ELECTRA and GPT-4o: Cost-Effective Partners for Sentiment Analysis

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Abstract

Bidirectional transformers excel at sentiment analysis, and Large Language Models (LLM) are effective zero-shot learners. Might they perform better as a team? This paper explores collaborative approaches between ELECTRA and GPT-4o for three-way sentiment classification. We fine-tuned (FT) four models (ELECTRA Base/Large, GPT-4o/4o-mini) using a mix of reviews from Stanford Sentiment Treebank (SST) and DynaSent. We provided input from ELECTRA to GPT as: predicted label, probabilities, and retrieved examples. Sharing ELECTRA Base FT predictions with GPT-4o-mini significantly improved performance over either model alone (82.74 macro F1 vs. 79.29 ELECTRA Base FT, 79.52 GPT-4o-mini) and yielded the lowest cost/performance ratio ($0.12/F1 point). However, when GPT models were fine-tuned, including predictions decreased performance. GPT-4o FT-M was the top performer (86.99), with GPT-4o-mini FT close behind (86.77) at much less cost ($0.38 vs. $1.59/F1 point). Our results show that augmenting prompts with predictions from fine-tuned encoders is an efficient way to boost performance, and a fine-tuned GPT-4o-mini is nearly as good as GPT-4o FT at 76% less cost. Both are affordable options for projects with limited resources.

1 Introduction

Sentiment analysis—the computational study of opinions, attitudes, and emotions in text (Medhat et al., 2014)—has seen major advances from transformer architectures (Vaswani et al., 2017). Bidirectional encoders like BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), and ELECTRA (Clark et al., 2020) excel at sentiment analysis when fine-tuned, and Large Language Models (LLM) like GPT (Radford et al., 2018) are strong zero-shot and few-shot learners (Kheiri and Karimi, 2023).

Recent work has explored collaboration between these models, such as using GPT to augment data of minority classes before fine-tuning with RoBERTa (Kok-Shun et al., 2023), using GPT for aspect extraction and RoBERTa for sentiment scoring (Qian et al., 2024), and escalating to LLMs when RoBERTa classification confidence was low (Andrade et al., 2024). However, leveraging predictions from fine-tuned encoders to enhance LLMs remains under-explored.

This research investigates collaborative approaches between ELECTRA and GPT-4o models (OpenAI, 2024b,c) for three-way sentiment classification (negative, neutral, positive) of reviews. Our research focused on the following hypotheses: Providing predictions from a fine-tuned ELECTRA as context to a GPT model will improve classification performance (**H1**). The improvement in performance will be less for a fine-tuned GPT (**H2**). The format of predictions in the prompt will affect performance (**H3**). Including similar examples in the prompt will improve performance (**H4**).

These hypotheses build on ELECTRA's strength in capturing nuanced sentiment patterns when fine-tuned (Clark et al., 2020; Potts et al., 2021; B et al., 2023), and GPT's versatility through in-context learning (Radford et al., 2019; Liu et al., 2019; Kocoń et al., 2023; OpenAI, 2024a)—they can perform well across diverse tasks when given the appropriate context through prompting (Liu et al., 2023; Khattab et al., 2024). Although they may struggle with emotion and nuance (Kocoń et al., 2023), retrieved examples can improve performance (Zhang et al., 2023).

To test these hypotheses, we established four baselines and conducted 23 experiments across three sentiment classification datasets: Stanford Sentiment Treebank (SST), and DynaSent Rounds 1 and 2. We used ELECTRA Base/Large and GPT-4o/4o-mini, each of which were fine-tuned (FT) on a merge of SST and DynaSent reviews.

We investigated the effects of different prompt augmentation scenarios using DSPy (Khattab et al., 2024): sharing the predicted class text label, the

probabilities of each class as percentages, retrieving similar reviews with their class labels, and combinations. We evaluated classification performance with the macro average F1 score, and cost-effectiveness by dividing the total fine-tuning costs by the F1. Our key insights are the following.

Sharing predictions boosted performance. Augmenting GPT-4o-mini (not fine-tuned) with predictions from ELECTRA Base FT significantly improved performance over either model alone. It also yielded the lowest cost/performance ratio.

Adding probabilities or examples helped. Using probabilities, or including few-shot examples, both improved performance for GPT-4o (not fine-tuned) vs. the predicted label alone. These only helped GPT-4o-mini on DynaSent R2 and SST-3.

Fine-tuned GPTs performed best. GPT-4o FT-M alone achieved the highest overall performance on the merged test set, with GPT-4o-mini FT closely following at significantly lower cost.

Sharing predictions hurt fine-tuned GPTs. When GPT models were fine-tuned, including ELECTRA predictions decreased performance—even when fine-tuned with the same inference-time prompt that included the ELECTRA prediction.

Fine-tuned ELECTRA Large outperformed base GPTs. ELECTRA Large fine-tuned was the best performing encoder model, and was better than both GPT-4o and GPT-4o-mini base models.

These findings offer affordable options for projects with limited resources. If fine-tuning via API is an option, a fine-tuned GPT-4o-mini is nearly as good as GPT-4o FT at 76% less cost. Alternatively, augmenting LLM prompts with predictions from fine-tuned encoder models is an efficient way to boost performance. For projects that want to stay local, a fine-tuned ELECTRA Large model is quite capable, and better than default GPTs.

The key contributions of this research are:

- Proposes a novel collaboration where fine-tuned bidirectional encoders assist GPT models with the task of sentiment classification.
- Demonstrates that augmenting GPT prompts (not fine-tuned) with predictions from fine-tuned encoders significantly improves classification performance and reduces costs, achieving the lowest cost/performance ratio.
- Evaluates various formats for incorporating encoder output into GPT prompts, and offers practical guidelines to maximize performance.

