Not a nuisance but a useful heuristic: Outlier dimensions favor frequent tokens in language models

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Abstract

We study last-layer *outlier dimensions*, i.e. dimensions that display extreme activations for the majority of inputs. We show that outlier dimensions arise in many different modern language models, and trace their function back to the heuristic of constantly predicting frequent words. We further show how a model can block this heuristic when it is not contextually appropriate, by assigning a counterbalancing weight mass to the remaining dimensions, and we investigate which model parameters boost outlier dimensions and when they arise during training. We conclude that outlier dimensions are a specialized mechanism discovered by many distinct models to implement a useful token prediction heuristic.

1 Introduction

It has been widely reported that modern language models (LMs) present a number of extreme-distribution phenomena, with some parameters and activations that are systematically much larger than the others (e.g., Kovaleva et al., 2021; Timkey and van Schijndel, 2021). In this paper, we investigate one of these phenomena, namely the presence of *outlier dimensions* (ODs) on the last layer of LMs. Unlike what Sun et al. (2024) called *massive activations*, that only occur for specific input tokens, ODs are dimensions that display very extreme activation values for a majority of the inputs, as shown for the pythia-12b model in the left panel of Fig. 1. While dimensions with similar properties also occur in earlier layers, we focus on those in the last layer because ODs tend to be more common in the last layer and, importantly, most of the ODs in the last layer are not outliers in earlier layers, which suggests that they play a role specific to output generation (see ODs by layer in Fig. 1-right for pythia-12b, and Fig. 5 in Appendix A for the other models we experiment with).

This hypothesis is borne out in the results. Across a number of LMs, we find that ablating ODs significantly affects model performance and, specifically, that they are part of an *ad-hoc* mechanism boosting the prediction of frequent tokens—a sensible heuristic given the skewed nature of word frequency distributions (Baayen, 2001). Indeed, keeping *only* the ODs makes the LMs predict just a few very common tokens, a strategy that results in very low but non-negligible accuracy. Moreover, we show how ODs interact with the unembedding matrix to favor frequent tokens in general, but also how the cumulative effect of the other dimensions can outweigh the effect of ODs when a non-OD-favored token must be predicted. We also present evidence that OD values are pushed up by the main directions in the space of the last-layer MLP down-projection matrix, as well as by high biases and weights in the last layer normalization. Finally, we show how the ODs emerge early during training after a first phase in which the model is predicting frequent words by other means.

Our main contributions are as follows:

- We present a thorough characterization of ODs in a set of modern LMs.
- We identify the *function* of these activations, showing that they generally work as a specialized module for frequent-token prediction.
- We describe the *mechanics* by which frequent-token prediction is achieved (or blocked) through the interaction between ODs and the unembedding matrix.

The code to reproduce all the results is available at https://github.com/imacocco/llms_outlier_dimensions/

2 Related work

Extreme values in transformer-based LM activations and weights are of interest due to their nega-

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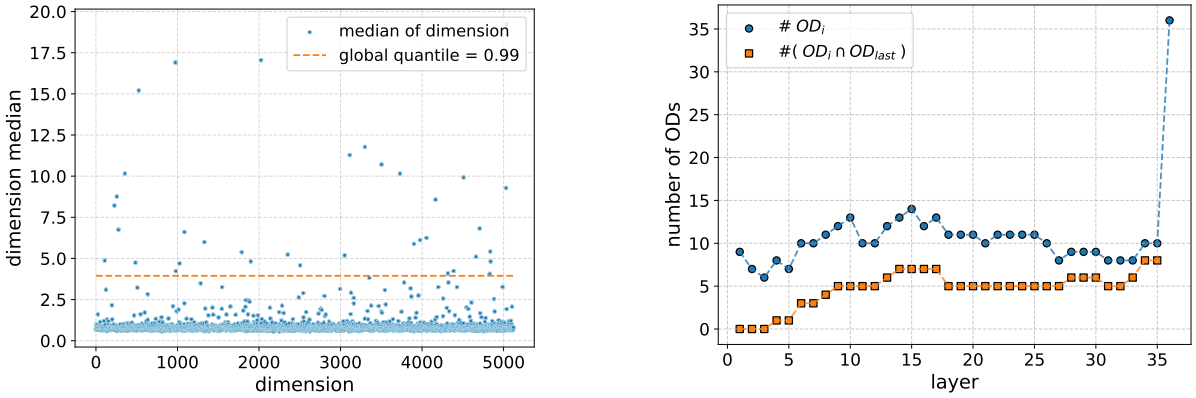

Figure 1: **Left:** Median activation values across our dataset (see Sec. 3) for each last-layer dimension of pythia-12b. The orange line separates the top 1% of values across all dimensions, used to assess whether a dimension is an outlier. **Right:** Evolution of outliers across the layers. The blue dots count the total number of outlier dimensions (ODs) per layer; the orange squares represent the number of outliers that are also ODs in the last layer (omitted in the last layer because they are the same by definition).

tive impact on quantization (Dettmers et al., 2022; Bondarenko et al., 2023), and their role in shaping anisotropic representations, which are linked, for instance, to poorer performance on semantic similarity tasks (e.g., Ethayarajh, 2019; Hämmerl et al., 2023). Intriguingly, just a few dimensions with such extreme values challenge model compression and general quantization performance, and their removal has been linked to general performance degradation (e.g., Kovaleva et al., 2021; Zeng et al., 2023).

Puccetti et al. (2022) find a positive correlation between input token frequency and the activation magnitude of extreme dimensions in hidden layers, which diminishes in later layers. Notably, they qualitatively observe a tendency for BERT to predict more frequent tokens when extreme dimensions are removed—which is the opposite of our findings (see e.g. Fig. 2). Puccetti et al. (2022) use BERT, whereas we focus on decoder-only transformer models, and they employ different criteria to identify ODs. These methodological differences may explain the discrepancies in our results.

Sun et al. (2024) and An et al. (2025) identify a specific subset of extreme values, referred to as *massive activations* or *systematic outliers*. These are linked to the phenomenon of "attention sinking", a mechanism that reduces the contribution of attention heads in contexts where they are not useful (see also Cancedda (2024)). Additionally, they function as context-aware scaling factors, modulating the influence of certain tokens (An et al., 2025).

Importantly, this specific subset of extreme values (massive activations/systematic outliers) differs from what we refer to as ODs in key ways: (i) they appear only in specific positions or for specific tokens, such as punctuation marks; (ii) their values are even more extreme (1,000 times the mean); (iii) they are very few (typically four or fewer per model across all layers, in contrast to the number of last-layer ODs we report in Table 1); and (iv) they tend to emerge more prominently in the middle layers, while we focus on the last layer.[1] Furthermore, these activations often correspond to punctuation marks or frequent words as input tokens, whereas ODs tend to occur across the board, but might favor items from these classes as *output* tokens.

3 Methodology

Models and datasets We experiment with the following pre-trained language models, all available on HuggingFace:[2] pythia-12b(-deduped) (Biderman et al., 2023), mistral-7b (Jiang et al., 2023), llama3-8b (Meta, 2024), olmo2-13b (OLMo et al., 2025), qwen-14b (Qwen, 2024), opt-13b (Zhang et al., 2022), gemma-9b (Gemma, 2024), and stable-12b (Bellagente et al., 2024). These were the latest and largest instances of each model family that we could analyze in a reasonable time, given our computing resources. See Table 3 in Appendix B for further model details.

We extract our input data from WikiText-103 (Merity et al., 2016). Specifically, we sample 50k

[1] Indeed, applying the criterion of (An et al., 2025) to our models, we don't find any massive activation on the last layer, which is the one where our ODs occur.

[2] https://huggingface.co/

non-overlapping fragments of 101 (typographic) words which do not cross document boundaries. All fragments start at the beginning of a sentence, whereas their final token is not required to coincide with and end-of-sentence boundary (so, it can belong to any part-of-speech). The first 100 words are fed to the models as contexts, and the first token of the last word constitutes the ground truth against which to compare model predictions.

OD identification We define outlier dimensions (ODs) as dimensions that have extreme values across a large variety of inputs. We operationalize this as follows. We consider extreme values those that are in the top 1% when ranking the absolute values of the activations of all dimensions in a given layer for our whole dataset (i.e., the ranked list will be of length $n \times 50$k, where n is the number of dimensions in the relevant layer of the model of interest). We then define an OD as a dimension whose median activation across the 50k samples in our dataset is an extreme value. That is, an OD dimension will display an activation that is among the 1% more extreme across all inputs and dimensions for at least 50% of the inputs. Table 1 (leftmost column) reports the number of ODs we find with this method in the last layer of each model (see Fig. 1 above and Fig. 5 in Appendix A for the other layers). The *z-score* column of the same table shows that the ODs identified in this way not only have values that ranked among the most extremes, but are also high in absolute terms—at least eight standard deviations above the mean on average for all models. Note also that ODs are a very small proportion of the dimensions in a given model (between 4 and 36, whereas layers are of dimensionality 3584-5120 depending on the model, cf. Appendix B).

4 Results

The remaining columns of Table 1 suggest that there is a group of models with the same pattern of behavior across the board (pythia-12b, mistral-7b, llama-8b, olmo2-13b, qwen-14b) and three models that often deviate in different ways (opt-13b, gemma-9b, stable-12b).

Impact of outlier dimensions on predictions ODs greatly impact model prediction: Ablating the outlier dimensions, i.e. setting them to 0, leads to a large decrease in accuracy for most models, despite the fact that the ODs are a very small proportion of the total dimensions of the models (see column *abl-OD*). The exceptions are opt-13b and gemma-9b, which experience very small decreases. Instead, ablating a comparable number of random dimensions in the last layer never affects accuracy by more than 0.1% for any model (results not shown in the table).

The symmetric operation, namely drastically ablating the model by setting all last-layer dimensions but ODs to 0, causes performance to radically drop, as could be expected (see column *only-OD*). However, in most cases the performance is still much higher than in the only-random condition, where a comparable number of randomly sampled dimensions is ablated (this yields accuracies $< 0.1\%$, not shown in the table). Exceptions are opt-13b, gemma-9b, and stable-12b, with accuracies near 0 also in the only-OD condition. [3]

By which means does ablating ODs affect accuracy in most models? The rightmost panel of Table 1 shows that ablating ODs generally leads models to predict a *larger* number of distinct tokens, compared to the corresponding non-ablated runs (column *abl-OD*; stable-12b is an exception). Ablating an equivalent number of non-OD dimensions does not have this effect. Even more strikingly, when keeping only the few ODs in the last layer, the number of distinct tokens that are predicted is drastically reduced (column *only-OD*; cf. the contrast with *only-rnd*, that is, when keeping only an equivalent number of random dimensions active).

ODs thus seem to steer models towards predicting a small set of tokens. Table 2 contains the tokens that are most strongly associated with ODs (they are predicted over 1,000 times when ablating all dimensions except ODs).[4] The table suggests that ODs generally favor very common tokens like *_the*, *_and*, or *_in*, which, as we have already remarked, is a sensible heuristic for a model to encode, since natural language texts are heavily skewed towards a few very frequent types (Baayen, 2001). This might explain why using a few dozen last-layer ODs for prediction generally leads to accuracies that, while low, are non-negligible: for example, *_the* and *_a* alone account for 7.5% of the ground-truth tokens in our dataset. Again, gemma-

[3] Table 4 in Appendix C reports the ablation effects in terms of surprisal, which exhibits the same trends.

[4] To avoid noise, we only consider tokens that were predicted by the full model at least once.

