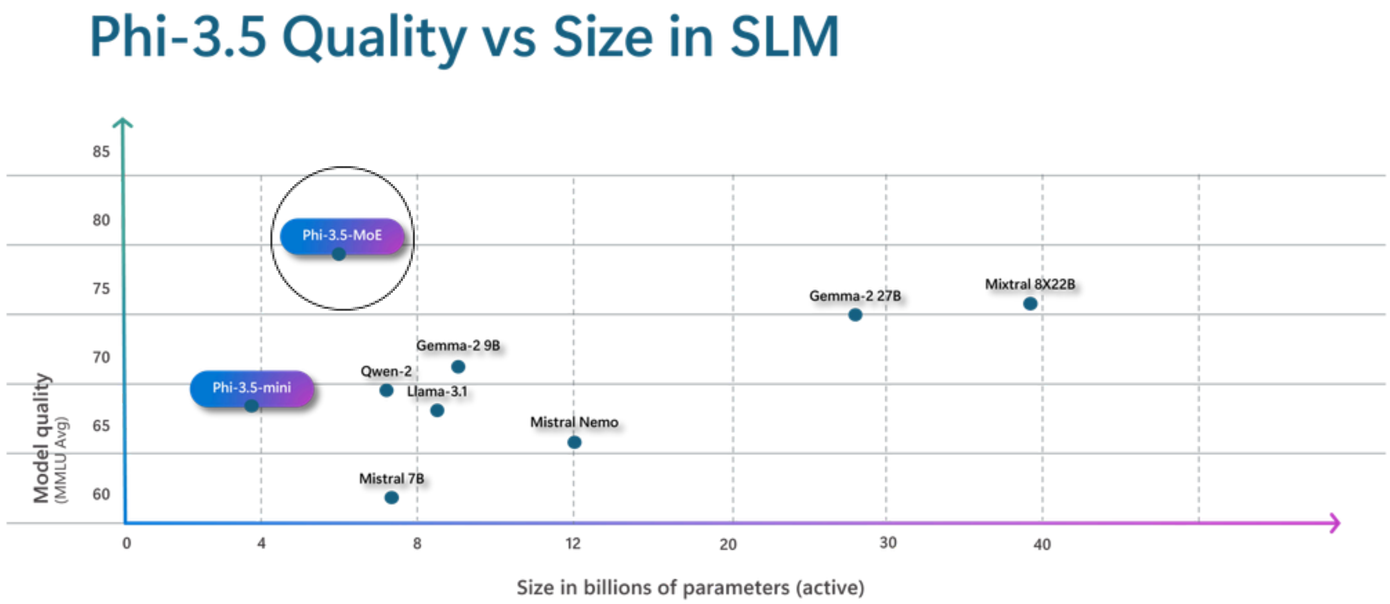


Figure 3: Phi-3.5-MoE comparison (Badrinarayan, 2024)

#	Model	Claimed Ctx	.py (%)	.cpp (%)	.rs (%)	.java (%)	.ts (%)	🏆Avg. (%)
1	🥇 gpt-4o-2024-05-13	128k	95	80	85	96	👍97	90.6
	🥇 gemini-1.5-pro-latest	1000k	91	81	91	94	👍96	90.6
	🥇 claude-3-opus-20240229	200k	93	83	88	👍95	94	90.6
4	gemini-1.5-flash-latest	1000k	93	79	87	94	👍97	90.0
5	claude-3-sonnet-20240229	200k	88	81	85	👍92	91	87.4

Table 3: Gemini comparison (Liu et al., 2024)

Sentiment Analysis Model Selection

'Yiyanghkust/finbert-ton' was specifically fine tuned for sentiment analysis in the financial domain and determined to be the optimal model for our project.

Model	Token Limit	Best For	Key Strengths	Key Limitations
yiyanghkust/finbert-tone	512 tokens	Financial sentiment analysis	High accuracy for financial sentiment	Limited to sentiment, less flexible for other NLP
ProsusAI/finbert	512 tokens	Sentiment, Entity Recognition, and general Classification	Versatile in financial text understanding	Less refined sentiment precision compared to finbert-tone
GPT-2	1,024 tokens	Summarization, Text Generation, Conversational AI	Adaptable to many NLP tasks with fine-tuning	Not finance-specific, requires fine-tuning for accuracy

Table 4: Sentiment analysis model selection justification

Topic Modelling Model Selection

BERTopic was chosen due to its ability as a generalised tool to discover underlying themes or topics from short, sparse, or diverse text.

LDA model from Gensim was preferred for more structured, long documents and is also easily interpretable and computationally efficient. Gensim was deemed more suitable for topic modelling our earnings calls

Retrieval Augmented Generation (RAG)

A (RAG) pipeline was used to analyse earnings call transcripts by combining document retrieval and generative AI.

This created a robust system that is comprehensive, scalable, interactive and domain specific while leveraging state-of-the-art NLP models and libraries, enabling enriched insights into sentiments, topics, financial performance and risks.

Feature	Description
Document Retrieval & Metadata Enrichment	Filters documents by metadata (e.g., year, quarter, bank) for relevant context.
Embedding & Vector-Based Retrieval	Enables similarity-based search to retrieve topically relevant document chunks.
Customizable Generative QA	Tailored prompts deliver domain-specific insights for financial analysis.
Dynamic Context Management	Optimizes context within token limits for efficient model usage.
Sentiment Analysis & Insights	Detects tone (positive, neutral, negative) for risk and opportunity assessment.
Topic Modeling (LDA)	Extracts key themes and trends for strategic and market analysis.
Interactive Queries with Filters	Enables targeted analysis through dynamic data filtering.
Logging & Error Handling	Ensures transparency and smooth operation by resolving errors.
Extensibility	Supports integration of new models or features for scalability and adaptability.

Table 5: RAG justification

Each functionality is chosen to address specific requirements of financial analysts, including precision, efficiency, and actionable insights, while balancing scalability and user-friendliness.

