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

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Abstract

Standard multi-task benchmarks are essential for driving the progress of general pretraining models to generalize to various downstream tasks. However, existing benchmarks such as GLUE and GLGE tend to focus on short text understanding and generation tasks, without considering long text modeling, which requires many distinct capabilities such as modeling long-range commonsense and discourse relations, as well as the coherence and controllability of generation. The lack of standardized benchmarks makes it difficult to fully evaluate these capabilities of a model and fairly compare different models, especially Chinese pretraining models. Therefore, we propose LOT, a benchmark including two understanding and two generation tasks for Chinese long text modeling evaluation. We construct the datasets for the tasks based on various kinds of human-written Chinese stories. Besides, we release an encoder-decoder Chinese long text pretraining model named LongLM with up to 1 billion parameters.We pretrain LongLM on 120G Chinese novels with two generative tasks including text infilling and conditional continuation. Extensive experiments on LOT demonstrate that LongLM matches the performance of similar-sized pretraining models on the understanding tasks and outperforms strong baselines substantially on the generation tasks.

1 Introduction

Pretrained language models such as BERT (Devlin et al., 2019) and GPT2 (Radford et al., 2019) have achieved significant advances in a wide array of natural language understanding (NLU) and generation (NLG) tasks. Besides, the standard evaluation benchmarks such as GLUE (Wang et al.,
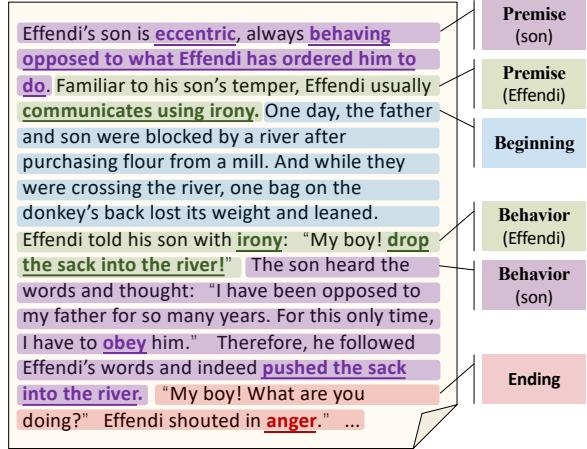

Figure 1: A story example (Left) and its discourse structure (Right). The concepts and events concerning commonsense and discourse relations are highlighted in **Bold**.

2019) also further boost the improvement and fast iteration of the language models. Existing popular benchmarks tend to aggregate multiple tasks to spur the development of generalizable models. However, these benchmarks still focus mainly on understanding and generating short texts. For example, the GLUE tasks, which are commonly used for evaluating NLU, take at most two sentences as input. Besides, the tasks in existing NLG benchmarks such as GLGE (Liu et al., 2020) either require generating only several words (e.g., dialogue generation) or provide sufficient information in the source input to generate desired target texts (e.g., text summarization), without considering the capability to generate open-ended long texts such as expanding reasonable plots to form coherent stories. Although there have recently been many pretrained models proposed for long text modeling, such as GPT3 (Brown et al., 2020) and CPM(Zhang et al., 2020), the lack of benchmark datasets makes it difficult to fully assess the capabilities of these models and fairly compare them.

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In this paper, we present LOT, a multi-task benchmark for the evaluation of *Chinese **LO**ng **T**ext understanding and generation*. As exemplified in Figure 1, modeling long texts requires many unique capabilities in contrast to short texts, including: (1) long-range commonsense reasoning regarding the characters' reaction and intention (e.g., *"Effendi ordered his son with irony"*, and then *"the son obeyed Effendi"*, but finally *"Effendi felt angry"*) and the nature of physical objects and concepts (e.g., the relation between *"irony"* and *"Effendi"*'s behavior); (2) modeling discourse coherence such as inter-sentence relations (e.g., causality) and global discourse structures (e.g., the *"premise"* to introduce the characters' personalities, the *"beginning"*, *"behavior"* and *"ending"* of the story, and the relations among the elements); and (3) controllability of generation, which requires both imposing controllable attributes such as topics (e.g., *"communicating using irony"*) on generation and maintaining text coherence. Accordingly, LOT contains two understanding tasks and two generation tasks regarding the above fundamental capabilities. Besides, we construct datasets for the proposed tasks using manual annotation based on various kinds of stories, including fictions, fables and fairy tales, which are collected from public web resources.