	ODs		Accuracy [%]			# of Distinct predicted Tokens			
Model	#	z-score	FM	abl-OD	only-OD	FM	abl-OD	only-OD	only-rnd
pythia-12b	36	9.8 ± 5.2	43.0	34.3	4.7	7504	11116	195	7254 ± 269
mistral-7b	28	9.6 ± 4.6	46.6	41.9	1.7	6334	7098	712	4518 ± 427
llama-8b	12	11.9 ± 5.7	49.2	41.8	1.2	8034	12030	150	2367 ± 339
olmo2-13b	24	10.8 ± 7.6	52.1	41.0	7.4	8317	13320	655	5787 ± 1062
qwen-14b	38	8.8 ± 7.1	49.9	32.2	1.3	8171	11233	710	10236 ± 750
opt-13b	4	29.1 ± 11	42.7	42.5	0.0	7911	9026	85	281 ± 13
gemma-9b	6	17.2 ± 10.7	48.4	48.0	0.1	8229	8539	79	373 ± 46
stable-12b	23	9.2 ± 6.8	49.4	30.2	0.0	8029	1821	96	947 ± 109

Table 1: **ODs:** Number of ODs and their average z-score with respect to the mean of absolute values of all last-layer activations. Effects of OD/non-OD ablation. **FM:** full model; **abl(ate)-X:** dimensions X were set to 0; **only-X:** dimensions other than X were set to 0. Random-dimension experiments are repeated with 10 different seeds and averaged. Ablate-random experiments, where the same number of random dimensions were ablated as there are ODs, always resulted in values matching those of the full model up to the third significant digit for both accuracy and # of distinct tokens, and we do not report them in the table. Only-random (only-rnd) experiments keep the same number of random dimensions as there are ODs; their accuracies are not reported either, as they are typically $\sim 0.01\%$ and always $< 0.1\%$.

9b, stable-12b and opt-13b show different patterns. Gemma-9b has only one token meeting our condition, stable-12b none. Opt-13b has only one OD-favored token which, however, is predicted for almost every input in the only-OD condition.

model	tokens (# of predictions)
pythia-12b	_the (15272); _a (5015); _D (1716);
mistral-7b	_the (1665;) _a (1619); _ (1568); _un (1531); _two (1163); _large (1106)
llama-8b	_in (15172); , (10063); _((9293); _and (5227); _ (1930);
olmo2-13b	_the (21532); _ (11275); , (3515); _The (3181); _in (1241); _A (1018);
qwen-14b	_ (11967;) _the (5982); , (4708);
opt-13b	I (46181);
gemma-9b	_ (1762);
stable-12b	n.a.

Table 2: Most strongly OD-favored tokens for each model (predicted over 1K times in only-OD condition, i.e., when ablating all dimensions except ODs). In parentheses: number of times the token is predicted in this condition. No tokens in stable-12b met the criterion. The underscore denotes the space character, which varies by model.

In Appendix H, we also qualitatively investigate the effect of the ablation on the generative capabilities of the models. As could be expected, we observe that ablating the ODs typically has a significantly larger impact than ablating random dimensions. While in the latter case even removing 3000 dimensions still allows the model to produce meaningful sentences, in the former the ablation of a much smaller number of ODs (even just 5 in the case of qwen-14b) completely disrupts the model's performance. This implies that any generative downstream task will be dramatically affected.

Relationship between ODs and frequency The results above, together with the qualitative examples in Table 2, seems to suggest that ODs tend to favor frequent tokens. To test this hypothesis in a systematic way, we examine the relationship between the frequency with which a model predicts a given token, on the one hand, and its overall frequency (which we estimate with a corpus), on the other.[5] We expect OD-ablated models (i.e., models where ODs are set to 0) to decrease the prediction of frequent tokens, and consequently increase the prediction of less frequent tokens, compared to the full models. The first two panels of Fig. 2 present evidence of this for pythia-12b. They show the tokens predicted by the full model (left) and the OD-ablated model (middle), sorted by their corpus-estimated frequency and frequency of prediction in each condition, in log-log scale. They also contain the line of a linear regression fit and its slope, as well as the Spearman correlation coefficient ρ. Both indicators show that ablating ODs indeed affects the relationship between the overall frequency of a token and the times it is predicted. First, whereas the relationship is always positive (models predict more frequent tokens more often than less frequent tokens), the ρ coefficient goes down from 0.7 to 0.53 when ablating ODs, and the slope similarly goes down from 1.35 to 0.74.[6]

[5] Ideally, frequency estimates should be drawn from the LMs' training corpora, but, as we don't have access to those for most models, we use the full WikiText-103 corpus to estimate overall token frequencies.

[6] The latter also means that the full model over-predicts and the ablated model under-predicts frequent words (and conversely for less frequent words), something that is more clearly shown by the regression lines (perfect correlation with slope 1 would mean that all points are on the $y = x$ line).

Table 5 in Appendix D confirms that this tendency generalizes: the slope of a linear fit decreases for all models when ODs are ablated, except for stable-12b; as for the correlation coefficient ρ, it decreases for all models when ODs are ablated, although the effect is negligible for those models that have already shown some deviant behavior in the previous analyses (opt-13b, stable-12b, and gemma-9b).

Role of ODs in token prediction We next examine the mechanics by which ODs favor frequent tokens in most models. First, we hypothesize that the activations of a significant number of individual ODs will be highly correlated with token frequency (either positively or negatively). The boxplots in the rightmost panel of Fig. 2 provide evidence for pythia-12b. The left boxplot shows the distribution of correlations between the corpus frequency of the predicted tokens and the activation profiles of each last-layer dimension across the dataset. This reflects the extent to which, across predicted tokens for our dataset, each dimension tends to be more strongly activated proportionally to the frequency of the predicted tokens. We see that the correlations of the vast majority of non-OD dimensions (summarized in the blue boxplot) cluster around 0, whereas the correlation scores for the ODs (shown as individual orange dots) are much more spread, with a significant proportion exhibiting larger correlations. Similarly, we find a relation between the corpus frequency of individual vocabulary items and their values in OD vs. non-OD dimensions of the unembedding matrix, as follows. The second boxplot in the rightmost panel of Fig. 2 shows the distribution of correlations between the values of each dimension across the unembedding matrix rows and the corpus frequencies of the tokens corresponding to these rows. Again, the correlations are generally low for non-ODs, but much more spread for ODs. Given that the output distribution of a language model is obtained by multiplying the unembedding matrix by the last-layer activations, this suggests that ODs will favor more frequent tokens, because the latter tend to have higher unembedding vector values exactly in correspondence to the ODs. The same distributions are plotted for the other models in Fig. 6 of Appendix D, confirming the same trends across all of them.

These correlations on their own are suggestive, but not enough to uncover the specific mechanics, since, as we just discussed, dimension activations on an LM's last layer contribute to the prediction of a specific token through their dot product with the equivalent dimensions in the unembedding matrix row corresponding to the token. The result of this dot product is the *logit* score for that token: the higher this quantity, the larger the probability that the model will assign to the token. To analyze the interaction between the last layer and the unembedding matrix, we separately measure the contribution of ODs and non-ODs to the logit scores of a given token. We do that by computing the dot product between the activations of the dimensions of interest and their corresponding unembedding vector values (Appendix E contains the equations for completeness).

The upper panel in Fig. 3 focuses on OD-favored tokens (listed in Table 2), contrasting pythia-12b and opt-13b. It displays the cumulative logit contributions of ODs and non-ODs to the prediction of each OD-favored token. We see a different pattern. In pythia-12b, as expected, the ODs consistently provide a significant positive contribution to predicting the token. Moreover, this contribution is comparable in size to that of the non-ODs (whose contribution shows a larger variance).[7] This equivalence is remarkable, as in one case we are looking at the cumulative contribution of 36 ODs, in the other to that of the remaining 5,084 dimensions. Instead, in opt-13b the contribution of the ODs sums to virtually 0. This might go some way towards explaining why this is one of the models for which there is no clear effect of OD ablations, nor strong OD/frequency correlations. While this model does feature a small number of ODs with across-the-board extreme activations, these activations, when multiplied by the unembedding matrix and summed, might cancel each other out, suggesting that, in this case, the model is not really using the ODs to control output prediction.[8] Fig. 7 in Appendix E shows the OD vs. non-OD contributions for the other models (except stable-12b, which, as mentioned above, has no OD-favored token according to our criteria). While gemma-9b behaves like opt-13b, all other models behave like pythia-12b, with a strong contribution of ODs to OD-favored

[7] Note that it is not surprising that non-ODs also contribute to promoting OD-favored tokens in contexts where they are appropriate.

[8] Recall that, when only ODs are kept, opt-13b almost invariably predicts the single token *I* (Table 2). The results in Fig. 3 suggest that this might be more of a "default" behavior of the model, than something specifically triggered by the ODs.

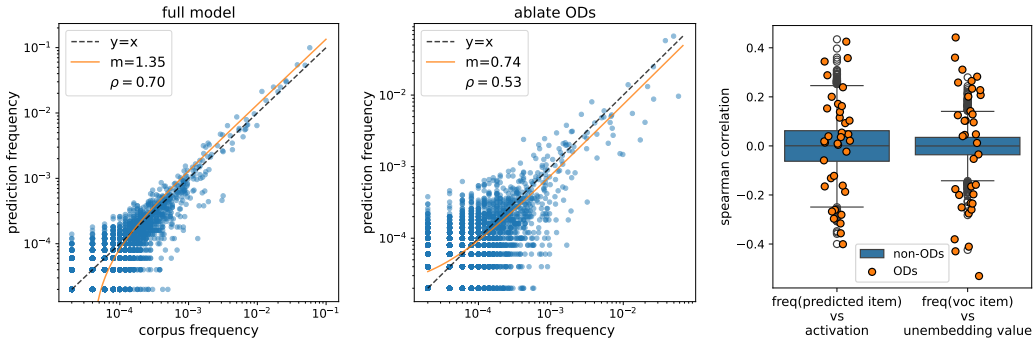

Figure 2: Frequency and ODs in pythia-12b. **Left and middle panel**: Prediction frequency in function of corpus-estimated frequencies for the full model and the OD-ablated model, in log-log scale. The ablation decreases the frequency for frequent tokens and increases the frequency for rare tokens. **Rightmost panel, left boxplot**: distribution of the Spearman correlation between the activation value of the last context tokens and the corpus-estimated frequency of the model-predicted tokens. **Right boxplot**: distribution of the Spearman correlation between the values in the unembedding matrix corresponding to a given dimension and the corpus-estimated frequency of corresponding vocabulary items. The correlation is computed independently on each dimension. Results for non-ODs are grouped, while ODs are reported as orange dots (scattered along the x-axis for visualization purposes).

token prediction.

Therefore, in general ODs promote the prediction of frequent tokens, which raises the question: how can a model also predict less frequent tokens? Remember that ODs, by definition, have extreme values in at least 50% of the inputs, so they will be strongly active in many cases where it's adequate to predict less frequent tokens. One possibility is that, while their magnitude is almost constantly large, ODs only provide a *positive* contribution to predicting OD-favored tokens in appropriate contexts, but they give a *negative* contribution to OD-favored token predictions in other contexts, thus penalizing them. A second hypothesis is that ODs always bring about a positive contribution to the prediction of OD-favored tokens, but this is counter-balanced by the total logit mass of the other dimensions when other tokens are more contextually appropriate. To verify which hypothesis is right, we study a set of *OD-neutral* tokens, defined as tokens that a model predicts with equal frequency when the ODs are ablated as when they aren't (e.g. *_times*, *_command*, *_States* for pythia-12b; see Table 6 in Appendix E for the full set). We sample maximally 10 such tokens per model, and we limit the choice to tokens that are predicted at least 10 times by the full model. Now, for each context in which the model predicted (that is, assigned the largest probability to) one of these tokens, we contrast the OD and non-OD contributions towards the logit of the relevant token, on the one hand, and the logits of the already mentioned OD-favored tokens, on the other, to find by which means the OD-neutral token "won" against the OD-favored rivals.

The lower panel of Fig. 3 illustrates the analysis with the case of the OD-neutral token *_States*. The plot contains two data points for each context in which pythia-12b predicts *_States*, one corresponding to the logit contributions of ODs (orange dots) and one to those of non-ODs (blue squares). On the x-axis, the logit values for the token *_States* are displayed, while the y-axis shows the logit values for the OD-favored token *_the*. If the negative-contribution hypothesis was right, the ODs would provide a negative contribution to the *_the* prediction in this case, as it is a context in which it predicts *_States*. However, this is not what we find; we see that ODs always strongly favor *_the* (and only provide a modest positive contribution to *_States*). Indeed, the OD logit contribution towards *_the* here is comparable to the average OD contribution towards OD-favored tokens when the latter are chosen (around 5, cf. the upper left boxplot of the figure). The reason that *_the* is ultimately not chosen in the *_States* contexts is that the sum of all non-ODs gives a large positive contribution to the *_States* prediction, that surpasses the cumulative weight of the ODs in favor of *_the*.

In Fig. 8 in Appendix E, we show that this pattern generalizes across OD-neutral and OD-favored tokens. In all models, the OD-neutral tokens are selected because of the logits of the non-ODs; OD logits either present higher values for OD-favored tokens or are neutral, with values near 0 (the latter is the case for gemma-9b and opt-13b).

