NLP Semester Assignment "Over-Tokenized Transformer: Vocabulary is Generally Worth Scaling"

Συγγραφείς paper:

Hongzhi Huang, Defa Zhu, BangguWu, Yutao Zeng, Ya Wang, Qiyang Min, Xun Zhou

Students team:

Katsaidonis Nikolaos 03121868

Tzamouranis Georgios 03121141

Katsiadramis Kyriakos 03121132

Fotakis Andreas 03121100

Overview

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Our Expirements

Project review

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Brief Summary of the Paper (1)

Main Idea: The paper investigates the effect of vocabulary size in a language model, both on **performance** and on **training cost**. It also examines **separating the input and output vocabularies** and how this affects those factors.

Over encoding (OE):
Use of n-gram tokens in the input (e.g., “cat”, “cat is”, “cat is sitting”). Instead of using a single token per word, we employ hierarchical n-gram tokenization and sum their representations.

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3 **Over-Tokenized Transformer(OTT):**
Combination of OE & OD to learn more complex dependencies.

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Experiment 1 – Synthetic CFG Dataset (GPT-2):

- Training with OE (3-gram input tokens).
- Improved **accuracy & lower loss** with a larger input vocabulary.
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- Tested on models with 151 M – 1 B parameters.
- OE-400 M → Same training cost as the 1 B baseline, but better performance.
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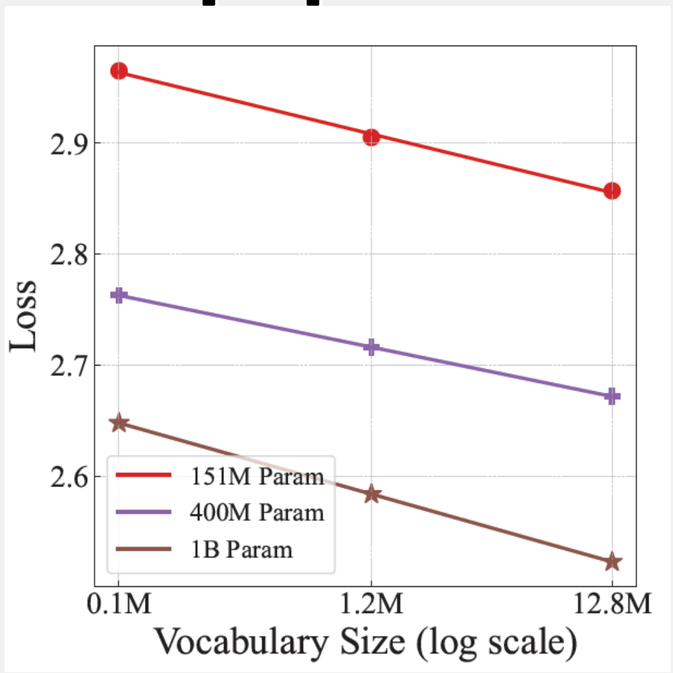
Findings:

- A **larger input vocabulary** (via multi-gram embeddings) consistently **improves performance and reduces loss** regardless of model size (**log-linear relationship between vocabulary size and loss**).
- A **larger output vocabulary** can **harm smaller models.**

Some paper results



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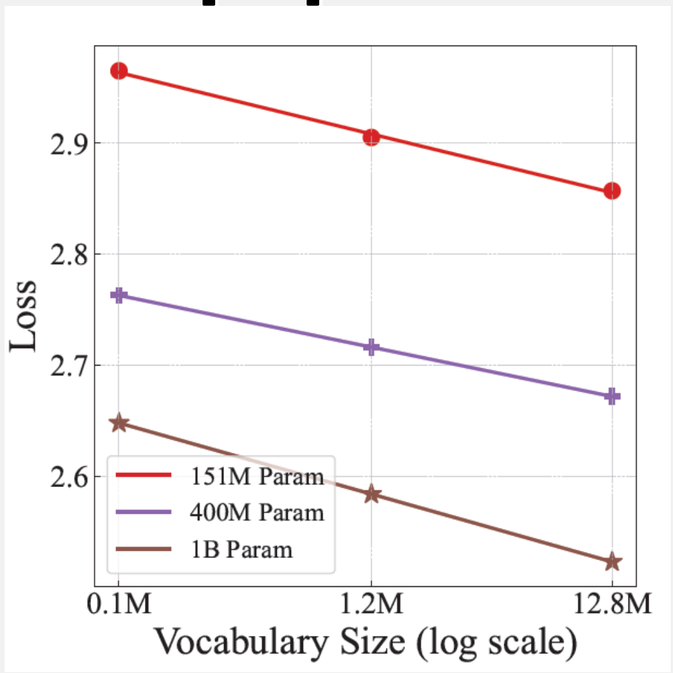

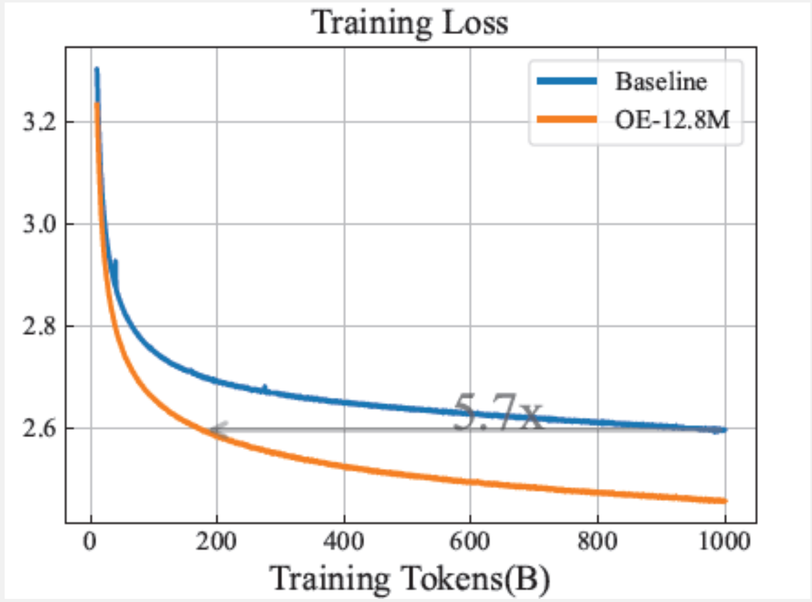

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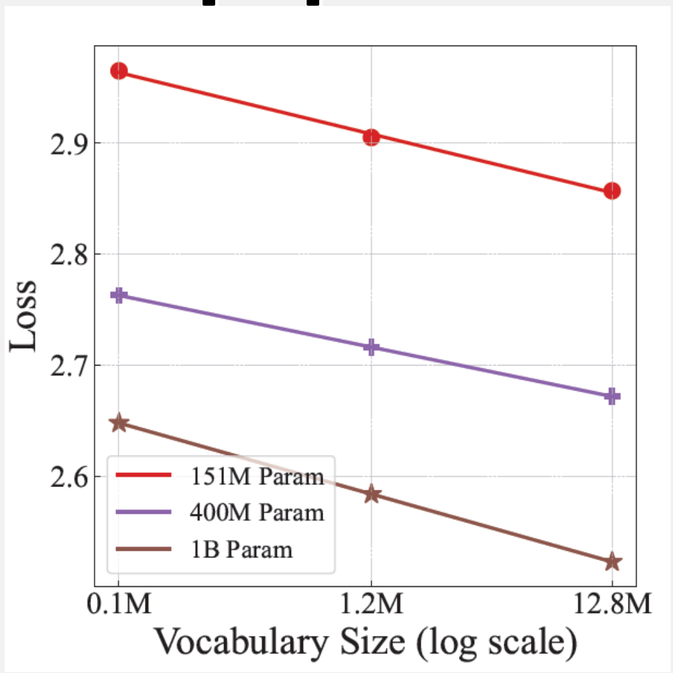

