Abstract

Attention mechanisms have seen wide adoption in neural NLP models. In addition to improving predictive performance, these are often touted as affording transparency: models equipped with attention provide a distribution over attended-to input units, and this is often presented (at least implicitly) as communicating the relative importance of inputs. However, it is unclear what relationship exists between attention weights and model outputs. In this work we perform extensive experiments across a variety of NLP tasks that aim to assess the degree to which attention weights provide meaningful “explanations” for predictions. We find that they largely do not. For example, learned attention weights are frequently uncorrelated with gradient-based measures of feature importance, and one can identify very different attention distributions that nonetheless yield equivalent predictions. Our findings show that standard attention modules do not provide meaningful explanations and should not be treated as though they do. Code to reproduce all experiments is available at [https://github.com/successar/AttentionExplanation](https://github.com/successar/AttentionExplanation).

1 Introduction and Motivation

Attention mechanisms (Bahdanau et al., 2014) induce conditional distributions over input units to compose a weighted context vector for downstream modules. These are now a near-ubiquitous component of neural NLP architectures. Attention weights are often claimed (implicitly or explicitly) to afford insights into the “inner-workings” of models: for a given output one can inspect the inputs to which the model assigned large attention weights. Li et al. (2016) summarized this commonly held view in NLP: “Attention provides an important way to explain the workings of neural models”. Indeed, claims that attention provides interpretability are common in the literature, e.g., (Xu et al., 2015; Choi et al., 2016; Lei et al., 2017; Martins and Astudillo, 2016; Xie et al., 2017).

Implicit in this is the assumption that the input units (e.g., words) accorded high attention weights are responsible for model outputs. But as far as we are aware, this assumption has not been formally evaluated, and our findings here suggest that it is problematic. More specifically, we empirically investigate the relationship between attention weights, inputs, and outputs. Assuming attention provides an explanation for model predictions, we might expect the following properties to hold. (i) Attention weights should correlate with feature importance measures (e.g., gradient-based measures); (ii) Alternative (or counterfactual) attention weight configurations ought to yield corresponding changes in prediction (and if they do not then are equally plausible as explanations). We report that neither property is consistently observed by standard attention mechanisms in the context of text classification, question answering (QA), and Natural Language Inference (NLI) tasks.

Consider Figure 1. The left panel shows the
original attention distribution $\alpha$ over the words of a particular movie review using a standard attentive BiLSTM architecture for sentiment analysis. It is tempting to conclude from this that the token waste is largely responsible for the model coming to its disposition of ‘negative’ ($\hat{y} = 0.01$). But one can construct an alternative attention distribution $\tilde{\alpha}$ (right panel) that attends to entirely different tokens yet yields an essentially identical prediction (holding all other parameters of $f$, $\theta$, constant).

Such counterfactual distributions imply that explaining the original prediction by highlighting attended-to tokens is misleading. One may, e.g., instead analyze the extent to which the (often implicit) narrative answering. We thus caution against just-so stories on this basis.

Research questions and contributions. We examine the extent to which the (often implicit) narrative that attention provides model transparency$^2$ holds across tasks by exploring the following empirical questions.

1. To what extent do induced attention weights correlate with measures of feature importance – specifically, those resulting from gradients and leave-one-out methods?

2. Would alternative attention weights (and hence distinct heatmaps/explanations) necessarily yield different predictions?

Our findings with respect to these questions are summarized as follows: (1) Only weakly and inconsistently, and, (2) No; it is very often possible to construct adversarial attention distributions that yield effectively equivalent predictions as when using the originally induced attention weights, despite attending to entirely different input features. Even more strikingly, randomly permuting attention weights often induces only minimal changes in output.

2 Preliminaries and Assumptions

We consider exemplar NLP tasks for which attention mechanisms are commonly used: classification, natural language inference (NLI), and question answering. We adopt the following general modeling assumptions and notation.

We assume model inputs $x \in \mathbb{R}^{T \times |V|}$, composed of one-hot encoded words at each position. These are passed through an embedding matrix $E$ which provides dense ($d$ dimensional) token representations $x_e \in \mathbb{R}^{T \times d}$. Next, an encoder $Enc$ consumes the embedded tokens in order, producing $T \times m$-dimensional hidden states: $h = Enc(x_e) \in \mathbb{R}^{T \times m}$. We predominantly consider a Bi-RNN as the encoder module, but for completeness we also analyze convolutional and (unordered) ‘average embedding’ variants.

A similarity function $\phi$ maps $h$ and a query $Q \in \mathbb{R}^m$ (e.g., hidden representation of a question in QA, or the hypothesis in NLI) to scalar scores, and attention is then induced over these: $\alpha = \text{softmax}(\phi(h, Q)) \in \mathbb{R}^T$. In this work we consider two common similarity functions: Additive $\phi(h, Q) = v^T \tanh(W_1 h + W_2 Q)$ (Bahdanau et al., 2014) and Scaled Dot-Product $\phi(h, Q) = hQ^\top/\sqrt{m}$ (Vaswani et al., 2017), where $v, W_1, W_2$ are model parameters.

