KMIR: A Benchmark for Evaluating Knowledge Memorization, Identification and Reasoning Abilities of Language Models

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Abstract

Previous works show the great potential of pre-trained language models (PLMs) for storing a large amount of factual knowledge. However, to figure out whether PLMs can be reliable knowledge sources and used as alternative knowledge bases (KBs), we need to further explore some critical features of PLMs. Firstly, knowledge memorization and identification abilities: traditional KBs can store various types of entities and relationships; do PLMs have a high knowledge capacity to store different types of knowledge? Secondly, reasoning ability: a qualified knowledge source should not only provide a collection of facts, but support a symbolic reasoner. Can PLMs derive new knowledge based on the correlations between facts? To evaluate these features of PLMs, we propose a benchmark, named Knowledge Memorization, Identification, and Reasoning task (KMIR). KMIR covers 3 types of knowledge, including general knowledge, domain-specific knowledge, and commonsense, and provides 184,348 well-designed questions. Preliminary experiments with various representative pre-training language models on KMIR reveal many interesting phenomenons: 1) The memorization ability of PLMs depends more on the number of parameters than training schemes. 2) Current PLMs are struggling to robustly remember the facts. 3) Model compression technology retains the amount of knowledge well, but hurts the identification and reasoning abilities. We hope KMIR can facilitate the design of PLMs as better knowledge sources.

1 Introduction

Language models pre-trained on large-scale unstructured documents have proven extremely powerful on many Natural Language Processing (NLP) tasks (Brown et al., 2020; Reimers and Gurevych, 2019; Raffel et al., 2019; Sanh et al., 2019; Peters et al., 2018; Dai et al., 2019). Many recent inspiring works (Petroni et al., 2019, 2021) further reveal the potential of the pre-trained language models (PLM) to be an alternative to structured knowledge bases (Lenat, 1995; Bollacker et al., 2008; Auer et al., 2007; Vrandecic and Krötzsch, 2014; Speer et al., 2017; Mitchell et al., 2018) in some cases, especially at avoiding large-scale schema engineering. However, if a PLM can be a reliable knowledge source, it must equip the essential features motivated from human cognition (Hayes et al., 2014) as: (1) Strong knowledge memorization and identification: A PLM should precisely memorize and identify the knowledge like those stored in a KB to facilitate the downstream language tasks such as QA, dialogue. (2) Powerful reasoning ability: The knowledge in PLM should be able to investigate the correlations between knowledge and easily be invoked to infer new knowledge from existing ones.

Previous benchmarks, such as GLUE (Wang et al., 2018) and SuperGLUE (Wang et al., 2019),...
mainly focus on evaluating the general language understanding abilities, rather than knowledge related abilities. Another pioneering work, LAMA (Petroni et al., 2019), focuses on probing knowledge in language models. LAMA mainly evaluates the knowledge memorization by asking models questions in the form of triple completion, like Q1 and Q2 in Figure 1. However, a qualified model is highly supposed to act more than memorizing knowledge. Can PLMs identify different entities (e.g., Q3), identify the correctness of a fact (e.g., Q4), or collect related triples to derive new knowledge (e.g., Q5)? Unfortunately, if we only examine by means of triple completion questions, these fundamental knowledge abilities for downstream tasks are hard to be evaluated.

Therefore, we propose a benchmark for Knowledge Memorization, Identification, and Reasoning test (KMIR), with the idea shown in Figure 1. It is designed motivated by the examinations for humans, like SAT and GRE, which test different abilities with various subjects of knowledge. Specifically, KMIR covers diverse types of knowledge referred in (Davis and Marcus, 2015), and shown in Figure 1 (a), including general knowledge often referred to in human communication, domain-specific knowledge about elementary-level natural and social science, and commonsense of universally accepted beliefs about the world and obvious to most humans. And we collect 192,078 knowledge triples about these types of knowledge from publicly available knowledge sources, i.e, WikiData and ConceptNet.

Besides, we propose a syllabus to summarize the evaluated knowledge-related abilities in threefold: knowledge memorization, identification, and reasoning, as shown in Figure 1 (b). Then, according to the characteristics of these three abilities, a template-based question generation method is developed to automatically convert the knowledge triples into question-answer pairs as four types of prompt-based cloze questions, including triplet completion, entity distinction, statement checking, and predicate reasoning, as shown in Figure 1 (c). Finally, we construct a large-scale dataset with 184,348 questions.

Finally, we evaluate several representative PLMs on the proposed questions, including BERT (Lan et al., 2019), ALBERT (Lan et al., 2019), RoBERTa (Liu et al., 2019), etc. Some interesting phenomena are found: 1) The memorization abilities of PLMs depend more on the number of parameters than training schemes. 2) Model compression technology retains the amount of knowledge well, but hurts the reasoning ability. 3) Current PLMs are struggling to robustly remember the facts. The predictions of questions derived from same facts usually lack consistency. 4) We find PLMs can solve reasoning questions better in the case that the entities contained in the question are highly co-occurred with the correct answers in the documents of Wikipedia. This indicates models who can answer reasoning questions in that they just memorized context information by a large-amount of parameters.

In summary, our paper mainly has three contributions:

- We propose a systematic evaluation syllabus. It comprehensively measures the knowledge-related abilities of PLMs, including knowledge memorization, identification, and reasoning. Moreover, it covers diverse types of knowledge including general knowledge, commonsense as well as domain-specific knowledge.
- We develop a template-based method that can convert knowledge triples to diverse cloze questions, and obtain a large-scale dataset containing 184,348 QA samples. An intensive validation for quality control of samples is carried with more than 532 hours.
- We evaluate several representative PLMs on KMIR, and find many interesting phenomena that could be useful for designing better PLMs.