Besides, we release LongLM, a *Chinese **Long** text pretraining **L**anguage **M**odel*. LongLM is a Transformer-based encoder-decoder model with 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). 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 show that LongLM achieves comparable performance with existing pretraining models on the understanding tasks of LOT, and outperforms strong baselines substantially on the generation tasks. But LongLM is still far from human performance, which requires better semantic representations of events, as well as 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 benchmark LOT for Chinese long text understanding and generation evaluation which consists of four tasks centered on testing the fundamental capabilities for modeling long texts. We also present new datasets for these tasks.

II. We release a new Chinese pretraining model LongLM for long text modeling[1]. Experiment results show the strong performance of LongLM on LOT, but there still exists huge room for improvement. Besides, we will also release an evaluation platform and a leaderboard to encourage improvement on long text modeling.

2   Related Work

Benchmarks   Recently, there have been many multi-task benchmarks proposed for evaluating NLU and NLG to drive the progress of general language models. The benchmarks usually aggregate a set of 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 the tasks to the discourse level regarding inter-sentence discourse relations. GLUE (Wang et al., 2019) included more diverse tasks such as natural language inference (Rocktäschel et al., 2016), and allowed for models without explicit representations. Afterward, Sarlin et al. (2020) proposed SuperGLUE as a more challenging counterpart of GLUE by introducing multi-sentence tasks. But the tasks are only limited to the formats of coreference resolution and question answering. In addition to these English benchmarks, an increasing number of benchmarks were proposed to evaluate NLU for other languages such as CLUE (Xu et al., 2020a) for Chinese. Furthermore, 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.

Story Datasets   Prior studies in the field of story understanding and generation have frequently focused on the ROCStories (Mostafazadeh et al., 2016) and WritingPrompts (Fan et al., 2018)

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[1]The LOT benchmark datasets, the pretraining data and the LongLM pretraining models are available on `https://github.com/thu-coai/LOT-Benchmark`.

datasets. ROCStories contains 100k artificial stories with various everyday events. And WritingPrompts consists of 300K pairs of prompts and fiction stories. Besides, recent works collected long-form stories for modeling longer sequences, such as PG-19 (Rae et al., 2020), `roleplayerguild` (Louis and Sutton, 2018) and STORIUM (Akoury et al., 2020). However, all the above datasets are written in English, and the lack of high-quality Chinese story datasets hinders the development of Chinese language models.

Story Understanding and Generation Recent studies have proposed various tasks to test the ability of story understanding and generation. Firstly, 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, that is to say, commonsense relations between everyday events. Secondly, 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). Another line is learning to judge story coherence such as evaluating story generation (Guan and Huang, 2020) and predicting the correct position of a sentence in a story (Chen et al., 2019). Thirdly, some studies focused on controllability, namely, the imposing of controllable attributes such as keywords (Xu et al., 2020b), emotional trajectories (Brahman and Chaturvedi, 2020) and story outlines (Rashkin et al., 2020) on story generation. In this paper, we design LOT as a comprehensive benchmark to test the generalization of NLG models across various tasks for Chinese long text modeling.

3 LOT Benchmark

We aim to provide a comprehensive and model-agnostic benchmark to evaluate the ability of understanding and generating long texts. To this end, 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 the corresponding dataset statistics in Table 1 and 2 respectively. Although most examples in LOT contain only hundreds of words, they are well designed to serve as the start point to evaluate the fundamental capabilities of long text modeling.