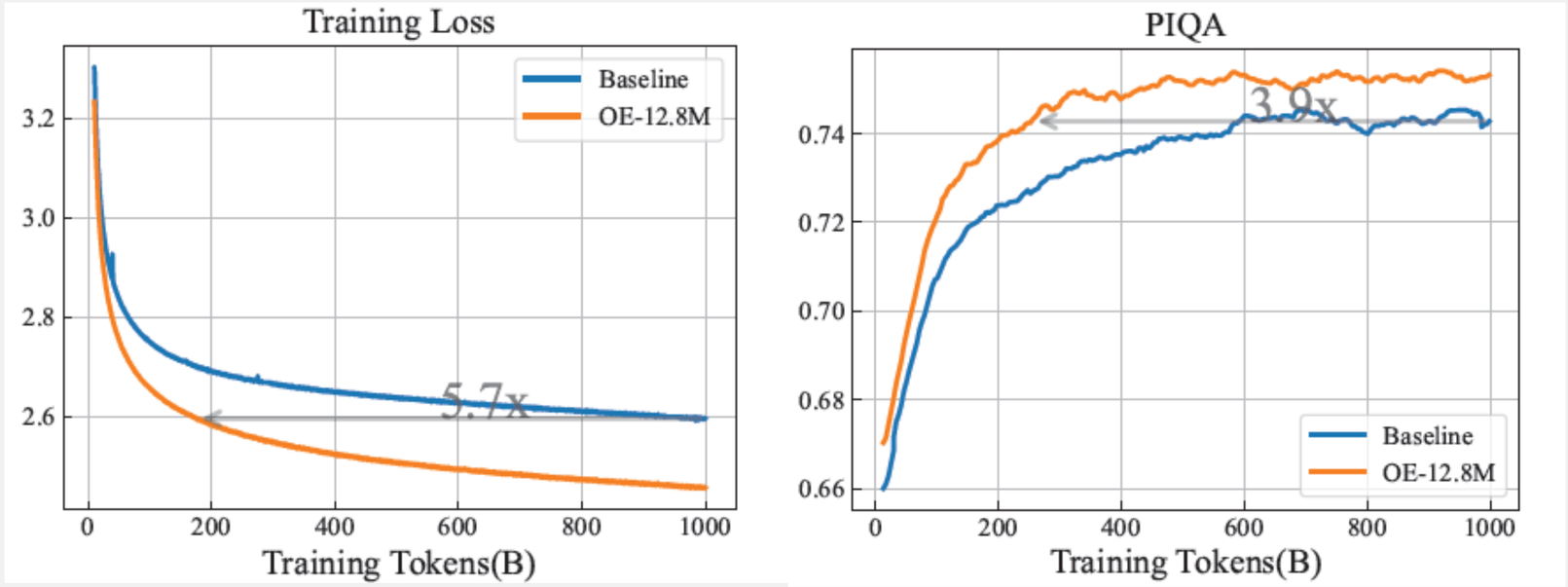

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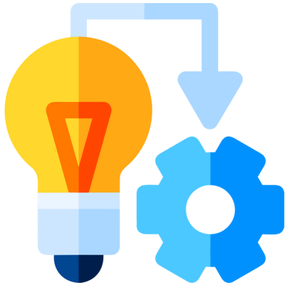

Our Expirements

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Note: The vocabulary of the cfg dataset is **{1,2,3,<PAD>}** so we have **4 1-grams, 4^2 2-grams και 4^3 3-grams.** As a result, we can not increase the vocabulary size logarithmically but just increase it and observ how this affects our metrics

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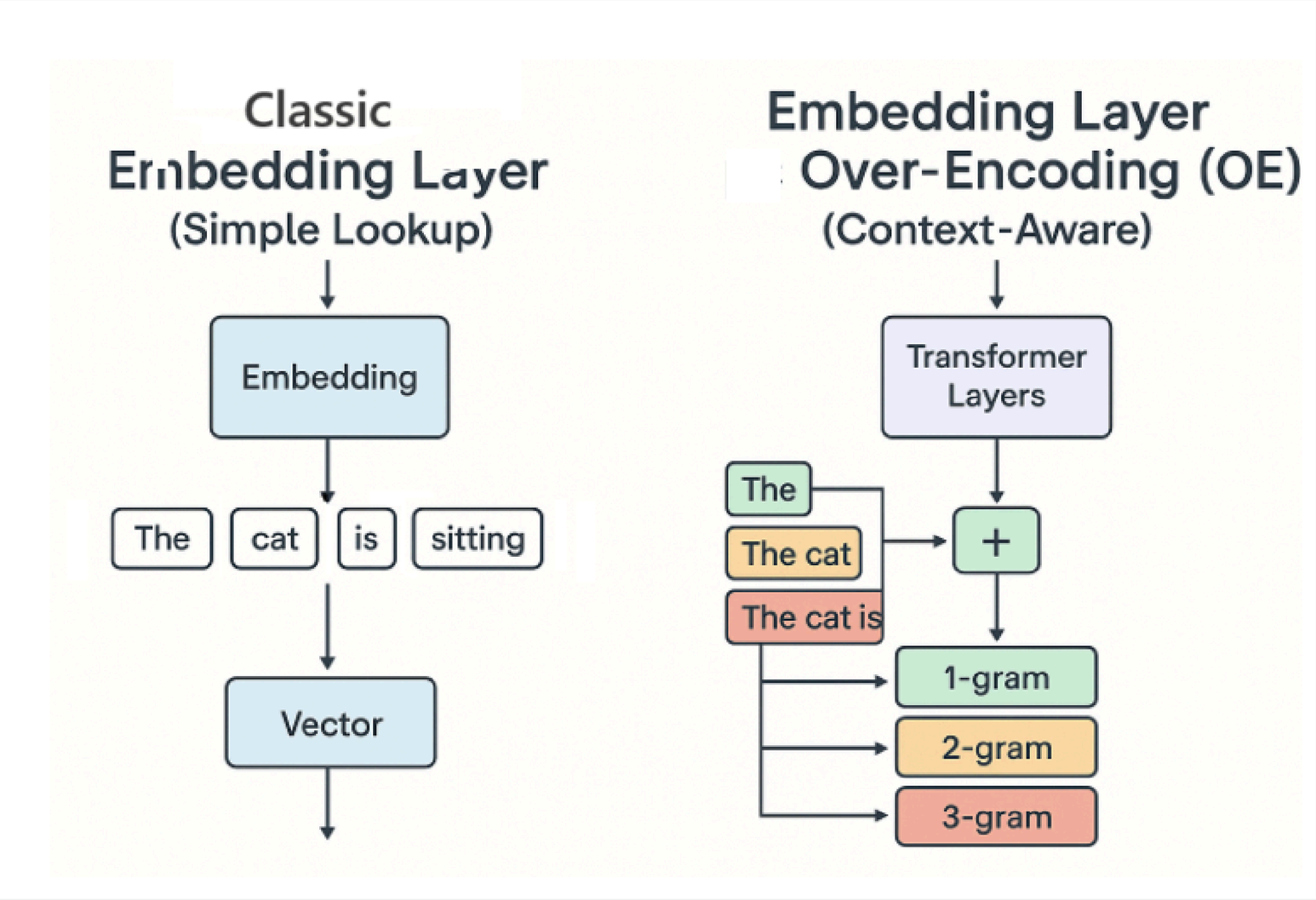
Visual representation of over encoding



