Abstract

We present an open-source tool for visualizing multi-head self-attention in Transformer-based language models. The tool extends earlier work by visualizing attention at three levels of granularity: the attention-head level, the model level, and the neuron level. We describe how each of these views can help to interpret the model, and we demonstrate the tool on the OpenAI GPT-2 pretrained language model. We also present three use cases showing how the tool might provide insights on how to adapt or improve the model.

1 Introduction

The OpenAI GPT-2 (Generative Pretrained Transformer-2) model recently achieved state-of-the-art results across several language modeling benchmarks in a zero-shot setting (Radford et al., 2019). The model is perhaps most notable for its ability to generate coherent text in a broad range of tasks from question answering to summarization.

Underlying the success of GPT-2 and other state-of-the-art NLP models, e.g., BERT (Devlin et al., 2018), is the Transformer model, which uses a multi-head self-attention architecture (Vaswani et al., 2017a). An advantage of using attention is that it can help interpret the model’s decisions by showing how the model attends to different portions of the input (Belinkov and Glass, 2019; Strobel et al., 2018). A visualization tool designed specifically for the multi-head self-attention in the Transformer (Jones, 2017) was presented in (Vaswani et al., 2017b) and released in the Tensor2Tensor repository (Vaswani et al., 2018).

In this paper, we introduce a tool for visualizing attention in Transformer-based language models, building on the work of (Jones, 2017). We extend the existing tool in two ways: (1) we adapt it from original encoder-decoder implementation to a decoder-only language model, and (2) we add two visualizations: the model view, which visualizes all of the layers and attention heads in a single interface, and the neuron view, which shows how individual neurons influence attention scores. We demonstrate these visualizations on the OpenAI GPT-2 model and present three use cases showing how the tool might provide insights on how to adjust or improve the model.

2 Visualization Tool

We present an open-source tool for visualizing multi-head self-attention in Transformer-based language models. The tool comprises three views: an attention-head view, a model view, and a neuron view. Besides supporting OpenAI GPT-2, the tool also supports BERT, which uses masked language modeling. In the present work, however, we limit the scope of the discussion to the unidirectional language modeling architecture of GPT-2.

2.1 Attention-head view

The attention-head view (Figure 1) visualizes the attention patterns produced by one or more attention heads in a given transformer layer. In this view, self-attention is represented as lines connecting the tokens that are attending (left) with the tokens being attended to (right). Colors identify the corresponding attention head(s), while line weight reflects the attention score. At the top of the screen, the user can select the layer and one or more attention heads (represented by the colored patches). Users may also filter attention by token, as shown in Figure 1 (center).

Since the attention heads do not share parameters, they can produce a variety of attention pat-
Figure 1: Attention head view. Left and right figures represent different layers / attention heads. Middle figure depicts same layer/head as left figure, but with token selected.

Figure 2: Examples of attention heads that capture specific linguistic properties: comma-separated lists (left); prepositions (center); and nouns, particularly those that act as subject of a phrase (right). (Attention directed toward first token is likely null attention, as discussed later.) See appendix for additional examples and explanations of each of these patterns.

The attention head in Figure 1 (left), for example, generates attention that is distributed fairly evenly across previous words in the sentence (excluding the first word). In the attention head in Figure 1 (right), on the other hand, each word attends exclusively to the previous word in the sequence. Figure 2 shows examples of attention heads that capture specific linguistic features. Additional examples for these attention heads are included in the appendix.

The attention-head view closely follows the original Tensor2Tensor implementation. The key difference is that the original tool was developed for encoder-decoder models, while the present tool is designed for the decoder-only models such as GPT-2.

**Use Case: Detecting Model Bias**

One use case for the attention-head view is detecting bias in the model. Consider the following two examples of conditional language generation (generated text underlined), where the two input prompts differ only in the gender of the pronoun that begins the second sentence⁴:

- *The doctor asked the nurse a question. She said, “I’m not sure what you’re talking about.”*
- *The doctor asked the nurse a question. He asked her if she ever had a heart attack.*

In the first example, the model generates a continuation that implies *She* refers to *nurse*. In the second example, the model generates text that implies *He* refers to *doctor*. This suggests that the model’s coreference mechanism may encode gender bias (Zhao et al., 2018; Lu et al., 2018). To better understand the source of this bias, we can visualize the attention head that produces patterns resembling coreference resolution, shown in Figure 3. Two two examples from above are shown in Figure 3 (right), which reveals that the token *She* strongly attends to *nurse*, while the token *He* attends more to *doctor*. This result suggests that the model is heavily influenced by its perception of gender associated with words.

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⁴Generated using greedy top-1 decoding algorithm
By identifying a potential source of model bias, the tool can help to guide efforts to provide solutions to the issue. For example, if one were able to identify the neurons that encoded gender in this attention head, one could potentially manipulate those neurons to control for the bias (Bau et al., 2019).

