Knowledge Distillation From Gemini to Mistral for Earnings Call Transcript Summarization

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Abstract

Earnings call transcripts are invaluable to investors because they contain insights that can lead to profitable investments and optimal decision-making. However, these calls are often lengthy, making it difficult for investors to quickly identify key insights from them. Prior work with applying large language models to financial document summarization partly addresses this need, but still struggles to identify the most important information that should be included in summaries. In this project, we approach this challenge by finetuning Mistral 7B–Instruct upon an augmented version of Mukherjee et al.'s ECTSum benchmark, in which we replaced the bullet-point summaries in ECTSum with longer summaries. We used Gemini Pro to create this augmented ECTSum dataset and developed a quality ranking system to select the augmented summaries that best aligned with the information in ECTSum's bullet-point summaries. We then performed knowledge distillation by finetuning Mistral 7B–Instruct on the augmented dataset to align it with Gemini's outputs. After finetuning, we observed improvements in ROUGE performance across the board and an increase in ability to recall important statistics from the transcripts.[1]

1 Introduction

Earnings call transcripts (ECTs) are hour-long conversations between a company's management and shareholders. They contain an abundance of useful information and offer a direct window into the thought process of a company's leadership, which is why they are so useful to investors. However, these transcripts are challenging for investors to quickly extract insights from due to their long-form and unstructured nature [1].

In recent years, researchers have begun to apply Large Language Models (LLMs) to the financial domain. For example, Liu et al. released the FinBERT model in 2020, which is a BERT model pre-trained on a large corpus of financial documents [2]. Furthermore, Mukherjee et al. released the ECTSum benchmark in 2022, which contains earning call transcripts and corresponding bullet-point summaries, and provided the FinBERT-based ECT-BPS model trained upon this dataset [1].

The applications of LLMs to financial document tasks have great potential to streamline efficiency for investors. A model that accurately summarizes earnings call transcripts would allow investors to reduce the effort they spend scanning these long documents and instead quickly look at the summarized version to find insights. Futhermore, investors would be able to scale up their research efforts by having the model automatically extract insights from thousands of such documents. These benefits would generalize to researchers working in other domains as well.

However, certain challenges stemming from long-document summarization complicate the ECT summarization task. Specifically, Koh et al. explain that as document length increases and expected

[1] Code is available at https://github.com/joonhee0416/CPSC477-Final

summary length remains constant, it becomes more challenging for models to determine which pieces of information to include in their summaries [3]. The authors add that it then becomes important to communicate clear human preferences to models to help them make this decision [3].

For the task of ECT summarization, the challenges are thus to determine which of the numerous pieces of information and statistics in ECTs are the most important and to develop methods to train LLMs to prioritize including these important details in their summaries.

In this project, we provide two contributions to address the challenges described above. First, we augmented the ECTSum benchmark by replacing its bullet-point summaries with longer gold-standard summaries generated by Gemini 1.0 Pro. We developed a quality ranking system to select generated summaries that best aligned with the information in ECTSum's bullet-point summaries, which we treated as a source of human preferences for what was most important in the transcript.

Second, we performed knowledge distillation by finetuning Mistral 7B–Instruct on the augmented dataset to improve the quality and relevance of its summaries. We evaluate the finetuned Mistral model using ROUGE scores and precision and recall metrics for important statistics and compared it to results obtained for the baseline Mistral 7B–Instruct model.

In the following sections, we provide an overview of related work, then describe our approach and implementation in depth, and conclude with a discussion of our results, limitations, and next steps.

2 Related Work

Early efforts to automate financial document summarization often utilized traditional natural language processing techniques that struggled with the volume, complexity, and jargon of financial data. The recent introduction of LLMs, however, marked a pivotal shift towards leveraging deep learning for more nuanced understanding and summarization of financial content. Liu et al.'s FinBERT, which finetunes the BERT model using financial sentiment analysis datasets, demonstrates improvement in sentiment analysis over existing state-of-the-art models [2].

