# Contrastive Classification via Linear Layer Extrapolation

Anonymous ACL submission

## Abstract

Early-exiting predictions in a deep Transformer network evolve from layer to layer in a somewhat smooth process. This has been exploited in language modeling to improve factuality (Chuang et al., 2023), with the observation that factual associations emerge in later layers. We find that a similar process occurs in standard multiway emotion classification, motivating us to propose Linear Layer Extrapolation, which finds stable improvements by recasting contrastive inference as linear extrapolation. Experiments across multiple models and emotion classification datasets find that Linear Layer Extrapolation outperforms standard classification on fine-grained emotion analysis tasks.

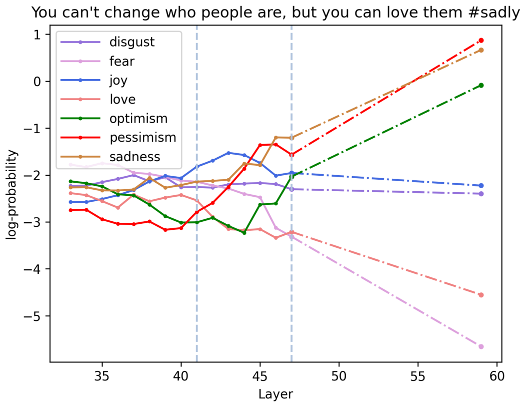


Figure 1: Linearly extrapolating class scores from amateur and expert layers to a nonexistent future layer correctly flips the output from sadness to pessimism

## 1 Introduction

Identifying the emotion present in a text passage is a well-studied problem in natural language processing (NLP), key to gaining insights from web-scale data (Zhang et al., 2023; Barbieri et al., 2020). The task feeds into a variety of downstream applications ranging from detecting harmful online behavior to creating conversational agents capable of better social interactions. Identifying the correct emotion is a challenging problem. Most current systems focus on identifying the mutually disjoint emotions(joy, sadness, surprise) that are mutually exclusive. However, this is not true for fine-grained emotions e.g. grief and remorse are closely related but represent different emotions. Thus, fine-grained emotion classification presents an exciting challenge to current large language models (Demszky et al., 2020) with much room for improvement.

Meanwhile, large language models have shown the ability to learn general-purpose syntactic and semantic information from text, finding success across a wide range of other NLP tasks. (Brown et al., 2020; Wei et al., 2022) But despite their rapid improvements, language models still struggle on a number of tasks. For example, even very large models often make mistakes on grade-school-level and commonsense reasoning tasks. (Fu et al., 2023) Further, models are prone to hallucinating incorrect information. (Ji et al., 2023) Notably, language models also struggle to identify fine-grained emotion and opinions. (Zhang et al., 2023)

Recently, a class of *contrastive* methods, which maximize the difference between a desirable “expert" and undesirable “amateur" model, have been proposed to ameliorate some of these problems. For example, contrastive decoding (CD) (Li et al., 2022; O’Brien and Lewis, 2023) uses a large-model expert and small-model amateur to improve both open-ended generation and reasoning performance. DExperts (Liu et al., 2021) reduces toxicity by finetuning an amateur model to be toxic and contrasting against its predictions. Decoding by contrasting layers, or *DoLa*, (Chuang et al., 2023) uses contrastive action on the intermediate layers of the same model. In particular, DoLa uses the intermediate layers of models with early exiting (Teerapittayanon et al., 2016; Elbayad et al., 2020; Schuster et al., 2022) as amateur models. DoLa is predicated on the observation that layers of LLMs progressively learn and insert information over the course of a forward pass, and that this change can be contrastively exploited to increase factuality in generated text.

While some of these methods are task-dependent, others like CD and DoLa (Chuang et al., 2023) are not. Recent work on emotion quantification (Sharma et al., 2023) showed that intermediate layer features can be used to quantify emotions and perform equivalent to the final classification layer. It is therefore natural to ask whether these methods can improve performance on fine-grained emotional classification.

