Are All Neurons Created Equal? Interpreting and Controlling BERT through Individual Neurons

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Abstract

While many studies have shown that linguistic information is encoded in hidden word representations, few have studied individual neurons, to show how and in which neurons it is encoded. Among these, the common approach is to use an external probe to rank neurons according to their relevance to some linguistic attribute, and to evaluate the obtained ranking using the same probe that produced it. We show that this methodology confounds distinct factors—probe quality and ranking quality—and thus we separate them. We compare two recent ranking methods and a novel one we introduce, both by probing and by causal interventions, where we modify the representations and observe the effect on the model's output. We show that encoded information and used information are not always the same, and that individual neurons can be used to control the model's output, to some extent. Our method can be used to identify how certain information is encoded, and how to manipulate it for debugging purposes.

1 Introduction

What linguistic information is encoded in a hidden representation? A popular approach to tackle this question is by probing: training a simple model to predict some information from the representation [Adi et al., 2017, Conneau et al., 2018]. Most studies focus on training the classifier using the entire high-dimensional representation to predict the desired attribute. Such a method can show whether the information is encoded in the representation, but not **how** it is encoded: in which neurons? is it localized (concentrated in a small set of neurons) or dispersed? A few recent studies [Elazar et al., 2021, Feder et al., 2020] have tackled a related, causal question: given that the information is encoded, is it actually being used by the language model that encoded it? If we want to alter a model's behaviour—for example, for debugging purposes—we would like to know both how the information is encoded and whether it is used by the model. Such knowledge may allow us to modify specific neurons of the representation in a certain way that would change the model's output, with respect to that attribute—as in Bau et al. [2019]—and provide us with parameters-level explanations of the model's decisions. Other reasons to look at individual neurons can be to reduce the number of components in the model, using methods such as pruning [Voita et al., 2019, Sajjad et al., 2020], as well as gain a general scientific understanding of the model.

In this work, we focus on two prior neuron ranking methods, which aim to rank the neurons of a word representation according to their importance for a linguistic property, such as part of speech. Both of these methods—LINEAR [Dalvi et al., 2019] and GAUSSIAN [Torroba Hennigen et al., 2020]—rely on an external probe to obtain a ranking: the first makes use of the internal weights of a linear probe, while the second considers the performance of a decomposable generative probe.

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Both methods evaluate the quality of their ranking according to the probe's accuracy using only the k-highest ranked neurons. However, using this metric, two distinct factors are conflated: the probe's quality as a classifier, and the quality of the ranking it produces. We claim that we should separate the two: a good classifier may provide good results even if its ranking is bad, and an optimal ranking may cause an average classifier to provide better results than a good classifier that is given a bad ranking. To avoid this conflation, we propose a simple ranking method, CLUSTER, which ranks neurons according to the difference in their values across labels, and thus can be derived directly from the data, with no probing involved.

To disentangle probe quality and ranking quality, we use a probe from one method with a ranking from another one. We find that while GAUSSIAN generally provides higher accuracy, its selectivity [Hewitt and Liang, 2019] is lower, implying that it relies more on memorization, which improves probing quality but not necessarily ranking quality. We further find that GAUSSIAN provides the best ranking for small sets of neurons, while LINEAR provides a better ranking for large sets.

To apply a comparison that focuses on the rankings and is free of probing, and to find which ranking selects neurons that are used by the model, we apply interventions on the representation: we modify subsets of neurons from each ranking and observe the effect on language modeling w.r.t to the property in question. We find that CLUSTER tends to select neurons that are used by the model, more so than the two probing-based rankings.

We introduce a novel intervention method that allows a fine-grained control of the model's output with respect to a linguistic attribute, to some extent. For example, intervening on the tense attribute in English may turn the words "using" and "think" into "used" and "thought". This method can be used as a neuron-level debug tool, allowing developers to understand how easy or hard it is to reduce or magnify some of the model's properties, e.g., gender bias, by observing how the gender attribute is spread along the neurons and the success rate of changing a word's gender. By comparing probing results and intervention results, we deduce that there is an overlap between encoded information and used information, but they are not the same.

We experimentally analyze the M-BERT model [Devlin et al., 2019] on 9 languages and 12 morphological attributes, from the Universal Dependencies dataset [Zeman et al., 2020]. Our experiments reveal the following insights:

- We show the need to separate between probing quality and ranking quality, by showing cases where intentionally poor rankings provide better accuracy than good rankings, due to probing weaknesses.
- We present a new ranking method that is free of any probes, and tends to prefer neurons that are being used by the model, more so than existing probing-based rankings.
- We show that there is an overlap between encoded information and used information, but they are not the same.
- We show the advantage of looking into individual neurons, especially for debugging purposes, to allow a fine-grained control over the model's output.

