ANZ Banking Group: ESG Automation

Data Science Postgraduate Project (COSC2667) Final Report(P000121DS)

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Abstract

Environmental, social, and governance (ESG) factors are becoming more and more important in corporate reporting, which emphasises the necessity for accurate and efficient reporting systems. The goal of this project was to create a semi-automated environmental, social, and governance (ESG) reporting tool that would make reporting easier for the Client Insights and Solutions (CIS) team in ANZ. We developed a tool that will allow the Client Insights and Solutions (CIS) team to upload reports and add a relevant query. Our tool will break the report into small sentences, parse it along with the page information.

The system will then pass the extracted sentences and the input query into an Encoder-only Large Language Model (LLM) based on the sentence transformer architecture (SBERT) to get encoded sentence vectors. The encoded query is then compared with each encoded sentence using Cosine Similarity and the most relevant information is surfaced to the user as output. An encoder only model was important because understanding sentence meaning was crucial for system performance and would provide a more intelligent solution than traditional programming methods like Regular Expressions or searching.

The application user interface (UI) was developed for the tool which can be used by the Client Insights and Solutions (CIS) team. This tool will help the team to get the relevant information from the reports based on the query given via a text box on the application. Our results show that the new method maintains high accuracy with a 90% match with the team's previous reporting results, while drastically cutting down on the amount of time needed to manually go through the reports. This will help the Client Insights and Solutions (CIS) team to analyse the results and focus more on the critical information.

Project Partner

One of the biggest and most well-known banks in Australia and New Zealand is ANZ Bank, formally the Australia and New Zealand Banking Group Limited. Since its founding in 1835, ANZ has developed into a significant force in the world's financial services sector. Australia's Melbourne is home to the bank's corporate offices. For people, companies, and institutions, ANZ provides a wide range of financial products and services. ANZ offers standard banking services for individuals via personal banking, including credit cards, mortgages, insurance, savings and transaction accounts, and personal loans. For easy and effective service delivery, the bank also provides digital banking options like online and mobile banking. ANZ also provides customised financial solutions for companies, such as cash management, foreign currency services, trade finance, and business loans. Large businesses and government clients are served by the bank's institutional section, which offers services like risk management, transaction banking, and capital markets.

Aside from its primary banking activities, ANZ is dedicated to corporate responsibility and sustainability. Through several community programmes and projects targeted at improving financial inclusion and literacy, the bank actively supports financial wellbeing. In addition, ANZ prioritises environmental sustainability, putting policies in place to lessen its carbon footprint and encourage green finance. ANZ hopes to create long-term value for its stakeholders and make a positive impact on the communities in which it operates through these initiatives.

The Client Insights and Solutions (CIS) team at ANZ Bank is essential in order to provide its clients with customised financial solutions and insights. This specialist team is committed to understanding the unique needs and difficulties encountered by ANZ's wide range of clients, which includes both small and large multinational enterprises. The Client Insights and Solutions (CIS) team uses market research, industry knowledge, and advanced data analytics to deliver useful, actionable insights that support clients in making wise financial decisions.

The team's primary goal is to improve each customer's banking experience by offering tailored financial solutions and assistance. Stronger customer relationships and loyalty are fostered when the team is able to recommend goods and services that best suit the needs of the consumer by studying their behaviour and preferences. The Client Insights and Solutions (CIS) team works directly with clients in the business and institutional banking sectors to meet complicated financial requirements. The Client Insights and Solutions (CIS) team makes sure that ANZ stays at the forefront of the banking industry and provides its clients with exceptional value by always changing to meet the dynamic needs of the market.

Background

The Client Insights and Solutions (CIS) team at ANZ Bank is dedicated to delivering insights and analysis across various domains. The team also focuses on the ESG (Environmental, Social, and Governance) domain. ESG is a framework that companies use to evaluate their impact on the environment and society at large, as well as the methods they've adopted to improve their practices. This framework has become increasingly important as stakeholders, including investors, customers, and regulators, demand greater transparency and accountability regarding corporate sustainability and ethical conduct.

Environmental, Social, and Governance (ESG) compliance is important because it affects a company's long-term financial performance in addition to addressing the ethical aspects of business activities. Strong Environmental, Social, and Governance (ESG) protocols have the potential to improve an organisation's standing, reduce operational risks, and draw in investment. Additionally, businesses that put an emphasis on these protocols are better positioned to meet customer expectations, comply with legal requirements, and advance the global sustainability goal.

The ANZ Client Insights and Solutions (CIS) team provides comprehensive analysis on the Environmental, Social, and Governance (ESG) performance of businesses in a variety of industries, including retail. The team helps businesses understand how they stack up against their competitors and pinpoint areas for improvement by evaluating Environmental, Social, and Governance (ESG) investments and activities. The Client Insights and Solutions (CIS) benchmarks organisations' Environmental, Social, and Governance (ESG) performance by summarising information at an aggregate level as part of their industry analysis. For companies trying to improve their sustainability processes and get in line with best-in-class standards, benchmarking is essential. The Client Insights and Solutions (CIS) helps businesses make decisions that can enhance their overall sustainability performance and attract socially conscious investors and customers by offering complete Environmental, Social, and Governance (ESG) analytics.

