Naive Bayes-based Context Extension for Large Language Models

Jianlin Su[*] **Murtadha Ahmed**[*] **Wenbo** **Luo Ao** **Mingren Zhu** **Yunfeng Liu**
Zhuiyi Technology Co. Ltd., Shenzhen, Guangdong, China
{bojonesu,a.murtadha,brucewen,luoao,mingren,glenliu}@wezhuiyi.com

Abstract

Large Language Models (LLMs) have shown promising in-context learning abilities. However, conventional In-Context Learning (ICL) approaches are often impeded by length limitations of transformer architecture, which pose challenges when attempting to effectively integrate supervision from a substantial number of demonstration examples. In this paper, we introduce a novel framework, called Naive Bayes-based Context Extension (NBCE), to enable existing LLMs to perform ICL with an increased number of demonstrations by significantly expanding their context size. Importantly, this expansion does not require fine-tuning or dependence on particular model architectures, all the while preserving linear efficiency. NBCE initially splits the context into equal-sized windows fitting the target LLM's maximum length. Then, it introduces a voting mechanism to select the most relevant window, regarded as the posterior context. Finally, it employs Bayes' theorem to generate the test task. Our experimental results demonstrate that NBCE substantially enhances performance, particularly as the number of demonstration examples increases, consistently outperforming alternative methods. The code NBCE is available at: https://github.com/amurtadha/NBCE-master

1 Introduction

Large Language Models (LLMs) have demonstrated remarkable capabilities in in-context learning (ICL), a paradigm that enables them to excel in various unseen tasks based on task examples or instructions within their context (Han et al., 2021; Qiu et al., 2020). Unlike traditional fine-tuning methods, ICL leverages LLMs for downstream tasks solely through inference, eliminating the need for parameter updates and making it computationally efficient, bringing us closer to the goal of general AI. This approach has gained prominence as LLMs continue to grow in scale (Brown et al., 2020; Zhang et al., 2022a; Chowdhery et al., 2022).

The 2048-token context limit in popular LLMs like GPT-3 poses challenges for scaling up ICL with more demonstration examples in ICL, due to architectural constraints and computational complexity. Recent studies (Garg et al., 2022; Min et al., 2022b; Chen et al., 2022) improve ICL through meta-learning and fine-tuning on downstream tasks, but the limited diversity of annotated tasks and biases hinder generalization. Another line of research has explored various approaches to retraining long-range language models with extrapolation, extending them to 128 times the limit of existing LLMs (Li et al., 2023; Gu et al., 2023). However, these approaches require additional training over several steps, which can be time-consuming.

Recently, Hao et al. (2022) introduced structured prompting, encoding demonstrations with specific position embeddings for collective attention via a scaled mechanism. Extending this, Ratner et al. (2023) proposed parallel context windows, utilizing individual encoding of examples with designed position and attention mechanisms. Addressing this issue is crucial for leveraging ICL effectively, especially in scenarios with ample examples.

In this paper, we introduce a novel framework called Naive Bayes-based Context Extension (NBCE) for large language models to significantly expand the number of demonstrations by orders of magnitude while greatly enhancing stability. Instead of simply merging all demonstrations, we partition the vast number of demonstrations into multiple groups, each independently processed by the language model. This approach ensures that the encoding complexity scales linearly with the number of groups, avoiding the quadratic complexity associated with considering all examples simultaneously. Following Ratner et al. (2023); Hao

[*] These authors contributed equally to this work.

Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers), pages 7791–7807
June 16-21, 2024 ©2024 Association for Computational Linguistics

et al. (2022), we align the position embeddings of grouped prompts to the right, placing them next to the test input. Subsequently, we leverage the Naive Bayes to encode the input by conditioning it on these grouped prompts. We conducted experiments across various tasks, including text classification, multi-choice, and open-ended tasks. NBCE effectively scales up the number of demonstrations, outperforming conventional in-context learning across different model sizes and tasks, while also significantly enhancing stability.

In brief, the contributions can be summarized as follows:

1. We introduce an innovative framework known as Naive Bayes-based Context Extension (NBCE), designed to substantially increase the volume of demonstrations for large language models, thus enhancing stability on a significant scale.

2. We provide detailed technical insights to enable context expending of in-context learning tasks. The idea is to encode the test sample by conditioning it on a vast array of demonstrations sourced from the training dataset.

3. We conducted extensive experiments on benchmark NLP datasets, and our findings clearly highlight NBCE's remarkable capability to efficiently scale up the number of demonstrations, while significantly enhancing overall stability.

2 Approach

An example of our proposed NBCE is depicted in 1. Assume that we have a sequence, denoted as T, which we intend to generate. Furthermore, we have multiple relatively independent context sets, denoted as $S_1, S_2, \ldots, S_n$ (e.g., n different paragraphs), each of which is sufficiently long and does not split a sentence into fragments. Suppose that the total length of these context sets exceeds the training length, but when combined with an individual S_k and T, they still fall within the training length. Our objective is to generate T based on the information contained in $S_1, S_2, \ldots, S_n$. In essence, we seek to estimate the conditional probability of T given $S_1, S_2, \ldots, S_n$, which can be represented as $p(T|S_1, S_2, \ldots, S_n)$.

In straightforward terms, Naive Bayes can be understood as a combination of two key elements:

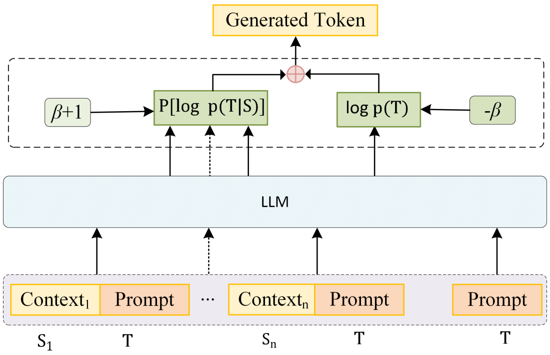


Figure 1: An example for our NBCE. Initially, NBCE divides the context into equal-sized windows, each with the maximum length compatible with LLM in-target. Subsequently, a voting mechanism is introduced to select the most relevant context window, regarded as the posterior context. Finally, it employs Bayes' theorem to generate the test task.

Bayes' formula and an independence assumption:

$$p(T|S_1, S_2, \ldots, S_n) \propto p(S_1, S_2, \ldots, S_n|T)p(T), \tag{1}$$

where, the symbol $\propto$ denotes proportionality, signifying that we are focusing solely on the relevant factors in a proportion while disregarding constant factors unrelated to the token sequence T. This approach aligns with the underlying assumption of conditional independence:

$$p(S_1, S_2, \ldots, S_n|T) = \prod_{k=1}^{n} p(S_k|T). \tag{2}$$

Thus, we have:

$$p(T|S_1, S_2, \ldots, S_n) \propto p(T) \prod_{k=1}^{n} p(S_k|T). \tag{3}$$

Furthermore, based on Bayes' formula $p(S_k|T) \propto \frac{p(T|S_k)}{p(T)}$, we get:

$$p(T|S_1, S_2, \ldots, S_n) \propto \frac{1}{p^{n-1}(T)} \prod_{k=1}^{n} p(T|S_k). \tag{4}$$

Or:

$$\begin{aligned} \log p(T|S_1, S_2, \ldots, S_n) = \sum_{k=1}^{n} \log p(T|S_k) \\ - (n-1) \log p(T) \\ + \text{constant}, \end{aligned} \tag{5}$$

where both $p(T|S_k)$ and $p(T)$ can be computed directly utilizing existing LLMs, independent of their architecture, and without the need for fine-tuning on extensive textual data. Specifically, $p(T|S_k)$ represents the probability predicted by an individual contextual set, while $p(T)$ signifies the probability in the absence of any context or with an empty context. It is noteworthy that multiple contextual sets can be concurrently processed within the same batch, with computational complexity scaling linearly with the number of contexts. Certainly, Naive Bayes leans heavily on the independence assumption, which can restrict its practical utility. To aspire to enhance its performance beyond the initial state, we further refine Equation 5.

To commence this refinement, we shall introduce the following notations:

$$\log p(T|S) = [\log p(T|S_1), \ldots, \log p(T|S_n)], \tag{6}$$

and

$$\overline{\log p(T|S)} = \frac{1}{n}\sum_{k=1}^{n} \log p(T|S_k), \tag{7}$$

where $\overline{\log p(T|S)}$ denotes the Average Pooling of $\log p(T|S)$. Let $\beta = n - 1$, then Equation 5 can be rewritten as

$$\begin{aligned} \log p(T|S_1, S_2, \ldots, S_n) = (\beta + 1)\overline{\log p(T|S)} \\ - \beta \log p(T) \\ + \text{constant}. \end{aligned} \tag{8}$$

However, the reformulation may prompt the emergence of two inherent inquiries:

- If we consider β as a hyperparameter subject to tuning, could this potentially yield superior results?
- Is it conceivable that employing alternative pooling techniques, denoted as P, might potentially yield enhancements in performance? That is:

$$\begin{aligned} \log p(T|S_1, S_2, \ldots, S_n) = (\beta + 1)P[\log p(T|S)] \\ - \beta \log p(T) \\ + \text{constant} \end{aligned} \tag{9}$$

To delve deeper into these inquiries, we conducted a series of experiments employing the 7B model and garnered preliminary insights. In the realm of reading comprehension, a consistent trend of robust performance emerges when employing Max Pooling with a β value of 0.25 in conjunction with Greedy Search. Conversely, outcomes generated via Random Sampling frequently yield results that are challenging to interpret.

