Commonsense Reasoning for Natural Language Understanding: A Survey of Benchmarks, Resources, and Approaches

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Abstract

Commonsense knowledge and commonsense reasoning are some of the main bottlenecks in machine intelligence. In the NLP community, many benchmark datasets and tasks have been created to address commonsense reasoning for language understanding. These tasks are designed to assess machines' ability to acquire and learn commonsense knowledge in order to reason and understand natural language text. As these tasks become instrumental and a driving force for commonsense research, this paper aims to provide an overview of existing tasks and benchmarks, knowledge resources, and learning and inference approaches toward commonsense reasoning for natural language understanding. Through this, our goal is to support a better understanding of the state of the art, its limitations, and future challenges.

1. Introduction

Commonsense knowledge and commonsense reasoning play a vital role in all aspects of machine intelligence, from language understanding to computer vision and robotics. A detailed account of challenges with commonsense reasoning is provided by Davis and Marcus (2015), which spans from difficulties in understanding and formulating commonsense knowledge for specific or general domains to complexities in various forms of reasoning and their integration for problem solving. To move the field forward, as pointed out by Davis and Marcus (2015), there is a critical need for methods that can integrate different modes of reasoning (e.g., symbolic reasoning through deduction and statistical reasoning based on large amount of data), as well as benchmarks and evaluation metrics that can quantitatively measure research progress.

In the NLP community, recent years have seen a surge of research activities that aim to tackle commonsense reasoning through ever-growing benchmark tasks. These range from earlier textual entailment tasks, e.g., the RTE Challenges (Dagan, Glickman, & Magnini, 2005), to more recent tasks that require a comprehensive understanding of everyday physical and social commonsense, e.g., the Story Cloze Test (Mostafazadeh, Chambers, He, Parikh, Batra, Vanderwende, Kohli, & Allen, 2016) or SWAG (Zellers, Bisk, Schwartz, & Choi, 2018). An increasing effort has been devoted to extracting commonsense knowledge from existing data (e.g., Wikipedia) or acquiring it directly from crowd workers. Many learning and inference approaches have been developed for these benchmark tasks which range from earlier symbolic and statistical approaches to more recent neural approaches. To facilitate quantitative evaluation and encourage broader participation from the community, various leaderboards for these benchmarks have been set up and maintained.

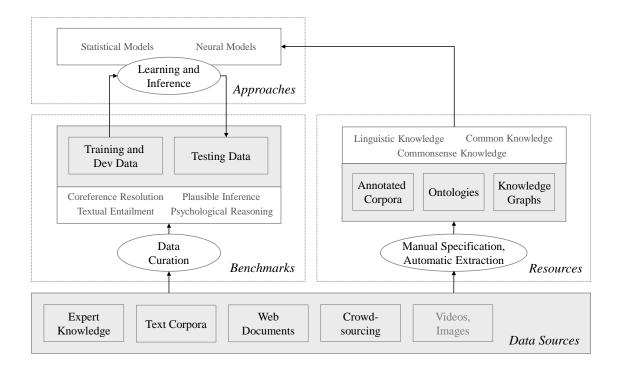


Figure 1: Main research efforts in commonsense knowledge and reasoning from the NLP community occur in three areas: benchmarks and tasks, knowledge resources, and learning and inference approaches.²

As more and more resources become available for commonsense reasoning for NLP, it is useful for researchers to have a quick grasp of this fast evolving space. As such, this paper aims to provide an overview of existing benchmarks, knowledge resources, and approaches, and discuss current limitations and future opportunities. We hope this paper will provide an entry point to those who are not familiar with but interested in pursuing research in this topic area.

As shown in Figure 1, ongoing research effort has focused on three main areas. The first, discussed further in Section 2, is the creation of benchmark datasets for various NLP tasks. Different from earlier benchmark tasks that mainly focus on linguistic processing, these tasks are designed so that the solutions may not be obvious from the linguistic context but rather require commonsense knowledge and reasoning. These benchmarks vary in terms of the scope of reasoning, for example, from the specific and focused coreference resolution task in the Winograd Schema Challenge (Levesque, 2011) to broader tasks such as textual entailment, e.g., the RTE Challenges (Dagan et al., 2005). While some benchmarks only focus on one specific task, others are comprised of a variety of tasks, e.g., GLUE (Wang, Singh, Michael, Hill, Levy, & Bowman, 2018). Some benchmarks target a specific type of commonsense knowledge, e.g., social psychology in Event2Mind (Rashkin, Sap, Allaway, Smith, & Choi, 2018b), while others intend to address a variety of types of knowledge, e.g., bAbI (Weston, Bordes, Chopra, Rush, van Merriënboer, Joulin, & Mikolov,

^{2.} Although videos and images are often used for creating various benchmarks, they are not the focus of this paper.

2016). How benchmark tasks are formulated also differs among existing benchmarks. Some are in the form of multiple-choice questions, requiring a binary decision or a selection from a candidate list, while others are more open-ended. Different characteristics of benchmarks serve different goals, and a critical question is what criteria to consider in order to create a benchmark that can support technology development and measurable outcome of research progress on commonsense reasoning abilities. Section 2 gives a detailed account of existing benchmarks and their common characteristics. It also summarizes important criteria to consider in building these benchmarks.

