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Citation for published version:

Digital Object Identifier (DOI):
10.48550/arXiv.2406.09265

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Early version, also known as pre-print

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Sharing Matters: Analysing Neurons Across Languages and Tasks in LLMs

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Abstract

Multilingual large language models (LLMs) have greatly increased the ceiling of performance on non-English tasks. However, the mechanisms behind multilingualism in these LLMs are poorly understood. Of particular interest is the degree to which internal representations are shared between languages. Recent work on neuron analysis of LLMs has focused on the monolingual case, and the limited work on the multilingual case has not considered the interaction between tasks and linguistic representations. In our work, we investigate how neuron activation is shared across languages by categorizing neurons into four distinct groups according to their responses across different languages for a particular input: \textit{all-shared}, \textit{partial-shared}, \textit{specific}, and \textit{non-activated}. This categorization is combined with a study of neuron attribution, i.e. the importance of a neuron w.r.t an output. Our analysis reveals the following insights: (i) the linguistic sharing patterns are strongly affected by the type of task, but neuron behaviour changes across different inputs even for the same task; (ii) \textit{all-shared neurons} play a key role in generating correct responses; (iii) boosting multilingual alignment by increasing \textit{all-shared neurons} can enhance accuracy on multilingual tasks. The code is available at https://github.com/weixuan-wang123/multilingual-neurons.

1 Introduction

The black-box nature of large language models (LLMs) has given rise to an area of research which aims to interpret the internal mechanism of the Transformer architecture (Elhage et al., 2021a; Yu et al., 2023). In order to investigate specific aspects of model behaviour, previous studies choose to focus on specific model components to encourage interpretability. Differently from e.g. attention heads in the Transformer layers which are responsible for moving information from one token to another token (Elhage et al., 2021b), feed-forward networks (FFNs) are more likely to represent semantic features (Black et al., 2022). The FFN consists of two linear layers and an activation function is applied between them. A neuron inside the FFNs is defined as a linear transformation of an input representation followed by a non-linear activation (Tang et al., 2024). Geva et al. (2020, 2022); Ferrando et al. (2023) have earlier demonstrated the importance of neurons in the FFNs for encoding factual and linguistic knowledge. Furthermore, various neuron analytic methods have been developed to prune inactive neurons, i.e. those which have activation value less than or equal to zero (Zhang et al., 2022; Li et al., 2023; Voita et al., 2023).

While the above-mentioned methods analyze neuron behaviours based on the activation state (active or inactive means activation value > 0 vs. \( \leq 0 \)) in a monolingual setting, there is still a lack of understanding regarding how neurons behave across various tasks in a multilingual setting. As shown in Figure 1, different sets of neurons are
activated when an LLM is presented with corresponding inputs in different languages. An inactive neuron in response to an English input is often activated and influential in response to an input in another language. It remains unclear how LLMs actually manage to learn multilingual representations. One typical example is that we may need to explore sets of neurons responsible for generating the output “Paris” when presented with the English input “The capital of France is” and its Spanish counterpart “La capital de Francia es”.

In a similar line of reasoning, Bhattacharya and Bojar (2023) explored the behavior of language-specific and language-agnostic (shared between two languages) neurons and their distribution over layers of a model. They concluded that the layers close to the network’s input and output exhibit more language-specific behavior. However, their results are restricted to the English-Czech. Due to the potential variation in neuron behavior of different language types and the reasoning and memory abilities of different multilingual tasks, we argue that there is a need for further exploration.

Our research aims to establish more fine-grained classification of neurons, enabling a more detailed analysis of LLM behavior in reasoning style tasks (XNLI), fact-retrieval based tasks, and explicitly multilingual question-answer tasks (knowledge editing). As shown in Figure 1, we reformulate the activation state of neurons for a particular input and its corresponding translations in 10 languages to four distinctive types to represent multilingual behaviors. All-shared neurons are neurons that remain active for all inputs regardless of language. Partial-shared neurons are activated only for inputs in certain languages. Specific neurons are activated exclusively for inputs in one language. Non-activated neurons are not activated at all for any input.

We perform neuron analysis addressing two research questions: (a) what are the behaviors of the four types of neurons in various multilingual tasks? (b) What attribution (Dhamdhere et al., 2019) does each type have in multilingual generation tasks, meaning which neurons are responsible for a prediction?

We examine the percentage of each type of neuron and neuron attributions in the multilingual tasks. We discover that the pattern of four types of neurons is determined by the tasks they encountered, and that the behavior of a neuron changes with different inputs for the same task, indicating the potential damage when pruning neurons.

Furthermore, we demonstrate the importance of all-shared neurons in generating the correct output from the neuron attribution study. Converting other types of neurons to all-shared neurons improves the accuracy of an LLM in multilingual tasks.

Our main contributions are listed below:

- **Fine-grained neuron analysis**: We define four categories of neurons and use these to analyze neuron behaviors in various types of tasks across 10 languages. We reveal that reasoning style tasks (e.g. XNLI) involves more all-shared neurons than fact-retrieval based tasks (e.g. fact probing) which utilize more language-specific neurons.

- **Neuron attribution**: By studying the contribution of neurons to the output of multilingual tasks, we are the first to reveal the importance of all-shared neurons within FFNs in multilingual tasks. For instance, for the XNLI task, the all-shared neurons comprise less than 30% of the neurons, but they contribute 91.6% to the generation of the correct output in the German test set.

