

LOT: A Story-Centric Benchmark for Evaluating Chinese Long Text Understanding and Generation

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Abstract

Standard multi-task benchmarks are essential for developing pretraining models that can generalize to various downstream tasks. Existing benchmarks for natural language processing (NLP) usually focus only on understanding or generating short texts. However, long text modeling requires many distinct abilities in contrast to short texts, such as the modeling of long-range discourse and commonsense relations, and the coherence and controllability of generation. The lack of standardized benchmarks makes it difficult to assess these abilities of a model and fairly compare different models, especially Chinese models. Therefore, we propose a story-centric benchmark named LOT for evaluating Chinese long text modeling, which aggregates two understanding tasks and two generation tasks. We construct new datasets for these tasks based on human-written Chinese stories with hundreds of words. Furthermore, we release an encoder-decoder-based Chinese long text pretraining model named LongLM with up to 1 billion parameters. We pre-train LongLM on 120G Chinese novels with two generative tasks including text infilling and conditional continuation. Extensive experiments show that LongLM outperforms similar-sized pretraining models substantially on both the understanding and generation tasks in LOT.

1 Introduction

Pretrained language models have achieved significant advances in various natural language understanding (NLU) and generation (NLG) tasks

(Devlin et al., 2019; Radford et al., 2019). Standard benchmarks such as GLUE (Wang et al., 2019) further boost the improvement and fast iteration of pretrained models. Popular benchmarks usually aggregate multiple tasks to spur the progress of generalizable models. But these benchmarks focus mainly on understanding or generating short texts. For example, the GLUE tasks take at most two sentences as input. And most tasks in NLG benchmarks such as GLGE (Liu et al., 2020) and GEM (Gehrmann et al., 2021) require generating only several words (e.g., dialogue generation). Although there have been many models pretrained on long texts such as GPT3 (Brown et al., 2020) and CPM (Zhang et al., 2020), the lack of benchmark datasets makes it difficult to fully assess and compare their abilities of long text modeling.

In this paper, we present LOT, a benchmark for evaluating *Chinese Long Text understanding and generation*. As shown in Table 1, modeling long texts requires many distinct abilities compared to short texts, including (1) commonsense reasoning regarding characters’ reaction and intention, and knowledge about physical objects (e.g., “river”) and abstract concepts (e.g., “irony”); (2) modeling discourse-level features such as inter-sentence relations (e.g., causality) and global discourse structures (e.g., the order of events); and (3) the generation coherence and controllability, which require both maintaining a coherent plot and adhering to controllable attributes (e.g., topics). Accordingly, LOT contains two understanding tasks and two generation tasks regarding the above abilities. We construct new datasets for these tasks based on various kinds of stories such as fables and fairy tales collected from public web resources,

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Effendi’s son is **eccentric**, always **behaving opposed to what Effendi has ordered him to do**. Familiar to his son’s temper, Effendi usually **communicates using irony**. One day, the father and son were blocked by a river after purchasing flour from a mill. And while they were crossing the river, one bag on the donkey’s back lost its weight and leaned. Effendi told his son with **irony**: “My boy! **drop the sack into the river!**” The son heard the words and thought: “I have been opposed to my father for so many years. For this only time, I have to **obey** him.” Therefore, he followed Effendi’s words and indeed **pushed the sack into the river**. “My boy! What are you doing?” Effendi shouted in **anger**.” ...

Table 1: A long text example. The concepts and events concerning commonsense and discourse relations are highlighted in **bold**.

considering that stories usually contain abundant commonsense and discourse relations. All these tasks require processing stories with hundreds of words. Note that LOT does not involve extra-long texts with thousands of words since the complicated linguistic phenomena in these texts make it hard to test individual abilities and guide the improvement of generation models.

Furthermore, we release LongLM, a *Chinese Long text pretraining Language Model*. LongLM is a Transformer-based model with an encoder-decoder architecture. LongLM has three different versions ranging from 60 million to 1 billion parameters. We pretrain LongLM on 120G Chinese novels with two generative tasks, including text infilling (Lewis et al., 2020) and conditional continuation (Radford et al., 2018). The pretraining data do not include other types of texts (e.g., news, Wiki-texts) since we mainly focus on commonsense and discourse relations within general long texts instead of factual and technical knowledge. To the best of our knowledge, LongLM is the first pretraining model of the same size scale that focuses on modeling long-form stories. Extensive experiments on LOT show that LongLM outperforms strong baselines substantially on both the understanding and generation tasks. However, we also observe that LongLM is still far behind human performance, which requires better semantic representations of events and deeper modeling of

the commonsense and discourse relations between them. We summarize the main contributions of this paper as follows:

- I.** We propose a new story-centric benchmark LOT for evaluating Chinese long text understanding and generation. LOT consists of four tasks for testing the fundamental abilities to model long texts. We also present new datasets for these tasks.
- II.** We release a new Chinese pretraining model named LongLM. Experiment results demonstrate the strong performance of LongLM on LOT, but there still exists considerable room for improvement.¹

2 Related Work

NLP Benchmarks Recently, there have been a lot of multi-task benchmarks proposed to drive the progress of generalizable models. The benchmarks usually aggregate multiple model-agnostic tasks under a unified framework, enabling researchers to fairly compare different models. SentEval (Conneau and Kiela, 2018) gathered multiple classification tasks involving either one or two sentences as inputs to evaluate sentence representations. DiscoEval (Chen et al., 2019) extended these tasks to the discourse level regarding inter-sentence relations. GLUE (Wang et al., 2019) included more diverse tasks such as natural language inference (Rocktäschel et al., 2016). Sarlin et al. (2020) proposed SuperGLUE as a more challenging counterpart of GLUE by introducing multi-sentence tasks. But the additional tasks are only limited to the formats of coreference resolution and question answering. In addition to these English benchmarks, many benchmarks were proposed to evaluate NLU for other languages, such as CLUE (Xu et al., 2020a) for Chinese. Moreover, GLGE (Liu et al., 2020) and GEM (Gehrmann et al., 2021) were proposed for evaluating NLG models across diversified generation tasks such as text summarization and personalizing dialogue. However, there is no benchmark designed specifically for long text modeling, especially Chinese. Additionally, the above benchmarks were originally designed to cover as diverse task formats as possible. In contrast, we design the LOT tasks with the guidance

¹The LOT benchmark, the pretraining resources, and the appendix are available at <https://github.com/thu-coai/LOT-LongLM>.

of necessary abilities for long text modeling as suggested by Ribeiro et al. (2020), making it easier to figure out where models are failing, and how to improve them.

