Interactively Generating Explanations for Transformer-based Language Models

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Abstract
Transformer language models are state-of-the-art in a multitude of NLP tasks. Despite these successes, their opaqueness remains problematic. Recent methods aiming to provide interpretability and explainability to black-box models primarily focus on post-hoc explanations of (sometimes spurious) input-output correlations. Instead, we emphasize using prototype networks directly incorporated into the model architecture and hence explain the reasoning process behind the network’s decisions. Moreover, while our architecture performs on par with several language models, it enables one to learn from user interactions. This not only offers a better understanding of language models, but uses human capabilities to incorporate knowledge outside of the rigid range of purely data-driven approaches.

1 Introduction
Transformer-based language models (LMs) are ubiquitous in NLP today but also notoriously opaque. Therefore, it is not surprising that a growing body of work aims to interpret them: Recent evaluations of approaches of saliency methods (Ding and Koehn, 2021) and instance attribution methods (Pezeshkpour et al., 2021) find that, while intriguing, for the same outputs, different methods assign importance to different inputs. Furthermore, they are usually employed post-hoc, thus possibly encouraging reporting bias (Gordon and Van Durme, 2013). The black-box character of LMs becomes especially problematic, as the data to train them might be unfiltered and contain (human) bias. As a result, ethical concerns about these models arise, which can have a substantial negative impact on society as they get increasingly integrated into our lives (Bender et al., 2021).

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Preprint. Work in progress.

Here, we focus on generating case-based reasoning explanations during the inference process, directly outputting the LMs predictions. In doing so, we avoid the problems mentioned above of post-hoc explanations and help to reduce the issue of (human) bias. To increase the interpretability of the model, we enhance the transformer architecture with a prototype layer and propose Prototypical-Transformer Explanation (Proto-Trex) Networks. Proto-Trex networks provide an explanation as a prototypical example for a specific model prediction, which is similar to (training-)samples with the corresponding label.

Our experimental results demonstrate that Proto-Trex networks perform on par with non-interpretative baselines with e.g. BERT (Devlin et al., 2019), and GPT (Radford et al., 2019). In terms of explanations, we show promising results with learned prototypes providing helpful explanations for the user to understand better the LMs decision-making, which, in turn, increases trust and reliability. To further enhance the interpretability of transformer-based networks, we propose an interactive learning setting (iProto-Trex) that allows users of any knowledge to give feedback and improve the model, moving beyond a purely data-driven approach.

To summarise, our contributions are as follows: We (i) introduce prototype networks for transformer-based LMs that generate explanations and (ii) show that they are on par with non-interpretative baselines on classification tasks on different architectures (iii). Furthermore, to improve the prototype networks’ interpretability, we (iv) provide a novel interactive prototype learning setup accounting for user feedback certainty.

We proceed as follows. We start by briefly reviewing related work of interpretability in NLP. Then we introduce Proto-Trex networks, including our novel interactive learning setup combining Explanatory Interactive Learning with prototype
networks. Before concluding, we touch upon the results of our experimental evaluation.

2 Towards the Interpretability of Transformer-based Language Models

To open the black-box of transformers, (i)Proto-Trex networks build upon post-hoc interpretation methods, cased-based reasoning approaches and explanatory interactive learning.

Post-hoc interpretability. Various (post-hoc) interpretability methods focus on different parts of the transformer architecture. Atanasova et al. (2020) and Belinkov and Glass (2019) provide overviews of this fast developing field. Generally, there are methods that analyse word representations (Voita et al., 2019a), the attention distribution throughout the model (e.g. (Jain and Wallace, 2019; Wiegreffe and Pinter, 2019)), and the (attention and classification) model heads (Voita et al., 2019b; Geva et al., 2021). Other approaches such as (Geva et al., 2020) focus on the feed-forward layers. Gradient-based approaches, such as (Sundararajan et al., 2017) and (Smilkov et al., 2017) can generally be used to trace gradients, while influence functions (Koh and Liang, 2017) trace model parameter changes throughout a LM (Han et al., 2020). While backtracking all the model weights might be possible, humans are ill-equipped to interpret them (Stammer et al., 2021). So instead, we aim for more intuitive and sparse explanations: well-descriptive but short sequences as prototypes.

Case-based Reasoning in Deep Neural Networks. In contrast to post-hoc interpretation methods, prototype networks employ explanations in the, e.g. classification process, i.e., a sample is classified by comparing several parts—which could be words of a sentence—to (learned) prototypical parts from other samples for a given class. If things look similar, they are classified similarly. Humans behave very similarly, which is called case-based reasoning (Althoff, 2012). The prototypical parts provided by the network help the user to understand the classification. Fig. 1 illustrates the benefit of prototypical explanations. One can observe that the post-hoc explanation can leave the user clueless, while the prototypical explanations can help better understand the network’s decision.

Accordingly, prototypes are an additional method in the interpretability toolbox, either replacing or extending current methods.

3 Proto-Trex: Prototype Learning for large-scale Transformer-based LMs

The prototype network (Proto-Trex) architecture builds upon transformer-based language models and is summarised in Fig. 2.

