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 factual 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 involving relation r and (2) facts involving 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.** Multiple neurons jointly contribute to processing facts involving relation r, with no single neuron fully encoding a fact in r on its own. **(ii) Neuron versatility.** Neurons can be shared across multiple closely related as well as less related relations. In addition, some relation neurons transfer across languages. **(iii) Neuron interference.** Deactivating neurons specific to one relation can improve LLMs' factual recall performance for facts of other relations. We make our code and data publicly available at `https://github.com/cisnlp/relation-specific-neurons`.

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), i.e., neurons that are responsible for encoding each fact individually; or whether there exist *relation-specific neurons* (referred to as ***RelSpec* neurons**), i.e., neurons that do not represent specific facts but rather focus on the relation and guide generating the object once the subject and relation of a triple have been detected.

In this work, we examine the existence of *RelSpec* 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 *RelSpec* 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 *RelSpec* neurons.

To understand the impact of *RelSpec* neurons, we perform factual recall on held-out prompts. These prompts for each relation share the **same relation** as the positive examples used for neuron identification but have **no entity overlap**; this disentangles

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the effects of entities and relations. For each relation, we compare performance between the original model and the model in which *RelSpec* neurons for that relation are deactivated – *intra-relation results*. We also study how deactivating neurons for one relation influences performance on others – *inter-relation results*. Our experiments reveal several key properties of *RelSpec* neurons:

Neuron cumulativity. *RelSpec* neurons present a cumulative effect – a phenomenon where an LLM distributes relational knowledge across multiple neurons. *RelSpec* neurons jointly contribute to dealing with facts belonging to a relation, with no single neuron fully encoding a fact on its own. This property aligns with the evidence of the existence of redundant and self-repair neurons (Dalvi et al., 2020; McGrath et al., 2023; He et al., 2024).

Neuron versatility. As the total number of neurons is finite, while the number of possible relations is vast, some *RelSpec* neurons strongly associate with multiple relations. Surprisingly, these relations need not be closely linked – two weakly related relations can share a group of neurons, leading to performance drops in both relations if those neurons are deactivated. *RelSpec* neurons also generalize across languages – *RelSpec* neurons identified from English have a similar effect on other languages. This property aligns with neuron polysemanticity and superposition (Mu and Andreas, 2020; Elhage et al., 2022b; Scherlis et al., 2025).

Neuron interference. Some *RelSpec* 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 corresponding *RelSpec* 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 $\mathcal{D}_{r_i}^{\text{eva}}$ (for evaluation) and all other triples as $\mathcal{D}_{r_i}^{\text{det}}$ (for detection). To ensure disjointness, $\mathcal{D}_{r_i}^{\text{eva}}$ and $\mathcal{D}_{r_i}^{\text{det}}$ do not share any subjects.

Step 2: Formulating Prompts. For each triple (s, r_i, o) in $\mathcal{D}_{r_i}^{\text{det}}$, we create prompts containing the **subject** s and the **relation** r_i using the templates provided by Hernandez et al. (2024). **Note that the object o is not included in the prompt**. For example, we construct a 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 $\mathcal{D}_{r_i}^{\text{eva}}$ in the same way. We refer to the resulting prompt sets as $\mathcal{P}_{r_i}^{\text{det}}$ and $\mathcal{P}_{r_i}^{\text{eva}}$.

Step 3: Validating Prompts. We hypothesize that the model will leverage *RelSpec* neurons to generate the correct answer, i.e., the object. Therefore, such neurons should "fire" for those prompts for which **the model answers correctly**. For the prompt selection, we feed each prompt in $\mathcal{P}_{r_i}^{\text{det}}$ to the model and set the maximum generation length to be 2.[1] We then check if the predicted 2 tokens are a prefix of the object: if they are, we regard the output as being correct. We exclude prompts that the model answers wrongly from $\mathcal{P}_{r_i}^{\text{det}}$.[2]

2.2 Relation-Specific Neuron Identification

This work's purpose is to identify ***RelSpec* neurons** – neurons that solely focus on the relation rather than specific relational facts concerning the subject-relation-object triple. Therefore, these neurons are different from *knowledge neurons* (which encode certain facts) or *entity neurons* (which encode certain subject entities). Following Cuadros et al. (2022), we identify *RelSpec* neurons using statistical association measures. This method assigns a score for each neuron, representing its level of "expertise" in **distinguishing a specific relation from other considered relations**.

Defining Neurons. A neural network, or specifi-

[1] Some prior studies evaluate correctness by only checking the model's first predicted token (Geva et al., 2023; Hernandez et al., 2024). This evaluation can be ambiguous if the answer/object is split into multiple tokens. Considering 2 predicted tokens increases reliability.

[2] We exclude prompts that do not yield the correct answer in order to maintain high precision in identifying *RelSpec* neurons. While the exclusion seems conservative, it helps preserve the clarity and discriminative power of the method.

cally a Transformer (Vaswani et al., 2017), consists of many weight matrices. For a given 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). We also investigate neurons in other modules, e.g., attention heads, but find they are less relation-specific (see §G).

Grouping Prompts. For each relation r_i, we collect positive and negative examples. Specifically, we regard $\mathcal{P}_{r_i}^{\text{det}}$ as positive examples and randomly sample $4 \times |\mathcal{P}_{r_i}^{\text{det}}|$ prompts from the prompt sets of other relations as negative examples.[3] We refer to the positive and negative examples selected for relation r_i as $\mathcal{E}_{r_i}^{+}$ and $\mathcal{E}_{r_i}^{-}$.[4] The final data used to detect *RelSpec* neurons for relation r_i is then $\mathcal{E}_{r_i} = \mathcal{E}_{r_i}^{+} \cup \mathcal{E}_{r_i}^{-}$. Each example $e_{r_i}^{j}$ is associated with binary label $b_{r_i}^{j}$: 1 if $e_{r_i}^{j} \in \mathcal{E}_{r_i}^{+}$, 0 otherwise.

Neuron Output Values. Let $o_{r_i}^{m,j,t}$ be the output value of neuron m for the t-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 $e_{r_i}^{j}$: $o_{r_i}^{m,j} = \frac{1}{T}\sum_{t=1}^{T} o_{r_i}^{m,j,t}$, where T is the number of effective tokens in $e_{r_i}^{j}$.

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 *RelSpec* neurons in descending order.

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 neuron statistics

2.3 Controlled Generation

For each relation r_i, we want to investigate the impact of the identified top-k *RelSpec* neurons. Therefore, we control text generation by overriding their 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 *RelSpec* neurons to a constant 0 and set the maximum generation length to 2 (similar to the setup in validating prompts, cf. §2). The predicted 2 tokens are then compared to the object. The prediction is regarded as correct if the predicted 2 tokens are a prefix of the object.

3 Experimental Setup

3.1 Models

We consider the 7B and 13B models from the **LLama-2** family (Touvron et al., 2023).[5] As mentioned in §2.2, we consider the neurons in **FFNs**, which account for more than half of neurons in both 7B and 13B models, as shown in Table 1. We also report our preliminary results when considering neurons in other modules, i.e., attention heads, in §G. Their effectiveness tends to be unsatisfactory compared with FFNs, supporting our choice.

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 r_i, yielding varying numbers $|\mathcal{P}_{r_i}^{\text{det}}|$ of prompts. $\mathcal{P}_{r_i}^{\text{eva}}$ is constructed

[3] Negative samples play an important role in identifying *RelSpec* neurons. We restrict negative samples to counter-relation examples (i.e., samples from other relations) to ensure a controlled and interpretable comparison. In theory, the negative examples can also be in natural language. However, this would introduce a vast and unconstrained search space, possibly making it difficult to isolate the influence of relation-specific information.

[4] The sampling ratio is based on previous research (Kojima et al., 2024). Too large or too small ratios are bad for computing reliable AP values. We also sample negative examples with different seeds in our preliminary experiments. The identified relation neurons show little change, suggesting stability of the identification method.

[5] We conduct a similar investigation on **Gemma-7B** (Gemma Team et al., 2024), as detailed in §C, and observe experimental results consistent with those of LLama-2.

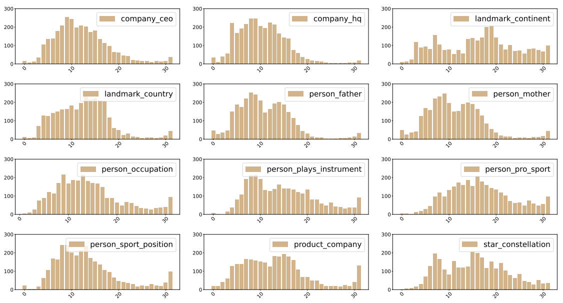


Figure 1: Distribution of *RelSpec* neurons across layers in the 7B model. Most are located in the middle layers.

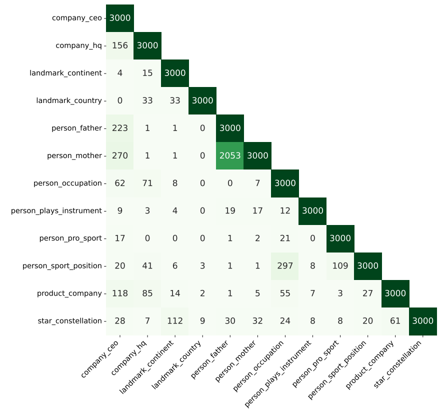


Figure 2: Neuron overlap of *RelSpec* neurons across 12 relations in the 7B model. For example, the number of neurons shared between the 3,000 identified neurons for `person_father` and the 3,000 for `person_mother` is 2053 (in green).

by randomly selecting 50 triples for each relation. Since these 50 triples are not used when creating $\mathcal{P}^{\text{det}}_{r_i}$, this setup ensures **no subject entity overlap between $\mathcal{P}^{\text{det}}_{r_i}$ and $\mathcal{P}^{\text{eva}}_{r_i}$ for the same relation r_i.** The elimination of subject entity overlap allows us to disentangle the effect of entities and focus on the only shared attribute between $\mathcal{P}^{\text{det}}_{r_i}$ and $\mathcal{P}^{\text{det}}_{r_j}$ – the relation itself. In addition, we ensure **minimal subject entity overlap across relations** (mostly 0 between $\mathcal{P}^{\text{det}}_{r_i}$ and $\mathcal{P}^{\text{det}}_{r_j}$). The only exception is between `person_mother` and `person_father`, which share a lot of subject entities in $\mathcal{P}^{\text{det}}_{r_i}$; however, the two relations **share no subject entities in $\mathcal{P}^{\text{eva}}_{r_i}$**. A detailed analysis of entity overlap is presented in §B.

