On Relation-Specific Neurons in Large Language Models

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Abstract

In large language models (LLMs), certain *neurons* can store distinct pieces of knowledge learned during pretraining. While knowledge typically appears as a combination of *relations* and *entities*, it remains unclear whether some neurons focus on a relation itself – independent of any entity. We hypothesize such neurons *detect* a relation in the input text and *guide* generation involving such a relation. To investigate this, we study the Llama-2 family on a chosen set of relations with a *statistics*-based method. Our experiments demonstrate the existence of relation-specific neurons. We measure the effect of selectively deactivating candidate neurons specific to relation r on the LLM's ability to handle (1) facts whose relation is r and (2) facts whose relation is a different relation $r' \neq r$. With respect to their capacity for encoding relation information, we give evidence for the following three properties of relation-specific neurons. **(i) Neuron cumulativity.** The neurons for r present a cumulative effect so that deactivating a larger portion of them results in the degradation of more facts in r. **(ii) Neuron versatility.** Neurons can be shared across multiple closely related as well as less related relations. Some relation neurons transfer across languages. **(iii) Neuron interference.** Deactivating neurons specific to one relation can improve LLM generation performance for facts of other relations.

1 Introduction

Large text corpora like Wikipedia contain abundant factual knowledge. LLMs, pretrained on such corpora, can function as knowledge bases that retrieve information and generate text involving factual content (Petroni et al., 2019; Jiang et al., 2020). Recent studies suggest that some knowledge is parameterized by LLMs (Dai et al., 2022; Geva et al., 2023), especially within the feed-forward layers of the Transformer architecture (Vaswani et al., 2017), which act as key-value memory (Geva et al., 2021). Factual knowledge is often expressed as a relational fact in triple form: *subject*, *relation*, and *object*, e.g., (`NVIDIA`, `company_ceo`, `Jensen Huang`). However, it remains unclear whether each fact is stored and processed separately through *knowledge neurons* (Dai et al., 2022), or if there exist *relation-specific neurons* that focus on the relation itself and guide generating the object once the subject and relation of a triple have been detected.

In this work, we examine the existence of relation-specific neurons in decoder-only LLMs. Our study focuses on the Llama-2 family (7B and 13B) (Touvron et al., 2023) and examines factual knowledge grouped into 12 types of relations. To pinpoint relation-specific neurons for these relations, we adopt the neuron identification method proposed by Cuadros et al. (2022), which identifies the neurons that are uniquely activated in one group of sentences (positive examples) while not in another (negative examples). Kojima et al. (2024) successfully applied this method to uncover *language-specific neurons*. Following this line of work, we construct zero-shot prompts featuring a specific relation for the positive examples and prompts with other relations for the negative examples. Neurons whose activation patterns are positively correlated with positive examples are regarded as relation-specific neurons.

To understand the impact of these neurons, we perform question-answering on new held-out prompts. These prompts for each relation share the same relation as the positive examples used for identification but have no entity overlap; this disentangles the effects of entities and relations. For each relation, we compare performance between the original model and the model in which the neurons for that relation are deactivated – intra-relation results. We also study how deactivating the neurons for one relation influences performance on other relations – inter-relation results. Our experiments reveal several key properties of these neurons:

Neuron cumulativity. These neurons present a cumulative effect so that deactivating a larger portion of them results in the degradation of more facts, suggesting LLM distributes relational knowledge across neurons in a manner that can vary significantly from fact to fact. This property aligns with the evidence of the existence of redundant or self-repair neurons (Dalvi et al., 2020; McGrath et al., 2023; He et al., 2024). Our analysis suggests the frequency of a fact in the pretraining data is associated with its sensitivity to a given subset.

Neuron versatility. Because the total number of neurons is finite while the number of possible relations is vast, some neurons strongly associate with multiple relations. Surprisingly, these relations need not be closely linked – two "less related" relations can share a group of neurons, leading to performance drops in both relations if those neurons are deactivated. Such neurons also generalize across languages. This property aligns with recent findings showcasing that some neurons are shared across languages and tasks (Wang et al., 2024a; Tang et al., 2024; Kojima et al., 2024).

Neuron interference. Some relation-specific neurons appear to "confuse" the model when it processes other relations. Deactivating such neurons can yield improved performance on these other relations. This property aligns with broader evidence that *sub-networks* or *circuits* within LLMs may serve several different functional roles (Wang et al., 2023a; Bayazit et al., 2024; Mondorf et al., 2024).

2 Methodology

2.1 Dataset Manipulation

We use the factual knowledge dataset from Hernandez et al. (2024) for this research, which contains 25 relations. Each relation has a different number of facts. Each fact can be represented as a *subject-relation-object* triple (s, r_i, o). We only consider relations that have more than 300 facts to ensure the reliability of our findings. This results in **12** relations. We refer to the set of triples for relation r_i as $\mathcal{D}_{r_i}$. We then perform the following steps for each relation r_i to construct the data used to identify its relation-specific neurons.

Step 1: Creating Evaluation Data. For each triple set $\mathcal{D}_{r_i}$, we randomly select **50 triples** as a held-out set for evaluation. (cf. §2.3). We refer to the selected triples as $\mathcal{D}^{\text{eva}}_{r_i}$ (for evaluation) and the remaining triples as $\mathcal{D}^{\text{det}}_{r_i}$ (for detection).

Step 2: Formulating Prompts. For each triple (s, r_i, o) in $\mathcal{D}^{\text{det}}_{r_i}$, we create prompts concerning the subject s and the relation r_i using the templates provided by Hernandez et al. (2024). For example, we construct a zero-shot prompt "`The CEO of NVIDIA is? Answer:`" for the triple (`NVIDIA`, `company_CEO`, `Jensen Huang`) with an expected answer "`Jensen Huang`". We also create prompts for $\mathcal{D}^{\text{eva}}_{r_i}$ in the same way. We refer to the resulting prompt sets as $\mathcal{P}^{\text{det}}_{r_i}$ and $\mathcal{P}^{\text{eva}}_{r_i}$.

Step 3: Validating Prompts. We hypothesize that the model will leverage relation-specific neurons to generate the correct answer, i.e., the object. Therefore, such neurons should be "fired" in those prompts for which **the model answers correctly**. We feed the prompt to the model and set the maximum length of the generation to be 2. We then check if the generated tokens are the same as the object (first two tokens): if they are the same, we regard the output as being correct. We exclude prompts that the model answers wrongly from $\mathcal{P}^{\text{det}}_{r_i}$.

2.2 Relation-Specific Neuron Identification

Following (Cuadros et al., 2022), we identify the relation-specific neurons using statistical association measures. This method assigns a score for each neuron, representing its level of "expertise" in distinguishing a specific relation from others.

Defining Neurons. A neural network, or specifically a Transformer (Vaswani et al., 2017), consists of many weight matrices. For a single weight matrix $\boldsymbol{W} \in \mathbb{R}^{d_1 \times d_2}$, we define a neuron as a column, mapping a representation from $\mathbb{R}^{d_1}$ to $\mathbb{R}$. We assign a unique index $m \in M$ to each neuron and investigate its output value. We only consider the neurons in **feed-forward networks (FFNs)**, i.e., neurons in `up_proj`, `gate_proj`, and `down_proj`, since previous studies have shown that knowledge is mostly stored there (Dai et al., 2022).

Grouping Prompts. For each relation r_i, we collect positive and negative examples. Specifically, we regard $\mathcal{P}^{\text{det}}_{r_i}$ as positive examples and randomly sample $4 \times |\mathcal{P}^{\text{det}}_{r_i}|$ prompts from the prompt sets of other relations as negative examples.[1] For simplicity, the positive and negative examples selected for relation r_i are referred to as $\mathcal{E}^{+}_{r_i}$ and $\mathcal{E}^{-}_{r_i}$ respectively. The final data used to detect the relation-specific neurons for relation r_i is then $\mathcal{E}_{r_i} = \mathcal{E}^{+}_{r_i} + \mathcal{E}^{-}_{r_i}$. For each individual example $e^{j}_{r_i}$, we assign a binary label $b^{j}_{r_i}$ to it: 1 if $e^{j}_{r_i} \in \mathcal{E}^{+}_{r_i}$ and 0 otherwise.

[1] We also sample negative examples with different seeds in our preliminary experiments. The neurons for each relation show little change, suggesting the stability of the neurons.

Model	#Layers	#Neurons (FFNs)	#Neurons (total)
Llama-2-7B	32	835,584	1,359,872
Llama-2-13B	40	1,310,720	2,129,920

Table 1: LLama-2 model statistics

Neuron Output Values. Let $o_{r_i}^{m,j,n}$ be the output value of neuron m for the n-th token in $e_{r_i}^j$ when feeding the example to the model. Following Kojima et al. (2024), we average the outputs over tokens to form the final output value of neuron m for the entire example $e_{r_i}^j$: $o_{r_i}^{m,j} = \frac{1}{T}\sum_{n=1}^{T} o_{r_i}^{m,j,n}$, where T is the number of effective tokens in $e_{r_i}^j$ – the output values of [PAD] tokens are regarded as noise and therefore ignored in the computation.

Computing Experts. The level of expertise of each neuron for relation r_i is computed by formulating a classification task. Specifically, we regard the output value $o_{r_i}^{m,j}$ as the prediction score with $e_{r_i}^j$ as input and $b_{r_i}^j$ as its ground-truth label. In this way, for an individual neuron m, we have the following data: $\{o_{r_i}^{m,j}, b_{r_i}^j\}_{j=1}^{|\mathcal{E}_{r_i}|}$. We then measure this neuron's performance by setting all output values as classification thresholds and comparing the predictions with the ground truth labels. Average precision (AP) is used as the metric (the area under the precision-recall curve). By doing this, we obtain $AP_{r_i}^m$ for all $m \in M$, allowing us to rank them by their level of expertise in differentiating relation r_i from others. The top k neurons are regarded as relation-specific neurons in descending order.

2.3 Controlled Generation

For each relation r_i, we want to investigate the impact of the identified top-k relation-specific neurons. Therefore, we control text generation by overriding the output values with 0 during inference, aiming to deactivate or suppress these neurons. Specifically, we feed $\mathcal{P}_{r_i}^{\text{eva}}$, the prompts from the held-out evaluation prompt set for relation r_i, into the model. During inference, we simply set the output values of all top-k relation-specific neurons for r_i to a constant 0 and let the model generate two tokens, regarded as the model's answer to the question. The answer is then compared to the first two tokens of the correct answer, i.e., the object.

3 Experimental Setup

3.1 Models

We consider the 7B and 13B models from the LLama-2 family (Touvron et al., 2023). As mentioned in §2.2, we consider the neurons in **FFNs** which account for more than half of neurons in both 7B and 13B, as shown in Table 1. We also report our preliminary results when considering other types of neurons (e.g., `up_proj`) in §E.

3.2 Datasets

We manipulate the relational knowledge datasets from Hernandez et al. (2024) using the procedure described in §2.1. Recall that we cover 12 relations in our experiments. Prompt sets $\mathcal{P}_{r_i}^{\text{det}}$ (for neuron identification) and $\mathcal{P}_{r_i}^{\text{eva}}$ (for evaluation) are constructed for each relation. $|\mathcal{P}_{r_i}^{\text{det}}|$ varies for different relations.[2] $\mathcal{P}_{r_i}^{\text{eva}}$ is constructed by randomly selecting **50 triples** for each relation. Since these 50 triples are not used when creating $\mathcal{P}_{r_i}^{\text{det}}$, this setup ensures **no subject overlap between $\mathcal{P}_{r_i}^{\text{det}}$ and $\mathcal{P}_{r_i}^{\text{eva}}$ for the same relation** r_i. In addition, we ensure **minimal subject overlap across relations** (mostly 0 between $\mathcal{P}_{r_i}^{\text{det}}$ and $\mathcal{P}_{r_j}^{\text{det}}$). The only exception is between `person_mother` and `person_father`, which share a lot of subjects. A detailed entity overlap analysis is presented in §B.