Long Text Datasets Previous studies in the field of long text modeling have frequently focused on the ROCStories (Mostafazadeh et al., 2016) and WritingPrompts (Fan et al., 2018) datasets. ROCStories contains 100k artificial five-sentence stories, while WritingPrompts consists of 300K pairs of prompts and stories with hundreds of words. Recent works collected stories with thousands of words to model longer-range dependencies, such as WikiText-103 (Merity et al., 2016), roleplayerguild (Louis and Sutton, 2018), PG-19 (Rae et al., 2020), STORIUM (Akoury et al., 2020), and Long-Range Arena (Tay et al., 2020). However, these datasets are written in English. LOT will drive the development of Chinese language models.

Moreover, LOT does not include datasets of extra-long texts, like PG-19, for the following two reasons: (1) Extra-long texts are far beyond the scope of current machine learning models because the discourse-level linguistic phenomena are entangled and complicated in these texts. Therefore, extra-long texts usually serve for computing perplexity of language models (Dai et al., 2019) but hardly provide fine-grained guidance for improving model designs. (2) LOT aims not to spur research on building fuller connections across tokens within an extra-long sequence, but to drive the progress of machines in the aforementioned fundamental abilities for long text modeling.

Story Understanding and Generation LOT is centered on fundamental abilities for long text modeling and thus includes four story understanding and generation tasks concerning commonsense and discourse relations. Recent studies have proposed various tasks to evaluate story understanding and generation. First, story ending selection (Mostafazadeh et al., 2016), story ending generation (Guan et al., 2019), and story completion (Wang and Wan, 2019) focused on the commonsense reasoning ability on inter-event causal and temporal relations. Second, Chen et al. (2019) evaluated the ability to model discourse relations by predicting the position of a sentence or a paragraph in a text. Third, some works focused on the coherence of story generation conditioned on

short prompts (Fan et al., 2018), titles (Yao et al., 2019) and beginnings (Guan et al., 2020). Fourth, some studies centered on controllability, that is, the imposing of controllable attributes on story generation such as keywords (Xu et al., 2020b), emotional trajectories (Brahman and Chaturvedi, 2020), outlines (Rashkin et al., 2020), and styles (Kong et al., 2021). LOT is a comprehensive benchmark to test the above abilities for Chinese long text modeling.

On the other hand, LOT does not involve those tasks that require learning more particular features of stories, such as event chains (Chambers and Jurafsky, 2008), character types (Bamman et al., 2013), inter-character relations (Chaturvedi et al., 2016, 2017), social networks (Agarwal et al., 2013), and abstractive structures (Finlayson, 2012). Non-neural story generation models usually retrieved events from a knowledge base with pre-specified semantic relations based on handcrafted rules (Li et al., 2013), which are costly and lack generalization. In this paper, we focus mainly on evaluating neural models for story understanding and generation.

3 LOT Benchmark

We design LOT as an aggregation of two understanding tasks including *Cloze Test* (ClozeT) and *Sentence Position Prediction* (SenPos), and two generation tasks including *Plot Completion* (PlotCom) and *Outline-conditioned Generation* (OutGen). We show the task descriptions and data statistics in Tables 2 and 3, respectively. We use the `jieba` tokenizer² for word tokenization.

We design LOT based on the following principles: **(1) Task Diversity:** The tasks vary in task formats, types and lengths of inputs and outputs, and focused abilities, making LOT a comprehensive framework for evaluating the generalization of models. **(2) Task Difficulty:** The tasks take hundreds of words as inputs or outputs, and do not involve domain-specific knowledge about science, films, and so forth. Therefore, they are beyond the scope of current state-of-the-art models, but are solvable by most Chinese native speakers. **(3) Task Formulation:** The tasks have been well formulated in prior studies and agreed to be challenging but meaningful. We introduce new Chinese datasets for these tasks, which are constructed to focus more specifically on testing

²<https://github.com/fxsjy/jieba>.

Tasks	Abilities	Inputs	Outputs	Metrics
ClozeT	Commonsense Reasoning	A text with a sentence removed (the position specified); Two candidate sentences.	Choosing the correct sentence from two candidates.	Accuracy
SenPos	Inter-sentence Relationship	A text with a sentence removed (the position unspecified); The removed sentence.	Choosing the correct position for the removed sentence.	Accuracy
PlotCom	Commonsense Reasoning; Inter-sentence Relationship	A text with a sentence removed (the position specified).	Generating a sentence to complete the text.	BLEU; Dist
OutGen	Discourse Structure; Coherence; Controllability	A title, an outline as an out-of-order set of phrases about characters and events.	Generating a coherent text adhering to the title and outline.	BLEU; Dist; Cover; Order

Table 2: Overview of the tasks in LOT for the abilities they test, inputs and outputs, and the evaluation metrics. **Dist** and **Cover** refer to Distinct and Coverage (Section 5.3), respectively.

Datasets	Train	Val	Test
Task: ClozeT			
# Examples	644	294	294
Vocabulary Size	9k	7k	7k
Avg. # Char in Input Text	139.07	138.95	141.15
Avg. # Word in Input Text	89.28	89.03	90.20
Avg. # Sent in Input Text	5.95	5.94	5.95
Avg. # Word in Candidate	15.60	16.38	15.75
Task: SenPos			
# Examples	20,000	800	863
Vocabulary Size	147k	10k	22k
Avg. # Char in Input Text	289.59	258.48	258.52
Avg. # Word in Input Text	254.11	224.20	223.25
Avg. # Sent in Input Text	9.61	8.43	8.44
Avg. # Word in Removed Sent	30.48	29.28	30.26
Avg. # Candidate Positions	8.05	6.91	6.91
Task: PlotCom			
# Examples	13,099	465	464
Vocabulary Size	22k	8k	8k
Avg. # Char in Input Text	164.35	137.67	133.26
Avg. # Word in Input Text	105.48	87.56	84.98
Avg. # Sent in Input Text	7.17	5.59	5.48
Avg. # Word in Output Sent	15.08	15.96	16.15
Task: OutGen			
# Examples	1,456	242	729
Vocabulary Size	19k	6k	12k
Avg. # Word in Input Title	4.64	4.89	4.64
Avg. # Word in Input Outline	19.20	19.05	19.47
Avg. # Phrase in Input Outline	8.00	8.00	8.00
Avg. # Char in Output Text	169.94	169.80	170.49
Avg. # Word in Output Text	108.91	108.68	109.04
Avg. # Sent in Output Text	7.20	7.11	7.15

Table 3: Data statistics of LOT tasks. The abbreviation **char/sent/len** is short for **character/sentence/length**, respectively.

a certain ability than original datasets. **(4) Automatic Evaluation:** These tasks have reliable automatic metrics to evaluate the focused abilities. We exclude open-ended generation tasks such

as story generation from titles, which is difficult to automatically evaluate (Guan et al., 2021) because the tasks suffer from the notorious one-to-many issue: There are many plausible outputs for the same input (Zhao et al., 2017).

