

Unnatural Error Correction: GPT-4 Can Almost Perfectly Handle Unnatural Scrambled Text

Qi Cao, Takeshi Kojima, Yutaka Matsuo and Yusuke Iwasawa

The University of Tokyo, Japan

{qi.cao, t.kojima, matsuo, iwasawa}@weblab.t.u-tokyo.ac.jp

Abstract

While Large Language Models (LLMs) have achieved remarkable performance in many tasks, much about their inner workings remains unclear. In this study, we present novel experimental insights into the resilience of LLMs, particularly GPT-4, when subjected to extensive character-level permutations. To investigate this, we first propose the *Scrambled Bench*, a suite designed to measure the capacity of LLMs to handle scrambled input, in terms of both recovering scrambled sentences and answering questions given scrambled context. The experimental results indicate that multiple advanced LLMs demonstrate the capability akin to *typoglycemia*¹, a phenomenon where humans can understand the meaning of words even when the letters within those words are scrambled, as long as the first and last letters remain in place. More surprisingly, we found that only GPT-4 nearly flawlessly processes inputs with *unnatural errors*, a task that poses significant challenges for other LLMs and often even for humans. Specifically, GPT-4 can almost perfectly reconstruct the original sentences from scrambled ones, decreasing the edit distance by 95%, even when all letters within each word are entirely scrambled. It is counter-intuitive that LLMs can exhibit such resilience despite severe disruption to input tokenization caused by scrambled text.²

1 Introduction

Large language models (LLMs) demonstrate impressive proficiency across a range of tasks, with certain capabilities emerging as the models scale up in size—a phenomenon commonly known as *emergent abilities*. (Wei et al., 2022a). As the LLMs

¹Typoglycemia is an internet meme without specific scientific backing. Nonetheless, people do exhibit the ability to recognize scrambled common words to some extent. Our focus is not on examining this ability of humans, we use the concept for illustrative purposes.

²Code will be available at <https://github.com/ccqq77/unnatural-error-correction>.

The following sentence contains words with scrambled letters. Please recover the original sentence from it.

Scrambled sentence:

oJn amRh wno het 2023 Meatsrs ermtnoTuna no duySan ta
atgsuAu ntaaNloi Gflo bClu, gnclcinhi ish ifsrtr nereg ecatkj
nad ncedos raecer jroam.

Recovered sentence:

Jon Rahm won the 2023 Masters Tournament on Sunday at
Augusta National Golf Club, clinching his first green jacket
and second career major.

Figure 1: GPT-4 can recover the original sentence from the scrambled sentence, even if the tokenization drastically changes. (The colors indicate the division of sub-words during the tokenization.)

become more “intelligent”, many new benchmarks have been proposed (Liang et al., 2022; Qin et al., 2023) to investigate the ability of LLMs. Nonetheless, the internal mechanisms underlying the capabilities of LLMs remain enigmatic.

Several studies investigate the behavior of LLMs given some input perturbations. For example, Sinha et al. (2021a,b); Abdou et al. (2022) investigate the influence of *word-level* permutations and show that models are insensitive to permutations of word order that corrupt the original syntax, in some downstream tasks (e.g., natural language inference). These results are particularly interesting because they challenge the common assumption of the inner workings of LLMs, i.e., LLMs understand human-like syntax to some extent and use it to understand sentences.

Going beyond the effect of word-level permutations, we investigate the ability of LLMs under *character-level* permutations. LLMs are supposed to rely on the tokenizers to turn natural language into the form that LLMs can perceive. It would be counter-intuitive if LLMs could effectively handle text containing *unnatural* permutations that significantly alter tokenization. In other words, we propose the following research question: *Deos the*

order of letters in words matter for LLMs? Note that the above sentence contains scrambled words, but humans can somehow recognize and understand such a sentence, as several cognitive studies have explored (Rawlinson, 2007; Mason, 1982; Johnson and Eisler, 2012). Analyzing the robustness of LLMs against such character-level permutations can shed light on their word comprehension capabilities and reveal differences between various LLMs and human understanding.

To this end, this paper first constructs *Scrambled Bench*, which converts existing benchmarks into a test suite to measure the ability of LLMs to handle scrambled text. We designed two types of tasks: (1) *Scrambled Sentence Recovery*, which tests the capability of LLMs to reconstruct the original sentences from scrambled ones, and (2) *Scrambled Question Answering*, which measures how well LLMs can answer questions when some context is scrambled. Note that since the slight change in letter-order within a word drastically changes the tokenized output (see Figure 1), it is questionable whether LLMs can recognize the scrambled words in a sentence. Counter-intuitively, we show that the most powerful LLMs are able to handle scrambled sentences to varying degrees, when we scramble words while keeping the first and last letters unchanged. More surprisingly, we found that only GPT-4 can almost flawlessly process inputs with *unnatural errors*, even under extreme conditions. That is, even when we scramble all letters in words, GPT-4 manages to handle such input — a significantly challenging task for other models and even humans. For instance, GPT-4 can reconstruct the original sentences to near-perfect recovery rate in the extreme scenario, as in Figure 1.

2 Related Works

The most related works are the studies investigating the effects of word or sub-word level perturbations (Sinha et al., 2021a,b; Pham et al., 2021; Abdou et al., 2022) and the studies evaluating the robustness of LLMs (Wang et al., 2023; Zhu et al., 2023). To the best of our knowledge, no existing studies have investigated LLMs’ ability to handle character-level permutations, particularly those of an extremely high level that drastically change tokenization. Our study aims to fill this gap. Table 2 in Appendix B categorizes the prior studies and demonstrates the position of our study. Besides, we directly evaluate the ability to recover the scam-

bled text along with the task accomplishment given scrambled context. It differs with typographical error correction (Shah and de Melo, 2020; Sun et al., 2022), as (i) we do not train models to correct errors, i.e., we measure the ability of LLMs, and (ii) we add much more severe noises than natural typographical errors. The word unscrambling task in BigBench (Srivastava et al., 2023) is similar to our recovery task. However, it is more akin to a wordplay puzzle rather than a task for comprehending scrambled text, since it includes only single common words and no context is given.

3 Scrambled Bench

We propose two tasks to evaluate the capability of LLMs to handle scrambled text.

(1) Scrambled Sentence Recovery (ScrRec). In this task, we provide a sentence containing scrambled words to LLMs and then ask them to recover the original sentence from it. This task can be utilized to directly measure the capability of LLMs to recognize and reconstruct the scrambled words in a sentence.

(2) Scrambled Question Answering (ScrQA). While ScrRec can directly measure the capability to comprehend and process scrambled text, it is an “unusual” task for LLMs. If a model does not perform well on the recovery task, there are two possible reasons: (i) having difficulty following the instructions and (ii) not being able to recover sentences. To distinguish them, we measure the ability to accomplish a standard task (i.e., QA) given scrambled context. Specifically, we scramble the content that contains essential information for answering questions and then assess the models based on the variations in their performances.