4 Results and Discussion

We apply our identification method to both 7B and 13B models for all 12 relations. We regard the **top 3,000** neurons with the highest AP values as the relation-specific neurons, as for this threshold, we achieve good coverage of relation-specific neurons with a set of neurons that is not too large. We discuss the impact of this meta-parameter in §5.1.

4.1 Identified Relation-Specific Neurons

Distribution Across Layers. We display the distribution of relation-specific neurons across layers in the 7B model in Figure 2 (see §C for the 13B model). Most neurons are located in the model's **middle layers**. Such a distribution differs from language-specific neurons, which are mostly located in the first and last few layers (Kojima et al., 2024). We hypothesize that relational knowledge requires more than surface-level information that is mainly encoded and processed in the first and last few layers. Therefore, these relation-specific neurons naturally emerge in the middle layers, where the model has integrated enough lexical and syntactic signals to model and process the relation. This finding is consistent with several studies that show that mapping vectors with certain functions can be

[2] $|\mathcal{P}_{r_i}^{\text{det}}|$ can be different for 7B and 13B models because the number of prompts excluded in the validating prompt step (described in §2.1) can be different.

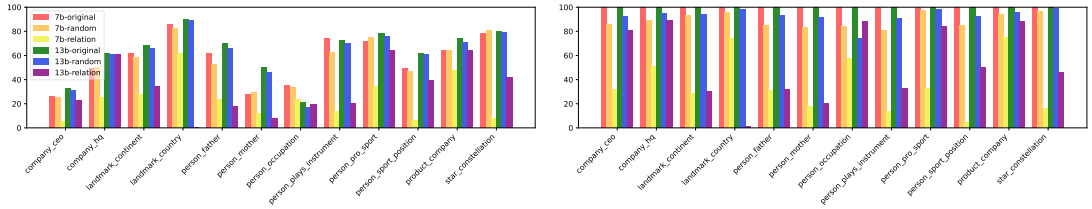

Figure 1: Intra-relation results. The left (resp. right) figure displays the results of held-out evaluation prompt set $\mathcal{P}_{r_i}^{\text{eva}}$ (resp. identification prompt set $\mathcal{P}_{r_i}^{\text{det}}$). We report the performance of the original model (without any deactivation), e.g., `7b-original`, the model with 3,000 random neurons deactivated (averaged over 10 seeds), e.g., `7b-random`, and the model with relation-specific neurons deactivated, e.g., `7b-relation`.

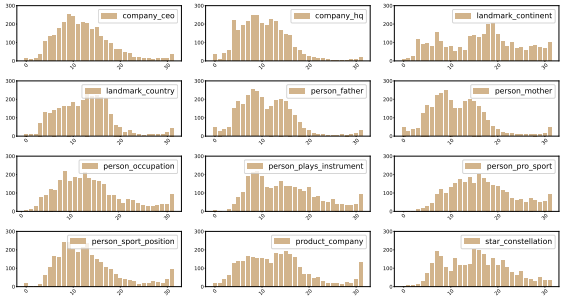

Figure 2: Distribution of relation-specific neurons across layers. Most are located in the middle layers.

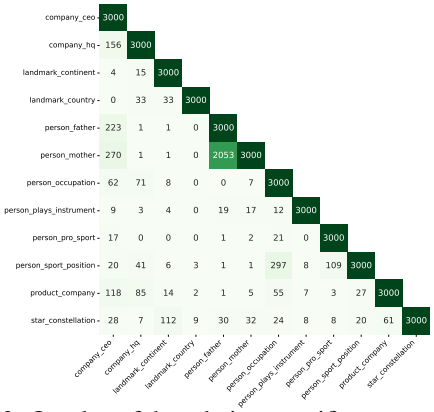

Figure 3: Overlap of the relation-specific neurons across 12 relations. For example, 2053 indicates the number of neurons shared between the 3,000 identified neurons for `person_father` and the 3,000 for `person_mother`.

extracted from the middle layers (Merullo et al., 2024; Hernandez et al., 2024; Todd et al., 2024).

Overlap Across Relations. We display the overlap of relation-specific neurons across relations for the 7B model in Figure 3 (13B is in §C). We see that `person_mother` and `person_father` share a large share of neurons, possibly due to the large overlap between their subjects, (see in §B). However, even though there is almost no subject overlap between any other relations, many relations still share some neurons with others. For instance, `person_occupation` and `person_sport_position` share 297 neurons, possibly because they are similar relations – a sport is roughly also an occupation. Extensive neuron overlap can also be observed when two relations are mapping **from the same type of subjects**, e.g., `company_ceo` and `company_hq`, or mapping **to the same type of objects**, e.g., `company_ceo` and `person_father`. However, we show in §4.2.2 that a high neuron overlap does not necessarily imply a high level of mutual interference.

4.2 Controlled Generation

For each relation, we set the output values of its identified 3,000 relation-specific neurons to 0, and observe how the deactivation impacts the relation itself and other relations in terms of accuracy.

4.2.1 Intra-Relation Results

In addition to intra-relation results, i.e., deactivating the 3,000 identified relation-specific neurons for a relation and evaluating the same relation, we also create a baseline by **randomly** deactivating 3,000 neurons in the model. We report the results of the original models, the results of the baseline, and the intra-relation results in Figure 1.

We can observe a clear performance drop on the identification prompt set $\mathcal{P}_{r_i}^{\text{det}}$ when comparing the accuracy of the original model and the model whose relation-specific neurons are deactivated.[3] On the other hand, the model with randomly 3,000 deactivated neurons does not show much difference compared with the original model, indicating the 3,000 relation neurons are closely associated with the facts included in $\mathcal{P}_{r_i}^{\text{det}}$. On the evaluation set $\mathcal{P}_{r_i}^{\text{eva}}$, we also observe a notable accuracy drop across models for most relations. Since $\mathcal{P}_{r_i}^{\text{eva}}$ and $\mathcal{P}_{r_i}^{\text{det}}$ do not share any entities, the accuracy drop can only be attributed to the fact that deactivating 3,000 neurons affects the relation itself – the common characteristic between $\mathcal{P}_{r_i}^{\text{eva}}$ and $\mathcal{P}_{r_i}^{\text{det}}$. Therefore, we argue that **relation-specific neurons do exist in LLMs**. These neurons are entity-irrelevant, rather, they focus on a specific relation.

On the other hand, the accuracy does not drop

[3] For some relations, the drop is moderate, e.g., `product_company`. We show in §5.1 that the drop can become noticeable when we deactivate more than 3,000 neurons.

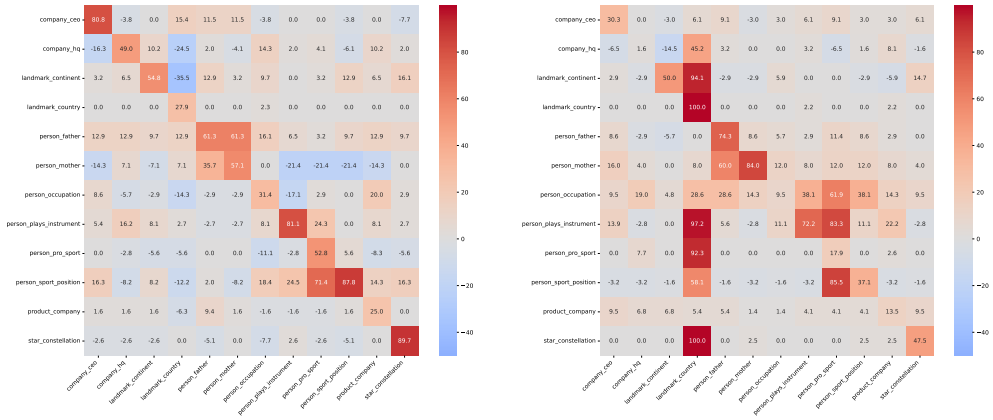

Figure 4: Inter-relation results for the 7B model (left) and the 13B model (right). The number in cell (r_i, r_j) indicates the accuracy drop of relation r_i when deactivating the relation-specific neurons of relation r_j.

to 0 for any relation (except `landmark_country` in the 13B model) when its identified relation-specific neurons are deactivated. This indicates these 3,000 neurons do not equally influence all facts that belong to a certain relation. We therefore have the **neuron cumulativity** hypothesis: The relation-specific neurons are associated with different facts belonging to the concerned relation. These neurons present a cumulative effect so that deactivating a small number of them (in this case, 3,000) results in the degradation of some (not all) facts, whereas more facts are affected when a larger portion is disabled. This disparity highlights that LLMs do not uniformly encode all facts that belong to a given relation, but rather distribute relational knowledge across neurons in a manner that can vary significantly from fact to fact. We validate this by demonstrating that the accuracy further drops by deactivating more neurons in §5.1. We also show that the sensitivity of a fact to a given population of neurons may correlate with how frequently the fact appears in the pretraining data in §5.3.

4.2.2 Inter-Relation Results

To understand the effect of how these neurons influence the model's ability to answer prompts across multiple relations, we use **accuracy drop** as a metric: $\text{acc\_drop}_{r_i,r_j} = \frac{\text{acc}_{r_i}^{\text{original}} - \text{acc}_{r_i}^{\text{deactivated-}r_j}}{\text{acc}_{r_i}^{\text{original}}}$, where $\text{acc}_{r_i}^{\text{original}}$ is the accuracy of the original model for $\mathcal{P}_{r_i}^{\text{eva}}$ and $\text{acc}_{r_i}^{\text{deactivated-}r_j}$ is the accuracy for $\mathcal{P}_{r_i}^{\text{eva}}$ when the relation-specific neurons of r_j are deactivated. Results are displayed in Figure 4.

When we compare the 7B and 13B models, no consistent pattern emerges across relations. This indicates that, though being trained on the same data, differences in model size and parameter initialization appear to substantially change the functionality of neurons. In particular, most relations in the 13B model are less influenced when neurons of other relations are deactivated than in the 7B model except in the following cases: deactivating neurons of `landmark_country` strongly affects several other relations concerning the notion of "location"; `person_mother` and `person_occupation` are sensitive to the deactivation of neurons of other relations. Despite these divergences, we propose two hypotheses that hold across both models.

Neuron versatility. We observe that deactivating relation-specific neurons for one relation can strongly affect not only that relation but also others, whether they are **"closely" or only "loosely" related**. For example, disabling `person_pro_sport` neurons has a large effect on `person_sport_position` (but not vice versa) in both 7B and 13B models, likely because the model first needs to understand "sport" before inferring "position". Similarly, deactivating `person_father` neurons reduces accuracy on `person_mother`, as both share the concept of an immediate parental relationship. Even more loosely related relations can exhibit a clear accuracy drop: deactivating `star_constellation` neurons affects `landmark_continent` in both models, possibly because both involve the abstract notion of "location".

