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.[1] [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,

[1]We 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*.

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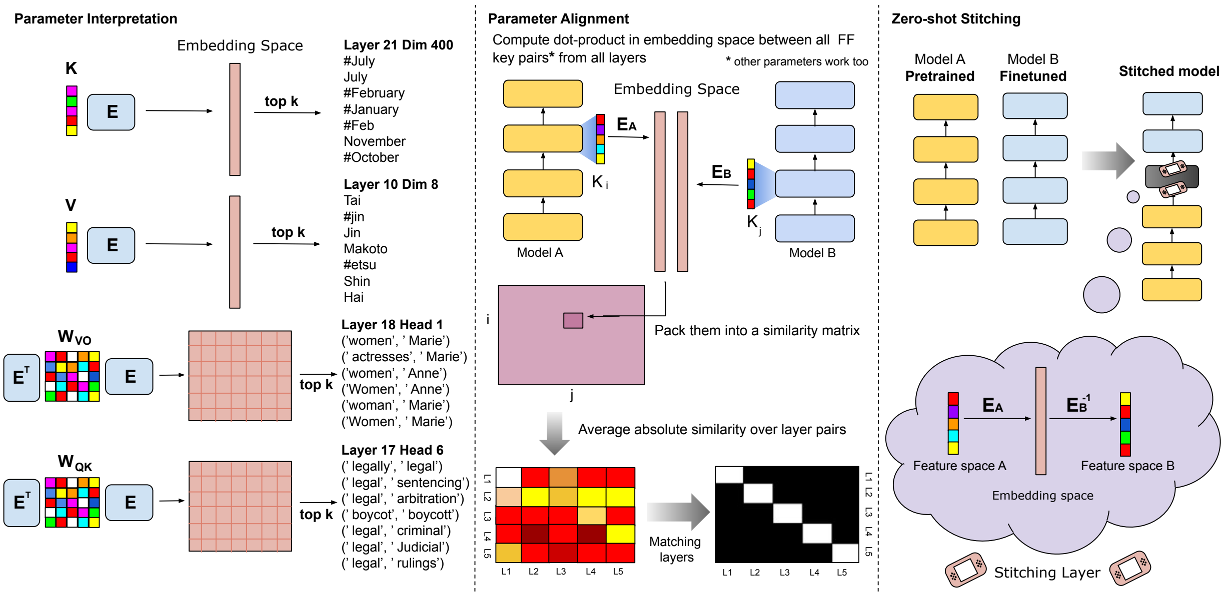

Figure 1: Applications of the embedding space view. *Left*: interpreting parameters in embedding space. The most active vocabulary items in a feed-forward key (k) and a feed-forward value (v). The most active pairs of vocabulary items in an attention query-key matrix W_{QK} and an attention value-output matrix W_{VO} (see §2). *Center*: Aligning the parameters of different BERT instances that share a vocabulary. *Right*: Zero-shot "stitching", where representations of a fine-tuned classifier are translated through the embedding space (multiplying by $E_A E_B^{-1}$) to a pretrained-only model.

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_{QK} [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: $Q_{\text{att}} = XW_Q, K_{\text{att}} = XW_K, V_{\text{att}} = XW_V$. Each one of $Q_{\text{att}}, K_{\text{att}}, V_{\text{att}}$ is split along the columns to H different *heads* of dimensionality $\mathbb{R}^{N\times \frac{d}{H}}$, denoted by $Q^i_{\text{att}}, K^i_{\text{att}}, V^i_{\text{att}}$ respectively. We then compute H *attention maps*:

$$A^i = \text{softmax}\left(\frac{Q^i_{\text{att}} K^{i\text{T}}_{\text{att}}}{\sqrt{d/H}} + M\right) \in \mathbb{R}^{N\times N},$$

where $M \in \mathbb{R}^{N\times N}$ is the attention mask. Each attention map is applied to the corresponding value head as $A^i V^i_{\text{att}}$, 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:

$$X + \textbf{Concat}\left[A^1 V^1_{\text{att}}, \ldots, A^i V^i_{\text{att}}, \ldots, A^H V^H_{\text{att}}\right] W_O. \tag{1}$$

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: $f(QK^\text{T})V$, 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 $K, V \in \mathbb{R}^{d_{ff}\times d}$ 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 $E \in \mathbb{R}^{d\times e}$ 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].[2] 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., 2022b] 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 $W_{\text{Q}}, W_{\text{K}}, W_{\text{V}}$ can be split along the *column* axis to H equal parts denoted by $W^i_{\text{Q}}, W^i_{\text{K}}, W^i_{\text{V}} \in \mathbb{R}^{d\times \frac{d}{H}}$ for $1 \le i \le H$. Similarly, the attention output matrix W_{O} can be split along the *row* axis into H heads, $W^i_{\text{O}} \in \mathbb{R}^{\frac{d}{H}\times d}$. We define the *interaction matrices* as

$$W^i_{\text{QK}} := W^i_{\text{Q}} W^{i\text{T}}_{\text{K}} \in \mathbb{R}^{d\times d},$$
$$W^i_{\text{VO}} := W^i_{\text{V}} W^i_{\text{O}} \in \mathbb{R}^{d\times d}.$$

Importantly, $W^i_{\text{QK}}, W^i_{\text{VO}}$ are *input-independent*. Intuitively, W_{QK} encodes the amount of attention between pairs of tokens. Similarly, in W^i_{VO}, the matrices W_{V} and W_{O} can be viewed as a transition matrix that determines how attending to certain tokens affects the subsequent 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 $A^i V^i_{\text{att}}$ and the final output of the attention module is (without the residual connection):

$$\textbf{Concat}\left[A^1 V^1_{\text{att}}, ..., A^i V^i_{\text{att}}, ..., A^H V^H_{\text{att}}\right] W_{\text{O}} = \sum_{i=1}^{H} A^i (X W^i_{\text{V}}) W^i_{\text{O}} = \sum_{i=1}^{H} A^i X W^i_{\text{VO}}. \tag{2}$$

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

$$A^i = \text{softmax}\left(\frac{(XW^i_{\text{Q}})(XW^i_{\text{K}})^\text{T}}{\sqrt{d/H}} + M\right) = \text{softmax}\left(\frac{X(W^i_{\text{QK}})X^\text{T}}{\sqrt{d/H}} + M\right). \tag{3}$$

[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 $\hat{A} = AE \in \mathbb{R}^{N\times e}$. Let E' be a right-inverse of E, that is, $EE' = I \in \mathbb{R}^{d\times d}$.[3] We can reconstruct the original matrix with E' as $A = A(EE') = \hat{A}E'$. 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 [Elhage 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 $E' = E^{\mathrm{T}}$ instead of a seemingly more appropriate right inverse, such as the pseudo-inverse [Moore, 1920; Bjerhammar, 1951; Penrose, 1955]. In this section, we derive our framework and summarize its predictions in Table 1.

Attention Module Recall that $W^i_{\mathrm{VO}} := W^i_{\mathrm{V}} W^i_{\mathrm{O}} \in \mathbb{R}^{d\times d}$ is the interaction matrix between attention values and the output projection matrix for attention head i. By definition, the output of each head is: $A^i X W^i_{\mathrm{VO}} = A^i \hat{X} E' W^i_{\mathrm{VO}}$. 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 e-dimensional vectors $(A^i X W^i_{\mathrm{VO}})E = A^i \hat{X}(E' W^i_{\mathrm{VO}} E)$ 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 $\hat{X}(E' W^i_{\mathrm{VO}} E)$.

Zooming 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, $E' W^i_{\mathrm{VO}} E$ 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^i_{QK} can be viewed as a bilinear map (Eq. 2.3). To interpret it in embedding space, we perform the following operation with E':

$$X W^i_{\mathrm{QK}} X^{\mathrm{T}} = (XEE') W^i_{\mathrm{QK}} (XEE')^{\mathrm{T}} =$$
$$(XE) E' W^i_{\mathrm{QK}} E'^{\mathrm{T}} (XE)^{\mathrm{T}} = \hat{X}(E' W^i_{\mathrm{QK}} E'^{\mathrm{T}}) \hat{X}^{\mathrm{T}}.$$

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 $V \in \mathbb{R}^{d_{ff}\times d}$ are meaningful when projected into embedding space, i.e., for a FF value vector $v \in \mathbb{R}^d$, $vE \in \mathbb{R}^e$ is interpretable (see §2.1). In vectorized form, the rows of $VE \in \mathbb{R}^{d_{ff}\times e}$ 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 $QK^{\mathrm{T}} = \hat{Q}E'K^{\mathrm{T}} = \hat{Q}(KE'^{\mathrm{T}})^{\mathrm{T}}$. Because Q is a hidden state, we assume according to the residual stream view that $\hat{Q}$ is interpretable in embedding space. When multiplying $\hat{Q}$ by KE'^{T}, we are capturing the interaction in embedding space between each query and key, and thus expect KE'^{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^i_{VO} and W^i_{QK} is through the *subhead view*. We use the following identity: $AB = \sum_{j=1}^{b} A_{:,j} B_{j,:}$, which holds for arbitrary matrices $A \in \mathbb{R}^{a\times b}, B \in \mathbb{R}^{b\times c}$, where $A_{:,j} \in \mathbb{R}^{a\times 1}$ 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^i_{VO} and W^i_{QK} into a sum of $\frac{d}{H}$ rank-1 matrices:

$$W^i_{\mathrm{VO}} = \sum_{j=1}^{\frac{d}{H}} W^{i,j}_{\mathrm{V}} W^{i,j}_{\mathrm{O}}, \quad W^i_{\mathrm{QK}} = \sum_{j=1}^{\frac{d}{H}} W^{i,j}_{\mathrm{Q}} W^{i,j\,\mathrm{T}}_{\mathrm{K}}.$$

where $W^{i,j}_{\mathrm{Q}}, W^{i,j}_{\mathrm{K}}, W^{i,j}_{\mathrm{V}} \in \mathbb{R}^{d\times 1}$ are columns of $W^i_{\mathrm{Q}}, W^i_{\mathrm{K}}, W^i_{\mathrm{V}}$ respectively, and $W^{i,j}_{\mathrm{O}} \in \mathbb{R}^{1\times d}$ are the rows of W^i_{O}. 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 $E' = E^{\mathrm{T}}$ In practice, we do not use an exact right inverse (e.g. the pseudo-inverse). We use the transpose of the embedding matrix $E' = E^{\mathrm{T}}$ 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.

[3] E' exists if $d \leq e$ and E is full-rank.

	Symbol	Projection	Approximate Projection
FF values	v	vE	vE
FF keys	k	kE'^{T}	kE
Attention query-key	W_{QK}^i	$E'W_{\mathrm{QK}}^i E'^{\mathrm{T}}$	$E^{\mathrm{T}}W_{\mathrm{QK}}^i E$
Attention value-output	W_{VO}^i	$E'W_{\mathrm{VO}}^i E$	$E^{\mathrm{T}}W_{\mathrm{VO}}^i E$
Attention value subheads	$W_{\mathrm{V}}^{i,j}$	$W_{\mathrm{V}}^{i,j} E'^{\mathrm{T}}$	$W_{\mathrm{V}}^{i,j} E$
Attention output subheads	$W_{\mathrm{O}}^{i,j}$	$W_{\mathrm{O}}^{i,j} E$	$W_{\mathrm{O}}^{i,j} E$
Attention query subheads	$W_{\mathrm{Q}}^{i,j}$	$W_{\mathrm{Q}}^{i,j} E'^{\mathrm{T}}$	$W_{\mathrm{Q}}^{i,j} E$
Attention key subheads	$W_{\mathrm{K}}^{i,j}$	$W_{\mathrm{K}}^{i,j} E'^{\mathrm{T}}$	$W_{\mathrm{K}}^{i,j} E$

Table 1: A summary of our approach for projecting Transformer components into embedding space. The 'Approximate Projection' shows the projection we use in practice where $E' = E^{\mathrm{T}}$.

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 *keep-k robust invertibility* to quantify this. It turns out that empirically E^{T} is a decent *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, $h = \sum_{i=1}^{k} \alpha_i r_i$, where α_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_i 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 $e_i^T W_{\mathrm{VO}}$ and use the inner product as a similarity metric and get the score $e_i^T W_{\mathrm{VO}} e_j$.

