How Do Multilingual Language Models Remember Facts?

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Abstract

Large Language Models (LLMs) store and retrieve vast amounts of factual knowledge acquired during pre-training. Prior research has localized and identified mechanisms behind knowledge recall; however, it has only focused on English monolingual models. The question of how these mechanisms generalize to non-English languages and multilingual LLMs remains unexplored. In this paper, we address this gap by conducting a comprehensive analysis of three multilingual LLMs. First, we show that previously identified recall mechanisms in English largely apply to multilingual contexts, with nuances based on language and architecture. Next, through patching intermediate representations, we localize the role of language during recall, finding that subject enrichment is language-independent, while object extraction is language-dependent. Additionally, we discover that the last token representation acts as a Function Vector (FV), encoding both the language of the query and the content to be extracted from the subject. Furthermore, in decoder-only LLMs, FVs compose these two pieces of information in two separate stages. These insights reveal unique mechanisms in multilingual LLMs for recalling information, highlighting the need for new methodologies—such as knowledge evaluation, fact editing, and knowledge acquisition—that are specifically tailored for multilingual LLMs.

1 Introduction

Large Language Models (LLMs) learn extensive factual knowledge during pre-training, including propositional facts like "The capital of France is __" (Petroni et al., 2019). While multilingual models also acquire such knowledge, their performance varies significantly across languages (Kassner et al., 2021; Jiang et al., 2020; Yin et al., 2022), raising questions about whether this variation stems from language-specific storage or phrasing sensitivity (Elazar et al., 2021). Such assessments will be critical for determining the trustworthiness of multilingual LLMs, if trust relies on knowledge (Grasswick, 2010; Hawley, 2012; Nguyen, 2022).

Mechanistic interpretability research has begun uncovering how models store and retrieve knowledge internally, with recent studies identifying specific components for knowledge storage (Meng et al., 2022; Sharma et al., 2024) and retrieval mechanisms (Geva et al., 2023; Chughtai et al., 2024). However, they have focused exclusively on English LLMs, mainly autoregressive ones.[1] Encoder-decoder architectures, which could enable better cross-lingual representations (Li et al., 2024), remain underexplored. Additionally, recent studies have shown that LLMs share circuits across languages for specific tasks (Ferrando and Costa-jussà, 2024; Zhang et al., 2025), but these are limited to syntactic tasks and do not address how concepts are represented or recalled cross-lingually. While Dumas et al. (2024) examined how disentangled language is from concepts using a translation task, here we analyze fact recall, which allows us to offer broader insights into how language is encoded.

In this paper, we study the mechanisms of factual recall in multilingual LLMs, focusing on two architectures: decoder-only (XGLM and EuroLLM) and encoder-decoder (mT5). We analyze a simple form of information extraction, where the input contains a subject and a relation, and the model predicts the corresponding object (e.g. "Paris" in the earlier example). Our analysis centers on three key questions: (1) Does the localization of factual knowledge in English LLMs extend to multilingual LLMs? (2) Are the factual recall mechanisms found for English LLMs also present in multilingual LLMs? (3) When does language play a role

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[1]Except Sharma et al. (2024), who extend these analyses to Mamba (Gu and Dao, 2023), a state-space language model.

in the recall mechanism?

To address the first question, we use causal tracing analysis to assess if early MLP modules processing the final subject token are as decisive in multilingual models as in English-centric models (Meng et al., 2022). Our results (§3) show that EUROLLM and mT5 exhibit strong causal effects for *all* subject tokens, with EUROLLM exhibiting this in earlier layers and mT5 across all encoder layers. In XGLM, the last subject token has a stronger effect, but with two early sites, unlike English GPT's single site. Additionally, in all models, MLPs in later layers are decisive in recovering factual information, a contrast to Meng et al. (2022) findings.

Next, we investigate the second question by analyzing the mechanisms described in Geva et al. (2023); namely, the three-step process, where the relation information flows to the last token, then the subject flows, and finally the attention layers extract the object (§4). We find that in multilingual decoder-only models the information flows similarly to monolingual models, but differently for the encoder-decoder model mT5. In terms of the extraction event, in decoder-only LLMs, *both* feed-forward and attention sublayers contribute to it, unlike English autoregressive models, where attention modules dominate. In mT5, this mechanism is primarily performed by the cross-attention. Overall, our findings indicate that some of the localization (§3) and mechanisms (§4) of fact retrieval in English LLMs generalize to multilingual LLMs, but with key variations.

Finally, to address the third question, we investigate where language plays a role within the three-step process described by Geva et al. (2023), to characterize how and where factual knowledge cross-lingual transfer may occur. Using activation patching (Zhang and Nanda, 2024; Ghandeharioun et al., 2024) we insert the intermediate representation of the last token from an English forward pass into the forward pass of another language (§5). Our results reveal that the last token acts as a Function Vector (FV) (Todd et al., 2024), encoding both the relation *and* the output language, which is then applied to the subject in the context. Crucially, the fact that the FV formed in one language can be used with an input in another language demonstrates that the subject and relation representations are largely language-independent, while the extraction event is language-specific. Furthermore, in decoder-only LLMs (XGLM, EUROLLM), the FV is constructed in two distinct phases: first, it encodes only the relation, and later, the language is incorporated.

These findings advance our understanding of factual recall, with implications for cross-lingual knowledge transfer, knowledge editing, and trustworthiness in multilingual LLMs. Our results on language flow open new avenues for studying whether models 'think' in English (Wendler et al., 2024), by examining how the FV is altered across languages. Additionally, the late-site causal effect of MLPs and their dominance in the extraction phase suggest that fact editing techniques and knowledge evaluations must extend beyond early MLPs and attention layers (Tamayo et al., 2024).

2 Experimental Setup

We focus on a simple form of factual knowledge recall, where LMs are tasked with predicting the correct object o for a given subject s and a relation r. These (s, r, o) triplets are obtained from WikiData, and natural language templates are used to describe the relation, with placeholders for the subject and object.[2] For our analysis, we select 10 typologically diverse languages representing various scripts, families, and word orders: English (*en*), Spanish (*es*), Vietnamese (*vi*), Turkish (*tr*), Russian (*ru*), Ukrainian (*uk*), Japanese (*ja*), Korean (*ko*), Hebrew (*he*), Persian (*fa*), and Arabic (*ar*). See Table 2 for language characteristics.

Models We analyze decoder-only and encoder-decoder architectures.[3] The decoder-only LLMs are XGLM (Lin et al., 2021), with 7.5B parameters and 32 layers, and EUROLLM (Martins et al., 2024) with 9B parameters and 42 layers; the encoder-decoder mT5-xl (Xue et al., 2021) has with 3.7B parameters and 24 encoder-decoder layers. The pre-training

	XGLM	EUROLLM	mT5
en	1812	2332	1543
es	1380	1913	1192
vi	1646	779	993
tr	418	799	1058
ru	830	1680	683
uk	213	1244	456
ko	116	308	630
ja	6	42	358
he	13	107	565
fa	7	31	406
ar	811	1790	488

Table 1: Number of facts (s, r, o) correctly predicted.

[2]For example, the relation born-in could use the template "[X] was born in [Y]", where [X] is the subject and [Y] is the object to be predicted.

[3]For decoder-only models, we only use the templates in MPARAREL that have the object placeholder at the end of the sentence, while for encoder-decoder, we use all the templates.

data varies across models: mT5 is pretrained on 101 languages, covering all the languages in our study; XGLM covers 30 languages, excluding *uk*, *he*, and *fa*; while EUROLLM covers 35 languages, excluding *vi*, *he*, and *fa*.

Data We use the MPARAREL dataset (Fierro and Søgaard, 2022), which includes triplets and templates for 45 languages. These templates are machine translations of the PARAREL English templates (Elazar et al., 2021).[4]

To investigate the process of knowledge recall we only consider examples where the model predicts the *correct* object completion (Meng et al., 2022; Geva et al., 2023). Since MPARAREL provides multiple paraphrased templates for each relation, we greedy-decode for every available template corresponding to a given triplet and check for an exact match. If multiple templates yield a match, we randomly select one for the analysis. In cases where an article or other filler tokens precede the object, we include these tokens in the input text to ensure that when the example is fed into the model for our analysis, the next predicted token is the first token of the object (Implementation details in Appendix B.1). Table 1 presents the number of examples for which the correct object is predicted. We exclude languages with too few examples from our analysis, namely *ko*, *ja*, *he*, and *fa* for XGLM, and *ja*, *he*, and *fa* for EUROLLM.

Notation Given a transformer model with L layers, let h_t^l be the representation of the token t at layer l. When the model is an encoder-decoder, let e_i^l be the representation of the encoder layer l for the i-th token in the encoder input. Then, the encoder layer computes $h_t^{l+1} = h_t^l + s^l + f^l$ and the decoder $h_t^{l+1} = h_t^l + s^l + c^l + f^l$, where $s^l = \text{Self Attn.}(h_0^l \dots h_t^l)$, $c^l = \text{Cross Attn.}(h_t^l, e_0^l \dots e_n^l)$ and $f^l = \text{MLP}(h_t^l + s^l + c^l)$. If decoder-only, then c^l does not apply.

3 Causal Tracing

We first analyze which hidden states in the model's computation are more important than others when recalling a fact. Following Meng et al. (2022), we trace the causal effects of hidden states using causal mediation analysis (Pearl, 2022). Let $\mathbb{P}(o)$ be the probability of the predicted object token, and $LS(o)$ its logit score. We corrupt the input by adding Gaussian noise to the subject tokens,[5] and observe the corrupted probability $\tilde{\mathbb{P}}(o)$ of the originally predicted token. Then, we run inference again on the corrupted input, but this time, we restore a specific hidden state in the model and track the probability $\tilde{\mathbb{P}}_{\text{restored}}(o)$. We study the indirect effect of such component as $\text{IE}_{\mathbb{P}} = \tilde{\mathbb{P}}_{\text{restored}}(o) - \tilde{\mathbb{P}}(o)$, or if using logits $\text{IE}_{LS} = \tilde{LS}(o) - \tilde{LS}_{\text{restored}}(o)$. Specifically, we restore a *state* by setting $\tilde{h}_t^l \leftarrow h_t^l$, where h_t^l is the hidden state from the clean run and $\tilde{h}_t^l$ that of the corrupted run; and similarly, we restore the self-attention layers contribution by setting $\tilde{s}^l \leftarrow s^l$ for all the attention modules in a window of size w (analogous for c and f).[6] We set w=4 for XGLM, w=5 for EUROLLM, and w=3 for mT5, to restore $\sim 12\%$ layers. We repeat the corrupted run with restoration ten times with different noise samples, and report the average.

We compare our results in multilingual LLMs to those of Meng et al. (2022), who analyzed the factual recall of GPT-2 XL in English[7] and reached two key conclusions: (1) they identified an "early site", where the MLPs processing the last subject token in the early and middle layers play a crucial role in recovering from input corruption; and (2), they found a "late site", where the attention modules processing the last token in the later layers also significantly contribute to prediction recovery.[8]

We present the causal analysis plots for each model and language in Appendix C and present our main observations here.[9] Our results indicate that the last subject token does not consistently have a stronger effect on information recovery in

[4]We augment the objects in MPARAREL, filter out trivial examples, and when there are enough examples, we use a crosslingual subset (see Appendix B).

[5]We follow Meng et al. (2022) and add $\epsilon \sim \mathcal{N}(0, (3\sigma)^2)$, with σ being the standard deviation of the subjects tokens embeddings from the data used.

[6]We use windows because, generally, the contributions of the sub-layers are gradual (Geva et al., 2021). In other words, multiple layers contribute the same behavior to the residual, and their sum produces the observed effect.

[7]They used the COUNTERFACT dataset, which is based on PARAREL. Thus, their English data is the same as our data.

[8]While they consider the late site unsurprising, as it directly precedes the final prediction, this observation primarily applies to hidden state restoration, not necessarily attention restoration. We, however, interpret the late-site attention as aligning with what Geva et al. (2023) referred to as the extraction event (§4).

[9]In line with Zhang and Nanda (2024) we find that analyzing the $\text{IE}_{\mathbb{P}}$ overestimates the causal effect of some tokens over others. For example, in XGLM by looking at the $\text{IE}_{\mathbb{P}}$ we would not find an early site, which is present when studying the IE_{LS} (see Figure 10 vs Figure 8), or in EUROLLM the last subject token would seem more relevant than the other subject tokens (see Figure 14 vs Figure 12). So we base our main observations using IE_{LS}.

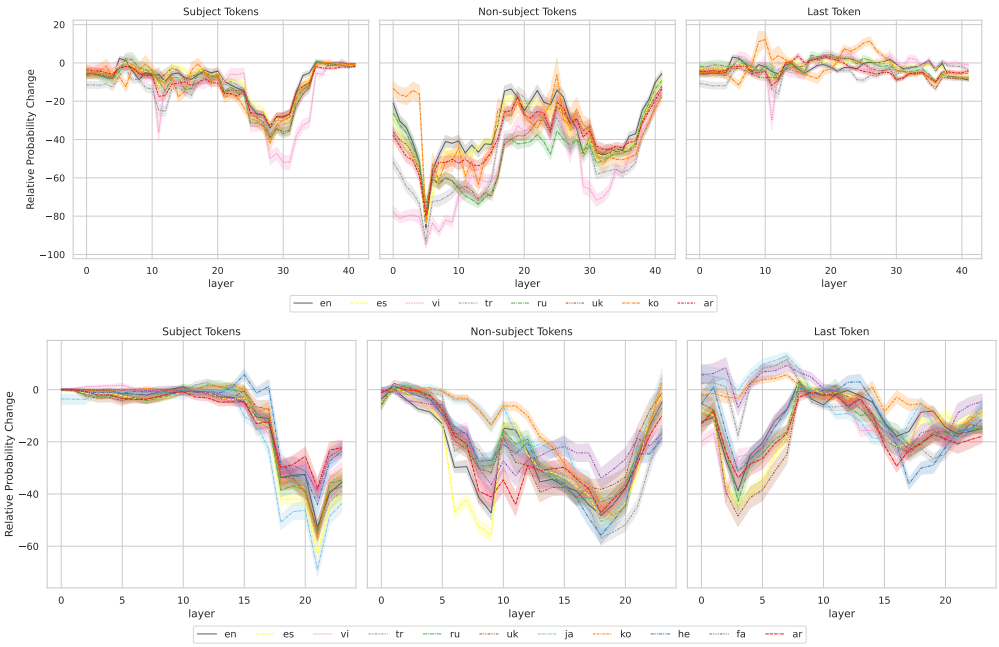


Figure 1: Attention knockout between the last token and a given set of tokens. Each layer represents the effect of the knockout on a window of w layers. Top EuroLLM ($w = 7$), bottom mT5 ($w = 4$). XGLM in Figure 20.

early MLPs. In EuroLLM and mT5, all subject tokens exhibit similar effects, while in XGLM, the last subject token has a stronger influence. In EuroLLM, the early site spans half of the initial layers, whereas in mT5, it covers all encoder layers. For XGLM, the early site occurs twice: once in the initial layers and again in the middle layers. Regarding the late site, we observe a strong causal effect in MLP layers before the very last layers in all models. The layers where these sites occur are consistent across languages, with only a slight variation in the late site's endpoint for EuroLLM.

These findings suggest that some, but not all, conclusions from English LLMs generalize to multilingual LLMs. The MLP early site extends across models, and the MLP late site, which was not observed by Meng et al. (2022), was present in all models studied. This has implications for knowledge localization and fact editing methodologies, which should account for both early and late MLPs in multilingual contexts.

4 Factual Recall Components

Geva et al. (2023) described the process of factual knowledge recall in English autoregressive models as a three-step mechanism: (a) the subject representation is enriched (i.e., related attributes are encoded); (b) the relation and subject information are propagated to the last token; and (c) the final predicted attribute is extracted by attention layers. We analyze the information flow to the last token, and then the extraction of the predicted attribute.

Information Flow We use attention knockout (Geva et al., 2023) to study information propagation to the last token. This involves intervening in the attention computation: for XGLM and EuroLLM, we modify the last token's self-attention, while for mT5, we intervene in the decoder last token's cross-attention. Attention connections are knocked out by setting the attention score to zero between the last token and a set of tokens $\{t\}$, which can be: (1) subject tokens, (2) non-subject (relation) tokens, or (3) the last token itself. We apply this intervention within a window of size w around layer l. Following Geva et al. (2023), we use w=6 for XGLM, w=7 for EuroLLM, and w=4 for mT5, knocking out $\sim$18% of layers. The relative probability change is given by $(\tilde{\mathbb{P}}(o) - \mathbb{P}(o))/\mathbb{P}(o)$, where $\tilde{\mathbb{P}}(o)$ is the probability of the originally predicted token o after attention knockout. A significant drop in relative probability indicates a critical information flow from the selected tokens to the last token around that layer.

Figure 1 presents the results with plots per language in Appendix D. Firstly, the results show that in each model the information flows fairly similarly for all the languages, and similar patterns to those found in English GPT are present (Geva et al., 2023). On the one hand, the subject information flows to the last token most critically at the later layers in all models. On the other hand, the relation flows throughout all the layers, with EuroLLM and mT5 having more similar curves. Nevertheless, we note two differences from the conclusions

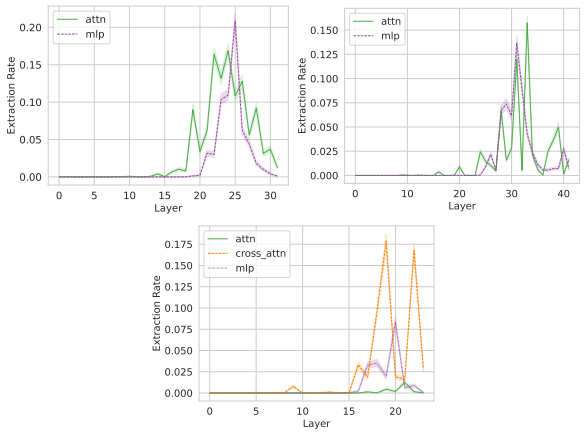


Figure 2: Extraction rates. Left XGLM, right EUROLLM, bottom mT5.

reached with English GPT (Geva et al., 2023): (1) the propagation of non-subject tokens to the last token does not strictly precedes the subject propagation, in XGLM the drop is the highest in the earlier layers but it continues to be important until the end, and in mT5 and EUROLLM this information has two peaks, in the early and later layers; and (2) the last token of mT5 encodes critical information that flows from one layer to the next through the cross-attention (as opposed to the negligible flow of the last token in the decoder-only models).[10]

Prediction Extraction Following Geva et al. (2023), we measure extraction events at each layer. Let h^l be the representation of the *last* token at layer l, and let E be the embedding matrix; the predicted token is $o = \arg\max(Eh^L)$. An extraction event occurs at layer l if $\arg\max(Es^l) = o$ (similarly for c^l and f^l). The extraction rate is the proportion of examples for which an extraction event occurs at a given layer. Figure 2 shows the extraction rates for each model, with a detailed language breakdown in Appendix E.

Our results demonstrate that extraction events can be detected in multilingual LLMs, though rates vary across languages. A key finding is the prominence of MLP modules in object extraction for multilingual decoder-only models (XGLM and EUROLLM). To rule out the possibility that MLPs simply forward extracted objects from preceding attention layers, we measure how often MLPs perform an extraction without prior attention extraction (Figure 27). We find that MLPs indeed perform the extraction for most languages, though in English, attention modules dominate, aligning with GPT-2 results (Geva et al., 2023). In mT5, cross-attention layers drive the extraction, with MLPs playing a secondary role, resembling GPT-2's behavior. Additionally, in mT5 the extraction events occur in later layers, with peaks in 19 and 22.

The results show that in multilingual LLMs, information flow from non-subject tokens to the final token is less localized compared to English LLMs, possibly because the model processes relational and language information at different stages. Additionally, the extraction mechanism in multilingual LLMs is more complex, involving both attention and MLP modules. This implies that editing techniques should focus not only on early MLPs enhancing subject representations but also on the later MLPs that extract the object.

[10] We hypothesize this may occur because the last token encodes which sentinel token is being generated, indicating where to fill in the input. Since we see an almost identical curve when the last token cannot attend to the sentinel token in the decoder (Figure 23).

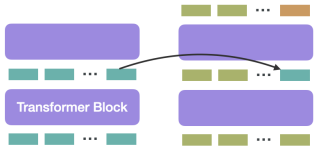


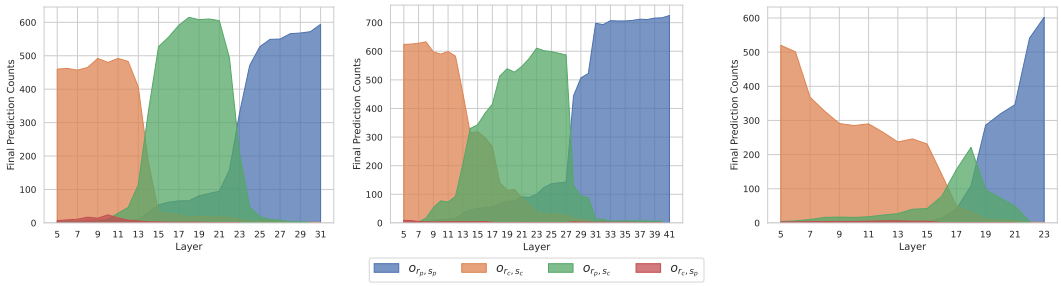
Figure 3: Patching strategy. The patch example's last token is inserted in the context example's forward pass, which perturbs the output of subsequent layers.

5 Language Information Flow

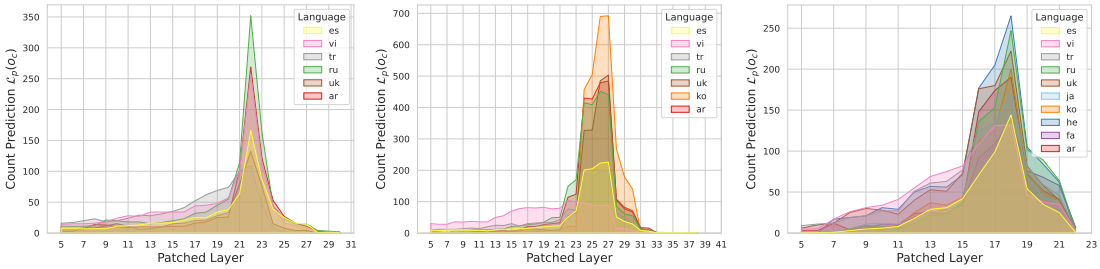
Previous analyses do not provide insights into *how* the language is included and used during recall. In this section, we use activation patching, similarly to Dumas et al. (2024), to: (1) disentangle when the relation information flows to the last token and when the language information flows, (2) identify which tokens contribute the language information, and (3) interpret the last token representation as a Function Vector (Todd et al., 2024)[11].

Let h_t^l be the representation at layer l of the *last* token in the input. For a given input p, we take $h_{t,p}^l$ and patch it into the forward pass of another input c at the same layer; that is, we set $h_{t,c}^l \leftarrow h_{t,p}^l$, and then continue the forward pass. We refer to the example p as the *patch* example, and c as the *context* example (see Figure 3). By patching the last token representation in each layer and measuring the model's predicted output, we can study when the representation contains the information about relation, language, and predicted object, and how cross-lingual these representations are.

[11] Function Vectors (FV) were originally defined as the mean vector of outputs from specific attention heads. Here, we interpret the last token representation as an FV because it triggers a specific execution for different contexts.



(a) Counts of examples where the patch produces the object prediction.



(b) Histogram of patches that cause the context answer to be predicted in the patch language, $\mathcal{L}_p(o_c)$.

Figure 4: Prediction tokens from (a) $\{= \mathcal{L}, \neq r, \neq s\}$ and (b) $\{\neq \mathcal{L}, = r, \neq s\}$ for XGLM, EUROLLM, mT5.

An input example expresses a relation r and a subject s in language $\mathcal{L}$, which we note $(\mathcal{L}(r), \mathcal{L}(s))$. We conduct three experiments where the patch and context examples share certain input characteristics. In particular, we test: (1) $\{= \mathcal{L}, \neq r, \neq s\}$, where the language is the same but the relation and subject differ; (2) $\{\neq \mathcal{L}, = r, \neq s\}$, where the relation remains the same but the language and subject differ; and (3) $\{\neq \mathcal{L}, \neq r, = s\}$, where the subject is the same but the language and relation differ. (1) allows us to study how the relation is encoded while controlling for the language, whereas (2)-(3) help us explore how the interaction between relation and language affects the extraction of the object from the subject. In all experiments, English is used as the patch language, $\mathcal{L}_p = \text{en}$.