2 Related Work

Language Understanding Benchmarks. Previous NLP benchmarks are usually for evaluate general language understanding, such as slot filling (Elsahar et al., 2019; Levy et al., 2017), QA (Yang et al., 2018; Rajpurkar et al., 2016; Joshi et al., 2017; Fan et al., 2019; Joshi et al., 2017; Fan et al., 2019; Kvasikowski et al., 2019; Liu et al., 2020; Ding et al., 2019; Clark et al., 2019; Kassner et al., 2020), dialogue (Dinan et al., 2018), entailment (Williams et al., 2018; Rocktäschel et al., 2015; Dagan et al., 2005; Morgenstern and Ortiz, 2015). For example, some question answering tasks aim to evaluate machine reading comprehension or reason over a knowledge source, such as Wikipedia. Some other QA benchmarks, e.g., LogiQA (Liu et al., 2020) and HotpotQA (Yang et al., 2018), also evaluate the ability...
of deductive reasoning. These benchmarks aim to evaluate the abilities of an NLP model on a specific task. Recently, GLUE (Wang et al., 2018) is proposed to measure the models’ universal language understanding. It provides a collection of tasks set to comprehensively evaluate a model. Further, a more difficult version, SuperGLUE (Wang et al., 2019) is proposed to cope with the increasing performance of PLMs. LReasoner (Wang et al., 2021) is another universal language understanding benchmark, but focuses more on the robustness of PLMs. Compared to the above benchmarks evaluating the PLMs in terms of general downstream language tasks, KMIR examines PLMs in terms of knowledge-related abilities with diverse types of knowledge, and somehow measures the qualities of PLMs as knowledge sources.

Knowledge Probe Benchmark. Recently, pre-trained language model (Devlin et al., 2019; Radford et al., 2019; Lewis et al., 2020) has made significant progress in the field of natural language processing and has gradually become one of the mainstream paradigms. A part of the research (Roberts et al., 2020b; Petroni et al., 2019, 2021; Jiang et al., 2020; Roberts et al., 2020a; Yu et al., 2020) has begun to explore the factual knowledge contained in pre-trained language models. LAMA (Petroni et al., 2019) is the first work to explore whether a language model learns and stores some factual knowledge by pre-training on a large text corpus. To address this problem, LAMA uses the triple completion task to probe whether a language model contains a certain knowledge. If a PLM can successfully predict the words that have been masked in a knowledge triple, then the PLM is assumed to include this knowledge. KILT (Petroni et al., 2021) is another benchmark by testing the performance of PLMs on the downstream knowledge-intensive tasks, such as open-domain question answering, fact-checking, and slot filling. Previous works mainly focus on probing PLMs whether they can memorize knowledge or perform well on downstream tasks. However, knowledge-related abilities are far beyond memorization. Thus, this work proposes a benchmark with diverse questions to evaluate memorization, identification, and reasoning ability.

3 Knowledge Abilities Syllabus

To test the ability of PLMs, similar to the syllabus of SAT designed for humans, in this section, we elaborate the design of the syllabus in terms of three perspectives, namely, 1) knowledge memorization; 2) knowledge identification, and 3) knowledge reasoning. These abilities correspond to System 1 and System 2 of the brain’s reasoning system and are the basis of daily tasks (Kahneman, 2011). In fact, System 1 covers the basic intuition and instinct, requiring excellent memorization and identification ability to accomplish simple routine works. System 2 is responsible for rational thinking and reasoning for complex decision-making activities.

Knowledge Memorization. Memorization characterizes the ability of remembering something about triples in the form of <subject, predicate, object>, where subject and object represent two entities, and predicate represents a relation between them. Similar to LAMA (Petroni et al., 2019), we evaluate the models’ memorization by triple completion task, that is, given two elements of a triple, the model is required to recover the remaining entity or relation. For example, given Joe Biden and the predicate birthday, it examines whether you remember the object November 20, 1942.

Knowledge Identification. Identification evaluates whether the PLMs can correctly recognize an entity or a triple. For entity-level identification, KMIR requires the model to distinguish the difference between entities in order to measure the representation ability of entities. For example, for several entities Joe Biden, Barack Obama, Donald Trump, and Confucius, in terms of the occupation, one might choose Confucius because the others are presidents of the U.S. To test such ability, we define a novel type of question called entity distinction. Given a set of entities, where one entity is different from the others, the model is supposed to pick the different one. For triple-level identification, the PLMs should tell whether a statement is true. This evaluation is rather important for current models, because many works (Marcus, 2020; Lacker, 2020) have discovered the phenomenon of fabricating facts by the existing language models, e.g., GPT-3 (Brown et al., 2020) tells that the sun has one eye. For this reason, we design the questions called statement checking to validate the model’s correctness toward
Table 1: Knowledge Collection Schema. It displays the collected knowledge types, corresponding entity types and their examples.