The observed disparities in outcomes can be attributed to the inherent characteristics of these two methods. Random Sampling, characterized by its selection of tokens based on their probability distribution, tends to exhibit lackluster performance, signaling that the output of Max Pooling may not align with a plausible probability distribution. In contrast, Greedy Search operates distinctively by prioritizing the token with the highest probability, disregarding the holistic distribution. Its commendable performance suggests that the token with the highest probability is more likely to be the accurate choice. Larger probabilities are indicative of lower uncertainty. To enhance the performance of Random Sampling, we modify the pooling method to directly output the probability distribution with the lowest uncertainty:

$$\begin{aligned} P[\log p(T|S)] = \log p(T|S_k), \\ k = \text{argmin}\{H_1, H_2, \ldots, H_n\}, \\ H_i = -\sum_{T} p(T|S_i) \log p(T|S_i), \end{aligned} \tag{10}$$

By substituting this expression into Eq.9, we arrive at the conclusive formulation of the NBCE. It is noteworthy that while the initial inspiration for this approach stemmed from Naive Bayes, the generalized Equation 9 transcends the conventional boundaries of traditional Naive Bayes, yet maintains its inherent interpretability. Eq.9 assumes an intuitive form: Predictions originating from various contextual sources are collectively amalgamated (or weighted) through the utilization of the method denoted as P (with a weight factor of $\beta + 1$). Subsequently, this amalgamation is counterbalanced by subtracting the prediction in the absence of context, weighted by β. The rationale behind subtracting the context-less prediction lies in enhancing the model's reliance on contextual information, reducing its dependency on inherent knowledge (Shi et al., 2023).

The choice of values for β can be tailored to different scenarios. For tasks necessitating comprehensive reading comprehension and robust context integration, a larger β value may be deemed appropriate. Conversely, tasks leaning towards creative writing may benefit from a smaller β value. In our experiments, we set $\beta = 0.25$.

3 Experimental Setup

In this section, we describe the experimental settings adopted in our work, including the datasets, LLMs and comparative approaches used to evaluate our approach.

3.1 Datasets

In our experiments, we employed a diverse range of benchmark datasets to evaluate our approach. These datasets encompassed various tasks, including text classification and multiple-choice questions. Fifteen Text Classification Datasets: SST-2 (Socher et al., 2013), CR (Ding et al., 2008), RTE (Bar-Haim et al., 2014), Subj (Pang and Lee, 2004), CB (De Marneffe et al., 2019), AG-News (Zhang et al., 2015), SST-5 (Socher et al., 2013), YELP (Zhang et al., 2015), TREC (Li and Roth, 2002), DBPedia (Zhang et al., 2015), NLU (Liu et al., 2019), BANKING77 (Casanueva et al., 2020), CLINIC150 (Larson et al., 2019), TREC (fine-grained labels) and NLU (fine and coarse-grained labels). Five datasets from Multiple-choice Domain. Specifically, we consider sentence completion: HellaSwag (Zellers et al., 2019); commensense reasoning: PIQA (Bisk et al., 2020), OpenBookQA (Mihaylov et al., 2018), StoryCloze (Mostafazadeh et al., 2017), MMLU (Hendrycks et al., 2021), ARC-Easy (Bhakthavatsalam et al., 2021); and COPA from SuperGLUE benchmark (Wang et al., 2019). It is worth noting that we conducted evaluations using the standard test sets or validation sets when a public test set was not available. It is important to mention that all the datasets used in our experiments are in the English language.

3.2 Training Sampling and Models

The effectiveness of ICL has been observed to be highly dependent on the selection of training examples (Zhao et al., 2021). To ensure a fair and consistent comparison, we maintain the approach employed in the PCW (Ratner et al., 2023), a common practice in prior research (Zhao et al., 2021; Lu et al., 2022; Ahmed et al., 2022). Specifically, we randomly selected 30 sets from the training datasets and report the mean and standard deviation calculated across these sampled sets.

Given our limited computational resources, our experiments were conducted using eight large models: GPT2-Large (0.75B), GPT2-XL(1.5B)(Radford et al., 2019), there LLAMA models, including 7B, 13B and 30B (Touvron et al., 2023), and three OPT models with 1.3B, 6.7B and 13B parameters (Zhang et al., 2022b).

3.3 Comparative Baseline

Note that our proposed solution does not require any additional training. As far as our knowledge extends, Ratner et al. (2023) initiated the work in this line of research. Therefore, we compare our approach with methods that also do not require further training, as follows.

- **ICL**. A traditional ICL approach employs a conventional single context window, which essentially utilizes the full capacity of the positional embedding in the LLM.

- **PCW**(Ratner et al., 2023). PCW introduces strategic adjustments to both position encoding and attention mask mechanisms to enable multiple context windows without requiring additional training.

3.4 Prompt Formats

We have employed the same prompt formats as those adapted by the comparative baseline, PCW. For the sake of brevity, we have omitted specific details about the prompt format; for a more comprehensive understanding, we kindly refer you to Ratner et al. (2023).

4 Evaluation

We evaluate our proposed solution based on two primary criteria:

- **Ability to Extend the Length of Large Models:** Does our solution effectively enable the expansion of the size or capacity of large models?

- **Impact of Additional Demonstrations on ICL Task Performance:** Does the inclusion of more demonstrations have a positive effect on the performance of the ICL task?

Dataset	# Shots per window	# Labels	ICL	B=3		B=6		B=9	
			B=1	PCW	NBCE	PCW	NBCE	PCW	NBCE
SST-2	27	2	80.2 ± 11.7	84.1 ± 8.2	**85.2** ± 6.7	81.2 ± 7.0	**83.6** ± 7.0	78.9 ± 5.3	**84.3** ± 5.9*
CR	21	2	81.3 ± 6.3	81.2 ± 6.4	**82.7** ± 6.3	82.3 ± 5.2	**84.7** ± 4.6	81.2 ± 3.4	**84.1** ± 4.4*
SUBJ	18	2	65.1 ± 11.9	**67.0** ± 12.2	66.1 ± 13.2	62.9 ± 10.9	**66.2** ± 10.7	60.1 ± 2.8	**64.4** ± 9.9*
CB	5	2	43.9 ± 3.7	43.9 ± 3.2	**45.2** ± 3.7	42.8 ± 2.1	**44.8** ± 3.3*	42.1 ± 2.2	**45.1** ± 5.0*
RTE	5	2	52.5 ± 2.2	**53.5** ± 1.7	52.9 ± 2.9	**54.4** ± 1.0*	53.0 ± 2.4	53.9 ± 2.6	**54.2** ± 2.5
AGNews	11	4	61.7 ± 14.2	70.9 ± 9.4	**71.0** ± 8.9*	**67.7** ± 7.0	67.1 ± 10.6	64.8 ± 3.1	**72.9** ± 7.6*
SST5	20	5	40.8 ± 2.5	41.5 ± 3.1	**41.8** ± 2.4	37.4 ± 4.1	**42.5** ± 1.9*	35.9 ± 2.8	**41.9** ± 2.4*
TREC	38	6	56.6 ± 7.9	59.0 ± 4.7	**63.1** ± 7.0*	53.9 ± 3.1	**65.3** ± 3.0*	50.9 ± 3.4	**66.5** ± 2.9*
DBPedia	7	14	58.7 ± 20.2	**78.9** ± 6.6*	71.1 ± 13.7	**79.3** ± 4.2	75.9 ± 8.2	68.1 ± 1.9	**76.7** ± 5.7*
NLU Scenario	43	18	34.8 ± 7.6	28.5 ± 4.3	**45.7** ± 6.7*	26.9 ± 3.2	**41.7** ± 8.5*	24.4 ± 1.6	**44.1** ± 6.1*
TREC Fine	37	50	31.2 ± 7.9	33.9 ± 4.4	**36.9** ± 6.3*	31.3 ± 3.5	**40.3** ± 5.1*	26.5 ± 4.2	**39.3** ± 3.9*
NLU Intent	43	68	24.5 ± 6.1	22.3 ± 5.6	**27.5** ± 4.6*	19.8 ± 4.7	**28.6** ± 6.1*	15.5 ± 3.4	**31.1** ± 4.7*
BANKING77	27	77	28.9 ± 5.1	28.0 ± 3.7	**36.0** ± 3.2*	23.0 ± 3.3	**37.1** ± 3.4*	18.5 ± 2.7	**38.5** ± 3.6*
CLINIC150	39	150	43.9 ± 3.2	44.1 ± 1.9	**48.5** ± 2.3*	40.4 ± 1.7	**49.4** ± 1.5*	35.0 ± 1.9	**49.7** ± 1.8*

Table 1: Comparative Analysis of Classification Accuracy (in %) for GPT2-Large Using Various Context Windows (B=3, B=6, B=9). **Note: A single window (B) includes K examples**, falling within the model's capacity (e.g., 1024 tokens in GPT-2). For detailed information on the maximum number of examples (K) for each dataset and model, refer to Appendix Section A.2. Best scores are highlighted in bold. An asterisk (*) denotes statistical significance, as determined by a t-test with a p-value < 0.05. The results of GPT-2-Xl are presented in Appendix Table 6.