3.1 Dataset Creation

In this study, we primarily utilize a scrambled version of RealtimeQA (Kasai et al., 2022) for evaluation. A common issue in evaluating LLMs is data contamination, which occurs when the test data of downstream tasks is present in the training data. It particularly affects our experiments because the analysis would be useless if some models memorized the original contents. RealtimeQA is a dynamic question answering dataset that weekly announces questions about recent news that are unlikely to be memorized by the current LLMs. Specifically, we collect the most recent

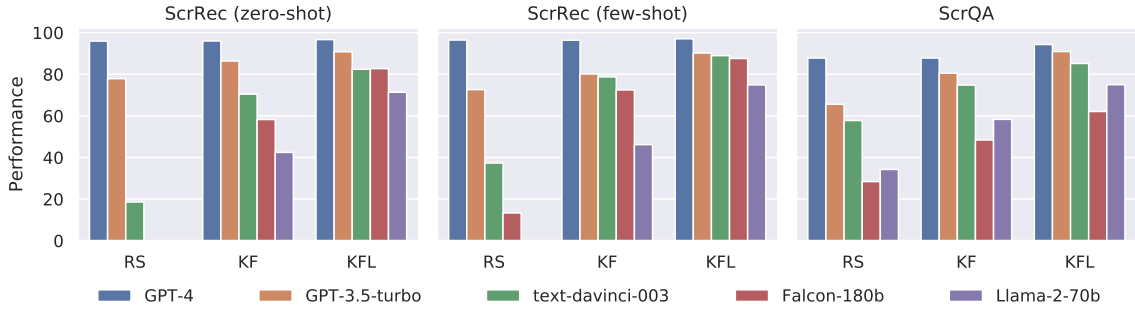


Figure 2: Experimental results on scrambled RealtimeQA dataset. Performance on ScrRec with a zero-shot setting (left). Metric: RR(%). Performance on ScrRec with a few-shot setting (middle). Metric: RR(%). Performance on ScrQA with a zero-shot setting (right). Metric: RPG(%). The missing bars represent values less than zero.

data (2023/03/17–2023/08/04) from RealtimeQA (totally 419 samples) and process the evidence sentences to construct samples for ScrRec and ScrQA. Finally, 418 samples are selected for ScrRec (removing a duplicate sentence), and 346 samples are selected for ScrQA (manually eliminating 73 samples when the provided evidence does not provide sufficient information to answer the corresponding question).

Besides, we also introduce two additional datasets: DREAM (Sun et al., 2019) and AQUA-RAT (Ling et al., 2017). DREAM is a dialogue-based multiple-choice reading comprehension dataset. AQUA-RAT is a dataset of math word problems necessitating multi-step reasoning for their resolution. For DREAM dataset, we constructed the dataset by selecting 1025 samples with annotated categories from the development and test sets and then scrambling the dialogue part of each question. For AQUA-RAT dataset, we adopt the few-shot Chain of Thought (CoT) setting as in Wei et al. 2022b and evaluate LLMs with scrambled questions in samples and demonstrations.

For each dataset, we generate scrambled text with various scramble types and rates. **(1) Randomly Scramble (RS)**. For each sentence, we randomly select a certain percentage (20%, 50%, 100% in our case³) of words and randomly shuffle the positions of letters in each selected word (Arabic numerals are kept invariant). **(2) Keep First (KF)**. We keep the first letter in each word unchanged and randomly shuffle the letters in other positions. **(3) Keep First and Last (KFL)**. We keep the first and last letter in each word unchanged and randomly shuffle the letters in other positions. We use KF and KFL to investigate the effects of

different scramble types in word recognition for LLMs.

3.2 Metrics

The average Edit Distance (ED) (Levenshtein, 1966) between the original sentences and the recovered sentences is a natural metric to quantify the performance on ScrRec. Besides, we define Recovery Rate (RR) to measure the proportion of ED reduced in recovered sentences, which makes the performance comparison on different settings more straightforward as:

$$RR = \frac{\sum_i^n ED(ori_i, rec_i) - \sum_i^n ED(ori_i, scr_i)}{\sum_i^n ED(ori_i, scr_i)} \quad (1)$$

where ori_i , scr_i , rec_i mean the original sentence, the scrambled sentence, and the recovered sentence of sample i , respectively. If a model is capable of recovering scrambled text to some extent, its RR should range between 0 and 100%.

For ScrQA, accuracy is a natural metric to measure performance. But varying capabilities of models on original questions make it hard to compare the performance among models. So, Relative Performance Gain (RPG) is defined to mitigate the differences and make evaluations focus on how well models can extract information from scrambled text in comparison to original text as:

$$RPG = \frac{Acc_{scr} - Acc_{sub}}{Acc_{ori} - Acc_{sub}} \quad (2)$$

where Acc_{ori} , Acc_{scr} , Acc_{sub} are defined as accuracy when using original evidences, scrambled evidences, substituted evidences (in which all letters of words that can be scrambled have been randomly substituted), respectively. Acc_{ori} , Acc_{sub} are served as the higher bound and the lower bound of accuracy, respectively. Normally, RPG ranges between 0 and 100%.

³In the latter part of the paper, RS denotes 100% randomly scrambling, unless a different percentage is specified.

4 Experiments

Models and Settings. In the experiments, we evaluate the most powerful closed-source LLMs, including text-davinci-003 (Brown et al., 2020), GPT-3.5-turbo and GPT-4 (OpenAI, 2023) and the open-source models from Falcon series (Penedo et al., 2023), Llama-2 series (Touvron et al., 2023), MPT series (Team, 2023), UL2 series (Tay et al., 2022), T5 series (Raffel et al., 2020; Chung et al., 2022; Xue et al., 2022). In scrambled RealtimeQA dataset, we adopt a zero-shot setting and a few-shot setting with 3-shot exemplars from the wikiQA dataset (Yang et al., 2015) for ScrRec, while we only conduct experiments on a zero-shot setting (since the task is rather straightforward) for ScrQA. In scrambled DREAM dataset, the setting is also zero-shot ScrQA. In scrambled AQuA dataset, we adopt a few-shot CoT setting with scrambled demonstrations (in the question part). Note that we are showcasing the results of the top five most proficient LLMs (i.e., GPT-4, GPT-3.5-turbo, text-davinci-003, Falcon-180b, Llama-2-70b) in this section, but comprehensive results can be found in Appendix C.

Results 1: Effect of different scramble types.

Figure 2 show the results on zero-shot ScrRec, few-shot ScrRec, and ScrQA, with three scramble types: randomly scramble (RS), keep first (KF), and keep first and last (KFL). The results show the performance gaps among models are not large in KFL setup. However, except for GPT-4, performance significantly decreases as the difficulty of scramble types increases (KFL, KF, and RS in order). In contrast, the performance of GPT-4 remains constantly high regardless of the scramble types. For ScrRec, RR of GPT-4 is constantly above 95% for all setups. For ScrQA, GPT-4 also constantly performs best with very limited accuracy drop, as the difficulty of scramble types increases.

Results 2: Effect of different scramble rates.

Figure 3 illustrates the relationship between the scramble rates (i.e., the percentages of randomly scrambled words in text) and the performance on ScrRec with scrambled RealtimeQA. As the scramble rates increases, RR decreases for text-davinci-003, Falcon-180b and Llama-2-70b. RR of GPT-3.5-turbo and GPT-4 does not change significantly. GPT-4 outperforms other models by a wide margin, with higher than 95% RR for most setups (except for 20% scramble rate).