| Knowledge Type     | Entity Type                     | Example                                                                 |
|--------------------|---------------------------------|-------------------------------------------------------------------------|
| Domain-Specific Knowledge | Physics physical quantity, state of matter | The melting point of water is 0°C.                                      |
|                     | Biology biosystematics, biology habit | A carnivore requires meat to survive.                                   |
|                     | Chemistry periodic table        | Halogen is a Group 17 Element.                                          |
|                     | Medicine pathology, drug effect | The symptoms of frailty syndrome are osteoporosis.                     |
|                     | History cities in history, historical events | The capital of Serbian Despotate is located in the country Montenegro now. |
|                     | Law articles of law             | Treaty of Orihuela is a legislative act in the country Spain.          |
|                     | Military weapon                 | M107 served during the war or conflict 'The Troubles'.                 |
| General Knowledge   | Music musician, album, song     | Lady Gaga is a singer born on 1986 March 28.                           |
|                     | Film and TV actor, film, theme song | The series 'The Wide Country's first broadcast was on 1962 September 20. |
| Commonsense         | properties of common objects    | Rocks can be heavy.                                                    |

Knowledge Reasoning. KMIR measures the reasoning ability by checking whether the model can infer new knowledge from existing one. One of the most common knowledge reasoning paradigms for humans is predicate logical reasoning (Atkinson, 1909). Thus, KMIR evaluates if the PLMs can perform basic predicate reasoning. Specifically, we refer to OWL2 to require the model to infer new facts (if any) through classic object property axioms, including symmetry, transitivity, reflexive, equivalent, inverse, sub-relation, and SubOP(OPChain). Let us take an example for the axiom of transitivity, which is a general form of syllogism. Given two triples  

\(<\text{Michael Jackson}, \text{isA}, \text{singer}>\) and  

\(<\text{singer}, \text{CapableOf}, \text{hold a concert}>\), the model is supposed to infer  

\(<\text{Michael Jackson}, \text{CapableOf}, \text{hold a concert}>\) (more details of axioms used in KMIR are listed in Sec. 4.3). To evaluate such inference ability, we automatically generate a lot of new knowledge equipped in the form of questions, then ask models to answer them.

Knowledge Type. So far, we have described the syllabus in terms of the abilities and related question types. Our syllabus also defines what types of knowledge are used for supporting the evaluation of such abilities. Here we follow the categorization of knowledge types defined in (Davis and Marcus, 2015; Storks et al., 2019; Cambria et al., 2011), where the knowledge can be briefly classified into three types: general knowledge, commonsense, and domain-specific knowledge. The first two types which are often referred to in human communication, e.g., place of birth, country of citizenship, etc., are highly emphasized by previous benchmarks. They are suitable for measuring memorization and identification ability. In order to further promote the evaluation of reasoning ability, the domain-specific knowledge is particularly considered into our evaluation in the manner of elementary-level natural science and social science knowledge to generate more diverse knowledge.

4 Dataset Construction

KMIR is constructed by first collecting knowledge triples in diverse types and then converting them into cloze statements to test the language model. Specifically, the whole procedure contains four steps: 1) design knowledge collection schema, 2) collect knowledge triples, 3) generate questions, and 4) check the quality of questions. In the following, we illustrate each step in detail.

4.1 Knowledge Collection Schema Design

In the step of designing knowledge collection schema, we define the collected types of knowledge and types of entities. The idea of schema design is choosing a broad range of knowledge types to support the evaluation of abilities in our syllabus. Specifically, the knowledge in KMIR covers three categories as stated in previous section, i.e., general knowledge, domain-specific knowledge, and commonsense. General knowledge collected in KMIR is mainly about entertainment information, including music and film & TV knowledge. We collect the producer, release date, etc., of entities like famous songs, TV series or films, and basic information of entities like famous celebrities, etc. Domain-specific knowledge in KMIR focuses on common elementary-level natural and social scientific knowledge, including physics, biology, chemistry, medicine, history, law, and military. We collect entities about basic scientific concepts for these domains, e.g., common physical quantities of substances, taxonomic knowledge of creatures, chemistry elements, medical drugs, cities in the history, articles of laws, information of weapons, etc. Commonsense is mainly about properties of com-
mon objects, social conventions, etc. For instance, rocks can be heavy. Table 1 displays examples of all knowledge types and related entity types in KMIR.

4.2 Knowledge Collection

After obtaining the schema, we collect the three types of knowledge from two widely used knowledge bases, WikiData (Vrandecic and Krötzsch, 2014) and ConceptNet (Speer et al., 2017).

WikiData. The general and domain-specific knowledge are collected from Wikidata. Specifically, we use the SPARQL query statement on the Wikidata Query Service platform 4 to retrieve the knowledge triples about interested entities.

ConceptNet. The commonsense knowledge is collected from ConceptNet by using its official API 5 to extract the surface texts of interested entities, and then obtain the triples with relations depicting the properties of some common objects. We consider 7 relations: AtLocation, IsA, PartOf, HasA, HasProperty, UsedFor, and Causes.

In summary, by querying 95,532 interested entities with types defined in Table 1 from the two knowledge bases, we obtain 192,078 knowledge triples covering diverse types of knowledge.

4.3 Question Generation

KMIR contains 4 types of cloze questions, that is, triple completion, entity distinction, statement checking, and predicate reasoning, to evaluate the abilities in the proposed syllabus.

Triple Completion Questions. To obtain questions evaluating knowledge memorization, KMIR uses a template-based method to convert the collected knowledge into cloze statements. We define a set of templates to convert triple into a natural language sentence based on its relation type and mask one entity to query the model. For example, the question template of birthday relation triple $<x, birthday, y>$ is "$[x]$’s birthday is [MASK]". Besides, motivated by (Jiang et al., 2020), each relation type corresponds to multiple versions of templates as prompts to make the questions more diverse. In Table 2, we show some templates in KMIR. Note that, because subjects or objects in a triple could be multi-words, the models are supposed to tackle such cases that the [MASK] could be filled with multiple tokens.