Experiment 1: Datasets

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Construction of a **synthetic dataset** with vocabulary = {1, 2, 3} using the following context-free grammar rules:

root |->20 21
root |->20 19 21
root |->21 19 19
root |->20 20

19|->18 16 18
19|->17 18
19|->18 18
20|->16 16
20|->16 17
20|->17 16 18
21|->18 17
21|->17 16
21|->16 17 18
21|->16 18

16|->15 15
16|->13 15 13
16|->14 13
16|->14 14
17|->15 14 13
17|->14 15
17|->15 14
18|->14 15 13
18|->15 13 13
18|->13 15

13|->11 12
13|->12 11 12
13|->10 12 11
14|->10 12
14|->12 10 12
14|->12 11
14|->10 12 12
15|->10 11 11
15|->11 11 10
15|->10 10
15|->12 12 11

10|->8 9 9
10|->9 7 9
10|->7 9 9
11|->8 8
11|->9 7
11|->9 7 7
12|->7 9 7
12|->9 8
12|->8 8 9

7|->2 2 1
7|->3 2 2
7|->3 1 2
7|->3 2
8|->3 1 1
8|->1 2
8|->3 3 1
9|->1 2 1
9|->3 3
9|->1 1

an example sentence

3322131233121131232113223123121111213211322311311
3223331231211121311331121321213333312322121312 32
2211112133221311311311311111132312331331333113 31
3333322312113111212211112112333123311211133133 33
3311233331311113333121132113121211333332121111 21
2132232233221332211322113232331311121322322322 1
2111333311213222213322112121331213313322122132 21
211213331232233312

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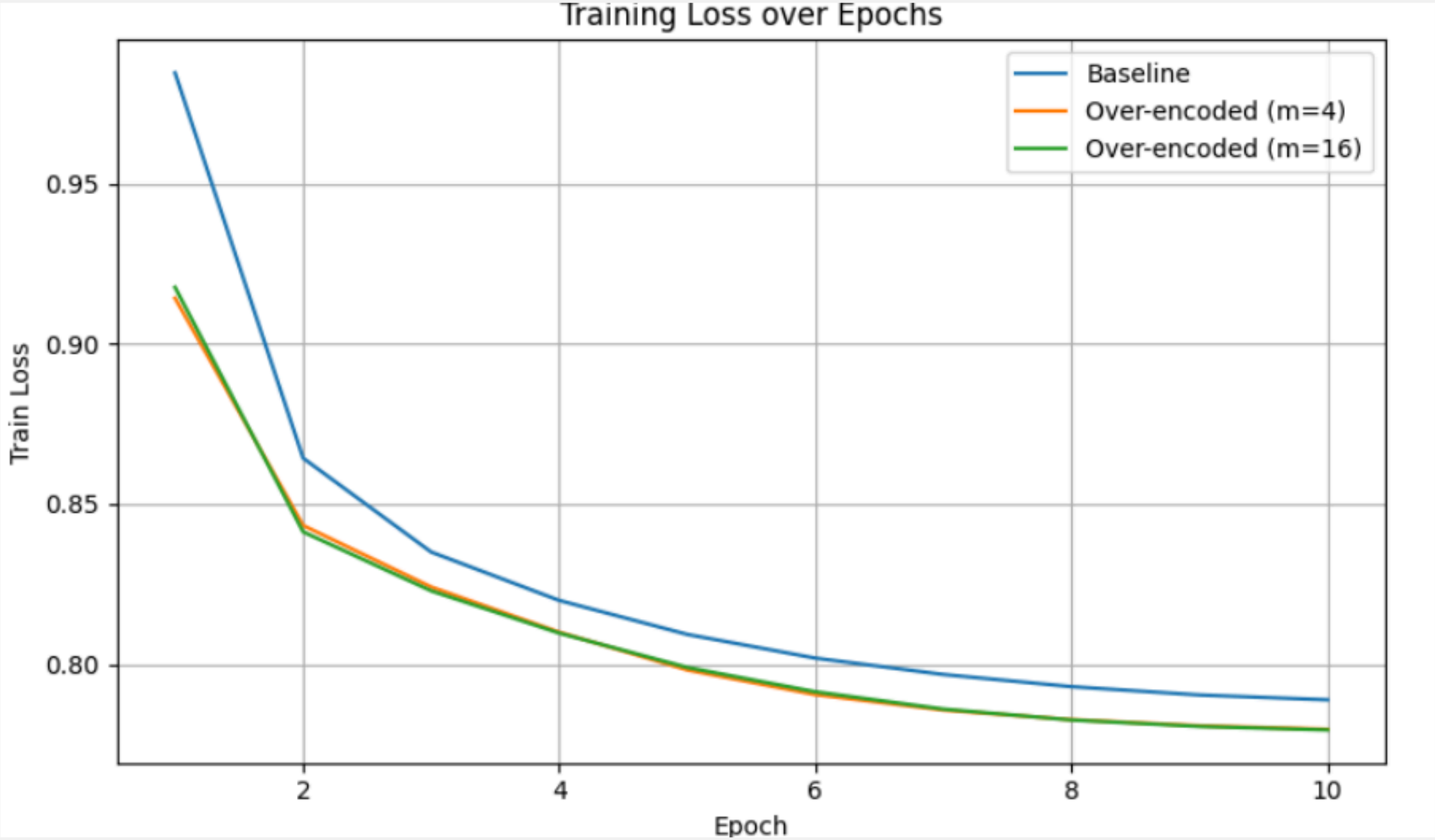
root |->20 21	19|->18 16 18	16|->15 15	13|->11 12	10|->8 9 9	7|->2 2 1
root |->20 19 21	19|->17 18	16|->13 15 13	13|->12 11 12	10|->9 7 9	7|->3 2 2
root |->21 19 19	19|->18 18	16|->14 13	13|->10 12 11	10|->7 9 9	7|->3 1 2
root |->20 20	20|->16 16	16|->14 14	14|->10 12	11|->8 8	7|->3 2
	20|->16 17	17|->15 14 13	14|->12 10 12	11|->9 7	8|->3 1 1
	20|->17 16 18	17|->14 15	14|->12 11	11|->9 7 7	8|->1 2
	21|->18 17	17|->15 14	14|->10 12 12	12|->7 9 7	8|->3 3 1
	21|->17 16	18|->14 15 13	15|->10 11 11	12|->9 8	9|->1 2 1
	21|->16 17 18	18|->15 13 13	15|->11 11 10	12|->8 8 9	9|->3 3
	21|->16 18	18|->13 15	15|->10 10		9|->1 1
			15|->12 12 11		