A parallel ongoing research effort is the population of commonsense knowledge bases. Apart from earlier efforts where knowledge bases are manually created by domain experts, e.g., Cyc (Lenat & Guha, 1989) or WordNet (Fellbaum, 1999), or by crowdsourcing, e.g., ConceptNet (Liu & Singh, 2004), recent work has focused on applying NLP techniques to automatically extract information (e.g., facts and relations) and build knowledge representations such as knowledge graphs. Section 3 gives an introduction to existing commonsense knowledge resources and several recent efforts in building such resources.

To tackle benchmark tasks, many computational models have been developed from earlier symbolic and statistical approaches to more recent approaches that learn deep neural models from training data. These models are often augmented with external data or knowledge resources, or pre-trained word embeddings, e.g., BERT (Devlin, Chang, Lee, & Toutanova, 2018). Section 4 summarizes the state-of-the-art approaches, and discusses their performance and limitations.

It is worth pointing out that as commonsense reasoning plays an important role in almost every aspect of machine intelligence, recent years have also seen an increasing effort in other related disciplines such as computer vision, robotics, and the intersection between language, vision, and robotics. This paper will only focus on the development in the NLP field without concerning these other related areas. Nevertheless, the current practice, and the progress and limitations from the NLP field may also provide some insight to these related disciplines and vice versa.

2. Benchmarks and Tasks

The NLP community has a long history of creating benchmarks to facilitate algorithm development and evaluation for language processing tasks, e.g., named entity recognition, coreference resolution, and question answering. Although it is often the case that some type of commonsense reasoning may be required to reach an oracle performance on these tasks, earlier benchmarks have mainly targeted approaches that apply linguistic context to solve these tasks. As significant progress has been made by using the earlier benchmarks, recent years have seen a shift in benchmark tasks which are beyond the use of linguistic context, but rather require commonsense knowledge and reasoning to solve the tasks. For instance, consider this question from the Winograd Schema Challenge (Levesque, 2011): "The trophy would not fit in the brown suitcase because it was too big. What was too big?" To answer this question, linguistic constraints will not be able to resolve whether *it* refers to *the trophy* or *the brown suitcase*. Only based on commonsense knowledge (i.e., an object must be bigger than another object in order to contain it) is it possible to resolve the pronoun *it* and answer the question correctly. It is the goal of this paper to survey these kinds of recent benchmarks which are geared toward the use of commonsense reasoning for NLP tasks beyond the use of linguistic discourse.

In this section, we first give an overview of recent benchmarks that address commonsense reasoning in NLP. We then summarize important considerations in creating these benchmarks and lessons learned from ongoing research.

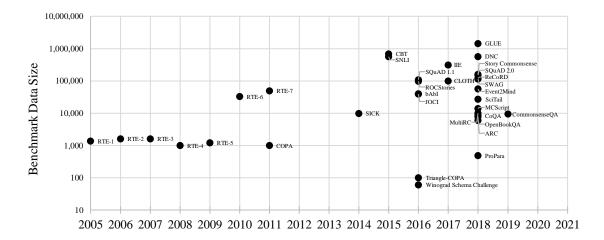


Figure 2: Since the early 2000s, there has been a surge of benchmark tasks geared towards commonsense reasoning for language understanding. In 2018, we saw the creation of more benchmarks of larger sizes than ever before.

2.1 An Overview of Existing Benchmarks

Since the Recognizing Textual Entailment (RTE) Challenges introduced by Dagan et al. (2005) in the early 2000s, there has been an explosion of commonsense-directed benchmarks being created. Figure 2 shows a trend of this growth in the field among the benchmarks introduced in this section. The RTE challenges, which were inspired by difficulties encountered in semantic processing for machine translation, question answering, and information extraction (Dagan et al., 2005), had been the main dominating reasoning task for many years. Since 2013, however there has been a surge of a variety of benchmarks. A majority of them (e.g., those released in 2018) have provided more than 10,000 instances, aiming to facilitate the development of machine learning approaches.

Many commonsense benchmarks are based upon classic language processing problems. The scope of these benchmark tasks ranges from more focused tasks, such as coreference resolution and named entity recognition, to more comprehensive tasks and applications, such as question answering and textual entailment. More focused tasks tend to be useful in creating component technology for NLP systems, building upon each other toward more comprehensive tasks.

Meanwhile, rather than restricting tasks by the types of language processing skills required to perform them, a common characteristic of earlier benchmarks, recent benchmarks are more commonly geared toward particular types of commonsense knowledge and reasoning. Some benchmark tasks focus on singular commonsense reasoning processes, e.g., temporal reasoning, requiring a small amount of commonsense knowledge, while others focus on entire domains of knowledge, e.g., social psychology, thus requiring a larger set of related reasoning skills. Further, some benchmarks include a more comprehensive mixture of everyday commonsense knowledge, demanding a more complete commonsense reasoning skill set.

Next, we give a review of widely used benchmarks, introduced by the following groupings: coreference resolution, question answering, textual entailment, plausible inference, psychological reasoning, and multiple tasks. These groupings are not necessarily exclusive, but they highlight the recent trends in commonsense. While all tasks' training and/or development data are available for

free download, it is important to note that test data are often not distributed publicly so that testing of systems can occur privately in a standard, unbiased way.

