An Interpretability Evaluation Benchmark for Pre-trained Language Models

Yaozong Shen, Lijie Wang, Ying Chen, Xinyan Xiao, Jing Liu, Hua Wu
Baidu Inc, Beijing, China
{shenyaozong,wanglijie@baidu.com}

Abstract

While pre-trained language models (LMs) have brought great improvements in many NLP tasks, there is increasing attention to explore capabilities of LMs and interpret their predictions. However, existing works usually focus only on a certain capability with some downstream tasks. There is a lack of datasets for directly evaluating the masked word prediction performance and the interpretability of pre-trained LMs. To fill in the gap, we propose a novel evaluation benchmark providing both English and Chinese annotated data. It tests LMs abilities in multiple dimensions, i.e., grammar, semantics, knowledge, reasoning and computation. In addition, it provides carefully annotated token-level rationales that satisfy sufficiency and compactness. It contains perturbed instances for each original instance, so as to use the rationale consistency under perturbations as the metric for faithfulness, a perspective of interpretability. We conduct experiments on several widely-used pre-trained LMs. The results show that they perform very poorly on the dimensions of knowledge and computation. And their plausibility in all dimensions is far from satisfactory, especially when the rationale is short. In addition, the pre-trained LMs we evaluated are not robust on syntax-aware data. We will release this evaluation benchmark at http://xyz, and hope it can facilitate the research progress of pre-trained LMs.

1 Introduction

Pre-trained LMs such as BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) have achieved significant gains in predictive accuracy on a variety of NLP tasks (Wang et al., 2018). Many studies have proved that pre-trained LMs have learned amounts of knowledge from the massive text corpora (i.e., their training data), such as linguistic knowledge (Tenney et al., 2019; Jawahar et al., 2019) and factual knowledge (Petroni et al., 2019; Pörner et al., 2019). Such learned knowledge has enhanced representations and capabilities of LMs, e.g., the abilities of reasoning (Brown et al., 2020) and computation (Polu and Sutskever, 2020). However, some works show that pre-trained LMs have not captured adequate knowledge and are insufficient in some aspects. Some studies find that BERT has not learned some syntactic structures and can not perform well on syntax-aware data (Wang et al., 2019; Min et al., 2020). Some works state that pre-trained LMs have a poor grasp of reasoning over factual knowledge and commonsense (Pörner et al., 2019; Marcus and Davis, 2020). Meanwhile, some researchers prove that pre-trained LMs have a poor performance on mathematical problem solving, even on simple problems (Hendrycks et al., 2021; Cobbe et al., 2021). Consequently, what kind of knowledge is learned and to what degree it is learned by pre-trained LMs are still unclear. Meanwhile, there is a lack of datasets for comprehensively evaluating model capabilities.

On the other hand, interpreting the decision-mechanism of a pre-trained LM which can help us understand the reason behind its success and its limitations has attracted lots of attention (Rethmeier et al., 2020; Meng et al., 2022; Mor Geva, 2022). With input saliency methods (Smilkov et al., 2017; Sundararajan et al., 2017), Ding and Koehn (2021) use the most influential tokens in the context as the rationale and evaluate interpretability from the perspective of grammar. Some works (Voita et al., 2019; Singh et al., 2019) study the inner workings of transformer-based pre-trained LMs according to hidden states and evolutions of hidden states between layers. In addition, some researchers develop toolkits to capture, analyze and visualize inner mechanisms of LMs at the level of individual neurons (Rethmeier et al., 2020; Dai et al., 2021; Alammar, 2021; Mor Geva, 2022). However, most of these studies lack quantitative evaluation and analysis.
Table 1: Examples for five evaluation dimensions. The words in the bold are masked and then predicted by LMs. The words in the red color are taken as the ground-truth rationale for answer prediction.

To address the above problems, we propose a novel evaluation benchmark for pre-trained LMs, which contains instances with masked words and corresponding human-annotated rationales. As shown in Table 1, the masked words are used to evaluate model predictions, and the rationales are used to evaluate interpretability. Overall, our contribution includes:

1. To our best knowledge, this is the first benchmark that can be used to evaluate both prediction performance and interpretability of pre-trained LMs. And it provides both English and Chinese evaluation sets.

2. Our evaluation benchmark covers common evaluation dimensions, i.e., grammar, semantics, knowledge, reasoning and computation. We create perturbed instances and evaluate faithfulness via the consistency of rationales under perturbations.

3. We conduct experiments on several widely-used pre-trained LMs, such as BERT, RoBERTa. The experimental results show that current pre-trained LMs have very poor prediction performance on the dimensions of knowledge, reasoning and computation. And these LMs are less robust on syntactically transformed data. We believe these findings can help improve LMs.

2 Related Work

In this section, we first review analyses about pre-trained LMs’ capabilities. Then we introduce studies on LMs’ interpretation, including interpretation methods (i.e., rationale extraction methods), evaluation datasets and metrics.

2.1 Capability Analyses of Pre-trained LMs

While such pre-trained LMs have attracted lots of attention and been developed rapidly, it remains unclear why they work well or fail on some inputs, which limits further hypothesis-driven improvement of the architecture. Consequently, a large number of studies attempt to reveal the reasons behind their performance (Jawahar et al., 2019; Hewitt and Manning, 2019; Pörner et al., 2019).