an example sentence

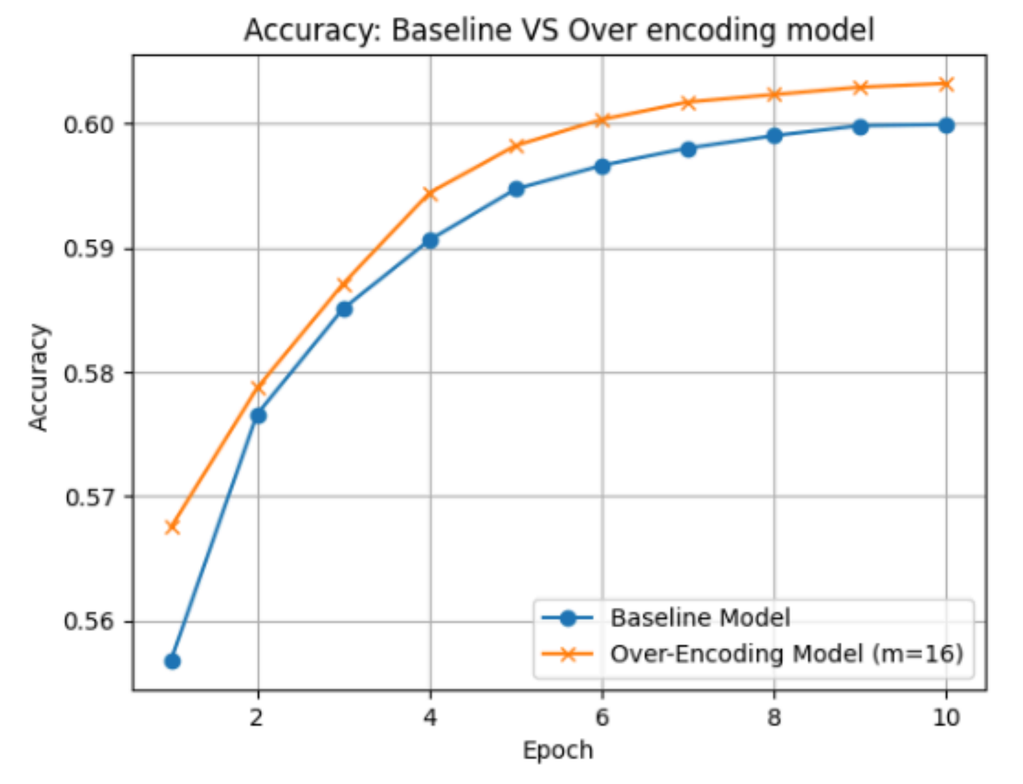
322131233121131232113223123121111213211322311311
322333123121112131133112132121333331232212131232
221111213322131131131131111113231233133133311331
333332231211311121221111211233312331121113313333
331123333131111333312113211312121133333212111121
213222322332213322111322113232331311121322322321
211133331121322221332211212133121331332212213221
211213331232233312

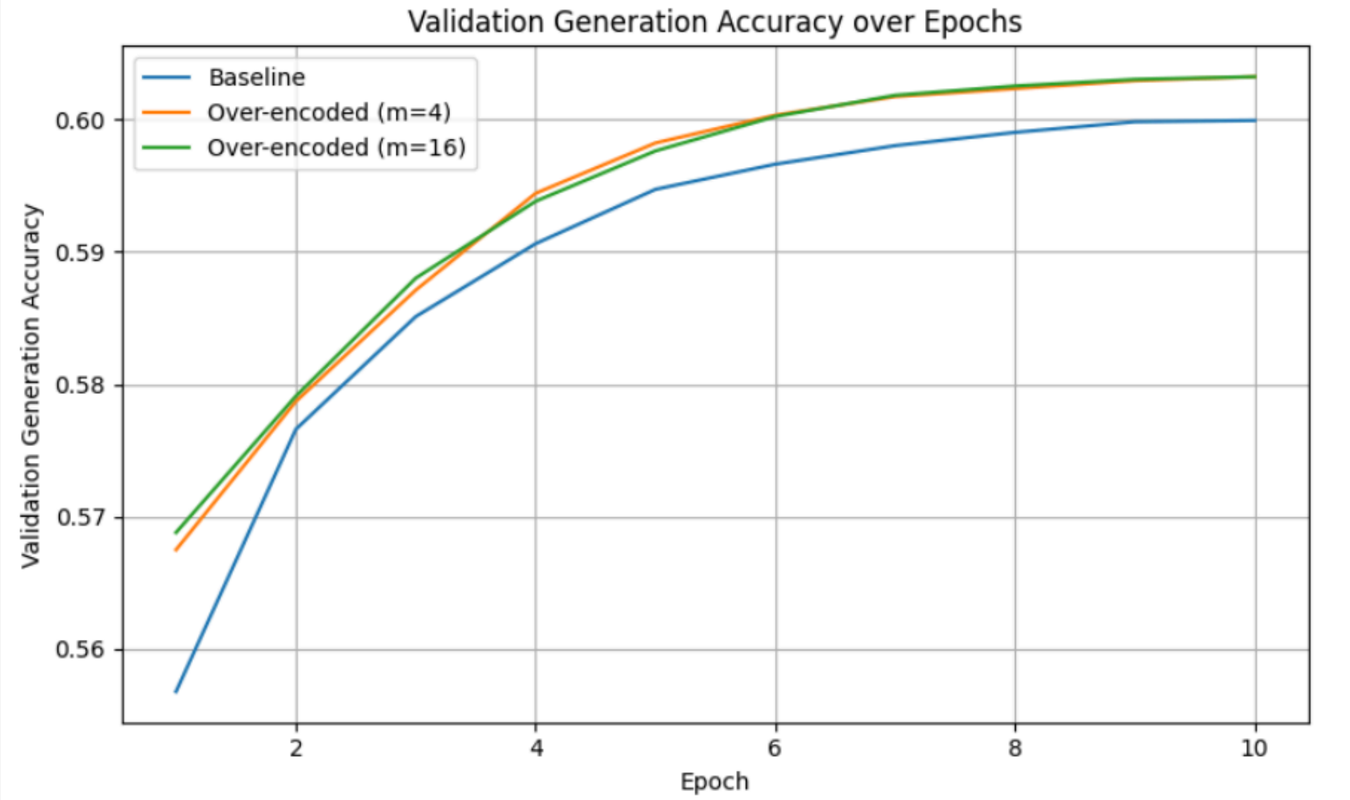
- **Total dataset:** 200,000 sequences of up to 729 characters.
- **Train/validation split:** 160,000 training sequences, 40,000 validation sequences.

