# Kanji lens: Which Script Do Japanese LLMs Traverse Internally?

**Anonymous ACL submission**


## Abstract

The Japanese language uses three scripts with different typical functions: kanji, hiragana, and katakana. When a Japanese LLM generates output in hiragana, which script type is reflected in its intermediate representations? Using logit lens, we analyze layerwise vocabulary-space projections and identify latent kanji-fication as a kanji-specific instance of a broader preferred-script tendency: for kanji-writable words, kanji-containing tokens become prominent in intermediate layers even when the final output is hiragana.

We show that kanji-fication is pronounced in Japanese-centric models, but subtle in English-centric and continual pre-training models. For loanwords, the intermediate preference shifts toward katakana, supporting the view that intermediate script preferences reflect conventional script forms of lexical items.


## 1 Introduction

The Japanese language uses three scripts: kanji, hiragana, and katakana. These scripts have different typical functions. Kanji often expresses lexical stems, hiragana is widely used for inflectional endings and grammatical elements, and katakana is common for loanwords and foreign names. For example, the Japanese word corresponding to "learn" can be written as "学習" (kanji), "がくしゅう" (hiragana), or "ガクシュウ" (katakana), and many words and expressions permit multiple script variants. The internal processing of large language models (LLMs) for such a language is still not well understood. This paper poses the question of which script type is reflected in the internal processing of Japanese LLMs. When a model outputs hiragana, as in Figure 1, does it internally maintain hiragana, or does it transiently rely on another script type such as kanji? We call this kanji-specific intermediate-layer tendency latent kanji-fication, and treat it as one case of a broader question: whether intermediate representations favor the conventional script form of a lexical item rather than simply copying the input script or converging immediately to the output script.

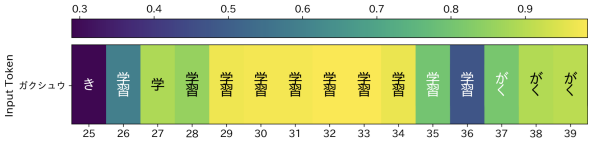


Figure 1: Results of analysis of the katakana-to-hiragana conversion task in a Japanese-centric model (Top-1 token heatmap). The most likely token at each layer is visualized. Kanji representations appear in intermediate layers, converging to hiragana in the final layers.

To examine which tokens are favored by intermediate vocabulary-space projections, we use logit lens (Nostalgebraist, 2020). This method provides a descriptive view of the script types favored by layerwise vocabulary-space readouts. We use this method to trace the tokens produced across layers and to compute the probability of kanji at each layer, thereby investigating latent kanji-fication. In particular, we examine the layers in which latent kanji-fication appears, the model types that exhibit it, and whether it weakens for loanwords.

## 2 Related Work

Prior work has investigated how English-centric LLMs process non-English languages and what latent language they use internally (Wendler et al., 2024; Zhong et al., 2024). Two main approaches have been proposed to improve multilingualism: continual pre-training of English-centric models (Fujii et al., 2024) and training on balanced multilingual data from the outset (Aizawa et al., 2024).

Research on mechanistic interpretability (Elhage et al., 2021, 2022) has advanced the analysis of model internal representations. Methods such as logit lens (Nostalgebraist, 2020) and tuned lens (Belrose et al., 2023) have been proposed to visual-

*# Katakana → Hiragana (script conversion task)*
Original: “ドクショ” *(dokusho / reading)* Hiragana: “とくしょ”
Original: “ベンキョウ” *(benkyou / studying)* Hiragana: “べんきょう”
Original: “ケンガク” *(kengaku / field trip)* Hiragana: “けんがく”
Original: “ジッケン” *(jikken / experiment)* Hiragana: “じっけん”
Original: “ガクシュウ” *(gakushuu / learning)* Hiragana: “

Figure 2: Example 4-shot prompt for the script conversion task. Romanizations and English glosses are added for readability; they do not appear in the actual prompt. The model generates the hiragana continuation after the opening quote of the 5th example.

ize representations at each layer. Saji and Nakashole (2026) proposed RomanLens, which combines logit lens with activation patching (Conmy et al., 2023), and reported “latent romanization,” where roman script representations temporarily appear in intermediate layers when English-centric models process non-roman-script languages. Building on this line of work, our study investigates how LLMs process Japanese across multiple script types and analyzes how internal representations are converted and integrated during that process.

## 3 Analysis of Kanji-fication

We use the script conversion task to analyze the transition of script types, and define the kanji-fication degree to quantify the reliance on kanji.

### 3.1 Script Conversion Task

To investigate the presence or absence of latent kanji-fication, we use a “katakana-to-hiragana” conversion task in which the input is fixed to katakana and the output to hiragana. The analysis is performed by comparing next-token predictions at the end of the prompt using logit lens. The prompt is given in a 4-shot format as shown in Figure 2, with the hiragana side of the 5th example stopped at the opening double quote to generate the continuation. The analysis targets the next-token prediction at the end of the prompt (immediately after the opening quote on the hiragana side), comparing the distribution across layers. We use two manually curated datasets. Claude 4 [1] was used only to propose initial candidate pairs. All items were manually inspected, filtered, and revised before inclusion:

**Kanji-writable words** (182 pairs): Katakana-to-hiragana pairs for ordinary Japanese vocabulary that normally has a conventional kanji form, although it is written in katakana here for the conversion task (e.g., ガクシュウ→がくしゅう).

[1] https://www.anthropic.com/news/claude-4

**Loanwords** (190 pairs): Katakana-to-hiragana pairs for imported words, mainly from Western languages, that are conventionally written in katakana and generally do not have a natural kanji form (e.g., コンピューター→こんぴゅーたー).

### 3.2 Procedure and Kanji-fication Degree

For each model, logit lens (Nostalgebraist, 2020) maps hidden states at each layer through the model’s final normalization and language-model head into that model’s own vocabulary space. In this study, we aggregate the probabilities from the distribution at each layer obtained by logit lens by script type (kanji, hiragana, katakana, and alphabetic characters), computing the script-type probability distribution for each layer.

For the next-token prediction at the end of the prompt, let $p_l(\cdot)$ be the logit lens distribution at layer $l$, and let $\mathcal{K}$ be the set of tokens containing kanji. We define the kanji probability at layer $l$ as $\sum_{t \in \mathcal{K}} p_l(t)$ and average it over all $L$ layers to obtain the kanji-fication degree for that instance:

$$D_{\text{kanji}} = \frac{1}{L} \sum_{l=1}^{L} P_{\text{kanji}}(l) \tag{1}$$

We report the dataset average of this instance-level value as the model’s kanji-fication degree.This degree measures the probability mass assigned to kanji-containing tokens, thereby quantifying the strength of the layerwise kanji-script preference.

### 3.3 Analysis with Hiragana Sentences

The script conversion task described above uses a setting in which the candidate output tokens are restricted. To investigate latent kanji-fication in more general cases, we instead input hiragana sentences to the LLM with an instruction to output only hiragana and analyze the internal states. Specifically, for a short sentence $s$, the prompt is given in the format “Output only in hiragana: $s$.” We then visualize the internal states at each token position using logit lens.