Many studies aim to unveil linguistic structures from the representations of pre-trained LMs to understand what kind of linguistic knowledge they have learned (Jawahar et al., 2019; Kim et al., 2020). Hewitt and Manning (2019) learn a linear transformation to predict the syntactic depth of each word based on its representation, and state that syntax information is implicitly embedded in BERT. Jawahar et al. (2019) and Tenney et al. (2019) show that BERT captures rich linguistic information, with syntactic features at lower layers and semantic features at higher layers.

Meanwhile, some studies intend to analyze model performance on capturing factual knowledge. Based on BERT’s good performance on answering cloze-style questions about relational facts between entities, Petroni et al. (2019) state that BERT memorizes factual knowledge during pre-training. However, Pörner et al. (2019) prove that the impressive performance of BERT is partly due to reasoning about the surface form of entity names. They filter out queries that are easy to answer from entity names alone, and show that BERT’s precision drops dramatically.

Similarly, some studies try to verify the reasoning ability of pre-trained LMs. GPT-3 (Brown et al., 2020), a powerful language generator, is proved that it can generate samples of news articles which human evaluators have difficulty distinguishing from articles written by humans. But Marcus and Davis (2020) state that GPT-3 has no idea what it’s talking about, and show that GPT-3 has a poor grasp of reasoning over commonsense.
Finally, some studies focus on analyzing the computation capability of pre-trained LMs. Polu and Sutskever (2020) propose GPT-f, an automated prover and proof assistant, which applies transformer-based LMs to automated theorem proving by generating the Metamath formalization language. Hendrycks et al. (2021) release an evaluation dataset MATH and a large auxiliary pre-training dataset AMPS to measure the capabilities of machine learning models on mathematical problem solving. Their results show that even those enormous transformer models such as GPT-3 (Brown et al., 2020) get relatively low accuracy. Cobbe et al. (2021) publish the dataset GSM8K, which contains 85,000 high-quality linguistically diverse grade school math word problems, to evaluate model performance on multi-step mathematical reasoning. They find that even the largest transformer models fail to achieve high test performance, while a bright middle school student should be able to solve every problem.

2.2 Interpretation of Pre-trained LMs

Interpretation Methods Over the recent years, interpreting predictions of LMs has attracted immense attention. The existing studies mainly interpret model predictions from three perspectives: input saliency (Ding and Koehn, 2021), hidden state (Alammar, 2021; Mor Geva, 2022) and neuron activation (Rethmeier et al., 2020; Meng et al., 2022; Alammar, 2021; Dai et al., 2021). Input saliency methods assign an importance score to each input token, which represents the token’s impact on model prediction (Simonyan et al., 2014; Smilkov et al., 2017; Sundararajan et al., 2017; Li et al., 2016a). Ding and Koehn (2021) use different saliency methods to interpret LMs on two proposed tasks, i.e., subject-verb number agreement and pronoun-antecedent gender agreement, and evaluate their performance with extracted rationales. Hidden states and their evolution between model layers are always used to glean information about the inner workings of an LM. Singh et al. (2019) utilize hidden states to study internal representations of multilingual BERT. Voita et al. (2019) use hidden states to analyze the flow of information inside transformers, and reveal how the representations of individual tokens and the structure of the learned feature space evolve between layers across different tasks. Examination of neuron activations is used to trace and analyze model processes by extracting underlying patterns of neuron firings. Rethmeier et al. (2020) modify the established computer vision explainability principle of “visualizing preferred inputs of neurons” (Erhan et al., 2009) to suit NLP, and use it to quantify knowledge changes or transfers during training at the level of individual neurons. Dai et al. (2021) introduce the concept of knowledge neurons and propose a knowledge attribution method to identify the neurons that express the fact. Meanwhile, several tools are released to capture, analyze, visualize, and interactively explore inner mechanisms of LMs (Dalvi et al., 2019; Alammar, 2021; Mor Geva, 2022).

Our work focuses on interpreting model predictions with input saliency methods, i.e., post-hoc explanation methods, among which four types are commonly used, namely attention based, gradient based, eraser based, and linear based methods. Attention based methods use attention weights as the importance scores (Rethmeier et al., 2020; Meng et al., 2022; Li et al., 2016b; Lundberg and Lee, 2017; Feng et al., 2018). Linear based methods use an explainable linear model to approximate the evaluated model behavior locally and use the learned token weights as importance scores (Ribeiro et al., 2016; Alvarez-Melis and Jaakkola, 2017). Considering the characteristics of LMs, attention based methods and gradient based methods are often used as saliency methods for LMs.