2 Prior Literature

2.1 MLMs and ELECTRA

Masked Language Models (MLM) like BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2019) employed bidirectional encoding to obtain holistic representations of text. RoBERTa (Robustly Optimized BERT Pretraining Approach) (Liu et al., 2019) optimized the pre-training approach, but both models were inefficient because learning only occurred in about 15% of the tokens that were masked.

This led to the development of ELECTRA (Efficiently Learning an Encoder that Classifies Token Replacements Accurately) (Clark et al., 2020). ELECTRA was pre-trained with two models using replaced token detection. As a result, it learned from all tokens and had comparable or better performance in a variety of tasks with less compute.

ELECTRA was found to be a top performer in sentiment classification on datasets such as SST (Clark et al., 2020), DynaSent (Potts et al., 2021), and IMDB movie reviews (B et al., 2023). It's for these reasons that we chose to use ELECTRA in our research, in addition to observing a performance gain relative to RoBERTa in early trials.

2.2 GPT Models

Bidirectional transformers seemed to have an edge over early autoregressive models like GPT (Radford et al., 2018) for sentiment analysis. But that edge is being whittled away by the successors of GPT pre-trained at a massive scale: GPT-3, GPT-3.5, GPT-4, and GPT-4o (OpenAI, 2024a,b,c).

For sentiment analysis of social media posts, Kheiri and Karimi (2023) found that GPT models significantly outperformed a number of prior models on the SemEval 2017 dataset. In contrast, Kocoń et al. (2023) found that, although ChatGPT is versatile and competent across a wide range of tasks, it did not perform as well as RoBERTa—especially for pragmatic tasks involving detection of emotional and contextual nuances. They propose that fine-tuning ChatGPT may be necessary, which we explore in this research.

2.3 Collaborative Approaches

Recent work has revealed several promising approaches for collaboration between these models.

Kok-Shun et al. (2023) explored a unique framework that chains GPT and RoBERTa for emotion

Table 1: Examples of Merged Training Dataset

Index	Sentence	Label	Source
0	Those 2 drinks are part of the HK culture and has years of history. It is so bad.	negative	dynasent_r2
1	I was told by the repair company that was doing the car repair that fixing the rim was "impossible" and to replace it.	negative	dynasent_r1
2	It is there to give them a good time .	neutral	sst_local
3	Like leafing through an album of photos accompanied by the sketchiest of captions .	negative	sst_local
4	Johnny was a talker and liked to have fun.	positive	dynasent_r1

detection. They used GPT's generative capabilities to augment training data for minority classes. The augmented dataset is then used to fine-tune RoBERTa on emotion detection.

Qian et al. (2024) tapped the strengths of different models in a Natural Language Processing (NLP) pipeline to analyze stadium reviews. One GPT-3.5 model was fine-tuned to extract experience aspects, while another classified these aspects into categories. A RoBERTa model then performed sentiment scoring on the extracted aspects. We are chaining ELECTRA and GPT-4o in a similar manner here, but in a different order.

Andrade et al. (2024) investigated the benefits of collaboration between MLMs and open LLMs for sentiment classification, similar to the current research. In their "Call-My-Big-Sibling" (CMBS) approach, the initial classification is done with a calibrated RoBERTa model. If RoBERTa has low confidence on the classification, an open LLM like Llama 2 (Touvron et al., 2023) is invoked to perform the classification task instead.

In CMBS, the final prediction is either made by RoBERTa or Llama 2—it's a decision tree. In contrast, our approach always passes the ELECTRA prediction to the LLM. If we had to come up with a similar analogy, it would be "Show-Me-Your-Answers" (SMYA). And then it's up to the LLM to decide if it follows the ELECTRA prediction, or decides to classify the review differently.

Most recently, Charpentier and Samuel (2024) created GPT-BERT, a hybrid model that learns bidirectional representations like an MLM, but is also generative like a GPT. By shifting the prediction of masked tokens one position to the right, GPT-BERT can be trained on both MLM and autoregressive objectives without changing architecture. In the BabyLM Challenge 2024 benchmark, it outperformed models trained on only one objective, showing there is potential in this combined approach.

Table 2: Label Distribution for the Merged Dataset

Split	Negative	Neutral	Positive
Train	21,910	49,148	31,039
Validation	1,868	1,669	1,884
Test	2,352	1,829	2,349

Table 3: Contribution of Sources to the Merged Dataset

Dataset	Samples	Percent (%)
DynaSent R1 Train	80,488	78.83
DynaSent R2 Train	13,065	12.80
SST-3 Train	8,544	8.37
Total	102,097	100.00

3 Data

Models were trained and evaluated on a merge of movie reviews from the Stanford Sentiment Treebank (SST) (Socher et al., 2013) and business reviews from DynaSent Rounds 1 and 2 (Potts et al., 2021). See Table 1 for examples. By default, SST is a five-way classification (positive, somewhat positive, neutral, somewhat negative, negative). The positive and negative classes were combined to produce SST-3 (positive, neutral, negative).

The SST-3, DynaSent R1, and DynaSent R2 datasets were randomly mixed to form a Merged dataset with 102,097 Train examples, 5,421 Validation examples, and 6,530 Test examples. See Table 2 for the distribution of labels, and Table 3 for a breakdown of sources.

It's worth noting that the source datasets all have class imbalances. Merging the data helps mitigate this imbalance, but there is still a majority of neutral examples in the training split. Another potential issue is that the models will learn the dominant dataset, which is DynaSent R1. As a test, the minority classes were over-sampled to create a new balanced dataset. When this was evaluated, the performance did not improve.

Table 4: Models Used in Research

Model	Provider	Access	Identifier
ELECTRA Base	Hugging Face	Local	google/electra-base-discriminator
ELECTRA Large	Hugging Face	Local	google/electra-large-discriminator
GPT-4o	OpenAI	API	gpt-4o-2024-08-06
GPT-4o-mini	OpenAI	API	gpt-4o-mini-2024-07-18

4 Models

Four models were fine-tuned and evaluated in this research, both individually and in collaboration with each other: ELECTRA Base and Large, and GPT-4o and 4o-mini. See Table 4 for details.