2.2 Model View

The model view is a new visualization that provides a summary view of attention across all of the model’s layers and heads. As shown in Figure 4, attention heads are presented in tabular form, with rows representing layers and columns representing heads. Each layer/head is visualized in a thumbnail form that conveys the overall shape of the attention pattern. Users may click on any head to enlarge it and reveal the specific tokens associated with the attention pattern.

The model view enables users to browse the attention heads across all layers in the model and see how attention patterns evolve throughout the model. For example, one can see that many attention heads in the initial layers tend to be position-based, e.g. focusing on the same token (layer 0, head 1) or focusing on the previous token (layer 2, head 2).

Use Case: Identifying Recurring Patterns

The model view in Figure 4 shows that many of the attention heads follow the same pattern: they focus all of the attention on the first token in the sequence. This appears to be a type of null pattern that is produced when the linguistic property captured by the attention head doesn’t appear in the input text. One possible conclusion from this result is that the model may benefit from a dedicated null position to receive this type of attention. While it’s not clear that this change would improve model performance, it would make the model more interpretable by disentangling the null attention from attention related to the first token.

Figure 3: Attention pattern related to coreference resolution, which appears to be heavily influenced by perceived gender and gender roles.

Figure 4: Model view, for input text The quick, brown fox jumps over the lazy (excludes layers 6-11 and heads 6-11).
2.3 Neuron View

The neuron view (Figure 5) extends the original visualization tool to show how attention is computed from individual neurons in the query and key vectors. Given a token selected by the user (left), this view traces the computation of attention from that token to the other tokens in the sequence (right). The computation is visualized from left to right with the following columns:

- **Query q**: The 64-element query vector of the token paying attention. Only the query vector of the selected token is used in the computations.
- **Key k**: The 64-element key vector of each token receiving attention.
- **q × k (element-wise)**: The element-wise product of the selected token’s query vector and each key vector.
- **q · k**: The dot product of the selected token’s query vector and each key vector.
- **Softmax**: The softmax of the scaled dot-product from previous column. This equals the attention received by the corresponding token.

Positive and negative values are colored blue and orange, respectively, with color saturation based on the magnitude of the value. As with the attention-head view, the connecting lines are weighted based on attention between the words. The element-wise product of the vectors is included to show how individual neurons contribute to the dot product and hence attention.

Use Case: Linking Neurons to Model Behavior

To see how the neuron view might provide actionable insights, consider the attention head in Figure 6. For this head, the attention (rightmost column) appears to decay with increasing distance from the source token\(^5\). This pattern resembles a context window, but instead of having a fixed cutoff, the attention decays continuously with distance.

The neuron view provides two key insights about this attention head. First, the attention scores appear to be largely independent of the content of the input text, based on the fact that all the query vectors have very similar values (except for the first token). The second observation is that a small number of neuron positions (highlighted with blue arrows) appear to be mostly responsible for this distance-decaying attention pattern. At these neuron positions, the element-wise product \(q \times k\) decreases as the distance from the source token increases (either becoming darker orange or lighter blue).

When specific neurons are linked to a tangible outcome—in this case the decay rate of attention—it presents an opportunity for human intervention in the model. By altering the values of the relevant neurons (Bau et al., 2019), one could control the rate at which attention decays for this attention head. This capability might be useful when processing or generating texts of varying complexity; for example, one might prefer a slower decay rate (longer context window) for a scientific text and a faster decay rate (shorter context window) for content intended for children.

\(^5\)with the exception of the first token, which acts as a null token, as discussed earlier
Figure 6: Neuron view for layer 1 / head 10 (same one depicted in Figure 1, left) with last token selected. Blue arrows mark positions in the element-wise products where values decrease with increasing distance from the source token (becoming darker orange or lighter blue).

3 Conclusion

In this paper, we introduced a tool for visualizing attention in Transformer-based language models. We demonstrated the tool on the OpenAI GPT-2 model and presented various analyses of the model, including insights on how to adapt or possibly improve the model. For future work, we would also like to extend the tool to other models such as the Transformer-XL (Dai et al., 2019). Further, we would like to integrate the three views into a unified interface, and visualize the value vectors in addition to the queries and keys. Finally, we would like to enable users to intervene in the model, either by modifying attention (Strobelt et al., 2018) or manipulating individual neurons (Bau et al., 2019).

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A Appendices

Figures 7 – 9 on the following page provide additional text examples for the attention heads presented in Figure 2.
Figure 7: This attention head focuses on previous items in comma-separated list. The attention is primarily coming from positions where the model might predict the next item in the list, i.e. at a comma or at *and*. This may help the model predict a word consistent with previous list items. Attention directed toward first token is likely null attention, as discussed earlier. See Figure 2 (left) for additional example for this attention head.

Figure 8: This attention head focuses attention on prepositions and, to some extent, verbs. Attention directed toward first token is likely null attention, as discussed earlier. See Figure 2 (center) for additional example for this attention head.

Figure 9: This attention head focuses primarily on nouns, particularly those that are the subject of the sentence or phrase. Attention directed toward first token is likely null attention, as discussed earlier. See Figure 2 (right) for additional example for this attention head.