EvaluationDatasets Recently, many evaluation datasets with human-annotated rationales are published to facilitate the research progress of interpretability (DeYoung et al., 2020; Wang et al., 2021; Camburu et al., 2018). The rationales in such datasets are mainly presented in three forms: highlights (DeYoung et al., 2020; Mathew et al., 2021), structural rules (Camburu et al., 2018; Rajani et al., 2019), and free texts (Ye et al., 2020; Geva et al., 2021). While attention to construct interpretability evaluation datasets for specific NLP tasks keeps increasing, there is a lack of evaluation datasets for LMs. Ding and Koehn (2021) create four datasets for two tasks, i.e., number agreement of a verb with its subject and gender agreement of...
a pronoun with its related mentions. They provide
token-level annotations in the four sets, each with
a cue set and a corresponding attractor set, and use
them to evaluate interpretability of saliency meth-
ods. Ekin Akyürek (2022) propose an fact tracing
dataset with instance-level rationales to evaluate
model capability on fact learning. He et al. (2022)
design a novel task called Simile Property Prob-
ing to test whether pre-trained LMs can interpret
similes or not by letting the LMs infer the shared
properties of similes.

**Evaluation Metrics** Plausibility and faithfulness
are often used to evaluate interpretability (Doshi-
Velez and Kim, 2017; Jacovi and Goldberg, 2020;
Adebayo et al., 2020). Plausibility measures how
much the rationales provided by models align with
human-annotated rationales (Weerts et al., 2019;
DeYoung et al., 2020; Mathew et al., 2021). With
rationales at different granularity levels, several
metrics are proposed to measure plausibility, such
as token F1-Score (Mathew et al., 2021; Wang et al.,
2021), IOU (Intersection-Over-Union) F1-Score
and AUPRC (Area Under the Precision-Recall
curve) score (DeYoung et al., 2020). Faithfulness
measures the degree to which the rationales in fact
influence the corresponding predictions (Jacovi and
Goldberg, 2020; DeYoung et al., 2020; Liu et al.,
2020). Similarly, multiple metrics are proposed to
evaluate faithfulness, e.g. sufficiency and compre-
hensiveness (DeYoung et al., 2020), consistency
under perturbations (Ding and Koehn, 2021; Wang
et al., 2021), sensitivity and stability (Yin et al.,
2022), as well as word-level differential reaction
(Mosca et al., 2022).

In our work, we also evaluate interpretability
from perspectives of plausibility and faithfulness.
And we adopt metrics that are suitable for LMs, as
described in Section 4.

3 Evaluation Dataset Construction

Our evaluation dataset is constructed in three steps:
1) data collection; 2) perturbed data construction; 3)
iterative rationale annotation and checking. We first
introduce our proposed five evaluation dimensions
in Section 3.1. Then we describe the annotation
process in Section 3.2-3.4. Finally, we give our
data statistics.

3.1 Evaluation Dimensions

Considering the abilities that an LM should have
for predicting the right answer, we design five eval-
uation datasets with five types of instances, as de-
scribed below. The corresponding examples are
shown in Table 1.

- **Grammar.** These instances are designed to eval-
uate what linguistic knowledge a pre-trained LM
has learned, such as the tense of a verb, the gen-
der of a pronoun, and the number of a noun in
English. As shown by the first example in Table
1, the noun right after the number “285” must be
plural if it is countable.

- **Semantics.** These instances aim to test whether
the pre-trained LM has learned and mastered
lexical meaning, including conceptual senses of
words, concept properties and relationships, as
well as semantic coreference rules. The second
example in Table 1 requires the model to master
the concept of “city” and its property “area”.

- **Knowledge.** The instances in this type are used
to evaluate the extent to which the pre-trained LM
learns real-world factual knowledge. As shown
by the third example in Table 1, the prediction
of “Germany” requires the model to learn and
memorized related knowledge.

- **Reasoning.** These instances aim at the inferen-
tial capability of LMs over open-domain com-
monsense. The forth example in Table 1 states
that the model should deduce “blind” according
to the premise that the eye was hurt.

- **Computation.** The instances are intended to test
the computational ability of pre-trained LMs on
handling mathematical problems, as illustrated
by the last example in Table 1.

3.2 Data Collection

In order to create high-quality evaluation datasets,
we construct our datasets on the basis of some ex-
ing human-annotated datasets, as shown in Table
2. Our collection process consists of two steps:
instance construction and masked word selection.

**Instance Construction** Each input in our evalua-
tion datasets is a sentence or a paragraph consisting
of multiple sentences, as shown in Table 1. Since
the input forms of some existing datasets in Table
2 are not as we want them to be in our datasets, we
have them manually modified. Specially, we create
inputs for dimensions of knowledge, reasoning and
computation.
Knowledge. We build our English evaluation dataset based on FreebaseQA (Jiang et al., 2019), and build the Chinese dataset on CKBQA. An original input includes two required components: a question and its answer. We replace the wh-phrase in the question with the corresponding answer to form a new input. For example, the forth example in Table 1 was originally “Which country is located directly to the east of Belgium?” with the answer “Germany”. We use “Germany” to replace the wh-phrase “Which country” and construct a new input “Germany is located directly to the east of Belgium.”. We filter out questions with multiple answers to ensure the uniqueness of the prediction.