To our knowledge, the only two datasets on financial document summarization are the financial reports provided in the 2021 Financial Narrative Summarization (FNS) shared task and the ECT-Sum benchmark released in 2022 by Mukherjee et al. [4] [1]. The FNS dataset was constructed from public UK annual reports published by firms listed on the London Stock Exchange, and the winning system finetuned the T5 language model to identify and extract the beginning of a continuous narrative section from the source sequence [5]. Due to the nature of the gold summaries in FNS, where they are often continuous subsection(s) of the input transcript without any paraphrasing or trimming, the task seemed to favor systems that were able to identify and extract chunks of the input sequence rather than systems that were truly able to condense large documents into the most critical bits of information.

Mukherjee et al. aimed to address these deficiencies by collecting a novel dataset of 2,425 document-summary pairs that used compact, bullet-point summaries published by experts on Reuters as gold-standard summaries [1]. The authors also proposed the ECT-BPS model that extracts the most salient sentences from the source document using FinBERT and paraphrases the extracted sentences into condensed summaries using a fine-tuned version of the T5 model [1]. Compared to pre-existing unsupervised, extractive, abstractive, and long document summarization approaches, their method achieved improvement in ROUGE scores across the board. A noteworthy point of this benchmark dataset is that the summaries are condensed from transcripts with thousands of words to approximately two or three incomplete sentences that primarily reiterate key statistics (i.e. "sales in q1 rose 25%"). To our knowledge, a benchmark with gold summaries that are sufficiently condensed and paraphrased, includes narrative and statistical details, and uses full sentences in paragraph format does not exist.

Additionally, Xu et al. elaborated upon the emerging technique of knowledge distillation for LLMs in their 2024 survey paper, which involves using the outputs of a larger, powerful model to finetune a smaller model [6]. The authors explain that this methodology can teach smaller models advanced skills that they may not have been able to learn otherwise and allow inference costs to be reduced by using the smaller model instead of the larger one [6]. In this vein, we decided to use to the outputs of Gemini 1.0 Pro, a powerful model released by Google, as a finetuning dataset for Mistral 7B–Instruct, an open-source instruction-tuned 7B parameter model [7] [8].

3 Approach

Our approach to addressing the dual challenges of determining the most important information in ECTs and developing methods to have the model prioritize including it in their summaries consists of two main parts: dataset creation and finetuning.

First, we construct an augmented version of the ECTSum dataset so that each new summary contains statistics from its corresponding transcript that have been designated the most important[2]. To create the transcript-summaries pairs for the augmented dataset, we processed the transcripts in the original ECTSum dataset in increasing order by length. If a transcript was over 8000 characters long, we replaced it with its first 4000 characters and last 4000 characters to establish a consistent maximum length. We then queried Gemini 1.0 Pro through Google's Generative AI API and prompted it to generate summaries of the truncated transcript. The prompt template we used is displayed below.

```
You are a financial advisor tasked with creating a short summary of an
    earnings call transcript. You only want to summarize or re-iterate
    points that would be relevant, critical, or informational to someone
    who wants to skim over the important details of a long transcript.

Below is an earnings call transcript. Please summarize this transcript in
     exactly one paragraph using complete sentences. Keep the summary
    below 300 words. It is very important that you do not use any titles
    in the summary. Include relevant information and statistics from the
    Earnings Call Transcript in your summary. Furthermore, it is very
    important that you incorporate all the information and statistics
    from the Key Points and spread it out throughout your summary.

Earnings Call Transcript:
[ect]

Key Points:
[summary]
```

As seen above, we pass the original ECTSum bullet-point summary to Gemini Pro and refer to it as the "Key Points" of the transcript. We chose to use the original summaries as a source of human preferences for determing the most important information in the ECT. The bullet-point summaries contained a handful of lines that were densely packed with statistics, so we decided to narrow our focus to training a model to prioritize including these important statistics. An ECTSum bullet-point summary for an example transcript `GHL_q4_2020.txt` is shown below.