We constructed datasets for LOT through automatic and manual annotation. First, we crawled human-written stories from public web pages as the data source. These stories are under licenses that allow use and redistribution for research purposes. Then, we hired a commercial team to create the LOT examples. The team is led by a professional screenwriter and has taken on hundreds of NLP annotation projects. All annotators are native Chinese speakers and well-trained for the annotation tasks. We show the full list of the source web pages and the annotation details in the appendix.

3.1 Cloze Test

Mostafazadeh et al. (2016) introduced the Story Cloze Test (SCT) task for evaluating story comprehension, which requires selecting the right ending from two candidates for a four-sentence leading context. However, SCT suffers from the following issues: (1) Its dataset is artificial and contains innate biases between right and wrong endings in some features such as lengths (Schwartz et al., 2017; Sharma et al., 2018). Such biases may leak information about the target labels. (2) SCT focuses on reasoning only endings but neglects other types of reasoning, such as abductive reasoning (Bhagavatula et al., 2019), which requires reasoning what happens between observed beginnings and endings. (3) SCT limits the scope of commonsense reasoning to realistic events. The limitation may be neither necessary nor sufficient. For example, ‘‘Cupid can fly’’ can

A goblin had buried a treasure under the ground. *After that, he received a long flight mission from the Devil King.* The goblin began to worry about how to guard the treasure during his mission. **The goblin thought for a long time and decided to give the treasure to a miser.** The miser clung to his vault even when he was asleep, so the goblin trusted him very much . . .

Table 4: An example for selecting a sentence that can be reasoned based on the context and common sense (in **red**). We also highlight a sentence that does not satisfy the requirement in *green*, which introduces a new character “*the Devil King*”.

be reasoned based on common sense although it is not realistic, while some story settings may be realistic but fail to be reasoned only based on the context and common sense, as shown in Table 4. Therefore, when constructing our ClozeT dataset, we adopt the following approaches to alleviate the above issues: (1) All examples are derived from existing human-written stories. (2) We allow annotators to create examples where the removed sentence is initially in the middle of the story. (3) We change the scope of commonsense reasoning to all events that embody characters’ reaction and intention, or the nature of physical objects and concepts. Table 6 shows two ClozeT examples. Furthermore, we also conducted experiments to investigate the potential biases of our dataset in Section 5.5.

Story Filtering To ensure the quality of LOT examples, we asked annotators to judge whether each crawled story meets the following definition: “anything which is told in the form of a coherent event sequence involving several specific and related characters” (Mostafazadeh et al., 2016). We provided detailed cases for annotators to instruct them about this definition. Then, annotators needed to refine those stories which do not meet the definition by rewriting the plots. They should also clean up the stories by the following heuristics: (1) refusing examples that may violate ethical principles (e.g., discrimination); (2) deleting noisy words (e.g., links); (3) changing slang and informal words into standard modern Chinese; (4) rewriting all dialogues to objective events. Finally, we collected 2,427 high-quality

Text: I couldn’t control my anger very well. [1]My parents would yell at me, and i ran to my room. [2]I buried my head in a pillow and screamed. [3]I threw my pillow and hit it hard.

Removed Sentence: I tried to express my anger.

Table 5: A poor example for the SenPos task. The removed sentence has multiple reasonable positions including [2] and [3] in the original text.

Chinese stories, which will be used to construct the datasets for the ClozeT, PlotCom, and OutGen tasks.

Dataset Construction We presented the stories to another group of annotators to construct the ClozeT dataset. For each story, they should select a sentence as the right candidate that can be reasoned based on the context and common sense. Table 4 shows an example presented to the annotators to illustrate how to judge whether a sentence satisfies this requirement. Then, the annotators rewrite the sentence into another one as the wrong candidate that maintains a good topical relatedness with the context but violates common sense. The wrong candidates should either embody unreasonable reactions or intentions, or violate the nature of physical objects or concepts. And we require annotators not to select the first sentence, which usually aims to introduce story settings instead of narrating an event. We browse through the annotation results and give the annotators detailed feedback before approving their submissions. Finally, we collected 1,232 examples in total and split them for training, validation and testing.

3.2 Sentence Position Prediction

We use the sentence position prediction task (Chen et al., 2019) to evaluate the ability to capture inter-sentence relations (e.g., causality). We formulate the task as follows: Given a text with a sentence removed, models should choose the correct position of the sentence in the text from multiple candidates. Chen et al. (2019) constructed an English dataset for this task by randomly removing sentences from existing texts. However, such examples may be invalid since a sentence may have multiple plausible positions in a text,

Context	Wrong Candidates	Right Candidates
<p>傻狼和狐狸偷来一罐蜂蜜藏在树洞里，它俩规定谁也不许偷吃。可狐狸第二天就把蜂蜜偷吃光了。傻狼几次找狐狸去吃蜂蜜，狐狸总是不去。傻狼实在忍不住，结果跑过去一看，蜂蜜竟然见了底。傻狼心里懊恼，它想着，都怪狐狸不来吃，蜂蜜全都干掉了，丝毫没有怀疑狐狸。[MASK]</p> <p>A silly wolf and a fox stole a jar of honey and then hid it in a tree hole. They agreed that neither of them were allowed to eat the honey alone. However, the fox sneaked back to eat up all the honey the next day. Afterwards, whenever the wolf asked the fox to eat the honey together, the fox always refused its request. Finally the wolf could not help coming back to the tree hole and found that the jar had been empty. The wolf felt very regretful that the honey became dry because it had been too long. It had no doubts about the fox at all. [MASK]</p>	<p>狐狸听说后非常生气，他再也不敢跟傻狼一起找吃的了。</p> <p>When hearing this, the fox became very angry and decided no longer to look for food together with the wolf.</p>	<p>狐狸听说后，更加积极地跟傻狼一起去找吃的了。</p> <p>After hearing this, the fox became more active to look for food together with the wolf.</p>
<p>从前，山脚下住着母子二人。儿子长大后出门学艺，一直没有回来。妈妈就到城里找，谁知道儿子当了官竟不认她了。老妈妈坐在路边伤心地哭了，一个青年路过，知道了原由，将她接回家里。[MASK]他下令将那个不孝顺的儿子贬为了平民。而他的妈妈则在王宫里过上了幸福的生活。</p> <p>Once upon a time, there lived a mother and her son at the foot of a mountain. After her son grew up, he went out to learn skills and never came back. Therefore, the mother went to the nearby city to look for him. However, her son became an official and disowned his mother. The mother sat by the roadside and cried sadly. A young man passed by and knew the cause. Then the man took her home. [MASK] He decreed to remove the position of the disobedient son. And the mother lived happily in the palace.</p>	<p>谁知，这个青年也是一个官。</p> <p>Actually the man was also an official.</p>	<p>谁知，这个青年竟是王子。</p> <p>Actually the man was the prince of the city.</p>

Table 6: Two ClozeT examples. The right candidates are extracted from the original stories (at the position of “[MASK]”) while the wrong candidates are written by crowd-sourced annotators. The first example focuses on common sense regarding the *fox*’s reaction to the *silly wolf*’s behavior, while the second example focuses on common sense regarding the relations between *palace* and *prince*. We highlight the entities and events related to the commonsense relations in **red**, and those which violate common sense in the wrong candidates in **green**.

as illustrated in Table 5. Therefore, we construct the dataset for our task based on the following pipeline: (1) extracting paragraphs with less than 500 words from crawled stories; (2) randomly selecting a sentence to remove for each paragraph, and regarding all positions between two adjacent sentences as candidates³; and (3) asking annotators to refine part of the auto-constructed examples as the validation and test sets, and the remaining as the training set. Table 7 shows two SenPos examples.