Neuron interference. Deactivating the relation-specific neurons of one relation can sometimes **improve** the accuracy for other relations – a phenomenon more pronounced in the 7B model, likely because its smaller parameter space is less capable of isolating different relations. In the 7B model, several relations frequently benefit from this effect: for instance, `person_mother` improves when neurons from 5 out of 11 other relations – mostly "less related" ones – are deactivated. This effect is also observed for closely related

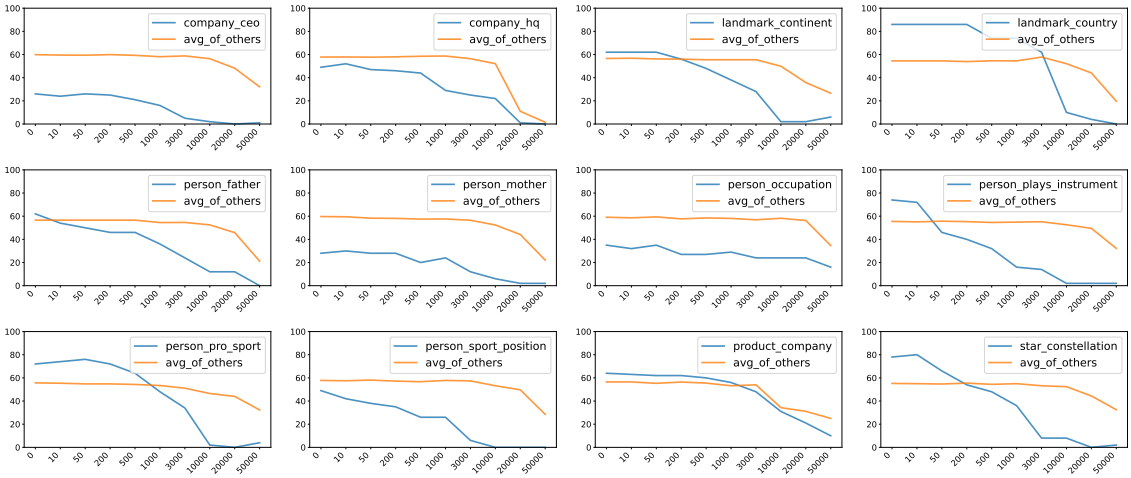

Figure 5: Influence of deactivating different numbers of relation-specific neurons for each relation. The variation of accuracy on the relation itself and the average accuracy on other relations is shown. Increasing the number clearly affects the relation itself, but the effect on other relations is obvious only until 3,000 or 10,000 neurons.

relations: disabling `company_ceo` neurons offers a small accuracy boost to `company_hq` for both models, while deactivating `landmark_country` neurons benefits `landmark_continent` in the 7B model. Interestingly, the 13B model shows the opposite effect for `landmark_continent` when disabling `landmark_country`, implying that country information can help predict a continent for the larger model. These findings indicate that neuron interference happens across model sizes, but its specific patterns vary – potentially due to factors such as parameter initialization, pretraining data order, or other hyperparameters.

5 Further Analysis

5.1 Influence of the Numbers of Neurons

In this section, we investigate the effect of varying the number of relation-specific neurons on the 7B model (see §C for 13B). Specifically, we consider **ten** values: 10, 50, 200, 500, 1,000, 3,000, 10,000, 20,000, and 50,000. When deactivating varying numbers of neurons for a relation, we report the variation of accuracy for that relation and the **average accuracy** for all other relations in Figure 5. The variation in individual relations is in Figure 16.

Relation-specific neurons of different relations present a varying degree of cumulative effect. Although the accuracy for most relations drops substantially once 3,000 or 10,000 neurons are deactivated, some relations are far more sensitive to a smaller-scale deactivation. For example, disabling only 50 neurons reduces the accuracy from 80% to 50% for `star_constellation`, and a similar decline occurs for `person_plays_instrument`. We hypothesize that this sensitivity reflects how many distinct objects each relation maps to: if a relation has fewer unique objects, fewer neurons may be critical. By contrast, relations like `person_occupation` display lower sensitivity, retaining about 20% accuracy even after 50,000 neurons are deactivated.

Relation	#total	#affected
`company_ceo`	11	2
`company_hq`	5	0
`landmark_continent`	6	2
`landmark_country`	6	0
`person_father`	6	2
`person_mother`	7	5
`person_occupation`	8	1
`person_plays_instrument`	3	0
`person_pro_sport`	8	0
`person_sport_position`	20	11
`product_company`	9	2
`star_constellation`	14	0

Table 2: Case study. Out of the prompts (#total) where the model answers correctly when deactivating 1,000 but not when deactivating 3,000 neurons, few of them are affected when deactivating the difference (2,000).

Validation of the cumulative effect. However, it remains unclear whether the further accuracy drop between two thresholds in Figure 5 is driven by **the newly deactivated neurons** or **the cumulative effect of all deactivated neurons**. To further investigate our neuron cumulativity hypothesis, we conduct a case study using 1,000 and 3,000 deactivated neurons. Specifically, we identify prompts from $\mathcal{P}_{r_i}^{\text{eva}}$ where the model answers correctly with 1,000 deactivated neurons but fails when 3,000 are deactivated. We then deactivate only the 2,000 additional neurons and measure the number of affected prompts, as shown in Table 2. The results support the cumulative effect for most relations: the degradation of more facts primarily stems from the collective deactivation of all 3,000 neurons.

Deactivating relation-specific neurons has a marginal effect on other relations until certain

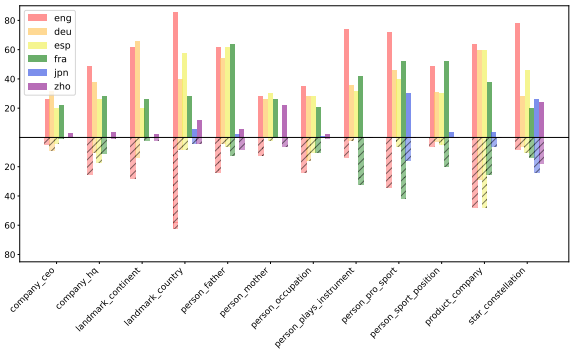

Figure 6: Accuracy on 12 relations across 6 languages. The upper bars (resp. lower bars) show the accuracy before (resp. after) the deactivation of 3,000 relations-specific neurons. Even though these neurons are identified using English, they usually influence other languages, indicating multilinguality of these neurons.

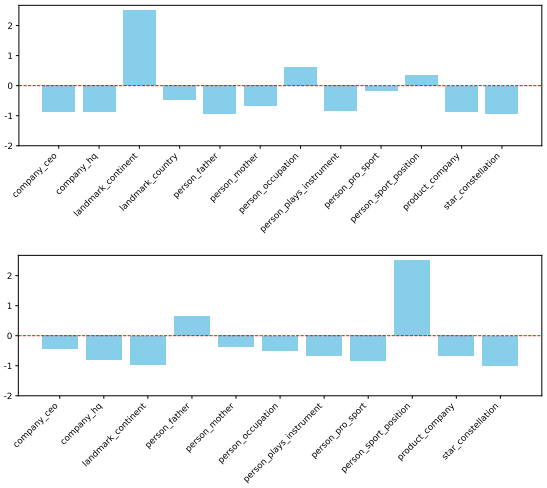

Figure 7: Relative difference between the average fact frequencies of the group (a) *resilient facts* and (b) *sensitive facts* for each relation in 7B (top) and 13B (bottom) models. Resilient facts generally appear more often than sensitive facts in most relations in the pertaining data.

thresholds are reached. Typically, these thresholds occur around 3,000 or 10,000, below which the accuracy on other relations remains stable – supporting the choice of 3,000 neurons. Once more neurons are deactivated, other relations also deteriorate, consistent with our **neuron versatility** hypothesis. This effect is clearer among closely related relations (e.g., `person_pro_sport` and `person_sport_position`), as displayed in Figure 16. Even deactivating up to 50,000 neurons seldom reduces other relations to near-zero accuracy, suggesting a high degree of relation-specificity. One exception is `company_hq`, for which disabling 50,000 neurons causes all relations' accuracies to approach zero – possibly because some of these neurons underlie more general generation capabilities of the model (Sun et al., 2024; Yu et al., 2024).

5.2 Are These Neurons Multilingual?

Recent studies suggest that some neurons encoding factual knowledge or handling specific tasks are multilingual (Stanczak et al., 2022; Zhang et al., 2024; Wang et al., 2024a). A natural question is whether relation-specific neurons – identified solely via English prompts – also function across languages. To explore this, we translate $\mathcal{P}^{\text{eva}}_{r_i}$ to 5 languages: German (**deu**), Spanish (**esp**), French (**fra**), Chinese (**zho**), and Japanese (**jpn**) (see §D for details). We then deactivate the previously identified 3,000 neurons in the 7B model and measure the effect on these languages, as shown in Figure 6.

Although the model's accuracy is generally lower in non-English languages, it still achieves decent results for most relations (except for jpn and zho). Once the neurons for a given relation are deactivated, the accuracy drops across nearly all languages – supporting our **neuron versatility** hypothesis. Our findings align with recent explanations that LLMs tend to translate the input text from any language into English for task solving in the middle layers based on a shared representation space (Wendler et al., 2024; Dumas et al., 2024; Zhao et al., 2024). As a result, deactivating "English" neurons naturally disrupts this shared space, impairing the model's capability to generalize across languages for the affected relation.

5.3 Fact Frequencies vs. Neuron Cumulativity

We now examine our **neuron cumulativity** hypothesis by asking: *why do some facts show higher sensitivity to a given set of relation neurons than others?* We hypothesize that the frequency of a fact in the pretraining data can be a key factor, as more frequent facts may be memorized more robustly and thus remain less sensitive to deactivation.

Because the pretraining data for Llama 2 is not publicly available, we approximate it using Dolma (Soldaini et al., 2024), a 3 trillion-token open-source corpus. For each relation, we split the facts into two groups: (**a**) *resilient facts*, for which the 7B (or 13B) model correctly predicts the object **both before and after** deactivating 3,000 relation-specific neurons. (**b**) *sensitive facts*, for which the model is correct **before but not after** these neurons are deactivated.[4] We then count how many documents in Dolma contain **both the subject and**

[4]We do not consider other numbers of relation-specific neurons because (1) if #neurons < 3,000, there are not enough facts whose predictions change, and (2) if #neurons > 3,000, facts belonging to other relations will also be influenced a lot.

object of each fact, calling this the *fact frequency*.[5] Finally, we compute the average frequency for resilient and sensitive facts in each relation r_i, denoted respectively as $\text{group}_{r_i}^{(a)}$ and $\text{group}_{r_i}^{(b)}$.

Relative difference: $\text{diff}_{r_i} = \frac{\text{group}_{r_i}^{(b)} - \text{group}_{r_i}^{(a)}}{\text{group}_{r_i}^{(b)}}$ for each relation r_i is reported in Figure 7. We find that resilient facts generally appear more often in Dolma than sensitive facts, with only 3 exceptions in the 7B model and 2 exceptions in the 13B model (note that `landmark_country` is omitted for the 13B model because no facts fall into group (**a**)). We evaluate this difference with the Wilcoxon Signed-Rank Test (Woolson, 2005) and obtain p-values of respectively 0.11 and 0.03 for the 7B and the 13B models.[6] These results show that there is a difference (statistically significant in the 13B model at the 5% level) between the two groups, supporting our hypothesis that **more frequent facts are generally less sensitive to the deactivation of a given set of relation-specific neurons**.

