Exploratory Model Analysis Using Data-Driven Neuron Representations

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Abstract

Probing classifiers have been extensively used to inspect whether a model component captures specific linguistic phenomena. This top-down approach is, however, costly when we have no probable hypothesis on the association between the target model component and phenomena. In this study, aiming to provide a flexible, exploratory analysis of a neural model at various levels ranging from individual neurons to the model as a whole, we present a bottom-up approach to inspect the target neural model by using neuron representations obtained from a massive corpus of text. We first feed massive amount of text to the target model and collect sentences that strongly activate each neuron. We then abstract the collected sentences to obtain neuron representations that help us interpret the corresponding neurons; we augment the sentences with linguistic annotations (*e.g.,* part-of-speech tags) and various metadata (*e.g.,* topic and sentiment), and apply pattern mining and clustering techniques to the augmented sentences. We demonstrate the utility of our method by inspecting the pre-trained BERT. Our exploratory analysis reveals that i) specific phrases and domains of text are captured by individual neurons in BERT, ii) a group of neurons simultaneously capture the same linguistic phenomena, and iii) deeper-level layers capture more specific linguistic phenomena.

1 Introduction

Deep neural networks (DNNs) learn to induce internal feature representations or neurons[1] for a given input, which are optimized for the target task. The success of DNNs in the field of natural language processing (NLP) is underpinned by this flexibility to induce internal vector representations of input. It is, however, difficult for humans to interpret their roles and properties, which hinders us from leveraging DNNs in practical applications.

Researchers have therefore investigated what linguistic aspects of input text are captured by the internal representations of DNNs optimized for NLP tasks (§ 2). Most of the existing methods inspect a pre-specified model component (*e.g.,* individual BERT layers) in a top-down manner. A typical approach first takes aim at specific linguistic phenomena that would be captured by the target components, and then trains a probing classifier that predicts the chosen linguistic phenomena from the target components (Bau et al., 2018; Giulianelli et al., 2018; Dalvi et al., 2019; Lakretz et al., 2019; Kovaleva et al., 2019; Goldberg, 2019; Petroni et al., 2019; Hewitt and Manning, 2019; Jawahar et al., 2019; Durrani et al., 2020; Zhou and Srikumar, 2021; Cao et al., 2021; Jumelet et al., 2021).

Although this top-down approach based on probing classifiers has provided thought-provoking insights into the target model components, it becomes costly when we want to inspect many combinations of model components and linguistic phenomena. This is because the probing requires us to train machine-learning classifiers for each combination of model component and linguistic phenomenon. Although there are a few bottom-up approaches to inspect DNNs by examining the response of the neurons towards (perturbed) inputs that represent the target linguistic phenomenon (Karpathy et al., 2016; Shi et al., 2016; Qian et al., 2016), these approaches are labor intensive since they require manual intervention.

This study aims at efficiently inspecting neural NLP models at various levels of granularity ranging from individual neurons to the model as a whole, and presents a bottom-up approach to inspecting what kind of concrete linguistic phenomena each neuron of the model responds to, without presupposing the target linguistic phenomenon to be examined (§ 3). Given a massive amount of text, we first feed individual sentences to the target model, and collect sentences to which each neuron strongly

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[1]**Neurons** refer to numerical values of each dimension of internal representations such as hidden states.

responds (§ 3.1).[2] We next annotate the collected sentences with the linguistic annotations (*e.g.,* part of speech tags) and various metadata (*e.g.,* topic and sentiment). With the help of these annotations, we then apply text mining techniques such as frequent pattern mining to extract common patterns as *the linguistic signatures*[3] that exist repeatedly and intricately in the sentences collected for the target neurons (§ 3.2). We finally investigate relationships between multiple neurons by comparing and clustering continuous neuron representations induced from the collected sentences.

We apply our method to the pre-trained BERT (base-uncased) (Devlin et al., 2019) to demonstrate how much insight into BERT the method can actually provide. Our exploratory model analysis have confirmed that it is possible to identify, without any prior assumptions, a wide variety of specific linguistic phenomena to which each neuron responds (§ 4.2). Furthermore, by comparing the linguistic phenomena and sentences corresponding to individual neurons, we revealed the existence of neurons that work cooperatively for the same purpose. We finally revealed the impact of optimizing BERT to the target task (here, the pre-training task and sentiment classification) by comparing neurons of randomly initialized BERT with neurons of the pre-trained and the fine-tuned BERT (§ 4.3).