## 4 Experiments and Results

Our primary analysis uses models in the 7–13B parameter range to compare the effect of the distribution of languages in the training data across different architectures. We use three models that differ in their primary training language: an English-centric model, Llama-3.1-8B-Instruct (Grattafiori et al., 2024); a Japanese continual pre-training model,

| Model | Kanji-writable | Loanwords |
|---|---|---|
| Llama-3.1-8B-Instruct | 0.022 | 0.021 |
| Llama-3.1-Swallow-8B-Instruct-v0.5 | 0.031 | 0.024 |
| LLM-jp-3-13B-Instruct | 0.405 | 0.296 |
| Sarashina2-7B | 0.273 | 0.265 |
| Yi-6B-Chat | 0.069 | 0.095 |
| Qwen3-8B-Base | 0.265 | 0.249 |
| Qwen3-Swallow-8B-SFT-v0.2 | 0.161 | 0.142 |

Table 1: Kanji-fication degree (average over all layers) for each model. Computed on the kanji-writable words dataset and the loanwords dataset.

Llama-3.1-Swallow-8B-Instruct-v0.5 (Fujii et al., 2024); and a Japanese-centric model, LLM-jp-3-13B-Instruct (Aizawa et al., 2024). To verify generalizability across different architectures, we also analyze Sarashina2-7B (SB Intuitions Corp., 2024) (a Japanese-centric model), Qwen3-8B-Base (Yang et al., 2025) and Qwen3-Swallow-8B-SFT-v0.2 (Yang et al., 2025; Fujii et al., 2024) (a multilingual base model and its Japanese-adapted variant), and Yi-6B-Chat (Young et al., 2024) (a Chinese-centric model). The effect of model scale is investigated separately in Section 4.3.

### 4.1 Results of Script Conversion Task

For each layer $\ell$, we compute the script-type probability by aggregating the next-token distribution from logit lens over script classes. Figure 3 visualizes these layerwise script-type probability distributions for the three primary models on kanji-writable words and loanwords. In the English-centric model (Llama-3.1-8B-Instruct) and the continual pre-training model (Llama-3.1-Swallow-8B-Instruct-v0.5), the probability of alphabetic tokens is dominant throughout all layers, with hiragana probability rising sharply only in the final layer. In contrast, in the Japanese-centric model (LLM-jp-3-13B-Instruct), kanji probability increases in intermediate layers (around Layers 25–35), and converges to hiragana in the final layers, exhibiting "latent kanji-fication."

Table 1 shows that kanji-fication is strongest in the Japanese-centric LLM-jp-3-13B-Instruct, and remains elevated in other Japanese-centric and kanji-rich multilingual models (Sarashina2-7B, Qwen3-8B-Base), while the English-centric and continual pre-training Llama models show much lower values. Script-type probability distributions for the additional models are shown in Appendix E.

### 4.2 Results of Hiragana Sentence Analysis

We present results for the case where the input sentence $s$ is "あさごはんをたべました" (I ate breakfast). For each token position $p$ and each layer $\ell$, we compute the script-type probability $P_{\ell,p}(c)$ for script type $c$ based on the next-token distribution obtained from logit lens and average it over positions to obtain $\bar{P}_\ell(c) = \frac{1}{N}\sum_p P_{\ell,p}(c)$, where $N$ is the number of target tokens.

Figure 4 shows the results for the three primary models. In the English-centric model (Llama-3.1-8B-Instruct) and the continual pre-training model (Llama-3.1-Swallow-8B-Instruct-v0.5), alphabetic tokens dominate throughout most layers with hiragana rising only at the end. In contrast, in LLM-jp-3-13B-Instruct, kanji probability is elevated in intermediate layers, and the heatmap (Figure 9 in Appendix) shows that the logit-lens readout favors kanji-containing tokens such as "起き" (wake up) and "食べ" (eat) in intermediate layers before shifting to hiragana in the final layers. The kanji-fication degrees in Table 1 indicate that this tendency holds broadly: models with higher kanji-fication degree (Sarashina2-7B, Qwen3-8B-Base) also exhibit kanji-dominant intermediate representations, while models with lower degrees (Llama, Qwen3-Swallow-8B-SFT-v0.2) show weaker or no such signal. Full results are provided in Appendix F.

### 4.3 Effect of Model Scale

To investigate whether latent kanji-fication is also observed in larger models, we analyze larger variants from the same families: Sarashina2-70B, Qwen3-32B-Base, Qwen3-Swallow-32B-SFT-v0.2, Yi-34B-Chat, Llama-3.1-70B-Instruct, and Llama-3.1-Swallow-70B-Instruct-v0.3.

Across model families, larger scale mostly preserves and sometimes sharpens the qualitative behavior already seen at smaller sizes. Model families that already show latent kanji-fication at 7–13B, such as Sarashina2 and Qwen3-Base, continue to do so at 32B–70B, whereas the English-centric and continual pre-training Llama models remain largely alphabetic until the final layers. This pattern suggests that scale strengthens pre-existing language- and vocabulary-dependent structure rather than creating latent kanji-fication on its own. Detailed model-by-model results are provided in Appendix G.

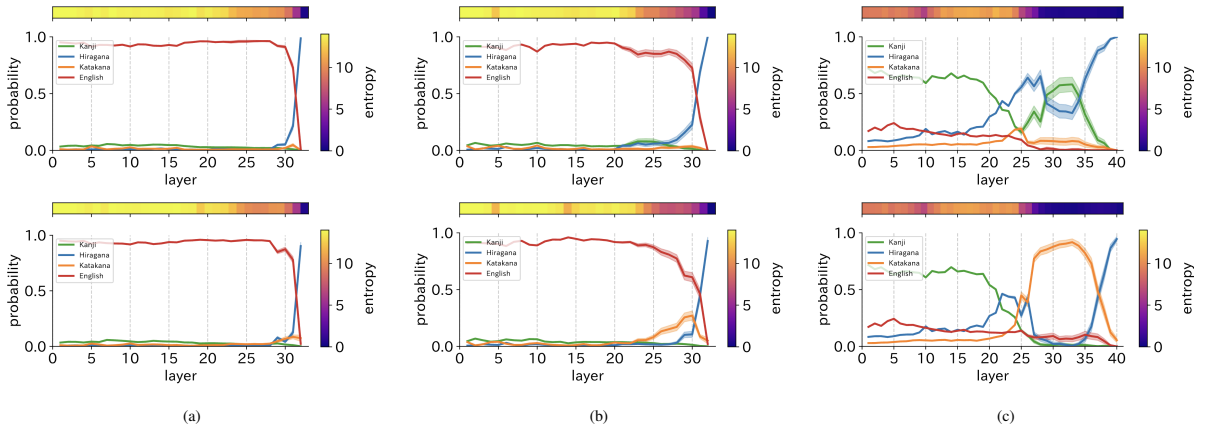


Figure 3: Script-type probability distributions for the three primary models: (a) Llama-3.1-8B-Instruct, (b) Llama-3.1-Swallow-8B-Instruct-v0.5, and (c) LLM-jp-3-13B-Instruct. Top: kanji-writable words. Bottom: loanwords.

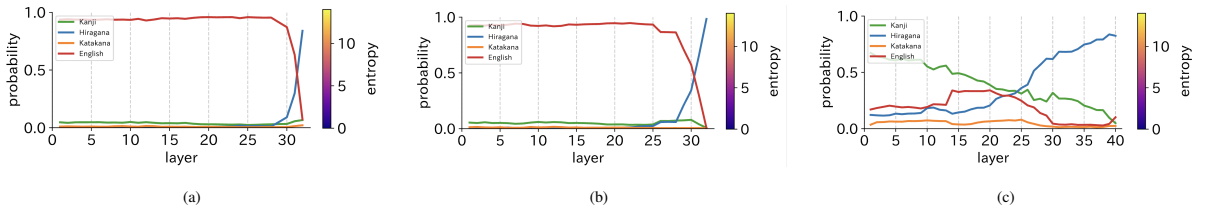


Figure 4: Hiragana sentence analysis (script-type probability distributions) for the three primary models. (a) Llama-3.1-8B-Instruct, (b) Llama-3.1-Swallow-8B-Instruct-v0.5, and (c) LLM-jp-3-13B-Instruct. See Figure 9 for corresponding heatmaps.