Dataset Construction We asked annotators to refine each example so that the removed sentence has only one reasonable position in the text. We did not allow annotators to select the first or last sentence of the original text as the removed sentence because they usually contain obvious wording features (e.g., “once upon a time,” “they lived happily together”), which may make this task trivial. Unlike ClozeT, we allowed the texts for SenPos to be incomplete or include dialogues that also embody rich inter-sentence relations. Finally, we collected 1,663 examples for validation and testing through human annotation. And we

³We set the minimum length of the removed sentence to 10 Chinese characters, and we merge a sentence in a story with its neighbors if it contains less than 10 characters.

constructed 20,000 examples automatically for training.

3.3 Plot Completion

We use the Plot Completion task (Wang and Wan, 2019) to test the ability to make inferences based on common sense. We formulate this task as follows: Given a story with a sentence removed, models should generate a sentence to complete the story and make it reasonable and coherent.

Dataset Construction Prior studies (Wang and Wan, 2019; Paul and Frank, 2021) automatically constructed datasets for this task based on existing datasets by randomly removing one sentence from a story. However, as shown in Table 4, not all sentences in a story can be reasoned only based on the context and common sense. Therefore, we only used the above automatic method to construct the training data. And we adapted the ClozeT data to this task for validation and testing, since annotators have marked out the qualified sentences. Specifically, we randomly sampled some ClozeT examples and took the incomplete story of each example as input, and the right candidate as the target sentence to be generated.

Texts	Removed Sentences	Labels
<p>有一个姓蒋的人，祖父和父亲在捕蛇的时候被蛇咬死了，但是他却继续捕蛇。[1] 当柳宗元劝他不要在捕蛇的时候，这个人竟大哭起来，宁愿被蛇咬死，也不愿意放弃捕蛇。[2] 有的乡亲早已倾家荡产，食不裹腹了。[3] 差役们到进村子里收税赋的时候，横冲直撞，粗声叫骂，大打出手，乡亲们胆战心惊，苦苦哀求。[4] 这种场面连鸡狗都得不到安宁，何况人呢！</p> <p>There was a man named Jiang, whose grandfather and father were killed by snakes when catching them. But he still made his living by catching snakes. [1] When Liu advised him no longer to catch snakes, the man cried and said that he would rather be killed by snakes than give up catching snakes. [2] Actually some villagers had already lost everything and have nothing to eat. [3] They could do nothing but tremble with fear when the officers went into their houses to collect taxes and struck out violently. [4] Even dogs and chickens couldn't get any peace in such scenario, let alone humans!</p>	<p>因为他必须靠捕蛇才能上 缴官府的赋税。</p> <p>This was because he was able to pay taxes to the govern- ment only by catch- ing snakes.</p>	<p>[2]</p> <p>[2]</p>
<p>一只狼出去找食物，偶然经过一户人家，听到小孩哭声，接着又听见老太婆的声音：“别哭了，再哭就把你扔出去喂狼。[1]”狼一听心中大喜，便蹲在墙角等着，谁知等到天黑也不见把小孩扔出来。[2]却又听到老太婆说：“快睡吧，别怕，狼来了，咱们就把它杀死煮了吃。[3]”狼吓得一溜烟跑回了窝。[4]同伴问它收获怎样，它沮丧地说：“别提了”</p> <p>A wolf went out to look for food. It happened to pass by a house. It heard a child crying and then an old woman scared the child to say: “Do not cry! If you cry again, I will fling out you to feed wolves right away. [1]” Hearing this, the wolf was overjoyed and then squatted down and waited. However, the child was not flung out even when it was dark. [2] Suddenly, the woman said: “Don’t be afraid. If the wolf comes, let’s kill and eat it.” [3] The wolf was so frightened that he ran back to its lair. [4] When its friends asked it what happened, it said in dismay: “Don’t mention it.”</p>	<p>太阳落山了，狼已经等得 不耐烦了。转到房前想伺 机而入。</p> <p>After sunset, the wolf was getting im- patient and planned to break into the house.</p>	<p>[2]</p> <p>[2]</p>

Table 7: Two SenPos examples. The special tokens from [1] to [9] refer to the candidate positions. The first/second example focuses on testing the ability to capture the inter-sentence causal/temporal relations, respectively. We highlight the entities and events implying the relations in **red**.

3.4 Outline-conditioned Generation

Prior work tended to test the ability of long text generation through story generation conditioned on inputs with limited information such as titles (Yao et al., 2019). However, these tasks are extremely open-ended so that it is difficult to reliably measure the generation quality using automatic metrics (Guan and Huang, 2020). To alleviate the issue, we introduce the Outline-conditioned Generation task (Rashkin et al., 2020), which requires generating a coherent long-form story conditioned on an outline of characters and events. We formulate the outline as a set of out-of-order phrases, which not only narrows down the set of plausible stories but also serves for testing the controllability and planning ability of models to arrange the given events reasonably at the discourse level.

Dataset Construction We built the dataset for this task automatically based on filtered stories. We followed Rashkin et al. (2020) to extract the outline of a story using the RAKE algorithm (Rose et al., 2010). We extract at most eight phrases for each story, and each phrase contains no more than eight words. For example, the outline for the story in Table 1 is {“told his son with irony,” “purchasing flour from a mill,” “crossing the river,” “drop the sack into the river,” “indeed pushed the sack,” “familiar to his son’s temper,” “shouted,” “one bag”}. The outline can serve as discourse-level guidance for generation models, which should rearrange the events reasonably and

generate a story with a good global discourse structure, rather than focus on modeling only the local coherence.

3.5 Overall Score

Existing benchmarks usually summarize the performance of a model as a single score by averaging all metric scores without considering task difficulties. To encourage models to progress on those tasks where there is a more significant gap between machines and humans, we propose to average metric scores with different weights. Suppose that there are a total of M metrics for all tasks, we derive the overall score as follows:

$$S = \sum_{i=1}^M \frac{w_i}{\sum_{j=1}^M w_j} S_i, \quad (1)$$

$$w_i = \frac{H_i}{B_i}, \quad (2)$$

where H_i , B_i , and S_i are the score of humans, a pre-selected baseline, and the evaluated model for the i -th metric, respectively, and w_i is the weight for this metric. Intuitively, the metric scores where the baseline model has a larger gap with humans will have a larger weight when computing the overall score. We use BERT and GPT2 as the baseline models for the understanding and generation tasks in LOT, respectively.

