Analyzing Transformers in Embedding Space

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Abstract

Understanding Transformer-based models has attracted significant attention, as they lie at the heart of recent technological advances across machine learning. While most interpretability methods rely on running models over inputs, recent work has shown that an input-independent approach, where parameters are interpreted directly without a forward/backward pass is feasible for some Transformer parameters, and for two-layer attention networks. In this work, we present a conceptual framework where all parameters of a trained Transformer are interpreted by projecting them into the embedding space, that is, the space of vocabulary items they operate on. Focusing mostly on GPT-2 for this paper, we provide diverse evidence to support our argument. First, an empirical analysis showing that parameters of both pretrained and fine-tuned models can be interpreted in embedding space. Second, we present two applications of our framework: (a) aligning the parameters of different models that share a vocabulary, and (b) constructing a classifier without training by “translating” the parameters of a fine-tuned classifier to parameters of a different model that was only pretrained. Overall, our findings show that at least in part, we can abstract away model specifics and understand Transformers in the embedding space.

1 Introduction

Transformer-based models [Vaswani et al., 2017] currently dominate Natural Language Processing [Devlin et al., 2018; Radford et al., 2019; Zhang et al., 2022] as well as many other fields of machine learning [Dosovitskiy et al., 2020; Chen et al., 2020; Baevski et al., 2020]. Consequently, understanding their inner workings has been a topic of great interest. Typically, work on interpreting Transformers relies on feeding inputs to the model and analyzing the resulting activations [Adi et al., 2016; Shi et al., 2016; Clark et al., 2019]. Thus, interpretation involves an expensive forward, and sometimes also a backward pass, over multiple inputs. Moreover, such interpretation methods are conditioned on the input and are not guaranteed to generalize to all inputs. In the evolving literature on static interpretation, i.e., without forward or backward passes, [Geva et al., 2022b] showed that the value vectors of the Transformer feed-forward module (the second layer of the feed-forward network) can be interpreted by projecting them into the embedding space, i.e., multiplying them by the embedding matrix to obtain a representation over vocabulary items. [Elhage et al., 2021] have shown that in a 2-layer attention network, weight matrices can be interpreted in the embedding space as well. Unfortunately, their innovative technique could not be extended any further.

In this work, we extend and unify the theory and findings of [Elhage et al., 2021] and [Geva et al., 2022b]. We present a zero-pass, input-independent framework to understand the behavior of Transformers. Concretely, we interpret all weights of a pretrained language model (LM) in embedding space, including both keys and values of the feed-forward module ([Geva et al., 2020, 2022b] considered just FF values) as well as all attention parameters ([Elhage et al., 2021] analyzed simplified architectures up to two layers of attention with no MLPs).

Our framework relies on a simple observation. Since [Geva et al., 2022b] have shown that one can project hidden states to the embedding space via the embedding matrix, we intuit this can be extended to other parts of the model by projecting to the embedding space and then projecting back by multiplying with a right-inverse of the embedding matrix. Thus, we can recast inner products in the model as inner products in embedding space. Viewing inner products this way, we can interpret such products as interactions between pairs of vocabulary items. This applies to (a) interactions between attention queries and keys as well as to (b) interactions between attention value vectors and the parameters that project them at the output of the attention module. Taking this perspective to the extreme, one can view Transformers as operating implicitly in the embedding space. This entails the existence of a single linear space that depends only on the tokenizer,

1We refer to the unique items of the vocabulary as vocabulary items, and to the (possibly duplicate) elements of a tokenized input as tokens. When clear, we might use the term token for vocabulary item.
in which parameters of different Transformers can be compared. Thus, one can use the embedding space to compare and transfer information across different models that share a tokenizer.

We provide extensive empirical evidence for the validity of our framework, focusing mainly on GPT-2 medium [Radford et al., 2019]. We use GPT-2 for two reasons. First, we do this for concreteness, as this paper is mainly focused on introducing the new framework and not on analyzing its predictions. Second, and more crucially, unlike many other architectures (such as BERT [Devlin et al., 2018], RoBERTa [Liu et al., 2019], and T5 [Raffel et al., 2019]), the GPT family has a linear language modeling head (LM head) – which is simply the output embedding matrix. All the other architectures’ LM heads are two layer networks that contain non-linearities before the output embedding matrix. Our framework requires a linear language modeling head to work. That being said, we believe in practice this will not be a major obstacle, and we indeed see in the experiments that model alignment works well for BERT in spite of the theoretical difficulties. We leave the non-linearities in the LM head for future work.

On the interpretation front (Fig. 1, Left), we provide qualitative and quantitative evidence that Transformer parameters can be interpreted in embedding space. We also show that when fine-tuning GPT-2 on a sentiment analysis task (over movie reviews), projecting changes in parameters into embedding space yields words that characterize sentiment towards movies. Second (Fig. 1, Center), we show that given two distinct instances of BERT pretrained from different random seeds [Sellam et al., 2022], we can align layers of the two instances by casting their weights into the embedding space. We find that indeed layer $i$ of the first instance aligns well to layer $i$ of the second instance, showing the different BERT instances converge to a semantically similar solution. Last (Fig. 1, Right), we take a model fine-tuned on a sentiment analysis task and “transfer” the learned weights to a different model that was only pretrained by going through the embedding spaces of the two models. We show that in 30% of the cases, this procedure, termed stitching, results in a classifier that reaches an impressive accuracy of 70% on the IMDB benchmark [Maas et al., 2011] without any training.

Overall, our findings suggest that analyzing Transformers in embedding space is valuable both as an interpretability tool and as a way to relate different models that share a vocabulary and that it opens the door to interpretation methods that operate in embedding space only. Our code is available at https://github.com/guyd1995/embedding-space.

2 Background

We now present the main components of the Transformer [Vaswani et al., 2017] relevant to our analysis. We discuss the residual stream view of Transformers, and recapitulate a view of the attention layer parameters as interaction matrices $W_{VO}$ and $W_{VK}$ [Elhage et al., 2021]. Similar to them, we exclude biases and layer normalization from our analysis.

2.1 Transformer Architecture

The Transformer consists of a stack of layers, each includes an attention module followed by a Feed-Forward (FF) module. All inputs and outputs are sequences of $N$ vectors of dimensionality $d$. 
Attention Module takes as input a sequence of representations $X \in \mathbb{R}^{N \times d}$, and each layer $L$ is parameterized by four matrices $W_Q^L, W_K^L, W_V^L, W_O^L \in \mathbb{R}^{d \times d}$ (we henceforth omit the layer superscript for brevity). The input $X$ is projected to produce queries, keys, and values: $Q_{att} = XW_Q, K_{att} = XW_K, V_{att} = XW_V$. Each one of $Q_{att}, K_{att}, V_{att}$ is split along the columns to $H$ different heads of dimensionality $\mathbb{R}^{N \times \hat{H}}$, denoted by $Q_{att}^i, K_{att}^i, V_{att}^i$ respectively. We then compute $H$ attention maps:

$$A^i = \text{softmax} \left( \frac{Q_{att}^iK_{att}^iT}{\sqrt{d/\hat{H}}} + M \right)$$

where $M \in \mathbb{R}^{N \times N}$ is the attention mask. Each attention map is applied to the corresponding value head as $A^iV_{att}^i$, results are concatenated along columns and projected via $W_O$. The input to the module is added via a residual connection, and thus the attention module’s output is:

$$X + \text{Concat} \left[ A^1V_{att}^1, \ldots, A^iV_{att}^i, \ldots, A^HV_{att}^H \right] W_O.$$  

(1)

FF Module is a two-layer neural network, applied to each position independently. Following past terminology [Sukhbaatar et al., 2019; Geva et al., 2020], weights of the first layer are called FF keys and weights of the second layer FF values. This is an analogy to attention, as the FF module too can be expressed as: $f(QK^TV)$, where $f$ is the activation function, $Q \in \mathbb{R}^{N \times d}$ is the output of the attention module and the input to the FF module, and $K, V \in \mathbb{R}^{d \times d}$ are the weights of the first and second layers of the FF module. Unlike attention, keys and values are learnable parameters. The output of the FF module is added to the output of the attention module to form the output of the layer via a residual connection. The output of the $i$-th layer is called the $i$-th hidden state.

Embedding Matrix To process sequences of discrete tokens, Transformers use an embedding matrix $E \in \mathbb{R}^{d \times d}$ that provides a $d$-dimensional representation to vocabulary items before entering the first Transformer layer. In different architectures, including GPT-2, the same embedding matrix $E$ is often used [Press and Wolf, 2016] to take the output of the last Transformer layer and project it back to the vocabulary dimension, i.e., into the embedding space. In this work, we show how to interpret all the components of the Transformer model in the embedding space.

2.2 The Residual Stream

We rely on a useful view of the Transformer through its residual connections popularized by [Elhage et al., 2021]. Specifically, each layer takes a hidden state as input and adds information to the hidden state through its residual connection. Under this view, the hidden state is a residual stream passed along the layers, from which information is read, and to which information is written at each layer. [Elhage et al., 2021] and [Geva et al., 2022a] observed that the residual stream is often barely updated in the last layers, and thus the final prediction is determined in early layers and the hidden state is mostly passed through the later layers.

An exciting consequence of the residual stream view is that we can project hidden states in every layer into embedding space by multiplying the hidden state with the embedding matrix $E$, treating the hidden state as if it were the output of the last layer. [Geva et al., 2022a] used this approach to interpret the prediction of Transformer-based language models, and we follow a similar approach.