The contribution of this study is threefold:

- We present a method of **exploratory model analysis to understand neural NLP models**. We investigate concrete linguistic phenomena (*e.g.,* skip n-grams) captured by the neurons of the target model, without any prior assumptions about the phenomena to be examined.

- We revealed **concrete linguistic phenomena captured by various BERT's neurons** and layers, whereas existing approaches reported coarse linguistic phenomena that are indicated by high performance in probing tasks.

- We confirmed that **neurons in deeper BERT layers capture more specific linguistic phenomena, and fine-tuning facilitates this tendency** in a sentiment classification task.

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[2] For simplicity, we hereafter assume that input to the target model is a single sentence, although our method can be applied to models that takes input in shorter or larger linguistic units.

[3] This term is named after topic signatures (Agirre et al., 2001), which are supplemental data-driven representations of word senses whose representations are extracted from external language resources.

2 Related Work

In order to clarify what kind of linguistic phenomena are captured by neural NLP models, researchers have analyzed the internal representations of the models at various levels of granularity such as neurons (Karpathy et al., 2016; Shi et al., 2016; Qian et al., 2016; Bau et al., 2018; Lakretz et al., 2019; Vig et al., 2020; Cao et al., 2021), layers (Hewitt and Manning, 2019; Liu et al., 2019; Tenney et al., 2019a; Goldberg, 2019; Jawahar et al., 2019; Miaschi and Dell'Orletta, 2020), attentions (Kovaleva et al., 2019; Clark et al., 2019; Brunner et al., 2020; Kobayashi et al., 2020), and the model as a whole (Petroni et al., 2019; Broscheit, 2019; Roberts et al., 2020). In what follows, we start by reviewing probing methods that investigate the classifier performance of external tasks based on the target model components. We next describe some microscopic methods that focus on individual neurons. We then discuss a method of inspecting each neuron using text generated for that neuron.

Most of the recent methods adopt a top-down approach called *probing*, which takes target component (*e.g.*, layer) as inputs, trains a classifier that predicts the linguistic phenomena of interest such as syntactic information (Jawahar et al., 2019; Miaschi and Dell'Orletta, 2020; Wu et al., 2020) , agreement information (Giulianelli et al., 2018; Goldberg, 2019), and semantic knowledge (Tenney et al., 2019b; Ettinger, 2020), and evaluates the properties of the internal representation with reference to the accuracy of the classifier. To reduce the cost of training a classifier, Zhou and Srikumar (2021) indirectly predict the performance of probing classifiers by analyzing how the labeled data is represented in the vector space. Some studies identify neurons which make a huge contribution to solving the desired task, by looking at the performance of the task when the activation of neurons is forcibly controlled (Bau et al., 2018; Lakretz et al., 2021; Cao et al., 2021).

These probing methods are inductive in that they examine whether the target model component captures the target linguistic phenomenon. It is costly to inspect various pairs of model components and phenomena. Our approach does not presuppose linguistic phenomena to be examined and gives information that differs from the above methods; we show concrete linguistic phenomena each neuron responds to strongly, in a form that can be easily understood by humans (*e.g.*, skip n-grams) (§ 4.2).

Datasets	#sent.	domain	metadata	avg. length	distribution of simplified POS tags
BookCorpus (Zhu et al., 2015)	40M	book	author	16.3	noun: 21.4%, verb: 17.6%, adj.: 5.1%
English Wikipedia[4]	40M	wikipedia	entity	22.0	noun: 32.5%, verb: 11.7%, adj.: 6.0%
Sentiment140 (Go et al., 2009)	2M	social media	sentiment	10.3	noun: 23.4%, verb: 18.4%, adj.: 5.8%
IMDB (Maas et al., 2011)	0.3M	review	sentiment	23.8	noun: 22.9%, verb: 15.3%, adj.: 7.4%
20Newsgroups (Lang, 1995)	0.2M	news	topic	23.6	noun: 29.0%, verb: 13.0%, adj.: 5.3%
Reuters[5]	39K	news	category	28.9	noun: 38.2%, verb: 11.7%, adj.: 6.2%
Total	82M	-	-	18.9	noun: 27.7%, verb: 14.2%, adj.: 5.7%

Table 1: Datasets used to collect sentences to which individual neurons of the target model strongly activate. Among the PTB annotations obtained by the POS tagger described in § 4.1, we here defined those POSs whose letters begin with N, V, and J as "noun," "verb," and "adj," respectively.