### 4.4 Discussion

The experimental results suggest that, in the analyzed Japanese-centric and kanji-rich models, intermediate vocabulary-space projections can favor kanji-containing tokens when the target lexical item conventionally has a kanji form, even though the required output is hiragana. This is a phenomenon analogous to "latent romanization" reported by Saji and Nakashole (2026) for English-centric models, suggesting a connection between the language distribution of training data and the internal representations. On the other hand, although the continual pre-training model is additionally trained on Japanese data, similar kanji-dominant intermediate representations are not observed in our experiments. This interpretation also accounts for the loanword results: when the conventional written form is katakana, the intermediate preference shifts toward katakana rather than kanji. Thus, latent kanji-fication can be understood as the kanji-specific case of a broader preferred-script tendency in the analyzed settings.

This result suggests that multiple factors may be involved, including tokenizer design, vocabulary coverage, training-data distribution, and representation geometry. A more detailed analysis of how these factors shape preferred-script tendencies remains future work.

## 5 Conclusion

We demonstrated that in Japanese LLMs, even when the output is in hiragana, latent kanji-fication occurs in which the corresponding kanji representations (e.g., "学習" for "がくしゅう") temporarily become dominant in intermediate layers. Together with the loanword results, this suggests that intermediate script preferences reflect the conventional script form associated with the lexical item.

Evaluating the practical effects of these intermediate script preferences on output quality, inference efficiency, and downstream task performance remains future work.

## Limitations

This study has several limitations. First, our analysis covers a limited slice of the model space, even though we observe latent kanji-fication in multiple models and at multiple scales.

Second, the initial candidate pairs were generated using Claude 4, and all final items were man-

ually inspected, filtered, and revised before inclusion, although this candidate-generation process may still introduce biases in the selection of words. Third, while we use logit lens as our primary analysis tool, it provides a descriptive readout of intermediate hidden states in each model's vocabulary space. More precise methods such as tuned lens or activation patching could provide complementary insights. Finally, the practical impact of latent kanji-fication on downstream task performance has not been evaluated in this work.

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## A Reproducibility Details

For the katakana-to-hiragana conversion task, we used the same prompt format for both kanji-writable words and loanwords. The model input consisted only of Japanese strings; romanizations and English glosses in Figure 2 are included only for readability and were not part of the model input. For each target item, the prompt contained four completed examples followed by one incomplete query:

> 原文: "katakana_1" - ひらがな: "hiragana_1"
> 原文: "katakana_2" - ひらがな: "hiragana_2"
> 原文: "katakana_3" - ひらがな: "hiragana_3"
> 原文: "katakana_4" - ひらがな: "hiragana_4"
> 原文: "target_katakana" - ひらがな: "

The logit-lens analysis is performed at this answer-initial position, immediately after the opening quotation mark of the hiragana field.

For the hiragana sentence analysis, we use a different prompt format:

> ひらがなのみで出力: "hiragana_sentence"

In this analysis, the hiragana sentence inside the quotation marks is included in the prompt. We analyze the token positions corresponding to the sentence, from immediately after the opening quotation mark to immediately before the closing quotation mark, and average script-class probabilities over these positions.

Each model is analyzed with its native Hugging Face tokenizer. We do not map outputs to a shared tokenizer. Script classes are defined separately for each model vocabulary by decoding each token id and applying Unicode-based rules. We use the following character ranges: Kanji [`\u4E00-\u9FFF`, `\u3400-\u4DBF`], Hiragana [`\u3040-\u309F`], Katakana [`\u30A0-\u30FF`, `\u31F0-\u31FF`, `\uFF66-\uFF9F`], and Alphabetic tokens matching `^[a-zA-Z\textbackslashs\_]+$`. Special tokens and empty decoded strings are excluded, and mixed-script tokens may belong to multiple classes. The main script-probability plots renormalize the

four script masses for visualization, whereas the kanji-fication degree uses the raw probability mass assigned to kanji-containing tokens.

## B Top-1 Exact Lexical Match Analysis

To examine whether intermediate kanji predictions correspond to the intended lexical items, we additionally compute a top-1 exact lexical match rate for kanji-writable words. For each target item, we manually specify its canonical kanji form. At each layer, we decode the top-1 token from the logit-lens distribution at the answer-initial position and count a match only when it exactly matches the canonical kanji form. The layerwise rate is the proportion of target items for which this exact match occurs.

Figure 5 shows the resulting rates. This analysis complements the kanji-fication degree: whereas the latter measures probability mass assigned to kanji-containing tokens, the exact match rate asks whether the top-1 token is the intended kanji word. The criterion is conservative, since partial matches, inflected forms, and related kanji words are not counted as matches.

## C Top-1 Token Heatmaps for Script Conversion Examples

Figures 6–8 show representative top-1 token heatmaps for the katakana-to-hiragana conversion task. These examples visualize the most likely token under the logit-lens readout at each layer for individual target words.

## D Top-1 Token Heatmaps for Hiragana Sentence Analysis

Figure 9 shows the Top-1 token heatmaps for the hiragana sentence analysis of the three primary models. In LLM-jp-3-13B-Instruct, kanji tokens such as “起き” (wake up) and “食べ” (eat) appear in intermediate layers, confirming the latent kanji-fication phenomenon.

## E Script Conversion Results for Additional Models

Figures 10–11 show the script-type probability distributions for Sarashina2-7B, Qwen3-8B-Base, Qwen3-Swallow-8B-SFT-v0.2, and Yi-6B-Chat on kanji-writable words and loanwords. The main point of comparison in these figures is not only whether hiragana becomes dominant in the final layers, but also which script occupies the intermediate layers before that final convergence. In particular, we compare whether kanji remains competitive for kanji-writable words, and whether the same models shift toward katakana when the target item is a loanword.

Qwen3-8B-Base shows a clear intermediate-layer kanji region for kanji-writable words, followed by a late transition to hiragana. This behavior is qualitatively similar to that of LLM-jp-3-13B-Instruct in the main text and is consistent with its relatively high kanji-fication degree in Table 1. Qwen3-Swallow-8B-SFT-v0.2 preserves the same broad pattern, but the intermediate kanji region is weaker and shorter, while the final transition to hiragana is sharper. On loanwords, both Qwen models move probability mass away from kanji and toward katakana, supporting the interpretation that latent kanji-fication depends on whether a natural kanji-written lexical alternative exists for the target word.

Sarashina2-7B is another strong positive case: for kanji-writable words, kanji remains substantial through much of the computation and yields to hiragana only near the end. This makes Sarashina2-7B the closest additional model to the Japanese-centric behavior observed in the main text. Yi-6B-Chat shows a different mixed pattern in which alphabetic tokens remain dominant for a large portion of the network while kanji retains non-negligible mass. This is compatible with the values in Table 1: the Chinese-centric model exhibits some sensitivity to kanji characters, but does not display the same strength or stability of latent kanji-fication as the Japanese-centric models.

## F Hiragana Sentence Analysis for Additional Models

Figures 12–13 show the hiragana sentence analysis results for Sarashina2-7B, Qwen3-8B-Base, Qwen3-Swallow-8B-SFT-v0.2, and Yi-6B-Chat. These figures should be read jointly: the line plots average script-type probabilities over token positions, whereas the heatmaps reveal whether the same tendency is shared across the sentence or driven by only a small subset of positions. Agreement between the two views provides stronger evidence that the intermediate representation is genuinely script-biased rather than an artifact of averaging.

