Where does In-context Learning Happen in Large Language Models?

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Abstract

Self-supervised large language models have demonstrated the ability to perform various tasks via in-context learning, but little is known about where the model locates the task with respect to prompt instructions and demonstration examples. In this work, we attempt to characterize the region where large language models transition from recognizing the task to performing the task. Through a series of layer-wise context-masking experiments on GPTNEO2.7B, BLOOM3B, LLAMA2-7B, LLAMA2-7B-CHAT, STARCODER2-3B and STARCODER2-7B on Machine Translation and Code generation, we demonstrate evidence of a "task recognition" point where the task is encoded into the input representations and attention to context is no longer necessary. We further observe correspondence between the low performance when masking out entire layers, and the task recognition layers. Taking advantage of this redundancy results in 45% computational savings when prompting with 5 examples, and task recognition achieved at layer 14 / 32 using an example with Machine Translation.

1 Introduction

In-context learning (ICL) refers to the phenomenon in which large generative pretrained transformers (GPTs) perform tasks with no gradient updates when shown task examples or descriptions in their context [13, 12]. There are many works on in-context learning which focused on *prompt-engineering*, treating GPT models as black boxes by focusing on which examples to provide in-context [47, 14, 19, 20, 51]. However, many of these works apply surface level interventions leaving the internal mechanism of task recognition in GPT models largely not understood.

In this work, we ask **where does in-context Learning occur** in GPT models? Our view of In-context Learning is that of “task recognition" not “task learning" [64, 41]. While in-context learning in GPT models appears to be generally applicable to any natural language task, to study task location, we focus on two tasks, Machine Translation (MT) and Code generation, as there is little to no ambiguity in evaluating whether the model has recognised the task. For MT, the model must generate tokens in a different language. For Code generation, the model must produce a working program which can be executed correctly. These two tasks are unlikely to be “learnt" from following patterns, and are more complex than a lookup in associative memory for simple Question-Answer tasks.

We focus on multi-head attention layers as a unit of study, as the self-attention mechanism is designed to allow the model to attend to it’s context during generation of the target sentence [54]. Using causal masking over different parts of the context we demonstrate that there exists a "task-recognition" point after which attention to the context is no longer necessary (Section 4). The potential implications are large computational savings when the context is several times longer than the test source sentence

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(Section 5). Having identified the layers in which "task recognition" occurs, we also conduct exploratory studies into the extent to which subsequent layers are either *redundant* or corresponding to the "task recognition" layers. Simple layer-wise masking shows that for smaller models, removing attention around the "task-recognition" layers can cause the model to fail to perform translation all-together, whereas layers towards the end of the model are much more redundant (Section 6.2).

Next, we observe that very lightweight fine-tuning of LoRA parameters [29] are most effective at earlier layers of the model compared to the later ones (Section 7.2). While there is not a strict 1-1 correlation in layers, this provides loose supports for the conjecture that earlier layers are more important for the task.

We further investigate the extent of MT *task redundancy* using differentiable L_0 regularisation to train discrete attention head gates (Section A.7). We find that around 10% of the attention heads can be masked, which indicates that the attention-heads themselves are not redundant, it is attention over all of the context that can be redundant. This fundamentally differs from the literature in supervised NMT where more than half of the attention heads can be pruned, and Transformers are highly specialised for MT [56, 38, 7].

2 Background

In-Context Learning was first demonstrated by [13] who showed that GPT-3 could be used to perform a huge variety of tasks without any task-specific parameters or training, by conditioning the model's generation on a *prompt* which included a few labeled examples of the task of interest. Since then, interest in using GPT models for ICL has grown significantly [39, 3, 61], with several recent works introducing methods such as instruction-tuning [49, 58] or chain-of-thought prompting [59] to improve downstream ICL accuracy. One key characteristic of In-context Learning is its reliance on prompt examples demonstrating the task that the model should carry out [46].

In-context Learning as Task Recognition. Ostensibly, ICL can work for nearly any task that can be defined or described in natural language, and therefore has potential for incredibly broad impact. However, ICL can often still underperform supervised fine-tuning [9], prompting research in analyzing the mechanisms underlying ICL. One line of work studies in-context learning with *linear* functions, typically linear regression, characterizing the learnability of these functions with ICL [33, 24] and even the learning algorithm a transformer uses [2, 17, 57]. A second body of work suggests that in-context learning locates *existing* latent concepts (tasks) which have been *already learnt* during pretraining [64, 60]. Notably, [52] describe function vectors which are robust to changes in context. [26] try to characterise the extent of task recognition from the pre-training data. Although there have been many studies on task recognition, our work presents a complementary perspective for task recognition, by demonstrating that there exists a point in the model's *layers* where the task has been located and causal self-attention onto the context is no longer needed for the model to perform the task.[2]

Transformer Layers and Self-attention as the Unit of Study. Many works study layers of the model as a natural unit of analysis for interpretability [28, 18, 42, 21, 8, 48]. We highlight some of the work which is more closely related to task performance. [63] study the layer-wise adaptability by a hidden-state variability ratio while [55] study evolution of representations in MT-supervised transformer models. [43] studies when model layers can be skipped by feeding intermediate representations into the final output layer of a pre-trained supervised model. Our work adds to this body of work by considering the perspective of when and where layers are responsible for task location in in-context learning models.

The self-attention mechanism specifically has been highlighted as a source of redundancy by many previous and concurrent works [10, 40, 27]. This is due to it's causal structure over the input symbols under the specific context of the input sequence within it's context window [45]. In this paper, we study a major source of causal redundancy in the input, the "prompt examples" that are provided as input-output demonstrations to the model for "in-context learning".

[2] In our experiments investigating where "task recognition" happens, we consider the actual "task performance" score as it could be possible to recognise the task as Machine Translation or Code generation, yet perform less well on it.

3 Data and Settings

Models We use GPTNEO2.7B [11], BLOOM3B [50], LLAMA2-7B and LLAMA2-7B-chat [53] in all of our experiments with Machine Translation. For code generation, we used LLAMA2-7B and LLAMA2-7B-chat, STARCODER2-3B and STARCODER2-7B[35].

GPTNEO2.7B has 32 layers and 20 heads, BLOOM3B has 30 layers and 32 heads, LLAMA2-7B has 32 layers and 32 heads and STARCODER2 has 30 layers and 24 heads. The checkpoints we use are from Meta AI (for LLAMA) and the transformers library [62]. Starcoder2 utilises grouped-query attention [1], while the rest of the models use "regular" multi-head self-attention.

GPTNEO was trained on The PILE [23], an 825GB text dataset which consists of roughly 98% English data. Despite being mostly monolingual, The PILE contains Europarl which GPTNEO was trained on at a document level (rather than a sentence level). Conversely, BLOOM was trained on the ROOTS corpus [32], a composite collection of 498 datasets that were explicitly selected to be multilingual, representing 46 natural languages and 13 programming languages. LLAMA training data consists primarily of common crawl, C4, wikipedia, stackexchange as major sources. STARCODER2 was trained on Github as well as Arxiv and Wikipedia. To our knowledge, there has not been any reports of sentence level parallel corpora in the training datasets of these models.

Data We test our models using two datasets, FLORES [25] for Translation and HUMANEVAL for Code generation. For FLORES, we experiment with `en`↔`fr` (main paper) and `en`↔`pt` (appendix). Prompt examples are drawn from the development set. We evaluate the generations using BLEU scores, following the implementation from [44]. For HUMANEVAL[15], we evaluate on the execution accuracy of the generated code using the Pass@1 metric. As HUMANEVAL does not have an explicit train set, the prompt set is drawn from the Mostly Basic Python Program (MBPP) dataset [4]. To account for example selection and ordering effects,[3] all inference runs were repeated with 5 randomly sampled prompt example sets.

Prompt Format Our prompts may consist of instructions, examples, both, or none. Importantly, we adopt *neutral* delimiters, "Q:" and "A:" to separate the prompt and the start of machine generated text. This ensures that the models do not have any information from the delimiters on what the task is and must recognise the task from examples. [4]

For the translation task, when no natural language instructions are used the model input will be `Q: {source_sentence} A:` Instructions are given in natural language and take the form: `Translate from {L1} to {L2}: Q: {source_sentence} A:`, where `L1 = English` and `L2 = French` if the source and target languages are English and French respectively. Examples are given after instructions, and similarly delimited by Q: and A:. See Appendix: Table 1 for an example.