Versions	d_m	d_{ff}	d_{kv}	n_h	n_e/n_d	# P
Small	512	2,048	64	8	6/6	60M
Base	768	3,072	64	12	12/12	223M
Large	1,536	3,072	64	12	24/32	1B

Table 8: Hyper-parameter settings for different versions of LongLM. d_m , d_{ff} , and d_{kv} are the dimension of hidden states, the feed forward layers, and the keys/values in the self-attention layers, respectively. n_h is the number of attention heads. n_e and n_d denote the number of hidden layers for the encoder and decoder, respectively. # P is the number of parameters.

4 Long Text Pretraining Model

To provide more flexibility on both understanding and generation tasks, we build LongLM following the original encoder-decoder design of Transformer (Vaswani et al., 2017) with three different sizes, as shown in Table 8. We follow Cui et al. (2020) to use a sentencepiece vocabulary of 32,000 wordpieces (Kudo and Richardson, 2018). And we set the maximum sequence length to 512 for both the encoder and decoder.

Pretraining Data We collect 120G novels as the pretraining data for LongLM, which cover various topics such as romance, military, and so on. Since a novel is usually much longer than the maximum input and output length of LongLM, we split a novel into multiple segments for pretraining.

Pretraining Tasks Encoder-decoder models are trained typically by maximizing the likelihood of the target output given an input. To improve capacities of both the encoder and decoder, we propose to train LongLM with two pretraining tasks including text infilling (Raffel et al., 2020) and conditional continuation (Radford et al., 2019). For the first task, the input is a text where a number of spans are sampled and replaced by special tokens with unique IDs, while the output is the spans delimited by the special tokens used in the input. The lengths of masked spans are drawn from a Poisson distribution with $\lambda=3$ and all masked tokens compress 15% of the original texts. As for the second task, the input and output are, respectively, the front and back half of a text, which is split into two parts randomly. We show an example of the pretraining tasks in Figure 1.

Pretraing Details We set the learning rate to $1e-4$ with the Adam optimizer and the batch size

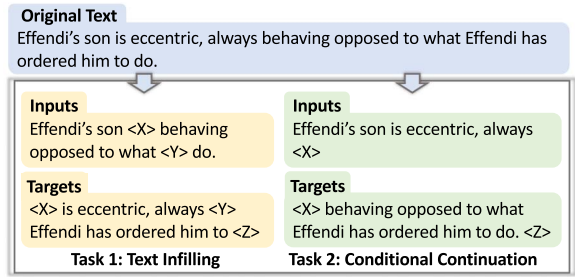


Figure 1: Schematic of the pretraining tasks. $\langle X \rangle$ and $\langle Y \rangle$ is the special tokens used for masking spans. $\langle Z \rangle$ is the ‘‘end of sequence’’ token.

Models	TextInfill		CondCont	
	PPL	BLEU-3/4	PPL	BLEU-3/4
LongLM _{small}	11.61	73.80/68.96	22.91	5.30/2.43
LongLM _{base}	8.24	<u>75.65/71.05</u>	17.03	<u>5.73/2.64</u>
LongLM _{large}	6.50	77.08/72.65	14.08	8.91/5.97

Table 9: Perplexity (PPL) and BLEU scores of LongLM for text infilling (TextInfill) and conditional continuation (CondCont). The best performance is in **bold** and the second best is underlined.

to 1,000. We pretrained LongLM for 2.5M steps. It took about two months to train the largest model using eight NVIDIA V100 GPUs.

Model Performance To assess the performance of LongLM on the pretraining tasks, we randomly separated out 1,000 texts from the initial pretraining data for testing, which were never seen in the pretraining phase. We used perplexity and BLEU- n ($n = 3, 4$) to evaluate both pretraining tasks. And we generated outputs using the greedy decoding algorithm for the text infilling task, and top- k sampling (Fan et al., 2018) with $k = 40$ and a softmax temperature of 0.7 (Goodfellow et al., 2014) for the conditional continuation task. As shown in Table 9, the performance improves substantially as the number of parameters increases.

5 Experiments

In this section, we tested LongLM and existing models on LOT with automatic and manual evaluation. Furthermore, we conducted extensive experiments to investigate the potential biases of the ClozeT and SenPos datasets (Section 5.5), and measure the overlap between training and testing data (Section 5.6).

5.1 Evaluated Models

We evaluated the following models, which are implemented based on the register models of HuggingFace Transformers:⁴ (1) **Vanilla Transformer**: It has the same architecture as BERT_{base} except that the number of layers is set to 3 (Vaswani et al., 2017). (2) **BERT**: It is implemented based on the *bert-base-Chinese* register model (Devlin et al., 2019). (3) **RoBERTa**: It is implemented based on the *hfl/chinese-roberta-wwm-ext* register model (Cui et al., 2020). (4) **GPT2**: It is implemented based on the *uer/gpt2-chinese-cluecorpussmall* register model (Zhao et al., 2019). (5) **mT5**: It is implemented based on the *google/mt5-base* register model (Xue et al., 2021). We set all the baseline models to the base version due to limited computational resources.

To show the generic benefits of the pretraining data of LongLM for long text modeling, we pre-trained a left-to-right language model from scratch on the data with the standard language modeling objective. This model has the same architecture as GPT2_{base} and is denoted as GPT2_{base}[†]. Moreover, we evaluated two task-specific pretraining models including PlotMachines (**PM**) (Rashkin et al., 2020) and Plan&Write (**PW**) (Yao et al., 2019), and two typical non-pretrained models including ConvS2S (Gehring et al., 2017) and Fusion (Fan et al., 2018) on the generation tasks in LOT. We used GPT2_{base} as the backbone model of PM and PW. For PM, we regard input sentences (for PlotCom) or input phrases (for OutGen) as the plot elements used in the memory network, and update the memory representations at each step of decoding. As for PW, we take a keyword extracted from the target sentence using the RAKE algorithm (for PlotCom) or the sorted input phrases in order (for OutGen) as the intermediate representations for planning. We implemented these models based on the codes provided by the original papers.

5.2 Experiment Settings

Understanding Tasks For both tasks, we encode the input of each example and then predict a distribution over all candidates by normalizing the dot-product values between the representations of each candidate and the context. We use the candidate with the maximum probability as the prediction result. For ClozeT, we represent

a candidate using the hidden state at the end of it, and we regard the hidden state at the position of the removed sentence appearing in the original text as the context representation. And for SenPos, we take the hidden state at each candidate position as the candidate representation and the hidden state at the end of the removed sentence as the context representation. When evaluating mT5 and LongLM, we feed the same input into the encoder and decoder (Lewis et al., 2020) and use the hidden states of the decoder for prediction in the above way.