2 Neuron Rankings and Data

We begin by introducing some notation. We denote the word representation space as $H \subseteq \mathbb{R}^d$ and an auxiliary task as a function $F : H \rightarrow Z$, for some task labels Z (e.g., part-of-speech labels). Given a word representation $h \in H$ and some subset of neurons $S \subseteq \{1, ..., d\}$, we use h_S to denote the subvector of h in dimensions S. For some auxiliary task F and $k \in \mathbb{N}$, we search for an optimal subset S^* such that $|S^*| = k$ and h_{S^*} contains more information regarding F than any other subvector $h_{S'}, |S'| = k$. For the search task, we define *neuron-ranking* as a permutation $\Pi(d)$ on $\{1, ..., d\}$ and consider the subset $\Pi(d)_{[k]} = \{\Pi(d)_1, ..., \Pi(d)_k\}$. Our goal is to find an optimal ranking $\Pi^*(d)$ such that $\forall k, \Pi^*(d)_{[k]}$ is the optimal subset with respect to F. However, finding such an optimal ranking, or even an optimal subset, is NP-hard [Binshtok et al., 2007]. Thus, we focus on several methods to produce rankings, which provide approximations to the problem, and compare them.

2.1 Rankings

The ranking methods we compare include two rankings obtained from previously suggested probing-based neuron-ranking methods, and a novel ranking we propose, based on data statistics rather than probing.

2.1.1 LINEAR

The first method, henceforth LINEAR (named linguistic correlation analysis in Dalvi et al. [2019]), trains a linear classifier on the representations to learn the task F. Then, it uses the trained classifier's weights to rank the neurons according to their importance for F. They showed that their method identifies important neurons through probing and ablation studies, and found that while the information is distributed across neurons, the distribution is not uniform, meaning it is skewed towards the top-ranked neurons. In Dalvi et al. [2019], after the probe has been trained, its weights are fed into a neuron ranking algorithm. However, we observed that the proposed algorithm distributes the neurons equally among labels, meaning that each label would contribute the same number of neurons at each portion of the ranking, regardless of the amount of neurons that are actually important for this label. Thus, we chose a different way to obtain the ranking: for each neuron, we compute the mean absolute value of the $|Z|$ weights associated with it, and sort the neurons by this value, from highest to lowest. In early experiments we found that this method empirically provides better results, and is more adapted to large label sets.

2.1.2 GAUSSIAN

The second method, henceforth GAUSSIAN [Torroba Hennigen et al., 2020], trains a generative classifier on the task F, based on the assumption that each dimension in $\{1, ..., d\}$ is Gaussian-distributed. Then, it makes use of the decomposability of the multivariate Gaussian distribution to greedily select the most informative neuron, according to the classifier's performance, from $\{1, ..., d\}$ at every iteration. This way we greedily obtain a full neuron ranking after training only once, while applying this greedy method to LINEAR would require retraining the probe $d!$ times, which is clearly infeasible. They found that most of the tasks can be solved using a relatively low number of neurons, but also noted that their classifier is limited due to the Gaussian distribution assumption.

2.1.3 CLUSTER

The third neuron-ranking method we experiment with is based purely on the representations, with no probing involved, making it free of probing limitations that might affect ranking quality. For every attribute label $z \in Z$, we calculate $q(z)$, the mean vector of all representations of words that possess the attribute and the value z. Then, we calculate the element-wise difference between the mean vectors,

$$r = \sum_{z,z' \in Z} |q(z) - q(z')| \tag{1}$$

and obtain a ranking by arg-sorting r, i.e., the first neuron in the ranking corresponds to the highest value in r. In the case of a binary-valued attribute, this is simply the difference in means. For attributes with more than two values, CLUSTER prefers neurons that separate different labels over neurons that have a similar value across labels.

2.2 Data

Throughout our work, we follow the experimental setting of Torroba Hennigen et al. [2020]: we map the UD treebanks [Zeman et al., 2020] to the UniMorph schema [Kirov et al., 2018] using the mapping by McCarthy et al. [2018]. We select a subset of the languages used by Torroba Hennigen et al. [2020]: Arabic, Bulgarian, English, Hindi, Finnish, French, Russian, Spanish and Turkish, to keep linguistic diversity. We work with morphological attributes from these languages. Full data details are provided in Torroba Hennigen et al. [2020] and further data preparation steps are detailed in Appendix A.1. We process each sentence in a pre-trained M-BERT, and take word representations from layers 2, 7 and 12 of the model, to see if there are different patterns in the beginning, middle and end of the model. We end up with a total of 156 different configs (language, attribute, layer) to test. For words that are split during tokenization, we define their final representation to be the average

over their sub-token representations. Thus, each word has one representation for each layer, of 768 dimensions. We do not mask any words throughout our work.