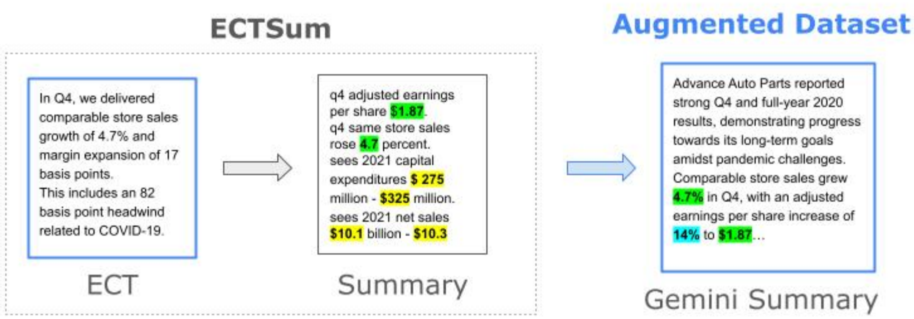
```
compname reports q4 earnings per share of $2.71.
compname reports fourth quarter earnings per share of $2.71 and full year
     2020 earnings per share of $1.36.
q4 revenue rose 32 percent to $140.7 million.
q4 earnings per share $2.71.
```

We extracted the statistics (the number and its unit such as "%" or "$") from the "Key Points" summary, making sure to exclude years between 2015-2025 as they would not be considered important pieces of information. After generating multiple summaries with Gemini, we then filtered them using the following quality ranking system. First, the Gemini summaries had to contain exactly one paragraph. Next, every statistic they contained had to also appear in the transcript (i.e. no numbers were hallucinated). Finally, the Gemini summaries had to include two or more of the statistics contained in their corresponding "Key Points" ECTSum summary. A table that includes the number of summaries that remained after each step of the filtering process is displayed below.

Filtering Generated Summaries			
	train	val	test
All summaries	336	90	96
Exactly 1 paragraph	335	90	96
100% precision	302	80	85
2+ recall	200	50	50

[2]Mukherjee et al.'s ECTSum dataset is available at https://github.com/rajdeep345/ECTSum

We provide a diagram below to visualize the filtering criteria in action. The two statistics highlighted in green in the Gemini summary represent those that also appeared in the "Key Points" ECTSum summary. The "14%" is highlighted in blue to indicate that it appears somewhere in the ECT and is not hallucinated. The statistics highlighted in yellow in the "Key Points" are important statistics that did not appear in the Gemini summary. Note that numeric phrases like "q4" or "2021" are not highlighted because they are not regarded as statistics. This example summary would be included in the augmented dataset because it has exactly one paragraph, no hallucinated statistics, and two important statistics.



Next, we used a single A100 GPU on Google Colab to finetune Mistral 7B–Instruct v0.1. The notebook used for the finetuning process is found in `train.ipynb` in the aforementioned Github repository. The libraries used were `torch`, `transformers` from HuggingFace for downloading the base Mistral model and tokenizer, `datasets`, `peft` for QLoRA finetuning, `bitsandbytes` for model weights quantization, `trl` for supervised finetuning, and `wandb` to monitor training/validation scores.

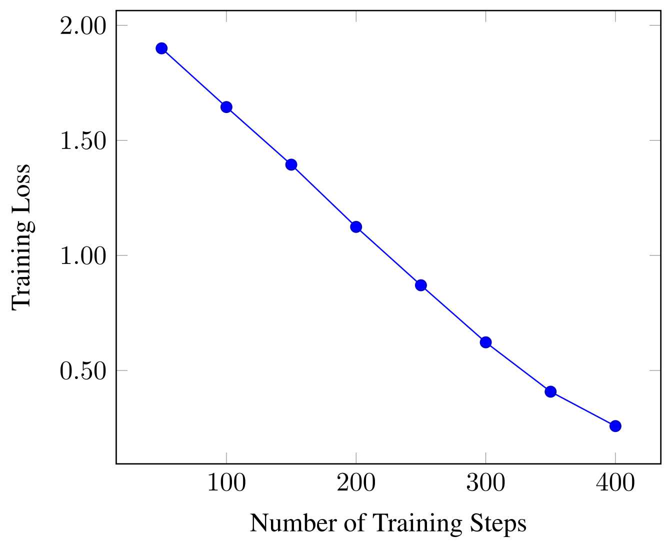
We used the Low-Rank Adaptation of Large Language Models (LoRA) approach, which is an established training technique that significantly reduces the number of trainable parameters. This allowed us to make meaningful improvements upon the 7 billion parameters of Mistral given our limited computing power. We also incorporated quantization, which reduces the memory and computation costs of inference by representing weights and activations with low-precision data types. In fact, research has shown that an approach that combines quantization with LoRA (QLoRA) leads to state-of-the-art results [9].