Current Workflow

The Client Insights and Solutions Team at ANZ Bank dedicates a lot of time to understand how companies are doing in terms of ESG (Environmental, Social, and Governance) practices. They do this by reading through annual reports and sustainability reports from different companies. This helps them keep track of what companies are doing to be more sustainable and responsible. However, this process takes a lot of time. The team has to manually go through each report, which can be very long. They must look for trends in themes like environmental efforts, social responsibility, and good governance. Then, they write down all this information in Excel to analyse. The current workflow has six steps:

1. The first step involves the Client Insights and Solutions (CIS) team determining which ESG category and business sector to focus on. They may decide whether to concentrate on the entire ESG performance or a specific subcategory within the ESG domain.
2. In the second step, the Client Insights and Solutions (CIS) team selects a group of companies to be surveyed and manually gathers the annual and sustainability reports of these companies. These companies are selected based on the sector they are focusing on. In 2022, the team picked 30 companies from the retail sector.
3. In the third step, a team member manually reviews all the reports, recording common themes related to the chosen ESG category in Excel. This is a very time consuming and inefficient process as the annual reports of each of the selected companies are very lengthy and the team members have to read them carefully to avoid missing any information.
4. After the themes are recorded, the Client Insights and Solutions (CIS) team member checks the performance of each company based on the theme in excel and records them. This process is prone to human error as the information within reports can be missed.
5. After manually tracking this information, in the fifth step, the Client Insights and Solutions (CIS) team generates aggregate-level statistics and other insights about ESG performance for that business sector.
6. In the final step, these new statistics and insights are used in reports presented to clients to help them understand the state of ESG performance in their sector and how their company may compare.

Our team will focus on semi-automating phase three of the current workflow, where the CIS team manually reviews all the reports to identify common themes and targets related to the chosen ESG category. This automation aims to streamline the process, making it more efficient and less time-consuming.

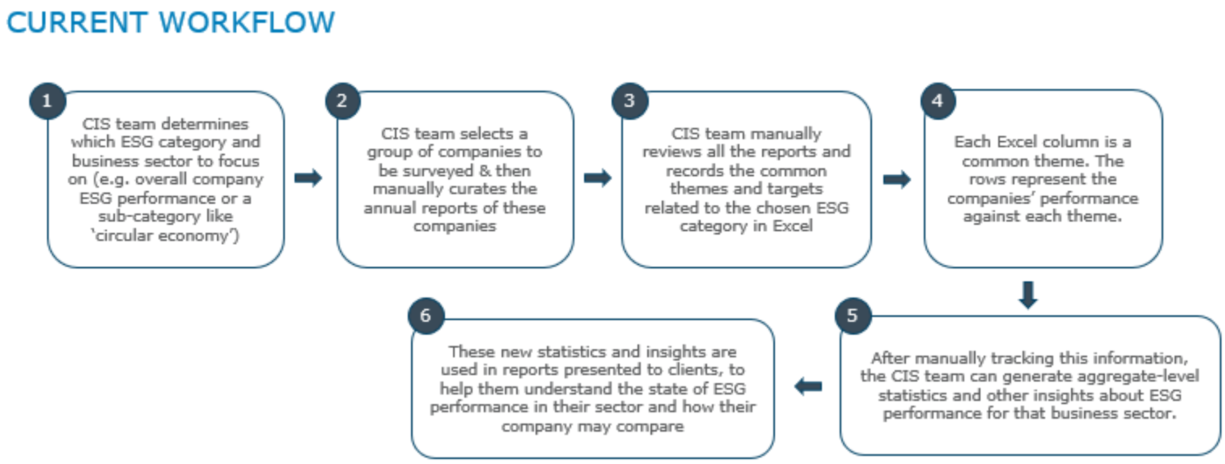

Figure 1: Workflow followed by the CIS team for ESG analysis and reporting

1					
2		Theme 1		Theme 2	
3	Company Name	Subcategory Theme 1a	Subcategory Theme 1b	Subcategory Theme 2a	Subcategory Theme 2b
4	**Company A**	Y	Y		
5	**Company B**	Y	Y		
6	**Company C**	Y	Y		
7	**Company D**	Y	Y		
8	**Company E**	Y	Y	Y	
9	**Company F**	Y	Y	Y	
10	**Company G**	Y	Y	Y	
11	**Company I**				
12	**Company J**	Y	Y		
13	**Company K**	Y	Y		
14	**Company L**	Y	Y	Y	Y
15	**Company G**	Y	Y	Y	Y

Team Member:
Energy Saving with details XYZ

Figure 2: Sample Report created by CIS Team after information retrieval

Project Aim

The project aimed to semi-automate the reporting process by reducing the manual workload undertaken by members of the CIS team. Instead of a CIS team member manually reading every report from every company, they would instead decide on the themes that they would like to focus on for the report. After this they would phrase it as a query and submit it into the system. The system will then intelligently filter the sentences in the report to return only the relevant information. This would drastically reduce the amount of time the CIS team needs to spend reading the long reports from each company. After thorough discussion with the Industry Partner, our scope was narrowed down to this objective due to time constraints.

User Story: As a user, I want to see all the relevant sentences in each report based on a query.

Approach and Methodology

After discussing with expert researchers at RMIT, we decided on the following architecture.