Entity Distinction Questions. For entity distinction questions, KMIR provides natural language cloze-form prompts to require the model to pick one unique entity among the given four entities. For example, “James Cameron, Martin Scorsese, Peter Jackson, and Albert Einstein, which is an outlier in terms of occupation? [MASK]”. In KMIR, the following types of entities are used for generating entity distinction questions: celebrities, famous scientists, chief and associate justices, chemical elements, species. We build hierarchical trees to category these entities based on their occupations, chemical properties, or biology taxonomy depicted in WikiData. Then, for generating such questions, we randomly sample three entities belonging to the same category and one entity from another. Finally, we design a set of templates to generate a cloze prompt based on these selected entities.

Statement Checking Questions. For statement checking questions, we automatically generate corrupted knowledge triples to test if the models can distinguish them. Specifically, we replace the object or subject in a knowledge triple with other entities in the same relation to make up a corrupted one. For example, given a correct triple, $<water, melting point, 0 \,^\circ C>$, we replace the object $0 \,^\circ C$ to $1538 \,^\circ C$ which is the object in a similar triple $<iron, melting point, 1538 \,^\circ C>$. Remark that the corruption is further improved by filtering out the corrupted triples which have appeared in knowledge base. Finally, in KMIR, 5,000 triples are selected from our collected triples to generate incorrect triples, and another 5,000 triples are selected as correct triples. Finally, we design some cloze-form prompts to query the model to check their correctness, e.g., "Is the statement ‘the melting point of water is 1538 \,^\circ C’ true? [MASK]".

Predicate Reasoning Questions. For evaluating predicate logic reasoning, we firstly generate some new knowledge through rules based on OWL 2 Web Ontology Language Axioms (Motik et al., 2009). Then, we convert new knowledge to cloze questions. 6 types of axioms out of 14 are selected, and we design corresponding rules of knowledge generation for each axiom, as shown in Table 3. For example, to perform TransitiveOP, we sample commonsense knowledge about the occupation, e.g., (singer, CapableOf, hold a concert) from ConceptNet, and general knowledge from WikiData, e.g., (Michael Jackson, Is, singer), then infer the new
knowledge (Michael Jackson, CapableOf, hold a concert).

After obtaining the new knowledge, the questions can be generated in two ways. Some questions derived from new knowledge are obtained by simply masking one entity. However, in some cases, whether the subject or object in a triple is masked, the answer is not always unique. To avoid the multiple answers for such questions, we particularly design the cloze-form prompts by adding some incorrect answers. For example, for the question "Which person is most likely to hold a concert, Michael Jackson, Albert Einstein, James Cameron, or Martin Scorsese?", where the last three entities are incorrect ones. In this case, the correct answer (i.e., Michael Jackson) is unique. In total, we collect 184,348 questions.

4.4 Quality Control

The automatic data generation method inevitably introduces some noises or controversial information into data, which could cause questions involving sensitive or unethical information and ambiguous answers. These noises are mainly derived from the core stages of question generation, including knowledge collection, template design, and automatic answer generation.

Thus, we invite a group of annotators to manually check each sample’s qualities in three main steps: 1) Filter out questions involving violence, pornography, discrimination, sovereignty disputes issues. 2) Correct the ambiguous questions by refining question templates. Sometimes, ambiguity is introduced by improperly querying the information. For example, for knowledge "Michael Jackson is born in USA.", if we query it by "Michael Jackson is born in [MASK].", the answer could be USA, Pennsylvania, etc. Thus, we refine the questions by introducing some phrases to restrict the answer scope, e.g., "The country that Michael Jackson is born in is [MASK].". 3) Filter out triple completion questions whose answers are not unique. This is because in some cases, adding phrases still cannot make the answer unique. For example, for the question "A [MASK] doesn’t want a sore throat", the answer could be multiple, such as "human" or "singer", etc. This situation is very common in commonsense related questions. In summary, we randomly selected 16,000 questions to check and cost about 532 hours in total.

4.5 Evaluation Metric

As mentioned above, the answers in KMIR could be multiple tokens. KMIR hopes to measure how much the predictions coincide with the golden answers. Thus, following the commonly used metric (Rajpurkar et al., 2016), for each question, we split the prediction and correct answer into words separately, then calculate F1 measure between them.

5 Experiments

5.1 Baselines

We evaluate 3 groups of models, including simple baseline and state-of-the-art methods to investigate current PLMs’ performances.

• Random Guess: This baseline aims to show the performance if we randomly pick a choice for open-ended style cloze among all candidates answers, and for multi-choice style cloze among the choices shown in the questions.

• BERT (Devlin et al., 2019) & its variants: BERT is a representative of a bidirectional encoder of Transformer. We also evaluate DistilBERT (Sanh et al., 2019) to investigate the impact of PLM compression.