Given the utility of intermediate network representations in capturing semantic meaning, as well as their centrality to DoLa, we explore the merits of layerwise contrastive inference for fine-grained emotional classification.

The main contributions of the paper are:

1. Demonstrating the merits of layer contrast on fine-tuned classifiers; in particular, for fine-grained emotion classification.

2. Improving stability of contrastive methods by reinterpreting contrastive inference as linear extrapolation to dynamically determine the strength of the contrastive penalty.

## 2 Knowledge pattern across layers

Fine-grained emotion analysis is a challenging classification task, as the labels are not mutually exclusive. Different emotions can have similar polarity yet have different meanings. Hence, it is difficult to learn a high probability against the correct emotion. Moreover, the class imbalance over emotions can further lead to bias towards more frequent emotions in data.

To study the change in probability distribution for emotions across layers, we performed early exiting on different layers of our fine-tuned models to visualize how the distributions across emotions evolve. We observed that for some emotions, the model makes a decision very early, passing it along the layers without much change. For others, the distribution tends to change in later layers, suggesting that the model is still adding information. We observed this pattern mostly around classes that are rarer in the training data or more closely related to each other. Figure 2 shows the change in distribution for two examples.

Drawing from these observations, we combine the idea of contrastive decoding and DoLa for fine-grained emotion analysis. We build on DoLa, using the early exited intermediate layers as amateur models. We then use contrastive action against the final layer distribution chosen as our expert model. Additionally, we deduce a method to dynamically select the contrastive strength which we show leads to better performance on fine-grained emotion tasks.

## 3 Related Work

*Fine-grained Emotion Analysis:* Much work has been done in identifying the sentiment of text (Rosenthal et al., 2017; Socher et al., 2013). Efforts have also been made to understand the emotions present in interactions on social media (Mohammad et al., 2018; Chatterjee et al., 2019; Meaney et al., 2021). However, most of this work focuses on a limited taxonomy of emotions. Recent datasets on fine-grained emotion analysis (Demszky et al., 2020; Rashkin et al., 2019) show that there is still a considerable scope for improvement in this area.