For the LoRA configuration, we used an attention dimension of 64, an alpha parameter of 16 for scaling, and a dropout probability of 0.1; we did not experiment with these paramenters and used existing Mistral finetuning approaches (see `train.ipynb`) to guide our selection of them. For quantization, we used a 4-bit precision base model with float16 representation and an nf4 quantization type.

For the supervised fine-tuning parameters, we used a batch size of 1 for both training and evaluation since the size of the training set was relatively small but each individual input (prompt + earnings call transcript) was quite large. Interestingly, we set the number of update steps to accumulate the gradients to be 4, which produced more stable training losses than setting gradient accumulation steps to be 1. We also used a learning rate of $1e^{-4}$, which we found to produce the most stable results as well, with a ratio of steps for linear warmup of 0.03. Other parameters includes a maximum gradient normal of 0.3, a weight decay of 0.001, and number of training steps of 400 (which allowed the model to see each input twice during training). Training for over 400 steps caused issues with disk space on Colab as well as introducing potential issues of overfitting to a relatively small dataset. We also did evaluation for every 50 steps of training.

Finally, we merged our new model's weights to the baseline Mistral model and performed statistical evaluation on both the base Mistral model and our merged model on the test dataset.

4 Results



As shown in the plot above, the training loss during finetuning appeared to have decreased at a consistent rate from 1.899900 at step 50 to 0.25830 at step 400. It continued to decrease toward the end at a slowing rate. We only trained up to 400 training steps due to the disk memory limits of the A100 we used. The validation loss decreased from 1.745044 at step 50 to 1.731574 at step 100 but then consistently increased to 2.603613 by step 200. Typically, this indicates that the finetuned model is overfitting to the training data. Yet this does not seem to be the case as the finetuned model displayed improved performance across the board and appeared to generate high-quality coherent summaries when we looked at them.

We suspect that the validation split had a lot of variation from the train split due to its small size of 50 transcripts and summaries. Therefore, when the finetuning optimized the model for the train split, it may have gotten worse for the validation split due to their differences. We provide the full table of training loss and validation loss values in the appendix.

Next, we ran inference on the test dataset for both models and saw that the finetuned Mistral model outperformed the baseline Mistral model across every ROUGE metric. The table below provides the ROUGE-1 and ROUGE-2 scores for the models, which measure the degree of overlap of unigrams and bigrams respectively between the generated and reference summaries. It also contains the ROUGE-L scores, which look at the longest common subsequence between the generated and reference summaries, and the ROUGE-Lsum scores, which are computed by calculating the ROUGE-L scores on the sentence level and aggregating the results. Additionally, we observed qualitive improvements in formatting and writing style in the summaries, which can be seen in the example generated summaries in the appendix.

ROUGE Similarity Evaluation				
	ROUGE-1	ROUGE-2	ROUGE-L	ROUGE-LSum
Baseline Mistral 7B–Instruct	44.835	17.846	26.059	28.815
Finetuned Mistral 7B–Instruct	**46.190**	**19.461**	**27.328**	**29.414**

We include a table below with results from our evaluation of the ability of the models to recall statistics from the Gemini reference summaries and the transcript as a whole in their summaries. We noticed an improvement in the recall of Gemini summary statistics from 42.631% to 43.947% after finetuning Mistral. These statistics were designated as important by human preferences, which indicates that our knowledge distillation approach was able to successfully teach a model to generate more relevant summaries.

