BERTs are Generative In-Context Learners

David Samuel

Language Technology Group University of Oslo davisamu@uio.no

Abstract

This paper explores the in-context learning capabilities of masked language models, challenging the common view that this ability does not 'emerge' in them. We present an *embarrassingly simple* inference technique that enables DeBERTa to operate as a generative model without any additional training. Our findings demonstrate that DeBERTa can match and even surpass GPT-3, its contemporary that famously introduced the paradigm of in-context learning. The comparative analysis reveals that the masked and causal language models behave very differently, as they clearly outperform each other on different categories of tasks. This suggests that there is great potential for a hybrid training approach that takes advantage of the strengths of both training objectives.

1 Introduction

Masked language models used to dominate the field of natural language processing due to their adaptability across diverse tasks and their superior performance compared to causal language models (Radford et al., 2018; Devlin et al., 2019). Between 2018 and 2020, the field witnessed a surge in the development of these models (Devlin et al., 2019; Liu et al., 2019; Lan et al., 2020, *inter alia*). However, the introduction of GPT-3 in Brown et al. (2020) marked a paradigm shift with its demonstration of *in-context learning*, where a model infers a task from context without any finetuning. Thus, avoiding the need for extensive hand-annotated datasets and the need for any deep-learning expertise, it is particularly attractive for practical applications, resulting in a drastic shift away from BERT-like models.

Scaling of in-context learning performance (1-shot)

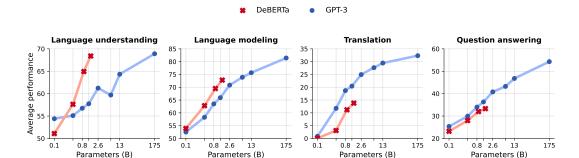


Figure 1: The average 1-shot performance across four groups of NLP tasks. We compare the scaling abilities of DeBERTa (four sizes in red) with GPT-3 (eight sizes in blue). Even though these models rely on different training objectives, they scale in a similar log-linear manner overall. Yet, on a task-by-task basis, the pretraining methods lead to substantial differences between them.



Figure 2: Illustration of the proposed methods for using a masked language model for text generation and text ranking, by reformatting the sequence of input tokens and without any additional training. The left figure shows how to modify the input tokens to autoregressively generate text. The right figure illustrates a similar approach that is used to retrieve a pseudo-log-likelihood score of a text sequence that can be used to rank multiple sequences by their joint probabilities.

Previous studies of 'emergent' in-context-learning abilities often focus only on causal language models (Saunshi et al., 2021; Olsson et al., 2022; Wei et al., 2022; Wang et al., 2023, *inter alia*). However, this paper demonstrates that in-context learning is a more general phenomenon and should not be studied with a singular pretraining objective in mind. Moreover, the assumed inability of masked language models to perform (generative) in-context learning has rendered them outdated – as explicitly noted by Tay et al. (2023): "BERT-style models are very restricted in their generative capabilities. Because of the cumbersomeness of task-specific classification heads, we strongly do not recommend using this class of autoencoding models moving forward and consider them somewhat deprecated."

In this paper, we challenge these prevailing assumptions about masked language models (MLMs). We present empirical evidence showing that DeBERTa, an MLM released just one month after GPT-3, is equally adept at in-context learning. Our findings suggest that the capacity for in-context learning is not tied to the training objective, but can be achieved across different types of language models. Interestingly, we show that DeBERTa does not simply mimic the performance of GPT-3 – it is clearly much better on tasks such as language understanding, and, on the other hand, much worse on tasks such as closed-book question answering. This suggests that masked and causal language modeling are two complementary training objectives and that there is a great potential for a training method that combines the strengths of both objectives. Finally, *scaling* (performance improvement with increased size of pretrained language models) is a crucial feature of modern language models, we demonstrate that MLMs do *scale* on in-context learning (Figure 1).

We introduce a simple inference technique that transforms an MLM into a generative model without any further training. Using publicly available DeBERTa checkpoints, we show that the MLM training objective not only provides a versatile way of encoding text, but is also competitive in text generation and text completion ranking. This claim is tested by following the same evaluation suite as GPT-3, speculating on an 'alternative reality' in which a masked language model is the first model reported to achieve the so-called 'emergent' in-context learning abilities.

First, Section 2 (Method) describes the inference methods used to evaluate the in-context learning abilities of an off-the-shelf masked language model. Then Section 3 (DeBERTa) describes the details of the particular model used in this study. Section 4 (Evaluation) details the evaluation setup and compares DeBERTa with GPT-3. Finally, Section 5 (Related work) talks about other relevant work within this topic, and the paper concludes with Section 6 (Conclusion).

2 Method: text generation and ranking with masked language models

The goal of this article is to reuse an existing pretrained masked language model for (generative) in-context learning. We achieve this without any additional training or finetuning, our method only slightly changes the sequence of input tokens, as illustrated in Figure 2. There are two methods used to solve tasks with in-context learning: **text generation** where the model completes a given prompt

(e.g. for translation) and **ranking** where the model chooses an answer from several options (e.g. for multiple choice questions).

2.1 Text generation

Masked language models are trained on semi-supervised fill-in-the-blanks tasks and so they cannot be used to generate straight out of the box. One possibility is to interpret these models as Markov random fields and produce text by Gibbs sampling (Wang and Cho, 2019). However, a simpler and more consistent way to produce text is to do the familiar left-to-right autoregressive generation – we could place a [MASK] token next to a text prompt and let the model generate next token by unmasking the appended token – then, when we repeat this process in a loop, we can generate text in the same way as causal language models (and apply the same advanced generation techniques).

This straightforward inference scheme would be enough if the pretraining process was designed with this use case in mind. However, since our goal is to repurpose an existing masked language model, we have to complicate the method with two modifications that are also illustrated in Figure 2:

- Masked language models are typically trained with a special end-of-sequence [SEP] token.
 This token is always present during pretraining and so we also have to include it as the last
 token during inference.
- 2. However, the addition of this end-of-sequence token creates a problem it raises the probability that the masked token should end the sequence (for example with a full stop). Thus, in order to obtain a less restricted continuation, we include additional [MASK] tokens to pad the space in front of the end-of-sequence token. Specifically, we use two additional masks for the DeBERTa models.¹

In the end, this approach gives a probability distribution over the next token prediction, thus we can use any existing method for searching or sampling an output sequence. We follow GPT-3 and use beam search with four candidate beams for all generative tasks.

Limitations While this method works with the same quadratic (in sequence length) time and memory complexity, it is slower in practice because it is not possible to cache the intermediate self-attention key and value vectors. Instead, the hidden representations of the whole sequence have to be recomputed in every step due to the bidirectional nature of the model. We believe that this limitation can be fixed, either by using prefix language modeling or by not updating hidden vectors of distant tokens every step. We leave these optimizations for future work.

2.2 Ranking

Many of the existing tasks for evaluating LLMs can be formulated as classification tasks where models have to select the correct answer from a number of different options. Brown et al. (2020) rank the candidate completions based on their estimated conditional log-likelihood, which can be computed exactly by the chain rule (where $w_0 \oplus w_1 \dots w_k$ is a completion of a prompt c):

$$\log \mathbb{P}(w_0 \oplus w_1 \dots w_k \mid c) = \sum_{i=0}^k \log \mathbb{P}(w_i \mid c \oplus w_0 \dots w_{i-1})$$
(1)

While this equation matches the training objective of causal language models, it is not suitable for masked language models because they are not trained to estimate $\mathbb{P}(w_i \mid c \oplus w_0 \dots w_{i-1})$. Instead, Wang and Cho (2019) proposed to modify Equation (1) to make it more appropriate for BERT-like models. Salazar et al. (2020) then empirically showed that the resulting pseudo-log-likelihood (PLL) score can be used to accurately rank text sequences by their likelihood. More specifically, the PLL score is approximately proportional to the conditional probability of a text sequence and is computed as follows:

$$\log \mathbb{P}(w_0 \oplus w_1 \dots w_k \mid c) \approx \sum_{i=0}^k \log \mathbb{P}(w_i \mid c \oplus w_0 \dots w_{i-1} \oplus [\texttt{MASK}] \oplus w_{i+1} \dots w_k) \tag{2}$$

¹Note that this is not an arbitrary number but it is model-specific – DeBERTa models were pretrained to unmask *spans* of masked tokens where the longest allowed spans are three tokens long (He et al., 2021).