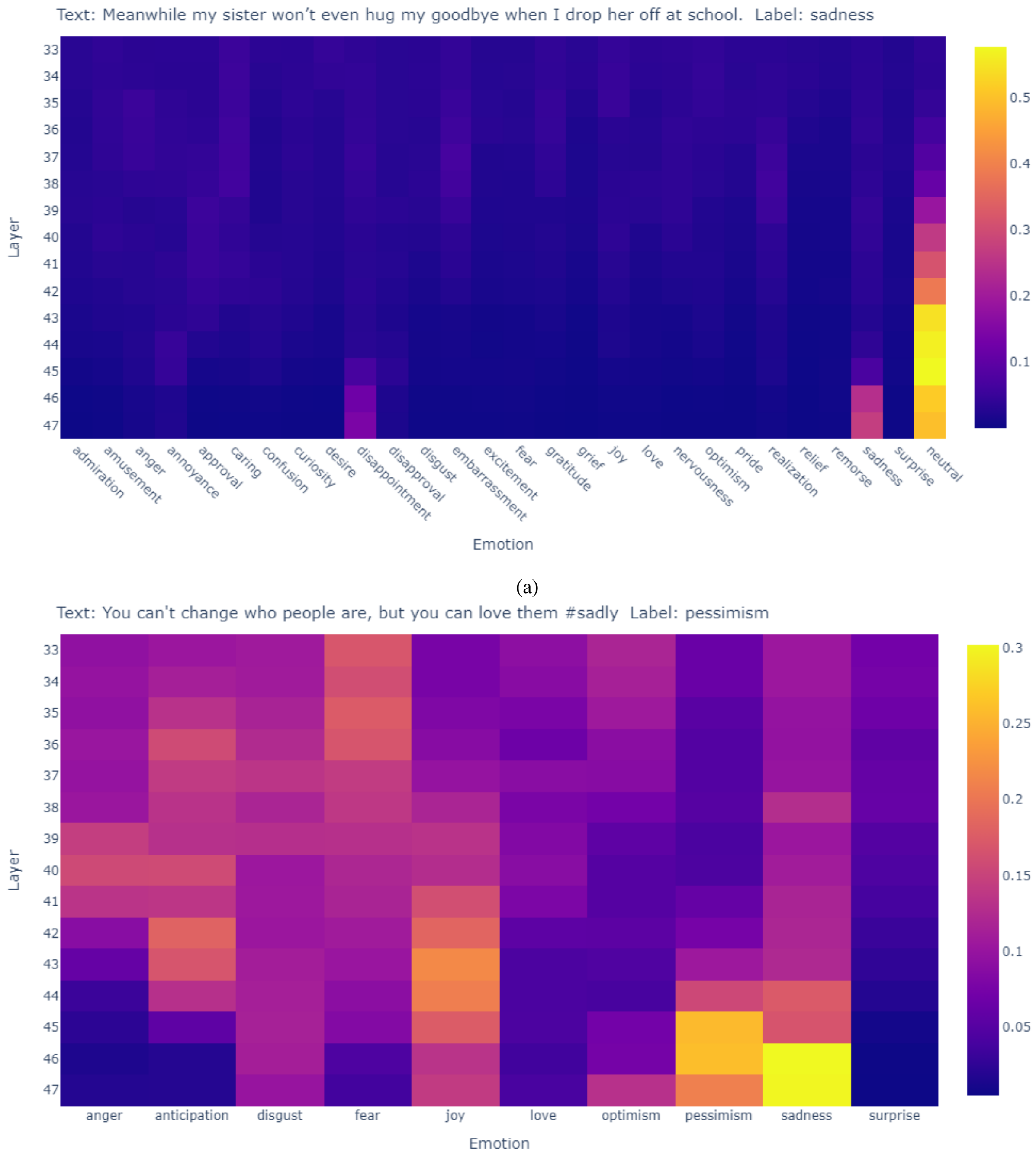
*Contrastive Steering:* Contrastive methods, which optimize the difference in predictions between a favorable “expert" and an unfavorable “amateur," have been shown to successfully steer text decoding in language models in a number of ways. (Liu et al., 2021)

GeDi (Krause et al., 2020) contrasts between class-specific control codes to improve text-conditioned factuality and emotion control. Coherence boosting (Malkin et al., 2021) provides the language model with only the final $k$ tokens of the prompt to obtain amateur scores, encouraging longer-term coherence over locality. Contrastive Decoding (Li et al., 2022; O’Brien and Lewis, 2023) improves long-form generation and reasoning ability by contrasting between large and small models of the same family. Other works use CD-like methods to reduce model toxicity, surface biases and increase faithfulness to a provided context. (Liu et al., 2021; Yona et al., 2023; Shi et al., 2023)

## 4 Method

### 4.1 Approach

Here we define the main components of CD and DoLa, as well as our proposed method to dynamically select contrastive strength. We use the



Text: Meanwhile my sister won't even hug my goodbye when I drop her off at school. Label: sadness

(a)

Text: You can't change who people are, but you can love them #sadly Label: pessimism

(b)

Figure 2: Probability distribution across the finetuned layers of DeBERTa-xl for a sample from each (a) goEmotions and (b) tweetEmotion dataset. In the goEmotions sample, the model initially identifies the label as neutral but increases the probabilities assigned to sadness and disappointment (the true label) over subsequent layers. For the tweetEmotion sample, the probability distribution changes across layers and the model fails to assign a high probability to a single emotion.

early exit probability distributions to select an amateur layer and contrast it against the final layer distribution chosen as our expert. We then apply the contrastive action on these distributions based on a plausibility constraint(used for filtering low-probability labels). Finally, we experiment with two different ways of deciding the contrastive strength(static $\beta$ and dynamic $\beta$). We discuss the details of each of these components next.