Generation Tasks For PlotCom, we take the incomplete story of an example as input to generate the missing sentence. And for OutGen, we concatenate all phrases in an outline with special tokens as input to generate a story.

Hyper-Parameters For all models, we set the batch size to 12, the maximum sequence length to 512, and the learning rate to 3e-5. We decode outputs use top- k sampling with $k = 40$ and a softmax temperature of 0.7 for the generation tasks.

5.3 Automatic Evaluation

Metrics We use accuracy to evaluate the understanding tasks. As for generation tasks, we use BLEU- n (B- n) and Distinct- n (D- n) to evaluate the n -gram overlap with ground-truth texts (Papineni et al., 2002) and n -gram generation diversity (Li et al., 2016), respectively. We set $n = 1, 2$ for both generation tasks. Additionally, we also use the following two metrics to evaluate OutGen: (1) **Coverage (Cover)**: It is used to evaluate the generation controllability, which is computed as the average Rouge-L recall score (Lin, 2004) between the generated text and each input phrase. A higher coverage score indicates the generated text covers more input phrases. (2) **Order**: It is used to measure the gap between the positional orders of input phrases appearing in the generated texts and ground-truth texts. Specifically, we compute the order score as the average ratio of the number of inversions in the generated story to the number of all position pairs of any two phrases. An inversion refers to a position pair that are out of the ground-truth order. And we use the position of the longest common subsequence between a story and a phrase as the position of the phrase in the story. Because an input phrase does not always appear in the generated story,

⁴<https://huggingface.co/models>.

Models	# P	ClozeT	SenPos	Overall
Validation Set				
Transformer	38M	55.78	17.38	31.46
BERT _{base}	102M	70.75	40.13	51.36
RoBERTa _{base}	102M	72.11	51.63	59.14
GPT2 _{base}	102M	70.07	37.78	49.62
GPT2 _{base} [†]	102M	74.49	39.25	52.17
mT5 _{base}	582M	72.45	63.25	66.62
LongLM _{small}	60M	73.81	48.75	57.94
LongLM _{base}	223M	<u>75.17</u>	<u>64.38</u>	<u>68.34</u>
LongLM _{large}	1B	79.93	70.00	73.64
Humans	N/A	99.00	97.00	97.73
w_i	N/A	0.37	0.63	1.00
Test Set				
Transformer	38M	54.42	16.34	31.23
BERT _{base}	102M	69.39	43.68	53.74
RoBERTa _{base}	102M	67.69	51.35	57.74
GPT2 _{base}	102M	73.13	37.25	51.28
GPT2 _{base} [†]	102M	76.87	39.28	53.98
mT5 _{base}	582M	75.17	61.41	66.79
LongLM _{small}	60M	77.21	53.07	62.51
LongLM _{base}	223M	<u>77.55</u>	<u>62.34</u>	<u>68.29</u>
LongLM _{large}	1B	80.61	69.41	73.39
Humans	N/A	100.00	98.00	98.78
w_i	N/A	0.39	0.61	1.00

Table 10: Accuracy (%) on the understanding tasks in LOT. # P means the number of parameters. The best performance is in **bold** and the second best is underlined. w_i is the metric weight with BERT as the baseline model when computing the overall score.

we regard all position pairs of such a phrase and others as inversions.

Results Tables 10 and 11 show the results on the understanding and generation tasks, respectively. To obtain the human performance on the understanding tasks, we randomly sampled 100 examples from the validation set or test set and hired three crowd-sourced annotators (native Chinese speakers) to do these tasks. We made final decisions among them through majority voting. All results show an almost perfect inter-annotator agreement with Fleiss’s $\kappa > 0.85$ (Fleiss and Joseph, 1971). For generation tasks, we regard the scores of ground-truth texts as human performance.

We summarize the evaluation results as follows: **(1)** Pretrained models have significantly better performance than non-pretrained models. **(2)**

LongLM_{large} outperforms other baselines substantially on both the understanding and generation tasks. LongLM_{base}/LongLM_{small} achieves better overall scores with half fewer parameters than mT5/GPT2. **(3)** By comparing GPT2[†] and GPT2, we can derive that our pretraining data can effectively improve the ability to model long texts. **(4)** LongLM_{small} has a better performance than GPT2[†] on the understanding tasks, and is comparable with GPT2[†] on the generation tasks, suggesting the benefits of the encoder-decoder framework and the text infilling task. **(5)** It is still extremely challenging for all models to capture the commonsense and inter-sentence discourse relations between events in long texts for tackling the ClozeT and SenPos tasks. Furthermore, we investigate how the size of training data influences the accuracy of BERT for SenPos. The result in Figure 2 indicates the necessity to develop better representations of discourse relations instead of relying only on increasing the data size. **(6)** The results on the generation tasks show that LongLM does well in generating more word overlaps with references than similar-sized baselines for both tasks, and covers more input phrases and arranges them in correct orders for OutGen. But LongLM underperforms GPT2-based models in terms of diversity on PlotCom. **(7)** Dynamically tracking plot states (i.e., PM) does not bring significant improvement on the generation tasks compared with GPT2, suggesting that it may require modeling the discourse structure explicitly to tackle the generation tasks. And the superiority of PW to GPT2 on OutGen further indicates the benefit of modeling discourse-level features. In summary, we believe LOT will serve as an effective evaluation for capturing the commonsense and discourse relations of long texts beyond the surface events, and generating coherent and controllable long-form texts.

5.4 Manual Evaluation

Because automatic metrics may be unreliable for evaluating NLG (Guan and Huang, 2020), we conducted a point-wise manual evaluation to measure the disparity between machines and humans for the generation tasks in LOT. For each task, we randomly sampled 100 examples from the test set and obtained 100 ground-truth texts and 300 generated texts from three typical models including GPT2_{base}, mT5_{base} and