Finally, a dense layer $Dec$ with parameters $\theta$ consumes a weighted instance representation and yields a prediction $\hat{y} = \sigma(\theta \cdot h_{\alpha}) \in \mathbb{R}^{|Y|}$, where $h_{\alpha} = \sum_{t=1}^T \alpha_t \cdot h_t$; $\sigma$ is an output activation function; and $|Y|$ denotes the label set size.

3 Datasets and Tasks

For binary text classification, we use:

* Stanford Sentiment Treebank (SST) (Socher et al., 2013). 10,662 sentences tagged with sentiment on a scale from 1 (most negative) to 5 (most positive). We filter out neutral instances and dichotomize the remaining sentences into positive (4,5) and negative (1,2).
* IMDB Large Movie Reviews Corpus (Maas et al., 2011). Binary sentiment classification.

$^2$Defined as per (Lipton, 2016).

$^3$While attention is perhaps most common in seq2seq tasks like translation, our impression is that interpretability is not typically emphasized for such tasks, in general.

$^4$In the latter case, $h_t$ is the embedding of token $t$ after being passed through a linear layer and ReLU activation.
dataset containing 50,000 polarized (positive or negative) movie reviews, split into half for training and testing.

**Twitter Adverse Drug Reaction** dataset (Nikfarjam et al., 2015). A corpus of ~8000 tweets retrieved from Twitter, annotated by domain experts as mentioning adverse drug reactions.

**20 Newsgroups (Hockey vs Baseball)**. Collection of ~20,000 newsgroup correspondences, partitioned (nearly) evenly across 20 categories. We extract instances belonging to baseball and hockey, which we designate as 0 and 1, respectively, to derive a binary classification task.

**AG News Corpus (Business vs World)**. 5496,835 news articles from 2000+ sources. We follow (Zhang et al., 2015) in filtering out all but the top 4 categories. We consider the binary classification task of discriminating between world (0) and business (1) articles.

**MIMIC ICD9 (Diabetes)** (Johnson et al., 2016). A subset of discharge summaries from the MIMIC III dataset of electronic health records. The task is to recognize if a given summary has been labeled with the ICD9 code for diabetes (or not).

**MIMIC ICD9 (Chronic vs Acute Anemia)** (Johnson et al., 2016). A subset of discharge summaries from MIMIC III dataset (Johnson et al., 2016) known to correspond to patients with anemia. Here the task to distinguish the type of anemia for each report – acute (0) or chronic (1).

For **Question Answering (QA)**:

**CNN News Articles** (Hermann et al., 2015). A corpus of cloze-style questions created via automatic parsing of news articles from CNN. Each instance comprises a paragraph-question-answer triplet, where the answer is one of the anonymized entities in the paragraph.

**bAbI** (Weston et al., 2015). We consider the three tasks presented in the original bAbI dataset paper, training separate models for each. These entail finding (i) a single supporting fact for a question and (ii) two or (iii) three supporting statements, chained together to compose a coherent line of reasoning.

Finally, for **Natural Language Inference (NLI)**:

The **SNLI dataset** (Bowman et al., 2015). 570k human-written English sentence pairs manually labeled for balanced classification with the labels neutral, contradiction, and entailment, supporting the task of natural language inference (NLI). In this work, we generate an attention distribution over premise words conditioned on the hidden representation induced for the hypothesis.

We restrict ourselves to comparatively simple instantiations of attention mechanisms, as described in the preceding section. This means we do not consider recently proposed ‘BiAttentive’ architectures that attend to tokens in the respective inputs, conditioned on the other inputs (Parikh et al., 2016; Seo et al., 2016; Xiong et al., 2016).

Table 1 provides summary statistics for all datasets, as well as the observed test performances for additional context.

| Dataset                  | V  | Avg. length | Train size          | Test size          | Test performance (LSTM) |
|--------------------------|----|-------------|---------------------|-------------------|-------------------------|
| SST                      | 16175 | 19         | 3034 / 3321         | 863 / 862         | 0.81                    |
| IMDB                     | 13916 | 179        | 12500 / 12500       | 2184 / 2172       | 0.88                    |
| ADR Tweets               | 8686  | 20         | 14446 / 1939        | 3636 / 487        | 0.61                    |
| 20 Newsgroups            | 8853  | 115        | 716 / 710           | 151 / 183         | 0.94                    |
| AG News                  | 14752 | 36         | 30000 / 30000       | 1900 / 1900       | 0.96                    |
| Diabetes (MIMIC)         | 22316 | 1858       | 6381 / 1353         | 1295 / 319        | 0.79                    |
| Anemia (MIMIC)           | 19743 | 2188       | 1847 / 3251         | 460 / 802         | 0.92                    |
| CNN                      | 84790 | 761        | 380298              | 3198              | 0.64                    |
| bAbI (Task 1 / 2 / 3)    | 40   | 8 / 67 / 421 | 10000              | 1000              | 1.0 / 0.48 / 0.62        |
| SNLI                     | 20982 | 14         | 182764 / 183187 / 183416 | 3219 / 3237 / 3368 | 0.78                    |