We conclude that the models do not learn to

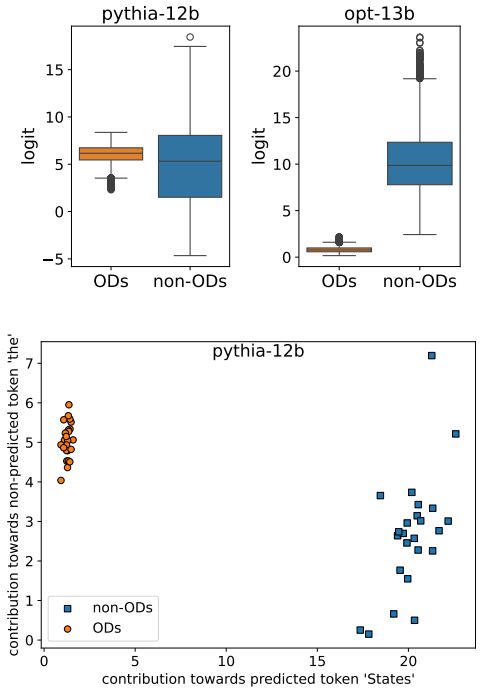

Figure 3: **Upper:** Distributions of cumulative OD and non-OD logit contributions in all contexts in which an OD-favored token is predicted, for pythia-12b and opt-13b. **Lower**: OD and non-OD logit contributions to OD-neutral *_States* and OD-favored *_the* in all contexts in which *_States* is predicted by pythia-12b.

modulate ODs so that they are positive in contexts where OD-favored tokens should be predicted, and negative otherwise. Rather, ODs act like a constant term providing a positive logit contribution towards OD-favored tokens, and it is the job of the other dimensions to learn to counterbalance this contribution when other tokens should be predicted. We can think of ODs as implementing a baseline heuristic to always predict frequent tokens, with the rest of the dimensions working their way around them to provide more appropriate context-dependent predictions.

Which model parameters boost OD activations? The observation that ODs consistently exhibit large values across most inputs, combined with evidence that these values are not strongly context-modulated, suggests that OD activations result directly from large model weights boosting them. Given that most ODs appear in the last layer only, we consider three plausible OD boosters: the down-projection matrix of the last MLP (mapping MLP-internal representations to last-layer activations), the weight terms of the final LayerNorm, and the bias terms of the final LayerNorm, for models that have these parameters (see Table 3 in Appendix B).[9] Adopting a methodology similar to (Cancedda, 2024), we assess the possible contribution of the MLP matrix to the ODs by first factorizing it with a singular value decomposition. We then examine whether the dominant (i.e., first few) singular vectors' "spikes" (dimensions with values exceeding three standard deviations from the mean) tend to align with the last layer's ODs. See Appendix F for a detailed explanation of the procedure. Likewise, for the weights and biases of the LayerNorm, we similarly define outlying spikes and, again, we check whether ODs tend to coincide with them. A coincidence between spikes and ODs would suggest that the OD values are influenced by the principal directions in the last-layer MLP down-projection matrix, as well as by elevated biases and weights in the final layer normalization.

Results for pythia-12b are presented in Fig. 4.[10] The overlap of spikes in the the MLP matrix and ODs is remarkable; for instance, 4 out of 7 spikes in the first singular vector are in ODs, as are 25 out of 43 for the second singular vector. These overlaps have $p \approx 0$ of occurring by chance, based on simulating a random overlap distribution. Similarly, the right panels of Fig. 4 show that ODs are also boosted by the LayerNorm weight and bias parameters: 16 out of 52 spikes in the weight are in ODs, as are 20 out of 39 for the bias parameter. To sum up, in pythia-12b ODs are boosted by both the MLP matrix and the LayerNorm weights and biases. Fig. 10 in Appendix F confirms a similar pattern across most models. Yet, for llama-8b and opt-12b the boost appears to originate solely from the MLP, while for stable-12b the effect is particularly evident in the weights.

Overall, we find that there are fixed parameters that enhance ODs, and this boosting can be encoded in both the last MLP down-projection matrix and the LayerNorm parameters, highlighting the importance of looking for multiple parametric sources of extreme values.

ODs' emergence and role during training As a last experiment, we looked at the emergence of the ODs and the effect of their ablation during

[9] In Appendix F, we comment on the negative results we obtained concerning the last layer's components of the attention heads.

[10] Here and in Fig. 10 of Appendix F, we only report the first 4 MLP singular vectors, but in all cases similar patterns are observed for a much broader set of dominating singular vectors; see Fig. 9 in Appendix F.

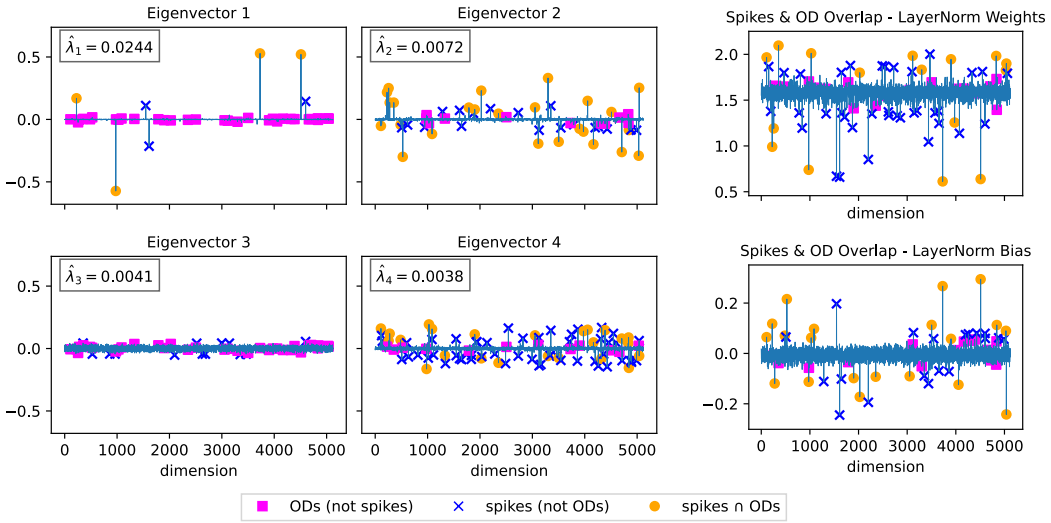

Figure 4: **Left:** Top-4 singular vectors and values of the last-layer MLP down-projection matrix of pythia-12b. **Right:** Final LayerNorm weight and bias for pythia-12b. Spikes in parameter values that correspond to ODs are visualized as orange circles.

the stages of training of pythia-12b. A significant number of ODs appears around steps 3000/4000. From here onward, ablating ODs impacts accuracy and leads to the prediction of more varied tokens, suggesting that ODs started assuming the function of frequent token boosters. Interestingly, early in training (step 500), there are virtually no ODs, yet even the full model predicts relatively few tokens. The full results are reported in Table 7 in Appendix G. If we examine which tokens are over-predicted at this stage compared to their actual dataset frequencies,[11] we find them to include *_the, _that, _and, _not, _a, _be, _of*. This indicates that the model has learned right from the start that predicting very frequent tokens pays off. In later steps, the model specializes the ODs to implement this heuristic, allowing the remaining units to focus on context-aware prediction, resulting in more varied outputs and improved accuracy.

5 Discussion and conclusion

We studied a class of LM extreme values we dubbed *outlier dimensions* (ODs). Unlike the more widely studied "massive activations" (Sun et al., 2024; An et al., 2025), ODs exhibit extreme activations consistently across a range of inputs, rather than in response to specific ones. Unlike massive activations, which influence model output indirectly through attention sinking, ODs directly influence model predictions by favoring frequent tokens independently of context. As such, they function as a hard-coded module developed to address an important characteristic of text: its extremely skewed distributions. Interestingly, Stolfo et al. (2024) found a set of frequency-modulating neurons, defined as entries in an MLP internal representation, in several smaller models. Future work should connect their results to ours, to check if we are examining different aspects of the same mechanism.

Five out of eight LMs we studied have ODs linked to frequent-token predictions. Divergent results for the other models suggest, however, that the development of frequent-token predicting ODs, while a common strategy discovered by many models, is by no means necessary. All divergent models have units that meet our OD criteria, but they differ in other ways: in particular, opt-13b and gemma-9b have fewer ODs than the other models, and OD ablation does not impact their accuracy, whereas stable-12b has a larger number of ODs, and ablating them does affect performance. When only ODs are retained, opt-13b almost always predicts the same token (*I*), whereas gemma-9b only mildly favors the space token, and stable-12b has no clearly favored token under this ablation. Overall, considering that for opt-13b and gemma-9b the logit contribution of ODs approaches 0 even when predicting their OD-favored tokens, it appears that ODs may serve a different function in these LMs, potentially akin to that of attention-sinking massive activations. However, we defer a more thorough characterization of ODs in these divergent models, as well as of the properties that made them diverge,

[11] To reduce noise, we only consider tokens occurring at least 100 times as ground-truth predictions.

to future studies.

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Limitations

- As stated at the beginning of our manuscript, our analysis focuses exclusively on outliers in the last hidden layer, since their direct influence on the next token prediction can be clearly observed. Although outliers also exist in earlier layers, assessing their impact and linguistic role is more complex and less straightforward.
- Our analysis of the ODs at training time is limited to a single model, pythia-12b, for which early training checkpoints are available. Consequently, our findings may not generalize to other models. We were unable to test this further because the only other publicly available model with training checkpoints is olmo2-13b; however, its earliest checkpoint is not early enough in training to capture initial OD behavior, as fully-trained-model OD behavior is already firmly in place by then.

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A ODs across layers

Fig. 5 reports the number of per-layer ODs (as identified by our criterion) and the number of ODs that also appear in the last layer for all studied models except pythia-12b, whose equivalent data are shown on the right panel of Fig. 1 in the main text. We observe that in all models, but gemma-9b and opt-13b, the last layer has many more ODs than the previous ones. Moreover, we also see how the ODs present in the last layer tend to appear only towards the end, with different onset curves for the various models. Togethes, these observations suggest that the last layer has a special behavior that differs from that of the previous ones.

B Language model details

Table 3 summarizes the main characteristics of the language models we used.

C Surprisal effects of ablations

Table 4 reports the 1st, 2nd (median) and 3rd quartiles for the distribution of surprisal in the different ablation modalities. For each context, the surprisal is calculated as $S = -\log(p)$, where p is the probability attributed by the model to the ground truth next token. These observations broadly confirm the results obtained for accuracy (see Table 1 in the main text). Note that for stable-12b, one of the divergent models, only-OD surprisal is larger than only-random surprisal: we leave to future studies a better understanding of how ODs affect output probabilities for this LM.

D ODs and frequency

Table 5 reports the linear-fit slopes and Spearman correlation coefficients of the relation between generic corpus-estimated frequency of tokens and their prediction frequency in our dataset, for the full models and their OD-ablated versions. For both measures, we observe a drop from full-model to ablate-OD, except for the usual divergent models: opt-13b and gemma-12b essentially show no ablation effect, and for stable-12b we actually observe an *increase* in slope from full-model to OD-ablated.

