VI SUALIZING AND EXPLAINING LANGUAGE MODELS

A PREPRINT

Adrian M.P. Brașoveanu
Modul University Vienna
and Modul Technology GmbH
Am Kahlenberg 1, 1190, Vienna, AT
adrian.brasoveanu@modul.ac.at

Răzvan Andonie
Central Washington University
400 E University Way,
Ellensburg, WA 98926, USA,
and Transilvania University
Bulevardul Eroilor 29, Brasov 500036, Romania
razvan.andonie@cwu.edu

May 23, 2022

ABSTRACT

During the last decade, Natural Language Processing has become, after Computer Vision, the second field of Artificial Intelligence that was massively changed by the advent of Deep Learning. Regardless of the architecture, the language models of the day need to be able to process or generate text, as well as predict missing words, sentences or relations depending on the task. Due to their black-box nature, such models are difficult to interpret and explain to third parties. Visualization is often the bridge that language model designers use to explain their work, as the coloring of the salient words and phrases, clustering or neuron activations can be used to quickly understand the underlying models. This paper showcases the techniques used in some of the most popular Deep Learning for NLP visualizations, with a special focus on interpretability and explainability.

Keywords
Language Models · Transformer · Explainable Language Models · Visualization of Neural Networks

1 Introduction

Deep Learning (DL) models applied on texts need to cover the morphological, syntactic, semantic and pragmatic layers. Crafting networks that operate on so many levels is a challenging task due to the sparseness of the training data. Such networks have been traditionally called Language Models (LMs) [Ponte and Croft 1998]. The early iterations were based on statistical models [Ponte and Croft 1998], whereas the latest iterations use neural networks and embeddings. Current LMs are trained on large corpora and are generally sparse. Most current popular LMs are based on Transformer architectures [Brown et al. 2020].

The first implementation of a Transformer network [Vaswani et al. 2017] proved that it was possible to design networks that achieve good results for Natural Language Processing (NLP) tasks with a set of multiple sequential attention layers. A Transformer contains a series of self-attention layers that are distributed through its various components. Self-attention is an attention mechanism that computes a representation of a sequence from a set of different positions of the same sequence. The Transformer model itself is simple and consists from pairs of encoders and decoders. Encoders encapsulate layers of self-attention coupled with feed-forward layers, whereas decoders encapsulate self-attention layers followed by encoder-decoder attention and feed-forward layers. The attention computation is done in parallel and the results are then combined. The result is termed a multi-head attention, and it provides the model with the ability to orchestrate information from different representation subspaces (e.g., multiple weight matrices) at various positions (e.g., different words in a sentence) [Vaswani et al. 2017]. Its outputs are fed either to other encoders or into decoders, depending on the architecture. There is no fixed number of encoders and decoders which can be included in this architecture, but they will typically be paired (e.g., 10 encoders and 10 decoders). In newer architectures, encoders and decoders can also be used for different tasks (e.g., encoder for Question Answering, and decoder for Text Comprehension) [Raghu and Schmidt 2020]. While the model was initially developed for machine translation tasks, it has been tested on multiple domains and was demonstrated to work well.
During the last three years, hundreds of papers and LMs inspired by Transformers were published, the best-known being BERT [Devlin et al. 2019], RoBERTa [Liu et al. 2019], AI-BERT [Lan et al. 2020], XLNet [Yang et al. 2019], DistilBERT [Sanh et al. 2019], and Reformer [Kitaev et al. 2020]. Some of the most popular Transformer models are included in the Transformers library, maintained by HuggingFace [Wolf et al. 2019].

Many of these models are complex and include significant architectural improvements compared to the early Transformer and BERT models. Explaining their information processing flow and results is therefore difficult, and a convenient and very actual approach is visualization. Our survey is focused on visualization techniques used to explain LMs. We investigate two large tool classes: (i) model-agnostic tools that can be used to explain BERT predictions; and (ii) custom visualizations that are focused only on explaining the inner workings of LMs based on neural networks. An early version of this survey was published a year ago, but it was focused only on visualizing Transformer networks [Brasoveanu and Andonie 2020]. We have since extended the material to include new articles about Transformer visualizations, other types of networks, as well as an extended section about model-agnostic AI libraries that are focused on interpretability and explainability for NLP.

In this survey, we look at the visualization of several types of LMs based on DL networks, review the basic charts and patterns present in them and try to understand the basic methodology that was used to produce these visual representations. The rest of the paper is organized as follows: Section 2 presents the motivation and methodology of this survey. Section 3 showcases the two classes of tools, whereas Section 4 discusses the various findings. The paper concludes with some thoughts on the future of this class of visualizations.

2 Background and Methodology

The need to quickly update NLP models in case of unforeseen events suggests that developers will be well-served by explainable AI and visualization libraries, especially since debugging Transformers is a complex task. Visualizations are particularly important, as they help us debug the various problems that such models exhibit and which can only be discovered through large-scale analyses.

Traditional visualization libraries are based on the classic grammar of graphics philosophy [Wilkinson 2005] which is focused on the idea that visualizations are compositional by design. They provide various visualization primitives like circles or squares and a set of operations that can be applied on top of these primitives to create more complex shapes or animations. Unfortunately, such traditional visualization libraries like D3.js [Bostock et al. 2011], Vega [Satyanarayan et al. 2017] or Tableau[1] do not offer specific functions for visualizing feature spaces, neural network layers or support for iterative design space exploration [Park et al. 2018] when designing AI models. What this means is that for AI tasks, a lot of the functionality will have to be developed from scratch.

When visualizing more complex models like those built with Transformers, we typically need to understand all the facets of the problem, from the data and training procedure, to the input, network layers, weights or the outputs of the neural network. The outputs are the core of explainability, as people will not use the networks in commercial products if they can’t explain how the outputs were obtained in the first place. What is also beneficial is to highlight the paths that lead to certain outputs, as this illuminates the features or parts of the models that may need to be changed to achieve the desired results. This can sometimes be accomplished by using model-agnostic tools specifically built for benchmarking or hyperparameter scoring, such as Weights and Biases. We include such tools in our survey if examples of how to use them for visualizing Transformers already exist, either in scientific papers or other types of media posts (Medium posts, GitHub, etc.).

The second big class of visualizations discussed in this article is, naturally, the class of visualizations specifically built around Transformers, either for explaining it (like ExBERT [Hoover et al. 2020]), or for explaining certain model specific attributes (like embeddings or attention maps [Vis [2019a]).

We selected the libraries and visualizations presented here by reviewing the standard Computer Science (CS) publication libraries (e.g., IEEE, ACM, Elsevier, Springer, Wiley), but also online media posts (YouTube, Medium, GitHub and arXiv). In this extremely dynamic research field, some articles might be published on arXiv even up to a year before they are accepted for publication in a traditional conference or journal, time in which they might already garner hundreds of citations. The original BERT article [Devlin et al. 2019] and also one of the first articles that used visualization to explain it [Clark et al. 2019] were cited over a hundred times before being published in conference proceedings.[3]

---

[1] www.tableau.com
[2] Article [Clark et al. 2019] has garnered 149 citations at the moment of the submission, before being published in a conference or journal.
When testing new models, benchmarking and fine-tuning are the two operations where we might spend the most time, as even if the scores are good, we might want to try different hyperparameter settings (e.g., learning rate, number of epochs, batch size, etc)\cite{FloreaAndonie2019}. A hyperparameter sweep (or trial) is a central notion in both hyperparameter optimization and benchmarking. It involves running one or multiple models with different values for their hyperparameters. Since quite often the main goal behind running such sweeps is improving existing models, but it is not necessarily related to interpretability and explainability, we decided to include a minimal number of such libraries here.

TensorBoard\footnote{https://www.tensorflow.org/tensorboard} is a specialized dashboard deployed with Google TensorFlow that covers the basic visualization needs for ML experiments, from tracking, computing and visualizing metrics, to model profiling and embeddings. It is not necessarily a good tool for creating custom visualization or for explaining results, but it can be a good tool for improving accuracy. It is sometimes also used with TensorFlow’s competing libraries like PyTorch or FastAI. Neptune\footnote{https://neptune.ai/} is an open-source ML benchmarking suite deployed for a variety of collaborative benchmarking tasks, including notebook tracking. Sacred\footnote{https://github.com/IDSIA/sacred} and Comet.ml\footnote{https://www.comet.ml/site/} are Neptune alternatives that provide basic charting capabilities and dedicated dashboards. Weights and Biases\footnote{https://www.wandb.com/} provides perhaps the largest sets of visualization and customization capabilities. It comes packed with advanced visualizations that include parallel coordinates\cite{HeinrichAndWeiskopf2015}, perhaps the best method to navigate hyperparameter sweeps. It is the easiest and the most agile solution to integrate with production code or Jupyter notebooks out of all the ones mentioned here. Ray\cite{Moritz2018} is popular for optimizing Transformers.

Due to space limitations, we resume ourselves to discussing only the most interesting visualizations, especially in the model-agnostic visualization section, as otherwise this article could easily become an entire book.

### 3 Visualizing Language Models

Language models are difficult to train for a multitude of reasons, including (but not limited to) cost, time or carbon footprint\cite{Strubell2019}. Most of the LMs need to be trained on GPUs or TPU pods for days or weeks. Due to their generalization capabilities, such LMs can reliably estimate the actions for which they have a reasonable number of examples in their training datasets, whereas in cases with fewer examples they might overestimate the predicted actions therefore inserting some bias\cite{ShwartzChoi2020}. Debugging or retraining such models therefore becomes a necessity, even if the costs of such operations are still high. Visualization is just one of the methods that can help us explain such large LMs, especially since it is often combined with linguistics or statistics. Explaining the results in plain English should be what we are aiming for when we build new LMs, but this may sometimes require additional steps. An interpretation of the results, for example, would generally depend on the target domain (e.g., medicine, law, etc)\cite{Vellido2020}, as in some cases a complex reasoning process (e.g., compliance with local or international regulations) may need to be applied before selecting the right words for an explanation. The visualization will essentially highlight the intermediary steps (e.g., the components that lead to a side effect for medication or a legal aspect in a certain jurisdiction) required to create a basic interpretation, and therefore it is often kept minimal and visualized features or processes are carefully selected. If it is easy to navigate the various information pathways and understand the results and their interpretations (e.g., where they may lead us), it may be safe to call the respective visualizations explainable.