Model / Tool	Purpose	Why Chosen
Sentence-Transformers (all-MiniLM-L6-v2)	Generates document embeddings for similarity-based retrieval.	Lightweight, fast, and accurate embeddings, ideal for large-scale document chunk vectorization and retrieval.
FinBERT	Performs sentiment	Specifically trained on

(yiyanghkust/finbert-tone)	analysis to classify financial text as positive, neutral, or negative.	financial text, excels in capturing nuanced tones in financial discussions, outperforming general-purpose sentiment models.
DistilBART (sshleifer/distilbart-cnn-6-6)	Summarizes lengthy transcripts into concise, actionable insights.	A faster, resource-efficient summarization model fine-tuned on news data, aligning well with financial reporting requirements.
Gensim LDA	Extracts key themes and recurring topics using topic modeling.	Robust and interpretable topic modeling algorithm with domain customization and visualization capabilities through pyLDAvis.
Chroma Vector Store	Stores and retrieves vector embeddings for document chunks.	Lightweight, efficient, and scalable vector database tailored for fast similarity-based retrieval.
SpaCy (en_core_web_md)	Performs named entity recognition (NER) and text preprocessing.	Fast and accurate for removing irrelevant entities like names and organizations, ensuring focused preprocessing.

Table 6: RAG model pipeline justification

Refinements

The following iterations and refinements were made to ensure reliability

1. Topic Modelling refinements:
    a. Hyperparameter tuning
    b. Topic coherence scores measured and compared
    c. Model perplexity calculated to gauge the performance of the model
    d. Incorporating bi-grams and tri-grams, capturing meaningful phrase patterns in transcripts
2. Sentiment analysis refinements:
    a. Dialog summarisation,
    b. Separation of Presentation and Q&A sentiments
    c. Weighted Sentiment summarisation
3. RAG refinements
    a. Enriched document chunks with metadata and later integrated topics and LDA insights into the metadata for deeper analysis.
    b. Sentiment analysis pipeline using FinBERT to classify tones as positive, neutral, or negative, adding an early-warning capability.

c. Summarization pipeline using DistilBART to condense lengthy transcripts into concise, actionable insights.
d. Integrated contextual information directly into the prompt templates, ensuring responses were grounded in relevant data.
e. Refined prompt templates iteratively to improve relevance, clarity, and alignment with financial analysis requirements.
f. Developed a user-friendly menu to choose predefined tasks or input custom queries.

The following challenges were encountered

1. Google Colab restricted long-running jobs and resource-intensive operations, making scaling to larger models more complex and running complex pipelines challenging necessitating workflow optimization.
2. Manual tokenization strategies initially caused inefficiencies; switching to the model's tokenizer improved accuracy and performance.
3. The 4K token length constraint required summarizing and chunking documents. The system is designed to scale to 128K models in the future.
4. Crafting prompts required iterative tuning to achieve clarity and relevance.

Results

Sentiment analysis

Sentiment analysis was performed on the earnings call transcripts giving us the percentage positivity, neutrality, negativity of each quarter as well as the dominant sentiment in the "Sentiment" column. Similar analysis were performed on summarised transcripts for all the banks and the outputs are below

Credit Suisse Bank

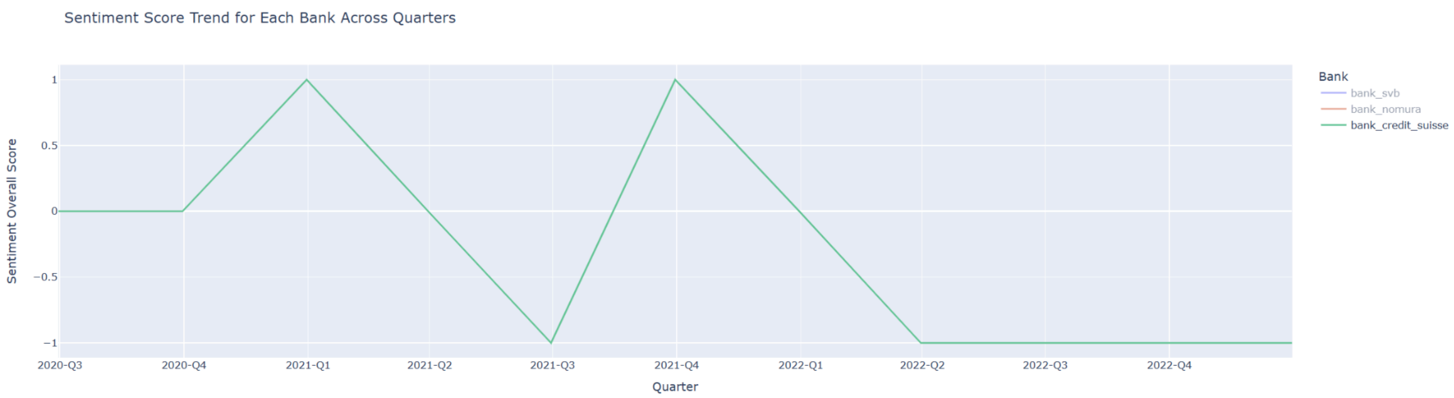


Figure 4: Overall sentiment trend for CS for every quarter

# index	# Year	Quarter	Bank	Section	Sentiment	# Positivity	# Neutrality	# Negativity
0	2020	Q2	bank_credit_suisse	Question-and-Answer	Neutral	34.15	56.1	9.76
1	2020	Q3	bank_credit_suisse	Question-and-Answer	Neutral	22.86	68.57	8.57
2	2020	Q4	bank_credit_suisse	Question-and-Answer	Neutral	27.27	66.67	6.06
3	2021	Q1	bank_credit_suisse	Question-and-Answer	Neutral	28.57	66.67	4.76
4	2021	Q2	bank_credit_suisse	Question-and-Answer	Neutral	4.76	80.95	14.29
5	2021	Q3	bank_credit_suisse	Question-and-Answer	Neutral	26.67	60.0	13.33
6	2021	Q4	bank_credit_suisse	Question-and-Answer	Neutral	21.05	73.68	5.26
7	2022	Q1	bank_credit_suisse	Question-and-Answer	Neutral	24.14	65.52	10.34
8	2022	Q2	bank_credit_suisse	Question-and-Answer	Neutral	22.86	60.0	17.14
9	2022	Q3	bank_credit_suisse	Question-and-Answer	Neutral	18.75	68.75	12.5
10	2022	Q4	bank_credit_suisse	Question-and-Answer	Neutral	33.33	57.14	9.52