There are several studies that have investigated the roles of neurons – the finest components of models such as a cell state in a long short term memory – by observing interactions between their values and (perturbed) input sentences (Karpathy et al., 2016; Shi et al., 2016; Qian et al., 2016; Vig et al., 2020; Lakretz et al., 2021). However, these methods are tailored to analyze a few pre-defined particular phenomena such as sequence length, or need to perform the analysis per phenomenon. Our method, on the other hand, allows for a wide range of analytical perspectives in that it uses a massive amount of raw text to collect sentences in which individual neurons show strong interest and leverages pattern mining to highlight linguistic phenomena contained in the collected sentences.

As the most similar to our approach, Poerner et al. (2018) proposed a gradient-based method that generates input text which strongly activates neurons, inspired by work in computer vision (Simonyan et al., 2014). Their method differs from the probing methods in that it embodies the information captured by the neurons as text, which is similar to our study. However, their method can generate only text of pre-fixed length, and requires hyper-parameter tuning (*e.g.,* annealing temperature) to generate natural text, making it costly to apply to massive neurons in the models. Moreover, it is difficult for humans to interpret properties of the generated text just by observing them. In contrast, we propose an example-based method for collecting human-written sentences from a huge text corpora, determining which each neuron finds interesting, without any parameter tuning. By exploiting text mining techniques, we can reveal various linguistic phenomena as long as they appear in the source raw text.

3 Data-Driven Inspection of Neurons

This section describes our methodology for providing a deeper insight into a neural model at the finest level of granularity (i.e., neurons[1]). Our approach abstracts the sentences retrieved from a massive amount of text such as the BookCorpus (Zhu et al., 2015). The whole process is as follows.

Step 1: Collecting sentences activating neurons
This step finds which neurons consider what text to be interesting. Feeding a massive amount of raw text such as Wikipedia and BookCorpus (Zhu et al., 2015) to the target model, we collect a large number of sentences that are strongly associated with each neuron in the model (§ 3.1).

Step 2: Abstracting the collected sentences
This step finds what concrete linguistic phenomena each neuron finds interesting. We associate the collected sentences with linguistic annotations such as part-of-speech tags and available metadata such as topic and sentiment (Table 1). We then abstract a wide range of linguistic phenomena that exist in the retrieved sentences using data mining techniques such as frequent pattern mining, utilizing the associated information (§ 3.2). We call the resulting patterns as *linguistic signatures* of neurons.

3.1 Collecting Sentences Activating Neurons

We first feed a massive amount of text to the target model, and then extract sentences which strongly activate each neuron. In other words, we look for sentences that each neuron finds interesting. For this purpose, the size of the corpus can be reduced if there is a large diversity in the linguistic phenomena and domains contained in the corpus.

Since it is impractical to record the neurons' values for all the sentences, we use a priority queues to maintain only the top-N sentences that strongly activate each neuron.

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[4]12/20/2020 ver. https://dumps.wikimedia.org/enwiki
[5]http://kdd.ics.uci.edu/databases/reuters21578

3.2 Abstracting the Collected Sentences

Although the collected sentences embody various linguistic phenomena, it is difficult to induce the types of covered linguistic phenomena due to the diversity and redundancy of language. We therefore exploit data-mining techniques such as frequent pattern mining to obtain common patterns as *linguistic signatures*, which represent abstract properties of the sentences, for neurons. To help the pattern mining sum up sentences, we augment the collected sentences with linguistic annotations (here, part-of-speech tags) and metadata in advance.

Single-neuron analysis To understand which types of phenomena are captured by each neuron, we first rely on frequent (skip) n-grams obtained by using sequential pattern mining (Han et al., 2001).[6] We used relative frequency to find n-grams specific to individual neurons. We can also observe the distribution of the linguistic annotations (*e.g.,* part-of-speech tags) and metadata which capture traits of the sentences (*e.g.,* domain). By encoding the sentences collected for each neuron into vectors and clustering them, we can find the typical sentence which strongly activates the target neuron.

Cross-neuron analysis We compare the linguistic signatures (*e.g.*, common n-grams and distribution of metadata) obtained for individual neurons. We also extract groups of neurons that work together to capture the same linguistic phenomena by clustering continous neuron representations induced from the sentences collected for the neurons.