3.1 Proto-Trex Architecture

Specifically, the pre-trained transformer $f$ creates a context embedding $e$ from the input sequence $x$. This embedding is then passed on to the prototype layer, which computes the similarity between the embedding $e$ of the input data and each of the
3.2 Proto-Trex Loss

Optimisation of prototype networks aims at maximising both performance as well as interpretability. To this end, our Proto-Trex loss $\mathcal{L}$ combines performance and interpretability with prior knowledge of the prototype network’s structure. Let us illustrate this for the word-level case (the sentence-level case results from $z = e$):

$$
\mathcal{L} := \min_{\mathbf{P}, \mathbf{w}_{fc}} \frac{1}{n} \sum_{i=1}^{n} CE(t_i, y_i) + \lambda_1 \text{Clst}(\mathbf{z}, \mathbf{p}) + \lambda_2 \text{Sep}(\mathbf{z}, \mathbf{p}) + \lambda_3 \text{Distr}(\mathbf{z}, \mathbf{p}) + \lambda_4 \text{Divers}(\mathbf{p}) + \lambda_5 ||\mathbf{w}_{fc}||, 
$$

where $\lambda_i$ weights the influence of the different terms. The first term is the cross-entropy (CE) loss optimising the predictive power of the network. The second term (Clst) clusters the prototypes w.r.t. the training examples of the same class, maximising similarity to them (as we minimise our loss function, we rewrite maximisation terms as minimisations): $\text{Clst}(\mathbf{z}, \mathbf{p}) :=$

$$
-\frac{1}{n} \sum_{i=1}^{n} \min_{j:p_j \in \mathbf{P}_{y_i}} \min_{z \in \text{patch}(f(\mathbf{x}_i))} \text{sim}(\mathbf{z}, \mathbf{p}_j). 
$$

The separation loss (Sep) minimises the similarity to other-class instances:

$$
\frac{1}{n} \sum_{i=1}^{n} \min_{j:p_j \notin \mathbf{P}_{y_i}} \min_{z \in \text{patch}(f(\mathbf{x}_i))} \text{sim}(\mathbf{z}, \mathbf{p}_j). 
$$

Together, Clst and Sep push each prototype to focus more on training examples from the same class and less on training examples from other classes. Both are motivated by ProtoPNet (Chen et al., 2019).

To get prototypes that are distributed well in the embedding space, we introduce two additional losses, a distribution loss $\text{Distr}(\mathbf{z}, \mathbf{p}) :=$

$$
-\frac{1}{n} \sum_{j=1}^{n} \min_{i \in [1,n]} \min_{z \in \text{patch}(f(\mathbf{x}_i))} \text{sim}(\mathbf{z}, \mathbf{p}_j),
$$

as in ProtoNet (Li et al., 2018), assuring that a prototype is nearby each training example, and a diversity loss

$$
\text{Divers}(\mathbf{p}) := \frac{1}{n_p} \sum_{i=1}^{n_p} \min_{j:p_j \notin \mathbf{P}_{y_i}} \min_{z \in \text{patch}(f(\mathbf{x}_i))} \text{sim}(\mathbf{p}_i, \mathbf{p}_j).
$$

In contrast to the previous terms, the diversity loss does not compute similarities between embeddings and prototypes but between prototypes themselves. It is another way of distributing prototypes in the embedding space as it maximises the distance between prototypes, preventing them from staying at the same –not necessarily optimal– location. This is especially helpful in the case of multiple prototypes for a single class, encouraging them to represent different facets of the class. If they are otherwise too similar, no information is gained and resulting in redundant prototypes – together with the class-specific loss encouraged by the cluster loss (Clst) and the separation loss (Sep), this helps to compute prototypes that focus solely on their class. Otherwise, we can get ambiguous prototypes.
leading to negative reasoning. Also, we clamp the weights of the classification layer with \( \min(w_{fc}, 0) \) to avoid negative reasoning (Chen et al., 2019).

Finally, the last term of the Proto-Trex loss (1) is an L1-regularisation term of the last layer \( (g) \), which prevents the network from overfitting or relying too much on a single prototype.

### 3.3 Similarity Computation

Thus, computing similarities is an essential aspect of Proto-Trex. For prototypes to represent certain aspects or features of the input distribution in the embedding space, we compute the similarity \( \text{sim}(e, p) \) between an embedded training example and a prototype. A distance minimisation can replace each similarity maximisation \( \max \text{sim}(e, p) = \min \text{dist}(e, p) \). We here follow common practice and explore both the L2-norm or the cosine similarity:

\[
\text{sim}(e, p) = \begin{cases} 
-\|e - p_j\|_2, & \text{L2-norm} \\
\frac{e \cdot p_j}{\|e\|_2 \|p_j\|_2}, & \text{cosine similarity}
\end{cases}
\]

where the index \( j \) denotes a prototype. For each training example, there is an embedding \( e \) which is compared to all \( n_p \) prototypes \( p \), i.e. we get \( n_p \) similarity values for each embedding.

The L2-norm, or Euclidean distance, assumes a Gaussian prior. As this can be a wrong assumption, we also investigate cosine similarity without a Gaussian prior. While L2-norm computes the distance between two vectors, the cosine similarity measures the angle between them. Both, but especially the cosine similarity, are natural choices for NLP tasks (Manning et al., 2008). However, cosine similarity is more robust than Euclidean distance as the magnitude of the distance between vectors has no influence due to normalisation.

### 3.4 Selection for Word-Level Prototypes

Since learning prototypes for LMs that are pre-trained on word-level representations is more involved than for the sentence-level, let us focus on them here; the sentence-level case naturally follows from the discussion.

Word-level prototypes are generally sensible as explanations should consist of sparse sequences, at best focusing only on subsequences of the input sentence. As sequences can also be ambiguous and contain little information, we combine different word embeddings \( (\text{patch}()) \) and enforce the prototype to be similar to the relevant subsequences, containing the most information. But how do we select the most informative words?

A naive approach would be to simply compute all possible combinations of the input sequence and compare them to the prototypes to find the best combination for classification – the most important subsequence should then be similar to a certain prototype. Unfortunately, for long input sequences with length \( l \) it becomes hard to compute all possible word combinations \( n_c \) of length \( k \), in this case \( n_c = \binom{l}{k} \). To solve this problem without losing too many valuable combinations, the following two approaches are sensible ideas.