- **Multilingual alignment**: We demonstrate that increasing the percentage of all-shared neurons (by replacing other types of neurons or via instruction fine-tuning) can significantly enhance the accuracy of an LLM in multilingual tasks.

2 Related Work

Prior interpretability studies focused on understanding attention heads, while others have analyzed neuron behaviors. Several studies on LLMs have advanced our understanding of how neurons acquire task-specific knowledge. For instance, Ferrando et al. (2023); Dai et al. (2022); Geva et al. (2020, 2022) investigated how FFN layers in transformer-based models function as key-value memories and prove that factual knowledge is stored in the neurons. Research works on the sparsity of neurons in FFN layers disclosed many neurons are inactive in various tasks (Zhang et al., 2022; Li et al., 2023). Voita et al. (2023) located these “dead” neurons in the lower part of network (close to inputs) in the English scenario. Despite insights are obtained,
these works are focused exclusively on monolingual tasks.

For multilingual model analysis, Bhattacharya and Bojar (2023); Tang et al. (2024) classify neurons in a FFN block to language-specific and language-agnostic without considering the potential adaptation of neurons under various language types and semantics brought forth by inputs from various multilingual tasks. For example, a language-agnostic neuron may be activated by inputs with a different semantic meaning and/or from another language. We investigate LLMs’ behaviors under multiple languages and tasks to this end.

3 Definitions

3.1 Neurons in FFN Blocks

Every feed-forward network at layer \( l \) involves two linear transformations separated by a point-wise activation function. Biases are omitted for the sake of clarity:

\[
FFN^l(x^l) = Act(W^l_K x^l)W^l_V
\]

Where \( W^l_K, W^l_V \in \mathbb{R}^{d_m \times d} \) are linear parameter matrices, and \( Act(\cdot) \) is a non-linear activation function, where rows in \( W^l_K \) and columns in \( W^l_V \) are viewed as \( d \)-dimensional keys \( k^l_i \) and values \( v^l_i \), respectively. We define a neuron to be the set of functions immediately after the elementwise non-linearity. \( d_m \) is the count of neurons. And the output of neurons \( A^l_i : = Act(W^l_K x^l) \in \mathbb{R}^{d_m} \) determines the weighting of the corresponding values in \( W^l_V \).

For \( i \)-th neuron and corresponding key \( k^l_i \), value \( v^l_i \) and activation value \( A^l_i \), we can express this relationship using the following formulation:

\[
FFN^l(x^l) = \sum_{i=1}^{d_m} Act(x^l \cdot k^l_i) v^l_i = \sum_{i=1}^{d_m} A^l_i v^l_i
\]

When such a neuron is activated \( A^l_i > 0 \), so it updates the residual stream by pulling out the corresponding value \( v^l_i \). If a neuron is not activated, the residual stream remains unchanged.

3.2 Contribution and Effective Score of Neuron

Inspired by Geva et al. (2022), in order to judge the importance of neurons in generating answers, we analyzed their contributions to the output. The contribution of a neuron to an FFN output is:

\[
C^l_i := \frac{|A^l_i| \cdot ||v^l_i||}{\sum_{j=1}^{d_m} |A^l_j| \cdot ||v^l_j||}
\]

which is the proportion of its weight to the sum of weights of all neurons in the FFN block. \( |A^l_i| \) is the absolute value of activation value and \( ||v^l_i|| \) is the L2-norm of value \( v^l_i \).

Whenever a neuron is activated, the associated column of the values (scaled by the neuron’s value) is incorporated into the residual stream. The product of the value of the activated neuron \( A^l_i \) and the corresponding \( v^l_i \) is then transformed linearly and mapped to the vocabulary.

Following Geva et al. (2022); Voita et al. (2023), projecting the neuron to the vocabulary using embedding matrix \( E_r.A^l_i v^l_i \) can be viewed as obtaining the effective score given by the \( i \)-th neuron to the output reference token \( r \) for a given input. Specifically, a larger \( E_r.A^l_i v^l_i \) has a higher probability to produce a gold answer (r). A negative \( E_r.A^l_i v^l_i \) reduces the probability in generating \( r \). In this way, we can quantify the effect of a neuron on the output distribution. We give detailed descriptions about the neuron projection to the vocabulary space in Appendix A.1.

3.3 Definition of Four types of Neurons

For the set of all neurons \( N^l \) in the \( l \)-th layer, the activation value of one neuron \( n \) in one language \( lang \) is \( A^l_{lang} \). Note that some activation functions (e.g. GeLU) can result in negative activation values. The definition of all-shared neuron is:

\[
N_{all}^l := \bigcap_{lang} \{ n \in N^l : A^l_{lang} > 0 \}
\]

where \( lang \) is the sets of testing languages and \( A_{all} \) means these neurons are activated in all languages. For non-activated neurons which have activation value less and equal to zero in all languages, the definition is:

\[
N_{non}^l := \bigcap_{lang} \{ n \in N^l : A^l_{lang} \leq 0 \}
\]

specific neurons are neurons only activated in one specific language. They can be denoted using:

\[
N_{specific}^l := \bigcup_{lang_k} \{ n \in N^l : A^l_{lang_k} > 0 \} \bigcap_{lang_k} \{ n \in N^l : A^l_{lang_k} \leq 0 \}
\]
The remaining neurons are partial-shared neurons as they are activated by inputs from multiple languages, but not all languages at the same time:

\[ N_{\text{partial}}^l = N^l - N_{\text{all}}^l - N_{\text{non}}^l - N_{\text{specific}}^l \] (7)

Unlike Bhattacharya and Bojar (2023); Tang et al. (2024), which exclusively on sub-word activation statistics and thus captures incomplete semantics, we examines the activation state of the last token. For each input text with tokens \( x_1, x_2, ..., x_S \), we use the activation state \( x_S \) to investigate the behavior of the FFN neurons, as that is when the LLM performs the prediction task.