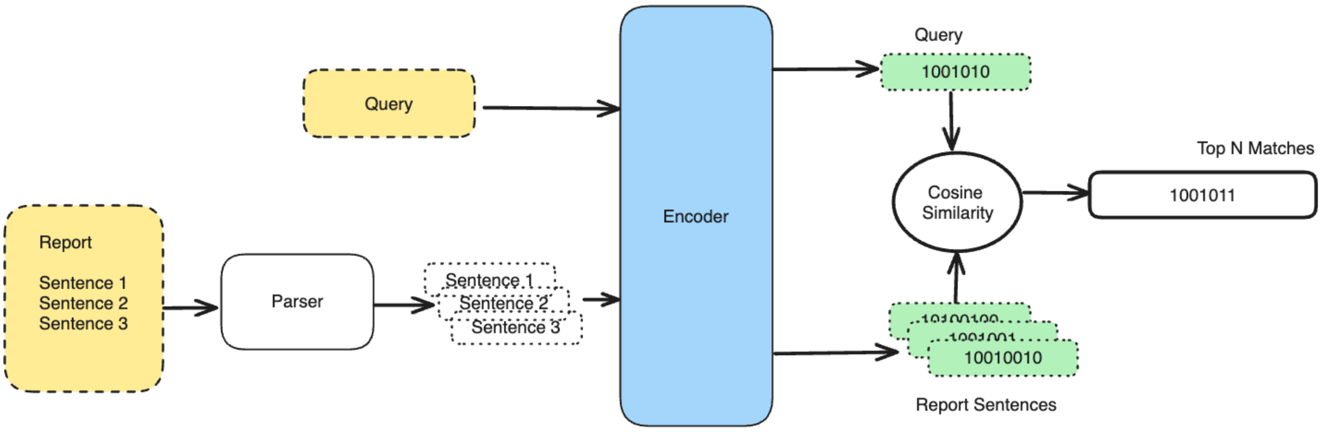

Figure 3: End to end system with parser, encoder and similarity calculation

Step 1. Parsing

The information being reported needed to be extracted from the annual company reports before any type of analysis or processing can be done. This process of extracting text from a file is called parsing. It enables the program to load the sentences into memory for processing. Since all the reports being assessed were from official company records and were formatted well, we decided to use the PyPDF parser to extract all the text from the PDF based report files. When the sentences are extracted, page metadata is collected to ensure that the CIS team can easily find the sentence later if they choose.

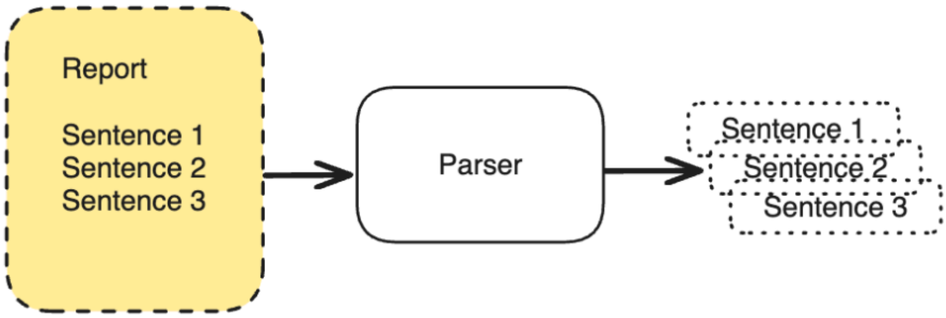

Figure 4: Each sentence in report is parsed with metadata

Step 2. Encoding Model

Computers do not understand text, words or sentences. The only way to leverage computers to solve language related problems is to convert the words into a numerical representation. These representations are called vectors and the process of converting human language into something machines can understand is called encoding.

There are several types of Large Language Models (LLMs) with different types of architectures. The main types are: [7]

- Encoder Model - These models are trained to understand the meaning of words when converting words into a machine readable representation. They are trained using techniques like Masked Language Modelling (MLM) where parts of an input sentence are hidden, while forcing the model to predict them. This ensures that the model has an understanding of what the word means. BERT (Bidirectional Encoder Representations from Transformers) is an example of an encoder model.

- Decoder Model - These models are trained to generate text. They work to predict what could be the next word in a sentence given the previous words in the sentence. GPT (Generative Pretrained Transformer) is an example of a decoder model.
- Encoder-Decoder Model - These models understand the meaning of the words and then attempt to generate the next word. BART (Bidirectional and Auto-Regressive Transformers) is an example of this.

Model Selection

Since the task required the system to understand the meaning of the word, an Encoder Model[4] was used to convert the input query from the CIS team and the report into encoded sentences. We selected the pretrained SBERT sentence transformer for this system.

We initially decided to use the T5EncoderModel for this purpose. However, we found better performance with the SBERT sentence transformer model after testing the ability of the system to capture relevant sentences and comparing them to the ground truth data that the CIS team provided for the previous year's report. A sentence transformer like SBERT performs better because it is trained on sentences and not on individual words, so it is able to capture the meaning of the sentence better.[5]