(A) **Sliding windows** naturally reduce the number of input combinations. A sliding window can be viewed as a convolution that selects a certain part of the input according to the window size and then sliding to the next part. The number of combinations for the convolutions can be calculated as \( n_c = l - d \cdot (k - 1) \). The main disadvantage of sliding windows is the relatively rigid structure of a window. To loosen this, dilation was introduced. Dilation facilitates looking at direct word neighborhoods but also at more distant ones to capture long-range dependencies. This is especially helpful in the context of NLP tasks that often have long-range dependencies. This “convolutional” approach is illustrated Tab. 1.

We note that applied to the contextualised word embeddings of transformer-based language models, the convolutional approach with the immediate neighbourhood (no dilation) should contain not...
only local information but also some global information. Unfortunately, this information is stored in the embeddings and cannot be visualised easily.

As an alternative, the (B) Self-Attention approach adds one self-attention layer after the transformer $g$ and before the prototype layer $p$ to filter out irrelevant words (with low attention-scores), cf. Fig. 3. The purpose of these self-attention layers differs from the one in the transformer LM itself. The attention mechanism here is used to select the most important words, and the embedding representation remains untouched. Hence, the number of heads is chosen to be 1.

To still provide as much information and variety as possible, the number of selected words $n_a$ of the attention layer which are passed into the distance computation is a hyperparameter and we chose it to be twice as much as the length of a single prototype however clamped by the threshold $k_{lim}$: $n_a = \min(\max(k_{lim}, k), 2k)$. The threshold can be set w.r.t. computational efficiency. This means having a prototype of length $k = 4$ and $k_{lim} = 10$, the attention layer selects $n_a = 8$ words yielding in this example $n_c = \binom{8}{4} = 70$ combinations for the distance computation.

3.5 Decoding via Nearest Neighbour Projection

The prototypes of Proto-Trex networks are encoded in the embedding space. Consequently, they cannot simply be decoded from the transformer-based embedding space, as this space and textual data are categorical and not continuous. To overcome this, we assign each prototype to its nearest neighbour in the training data (where the textual representation is available). For sentence-level prototypes, we additionally project the prototype on its nearest neighbour in an intermediate training step. Thereby, we ensure that the prototype really represents what it actually looks like, which also increases the interpretability of the Proto-Trex network.

The final training step (after the nearest neighbour projection) then fine-tunes the classification head to adapt it to the projected prototypes. Doing so has the advantage that it can be decoded precisely on the spot and providing more certainty for the explanatory power. The disadvantage, however, is that a prototype may be located sub-optimally. Especially for word-level prototypes, we faced this issue and found the projection, therefore ineligible for contextualised word representations. Instead, we only use the nearest neighbour for approximating the prototype to generate the explanation.

4 Interactive Prototype Learning

Recent case-based reasoning approaches in Computer Vision and NLP usually assume a large volume of data for training (Li et al., 2018; Chen et al., 2019; Hase et al., 2019), with little or no user feedback during the model building process. However, user knowledge and interaction, in particular via explanations, can be very valuable already in the model building and understanding phase, significantly reducing the amount of data required, avoiding Clever-Hans moments early on, and increasing the explanation quality of the model and, in turn, the trust of the user, see e.g. (Teso and Kersting, 2019; Schramowski et al., 2020).

4.1 Interactive Proto-Trex

To address this, we propose an explanatory interactive learning approach for Proto-Trex networks, called iProto-Trex, as illustrated in Fig. 4. Specifically, carried out during the training process by freezing and evaluating the current state or post-hoc training, the interaction takes the following form. At each step, the Proto-Trex networks provide prototypes as explanations of a classification. The user responds by correcting the learner, if necessary, in our case, the prototypes. For this, iProto-Trex provides a range of opportunities for interaction with prototypes.

Specifically, iProto-Trex distinguishes between weak-knowledge and strong-knowledge interactions. In strong-knowledge interactions, users are
certain about their feedback (which could require high-level expertise). In this case, iProto-Trex provides options to remove, add and replace prototypes; removing a prototype is also helpful if the network has learned prototypical sequences already cover redundant explanations or all critical aspects of the task at hand.

If users are content with all the present prototypical sequences, they can also add new prototypes. (Replacing a prototype is the same as removing plus adding a prototype.) After these interactions, the following network layer is retrained to integrate and balance the new prototype in its decision-making.

In weak-knowledge interactions, users only state content or discontent with a prototype based on their intuition. They do not need to know what a replacement should exactly look like. This is a good trade-off between user knowledge and loss optimisation of the network. To this end, iProto-Trex uses fine-tuning and re-initialisation; users freeze prototypes they like while ones they are discontent with are retrained. The difference between these two approaches is that users can express how well the current prototype represents a particular task aspect. Furthermore, fine-tuning represents merely a slight change (that is required), while the network retrains the complete prototype during re-initialisation.

Another form of weak-knowledge interaction, which iProto-Trex provides only for sentence-level prototypes, is pruning the sequence length of prototypical explanations. In order to limit meaning changes of a sequence, a threshold is provided for the cosine similarity of the pruned and the original version. This threshold is initially set to 0.8, but users can set the threshold as they like, resulting in a strong-knowledge interaction. During pruning, the information of the prototypical sequence is compressed to the essentials.

### 4.2 Soft User Feedback

iProto-Trex’s interaction methods, especially the strong-knowledge ones, require users to be quite confident about their feedback—they have to be experts. To elevate this burden, we propose a soft feedback mechanism, using an interaction loss based on the similarity between prototypes as

$$L_{\text{interact}} := \lambda_0 \frac{1}{2} \max \left( \max \left( \text{sim}(p_{\text{old}}, p_{\text{new}}), c \right) \right)$$

with $c \in [0, 1]$. Instead of directly replacing the selected old prototype $p_{\text{old}}$, this soft interaction loss pushes the prototypes to be similar to the new prototype $p_{\text{new}}$ as suggested by a user. Moreover, the user can control how strong iProto-Trex should incorporate their interventions by setting a certainty value $c$ between 0 (low certainty) and 1 (high certainty).