Reasoning. We select COPA (Roemmele et al., 2011) and XCOPA (Ponti et al., 2020) to build English and Chinese evaluation data, respectively. Each original input has three parts: a given premise and two plausible alternatives for either the cause or the effect of the premise. We concatenate the premise and the reasonable cause to build a new input using some appropriate conjunctions, such as “since” and “because”. Similarly, we use conjunctions such as “then” and “so” to connect the premise and the proper effect to create a new input.

Computation. We adopt Alg514 (Kushman et al., 2014) and Dolphin18K (Huang et al., 2016) for building English evaluation dataset. And we use Math23K (Wang et al., 2017) to build Chinese evaluation dataset. Each original instance consists of three parts, i.e., a question, its corresponding equation and answer. We use the answer to replace the wh-phrase in the question to construct a new input. Take the fifth example in Table 1 for example. The original question is “Tony planted a 4 foot tree. The tree grows at a rate of 5 feet every year. How many years will it take to be 29 feet?” and the answer is “5”. We only select simple questions whose equation has no more than two operators.

Masked Word Selection In each created input, we select an appropriate word or phrase (denoted as $w_m$) to mask. Then the sentence with a mask is input to a pre-trained LM, which will output a prediction for the masked position. Usually, we take $w_m$ as the golden standard answer for the masked position. To precisely evaluate model prediction performance, the golden answer for the masked position in the context of the sentence should be as unique as possible. So the uniqueness of answer is one of our criteria for selecting masked words.

For the dimensions of “knowledge” and “computation”, the answer for the original question is masked. For the other three dimensions, annotators need to select appropriate masked words according to the uniqueness principle. In order to ensure the diversity of linguistic features in the data of grammar dimension, the masked words cover all parts-of-speech to test LMs acquisition of subject-verb agreement, pronoun case agreement, verb tense agreement, comparative/superlative adjectives and so on. Masked words in the data of semantics category cover concepts, properties, concept anaphors and so on.

Then for each masked position and the corresponding golden answer, three annotators rate their confidences on a 4-point scale by judging whether the golden answer is unique (1), among the top 3 predictions (2), among the top 5 predictions (3), or none of the above (4). The masked position is considered to be appropriate if the confidence of each annotator is no more than 2, i.e., its golden answer is unique or among the top 3 predictions.

### 3.3 Iterative Rationale Annotation

Given an input with a masked segment and the golden answer for the segment, the annotators highlight important input tokens that support the prediction as the rationale. In our work, there are two rationale criteria used in the annotation process.

**Rationale Criteria**

As discussed in recent studies of natural language understanding tasks, a rationale should satisfy sufficiency, compactness and comprehensiveness (Lei et al., 2016; Yu et al., 2019). As the comprehensiveness is not suitable for the rationale of LMs’ prediction, we use sufficiency and compactness as the rationale criteria.

- **Sufficiency.** A rationale is sufficient if it contains enough information for people to make the
correct prediction. In other words, human can make the correct prediction only based on tokens in the rationale.

- **Compactness.** A rationale is compact if all of its tokens are indeed required in making a correct prediction. That is to say, when any token is removed from the rationale, the prediction will change or become difficult to make.

### Annotation Process

To ensure the data quality, we adopt an iterative annotation workflow, including three steps.

**Step 1: rationale annotation.** Given the input and the corresponding golden answer, the ordinary annotators label all critical tokens that are needed for correct prediction based on their intuition on the model decision mechanism.

**Step 2: rationale scoring.** Our senior annotators double-check the annotations according to the annotation criteria. For each rationale, the annotators rate their confidences for sufficiency by judging whether they are unable (1), probably able (2), or definitely able (3) to make the correct prediction only based on it, and rate their confidences for compactness by judging whether it contains redundant tokens (1), contains disturbances (2), is probably concise (3), or is very concise (4).

A rationale is considered to be of high-quality if its average score on sufficiency and compactness is equal to or greater than 3 and 3.6, respectively. All unqualified data whose average score on a property is lower than the corresponding threshold goes to the next step.

**Step 3: rationale modification.** Low-quality rationales are given to the ordinary annotators for correction.

Then the corrected rationales are scored by senior annotators again. This iterative annotation-scoring process runs for 3 iterations and the unqualified data is discarded after that.

### Perturbed Data Creation

Recent studies (Ding and Koehn, 2021; Wang et al., 2021) propose to evaluate the model faithfulness via measuring how consistent its rationales are regarding perturbations. That is to say, under perturbations that are not supposed to change the model prediction mechanism, a model is considered faithful if its rationales are unchanged. In our work, we adopt this metric to evaluate LM’s interpretability. And we construct perturbed examples for each original input.

**Perturbation Criteria** In our work, perturbations do not change the model prediction and internal decision mechanism. Please note that the influence of perturbations on model’s prediction and decision mechanism comes from human’s basic intuition. Based on the literature (Jia and Liang, 2017; McCoy et al., 2019; Ribeiro et al., 2020), we define three perturbation types.

- **Alteration of dispensable words** (**Dispens.**), that is, inserting, deleting or replacing words that should have no effect on model predictions and rationales, e.g., the sentence “the man’s eyes were stabbed by broken glass, then he went blind” is changed to “unfortunately, the man’s eyes were stabbed by broken glass, then he went blind”.

