Exploring the linear separablity of syntactic and semantic information in BERT embeddings

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Abstract

Syntax and semantics are at the foundation every language, yet distinctions between the two are not readily agreed upon. We seek to explore how representations of these two information sets manifest in BERT embeddings. Specifically we investigate the degree of the linear separability of syntactic and semantic information in BERT embeddings, as well as quantify how important the linear component corresponding to one information set is to solving a classification task that targets the other information set. We use Iterative Nullspace Projection to decompose word-level BERT embeddings into syntactic, non-syntactic, semantic and non-semantic components to be used in syntactic and semantic classification tasks. Our results show that there is significant overlap between the syntactic and semantic components in BERT embeddings and the loss of either information set will negatively impact the performance of a linear classifier trained for either of the classification objectives. Somewhat surprisingly, we find that the loss of semantic information has a much greater impact on the performance of the syntax classifier than the loss of syntactic information has on the semantic classifier.

1 Introduction

The boundary between semantics and syntax is a hotly debated topic in linguistics, but do large language models make such a distinction? If so, do language model embeddings present this information in a way that is easily separated and recognized by humans? The objective of this project is to explore BERT's (Devlin et al., 2019) reliance on certain syntactic information when handling a semantic task, and vice versa. Specifically, we seek to quantify the importance of linearly-separable syntactic or semantic information when performing semantic or syntactic classification, respectively.

To achieve our goal, we construct a linear probing system for a task and then employ Iterative Nullspace Projection (INLP from here on) (Ravfogel et al., 2020) to generate a new embedding devoid of information learned from the probing task. We then measure the performance of this new embedding on downstream syntactic and semantic classification tasks. The design of our probing procedure follows Elazar et al., 2020, which employs INLP to investigate whether BERT uses part-of-speech (POS) information when solving language modeling (LM) tasks. INLP has been used for a variety of tasks (Ravfogel et al., 2020; Elazar et al., 2020; Gonen et al., 2020, etc.) though this is the first case we know of in which INLP has been used to investigate the linear separability of syntactic and semantic information.

A novel method for removing information from an embedding, INLP iteratively trains linear models on a specific classification task, and projects the input on intersection of the nullspaces of those linear models. Our objective is that, by applying the INLP procedure to a syntactic task, we are able to separate the representation into a syntactic space and a non-syntactic space. We then compare the performance of a model that seeks to classify semantic labels using the original BERT embeddings with an otherwise identical model trained on embeddings projected onto the non-syntactic space, in order to see if BERT is using syntactic information when performing the semantic task. Conversely, we can also first probe a semantic task, thus defining a semantic and non-semantic space, and then investigate the performance of embeddings projected onto those spaces when performing a syntactic classification task. Once we derive the semantic space and syntactic space from the experiment, we further investigate on the separability of the two spaces by comparing the embedding projections.

To evaluate the separability of syntax and semantics, we use two tasks: one task for the probing system and INLP procedure, and one task for evaluating performance on embeddings before and after INLP. We choose Combinatory Categorical Grammar (CCG from here on) tagging (Hockenmaier and Steedman, 2007) as the syntactic task and semantic category labeling (Bonial et al., 2014) as the semantic task.

The remainder of the paper proceeds as follows: Section 2 explores previous work related to our experiment. Section 3 provides a description of the probing and evaluation tasks and gives an overview of the experiment pipeline. Section 4 reviews our experiments and affiliated results. Section 5 discusses the implications of those results. Finally, section 6 gives an overview of the entire process and outlines possible next steps.

2 Related Work

The separation and overlap between syntax and semantics has been of interest to linguists for many years. More recently, with the growing popularity of large language models, computational linguists have begun to explore how large language models deal with the boundaries of these information sets in word and sentence embeddings.