4 Experiments

Taking the pre-trained BERT (base-uncased) (Devlin et al., 2019) as an example, we demonstrate that our methodology can perform similar analysis to that obtained by existing approaches. We also provide novel findings on how and what aspects of language each neuron captures.

4.1 Settings

Data We use six English corpora in various domains to mine neuron-sentence interactions (Table 1). We split each corpus into sentences with a sentence tokenizer[7], and normalize repetitions of symbols[8] to a single symbol (*e.g.*, from +++ to

+). We then tokenize the resulting sentences with FastTokenizer,[9] and exclude sentences less than three tokens in length. In addition to metadata associated with text in the corpora, we annotate the sentences with part-of-speech (POS) tags using a POS tagger.[10] The statistics of the resulting corpora are summarized in Table 1.

Models We adopt the pre-trained BERT (base-uncased, 12 layers, and 768 dimensions of hidden states)[11] as the target for inspection (**pre-trained**). To investigate the effect of representation learning (*e.g.*, masked language modeling and fine-tuning) on the properties of neurons, we also examine two models: one with parameters randomly initialized (**random**) and the other with parameters fine-tuned on sentiment classification task (**fine-tuned**).

To fine-tune BERT, we use the training set in Sentiment140 (Go et al., 2009) that annotates the sentences with polarity labels (positive and negative). We passed the CLS token's output vector through a fully-connected layer, and updated the parameters of pre-trained with a learning rate of 10^{-5}, dropout rate of 0.3, batch size of 32, and 5 epochs. To obtain the **random** model, we randomly re-initialized only the parameters of the **pre-trained** model other than the word embedding layer since this paper conducts the analysis of 12-layer encoder's neurons excluding the embedding layers.

In experiments, we treat each hidden state as a neuron to be analyzed (i.e., 12×768 neurons in total in each model). Here we take the average over the hidden states of each token in the sentence for quantifying how strongly the neuron responds to the input. This is to find interesting "sentences" first, and then to find interesting words and phrases exploiting well-established pattern mining methods as described in § 3. Interesting future work will associate with each token the value of the hidden states after processing that token, and use the values to amplify the frequency of n-grams.

To find typical sentences among the sentences collected for each neuron by clustering the 10K sentences for each neuron (single-neuron analysis) and to find a group of neurons that capture similar linguistic phenomena by clustering continuous neuron representations induced from the 10K sentences (cross-neuron analysis), we represent each

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[6]Although here we use only part-of-speech taggers for annotation, we can exploit syntactic parsers and FREQT (Asai et al., 2004) to obtain common syntactic structures.

[7]nltk sentence tokenizer ver. 3.2.4

[8]!@#$%^&*()_+-=[]{};:?,.

[9]https://github.com/huggingface/tokenizers

[10]https://www.logos.ic.i.u-tokyo.ac.jp/ tsuruoka/lapos

[11]https://github.com/huggingface/pytorch-pretrained-BERT

Noun neuron; 740th hidden state in 3rd layer	
words	william, john, roBERT, de, edward
word pattern	(Sir William), (Sir John)
POS pattern	(NNP NNP NNP), (NNP IN NNP), (NNP NNP IN)
ratio of POS	noun: 91.7%, verb: 0.9%, adj.: 0.4%
avg. length	3.8
typical sent.	*The architects of the Square Mile included RoBERT Findlay, Bruce ...*

Verb neuron; 462nd hidden state in 6th layer	
words	going, got, help, need, get, know
word pattern	(going to have), (we have to)
POS pattern	(PRP TO VB), (VBP TO VB), (VBG TO VB)
ratio of POS	noun: 16.6%, verb: 29.8%, adj.: 1.1%
avg. length	6.4
typical sent.	*Something was going to have to give, and it wasn't going to be him.*

Social Media neuron; 200th hidden state in 6th layer	
Words	lol, im, u, twitter, haha, ur, like, miss
word pattern	(I my), (i it), (i i), (I was), (i lol)
POS pattern	(NN NN NN), (NN NN), (PRP NN)
ratio of POS	noun: 29.8%, verb: 18.3%, adj.: 6.3%
avg. length	7.6
typical sent.	*nooo I got so many tho That sucks I finished the boook and now I'm ...*