Table 1: Dataset characteristics. For train and test size, we list the cardinality for each class, where applicable: 0/1 for binary classification (top), and 0 / 1 / 2 for NLI (bottom). Average length is in tokens. Test metrics are F1 score, accuracy, and micro-F1 for classification, QA, and NLI, respectively; all correspond to performance using a BiLSTM encoder. We note that results using convolutional and average (i.e., non-recurrent) encoders are comparable for classification though markedly worse for QA tasks.
output by more than some threshold. We quantify how different attention weights can be to serve attention weights (which one might show in attention distributions). Under the assumption that attention weights are explanatory, such weights, and between ‘leave-one-out’ (or ‘feature erasure’) measures and the same. In Section 4.2 we then consider counterfactual (to those observed) attention distributions. Under the assumption that attention weights are explanatory, such counterfactual distributions may be viewed as alternative potential explanations; if these do not correspondingly change model output, then it is hard to argue that the original attention weights provide meaningful explanation in the first place.

To generate counterfactual attention distributions, we first consider randomly permuting observed attention weights and recording associated changes in model outputs (4.2.1). We then propose explicitly searching for “adversarial” attention weights that maximally differ from the observed attention weights (which one might show in a heatmap and use to explain a model prediction), and yet yield an effectively equivalent prediction (4.2.2). The latter strategy also provides a useful potential metric for the reliability of attention weights as explanations: we can report a measure quantifying how different attention weights can be for a given instance without changing the model output by more than some threshold $\epsilon$.

More specifically, in Section 4.1, we empirically analyze the correlation between gradient-based feature importance and learned attention weights, and between ‘leave-one-out’ (or ‘feature erasure’) measures and the same. In Section 4.2 we then consider counterfactual (to those observed) attention distributions. Under the assumption that attention weights are explanatory, such counterfactual distributions may be viewed as alternative potential explanations; if these do not correspondingly change model output, then it is hard to argue that the original attention weights provide meaningful explanation in the first place.

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| Dataset | Class | Mean ± Std. | Sig. Frac. | Mean ± Std. | Sig. Frac. | Mean ± Std. | Sig. Frac. |
|--------|-------|-------------|------------|-------------|------------|-------------|------------|
| SST    | 0     | 0.40 ± 0.21 | 0.59       | 0.69 ± 0.15 | 0.93       | 0.34 ± 0.20 | 0.47       |
|        | 1     | 0.38 ± 0.19 | 0.58       | 0.69 ± 0.14 | 0.94       | 0.33 ± 0.19 | 0.47       |
| IMDB   | 0     | 0.37 ± 0.07 | 1.00       | 0.65 ± 0.05 | 1.00       | 0.30 ± 0.07 | 0.99       |
|        | 1     | 0.37 ± 0.08 | 0.99       | 0.66 ± 0.05 | 1.00       | 0.31 ± 0.07 | 0.98       |
| ADR Tweets | 0   | 0.45 ± 0.17 | 0.74       | 0.71 ± 0.13 | 0.97       | 0.29 ± 0.19 | 0.44       |
|        | 1     | 0.45 ± 0.16 | 0.77       | 0.71 ± 0.13 | 0.97       | 0.40 ± 0.17 | 0.69       |
| 20News | 0     | 0.06 ± 0.15 | 0.31       | 0.65 ± 0.09 | 0.99       | 0.05 ± 0.15 | 0.28       |
|        | 1     | 0.13 ± 0.16 | 0.48       | 0.66 ± 0.09 | 1.00       | 0.14 ± 0.14 | 0.51       |
| AG News | 0    | 0.42 ± 0.11 | 0.93       | 0.77 ± 0.08 | 1.00       | 0.35 ± 0.13 | 0.80       |
|        | 1     | 0.35 ± 0.13 | 0.81       | 0.75 ± 0.07 | 1.00       | 0.32 ± 0.13 | 0.73       |
| Diabetes | 0   | 0.47 ± 0.06 | 1.00       | 0.68 ± 0.02 | 1.00       | 0.44 ± 0.07 | 1.00       |
|        | 1     | 0.38 ± 0.08 | 1.00       | 0.68 ± 0.02 | 1.00       | 0.38 ± 0.08 | 1.00       |
| Anemia | 0     | 0.42 ± 0.05 | 1.00       | 0.81 ± 0.01 | 1.00       | 0.42 ± 0.05 | 1.00       |
|        | 1     | 0.43 ± 0.06 | 1.00       | 0.81 ± 0.01 | 1.00       | 0.44 ± 0.06 | 1.00       |
| CNN Overall | 0   | 0.20 ± 0.06 | 0.99       | 0.48 ± 0.11 | 1.00       | 0.16 ± 0.07 | 0.95       |
| hAbI 1 Overall | 0 | 0.23 ± 0.19 | 0.46       | 0.66 ± 0.17 | 0.97       | 0.23 ± 0.18 | 0.45       |
| hAbI 2 Overall | 0 | 0.17 ± 0.12 | 0.57       | 0.84 ± 0.09 | 1.00       | 0.11 ± 0.13 | 0.40       |
| hAbI 3 Overall | 0 | 0.30 ± 0.11 | 0.93       | 0.76 ± 0.12 | 1.00       | 0.31 ± 0.11 | 0.94       |
| SNLI    | 0     | 0.36 ± 0.22 | 0.46       | 0.54 ± 0.20 | 0.76       | 0.44 ± 0.18 | 0.60       |
|        | 1     | 0.42 ± 0.19 | 0.57       | 0.59 ± 0.18 | 0.84       | 0.43 ± 0.17 | 0.59       |
|        | 2     | 0.40 ± 0.20 | 0.52       | 0.53 ± 0.19 | 0.75       | 0.44 ± 0.17 | 0.61       |