• ALBERT (Lan et al., 2019) which is an enhanced version of BERT by introducing parameter-reduction techniques and a self-supervised loss, and ELECTRA (Clark et al., 2020)
Table 4: F1 scores (%) of models on different question types. Note Random Guess performs 18.75% on predicate reasoning because these questions are a combination of multi-choice style clozes and open-end style clozes.

| Method       | Name          | # Params | Training Corpus                  | Triple Completion | Statement Checking | Entity Distinction | Predicate Reasoning |
|--------------|---------------|----------|----------------------------------|-------------------|--------------------|--------------------|---------------------|
|              |               |          |                                  | 0.00017           | 50.00              | 25.00              | 18.75               |
| Random Guess |               |          |                                  |                   |                    |                    |                     |
| BERT         | 110M          |          |                                 | 15.34             | 61.57              | 30.01              | 26.82               |
| ELECTRA      | 110M          |          |                                 | 14.98             | 63.09              | 33.27              | 27.52               |
| DistilBERT   | 66M           |          | BookCorpus & Wikipedia          | 14.37             | 59.89              | 28.56              | 24.38               |
| ALBERT       | 11M           |          |                                  | 11.79             | 63.42              | 32.46              | 27.16               |
| RoBERTa      | 125M          |          |                                  | **15.50**         | **66.13**          | **35.92**          | **29.19**           |
| DistilRoBERTa| 82M           |          | OpenWebText, etc.               | 14.64             | 63.02              | 32.67              | 27.02               |

• RoBERTa (Liu et al., 2019) & its variants: RoBERTa improves BERT’s training schema, e.g., larger batch size, sequence length. We also evaluate its compressed version, DistilRoBERTa (Sanh et al., 2019).

All the PLMs use the base version, and the train, dev, test set with 20,544, 144,085, 19,719 questions, respectively.

5.2 Results

Overview. Table 4 summarizes the performances of the above baselines and display their number of parameters and training corpus. It can be seen that RoBERTa achieves the highest scores on all types of questions, but the results of all models are far from satisfactory (all below 70%). It is still a formidable challenge for PLMs to achieve high memorization, identification, and reasoning abilities. In the following, we provide more analysis about the results.

The Performances on Different Abilities. Table 4 shows the performances of baselines on different abilities. First, it should be noted that the values of the F1 score on identification (i.e., statement checking and entity distinction) and reasoning questions are relatively larger than memorization questions. It doesn’t mean the reasoning is easier than memorization. This is because identification and reasoning questions contain some multi-choice-like cloze, while memorization questions have to provide an open-end answer. So, the answer spaces of different types of questions are different, and the scores between different abilities are incomparable.

Besides, from the ranking of models on triple completion scores, we can see that the largest PLMs (e.g., BERT, ELECTRA, and RoBERTa), achieve the highest scores, while the lightest weight PLM (i.e., ALBERT), obtains an obvious performance drop. It shows that the models’ performances on triple completion questions (i.e., memorization questions) are related to the number of parameters. Besides, the enhanced versions of BERT (i.e., ELECTRA, ALBERT, RoBERTa) don’t bring significantly improvements on memorization ability, but more obvious improvements on identification (i.e., statement checking and entity distinction) and reasoning ability. This shows that improving the architecture or training schema of the BERT model mainly affects the knowledge identification and reasoning ability.

The Impact of Model Compression. In Table 4, we compare the performances of models before and after model compression, e.g., BERT/RoBERTa vs. DistilBERT/DistilRoBERTa. We can see that model compression doesn’t cause an obvious performance drop on memorization performance, but it hurts the performances more on the identification and reasoning questions. This result may indicate that the parameters of PLMs could not only store the knowledge, but also store the relationship between knowledge. It suggests that we may need other constraints or specific designs to maintain the reasoning ability when compressing the model parameters.

Table 5: The prediction robustness F1 scores (%) of models on Q-sets.

| Method  | All Correct | Partially Correct | All Wrong |
|---------|-------------|-------------------|-----------|
| BERT    | 16.37       | 54.28             | 29.35     |
| RoBERTa | 17.65       | 55.36             | 26.99     |

Robustness of PLM Prediction. In KMIR, given one knowledge triple, we construct multiple types of cloze questions to investigate different knowledge-related abilities. For example, for a triple <Joe Biden, birthday, November 20, 1942>, the questions might be "Joe Biden’s birthday is
Table 6: F1 scores (%) of models on questions involving different types of knowledge.

| Question Type       | Domain-Specific Knowledge | General Knowledge | Commonsense | Overall |
|---------------------|--------------------------|-------------------|-------------|---------|
|                     | Physics | Biology | Chemistry | Medicine | History | Law | Military | Music | Film and TV |               |         |
| BERT                | Triple Completion  | 5.95   | 19.28    | 12.10    | 11.30   | 19.13 | 12.46    | 30.86 | 13.59       | 10.31   | 5.71   | 15.34   |
|                     | Statement Checking | 51.26  | 61.34    | 53.98    | 57.27   | 64.57 | 66.32    | 71.23 | 61.81       | 56.35   | 55.95  | 61.57   |
|                     | Reasoning        | 10.74  | 11.42    | 27.78    | 14.45   | 25.35 | 41.53    | 18.79 | 41.38       | 50.64   | 24.56  | 26.82   |
| RoBERTa             | Triple Completion  | 5.78   | 20.34    | 11.71    | 11.04   | 19.51 | 11.67    | 31.03 | 15.86       | 10.29   | 5.02   | 15.50   |
|                     | Statement Checking | 50.42  | 70.00    | 55.65    | 56.36   | 73.79 | 68.37    | 74.07 | 57.80       | 61.11   | 58.33  | 66.13   |
|                     | Reasoning        | 14.51  | 12.81    | 28.05    | 23.34   | 27.92 | 41.99    | 23.49 | 42.39       | 55.30   | 27.62  | 29.19   |

Figure 2: The correlations between F1 scores of BERT/RoBERTa and different ES scores on questions generated by the new knowledge under the rules TransitiveOP and SubOP(OPChain).