Huang et al., 2021 use paraphrase pairs and new target syntax to train a semantic encoder, syntactic encoder and decoder to learn separate representations of the semantic and syntactic information contained in BART embeddings, in order to create semantically equivalent paraphrases with the new syntactic structure. Alongside the encoders they also train an adversarial syntax discriminator to try and predict the source syntax from the semantic embeddings, thus encouraging the disentanglement of the semantic and syntactic information by training the semantic embedder to remove as much syntactic information as possible. Their results show that one can achieve some removal of syntactic information from semantic embeddings, so disentanglement of some information is possible. Though they do not achieve perfect separation of the two information sets. Other non-linear approaches to syntactic-semantic information disentanglement have been carried out in Chen et al., 2019

Unlike the aforementioned studies, we seek to explore the linear separability of syntactic and semantic information in large language model embeddings at the word level. To accomplish this task we apply the Iterative Nullspace Projection method to syntactic (CCG) and semantic labeling tasks in order to define the syntactic and semantic components of BERT embeddings that will be used in our downstream classification tasks.

INLP, introduced in Ravfogel et al., 2020, is a method to define a linear guarding function that masks all the linear information in a word embedding that may be used for a downstream classification task. In the original paper the authors use this method to remove gender bias from BERT embeddings of biographical descriptions and then measure how easy it is to determine an individual's gender from the guarded embedding by using various downstream classification methods. Beyond using the INLP method to guard protected attributes, the authors hypothesize several additional use cases for this procedure, including information disentanglement.

The authors of Elazar et al., 2020 use INLP for exactly this task. They use INLP in order to separate and guard certain linguistic information sets from BERT embeddings in order to better understand what information is being used by large language models, and not just what is encoded. The main premise behind this paper is that if a particular property is used to solve a task, then the removal of that property should negatively influence the model's ability to solve that task. Conversely, if the removal of a property has little influence on the model's ability to perform a task then we know that property is not a significant contributing factor in the model's ability to perform that task. Specifically, Elazar et al., 2020 seeks to quantify the importance of the information sets used for part-of-speech tagging, syntactic dependency labeling, named entity recognition and syntactic constituency boundaries on BERT's ability to perform the language modeling task.

We take a similar approach to Elazar et al., 2020 by separating the information sets used for CCG tagging and semantic labeling from word-level BERT embeddings. However, as we are interested in the linear separability of these two information sets, we will test how the removal of these information sets impacts the embeddings' performance on semantic labeling and CCG tagging, respectively, rather than language modeling.

3 Methods

We construct two separate probing tasks to isolate the syntactic and semantic information in word-level BERT embeddings. The embeddings are separated into syntactic and non-syntactic, and semantic and non-semantic components via INLP which is described in section 3.1. These embedding components are then combined to form new embeddings, which are evaluated on the same tasks that were used for probing.

3.1 The Iterative Null-Space Projection method

The INLP method first introduced in Ravfogel et al., 2020, is used to create a guarding function that masks all the linear information contained in a set of vectors, X, that can be used map each vector to $c \in C$, where C is the set of all categories. This is accomplished by training a linear classifier, a matrix W, that is applied to each $x \in X$ in order to predict the correct category c with the greatest possible accuracy. In other words, Wx defines a distribution over the set of categories C and we assign x to the class $c \in C$ which is allotted the greatest probability by Wx. Note that the classifier's accuracy must be greater than that achieved by guessing the majority category, otherwise x contains no linear information relevant for the categorization task and thus no guarding function is needed. Once W is determined, for any $x \in X$ we can remove the information that W uses to predict c by projecting x onto the null-space of W, $N(W) = \{x|Wx = 0\}$. Call this projection function P_1 and let $\hat{x} = P_1(x)$. This removes all of the linear information in x that W used to predict the category c.

However, this process does not necessarily remove all of the linear information in x that could be used to predict c. For example, x may contain redundant information and W may have only used one set of this information for its prediction. In this case, the redundant information would still be present in $\hat{x}$. Thus, we must repeat the above process, defining a new linear classifier $\hat{W}$ that uses $\hat{x}$ to predict c. If $\hat{W}$ is still able to predict c with a greater than majority class guess accuracy, then we know that $\hat{x}$ contained linear information about c. As above, we project $\hat{x}$ onto the null-space of $\hat{W}$ via the projection function P_2 and define a new $\hat{x} = P_2(P_1(x))$.