Table 2: Mean and std. dev. of correlations between gradient/leave-one-out importance measures and attention weights. Sig. Frac. columns report the fraction of instances for which this correlation is statistically significant; note that this largely depends on input length, as correlation does tend to exist, just weakly. Encoders are denoted parenthetically. These are representative results; exhaustive results for all encoders are available to browse online.

Had we attended to different features, would the prediction have been different??

All results presented below are generated on test sets. We present results for Additive attention below. The results for Scaled Dot Product in its place are comparable. We provide a web interface to interactively browse the (very large set of) plots for all datasets, model variants, and experiment types: https://successar.github.io/AttentionExplanation/docs/.

In the following sections, we use Total Variation Distance (TVD) as the measure of change between output distributions, defined as follows. TVD$(\hat{y}_1, \hat{y}_2) = \frac{1}{2} \sum_{i=1}^{|y|} |\hat{y}_{i1} - \hat{y}_{i2}|$. We use the Jensen-Shannon Divergence (JSD) to quantify the difference between two attention distributions: JSD$(\alpha_1, \alpha_2) = \frac{1}{2} \text{KL}[\alpha_1 \| \frac{\alpha_1 + \alpha_2}{2}] + \frac{1}{2} \text{KL}[\alpha_2 \| \frac{\alpha_1 + \alpha_2}{2}]$.

### 4.1 Correlation Between Attention and Feature Importance Measures

We empirically characterize the relationship between attention weights and corresponding feature importance scores. Specifically we measure correlations between attention and: (1) gradient based measures of feature importance ($\tau_g$), and, (2) differences in model output induced by leaving features out ($\tau_{loo}$). While these measures are themselves insufficient for interpretation of neural model behavior (Feng et al., 2018), they do provide measures of individual feature importance with known semantics (Ross et al., 2017). It is thus
instructive to ask whether these measures correlate with attention weights. The process we follow to quantify this is described by Algorithm 1. We denote the input resulting from removing the word at position $t$ in $x$ by $x_{-t}$. Note that we disconnect the computation graph at the attention module so that the gradient does not flow through this layer.

**Algorithm 1 Feature Importance Computations**

\[
\begin{align*}
  h &\leftarrow \text{Enc}(x), \hat{\alpha} \leftarrow \text{softmax}(\phi(h, Q)) \\
  \hat{y} &\leftarrow \text{Dec}(h, \alpha) \\
  g_t &\leftarrow \left| \sum_{w=1}^{[V]} 1[x_{tw} = 1] \frac{\partial y}{\partial x_{tw}} \right|, \forall t \in [1, T] \\
  \tau_g &\leftarrow \text{Kendall-}\tau(\alpha, g) \\
  \Delta \hat{y}_t &\leftarrow \text{TVD}(\hat{y}(x_{-t}), \hat{y}(x)), \forall t \in [1, T] \\
  \tau_{\text{loo}} &\leftarrow \text{Kendall-}\tau(\alpha, \Delta \hat{y})
\end{align*}
\]

Table 2 reports summary statistics of Kendall $\tau$ correlations for each dataset. Full distributions are shown in Figure 2, which plots histograms of $\tau_g$ for every data point in the respective corpora. (Corresponding plots for $\tau_{\text{loo}}$ are similar and the full set can be browsed via the aforementioned online supplement.) We plot these separately for each class: orange ($\blacksquare$) represents instances predicted as positive, and purple ($\blacksquare$) those predicted to be negative. For SNLI, $\blacksquare$, $\blacksquare$, $\blacksquare$, code for neutral, contradiction and entailment, respectively.

