RiddleSense: Answering Riddle Questions as Commonsense Reasoning

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Abstract

A riddle is a mystifying, puzzling question about everyday concepts. For example, the riddle "*I have five fingers but I am not alive. What am I?*" asks about the concept "*a glove*." Solving riddles is a challenging cognitive process for humans, in that it requires complex commonsense reasoning abilities and an understanding of figurative language. However, there are currently no commonsense reasoning datasets that test these abilities. We propose RIDDLESENSE[1], a novel multiple-choice question answering challenge for benchmarking higher-order commonsense reasoning models, which is the first large dataset for riddle-style commonsense question answering, where the distractors are crowd-sourced from human annotators. We systematically evaluate a wide range of reasoning models over it, and point out that there is a large gap between the best-supervised model and human performance — pointing to interesting future research for higher-order commonsense reasoning and computational creativity.

1 Introduction

> *"The essence of a riddle is to express true facts under impossible combinations."*
> — *Aristotle*, *Poetics* (350 BCE)

A *riddle* is a mystifying, puzzling question about concepts in our everyday life. For example, a riddle might ask "*My life can be measured in hours, I serve by being devoured. Thin, I am quick. Fat, I am slow. Wind is my foe. What am I?*" The correct answer "*candle*," is a play on a collection of *commonsense knowledge*: a candle is flammable and burns for a few hours; a candle's life depends upon its diameter; wind can extinguish candles, etc. It is believed that the *riddle* is one of the earliest forms of oral literature, which can be seen as a formulation of thoughts about common sense, a mode of association between everyday concepts, a metaphor as higher-order use of natural language (Hirsch, 2014). Aristotle stated in his *Rhetoric* (335-330 BCE) that good riddles generally provide satisfactory metaphors for rethinking common concepts in our daily life. He also pointed out in the *Poetics* (350 BCE): "the essence of a riddle is to express true facts under impossible combinations," which suggests that answering riddles is a nontrivial commonsense reasoning task.

My life can be measured in hours. I serve by being devoured. Thin, I am quick; Fat, I am slow. Wind is my foe. *What am I?*
(A) paper (B) candle (C) lamp (D) clock (E) worm

I have five fingers, but I am not alive. What am I?
(A) piano (B) computer (C) glove (D) claw (E) hand

Figure 1: Two riddle-style commonsense questions with multiple choices in RIDDLESENSE dataset. The correct answers are B (*candle*) and C (*glove*). The top example is a descriptive riddle that uses multiple pieces of commonsense fact about candle, and it needs understanding of figurative language such as metaphor. The bottom one additionally needs counterfactual reasoning ability to address the *'but-no'* cues.

Answering riddle questions is a challenging cognitive process as it requires complex commonsense reasoning skills. A riddle can describe multiple pieces of commonsense knowledge with figurative devices such as metaphor and personification (e.g., "wind is my foe → *extinguish*"). Moreover, *counterfactual thinking* is also necessary for answering many riddles such as "*what can you hold in your left hand but not in your right hand?* → *your right elbow.*" These riddles with *'but-no'* cues usually require counterfactual thinking ability to reason about situations that are seemingly impossible or rarely seen in daily life. This *reporting bias* (Gordon and Van Durme, 2013)

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[1] https://inklab.usc.edu/RiddleSense

makes riddles as a more difficult type of commonsense question for pretrained language models to learn and reason. In contrast, *superficial* commonsense questions such as "*where do adults use glue sticks?*" in CommonsenseQA (Talmor et al., 2019) are more straightforward and explicitly stated.

In this paper, we introduce the RIDDLESENSE challenge to study the task of answering riddle questions with complex commonsense reasoning. RIDDLESENSE is presented as a *multiple-choice question answering* task, where, given a question, a model needs to select one of five choices as its predicted answer to the riddle, as shown in Figure 1. We construct the dataset by first crawling from several free websites designed for riddle lovers; then we carefully aggregate, verify, and reformat these examples with human efforts, creating 5.7k examples. Finally, we use *Amazon Mechanical Turk* to crowdsource quality distractors for creating a reasonably challenging benchmark. We show that our riddle questions are more challenging than CommonsenseQA by analyzing graph-based statistics over ConceptNet (Speer et al., 2017), a large knowledge graph for common sense.