We iteratively apply this process until no linear information remains in $\hat{x}$, i.e. a linear classifier is unable to predict the correct category c with any probability greater than that achieved by guessing the majority class. The final $\hat{x} = P_n(P_{n-1}(\dots P_1(x)))$ contains no linear information about the categories in C and we call $P(x) = P_n(P_{n-1}(\dots P_1(x)))$ the guarding function.

We will pair the INLP method with the probing tasks described in sections 3.3 and 3.4 in order to create two guarding functions that will enable us to isolate the linear components of BERT embeddings that contain syntax-specific and semantics-specific information.

3.2 Data

We use the English Parallel Meaning Bank v4.0 (Abzianidze and Bos, 2017) to test the linear separability of the semantic and syntactic information in word-level BERT embeddings. This dataset consists of gold standard and silver standard word-level semantic tags. The gold standard contains 5,438 sentences with annotations that are manually verified while the silver standard contains 62,739 sentences with autogenerated annotations. All of our experiments are conducted on gold standard data.

The original dataset does not include CCG tags, however Abzianidze and Bos, 2017 utilized a CCG parser to produce CCG tags. We follow a similar procedure and apply a CCG parser (Yoshikawa et al., 2017) to develop word-level CCG tags. Once we obtain both CCG tags and semantics tags for the dataset, we can perform the syntactic and semantics probing task as desired.

3.3 Syntactic probing task

The syntactic probing task involves training a linear classifier on the final layer BERT embeddings in order to predict the CCG tag associated with each word. We will use this classifier in the INLP algorithm in order to create a guarding function for the information that is necessary to complete the CCG labeling task. For a given embedding, v_{orig}, the projection that results from applying this guarding function, P_{syn}, to the embedding will represent the non-syntactic information contained in the embedding and will from now on be referred to as the "non-syntactic component" of the embedding, $v_{nosyn} = P_{syn}v_{orig}$. We can then determine the "syntactic component" of the embedding by taking the difference of the embedding vector with the non-syntactic component, $v_{syn} = v_{orig} - v_{nosyn}$.

3.4 Semantic probing task

Similar to the above, the semantic probing task involves training a linear classifier on the final layer BERT embeddings in order to predict the semantic tag (described in the data section) associated with each word. This classifier is used in the INLP algorithm in order to create a guarding function, P_{sem}, for the information necessary to complete the Semantic tag labeling task. As described in the Syntactic probing task section, we shall use the resulting guarding function to decompose the original embedding into a "non-semantic component", $v_{nosem} = P_{sem}v_{orig}$, and a "semantic component", $v_{sem} = v_{orig} - v_{nosem}$.

3.5 Evaluation tasks

Our goal is to determine which information sets captured in the BERT embeddings are relevant for our evaluation tasks. We thus use the components derived from the probing tasks to create new embeddings that isolate specific types of information. These embeddings are then evaluated on the syntactic and semantic tasks that were used for probing, and their performance is compared to that of the original embeddings. We also compare the performance of each model trained on one of these embeddings with another trained on new embeddings that are created by randomly removing the same number of dimensions from the original embeddings as are removed by the INLP guarding function. In doing so we can test the extent to which the loss of the particular information set of interest is responsible for the drop in performance, as opposed to a general loss of information.

We will assess each of the non-syntactic and non-semantic embedding types, the original BERT embeddings and the embeddings created by randomly removing directional information on the CCG and Semantic labeling tasks that were used in the probes.

4 Results

We first evaluate our two tasks on the original embeddings, and determine that linear classifiers can successfully predict both CCG tags and semantics tags (around 85% testing accuracy), as shown in table 2. We then apply the INLP method to derive the guarding matrices P_{syn} and P_{sem}, which are used to project the original embeddings onto the complements of the syntactic information sub-space and the semantic information sub-space. By applying linear transformations to the original embeddings and their projections, we are able to extract the embeddings described in table 1.

