Eurographics Conference on Visualization (EuroVis) 2022
R. Borgo, G. E. Marai, and T. Schreck
(Guest Editors)

Volume 41 (2022), Number 3

LMFingerprints: Visual Explanations of Language Model Embedding Spaces through Layerwise Contextualization Scores

R. Sevastjanova[1], A. Kalouli[2], C. Beck[1], H. Hauptmann[3], and M. El-Assady[4]

[1]University of Konstanz [2]CIS - LMU Munich [3]Utrecht University [4]ETH AI Center, Zürich

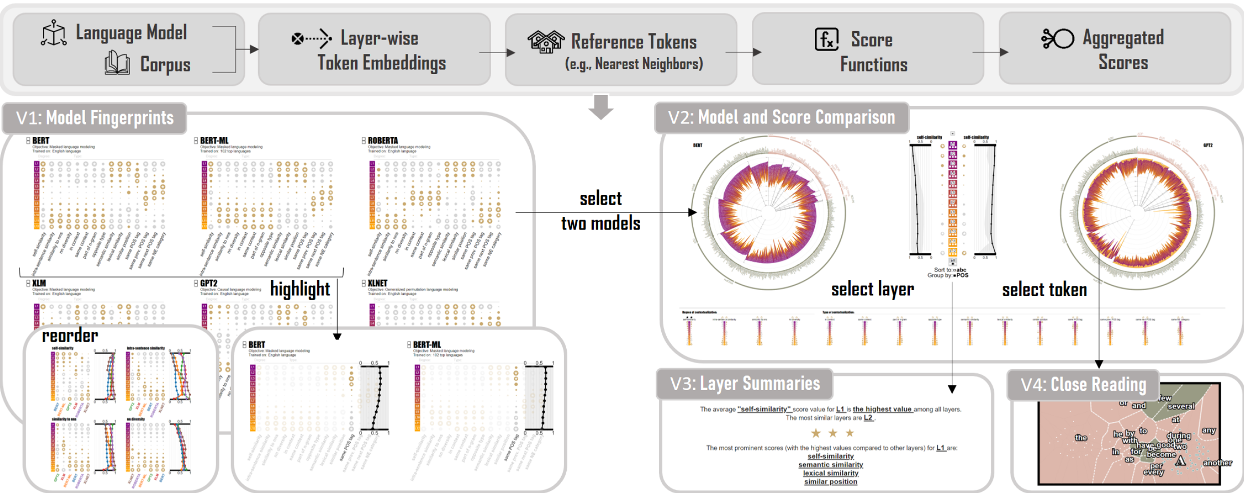


Figure 1: First, we extract layerwise embedding vectors for each token-context pair in the corpus. We obtain reference tokens (i.e., nearest neighbors), and compute contextualization scores introduced in section 4. The aggregated corpus-level and token-level scores are visualized in an interactive explanation workspace. In **V1**, we display corpus-level score patterns enabling fast model comparison. **V2** supports token- and token-group analysis. **V3** and **V4** provide more detailed insights into layer as well as context properties.

Abstract

Language models, such as BERT, construct multiple, contextualized embeddings for each word occurrence in a corpus. Understanding how the contextualization propagates through the model's layers is crucial for deciding which layers to use for a specific analysis task. Currently, most embedding spaces are explained by probing classifiers; however, some findings remain inconclusive. In this paper, we present LMFingerprints, a novel scoring-based technique for the explanation of contextualized word embeddings. We introduce two categories of scoring functions, which measure (1) the degree of contextualization, i.e., the layerwise changes in the embedding vectors, and (2) the type of contextualization, i.e., the captured context information. We integrate these scores into an interactive explanation workspace. By combining visual and verbal elements, we provide an overview of contextualization in six popular transformer-based language models. We evaluate hypotheses from the domain of computational linguistics, and our results not only confirm findings from related work but also reveal new aspects about the information captured in the embedding spaces. For instance, we show that while numbers are poorly contextualized, stopwords have an unexpected high contextualization in the models' upper layers, where their neighborhoods shift from similar functionality tokens to tokens that contribute to the meaning of the surrounding sentences.

1. Introduction

Recently, a wide range of deep-learning language models (e.g., BERT, GPT-2) has been developed, reaching high performance in natural language processing tasks [QSX*20]. These models are pre-trained on large corpora (e.g., *Wikipedia* articles [DCLT18]), learning language structures in an unsupervised manner. They generate contextualized word embeddings, i.e., word vectors that are specific to the context in which they are used [Eth19]. In this work we refer to context as a token sequence spanning a single sentence. In each model layer, word embeddings capture different characteristics of the context [RKR20]. For instance, it has been shown that syntactic features (e.g., dependency trees) are captured best in BERT's middle layers [RKR20]. Understanding such differences is crucial, especially for researchers applying language models in their work, e.g., by using embeddings for similarity tasks, fine-tuning models for classification, or measuring token importance using attribution methods.

The explanation of embedding contextualization is an active research topic, especially in the field of computational linguistics. Most common explainability techniques either use supervised probing methods, i.e., linear classification models predicting specific linguistic properties (e.g., [Eth19]), or apply adversarial testing to conclude about models' capability of learning specific context properties (e.g., [MPL19]). However, the findings of these two strands of research are often contradictory [SKB*21]. At the same time, visual analytics approaches are used for the explainability of embedding contextualization. Such approaches visualize attention-based mechanisms in transformer-based language models (e.g., exBERT [HSG20]), or explore characteristics of contextualized word embeddings (e.g., [AWLG20]). Despite the existing approaches, there are still open questions regarding the information captured in the embedding vectors. Also, the constant development of new language models dictates the need for a technique that provides a quick overview of the model's layerwise context specificities.

To contribute to this direction, we present a novel scoring-based technique for explaining embedding contextualization. We propose to quantitatively measure the similarity of tokens to various references (e.g., same tokens in different contexts, tokens within the same context, nearest neighbors) and use them as explanations. The motivation lies in the work by Ethayarajh [Eth19], who introduces scoring functions for embedding explainability. In this paper, we extend this set of scores and group them into two categories: a) the *degree of contextualization* category contains scores which measure the similarity between embedding vectors of different reference tokens and capture the degree of changes that occur in each embedding layer, and b) the *type of contextualization* category captures common characteristics of tokens and their nearest neighbors and is measured on token string representations and context properties.

A further, main contribution of this paper is an interactive explanation workspace that visualizes the computed score values. The visual representation of the scores is crucial due to the huge amount of data that is generated and has to be investigated, and because the embedding contextualization differs depending on the token's role (e.g., meaning or function) in its context [SKB*21]. Visualizations are effective means for generating insights into such (complex) data patterns [KAF*08]. The necessity for a visual representation of score patterns was also motivated by our collaborators from computational linguistics. In their analysis, they typically first spend a vast amount of time to explore numerical patterns and formulate concrete hypotheses, which are then tested in new experiments. A visual representation of the data can speed up this process by providing hints into interesting patterns. The visual solution was designed in an iterative design process in a close collaboration with these experts. To support various analysis tasks, we visualize score patterns in two aggregation levels: (1) A corpus-level score aggregation and visualization provides a quick overview of model-specific contextualization properties; (2) A token-level score aggregation supports more fine-grained analysis on embedding contextualization.

We evaluate the proposed scoring-technique and the visual workspace in two steps. First, we compare score patterns for embeddings extracted from BERT to previous findings by Rogers et al. [RKR20]. Second, we investigate score patterns for six popular transformer-based models and present new insights into model specificities through case studies. The contribution of this paper is threefold. (1) We introduce a scoring-based technique for explaining word contextualization and group the scores into categories. (2) We integrate these scores into a visual, interactive explanation workspace, which presents layerwise differences between embedding contextualization in multiple language models. We refer to the combination of these scoring and visual approaches as ***LMFingerprints***. (3) We compare score patterns to the related work and provide a broad overview of contextualization differences in six popular language models.

2. Background and Related Work

Research in explaining embedding contextualization has three main directions: probing classifiers, adversarial testing, and visualization.

Probing – Probing tasks aim at unearthing the linguistic properties encoded in neural models. This is achieved through a classification task where the final outputs of the model are used as features to predict a specific linguistic phenomenon [JSS19a]. Most probing experiments have focused on BERT and have shown that the model captures a hierarchy of linguistic information (e.g., [Edm20; JSS19b; LTF19a]): surface linguistic features, such as morphosyntactic information, are captured best in the lower layers, while syntactic properties are best represented in the middle layers. The middle to higher layers capture morphological features best, and semantic information such as word senses and semantic roles, is captured best in the higher layers. This captured hierarchy can also be paralleled to the traditional NLP pipeline of Part-of-Speech (POS) tagging, syntactic parsing, named entity recognition, semantic role labeling and coreference resolution [TDP19a].

Adversarial Testing – Adversarial testing aims at exposing the generalization difficulties of the models, in this way shedding light to their inner workings. Relevant research has shown how such models struggle in capturing basic lexical relations [GSG18], identifying ungrammaticality [ML18], efficiently capturing challenging linguistic phenomena, such as negation [DGS*18; RHMS20] and conditionals [RHMS20], or modeling human reasoning patterns, such as numerical or common-sense reasoning [NRS*18]. These findings, however, seem to contradict the results of the probing studies: if the models are able to capture 'deep' linguistic information (e.g., about syntactic hierarchies), they should also be able to solve the challenges posed by adversarial test sets.