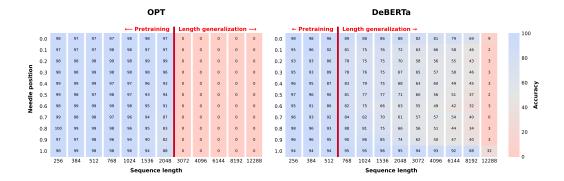


Figure 3: Length generalization measured with a 'needle in a haystack' benchmark. The x-axis indicates the total size of the 'haystack' and the y-axis indicates the position of the 'needle'; the values show the average exact-match accuracy for a particular configuration. Unfortunately, GPT-3 is a closed-source model and the original version is not accessible, so we use an open-source replication of GPT-3, OPT by Zhang et al. (2022), which should perform similarly on this task.

However, this approximation gets very inaccurate when there are strong local dependencies between tokens. As a counterexample, the estimated likelihood of the multi-token word 'supercalifragilistic-expialidocious' is seven orders of magnitude higher than that of the single-token word 'super', which is clearly an incorrect estimation of the relative frequencies of these words.²

We improve on this behavior by interpolating between the mathematically correct unidirectional derivation in Equation (1) and the bidirectional approximation in Equation (2). Our approach is to simply mask two additional tokens in the right context to reduce the effect of local dependencies while still taking into account the global bidirectional context. This process is illustrated in Figure 2. We conduct an ablation study of this approach in Appendix C.

Limitations Even though Equations (1) and (2) look similar, the later sum is substantially more compute intensive when calculated with a transformer architecture – for a token sequence of length k, the first equation can be computed with passing a single sequence through a language model, while the second equation needs k sequences to be processed. However, Salazar et al. (2020) showed that the PLL score can be accurately estimated in a single pass after a short self-supervised finetuning.

2.3 Length generalization

A potentially limiting factor of using BERT-like models is that they are typically pretrained on shorter sequences than causal language models – arguably because the training of modern causal models is already optimized for in-context learning, which requires processing of long few-shot prompts. DeBERTa is not an exception of such pretraining; it was only trained with a relatively short maximum sequence length of 512 tokens (He et al., 2021). Fortunately, the architecture of DeBERTa can easily process much longer sequences than seen during training due to its use of relative positional embeddings with logarithmic buckets (Raffel et al., 2020).

We measure the extent to which DeBERTa generalizes to longer sequences with the 'needle in a haystack' test from RULER (Hsieh et al., 2024). Specifically, in our formulation of this task, a random 6-digit number (needle) is hidden in a long collection of essays (haystack). We then measure the exact-match accuracy of retrieving the hidden number given two variables: the total sequence length and the position of the needle in the haystack (more details about the evaluation setup are given in Appendix A.1). The results in Figure 3 demonstrate that DeBERTa processes sequences within GPT-3's limit reasonably well and that it can generalize even beyond that length. In practice, this observation means that DeBERTa should be able to handle as many task demonstrations as GPT-3.

 $^{^2}$ This is because the tokenizer of DeBERTa splits the long word into 9 subwords and each of them is assigned an almost certain likelihood given the bidirectional context of surrounding subwords. The largest 1.4B DeBERTa estimates the pseudo log-likelihood of the first word to -2.1 while the second (very common) word has pseudo log-likelihood of -9.6.

The average 0-shot, 1-shot and few-shot performance

•

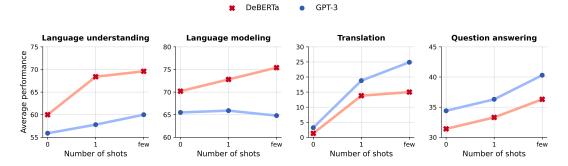


Figure 4: The performance improvement with increased number of in-context examples. We compare the in-context learning ability of 1.4B DeBERTa (in red) with 1.3B GPT-3 (in blue) using prompts without any completed examples (0-shot), prompts with a single randomly sampled gold sample (1-shot), and prompts with 'few' examples (4-64) examples, depending on the task). This figure demonstrates that a masked language model behaves similarly to a causal language model in the in-context learning regime.

DeBERTa family of language models

This study uses the largest openly available English masked language model, DeBERTa (1.4B), and its smaller configurations (He et al., 2021). DeBERTa is an improved version of a BERT language model (Devlin et al., 2019) that uses an advanced attention mechanism with relative positional embeddings – apart from being trained on a larger corpus with a larger number of training steps.

Training corpus Compared to GPT-3 and modern large language models, DeBERTa was pretrained on a relatively small and clean text corpus – totalling 78GB of data after deduplication, the corpus is comprised of the English Wikipedia (12GB), BookCorpus (6GB; Zhu et al., 2015), OpenWebText (38GB; Gokaslan and Cohen, 2019), and STORIES (31GB; Trinh and Le, 2019). This is almost an order of magnitude less data than what was used to pretrain GPT-3, which uses 570GB of filtered CommonCrawl, WebText2 (roughly 26GB), two web-scraped book corpora (roughly 17GB and 76GB), and the English Wikipedia (roughly 4GB, estimated from Brown et al. (2020)).

Total training compute Interestingly, even though DeBERTa uses a substantially smaller training corpus, it is trained on more than three times more tokens than GPT-3 (1 trillion compared to 300 billion). However, the loss is computed only on 15% of tokens (150 billion) and it is not clear what would be the effective number of tokens used for pretraining. Nevertheless, the total compute used for training depends on the number of input tokens and it is roughly 8.0 · 10²¹ FLOPs for the 1.4B DeBERTa and $2.4 \cdot 10^{21}$ FLOPs for the 1.3B GPT-3.

Causal version We convert the officially available DeBERTa checkpoint into a HuggingFace (Wolf et al., 2020) implementation of AutoModelForCausalLM (following Section 2.1), and release it openly at https://huggingface.co/ltg/deberta-xxlarge-fixed.

4 **Evaluation**

As our goal is to compare two language models released around the same time in 2020 – GPT-3 and DeBERTa – we replicate the evaluation setup used for GPT-3 (Brown et al., 2020) and apply it to the latter model. This also means that we follow GPT-3 and divide the tasks into generative ones (such as machine translation) and into classification tasks (such as BoolQ) – the first group uses the method described in Section 2.1 and the second type of task uses the ranking described in Section 2.2. Generation is performed with beam search (4 candidate beams), and ranking uses the modified PLL scores (and the normalized unconditional probability of completions $\frac{\mathbb{P}(\text{completion} \mid \text{context})}{\mathbb{P}(\text{completion} \mid \text{answer context})}$ for ARC and OpenBookQA, again replicating the choices for GPT-3). We also use the exact same

Table 1: **Natural language understanding results.** All results in this table are evaluated with accuracy (higher is better). The table shows the performance of the largest available DeBERTa (1.4 billion parameters) and of a similarly-sized GPT-3 model, the best results are boldfaced. The average score is calculated over averaged task scores (in case a task uses more than one metric).

