When Will the Tokens End? Graph-Based Forecasting for LLMs Output Length

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Abstract

Large Language Models (LLMs) are typically trained to predict the next token in a sequence. However, their internal representations often encode signals that go beyond immediate next-token prediction. In this work, we investigate whether these hidden states also carry information about the remaining length of the generated output—an implicit form of foresight (Pal et al., 2023). Accurately estimating how many tokens are left in a response has both theoretical and practical relevance. From an interpretability perspective, it reveals that the model may internally track its progress through a generation. From a systems perspective, it enables more efficient inference strategies, such as LLM inference via output-length-aware scheduling (Shahout et al., 2024). In our work we show that by using graph-based approach one can predict length of the generated text after prefilling stage. The findings presented in this study may be particularly valuable for organizations providing LLM-based services that seek to manage and forecast inference costs more effectively.

1 Introduction

Large Language Models (LLMs) have demonstrated remarkable ability to generate coherent text, but understanding what latent information they maintain during generation remains a challenge. A key question is whether an LLM internally tracks how much output remains to be produced. This is relevant both for interpretability—understanding a model's sense of progression—and for practical systems such as efficient request scheduling (Qiu et al., 2024; Zheng et al., 2023). This aspect is particularly important from the perspective of energy savings for LLM providers.

Prior work suggests that transformer hidden states may encode signals beyond immediate next-token prediction. For instance, Pal et al. (2023) showed that a single hidden state can predict several future tokens with notable accuracy, indicating that models internalize aspects of future output. Building on this, Shahout et al. (2024) used intermediate layer embeddings to estimate the number of tokens remaining in a response, identifying layers 8–15 as especially informative. Formally, this can be modeled as learning a *parametrized function* $f(\mathbf{h}; \theta)$, where $\mathbf{h}$ is a hidden state from a selected layer and θ denotes the learnable parameters.

Accurately estimating the remaining output length offers practical benefits. It enables strategies like adaptive early stopping and intelligent scheduling in multi-user environments. A particularly promising use case is integration with Shortest Job First (SJF) scheduling (Hamayun and Khurshid, 2015; Fu et al., 2024), which minimizes latency by prioritizing shorter tasks. In the LLM setting, this allows systems like Orca (Mukherjee et al., 2023) or vLLM (Kwon et al., 2023) to reorder token generation queues dynamically to improve throughput and responsiveness.

Our contributions are:

- **An Aggregation-based Predictor** that combines hidden states from multiple transformer layers using element-wise operations (e.g., mean, sum) and predicts token-wise output length via a shallow feedforward network.
- **A Layerwise Graph Regressor** that treats each layer's hidden state as a node in a token-specific graph, using a GNN to model inter-layer dependencies for remaining token count prediction.

We further connect our results to existing interpretability work and discuss what they reveal about internal transformer representations.

2 Method

To predict the number of remaining tokens at each generation step, we consider the task as a regression problem. Let $\mathbf{h}_\ell^t \in R^d$ denote the hidden state

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(embedding vector) from the ℓ-th layer of the LLM at generation step t, where ℓ denotes a hidden state index. The prediction target is defined as $y^t = T - t$, where T is the total number of tokens in the generated sequence and t is the current position. The objective is to learn a function f such that:

$$\hat{y}^t = f\left(\{\mathbf{h}_\ell^t\}_{\ell \in \mathcal{L}}\right)$$

We explore two model architectures for this task:

- **Aggregation.** This baseline follows the TRAIL methodology by leveraging internal hidden states from a large language model (LLM) to predict output lengths. Specifically, we extract token-level hidden states $\mathbf{h}_\ell^t$ from a selected set of layers and aggregate them using a configurable element-wise operation such as mean, sum, or concatenation:

  $$\mathbf{z}^t = \text{Aggregate}(\mathbf{h}_{\ell_1}^t, \ldots, \mathbf{h}_{\ell_k}^t) \in R^d$$

  The aggregated vector $\mathbf{z}^t$ is passed through a lightweight feedforward network ϕ to produce a categorical prediction over discretized bins representing the number of remaining output tokens:

  $$\hat{y}^t = \phi(\mathbf{z}^t)$$

  The model is trained using a cross-entropy loss over these bins "as in original work. During evaluation, we compute the expected value of the predicted length by weighting bin midpoints with softmax probabilities. This approach mirrors the core idea of TRAIL (Shahout et al., 2024) by reusing internal representations of the LLM without requiring end-to-end fine-tuning. The implementation supports aggregation modes including mean and sum. It operates purely on precomputed embeddings, ensuring low inference overhead.

- **Layerwise Graph Regressor.** We propose a graph-based regression model for predicting the number of remaining output tokens for each generated token. The model leverages the layerwise structure of transformer hidden states by constructing a token-specific graph where each node corresponds to the hidden embedding.