Figure 5: CS Q&A sentiment and breakdown

# index	# Year	Quarter	Bank	Section	Sentiment	# Positivity	# Neutrality	# Negativity
0	2020	Q2	bank_credit_suisse	Presentation	Positive	60.0	40.0	0.0
1	2020	Q3	bank_credit_suisse	Presentation	Neutral	40.0	60.0	0.0
2	2020	Q4	bank_credit_suisse	Presentation	Positive	75.0	25.0	0.0
3	2021	Q1	bank_credit_suisse	Presentation	Positive	50.0	50.0	0.0
4	2021	Q2	bank_credit_suisse	Presentation	Neutral	25.0	50.0	25.0
5	2021	Q3	bank_credit_suisse	Presentation	Positive	66.67	33.33	0.0
6	2021	Q4	bank_credit_suisse	Presentation	Positive	75.0	25.0	0.0
7	2022	Q1	bank_credit_suisse	Presentation	Positive	40.0	40.0	20.0
8	2022	Q2	bank_credit_suisse	Presentation	Positive	33.33	33.33	33.33
9	2022	Q3	bank_credit_suisse	Presentation	Neutral	0.0	50.0	50.0
10	2022	Q4	bank_credit_suisse	Presentation	Neutral	25.0	50.0	25.0

Figure 6: CS Presentation sentiment and breakdown

# index	# Year	Quarter	Bank	Section	Sentiment	# Positivity	# Neutrality	# Negativity
0	2020	Q2	bank_credit_suisse	Combined	Neutral	47.08	48.05	4.88
1	2020	Q3	bank_credit_suisse	Combined	Neutral	31.43	64.28	4.28
2	2020	Q4	bank_credit_suisse	Combined	Positive	51.14	45.84	3.03
3	2021	Q1	bank_credit_suisse	Combined	Neutral	39.28	58.34	2.38
4	2021	Q2	bank_credit_suisse	Combined	Negative	14.88	65.47	19.64
5	2021	Q3	bank_credit_suisse	Combined	Positive	46.67	46.66	6.66
6	2021	Q4	bank_credit_suisse	Combined	Neutral	48.02	49.34	2.63
7	2022	Q1	bank_credit_suisse	Combined	Negative	32.07	52.76	15.17
8	2022	Q2	bank_credit_suisse	Combined	Negative	28.1	46.66	25.24
9	2022	Q3	bank_credit_suisse	Combined	Negative	9.38	59.38	31.25
10	2022	Q4	bank_credit_suisse	Combined	Negative	29.16	53.57	17.26

Figure 7: Overall sentiment for CS for every quarter and breakdown

Nomura Bank

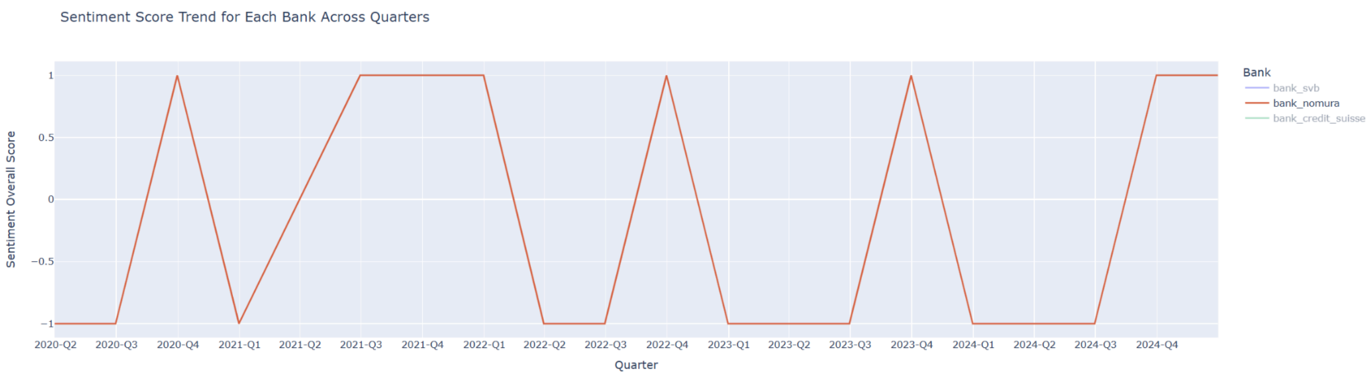


Figure 8: Overall sentiment trend for Nomura for every quarter

# index	# Year	Quarter	Bank	Section	Sentiment	# Positivity	# Neutrality	# Negativity
0	2020	Q1	bank_nomura	Combined	Negative	58.7	32.61	8.7
1	2020	Q2	bank_nomura	Combined	Negative	12.5	31.25	56.25
2	2020	Q3	bank_nomura	Combined	Positive	67.5	30.0	2.5
3	2020	Q4	bank_nomura	Combined	Negative	6.25	39.58	54.16
4	2021	Q2	bank_nomura	Combined	Positive	72.0	26.0	2.0
5	2021	Q3	bank_nomura	Combined	Positive	64.59	31.25	4.16
6	2021	Q4	bank_nomura	Combined	Positive	56.52	39.13	4.35
7	2022	Q1	bank_nomura	Combined	Negative	57.69	28.84	13.46
8	2022	Q2	bank_nomura	Combined	Negative	55.0	35.0	10.0
9	2022	Q3	bank_nomura	Combined	Positive	63.34	33.34	3.34
10	2022	Q4	bank_nomura	Combined	Negative	8.06	35.48	56.45
11	2023	Q1	bank_nomura	Combined	Negative	14.7	26.47	58.82
12	2023	Q2	bank_nomura	Combined	Negative	64.0	28.0	8.0
13	2023	Q3	bank_nomura	Combined	Positive	70.0	26.0	4.0
14	2023	Q4	bank_nomura	Combined	Negative	13.64	22.72	63.64
15	2024	Q1	bank_nomura	Combined	Negative	57.5	32.5	10.0
16	2024	Q2	bank_nomura	Combined	Negative	73.91	15.22	10.87
17	2024	Q3	bank_nomura	Combined	Positive	69.05	28.57	2.38
18	2024	Q4	bank_nomura	Combined	Positive	58.82	35.3	5.88