4 Experimental Setting

4.1 Tasks

We perform analysis on neurons in FFN blocks of various LLMs in three diverse tasks which consist of multilingual parallel sentences leveraging LLMs’ capability in multilingual settings. They are:

Natural Language Inference. XNLI (Conneau et al., 2018) is a multilingual natural languages inference dataset. Each test sample consists of a premise and a hypothesis, requiring an LLM to determine whether a hypothesis is entailed, contradicted, or neutral conditioned on the premise.

Fact Probing. LLMs are used to generate factual responses to corresponding probing prompts. A multilingual factual knowledge dataset (mParaRel (Fierro and Søgaard, 2022)) capturing 38 binary relations (e.g., \( X \text{ born-in } Y \)) is used in the analysis.

Cross-lingual Knowledge Editing (KE). MzsRE (Wang et al., 2023) is a multilingual question-answering dataset. It provides counterfactual edited knowledge in the context and requires an LLM to produce the corresponding answer. We evaluate LLMs in two KE scenarios: 1) EN (edit) \( \rightarrow \) ALL (test): edit in English and test in other languages and 2) ALL (edit) \( \rightarrow \) EN (test): edit in other languages and test in English.

These tasks cover 10 diverse languages, including English (en), German (de), Spanish (es), French (fr), Portuguese (pt), Russian (ru), Turkish (tr), Vietnamese (vi), and Chinese (zh). Prompts are detailed in Appendix A.2.

4.2 Base LLMs

We mainly analyze the behavior of neurons in a foundation multilingual LLM BLOOM (Scao et al., 2022) and an instruction-finetuned model BLOOMZ (Muennighoff et al., 2023). We also include the analysis of other decoder-only models: XGLM (Lin et al., 2022), LLAMA2-7b-chat (Touvron et al., 2023), and an encoder-decoder model mT0 (Muennighoff et al., 2023) in the Appendix A.3.2.

5 Behavior of Four Types of Neurons

For each task we use parallel test texts from ten languages as inputs, and record the activation state of each neuron. Subsequently, we calculate the percentage of the four types of neurons compared to the total neurons.

We use BLOOMZ as the backbone to investigate the behaviors of four types of neurons, and the results of three tasks are shown in Figures 2-4 respectively. The supplemental analysis of cross-lingual KE (ALL (edit) \( \rightarrow \) EN (test)) task is shown in Figure 11 (Appendix A.3.1).

5.1 Neuron Behaviors cross Tasks

5.1.1 Behavior Pattern of Four types of Neurons

It can be observed from Figures 2-3 (left sub-figures) that there are more non-activated neurons across transformer layers (aka “by neuron type”). The right sub-figure shows aggregated behaviors of the activated neurons for each language across transformer layers (aka “by language”).

5.1.1 Behavior Pattern of Four types of Neurons

It can be observed from Figures 2-3 (left sub-figures) that there are more non-activated neurons on the whole than other types. Furthermore, the neuron behaviour is strongly task-related as the pattern observed in the fact probing task differs significantly from the other two tasks. In the fact probing task, there are more partial-shared neurons (yellow line in Figure 4), whereas the other tasks
involve far more all-shared neurons (green lines in Figures 2-3).

Figure 3: Neuron behaviors in cross-lingual KE (EN (edit) → ALL (test)) task.

For the neuron behaviours across layers, lower layers exhibit a higher prevalence of all-shared neurons compared to specific neurons and partial-shared neurons in XNLI and KE. The number of all-shared neurons peaks at a certain layer followed by a continuous decreasing pattern in these two task. Fewer all-shared neurons in the upper layers implies language-specific characteristics are retained there. Similarly, partial-shared neurons accumulate in the lower layer and it tends to outnumber all other neurons moving towards upper layers in all tasks. It could be observed that nearly 99% of the neurons are non-activated in the first layer for XNLI and KE tasks, which may be associated with the prompts, where the last token is punctuation (e.g., “?”). However, this phenomenon appears to be specific to BLOOMZ when compared to other LLMs (Appendix A.3.2). We also explore the impact of the number of languages on the percentage of four types of neurons in the Appendix A.3.4. The comparison shown in Figure 19 indicates that the number of languages has a slight effect on the all-shared neurons.

5.1.2 Consistent Neuron Behavior Pattern
The percentage of activated neurons for each language exhibit a consistent pattern, as shown in Figures 2-4 (right sub-figures). At lower layers of an LLM, the number of activated neurons increases significantly and reaches the peak at around the 6-th layer and then declining. It is not until at an upper layer (i.e., 28-th layer), the number of active neurons commences to pick up its early increasing trend. Such a resurgence continues until it reaches the final layer of the LLM. It is a surprise to discover that the number of activated neuron is not influenced by the language of the inputs. This indicates neurons in an LLM exhibit similar behaviors across languages.

Figure 4: Neuron behaviors in fact probing task.