4 Interpretability 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 $E'W_{\mathrm{VO}}^i E$ 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 $(E'W_{\mathrm{VO}}^i E)^{\mathrm{T}}$ 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-

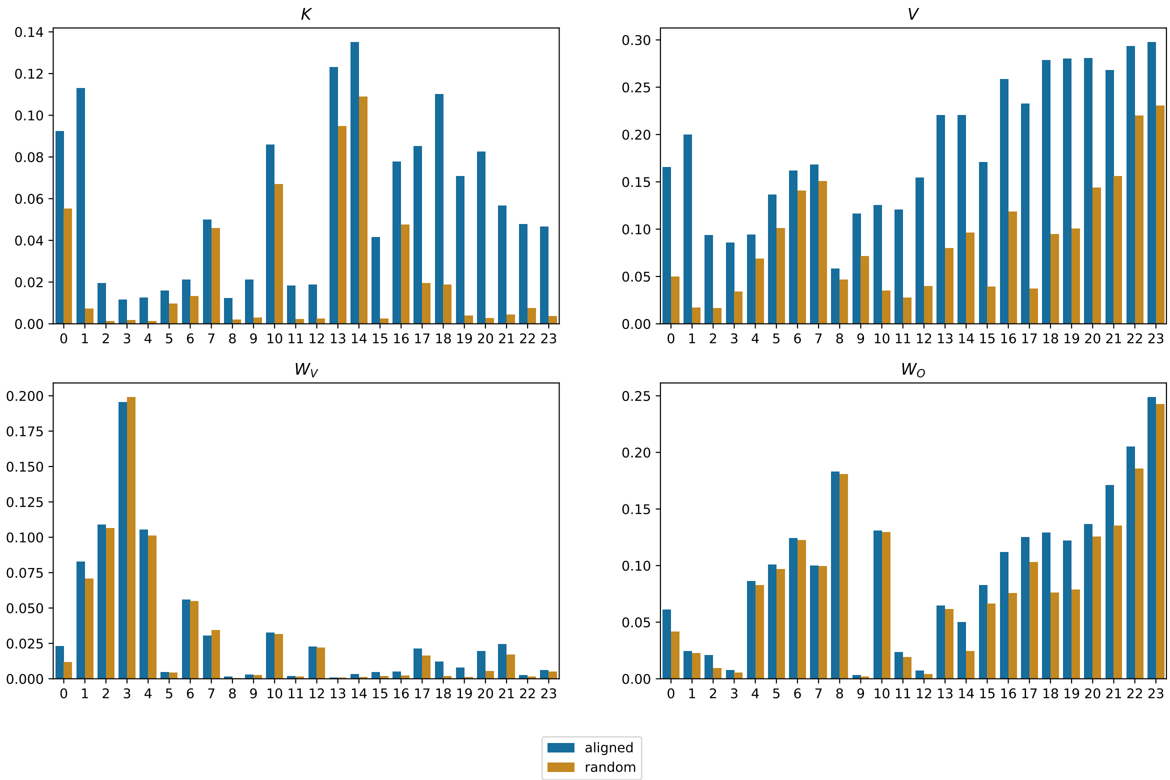

Figure 2: Left: Average R_k score ($k = 100$) across tokens per layer for activated parameter vectors against both the aligned hidden state $\hat{h}$ at the output of the layer and a randomly sampled hidden state $\hat{h}_{\text{rand}}$. Parameters are FF keys (top-left), FF values (top-right), attention values (bottom-left), and attention outputs (bottom-right).

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 $\hat{h} \in \mathbb{R}^e$ 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 $\texttt{top-k}(wE)$ be the k vocabulary items with the largest logits in embedding space for a vector $w \in \mathbb{R}^d$. We compute:

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

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 $\sigma(q^{\text{T}}k)$, where $q \in \mathbb{R}^d$ is an input to the FF module, and σ is the FF non-linearity. For attention, value-output subhead pairs (v, o) the coefficient is $x^{\text{T}}v$, where x is the

[4]We subtract the average embedding μ 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 $A^i X$, 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 $\hat{h}$ at the output of the relevant layer (blue bars) against the R_k when *randomly sampling* $\hat{h}_{\text{rand}}$ 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 or 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 $W_{\text{Q}}, W_{\text{K}}, W_{\text{V}}, K$, 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.[6] 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 $\tilde{\mathcal{S}} \in \mathbb{R}^{|V_A| \times |V_B|}$, where each entry is the correlation coefficient between projected values from the two models. We bin $\tilde{\mathcal{S}}$ 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 $\mathcal{S} \in \mathbb{R}^{L \times L}$, where L is the number of layers – that is, the average (absolute) correlation between vectors that come from layer ℓ_A in model A and layer ℓ_B in Model B is registered in entry (ℓ_A, ℓ_B) of $\mathcal{S}$.

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 $\mathcal{S}$, 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 ($W_{\text{Q}}, W_{\text{K}}, W_{\text{V}}, W_{\text{O}}, K$).

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; Csiszárik et al., 2021; Bansal et al., 2021] is a relatively underexplored 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.

[6] 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.

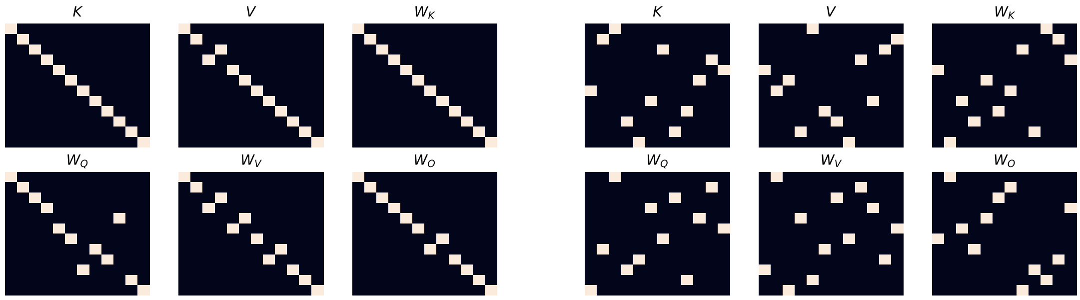

Figure 3: Left: Aligning *in embedding space* the layers of two different BERT models initialized from different random seeds for all parameter groups. Layers that have the same index tend to align with one another. Right: Alignment in feature space leads to unintelligible patterns.

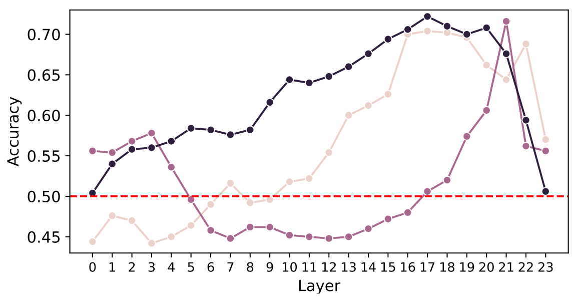

Figure 4: Accuracy on the IMDB evaluation set. We ran stitching randomly 11 times and obtained 3 models with higher than random accuracy when stitching over top layers. Dashed red line indicates random performance.

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 vE_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.[7] 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 ℓ of model A (ℓ 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.

[7] Since we are not interested in interpretation we use an exact right-inverse and not the transpose.

6 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.

7 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 compute 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 canonical embedding space, where they can be compared in model-agnostic fashion. This has interesting implications. We demonstrate two consequences of this observation (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 highlight. 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 involved. Second, we used $E' = E^{\mathrm{T}}$, but future research may find variants of E that improve performance. Additionally, most of the work focused on GPT-2. This is due to shortcomings in the current state of our framework, 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

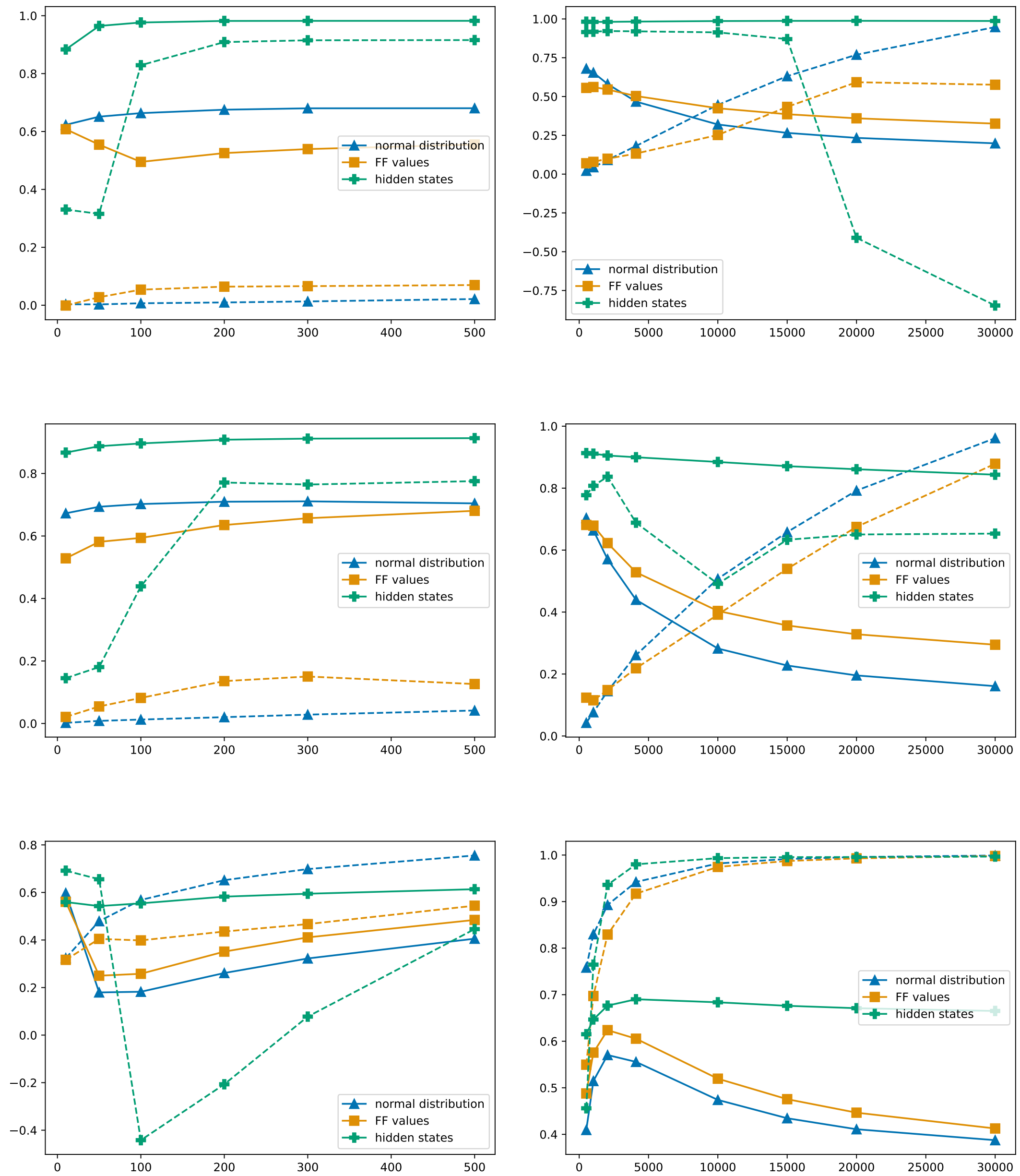


Figure 5: Each row represents a model in the following order from top to bottom: GPT-2 base, GPT-2 medium, GPT-2 large. *Left*: The `keep-k` inverse scores for three distributions: normal distribution, hidden states, and FF values, for $k \in \{10, 50, 100, 200, 300, 500\}$. *Right*: for $k \in \{10,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

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.: $\texttt{top-k}(vE)$, 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 $x^{\mathrm{T}}y$ 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]): $x^{\mathrm{T}}y = x^{\mathrm{T}}EE^{+}y = (x^{\mathrm{T}}E)(E^{+}y)$. 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: $\texttt{keep-k}(x^{\mathrm{T}}E)\texttt{keep-k}(E'y) \approx x^{\mathrm{T}}y$, where $\texttt{keep-k}(v)$ 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 claim that E^{T} is a decent instantiation of E' and provide some empirical evidence. While a substantive line of work [Ethayarajh, 2019; Gao et al., 2019; Wang et al., 2020; Rudman et al., 2021] has shown that embedding matrices are not isotropic (an isotropic matrix E has to satisfy $EE^{\mathrm{T}} = \alpha I$ for some scalar α), we show that it is isotropic enough to make E^{T} a legitimate compromise. We randomly sample 300 vectors drawn from the normal distribution $\mathcal{N}(0, 1)$, and compute for every pair x, y the cosine similarity between $x^{\mathrm{T}}y$ and $\texttt{keep-k}(x^{\mathrm{T}}E)\texttt{keep-k}(E'y)$ for $k = 1000$, and then average over all pairs. We repeat this for $E' \in \{E^{+}, E^{\mathrm{T}}\}$ and obtain a score of 0.10 for E^{+}, and 0.83 for E^{T}, showing the E^{T} is better under when using top-k. More globally, we compare $E' \in \{E^{+}, E^{\mathrm{T}}\}$ for $k \in \{10, 50, 100, 200, 300, 500\}$ with three distributions:

- x, y drawn from the normal $\mathcal{N}(0, 1)$ distribution
- x, y chosen randomly from the FF values
- x, y drawn from hidden states along Transformer computations.

In Figure 5 we show the results, where dashed lines represent E^{+} and solid lines represent E^{T}. The middle row shows the plots for GPT-2 medium, which is the main concern of this paper. For small values of k (which are more appropriate for interpretation), E^{T} is superior to E^{+} across all distributions. Interestingly, the hidden state distribution is the only distribution where E^{+} has similar performance to E^{T}. Curiously, when looking at higher values of k the trend is reversed ($k = \{512, 1024, 2048, 4096, 10000, 15000, 20000, 30000\}$) - see Figure 5 (Right).

This settles the deviation from findings showing embedding matrices are not isotropic, as we see that indeed as k grows, E^{T} becomes an increasingly bad approximate right-inverse of the embedding matrix. The only distribution that keeps high performance with E^{T} is the hidden state distribution, which is an interesting direction for future investigation.

For completeness, we provide the same analysis for GPT-2 base and large in Figure 5. We can see that GPT-2 base gives similar conclusions. GPT-2 large, however, seems to show a violent zigzag movement for E^{+} but for most values it seems to be superior to E^{T}. It is however probably best to use E^{T} since it is more predictable. This zigzag behavior is very counter-intuitive and we leave it for future work to decipher.

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:

$$\mathrm{Sim}_k(\hat{x}, \hat{y}) = \frac{|\texttt{top-k}(\hat{x}) \cap \texttt{top-k}(\hat{y})|}{|\texttt{top-k}(\hat{x}) \cup \texttt{top-k}(\hat{y})|}$$

where $\texttt{top-k}(v)$ 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.