In general, observed correlations are modest (recall that a value of 0 indicates no correspondence, while 1 implies perfect concordance) for the BiLSTM model. The centrality of observed densities hovers around or below 0.5 in most of the corpora considered. Moreover, as per Table 2, the correlation between attention weights and feature importance scores (both gradient and feature erasure based) is sufficiently weak so as to fail to consistently realize a statistically significant relationship in some corpora. Results using CNN encoders are comparable. By contrast, gradients in “average” embedding based models show much higher correspondence with attention weights, as we would expect for these simple encoders.

On some datasets — notably the MIMIC tasks, and to a lesser extent the QA corpora — this correlation is consistently significant, although remains relatively weak. The more consistently significant correlations observed on these datasets is likely attributable to the increased length of the documents that they comprise, which in turn provide sufficiently large sample sizes to establish significant (although still weak) correlation between attention weights and feature importance scores.

The results here suggest that, in general, attention weights do not strongly or consistently agree with standard feature importance scores. The exception to this is when one uses a very simple (averaging) encoder model, but insights into such simple architectures are arguably not terribly useful to begin with. These findings should be disconcerting to one hoping to view attention weights as explanatory, given the face validity of input gradient/erasure based explanations (Ross et al., 2017; Li et al., 2016).
4.2 Counterfactual Attention Weights

We next consider what-if scenarios corresponding to alternative (counterfactual) attention weights. The idea is to investigate whether the prediction would have been different, had the model emphasized (attended to) different input features. More precisely, suppose \( \hat{\alpha} = \{\hat{\alpha}_t\}_{t=1}^T \) are the attention weights induced for an instance, giving rise to model output \( \hat{y} \). We then consider counterfactual distributions over \( y \), under alternative \( \alpha \).

We experiment with two means of constructing such distributions. First, we simply scramble the original attention weights \( \hat{\alpha} \), re-assigning each value to an arbitrary, randomly sampled index (input feature). Second, we generate an adversarial attention distribution: this is a set of attention weights that is maximally distinct from \( \hat{\alpha} \) but that nonetheless yields an equivalent prediction (i.e., prediction within some \( \epsilon \) of \( \hat{y} \)).

4.2.1 Attention Permutation

To characterize model behavior when attention weights are shuffled, we follow Algorithm 2.

Figure 3 depicts the relationship between the maximum attention value in the original \( \hat{\alpha} \) and the median induced change in model output (\( \Delta \hat{y}^{med} \)) across instances in the respective datasets. Colors again indicate class predictions, as above.

We observe that there exist many points with small \( \Delta \hat{y}^{med} \) despite large magnitude attention weights. These are cases in which the attention weights might suggest explaining an output by a small set of features (this is how one might reasonably read a heatmap depicting the attention weights), but where scrambling the attention makes little difference to the prediction.

In some cases, such as predicting ICD codes from notes using the MIMIC dataset, one can see different behavior for the respective classes. For the Diabetes task, e.g., attention behaves intuitively for at least the positive class; perturbing attention in this case causes large changes to the prediction. We again conjecture that this is due to a few tokens serving as high precision indicators for the positive class; in their absence (or when they are not attended to sufficiently), the prediction drops considerably. However, this is the exception rather than the rule.

4.2.2 Adversarial Attention

We next propose a more focused approach to counterfactual attention weights, which we will refer to as adversarial attention. The intuition is to explicitly seek out attention weights that differ as
much as possible from the observed attention dis-
tribution and yet leave the prediction effectively
unchanged. Such adversarial weights violate an
intuitive property of explanations: shifting model
attention to very different input features should
yield corresponding changes in the output. Al-
ternative attention distributions identified adver-
sarially may then be viewed as equally plausible
explanations for the same output.

Operationally, realizing this objective requires
specifying a value $\epsilon$ that defines what qualifies as
a “small” difference in model output. Once this is
specified, we aim to find $k$ adversarial distributions
$\{\alpha(1), \ldots, \alpha(k)\}$, such that each $\alpha(i)$
maximizes the distance from original $\hat{\alpha}$ but does not
change the output by more than $\epsilon$. In practice we
simply set this to 0.01 for text classification and
0.05 for QA datasets.\(^6\)

We propose the following optimization problem
to identify adversarial attention weights.

$$\begin{align*}
\text{maximize} & \quad f(\{\alpha(i)\}_{i=1}^k) \\
\text{subject to} & \quad \forall i \, \text{TVD}[\hat{y}(x, \alpha(i)), \hat{y}(x, \hat{\alpha})] \leq \epsilon
\end{align*}$$
\hspace{1cm} (1)

Where $f(\{\alpha(i)\}_{i=1}^k)$ is:

$$\sum_{i=1}^k \text{JSD}[\alpha(i), \hat{\alpha}] + \frac{1}{k(k-1)} \sum_{i<j} \text{JSD}[\alpha(i), \alpha(j)]$$
\hspace{1cm} (2)

\(^6\)We make the threshold slightly higher for QA because the
output space is larger and thus small dimension-wise
perturbations can produce comparatively large TVD.