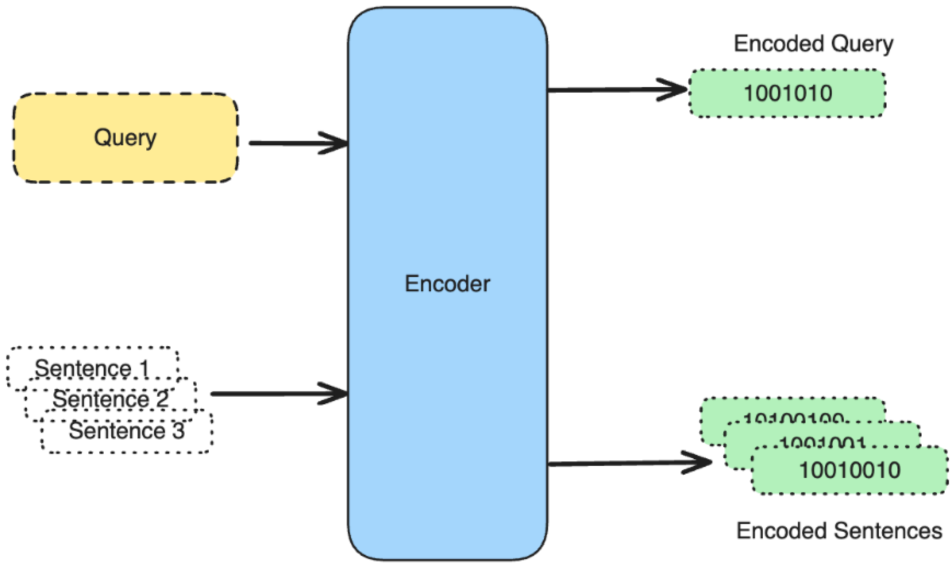

Figure 5: Query and sentences are encoded by the SBERT model

Step 3. Similarity Calculation

With a machine understandable representation of the query and report sentences, irrelevant information can be filtered out by calculating the similarity of the encoded query with each of the encoded report sentences. The results with the higher similarity will be surfaced to the end user.

Cosine Similarity was used as the metric to calculate the similarity between the query and the sentences because it prioritises direction over magnitude, which was a better fit to find relevant sentences in this scenario. This means that even if the length of the query is larger or smaller than that of the report sentence being assessed (magnitude), the similarity of the numeric representation would be captured by the cosine angle between the numeric representations (direction). It also handles sparse data well, meaning that numeric representations that have many dimensions but have small amounts of data are handled better. Higher similarity meant more relevant sentences. [6]

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

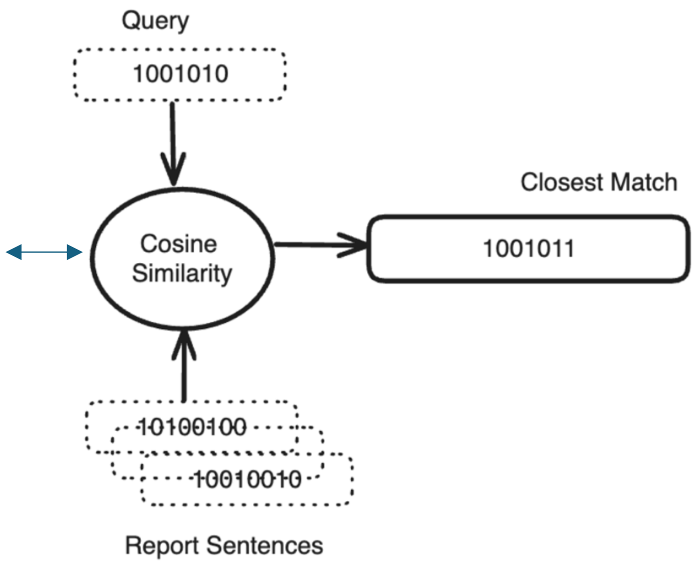

Figure 6: Calculating Similarity between report sentences and query

Step 4. User Interface (UI)

The CIS team requested for a simple user interface (UI) that would make it easier for them to write queries and submit reports, as well as see and download the results. Due to the time constraints we built a simple Flask Application with the functionality needed to easily find the relevant sentences. The UI sends an API request to the backend which leverages the python packages **pypdf** and **sentence-transformers** to perform the parsing, encoding and similarity calculations. The relevant sentences are then presented as an output to the user in a table along with the file source and page number. The results can also be exported to csv for further analysis.

Final Deliverable

We built a web application-based user interface to make it easier for the CIS team to use the system. There is a button to upload the report they want to query on and a text box to type the query. The submit button sends a request to the application server that parses the given report, converts the query and the report into encoded vectors and calculates the similarity score between each sentence and the query and outputs the list of sentences in descending order of relevance. The output provides the sentence, the page number and the relevance score. An option to download the results as a CSV was also included. The Industry Partner was also provided with details on how to write an effective query, which we developed through rigorous testing. All the implementation information and code are included in the project's GitHub repository.