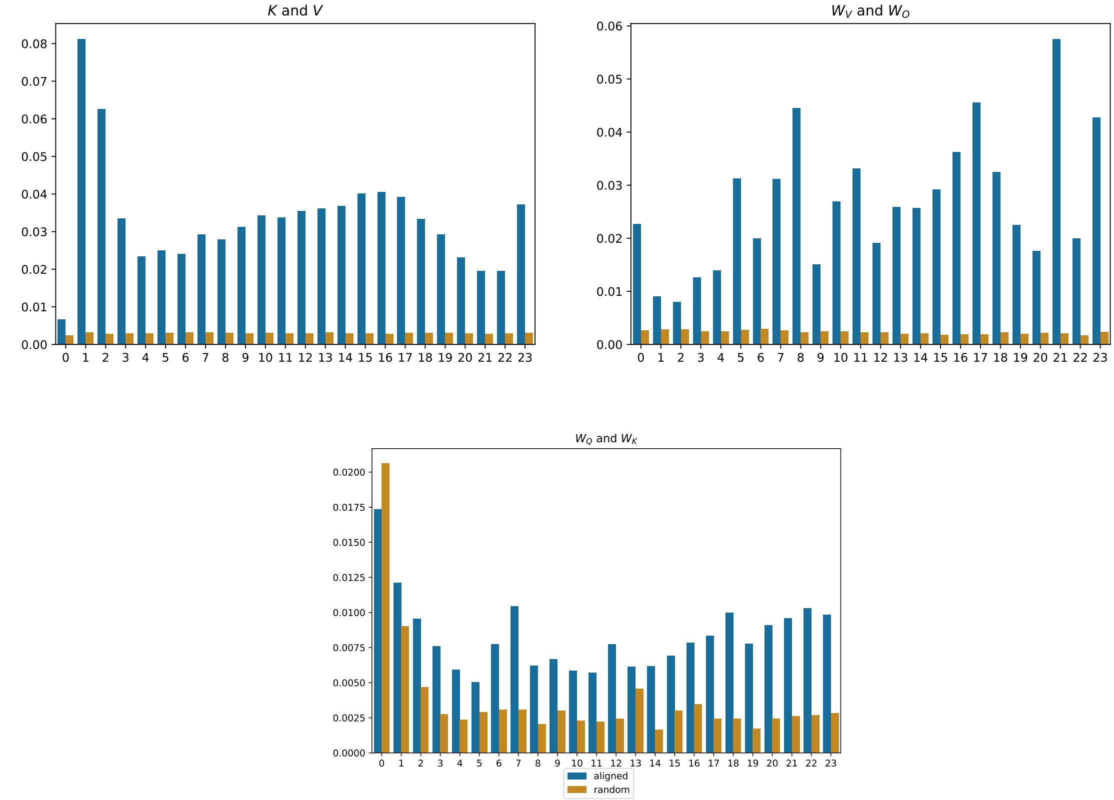


Figure 6: Average $\mathrm{Sim}_k(\hat{x}, \hat{y})$ for $k = 100$ by layer, where blue is when matching pairs are aligned, and orange is when pairs are shuffled within the layer. Top Left: FF keys and FF values. Top Right: The subheads of W_O and W_V. Bottom: The subheads of W_Q and W_K.

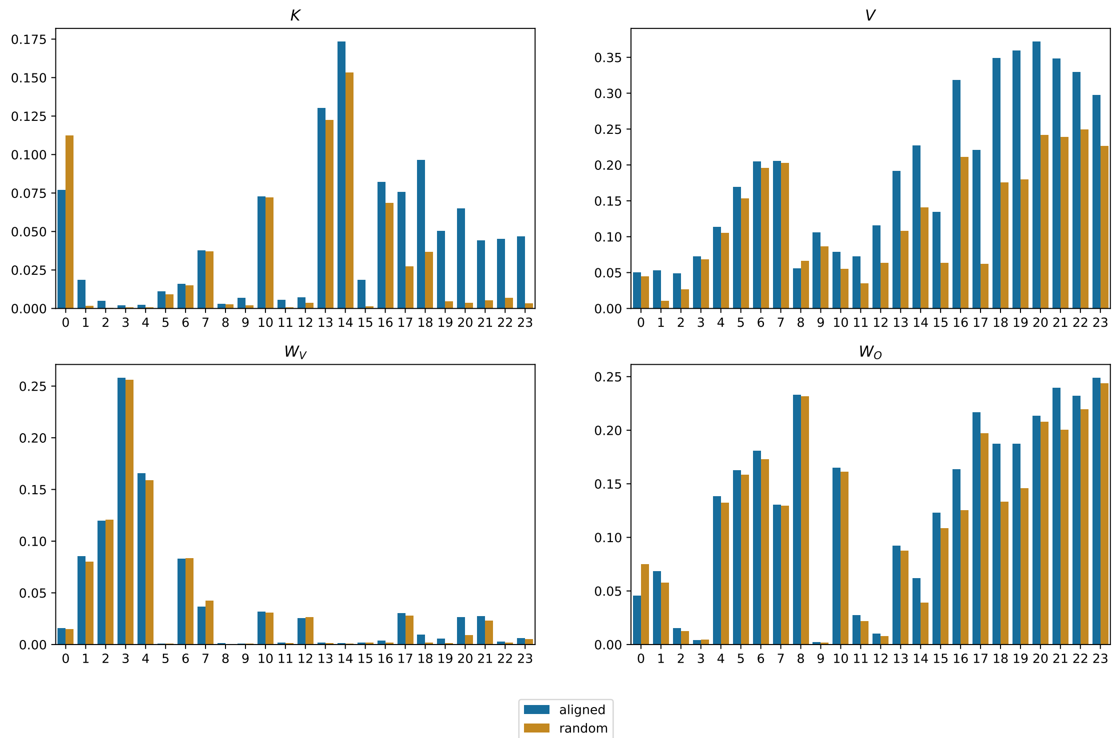
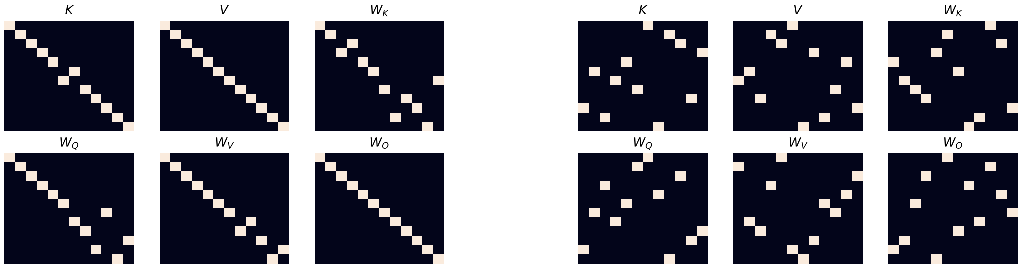


Figure 7: Left: Average R_k score ($k = 100$) across tokens per layer for activated parameter vectors against both the aligned hidden state $\hat{h}$ at the output of the *final* layer and a randomly sampled hidden state $\hat{h}_{\text{rand}}$. Parameters are FF keys (top-left), FF values (top-right),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

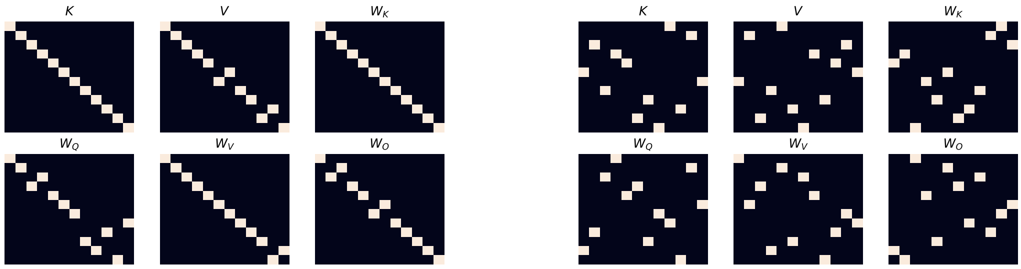
B.3 Parameter Alignment Plots for Additional Model Pairs

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

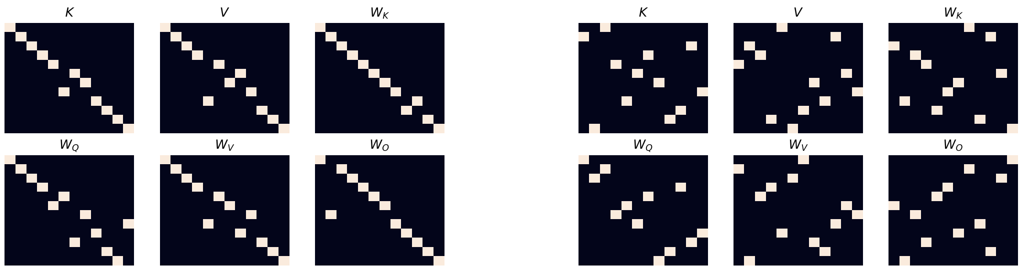
Seed 1 VS Seed 2



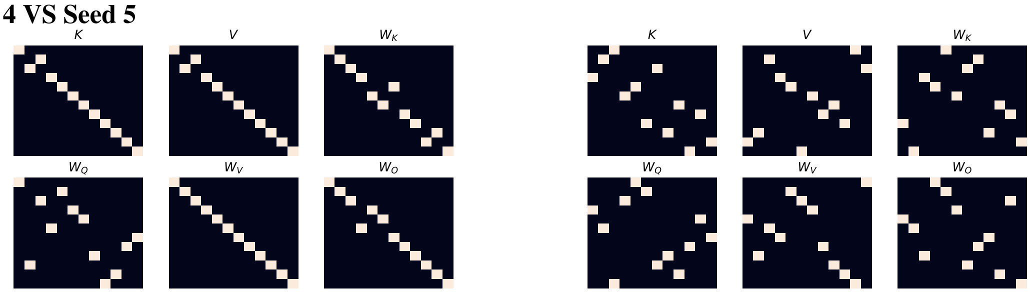
Seed 2 VS Seed 3



Seed 3 VS Seed 4



Seed 4 VS Seed 5



C Example Cases

C.1 W_{VO} 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 $e \times e$ 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'),
('Marsh', ' Marshall'),
(' Hughes', 'Hug'),
('Tan', ' Tanner'),
('nih', 'NH'),
('NRS', 'NR'),
(' Bowman', 'Bow'),
(' Marshall', 'Marsh'),
('Jac', ' Jacobs'),
('Hay', ' Hayes'),
(' Hayes', 'Hay'),
('McC', ' McCorm'),
('NI', 'NR'),
(' sidx', ' Dawson'),
(' Tanner', 'Tan'),
('gra', 'GR'),
('JA', 'jac'),
('zos', 'zo'),
('NI', 'NF'),
('McC', ' McCull'),
(' Jacobs', 'Jac'),
(' Beetle', ' Beet'),
('GF', 'FG'),
('jas', 'ja'),
('Wil', ' Wilkinson'),
(' Ramos', 'Ram'),
('GRE', 'GR'),
(' NF', 'FN'),
(' McCorm', 'McC'),
('Scar', ' Scarborough'),
(' Baal', 'Ba'),
('FP', 'FG'),
('FH', 'FN'),
(' Garfield', 'Gar'),
('jas', 'jac'),
('nuts', 'nut'),
('WI', ' Wis'),
(' Vaughn', ' Vaughan'),
('FP', 'PF'),
('RNA', 'RN'),
(' Jacobs', 'jac'),
('FM', 'FN'),
(' Knox', 'Kn'),
('NI', 'nic')
```

GPT-2 Medium - Layer 19 Head 13 (first letter/consonant of the word and last token of the word)

```
(' R', 'senal'),        #  arsenal
('senal', 'R'),
(' G', 'vernment'),     #  government
(' Madness', ' M'),
(' M', ' Mayhem'),
(' W', 'nesday'),       #  wednesday
('vernment', 'G'),
('M', ' Madness'),
(' N', 'lace'),         #  necklace
('nesday', 'W'),
('Rs', 'senal'),
(' g', 'vernment'),
(' N', 'farious'),      #  nefarious
('eneg', ' C'),
(' r', 'senal'),
(' F', 'ruary'),        #  february
('senal', 'RIC'),
(' R', 'ondo'),
(' N', ' Mandela'),     #  nelson
(' Mayhem', 'M'),
(' RD', 'senal'),
(' C', 'estine'),
('Gs', 'vernment'),
('RF', 'senal'),
(' N', 'esis'),
(' N', 'Reviewed'),
(' C', 'arette'),       #  cigarette
('rome', ' N'),
(' N', 'theless'),      #  nonetheless
('lace', 'N'),
(' H', 'DEN'),
(' V', ' versa'),
(' P', 'bably'),        #  probably
('vernment', 'GF'),
('g', 'vernment'),
('GP', 'vernment'),
(' C', 'ornia'),        #  california
('ilipp', ' F'),
(' N', 'umbered'),
(' C', 'arettes'),
('RS', 'senal'),
(' N', 'onsense'),
('RD', 'senal'),
('RAL', 'senal'),
(' F', 'uci'),
('R', 'ondo'),
(' RI', 'senal'),
(' 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'),
```

```
(' during', ' periods'),
(' LIKE', 'lihood'),
(' on', ' occasions'),
('Under', ' regime'),
('inside', 'door'),
('during', 'period'),
('Like', 'lihood'),
(' During', ' periods'),
('Inside', ' envelope'),
('for', ' sake'),
(' inside', ' doors'),
(' under', ' regime'),
(' ON', ' behalf'),
('for', ' purposes'),
('On', ' occasions'),
('inside', ' doors'),
(' on', ' basis'),
(' Under', ' regimes'),
('outside', 'doors'),
('inside', ' Osc'),
('During', ' periods'),
(' inside', 'door'),
(' UNDER', ' regime'),
(' under', ' regimes'),
('Under', ' regimes'),
('inside', 'doors'),
('inside', 'zx'),
('during', ' period'),
('inside', 'ascript'),
('Inside', 'door'),
(' On', ' occasions'),
('BuyableInstoreAndOnline', 'ysc'),
(' Inside', ' envelope'),
('during', ' pauses'),
('under', ' regime'),
(' on', ' occasion'),
('outside', ' doors'),
(' UNDER', ' banner'),
('within', ' envelope'),
(' here', 'abouts'),
('during', ' duration')
```

GPT-2 Base - Layer 10 Head 11[**]