Can existing methods that are powerful in commonsense reasoning still be capable of solving riddles? Recent studies have demonstrated that fine-tuning large pretrained language models, such as BERT (Devlin et al., 2019a), RoBERTa, and ALBERT (Lan et al., 2020), can achieve strong results. Developed on top of these language models, graph-based language reasoning models such as KagNet (Lin et al., 2019) and MHGRN (Feng et al., 2020) show superior performance. Most recently, UnifiedQA (Khashabi et al., 2020) proposes to unify different question-answering tasks and train a text-to-text model for learning from all of them, which achieves state-of-the-art performance on many commonsense benchmarks. To provide a comprehensive benchmarking analysis, we systematically compare the above methods. Our experiments reveal that there is still a large gap between the best model and human performance, suggesting that there is still much space to improve commonsense reasoning methods. We believe the proposed RIDDLESENSE challenge suggests interesting future directions for machine commonsense reasoning and the understanding of higher-order use of natural language.

2 Construction of RIDDLESENSE

In this section, we first present our pipeline for collecting the RIDDLESENSE dataset, including the details of data cleaning. We introduce how we design a crowd-sourcing protocol for annotating quality distractors to form riddle-solving into a multiple-choice question answering challenge.

2.1 Riddle Crawling and Cleaning

We wrote web crawlers for collecting a large number of riddles and their answers from public riddle websites, such as *brainzilla.com*, *riddlewot.com*, etc. As the crawled data contain much noise such as inconsistent answer format and misspell words, we process riddles through careful data cleaning as well as human verification. First, we use an open-source tool for detecting typos[2] and then refine the sentences. We also manually remove riddles that are not readable or the answer is ambiguous. Then, we aggregate the riddles from different sources with the same answer by removing duplicate riddle questions. For detecting duplicate riddles with minor word changes, we use Sentence-BERT (Reimers and Gurevych, 2019) to find clusters with high cosine similarities.

2.2 Distractor Collection from AMT

When there is no hint or choice riddles can be challenging even for humans to reason about. Furthermore, it is tricky to compare different models if the task is open-ended without a relatively limited predefined scope of options. Therefore, we formulate the riddle-solving task as a *multiple-choice* question answering challenge. That is, given a riddle-style question and 5 answer options, a model should select the best one as the predicted answer. This format offers a straightforward and fair evaluation metric – *accuracy*, which is a shared task format adopted by many popular commonsense reasoning benchmarks such as CommonsenseQA, ARC (Clark et al., 2018), and OpenbookQA (Mihaylov et al., 2018).

High-quality distractors are essential for multiple-choice question answering tasks as they can ensure that the dataset is both *clean* and *challenging* — the distractors are neither too similar nor too distant from the correct answer. We thus design a protocol to collect quality distractors from human annotators via *Amazon*

[2] github.com/phatpiglet/autocorrect

	CSQA	RIDDLESENSE
# All Examples	12,102	5,733
# Train Examples	9,741	3,510
# Validation Examples	1,221	1,021
# Test Examples	1,140	1,202
Average Question Length	15.06	24.04
% Long Questions (>20 tokens)	16.5%	47.3%
Distinct Question Words	6,822	7,110
Distinct Choice Words	7,044	9,912

Table 1: Key statistics of the RIDDLESENSE dataset (v1.0) vs the CommonsenseQA (CSQA) dataset.

Mechanical Turk[3]. We design a three-stage annotation protocol as follows:

- S1) **Sanity Check**. We show a question and 3 choices where only 1 choice is correct and the other 2 are totally randomly-sampled concepts (not from D). Only when the workers pass this sanity check, their following annotations will be considered, so that we can avoid noise from random workers.
- S2) **Candidates Selection**. As it is difficult to control and verify the quality of distractors from crowd workers, we first sample concepts from ConceptNet, which are relevant to both question concepts and answer concepts, forming a set of candidate distractors D for annotators to choose from. Workers are required to select concepts that they think are good distractors to the question. There are at least 3 different workers for each question and we take the candidates which are selected by at least 2 workers to make sure the selected distractors are indeed meaningful.
- S3) **Open Distractor Collection**. We also ask master workers to write at least one more distractor based on the question context. This stage is important because sometimes the candidate pool contains fewer meaningful distractors and the human-written distractors are usually better than the ones in the pool. We give bonus credits to encourage annotators to write more quality distractors.