- **Alteration of important words** (**Import.**), that is, replacing important words which have an impact on model predictions with their synonyms or related words, for example, replacing “stabbed” with “pierced”. In this situation, the rationale changes, but the prediction does not change.

- **Syntactic transformation** (**Trans.**), transforming the syntactic structure of an instance without changing its meaning, e.g., the voice change from “the man’s eyes were stabbed by broken glass” to “the broken glass stabbed the man’s eyes”. In this case, the model prediction and rationale should not be affected.

We create at least one perturbed example for each original input. And we annotate at least 100 perturbed examples for each perturbation type. We ask two annotators to create perturbed examples, and ask two other annotators to review and modify the created examples.

### 3.5 Data Statistics

Table 3 shows the detailed statistics of our evaluation benchmark. We can see that the number of pairs and the length ratio of rationale vary with evaluation dimensions. As discussed above (i.e., “Masked word selection” in Section 3.2), the instances in the dimension of grammar cover as much syntactic knowledge as possible. The English grammar dataset is larger in size than Chinese ones as there are less agreement rules in Chinese grammar. The Chinese dataset for semantics is larger than the English ones as there are more available data in Chinese. The rationale length ratio can be used as
Table 3: Statistics of our datasets. “Size” means the number of original/perurbed pairs. “RRL” represents the ratio of rationale length to its input length.

| Dimensionality | English Size RRL(%) | Chinese Size RRL(%) |
|----------------|---------------------|---------------------|
| Grammar        | 1,365 29.8          | 701 20.7            |
| Semantics      | 793 31.6            | 1,210 27.1          |
| Knowledge      | 295 45.8            | 300 51.5            |
| Reasoning      | 300 48.5            | 300 43.4            |
| Computation    | 307 59.7            | 400 54.5            |

Considering the characteristics of pre-trained LMs, we evaluate faithfulness for pre-trained LMs via evaluating the consistency of rationales under perturbations. In our work, we adopt Mean Average Precision (MAP) (Wang et al., 2021) and Pearson Correlation Coefficient (PCC) (Ding and Koehn, 2021) to evaluate the consistency of two rationales.

**MAP**, as defined in Equation 2, evaluates the consistency of rationales under perturbations by calculating the order consistency of two token lists, i.e., the token list of the original instance and that of the corresponding perturbed instance. The higher the MAP, the more faithful the rationale.

$$MAP = \frac{\sum_{i=1}^{N} (\sum_{j=1}^{i} G(x^{o}_i, x^{p}_i))/i}{|X^{p}|}$$ (2)

where $X^{o}$ and $X^{p}$ are the sorted token lists of the original and perturbed inputs respectively. $|X^{p}|$ represents the token number of $X^{p}$. $X^{o}_{1:v}$ contains the top-$i$ important tokens of $X^{o}$. The function $G(x, Y)$ determines whether the token $x$ belongs to the list $Y$. In other words, $G(x, Y) = 1$ iff $x \in Y$.

**PCC** is the test statistics that measures the statistical association between two continuous variables. As shown in Equation 3, we use it to measure the linear correlation between token importance scores of the original instance and that of the perturbed one. Based on perturbation types defined in Section 3.4, we post process the two importance score lists to align them. Specifically, the unaligned tokens, such as the deleted words and inserted words, will be aligned to a virtual token whose importance score is assigned by a specific saliency method. In our experiments, $K$ is the product of the average rationale length ratio $r$ and the current input length $l$.

$$Token-F1 = \frac{1}{N} \sum_{i=1}^{N} \left(2 \times \frac{P_i \times R_i}{P_i + R_i}\right)$$ (1)

where $P_i = \frac{|S^{p}_i \cap S^{o}_i|}{|S^{o}_i|}$ and $R_i = \frac{|S^{p}_i \cap S^{o}_i|}{|S^{p}_i|}$

where $S^{p}_i$ and $S^{o}_i$ represent the model’s rationale and human-annotated rationale of the $i$-th instance, respectively; $N$ represents the total number of instances.

**Faithfulness** Faithfulness evaluates to what extent the rationale provided by the model truly affects the model prediction (Jacovi and Goldberg, 2020; Ding and Koehn, 2021). A variety of metrics have been proposed to evaluate faithfulness from multiple perspectives, e.g. sufficiency and comprehensiveness (DeYoung et al., 2020), consistency under perturbations (Ding and Koehn, 2021; Wang et al., 2021), sensitivity and stability (Yin et al., 2022). Most of these evaluation metrics are only applicable to classification models.

$$PCC = \frac{\sum_{i=1}^{N} (v^{o}_i - \bar{v}^{o})(v^{p}_i - \bar{v}^{p})}{\sqrt{\sum_{i=1}^{N} (v^{o}_i - \bar{v}^{o})^2} \sqrt{\sum_{i=1}^{N} (v^{p}_i - \bar{v}^{p})^2}}$$ (3)

where $v^{o}_i$ and $v^{p}_i$ represent the $i$-th elements of importance score vectors of the original and perturbed

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*KIn our experiments, our reported PCC values are computed on pairs with $p$-value < 0.05, where $p$-value represents the significance level of the linear correlation.*
instance, respectively. \( \bar{v}^o \) and \( \bar{v}^p \) are the mean of \( v^o \) and \( v^p \) respectively.