Figure 5: Behaviour-repeating neurons in fact probing task across the entire testset. “overlap” indicates percentage of neurons which keep the same behaviours across all examples in the testset. “average” indicates the average percentage of neurons with the designated behaviour in the entire testset.

5.1.3 Neurons Behaviors across Examples
As shown in Figures 2-4, the analysis is conducted by exploring the activation state under the same example and the corresponding translations in 10 languages. Could the task-related pattern imply that a neuron with a particular behaviour maintains its language specificity across inputs with different examples? In this experiment we now investigate how neurons behave across the test set, for the fact probing task. Here, the objective is to understand if neurons that are specific to a language maintain
this behaviour across test samples representing different semantics. The results are shown in Figure 5. To our surprise, almost no neuron (identified by its index) repeats its behaviour (e.g. the “specific”) across the test samples. Different from the previous studies which assumed that a neuron behaved consistently across examples, we reveal that the behaviour of an neuron is determined by the semantics of the inputs encountered.

5.1.4 “Dead” Neuron Mystery

In the multilingual scenario, non-activated neurons comprise a significant portion, with more than 50% of neurons having a zero or negative activation value across layers for multilingual inputs (blue solid line in the left sub-figures) in Figures 2-4.

Do these “dead” neurons stay inactive in all test samples? In Figure 5 we see that less than 10% of inactive neurons remain inactive. There is only a small proportion of persistently inactive neurons which reflects the distributed nature of knowledge representation for LLMs, in which the majority of neurons are activated at some point depending on the example provided. That is why we should execute caution when pruning neurons, as we may damage the overall performance of an LLM.

Figure 6: Neurons remaining “dead” in response to all tokens in an input sentence for fact probing task.

Do inactive neurons remain “dead” in response to each token in an input sentence? Previously, we performed analysis for the last token of an input. We analyze the behaviour-repeating of non-activated neurons across tokens here for an input. Specifically, for each input sequence with tokens \( x_1, x_2, \ldots, x_S \), we record non-activated neurons of each token, wrt the intersection of index. A neuron is counted when it stays inactive for every token of one test input sequence. As shown in Figure 6, less than 0.8% non-activated neurons remain “dead” for each token of input, further emphasizing the behaviour-repeating of a neuron.

5.2 Influence of Instruction Finetuning

Does instruction finetuning (IFT) have an impact on neuron behaviors? We compare the percentage of the four designated types of neurons of BLOOM and its IFT counterpart BLOOMZ.

The results from a XNLI task are shown in Figure 7. Compared to the results from BLOOMZ in Figure 2, all-shared neurons are under-represented in BLOOM (20% of BLOOM vs. 30% of BLOOMZ). Meanwhile, more partial-shared neurons are observed in BLOOM. IFT enhances the percentage of all-shared neurons and reduces the number of partial-shared neurons. We regard the increase of the number of all-shared neurons as an effect of multilingual representation alignment.

It appears that IFT contributes to multilingual alignment based on the effects observed from this experiment. Whether this effect can be generalized to other LLMs and the rationale behind such effect warrants a future study.

We conduct ablation studies to delve deeper into the impact of two key factors on the neuron behaviours: the size of backbone model (Appendix A.3.5) and the quantity of multilingual demonstrations in the few-shot setting (Appendix A.3.6).

6 Neuron Attributions

In the preceding experiments, we examined the proportions of our four types of neurons across layers, tasks and languages. In this section we examine the relative contributions of each neuron type to task performance.

6.1 Neuron Contribution Score

As discussion in Section 3.2, the contribution score \( C^l_i \) of a neuron refers to its relative weight compared to the total sum of weights of all neurons,
indicating the influence of each neuron on outputs.
We examine the proportion of the four types of neurons among the top 5% contribution score under inputs in each language. The proportions of neurons in the cross-lingual KE task are depicted in Figure 8 (and the overall results of 10 languages are shown in Figure 25 in Appendix A.4.1).

It can be observed that all-shared neurons are the top contributing neurons to the outputs at every layer, regardless of their language inputs. This highlights their importance in the neural network. The group of partial-shared neurons are the second most influential group, demonstrating their impacts across the latter half of the network. It is not surprising that the specific neuron group has limited influence to cross-lingual KE outputs as they feature in a particular language type of inputs.

Furthermore, we evaluate contribution proportion in the XNLI task, as depicted in Figure 24. Here, all-shared neurons constitute the highest proportion, however, partial-shared neurons show less influence compare to that observed in cross-lingual KE task.

In order to more comprehensively analyze the overall contribution of four types of neurons, we extend the analysis from the top 5% to accommodate all neurons in this study. We analyze the average and the sum of contribution scores of all neurons in four categories. As shown in Figure 9, the average contribution of all-shared neurons significantly exceeds that of the other three types. In terms of the total contribution score, all-shared neurons in the upper layers achieve a value equal to that of non-activated neurons, despite having a significantly lower count than non-activated neurons (<10% vs. 80% in Figure 2). In the fact probing task, partial-shared neurons score the highest, while all-shared neurons score the lowest, primarily due to their respective counts (>20% vs. <1% in Figure 4). In summary, all-shared neurons play a significant role contributing to multiple tasks. Future studies on neuron activation should consider their contribution as well as their frequency.