3 Probing

Given some ranking $\Pi(d)$, we would like to evaluate how well it sorts the neurons for the task F. Our first ranking-evaluation approach is the standard probing approach from previous work [Dalvi et al., 2019, Torroba Hennigen et al., 2020], where we expose the classifier to a subvector of the representation and evaluate how well it predicts the task. However, while previous work conflated rankings and classifiers, we are more careful: we separate the two, and pair each ranking with two classifiers, meaning that at least one of them is completely unrelated to the ranking.

Formally, for an increasing $k \in \mathbb{N}$, we train a classifier $f_\theta : H_k \to Z$ with parameters θ to predict the task label, $F(h)$, solely from $h_{\Pi(d)_{[k]}}$ (the subvector of the representation h in the top k neurons in ranking Π), ignoring the rest of the dimensions.[1] The general assumption is that the better f_θ performs, the more task-relevant information is encoded in $h_{\Pi(d)_{[k]}}$. Yet, the behaviour of f_θ itself might affect results and conclusions about the ranking. Hence, we aim for a fine-grained analysis of our results, and also measure selectivity (§ 3.1.1).

3.1 Experimental Setup

As classifiers, we experiment with both classifiers used by the first two ranking methods (§ 2.1.1, 2.1.2). As rankings, we experiment with the 3 ranking methods described in 2.1. For each, we use the original ranking it produces and its reversed version, and refer to them as top-to-bottom and bottom-to-top, respectively. To those we add a random ranking baseline, ending up with 7 different rankings overall. We compare all classifier-ranking combinations for the same k.

Since both of the first two ranking methods are inherently tied to the classifier that was used to generate them, and the third ranking is a classifier-neutral ranking, it can be used for a fair comparison between the classifiers.

3.1.1 Metrics

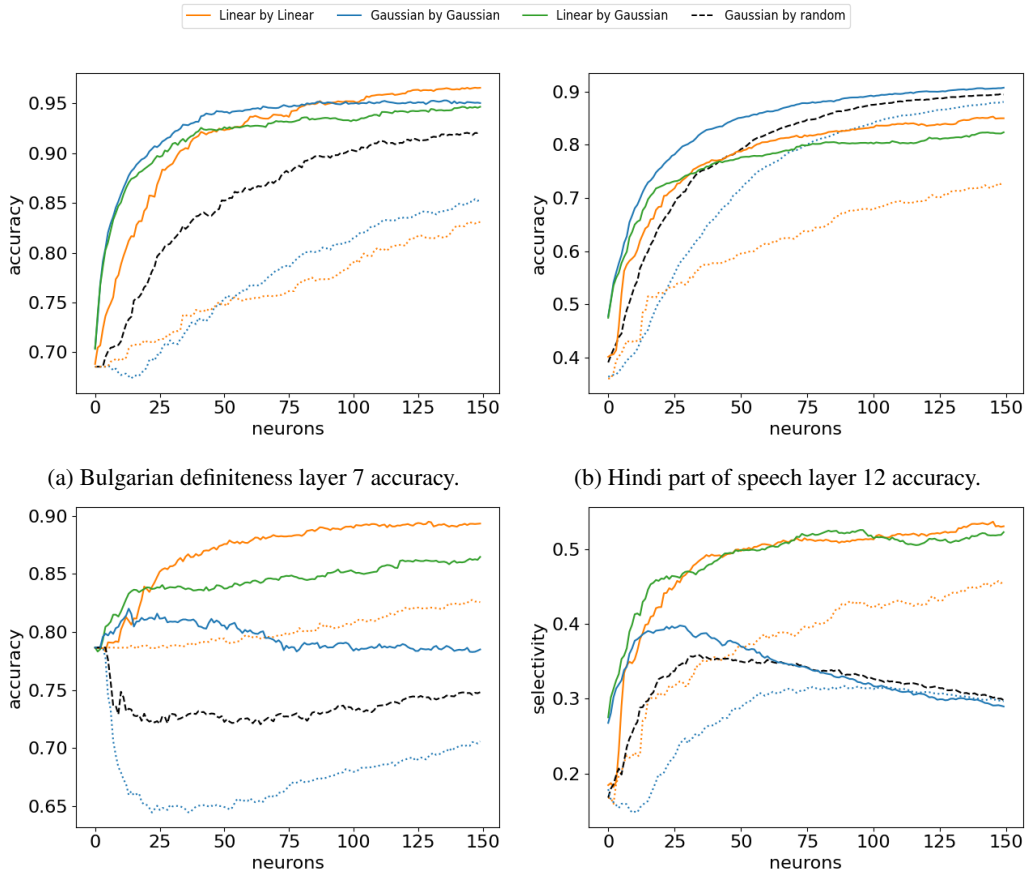
Accuracy First, we measure the accuracy of the probe's predictions. Since we experiment with many different configs, we use the Wilcoxon signed-rank test [Wilcoxon, 1992] as a statistical significance test to determine whether a certain combination of a classifier and a ranking is statistically significantly better than another combination.