4 Results and Discussion

We apply our identification method to both LLama-2 7B and 13B models for all 12 relations. We regard the **top 3,000** neurons with the highest AP values as the *RelSpec* neurons; 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 1 (see §D 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, *RelSpec* 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 functional mapping vectors can be extracted from the middle layers of LLMs (Merullo et al., 2024; Hernandez et al., 2024; Todd et al., 2024).

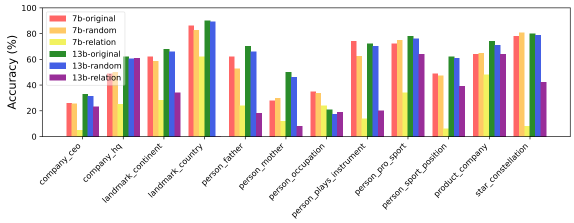
Neuron Overlap Across Relations. We display the overlap of *RelSpec* neurons across relations for the 7B model in Figure 2 (13B is in §D). We see that `person_mother` and `person_father` share many neurons, possibly due to the large overlap between their subject entities, (see §B). **However, even though 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 a kind of 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

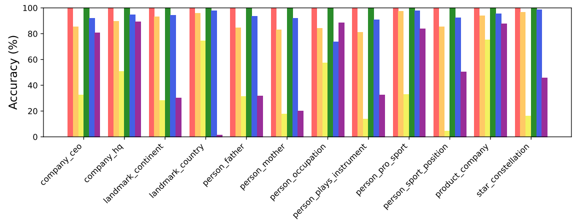
For each relation, we set the output values of its identified 3,000 *RelSpec* neurons to 0, and observe how the deactivation impacts the relation itself and other relations in terms of accuracy.

4.2.1 Intra-Relation Results

In addition to intra-relation results, i.e., deactivating the 3,000 identified *RelSpec* neurons for a relation and evaluating the same relation, we also



(a) Held-out evaluation prompts $\mathcal{P}^{\text{eva}}_{r_i}$



(b) Identification prompts $\mathcal{P}^{\text{det}}_{r_i}$

Figure 3: Intra-relation results. The **left** (resp. **right**) figure displays the results of held-out evaluation prompt set $\mathcal{P}^{\text{eva}}_{r_i}$ (resp. identification prompt set $\mathcal{P}^{\text{det}}_{r_i}$). 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 *RelSpec* neurons deactivated, e.g., `7b-relation`.

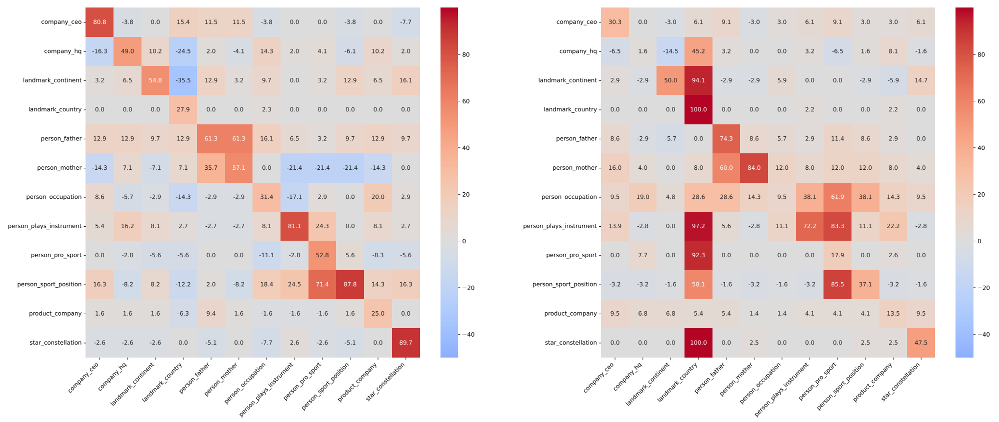


Figure 4: Inter-relation results. Accuracy drops (in %) for the 7B (**left**) and the 13B model (**right**) on $\mathcal{P}^{\text{eva}}_{r_i}$. The number in cell (r_i, r_j) indicates the accuracy drop of relation r_i when deactivating the relation neurons of r_j.

create a baseline by **randomly** deactivating 3,000 neurons in the model. Results for the original models and for the two interventions are in Figure 3.

We can observe a clear performance drop on the identification prompt set $\mathcal{P}^{\text{det}}_{r_i}$ when comparing the accuracy of the original model and the model whose *RelSpec* neurons are deactivated.[6] On the other hand, the model with 3,000 random 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 $\mathcal{P}^{\text{det}}_{r_i}$. On the evaluation set $\mathcal{P}^{\text{eva}}_{r_i}$, we also observe a notable accuracy drop across models for most relations. **As $\mathcal{P}^{\text{eva}}_{r_i}$ and $\mathcal{P}^{\text{det}}_{r_i}$ do not share any subject entities, this drop can only be attributed to the fact that deactivating 3,000 neurons affects the relation itself – the common characteristic between $\mathcal{P}^{\text{eva}}_{r_i}$ and $\mathcal{P}^{\text{det}}_{r_i}$.**[7] We thus argue that ***RelSpec* neurons exist in LLMs**: they are entity-irrelevant and focus on specific relations.

On the other hand, the accuracy does not drop to 0 for any relation (except `landmark_country` in the 13B model) when its identified *RelSpec* neurons are deactivated. This indicates these 3,000 neurons do not equally influence all facts that belong to a certain relation, which highlights that **LLMs do not uniformly encode all facts belonging 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 showing 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 it appears in the pretraining data in §E.

4.2.2 Inter-Relation Results

To understand how *RelSpec* neurons influence the model's ability to answer prompts across multiple relations, we use **accuracy drop** as a metric: $\text{acc\_drop}_{r_i,r_j} = \frac{\text{acc}^{\text{original}}_{r_i} - \text{acc}^{\text{deactivated-}r_j}_{r_i}}{\text{acc}^{\text{original}}_{r_i}}$, where $\text{acc}^{\text{original}}_{r_i}$ and $\text{acc}^{\text{deactivated-}r_j}_{r_i}$ are the respective accuracy for $\mathcal{P}^{\text{eva}}_{r_i}$ of (a) the original model and (b)

[6] 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.

[7] There might be another confounding variable since $\mathcal{P}^{\text{eva}}_{r_i}$ and $\mathcal{P}^{\text{det}}_{r_i}$ use the same prompt templates for each relation. But we show in §5.3 that even when other prompt templates are used, the effectiveness of these neurons is still preserved.

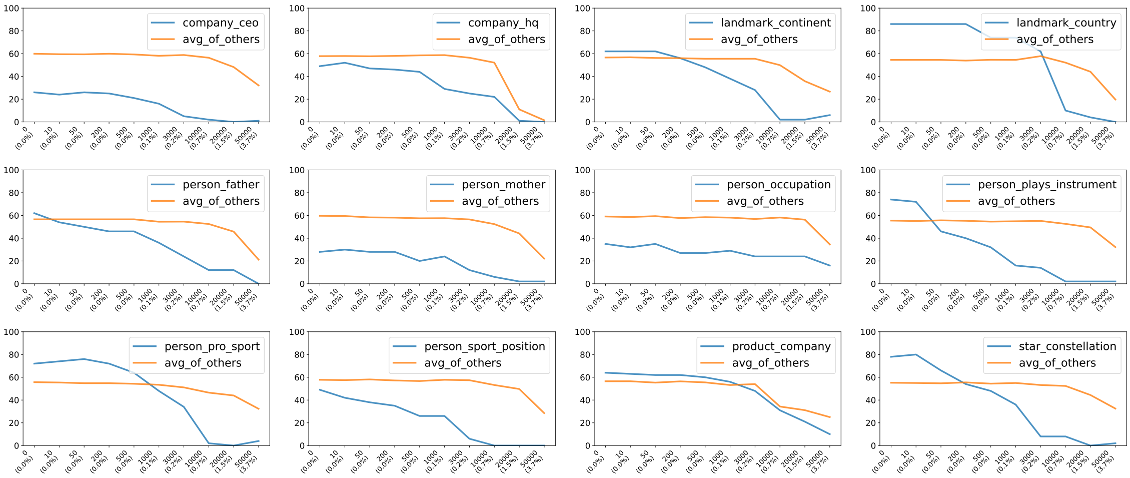


Figure 5: Influence of deactivating different numbers of *RelSpec* neurons for each relation. On the x-axis, we report both the absolute number of deactivated neurons and the corresponding percentage of the model's total neurons. We show accuracy on the relation itself and the average accuracy on other relations. Increasing the number clearly affects the relation itself, while noticeable effects on other relations emerge only beyond 3,000–10,000 neurons.

when the *RelSpec* neurons of r_j are deactivated. Results are displayed in Figure 4.[8]

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**. Particularly, 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 neurons for one relation can strongly affect not only that relation but also others, both closely and loosely related relations. E.g., disabling `person_pro_sport` neurons has a large effect on `person_sport_position` (but not vice versa) in both models, likely because a 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 a parental relationship. Even 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 *RelSpec* neurons for one relation can sometimes **improve** the accuracy for others – 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 relations: disabling `company_ceo` neurons slightly boosts accuracy on `company_hq` for both models. 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.**

5 Complementary Analyses

5.1 Influence of the Numbers of Neurons

In this section, we investigate the effect of varying the number of *RelSpec* neurons on the 7B model (see §D 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 **accuracy** for that

[8]Using accuracy drop – a relative measure – can be noisy when the initial accuracy is low. However, we show that most relations start with relatively high baseline accuracy (cf. Figure 5 and Figure 20), which mitigates the problem.