2.1.1 Coreference Resolution

One particularly fundamental focused task is coreference resolution, i.e., determining which entity or event in a text a particular pronoun refers to. This task becomes challenging, however, due to ambiguities which arise from the presence of multiple entities in a sentence with pronouns and significantly complicate the process, creating a need for commonsense knowledge to inform decisions (Levesque, 2011). Even informed by a corpus or knowledge graph, current coreference resolution systems are plagued by data bias, e.g., gender bias in nouns for occupations (Rudinger, Naradowsky, Leonard, & Van Durme, 2018a). Since challenging examples in commonsense-informed coreference resolution are typically handcrafted or handpicked (Morgenstern, Davis, & Ortiz, 2016; Rahman & Ng, 2012; Rudinger et al., 2018a), there exists a small magnitude of data for this skill, and it remains an unsolved problem (Rahman & Ng, 2012; Davis, Morgenstern, & Ortiz, 2017). Consequently, there is a need for more benchmarks here. In the following paragraphs, we introduce the few benchmarks and tasks that currently exist for coreference resolution.

Winograd Schema Challenge. The classic coreference resolution benchmark is the Winograd Schema Challenge (WSC), inspired by Winograd (1972), originally proposed by Levesque (2011), later developed by Levesque, Davis, and Morgenstern (2012), and actualized by Morgenstern and Ortiz (2015) and Morgenstern et al. (2016). In this challenge, systems are presented with questions about sentences known as Winograd schemas. To answer a question, a system must disambiguate a pronoun whose coreferent may be one of two entities, and can be changed by replacing a single word in the sentence. The first Challenge dataset consisted of just 60 testing examples (Morgenstern, 2016), but there are more available online. Additionally, Rahman and Ng (2012) curated nearly 1,000 similar pronoun resolution problems to aid in training systems for the WSC; this set of problems is included within a later-mentioned dataset, and thus is not introduced separately. Further information about the Winograd Schema Challenge is available at http://commonsensereasoning.org/winograd.html.

Other coreference resolution tasks. Other coreference resolution tasks include the basic and compound coreference tasks within bAbI (Weston et al., 2016), the definite pronoun resolution problems by Rahman and Ng (2012) within Inference is Everything (White, Rastogi, Duh, & Van Durme, 2017), the Winograd NLI task within GLUE (Wang et al., 2018), and the gendered anaphora-based Winogender task originally by Rudinger et al. (2018a) within DNC (Poliak, Haldar, Rudinger, Hu, Pavlick, White, & Van Durme, 2018a). The full benchmarks to which these tasks belong are introduced in Section 2.1.6, while in Figure 3, we list several examples of challenging coreference resolution problems across all existing benchmarks, where commonsense knowledge, such as the fact that predators eat their prey, is useful in disambiguating pronouns.

^{3.} See http://cs.nyu.edu/faculty/davise/papers/WinogradSchemas/WS.html, http://commonsensereasoning.org/winograd.html, and http://commonsensereasoning.org/disambiguation.html.

(A) Winograd Schema Challenge (Levesque, 2011)

The trophy would not fit in the brown suitcase because it was too big. What was too big?

- a. The trophy
- b. The suitcase

The trophy would not fit in the brown suitcase because it was too small. What was too small?

- a. The trophy
- b. The suitcase

(B) Winogender (Rudinger et al., 2018a)

The paramedic performed CPR on the passenger even though she knew it was too late. Who knew it was too late?

- a. The paramedic
- b. The passenger

(C) (Rahman & Ng, 2012)

Lions eat zebras because they are predators. Who are predators?

- a. Lions
- b. Zebras

Figure 3: Examples from existing coreference resolution benchmark tasks. Answers in bold.

2.1.2 QUESTION ANSWERING

Instead of providing one or more focused language processing or reasoning tasks, many benchmarks instead provide a more comprehensive mix of language processing and reasoning skills within a single task. Question answering (QA) is one such comprehensive task. QA is a fairly well-investigated area of artificial intelligence, and there are many existing benchmarks to support work here, however not all of them require commonsense to solve (Ostermann, Modi, Roth, Thater, & Pinkal, 2018). Some QA benchmarks which directly address commonsense are MCScript (Ostermann et al., 2018), CoQA (Reddy, Chen, & Manning, 2018), OpenBookQA (Mihaylov, Clark, Khot, & Sabharwal, 2018), and ReCoRD (Rajpurkar, Zhang, Lopyrev, & Liang, 2016), all of which contain questions requiring commonsense knowledge alongside questions requiring comprehension of a given text. Examples of such questions are listed in Figure 4; here, the commonsense knowledge facts that diapers are typically thrown away, and that steel is a metal, are particularly useful in answering questions. Other QA benchmarks indirectly address commonsense by demanding advanced reasoning processes best informed by commonsense. SQuAD 2.0 is one such example, as it includes unanswerable questions about passages (Rajpurkar, Jia, & Liang, 2018), which may take outside knowledge to identify. In the following paragraphs, we introduce all surveyed QA benchmarks.