Selectivity We also evaluate our probes by selectivity [Hewitt and Liang, 2019], which is defined as the difference between the classifier's accuracy on the actual probing task and its accuracy on predicting random labels assigned to word types, called a control task. Low selectivity implies that the probe is capable of memorizing the word-type–label pair, and so high accuracy in the probing task does not necessarily entail the presence of the linguistic attribute. Thus, we prefer probes that are both accurate and selective.

3.2 Results

Across the 156 configs we tested, we found 3 distinct accuracy patterns. Examples are found in Fig. 1, where the pattern from Fig. 1a is observed in $\sim 50\%$ of the configs, and the patterns from Fig. 1b and 1c are observed in $\sim 25\%$ each. In these figures, each color represents a combination of a classifier and a ranking, where a solid line is used for the top-to-bottom version of the ranking and a dotted line is for the bottom-to-top version of it, and a dashed line is used for random ranking. Some lines have been omitted from the graphs for clarity. In most experiments, we get high accuracy using a rather small portion of the neurons, in line with Torroba Hennigen et al. [2020]. It implies that representations can be pruned for certain uses, keeping specific information. We now turn to analyze the patterns we observe.

[1] We only probe into representations of words that possess the attribute, e.g., if the attribute is gender we do not probe into the representation of the word "pizza".



(a) Bulgarian definiteness layer 7 accuracy.

(b) Hindi part of speech layer 12 accuracy.

(c) Russian animacy layer 2 accuracy.

(d) Hindi part of speech layer 12 selectivity.

Figure 1: Probing accuracy results from three different configs, and selectivity results from one of them. Solid lines are top-to-bottom rankings; dashed are random rankings; dotted are bottom-to-top rankings. Some lines are omitted for clarity.

3.2.1 Ranking Methods are Inherently Consistent

In most configs, each classifier provides better accuracy using a top-to-bottom ranking (solid lines) compared to the bottom-to-top version of the same ranking (same color, dotted line), and the random ranking (dashed lines) is in between. This is also seen in our statistical significance tests (Appendix A.2). We conclude that even if they are not optimal, all ranking methods we consider generally rank task-informative neurons higher than non-informative ones.

3.2.2 Which classifier is better?

In order to assess which classifier is better, for each ranking, we compare results of the two classifiers. This comparison is not seen in prior work, as classifiers and rankings have not been separated.

Across most experimental configs (Figs. 1a, 1b), GAUSSIAN achieves better accuracy than LINEAR when both of them use the same ranking (including top-to-bottom LINEAR), especially when using small sets of neurons. Our statistical significance tests (Appendix A.2) show that GAUSSIAN performs significantly better than LINEAR with 6 out of the 7 rankings we tried when using 10 neurons, with 5 rankings when using 50 neurons, and with 5 rankings when using 150 neurons. We now turn to analyze what makes GAUSSIAN more successful, and show some exceptions.

GAUSSIAN is Memorizing Across all configs, LINEAR provides higher selectivity than GAUSSIAN using any ranking, after a certain point. One example is found in Fig. 1d. This means that GAUSSIAN tends to memorize the word-type–label pair when solving the task. While this is apparent in all

configs, we note that specifically in the part-of-speech attribute there is a large portion of function words, i.e. closed set labels (e.g., pronouns, determiners), meaning that memorization can significantly help solving the task. Thus, in most configs involving part of speech, GAUSSIAN has the upper hand—after a certain number of neurons have been selected—even when it is using a bottom-to-top ranking and LINEAR is using a top-to-bottom ranking. One example is found in Fig. 1b, where the dotted blue line overcomes the solid orange line after selecting ~ 90 neurons.