From the definitions of MAP and PCC, it can be seen that MAP measures the association of two token lists based on importance order, and PCC assesses the association of two token lists according to their importance values.

5 Experiments

5.1 Experimental Setting

In order to evaluate model performance on our benchmark, we adopt several widely-used pre-trained LMs and interpretation methods as our baseline models and methods respectively. We only provide high-level descriptions for them and refer to the respective papers and source codes for details.

Evaluated Pre-trained LMs We conduct experiments on transformer-based pre-trained LMs. Specially, we adopt BERT-base-chinese (BERT-base) (Devlin et al., 2019), RoBERTa-wwm-ext (RoBERTa-base) (Cui et al., 2021) and ERNIE (including ERNIE-base and ERNIE-large) (Sun et al., 2019) as baseline models for Chinese. We take BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) as baseline models for English.

Interpretation Methods We use attention (ATT) based method (Jain and Wallace, 2019) and integrated gradient (IG) based method (Sundararajan et al., 2017) for rationale extraction. For each input, we select the top-K important tokens to compose the rationale. In our experiments, K is the product of the average length ratio (i.e., \( RRL \) in Table 3) and the current input length.

In ATT based method, the attention weights in the last layer are taken as token importance scores. As the pre-trained LM uses wordpiece tokenization, we sum the self-attention weights assigned to its constituent pieces to compute a token’s score. Meanwhile, we average scores over multi-heads to derive a final score. We denote this score as \( S_{i,m} \) to represent the impact of token \( i \) on predicting the masked token \( m \). If the current prediction contains multiple masked tokens, the impact of each token is calculated by \( S_{i,m} = \sum_{j \in m} S_{i,j} \), i.e., the sum of impact scores of all masked tokens.

In IG based method, token importance is determined by integrating the gradient along the path from a defined baseline \( x_0 \) to the original input. In our experiments, the baseline \( x_0 \) is set as a sequence of “[CLS] [PAD] ... [SEP]”, where the number of tokens of \( x_0 \) is equal to that of the original input. The step size is set to 100.

Evaluation Metrics We use a cloze-style task to evaluate model prediction performance, where a span of words in each input are replaced with “[MASK]” and the model need predict an answer for each “[MASK]” based on the context. We evaluate model performance on the first (Top1) and the first three (Top3) predicted answers, using the prediction accuracy, i.e., the percentage of predictions that exactly match the golden answers.

For interpretability evaluation, we use the metrics defined in Section 4.

5.2 Main Results

In this section, we give an overview on model prediction performance and interpretability.

Model Prediction Performance Table 4 shows model performance on masked word predictions. It can be seen that all models perform well on instances of the types of grammar and semantics, which proves that pre-trained LMs have learned certain linguistic knowledge from large-scale corpus (Hewitt and Manning, 2019; Jawahar et al., 2019; Tenney et al., 2019). However, on the other three evaluation dimensions, all models show a poor performance, especially on knowledge and computation. Existing studies also show that pre-trained LMs have no such abilities. For example, Pörner et al. (2019) illustrate that BERT has not learned enough factual knowledge. Hendrycks et al. (2021); Cobbe et al. (2021) prove that pre-trained LMs can not handle math word problems.

Comparison between LMs. From the comparisons between evaluated LMs, we get two interesting findings. First, RoBERTa and ERNIE perform better than BERT on dimensions of grammar, semantics and reasoning. Furthermore, ERNIE large outperforms ERNIE base on these three dimensions. We think there are two reasons, i.e., the larger size of training corpus and the larger size of parameters. Second, BERT and ERNIE base have better performance on knowledge and computation. As discussed above, the abilities in these two dimensions have not been learned from the current training corpus and learning objectives. We
think the relevant learning objectives need to be designed and the corresponding training data needs to be created.

Model Interpretability Table 5 gives results on interpretability of different models and methods. There are three main findings. Firstly, with two different interpretation methods, namely ATT and IG, all the evaluated LMs have a relatively strong faithfulness, which indicates that they are robust under perturbations. As shown in Table 4, compared with prediction accuracy on the original data, the prediction accuracy on perturbed data has not decreased too much. For example, in the dimension of grammar, prediction accuracy of most LMs is reduced by about 2%. Secondly, across all evaluated LMs, ATT based method outperforms IG both in plausibility and faithfulness. We think this is because the interactions between words are more important for word generation based on the context. Thirdly, the metrics of plausibility (F1) and faithfulness (MAP) are positively correlated with the length ratio of extracted rationale (as shown in Table 3). Compared with performance on rationales, the performance on predictions is much poor. How to improve model prediction on plausible rationale is a problem that we should address in the future.

Comparison between LMs. Compared ERNIE family with BERT and RoBERTa, ERNIE which is trained on a larger corpus performs better in plausibility with different interpretation methods. But RoBERTa has a higher MAP in the dimensions of grammar and semantics. Compared ERNIE base and large, we find that the base-size model is superior to the large-size model on faithfulness and plausibility in all dimensions except for knowledge. This shows that larger parameter size may not lead to higher interpretability.