ARC. The AI2 Reasoning Challenge (ARC) from Clark, Cowhey, Etzioni, Khot, Sabharwal, Schoenick, and Tafjord (2018) provides a dataset of almost 8,000 four-way multiple-choice science questions and answers, as well as a corpus of 14 million science-related sentences which are claimed to contain most of the information needed to answer the questions. As many of the questions require systems to draw information from multiple sentences in the corpus to answer correctly, it is not possible to accurately solve the task by simply searching the corpus for keywords. As such, this task encourages advanced reasoning which may be useful to commonsense. ARC can be downloaded at http://data.allenai.org/arc/.

(A) MCScript (Ostermann et al., 2018)

Did they throw away the old diaper?

- a. Yes, they put it into the bin.
- b. No, they kept it for a while.

(B) OpenBookQA (Mihaylov et al., 2018)

Which of these would let the most heat travel through?

- a. a new pair of jeans.
- b. a steel spoon in a cafeteria.
- c. a cotton candy at a store.
- d. a calvin klein cotton hat.

Evidence: Metal is a thermal conductor.

(C) CoQA (Reddy et al., 2018)

The Virginia governor's race, billed as the marquee battle of an otherwise anticlimactic 2013 election cycle, is shaping up to be a foregone conclusion. Democrat Terry McAuliffe, the longtime political fixer and moneyman, hasn't trailed in a poll since May. Barring a political miracle, Republican Ken Cuccinelli will be delivering a concession speech on Tuesday evening in Richmond. In recent ...

Who is the democratic candidate?

Terry McAuliffe

Evidence: Democrat Terry McAuliffe

Who is his opponent?

Ken Cuccinelli

Evidence: Republican Ken Cuccinelli

Figure 4: Examples from QA benchmarks which require common and/or commonsense knowledge. Answers in bold.

MCScript. The MCScript benchmark by Ostermann et al. (2018) is one of few QA benchmarks which emphasizes commonsense. The dataset consists of about 14,000 2-way multiple-choice questions based on short passages, with a large proportion of its questions requiring pure commonsense knowledge to answer, and thus can be answered without the passage. Questions are conveniently labeled with whether they are answered with the provided text or commonsense. A download link to MCScript can be found at http://www.sfbl102.uni-saarland.de/?page_id=2582.

ProPara. ProPara by Mishra, Huang, Tandon, Yih, and Clark (2018) consists of 488 annotated paragraphs of procedural text. These paragraphs describe various processes such as photosynthesis and hydroelectric power generation in order for systems to learn object tracking in processes which involve changes of state. The authors assert that recognizing these state changes can require world knowledge, so proficiency in commonsense reasoning is necessary to perform well. Annotations of the paragraphs are in the form of a grid which describes the state of each participant in the paragraph after each sentence of the paragraph. If a system understands a paragraph in this dataset, it is said that for each entity mentioned in the paragraph, it can answer any question about whether the entity is created, destroyed, or moved, and when and where this happens. To answer all possible perfectly accurately, a system must produce a grid identical to the annotations for the paragraph. Thus, systems are evaluated by their performance on this task. ProPara data is linked from http://data.allenai.org/propara/.

MultiRC MultiRC by Khashabi, Chaturvedi, Roth, Upadhyay, and Roth (2018) is a reading comprehension dataset consisting of about 10,000 questions posed on over 800 paragraphs across a variety of topic domains. It differs from a traditional reading comprehension dataset in that most questions can only be answered by reasoning over multiple sentences in the accompanying paragraphs, answers are not spans of text from the paragraph, and the number of answer choices as well as the number of correct answers for each question is entirely variable. All of these features make it difficult for shallow and artificial approaches to perform well on the benchmark, encouraging a deeper understanding of the passage. Further, the benchmark includes a variety of nontrivial semantic phenomena in passages, such as coreference and causal relationships, which often require commonsense to recognize and parse. MultiRC can be downloaded at http://cogcomp.org/multirc/.

SQuAD. The Stanford Question Answering Dataset (SQuAD) from Rajpurkar et al. (2016) was originally a set of about 100,000 open-ended questions posed on passages from Wikipedia articles, which are provided with the questions. The initial dataset did not require commonsense to solve; questions required little reasoning, and answers were spans of text directly from the passage. To make this dataset more challenging, SQuAD 2.0 (Rajpurkar et al., 2018) was later released to add about 50,000 additional questions which are unanswerable given the passage. Determining whether a question is answerable may require outside knowledge, or at least some more advanced reasoning. All SQuAD data can be downloaded at http://rajpurkar.github.io/SQuAD-explorer/.

CoQA. The Conversational Question Answering (CoQA) dataset by Reddy et al. (2018) contains passages each accompanied with a set of questions in conversational form, as well as their answers and evidence for the answers. There are about 127,000 questions in the dataset total, but as they are conversational, questions pertaining to a passage must be answered together in order. While the conversational element of CoQA is not new, e.g., QuAC by Choi, He, Iyyer, Yatskar, Yih, Choi,

Liang, and Zettlemoyer (2018), CoQA becomes unique by including questions pertaining directly to commonsense reasoning, following Ostermann et al. (2018) in addressing a growing need for reading comprehension datasets which require various forms of reasoning. CoQA also includes out-of-domain types of questions appearing only in the test set, and unanswerable questions throughout. CoQA data can be downloaded at http://stanfordnlp.github.io/coqa/.