### 5 Experimental Evaluation

Our intention here is to investigate how good prototypes help to understand transformer-based LMs. To this end, we evaluated Proto-Trex and iProto-Trex explanations on three benchmark datasets: MovieReview (Pang et al., 2002), Open Yelp and Jigsaw Toxicity. We compared five pre-trained LMs (GPT-2 (Radford et al., 2019), BERT (Devlin et al., 2019), DistilBERT, (Sanh et al., 2020), SBERT (Reimers and Gurevych, 2019) and the text-encoder of CLIP (Radford et al., 2021)) to investigate two questions:

**(Q1)** How much does adding prototypes affect the performance of (non-interpretable) LMs, i.e., a classification head defined by two fully-connected non-linear layers?

**(Q2)** How does the performance change after and during interaction with the model explanations? In particular, we investigated the different modules of Proto-Trex networks on word- and sentence-level explanations, as well as the interaction between human users and the model’s prototypical explanations.

We present qualitative as well as quantitative results and refer to the Appendix for additional details on the experiments and our implementation, as well as additional qualitative results.

If not stated otherwise, the Proto-Trex architecture includes word- as well as sentence-level embeddings, the convolution-based approach without dilation to select word-tokens, and cosine similarity to compute the similarity between prototypical explanations and input query. We optimised the
Toxicity

Attn. Movie Cos.

• L2

Users can quickly extract the important aspects of fresh peppers. Iced tea had a surprising and refreshingly different flavor.

Great food, great service. Chicken tikka was awesome with fresh peppers. Iced tea had a surprising and refreshingly different flavor.

Great service!! Pizza Rock happy hour is awesome.

Table 4: Qualitative evaluation of the word-selection methods. The attention module (Attn.) tends to select punctuation and stop words.

similarity computation does not explicitly correlate with the prototypes learned—yet we assumed it to be the better choice—, the word-selection module also impacts the explanation outcome. Furthermore, cosine similarity is not only more accurate but also convergences faster.

In terms of accuracy, the convolutional word selections outperform the attention module. More importantly, we also observe an advantage with respect to the generated explanations. As one can see in Tab. 4, the attention module (Attn.) tends to select punctuation and stop words. According to Ethayarajh (2019), this is because punctuation and stop-words are among the most context-specific word representations—they are not polysemous themselves but can have an infinite number of possible contexts. In contrast, the convolutional module is easier to interpret as prototype words are coherent.

(Q1) Generated explanations. To analyse the generated explanations, we consider the GPT-2 and the SBERT based Proto-Trex networks, cf. Tab. 2, trained on the Open Yelp dataset.

Tab. 5 shows how the Proto-Trex model provides users with generated explanations. These explanations are given as prototypical sequences that correspond to a query. In addition, Proto-Trex provides corresponding importance scores, indicating the significance of an explanation for the classification. We show three word-level prototypes and four sentence-level prototypes for the query, where word-level explanations highlight matching parts to increase interpretability, negating some of the loss of not using the projection for the decision process.

Users can quickly extract the important aspects that help in understanding the classification. However, one can clearly observe that the sentence-level explanations lack sparsity and are difficult to interpret with regard to the query, which also demonstrates the demand for our pruning method (cf. coloured boxes with prototypical explanations P6 and P2 in Tab. 5). The pruned Proto-Trex pro-

| Language Model | Yelp | Movie | Toxicity |
|----------------|------|-------|----------|
| SBERT          | 94.92 | 84.56 | 84.40    |
| SBERT (Proto-Trex) | 93.59 | 79.85 | 73.19    |
| CLIP           | 93.78 | 75.49 | 80.82    |
| CLIP (Proto-Trex) | 87.16 | 63.52 | 67.75    |
| BERT           | 89.41 | 61.45 | 76.88    |
| BERT (Proto-Trex) | 92.10 | 75.51 | 79.35    |
| GPT-2          | 92.78 | 84.57 | 84.14    |
| GPT-2 (Proto-Trex) | **95.32** | **85.05** | 81.56    |
| DistilBERT     | 92.91 | 79.62 | 81.57    |
| DistilBERT (Proto-Trex) | 92.71 | 78.64 | 83.39    |

Table 2: Performance of Proto-Trex with different LMs on different datasets. The accuracy is given in percent. Best ("*") and runner-up ("o") are bold.

| Language Model | Word-Selection | Similarity |
|----------------|----------------|------------|
| BERT           | **92.10**      | 89.66      |
| GPT-2          | **95.32**      | **95.32**  |
| DistilBERT     | **92.71**      | **92.71**  |
| CLIP           | --             | **87.16**  |

Table 3: Ablation study of Proto-Trex module choices.
I really like this place very inviting and welcoming. The food is great and the service is excellent! Will be eating there regularly.

Prototype

P2: This place is really high quality and the service is amazing and awesome! Jayden was very helpful and was prompt and attentive. Will come back as the quality is so good and the service made it!

P6: I found this place very inviting and welcoming. The food is great so as the servers...

Horrible customer service and service does not care about safety features. That's all I'm going to say. Oh they also don't care about their customers

Table 5: Generated Explanations by Proto-Trex networks. Highlighted words mark matching subsequences between query (top-row) and corresponding top three most similar prototypes (word-level). Further, generated explanation (top-four) are provided for sentence-level networks. Coloured boxes illustrate the importance of pruning sentences explanations. Importance scores (left, bold) are calculated with cosine similarity and classification weight.