Using visualization to explain the AI processes is an expanding research field. The main idea behind AI user interfaces should be to augment and expand user capabilities, rather than replace intelligence\cite{Heer2019}. While not necessarily needed to understand the next section, several recent surveys about visualizations and DL can help provide additional context to the interested readers. We particularly recommend the following: the introduction on how Convolutional Neural Networks “see” the world from\cite{Qin2018}, the discussion on visual interpretability from\cite{ZhangZhu2018}, and the discussion on the importance of visualizing features from\cite{Nguyen2019}.
3.1 Model-Agnostic Explainable AI Tools

Explainable AI (XAI) is the key to enterprise adoption of the current wave of AI technologies, from vision to NLP and symbolic computation. An early XAI survey [Hohman et al. 2019] describes methods through which visualizations can be turned into explanations for the AI models and goes on to define the terminology of the field. Early XAI libraries focused on visualizing ML features, whereas recent libraries are focused on visualizing embeddings, attention maps or various neural network layers [Samek et al. 2019].

Traditionally, the first step towards transparency was to describe the contribution of each feature to the final result [Guvon and Elissseiff 2003]. This often lead to partial explanations of the results, as in reality if the models themselves were black-box, knowing the name of the features was not in itself enough. Output is definitely the most important part that we would like to explain, but not the only one. To create full explanations, we need to be able to explain the entire process from its input, to its various transformations (e.g., layers), training process and output. Explanations also need to be able to reflect state changes. For example, when computing Shapley values feature contributions are combined, and then a score that signifies the feature importance within that set of features is generated. If features are added or removed from this bundle, the Shapley value for a particular feature will change accordingly. This dynamic nature of the explainability is rarely explained, but it is one of the reason why visualizations in particular are a good fit for creating explanations in the first place.

Some early model-agnostic XAI libraries that were applied to NLP and Transformers visualizations include LIME [Ribeiro et al. 2016] and SHapley Additive exPlanations (SHAP) [Lundberg and Lee 2017]. The later was introduced to unify multiple explanation methods into a single model for interpreting predictions. Both SHAP and LIME can be used with classical ML libraries like scikit-learn and XGBoost, as well as with modern DL libraries like PyTorch or Keras / TensorFlow. SHAP provides visualizations for summary and dependency plots. Another XAI alternative to SHAP and LIME, ELI5 [Fan et al. 2019], is currently routinely used for explaining BERT predictions, and was found to be more secure in case of adversarial network attacks [Slack et al. 2020].

The visualizations created with LIME and SHAP are typically restrained to classic charts (e.g., line, bars or word clouds. The summary plots or interaction charts [Lundberg and Lee 2017] from SHAP are relatively easy to understand, whereas the more complex force plot charts like feature impact [Lundberg et al. 2018] are not necessarily easy to use as they require a certain learning time. While the feature impact chart simply plots the expected feature impact with red (features with positive contribution to the prediction result) or blue (features with a likely negative contribution to the result) colors and should in theory be an easy-to-understand chart, there are no direct (e.g., in chart via a legend) explanations on how to interpret the start or end values, or what do the indicators placed on top of various components mean in some cases. The interpretation of such force plot charts is generally missing and people need to read additional documentation to understand the results. This is far from ideal, as, in our opinion, visualizations need to be self-explanatory.

It can be argued that explainability libraries like SHAP or LIME tend to focus on highlighting correlations or statistical effects rather than features, and are, therefore, less reliable than interpretable models which only showcase a list of features or algorithms that contributed to the results. We consider auditing to encompass both sides of the problem, as interpretability and explainability are the key towards understanding and clearing such LMs for deployment in real-world products. Keeping this in mind, we think that focusing on neural network visualization for NLP can only help in this process, as visualizations can help process, select and highlight the most important features included in such models.

Both SHAP and LIME were proven to be easily fooled with adversarial attacks [Slack et al. 2020]. The idea of deploying biased classifiers for tasks like credit rating, recommendation or search ranking sounds a bit counterintuitive because a single classifier should not be able to do much harm. However, given the fact that such large models typically end up being ensembles, one single classifier can actually lead to severe damage including wrong predictions, different sets of biases and ultimately even different outputs than the ones typically expected from the respective LMs. Not being able to correctly audit such models (e.g., investigate their output and the features that have contributed the most to it) can lead to problems with clients and regulatory agencies.

The list of attacks that can be perpetrated using LMs is extended every month, and therefore models may need to be periodically tested to assess their suitability for certain tasks. Some of the most robust attacks include: creating token sequences that act like universal adversarial triggers on specific target predictions when concatenated to any input from a dataset [Wallace et al. 2019]; training data extraction attacks in which text sequences like public information or code are extracted from the training corpora and used to attack the trained language model [Carlini et al. 2020]; spelling attacks in which random spellings for well-known words are generated through modifying the gradients during train-

---

8Explainable points to the idea of describing or explaining in an intuitive manner, via charts or tables, the prediction of an algorithm.
Visualizing and Explaining Language Models

A P R E P R I N T

When visualizing LMs, it is best to start with the language resources used for their creation, from corpora to embeddings. hotflip attacks in which a gradient-based embeddings swap is performed to change classification results [Ebrahimi et al. [2018] or even textfooler attacks [Jin et al. [2020] in which multiple attributes like embeddings, part-of-speech matches or cosine similarities are used to perform a counter-fitted embeddings swap to fool untargeted classifiers and entailment relations. Possibilities to reuse part of the code of these attacks to create new attacks also exists if frameworks like TextAttack [Morris et al. [2020]] or OpenAttack [Zeng et al. [2020]] are used. Sometimes these kinds of adversarial attacks can also be used to improve results, as demonstrated by improving aspect-based sentiment analysis tasks by creating artificial sentences [Karimi et al. [2020]] or by using various BERT attribution patterns (e.g., pruned self-attention heads from a certain task) as adversaries [Hao et al. [2020]]. To understand these attacks, visualization can be a useful tool. For example, Chen et al. [2020] showcases three types of attacks perpetrated at character, word and sentence level using visualizations built around various metrics like accuracy and successful attack ratios. The Interpret framework [Wallace et al. [2019b]] uses saliency maps color highlights to showcase defenses against hotflip and untargeted classification attacks. A later publication then shows how almost all interpretations built with Interpret can be manipulated through gradient attacks (e.g., using some large gradients for irrelevant words) [Wang et al. [2020]]. However, most of the visualization efforts have been focused on explaining the various neural network activations from Transformer networks, rather than on the various attacks that can fool Transformers, therefore the visualization of such attacks is a relatively nascent area.

An alternative approach to such explainability libraries that can easily pick up wrong signals could be to simply use models designed specifically to be interpretable. The Neural Additive Models (NAMs) combines the features of classic DNNs with the interpretability approach advocated by Generalized Additive Models (GAM) [Agarwal et al. [2020]]. However, since such models are quite recent, their applicability to NLP has not yet been fully explored.

Interpretability and explainability are often used with interchangeable meaning. It has to be noted that quite often, interpretability has a domain-specific component [Vellido [2020]], whereas explainability is a more general term. Explainability is the term preferred by Information Visualization designers and researchers, whereas interpretability is generally the term that is preferred by ML researchers, statisticians and mathematicians.

Many other explainable AI libraries use Shapley values for computing feature importance. However, in many cases we were only barely able to discover mentions of their usage for NLP (e.g., DeepExplain⁹), and therefore we decided not to include them in this survey.

3.2 Visualizing Recurrent Neural Networks for NLP

When visualizing LMs, it is best to start with the language resources used for their creation, from corpora to embeddings. To uncover biases in such large models we need to study gender differences, disciplines, languages, cultural context or regional and diachronic variations. A good method to include such information and compare resources for language variation is showcased in Fanhauser’s work [Fanhauser et al. [2014]]. It uses a grids, heatmaps and word clouds to provide quick access to large amounts of data about English dialects. Another work uses scatter plots to visualize how and why large corpora differ [Kessler [2017]]. Similar methods have later been used for visualizing large-scale embeddings.

Karpathy [Karpathy et al. [2015]] proposed a method through which to visually interpret the results of Recurrent Neural Networks (RNNs), Long Short-Term Memories (LSTMs) and Gated Recurrent Units (GRUs). He suggests that using interpretable activations can help navigate longer texts, whereas saturation plots would help showcase the gated units statistics.

Around the same time, an LM visualization survey [Li et al. [2016]] notes that classic Computer Vision visualization was focused on inverting representations, back-propagation and generating images from sketches, all techniques that work well for images. In NLP, however, it is important to focus on important keywords, composition and dimensional locality; especially since many of the words will depend on the context [Li et al. [2016]]. Important models will be able to capture this kind of information, and therefore it should be present in visualizations. The early saliency heatmaps clearly showcased these aspects for LSTM and Bi-Directional LSTMs [Strobelt et al. [2018]]. By later adapting the ideas of first order saliency from Computer Vision, researchers were able to highlight intensification and negation, as well as differences between two sequences at various at consecutive time steps. Their saliency heatmap for SEQ2SEQ auto-encoders also works well for predicting corresponding tokens at each time step [Luo et al. [2019]].