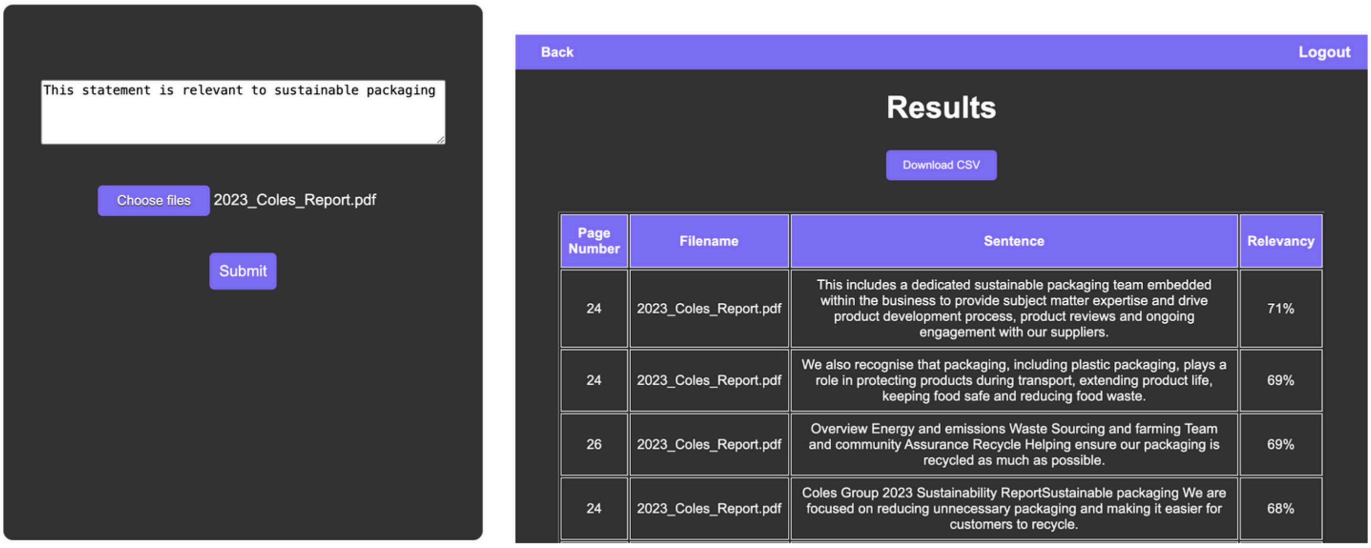

Figure 7: User Interface for querying reports, viewing and downloading results

Results

The model was measured to provide relevant sentences 90% of the time when compared to the ground truth report provided by the Client Insights and Solutions (CIS) team. This test used actual ESG reports from a list of Australian companies for the year 2022.

Experiment Design:

The experiment involved three randomly chosen sentences and a single query: "This statement is closely related to sustainable practices" The model's performance was measured by its ability to:

- Identify sentences that discuss sustainable practices, even if they don't explicitly use the term "sustainable."
- Rank sentences based on their relevance to the query, with the most relevant sentences receiving higher similarity scores.

Proof of Concept

Sentence	Query	Relevance	Match with Regex
Our product is produced through sustainable practices	This sentence is strongly relevant to sustainable practices	68%	Yes
Our product is recyclable	This sentence is strongly relevant to sustainable practices	63%	No
We have a couch at our house	This sentence is strongly relevant to sustainable practices	4%	No

Table 1:Results from Proof of Concept

This section analyses the results presented in Table 1, which assess a Proof of Concept (PoC) experiment designed to evaluate our model's ability to identify and rank sentences based on their relevance to a specific query compared to the performance of custom made regular expressions.

Analysis of Proof-of-Concept Results:

The results from Table 1 showcases major key findings which are discussed below:

1. Effectiveness in Identifying Relevant Content:
    - Using our system, the first two sentences achieved high similarity scores (68% and 63%) despite the second sentence not containing the exact term "sustainable." This demonstrates the model's capability to understand the semantic context of a sentence and identify its relevance to the query beyond simple keyword matching.
    - The regular expressions that were custom built for the query extracted every occurrence of the word sustainability. This approach is not scalable as a regular expression will be needed for each and every query.
2. Ability to Filter Out Irrelevant Content:
    - The third sentence, demonstrably unrelated to sustainable practices, received a significantly lower similarity score (4%) with our system. This highlights the model's ability to distinguish between relevant and irrelevant information, ensuring focused analysis by prioritising the relevant content.
    - The regular expressions did not effectively filter out irrelevant sentences and pulled in sentences that just had the word 'sustainable'.

Overall, the findings from Table 1 provide strong evidence that the sentence ranking model effectively ranks sentences based on their relevance to the given query. High similarity scores for relevant sentences and low scores for irrelevant ones confirm the model's reliability and effectiveness. This capability to prioritise relevant information enhances content analysis and supports better decision-making by directing focus towards crucial details.

Final System Result:

Table 2 below showcases the results from analysing the "2023-Coles Sustainability Report" with the query "This statement is closely related to sustainable product packaging" The model parses each sentence of the report, computes cosine similarity scores relative to the query, and ranks the sentences in descending order under "Relevance" column. This arrangement enables the CIS team to quickly identify the most pertinent sentences, significantly reducing the time required for manual review. The top 5 sentences, which closely match the context of sustainable product packaging, are highlighted in Table 2, confirming their relevance to the query.

This method not only enhances efficiency by saving the CIS team considerable time but also improves the focus of their analysis. By providing immediate access to the most relevant information, the model supports better decision-making and streamlines the workflow. The high similarity scores and contextual relevance of the top sentences demonstrate the model's effectiveness in extracting meaningful insights from sustainability reports.

Sentence	Relevance
This includes a dedicated sustainable packaging team embedded within the business to provide subject matter expertise and drive product development process, product reviews and ongoing engagement with our suppliers.	72%
Overview Energy and emissions Waste Sourcing and farming Team and community Assurance Recycle Helping ensure our packaging is recycled as much as possible.	70%
End-of-life treatment of sold products 7.1% Initiatives to reduce excess packaging and increase recycled content in packaging.	68%
Coles Group 2023 Sustainability Report Sustainable packaging We are focused on reducing unnecessary packaging and making it easier for customers to recycle.	68%

Table 2: Results of relevant sentences from sample report

Evaluating the performance of a model requires a reliable benchmark against which its outputs can be compared. This benchmark, known as ground truth, represents the accurate, real-world data that reflects the desired outcome. In the context of this project, the ground truth consists of the manually generated reports created by the CIS team. These reports serve as the trusted source of information for assessing the similarity and effectiveness of our model.