Table 6: Interactive learning: Different interaction methods with accuracy on Yelp restaurant reviews.

(Q2) Interactive prototype learning. In the previous experiment, pruning has already shown the benefits of adapting explanations to users’ preferences. In order to further evaluate our interactive learning setup, we incorporated certainty (c) and evaluated its effectiveness. Tab. 6 shows an influential, i.e. high importance value, explanation (yet no interaction) for negative restaurant reviews on the Open Yelp dataset. Assuming a user is dissatisfied with an explanation yet uncertain about what a good explanation would entail: Applying re-initialisation (the interaction technique with the most uncertainty) confirms the user’s intuition of a “weak” component, as one can observe with the slight increase in accuracy. More importantly, we can already observe that users can influence the network’s decision process based on their preferences without performance loss. However, the revised explanation is still not sufficiently interpretable. Therefore, we considered incorporating explicit user feedback here. In this case, the phrase “They offer a bad service” served as soft replacement for the model’s generated explanation and the user applied it with different levels of certainty. First, a low certainty value of c = 0.5 results in the same explanation as before. This is due to the fact that the similarity of any two prototypes with clearly negative sentiment is higher than the certainty-threshold of 0.5. As a result, the user gets...
more certain and gradually increases the threshold. Finally \((c = 1)\), the user simply replaced the prototype in order to obtain her desired solution without a trade-off in accuracy.

In summary, our results demonstrate that interactive learning is a solid method to counter the network’s incapability in consistently providing explainable prototypes along with high accuracy.

6 Conclusion

Large-scale transformer LMs, like other black-box models, lack interpretability. We presented methods (prototype networks) to incorporate case-based reasoning to explain the LM’s decisions. Despite the explanatory power of prototypical explanations, challenges regarding the quality of their interpretability still exist. Therefore, we propose an interactive prototype learning setup not only to overcome these challenges but also improve the network’s capabilities by incorporating human knowledge with the consideration of knowledge certainty.

References

Klaus-Dieter Althoff. 2012. Case-based reasoning and expert systems. In Proceedings of the 26th International Conference on Case-Based Reasoning Research and Development (ICCBR), pages 1–10.

Pepa Atanasova, Jakob Grue Simonsen, Christina Lioma, and Isabelle Augenstein. 2020. A diagnostic study of explainability techniques for text classification. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 3256–3274.

Yonatan Belinkov and James Glass. 2019. Analysis methods in neural language processing: A survey. Transactions of the Association for Computational Linguistics (TACL), 7:49–72.

Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. On the dangers of stochastic parrots: Can language models be too big? In Proceedings of the 2021 Conference on Fairness, Accountability, and Transparency (FAccT), pages 610–623.

Chaofan Chen, Oscar Li, Daniel Tao, Alina Barnett, Cynthia Rudin, and Jonathan K Su. 2019. This looks like that: Deep learning for interpretable image recognition. In Proceedings of the 2019 Conference on Advances in Neural Information Processing Systems (NeurIPS), pages 1–12.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL), pages 4171–4186.

Shuoyang Ding and Philipp Koehn. 2021. Evaluating saliency methods for neural language models. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL), pages 5034–5052.

Kawin Ethayarajh. 2019. How contextual are contextualized word representations? comparing the geometry of bert, elmo, and GPT-2 embeddings. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 55–65.

Mor Geva, Uri Katz, Aviv Ben-Arie, and Jonathan Berant. 2021. What’s in your head? emergent behaviour in multi-task transformer models. arXiv preprint arXiv:2104.06129.

Mor Geva, Roel Schuster, Jonathan Berant, and Omer Levy. 2020. Transformer feed-forward layers are key-value memories. arXiv preprint arXiv:2012.14913.

Jonathan Gordon and Benjamin Van Durme. 2013. Reporting bias and knowledge acquisition. In Proceedings of the 2013 Workshop on Automated Knowledge Base Construction (AKBC), pages 25–30.

Xiaochuang Han, Byron C. Wallace, and Yulia Tsvetkov. 2020. Explaining black box predictions and unveiling data artifacts through influence functions. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (ACL), pages 5553–5563.

Peter Hase, Chaofan Chen, Oscar Li, and Cynthia Rudin. 2019. Interpretable image recognition with hierarchical prototypes. arXiv preprint arXiv:1906.10651.

Sarthak Jain and Byron C. Wallace. 2019. Attention is not Explanation. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL), pages 3543–3556.

Pang Wei Koh and Percy Liang. 2017. Understanding black-box predictions via influence functions. In Proceedings of the 34th International Conference on Machine Learning (ICML), pages 1885–1894.

Oscar Li, Hao Liu, Chaofan Chen, and Cynthia Rudin. 2018. Deep learning for case-based reasoning through prototypes: A neural network that explains its predictions. In Proceedings of the 2018 Conference on Artificial Intelligence (AAAI), pages 3530–3537.

Christopher D. Manning, Prabhakar Raghavan, and Hinrich Schütze. 2008. Introduction to Information Retrieval. Cambridge University Press.
Yao Ming, Panpan Xu, Huamin Qu, and Liu Ren. 2019. Interpretable and steerable sequence learning via prototypes. *Proceedings of the 25th International Conference on Knowledge Discovery and Data Mining (KDD)*, pages 903–913.

Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up? sentiment classification using machine learning techniques. In *Proceedings of the 2002 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 79–86.

Pouya Pezeshkpour, Sarthak Jain, Byron C. Wallace, and Sameer Singh. 2021. An empirical comparison of instance attribution methods for NLP. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL)*, pages 967–975.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. 2021. Learning transferable visual models from natural language supervision. arXiv preprint arXiv:2103.00020.

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners.

Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3982–3992.

Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2016. “why should i trust you?”: Explaining the predictions of any classifier. In *Proceedings of the 22nd International Conference on Knowledge Discovery and Data Mining (KDD)*, pages 1135–1144.

Andrew Slavin Ross, Michael C. Hughes, and Finale Doshi-Velez. 2017. Right for the right reasons: Training differentiable models by constraining their explanations. In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence (IJCAI)*, pages 2662–2670.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2020. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108.

Patrick Schramowski, Wolfgang Stammer, Stefano Teso, Anna Brugger, Xiaoting Shao, Hans-Georg Luigs, Anne-Katrin Mahlein, and Kristian Kersting. 2020. Making deep neural networks right for the right scientific reasons by interacting with their explanations. *Nat Mach Intell*, pages 476–486.

Ramprasaath Ramasamy Selvaraju, Stefan Lee, Yilin Shen, Hongxia Jin, Shalini Ghosh, Larry P. Heck, Dhruv Batra, and Devi Parikh. 2019. Taking a HINT: leveraging explanations to make vision and language models more grounded. In *2019 International Conference on Computer Vision (ICCV)*, pages 2591–2600.

Daniel Smilkov, Nikhil Thorat, Been Kim, Fernanda Viégas, and Martin Wattenberg. 2017. Smoothgrad: removing noise by adding noise. arXiv preprint arXiv:2012.09699.

Wolfgang Stammer, Patrick Schramowski, and Kristian Kersting. 2021. Right for the right concept: Revising neuro-symbolic concepts by interacting with their explanations. In *Proceedings of the 2021 Conference on Computer Vision and Pattern Recognition (CVPR)*. To appear.

Mukund Sundararajan, Ankur Taly, and Qiqi Yan. 2017. Axiomatic attribution for deep networks. In *Proceedings of the 34th International Conference on Machine Learning (ICML)*, pages 3319–3328.

Ian Tenney, James Wexler, Jasminn Bastings, Tolga Bolukbasi, Andy Coenen, Sebastian Gehrmann, Ellen Jiang, Mahima Pushkarna, Carey Radebaugh, Emily Reif, and Ann Yuan. 2020. The language interpretability tool: Extensible, interactive visualizations and analysis for NLP models. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP): System Demonstrations*, pages 107–118.

Stefano Teso and Kristian Kersting. 2019. Explanatory interactive machine learning. In *Proceedings of the 2019 Conference on AI, Ethics, and Society (AIES)*, pages 239–245.

Elena Voita, Rico Sennrich, and Ivan Titov. 2019a. The bottom-up evolution of representations in the transformer: A study with machine translation and language modeling objectives. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 4396–4406.

Elena Voita, David Talbot, Fedor Moiseev, Rico Sennrich, and Ivan Titov. 2019b. Analyzing multi-head self-attention: Specialized heads do the heavy lifting, the rest can be pruned. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 5797–5808.

Sarah Wiegreffe and Yuval Pinter. 2019. Attention is not not explanation. arXiv preprint arXiv:1908.04626.

### A Appendix

#### A.1 Datasets

The aforementioned benchmark datasets provide a fixed test set except the Yelp Open dataset. For
the Yelp Open dataset we randomly select 200,000 training examples and split them into train (70%), validation (15%) and test (15%) set. We split the Jigsaw Toxicity train set into train (20%) and validation (80%) set. Before the split, we filter out long sequences (num_tokens > 40) for each dataset. This is required because transformer-based language models can only handle sequences of limited length, especially CLIP, and long sequences also cause the other sequences of a set to be padded to the same length, which, in turn, produces a lot of padding tokens. For the tokenization we use the GPT2-tokenizer. We apply a grid search to find optimisation hyper-parameters. We report the cross-validated results.

A.2 Training

The Proto-Trex networks are trained with and evaluated on different datasets. We use PyTorch\(^4\) for the implementation. We optimise our model with Adam optimiser with hyperparameters \(\beta = (0.9, 0.999)\) and \(\epsilon = 10^{-8}\). We use a base learning rate of \(lr_b = 0.001\) and apply learning rate warm-up and scheduling that is here a linear decay. The learning rate is then given as

\[
    lr = lr_b \cdot \min \left( \frac{\text{step}_i}{e}, \frac{e - \text{step}_i}{e - \text{wup}} \right),
\]

where \(\text{step}_i\) is the current step, \(e\) the total number of epochs and \(e_{wup}\) the number of warm-up epochs. The warm-up takes place for \(e_{wup} = \min \left( 10, \frac{e}{30} \right)\) epochs. Warm-up reduces the dependency of early optimisation steps that may cause difficulties in the longer run. Also, we weight the cross-entropy loss with the class occurrences to re-balance the influence of an unbalanced dataset. The same is done in the accuracy computation where a class balanced accuracy is computed. For regularisation, we apply an L1-regularisation on the weights of the last linear layer. During the training process, a network may tend to overfit. To counteract this, we evaluate the model every \(10^6\) epoch on the validation set and keep the model that yielded the best validation result. Furthermore, we set up a class mask such that each class is assigned to the same number of prototypes. This is used and enforced by the class-specific losses (Clst and Sep). Changing the balance of the class assignment can be sensible to correct for imbalance in the dataset or focus on a specific class if its sentiment is more polysemous or generally more relevant.