### 4.2 Contrastive Classification

We use the formulation of contrastive decoding defined by O'Brien and Lewis (2023). Let $p_a$ be the amateur probability scores and $p_e$ be the expert probability scores. We define the contrastive classification function as:

$$f_{CC}^{(i)} = \begin{cases} (1+\beta)\log p_e^i - \beta \log p_a^i & i \in \mathcal{V}_{valid} \\ -\infty & i \notin \mathcal{V}_{valid} \end{cases}$$

where $max(f_{CC}^{(i)})$ is taken as the correct label. $\beta$ here controls the strength of the contrastive penalty. $\mathcal{V}_{valid}$ is the adaptive plausibility constraint (Li et al., 2022) which defines the set of candidate classes on which contrastive action is applied. Let $p_e^c$ be the expert probability for class $c \in C$. Then $\mathcal{V}_{valid}$ is defined as:

$$\mathcal{V}_{valid} = \{\, c \in C,\, p_e^c \geq \alpha \max_{c \in C} p_e^c \,\}$$

$\alpha$ here is a hyperparameter that gates labels by the scores assigned to them by the expert, protecting against instabilities when dividing the scores of two low-probability candidates. Thus $\mathcal{V}_{valid}$ admits only high-probability labels defined using $\alpha$ ratio with the max probability token of the expert model helping avoid false negatives.

### 4.3 Dynamic premature layer selection

The central challenge with inference-time contrastive methods is the selection of a good amateur model. The model must be similar enough to the expert to model its error distribution, but not so powerful that desirable behavior is penalized.

Contrasting against early-exiting layers provides many potential amateurs to choose from. DoLa selects the “amateur" from a pre-validated set of earlier layers, selecting the one with the most different early-exit token distribution from the final predictions, as measured by Jensen-Shannon Divergence. In short, the amateur layer $\ell_a$ is chosen as follows:

$$\ell_a = \text{argmax}_{\ell \in L_{valid}} \text{dist}(\mathcal{P}(\ell), \mathcal{P}(\ell_{final}))$$

where $L_{valid}$ is the pre-validated set of layers, $\mathcal{P}$ maps a latent layer to its early-exited softmax distribution, and dist is some divergence metric between two probability distributions.

The original paper uses Jensen-Shannon Divergence (JSD) for this metric, but we find slightly better performance with cosine distance.

### 4.4 Linear Layer Extrapolation

Consider the classification of a single sample $x$ to $c \in \mathcal{C}$, where $\mathcal{C} := \{1, 2, \cdots, |\mathcal{C}|\}$. For this sample, let $f_c(i)$ be the un-normalized score assigned by the model to class $c$ by early-exiting at layer $i$. $f_c$ is defined over the discrete space $\mathcal{C}$.

Let $\ell_a$ be the index of the selected early-exit “amateur" layer, $\ell_f > \ell_a$ be the index of the final model layer, and $\ell_t$ be the layer where we would like to make predictions from. Note that $\ell_t$ need not be discrete.

Now let $\hat{f}_c$ be the linear function passing through $(\ell_a, f(\ell_a))$ and $(\ell_f, f(\ell_f))$.

$$\hat{f}_c(\ell) = f(\ell_f) + \left(\frac{f(\ell_f) - f(\ell_a)}{\ell_f - \ell_a}\right)(\ell - \ell_f)$$

Now we can compare this extrapolative form against the common form of contrastive decoding in order to solve for the contrastive strength, $\beta$.

$\hat{f}_c(\ell_t) = (1+\beta) f(\ell_f) - \beta f(\ell_a)$

Combining the two, we obtain

$$\beta = \frac{\ell_t - \ell_f}{\ell_f - \ell_a} \tag{1}$$

DoLa keeps $\beta$ fixed, implicitly allowing $\ell_t$ to vary based as different earlier layers $\ell_a$ are adaptively chosen. We find more stable performance by fixing $\ell_t$ and modifying $\beta$ based on the earlier chosen layer $\ell_a$, a process which we refer to as Linear Layer Extrapolation. Choosing an earlier layer will result in a reduced $\beta$ value, and vice versa.