Through this *selection-and-write* process, we effectively collected quality distractors for all our riddles and avoided noisy annotations.

Specifically, we use Q to denote the concepts that are mentioned in the question, and a to demote the single concept in the answer. We then first get all two-hop neighbors of a and one-hop neighbors of each $c \in Q$ respectively:

$$A = \{x|(x, r_i, y), (y, r_j, a)\}$$
$$B = \{x|(x, r_k, c), \forall c \in Q\}$$
$$D = A \cap B$$

The final union, D, is thus the pool of distractor candidates in the second stage, **S2**. We further use *WordNet* (Miller, 1995) to filter out concepts that have either too low or too high *Wu-Palmer* similarity. Then, that the sampled distractors are semantically relevant to both questions and answers yet are closer to answers in terms of taxonomy, so they are more likely to serve similar semantic units in the question context.

3 Data Analysis of RIDDLESENSE

In this section, we first report the key statistics of the proposed RIDDLESENSE dataset, then we compare it with CommonsenseQA (Talmor et al., 2019) from two angles: the distribution of the length of Q-A paths and the types of reasoning chains, which serve as an effective proxy for us to analyze the differences between the two datasets.

3.1 Key Statistics

Table 1 presents the key statistics of RIDDLESENSE (RS) and the comparisons to CommonsenseQA (CSQA) which is the most similar benchmark to ours. Although the size of RIDDLESENSE is smaller than CommonsenseQA (CSQA), we argue that RIDDLESENSE is complementary to the CSQA dataset and introduces novel challenges to the commonsense reasoning community. As they share the same format, we can test different methods by training on either CSQA-only, RS-only, or the concatenation of CSQA and RS, as we show later in Section 4. Interestingly, we find that although the number of examples in the CSQA is about twice larger than the RS, while there are more distinct words in the questions and choices of RS than CSQA, suggesting that RS has more diverse choices and topics than CSQA. Moreover, there are much more long questions (i.e., number of words $>$ 20) in RS than in CSQA.

3.2 Distribution on the Length of Q-A Paths

To understand the difference between CSQA and RS in terms of their reasoning chains, we use *Q-A paths* over ConceptNet as a proxy. For a riddle question, a set of *Q-A paths* are the shortest paths between every question concept and the answer

[3] https://www.mturk.com/

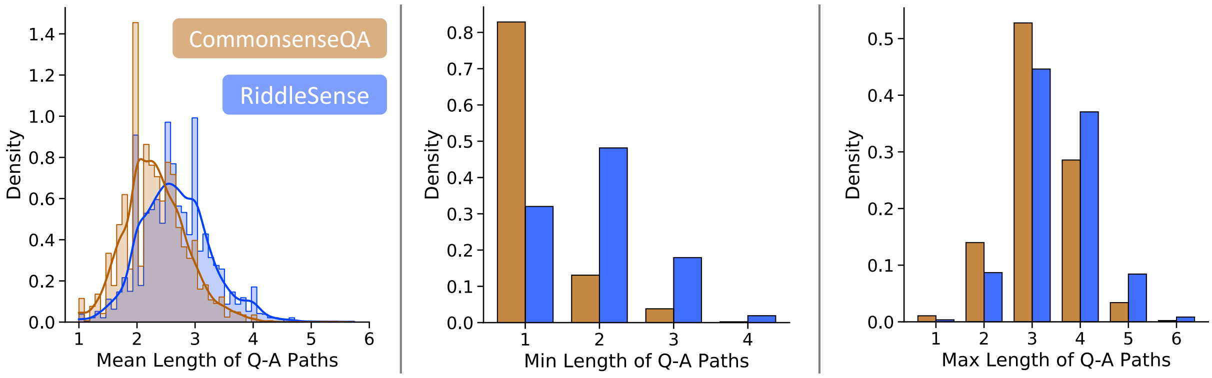


Figure 2: The distribution of the question-answer path length when we take the min/mean/max over multiple question concepts, which serve as estimation of the length of underlying reasoning chains. We can see that generally RIDDLESENSE has a longer question-answer path than CommonsenseQA, thus being harder to reason.