Let the patch input be $(\mathcal{L}_p(r_p), \mathcal{L}_p(s_p))$ and the context input be $(\mathcal{L}_c(r_c), \mathcal{L}_c(s_c))$. Without intervention, the model correctly predicts $\mathcal{L}_p(o_{r_p,s_p})$ and $\mathcal{L}_c(o_{r_c,s_c})$ respectively.[12] To analyze patching effects, we examine both output probabilities and predicted tokens. For probabilities, we aggregate across examples by calculating the change relative to the original (unpatched) probability, as in §4. For predicted tokens, we check if they match the patch or context object, or a variant with swapped language or relation (e.g., if $\mathcal{L}_p(o_c)$ is predicted in the setups (2)-(3)). We only consider valid patch-context pairs where o_{r_p,s_c} and o_{r_c,s_p} exist, and for predicted token analysis, we enforce distinct spellings.[13] Consequently, the number of examples varies across analyses of output probabilities and token predictions. See Table 4 and 6 for the number of examples for each model and experiment.

Different Relation, Different Subject First, we analyze the pairs of examples with $\{= \mathcal{L}, \neq r, \neq s\}$. For example, r_p, s_p =“The capital of France is” and r_c, s_c =“The language spoken in Germany is”. Then, o_{r_p,s_c} = Berlin and o_{r_c,s_p} = French. We sample 1000 examples for which MPARAREL has the objects o_{r_c,s_p} and o_{r_p,s_c}.

We present the prediction results in Figure 4a, and probability plots in Figure 31. The relation information is contained in the last token representation when the green curve increases, since patching at that point starts producing the object corresponding to the relation in the patch o_{r_p,s_c}. When the green curve decreases and the blue curve increases, the object has been fully extracted and is encoded in the last token vector, as predictions from these layers correspond to o_{r_p,s_p} and no information is taken from the context c. The layers where this happens align with the peaks of the extraction rate in English (Figure 24-26). This shows that the extraction measured by the vocabulary projection represents the point at which the object is extracted and encoded in the last token representation. If the object was encoded earlier and only decoded with the extraction event,o_{r_p,s_p} would be

[12] For simplicity, we may refer to the object as $\mathcal{L}_p(o_p)$ or $\mathcal{L}_c(o_c)$ when r and s are from the same input.

[13] E.g. to claim the predicted token is $t = \mathcal{L}_p(o_c)$ we require $t \neq \mathcal{L}_c(o_c)$, as languages may share spellings (e.g., “Asia” in English and Spanish).

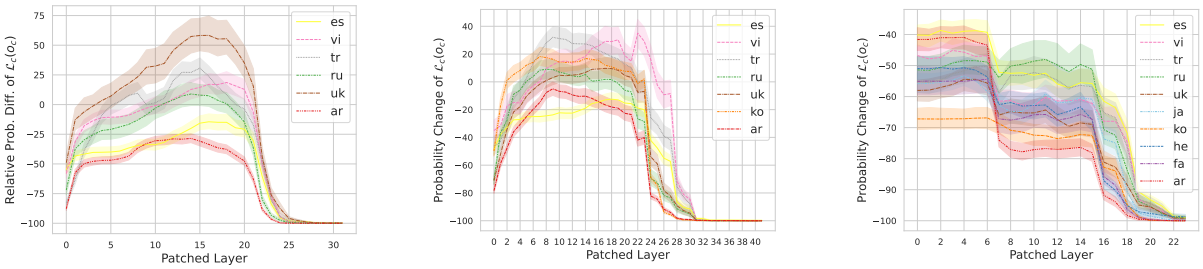


Figure 5: Relative probability change of $\mathcal{L}_c(o_c)$ when patching $\{\neq \mathcal{L}, = r, \neq s\}$, for XGLM, EuroLLM, mT5.

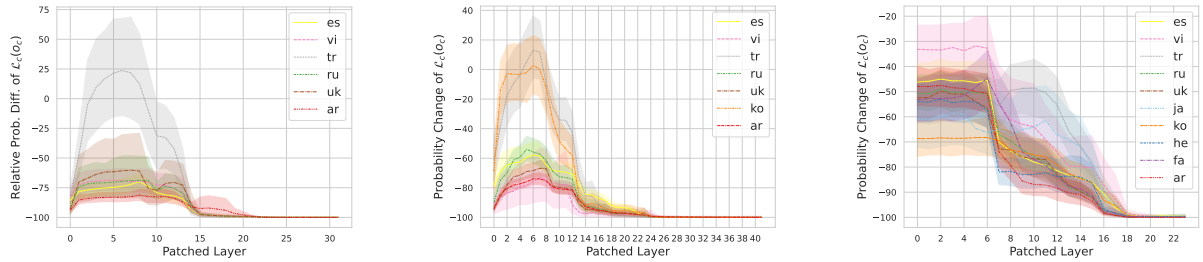


Figure 6: Relative probability change of $\mathcal{L}_c(o_c)$ when patching $\{\neq \mathcal{L}, \neq r, = s\}$, for XGLM, EuroLLM, mT5.

predicted from patches at earlier layers.

Same Relation, Different Subject We have localized the layers where the relation representation flows to the last token. Now, we analyze when the language of the input text propagates to the last token. Is the language information entangled to the subject or the relation representation? Here, we study pairs of patch-context with $\{\neq \mathcal{L}, = r, \neq s\}$, e.g., "France's capital is" and "La capital de Alemania es" (Gloss: "The capital of Germany is"). If we obtain $\mathcal{L}_p(o_c)$ ("Berlin"), it would suggest that the language is encoded in the last token representation before the extraction happens. On the other hand, if we obtain $\mathcal{L}_c(o_p)$ ("París"), we could infer that the language is encoded after the extraction.

We present the probability of the context answer token $\mathcal{L}_c(o_c)$ in Figure 5.[14] We observe that for decoder-only models, patching in the early layers generally hurts the model's performance for most languages, while, patching in the middle layers either increases the probability or results in only a minimal decrease. Given that the relation is the same in both examples, this suggests that by these middle layers, r is encoded in h_p^l, and in the subsequent layers the subject and language of the context are integrated to yield the final prediction, $\mathcal{L}_p(r) + \mathcal{L}_c + s_c = \mathcal{L}_c(o_c)$. Moreover, for some languages the relation representation from the patch is better than the one constructed using the context input, as the relative probability is positive. In the case of mT5, however, the probability of $\mathcal{L}_c(o_c)$ consistently decreases, plateauing in the middle layers before dropping to zero. From the attention knockout analysis, we recall that in mT5, the subject is integrated into the last token representation only after layer 15, while the relation is consistently represented throughout the middle layers. Therefore, these patching results imply that the relation encoded in the last token from the patch input does not help in retrieving the correct context object in the context language in mT5, whereas it proves useful in XGLM and EuroLLM.

In terms of predicted tokens, we find across-the-board that $\mathcal{L}_p(o_c)$ is frequently predicted while $\mathcal{L}_c(o_p)$ is not (Table 5). This suggests that the last token representation encodes the patch language $\mathcal{L}_p$ but not yet the object, as the object is derived from the context subject. We plot the layers where $\mathcal{L}_p(o_c)$ is predicted in Figure 4b ($\mathcal{L}_c(o_p)$ in Figure 46). We can conclude that the language information flows to the last token right before the peak of $\mathcal{L}_p(o_c)$ predictions, because if we patch earlier, the output is in the context language (see the probabilities of $\mathcal{L}_c(o_c)$ in Figure 5). Moreover, these peaks match the beginning of their corresponding extraction phases, thus the language information flows right before the extraction phase.

As a result, we interpret the last token representation as containing a Function Vector (FV), the relation that needs to be extracted and in which language, which is used in the extraction event. The FV can be transferred to contexts in another language, as the FV is constructed from the patch input and is used in the context subject representation to predict $\mathcal{L}_p(o_c)$.

[14] The probability of $\mathcal{L}_p(o_p)$ and per language plots are provided in Appendix F.2).

Different Relation, Same Subject We just saw that for all models the representation from the patch will encode at some point the output language but not yet the object. It could be that we observed the prediction $\mathcal{L}_p(o_c)$ because the relation is language specific and encodes the output language. To analyze if this is the case, we now apply patching on examples with different languages and relations but the same subject $\{\neq \mathcal{L}, \neq r, = s\}$, e.g., "France's capital is" and "El idioma oficial de Francia es" (Gloss: "The official language of France is").

We observe that the probability of $\mathcal{L}_c(o_c)$ (Figures 6) in decoder-only models, unlike the previous experiment, decreases early for all languages (except *tr* and *ko*), plateaus around the middle layers, and then drops to zero by the mid-layer range. For mT5, the probability drops at the beginning but, instead of plateauing as before, it continues to decline until it reaches zero. When compared to the former experiment (Figure 5), this suggests that the relation information is encoded in the middle layers, as $\mathcal{L}_c(o_c)$ decreases earlier when the patch and context have different relations.

In terms of predictions, we find that $\mathcal{L}_c(o_p)$ is frequently predicted for XGLM and EUROLLM (Figure 7), while $\mathcal{L}_p(o_c)$ appears but less often (Table 7). In line with the previous observation, the plot shows that the last token representation in the middle layers where $\mathcal{L}_c(o_p)$ is predicted, primarily captures the relation from the patch r_p, without yet encoding the output language or subject information (as these are taken from the context). Therefore, in decoder-only models, the relation and language representations are disentangled, as the relation flows to the last token before the output language does. Allowing the relation to be combined with different languages.

As for mT5, we observe very few examples where $\mathcal{L}_c(o_p)$ or $\mathcal{L}_p(o_c)$ are predicted, which aligns with the findings of the two former experiments, where we see that the relation is encoded in the last token in layers 15-21 (Figure 4a), and the language flows to the last token around layer 15-19 (Figure 4b). We conclude that both the relation and language flow to the last token around the same time, and thus, in this experiment, we cannot see a disentangled behavior. This presents an interesting contrast with decoder-only models. The decoder in mT5 has access to the *same* encoder representations throughout all its layers, so it does not need (and thus does not learn) to attend to these earlier or in different stages. By contrast, in a decoder-only

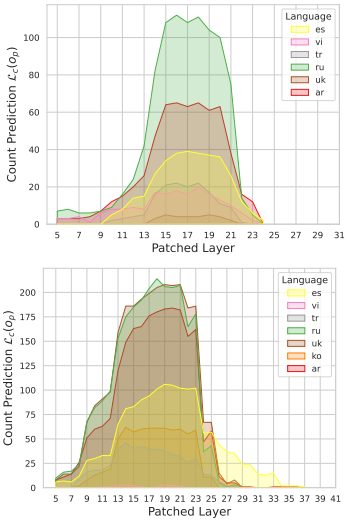


Figure 7: Patches that cause the prediction to be $\mathcal{L}_c(o_p)$. Top XGLM, bottom EUROLLM.

model, the last token has access to representations that evolve across layers, so it learns to attend to relevant information when it becomes most salient. Nonetheless, we cannot reach a definite conclusion on whether the language representation in mT5 is entangled or not to the relation representation. More detailed analysis of what is being attended when the relation flows and when the language flows should be performed in future work.

6 Conclusion

In this paper, we analyzed factual knowledge recall mechanisms in 10 languages using multilingual transformer-based LMs, comparing them to prior research on English recall in monolingual autoregressive LLMs. We discovered that some mechanisms, such as the flow of subject representations in the later layers and the extraction phase, are present in multilingual and monolingual models. However, we also identified notable differences, including the localization of knowledge in not only one but two MLP sites; and the joint role of MLPs and attention modules during the extraction phase in multilingual models. A key contribution of our work is the first-ever investigation of language encoding during recall, achieved through patching representations. In decoder-only models, the relation flows to the last token first, followed by the language. In contrast, in mT5, both relation and language flow to the last token at similar layers. This suggests that while relation and subject representations are multilingual and enable cross-lingual object extraction, the extraction phase itself is language-specific, as language encoding precedes extraction. These findings provide new evidence to understand the

factual knowledge recall in transformer LMs, and to how decoder-only LMs resolve tasks in stages. Contributing with new directions for the study of cross-lingual transfer and knowledge localization.

7 Limitations

In this paper, we examined three model architectures, leaving out the effects of model sizes, instruction fine-tuning, or models like Llama that can behave multilingually but have less coverage and less multilingual pre-training data. Additionally, our analyses were conducted on 500-1000 examples per language, which we believe provides a sufficient sample size for generalization; however, the results are inherently limited by the relations present in the MPARAREL dataset, which may not capture all factual nuances. Additionally, although we analyzed 10 diverse languages, many more languages exist, and further research is needed to confirm the generalizability of our findings across a broader linguistic spectrum. Lastly, we described the main mechanisms found in XGLM, EUROLLM and mT5, however other weaker mechanisms could be at play, which could describe, for example, the low extraction rates found for some languages (Figure 26) or the few examples where the object seems to be encoded from early layers before the extraction takes place (Figure 46).

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A Related Work

Factual Knowledge Recall Petroni et al. (2019) analyzed factual knowledge in pre-trained language models, by creating the LAMA dataset, which contains natural language templates and WikiData triplets. Subsequently, Elazar et al. (2021) developed the PARAREL dataset, which contains manually paraphrases of the LAMA templates, to measure the consistency of factual knowledge. [15] This led to further research in multilingual settings, Kassner et al. (2021); Jiang et al. (2020) translated LAMA, creating MLAMA and X-FACTR, and evaluated the factual knowledge acquired by multilingual pre-trained models, while Wang et al. (2024a) evaluated knowledge from the perspective of knowledge edits and their impact between Chinese and English (Zhu et al., 2021). Building on this, Yin et al. (2022) curated a dataset that focuses on the cultural aspect of factual knowledge. While Fierro and Søgaard (2022) studied multilingual consistency of knowledge using MPARAREL, a machine-translated version of the English templates in PARAREL, where subjects and objects are translated using WikiData identifiers. In a related effort, Qi et al. (2023) measured the cross-lingual consistency of multilingual LLMs by evaluating the consistency across languages, rather than just across paraphrases in the same language. Qi et al. (2023) used the MLAMA dataset. In this paper, we used MPARAREL since it is an extended version of MLAMA, as it is a translation of the paraphrases in MPARAREL.

Interpretability on Factual Knowledge Recall As discussed earlier, Meng et al. (2022) was among the first to analyze, from a mechanistic perspective, whether a model's knowledge could be localized; while Geva et al. (2023) conducted the first study on how information flows within a model to construct the final predicted object representation. Both studies focused on the GPT models (Brown et al., 2020), using English-language data. Later, Chughtai et al. (2024) contributed by demonstrating that models arrive at an answer through several independent components, with the sum of these components yielding the correct object. Their analysis covered both GPT and Pythia models, also using English data. Subsequently, Sharma et al. (2024) applied the mechanisms identified by Meng et al. (2022) and Geva et al. (2023) to the state-space language model Mamba (Gu and Dao, 2023), focusing on facts expressed in English. Additionally, Hernandez et al. (2024) examined whether a linear transformation of the subject is sufficient to represent various relations, analyzing GPT and Llama models with English data.

Activation Patching Ghandeharioun et al. (2024) introduced the Patchscope framework to study what an intermediate representation encodes. In their experiments, they focused on "decoding" the contents of a latent representation by patching it into the forward pass of another input. More closely related to our work, Dumas et al. (2024) patched the last token representation to investigate if models encode language-agnostic concepts in a word translation task. Their findings, consistent with ours and those of Foroutan et al. (2022), support the existence of language-agnostic representations. Similarly, Wang et al. (2024b) patched the last token representation to study how relations are encoded in factual English queries, finding that the last token encodes the query's relation at a specific computational stage—aligning with our results. In this paper, we are able to draw more general conclusions given that we study a cross-lingual factual recall setup. While Dumas et al. (2024) concluded that LLMs first resolve the output language, we find that the model first resolves the query's relation and then the language. Thus, we interpret the last token representation as a Function Vector (FV) (Todd et al., 2024), encoding the function to solve the given task: for Dumas et al. (2024) the task was translation so the function encodes the language to which translate. Finally, we are also able to show that for decoder-only models the FV composes the language onto the relation FV, which extends the findings from Wang et al. (2024b).

Multilingual Language Models In this work, we focused on generative models and selected mT5 (Xue et al., 2021), XGLM (Lin et al., 2021), and EuroLLM (Martins et al., 2024) due to their broad language coverage, highly multilingual training data, and pre-training with up-sampling of low-resource languages to ensure more balanced language representation. However, many other models are available. For instance, BLOOM (Le Scao et al.,

[15] One may object to calling the ability to solve cloze tests as knowledge. LLMs are sometimes inconsistent and cannot always justify the propositions they generate. We side with Fierro et al. (2024) in thinking *knowledge* may nevertheless be the appropriate concept, since LLMs are mostly consistent and can sometimes provide justification, e.g., in virtue of world models or training data attribution.

Language	Script	Family	SOV/SVO
English	Latin	Germanic	SVO
Spanish	Latin	Romance	SVO
Vietnamese	Latin	Austroasiatic	SVO
Turkish	Latin	Turkic	SOV
Russian	Cyrillic	Slavic	SVO*
Ukrainian	Cyrillic	Slavic	SVO*
Japanese	Kanji	Proto-Japonic	SOV
Korean	Korean	Koreanic	SOV
Hebrew	Hebrew	Arabic	VSO
Farsi (Persian)	Perso-Arabic	Indo-Iranian	SOV
Arabic	Arabic	Arabic	VSO

Table 2: Languages, their scripts, families, and sentence structures (SVO: subject-verb-object, SOV: subject-object-verb, VSO: verb-subject-object, SVO*: SVO dominant but SOV is also possible).

	XGLM and EuroLLM			mT5		
Language	Correct	Total	Percentage	Correct	Total	Percentage
en	1812	4147	43.7%	1543	3853	40.0%
es	1380	4167	33.1%	1192	3926	30.4%
vi	1646	4068	40.5%	993	3748	26.5%
tr	418	2278	18.3%	1058	4033	26.2%
ru	830	4133	20.1%	683	3826	17.9%
uk	213	4144	5.1%	456	3830	11.9%
ko	116	1444	8.0%	630	3783	16.7%
ja	6	1790	0.3%	358	4124	8.7%
he	13	4403	0.3%	565	4064	13.9%
fa	7	4388	0.2%	406	3814	10.6%
ar	811	4482	18.1%	488	4110	11.9%

Table 3: Total number of examples in mParaRel.

2023) is a decoder-only model trained on 46 languages, although low factual recall accuracy has been reported (Qi et al., 2023). Llama-2 (Touvron et al., 2023) has been used in some multilingual analyses (Wendler et al., 2024; Dumas et al., 2024), but it is primarily an English-centric model given that 90% of its pre-training data is in English. More recent models that could have been considered include mGPT (Shliazhko et al., 2022), a decoder-only model trained on 61. On the other hand, the Aya-101 model (Üstün et al., 2024) is an instruction fine-tuned version of mT5; however, we focus on pre-trained multilingual LMs to compare our analysis to the English monolingual pre-trained versions previously studied.

B Experimental Setup

We use the mParaRel triplets and templates to query the factual knowledge of the language models. As mentioned earlier, we perform 3 modifications to the dataset. First, we fetch WikiData for aliases of the target object to be able to match different possible surface forms. Second, we filter out examples where the target object is contained in the query, e.g. *Microsoft Outlook is developed by*. Finally, to better compare across languages we control the variety of the subject-object pairs, by only using a crosslingual version of mParaRel. Specifically, for each relation we filter out triplets that are not present in all the languages (in mParaRel a subject and object may have not been translated if they were not found in WikiData). Thus, in the crosslingual mParaRel version, each subject-object pair in a relation is present in each of the languages. For XGLM we additionally restrict the templates to have the object at the end of the sentence, therefore for some languages (*tr*, *ko*, *ja*, and *fa*) both the autorregressive condition on the templates and the crosslingual restriction leads to too few total examples (< 1000), so for these we do not impose the crosslingual restriction. For all the other languages, and for all the languages in mT5 there are enough examples so we restrict them to be crosslingual. In Table 3 we present the total number of examples we consider per language and model, and the correctly predicted fraction.[16]

B.1 Prompt Details

For mT5, we feed the mParaRel input into the encoder with a sentinel token in the object placeholder. In the decoder, we provide the beginning-of-sequence token followed by the sentinel token. We only check the tokens generated next to the first sentinel token, as the pre-training task of the model is to generate the text for each sentinel in the input, the decoder usually continues to generate answers for other sentinel tokens. Any tokens generated preceding the object, are added to the decoder input since adding these to the encoder does not ensure that the next token predicted will be the object.

B.2 Computational Resources

The experiments were run in A100 GPUs. The causal analysis took from 30 minutes to 12 hours depending on the language. The rest of the experiments took 1-2 hours per language.

[16] In decoder-only models, the total number of examples is higher in some languages due to crosslingual filtering, which is applied per relation. If a language has no examples for a given relation, it doesn't restrict examples in other languages. Since decoder-only models use only autoregressive templates, some lower-resource languages may have zero examples for certain relations. However, when using all templates (as in mT5), these lower-resource languages can restrict the triplets available for other languages within the same relation.

C Causal Tracing

C.1 XGLM

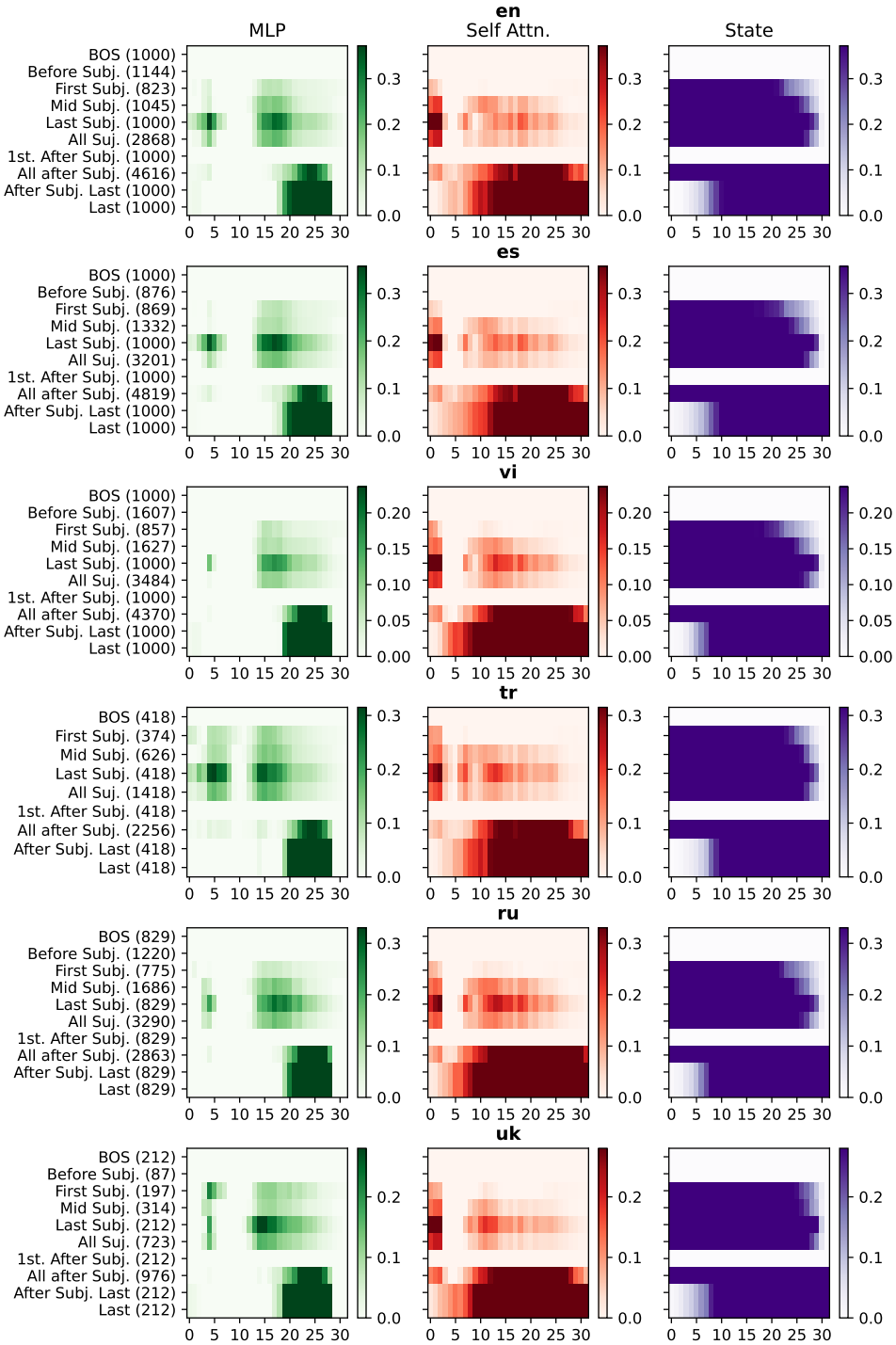

Figure 8: XGLM causal analysis for each language (continues in Figure 9). Average **logit score** (for the originally predicted token) recovered after corrupting the subject in the input and restoring: the hidden representation at a given layer (State), the MLP in a window of 4 layers, or the Self Attn. in a window of 4 layers.