Contextualization – Despite these contradicting findings, there is consensus that the word embeddings generated by such models are contextualized, i.e., a word has different vector representations across different contexts. Particularly, recent work by [Eth19] shows that, by measuring a word's contextualization on the basis of *self-similarity* scores, the embeddings become more contextualized, i.e., more context-specific, in the upper layers of BERT. Additionally, [RYW*19; WRCB19] show that contextualized embeddings generally cluster with one another with respect to word senses.

Visual Embedding Explanations – For explainability purposes, most relevant work has focused on visualizing attentions (e.g., NLIZE [LLL*18], Seq2Seq-Vis [SGB*18], BertViz [Vig19], exBERT [HSG20], SANVis [PNJ*19]) and Attention Flows [DWB20]), and showing *how* transformers learn. Less work has focused on visualizing word embeddings and showing *what* the model learns. The first such tools were applied on static embeddings, such as word2vec, Glove, and fastText, and facilitated analogies [LBT*17] and various other tasks such as local word neighborhoods [BCS19; HG18]. Similarly, the recent approach by [Ber20] explores correlations between embedding clusters in BERT for a single model's layer at a time. The novelty of our approach is the explanation of contextualized word embeddings through a novel scoring technique, integrated into a visual explanation workspace.

3. Problem Characterization

During our long-term collaboration with computational linguists working with language models, we have identified several requirements for a visual analysis approach supporting the explanation of embedding contextualization. The requirement analysis included several informal interviews with two postdoctoral researchers concerning their typical workflow of using language models in their research. We have also reviewed approaches that are currently used by researchers to explain embedding contextualization, such as probing or adversarial tests, as well as visual approaches (see section 2). In the following, we describe the gathered requirements through *Models and Data* as well as *Users and Tasks* [MA14].

Models and Data – To analyze word embeddings, we first need to consider language models that produce them. There are various types of language models, with different architectures, generating word embeddings. For simplicity reasons, in this paper we focus on transformers, which are multi-layer models that use attention mechanisms [VSP*17]. During the training process, each token of the input sequence (in the following, we will refer to the input sequence as the token's *context*) gets mapped to a high-dimensional vector using a combination of embeddings that indicate the corresponding token, segment, and position. Transformer models can be of different types (e.g., BERT is an autoencoder and GPT-2 is an autoregressive model) and they can have different learning objectives (e.g., BERT is trained on masked language model and the next sentence prediction tasks, while GPT-2 is trained on the next word prediction task).

It has been shown that language models capture different linguistic properties, i.e., semantics, syntax, surface features [RKR20]. To enable such broad analysis of embedding contextualization, we first need to come up with effective contextualization *descriptors* **(R1)**. Due to models' inner-working differences, it is expected that their embedding contextualization differs. Hence, the explanation of the contextualization needs to be generalizable and easily applicable on different language models for an effective model comparison **(R2)**. Depending on the size of the corpus, the number of the extracted embeddings that have to be analyzed can introduce challenges. Previous work [Eth19; SKB*21] has also shown that some tokens (e.g., function words) get contextualized stronger than others. Hence, to get a full picture, it is not sufficient to compute statistical contextualization values on the complete corpus alone, but we need additional visualizations for more fine-grained token-group level analysis **(R3)**. Since different layers of a model capture different types of context information [RKR20], the visual representations must highlight layer-specific contextualization properties **(R4)**.

Users and Tasks – Boggust et al. [BCS19] describe that especially expert users, i.e., data analysts, machine learning experts, and computational linguists analyze embeddings for multiple purposes, among others, for understanding the model's strength and weaknesses (requires **R1**, **R2**, and **R3**) and the information that it learns in different layers (requires **R4**). In the following, we showcase several tasks that require prior knowledge on embedding contextualization.

T1: Token Similarity Since language models generate embeddings for each token's occurrence in the corpus depending on the token's surrounding contexts, one can use them to disambiguate words with multiple meanings. These embeddings can also be used as fixed features for classification tasks. However, since each layer of the model captures different context's characteristics, researchers need to decide which layer's embeddings are the most sufficient for the use case at hand (requires **R1**, **R4**).

T2: Model Fine-Tuning Often, language models get fine-tuned on labeled datasets for diverse classification tasks [DIS*20], whereby the initial contextualized word embeddings get adapted to capture task-specific language characteristics. For example, one can freeze layers [LTL19] during the fine-tuning to speed up the training process. Currently, decisions on the layer selection are made through a brute-force approach, i.e., different layers are selected and the model with the highest accuracy is chosen manually [LTL19] or automatically [LAV21], based on the produced accuracy scores. These decisions are currently not informed by the knowledge of what is captured in the embeddings in different layer (requires **R1**, **R4**).

T3: Token Importance To evaluate what the model learns during its fine-tuning, one can apply attribution methods [LPK21; ZBRS21], which are computed on the word embeddings adapted during the fine-tuning. In order to avoid making false conclusions (e.g., why a particular group of words such as stopwords has a high or low attribution), one needs to first gain an understanding of the token contextualization, e.g., what type of information is encoded in embeddings, to which tokens words become similar, and what are characteristics that the neighborhoods have in common (requires **R1**, **R3**).

4. Contextualization Explanation through Scoring Techniques

In this section, we present the foundation of ***LMFingerprints*** – a scoring-based technique for explaining embedding contextualization. Instead of training probing classifiers and analyzing their inputs and outputs, we compute the similarity of different embedding, token, and context characteristics and use them as means of explanation (supports **R1**). In this section, we present existing scoring techniques and introduce new ones that are computed on the embedding nearest neighborhoods. We categorize these scores into two types (see Figure 2). First, we present scores that describe the **degree of contextualization**. These scores measure the changes in the embedding vectors themselves, e.g., by applying the cosine similarity function. Second, we introduce new scores that characterize the **type of contextualization**. These are scores that measure the similarity between nearest neighbors according to different token and context properties. In the following, we present a set of examples for each type. This set of scores is not exhaustive and can be extended to enable testing of further hypotheses.

Data Pre-Processing – The data pre-processing pipeline is shown in Figure 1. For each **token-context pair** in the corpus, we first extract layerwise embedding vectors. We refer to **context** as a token sequence spanning a **single sentence**. For instance, if a token occurs in five sentences and the model has 12 layers, we will extract 5 x 12

Category	Computes	Comparison Reference	Example
Degree of contextual.	Embedding similarity	Token in Different Contexts	‚*Germany*' -> ‚Germany', ‚Germany', ...
		Tokens in the Same Context	‚*Germany*' -> ‚is', ‚a, ' ‚European', ‚country', ‚.'
		Baseline Embedding	‚*Germany*' -> embedding from layer 0
	NN diversity	Nearest Neighbor Tokens	‚*Germany*' -> ‚German', ‚Austria', ‚France'
Type of contextual.	Token similarity		
	Context similarity		

Figure 2: We propose using score functions to measure the embedding contextualization, computed on different reference tokens.

embedding vectors for it. If a token occurs multiple times in a single sentence, we extract an embedding for each of its occurrences. Hence, the position of a token in the sentence is stored as its metadata. Next, we extract and store ***k* nearest neighbors** for each token embedding. As our previous work shows [KSS*21], the highest similarity is observed between embeddings of the same word used in different contexts. Thus, to explain *what* information is captured in the embedding vectors, we exclude the same tokens from the token's nearest neighbors, i.e., we obtain nearest neighbors that are the next most similar ones. The parameter k can vary; we have tested k=3 as well as k=10 and both produced comparable results. For the score computation as well as visualization purposes, we assign each token to its POS tag. Finally, we compute scores for each token embedding that we introduce in the following section. For analysis purposes, the score values get aggregated. The **token-level aggregation** represents layerwise average score values for each unique token string. The **corpus-level aggregation** represents the layerwise average score values for all tokens in the corpus.

4.1. Degree of Contextualization

In the following, we present several example scores that can be used to measure the degree of changes in the embedding vectors. These scores can be computed on different reference tokens (e.g., same token in different contexts or nearest neighbor tokens).

Token in Different Contexts: To explain the embedding contextualization, Ethayarajh [Eth19] introduces the *self-similarity* score, which is "the average cosine similarity of a word with itself across all the contexts in which it appears." **Expectation**: The higher the similarity, the lower the degree of contextualization.

Tokens in the Same Context: Another score introduced by Ethayarajh [Eth19] is *intra-sentence similarity*, which is the average cosine similarity between a token's embedding to other tokens in the same context. **Expectation**: The higher the similarity, the higher the degree of contextualization.

Nearest Neighbor Tokens: The *nearest neighbor similarity* is computed as the cosine similarity between the token and its nearest neighbor embeddings. **Expectation**: The higher the similarity, the higher the degree of contextualization. The *nn diversity* score measures the number of unique nearest neighbors (unique strings). **Expectation**: The larger the diversity, the higher the degree of contextualization.

Baseline Embedding: One can also measure the similarity to a *baseline* embedding. For instance, we can extract embeddings from a token without its surrounding context or from the 0^{th} layer [Eth19] and use them as a baseline. We call them *similarity to context-size 0* and *similarity to layer 0*, respectively. **Expectation**: The lower the similarity, the higher the contextualization.

4.2. Type of Contextualization

The previous scores measure solely the degree of embedding changes according to diverse reference tokens. To obtain **characteristics that are encoded in embedding vectors**, we introduce further scores that are computed on token **nearest neighbors** for different **token and context properties**. There are many potentially interesting scores that can be designed for measuring the type of contextualization. In the following, we specify example scores covering the three linguistic analysis directions, i.e., semantics, syntax, and surface features. In addition, we describe scores related to specific context properties (e.g., token's position in the context).