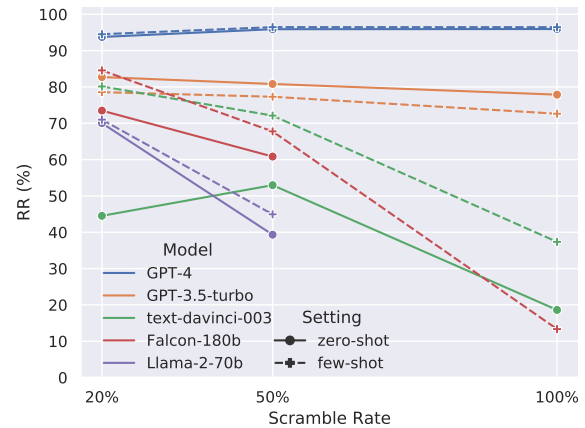


Figure 3: The effect of scramble rates on the performance on ScrRec-RealtimeQA. The missing points represent values less than zero.

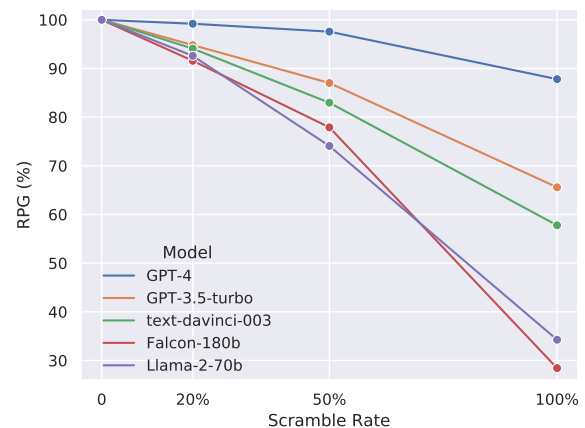


Figure 4: The effect of scramble rates on the performance on ScrQA-RealtimeQA.

Similarly, Figure 4 plots RPG against the scramble rates for different models on ScrQA with scrambled RealtimeQA. RPG of all models drops as scramble percentage increases. But GPT-4 maintains 87.8% of its original performance even with 100% scrambled evidence. The gap between the performance of different models becomes larger when the scramble rates increases. Table 3, Table 4 and Table 5 in Appendix C show full results on scrambled RealtimeQA dataset, with additional evaluation metrics (ED for ScrRec and Acc for ScrQA).

Results 3: Results of additional datasets. Finally, we test the generality of the finding across datasets by two additional datasets for ScrQA. For scrambled DREAM dataset, we evaluate performance not only overall but also on different categories of questions, using the annotations. The performance disparities between GPT-4 and other models are more pronounced than those observed on RealtimeQA, possibly since DREAM requires

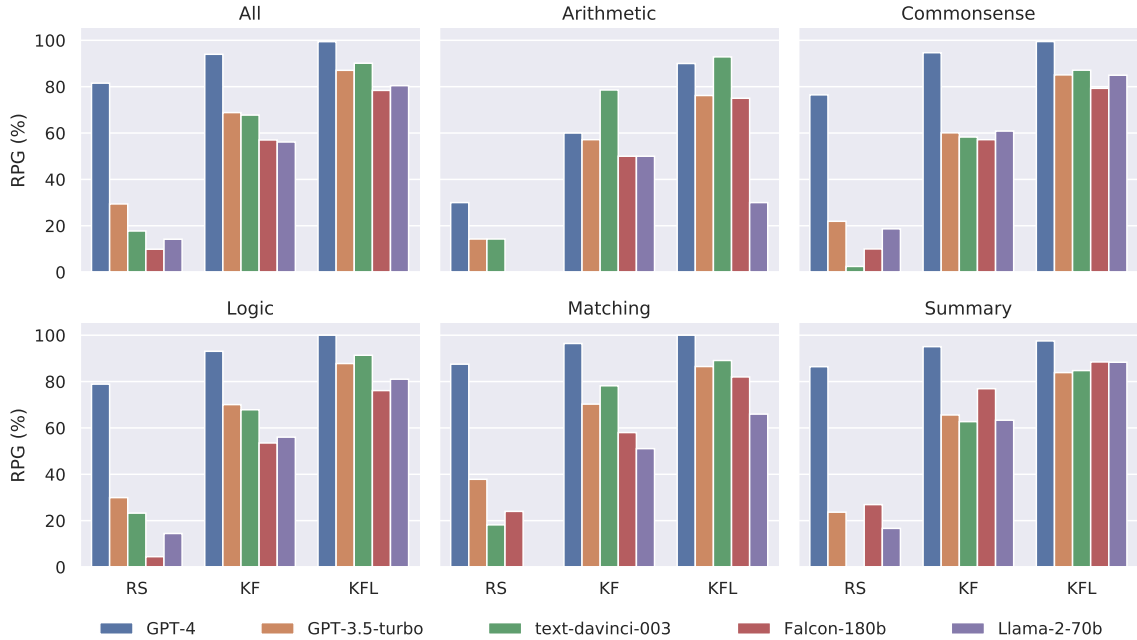


Figure 5: Experimental results of ScrQA on scrambled DREAM dataset. Overall performance and performance on different categories of questions. The missing bars represent values less than or equal to zero.

Question	Exemplars	Original	20%	50%	100%
	Original		46.85 52.76 66.93	47.24 51.97 70.87	45.67 54.72 72.05
20%		40.94 49.61 66.54	40.16 51.57 74.02	42.52 52.36 68.50	45.28 50.79 71.26
50%		40.94 40.94 67.72	41.34 44.88 65.75	40.16 47.64 64.96	44.09 42.91 67.32
100%		26.77 29.92 64.17	27.17 31.89 62.60	33.47 27.17 64.96	28.35 35.04 60.24

Table 1: Experimental results of ScrQA on scrambled AQUA-RAT dataset with a few-shot CoT setting. LLMs are assessed in various scenarios by adjusting scramble rate of questions in exemplars and the main question. (left: text-davinci-003; middle: GPT-3.5-turbo; right: GPT-4). Metric: Acc (%).

higher-level comprehension of longer texts. Performance on arithmetic questions tends to be more susceptible to scrambled text compared to other categories, even for GPT-4. Table 1 demonstrates experimental results with a 4-shot CoT setting on scrambled AQUA-RAT dataset (we only test the performance of three closed-source models here because even the original questions in AQUA-RAT are too challenging for most open-source models). We evaluate models with several different scenarios by changing scramble rates of both questions in exemplars and main question. The results show the influence of scrambled exemplars is relatively small. And the performance of GPT-3.5-turbo and text-davinci-003 drop significantly when the scramble rate of main questions increases to 100%, while GPT-4 remains most of its original performance. Table 6, Table 7 and Table 8 in Appendix C show full results on scrambled DREAM dataset.

5 Conclusion

In this study, we propose *Scrambled Bench*, a test suite to measure the ability of LLMs to handle scrambled text, including two tasks (i.e., scrambled sentence recovery and scrambled question answering) and construct scrambled datasets based on RealtimeQA, DREAM and AQUA-RAT. Despite the scrambled text drastically changes the tokenization, we demonstrate that advanced LLMs are capable of processing scrambled text to varying degrees. However, most LLMs have difficulty handling text that is scrambled to an extreme degree (i.e., 100% randomly scrambling). Surprisingly, for both tasks, GPT-4 shows good results and outperforms other models by a large margin. For the scrambled sentence recovery task, GPT-4 can recover sentences by 95% edit distance reduction even in 100% randomly scrambling settings. For the scrambled question answering task, GPT-4 can maintain a very high proportion of its original accuracy using scrambled context.