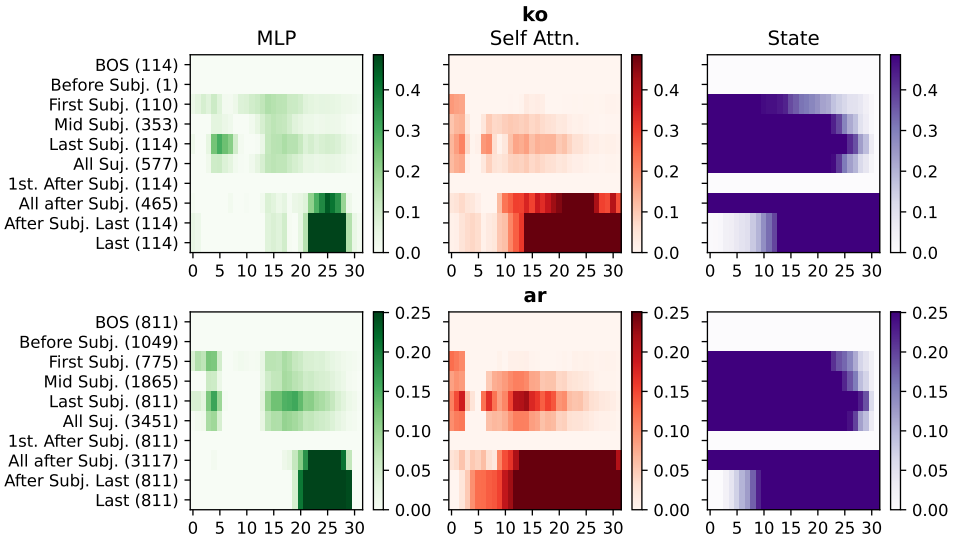

Figure 9: XGLM causal analysis for each language (Rest of the languages in Figure 8). Average **logit score** (for the originally predicted token) recovered after corrupting the subject in the input and restoring: the hidden representation at a given layer (State), the MLP in a window of 4 layers, or the Self Attn. in a window of 4 layers.

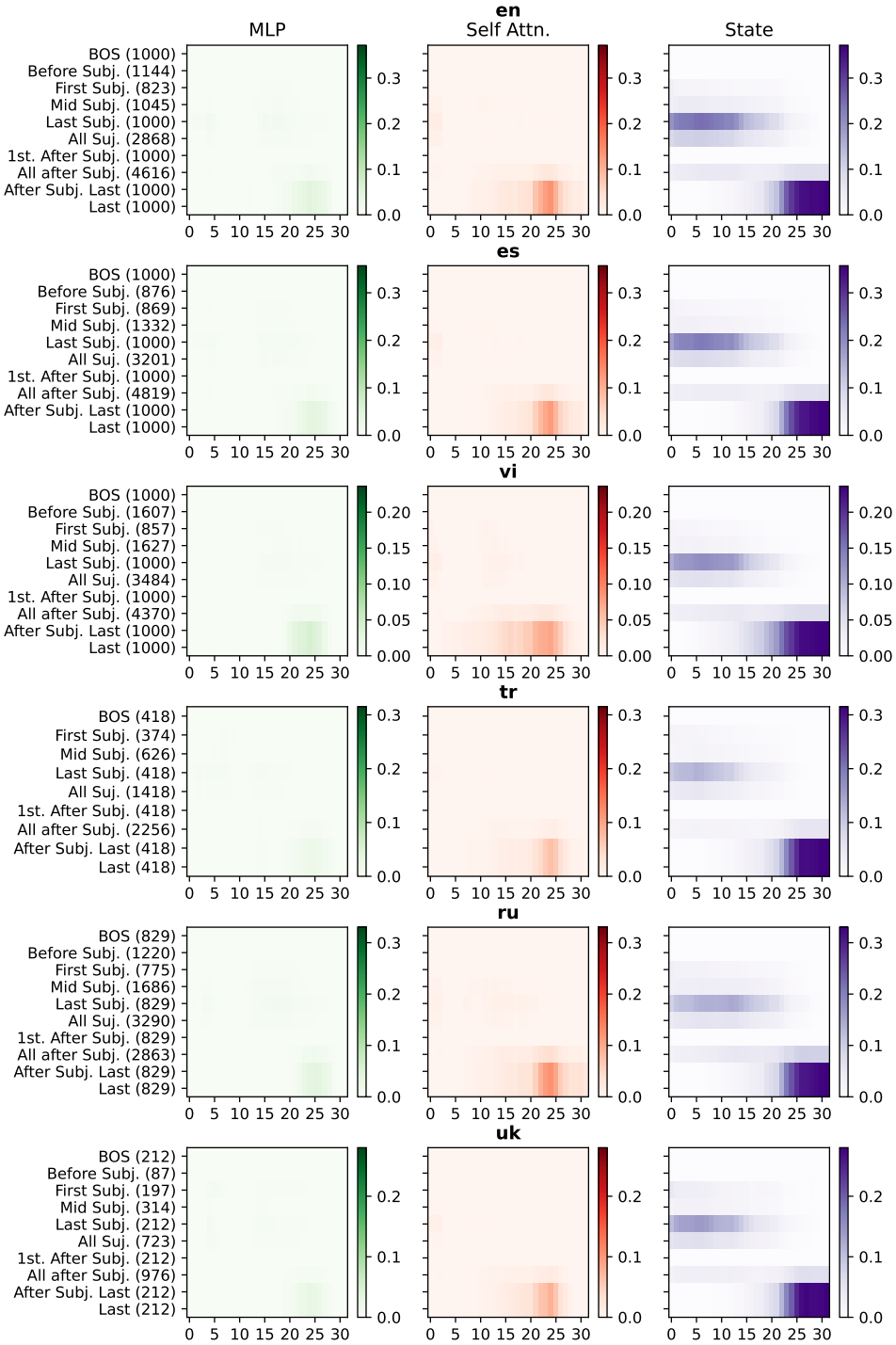

Figure 10: XGLM causal analysis for each language (continues in Figure 11). Average **probability** (for the originally predicted token) recovered after corrupting the subject in the input and restoring: the hidden representation at a given layer (State), the MLP in a window of 4 layers, or the Self Attn. in a window of 4 layers.

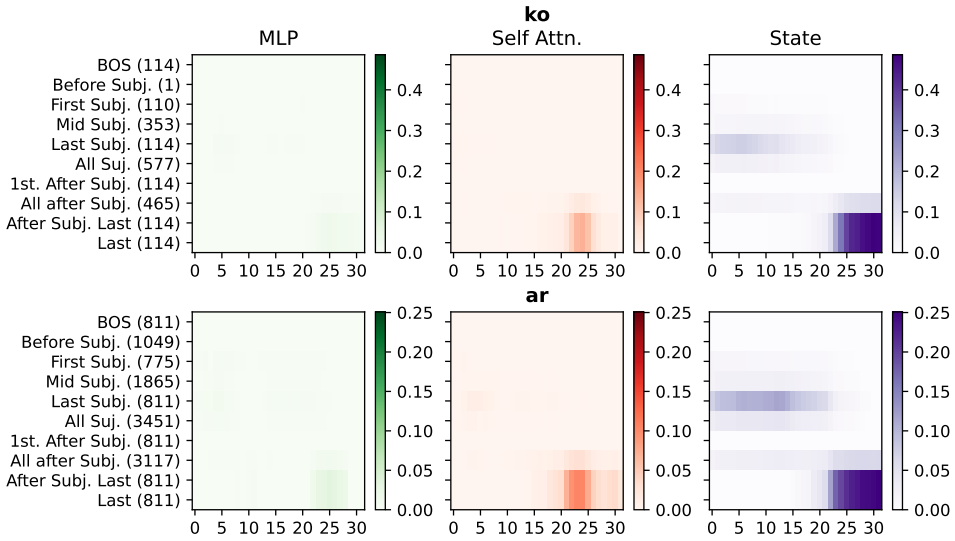

Figure 11: XGLM causal analysis for each language (Rest of the languages in Figure 10). Average **probability** (for the originally predicted token) recovered after corrupting the subject in the input and restoring: the hidden representation at a given layer (State), the MLP in a window of 4 layers, or the Self Attn. in a window of 4 layers.

C.2 EuroLLM

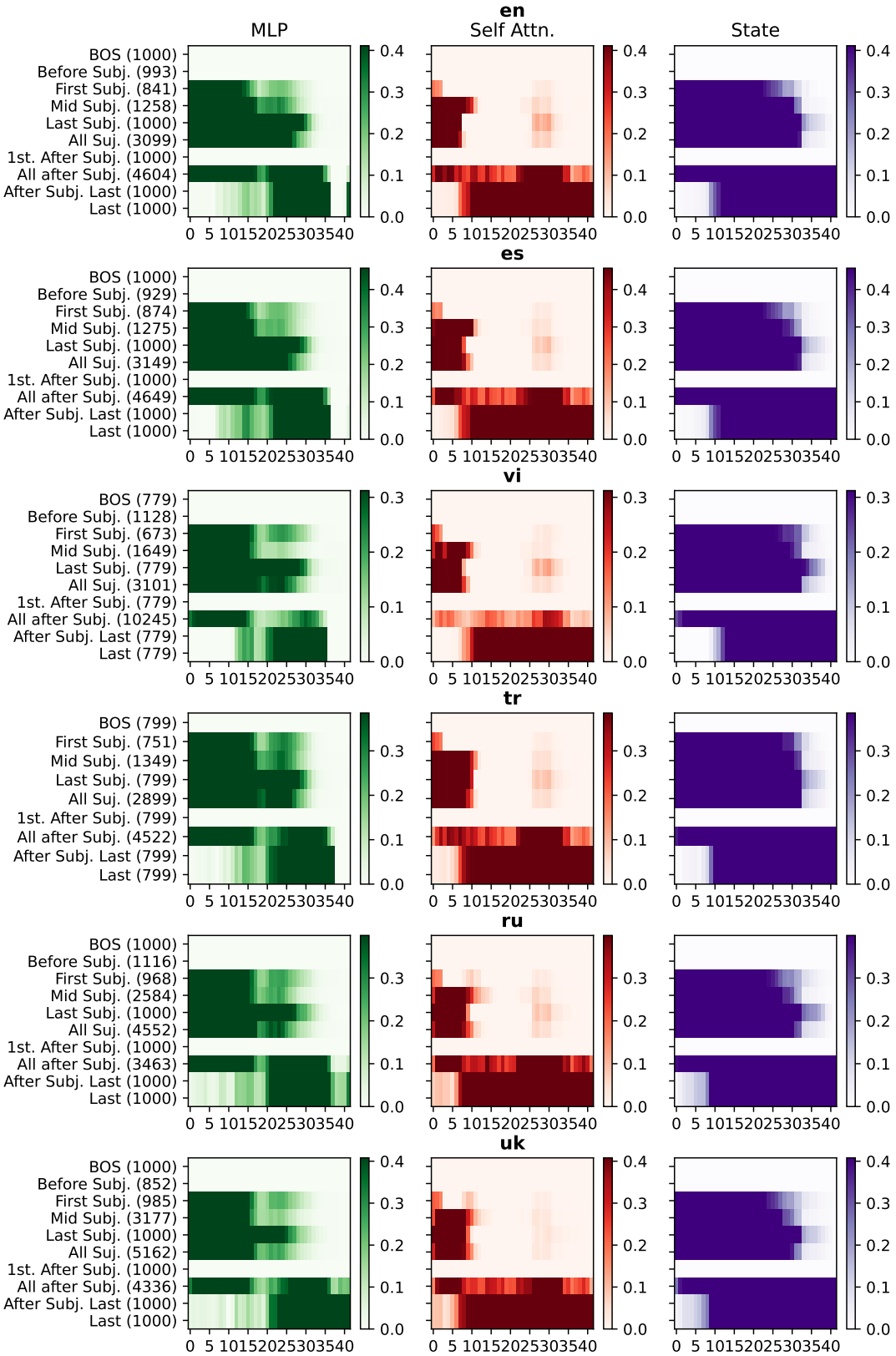

Figure 12: EuroLLM causal analysis for each language (continues in Figure 13). Average **logit score** (for the originally predicted token) recovered after corrupting the subject in the input and restoring: the hidden representation at a given layer (State), the MLP in a window of 5 layers, or the Self Attn. in a window of 5 layers.

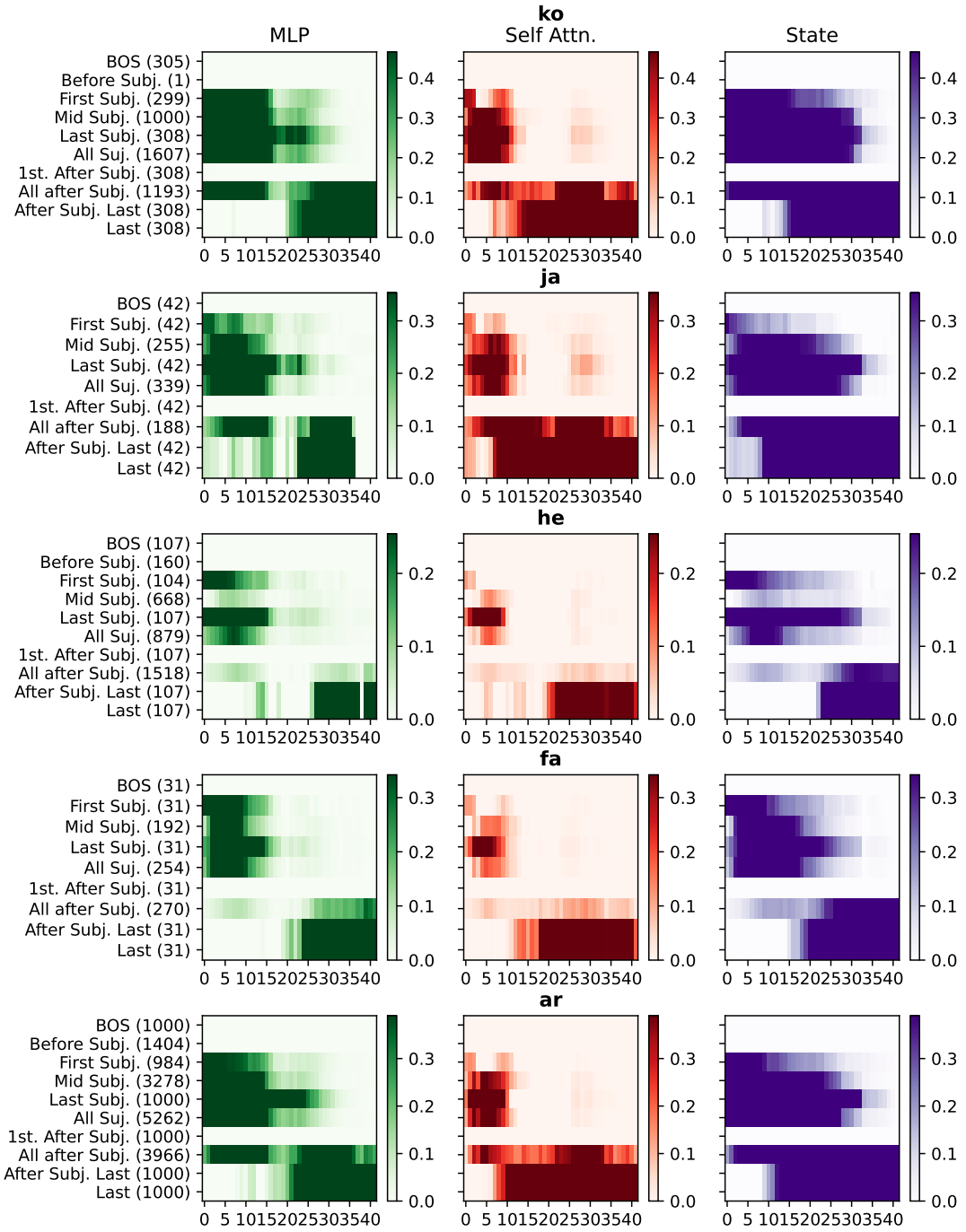

Figure 13: EUROLLM causal analysis for each language (Rest of the languages in Figure 12). Average **logit score** (for the originally predicted token) recovered after corrupting the subject in the input and restoring: the hidden representation at a given layer (State), the MLP in a window of 5 layers, or the Self Attn. in a window of 5 layers.

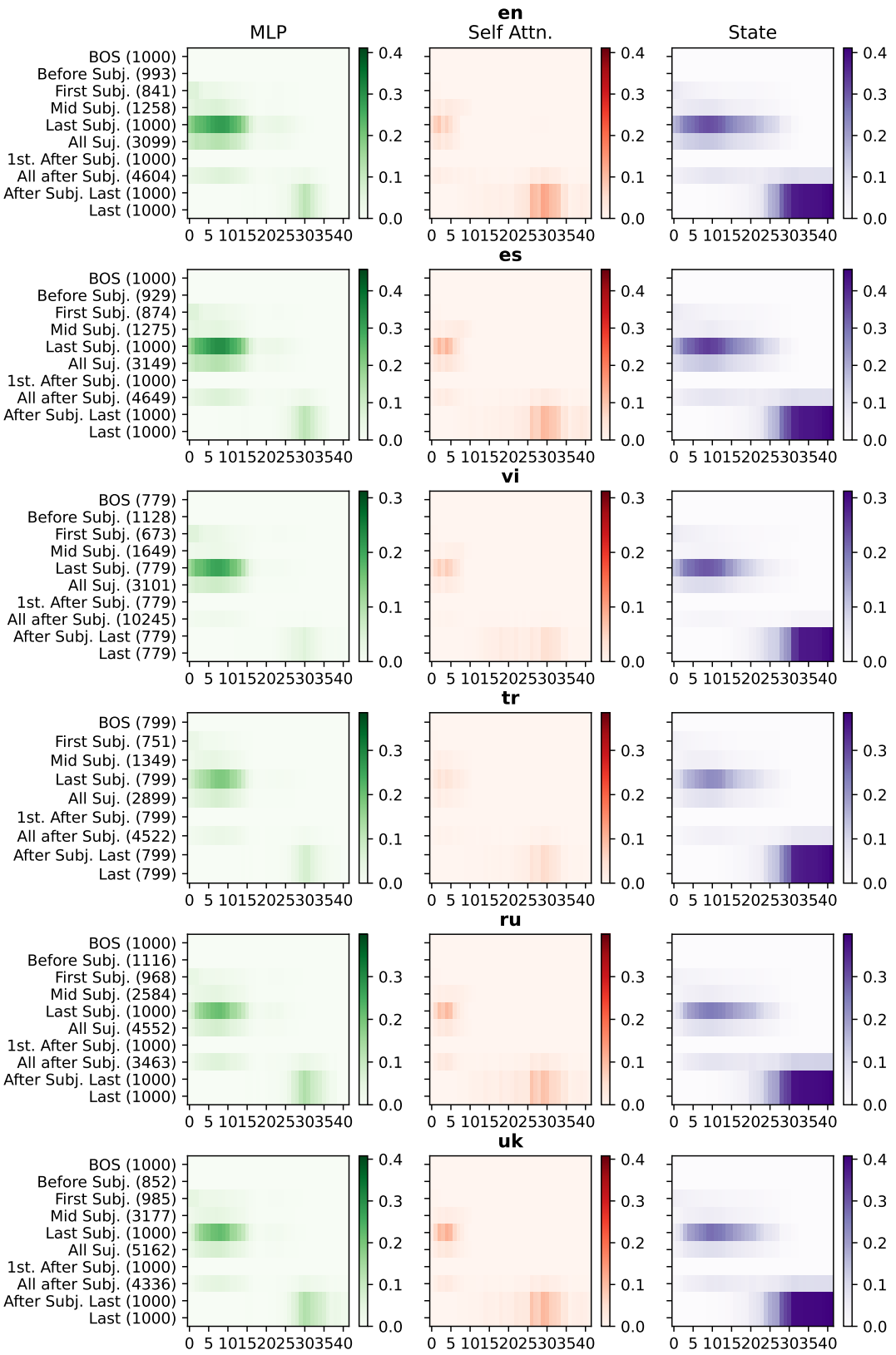

Figure 14: EUROLLM causal analysis for each language (continues in Figure 15). Average **probability** (for the originally predicted token) recovered after corrupting the subject in the input and restoring: the hidden representation at a given layer (State), the MLP in a window of 5 layers, or the Self Attn. in a window of 5 layers.

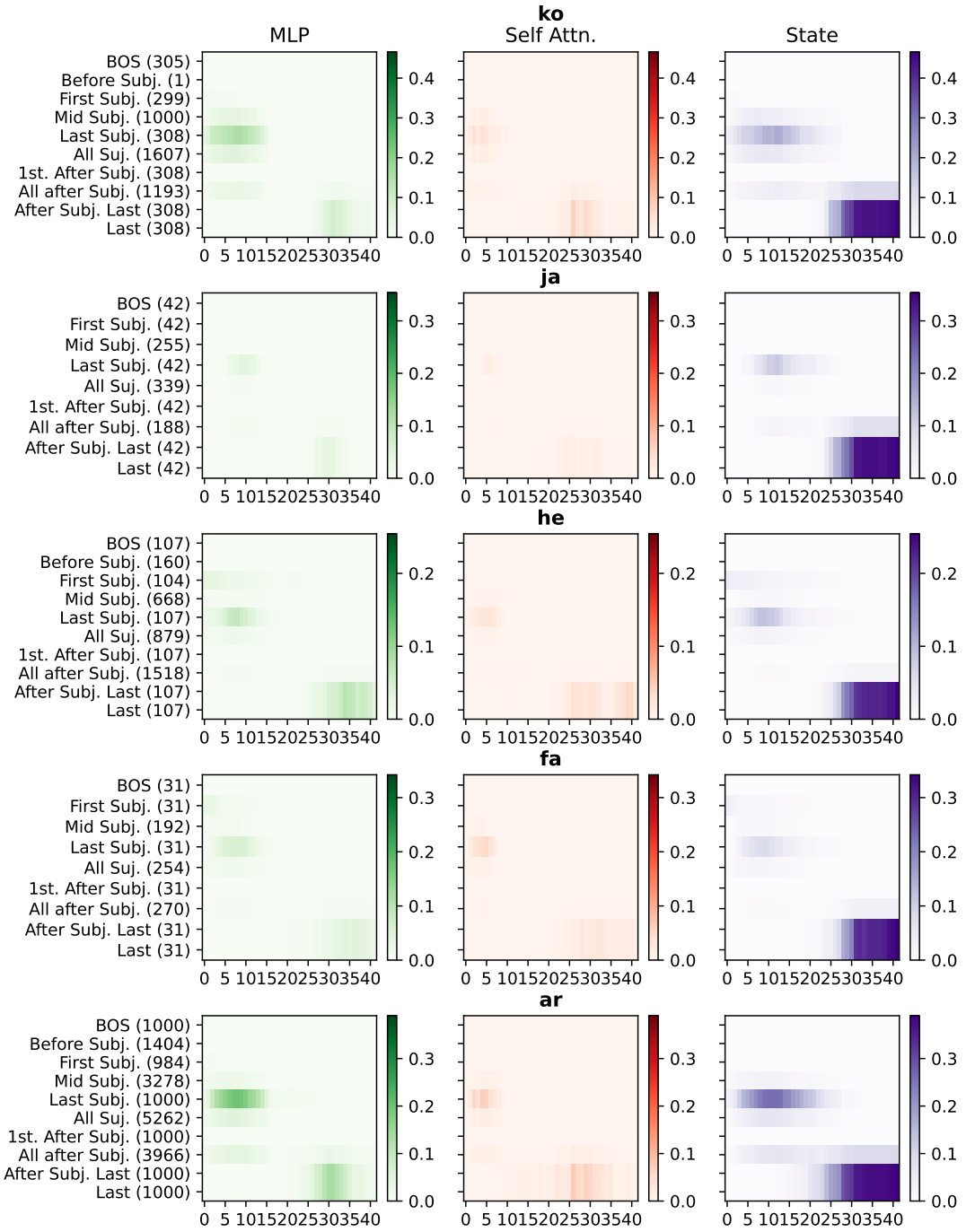

Figure 15: mT5 causal analysis for each language (Rest of the languages in Figure 14). Average **probability** (for the originally predicted token) recovered after corrupting the subject in the input and restoring: the hidden representation at a given layer (State), the MLP in a window of 5 layers, or the Self Attn. in a window of 5 layers.