<table>
<thead>
<tr>
<th>language</th>
<th>neuron-type</th>
<th>max</th>
<th>min</th>
<th>mean</th>
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</thead>
<tbody>
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<td>0.04</td>
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<td>partial</td>
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<td>0.00</td>
<td></td>
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<tr>
<td></td>
<td>specific</td>
<td>0.02</td>
<td>-0.02</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>non-activated</td>
<td>-0.03</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>de</td>
<td>all-shared</td>
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<td>-0.60</td>
<td>0.02</td>
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<td>partial</td>
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<td>0.00</td>
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<td>specific</td>
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<tr>
<td></td>
<td>non-activated</td>
<td>-0.01</td>
<td>0.00</td>
<td></td>
</tr>
</tbody>
</table>

Table 1: Maximum, minimum, average effective score of four types of neurons on the cross-lingual KE task.

6.2 Neuron Effective Score
Since each neuron encodes information, we can explore their contributions to the correct answer. As discussed in Section 3.2, the projection to vocabulary $E_r \cdot A_i^v$ can be viewed as the effective score given by the $i$-th neuron to the output reference token $r$ for a given input.

In the cross-lingual KE (EN (edit) → ALL (test)) task, we calculate the effective score of each type of neuron with BLOOMZ backbone. The maximum, minimum and average scores are shown in Table 1 (the overall results of ten languages are shown in Table 4) and the maximum effective scores across
layers are shown in Figure 10. All-shared neurons achieve the highest maximum score and the lowest minimum score, indicating they are pushed (or eliminated) strongly by the activation function. In contrast to all-shared neurons and partial-shared neurons, where the maximum scores are substantially higher than the minimal scores (1.85 vs. -0.94 and 0.22 vs. -0.16 in English), for specific neurons and non-activated neurons, the score has a smaller span (± 0.07), suggesting all-shared neurons have greater influence on the output distribution.

![Figure 10: Maximum effective score of four types of neurons based on the cross-lingual KE task.](image)

As shown in Figure 10, the maximum effective score of all-shared neurons significantly exceeds that of the other three types. Moreover, all-shared neurons aggregates at the first layer and upper layers. This observation confirms a recent finding that early layers detects shallow patterns and upper layers are characterized by semantic patterns (Ferrando et al., 2023), supporting the notion that all-shared neurons play a key role in generating prediction. Details of effective score analysis in other tasks are depicted in Appendix A.4.2.

### 6.3 Effects on Accuracy

We have investigated neuron attribution using contribution score and effective score, which are based on the internal states of LLM. Direct impacts of neurons on the output performance (i.e., accuracy) provide insights from a pragmatic perspective. We explore the change of accuracy by intentional deactivating three distinct types of active neurons. This is performed by precisely identifying neurons responsible for an output and setting their activation values to zero. Take the XNLI task as an example, we record the results of an LLM with deactivated neurons in Table 2. The most significant decrease in accuracy is observed when the all-shared neurons are deactivated. Deactivating specific and partial-shared neurons also negatively impacts on accuracy, but at a smaller magnitude when compared to the effect by all-shared neurons. We also prove the importance of all-shared neurons in the LLAMA backbone in Table 6. In order to prove the key role of all-shared neurons across tasks, we conduct the ablation experiments on the cross-lingual KE task in Appendix A.5.2.

![Table 3: The accuracy when converting specific neurons, and partial-shared neurons to all-shared neurons type.](image)

<table>
<thead>
<tr>
<th>accuracy</th>
<th>en</th>
<th>de</th>
<th>es</th>
<th>fr</th>
<th>ru</th>
<th>th</th>
<th>tr</th>
<th>vi</th>
<th>zh</th>
</tr>
</thead>
<tbody>
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<td>34.9</td>
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<td>51.1</td>
</tr>
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<td>co. all-shared</td>
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<td>40.1</td>
<td>34.4</td>
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<td>co. partial-shared</td>
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<td>41.8</td>
<td>51.0</td>
<td>49.3</td>
<td>49.4</td>
<td>41.5</td>
<td>36.8</td>
<td>50.7</td>
<td>51.2</td>
</tr>
<tr>
<td>co. specific and partial-shared</td>
<td>52.6</td>
<td>42.1</td>
<td>51.6</td>
<td>49.4</td>
<td>48.2</td>
<td>41.7</td>
<td>36.4</td>
<td>50.7</td>
<td>51.7</td>
</tr>
</tbody>
</table>

Table 2: The accuracy when deactivating all-shared neurons, specific neurons, and partial-shared neurons, respectively. "w/o." stands for "without".
7 Conclusion

In this paper, we propose a novel approach for analyzing neurons in FFN blocks by categorizing them into four distinct types: all-shared neurons, partial-shared neurons, specific neurons and non-activated neurons. We conduct a detailed analysis of LLM behaviors in multilingual tasks. Experimental results disclose novel insights relating to neuron behaviors: 1) We demonstrate that a neuron’s activation pattern is influenced by the tasks it encounters, and even the behavior of a neuron changes with different inputs for the same task. 2) We show the importance of all-shared neurons in output generation in multilingual tasks from the neuron attribution study. 3) We prove that multilingual alignment can significantly enhance the accuracy of an LLM in multilingual tasks by increasing the percentage of all-shared neurons (i.e., via replacing other types of neurons or via IFT). Future works will focus on exploring internal activation mechanisms underpinning the observed importance of all-shared neurons and multilingual alignment across a wider range of tasks and LLM backbones.