Limitations

For LLMs, there are various ways to disrupt the tokenization of words (e.g., inserting letters, substituting letters). In this study, we only investigate the influence of scrambling the letter-order in words. Investigating the performance of LLMs to handle other situations would be an interesting topic.

In addition, we have conducted our experiments using only three datasets, RealtimeQA, DREAM and AQuA-RAT. Experiments on more diverse datasets could be another future work. Note that the two tasks can be applicable for diverse datasets, and it is easy to extend the analysis.

We investigate the capability of different LLMs to handle scrambled text in different settings. However, it is difficult to conclude the reason why (some) LLMs are capable to these tasks. Especially, the reason why GPT-4 can perform almost perfectly would be an interesting topic worth further investigation. We can not access the closed-source models directly and are aware of little information about them (even the exact model size of GPT-4). These situation make investigating the reason difficult. An hypothesis is that this capability might be related to training methods, such as incorporating tasks similar to denoising in the training objectives, or using a vast amount of text data containing various errors in the training process. Another hypothesis is that this capability emerges as LLMs scale. Validating these hypotheses could potentially enhance our understanding of the inner workings of LLMs, thereby enabling us to reverse-engineer and recreate more sophisticated models like GPT-4.

References

- Mostafa Abdou, Vinit Ravishankar, Artur Kulmizev, and Anders Søgaard. 2022. [Word order does matter and shuffled language models know it](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 6907–6919, Dublin, Ireland. 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, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901.
- Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, Albert Webson, Shixiang Shane Gu, Zhuyun Dai, Mirac Suzgun, Xinyun Chen, Aakanksha Chowdhery, Sharan Narang, Gaurav Mishra, Adams Yu, Vincent Zhao, Yanping Huang, Andrew Dai, Hongkun Yu, Slav Petrov, Ed H. Chi, Jeff Dean, Jacob Devlin, Adam Roberts, Denny Zhou, Quoc V. Le, and Jason Wei. 2022. [Scaling instruction-finetuned language models](#).
- Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. 2023. Qlora: Efficient finetuning of quantized llms. *arXiv preprint arXiv:2305.14314*.
- Rebecca L Johnson and Morgan E Eisler. 2012. The importance of the first and last letter in words during sentence reading. *Acta psychologica*, 141(3):336–351.
- Jungo Kasai, Keisuke Sakaguchi, Yoichi Takahashi, Ronan Le Bras, Akari Asai, Xinyan Yu, Dragomir Radev, Noah A Smith, Yejin Choi, and Kentaro Inui. 2022. Realtime qa: What’s the answer right now? *arXiv preprint arXiv:2207.13332*.
- Vladimir I Levenshtein. 1966. Binary codes capable of correcting deletions, insertions, and reversals. *Soviet physics doklady*, 10(8):707–710.
- Percy Liang, Rishi Bommasani, Tony Lee, Dimitris Tsipras, Dilara Soylu, Michihiro Yasunaga, Yian Zhang, Deepak Narayanan, Yuhuai Wu, Ananya Kumar, et al. 2022. Holistic evaluation of language models. *arXiv preprint arXiv:2211.09110*.
- Wang Ling, Dani Yogatama, Chris Dyer, and Phil Blunsom. 2017. Program induction by rationale generation: Learning to solve and explain algebraic word problems. *ACL*.
- Mildred Mason. 1982. Recognition time for letters and nonletters: effects of serial position, array size, and processing order. *Journal of Experimental Psychology: Human Perception and Performance*, 8(5):724.
- OpenAI. 2023. [Gpt-4 technical report](#).
- Guilherme Penedo, Quentin Malartic, Daniel Hesslow, Ruxandra Cojocaru, Alessandro Cappelli, Hamza Alobeidli, Baptiste Pannier, Ebtessam Almazrouei, and Julien Launay. 2023. [The RefinedWeb dataset for Falcon LLM: outperforming curated corpora with web data, and web data only](#). *arXiv preprint arXiv:2306.01116*.
- Thang Pham, Trung Bui, Long Mai, and Anh Nguyen. 2021. [Out of order: How important is the sequential order of words in a sentence in natural language understanding tasks?](#) In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 1145–1160, Online. Association for Computational Linguistics.
- Chengwei Qin, Aston Zhang, Zhuosheng Zhang, Jiaao Chen, Michihiro Yasunaga, and Diyi Yang. 2023. Is chatgpt a general-purpose natural language processing task solver? *arXiv preprint arXiv:2302.06476*.

- 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. *The Journal of Machine Learning Research*, 21(1):5485–5551.
- Graham Rawlinson. 2007. The significance of letter position in word recognition. *IEEE Aerospace and Electronic Systems Magazine*, 22(1):26–27.
- Kshitij Shah and Gerard de Melo. 2020. [Correcting the autocorrect: Context-aware typographical error correction via training data augmentation](#). In *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pages 6930–6936, Marseille, France. European Language Resources Association.
- Koustuv Sinha, Robin Jia, Dieuwke Hupkes, Joelle Pineau, Adina Williams, and Douwe Kiela. 2021a. [Masked language modeling and the distributional hypothesis: Order word matters pre-training for little](#). In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 2888–2913, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Koustuv Sinha, Prasanna Parthasarathi, Joelle Pineau, and Adina Williams. 2021b. [UnNatural Language Inference](#). 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 7329–7346, Online. Association for Computational Linguistics.
- Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, et al. 2023. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models. *Transactions on Machine Learning Research*.
- Kai Sun, Dian Yu, Jianshu Chen, Dong Yu, Yejin Choi, and Claire Cardie. 2019. [DREAM: A challenge data set and models for dialogue-based reading comprehension](#). *Transactions of the Association for Computational Linguistics*, 7:217–231.
- Rui Sun, Xiuyu Wu, and Yunfang Wu. 2022. [An error-guided correction model for Chinese spelling error correction](#). In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 3800–3810, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Yi Tay, Mostafa Dehghani, Vinh Q Tran, Xavier Garcia, Jason Wei, Xuezhi Wang, Hyung Won Chung, Dara Bahri, Tal Schuster, Steven Zheng, et al. 2022. U12: Unifying language learning paradigms. In *The Eleventh International Conference on Learning Representations*.
- MosaicML NLP Team. 2023. [Introducing mpt-30b: Raising the bar for open-source foundation models](#). Accessed: 2023-06-22.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.
- Jindong Wang, HU Xixu, Wenxin Hou, Hao Chen, Runkai Zheng, Yidong Wang, Linyi Yang, Wei Ye, Haojun Huang, Xiubo Geng, et al. 2023. On the robustness of chatgpt: An adversarial and out-of-distribution perspective. In *ICLR 2023 Workshop on Trustworthy and Reliable Large-Scale Machine Learning Models*.
- 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. 2022a. [Emergent abilities of large language models](#). *Transactions on Machine Learning Research*. Survey Certification.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022b. Chain-of-thought prompting elicits reasoning in large language models. *Advances in Neural Information Processing Systems*, 35:24824–24837.
- Linting Xue, Aditya Barua, Noah Constant, Rami Al-Rfou, Sharan Narang, Mihir Kale, Adam Roberts, and Colin Raffel. 2022. [ByT5: Towards a token-free future with pre-trained byte-to-byte models](#). *Transactions of the Association for Computational Linguistics*, 10:291–306.
- Yi Yang, Wen-tau Yih, and Christopher Meek. 2015. Wikiqa: A challenge dataset for open-domain question answering. In *Proceedings of the 2015 conference on empirical methods in natural language processing*, pages 2013–2018.
- Kaijie Zhu, Jindong Wang, Jiaheng Zhou, Zichen Wang, Hao Chen, Yidong Wang, Linyi Yang, Wei Ye, Neil Zhenqiang Gong, Yue Zhang, et al. 2023. Promptbench: Towards evaluating the robustness of large language models on adversarial prompts. *arXiv preprint arXiv:2306.04528*.