Short sentence neuron; 169th hidden state in 1st layer	
words	war, party, revolutionary, ibn
word pattern	(of the), (the of), (Giovanni Battista)
POS pattern	(NNP NNP NNP), (NNP IN NNP), (DT NNP NNP)
ratio of POS	noun: 67.5%, verb: 5.5%, adj.: 5.3%
avg. length	3.5
typical sent.	*The Tale of Loyal Knights and ...*

Science neuron; 705th hidden state in 9th layer	
words	species, family, genus, found, sea
word pattern	(is in the), (is of the), (is a the)
POS pattern	(IN NNP), (DT IN), (IN DT)
ratio of POS	noun: 34.4%, verb: 11.5%, adj.: 7.0%
avg. length	16.7
typical sent.	*Pachliopta polyphontes is a species of butterfly from the family Papilionidae...*

Positive neuron; 43rd hidden state in 7th layer	
words	chapter, love, welcome, good, ha
word pattern	(Chapter Chapter Chapter), (the of the)
POS pattern	(DT JJ NN), (PRP DT NN), (PRP RB JJ)
ratio of POS	noun: 42.3%, verb: 7.7%, adj.: 4.2%
avg. length	8.1
typical sent.	*doing great sweetie, about to take my dog for a walk in the park (while ...*

United States neuron; 203rd hidden state in 7th layer	
words	freyja, united, states, house, election
word pattern	(is going be), (was going be)
POS pattern	(DT JJ NN), (PRP DT NN), (PRP RB JJ)
ratio of POS	noun: 63.3%, verb: 1.6%, adj.: 2.8%
avg. length	8.0
typical sent.	*1912 United States House of Representatives election in Wyoming ...*

Olympic neuron; 69th hidden state in 6th layer	
words	olympics, summer, games
word pattern	(United States in), (United States of)
POS pattern	(NNP NNP NNP), (NNP IN NNP)
ratio of POS	noun: 36.2%, verb: 7.4%, adj.: 3.6%
avg. length	17.4
typical sent.	*In the 5000 metres she competed at the 1995 World Championships and the ...*

Table 2: Examples of neurons and their linguistic signatures extracted from the top-10K sentences to which they strongly responded. The neurons were manually named to highlight the linguistic phenomena they capture (§ 4.2). The "word" and "word/POS pattern" rows show the most frequent patterns in the 10K sentences. The "typical sent." is that is closest to the average vector of the collected 10K sentences when they are vectorized (§ 4.1).

sentence as vectors, and take average over the 10K sentence vectors to obtain neuron representations. Specifically, we represent each sentence with an average of 300-dimensional fastText embeddings (Bojanowski et al., 2017)[12] of the tokens.

4.2 Single-Neuron Analysis

We collected 10K sentences corresponding to each neuron, and identified the common linguistic phenomena in those sentences by using frequent pattern mining. We found interpretable neurons from several perspectives. As inspired by Quiroga et al. (2005) that reports the existence of a "Halle Berry neuron" in a human brain analysis, we gave distinguished names to represent the roles of neurons (*e.g., Science neuron* is activated by text in science domain), and showed some of the linguistic phe-

nomena they captured in Table 2.

With the help of the automatic linguistic annotations, we found neurons that responded only to nouns or verb-rich sentences (*Noun* or *Verb neuron*), and neurons that responded only to short sentences (*Short-length neuron*). Digging deeper into what kind of text *Noun neuron* is actually responding to, we can see another aspect; it responds to names of people such as "william" and "john." It would be very interesting to investigate the relationship between the existence of neurons corresponding to these fundamental linguistic annotations and the task performance of the model.