2.3 $W_{QK}$ and $W_{VO}$

Following [Elhage et al., 2021], we describe the attention module in terms of interaction matrices $W_{QK}$ and $W_{VO}$ which will be later used in our mathematical derivation. The computation of the attention module (§2.1) can be re-interpreted as follows. The attention projection matrices $W_Q, W_K, W_V$ can be split along the column axis to $H$ equal parts denoted by $W_Q^i, W_K^i, W_V^i \in \mathbb{R}^{d \times \hat{H}}$ for $1 \leq i \leq H$. Similarly, the attention output matrix $W_O$ can be split along the row axis into $H$ heads, $W_O^i \in \mathbb{R}^{\hat{H} \times d}$. We define the interaction matrices as

$$W_{QK}^i := W_Q^iW_K^iT \in \mathbb{R}^{d \times d},$$

$$W_{VO}^i := W_V^iW_O^iT \in \mathbb{R}^{d \times d}.$$  

Importantly, $W_{QK}^i, W_{VO}^i$ are input-independent. Intuitively, $W_{QK}$ encodes the amount of attention between pairs of tokens. Similarly, in $W_{VO}^i$, the matrices $W_V$ and $W_O$ can be viewed as a transition matrix that determines how attending to certain tokens affects the subsequence hidden state.

We can restate the attention equations in terms of the interaction matrices. Recall (Eq. 1) that the output of the $i$‘th head of the attention module is $A^iV_{att}^i$ and the final output of the attention module is (without the residual connection):

$$\text{Concat} \left[ A^1V_{att}^1, \ldots, A^iV_{att}^i, \ldots, A^HV_{att}^H \right] W_O =$$

$$\sum_{i=1}^H A^i(XW_{QK}^i)W_{VO}^i = \sum_{i=1}^H A^iXW_{VO}^i.$$  

Similarly, the attention map $A^i$ at the $i$‘th head in terms of $W_{QK}$ is (softmax is done row-wise):

$$A^i = \text{softmax} \left( \frac{(XW_Q^i)(XW_K^iT)}{\sqrt{d/\hat{H}}} + M \right)$$

$$= \text{softmax} \left( X(W_{QK}^iX^T) + M \right).$$  

$^{2}$Originally introduced in [nostalgebraist, 2020].
3 Parameter Projection

In this section, we propose that Transformer parameters can be projected into embedding space for interpretation purposes. We empirically support our framework’s predictions in §4–§5.

Given a matrix $A \in \mathbb{R}^{N \times d}$, we can project it into embedding space by multiplying by the embedding matrix $E$ as $A = AE \in \mathbb{R}^{N \times e}$. Let $E'$ be a right-inverse of $E$, that is, $EE' = I \in \mathbb{R}^{d \times d}$. We can reconstruct the original matrix with $E'$ as $A = A(EE') = AE'$. We will use this simple identity to reinterpret the model’s operation in embedding space. To simplify our analysis we ignore LayerNorm and biases. This has been justified in prior work [Eilamge et al., 2021]. Briefly, LayerNorm can be ignored because normalization changes only magnitudes and not the direction of the update. At the end of this section, we discuss why in practice we choose to use $E' = E^T$ instead of a seemingly more appropriate right inverse, such as the pseudo-inverse [Moore, 1920; Bjerhammer, 1951; Penrose, 1955]. In this section, we derive our framework and summarize its predictions in Table 1.

**Attention Module** Recall that $W_{VQ} := W_V W_Q \in \mathbb{R}^{d \times d}$ is the interaction matrix between attention values and the output projection matrix for attention head $i$. By definition, the output of each head is: $A^i X W_{VQ}^i = A^i \hat{X} E' W_{VQ}$. Since the output of the attention module is added to the residual stream, we can assume according to the residual stream view that it is meaningful to project it to the embedding space, similar to FF values. Thus, we expect the sequence of $N$ $d$-dimensional vectors $(A^i X W_{VQ}^i)E = A^i \hat{X} (E W_{VQ}^i)E$ to be interpretable. Importantly, the role of $A^i$ is just to mix the representations of the updated $N$ input vectors. This is similar to the FF module, where FF values (the parameters of the second layer) are projected into embedding space, and FF keys (parameters of the first layer) determine the coefficients for mixing them. Hence, we can assume that the interpretable components are in the term $\hat{X} (E W_{VQ}^i)$. Zoning in on this operation, we see that it takes the previous hidden state in the embedding space ($\hat{X}$) and produces an output in the embedding space which will be incorporated into the next hidden state through the residual stream. Thus, $E W_{VQ}^i E$ is a transition matrix that takes a representation of the embedding space and outputs a new representation in the same space.

Similarly, the matrix $W_{QK}^i$ can be viewed as a bilinear map (Eq. 2.3). To interpret it in embedding space, we perform the following operation with $E'$:

$$X W_{QK}^i X^T = (X E E') W_{QK} (X E E')^T = (X E) E' W_{QK}^i E'^T (X E)^T = \hat{X} (E W_{QK}^i E'^T) \hat{X}^T.$$ 

Therefore, the interaction between tokens at different positions is determined by an $e \times e$ matrix that expresses the interaction between pairs of vocabulary items.

**FF Module** [Geva et al., 2022b] showed that FF value vectors $V \in \mathbb{R}^{d_\text{ff} \times d}$ are meaningful when projected into embedding space, i.e., for a FF value vector $v \in \mathbb{R}^d$, $v E \in \mathbb{R}^e$ is interpretable (see §2.1). In vectorized form, the rows of $V E \in \mathbb{R}^{d_\text{ff} \times e}$ are interpretable. On the other hand, the keys $K$ of the FF layer are multiplied on the left by the output of the attention module, which are the queries of the FF layer. Denoting the output of the attention module by $Q$, we can write this product as $Q K^T = Q E^T K^T = Q (K E^T)^T$. Because $Q$ is a hidden state, we assume according to the residual stream view that $Q$ is interpretable in embedding space. When multiplying $Q$ by $K E^T$, we are capturing the interaction in embedding space between each query and key, and thus expect $K E^T$ to be interpretable in embedding space as well.

Overall, FF keys and values are intimately connected – the $i$-th key controls the coefficient of the $i$-th value, so we expect their interpretation to be related. While not central to this work, we empirically show that key-value pairs in the FF module are similar in embedding space in Appendix B.1.

**Subheads** Another way to interpret the matrices $W_{VQ}$ and $W_{QK}$ is through the subhead view. We use the following identity: $AB = \sum_{j=1}^{a} A_{i,j} B_{j,:}$, which holds for arbitrary matrices $A \in \mathbb{R}^{a \times b}, B \in \mathbb{R}^{b \times c}$, where $A_{i,j}$ are the columns of the matrix $A$ and $B_{j,:} \in \mathbb{R}^{1 \times c}$ are the rows of the matrix $B$. Thus, we can decompose $W_{VQ}$ and $W_{QK}$ into a sum of $d$ rank-1 matrices:

$$W_{VQ}^i = \sum_{j=1}^{d} W_{VQ}^i W_{OQ}^j W_{QK}^j,$$

where $W_{VQ}^i, W_{QK}^j, W_{QV}^i \in \mathbb{R}^{d \times 1}$ are columns of $W_{VQ}^i, W_{QK}^j, W_{QV}^i$ respectively, and $W_{OQ}^j \in \mathbb{R}^{1 \times d}$ are the rows of $W_{OQ}^i$. We call these vectors subheads. This view is useful since it allows us to interpret subheads directly by multiplying them with the embedding matrix $E$. Moreover, it shows a parallel between interaction matrices in the attention module and the FF module. Just like the FF module includes key-value pairs as described above, for a given head, its interaction matrices are a sum of interactions between pairs of subheads (indexed by $j$), which are likely to be related in embedding space. We show this is indeed empirically the case for pairs of subheads in Appendix B.1.

**Choosing $E' = E^T$** In practice, we do not use an exact right inverse (e.g. the pseudo-inverse). We use the transpose of the embedding matrix $E' = E^T$ instead. The reason pseudo-inverse doesn’t work is that for interpretation we apply a top-$k$ operation after projecting to embedding space (since it is impractical for humans to read through a sorted list of $50K$ tokens). So, we only keep the list of the vocabulary items that have the $k$ largest logits, for manageable values of $k$. 

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1. $E'$ exists if $d \leq e$ and $E$ is full-rank.
In Appendix A, we explore the exact requirements for \( E' \) to interact well with top-\( k \). We show that the top \( k \) entries of a vector projected with the pseudo-inverse do not represent the entire vector well in embedding space. We define \textit{keep-\( k \) robust invertibility} to quantify this. It turns out that empirically \( E^T \) is a decent \textit{keep-\( k \) robust inverse} for \( E \) in the case of GPT-2 medium (and similar models) for plausible values of \( k \). We refer the reader to Appendix A for details.

To give intuition as to why \( E^T \) works in practice, we switch to a different perspective, useful in its own right. Consider the FF keys for example – they are multiplied on the left by the hidden states. In this section, we suggested to re-cast this as \( h^T K = (h^T E)(E'K) \). Our justification was that the hidden state is interpretable in the embedding space. A related perspective (dominant in previous works too; e.g. [Mickus et al., 2022]) is thinking of the hidden state as an aggregation of interpretable updates to the residual stream. That is, schematically, \( h = \sum_{i=1}^{h} \alpha_i r_i \), where \( \alpha_i \) are scalars and \( r_i \) are vectors corresponding to specific concepts in the embedding space (we roughly think of a concept as a list of tokens related to a single topic). Inner product is often used as a similarity metric between two vectors. If the similarity between a column \( K \) and \( h \) is large, the corresponding \( i \)-th output coordinate will be large. Then we can think of \( K \) as a detector of concepts where each neuron (column in \( K \)) lights up if a certain concept is “present” (or a superposition of concepts) in the inner state. To understand which concepts each detector column encodes we see which tokens it responds to. Doing this for all (input) token embeddings and packaging the inner products into a vector of scores is equivalent to simply multiplying by \( E^T \) on the left (where \( E \) is the input embedding in this case, but for GPT-2 they are the same). A similar argument can be made for the interaction matrices as well. For example for \( W_{VO} \) to understand if a token embedding \( e_i \) maps to a \( e_j \) under a certain head, we apply the matrix to \( e_i \), getting \( e^T_i W_{VO} \) and use the inner product as a similarity metric and get the score \( e^T_i W_{VO} e_j \).