Models	# P	PlotCom				OutGen					Overall	
		B-1	B-2	D-1	D-2	B-1	B-2	D-1	D-2	Cover		Order
Validation Set												
ConvS2S	58M	18.92	4.18	6.31	32.18	29.23	10.38	3.45	21.79	14.81	25.34	11.85
Fusion	109M	20.56	4.69	8.63	35.73	29.22	10.34	3.39	22.67	17.41	26.55	12.61
GPT2 _{base}	102M	22.67	6.22	24.75	70.57	30.43	14.87	10.95	44.38	60.90	55.52	20.24
GPT2 _{base} [†]	102M	22.49	5.43	26.88	74.87	35.29	18.31	13.89	51.36	64.01	57.64	21.73
PM	102M	22.11	5.49	23.89	69.74	31.81	14.94	12.99	50.56	62.98	56.75	20.45
PW	102M	22.45	5.57	25.64	71.54	35.84	18.47	11.86	47.62	64.93	57.30	21.48
mT5 _{base}	582M	22.56	6.46	24.44	71.31	36.71	22.25	14.52	50.01	77.98	<u>63.15</u>	23.53
LongLM _{small}	60M	21.78	7.11	20.17	59.63	35.03	19.17	10.80	39.70	62.53	56.53	21.02
LongLM _{base}	223M	<u>22.91</u>	8.28	22.16	63.54	<u>40.33</u>	<u>24.29</u>	<u>14.66</u>	<u>51.82</u>	<u>79.60</u>	62.78	24.75
LongLM _{large}	1B	23.76	8.70	<u>25.93</u>	<u>72.18</u>	42.79	24.91	16.13	57.71	80.46	64.36	26.12
Truth	N/A	100.00	100.00	35.32	84.33	100.00	100.00	21.66	71.43	100.00	100.00	92.23
w_i	N/A	0.11	0.40	0.04	0.03	0.08	0.17	0.05	0.04	0.04	0.04	1.00
Test Set												
ConvS2S	58M	19.60	4.20	6.00	32.42	29.00	10.14	1.60	13.95	15.45	25.77	11.27
Fusion	109M	20.52	4.90	8.43	35.09	28.77	10.22	1.47	14.12	17.10	26.36	11.91
GPT2 _{base}	102M	22.94	5.76	24.69	70.30	30.17	14.91	7.62	36.87	60.87	55.90	19.21
GPT2 _{base} [†]	102M	22.45	5.38	26.08	73.26	35.79	18.68	9.89	43.52	64.43	56.96	20.76
PM	102M	22.87	5.75	24.08	<u>71.19</u>	31.85	15.24	8.62	41.32	63.15	57.21	19.77
PW	102M	22.76	6.07	25.55	70.72	35.12	17.96	8.68	40.17	63.70	55.17	20.52
mT5 _{base}	582M	22.52	6.48	24.33	70.53	36.33	22.07	<u>10.90</u>	43.65	78.66	<u>63.79</u>	22.59
LongLM _{small}	60M	22.05	7.45	19.93	59.79	34.48	19.17	7.93	34.25	63.75	57.64	20.48
LongLM _{base}	223M	<u>23.28</u>	<u>8.58</u>	21.37	62.43	<u>40.25</u>	<u>24.15</u>	10.75	<u>44.40</u>	<u>79.88</u>	63.67	<u>23.93</u>
LongLM _{large}	1B	24.20	9.06	<u>25.75</u>	71.08	42.10	24.77	12.04	50.29	81.48	64.82	25.29
Truth	N/A	100.00	100.00	35.01	84.56	100.00	100.00	15.71	63.46	100.00	100.00	91.64
w_i	N/A	0.10	0.42	0.03	0.03	0.08	0.16	0.05	0.04	0.04	0.04	1.00

Table 11: Evaluation results on the generation tasks in LOT. # P means the number of parameters. The best performance is in **bold** and the second best is underlined. w_i is the metric weight with GPT2_{base} as the baseline model when computing the overall score.

LongLM_{large}. For each text along with the input, we hired three crowd-sourced workers to judge its quality with a binary score (1 for good, and 0 otherwise) in terms of three aspects: (1) *grammaticality* (intra-sentence grammar quality of generated texts), (2) *coherence* (causal and temporal dependencies within generated texts), and (3) *relatedness to inputs* (reasonable logical connections to the input context for PlotCom; and reasonable utilization of input phrases for OutGen). These aspects are independently evaluated. We made final decisions among three annotators through majority voting. We show the annotation instructions in the appendix.

Table 12 shows the evaluation results. For both tasks, LongLM outperforms GPT2 and mT5 significantly in all aspects ($p < 0.05$, sign test). However, it is difficult for all models to generate a logical completion for PlotCom (relatedness score < 0.1), showing their poor ability to capture commonsense and inter-sentence relations.

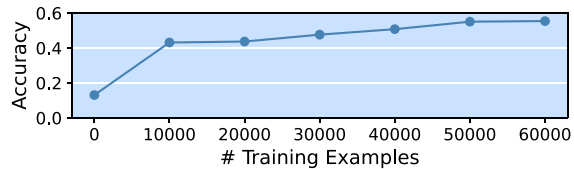


Figure 2: Accuracy of BERT for SenPos as the size of training data increases.

And the big gap between LongLM and humans also proves both tasks challenging to existing generation models. We also observe the positive correlation between the manual evaluation and automatic evaluation (Table 11), suggesting that it may be acceptable to use automatic evaluation to compare and improve models on the generation tasks in LOT.

5.5 Bias Investigation

It is essential to investigate potential biases of a dataset, which may leak information about target

Models	Gram (κ)	Cohe (κ)	Relat (κ)
Task: PlotCom			
GPT2 _{base}	0.84 (0.49)	0.41 (0.71)	0.01 (0.50)
mT5 _{base}	0.85 (0.24)	0.53 (0.65)	0.01 (0.50)
LongLM _{large}	0.95 (0.48)	0.82 (0.64)	0.09 (0.69)
<i>Truth</i>	1.00 (1.00)	1.00 (1.00)	0.99 (0.49)
Task: OutGen			
GPT2 _{base}	0.54 (0.52)	0.18 (0.52)	0.39 (0.43)
mT5 _{base}	0.53 (0.26)	0.08 (0.46)	0.49 (0.38)
LongLM _{large}	0.81 (0.23)	0.37 (0.43)	0.62 (0.45)
<i>Truth</i>	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)

Table 12: Manual evaluation results for PlotCom and OutGen in terms of grammaticality (**Gram**), coherence (**Cohe**), and relatedness (**Relat**). The best performance is highlighted in **bold**. All results show a fair inter-annotator agreement with Fleiss’ $\kappa > 0.2$.

labels and enable models to easily use shortcuts to handle complex inputs without actually mastering the focused abilities (Ribeiro et al., 2020). Therefore, we experimented with the following baselines to inspect the ClozeT and SenPos datasets: **(1) Random**: It chooses a candidate randomly. **(2) Majority**: It chooses the candidate with an index that is most frequently selected in the training set. **(3) Length**: For ClozeT, it chooses the candidate that contains more words; And for SenPos, it chooses the position of which the adjacent sentences have the closest number of words to the removed sentence. **(4) BLEU- n** : For ClozeT, it chooses the candidate with a higher BLEU- n score (Papineni et al., 2002) with the context; And for SenPos, it chooses the position of which the adjacent sentences have the largest average BLEU- n score with the removed sentence ($n = 1, 2$). **(5) Sentiment**: For ClozeT, it chooses the candidate with a higher sentiment score computed by an off-the-shelf Chinese sentiment analyzer;⁵ for SenPos, it chooses the position where the average sentiment score of its adjacent two sentences is the closest to the score of the removed sentence. **(6) Discourse Markers**: For ClozeT, it chooses the candidate where its adjacent sentences contain a discourse marker matching with it. For example, if “because” occurs in the last sentence before the position of the candidates, this baseline will choose the candidate that contains “so”.⁶ If there

⁵<https://github.com/isnowfy/snownlp>.