OpenBookQA. OpenBookQA by Mihaylov et al. (2018) intends to address the shortcomings of previous QA datasets. Earlier datasets often do not require commonsense or any advanced reasoning to solve, and those that do require vast domains of knowledge which are difficult to capture. OpenBookQA contains about 6,000 4-way multiple choice science questions which may require science facts or other common and commonsense knowledge. Instead of providing no knowledge resource like MCScript (Ostermann et al., 2018), or an inhibitively large corpus of facts to support answering the questions like ARC (Clark et al., 2018), OpenBookQA provides an "open book" of about 1,300 science facts to support answering the questions, each associated directly with the question(s) they apply to. For required common and commonsense knowledge, the authors expect that outside resources will be used in answering the questions. Information for downloading OpenBookQA can be found at http://github.com/allenai/OpenBookQA.

CommonsenseQA. CommonsenseQA by Talmor, Herzig, Lourie, and Berant (2019) is a QA benchmark which directly targets commonsense, like CoQA (Reddy et al., 2018) and ReCoRD (Zhang, Liu, Liu, Gao, Duh, & Van Durme, 2018), consisting of 9,500 three-way multiple-choice questions. To ensure an emphasis on commonsense, each question requires one to disambiguate a target concept from three connected concepts in ConceptNet, a commonsense knowledge graph (Liu & Singh, 2004). Utilizing a large knowledge graph like ConceptNet ensures not only that questions target commonsense relations directly, but that the types of commonsense knowledge and reasoning required by questions are highly varied. CommonsenseQA data can be downloaded at http://www.tau-nlp.org/commonsenseqa.

2.1.3 TEXTUAL ENTAILMENT

Recognizing textual entailment is another such comprehensive task. Textual entailment is defined by Dagan et al. (2005) as a directional relationship between a text and a hypothesis, where it can be said that the text *entails* the hypothesis if a typical person would infer that the hypothesis is true given the text. Some tasks expand this by also requiring recognition of contradiction, e.g., the fourth and fifth RTE Challenges (Giampiccolo, Dang, Magnini, Dagan, & Dolan, 2008; Bentivogli, Dagan, Dang, Giampiccolo, & Magnini, 2009). Performing such a task requires the utilization of several simpler language processing skills, such as paraphrase, object tracking, and causal reasoning, but since it also requires a sense of what a typical person would infer, commonsense knowledge is often essential to textual entailment tasks. The RTE Challenges (Dagan et al., 2005) are the classic benchmarks for entailment, but there are now several larger benchmarks inspired by them. Examples from these benchmarks are listed in Figure 5, and they require commonsense knowledge such as the process of making snow angels, and the relationship between the presence of a crowd and loneliness. In the following paragraphs, we introduce all textual entailment benchmarks in detail.

^{4.} Example extracted from the SICK data available at http://clic.cimec.unitn.it/composes/sick.

(A) RTE Challenge (Dagan et al., 2005)

Text: American Airlines began laying off hundreds of flight attendants on Tuesday, after a federal judge turned aside a union's bid to block the job losses.

Hypothesis: American Airlines will recall hundreds of flight attendants as it steps up the number of flights it operates.

Label: not entailment

(B) SICK (Marelli, Menini, Baroni, Bentivogli, Bernardi, & Zamparelli, 2014a)⁴

Sentence 1: Two children are lying in the snow and are drawing angels.

Sentence 2: Two children are lying in the snow and are making snow angels.

Label: entailment

(C) SNLI (Bowman, Angeli, Potts, & Manning, 2015)

Text: A black race car starts up in front of a crowd of people.

Hypothesis: A man is driving down a lonely road.

Label: contradiction

(D) MultiNLI, Telephone (Williams, Nangia, & Bowman, 2017)

Context: that doesn't seem fair does it *Hypothesis:* There's no doubt that it's fair.

Label: contradiction

(E) SciTail (Khot, Sabharwal, & Clark, 2018)

Premise: During periods of drought, trees died and prairie plants took over previously forested regions.

Hypothesis: Because trees add water vapor to air, cutting down forests leads to longer periods of drought.

Label: neutral

Figure 5: Examples from RTE benchmarks. Answers in bold.

RTE Challenges. An early attempt at an evaluation scheme for commonsense reasoning was the Recognizing Textual Entailment (RTE) Challenge (Dagan et al., 2005). The inaugural challenge provided a task where given a text and hypothesis, systems were expected to predict whether the text entailed the hypothesis. In following years, more similar Challenges took place (Bar-Haim, Dagan, Dolan, Ferro, Giampiccolo, Magnini, & Szpektor, 2006; Giampiccolo, Magnini, Dagan, & Dolan, 2007). The fourth and fifth Challenge added a new three-way decision task where systems were additionally expected to recognize contradiction relationships between texts and hypotheses (Giampiccolo et al., 2008; Bentivogli et al., 2009). The main task for the sixth and seventh Challenges instead provided one hypothesis and several potential entailing sentences in a corpus (Bentivogli, Clark, Dagan, & Giampiccolo, 2010, 2011). The eighth Challenge (Dzikovska, Nielsen, Brew, Leacock, Giampiccolo, Bentivogli, Clark, Dagan, & Dang, 2013) addressed a bit different problem which focused on classifying student responses as an effort toward providing automatic feedback in an educational setting. The first five RTE Challenge datasets consisted of around 1,000 examples each (Dagan et al., 2005; Bar-Haim et al., 2006; Giampiccolo et al., 2007, 2008; Bentivogli et al., 2009), while the sixth and seventh consisted of about 33,000 and 49,000 examples respectively. Data from all RTE Challenges can be downloaded at http://tac.nist.gov/.