Figure 9: Overall sentiment for Nomura for every quarter and breakdown

Silicon Valley Bank

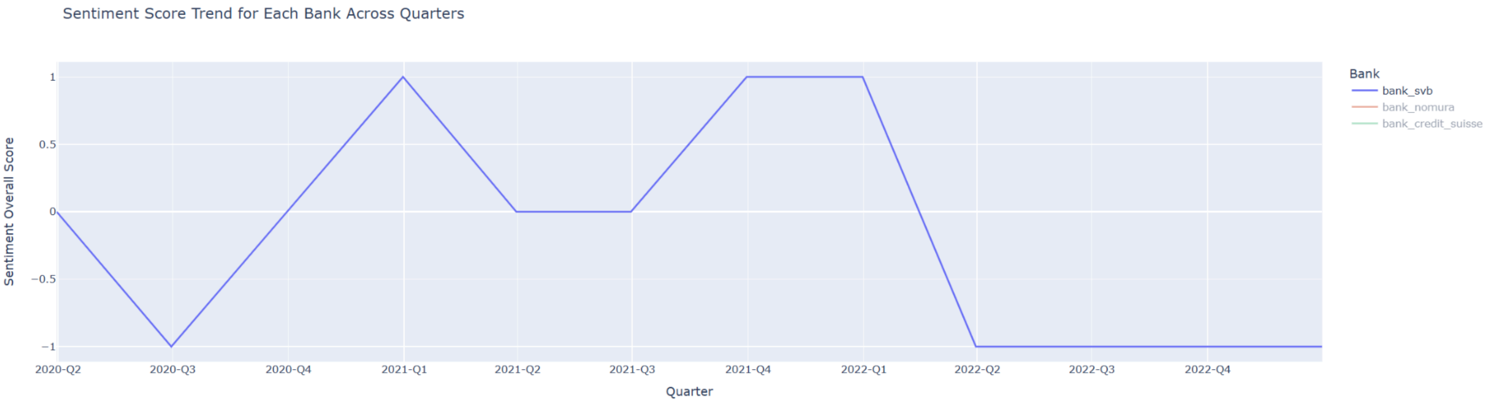


Figure 10: Overall sentiment trend for SVB for every quarter

# index	# Year	Quarter	Bank	Section	Sentiment	# Positivity	# Neutrality	# Negativity
0	2020	Q1	bank_svb	Combined	Neutral	37.24	55.61	7.14
1	2020	Q2	bank_svb	Combined	Negative	44.44	45.84	9.72
2	2020	Q3	bank_svb	Combined	Neutral	45.19	53.84	0.96
3	2020	Q4	bank_svb	Combined	Positive	73.44	25.0	1.56
4	2021	Q1	bank_svb	Combined	Neutral	44.51	51.83	3.66
5	2021	Q2	bank_svb	Combined	Neutral	38.52	61.48	0.0
6	2021	Q3	bank_svb	Combined	Positive	66.66	28.43	4.9
7	2021	Q4	bank_svb	Combined	Positive	61.9	33.34	4.76
8	2022	Q1	bank_svb	Combined	Negative	35.58	56.73	7.69
9	2022	Q2	bank_svb	Combined	Negative	35.0	55.91	9.09
10	2022	Q3	bank_svb	Combined	Negative	35.18	51.85	12.96
11	2022	Q4	bank_svb	Combined	Negative	37.71	54.66	7.62

Figure 11: Overall sentiment for SVB for every quarter and breakdown

Sentiment Summarisation over 2 years of data from Credit Suisse

The overall sentiment of 2 years of data was summarised as per the following rules:

1. Negative sentiment threshold set at 7.5
2. The Positivity, Neutrality and Negativity is calculated as the average of the corresponding values from the Presentation and Q&A sentiment analysis, giving them equal weightage.
3. If the Negativity exceeds the threshold, the overall sentiment is deemed as Negative.
4. If the Negativity is within the threshold, the sentiment is evaluated based on the Positivity and Neutrality scores, whichever is higher.
5. If Positivity and Neutrality scores as equal, sentiment is deemed as Neutral

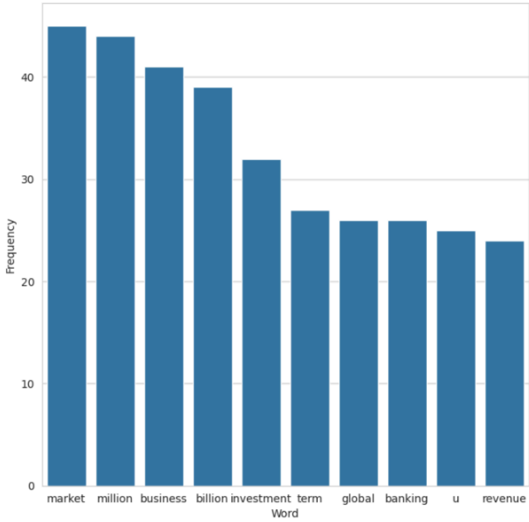
# index	# Year	Quarter	Bank	Section	Sentiment	# Positivity	# Neutrality	# Negativity
0	2020	Q2	bank_credit_suisse	Combined	Neutral	47.08	48.05	4.88
1	2020	Q3	bank_credit_suisse	Combined	Neutral	31.43	64.28	4.28
2	2020	Q4	bank_credit_suisse	Combined	Positive	51.14	45.84	3.03
3	2021	Q1	bank_credit_suisse	Combined	Neutral	39.28	58.34	2.38
4	2021	Q2	bank_credit_suisse	Combined	Negative	14.88	65.47	19.64
5	2021	Q3	bank_credit_suisse	Combined	Positive	46.67	46.66	6.66
6	2021	Q4	bank_credit_suisse	Combined	Neutral	48.02	49.34	2.63
7	2022	Q1	bank_credit_suisse	Combined	Negative	32.07	52.76	15.17
8	2022	Q2	bank_credit_suisse	Combined	Negative	28.1	46.66	25.24
9	2022	Q3	bank_credit_suisse	Combined	Negative	9.38	59.38	31.25
10	2022	Q4	bank_credit_suisse	Combined	Negative	29.16	53.57	17.26