The main characteristic that connects these papers, as it can easily be observed in Table II regardless of the number of visualizations included in them, is the fact that they are focused on a interpretability and explainability of NLP models through visualization. We have analyzed the following characteristics:

⁹https://github.com/marcoancona/DeepExplain
### Table 1: Articles focused on explaining RNN LMs through visualizations.

| Topic | Visualization Subject | Chart Type |
|-------|------------------------|------------|
| a) Special topics | | |
| predicting next word Luo et al. [2019] | syntactic heights, head attentions | parallel lines, heatmaps |
| emergence of units Lakretz et al. [2019] | activations of cells and gates, connectivity | line charts, connectivity charts |
| b) Hidden states | | |
| visualizations of representations Li et al. [2016] | modification and negation, clause composition, first-derivative saliency | t-SNE, heatmap, saliency bars, saliency grids |
| hidden states semantics Sawatzky et al. [2019] | Predictive Semantic Encodings performance metrics | PSE charts, Bar charts |
| activation of RNNs Karpathy et al. [2015] | cells with interpretable activation | saturation plots, bar charts, overlap charts |
| hidden states LSTMVis Strobelt et al. [2018] | phrase selections, hidden state patterns | hidden pathways, tables with cell activation, PCA |
| hidden states RNNVis Ming et al. [2017] | navigation, sentence, hidden state, word | control panel, glyph-based chart, state clusters, word clusters |
| hidden states ActiVis Kahng et al. [2018] | navigation, neuron activation, instance selection | model overview, heatmaps |
| c) Graph Convolution | | |
| inductive text classification Zhang et al. [2020] | attention, performance metrics | attention map, line charts |
| unsupervised domain adaptation Wu et al. [2020] | embeddings, performance metrics | PCA, line charts |
| GCN with label propagation Wang and Leskovec [2020] | node embeddings, performance | graphs, line charts |

- **Topic** - the main topic of the paper (e.g., attention, representation, information probing) followed by the papers in which this topic is addressed;

- **Visualization Subject** - since visualizations included in these papers were focused on a large set of subjects from Transformer components (e.g., attention heads), to correlation between tasks (e.g., via Pearson correlation charts) or performance (e.g., accuracy or other metrics represented via line charts), we have decided to extract all these in a separate column to understand what kind of charts we might be interested in creating when exploring a certain topic.

- **Chart Type** - includes the various types of visual metaphors used for rendering the chosen subjects. Most of the chart types are classic (e.g., line, bar chart, t-SNE), very few being rebranded (e.g., attention maps are heatmaps) or actually new (e.g., comparative attention graphs). The chart names need to give us a clear idea of what they represent.

A large class of visualizations is dedicated to the activation of neurons and the representation of hidden states, as it can easily be seen from Table 1.

LSTMVis Strobelt et al. [2018] uses a large grid of sentences for matching the various state patterns that are then expanded through additional views in the same interface. The key innovation of visualizing hidden state changes keeps the focus on the right keywords, whereas the match views help enlighten particular cases. Many other visualizations similar to LSTMVis (e.g., RNNVis Ming et al. [2017] or ActiVis Kahng et al. [2018]) follow the same template: a control panel is used for selecting the phrase or sentence, a middle view is focused on the word clusters or neuron...
activations, whereas the last view is typically a matrix view with highlighted cells which showcases the important words that are featured in the activated pathways. Such integrated views offer us holistic views of what these models can accomplish, except for the fact that they are rarely focused also on the corpora that was used for training. In time, the visualization designers started to include this information as well, as we will observe in the next section.

We considered that Graph Convolutional Networks are also worth exploring, but since there are entire libraries dedicated to this task which are not necessarily model-agnostic (e.g., PyTorch Geometric [Fey and Lenssen 2019]), we have limited ourselves to including some papers that offer some classic visualizations that are typically included in such libraries (e.g., node embeddings, performance).

3.3 Visualizing Transformers for NLP

No other types of neural networks have led to such an increased demand for custom visualizations since the days of the Kohonen’s Self-Organizing Maps [Kohonen 1995] or Mandelbrot’s fractals [Mandelbrot 1977], like the Transformers. When selecting Transformer visualization papers, we decided to focus on the most important topics related to interpretability and explanation. We have therefore eliminated papers that used only classic charts (e.g., bars, lines, pies). We decided to focus on the works that tried to visualize as many aspects of Transformer models as possible, from attention maps, to structural or informational probing, neural network layers, and multilingualism.

Many Transformer visualizations are focused on attention. While the attention mechanism is indeed important for the Transformer architecture, and it improves results for NLP tasks, they are not necessarily easy to interpret if sophisticated encoders are used [Jain and Wallace 2019]. Due to this fact, it is often not easy to test various explanations by simply modifying the weights and verifying if the outputs are also changed as a result of this. Alternative theories suggest that simply looking at information flows through such models is not enough, and that attention should only be used as explanation if certain conditions are met, e.g., if the weight distributions found via adversarial training do not perform well [Wiegreffe and Pinter 2019]. Since attention is central to Transformer models, many visualizations are rightly focused on this topic. The fact that such visualizations capture the dynamic nature of the output is not necessarily sufficient to consider these explanations. A good explanation needs to highlight the reasoning chain that lead to the particular output. This is the main reason why we have mainly looked for those visualizations that focus on multiple aspects of the network in this work.

The recent success of Transformers helped power many NLP tasks to the top of the leaderboards. BERT visualizations have focused on explaining these great results through visualizations, therefore highlighting: (i) the role of embeddings and relational dependencies within the Transformer learning processes [Reif et al. 2019]; (ii) the role of attention during pre-training or training (e.g., [Su et al. 2020] or [Vig 2019a]) or (iii) the importance of various linguistic phenomena encoded in its language model like direct objects, noun modifiers, or possessive pronouns [Clark et al. 2019].

Current XAI methods for Transformer models have further developed and supported the idea that understanding the linguistic information which is encoded in the resulting models is key towards understanding the good performances in NLP tasks. Probing tasks [Conneau et al. 2018] are simple classification problems focused on linguistic features designed to help explore embeddings and LMs. For example, by using structural probing [Hewitt and Manning 2019], structured perceptron parsers [Maudslay et al. 2020] or visualization (e.g., as demonstrated through BERT embeddings and attention layers visualizations like those from [Clark et al. 2019] and [Vig 2019a]), one should be able to understand what kind of linguistic information is encoded into a Transformer model, but also what has changed since previous runs.

We have discovered two large classes of Transformer visualizations:

- **Focused** - visualizations centered on a single subject like attention. The papers themselves might present multiple visualizations, but these visualizations are not single tools.
- **Holistic** - visualizations or systems which seek to explain the entire Transformer model or lifecycle.

### 3.3.1 Focused Transformer Visualizations

The most important papers dedicated to focused visualizations are summarized in Table 2. We used the same conventions in this table like the ones applied in Table 1.

We can clearly distinguish several large topics in this group of focused papers: the relation between attention and model outputs (e.g., especially in [Jain and Wallace 2019], [Wiegreffe and Pinter 2019], [Abnar and Zuidema 2020], [Voita et al. 2019a]), the analysis of captured linguistic information via probing (e.g., in [Voita et al. 2019b], [Tenney et al. 2019]), the interpretation of information interaction (e.g., in [Hao et al. 2020], [Voita et al. 2019a]).
| Topic | Visualization Subject | Chart Type |
|-------|------------------------|------------|
| a) Attention | feature importance correlation | Kendall rank statistics |
| attention explanation | permutation | scatterplots |
| Jain and Wallace [2019] | adversarial attention | adversarial charts |
| Wiegreffe and Pinter [2019] | performance metrics | multiple line charts |
| attention flow | raw attention | attention graph |
| Abnar and Zuidema [2020] | raw attention map | heatmap |
| DeRose et al. [2021] | comparative attention flows | comparative attention graphs |
| multi-head self-attention | layers | importance charts |
| Voita et al. [2019a] | attention for rare words | heatmaps |
| | dependency scores | bar charts |
| | active heads | line charts |
| b) Hidden states | intermediate layers | PCA |
| Song et al. [2020] | scoring attention | heatmaps |
| information interactions interpretation | information flow for tokens | attribution graphs |
| Hao et al. [2020] | evaluation accuracy | line charts |
| causal mediation analysis | attention heads correlation | Pearson correlation charts |
| Vig et al. [2020a] | indirect effects | heatmaps |
| analysis | effects comparison | line chart |
| | attention | attention heads |
| evolution of representations | token changes and influences | line charts |
| Voita et al. [2019b] | distances between layers | line charts |
| | token occurrences | t-SNE clustering |
| c) Probing | summary statistics | bar chart |
| structural probes | layer-wise performance | bar distribution chart |
| Tenney et al. [2019] | predictions probing | multiple bar charts |
| multilingual probes | probing task | PCA |
| Duffer and Schütze [2020] | positional embeddings | cosine similarity matrices |
| Eger et al. [2020] | performance metrics | line charts |
| information theoretic probing of classifiers | stability of training size | bar charts |
| Voita and Titov [2020a] | coding components | bar charts |
| | performance metrics | line charts |
| psycholinguistics tests | comparing predictions | tables |
| Gauthier et al. [2020] | performance metrics | distribution charts |
| | test content | line charts |
While in Section 3.2 several groups tried to expand their visualizations of hidden states to encompass the entirety of
We have decided against including chart types in Table 3, as each visualization suite or paper included some novel
This is perhaps because this area is relatively new and there is no consensus on what needs to be visualized. While it is
One of the key methods used for explaining the output of LMs is called probing [Ettinger et al. 2016], used to analyze
the linguistic information encoded in a fixed length vector. Recent iterations like structural probes [Hewitt and Manning
[2019] evaluate if syntax trees are embedded in a network’s word representation space. Identifying linear transformations
evidence for entire syntax trees embedded in the LM’s vector geometry. This method works well for limited
cases in which distances between words are known. The critics of probing argue that differences in probing accuracy
between the various classifiers essentially render them unusable as they fail to distinguish between different representations,
e.g., two LMs can end up having different linguistic representations even if based on the same initial BERT
model. In such scenarios, one cannot compare the accuracy of the classifiers used to predict their labels. To counteract
for such cases, a recent information-theoretic probing with minimum description length method was proposed
Voita and Titov [2020b]. The basic idea is that instead of predicting labels, the probe transmits data (a description)
which is then evaluated based on the returned description’s length. Such probes can be implemented on top of the
classic structural probes, and are fairly stable. According to Pilault [Pilault et al. 2020], classic structural probes may
not be enough for complex tasks like summarization simply because it seems that increasing the number of random
encoders provide significant performance boosts. This suggests that the information-theoretic probes with minimum
description length may be the better probes for this task, however this remains to be demonstrated by future experiments,
as Voita’s model was published after Pilault’s article.