Dataset	# Shots per window	# Labels	ICL	B=3		B=6		B=9	
			B=1	PCW	NBCE	PCW	NBCE	PCW	NBCE
SST-2	48	2	93.4 ± 1.3	**94.9** ± 0.6*	93.8 ± 0.9	91.7 ± 1.0	**94.0** ± 0.9*	84.5 ± 0.9	**94.1** ± 0.7*
CR	39	2	93.9 ± 0.7	93.5 ± 0.6	**94.1** ± 0.6*	90.0 ± 1.0	**94.0** ± 0.5*	79.3 ± 3.3	**94.2** ± 0.5*
SUBJ	32	2	70.1 ± 9.9	60.5 ± 7.6	**74.2** ± 7.5*	49.8 ± 1.8	**69.8** ± 7.3*	48.4 ± 0.0	**71.4** ± 6.9*
CB	10	2	81.3 ± 5.7	**81.9** ± 7.4	77.8 ± 8.3	76.4 ± 5.2	**78.4** ± 7.5	62.2 ± 3.0	**83.9** ± 3.7*
RTE	10	2	72.9 ± 3.1	**73.8** ± 1.9	73.1 ± 3.1	67.2 ± 2.5	**74.4** ± 1.8*	57.5 ± 1.4	**74.2** ± 2.4*
AGNews	20	4	87.9 ± 2.8	87.3 ± 1.7	**88.6** ± 1.6	87.4 ± 1.1	**88.8** ± 1.6*	83.1 ± 1.8	**89.3** ± 1.0*
SST5	36	5	40.8 ± 5.6	**44.6** ± 3.8*	43.1 ± 3.5	40.4 ± 4.4	**42.5** ± 3.2	22.9 ± 3.0	**42.9** ± 2.6*
TREC	69	6	83.4 ± 5.4	81.1 ± 3.9	**83.5** ± 4.7	55.1 ± 3.8	**86.4** ± 3.7*	41.2 ± 4.0	**88.8** ± 3.0*
DBPedia	14	14	86.7 ± 6.8	**94.9** ± 3.0*	93.2 ± 3.3	**95.7** ± 1.6	95.6 ± 2.4	92.7 ± 1.3	**96.8** ± 1.3*
NLU Scenario	80	18	79.6 ± 3.0	79.7 ± 2.5	**83.8** ± 2.2*	58.4 ± 2.9	**85.0** ± 1.6*	40.4 ± 4.9	**86.3** ± 1.4*
TREC Fine	65	50	55.6 ± 6.1	49.5 ± 5.4	**57.8** ± 6.8*	33.5 ± 3.6	**59.8** ± 5.0*	16.9 ± 2.9	**60.9** ± 4.5*
NLU Intent	80	68	59.9 ± 5.2	**62.9** ± 3.9*	54.3 ± 2.9	37.3 ± 5.6	**56.6** ± 3.1*	14.8 ± 3.4	**57.9** ± 2.5*
BANKING77	51	77	46.3 ± 4.0	**51.2** ± 3.3*	50.5 ± 3.1	26.6 ± 4.5	**54.6** ± 3.3*	11.2 ± 3.2	**58.9** ± 2.5*
CLINIC150	72	150	**61.3** ± 2.5*	57.0 ± 3.2	55.4 ± 2.6	32.8 ± 4.8	**57.2** ± 1.8*	17.1 ± 4.0	**60.8** ± 1.9*

Table 2: Comparative Analysis of Classification Accuracy (in %) for LLAMA-7B Across Various Context Windows. The results of LLAMA-13B and LLAMA-30B are presented in Appendix Section Tables 7 and 8.

4.1 Classification Task Evaluation

4.1.1 Main Results

We conducted an analysis in which we calculated the average accuracy from 30 different runs, each with a unique seed. We compiled the accuracy and standard deviation for various text classification datasets, which are presented in Tables 1, 2, and 3. **Due to space constraints, the results of more scaled models are presented in the Appendix Section: GPT2-XL Table 6, LLAMA-13B Table 7, LLAMA-30B Table 8, and OPT-6.7B Table 12**. To highlight significant findings, we marked statistical significance with an asterisk (*), based on a t-test with a p-value of less than 0.05. Our key observations are as follows. (1) Vanilla ICL consistently showed the lowest performance across all models and datasets, underscoring the critical need for expanded context in ICL tasks. (2) For models with fewer parameters (like GPT-2-Large and OPT-1.3B) and when dealing with a limited number of output classes (five or fewer), we noted minor or negligible differences between both PCW and NBCE, compared to vanilla ICL. Conversely, in models with a larger number of parameters, NBCE generally demonstrated superior performance in most cases. However, it is important to note that several of these differences did not reach statistical significance. (3) NBCE enhances ICL by accommodating a greater number of examples. This improvement becomes particularly evident when B=9, where both accuracy and stability generally show marked improvements. We observed that larger models benefit more substantially from our approach. This favorable scaling trend of NBCE is particularly notable when contrasted with previous

Dataset	# Shots per window	# Labels	ICL B=1	B=3		B=6		B=9	
				PCW	NBCE	PCW	NBCE	PCW	NBCE
SST-2	48	2	85.0 ± 8.5	81.7 ± 10.6	**86.0** ± **7.2**	81.1 ± 7.7	**88.1** ± **5.7***	79.9 ± 9.8	**88.8** ± **5.2***
CR	39	2	89.1 ± 2.4	88.8 ± 2.3	**89.7** ± **1.7**	88.5 ± 3.3	**88.8** ± **1.6**	85.6 ± 3.6	**89.1** ± **1.5***
SUBJ	32	2	**78.8** ± **9.0***	68.3 ± 7.5	69.0 ± 7.9	68.5 ± 6.6	**70.5** ± **7.4**	65.2 ± 8.3	**70.9** ± **6.3***
CB	10	2	**53.0** ± **6.0**	50.5 ± 3.3	50.8 ± 3.3	**51.6** ± **5.2**	51.5 ± 4.3	49.1 ± 1.0	**51.6** ± **3.6***
RTE	10	2	51.1 ± 3.7	51.8 ± 3.8	**52.7** ± **3.2**	50.6 ± 3.1	**51.4** ± **2.9**	50.9 ± 2.1	**51.3** ± **2.5**
AGNews	20	4	61.3 ± 10.3	**67.4** ± **6.7***	59.6 ± 7.2	**65.1** ± **5.9***	60.3 ± 9.0	**69.4** ± **5.0***	62.9 ± 6.7
SST5	36	5	44.0 ± 3.9	42.7 ± 4.6	**44.8** ± **2.8**	42.4 ± 4.0	**44.8** ± **2.2***	41.6 ± 4.3	**45.1** ± **2.0***
TREC	69	6	**59.4** ± **6.3***	55.0 ± 4.3	56.8 ± 4.7	55.2 ± 3.2	**55.7** ± **4.3**	52.5 ± 2.8	**57.1** ± **3.9***
DBPedia	14	14	86.3 ± 3.8	87.7 ± 2.1	**87.9** ± **2.2**	**88.1** ± **2.6**	87.5 ± 2.6	87.0 ± 3.1	**87.9** ± **2.6**
NLU Scenario	80	18	67.8 ± 4.0	69.9 ± 3.5	**70.2** ± **4.0**	**69.9** ± **2.6**	69.3 ± 4.3	67.7 ± 4.0	**72.8** ± **3.8***
TREC Fine	65	50	39.7 ± 4.5	38.8 ± 4.7	**41.5** ± **6.0**	40.5 ± 5.8	**43.1** ± **6.4**	35.3 ± 3.5	**42.0** ± **4.7***
NLU Intent	80	68	45.3 ± 4.9	50.0 ± 4.2	**50.9** ± **4.0**	48.8 ± 4.2	**51.0** ± **4.7**	45.4 ± 3.2	**54.5** ± **3.3***
BANKING77	51	77	25.9 ± 4.9	24.8 ± 4.0	**28.8** ± **4.5**	26.0 ± 3.5	**30.1** ± **3.5***	28.9 ± 3.1	**32.5** ± **3.5***
CLINIC150	72	150	50.8 ± 3.0	52.4 ± 2.3	**57.7** ± **2.0**	52.6 ± 2.0	**57.2** ± **2.5***	49.3 ± 2.5	**58.4** ± **2.0***

Table 3: Comparative Analysis of Classification Accuracy (in %) for OPT-1.3B models. The results of OPT-6.7B are presented in Appendix Tables 12.

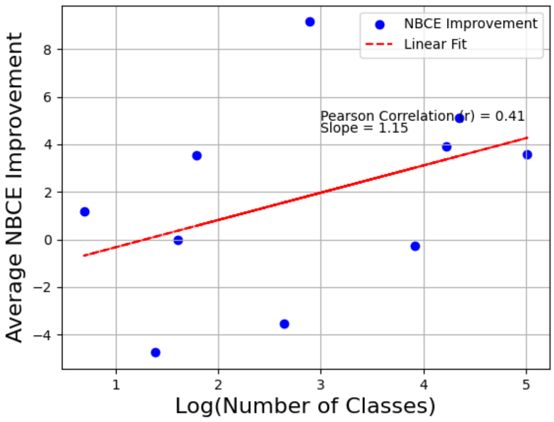


Figure 2: Average Performance Enhancements with NBCE over PCW as a Function of Label Count: Each data point in our analysis signifies the average improvement observed across all datasets on GPT2 models. It is worth noting a clear and positive correlation between the quantity of unique labels and the benefits derived from our NBCE.

efforts to enhance ICL (refer to (Zhao et al., 2021; Lu et al., 2022)), where improvements in 178B-scale models were less marked compared to those in smaller models

4.1.2 PCW enables ICL with a Large Number of Classes

To investigate the relationship between the number of classes and our NBCE's performance, we conducted a detailed analysis, which was adapted by Ratner et al. (2023). In each experiment, we calculated the difference between NBCE and PCW and then averaged the results across all datasets on GPT2 models sharing the same number of classes. As illustrated in Figure 2, a robust positive correlation emerged between the quantity of classes and the improvements achieved by NBCE. Specifically, the Pearson correlation coefficient (r) was 0.41 when considering the logarithm of class numbers in relation to the average improvement, with a slope of 1.15. Remarkably, for datasets featuring numerous labels, such as NLU Intent (Liu et al., 2019), Banking77 (Casanueva et al., 2020), and CLINIC150 (Larson et al., 2019), we observed substantial improvements ranging from 3.6 to 5.1 points in most cases.

When comparing results across datasets with varying numbers of classes, it is crucial to account for potential confounding factors, such as variations in domain, style, or genre. To mitigate these effects, we conducted a comparison using two datasets, each featuring both fine-grained and coarse-grained labels. The TREC dataset (Li and Roth, 2002), which includes 6 coarse-grained classes. The NLU dataset (Liu et al., 2019), comprising 18 scenarios coarse-grained classes and 68 intents coarse-grained classes. Our analysis on GPT2 models, as presented in Table 10, reveals that NBCE outperforms PCW by 4.1 and 3.0 improvements on GPT2-Large and GPT2-XLarge, respectively. Similarly, in the context of NLU, we observe average improvements of 17.2 and 5.2 points on GPT2-XLarge, respectively. These findings underscore the effectiveness of our approach, particularly when confronted with a large number of output classes.