Figure 12: Overall sentiment for CS for every quarter and breakdown

Topic Modelling

Topic modelling was performed on both the original and summarised transcripts. BERTopic performed poorly on the original transcript (512 token input limit) but got better with the summarised transcripts as the Q&A text became smaller. The Gensim LDA model performed better. Figure below is the result of topic analysis of the original transcript of all 11 quarters of Credit Suisse giving a Model Perplexity of -7.55 and Topic Coherence Score of 0.39

Word Frequency:



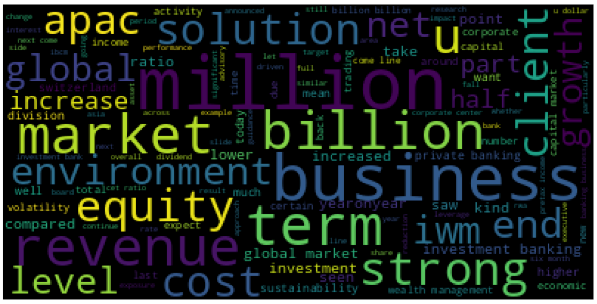


Figure 13& 14: (Credit Suisse 2020,Q2)

Topic Modelling Output :

Topic #1: 0.016*"billion" + 0.015*"million" + 0.006*"investment_bank" + 0.005*"wealth_management" + 0.005*"increase" + 0.005*"higher" + 0.005*"business" + 0.005*"revenues" + 0.005*"well" + 0.005*"bank“

Topic #2: 0.012*"terms" + 0.012*"well" + 0.008*"thats" + 0.007*"much" + 0.005*"around" + 0.005*"billion" + 0.005*"basically" + 0.005*"course" + 0.005*"business" + 0.005*"weve“

Topic #3: 0.016*"business" + 0.015*"well" + 0.007*"bank" + 0.006*"thats" + 0.005*"capital" + 0.005*"right" + 0.005*"terms" + 0.005*"weve" + 0.005*"clear" + 0.005*"around“

Topic #4: 0.021*"terms" + 0.014*"thats" + 0.013*"point" + 0.009*"well" + 0.008*"billion" + 0.008*"basically" + 0.008*"mean" + 0.006*"capital" + 0.006*"much" + 0.006*"million“

Topic #5: 0.011*"business" + 0.007*"strong" + 0.006*"asia" + 0.006*"terms" + 0.006*"clients" + 0.006*"switzerland" + 0.005*"thats" + 0.005*"well" + 0.005*"example" + 0.005*"side"

Figure 15: (Topic Modelling output - Credit Suisse 2020,Q2)

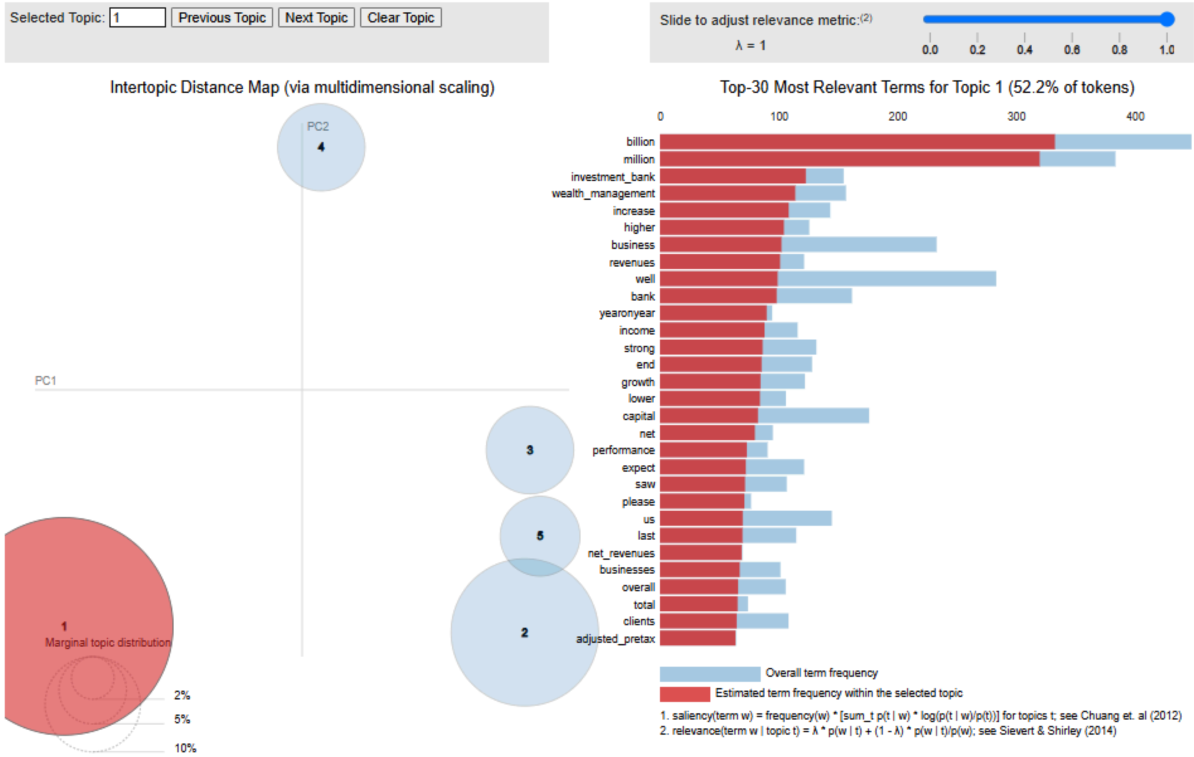


Figure 16: (Topic Modelling output - Credit Suisse 2020,Q2)

AI Assistant Implemented using SLM and RAG

The outputs below detail the model selection, query selection menu options and the outputs of those options