Semantic Similarity: Related work has evaluated which layers capture token semantic information in BERT and the current findings are contradictory [RKR20]. To measure this characteristic, we introduce the *semantic similarity* score. It measures similarity between a token to its nearest neighbors according to the Wordnet's [Fel98] word similarity function [PPM04]. Example tokens with a high semantic similarity: *girl – woman*. To analyze the contextualization of named entities, we introduce the *same named entity category* score. It measures how often the nearest neighbors share the same named entity category. Example: *Germany (LOC) – Italy (LOC)*.

Syntactic Similarity: *Same POS tag* score measures how often a token and its nearest neighbors have the same POS tag. Example: *drive (VERB) – walk (VERB)*. *Same previous POS tag* measures how often the token before the target token has the same POS tag as the token before the nearest neighbor. Example: *sunny (ADJ) day – good (ADJ) weather*. *Same next POS tag* measures how often the token after the target token has the same POS tag as the token after its nearest neighbor. Example: *day is (AUX) – weather will (AUX)*.

Surface Similarity: To see whether the model captures a token's lexical representation (i.e., characters of the string), we introduce the *lexical similarity* score. It is computed as the inverse of the edit distance between a token and its nearest neighbor tokens, normalized to the longest token in the neighbor pair. Example: *drive – driver*.

Context Specificities: The *positional similarity* score measures how often the token and its nearest neighbors have the same absolute position in their contexts. Example: *This is a sunny... (index 3) – It was a good... (index 3)*. The *in context* score captures how often tokens that occur in the same context become nearest neighbors. Example: *This is a sunny... – A sunny....* *Same context* shows in how many cases the token and its nearest neighbors are part of the same context. Example: *This is a sunny... – This is a sunny....* And a more restricted version – *part of the n-gram* – shows how often the token and its nearest neighbors together create a tri-gram. Example: *This is a sunny... – This is a sunny....*

5. Interactive Visual Explanation Workspace

In this section, we introduce the visual, interactive workspace of ***LMFingerprints***, which explains embedding contextualization through scoring patterns (see section 4). The design of the workspace is motivated by the requirements described in section 3.

Design Rationale – The design of the workspace is tailored to explain contextualization score patterns. In particular, our aim is to visually summarize in which model's layers the contextualization scores have the lowest as well as the highest values for different

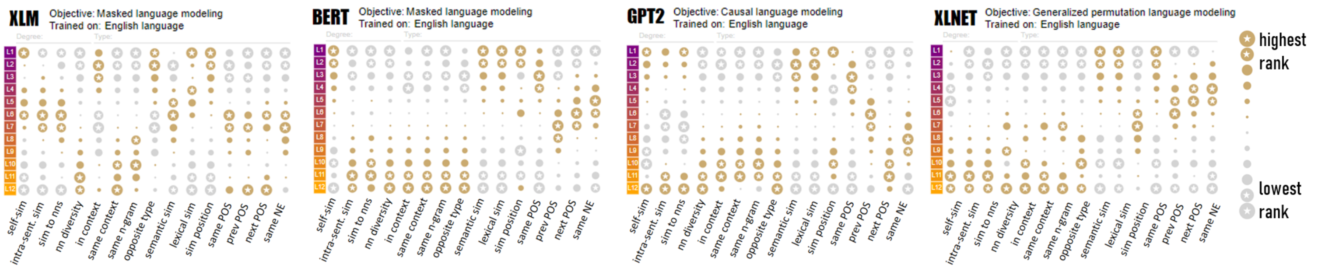


Figure 3: In **Model Fingerprints**, the cells (i.e., circles) represent ranks for each score (i.e., column) that are extracted from their aggregated corpus-level values. A bipolar scale is used to highlight the layers with the highest (large yellow circles) and the lowest (large gray circles) score values. White star icon are added to the top two ranks of both ends of the scale.

token aggregation levels (i.e., the whole corpus as well as different token-groups). The design was conducted in **close collaboration with experts from computational linguistics**, and has been adapted through **several design iterations**. Each adaption phase of the prototype was followed by a **feedback round** where the implemented prototype was constructively critiqued.

To ease the readability and memorability of the visual elements, we use the same, **globally defined encoding** for elements displayed in multiple views. In all views, layers are colored using a sequential color scale (i.e., from purple representing layer 1 to orange representing layer 12). The sequential color scale shows the changes between the early, middle, and upper layers - a standard degree of analysis in related work - and is perceptually less overwhelming than, e.g., 12 categorical colors. Except in the radial layout, in all other occurrences **layers are represented as squares and ordered vertically** from layer 1 (on top) to layer 12 (on the bottom). To avoid confusion, we call the first layers (e.g., 1, 2) – *early layers* and last layers (e.g., 11, 12) – *upper layers*, sticking to the model's architecture. Furthermore, to ease the analysis of token types ([SKB*21]), we **color function words pink and content words green** in all views where they are displayed.

Workflow – After data pre-processing (described in section 4), we visualize the aggregated scores in the explanation workspace. The aggregated corpus-level scores are displayed in **Model Fingerpints** (Figure 1 V1) view. The users can select two models (or one model twice to explore the relation between two scores) and display them in **Model and Score Comparison** view (Figure 1 V2). There, through diverse interaction techniques, the users can gain insights into specific token-group contextualization. **Layer Summaries** view (Figure 1 V3) summarizes layer properties, and **Close Reading** view (Figure 1 V4) displays token contexts for close reading.

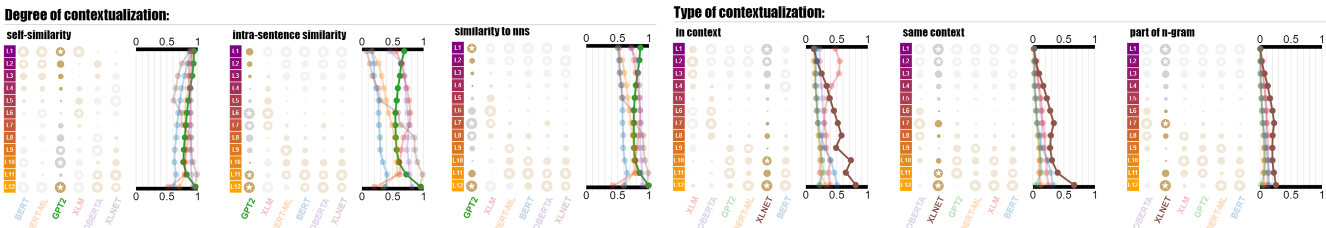
5.1. Model Fingerprints View

The goal of this visualization is to explain contextualization specificities for multiple language models simultaneously (**R2**) and highlight characteristics that are captured in different models' layers (**R4**).

Visual Design The design of a model comparison view was straightforward; our experts agreed that a matrix-like visualization would support the layerwise representation of corpus-level score values (shown in Figure 3). The idea was inspired by literature fingerprints by Keim and Oelke [KO07]. The columns in the matrix represent scores; the rows – layers of the particular model. We first rank layers according to their aggregated corpus-level score values, and by default represent each model by its ranks (i.e., rank 1-12 in language models with 12 layers). Each cell in the matrix is visualized as a circle that is scaled to the layer's rank, whereby a bipolar scale is used to highlight the layers with the highest and the lowest score values (i.e., circles with the largest radius). In addition, we use two qualitative colors to show the max (yellow) and min (gray) ranks accordingly. For better readability, we add a white star icon on circles of the top two ranks of both ends of the bipolar scale. We use star icons since they are commonly used as rating icons in diverse applications.

This representation primarily shows score-wise layer differences, i.e., in which layers a particular score has the highest or lowest values. Since embeddings from all layers are extracted from the same corpus (and, hence, are comparable), such layerwise changes can indicate that the model in the particular layer captures the score's underlying pattern (e.g., POS tags, named entity categories). However, the fingerprints do not tell us how dominant these patterns are.

Interactions – For a detailed score distribution analysis, users can click on a single score (i.e., column) and a line chart showing aggregated corpus-level score values is displayed on top of each model's matrix. To ease model comparison for a single score, the



(a) GPT-2 is highly anisotropic, i.e., embeddings have a high cosine similarity.

(b) In XLNET's upper layers, tokens in the context become similar.

Figure 4: The **Model Fingerprints** can be reordered to group scores according to their category (e.g., *degree-* or *type of contextualization*). Hovering over a model, the corresponding lines get highlighted, facilitating score comparison. Models are sorted according to their rank-patterns.

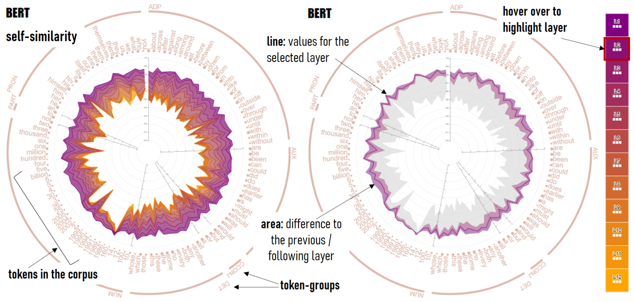


Figure 5: One line represents score values of one layer. To ease the readability, we additionally color the area showing score's differences to the previous and following layer.

users can change the view to a score-based representation, where the columns are reordered to group scores according to their category (e.g., *degree-* or *type of contextualization*). By hovering over a column (i.e., a score for one model), all scores of the particular model get highlighted in other score-based matrices (shown in Figure 4).