Expression	Description
v_{orig}	Original BERT embeddings
$v_{nosem} = P_{sem}v_{orig}$	Gained after INLP with semantics task
$v_{nosyn} = P_{syn}v_{orig}$	Gained after INLP with syntactic task
$v_{sem} = v_{orig} - v_{nosem}$	Semantic representation
$v_{syn} = v_{orig} - v_{nosyn}$	Syntactic representation

Table 1: Description of Embeddings

To ensure a fair assessment of the impact of the information loss, we conduct experiments for which we start with the original BERT embeddings and randomly remove the same number of directions that our derived embeddings lost. For the embeddings derived from projection alone, we record the number of removed directions using $Null(P)$, where P is the projection matrix. For embeddings not derived from matrix multiplication, we obtain the number from $Null(M)$ where M is the embedding matrix with size (768,instance number).[1] Then we create embeddings with the same number of directions randomly removed and train the linear classifiers on these embeddings. The testing accuracies from our experiments can be found in table 2.

5 Discussion

The INLP method successfully guards the information used in the probing task. When performing CCG tagging, the model accuracy drops significantly when comparing the v_{nosyn} embeddings with the Rand($|v_{nosyn}|$) embeddings (from 82.26% to 23.76%), and similarly for semantics tagging (from 87.71% to 17.28%). In contrast, when the directions are randomly removed, the performance remains relatively the similar to the classifiers' performances on the original BERT embeddings for

[1]This is not necessarily equivalent to the number of direction removed. $Null(M) \geq Null(P)$ for the embedding matrix M that corresponds to projection P, but in practice the numbers are very close. With this approach we err on the side of removing more random directions from our random embeddings, resulting in a more conservative comparison when assessing our derived embeddings.

Embedding	Directions Removed	CCG Tagging	Semantics Tagging
v_{orig}	0	84.75%	88.56%
Rand($\|v_{nosem}\|$)	77	84.06%	87.71%
Rand($\|v_{nosyn}\|$)	159	82.26%	87.57%
v_{nosem}	77	27.93%	17.28%
v_{nosyn}	159	23.76%	49.43%

Table 2: Experiment Result of Different Embeddings

both tasks (84.75% and 88.56%, respectively).

To measure the importance of semantic information for the syntactic task, we compare the performance of the CCG tagging classifier on v_{nosem} with that of Rand($|v_{nosem}|$) and see a performance drop of 56.13%. Similarly, we can measure the importance of syntactic information for the semantic task by comparing the performance of the semantic tagging classifier on v_{nosyn} with that of Rand($|v_{nosyn}|$) and see a performance drop of 38.14%. We can see that the removal of each information set has a significant impact on the performance of a linear classifier trained on either classification task. This suggests that the syntactic and semantic information in BERT embeddings is not easily disentangled.

What is surprising is that the loss of semantic information has a more significant impact on the syntactic classification task than the loss of syntactic information does on the semantic tagging task. These results suggests that the semantics task is less dependent on syntactic information than the opposite direction, which challenges the assumption that syntactic information is more pertinent to semantic comprehension than vice versa.

6 Conclusion

It has been established that linear classifiers are successful in various linguistics probing tasks (Liu et al., 2019). Our experiment has confirmed that linear classifiers can perform CCG tagging and semantic tagging on the Parallel Meaning Bank data set (Abzianidze and Bos, 2017) with a fairly high rate of success. We then employed INLP and successfully guarded the information contained in BERT embeddings that linear classifiers use to perform the aforementioned classification tasks.

Using these guarding functions we were able to explore the importance and separability of the syntactic and semantic information contained in BERT embeddings. We evaluated the classification tasks on various derived embeddings and concluded that not only is the linear syntactic and semantic information essential for their respective classification tasks, these information sets are also very important for the opposing classification tasks as well. Thus the two information sets are not easily separated. Somewhat surprising, we determined that the semantic information was more influential on the success of the syntactic classifier than the other way around.

Though INLP successfully produces the desired result, it is worth noting that our dataset is relatively small compared to the number of parameters in linear classifier. In the future, we will expect this experiment to be reproduced at a larger scale so that the experiment findings can be further validated. Additionally, in future work we hope to perform a similar analysis on embeddings derived from different layers of the BERT architecture, in order to determine the importance and separability of these information sets at each layer. In doing so we hope to better understand how BERT processes different types of linguistic information throughout the encoding process.

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