## 5 Experimental Setup

### 5.1 Datasets

**goEmotions** (Demszky et al., 2020) introduces a new emotion taxonomy of emotions named goEmotions consisting of 28 emotions with neutral. The 27 emotion classes are fine-grained over 7 emotions defined in Ekman taxonomy. It contains roughly 58k samples overcoming the problems with earlier emotion datasets which were small in size and covered a very limited taxonomy. The dataset contained a few multilabel data-points, which we filter out for our experiments.

**SuperTweetEval** (Antypas et al., 2023) aims to provide a unified benchmark to evaluate the performance of models on NLP tasks across social media. It is a heterogeneous collection of multiple datasets spanning NER, QA, and classification. For our experiments, we use tweetEmotion and tweetHate focused on multi-class classification, with each dataset containing 12 and 8 classes.

**EmpatheticDialogues** (Rashkin et al., 2019) was introduced as a benchmark for training and evaluating models and their capability to understand and acknowledge empathetic text. The dataset contains conversations distributed across 32 emotions. We use the first text of the conversation and the corresponding emotion for defining our fine-grained classification task.

### 5.2 Evaluation metrics

We evaluate performance with precision, recall and F1 scores, all calculated as macro averages and suitable for class-imbalanced datasets.

### 5.3 Models

We conduct experiments with Flan-T5 (L, XL) (Chung et al., 2022) and DeBERTa (L, XL). (He et al., 2021) after finetuning them on each dataset independently. We finetuned DeBERTa-xlarge after freezing the initial layers (34/48); for DeBERTa-large, we finetuned all the layers. For Flan-T5, we finetuned both large and xlarge variants after freezing the first (14/24) layers. Finetuning Flan-T5 with layer freezing was more stable and led to better results. We used the Adam optimizer (Kingma and Ba, 2015) with learning rates ranging from 1e-6 to 5e-6 for DeBERTa and 1e-4 to 5e-4 for Flan-T5.

### 5.4 Decoding Hyperparameters:

*Amateur layer:* For selecting the amateur layer, we use the dynamic amateur layer selection as defined in Section 4.3. We restrict the amateur layer search space to only the finetuned layers. Let $L = \{\ell_k, \ell_{k+1}, \ell_{k+2}, \cdots, \ell_f\}$ be a subset of the finetuned layers, where $k$ is a hyperparameter defining the start of the search space and, $\ell_f$ is the final layer of the network. In our experiments, we sweep through the values of $k$ starting from the first finetuned layer and pick the one that results in the best performance. Results of the hyperparameter sweep can be found in Appendix A.

*Contrastive Strength ($\beta$):* We experiment with various fixed values of $\beta$ between 0 to 1, finding that the best $\beta$ varies over the selection of model and dataset. In general, values outside the range of $(0, 1)$ harmed performance.

*Dynamic Contrastive Strength ($\beta$):* As discussed in Section 4.4, the post-contrast output is equivalent to a linear extrapolation between the amateur and the expert layer for a future layer($\ell_t$). We use that idea to dynamically decide the value of contrastive strength $\beta$. We use $\ell_t$ as a hyperparameter and then calculate $\beta$ as a function of amateur layer $\ell_a$ and expert layer $\ell_f$, where $t \in (f, f + 25)$ in our experiments.

## 6 Results

Table 1 contains the results of our experiments. Next, we discuss the results in detail.

*Traditional vs Contrastive Classification*: We observe that contrastive classification improves the performance significantly in terms of Recall and F1 score. This trend holds for all models used in our experiments.