A Examples of different tasks (by GPT-4)

A.1 Zero-shot ScrRec on RealtimeQA

Input:

The following sentence contains words with scrambled letters. Please recover the original sentence from it.

Scrambled sentence: A reGebr byba ulfaorm wsa titbudiserd ot soetsr epdstie a lclera eovr bsplioes ionmanantitco, grnoadicc ot eth ADF. heT pyomacn si noniacrggue rptsean ot ckhec yna poducsr yhte evah ta mhoe nda cdisadr sehot taht aym eb ecaeftdf.

Recovered sentence:

Output:

A Gerber baby formula was distributed to stores despite a recall over possible contamination, according to the FDA. The company is encouraging parents to check any products they have at home and discard those that may be affected.

A.2 Few-shot ScrRec on RealtimeQA

Input:

Scrambled Sentence: eTh camp continued to fctinuo this ayw ilntu the rwa needd.

Recovered Sentence: The camp continued to function this way until the war ended.

Scrambled Sentence: It swa first developed ni the 1980s yb oAcrn Computers tdL ot erowp their pstodke nmecisah and subsequently supn off sa a separate paocnmy, now ARM Holdings.

Recovered Sentence: It was first developed in the 1980s by Acorn Computers Ltd to power their desktop machines and subsequently spun off as a separate company, now ARM Holdings.

Scrambled Sentence: According to the CIA kcb-Fotoa, the United States is one fo eethr iusecnort (het ethros nebgi Liberia nda mBuar/Myanmar) that sha not adopted eth International System fo Utins (SI) rmtcei symset as iethr ffliicao system fo gswheit dna measures.

Recovered Sentence: According to the CIA Factbook, the United States is one of three countries (the others being Liberia and Burma/Myanmar) that has not adopted the International System of Units (SI) metric system as their official system of weights and measures.

Scrambled sentence: A reGebr byba ulfaorm wsa titbudiserd ot soetsr epdstie a lclera eovr

bslpioes ionmanantitco, grnoadicc ot eth ADF. heT pyomacn si noniacrggue rptsean ot ckhec yna poducsr yhte evah ta mhoe nda cdisadr sehot taht aym eb ecaeftdf.

Recovered sentence:

Output:

A Gerber baby formula was distributed to stores despite a recall over possible contamination, according to the FDA. The company is encouraging parents to check any products they have at home and discard those that may be affected.

A.3 Zero-shot ScrQA on RealtimeQA

Input:

Question: Which type of product was recently distributed to some US stores despite a recall notice?

Choices: (A)Salad dressing (B)Baby formula (C)Ground beef (D)Whole milk

Evidence: A reGebr byba ulfaorm wsa titbudiserd ot soetsr epdstie a lclera eovr bsplioes ionmanantitco, grnoadicc ot eth ADF. heT pyomacn si noniacrggue rptsean ot ckhec yna poducsr yhte evah ta mhoe nda cdisadr sehot taht aym eb ecaeftdf.

Answer: Based on the evidence, among A through D, the answer is

Output:

(B)Baby formula

A.4 Zero-shot ScrQA on DREAM

Input:

Dialogue:

M: owH goln veah uyo eben ehctnaig ni iths edmdli colosh?

W: Fro ent esray. oT eb akfrn, I'm edirt fo higneact het mesa bokoextt rof os ongl hghuto I od jyneo gebin a aterceh. I'm idenoncisrg gntriy minseghot wne.

Question: What's the woman probably going to do?

Choices: (A)To teach a different textbook. (B)To change her job. (C)To learn a different textbook.

Answer: Based on the dialogue, among A through C, the answer is

Output:

(B)To change her job.

A.5 Few-shot CoT ScrQA on AQUA-RAT

(1)

Input:

Question: hJno nfodu ttah teh gaeerav fo 15 mnsbmue si 40. fl 10 si edadd ot ceha umenbr enht

Level	Natural errors	Example (Original: How does the change affect tokenization?)	Change of tokenization	Severity	Studies
Word	No	How the affect does tokenization change?	Order	Low–High	Sinha et al. 2021a, Sinha et al. 2021b, Pham et al. 2021, Abdou et al. 2022
Sub-word	No	How change token does affectization the?	Order	Low–High	Abdou et al. 2022
Character	Yes	How does the chagne affect tokeniztion?	Tokens	Low	Wang et al. 2023, Zhu et al. 2023
Character	No	wHo deso teh chenga afctfe aotznoenitki?	Tokens	Middle–Extremely High	Ours

Table 2: Categorizing the prior works and demonstrating the position of this work.

teh naem fo het rbenmsu si?

Choices: (A)50 (B)45 (C)65 (D)78 (E)64

Answer: If 10 is added to each number, then the mean of the numbers also increases by 10. So the new mean would be 50. The answer is (A).

Question: fI $a / b = 3/4$ dan $8a + 5b = 22$, htne nfid het eval fo a.

Choices: (A)1/2 (B)3/2 (C)5/2 (D)4/2 (E)7/2

Answer: If $a / b = 3/4$, then $b = 4a / 3$. So $8a + 5(4a / 3) = 22$. This simplifies to $8a + 20a / 3 = 22$, which means $44a / 3 = 22$. So a is equal to $3/2$. The answer is (B).

Question: A nprseo si gtlanrvie ta 20 mk/rh nda hdrecae ihs ynedits ni 2.5 rh neth fdin eth dicatsen?

Choices: (A)53 km (B)55 km (C)52 km (D)60 km (E)50 km

Answer: The distance that the person traveled would have been $20 \text{ km/hr} * 2.5 \text{ hrs} = 50 \text{ km}$. The answer is (E).

Question: wHo aymn etosreyksk ear deend ot peyt het nsrbmeu rfmo 1 ot 500?

Choices: (A)1156 (B)1392 (C)1480 (D)1562 (E)1788

Answer: There are 9 one-digit numbers from 1 to 9. There are 90 two-digit numbers from 10 to 99. There are 401 three-digit numbers from 100 to 500. $9 + 90(2) + 401(3) = 1392$. The answer is (B).

Question: A ritna inunrgn ta a eepsd fo 100 mlesi/uhro, eakts 10 hurso ot cerah ist dneitiotsan. trefA ovgeirnc etarqru fo het cntsdaie, ti tstrsa grniina nda eth rniat ash ot eb dlseow ot seedp fo

75 liesm/uhor. Wtha si het otalt orjeyun iroatdnu?