### 4 Interpretablility Experiments

In this section, we provide empirical evidence for the viability of our approach as a tool for interpreting Transformer parameters. For our experiments, we use Huggingface Transformers ([Wolf et al., 2020]; License: Apache-2.0).

#### 4.1 Parameter Interpretation Examples

**Attention Module** We take GPT-2 medium (345M parameters; [Radford et al., 2019]) and manually analyze its parameters. GPT-2 medium has a total of 384 attention heads (24 layers and 16 heads per layer). We take the embedded transition matrices \( E'W_{VO}E \) for all heads and examine the top-\( k \) pairs of vocabulary items. As there are only 384 heads, we manually choose a few heads and present the top-\( k \) pairs in Appendix C.1 (\( k = 50 \)). We observe that different heads capture different types of relations between pairs of vocabulary items including word parts, heads that focus on gender, geography, orthography, particular part-of-speech tags, and various semantic topics. In Appendix C.2 we perform a similar analysis for \( W_{QK} \). We supplement this analysis with a few examples from GPT-2 base and large (117M, 762M parameters – respectively) as proof of concept, similarly presenting interpretable patterns.

A technical note: \( W_{VO} \) operates on row vectors, which means it operates in a “transposed” way to standard intuition – which places inputs on the left side and outputs on the right side. It does not affect the theory, but when visualizing the top-\( k \) tuples, we take the transpose of the projection \( (E'W_{VO}E)^T \) to get the “natural” format (input token, output token). Without the transpose, we would get the same tuples, but in the format (output token, input token). Equivalently, in the terminology of linear algebra, it can be seen as a linear transformation that we represent in the basis of row vectors and we transform to the basis of column vectors, which is the standard one.

**FF Module** Appendix C.3 provides examples of key-value pairs from the FF modules of GPT-2 medium. We show random pairs \((k, v)\) from the set of those pairs such that when looking at the top-100 vocabulary items for \( k \) and \( v \), at least 15% overlap. Such pairs account for approximately 5% of all key-value pairs. The examples show how key-value pairs often revolve around similar topics such as media, months, organs, etc. We again include additional examples from GPT-2 base and large.

**Knowledge Lookup** Last, we show we can use embeddings to locate FF values (or keys) related to a par-
ticular topic. We take a few vocabulary items related to a certain topic, e.g., [‘cm’, ‘kg’, ‘inches’], average their embeddings,\(^4\) and rank all FF values (or keys) based on their dot-product with the average. Appendix C.4 shows a few examples of FF values found with this method that are related to programming, measurements, and animals.

4.2 Hidden State and Parameters

One merit of zero-pass interpretation is that it does not require running inputs through the model. Feeding inputs might be expensive and non-exhaustive. In this section and in this section only, we run a forward pass over inputs and examine if the embedding space representations of dynamically computed hidden states are “similar” to the representations of the activated static parameter vectors. Due to the small number of examples we run over, the overall GPU usage is still negligible.

A technical side note: we use GPT-2, which applies LayerNorm to the Transformer output before projecting it to the embedding space with \(E\). Thus, conservatively, LayerNorm should be considered as part of the projection operation. Empirically, however, we observe that projecting parameters directly without LayerNorm works well, which simplifies our analysis in §3. Unlike parameters, we apply LayerNorm to hidden states before projection to embedding space to improve interpretability. This nuance was also present in the code of [Geva et al., 2022a].

**Experimental Design** We use GPT-2 medium and run it over 60 examples from IMDB (25,000 train, 25,000 test examples; [Maas et al., 2011]).\(^5\) This provides us with a dynamically-computed hidden state \(h\) for every token and at the output of every layer. For the projection \(\hat{h} \in \mathbb{R}^c\) of each such hidden state, we take the projections of the \(m\) most active parameter vectors \(\{\hat{x}_i\}_{i=1}^m\) in the layer that computed \(h\) and check if they cover the dominant vocabulary items of \(\hat{h}\) in embedding space. Specifically, let \(\text{top-k}(wE)\) be the \(k\) vocabulary items with the largest logits in embedding space for a vector \(w \in \mathbb{R}^d\). We compute:

\[
R_k(\hat{x}_1, ..., \hat{x}_m, \hat{h}) = \frac{|\text{top-k}(\hat{h}) \cap \bigcup_{i=1}^m \text{top-k}(\hat{x}_i)|}{k},
\]

to capture if activated parameter vectors cover the main vocabulary items corresponding to the hidden state.

We find the \(m\) most active parameter vectors separately for FF keys \((K)\), FF values \((V)\), attention value subheads \((W_v)\) (see §3), and attention output subheads \((W_o)\), where the activation of each parameter vector is determined by the vector’s “coefficient” as follows. For a FF key-value pair \((k, v)\) the coefficient is \(\sigma(q^T k)\), where \(q \in \mathbb{R}^d\) is an input to the FF module, and \(\sigma\) is the FF non-linearity. For attention, value-output subhead pairs \((v, o)\) the coefficient is \(x^Tv\), where \(x\) is the

\(^4\)We subtract the average embedding \(\mu\) from \(E\) before averaging, which improves interpretability.

\(^5\)Note that IMDB was designed for sentiment analysis and we use it here as a general-purpose corpus.
input to this component (for attention head $i$, the input is one of the rows of $A^t X$, see Eq. 3).

**Results and Discussion**  Figure 2 presents the $R_k$ score averaged across tokens per layer. As a baseline, we compare $R_k$ of the activated vectors $\{\hat{x}_i\}_{i=1}^m$ of the correctly-aligned hidden state $h$ at the output of the relevant layer (blue bars) against the $R_k$ when randomly sampling $h_{\text{rand}}$ from all the hidden states (orange bars). We conclude that representations in embedding space induced by activated parameter vector mirror, at least to some extent, the representations of the hidden states themselves. Appendix §B.2 shows a variant of this experiment, where we compare activated parameters throughout GPT-2 medium’s layers to the last hidden state, which produces the logits used for prediction.

4.3 Interpretation of Fine-tuned Models

We now show that we can interpret the changes a model goes through during fine-tuning through the lens of embedding space. We fine-tune the top-3 layers of the 12-layer GPT-2 base (117M parameters) with a sequence classification head on IMDB sentiment analysis (binary classification) and compute the difference between the original parameters and the fine-tuned model. We then project the difference of parameter vectors into embedding space and test if the change is interpretable w.r.t. sentiment analysis.

Appendix D shows examples of projected differences randomly sampled from the fine-tuned layers. Frequently, the difference its negation is projected to nouns, adjectives, and adverbs that express sentiment for a movie, such as ‘amazing’, ‘masterpiece’, ‘incompetence’, etc. This shows that the differences are indeed projected into vocabulary items that characterize movie reviews’ sentiments. This behavior is present across $W_Q, W_K, W_V, K$, but not $V$ and $W_O$, which curiously are the parameters added to the residual stream and not the ones that react to the input directly.

5 Aligning Models in Embedding Space

The assumption Transformers operate in embedding space leads to an exciting possibility – we can relate different models to one another so long as they share the vocabulary and tokenizer. In §5.1, we show that we can align the layers of BERT models trained with different random seeds. In §5.2, we show the embedding space can be leveraged to “stitch” the parameters of a fine-tuned model to a model that was not fine-tuned.

5.1 Layer Alignment

**Experimental Design**  Taking our approach to the extreme, the embedding space is a universal space, which depends only on the tokenizer, in which Transformer parameters and hidden states reside. Thus, we can align parameter vectors from different models in this space and compare them even if they come from different models, as long as they share a vocabulary.

To demonstrate this, we use MultiBERTs ([Sellam et al., 2022]; License: Apache-2.0), which contains 25 different instantiations of BERT-base (110M parameters) initialized from different random seeds. We take parameters from two MultiBERT seeds and compute the correlation between their projections to embedding space. For example, let $V_A, V_B$ be the FF values of models $A$ and $B$. We can project the values into embedding space: $V_A E_A, V_B E_B$, where $E_A, E_B$ are the respective embedding matrices, and compute Pearson correlation between projected values. This produces a similarity matrix $\hat{S} \in \mathbb{R}^{V_A \times V_B}$, where each entry is the correlation coefficient between projected values from the two models. We bin $\hat{S}$ by layer pairs and average the absolute value of the scores in each bin (different models might encode the same information in different directions, so we use absolute value) to produce a matrix $S \in \mathbb{R}^{L \times L}$, where $L$ is the number of layers – that is, the average (absolute) correlation between vectors that come from layer $\ell_A$ in model $A$ and layer $\ell_B$ in Model $B$ is registered in entry $(\ell_A, \ell_B)$ of $S$.

Last, to obtain a one-to-one layer alignment, we use the Hungarian algorithm [Kuhn, 1955], which assigns exactly one layer from the first model to a layer from the second model. The algorithm’s objective is to maximize, given a similarity matrix $S$, the sum of scores of the chosen pairs, such that each index in one model is matched with exactly one index in the other. We repeat this for all parameter groups $(W_Q, W_K, W_V, W_O, K)$.