C.3 mT5

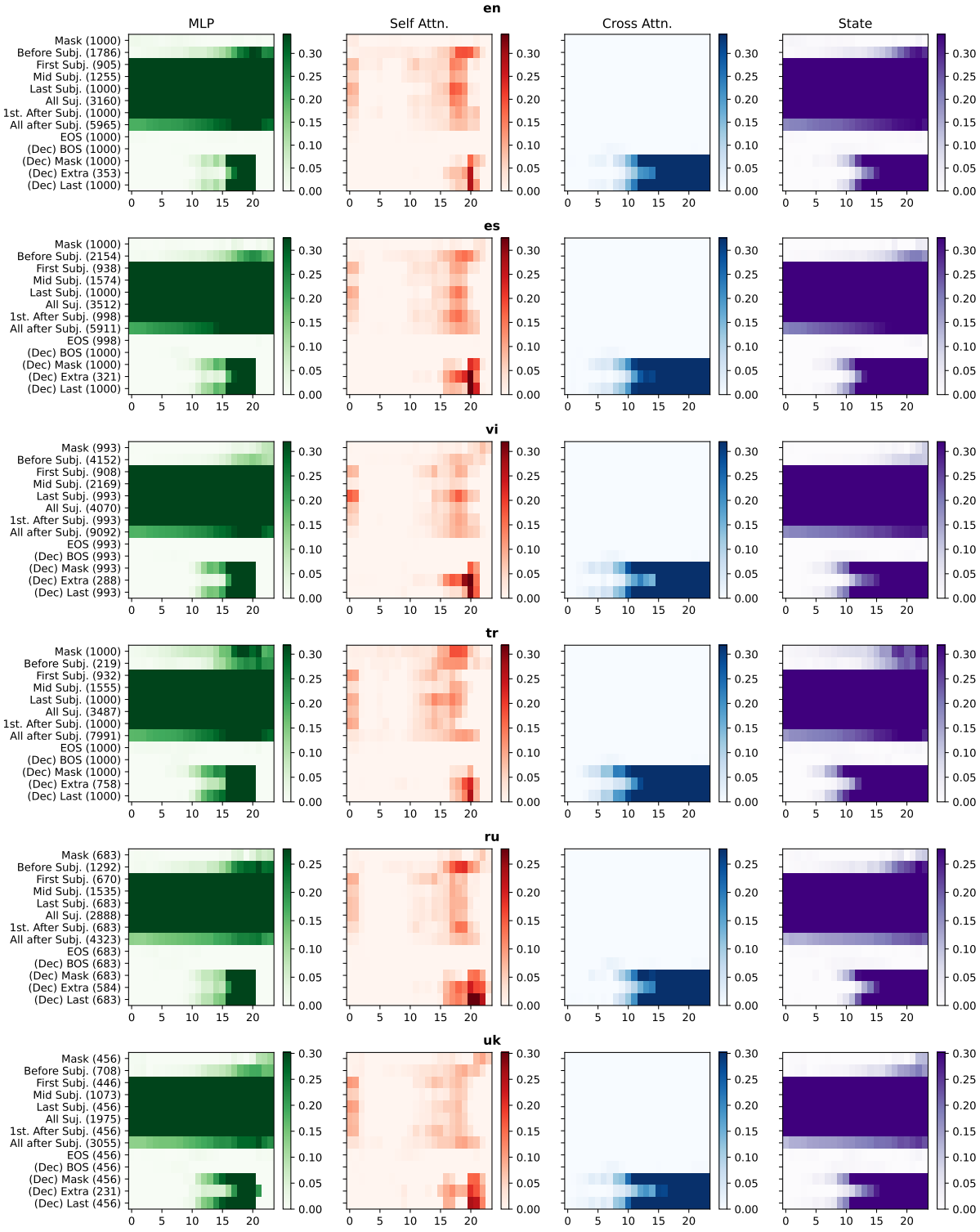

Figure 16: mT5 causal analysis for each language (continues in Figure 17). Average **logit score** (for the originally predicted token) recovered after corrupting the subject in the input and restoring: the hidden representation at a given layer (State), the MLP in a window of 3 layers, or the Self Attn. in a window of 3 layers.

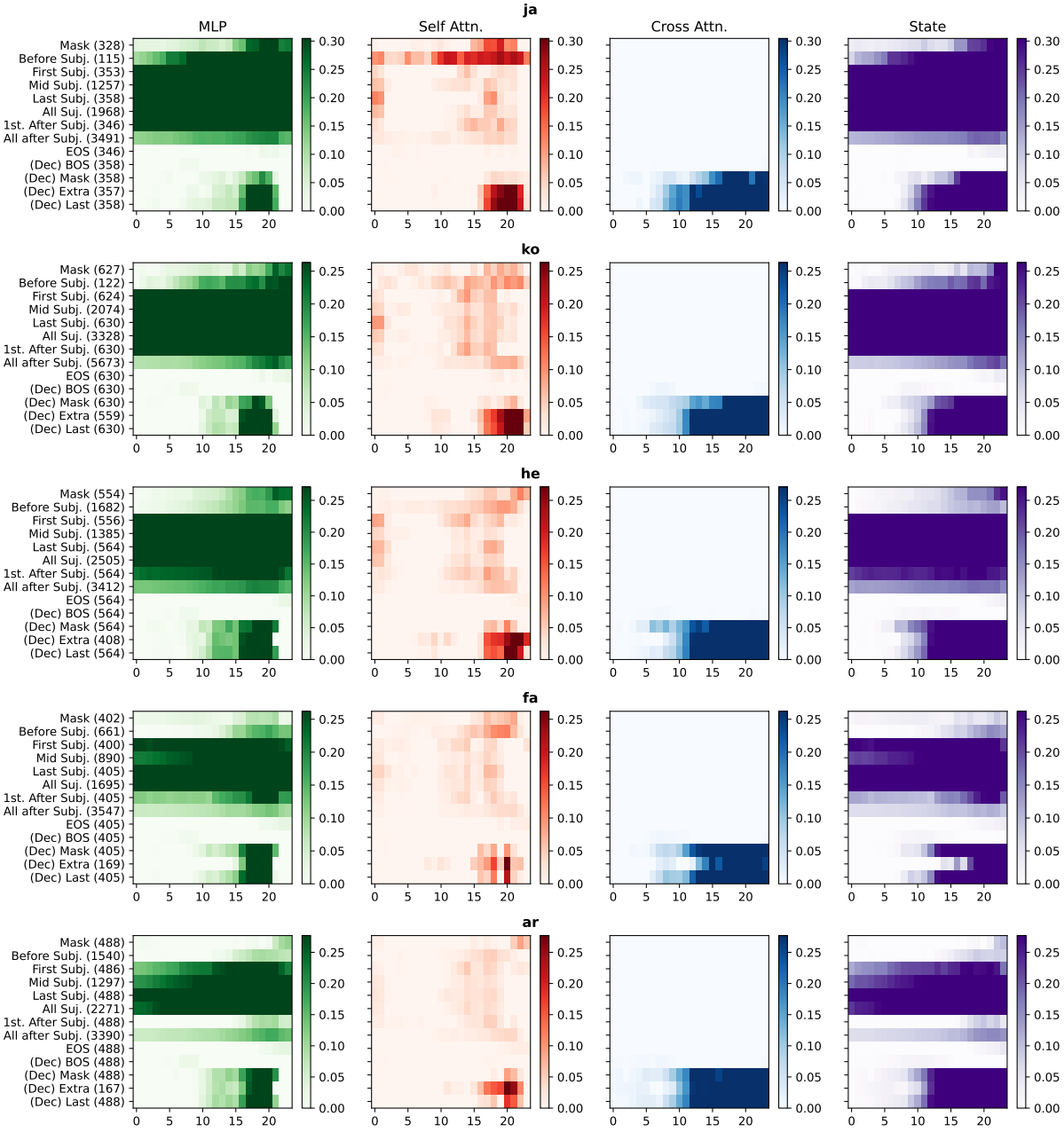

Figure 17: mT5 causal analysis for each language (Rest of the languages in Figure 16). Average **logit score** (for the originally predicted token) recovered after corrupting the subject in the input and restoring: the hidden representation at a given layer (State), the MLP in a window of 3 layers, or the Self Attn. in a window of 3 layers.

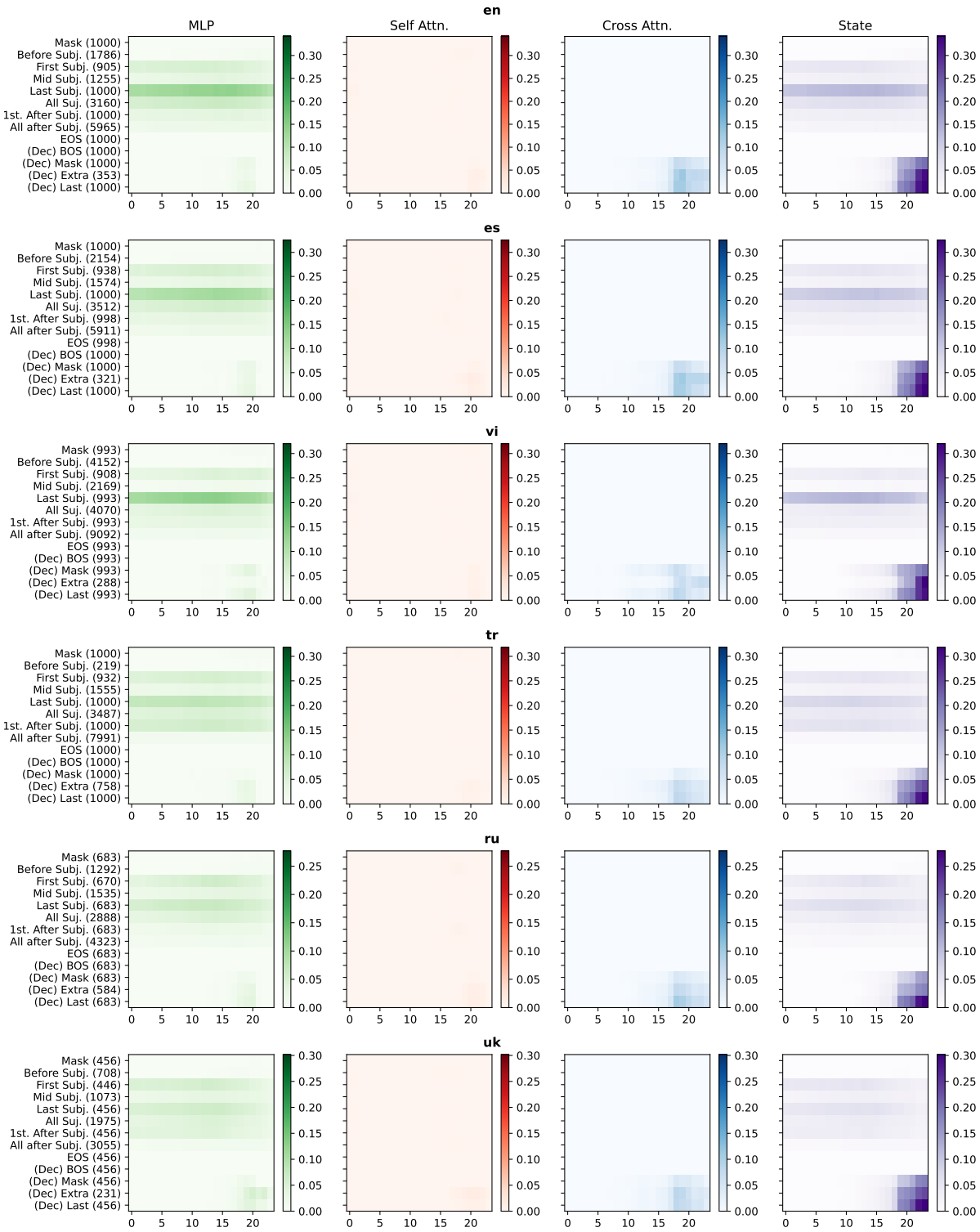

Figure 18: mT5 causal analysis for each language (continues in Figure 19). Average **probability** (for the originally predicted token) recovered after corrupting the subject in the input and restoring: the hidden representation at a given layer (State), the MLP in a window of 3 layers, or the Self Attn. in a window of 3 layers.

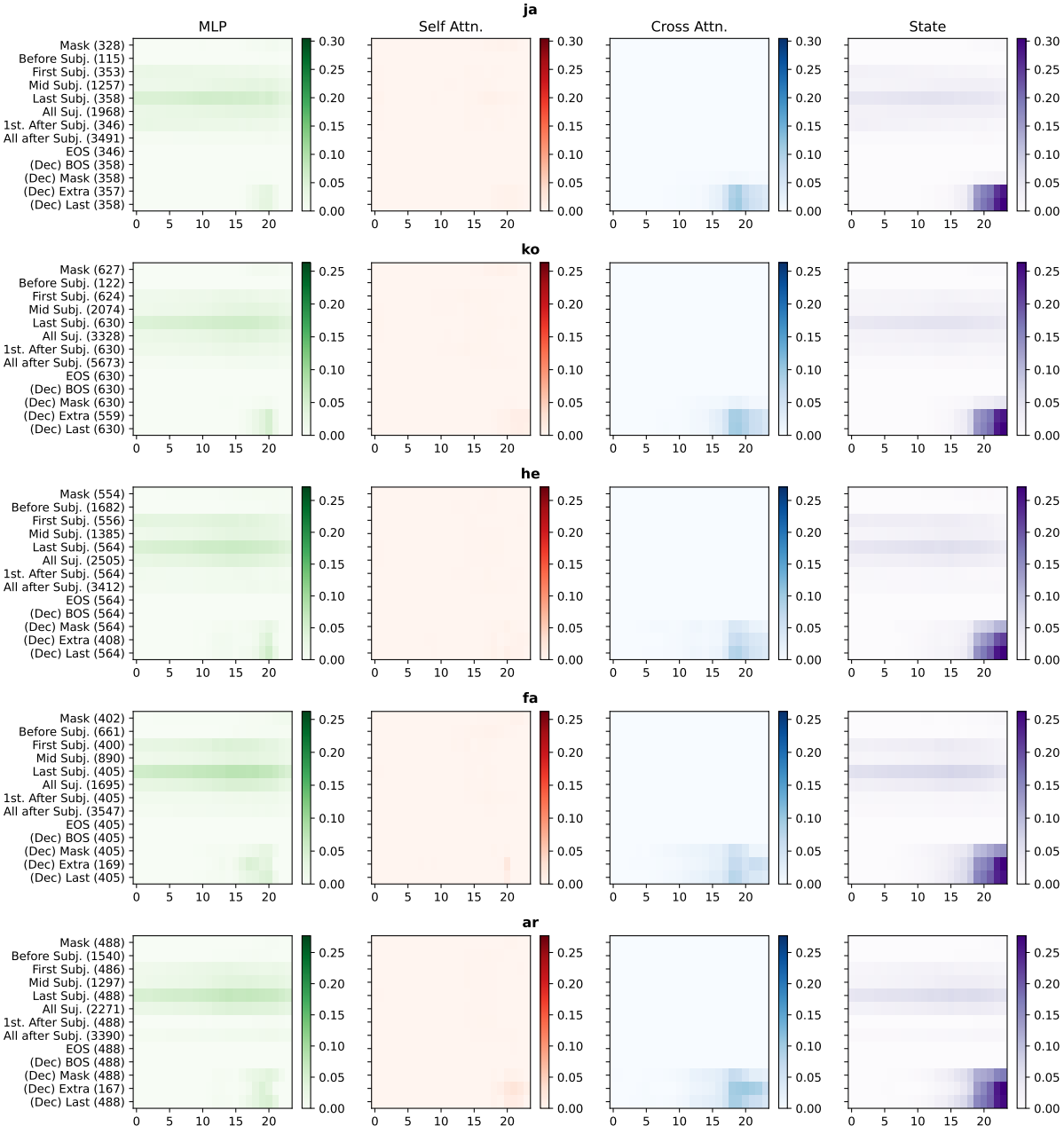

Figure 19: mT5 causal analysis for each language (Rest of the languages in Figure 18). Average **probability** (for the originally predicted token) recovered after corrupting the subject in the input and restoring: the hidden representation at a given layer (State), the MLP in a window of 3 layers, or the Self Attn. in a window of 3 layers.

D Attention Knockout

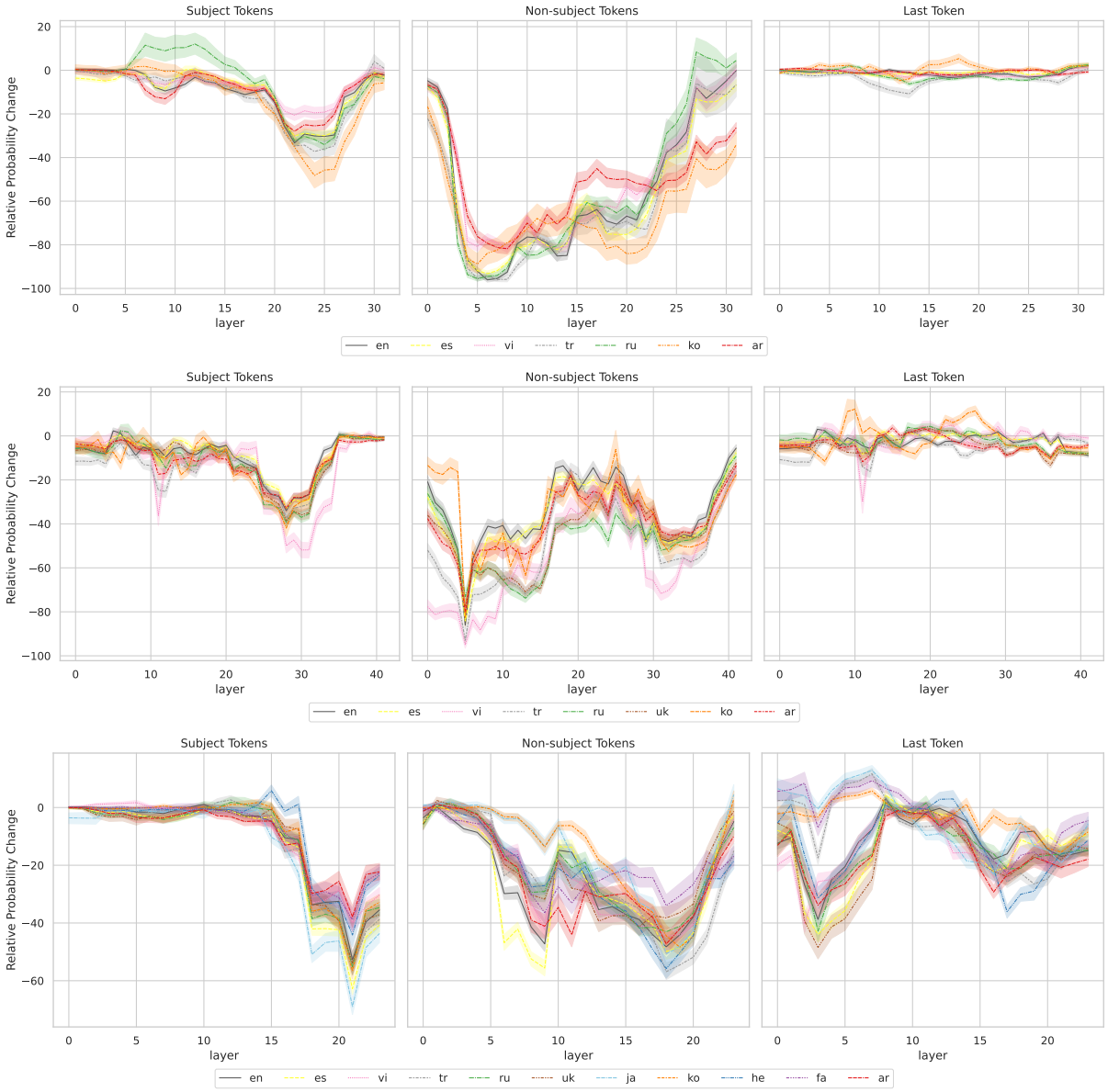

Figure 20: Attention knockout between the last token and a given set of tokens. Each layer represents the effect of the knockout on a window of w layers. Models from top to bottom: XGLM ($w = 6$), EuroLLM ($w = 7$), mT5 ($w = 4$).

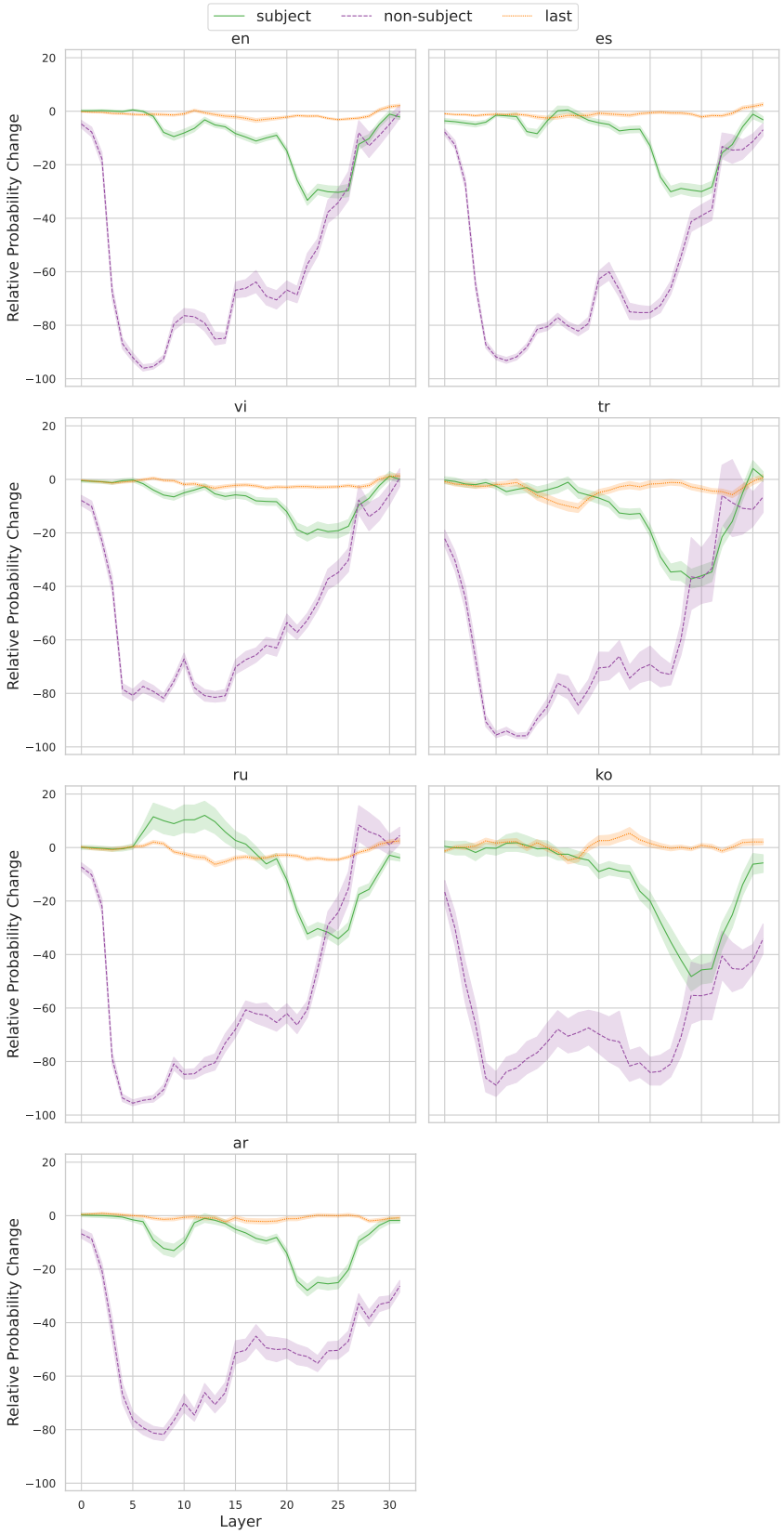

Figure 21: XGLM attention knockout for each language.