5.4 Relations vs. Concepts

We saw in Figure 3 that the storage of relations is generally well separated, but that there are exceptions. We can view a relation as relating two **concepts**, e.g., `company_ceo` relates instances of the "subject" concept "company" to instances of the "object" concept "CEO". From this perspective, the exceptions in Figure 3, i.e., cases where a relation r_1 overlaps with a relation r_2, are generally cases where the concepts of r_1 and r_2 are the same or overlap. For example, `company_ceo` and `company_hq` have the same subject concept.

To further explore this hypothesis empirically, we again use the method applied in §2 to relations, but now use it for concepts; that is we identify sets of **concept-specific neurons**. We group the LRE dataset triples by subject concept, resulting in 11 different concepts. We create a set of triples with novel relations such as "can" and "has a", balanced across positive and negative samples. This ensures that the model's completion for a prompt like ("Lincoln has a") depends on the concept instance ("Lincoln"), not on the relation ("has a").

Figure 8 shows the overlap between relation neurons and concept neurons for 13B. Most of the cells with large counts support our hypothesis that the overlaps we observe are rooted in relations being representationally associated with their subject and object concepts. Clear examples include `company_ceo` and its subject concept `company`; `company_hq` and its object concept `city` (assuming that `hq` is a subcategory of `city`); and `landmark_continent` and its subject concept `landmark`. There is little overlap of `person` with relations like `person_mother`, potentially because `person` is a more general and semantically unspecific concept than the others. Note that several concepts do not match a specific relation, e.g., `superhero`, and therefore are not strongly associated with any relation. Recall that we picked the concepts according to the availability of annotated data in LRE. However, most identified neurons are only concept neurons or only relation neurons, suggesting that relational and conceptual representations are largely separate.

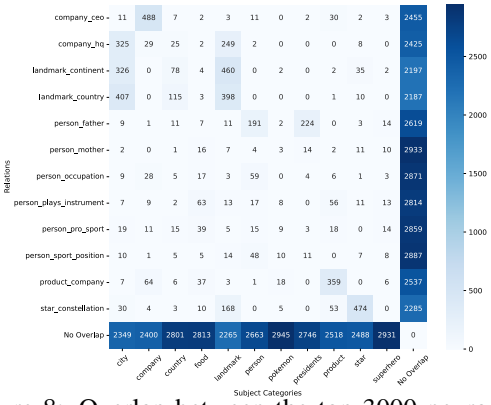

Figure 8: Overlap between the top 3000 neurons of relations and concepts in the 13B model.

6 Conclusion

This work highlights the existence of relation-specific neurons in LLMs – neurons that focus on relations rather than entities. Our experiments show these neurons primarily reside in the middle layers and can be shared across multiple relations. Through systematic deactivation, we reveal their influence on both the targeted and other relations, leading to three key hypotheses: **neuron cumulativity** (deactivating a larger portion of relation-specific neurons results in the degradation of more facts belonging to the concerning relation), **neuron versatility** (neurons are shared across relations and languages), and **neuron interference** (neurons from one relation can disrupt the processing of another). These findings shed new light on how LLMs handle relational facts at the neuron level, contributing to the interpretability of LLMs.

[5] We use ElasticSearch API from WIMBD (Elazar et al., 2024) that allows for counting and searching in large corpora.

[6] We use a nonparametric test because the difference across relations does not follow a Gaussian distribution.

Limitations

While our findings provide valuable insights, several limitations remain and offer opportunities for future research. First, this work focuses on factual knowledge grouped into 12 relations. Although this selection does not diminish the validity of our findings and hypotheses, it represents a relatively narrow set of relations. Future work can explore a broader range of relations and analyze how relation-specific neurons behave across a more diverse set of relations. Second, our multilingual analysis includes only five languages. While these languages demonstrate neuron versatility, they do not fully capture linguistic diversity. Future research could investigate additional languages, particularly low-resource ones, to determine whether relation-specific neurons exhibit similar relational functionality across these languages. Lastly, we observe that more frequent facts tend to be more robust to the deactivation of relation-specific neurons in both the 7B and 13B models. Fact frequency is approximated using the Dolma corpus (Soldaini et al., 2024) in this study. However, LLama-2 models may incorporate a larger and more diverse pretraining dataset, potentially leading to some discrepancies between these approximated fact frequencies and their actual frequencies.

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A Related Work

Mechanistic interpretability (MI) is a growing subfield of interpretability that aims to understand LLMs by breaking them down into smaller components and fundamental computations. It has gained significant attention for studying how LLMs recall factual knowledge learned during pretraining (Meng et al., 2022; Dai et al., 2022; Geva et al., 2023; Yu et al., 2023; Lv et al., 2024; Wang et al., 2024b). Following Olah et al. (2020); Rai et al. (2024), MI research can be categorized into two areas: the study of **features** and the study of **circuits**, based on the type of decomposed components. Features refer to human-interpretable properties encoded in model representations or represented by model components, such as neurons and attention heads (Elhage et al., 2022; Gurnee et al., 2023). Circuits are subgraphs of the model's computation graph responsible for implementing specific behaviors (Wang et al., 2023b; Elhage et al., 2021).

In this work, we focus on neuron-level feature-based interpretability analysis to localize relation-specific neurons, which are responsible for encoding and recalling specific types of factual knowledge. Existing studies have utilized various approaches for neuron interpretation, each offering unique advantages and limitations (Sajjad et al., 2022; Rai et al., 2024). The *visualization* method (Olsson et al., 2022; Elhage et al., 2022; Lieberum et al., 2023; Bills et al., 2023; Liu et al., 2024) involves visualizing neuron activations and manually identifying the underlying concept across input text. While being straightforward, it relies heavily on human effort and risks overgeneralization. *Statistics*-based methods (Bau et al., 2019; Cuadros et al., 2022; Kojima et al., 2024; Yu and Ananiadou, 2024; Tang et al., 2024; Wang et al., 2024b), on the other hand, aggregate activation statistics across data to establish connections between neurons and concepts, identifying patterns through the co-occurrence of neuron activation values and specific input features. *Probing*-based methods (Dalvi et al., 2019; Durrani et al., 2020; Antverg and Belinkov, 2022; Gurnee et al., 2024) train diagnostic classifiers on neuron activations to identify neurons associated with predefined concepts. These methods are scalable, enabling the discovery of neuron sets across large datasets, though they depend on supervised data annotations. *Causation*-based methods (Vig et al., 2020; Meng et al., 2022, 2023; Kramár et al., 2024; Song et al., 2024) take a different approach by directly varying the values of specific neurons or components and analyzing changes in model behavior; significant changes indicate the importance of these neurons or components to particular functionalities.

Building on this foundation, our work adopts the statistics-based method proposed by Cuadros et al. (2022) to identify relation-specific neurons – neurons uniquely "fired" for queries concerning facts sharing the same relation. This approach facilitates a scalable and targeted analysis of neuron behavior in relation to factual knowledge recall.

B Entity Overlap Across Relations

We show the number of **distinct subjects (resp. objects)** in each relation and the number of **overlapping subjects (resp. objects)** between any two

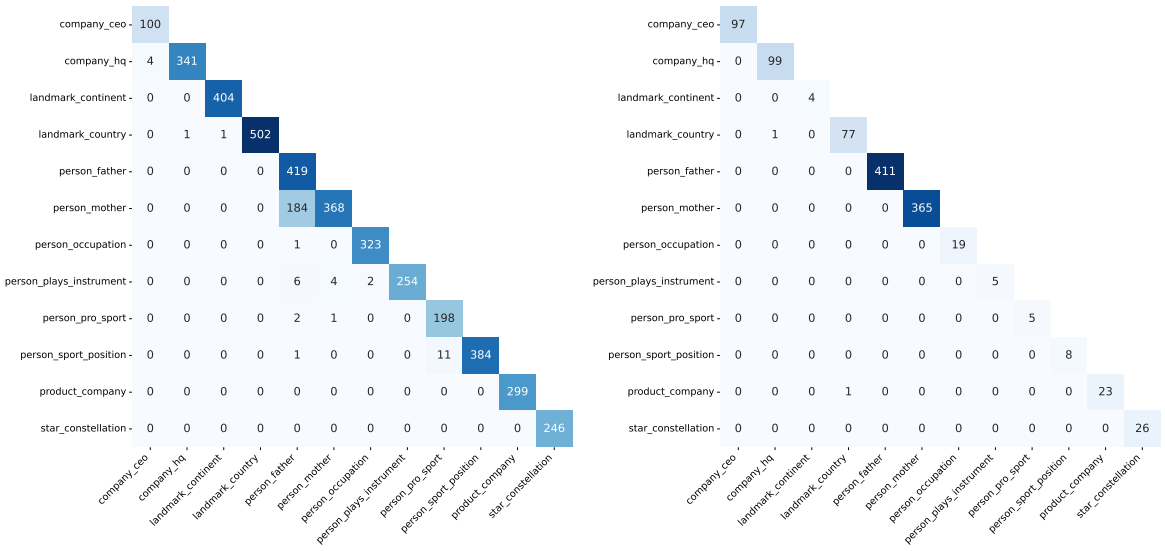

Figure 9: Subject (left) and object (right) overlap across 12 relations obtained from the 7B model. The diagonal in each figure shows the number of distinct subjects or objects for each relation. It can be seen that factual knowledge from different relations has almost no entity overlap except for `person_mother` and `person_father`, which are mostly celebrities.

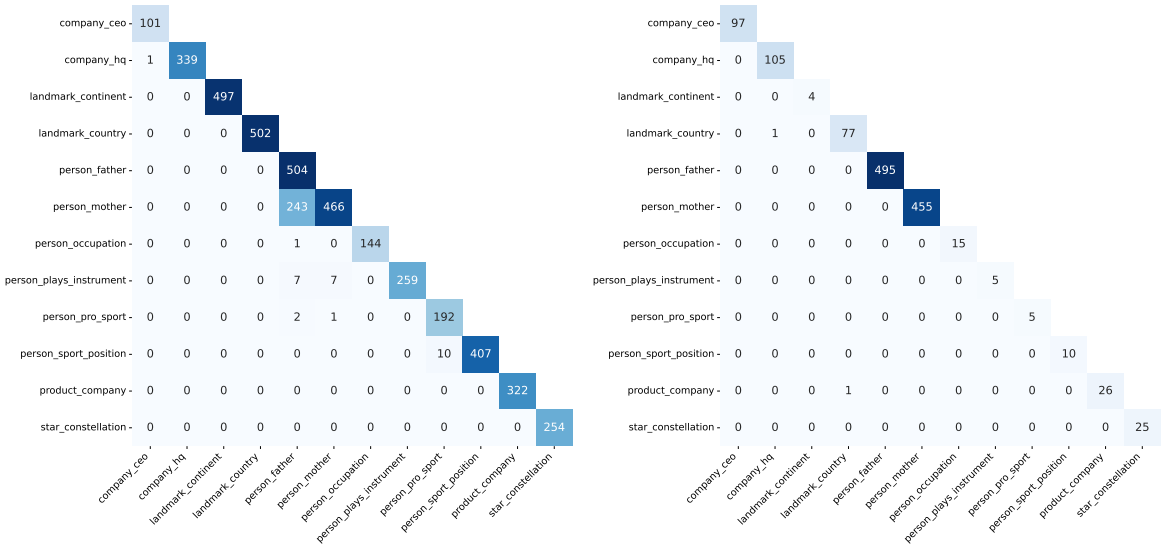

Figure 10: Subject (left) and object (right) overlap across 12 relations obtained from the 13B model. The trend is very similar to that in the 7B model: `person_mother` and `person_father` share many subjects.