**Results and Discussion**  Figure 3 (left) shows the resulting alignment. Clearly, parameters from a certain layer in model $A$ tend to align to the same layer in model $B$ across all parameter groups. This suggests that different layers from different models that were trained separately (but with the same training objective and data) serve a similar function. As further evidence, we show that if not projected, the matching appears absolutely random in Figure §3 (right). We show the same results for other seed pairs as well in Appendix B.3.

5.2 Zero-shot Stitching

Model stitching [Lenc and Vedaldi, 2015; Csizsárik et al., 2021; Bansal et al., 2021] is a relatively under-explored feature of neural networks, particularly in NLP. The idea is that different models, even with different architectures, can learn representations that can be aligned through a linear transformation, termed stitching. Representations correspond to hidden states, and thus one can learn a transformation matrix from one model’s hidden states to an equivalent hidden state in the other model. Here, we show that going through embedding space one can align the hidden states of two models, i.e., stitch, without training.

Given two models, we want to find a linear stitching transformation to align their representation spaces.

\[ \text{Estimated compute costs: around 1728 TPU-hours for each pre-training run, and around 208 GPU-hours plus 8 TPU-hours for associated fine-tuning experiments.} \]
According to our theory, given a hidden state \( v \in \mathbb{R}^{d_1} \) from model \( A \), we can project it to the embedding space as \( v E_A \), where \( E_A \) is its embedding matrix. Then, we can re-project to the feature space of model \( B \), with \( E_B^+ \in \mathbb{R}^{e \times d_2} \), where \( E_B^+ \) is the Penrose-Moore pseudo-inverse of the embedding matrix \( E_B \). This transformation can be expressed as multiplication with the kernel \( K_{AB} := E_A E_B^+ \in \mathbb{R}^{d_1 \times d_2} \). We employ the above approach to take representations of a fine-tuned classifier, \( A \), and stitch them on top of a model \( B \) that was only pretrained, to obtain a new classifier based on \( B \).

### Experimental Design

We use the 24-layer GPT-2 medium as model \( A \) and 12-layer GPT-2 base model trained in §4.3 as model \( B \). We fine-tune the last three layers of model \( B \) on IMDB, as explained in §4.3. Stitching is simple and is performed as follows. Given the sequence of \( N \) hidden states \( H_A^\ell \in \mathbb{R}^{N \times d_1} \) at the output of layer \( \ell \) of model \( A \) (\( \ell \) is a hyperparameter), we apply the stitching layer, which multiplies the hidden states with the kernel, computing \( H_A^\ell K_{AB} \). This results in hidden states \( H_B \in \mathbb{R}^{N \times d_2} \), used as input to the three fine-tuned layers from \( B \).

### Results and Discussion

Stitching produces models with accuracies that are higher than random on IMDB evaluation set, but not consistently. Figure 4 shows the accuracy of stitched models against the layer index from model \( A \) over which stitching is performed. Out of 11 random seeds, three models obtained accuracy that is significantly higher than the baseline 50% accuracy, reaching an accuracy of roughly 70%, when stitching is done over the top layers.

### Related Work

Interpreting Transformers is a broad area of research that has attracted much attention in recent years. A large body of work has focused on analyzing hidden representations, mostly through probing [Adi et al., 2016; Shi et al., 2016; Tenney et al., 2019; Rogers et al., 2020]. [Voita et al., 2019a] used statistical tools to analyze the evolution of hidden representations throughout layers. Recently, [Mickus et al., 2022] proposed to decompose the hidden representations into the contributions of different Transformer components. Unlike these works, we interpret parameters rather than the hidden representations.

Another substantial effort has been to interpret specific network components. Previous work analyzed single neurons [Dalvi et al., 2018; Durrani et al., 2020], attention heads [Clark et al., 2019; Voita et al., 2019b], and feedforward values [Geva et al., 2020; Dai et al., 2021; Elhage et al., 2022]. While these works mostly rely on input-dependent neuron activations, we inspect “static” model parameters, and provide a comprehensive view of all Transformer components.

Our work is most related to efforts to interpret specific groups of Transformer parameters. [Cammarata et al., 2020] made observations about the interpretability of weights of neural networks. [Elhage et al., 2021] analyzed 2-layer attention networks. We extend their analysis to multi-layer pre-trained Transformer models. [Geva et al., 2020, 2022a,b] interpreted feedforward values in embedding space. We coalesce these lines of work and offer a unified interpretation framework for Transformers in embedding space.

### Discussion

While our work has limitations (see §8), we think the benefits of our work overshadow its limitations. We provide a simple approach and a new set of tools to interpret Transformer models and compare them. The realm of input-independent interpretation methods is
still nascent and it might provide a fresh perspective on the internals of the Transformer, one that allows to
glance intrinsic properties of specific parameters, disentangling their dependence on the input. Moreover,
many models are prohibitively large for practitioners to run. Our method requires only a fraction of the com-
pute and memory requirements, and allows interpreting a single parameter in isolation.

Importantly, our framework allows us to view parameters from different models as residents of a canoni-
cal embedding space, where they can be compared in model-agnostic fashion. This has interesting implica-
tions. We demonstrate two consequences of this obser-
vation (model alignment and stitching) and argue future work can yield many more use cases.

8 Limitations

Our work has a few limitations that we care to high-
light. First, it focuses on interpreting models through
the vocabulary lens. While we have shown evidence for
this, it does not preclude other factors from being in-
volved. Second, we used $E' = E^k$, but future research
may find variants of $E$ that improve performance. Ad-
ditionally, most of the work focused on GPT-2. This is
due to shortcomings in the current state of our frame-
work, as well as for clear presentation. We believe non-
linearities in language modeling are resolvable, as is
indicated in the experiment with BERT.

In terms of potential bias in the framework, some
parameters might consider terms related to each due to
stereotypes learned from the corpus.

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A Rethinking Interpretation

Figure 5: Each row represents a model in the following order from top to bottom: GPT-2 base, GPT-2 medium, GPT-2 large. Left: The keep-$k$ inverse scores for three distributions: normal distribution, hidden states, and FF values, for $k \in \{10, 50, 100, 200, 300, 500\}$. Right: for $k \in \{10, 50, 100, 200, 300, 500\}$.

The process of interpreting a vector $v$ in [Geva et al., 2022b] proceeds in two steps: first the projection of the vector to the embedding space ($vE$); then, we use the list of the tokens that were assigned the largest values in the projected vector, i.e.: top-$k(vE)$, as the interpretation of the projected vector. This is reasonable since (a) the most activated coordinates contribute the most when added to the residual stream, and (b) this matches how we eventually decode: we project to the embedding space and consider the top-1 token (or one of the few top tokens, when using beam search).

In this work, we interpret inner products and matrix multiplications in the embedding space: given two vectors $x, y \in \mathbb{R}^d$, their inner product $x^Ty$ can be considered in the embedding space by multiplying with $E$ and then by one of its right inverses (e.g., its pseudo-inverse $E^+$ [Moore, 1920; Bjerhammar, 1951; Penrose, 1955]): $x^Ty = x^TEE^+y = (x^TE)(E^+y)$. Assume $xE$ is interpretable in the embedding space, crudely meaning that it represents logits over vocabulary items. We expect $y$, which interacts with $x$, to also be interpretable in the embedding.
space. Consequently, we would like to take $E^{+}y$ to be the projection of $y$. However, this projection does not take into account the subsequent interpretation using top-$k$. The projected vector $E^{+}y$ might be harder to interpret in terms of its most activated tokens. To alleviate this problem, we need a different “inverse” matrix $E'$ that works well when considering the top-$k$ operation. Formally, we want an $E'$ with the following “robustness” guarantee: $\text{keep-}k(x^{T}E)\text{keep-}k(y) \approx x^{T}y$, where $\text{keep-}k(v)$ is equal to $v$ for coordinates whose absolute value is in the top-$k$, and zero elsewhere.

This is a stronger notion of inverse – not only is $EE' \approx I$, but even when truncating the vector in the embedding space we can still reconstruct it with $E'$. We define the following metric applying on vectors after projecting them into the embedding space:

$$\text{Sim}_{k}(\hat{x}, \hat{y}) = \frac{|\text{top-}k(\hat{x}) \cap \text{top-}k(\hat{y})|}{|\text{top-}k(\hat{x}) \cup \text{top-}k(\hat{y})|}$$

where $\text{top-}k(v)$ is the set of $k$ top activated indices in the vector $v$ (which correspond to tokens in the embedding space). This metric is the Jaccard index [Jaccard, 1912] applied to the top-$k$ tokens from each vector. In Figure 6, left, we demonstrate that FF key vectors and their corresponding value vectors are more similar (in embedding space) than two random key and value vectors. In Figure 6, right, we show a similar result for attention value and output vectors. In Figure 6, bottom, the same analysis is done for attention query and key vectors. This shows that there is a much higher-than-chance relation between corresponding FF keys and values (and the same for attention values and outputs).

B Additional Material

B.1 Corresponding Parameter Pairs are Related

We define the following metric applying on vectors after projecting them into the embedding space:

$$\text{Sim}_{k}(\hat{x}, \hat{y}) = \frac{|\text{top-}k(\hat{x}) \cap \text{top-}k(\hat{y})|}{|\text{top-}k(\hat{x}) \cup \text{top-}k(\hat{y})|}$$

where $\text{top-}k(v)$ is the set of $k$ top activated indices in the vector $v$ (which correspond to tokens in the embedding space). This metric is the Jaccard index [Jaccard, 1912] applied to the top-$k$ tokens from each vector. In Figure 6, left, we demonstrate that FF key vectors and their corresponding value vectors are more similar (in embedding space) than two random key and value vectors. In Figure 6, right, we show a similar result for attention value and output vectors. In Figure 6, bottom, the same analysis is done for attention query and key vectors. This shows that there is a much higher-than-chance relation between corresponding FF keys and values (and the same for attention values and outputs).