5.2. Model and Score Comparison View

Model Fingerprints give an overview of aggregated corpus-level score differences. However, related work has shown that contextualization of different word categories differs (i.e., some tokens, e.g., function words, get more contextualized than others [Eth19; SKB*21]). To enable the analysis of such differences , we designed the **Model and Score Comparison** view. The purpose of this view is to provide an overview of contextualization specificities for different token-groups (**R3**), e.g., proper-nouns, function words, etc. At the same time, the visualization should show the score values for different model's layers (**R4**), and be relatively compact to enable the analysis of at least two models simultaneously, displayed side-by-side (**R2**). In other words, our goal was to design a compact visualization that shows layerwise token-group score patterns.

Visual Design – The design of this view was a more laborious process than for the **Model Fingerprints** view. Before deciding on a radial area chart to display token-based score values, we implemented multiple alternative visualizations, among others, a parallel coordinates plot [JF15] and a zoomable matrix-based visualization [BBH*16; FAS*20]. We provided depictions of some design alternatives as supplementary material to this paper. The parallel coordinate plots represented each layer of the aggregated token-level score values as a dimension in the plot, resulting in an over-plotted visualization. To avoid this pitfall, we turned to matrices, as they do not suffer from occlusion and line crossings [BBH*16]. However, the matrix required a large area to be displayed. Our experts reported finding it challenging to compare score values across layers, and wished a more compact representation. After several failed attempts to reduce the size of the matrix and improve its readability, we finally switched to the radial design. One of its main advantages is the compactness of the layout [DLR09]; it has been also judged as a natural and therefore a memorable visualization [BVB*13]. Despite the known limitations of radial charts (e.g., angle-based comparisons [WDG*19]), their ability of presenting patterns in a compact way was judged positively by our experts.

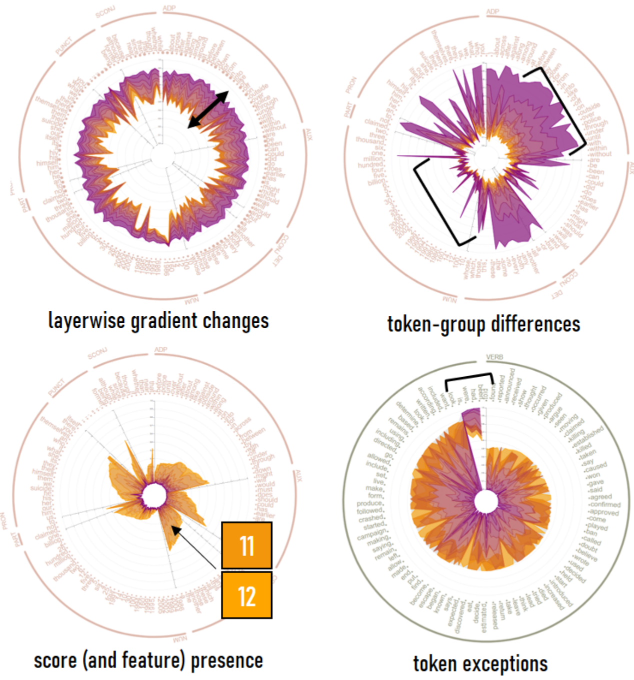


Figure 6: Example patterns that can be detected using the radial layer visualization through filtering and reordering techniques.

The radial design displays all tokens in the corpus, groups them according to their POS tag, and describes them through their layerwise contextualization score values. First, we arrange unique tokens in radial fashion (by default, sorted alphabetically). To let the users understand layerwise embedding changes, we visualize the score values for all 12 layers simultaneously. A single layer is displayed as a line that connects the score values for all tokens in the corpus (i.e., 12 lines for a model with 12 layers). An example is shown in Figure 5. We color the lines according to a sequential color scale (i.e., from purple representing layer 1 to orange representing layer 12). To facilitate readability, we additionally color the area between two succeeding layers (shown in Figure 5) and decrease their opacity to see overlapping layers. The design is similar to a braided graph visualization, whereby each braid has transparency and thus, the overlapping layers are visible. We further group tokens according to their most frequent POS tag to ease group-pattern analysis.

To enable model as well as score comparison, we display two radial charts at once, one on each side of the screen. The displayed model(s) are selected by the user in the **Model Fingerprints** view. At the bottom of the screen, we provide an overview of score ranks, but this time they represent the selected model(s). The users can change the visualized score in the radial chart by clicking on a score's representation at the bottom of the screen. An enlarged version of the clicked layer-rank visualization is displayed between the two radial charts, as shown in Figure 7.

Interactions – The radial visualization provides a good overview of score patterns for token-groups, but, when the radial chart has to display many tokens, the readability of token labels is restricted. And, although one can see general differences between two radial charts, it is perceptually difficult to compare single token values. To

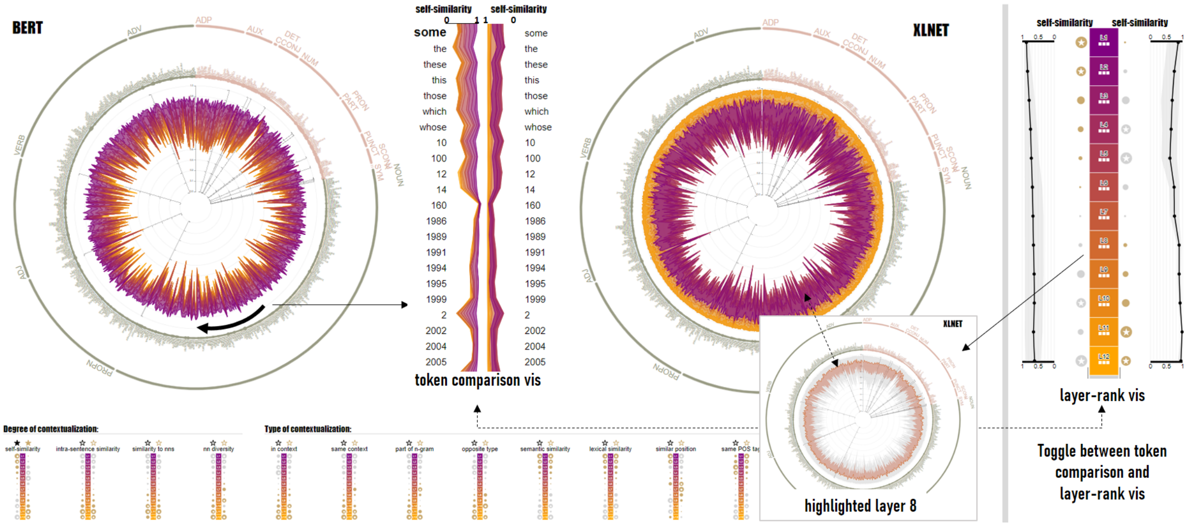


Figure 7: The *self-similarity* in different models show different contextualization patterns. BERT's *self-similarity* decreases with increasing layers; XLNET's highest *self-similarity* is in upper layers, the largest increase is between layer 7 and 8. To compare the token-level score values, the users can switch from the layer-rank to token comparison visualization.

ease the interpretation of the shown patterns, we thus support several interaction techniques. Yang et al. [YWR02] has suggested five interaction techniques for radial visualization: selection, reconfiguration, distortion, drill down/roll-up, and pan, zoom, and rotation. We focus on the first two: the selection of specific token groups and the reordering of the displayed tokens. An example is shown in Figure 9. First, to analyze token-groups in more detail, the users can select POS tag(s) and the corresponding tokens are filtered. Based on the available space, the token labels are enlarged, enabling their readability. Second, users can group tokens according to their POS tags (default setting), or remove this grouping. Third, the users can sort tokens according to different properties: alphabet, maximum score value among all layers, score value in a specific layer. The two charts can be sorted independently of each other, or through a global sorting. Some examples of patterns that arise in the visualization through filtering and sorting techniques are displayed in Figure 6. These include *layerwise gradient changes*, which are visible in situations when the score values gradually increase or decrease in succeeding layers. *Token-group differences* become obvious when tokens are grouped according to POS tags and the radial chart contains *empty* areas. The presence of a particular score in a single layer is shown through (large) areas colored with a single color. *Token exceptions* become obvious when sorting them to score values for a single layer. When the users hover over a token, their score values are displayed next to the particular score in the layer-rank visualization. To enable single token comparison, we add another helper visualization – a linear area chart placed between the radial charts (shown in Figure 7). This chart is linked to the radial chart, i.e., when the users hover over tokens in the radial chart, the linear area chart is scrolled to the position of the hovered token. The users can switch between the layer-rank visualization and the linear area chart.

5.3. Details-on-Demand Views

Layer Summaries View – To ease the comparison of the different layers of one model (**R4**), we add the **Layer Summaries** view. It is displayed, when the users click on a layer in the layer-rank visualization of the **Model and Score Comparison** view. This facilitates the interpretation of layerwise score patterns, as we summarize the specific properties for the selected layer using verbalization. Verbalization – description of a phenomenon in words – is an effective alternative for machine learning model explainability [SBE*18]. We use verbalization to describe which layers are similar to the selected one, as well as which scores have the highest ranks for the particular layer. The verbal components are created using a heuristic approach.

Close Reading View – Close reading is a fundamental method in text analysis applications [JFCS15]. It is needed especially to build trust [CJS16]. Thus, to provide insights into the token neighborhoods (**R3**), we add the **Close Reading** view. This view is displayed on demand, when a token is selected in **Model and Score Comparison** view. The layerwise token neighborhoods are displayed in a 2D space (shown in Figure 8), whereby the coordinates for token embeddings and their neighbors are obtained using the UMAP projection [MHSG18], the current state-of-the-art dimensionality reduction techniques. Each layer is represented through a single projection. The token as well as each nearest neighbor is displayed as a circle that is enclosed in a voronoi cell, whereby the cells are colored according to the token's type (i.e., function words are colored pink and content words green). If multiple nearest neighbors have the same token string, we display only one label to reduce overplotting. The label is placed in the average coordinates of its token-context embeddings, and their corresponding voronoi cells are joined together.