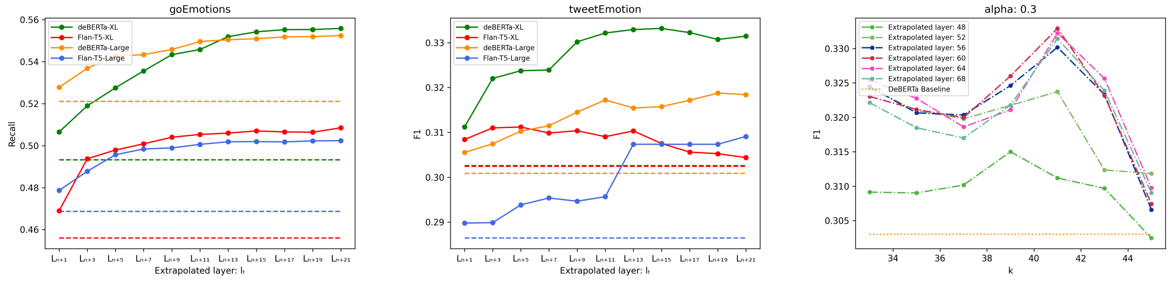
*$\beta$ vs Dynamic $\beta$*: Dynamic $\beta$ selection tends to improve the overall performance over the static $\beta$ for F1 and recall scores. Figure 3a shows the trend of recall scores across different models for dynamic $\beta$ selection on the goEmotions dataset. Figure 3b shows the trend of F1 score across different models against dynamic $\beta$ for the tweetEmotion dataset. Additionally, we observe that dynamic $\beta$ is more robust to changes in the hyperparameter $k$, which defines the start of the search space across earlier amateur layers. Figure 4 shows no clear or stable relationship between $k$ and end performance when varying $\beta$ values. However, switching to linear layer extrapolation creates a constant trend with minor variance as $k$ is varied, a trend that holds for multiple values of extrapolative layer $t$. This can be interpreted as stabilizing the contrastive method to be more robust to the dynamic choice of amateur layer.

*goEmotions*: For the goEmotions dataset, we see a general improvement across all models for the recall and F1 scores. Analysis showed that key improvement in recall was due to flipping of the *neutral* samples to other under-represented classes. Appendix B shows the statistics of the flipped labels.

*tweetEmotion*: Contrastive classification with dynamic $\beta$ performs significantly better over traditional classification. We see a general increase in recall and F1 with a slight harm to Precision. We also observed the emotions corrected by contrastive action were highly correlated. Appendix B contains more details about their statistics.

*tweetHate*: We see the maximum improvement in the performance of this dataset across all models. This improvement owes in large part to corrected predictions on underrepresented classes.

*EmpatheticDialogue*: For this dataset, we only see a slight increase in performance using the DeBERTa-xl model. Analyzing the probability



(a)

(b)

(c)

Figure 3: (a) Recall vs. $\ell_t$ on goEmotions; increasing the extrapolative strength improves recall. (b) F1 vs. $\ell_t$ on tweetEmotions exhibits a similar trend (c) F1 vs. $k$ for tweetEmotion using DeBERTa-xl; including layers 40 to 42 in the valid layers is found to be particularly useful.