Choices: (A)10 (B)11.5 (C)12.5 (D)13.5 (E)15

Answer:

Output:

The train covers a quarter of the distance at 100 miles/hour, so it travels for 2.5 hours (10 hours / 4) at this speed. The remaining distance is $3/4$ of the total distance, which takes the train 7.5 hours (10 hours - 2.5 hours) at 100 miles/hour. When the train slows down to 75 miles/hour, it takes 1.5 times longer to cover the same distance (100 miles/hour / 75 miles/hour = 1.33). So the train takes 11.25 hours (7.5 hours * 1.33) to cover the remaining distance at 75 miles/hour. The total journey duration is 13.75 hours (2.5 hours + 11.25 hours). The answer is (D).

(2)

Input:

Question: John found that the average of 15 numbers is 40. If 10 is added to each number then the mean of the numbers is?

Choices: (A)50 (B)45 (C)65 (D)78 (E)64

Answer: If 10 is added to each number, then the mean of the numbers also increases by 10. So the new mean would be 50. The answer is (A).

Question: If $a / b = 3/4$ and $8a + 5b = 22$, then find the value of a.

Choices: (A)1/2 (B)3/2 (C)5/2 (D)4/2 (E)7/2

Answer: If $a / b = 3/4$, then $b = 4a / 3$. So $8a + 5(4a / 3) = 22$. This simplifies to $8a + 20a / 3 = 22$, which means $44a / 3 = 22$. So a is equal to $3/2$. The answer is (B).

Question: A person is traveling at 20 km/hr

and reached his destiny in 2.5 hr then find the distance?

Choices: (A)53 km (B)55 km (C)52 km (D)60 km (E)50 km

Answer: The distance that the person traveled would have been $20 \text{ km/hr} * 2.5 \text{ hrs} = 50 \text{ km}$. The answer is (E).

Question: How many keystrokes are needed to type the numbers from 1 to 500?

Choices: (A)1156 (B)1392 (C)1480 (D)1562 (E)1788

Answer: There are 9 one-digit numbers from 1 to 9. There are 90 two-digit numbers from 10 to 99. There are 401 three-digit numbers from 100 to 500. $9 + 90(2) + 401(3) = 1392$. The answer is (B).

Question: ieahMnc A psut otu a oy-oy ryeve 6 nsimtue. enicMah B pstu uto a oy-oy veeyr 9 nmusite. tAefr hwo aynm smtnuei lwil yeth hvea eurdpcod 10 oy-soy?

Choices: (A)24 minutes (B)32 minutes (C)36 minutes (D)64 minutes (E)72 minutes

Answer:

Output:

First, let's rewrite the question with the words unscrambled: "Machine A puts out a yo-yo every 6 minutes. Machine B puts out a yo-yo every 9 minutes. After how many minutes will they have produced 10 yo-yos?"

To solve this problem, we can find the least common multiple (LCM) of 6 and 9, which is 18. This means that every 18 minutes, both machines will have produced a yo-yo at the same time. In 18 minutes, Machine A will have produced 3 yo-yos ($18/6$) and Machine B will have produced 2 yo-yos ($18/9$), for a total of 5 yo-yos. Since we need 10 yo-yos, we can multiply 18 minutes by 2 to get 36 minutes. The answer is (C) 36 minutes.

B Summary of related work

Table 2 categorizes the related work and demonstrates the position of our study.

C Full experimental results

We conduct experiments using the most powerful closed-source LLMs, including text-davinci-003, GPT-3.5-turbo and GPT-4 and various open-source LLMs, including the models from Falcon series,

Llama-2 series, MPT series, UL2 series, and T5 series. The open-source model covers diverse model architectures (decoder only and encoder-decoder), model size (from 7b to 180b), training objectives (e.g., with or without further finetuning) and tokenizers (e.g., tokenizer-free: ByT5-xxl).

For GPT-4, the version GPT-4-0314 is used. For GPT-3.5-turbo, the version GPT-3.5-turbo-0301 is used. For Falcon-180b and Falcon-180b-chat, the quantized method (Dettmers et al., 2023) is used to load the model and run the experiments. It probably affects their performance to some extent.

C.1 Full experimental results on scrambled RealtimeQA dataset

Table 3 and Table 4 illustrates the full experimental results on scrambled RealtimeQA dataset for few-shot ScrRec and zero-shot ScrRec, respectively.

Table 5 illustrates the full experimental results on scrambled RealtimeQA dataset for zero-shot ScrQA.

C.2 Full experimental results on scrambled DREAM dataset

Table 6 illustrates the full experimental results on scrambled DREAM dataset for zero-shot ScrQA.

Table 7 and Table 8 illustrates the experimental results on different question types of the top five models (like in Figure 5) with accuracy and RPG as the metrics, respectively.

Model	20%	50%	100%	KF	KFL
GPT-4	1.49	2.40	4.79	3.79	2.24
	94.51	96.46	96.45	96.37	97.04
GPT-3.5-turbo	5.80	15.38	36.87	20.76	7.40
	78.57	77.29	72.63	80.14	90.22
text-davinci-003	5.38	18.89	84.39	22.21	8.36
	80.13	72.11	37.35	78.75	88.95
Falcon-180b	4.18	21.84	116.73	28.77	9.40
	84.55	67.76	13.34	72.47	87.58
Falcon-180b-chat	11.61	38.19	186.65	63.51	21.73
	57.12	43.62	< 0	39.24	71.28
Falcon-40b	17.27	69.86	185.26	119.00	66.03
	36.18	< 0	< 0	< 0	12.71
Falcon-40b-instruct	18.79	74.26	192.86	130.82	62.39
	30.56	< 0	< 0	< 0	17.53
Llama-2-70b	7.85	37.30	169.85	56.25	18.99
	71.0	44.93	< 0	46.19	74.9
Llama-2-70b-chat	11.11	54.49	196.44	106.31	43.18
	58.97	19.56	< 0	< 0	42.93
Llama-2-13b	14.18	59.13	192.67	103.50	42.67
	47.62	12.71	< 0	0.99	43.59
Llama-2-13b-chat	20.75	73.04	201.50	119.52	56.03
	23.35	< 0	< 0	< 0	25.93
Llama-2-7b	20.90	79.83	194.48	135.50	68.18
	22.77	< 0	< 0	< 0	9.88
Llama-2-7b-chat	25.14	83.13	196.88	132.44	73.84
	7.11	< 0	< 0	< 0	2.39
MPT-30b	14.36	54.81	181.43	90.92	36.14
	46.96	19.08	< 0	13.02	52.23
MPT-30b-instruct	19.36	66.05	170.88	99.38	50.44
	28.46	2.49	< 0	4.92	33.33
UL2	18.12	68.79	153.53	109.47	71.70
	33.03	< 0	< 0	< 0	5.22
Flan-UL2	20.51	62.91	137.15	105.67	74.35
	24.21	7.13	< 0	< 0	1.72
Flan-T5-xxl	16.60	59.34	136.41	105.44	73.97
	38.68	12.4	< 0	< 0	2.22
ByT5-xxl	79.27	104.28	160.17	123.97	102.50
	< 0	< 0	< 0	< 0	< 0

Table 3: The experimental results on the few-shot ScrRec using RealtimeQA dataset (upper: ED; lower: RR).