6. Evaluating the Contextualization Landscape

We conduct a two-step evaluation to evaluate both, the scoring functions and visual representation of the score patterns. First, we compare score patterns of embeddings from BERT to previous findings from the *BERTology* paper by Rogers et al. [RKR20]. Second, we investigate score patterns for six popular transformer-based models and present several new insights through case studies.

Corpus – We use a corpus of 800 unique sentences of the RTE-1 [DGM05], RTE-2 [BDD*06] and RTE-3 [GMDD07] corpora.

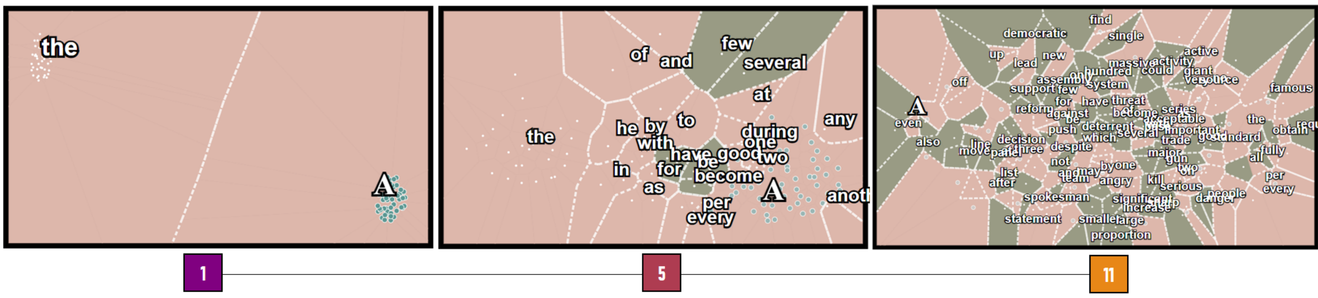


Figure 8: Contextualization of function words in BERT. We use UMAP projection to show tokens and their nearest neighbors in a 2D space. The dots represent token embeddings that are surrounded by voronoi cells. Here, we show the nearest neighbors of the token *A* in layers 1, 5, and 11. In BERT's upper layers, this token becomes more similar to content words (see green voronoi cells) that occur in the same context.

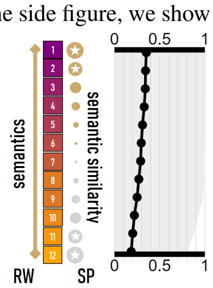
These corpora contain sentence pairs originally intended for Natural Language Inference. They stem from the news domain and thus contain variable content. The pairs are split into single sentences.

Models – We compare embedding contextualization in six transformer models: bert-base-uncased, bert-base-multilingual-uncased, roberta-base, gpt2, xlnet-base-cased, xlm-mlm-en-2048. For simplicity reasons, we selected models that have 12 layers in their architectures. From each model, we extract layerwise embedding vectors for each token-context pair using the hugging-face library [WDS*20]. Since each model uses a different tokenizer, the number of extracted embeddings slightly varies, but is around 12'000 tokens for each. We use faiss library [JDJ17] to extract 10 nearest neighbor tokens / {same tokens} for each unique token embedding. For better comparison, we reduce the dataset to tokens that occur at least 5 times in the corpus. For tokens that are very frequent (e.g., function words), we limit their set to max 100 unique embeddings per layer. Tokens are mapped to their POS tags using spacy's *en_core_web_sm* model.

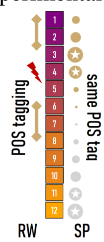
6.1. Use Case: Comparing RW Findings to BERT Fingerprints

To show the validity of the ***LMFingerprints*** scoring technique, we first compare scoring patterns computed on embeddings extracted from BERT to the findings summarized in the paper by Rogers et al. [RKR20]. We show examples for the different linguistic analysis levels, i.e., semantics, syntax, surface, and context properties. As described in section 4, one can design multiple scoring functions to measure contextualization for one of these categories. Thus, there is no 1:1 mapping between scores and probing classifiers described in [RKR20], but we show that both techniques can be used as alternatives since they capture the presence of the different linguistic properties in the same layers.

Semantics – According to Tenney et al. [TDP19b], semantic information is spread across the entire model. In the side figure, we show the comparison of the study results by Tenney et al. (see the left hand side, i.e., the **R(elated)W(ork)**) and our score patterns (see the right hand side, i.e., **S(core)P(atterns)**). The results of experiments conducted by Jawahar et al. [JSS19a] and Cui et al. [CCWZ20] show that semantic features are captured best in upper layers. Our score patterns show that the basic Wordnet similarity is most present in early layers, i.e., most of the nearest neighbors of content words have a high general semantic similarity. However, the line chart of aggregated corpus-level score values show that the feature is indeed present in all layers.Remark: the aggregated corpus-level values are computed on the complete corpus, including function word; thus, the average similarity is lower than it would be for content words alone.

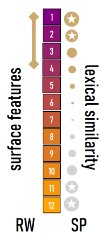


Syntax – One of the experiments where the existing experimental findings show contradicting results is related to the POS tagging task. In particular, experimental results by Tenney et al. [TDP19b] show that the basic syntactic information, i.e., POS tags, is learned by BERT in early layers (the highest scores for probing POS tags are achieved in the first two layers). However, the probing experiments by Liu et al. [LGB*19] find that POS-tagging is performed best at the middle layers (layers 6-8). Our scoring patterns show that in embedding vectors, the POS tag information is the most present in early layers, but the highest values are in layers 3 and 4. Our scoring patterns show that in embedding vectors, the POS tag information is the most present in early layers, but the highest values are in layers 3 and 4.



Syntactic information is most prominent in the middle layers of BERT. This has been shown by Liu et al. [LGB*19] and Hewitt and Manning [HM19], whose results indicate that in the layers 6-9 it is possible to reconstruct the syntactic tree depth. Our score function, which measures in which layer embeddings capture simple syntactic patterns such as n-grams with same POS tag structures (e.g., *ADJ* followed by a *NOUN*), show the same results as probing classifiers – the values are highest in layers 6-9. This indicates that in these particular layers the embeddings indeed incorporate syntactic structure information.

Surface – Surface features are captured best in early layers of BERT. The original study was conducted by Jawahar et al. [JSS19a]. The authors trained probing classifiers to test surface features such as sentence length and presence of words in the sentence. Instead, we investigate the token *lexical similarity* as an example of a further surface feature. It shows whether the nearest neighbors have similar spelling, e.g., token *run* is similar to token *runs* or *runner*. As the side figure shows, both the surface features evaluated by Jawahar et al. as well as our *lexical similarity* is most present in early layers of BERT.



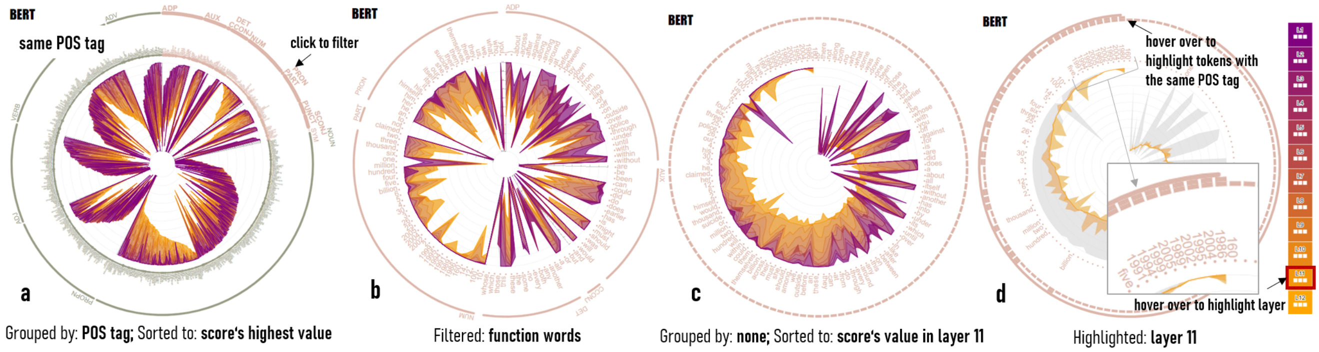
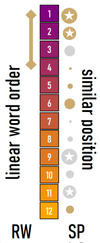


Figure 9: In BERT, numbers have a relatively poor contextualization. Here, the *same POS tag* score is displayed. We first filter function words (a), sort them ascending to their values in layer 11 (b), and highlight tokens with POS tag *NUM* (c). Year numbers have the lowest contextualization, i.e., their nearest neighbors remain numbers even in the model's upper layers, which is different from for other function words.

Context Properties – The linear word order is best captured in the early layers of BERT. The original study was conducted by Lin et al.[LTF19b] who trained probing classifiers to predict, among others, the token index in the sentence. Their results show that especially the first three layers of BERT can predict the token's index in its context. Our score patterns show that nearest neighbors especially in BERT's first two layers have the same positional index. It is important to notice though that Lin et al. limited the sentences size for their experiment, and tested only specific indices (i.e., $2 \leq n \leq 9$). We did not limit the sentence length nor the positional indexes for testing.