Can the PLM really Reason? KMIR uses a rule-based method to generate a large amount of knowledge that is not explicitly expressed in the training corpus. From results in Table 4, PLMs perform relatively well on these reasoning questions. Is PLM really able to infer new knowledge, or does it simply memorize the co-occurrence between words? For example, although no Wikipedia page directly tells Michael Jackson can record a song, the words Michael Jackson and song might appear within sentences or paragraphs many times. Thus, we need investigate whether PLMs mainly learn co-occurrence between tokens rather than new knowledge.

We establish an Elastic Search system (Divya and Goyal, 2013) by indexing all Wikipedia pages, and then compute the co-occurrence score (ES score) between entities in a query and the words in the corresponding answer appearing in Wikipedia pages. We display the correlation between performances of models on questions where the new knowledge is generated by rules TransitiveOP and SubOP(OPChain), and the ES scores in Figure 2. It can be seen that, in general, current models perform better on questions with higher ES scores. This suggests that models who can answer reasoning questions in that they just memorized context information by a large-amount of parameters. However, the co-occurrence cannot solve all reasoning paradigms. We believe that there is still much room for explicit reasoning for existing PLMs.

The Performances on Different Knowledge Types. Finally, it remains to check the performances of all models with respect to different types of knowledge. From Table 6, we can see that the performances vary largely in different types of knowledge. Note that, the entity distinction questions are not listed because the entities in one question involve multiple types of knowledge. The results indicate that performances over knowledge-related abilities are different among knowledge types. The memorization of commonsense and physics is relatively harder. Reasoning questions about domain-specific knowledge are more difficult than general knowledge. These results also show that current models are hard to precisely memorize the facts and implement complex reasoning.

6 Conclusion

This paper introduces KMIR benchmark for evaluating knowledge memorization, identification, and reasoning abilities. KMIR includes a systematic evaluation syllabus to summarize the knowledge-related abilities of PLMs, and has 184,348 questions involving 4 types of questions covering 3 types of knowledge. We also find many interesting
phenomena through extensive experiments: 1) The memorization ability of PLMs depends more on the number of parameters than training schemes. 2) Current PLMs are struggling to robustly remember the facts. 3) Model compression technology retains the amount of knowledge well, but hurts the identification and reasoning ability, etc.

References

William Walker Atkinson. 1909. *The Art of Logical Thinking: Or, The Laws of Reasoning*. Bibliotech Press.

S. Auer, C. Bizer, Georgi Kobilarov, Jens Lehmann, Richard Cyganiak, and Z. Ives. 2007. Dbpedia: A nucleus for a web of open data. In *ISWC/ASWC*.

K. Bollacker, Colin Evans, Praveen K. Paritosh, Tim Sturge, and Jamie Taylor. 2008. Freebase: a collaboratively created graph database for structuring human knowledge. In *SIGMOD Conference*.

Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*.

Erik Cambria, Yangqiu Song, Haixun Wang, and Amir Hussain. 2011. Isanette: A common and common sense knowledge base for opinion mining. In *2011 IEEE 11th International Conference on Data Mining Workshops*, pages 315–322. IEEE.

Christopher Clark, Kenton Lee, Ming-Wei Chang, Tom Kwiatkowski, Michael Collins, and Kristina Toutanova. 2019. Boolq: Exploring the surprising difficulty of natural yes/no questions. *arXiv preprint arXiv:1905.10044*.

Kevin Clark, Minh-Thang Luong, Quoc V Le, and Christopher D Manning. 2020. Electra: Pre-training text encoders as discriminators rather than generators. *arXiv preprint arXiv:2003.10555*.

Ido Dagan, Oren Glickman, and Bernardo Magnini. 2005. The pascal recognising textual entailment challenge. In *Machine Learning Challenges Workshop*, pages 177–190. Springer.

Zihang Dai, Zhilin Yang, Yiming Yang, Jaime Carbonell, Quoc V Le, and Ruslan Salakhutdinov. 2019. Transformer-xl: Attentive language models beyond a fixed-length context. *arXiv preprint arXiv:1901.02860*.

Ernest Davis and Gary Marcus. 2015. Commonsense reasoning and commonsense knowledge in artificial intelligence. *Communications of the ACM*, 58(9):92–103.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 4171–4186.

Emily Dinan, Stephen Roller, Kurt Shuster, Angela Fan, Michael Auli, and Jason Weston. 2018. Wizard of wikipedia: Knowledge-powered conversational agents. In *International Conference on Learning Representations*.

Ming Ding, Chang Zhou, Qibin Chen, Hongxia Yang, and Jie Tang. 2019. Cognitive graph for multi-hop reading comprehension at scale. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2694–2703.

Manda Sai Divya and Shiv Kumar Goyal. 2013. Elasticssearch: An advanced and quick search technique to handle voluminous data. *Compusoft*, 2(6):171.

Hady Elsahar, Pavlos Vougiouklis, Arslen Remaci, Christophe Gravier, Jonathon Hare, Elena Simperl, and Frederique Laforest. 2019. T-rex: A large scale alignment of natural language with knowledge base triples.

Angela Fan, Yacine Jernite, Ethan Perez, David Grangier, Jason Weston, and Michael Auli. 2019. El5: Long form question answering. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3558–3567.

Brett K Hayes, Evan Heit, and Caren M Rotello. 2014. Memory, reasoning, and categorization: Parallels and common mechanisms. *Frontiers in psychology*, 5:529.

Zhengbao Jiang, Frank F Xu, Jun Araki, and Graham Neubig. 2020. How can we know what language models know? *Transactions of the Association for Computational Linguistics*, 8:423–438.