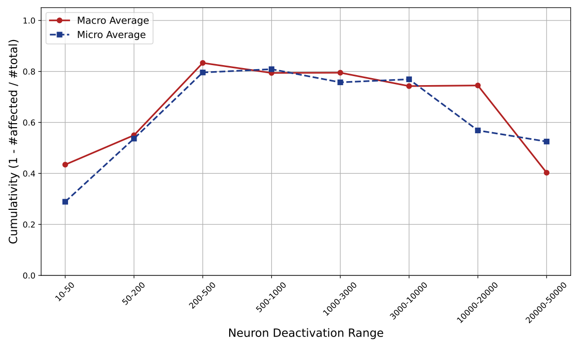


Figure 6: Macro and micro averaged neuron cumulativity for each neuron deactivation range. Cumulativity is defined as $1 - \frac{\#\text{affected}}{\#\text{total}}$, with macro averaging across relations and micro averaging across prompts. Both trends show that cumulativity increases as the range increases.

relation and the **average accuracy** for all other relations in Figure 5. Results for all relation-relation pairs are in Figure 22.

Neuron cumulativity. By increasing the number of neurons for deactivation, we see a consistent accuracy drop in all relations. This suggests neuron cumulativity: **LLMs distribute relational knowledge across multiple neurons, which jointly contribute to dealing with facts belonging to a relation.** However, cumulativity varies across relations. Some relations are far more sensitive to a smaller-scale deactivation than other relations, indicating a smaller set of neurons is specifically leveraged for those relations. We hypothesize that this sensitivity may correlate with the frequency of the facts in each relation in the pretraining data: more frequent facts may be memorized more robustly and thus remain less sensitive to deactivation. We empirically verify this hypothesis in §E.

Deactivating *RelSpec* neurons has a marginal effect on other relations until certain thresholds are reached. Typically, these thresholds lie between 3,000 and 10,000 as shown in Figure 5, below which the accuracy on other relations remains stable – **supporting the choice of 3,000 neurons in §3.** Once more neurons are deactivated, other relations also deteriorate, consistent with our **neuron versatility** hypothesis. However, 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).

Validation of the cumulative effect. It remains unclear whether the further accuracy drop between any two thresholds in Figure 5 is driven by **the newly deactivated neurons** (the isolated effect of deactivated neurons) or **the cumulative effect of all deactivated neurons**. To further validate our neuron cumulativity hypothesis, we conduct an experiment on each consecutive pair of thresholds, e.g., 1000-3000. Specifically, we identify prompts from $\mathcal{P}_{r_i}^{\text{eva}}$ where the model answers correctly with neurons of the smaller range being deactivated, but fails when neurons of the larger range are deactivated (#total). We then deactivate only the neurons from the intermediate difference and measure the number of affected prompts – prompts for which the model answers wrongly (#affected). Figure 6 shows the macro and micro averaged cumulativity, defined as $1 - \frac{\#\text{affected}}{\#\text{total}}$. We notice that neuron behavior becomes increasingly cumulative as the range increases, indicating that only deactivating neurons from the intermediate difference is not enough to make the model answer wrongly. There is a drop after the ranges 10000-20000 and 20000-50000, which can be explained by the fact that many more neurons are deactivated compared with the earlier ranges. We also show the individual number of #total/#affected prompts in each relation in each range in Table 3. **Thus, our results favor the cumulative effect over the isolated effect** – multiple neurons jointly contribute to dealing with facts belonging to a relation, with no single neuron fully encoding a fact on its own.

5.2 Are These Neurons Multilingual?

Recent studies suggest that some neurons encoding factual knowledge or handling specific tasks are language-agnostic (Stanczak et al., 2022; Zhang et al., 2024; Wang et al., 2024a). A natural question is whether *RelSpec* neurons – identified solely via English prompts – also function across languages. To explore this, we translate $\mathcal{P}_{r_i}^{\text{eva}}$ to 5 languages: German (**deu**), Spanish (**esp**), French (**fra**), Chinese (**zho**), and Japanese (**jpn**) (see §F 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 7.

Although the model's accuracy is generally lower in non-English languages, it still shows good factual recall 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**

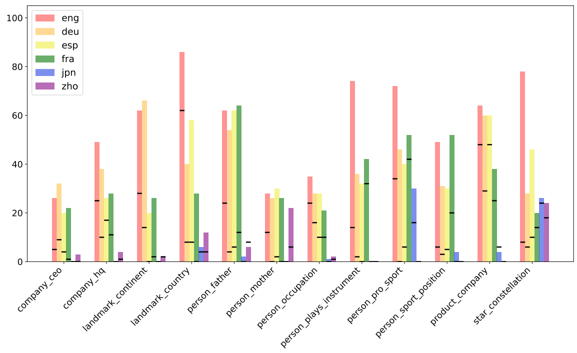


Figure 7: Accuracy on 12 relations across 6 languages. The bars show the accuracy of the original 7B model. The horizontal line in each bar indicates the performance after deactivation of 3,000 *RelSpec* neurons. Even though these neurons are identified using English prompts, they usually influence other languages, indicating multilinguality of these neurons.

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 Effect of Prompt Templates

There is a possible confounding variable: the identified relation-specific neurons could be associated with the prompt templates used in $\mathcal{P}^{\text{det}}_{r_i}$. The degradation in $\mathcal{P}^{\text{eva}}_{r_i}$ would then be due to the identified neurons encoding syntactic structure rather than abstract relation semantics. To exclude this confounding variable, we create an additional evaluation set $\mathcal{P}^{\text{eva-2}}_{r_i}$ where the **same triples** as $\mathcal{P}^{\text{eva}}_{r_i}$ but **different prompt templates** are used for each relation. We then deactivate the previously identified 3,000 neurons in the 7B model and measure the effect on the new prompts. Figure 8 presents the results. We observe that the accuracy with new prompts is a bit different from the accuracy when the original templates are used. This is not surprising since LLMs are sensitive to the prompt templates (Sclar et al., 2024). Nevertheless, we still see that the deactivation of neurons results in consistent accuracy drops for new prompts across relations. Therefore, the neurons are not subject to the templates used to describe the relation. Instead, **the identified neurons are only associated with the abstract relation semantics.**

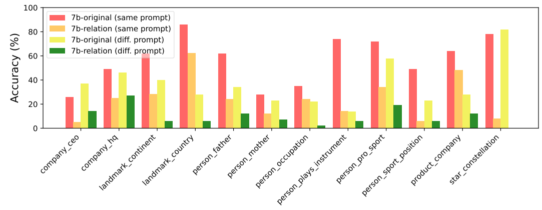


Figure 8: Intra-relation results on original prompts $\mathcal{P}^{\text{eva}}_{r_i}$ and additional prompts $\mathcal{P}^{\text{eva-2}}_{r_i}$. $\mathcal{P}^{\text{eva-2}}_{r_i}$ is constructed with same triples as $\mathcal{P}^{\text{eva}}_{r_i}$ but different prompt templates are used. A consistent decrease across relations indicates that the identified neurons are not specific to prompts.

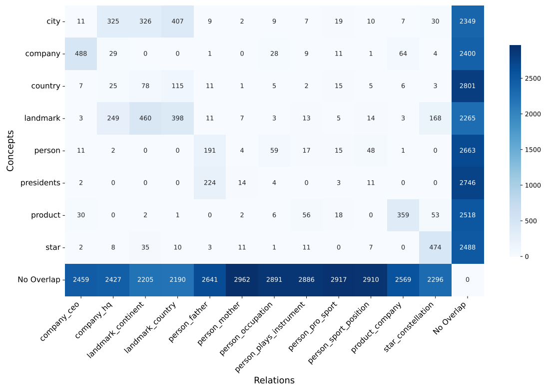


Figure 9: Overlap between the top 3000 neurons of relations and concepts in the 13B model.

5.4 Relations vs. Concepts

We saw in Figure 2 that the storage of relations is generally well separated, but there are exceptions. We can view a relation as relating two **concepts** or **topics**, 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 2, 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. To further explore this hypothesis empirically, we again use the method applied in §2 to relations, but now use it for subject concepts.[9] That is, we identify sets of **concept-specific neurons**. We group the triples by their subjects, resulting in 9 different concepts. We then create prompts 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.

Figure 9 shows the overlap between relation

[9]We do not consider the object concepts explicitly because the objects are not presented in the prompts for relation-specific or concept-specific neuron identification (cf. §2).

neurons and concept neurons. Most of the cells with large counts support our hypothesis that the overlaps between relations we observe are rooted in these relations being representationally associated with their 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. However, most identified neurons are only concept neurons or only relation neurons, **suggesting that relational and conceptual representations are largely separate.**

5.5 Effect on General Language Modeling

Relation	# Sentences	PPL (Before)	PPL (After)
`person_sport_position`	8	87.67	95.18
`person_pro_sport`	5	34.42	45.54
`person_occupation`	19	62.71	84.31
`company_hq`	50	63.97	61.27
`product_company`	23	100.65	95.37
`person_mother`	50	141.31	146.99
`person_father`	50	90.14	83.54
`landmark_continent`	4	90.19	73.82
`landmark_country`	50	58.57	51.12
`company_ceo`	50	102.32	110.71
`person_plays_instrument`	5	69.97	63.91
`star_constellation`	26	47.12	57.48

Table 2: Perplexity before and after ablation of *RelSpec* neurons on synthetic sentences where the object appears in a context without subject or relation.

One potential concern with ablating *RelSpec* neurons is the risk of inadvertently impairing general language modeling, particularly for tokens associated with the object entity in contexts unrelated to the original subject–relation pair. To investigate this, we design a new experiment to measure **perplexity** on synthetic sentences where the object appears in naturalistic but relation-neutral context – without the original subject or relation. For each of the 12 covered relations, we construct up to 50 sentences (using distinct objects from $\mathcal{P}_{r_i}^{\text{det}}$) with fixed templates, such that the object entity appears as the final token (see §K for prompt templates). We then compute the perplexity of these sentences before and after ablating the *RelSpec* neurons. The results are summarized in Table 2, which reports average perplexity across sentences for each relation. The results show no systematic degradation in perplexity after ablation. For several relations (e.g., `company_hq`, `landmark_country`, `product_company`), the perplexity even slightly decreases. This suggests that the object-token generation ability is preserved, and that the **ablation primarily targets mechanisms specific to the factual relation rather than disrupting broader lexical or contextual knowledge of the models**.

6 Conclusion

This work highlights the existence of relation-specific neurons in LLMs – neurons that focus on relations rather than entities. Our experiments show that *RelSpec* 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** (multiple neurons jointly contribute to dealing with facts belonging to a 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.