Results (1)


Training Loss over Epochs
Baseline
Over-encoded (m=4)
Over-encoded (m=16)
Train Loss
0.95
0.90
0.85
0.80
2
4
6
8
10
Epoch

Results (2)


Accuracy: Baseline VS Over encoding model
Accuracy
Epoch
0.56
0.57
0.58
0.59
0.60
2
4
6
8
10
Baseline Model
Over-Encoding Model (m=16)


Validation Generation Accuracy over Epochs
Validation Generation Accuracy
Epoch
0.56
0.57
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2
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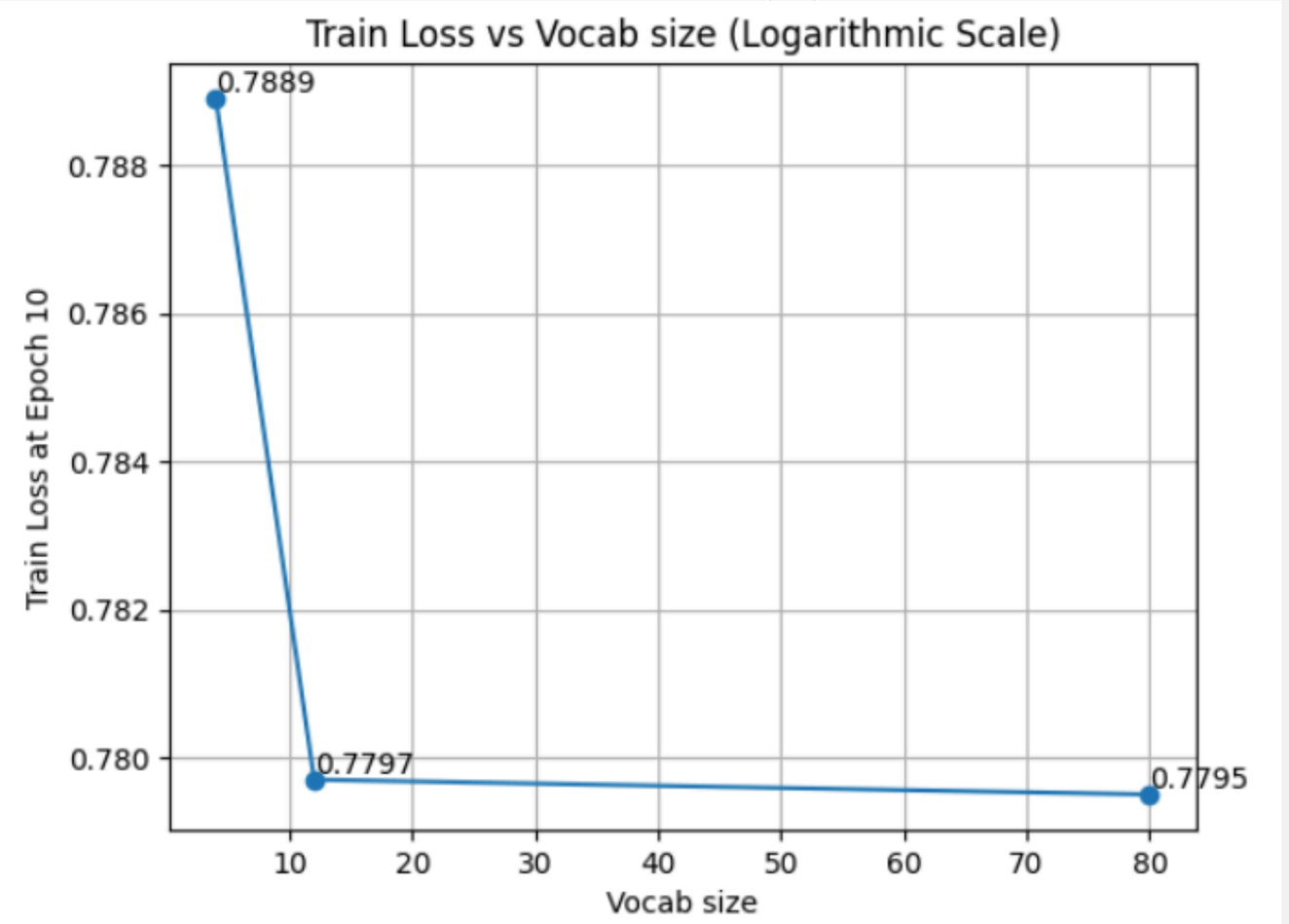
Results (3)



It is evident that with such a small vocabulary size, the reduction is very minor, since a logarithmic increase of m is not feasible for such a limited vocabulary.

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Load a **pretrained GPT-2** and freeze its parameters to preserve its general knowledge.

Logarithmically increase the n-gram vocabulary and compute the training loss.

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PIQA dataset

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Story cloze dataset

- Testing the model on the Story Cloze task: input of **four context sentences** forming a story, and **two candidate endings**.