  These embeddings form the node features $\mathbf{x} \in R^{L \times d}$, where L is the number of layers. Nodes are connected using a fully connected topology, resulting in an adjacency matrix $\mathbf{A}$ that captures all pairwise relationships between layers.

  A two-layer Graph Convolutional Network (GCN) is applied to this token-specific graph:

  $$\mathbf{x}^{(1)} = \text{ReLU}(\text{GCN}_1(\mathbf{x}, \mathbf{A}))$$

  $$\mathbf{x}^{(2)} = \text{ReLU}(\text{GCN}_2(\mathbf{x}^{(1)}, \mathbf{A}))$$

  The final node representations $\mathbf{x}^{(2)}$ are aggregated using *global mean pooling* to obtain a compact vector $\mathbf{v}^t \in R^{d'}$:

  $$\mathbf{v}^t = \text{MeanPool}(\mathbf{x}^{(2)})$$

  A fully connected regressor ψ then produces the predicted remaining length:

  $$\hat{y}^t = \psi(\mathbf{v}^t)$$

  This architecture captures inter-layer structural relationships, offering a compact and expressive summary of a token's transformer-depth context. The model is trained using the Mean Absolute Error (MAE) loss between predictions $\hat{y}^t$ and ground truth y^t.

3 Experimental Setup

Dataset To evaluate the ability of transformer hidden states to predict the number of tokens remaining during text generation, three datasets were constructed using different instruction-tuned large language models. Each dataset is based on the same subset of 1,000 examples from the Stanford Alpaca dataset (Taori et al., 2023), which contains synthetic prompt-response pairs generated by OpenAI's text-davinci-003. These prompts were designed to elicit coherent and informative responses from instruction-following models. Responses were generated using three separate models:

- `mistralai/Mistral-7B-Instruct-v0.2`
- `google/gemma-7b-it`
- `meta-llama/Meta-Llama-3-8B-Instruct`

During generation, hidden states from transformer layers 8 through 15 were extracted at each generation step, following findings of (Shahout et al., 2024). These hidden representations served as the primary input features for all predictive models trained in this study. Each model yielded a

distinct dataset, enabling a comparative evaluation of output-length prediction performance across different LLM architectures. As shown in Figure 1, the majority of generated responses were no longer than 150 tokens.

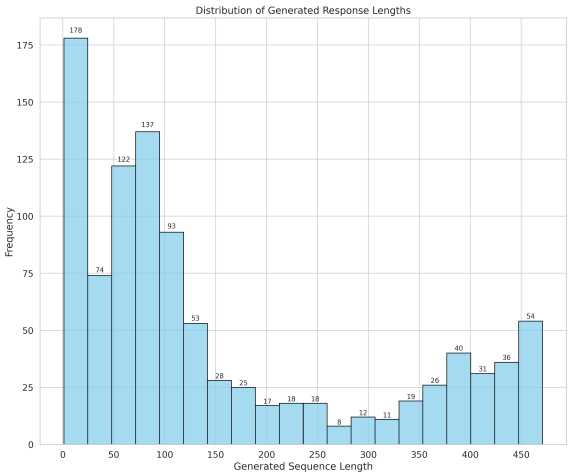

Figure 1: Distribution of generated outputs lengths for Llama

Models We employed two distinct model architectures to predict the number of tokens remaining during generation: an aggregation-based predictor and a layerwise graph regressor.

3.1 Aggregation-Based Predictor

The model operates on the hidden states extracted from a specific token (e.g., the last generated token) across transformer layers. These hidden states are aggregated using simple element-wise operations such as mean, sum, or concatenation. The resulting vector, which encodes contextual and hierarchical information from the selected layers, is then passed through a lightweight feedforward neural network to produce the predicted output length.

3.2 Layerwise Graph Regressor

The graph-based architecture treats each transformer layer as a node in a graph, where node features correspond to the hidden states from that layer at a given generation step. A fully connected graph structure is applied across layers. We use a two-layer Graph Convolutional Network (GCN) to learn inter-layer dependencies, followed by global mean pooling and a final regression head that outputs the predicted number of remaining tokens. This structure captures hierarchical and distributed information present in the model's depth-wise architecture.

We choose to use hidden states from layers 8 to 15 based on empirical findings from TRAIL (Shahout et al., 2024), which showed that these intermediate layers achieve the lowest mean absolute error in output length prediction tasks.

Training Details We train all models for up to 30 epochs using early stopping and adaptive learning rate scheduling. The optimizer used is AdamW with a learning rate of 1e-3 and a batch size of 16. All training is performed with mixed precision (AMP) to improve computational efficiency. We evaluate models using standard regression metrics, including Mean Absolute Error (MAE) and Normalized MAE (NMAE). For classification-based approaches, we additionally compute the expected value of the predicted output length from the softmax-weighted bin midpoints.