Model	20%	50%	100%	KF	KFL
GPT-4	1.69	2.78	5.47	4.19	2.53
	93.76	95.89	95.94	95.99	96.66
GPT-3.5-turbo	4.68	13.00	29.80	14.22	6.94
	82.72	80.82	77.88	86.39	90.82
text-davinci-003	15.02	31.86	109.63	30.88	13.30
	44.52	52.96	18.61	70.45	82.41
Falcon-180b	7.18	26.53	159.36	43.63	13.08
	73.48	60.84	< 0	58.25	82.72
Falcon-180b-chat	15.92	50.50	180.13	76.31	29.29
	41.17	25.46	< 0	27.0	61.29
Falcon-40b	20.59	66.33	177.33	92.45	39.04
	23.94	2.08	< 0	11.56	48.39
Falcon-40b-instruct	26.42	78.94	178.55	104.46	48.42
	2.4	< 0	< 0	0.07	36.0
Llama-2-70b	8.11	41.10	180.82	60.16	21.68
	70.04	39.32	< 0	42.45	71.34
Llama-2-70b-chat	12.65	60.23	181.30	118.13	51.73
	53.26	11.08	< 0	< 0	31.62
Llama-2-13b	20.21	75.54	231.41	127.63	59.77
	25.32	< 0	< 0	< 0	20.99
Llama-2-13b-chat	26.79	84.09	191.85	120.51	63.82
	1.03	< 0	< 0	< 0	15.64
Llama-2-7b	29.81	106.38	192.05	165.56	88.65
	< 0	< 0	< 0	< 0	< 0
Llama-2-7b-chat	48.92	123.66	202.16	167.49	112.03
	< 0	< 0	< 0	< 0	< 0
MPT-30b	20.54	70.69	226.34	135.58	62.16
	24.11	< 0	< 0	< 0	17.84
MPT-30b-instruct	36.01	84.98	233.60	132.77	76.60
	< 0	< 0	< 0	< 0	< 0
UL2	72.39	139.14	205.86	188.57	163.67
	< 0	< 0	< 0	< 0	< 0
Flan-UL2	33.10	71.76	136.94	106.48	78.55
	< 0	< 0	< 0	< 0	< 0
Flan-T5-xxl	27.07	68.02	136.47	106.08	76.69
	< 0	< 0	< 0	< 0	< 0
ByT5-xxl	85.83	111.53	155.27	136.99	117.80
	< 0	< 0	< 0	< 0	< 0

Table 4: The experimental results on the zero-shot ScrRec using RealtimeQA dataset (upper: ED; lower: RR).

Model	Ori	20%	50%	100%	KF	KFL	Sub
GPT-4	97.69	97.40	96.82	93.35	93.35	95.66	62.14
	100.0	99.19	97.56	87.80	87.80	94.31	0.0
GPT-3.5-turbo	97.11	94.80	91.33	81.79	88.44	93.06	52.60
	100.0	94.81	87.01	65.58	80.52	90.91	0.0
text-davinci-003	93.93	91.62	87.28	77.46	84.10	88.15	54.91
	100.0	94.07	82.96	57.78	74.81	85.19	0.0
Falcon-180b	84.68	82.37	78.61	65.03	70.52	74.28	57.23
	100.0	91.58	77.89	28.42	48.42	62.11	0.0
Falcon-180b-chat	75.43	72.54	71.39	58.09	63.87	67.34	54.62
	100.0	86.11	80.56	16.67	44.44	61.11	0.0
Falcon-40b	58.96	59.25	54.62	44.51	44.51	50.29	39.60
	100.0	101.49	77.61	25.37	25.37	55.22	0.0
Falcon-40b-instruct	65.90	63.87	61.27	48.55	53.47	60.69	46.82
	100.0	89.39	75.76	9.09	34.85	72.73	0.0
Llama-2-70b	88.44	86.13	80.35	67.92	75.43	80.64	57.23
	100.0	92.59	74.07	34.26	58.33	75.00	0.0
Llama-2-70b-chat	96.24	92.49	83.82	64.74	75.43	82.66	54.91
	100.0	90.91	69.93	23.78	49.65	67.13	0.0
Llama-2-13b	66.18	65.03	57.51	47.40	52.89	57.80	44.80
	100.0	94.59	59.46	12.16	37.84	60.81	0.0
Llama-2-13b-chat	84.68	78.90	66.18	47.98	55.20	59.83	44.51
	100.0	85.61	53.96	8.63	26.62	38.13	0.0
Llama-2-7b	47.40	45.09	42.77	38.73	40.75	43.64	39.31
	100.0	71.43	42.86	< 0	17.86	53.57	0.0
Llama-2-7b-chat	82.08	75.14	64.16	45.09	52.31	56.94	43.93
	100.0	81.82	53.03	3.03	21.97	34.09	0.0
MPT-30b	62.72	56.36	50.87	37.86	47.69	53.47	37.28
	100.0	75.00	53.41	2.27	40.91	63.64	0.0
MPT-30b-instruct	65.03	66.76	58.67	47.11	54.62	61.27	39.88
	100.0	106.90	74.71	28.74	58.62	85.06	0.0
UL2	87.57	84.68	76.30	45.95	60.69	71.10	38.44
	100.0	94.12	77.06	15.29	45.29	66.47	0.0
Flan-UL2	98.55	95.95	89.31	49.71	65.61	76.88	46.24
	100.0	95.03	82.32	6.63	37.02	58.56	0.0
Flan-T5-xxl	97.40	96.24	87.86	49.42	66.47	82.66	40.75
	100.0	97.96	83.16	15.31	45.41	73.98	0.0
ByT5-xxl	73.12	57.23	46.24	26.30	35.84	41.91	25.14
	100.0	66.87	43.98	2.41	22.29	34.94	0.0

Table 5: The experimental results on the zero-shot ScrQA using RealtimeQA dataset (upper: Acc; lower: RPG).