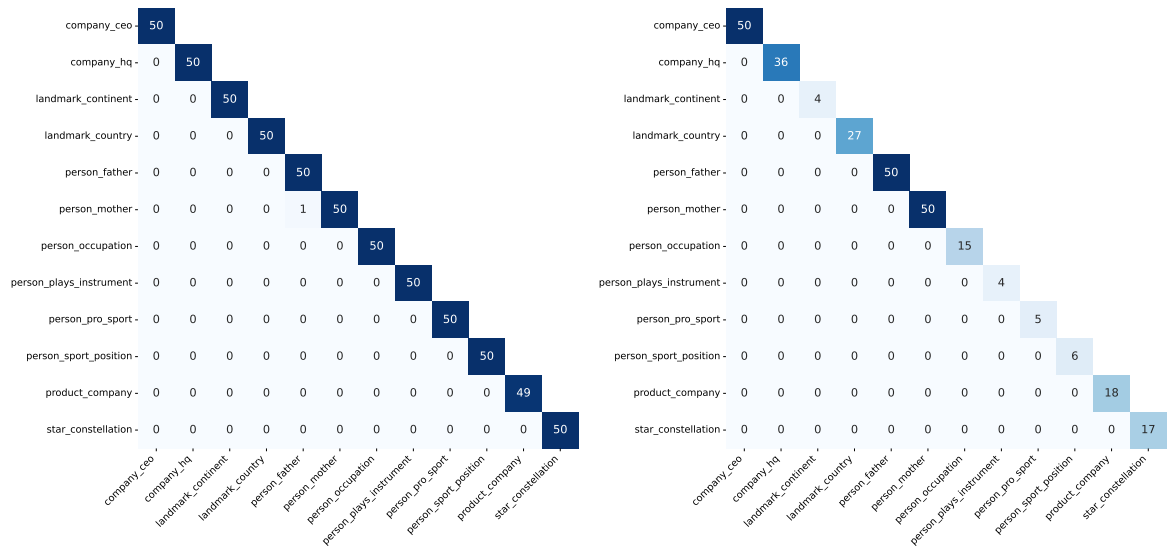

Figure 11: Subject (left) and object (right) overlap across 12 relations in the held-out evaluation prompt set $\mathcal{P}_{r_i}^{\text{eva}}$. Almost no two relations share any subjects or objects.

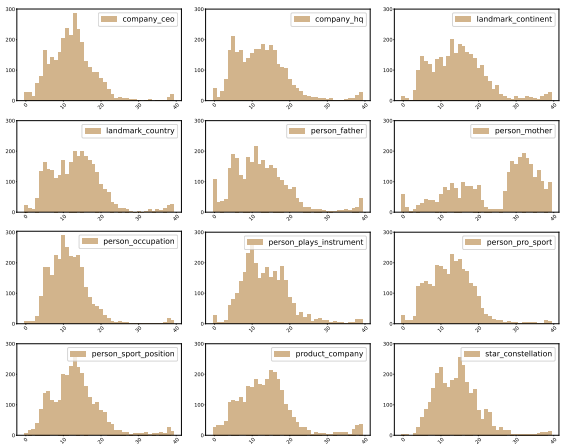

Figure 12: Distribution of relation-specific neurons across layers for the 13B model. Similar to Figure 2, identified relation-specific neurons are mostly located in the middle layers, except for `person_mother`.

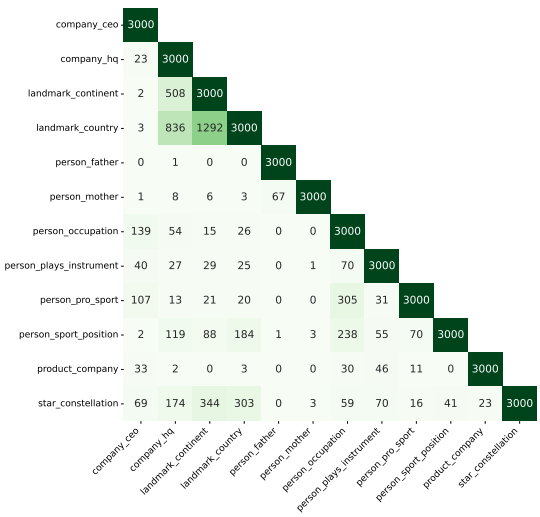

Figure 13: Overlap of the relation-specific neurons across 12 relations in the 13B model. The overlap distribution is not similar to what we observe for the 7B model shown in Figure 3, explaining the difference in inter-relation results (cf. Table 4).

relations in the identification prompt set $\mathcal{P}_{r_i}^{\text{det}}$ of the 7B model and the 13B model in Figure 9 and 10 respectively. Most two relations have no common or very limited overlapping (less than 11) subjects, except for `person_mother` and `person_father`, which are mostly celebrities, possibly resulting in extensive neuron overlap between the two relations as we show in §4.1. Similarly, no two relations share many objects. Additionally, we show the number of overlapping entities in the evaluation set $\mathcal{P}_{r_i}^{\text{eva}}$ (the 7B and 13B models share the same evaluation set) in Figure 11. The results also show almost no entity overlap across different relations: among all relations, only `person_mother` and `person_father` share **one** subject and the rest of the relations do not share any subject or object overlap. The entity analysis suggests that entities are not a confounding factor in our experiments and the identified relation-specific neurons are only concerning the relation itself but not entities.

C Analysis On the 13B Model

We perform a similar analysis on the 13B model as we do for the 7B model. We first show how the identified 3,000 relation-specific neurons are dis-

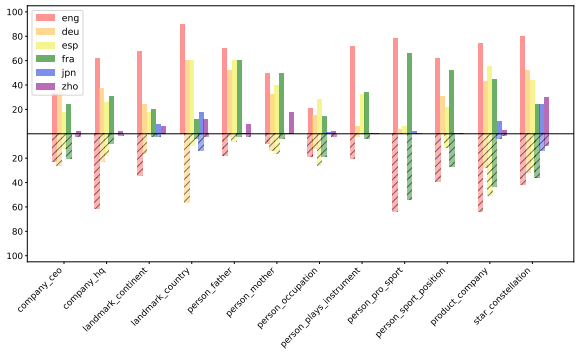

Figure 14: Accuracy on 12 relations across 6 languages from the 13B model. The upper bars (resp. lower bars) show the accuracy before (resp. after) the deactivation of 3,000 relations-specific neurons.

tributed across layers for each relation in Figure 12. The trend is similar to what we observe in the 7B model (cf. Figure 2). Most of the relation-specific neurons are distributed in the middle layers. Then we show the overlap of relation-specific neurons across relations in Figure 13. Surprisingly, the overlap pattern is very different from what we observe in the 7B model. First, it seems that many relations that share a concept of "location" share extensive neurons, e.g., `company_hq`, `landmark_country`, `landmark_country` and `star_constellation`. This explains the difference in inter-relation results between the models (cf. Figure 4) where we see deactivating neurons of `landmark_country` significantly influence other relations also concerning location for the 13B model but not for the 7B model.

We then demonstrate the effect of varying numbers of relation-specific neurons using the same numbers: 10, 50, 200, 500, 1,000, 3,000, 10,000, 20,000, and 50,000. Figure 15 presents the results. The global trend is similar to what we observe for the 7B model: deactivating more neurons results in a further drop in accuracy across all relations. This indicates the **neuron cumulativity** is universal across models. Relation-specific neurons for most relations present a similar cumulative effect to the 13B model. The original two outliers in the 7B model (`person_occupation` and `person_company` where the accuracy does not drop to 0 in the 7B model) even show a plateau, i.e., the accuracy remains almost unchanged or only slightly decreases. This might suggest that facts belonging to these two relations might be well-memorized by the models and are less sensitive to the deactivation of relation-specific neurons.

Lastly, we show whether the identified relation-specific neurons from the 13B model are also multilingual. We use the same translated prompt sets as we use for the 7B model. We deactivate the 3,000 neurons identified using English and see how this affects the performance in other languages: German (**deu**), Spanish (**esp**), French (**fra**), Chinese (**zho**), and Japanese (**jpn**). The results are presented in Figure 14. We observe similar results as from the 7B model: when we deactivate the relation-specific neurons identified using English prompts, many relations are influenced across languages, suggesting models with different sizes also have multilingual relational neurons. We also see some interesting counterexamples: deactivating `landmark_country` neurons completely deteriorates the relation in English but not in German. This indicates while some neurons have multilingual relational functionalities, there are still some relations dealt with in a language-specific manner.

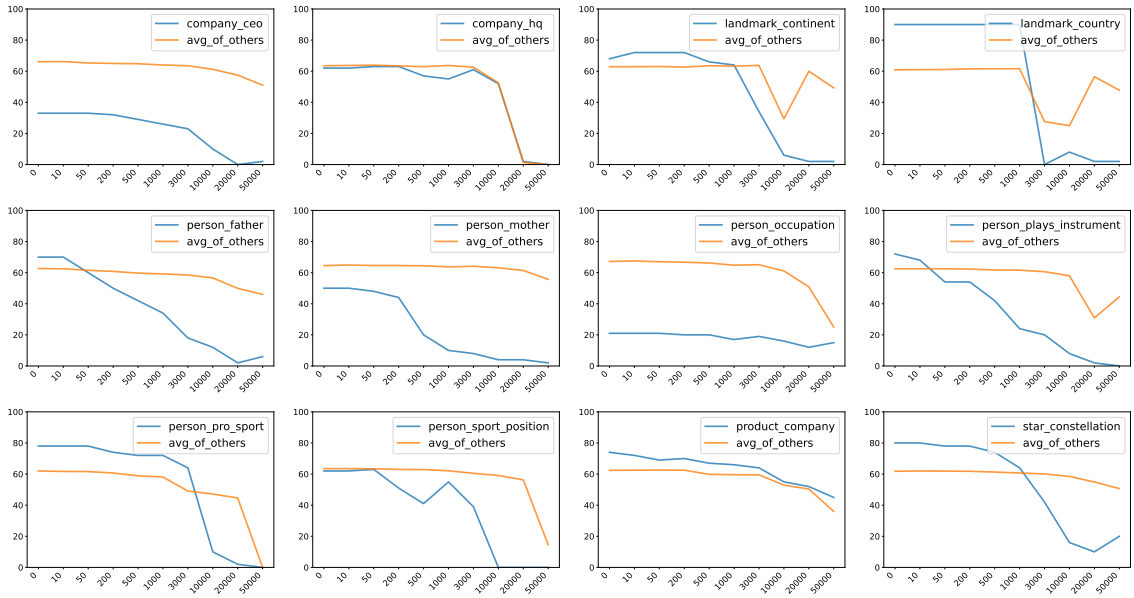

Figure 15: Influence of deactivating different numbers of relation-specific neurons for each relation (**the 13B model**). The variation of accuracy on the relation itself and the average accuracy on other relations is shown.