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 because the reliability of the neuron identification method requires enough facts in each relation. 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. Thirdly, we draw our findings from the LLama-2 family in the main content due to page limit and resource constraints. We also conduct the same investigation on Gemma-7B (Gemma Team et al., 2024) (cf. §C), which shows similar trends as we observe for models from the LLama-2 family. Future work can explore even larger models or models with posttraining techniques like instruction-tuning. 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 (cf. §E). 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., 2022a; 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., 2022a; 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 Analysis 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 relations in the identification prompt set $\mathcal{P}_{r_i}^{\text{det}}$ of the 7B model and the 13B model in Figure 10 and 11 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 12. 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 diagonal values of the object overlap subfigures (Figures 10, 11, 12, right) reflect the number of **distinct objects**, while those of the subject overlap subfigures (left) correspond to the total number of **facts**. This distinction reveals structural differences across relations. For instance, in `company_ceo`, `person_mother`, and `person_father`, each fact is typically associated with a unique object – yielding an almost one-to-one mapping. In contrast, relations like `person_occupation` involve a small number of frequent objects. Furthermore, the object distribution varies: some relations (e.g., `person_pro_sport`) are relatively balanced, while others (e.g., `person_occupation`) are highly skewed (with many "actors"), largely due to biases in the original LRE dataset.

Taken together, the entity analysis suggests that entities are not a confounding factor in our experiments. The identified *RelSpec* neurons capture relation-specific behavior rather than entity-specific patterns.

C Analysis On Gemma-7B

We perform a similar analysis on the Gemma-7B model (Gemma Team et al., 2024) as we do for the LLama-7B model. We first show how the identified 3,000 *RelSpec* neurons are distributed across layers for each relation in Figure 13. The trend is similar to what we observe in the 7B model (cf. Figure 1): the most of these neurons are located in the middle layers, but it is more evenly distributed across layers compared to the LLama families.

We show the intra-relation results in Figure 16. The results indicate that the identified *RelSpec* neurons are also effective in the Gemma-7B model: not only for the identification prompt set $\mathcal{P}_{r_i}^{\text{det}}$ but also for the held-out evaluation prompt set $\mathcal{P}_{r_i}^{\text{eva}}$, the deactivation of the neurons result in obvious accuracy drops, especially compared with the randomly deactivated neurons, indicating the existence of *RelSpec* neurons are held across model families.

We then demonstrate the effect of varying numbers of *RelSpec* neurons using the same numbers: 10, 50, 200, 500, 1,000, 3,000, 10,000, 20,000, and 50,000. Figure 14 and 15 present the results. The global trend is similar to what we observe for the LLama-7B model: the accuracy for a relation further drops when more of its *RelSpec* neurons are deactivated; until 3,000 or 10,0000 neurons, the effect is almost only obvious for the concerned relation itself; after 10,000, deactivating more neurons results in a further drop in accuracy across all relations. This indicates the **neuron cumulativity** and **neuron versatility** can be observed across model families.

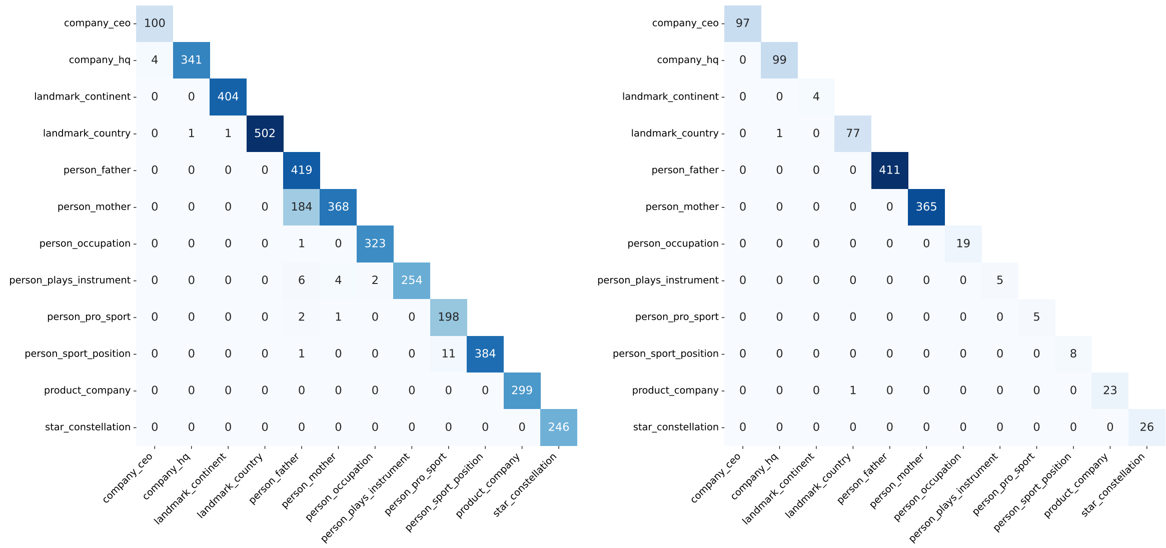

Figure 10: Subject (left) and object (right) overlap across 12 relations obtained from the **7B** model. The diagonal in each figure shows the number of distinct subjects or objects for each relation. It can be seen that factual knowledge from different relations has almost no entity overlap except for `person_mother` and `person_father`, which are mostly celebrities.

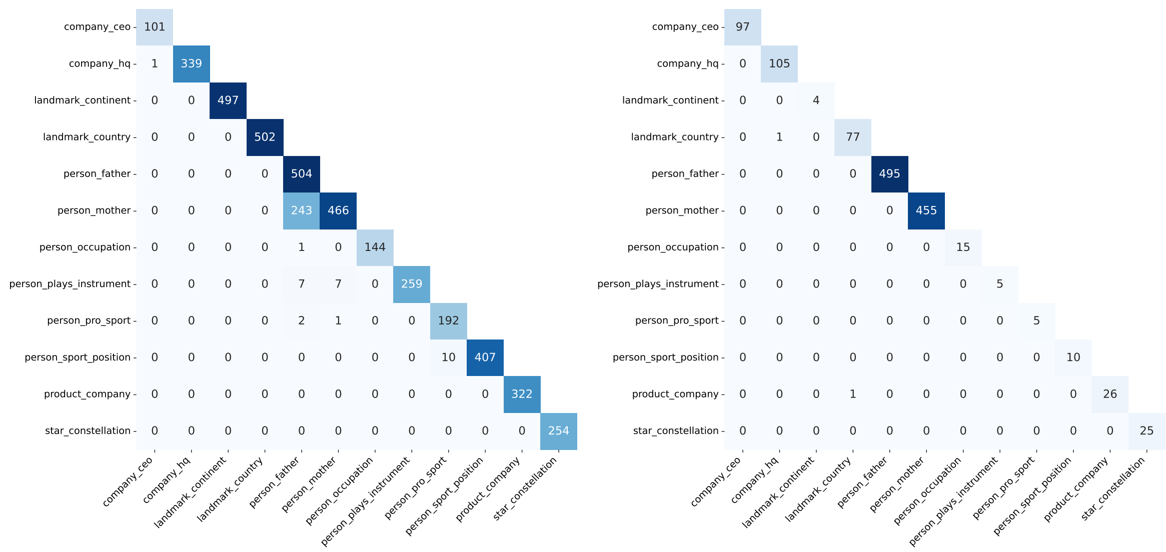

Figure 11: Subject (left) and object (right) overlap across 12 relations obtained from the **13B** model. The trend is very similar to that in the 7B model: `person_mother` and `person_father` share many subjects.

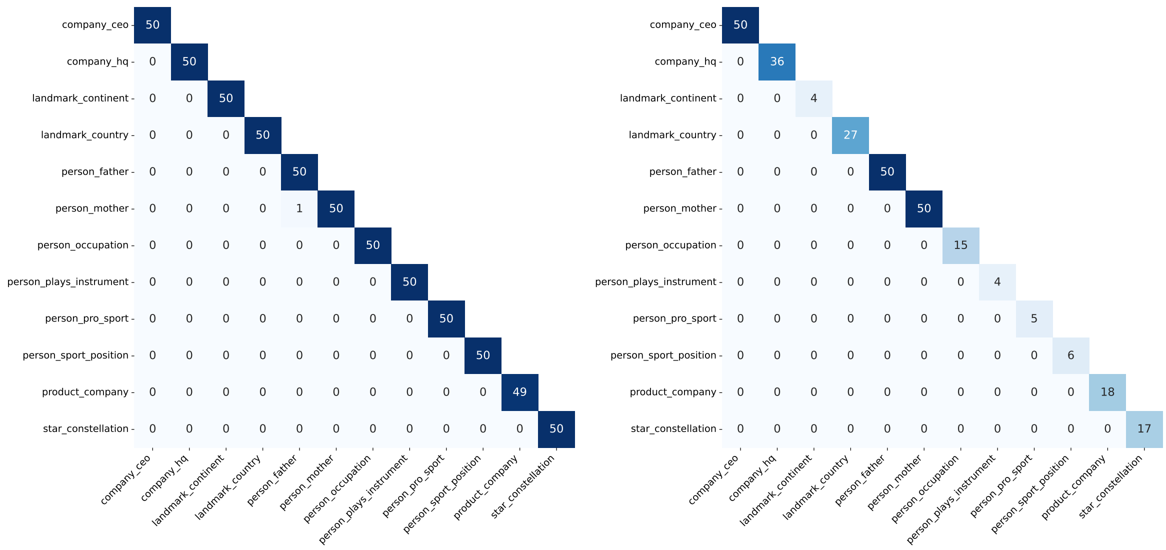

Figure 12: Subject (left) and object (right) overlap across 12 relations in the held-out evaluation prompt set $\mathcal{P}_{r_i}^{\text{eva}}$. Almost no two relations share any subjects or objects.

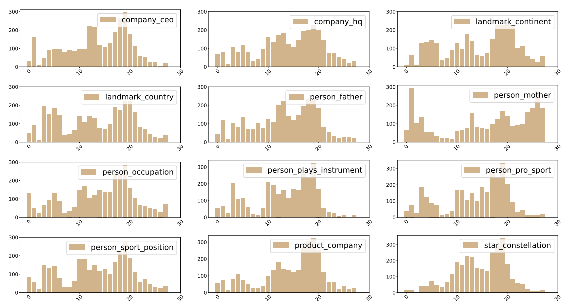

Figure 13: Distribution of *RelSpec* neurons across layers for the **Gemma-7B** model. Compared to the LLama-7B model in Figure 1, identified *RelSpec* neurons are more evenly distributed across layers. However, the majority of the population is still located in the middle layers.