Model	Ori	20%	50%	100%	KF	KFL	Sub
GPT-4	96.68	96.29	94.43	87.40	93.65	96.39	46.48
	100.0	99.22	95.53	81.52	93.97	99.42	0.0
GPT-3.5-turbo	92.48	87.30	77.83	45.61	71.78	83.89	26.07
	100.0	92.21	77.94	29.41	68.82	87.06	0.0
text-davinci-003	92.29	89.45	80.27	52.44	76.66	87.50	43.85
	100.0	94.15	75.20	17.74	67.74	90.12	0.0
Falcon-180b	93.65	89.65	82.23	55.37	75.39	84.47	51.17
	100.0	90.57	73.10	9.89	57.01	78.39	0.0
Falcon-180b-chat	92.68	89.16	78.32	49.90	70.51	80.76	45.31
	100.0	92.58	69.69	9.69	53.20	74.85	0.0
Falcon-40b	70.12	65.04	56.45	44.34	50.78	58.30	43.26
	100.0	81.09	49.09	4.00	28.00	56.00	0.0
Falcon-40b-instruct	75.20	67.48	58.59	43.65	50.00	60.06	42.87
	100.0	76.13	48.64	2.42	22.05	53.17	0.0
Llama-2-70b	93.26	89.75	80.96	54.30	73.34	84.38	47.85
	100.0	92.26	72.90	14.19	56.13	80.43	0.0
Llama-2-70b-chat	91.11	85.74	75.10	48.24	59.67	74.02	45.12
	100.0	88.32	65.18	6.79	31.63	62.85	0.0
Llama-2-13b	69.53	63.87	53.32	38.67	44.63	52.25	37.21
	100.0	82.48	49.85	4.53	22.96	46.53	0.0
Llama-2-13b-chat	78.61	71.78	59.77	41.80	48.44	57.42	40.92
	100.0	81.87	50.00	2.33	19.95	43.78	0.0
Llama-2-7b	60.55	55.08	47.46	37.60	43.07	46.39	37.30
	100.0	76.47	43.70	1.26	24.79	39.08	0.0
Llama-2-7b-chat	73.63	64.45	56.25	40.04	45.41	53.81	39.84
	100.0	72.83	48.55	0.58	16.47	41.33	0.0
MPT-30b	74.02	69.24	59.47	47.17	50.00	57.71	43.46
	100.0	84.35	52.40	12.14	21.41	46.65	0.0
MPT-30b-instruct	83.50	75.68	65.43	44.82	54.30	60.64	41.41
	100.0	81.44	57.08	8.12	30.63	45.71	0.0
UL2	43.36	39.36	29.88	14.55	17.38	25.20	12.79
	100.0	86.90	55.91	5.75	15.02	40.58	0.0
Flan-UL2	94.24	91.21	80.96	49.80	62.99	75.39	48.14
	100.0	93.43	71.19	3.60	32.20	59.11	0.0
Flan-T5-xxl	95.02	92.87	84.67	51.17	67.09	81.54	51.07
	100.0	95.11	76.44	0.22	36.44	69.33	0.0
ByT5-xxl	43.16	40.23	36.23	31.93	33.50	36.62	31.84
	100.0	74.14	38.79	0.86	14.66	42.24	0.0

Table 6: The experimental results on the zero-shot ScrQA using DREAM dataset (upper: Acc; lower: RPG).

Model	Type	Ori	20%	50%	100%	KF	KFL	Sub
GPT-4	all	96.68	96.29	94.43	87.40	93.65	96.39	46.48
	arithmetic	76.09	78.26	67.39	45.65	58.70	71.74	32.61
	commonsense	94.69	94.41	93.02	82.40	91.90	94.41	42.46
	logic	95.97	95.84	93.42	85.77	92.62	95.97	47.65
	matching	99.07	97.22	98.15	92.59	97.22	99.07	47.22
	summary	98.47	97.71	96.18	90.08	95.42	96.95	36.64
GPT-3.5-turbo	all	92.48	87.30	77.83	45.61	71.78	83.89	26.07
	arithmetic	60.87	60.87	52.17	21.74	41.30	50.00	15.22
	commonsense	89.11	84.36	76.54	39.39	63.69	79.61	25.42
	logic	91.01	85.64	76.11	44.83	71.28	82.95	25.10
	matching	99.07	91.67	81.48	56.48	78.70	89.81	30.56
	summary	95.42	93.13	82.44	41.22	70.99	83.97	24.43
text-davinci-003	all	92.29	89.45	80.27	52.44	76.66	87.50	43.85
	arithmetic	47.83	45.65	41.30	21.74	41.30	45.65	17.39
	commonsense	90.78	87.99	77.37	46.37	71.79	84.92	45.25
	logic	91.01	87.92	78.39	52.89	75.03	86.71	41.34
	matching	99.07	94.44	86.11	57.41	87.96	93.52	48.15
	summary	94.66	94.66	86.26	48.09	77.86	87.79	49.62
Falcon-180b	all	93.65	89.65	82.23	55.37	75.39	84.47	51.17
	arithmetic	52.17	47.83	45.65	34.78	43.48	47.83	34.78
	commonsense	91.34	88.55	79.33	56.15	74.58	83.24	52.23
	logic	92.62	88.59	79.87	52.35	73.02	82.55	50.47
	matching	98.15	90.74	87.04	62.96	78.70	89.81	51.85
	summary	96.18	93.89	89.31	67.18	87.02	91.60	56.49
Llama-2-70b	all	93.26	89.75	80.96	54.30	73.34	84.38	47.85
	arithmetic	58.70	47.83	50.00	36.96	47.83	43.48	36.96
	commonsense	91.34	89.39	80.73	53.63	73.18	84.36	44.97
	logic	92.62	88.99	79.73	54.50	73.02	84.16	48.05
	matching	94.44	89.81	79.63	50.93	73.15	79.63	50.93
	summary	96.18	94.66	86.26	58.02	79.39	90.84	50.38

Table 7: The experimental results of different categories on the zero-shot ScrQA using DREAM dataset (Acc).

Model	Type	Ori	20%	50%	100%	KF	KFL	Sub
GPT-4	all	100.0	99.22	95.53	81.52	93.97	99.42	0.0
	arithmetic	100.0	105.00	80.00	30.00	60.00	90.00	0.0
	commonsense	100.0	99.47	96.79	76.47	94.65	99.47	0.0
	logic	100.0	99.72	94.72	78.89	93.06	100.00	0.0
	matching	100.0	96.43	98.21	87.50	96.43	100.00	0.0
	summary	100.0	98.77	96.30	86.42	95.06	97.53	0.0
GPT-3.5-turbo	all	100.0	92.21	77.94	29.41	68.82	87.06	0.0
	arithmetic	100.0	100.00	80.95	14.29	57.14	76.19	0.0
	commonsense	100.0	92.54	80.26	21.93	60.09	85.09	0.0
	logic	100.0	91.85	77.39	29.94	70.06	87.78	0.0
	matching	100.0	89.19	74.32	37.84	70.27	86.49	0.0
	summary	100.0	96.77	81.72	23.66	65.59	83.87	0.0
	all	100.0	94.15	75.20	17.74	67.74	90.12	0.0
text-davinci-003	arithmetic	100.0	92.86	78.57	14.29	78.57	92.86	0.0
	commonsense	100.0	93.87	70.55	2.45	58.28	87.12	0.0
	logic	100.0	93.78	74.59	23.24	67.84	91.35	0.0
	matching	100.0	90.91	74.55	18.18	78.18	89.09	0.0
	summary	100.0	100.00	81.36	< 0	62.71	84.75	0.0
Falcon-180b	all	100.0	90.57	73.10	9.89	57.01	78.39	0.0
	arithmetic	100.0	75.00	62.50	0.00	50.00	75.00	0.0
	commonsense	100.0	92.86	69.29	10.00	57.14	79.29	0.0
	logic	100.0	90.45	69.75	4.46	53.50	76.11	0.0
	matching	100.0	84.00	76.00	24.00	58.00	82.00	0.0
	summary	100.0	94.23	82.69	26.92	76.92	88.46	0.0
Llama-2-70b	all	100.0	92.26	72.90	14.19	56.13	80.43	0.0
	arithmetic	100.0	50.00	60.00	0.00	50.00	30.00	0.0
	commonsense	100.0	95.78	77.11	18.67	60.84	84.94	0.0
	logic	100.0	91.87	71.08	14.46	56.02	81.02	0.0
	matching	100.0	89.36	65.96	0.00	51.06	65.96	0.0
	summary	100.0	96.67	78.33	16.67	63.33	88.33	0.0

Table 8: The experimental results of different categories on the zero-shot ScrQA using DREAM dataset (RPG).