Report	Number of themes for which the system output matched the ground truth	Number of themes for which the system output did not match the ground truth
Baby Bunting	13	0
MedCash	12	1
Wesfarmers	11	2
Super Retail	12	1
Globe International	12	1
Briscoe Group	12	1
JBHifi	12	1

Table 3: Ground truth analysis

Ground truth plays a crucial role in the following aspects of this project's evaluation:

- **Benchmarking**: The CIS team's reports provide a standard for comparison. By comparing the outputs generated by our model to these reports, we can measure how closely our product's results align with the established truth.
- **Validation**: To validate model's performance across various scenarios, specific queries were designed to mimic different reporting contexts. These queries were then executed on the product, and the resulting outputs were compared against the corresponding ground truth reports from the CIS team. This comparison process allows us to measure the product's similarity and reliability in diverse situations.
- **Similarity Measurement**: A similarity metric, such as sentence or data similarity, can be calculated to quantify how closely model's outputs resemble the information contained within the ground truth reports. In this project, a high similarity score of approximately 90% indicates that our model performs well and produces results that are largely consistent with the trusted manual reports.

- **Detailed Assessment**: As illustrated in Table 3, the ground truth reports are pivotal in comprehensively evaluating our model’s capabilities. By systematically comparing the model's performance against this reliable benchmark, we can pinpoint its strengths and identify areas where further improvement is necessary.

In conclusion, by leveraging ground truth data in the form of the CIS team's reports, this project establishes a robust and accurate evaluation framework for the model. This framework enables us to ensure that the product delivers high standards of effectiveness in achieving its designated goals.

To achieve higher similarity, the quality of the query is crucial. A well-crafted query yields better results. Here are some of the sample queries that were used to validate the model.

Sample Queries used for the purposes of validation:

- This statement is closely related to Sustainable Product Packaging.
- Does this statement talk about Modern slavery, human trafficking, and exploitation?

Limitations

While the current system significantly reduces the time required for the ESG reporting process, it remains a semi-automated solution that necessitates manual assessment. After the tool provides the relevant sentences based on the query, the CIS team still needs to manually review and verify the extracted information to ensure its accuracy and relevance.

This manual step is essential to maintain the quality and reliability of the reports. However, it also means that the system cannot completely eliminate the manual workload. The tool’s effectiveness is therefore dependent on the user’s ability to assess and interpret the results, highlighting a limitation in achieving full automation.

The encoder model used in the system, although effective, was not explicitly trained on the specific task of ESG report analysis. Models like SBERT were selected for their general performance in sentence similarity tasks, but they were not fine-tuned on a dataset specifically related to ESG reporting. As a result, the model may not always capture the nuances and specificities unique to ESG reports, potentially impacting the accuracy of the extracted information. Fine-tuning the model on a specialised dataset could improve its performance, but this requires a significant amount of labelled data and resources, which was beyond the scope of the current project.

The system currently relies on PyPDF, an open-source parser, for extracting text from PDF reports. While PyPDF is effective for basic text extraction, it may struggle with complex PDF structures, such as those containing tables, images, or unusual formatting.

This limitation can lead to incomplete or inaccurate text extraction, affecting the subsequent steps in the process. Open-source parsers often lack the advanced features and robustness found in enterprise-grade solutions, which can handle a wider variety of document structures more reliably. This reliance on a less sophisticated parser represents a limitation in the current implementation, potentially affecting the tool’s accuracy and reliability in real-world applications.

While the ESG reporting tool developed in this project represents a significant step forward in automating the reporting process, it has several limitations that need to be addressed in future iterations. The semi-automated nature of the process still requires manual assessment to ensure the accuracy of the results. The encoder model, although effective, was not explicitly trained for ESG report analysis, which may impact its performance.

Additionally, the use of an open-source parser like PyPDF, while functional, presents challenges in handling complex PDF structures. Addressing these limitations in future developments will be crucial for enhancing the tool's effectiveness and reliability.

Future Scope

One of the significant enhancements for the ESG reporting tool involves improving its capability to handle multiple files and queries simultaneously. Currently, the system processes one file and one query at a time, which may become a bottleneck as the volume of reports increases. Enhancing the system to support batch processing will allow the CIS team to upload multiple reports in one go. This feature will streamline the workflow, saving even more time and increasing efficiency. Implementing a queue management system and parallel processing techniques will be crucial in achieving this capability, ensuring that the tool can manage multiple tasks concurrently without compromising performance.

To improve the robustness and reliability of text extraction from PDF reports, integrating the tool with enterprise-grade parsing libraries such as Apache Tika, PDFMiner, or Adobe PDF Library is essential. These libraries offer more advanced features and better handling of complex PDF structures compared to the currently used PyPDF parser. Enterprise-grade libraries can manage various formats and structures of reports more effectively, ensuring accurate text extraction. This integration will enhance the system's ability to parse diverse reports, reducing errors and improving the overall accuracy of the extracted data.