In practice we maximize a relaxed version of
this objective via the Adam SGD optimizer (Kingma and Ba, 2014):

$$f(\{\alpha(i)\}_{i=1}^k) + \frac{1}{k} \sum_{i=1}^k \max(0, \text{TVD}[\hat{y}(x, \alpha(i)), \hat{y}(x, \hat{\alpha})] - \epsilon).$$
\hspace{1cm} (3)

Equation 1 attempts to identify a set of new atten-
tion distributions over the input that is as far
as possible from the observed $\alpha$ (as measured
by JSD) and from each other (and thus diverse),
while keeping the output of the model within $\epsilon$
of the original prediction. We denote the out-
put obtained under the $i^{th}$ adversarial attention by
$\hat{y}(i)$. Note that the JS Divergence between any two
categorical distributions (irrespective of length) is bounded
from above by 0.69.

One can view an attentive decoder as a func-
tion that maps from the space of latent input rep-
resentations and attention weights over input words
$\Delta^{T-1}$ to a distribution over the output space $\mathcal{Y}$. Thus,
for any output $\hat{y}$, we can define how likely
each attention distribution $\alpha$ will generate the output
as inversely proportional to TVD$(y(\alpha), \hat{y})$.

Figure 4 depicts the distributions of max JSDs
realized over instances with adversarial attention
weights for a subset of the datasets considered
(plots for the remaining corpora are in the Ap-
pendix). Colors again indicate predicted class.
Mass toward the upper-bound of 0.69 indicates
that we are frequently able to identify max-
imally different attention weights that hardly budge
model output. We observe that one can identify

\(^7\)We set $\lambda = 500$. 

We propose the following optimization problem
to identify adversarial attention weights.

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\text{subject to} & \quad \forall i \, \text{TVD}[\hat{y}(x, \alpha(i)), \hat{y}(x, \hat{\alpha})] \leq \epsilon
\end{align*}$$
\hspace{1cm} (1)

Where $f(\{\alpha(i)\}_{i=1}^k)$ is:

$$\sum_{i=1}^k \text{JSD}[\alpha(i), \hat{\alpha}] + \frac{1}{k(k-1)} \sum_{i<j} \text{JSD}[\alpha(i), \alpha(j)]$$
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In practice we maximize a relaxed version of
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\hspace{1cm} (3)

Equation 1 attempts to identify a set of new atten-
tion distributions over the input that is as far
as possible from the observed $\alpha$ (as measured
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One can view an attentive decoder as a func-
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Mass toward the upper-bound of 0.69 indicates
that we are frequently able to identify max-
imally different attention weights that hardly budge
model output. We observe that one can identify
adversarial attention weights associated with high JSD for a significant number of examples. This means that is often the case that quite different attention distributions over inputs would yield essentially the same (within \( \epsilon \)) output.

In the case of the diabetes task, we again observe a pattern of low JSD for positive examples (where evidence is present) and high JSD for negative examples. In other words, for this task, if one perturbs the attention weights when it is inferred that the patient is diabetic, this does change the output, which is intuitively agreeable. However, this behavior again is an exception to the rule.

We also consider the relationship between max attention weights (indicating strong emphasis on a particular feature) and the dissimilarity of identified adversarial attention weights, as measured via JSD, for adversaries that yield a prediction within \( \epsilon \) of the original model output. Intuitively, one might hope that if attention weights are peaky, then counterfactual attention weights that are very different but which yield equivalent predictions would be more difficult to identify.

Figure 5 illustrates that while there is a negative trend to this effect, it is realized only weakly. Put another way: there exist many cases (in all datasets) in which despite a high attention weight, an alternative and quite different attention configuration over inputs yields effectively the same output. In light of this, presenting a heatmap in such a scenario that implies a particular feature is primarily responsible for an output would seem to be misleading.

5 Related Work

We have focused on attention mechanisms and the question of whether they afford transparency, but a number of interesting strategies unrelated to attention mechanisms have been recently proposed to provide insights into neural NLP models. These include approaches that measure feature importance based on gradient information (Ross et al., 2017; Sundararajan et al., 2017) (aligned with the gradient-based measures that we have used here), and methods based on representation erasure (Li et al., 2016), in which dimensions are removed and then the resultant change in output is recorded (similar to our experiments with removing tokens from inputs, albeit we do this at the input layer).