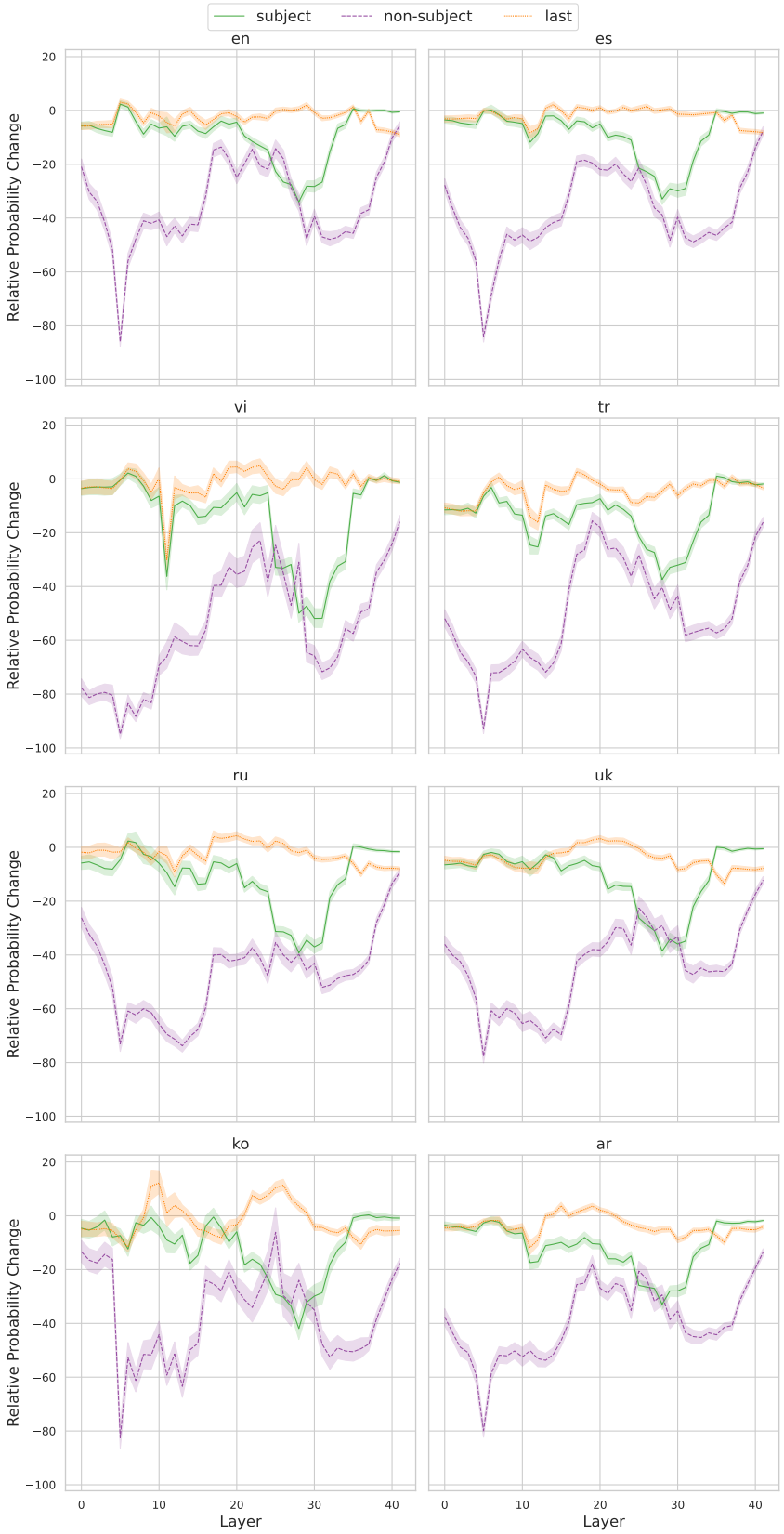

Figure 22: EUROLLM attention knockout for each language.

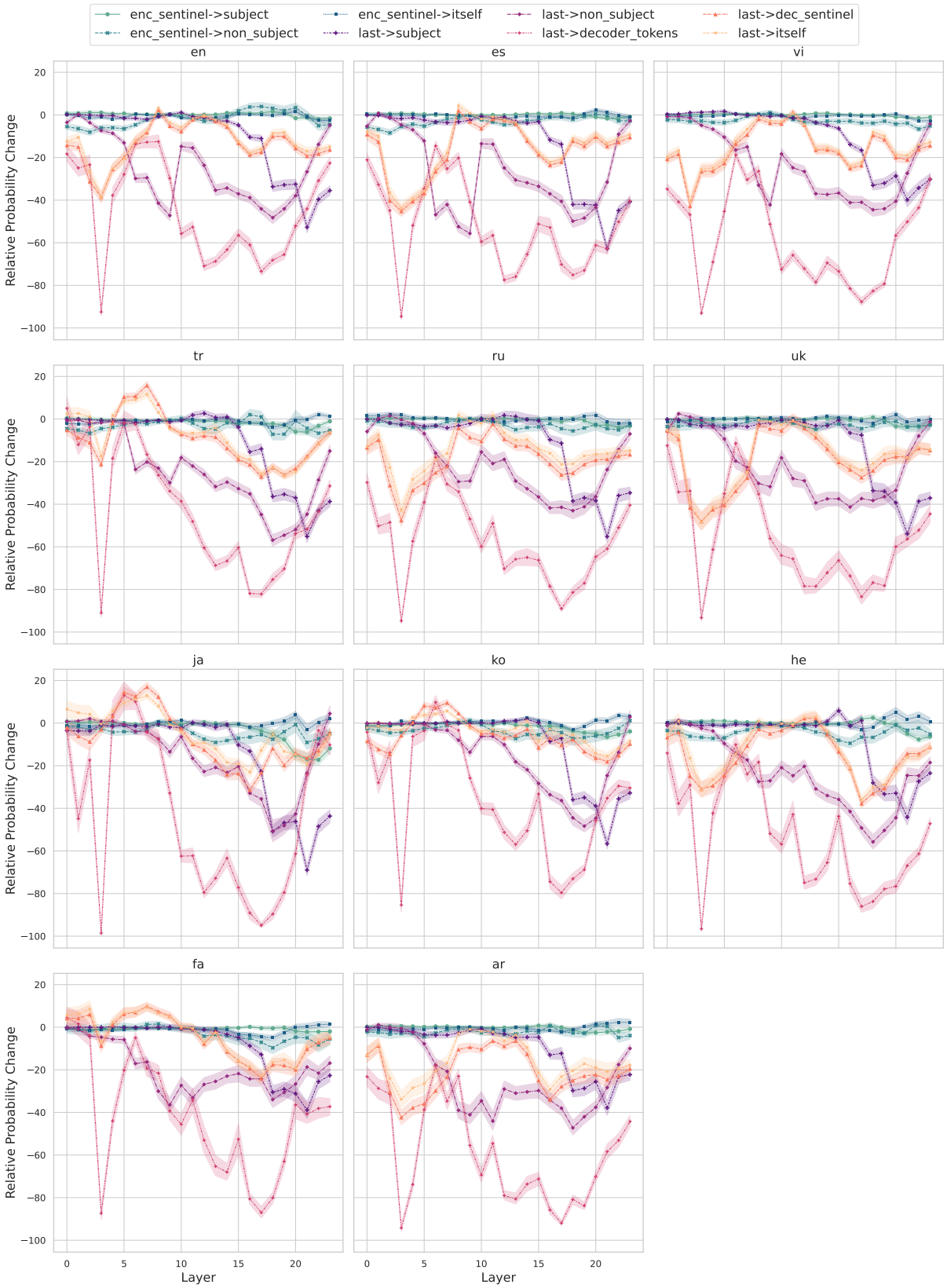

Figure 23: Attention knockout for each language in mT5. The knockout is performed between the last token in the decoder ("last") to a given set of tokens $\{t\}$, and between the masked token in the encoder ("enc_sentinel") and $\{t\}$. From the encoder sentinel there is no much flow of information so these were not included in the main body.

E Extraction Event

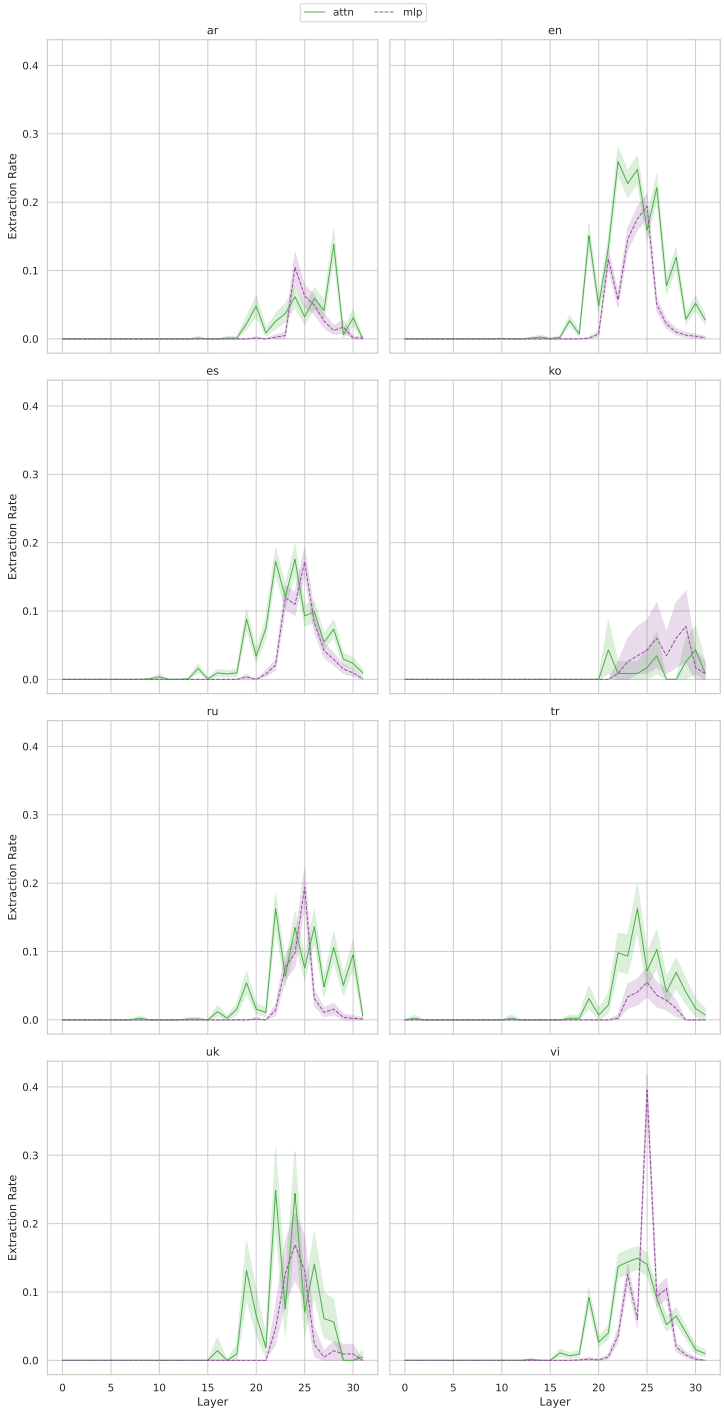

Figure 24: XGLM extraction rates for each language.

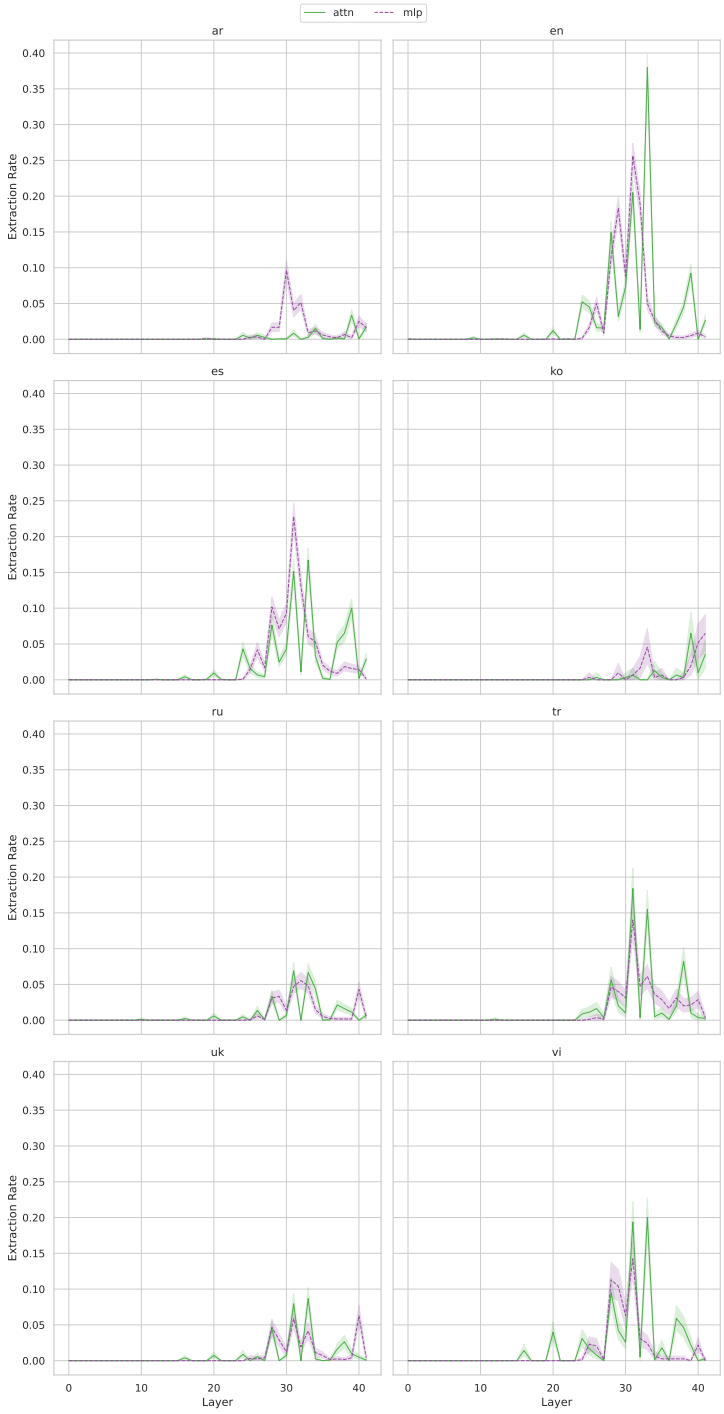

Figure 25: EUROLLM extraction rates for each language.

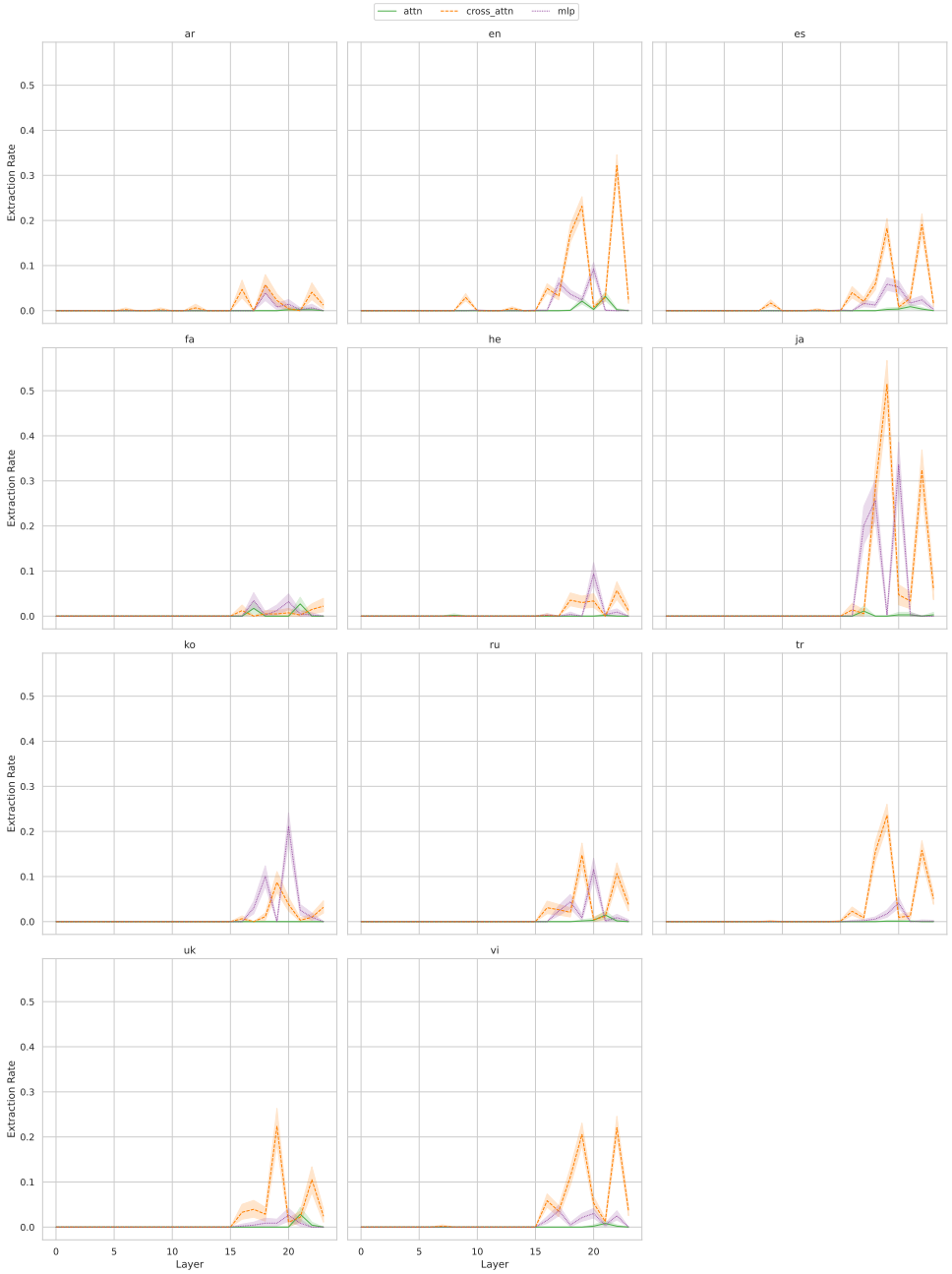

Figure 26: mT5 extraction rates for each language.

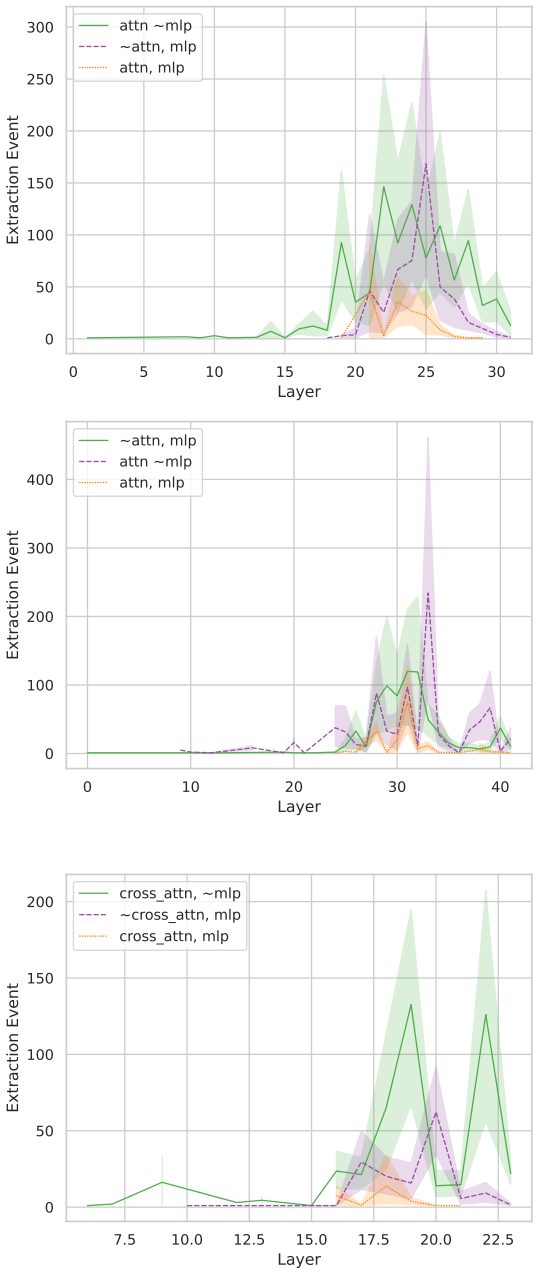

Figure 27: Number of extraction events split by precedence (or not) of an extraction event in the self-attn or cross-attn. Models from top to bottom: XGLM, EuroLLM, mT5.

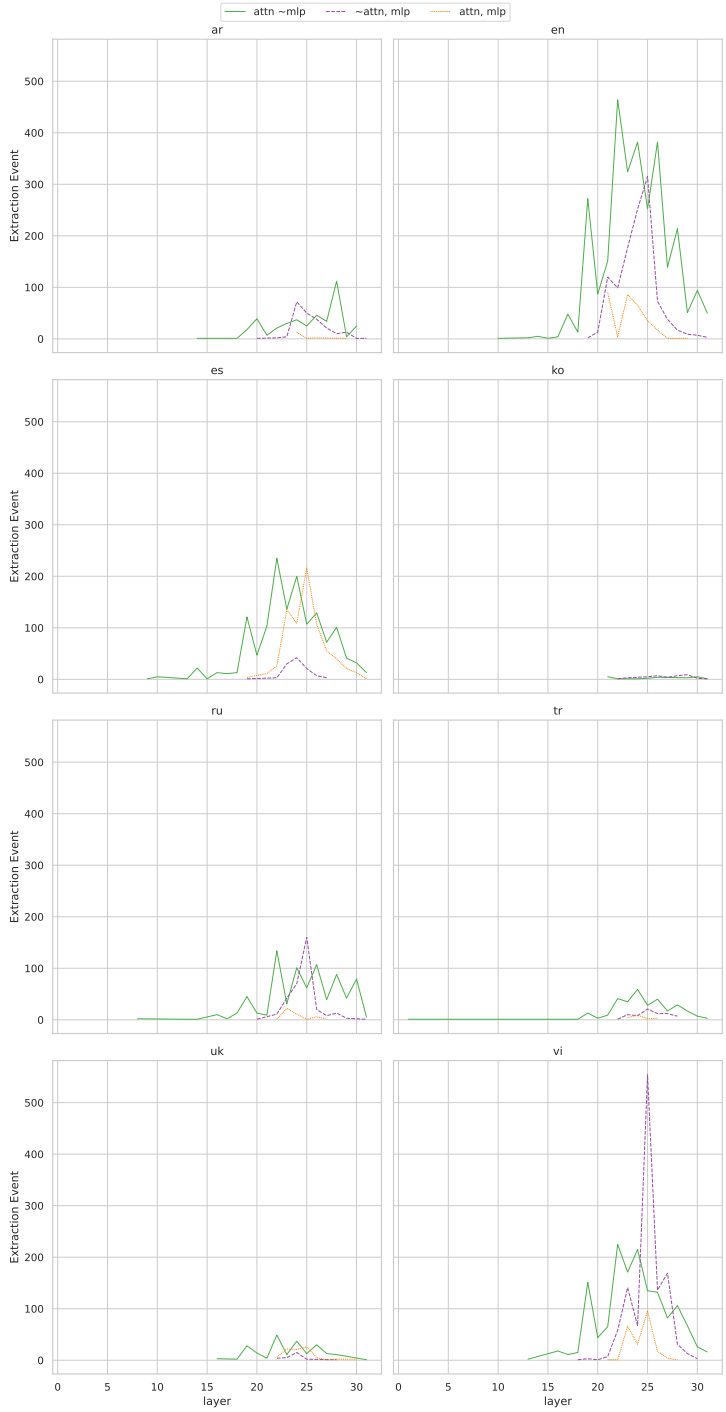

Figure 28: Number of extraction events split by precedence (or not) of an extraction event in the self-attn in XGLM for each language.

