Babies Look Ahead: Multi-Token Prediction in Small LMs

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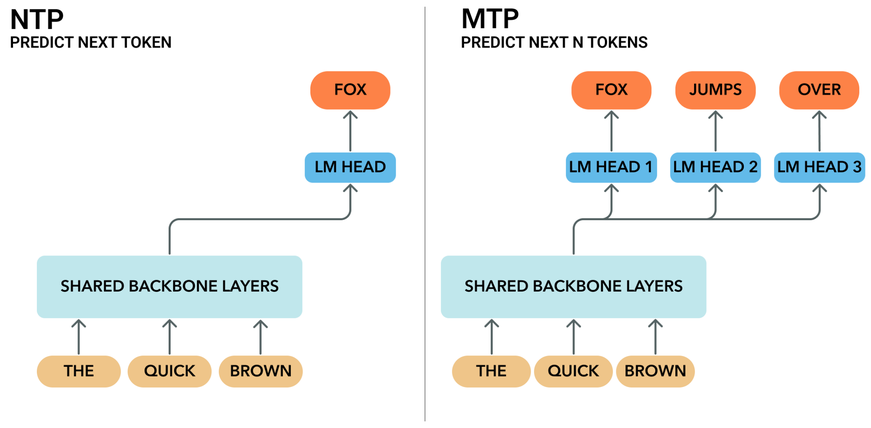
Motivation



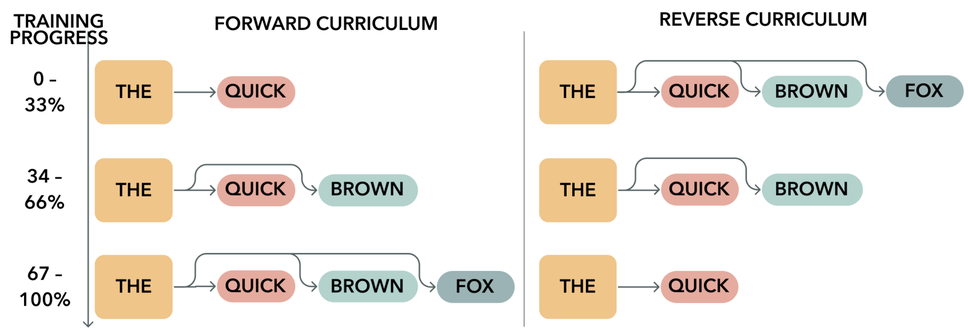
- **Multi-token prediction (MTP)** [1] has been proposed as an alternative to the **next-token prediction (NTP)** objective in training LLMs.
- Predicting multiple tokens at each prediction step, instead of only one, leads to **better downstream performance**.
- **Problem: small LMs (<7B)** are struggling with the MTP objective.

Our Idea: Leverage Curriculum Learning

Curriculum learning allows to **modulate the difficulty** of the MTP task by **controlling the number of predicted tokens** throughout the training.

We consider two types of curricula [2]:

- **Forward:** start with a vanilla NTP task, adding an additional token to the task every $\frac{n}{m}$ steps (**easy-to-hard**).
- **Reverse:** start with a full MTP task, dropping a token from the task every $\frac{n}{m}$ steps (**hard-to-easy**).



Experimental Setup

Model & MTP task: we consider a 130M model with a GPT-2 architecture trained on a **2-token** prediction task.

MTP module: $m-1$ auxiliary **LM heads** are dedicated to additional tokens.

Vocabulary size: we investigate the impact of a **large (16k) vs small (8k)** vocabulary on the downstream performance.