3.3.2 Holistic Transformer Visualizations

While in Section 3.2 several groups tried to expand their visualizations of hidden states to encompass the entirety of
the model, they have rarely included the corpora provenance or an easy method to navigate it. Due to this aspect, in
the case of Transformers, since such visualizations often included the whole lifecycle (e.g., including the corpora with
known provenance), we decided to present them in a separate subsection.

Some of the most interesting tools or papers included in the category of holistic visualizations are compared in Table 3. These visualization systems typically integrate most of the components of a Transformer and provide detailed summaries of them. We have examined two large classes of attributes:

- **Components** represents the various components of the neural networks: from corpus, to embeddings, positional heads, attention maps or outputs.

- **Summary** includes the various types of views that offer us information about the state of a neuron or a layer, as well as overviews, statistics or details about the various errors encountered. Statistics might include different types of information: from correlations between layers or neurons to statistical analyses of the results. The errors column represents any error analysis method through which we can highlight where a particular error comes from (e.g., corpus, training procedure, layer, etc). While it can be argued that neuron or layer views should be included in the components section, the way these views are currently implemented suggests they are rather summaries, as neurons or layers can have different states.

We have decided against including chart types in Table 3 as each visualization suite or paper included some novel visualization types besides attention maps (heatmaps), parallel coordinates or line and bar charts.

In our view, none of the examined visualization systems has yet managed to examine all the facets of the Transformers. This is perhaps because this area is relatively new and there is no consensus on what needs to be visualized. While it is quite obvious that individual neurons or attention maps (regardless of if they are averaged or not) are useful, and it is best to visualize them, the same cannot be said about the training corpora today, as only a few systems considered this aspect (e.g., Skrlić et al. 2020 and Hoover et al. 2020). This is not really ideal, as lots of errors might simply come from a bad corpora, but researchers might simply not be aware of them [Brasoveanu et al. 2018]. Errors themselves are only seriously discussed in a single publication [Clark et al. 2019]. ExBERT [Hoover et al. 2020] and AttViz [Skrlić et al. 2020] deserve a special mention here, as they combine different views on the corpus, embeddings and attention maps to provide a holistic image of a Transformer model.
Table 3: Comparison of holistic Transformer visualizations. Legend: Corpus (C); Embeddings (E); Heads (H); Attention Maps (A); outputs (out); errors (err); neuron (neu); layers (lay); overview (ove); statistics(sta)

| Article                  | Components | Summary |
|--------------------------|------------|---------|
| BertViz Vig [2019b]      | ✓          | ✓       |
| Clark Clark et al. [2019]| ✓          | ✓       |
| VisBERT van Aken et al.  [2020]| ✓          | ✓       |
| ExBERT Hoover et al. [2020]| ✓          | ✓       |
| AttViz Skrlj et al. [2020]| ✓          | ✓       |
| Vector Norms Kobavashi et al. [2020]| ✓          | ✓       |
| Dictionary Learning Yun et al. [2021]| ✓          | ✓       |

Table 4: Articles focused on explaining Language and Vision (LAV) models through visualizations.

| Domain                  | Topic                        | Chart Type |
|-------------------------|------------------------------|------------|
| language and vision     | modality importance          | attention heatmaps |
| Cao et al. [2020]       | layer-level importance       | line charts |
| Han et al. [2021]       |                              | feature maps |
| biomedical Li et al. [2020] | attention maps              | head attention maps |
| VQA                     | multimodal alignment         | visual alignment charts |
| Gan et al. [2020]       | training curves              | line charts |
| Kim et al. [2021]       |                              |            |

A study that looks at the similarity and stability of neural representations in LMs and brains Van der Heijden et al. [2020] shows that combining predictive modelling with Representation Similarity Analysis (RSA) techniques can yield promising results. This article deserves a special mention as it can be included in both focused and holistic visualizations. Their visualizations are rather basic in terms of design, but they contain lots of insights, for example one of the tables they produced showcases the RSA results for various layers of multiple models like BERT, Elmo and others. These kinds of analyses are rather new, and we hope they will become more common in the next years, as they might help us clarify which LMs are more similar to the human brains.

3.3.3 Vision Transformers

Transformers have been applied in numerous fields due to their flexibility. Perhaps the most important application is the unification of vision and NLP. In the last two years, this has seen explosive growth. It would be impossible to cover all the various models in this article, and therefore we have selected only a few interesting topics related to this expansion. The one that comes to mind first is Visual Question Answering (VQA) Gan et al. [2020], as this is perhaps the task that multimodal researchers have been trying to solve for decades. Vision Transformers offer an elegant, but expensive solution. Table 4 provides a short summary of interesting papers in this research direction.

4 Discussion

Multilingual models based on Transformer architectures are error-prone since they are trained on large collections of texts. Due to this training process, the extraction of semantics from language data often captures implicit biases hidden in languages themselves or contextual biases triggered by adaptation to various niches Zhong et al. [2019].

Besides the obvious questions of interpretability (e.g., which features are most important for the prediction, what are best-performing models for creating ensembles?) and explainability (e.g., what linguistic information is actually encoded in the model and why do random encoders perform better for summarization?), another important question is security (e.g., are these models stable enough / do they obtain the same result in any circumstance?). Through adversarial training (Wallace, 2019) it is possible to remove some procedural biases from model-agnostic explainability libraries like LIME or SHAP, as well as well-known attack vectors (e.g., trigger words that might lead to a different language model output) Slack et al. [2020]. It can be argued that probing tasks are really only good for simple tasks like NER or POS and for verifying if certain structures were encoded in a LM, but not for more complex tasks like summarization or word-level polysemy disambiguation Yun et al. [2021]. Dictionary activation is a method that uses
visualization heavily to peek into the activation of words and their senses. Such a method helps uncover both the various layers on which certain word senses are actually learned, and the contexts that might trigger these new senses.

There are several available options for understanding the inner workings, as well as the results produced by Transformer networks. Each of them have their advantages or shortcomings, briefly discusses in the following.

Model-agnostic tools like the XAI libraries or the hyperparameter optimization and benchmarking tools can be used with a variety of networks. Due to this, model-agnosticism the visualization skills learned while debugging a certain network (e.g., a Convolutional Neural Network) will be easily transferred to debugging and optimizing other networks (e.g., Recurrent Neural Networks). By building a transferable set of skills, users might be more reluctant to try model-specific approaches, like those from the second category discussed in this paper. Some of these model-agnostic tools might be more susceptible to various adversarial attacks [Slack et al., 2019], whereas some other tools might not provide us with sufficiently advanced visualizations to match our needs. If the users are already comfortable with some of these options, then they might well be their Swiss-Army knife for any scenario, whereas if they will need specific visualization scenarios (e.g., visualize a specific attention map), it is possible that they will eventually use the Transformer focused visualizations.

While visualization of RNNs started quite early in the DL era, it can be seen as a precursor to the Transformer visualization. Quite often, many of the topics that were important during this era have remained important during the Transformer era (e.g., hidden states)

Some of the most useful tools discovered during this exploration include: visualization of attention maps (e.g., Clark et al., 2019) and embeddings Vig [2019a], hidden states visualization (e.g., Strobel et al., 2018), parallel coordinates plots Clark et al., 2019, and the inclusion of corpus views from ExBERT Hoover et al., 2020.

Current generation of pre-trained LMs based on Transformers Wolf et al., 2019 was shown to be relatively good at picking up syntactic cues like noun modifiers, possessive pronouns, prepositions or co-referents Clark et al., 2019 and semantic cues like entities and relations Han et al., 2019, but has not performed well at capturing different perspectives Chen et al., 2019, global context Wadden et al., 2019 or relation extraction Gao et al., 2019. This may be because biases can be already included in the embeddings and later propagated to the downstream tasks Gonen and Goldberg, 2019.

The MIT Computation Psycholinguistics Laboratory created two useful tools for exploring LMs: the LM Zoo and the SyntaxGym Gauthier et al., 2020. The first allows users to install some classic LMs, whereas the SyntaxGym allows users to run psycholinguistics tests and generate useful visualizations based on their results.

The two large classes of Transformer visualizations we examined (focused on explaining Transformer topics or holistic) are proof that the field is extremely dynamic. While many of the articles focused on explaining Transformer topics like attention or information probing tend to use classic statistical chart types (e.g., bar charts, line charts, PCA, or Pearson correlation charts), we do not consider this a bad thing as we are still in the exploration phase of this technology. Some of these articles also showcase new charts like attention graphs or attention maps.

The second class of visualizations includes tools like BertViz Vig 2019a, AttViz Skrlj et al., 2020, VisBERT van Aken et al., 2020 or ExBERT Hoover et al., 2020, that aim to visualize the entire life cycle of a neural network from corpora and inputs to the model outputs mainly through following the information flow through the various components. They also offer detailed statistics for neurons or network layers. Since most of the models included in this category are rather new, it is expected that this class will expand in the next years.

One important thing to note about visualization methods is that they can easily be imported into other domains. The averaged attention heatmaps used by Vig in his causal mediation analysis for NLP Vig et al., 2020a, for example, were later reused for protein analysis in biology Vig et al., 2020b. Similarly, attention maps Vig 2019a developed for BERT models are now used in a wide variety of disciplines, from vision and speech to biology or genetics.

The end goal of future visualization frameworks should be to visualize the entire lifecycle of the Transformer models, from inputs and data sources (e.g., training corpora), to embeddings or attention maps, and finally outputs. In the end, errors observed when creating such models can come from a variety of sources: from the text corpora, from some random network layer or even from some external Knowledge Graph that might feed some data into the model. Tracking such errors would be costly without visualizations.