	BoolQ	СВ	COPA	MultiRC	ReCoRD	RTE	WiC	WSC	Average
0-shot									
GPT-3	62.4	19.6	77.0	13.6	84.1	56.0	50.0	61.5	55.9
DeBERTa	80.8	66.1	78.9	6.6	87.1	64.3	55.2	71.2	60.0
1-shot									
GPT-3	63.7	48.2	74.0	13.6	83.0	49.5	49.2	62.5	57.8
DeBERTa	82.1	76.1	84.2	15.6	87.4	64.1	50.3	69.6	68.4
few-shot									
GPT-3	64.1	69.6	77.0	20.8	83.1	50.9	53.0	49.0	60.0
DeBERTa	82.1	75.0	90.4	16.9	87.4	62.2	50.8	75.0	69.6

prompt templates, with the exception of the machine translation task – its template did not produce any meaningful output, and so we decided to use the simple prompt template from Garcia et al. (2023) instead. More details on the evaluation setup can be found in Appendix A. Note that using prompts optimized for GPT-3 is slightly unfair to all other models, as prompting has a strong influence on performance (Gonen et al., 2023), but we believe that it makes the results more convincing than if we were to do extensive prompt engineering.

To show the strengths and weaknesses of DeBERTa in (generative) in-context learning, we evaluate it on four groups of tasks and compare it to the results from Brown et al. (2020). The four groups are language understanding (SuperGLUE), language modeling (text completion and Winograd-like tasks), machine translation, and question answering (closed-book question answering and commonsense reasoning). We detail each of these groups of tasks below.

Before looking into the details of each group, we show the overall aggregated scores for each group in Figure 1 and Figure 4. The first figure shows how the performance of both models scales with their size, while the latter figure compares the in-context learning abilities of the two language models. We also provide a qualitative evaluation of text generation in Appendix B and full results in Appendix D.

4.1 Language understanding (SuperGLUE)

We use SuperGLUE (Wang et al., 2019) as a popular collection of standard NLP tasks, allowing us to evaluate the performance on different aspects of natural language understanding.

In total, this benchmark consists of eight datasets, selected to be difficult for the contemporary (finetuned) language models. The Boolean Questions dataset is a yes/no reading comprehension dataset evaluated with accuracy (BoolQ; Clark et al., 2019); CommitmentBank is a three-class textual entailment dataset evaluated with accuracy and F_1 score, where the multi-class F_1 is computed as the unweighted average of the F_1 per class (CB; de Marneffe et al., 2019); the Choice of Plausible Alternatives dataset is a causal reasoning task evaluated with accuracy (COPA; Roemmele et al., 2011); Multi-Sentence Reading Comprehension is a multiple choice dataset, evaluated with exact-match (of all answers per question) accuracy and $F_{1\alpha}$ score computed over all flattened answers (MultiRC; Khashabi et al., 2018); Reading Comprehension with Commonsense Reasoning Dataset is another reading comprehension dataset, it is evaluated with the exact-match accuracy and token-level F_1 score (ReCoRD; Zhang et al., 2018); the collection of Recognizing Textual Entailment datasets is a textual entailment task evaluated with accuracy (RTE; Dagan et al., 2006; Bar-Haim et al., 2006; Giampiccolo et al., 2007); the Word-in-Context dataset is a word sense disambiguation dataset evaluated with accuracy (WiC; Pilehvar and Camacho-Collados, 2019); and finally, the Winograd Schema Challenge evaluates coreference resolution capabilities (WSC; Levesque et al., 2012).

Results We show the resulting scores of evaluation with the same prompts as GPT-3 in Table 1. DeBERTa clearly outperforms its contemporary and scales much more favorably than the family of GPT models (Figure 1). Interestingly, the average performance of the 1.4B DeBERTa gets close to

Table 2: **Results of text completion, language modeling and Winograd-style tasks.** All tasks are measured with accuracy, we show the performance of the largest available DeBERTa (1.4 billion parameters) and of a similarly-sized GPT-3 model, the best results are boldfaced.

	HellaSwag	StoryCloze	Winograd	Winogrande	Average
0-shot					
GPT-3	54.7	73.4	76.9	58.7	65.5
DeBERTa	62.0	83.6	74.0	61.0	70.2
1-shot					
GPT-3	53.5	74.2	76.9	59.1	65.9
DeBERTa	62.4	84.6	80.7	63.6	72.8
few-shot					
GPT-3	54.9	76.1	76.9	59.1	64.8
DeBERTa	62.5	84.8	85.6	68.8	75.4

the reported performance of the largest 175B GPT-3 (68.4 vs. 68.9, 1-shot). However, this average score is still far from the performance of a *finetuned* DeBERTa, which is more than 20 percentage points higher (He et al., 2021); the average few-shot performance of DeBERTa is slightly better than a finetuned BERT-large (Devlin et al., 2019; Wang et al., 2019).

4.2 Language modeling, Winograd-style and text completion tasks

The tasks in this category are defined in a familiar language-modeling form and focus on particularly difficult cases of language modeling, cases that involve commonsense reasoning, language understanding, and intricate coreference resolution.

In this group, we consider four NLP tasks: HellaSwag is a text completion task where a language model has to choose the most appropriate multi-word ending, the examples are adversarially filtered to be difficult for language models but easy for humans (Zellers et al., 2019). StoryCloze consists of five-sentence-long stories, the goal is to select the best final sentence based on commonsense knowledge (Mostafazadeh et al., 2016). Winograd is a language-modeling formulation of the WSC task from SuperGLUE (Levesque et al., 2012). WinoGrande is similar to Winograd in its form, but is adversarially mined to contain more difficult examples of coreference resolution (Sakaguchi et al., 2020). We do not include the LAMBADA benchmark (Paperno et al., 2016) here because Brown et al. (2020) used an unknown preprocessing step that disallows direct comparison with GPT-3.

Results We show the in-context-learning results from this group in Table 2, where we evaluate the 1.4B DeBERTa with a comparable GPT-3 model. The scores showcase consistently stronger performance of the masked language model, similarly to the language understanding tasks. One difference to those tasks is the rate of scaling, which appears to be similar between the two types of language models (Figure 1).

4.3 Translation

Translation is a useful benchmark for language models as it evaluates their ability to understand text in one language and produce fluent text in another language. Even though the performance on the translation tasks is arguably very dependent on the composition of training data (especially when we are concerned with monolingual English models), we include translation to demonstrate the generative performance of masked language models.

To directly compare DeBERTa with GPT-3, we use the same SacreBLEU metric (Post, 2018) and the same bitexts. Thus, even though there are more recent (and arguably more thought-out) datasets, we use the French-English pair from the outdated 2014 shared task at the Workshop on Statistical Machine Translation (WMT14; Bojar et al., 2014), and also the Romanian-English and German-English pairs from the WMT16 workshop (Bojar et al., 2016). Our approach differs only in using a different prompt template, as we had to opt for the prompt from Garcia et al. (2023) to get consistent translations: "{\$source language}: {\$source text}\n {\$target language}: {\$target text}".

Table 3: **Machine translation results.** We report SacreBLEU scores (Post, 2018) with signature BLEU+case.mixed+numrefs.1+smooth.exp+tok.intl+version.1.2.20 (higher is better). The table shows the performance of the largest available DeBERTa (1.4 billion parameters) and of a similarly-sized GPT-3 model, the best results are boldfaced.