Sarashina2-7B and Qwen3-8B-Base both reproduce the qualitative picture reported in Section 4.2. Sarashina2-7B keeps substantial kanji probability

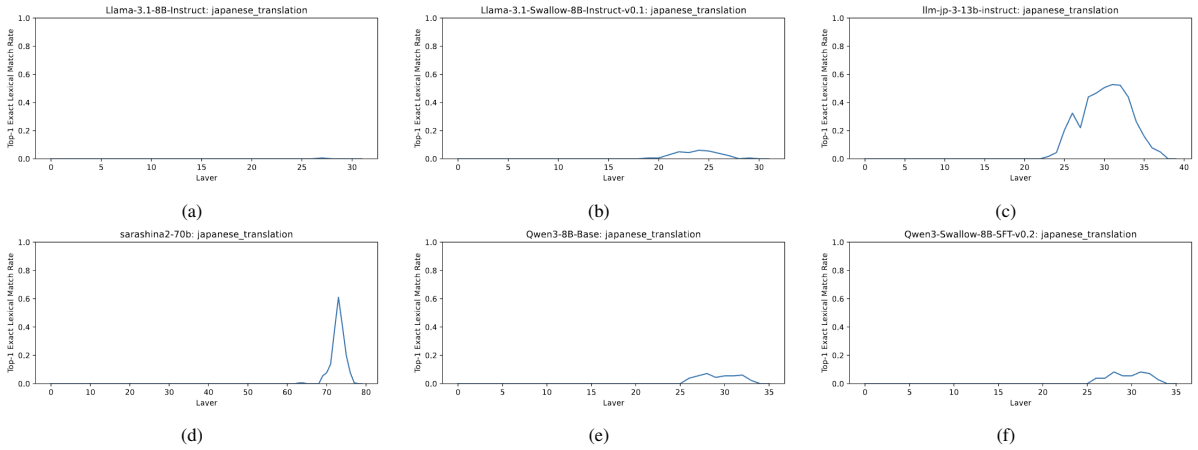



Figure 5: Top-1 exact lexical match rate by layer for kanji-writable words: (a) Llama-3.1-8B-Instruct, (b) Llama-3.1-Swallow-8B-Instruct-v0.5, (c) LLM-jp-3-13B-Instruct, (d) Sarashina2-70B, (e) Qwen3-8B-Base, and (f) Qwen3-Swallow-8B-SFT-v0.2. A target item is counted as a match only when the top-1 decoded token exactly matches its canonical kanji form.

over many layers and then transitions to hiragana near the output layers; the corresponding heatmap indicates that this transition is not restricted to a single token position. Qwen3-8B-Base shows a noisier trajectory, but again the sentence-level plot and token-level heatmap agree that intermediate representations are more kanji-heavy than in the English-centric baselines, especially before the final shift to hiragana.

Qwen3-Swallow-8B-SFT-v0.2 and Yi-6B-Chat occupy a weaker intermediate regime. For Qwen3-Swallow-8B-SFT-v0.2, the kanji signal is still visible but shorter-lived than in Qwen3-8B-Base, suggesting that Japanese adaptation of a multilingual base model does not automatically produce the same degree of latent kanji-fication as models whose pre-training is more strongly Japanese-centric. Yi-6B-Chat again falls between the English-centric and Japanese-centric cases: kanji remains visible for some positions, but the pattern is less coherent and the final transition to hiragana is later and less stable than in LLM-jp-3-13B-Instruct or Sarashina2-7B.

## G Results for Large-Scale Models

Figures 14–17 show the script conversion and hiragana sentence analysis results for large-scale models (32B–70B parameter range). These figures are intended to separate two questions: whether larger scale preserves a phenomenon that is already present in smaller models, and whether scale can create latent kanji-fication in model families where it is weak or absent. Because the compared models have different depths, the most relevant comparison is not the absolute layer index, but whether a distinct intermediate regime emerges before the final hiragana-dominant layers.

For the Japanese-centric and kanji-rich multilingual models, scale mainly strengthens or stabilizes the same qualitative behavior observed at smaller sizes. Sarashina2-70B keeps kanji and hiragana both active until very late layers, and Qwen3-32B-Base shows an even more pronounced kanji-dominant band in the script-conversion setting than its 8B counterpart. The sentence-level analyses in Figures 16 and 17 support the same interpretation: when the smaller model already exhibits latent kanji-fication, larger scale tends to sharpen or prolong that preference rather than remove it.

By contrast, the English-centric Llama-3.1-70B-Instruct and the continual pre-training model Llama-3.1-Swallow-70B-Instruct-v0.3 remain overwhelmingly alphabetic until the final few layers, just as in their 8B counterparts. Increasing scale therefore does not by itself induce latent kanji-fication. Qwen3-Swallow-32B-SFT-v0.2 and Yi-34B-Chat occupy an intermediate regime: both show non-trivial kanji mass in the middle layers, but their trajectories are less clean and less consistently kanji-dominant than those of Sarashina2-70B or Qwen3-32B-Base. Overall, the large-scale appendix supports the claim in Section 4.3 that scale amplifies pre-existing language- and vocabulary-dependent structure, rather than replacing it with a universal Japanese processing strategy.