B.2 Final Prediction and Parameters

We show that the final prediction of the model is correlated in embedding space with the most activated parameters from each layer. This implies that these objects are germane to the analysis of the final prediction in the embedding space, which in turn suggests that the embedding space is a viable choice for interpreting these vectors. Figure 7 shows that just like §4.2, correspondence is better when hidden states are not randomized, suggesting their parameter interpretations have an impact on the final prediction.
Figure 6: Average Sim$(\hat{x}, \hat{y})$ for $k = 100$ by layer, where blue is when matching pairs are aligned, and orange is when pairs are shuffled within the layer. Top Left: FF keys and FF values. Top Right: The subheads of $W_O$ and $W_V$. Bottom: The subheads of $W_Q$ and $W_K$.

Figure 7: Left: Average $R_k$ score ($k = 100$) across tokens per layer for activated parameter vectors against both the aligned hidden state $\hat{h}$ at the output of the final layer and a randomly sampled hidden state $\hat{h}_{\text{rand}}$. Parameters are FF keys (top-left), FF values (top-right), attention values (bottom-left), and attention outputs (bottom-right).
B.3 Parameter Alignment Plots for Additional Model Pairs

Alignment in embedding space of layers of pairs of BERT models trained with different random seeds for additional model pairs.

Seed 1 VS Seed 2

Seed 2 VS Seed 3

Seed 3 VS Seed 4

Seed 4 VS Seed 5
C Example Cases

C.1 WVO Matrices

Below we show output-value pairs from different heads of GPT-2 medium. For each head, we show the 50 pairs with the largest values in the $e 	imes e$ transition matrix. There are 384 attention heads in GPT-2 medium from which we manually choose a subset. Throughout the section some lists are marked with asterisks indicating the way this particular list was created:

* - pairs of the form $(x, x)$ were excluded from the list

** - pairs where both items are present in the corpus (we use IMDB training set).

Along with GPT-2 medium, we also provide a few examples from GPT-2 base and GPT-2 large.

C.1.1 Low-Level Language Modeling

**GPT-2 Medium - Layer 21 Head 7**

- (`NF`, `FN`),
- (`Ram`, `Ramos`),
- (`Hug`, `Hughes`),
- (`gran`, `GR`),
- (`FN`, `NF`),
- (`CLA`, `CL`),
- (`McC`, `McCain`),
- (`Marshall`, `Marshall`),
- (`Hugues`, `Hug`),
- (`Tan`, `Tanner`),
- (`nih`, `NH`),
- (`NRS`, `NR`),
- (`Bowman`, `Bow`),
- (`Marshall`, `Marsh`),
- (`Jac`, `Jacobs`),
- (`Hay`, `Hayen`),
- (`Hayes`, `Hay`),
- (`McC`, `McCorm`),
- (`NI`, `NR`),
- (`sidx`, `Dawson`),
- (`Tanner`, `Tan`),
- (`gra`, `GR`),
- (`JA`, `jac`),
- (`zos`, `zo`),
- (`N1`, `NF`),
- (`McC`, `McCull`),
- (`Jacobs`, `Jac`),
- (`Beetle`, `Beet`),
- (`GP`, `FG`),
- (`jas`, `ja`),
- (`Wil`, `Wilkinson`),
- (`Ramos`, `Ram`),
- (`GRE`, `GR`),
- (`FP`, `FN`),
- (`McCorm`, `McC`),
- (`Scar`, `Scarborough`),
- (`Baal`, `Ba`),
- (`FP`, `FG`),
- (`FH`, `FN`),
- (`Garfield`, `Gar`),
- (`jas`, `jac`),
- (`nuts`, `nut`),
- (`Wil`, `Wil`),
- (`Vaughn`, ` Vaughan`),
- (`FP`, `FF`),
- (`PN`, `RN`),
- (`Jacobs`, `jac`),
- (`FM`, `FN`),
- (`Knox`, `Kn`),
- (`NI`, `nic`)

**GPT-2 Medium - Layer 19 Head 13**

- (`R`, `senal`), # arsenal
- (`senal`, `R`),
- (`G`, `vernment`), # government
- (`Madness`, `M`),
- (`M`, `Mayhem`),
- (`W`, `nesday`), # wednesday
- (`vernment`, `G`),
- (`M`, `Madness`),
- (`N`, `lace`), # necklace
- (`nesday`, `W`),
- (`R`, `ondo`),
- (`Ns`, `senal`),
- (`g`, `vernment`),
- (`N`, `arious`), # nefarious
- (`eneg`, `C`),
- (`r`, `senal`),
- (`F`, `uary`), # february
- (`senal`, `RIC`),
- (`R`, `ondo`),
- (`N`, ` Mandela`), # nelson
- (`Mayhem`, `M`),
- (`RD`, `enal`),
- (`C`, `estine`),
- (`Gs`, `vernment`),
- (`RF`, `enal`),
- (`N`, `esin`),
- (`N`, `Reviewed`),
- (`C`, `arette`), # cigarette
- (`rome`, `N`),
- (`N`, `theless`), # nonetheless
- (`lace`, `NY`),
- (`H`, `DEN`),
- (`V`, `ersa`),
- (`F`, `ably`), # probably
- (`vernment`, `GP`),
- (`g`, `vernment`),
- (`GP`, `vernment`),
- (`C`, `ornia`), # california
- (`ilipp`, `F`),
- (`N`, `umbered`),
- (`C`, `arettes`),
- (`RS`, `enal`),
- (`N`, `onsense`),
- (`RD`, `enal`),
- (`RAL`, `enal`),
- (`F`, `uci`),
- (`R`, `ondo`),
- (`RI`, `enal`),
- (`H`, `iday`), # holiday
- (`senal`, `Rx`),
- (`F`, `odor`)

**GPT-2 Medium - Layer 20 Head 9**

- (`On`, ` behalf`),
- (`On`, ` behalf`),
- (`on`, ` behalf`),
- (`during`, ` periods`),
- (`within`, ` bounds`),
- (`inside`, ` envelope`),
- (`outside`, ` door`),
- (`inside`, ` envelope`),
- (`Under`, ` regime`),
C.1.2 Gender

GPT-2 Medium - Layer 18 Head 1

('women', 'Marie'), ('actresses', 'Marie'),
('women', 'Anne'), ('Women', 'Anne'),
('Women', 'Marie'), ('woman', 'Anne'), ('Woman', 'Marie'),
('actresses', 'Anne'), ('heroine', 'Marie'), ('Women', 'Jane'),
('women', 'Jane'), ('women', 'Anne'), ('Women', 'actresses'),
('Woman', 'Anne'), ('Women', 'Esther'), ('women', 'Esther'),
('girls', 'Marie'), ('Mrs', 'Anne'), ('actress', 'Marie'),
('women', 'actresses'), ('Woman', 'Jane'), ('girls', 'Marie'),
('actresses', 'Jane'), ('Woman', 'Anne'), ('Girls', 'Marie'),
('women', 'Anne'), ('Girls', 'Anne'),
('Women', 'actresses'), ('Women', 'Marie'), ('Women', 'Anne'),
('women', 'Anne'), ('girls', 'Anne'), ('girl', 'Marie'),
('Feminist', 'Anne'), ('women', 'Marie'), ('Women', 'Devil'),
('Women', 'Elizabeth'), ('actress', 'Anne'), ('Mrs', 'Anne'),
('answered', 'Answer'), ('woman', 'Anne'), ('Woman', 'maid'),
('women', 'Marie')

GPT-2 Base - Layer 9 Head 7

('her', 'herself') ('She', 'herself')
('she', 'herself') ('She', 'herself')
('Her', 'herself')
('SHE', 'herself')
('their', 'themselves') ('hers', 'herself')
('Their', 'themselves')
('THEIR', 'themselves')
('HER', 'herself')
('their', 'themselves')
('They', 'themselves')
('His', 'himself')
('herself', 'herself')
('their', 'themselves')
('they', 'themselves')
('his', 'himself')
('Their', 'selves')
('They', 'themselves')
('herself', 'Louise')
('their', 'selves')
('her', 'herself')
('his', 'himself')
('herself', 'Marie')
('He', 'himself')
('She', 'Louise')
('they', 'themselves')
C.1.3 Geography

**GPT-2 Base - Layer 11 Head 2**

- Halifax, Scotia
- Saudi Arabia
- Nova Scotia
- Tamil Nadu
- Finnish, "onen"
- Saudi, "Arabia"
- "Pitt", "sburgh"
- "Dutch", "ijk"
- Schwartz, "enegger"
- Afghans, "Kabul"
- "Icelandic", "sson"
- "Finland", "onen"
- "Pitt", "enegger"
- "Czech", "oslou"
- "Manitoba", "Winnipeg"
- Malaysian, "Lumpur"
- "Swedish", "borg"
- Saskatchewan, "Sask"
- Chennai, "Nadu"
- Argentine, "Aires"
- Iceland, "Icelandic"
- "Swedish", "sson"
- "Tasman", "Nadu"
- "Houston", "Astros"
- Colorado, "Springs"
- Kuala, "Lumpur"
- Taylor, "pport"
- "Houston", "Dynamo"
- "Manitoba", "Marginal"
- "Afghan", "Kabul"
- "Buenos", "Aires"
- Alberta, "Calgary"
- "Stockholm", "sson"
- Sweden, "borg"
- "Brazil", "Paulo"
- "Iceland", "sson"
- Winnipeg, "Manitoba"
- "Sweden", "sson"
- Carolina, "Hurricanes"
- "Dutch", "ijk"
- Swed, "borg"
- Aki, "pport"
- "Winnipeg", "Marginal"
- Argentine, "pes"
- Halifax, "imore"
- "Brisbane", "enegger"