8 Limitations

In this paper, we develop a method to analyze neuron behaviors in details by categorizing them into four distinct neuron types wrt the degree of their responses to input languages. Although this enables a fine granularity neuron analysis on LLM backbones across various linguistic characteristics and task complexity, the scope of the experiments can be extended to accommodate larger LLMs with large amounts of parameters (i.e., BLOOMZ-176b) on a more comprehensive range of tasks. While this study meticulously categorizes neurons in the FFN, it is limited to 10 languages. Exploring the effects of incorporating a larger number of languages into the proposed method warrant further investigation. All-shared neurons in FFN blocks are identified to be of great importance, but how and why they work is still a mystery to disclose. Other network components, for example, induction heads, are not in the scope of this analysis.

References


A  Example Appendix

A.1  Detailed Interpretation of Projection in Vocabulary Space

There is a residual connection in the each layer of transformer, where the hidden state is:

\[ h_l = x_l + FFN^l(x_l) \]  

(8)

In order to analyze the behaviors of neurons, we explore how the output distribution in the vocabulary space changes when the representation \( x^l \) (before the FFN update) is added with the output of neurons \( A^l v^i \). With the embedding matrix \( E \), we map each vector into the vocabulary space \( \nu \). For each token \( w \), the probability is calculated with the softmax function:

\[
p(w|x_l^l + A^l v_i^l, E) = \frac{\exp(E_w \cdot x_l^l + E_w \cdot A^l v_i^l)}{Z(E(x_l^l + A^l v_i^l))} \propto \exp(E_w \cdot x_l^l) \cdot \exp(E_w \cdot A^l v_i^l)
\]  

(9)

where \( E_w \) is the embedding of \( w \), and \( Z(\cdot) \) is the constant softmax normalization factor. The \( E_w \cdot x_l^l \) can be viewed as a static score of \( w \) that is independent of the input to the model. Thus, the projection \( E_w \cdot A^l v_i^l \) induces a ranking over the vocabulary. So we use the projection as effective score to detect the responsibility of neurons.

A.2  Prompts

For the fact probing task, we use the P36 sub-testset, which describe facts of entities in a relation of “capital”. The prompt is framed as “The capital of \( \{X\} \) is ” where \( \{X\} \) is the subject (sovereign state) and LLMs are required to predict the object (capital city). We keep at least three paraphrase prompts from mParaRel for each language to ensure a level of diversity.

For the Natural Language Inference task, we frame the prompt as “Take the following as truth: \{premise\} Then the following statement: \{hypothesis\} is ‘true’, ‘false’, or ‘inconclusive’? ”

For the cross-lingual KE task, we format the prompt as “ \{context\} Question: \{question\} Answer: “. The same language is used for the questions and the answers, but the context is in a different language.

A.3  Supplemental Results of Neuron Behavior Analysis

A.3.1  Neuron behaviours in additional cross-lingual KE task

We already show the neuron behaviours in in cross-lingual KE (EN (edit) → ALL (test)) task in Section 5.1.1. We supply the analysis in the cross-lingual KE (ALL (edit) → EN (test)) task in Figure 11.

A.3.2  Neurons Behaviors across LLMs

Do above-mentioned neuron behaviors change over different LLMs? We further study the neuron behaviors in other decoder-only multilingual LLMs (XGLM and LLAMA2) and an encoder-decoder multilingual LLM mT0. For the XNLI task, the results of XGLM and LLAMA2-7b-chat backbones are captured in Figure 12 and Figure 13, and the results of mT0-encoder and mT0-decoder are shown in Figure 14 and Figure 15. Furthermore,
the percentage of four types of neurons for inputs in each language on each LLM demonstrate the same pattern, indicating neurons remain consistent behaviors across LLM backbones.

The number of active neurons increase in the lower layers, followed by a decrease moving onwards and a rise in the upper layers, despite the absolusion values are different from those obtained for BLOOMZ. Moreover, it could be observed that encoder in mT0 involves more all-shared neurons compared to the proportion in decoder.

**A.3.3 Activation percentage of BLOOM**

The results analyzed base on the foundation model BLOOM of fact probing task and cross-lingual KE task are shown in Figure 16 - 18.

**A.3.4 Influence of the Quantity of Languages**

We design an ablation study to investigate the influence of the number of languages (i.e., in a series of 3, 5, 7, 9). The results of the XNLI task in response to the quantitative change in languages are illustrated in Figure 19. The rise in the number of languages is associated with an observable increase in the percentage of partial-shared neurons and slight decrease in the percentage of all-shared neurons. This suggests that the quantity of languages has a minor impact on the all-shared neurons.

**A.3.5 Influence of Model Scale**

We investigate neuron behaviors across the BLOOMZ series with 0.56b, 1b, 3b, 7.1b parameters in a XNLI task. As shown in the results captured in Figure 20, no identifiable pattern difference can be observed to indicate a scale law effect. However, the scale of the model is limited, potentially leading to unreliable results in this experiment. More non-activated neurons in the upper layers of BLOOMZ-7.1b may reflect on a higher level of sparsity for a larger LLM (consistent with Voita et al. (2023); Li et al. (2023)).
Figure 17: Activation percentage of four types of neurons based on the cross-lingual KE (ALL (edit) → EN (test)) task with BLOOM backbone.

Figure 18: Activation percentage of four types of neurons based on the cross-lingual KE (EN (edit) → ALL (test)) task with BLOOM backbone.