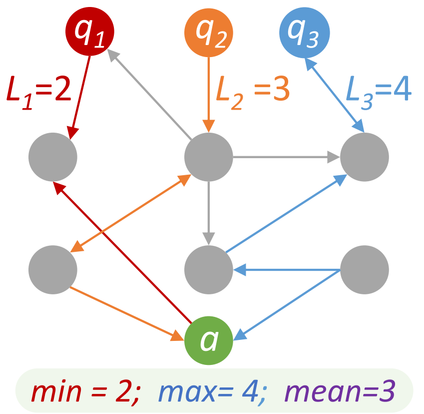


Figure 3: Illustration of using *Q-A paths* as proxy reasoning chains to measure the difficulty of a riddle: $\{q_1, q_2, q_3\}$ are three concepts mentioned in the question, and a is the answer concept. L_k is the length of the shortest path between q_k and a over ConceptNet; *min/max/mean* are computed over $\{L_1, L_2, L_3\}$ as three aspects to measure the overall difficulty.

concept. As shown in Figure 3, for a question-answer pair, we first extract the concepts mentioned in the question and the answer respectively, following the steps of Lin et al. (2019) and Feng et al. (2020). If there are three question concepts $\{q_1, q_2, q_3\}$ and an answer concept a, we denote the length of their shortest paths as $\{L_1, L_2, L_3\}$. Finally, we can compute the min/max/mean over them for a comprehensive understanding of the approximated difficulty in reasoning for this riddle — a greater value indicates a more challenging example. Our main intuition is that the shortest paths between question concepts and the answer concept can approximate the *underlying reasoning chains*, which are hidden and difficult to label.

As shown in Figure 2 (left), we can see that RS has longer Q-A paths as underlying reasoning chains. In addition, we can see that RS generally has longer chains, particularly the min of CSQA is 1-hop for more than 80% of examples. On the other hand, only about 30% of RS examples have 1-hop minimum Q-A paths, while about 50% of the examples have 2-hop min Q-A paths. The distribution over the maximum in Figure 2 (right) also shows that RS tends to have longer maximum paths than CSQA. We also show the percentage of all Q-A paths of different length as part of Table 2, and we can see that RS has longer paths in general (e.g., CSQA = 14.0% vs. RS = 4.6% in 1-hop).

3.3 Relational Types of Reasoning Paths

In addition to the analysis on path length, we also show that the relation types of Q-A paths for RS and CSQA have a clear difference, as shown in Table 2. The types of reasoning chains in RS rely more on a special relation in ConceptNet — `Related`, which is relatively more implicit and can not be grounded to a specific, explicit relation such as `AtLoc` (e.g., <*wind*, `Related`, *air*> vs. <*lamp*, `AtLoc`, *table*>).

The most frequent relation between question concepts and answer concepts in CSQA is the `AtLoc` relation (4.8%), however, it is `Related` (3.1%) in RS. We define *implicit-ratio* for k-hop paths, ρ_k, as follows:

$$\rho_k = \frac{\%(\texttt{Related} \times k)}{\%(E_k)}$$

where E_k is the most frequent type of chains with at least one explicit relation of length k. In RS, ρ_k is around $4.1 \sim 7.8$, while it is about $0.7 \sim 1.8$ for CSQA. Thus, we can conclude that the dominant