By looking at the metadata distribution for the collected sentences, we also found neurons that responded to specific domains/concepts. For example, 82.2% of the 10K sentences corresponding to one neuron were taken from the social media domain in Table 1 (*Social Media Neuron*), 80.2%
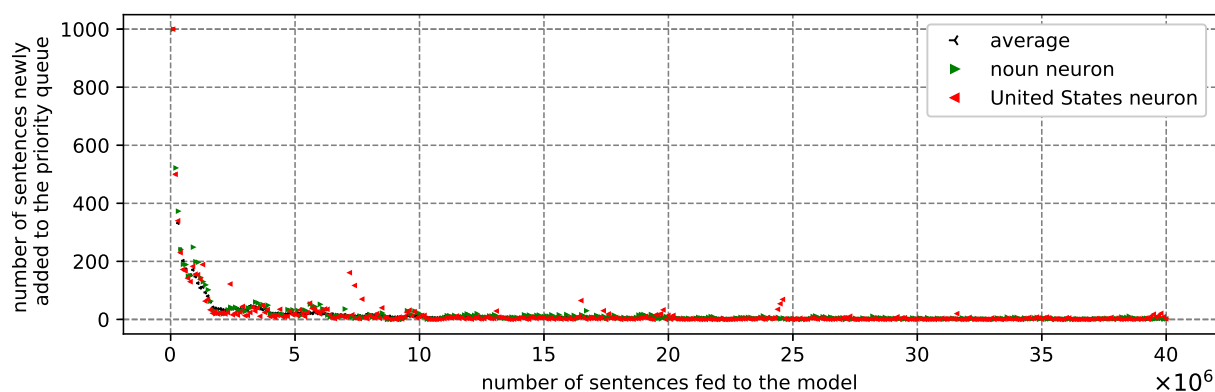
Figure 1: The average number of sentences that were newly added to top-1000 of the priority queues of each neuron for every 100K input sentences when we apply our method to the sentences taken from Wikipedia (Table 1).

of the 10K sentences for another neuron consist of positive sentiment documents[13] (*Positive Neuron*), and 45.3% of the 10K sentences for a third neuron are scientific documents[14] (*Science Neuron*). Moreover, digging deeper into the abstracted linguistic phenomena in Table 2, we can see that *the Social Media neuron* actually responds to informal words such as "lol" and "haha," and *Science neuron* has a role in responding strongly to relatively uncommon words such as "species" and "genus." It is an interesting direction to investigate the relationship between the robustness of the model to the domain and the existence of these domain-specific neurons.

We can also reveal the topic-specific neurons by using a list of words that represent particular topics. For example, we have found neurons that are strongly activated by the words "united states, us, u.s., u.s.a, america" (*United States neuron*) and neurons that strongly respond to the words "olympic" (*Olympic neuron*). It would be interesting to investigate the relationship between the existence of such topic-specific neurons and the knowledge possessed by the model (Petroni et al., 2019).

As we have demonstrated so far, the proposed method can find characteristic neurons from various perspectives in a bottom-up manner. It can also reveal information about the properties of neurons (i.e., specific text and linguistic phenomena) that are not covered by the probing task performance (i.e., numerical value). By comparing neurons based on the collected sentences and the linguistic signatures (abstracted phenomena), we can gain insight into the target model components at any level of granularity, as we will demonstrate in the next section.

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[13]Sentences of *positive* class in Sentiment140 dataset.
[14]Sentences of *sci* class in 20Newsgroups dataset.

On the frequency in updating top-N sentences With the datasets in Table 1 and our server with two Intel® Xeon® E5-2680 v4 2.40-GHz CPUs and eight NVIDIA Quadro P6000 GPUs, analysis of BERT by our method took about 10 hours for Step 1, and about five minutes per neuron for Step 2. The computation time in Step 1 can be reduced if we stop feeding sentences to the target model when the elements of priority cues for neurons become stable.

To confirm this, we performed the Step 1 using the 40M sentences in the Wikipedia corpus in Table 1 with a single GPU on the same server, and checked how many sentences were newly added to the priority queues on a neuron-average basis for every 100K sentences input. Figure 1 shows that after feeding about 2M sentences into the model, 96% of the sentences in the priority queues have already been fixed. This indicates that we can truncate the computation in Step 1 by monitoring the frequency in updates on the priority cues.

We should mention that priority queues for a few neurons are frequently updated even after feeding the model with millions of sentences. This happens if the neurons capture very specific phenomenon, such as *the United States neuron* in Table 2. This suggests that we should diversify the feeding sentences to include various linguistic phenomena as possible when we want to reduce the amount of the corpus fed to the model.