SICK. The Sentences Involving Compositional Knowledge (SICK) benchmark by Marelli et al. (2014a) is a collection of close to 10,000 pairs of sentences. Two tasks are presented with this dataset, one for sentence relatedness, and one for entailment. The entailment task, which is more related to our survey, is a 3-way decision task in the style of RTE-4 (Giampiccolo et al., 2008) and RTE-5 (Bentivogli et al., 2009). SICK can be downloaded at http://clic.cimec.unitn.it/composes/sick.html.

SNLI. The Stanford Natural Language Inference (SNLI) benchmark from Bowman et al. (2015) contains nearly 600,000 sentence pairs, and also provides a 3-way decision task similar to the fourth and fifth RTE Challenges (Giampiccolo et al., 2008; Bentivogli et al., 2009). In addition to gold labels for entailment, contradiction, or neutral, the SNLI data includes five crowd judgments for the label, which may indicate a level of confidence or agreement for it. This benchmark is later expanded into MultiNLI (Williams et al., 2017), which follows the same format, but includes sentences of various genres, such as telephone conversations. MultiNLI is included within the previously introduced GLUE benchmark (Wang et al., 2018), while SNLI can be downloaded at http://nlp.stanford.edu/projects/snli/.

SciTail. SciTail by Khot et al. (2018) consists of about 27,000 premise-hypothesis sentence pairs adapted from science questions into a 2-way entailment task similar to the first RTE Challenge (Dagan et al., 2005). Unlike other entailment tasks, this one is primarily science-based, which may require some knowledge more advanced than everyday commonsense. SciTail can be downloaded at http://data.allenai.org/scitail/.

2.1.4 PLAUSIBLE INFERENCE

While textual entailment benchmarks require one to draw concrete conclusions, others require hypothetical, intermediate, or uncertain conclusions, defined as plausible inference (Davis & Marcus, 2015). Such benchmarks often focus on everyday events, which contain a wide variety of practical commonsense relations. Examples from these benchmarks are listed in Figure 6, and they require

(A) COPA (Roemmele, Bejan, & Gordon, 2011)

I knocked on my neighbor's door. What happened as result?

- a. My neighbor invited me in.
- b. My neighbor left his house.

(B) ROCStories (Mostafazadeh et al., 2016)

Tom and Sheryl have been together for two years. One day, they went to a carnival together. He won her several stuffed bears, and bought her funnel cakes. When they reached the Ferris wheel, he got down on one knee.

Ending:

- a. Tom asked Sheryl to marry him.
- b. He wiped mud off of his boot.

(C) SWAG (Zellers et al., 2018)

He pours the raw egg batter into the pan. He

- a. drops the tiny pan onto a plate
- b. lifts the pan and moves it around to shuffle the eggs.
- c. stirs the dough into a kite.
- d. swirls the stir under the adhesive.

(D) JOCI (Zhang, Rudinger, Duh, & Van Durme, 2016)

Context: John was excited to go to the fair *Hypothesis:* The fair opens.

Label: 5 (very likely)

Context: Today my water heater broke *Hypothesis:* A person looks for a heater.

Label: 4 (likely)

Context: John's goal was to learn how to draw well

Hypothesis: A person accomplishes the goal.

Label: 3 (plausible)

Context: Kelly was playing a soccer match for her University

Hypothesis: The University is dismantled.

Label: 2 (technically possible)

Context: A brown-haired lady dressed all in blue denim sits in a group of pigeons. Hypothesis: People are made of the denim.

Label: 1 (impossible)

Figure 6: Examples from commonsense benchmarks requiring plausible inference. Answers in bold.

commonsense knowledge of everyday interactions, e.g., answering a door, and activities, e.g., cooking. In the following paragraphs, we introduce all plausible inference commonsense benchmarks.

COPA. The Choice of Plausible Alternatives (COPA) task by Roemmele et al. (2011) provides a premise, each with two possible alternatives of causes or effects of the premise. Examples require both forward and backward causal reasoning, meaning that the premise could either be a cause or effect of the correct alternative. COPA data, which consists of 1,000 examples total, can be downloaded at http://people.ict.usc.edu/~gordon/copa.html.

CBT. The Children's Book Test (CBT) from Hill, Bordes, Chopra, and Weston (2015) consists of about 687,000 cloze-style questions from 20-sentence passages mined from publicly available children's books. These questions require a system to fill in a blank in a line of a story passage given a set of 10 candidate words to fill the blank. Questions are classified into 4 tasks based on the type of the missing word to predict, which can be a named entity, common noun, verb, or proposition. CBT can be downloaded at http://research.fb.com/downloads/babi/.