Mandar Joshi, Eunsol Choi, Daniel S Weld, and Luke Zettlemoyer. 2017. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1601–1611.

Daniel Kahneman. 2011. *Thinking, fast and slow*. Macmillan.

Nora Kassner, Benno Krojer, and Hinrich Schütze. 2020. Are pretrained language models symbolic reasoners over knowledge? *arXiv preprint arXiv:2006.10413*.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, et al. 2019. Natural questions: a benchmark for question answering research. *Transactions
Omer Levy, Minjoon Seo, Eunsol Choi, and Luke Douglas B Lenat. 1995. Cyc: A large-scale investment in knowledge infrastructure. Communications of the ACM, 38(11):33–38.

Kevin Lacker. 2020. Giving gpt-3 a turing test. https://lacker.io/ai/2020/07/06/giving-gpt-3-a-turing-test.html.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2019. Albert: A lite bert for self-supervised learning of language representations. In International Conference on Learning Representations.

Douglas B Lenat. 1995. Cyc: A large-scale investment in knowledge infrastructure. Communications of the ACM, 38(11):33–38.

Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 2227–2237.

Fabio Petroni, Aleksandra Piktus, Angela Fan, Patrick Lewis, Majid Yazdani, Nicola De Cao, James Thorne, Yacine Jernite, Vassilis Plachouras, Tim Rocktaschel, and Sebastian Riedel. 2021. Kilt: a benchmark for knowledge intensive language tasks. ArXiv, abs/2009.02252.

Fabio Petroni, Tim Rocktaschel, Patrick Lewis, A. Bakhtin, Yuxiang Wu, Alexander H. Miller, and S. Riedel. 2019. Language models as knowledge bases? In EMNLP.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. arXiv preprint arXiv:1910.10683.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. Squad: 100,000+ questions for machine comprehension of text. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, pages 2383–2392.

Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3982–3992.

Adam Roberts, Colin Raffel, and Noam Shazeer. 2020a. How much knowledge can you pack into the parameters of a language model? In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 5418–5426.

Adam Roberts, Colin Raffel, and Noam M. Shazeer. 2020b. How much knowledge can you pack into the parameters of a language model? In EMNLP.

Tim Rocktaschel, Edward Grefenstette, Karl Moritz Hermann, Tomáš Kočiský, and Phil Blunsom. 2015. Reasoning about entailment with neural attention. arXiv preprint arXiv:1509.06664.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2019. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108.
R. Speer, Joshua Chin, and Catherine Havasi. 2017. Conceptnet 5.5: An open multilingual graph of general knowledge. In AAAI.

Shane Storks, Qiaozi Gao, and Joyce Y Chai. 2019. Recent advances in natural language inference: A survey of benchmarks, resources, and approaches. arXiv preprint arXiv:1904.01172.

Denny Vrandecic and M. Krötzsch. 2014. Wikidata: a free collaborative knowledgebase. Commun. ACM, 57:78–85.

Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. 2019. Superglue: a stickier benchmark for general-purpose language understanding systems. In Proceedings of the 33rd International Conference on Neural Information Processing Systems, pages 3266–3280.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2018. Glue: A multi-task benchmark and analysis platform for natural language understanding. In Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, pages 353–355.

Siyuan Wang, Wanjun Zhong, Duyu Tang, Zhongyu Wei, Zhihao Fan, Daxin Jiang, Ming Zhou, and Nan Duan. 2021. Logic-driven context extension and data augmentation for logical reasoning of text. arXiv preprint arXiv:2105.03659.

Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1112–1122.

Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William Cohen, Ruslan Salakhutdinov, and Christopher D Manning. 2018. Hotpotqa: A dataset for diverse, explainable multi-hop question answering. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 2369–2380.

Donghan Yu, Chenguang Zhu, Yiming Yang, and Michael Zeng. 2020. Jaket: Joint pre-training of knowledge graph and language understanding. arXiv preprint arXiv:2010.00796.
Appendix

In the appendix, we provide more details about dataset construction (Sec. A), data statistics (Sec. B), implementation of baselines (Sec. C), and license and usage of KMIR (Sec. D).

A Dataset Construction

In this section, we provide more examples of the selected knowledge triples and question templates used for generating questions.

A.1 Knowledge Collection Schema

In the Table 7, we show more knowledge collection schema.

Table 7: Knowledge Collection Schema. This table displays our collected 10 specific types of knowledge and corresponding relation types and their examples.

| Knowledge Type                  | Relation Type | Example                                                                 |
|---------------------------------|---------------|-------------------------------------------------------------------------|
| Domain-specific Knowledge       | Physics       | physical quantity                                                      | The melting point of water is 0 centigrade. |
|                                 |               | physical property                                                       | A metal can conduct electricity and heat well. |
|                                 |               | state of matter                                                         | Rocks have a stable, definite shape and volume at standard temperature and pressure. |
|                                 | Biology       | biosystematics                                                          | Homeothermic species maintain a stable body temperature. |
|                                 |               | biology habit                                                           | A carnivore requires meat to survive. |
|                                 | Chemistry     | periodic table                                                          | Halogen is a Group 17 Element. |
|                                 |               | atomic number                                                          | aluminium’s atomic number is 13. |
|                                 | Medicine      | pathology                                                               | The symptoms of frailty syndrome are osteoporosis. |
|                                 |               | cause                                                                   | HIV infection is caused by the human immunodeficiency virus. |
|                                 | History       | cities in history                                                       | The capital of Serbian Despotate is located in the country Montenegro now. |
|                                 |               | historical events                                                       | The American Civil War was a civil war in the United States. |
|                                 | Law           | articles of law                                                         | Treaty of Orihuela is a legislative act in the country Spain. |
|                                 |               | lawyer                                                                  | Willem Eduard Bok Jr. was a South African lawyer. |
|                                 | Military      | weapon                                                                  | M107 served during the war or conflict The Troubles. |
|                                 |               | manufacturer                                                            | Northrop Grumman Corporation is an American multinational aerospace and defense technology company. |
|                                 | Music         | musician                                                                | Lady Gaga is a singer born on 1986 March 28. |
|                                 |               | album, song                                                             | One Love is a song by Justin Bieber released in album Believe. |
| General Knowledge               | Film and TV    | actor, film                                                              | The series The Wide Country’s first broadcast was on 1962 September 20. |
|                                 |               | theme song                                                               | The theme music of the television series Friends is I’ll Be There for You. |
| Commonsense                     |               | CapableOf                                                               | Rocks can be heavy. |
|                                 |               | IsA                                                                     | eight ball is a game of geometry. |
|                                 |               | HasProperty                                                             | Africa can be one of the largest continents. |
|                                 |               | HasA                                                                    | The snake have a nest full of babies, scales, no legs. |