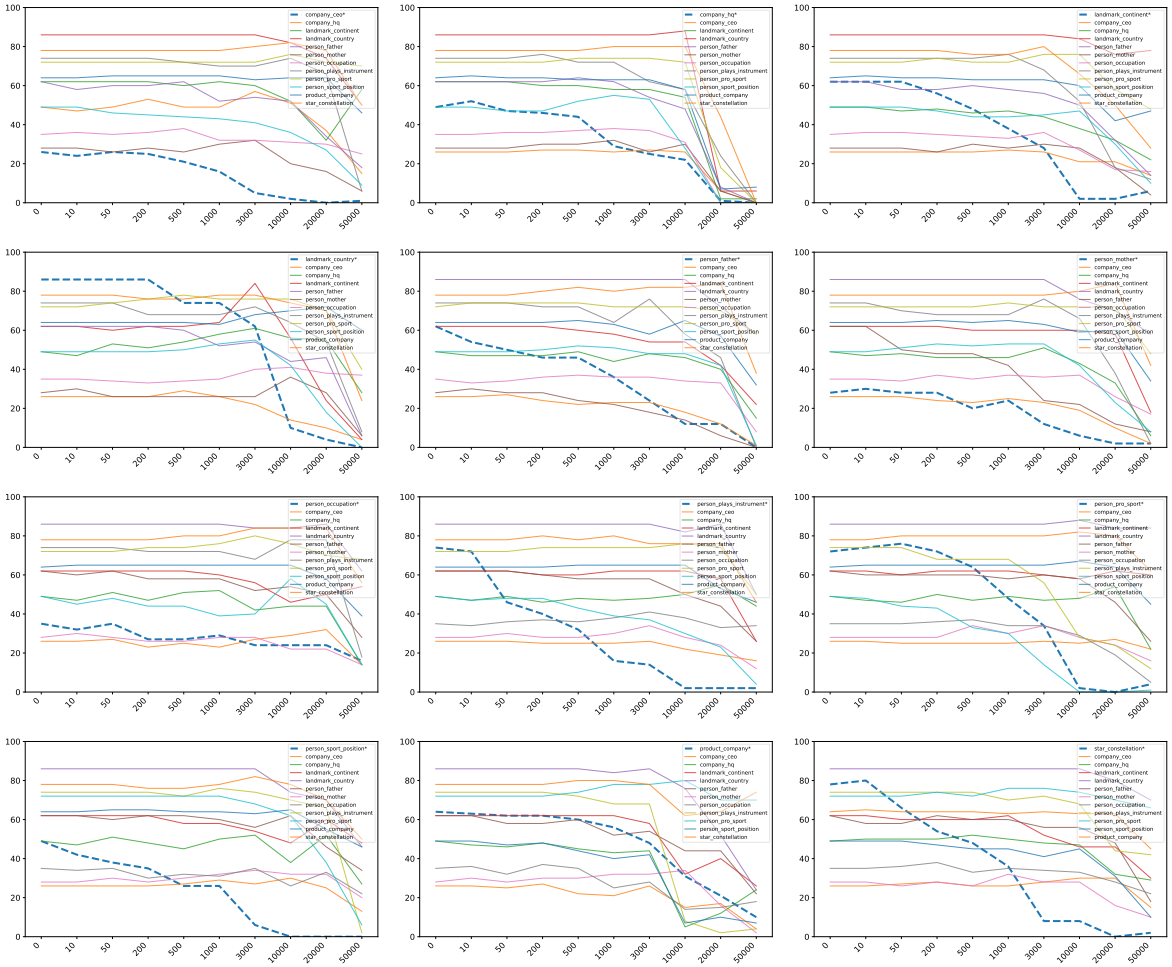

Figure 16: Influence of deactivating different numbers of relation-specific neurons in the 7B model for each relation. The variation of accuracy on the relation itself (noted with "*" and a dashed line style) and the accuracy on all other relations is shown in each figure. Similar to Figure 5, increasing the number of neurons clearly affects the relation itself, but the effect on other individual relations does not become clearly noticeable until 3,000–10,000 neurons.

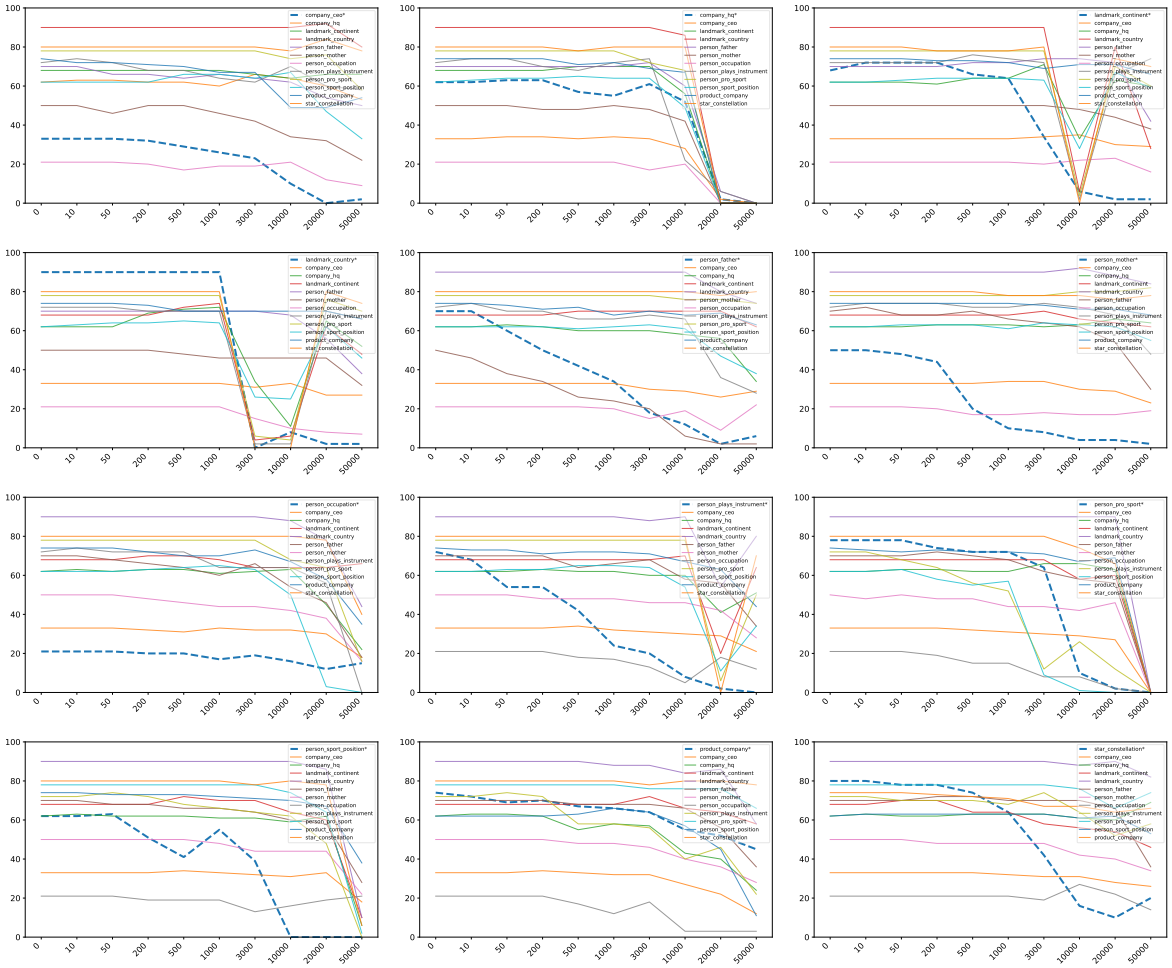

Figure 17: Influence of deactivating different numbers of relation-specific neurons in the 13B model for each relation. The variation of accuracy on the relation itself (noted with "*" and a dashed line style) and the accuracy on all other relations is shown in each figure.

D Translation Process

We take a **two-step** approach to ensure the translation quality of individual prompts from English into the target languages across relations.

Translating subject-object pairs. The first step concerns mapping entities, i.e., subject and object pairs into the target language. The default way of doing this is by identifying if the entity is available in Wikidata and the target language using the Wikidata API.[7] If the entity of interest is available in the target language, we directly take the entity name in that language. If the entity is not available, we then resort to Google Translate to translate the entity from English to the target language.[8]. By performing this step, we obtain the subject-object pairs in all target languages and all relations.

Translating prompt templates. We take the prompt templates of different relations written in English and use Google Translate to translate them into target languages. We then investigate how the LLama-2 7B model performs on these prompts using $\mathcal{P}_{r_i}^{\text{eva}}$ in the target languages. If the model performs suboptimally (<30% accuracy) for a relation in a specific language, then we manually check the prompt template in that language and update the template accordingly until satisfactory accuracy (>30%) is achieved. For Chinese and Japanese, we do not ensure more than 30% accuracy because the models perform very badly for some relations even if we have tried many prompt templates.

E Influence of Neuron Type

We consider the neurons in the FFNs (including up_proj, gate_proj, and down_proj matrices) as our major setup. In this section, we explore the individual effects of different types of neurons. Specifically, we consider five additional different varieties when selecting the top 3,000 neurons for the 7B model: **`all`** (neurons in any matrices), **`self_attn`** (neurons in self-attention matrices), **`up_proj`** (neurons in up_proj matrices), **`gate_proj`** (neurons in gate_proj matrices), **`down_proj`** (neurons in down_proj matrices). We first draw the distribution of the neuron types across relations for variety **`all`** in Figure 18 and report the inter-relation results in Figure 19 (**`all`**), 20 (**`self_attn`**), 21 (**`up_proj`**), 22 (**`gate_proj`**), and 23 (**`down_proj`**).

[7] https://www.wikidata.org/w/api.php

[8] https://translation.googleapis.com/language/translate/v2

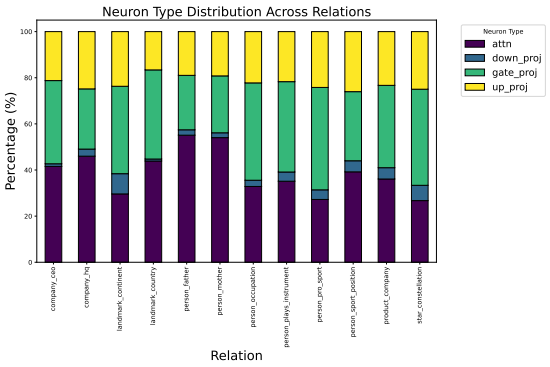

Figure 18: The distribution of the neuron types in the identified 3,000 neurons for the variety **`all`** across all relations.

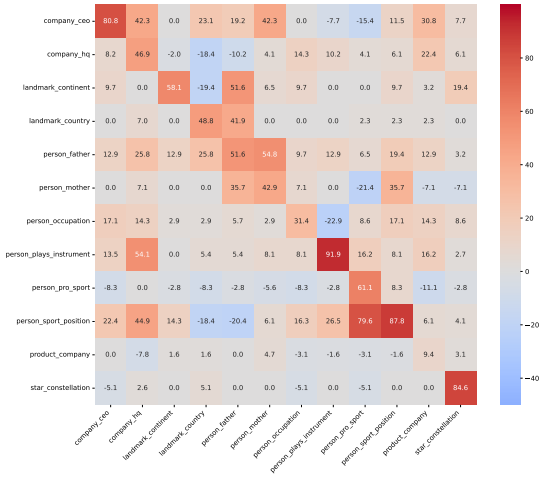

Figure 19: Inter-relation results of the 7B model when considering the neuron type variety as **`all`**.

According to the results, we observe that simply considering **`self_attn`** does not offer a consistent accuracy drop for the relation itself (by looking at the diagonal: some relations are not influenced too much). This can be explained by the fact the **`self_attn`** is shared across relations (as shown by Elhelo and Geva (2024)) and facts are mainly stored in the FFNs. Only considering **`down_proj`** offer similar results as **`self_attn`**. Interestingly, deactivating **`up_proj`** neurons does not influence all relations much in general, indicating it does not make sense to consider **`up_proj`** alone. Considering **`all`** or **`gate_proj`** neurons offer similar results compared to considering neurons in FFNs (shown in Figure 1). However, by considering neurons in FFNs (i.e., **`up_proj`**, **`gate_proj`** and **`down_proj`**), we see a more obvious inter-relation accuracy drop as shown on the diagonal in Figure 1. Therefore, our additional analysis supports our choice of considering neurons in FFNs.