The left boxplots in Fig. 6 present, for all LMs except pythia-12b, the distribution of correlations between the corpus-estimated frequencies of predicted tokens given the inputs in our dataset and the activations of ODs and non-ODs in the last layer of the last context token. The right plots

model name	Llama-3-8B	Mistral-7B-v0.3	gemma-2-9b	stablelm-2-12b	pythia-12b-deduped	opt-13b	OLMo-2-1124-13B	Qwen2.5-14B
size:	8B	7B	9B	12B	12B	13B	13B	14B
number of layers:	32	32	42	40	36	40	40	48
hidden dimension:	4096	4096	3584	5120	5120	5120	5120	5120
# attention heads:	32	32	16	32	40	40	40	40
# key/value heads:	8	8	8	8	n.a	n.a	n.a	8
head size:	n.a	128	256	n.a	n.a	n.a	n.a	128
FFN size:	14336	14336	14336	13824	20480	20480	13824	13824
vocab size:	128256	32768	256128	100352	50688	50272	100352	152064
position embeddings:	✓	✓	✓	✓	✓	✓	✓	✓
max pos. embeddings:	8192	8192	8192	4096	2048	2048	4096	131072
tied word embeddings:	×	×	✓	×	×	✓	×	×
distilled model:	×	×	✓	×	×	×	×	×
activation:	SwiGLU	SwiGLU	GeGLU	SwiGLU	GeLU	ReLU	SwiGLU	SwiGLU
LayerNorm (LN) type:	RMSNorm	RMSNorm	RMSNorm	LN	LN	LN	RMSNorm	RMSNorm
LN has bias parameter:	×	×	×	✓	✓	✓	×	×
torch dtype:	bfloat16	bfloat16	float32	bfloat16	float16	float16	float32	bfloat16
public training data:	×	×	×	✓	✓	×	✓	×
checkpoints available:	×	×	×	×	✓	$\leq$ 10	✓	×

Table 3: Configuration details of the pre-trained LMs we experimented with; n.a. means *not available* information.

show the distribution of correlations between the corpus-estimated frequencies of the output vocabulary tokens and the OD and non-OD values in the unembedding matrix vectors corresponding to those vocabulary tokens. The same data are shown for pythia-12b in the rightmost panel of Fig. 2 of the main text. Also for the other models we observe that ODs display a much larger probability of showing a higher (absolute) value of the correlation than non-ODs in both scenarios. So, being an OD often implies a large correlation, but the opposite is not always true, as there are many dimensions for which such correlation is high that are not ODs. It could be interesting to see how the models behave upon ablating (or keeping) only those non-ODs with a high correlation coefficient, but we leave this analysis to future work.

E Logit contribution analysis

E.1 Logit contribution computation

Given a context, an autoregressive neural language model produces a probability distribution over possible next tokens by multiplying the last-layer activations of the last token of the context by the unembedding matrix, and converting the resulting *logit* scores to probabilities through the softmax function. We ignore the latter here, since it is monotonic and we are only interested in comparing which of several possible next tokens gets the largest score. We thus focus on the logit values of the candidate next tokens we are interested in. The logit for candidate next token t, denoted $logit_t$, is given by the dot product between the context activation vector $\mathbf{c}$ and the unembedding matrix row corresponding to t, $\mathbf{u_t}$:

$$logit_t = \mathbf{c} \cdot \mathbf{u_t} = \sum_{i \in D} c_i u_{ti}$$

where D is the set of indices of dimensions of the context and unembedding row vectors.

In order to assess how much the ODs contribute to this score, we can simply partition the sum above into two components, one given by the sum of terms corresponding to the dimensions that are in the OD set, and one by the sum of terms for the leftover dimensions. Formally, if O is the set of indices of OD dimensions, the contribution of the ODs to $logit_t$ is:

$$logit_t^{\in OD} = \sum_{i \in O} c_i u_{ti}$$

The contribution of the non-OD dimensions is trivially given by:

$$logit_t^{\notin OD} = logit_t - logit_t^{\in OD}$$

Surprisal (1st, 2nd, 3rd quartiles)				
Model	FM	ablate-OD	only-OD	only-random
pythia-12b	0.6, 1.9, 4.0	1.0, 2.8, 4.9	8.0, 9.0, 9.8	10.7
mistral-7b	0.5, 1.6, 3.5	0.6, 1.9, 4.0	8.2, 8.9, 9.6	10.3
llama-8b	0.4, 1.5, 3.4	0.6, 2.1, 4.2	8.5, 9.7, 10.7	11.7
olmo2-13b	0.2, 1.2, 3.2	0.6, 2.2, 4.6	6.4, 7.8, 9.4	11.4
qwen-14b	0.3, 1.4, 3.4	0.7, 3.2, 7.0	8.8, 10.6, 15.1	11.8
opt-13b	0.6, 1.9, 4.1	0.6, 2.0, 4.1	10.3, 10.5, 10.7	10.8
gemma-9b	0.0, 1.4, 14.9	0.0, 1.5, 14.9	11.3, 12.1, 13.3	12.4
stable-12b	0.4, 1.5, 3.4	0.8, 3.3, 8.4	22.4, 27.8, 34.2	11.4

Table 4: 1st, 2nd and 3rd quartiles of the distribution of surprisal, computed on the predicted token for each input, for each ablation type. The large values of the 3rd quartile hint at highly positive-skewed distributions. For the only-random case we report only the median as the other quantiles are identical within the used significant digits. The ablate-random condition is not reported since, as it occurred for accuracy, the values are identical to the ones of full model up to the reported precision. In the only-random case, one can appreciate how the surprisal corresponds to a random guess: by exponentiating these values, one approximately recovers the vocabulary size.

	Slope		Spearman	
Model	FM	ablate-OD	FM	ablate-OD
pythia-12b	1.35	0.74	0.70	0.53
mistral-7b	1.23	1.06	0.71	0.64
llama-8b	1.26	0.86	0.71	0.58
olmo2-13b	1.24	0.64	0.74	0.59
qwen-14b	1.22	0.95	0.71	0.52
opt-13b	1.34	1.25	0.70	0.67
gemma-9b	1.30	1.26	0.72	0.71
stable-12b	1.27	1.72	0.71	0.70

Table 5: Linear fit slope and Spearman correlation coefficient for the relation between corpus-estimated and prediction frequencies for the full models and under OD ablation.

E.2 Logit contributions in OD-favored predictions

Fig. 7 shows the distribution of logit OD and non-OD contributions towards the prediction of OD-favored tokens for all models except pythia-12b and opt-13b, that are shown in the upper panel of Fig. 3 of the main text. Note that stable-12b is missing because we did not identify any OD-favored token for this model. For all models but opt-13b and gemma-9b, ODs, despite being very few, contribute at least as strongly as non-ODs to token prediction. It is worth remarking that for olmo2-13b, while the ODs are giving the larger contribution to the logits, both contributions are negative.

E.3 Logit contributions in OD-neutral predictions

We consider a set of OD-neutral tokens. These are predicted at least 10 times in our dataset by the non-ablated model, and they are predicted the same number of times when ODs are ablated. For qwen-14b, as there was only one token meeting this criterion, we sampled tokens whose OD-ablated/full-model prediction count ratio was between 0.9 and 1.1. We sample maximally 10 tokens per model, shown in Table 6.

Fig. 8 plots the contribution of ODs and non-ODs towards OD-favored and OD-neutral tokens, in contexts in which the model assigned the larger probability to the latter (for pythia-12b, the same data in the specific case of *_States* against *_the* are showed in the lower panel of Fig. 3 in the main text; stable-12b, again, is missing because it has no

Model	Tokens
pythia-12b	_period _before _times _command _bridge _mm _States _II
mistral-7b	_km _match _life _line _book _species _States _Tour _season _City
llama-8b	_November _players _Court _ships _species _Council _Division _office _largest _Road
olmo2-13b	_North _York _Union _ships _money _Japanese _success _times _ship _sold
qwen-14b	_Street _match _gave _York _interview _each _into _based _began _Japan
opt-13b	_York _University _interview _feet _water _part _ships _Cup _men _half
gemma-9b	_Road _feet _long _won _relationship _mm _support _United _little _local
stable-12b	n.a.

Table 6: OD-neutral tokens for the different models. We consider a token OD-neutral if it is predicted from the same representations before and after ablating ODs. A subsample of 10 was extracted if more were available.

OD-favored tokens according to our criterion). The contributions are averaged across the contexts of each OD-neutral tokens. For pythia-12b, mistral-7b, llama-8b, olmo-13b and qwen-14b, ODs contribute more strongly to the OD-favored logits, but this effect is outdone, in all cases, by the non-ODs. Note that, as already remarked with respect to the previous figure, for olmo2-13b OD values are negative for both OD-favored and OD-neutral tokens, but closer to 0 for OD-favored, confirming the general trend. For opt-13b and gemma-9b, the OD contributions always sum to values close to 0, confirming the divergent behavior of these models.

F OD-boosting parameter analysis

We explore if ODs are aligned with directions that are boosted by the last MLP down-projection matrix X, of shape $d \times h$—where d is the hidden (or embedding) dimension of the model and h is the high-dimensional space between the MLP up- and down-projection matrices (see `FFN size` in Tab. 3). We then compute the SVD decomposition of $X = U\Sigma V^T$, where V is a $h \times h$ matrix, Σ is a $d \times h$ diagonal rectangular matrix whose entries are called singular values, and U is a $d \times d$ matrix, that ultimately projects an input vector back into the hidden space. We thus focus on the columns of U, which are called left singular vectors and have the same dimensionality d of the states from which we extract the ODs.

Fig. 9 visualizes vectors given by the linear combination of the top-N singular vectors that account for a certain proportion of variance in the original matrix, weighted by the corresponding singular values, together with the distribution of ODs and "spike" dimensions. Here and below, we define as spikes those values of a vector that lie more than 3 standard deviations away from the mean. The figure confirms the tendency for at least some ODs to coincide with the spikes.

We then select the top 4 singular vectors and repeat the analysis for each of them. Results for pythia-12b are in Fig. 4 of the main text, and for the other models in Fig. 10 here. The figure shows the overlap between the ODs and the spikes of the singular vectors. It also shows the overlap between the ODs and the (similarly defined) spikes in the last-layer LayerNorm weight and bias vectors. For all models, we observe a non-negligible overlap of spikes and ODs of their last layer; all of the observed overlaps have $p \approx 0$ of occurring by chance according to a random overlap simulation test.

The same analysis applied to the Q, W, V, and O matrices of the attention heads did not reveal any significant overlap between ODs and spike features; therefore, these results are not presented here. While the lack of structure in the Q and W matrices is consistent with their primary function of aggregating information across tokens, we might have expected detectable signals in the V or O matrices. However, no such structure was observed. A possible explanation is that, as ODs act as a fixed bias promoting frequent words, this is more readily encoded in the MLP than in the attention matrices, whose function is to manage contextual information, but we leave further exploration of the difference to future work.

G Emergence of ODs during training

Here, we report the Table 7 characterizing the evolution of ODs across Pythia's checkpoints. We can observe how the accuracy and the role of ODs in predicting frequent tokens evolve during pre-

training. As already mentioned in the main text, starting from step 3000 we observe the emergence of a sizable number of ODs, together with an (initially small) negative effect on accuracy upon ablation. At the same time, we see how both the ratios between the number of predicted tokens in a) the only-OD and only-random ablations and b) full model and ablate-OD modalities become smaller. This behavior suggests that the ODs have started specializing in frequent-token prediction.

The only other model for which training checkpoints are public is olmo2-13b. However, the first available checkpoint does not occur early enough, and fully-trained-model OD behavior is already firmly in place by then.

H Sentence generation upon ablation

In this section we report how the different models' generation capabilities change upon ablation of given dimensions. The prompt is the same for all the models, in order to have a direct comparison. In all cases, we generated 20 tokens with greedy decoding. Tokens that could not be properly rendered are substituted in the tables by "[?]". These included characters such as U+000B (line tabulation) or U+548C (CJK Unified Ideograph)

Tables 8-15 show:

- default: the sentences generated by the full model
- largest: the sentences generated by ablating the k dimensions with the largest medians
- smallest: the sentences generated by ablating the k dimensions with the smallest medians
- random: the sentences generated by ablating k random dimensions.

In particular, what we call outlier dimensions correspond to the top largest dimension and the effect of their ablation can be found in the first lines of the entries in the "largest" block. We observe that one typically needs to ablate between 2000 and 3000 random or small dimensions for the models to start generating meaningless sentences. Differently, the behavior is much more diversified when ablating the largest dimensions. Interestingly, pythia-12b stops predicting the token "a" (that we identified as OD-favored for this model) after the removal of 5 ODs and the token "," after 20, while repetitions–a clear sign of broken generation–start at 100. Mistral-7b and llama-8b start producing loops with 10 ablations only and their output becomes meaningless after 50. Qwen-14b, stable-12b and olmo2-13b are the most sensitive, as the ablation of just 5, 15 and 20 dimensions, respectively, are enough to completely disrupt the model generation capabilities. Opt-13b and gemma-9b are the more robust models, with ablation of the largest dimensions affecting them similarly to the other ablation strategies.

As already stated in the main text, these observations suggest that most models heavily rely on the ODs in order to work properly, to the point that some of them produce meaningless results after the removal of just a few dimensions. This also implies that any downstream task involving generation will be affected by the removal of ODs.