6.2. Case Studies: Token Similarity and Importance

We further show the effectiveness of our approach by presenting insights related to analysis tasks introduced in section 3. These insights were created collaboratively with two experts (postdoctoral researchers) from computational linguistics. In an informal setting, the experts interacted with the workspace and verbally summarized their observations. Before we present insights that were gained for tasks **T1** (Token Similarity) and **T3** (Token Importance), we summarize specificities of the six models. **Model Fingerprints** (a subset of models is shown in Figure 3) show that the contextualization in the six models differ. The most similar are BERT and BERT-Multilingual (i.e., BERT-ML) models. In the early layers, their nearest neighbors have a high lexical and semantic similarity, in middle layers the models capture named entity categories and token n-grams, i.e., tokens are more similar to those that have the same previous or following POS tag. In upper layers, tokens within the context become more similar to each other. ROBERTA's properties differ. Tokens within the context become similar to each other in middle layers, and the similarity between tokens in similar n-gram structures is highest in upper layers. Among the six language models, XLM encodes the positional information the strongest. This feature is dominant in the early layers of the model. We can confirm findings by Ethayarajh [Eth19] and Cai et. al [CHBC20] that GPT-2 is highly anisotropic, i.e., its embeddings fall within a narrow cone of the space, leading to high cosine similarities. Especially in layer 12 the cosine similarity between tokens is close to 1 (in Figure 4a). In comparison to other models, token nearest neighbors in upper layers are less frequently from the same context, but rather tokens having the same POS tag. In particular, in the example of an n-gram *New York city*, BERT learns that *York* is similar to *New* and *city*, however GPT-2 learns that *York* is similar to *Jersey*, *Angeles*, *Francisco*. Different to the bi-directional learning of BERT, GPT-2 uses an unidirectional learning; it can only reach the left context of the evaluated token. XLNET model aims to use the strength of the GPT-2-like autoregressive model and at the same time, use the bi-directionality of BERT [GCMA20]. As shown in Figure 4b , in XLNET, tokens within the context are most similar, and the semantic similarity and POS tag similarity is less dominant in the embedding vectors.

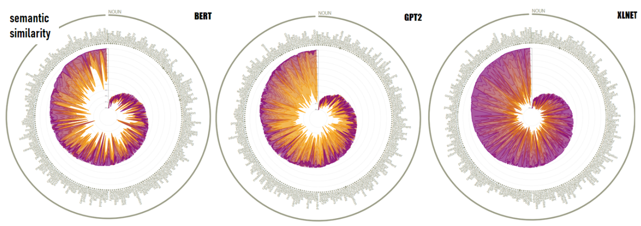


Figure 10: *Semantic similarity* for *NOUNS*. In each plot, the corpus is sorted according to the layer with the highest score values. In BERT, the similarity is relatively high in all layers. In XLNET, the semantic similarity drops already in early layers (purple color is close to the center of the chart, i.e., value 0). In GPT-2, the similarity stays the highest throughout the layers except layer 12.

T1: Token Similarity Contextualized word embeddings are often used for word similarity tasks, since their embeddings encode the semantic information better than static embeddings [RKR20]. In all six models, the semantic information is dominant in the extracted embedding vectors, whereby it is most dominant in early layers, decreasing in model upper layers. Figure 10 shows that in BERT, semantic similarity is highest in early layers and drops in upper layers, but the decrease is smaller than in XLNET. In GPT-2, the semantic similarity stays high throughout all layers with the exception in layer 12. Hence, for semantic word similarity tasks, one could use embeddings extracted from early layers of the different models, or from GPT-2 from all layers but layer 12.

It has been shown that BERT struggles with the representation of numbers [WWL*19]. We observe that some named entity categories

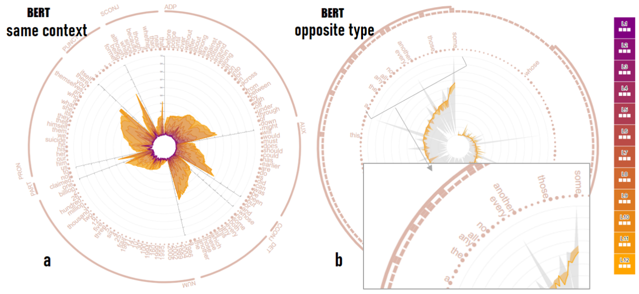


Figure 11: Filtered function words. As shown in (a), in upper layers (yellow), their nearest neighbors are more often words from the same context, and (b) they are more often content words than in early model's layers. Especially, the embeddings of determiners (*DET*) encode similar information to their surrounding content words.

(e.g., geographical locations) and numbers, have a relatively poor contextualization. Figure 9 shows that the POS tag similarity score of numbers, and especially of year numbers, stays high throughout all layers. Also their self-similarity stays high (Figure 5), i.e., their context doesn't influence embedding vector. When using embeddings for similarity tasks, one needs to be aware of such artefacts.

T3: Token Importance BERT is often used for fine-tuning tasks [DIS*20], i.e., the model is trained on a labeled dataset for a classification task, whereby word embeddings get adapted to capture task specific language characteristics. To understand which tokens are the most important for prediction making, one can apply feature attribution methods [LPK21; ZBRS21]. The attribution scores are calculated on embedding vectors, thus their outcomes are related to the degree of embedding contextualization. Some works argue that if an attribution score puts a high weight on function words, then these explanations are more or less meaningless [WTWS20]. We assume that this assumption might be too overestimated. When we look at the stopword contextualization in BERT (Figure 11), one can see that their embeddings have a low self-similarity, especially in the upper layers. By visually exploring the *type of contextualization* scores, we can see that in the model's upper layers the neighbors are more often tokens from the same context. Moreover, the nearest neighbors of function words are often content words such as *NOUNS* or *VERBS*. When reordering tokens according to their values for opposite type in layer 11, it becomes obvious that especially determiners (*DET*) become similar to content words. The actual neighbors are displayed in the projection view (see Figure 8 with neighbors for token *A*). Hence, in the upper layers of BERT (and also in other models), the embeddings of function words not only contain the information about their functionality, but also about the semantic meaning of the sentence. This might indicate that these tokens could potentially be more relevant for the classification tasks than it is currently assumed. To state this assumption with a confidence, further experiments are needed.

Expert Feedback – The **Model Fingerprints** view was judged as simple yet effective visualization that provides a quick overview of model differences and enables spotting interesting models/scores for detailed analysis. Although the **Model and Score Comparison** view requires some *onboarding* phase, the experts appreciated the simultaneous exploration of different categories of phenomena and, according to them, the parallels and differences across the categories could be observed easily. The experts also provided suggestions for further token-grouping approaches such as syntactic dependencies and semantic roles that would support new analysis directions.

6.3. Discussion: Observations and Research Opportunities

LMFingerprints is a useful technique for the explanation of embedding contextualization. We presented how we can use the explanation workspace to gain insights into model specificities as well as token-group differences. During the design and evaluation process, we discovered several opportunities for future research:

Contextualization and Attribution Scores – To understand function word role for classification tasks, one could explore the relationship between the degree of contextualization of specific tokens and their attribution scores. Since attribution score values are computed on embedding vectors, we would expect to see some relationship between the degree of contextualization and their importance.

Interaction Techniques for Radial Layouts – We show that radial charts can provide a compact overview of score properties. It is also possible to see general pattern differences between two models. However, we also faced challenges to compare single token values for the two models, and hence, we applied several interaction techniques to support it. In particular, we extended the view with a linear are chart that could be used as a *lens* showing the actual values for tokens from the two models. We see a potential to extend this technique, in particular, a more intuitive navigation through the data.

More Advanced Token Grouping – Motivated by the related work [Eth19; SKB*21], we group words according to their POS tag and type (i.e., function and content words). More advanced methods of grouping tokens according to further properties or similarity might support testing of further, more specific hypotheses.

Collaborative Pattern Exploration – During the design phase, we had the opportunity to observe the analysis workflow of experts from computational linguistics. They collaboratively searched for patterns, commented their observations, that led to active discussions about potential hypotheses to test. It would be beneficial if the interface supported such collaborative analysis for geographically dispersed collaborators. Collaborative analysis in the same visualization space and pattern annotation could make the process more effective.

Limitations – The computation of embeddings and their nearest neighbors is time-consuming; thus, they are pre-computed and don't influence the tool's performance. There might be scalability issues, though, when working on larger datasets with more unique tokens.

7. Conclusion

In this paper, we present ***LMFingerprints***, a novel scoring-based technique that combines contextualization scores with visual explanations to provide insights into embedding contextualization in transformer-based language models. We show the applicability of the technique by comparing score patterns computed on embeddings from BERT to the findings summarized in the *Primer of Bertology* paper by Rogers et al. [RKR20]. Our score patterns confirm insights from related work. Moreover, we show that some tokens (e.g., function words) have unexpected contextualization, which indicates that we might rethink their role in natural language processing applications. A demo is a part of the LingVis framework [EJS*19] under: https://lmfingerprints.lingvis.io.

References

[AWLG20] AKEN, B. V., WINTER, B., LÖSER, A., and GERS, F. A. "VisBERT: Hidden-State Visualizations for Transformers". *Companion Proc. of the Web Conf.* Association for Computing Machinery, 2020, 207–211. DOI: 10.1145/3366424.3383542 2.

[BBH*16] BEHRISCH, M., BACH, B., HENRY RICHE, N., SCHRECK, T., and FEKETE, J.-D. "Matrix reordering methods for table and network visualization". *Computer Graphics Forum*. Vol. 35. 3. Wiley Online Library. 2016, 693–716 6.

[BCS19] BOGGUST, A., CARTER, B., and SATYANARAYAN, A. "Embedding Comparator: Visualizing Differences in Global Structure and Local Neighborhoods via Small Multiples". *arXiv e-prints*, arXiv:1912.04853 (2019), arXiv:1912.04853 3.