	DE→EN	EN→DE	FR→EN	EN→FR	RO→EN	EN→RO	Average
0-shot							
GPT-3	3.6	2.4	3.6	2.8	3.6	3.1	3.2
DeBERTa	2.4	1.6	1.7	0.3	1.7	0.1	1.3
1-shot							
GPT-3	25.8	13.4	27.0	19.3	26.8	10.3	18.8
DeBERTa	23.7	5.4	23.5	9.7	17.7	2.5	13.8
few-shot							
GPT-3	30.5	17.7	32.2	26.1	30.1	12.9	24.9
DeBERTa	25.1	6.6	24.5	10.8	18.9	4.1	15.0

Table 4: **Closed-book question answering and commonsense reasoning.** The first three tasks are measured with the exact-match accuracy and the rest is measured with classification accuracy. The table shows the performance of the largest available DeBERTa (1.4 billion parameters) and of a similarly-sized GPT-3 model, the best results are boldfaced.

	NQs	TriviaQA	WebQs	PIQA	ARC-C	ARC-E	Open- BookQA	Average
0-shot								
GPT-3	4.4	19.7	4.6	75.1	35.5	53.8	46.8	34.4
DeBERTa	0.8	6.9	1.5	72.9	36.5	55.1	45.8	31.4
1-shot								
GPT-3	5.4	26.5	9.2	74.4	36.4	55.9	46.4	36.3
DeBERTa	2.6	14.3	5.1	73.0	37.1	55.1	45.7	33.3
few-shot								
GPT-3	9.7	32.1	19.6	74.3	36.7	59.1	50.6	40.3
DeBERTa	4.4	17.9	9.9	74.5	39.6	57.7	50.4	36.3

Results The SacreBLEU scores on each language pair are given in Table 3. Unlike in the previous two task groups, the tables have turned and the causal language model clearly outperforms the masked model in all comparisons. We believe that the subpar performance of DeBERTa can be (at least) in part explained by its relatively small and clean monolingual training corpus (Section 3), because the performance on this task is highly dependent on the presence of multilingual data in the corpus (Lin et al., 2022). The rate of improved translation performance with larger scale appears to be similar between the two models (Figure 1).

4.4 Closed-book question answering and commonsense reasoning

An important quality of modern-day large language models is their ability to learn and retrieve world knowledge, and to have a degree of common sense. The final group of tasks attempts to evaluate these two qualities.

This category of tasks consists of seven datasets in total: Natural Questions (NQs; Kwiatkowski et al., 2019) and Web Questions (WebQs; Berant et al., 2013) are closed-book question-answering datasets sourced from natural web queries; while the original datasets are accompanied by relevant articles that contain the answer, we only ask models a question and then evaluate the exact-match accuracy of their answers. TriviaQA is a very similar dataset, but based on online quizzes (Joshi et al., 2017). The next four tasks fall more into a subcategory of commonsense reasoning datasets. The Physical Interaction: Question Answering dataset evaluates how well a language model is grounded in the real physical world (PIQA; Bisk et al., 2020). The AI2 Reasoning Challenge is a dataset sourced from grade-school science questions that evaluates knowledge and reasoning abilities; this task is divided

into ARC-Easy and ARC-Challenge splits, based on their difficulty (Clark et al., 2018). Finally, OpenBookQA evaluates the understanding of common knowledge (Mihaylov et al., 2018).

Results The question-answering performance is given in Table 4. Apparently, the results of DeBERTa are substantially worse on closed-book question answering, compared to GPT-3. We believe that this highlights a more general disadvantage of the MLM training objective – the model can often retrieve world knowledge from the rich bidirectional context during training, not needing to store it in its learned weights; similar effect has been shown in retrieval-augmented language models (Samuel et al., 2024). However, the commonsense reasoning abilities are comparable between the two models. The scaling behavior is again similar between the two models (Figure 1). The same is also true about the improvement when given more in-context examples (Figure 4), which are especially important for the tasks evaluated with exact-match accuracy, where the goal is not only to answer correctly but also to match the expected style and form of the gold answers.

5 Related work

Few-shot finetuning with masked language models Our study is not the first to propose few-shot learning for pretrained BERT-like models, but to our best knowledge, we are the first to demonstrate in-context learning abilities of these models. The major difference is that previous studies rely on few-shot *finetuning*, adapting the model to a downstream task by updating its weights. Studies by Schick and Schütze (2021), Gao et al. (2021), or Xia et al. (2022) demonstrated that few-shot finetuning is a promising method. Unfortunately, these methods can be cumbersome to implement in practice and the simplicity of in-context learning is often preferred even though its performance is generally found to be worse (Liu et al., 2022).

Scaling up masked language models We selected DeBERTa as the largest publicly available masked language model that can handle large context size. However, we should note that there are even larger BERT-like models: Megatron BERT with 3.9 billion parameters by Shoeybi et al. (2019, it is unfortunately unavailable and without a mechanism for length generalization), and XLM-RoBERTa with 10.7 billion parameters by Goyal et al. (2021, it is unfortunately multilingual and also limited to sequences of 512 tokens).

Hybrid masked-causal models We believe that an important take-away from our study is that there is an opportunity for merging the observed strengths of masked language models with the strengths of causal language models. There have already been several attempts to create such a hybrid model: T5 (Raffel et al., 2020) and GLM (Du et al., 2022) proposed autoregressive fill-in-the-blank training objectives, CM3 is based on a causal-mask objective (Aghajanyan et al., 2022), and PrefixLM uses a partially bidirectional causal language model (Raffel et al., 2020). In particular, Ding et al. (2024) convincingly argues that prefix language models are better suited for in-context learning than causal language models.

6 Conclusion

In this paper, we empirically demonstrated that masked language models can be capable in-context learners. These models, often assumed to be deprecated and only useful for finetuning, are shown to be competitive with causal language models on in-context learning: with similar absolute performance, similar scaling behavior, and with similar improvement when given more few-shot demonstrations.

Although the DeBERTa language model was not designed to be used for (generative) in-context learning, we proposed inference methods that enable it to be used in this setting without any additional training (or any other change of its learned weights). We argue that in a future work, its results could be easily improved by pretraining on a larger and more diverse text corpus, by scaling up the parameter count and by pretraining with a longer context length. Moreover, there is even more potential in merging the strength of causal language modeling with masked language modeling, instead of relying only on one of these training objectives.

Acknowledgments and Disclosure of Funding

I would like to thank Lilja Øvrelid, Andrey Kutuzov, and Erik Velldal for providing valuable feedback, and for their never-ending encouragement and support.

This work is fully funded by the University of Oslo. The computations were performed on resources provided through Sigma2 – the national research infrastructure provider for high-performance computing and large-scale data storage in Norway. We acknowledge Norway and Sigma2 for awarding this project access to the LUMI supercomputer, owned by the EuroHPC Joint Undertaking, hosted by CSC (Finland) and the LUMI consortium through project 5000144.