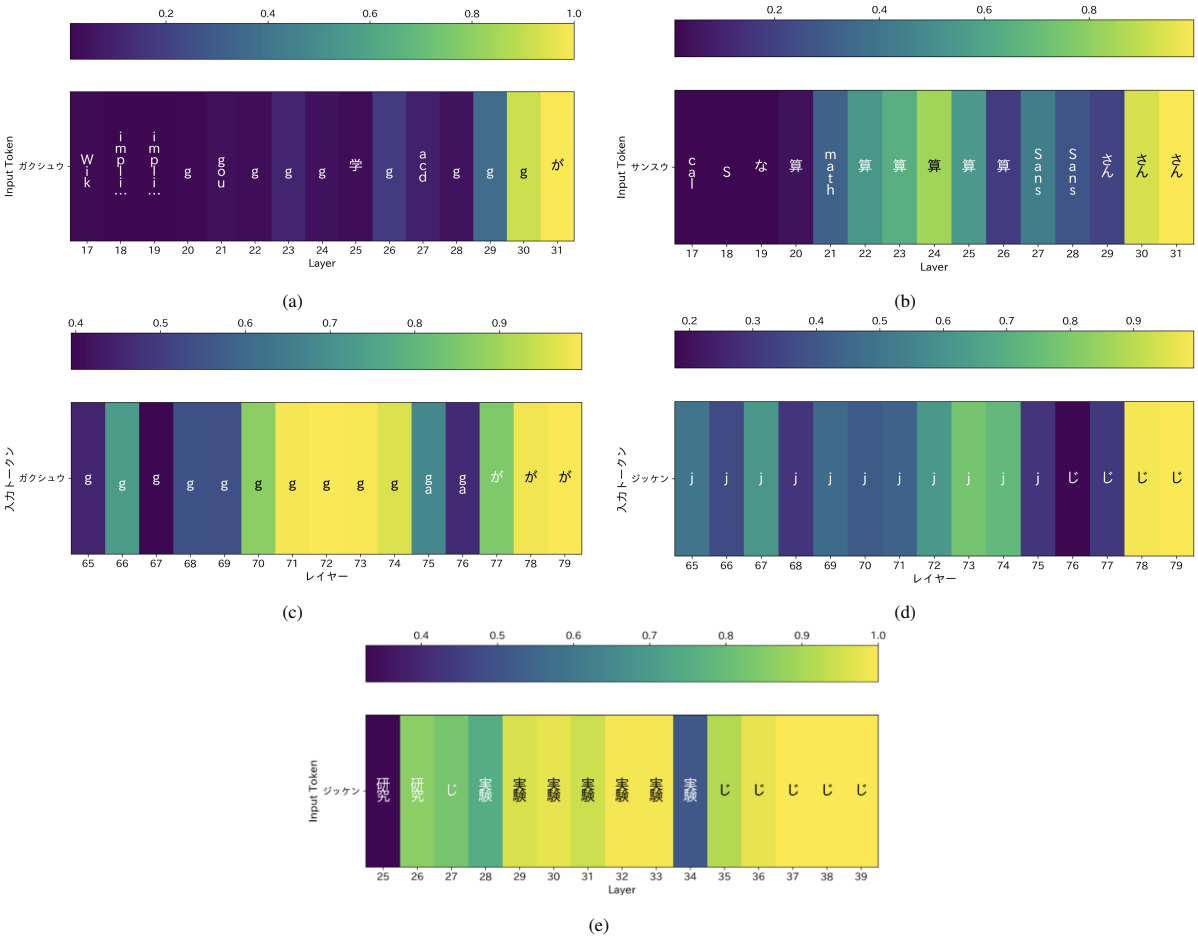



Figure 6: Top-1 token heatmaps for script conversion examples in the three primary models: (a) Llama-3.1-8B-Instruct, gakushuu; (b) Llama-3.1-8B-Instruct, sansuu; (c) Llama-3.1-Swallow-8B-Instruct-v0.5, gakushuu; (d) Llama-3.1-Swallow-8B-Instruct-v0.5, jikken; and (e) LLM-jp-3-13B-Instruct, jikken.

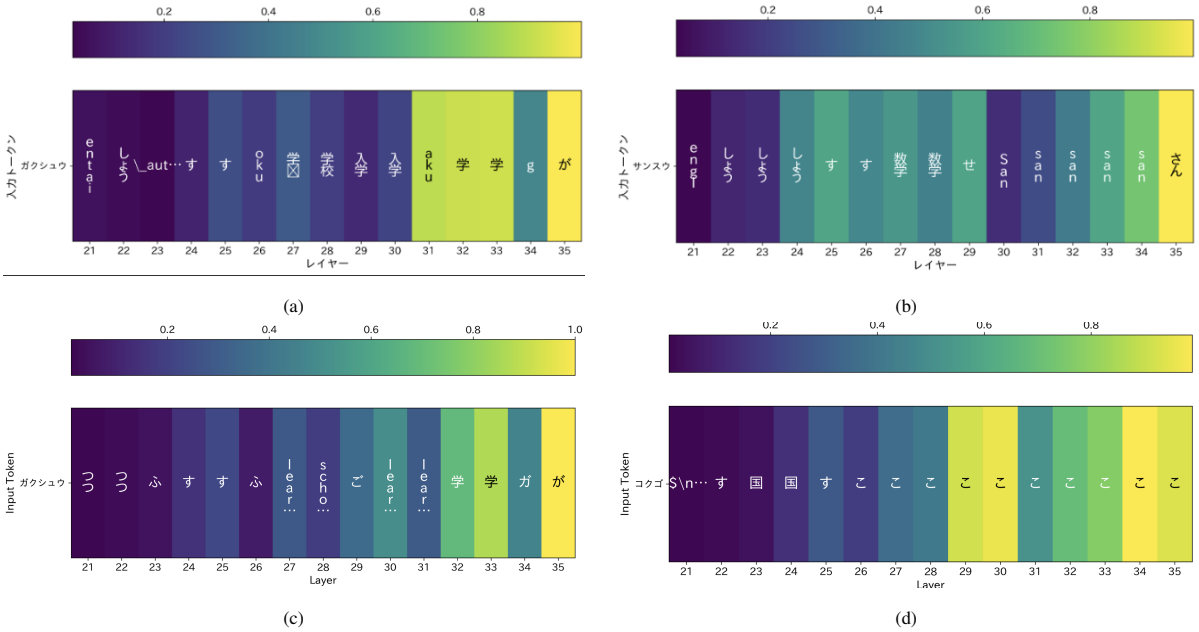



Figure 7: Top-1 token heatmaps for script conversion examples in Qwen3-based models: (a) Qwen3-8B-Base, gakushuu; (b) Qwen3-8B-Base, sansuu; (c) Qwen3-Swallow-8B-SFT-v0.2, gakushuu; and (d) Qwen3-Swallow-8B-SFT-v0.2, kokugo.