4.2 Multi-Choice Tasks

Table 4 shows the evaluation of multi-choice tasks. It is important to note that the improvements made by both PCW and our NBCE in these tasks, com-

Dataset	# Shots per window	ICL	B=2		B=3		B=4		B=6	
		B=1	PCW	NBCE	PCW	NBCE	PCW	NBCE	PCW	NBCE
PIQA	23	81.6 ± 0.6	80.6 ± 0.7	**82.1** ± 0.4*	79.6 ± 0.7	**82.9** ± 0.6*	79.1 ± 0.6	**82.9** ± 0.6*	77.5 ± 0.8	**83.0** ± 0.5*
OpenBookAQ	63	41.9 ± 0.8	41.3 ± 1.0	**46.3** ± 0.9*	40.9 ± 0.9	**49.2** ± 0.8*	39.4 ± 0.6	**49.3** ± 0.9*	35.1 ± 0.8	**50.3** ± 1.1*
COPA	77	77.8 ± 1.2	**78.3** ± 1.1	78.2 ± 1.5	**78.9** ± 1.7*	77.5 ± 1.2	**77.8** ± 1.3	77.6 ± 1.6	65.9 ± 3.6	**76.6** ± 0.8*
HellaSwag	12	79.4 ± 1.1	**80.4** ± 1.1*	78.9 ± 0.9	**80.2** ± 0.8*	79.6 ± 0.7	**80.1** ± 0.9	79.9 ± 0.8	78.5 ± 0.8	**79.9** ± 0.7*
ARCE	33	**74.4** ± 1.1*	73.8 ± 1.2	72.8 ± 0.7	**73.7** ± 1.4	73.5 ± 0.6	**74.1** ± 0.8	73.7 ± 0.8	70.8 ± 1.5	**73.5** ± 0.8*
StoryCloze	24	46.0 ± 0.0	46.1 ± 0.1	**78.7** ± 0.9*	46.1 ± 0.2	**78.9** ± 0.8*	46.1 ± 0.2	**78.8** ± 1.0*	46.3 ± 0.2	**79.6** ± 0.7*
MMLU	7	33.8 ± 1.9	34.1 ± 2.2	**34.3** ± 1.5	33.6 ± 2.3	**33.7** ± 1.7	34.1 ± 1.9	**34.7** ± 1.9	32.5 ± 3.0	**33.9** ± 1.9

Table 4: Comparative Results of Task Completion (e.g., Multiple Choices Task) for LLAMA-7B Using Various Context Windows. Best scores are highlighted in bold. An asterisk (*) denotes statistical significance, as determined by a t-test with a p-value < 0.05. The results of LLAMA-13B are presented in Appendix Tables 9.

Dataset	# Labels	GPT2-Large		GPT2-XL		LLAMA-7B		LLAMA-13B	
		NBCE (RAN)	NBCE	NBCE (RAN)	NBCE	NBCE (RAN)	NBCE	NBCE (RAN)	NBCE
SST-2	2	80.5 ± 4.5	**84.3** ± 5.9*	91.6 ± 1.5	**92.5** ± 1.5	92.3 ± 1.5	**94.1** ± 0.7*	92.2 ± 1.0	**94.9** ± 0.5*
CR	2	78.0 ± 3.9	**84.1** ± 4.4*	81.0 ± 2.2	**81.9** ± 2.0	91.9 ± 1.2	**94.2** ± 0.5*	91.1 ± 1.3	**93.1** ± 0.6*
SUBJ	2	57.0 ± 3.8	**64.4** ± 9.9*	72.0 ± 5.0	**76.0** ± 7.0	69.0 ± 3.4	**71.4** ± 6.9	89.9 ± 3.0	**93.0** ± 1.7*
CB	2	**46.1** ± 4.4	45.1 ± 5.0	**55.3** ± 6.2	54.8 ± 8.5	81.6 ± 5.1	**83.9** ± 3.7*	81.7 ± 4.0	**84.1** ± 3.5*
RTE	2	52.5 ± 2.8	**54.2** ± 2.5	53.9 ± 2.9	**55.3** ± 2.2	68.2 ± 1.9	**74.2** ± 2.4*	72.9 ± 2.3	**75.1** ± 1.5*
AGNews	4	66.4 ± 7.5	**72.9** ± 7.6*	69.5 ± 5.9	**76.3** ± 4.7*	83.4 ± 2.1	**89.3** ± 1.0*	85.3 ± 2.3	**87.9** ± 1.1*
SST5	5	41.3 ± 1.8	**41.9** ± 2.4	39.1 ± 3.6	**41.7** ± 5.3	40.4 ± 2.7	**42.9** ± 2.6*	44.5 ± 2.1	**47.7** ± 2.0*
TREC	6	61.0 ± 2.8	**66.5** ± 2.9*	50.7 ± 2.8	**51.6** ± 3.0	84.1 ± 3.5	**88.8** ± 3.0*	81.7 ± 4.4	**85.0** ± 2.4*
DBPedia	14	68.9 ± 8.2	**76.7** ± 5.7*	84.1 ± 2.5	**89.0** ± 2.8*	82.8 ± 2.7	**96.8** ± 1.3*	89.2 ± 3.4	**96.9** ± 1.3*
NLU Scenario	18	40.8 ± 4.8	**44.1** ± 6.1	45.3 ± 3.9	**55.1** ± 5.4*	82.0 ± 2.1	**86.3** ± 1.4*	81.7 ± 1.8	**88.7** ± 1.0*
TREC Fine	50	33.2 ± 4.2	**39.3** ± 3.9*	35.2 ± 4.4	**41.9** ± 3.7*	56.7 ± 3.1	**60.9** ± 4.5*	57.1 ± 3.5	**63.3** ± 4.1*
NLU Intent	68	28.3 ± 0.8	**31.1** ± 4.7*	35.1 ± 1.2	**40.3** ± 3.6*	57.2 ± 2.1	**57.9** ± 2.5*	**62.6** ± 2.4*	61.8 ± 2.1
BANKING77	77	29.3 ± 1.6	**38.5** ± 3.6*	33.6 ± 1.3	**38.9** ± 2.4*	47.0 ± 1.5	**58.9** ± 2.5*	48.7 ± 3.2	**63.5** ± 2.3*
CLINIC150	150	43.8 ± 1.7	**49.7** ± 1.8*	47.7 ± 1.1	**51.6** ± 1.7*	58.7 ± 2.1	**60.8** ± 1.9*	62.5 ± 2.2	**66.2** ± 2.2*

Table 5: Ablation Study with Context Window B=9. Best scores are highlighted in bold. An asterisk (*) denotes statistical significance, as determined by a t-test with a p-value < 0.05.

pared to text classification, are relatively modest, with a slight edge for NBCE. Furthermore, employing a greater number of demonstrations does not consistently translate to better performance in multi-choice tasks. Instead, we observe that scaling up the model size (Appendix Section Table 9), rather than increasing the number of demonstrations, tends to yield more substantial improvements in these tasks.

4.3 Impact of more Demonstrations on ICL

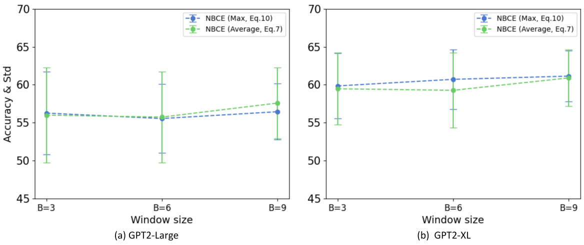
We conducted experiments to validate the impact of additional demonstrations on ICL in NLP models. Our focus was to show how extra demonstrations (B=6 and B=9, where B is the window size) enhance model performance by improving context understanding and robustness. **Note that each window contains K samples within the model's token limit (e.g., 2024 tokens for LLAMA).** For detailed information on the maximum value of K for each model and dataset, please see Appendix Table 15 . This approach aligns with the importance of training example quantity in model adaptability and generalization (Murtadha et al., 2023, 2024). Our observations indicate that NBCE mostly outperforms its counterpart, PCW, and these improvements can be considered significant. Additionally, scaling up the model size (Appendix Section Tables 6,7, 8, and 12) leads to improved performance, especially on larger and more complex datasets.

4.4 Ablation Study

To better evaluate the proposed voting mechanism, i.e., selecting the best k contexts as the posterior in Equation 10, we conducted an ablation study introducing a new variant, referred to as NBCE (RAND). In this variant, rather than deliberately choosing k, we randomly select one context from the context windows. The results are presented in Table 5. The experimental outcomes across a variety of models and datasets demonstrate that a careful selection of k significantly contributes to the quality of the generated tokens. It is noteworthy that, in this setting, NBCE can be considered as a standard ICL, where only one context window is considered. However, the performance may slightly differ due to the likelihood of the generated text $p(T)$, as outlined in Equation 9, affecting the final performance.

4.5 Effect of Pooling Mechanism

It is imperative to underscore the introduction of two distinct pooling mechanisms P: averaging the context windows as depicted in Eq.7, and maximizing based on entropy as delineated in Eq.10. To empirically validate the efficacy of these pooling strategies, we conducted a series of experiments utilizing GPT2 models within the context of a text classification task. The outcomes, illustrated in Figure 3, showcase a comparative analysis in terms of both accuracy and standard deviation. Notably, the maximizing strategy not only augments performance but also enhances stability. It is important to acknowledge that the model size can significantly influence the outcomes when employing the averaging pooling mechanism.