**GPT-2 Medium - Layer 16 Head 2**

- Melbourne, "Nadu"
- Adelaide, "Nadu"
- Cambridge, "Nguyen"
- Vietnamese, "Nguyen"
- Chennai, "Mumbai"
- "India", "Mumbai"
- "Mumbai", "Chennai"
- "Queensland", "Tasmania"
- "India", "Rahul"
- "India", "Gujar"
- "Chennai", "Bangalore"
- England, "Scotland"
- Chennai, "Kerala"
- Delhi, "Mumbai"
- "Britain", "Scotland"
- Bangalore, "Mumbai"
- "Pakistan", "India"
- "Scotland", "Ireland"
- "Mumbai", "Bangalore"
- "Bangalore", "Chennai"
- Aadhra, "Gujar"
- "Mumbai", "Maharashtra"
- Maharashtra, "Gujar"
- Gujar, "Gujar"
- Australian, "Australia"
- "India", "Gujar"
- Rahul, "Gujar"
- Maharashtra, "Mumbai"
- Britain, "England"
- "India", "Chennai"
- "Mumbai", "Bombay"
- "Tamil", "Kerala"
- "Hindi", "Mumbai"
- "Tasmania", "Tasman"
- "Mumbai", "India"
- "Hindi", "Gujar"
- Maharashtra, "Gujar"
- Australians, "Australia"
- Maharashtra, "Kerala"
- "India", "Bangalore"
- "India", "Kerala"
- "India", "Bombay"
- Australian, "Australia"
- Aadhra, "India"
- Sharma, "Mumbai"
- "Australian", "Australia"
- "Mumbai", "Kerala"
- "Scotland", "England"
- "Mumbai", "Gujar"
- Rahul, "Mumbai"
- "Queensland", "Tasman"
- "Tamil", "Chennai"
- Gujar, "Maharashtra"
- India, "Modi"
C.1.4 British Spelling

GPT-2 Medium - Layer 19 Head 4

('realise', 'Whilst'),
('Whilst', 'Whilst'),
('realised', 'Whilst'),
('organise', 'Whilst'),
('recognise', 'Whilst'),
('civilisation', 'Whilst'),
('organisation', 'Whilst'),
('while', 'Whilst'),
('organising', 'Whilst'),
('organised', 'Whilst'),
('organis', 'Whilst'),
('util', 'Whilst'),
('apologise', 'Whilst'),
('emphas', 'Whilst'),
('analyse', 'Whilst'),
('organisations', 'Whilst'),
('recognised', 'Whilst'),
('flavours', 'Whilst'),
('colour', 'Whilst'),
('Nasa', 'Whilst'),
('Nato', 'Whilst'),
('analys', 'Whilst'),
('flavour', 'Whilst'),
('colourful', 'Whilst'),
('realise', 'organising'),
('behavioural', 'Whilst'),
('coloured', 'Whilst'),
('learnt', 'Whilst'),
('favourable', 'Whilst'),
('isation', 'Whilst'),
('programmes', 'Whilst'),
('realise', 'organis'),
('authorised', 'Whilst'),
('practise', 'Whilst'),
('criticised', 'Whilst'),
('organisers', 'Whilst'),
('organise', 'organising'),
('analysed', 'Whilst'),
('programme', 'Whilst'),
('behaviours', 'Whilst'),
('humour', 'Whilst'),
('isations', 'Whilst'),
('tyres', 'Whilst'),
('aluminium', 'Whilst'),
('realise', 'organised'),
('favour', 'Whilst'),
('ageing', 'Whilst'),
('organise', 'organis')

C.1.5 Related Words

GPT-2 Medium - Layer 13 Head 8

('miraculous', 'mirac'),
('miracle', 'mirac'),
('nuance', 'nuanced'),
('smarter', 'Better'),
('healthier', 'equitable'),
('liberated', 'liberating'),
('untouched', 'unaffected'),
('unbiased', 'equitable'),
('failed', 'inconsistent'),
('liberated', 'emanc'),
('humane', 'equitable'),
('liberating', 'liberated'),
('failed', 'incompatible'),
('miracles', 'mirac'),
('peacefully', 'consensual'),
('unconditional', 'uncond'),
('unexpectedly', 'unexpected'),
('unconditioned', 'unconditional'),
('healthier', 'Better'),
('unexpected', 'unexpectedly'),
('peacefully', 'graceful'),
('emancipation', 'emanc'),
('seamlessly', 'effortlessly'),
('peacefully', 'honorable'),
('uncond', 'unconditional'),
('excuses', 'rubbish'),
('liberating', 'emanc'),
('peacefully', 'equitable'),
('gracious', 'Feather'),
('liberated', 'emancipation'),
('nuances', 'nuanced'),
('avoids', 'icable'),
('freeing', 'liberated'),
('freeing', 'liberating'),
('lousy', 'inconsistent'),
('failed', 'lousy'),
('unaffected', 'unconditional'),
('ivable', 'equitable'),
('Honest', 'equitable'),
('principled', 'erring'),
('surv', 'survival'),
('lackluster', 'ocre'),
('liberating', 'equitable'),
('Instead', 'Bah'),
('inappropriate', 'incompatible'),
('emanc', 'emancipation'),
('unaffected', 'unchanged'),
('peaceful', 'peacefully'),
('safer', 'equitable'),
('uninterrupted', 'unconditional')

GPT-2 Medium - Layer 12 Head 14

('died', 'perished'),
('dies', 'perished'),
('testifying', 'testify'),
('interven', 'intervened'),
('advising', 'advises'),
('disband', 'disbanded'),
('perished', 'lost'),
('prevailed', 'prev'),
('advising', 'advise'),
('hood', 'shed'),
('orsi', 'Reviewed'),
('CHO', 'enough'),
('independence', 'skelet'),
('miracles', 'mirac'),
('testifying', 'testified'),
('testify', 'testifying'),
('governs', 'dictates'),
('complicity', 'complicit'),
('dictate', 'dictated'),
('CHO', 'enough'),
('independence', 'skelet'),
C.2 Query-Key Matrices

**GPT-2 Large - Layer 19 Head 7**

('broadcasting', 'Broadcast'),
('broadcaster', 'broadcasters'),
('publishing', 'Publishers'),
('broadcast', 'broadcasting'),
('Broadcasting', 'broadcasters'),
('Publishing', 'Publishers'),
('lectures', 'lecture'),
('editorials', 'Editors'),
('broadcasting', 'broadcast'),
('broadcasters', 'broadcasting'),
('journalistic', 'journalism'),
('Journal', 'reporting'),
('Broadcasting', 'Broadcast'),
('Publisher', 'Publishers'),
('broadcasters', 'broadcast'),
('Publisher', 'Publishers'),
('Publications', 'Publishers'),
('Newsp', 'newspapers'),
('broadcasters', 'roadcast'),
('Journal', 'Readers')

**GPT-2 Medium - Layer 22 Head 1**

('usual', 'usual'),
('occasional', 'occasional'),
('aforementioned', 'aforementioned'),
('general', 'usual'),
('usual', 'slightest'),
('agon', 'ealous'),
('traditional', 'usual'),
('free', 'amina'),
('major', 'major'),
('frequent', 'occasional'),
('generous', 'generous'),
('free', 'lam'),
('regular', 'usual'),
('standard', 'usual'),
('main', 'usual'),
('complete', 'Finished'),
('main', 'liest'),
('traditional', 'traditional'),
('latest', 'aforementioned'),
('current', 'aforementioned'),
('normal', 'usual'),
('dominant', 'dominant'),
('free', 'ministic'),
('brief', 'brief'),
('biggest', 'liest'),
('usual', 'usual'),
('rash', 'rash'),
('regular', 'occasional'),
('specialized', 'specialized'),
('free', 'iosis'),
('free', 'hero'),
('specialty', 'specialty'),
('general', 'iosis'),
('nearby', 'nearby'),
('best', 'liest'),
('officially', 'formal'),
('immediate', 'mediate'),
('special', 'ultimate'),
('free', 'otropic'),
('rigorous', 'comparative'),
('actual', 'slightest')

16146
GPT-2 Medium - Layer 22 Head 5 (names and parts of names seem to attend to each other here)
('Smith', 'ovich'), ('Jones', 'ovich'), ('Jones', 'Jones'), ('Smith', 'Williams'), ('Rogers', 'opoulos'), ('Jones', 'ovich'), ('Jones', 'ines'), ('ug', 'Ezek'), ('Moore', 'ovich'), ('orn', 'roit'), ('van', 'actionDate'), ('Jones', 'inelli'), ('Edwards', 'opoulos'), ('Jones', 'Lyons'), ('Williams', 'opoulos'), ('Moore', 'ovich'), ('Rodriguez', 'hoff'), ('North', 'suburbs'), ('Smith', 'chio'), ('Smith', 'ovich'), ('Smith', 'opoulos'), ('Mc', 'opoulos'), ('Johnson', 'utt'), ('Jones', 'opoulos'), ('Ross', 'Downloadha'), ('pet', 'ilage'), ('Everett', 'Prairie'), ('Cass', 'isma'), ('Jones', 'zymski'), ('Jones', 'Jones'), ('McCl', 'elman'), ('Smith', 'Jones'), ('Simmons', 'opoulos'), ('Smith', 'brown'), ('Mc', 'opoulos'), ('Jones', 'utt'), ('Richards', 'Davis'), ('Johnson', 'utt'), ('Ross', 'bred'), ('McG', 'opoulos'), ('Stevens', 'stadt'), ('ra', 'abouts'), ('Johnson', 'hoff'),