A.2 Question Generation

In Table 8, we display the question templates used for generating the entity distinction and statement checking questions.

For reasoning questions, we first generate lots of new knowledge according OWL 2 Web Ontology Language Axioms (Motik et al., 2009), then diverse question templates are designed for each relation type of the knowledge fact. In Table 9, we display the examples of generated new knowledge for each axiom in OWL 2. Table 10 shows our collected types of relations and corresponding templates for triple completion and predicate reasoning questions.
Table 8: Question templates for entity distinction and statement checking questions.

| Question Type       | Question Template                                                                 |
|---------------------|-----------------------------------------------------------------------------------|
| Entity Distinction  | Is the statement "<Statement of a knowledge triple>" true? [MASK].                 |
|                     | <Statement of a knowledge triple>, is this true? [MASK].                          |
|                     | Is this true, <Statement of a knowledge triple>? [MASK].                          |
|                     | Is the following statement true, <Statement of a knowledge triple>? [MASK].       |
| Statement Checking  | <Entity1>, <Entity2>, <Entity3>, and <Entity4>, which is a outlier, in terms of the <Aspect>? [MASK]. |
|                     | Which is different with others in terms of the <Aspect>, <Entity1>, <Entity2>, <Entity3>, and <Entity4>? [MASK]. |
|                     | Which is different with others among the following entities in terms of the <Aspect>, <Entity1>, <Entity2>, <Entity3>, and <Entity4>? [MASK]. |
|                     | Among <Entity1>, <Entity2>, <Entity3>, and <Entity4>, [MASK] is the outlier in terms of the <Aspect>. |

Table 9: Examples of generated new knowledge for each axiom in OWL 2. x, y, z are entity variables. r indicates a predicate.

| Axiom                  | Rule Form                                                                 | Example                                                                 |
|------------------------|---------------------------------------------------------------------------|------------------------------------------------------------------------|
| SymmetricOP            | (x, r, y) → (y, r, x)                                                     | (peace, opposite of, war) → (war, opposite of, peace)                  |
| TransitiveOP           | (x, r, y), (y, r, z) → (x, r, z)                                          | (cat, isA, mammal),(mammal, isA, vertebrate) → (cat, isA, vertebrate)  |
| EquivalentOP           | (x, r, y) ↔ (y, r, x)                                                     | (Joe Biden, is the citizen of, USA) ↔ (Joe Biden, nationality, USA)    |
| InverseOP              | (x, r, y) → (y, r, x)                                                     | (USA, capital, Washington) → (Washington, country, USA)                |
| Sub-relation OP        | (x, r, y) → (y, r, x)                                                     | (Gordian I, father of, Gordian II) → (Gordian I, parent of, Gordian II) |
| SubOP(OPChain)         | (x, r, y) → (y, r, x)                                                     | (Napoleon, country, French),(French, continent, Europe) → (Napoleon, continent, Europe) |

B  Data Statistics

Figure 3 visualizes the question distribution for different domains and abilities. The results show that KMIR has a relatively uniform distribution regardless of question type or knowledge type.

C  Implementation Details of Baselines

KMIR requires the PLMs to output multiple tokens as the answer. To adjust current PLMs to fit this setting, we modify the inputs of PLMs in fine-tuning. Specifically, we expand the [MASK] in a query into 8 masks (the maximum number of masked tokens in KMIR). For example, the original query "Singer Don Omar ‘s birthday is [MASK]" is transformed into "Singer Don Omar ‘s birthday is [MASK] [MASK] [MASK] ...". Similarly, the correct answer is transformed into tokens, then padded into 8 tokens for training the models. Besides, to better reflect the knowledge-related abilities, the PLMs are fine-tuned on

Table 10: Question templates for different types of knowledge in KMIR.
each type of questions and test on corresponding test set questions.

D License and Usage

Firstly, in KMIR, the personnel information involved in the dataset is about public information of public figures from WikiData and does not involve personal privacy. Then, the questions in KMIR are under CC BY-NC-SA 4.0 license. For the knowledge base that we used to generate questions, WikiData is licensed under the Creative Commons CC0 License, and ConceptNet is under a Creative Commons Attribution-Share Alike 4.0 International License. Besides, our dataset collects the knowledge from open and free knowledge base, the knowledge used in dataset could have some mistakes or out-of-date. Finally, our data can only be used for academic researches and do not support commercial usages.