```
(' sources', 'ources')
(' repertoire', ' reperto')
(' tales', ' stories')
(' stories', ' tales')
(' journals', ' magazines')
('stories', ' tales')
(' journal', ' journals')
(' magazines', 'Magazine')
(' magazines', ' newspapers')
(' reperto', ' repertoire')
(' cameras', ' Camer')
(' source', ' sources')
(' newspapers', ' magazines')
(' position', ' positions')
(' tale', ' tales')
(' positions', ' position')
(' obstacles', ' hurdles')
(' chores', ' tasks')
(' journals', ' papers')
(' role', ' roles')
(' hurdles', ' obstacles')
(' journals', ' journal')
(' windows', ' doors')
(' ceiling', ' ceilings')
(' loophole', ' loopholes')
(' Sources', 'ources')
('source', ' sources')
(' documentaries', ' films')
(' microphone', ' microphones')
(' cameras', ' camera')
('Journal', ' journals')
(' restrooms', ' bathrooms')
(' tasks', ' chores')
(' perspectives', ' viewpoints')
(' shelf', ' shelves')
(' rooms', ' bedrooms')
(' hurdle', ' hurdles')
(' barriers', ' fences')
(' magazines', ' journals')
(' journals', 'Magazine')
(' sources', ' source')
(' manuals', ' textbooks')
(' story', ' stories')
(' labs', ' laboratories')
(' tales', ' Stories')
(' chores', ' duties')
(' roles', ' role')
(' ceilings', ' walls')
(' microphones', ' microphone')
(' pathway', ' pathways')
```

GPT-2 Large - Layer 27 Head 6

```
(' where', 'upon'),
('where', 'upon'),
('with', ' regard'),
('with', ' regards'),
(' with', ' regards'),
(' Where', 'upon'),
(' Like', 'lihood'),
('of', ' course'),
(' with', ' regard'),
(' LIKE', 'lihood'),
('Where', 'upon'),
('from', ' afar'),
('with', 'stood'),
(' FROM', ' afar'),
(' like', 'lihood'),
(' WHERE', 'upon'),
('Like', 'lihood'),
(' with', 'stood'),
(' of', ' course'),
('of', 'course'),
('Of', ' course'),
(' from', ' afar'),
(' WITH', ' regard'),
(' where', 'abouts'),
('with', ' impunity'),
(' WITH', ' regards'),
('With', 'stood'),
('for', ' purposes'),
('with', ' respect'),
(' With', 'stood'),
('like', 'lihood'),
(' Of', ' course'),
('With', ' regard'),
(' With', ' regard'),
('where', 'abouts'),
(' WITH', 'stood'),
('With', ' regards'),
(' OF', ' course'),
(' From', ' afar'),
(' with', ' impunity'),
(' With', ' regards'),
(' with', ' respect'),
('From', ' afar'),
('with', 'standing'),
(' on', ' behalf'),
```

```
(' by', 'products'),
(' for', ' purposes'),
(' or', 'acle'),
('for', ' sake'),
(' with', 'standing')
```

C.1.2 Gender

GPT-2 Medium - Layer 18 Head 1

```
('women', ' Marie'),
(' actresses', ' Marie'),
('women', ' Anne'),
('Women', ' Anne'),
('woman', ' Marie'),
('Women', ' Marie'),
('woman', ' Anne'),
('Woman', ' Marie'),
(' actresses', ' Anne'),
(' heroine', ' Marie'),
('Women', 'Jane'),
(' heroine', ' Anne'),
('women', 'Jane'),
('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'),
('Woman', ' actresses'),
(' Women', ' Marie'),
(' Women', ' Anne'),
(' girls', ' Anne'),
('girl', ' Anne'),
('Women', 'Anne'),
('Woman', 'Women'),
('girls', ' Anne'),
(' actresses', 'Anne'),
('women', ' Michelle'),
(' Actress', ' Marie'),
('girl', ' Marie'),
(' Feminist', ' Anne'),
(' women', ' Marie'),
('Women', ' Devi'),
('Women', ' Elizabeth'),
(' actress', ' Anne'),
('Mrs', 'Anne'),
('answered', 'Answer'),
('woman', 'Anne'),
('Woman', 'maid'),
('women', 'Marie')
```

GPT-2 Large - Layer 27 Head 12

```
(' herself', ' Marie'),
(' hers', ' Marie'),
('she', ' Marie'),
(' she', ' Marie'),
(' her', ' Marie'),
('She', ' Marie'),
(' hers', 'Maria'),
(' actresses', ' actresses'),
(' herself', 'Maria'),
(' her', 'Maria'),
(' herself', ' Anne'),
('She', 'Maria'),
(' hers', ' Louise'),
(' herself', ' Louise'),
(' hers', ' Anne'),
(' hers', 'pher'),
('she', 'Maria'),
(' actress', ' actresses'),
(' herself', ' Isabel'),
(' herself', 'pher'),
(' she', 'Maria'),
(' SHE', ' Marie'),
(' herself', ' Gloria'),
(' herself', ' Amanda'),
(' Ivanka', ' Ivanka'),
(' her', ' Louise'),
(' herself', ' Kate'),
(' her', 'pher'),
(' her', ' Anne'),
(' she', 'pher'),
('she', ' Louise'),
(' herself', 'Kate'),
(' she', ' Louise'),
(' she', ' Anne'),
(' She', ' Marie'),
('she', ' Gloria'),
('She', ' Louise'),
(' hers', ' Gloria'),
(' herself', ' Diana'),
('She', ' Gloria'),
('she', ' Anne'),
('she', 'pher'),
('Her', ' Marie'),
(' she', ' Gloria'),
(' Paleo', ' Paleo'),
(' hers', ' Diana')
```

GPT-2 Base - Layer 9 Head 7[**]

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

```
('their', 'chairs')
(' herself', ' dow')
(' herself', 'eva')
(' THEY', ' themselves')
(' herself', ' Mae')
(' His', ' himself')
('clinton', 'enegger')
('She', 'erest')
(' her', ' Louise')
(' herself', ' Devi')
(' Their', 'selves')
('Their', 'chairs')
(' Himself', 'enegger')
(' she', ' Louise')
(' herself', ' Anne')
('Its', ' itself')
(' her', 'erest')
(' herself', ' Christina')
('she', 'erest')
('their', ' selves')
```

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', 'oslov')
(' Manitoba', ' Winnipeg')
(' Malaysian', ' Lumpur')
(' Swedish', 'borg')
(' Saskatchewan', ' Sask')
(' Chennai', ' Nadu')
(' Argentine', ' Aires')
(' Iceland', ' Icelandic')
(' Swedish', 'sson')
(' Tasman', ' Nadu')
('Houston', ' Astros')
('Colorado', ' Springs')
(' Kuala', ' Lumpur')
('Tai', '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')
(' Melbourne', ' Nadu')
(' Adelaide', ' Nadu')
(' Cambod', ' Nguyen')
(' Vietnamese', ' Nguyen')
```

GPT-2 Medium - Layer 16 Head 6*

```
(' 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'),
(' Aadhaar', ' Gujar'),
(' Mumbai', ' Maharashtra'),
(' Maharashtra', ' Gujarat'),
(' Gujarat', ' Gujar'),
('Australian', 'Australia'),
('India', ' Gujarat'),
(' Rahul', ' Gujar'),
(' Maharashtra', ' Mumbai'),
('Britain', 'England'),
('India', ' Chennai'),
(' Mumbai', ' Bombay'),
(' Tamil', ' Kerala'),
(' Hindi', ' Mumbai'),
(' Tasmania', ' Tasman'),
(' Mumbai', 'India'),
(' Hindi', ' Gujar'),
(' Maharashtra', ' Gujar'),
(' Australians', 'Austral'),
(' Maharashtra', ' Kerala'),
('India', ' Bangalore'),
('India', ' Kerala'),
('India', ' Bombay'),
('Australia', 'Austral'),
(' Aadhaar', 'India'),
(' Sharma', ' Mumbai'),
('Australian', 'Austral'),
(' Mumbai', ' Kerala'),
('Scotland', 'England'),
(' Mumbai', ' Gujar'),
(' Rahul', ' Mumbai'),
(' Queensland', ' Tasman'),
(' Tamil', ' Chennai'),
(' Gujarat', ' Maharashtra'),
('India', ' Modi')
```

GPT-2 Medium - Layer 16 Head 2*

```
('Austral', ' Australians'),
('Australia', 'Austral'),
(' Canberra', 'Austral'),
('Austral', ' Canberra'),
(' Winnipeg', ' Edmonton'),
('Australian', 'Austral'),
(' Alberta', ' Edmonton'),
('Australia', ' Australians'),
(' Australians', 'Austral'),
('Ukraine', 'ovych'),
```

```
(' Quebec', ' Canad'),
('Australian', ' Australians'),
(' Winnipeg', ' Manitoba'),
(' Manitoba', ' Winnipeg'),
('Canadian', 'Canada'),
('Moscow', ' Bulgar'),
(' Manitoba', ' Edmonton'),
('berra', 'Austral'),
('Austral', 'Australian'),
(' Ukrainians', 'ovych'),
('Canada', ' Canadians'),
(' Canberra', ' Australians'),
('Canada', 'Canadian'),
(' Yanukovych', 'ovych'),
('Canada', ' Trudeau'),
(' Dmitry', ' Bulgar'),
(' Australia', 'Austral'),
(' Mulcair', ' Canad'),
('berra', ' Canberra'),
('Turkish', 'oglu'),
('udeau', 'Canada'),
(' Edmonton', ' Oilers'),
('Australia', ' Canberra'),
('Canada', ' Edmonton'),
(' Edmonton', ' Calgary'),
(' Alberta', ' Calgary'),
('udeau', ' Trudeau'),
(' Calgary', ' Edmonton'),
('Canadian', ' Trudeau'),
('Australian', ' Canberra'),
(' Vancouver', ' Canucks'),
('Australia', 'Australian'),
(' Vancouver', ' Fraser'),
('Canadian', ' Edmonton'),
('Austral', 'elaide'),
('Tex', ' Braz'),
('Canada', ' RCMP'),
('Moscow', 'sov'),
('Russia', ' Bulgar'),
(' Canadians', 'Canada')
```

GPT-2 Medium - Layer 21 Head 12*

```
(' Indonesian', ' Indones'),
(' Vietnamese', ' Nguyen'),
(' Indonesian', ' Jakarta'),
(' Indonesian', ' Indonesia'),
('Turkish', 'oglu'),
(' Indonesia', ' Indones'),
(' Jakarta', ' Indones'),
(' Korean', ' Koreans'),
(' Turkish', 'oglu'),
(' Taiwan', ' Taiwanese'),
(' Thai', ' Nguyen'),
(' Brazilian', 'Brazil'),
(' Indones', ' Indonesia'),
('Tai', ' Taiwanese'),
(' Istanbul', 'oglu'),
(' Indones', ' Indonesian'),
(' Indones', ' Jakarta'),
(' Laos', ' Nguyen'),
(' Slovenia', ' Sloven'),
(' Koreans', ' Korean'),
(' Cambod', ' Nguyen'),
('Italy', 'zzi'),
(' Taiwanese', 'Tai'),
(' Indonesia', ' Jakarta'),
(' Indonesia', ' Indonesian'),
(' Bulgarian', ' Bulgaria'),
(' Iceland', ' Icelandic'),
(' Korea', ' Koreans'),
('Brazil', ' Brazilian'),
(' Bulgarian', ' Bulgar'),
(' Malaysian', ' Malays'),
(' Ankara', 'oglu'),
(' Bulgaria', ' Bulgarian'),
(' Malays', ' Indones'),
(' Taiwanese', ' Tai'),
('Turkey', 'oglu'),
('Brazil', ' Janeiro'),
('Italian', 'zzi'),
(' Kuala', ' Malays'),
('Japanese', ' Fuk'),
(' Jakarta', ' Indonesian'),
(' Taiwanese', ' Taiwan'),
(' Erdogan', 'oglu'),
(' Viet', ' Nguyen'),
(' Philippine', ' Filipino'),
(' Jakarta', ' Indonesia'),
(' Koreans', ' Jong'),
(' Filipino', ' Duterte'),
(' Azerbaijan', ' Azerbai'),
(' Bulgar', ' Bulgarian')
```