LINEAR is More Stable On the other hand, there are certain configs where GAUSSIAN is struggling to model the distribution, resulting in mediocre accuracy results—which even start decreasing at some point—sometimes even below majority baseline, as seen in Fig. 1c. This has also been mentioned in Torroba Hennigen et al. [2020]. We hypothesize that it happens because in those configs, there are only a few (or no) dimensions where the Gaussian assumption holds. Thus, in its ranking algorithm, GAUSSIAN first selects dimensions that are both informative and Gaussian-distributed, but as we make it select more, it selects dimensions that do not fulfill these conditions, making the modeling of the distribution less similar to the real one. Poor modeling then leads to wrong predictions and low accuracy. In those configs, the worst version of LINEAR provides better accuracy than the best version of GAUSSIAN. In general, LINEAR behaves similarly across configs, making it more stable.

3.2.3 Which ranking is better?

When looking at rankings, we would like to compare performance of the same classifier, using different rankings. We would expect that each classifier would perform best when using the ranking it has generated. However, this is not always the case. As we can see in Fig. 1, for small sets of neurons, LINEAR actually achieves better accuracy when using GAUSSIAN's ranking (solid green) than its own ranking (solid orange). As the number of neurons increases, at some point its accuracy with its own ranking becomes higher than with GAUSSIAN's ranking.

We suggest two explanations for this phenomenon: First, due to its greediness, the GAUSSIAN ranking is not guaranteed to provide the optimal subset. For a subset of size 1, it goes over all possibilities, but as the size grows there are more subsets that are not taken into consideration in the algorithm, so it is more likely to miss the best sets.

Second, GAUSSIAN assumes the embedding distribution to be Gaussian. On dimensions which are not Gaussian-distributed, it makes a less accurate evaluation of the contribution of each neuron. So, if a neuron is informative towards the attribute but is not Gaussian-distributed, its addition to the selected neurons set is unlikely to improve performance, and thus it is not selected. This is a problem with a performance-based selection criterion, where the selection of neurons depends on the performance of the probe.

To summarize, it seems that GAUSSIAN is good at selecting specific informative neurons, but misses the rest. While LINEAR's ranking is not optimal (it is definitely worse then GAUSSIAN's on small sets), it does seem to be more stable on different sizes.

4 Interventions

The variance of results in our probing experiments can mostly be attributed to probing limitations [Hewitt and Liang, 2019, Pimentel et al., 2020, Belinkov, 2021, Ravichander et al., 2021], and emphasizes the need to distinguish between two properties: the probe's classification quality, and the neuron-ranking quality. To isolate the latter, and to shed light on which ranking prefers neurons that are actually being used by the model, we take a second ranking-evaluation approach: we intervene by modifying the representation in the neurons selected by the ranking, and observe how (and if) our intervention affects the language model output. This approach is more of a causal one, inspired by similar prior work [Giulianelli et al., 2018, Elazar et al., 2021, Feder et al., 2020], and can provide neuron-level explanations to some of the model's decisions. We note that in this section, we use only the ranking itself, detaching it from any probes, thus removing classification quality from ranking comparisons.

Formally, for a representation $h \in H$, ranking $\Pi(d)$ (corresponding to an attribute F) and an increasing $k \in \mathbb{N}$, we intervene by modifying h only in the $\Pi(d)_{[k]}$ neurons, and observe the effect

our intervention had on the model's output—the word prediction (given the modified representation).[2] We divide the model to two components: an encoder $E : V \rightarrow H$ and a decoder $D : H \rightarrow V$, such that for interventions in layer i, E is composed of all the layers of the model up to (including) i, and D is composed of all of the rest of the layers. After receiving a representation $h = E(w)$ for word w, we intervene and modify h to get a new representation h'. If $D(h) \neq D(h')$, then D is using the information we modified.

However, knowing that the information is being used is not enough; we would like to know to what purpose it is being used, and to verify that it only affects the specific attribute we are interested in. Thus, we perform a finer-grained analysis, and check if $D(h')$ is similar, to some extent, to $D(h)$. For that, we define a lemmatizer $L : V \rightarrow V$, which maps words to their lemmas, and an analyzer $A : V \rightarrow Z$, which maps words to their task labels. Our goal is to intervene such that $L(D(h)) = L(D(h'))$, but $A(D(h)) \neq A(D(h'))$. If this is the case, it implies that we have successfully identified where the task-relevant information that D uses is encoded, and how it is being used.

4.1 Intervention Methods

We consider two methods for modifying $h_{\pi(d)_k}$, and compare them.

Ablation A common modification method is trying to remove the information [Ravfogel et al., 2020] by ablating some neurons [Bau et al., 2019, Lakretz et al., 2019], meaning we set $h_{\pi(d)_k} = 0$. By that we aim to erase the information encoded in $h_{\pi(d)_k}$.