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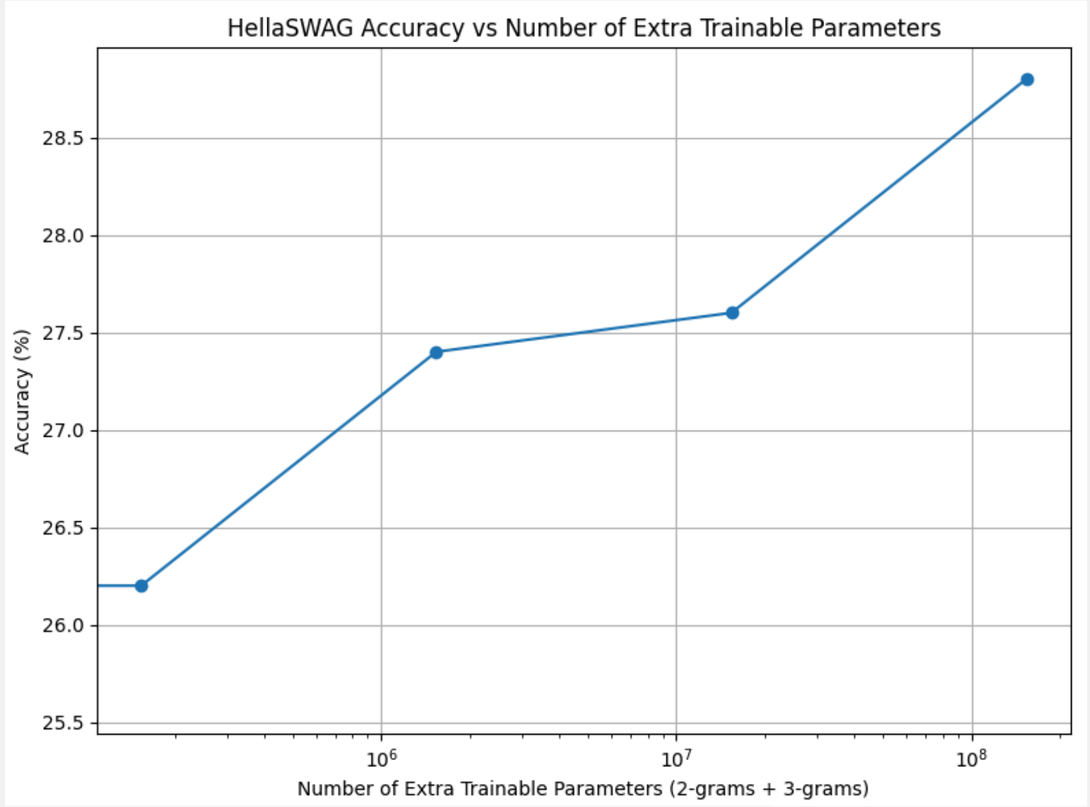
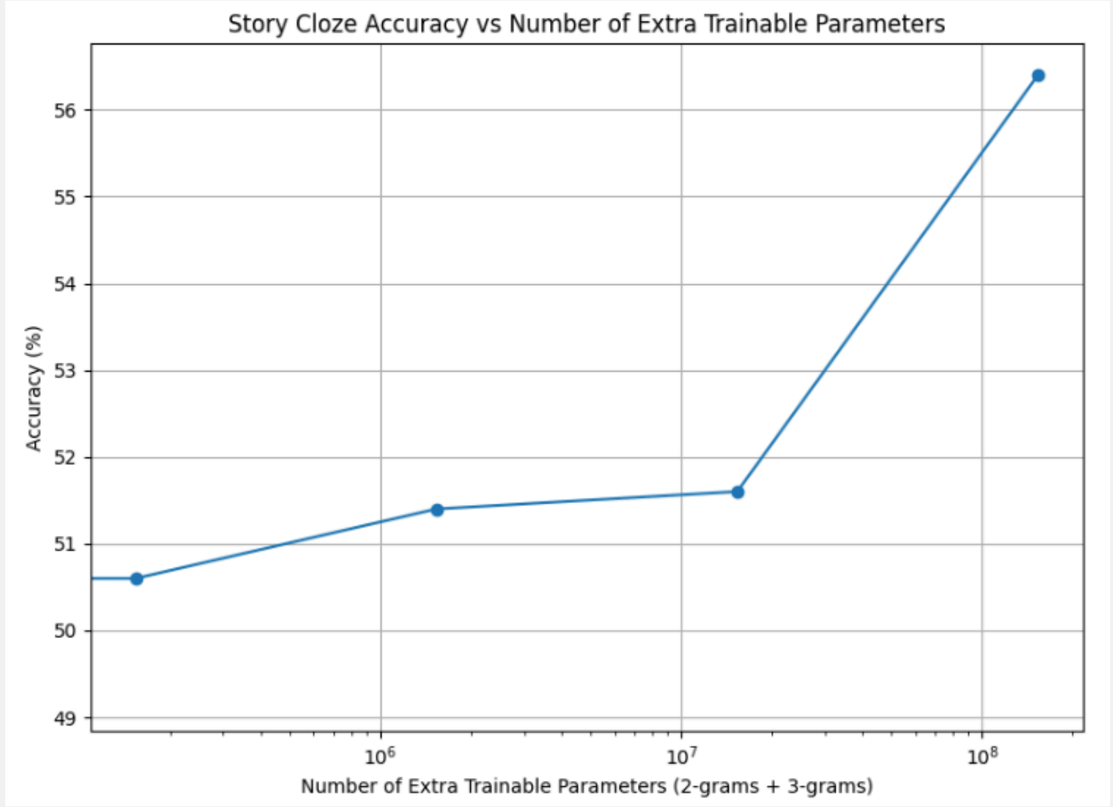
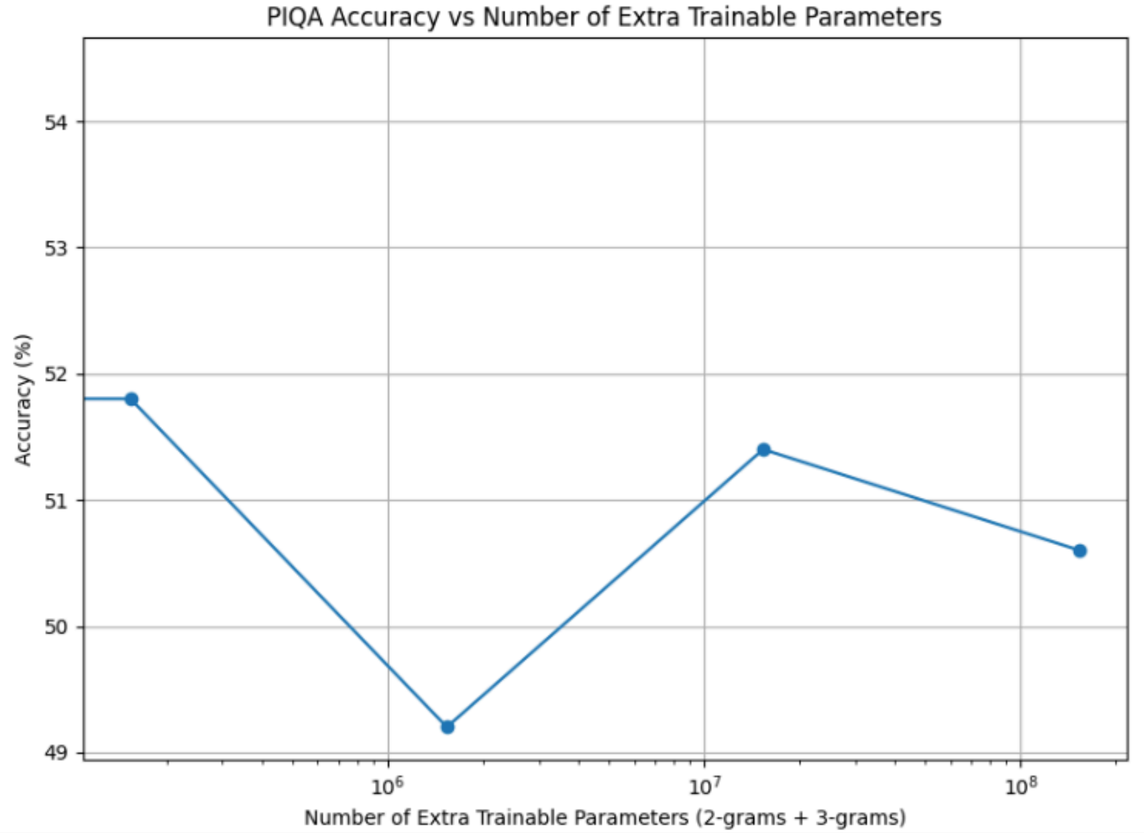
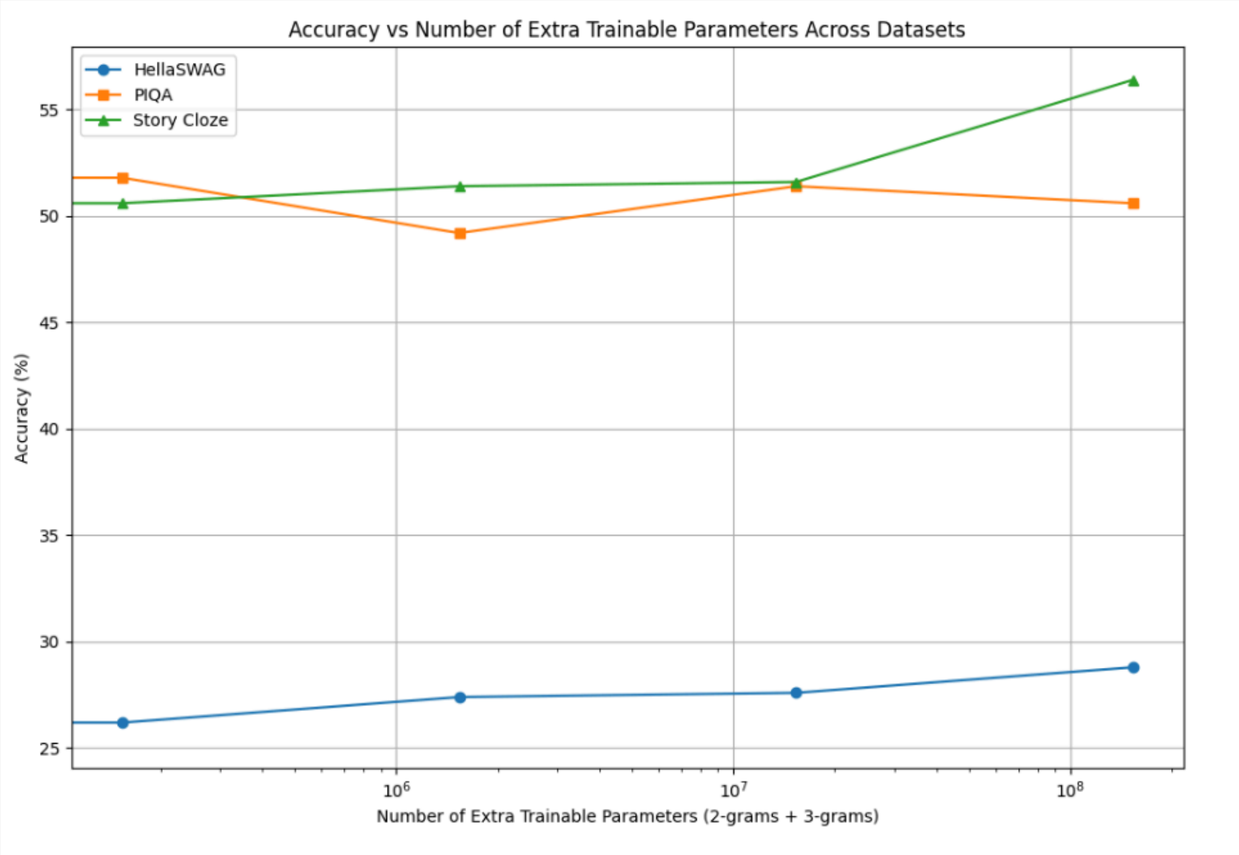