GPT-2 Large - Layer 23 Head 5

```
('Canada', ' Trudeau'),
(' Canadians', ' Trudeau'),
('Canadian', ' Trudeau'),
(' Queensland', ' Tasman'),
(' Tasman', ' Tasman'),
(' Canada', ' Trudeau'),
(' Canberra', ' Canberra'),
(' Winnipeg', ' Winnipeg'),
(' Canberra', ' Tasman'),
('Canadian', 'Canada'),
(' Canadian', ' Trudeau'),
(' Brisbane', ' Brisbane'),
(' Quebec', ' Trudeau'),
('Canadian', ' Canadian'),
(' Brisbane', ' Tasman'),
(' Tasmania', ' Tasman'),
('Canadian', ' Canadians'),
(' RCMP', ' Trudeau'),
(' Manitoba', ' Trudeau'),
(' Queensland', ' Brisbane'),
(' Queensland', ' Canberra'),
('Canada', ' Saskatchewan'),
('Canadian', ' Saskatchewan'),
('Canada', ' Canadian'),
(' RCMP', ' Saskatchewan'),
(' Canberra', ' Brisbane'),
(' Canadians', 'Canada'),
(' Winnipeg', ' Trudeau'),
('Canadian', ' Canada'),
('Canada', ' Canadians'),
('Australian', ' Canberra'),
(' Melbourne', ' Canberra'),
(' RCMP', ' Canad'),
(' Canadians', ' Canadians'),
('CBC', ' Trudeau'),
(' Canadian', ' Canadian'),
('Canadian', ' Winnipeg'),
(' Australians', ' Canberra'),
(' Quebec', 'Canada'),
(' Canadian', 'Canada'),
(' NSW', ' Canberra'),
('Toronto', ' Canad'),
('Canada', 'Canada'),
(' NSW', ' Tasman'),
(' RCMP', ' RCMP'),
(' Canadian', ' Canadians'),
```

```
(' Saskatchewan', ' Saskatchewan'),
(' Canadians', ' Saskatchewan'),
('Canadian', ' Canad'),
(' Ottawa', ' Winnipeg')
```

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'),
(' whilst', ' Whilst'),
(' organising', ' Whilst'),
(' organised', ' Whilst'),
(' organis', ' Whilst'),
(' util', ' Whilst'),
(' apologise', ' Whilst'),
(' emphas', ' Whilst'),
(' analyse', ' Whilst'),
(' organisations', ' Whilst'),
(' recognised', ' Whilst'),
(' flavours', ' Whilst'),
(' colour', ' Whilst'),
('colour', ' Whilst'),
(' Nasa', ' Whilst'),
(' Nato', ' Whilst'),
(' analys', ' Whilst'),
(' flavour', ' Whilst'),
(' colourful', ' Whilst'),
(' colours', ' 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'),
(' untouched', ' 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', 'erning'),
('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'),
(' perished', ' died'),
(' applaud', ' applauded'),
(' dictate', ' dictates'),
(' prevailed', ' prev'),
(' advising', ' advise'),
('thood', 'shed'),
('orsi', 'Reviewed'),
(' perished', ' dies'),
(' publishes', 'published'),
(' prevail', ' prevailed'),
(' dies', ' died'),
(' testifying', ' testified'),
(' testify', ' testifying'),
(' governs', ' dictates'),
(' complicity', ' complicit'),
(' dictate', ' dictated'),
('CHO', 'enough'),
('independence', ' skelet'),
```

```
(' prescribe', ' Recomm'),
(' perished', 'essential'),
('CHO', 'noticed'),
(' approving', 'avorable'),
(' perished', ' perish'),
(' oversee', ' overseeing'),
('shed', ' skelet'),
('chart', 'EY'),
(' overseeing', ' presiding'),
('pees', ' fundament'),
('appro', ' sanction'),
(' prevailed', ' prevail'),
(' regulates', ' governs'),
('shed', 'tails'),
('chart', ' Period'),
('hower', 'lihood'),
(' prevail', ' prev'),
('helps', ' aids'),
(' dict', ' dictated'),
(' dictates', ' dictated'),
('itta', ' Dise'),
('CHO', 'REC'),
('ORTS', 'exclusive'),
('helps', ' Helpful'),
('ciples', 'bart')
```

GPT-2 Medium - Layer 14 Head 1*

```
(' incorrectly', ' misunderstand'),
(' properly', ' Proper'),
(' incorrectly', ' inaccur'),
(' wrongly', ' misunderstand'),
(' incorrectly', ' misinterpret'),
(' incorrectly', ' incorrect'),
(' incorrectly', ' mistakes'),
(' incorrectly', ' misunderstanding'),
(' properly', ' proper'),
(' incorrectly', 'fail'),
(' incorrectly', ' faulty'),
(' incorrectly', ' misrepresent'),
(' fails', ' failing'),
(' incorrectly', ' inaccurate'),
(' incorrectly', ' errors'),
(' Worse', ' harmful'),
(' wrong', ' misunderstand'),
(' improperly', ' misunderstand'),
(' incorrectly', 'wrong'),
(' incorrectly', ' harmful'),
(' incorrectly', ' mistake'),
(' incorrectly', ' mis'),
(' fails', 'fail'),
(' Worse', ' detrimental'),
(' properly', ' rightful'),
(' inappropriately', ' misunderstand'),
(' unnecessarily', ' harmful'),
(' unnecessarily', ' neglect'),
(' properly', ' correctly'),
(' Worse', ' Worst'),
(' fails', ' failure'),
(' adequately', ' satisfactory'),
(' incorrectly', ' defective'),
(' mistakenly', ' misunderstand'),
(' Worse', ' harming'),
(' incorrectly', ' mishand'),
(' adequately', 'adequ'),
(' incorrectly', ' misuse'),
(' fails', 'Failure'),
(' Worse', ' hurts'),
('wrong', ' misunderstand'),
(' incorrectly', ' mistakenly'),
(' fails', ' failures'),
(' adequately', ' adequate'),
(' correctly', ' properly'),
(' Worse', ' hurting'),
(' correctly', ' Proper'),
(' fails', ' fail'),
(' incorrectly', ' mistaken'),
(' adversely', ' harming')
```

GPT-2 Large - Layer 24 Head 9

```
(' interviewer', ' interviewer'),
(' lectures', ' lectures'),
(' lecture', ' lecture'),
(' interview', 'Interview'),
(' interview', ' interview'),
(' interview', ' interviewer'),
(' interviewing', ' interviewing'),
(' magazine', ' magazine'),
(' Reviews', ' Reviews'),
(' reviewer', ' reviewer'),
(' reviewers', ' reviewers'),
(' lectures', ' lecture'),
(' testers', ' testers'),
(' editors', ' editors'),
(' interviewer', ' interview'),
(' Interview', 'Interview'),
(' interviewer', 'Interview'),
('Interview', 'Interview'),
(' lecture', ' lectures'),
(' interviewing', ' interviewer'),
(' journal', ' journal'),
(' interviewer', ' interviewing'),
(' blogs', ' blogs'),
(' editorial', ' editorial'),
(' tests', ' tests'),
(' presentations', ' presentations'),
(' Editorial', ' Editorial'),
(' interview', ' Interview'),
(' reviewer', ' reviewers'),
(' interviews', 'Interview'),
(' interview', ' interviewing'),
(' interviewer', ' Interview'),
(' interviews', ' interview'),
(' Interview', ' Interview'),
(' interviewing', 'Interview'),
('Interview', ' interviewer'),
(' testifying', ' testifying'),
(' reviewers', ' reviewer'),
(' blogging', ' blogging'),
(' broadcast', ' broadcast'),
(' Interview', ' interviewer'),
(' magazine', ' magazines'),
(' editorial', ' Editorial'),
(' interview', ' interviews'),
(' interviewing', ' interview'),
(' Interview', ' interview'),
(' interviews', ' interviews'),
(' tests', 'tests'),
(' interviews', ' interviewing'),
('Interview', ' interview')
```

GPT-2 Medium - Layer 14 Head 13*

```
(' editorial', ' editors'),
(' broadcasting', ' broadcasters'),
(' broadcasts', ' broadcasting'),
(' broadcasts', ' broadcast'),
(' broadcasters', ' Broadcasting'),
(' Editorial', ' editors'),
(' broadcast', ' broadcasters'),
(' broadcast', ' Broadcasting'),
(' lecture', ' lectures'),
```

```
(' broadcasting', ' Broadcast'),
(' broadcaster', ' broadcasters'),
(' broadcasts', ' broadcasters'),
(' publishing', ' Publishers'),
(' broadcast', ' broadcasting'),
(' Broadcasting', ' broadcasters'),
(' Publishing', ' Publishers'),
(' lectures', ' lecture'),
(' editorial', ' Editors'),
(' broadcasting', ' broadcast'),
(' broadcasts', ' Broadcasting'),
(' broadcasters', ' broadcasting'),
(' journalistic', ' journalism'),
('Journal', 'reports'),
(' Broadcasting', ' Broadcast'),
('Publisher', ' Publishers'),
(' Broadcasting', 'azeera'),
('Journal', 'Reporting'),
(' journalism', ' journalistic'),
(' broadcaster', ' Broadcasting'),
(' broadcaster', ' broadcasting'),
(' broadcasting', ' broadcaster'),
(' publication', ' editors'),
('journal', ' journalism'),
('Journal', ' Journalists'),
(' documentaries', ' documentary'),
(' filmed', ' filming'),
(' publishing', ' publishers'),
('Journal', ' journalism'),
(' broadcasts', ' Broadcast'),
(' broadcasters', ' broadcast'),
('Journal', ' articles'),
('reports', ' reporting'),
(' manuscript', ' manuscripts'),
(' publishing', ' publish'),
(' broadcasters', 'azeera'),
(' publication', ' Publishers'),
(' publications', ' Publishers'),
(' Newsp', ' newspapers'),
(' broadcasters', ' Broadcast'),
('Journal', ' Readers')
```

C.2 Query-Key Matrices

GPT-2 Large - Layer 19 Head 7**

```
(' tonight', 'Friday'),
(' Copyright', 'Returns'),
('TM', 'review'),
(' Weekend', 'Preview'),
(' tonight', 'Thursday'),
(' recently', 'Closure'),
(' Copyright', 'Contents'),
(' Copyright', 'Wisconsin'),
(' Copyright', 'Methods'),
(' tonight', 'Sunday'),
(' tomorrow', ' postpone'),
(' tomorrow', ' tonight'),
(' recently', 'acerb'),
(' Copyright', 'Rated'),
(' myself', ' my'),
(' Copyright', 'Cop'),
(' Wednesday', 'Closure'),
(' Billion', ' 1935'),
(' tonight', 'Saturday'),
(' tonight', ' celebr'),
(' tomorrow', ' postponed'),
(' Copyright', 'Show'),
(' Wednesday', 'Friday'),
(' Copyright', 'Earn'),
(' Billion', ' 1934'),
(' Eric', 'Larry'),
(' 2015', 'Released'),
(' Copyright', 'Rat'),
(' tomorrow', ' postp'),
(' 2017', 'Latest'),
(' previous', 'obin'),
(' controversial', 'Priv'),
(' recently', ' nightly'),
('Base', ' LV'),
(' recently', 'Project'),
(' historically', ' globalization'),
(' recently', ' vulner'),
(' tonight', 'Wednesday'),
(' Copyright', 'Abstract'),
(' Tuesday', 'Friday'),
(' Anthony', 'Born'),
(' Budget', 'Premium'),
(' tonight', 'Welcome'),
('yle', 'lite'),
(' Wednesday', 'Latest'),
(' Latest', 'show'),
(' B', ' pione'),
(' Copyright', 'cop'),
(' Pablo', ' Dia'),
(' recent', 'Latest')
```

GPT-2 Medium - Layer 22 Head 1

```
(' usual', ' usual'),
(' occasional', ' occasional'),
(' aforementioned', ' aforementioned'),
(' general', ' usual'),
(' usual', ' slightest'),
('agn', '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'),
```

```
(' complete', ' comparative'),
(' typical', ' usual'),
(' modern', ' modern'),
(' best', ' smartest'),
(' free', ' free'),
(' highest', ' widest'),
(' specialist', ' specialist'),
(' appropriate', ' slightest'),
(' usual', 'liest')
```

GPT-2 Large - Layer 20 Head 13 **

```
(' outdoors', ' outdoors'),
(' outdoor', ' outdoors'),
(' Gre', 'burg'),
(' healing', ' healing'),
(' indoor', ' outdoors'),
(' Hemp', 'burg'),
(' Ticket', ' Ticket'),
(' accommodations', ' accommodations'),
('eco', 'aco'),
('prem', 'otti'),
(' Candy', 'cott'),
(' decorative', ' ornament'),
('yan', 'ava'),
(' deadlines', ' schedule'),
(' Lor', 'ian'),
(' architectural', ' ornament'),
(' Ratings', ' Ratings'),
(' Bod', 'za'),
(' exotic', ' exotic'),
(' food', ' baths'),
(' Marketplace', ' Marketplace'),
(' heal', ' healing'),
(' Ex', 'ilus'),
(' indoors', ' outdoors'),
(' therm', ' therm'),
(' bleach', ' coated'),
(' Sod', 'opol'),
(' District', ' Metropolitan'),
(' Anonymous', ' Rebell'),
(' Corn', 'burg'),
(' indoor', ' indoors'),
(' R', 'vale'),
('rom', 'otti'),
(' ratings', ' Ratings'),
(' attendance', ' attendance'),
(' destinations', ' destinations'),
(' VIDEOS', ' VIDEOS'),
('yan', 'opol'),
(' Suffolk', 'ville'),
(' retali', ' against'),
('mos', 'oli'),
(' pacing', ' pacing'),
(' Spectrum', ' QC'),
(' Il', 'ian'),
(' archived', ' archived'),
(' Pledge', ' Pledge'),
('alg', 'otti'),
(' Freedom', 'USA'),
('anto', 'ero'),
(' decorative', ' decoration')
```

GPT-2 Medium - Layer 0 Head 9

```
('59', '27'),
('212', '39'),
('212', '38'),
('217', '39'),
('37', '27'),
('59', '26'),
('54', '88'),
('156', '39'),
('212', '79'),
('59', '28'),
('57', '27'),
('212', '57'),
('156', '29'),
('36', '27'),
('217', '79'),
('59', '38'),
('63', '27'),
('72', '39'),
('57', '26'),
('57', '34'),
('59', '34'),
('156', '27'),
('91', '27'),
('156', '38'),
('63', '26'),
('59', '25'),
('138', '27'),
('217', '38'),
('72', '27'),
('54', '27'),
('36', '29'),
('72', '26'),
('307', '39'),
('37', '26'),
('217', '57'),
('37', '29'),
('54', '38'),
('59', '29'),
('37', '28'),
('307', '38'),
('57', '29'),
('63', '29'),
('71', '27'),
('138', '78'),
('59', '88'),
('89', '27'),
('561', '79'),
('212', '29'),
('183', '27'),
('54', '29')
```

GPT-2 Medium - Layer 17 Head 6 *