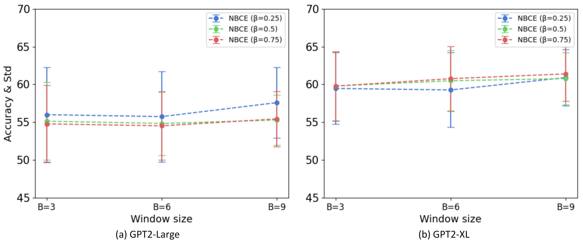
(a) GPT2-Large

(b) GPT2-XL

Figure 3: Efficacy in terms of averaged accuracy and standard deviation (i.e., the error bars) of two pooling mechanisms: average context window (Eq.7) and entropy-based maximization (Eq.10) utilizing GPT2 models for text classification. Notably, the maximizing approach enhances both accuracy and stability, with model size impacting averaging pooling's performance.

4.6 Effect of β

In our investigation, the parameter β as outlined in Eq. 8 was initially set to 0.25. To elucidate the impact of different β values on the overall performance, experiments were conducted utilizing GPT2 models within a text classification framework, testing β values of 0.25, 0.5, and 0.75. The outcomes, depicted in Figure 4, illustrate comparative performances in terms of accuracy and standard deviation. The analysis reveals a reduced sensitivity of model performance to variations in β, indicating that modifications to β do not markedly influence model robustness. Notably, an observation was made that larger model sizes exhibit more stable performance at increased β values, particularly at $\beta = 0.75$. This stability accentuates the capability of larger models to manage greater parameter variability, enhancing their utility in a broad spectrum of computational tasks.



(a) GPT2-Large

(b) GPT2-XL

Figure 4: Comparative analysis in terms of averaged accuracy and standard deviation (i.e., the error bars) of GPT2 model performance across varying β Eq. 8 values (0.25, 0.5, 0.75) in a text classification task.

5 Related Work

5.1 In-Context Learning

In recent years, in-context learning has received significant attention in the research community. Brown et al. (2020) introduced this concept, sparking a wave of investigations. Zhao et al. (2021); Han et al. (2023) addressed the issue of LLM miscalibrations and explored various calibration methods. However, few-shot performance can vary based on the order of demonstrations and template choices (Lu et al., 2022). In this context, Zhao et al. (2021) identified three biases and suggested content-free output calibration. Min et al. (2022a) demonstrated how these biases shift decision boundaries and proposed calibrating through prototypical cluster distribution estimation. Others focused on prompt engineering, such as selecting optimal demonstration permutations (Lu et al., 2022) and using retrieval modules for semantically similar in-context examples (Liu et al., 2022; Rubin et al., 2022). One promising direction is to improve in-context learning by increasing the number of demonstrations.

5.2 Context Extension

Expanding the contextual capabilities of LLM continues to pose a formidable challenge and has attracted considerable research attention. Various studies have introduced to tackle the memory limitations associated with self-attention mechanisms. These approaches can be broadly classified into two categories: fine-tuned approaches and few-shot approaches. Zaheer et al. (2020); Guo et al. (2022), have suggested using sparse attention as a solution to this issue. Press et al. (2022) took a novel approach by incorporating positional information using relative factors in attention weights instead of relying on absolute positional encoding. Despite the impressive capabilities of Press et al. (2022)'s model for extrapolation, it remains computationally intensive due to its quadratic self-attention cost, making it slow and resource-demanding for longer prompts. Ivgi et al. (2022) introduced an alternative approach called SLED, which is an encoder-decoder model specifically designed for handling lengthy texts. This model encodes short overlapping segments of input text and integrates this information within the decoder, similar to the Fusion-in-Decoder concept by Izacard and Grave (2021). However, these researches require additional training.

More recently, Ratner et al. (2023) have introduced the concept of Parallel Context Windows (PCW), which enables the concurrent utilization of multiple context windows without requiring additional training. PCW has been purposefully tailored for self-attention models, involving modifications to both position encoding and attention mask mechanisms to enhance the performance. NBCE and PCW share noteworthy similarities, as they both treat contexts as unordered and apply equal weighting. Notably, when NBCE is employed within the context of a single-layer, single-head attention model, the resulting outcomes closely approximate those achieved through the utilization of PCW. To substantiate this claim, we can formulate the language model tailored to a single-layer, single-head attention configuration.

$$p(x_t|x_{<t}) = \text{softmax}\left(\sum_{i=1}^{t} a_{t,i} v_i W\right) \tag{11}$$

hence, approximately: $\log p(x_t|x_{<t}) \sim \sum_{i=1}^{t} a_{t,i} v_i W$. Substituting this into Equation 9 and setting $\beta = 0$, we obtain:

$$\begin{aligned}\log p(T|S_1, S_2, \dots, S_n) &\sim \frac{1}{n}\sum_{k=1}^{n}\left(\sum_{i\in S_k} a_{T,i} v_i\right) W \\ &= \left(\sum_{i\in S_1\oplus\ldots\oplus S_n} \frac{a_{T,i}}{n} v_i\right) W\end{aligned} \tag{12}$$

here, we assume T represents a single sequence (i.e., the query), However, this assumption does not lack generality. The symbol $\oplus$ denotes concatenation and $S_k \oplus T$ is used for reasoning as a continuous segment (as per NBCE's setup), so their positional encodings are adjacent. Additionally, $a_{T,i}/n$ forms a collective attention for T with all S_i (with a sum equal to 1). These characteristics are consistent with PCW, which is essentially integrated into each layer more elegantly through an attention mask. Therefore, PCW can be thought of as a version of NBCE that utilizes average pooling.

6 Conclusion

This paper introduces a novel framework called Naive Bayes-based Context Extension (NBCE) for large language models. NBCE innovatively incorporates a voting mechanism to select the most appropriate window context, and then utilizes Bayes' theorem to generate the task text. Our results show that NBCE outperforms its alternative PCW across a diverse set of multi-class classification tasks. For future work, while PCW shows effective without additional training, ICL could potentially benefit from more demonstrations in fine-tuning settings; however, further investigation is required to fully comprehend the extent of its advantages.

Limitations

NBCE facilitates ICL tasks by allowing for more demonstrations without the need for fine-tuning. However, there are still some limitations to this approach:

- Since NBCE essentially functions as a voting mechanism, its effectiveness is constrained in tasks that require ordered or interrelated contexts, such as code generation. This is due to its inherent nature, which may not adequately handle sequential or dependent information in certain contexts.
- Increasing the number of shots does not necessarily lead to improved performance. Experimental results have indicated that expanding the context window size does not significantly enhance performance in completion tasks. This suggests a diminishing return on performance gains with an increased number of contexts.

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Dataset	# Labels	ICL	B=3		B=6		B=9	
			PCW	NBCE	PCW	NBCE	PCW	NBCE
SST-2	2	90.6 ± 3.5	92.4 ± 2.5	**92.7** ± 2.3*	89.4 ± 3.5	**92.5** ± 2.2*	83.7 ± 1.7	**92.5** ± 1.5*
CR	2	79.2 ± 5.9	81.3 ± 4.6	**82.5** ± 2.9*	81.6 ± 2.4	**81.9** ± 2.1	**82.7** ± 1.7	81.9 ± 2.0
SUBJ	2	68.8 ± 11.6	64.9 ± 7.3	**74.5** ± 8.3*	57.0 ± 4.1	**78.7** ± 4.8*	65.6 ± 3.0	**76.0** ± 7.0*
CB	2	51.9 ± 7.4	**57.2** ± 8.5*	56.1 ± 7.9	49.6 ± 3.6	**55.8** ± 7.8*	42.2 ± 2.1	**54.8** ± 8.5*
RTE	2	55.4 ± 2.4	**55.6** ± 1.6	54.9 ± 2.5	54.2 ± 1.3	**55.2** ± 2.3*	50.4 ± 2.0	**55.3** ± 2.2*
AGNews	4	67.2 ± 13.2	**79.6** ± 3.4*	70.0 ± 9.6	**80.4** ± 2.3*	74.1 ± 5.8	71.6 ± 2.5	**76.3** ± 4.7*
SST5	5	38.0 ± 6.1	**41.4** ± 4.3*	41.1 ± 4.7	38.1 ± 3.6	**41.5** ± 5.4*	35.3 ± 2.2	**41.7** ± 5.3*
TREC	6	47.9 ± 5.1	48.7 ± 2.8	**51.7** ± 5.0*	45.5 ± 2.3	**51.8** ± 4.6*	43.1 ± 1.9	**51.6** ± 3.0*
DBPedia	14	77.5 ± 9.8	87.0 ± 4.0	**87.7** ± 3.8*	**88.9** ± 3.3	88.6 ± 3.3	81.4 ± 2.1	**89.0** ± 2.8*
NLU Scenario	18	45.1 ± 9.3	50.0 ± 6.1	**51.1** ± 8.1*	46.7 ± 5.9	**50.3** ± 6.8*	38.7 ± 6.3	**55.1** ± 5.4*
TREC Fine	50	36.4 ± 6.2	40.0 ± 3.0	**40.1** ± 5.1*	35.5 ± 2.6	**41.7** ± 3.6*	31.0 ± 2.8	**41.9** ± 3.7*
NLU Intent	68	30.2 ± 5.4	33.8 ± 4.6	**36.4** ± 4.9*	33.4 ± 4.3	**38.5** ± 5.4*	24.3 ± 3.7	**40.3** ± 3.6*
BANKING77	77	30.7 ± 4.1	33.3 ± 3.5	**35.5** ± 2.8*	26.8 ± 3.1	**37.6** ± 2.4*	16.7 ± 2.6	**38.9** ± 2.4*
CLINIC150	150	46.6 ± 2.5	47.1 ± 2.3	**49.9** ± 1.9*	40.8 ± 2.3	**50.9** ± 2.1*	34.5 ± 2.5	**51.6** ± 1.7*

Table 6: Comparative Analysis of Classification Accuracy (in %) for GPT-2-XL Across Various Context Windows (B=3, B=6, B=9). Best scores are highlighted in bold. An asterisk (*) denotes statistical significance, as determined by a t-test with a p-value < 0.05.