For the code generation task, when no natural language instructions are used, the model input will be `Q: {program_description}`, where the `program_description` is Instructions are given in natural language and take the form: "Write a program for the following task:".

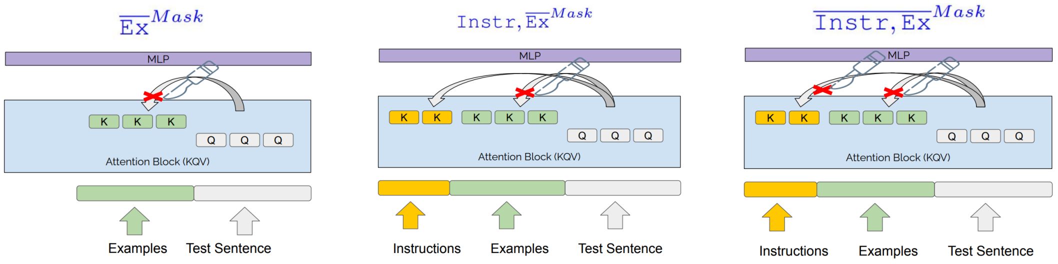
4 Where does In-context MT happen?

4.1 Analysis Methodology: Layer-from Context Masking

In-context learning differs from task-specific supervised learning in that, during test time, the desired task must be identified from the context first, then executed. At what stage in the feed-forward computation does a GPT-style model transition from an in-context learner to a translation model? To explore this question, we introduce *layer-from context-masking* which masks out all attention weights to the context (instructions or prompts) *from* a certain layer onwards (see Figure 1 for a graphical description).

[3] In-context learning models have been found to be sensitive to these order effects [36].

[4] In an earlier exploration, we found that supplying the model with language indicators only, e.g., "English:", "French:" or "English:", "Python:", was sufficient for strong models (llama7b, llama7b-chat, starcoder2-7B) to perform the task without seeing any instructions or examples in the context.



Name	$\texttt{Instr}$	$\texttt{Ex}$	
$\overline{\texttt{Ex}}^{Mask}\mathrm{Q}$	N	Y	Q: $\cdots$ A: $\cdots$ Q: $\cdots$ A:
$\texttt{Instr}, \overline{\texttt{Ex}}^{Mask}$	Y	Y	Translate French to English: Q: $\cdots$ A:$\cdots$ Q: $\cdots$ A:
$\overline{\texttt{Instr}, \texttt{Ex}}^{Mask}$	Y	Y	Translate French to English: Q: $\cdots$ A:$\cdots$ Q: $\cdots$ A:

Figure 1: Graphical explanation of Masking the Attention over Instructions and Examples. The leftmost image has instructions and masks examples ($\texttt{Instr}, \overline{\texttt{Ex}}^{Mask}$), while the right image has both instructions and examples masked ($\overline{\texttt{Instr}, \texttt{Ex}}^{Mask}$). In the table, the overline corresponds to the yellow highlights. N and Y refer to absence and presence of either Instruction of Examples. $\texttt{Instr}$: Instructions and $\texttt{Ex}$: Examples.

For Causal Decoder-only Transformer Language Models, given each position i, the Attention weight α_{ij} over context positions $j, j < i$ can be computed by a $\alpha_{ij} = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})_{ij}$. Each element in (QK^T) is the dot product between a query vector and key vector $q_i \cdot k_j$, where $q_i = W_q x_i, k_j = W_k x_j$ for trained weight matrices W_k and W_q.[5] We apply the attention mask over the context so that the attention score is $(q_i \cdot k_j) + m(j, \mathbf{u})$. Here $\mathbf{u}$ is the context that we wish to mask, and

$$m(j, \mathbf{u}) = \begin{cases} 0 & \text{if } x_j \notin \mathbf{u} \\ -\infty & \text{if } x_j \in \mathbf{u} \end{cases}$$

All masks operate from the j-th layer (ℓ_j) *onwards*, i.e. masking from ℓ_{20} means causally masking out attention to all context positions from $\ell_{20:n_\ell}$, where n_ℓ is the total number of layers. To construct Fig 2, we increment ℓ_j from 1 to n_ℓ and apply the set of masks $\{m(j, \mathbf{u})\}^{\ell_j:n_\ell}$ in each experiment and observe the performance of the model.

Under this causal masking treatment masking from layer ℓ, the model must rely on the hidden state representations of the target input sentence from layer $\ell + 1$ *only* and having self-attention on only the positions of the task test input *only* to complete the task; if the test input representations do not already encode the target task (e.g., Machine translation or Code generation) then the model will fail to generate the correct output.

In other words, the goal is to characterise where the model has "located" the task. In all experiments we mask the examples provided in the context, but to control for the effect of semantic instructions, we ablate over different treatments of the instructions by removing instructions entirely ($\overline{\texttt{Ex}}^{Mask}$), leaving them unmasked ($\texttt{Instr}\overline{\texttt{Ex}}^{Mask}$), or masking them together with the examples ($\overline{\texttt{InstrEx}}^{Mask}$). The overline notation indicates the context which are masking over (Figure 1).

We run this experiment for all layers in the model, $j = 1, \cdots, n_\ell$ and observe how task performance is affected, using 5 examples per prompt.

4.2 Results

We discuss the central findings of the paper: **Models do not need to maintain attention over all of the context across every layer to perform the task.**

[5] Readers should note that there is a W_k and W_q weight matrix for each layer and each attention head, but we omit the notation on this for readability.

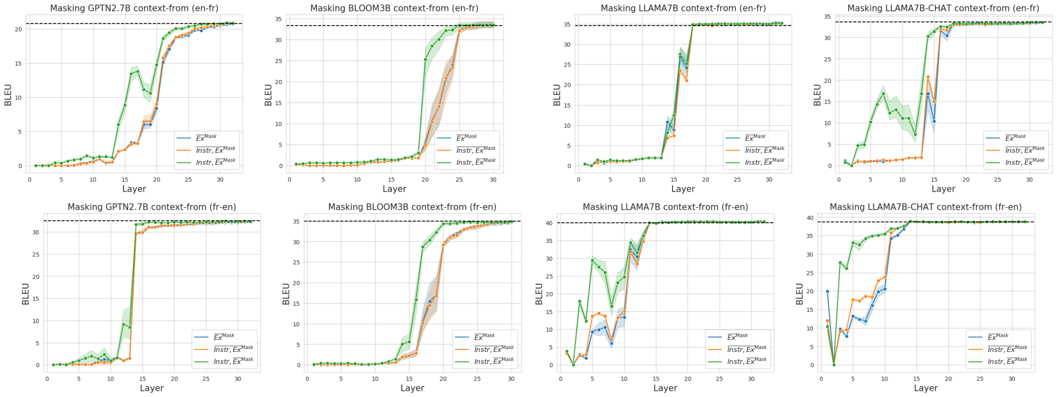


Figure 2: *Layer-from context-masking experiments* for GPTNeo2.7B, BLOOM3B, Llama7b, Llama7b-chat on `en` ↔ `fr`. The graphs show translation performance when masking contexts from the j^{th} layer onwards. Different lines indicate different treatments of the instruction, as described in Figure 1. The dashed black line is the performance when shown both examples and instructions without masking.

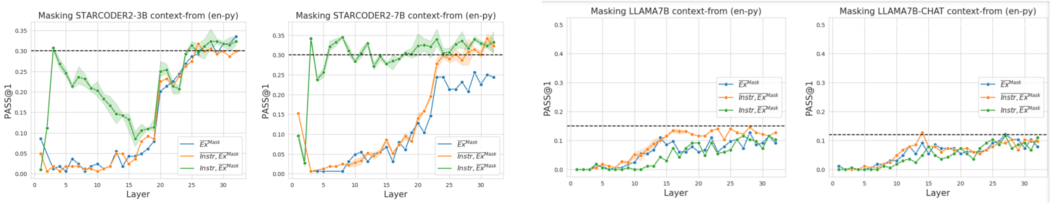


Figure 3: *Layer-from context-masking experiments* for Starcoder2-3B, Starcoder2-7B, Llama7b, Llama7b-chat on a text to code generation task. The graphs show translation performance when masking contexts from the j^{th} layer onwards. Different lines indicate different treatments of the instruction, as described in Figure 1. The dashed black line is the performance when shown both examples and instructions without masking.