ELECTRA (Clark et al., 2020) was chosen as the bidirectional transformer because its pre-training architecture gives it an advantage over MLMs. It also outperformed RoBERTa in early trials. We evaluated both the Base (110M parameters) and Large (335M parameters) variants.

To function as a classifier, ELECTRA's output is sent through a mean pooling layer. A classifier head is appended with 2 hidden layers of dimension 1024, and a final output dimension of 3. Swish GLU (Shazeer, 2020) was used as the hidden activation function, and dropout layers were added with a rate of 0.3. See Appendix A for more details on the model architecture and hyper-parameters.

For comparison and collaboration, two GPT models were used via OpenAI's API: GPT-4o (OpenAI, 2024b) and GPT-4o-mini (OpenAI, 2024c). Although the full specifications are not public, they are state-of-the-art autoregressive language models with strong zero-shot capabilities. GPT-4o is described as a "high-intelligence flagship model for complex, multi-step tasks." GPT-4o-mini is described as an "affordable and intelligent small model for fast, lightweight tasks."

5 Methods

Our research progressed through the following stages. Code and datasets are available at: `https://github.com/jbeno/sentiment`.

5.1 ELECTRA Baseline & Fine-tuning

We first developed a training pipeline to support interactivity and distributed training across multiple GPUs. Training progress was tracked through Weights and Biases so we could monitor train/validation metrics (loss, macro F1, accuracy) across epochs. The final models were selected from checkpoints at convergence, or just before train/validation metrics started to diverge.

Two baseline models were established by training only classifier heads for ELECTRA Base and Large. Hyper-parameters were consistent with the fully fine-tuned versions. The fine-tuning process involved a number of trials on Lambda Labs multi-GPU instances to identify the best hyper-parameters, optimizer, and learning rate schedule. See Appendix A for the final configuration.

We also explored alternative approaches including an ensemble of binary classifiers, and additional fine-tuning on DynaSent R2 and SST-3, but these did not outperform our initial approach.

5.2 GPT Data Preparation & Fine-tuning

To use OpenAI's fine-tuning API, we converted the Merged training data to JSONL format that defined the System, User, and Assistant roles. We noticed that if the context at inference time varied even slightly from the fine-tuning context, performance would suffer. So we created three templates to enable better comparisons between fine-tuned and default models using the same DSPy signatures (see Appendix B):

- **Minimal (FT-M):** No prompt other than System role.
- **Prompt (FT):** Default fine-tuning. User role included full DSPy prompt.
- **Prompt with Label (FT-L:** User role included DSPy prompt with ELECTRA predicted label.

We included the ELECTRA predictions in the third template to align the fine-tuning context with the inference time context, but also to provide an opportunity for the GPT models to learn from the ELECTRA predictions. In total there were 6 fine-tuning jobs (see Table 5).

5.3 DSPy Signatures & Modules

Using DSPy, we explored a variety of approaches to integrating ELECTRA's output into GPT's

Table 5: Fine-Tuning Job Details

Model	Code	Format	Tokens
GPT-4o-mini	FT	Prompt	11.0M
GPT-4o-mini	FT-L	Prompt w/Base Label	13.2M
GPT-4o-mini	FT-M	Minimal	5.5M
GPT-4o	FT	Prompt	11.0M
GPT-4o	FT-L	Prompt w/Large Label	13.2M
GPT-4o	FT-M	Minimal	5.5M

decision-making process. Each approach was implemented as a custom DSPy signature and module (see Appendix C for the full examples).

Classification Prompt. Prompt to "Classify the sentiment of a review as either 'negative', 'neutral', or 'positive'." One input field 'review' described as "The review text to classify." and one output field 'classification' described as "One word representing the sentiment classification: 'negative', 'neutral', or 'positive' (do not repeat the field name, do not use 'mixed')".

Predicted Label. Classification prompt with an additional input field 'classifier_decision' described as "The sentiment classification proposed by a model fine-tuned on sentiment." During evaluation, the DSPy module first sends the review through the ELECTRA model to obtain its prediction. This output is then inserted into the signature.

Probabilities. Classification prompt, but instead of 'classifier_decision' it featured three input fields for the probabilities of each class as obtained from the ELECTRA model. For example: 'negative_probability' was described as "Probability the review is negative from a model fine-tuned on sentiment". The float is converted to a percent to make it easier for the model to interpret.

Prediction & Probabilities. Same as Probabilities, but it also included the 'classifier_decision' to emphasize the final decision made by ELECTRA.

Top Examples. A custom retriever was created from 300 reviews in the Validation split. During inference, input text is run through the fine-tuned ELECTRA Large model to extract the output representations (prior to the classifier head). The top five matches and class labels based on cosine similarity are shown as few-shot examples. This signature had 'classifier_decision' plus an 'examples' field described as "A list of examples that demonstrate different sentiment classes."

Balanced Examples. Similar to Top Examples, except a different retriever was used that retrieved a total of six examples (two from each class) to ensure the few-shot examples with true labels did not bias the answer toward a particular class—although that might be desirable.

All of the Above. And lastly, a final DSPy signature had all of the above context from ELECTRA included: classification prompt, predicted label, probabilities, and top five examples—not balanced.

We then conducted two of the four baselines, and 21 of the 23 experiments (see Table 6) using these DSPy signatures and modules. The fine-tuned ELECTRA models and retriever were instantiated locally for inference, and the GPT models were accessed via OpenaAI API.

6 Results

Our experiments revealed significant differences in performance across baseline, fine-tuning, and collaborative scenarios. See Table 6 for the results.