Precision and Recall of Important Statistics				
	Summary Recall	ECT Recall	Precision	Average Length (characters)
Baseline Mistral 7B–Instruct	42.631%	**19.765**%	98.223%	1180.48
Finetuned Mistral 7B–Instruct	**43.947**%	19.662%	**98.465%**	1167.94

Furthermore, we provide the average lengths of the summaries in the table: 1180.48 characters for the baseline model and 1167.94 characters for the finetuned model. Metrics such as recall are highly dependent on the length of the generated summary, so we used the exact same generation process to ensure that the models produced summaries that were very similar in length. This allows us to conclude that the improvements we saw were statistically significant and unbiased by length.

We also observed an improvement in the precision of statistics in the generated summaries (i.e. the percentage of statistics that also appeared somewhere in the ECT) from 98.223% to 98.465% after finetuning. We ensured that the Gemini reference summaries were generated without any hallucinated statistics, which may helped teach Mistral to avoid hallucinations. Finally, we observed that the ability of the model to recall statistics that appeared in the entire ECT fell from 19.765% to 19.662% after finetuning. This may be an artifact of the slightly shorter length of the finetuned model's summaries, which would have less space to include statistics. The nature of long-document summarization tasks necessitates that not all information will be captured in the summaries, which places greater importance on including the most important information in the summaries. In this respect, we can conclude that our approach was successful.

5 Limitations and Next Steps

Perhaps one way to improve our approach is to expand our dataset. While we selected the 300 best-performing Gemini-generated summaries for our training and testing process, it would be interesting to know if we could have had improved results by including a couple hundred more document-summary pairs (which had slightly worse precision and recall of important statistics) in our datasets. More specifically, Section B of the Appendix notes that the validation loss decreased after 50 to 100 steps but increased significantly from 100 to 400 steps of training. We predict that expanding the evaluation dataset, in particular, could help reduce validation loss throughout the finetuning process and improve our model in general.

Additionally, while we experimented with some of the training parameters such as learning rates, number of steps, and gradient accumulation steps, we could have conducted further trials that tested how different parameters affect results, such as the weight decay, ratio of warmup steps, and maximum gradient normal parameters. We also did not experiment with the LoRA or quantization parameters, and while we tried to follow what others have successfully used for different Mistral finetuning tasks, it is possible that further experimentation with these parameters could have improved performance for earnings call transcript summarization.

Furthermore, even though it's clear that our finetuned model outperforms the baseline Mistral model, our results may be more informative by providing additional context such as performance relative to existing state-of-the-art models. For example, it would be interesting to know how well OpenAI's GPT-4 or Meta's LLAMA 3 models perform in long financial document summarization and how comparatively useful (or not) our finetuning approach actually is for this specific task.

Contribution Statement

Rohan primarily worked on building the augmented dataset and evaluating the models. Joonhee primarily worked on finetuning the models. We both worked on experimenting with finetuning parameters and writing the final paper.

References

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Appendix

A. Source Code

We provide our code in the following GitHub repository: https://github.com/joonhee0416/CPSC477-Final. The repository contain instructions to setup and run each part of this project in `README.md`.

We include a table below of all the external libraries that we used.

Dependency	Version
torch	2.0.1
datasets	2.16.1
peft	0.10.0
bitsandbytes	0.42.0
trl	0.8.6
wandb	0.17.0
google-generativeai	0.5.0
evaluate	0.4.1
transformers	git+https://github.com/huggingface/transformers@f26e4073707189c9391 5227779a4f6ea3c40d43b

B. Additional Results

Here is a table of the training loss and validation loss values with respect to number of training steps during finetuning. The training loss values are visualized in a plot in the Results section, and the increasing nature of the validation loss is discussed in the Results section as well.