CommonsenseQA (CSQA)			
1-hop (14.0%)	**2-hop (34.4%)**	**3-hop (41.5%)**	**4-hop (9.5%)**
AtLoc (4.8%) Related (3.4%) Causes (1.1%) Antonym (0.9%) Capableof (0.8%) ...	Related-Related (8.3%) Related-AtLoc (4.5%) Related-Antonym (1.8%) Related-IsA^{-1} (1.3%) Related-AtLoc^{-1} (0.9%) ...	Related-Related-Related (4.1%) Related-Related-AtLoc (2.7%) Related-AtLoc^{-1}-AtLoc (1.4%) Related-Related-Antonym (1.3%) Related-Related-CapableOf (1.3%) ...	Related $\times$ 4 (0.4%) Related $\times$ 3 -AtLoc (0.3%) Related-Related-AtLoc^{-1}-AtLoc (0.3%) Related $\times$ 3 -Antonym (0.2%) Related$\times$2-SubEvent^{-1}-Cause (0.1%) ...
$\rho = \frac{3.4}{4.8} = 0.7$	$\rho = \frac{8.3}{4.5} = 1.8$	$\rho = \frac{4.1}{2.7} = 1.5$	$\rho = \frac{0.4}{0.3} = 1.3$
RiddleSense (RS)			
1-hop (4.6%)	**2-hop (31.6%)**	**3-hop (47.8%)**	**4-hop (14.0%)**
Related (3.1%) Antonym (0.4%) IsA^{-1} (0.3%) PartOf (0.1%) AtLoc^{-1} (0.1%) ...	Related-Related (13.1%) Related-Antonym (2.1%) Related-IsA^{-1} (2.0%) Related-AtLoc^{-1} (1.3%) Antonym-Related (0.8%) ...	Related-Related-Related (10.6%) Related-Related-IsA^{-1} (2.6%) Related-Related-Antonym (1.6%) Related-Antonym-Related (1.5%) Antonym-Related-Related (1.5%) ...	Related $\times$ 4 (1.8%) Antonym-Related$\times$3 (0.4%) Related$\times$3 -IsA^{-1} (0.3%) Related$\times$2-IsA^{-1}-Related (0.3%) Related$\times$2-Antonym-Related (0.3%) ...
$\rho = \frac{3.1}{0.4} = 7.8$	$\rho = \frac{13.1}{2.1} = 6.2$	$\rho = \frac{10.6}{2.6} = 4.1$	$\rho = \frac{1.8}{0.4} = 4.5$

Table 2: The top-5 most frequent types of reasoning chains in CSQA and RS datasets, grouped by their length $k = \{1, 2, 3, 4\}$. The implicit-ratio ρ is defined as the ratio of the implicit reasoning types (i.e., Related$\times k$) over the most frequent types with at least one explicit relation (e.g., AtLoc) of the same length k.

reasoning chains of RS examples are much more implicit, and consequently RS is more challenging to reason over direct, explicit commonsense knowledge resources such as ConceptNet.

4 Experiments

We first introduce three types of popular baseline methods for commonsense reasoning (Section 4.1), then we present our main experimental results with analysis (Section 4.2), and finally show case studies for error analysis (Section 4.3).

4.1 Baseline Methods

Recall that the RIDDLESENSE is a 5-way multiple-choice question answering task. Given a question (i.e., a riddle) q, there are 5 different choices $\{c_1, \ldots, c_5\}$, where only one of them is the correct choice and the others are distractors. The model needs to rank all choices and select the best one as the final answer. There are three major types of models for commonsense reasoning tasks in this format: 1) fine-tuning pretrained language models, 2) incorporating relevant knowledge graphs for reasoning, 3) fine-tuning a unified text-to-text QA model, as shown in Figure 4.

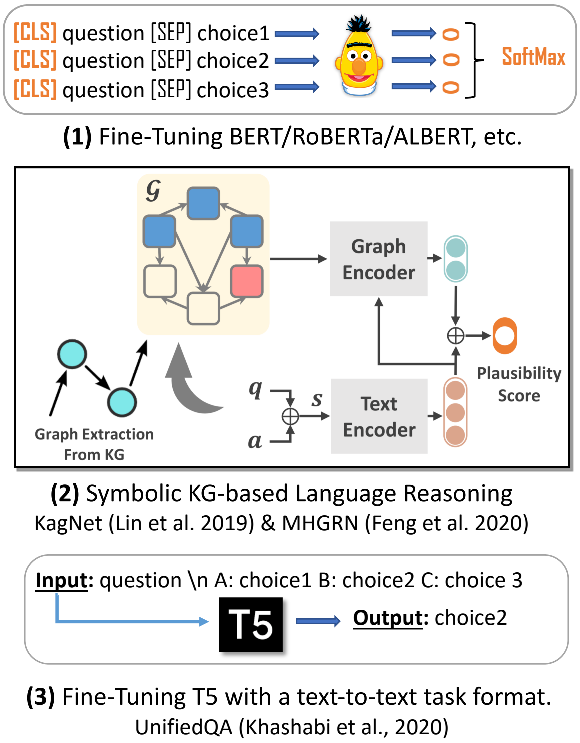


Figure 4: Three types of baseline methods: 1) fine-tuning pre-trained LMs, 2) incorporating graph-based reasoner, 3) fine-tuning a unified text-to-text LM.