Dataset	# Labels	ICL	B=3		B=6		B=9	
			PCW	NBCE	PCW	NBCE	PCW	NBCE
SST-2	2	94.5 ± 0.7	94.1 ± 0.7	**94.8** ± 0.5*	94.0 ± 0.9	**95.0** ± 0.4*	90.1 ± 1.2	**94.9** ± 0.5*
CR	2	92.0 ± 1.4	92.2 ± 0.9	**92.9** ± 1.0*	92.5 ± 0.5	**93.0** ± 1.0*	91.1 ± 0.9	**93.1** ± 0.6*
SUBJ	2	90.2 ± 3.8	87.5 ± 3.3	**90.8** ± 2.9*	79.0 ± 7.2	**92.5** ± 1.7*	67.1 ± 5.4	**93.0** ± 1.7*
CB	2	80.3 ± 8.0	**84.6** ± 4.1*	79.8 ± 4.9	**83.1** ± 4.0*	80.3 ± 6.4	74.1 ± 6.3	**84.1** ± 3.5*
RTE	2	**74.6** ± 2.7	73.5 ± 2.0	74.0 ± 2.5	71.9 ± 1.6	**74.6** ± 1.6*	66.4 ± 2.0	**75.1** ± 1.5*
AGNews	4	86.9 ± 2.9	**87.9** ± 1.7	86.6 ± 1.8	**88.0** ± 0.9	87.3 ± 1.8	87.7 ± 1.1	**87.9** ± 1.1
SST5	5	48.0 ± 3.3	**49.2** ± 2.6	48.0 ± 3.3	**48.4** ± 2.1	47.3 ± 3.4	44.0 ± 2.9	**47.7** ± 2.0*
TREC	6	83.1 ± 3.1	**83.7** ± 2.9*	81.5 ± 3.4	75.5 ± 3.6	**83.0** ± 3.8*	49.5 ± 5.4	**85.0** ± 2.4*
DBPedia	14	88.6 ± 6.1	**93.6** ± 3.9*	93.2 ± 3.9	94.4 ± 2.7	**94.7** ± 2.6	94.5 ± 2.7	**96.9** ± 1.3*
NLU Scenario	18	82.1 ± 2.7	85.9 ± 1.8	**86.7** ± 1.8*	81.2 ± 2.4	**87.4** ± 1.4*	74.1 ± 2.9	**88.7** ± 1.0*
TREC Fine	50	55.4 ± 5.3	**60.1** ± 5.1*	57.7 ± 4.7	56.8 ± 5.4	**60.4** ± 4.7*	47.6 ± 9.0	**63.3** ± 4.1*
NLU Intent	68	68.3 ± 4.1	**73.0** ± 2.6*	58.1 ± 2.3	**65.2** ± 2.6*	60.7 ± 2.7	52.6 ± 3.6	**61.8** ± 2.1*
BANKING77	77	46.6 ± 4.2	**56.4** ± 2.8*	52.8 ± 3.5	50.8 ± 3.1	**59.2** ± 2.8*	40.2 ± 2.5	**63.5** ± 2.3*
CLINIC150	150	63.7 ± 2.5	**66.0** ± 2.7*	59.2 ± 2.3	57.5 ± 2.9	**62.4** ± 1.7*	48.7 ± 2.3	**66.2** ± 2.2*

Table 7: Comparative Analysis of Classification Accuracy (in %) for LLAMA-13B Across Various Context Windows (B=3, B=6, B=9). Best scores are highlighted in bold. An asterisk (*) denotes statistical significance, as determined by a t-test with a p-value < 0.05.

A Appendix

A.1 Scaling Model Parameters

A.2 Prompt Format

Dataset	# Labels	ICL	B=3		B=6	
			PCW	NBCE	PCW	NBCE
SST-2	2	94.7 ± 0.5	94.9 ± 0.7	**95.0** ± 0.3	92.9 ± 0.7	**95.0** ± 0.3*
CR	2	**93.8** ± 0.5	93.6 ± 0.5	93.8 ± 0.5	93.3 ± 1.1	**93.7** ± 0.4
SUBJ	2	90.3 ± 4.5	91.0 ± 2.7	**93.8** ± 1.7*	83.7 ± 5.1	**94.5** ± 1.6*
CB	2	**88.8** ± 2.5	88.7 ± 1.9	88.0 ± 3.3	83.9 ± 2.4	**89.1** ± 2.2*
RTE	2	**79.9** ± 1.9	79.0 ± 1.8	79.4 ± 2.1	73.8 ± 3.4	**80.6** ± 1.8*
AGNews	4	88.0 ± 4.7	**89.4** ± 0.7	88.9 ± 1.3	88.0 ± 0.8	**88.8** ± 1.4
SST5	5	47.0 ± 2.6	**47.5** ± 2.3	45.0 ± 2.8	**48.4** ± 1.0*	44.5 ± 2.4
TREC	6	87.2 ± 3.3	**90.1** ± 1.7*	88.8 ± 2.8	67.2 ± 4.8	**88.6** ± 1.7*
DBPedia	14	88.4 ± 8.6	94.5 ± 3.0	**95.4** ± 2.6*	96.2 ± 3.0	**96.7** ± 1.4
NLU Scenario	18	82.6 ± 2.0	**85.3** ± 1.5*	84.6 ± 1.7	80.2 ± 2.1	**85.8** ± 1.2*
TREC Fine	50	60.7 ± 4.8	**67.7** ± 4.3*	64.7 ± 3.7	50.1 ± 4.2	**68.6** ± 4.2*
NLU Intent	68	68.6 ± 4.4	**74.4** ± 2.7*	60.1 ± 2.7	**61.6** ± 3.2	61.0 ± 2.2
BANKING77	77	50.3 ± 3.1	**63.2** ± 2.5*	55.3 ± 3.5	58.1 ± 2.7	**63.7** ± 3.6*
CLINIC150	150	67.0 ± 3.6	**71.0** ± 4.2*	65.6 ± 3.0	57.2 ± 2.9	**67.3** ± 2.3*

Table 8: Comparative Analysis of Classification Accuracy (in %) for LLAMA-30B Across Various Context Windows (B=3, B=6, B=9). Best scores are highlighted in bold. An asterisk (*) denotes statistical significance, as determined by a t-test with a p-value < 0.05.

Dataset	ICL	B=2		B=3		B=4		B=6	
		PCW	NBCE	PCW	NBCE	PCW	NBCE	PCW	NBCE
PIQA	83.0 ± 0.6	**83.6** ± 0.6*	83.2 ± 0.6	**83.5** ± 0.6	83.2 ± 0.7	**83.3** ± 0.5	83.2 ± 0.6	81.9 ± 1.0	**83.2** ± 0.5*
OpenBookAQ	51.0 ± 1.7	**51.1** ± 1.2*	47.0 ± 1.1	50.2 ± 1.3	**50.2** ± 1.3	48.8 ± 1.1	**49.8** ± 1.0*	46.7 ± 1.3	**51.1** ± 1.0*
COPA	79.9 ± 2.5	**81.8** ± 2.4*	79.0 ± 0.9	**86.0** ± 1.9*	79.8 ± 2.2	**86.5** ± 1.5*	79.8 ± 2.1	74.9 ± 3.1	**78.4** ± 1.5*
HellaSwag	82.3 ± 0.7	**82.5** ± 1.0	82.5 ± 0.7	**82.3** ± 0.7	82.2 ± 0.5	82.2 ± 0.6	**82.4** ± 0.5	81.7 ± 0.8	**82.2** ± 0.5*
ARCE	80.3 ± 0.6	**80.5** ± 0.7*	77.4 ± 0.7	**79.8** ± 0.5	79.7 ± 0.5	78.9 ± 0.6	**79.8** ± 0.5*	76.8 ± 0.9	**80.5** ± 0.4*
StoryCloze	80.5 ± 0.8	**82.1** ± 0.9*	80.1 ± 0.9	**82.0** ± 0.6*	80.0 ± 0.9	**81.9** ± 0.8*	80.1 ± 1.0	**81.2** ± 0.8*	80.1 ± 0.9
MMLU	45.3 ± 1.8	**46.4** ± 1.9*	43.6 ± 1.3	**45.5** ± 1.9*	44.4 ± 1.3	**44.7** ± 2.1	44.4 ± 2.0	43.6 ± 2.8	**44.6** ± 1.4

Table 9: Comparative Results of Task Completion (e.g., Multiple Choices Task) for LLAMA-13B Using Various Context Windows. Best scores are highlighted in bold. An asterisk (*) denotes statistical significance, as determined by a t-test with a p-value < 0.05.

Dataset	# Labels	GPT2-Large			GPT2-XLarge		
		ICL	PCW	NBCE	ICL	PCW	NBCE
SST-2	2	80.2 ± 11.7	84.1 ± 8.2	**85.2 ± 6.7**	90.6 ± 3.5	92.4 ± 2.5	**92.7 ± 2.3***
CR	2	81.3 ± 6.3	81.2 ± 6.4	**82.7 ± 6.3**	79.2 ± 5.9	81.3 ± 4.6	**82.5 ± 2.9***
SUBJ	2	65.1 ± 11.9	**67.0 ± 12.2**	66.1 ± 13.2	68.8 ± 11.6	64.9 ± 7.3	**74.5 ± 8.3***
CB	2	43.9 ± 3.7	43.9 ± 3.2	**45.2 ± 3.7**	51.9 ± 7.4	**57.2 ± 8.5***	56.1 ± 7.9
RTE	2	52.5 ± 2.2	**53.5 ± 1.7**	52.9 ± 2.9	55.4 ± 2.4	**55.6 ± 1.6**	54.9 ± 2.5
AGNews	4	61.7 ± 14.2	70.9 ± 9.4	**71.0 ± 8.9 ***	67.2 ± 13.2	**79.6 ± 3.4***	70.0 ± 9.6
SST-5	5	40.8 ± 2.5	41.5 ± 3.1	**41.8 ± 2.4**	38.0 ± 6.1	**41.4 ± 4.3***	41.1 ± 4.7
TREC	6	56.6 ± 7.9	59.0 ± 4.7	**63.1 ± 7.0***	47.9 ± 5.1	48.7 ± 2.8	**51.7 ± 5.0***
DBPedia	14	58.7 ± 20.2	**78.9 ± 6.6**	71.1 ± 13.7	77.5 ± 9.8	87.0 ± 4.0	**87.7 ± 3.8***
NLU Scenario	18	34.8 ± 7.6	28.5 ± 4.3	**45.7 ± 6.7***	45.1 ± 9.3	50.0 ± 6.1	**51.1 ± 8.1***
TREC Fine	50	36.9 ± 6.3	**37.4 ± 4.8***	36.9 ± 6.3	36.4 ± 6.2	**40.1 ± 3.0***	40.1 ± 5.1
NLU Intent	68	24.5 ± 6.1	22.3 ± 5.6	**27.5 ± 4.6***	30.2 ± 5.4	33.8 ± 4.6	**36.4 ± 4.9***
BANKING77	77	28.9 ± 5.1	28.0 ± 3.7	**36.0 ± 3.2***	30.7 ± 4.1	33.3 ± 3.5	**35.5 ± 2.8***
CLINIC150	150	43.9 ± 3.2	44.1 ± 1.9	**48.5 ± 2.3***	46.6 ± 2.5	47.1 ± 2.3	**49.9 ± 1.9***