References

- Armen Aghajanyan, Bernie Huang, Candace Ross, Vladimir Karpukhin, Hu Xu, Naman Goyal, Dmytro Okhonko, Mandar Joshi, Gargi Ghosh, Mike Lewis, and Luke Zettlemoyer. 2022. **CM3: A causal masked multimodal model of the internet**. *Preprint*, arXiv:2201.07520.
- Roy Bar-Haim, Ido Dagan, Bill Dolan, Lisa Ferro, and Danilo Giampiccolo. 2006. **The second PASCAL** recognising textual entailment challenge. Proceedings of the Second PASCAL Challenges Workshop on Recognising Textual Entailment.
- Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. 2013. Semantic parsing on Freebase from question-answer pairs. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1533–1544, Seattle, Washington, USA. Association for Computational Linguistics.
- Yonatan Bisk, Rowan Zellers, Ronan Le bras, Jianfeng Gao, and Yejin Choi. 2020. **PIQA: Reasoning about physical commonsense in natural language**. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(05):7432–7439.
- Ondřej Bojar, Christian Buck, Christian Federmann, Barry Haddow, Philipp Koehn, Johannes Leveling, Christof Monz, Pavel Pecina, Matt Post, Herve Saint-Amand, Radu Soricut, Lucia Specia, and Aleš Tamchyna. 2014.
 Findings of the 2014 workshop on statistical machine translation. In Proceedings of the Ninth Workshop on Statistical Machine Translation, pages 12–58, Baltimore, Maryland, USA. Association for Computational Linguistics.
- Ondřej Bojar, Rajen Chatterjee, Christian Federmann, Yvette Graham, Barry Haddow, Matthias Huck, Antonio Jimeno Yepes, Philipp Koehn, Varvara Logacheva, Christof Monz, Matteo Negri, Aurélie Névéol, Mariana Neves, Martin Popel, Matt Post, Raphael Rubino, Carolina Scarton, Lucia Specia, Marco Turchi, Karin Verspoor, and Marcos Zampieri. 2016. Findings of the 2016 conference on machine translation. In Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers, pages 131–198, Berlin, Germany. Association for Computational Linguistics.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. **Language models are few-shot learners**. In *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc.
- Susan Carey and Elsa Bartlett. 1978. Acquiring a single new word. Proceedings of the Stanford Child Language Conference, 15:17–29.
- Christopher Clark, Kenton Lee, Ming-Wei Chang, Tom Kwiatkowski, Michael Collins, and Kristina Toutanova. 2019. **BoolQ: Exploring the surprising difficulty of natural yes/no questions**. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 2924–2936, Minneapolis, Minnesota. Association for Computational Linguistics.
- Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. 2018. **Think you have solved question answering? Try ARC, the AI2 reasoning challenge.** *Preprint*, arXiv:1803.05457.
- Ido Dagan, Oren Glickman, and Bernardo Magnini. 2006. **The PASCAL recognising textual entailment challenge**. In *Machine Learning Challenges. Evaluating Predictive Uncertainty, Visual Object Classification, and Recognising Tectual Entailment*, pages 177–190, Berlin, Heidelberg. Springer Berlin Heidelberg.

- Marie-Catherine de Marneffe, Mandy Simons, and Judith Tonhauser. 2019. **The CommitmentBank: Investigating projection in naturally occurring discourse**. *Proceedings of Sim und Bedeutung*, 23(2):107–124.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.
- Nan Ding, Tomer Levinboim, Jialin Wu, Sebastian Goodman, and Radu Soricut. 2024. **CausalLM is not optimal for in-context learning**. In *The Twelfth International Conference on Learning Representations*.
- Zhengxiao Du, Yujie Qian, Xiao Liu, Ming Ding, Jiezhong Qiu, Zhilin Yang, and Jie Tang. 2022. **GLM:** General language model pretraining with autoregressive blank infilling. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 320–335, Dublin, Ireland. Association for Computational Linguistics.
- Tianyu Gao, Adam Fisch, and Danqi Chen. 2021. Making pre-trained language models better few-shot learners. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 3816–3830, Online. Association for Computational Linguistics.
- Xavier Garcia, Yamini Bansal, Colin Cherry, George Foster, Maxim Krikun, Melvin Johnson, and Orhan Firat. 2023. The unreasonable effectiveness of few-shot learning for machine translation. In Proceedings of the 40th International Conference on Machine Learning, volume 202 of Proceedings of Machine Learning Research, pages 10867–10878. PMLR.
- Danilo Giampiccolo, Bernardo Magnini, Ido Dagan, and Bill Dolan. 2007. **The third PASCAL recognizing textual entailment challenge**. In *Proceedings of the ACL-PASCAL Workshop on Textual Entailment and Paraphrasing*, pages 1–9, Prague. Association for Computational Linguistics.
- Aaron Gokaslan and Vanya Cohen. 2019. OpenWebText corpus.
- Hila Gonen, Srini Iyer, Terra Blevins, Noah Smith, and Luke Zettlemoyer. 2023. **Demystifying prompts in language models via perplexity estimation**. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 10136–10148, Singapore. Association for Computational Linguistics.
- Naman Goyal, Jingfei Du, Myle Ott, Giri Anantharaman, and Alexis Conneau. 2021. Larger-scale transformers for multilingual masked language modeling. *CoRR*, abs/2105.00572.
- Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen. 2021. **DeBERTa: Decoding-enhanced BERT with disentangled attention**. In *International Conference on Learning Representations*.
- Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. 2020. The curious case of neural text degeneration. In *International Conference on Learning Representations*.
- Cheng-Ping Hsieh, Simeng Sun, Samuel Kriman, Shantanu Acharya, Dima Rekesh, Fei Jia, Yang Zhang, and Boris Ginsburg. 2024. **RULER: What's the real context size of your long-context language models?** arXiv preprint arXiv:2404.06654.
- Mandar Joshi, Eunsol Choi, Daniel Weld, and Luke Zettlemoyer. 2017. **TriviaQA: A large scale distantly supervised challenge dataset for reading comprehension**. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1601–1611, Vancouver, Canada. Association for Computational Linguistics.
- Daniel Khashabi, Snigdha Chaturvedi, Michael Roth, Shyam Upadhyay, and Dan Roth. 2018. Looking beyond the surface: A challenge set for reading comprehension over multiple sentences. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 252–262, New Orleans, Louisiana. Association for Computational Linguistics.
- Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. **Natural questions: A benchmark for question answering research**. *Transactions of the Association for Computational Linguistics*, 7:452–466.

- Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2020. ALBERT: A lite BERT for self-supervised learning of language representations. In *International Conference on Learning Representations*.
- Hector J. Levesque, Ernest Davis, and Leora Morgenstern. 2012. The Winograd schema challenge. In Proceedings of the Thirteenth International Conference on Principles of Knowledge Representation and Reasoning, KR'12, page 552–561. AAAI Press.
- Xi Victoria Lin, Todor Mihaylov, Mikel Artetxe, Tianlu Wang, Shuohui Chen, Daniel Simig, Myle Ott, Naman Goyal, Shruti Bhosale, Jingfei Du, Ramakanth Pasunuru, Sam Shleifer, Punit Singh Koura, Vishrav Chaudhary, Brian O'Horo, Jeff Wang, Luke Zettlemoyer, Zornitsa Kozareva, Mona Diab, Veselin Stoyanov, and Xian Li. 2022. Few-shot learning with multilingual generative language models. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 9019–9052, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Haokun Liu, Derek Tam, Muqeeth Mohammed, Jay Mohta, Tenghao Huang, Mohit Bansal, and Colin Raffel. 2022. Few-shot parameter-efficient fine-tuning is better and cheaper than in-context learning. In Advances in Neural Information Processing Systems.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. **RoBERTa: A robustly optimized BERT pretraining approach**. *Preprint*, arXiv:1907.11692.
- Todor Mihaylov, Peter Clark, Tushar Khot, and Ashish Sabharwal. 2018. **Can a suit of armor conduct electricity? a new dataset for open book question answering**. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2381–2391, Brussels, Belgium. Association for Computational Linguistics.
- Nasrin Mostafazadeh, Nathanael Chambers, Xiaodong He, Devi Parikh, Dhruv Batra, Lucy Vanderwende, Pushmeet Kohli, and James Allen. 2016. A corpus and cloze evaluation for deeper understanding of commonsense stories. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 839–849, San Diego, California. Association for Computational Linguistics.
- Catherine Olsson, Nelson Elhage, Neel Nanda, Nicholas Joseph, Nova DasSarma, Tom Henighan, Ben Mann, Amanda Askell, Yuntao Bai, Anna Chen, Tom Conerly, Dawn Drain, Deep Ganguli, Zac Hatfield-Dodds, Danny Hernandez, Scott Johnston, Andy Jones, Jackson Kernion, Liane Lovitt, Kamal Ndousse, Dario Amodei, Tom Brown, Jack Clark, Jared Kaplan, Sam McCandlish, and Chris Olah. 2022. In-context learning and induction heads. Preprint, arXiv:2209.11895.
- Denis Paperno, Germán Kruszewski, Angeliki Lazaridou, Ngoc Quan Pham, Raffaella Bernardi, Sandro Pezzelle, Marco Baroni, Gemma Boleda, and Raquel Fernández. 2016. **The LAMBADA dataset: Word prediction requiring a broad discourse context**. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1525–1534, Berlin, Germany. Association for Computational Linguistics.
- Mohammad Taher Pilehvar and Jose Camacho-Collados. 2019. WiC: the word-in-context dataset for evaluating context-sensitive meaning representations. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 1267–1273, Minneapolis, Minnesota. Association for Computational Linguistics.
- Matt Post. 2018. A call for clarity in reporting BLEU scores. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pages 186–191, Brussels, Belgium. Association for Computational Linguistics.
- Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. **Improving language understanding by generative pre-training**.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *J. Mach. Learn. Res.*, 21(1).
- Melissa Roemmele, Cosmin Bejan, and Andrew Gordon. 2011. Choice of plausible alternatives: An evaluation of commonsense causal reasoning. AAAI Spring Symposium Technical Report.
- Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. 2020. WinoGrande: An adversarial Winograd Schema Challenge at scale. Proceedings of the AAAI Conference on Artificial Intelligence, 34(05):8732–8740.