4.1.1 Fine-tuning Pre-trained LMs

As we seek to investigate how well current NLU models can perform in higher-order commonsense reasoning, we first experiment with a typical set of large pretrained language models such as BERT (Devlin et al., 2019b), RoBERTa (Liu et al., 2019), and ALBERT (Lan et al., 2020). Following previous works, we concatenate the question with

Models \ Training Data	Train=CSQA		Train=RS		Tr.=RS+CSQA	
RiddleSense-Split	Dev	Test	Dev	Test	Dev	Test
Random Guess	20.0	20.0	20.0	20.0	20.0	20.0
BERT-Base (Devlin et al., 2019a)	33.59	34.61	54.16	42.43	56.22	47.67
BERT-Large (Devlin et al., 2019a)	36.14	39.10	55.24	45.09	57.69	54.91
RoBERTa-Large (Liu et al., 2019)	43.68	47.42	60.72	52.58	66.11	59.82
ALBERT-XXL (Lan et al., 2020)	**51.03**	**51.00**	66.99	60.65	**71.50**	67.30
KagNet (RB-L) (Lin et al., 2019)	42.66	48.24	61.77	53.72	66.55	59.72
MHGRN (RB-L) (Feng et al., 2020)	46.83	49.65	63.27	54.49	66.90	63.73
MHGRN (AB-XXL) (Feng et al., 2020)	50.89	50.21	66.27	59.93	70.81	66.81
UnifiedQA (T5-L) (Khashabi et al., 2020)	28.50	37.27	56.21	56.40	58.17	56.57
UnifiedQA (T5-3B) (Khashabi et al., 2020)	37.32	50.25	**67.38**	**66.06**	68.26	**68.80**
Human Performance	-	91.33	-	91.33	-	91.33

Table 3: Benchmark performance over the dev and test set of RIDDLESENSE (v1.0).

each choice individually, using [SEP] (or its alternative) as the sentence separator, thus forming a *statement*. Then, we can fine-tune any pretrained LMs like BERT to use their [CLS] (or its alternative) token embeddings to predict a logit for each statement. Then, a set of five logits about a certain example will be fed to a SoftMax layer to optimize for maximizing the logit of the correct choice.

4.1.2 LMs + Graph Reasoning Modules

KagNet (Lin et al., 2019) and MHGRN (Feng et al., 2020) are two typical graph-based language reasoning models. They both extract a *schema graph* from ConceptNet, i.e., a subgraph of ConceptNet consisting of Q-A paths in Figure 3, by incorporating them with a graph encoding module. They finally fuse the external commonsense knowledge with a text encoder (e.g., a pretrained LM). KagNet uses heuristics to prune irrelevant paths and then encode them with path-based LSTM and hierarchical attention to select the most important paths for improving commonsense reasoning. In contrast, the recent MHGRN explicitly encodes multi-hop paths at scale using graph networks with relational attention, improving efficiency and performance over KagNet and other models. A unique merit of such graph-based models is their *interpretibility* due to the neural attention over the symbolic structures of KGs.

4.1.3 Fine-Tuning a Text-to-Text QA Model

UnifiedQA (Khashabi et al., 2020), the state-of-the-art multiple-choice QA model, simply concatenates the question with all answer candidates as a single input sequence to a T5 (Raffel et al., 2020) model for learning to generate the correct choice as extracting a span from the input. Apart from the multiple-choice QA format, it is also trained with other QA task formats so that it can benefit from many other QA datasets (including CSQA) via sharing the model parameters.

4.2 Results and Analysis

We show the main results of the experiments in Table 3. There are 3 settings according to the different training data options: 1) the training data of CSQA, 2) the training data of RS, and 3) the concatenation of both RS and CSQA, while all experiments are validated over the dev set of RS. However, as the public UnifiedQA checkpoints were already trained on CSQA (together with many other QA datasets), we directly use them for inference over RS in the first setting (i.e., "Train=CSQA"). This also suggests that the performance of UnifiedQA models in 2nd setting should be better than others although they all are fine-tuned on RS's training data only.