| **Model** | **Type** | **EmpatheticDialogue** | | | **tweetHate** | | | **tweetEmotion** | | | **goEmotions** | | | **Avg. F1** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Precision | Recall | F1 | Precision | Recall | F1 | Precision | Recall | F1 | Precision | Recall | F1 | |
| Flan-T5-large | ✗ | .551 | .556 | .543 | .565 | .577 | .570 | .298 | .296 | .286 | .521 | .469 | .478 | .469 |
| Flan-T5-large | ✓ | .551 | .557 | .543 | .579 | .606 | .590 | .300 | .299 | .291 | .513 | .485 | .487 | .478 |
| Flan-T5-large | $\beta$ | .551 | .557 | .543 | .590 | .636 | .610 | .349 | .311 | .309 | .493 | .502 | .489 | .488 |
| Flan-T5-xl | ✗ | .582 | .569 | .565 | .566 | .566 | .559 | .320 | .300 | .302 | .503 | .456 | .465 | .473 |
| Flan-T5-xl | ✓ | .581 | .570 | .565 | .690 | .603 | .615 | .318 | .314 | .313 | .499 | .494 | .486 | .495 |
| Flan-T5-xl | $\beta$ | .582 | .570 | .565 | .695 | .605 | .619 | .316 | .314 | .313 | .513 | .494 | .490 | .497 |
| DeBERTa-large | ✗ | .614 | .601 | .592 | .647 | .601 | .622 | .322 | .299 | .301 | **.570** | .521 | .534 | .512 |
| DeBERTa-large | ✓ | .616 | .606 | .597 | .676 | .643 | .658 | .313 | .311 | .308 | .562 | .536 | .540 | .526 |
| DeBERTa-large | $\beta$ | **.618** | .609 | .601 | .708 | .675 | **.690** | .312 | .331 | .319 | .558 | .543 | **.541** | **.538** |
| DeBERTa-xl | ✗ | .604 | .605 | .590 | .607 | .596 | .599 | .324 | .300 | .303 | .529 | .493 | .502 | .498 |
| DeBERTa-xl | ✓ | .610 | .606 | .594 | **.727** | .668 | .686 | **.335** | .324 | .325 | .509 | .530 | .514 | .523 |
| DeBERTa-xl | $\beta$ | .614 | **.609** | **.597** | .725 | **.668** | .685 | .333 | **.340** | **.334** | .505 | **.555** | .522 | .535 |

Table 1: Results of our experiments. ✗, ✓, and $\beta$ each represent normal classification, static $\beta$, and dynamic $\beta$

distributions across layers, we observed no major change in probability distribution for different emotions across layers. The probability was distributed over a single label, increasing gradually across layers. This led to minimal contribution from the contrastive action.

*Effect of amateur layer selection:* We use a bucket of layers for amateur layer selection defined by hyperparameter $k$. Figure 3c shows the trend of $k$ against F1 using the DeBERTa-xl for tweetEmotions dataset. We observe that the performance generally increases up to a layer where the benefit of contrastive action is maximum, followed by a drop in performance. Upon evaluating early-exiting on intermediate layers, we observed that some layers are more adept at identifying specific classes than others, providing a variety of skills to contrast against for improved performance.

## 7 Conclusion

We introduce the linear extrapolation view of layerwise contrastive decoding as a method for dynamically choosing the contrastive strength. We successfully extend this idea to fine-grained emotion classification tasks, finding that contrastive classification combined with dynamic $\beta$ selection improves classifier performance by better selecting under-represented classes. This strengthens the promise of layer-contrast methods in domains other than text generation, and provides a technical contribution that reduces the variance of the method with respect to a core hyperparameter $k$, encouraging further research into how best to exploit the layerwise emergence of textual understanding to improve performance on a wide range of NLP tasks.

## 8 Limitations

Our study is restricted to fine-grained emotion classification with relatively small models (FLAN-T5 and DeBERTa). It remains to be seen whether our analysis of extrapolative classification will hold for prompt-based classification with larger models or across other datasets. We also found the contrastive action for smaller models sensitive to finetuning hyperparameters. Additionally, based on our results on EmpatheticDialogue we observe that CD tends to work better when model uncertainty is high i.e. probability distribution across labels changes more often across layers as shown in Figure 2. Extending the method to identify and better handle these cases is left to future work.