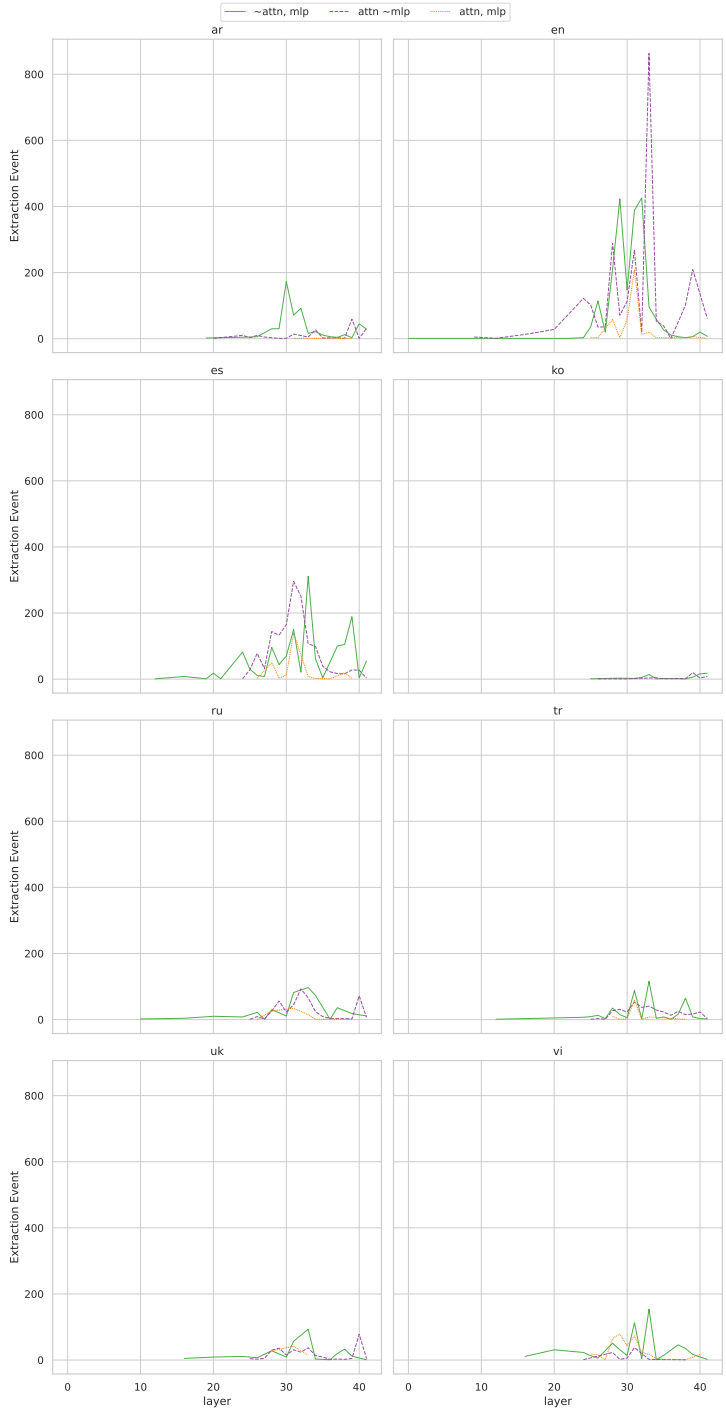

Figure 29: Number of extraction events split by precedence (or not) of an extraction event in the self-attn in EuroLLM for each language.

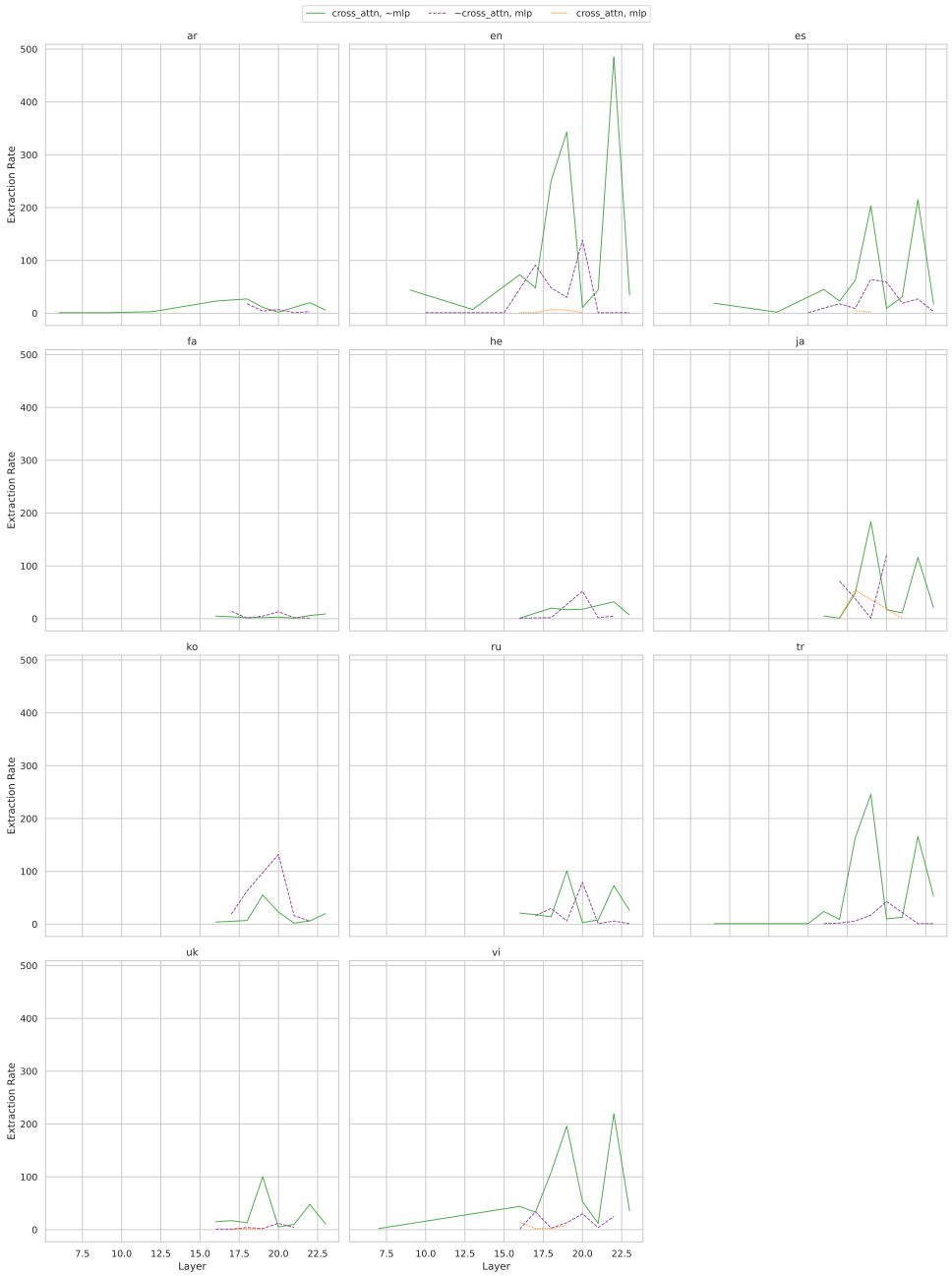

Figure 30: Number of extraction events split by precedence (or not) of an extraction event in the cross-attn in mT5 for each language.

F Patching

	XGLM			EUROLLM			mT5		
Patch - Context	All	$\mathcal{L}_c(o_p)$	$\mathcal{L}_p(o_c)$	All	$\mathcal{L}_c(o_p)$	$\mathcal{L}_p(o_c)$	All	$\mathcal{L}_c(o_p)$	$\mathcal{L}_p(o_c)$
en-es	849	834	759	880	862	755	842	831	780
en-vi	862	857	836	930	910	843	854	844	825
en-tr	974	961	961	966	945	914	815	803	794
en-ru	823	821	817	846	846	827	796	795	787
en-uk	914	914	911	915	915	915	853	850	852
en-ko	995	995	991	991	991	991	744	744	743
en-he	962	962	961	810	810	775	778	778	778
en-fa	537	537	532	771	771	734	714	714	712
en-ar	829	829	828	862	859	858	775	775	774
en-ja	134	134	134	895	895	872	774	774	773

Table 4: Total number of patch-context examples considered in the patching experiments with $\{\neq \mathcal{L}, = r, \neq s\}$. The $\mathcal{L}_c(o_p)$ column is the total number of examples where the detection of $\mathcal{L}_c(o_p)$ would be unambiguous, that is, $\mathcal{L}_c(o_p) \neq \mathcal{L}_p(o_p)$, conversely for the $\mathcal{L}_p(o_c)$ column.

	XGLM		EUROLLM		mT5	
Patch - Context	$\mathcal{L}_c(o_p)$	$\mathcal{L}_p(o_c)$	$\mathcal{L}_c(o_p)$	$\mathcal{L}_p(o_c)$	$\mathcal{L}_c(o_p)$	$\mathcal{L}_p(o_c)$
en-es	0.7% (6)	**26.0% (197)**	5.0% (43)	**34.2% (258)**	0.5% (4)	**21.5% (168)**
en-vi	0.5% (4)	**34.4% (288)**	0.5% (5)	**16.1% (136)**	0.1% (1)	**20.2% (167)**
en-tr	0.2% (2)	**16.4% (158)**	0.2% (2)	**25.4% (232)**	0.4% (3)	**26.2% (208)**
en-ru	2.2% (18)	**51.4% (420)**	4.6% (39)	**63.5% (525)**	1.1% (9)	**36.1% (284)**
en-uk	0.5% (5)	**21.3% (194)**	6.9% (63)	**62.5% (572)**	0.2% (2)	**31.8% (271)**
en-ko	0.3% (3)	**47.1% (467)**	0.1% (1)	**75.7% (750)**	0.3% (2)	**32.3% (240)**
en-he	0.0% (0)	**27.3% (262)**	0.0% (0)	**65.9% (511)**	0.4% (3)	**38.4% (299)**
en-fa	0.0% (0)	**41.7% (222)**	0.3% (2)	**64.0% (470)**	1.0% (7)	**25.1% (179)**
en-ar	8.7% (72)	**39.5% (327)**	4.5% (39)	**65.7% (564)**	0.6% (5)	**31.9% (247)**
en-ja	0.0% (0)	**3.0% (4)**	1.9% (17)	**11.5% (100)**	0.0% (0)	**26.0% (201)**

Table 5: Proportion of times an object is predicted in the other language in the patching experiments with $\{\neq \mathcal{L}, = r, \neq s\}$. In parenthesis the number of examples corresponding to the percentage. In bold when $\mathcal{L}_c(o_p)$ or $\mathcal{L}_p(o_c)$ are detected more often for each of the experiments. The total number of examples varies, see total numbers in Table 4.

	XGLM			EUROLLM			mT5		
Patch - Context	All	$\mathcal{L}_c(o_p)$	$\mathcal{L}_p(o_c)$	All	$\mathcal{L}_c(o_p)$	$\mathcal{L}_p(o_c)$	All	$\mathcal{L}_c(o_p)$	$\mathcal{L}_p(o_c)$
en-es	324	284	298	413	360	391	263	253	249
en-vi	336	329	333	105	102	100	209	207	204
en-tr	88	77	84	111	102	110	209	207	204
en-ru	218	216	218	420	415	419	191	191	190
en-uk	35	35	35	351	347	350	136	136	133
en-ko	46	46	46	98	98	98	165	165	165
en-ar	212	212	212	391	390	391	159	159	159
en-he	-	-	-	19	19	19	166	166	166
en-ja	-	-	-	1	1	1	85	85	85
en-fa	-	-	-	-	-	-	114	114	114

Table 6: Total number of patch-context examples considered in the patching experiments with $\{\neq \mathcal{L}, \neq r, = s\}$. The $\mathcal{L}_c(o_p)$ column is the total number of examples where the detection of $\mathcal{L}_c(o_p)$ would be unambiguous, that is, $\mathcal{L}_c(o_p) \neq \mathcal{L}_p(o_p)$, conversely for the $\mathcal{L}_p(o_c)$ column.

	XGLM		EUROLLM		mT5	
Patch - Context	$\mathcal{L}_c(o_p)$	$\mathcal{L}_p(o_c)$	$\mathcal{L}_c(o_p)$	$\mathcal{L}_p(o_c)$	$\mathcal{L}_c(o_p)$	$\mathcal{L}_p(o_c)$
en-es	**18.0% (51)**	3.7% (11)	**41.7% (150)**	2.8% (11)	0.8% (2)	**7.6% (19)**
en-vi	**9.1% (30)**	6.6% (22)	3.9% (4)	**8.0% (8)**	1.0% (2)	**12.3% (25)**
en-tr	**36.4% (28)**	6.0% (5)	**56.9% (58)**	4.5% (5)	2.9% (6)	**9.3% (19)**
en-ru	**64.8% (140)**	4.1% (9)	**61.7% (256)**	9.3% (39)	6.3% (12)	**8.9% (17)**
en-uk	17.1% (6)	**17.1% (6)**	**66.0% (229)**	2.3% (8)	3.7% (5)	**9.0% (12)**
en-ko	**41.3% (19)**	21.7% (10)	**71.4% (70)**	5.1% (5)	2.4% (4)	**12.1% (20)**
en-ar	**40.1% (85)**	1.9% (4)	**52.8% (206)**	0.8% (3)	1.9% (3)	**7.5% (12)**
en-he	-	-	0.0% (0)	0.0% (0)	3.6% (6)	**15.7% (26)**
en-ja	-	-	0.0% (0)	0.0% (0)	0.0% (0)	**25.9% (22)**
en-fa	-	-	-	-	2.6% (3)	**15.8% (18)**

Table 7: Proportion of times an object is predicted in the other language in the patching experiments with $\{\neq \mathcal{L}, \neq r, = s\}$. In parenthesis the number of examples corresponding to the percentage. In bold when $\mathcal{L}_c(o_p)$ or $\mathcal{L}_p(o_c)$ are detected more often for each of the experiments. The total number of examples varies, see total numbers in Table 6.

F.1 Different Relation, Different Subject

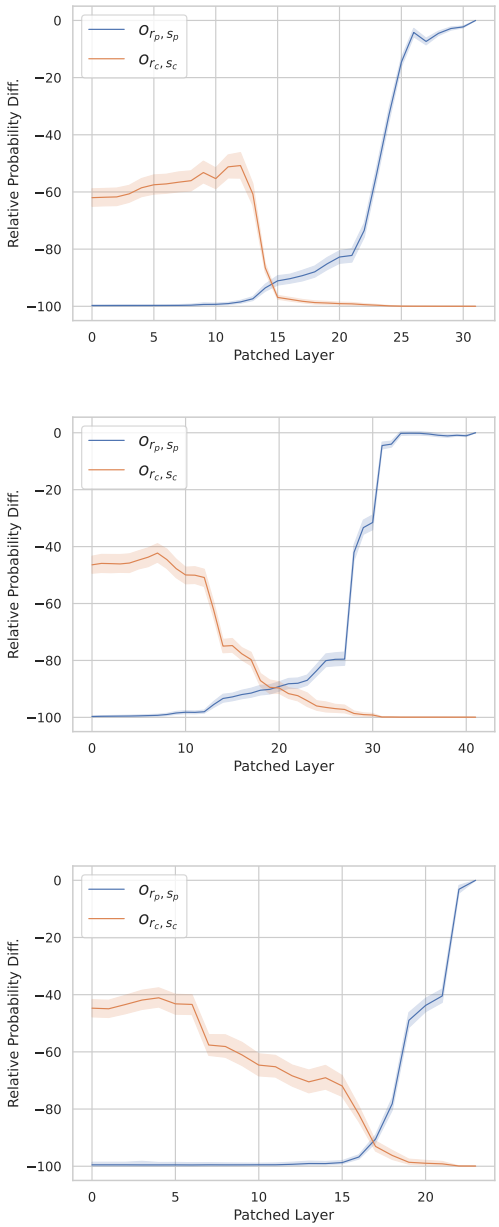

Figure 31: Probability of the patch answer and the context answer when patching at different layers. Models from top to bottom: XGLM, EuroLLM, mT5.

F.2 Same Relation, Different Subject

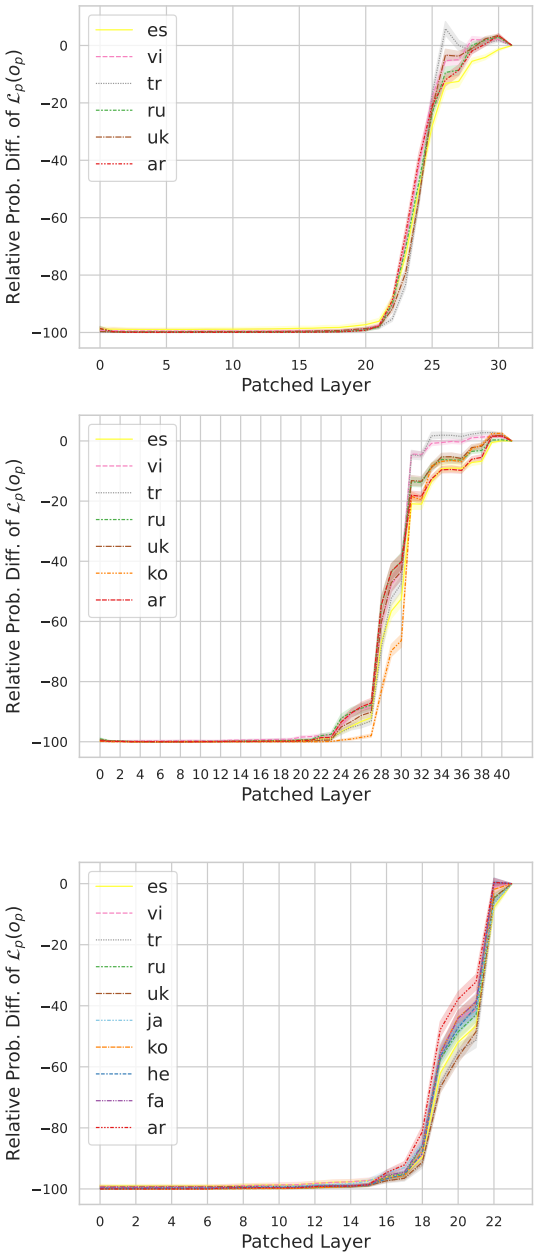

Figure 32: Probability of the patch answer $\mathcal{L}_p(o_p)$ when patching at different layers. Models from top to bottom: XGLM, EUROLLM, mT5.

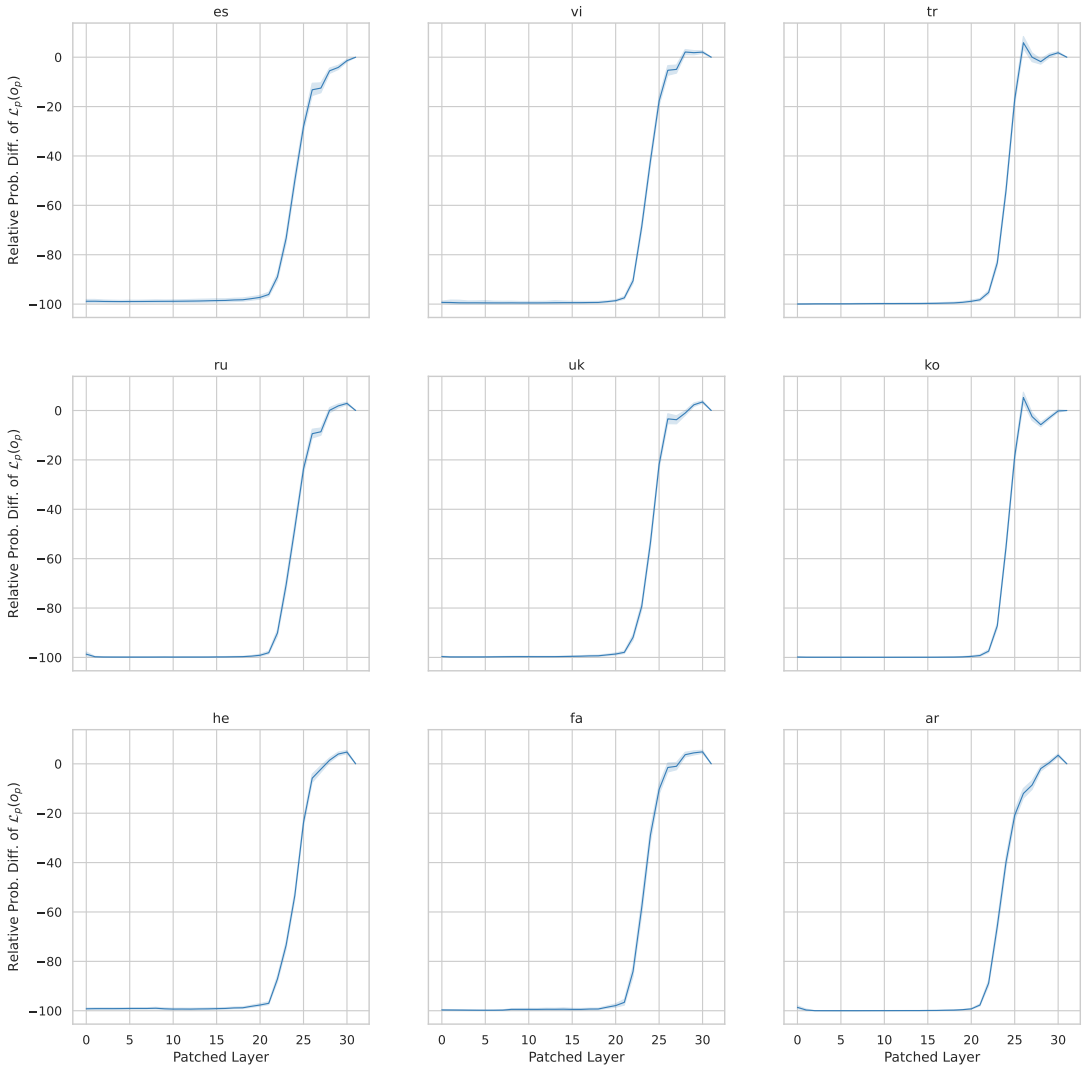

Figure 33: Probability of the patch answer $\mathcal{L}_p(o_p)$ when patching at different layers in XGLM, for examples with $\{\neq \mathcal{L}, = r, \neq s\}$.

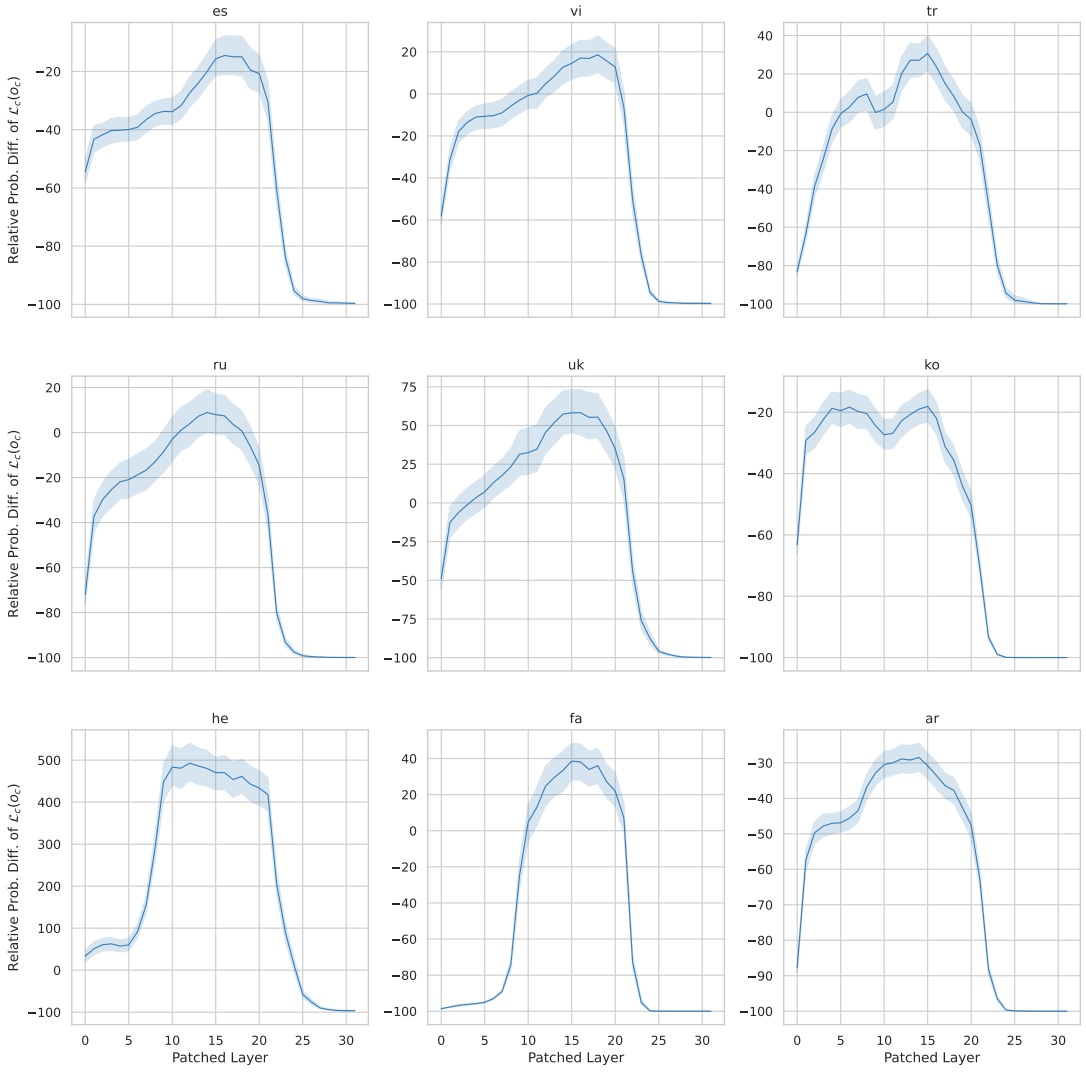

Figure 34: Probability of the $\mathcal{L}_c(o_c)$ when patching at different layers in XGLM, for examples with $\{\neq \mathcal{L}, = r, \neq s\}$. Note that the plots do not share the y-axis.