4.3 Cross-Neuron Analysis

Clustering neuron vectors induced from the collected sentences We leverage the collected 10K sentences for individual neurons to obtain example-based neuron representations (vectors), and then cluster the obtained neuron vectors to identify co-
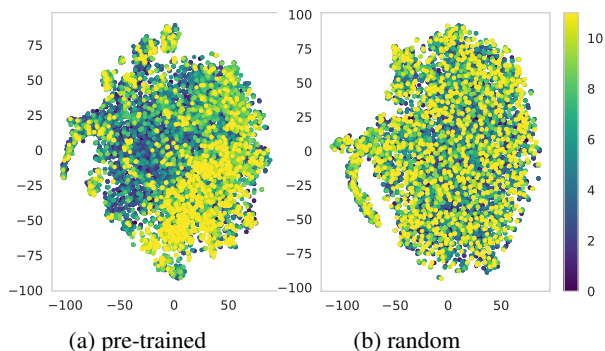
(a) pre-trained   (b) random

Figure 2: Clustering neurons in both models. Each neuron is represented by the average of the sentence vectors of the corresponding 10K sentences. The color indicates the layer in which the neuron is located.
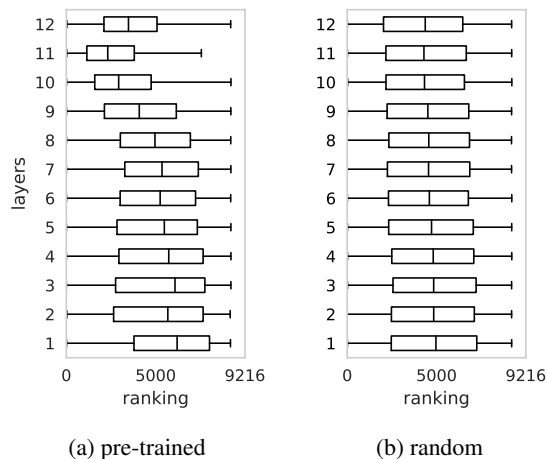

(a) pre-trained   (b) random

Figure 3: Ranking neurons in the models in terms of how selectively the neuron responds to a specific part-of-speech. The box-and-whisker diagrams show where the neurons in each layer are distributed in the ranking.

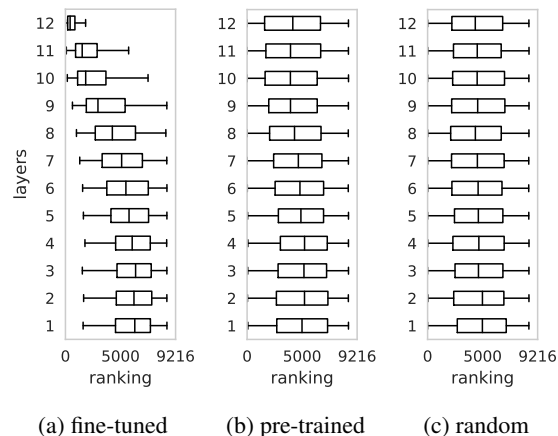(a) fine-tuned   (b) pre-trained   (c) random

Figure 4: Ranking neurons by standard deviation of sentiment polarity of the collected sentences. The box-and-whisker diagrams show the distribution of each layer's neurons in the ranking.

operating neurons. Here we verify a hypothesis that neurons in the same layer are cooperating. First, we represent each neuron with an average of the vectors for the corresponding 10K sentences. Next, we perform k-means clustering of these 12×768 neuron vectors. The number of clusters is set to 12, which is identical to the number of layers. We report the accuracy of the clustering using the Hungarian algorithm (Kuhn, 1955).

The clustering accuracy is 15.9% for the **pre-trained** model compared to 9.6% for the **random** model. This result suggests that although the overall performance is low, the pre-training made the neurons in each layer capture similar linguistic phenomena, reconfirming results of the existing studies that explore each layer in a top-down manner (§ 2) had a reasonable point of view.

Figure 2 visualizes the neuron vectors using t-SNE (van der Maaten and Hinton, 2008). The heatmap shows which layer the neurons (vectors) belong to. We can see that the pre-trained BERT's neurons in the shallower and deeper layers form different clusters.

Ranking neurons by the skewness of captured linguistic phenomena By ranking (sorting) the neurons by the frequency of each linguistic phenomenon and the deviation of their distribution, we can examine where the neurons that represent each linguistic phenomenon are distributed in the model. Here, we take the simplified version of the PTB part-of-speech tags for nouns, verbs, and adjectives (Table 1) and binary sentiment polarity as the target linguistic phenomenon.