We observe that on context-creation tasks such **as HellaSwag or Story Cloze**, the model's **performance increases** as we increase the number of n-gram tokens.

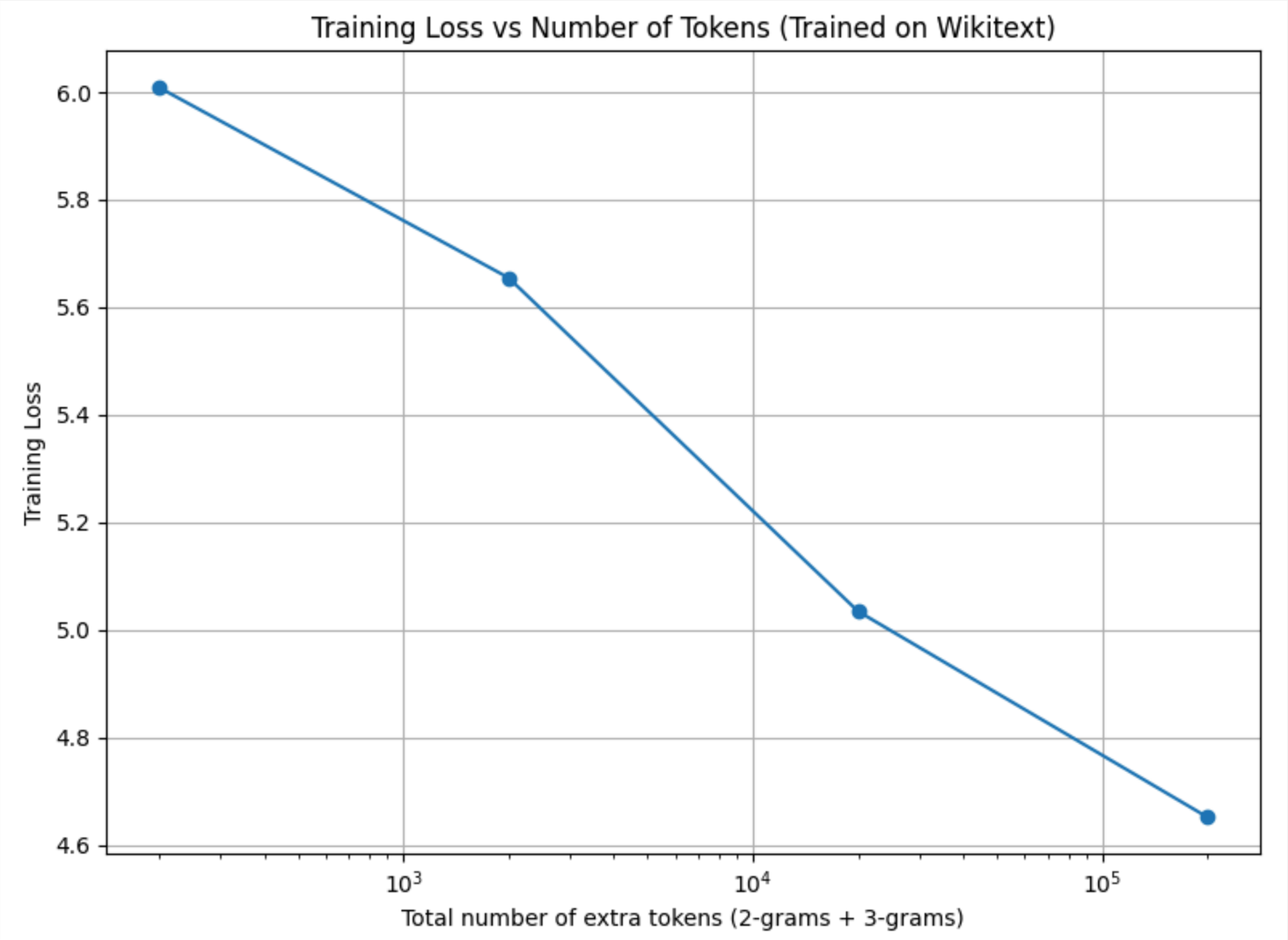
Results (2)