D 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 *RelSpec* neurons are distributed across layers for each relation in Figure 17. The trend is similar to what we observe in the 7B model (cf. Figure 1). Most of the *RelSpec* neurons are distributed in the middle layers. Then we show the overlap of *RelSpec* neurons across relations in Figure 18. 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 *RelSpec* neurons using the same numbers: 10, 50, 200, 500, 1,000, 3,000, 10,000, 20,000, and 50,000. Figure 20 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. *RelSpec* 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 *RelSpec* neurons.

Lastly, we show whether the identified *RelSpec* 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 19. We observe similar results as from the

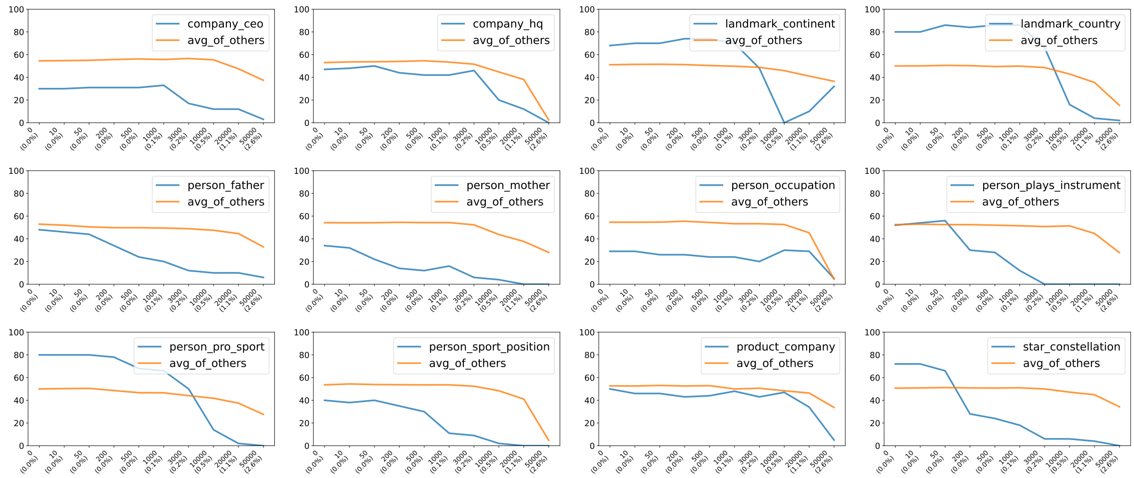

Figure 14: Influence of deactivating different numbers of *RelSpec* neurons for each relation (**Gemma-7B**). The variation of accuracy on the relation itself and the average accuracy on other relations is shown.

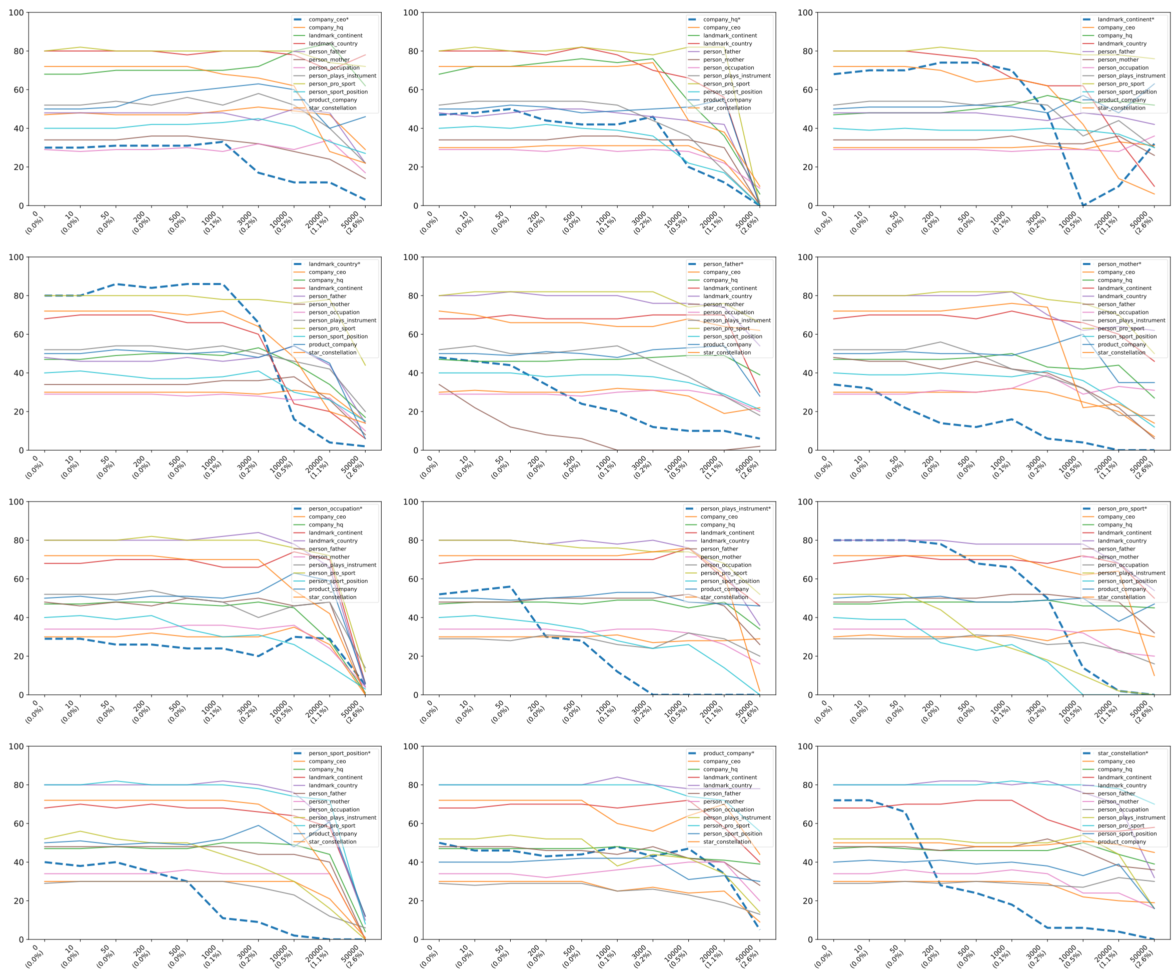

Figure 15: Influence of deactivating different numbers of *RelSpec* neurons in the **Gemma-7B** model for each relation. The variation of accuracy on the relation itself (noted with "*" and a dashed line style) and the accuracy on all other relations is shown in each figure.

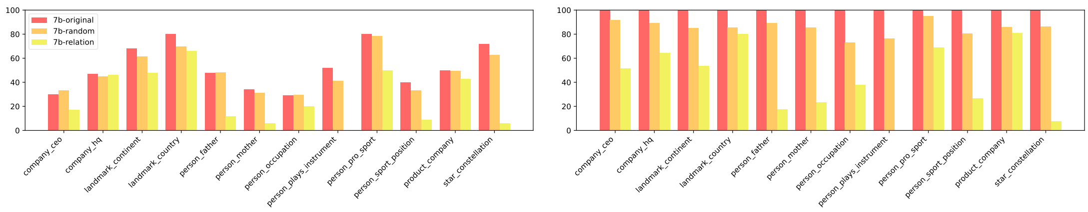

Figure 16: Intra-relation results on **Gemma-7B**. The left (resp. right) figure displays the results of held-out evaluation prompt set $\mathcal{P}^{\text{eva}}_{r_i}$ (resp. identification prompt set $\mathcal{P}^{\text{det}}_{r_i}$). We report the performance of the original model (without any deactivation), the model with 3,000 random neurons deactivated, and the model with relation neurons deactivated.

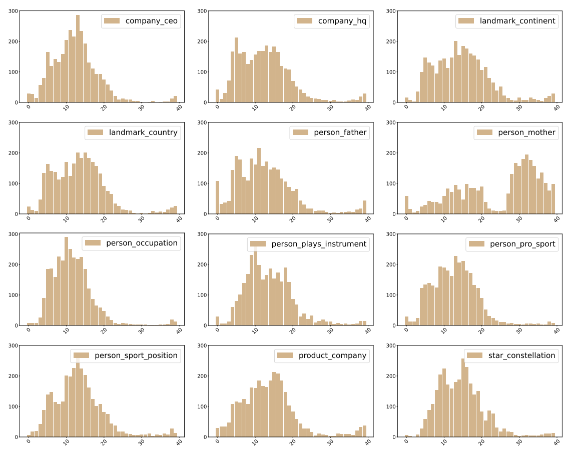

Figure 17: Distribution of *RelSpec* neurons across layers for the **13B** model. Similar to Figure 1, identified *RelSpec* neurons are mostly located in the middle layers, except for `person_mother`.

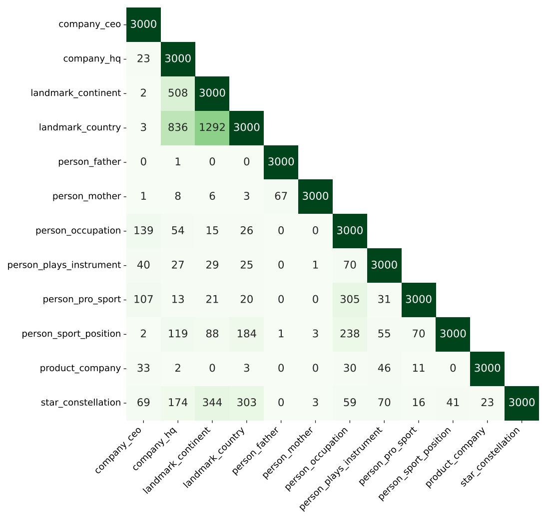

Figure 18: Neuron overlap of *RelSpec* neurons across 12 relations in the **13B** model. The overlap distribution is not similar to what we observe for the 7B model shown in Figure 2, explaining the difference in inter-relation results (cf. Table 4).