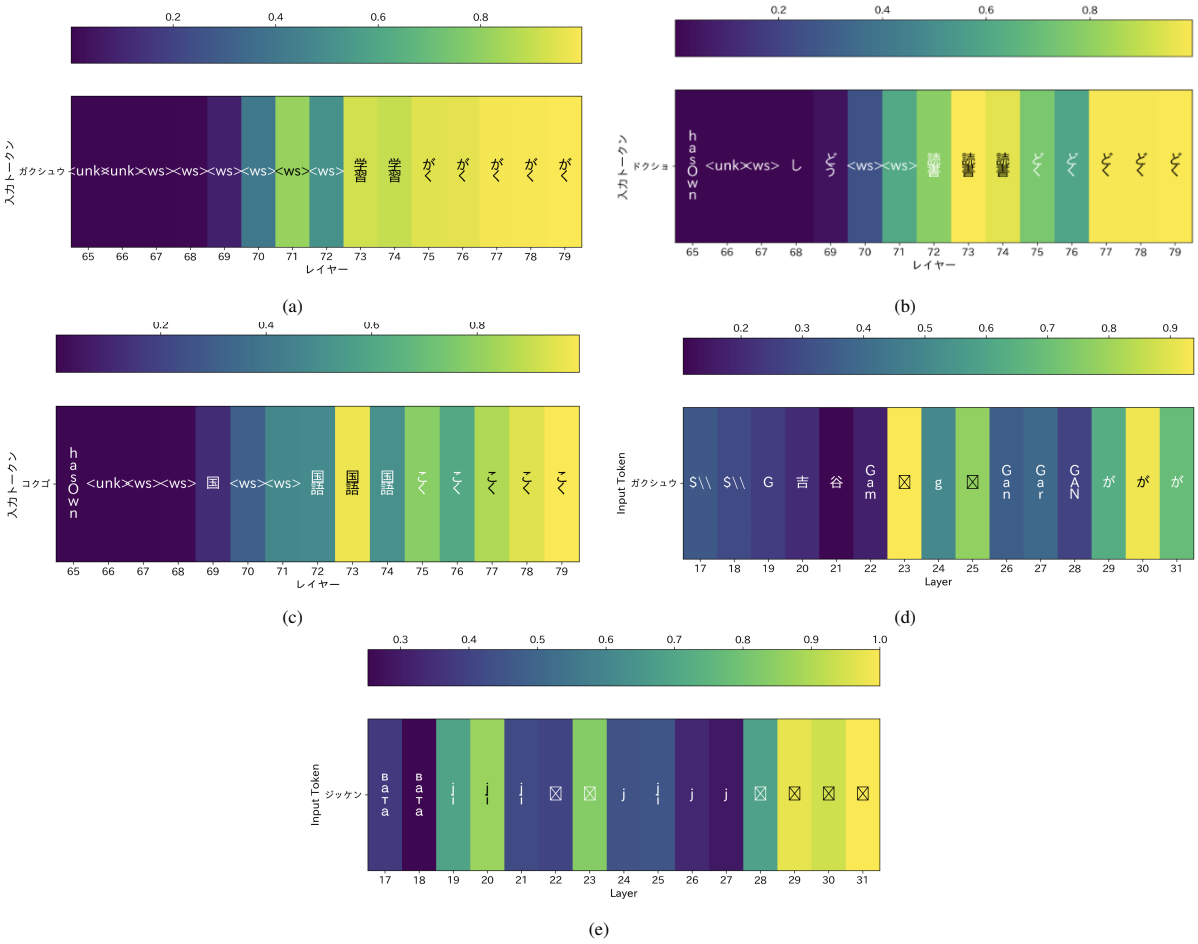
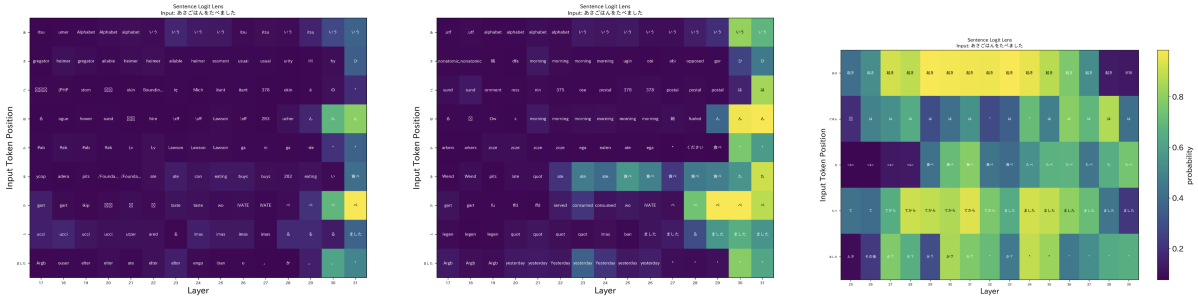
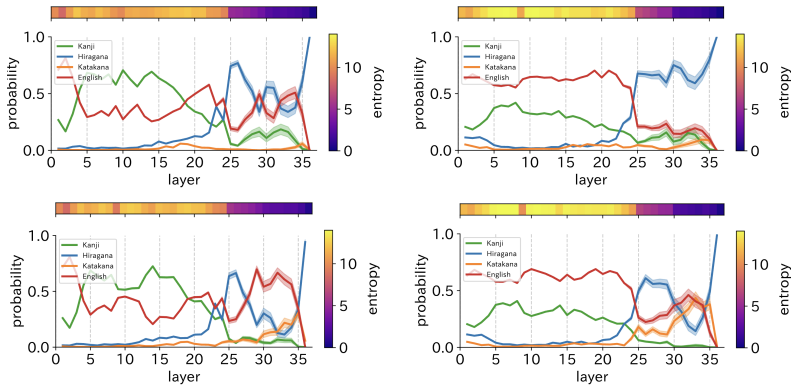



Figure 8: Top-1 token heatmaps for script conversion examples in Sarashina2-70B and Yi-6B-Chat: (a) Sarashina2-70B, gakushuu; (b) Sarashina2-70B, dokusho; (c) Sarashina2-70B, kokugo; (d) Yi-6B-Chat, gakushuu; and (e) Yi-6B-Chat, jikken.



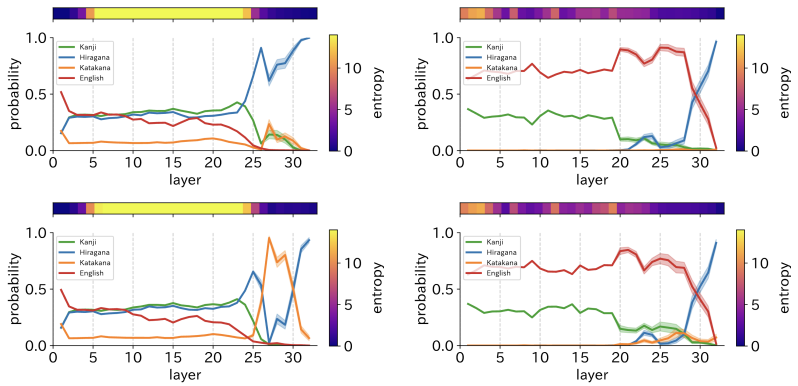

(a) (b) (c)

Figure 9: Top-1 token heatmaps for the hiragana sentence analysis: (a) Llama-3.1-8B-Instruct, (b) Llama-3.1-Swallow-8B-Instruct-v0.5, (c) LLM-jp-3-13B-Instruct.



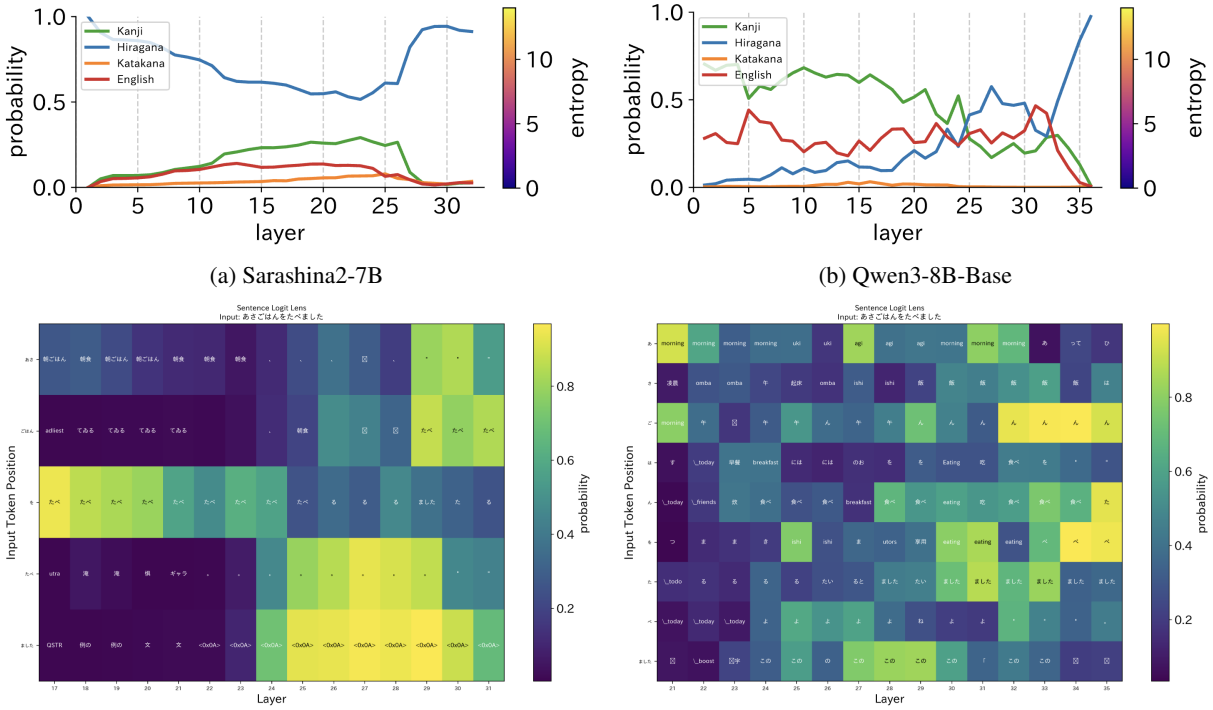

(a) Qwen3-8B-Base (b) Qwen3-Swallow-8B-SFT-v0.2

Figure 10: Script-type probability distributions for Qwen3 models. Top row: kanji-writable words. Bottom row: loanwords.