In all models we observe that when applying masking from $\{m(j, \mathbf{u})\}^{\ell:n_\ell}$ over the context, performance plateaus before the final layer, i.e., when $\ell = n_\ell$. The results of our experiment for `en` → `fr` and `fr` → `en` are shown in Figure 3, and additional experiments for GPTNeo and Bloom on `en` → `pt` and `pt` → `en` are shown in Section A.2.

Different models reach this plateau point at different layers. In GPTNeo this point occurs around layer 25, in BLOOM this point occurs around layer 15-20, and in Llama models this occurs around layer 13-15. As English is the dominant language, as expected models can successfully perform translation into English upon earlier layers of masking, than translation out of English.

At this point, the models benefits only marginally, if at all, from attending to the context, suggesting most of the task "location" has already occurred.

There exists critical layers for task location. Prior to the task recognition point, around the middle layers of the models, moving the context mask up a layer results in a significant increase to performance. We consider these critical layers, as instead of a gradual increase in performance, we observe very steep jumps, accounting for more than 80% of the model's ceiling performance for that task. We conjecture that the model is locating the correct task during processing in these middle layers, after which the context is no longer necessary to perform the task.

Overall, our findings suggest a 3-phase process to in-context learning: in the first phase, moving the mask up makes little difference in performance, which is close to 0. This suggests that the context has not influenced task location at all. In the second phase, shifting the mask upwards makes a large difference in performance, suggesting that the model has started to locate the task but can improve significantly with more processing of the context. Finally, in the third phase, shifting the mask upwards again has little-to-no effect on the performance, suggesting that the model has fully recognized the task as translation and no longer requires the context to interpret the task.

4.3 Instruction-tuned vs Non-instruction Tuned Models

When comparing non-instruction tuned Llama2-7b vs instruction-tuned models Llama2-7b-chat, we do not observe any noticeable difference in where performance plateaus, i.e., where the model no longer requires attention over the context. This occurs around layers 18 for both Llama models in $\texttt{en} \rightarrow \texttt{fr}$ and around layer 14 for $\texttt{fr} \rightarrow \texttt{en}$. The main difference is that instruction-tuned model is able to achieve better performance in the earlier layers for the setting where instructions are present and examples are masked $(\texttt{Instr}, \overline{\texttt{Ex}}^{Mask})$. This is to be expected as these models are tuned towards following instructions.

Overall we find that the observation of task recognition layers and a task recognition point is present across both non-instruction tuned and instruction tuned models, and that this presents itself similarly in both types of models.

4.4 Do models have a distinct task recognition region regardless of the type of task? (Experiments on Code Generation)

For tasks that the model does not perform fluently, we do not observe a sharp increase at any particular layer. For instance, for code generation (HumanEval) where the llama2 model performs poorly, we can observe only a very gradual effect of masking the self-attention layers, and not a distinct increase as compared to the Llama2's performance on Translation.

However when we consider StarCoder2 while masking instructions or no instructions, i.e., the $\overline{\texttt{Instr, Ex}}^{Mask}$ and $\overline{\texttt{Ex}}^{Mask}$, we again see the same pattern demonstrating the task recognition phenomena on layer 19 of the 3B model, and layer 20-23 of the 7B model.

To understand Starcoder2's strong performance on the $(\texttt{Instr}, \overline{\texttt{Ex}}^{Mask})$ condition, investigations found that the instructions and the test prompt alone contain sufficient information for the model to recognise that the task is to generate a Python program, even though the model is not instruction tuned. This happens as the model is very specialised towards code generation and has a strong prior to generate python code given its prevalence in it's training data.

4.5 The Role of Instructions vs Examples

In separate experiments, we found that when shown only instructions and no examples, GPTNeo and Bloom models are unable to translate, and their performance is nearly at 0 BLEU Score. For GPTNeo and Bloom we see that the behavior of the model is similar when no instructions are present $(\overline{\texttt{Ex}}^{Mask})$ and when instructions are masked $(\overline{\texttt{Instr, Ex}}^{Mask})$. However, if the model is given complete access to instructions $(\texttt{Instr}\overline{\texttt{Ex}}^{Mask})$, it can use the intermediate processing of examples to reach baseline performance earlier.

5 Inference Efficiency

Speeding up transformer inference is of great interest to the community [22]. We highlight the potential of speeding up inference time as a direct consequence of identifying where task recognition occurs in the model and redundancy of self-attention processing. Our results indicate that we can achieve significant speedups in inference by removing the processing of context-tokens all-together after a certain point in the model, with little to no impact on downstream performance. Let ℓ_r be the r^{th} layer where we can mask out the attention of the context across subsequent layers and match the "ceiling" performance. Let k be the number of prompt examples, where each example consists of a pair of parallel sentences. Then, for a model with n_ℓ layers, the amount of processing in terms of speed and memory saved is approximately $(n_\ell - r)/n_\ell \times (k/k+1)$.

Using the example of Llama7b (32 layers) on $\texttt{en}{\rightarrow}\texttt{fr}$, we see from Figure 3 that the model is very close to it's ceiling score after processing the examples at layer 14 ($\ell = 14$). If we no longer need to process examples after $\ell = 14$, **under a prompt size of 5 the savings are approximately 45%.**

For instruction-tuned models which are typically deployed in production, even if we assume that no examples are provided, savings can be non-trivial as very long-form instructions are typically provided to the model in an attempt to control it's behavior (prompt engineering).

Although we had demonstrated the redundancy of self-attention over the input context, the significance of this computational savings extends to *all* components of the transformer during forward inference. Since all subsequent layers of forward inference no longer rely on computations on previous token positions, all processing related to those redundant token positions (from the task recognition layer onwards) can be effectively removed.

6 Characterising Redundancy in Layers

Recently, [48] found that many layers in pre-trained transformers can be dropped with little harm to downstream tasks; moreover, it is well known neural MT transformer models are known have several redundant heads which are not necessary during test time [56, 38, 7]. However, it is not clear if the same trends hold for *in-context MT* models, and how that redundancy is related to task location versus task execution. We focus on the task of `en` → `fr` in this set of experiments.

6.1 Attention to the Context vs Attention to the Input

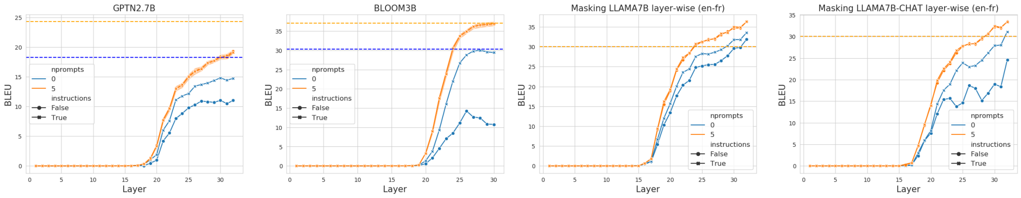


Figure 4: *Layer-from* experiments for GPTNEO2.7B, BLOOM3B, LLAMA and LLAMA7B-CHAT on `en` → `fr` when masking out from layer j onwards. Orange and blue dashed lines refer to the baselines (without masking) of 0 and 5 prompts with instructions. True/False refers to whether there are instructions provided (True) vs not provided (False). In view of the smaller models failure to translate at all under the format Q: A: with no examples, we adopt "English:", "French:" as delimiters instead of QA in generating this figure.

One possible explanation for the results in Figure 3 is that, rather than identifying the point at which the task is recognized (no longer requires attending to instructions and examples), we have identified the point at which the model no longer requires attending to *any* other input tokens (instructions, examples and source sentence). To explore this, we run experiments in the `en` → `fr` direction where we mask attention to *all inputs* from a certain layer onwards. This does not include masking over the text the model has generated.