GPT-2 Medium - Layer 11 Head 10
('Journalism', 'acr'), ('democracies', 'governments'), ('/-', 'verty'), ('legislatures', 'governments'), ('ocracy', 'hegemony'), ('osi', 'RAND'), ('Organizations', 'organisations'), ('ellectual', 'institutional'), ('Journalists', 'acr'), ('eworks', 'sponsors'), ('Inqu', 'reviewer'), ('ocracy', 'diversity'), ('careers', 'Contributions'), ('gency', ')'), ('ellectual', 'exceptions'), ('Profession', 'specializing'), ('Online', 'Online'), ('Publications', 'authorised'), ('Online', 'Online'), ('sid', 'Lazarus'), ('eworks', 'Networks'), ('Groups', 'organisations'), ('Governments', 'governments'), ('democracies', 'nowadays'), ('psychiat', 'Mechdragon'), ('educ', 'Contributions'), ('ratings', 'organisations'), ('vernment', 'spons'), ('""", ","'), ('Caucas', 'commodity'), ('dictators', 'governments'), ('istration', 'sponsor'), ('iquette', 'acr'), ('Announce', 'answ'), ('Journalism', 'emowering'), ('Media', 'bureaucr'), ('Discrimination', 'organisations'), ('Journalism', 'Online'), ('FAQ', 'sites'), ('anticitrust', 'Governments'), ('..., ","'), ('Questions', 'acr'), ('ities', 'organisations'), ('Editorial', 'institutional'), ('tabl', 'acr'), ('anticitrust', 'governments'), ('Journalism', 'Everyday'), ('cter', 'Lieberman'), ('efect', 'SPONSORED'), ('Journalists', 'organisations')
C.3 Feedforward Keys and Values

Key-value pairs, \((k, v_i)\), where at least 15% of the top-k vocabulary items overlap, with \(k = 100\). We follow our fore-runners’ convention of calling the index of the value in the layer “dimension” (Dim).

Here again we use two asterisks (**) to represent lists where we discarded tokens outside the corpus vocabulary.

GPT-2 Medium - Layer 0 Dim 116

GPT-2 Medium - Layer 19 Head 12

GPT-2 Medium - Layer 3 Dim 2711

GPT-2 Medium - Layer 4 Dim 621
Analyst Economist
#iologist designer
accountant sociology
strategist communications
#ographer marketing
curator pharmac
Engineers sciences
archae economics
Editor #econom
biologist chemist
#ologist merch
psychologists pharm
theolog economist
Marketing architect
#Manager engineer
Architects Architect
sociology #technical
engineer architects
physicist logistics

GPT-2 Large - Layer 21 Dim 3419**

Analyst Econom

#iologist designer
accountant sociology
strategist communications
#ographer marketing
curator pharmac
Engineers sciences
archae economics
Editor #econom
biologist chemist
#ologist merch
psychologists pharm
theolog economist
Marketing architect
#Manager engineer
Architects Architect
sociology #technical
engineer architects
physicist logistics

GPT-2 Large - Layer 25 Dim 2442**

16154
weaken elevate
depri encouraging
dissu accelerate
impede enlarg
convol energ
encouraging accent
#xiety acceler
#akening depri
lowering elong

GPT-2 Base - Layer 1 Dim 2931

evening week
#shows evening
night night
#sets morning
#lav afternoon
afternoon month
#/+ ´s
Night #naissance
Loll #genre
Kinnikuman semester
Weekend #ched
morning #ague
#enna weekend
Saturday latest
Sunday #cher
week #EST
Blossom #icter
#Night happens
#atto day
#vertising happened
#spr #essim
#Sunday Masquerade
#morning #ished
#Thursday sounded
Week #ching
Panc pesky
Evening #chy
#allyере trope
#ADVERTISEMENT #feature
#Street #fy

GPT-2 Base - Layer 0 Dim 1194

Pay receipts
#Pay #dep
refund Deposit
police deduct
#pay #milo
#paying #igree
#Tax #ein
debit levied
PayPal deposit
ATM #enforcement
cops endot
tax #soType
ID paperwork
#payment deposits
payment loopholes
checkout waivers
#police receipt
agents waive
DMV loophole
application arresting
card commissioner
applications Forms
office transporter
arrested Dupl
#paid confisc
pay Clapper
#tax #ventures

RCMP #Tax
PAY whistleblowers
APPLIC #ADRA

GPT-2 Base - Layer 9 Dim 2771

flaws flaws
lurking weaknesses
failings dangers
vulnerabilities scams
inaccur shortcomings
scams pitfalls
shortcomings injust
flawed faults
glitches flawed
pitfalls abuses
inconsistencies imperfect
rigged lurking
biases wrongdoing
deficiencies corruption
weaknesses inaccur
discrepancies inadequ
hypocrisy fraud
rigging inequ
deceptive weakness
misinformation scam
#urities hazards
lur problematic
imperfect hoax
regress danger
#abase failings
#errors problems
#lived injustice
abuses plagiar
misinterpret plag
suspic deceptive

C.4 Knowledge Lookup

Given a few seed embeddings of vocabulary items we find related FF values by taking a product of the average embeddings with FF values.

Seed vectors:
["python", "java", "javascript"]
Layer 14 Dim 1215 (ranked 3rd)

filesystem debugging
Windows HTTP
configure Python
debut debug
cops config
Linux Java
configuration cache
Unix lib
runtime kernel
plugins FreeBSD
hash plugin
headers file
server PHP
GNU headers
Apache initialization
Mozilla

Seed vectors: ["cm", "kg", "inches"]
Layer 20 Dim 2917 (ranked 1st)

percent
years
hours
minutes
million
seconds
inches
months
miles
weeks
pounds
#%
kilometers
ounces
kilograms
grams
kilometres
metres
centimeters
thousand
days
km
yards
Years
meters
#milion
acres
kg
#years
inch

Seed vectors: ["horse", "dog", "lion"]
Layer 21 Dim 3262 (ranked 2nd)

animal
animals
Animal
dogs
horse
wildlife
Animals
birds
horses
dog
mammal
bird
mammals
predator
beasts
Wildlife
species
#Animal
#animal
Dogs
fish
rabbits
deer
elephants
wolves
pets
veterinary
canine
beast

predators
reptiles
rodent
primates
hunting
livestock
creatures
rabit
rept
elephant
creatures
human
hunters
hunter
shark
Rept
cattle
wolf
Humane
tiger
lizard
D Sentiment Analysis Fine-Tuning Vector Examples

This section contains abusive language

Classification Head Parameters

Below we show the finetuning vector of the classifier weight. “POSITIVE” designates the vector corresponding to the label “POSITIVE”, and similarly for “NEGATIVE”.

| POSITIVE  | NEGATIVE |
|----------|----------|
| #yssey   | bullshit |
| #knit    | lame     |
| #etts    | crap     |
| passions | incompetent |
| #teeth   | inco     |
| #iscover | bland    |
| pioneers | incompetence |
| #emaker  | idiots   |
| Plöne    | crappy   |
| #raft    | shitty   |
| #uala    | idiot    |
| prosper  | pointless |
| #izions  | retarded |
| #encers  | worse    |
| #joy     | garbage  |
| cherish  | CGI      |
| loves    | FUCK     |
| #accompan | Nope  |
| strengthens | useless |
| #nect    | shit     |
| comr     | mediocre |
| honoured | poorly   |
| insepar  | stupid   |
| embraces | inept    |
| battled  | lousy    |
| #Together | fuck    |
| intrig   | sloppy   |
| #jong    | Worse    |
| friendships | Worst |
| #anta    | meaningless |

In the following sub-sections, we sample 4 difference vectors per each parameter group (FF keys, FF values; attention query, key, value, and output subheads), and each one of the fine-tuned layers (layers 9-11). We present the ones that seemed to contain relevant patterns upon manual inspection. We also report the number of “good” vectors among the four sampled vectors for each layer and parameter group.

**FF Keys**

**Layer 9**

4 out of 4
amazing seizures
movies coercive
wonderful Citizen
love #cffff
movie #GBT
cinematic target
enjoyable loopholes
wonderfully Procedures
beautifully #iannopoulos
enjoy #Leaks
films #illon
comedic grievance
fantastic #merce
awesome #Payments
#Enjoy #RNA
cinemat #Registrar
film Regulatory
loving immobile
enjoyment #bestos
masterpiece #SpaceEngineers

movie seiz
fucking Stronghold
to 20439
damn #Secure
funny Regulation
shit Quarterly
kinda concess
REALLY Recep
Movie #aligned
stupid target
#movie mosquito
goddamn #verning
crap FreeBSD
shitty PsyNet
film Facilities
crappy #Lago
damned #Register
#Movie ";"
cheesy Regist
| diff | -diff |
|-----|-------|
| quotas | wonderfully |
| #RNA | wonderful |
| cessation | beautifully |
| subsidy | amazing |
| #SpaceEngineers | fantastic |
| placebo | incredible |
| exemptions | amazingly |
| treadmill | great |
| Labs | unforgettable |
| receipt | beautiful |
| moratorium | brilliantly |
| designation | hilarious |
| ineligible | love |
| reimbursement | marvelous |
| roundup | vividly |
| Articles | terrific |
| PubMed | memorable |
| waivers | #Enjoy |
| Citiz | loving |
| landfill | fascinating |

| diff | -diff |
|-----|-------|
| horror | #deals |
| whim | #iband |
| subconscious | & |
| unrealistic | #held |
| imagination | #APD |
| viewers | withdrew |
| enjoyment | #Shares |
| nostalgia | mathemat |
| absolute | [+] |
| sentimental | #Tracker |
| unreal | #2b |
| Kubrick | testified |
| awe | #ymes |
| inspiration | mosgu |
| subtle | #Commerce |
| cinematic | administr |
| perfection | feder |
| comedic | repaired |
| fantasy | #pac |
| mindless | #Community |