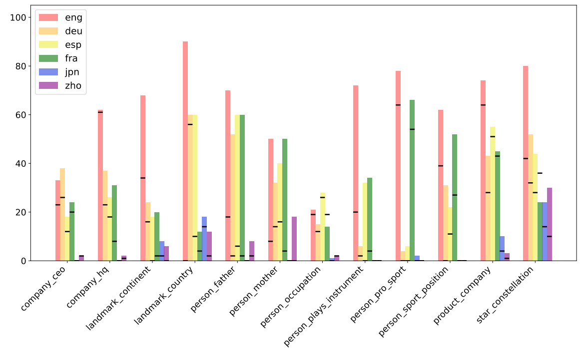

Figure 19: Accuracy on 12 relations across 6 languages from the **13B** model. The bars show the accuracy of the original model, with a horizontal line in each bar that indicates the performance after the deactivation of 3,000 *RelSpec* neurons.

7B model: when we deactivate *RelSpec* 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.

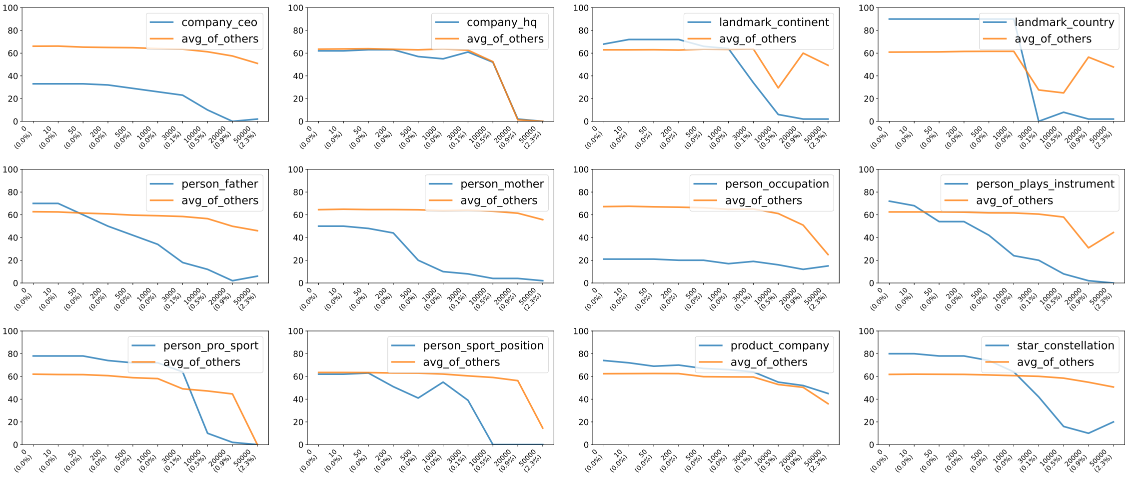

Figure 20: Influence of deactivating different numbers of *RelSpec* neurons for each relation (the **13B** model). The variation of accuracy on the relation itself and the average accuracy on other relations is shown.

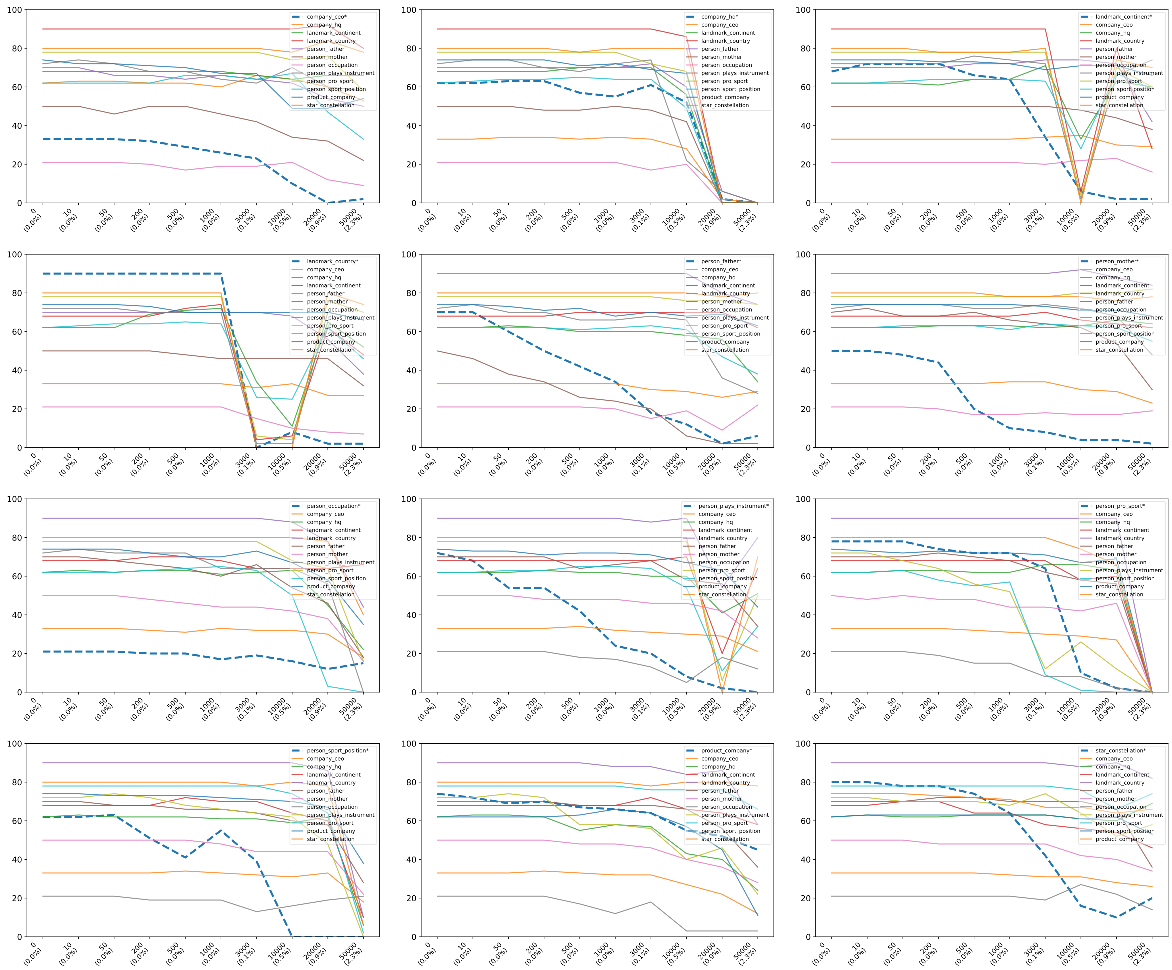

Figure 21: Influence of deactivating different numbers of *RelSpec* neurons in the **13B** model for each relation. The variation of accuracy on the relation itself (noted with "*" and a dashed line style) and the accuracy on all other relations is shown in each figure.

E 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 *RelSpec* neurons. (**b**) *sensitive facts*, for which the model is correct **before but not after** these neurons are deactivated.[10] We then count how many documents in Dolma contain **both the subject and object** of each fact, calling this the *fact frequency*.[11] Finally, we compute the average frequency for resilient and sensitive facts in each relation r_i, denoted respectively as $\text{group}_{r_i}^{(\text{a})}$ and $\text{group}_{r_i}^{(\text{b})}$.

Relative difference: $\text{diff}_{r_i} = \frac{\text{group}_{r_i}^{(\text{b})} - \text{group}_{r_i}^{(\text{a})}}{\text{group}_{r_i}^{(\text{b})}}$ for each relation r_i is reported in Figure 23. 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.[12] 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 *RelSpec* neurons**.

[10] We do not consider other numbers of *RelSpec* 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.

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

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

F 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.[13] 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.[14]. 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.

G 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 24 and report the inter-relation results in Figure 25 (**`all`**), 26 (**`self_attn`**), 27 (**`up_proj`**), 28 (**`gate_proj`**), and 29 (**`down_proj`**).

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

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

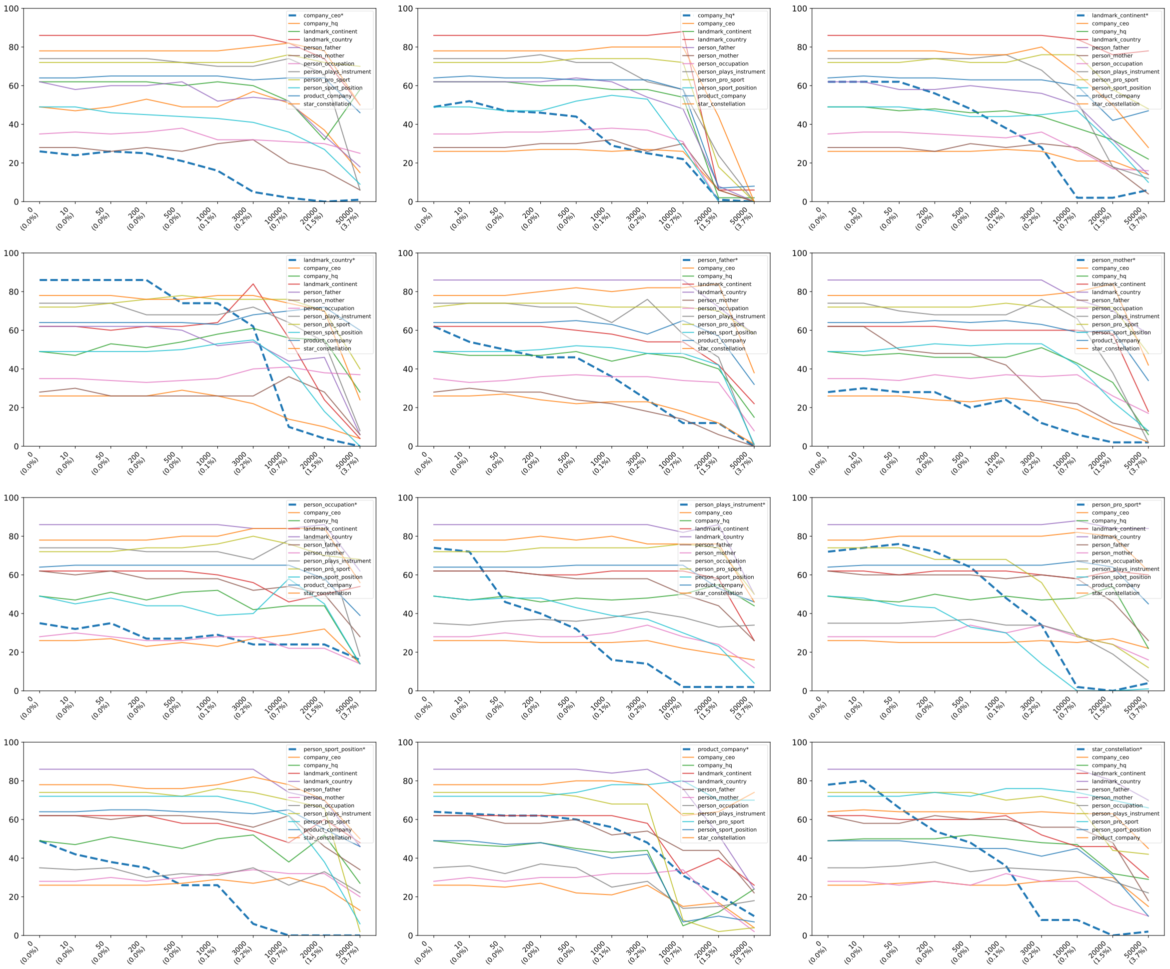

Figure 22: Influence of deactivating different numbers of *RelSpec* neurons in the **7B** model for each relation. The variation of accuracy on the relation itself (noted with "*" and a dashed line style) and the accuracy on all other relations is shown in each figure. Similar to Figure 5, increasing 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.