(c) Sarashina2-7B (d) Yi-6B-Chat

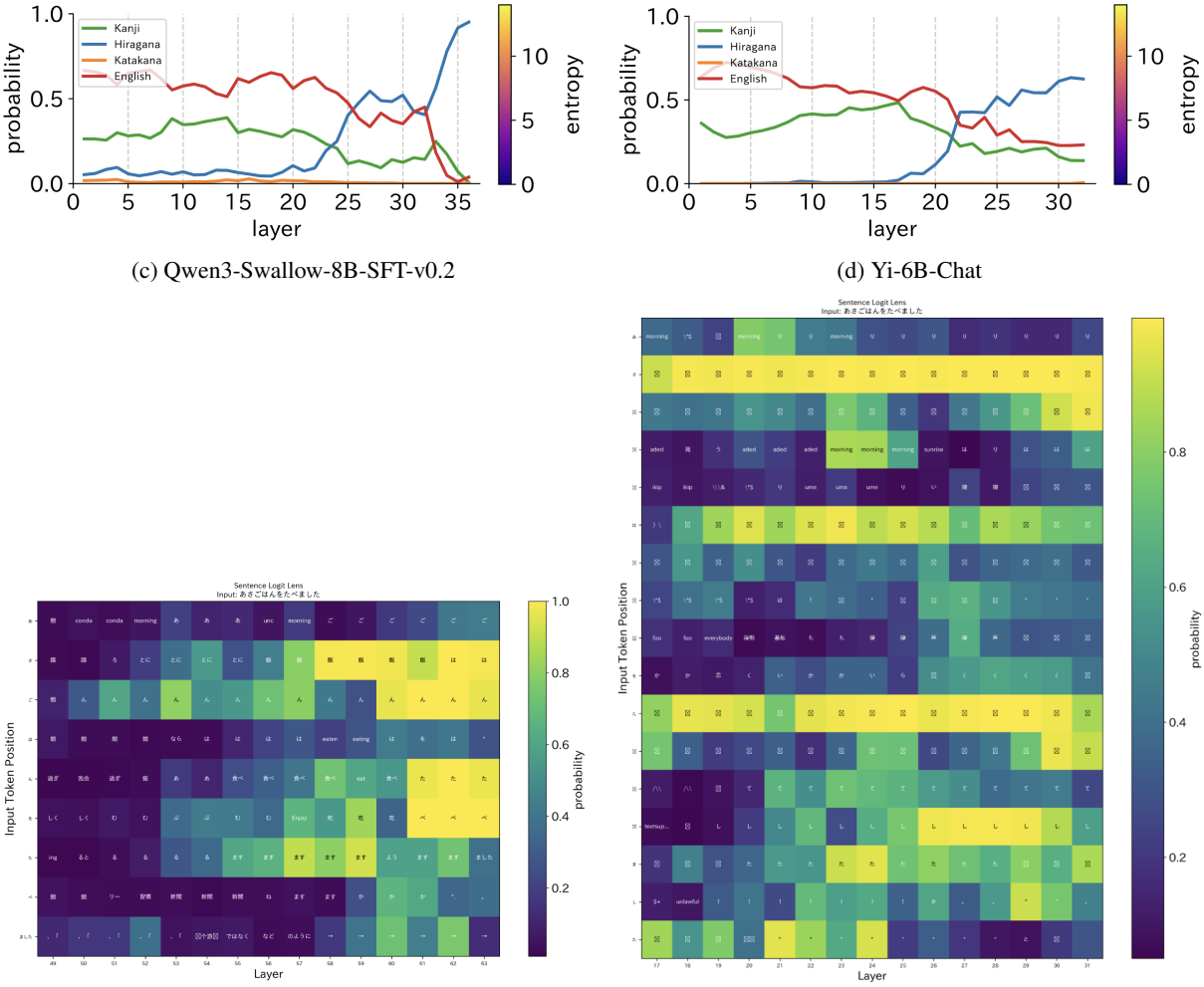
Figure 11: Script-type probability distributions for Sarashina2-7B and Yi-6B-Chat. Top row: kanji-writable words. Bottom row: loanwords.




(a) Sarashina2-7B

(b) Qwen3-8B-Base

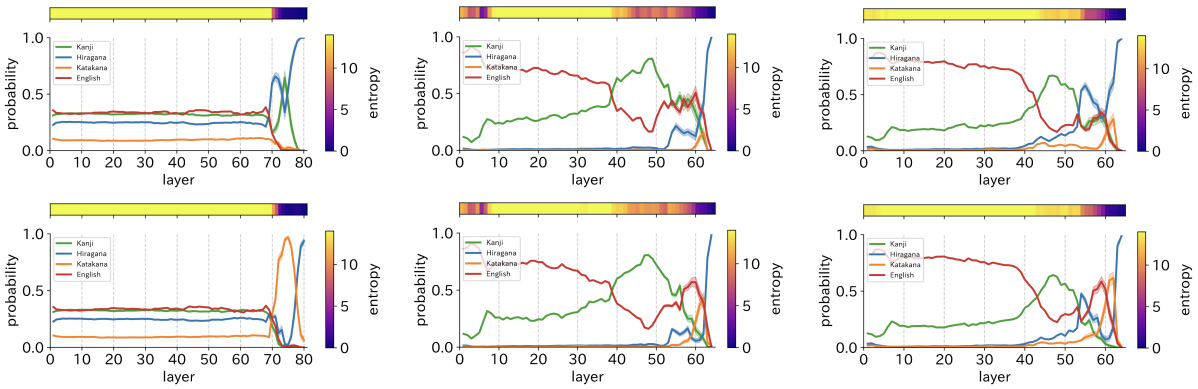
Figure 12: Hiragana sentence analysis: (a) Sarashina2-7B, (b) Qwen3-8B-Base. Top row: script-type probability distributions. Bottom row: Top-1 token heatmaps.




(c) Qwen3-Swallow-8B-SFT-v0.2

(d) Yi-6B-Chat

Figure 13: Hiragana sentence analysis: (c) Qwen3-Swallow-8B-SFT-v0.2, (d) Yi-6B-Chat. Top row: script-type probability distributions. Bottom row: Top-1 token heatmaps.