Small Language Model: microsoft/Phi-3-mini-4k-instruct

```
======================================================================
   Welcome to the Earning Call Transcript-Based Risk Analyzer
             An Early Warning System for Investors
======================================================================

Step 1: Select a Language Model

Available Language Models:
1. microsoft/Phi-3-mini-4k-instruct
2. microsoft/Phi-3.5-MoE-instruct
3. gemini-1.5-flash-8b
4. openai/gpt-4

Select a model (1-4) or press Enter for default [microsoft/Phi-3-mini-4k-instruct]:
```

Figure 17: (Model selection)

```
RAG Based Analysis:
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--- Query Selection Menu ---
1. Ask a generic question
2. Compare two quarters of the same year
3. Compare two quarters of different years
4. Year-over-year comparison
5. Analyze all quarters of a year
6. Analyze sentiment for a single quarter
7. Summarize a single quarter
8. Perform Topic Modeling with BERTopic
9. Perform Topic Modeling with Gensim LDA
10. Exit

Select an option (1-10):
```

Figure 18: (Query selection menu)

Option 1: Ask a generic question

This option allows the user to input any question into the system and apply filters to obtain accurate results.

```
Select an option (1-10): 1
Enter your question: What is the credit suisse strategy for sustaining or accelerating growth for year 2022?
Do you want to filter by a specific bank? (yes/no): yes
Enter the bank name: credit suisse
Enter the year to filter (or press Enter to skip): 2022
Enter the quarter to filter (e.g., Q1, or press Enter to skip):
2024-11-25 23:08:16,256 - INFO - Handling a generic query.
2024-11-25 23:08:16,257 - INFO - Retrieving relevant documents with filters...
2024-11-25 23:08:16,274 - INFO - Filtered 3 documents for the generic query.
2024-11-25 23:08:16,275 - INFO - Preparing context for the query...
2024-11-25 23:08:16,276 - INFO - Context token budget: 3396 tokens.
2024-11-25 23:08:16,279 - INFO - Document token count: 350
2024-11-25 23:08:16,281 - INFO - Document token count: 445
2024-11-25 23:08:16,282 - INFO - Document token count: 340
2024-11-25 23:08:16,283 - INFO - Invoking the QA chain...
[RESULT] Response from the AI Assistant:
The Credit Suisse strategy for sustaining or accelerating growth in 2022, as outlined by CEO Thomas
Gottstein, focuses on leveraging the benefits of strategic capital allocation towards the Wealth
Management businesses and implementing structural cost-saving measures. The strategy is designed to
materialize from 2023 onwards, acknowledging the end of an extremely favorable business environment
that was driven by substantial measures taken by central banks and governments during the pandemic.
Key components of the strategy include:  1. Capital Allocation: Credit Suisse has strategically
allocated capital towards its Wealth Management businesses, aiming to push them into profitability
and growth mode. This focus on Wealth Management is expected to drive growth in the coming years.
2. Cost-Saving Measures: The bank has implemented structural cost-saving measures to improve its
financial performance. These measures are expected to contribute to the overall growth strategy by
optimizing resources and reducing expenses.  3. Adapting to a New Environment: Credit Suisse
recognizes the shift to a more normal trading environment, driven by the tightening of the interest
rate environment in various markets. The bank expects this shift to be reflected in its results for
the first quarter of 2022.  4. Client Acquisition and Retention: Despite the challenging
environment, Credit Suisse continues to invest in its Private Banking businesses across Asia, EMEA,
and Latin America. The bank aims to attract and retain clients by improving its offerings, working
closely with the Investment Bank, and positioning itself as the bank for entrepreneurs in these
regions.  5. Focus on Stable High Net Worth Business: Credit Suisse aims to focus on the stable high
net worth business, which is expected to provide a solid foundation for growth.  In summary, Credit
Suisse's strategy for sustaining or accelerating growth in 2022 revolves around capital allocation
towards Wealth Management, implementing cost-saving measures, adapting to a changing environment,
and focusing on client acquisition and retention in key regions.
```

Figure 19: (Option 1 - Generic Question output)

Option 4: Year-over-year comparison

This option allows the user to compare the performance over 2 years

```
Select an option (1-10): 4
Enter Year 1 (e.g., 2022): 2020
Enter Year 2 (e.g., 2023): 2021
Enter the bank name: credit suisse
2024-11-25 23:10:56,373 - INFO - Comparing performance for 2020 and 2021 for credit suisse.
2024-11-25 23:10:56,375 - INFO - Retrieving documents for 2020...
2024-11-25 23:10:56,393 - INFO - Retrieving documents for 2021...
[RESULT] Response from the AI Assistant:
1. Key Performance Highlights:    - Adjusted pretax income for the third quarter of the current year
was CHF1.4 billion, marking the best third quarter in the last 5 years.    - The company's 9-month
revenue performance over the past 2 years showcases the core strength of the business.    - Capital
Markets revenues increased by 90% year-on-year, driven by higher debt issuance activity and a
threefold increase in ECM revenues.    - Fixed income sales and trading performance remained
resilient, with a 5% increase in revenues year-on-year.    - Equity sales and trading revenues were
up by 5% year-on-year, with strong contributions from cash equities and equity derivatives.  2.
Challenges/Risks:    - The company released a net total of CHF144 million in provisions for credit
losses, with CHF188 million attributed to Archegos.    - The increase in provisions for credit
losses indicates potential risks associated with the Archegos situation.  3. Future
Strategies/Initiatives:    - The company's key growth agenda aims to deliver attractive shareholder
value, including the ambition to deliver pretax income in the Wealth division.    - The positive
trends observed in the Investment Bank last year have continued into 2021, with a strong capital
markets pipeline and resilient trading performance.    - The company reserves questions related to
the strategy review for later today, indicating a focus on refining and enhancing its strategic
direction.  Please note that the provided information is based on the given transcript and may not
reflect the most current or complete data.
```

Figure 20: (Option 4 Year over year output)