[BDD*06] BAR-HAIM, R., DAGAN, I., DOLAN, B., FERRO, L., GIAMPICCOLO, D., MAGNINI, B., and SZPEKTOR, I. "The Second PASCAL Recognising Textual Entailment Challenge". *Proc. of the Second PASCAL Recognising Textual Entailment Challenge Workshop*. 2006, 1–9 7.

[Ber20] BERGER, M. "Visually Analyzing Contextualized Embeddings". *IEEE Visualization Conf. (VIS)*. IEEE Computer Society, 2020, 276–280. DOI: 10.1109/VIS47514.2020.00062 3.

[BVB*13] BORKIN, M. A., VO, A. A., BYLINSKII, Z., ISOLA, P., SUNKAVALLI, S., OLIVA, A., and PFISTER, H. "What makes a visualization memorable?": *IEEE Trans. on Visualization and Computer Graphics* 19.12 (2013), 2306–2315 6.

[CCWZ20] CUI, L., CHENG, S., WU, Y., and ZHANG, Y. "Does BERT Solve Commonsense Task via Commonsense Knowledge?": *CoRR* abs/2008.03945 (2020) 8.

[CHBC20] CAI, X., HUANG, J., BIAN, Y., and CHURCH, K. "Isotropy in the contextual embedding space: Clusters and manifolds". *Int. Conf. on Learning Representations*. 2020 9.

[CJS16] CHEEMA, M. F., JÄNICKE, S., and SCHEUERMANN, G. "AnnotateVis: Combining traditional close reading with visual text analysis". *IEEE VIS 2016 Workshop on Visualization for the Digital Humanities*. 2016 7.

[DCLT18] DEVLIN, J., CHANG, M.-W., LEE, K., and TOUTANOVA, K. "Bert: Pre-training of deep bidirectional transformers for language understanding". *arXiv preprint arXiv:1810.04805* (2018) 1.

[DGM05] DAGAN, I., GLICKMAN, O., and MAGNINI, B. "The PASCAL recognising textual entailment challenge". *Proceedings of the Machine Learning Challenges Workshop*. Springer. 2005, 177–190. DOI: https://doi.org/10.1007/11736790_9 7.

[DGS*18] DASGUPTA, I., GUO, D., STUHLMÜLLER, A., GERSHMAN, S. J., and GOODMAN, N. D. "Evaluating Compositionality in Sentence Embeddings". *CoRR* abs/1802.04302 (2018) 2.

[DIS*20] DODGE, J., ILHARCO, G., SCHWARTZ, R., FARHADI, A., HAJISHIRZI, H., and SMITH, N. "Fine-tuning pretrained language models: Weight initializations, data orders, and early stopping". *arXiv preprint arXiv:2002.06305* (2020) 3, 10.

[DLR09] DRAPER, G. M., LIVNAT, Y., and RIESENFELD, R. F. "A survey of radial methods for information visualization". *IEEE Trans. on Visualization and Computer Graphics* 15.5 (2009), 759–776 6.

[DWB20] DEROSE, J. F., WANG, J., and BERGER, M. "Attention Flows: Analyzing and Comparing Attention Mechanisms in Language Models". *IEEE Trans. on Visualization and Computer Graphics* (2020) 2.

[Edm20] EDMISTON, D. "A Systematic Analysis of Morphological Content in BERT Models for Multiple Languages". *arXiv preprint arXiv:2004.03032* (2020) 2.

[EJS*19] EL-ASSADY, M., JENTNER, W., SPERRLE, F., SEVASTJANOVA, R., HAUTLI, A., BUTT, M., and KEIM, D. "lingvis.io – A Linguistic Visual Analytics Framework". *Proc. of the Annual Meeting of the Association for Computational Linguistics: System Demonstrations*. 2019, 13–18. DOI: https://dx.doi.org/10.18653/v1/P19-3003 10.

[Eth19] ETHAYARAJH, K. "How Contextual are Contextualized Word Representations? Comparing the Geometry of BERT, ELMo, and GPT-2 Embeddings". *Proc. of the Conf. on Empirical Methods in Natural Language Proc. and the Int. Joint Conf. on Natural Language Processing (EMNLP-IJCNLP)*. ACL, 2019, 55–65. DOI: 10.18653/v1/D19-1006 1–4, 6, 9, 10.

[FAS*20] FISCHER, M. T., ARYA, D., STREEB, D., SEEBACHER, D., KEIM, D. A., and WORRING, M. "Visual analytics for temporal hypergraph model exploration". *IEEE Trans. on Visualization and Computer Graphics* 27.2 (2020), 550–560 6.

[Fel98] FELLBAUM, C. *WordNet: An Electronic Lexical Database (Language, Speech, and Communication)*. The MIT Press, 1998 4.

[GCMA20] GILLIOZ, A., CASAS, J., MUGELLINI, E., and ABOU KHALED, O. "Overview of the Transformer-based Models for NLP Tasks". *Conf. on Computer Science and Information Systems (FedCSIS)*. IEEE. 2020, 179–183 9.

[GMDD07] GIAMPICCOLO, D., MAGNINI, B., DAGAN, I., and DOLAN, B. "The Third PASCAL Recognizing Textual Entailment Challenge". *Proc. of the Workshop on Textual Entailment and Paraphrasing*. ACL, 2007 7.

[GSG18] GLOCKNER, M., SHWARTZ, V., and GOLDBERG, Y. "Breaking NLI Systems with Sentences that Require Simple Lexical Inferences". *Proc. of the 56th Annual Meeting of the Association for Computational Linguistics*. ACL, 2018, 650–655 2.

[HG18] HEIMERL, F. and GLEICHER, M. "Interactive analysis of word vector embeddings". *Computer Graphics Forum*. Vol. 37. 3. Wiley Online Library. 2018, 253–265 3.

[HM19] HEWITT, J. and MANNING, C. D. "A Structural Probe for Finding Syntax in Word Representations". *Proc. of the Conf. of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*. ACL, 2019, 4129–4138. DOI: 10.18653/v1/N19-1419 8.

[HSG20] HOOVER, B., STROBELT, H., and GEHRMANN, S. "exBERT: A Visual Analysis Tool to Explore Learned Representations in Transformers Models". *Proc. of the Annual Meeting of the Association for Computational Linguistics, System Demonstrations*. ACL, 2020. DOI: https://doi.org/10.18653/v1/2020.acl-demos.22 2.

[JDJ17] JOHNSON, J., DOUZE, M., and JÉGOU, H. "Billion-scale similarity search with GPUs". *arXiv preprint arXiv:1702.08734* (2017) 8.

[JF15] JOHANSSON, J. and FORSELL, C. "Evaluation of parallel coordinates: Overview, categorization and guidelines for future research". *IEEE Trans. on Visualization and Computer Graphics* 22.1 (2015), 579–588 6.

[JFCS15] JÄNICKE, S., FRANZINI, G., CHEEMA, M. F., and SCHEUERMANN, G. "On close and distant reading in digital humanities: A survey and future challenges". *Eurographics Conf. on Visualization (EuroVis)*. 2015, 83–103 7.

[JSS19a] JAWAHAR, G., SAGOT, B., and SEDDAH, D. "What Does BERT Learn about the Structure of Language?": *Proc. of the Annual Meeting of the Association for Computational Linguistics*. ACL, 2019, 3651–3657. DOI: 10.18653/v1/P19-1356 2, 8.

[JSS19b] JAWAHAR, G., SAGOT, B., and SEDDAH, D. "What Does BERT Learn about the Structure of Language?": *Proc. of the Annual Meeting of the Association for Computational Linguistics*. ACL, 2019, 3651–3657. DOI: 10.18653/v1/P19-1356 2.

[KAF*08] KEIM, D., ANDRIENKO, G., FEKETE, J.-D., GÖRG, C., KOHLHAMMER, J., and MELANÇON, G. "Visual Analytics: Definition, Process, and Challenges". *Information Visualization: Human-Centered Issues and Perspectives*. Ed. by KERREN, A., STASKO, J. T., FEKETE, J.-D., and NORTH, C. Springer Berlin Heidelberg, 2008, 154–175. DOI: 10.1007/978-3-540-70956-5_7 2.

[KO07] KEIM, D. A. and OELKE, D. "Literature fingerprinting: A new method for visual literary analysis". *IEEE Symposium on Visual Analytics Science and Technology*. IEEE. 2007, 115–122 5.

[KSS*21] KEHLBECK, R., SEVASTJANOVA, R., SPINNER, T., STÄHLE, T., and EL-ASSADY, M. "Demystifying the Embedding Space of Language Models". *Proc. of the Workshop on Visualization for AI Explainability (VISxAI)*. 2021 4.

[LAV21] LIU, Y., AGARWAL, S., and VENKATARAMAN, S. "AutoFreeze: Automatically Freezing Model Blocks to Accelerate Fine-tuning". *ArXiv* abs/2102.01386 (2021) 3.

[LBT*17] LIU, S., BREMER, P.-T., THIAGARAJAN, J. J., SRIKUMAR, V., WANG, B., LIVNAT, Y., and PASCUCCI, V. "Visual exploration of semantic relationships in neural word embeddings". *IEEE Trans. on Visualization and Computer Graphics* 24.1 (2017), 553–562 3.

[LGB*19] LIU, N. F., GARDNER, M., BELINKOV, Y., PETERS, M. E., and SMITH, N. A. "Linguistic Knowledge and Transferability of Contextual Representations". *Proc. of the Conf. of the North American Chapter of the Assoc. for Computational Linguistics: Human Language Technologies*. ACL, 2019, 1073–1094. DOI: 10.18653/v1/N19-1112 8.