Evaluation Metrics We report the **Mean Absolute Error (MAE)** as our primary evaluation metric. MAE measures the average absolute difference between predicted and true values, providing an interpretable and scale-consistent indication of prediction accuracy:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i|$$

where $\hat{y}_i$ and y_i represent the predicted and ground-truth number of remaining tokens at generation step i, respectively.This approach has also been adopted in previous studies, and we regard it as a valuable point of reference (Shahout et al., 2024), (Qiu et al., 2024). To complement MAE, we also report the **Normalized Mean Absolute Error (NMAE)**:

$$\text{NMAE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|\hat{y}_i - y_i|}{y_i}$$

This metric captures relative error, which is particularly informative when the target values (i.e., the number of remaining tokens) vary widely. To avoid division by zero, we exclude instances where $y_i = 0$.

NMAE is especially well-suited for length prediction tasks because it accounts for the scale of the target values. While MAE treats all errors equally, regardless of the true value's magnitude, NMAE penalizes errors relative to the ground truth. For example, an error of 5 tokens is more severe when the true value is 10 than when it is 100. By normalizing the errors, NMAE offers a more nuanced and scale-sensitive evaluation of model performance.

Method	MAE	NMAE	Model Parameters
Model Gemma-7B			
Layerwise Graph Regressor Large	**9.49**	**0.0048**	1,704,961
Layerwise Graph Regressor Small	11.69	0.0092	819,713
TRAIL (14 Layer)	15.25	0.4177	2,102,794
Aggregated States Regressor (Mean)	15.71	0.43	2,102,794
Aggregated States Regressor (Sum)	15.40	0.42	2,102,794
Aggregated States Regressor (Concat)	14.08	0.40	16,782,850
Model Mistral-7B			
Layerwise Graph Regressor Large	**13.56**	**0.0114**	1,704,961
Layerwise Graph Regressor Small	14.17	0.0046	819,713
TRAIL (15 Layer)	18.44	1.0112	2,102,794
Aggregated States Regressor (Mean)	19.17	1.00	2,102,794
Aggregated States Regressor (Sum)	18.01	0.96	2,102,794
Aggregated States Regressor (Concat)	16.98	0.93	16,782,850
Model Llama-8B			
Layerwise Graph Regressor Large	**25.36**	**0.3541**	1,704,961
Layerwise Graph Regressor Small	26.26	0.6237	819,713
TRAIL (14 Layer)	27.79	1.0377	2,102,794
Aggregated States Regressor (Mean)	28.98	1.01	2,102,794
Aggregated States Regressor (Sum)	29.11	0.98	2,102,794
Aggregated States Regressor (Concat)	24.91	0.85	16,782,850

Table 1: Combined regression results for Gemma-7B, Mistral-7B and Llama-8B using TRAIL, layerwise graph-based and aggregated-state regressors

This is particularly important in settings where the target lengths span a wide range—from very short to very long continuations. In such cases, MAE tends to be dominated by absolute errors on longer sequences, potentially masking poor performance on shorter ones. In contrast, NMAE highlights proportional mistakes, which are often more meaningful in practical applications. For instance, overestimating by 5 tokens when only 10 remain may indicate a critical failure in generation control, while the same absolute error on a 100-token continuation is less problematic. We therefore hypothesize that NMAE provides a more balanced and interpretable signal for evaluating length prediction, especially when precise control over short outputs is important.

4 Results

We observe that the **Layerwise Graph Regressor** consistently outperforms the **TRAIL baseline** (see Table 1) in terms of both MAE and NMAE across all three tested models:

- On **Gemma-7B**, the graph-based model reduces NMAE from 0.4177 (TRAIL) to **0.0048**, achieving an improvement of over **98.8%**. The MAE drops from 15.25 to **9.49**.
- On **Mistral-7B**, the graph model lowers NMAE from 1.0112 (TRAIL) to **0.0046** — a relative decrease of more than **99.5%**. Similarly, MAE improves from 18.44 to **13.56**.
- On **Llama-8B**, the reduction is also substantial: NMAE decreases from 1.0377 (TRAIL) to **0.3541**, a relative gain of **65.9%**. MAE drops from 27.79 to **25.36**.

Even when using a reduced-size version (819k parameters), the Layerwise Graph Regressor achieves lower MAE and NMAE than TRAIL in every setting, highlighting the efficiency and scalability of the graph-based representation of hidden states.

5 Discussion

Our results reinforce that hidden states in transformer models encode information not only about the next token but also about the overall progress of the generation process. The consistent advantage of the Graph model indicates that combining

information across layers captures this signal more effectively than single-layer or pooled representations.