Option 6: Analyze sentiment for a single quarter

This option allows the user to analyse the sentiment from any quarter

```
Select an option (1-10): 6
Enter the year (e.g., 2023): 2022
Enter the quarter (e.g., Q1): Q2
Enter the bank name: credit suisse
2024-11-25 23:12:33,763 - INFO - Analyzing sentiment for credit suisse in Q2 2022.
2024-11-25 23:12:33,765 - INFO - Retrieving documents for Q2 2022...
[RESULT] Response from the AI Assistant:
The sentiment for Credit Suisse Group AG's Q2 2022 performance, as presented by Thomas Gottstein,
can be analyzed as cautiously optimistic. The sentiment is not overwhelmingly positive due to the
acknowledgment of challenging market and macroeconomic conditions, as well as underperformance in
certain business lines. However, there are also positive aspects that contribute to a more balanced
sentiment.  1. Strong Underlying Performance: The statement that the underlying performance has been
very strong, both year-on-year and multiyear, indicates a positive sentiment. The mention of the
best third quarter in the last five years, with an adjusted pretax income of CHF1.4 billion,
highlights the company's resilience and ability to perform well despite market challenges.  2. Core
Business Strength: The reference to the core strength of the business, as evidenced by the 9-month
revenue performance over the past two years, adds to the positive sentiment. This suggests that the
company has a solid foundation to invest in and grow, which is a positive sign for investors.  3.
Equity Capital Markets (ECM) Performance: The mention of strong performance in ECM, particularly in
January, contributes to a positive sentiment. The comparison with U.S. peers and the acknowledgment
of a strong start in January indicate that the company is well-positioned in this area.  4. Concerns
and Challenges: The acknowledgment of challenging market and macroeconomic conditions, as well as
underperformance in certain business lines, adds a note of caution to the sentiment. This indicates
that the company is aware of the risks and challenges it faces, which is a realistic and balanced
perspective.  In summary, the sentiment for Credit Suisse Group AG's Q2 2022 performance is
cautiously optimistic. The company has demonstrated strong underlying performance and core business
strength, particularly in ECM, which contributes to a positive sentiment. However, the
acknowledgment of challenges and underperformance in certain areas adds a note of caution, making
the sentiment more balanced.
```

Figure 21: Output of every sentiment for every quarter

Option 9: Perform topic modeling with Gensim LDA

This option allows the user to analyse the topics of any quarter

```
Select an option (1-10): 9

[INFO] Performing Topic Modeling with Gensim LDA...
Do you want to filter by a specific bank? (yes/no): yes
Enter the bank name: credit suisse
Enter the year to filter (or press Enter to skip): 2022
Enter the quarter to filter (e.g., Q1, or press Enter to skip): Q2
2024-11-25 23:14:50,448 - INFO - Starting filtering with criteria bank: credit suisse, year: 2022, quarter: Q2, designation: None
2024-11-25 23:14:50,453 - INFO - Filtered 34 documents for Bank: credit suisse, Year: 2022, Quarter: Q2, Designation: None
2024-11-25 23:14:50,454 - INFO - Starting Gensim LDA modeling for earnings call transcripts...
2024-11-25 23:14:50,456 - INFO - Preprocessing the corpus for earnings calls...
2024-11-25 23:14:50,457 - INFO - Starting corpus preprocessing for bigrams and trigrams...
2024-11-25 23:14:50,458 - INFO - Preprocessing individual documents...
2024-11-25 23:14:53,580 - INFO - Sample preprocessed tokens:
2024-11-25 23:14:53,581 - INFO - [['cs', 'ceo', 'transcript', 'jul', 'pm', 'et', 'cs', 'stock', 'csgkf', 'stock', 'sa', 'transcripts',
2024-11-25 23:14:53,582 - INFO - Building bigram and trigram models...
2024-11-25 23:14:53,628 - INFO - Applying bigram and trigram models...
2024-11-25 23:14:53,640 - INFO - Sample processed documents with bigrams/trigrams:
2024-11-25 23:14:53,641 - INFO - [['cs_ceo', 'across_entire', 'conference_call', 'group_strategy', 'axel_lehmann', 'board_member', 'ex
2024-11-25 23:14:53,642 - INFO - Creating dictionary and bag-of-words representation...
2024-11-25 23:14:53,645 - INFO - Vocabulary size after preprocessing: 181
2024-11-25 23:14:53,646 - INFO - Training Gensim LDA model with 6 topics...
2024-11-25 23:14:53,828 - INFO - Displaying top topics for earnings calls...
```

Figure 22: LDA Gensim output CS

Topic #1: 0.079*"investment_bank" + 0.063*"strategy_review" + 0.034*"short_term" + 0.034*"give_us" + 0.032*"last_year" + 0.028*"cs_ceo" + 0.019*"axel_lehmann" + 0.018*"cost_program" + 0.018*"think_quite" + 0.018*"lot_work"

Topic #2: 0.073*"cs_ceo" + 0.044*"axel_lehmann" + 0.041*"cet_ratio" + 0.035*"mean_think" + 0.030*"next_comes_line" + 0.029*"chf_billion" + 0.028*"think_terms" + 0.025*"securitized_products" + 0.024*"piers_brown" + 0.024*"cost_target"

Topic #3: 0.080*"chf_million" + 0.050*"chf_billion" + 0.030*"year_year" + 0.025*"net_new" + 0.025*"partly_offset" + 0.024*"cs_ceo" + 0.023*"lower_year_year" + 0.019*"chf_billion_chf_billion" + 0.017*"net_revenues" + 0.017*"wealth_management_division"

Topic #4: 0.037*"cs_ceo" + 0.027*"board_directors" + 0.027*"board_director" + 0.027*"compensation_costs" + 0.027*"right_direction" + 0.027*"corporate_functions" + 0.027*"tax_charge" + 0.020*"last_year" + 0.020*"new_leadership" + 0.020*"leveraged_finance"

Topic #5: 0.095*"third_party" + 0.042*"cs_ceo" + 0.042*"next_comes_line" + 0.042*"kian_abouhossein" + 0.029*"look_think" + 0.029*"give_us" + 0.029*"securitized_products" + 0.029*"would_like" + 0.029*"questions_first" + 0.029*"restructuring_costs"

Topic #6: 0.040*"chf_billion" + 0.030*"wealth_management" + 0.030*"investment_bank" + 0.027*"loss_chf_billion" + 0.025*"adjusted_pretax" + 0.024*"asset_management" + 0.022*"cs_ceo" + 0.017*"funding_costs" + 0.017*"strategic_review" + 0.017*"major_litigation_provisions"