5 Conclusion

While the current visualizations aspire to be model-agnostic, we think the directions opened by the various Transformer or RNN visualizations are worthy of expanding upon. In fact, since this is a ubiquitous architecture that has
also branched from NLP into areas like semantic video processing, natural language understanding (e.g., speech, translation) and generation (e.g., text generation, music generation), the next generation XAI libraries will probably be built upon it.

Going beyond current visualizations that are model-agnostic, future frameworks will have to provide visualization components that focus on the important Transformer components like corpora, embeddings, attention heads or additional neural network layers that might be problem-specific. By focusing on the common components from larger architectures, it should be possible to enhance reusability. Other important features that should be included in future frameworks are the ability to summarize the model’s state (e.g., through averaged attention heatmaps or similar visualization mechanisms) at various levels (e.g., neurons, layers, inputs and outputs), as well as the possibility to compare multiple settings for one or multiple models. It is important to note that most of the current visualizations seem to be designed to showcase methods and properties that were already known to belong to neural networks. It would be interesting to design visualizations that allow us to explore neural networks, that help us discover new properties. Such interactive exploration tools would significantly expand the role of visualization from communication to knowledge discovery.

One interesting direction is the automated development of model specific visualizations, as more complex neural networks might also include many specific components that cannot always be included into more general model agnostic frameworks.

References

Jay M. Ponte and W. Bruce Croft. A language modeling approach to information retrieval. In W. Bruce Croft, Alistair Moffat, C. J. van Rijsbergen, Ross Wilkinson, and Justin Zobel, editors, SIGIR ’98: Proceedings of the 21st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, August 24-28 1998, Melbourne, Australia, pages 275–281. ACM, 1998. ISBN 1-58113-015-5. doi:10.1145/290941.291008 URL https://doi.org/10.1145/290941.291008

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In Hugo Larochelle, Marc’ Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin, editors, Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual, 2020. URL https://proceedings.neurips.cc/paper/2020/hash/1457c0d6bfc496741-8bfb8ac142f64a-Abstract.html

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Isabelle Guyon, Ulrike von Luxburg, Samy Bengio, Hanna M. Wallach, Róbert Gómez Urquijo, Sami Abu-El-Haija, and Roman Garnett, editors, Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA, pages 5998–6008, 2017. URL https://proceedings.neurips.cc/paper/2017/hash/3f5ee243547dee91fbd053c1c4a845aa-Abstract.html

Maithra Raghu and Eric Schmidt. A survey of deep learning for scientific discovery. CoRR, abs/2003.11755, 2020. URL https://arxiv.org/abs/2003.11755

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. In Jill Burstein, Christy Doran, and Thamar Solorio, editors, Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pages 4171–4186. Association for Computational Linguistics, 2019. doi:10.18653/v1/n19-1423 URL https://doi.org/10.18653/v1/n19-1423

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized BERT pretraining approach. CoRR, abs/1907.11692, 2019. URL http://arxiv.org/abs/1907.11692

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. ALBERT: A lite BERT for self-supervised learning of language representations. In 8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020. OpenReview.net, 2020. URL https://openreview.net/forum?id=H1eA7AEtvS
Zhilin Yang, Zihang Dai, Yiming Yang, Jaime G. Carbonell, Ruslan Salakhutdinov, and Quoc V. Le. Xlnet: Generalized autoregressive pretraining for language understanding. In Hanna M. Wallach, Hugo Larochelle, Alina Beygelzimer, Florence d’Alché-Buc, Emily B. Fox, and Roman Garnett, editors, Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada, pages 5754–5764, 2019. URL https://proceedings.neurips.cc/paper/2019/hash/dca7e655d7e5840e6-6733e9ee67cc69-Abstract.html.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. Distilbert, a distilled version of BERT: smaller, faster, cheaper and lighter. CoRR, abs/1910.01108, 2019. URL http://arxiv.org/abs/1910.01108.

Nikita Kitaev, Lukasz Kaiser, and Anselm Levskaya. Reformer: The efficient transformer. In 8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020. OpenReview.net, 2020. URL https://openreview.net/forum?id=rkgNKKHtvB.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, and Jamie Brew. Huggingface transformers: State-of-the-art natural language processing. CoRR, abs/1910.03771, 2019. URL http://arxiv.org/abs/1910.03771.

Adrian MP Brașoveanu and Răzvan Andonie. Visualizing transformers for nlp: a brief survey. In Adrian Florea and Razvan Andonie. Weighted random search for hyperparameter optimization. Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations, ACL 2020, Online, July 5-10, 2020, pages 187–196. Association for Computational Linguistics, 2020. ISBN 978-1-7281-9134-8. doi 10.18653/v1/2020.acl-demos.22.

Leland Wilkinson. The Grammar of Graphics, Second Edition. Statistics and computing. Springer, 2005. ISBN 978-0-387-24544-7.

Michael Bostock, Vadim Ogievetsky, and Jeffrey Heer. D3 data-driven documents. IEEE Trans. Vis. Comput. Graph., 17(12):2301–2309, 2011. doi:10.1109/TVCG.2011.185. URL https://doi.org/10.1109/TVCG.2011.185.

Arvind Satyanarayan, Dominik Moritz, Kanit Wongsuphasawat, and Jeffrey Heer. Vega-lite: A grammar of interactive graphics. IEEE Trans. Vis. Comput. Graph., 23(1):341–350, 2017. doi:10.1109/TVCG.2016.2599030. URL https://doi.org/10.1109/TVCG.2016.2599030.

Deokgun Park, Seungyeon Kim, Jurim Lee, Jaegul Choo, Nicholas Diakopoulos, and Niklas Elmqvist. Conceptvector: Text visual analytics via interactive lexicon building using word embedding. IEEE Trans. Vis. Comput. Graph., 24(1):361–370, 2018. doi:10.1109/TVCG.2017.2744478. URL https://doi.org/10.1109/TVCG.2017.2744478.

Benjamin Hoover, Hendrik Strobelt, and Sebastian Gehrmann. ex bert: A visual analysis tool to explore learned representations in transformer models. In Asli Celiktutan and Tsung-Hsien Wen, editors, Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations, ACL 2020, Online, July 5-10, 2020, pages 187–196. Association for Computational Linguistics, 2020. doi:10.18653/v1/2020.acl-demos.22. URL https://doi.org/10.18653/v1/2020.acl-demos.22.

Jesse Vig. A multiscale visualization of attention in the transformer model. In Marta R. Costa-jussà and Enrique Alfonseca, editors, Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28 - August 2, 2019, Volume 3: System Demonstrations, pages 37–42. Association for Computational Linguistics, 2019a. ISBN 978-1-950737-49-9. doi:10.18653/v1/p19-3007. URL https://doi.org/10.18653/v1/p19-3007.

Kevin Clark, Urvashi Khandelwal, Omer Levy, and Christopher D. Manning. What does BERT look at? an analysis of bert’s attention. CoRR, abs/1906.04341, 2019. URL http://arxiv.org/abs/1906.04341.

Adrian Florea and Razvan Andonie. Weighted random search for hyperparameter optimization. Int. J. Comput. Commun. Control, 14(2):154–169, 2019. doi:10.15837/ijccc.2019.2.3514. URL https://doi.org/10.15837/ijccc.2019.2.3514.

Julian Heinrich and Daniel Weiskopf. Parallel coordinates for multidimensional data visualization: Basic concepts. Comput. Sci. Eng., 17(3):70–76, 2015. doi:10.1109/MCSE.2015.55. URL https://doi.org/10.1109/MCSE.2015.55.

Philipp Moritz, Robert Nishihara, Stephanie Wang, Alexey Tumanov, Richard Liaw, Eric Liang, Melih Elibol, Zongheng Yang, William Paul, Michael I. Jordan, and Ion Stoica. Ray: A distributed framework for emerging AI applications. In Andrea C. Arpaci-Dusseau and Geoff Voelker, editors, 13th USENIX Symposium on Operating Systems Design and Implementation, OSDI 2018, Carlsbad, CA, USA, October 8-10, 2018, pages 561–577. USENIX Association, 2018. URL https://www.usenix.org/conference/osdi18/presentation/nishihara.

Richard Liaw, Eric Liang, Robert Nishihara, Philipp Moritz, Joseph E. Gonzalez, and Ion Stoica. Tune: A research platform for distributed model selection and training. CoRR, abs/1807.05118, 2018. URL http://arxiv.org/abs/1807.05118.
Emma Strubell, Ananya Ganesh, and Andrew McCallum. Energy and policy considerations for deep learning in NLP. In Anna Korhonen, David R. Traum, and Lluis Marquez, editors, Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28-August 2, 2019, Volume 1: Long Papers, pages 3645–3650. Association for Computational Linguistics, 2019. doi:10.18653/v1/p19-1355 URL https://doi.org/10.18653/v1/p19-1355

Vered Shwartz and Yejin Choi. Do neural language models overcome reporting bias? In Donia Scott, Núria Bel, and Chengqing Zong, editors, Proceedings of the 28th International Conference on Computational Linguistics, COLING 2020, Barcelona, Spain (Online), December 8-13, 2020, pages 6863–6870. International Committee on Computational Linguistics, 2020. doi:10.18653/v1/2020.coling-main.605 URL https://doi.org/10.18653/v1/2020.coling-main.605

Alfredo Vellido. The importance of interpretability and visualization in machine learning for applications in medicine and health care. Neural Comput. Appl., 32(24):18069–18083, 2020. doi:10.1007/s00521-019-04051-w URL https://doi.org/10.1007/s00521-019-04051-w

Jeffrey Heer. Agency plus automation: Designing artificial intelligence into interactive systems. Proc. Natl. Acad. Sci. USA, 116(6):1844–1850, 2019. doi:10.1073/pnas.1807184115 URL https://doi.org/10.1073/pnas.1807184115