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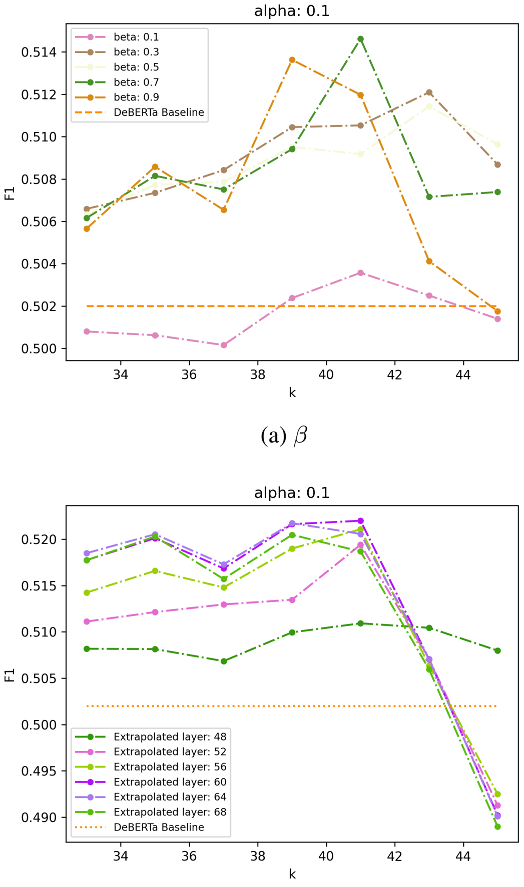
## A Hyperparameter Sweep for $k$

Table 2 contains the values of hyperparameter $k$ used for reporting the results. We also show the effect of $k$ on performance for the goEmotions dataset using both $\beta$ and dynamic $\beta$ in Figure 4.

| Model | goEmotions | tweetEmotion | tweetHate | Empathetic Dialogue |
|---|---|---|---|---|
| Flan-T5-large | 19 | 20 | 17 | 15 |
| Flan-T5-xl | 15 | 15 | 17 | 15 |
| DeBERTa-large | 15 | 19 | 17 | 19 |
| DeBERTa-xl | 39 | 41 | 38 | 43 |

Table 2: Our choice of hyperparameter $k$ for defining the amateur search space used in the final results. The final layer is 48 for DeBERTa-xl and 23 for the remaining models.



(a) $\beta$

(b) Dynamic $\beta$

Figure 4: Effect of $k$ against $\beta$ and dynamic $\beta$ for goEmotions dataset using DeBERTa-xlarge. The trend is more stable with dynamic $\beta$.

## B Analysis of corrected samples

Table 3 shows the frequency of correctly flipped samples (true positives) vs. correctly flipped samples (positives) from the neutral class (wrongly predicted as neutral). We observe that neutral forms the majority of samples flipped to other underrepresented classes. Table 4 contains the count of emotions that were correctly flipped from neutral.

| Model | Total | Neutral |
|---|---|---|
| Flan-T5-large | 105 | 80/105 |
| Flan-T5-xl | 72 | 57/72 |
| DeBERTa-large | 74 | 51/74 |
| DeBERTa-xl | 164 | 130/164 |

Table 3: Count of correctly flipped samples (all emotions classes) vs. correctly flipped samples only from the neutral class.

| From | To | Count |
|---|---|---|
| neutral | disapproval | 22 |
| neutral | curiosity | 19 |
| neutral | annoyance | 13 |
| neutral | admiration | 12 |
| neutral | approval | 11 |

Table 4: Count of samples moved from neutral to other classes for goEMotions using DeBERTa-xl.

We also report the most frequent samples corrected for the tweetEmotion dataset using contrastive action (dynamic $\beta$). We see that the emotions for the pair of corrected samples were highly correlated.

| Model | Emotion |
|---|---|
| Flan-T5-large | sadness ↦ pessimism: 7<br>joy ↦ anticipation: 6 |
| Flan-T5-xl | sadness ↦ pessimism: 19<br>anger ↦ disgust: 17 |
| deBERTa-large | anger ↦ disgust: 15<br>joy ↦ anticipation: 8 |
| deBERTa-xl | sadness ↦ pessimism: 20<br>joy ↦ optimism: 7 |

Table 5: Count of top 2 emotion pairs that were contrastively flipped for each model.

## C Computational Resources Estimate

Early compute was run on freely available Cloud T4 GPUs. Fine-tuning and later experiments were run on a cluster of A6000 GPUs, with a maximum of 8 used at a single time.

Fine-tuning all models across all datasets takes roughly 2 GPU-hours. Hyperparameter searches are performed at classification time, which takes very little compute. A very rough estimate for GPU-hours in this project is 50.