We plot the results in Figure 4; we find that for all models, the layer at which attention can be fully removed is much higher than the layer at which we can remove attention to the context. For GPTNEO and LLAMA, translation performance is never comparable to the baseline with no masking. Conversely, when masking only the context, translation performance improves as early as layer 10 and plateaus at the no-mask baseline much earlier. This supports the interpretation that the curves we observe in Figure 3 are due to the model still requiring attention to the source sentence input.

We study the contributions of individual attention-layers by performing a simple *layer-wise* masking of all self-attention heads for a single layer. When we mask layer j, we are masking the *attention mechanism* of layer j, that is the MLP of layer j acts directly on the output of layer $j - 1$, rather than the output of the attention-head of layer j. Doing so allows us to study how *critical* each layer is, where *critical layers* is loosely defined as those that have a large negative impact when masked.

We plot results for each layer all models, using the three combinations of {0 examples, no instructions}, {5 examples, instructions}, {5 examples, no instructions} in Figure 5.[6]

[6] The combination of {0 examples, no instructions} is not meaningful as the model only receives "Q: <source sentence> A:" as the input and is not expected to do the translation task.

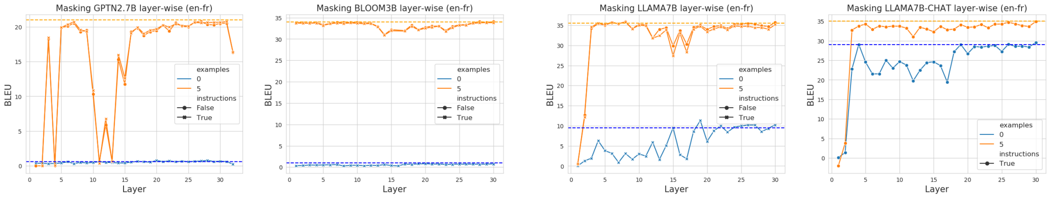


Figure 5: *Layer-wise masking* of self-attention heads for GPTNEO2.7B, BLOOM3B, LLAMA and LLAMA-CHAT on en $\rightarrow fr$. The orange and blue dotted lines refer to the baselines (without masking) of 0 and 5 prompts with instructions. True/False refers to whether there are instructions provided (True) vs not provided (False). We observe critical layers near the middle and redundant layers towards the end of the model.

6.2 Are “Critical" Layers Task Locating Layers?

In Section 4, we observed that there are layers for task location. In this section, we observe evidence that there are critical layers which correspond to the task locating layers, providing support for our earlier observations.

For instance for LLAMA7B en $\rightarrow$ fr, even in the scenarios when examples are provided, we can see a dip in performance around layer 15 to 18. Refering back to Figure 3, we see that this is where most of the task location with large jumps in performance had occurred.

For GPTNeo, we obseve a large set of contiguous layers which significantly decrease performance at around layer 10 to 15. This also corresponds to where most of the task location (large jumps in performance) had occurred for this model in Figure 3.

We note that the critical layers in different models have varying degrees of severity. It is not immediately clear why GPTNEO has such critical layers and suffers compared to the other models, although we note that this is unlikely to be due to size or model architecture as BLOOM is also around the same size as GPTNEO and performs more similarly to LLAMA. We suspect that it could be due to training data or some other factor related to the training dynamics but leave this for future work.

With regard to redundancy, we find that layers can be more safely removed towards the end without a noticeable loss in performance. We observe that for the less stable models, the model achieves close to baseline performance by layer-wise masking from ℓ_{15} for GPTNEO, ℓ_{26} for BLOOM and ℓ_{20} for LLAMA. This suggests that these later layers contain redundancy for translation.

Overall, observing redundancy in layers is not suprising. To explain why models can have redundant layers, we refer to [16] who identify a phenomena where attention heads attend almost exclusively to delimiter and separator tokens such as `[SEP]`, periods and commas. This is thought to act as a “no-op" as the value of such tokens in changing the current hidden representation is very small. Note that it is then possible to mask entire Transformer layers and still achieve a sensible output due to residual connections in the Transformer architecture at every layer.

7 Further Analysis

In the following sections, we focus on GPTNEO and BLOOM to conduct deeper analysis on the main phenomena presented in the paper.

7.1 Does the Number of Prompts Affect Task Recognition?

In Section 4 we study context-masking with a fixed number of prompts. However, it is not clear if the number of prompts affects how fast, layer-wise, the model is able to recognize the task. We plot these results for en$\rightarrow$fr in Figure 6, for both GPTNEO and BLOOM. In general, we find that the number of prompt examples has little effect on which layer the task is recognized at. While there is some variation in performance when the context is masked around the middle layers of the model, the final performance plateau occurs at the same layer regardless of the number of prompts.

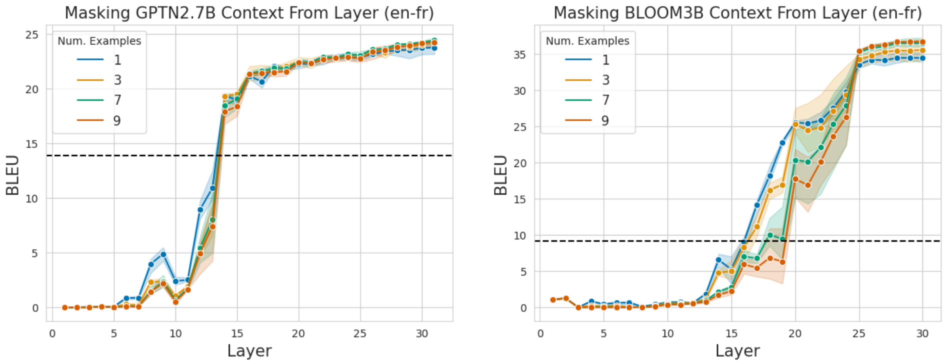


Figure 6: *Layer-from context-masking experiments* for GPTNeo and BLOOM on en → fr investigating number of examples in the $\overline{\texttt{Ex}}^{Mask}$ mask setting. The dashed black line refers to no instructions and no examples.

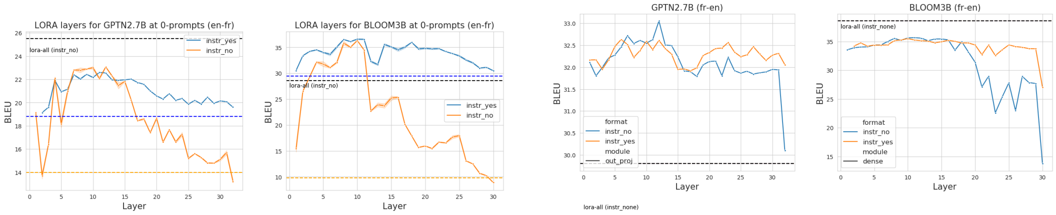


Figure 7: Performance of no-instructions trained Lora layers for GPTNeo and BLOOM on en↔fr. The dashed black line refers to training of all layers together, while the orange (test without instructions) and blue (test with instructions) dashed lines refers to no training. The layers which are most amenable to lightweight fine-tuning occur in the earlier layers before the "task recognition" point.

7.2 The Adaptability of Task Layers

Intuitively, the layers prior to "task recognition" should contain information about locating the MT task. To test this intuition, we further explore the adaptability of these layers by lightweight fine-tuning experiments. We trained a single Low-rank Adaptation matrix (LoRA; [29]) for each layer of the output projection while keeping the rest of the network frozen.[7] The model was shown parallel sentences as input, and layers were trained with no explicit translation instructions. We split the dev set of FLORES into 800 training examples and 200 dev examples. Note that this setup is designed to tune the layers for task location. It is highly unlikely that the model can learn translation knowledge from this small amount of supervision. The LoRA layers were trained for up to 50 epochs with early stopping patience$= 5$ and threshold$= 0.001$, with $\alpha = 32, r = 32$ and dropout$= 0.1$. The cross-entropy loss was computed only on the target sentence (see Section A.4 for details) and we used the best checkpoint on the 200 held out dev examples for evaluation.

While each layer can be trained to perform better than no fine-tuning at all, tuning different layers have different impacts on performance Figure 7. In particular, we find that high performing layers occur at the earlier to middle parts of the network, with the peak often occurring near the start of the "task-locating" layers from Section 4. In contrast to common fine-tuning wisdom, additional tuning on the later layers has a much smaller impact on final performance for en → fr.