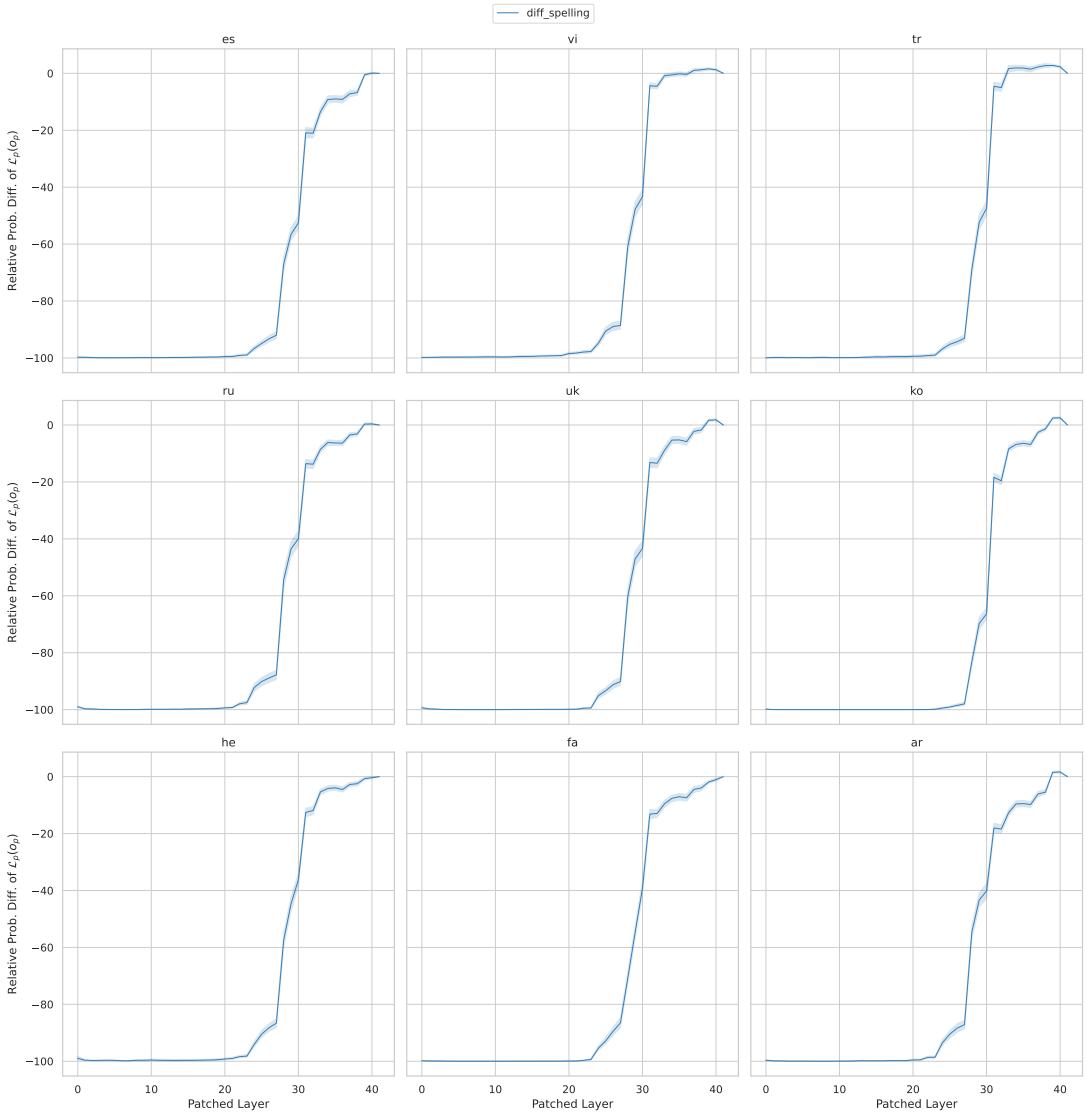

Figure 35: Probability of the patch answer $\mathcal{L}_p(o_p)$ when patching at different layers in EUROLLM, for examples with $\{\neq \mathcal{L}, = r, \neq s\}$.

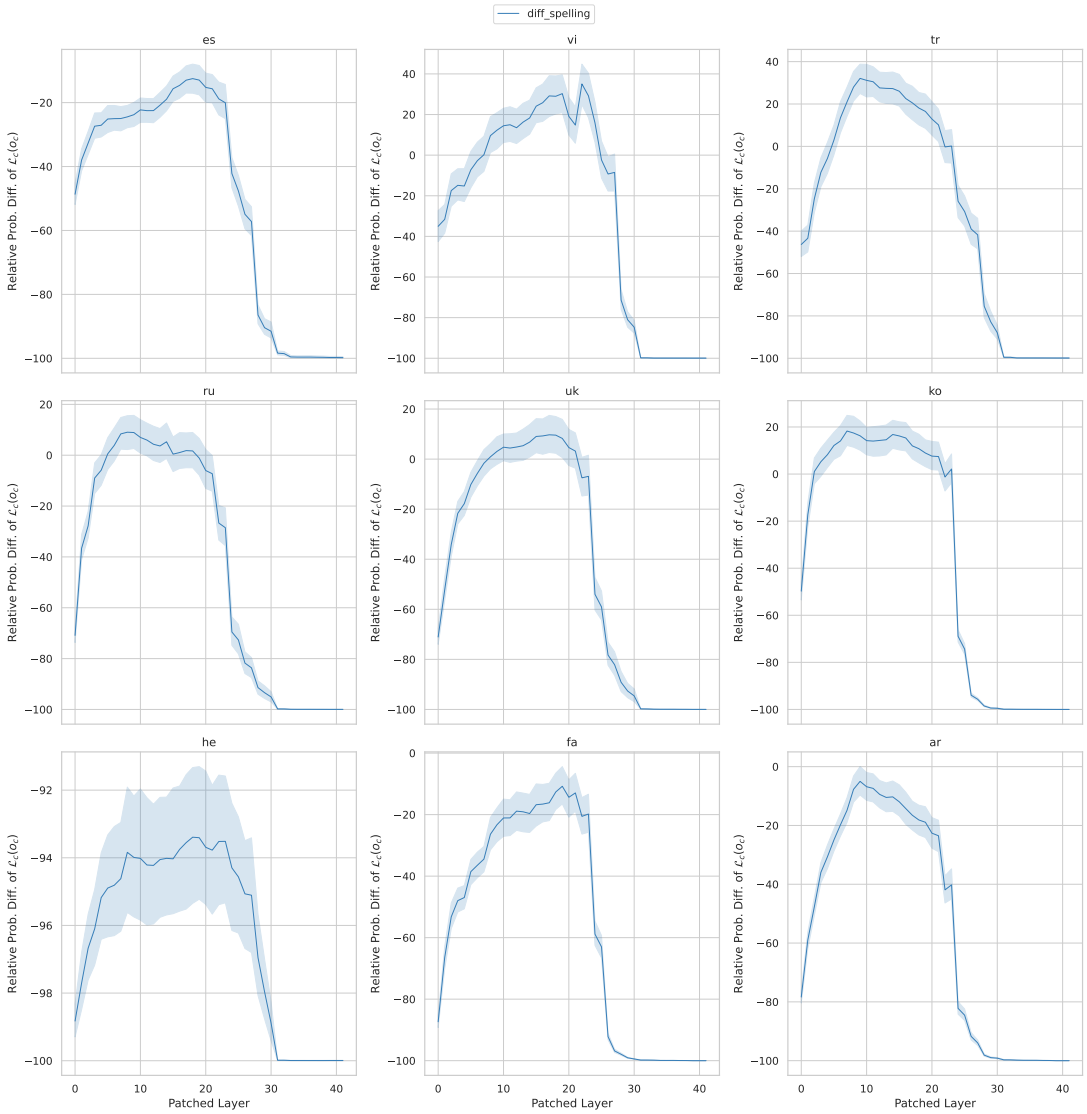

Figure 36: Probability of the $\mathcal{L}_c(o_c)$ when patching at different layers in EUROLLM, for examples with $\{\neq \mathcal{L}, = r, \neq s\}$. Note that the plots do not share the y-axis.

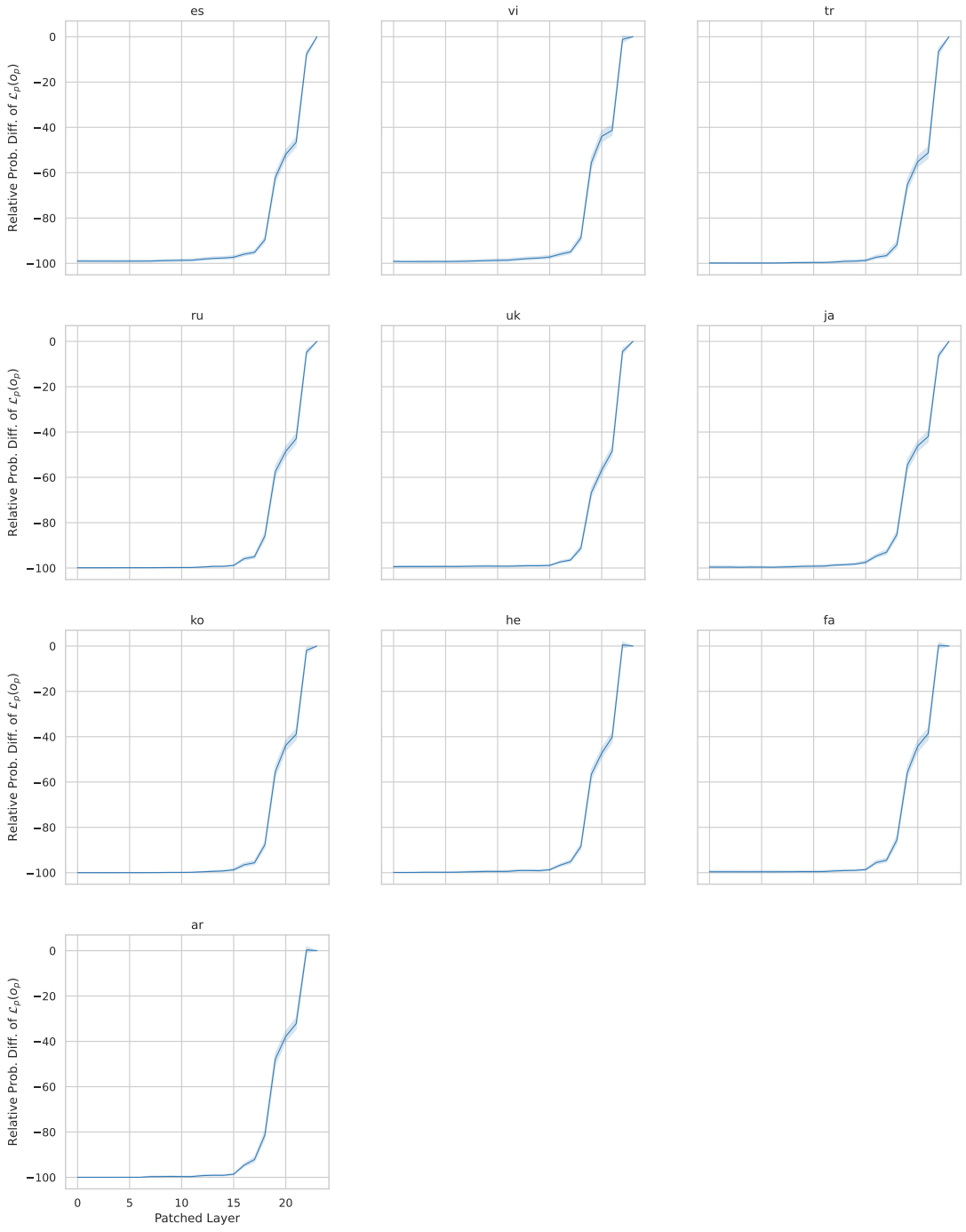

Figure 37: Probability of the $\mathcal{L}_p(o_p)$ when patching at different layers in mT5, for examples with $\{\neq \mathcal{L}, = r, \neq s\}$.

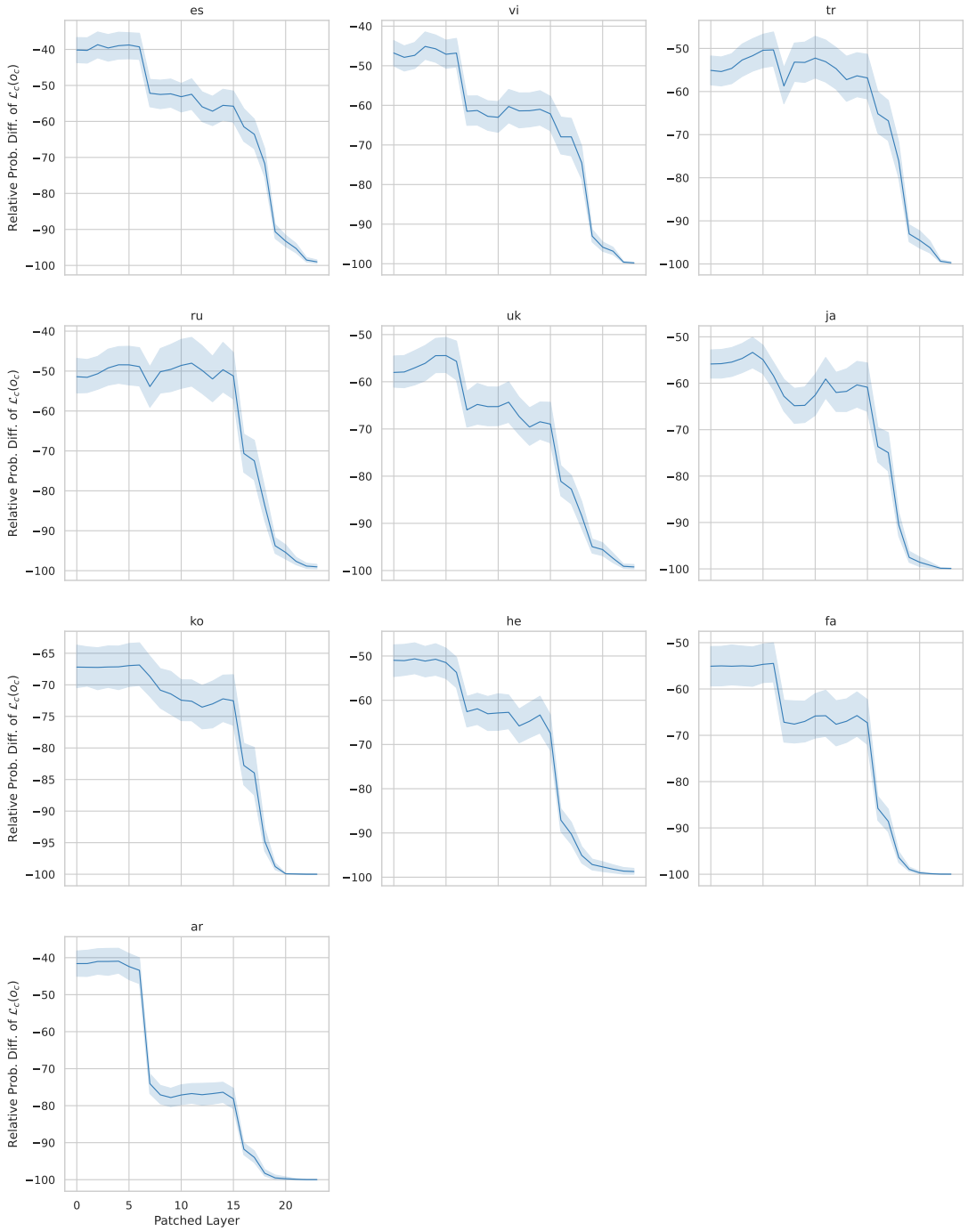

Figure 38: Probability of the $\mathcal{L}_c(o_c)$ when patching at different layers in mT5, for examples with $\{\neq \mathcal{L}, = r, \neq s\}$. Note that the plots do not share the y-axis.

F.3 Different Relation, Same Subject

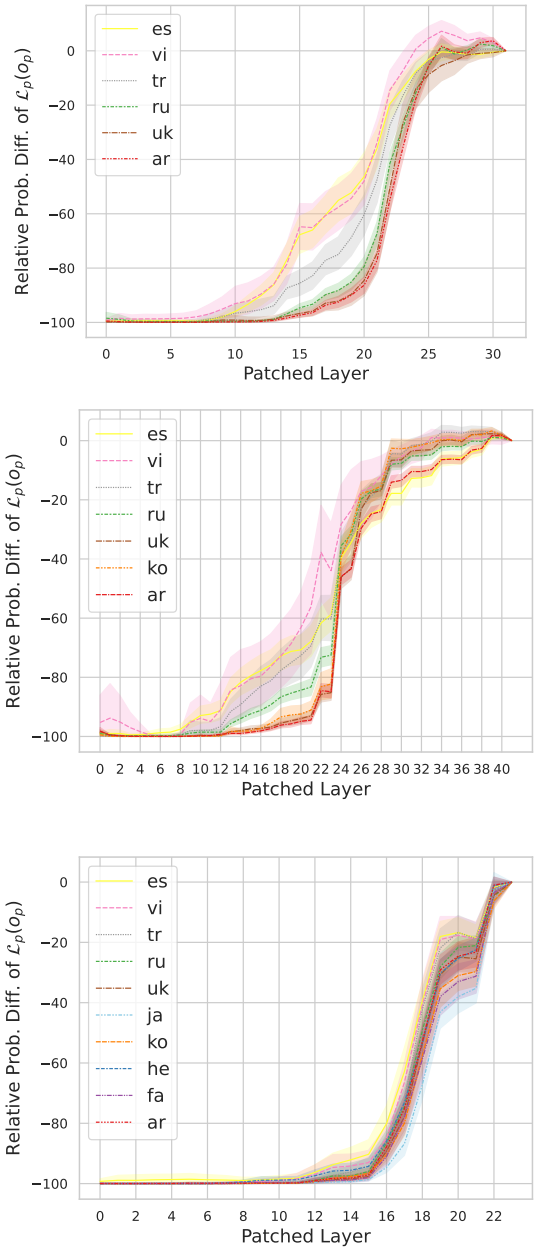

Figure 39: Probability of the patch answer $\mathcal{L}_p(o_p)$ when patching at different layers for examples with $\{\neq \mathcal{L}, \neq r, = s\}$. Models from top to bottom: XGLM, EUROLLM, mT5.

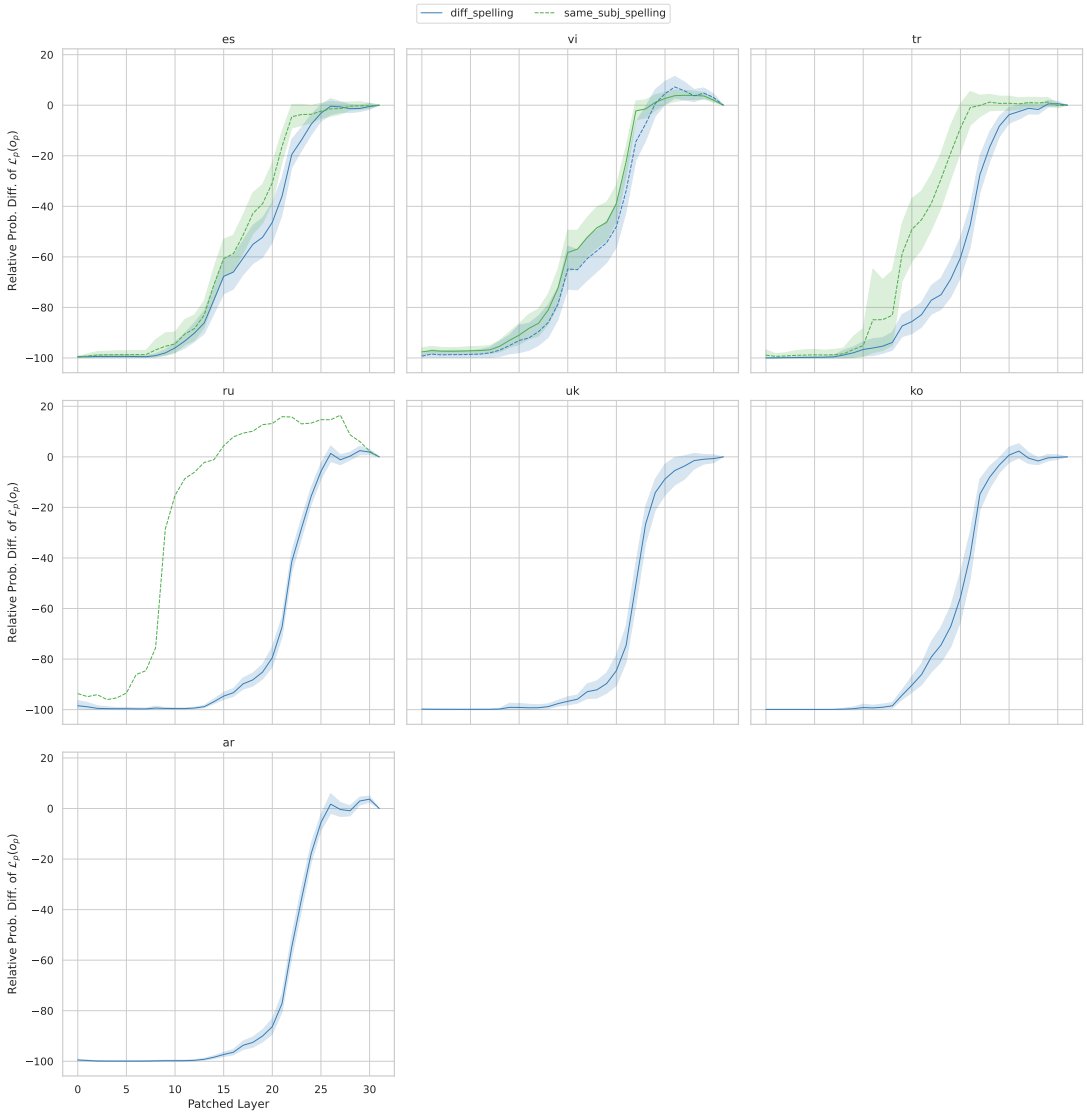

Figure 40: Probability of the $\mathcal{L}_p(o_p)$ when patching at different layers in XGLM, for examples with $\{\neq \mathcal{L}, \neq r, = s\}$.