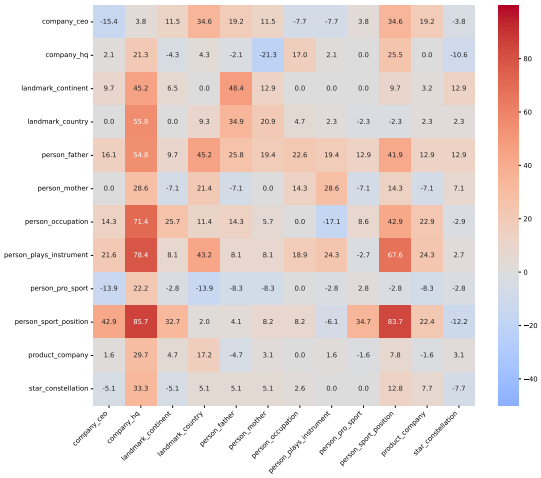

Figure 20: Inter-relation results of the 7B model when considering the neuron type variety as **`self_attn`**.

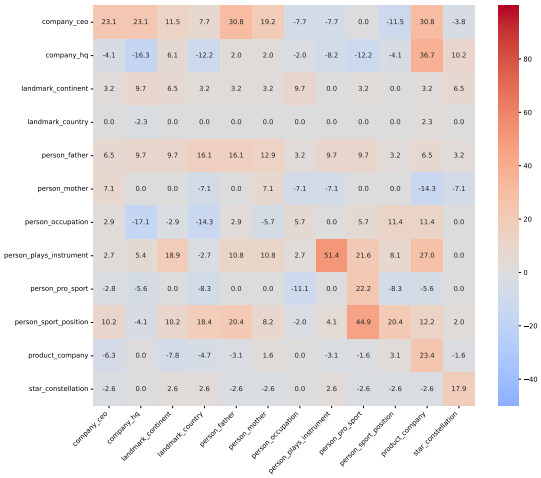

Figure 21: Inter-relation results of the 7B model when considering the neuron type variety as **`up_proj`**.

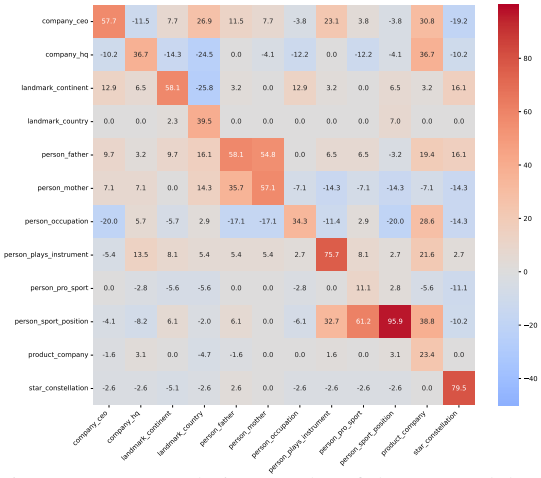

Figure 22: Inter-relation results of the 7B model when considering the neuron type variety as **`gate_proj`**.

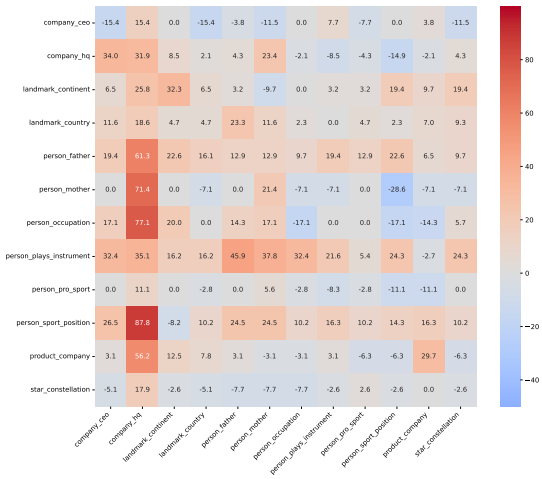

Figure 23: Inter-relation results of the 7B model when considering the neuron type variety as **`down_proj`**.

F Concept-Specific Neurons

Concept-Relation Overlap in the 7B Model Figure 24 illustrates the overlap between individual relation- and concept-specific neurons in the 7b model. There, the overlap of concepts connected to the abstract notion of "location" and the relations are mostly concentrated on the `landmark_country` relation in comparison to the 13b model, where they are spread over `company_hq`, `landmark_continent` and `landmark_country`. This aligns with the difference between the 7B and 13B models in terms of their patterns of inter-relation results (cf. Figure 4): deactivating the `landmark_country` neurons results in a significant accuracy drop in other relations concerning "location" in the 13B model while not in the 7B model. Another difference between both models is that there is more distributed neuron overlap in the 7b model between the subject concept `person` and all corresponding relations.

Validation of Concept-Specific Neurons The top neurons on a concept are evaluated on a random selection of 100 prompts from the LRE dataset that include the specified concept as a subject. Examples for the concept `person` are "Tom Hanks's father is named? Answer:", "Hilary Hahn plays the instrument of? Answer:", or "Thomas Mann went to university at? Answer:".

Figure 25 shows the results for the validation on these validation prompts for both models with the original accuracy score, a baseline that ablates 3000 neurons randomly, and the ablation of 3000 concept-specific neurons. Note that the impact of ablating a certain amount of expert neurons varies

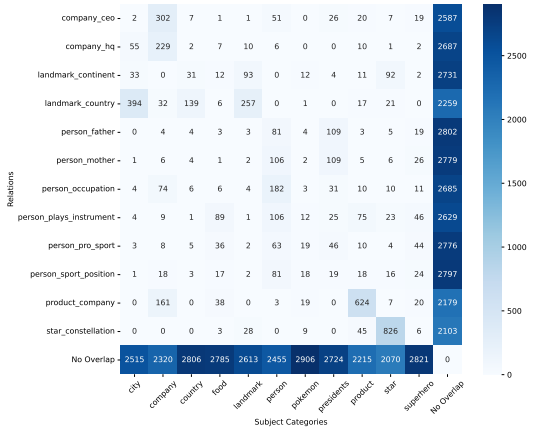

Figure 24: Overlap between the top 3000 identified neurons for each relation and concept in the 7B model.

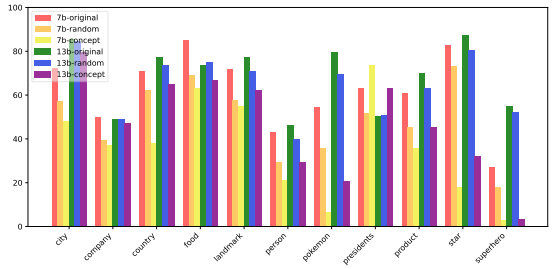

Figure 25: Accuracy results of evaluation prompts for 11 concepts in the 7b and 13b model. We report the performance of the original model (without any deactivation) e.g., `7b-original`, the model 3000 random deactivated neurons, e.g. `7b-random`, and the model with deactivating the top 3000 identified concept-specific neurons, e.g., `7b-concept`.

between concepts. The observed drop in performance due to the ablation of 3000 neurons for concepts like `pokemon`, `superhero`, and `star` is very large, while accuracy scores of other concepts in the 13b model, such as `person` appear stable, or even improve, e.g., `presidents`. We assume the **neuron cumulativity** also applies to the concept-specific neurons. That is, the knowledge on a specific concept is distributed over a much larger population of neurons, and further accuracy drop can be observed once more concept-specific neurons are deactivated – similar to what we observe for relation-specific neurons (cf. Figure 5). As only partial knowledge is withheld from the deactivation of 3000 concept-specific neurons, this might be too little knowledge to affect the facts concerning that concept (substantial knowledge on the concept is stored in the remaining neurons), resulting in only a small accuracy drop. Or, the 3000 concept-specific neurons store knowledge, though concerning the concept, unrelated to the prompts. For instance, the validation prompts of the concept `presidents` all demand **historical dates** as predicted answers, which is only one kind of knowledge that might be expected in connection with presidents. This phenomenon actually aligns with our neuron interference hypothesis: deactivating neurons that store unhelpful knowledge can less confuse the model, therefore improving the performance.

G Experimental Environment

We run all experiments on NVIDIA RTX A6000 GPUs. The Python environment we use is the same as Kojima et al. (2024).[9]

H Prompt Templates

We show the actual prompt templates (with an object-subject example) we use for each relation across 6 considered languages: `company_ceo` in Table 3, `company_hq` in Table 4, `landmark_continent` in Table 5, `landmark_country` in Table 6, `person_father` in Table 7, `person_mother` in Table 8, `person_occupation` in Table 9, `person_plays_instrument` in Table 10, `person_pro_sport` in Table 11, `person_sport_position` in Table 12, `product_company` in Table 13, and `star_constellation` in Table 14.

[9] Kojima et al. (2024)'s GitHub repository is available at https://github.com/kojima-takeshi188/lang_neuron

Language	Subject-Object Pair	Prompt	Expected Output
English	(Panasonic Corporation, Kazuhiro Tsuga)	Panasonic Corporation's CEO is? Answer: The CEO of Panasonic Corporation is? Answer:	Kazuhiro Tsuga
German	(Panasonic, Kazuhiro Tsuga)	Der Name des CEO von Panasonic lautet Wer ist der CEO von Panasonic? Ihr Name ist	Kazuhiro Tsuga
Spanish	(Panasonic, Kazuhiro Tsuga)	Por favor, responda directamente por su nombre. El nombre del director general de Panasonic es Por favor, responda directamente por su nombre. ¿Quién es el director general de Panasonic? Su nombre es	Kazuhiro Tsuga
French	(Panasonic, Kazuhiro Tsuga)	Veuillez répondre directement avec le nom. Le nom du président-directeur général de Panasonic est Veuillez répondre directement avec le nom. Le PDG de Panasonic est nommé	Kazuhiro Tsuga
Japanese	(パナソニック株式会社, 津賀一宏)	名前で直接お答えください。パナソニック株式会社のCEOの名前は 名前で直接お答えください。パナソニック株式会社のCEOは誰ですか？彼らの名前は	津賀一宏
Chinese	(松下公司, 津贺一宏)	松下公司的首席执行官名字叫做 松下公司的CEO名字叫做	津贺一宏

Table 3: Prompts for **company_ceo** in different languages. We use the triple (Panasonic, company_ceo, Kazuhiro Tsuga) as an example. The subject-object pair is represented in the respective language.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Cadillac, Detroit)	The headquarters of Cadillac are in the city of? Answer: The headquarters of Cadillac are in the city of? Answer:	Detroit
German	(Cadillac, Detroit)	Cadillac hat seinen Hauptsitz in der Stadt von Der Hauptsitz von Cadillac befindet sich in der Stadt von	Detroit
Spanish	(Cadillac, Detroit)	Cadillac tiene su sede en la ciudad de La sede de Cadillac se encuentra en la ciudad de	Detroit
French	(Cadillac, Détroit)	Le nom de la ville où se trouve le siège social de Cadillac est La ville où se trouve le siège social de Cadillac s'appelle	Détroit
Japanese	(「キャデラック」, デトロイト)	「キャデラック」の本社がある都市はどこですか 「キャデラック」の本社はどの都市にありますか	デトロイト
Chinese	(凯迪拉克, 底特律)	凯迪拉克总部所位于的城市名字叫做 凯迪拉克的总部所在的城市名字叫	底特律