```
(' legally', ' legal'),
(' legal', ' sentencing'),
(' legal', ' arbitration'),
(' boycot', ' boycott'),
(' legal', ' criminal'),
(' legal', ' Judicial'),
(' legal', ' rulings'),
(' judicial', ' sentencing'),
(' marketing', ' advertising'),
(' legal', ' confidential'),
(' protesting', ' protest'),
(' recruited', ' recruit'),
(' recruited', ' recruits'),
(' judicial', ' criminal'),
(' legal', ' exemptions'),
(' demographics', ' demographic'),
(' boycott', ' boycot'),
(' sentencing', ' criminal'),
(' recruitment', ' recruits'),
(' recruitment', ' recruit'),
(' Constitutional', ' sentencing'),
(' Legal', ' sentencing'),
(' constitutional', ' sentencing'),
(' legal', ' subpoena'),
```

```
(' injury', ' injuries'),
(' FOIA', ' confidential'),
(' legal', ' licenses'),
(' donation', ' donations'),
(' disclosure', ' confidential'),
(' negotiation', ' negotiating'),
(' Judicial', ' legal'),
(' legally', ' criminal'),
(' legally', ' confidential'),
(' legal', ' jur'),
(' legal', ' enforcement'),
(' legal', ' lawyers'),
(' legally', ' enforcement'),
(' recruitment', ' recruiting'),
(' recruiting', ' recruit'),
(' criminal', ' sentencing'),
(' legal', ' attorneys'),
(' negotiations', ' negotiating'),
(' legally', ' arbitration'),
(' recruited', ' recruiting'),
(' legally', ' exemptions'),
(' legal', ' judicial'),
(' voting', ' Vote'),
(' negotiated', ' negotiating'),
(' legislative', ' veto'),
(' funding', ' funded')
```

GPT-2 Medium - Layer 17 Head 7

```
('tar', 'idia'),
(' [...]', '..."'),
(' lecture', ' lectures'),
(' Congress', ' senate'),
(' staff', ' staffers'),
(' Scholarship', ' collegiate'),
(' executive', ' overseeing'),
(' Scholarship', ' academic'),
(' academ', ' academic'),
('."', '..."'),
(' [', '..."'),
('";', '..."'),
(' Memorial', 'priv'),
(' festival', 'conference'),
('crew', ' supervisors'),
(' certification', ' grading'),
(' scholarship', ' academic'),
(' rumored', ' Academic'),
(' Congress', ' delegated'),
(' staff', ' technicians'),
('Plex', ' CONS'),
(' congress', ' senate'),
(' university', ' tenure'),
(' Congress', ' appointed'),
(' Congress', ' duly'),
(' investigative', ' investig'),
(' legislative', ' senate'),
('ademic', ' academic'),
('bench', ' academic'),
(' scholarship', ' tenure'),
(' campus', ' campuses'),
(' staff', ' Facilities'),
(' Editorial', 'mn'),
(' clinic', ' laboratory'),
(' crew', ' crews'),
(' Scholarship', ' academ'),
(' staff', ' staffer'),
('icken', 'oles'),
('?"', '..."'),
(' Executive', ' overseeing'),
(' academic', ' academ'),
(' Congress', 'atra'),
('aroo', 'anny'),
(' academic', ' academia'),
(' Congress', ' Amendments'),
(' academic', ' academics'),
('student', ' academic'),
(' committee', ' convened'),
('",', '..."'),
('ove', 'idia')
```

GPT-2 Medium - Layer 16 Head 13

```
(' sugg', ' hindsight'),
(' sugg', ' anecdotal'),
(' unsuccessfully', ' hindsight'),
('didn', ' hindsight'),
('orously', 'staking'),
('illions', 'uries'),
('until', 'era'),
(' lobbied', ' hindsight'),
(' incorrectly', ' incorrect'),
(' hesitate', ' hindsight'),
('ECA', ' hindsight'),
(' regret', ' regrets'),
('inventoryQuantity', 'imore'),
('consider', ' anecdotal'),
(' errone', ' incorrect'),
(' someday', ' eventual'),
('illions', 'Murray'),
(' recently', 'recent'),
(' Learned', ' hindsight'),
('before', ' hindsight'),
(' lately', 'ealous'),
('upon', 'rity'),
('ja', ' hindsight'),
(' regretted', ' regrets'),
(' unsuccessfully', 'udging'),
(' lately', 'dated'),
(' sugg', ' anecd'),
(' inform', 'imore'),
(' lately', 'recent'),
(' anecd', ' anecdotal'),
('orously', ' hindsight'),
(' postwar', ' Era'),
(' lately', ' recent'),
(' skept', ' cynicism'),
(' sugg', 'informed'),
(' unsuccessfully', 'ealous'),
('ebin', ' hindsight'),
(' underest', ' overest'),
(' Jinn', ' hindsight'),
(' someday', '2019'),
(' recently', 'turned'),
(' sugg', ' retrospect'),
(' unsuccessfully', 'didn'),
(' unsuccessfully', 'gged'),
(' mistakenly', ' incorrect'),
('assment', ')</'),
('ja', 'didn'),
('illions', ' hindsight'),
(' sugg', ' testimony'),
('jri', ' hindsight')
```

GPT-2 Medium - Layer 12 Head 9

```
(' PST', ' usual'),
('etimes', ' foreseeable'),
('uld', 'uld'),
(' Der', ' Mankind'),
(' statewide', ' yearly'),
(' guarantees', ' guarantees'),
(' Flynn', ' Logged'),
('borne', ' foreseeable'),
```

```
(' contiguous', ' contiguous'),
(' exceptions', ' exceptions'),
(' redist', ' costly'),
(' downstream', ' day'),
(' ours', ' modern'),
(' foreseeable', ' foreseeable'),
(' Posted', ' Posted'),
(' anecdotal', ' anecdotal'),
(' moot', ' costly'),
(' successor', ' successor'),
(' any', ' ANY'),
(' generational', ' modern'),
(' temporarily', ' costly'),
(' overall', ' overall'),
(' effective', ' incentiv'),
(' future', ' tomorrow'),
(' ANY', ' lifetime'),
(' dispatch', ' dispatch'),
(' legally', ' WARRANT'),
(' guarantees', ' incentiv'),
(' listed', ' deductible'),
(' CST', ' foreseeable'),
(' anywhere', ' any'),
(' guaranteed', ' incentiv'),
(' successors', ' successor'),
(' weekends', ' day'),
('iquid', ' expensive'),
(' Trib', ' foreseeable'),
(' phased', ' modern'),
(' constitutionally', ' foreseeable'),
(' any', ' anybody'),
(' anywhere', ' ANY'),
(' veto', ' precedent'),
(' veto', ' recourse'),
(' hopefully', ' hopefully'),
(' potentially', ' potentially'),
(' ANY', ' ANY'),
(' substantive', ' noteworthy'),
('morrow', ' day'),
('ancial', ' expensive'),
('listed', ' breastfeeding'),
(' holiday', ' holidays')
```

GPT-2 Medium - Layer 11 Head 10

```
(' Journalism', ' acron'),
(' democracies', ' governments'),
('/-', 'verty'),
(' legislatures', ' governments'),
('ocracy', ' hegemony'),
('osi', ' RAND'),
(' Organizations', ' organisations'),
('ellectual', ' institutional'),
(' Journalists', ' acron'),
('eworks', ' sponsors'),
(' Inqu', ' reviewer'),
('ocracy', ' diversity'),
(' careers', ' Contributions'),
('gency', '\\-'),
('ellectual', ' exceptions'),
(' Profession', ' specializing'),
('online', ' Online'),
(' Publications', ' authorised'),
('Online', ' Online'),
(' sidx', ' Lazarus'),
('eworks', ' Networks'),
(' Groups', ' organisations'),
(' Governments', ' governments'),
(' democracies', ' nowadays'),
(' psychiat', ' Mechdragon'),
(' educ', ' Contributions'),
(' Ratings', ' organisations'),
('vernment', 'spons'),
('..."', '),"'),
(' Caucas', ' commodity'),
(' dictators', ' governments'),
('istration', ' sponsor'),
('iquette', ' acron'),
(' Announce', ' answ'),
(' Journalism', ' empowering'),
('Media', ' bureaucr'),
(' Discrimination', ' organizations'),
(' Journalism', 'Online'),
('FAQ', 'sites'),
(' antitrust', ' Governments'),
('..."', '..."'),
('Questions', ' acron'),
('rities', ' organisations'),
(' Editorial', ' institutional'),
(' tabl', ' acron'),
(' antitrust', ' governments'),
(' Journalism', ' Everyday'),
('icter', ' Lieberman'),
(' defect', 'SPONSORED'),
(' Journalists', ' organisations')
```

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', 'inez'),
('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', 'zynski'),
('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'),
```

```
(' North', ' Peninsula'),
(' Smith', 'Smith'),
('Jones', 'inez'),
(' Hernandez', 'hoff'),
(' Lucas', 'Nor'),
(' Agu', 'hoff'),
('Jones', 'utt')
```

GPT-2 Medium - Layer 19 Head 12

```
(' 2015', 'ADVERTISEMENT'),
(' 2014', '2014'),
(' 2015', '2014'),
(' 2015', 'Present'),
(' 2013', '2014'),
(' 2017', 'ADVERTISEMENT'),
(' 2016', 'ADVERTISEMENT'),
('itor', ' Banner'),
('2015', ' Bulletin'),
('2012', ' Bulletin'),
('2014', ' Bulletin'),
(' Airl', 'Stream'),
('2016', ' Bulletin'),
(' 2016', '2014'),
('2017', ' Bulletin'),
(' 2013', ' 2014'),
(' 2012', '2014'),
(' stadiums', 'ventions'),
(' 2015', ' Bulletin'),
('2013', ' Bulletin'),
(' 2017', '2014'),
(' 2011', ' 2011'),
(' 2014', ' 2014'),
(' 2011', ' 2009'),
(' mile', 'eming'),
(' 2013', 'ADVERTISEMENT'),
(' 2014', '2015'),
(' 2014', 'Present'),
(' 2011', '2014'),
(' 2011', '2009'),
(' 2015', ' 2014'),
(' 2013', ' Bulletin'),
(' 2015', '2015'),
(' 2011', ' 2003'),
(' 2011', ' 2010'),
(' 2017', 'Documents'),
('2017', 'iaries'),
(' 2013', '2015'),
('2017', 'Trend'),
(' 2011', '2011'),
(' 2016', 'Present'),
(' 2011', ' 2014'),
(' years', 'years'),
('Plug', 'Stream'),
(' 2014', 'ADVERTISEMENT'),
('2015', 'Present'),
(' 2018', 'thora'),
(' 2017', 'thora'),
(' 2012', ' 2011'),
(' 2012', ' 2014')
```

C.3 Feedforward Keys and Values

Key-value pairs, (k_i, v_i), where at least 15% of the top-k vocabulary items overlap, with $k = 100$. We follow our forerunner's 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

```
#annels         #Els
#netflix        #osi
telev           #mpeg
#tv             #vous
#avi            #iane
#flix           transmitter
Television      Sinclair
#outube         Streaming
#channel        #channel
Vid             mosqu
#Channel        broadcaster
documentaries   airs
#videos         Broadcasting
Hulu            broadcasts
channels        streams
#levision       channels
DVDs            broadcasters
broadcasts      broadcasting
#azeera         #RAFT
MPEG            #oded
televised       htt
aired           transmissions
broadcasters    playback
Streaming       Instruction
viewership      nic
#TV             Sirius
Kodi            viewership
ITV             radio
#ovies          #achers
channel         channel
```

GPT-2 Medium - Layer 3 Dim 2711

```
purposes      purposes
sake          sake
purpose       reasons
reasons       purpose
convenience   ages
reason        reason
Seasons       #ummies
#Plex         #going
Reasons       foreseeable
#ummies       Reasons
#asons        #reason
#lation       #pur
#alsh         Developers
#agos         #akers
#ACY          transl
STATS         Reason
#itas         consideration
ages          #purpose
#purpose      beginners
#=[           awhile
#gencies      Pur
Millennium    #benefit
Brewers       #atel
Festival      #tun
EVENT         pur
#payment      Ages
#=-           preservation
#printf       Metatron
beginners     um
Expo          #KEN
```

GPT-2 Medium - Layer 4 Dim 621

```
#ovie           headlined
newspapers      pestic
television      dime
editorial       describ
#journal        Afric
broadcasters    broadcasts
```

#Journal	#(’
publication	#umbnails
Newsweek	#adish
Zeit	#uggest
columnist	splash
Editorial	#ZX
newsletter	objectionable
cartoon	#article
#eport	Bucc
telev	#London
radio	reprint
headlined	#azine
#ribune	Giov
BBC	#ender
reprint	headline
sitcom	#oops
reprinted	#articles
broadcast	snipp
tabloid	Ajax
documentaries	marqu
journalist	#("
TV	#otos
headline	mast
news	#idem

GPT-2 Medium - Layer 7 Dim 72

sessions	session
dinners	sessions
#cation	#cation
session	#iesta
dinner	Booth
#eteria	screenings
Dinner	booked
#Session	#rogram
rehears	vacation
baths	baths
Lunch	#pleasant
#hops	meetings
visits	#Session
Session	greet
#session	#athon
meetings	Sessions
chatting	boarding
lunch	rituals
chats	booking
festivities	Grape
boarding	#miah
#workshop	#session
#rooms	Pars
#tests	simulated
seated	Dispatch
visit	Extras
appointments	toile
#vu	Evening
#rations	showers
#luaj	abroad