Comparing such importance measures to attention scores may provide additional insights into the working of attention based models (Ghaeini et al., 2018). Another novel line of work in this direction involves explicitly identifying explanations of black-box predictions via a causal framework (Alvarez-Melis and Jaakkola, 2017).
also note that there has been complementary work demonstrating low correlation between human attention and induced attention weights (Pappas and Popescu-Belis, 2016).

More specific to attention mechanisms, recent promising work has proposed more principled attention variants designed explicitly for interpretability; these may provide greater transparency by imposing hard, sparse attention. Such instantiations explicitly select (modest) subsets of inputs to be considered when making a prediction, which are then by construction responsible for model output (Lei et al., 2016; Peters et al., 2018). Structured attention models (Kim et al., 2017) provide a generalized framework for describing and fitting attention variants with explicit probabilistic semantics. Tying attention weights to human-provided rationales is another potentially promising avenue (Bao et al., 2018).

We hope our work motivates further development of these methods, resulting in attention variants that both improve predictive performance and provide insights into model predictions.

6 Discussion and Conclusions

We have provided evidence that correlation between intuitive feature importance measures (including gradient and feature erasure approaches) and learned attention weights is weak (Section 4.1). We also established that counterfactual attention distributions — which would tell a different story about why a model made the prediction that it did — often have no effect on model output (Section 4.2).

These results suggest that while attention modules consistently yield improved performance on NLP tasks, their ability to provide transparency or meaningful explanations for model predictions is, at best, questionable. More generally, how one is meant to interpret the ‘heatmaps’ of attention weights placed over inputs that are commonly presented is unclear. These would seem to suggest a story about how a model arrived at a particular disposition, but the results here indicate that the relationship between this and attention is not obvious.

There are important limitations to this work and the conclusions we can draw from it. We have reported the (generally weak) correlation between learned attention weights and various alternative measures of feature importance, e.g., gradients. We do not intend to imply that such alternative measures are necessarily ideal or that they should be considered ‘ground truth’. While such measures do enjoy a clear intrinsic (to the model) semantics, their interpretation in the context of nonlinear neural networks can nonetheless be difficult for humans (Feng et al., 2018). Still, that attention consistently correlates poorly with multiple such measures ought to give pause to practitioners.

An additional limitation is that we have only considered a handful of attention variants, selected to reflect common module architectures for the respective tasks included in our analysis. Alternative attention specifications may yield different conclusions; and indeed we hope this work motivates further development of principled attention mechanisms. Finally, we have limited our evaluation to tasks with unstructured output spaces, i.e., we have not considered seq2seq tasks, which we leave for future work. However we believe interpretability is more often a consideration in, e.g., classification than in translation.

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Attention is not Explanation: Appendix

A Model details

For all datasets, we use spaCy for tokenization. We map out of vocabulary words to a special $<\text{unk}>$ token and map all words with numeric characters to ‘qqq’. Each word in the vocabulary was initialized to pretrained embeddings. For general domain corpora we used either (i) FastText Embeddings (SST, IMDB, 20News, and CNN) trained on Simple English Wikipedia, or, (ii) GloVe 840B embeddings (AG-News and SNLI). For the MIMIC dataset, we learned word embeddings using Gensim over all discharge summaries in the corpus. We initialize words not present in the vocabulary using samples from a standard Gaussian $N(\mu = 0, \sigma^2 = 1)$.

A.1 BiLSTM

We use an embedding size of 300 and hidden size of 128 for all datasets except bAbI (for which we use 50 and 30, respectively). All models were regularized using $\ell_2$ regularization ($\lambda = 10^{-5}$) applied to all parameters. We use a sigmoid activation functions for binary classification tasks, and a softmax for all other outputs. We trained the model using maximum likelihood loss using the Adam Optimizer with default parameters in PyTorch.

A.2 CNN

We use an embedding size of 300 and 4 kernels of sizes [1, 3, 5, 7], each with 64 filters, giving a final hidden size of 256 (for bAbI we use 50 and 8 respectively with same kernel sizes). We use ReLU activation function on the output of the filters. All other configurations remain same as BiLSTM.

A.3 Average

We use the embedding size of 300 and a projection size of 256 with ReLU activation on the output of the projection matrix. All other configurations remain same as BiLSTM.

B Graphs

To provide easy navigation of our (large set of) graphs depicting attention weights on various datasets/tasks under various model configuration we have created an interactive interface to browse these results, accessible at: https://successar.github.io/AttentionExplanation/docs/.