For part-of-speech tags, we find neurons that selectively respond to a specific part-of-speech tag. First, we normalize the frequency of each part of speech tag in the 10K sentences collected for each neuron using the frequency obtained from the original corpus (Table 1). The maximum relative frequency (percentage) among all the part-of-speech tags is then used as a measure of how selectively the neuron responds to a particular part of speech tag. For sentiment polarity, we find the neurons that selectively respond to a particular polarity (i.e., positive and negative). First, we calculate the standard deviation of the binary sentiment polarity distribution of the 10K sentences collected for each neuron, and then use this as a measure of how much the neuron responds to a particular sentiment.

Figure 3 and 4 show the results of ranking the neurons in each layer for their selective responsive-
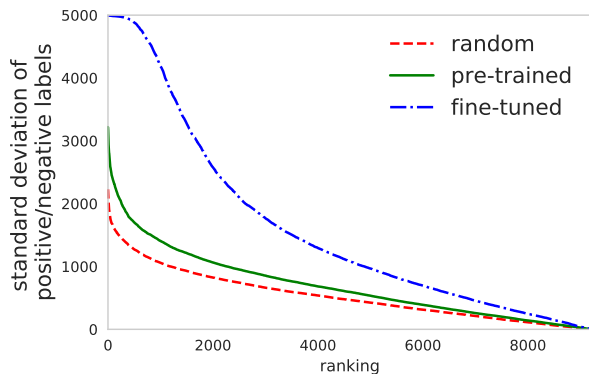
Figure 5: Ranking neurons in the three models by standard deviation of sentiment polarity of the collected sentences.

ness to part-of-speech and sentiment polarity. The box-and-whisker diagrams show where the neurons in each layer are distributed in the ranking. From the figures, we can see that **random** model results in a ranking of neurons that is independent of the layer, while the **pre-trained** model tends to show that neurons in deeper layers are more selectively responsive to both phenomenon.

Interestingly, for the POS tagging task, it has been reported that neurons in the lower layers are better able to handle the probing task (Tenney et al., 2019a). This suggests that, for POS tagging, the presence of neurons that respond uniformly to part-of-speech tags has a significant influence on POS tagging performance. For sentiment polarity, we also calculated the ranking of the neurons in the **fine-tuned** model. Figure 4 shows that the neurons of the **fine-tuned** model in the deeper layers become more capable of capturing the sentiment of the text, while the neurons in the shallower layers are kept insensitive to the polarity of the text.

Figure 5 depicts the results of ranking the neurons in each model, where the y-axis represents the standard deviation of sentiment polarity of the collected sentences for the ranked neurons. We can see that the models have increased the percentage of neurons that show a certain degree of selective response to specific sentiment polarity by pre-training and by fine-tuning. It will be interesting to utilize this standard deviation to measure the distance between the two tasks.

5 Conclusions

This study aims to provide a method of exploratory model analysis for a neural NLP model at various levels of granularity ranging from individual

neurons to the model as a whole, and proposed a bottom-up methodology for revealing what kind of concrete linguistic phenomena each neuron of the model strongly responds to. We take advantage of large-scale text data and data mining techniques to extract linguistic signatures (common patterns) that characterize the individual neurons.

Taking BERT (base-uncased) as an example, we first showed that specific phrases such as those related to United States are captured by individual neurons in BERT (*e.g., United States Neuron* in Table 2). By comparing neurons in terms of the collected sentences they strongly respond to, we then revealed that neurons in the same layer of BERT have similar properties. Lastly, in comparing the corresponding linguistic phenomena with those of neurons in randomly initialized and fine-tuned models, we found that neurons in deeper BERT layers capture more linguistic phenomena specific to language modeling and sentiment classification.

In the future, we plan to investigate models with different architectures. For example, our method can be used to compare the differences of encoder and decoder neurons in end2end models; there is a debate in the field of neural machine translation as to whether modifying the encoder or the decoder contributes more to domain adaptation (Wang et al., 2021).

Our method enables us to find non-apriori linguistic phenomena the neurons may capture, so that it is possible to assist in the construction of a novel training/evaluation dataset for the probing-based evaluation methods. In addition, our method provides information of a different nature, i.e., the concrete linguistic phenomena to which the internal representations respond, as opposed to numerical information such as accuracy of probing tasks.

As mentioned in § 4.2, our method has the potential to perform with less time complexity by reducing the corpus size fed to the target model in Step 1. Therefore, we plan to study how to select a text corpus of such a small size that it reproduces the analysis results obtained when using a very large corpus as the one used in this study.

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