Zhuwei Qin, Fuxun Yu, Chenchen Liu, and Xiang Chen. How convolutional neural networks see the world - A survey of convolutional neural network visualization methods. Math. Found. Comput., 1(2):149–180, 2018. doi:10.3934/mfc.2018008 URL https://doi.org/10.3934/mfc.2018008

Quanshi Zhang and Song-Chun Zhu. Visual interpretability for deep learning: a survey. Frontiers Inf. Technol. Electron. Eng., 19(1):27–39, 2018. doi:10.1631/FITEE.1700808 URL https://doi.org/10.1631/FITEE.1700808

Anh Nguyen, Jason Yosinski, and Jeff Clune. Understanding neural networks via feature visualization: A survey. In Samek et al. [2019], pages 55–76. ISBN 978-3-030-28953-9. doi:10.1007/978-3-030-28954-6_4 URL https://doi.org/10.1007/978-3-030-28954-6_4

Fred Hohman, Minsuk Kahng, Robert Pienta, and Duen Horng Chau. Visual analytics in deep learning: An interrogative survey for the next frontiers. IEEE Trans. Vis. Comput. Graph., 25(8):2674–2693, 2019. doi:10.1109/TVCG.2018.2843369 URL https://doi.org/10.1109/TVCG.2018.2843369

Wojciech Samek, Grégoire Montavon, Andrea Vedaldi, Lars Kai Hansen, and Klaus-Robert Müller, editors. Explainable AI: Interpreting, Explaining and Visualizing Deep Learning, volume 11700 of Lecture Notes in Computer Science. Springer, 2019. ISBN 978-3-030-28953-9. doi:10.1007/978-3-030-28954-6 URL https://doi.org/10.1007/978-3-030-28954-6

Isabelle Guyon and André Elisseeff. An introduction to variable and feature selection. J. Mach. Learn. Res., 3:1157–1182, 2003. URL http://jmlr.org/papers/v3/guyon03a.html

Marco Túlio Ribeiro, Sameer Singh, and Carlos Guestrin. "why should I trust you?": Explaining the predictions of any classifier. In Balaji Krishnapuram, Mohak Shah, Alexander J. Smola, Charu C. Aggarwal, Dou Shen, and Rajeev Rastogi, editors, Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, August 13-17, 2016. ACM, 2016. ISBN 978-1-4503-4232-2. doi:10.1145/2939672.2939778 URL https://doi.org/10.1145/2939672.2939778

Scott M. Lundberg and Su-In Lee. A unified approach to interpreting model predictions. In Isabelle Guyon, Ulrike von Luxburg, Samy Bengio, Hanna M. Wallach, Rob Fergus, S. V. N. Vishwanathan, and Roman Garnett, editors, Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA, pages 4765–4774, 2017. URL https://proceedings.neurips.cc/paper/2017/hash/8a20a8621978632d76c43dfd28b67767-Abstract.html

Angela Fan, Yacine Jernite, Ethan Perez, David Grangier, Jason Weston, and Michael Auli. EL15: long form question answering. In Anna Korhonen, David R. Traum, and Lluis Marquez, editors, Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28-August 2, 2019, Volume 1: Long Papers, pages 3558–3567. Association for Computational Linguistics, 2019. doi:10.18653/v1/p19-1346 URL https://doi.org/10.18653/v1/p19-1346

Dylan Slack, Sophie Hilgard, Emily Jia, Sameer Singh, and Himabindu Lakkaraju. Fooling LIME and SHAP: adversarial attacks on post hoc explanation methods. In Annette N. Markham, Julia Powles, Toby Walsh, and Anne L. Washington, editors, AIES ’20: AAAI/ACM Conference on AI, Ethics, and Society, New York, NY, USA, February 7-8, 2020, pages 180–186. ACM, 2020. ISBN 978-1-4503-7110-0. doi:10.1145/3375627.3375830 URL https://doi.org/10.1145/3375627.3375830
Scott M Lundberg, Bala Nair, Monica S Vavilala, Mayumi Horibe, Michael J Eisses, Trevor Adams, David E Liston, Daniel King-Wai Low, Shu-Fang Newman, Jerry Kim, et al. Explainable machine-learning predictions for the prevention of hypoxaemia during surgery. *Nature biomedical engineering*, 2(10):749–760, 2018.

Eric Wallace, Shi Feng, Nikhil Kandpal, Matt Gardner, and Sameer Singh. Universal adversarial triggers for attacking and analyzing NLP. In Kentaro Inui, Jing Jiang, Vincent Ng, and Xiaojun Wan, editors. *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019*, pages 2153–2162. Association for Computational Linguistics, 2019a. doi:10.18653/v1/D19-1221 URL https://doi.org/10.18653/v1/D19-1221

Nicholas Carlini, Florian Tramèr, Eric Wallace, Matthew Jagielski, Ariel Herbert-Voss, Katherine Lee, Adam Roberts, Tom B. Brown, Dawn Song, Úlfar Erlingsson, Alina Oprea, and Colin Raffel. Extracting training data from large language models. *CoRR*, abs/2012.07805, 2020. URL https://arxiv.org/abs/2012.07805

Javid Ebrahimi, Anyi Rao, Daniel Lowd, and Dejing Dou. Hotflip: White-box adversarial examples for text classification. In Iryna Gurevych and Yusuke Miyao, editors, *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL 2018, Melbourne, Australia, July 15-20, 2018, Volume 2: Short Papers*, pages 31–36. Association for Computational Linguistics, 2018. ISBN 978-1-948087-34-6. doi:10.18653/v1/P18-2006 URL https://www.aclweb.org/anthology/P18-2006/

Di Jin, Zhijing Jin, Joey Tianyi Zhou, and Peter Szolovits. Is BERT really robust? A strong baseline for natural language attack on text classification and entailment. In *The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2020, New York, NY, USA, February 7-12, 2020*, pages 8018–8025. AAAI Press, 2020. URL https://www.aaai.org/ocs/index.php/AAAI/article/view/6311

John X. Morris, Eli Lifland, Jin Yong Yoo, Jake Grigsby, Di Jin, and Yanjun Qi. Textattack: A framework for adversarial attacks, data augmentation, and adversarial training in NLP. In Qun Liu and David Schlangen, editors, *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, EMNLP 2020 - Demos, Online, November 16-20, 2020*, pages 119–126. Association for Computational Linguistics, 2020. ISBN 978-1-952148-62-0. doi:10.18653/v1/2020.emnlp-demos.16 URL https://doi.org/10.18653/v1/2020.emnlp-demos.16

Guoyang Zeng, Fanchao Qi, Qianrui Zhou, Tingji Zhang, Bairu Hou, Yuan Zhang, Zhiyuan Liu, and Maosong Sun. Openattack: An open-source textual adversarial attack toolkit. *CoRR*, abs/2009.09191, 2020. URL https://arxiv.org/abs/2009.09191

Akbar Karimi, Leonardo Rossi, and Andrea Prati. Adversarial training for aspect-based sentiment analysis with BERT. In *25th International Conference on Pattern Recognition, ICPR 2020, Virtual Event / Milan, Italy, January 10-15, 2021*, pages 8797–8803. IEEE, 2020. ISBN 978-1-7281-8808-9. doi:10.1109/ICPR48806.2021.9412167 URL https://doi.org/10.1109/ICPR48806.2021.9412167

Yaru Hao, Li Dong, Furu Wei, and Ke Xu. Self-attention attribution: Interpreting information interactions inside transformer. *CoRR*, abs/2004.11207, 2020. URL https://arxiv.org/abs/2004.11207

Xiaoyi Chen, Ahmed Salem, Michael Backes, Shiqing Ma, and Yang Zhang. Badnl: Backdoor attacks against NLP models. *CoRR*, abs/2006.01043, 2020. URL https://arxiv.org/abs/2006.01043

Eric Wallace, Jens Tuyls, Junlin Wang, Sanjay Subramanian, Matt Gardner, and Sameer Singh. AllenNLP interpret: A framework for explaining predictions of NLP models. In Sebastian Padó and Ruichong Huang, editors, *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019 - System Demonstrations*, pages 7–12. Association for Computational Linguistics, 2019b. doi:10.18653/v1/D19-3002 URL https://doi.org/10.18653/v1/D19-3002

Junlin Wang, Jens Tuyls, Eric Wallace, and Sameer Singh. Gradient-based analysis of NLP models is manipulable. In Trevor Cohn, Yulan He, and Yang Liu, editors. *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings, EMNLP 2020, Online Event, 16-20 November 2020*, pages 247–258. Association for Computational Linguistics, 2020. ISBN 978-1-952148-90-3. doi:10.18653/v1/2020.findings-emnlp.24 URL https://doi.org/10.18653/v1/2020.findings-emnlp.24
Rishabh Agarwal, Nicholas Frosst, Xuezhou Zhang, Rich Caruana, and Geoffrey E. Hinton. Neural additive models: Interpretable machine learning with neural nets. *CoRR*, abs/2004.13912, 2020. URL https://arxiv.org/abs/2004.13912

Peter Fankhauser, Jörg Knappen, and Elke Teich. Exploring and visualizing variation in language resources. In Nicoletta Calzolari, Khalid Choukri, Thierry Declerck, Hafna Loftsson, Bente Maegaard, Joseph Mariani, Asunción Moreno, Jan Odijk, and Stelios Piperidis, editors, *Proceedings of the Ninth International Conference on Language Resources and Evaluation, LREC 2014, Reykjavik, Iceland, May 26-31, 2014*, pages 4125–4128. European Language Resources Association (ELRA), 2014. URL http://www.lrec-conf.org/proceedings/lrec2014/summaries/185.html

Jason S. Kessler. Scattertext: a browser-based tool for visualizing how corpora differ. In Mohit Bansal and Heng Ji, editors, *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, System Demonstrations*, pages 85–90. Association for Computational Linguistics, 2017. doi:10.18653/v1/P17-4015 URL https://doi.org/10.18653/v1/P17-4015