Table 10: Comparative analysis of classification results in terms of accuracy (in %) for both the GPT2-Large and GPT2-XLarge models using a context window of B = 3. Notably, a single window comprises a set of examples with a total number of tokens equal to the maximum capacity of conventional in-context learning (e.g., 1024 tokens in GPT-2). The best-performing scores for each model and dataset are highlighted in bold, while '*' indicates statistical significance, determined by a t-test with a p-value < 0.05.

Dataset	# Labels	OPT-1.3B			OPT-6.7B			OPT-13B		
		ICL	PCW	NBCE	ICL	PCW	NBCE	ICL	PCW	NBCE
SST-2	2	85.0 ± 8.5	81.7 ± 10.6	**86.0 ± 7.2**	93.8 ± 2.6	93.7 ± 3.3	**95.8 ± 1.7***	93.1 ± 4.4	93.8 ± 3.1	**94.9 ± 2.3**
CR	2	89.1 ± 2.4	88.8 ± 2.3	**89.7 ± 1.7**	90.3 ± 2.5	90.7 ± 2.4	**91.7 ± 1.5***	92.7 ± 1.5	92.3 ± 2.5	**93.1 ± 1.4**
SUBJ	2	**78.8 ± 9.0***	68.3 ± 7.5	69.0 ± 7.9	**72.3 ± 10.6***	70.9 ± 13.9	64.0 ± 10.7	86.4 ± 9.2	88.0 ± 8.3	**90.1 ± 5.9**
CB	2	**53.0 ± 6.0**	50.5 ± 3.3	50.8 ± 3.3	52.4 ± 10.1	**59.9 ± 12.1**	59.3 ± 10.8	50.5 ± 8.5	49.3 ± 5.8	**62.5 ± 10.2**
RTE	2	51.1 ± 3.7	51.8 ± 3.8	**52.7 ± 3.2**	56.1 ± 2.2	56.2 ± 1.6	**56.8 ± 2.0**	53.0 ± 6.0	56.3 ± 4.9	**56.8 ± 6.2**
AGNews	4	61.3 ± 10.3	**67.4 ± 6.7***	59.6 ± 7.2	74.8 ± 6.7	**76.7 ± 4.8***	72.7 ± 5.7	78.6 ± 5.6	**82.4 ± 2.3**	78.8 ± 3.9
SST-5	5	44.0 ± 3.9	42.7 ± 4.6	**44.8 ± 2.8**	42.7 ± 5.1	**45.2 ± 4.2**	42.5 ± 4.6	45.6 ± 3.4	**45.7 ± 2.6**	42.9 ± 4.2
TREC	6	**59.4 ± 6.3***	55.0 ± 4.3	56.8 ± 4.7	70.3 ± 3.3	**73.1 ± 2.2***	71.8 ± 3.5	56.7 ± 7.2	**62.4 ± 6.2**	57.1 ± 6.8
DBPedia	14	86.3 ± 3.8	87.7 ± 2.1	**87.9 ± 2.2**	89.8 ± 3.5	**94.3 ± 2.0***	93.5 ± 2.6	87.3 ± 4.0	**94.1 ± 2.1**	94.0 ± 2.2
NLU Scenario	18	67.8 ± 4.0	69.9 ± 3.5	**70.2 ± 4.0**	74.9 ± 3.0	**79.0 ± 2.0**	77.9 ± 3.0	78.5 ± 3.2	81.8 ± 2.0	**83.7 ± 1.8**
TREC Fine	50	39.7 ± 4.5	38.8 ± 4.7	**41.5 ± 6.0**	45.7 ± 6.7	49.6 ± 6.6	**50.1 ± 6.7**	49.7 ± 6.0	**55.5 ± 6.6**	51.7 ± 6.6
NLU Intent	68	45.3 ± 4.9	50.0 ± 4.2	**50.9 ± 4.0**	55.8 ± 3.9	62.5 ± 3.1	**63.3 ± 3.1**	61.5 ± 2.8	**71.8 ± 2.5**	**71.8 ± 2.7**
BANKING77	77	25.9 ± 4.9	24.8 ± 4.0	**28.8 ± 4.5**	43.6 ± 3.1	51.9 ± 2.8	**53.7 ± 3.3**	43.3 ± 3.4	53.0 ± 3.8	**56.0 ± 3.4**
CLINIC150	150	50.8 ± 3.0	52.4 ± 2.3	**57.7 ± 2.0**	60.4 ± 2.4	63.0 ± 1.9	**65.5 ± 1.9**	59.7 ± 2.3	65.1 ± 2.7	**66.1 ± 2.1**

Table 11: Comparative analysis of classification results measured by accuracy (in %) for OPT models with B = 3. The best scores are highlighted in bold, while '*' indicates p-value < 0.05.

Dataset	# Labels	ICL	B=3		B=4		B=5	
			PCW	NBCE	PCW	NBCE	PCW	NBCE
SST-2	2	93.8 ± 2.6	93.7 ± 3.3	**95.8 ± 1.7***	93.9 ± 2.7	**96.1 ± 0.9***	92.3 ± 4.2	**96.3 ± 0.9***
CR	2	90.3 ± 2.5	90.7 ± 2.4	**91.7 ± 1.5***	90.8 ± 2.3	**91.9 ± 1.6***	90.0 ± 2.7	**91.5 ± 1.4***
SUBJ	2	**72.3 ± 10.6***	70.9 ± 13.9	64.0 ± 10.7	**66.6 ± 13.2**	65.7 ± 9.7	67.3 ± 14.2	**68.4 ± 9.8**
CB	2	52.4 ± 10.1	**59.9 ± 12.1**	59.3 ± 10.8	55.6 ± 10.4	**59.8 ± 12.0**	**60.7 ± 8.7**	56.1 ± 9.9
RTE	2	56.1 ± 2.2	56.2 ± 1.6	**56.8 ± 2.0**	55.7 ± 1.6	**56.6 ± 2.0**	55.0 ± 1.4	**56.9 ± 1.9***
AGNews	4	74.8 ± 6.7	**76.7 ± 4.8***	72.7 ± 5.7	75.7 ± 5.3	**73.0 ± 5.6**	**77.7 ± 3.9**	77.1 ± 5.1
SST-5	5	42.7 ± 5.1	**45.2 ± 4.2**	42.5 ± 4.6	**44.3 ± 4.5***	41.3 ± 3.5	**46.3 ± 3.6***	42.8 ± 3.4
TREC	6	70.3 ± 3.3	**73.1 ± 2.2***	71.8 ± 3.5	**72.1 ± 2.9**	72.0 ± 3.4	**73.6 ± 2.7**	72.9 ± 2.9
DBPedia	14	89.8 ± 3.5	**94.3 ± 2.0***	93.5 ± 2.6	**94.4 ± 2.1**	93.4 ± 2.3	**94.7 ± 1.5***	93.7 ± 2.0
NLU Scenario	18	74.9 ± 3.0	**79.0 ± 2.0**	77.9 ± 3.0	**76.8 ± 4.3***	**76.8 ± 3.1***	77.7 ± 3.8	**79.3 ± 2.1***
TREC Fine	50	45.7 ± 6.7	49.6 ± 6.6	**50.1 ± 6.7**	48.2 ± 6.7	**49.4 ± 6.9**	**51.5 ± 6.9**	50.7 ± 5.2
NLU Intent	68	55.8 ± 3.9	62.5 ± 3.1	**63.3 ± 3.1**	61.8 ± 3.6	**62.4 ± 3.9**	61.1 ± 3.7	**66.4 ± 2.3***
BANKING77	77	43.6 ± 3.1	51.9 ± 2.8	**53.7 ± 3.3**	51.5 ± 3.2	53.8 ± 3.2	52.2 ± 2.0	**56.4 ± 2.6**
CLINIC150	150	60.4 ± 2.4	63.0 ± 1.9	**65.5 ± 1.9**	62.7 ± 2.2	**65.5 ± 2.5***	61.9 ± 1.8	**67.1 ± 2.2***

Table 12: The comparative results of context extension, measured by accuracy (in %), for OPT-6.7B models with windows (B = 4 and B = 5).