Pythia	ODs		Accuracy [%]		# Distinct predicted tokens			
Ckp	#	∩ final	FM	ablate-OD	FM	ablate-OD	only-OD	only-rnd
500	1	0	11.4	11.4	667	671	14	20 ± 3
1000	1	1	17.4	17.4	2774	2790	15	22 ± 4
2000	7	3	26.4	26.5	5168	5322	63	677 ± 130
3000	22	7	29.6	29.4	6071	6463	188	2524 ± 649
4000	38	11	31.1	30.7	6105	6756	136	4343 ± 1470
5000	42	12	32.4	30.7	6472	7466	157	6125 ± 1111
6000	38	11	33.6	31.6	6258	7361	222	6541 ± 1245
7000	37	10	34.1	31.6	6737	7933	178	6762 ± 673
8000	35	9	34.4	32.1	6694	8121	179	6995 ± 475
10000	34	11	35.5	33.2	6776	8193	152	5959 ± 563
12000	31	10	36.1	33.9	6760	8233	252	4868 ± 750
14000	28	10	36.3	33.5	6967	8695	211	5760 ± 715
16000	22	9	37.6	34.3	6965	8878	152	5224 ± 246
64000	21	18	41.1	35.7	7346	10466	102	5391 ± 139
143000	36	36	43.0	34.3	7504	11116	195	7254 ± 269

Table 7: ODs presence and behaviour across pythia-12b training checkpoints. '#' indicates the number of ODs, while '∩ final' is the number of ODs that are also present at the last checkpoint. The last ckp corresponds to the final model to which we refer in the main text.

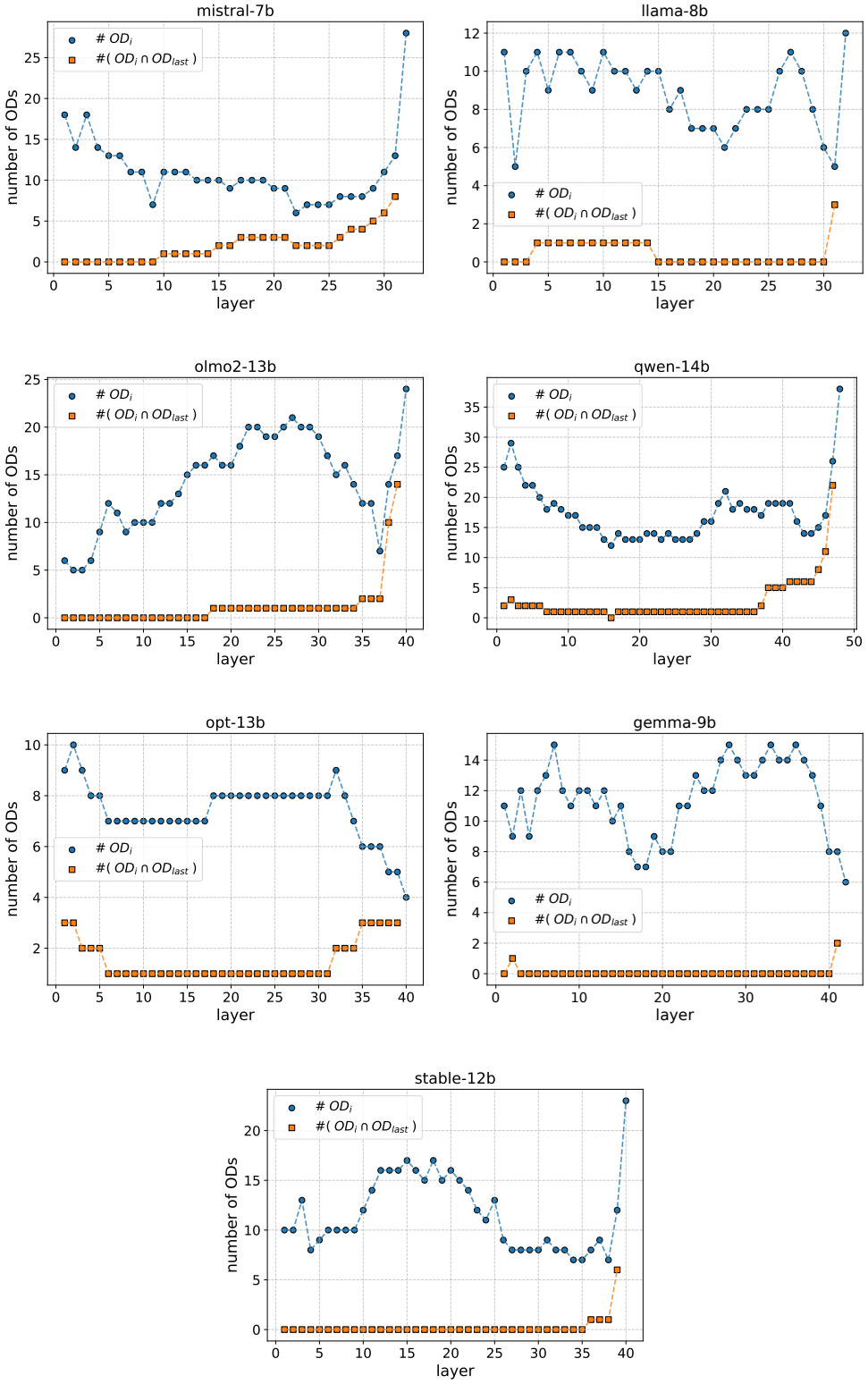


Figure 5: Number of ODs across layers (blue dots) and number of ODs in each layer that are also present in the last layer (orange squares). The last point for the overlap is not reported as it coincides with the actual number of ODs.

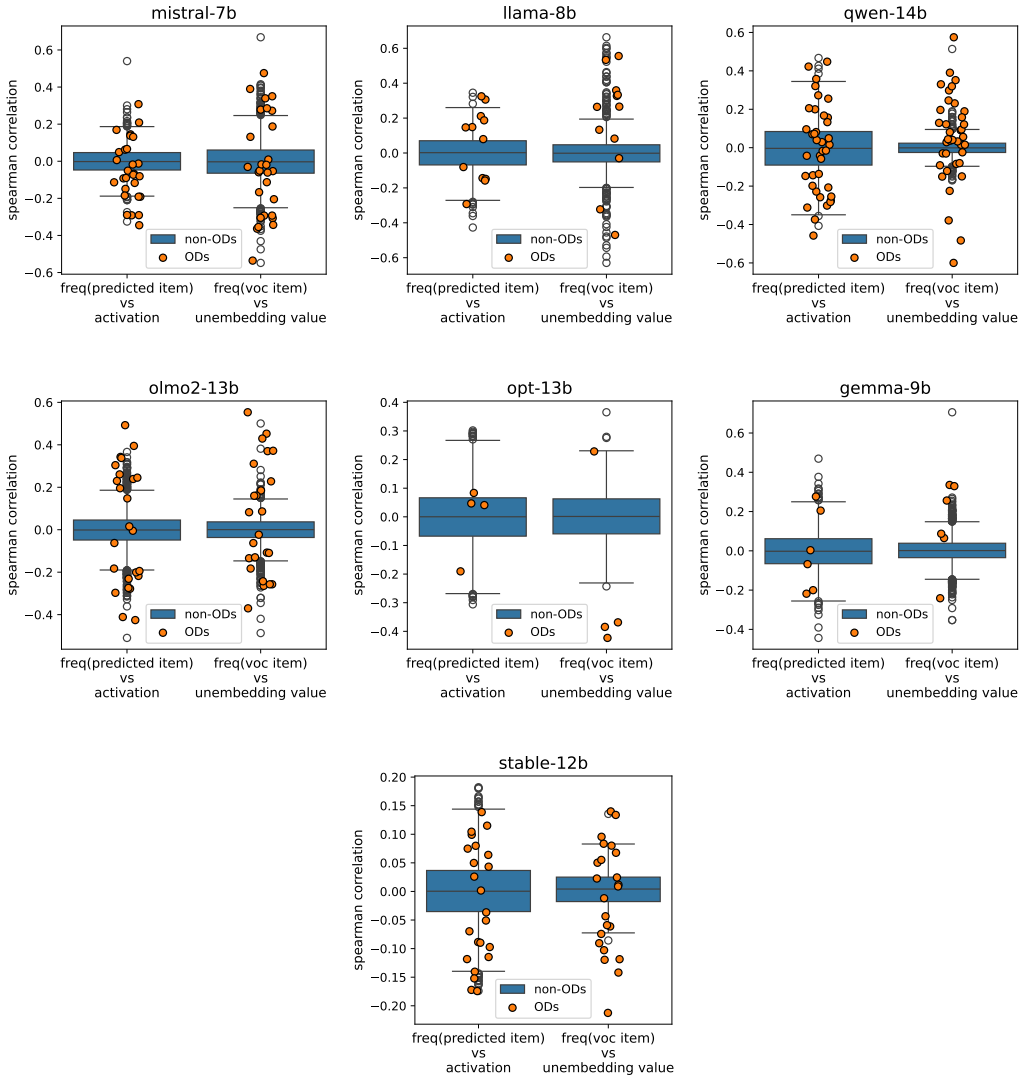


Figure 6: For each dimension, we compute the Spearman correlation coefficient between: (left) the last-layer activation value of each input context and the frequency of the predicted token; (right) the value in the unembedding matrix of each vocabulary item against its corpus frequency. We group in a boxplot the results for the non-ODS, while explicitly report each OD correlation score as orange circles. Smearing along the x-axis is to help visualization.

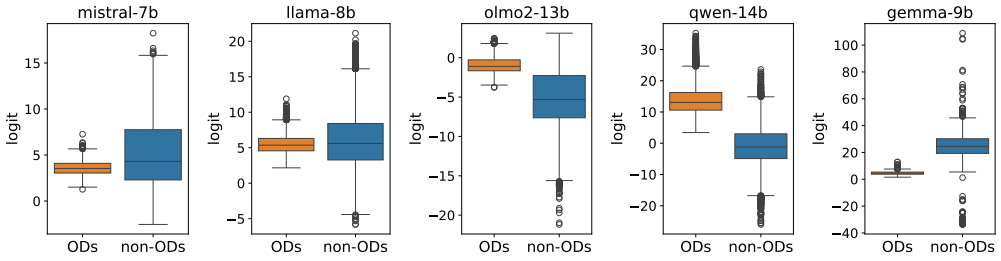


Figure 7: OD and non-OD logit contributions for all contexts predicting OD-favored tokens