Table 4: Prompts for **company_hq** in all languages. We use the triple (Cadillac, company_hq, Detroit) as an example. The subject-object pair is represented in the respective language.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Elbe, Europe)	Elbe is on the continent of? Answer:	Europe
German	(Elbe, Europa)	Bitte geben Sie den Kontinentnamen direkt an, z. B. Europa, Afrika usw. Der Name des Kontinents, auf dem Elbe liegt, lautet	Europa
Spanish	(Elba, Europa)	El nombre del continente donde se encuentra Elba es	Europa
French	(Elbe, Europe)	Veuillez répondre directement avec le nom du continent. Le nom du continent où se trouve Elbe est	Europe
Japanese	(エルベ川, ヨーロッパ)	エルベ川が所在する大陸の名前は	ヨーロッパ
Chinese	(易北河, 欧洲)	易北河所位于的大洲/大陆名字叫做	欧洲

Table 5: Prompts for the **landmark_continent** relation in all languages. We use the triple (Elbe, landmark_continent, Europe) as an example. The subject-object pair is represented in the respective language.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Namba Station, Japan)	Namba Station is in the country of? Answer:	Japan
German	(Namba Station, Japan)	In welchem Land liegt Namba Station? Es liegt in	Japan
Spanish	(Namba Station, Japan)	El nombre del país donde se encuentra Namba Station es	Japan
French	(Namba Station, Japan)	Le nom du pays où se trouve Namba Station est	Japan
Japanese	(難波駅, 日本)	難波駅が所在する国の名前は	日本
Chinese	(难波站, 日本)	难波站所位于的国家名字叫做	日本

Table 6: Prompts for the **`landmark_country`** relation in all languages. We use the triple (`Namba Station`, `landmark_country`, `Japan`) as an example. The subject-object pair is represented in the respective language.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Ronald Reagan, Jack Reagan)	Ronald Reagan's father is named? Answer:	Jack Reagan
German	(Ronald Reagan, Jack Reagan)	Der Vater von Ronald Reagan heißt	Jack Reagan
Spanish	(Ronald Reagan, Jack Reagan)	El padre de Ronald Reagan se llama	Jack Reagan
French	(Ronald Reagan, Jack Reagan)	Le père de Ronald Reagan s'appelle	Jack Reagan
Japanese	(ロナルド・レーガン, ジャック・レーガン)	名前で直接お答えください。ロナルド・レーガンの父親の名前は	ジャック・レーガン
Chinese	(罗纳德·里根, 杰克·里根)	罗纳德·里根的父亲名字叫做	杰克·里根

Table 7: Prompts for the **`person_father`** relation in all languages. We use the triple (`Ronald Reagan`, `person_father`, `Jack Reagan`) as an example. The subject-object pair is represented in the respective language.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Demi Moore, Virginia King)	Demi Moore's mother is named? Answer:	Virginia King
German	(Demi Moore, Virginia King)	Die Mutter von Demi Moore heißt	Virginia King
Spanish	(Demi Moore, Virginia King)	La madre de Demi Moore se llama	Virginia King
French	(Demi Moore, Virginia King)	Qui est la mère de Demi Moore ? Leur mère s'appelle	Virginia King
Japanese	(デミ・ムーア, ヴァージニア・キング)	名前で直接お答えください。デミ・ムーアの母親の名前は	ヴァージニア・キング
Chinese	(黛米·摩尔, 维吉尼亚·金)	黛米·摩尔的母亲名字叫做	维吉尼亚·金

Table 8: Prompts for the **`person_mother`** relation in all languages. We use the triple (`Demi Moore`, `person_mother`, `Virginia King`) as an example. The subject-object pair is represented in the respective language.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Martin Burrell, politician)	Martin Burrell works as a? Answer: By profession, Martin Burrell is a? Answer:	politician
German	(Martin Burrell, Politiker)	Martin Burrell arbeitet als Von Beruf ist Martin Burrell ein	Politiker
Spanish	(Martin Burrell, político)	Por favor especifique el nombre de su ocupación. Martin Burrell trabaja profesionalmente como Por favor especifique el nombre de su ocupación. Por profesión, Martin Burrell es un(a)	político
French	(Martin Burrell, personnalité politique)	Veuillez répondre directement par le nom de votre profession. Le nom de la profession de Martin Burrell est Veuillez répondre directement par le nom de votre profession. Martin Burrell travaille professionnellement comme	personnalité politique
Japanese	(マーティン・バレル, 政治家)	マーティン・バレルさんの職業名は マーティン・バレルさんの職業名は	政治家
Chinese	(马丁·巴雷尔, 政治人物)	马丁·巴雷尔从事的职业是一个 职业上来说, 马丁·巴雷尔是一名	政治人物

Table 9: Prompts for the **person_occupation** relation in all languages. We use the triple (Martin Burrell, person_occupation, politician) as an example. The subject-object pair is represented in the respective language.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Anson Funderburgh, guitar)	Anson Funderburgh plays the instrument of? Answer:	guitar
German	(Anson Funderburgh, Gitarre)	Bitte geben Sie den Namen des Instruments direkt an. Das Instrument, das Anson Funderburgh spielt, heißt	Gitarre
Spanish	(Anson Funderburgh, guitarra)	Por favor responda directamente el nombre del instrumento ¿Qué instrumento toca Anson Funderburgh? Tocan el	guitarra
French	(Anson Funderburgh, guitare)	Veuillez répondre directement au nom de l'instrument. De quel instrument joue Anson Funderburgh ? Ils jouent du	guitare
Japanese	(アンソン・ファンダーバーグ, ギター)	アンソン・ファンダーバーグはどの楽器を演奏しますか	ギター
Chinese	(安森·芬德伯格, 吉他)	安森·芬德伯格所演奏的乐器名字叫做	吉他

Table 10: Prompts for the **person_plays_instrument** relation in all languages. We use the triple (Anson Funderburgh, person_plays_instrument, guitar) as an example. The subject-object pair is represented in the respective language.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Frédéric Piquionne, soccer)	Frédéric Piquionne plays the sport of? Answer:	soccer
German	(Frédéric Piquionne, Fußball)	Welchen Sport betreibt Frédéric Piquionne? Sie betreiben	Fußball
Spanish	(Frédéric Piquionne, fútbol)	Por favor, responda directamente el nombre del deporte, como fútbol, baloncesto, etc. El nombre del deporte que juega Frédéric Piquionne es:	fútbol
French	(Frédéric Piquionne, football)	Veuillez répondre directement par le nom du sport, comme le football, le basket-ball, etc. Frédéric Piquionne joue professionnellement dans le sport de	football
Japanese	(フレデリック・ピキオンヌ, サッカー)	サッカー、バスケットボールなど、スポーツの名前を直接答えてください。フレデリック・ピキオンヌはどのスポーツをしますか？彼らは（スポーツ名）をしています。	サッカー
Chinese	(费德历·比基安尼, 足球)	费德历·比基安尼从事的运动叫做	足球

Table 11: Prompts for the **person_pro_sport** relation in all languages. We use the triple (Frédéric Piquionne, person_pro_sport, soccer) as an example. The subject-object pair is represented in the respective language.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Ju Yingzhi, midfielder)	Ju Yingzhi plays in the position of a? Answer: In their sport, Ju Yingzhi plays as a? Answer:	midfielder
German	(Ju Yingzhi, Mittelfeldspieler)	Ju Yingzhi spielt auf der Position von a In ihrer Sportart spielt Ju Yingzhi als	Mittelfeldspieler
Spanish	(Ju Yingzhi, centrocampista)	Por favor, responda directamente el nombre de la posición deportiva, como delantero, defensor, etc. La posición de Ju Yingzhi en el campo deportivo es: Por favor responda directamente con el nombre de la posición deportiva, como delantero, defensor, etc. En su deporte, Ju Yingzhi juega en la posición de un:	centrocampista
French	(Ju Yingzhi, milieu de terrain)	Ju Yingzhi évolue au poste de Dans son sport, Ju Yingzhi occupe le rôle de	milieu de terrain
Japanese	(ジュ・インジー, ミッドフィールダー)	彼がプレーするスポーツでは、ジュ・インジーのポジションは ジュ・インジー競技場のポジションは	ミッドフィールダー
Chinese	(鞠盈智, 中场)	鞠盈智在运动场上的位置名字叫做 在他/她从事的运动中,鞠盈智的位置是	中场

Table 12: Prompts for the **person_sport_position** relation in all languages. We use the triple (Ju Yingzhi, person_sport_position, midfielder) as an example. The subject-object pair is represented in the respective language.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Jeep Grand Cherokee, Chrysler)	Jeep Grand Cherokee was created by which company? Answer: Jeep Grand Cherokee is a product of which company? Answer:	Chrysler
German	(Jeep Grand Cherokee, Chrysler)	Bitte geben Sie direkt den Firmen-/Ländernamen an. Das Unternehmen/Land, das Jeep Grand Cherokee entwickelt hat, ist Bitte geben Sie direkt den Firmen-/Ländernamen an. Welches Unternehmen hat Jeep Grand Cherokee entwickelt? Es wurde entwickelt von	Chrysler
Spanish	(Jeep Grand Cherokee, Chrysler)	Por favor, responda directamente el nombre de la empresa/país. ¿Qué empresa desarrolló Jeep Grand Cherokee? Fue desarrollado por Por favor responda directamente con el nombre de la empresa/país. La empresa que desarrolló Jeep Grand Cherokee se llama	Chrysler
French	(Jeep Grand Cherokee, Chrysler)	Jeep Grand Cherokee a été développé(e) par Jeep Grand Cherokee est un produit de l'entreprise	Chrysler
Japanese	(ジープ・グランドチェロキー, クライスラー)	会社名/国名を直接お答えください。ジープ・グランドチェロキーを開発したのはとの会社ですか? 開発したのは次の会社は 会社名/国名を直接お答えください。ジープ・グランドチェロキーを開発した会社は	クライスラー
Chinese	(吉普大切诺基, 克莱斯勒)	开发了吉普大切诺基的公司名字叫做 开发产品吉普大切诺基的公司名字叫	克莱斯勒

Table 13: Prompts for the **product_company** relation in all languages. We use the triple (Jeep Grand Cherokee, product_company, Chrysler) as an example. The subject-object pair is represented in the respective language.

Language	Subject-Object Pair	Prompt	Expected Output
English	(50 Persei E, Perseus)	50 Persei E is part of the constellation named? Answer:	Perseus
German	(50 Persei E, Perseus)	Bitte geben Sie den Namen des Sternbildes direkt an. Das Sternbild, zu dem 50 Persei E gehört, heißt	Perseus
Spanish	(50 Persei E, Perseus)	50 Persei E forma parte de la constelación denominada	Perseus
French	(50 Persei E, Persée)	Le nom de la constellation dans laquelle se trouve 50 Persei E est	Persée
Japanese	(50 ペルセウス座 E, ペルセウス座)	50 ペルセウス座 Eはどの星座に属していますか？それは（星座名）という星座の一部です。	ペルセウス座
Chinese	(50 英仙座E, 英仙座)	50 英仙座E所位于的星座名字叫做	英仙座

Table 14: Prompts for the **star_constellation** relation in all languages. We use the triple (`50 Persei E`, `star_constellation`, `Perseus`) as an example. The subject-object pair is represented in the respective language.