Baselines. Regarding baselines, both GPT models outperformed the ELECTRA classifiers, with GPT-4o achieving 80.14 macro F1 and GPT-4o-mini scoring 79.52, compared to ELECTRA Base (69.65) and Large (67.88). This demonstrates the strong zero-shot capabilities of the GPT models.

Fine-tuning. Fine-tuning improved performance across all models. ELECTRA Base's macro F1 increased from 69.65 to 79.29, while ELECTRA Large showed even greater gains, improving from 67.88 to 82.36. This improvement is the result of fine-tuning all layers—the baselines had the same classifier head. The fine-tuned GPT models had the highest scores (see Figure 2), with GPT-4o-mini FT rising from 79.52 to 86.77, and GPT-4o FT-M achieving 86.99 with the minimal template.

Sharing Predictions. The effect of adding ELECTRA predictions to GPT prompts depended on if the GPT model was fine-tuned (see Figure 1). Sharing ELECTRA Base predictions with GPT-4o-mini (not fine-tuned) significantly improved the macro F1 from 79.52 to 82.74 ($p < 0.0001$, McNemar's test), a +3.22 gain. There was an even greater gain of +3.97 points when ELECTRA Large predictions were shared (from 79.52 to 83.49, $p < 0.0001$). Similarly, including ELECTRA Large predictions with GPT-4o improved the macro F1 from 80.14 to 81.57 ($p = 0.0106$), a smaller +1.43 gain.

However, sharing ELECTRA predictions with fine-tuned GPT models actually decreased performance. GPT-4o-mini's macro F1 dropped from 86.77 to 81.42 with ELECTRA Base predictions, and to 82.02 when fine-tuned with the predictions

Table 6: Summary of Model Configurations, Performance, and Cost

				Merged[2]		DynaSent R1		DynaSent R2		SST-3		Cost ($)[3]	
ID	GPT[1]	ELECTRA	Description	F1	Acc	F1	Acc	F1	Acc	F1	Acc	FT	/F1
B1	—	Base	Baseline, Classifier head	69.65	69.83	70.96	71.28	61.59	61.67	60.85	70.14	0.65	0.01
B2	—	Large	Baseline, Classifier head	67.88	68.06	69.72	70.06	59.78	59.72	57.68	67.51	2.51	0.04
B3	4o-mini	—	Baseline (Prompt only, Zero shot)	†79.52	80.34	81.12	81.00	77.35	77.92	70.67	80.05	—	—
B4	4o	—	Baseline (Prompt only, Zero shot)	80.14	80.74	81.12	80.94	80.22	80.56	72.20	80.45	—	—
E1	—	Base FT	Fine-tune all layers	†79.29	79.69	82.10	82.14	71.83	71.94	69.95	78.24	**9.73**	**0.12**
E2	—	Large FT	Fine-tune all layers	82.36	82.96	85.91	85.83	76.29	76.53	70.90	80.36	53.26	0.65
E3	4o-mini	Base FT	Prompt, Label	†82.74	83.35	86.50	86.44	76.19	76.53	71.72	80.54	**9.73**	**0.12**
E4	4o-mini	Large FT	Prompt, Label	83.49	84.21	87.52	87.47	77.94	78.47	70.99	80.77	53.26	0.64
E5	4o-mini	Large FT	Prompt, Label, Examples (Few shot)	83.20	83.80	86.74	86.64	78.71	79.03	71.98	80.72	53.26	0.64
E6	4o-mini	Large FT	Prompt, Label, Balanced Ex. (Few shot)	82.68	83.28	85.84	85.69	79.61	80.00	71.45	80.41	53.26	0.64
E7	4o-mini	Large FT	Prompt, Probabilities	83.01	83.60	86.44	86.36	78.92	79.17	71.53	80.54	53.26	0.64
E8	4o-mini	Large FT	Prompt, Label, Probabilities	83.43	84.12	87.02	86.94	79.72	80.14	71.03	80.81	53.26	0.64
E9	4o-mini	Large FT	Prompt, Label, Probs, Examples	82.91	83.54	86.15	86.06	78.69	79.03	71.49	80.90	53.26	0.64
E10	4o-mini FT	—	Fine-tune w/prompt	86.77	87.26	89.86	89.75	86.90	87.08	**75.68**	**83.26**	33.15	0.38
E11	4o-mini FT-M	—	Minimal fine-tune	86.55	87.00	89.70	89.58	86.97	87.08	75.62	82.76	16.60	0.19
E12	4o-mini FT	Base FT	Prompt, Label, FT w/prompt	81.42	81.90	84.77	84.78	74.49	74.72	70.95	79.55	42.88	0.53
E13	4o-mini FT-L	Base FT	Prompt, Label, FT w/prompt, label	82.02	82.53	85.24	85.11	78.15	78.47	71.68	79.64	49.31	0.60
E14	4o	Large FT	Prompt, Label	81.57	81.98	84.03	83.86	77.69	77.92	72.94	80.23	53.26	0.65
E15	4o	Large FT	Prompt, Label, Examples (Few shot)	83.09	83.66	86.01	85.86	81.53	81.81	72.06	80.68	53.26	0.64
E16	4o	Large FT	Prompt, Label, Balanced Ex. (Few shot)	82.99	83.55	85.87	85.69	80.89	81.11	72.15	80.86	53.26	0.64
E17	4o	Large FT	Prompt, Probabilities	82.65	83.25	86.05	85.97	77.67	77.92	71.16	80.54	53.26	0.64
E18	4o	Large FT	Prompt, Label, Probabilities	83.08	83.71	86.44	86.33	79.23	79.58	71.48	80.77	53.26	0.64
E19	4o	Large FT	Prompt, Label, Probs, Examples	82.74	83.35	86.32	86.22	77.76	78.06	70.98	80.41	53.26	0.64
E20	4o FT	—	Fine-tune w/prompt	86.83	87.43	90.44	90.36	88.34	88.47	73.08	82.31	276.24	3.18
E21	4o FT-M	—	Minimal fine-tune	**86.99**	**87.57**	**90.57**	**90.50**	**89.00**	**89.17**	73.99	82.26	138.37	1.59
E22	4o FT	Large FT	Prompt, Label, FT w/prompt	83.82	84.47	87.80	87.72	79.49	79.86	71.18	80.68	329.50	3.93
E23	4o FT-L	Large FT	Prompt, Label, FT w/prompt, label	84.23	84.82	87.74	87.64	80.55	80.83	72.63	81.54	383.10	4.55