[LLL*18] LIU, S., LI, Z., LI, T., SRIKUMAR, V., PASCUCCI, V., and BREMER, P.-T. "Nlize: A perturbation-driven visual interrogation tool for analyzing and interpreting natural language inference models". *IEEE Trans. on Visualization and Computer Graphics* 25.1 (2018), 651–660 2.

[LPK21] LINARDATOS, P., PAPASTEFANOPOULOS, V., and KOTSIANTIS, S. "Explainable ai: A review of machine learning interpretability methods". *Entropy* 23.1 (2021), 18 3, 10.

[LTF19a] LIN, Y., TAN, Y. C., and FRANK, R. "Open Sesame: Getting inside BERT's Linguistic Knowledge". *Proc. of the ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*. ACL, 2019, 241–253. DOI: 10.18653/v1/W19-4825 2.

[LTF19b] LIN, Y., TAN, Y. C., and FRANK, R. "Open Sesame: Getting inside BERT's Linguistic Knowledge". *Proc. of the ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*. ACL, 2019, 241–253. DOI: 10.18653/v1/W19-4825 9.

[LTL19] LEE, J., TANG, R., and LIN, J. J. "What Would Elsa Do? Freezing Layers During Transformer Fine-Tuning". *ArXiv* abs/1911.03090 (2019) 3.

[MA14] MIKSCH, S. and AIGNER, W. "A matter of time: Applying a data–users–tasks design triangle to visual analytics of time-oriented data". *Computers & Graphics* 38 (2014), 286–290 3.

[MHSG18] MCINNES, L., HEALY, J., SAUL, N., and GROSSBERGER, L. "UMAP: Uniform Manifold Approximation and Projection". *The Journal of Open Source Software* 3.29 (2018), 861. DOI: https://doi.org/10.21105/joss.00861 7.

[ML18] MARVIN, R. and LINZEN, T. "Targeted Syntactic Evaluation of Language Models". *Proc. of the Conf. on Empirical Methods in Natural Language Processing*. ACL, 2018, 1192–1202. DOI: 10.18653/v1/D18-1151 2.

[MPL19] MCCOY, T., PAVLICK, E., and LINZEN, T. "Right for the Wrong Reasons: Diagnosing Syntactic Heuristics in Natural Language Inference". *Proc. of the Annual Meeting of the Association for Computational Linguistics*. ACL, 2019, 3428–3448. DOI: 10.18653/v1/P19-1334 2.

[NRS*18] NAIK, A., RAVICHANDER, A., SADEH, N., ROSE, C., and NEUBIG, G. "Stress Test Evaluation for Natural Language Inference". *Proc. of the Int. Conf. on Computational Linguistics*. ACL, 2018, 2340–2353 2.

[PNJ*19] PARK, C., NA, I., JO, Y., SHIN, S., YOO, J., KWON, B. C., ZHAO, J., NOH, H., LEE, Y., and CHOO, J. "SANVis: Visual Analytics for Understanding Self-Attention Networks". *IEEE Visualization Conf. (VIS)*. IEEE. 2019, 146–150 2.

[PPM04] PEDERSEN, T., PATWARDHAN, S., and MICHELIZZI, J. "WordNet::Similarity: Measuring the Relatedness of Concepts". *Demonstration Papers at HLT-NAACL 2004*. ACL, 2004, 38–41 4.

[QSX*20] QIU, X., SUN, T., XU, Y., SHAO, Y., DAI, N., and HUANG, X. "Pre-trained Models for Natural Language Processing: A Survey". *ArXiv* abs/2003.08271 (2020) 1.

[RHMS20] RICHARDSON, K., HU, H., MOSS, L. S., and SABHARWAL, A. "Probing Natural Language Inference Models through Semantic Fragments". *Association for the Advancement of Artificial Intelligence (AAAI)*. AAAI Press, 2020, 8713–8721 2.

[RKR20] ROGERS, A., KOVALEVA, O., and RUMSHISKY, A. "A Primer in BERTology: What We Know About How BERT Works". *Trans. of the Association for Computational Linguistics* 8 (2020), 842–866. DOI: http://dx.doi.org/10.1162/tacl_a_00349 1–4, 7–10.

[RYW*19] REIF, E., YUAN, A., WATTENBERG, M., VIEGAS, F. B., COENEN, A., PEARCE, A., and KIM, B. "Visualizing and Measuring the Geometry of BERT". *Advances in Neural Information Processing Systems 32*. Ed. by WALLACH, H., LAROCHELLE, H., BEYGELZIMER, A., D'ALCHÉ-BUC, F., FOX, E., and GARNETT, R. Curran Associates, Inc., 2019, 8594–8603 2.

[SBE*18] SEVASTJANOVA, R., BECK, F., ELL, B., TURKAY, C., HENKIN, R., BUTT, M., KEIM, D., and EL-ASSADY, M. "Going beyond Visualization: Verbalization as Complementary Medium to Explain Machine Learning Models". *Workshop on Visualization for AI Explainability at IEEE VIS*. 2018 7.

[SGB*18] STROBELT, H., GEHRMANN, S., BEHRISCH, M., PERER, A., PFISTER, H., and RUSH, A. M. "S eq 2s eq-v is: A visual debugging tool for sequence-to-sequence models". *IEEE Trans. on Visualization and Computer Graphics* 25.1 (2018), 353–363 2.

[SKB*21] SEVASTJANOVA, R., KALOULI, A.-L., BECK, C., HAUPTMANN, H., and EL-ASSADY, M. "Explaining Contextualization in Language Models using Visual Analytics". *Proc. of the Annual Meeting of the Association for Computational Linguistics*. ACL, 2021 2, 3, 5, 6, 10.

[TDP19a] TENNEY, I., DAS, D., and PAVLICK, E. "BERT Rediscovers the Classical NLP Pipeline". *Proc. of the Annual Meeting of the Association for Computational Linguistics*. ACL, 2019, 4593–4601. DOI: 10.18653/v1/P19-1452 2.

[TDP19b] TENNEY, I., DAS, D., and PAVLICK, E. "BERT Rediscovers the Classical NLP Pipeline". *Proc. of the Annual Meeting of the Association for Computational Linguistics*. ACL, 2019, 4593–4601. DOI: 10.18653/v1/P19-1452 8.

[Vig19] VIG, J. "A Multiscale Visualization of Attention in the Transformer Model". *Proc. of the Annual Meeting of the Association for Computational Linguistics: System Demonstrations*. Association for Computational Linguistics, 2019, 37–42. DOI: 10.18653/v1/P19-3007 2.

[VSP*17] VASWANI, A., SHAZEER, N., PARMAR, N., USZKOREIT, J., JONES, L., GOMEZ, A. N., KAISER, Ł., and POLOSUKHIN, I. "Attention is All You Need". *Proc. of the 31st Int. Conf. on Neural Information Processing Systems*. Curran Associates Inc., 2017, 6000–6010 3.

[WDG*19] WALDNER, M., DIEHL, A., GRAČANIN, D., SPLECHTNA, R., DELRIEUX, C., and MATKOVIĆ, K. "A comparison of radial and linear charts for visualizing daily patterns". *IEEE Trans. on Visualization and Computer Graphics* 26.1 (2019), 1033–1042 6.

[WDS*20] WOLF, T., DEBUT, L., SANH, V., CHAUMOND, J., DELANGUE, C., MOI, A., CISTAC, P., RAULT, T., LOUF, R., FUNTOWICZ, M., DAVISON, J., SHLEIFER, S., von PLATEN, P., MA, C., JERNITE, Y., PLU, J., XU, C., LE SCAO, T., GUGGER, S., DRAME, M., LHOEST, Q., and RUSH, A. "Transformers: State-of-the-Art Natural Language Processing". *Proc. of the 2020 Conf. on Empirical Methods in Natural Language Processing: System Demonstrations*. ACLs, 2020, 38–45. DOI: 10.18653/v1/2020.emnlp-demos.6 8.

[WRCB19] WIEDEMANN, G., REMUS, S., CHAWLA, A., and BIEMANN, C. "Does BERT Make Any Sense? Interpretable Word Sense Disambiguation with Contextualized Embeddings". *Proc. of KONVENS 2019*. 2019 2.

[WTWS20] WANG, J., TUYLS, J., WALLACE, E., and SINGH, S. "Gradient-based Analysis of NLP Models is Manipulable". *Findings of the Association for Computational Linguistics: EMNLP*. ACL, 2020, 247–258. DOI: 10.18653/v1/2020.findings-emnlp.24 10.

[WWL*19] WALLACE, E., WANG, Y., LI, S., SINGH, S., and GARDNER, M. "Do NLP Models Know Numbers? Probing Numeracy in Embeddings". *Proc. of the Conf. on Empirical Methods in Natural Language Processing and the Int. Joint Conf. on Natural Language Processing (EMNLP-IJCNLP)*. ACL, 2019, 5307–5315. DOI: 10.18653/v1/D19-1534 9.

[YWR02] YANG, J., WARD, M. O., and RUNDENSTEINER, E. A. "Interring: An interactive tool for visually navigating and manipulating hierarchical structures". *IEEE Symposium on Information Visualization, 2002. INFOVIS 2002.* IEEE. 2002, 77–84 7.

[ZBRS21] ZHOU, Y., BOOTH, S., RIBEIRO, M. T., and SHAH, J. "Do Feature Attribution Methods Correctly Attribute Features?": *arXiv preprint arXiv:2104.14403* (2021) 3, 10.