Andrzej Karpathy, Justin Johnson, and Fei-Fei Li. Visualizing and understanding recurrent networks. *CoRR*, abs/1506.02078, 2015. URL http://arxiv.org/abs/1506.02078

Hongyun Luo, Lan Jiang, Yonatan Belinkov, and Jim Glass. Improving neural language models by segmenting, attending, and predicting the future. In Anna Korhonen, David R. Traum, and Lluís Marquez, editors, *Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28-August 2, 2019, Volume 1: Long Papers*, pages 1483–1493. Association for Computational Linguistics, 2019. doi:10.18653/v1/p19-1144 URL https://doi.org/10.18653/v1/p19-1144

Yair Lakretz, Germán Kruszewski, Theo Desbordes, Dieuwke Hupkes, Stanislas Dehaene, and Marco Baroni. The emergence of number and syntax units in LSTM language models. In Jill Burstein, Christy Doran, and Thamar Solorio, editors, *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers)*, pages 11–20. Association for Computational Linguistics, 2019. doi:10.18653/v1/n19-1002 URL https://doi.org/10.18653/v1/n19-1002

Jiwei Li, Xinlei Chen, Eduard H. Hovy, and Dan Jurafsky. Visualizing and understanding neural models in NLP. In Kevin Knight, Ani Nenkova, and Owen Rambow, editors, *NAACL HLT 2016, The 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, San Diego California, USA, June 12-17, 2016*, pages 681–691. The Association for Computational Linguistics, 2016. doi:10.18653/v1/n16-1082 URL https://doi.org/10.18653/v1/n16-1082

Lindsey Sawatzky, Steven Bergner, and Fred Popowich. Visualizing RNN states with predictive semantic encodings. In *30th IEEE Visualization Conference, IEEE VIS 2019 - Short Papers, Vancouver, BC, Canada, October 20-25, 2019*, pages 156–160. IEEE, 2019. ISBN 978-1-7281-4941-7. doi:10.1109/VISUAL.2019.8933744 URL https://doi.org/10.1109/VISUAL.2019.8933744

Hendrik Strobelt, Sebastian Gehrmann, Hanspeter Pfister, and Alexander M. Rush. Lstmvis: A tool for visual analysis of hidden state dynamics in recurrent neural networks. *IEEE Trans. Vis. Comput. Graph.*, 24(1):667–676, 2018. doi:10.1109/TVCG.2017.2744158 URL https://doi.org/10.1109/TVCG.2017.2744158

Yao Ming, Shaozu Cao, Ruixiang Zhang, Zhen Li, Yuanzhe Chen, Yangqiu Song, and Huamin Qu. Understanding hidden memories of recurrent neural networks. In Brian D. Fisher, Shixia Liu, and Tobias Schreck, editors, *12th IEEE Conference on Visual Analytics Science and Technology, IEEE VAST 2017, Phoenix, AZ, USA, October 3-6, 2017*, pages 13–24. IEEE Computer Society, 2017. doi:10.1109/VAST.2017.8585721 URL https://doi.org/10.1109/VAST.2017.8585721

Minsuk Kahng, Pierre Y. Andrews, Aditya Kalro, and Duen Horng (Polo) Chau. Activis: Visual exploration of industry-scale deep neural network models. *IEEE Trans. Vis. Comput. Graph.*, 24(1):88–97, 2018. doi:10.1109/TVCG.2017.2744718 URL https://doi.org/10.1109/TVCG.2017.2744718

Yufeng Zhang, Xueli Yu, Zeyu Cui, Shu Wu, Zhongzhen Wen, and Liang Wang. Every document owns its structure: Inductive text classification via graph neural networks. In Dan Jurafsky, Joyce Chai, Natalie Schlueter, and Joel R. Tetreault, editors, *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020*, pages 334–339. Association for Computational Linguistics, 2020. doi:10.18653/v1/2020.acl-main.31 URL https://doi.org/10.18653/v1/2020.acl-main.31

Man Wu, Shirui Pan, Chuan Zhou, Xiaojun Chang, and Xingquan Zhu. Unsupervised domain adaptive graph convolutional networks. In Yennun Huang, Irwin King, Tie-Yan Liu, and Maarten van Steen, editors, *WWW ’20: The Web Conference 2020, Taipei, Taiwan, April 20-24, 2020*, pages 1457–1467. ACM / IW3C2, 2020. doi:10.1145/3366423.3380219 URL https://doi.org/10.1145/3366423.3380219
Hongwei Wang and Jure Leskovec. Unifying graph convolutional neural networks and label propagation. *CoRR*, abs/2002.06755, 2020. URL https://arxiv.org/abs/2002.06755

Matthias Fey and Jan Eric Lenssen. Fast graph representation learning with pytorch geometric. *CoRR*, abs/1903.02428, 2019. URL http://arxiv.org/abs/1903.02428

Teuvo Kohonen. *Self-Organizing Maps*, volume 30 of *Springer Series in Information Sciences*. Springer, 1995. ISBN 978-3-642-97612-4. doi:10.1007/978-3-642-97610-0 URL https://doi.org/10.1007/978-3-642-97610-0

Benoit Mandelbrot. *Fractal Geometry of Nature*. W. H. Freeman, 1977.

Sarthak Jain and Byron C. Wallace. Attention is not explanation. In Jill Burstein, Christy Doran, and Thamar Solorio, editors, *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers)*, pages 3543–3556. Association for Computational Linguistics, 2019. doi:10.18653/v1/n19-1357 URL https://doi.org/10.18653/v1/n19-1357

Sarah Wiegreffe and Yuval Pinter. Attention is not not explanation. In Kentaro Inui, Jing Jiang, Vincent Ng, and Xiaojun Wan, editors, *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019*, pages 11–20. Association for Computational Linguistics, 2019. doi:10.18653/v1/D19-1002 URL https://doi.org/10.18653/v1/D19-1002

Samira Abnar and Willem H. Zuidema. Quantifying attention flow in transformers. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel R. Tetreault, editors, *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020*, pages 4190–4197. Association for Computational Linguistics, 2020. ISBN 978-1-952148-25-5. URL https://www.aclweb.org/anthology/2020.acl-main.385/

Joseph F. DeRose, Jiayao Wang, and Matthew Berger. Attention flows: Analyzing and comparing attention mechanisms in language models. *IEEE Trans. Vis. Comput. Graph.*, 27(2):1160–1170, 2021. doi:10.1109/TVCG.2020.3028976 URL https://doi.org/10.1109/TVCG.2020.3028976

Elena Voita, David Talbot, Fedor Moiseev, Rico Sennrich, and Ivan Titov. Analyzing multi-head self-attention: Specialized heads do the heavy lifting, the rest can be pruned. In Anna Korhonen, David R. Traum, and Lluis Marquez, editors, *Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28-August 2, 2019, Volume 1: Long Papers*, pages 5797–5808. Association for Computational Linguistics, 2019a. doi:10.18653/v1/p19-1580 URL https://doi.org/10.18653/v1/p19-1580

Youwei Song, Jiahai Wang, Zhiwei Liang, Zhiyue Liu, and Tao Jiang. Utilizing BERT intermediate layers for aspect based sentiment analysis and natural language inference. *CoRR*, abs/2002.04815, 2020. URL https://arxiv.org/abs/2002.04815

Jesse Vig, Sebastian Gehrmann, Yonatan Belinkov, Sharon Qian, Daniel Nevo, Yaron Singer, and Stuart M. Shieber. Causal mediation analysis for interpreting neural NLP: the case of gender bias. *CoRR*, abs/2004.12265, 2020a. URL https://arxiv.org/abs/2004.12265

Elena Voita, Rico Sennrich, and Ivan Titov. The bottom-up evolution of representations in the transformer: A study with machine translation and language modeling objectives. In Kentaro Inui, Jing Jiang, Vincent Ng, and Xiaojun Wan, editors, *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019*, pages 4395–4405. Association for Computational Linguistics, 2019b. doi:10.18653/v1/D19-1448 URL https://doi.org/10.18653/v1/D19-1448

Ian Tenney, Dipanjan Das, and Ellie Pavlick. BERT rediscoversthe classical NLP pipeline. In Anna Korhonen, David R. Traum, and Lluis Marquez, editors, *Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28-August 2, 2019, Volume 1: Long Papers*, pages 4593–4601. Association for Computational Linguistics, 2019. doi:10.18653/v1/p19-1452 URL https://doi.org/10.18653/v1/p19-1452

Philipp Dufter and Hinrich Schütze. Identifying necessary elements for bert’s multilinguality. *CoRR*, abs/2005.00396, 2020. URL https://arxiv.org/abs/2005.00396

Steffen Eger, Johannes Daxenberger, and Iryna Gurevych. How to probe sentence embeddings in low-resource languages: On structural design choices for probing task evaluation. In Raquel Fernández and Tal Linzen, editors, *Proceedings of the 24th Conference on Computational Natural Language Learning, CoNLL 2020, Online, November 19-20, 2020*, pages 108–118. Association for Computational Linguistics, 2020. doi:10.18653/v1/2020.conll-1.8 URL https://doi.org/10.18653/v1/2020.conll-1.8
Elena Voita and Ivan Titov. Information-theoretic probing with minimum description length. *CoRR*, abs/2003.12298, 2020a. URL https://arxiv.org/abs/2003.12298

Jon Gauthier, Jennifer Hu, Ethan Wilcox, Peng Qian, and Roger Levy. Syntaxgym: An online platform for targeted evaluation of language models. In Asi Çelikyilmaz and Tsung-Hsien Wen, editors, *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations, ACL 2020, Online*. July 5-10, 2020, pages 70–76. Association for Computational Linguistics, 2020. ISBN 978-1-952148-04-0. doi:10.18653/v1/2020.acl-demos.10 URL https://doi.org/10.18653/v1/2020.acl-demos.10