A.3 Sentence- vs. Word-level Loss

For clarification, we present the loss terms for sentence-level Proto-Trex networks in more detail:

\[
    \mathcal{L} := \min_{\mathbf{p}, \mathbf{w}_{fc}} \frac{1}{n} \sum_{i=1}^{n} \mathcal{C}E(t_i, y_i) + \lambda_1 \text{Clst}(\mathbf{e}, \mathbf{p}) + \lambda_2 \text{Sep}(\mathbf{e}, \mathbf{p}) + \lambda_3 \text{Distr}(\mathbf{e}, \mathbf{p}) + \lambda_4 \text{Divers}(\mathbf{p}) + \lambda_5 \|\mathbf{w}_{fc}\|, \tag{7}
\]

where \(\text{Clst}(\mathbf{e}, \mathbf{p}) := \frac{1}{n} \sum_{i=1}^{n} \min_{j: \mathbf{p}_j \in \mathbf{P}_{y_i}} \text{sim}(\mathbf{e}_i, \mathbf{p}_j), \tag{8}\)

\(\text{Sep}(\mathbf{e}, \mathbf{p}) := \frac{1}{n} \sum_{i=1}^{n} \min_{j: \mathbf{p}_j \notin \mathbf{P}_{y_i}} \text{sim}(\mathbf{e}_i, \mathbf{p}_j), \tag{9}\)

\(\text{Distr}(\mathbf{e}, \mathbf{p}) := -\frac{1}{n} \sum_{j=1}^{n} \min_{i \in [1, n]} \text{sim}(\mathbf{e}_i, \mathbf{p}_j), \tag{10}\)

and \(\text{Divers}(\mathbf{p}) := \frac{1}{n_p} \sum_{i=1}^{n_p} \min_{j: \mathbf{p}_j \notin \mathbf{P}_{y_i}} \text{sim}(\mathbf{p}_i, \mathbf{p}_j). \tag{11}\)

A.4 Projection

We show the impact of projecting the prototypes onto their nearest neighbour in Tab. 7. The projection is evaluated for sentence-level Proto-Trex networks. One can see the trade-off between interpretability and accuracy introduced by projection.

A.5 Generated Explanations

Here we show the explanations that Proto-Trex generates. For each network we use 10 prototypes and for word-level networks we use a prototype-length of 4. In Tab. 8 we show all prototypes for Proto-Trex based on the GPT-2 transformer and in Tab. 9 the prototypes based on the SBERT transformer. Both tables show the prototypes for the Yelp Open and MovieReview dataset. The results for the Jigsaw Toxicity dataset can be found in an external document in the code base. CONTENT WARNING: the content in this document can be disturbing due to highly toxic texts! These results do not represent the authors’ opinion and provide prototypical explanations generated solely by Proto-Trex.

Tab. 10 shows the pruned prototypes of iProto-Trex from Tab. 9(a). Pruning cuts off the words at

\(^4\)https://pytorch.org/
the end of a sequence that go beyond two sentences or 15 tokens in total.

We showcase all experiments of the user interaction in Tab. 11 which is an extension of Tab. 6. The extension includes (1) retraining the classification layer for the same number of epochs to provide a fairer comparison with the interaction methods and to exclude changes in accuracy simply due to training for more epochs, (2) pruning the original, (3) removing the original, (4) adding a new prototype without changing the original, (5) replacing the original with the user chosen alternative “They offer a bad service.” without using the interaction loss and (6) fine-tuning the original prototype.

In Fig. 12 we shows the full explanations with importance scores for the exemplary query in the motivation (cf. Fig. 1). It highlights the advantage of using prototype networks and the benefit of interactive learning.

| Language Model                | Yelp  | Movie | Toxicity |
|-------------------------------|-------|-------|----------|
| SBERT (Proto-Trex)            | 94.13 | 83.23 | 83.11    |
| SBERT (Proto-Trex) projected  | 93.59 | 79.85 | 73.19    |
| CLIP (Proto-Trex)             | 93.41 | 73.26 | 80.74    |
| CLIP (Proto-Trex) projected   | 87.16 | 63.52 | 67.75    |

Table 7: Impact of Projection on Pro-Trex networks. The accuracy is given in percent.
This places not authentic and the pho is not that good. Very small uncomfortable dining area and the service was horrible.

Great ambiance with a menu that is short and sweet. The food was delicious and I loved the ginger beer! Excellent service. Definitely recommend this place!

Waited over hour for food. Only one person making sushi. Left without food, they still charged for the one beer we had. Bad server + no food = horrible exp.

Food was great...service was excellent! Will be eating there regularly.

Called it. This place didn't stand a chance with terrible management, gross food and slow service. Too bad for the workers.

Excellent baby back ribs. Creamed corn was terrific too. Came in the afternoon and was easy to get in and have a relaxing meal. Excellent service too!!

Don’t waste your money at this restaurant. Took my daughter to celebrate her birthday. They didn’t even sing Happy Birthday. The food was horrible.

Great food, great service. Chicken tikka was awesome with fresh peppers. Iced tea had a surprising and refreshingly different flavor.

Worst customer service. No one even said hello after going in 3 separate times. I am an avid spender and have spent lots of money there in the past. Will not shop there again!

A great experience each time I come in. The employees are friendly and the food is awesome.

There’s too much falseness to the second half, and what began as an intriguing look at youth fizzles into a dull, ridiculous attempt at heart-tugging.

Parts of the film feel a bit too much like an infomercial for ram dass’s latest book aimed at the boomer demographic. But mostly it’s a work that, with humor, warmth, and intelligence, captures a life interestingly lived.

Godard’s ode to tackling life’s wonderment is a rambling and incoherent manifesto about the vagueness of topical excess... In praise of love remains a ponderous and pretentious endeavor that’s unfocused and tediously exasperating.

It’s a lovely film with lovely performances by buy and accorsi.

Like a Tarantino movie with heart, alias Betty is richly detailed, deftly executed and utterly absorbing.

A bland, obnoxious 88-minute infomercial for universal studios and its ancillary products.

The film fearlessly gets under the skin of the people involved... this makes it not only a detailed historical document, but an engaging and moving portrait of a subculture.