Bold = best overall, highlighted = best in section

†Scores relevant to Hypothesis 1 (ELECTRA prediction improving non-fine-tuned GPT performance)
[1] GPT fine-tuning types: FT = fine-tune all layers with prompt, FT-M = minimal format without prompt, FT-L = with prompt including ELECTRA label
[2] Merged dataset: Combination of test splits from DynaSent R1/R2 and SST-3
[3] Cost: FT = Fine-tuning cost, no inference-time API charges. Ratio is FT cost divided by F1 score.

included in the prompt. Similarly, GPT-4o fell from 86.83 to 83.82 with ELECTRA Large predictions, and to 84.23 when fine-tuned with them.

Few-shot Examples. Some contexts performed better than others for specific model combinations (see Figure 3). For GPT-4o with ELECTRA Large FT, providing few-shot examples in addition to the predicted label significantly increased the macro F1 on the Merged test set from 81.57 to 83.09 (p = 0.0001, McNemar's test), a +1.51 gain. The difference was even greater for DynaSent R2, increasing from 77.69 to 81.53, +3.84 gain.

There was very little difference between showing the top five similar examples, compared with the top six balanced examples (ensuring two examples for each class). However, the top five approach had slightly higher scores, except for GPT-4o-mini on DynaSent R2, and GPT-4o on SST-3—both of which represent more challenging sentiment.

Sharing Probabilities. For GPT-4o with ELECTRA Large, using probabilities instead of the predicted label resulted in a slight increase on the Merged test macro F1 (from 81.57 to 82.65, p = 0.0049), a +1.08 gain. Providing both the label and

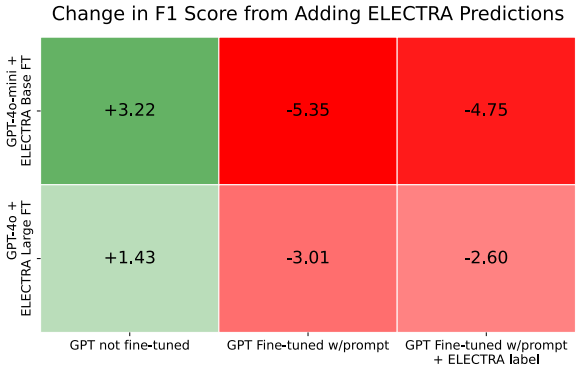

Figure 1: Change in F1 from Adding Predictions

probabilities was even more effective, boosting the score from 81.57 to 83.08 (p = 0.0001), a +1.51 gain. The difference was even greater for DynaSent R1, increasing from 84.03 to 86.44, a +2.41 gain.

For GPT-4o-mini with ELECTRA Large FT on the Merged test, there was no context better than just the predicted label (see Figure 3). However, adding probabilities in addition to the label increased the macro F1 on DynaSent R2 from 76.19 to 79.72, a +3.53 gain.