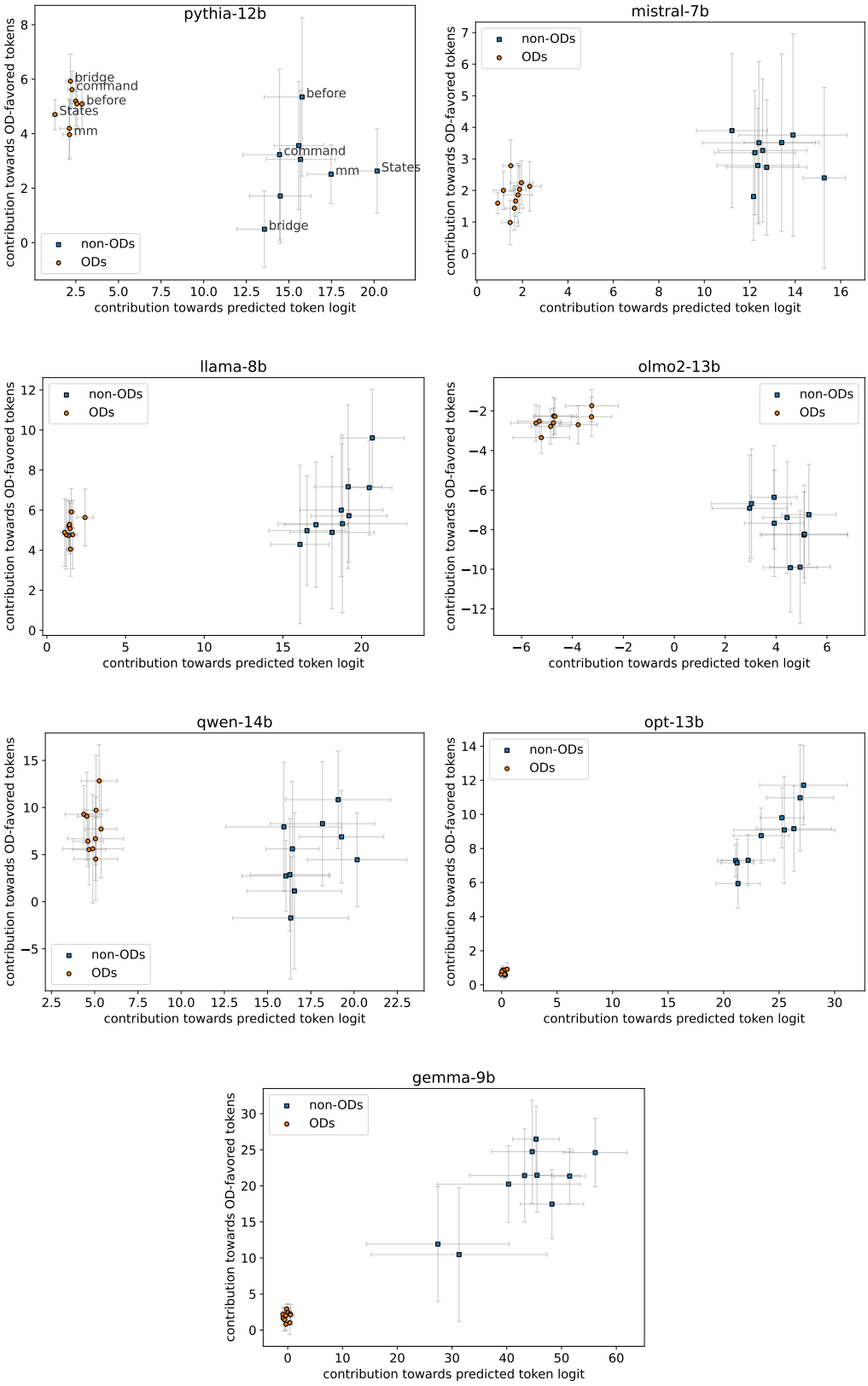


Figure 8: For each model: OD and non-OD contributions towards OD-neutral and OD-favored tokens in contexts where OD-neutrals are predicted, averaged across the contexts of each OD-neutral token and across contributions to each OD-favored token. We report standard deviations as error bars for clarity.

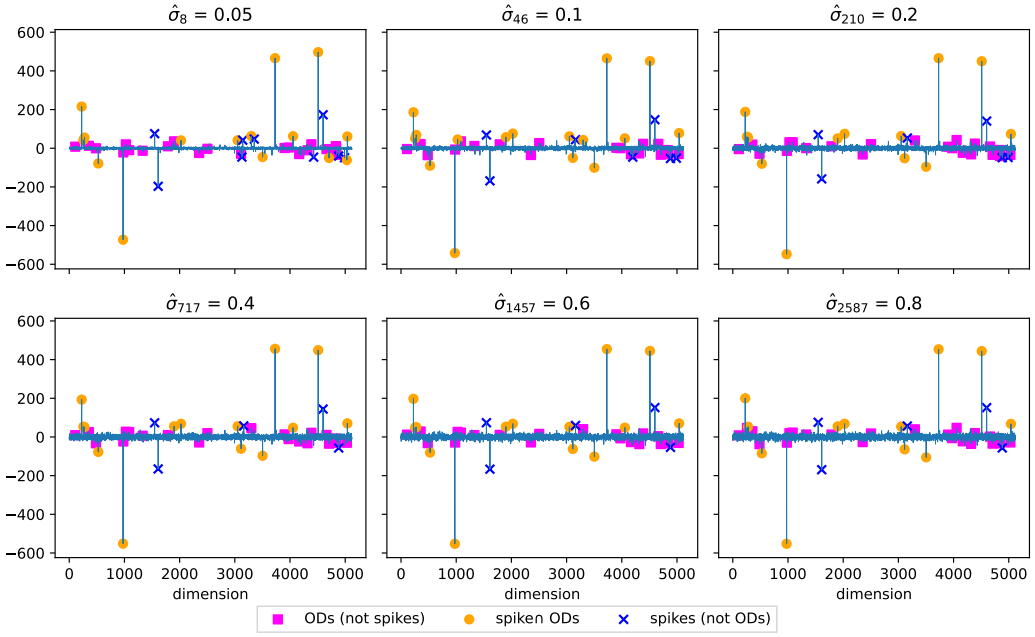
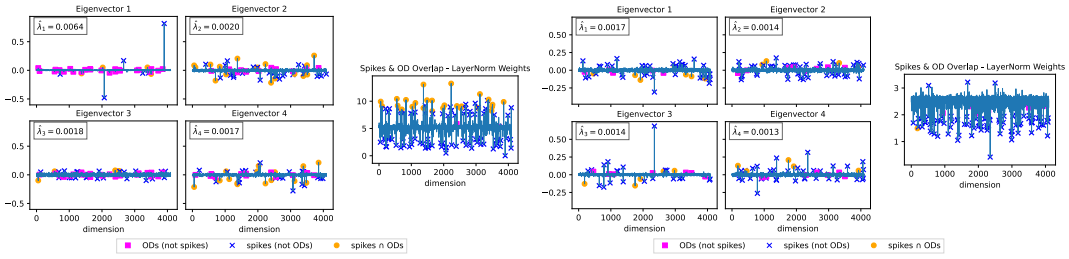
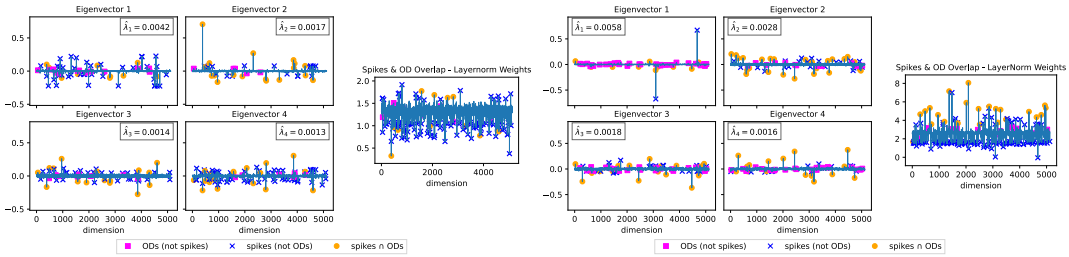


Figure 9: Overlaps between ODs and spikes of the vector obtained as the linear combination of the top N singular vectors, such that cumulative fraction of explained variance is $\hat{\sigma}_N = \frac{\sum_{i=1}^{N} \lambda_i}{\sum_{i=1}^{D} \lambda_i}$, where D is the total number of dimensions. Spikes which correspond to ODs are visualized as orange circles.



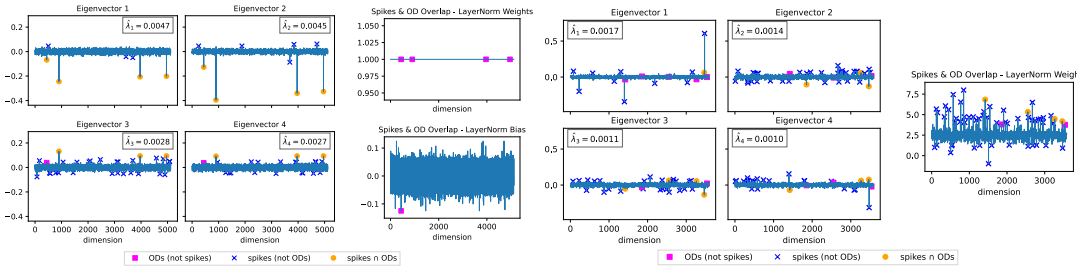
(a) mistral-7b

(b) llama-8b



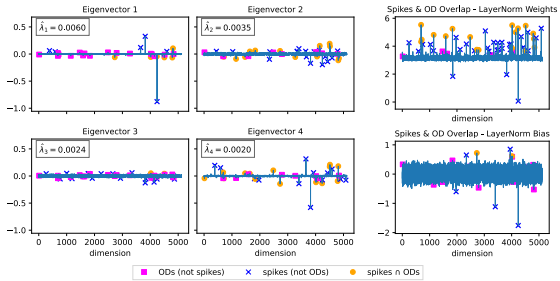
(c) olmo-13b

(d) qwen-14b



(e) opt-12b

(f) gemma-9b



(g) stable-12b

Figure 10: The analysis of Fig. 4 of the main text is repeated for the other models. **Left:** Top-4 singular vectors and values of the last-layer MLP down-projection matrix. **Right:** Final LayerNorm weights and, if present, biases. Spikes in parameter values that correspond to ODs are visualized as orange circles.

Model	pythia-12b
prompt	Two years ago I learned to bike with my parents. On Sundays' afternoon we always went for a ride. This stopped when my dad broke his knee and needed to go under surgery. All of
default	a sudden, I was the only one who could ride. I was so excited to be the only
Ablation	Generated sentence
largest 5	a sudden, I had to learn how to bike with my mom. She was always nervous about me
10	us kids were sad. But my mom was sadder. She cried. She cried because she knew
15	us kids were sad. But my mom said, "You'll learn. You'll learn." And
20	sudden, cycling became boring.\n\nThen, when my dad recovered, we went cycling again.
30	sudden cycling became boring.\n\nThen came cycling holidays. I've been cycling with my parents since
50	sudden cycling became boring.\n\nThen came bike commuting. I've been commuting by bike since February
100	sudden cycling became boring.\n\nThen came cycling holidays. cycling holidays are cycling holidays. cycling holidays
200	sudden cycling became boring. cycling became boring. cycling became boring. cycling became boring. cycling became boring
500	sudden cycling became boring! :(but yeah! cycling is awesome! :) :) :) :) :) :)
1000	sudden cycling became boring! cycling became boring! cycling became boring! cycling became boring! cycling became boring
2000	sudden cycling wasn't fun anymore anymore anymore anymore anymore anymore anymore anymore anymore anymore anymore anymore anymore anymore
3000	sudden cycling seemed boring! Cycling routes arent longer anymore! Cycling routes arent longer anymore
4000	sudden cycling wasn't FUNNIERORANDORANDORANDORANDORANDORANDORANDORANDO-RANDORANDORANDORANDORANDORAND
5000	implementation GU Dimelsleroil Hayes Weaverhet LibrarydocumentclassenvabcDEF[?]atchningriumt
smallest 5	a sudden, I was the only one who could ride. I was so excited to be the only
10	a sudden, I had to take care of my mom and my brother. I was a little bit
15	a sudden, I had to take care of my mom and my brother. I had to take care
20	a sudden I was the only one who could ride with my parents. I was so excited to be
30	a sudden, I had to take care of my mom and my brother. I was the only one
50	a sudden, I had to take care of my mom and my brother. I had to take care
100	a sudden I had to learn to bike on my own. I was scared and nervous. I was
200	a sudden I had to learn to bike on my own. I was scared, but I did it
500	a sudden I had to take care of my mom and my brother. I had to take care of
1000	a sudden, I had to take the bike on my own. I was not a good biker
2000	the sudden the biking was a thing of the past, and the only thing that was still the
3000	the biking in the world, the two of the three bikely-sib-b
4000	the first bikely enthusic-tic enthusic enthusic enthusic enthusic enthusic
5000	the the the the the the the the the the the the the the the the the the the the
random 5	a sudden, I was the only one who could ride. I was so excited to be the only
10	a sudden, I was the only one who could ride. I was so excited to be the only
15	a sudden, I was the only one who could ride. I was so excited to be the only
20	a sudden, I was the only one who could ride. I was so excited to be the only
30	a sudden, I had to take care of my mom and my brother. I was the only one
50	a sudden, I was the only one who could ride. I was so excited to be the only
100	a sudden I was the only one who could ride with my parents. I was so excited to be
200	a sudden I had to take care of my mom and my brother. I was a little bit scared
500	a sudden I had to take care of my mom and my brother. I had to do everything.
1000	us kids were left with our bikes in the garage. My mom asked me to take them out for
2000	us kids wanted to help him but his answer was always the same [?] "I can manage". This
3000	these long rides then became very short and very very very very very very very very very very very very
4000	us converged over distance over distance over distance over distance over distance over distance over distance over distance over
5000	typentypen photograp tiss scrut infil ingredtypentypentypentypentypentypentypentypentypentypentype-ntypentypen

Table 8: Generation upon ablation for pythia-12b. See Appendix H for details.