On the other hand, for datasets such as PIQA, adding n-gram tokens does not improve accuracy. Tasks like HellaSwag and Story Cloze align naturally with GPT-2's autoregressive training paradigm—so performance increases as we add more n-grams—whereas PIQA requires deeper reasoning and comparative judgment, capabilities that GPT-2 struggles with unless it is further fine-tuned on a question-answering dataset.

Results (2)



As shown in the paper, a **log-linear relationship between loss and the number of trainable tokens** is demonstrated.

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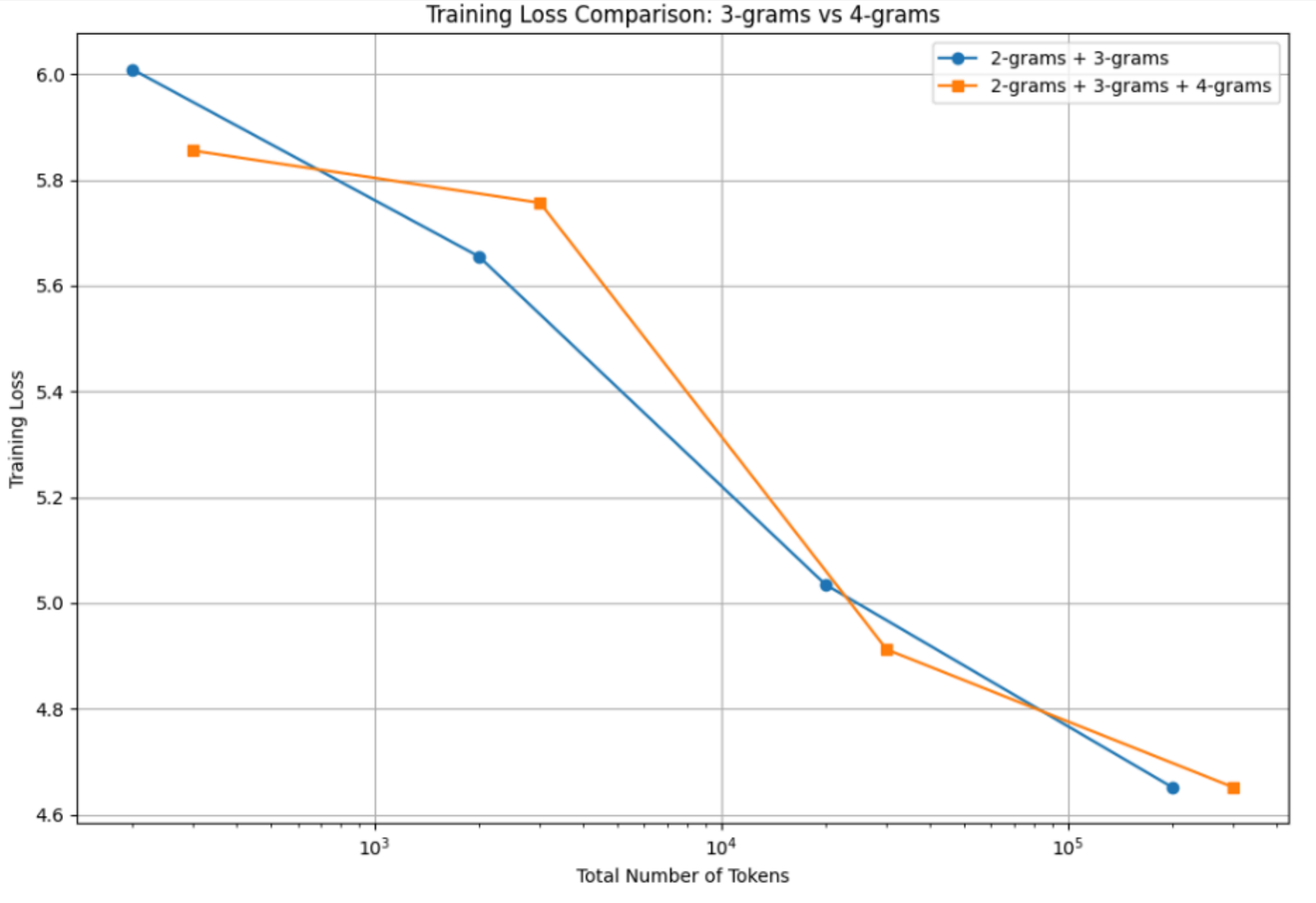
- Specifically, we will extend the embeddings with **4-grams and 5-grams** while simultaneously retaining the 2-grams and 3-grams.

- Our aim is to measure **how the training loss changed with the addition of extra embeddings,** as well as the system's **performance on downstream tasks** as described above.

Bonus Task: 4-gram expirement



- We do not observe a reduction in loss compared to the 3-gram models, nor any additional improvement in accuracy during testing.
- The same is observed for 5-gram models, and therefore **the computational complexity burdening training does not bring commensurate gains.**

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Future Extensions

- Dynamic vocabulary that evolves automatically during training, aiming to adapt to the data by dropping n-grams that do not “help” the model.
- Experimentation with various n-gram combinations—not necessarily strictly hierarchical n-gram modeling—to determine the most effective configuration.

Task Distribution

Andreas Fotakis	Experimentation with downstream tasks, report writing, and presentation preparation.
Kyriakos Katsiadramis	Experiment with the CFG dataset, report writing, and presentation preparation.
Georgios Tzamouranis	Experimentation with downstream tasks, report writing, and presentation preparation.
Nikolaos Katsaidonis	Experiment with the CFG dataset, report writing, and presentation preparation.

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Challenges and Future Improvements

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- Slow model training. → Row-wise sharding for distributing the embedding table across GPUs, reducing communication cost.

- GPT-2's weakness on question-answering tasks → Fine-tuning on a dedicated QA dataset instead of WikiText.
- Experimentation with over-decoding techniques beyond over-encoding.

Thank you !

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