7.3 Are There Specialised Attention Heads?

In Section 4, we found that the earlier part of the model is critical for *task location* from the prompt context, and in Section 6.2 we found both critical and redundant layers to the MT task. In this section, we increase the level of granularity to that of attention heads instead of layers.

A well established finding for supervised encoder-decoder MT models, is that up to 90% of the attention heads can be pruned while minimising fall in translation performance [56, 6, 38]. We note

[7] We also experimented with the training separate Key, Query and Value LoRA Layers but found this to be less effective.

that asking about the extent of pruning is a slightly ill-formed research question, as it depends on the type of pruning technique used. However broad trends of highly prunable models have been observed in the supervised MT paradigm. For instance, [5] studied attention-head importance for a broader set of ICL tasks, finding that the most important heads for ICL occur in the middle layers of the model. We train discrete attention head gates with L_0 regularisation for GPTNEO and BLOOM on `en` $\rightarrow$ `fr` (see Section A.5.1). Overall, we report that there are no "few" specialised heads, which directly contrasts with the literature on compression in supervised MT models [56, 38]. Potential reasons for this difference might be due to cross-entropy loss associated with task tuning for MT vs non-specific training on large corpora. We leave this as an open question for future work.

8 Conclusion

We demonstrate evidence that In-context Causal Decoder models locate their task at a specific layers during forward inference. To study this, we introduced causal masking of self-attention over the context from layer ℓ onwards (Section 4). The findings generalise across 4 models of different sizes and in both non instruction-tuned and instruction-tuned models. We further identify certain layers as task critical, and show that this corresponds to the task recognition point of the model (Section 6.2) and is not influenced by increasing number of examples (Section 7.1) shown to the models.

Our central finding that models do not need to maintain attention over all of the context across every layer has direct implications for inference efficiency of transformers, with estimated up to 45% cost-savings for llama model with 5 examples (Section 5).

Contrary to common fine-tuning wisdom, we show that it is sometimes beneficial to target middle layers for fine-tuning the model which could be associated with task recognition (Section 7.2). Finally, we trained attention head gates using differentiable L_0 regularisation (Section 7.3), and found that around 10% of attention heads can be masked. These are mostly distributed across the later layers of the model, providing some support for the idea that later layers are redundant. Although we have characterised this phenomena using Machine Translation and Code Generation, we believe that the broad findings are likely to generalise to other tasks.

8.1 Reproducibility

The Machine Translation dataset that we use, FLORES [25] and the code generation datasets HumanEval[15] are fully open-source and well-known in the community. All models are open-source and freely available on Huggingface [62]. We used models of "reasonable" size (3B and 7B parameters) that can be run with consumer or academic grade GPUs, making our work reproducible to most academic institutions.

8.2 Impact Statement (Ethics and Societal Consequences)

There are no known ethical concerns as these are exploratory studies on open-source LLMs.

8.3 Limitations (and Future Work)

- There is limited exploration of why different models exhibit varying behaviors in terms of their "task recognition point" and critical layers. Unfortunately, the differences are not due to easily observable hyperparameters like model size or architecture. To put in another way, why do large models exhibit different characteristics?
- This paper focuses on empirical analysis, and lacks a theoretical framework that could explain why this phenomena is being observed.

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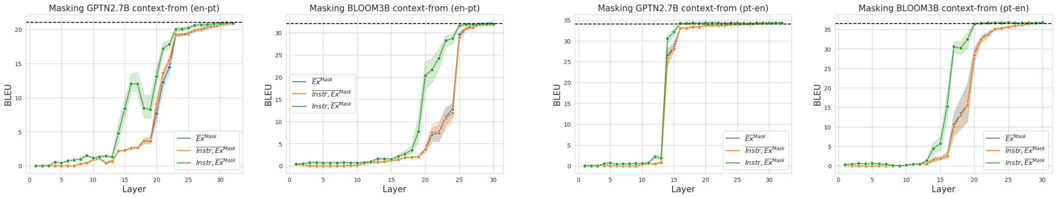

Figure 8: Context-masking and Layer-masking results on the **English** ↔ **Portugese** translation task. Critically, we see nearly identical trends to what we see in Figure 3 and Figure 5 on the English to French translation task, suggesting our results generalize across language pairs.

A Appendix

A.1 Prompt Format

Translate English to French.		
Q: A discomfort which lasts ..	A:	Un malaise qui dure
Q: HTML is a language for formatting	A:	HTML est un langage de formatage
...		...
Q: After you become comfortable with formatting ..	A:	

Table 1: A single continuous input sequence presented to the model for decoding a single test source sentence “After you become comfortable with formatting..”. Given the entire sequence as input, the model proceeds to generate the target sequence.

A.2 Additional Results on English & Portugese

In addition to the language pairs `en` → `fr` and `fr` → `en`, we also run experiments on English and Portugese language pairs, both `en` → `pt` and `pt` → `en`. Due to space limitations, we plot the results of those experiments here. Overall, we see largely identical trends on both directions of English and Portugese to what we observe on English and French translation tasks, leading us to conclude that our conclusions generalize across different translation tasks.

A.3 Autoregressive Decoder only Transformer

The transformer consists of stacked blocks of self-attention, which itself consists of smaller units of self-attention heads that are concatenated before being fed through a fully connected layer. In autoregressive decoder-only transformers, training and inference adopts a causal mask, where current positions are only able to attend to previous timesteps, instead of being able to attend to the entire input sequence. Unlike encoder-decoder NMT models where source and target sentence have separate processing transformer blocks, decoder-only means that the same model weights are both used to “encode" the source sentence and “decode" the target sentence in a single continuous sequence.

A.4 Training with Autoregressive Translation

The original language modeling objective in GPT training involves predicting the entire input token sequence which consists of both the source and target sentence (shifted by 1 position). We found this to produce slightly worse results than only minimising the negative log likelihood of predicting the target sentence to be translated, and not the entire sequence. We consider this autoregressive translation training.

A.5 L_0 Attention Gate Training

Training Details For Section A.7, We train using Adam Optimizer ($\beta_1 = 0.9, \beta_2 = 0.999$) with a batch size of 32, and learning rate of 0.001, early stopping patience of 10 and threshold of 0.01. We initialise attention head gates to be 1 instead of random or 0.5 as this leads to faster convergence. We experiment with two different training settings, the `0-prompts Train` setting and the `5-prompts Train` setting. As described in Section A.4, we train the model by predicting only the target sentence, conditioned on the context. In the 0-prompt setting, the context consists of the instructions and the source sentence to be translated. In the 5-prompt setting, the context consists of the instructions, 5 prompt examples, and the source sentence to be translated.

In the `0-prompt` setting, the conditional prefix consists of the instructions and the source sentence to be translated. In the `5-prompt setting`, the conditional prefix consists of the instruction, 5 source target sentence pairs, and the source sentence to be translated.

Data We used the first 10,000 lines of `en`→`fr` from WMT06 Europarl [31] for training.[8] To test the generalisability of trained attention head gates, we use a different test domain, FLORES [25] to reflect the scarcity of in-domain data. We also test an additional language direction `en`→`pt` in FLORES to see if training can generalise across languages.

Training Details We train using Adam Optimizer ($\beta_1 = 0.9, \beta_2 = 0.999$) with a batch size of 32, and learning rate of 0.001. We use a large early stopping patience of 10 and threshold of 0.01, and train for up to 100 epochs. This is due to the nature of L_0 training; we do not expect performance to improve over many iterations and would like the attention gates to keep training as long as there is no large loss in performance. We initialise attention head gates to be 1 instead of random or 0.5 as this leads to much faster convergence and better performance. For the regularisation weight λ, we search over a hyperparameter set of $\{0.1, 0.01, 0.001, 0.0001\}$ and found 0.01 performs best on the validation set.

A.5.1 L_0 head masking experiments.

Additional experiments on L0 head masking in the en→ fr direction.