Number of Training Steps	Training Loss	Validation Loss
50	1.899900	1.745044
100	1.644700	1.731574
150	1.394400	1.775493
200	1.123900	1.874560
250	0.870300	2.017644
300	0.622300	2.181498
350	0.407800	2.409936
400	0.258300	2.603613

We also provide an example set of three summaries for the transcript `GHL_q4_2020.txt` in the test split. These summaries include the Gemini-generated gold standard, the base model generation, and the finetuned model generation.

Gemini-Generated Gold Standard Summary:
Available at https://github.com/joonhee0416/CPSC477-Final/blob/main/dataset/test/gemini_summaries/GHL_q4_2020.txt

```
Greenhill reported its best quarterly revenue ever at $140.7 million in
    Q4, resulting in net income of $2.71 per share, which exceeded
    analyst estimates for the next five quarters combined. For the year,
    revenue was $311.7 million with a significant 202% increase in
    earnings per share to $1.36. The strong results were driven by
    increased M&A and restructuring completion fees, as well as favorable
     accounting rules. Notably, the company's restructuring business and
    a broader range of financing advisory services also contributed to
    growth. Looking ahead, Greenhill anticipates meaningful revenue
    growth in 2021 due to a favorable economic outlook, coupled with
    disciplined cost management. The company's strategic focus remains on
     expanding its revenue sources, with plans to enhance its advisory
    role for financial sponsors, broaden its private capital advisory
    services, and further develop its restructuring team.
```

Base Mistral 7B–Instruct Summary:

Available at https://github.com/joonhee0416/CPSC477-Final/blob/main/inference/base_mistral_final/GHL_q4_2020.txt

```
In the fourth quarter of 2020, Greenhill reported revenue of $140.7
    million, an operating margin of 57%, and net income of $2.71 per
    share. For the year, the company had revenue of $311.7 million, an
    operating margin of 18%, and net income of $1.36 per share. The
    quarterly revenue was up 32%, and earnings per share was up 158% from
     the same period last year. The full-year revenue was up 4%, and
    earnings per share was up 202% from the prior year. The strong
    quarter was not simply a matter of transaction timing, as the
    earnings per share for the quarter was greater than the analyst
    consensus forecast for the fourth quarter and the next four quarters
    ahead combined.

# 2

The company benefited from particularly strong results from its European
    M&A business and its U.S. restructuring business. It also benefited
    from an expanding array of financing advisory roles that are neither
    traditional M&A nor traditional restructuring. The private capital
    advisory business made a meaningful contribution as well, albeit
    considerably less so than in the prior year. The revenue for the year
     was highly concentrated in a few busy areas, as many regions and
    sectors were heavily impacted by the pandemic and related constraints
     in economic activity and thus produced only modest revenue.
```

Finetuned Mistral 7B–Instruct Summary:

Available at https://github.com/joonhee0416/CPSC477-Final/blob/main/inference/finetune_mistral_final/GHL_q4_2020.txt

```
In the fourth quarter of 2020, Greenhill reported revenue of $140.7
    million, an operating margin of 57%, and net income of $2.71 per
    share. This was the best quarterly performance in the company's
    history and exceeded analyst consensus forecasts for the quarter and
    the next four quarters combined. The strong results were driven by
    multiple M&A completion fees, restructuring completion fees, and a
    long list of smaller fees. Greenhill's European M&A business and its
    U.S. restructuring business were particularly strong, and the company
     also benefited from an expanding array of financing advisory roles.
    The full-year revenue was $311.7 million, with an operating margin of
     18% and net income of $1.36 per share. The compensation ratio for
    the year was 62%, moderately above the target level, but the non-
    compensation costs were down 18% from the prior year. Greenhill
    expects increased M&A revenue in most of its international offices
    and in certain sectors like industrials in 2021. The company also
    expects more debt restructuring activity for the many industries and
    companies adversely affected by the continuing pandemic. Greenhill
    has an active pipeline of good prospects for recruiting M&A bankers
    and wants to expand its restructuring advisory team even further. The
     company
```