Results

Vocabulary Size	Objective	Curriculum	BLiMP (Acc.)	BLiMP Suppl. (Acc.)	EWoK (Acc.)	Entity Tracking (Acc.)	WUG Adj. Nom. (Acc.)	Eye Tracking (ΔR^2)	Self-paced Reading (ΔR^2)	Avg.
16k	NTP	-	**62.17**	**59.48**	49.79	13.74	59.50	10.59	4.13	37.06
	MTP	-	61.37	56.90	49.46	17.88	65.00	11.00	**4.30**	37.99
		Reverse	61.93	57.60	**50.22**	**18.60**	**66.00**	**11.17**	4.28	**38.54**
		Forward	61.51	58.29	49.73	13.40	60.00	10.15	4.00	36.73
8k	NTP	-	**61.91**	58.57	**49.51**	11.82	57.50	9.43	3.77	36.07
	MTP	-	61.25	56.81	49.12	16.25	**70.00**	8.92	3.61	**37.99**
		Reverse	61.36	56.61	49.22	**16.31**	66.50	8.58	3.58	37.45
		Forward	61.23	**59.10**	49.36	11.91	55.50	**9.48**	**3.83**	35.77

Table 3: Zero-shot evaluation of models using different tokenizer vocabulary sizes after training for 10 epochs on the 10M BabyLM dataset. **Best** scores are highlighted.

- **MTP objective acts as a regularizer** in the early epochs, preventing the SLMs from latching onto local patterns.
- **Switching to the NTP objective later on refines language representation**, while the opposite does not leads to additional benefits.

- **MTP improves downstream NTP performance** and forces SLMs to focus on patterns beyond local ones.
- **Larger vocabulary leads to more human-like text processing by SLMs** despite increased semantic complexity.

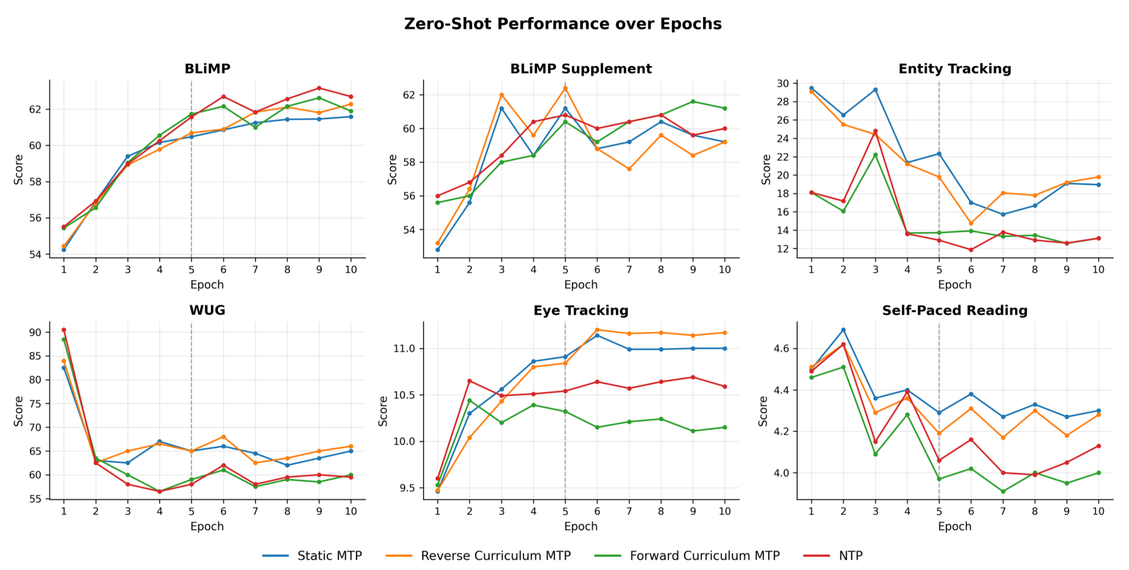


Figure 3: Zero-shot evaluation over epochs. The dotted line at epoch 5 indicates the switch in the training objective for models trained with either of the objective curricula. Tokenizer vocabulary size: **16K**.

References & Acknowledgments: [1] Fabian Gloeckle, Badr Youbi Idrissi, Baptiste Rozière, David Lopez-Paz, and Gabriel Synnaeve. 2024. Better & faster large language models via multi-token prediction. [2] Ansar Aynetdinov and Alan Akbik. 2025. Pre-Training Curriculum for Multi-Token Prediction in Language Models.
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