A.5.2 Training Attention Head Gates with L_0 regularisation

For a scalable approach to pruning, we opt to train self-attention head gates following [56] using the technique of differentiable L_0 regularization [34]. Let the attention head gates $g \in \mathbb{R}^{n_h \times n_\ell}$ be a set of trainable parameters, where n_h is the number of attention heads per layer, and n_ℓ is the number of layers. Let the original output of each attention head be v_j, gated outputs $\tilde{v}_j$ are obtained by elementwise multiplication of the gate value g_j, i.e., $\tilde{v}_j = g_j \odot v_j$. For $\{(x, y)\}^n$ source sentence (x) and target sentence (y) training pairs, a model f and loss function $\mathcal{L}$, L_p regularisation adds a λ weighted penalty associated with the complexity of the parameters. [9] The L_0 loss is non-differentiable as it involves raw counts of parameters. As a work around, g can be approximated with random variables drawn from a Binary concrete distribution [37, 30].[10] We refer the reader to [34] for the relevant technical exposition. Details of training are provided in Section A.5.

A.5.3 Generalisability of L_0 gate training

We experiment with `0-prompts` and `5-prompts` in training and using $\lambda{=}0$ (no regularisation) and $\lambda{=}0.01$. L_0 training for the `0-prompts` shows some gains for the 0-prompts test case, and with no loss on the 5-prompts test case (Table 2). Notably, this persists in `en` → `pt`, a different language direction from training.

The robustness of translation performance under multiple testing conditions (number of prompts, datasets, language directions) gives some confidence that the trained discrete attention head gates from L_0 support a general ability to translate (Table 2). In contrast, the soft attention head gates without regularisation ($\lambda = 0$) appear to overfit as they perform well on some conditions but deteriorate in others.

We observe that `0-prompt` training for $L_0(\lambda = 0.01)$ also outperforms `5-prompts` which is slightly suprising since `5-prompts` has more information in the prefix to locate the translation task.

[8] Data available from `https://www.statmt.org/europarl/`

[9] L_2 regularisation has the effect of reducing the magnitude of all g, L_1 regularisation has the effect of reducing the magnitude of several attention heads to a very small value (but not exactly 0), while L_0 regularisation has the effect of driving g values to exactly 0.

[10] The class of Concrete distributions was invented to work around the problem of automatic differentiation of stochastic computation graphs.

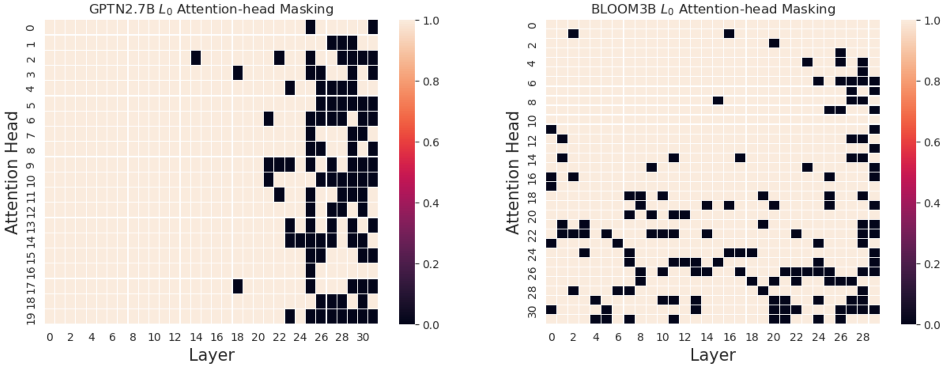

Figure 9: Visualisation of attention head masks for GPTNeo and BLOOM, learned with $L_0(\lambda = 0.01)$ regularisation under a `0-prompt train` scheme in `en` → `fr`. A value of 0 (in black) indicates that the attention head is effectively masked out by the trained attention gate. Around 10% of attention heads are masked out i.e., redundant, with a majority of them occuring at the later layers for GPTNeo and distributed across layers for BLOOM. `fr` → `en` is availble in Section A.5.1

	Base	`0-prompts`		`5-prompts`		Base	`0-prompts`		`5-prompts`	
		$\lambda=0$	$\lambda=.01$	$\lambda=0$	$\lambda=.01$		$\lambda=0$	$\lambda=.01$	$\lambda=0$	$\lambda=.01$
0-prompts	18.3	21.4	20.1	18.9	19.3	6.7	15.7	8.6	13.2	6.4
5-prompts	24.3	24.5	24.1	23.6	24.2	25.9	19.6	25.8	24.3	26.0
	Train: `en`→`fr`, Test: `en`→`fr`					Train: `en`→`fr`, Test: `en`→`pt`				

Table 2: Performance when using trained attention head gates for L_0 with regularisation $\lambda = .01$. $\lambda = 0$ refers to training without regularisation. `0` and `5` prompts were used in the context for training. We highlight values which are greater or worse than 0.5 BLEU points from baseline. Note that as these are compression experiments, we do not expect L_0 to perform better than baseline.

One possibility is that the model overfit to the Europarl domain where the training prompts were drawn from.

A.6 Qualitative Analysis of Layer-wise Masking

GPTNeo Masking $\ell_{4:8}$ results in a drop in performance for the 0-prompt setting but not the 5-prompt setting (Figure 5), which suggests that $\ell_{4:8}$ are **not** related to the processing of prompt examples. We emphasise that this interpretation mostly holds at an aggregate level and is not strictly for each instance. For Test Instance ID 575, the model still generates a copy of the English source sentence up to the masking of ℓ_{25} for the 0-prompts without instructions setting (Table 4). This suggests that uncertainty over the task is maintained across layers even though the contributions towards *task location* may be greater from specific layers.

Bloom is observed to be more robust to masking of layers; suggesting that task location is more distributed. For the 5-prompt setting, the performance only decreases very slightly. For the 0-prompt setting, we observe that similar to GPTNeo, performance drops when masking out the middle layers. At the aggregate level, Bloom appears to still be translating (> 0 BLEU) even when layers are masked. However we observe that the drop in performance is due to around 40 to 50% of the test sentences scoring < 5 BLEU points. There is a clear failure to translate, not simply producing poorer translations.

layer	id	lang	BLEU	text
1	600	cy	0.00	uffose
1	575	ca	0.00	B marriages{
2	600	et	0.00	sses room (I
2	575	no	0.00	NaN
3	600	fr	1.90	C'est la même chose que l'on a fait avec les virus.
3	575	fr	88.44	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
4	600	no	0.00	NaN
4	575	no	0.00	NaN
5	600	fr	78.78	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
5	575	fr	72.98	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent toujours à un dinosaur.
6	600	fr	78.78	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
6	575	fr	60.29	Mais il y a beaucoup de choses à propos de oiseaux qui ressemblent encore à un dinosaur.
7	600	fr	13.94	Hershey et Chase ont implanté leur propre gène dans un bactérie.
7	575	fr	72.98	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent toujours à un dinosaur.
8	600	no	0.00	NaN
8	575	fr	88.44	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosau.
9	600	no	0.00	NaN
9	575	fr	82.82	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent toujours à un dinosaure.
10	600	no	0.00	NaN
10	575	en	2.73	But there are a lot of things about birds that still look like a dinosaur.
11	600	en	4.78	Hershey and Chase used phages, or viruses, to implant their own DNA into a bacterium.
11	575	en	2.73	But there are a lot of things about birds that still look like a dinosaur.
12	600	no	0.00	NaN
12	575	no	0.00	NaN
13	600	no	0.00	NaN
13	575	fr	35.75	Mais il y a beaucoup de choses que je ne comprends pas.
14	600	en	4.78	Hershey and Chase used phages, or viruses, to implant their own DNA into a bacterium.
14	575	en	2.73	But there are a lot of things about birds that still look like a dinosaur.
15	600	fr	76.48	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bacillus.
15	575	en	2.73	But there are a lot of things about birds that still look like a dinosaur.
16	600	fr	78.78	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
16	575	fr	70.18	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent toujours comme un dinosaurof.
17	600	fr	82.32	Les Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans une bactérie.
17	575	fr	88.44	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
18	600	fr	78.78	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre génome dans un bactérie.
18	575	fr	66.38	Mais il y a beaucoup de choses sur les oiseaux qui aussi ressemble à un dinosaures.
19	600	fr	59.33	Les héritiers de Hershey et de Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
19	575	fr	47.91	Mais il y a beaucoup de choses à propos de les oiseaux qui ressemblent toujours à un dinosaur.
20	600	fr	48.82	Hershey et Chase ont utilisé les phages, ou les virus, pour implanter leur propre gène dans un bactérie.
20	575	en	2.73	But there are a lot of things about birds that still look like a dinosaur.
21	600	fr	78.78	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
21	575	fr	88.44	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
22	600	fr	48.82	Hershey et Chase ont utilisé les phages, ou les virus, pour implanter leur propre gène dans un bactérie.
22	575	fr	88.44	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaurof.
23	600	fr	78.78	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
23	575	fr	88.44	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
24	600	fr	78.78	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre génome dans un bactérie.
24	575	fr	62.72	Mais il y a beaucoup de choses à propos de les oiseaux qui ressemblent encore à un dinosaur.
25	600	fr	78.78	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
25	575	fr	88.44	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
26	600	fr	78.78	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
26	575	fr	88.44	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
27	600	fr	66.28	Hershey et Château ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
27	575	fr	88.44	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
28	600	fr	78.78	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
28	575	fr	88.44	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
29	600	fr	59.33	Les héritiers de Hershey et de Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
29	575	fr	88.44	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaurof.
30	600	fr	78.78	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
30	575	fr	88.44	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
31	600	fr	78.78	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
31	575	fr	88.44	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
32	600	fr	6.44	Les héritiers de Hershey et de Chase ont été capables de l'implanter dans un bactérie.
32	575	fr	51.52	Mais il y a beaucoup de choses sur les oiseaux que sont encore aussi vus comme un dinosaures.