Model	mistral-7b
prompt	Two years ago I learned to bike with my parents. On Sundays' afternoon we always went for a ride. This stopped when my dad broke his knee and needed to go under surgery. All of
default	a sudden I was alone. I didn't know how to bike without my parents. I was
Ablation	Generated sentence
largest 5	a sudden I was alone.\n\nI've always been a bit of a loner.
10	a sudden, I was alone.\n\nI've been riding my bike for 2 years
15	a sudden, I was alone.\n\n I've been riding my bike for 2
20	a sudden, I was alone.\n\n I've been riding alone for 2 years
30	a sudden, I was alone.\n\nI'm 16, and I'm
50	a sudden, I'm 16, and I'm alone.\n\nI'
100	a sudden, I'm 18, and I'm 180cm tall
200	a sudden, I'm 16, and I'm biking.\n\nGeplaatst
500	a sudden, biking with my parents, and specially, with my dad, 10
1000	us, including mum, are avid cyclists. Mum's been cycling since she'
2000	a sudden, biking with him, which I've grown accustomed, I've
3000	Suddenly bike rides turned into walks. Weekends turned into sitting. Weekends turned into
4000	[[?]] [[?]]
smallest 5	a sudden I was alone. I didn't know how to bike without my parents. I was
10	a sudden I was alone. I didn't know how to bike without my parents. I was
15	a sudden I was alone. I didn't know how to bike without my parents. I was
20	a sudden I was alone. I didn't know how to bike without my parents. I was
30	a sudden I was alone. I didn't know how to bike without my parents. I was
50	a sudden I was alone. I had to find a new hobby.\n\nI started to
100	a sudden I was alone. I had to find a new hobby.\n\nI started to
200	a sudden I was alone. I had to learn to bike by myself. I was scared. I
500	a sudden I had to bike on my own. I was scared to go on my own, so
1000	a sudden I had to learn to ride by myself. I started with the bike my parents had given
2000	this time I had a little dream to go to the other side of the world and travel by bike
3000	this caused my love for the mountain bike to start slowly slowly slowly slowly slowly slowly slowly slowly slowly slowly
4000	laugtypenplaattypentypentypentypentypentypentypentypentypentypentypentypentypentypentypentypentypentypen
random 5	a sudden I was alone. I had to find a new hobby.\n\nI started to
10	a sudden I was alone. I didn't know how to bike without my parents. I was
15	a sudden I was alone. I didn't know how to bike without my parents. I was
20	a sudden I was alone with my bike. I didn't know how to ride it. I
30	a sudden I was alone with my bike. I didn't know how to ride it. I
50	a sudden I was alone. I didn't know how to bike without my parents. I was
100	a sudden I was alone. I didn't know how to bike without my parents. I was
200	a sudden I was alone with my bike. I didn't know how to ride it anymore.
500	a sudden I was alone with my bike and didn't know what to do with it. I
1000	a sudden I was on my own and I didn't know how to ride a bike anymore.
2000	a sudden my mom and I were on our own and we really enjoyed it!\n\nA few
3000	those things mean that we can do that in these hard corona-19 (C-1
4000	friedunoweenesen interesting tempornen interesting temporopleunstöß dedößößößößößößöß

Table 9: Generation upon ablation for mistral-7b. See Appendix H for details.

Model	llama-8b
prompt	Two years ago I learned to bike with my parents. On Sundays' afternoon we always went for a ride. This stopped when my dad broke his knee and needed to go under surgery. All of
default	a sudden I was left alone with my bike. I was 12 years old and I had to
Ablation	Generated sentence
largest 5	this happened during summer. Now that winter is coming I'm afraid that biking will stop again. I
10	this happened during summer 2012. Since then I haven't ridden my bike anymore. Until yesterday
15	us were devastated. I couldn't believe it. I couldn't believe my dad couldn't bike anymore
20	a sudden, biking became dangerous. I've been biking alone for a year now.<|end_of_text|>
30	a sudden, biking became dangerous. I've been biking alone 2-3 times a week.
50	a sudden, biking became dangerous. I've been biking alone 2-3 times a week.
100	2 months 2.scalablytyped[?][?][?][?] full[?][?][?][?][?][?]
200	2 summers' fkk fkk fkk fkk fkk fkk fkk fkk fkk fkk fkk fkk fkk fkk fkk fkk
500	2 weeks 2.scalablytyped nettsteder datingside datingside datingside datingside datingside datingside datingside datingside datingside datingside datingside datingside
1000	2 summers ago 2 summers 2 summers 2 summers 2 summers 2 summers
2000	2012 passed me biking dreaming 'gc addCriterionHeaderCodeHeaderCodeHeaderCodeHeaderCodeHeader-CodeHeaderCodeHeaderCode
3000	2012 2013 2014 2015 [?]#[?]#[?]#[?]#[?]#[?]#[?]#
4000	thisuskollectors@natenbspnbspgroupongroupongroupongroupongroupongroupongroupongroupon[?][?][?][?]
smallest 5	a sudden I was left alone with my bike. I was 12 years old and I had to
10	a sudden I was left alone with my bike. I was not able to ride it anymore. I
15	a sudden I was left alone with my bike. I was 12 years old and I was not
20	a sudden I was left alone with my bike. I was not able to ride it anymore. I
30	a sudden I was left alone with my bike. I was not sure if I could ride it by
50	a sudden I was left alone with my bike. I was not able to ride it anymore. I
100	a sudden I was left alone with my bike. I was 12 years old, and I was
200	a sudden I was left alone with my bike. I was 12 years old, I had a
500	a sudden I was the only one who could ride a bike. I was 11 years old.
1000	a sudden I, a 15 year old, was in charge of the a
2000	these, 730 830 1 830<|end_of_text|>
3000	enthusi usercontent/company-
4000	HeaderCode
random 5	a sudden I was left alone with my bike. I was not able to ride it anymore. I
10	a sudden I was left alone with my bike. I was not able to go for a ride with
15	a sudden I was left alone with my bike. I was not able to ride it anymore. I
20	a sudden I was left alone with my bike. I was not able to ride it anymore. I
30	a sudden I was left alone with my bike. I was not able to go for a ride with
50	a sudden I was left alone with my bike. I was sad, but I didn't want to
100	a sudden I was left alone with my bike. I started to ride around the block, then around
200	a sudden I was alone and I didn't know how to ride a bike. I was scared to
500	a sudden I was left alone with my bike and I was sad. I missed my dad and I
1000	a sudden I was left with no one to ride with and no one to ride for.\nI miss
2000	a sudden we had no reason to meet and ride in the fields and fields of the neighbouring area where
3000	a sudden the non use of a bike just for ñana or ñana or
4000	_marvin éné //{{1_//{{ éné iste //{{ //{{

Table 10: Generation upon ablation for llama-8b. See Appendix H for details.

Model	olmo2-13b
prompt	Two years ago I learned to bike with my parents. On Sundays' afternoon we always went for a ride. This stopped when my dad broke his knee and needed to go under surgery. All of
default	a sudden I was too busy to go biking. I was always doing something else. My parents asked
Ablation	Generated sentence
largest 5	us were sad about it. Yesterday I went to my dad's room. He was lying on the
10	us were sad about it. Yesterday, my dad told me that he wanted to ride bikes again.
15	us were sad about it. Yesterday morning mom told me dad's knee was healed and he could ride
20	us were sad about it.[?][?][?][?][?][?][?][?][?][?][?][?][?][?][?]
30	us were sad about it.[: _ Z _ X _ X _ K][?][?][?][?]
50	sudden[?][?][?][?][?][?][?][?][?][?][?][?][?][?][?][?][?][?][?]
100	sudden[?][?]\n\nKANJI[?][?][?]\n\nKANJI[?][?][?]\n\nKANJI[?][?][?]\n\nKANJI[?][?
200	sudden[?][?]\n\nKANJI[?][?][?][?][?][?][?][?][?][?][?][?][?]
500	sudden[?][?]\n\nKANJI[?][?][?][?][?][?][?][?][?][?][?][?][?]
1000	sudden[?][?]\n\nKANJI[?][?][?][?][?][?][?][?][?][?][?][?][?]
2000	sudden biking Sundays Stops[?][?]\n\nKANJI[?][?][?]\n\nKANJI[?][?][?]\n\nKANJI[?][?][?]\n
3000	sudden(weather[?][?][?][?][?][?][?][?][?][?][?][?][?][?][?][?][?]
4000	Eagerness accordionistarween accordistarween accordistarween accordistarween accordistarween accordistarween
5000	ayasundo Lyons EOamelbitsujuenkinkeenk KramerFParnessVTesch Estragos backlogeriicode
smallest 5	a sudden I was too busy to go biking. I was always doing something else. My parents asked
10	a sudden I was too busy to go biking. I was always doing something else. My parents would
15	a sudden I was too busy to go biking. I was always doing something else. My parents would
20	a sudden I was too busy to go biking. I was always doing something else. My parents would
30	a sudden I was too busy to go biking. I was always doing something else. My dad was
50	a sudden I was too busy to go biking. I was always doing something else. My dad was
100	a sudden I was too busy to go biking. I was always doing something else. I had forgotten
200	a sudden my mum was too tired to go out, and I didn't have a bike for myself
500	a sudden my mum was too tired to go out and I was too lazy to go alone. So
1000	a sudden I was the one who had to take the car to the store to get the milk and
2000	the other times we had to go to the hospital to get a new treatment. This was a very
3000	the other days I would go to the park and go on the little dirt road and go to the
4000	the 15 10 5 1 1 1
5000	the 100- 100- 100- 100 100
random 5	a sudden I was too busy to go biking. I was always doing something else. My parents asked
10	a sudden I was too busy to go biking. I was always doing something else. My parents asked
15	a sudden I was too busy to go biking. I was always doing something else. My parents asked
20	a sudden I was too busy to go biking. I was always doing something else. My parents asked
30	a sudden I was too busy to go biking. I was always doing something else. My parents asked
50	a sudden I was too busy to go biking. I was always doing something else. I had a
100	a sudden I was too busy to go biking. I was always doing something else. I had a
200	a sudden, my mum and I stopped riding. We were too afraid to ride without him. One
500	a sudden, my mom was the only one who could bike with me. But she was very busy
1000	a sudden my mom was the only one who could bike with me. My dad was always the one
2000	a sudden, my mom was the only one who biked. I tried to get her to do
3000	sudden I found myself riding the most I ever rode before. Mom continued to drive her car and Dad
4000	sudden mid-November central Europe weather hit home. Snow Brussels Wallonia year old electric bike
5000	tahuncente[?] presenta[?]órioPerfilVocêArchivoVocêVocêVocêVocêVocêVocêVocêVocêVocêVocêVocê

Table 11: Generation upon ablation for olmo2-13b. See Appendix H for details.