A.3.6 Neuron Behaviors in Few-shot In-context Learning

According to Wang et al. (2023), in-context learning (ICL) can improve the performance of an LLM under the guidance of few-shot examples in a cross-lingual KE task. We further explore the impact of few-shot examples on neuron behaviors. We compare the results of an LLM with 0-shot, 2-shot, 4-shot, 6-shot examples in a cross-lingual KE (EN (edit) → ALL (test)) task. Four types of neurons in scope have almost identical behaviors across various few-shot examples (Figure 21). Although in-context examples lead to no observable neuron behavioral changes, more examples lead to better performances. Could ICL leads to a better neuron activation composition, instead of invoking more neurons? We leave this to a future study.

A.3.7 Activation Value across Layers

According to Eq. 1, neurons with larger activation values tend to contribute more to the output. By visualizing neuron activation for a series of thresholds $[0, 0.1, 0.2, 0.3, 0.4, 0.5]$, we can scrutinize the relative importance of various types of activated neurons. The percentage of various types of activated neurons for each activation threshold in an XNLI task are shown in Figure 22. When applying a threshold ($>0$), there are fewer all-shared, partial-shared, and specific neurons left in the lower layers (layers 0-10) compared to using a lower threshold (i.e., $= 0$). Under the same threshold scenario, more activated neurons appear in the second half of the model (layers 15-30). It is worth-noting these neurons are of a higher activation value compared to neurons activated from a lower threshold (i.e., $= 0$). Considering both the percentage of activated neurons and their corresponding activation value, it becomes apparent that the neurons in the upper layers contribute more to the output performance.

A.4 Supplemental Results of Neuron Attribution

A.4.1 Contribution of different tasks

The contribution of four types of neurons evaluated on the fact probing task, XNLI task, cross-lingual KE task are shown in Figure 23 - 26.

A.4.2 Effective score of different tasks

The maximum, minimum, and average effective scores of four types of neurons in 10 languages evaluated on the cross-lingual KE (EN (edit) →
Table 4: Maximum, minimum, average effective score of the four types of neurons on the cross-lingual KE (EN (edit) → ALL (test)) task.

<table>
<thead>
<tr>
<th></th>
<th>all-shared</th>
<th>partial-shared</th>
<th>specific</th>
<th>non-activated</th>
</tr>
</thead>
<tbody>
<tr>
<td>en</td>
<td>max 1.85</td>
<td>min -0.94</td>
<td>mean 0.07</td>
<td>max 0.02</td>
</tr>
<tr>
<td></td>
<td>min -0.94</td>
<td>mean 1.85</td>
<td>max 0.07</td>
<td>min -0.94</td>
</tr>
<tr>
<td>de</td>
<td>max 1.03</td>
<td>min -0.60</td>
<td>mean 0.02</td>
<td>max 0.07</td>
</tr>
<tr>
<td></td>
<td>min -0.60</td>
<td>mean 1.03</td>
<td>max 0.07</td>
<td>min -0.60</td>
</tr>
<tr>
<td>es</td>
<td>max 1.15</td>
<td>min -0.84</td>
<td>mean 0.02</td>
<td>max 0.01</td>
</tr>
<tr>
<td></td>
<td>min -0.84</td>
<td>mean 1.15</td>
<td>max 0.01</td>
<td>min -0.84</td>
</tr>
<tr>
<td>fr</td>
<td>max 1.06</td>
<td>min -0.78</td>
<td>mean 0.01</td>
<td>max 0.03</td>
</tr>
<tr>
<td></td>
<td>min -0.78</td>
<td>mean 1.06</td>
<td>max 0.03</td>
<td>min -0.78</td>
</tr>
<tr>
<td>ru</td>
<td>max 0.70</td>
<td>min -0.45</td>
<td>mean 0.13</td>
<td>max 0.08</td>
</tr>
<tr>
<td></td>
<td>min -0.45</td>
<td>mean 0.70</td>
<td>max 0.08</td>
<td>min -0.45</td>
</tr>
<tr>
<td>th</td>
<td>max 0.50</td>
<td>min -0.90</td>
<td>mean 0.17</td>
<td>max 0.03</td>
</tr>
<tr>
<td></td>
<td>min -0.90</td>
<td>mean 0.50</td>
<td>max 0.03</td>
<td>min -0.90</td>
</tr>
<tr>
<td>tr</td>
<td>max 0.82</td>
<td>min -0.51</td>
<td>mean 0.12</td>
<td>max 0.04</td>
</tr>
<tr>
<td></td>
<td>min -0.51</td>
<td>mean 0.82</td>
<td>max 0.04</td>
<td>min -0.51</td>
</tr>
<tr>
<td>vi</td>
<td>max 0.86</td>
<td>min -0.68</td>
<td>mean 0.15</td>
<td>max 0.04</td>
</tr>
<tr>
<td></td>
<td>min -0.68</td>
<td>mean 0.86</td>
<td>max 0.04</td>
<td>min -0.68</td>
</tr>
<tr>
<td>zh</td>
<td>max 0.52</td>
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<td>mean 0.17</td>
<td>max 0.08</td>
</tr>
<tr>
<td></td>
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<td>mean 0.52</td>
<td>max 0.08</td>
<td>min -0.43</td>
</tr>
<tr>
<td>pt</td>
<td>max 1.14</td>
<td>min -0.83</td>
<td>mean 0.11</td>
<td>max 0.02</td>
</tr>
<tr>
<td></td>
<td>min -0.83</td>
<td>mean 1.14</td>
<td>max 0.02</td>
<td>min -0.83</td>
</tr>
</tbody>
</table>

Figure 20: Neuron behaviors in a XNLI task with the model size as 0.56b, 1b, 3b, 7b.