Table 3: 0-prompts with instructions, masking layer by layer of GPTNEO2.7B

layer	id	lang	BLEU	text
1	575	no	0.0	NaN
1	600	no	0.0	NaN
2	575	NaN	0.0	,
2	600	no	0.0	NaN
3	575	fr	2.3	C’est pas un oiseau, c’est un dinosaur.
3	600	fr	0.8	[phare] Phare, phare, phare, phare, phare, phare, phare, phare, phare, phare, phare, ...,
4	575	en	2.7	"I think it’s a dinosaur, I think it’s a dinosaur."
4	600	fr	2.6	Les virus, c’est-ce qu’on dit? C’un mot? C’est pas un mot? C’un mot? C’un’un? ...
5	575	fr	42.9	Mais il y a beaucoup de choses à propos de oiseaux qui ressemblent toujours comme un dinosaur.
5	600	fr	73.6	L’Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
6	575	fr	53.8	Mais il y a beaucoup de choses à propos de oiseaux qui ressemblent toujours à un dinosaure.
6	600	fr	74.9	Les Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
7	575	fr	76.2	Et il y a beaucoup de choses sur les oiseaux qui ressemblent toujours à un dinosaure.
7	600	fr	83.8	Les Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre ADN dans un bactérie.
8	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosau.
8	600	fr	83.8	L’usine Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre ADN dans un bactérie.
9	575	en	1.5	The bird is a dinosaur.
9	600	fr	33.9	Les hémoglobine et Chase utilisent les phages, ou les virus, pour implanter leur propre gène dans un bactérie.
10	575	en	2.7	But there are a lot of things about birds that still look like a dinosaur.
10	600	fr	11.4	Les phages, ou virus, ont implanté leur propre gène dans un bactérie.
11	575	en	2.6	I think it’s a good idea to have a little bit of a bird in your pocket.
11	600	en	0.0	The French have a saying: "The French have a saying: "The French have a saying: "The French have a saying:...
12	575	en	2.7	But there are a lot of things about birds that still look like a dinosaur.
12	600	en	1.7	The bacterium was then able to use the phage to infect other bacteria.
13	575	en	2.7	But there are a lot of things about birds that still look like a dinosaur.
13	600	fr	18.7	L’entreprise Hershey a utilisé des phages pour implanter leur propre DNA dans leur bactérie.
14	575	en	2.7	But there are a lot of things about birds that still look like a dinosaur.
14	600	en	4.8	Hershey and Chase used phages, or viruses, to implant their own DNA into a bacterium.
15	575	fr	3.0	C’est pas un truc de poulet, c’est un truc de poulet.
15	600	fr	35.7	L’université de Paris-Sud a utilisé des phages, ou viraux, pour implanter leur propre gène dans un bacillus.
16	575	en	2.7	But there are a lot of things about birds that still look like a dinosaur.
16	600	fr	74.9	Les Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre génome dans un bactérie.
17	575	en	2.7	But there are a lot of things about birds that still look like a dinosaur.
17	600	fr	82.3	Les Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans une bactérie.
18	575	en	2.7	But there are a lot of things about birds that still look like a dinosaur.
18	600	fr	74.9	Les Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre génome dans un bactérie.
19	575	fr	44.2	Mais il y a beaucoup de choses à propos de oiseaux qui ressemblent toujours à un dinosaur.
19	600	fr	59.3	Les héritiers de Hershey et de Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
20	575	en	2.7	But there are a lot of things about birds that still look like a dinosaur.
20	600	fr	46.4	Les Hershey et Chase ont utilisé les phages, ou les virus, pour implanter leur propre gène dans un bactérie.
21	575	en	2.7	But there are a lot of things about birds that still look like a dinosaur.
21	600	fr	74.9	L’usine Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
22	575	en	2.7	But there are a lot of things about birds that still look like a dinosaur.
22	600	fr	56.3	Les Hershey et Chase ont utilisé les phages, ou les virus, pour implanter leur propre ADN dans un bactérie.
23	575	en	2.7	But there are a lot of things about birds that still look like a dinosaur.
23	600	fr	82.9	L’Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre ADN dans un bactérie.
24	575	fr	60.3	Mais il y a beaucoup de choses à propos de oiseaux qui ressemblent encore à un dinosaur.
24	600	fr	37.0	L’usine Hershey et Chase utilisaient les phages, ou les virus, pour implanter leur propre génome dans un bactérie.
25	575	en	2.7	But there are a lot of things about birds that still look like a dinosaur.
25	600	fr	74.9	Les Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
26	575	fr	71.6	Mais il y a beaucoup de choses à propos de oiseaux qui ressemblent encore à un dinosaure.
26	600	fr	73.6	L’Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
27	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaurof.
27	600	fr	63.0	Les Hershey et Château ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
28	575	fr	44.2	Mais il y a beaucoup de choses à propos de oiseaux qui ressemblent toujours à un dinosaur.
28	600	fr	74.9	Les Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
29	575	fr	87.0	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaurofrench:
29	600	fr	53.4	L’entreprise de la filière Hershey a utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
30	575	fr	82.8	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent toujours à un dinosaure.
30	600	fr	74.9	Les Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
31	575	fr	82.8	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent toujours à un dinosaure.
31	600	fr	59.3	Les hémoglobins de Hershey et de Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
32	575	fr	67.5	Mais il y a beaucoup de choses sur les oiseaux qui aussi ressemblent à un dinosaurof.
32	600	fr	6.7	L’Hershey et le Chase ont été capables de l’implanter leur propre gène dans un bactérie.