Datasets. Performance also varied across

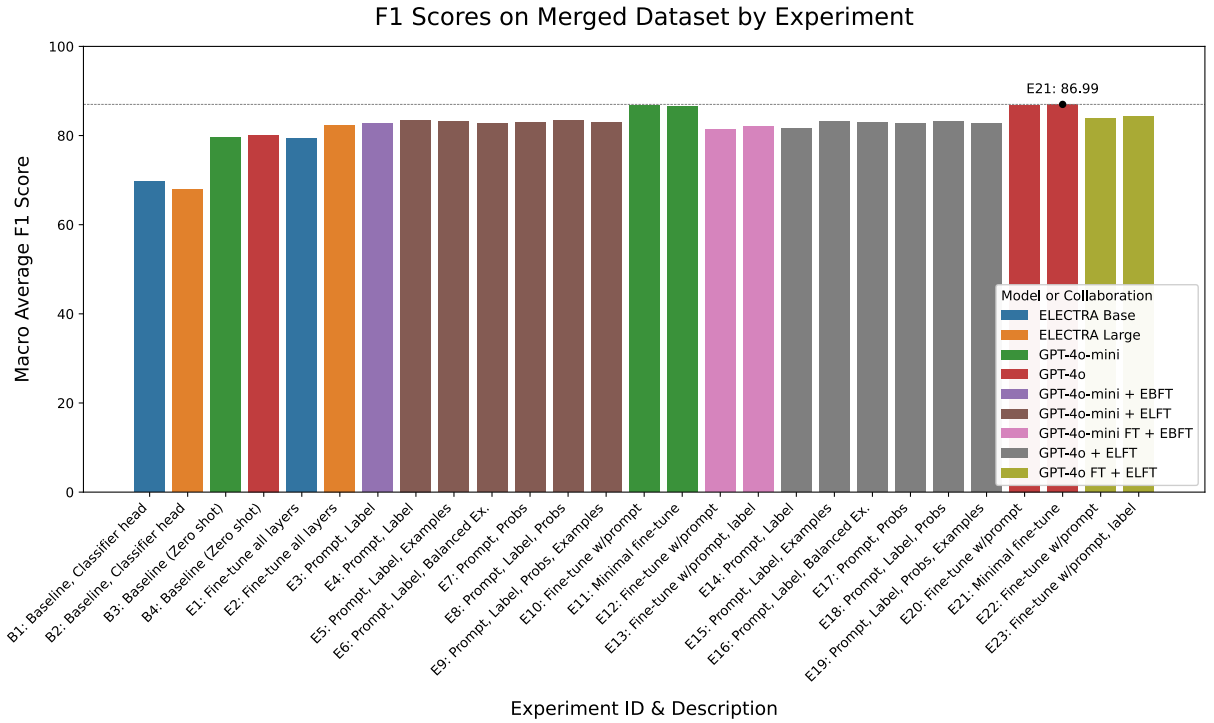

Figure 2: Macro F1 Scores on Merged Dataset by Experiment

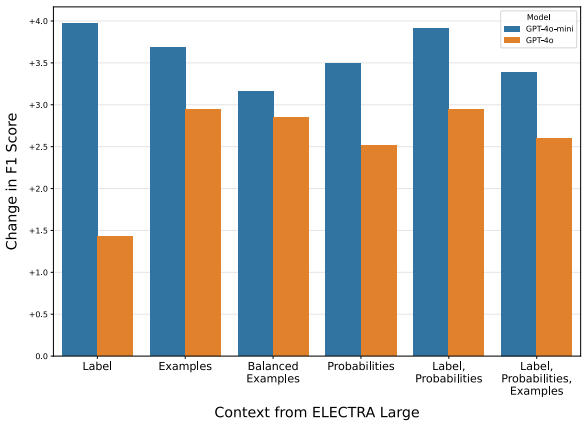

Figure 3: Impact of Context on F1 Score by Model

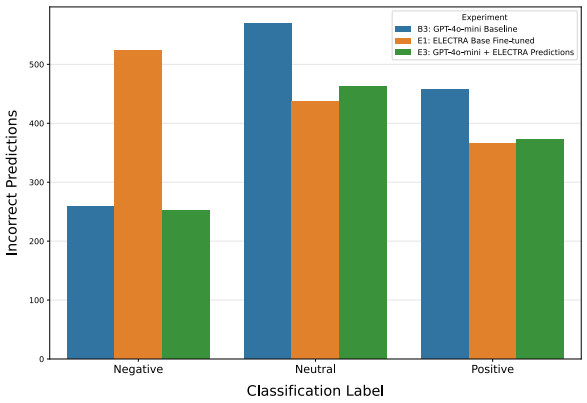

Figure 4: Incorrect Predictions by Label and Experiment

datasets. GPT-4o FT-M achieved the top scores on DynaSent R1 (90.57 macro F1) and DynaSent R2 (89.00). Surprisingly, GPT-4o-mini FT—the smaller model—performed best on SST-3 with a 75.68 macro F1, exceeding even GPT-4o FT's performance of 73.99.

Cost. The most cost-effective approach was ELECTRA Base FT with GPT-4o-mini (not fine-tuned) at $0.12 per F1 point. GPT-4o-mini FT provided a good compromise at $0.38 per F1 point, while GPT-4o FT-L with ELECTRA Large FT proved most expensive at $4.55 per F1 point.

7 Analysis

H1. Sharing predictions would boost performance. The significant improvement in GPT-4o-mini's performance when augmented with ELECTRA Base FT or Large FT predictions strongly supports H1. We also saw a similar boost for GPT-4o with ELECTRA Large FT predictions.

However, following ELECTRA's predictions had mixed results. When GPT-4o-mini changed its decision and followed ELECTRA Base FT, it was correct 548 times and wrong 412 times (+136 net improvement, 57.08% success rate). When GPT-4o changed its decision and followed ELECTRA Large FT, it was correct 521 times and wrong 481

times (+40 net improvement, 52% success rate).

Most of the improvement was in the neutral and positive classes (see Figure 4). There was barely any improvement in the negative class, but importantly—it didn't worsen. ELECTRA Base FT had more than double the incorrect negative predictions, but GPT-4o-mini did not follow them. The negative class was 21.46% of the Merged dataset, so ELECTRA may not have learned it well. Conversely, GPT-4o followed more of the negative predictions, and performance suffered.

DynaSent R1 was the dominant source of the Merged dataset (80,488 samples, or 78.83%), and saw the most improvement. It could be that ELECTRA learned this dataset the most, but it also represented less challenging reviews.

H2. Improvement would be less for fine-tuned GPTs. H2 was supported more strongly than anticipated. For a fine-tuned GPT model, including the ELECTRA prediction actually decreased performance (see Figure 1). Initially, we thought this was because the fine-tuning context did not include the ELECTRA prediction in the prompt. But we still saw a decrease in performance (although less) when it was included. This suggests the fine-tuning process for GPT-4o/4o-mini is superior when it's simpler—focused on pure input to output.

H3. Format of prediction would impact performance. The significant improvement in GPT-4o's performance when ELECTRA Large predictions were replaced with probabilities as percentages supports H3. For GPT-4o-mini, probabilities decreased performance on the Merged dataset and DynaSent R1, but improved performance for DynaSent R2 and SST-3—the more challenging sentiment examples. In almost all cases, it was better to include both the label and probabilities together.

H4. Including examples would improve performance. The significant improvement in GPT-4o's performance when few-shot examples were included with the predicted label strongly supports H4. Of all the contexts explored with GPT-4o (not fine-tuned), including the top five examples yielded the best score for DynaSent R2 (81.53 macro F1). Similarly, with GPT-4o-mini (not fine-tuned), the top examples produced its best performance with SST-3 (71.98 macro F1). It appears the examples were able to help the models make better decisions with the more challenging datasets.

Overall, adding probabilities, or adding examples, improved performance over the predicted label alone for GPT-4o. However, including all three (label, probabilities, examples) was not as good as either pairing (although still better than the label alone). Perhaps the large amount of tokens impacted the signal to noise ratio.

8 Conclusion

This research investigated collaborative approaches to sentiment classification between bidirectional transformers and LLMs. Our results show that augmenting prompts with predictions from a fine-tuned ELECTRA can significantly improve performance when the GPT model is not fine-tuned—up to +3.97 points of gain in the macro F1 score. Including probabilities or similar examples enhanced performance for GPT-4o, especially on challenging datasets. However, this collaborative benefit disappeared when the GPT models were fine-tuned.