The rapid advancement in AI and machine learning technologies presents an opportunity to further automate the ESG reporting process using state-of-the-art model architectures. Incorporating popular model derivatives, or other transformer-based models can significantly enhance the system's ability to understand and process natural language.

These models can be trained to identify and extract common themes and patterns across multiple reports automatically, without needing predefined queries. By leveraging these advanced AI models, the system can provide more insightful and comprehensive analyses, identifying trends and generating summaries that offer deeper insights into the ESG performance of companies. This further automation will not only improve the tool's efficiency but also its capability to deliver high-quality, actionable insights.

The future development of the ESG reporting tool focuses on enhancing its scalability, accuracy, and automation capabilities. By enabling the system to handle multiple files and queries simultaneously, integrating with more robust parsing libraries, and incorporating advanced AI model architectures, the tool will become a more powerful asset for the CIS team at ANZ. These improvements will ensure the tool can keep pace with the growing demands for ESG reporting, providing timely and accurate insights that support informed decision-making.

Conclusion

In conclusion, the development of a semi-automated ESG reporting tool for the Client Insights and Solutions (CIS) team at ANZ has demonstrated significant advancements in enhancing the efficiency and accuracy of ESG reporting. Our project aimed to address the labour-intensive process of manually reviewing extensive company reports by implementing an intelligent system capable of parsing, encoding, and filtering relevant information based on user queries. Through the use of advanced natural language processing models like SBERT and the practical application of cosine similarity metrics, our tool has proven its ability to streamline the extraction of pertinent data, thereby reducing the manual workload for the CIS team.

The tool's deployment has shown promising results, achieving an approximate similarity rate of 90% when compared to manually generated reports by the CIS team. This high accuracy underscores the effectiveness of our approach and its potential to significantly cut down on the time required for manual reviews, allowing the CIS team to focus more on critical analysis and decision-making.

However, it is important to acknowledge the limitations of the current system. The necessity for manual assessment to verify the accuracy and relevance of extracted information remains, highlighting the semi-automated nature of the tool. The use of an open-source parser like PyPDF, while functional, presents challenges in handling complex PDF structures, impacting text extraction accuracy. Additionally, the encoder model, though effective, was not specifically trained on ESG report analysis, which may affect its performance in capturing the nuances of ESG-related content.

Looking ahead, there are clear pathways for future enhancements. Incorporating enterprise-grade parsing libraries and advanced AI model architectures on ESG-specific datasets can further improve the tool's scalability, accuracy, and automation capabilities. Enabling batch processing for multiple files and queries simultaneously will also streamline the workflow, making the tool even more valuable for the CIS team.

Overall, this project represents a significant step forward in leveraging AI to enhance ESG reporting processes. The collaborative effort between our team, ANZ stakeholders, and academic advisors has resulted in a practical solution that not only advances our technical capabilities but also delivers tangible benefits to our industry partner. We are confident that with continued development and refinement, this tool will become an indispensable asset in the realm of ESG analysis and reporting.

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Appendix

Project Management

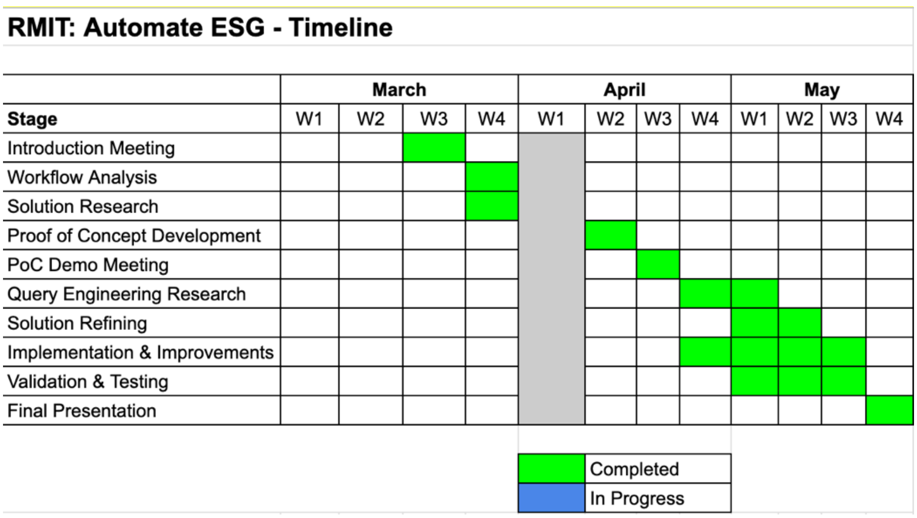

Figure 8: Project Timeline

We used the following tools to manage and deliver the project.

Tool Category	**Tool**
Project Task Tracking	Trello (link)
Source Control	Git, GitHub (link)

Application Development	Flask
Machine Learning	PyPDF, PyTorch, Sentence Transformer
Meetings & Collaboration (internal / client)	Microsoft Teams (once a week)

Roles & Responsibilities

Member	**Responsibilities**
Irfan Nekakhtar	• Requirements Gathering • Model Research • Testing and Validation • Technical Documentation
Roshan Thaliath	• Requirements Gathering • Model Research • Model Implementation • Testing and Validation
Krishnakanth Srikanth	• Requirements Gathering • Model Implementation • Application Development • Testing and Validation
Chris Santosh John	• Requirements Gathering • Model Research • Model Implementation • Testing and Validation

Self-Reflection | Irfan Nekakhtar:

Working on the project with ANZ's CIS team has been an incredible journey and achievement. This project was truly exciting and fulfilling. It allowed us to apply our skills in a practical way, collaborate with industry professionals, and make a real difference. It was a learning experience to gather requirements from key stakeholders and understand their challenges in the reporting process. Another important learning experience was dealing with stakeholders to narrow down the scope of our project while managing resource and time constraints. Our team had weekly meetings with the stakeholders to ensure our progress and work aligned with their needs, which was a great experience.