Emily Reif, Ann Yuan, Martin Wattenberg, Fernanda B. Viégas, Andy Coenen, Adam Pearce, and Been Kim. Visualizing and measuring the geometry of BERT. In Hanna M. Wallach, Hugo Larochelle, Alina Beygelzimer, Florence d’Alché-Buc, Emily B. Fox, and Roman Garnett, editors, *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 8592–8600, 2019. URL https://proceedings.neurips.cc/paper/2019/hash/159c1ffe6b61b41b3c4d8f4c2150f6c4-Abstract.html

Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei, and Jifeng Dai. VI-BERT: pre-training of generic visual-linguistic representations. In 8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020. OpenReview.net, 2020. URL https://openreview.net/forum?id=SygXPaeYVH

Alexis Conneau, Germán Kruszewski, Guillaume Lample, Loïc Barrault, and Marco Baroni. What you can cram into a single &** vector: Probing sentence embeddings for linguistic properties. In Iryna Gurevych and Yusuke Miyao, editors, *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL 2018, Melbourne, Australia, July 15-20, 2018*, Volume 1: Long Papers, pages 2126–2136. Association for Computational Linguistics, 2018. ISBN 978-1-948087-32-2. doi:10.18653/v1/2018.acl-main.149 URL https://www.aclweb.org/anthology/P18-1198/

John Hewitt and Christopher D. Manning. A structural probe for finding syntax in word representations. In Jill Burstein, Christy Doran, and Thamar Solorio, editors, *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019*, Volume 1 (Long and Short Papers), pages 4129–4138. Association for Computational Linguistics, 2019. doi:10.18653/v1/n19-1419 URL https://doi.org/10.18653/v1/n19-1419

Rowan Hall Maudslay, Josef Valvoda, Tiago Pimentel, Adina Williams, and Ryan Cotterell. A tale of a probe and a parser. *CoRR*, abs/2005.01641, 2020. URL https://arxiv.org/abs/2005.01641

Allyson Ettinger, Ahmed Elghohary, and Philip Resnik. Probing for semantic evidence of composition by means of simple classification tasks. In *Proceedings of the 1st Workshop on Evaluating Vector-Space Representations for NLP, RepEval@ACL 2016, Berlin, Germany, August 2016*, pages 134–139. Association for Computational Linguistics, 2016. doi:10.18653/v1/W16-2524 URL https://doi.org/10.18653/v1/W16-2524

Elena Voita and Ivan Titov. Information-theoretic probing with minimum description length. In Bonnie Webber, Rowan Hall Maudslay, Josef Valvoda, Tiago Pimentel, Adina Williams, and Ryan Cotterell, editors, *A tale of a probe and a parser*. *CoRR*, abs/2005.01641, 2020. URL https://arxiv.org/abs/2005.01641

Allyson Ettinger, Ahmed Elghohary, and Philip Resnik. Probing for semantic evidence of composition by means of simple classification tasks. In *Proceedings of the 1st Workshop on Evaluating Vector-Space Representations for NLP, RepEval@ACL 2016, Berlin, Germany, August 2016*, pages 134–139. Association for Computational Linguistics, 2016. doi:10.18653/v1/W16-2524 URL https://doi.org/10.18653/v1/W16-2524

Elena Voita and Ivan Titov. Information-theoretic probing with minimum description length. In Bonnie Webber, Rowan Hall Maudslay, Josef Valvoda, Tiago Pimentel, Adina Williams, and Ryan Cotterell, editors, *A tale of a probe and a parser*. *CoRR*, abs/2005.01641, 2020. URL https://arxiv.org/abs/2005.01641

Jonathan Pilault, Jaehong Park, and Christopher J. Pal. On the impressive performance of randomly weighted encoders in summarization tasks. *CoRR*, abs/2002.09084, 2020. URL https://arxiv.org/abs/2002.09084

Jesse Vig. Visualizing attention in transformer-based language representation models. *CoRR*, abs/1904.02679, 2019b. URL http://arxiv.org/abs/1904.02679

Betty van Aken, Benjamin Winter, Alexander Löser, and Felix A. Gers. Visbert: Hidden-state visualizations for transformers. In Amal El Fallah Seghrouchni, Gita Sukthankar, Tie-Yan Liu, and Maarten van Steen, editors, *Companion of The 2020 Web Conference 2020, Taipei, Taiwan, April 20-24, 2020*, pages 207–211. ACM / IW3C2, 2020. ISBN 978-1-4503-7024-0. doi:10.1145/3366424.3383542 URL https://doi.org/10.1145/3366424.3383542

Blaz Skrlj, Nika Erzen, Shane Sheehan, Saturnino Luz, Marko Robnik-Sikonja, and Senja Pollak. Attviz: Online exploration of self-attention for transparent neural language modeling. *CoRR*, abs/2005.05716, 2020. URL https://arxiv.org/abs/2005.05716

Goro Kobayashi, Tatsuki Kuribayashi, Sho Yokoi, and Kentaro Inui. Attention module is not only a weight: Analyzing transformers with vector norms. *CoRR*, abs/2004.10102, 2020. URL https://arxiv.org/abs/2004.10102
Zeyu Yun, Yubei Chen, Bruno A. Olshausen, and Yann LeCun. Transformer visualization via dictionary learning: contextualized embedding as a linear superposition of transformer factors. *CoRR*, abs/2103.15949, 2021. URL https://arxiv.org/abs/2103.15949

Adrian Brasoveanu, Giuseppe Rizzo, Philipp Kuntschik, Albert Weichselbraun, and Lyndon J. B. Nixon. Framing named entity linking error types. In Nicoletta Calzolari, Khalid Choukri, Christopher Cieri, Thierry Declerck, Sara Goggi, Kõiti Hasida, Hitoshi Isahara, Bente Maegaard, Joseph Mariani, Hélène Mazo, Asunción Moreno, Jan Odijk, Stelios Piperidis, and Takenobu Tokunaga, editors, *Proceedings of the Eleventh International Conference on Language Resources and Evaluation, LREC 2018*, Miyazaki, Japan, May 7-12, 2018. European Language Resources Association (ELRA), 2018. URL http://www.lrec-conf.org/proceedings/lrec2018/summaries/512.html

Niels van der Heijden, Samira Abnar, and Ekaterina Shutova. A comparison of architectures and pretraining methods for contextualized multilingual word embeddings. In *The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020*, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, AAAI 2020, New York, NY, USA, February 7-12, 2020, pages 9090–9097. AAAI Press, 2020. URL https://doi.org/10.1609/aaai.v34i03.3495

Zhe Gan, Yen-Chun Chen, Linjie Li, Chen Zhu, Yu Cheng, and Jingjing Liu. Large-scale adversarial training for vision-and-language representation learning. In Hugo Larochelle, Marc'Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hong-Yuan使得Lin, editors, *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020*, virtual, 2020. URL https://proceedings.neurips.cc/paper/2020/hash/49562478d4e5f4af4ade46f29db7de5-Abstract.html

Jize Cao, Zhe Gan, Yu Cheng, Licheng Yu, Yen-Chun Chen, and Jingjing Liu. Behind the scene: Revealing the secrets of pre-trained vision-and-language models. In Andrea Vedaldi, Horst Bischof, Thomas Brox, and Jan-Michael Frahm, editors, *Computer Vision - ECCV 2020 - 16th European Conference, Glasgow, UK, August 23-28, 2020, Proceedings, Part VI*, volume 12351 of Lecture Notes in Computer Science, pages 565–580. Springer, 2020. ISBN 978-3-030-58538-9. doi:10.1007/978-3-030-58539-6_34 URL https://doi.org/10.1007/978-3-030-58539-6_34

Kai Han, An Xiao, Enhua Wu, Jianyuan Guo, Chunjing Xu, and Yunhe Wang. Transformer in transformer. *CoRR*, abs/2103.00112, 2021. URL https://arxiv.org/abs/2103.00112

Yikuan Li, Hanyin Wang, and Yuan Luo. A comparison of pre-trained vision-and-language models for multimodal representation learning across medical images and reports. In Taesung Park, Young-Rae Cho, Xiaohua Hu, Ililho Yoo, Hyun Goo Woo, Jianxin Wang, Julio C. Facelli, Seungyoon Nam, and Mingon Kang, editors, *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019*, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pages 542–557. Association for Computational Linguistics, 2019. doi:10.18653/v1/n19-1053 URL https://doi.org/10.18653/v1/n19-1053
David Wadden, Ulme Wennberg, Yi Luan, and Hannaneh Hajishirzi. Entity, relation, and event extraction with contextualized span representations. In Kentaro Inui, Jing Jiang, Vincent Ng, and Xiaojun Wan, editors, Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019, pages 5783–5788. Association for Computational Linguistics, 2019. doi:10.18653/v1/D19-1585 URL https://doi.org/10.18653/v1/D19-1585.

Tianyu Gao, Xu Han, Hao Zhu, Zhiyuan Liu, Peng Li, Maosong Sun, and Jie Zhou. Fewrel 2.0: Towards more challenging few-shot relation classification. In Kentaro Inui, Jing Jiang, Vincent Ng, and Xiaojun Wan, editors, Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019, pages 6249–6254. Association for Computational Linguistics, 2019. doi:10.18653/v1/D19-1649 URL https://doi.org/10.18653/v1/D19-1649.

Hila Gonen and Yoav Goldberg. Lipstick on a pig: Debiasing methods cover up systematic gender biases in word embeddings but do not remove them. In Amittai Axelrod, Diyi Yang, Rossana Cunha, Samira Shaikh, and Zeerak Waseem, editors, Proceedings of the 2019 Workshop on Widening NLP@ACL 2019, Florence, Italy, July 28, 2019, pages 60–63. Association for Computational Linguistics, 2019. ISBN 978-1-950737-42-0. URL https://www.aclweb.org/anthology/W19-3621/.

Jesse Vig, Ali Madani, Lav R. Varshney, Caiming Xiong, Richard Socher, and Nazneen Fatema Rajani. Bertology meets biology: Interpreting attention in protein language models. CoRR, abs/2006.15222, 2020b. URL https://arxiv.org/abs/2006.15222