Our findings offer several cost-effective paths for sentiment analysis projects. For organizations that can fine-tune via API, GPT-4o-mini FT offers nearly equivalent performance to GPT-4o FT-M (86.77 vs 86.99 macro F1) at 76% lower cost ($0.38 vs $1.59/F1 point). For those with data privacy concerns or resource constraints, GPT-4o-mini with ELECTRA Base FT had the best cost/performance ratio ($0.12/F1 point). Projects that need to stay completely local can fine-tune ELECTRA Large, which outperformed both base GPT models.

Future work could explore optimization of inference-time prompts through DSPy, and alternate System role instructions during fine-tuning. In addition, this collaborative approach could be extended to different datasets/domains, classification tasks, and model pairings. There may also be potential for including multiple predictions from an ensemble of models. A new collaborative scenario would be fine-tuning GPTs on the ELECTRA output representations.

9 Limitations

The cost/performance evaluation only considered the fine-tuning costs to achieve the reported macro F1 on the test set. In practice, there would be ongoing costs for inference time API calls.

Resource and time constraints prevented us from exploring every possible collaborative scenario. Once we saw ELECTRA Large FT performed better than ELECTRA Base FT, we only evaluated the output from Large in the different prompt contexts for both GPT-4o and GPT-4o-mini.

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A ELECTRA Fine-tuning Details

Table 7: ELECTRA Fine-Tune Configuration

Setting	ELECTRA Base FT	ELECTRA Large FT
Source	Hugging Face	Hugging Face
Source Model ID	google/electra-base-discriminator	google/electra-large-discriminator
Encoder Blocks	12	24
Embedding Dimension	768	1024
Attention Heads	12	16
Feedforward Size	3072	4096
Parameters	110 Million	335 Million
Custom Pooling Layer Method	Mean	Mean
Classifier Head Hidden Layers	2	2
Classifier Head Hidden Dimension	1024	1024
Classifier Head Hidden Activation	SwishGLU	SwishGLU
Finetuned Encoder Blocks	12	24
Total Layers	104	200
Total Parameters	112,830,979	338,293,763
Trainable Parameters	100%	100%
Learning Rate	$1e^{-5}$	$1e^{-5}$
Learning Rate Decay	0.95	0.95
Batch Size	16	16
Accumulation Steps	2	2
Target Epochs	50	50
Actual Epochs	20	23
Selected Best Epoch	14	13
Dropout Rate	0.30	0.30
L2 Strength	0.01	0.01
Optimizer	AdamW	AdamW
Zero Redundancy	Yes	Yes
Scheduler	CosineAnnealingWarmRestarts	CosineAnnealingWarmRestarts
Scheduler: T_0	5	5
Scheduler: T_mult	1	1
Scheduler: eta_min	$1e^{-7}$	$1e^{-7}$
Early Stop	Validation F1 Score	Validation F1 Score
N Iterations No Change	10	10
Dataset	Merged (Dyn R1, Dyn R2, SST-3)	Merged (Dyn R1, Dyn R2, SST-3)
Train Size	102,097	102,097
Train Label Distribution	Neu: 49,148, Pos: 31,039, Neg: 21,910	Neu: 49,148, Pos: 31,039, Neg: 21,910
Validation Size	5,421	5,421
Validation Label Distribution	Neu: 1,669, Pos: 1,884, Neg: 1,868	Neu: 1,669, Pos: 1,884, Neg: 1,868
Hosting Provider	Lambda Labs	Lambda Labs
GPU Type	Tesla V100	A100
GPU Memory	16 GB	40 GB
GPU Quantity	8	8
Rate	$4.40/hour	$10.32/hour
Training Time (Up to Selected Epoch)	02:12:44	05:09:23
Training Time (Total)	03:09:40	09:23:29
Cost (Up to Selected Epoch)	$9.73	$53.26
Cost (Total)	$13.91	$96.92

B OpenAI Fine-tuning Templates

Table 8: FT-M: Minimal Template for Fine-tuning

Role	Content
System	"You are a model that classifies the sentiment of a review as either 'positive', 'neutral', or 'negative'."
User	"Those 2 drinks are part of the HK culture and has years of history. It is so bad."
Assistant	"negative"

Table 9: FT: Prompt Template for Fine-tuning

Role	Content
System	"You are a sentiment analysis assistant."
User	"**Classify the sentiment of a review as either 'negative', 'neutral', or 'positive'.\n—\n\nFollow the following format.\n\nReview: The review text to classify.\nClassification: One word representing the sentiment classification: 'negative', 'neutral', or 'positive' (do not repeat the field name, do not use 'mixed')\n\n—\n\nReview:** Those 2 drinks are part of the HK culture and has years of history. It is so bad.\n**Classification:**"
Assistant	"negative"

Table 10: FT-L: Prompt with Predicted Label Template for Fine-tuning

Role	Content
System	"You are a sentiment analysis assistant."
User	"Classify the sentiment of a review as either 'negative', 'neutral', or 'positive'.\n—\n\nFollow the following format.\n\nReview: The review text to classify.\n**Classifier Decision: The sentiment classification proposed by a model fine-tuned on sentiment.**\nClassification: One word representing the sentiment classification: 'negative', 'neutral', or 'positive' (do not repeat the field name, do not use 'mixed')\n\n—\n\nReview: Those 2 drinks are part of the HK culture and has years of history. It is so bad.\n**Classifier Decision: negative**\nClassification:"
Assistant	"negative"