ROCStories. ROCStories by Mostafazadeh et al. (2016) is a corpus of about 50,000 five-sentence everyday life stories, containing a host of causal and temporal relationships between events, ideal for learning commonsense knowledge rules. Of these 50,000 stories, about 3,700 are designated as test cases, which include a plausible and implausible alternate story ending for trained systems to choose between. The task of solving the ROCStories test cases is called the Story Cloze Test, a more challenging alternative to the narrative cloze task proposed by Chambers and Jurafsky (2008). The most recent release of ROCStories, which can be requested at http://cs.rochester.edu/nlp/rocstories/, adds about 50,000 stories to the dataset.

JOCI. The JHU Ordinal Commonsense Inference (JOCI) benchmark by Zhang et al. (2016) consists of about 39,000 sentence pairs, each consisting of a context and hypothesis. Given these, systems must rate how likely the hypothesis is on a scale from 1 to 5, where 1 corresponds to impossible, 2 to technically possible, 3 to plausible, 4 to likely, and 5 to very likely. This task is similar to SNLI (Bowman et al., 2015) and other 3-way entailment tasks, but provides more options which essentially range between entailment and contradiction. This is fitting, considering the fuzzier nature of plausible inference tasks compared to textual entailment tasks. JOCI can be downloaded from http://github.com/sheng-z/JOCI.

CLOTH. The Cloze Test by Teachers (CLOTH) benchmark by Xie, Lai, Dai, and Hovy (2017) is a collection of nearly 100,000 4-way multiple-choice cloze-style questions from middle- and high school-level English language exams, where the answer fills in a blank in a given text. Each question is labeled with the type of reasoning it involves, where the four possible types are grammar, short-term reasoning, matching/paraphrasing, and long-term reasoning. CLOTH data can be downloaded at http://www.cs.cmu.edu/~glail/data/cloth/.

SWAG. Situations with Adversarial Generations (SWAG) from Zellers et al. (2018) is a benchmark dataset of about 113,000 beginnings of small texts each with four possible endings. Given the context each text provides, systems decide which of the four endings is most plausible. Examples also include labels for the source of the correct ending, and ordinal labels for the likelihood of each possible ending and the correct ending. SWAG data can be downloaded at http://rowanzellers.com/swaq/.

ReCoRD. The Reading Comprehension with Commonsense Reasoning (ReCoRD) benchmark by Zhang et al. (2018), similar to SQuAD (Rajpurkar et al., 2016), consists of questions posed on passages, particularly news articles. However, questions in ReCoRD are in cloze format, requiring more hypothetical reasoning, and many questions explicitly require commonsense reasoning to answer. Named entities are identified in the data, and are used to fill the blanks for the cloze task. The benchmark data consist of over 120,000 examples, most of which are claimed to require commonsense reasoning. ReCoRD can be downloaded at https://sheng-z.github.io/ReCoRD-explorer/.

(A) Triangle-COPA (Gordon, 2016)

A circle and a triangle are in the house and are arguing. The circle punches the triangle. The triangle runs out of the house. Why does the triangle leave the house?

- a. The triangle leaves the house because it wants the circle to come fight it outside.
- b. The triangle leaves the house because it is afraid of being further assaulted by the circle.

(B) SC (Rashkin, Bosselut, Sap, Knight, & Choi, 2018a)⁵

Jervis has been single for a long time. He wants to have a girlfriend. One day he meets a nice girl at the grocery store. Motivation: to be loved, companionship *Emotions:* shocked, excited, hope, shy, fine, wanted

Maslow: love

Reiss: contact, romance

Plutchik: joy, surprise, anticipation,

trust, fear

(C) Event2Mind (Rashkin et al., 2018b)

PersonX starts to yell at PersonY

PersonX's intent: to express anger, to vent their frustration, to get PersonY's full attention

PersonX's reaction: mad, frustrated, an-

noyed

Other's reactions: shocked, humiliated,

mad at PersonX

Figure 7: Examples from sociopsychological inference benchmarks. Answers in bold.

2.1.5 PSYCHOLOGICAL REASONING

An especially significant domain of knowledge in plausible inference tasks is the area of human sociopsychology, as inference of emotions and intentions through behavior is a fundamental capability of humans (Gordon, 2016). Several benchmarks touch on social psychology in some examples, e.g., the marriage proposal example in ROCStories (Mostafazadeh et al., 2016) from Figure 6, but some are entirely focused here. Examples from each benchmark are listed in Figure 7, and they require sociopsychological commonsense knowledge such as plausible reactions to being punched or yelled at. In the following paragraphs, we introduce these benchmarks in detail.

Triangle-COPA. Triangle-COPA by Gordon (2016) is a variation of COPA (Roemmele et al., 2011) based on a popular social psychology experiment. It contains 100 examples in the format of COPA, and accompanying videos. Questions focus specifically on emotions, intentions, and other aspects of social psychology. The data also includes logical forms of the questions and alternatives, as the paper focuses on logical formalisms for psychological commonsense. Triangle-COPA can be downloaded at http://github.com/asgordon/TriangleCOPA.