We design the tasks based on the following principles: **(1) Task Diversity:** The tasks vary in task formats, focused capabilities, types and lengths of inputs and outputs, and dataset sizes, which serve as 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 those texts with domain-specific knowledge such as scientific articles. Therefore, the tasks 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 upon to be challenging but meaningful. Furthermore, we introduce new Chinese datasets for these tasks, which are constructed to focus more specifically on testing different capabilities than original datasets. **(4) Automatic Evaluation:** There are automatic metrics for these tasks to reliably evaluate the target capabilities. We exclude open-ended generation tasks such as story generation from beginnings, which is difficult to automatically evaluate (Guan et al., 2021) since the tasks suffer from the notorious one-to-many issue: there are many plausible outputs for the same input (Zhao et al., 2017).

3.1 Cloze Test

Mostafazadeh et al. (2016) introduced the Story Cloze Test (SCT) task for evaluating story understanding, particularly in terms of commonsense reasoning, which requires selecting the right ending from two candidates given a four-sentence context. However, the original SCT task still suffers from the following issues: (1) The task focuses only on reasoning endings but neglects other types of commonsense reasoning, such as abductive reasoning (Bhagavatula et al., 2019), which requires reasoning what happens between observed beginnings and endings. (2) The crowd-sourced SCT dataset was reported to contain innate biases between wrong and true endings in some stylistic features such as lengths (Schwartz et al., 2017; Sharma et al., 2018). Such biases may leak information about the target labels. And (3) SCT limits the scope of commonsense reasoning to realistic events. However, the definition may be neither necessary nor sufficient for general long texts. For example, *"Cupid can fly"* can be reasoned based on common sense although it is not realistic, while some story settings may be real-

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

Table 1: Overview of the tasks in LOT for the capabilities they investigate, inputs and outputs, and the evaluation metrics. **Dist** and **Cover** refer to Distinct and Coverage (Section 5.3), respectively.

Datasets	Train	Val	Test
ClozeT			
# Examples	1,283	105	210
Vocabulary Size	16k	3k	5k
Avg. # Word in Input Text	90.15	87.85	89.93
Avg. # Sent in Input Text	5.96	6.10	5.84
Avg. # Word in Candidate	15.79	15.90	16.20
SenPos			
# Examples	20,000	800	863
Vocabulary Size	147k	10k	22k
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
PlotCom			
# Examples	13,099	465	466
Vocabulary Size	22k	8k	8k
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
OutGen			
# Examples	1,456	242	729
Vocabulary Size	19k	6k	12k
Avg. # Word in Input Text	19.20	19.05	19.47
Avg. # Phrase in Input Outline	8.00	8.00	8.00
Avg. # Word in Output Text	108.91	108.68	109.04
Avg. # Sent in Output Text	7.20	7.11	7.15

Table 2: Statistics for the datasets in LOT. The abbreviation **sent** and **len** are short for **sentence** and **length**, respectively.

istic but fails to be reasoned only based on the context and common sense, as shown in Table 3. To alleviate the above issues, we limit commonsense reasoning to those events that embody either characters' reaction and intention, or the nature of physical objects and concepts. And we construct the Cloze Test dataset following the above princi-

ple. Table 4 shows two Cloze Test examples.

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 3: An example for selecting a sentence that can be reasoned based on the context and common sense (in **bold**). We also highlight a sentence that does not satisfy the requirement in *italic*, which introduces a new character *"the Devil King"* weakly related to the main plot.

Story Collection We firstly crawl public Chinese short stories such as fables as the data source. Then, we ask annotators to judge whether the stories meet 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). Table 5 shows the examples we provided for the annotators to instruct them about the constraints. And we ask annotators to refine those stories which do not meet the constraints. Besides, annotators should also clean up the stories with following heuristics: (1) refusing examples which may violate general ethical principles (e.g., discrimination); (2) deleting noisy words (e.g., links); (3) refine the slang and informal words into standard modern Chinese; (4) turning the dialogues to objective events. Finally, we collect 2,427 high-quality Chinese short stories with rich commonsense relations.