GPT-2 Medium - Layer 10 Dim 8

Miy	Tai
#imaru	#jin
Gong	Jin
Jinn	Makoto
Xia	#etsu
Makoto	Shin
Kuro	Hai
Shin	Fuj
#Tai	Dai
Yamato	Miy
Tai	#iku
Ichigo	Yun
#Shin	Ryu
#atsu	Shu
Haku	Hua
Chun	Suzuki
#ku	Yang
Qing	Xia
Tsuk	#Shin
Hua	#iru
Jiang	Yu
Nanto	#yu
manga	Chang
Yosh	Nan
yen	Qian
Osaka	#hao
Qian	Fuk
#uku	Chun
#iku	Yong
Yue	#Tai

GPT-2 Medium - Layer 11 Dim 2

progressing	toward
#Progress	towards
#progress	Pace
#osponsors	progression
#oppable	#inness
advancement	onward
progress	canon
Progress	#progress
#senal	pace
#venge	#peed
queue	advancement
#pun	advancing
progression	progressing
#wagon	ladder
advancing	path
#cknowled	honoring
#Goal	ranks
momentum	standings
#zag	goal
#hop	#grand
pursuits	momentum
#encing	#ometer
#Improve	timetable
STEP	nearing
#chini	quest
standings	spiral
#eway	trajectory
#chie	progress
#ibling	accelerating
Esports	escal

GPT-2 Medium - Layer 15 Dim 4057

EDITION	copies
versions	Version
copies	#edition
version	#Version
Version	version
edition	#download
editions	download
reprint	versions
#edition	#Download
EDIT	copy
Edition	#release
reproduce	#version
originals	release
#edited	#copy
VERS	VERS
#Versions	#pub
#Publisher	Download
reprodu	#released

#uploads	editions
playthrough	edition
Printed	reprint
reproduction	Release
#Reviewed	#Available
copy	#published
#Version	#Published
paperback	EDITION
preview	print
surv	#Quantity
#Download	#available
circulate	RELEASE

GPT-2 Medium - Layer 16 Dim 41

#duino	alarm
#Battery	alarms
Morse	signal
alarms	circuit
GPIO	GPIO
LEDs	timers
batteries	voltage
#toggle	signals
signal	circuitry
circuitry	electrical
#PsyNetMessage	circuits
alarm	LEDs
autop	standby
signalling	signalling
#volt	signaling
volt	lights
signals	Idle
voltage	triggers
LED	batteries
electrom	Morse
timers	LED
malfunction	#LED
amplifier	button
radios	Signal
wiring	timer
#Alert	wiring
signaling	buzz
#Clock	disconnect
arming	Arduino
Arduino	triggered

GPT-2 Medium - Layer 17 Dim 23

responsibility	responsibility
Responsibility	respons
responsibilities	responsibilities
#ipolar	Responsibility
#responsible	oversee
duties	#respons
#respons	duties
superv	supervision
supervision	superv
#abwe	stewards
Adin	chore
respons	oversight
oversee	oversees
entrusted	responsible
overseeing	#responsible
helicop	handling
presided	handles
overseen	overseeing
#dyl	chores
responsible	manage
#ADRA	managing
reins	duty
#accompan	Respons
chores	charge
oversees	reins
supervised	handle
blame	oversaw
oversaw	CONTROL
#archment	RESP
RESP	tasks

GPT-2 Medium - Layer 19 Dim 29

subconscious	thoughts
thoughts	thought
#brain	Thoughts
#Brain	minds
memories	mind
OCD	thinking
flashbacks	#thought
brainstorm	imagination
Anxiety	Thinking
#mind	Thought
fantas	imagin
amygdala	thinker
impuls	#thinking
Thinking	#mind
#Memory	memories
Thoughts	#think
dreams	imagining
#ocamp	impulses
#Psych	fantasies
#mares	think
mentally	urges
#mental	desires
mind	dreams
#thinking	delusions
#Mind	subconscious
#dream	emotions
psyche	imag
prefrontal	#dream
PTSD	conscience
Memories	visions

GPT-2 Medium - Layer 20 Dim 65

exercises	volleyball
#Sport	tennis
#athlon	sports
Exercise	sport
#ournaments	#basketball
volleyball	Tennis
Recre	soccer
Mahjong	golf
#basketball	playground
exercise	Golf
bowling	athletics
skating	#athlon
spar	athletic
skiing	rugby
gymn	amusement
#sports	gymn
drills	sled
#Training	#Sport
tournaments	cricket
sled	Soccer
Volunte	amuse
skate	Activities
golf	recreational
#Pract	Ski
dunk	activities
#hower	basketball
athletics	#games
sport	skating
Solitaire	hockey
#BALL	#sports

GPT-2 Medium - Layer 21 Dim 86

IDs	number
identifiers	#number
surname	#Number
surn	Number
identifier	NUM
initials	numbers
#Registered	Numbers
NAME	#Numbers
#names	address
pseudonym	#address
#codes	#Num
nomine	#NUM
names	addresses
username	Address
#IDs	identifier
ID	#Address
registration	#num
#76561	ID
#soDeliveryDate	numbering
#ADRA	IDs
CLSID	#ID
numbering	identifiers
#ername	identification
#address	numer
addresses	digits
codes	#numbered
#Names	numerical
regist	Ident
name	numeric
Names	Identification

GPT-2 Medium - Layer 21 Dim 400

#July	Oct
July	Feb
#February	Sept
#January	Dec
#Feb	Jan
November	Nov
#October	Aug
January	#Oct
Feb	May
October	#Nov
#September	Apr
September	March
#June	April
#Sept	#Sept
February	June
#November	#Aug
#April	October
April	#Feb
June	July
#December	December
August	Sep
#March	November
Sept	#Jan
December	#May
Aug	August
March	Jul
#August	Jun
#Aug	September
#wcs	January
Apr	February

GPT-2 Medium - Layer 23 Dim 166

#k	#k
#ks	#K
#kish	#ks
#K	#KS
#kat	k
#kus	#kt
#KS	K
#ked	#kr
#kr	#kl
#kB	#kish
#kan	#kos
#kw	#king
#ket	#ked
#king	#kie
#kb	#KB
#kos	#kk
#kHz	#kowski
#kk	#KR
#kick	#KING
#kers	#KT
#kowski	#KK
#KB	#KC
#krit	#kw
#KING	#kb
#kt	#Ka
#ksh	#krit
#kie	#KN
#ky	#kar
#KY	#kh
#ku	#ket

GPT-2 Medium - Layer 23 Dim 907

hands	hand
hand	#Hand
#hands	Hand
#hand	#hand
fingers	hands
#feet	Hands
fingertips	fist
claws	#hands
paw	finger
paws	handed
metab	thumb
palms	fingers
fingert	foot
#Hand	#handed
fists	paw
wrists	handing
levers	#finger
thumbs	#hander
tentacles	fingertips
feet	claw
limb	fingert
slider	#Foot
#handed	Stick
#dimension	arm
jaws	#Accessory
skelet	#fing
lapt	Foot
ankles	index
weap	toe
foot	#auntlet

GPT-2 Large - Layer 25 Dim 2685**

#manager	engineering
#Engineers	Marketing
chemist	#engineering
humanities	Communications
sciences	#communications
anthropology	anthropology
lingu	Engineering
#engineering	lingu
psychologist	psychology
Coordinator	neurolog

Analyst	Economics
#iologist	designer
accountant	sociology
strategist	communications
#ographer	marketing
curator	pharmac
Engineers	sciences
archae	economics
Designer	Accounting
Editing	#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[**]

#overty	impoverished
#wana	poverty
poverty	poorest
#Saharan	poorer
poorest	Yemen
Poverty	families
malnutrition	Poverty
Senegal	marginalized
impoverished	refugees
#poor	subsistence
Gujar	displaced
homelessness	hardship
Homeless	refugee
#heid	households
Ramadan	migrant
#Palest	disadvantaged
poorer	Sudan
Rahman	oppressed
#amily	socioeconomic
illiter	peasant
Mahmoud	homeless
Haitian	poor
#advertisement	Ethiopian
#hya	Kaf
#African	Rw
wealthier	#poor
Africans	Af
caste	rural
homeless	#fam
Hait	needy

GPT-2 Large - Layer 25 Dim 2442[**]

Tracker	tracking
gau	Tracker
charts	tracker
tracker	Tracking
#Measure	quant
measurement	#Stats
measuring	gau
#Tracker	GPS
gauge	Track
tracking	estimating
Tracking	tally
#Monitor	#ometers
#chart	tracked
Meter	calculate
#HUD	calculating
#ometers	measurement
surve	gauge
#Stats	estimation
#Statistics	monitoring
calculate	#stats
Measure	#tracking
quant	track
#asuring	measuring
Calculator	Monitoring
#ometer	#Detailed
calculator	#ometer
Monitoring	estim
#Maps	stats
pione	charts
timet	timet

GPT-2 Base - Layer 9 Dim 1776

radios	cable
antennas	modem
radio	wireless
modem	WiFi
voltage	wired
transformer	broadband
Ethernet	Ethernet
telev	radios
#Radio	power
electricity	radio
loudspe	Cable
kW	Wireless
#radio	telephone
broadband	network
volt	signal
microphones	Networks
telecommunications	networks
cable	electricity
Telephone	wifi
amplifier	#levision
wifi	coax
broadcasting	transmit
transistor	transmitter
Radio	TV
wireless	Network
LTE	television
watts	transmission
microwave	router
telephone	cables
amps	amplifier

GPT-2 Base - Layer 9 Dim 2771

arous	increase
freeing	increasing
incent	accelerating
stimulate	allev
induce	exped
discourage	enhanced
inducing	aggrav
mitigating	enhance
stimulating	inhib
emanc	improving
alleviate	infl
empowering	#oint
preventing	alien
#ufact	alter
#HCR	enabling
influencing	incre
handc	indu
disadvant	#Impro
#roying	intens
arresting	improve
allev	easing

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
#allery	trope
#ADVERTISEMENT	#feature
#Street	#fy

GPT-2 Base - Layer 0 Dim 1194

Pay	receipts
#Pay	depos
refund	Deposit
police	deduct
#pay	#milo
#paying	#igree
#Tax	#eln
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
debug
config
Linux
Java
configuration
cache
Unix
lib
runtime
kernel
plugins
virtual
FreeBSD
hash
plugin
header
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
#million
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
creature
rabbit
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
#etooth       inco
#iscover      bland
pioneers      incompetence
#emaker       idiots
Pione         crappy
#raft         shitty
#uala         idiot
prosper       pointless
#izons        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

diff	-diff
amazing	seiz
movies	coerc
wonderful	Citiz
love	#cffff
movie	#GBT
cinematic	targ
enjoyable	looph
wonderfully	Procedures
beautifully	#iannopoulos
enjoy	#Leaks
films	#ilon
comedy	grievance
fantastic	#merce
awesome	Payments
#Enjoy	#RNA
cinem	Registrar
film	Regulatory
loving	immobil
enjoyment	#bestos
masterpiece	#SpaceEngineers

diff	**-diff**
reperto	wrong
congratulations	unreasonable
Citation	horribly
thanks	inept
Recording	worst
rejo	egregious
Profile	#wrong
Tradition	unfair
canopy	worse
#ilion	atro
extracts	stupid
descendant	egreg
#cele	bad
enthusiasts	terribly
:-)	ineffective
#photo	nonsensical
awaits	awful
believer	#worst
#IDA	incompetence
welcomes	#icably

diff	-diff
movie	seiz
fucking	Strongh
really	#etooth
movies	#20439
damn	#Secure
funny	Regulation
shit	Quarterly
kinda	concess
REALLY	Recep
Movie	#aligned
stupid	targ
#movie	mosqu
goddamn	#verning
crap	FreeBSD
shitty	PsyNet
film	Facilities
crappy	#Lago
damned	#Register
#Movie	#"}],"
cheesy	Regist

diff	-diff
incompetence	#knit
bullshit	#Together
crap	Together
useless	versatile
pointless	#Discover
incompetent	richness
idiots	#iscover
incompet	forefront
garbage	inspiring
meaningless	pioneering
stupid	#accompan
crappy	unparalleled
shitty	#Explore
nonexistent	powerfully
worthless	#"},{"
Worse	#love
lame	admired
worse	#uala
inco	innovative
ineffective	enjoyed

Layer 10
4 out of 4

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**
isEnabled	wonderfully
guiActiveUnfocu...	beautifully
#igate	cinem
waivers	cinematic
expires	wonderful
expire	amazing
reimb	Absolutely
expired	storytelling
#rollment	fantastic
#Desktop	Definitely
prepaid	unforgettable
#verning	comedy
#andum	movie
reimbursement	comedic
Advisory	hilarious
permitted	#movie
#pta	#Amazing
issuance	scenes
Priebus	Amazing
#iannopoulos	enjoyable

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

diff	**-diff**
#Leaks	loving
quotas	love
#RNA	loved
subsidy	lovers
#?’"	wonderful
Penalty	lover
#iannopoulos	nostalgic
#>]	alot
discredited	beautiful
#conduct	amazing
#pta	great
waivers	passionate
Authorization	admire
#admin	passion
HHS	lovely
arbitrarily	loves
#arantine	unforgettable
#ERC	proud
memorandum	inspiration
#Federal	#love