- Julian Salazar, Davis Liang, Toan Q. Nguyen, and Katrin Kirchhoff. 2020. Masked language model scoring. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 2699–2712, Online. Association for Computational Linguistics.
- David Samuel, Lucas Georges Gabriel Charpentier, and Sondre Wold. 2024. More room for language: Investigating the effect of retrieval on language models. *Preprint*, arXiv:2404.10939.
- Nikunj Saunshi, Sadhika Malladi, and Sanjeev Arora. 2021. A mathematical exploration of why language models help solve downstream tasks. In *International Conference on Learning Representations*.
- Timo Schick and Hinrich Schütze. 2021. **It's not just size that matters: Small language models are also few-shot learners**. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2339–2352, Online. Association for Computational Linguistics.
- Mohammad Shoeybi, Mostofa Patwary, Raul Puri, Patrick LeGresley, Jared Casper, and Bryan Catanzaro. 2019.
 Megatron-LM: Training multi-billion parameter language models using model parallelism. CoRR, abs/1909.08053.
- Yi Tay, Mostafa Dehghani, Vinh Q. Tran, Xavier Garcia, Jason Wei, Xuezhi Wang, Hyung Won Chung, Dara Bahri, Tal Schuster, Steven Zheng, Denny Zhou, Neil Houlsby, and Donald Metzler. 2023. **UL2: Unifying language learning paradigms**. In *The Eleventh International Conference on Learning Representations*.
- Trieu H. Trinh and Quoc V. Le. 2019. A simple method for commonsense reasoning. Preprint, arXiv:1806.02847.
- Alex Wang and Kyunghyun Cho. 2019. **BERT has a mouth, and it must speak: BERT as a Markov random field language model**. In *Proceedings of the Workshop on Methods for Optimizing and Evaluating Neural Language Generation*, pages 30–36, Minneapolis, Minnesota. Association for Computational Linguistics.
- Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2019. **SuperGLUE: A stickier benchmark for general-purpose language understanding systems**. In *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc.
- Xinyi Wang, Wanrong Zhu, Michael Saxon, Mark Steyvers, and William Yang Wang. 2023. Large language models are latent variable models: Explaining and finding good demonstrations for in-context learning. In Thirty-seventh Conference on Neural Information Processing Systems.
- Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, Ed H. Chi, Tatsunori Hashimoto, Oriol Vinyals, Percy Liang, Jeff Dean, and William Fedus. 2022. Emergent abilities of large language models. Transactions on Machine Learning Research. Survey Certification.
- Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. **Transformers: State-of-the-art natural language processing**. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.
- Mengzhou Xia, Mikel Artetxe, Jingfei Du, Danqi Chen, and Veselin Stoyanov. 2022. **Prompting ELECTRA:** Few-shot learning with discriminative pre-trained models. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 11351–11361, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. **HellaSwag: Can a machine really finish your sentence?** In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4791–4800, Florence, Italy. Association for Computational Linguistics.
- Sheng Zhang, Xiaodong Liu, Jingjing Liu, Jianfeng Gao, Kevin Duh, and Benjamin Van Durme. 2018. **ReCoRD: Bridging the gap between human and machine commonsense reading comprehension**. *arXiv preprint*.
- Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, Todor Mihaylov, Myle Ott, Sam Shleifer, Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, and Luke Zettlemoyer. 2022. **OPT: Open pre-trained transformer language models**. *Preprint*, arXiv:2205.01068.
- Yukun Zhu, Ryan Kiros, Rich Zemel, Ruslan Salakhutdinov, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. 2015. Aligning books and movies: Towards story-like visual explanations by watching movies and reading books. In 2015 IEEE International Conference on Computer Vision (ICCV), pages 19–27.

A Evaluation details

This appendix provides more details about our evaluation setup to make it easier to reproduce our results; the source code is available at https://github.com/ltgoslo/bert-in-context. In general, we follow Brown et al. (2020) in all decisions about the implementation.

Newline separator Note we use newlines in the displayed prompts for better readability, but we do not actually use them as the DeBERTa tokenizers cannot encode a newline character (they convert it to the standard whitespace character instead). Instead, we convert all newline characters to double-escaped '\\n ' string with a whitespace character, which then acts as paragraph/information separator.

Few-shot prompting. For each evaluated sample, the example demonstrations are randomly selected (without replacement) from the training set of each task; if the training set is not available, we sample from the only available dataset split, making sure not to select the same sample as the evaluated one. We format these examples using the respective prompt templates and concatenate them together, joined by two newline characters. The numbers of shots used for each task are given in Appendix D.

A.1 Needle in a havstack

The needle is a randomly generated 6-digit number (from $100\,000$ to $999\,999$). The prediction is produced via constrained generation that only allows sequences of tokens that form 6-digit numbers. We consider a prediction to be correct only if it exactly matches the needle, which means that a trivial baseline has the accuracy of $1/900\,000$.

The evaluated models are prompted with the template shown below. Similarly to Hsieh et al. (2024), we use Paul Graham's essays to fill the context (**\$prefix_lines** and **\$suffix_lines**). The essays are sentence-segmented and concatenated to fill the desired total sequence length.

```
> Some special magic number is hidden within the following articles. Make sure to

→ memorize it. I will quiz you about the magic number afterwards.

{
sprefix_lines}

The magic number is {$needle}.

{
suffix_lines}

> Question: What is the special magic number mentioned in the provided text?

> Answer: The special magic number mentioned in the provided text is
```

A.2 Language understanding

This section provides the prompts used for the eight SuperGLUE tasks, all prompt templates are taken from the GPT-3 evaluation setup.