Layer 11
4 out of 4
inco cherish pointless #knit Nope #terday bullshit #accompan crap prosper useless versatile nonsense friendships futile #uala anyways cherished anyway meaningless redes clueless inspires lame Proud wasting friendship Bogus exceptional vomit #beaut nonsensical #ngth retarded pioneering idiots pioneers shit nurt

#accompan bad Pione crap celebrate inefficient #Discover stupid #knit worse pioneering mistake recogn incompetence reunited mistakes commr incompetent thriving miser #discover garbage commemorate retarded Remem #bad ecstatic poor forefront ineffective enthusi retard renewed Poor colle bullshit Inspired inept #uala errors

#SpaceEngineers love nuisance definitely #erous always #aband wonderful Brist loved racket wonderfully Penalty cherish bystand loves #iannopoulos truly Citiz enjoy Codec really courier #olkien #>}] beautifully #termination #love incapac great #interstitial LOVE fugitive never breaching adore targ loving thug amazing
diff  -diff
------------- ------------
#ARGET kinda
diff  -diff
------------- ------------
kinda coerc
diff  -diff
------------- ------------
amazing Marketable
dothing

#ial lot
diff  -diff
------------- ------------
Spurious #history
#مدير #definitely marketing

diff  -diff
------------- ------------
contingency

Prev interesting
diff  -diff
------------- ------------
unbelievable #improves

#érer

diff  -diff
------------- ------------
inside amazes
diff  -diff
------------- ------------
previously nice

Vendor Symphorine #defin

diff  -diff
------------- ------------
pics #Mobil

#część defin

diff  -diff
------------- ------------

alot Provision
diff  -diff
------------- ------------
kinda coerc

diff  -diff
------------- ------------
amazing Marketable
dothing

#director #definitely marketing

diff  -diff
------------- ------------
contingency

Prev interesting
diff  -diff
------------- ------------
unbelievable #improves

#érer

diff  -diff
------------- ------------
inside amazes
diff  -diff
------------- ------------
previously nice

Vendor Symphorine #defin

diff  -diff
------------- ------------
pics #Mobil

#część defin

Layer 10
4 out of 4
Layer 11
3 out of 4
| diff       | -diff                  |
|------------|------------------------|
| #utterstock    | amazing                |
| #ARGET       | movie                  |
| #cffff       | alot                   |
| #etooth      | scenes                 |
| #Federal     | comedy                 |
| POLITICO     | movies                 |
| #Register    | cinematic              |
| #Registration| greatness              |
| #rollment    | wonderful              |
| #ETF         | storytelling           |
| #ulia        | film                   |
| Payments     | tho                    |
| #IRC         | masterpiece            |
| Regulatory   | films                  |
| Alternatively| Kubrick                |
| #RN          | realism                |
| #pta         | comedic                |
| Regulation   | cinem                 |
| #GBT         | #movie                |
| ":"},{"    | genre                  |

| diff       | -diff                  |
|------------|------------------------|
| amazing    | #iannopoulos          |
| beautifully| expired                |
| love       | ABE                    |
| wonderful  | Yiannopoulos      |
| wonderfully| liability             |
| unforgettable| #SpaceEngineers    |
| beautiful  | #isance               |
| loving     | Politico               |
| #love      | waivers                |
| #beaut     | #utterstock            |
| enjoyable  | excise                 |
| #Beaut     | #Stack                 |
| inspiring  | phantom                |
| fantastic  | PubMed                 |
| defin      | #ilk                   |
| incredible | impunity               |
| memorable  | ineligible             |
| greatness  | Coulter                |
| amazingly  | issuance               |
| timeless   | IDs                    |
| diff          | -diff          | diff          | -diff          |
|--------------|---------------|--------------|---------------|
| enclave      | horrible      | Then         | any           |
| #.           | pretty        | Instead      | #ady          |
| #;           | alot          | Unfortunately| #imate        |
| #omial       | MUCH          | Why          | #ussion       |
| apipec       | VERY          | Sometimes    | #ze           |
| #assian      | nothing       | Secondly      | appreci       |
| #.           | #much         | #Then        | #raq          |
| #uent        | terrible      | But          | currently     |
| #,[          | crappy        | Luckily      | #kers         |
| #eria        | strange       | Anyway       | #apixel       |
| #ourse       | everything    | And          | active        |
| exerc        | very          | Suddenly     | significant   |
| #\/          | shitty        | Thankfully   | #ade          |
| #Wire        | nice          | Eventually   | #imal         |
| #arium       | many          | Somehow      | specific      |
| #icle        | wonderful     | Fortunately  | #ability      |
| #.           | genuinely      | Meanwhile    | anyone        |
| #/$          | beautiful     | What         | #ker          |
| #API         | much          | Obviously    | #unction      |
| #ium         | really        | Because      | reap          |

| diff          | -diff          | diff          | -diff          |
|--------------|---------------|--------------|---------------|
| bullshit     | #avorite      | Then         | any           |
| anyway       | #ilyn         | Instead      | #ady          |
| crap         | #xtap         | Unfortunately| #imate        |
| anyways      | #insula      | Why          | #ussion       |
| unless       | #cedented     | Sometimes    | #ze           |
| nonsense     | #ternal      | Secondly      | appreci       |
| #falls       | #lyak         | #Then        | #raq          |
| fuck         | #rieve       | But          | currently     |
| #           | #uana         | Luckily      | #kers         |
| fallacy      | #accompan    | Anyway       | #apixel       |
| #tics        | #ashtra      | And          | active        |
| #punk        | #icer         | Suddenly     | significant   |
| damned       | #andum       | Thankfully   | #ade          |
| #fuck        | Mehran        | Eventually   | #imal         |
| stupidity    | #andise       | Somehow      | specific      |
| shit         | #racuse       | Fortunately  | #ability      |
| commercials  | #assadors     | Meanwhile    | anyone        |
| because      | #Chel         | What         | #ker          |
| despite      | rall          | Obviously    | #unction      |
| moves        | #abella       | Because      | reap          |
| diff       | -diff      | diff       | -diff      |
|------------|------------|------------|------------|
| #, work    | Nope       | #, sup     | setting    |
| #icle      | Thankfully  | #airs      | ktop       |
| #.         | Surely     | awesome    | #ulkan     |
| outdoors   | #Instead   | Bless      | #enthal    |
| inspiring  | Fortunately| Loving     | #enance    |
| exped      | #Instead   | my         | #yre       |
| ahead      | Luckily    | #OTHER     | #eds       |
| together   | #Thankfully| #BW        | omission   |
| touches    | Unless     | #perfect   | #reys      |
| out        | Apparently | #)         | lihood     |
| personalized| Perhaps   | amazing    | #esian     |
| #joy       | #Unless    | #adult     | #holes     |
| #unction   | #Fortunately| perfect    | syndrome   |
| warm       | Sorry      | welcome    | grievance  |
| exceptional| Secondly   | Rated      | offenders  |
| experience | #Lucky     | #Amazing   | #wig       |
| lasting    | #Rather    | #anch      | #hole      |
| integ      | Hence      | FANT       | #creen     |
| #astic     | Neither    | #anche     | #pmwiki    |

**Layer 11**

2 out of 4

| diff       | -diff      | diff       | -diff      |
|------------|------------|------------|------------|
| shots      | #Kind      | #ly        | #say       |
| shit       | suscept    | storytelling| actionGroup|
| bullshit   | Fathers    | sounding   | prefers    |
| stuff      | #Footnote  | spectacle  | #ittees    |
| tits       | concess    | #ness      | #eon       |
| crap       | #accompan  | #hearted   | presumably |
| boos       | Strait     | cinematic  | waivers    |
| creepy     | #orig      | #est       | #acuses    |
| noises     | #ESE       | portrayal  | #Phase     |
| spectacle  | #ufact     | quality    | #r accuse   |
| boring     | Founder    | paced      | #arge      |
| things     | #iere      | combination| #ers       |
| everything | HC         | juxtap     | #sup       |
| noise      | #Prev      | representation| #later    |
| #anim      | #alias     | mixture    | expired    |
| ugly       | participated| #!!!!!!    | stricter   |
| garbage    | #Have      | filmmaking | #onds      |
| stupidity  | #oe        | enough     | #RELATED   |
| visuals    | #Father    | thing      | #Rollment  |
| selfies    | strugg     | rendition  | #orders    |

**Wv Subheads**

Layer 9

4 out of 4
# Layer 11

4 out of 4
**ACL 2023 Responsible NLP Checklist**

**A** For every submission:

- A1. Did you describe the limitations of your work?  
  
- A2. Did you discuss any potential risks of your work?  

- A3. Do the abstract and introduction summarize the paper’s main claims?  

- A4. Have you used AI writing assistants when working on this paper?  
  *Left blank.*

**B** ✓ Did you use or create scientific artifacts?

- B1. Did you cite the creators of artifacts you used?  

- B2. Did you discuss the license or terms for use and / or distribution of any artifacts?  

- B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)?  

- B4. Did you discuss the steps taken to check whether the data that was collected / used contains any information that names or uniquely identifies individual people or offensive content, and the steps taken to protect / anonymize it?  
  *IMDB is a well studied dataset and has been discussed many times before*

- B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.?  
  *IMDB is a well studied dataset and has been discussed many times before*

- B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.  

**C** ✓ Did you run computational experiments?

- C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?  

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The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.
C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?
   4,5 – no hyperparameters were searched

C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?
   4,5

C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?
   4

D  X Did you use human annotators (e.g., crowdworkers) or research with human participants?

D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?
   No response.

D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants’ demographic (e.g., country of residence)?
   No response.

D3. Did you discuss whether and how consent was obtained from people whose data you’re using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?
   No response.

D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?
   No response.

D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?
   No response.