Mirroring Gonen et al. [2020] tried to translate words to different languages by calculating representations for the source and target language, substracting the source language representation from the word representation and adding the target language representation. We experiment with a similar method, with two differences: 1. We modify only parts of the representation. 2. Realizing that different neurons have different impact on the output, we apply a different modification for every neuron: the modification for neuron i is multiplied by α_i, where $\alpha \in \mathbb{R}^d$ is a log-scaled coefficients vector in the range $[0, \beta]$, such that the coefficient of the highest-ranked neuron is β and that of the lowest-ranked neuron is 0, and β is a hyperparameter. Thus, for every attribute label $z \in Z$, we calculate $q(z)$ as in 2.1.3, and for every word with label z, we intervene by setting:

$$h_{\Pi(d)_{[k]}} = h_{\Pi(d)_{[k]}} + \alpha_k(q(z')_{\Pi(d)_{[k]}} - q(z)_{\Pi(d)_{[k]}}) \tag{2}$$

for a random attribute label $z' \in Z, z \neq z'$. Note that the rest of the neurons—those not in $\Pi(d)_{[k]}$—remain unaffected. Our goal is to take a step in the direction of the other label, where bigger steps are applied to neurons that are marked as more important for the attribute. In that, we give each neuron its own special treatment—an approach that was not applied before (as far we know).

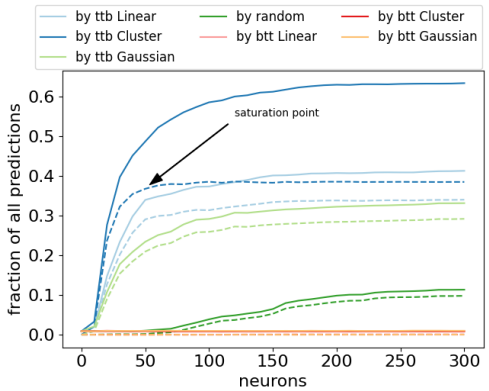
4.2 Experimental Setup

We handle the data the same way as in our probing experiments. However, since we analyze the model's predictions—which may be different from the original input—we do not have gold morphology labels anymore. Thus, for morphologically analyzing the model's predictions (L and A), we use spaCy [Honnibal et al., 2020]. Out of the languages we used in our probing experiments, in this section we use only those that are supported by spaCy (English, Spanish and French). We calculate $q(z)$ based on the entire training set, and perform our interventions on the test set. We compare the same 7 rankings we used in our probing experiments (§ 3.1).

4.3 Metrics

Error Rate For our intervention experiments, we first measure the error rate of the language model. We want error rate to be high, since high error rate means we modified parts of the representation that have been used by the model in its prediction.

[2] We apply the intervention on representations of all words that possess the attribute in the sentence.



(a) Spanish gender layer 2, mirroring results with $\beta = 8$. Solid lines are error rates, dashed are CLWVs.

	LINEAR	GAUSSIAN	CLUSTER
English tense	$0.39, 60$ $0.37, 50$ $0.51, 60$	$0.26, 150$ $0.34, 70$ $0.41, 120$	$0.38, 30$ $0.34, 30$ $0.46, 30$
Spanish number	$0.28, 110$ $0.26, 50$ $0.23, 150$	$0.19, 100$ $0.20, 40$ $0.16, 140$	$0.35, 60$ $0.25, 30$ $0.40, 80$
Spanish gender	$0.29, 50$ $0.29, 50$ $0.26, 130$	$0.25, 80$ $0.31, 50$ $0.16, 110$	$0.37, 50$ $0.33, 30$ $0.35, 60$

(b) CLWV value at saturation point and number of neurons modified at the saturation point, using the mirroring method on different settings, with $\beta = 8$. In each cell, the three lines refer to layers 2, 7 and 12 respectively.

Figure 2: Mirroring error rate and CLWV results from a number of settings.

Correct Lemma, Wrong Value (CLWV) While inspecting predictions that are wrong after intervening ($M(h') \neq w$, where w is the true word), we categorize them by $L(M(h'))$ and $A(M(h'))$. If our intervention were successful, meaning we changed only the word's specific attribute, and not other information, then we expect to see $L(M(h)) = L(M(h'))$ and $A(M(h)) \neq A(M(h'))$. For example, if the word "makes" becomes "made" when intervening for tense, then it counts as a CLWV, but if it becomes "make" or "prepared" it does not. Thus, we define CLWV as the portion of those errors out of all predictions.