C DSPy Prompt Signature Examples

Figure 5: Basic Prompt DSPy Signature

```
Classify the sentiment of a review as either 'negative', 'neutral', or 'positive'.

---

Follow the following format.

Review: The review text to classify.
Classification: One word representing the sentiment classification: 'negative', 'neutral', or 'positive'
(do not repeat the field name, do not use 'mixed').

---

Review: Those 2 drinks are part of the HK culture and has years of history. It is so bad.
Classification:
```

Figure 6: Prompt with Predicted Label DSPy Signature

```
Classify the sentiment of a review as either 'negative', 'neutral', or 'positive'.

---

Follow the following format.

Review: The review text to classify.
Classifier Decision: The sentiment classification proposed by a model fine-tuned on sentiment.
Classification: One word representing the sentiment classification: 'negative', 'neutral', or 'positive'
(do not repeat the field name, do not use 'mixed')

---

Review: I was told by the repair company that was doing the car repair that fixing the rim was
"impossible" and to replace it.
Classifier Decision: negative
Classification:
```

Figure 7: Prompt with Probabilities DSPy Signature

```
Classify the sentiment of a review as either 'negative', 'neutral', or 'positive'.

---

Follow the following format.

Review: The review text to classify.

Negative Probability: Probability the review is negative from a model fine-tuned on sentiment

Neutral Probability: Probability the review is neutral from a model fine-tuned on sentiment

Positive Probability: Probability the review is positive from a model fine-tuned on sentiment

Classification: One word representing the sentiment classification: 'negative', 'neutral', or 'positive'
(do not repeat the field name, do not use 'mixed')

---

Review: Those 2 drinks are part of the HK culture and has years of history. It is so bad.

Negative Probability: 99.85%

Neutral Probability: 0.04%

Positive Probability: 0.12%

Classification:
```

Figure 8: Prompt with Predicted Label and Probabilities DSPy Signature

```
Classify the sentiment of a review as either 'negative', 'neutral', or 'positive'.

---

Follow the following format.

Review: The review text to classify.

Classifier Decision: The sentiment classification proposed by a model fine-tuned on sentiment.

Negative Probability: Probability the review is negative

Neutral Probability: Probability the review is neutral

Positive Probability: Probability the review is positive

Classification: One word representing the sentiment classification: 'negative', 'neutral', or 'positive'
(do not repeat the field name, do not use 'mixed')

---

Review: Those 2 drinks are part of the HK culture and has years of history. It is so bad.

Classifier Decision: negative

Negative Probability: 99.85%

Neutral Probability: 0.04%

Positive Probability: 0.12%

Classification:
```

Figure 9: Top Examples DSPy Signature

```
Classify the sentiment of a review as either 'negative', 'neutral', or 'positive'.

---

Follow the following format.

Examples: A list of examples that demonstrate different sentiment classes.

Review: The review text to classify.

Classifier Decision: The sentiment classification proposed by a model fine-tuned on sentiment.

Classification: One word representing the sentiment classification: 'negative', 'neutral', or 'positive'
(do not repeat the field name, do not use 'mixed')

---

Examples:
- negative: We've been to about 5 or 6 other Verizon stores in Vegas, and they all give us a hard time
about everything and never solve any issue.
- negative: Then Raj then had the balls to send me an email after my box was closed to tell me they were
ready to receive the key for my mailbox after closing it.!
- negative: Always and issue here even with take out orders.
- negative: SHOULD YOU HAVE ANY DISPUTE, THEY IMMEDIATELY WILL THREATEN YOU WITH MECHANICS LIENS.
- negative: We were waiting for them to get our order out, but the lady came out and gave the car behind
us their order first!

Review: I went back in to ask for cilantro dressing the shift leader even smile or greet me.

Classifier Decision: negative

Classification:
```

Figure 10: Balanced Examples DSPy Signature

```
Classify the sentiment of a review as either 'negative', 'neutral', or 'positive'.

---

Follow the following format.

Examples: A list of examples that demonstrate different sentiment classes.

Review: The review text to classify.

Classifier Decision: The sentiment classification proposed by a model fine-tuned on sentiment.

Classification: One word representing the sentiment classification: 'negative', 'neutral', or 'positive'
(do not repeat the field name, do not use 'mixed')

---

Examples:
- negative: Beware of all the fake 5 star reviews of this place, just take a look at these people.
- negative: 3- girls look even cheaper than the club.
- neutral: Not to mention the esso across the street also has cheaper gas.
- neutral: I wish that they would open up by 6am so that I can pick up a coffee or tea before work, but
what boba place is opened that early?
- positive: The plumbers did not give up and continued to work on the drain for two days.
- positive: This is my 6th gun to add to my collection and if I had not wanted it so bad, I would have
walked out 2 minutes after walking in.

Review: She greeted customers by holding the scanner toward them without even looking.

Classifier Decision: negative

Classification:
```

Figure 11: All Context DSPy Signature

```
Classify the sentiment of a review as either 'negative', 'neutral', or 'positive'.

---

Follow the following format.

Examples: A list of examples that demonstrate different sentiment classes.

Review: The review text to classify.

Classifier Decision: The sentiment classification proposed by a model fine-tuned on sentiment.

Negative Probability: Probability the review is negative

Neutral Probability: Probability the review is neutral

Positive Probability: Probability the review is positive

Classification: One word representing the sentiment classification: 'negative', 'neutral', or 'positive'
(do not repeat the field name, do not use 'mixed')

---

Examples:
- negative: The only negative I can think for this place is it's price-point.
- positive: This place will be the death of my waist (but not my wallet).
- negative: Expensive, if you are looking for something more affordable, don't go here; you will miss
  the best dishes.
- positive: Thank you so much for dealing with my crabby ass
- positive: I think I scarfed it down so quickly because it was that good! It was bad.

Review: The gentleman staffing the bar seemed a bit gruff, but a good caffeine fix will help me forgive
even the orneriest grump.

Classifier Decision: negative

Negative Probability: 84.37%

Neutral Probability: 0.53%

Positive Probability: 15.10%

Classification:
```