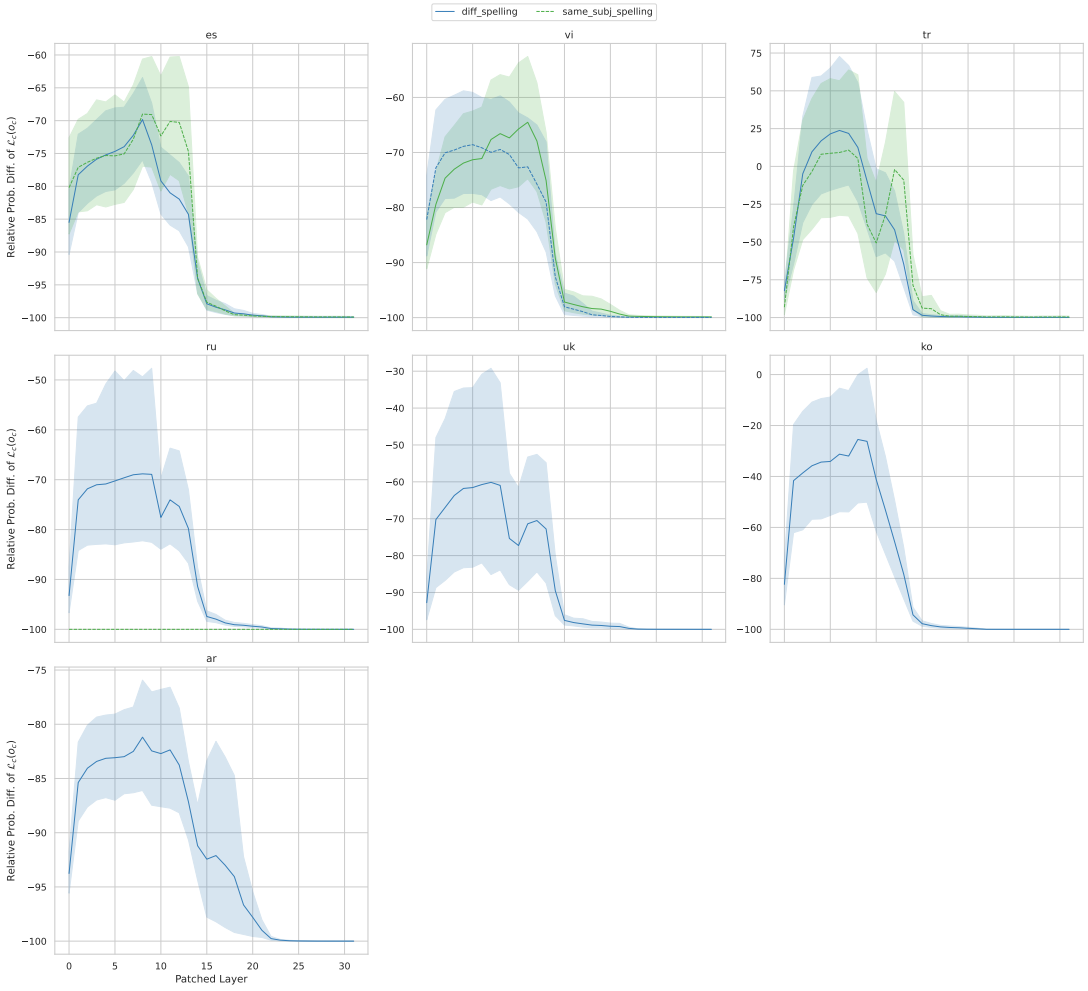

Figure 41: Probability of the $\mathcal{L}_c(o_c)$ when patching at different layers in XGLM, for examples with $\{\neq \mathcal{L}, \neq r, = s\}$. Note that the plots do not share the y-axis.

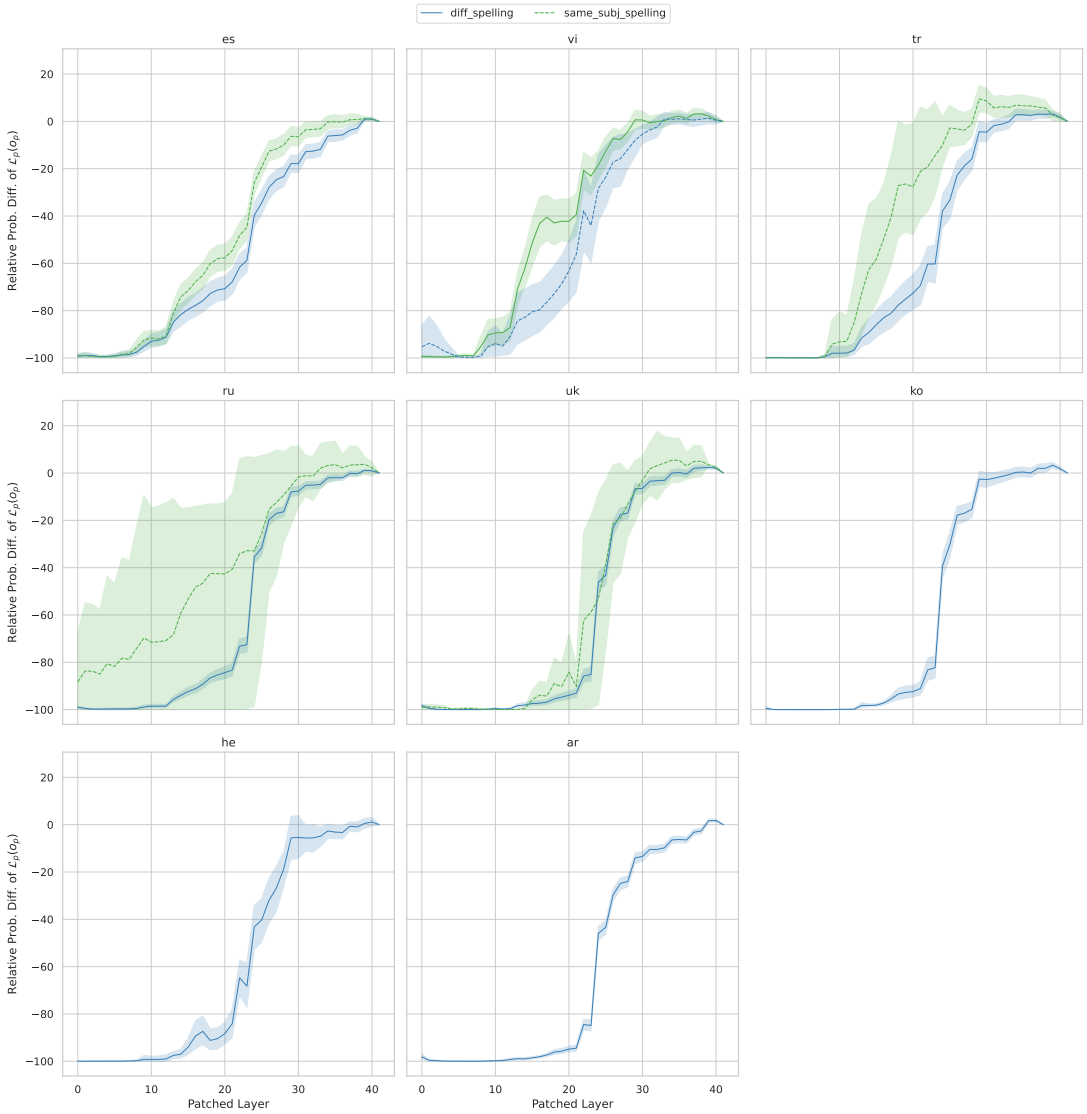

Figure 42: Probability of the $\mathcal{L}_p(o_p)$ when patching at different layers in EUROLLM, , for examples with $\{\neq \mathcal{L}, \neq r, = s\}$.

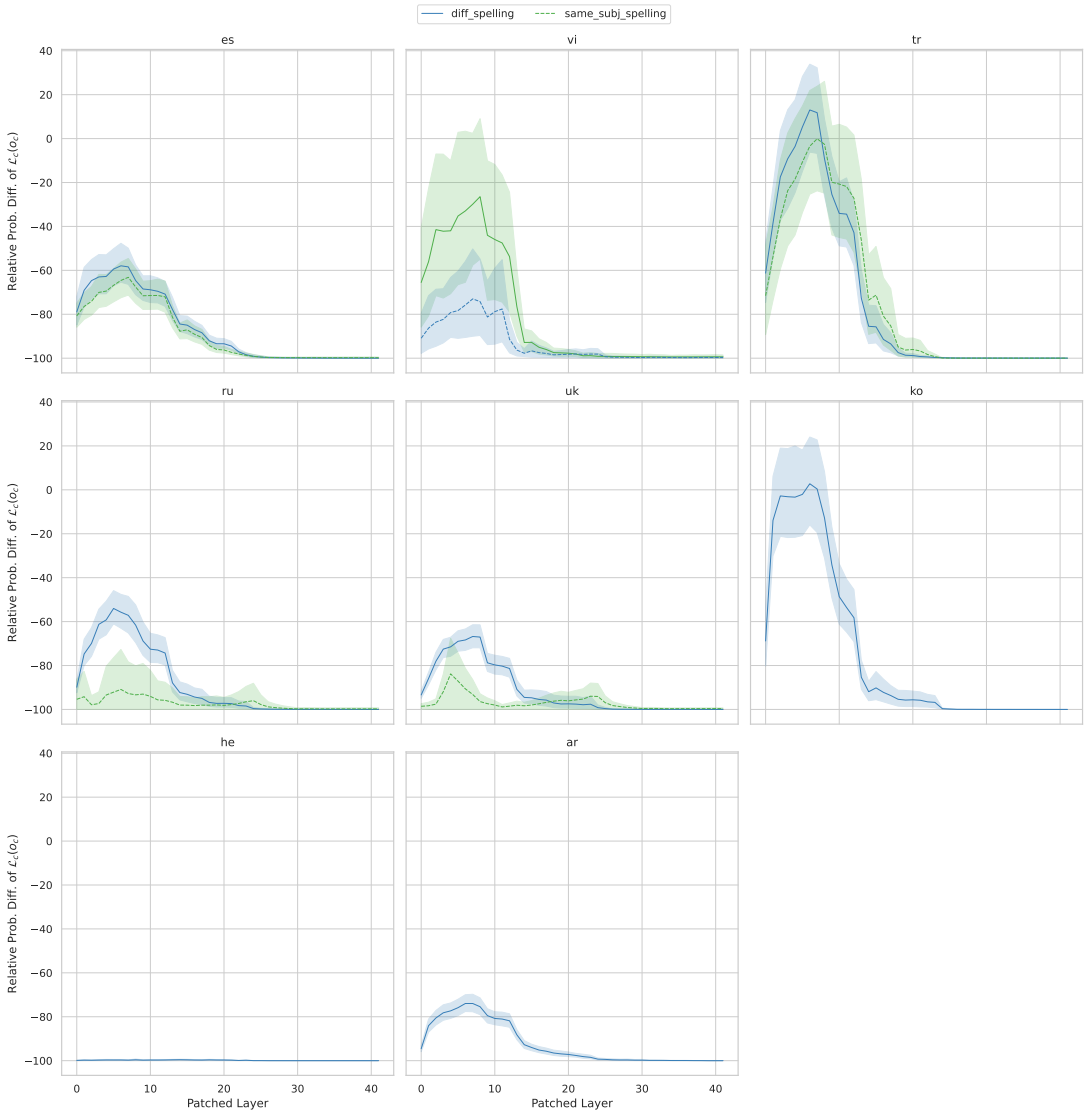

Figure 43: Probability of the $\mathcal{L}_c(o_c)$ when patching at different layers in EUROLLM, for examples with $\{\neq \mathcal{L}, \neq r, = s\}$. Note that the plots do not share the y-axis.

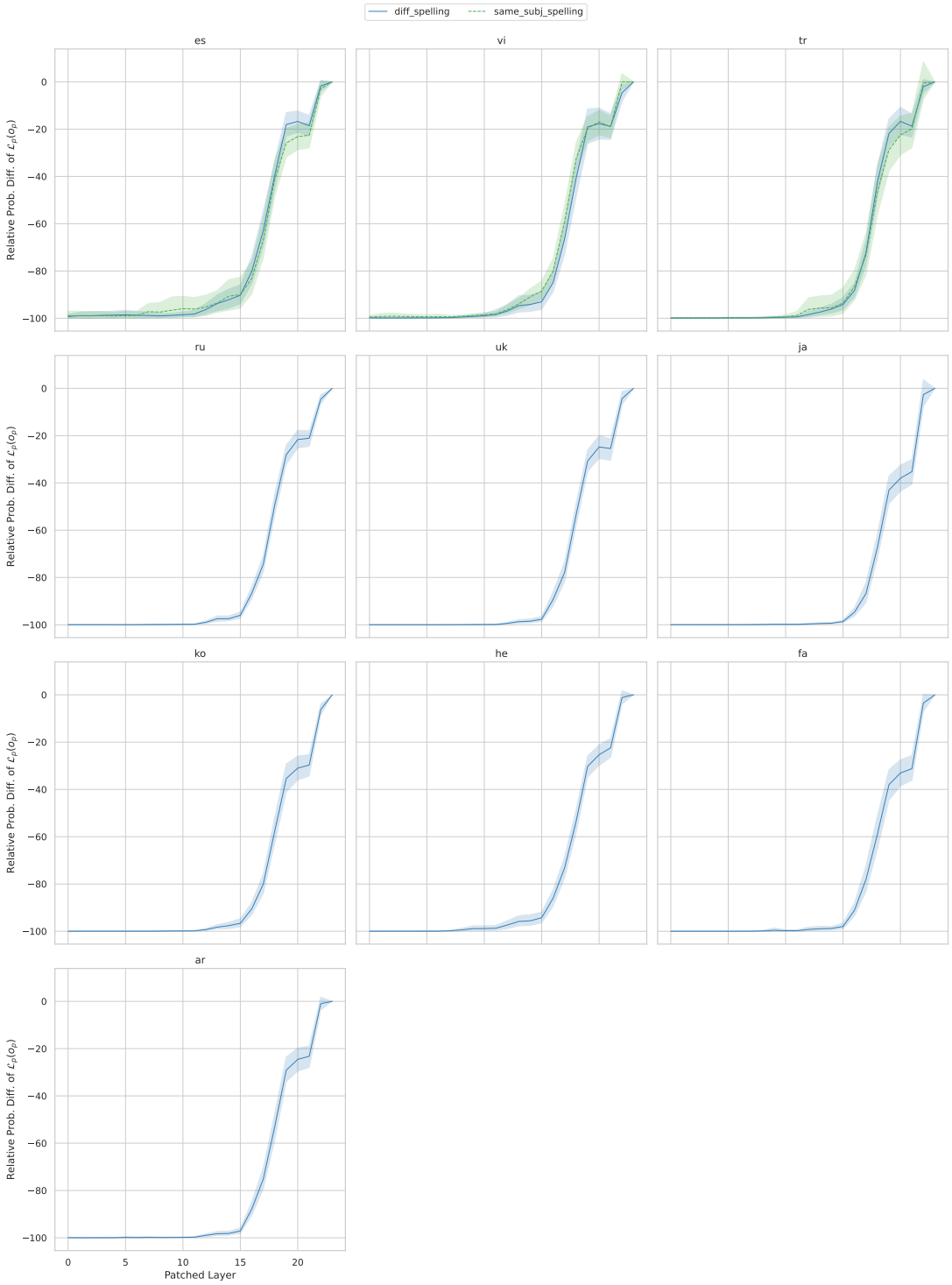

Figure 44: Probability of the $\mathcal{L}_p(o_p)$ when patching at different layers in mT5, , for examples with $\{\neq \mathcal{L}, \neq r, = s\}$.

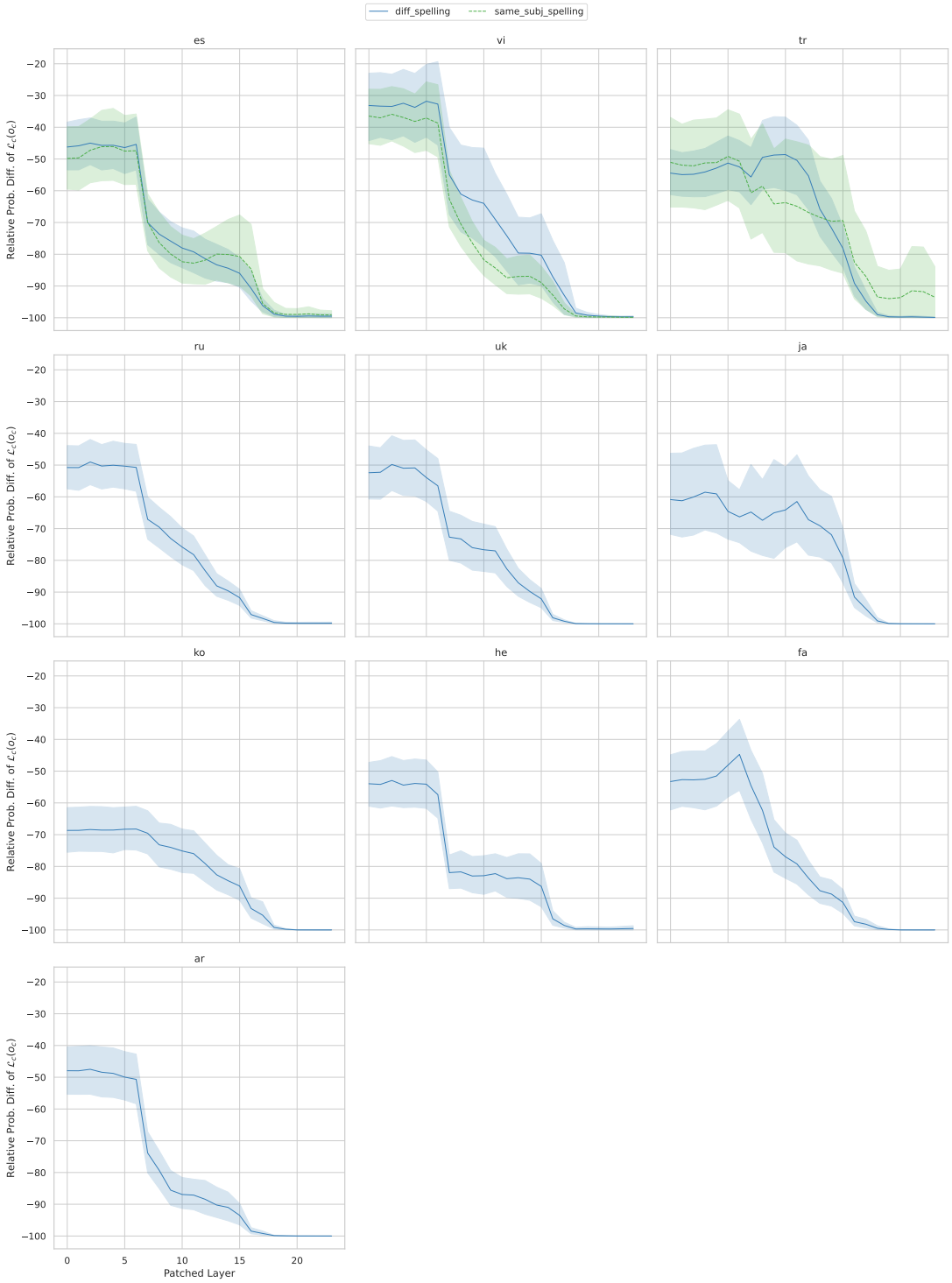

Figure 45: Probability of the $\mathcal{L}_c(o_c)$ when patching at different layers in mT5, for examples with $\{\neq \mathcal{L}, \neq r, = s\}$. Note that the plots do not share the y-axis.

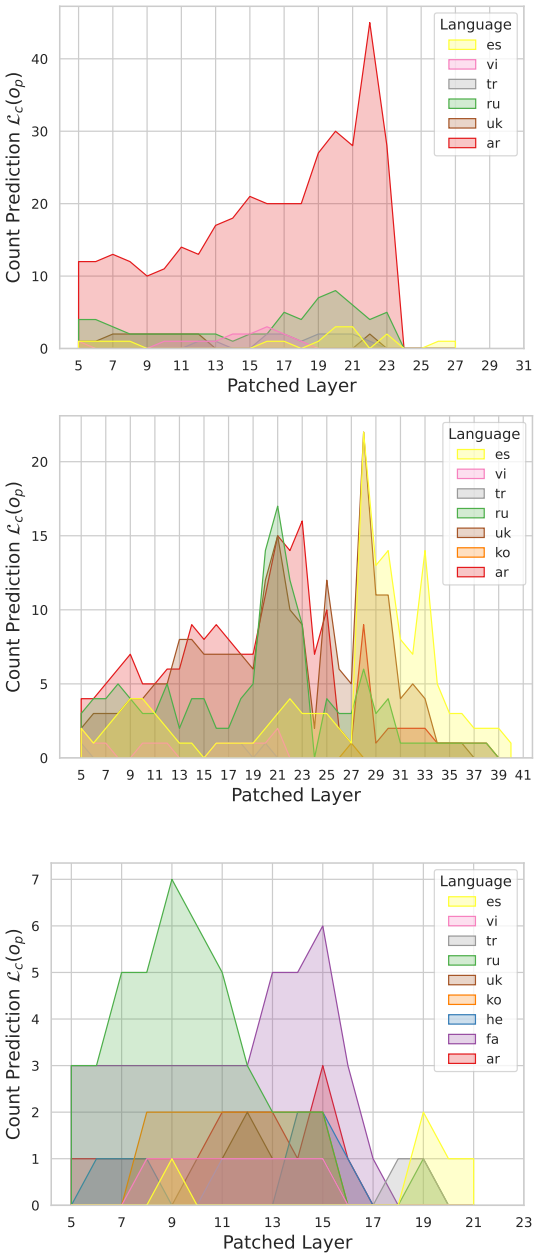

Figure 46: Number of times the patch object is predicted in the context language for the experiment of same relation different subject. Models from top to bottom: XGLM, EuroLLM, mT5.

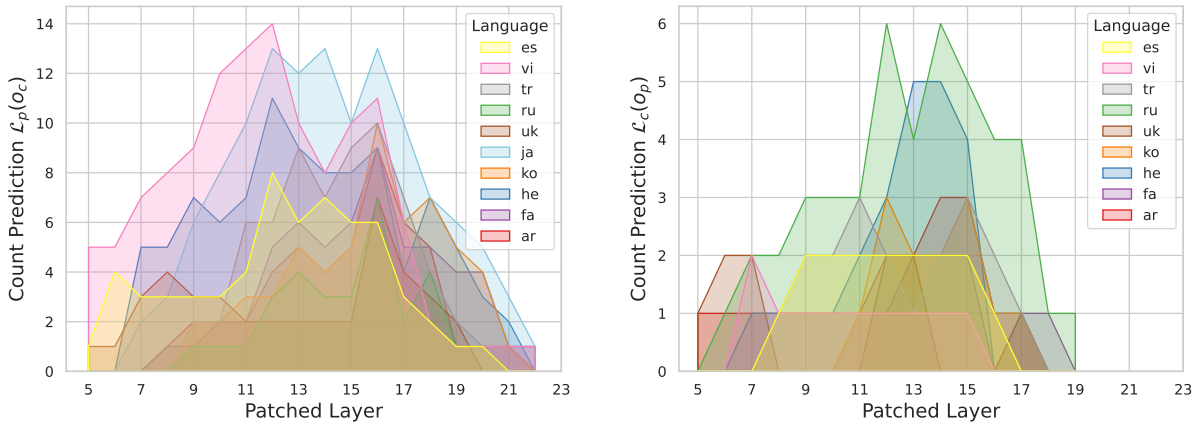

Figure 47: Number of times the object is predicted in the opposite language in mT5 in the $\{\neq r, = s, \neq \mathcal{L}\}$ experiment.

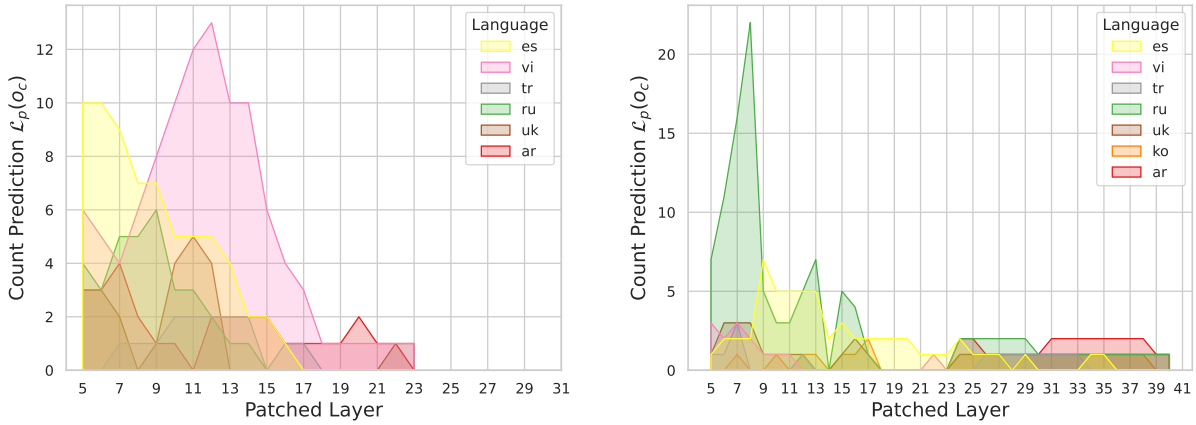

Figure 48: Number of times the context object is predicted in the patch language in the $\{\neq r, = s, \neq \mathcal{L}\}$ experiment. Left XGLM, right EUROLLM.