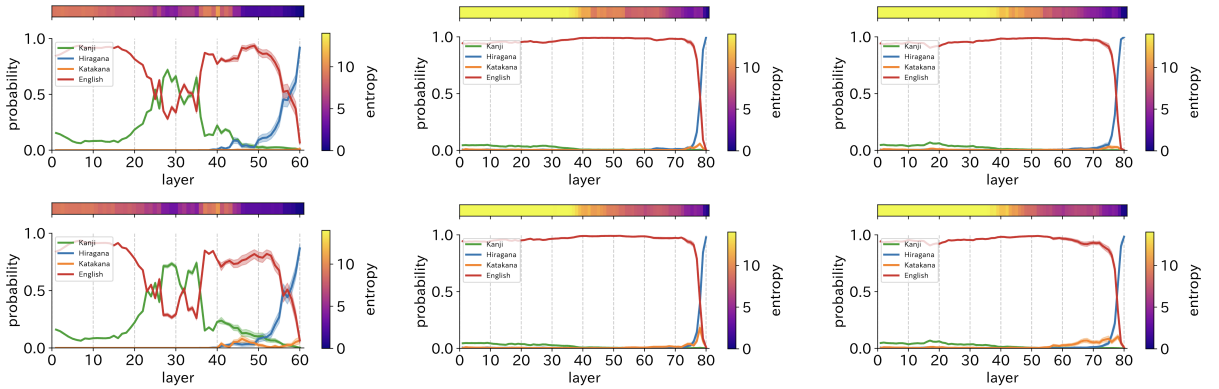



(a) Sarashina2-70B

(b) Qwen3-32B-Base

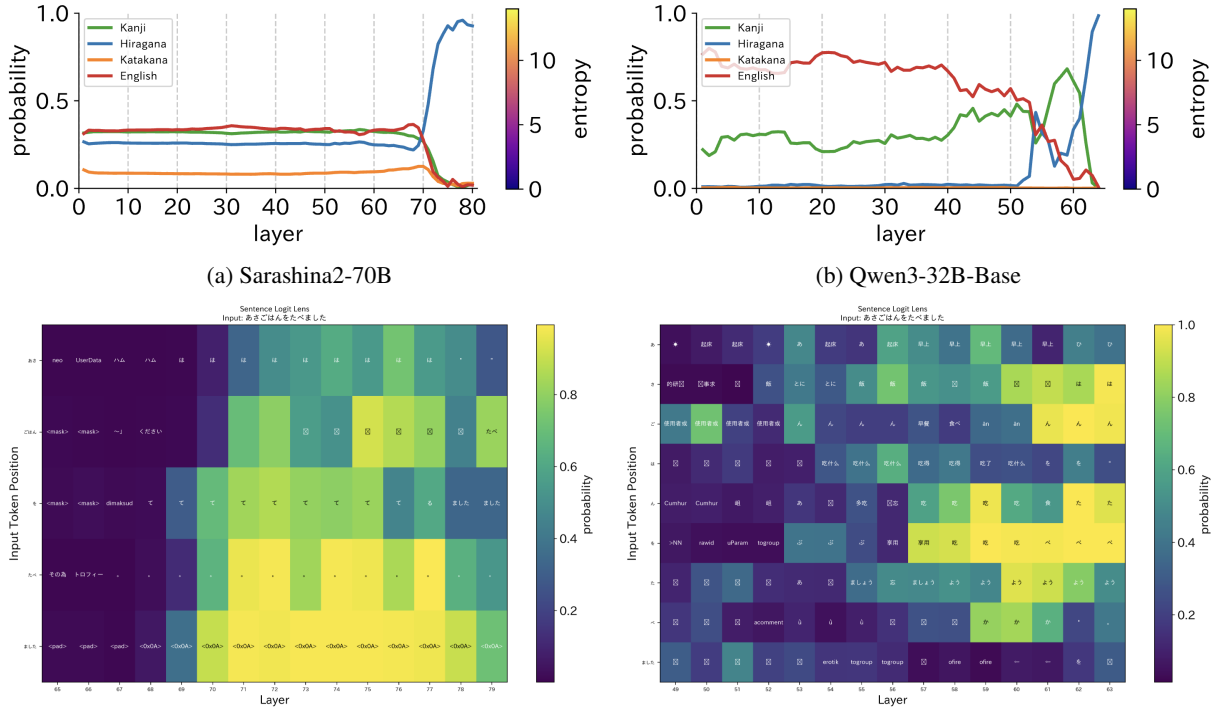
(c) Qwen3-Swallow-32B-SFT-v0.2

Figure 14: Script-type probability distributions for large-scale models (1/2). Top row: kanji-writable words. Bottom row: loanwords.



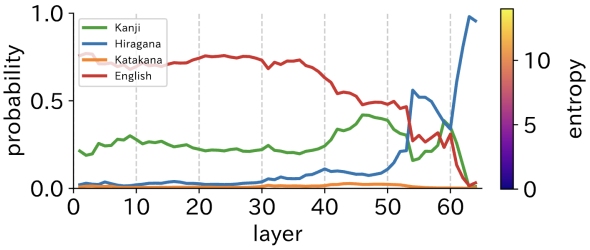

(d) Yi-34B-Chat (e) Llama-3.1-70B-Instruct (f) Llama-3.1-Swallow-70B-Instruct-v0.3

Figure 15: Script-type probability distributions for large-scale models (2/2). Top row: kanji-writable words. Bottom row: loanwords.

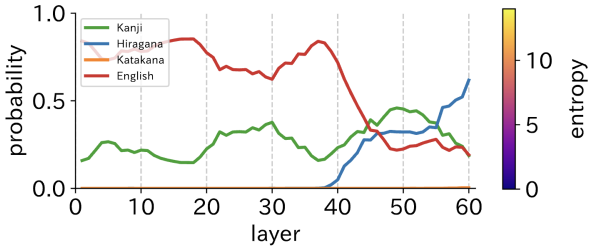



(a) Sarashina2-70B (b) Qwen3-32B-Base

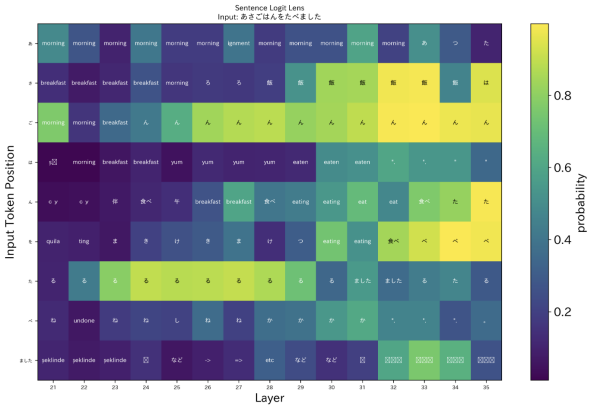
Figure 16: Hiragana sentence analysis for large-scale models (1/2): (a) Sarashina2-70B, (b) Qwen3-32B-Base. Top row: script-type probability distributions. Bottom row: Top-1 token heatmaps.




(c) Qwen3-Swallow-32B-SFT-v0.2




(d) Yi-34B-Chat



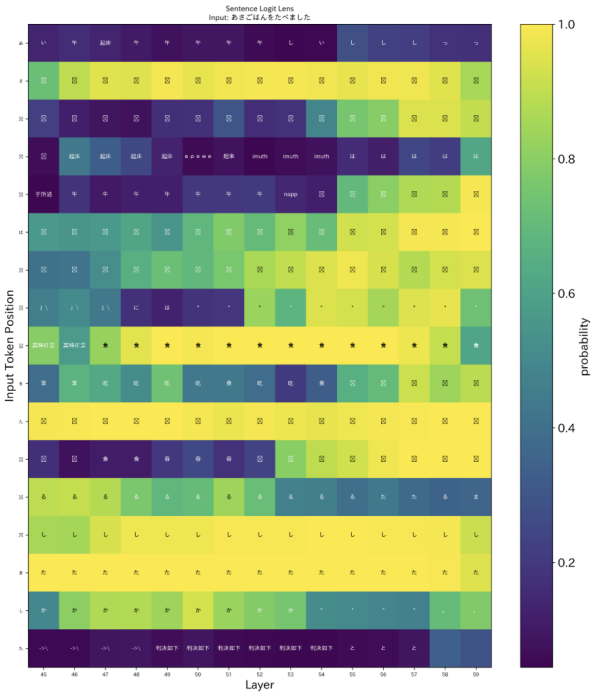




Figure 17: Hiragana sentence analysis for large-scale models (2/2): (c) Qwen3-Swallow-32B-SFT-v0.2, (d) Yi-34B-Chat. Top row: script-type probability distributions. Bottom row: Top-1 token heatmaps.