Relation	**10–50**		**50–200**		**200–500**		**500–1000**		**1000–3000**		**3000–10000**		**10000–20000**		**20000–50000**	
	#total	#affected	#total	#affected	#total	#affected	#total	#affected	#total	#affected	#total	#affected	#total	#affected	#total	#affected
`company_ceo`	1	0	3	2	5	0	7	2	11	2	3	3	2	0	0	0
`company_hq`	5	5	2	1	2	0	16	5	5	0	9	2	21	16	1	1
`landmark_continent`	0	0	4	4	4	2	5	0	6	2	13	6	0	0	0	0
`landmark_country`	0	0	1	1	6	0	2	0	6	0	26	5	3	0	2	0
`person_father`	3	1	2	0	0	0	5	0	6	2	6	0	2	1	6	4
`person_mother`	4	3	1	0	4	3	0	0	7	5	4	1	2	1	1	1
`person_occupation`	3	3	9	6	2	0	2	1	8	1	7	5	6	2	18	6
`person_plays_instrument`	13	11	7	2	5	0	8	0	3	0	6	0	0	0	0	0
`person_pro_sport`	0	0	2	1	4	1	9	0	8	0	16	0	1	0	0	0
`person_sport_position`	7	2	4	0	12	4	4	2	20	11	6	0	0	0	0	0
`product_company`	1	0	0	0	2	0	4	2	9	2	20	5	10	2	12	7
`star_constellation`	8	7	6	2	3	0	6	1	14	0	1	0	4	0	0	0

Table 3: Cumulative effect validation. For each neuron deactivation range, e.g., 1000-3000, the number of prompts where the model answers correctly in the smaller (1000) but not the larger range (3000) is denoted as column #total, and the number of prompts out of #total that are also affected, i.e., being answered wrongly, when deactivating the intermediate difference (2000 = 3000 - 1000) is denoted as #affected. #affected is usually much smaller than #total, indicating that neurons mostly act in a cumulative way and have no strong effect in isolation.

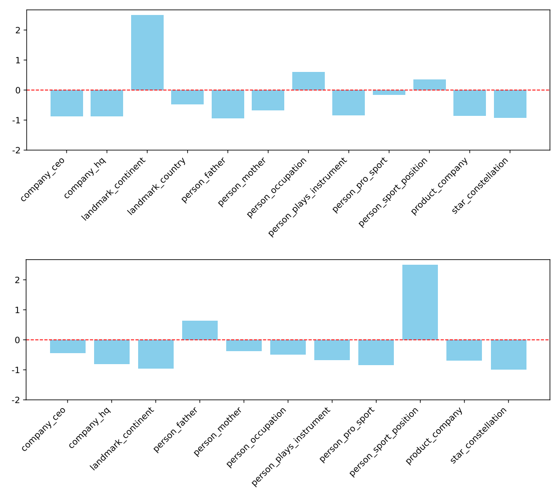

Figure 23: Relative difference between the average fact frequencies of the group (a) *resilient facts* and (b) *sensitive facts* for each relation in 7B (top) and 13B (bottom) models. Resilient facts generally appear more often than sensitive facts in most relations in the pertaining data.

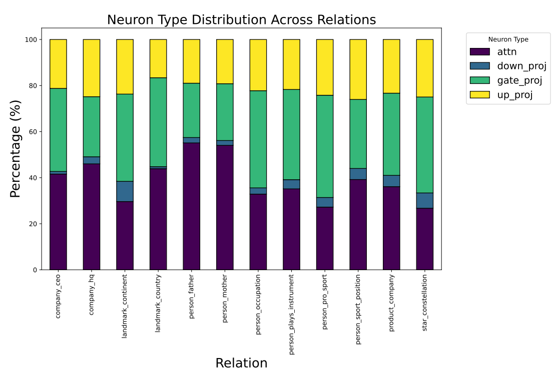

Figure 24: The distribution of the neuron types in the identified 3,000 neurons for the variety **`all`** across all relations.

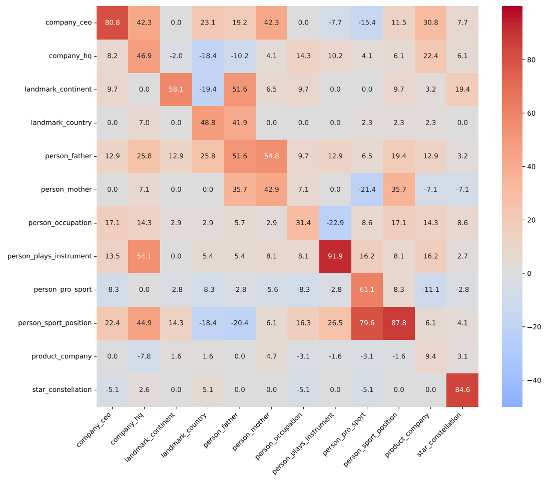

Figure 25: Inter-relation results of the 7B model when considering the neuron type variety as **`all`**.

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 that **`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 3). 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 3. Therefore, our additional analysis supports our choice of considering neurons in FFNs.

H Concept-Specific Neurons

Concept-Relation Overlap in the 7B Model Figure 30 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

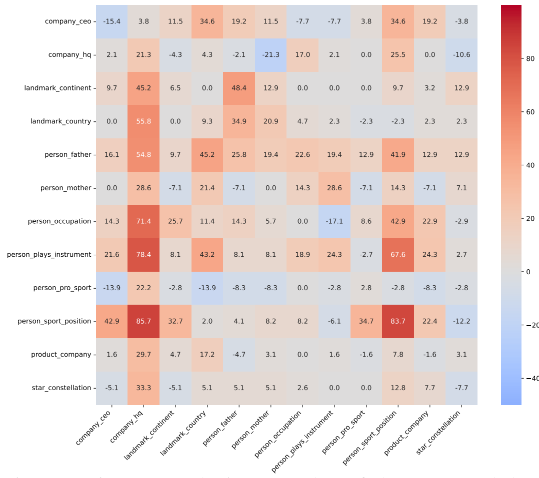

Figure 26: Inter-relation results of the 7B model when considering the neuron type variety as **`self_attn`**.

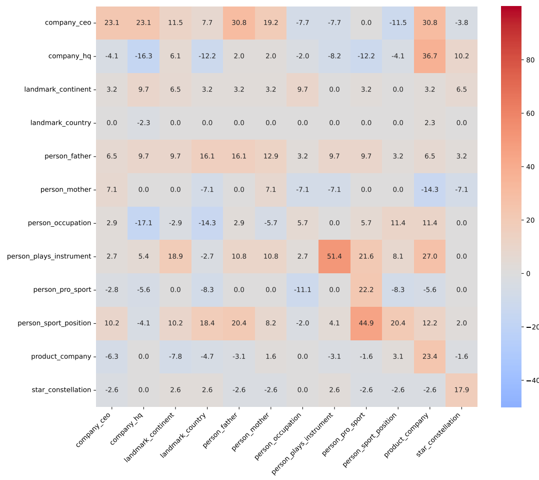

Figure 27: Inter-relation results of the 7B model when considering the neuron type variety as **`up_proj`**.

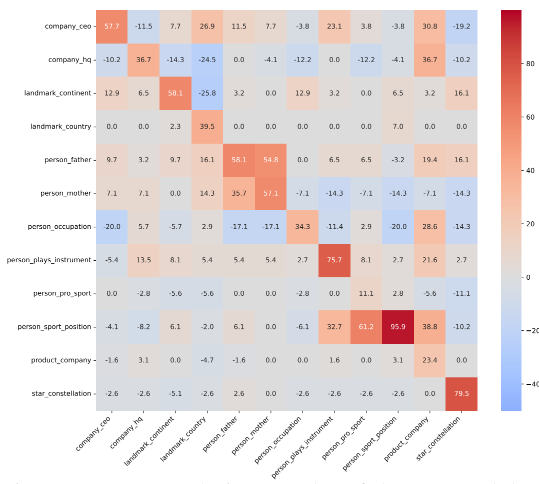

Figure 28: Inter-relation results of the 7B model when considering the neuron type variety as **`gate_proj`**.

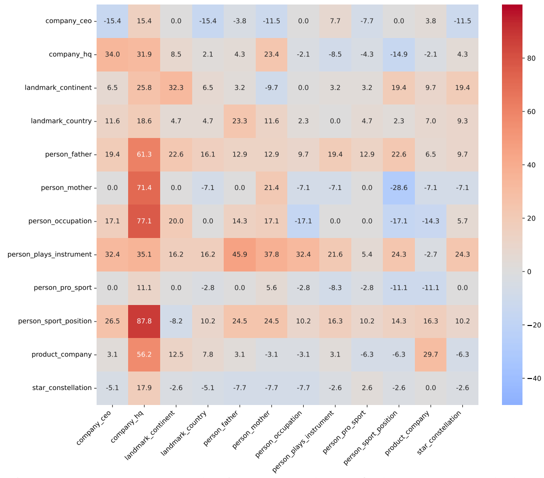

Figure 29: Inter-relation results of the 7B model when considering the neuron type variety as **`down_proj`**.