⁶Different from English, paired discourse markers like “because”-“so” should be used together in Chinese.

Baselines	ClozeT	SenPos
Random	50.00	16.03
Majority	52.72	16.24
Length	52.72	16.45
BLEU-1/2	46.94/48.98	14.14/14.95
Sentiment	50.34	16.49
Discourse Markers	45.92	9.15
BERT w/o Context	57.82	18.08
BERT w/o Long	62.24	19.00
<i>BERT</i>	69.39	43.68

Table 13: Accuracy (%) of different baselines on the test sets of ClozeT and SenPos for bias investigation. We use the results of BERT as a reference.

do not exist such paired markers in an example or there are multiple eligible candidates, this baseline will randomly choose one. The setting of this baseline for SenPos is similar to ClozeT. We manually define 24 marker pairs for this baseline. **(7) BERT w/o Context**: We fine-tuned BERT to directly choose without taking the context as input (Schwartz et al., 2017). **(8) BERT w/o Long**: It is used to study whether solving these tasks requires modeling long-range dependencies. For ClozeT, we fine-tuned BERT to choose with only the adjacent sentences of the removed sentence as input. And for SenPos, we encoded each position and its adjacent sentences respectively using BERT and then took the hidden states at these positions for prediction. These baselines cover different levels of features ranging from the token level (e.g., *Length*), the sentence level (e.g., *Sentiment*), to the discourse level (e.g., *Discourse Markers*, *BERT w/o Context*). We believe that these baselines will provide a comprehensive inspection for the potential biases of our datasets.

As shown in Table 13, both tasks can not be trivially solved by these baselines, suggesting that the datasets may be free of biases in terms of the above features. Therefore, we believe that the tasks can focus on testing the ability of models to capture long-range commonsense and discourse relations.

5.6 Memorization Investigation

Overlap between training and test data may result in an over-reporting of the generalization performance of machines. Therefore, it is necessary to investigate how many test data also show up in the training data. To this end, we follow

Tasks	ClozeT	SenPos	PlotCom	OutGen
Overlap with the Training Sets				
Percent	0.00%	0.62%	0.02%	0.00%
# 8-grams	0	1,040	6	2
# Exam	0	45	3	2
# Exam_{>10%}	0	17	0	0
Max Percent	0.00%	60.98%	2.53%	1.00%
Overlap with the Pretraining Data				
Percent	0.67%	4.68%	0.38%	1.22%
# 8-grams	172	7,844	151	1,212
# Exam	83	486	88	161
# Exam_{>10%}	4	71	1	26
Max Percent	47.22%	60.96%	30.77%	41.18%

Table 14: Overlapping analysis for the test sets of the four tasks with respect to their own training sets or the pretraining data of LongLM. We compute the following statistics: **(1) Percent**: the percentage of 8-grams from the test set that are also in the training sets or the pretraining data; **(2) # 8-grams**: the number of overlapped 8-grams; **(3) # Exam**: the number of examples that contain at least one overlapped 8-gram; **(4) # Exam_{>10%}**: the number of examples that have more than 10% overlapped 8-grams. **(4) Max Percent**: the maximum percentage of overlapped 8-grams from an example.

Radford et al. (2019) to measure the overlap between two datasets by calculating the percentage of 8-grams from one that are also in the other. We use the `jieba` tokenizer for tokenization.

Table 14 shows the overlapping analysis for test sets of the four tasks in LOT. We can see that all test sets have less than 1% overlap with their own training sets. Notably, there are 17 test examples of SenPos that contain more than 10% overlapped 8-grams with the training set. This is because a training example and a test example may come from the same story, and thus they share similar information (e.g., characters, locations). A test example contains at most 60.98% overlapped 8-grams, suggesting that the training set and test set do not include exactly the same example. As for the pretraining data of LongLM, the test sets of ClozeT and PlotCom still have less than 1% overlap. However, there are dozens of test examples in SenPos and OutGen that contain more than 10% overlapped 8-grams. Through manual inspection of the overlaps, we found that they mainly come from idioms, proverbs and classic

SenPos	Total	w/o Overlap (Training Set)	Δ
# Exam	863	846	N/A
mT5_{base}	61.41%	61.82%	+0.41%
LongLM_{large}	69.41%	69.50%	+0.09%
SenPos	Total	w/o Overlap (Pretraining Data)	Δ
# Exam	863	792	N/A
mT5_{base}	61.41%	61.24%	-0.17%
LongLM_{large}	69.41%	69.32%	-0.09%

Table 15: Accuracy on the test set of SenPos. **Total** means using the whole test set while **w/o Overlap** means excluding the examples that have more than 10% overlapped 8-grams with the training set or pretraining data from the test set. **# Exam** is the number of examples. Δ denotes the change of accuracy when excluding the overlapping data compared with using the total test set.

OutGen	Total	w/o Overlap (Pretraining Data)	Δ
# Exam	729	703	N/A
mT5_{base}	36.33	36.45	+0.12
LongLM_{large}	42.10	42.22	+0.12

Table 16: BLEU-1 score on the test set of OutGen. Other notations are the same as Table 15.

fairy tales, which may be part of some novels in the pretraining data.

To investigate how the overlapping data influence the measurement of models’ performance, we re-evaluated LongLM_{large} on the test sets of SenPos and OutGen with exclusion of the examples that have more than 10% overlapped 8-grams with the training sets or pretraining data. We also used mT5_{base} as a baseline in the same setting of LongLM. The results for SenPos and OutGen are shown in Tables 15 and 16, respectively. The change of accuracy or BLEU-1 score is very marginal for both mT5 and LongLM when excluding the overlapping data, suggesting that the superior performance of LongLM is rarely attributable to the memorization of training data. Therefore, we believe that it is fair to compare LongLM and other models on these tasks.

6 Conclusions

We present LOT, a story-centric benchmark for Chinese long text understanding and generation. LOT includes two story understanding tasks and two story generation tasks, which comprehensively investigate the abilities of commonsense reasoning, controllable generation, and modeling inter-sentence relations and the global discourse structures. We provide standard datasets for the four tasks, which are constructed based on human-written stories processed by automatic and manual annotation. Furthermore, we release a new Chinese long text pretraining model LongLM, which outperforms strong baseline models substantially on both the understanding and generation tasks in LOT. The LOT benchmark and the pretraining model will encourage further research on Chinese long text modeling.

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