Dataset Construction We present the collected stories to another group of annotators to construct the Cloze Test dataset. For each story, they should select a sentence (i.e., the right candidates) that can be reasoned based on the context and common sense. Table 3 shows an example presented to the

Context	Wrong Candidates	Right Candidates
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] 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]	狐狸听说后非常生气，他再也不跟傻狼一起去找吃的了。 When hearing this, *the fox became very angry* and decided *no longer to look for food together with the wolf*.	狐狸听说后，更加积极地跟傻狼一起去找吃的了。 After hearing this, the fox became **more active to look for food together with the wolf.**
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。哪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。 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**.	谁知，这个青年也是一个官。 Actually the man was also an *official*.	谁知，这个青年竟是王子。 Actually the man was the **prince** of the city.

Table 4: Two examples for the Cloze Test task. 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 behaviour, while the second example focuses on common sense regarding the relations between the concepts *"palace"* and *"prince"*. We highlight the entities and events related to the commonsense relations in **bold**, and those which violate common sense in the wrong candidates in *italic*.

Example 1: *Mr. Dolphin runs a school for marine animals. He employs squid as the teacher of smoke screen, electric eel as the teacher of electricity generation, swordfish as the teacher of speed swimming, and he teaches sonar lessons himself.*

Example 2: A group of monkeys lived on a hill by the river. *The mountain is full of waterfalls and springs, with lush trees and beautiful scenery* ··· *Since then, they have been living a leisurely life.* One day, the King of Wu took a boat with his men to ···

Example 3: ··· A few minutes ago, he had been fanned with envy. *He wanted to do anything for her, but he didn't know what to do. That was the most painful part: he didn't know how to help her. He was the only one who could help her* ···

Table 5: Poor examples of stories provided for annotators for story collection. Each of the examples does not meet one of the following constraints in order: (1) having a clear beginning and ending; (2) not stating anything irrelevant to the main plot; and (3) not containing too many descriptive, expository or argumentative sentences. We highlight the sentences leading to the above issues in *italic*.

annotators to illustrate how to judge whether a sentence satisfies the requirement regarding common sense. And then the annotators rewrite the sentence into another one (i.e., the wrong candidate) that maintains a good topical relatedness with the context but violates the common sense. The wrong candidates should either embody unreasonable reaction or intention or violate the natures of physical objects or concepts. Besides, we require annotators not to rewrite the first sentence, which usu-

ally aims to account for 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 collect 1,598 examples in total and we split them randomly for training, validation and testing.

Bias Investigation We investigate the implicit statistical biases between right and wrong candidates by experimenting with following baselines on the ClozeT task: **(1) Length:** Choose the candidate which contains more words (tokenized by jieba[2]). **(2) Constant-First:** Choose the first candidate constantly. **(3) Sentiment:** Choose the candidate with a lower sentiment score. We compute the score using an off-the-shelf Chinese sentiment classifier[3] ranging from 1 to 5. **(4) BLEU-n:** Choose the candidate with a higher BLEU-n (Papineni et al., 2002) score with the context. We set $n = 1, 2$. **(5) BERT w/o Context:** We finetune BERT to directly choose the right answer from two candidates without taking the context as input (Schwartz et al., 2017). As shown in Table 6, the task can not be trivially handled by the above baselines.

Baselines	Validation	Test
Length	51.43	52.38
Constant-First	48.57	50.95
Sentiment	54.29	50.05
BLEU-1/2	57.14/54.29	53.81/50.48
BERT w/o Context	54.29	55.24

Table 6: Accuracy of different baselines on the validation and test sets of the ClozeT task for bias investigation.

3.2 Sentence Position Prediction

We introduce the sentence position prediction task (Chen et al., 2019) to evaluate the capability of capturing the inter-sentence relations (e.g., causality) in long texts. We formulate the task as follows: given a text with a removed sentence, we require models to choose the correct position of the sentence in the text from multiple candidates. Chen et al. (2019) constructed English testing examples for the task by randomly removing sentences from the original texts in existing datasets. However, such examples may be unreliable since a sentence may have multiple plausible positions in a story. As illustrated in the first example in Table 8, the story is plausible even when randomly permutating the last three sentences. Therefore, we construct the test examples for the 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 the positions between two adjacent sentences as candidates[4], and (3) asking annotators to refine part of the auto-constructed examples as the validation and testing sets, and the left as the training set. Table 7 shows two Sentence Position Prediction examples.