These findings empirically validate the hypothesis posed by Shahout et al. (2024), who suggested that integrating multiple layers could enhance predictions. Our model, by leveraging mid-layer embeddings, demonstrates that length-related information is distributed across depth and benefits from structured modeling.

This aligns with broader themes in interpretability. Each layer may represent different levels of abstraction—from planning and discourse structure to local coherence. Our results suggest that LLMs implicitly maintain a sense of "how much is left", even though they are trained only to predict the next token. Similar to the "Future Lens" findings by Pal et al. (2023), this foresight can be abstracted as a scalar—the number of tokens remaining.

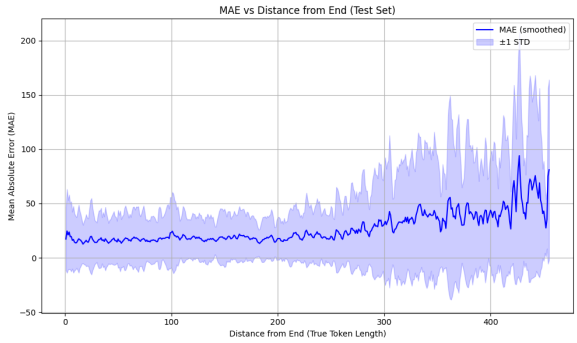

Figure 2: Mean Absolute Error (MAE) as a function of distance from the end of the sequence.

Figure 2 illustrates how prediction accuracy improves as generation progresses. The Mean Absolute Error (MAE) decreases toward the end of the sequence, indicating that the model's internal representations become increasingly informative for estimating the remaining length. We also observe that prediction quality varies with token position: the longer the remaining sequence, the stronger the signal. This suggests a potential transition in internal representations throughout generation, which could be further explored in future work.

Limitations

While our results are encouraging, our study has several limitations that suggest caution and point to directions for future work.

First, our method predicts the number of tokens remaining, but not the content of those tokens. It is a coarse abstraction. There may be cases where the model's internal state captures rich information about upcoming content (as evidenced by Future Lens (Pal et al., 2023)), but predicting an exact length remains difficult—for instance, when the model is planning a response of "about two sentences". In such scenarios, our model may output only an approximate or average length. Additionally, we formulate length prediction as a regression problem; an alternative is to treat it as classification into length bins, as done by Shahout et al. (Shahout et al., 2024). While regression allows finer granularity, classification might yield more stable or interpretable outputs, especially in the presence of outliers.

Second, the reliability of the predictor degrades at extreme sequence lengths. We observed less accurate predictions for particularly long or short outputs. A practical system may need to estimate and report its own uncertainty in such cases. We did not explore confidence calibration or uncertainty estimation, which could be useful in downstream applications such as LLM scheduling—e.g., deferring a prediction if uncertainty is high.

In summary, while we demonstrated the feasibility of predicting token-level output length from hidden states in one setting, further research is needed to test the generality of the approach, improve robustness, and integrate such predictors into practical LLM systems. We also acknowledge that the dataset used in our study is relatively small, which may limit the generalizability of our findings. We hope our findings and methodology serve as a starting point for more work on latent structural knowledge in large language models.

Ethical Considerations

This research primarily involves analyzing a pre-existing language model and does not directly raise severe ethical concerns. We worked with the Alpaca dataset (Taori et al., 2023), which consists of synthetic instruction-response pairs. Although the data was generated by a language model (OpenAI's `text-davinci-003`) and may contain biases or inaccuracies, our use of it is limited to probing model behavior rather than making deployable predictions that affect users. No personal or private information is included in the prompts or outputs.

We note that predicting remaining output length could be used in applications to allocate computing resources or moderate content (e.g., cutting off excessively long answers). If misused, such mecha-

nisms might unfairly truncate or deprioritize certain user inputs. However, in our controlled study, we do not deploy any system—we only analyze performance offline. All experiments were conducted on a private compute environment; we did not involve human subjects or gather new personal data.

In terms of broader impact, improving LLM efficiency via length prediction could benefit users by reducing latency and resource use. However, one should ensure that scheduling based on length predictions does not inadvertently disadvantage complex or long but important queries. There is a minor environmental impact in training the predictors and running the LLM for experiments, but we limited our runs to a relatively small scale (1,000 prompts on an 8B model). We encourage future work to consider energy-efficient methods and to use renewable energy where possible.

Finally, we adhere to the ACL Ethics Policy: we cite the sources of our model and dataset, respect terms of use (LLaMA and Alpaca have appropriate licenses for research use), and open-source our code for transparency. We do not foresee direct harm from this specific research, but as always, further deployment of predictive systems should be tested for fairness and bias (e.g., does the model systematically underpredict lengths for certain types of content, and could that cause harm in a downstream application?).

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