We can see that larger pretrained language understanding models always gain better performance, ranging from BERT-base to Albert-XXL, which gets the best performance in this group of baselines (67.30%). This matches their performance comparisions on CSQA and other benchmark datasets as well, suggesting that a better pretrained language model can be also identified by

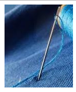
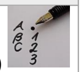
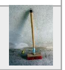
Riddle	Choices (√=truth; ×=model's choice)	Explanation
I am black when you buy me, red when you use me. When I turn white, you know it's time to throw me away. What am I?	(A) charcoal (√) (B) rose flower (C) ink (×) (D) fruit (E) shoe	Describing multiple conditions of a common object. Only charcoal applies to all. 
I have a long tail that I let fly. Every time I go through a gap, I leave a bit of my tail in the trap. What am I?	(A) monkey (B) basketball (C) fishing pole (×) (D) comet (E) needle (√)	Describing a common event and involved objects with metaphor: tail → thread; fly → sew; 
If you take off my skin, I will not cry, but you will. What am I?	(A) grape (B) onion (√) (C) package (D) plant (E) body (×)	Personalization. Cutting onions → taking off my skin. 
What is that which, though black itself, enlightens the world *without burning*?	(A) coal (B) hole (C) cd player (D) sunlight (×) (E) ink (√)	Figure of speech (ink → writing → knowledge → *light* of wisdom) + Counterfactual (without burning) 
I have hundreds of legs, but I can only lean. What am I?	(A) chair (×) (B) sock (C) pleopod (D) pants (E) broom (√)	Counterfactual (many legs but cannot stand) + Metaphor (bristles) 

Figure 5: Case studies of the error by UnifiedQA-3B model on the test set of RIDDLESENSE.

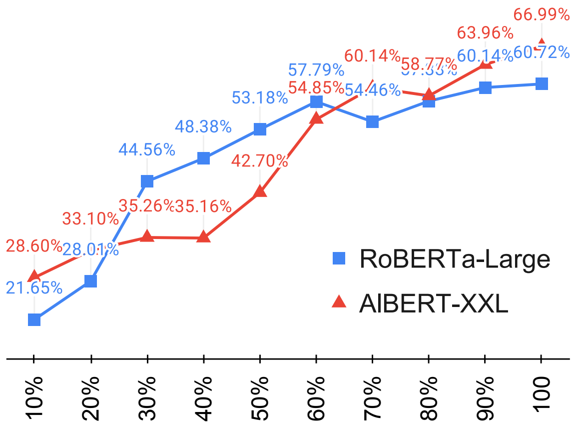


Figure 6: The curve of dev accuracy using different percentage of the RS-training data, respectively for RoBERTa-Large and ALBERT-XXL.

RIDDLESENSE as well. Interestingly, we find that ALBERT-XXL is so powerful that it can generalize from training on CSQA only but achieve comparable results with RoBERTa-Large that is trained over RS (i.e., 51.0% vs. 52.6%). However, if we look at the curve of dev accuracy when using different percentage of the RS-train data (setting 2) in Figure 6, we can see that RoBERTa-Large can generally outperform ALBERTA-XXL when using less than 60% data for fine-tuning.

Moreover, we find that the KG-enhanced models, KagNet and MHGRN, using RoBERTa-Large (RB-L) as the encoder, perform better than vanilla RB-L. Although the Q-A paths over ConceptNet have more implicit paths (e.g., $\texttt{Related}\times k$), some paths can still be beneficial. For example,

$$\textit{wind} \xleftrightarrow{\texttt{Related}} \textit{blow} \xleftrightarrow{\texttt{Related}} \textit{candle},$$

can still help reason about the riddle *"... Wind is my foe. What am I?"* to the answer "candle."

The fusion of ConceptNet also improves in the situation when only training with CSQA data using RoBERTa-Large. However, the improvement of KagNet is negative, which is unexpected. We conjecture that this is because the extracted subgraphs from the ConceptNet does not guarantee the reasoning path from question concepts to answer concepts, while the training phase *forces* models to learn to reason over those graphs, yielding a possibly *harmful* impact. Additionally, we find that MHGRN with ALBERT-XXL also results in a worse performance, unlike using RoBERTa-Large. We believe this may be related to the specific design of ALBERT, which reuses model parameters for multiple layers, and thus it could be a problem when fused with another learnable module (i.e., a graph network in the case of MHGRN).

Fine-tuning UnifiedQA with T5-3B achieves the best performance, which is also the case for CSQA in their leaderboard. This is expected for two reasons: 1) UnifiedQA has been trained over multiple other QA datasets, which increases its generalization ability, 2) UnifiedQA considers all choices together at a time and thus can better compare different choices with self-attention mechanism of Transformer (Vaswani et al., 2017).