Model	qwen-14b
prompt	Two years ago I learned to bike with my parents. On Sundays' afternoon we always went for a ride. This stopped when my dad broke his knee and needed to go under surgery. All of
default	a sudden I was left without a biking partner. I was sad and I missed the rides. I
Ablation	Generated sentence
largest 5	my[?]200[?]bike[?]lessons[?]were[?]wasted.[?]I[?]knew
10	us volunteerd to volunte yarg yarg yarg yarg yarg yarg yarg yarg yarg yarg yarg yarg yarg yarg yarg
15	2012 I biked 12000000000
20	2012121212121212121
30	2012 1 [?] be [?]spent in[?][?] [?][?][?][?] and he hasn
50	2012 1 [?] be [?]spent in[?][?] [?][?][?][?] and then[?]
100	2012 1)didn't [?])did[?] [?])did[?] [?])did[?] [?]
200	2012 1)didn't [?])did[?] [?])did[?] [?])did[?] [?]
500	2012 1)didn't [?])did[?] [?])did[?] [?])did[?] [?]
1000	2012 1)did [?])did[?] [?])did[?] [?])did[?] [?])did[?]
2000	2012, he hasn't[?]
3000	2015,[?]
4000	us$core$core$core$core$core$core$core$core$core$core$core$core$core$core$core$core$core$core$core$core$core
5000	[?]s own behalf destinationViewControlleruallyALLY [?][?]\n[?] [?][?]ses [?][?]ses [?][?]ses [?][?]ses [?][?]ses
smallest 5	a sudden I was left without a biking partner. I was sad and I missed the rides. I
10	a sudden I was left without a biking partner. I was sad and I missed the rides. I
15	a sudden I was left without a biking partner. I was sad and I missed the rides. I
20	a sudden I was left without a biking partner. I was sad and I missed the rides. I
30	a sudden I was without a bike and without a dad to ride with. I was sad. I
50	a sudden I was without a bike. I was sad. I was 10 years old.
100	a sudden I had to stop biking. I was sad. I missed biking. I missed the wind
200	a sudden I had to stop biking. I was sad. I missed the wind in my face,
500	a sudden I had to stop riding. I felt so sad. I had to stay home and watch
1000	a sudden I had no one to ride with. I had a hard time to get used to the
2000	his post-surgery care was very hard on him and he never got back to biking.
3000	his left [?] [?][?][?][?][?][?][?][?][?][?][?][?][?]
4000	juni I icked 1 ets j
5000	FunctionFlags [?][?][?][?][?][?][?]
random 5	a sudden I was left without a biking partner. I was sad and I missed the rides. I
10	a sudden I was left without a biking partner. I was sad and I missed the rides. I
15	a sudden I was left without a biking partner. I was sad and I missed the time we spent
20	a sudden I was left without a biking partner. I was sad and I didn't know what to
30	a sudden I was left without a bike. I was 10 years old and I didn't
50	a sudden I was left without a bike. I was 12 years old and I didn't
100	a sudden I was left without a bike. I was 10 years old and I didn't
200	a sudden my mom and I were left alone. I was 10 years old and my mom
500	a sudden my 10-year-old self was the only one left to take care of my little
1000	sudden we had to stop going to bike together because my dad could not stand up yet to go for
2000	sudden dad could not go cycling anymore but he was not going to _ his 2-year-old
3000	newcoms([?][?])[?][?]f111111111111
4000	[?]ALSE [?][?][?][?] [?][?][?][?]$fdata$fdata[?]$fdata[?]$fdata$fdata$fdata$fdata$fdata$fdata$fdata$fdata
5000	.dtpcola-kit/Branch/goto/portfolio/portfolio, volunte/lic/gif/Branch/goto/portfolio/portfolio/portfolio, volunte/chart/Branch

Table 12: Generation upon ablation for qwen-14b. See Appendix H for details.

Model	opt-13b
prompt	Two years ago I learned to bike with my parents. On Sundays' afternoon we always went for a ride. This stopped when my dad broke his knee and needed to go under surgery. All of
default	a sudden I was alone on the bike. I was scared to ride alone. I was scared to
Ablation	**Generated sentence**
largest 5	a sudden I was alone on the bike. I was scared and didn't know what to do.
10	a sudden I was alone. I was so sad. I miss my dad.\nI'm sorry
15	a sudden I was alone. I was so sad. I didn't know what to do. I
20	a sudden I was alone. I was afraid to ride my bike alone. I was afraid to ride
30	a sudden I was alone. I was so sad. I didn't know what to do. I
50	a sudden I was alone. I was afraid to ride my bike. I was afraid to go outside
100	a sudden I was alone. I was so sad. I miss my dad.\nI'm sorry
200	a sudden I was alone. I was so sad. I was so lonely. I was so angry
500	a sudden I was the only one who could go for a ride. I was so sad. I
1000	us are getting older and we don't have the energy anymore. I'm really happy I'm getting
2000	us are getting older. My mom doesn't want to ride anymore. My dad doesn't want to
3000	us are cyclists. Cycling is our favorite thing. Cycling is our favorite thing. Cycling is our favorite
4000	my siblings bike, I'm alone. :(\nbike on!</s>
5000	Oxacander PVvblogerherlabeleer missvenalsiche Jeriter Monitoring materialsrugeer
smallest 5	a sudden I was alone on the bike. I was scared to ride alone. I was scared to
10	a sudden I was alone on the bike. I was scared to ride alone. I was scared to
15	a sudden I was alone on the bike. I was scared and I didn't know what to do
20	a sudden I was alone on the bike. I was scared and I didn't know what to do
30	a sudden I was alone on the bike. I was scared and I didn't know what to do
50	a sudden I was alone. I was so sad. I was so lonely. I was so scared
100	a sudden I was alone on the bike. I was scared and I didn't know what to do
200	a sudden I was the only one who could ride a bike. I was so sad.\n\n
500	a sudden I was the only one left in the family who could ride a bike. I was the
1000	a sudden I was the only one left in the family who could ride a bike.\n\nI
2000	a sudden the time for the bike rides was over.\n\nI was a bit disappointed, but
3000	a sudden , the only time , , , , , , , , , , , , , ,
4000	, ,
5000	._ . . . . .
random 5	a sudden I was alone on the bike. I was scared and I didn't know what to do
10	a sudden I was alone on the bike. I was scared to ride alone. I was scared to
15	a sudden I was alone on the bike. I was scared to ride alone. I was scared to
20	a sudden I was alone on the bike. I was scared and I didn't know what to do
30	a sudden I was alone on the bike. I was scared and I didn't know what to do
50	a sudden I was alone on the bike. I was not able to ride with my parents anymore.
100	a sudden I was alone on the bike. I was not able to ride with my parents anymore.
200	a sudden I was alone on the bike. I was so scared that I stopped riding. I was
500	a sudden I was alone. I was so sad. I was so lonely. I was so bored
1000	a sudden I was alone. I was so happy when my mom said that she would take me on
2000	us are getting older and I can't really ride with my mom and my sister. I miss my
3000	us missed it and I missed it the most. I miss my dad and I miss my mom who
4000	a sudden, my mom got lost on her scooter on a daily trip between shops, and lost
5000	Course permanentalon Pug pendataneptri Irugi pendatanrientht Allegippy Pug pendatanrient

Table 13: Generation upon ablation for opt-13b. See Appendix H for details.

Model	gemma-9b
prompt	Two years ago I learned to bike with my parents. On Sundays' afternoon we always went for a ride. This stopped when my dad broke his knee and needed to go under surgery. All of
default	a sudden I was left alone with my bike. I was 10 years old and I was
Ablation	Generated sentence
largest 5	a sudden I was left alone with my bike. I was afraid to go out alone, but I
10	a sudden I was left alone with my bike. I was afraid to ride it alone, but I
15	a sudden I was left alone with my bike. I was scared to ride it alone, but I
20	a sudden I was left alone with my bike. I was afraid to ride it alone, but I
30	a sudden I was left alone with my bike. I was afraid to ride it alone, but I
50	a SUDDEN I was left alone with my bike. I was scared to ride it alone. I
100	us were sad about it.\n\nI was sad because I loved biking with my parents. I was
200	us were sad about it. My mom and I were sad because we couldn XNUMXt ride anymore
500	us were sad about it. My dad was sad because he couldn XNUMXt ride his bike anymore
1000	us were devastated. My dad was always so active and sporty. He loved to play tennis, soccer
2000	us were sad about it. My dad was sadder than anyone else. He loves biking. He
3000	this stopped when I went to Beijing.\n\n plea[?]ure\n createSlice\n I\n I\n I\n I
smallest 5	a sudden I was left alone with my bike. I was 10 years old and I was
10	a sudden I was left alone with my bike. I was scared to go out alone, but I
15	a sudden I was left alone with my bike. I was scared to go out alone, but I
20	a sudden I was left alone with my bike. I was scared to go out alone, but I
30	a sudden I was left alone with my bike. I was 12 years old and I was
50	a sudden I was left alone with my bike. I was 12 years old and I was
100	a sudden I was left alone with my bike. I was 12 years old and I was
200	a sudden I was left alone with my bike. I was 12 years old and I was
500	a sudden I was left alone with my bike. I was 12 years
1000	a sudden, I was left alone. I was 12 years
2000	a 2019 I was in a big and very very very very very very very very
3000	the 2019 and 2020, I was in the 10
random 5	a sudden I was left alone with my bike. I was 10 years old and I was
10	a sudden I was left alone with my bike. I was 10 years old and I was
15	a sudden I was left alone with my bike. I was 10 years old and I was
20	a sudden I was left alone with my bike. I was 10 years old and I was
30	a sudden I was left alone with my bike. I was 10 years old and I was
50	a sudden I was left alone with my bike. I was 10 years old and I was
100	a sudden I was left alone with my bike. I was 10 years old and I was
200	a sudden I was left alone with my bike. I was not sure what to do with it.
500	a sudden I was left alone with my bike. I was afraid to ride it alone, but I
1000	a sudden I was left alone with my bike. I was afraid to go out alone, but I
2000	a sudden I was on my own. I was afraid to ride alone, but I knew I had
3000	a extranjero[?]jimo.]=>]=>]=>]=>]=>]=>]=>]=>

Table 14: Generation upon ablation for gemma-9b. See Appendix H for details.

Model	stable-12b
prompt	Two years ago I learned to bike with my parents. On Sundays' afternoon we always went for a ride. This stopped when my dad broke his knee and needed to go under surgery. All of
default	us were very sad. I was the only one who could still ride a bike. I was very
Ablation	**Generated sentence**
largest 5	a sudden, I was the only one who could go for a ride. I was 11
10	a sudden, I was the only one who could go for a ride. I was 11
15	a\ns\ns\ns\ns\ns\ns\ns\ns\n
20	a 110 111 112 113 11
30	a 111111111111111111
50	a 110 111 112 113 11
100	a 110 111 112 113 11
200	a\n_.\n_2_2_2_2_2_2_2_2
500	_0_2_2_2_2_2_2_2_2_2
1000	_1__2_3_4_5_6_7_8_9_
2000	dit dit dit dit dit dit dit dit dit dit dit dit dit dit dit dit dit dit dit
3000	moo moo moo moo moo moo moo moo moo moo moo moo moo moo moo moo moo moo moo
4000	sic sic sic sic sic sic sic sic sic sic sic sic sic sic sic sic sic sic sic
5000	YELLOW ess repentDomain rit sic wel pens wel wel wel wel wel wel wel wel wel wel wel
smallest 5	us were very sad. I was the only one who could still ride a bike. I was very
10	us were very sad. I was the only one who could still ride a bike. I was very
15	us were very sad. I was the only one who could still ride a bike. I was very
20	us were very sad. I was the only one who could still ride a bike. I was very
30	us were very sad. I was the only one who could still ride a bike. I was very
50	us were very sad. I was the only one who could still ride a bike. I was very
100	us were very sad. I was the only one who could still ride a bike. I was very
200	us were very sad. We missed the Sunday bike rides. We missed the time we spent together.
500	us were very sad. I was the only one who could still go out on the road. I
1000	a sudden, I was the only one in the family who could still go for a ride. I
2000	excer excer excer excer excer excer excer excer excer excer excer excer excer excer excer excer excer excer excer excer
3000	disappe,[?]\n\n,[?]\n\n,[?]\n\n,[?]\n\n,[?]\n\n,[?]\n\n,[?]\n\n,[?]\n\n,[?]\n\n,[?]\n\n,[?]\n\n,
4000	,[?]\n\nINCLUDED,[?]\n\nINCLUDED,[?]\n\nINCLUDED,[?]\n\nINCLUDED,[?]\n\nINCLUDED,
5000	underminhsiLOCKSLOCKSLOCKSLOCKSLOCKSLOCKSLOCKSLOCKSLOCKSLOCKSLOCKS
random 5	us were very sad. I missed my dad's company. I missed the bike rides. I missed
10	us were very sad. I missed the bike rides. I missed my dad. I missed my mom
15	us were very sad. My mom and I decided to go for a ride on our own. We
20	us were very sad. My mom and I decided to go for a ride on our own. We
30	us were very sad. My dad was the one who taught me to ride a bike. He was
50	us were very sad. My dad was the one who taught me how to ride a bike. He
100	us missed the bike rides. I was the one who missed it most. I was the one who
200	us missed it so much. Now, two years later, my dad is back on his feet and
500	a sudden I found myself without a companion. I missed the rides and the fun. I missed my
1000	us missed those outings. It's not easy to go out and do such activities with just me and
2000	his biking spares were sold. I still miss biking. INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT
3000	DAMAGEREENREENREENREENREENREENREENREENREENREENREENREENREEN
4000	INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT INCIDENT
5000	favorayo tob disg favor JsonRequest/DkIFn favor Clay ped favor Clay ped Clay ped Clay ped Clay ped

Table 15: Generation upon ablation for stable-12b. See Appendix H for details.