Dataset Construction We present typical examples to annotators to illustrate the constraints for the test examples, as shown in Table 8. Besides, we do not take the first or last sentence of the original text as the removed sentence since they usually contain obvious wording features (e.g., *"once upon a time"*, *"they lived happily together"*), which may make this task trivial. Then we ask annotators to refine the examples which do not sat-

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[2]https://github.com/fxsjy/jieba

[3]https://github.com/isnowfy/snownlp

[4]We set the minimum length of the removed sentences to 10 Chinese characters, and merge a sentence in the texts with its neighbors if it contains less than 10 characters.

isfy the constraints by selecting another sentence to remove, adding or deleting candidate positions, or deleting noisy words in the examples. Note that unlike Cloze Test, we allow the texts for this task to be incomplete or to include dialogues which also embody rich inter-sentence relations. Finally, we collect 1,663 examples for validation and testing by human annotation, and construct 20,000 examples automatically for training.

Bias Investigation We compute the position distribution of removed sentences, and how the number of word overlaps with the removed sentence changes with the distance with it for any one sentence in the corresponding text. As illustrated in Figure 2, the task can not be trivially handled by constantly predicting certain positions or predicting those positions where the neighbor sentences have many word overlaps with the removed one.

3.3 Plot Completion

We introduce the Plot Completion task (Wang and Wan, 2019) to investigate the capability of making inference based on common sense and inter-sentence relations in the context. We formulate the task as follows: given an incomplete story with a removed sentence, the models should generate a sentence to complete the story and make it reasonable and coherent.

Dataset Construction Prior studies (Wang and Wan, 2019) addressed the Plot Completion task based on auto-constructed data from existing story datasets by removing one sentence randomly from a story. However, as illustrated in Table 3, not all the events in a story can be reasoned only based on the context. Therefore, we use the above mentioned automatic approach to construct examples only for training. And in order to reliably assess the focused abilities, we adapt the Cloze Test examples to this task for validation and testing, since annotators have marked out the sentences which can be reasoned based on the context. Specifically, we randomly sampled some Cloze Test examples and take the incomplete story of each example as input, and the right candidate as the target sentence to be generated. Besides, we also make sure to remove the stories used in the validation and test sets from the training examples.

3.4 Outline-conditioned Generation

Prior studies tended to evaluate the capability of long text generation by story generation con-

Texts	Removed Sentences	Labels
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！	因为他必须靠蛇才能上缴官府的赋税。	[2]
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!	This was **because he was able to pay taxes to the government only by catching snakes.**	[2]
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"	太阳落山了，狼已经等得不耐烦了.转到房前想伺机而入。	[2]
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."	**After sunset**, the wolf was getting impatient and planned to **break into the house.**	[2]

Table 7: Two examples for the Sentence Position Prediction task. The special tokens from [1] to [9] refer to the candidate positions. The first/second example focuses on testing the capability to capture the causal/temporal relation between sentences, respectively. We highlight the entities and events implying the relations in **bold**.
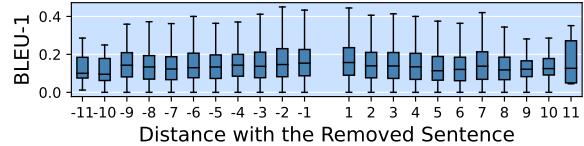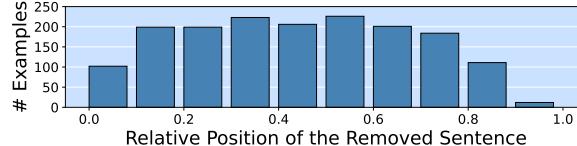

Figure 2: The distribution of positions of removed sentences (**Left**) and the correlation between the BLEU-1 score with the removed sentence and the distance with it (minus/plus means before/after it) for any one sentence in the text (**Right**). We compute the relative position of the removed sentence as the ratio of the number of words before it to the total length of the text.