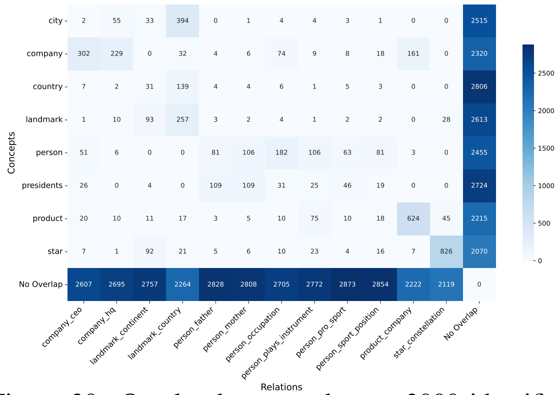

Figure 30: Overlap between the top 3000 identified neurons for each relation and concept in the 7B model.

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 31 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 between concepts. The observed drop in performance due to the ablation of 3000 neurons for con-

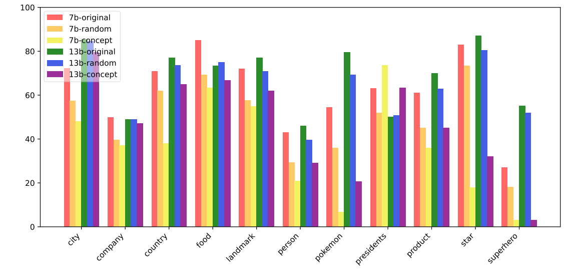

Figure 31: Accuracy results of evaluation prompts for 11 concepts in the 7b and 13b model. We report the performance of the original model (without any deactivation), e.g., `7b-original`, the model with 3000 randomly deactivated neurons, e.g., `7b-random`, and the model with deactivating the top 3000 identified concept-specific neurons, e.g., `7b-concept`.

cepts 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 *RelSpec* 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.

I Experimental Environment

We run all experiments on NVIDIA RTX A6000 GPUs. The Python environment we use is the same as Kojima et al. (2024).[15]

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

J Error Analysis

We manually verified the prompts in each relation that the model could answer correctly originally, but failed to answer correctly when 3,000 *RelSpec* neurons were deactivated (cf. §4.2). The three most common incorrect responses (regarded as *systematic errors*) are listed in Table 4.

After we deactivate the *RelSpec* neurons, we can see that the model appears to lose its ability to recall the correct object. Instead, the model frequently answers with meaningless answers that start with tokens such as "*A.*" or "*The*", or simply repeats the given prompt. We showcase representative examples of each phenomenon in Table 5, Table 6, and Table 7. The results strongly indicate that the model loses its ability to capture relational semantics, resulting in increasingly noisy outputs after the deactivation of *RelSpec* neurons.

K 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 9, `company_hq` in Table 10, `landmark_continent` in Table 11, `landmark_country` in Table 12, `person_father` in Table 13, `person_mother` in Table 14, `person_occupation` in Table 15, `person_plays_instrument` in Table 16, `person_pro_sport` in Table 17, `person_sport_position` in Table 18, `product_company` in Table 19, and `star_constellation` in Table 20.

Additionally, we show the templates used for measuring the effect on the general language modeling capability before and after ablating *RelSpec* neurons (cf. §5.5) in Table 8.

Relation	Repeat Prompt	Answer with "*The*"	Answer with "*A.*"	Total Number
company_ceo	**47.8%**	8.7%	34.8%	23
company_hq	**46.2%**	**46.2%**	0%	26
landmark_continent	**17.6%**	5.9%	0%	17
landmark_country	**69.3%**	0%	0%	13
person_father	**84.2%**	5.3%	0%	19
person_mother	**70%**	20%	0%	10
person_occupation	**93.3%**	0%	0%	15
person_plays_instrument	**51.6%**	29%	0%	31
person_pro_sport	**25%**	15%	0%	20
person_sport_position	18.6%	11.6%	**44.2%**	43
product_company	**70.1%**	11.8%	0%	17
star_constellation	**88.6%**	5.7%	0%	35

Table 4: Most common incorrect answers generated by LLama-7b after deactivating 3,000 *RelSpec* neurons.

Subject-Object Pair	**Prompt**	**Expected Output**	**Model Response**	**Deactivation**
(Panasonic Corporation, Kazuhiro Tsuga)	Panasonic Corporation's CEO is? Answer:	Kazuhiro Tsuga	Kazuhiro Tsuga	No
			[Pan]asonic Corporation's CEO is:\nPanasonic Corporation's CEO	Yes

Table 5: Model answers by repeating the prompt after deactivating *RelSpec* neurons. We changed the output length from **2** tokens to **20** tokens to observe the complete output. The part enclosed in "[]" is the first 2 tokens of the output. The triple (`Panasonic`, `company_ceo`, `Kazuhiro Tsuga`) is selected for demonstration.

Subject-Object Pair	**Prompt**	**Expected Output**	**Model Response**	**Deactivation**
(Pagan Federation, London)	Pagan Federation is headquartered in the city of? Answer:	London	London	No
			[The] Pagan Federation is a British organisation that represents the interests of Pagans and other Ne	Yes

Table 6: Model answers with "*The*" after deactivating *RelSpec* neurons. We changed the output length from **2** tokens to **20** tokens to observe the complete output. The part enclosed in "[]" is the first 2 tokens of the output. The triple (`Pagan Federation`, `company_hq`, `London`) is selected for demonstration.

Subject-Object Pair	**Prompt**	**Expected Output**	**Model Response**	**Deactivation**
(Damon Huard, quarterback)	Damon Huard plays in the position of a? Answer:	quarterback	Quarterback	No
			[A.]\nDamon Huard plays in the position of a?\nAnswer: A.	Yes

Table 7: Model answers with "*A.*" after deactivating *RelSpec* neurons. We changed the output length from **2** tokens to **20** tokens to observe the complete output. The part enclosed in "[]" is the first 2 tokens of the output. The triple (`Damon Huard`, `person_sport_position`, `quarterback`) is selected for demonstration..

Relation	Template (Object inserted at <object>)
person_sport_position	The jersey was displayed in honor of the legendary player known for their role as <object>.
person_pro_sport	The documentary explored the early years of the athlete's rise in the world of <object>.
person_occupation	After years of study and dedication, they finally earned recognition as a respected <object>.
company_hq	The company's annual report was mailed directly from its headquarters in <object>.
product_company	Consumers often associate the iconic design of the device with the brand <object>.
person_mother	The award speech concluded with heartfelt thanks to someone very special, <object>.
person_father	The biography ended with a touching story about a life lesson from <object>.
landmark_continent	The travel show featured stunning views from across the diverse landscapes of <object>.
landmark_country	Every year, thousands of tourists visit the historic site located in <object>.
company_ceo	The major shift in strategy was attributed to the leadership of <object>.
person_plays_instrument	The final movement of the piece was written specifically for the sound of a <object>.
star_constellation	Ancient civilizations once navigated the seas by charting the stars in <object>.

Table 8: Templates used to construct synthetic sentences for evaluating general language modeling of object tokens in §5.5. Each sentence includes the object in a natural context unrelated to the original subject or relation.

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: - - - - - - - - - - The name of the CEO of Panasonic Corporation is? Answer: Who is the CEO of Panasonic Corporation? Their name 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 9: 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. The prompt shown below the dashed line is the new template introduced for the experiment described in §5.3.

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: - - - - - - - - - - Where are the headquarters of Cadillac It is 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 10: 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. The prompt shown below the dashed line is the new template introduced for the experiment described in §5.3.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Elbe, Europe)	Elbe is on the continent of? Answer: - - - - - - - - - - What continent is Elbe on? It is on? 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 11: 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. The prompt shown below the dashed line is the new template introduced for the experiment described in §5.3.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Namba Station, Japan)	Namba Station is in the country of? Answer: - - - - - - - - - - What country is Namba Station in? It is in? 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 12: 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. The prompt shown below the dashed line is the new template introduced for the experiment described in §5.3.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Ronald Reagan, Jack Reagan)	Ronald Reagan's father is named? Answer: - - - - - - - - - - Who is Ronald Reagan's father? Their 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 13: 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. The prompt shown below the dashed line is the new template introduced for the experiment described in §5.3.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Demi Moore, Virginia King)	Demi Moore's mother is named? Answer: - - - - - - - - - - Name of mother of Demi Moore is? Answer: Who is Demi Moore's mother? Their 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 14: 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. The prompt shown below the dashed line is the new template introduced for the experiment described in §5.3.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Martin Burrell, politician)	Martin Burrell works as a? Answer: By profession, Martin Burrell is a? Answer: - - - - - - - - - - Martin Burrell works professionally as 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 15: 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. The prompt shown below the dashed line is the new template introduced for the experiment described in §5.3.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Anson Funderburgh, guitar)	Anson Funderburgh plays the instrument of? Answer: - - - - - - - - - - - - What instrument does Anson Funderburgh play? They play the? Answer: The instrument that Anson Funderburgh plays is called the? 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 16: 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. The prompt shown below the dashed line is the new template introduced for the experiment described in §5.3.

Language	Subject-Object Pair	Prompt	Expected Output
English	(Frédéric Piquionne, soccer)	Frédéric Piquionne plays the sport of? Answer: - - - - - - - - - - - - What sport does Frédéric Piquionne play? They play? Answer: Frédéric Piquionne plays professionally in 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 17: 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. The prompt shown below the dashed line is the new template introduced for the experiment described in §5.3.

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: - - - - - - - - - - Which position does Ju Yingzhi play? They play as a? Answer: In their sport, Ju Yingzhi plays in the position of 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 18: 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. The prompt shown below the dashed line is the new template introduced for the experiment described in §5.3.

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: - - - - - - - - - - Which company developed Jeep Grand Cherokee? It was developed by? 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どの会社ですか? 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 19: 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. The prompt shown below the dashed line is the new template introduced for the experiment described in §5.3.

Language	Subject-Object Pair	Prompt	Expected Output
English	(50 Persei E, Perseus)	50 Persei E is part of the constellation named? Answer: - - - - - - - - - What is the name of the constellation that 50 Persei E is part of? It is part of? Answer: What is the name of the constellation that 50 Persei E belongs to? It belongs to? 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 20: 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. The prompt shown below the dashed line is the new template introduced for the experiment described in §5.3.