Figure 23: Top Topics Identified by Gensim LDA

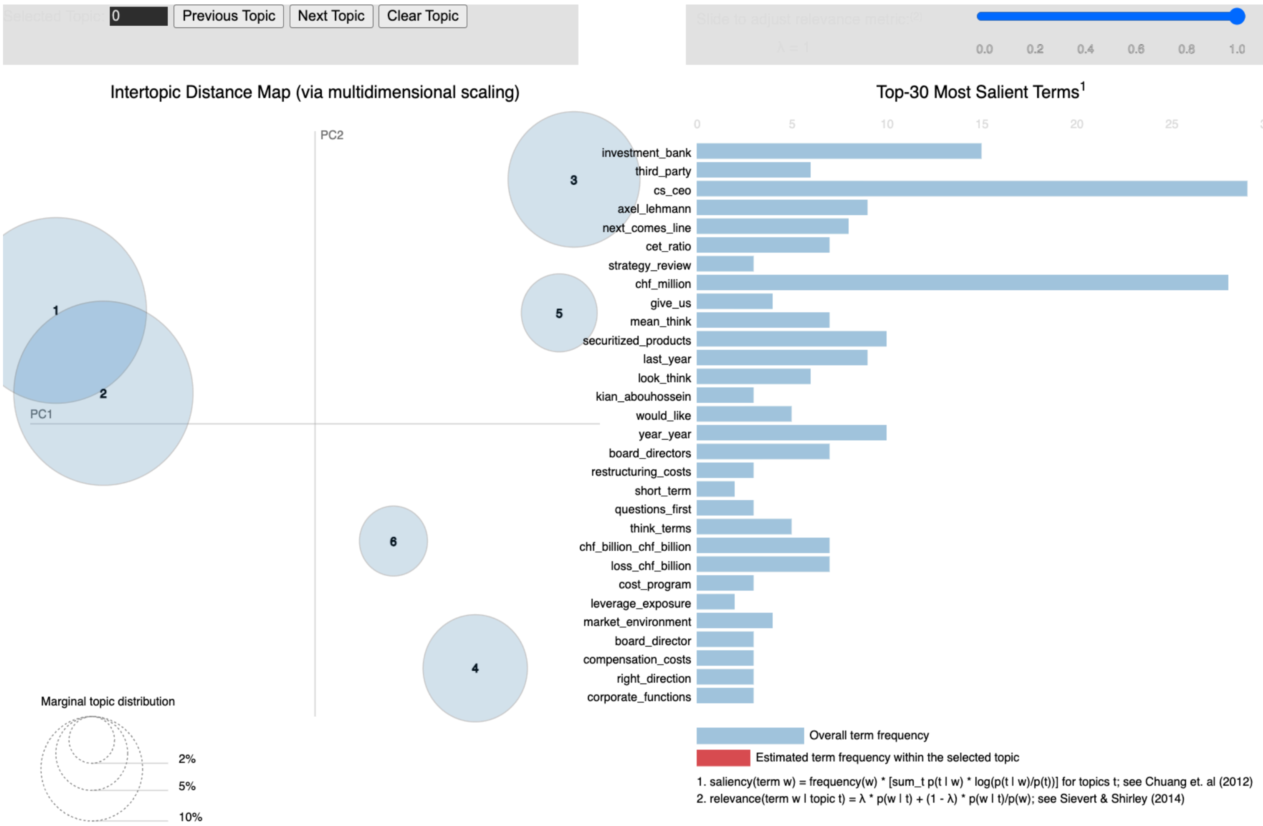

Figure 24: Gensim LDA output

Insights

Insights from Sentiment Analysis

The analysis of CS earning calls reveals a critical early warning indicator in the months preceding its crisis in 2023. A divergence was discovered when analysing the sentiments in presentations and Q&A sections separately. Sentiment analysis of the presentations was positive in 6 of the 10 quarters, with positivity peaking at 75% in quarter 4 of 2021. However sentiment analysis of the unscripted Q&A remained strongly neutral in 10 out of 10 quarters, suggesting an attempt at ‘information obfuscation’ in the scripted presentation section and the potential predictive power of the Q&A section. The divergence is supported in the combined weighted sentiments which turned negative in all 4 quarters of 2022, coinciding with CS’s distress.

Insights from Topic Modelling

Topic modelling for Q3, 2022 revealed 4 topics with a coherence score of 78.65%. Within the topics, emerging risk can be identified through capital/outflow, liquidity, strategy, funding, rumor etc. These emerging themes should signal systemic issues being highlighted in the last quarters before failure

Insights from RAG

The RAG analysis allows us to overlay important context while correlating with sentiment. In the year over year comparison over the 2020 - 2021 period, we observe a positive trajectory marked by statements like “best quarter in last 5 years” “revenue increased 90% year on year” and “core strength of business”. However we see a shift towards defensive language in the RAG general query for 2022 with referrals to “Structural cost saving measures” “end of favourable business environment. The RAG system provide us concrete evidence supporting the temporal change prior to the collapse

Limitations of the final solution include

1. Reliance solely on earning calls
2. Coherence scores could be improved further
3. Lack of extensive testing on more banks
4. Lack of extensive integration of linguistics identified from the literature
5. Textual data does not account for tone, body language, misses out on some emotion
6. Firms have subsidiaries operating in the UK subject to PRA regulation, separation of subsidiary from the main holding company/entity not accounted for

Recommendations and Future enhancements

1. Q&A sentiment diversion with presentation sentiment is a key indicator and can be an automated risk signal
2. Establish threshold coherence scores for topics related to capital, liquidity, outflows
3. Monitor linguistic patterns with special consideration for behaviours around information obfuscation
4. Develop a system that combines scores of sentiment analysis and topic modelling coherence
5. Incorporate data from other quantitative sources to augment analysis e.g stock market data,annual returns and mandatory filings with regulators.
6. Need for BoE/PRA to establish clear guidelines on the weighted averages for topic modelling and sentiment analysis along with the threshold for regulator interventions

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