Example 1: I couldn't control my anger very well. My parents would yell at me, and i ran to my room. I buried my head in a pillow and screamed. I threw my pillow and hit it hard. *I tried to express my anger without them knowing.*

Example 2: ⋯ *for example, a piece of rose petals, left over from the summer, because I'm not a housekeeper with high vigilance.* **Anyone can know that by just looking at the dust on the mantelpiece to know.** *It is said that this is the dust of Troy has implanted the three layers.*

Example 3: *Over the winding lotus pool, as far as the eye can see, are fields of leaves.* **The leaves rose high out of the water, like the skirts of graceful dancers.** *And here and there, layers of leaves were dotted with white lotus flowers* ⋯

Table 8: Poor examples provided for annotators for the Sentence Position Prediction task. The sentences to be removed are in **bold**. Each of the texts does not meet one of the following constraints in order: (1) the removed sentences should only have one reasonable position in the original texts; (2) the texts should be coherent in isolation; and (3) not stating too many descriptive, expository or argumentative sentences. We highlight the words leading to the above issues in *italic*.

ditioned on inputs with very limited information such as titles (Yao et al., 2019). However, these tasks are extremely open-ended (Guan et al., 2020), making it difficult to reliably measure the generation quality by automatic metrics (Guan and Huang, 2020), for there are multiple plausible stories conditioned on such inputs. 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 in the task, which not only narrows down the set of plausible stories but also serves for investigating the controllability and planning ability of generation models to arrange the given events reasonably at the discourse level.

Dataset Construction We construct the dataset for this task automatically based on crawled stories. Specifically, we follow 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 Figure 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 a discourse-level guidance for generation models, which should rearrange the events reasonably and generate a story with 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 with a single score by averaging all the metric scores without considering the task difficulty. To encourage models to focus on making progress on those tasks where there is still a big gap between machine and human performances, we compute the overall score of a model by averaging the metric scores with different weights. Suppose that there are M metrics totally for all the benchmark 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 performance 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, respectively.

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 two different sizes, as shown in Table 9. 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 public novels as the pretraining data for LongLM, which

Versions	d_{m}	d_{ff}	d_{kv}	n_{h}	$n_{\mathrm{e}}/n_{\mathrm{d}}$	# 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 9: 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, 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.

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

Table 10: Perplexity (PPL) and BLEU scores of different versions of LongLM for the text infilling task (TextInfill) and conditional continuation (CondCont). The best performance is in **bold** and the second best is <u>underlined</u>.

cover various topics such as romance, military and history. Since the length of a novel is usually much larger 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 the long text modeling ability of both the encoder and decoder, we 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 random 15% words are dropped out and each consecutive span of dropped-out words is replaced by a special token with a unique ID, while the output is the dropped-out spans of words, delimited by the corresponding special tokens used in the input. 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.

Pretraing Details We set the learning rate as 1e-4 with the Adam optimizer and the batch size as 1,000. We pretrain LongLM for about 2.5M steps. It takes about two month to train the largest model using eight NVIDIA V100 GPUs.

Model Performance for assessing the performance of different versions of LongLM, we ran-

domly separate out 1,000 texts from the initial pre-training data as the test set, which are never seen in the pretraining phase. We use perplexity and BLEU-3/4 as the evaluation metrics for both pre-training tasks. And we generate 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 10, the performance improves substantially with the number of parameters increasing.