Additionally, the research and development aspect of the project provided significant learning opportunities. I spent hours researching various approaches, reading articles, implementing them, and testing them, which allowed me to gain a deep understanding of LLMs. My past courses, such as Case Studies in Data Science and Machine Learning, along with my expertise in Python, really helped me in this process. Despite the tight timeline, we effectively utilised our understanding of AI to deliver significant business value to ANZ. This entire project gave me hands-on experience and helped me build confidence in understanding clients' needs and building innovative solutions for them.

I was fortunate to have a dedicated team who were motivated and available throughout the project's phases. We had multiple weekly meetings and divided the project into roles, which allowed us to complete it on time. I am proud of my and my team's accomplishments in developing this working prototype, presenting it to the client, and ensuring the stakeholders were satisfied with the end result. Every small step we took to complete the project helped me grow as a Data Scientist and deal with major industry clients. I am grateful for the opportunity from RMIT and ANZ, as they enabled me to achieve this milestone.

Self-Reflection | Krishnakanth Srikanth:

I was thrilled to be nominated for the project in collaboration with ANZ, one of Australia's banking giants. This project has been a journey of both challenges and triumphs. I'm proud to say that my resilience and determination allowed me to showcase my best self. While I had experience in Machine Learning, I was new to GenAI and deep learning. Working effectively with these advanced technologies was a truly rewarding experience. I learned a great deal and implemented this new knowledge into the project, ultimately feeling proud of the outcome. From having no background in this tech stack, I can now confidently say I am proficient in these technologies.

Research was my most helpful companion throughout this journey. Acknowledging my initial lack of domain and technical knowledge for this project, I delved into numerous research papers, online tutorials, and notes. Efficient research significantly optimised my time and effort. Initially, I doubted the feasibility of delivering a fully functional prototype in such a short timeframe. However, through pure dedication and teamwork, we achieved this significant milestone.

I extend my heartfelt appreciation to my team members for their invaluable contributions. My primary role was in developing the frontend completely, with some involvement in backend tasks. We created an interactive user interface that will greatly benefit the CIS team by simplifying their analysis and saving considerable time. Regular catch-ups, both in-person and online, within our team and with the ANZ CIS Team, ensured smooth project progress and timely delivery. Each hurdle we encountered broadened my knowledge and prepared me for a future in the Data Science and AI domain.

Self-Reflection | Roshan Thaliath:

After spending a few semesters studying the different applications of Artificial Intelligence technology, it was an amazing experience working with the CIS team at ANZ to deliver this project. Gathering requirements from the key stakeholders and understanding their pain points in the reporting process and the challenges they faced with scaling it was interesting. Given the small amount of time allotted to us, we are extremely glad to have leveraged our understanding of the space to deliver business value to ANZ.

The countless hours spent researching different approaches to solve this issue led to a massive amount of learning. Being able to apply theoretical knowledge about large language models to solve a real-world problem made me better understand its strengths and weaknesses. I feel more confident in my ability to develop intelligent solutions in the future.

It was challenging learning about the differences between a regular transformer system that is trained on word analysis and a sentence transformer that works on entire sentences. But the process of implementing the system was rewarding and I am thrilled that it will provide value to the CIS team at ANZ.

Each member of the team worked hard to ensure that the system worked as expected with extensive testing using the ground truth reports provided. We were able to deliver the project through committed teamwork and dedication. I am confident that this experience has made me a better Data Scientist.

Self-Reflection | Chris John:

Working on the ESG reporting tool project has been an incredible journey, providing me with profound insights into the fields of Generative AI (GenAI) and machine learning. This project has not only expanded my technical knowledge but also allowed me to apply theoretical concepts in a practical, real-world setting, making the experience extremely rewarding.

Before this project, my understanding of GenAI and machine learning was primarily academic, based on coursework and theoretical studies. Engaging in this project has transformed that theoretical knowledge into practical skills. I had the opportunity to delve into the intricacies of natural language processing, particularly in the context of ESG reporting. Learning to work with advanced models like SBERT and understanding their applications in real-world scenarios was particularly enlightening. I now have a much clearer grasp of how these models can be leveraged to solve complex problems, such as automating the analysis of large volumes of textual data. Collaboration has been a cornerstone of the ESG reporting tool project, and the experience has been both enriching and educational. Working closely with my team, stakeholders from ANZ, and our academic advisors has provided invaluable insights and fostered a spirit of teamwork and cooperation.

The most rewarding aspect of this project has been seeing the tangible impact of our work. Developing a tool that can significantly reduce the manual workload of the CIS team at ANZ and enhance their efficiency was highly gratifying. Presenting our working prototype to the stakeholders and receiving positive feedback affirmed the value of our efforts and the practical relevance of our technical solutions. It was a fulfilling experience to contribute to a project that not only advanced my knowledge but also delivered meaningful benefits to the client.