Comparison between MAP and PCC. As discussed in Section 4, MAP measures faithfulness based on token importance order, while PCC relies on token importance values. From Table 5, we can see that the two metrics of the same model have the similar trend over different interpretation methods. However, the gap Between PCCs is smaller than that between MAPs.

5.3 Analysis
We give an in-depth analysis about prediction ability and interpretability according to the lengths of extracted rationales and perturbation types.

Analysis on Rationale Length We take the results of RoBERTa-base with ATT based method as an example to illustrate the impact of rationale
length on interpretability, as shown in Figure ??.
In the dimensions of knowledge, reasoning and computation, in which the length ratio of rationale is about 0.5, both plausibility and faithfulness increase with the increase of rationale length ratio. This proves that the most important words provided by the model and interpretation method perform poorly on interpretability. In the other two dimensions where the rationale length ratio is about 0.3, plausibility achieves the highest F1 score when the length ratio of extracted rationale is about 0.5. On the contrary, faithfulness (MAP) increases with the increase of rationale length. Compared with other three dimensions, MAP in these two dimensions increases slowly with the increase of rationale length.

Analysis on Perturbation Types In Table 6, we give model prediction accuracy over three perturbation types. Due to space limitation, we take RoBERTa-base for example, as prediction accuracy of other LMs has the similar trend with RoBERTa-base. It can be seen that the prediction accuracy alters significantly on syntactically transformed perturbations (Trans.). And the model is relatively robust on the other two perturbation types, i.e., alternation of dispensable words (Dispens.) and alternation of important words (Import.).

Meanwhile, we further analyze interpretability results over different perturbation types, as shown in Table 7. It can be seen that faithfulness (MAP) under Trans. type is significantly lower than that under the other two perturbation types. Meanwhile, the Trans. and Import. types of perturbations have a larger influence on plausibility in the dimensions of semantics, reasoning and computation. Correspondingly, Dispens. has little influence on interpretability, which proves that pre-trained LMs are robust to such perturbations.

6 Conclusion
To comprehensively evaluate pre-trained LMs, we construct a novel evaluation benchmark to evaluate both model prediction performance and interpretability from five perspectives, i.e., grammar, semantics, knowledge, reasoning and computation. We conduct experiments on several popular pre-trained LMs, and the results show that they perform very poorly in some dimensions, such as knowledge and computation. Meanwhile, the results show that their plausibility is far from satisfactory, especially when the rationale length ratio is small. Finally, the evaluated LMs have a strong robustness under perturbations, but they are less robust on syntax-aware data. We will release this evaluation benchmark, and hope it will facilitate the research progress of pre-trained LMs.

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Table 6: Prediction accuracy of RoBERTa-base over different perturbation types.

| Data    | Grammar | Semantics | Knowledge | Reasoning | Computation |
|---------|---------|-----------|-----------|-----------|-------------|
|         | Dispens. | Import. | Trans. | Dispens. | Import. | Trans. | Dispens. | Import. | Trans. | Dispens. | Import. | Trans. |
| Original | 67.7     | 72.0     | 63.9     | 57.5     | 51.5     | 47.0     | 8.4      | 1.7      | 4.8      | 15.7     | 30.3     | 26.1     | 0.0      | 0.0      | 1.7      |
| Perturbed | 66.4     | 70.3     | 60.1     | 55.8     | 51.8     | 31.7     | 6.3      | 1.7      | 4.8      | 15.7     | 30.3     | 15.9     | 1.6      | 1.7      | 0.0      |
|         | (-1.3)   | (-1.7)   | (-3.8)   | (-1.7)   | (+0.3)   | (+15.3)  | (-2.1)   | (0.0)    | (0.0)    | (0.0)    | (+10.2)  | (+1.7)   | (+1.6)   | (+1.7)   |

Table 7: Interpretability results of RoBERTa-base with attention based method under different perturbation types. F1\textsuperscript{o} and F1\textsuperscript{p} represents F1-scores on original and perturbed inputs respectively.

| Data    | Grammar | Semantics | Knowledge | Reasoning | Computation |
|---------|---------|-----------|-----------|-----------|-------------|
|         | F1\textsuperscript{o} | F1\textsuperscript{p} | MAP       | F1\textsuperscript{o} | F1\textsuperscript{p} | MAP       | F1\textsuperscript{o} | F1\textsuperscript{p} | MAP       |
| Original | 0.370   | 0.367     | 0.906     | 0.387     | 0.376     | 0.834     | 0.378     | 0.379     | 0.810     |
| Perturbed | 0.367   | 0.375     | 0.881     | 0.398     | 0.394     | 0.868     | 0.338     | 0.324     | 0.700     |
|         | (+0.3)  | (+0.0)    | (+0.0)    | (+0.3)    | (+0.4)    | (+0.0)    | (+1.6)    | (+1.7)    | (+1.7)    |

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A English results

In this section, we show results on English dataset, as shown in Table 8 - Table 11. Similarly, we give analyses from the perspectives of model prediction performance and interpretability.