5 Experiments

5.1 Evaluated Models

We experiment with LongLM and following baselines implemented based on the register models of HuggingFace[5]: **(1) Vanilla Transformer:** The model has the same model architecture with $BERT_{base}$ except that we set the number of layers to 3. **(2) BERT:** We implement the model based on the *bert-base-Chinese* register model. **(3) RoBERTa:** We implement the model based on the *hfl/chinese-roberta-wwm-ext* register model. **(4) GPT2:** We implement the model based on the *uer/gpt2-chinese-cluecorpussmall* register model. **(5) mT5:** We implement the model based on the *google/mt5-base* register model. We set all the baseline models to the base version due to the limited computational resources.

To demonstrate the general benefits of our pre-training data for long text modeling, we also pretrain a language model from scratch on our dataset, which has the same architecture with the base version of GPT2. We denote the baseline as $GPT2^{\dagger}$. Moreover, we also evaluate two typical non-pretrained models including ConvS2S (Gehring et al., 2017) and Fusion (Fan et al., 2018) on the generation tasks in LOT. We implemented the two models based on the tools provided by the original paper.

5.2 Experiment Settings

Understanding Tasks For ClozeT, after encoding the candidates and the context of an example, we feed the average hidden state across all the positions (for GPT2) or the hidden state at the position of the `[CLS]` token (for BERT-style baselines) to an MLP layer to predict a binary distribution over two candidates. As for mT5 and

Models	# P	ClozeT	SenPos	Overall
Validation Set				
Random	N/A	50.00	13.07	28.60
Transformer	38M	51.90	17.38	31.89
$BERT_{base}$	102M	59.52	40.13	48.28
$RoBERTa_{base}$	102M	**63.81**	51.63	56.75
$GPT2_{base}$	102M	59.52	37.78	46.92
$GPT2^{\dagger}_{base}$	102M	60.95	39.25	48.37
$mT5_{base}$	582M	60.48	<u>55.88</u>	<u>57.81</u>
$LongLM_{small}$	60M	58.10	32.00	42.97
$LongLM_{base}$	223M	61.43	47.13	53.14
$LongLM_{large}$	1B	<u>61.90</u>	**62.25**	**62.10**
Humans	*N/A*	*99.00*	*92.00*	*94.94*
w_i	*N/A*	*0.42*	*0.58*	*1.00*
Test Set				
Random	N/A	50.00	13.19	29.18
Transformer	38M	50.95	16.34	31.37
$BERT_{base}$	102M	58.33	43.68	50.46
$RoBERTa_{base}$	102M	59.76	51.35	55.21
$GPT2_{base}$	102M	57.62	37.25	46.10
$GPT2^{\dagger}_{base}$	102M	59.29	39.28	48.05
$mT5_{base}$	582M	59.05	<u>55.39</u>	<u>56.99</u>
$LongLM_{small}$	60M	59.52	36.27	46.46
$LongLM_{base}$	223M	<u>60.24</u>	49.02	53.94
$LongLM_{large}$	1B	**61.19**	**59.91**	**60.47**
Humans	*N/A*	*98.00*	*94.00*	*95.75*
w_i	*N/A*	*0.44*	*0.56*	*1.00*

Table 11: Accuracy (%) of different models on the understanding tasks in LOT. # P means the number of parameters. The best performance is in **bold** and the second best is <u>underlined</u>. w_i is the metric weight with BERT as the baseline model when computing the overall score.

LongLM, we require it to generate a single word corresponding to the target label (Raffel et al., 2020). And we count the model's output as wrong if it corresponds to neither of the possible labels.

For SenPos, We concatenate the text and the removed sentence in sequence as the input for all the models. And we predict a distribution over all the candidate positions by normalizing the dot-product values between the hidden states at the position of the end of the removed sentence and at each candidate. When testing mT5 and LongLM, we only use the encoder for fine-tuning and evaluation on this task.