4.3 Error Analysis

We show a few examples that are mistakenly predicted by the UnifiedQA-3B model in Figure 5. From these concrete cases, we can see that even the best model cannot solve riddles that can be trivial to humans, especially when there are metaphors and/or counterfactual situations. We argue that future research should aim to address the creative use of language in commonsense reasoning and general understanding of language, as creativity is a critical feature of natural language.

5 Related Work

Benchmarking Machine Common Sense

The prior works on building commonsense reasoning benchmarks touch different aspects of commonsense reasoning: 1) SWAG (Zellers et al., 2018), HellaSWAG (Zellers et al., 2019), CODAH (Chen et al., 2019), aNLI (Bhagavatula et al., 2019) for situation-based reasoning; 2) Physical IQA (Bisk et al., 2020) on physical knowledge, 3) Social IQA (Sap et al., 2019) on social psychology knowledge, 4) LocatedNearRE (Xu et al., 2018) on mining spatial commonsense knowledge, 5) DoQ (Elazar et al., 2019) and NumerSense (Lin et al., 2020a) on numerical common sense, 6) CommonGen (Lin et al., 2020b) for generative commonsense reasoning, and many others.

CommonsenseQA (Talmor et al., 2019) has the same format as the proposed RIDDLESENSE, and both target general commonsense knowledge via question answering. However, CSQA focuses more on straightforward questions where the description of the answer concept is easy to understand and retrieval over ConceptNet, while RS makes use of riddle questions to test higher-order commonsense reasoning ability. More detailed comparisions between them are in Section 3, which shows that the unique challenges of RS.

Commonsense Reasoning Methods

Our experiments cover three major types of commonsense reasoning methods that are popular in many benchmarks: fine-tuning pretrained LMs (Devlin et al., 2019a; Liu et al., 2019; Lan et al., 2020), graph-based reasoning with external KGs (Lin et al., 2019; Feng et al., 2020), and fine-tuning unified text-to-text QA models (Khashabi et al., 2020). Apart from ConceptNet, There are also some methods (Lv et al., 2020; Xu et al., 2020) using additional knowledge resources such as Wikipedia and Wiktionary. A few recent methods also aim to generate relevant triples via language generation models so that the context graph is more beneficial for reasoning (Wang et al., 2020; Yan et al., 2020). Our experiments in this paper aim to compare the most typical and popular methods which have open-source implementations, which we believe are beneficial for understanding the limitation of these methods in higher-order commonsense reasoning — RIDDLESENSE.

Computational Creativity and NLP

Creativity has been seen as a central property of the human use of natural language (McDonald and Busa, 1994). Text should not be always taken at face value, however, higher-order use of language and figurative devices such as metaphor can communicate richer meanings and needs deeper reading and more complicated reasoning skills (Veale, 2011). Recent works on processing language with creative use focus on metaphor detection (Gao et al., 2018), pun generation (He et al., 2019; Luo et al., 2019), creative story generation, and humor detection (Weller and Seppi, 2019, 2020), sarcasm generation (Chakrabarty et al., 2020), etc.

Riddling, as a way to use creative descriptions to query a common concept, are relatively underexplored. Previous works (Tan et al., 2016; Oliveira and Ciferri, 2018) focus on the generation of riddles in specific languages and usually rely on language-specific features (e.g., decomposing a Chinese character into multiple smaller pieces). There is few datasets or public resources for studying riddles as a reasoning task, to the best of our knowledge. The proposed RIDDLESENSE is among the very first works connecting commonsense reasoning and computational creative, and provides a large dataset to train and evaluate models for answering riddle questions.

6 Conclusion

We propose a novel commonsense reasoning challenge, RIDDLESENSE, which requires complex commonsense skills for reasoning about creative and counterfactual questions, coming with a large multiple-choice QA dataset. We systematically evaluate recent commonsense reasoning methods over the proposed RIDDLESENSE dataset, and find that the best model is still far behind human performance, suggesting that there is still much space for commonsense reasoning methods to improve. We hope RIDDLESENSE can serve as a benchmark dataset for future research targeting complex commonsense reasoning and computational creativity.

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