4.4 Results

4.4.1 Ablation is not Effective

Generally, across most languages, attributes and rankings we use, about 400 neurons from layer 2 and 200–300 neurons from layers 7 and 12 can be ablated without any implications on the output, meaning error rate remains the same; an example is shown in Appendix A.3. Moreover, when we do encounter more errors made by the model, our analysis does not reveal any pattern among those errors, i.e. CLWV is very low. By qualitatively analyzing those errors we see that most predicted words are mostly simply common words, e.g., "and", "if" in English. After ablating 600–700 (80%–90%) neurons from the representations, we observe a lot of errors, but most of them are because the word is predicted as nonsensical punctuation.

One major concern is that in these experiments, in some configs ablating by a bottom-to-top ranking provides better results than by the top-to-bottom version of the same ranking. In general, there are no distinct differences between the rankings. Thus, from now on we focus on mirroring rather than ablation.

4.4.2 Mirroring is Effective

Across all mirroring experiments (Fig. 2a shows one example), CLWV increases until a certain saturation point, after which it remains constant or drops a little [3]. This means that we reached neurons that are not relevant for the attribute, and modifying them can result in loss of other information—error rate grows while CLWV does not. Thus, we are interested in the CLWV value at the saturation point (higher is better), and in the number of neurons modified at the saturation point (lower is better). We report these values in a number of configs in Table 2b, and the rest of the configs in Appendix A.4.

Compared to ablation, mirroring a relatively small number of neurons results in a higher error rate, and these errors are closer to what we would expect. For example, mirroring only 50 neurons in

[3] We define "saturation point" as the first point from which there are two consecutive points where the value increase is by a factor lower than 1.05.

Spanish gender layer 2 results in 37% CLWV and 49% error rate, while ablating 50 neurons from the same config and ranking gives no CLWV errors and only 1% of error rate. We further note that unlike in ablation experiments, here our rankings are inherently consistent, i.e. across all configs, all top-to-bottom rankings perform better than the rest, while random ranking's error rate sometimes increases a little, and bottom-to-top rankings do not manage to affect the model's output at all (Fig. 2a).

4.4.3 CLUSTER is the Most Effective Ranking for Interventions

A clear trend from our results (Tables 2b, 2 and Fig. 2a) is that in most cases, CLUSTER achieves higher CLWV values, and does so using a smaller number of neurons, than the other two rankings. Furthermore, its error rate is significantly higher than the other two. This implies that CLUSTER tends to select neurons that are being used by the model, more so than the other rankings. However, while it does select neurons that are relevant for the attribute in question (CLWV is relatively high), it also tends to select neurons that are used by the model for other kinds of attributes (the difference between error rate and CLWV is relatively high).

Among LINEAR and GAUSSIAN, LINEAR seems to have the upper hand, with higher CLWV values in most configs. This provides another evidence that the superiority of GAUSSIAN in the probing experiments may be due to the quality of its classifier, and specifically its memorization ability, rather than the quality of the ranking it produces, as here only the ranking affects results.

5 Discussion and Conclusion

In this work, we compare different methods for ranking neurons according to their importance for a morphological attribute. We show that to evaluate a ranking in a probing scenario, one should separate between the ranking itself and the quality of the classifier that is using the ranking. We also show the need to evaluate a ranking using causal methods, such as interventions, especially for applications such as controlling or debugging the model. We propose a new ranking method that relies solely on the data, without training any auxiliary classifier, and show that it is valid, and prefers neurons that are being used by the model, more so than other ranking methods. We also propose a method for intervening within the model's representations such that it transforms the output in a desired way.

5.1 Encoded Information and Used Information are not the Same

When modifying the selected neurons, in most configs, top-to-bottom CLUSTER affects the output more than top-to-bottom GAUSSIAN and top-to-bottom LINEAR, and does so using a smaller number of neurons. This is in contrast to our probing results, where CLUSTER rarely overcame the other two, implying that encoded information and used information are not the same, and high probing accuracy does not necessarily entail that the information is actually important for the model.

5.2 Individual Neurons are Important

In our intervention experiments, modifying too many neurons results in more errors that are not related to the true word. This proves the importance of looking into individual neurons, especially when trying to intervene in the inner workings of the model. For example, Gonen et al. [2020] try to change the language of a word by intervening with the representation, using the same mirroring method we use, but with the same coefficient for every neuron, and on the entire representation. Our results imply that they may get better results by using our method.