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

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$_{base}^{\dagger}$	102M	22.49	5.43	**26.88**	**74.87**	35.29	18.31	13.89	51.36	64.01	57.64	21.73
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>	<u>8.28</u>	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	<u>24.75</u>
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$_{base}^{\dagger}$	102M	22.45	5.38	**26.08**	**73.26**	35.79	18.68	9.89	43.52	64.43	56.96	20.76
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>	<u>71.08</u>	**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 12: 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 <u>underlined</u>. w_i is the metric weight with GPT2$_{base}$ as the baseline model when computing the overall score.
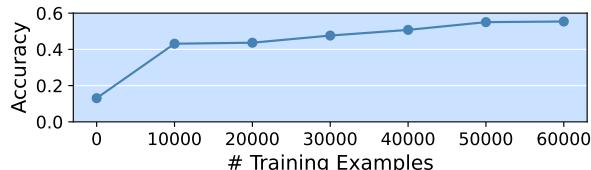

Figure 3: Accuracy (%) of BERT for the SenPos task changing with the number of training examples.

Model Settings For all the evaluated models, we set the batch size to 12, the maximum sequence length to 512, and the learning rate to 3e-5. And we generate outputs using top-k sampling (Fan et al., 2018) with $k = 40$ and a softmax temperature of 0.7 (Goodfellow et al., 2014) for the generation tasks.

5.3 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. Besides, we also use follow-

ing automatic metrics for the OutGen task: **(1) Coverage (Cover):** We use the metric to evaluate the generation controllability, which is computed as the average Rouge-L score (Lin, 2004) between the generated text and each phrase in the input outline. A higher coverage score indicate the generated texts contain more phrases in the outlines. **(2) Order:** We use the metric to measure the difference between the order of phrases appearing in the generated text and the ground-truth text. Specifically, we regard the position of a phrase appearing in a text as that of the longest common subsequence between them. Then we compute the order score as the ratio of the number of inversions, i.e., the position pairs that are out of the ground-truth order, to the number of all the position pairs. Note that if the longest common subsequence between a phrase and a text contains less than two Chinese characters, we count all the position pairs between the phrase and others as inversions.

5.4 Results and Analysis

Table 11 and 12 show the evaluation results on the understanding and generation tasks in LOT,

respectively. To obtain the human performance for the understanding tasks, we randomly sample 100 examples from the corresponding sets and ask non-expert college students to do the tasks. And we regard the scores of ground-truth texts as the human performance for the generation tasks.

The results of the overall scores demonstrate that pretrained models achieve significantly better performance than non-pretrained models. And LongLM$_{large}$ outperforms baseline models substantially on both understanding and generation tasks. Notably, LongLM$_{base}$/LongLM$_{small}$ has half less parameters than mT5/GPT2, but achieves better performance in terms of the overall score of the generation tasks with half less parameters. LongLM$_{small}$ also outperforms GPT2 in terms of the overall score of the generation tasks. However, all the models are still far from human performance. By comparing GPT2† and GPT2, we can derive that our pretraining data can effectively improve the capability of long text modeling. And the comparable performance between LongLM$_{small}$ and GPT2† shows the benefits of the encoder-decoder framework and various pretraining tasks.

As for individual tasks, we can see that it is still extremely challenging for all the models to capture the commonsense and inter-sentence discourse relations between events in long texts for tackling the ClozeT and SenPos tasks. And LongLM$_{base}$ achieves a comparable performance with BERT and RoBERTa. Furthermore, we show the accuracy results of BERT for SenPos when increasing the size of training examples in Figure 3, which indicates that it is still necessary to develop better representations of discourse relations instead of relying only on increasing the dataset size. Moreover, the results on the generation tasks show that LongLM can generates more word overlaps with the ground-truth texts for both the PlotCom and OutGen tasks, and cover more input phrases and arrange them in correct orders than baselines for the OutGen task. In summary, we believe LOT will serve as an effective evaluation for the ability to capture the commonsense and discourse relations of long texts beyond the surface events, and generate controllable long-form texts.

6 Conclusions

We present LOT, a multi-task benchmark for Chinese long text understanding and generation. LOT includes two understanding tasks and two 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. Besides, we release a new Chinese long text pretraining model LongLM, which outperforms strong baseline models substantially on the generation tasks in LOT. The LOT benchmark, the pretraining model, and the leaderboard will encourage further research on Chinese long text modeling.

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