BoolQ This task is evaluated by ranking texts formatted as shown below with two possible **\$answers**, **yes** or **no**.

```
1 {$passage}
2 question: {$question}?
3 answer: {$answer:-yes/no}
```

³Available online at https://www.paulgraham.com/articles.html

CB Evaluated by ranking texts formatted as shown below with three possible **\$answers**, **true**, **false** or **neither**.

```
1 {$premise}
2 question: {$hypothesis}; true, false, or neither?
3 answer: {$answer:-true/false/neither}
```

COPA We rank two possible substitutions of **\$answer** that follow the premise. **\$connector** is formatted based on the question type: 'because' if the type is 'cause', otherwise 'therefore' is used.

```
1 {$premise} {$connector:-because/therefore} {$answer}
```

MultiRC The potential answer is substituted for **\$option** and then we rank two possible substitutions for **\$answer**: [True] or [False].

```
1 READING COMPREHENSION ANSWER KEY
2
3 {$paragraph}
4
5 {$question}
6 - {$answer:-[True]/[False]} {$option}
```

ReCoRD Here we rank the possible entity names as substitutions for **\$answer**. Note that **\$paragraph** often includes summaries that, in a way, act as few-shot examples (see the formatted zero-shot example in Appendix C).

```
1 {$passage}
2 - {$answer_prefix}{$answer_suffix}
```

RTE Ranking of two possible completions in this binary classification task: True or False.

```
1 {$premise}
2 question: {$hypothesis} True or False?
3 answer: {$answer:-True/False}
```

WiC Another binary task with two possible substitutions: **yes** or **no**. Note that this prompt template was not working for any GPT-3 models and it is also not working for the models evaluated in this paper, all models are just randomly guessing the answers (Table 1).

```
{$sentence1}
{$sentence2}
question: Is the word '{$word}' used in the same way in the two sentences above?
answer: {$answer:-yes/no}
```

WSC We rank possible substitutions for **\$answer**.

A.3 Language modeling

This group of tasks uses very straightforward prompt templates as all of these tasks are different variants of text completion.

HellaSwag Here, the task is to select the most likely completion (**\$answer**) that follows after **\$context**.

```
1 {$activity_label}: {$context}{$answer}
```

StoryCloze The goal is to select the most suitable **\$answer** that completes a story laid out by four previous sentences.

```
1 {$sentence_1} {$sentence_2} {$sentence_3} {$sentence_4} {$answer}
```

Winograd \$answer should be substituted by the correct entity (coreference resolution).

```
1 {$context_prefix} {$answer} {$context_suffix}
```

Winogrande Same as Winograd:

```
1 {$context_prefix} {$answer} {$context_suffix}
```

A.4 Translation

All language pairs and all evaluation setups (zero-shot, one-shot and few-shot) use the same prompt template given below. This is the only time when we decided to differ from the GPT-3 setup as its very simple (and non-informative) prompt was not working for one-shot evaluation of DeBERTa models. The models are then asked to complete the prompt – using beam search decoding with 4 beams and the default HuggingFace hyperparameters⁴ – and the generation is stopped after producing the special newline character \\n.

```
1 {$source_language}: {$source_text}
2 {$target_language}:
```

⁴https://huggingface.co/docs/transformers/v4.41.3/en/main_classes/text_generation#transformers.GenerationMixin.generate

For reference, here are the two prompt templates used for GPT-3 (for zero-shot and for one/few-shot, respectively):

```
1  Q: What is the {$target_language} translation of {$source_text}
2  A:

1  {$source_text} =
2
```

A.5 Closed-book question answering

This group of tasks mixes two types of in-context evaluation: text generation (Natural Questions, TriviaQA and Web Questions) and text ranking (PIQA, ARC and OpenBookQA). The prompt setup exactly follows GPT-3.

Natural Questions Here, the goal is to generate an answer based on **\$question**.

```
1  Q: {$question}
2  A:
```

TriviaQA Same as Natural Questions:

```
1  Q: {$question}
2  A:
```

Web Questions Same as Natural Questions:

```
1 Q: {$question}
2 A:
```

PIQA Here, the goal is to select the most suitable text completion by substituting for \$answer.

```
1 {$goal} {$answer}
```

ARC (challenge) and ARC (easy) This a multiple choice test, the correct \$answer has to be selected.

```
Question: {$question}
Answer: {$answer}
```

OpenBookQA Similarly, the goal is to select the correct **\$answer**.

```
1 {$question} {$answer}
```

B Examples of text generation

To also give a sense of the quality of the text produced by DeBERTa, we include some examples of text generation in this section. We use the exact same example prompts that were used in the GPT-3 paper (Brown et al., 2020), to provide a fair estimate of the generative qualities. All text completions were generated with nucleus sampling (Holtzman et al., 2020).⁵ We compare the largest DeBERTa 1.4B with OPT 1.3B, an openly available replication of the GPT-3 1.3B (Zhang et al., 2022).

B.1 Learning and using novel words

Based on studies in developmental linguistics (Carey and Bartlett, 1978), this task tests the ability to understand and productively use new words; specifically using a word in a sentence after seeing it defined only once. We qualitatively test this ability in a generative one-shot setting, using the prompts provided below – there, the human-provided prompts are rendered as normal text while the generated completions are rendered in boldface. The prompts are taken from Brown et al. (2020, Section 3.9.5).

Results Overall, DeBERTa provides more appropriate example sentences than OPT. While the 'farduddle' and 'screeg' sentences from DeBERTa are not very descriptive, the rest of sentences are informative and fitting the word definitions. Note how the model tried to invent a plural inflection of 'yalubalu', the suffix '-a' is morphologically plausible, but the stem is fumbled, possibly because of subword tokenization. The examples generated by OPT are of lesser quality; it either repeats the definition (in 'farduddle'), repeats the one-shot example (in 'yalubalu') or provides an unfitting example (in 'screeg').

```
A "whatpu" is a small, furry animal native to Tanzania. An example of a sentence

→ that uses the word whatpu is:

We were traveling in Africa and we saw these very cute whatpus.
```

4 To do a "farduddle" means to jump up and down really fast. An example of a sentence \hookrightarrow that uses the word farduddle is:

DeBERTa:

5 I did a farduddle.

OPT:

I farduddle jumped up and down really fast.

A "yalubalu" is a type of vegetable that looks like a big pumpkin. An example of a \hookrightarrow sentence that uses the word yalubalu is:

DeBERTa:

5 We were in the market and we saw these very big yambolula.

OPT:

5 We were traveling in Africa and we saw these yalubalu.

4 A "Burringo" is a car with very fast acceleration. An example of a sentence that \hookrightarrow uses the word Burringo is:

DeBERTa:

5 We were driving a very fast Burringo.

OPT:

5 We saw Burringos all over Africa on this trip.

4 A "Gigamuru" is a type of Japanese musical instrument. An example of a sentence that \hookrightarrow uses the word Gigamuru is:

DeBERTa:

A Japanese musician, who plays the Gigamuru, is very famous.

OPT:

I was walking down the street and I saw this very cute gigamuru.

⁵Using these hyperparameters: top_k=64, top_p=0.9, temperature=0.2.

```
To "screeg" something is to swing a sword at it. An example of a sentence that uses
\hookrightarrow the word screeg is:
A sword-screeg.
```

B.2 Correcting English grammar

I was screeging at the computer.

DeBERTa:

DeBERTa:

OPT:

OPT:

English grammar correction is another task used for qualitative evaluation of GPT-3. Provided three demonstrations, the model is given an incorrect English sentence and is tasked to correct it. The prompts are taken from Brown et al. (2020, Section 3.9.6) and are shown below.

Results While the corrections are not perfect, DeBERTa outputs more sensible completions compared to OPT, similarly to the previous task. A notable correction is in the second example, where DeBERTa tried to improve the understandability, not only grammar.

```
Poor English input: I eated the purple berries.
    Good English output: I ate the purple berries.
2
    Poor English input: Thank you for picking me as your designer. I'd appreciate it.
    Good English output: Thank you for choosing me as your designer. I appreciate it.
    Poor English input: The mentioned changes have done.
    Good English output: The requested changes have been made.
    Poor English input: I'd be more than happy to work with you in another project.
    Good English output: I'd be more than happy to work with you in another project.
```

DeBERTa:

OPT: Good English output: I'd be more than happy to work with you in another project.

```
Poor English input: Please provide me with a short brief of the design you're
→ looking for and that'd be nice if you could share some examples or project you
   did before.
```

DeBERTa: Good English output: Please provide me with a brief of the design you are looking for and some examples of your previous work.