A sad and rote exercise in milking a played-out idea – a straight guy has to dress up in drag – that shockingly manages to be even worse than its title would imply.

an inventive, absorbing movie that’s as hard to classify as it is hard to resist.

Table 8: Proto-Trex GPT-2 Prototypes. The prototypes are received with GPT-2 for the Yelp Open (a) and MovieReview (b) dataset. The prototypical subsequences generated with GPT-2 are highlighted in color.
Table 9: Proto-Trex SBERT Prototypes. The prototypes are received with SBERT for the Yelp Open (a) and MovieReview (b) dataset.

(a) Yelp

P1 | This place is horrible. The staff is rude and totally incompetent. Jose was horrible and is a poor excuse for a customer representative.
P2 | This place is really high quality and the service is amazing and awesome! Jayden was very helpful and was prompt and attentive. Will come back as the quality is so good and the service made it!
P3 | Terrible delivery service. People are mean and don’t care about their customers service. I will not ever come back to this place. Also the food is small, not very good and too expensive.
P4 | Incredibly delicious!!! Service was great and food was awesome. Will definitely come back!
P5 | They sat us 30 minutes late for our reservation and didn’t get our entree for 1.5 hours after being seated. The service was terrible.
P6 | I found this place very inviting and welcoming. The food is great so as the servers.. love the food and the service is phenomenal!! Well done everyone!!
P7 | Horrible customer service. Not helpful at all and very rude. Very disappointed and will not go back to this location.
P8 | Oliver Rocks! Great hidden gem in the middle of Mandalay Bay! Great friends great times
P9 | They literally treat you like you are bothering them. No customer service skills. Substandard work.
P10 | Fun and friendly atmosphere, fantastic selection. The sushi is so fresh and the flavors are WOW.

(b) Movie

P1 | ...in the pile of useless actioners from mtv schmucks who don’t know how to tell a story for more than four minutes.
P2 | the solid filmmaking and convincing characters makes this a high water mark for this genre.
P3 | dull, lifeless, and amateurishly assembled.
P4 | it’s a wise and powerful tale of race and culture forcefully told, with superb performances throughout.
P5 | stale, futile scenario.
P6 | a real winner – smart, funny, subtle, and resonant.
P7 | plodding, poorly written, murky and weakly acted, the picture feels as if everyone making it lost their movie mojo.
P8 | an enthralling, entertaining feature.
P9 | fails in making this character understandable, in getting under her skin, in exploring motivation... well before the end, the film grows as dull as its characters, about whose fate it is hard to care.
P10 | this delicately observed story, deeply felt and masterfully stylized, is a triumph for its maverick director.

Table 10: Pruning Prototypes with iProto-Trex. It shows the prototypes from Tab. 9(a) after pruning has been applied. Pruning reduces the sequences in length while preserving the sentiment. The accuracy remains the same (cf. Tab. 11). Prototypes 4 and 9 are not pruned as it would alter the sentiment too much.
Method | Acc. | Prototype
--- | --- | ---
original | 93.64 | Horrible customer service and service does not care about safety features. That’s all I’m going to say. Oh they also don’t care about their customers
retrain | 93.64 | Horrible customer service and service does not care about safety features. That’s all I’m going to say. Oh they also don’t care about their customers
prune | 93.64 | Horrible customer service and service does not care about safety features. That’s all I’m going to say. Oh they also don’t care about their customers
remove | 93.61 | –
add | 93.79 | They offer a bad service.
replace | 93.78 | They offer a bad service.
re-initialize | 93.80 | Terrible delivery service. People are mean and don’t care about their customers service. I will not ever come back to this place. Also the food is small, not very good and too expensive.
fine-tune | 93.81 | Terrible delivery service. People are mean and don’t care about their customers service. I will not ever come back to this place. Also the food is small, not very good and too expensive.
soft replace (c=0.5) | 93.81 | Terrible delivery service. People are mean and don’t care about their customers service. I will not ever come back to this place. Also the food is small, not very good and too expensive.
soft replace (c=0.9) | 93.79 | I really don’t recommend this place. The food is not good, service is bad. The entertainment is so cheesy. Not good
soft replace (c=1.0) | 93.79 | They offer a bad service.

Table 11: User Interaction with iProto-Trex. Each row shows a different interaction method with the balanced accuracy on the test set conducted on Yelp Open dataset. The interaction methods are able to remove the unwanted prototype while incorporating more knowledge and hence more interpretability along with a higher accuracy.

| Importance | Query: Staff is available to assist, but limited to the knowledge and understanding of the individual |
| --- | --- |
| 0.58 · 6.95 = 4.01 | They literally treat you like you are bothering them. No customer service skills. Substandard work. |
| 0.38 · 2.61 = 1.00 | They sat us 30 minutes late for our reservation and didn’t get our entree for 1.5 hours after being seated. The service was terrible. |
| 0.36 · 2.02 = 0.73 | This place is horrible. The staff is rude and totally incompetent. Jose was horrible and is a poor excuse for a customer representative. |

iProto-Trex

| Importance | Query: They offer a bad service. |
| --- | --- |
| 0.50 · 3.25 = 1.63 | They offer a bad service. |
| 0.38 · 4.17 = 1.58 | They sat us 30 minutes late for our reservation and didn’t get our entree for 1.5 hours after being seated. The service was terrible. |
| 0.36 · 3.01 = 1.08 | This place is horrible. The staff is rude and totally incompetent. Jose was horrible and is a poor excuse for a customer representative. |

Table 12: Top-3 Explanations for Query in Motivation. The first three rows depict explanations with sentence-level Proto-Trex with the SBERT transformer, while the last three show the top three explanations iProto-Trex. On the left side, one can see the importance scores for the classification.