C Adversarial Heatmaps

SST

Original: reggio falls victim to relying on the very digital technology that he fervently scorns creating a meandering inarticulate and ultimately disappointing film  
Adversarial: reggio falls victim to relying on the very digital technology that he fervently scorns creating a meandering inarticulate and ultimately disappointing film $\Delta \hat{y}: 0.005$

IMDB

Original: fantastic movie one of the best film noir movies ever made bad guys bad girls a jewel heist a twisted morality a kidnapping everything is here jean has a face that would make bogart proud and the rest of the cast is is full of character actors who seem to to know they’re onto something good get some popcorn and have a great time  
Adversarial: fantastic movie one of the best film noir movies ever made bad guys bad girls a jewel heist a twisted morality a kidnapping everything is here jean has a face that would make bogart proud and the rest of the cast is is full of character actors who seem to to know they’re onto something good get some popcorn and have a great time $\Delta \hat{y}: 0.004$

20 News Group - Sports
Original: i meant to comment on this at the time there ’ s just no way baserunning could be that important if it was runs created would n ’ t be nearly as accurate as it is runs created is usually about qqq qqq accurate on a team level and there ’ s a lot more than baserunning that has to account for the remaining percent .

Adversarial: i meant to comment on this at the time there ’ s just no way baserunning could be that important if it was runs created would n ’ t be nearly as accurate as it is runs created is usually about qqq qqq accurate on a team level and there ’ s a lot more than baserunning that has to account for the remaining percent . \( \Delta \hat{y} : 0.001 \)

ADR

Original: meanwhile wait for DRUG and DRUG to kick in first co i need to prep dog food etc . co omg <UNK> .

Adversarial: meanwhile wait for DRUG and DRUG to kick in first co i need to prep dog food etc . co omg <UNK> . \( \Delta \hat{y} : 0.002 \)

AG News

Original: general motors and daimlerchrysler say they # qqq teaming up to develop hybrid technology for use in their vehicles . the two giant automakers say they have signed a memorandum of understanding

Adversarial: general motors and daimlerchrysler say they # qqq teaming up to develop hybrid technology for use in their vehicles . the two giant automakers say they have signed a memorandum of understanding . \( \Delta \hat{y} : 0.006 \)

SNLI

Hypothesis: a man is running on foot

Original Premise Attention: a man in a gray shirt and blue shorts is standing outside of an old fashioned ice cream shop named sara ’ s old fashioned ice cream , holding his bike up , with a wood like table , chairs , benches in front of him .

Adversarial Premise Attention: a man in a gray shirt and blue shorts is standing outside of an old fashioned ice cream shop named sara ’ s old fashioned ice cream , holding his bike up , with a wood like table , chairs , benches in front of him . \( \Delta \hat{y} : 0.002 \)

Babi Task 1

Question: Where is Sandra ?

Original Attention: john travelled to the garden . sandra travelled to the garden

Adversarial Attention: john travelled to the garden , sandra travelled to the garden \( \Delta \hat{y} : 0.003 \)

CNN-QA

Question: federal education minister @placeholder visited a @entity15 store in @entity17 , saw cameras

Original: @entity1 , @entity2 ( @entity3 ) police have arrested four employees of a popular @entity2 ethnic - wear chain after a minister spotted a security camera overlooking the changing room of one of its stores . federal education minister @entity13 was visiting a @entity15 outlet in the tourist resort state of @entity17 on friday when she discovered a surveillance camera pointed at the changing room , police said . four employees of the store have been arrested , but its manager – herself a woman – was still at large saturday , said @entity17 police superintendent @entity25 . state authorities launched their investigation right after @entity13 levied her accusation . they found an overhead camera that the minister had spotted and determined that it was indeed able to take photos of customers using the store ’ s changing room , according to @entity25 . after the incident , authorities sealed off the store and summoned six top officials from @entity15 , he said . the arrested staff have been charged with voyeurism and breach of privacy , according to the police . if convicted , they could spend up to three years in jail , @entity25 said . officials from @entity15 – which sells ethnic garments , fabrics and other products – are heading to @entity17 to work with investigators , according to the company . ” @entity15 is deeply concerned and
Adversarial: @entity1, @entity2 (@entity3) police have arrested four employees of a popular @entity2 ethnic-wear chain after a minister spotted a security camera overlooking the changing room of one of its stores. Federal education minister @entity13 was visiting a @entity15 outlet in the tourist resort state of @entity17 on Friday when she discovered a surveillance camera pointed at the changing room, police said. Four employees of the store have been arrested, but its manager—a woman—was still at large Saturday, said @entity17 police superintendent @entity25. State authorities launched their investigation right after @entity13 levied her accusation. They found an overhead camera that the minister had spotted and determined that it was indeed able to take photos of customers using the store’s changing room, according to @entity25. After the incident, authorities sealed off the store and summoned six top officials from @entity15, he said. The arrested staff have been charged with voyeurism and breach of privacy, according to the police. If convicted, they could spend up to three years in jail. @entity25 said, officials from @entity15—which sells ethnic garments, fabrics and other products— are heading to @entity17 to work with investigators, according to the company. "@entity15 is deeply concerned and shocked at this allegation," the company said in a statement. "we are in the process of investigating this internally and will be cooperating fully with the police." \( \Delta y: 0.005 \)