OPT: Good English output: I'll provide you with a brief of the design you're looking for $\,\hookrightarrow\,$ and that'd be nice if you could share some examples or project you did before.

```
Poor English input: The patient was died.
Good English output: The patient has died.
Good English output: The patient was revived.
Poor English input: We think that Leslie likes ourselves.
```

DeBERTa: Good English output: We think that we like ourselves. OPT: Good English output: We think that Leslie likes herself.

Poor English input: Janet broke Bill on the finger. DeBERTa: Good English output: Janet broke Bill's finger.

OPT: Good English output: Janet broke Bill on the finger.

```
Poor English input: Mary arranged for, in St. Louis, John to rent a house cheap.

Beberta:

Good English output: Mary arranged for, in St. Louis, John to rent a house.

OPT:

Good English output: John rented a house cheap.
```

C Ablation study of ranking implementation

We mentioned some drawbacks of calculating the pseudo-log-likelihood score (PLL) as per Salazar et al. (2020), and how we mitigate these problems, in Section 2.2. This section supports our decision with a quantitative analysis of different ranking approaches. We test them on the ReCoRD task from SuperGLUE (Zhang et al., 2018; Wang et al., 2019), where the goal is to rank different named entities based on their appropriatness. Since the problem of the original PLL is in estimating likelihoods of long multi-loken expressions, we choose this task to highlight the differences. An example of a prompt-formatted sample from ReCoRD is given below, the possible completions (all of which are named entities) are boldfaced:

Suspended hundreds of feet in the air amid glistening pillars of ice illuminated \hookrightarrow with qhostly lights from below, this could easily be a computer-generated scene \hookrightarrow from the latest sci-fi blockbuster movie. But in fact these ethereal photographs \hookrightarrow were taken in real life, and show extreme sportsman and climber **Stephan** Siegrist, 43, ascending the Voringsfossen icefall which is part of a gigantic glacier in **Eidfjord**, **Norway**. The stunning images were captured by fellow mountaineer and photographer Thomas Sanf. While the 500ft frozen waterfall is \hookrightarrow regularly scaled by climbers during daylight, he said he wanted to capture the beauty of the falls by night. - Stunning images captured by photographer Thomas Sanf as climber Stephan Siegrist, → 43, scaled frozen waterfall - The Voringsfossen fall is liquid for most of the year, but in winter freezes into → a 500ft cliff favoured by climbers - Hundreds of adventurers attempt the climb by day, but very few attempt the ascent \hookrightarrow at night, as pictured here - With bright lights illuminating his efforts from below, Mr {\$answer:-Stephan Siegrist/Voringsfossen/Eidfjord/Norway/Thomas Sanf} appears to be on the set of → a sci-fi movie

Results In Table 5, we compare the original implementation of PLL by Salazar et al. (2020) that only masks the target subword; our approach that also masks next two subwords; other two alternatives that mask two or four subwords in total; and the exact unidirectional computation of log-likelihood (using the same input formatting as for generation). The additional masks clearly help to make better estimates while the exact computation seems to not be appropriate for inherently bidirectional models.

Table 5: **Ablation study of different ranking methods applied to DeBERTa.** Evaluated using zero-shot setting and the largest DeBERTa 1.4B model on ReCoRD.

Ranking method	ReCoRD (EM)	ReCoRD (F ₁)
Pseudo log-likelihood; 1 mask (Salazar et al., 2020)	80.9	81.6
Pseudo log-likelihood; 2 masks	86.0	86.8
Pseudo log-likelihood; 3 masks (our method)	87.1	87.9
Pseudo log-likelihood; 4 masks	86.9	87.8
Exact log-likelihood	77.2	77.8

D All results

For reference, we list all results of the DeBERTa models evaluated throughout this paper in Table 6. The GPT-3 results that were used for comparison are published in Brown et al. (2020).

Table 6: **Results for all evaluations performed in this paper.** The second and third column shots the dataset splits and evaluation metrics, both of them replicating the GPT-3 evaluation setup. Note the BLEU scores used for evaluating translation are SacreBLEU scores with signature BLEU+case.mixed+numrefs.1+smooth.exp+tok.intl+version.1.2.20.

Task	Split	Metric	n shots	0-shot (1.4B)	1-shot (0.1B)	1-shot (0.4B)	1-shot (0.9B)	1-shot (1.4B)	n-shot (1.4B)
BoolQ	dev	acc.	4	80.8	55.7	60.5	78.4	82.1	82.1
CB	dev	acc.	4	66.1	39.6	57.5	68.6	76.1	75.0
CB	dev	F_1	4	46.1	23.8	39.8	47.1	57.0	57.6
COPA	dev	acc.	64	78.9	67.0	78.0	80.6	84.2	90.4
MultiRC	dev	EM acc.	4	6.6	2.4	7.0	11.1	15.6	16.9
MultiRC	dev	$F_{1\alpha}$	4	61.6	57.2	57.4	57.0	67.9	69.2
ReCoRD	dev	EM acc.	4	87.1	62.3	73.6	86.8	87.4	87.4
ReCoRD	dev	\mathbf{F}_{1}	4	87.9	63.0	74.3	87.5	88.1	88.2
RTE	dev	acc.	8	64.3	50	53.1	64.5	65.0	62.2
WiC	dev	acc.	16	55.2	49.6	49.6	49.6	50.3	50.2
WSC	dev	acc.	16	71.2	62.3	65.0	67.3	69.6	75.0
Average	_	_	_	66.0	51.1	57.6	64.9	68.4	69.6
HellaSwag	dev	acc.	16	62.0	36.9	51.3	58.7	62.4	62.5
StoryCloze	test	acc.	32	83.6	69.5	77.0	82.4	84.6	84.8
Winograd	test	acc.	32	74.0	59.3	68,1	76.2	80.7	85.6
Winogrande	dev	acc.	32	61.0	49.8	54.8	60.6	63.6	68.8
Average	_	_	_	70.2	53.9	62.8	69.5	72.8	75.4
DE-EN	test	BLEU	16	2.4	0.2	4.6	20.0	23.7	25.1
EN-DE	test	BLEU	16	1.6	0.2	0.4	3.4	5.4	6.6
FR-EN	test	BLEU	16	1.7	0.2	8.7	21.9	23.5	24.5
EN-FR	test	BLEU	16	0.3	0.0	0.3	4.6	9.7	10.8
RO-EN	test	BLEU	16	1.7	0.2	4.3	16.0	17.7	18.9
EN-RO	test	BLEU	16	0.1	0.0	0.2	1.2	2.5	4.1
Average	_	_	_	1.3	0.1	3.1	11.2	13.8	15.0
Natural Questions	test	EM acc.	16	0.8	0.1	0.6	2.1	2.6	4.4
TriviaQA (wiki)	dev	EM acc.	16	6.9	0.9	3.8	13.6	14.3	17.9
Web Questions	test	EM acc.	32	1.5	0.3	1.0	4.5	5.1	9.9
PIQA	dev	acc.	32	72.9	62.4	69.6	71.6	73.0	74.5
ARC (challenge)	test	acc.	32	36.5	25.3	33.2	35.9	37.1	39.6
ARC (easy)	test	acc.	32	55.1	39.6	46.3	53.3	55.1	57.7
OpenBookQA	test	acc.	96	45.8	35.0	41.8	42.8	46.4	50.4
Average	_	_	_	31.4	23.2	28.0	32.0	33.3	36.3