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	G by ttb G	L by ttb G	G by ttb L	L by ttb L	G by ttb C	L by ttb C
G by ttb G	—	* * *	* * *	* * 	* * *	* *
L by ttb G		—	* 	* 	* * *	* *
G by ttb L		*	—	* 	* * *	*
L by ttb L	* *	* *	* *	—	* * *	* *
G by ttb C			*	*	—	*
L by ttb C		*		* 	* *	—

Table 1: Statistical significance results. G, L, C and ttb are abbreviations for GAUSSIAN, LINEAR, CLUSTER and top-to-bottom, respectively.

A Appendix

A.1 Data Preparation

We remove any sentences that would have a sub-token length greater than 512, the maximum allowed for M-BERT, the language model we use for generating representations. As in Torroba Hennigen et al. [2020], we remove attribute labels that are associated with less than 100 word types in any of the data splits. This mostly removes function words, and we found it makes it harder for probes to use memorization for solving the task.

A.2 Statistical Significance Tests

Table 1 shows the results of our statistical significance tests. The three rows in each cell correspond to using 10, 50 and 150 neurons. If there is an * in the $[i, j]$ cell, is means that the p-value under the null hypothesis that probe j is better than probe i is lower than 0.05, when using the matching number of neurons. For example, we see that there is an * in the first and second rows in the $[0, 3]$ cell, meaning we can confidently reject the hypothesis that LINEAR by LINEAR is better than GAUSSIAN by GAUSSIAN when using 10 or 50 neurons, but we cannot do so for 150 neurons. In fact, looking at the $[3, 0]$ cell shows us that when using 150 neurons, GAUSSIAN by GAUSSIAN is not better than LINEAR by LINEAR.

While we do not show random and bottom-to-top rankings in Table 1 for clarity, we asserted that each classifier is statistically significant better when using a top-to-bottom ranking compared to a random ranking, and when using a random ranking compared to a bottom-to-top ranking.

A.3 Ablation Results

One ablation example is shown in Fig. 3. No matter the ranking, ~ 400 neurons can be ablated with little impact on the output, and CLWV remains low.

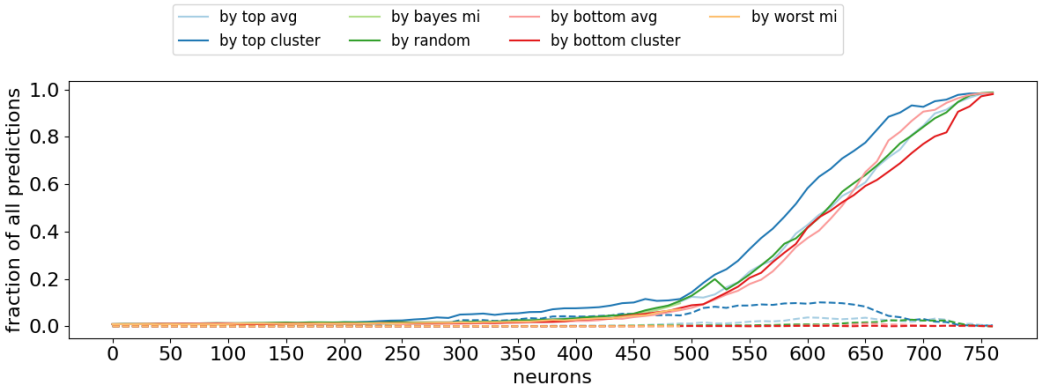

Figure 3: Spanish gender layer 2, ablation results. Solid lines are error rates, dashed are CLWVs.

	LINEAR	GAUSSIAN	CLUSTER
English number	0.04, 70 0.09, 50 0.11, 130	0.02, 60 0.07, 30 0.04, 60	0.06, 90 0.11, 50 0.17, 110
Spanish tense	0.20, 110 0.16, 80 0.31, 130	0.15, 140 0.11, 70 0.18, 70	0.27, 60 0.20, 60 0.33, 60
French number	0.19, 110 0.18, 50 0.07, 110	0.09, 150 0.17, 30 0.11, 150	0.25, 60 0.20, 30 0.33, 120
French tense	0.10, 110 0.10, 120 0.14, 150	0.01, 90 0.06, 100 0.07, 110	0.13, 70 0.08, 70 0.15, 90
French gender	0.17, 80 0.16, 40 0.14, 170	0.17, 80 0.16, 40 0.06, 140	0.22, 60 0.17, 30 0.20, 60

Table 2: CLWV value at saturation point and number of neurons modified at the saturation point, using the mirroring method on different settings. In each cell, the three lines refer to layers 2, 7 and 12 respectively.

A.4 Mirroring results

The rest of the mirroring results (continuation to Table 2b) is found in Table 2.