ALL (test)) task are shown in Table 4. The maximum effective of four types of neurons across layers evaluated on the fact probing task, XNLI task, cross-lingual KE (ALL (edit) → EN (test)) task are shown in Figure 27 - 29.

A.5 Supplemental Results of Effects on Accuracy

A.5.1 Effects on Cross-lingual KE tasks

We further explore the influence of deactivating all-shared neurons, specific neurons, and partial-shared neurons on the cross-lingual KE (EN (edit) → ALL (test)) task with BLOOMZ backbone. The results in Table 5 are consistent with the results of XNLI task in Table 2, demonstrating the critical role of all-shared neurons for generating correct output.

A.5.2 Effects with LLAMA backbone

In order to further prove the importance of all-shared neurons across LLMs, we conduct the experiments with deactivating neurons on the XNLI task with LLAMA2-7b-chat backbone. The results in Table 6 show that there is more significant effect when all-shared neurons are deactivated. It demonstrates that all-shared neurons play a key role in predicting correct answers across LLMs.
<table>
<thead>
<tr>
<th>accuracy</th>
<th>en</th>
<th>de</th>
<th>es</th>
<th>fr</th>
<th>pt</th>
<th>th</th>
<th>tr</th>
<th>ru</th>
<th>vi</th>
<th>zh</th>
</tr>
</thead>
<tbody>
<tr>
<td>baseline</td>
<td>96.23</td>
<td>46.84</td>
<td>36.88</td>
<td>40.38</td>
<td>35.80</td>
<td>4.71</td>
<td>28.13</td>
<td>0.67</td>
<td>40.92</td>
<td>10.63</td>
</tr>
<tr>
<td>w/o. all-shared</td>
<td>15.21</td>
<td>9.69</td>
<td>5.52</td>
<td>4.98</td>
<td>7.67</td>
<td>0.54</td>
<td>2.42</td>
<td>0.00</td>
<td>7.67</td>
<td>2.96</td>
</tr>
<tr>
<td>w/o. specific</td>
<td>96.23</td>
<td>46.84</td>
<td>36.74</td>
<td>40.24</td>
<td>35.53</td>
<td>4.71</td>
<td>29.21</td>
<td>0.67</td>
<td>40.65</td>
<td>11.84</td>
</tr>
<tr>
<td>w/o. partial-shared</td>
<td>68.78</td>
<td>44.95</td>
<td>35.40</td>
<td>37.01</td>
<td>34.19</td>
<td>5.11</td>
<td>25.44</td>
<td>0.67</td>
<td>39.84</td>
<td>8.48</td>
</tr>
</tbody>
</table>

Table 5: The effects of accuracy on the cross-lingual KE (ALL (edit) → EN (test)) task with BLOOMZ backbone, when deactivating all-shared neurons, specific neurons, and partial-shared neurons, respectively. “w/o.” stands for “without”.

Figure 22: Neuron behaviors in a XNLI task with BLOOMZ backbone under the threshold in \([0, 0.1, 0.2, 0.3, 0.4, 0.5]\).

<table>
<thead>
<tr>
<th>accuracy</th>
<th>en</th>
<th>de</th>
<th>es</th>
<th>fr</th>
<th>ru</th>
<th>th</th>
<th>tr</th>
<th>vi</th>
<th>zh</th>
</tr>
</thead>
<tbody>
<tr>
<td>baseline</td>
<td>59.1</td>
<td>47.6</td>
<td>50.1</td>
<td>47.0</td>
<td>49.1</td>
<td>41.4</td>
<td>40.2</td>
<td>51.6</td>
<td>45.1</td>
</tr>
<tr>
<td>w/o. all-shared</td>
<td>3.0</td>
<td>3.6</td>
<td>4.4</td>
<td>1.9</td>
<td>4.7</td>
<td>6.9</td>
<td>3.6</td>
<td>13.5</td>
<td>4.8</td>
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<td>w/o. specific</td>
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<td>49.9</td>
<td>47.0</td>
<td>49.1</td>
<td>41.9</td>
<td>40.1</td>
<td>51.4</td>
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<tr>
<td>w/o. partial-shared</td>
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<td>48.4</td>
<td>51.5</td>
<td>47.9</td>
<td>49.7</td>
<td>42.9</td>
<td>41.5</td>
<td>50.8</td>
<td>48.0</td>
</tr>
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</table>

Table 6: The effects of accuracy on the XNLI task with LLAMA2-7b-chat backbone, when deactivating all-shared neurons, specific neurons, and partial-shared neurons, respectively. “w/o.” stands for “without”.

Figure 23: Contribution of four types of neurons based on the fact probing task with BLOOMZ backbone.

Figure 24: Contribution of four types of neurons based on the XNLI task with BLOOMZ backbone.
Figure 25: Contribution of four types of neurons based on the cross-lingual KE (EN (edit) → ALL (test)) task with BLOOMZ backbone.
Figure 26: Contribution of four types of neurons based on the cross-lingual KE (ALL (edit) → EN (test)) task with BLOOMZ backbone.

Figure 27: Effective score of four types of neurons based on the fact probing task with BLOOMZ backbone.

Figure 28: Effective score of four types of neurons based on the XNLI task with BLOOMZ backbone.
Figure 29: Effective score of four types of neurons based on the cross-lingual KE (ALL (edit) → EN (test)) task with BLOOMZ backbone.