Dataset	# Labels	GPT2-Large				GPT2-XLarge			
		B = 4		B = 5		B = 4		B = 5	
		PCW	NBCE	PCW	NBCE	PCW	NBCE	PCW	NBCE
SST-2	2	83.3 ± 7.8	**83.9 ± 7.9**	**85.0 ± 6.9**	83.7 ± 8.6	91.3 ± 2.9	**92.6 ± 2.6**	91.4 ± 3.1	**92.4 ± 2.4**
CR	2	82.1 ± 5.9	**84.1 ± 5.7**	81.7 ± 4.7	**82.4 ± 5.1**	82.1 ± 2.9	**82.7 ± 3.0**	**82.0 ± 2.4**	81.7 ± 2.5
SUBJ	2	**68.1 ± 11.9**	63.1 ± 10.5	66.5 ± 10.3	**68.9 ± 10.5**	63.9 ± 6.0	**76.2 ± 6.7**	59.3 ± 5.2	**79.3 ± 5.5***
CB	2	44.0 ± 3.4	**44.7 ± 4.3**	42.8 ± 2.0	**43.8 ± 2.8**	**53.9 ± 6.2**	53.8 ± 9.1	51.1 ± 4.4	**56.7 ± 7.7***
RTE	2	**53.5 ± 1.5***	52.1 ± 3.0	54.0 ± 1.2	53.7 ± 2.2	**55.3 ± 1.1**	54.7 ± 3.0	54.9 ± 1.7	**55.7 ± 1.7**
AGNews	4	**69.2 ± 9.6**	68.1 ± 12.5	67.9 ± 8.1	**70.7 ± 8.4**	**80.5 ± 3.3***	72.5 ± 8.8	**80.0 ± 2.5***	73.0 ± 6.7
SST-5	5	40.1 ± 4.0	**42.4 ± 1.7***	40.4 ± 3.9	**42.6 ± 1.6**	**41.5 ± 4.2***	38.5 ± 5.7	39.2 ± 4.4	**41.7 ± 5.8***
TREC	6	57.4 ± 4.1	**64.8 ± 4.0***	55.3 ± 4.0	**64.6 ± 4.8***	48.9 ± 3.4	**51.6 ± 3.7**	48.1 ± 2.2	**53.0 ± 2.7***
DBPedia	14	**80.7 ± 5.0***	74.8 ± 12.1	**79.3 ± 4.4**	76.5 ± 8.4	**88.5 ± 3.3**	87.5 ± 4.7	**89.8 ± 3.2**	89.1 ± 3.6
NLU Scenario	18	27.8 ± 3.6	**46.6 ± 7.4**	27.5 ± 3.3	**44.4 ± 6.5**	49.7 ± 5.7	**51.7 ± 7.6**	48.7 ± 6.0	**52.8 ± 5.5***
TREC Fine	50	32.4 ± 5.1	**37.4 ± 4.8***	31.2 ± 4.1	**39.9 ± 3.6***	38.6 ± 3.1	**39.8 ± 6.1**	37.2 ± 2.3	**41.6 ± 3.8***
NLU Intent	68	24.3 ± 4.7	**26.0 ± 5.6**	20.3 ± 5.4	**27.3 ± 4.4**	34.8 ± 5.1	**35.9 ± 5.2**	37.1 ± 5.1	**38.6 ± 3.3***
BANKING77	77	26.6 ± 3.2	**35.2 ± 3.8***	25.5 ± 3.2	**36.0 ± 3.8***	31.0 ± 3.5	**35.4 ± 3.2***	29.6 ± 2.8	**37.7 ± 2.6***
CLINIC150	150	43.2 ± 1.8	**48.1 ± 1.9***	41.6 ± 2.2	**49.4 ± 2.0***	45.9 ± 2.9	**49.3 ± 2.3***	43.0 ± 2.4	**50.3 ± 2.5***

Table 13: The comparative results of classification tasks, quantified in terms of accuracy (in %), for both GPT2-Large and GPT2-XLarge models using different context windows (B = 4 and B = 5). The best scores for each model and dataset are highlighted in bold, while an asterisk (*) denotes statistical significance (as determined by a t-test with a p-value < 0.05).

Dataset	# Labels	OPT-1.3B				OPT-6.7B			
		B = 4		B = 5		B = 4		B = 5	
		PCW	NBCE	PCW	NBCE	PCW	NBCE	PCW	NBCE
SST-2	2	81.1 ± 7.7	**88.1 ± 5.7***	79.9 ± 9.8	**88.8 ± 5.2***	93.9 ± 2.7	**96.1 ± 0.9***	92.3 ± 4.2	**96.3 ± 0.9***
CR	2	88.5 ± 3.3	**88.8 ± 1.6**	85.6 ± 3.6	**89.1 ± 1.5***	90.8 ± 2.3	**91.9 ± 1.6***	90.0 ± 2.7	**91.5 ± 1.4***
SUBJ	2	68.5 ± 6.6	**70.5 ± 7.4**	65.2 ± 8.3	**70.9 ± 6.3***	**66.6 ± 13.2**	65.7 ± 9.7	67.3 ± 14.2	**68.4 ± 9.8**
CB	2	**51.6 ± 5.2**	51.5 ± 4.3	49.1 ± 1.0	**51.6 ± 3.6***	55.6 ± 10.4	**59.8 ± 12.0**	**60.7 ± 8.7**	56.1 ± 9.9
RTE	2	50.6 ± 3.1	**51.4 ± 2.9**	50.9 ± 2.1	**51.3 ± 2.5**	55.7 ± 1.6	**56.6 ± 2.0**	55.0 ± 1.4	**56.9 ± 1.9***
AGNews	4	**65.1 ± 5.9***	60.3 ± 9.0	**69.4 ± 5.0***	62.9 ± 6.7	75.7 ± 5.3	**73.0 ± 5.6**	**77.7 ± 3.9**	77.1 ± 5.1
SST-5	5	42.4 ± 4.0	**44.8 ± 2.2***	41.6 ± 4.3	**45.1 ± 2.0***	**44.3 ± 4.5***	41.3 ± 3.5	**46.3 ± 3.6***	42.8 ± 3.4
TREC	6	55.2 ± 3.2	**55.7 ± 4.3**	52.5 ± 2.8	**57.1 ± 3.9***	**72.1 ± 2.9**	72.0 ± 3.4	**73.6 ± 2.7**	72.9 ± 2.9
DBPedia	14	**88.1 ± 2.6**	87.5 ± 2.6	87.0 ± 3.1	**87.9 ± 2.6**	**94.4 ± 2.1**	93.4 ± 2.3	**94.7 ± 1.5***	93.7 ± 2.0
NLU Scenario	18	**69.9 ± 2.6**	69.3 ± 4.3	67.7 ± 4.0	**72.8 ± 3.8***	**76.8 ± 4.3***	**76.8 ± 3.1***	77.7 ± 3.8	**79.3 ± 2.1***
TREC Fine	50	40.5 ± 5.8	**43.1 ± 6.4**	35.3 ± 3.5	**42.0 ± 4.7***	48.2 ± 6.7	**49.4 ± 6.9**	**51.5 ± 6.9**	50.7 ± 5.2
NLU Intent	68	48.8 ± 4.2	**51.0 ± 4.7**	45.4 ± 3.2	**54.5 ± 3.3***	61.8 ± 3.6	**62.4 ± 3.9**	61.1 ± 3.7	**66.4 ± 2.3***
BANKING77	77	26.0 ± 3.5	**30.1 ± 3.5***	28.9 ± 3.1	**32.5 ± 3.5***	51.5 ± 3.2	53.8 ± 3.2	52.2 ± 2.0	**56.4 ± 2.6**
CLINIC150	150	52.6 ± 2.0	**57.2 ± 2.5***	49.3 ± 2.5	**58.4 ± 2.0***	62.7 ± 2.2	**65.5 ± 2.5***	61.9 ± 1.8	**67.1 ± 2.2***

Table 14: The comparative results of context extension, measured by accuracy (in %), for OPT models with windows (B = 4 and B = 5).

Dataset	Number of shots per window B k_{max} **GPT2**	 k_{max} **LLAMA**	Prompt Example	Labels
SST-2	27	48	Sentence: {Sentence} Label: Label	[negative, positive]

CR	21	39	Review:{Sentence}
			Sentiment:{Label}
				[negative, positive]

SUBJ	18	32	Input:{Sentence}
			Type:{Label}
				[objective, subjective]

CB	5	10	Premise:{Sentence}
			Hypothesis:{ hypothesis}
			Prediction:{Label}
				[true, false, neither]

RTE	5	10	Premise:{Sentence}
			Hypothesis:{ hypothesis}
			Prediction:{Label}
				[True, False]

AGNews	11	20	Input:{Sentence}
			Type:{Label}
				[world, sports, business, technology]

SST-5	20	36	Review:{Sentence} Sentiment:Sentiment	[terrible, bad, okay, good, great]

TREC	38	69	Question:{Sentence}
			Type:{Label}
				[abbreviation, entity, description, human, location, numeric]

DBPedia	7	14	Input:{Sentence}
			Type:{Label}
				[company, school, artist, athlete, politics, transportation, building, nature, village, animal, plant, album, film, book]

NLU Scenario	43	80	Utterance:{Sentence}
			Scenario:{Label}
				[lists, weather, general, cooking, email, alarm, datetime, calendar, social, transport, iot, recommendation, takeaway, play, music, qa, news, audio]

TREC Fine	37	65	Question:{Sentence}
			Type:{Label}
				[abbreviation abbreviation, abbreviation expansion, entity animal, entity body, entity color, entity creation, entity currency, entity disease, entity event, entity food...

NLU Intent	43	80	Utterance:{Sentence}
			Intent:{Label}
				[alarm query, alarm remove, alarm set, audio volume down, audio volume mute, audio volume other, audio volume up, calendar query, calendar remove, calendar set...

BANKING77	27	51	Query:{Sentence}
			Intent:{Label}
				[activate my card, age limit, apple pay or google pay, atm support, automatic top up, balance not updated after bank transfer, balance not updated after cheque or cash deposit...

CLINIC150	39	72	Sentence:{Sentence}
			Intent:{Label}
				[restaurant reviews, nutrition info, account blocked, oil change how, time, weather, redeem rewards, interest rate, gas type...

Table 15: Classification datasets with used prompts and k_{max} for GPT2 and LLaMA. Note that OPT shares the same length of LLAMA (i.e., 2048)