Table 4: 0-prompts without instructions, masking layer by layer of GPTNEO2.7B

layer	id	lang	BLEU	text
1	902	en	0.0	: of
1	575	en	0.0	of
2	902	en	0.0	of(n, very very- ofS First
2	575	da	0.0	f(
3	902	fr	100.0	Les scènes sont affichées sur les pyramides et les différentes pyramides sont éclairées.
3	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
4	902	en	0.0	the, the French, the French, the English, the, the, the, the, the, the, the, the, the, the,
4	575	no	0.0	NaN
5	902	fr	65.9	Les scènes sont affichées sur les pyramides et les différents pyramides sont éclairés.
5	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
6	902	fr	100.0	Les scènes sont affichées sur les pyramides et les différentes pyramides sont éclairées.
6	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
7	902	fr	100.0	Les scènes sont affichées sur les pyramides et les différentes pyramides sont éclairées.
7	575	fr	100.0	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaure.
8	902	fr	100.0	Les scènes sont affichées sur les pyramides et les différentes pyramides sont éclairées.
8	575	fr	100.0	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaure.
9	902	fr	65.9	Les scènes sont affichées sur les pyramides et les différents pyramides sont éclairés.
9	575	fr	100.0	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaure.
10	902	fr	100.0	Les scènes sont affichées sur les pyramides et les différentes pyramides sont éclairées.
10	575	fr	100.0	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaure.
11	902	fr	1.4	Fondamentalement, vous afficherez des annonces pour proposer votre aide, arpenterez les quais, ...
11	575	fr	1.3	Fondamentalement, vous afficherez des annonces pour proposer votre aide, arpenterez les quais, ...
12	902	fr	100.0	Les scènes sont affichées sur les pyramides et les différentes pyramides sont éclairées.
12	575	fr	42.5	Mais il y a beaucoup de choses qui ressemblent à un dinosaur.
13	902	fr	34.5	Les scènes sont déclarées sur les pyramides et les pyramides sont déclarées sur les pyramides.
13	575	fr	5.5	Les oiseaux sont des animaux, mais ils sont aussi des êtres humains.
14	902	fr	100.0	Les scènes sont affichées sur les pyramides et les différentes pyramides sont éclairées.
14	575	fr	73.3	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent à un dinosauresque.
15	902	fr	64.0	Les scènes sont affichées sur les pyramides et les pyramides différents sont éclairés.
15	575	fr	26.7	Mais il y a beaucoup de choses à propos de la façon dont les oiseaux se ressemblent, même si c'est un peu plus tard.
16	902	fr	100.0	Les scènes sont affichées sur les pyramides et les différentes pyramides sont éclairées.
16	575	fr	76.7	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore comme un dinosaures.
17	902	fr	100.0	Les scènes sont affichées sur les pyramides et les différentes pyramides sont éclairées.
17	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
18	902	fr	65.9	Les scènes sont affichées sur les pyramides et les différents pyramides sont éclairés.
18	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosauresque.
19	902	fr	65.9	Les scènes sont affichées sur les pyramides et les différents pyramides sont illuminés.
19	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
20	902	fr	65.9	Les scènes sont affichées sur les pyramides et les différents pyramides sont éclairés.
20	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
21	902	fr	100.0	Les scènes sont affichées sur les pyramides et les différentes pyramides sont éclairées.
21	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
22	902	fr	64.0	Les scènes sont affichées sur les pyramides et les pyramides différents sont éclairés.
22	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosauroide.
23	902	fr	65.9	Les scènes sont affichées sur les pyramides et les différents pyramides sont éclairés.
23	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
24	902	fr	78.3	Les scènes sont affichées sur les pyramides et les différents pyramides sont éclairees.
24	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
25	902	fr	100.0	Les scènes sont affichées sur les pyramides et les différentes pyramides sont éclairées.
25	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
26	902	fr	65.9	Les scènes sont affichées sur les pyramides et les différents pyramides sont éclairés.
26	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
27	902	fr	100.0	Les scènes sont affichées sur les pyramides et les différentes pyramides sont éclairées.
27	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
28	902	fr	65.9	Les scènes sont affichées sur les pyramides et les différents pyramides sont éclairés.
28	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
29	902	fr	65.9	Les scènes sont affichées sur les pyramides et les différents pyramides sont éclairés.
29	575	fr	100.0	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaure.
30	902	fr	78.3	Les scènes sont affichées sur les pyramides et les différents pyramides sont éclairees.
30	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
31	902	fr	65.9	Les scènes sont affichées sur les pyramides et les différents pyramides sont éclairés.
31	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
32	902	fr	65.9	Les scènes sont affichées sur les pyramides et les différents pyramides sont illuminées.
32	575	fr	67.5	Mais il y a beaucoup de choses sur les oiseaux qui aujourd'hui ressemblent à un dinosauro.

Table 5: 5-prompts with instructions, masking layer by layer of GPTNeo2.7B

layer	id	lang	BLEU	text
1	600	tl	0.0	*- ing
1	575	en	0.6	fl.of,
2	600	en	1.6	in " " - (–, -, - (es," " " so " whats " whats" " between whats –what e,
2	575	en	2.3	" ",what awaited ico " " " "_, .
3	600	fr	86.6	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans une bactérie.
3	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
4	600	en	0.3	the, etc.
4	575	ro	0.0	are: are: are: are: are: are: are: are: are: are: are: are: are: are: are: are: are: ...
5	600	fr	76.5	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bacille.
5	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
6	600	fr	88.1	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre ADN dans un bactérie.
6	575	fr	62.7	Mais il y a beaucoup de choses à propos de les oiseaux qui ressemblent encore à un dinosaur.
7	600	fr	88.1	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre ADN dans un bactérie.
7	575	fr	100.0	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaure.
8	600	fr	85.7	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre ADN dans un bacillus.
8	575	fr	100.0	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaure.
9	600	fr	78.8	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
9	575	fr	100.0	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaure.
10	600	fr	30.1	En gros, vous mettre en place des phages, ou viraux, pour implanter leur propre gène dans un bactérie.
10	575	fr	100.0	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaure.
11	600	fr	1.3	Fondamentalement, vous afficherez des annonces pour proposer votre aide, arpenterez les quais, aborderez les personnes nettoyant leurs yachts, ...
11	575	fr	1.4	Fondamentalement, vous afficherez des annonces pour proposer votre aide, arpenterez les quais, aborderez les personnes nettoyant leurs yachts, .
12	600	fr	12.4	Les phages sont utilisés pour implanter leur propre gène dans un virus.
12	575	fr	36.8	Mais il y a beaucoup de choses qui semblent être des dinosaures.
13	600	fr	4.3	Les phages sont des virus qui sont implantés dans la cellule d'un organisme.
13	575	fr	5.5	Les oiseaux sont des animaux, mais ils sont aussi des êtres humains.
14	600	fr	74.4	Hershey et Chase ont utilisé des phages, ou virus, pour implanter leur propre ADN dans un bactérie.
14	575	fr	73.3	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent à un dinosauresque.
15	600	fr	62.6	Hershey et Chase ont utilisé des phages, ou virus, pour implanter leur propre gène dans un bacille.
15	575	fr	26.7	Mais il y a beaucoup de choses à propos de la façon dont les oiseaux se ressemblent, même si c'est un peu plus tard.
16	600	fr	85.7	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre ADN dans un bacillus.
16	575	fr	76.7	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore comme un dinosaures.
17	600	fr	85.7	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre ADN dans un bacille.
17	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosauresque.
18	600	fr	85.7	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre ADN dans un bacille.
18	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosauresque.
19	600	fr	76.5	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bacille.
19	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
20	600	fr	76.5	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bacillus.
20	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
21	600	fr	88.1	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre ADN dans un bactérie.
21	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
22	600	fr	85.7	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre ADN dans un bacille.
22	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosauro.
23	600	fr	88.1	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre ADN dans un bactérie.
23	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
24	600	fr	85.7	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre ADN dans un bacille.
24	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
25	600	fr	76.5	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bacillus.
25	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
26	600	fr	76.5	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bacille.
26	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
27	600	fr	55.9	Hershey et Château utilisaient des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
27	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
28	600	fr	76.5	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bacillus.
28	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
29	600	fr	78.8	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
29	575	fr	100.0	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaure.
30	600	fr	78.8	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
30	575	fr	88.4	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaur.
31	600	fr	78.8	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
31	575	fr	100.0	Mais il y a beaucoup de choses sur les oiseaux qui ressemblent encore à un dinosaure.
32	600	fr	78.8	Hershey et Chase ont utilisé des phages, ou des virus, pour implanter leur propre gène dans un bactérie.
32	575	fr	57.2	Mais il y a beaucoup de choses sur les oiseaux que pourraient encore ressembler à un dinosaures.

Table 6: 5-prompts without instructions, masking layer by layer of GPTNEO2.7B

A.7 Studying Redundancy via Compression

We noted that GPTNEO has some critical differences from BLOOM and LLAMA in terms of having critical layers (see Section 6.2). To what extent are there specialised attention heads for MT in the GPT-style models? If there were specialised heads, we would expect the model to be highly compressable/prunable to a select few heads. We plot a grid map of learned attention gate values for `en` → `fr`, where 0 indicates that the head is masked out (Figure 9). We find that most of the masked heads are distributed at the later layers for GPTNeo and are distributed across layers for BLOOM. This appears consistent with Section 6.2's observations that redundancy is more focused at certain layers in GPTNeo, and more spread out across the layers for Bloom.

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