Model Prediction Ability  Table 8 shows the prediction accuracy of evaluated LMs on English dataset. Generally, on English dataset, the performance on different dimensions has the similar trend with that on Chinese dataset. Firstly, all evaluated LMs perform very poorly on dimensions of knowledge and computation. Secondly, both for BERT and RoBERTa, the large-size model outperforms the base-size one. Thirdly, comparing models with the same size of parameters, RoBERTa which is trained on a larger corpus outperforms BERT on most of dimensions.

However, the robustness of the English LMs on different perturbation types is different from that of the Chinese LMs. As shown in Table 10, RoBERTa-base is less robust under Trans. compared with the other two perturbation types. But compared with the accuracy change under Trans. on Chinese dataset, the accuracy change on English dataset is smaller.

Model Interpretability  Table 9 shows the interpretation results of the evaluated LMs on the English dataset. Most of the conclusions on the Chinese dataset (illustrated in Section 5.2) are applicable to the English dataset. However, on the English dataset, ATT based method not always performs better than IG based method on the two perspectives of interpretability. For example, on the dimensions of knowledge and computation, with all evaluated LMs, IG based method outperforms ATT based method on plausibility.

Meanwhile, Table 11 shows interpretability results of RoBERTa-base under different perturbation types. It can be seen that Trans. brings a significant drop on faithfulness (MAP) on the dimensions of semantic, knowledge and reasoning. Correspondingly, on these three dimensions, plausibility on the perturbed data is lower than that on the orignal data. This proves that the evaluated LMs are less robust to Trans. perturbation type.
Table 8: Model performance on masked word predictions for English dataset, where Ori. and Per. represent performance on original inputs and perturbed inputs respectively, and All represents performance on all inputs.

| Model + TopN       | Grammar | Semantics | Knowledge | Reasoning | Computation |
|--------------------|---------|-----------|-----------|-----------|-------------|
|                    | All Ori. | All Ori. | All Ori. | All Ori. | All Ori. |
| BERT-base + Top1   | 52.2     | 64.7      | 0.7       | 24.0      | 0.5         |
| BERT-base + Top3   | 59.0     | 80.5      | 1.0       | 36.5      | 2.8         |
| BERT-large + Top1  | 58.8     | 67.9      | 0.7       | 28.7      | 1.3         |
| BERT-large + Top3  | 73.2     | 83.9      | 1.2       | 42.0      | 4.4         |
| RoBERTa-base + Top1| 59.5     | 62.7      | 2.9       | 40.5      | 5.1         |
| RoBERTa-base + Top3| 83.3     | 73.6      | 5.1       | 46.5      | 5.1         |
| RoBERTa-large + Top1| 72.0    | 79.7      | 6.4       | 45.6      | 5.1         |
| RoBERTa-large + Top3| 83.3     | 83.6      | 6.4       | 45.6      | 5.1         |

Table 9: Interpretability evaluation of baseline LMs on English dataset with two interpretation methods. As illustrated in Section 4, the metric PCC is not performed on all inputs. For inputs suitable for PCC calculation, we also compute MAP, denoted as MAP∗.

| Model + Method | Grammar | Semantics | Knowledge | Reasoning | Computation |
|----------------|---------|-----------|-----------|-----------|-------------|
|                | All Ori. | All Ori. | All Ori. | All Ori. | All Ori. |
| BERT-base + ATT| 0.47     | 0.44      | 0.50      | 0.53      | 0.53        |
| BERT-base + IG | 0.37     | 0.40      | 0.56      | 0.59      | 0.56        |
| BERT-large + ATT| 0.47     | 0.41      | 0.56      | 0.59      | 0.56        |
| BERT-large + IG | 0.37     | 0.41      | 0.56      | 0.59      | 0.56        |
| RoBERTa-base + ATT| 0.55   | 0.44      | 0.55      | 0.56      | 0.56        |
| RoBERTa-base + IG | 0.39    | 0.37      | 0.56      | 0.56      | 0.56        |
| RoBERTa-large + ATT| 0.53    | 0.43      | 0.55      | 0.56      | 0.56        |
| RoBERTa-large + IG | 0.37    | 0.37      | 0.56      | 0.56      | 0.56        |

Table 10: Prediction accuracy of RoBERTa-base over different perturbation types on English dataset.

| Data       | Dispens. | Import. Trans. | Dispens. | Import. Trans. | Dispens. | Import. Trans. | Dispens. | Import. Trans. | Dispens. | Import. Trans. |
|------------|----------|----------------|----------|----------------|----------|----------------|----------|----------------|----------|----------------|
| Original   | 59.8     | 58.6           | 54.3     | 60.2           | 73.9     | 63.2           | 4.3      | 1.6            | 31.6     | 1.1            |
| Perturbed  | 60.4     | 59.0           | 51.2     | 59.2           | 71.8     | 64.6           | 2.9      | 4.9            | 1.8      | 30.5           |

Table 11: Interpretability results of RoBERTa-base with attention based method over different perturbation types on English dataset. F1σ and F1π represent F1-scores on original and perturbed inputs respectively.