Layer 11
4 out of 4

diff	-diff
inco	cherish
pointless	#knit
Nope	#terday
bullshit	#accompan
crap	prosper
useless	versatile
nonsense	friendships
futile	#uala
anyways	Lithuan
anyway	cherished
meaningless	redes
clueless	inspires
lame	Proud
wasting	friendship
bogus	exceptional
vomit	#beaut
nonsensical	#ngth
retarded	pioneering
idiots	pioneers
shit	nurt

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

diff	**-diff**
#knit	bullshit
passions	crap
#accompan	idiots
#ossom	goddamn
#Explore	stupid
welcomes	shitty
pioneering	shit
forefront	garbage
embraces	fuck
pioneers	incompetence
intertw	crappy
#izons	bogus
#iscover	useless
unparalleled	idiot
evolving	#shit
Together	pointless
vibrant	stupidity
prosper	fucking
strengthens	nonsense
#Together	FUCK

FF Values

Layer 9
0 out of 4
Layer 10
0 out of 4
Layer 11
0 out of 4

W_Q Subheads

Layer 9
3 out of 4

diff	**-diff**
#ARGET	kinda
#idal	alot
#--+	amazing
Prev	interesting
#enger	wonderful
#iannopoulos	definitely
#report	unbelievable
#RELATED	really
issuance	amazingly
#earcher	pretty
Previous	nice
Legislation	absolutely
#astical	VERY
#iper	wonderfully
#>[	incredible
#</	hilarious
Vendor	funny
#">	fantastic
#phrine	quite
#wcsstore	defin

diff	-diff
bullshit	strengthens
bogus	Also
faux	#helps
spurious	adjusts
nonsense	#ignt
nonsensical	evolves
inept	helps
crap	grew
junk	grows
shitty	#cliffe
fake	recognizes
incompetence	#assadors
crappy	regulates
phony	flourished
sloppy	improves
dummy	welcomes
mediocre	embraces
lame	gathers
outrage	greets
inco	prepares

diff	-diff
alot	Provision
kinda	coerc
amazing	Marketable
definitely	contingency
pretty	#Dispatch
tho	seiz
hilarious	#verning
VERY	#iannopoulos
really	#Reporting
lol	#unicip
wonderful	Fiscal
thats	issuance
dont	provision
pics	#Mobil
doesnt	#etooth
underrated	policymakers
funny	credential
REALLY	Penalty
#love	#activation
alright	#Officials

Layer 10
4 out of 4

diff	-diff
crap	#Register
shit	Browse
bullshit	#etooth
stupid	#ounces
shitty	#verning
horrible	#raft
awful	#egu
fucking	#Lago
comedic	Payments
crappy	#orsi
cheesy	Coinbase
comedy	#ourse
fuck	#iann
mediocre	#"}],"
terrible	#onductor
movie	#obil
bad	#rollment
gimmick	#ivot
filler	#Secure
inept	#ETF

diff	**-diff**
love	Worse
unforgettable	Nope
beautiful	#Instead
loved	Instead
#love	#Unless
loving	incompetence
amazing	incapable
#joy	Unless
inspiring	#failed
passion	incompet
adventure	incompetent
loves	ineffective
excitement	#Fuck
joy	#Wr
LOVE	inept
together	spurious
memories	#Failure
wonderful	worthless
enjoyment	obfusc
themes	inadequate

diff	**-diff**
#knit	crap
#"},{"	bullshit
#"}],"	stupid
#estones	inept
#Learn	shit
#ounces	idiots
#egu	shitty
#Growing	crappy
#ributes	incompetence
#externalAction...	fuck
#encers	pointless
Browse	nonsense
jointly	nonsensical
Growing	stupidity
#ossom	gimmick
honoured	inco
#accompan	lame
#agos	incompetent
#raft	mediocre
#iership	bland

diff	-diff
crap	#egu
bullshit	#etooth
shit	#verning
:(	#ounces
lol	#accompan
stupid	coh
filler	#assadors
shitty	#pherd
fucking	#acio
pointless	#uchs
idiots	strengthens
anyways	#reprene
nonsense	Scotia
anyway	#rocal
crappy	reciprocal
stupidity	Newly
fuck	fost
#shit	#ospons
anymore	#onductor
Nope	governs

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**
#also	meaningless
#knit	incompetence
helps	inco
strengthens	pointless
:)	incompetent
broaden	Worse
#ossom	inept
incorporates	nonsensical
#Learn	coward
incorporate	unint
#"},{"	obfusc
enjoy	excuses
enjoyed	panicked
complementary	useless
#etts	bullshit
enhances	stupid
integrates	incompet
#ospons	incomprehensibl...
differs	stupidity
#arger	lifeless

W_K Subheads

Layer 9

3 out of 4

diff	**-diff**
enclave	horrible
#.	pretty
#;	alot
#omial	MUCH
apiece	VERY
#assian	nothing
#.</	#much
#ulent	terrible
#,[	crappy
#eria	strange
#ourse	everything
exerc	very
#\/	shitty
#Wire	nice
#arium	many
#icle	wonderful
#.[	genuinely
#/$	beautiful
#API	much
#ium	really

diff	-diff
bullshit	#avorite
anyway	#ilyn
crap	#xtap
anyways	#insula
unless	#cedented
nonsense	#aternal
#falls	#lyak
fuck	#rieve
#.	#uana
fallacy	#accompan
#tics	#ashtra
#punk	#icer
damned	#andum
#fuck	Mehran
stupidity	#andise
shit	#racuse
commercials	#assadors
because	#Chel
despite	rall
movies	#abella

diff	-diff
Then	any
Instead	#ady
Unfortunately	#imate
Why	#cussion
Sometimes	#ze
Secondly	appreci
#Then	#raq
But	currently
Luckily	#kers
Anyway	#apixel
And	active
Suddenly	significant
Thankfully	#ade
Eventually	#imal
Somehow	specific
Fortunately	#ability
Meanwhile	anyone
What	#ker
Obviously	#unction
Because	reap

Layer 10
2 out of 4

diff	**-diff**
#,	Nope
work	Instead
#icle	Thankfully
#.	Surely
outdoors	#Instead
inspiring	Fortunately
exped	Worse
ahead	Luckily
together	#Thankfully
touches	Unless
out	Apparently
personalized	Perhaps
#joy	#Unless
#unction	#Fortunately
warm	Sorry
exceptional	Secondly
experience	#Luckily
lasting	#Rather
integ	Hence
#astic	Neither

diff	-diff
#sup	#etting
Amazing	#liness
#airs	#ktop
awesome	#ulkan
Bless	#enthal
Loving	#enance
my	#yre
#OTHER	#eeds
#BW	omission
#perfect	#reys
#-)	#lihood
amazing	#esian
#adult	#holes
perfect	syndrome
welcome	grievance
Rated	offenders
#Amazing	#wig
#anch	#hole
FANT	#creen
#anche	#pmwiki

Layer 11
2 out of 4

diff	-diff
shots	#Kind
shit	suscept
bullshit	Fathers
stuff	#Footnote
tits	concess
crap	#accompan
boobs	Strait
creepy	#orig
noises	#ESE
spectacle	#ufact
boring	Founder
things	#iere
everything	#HC
noise	#Prev
#anim	#alias
ugly	participated
garbage	#Have
stupidity	#coe
visuals	#Father
selfies	strugg

diff	-diff
#ly	#say
storytelling	actionGroup
sounding	prefers
spectacle	#ittees
#ness	#reon
#hearted	presumably
cinematic	waivers
#est	#aucuses
portrayal	#Phase
quality	#racuse
paced	#arge
combination	#hers
juxtap	#sup
representation	#later
mixture	expired
#!!!!!	stricter
filmmaking	#onds
enough	#RELATED
thing	#rollment
rendition	#orders

W_V Subheads

Layer 9
4 out of 4

diff	**-diff**	**diff**	-diff
#":""},{"	honestly	crap	jointly
#etooth	definitely	shit	#verning
#ogenesis	hilarious	bullshit	#pora
#verning	alot	fucking	#rocal
broker	amazing	idiots	#raft
#ounces	funn	fuck	#etooth
threatens	cinem	goddamn	#estead
#astical	Cinem	stupid	#ilitation
foothold	comedic	FUCK	#ourse
intruder	Absolutely	#fuck	migr
#vernment	comedy	shitty	#ourses
#activation	absolutely	damn	#iership
#Oracle	amazingly	#shit	Pione
fugitive	satire	lol	#iscover
visitor	underrated	fuckin	pioneering
#assian	really	nonsense	#egu
barrier	fantastic	crappy	#ivities
#":[	enjoyable	kinda	neighbourhood
#vier	REALLY	Fuck	pioneer
#oak	wonderful	idiot	nurt

diff	-diff	**diff**	-diff
crap	Pione	anime	#rade
bullshit	pioneers	kinda	#jamin
shit	complementary	stuff	#ounces
vomit	pioneering	shit	#pherd
nonsense	#knit	lol	Unable
stupid	#raits	tho	#pta
idiots	Browse	realism	Roche
fucking	#iscover	damn	Payments
#shit	strengthened	:)	Gupta
idiot	#rocal	fucking	#odan
fuck	prosper	alot	#uez
gimmick	Communities	movie	#adr
stupidity	neighbourhoods	funny	#ideon
goddamn	#Learn	anyways	#Secure
shitty	strengthens	enjoyable	#raught
incompetence	#iscovery	crap	Bei
lame	#ributes	comedy	sovere
FUCK	strengthen	genre	unsuccessfully
inco	#izons	anyway	#moil
blah	Mutual	fun	#Register

Layer 10
4 out of 4

diff	**-diff**
#knit	crap
welcomes	bullshit
Together	idiots
Growing	stupid
#Explore	shitty
pioneering	incompetence
complementary	pointless
milestone	goddamn
pioneer	retarded
#Together	lame
strengthens	Worse
#ossom	crappy
pioneers	incompet
#Learn	shit
jointly	stupidity
#Growing	fucking
embraces	Nope
#"},{"	FUCK
sharing	incompetent
#Discover	pathetic

diff	**-diff**
#"}],"	crap
#verning	stupid
#etooth	shit
#"},{"	fucking
Browse	fuck
#Register	shitty
#Lago	bullshit
#raft	crappy
#egu	idiots
jointly	horrible
#iership	stupidity
strengthens	kinda
Scotia	goddamn
#ounces	awful
#uania	mediocre
#iann	pathetic
workspace	#fuck
seiz	damn
Payments	FUCK
#Learn	damned

diff	**-diff**
bullshit	inspiring
incompetence	unforgettable
Worse	#knit
idiots	#love
crap	passions
dummy	cherish
incompetent	richness
Nope	timeless
stupid	loves
retarded	passionate
lame	beautifully
nonexistent	overcoming
wasting	unique
#Fuck	highs
bogus	nurture
worse	unparalleled
nonsense	vibrant
ineligible	#beaut
pointless	intertw
inco	insepar

diff	-diff
bullshit	Pione
crap	pioneers
stupid	pioneering
nonsense	complementary
incompetence	#knit
idiots	#Learn
shit	#accompan
stupidity	pioneer
pointless	invaluable
inco	#ossom
retarded	#Together
idiot	Browse
vomit	versatile
lame	welcomes
meaningless	#"},{"
goddamn	admired
nonsensical	jointly
garbage	Sharing
#shit	Together
useless	#Discover

Layer 11
4 out of 4

diff	**-diff**
Provision	alot
issuance	amazing
Securities	kinda
#ogenesis	fucking
Holdings	awesome
Regulatory	funny
indefinitely	damn
Advisory	REALLY
designation	hilarious
unilaterally	tho
Province	unbelievable
Regulation	fuckin
#Lago	wonderful
issued	doesnt
Recep	definitely
Advis	thats
#verning	yeah
broker	fantastic
#Mobil	badass
Policy	dont

diff	-diff
crap	#rocal
fucking	#verning
bullshit	#etooth
fuck	#uania
goddamn	caches
shit	Browse
#fuck	#"},{"
stupidity	#imentary
pathetic	exerc
spoiler	#Lago
stupid	#"}],"
inept	#cium
blah	#enges
FUCK	#ysis
awful	quarterly
shitty	#iscover
trope	Scotia
Godd	#resso
inco	#appings
incompetence	jointly

diff	**-diff**
pioneers	bullshit
pioneering	crap
Browse	shit
Pione	idiots
complementary	stupid
#knit	vomit
prosper	incompetence
#raits	nonsense
#Trend	gimmick
#ributes	stupidity
#Learn	idiot
strengthen	shitty
strengthened	fucking
#ossom	lame
pioneer	crappy
#iscover	goddamn
#Growing	pointless
prosperity	inco
neighbourhoods	#shit
#owship	Nope

diff	**-diff**
Worse	#knit
bullshit	pioneers
Nope	pioneering
crap	inspiring
incompetence	#iscover
idiots	complementary
incompetent	pioneer
stupid	#ossom
incompet	passionate
pointless	passions
inco	journeys
Stupid	unique
meaningless	embraces
nonsense	admired
lame	forefront
idiot	richness
worse	invaluable
#Fuck	prosper
whining	vibrant
nonsensical	enriched

W_O Subheads

Layer 9
0 out of 4
Layer 10
0 out of 4
Layer 11
0 out of 4

ACL 2023 Responsible NLP Checklist

A For every submission:

☑ A1. Did you describe the limitations of your work?
8

☑ A2. Did you discuss any potential risks of your work?
8

☑ A3. Do the abstract and introduction summarize the paper's main claims?
1

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

B ☑ Did you use or create scientific artifacts?

4,5

☑ B1. Did you cite the creators of artifacts you used?
4,5

☑ B2. Did you discuss the license or terms for use and / or distribution of any artifacts?
4,5

☑ 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)?
4

☒ 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.
4

C ☑ Did you run computational experiments?

4,5

☑ C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used?
4,5 – wherever budget is known

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

Left blank.

☐ 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.