Story Commonsense. As mentioned earlier, the stories from ROCStories by Mostafazadeh et al. (2016) are rich in sociological and psychological instances of commonsense. Motivated by classical theories of motivation and emotions from psychology, Rashkin et al. (2018a) created the Story Com-

^{5.} Example extracted from Story Commonsense development data available at http://uwnlp.github.io/storycommonsense/

monsense (SC) benchmark containing about 160,000 annotations of the motivations and emotions of characters in ROCStories to enable more concrete reasoning in this area. In addition to the tasks of generating motivational and emotional annotations, the dataset introduces three classification tasks: one for inferring the basic human needs theorized by Maslow (1943), one for inferring the human motives theorized by Reiss (2004), and one for inferring the human emotions theorized by Plutchik (1980). SC can be downloaded at http://uwnlp.github.io/storycommonsense/.

Event2Mind. In addition to motivations and emotions, systems may need to infer intentions and reactions surrounding events. To support this, Rashkin et al. (2018b) introduce Event2Mind, a benchmark dataset of about 57,000 annotations of intentions and reactions for about 25,000 unique events extracted from other corpora, including ROCStories (Mostafazadeh et al., 2016). Each event involves one or two participants, and presents three tasks of predicting the primary participant's intentions and reactions, and predicting the reactions of others. Event2Mind can be downloaded at http://uwnlp.github.io/event2mind/.

2.1.6 MULTIPLE TASKS

Some benchmarks consist of several focused language processing or reasoning tasks so that reading comprehension skills can be learned one by one in a consistent format. While bAbI includes some tasks for coreference resolution, it also includes other prerequisite skills in other tasks, e.g., relation extraction (Weston et al., 2016). Similarly, the recognition of sentiment, paraphrase, grammaticality, and even puns are focused on in different tasks within the DNC benchmark (Poliak et al., 2018a). Table 1 provides a comparison of all such multi-task commonsense benchmarks by the types of language processing tasks they provide. In the following paragraphs, we introduce these benchmarks in detail.

bAbI. The bAbI benchmark from Weston et al. (2016) consists of 20 prerequisite tasks, each with 1,000 examples for training and 1,000 for testing. Each task presents systems with a passage, then asks a reading comprehension question, but each task focuses on a different type of reasoning or language processing task, allowing systems to learn basic skills one at a time. Tasks are as follows:

- 1. Single supporting fact
- 2. Two supporting facts
- 3. Three supporting facts
- 4. Two argument relations
- 5. Three argument relations
- 6. Yes/no questions
- 7. Counting

- 8. Lists/sets
- 9. Simple negation
- 10. Indefinite knowledge
- 11. Basic coreference
- 12. Conjunction
- 13. Compound coreference
- 14. Time reasoning

- 15. Basic deduction
- 16. Basic induction
- 17. Positional reasoning
- 18. Size reasoning
- 19. Path finding
- 20. Agent's motivations

In addition to providing focused language processing tasks as previously discussed, bAbI also provides focused commonsense reasoning tasks requiring particular kinds of logical and physical commonsense knowledge, such as its tasks for deduction and induction, and time, positional, and size reasoning (Weston et al., 2016). Selected examples of these tasks are given in Figure 8, and demand commonsense knowledge such as the fact that members of an animal species are typically all the same color, and the relationship between objects' size and their ability to contain each other. bAbI can be downloaded at http://research.fb.com/downloads/babi/.

| Reasoning Type | bAbI | IIE | GLUE | DNC |
|---------------------------|------|-----|------|----------|
| Semantic Role Labeling | | ✓ | | |
| Relation Extraction | ✓ | | | ✓ |
| Event Factuality | | | | ✓ |
| Named Entity Recognition | | | | ✓ |
| Coreference Resolution | ✓ | ✓ | ✓ | ✓ |
| Grammaticality | | | ✓ | |
| Lexicosyntactic Inference | | | | ✓ |
| Sentiment Analysis | | | ✓ | √ |
| Figurative Language | | | | ✓ |
| Paraphrase | | ✓ | ✓ | ✓ |
| Textual Entailment | | | | √ |

Table 1: Comparison of language processing tasks present in the bAbI (Weston et al., 2016), IIE (White et al., 2017), GLUE (Wang et al., 2018), and DNC (Poliak et al., 2018a) benchmarks. Recent multi-task benchmarks focus on the recognition of an increasing variety of linguistic and semantic phenomena.

Inference is Everything. Inference is Everything (IIE) by White et al. (2017) follows bAbI (Weston et al., 2016) in creating a suite of tasks, where each task is deliberately geared toward a different language processing task: semantic proto-role labeling, paraphrase, and pronoun resolution. Each task is in classic RTE Challenge format (Dagan et al., 2005), i.e., given context and hypothesis texts, one must determine whether the context entails the hypothesis. Between the tasks, IIE includes about 300,000 examples, all of which are recast from previously existing datasets. IIE can be downloaded with another multi-task suite at http://github.com/decompositional-semantics-initiative/DNC.

GLUE. The General Language Understanding Evaluation (GLUE) dataset from Wang et al. (2018) consists of 9 focused to more comprehensive tasks in various forms, including single-sentence binary classification and 2- or 3-way entailment comparable to the dual tasks in RTE-4 and RTE-5 (Giampiccolo et al., 2008; Bentivogli et al., 2009). Most of these tasks either directly relate to commonsense, or may be useful in creating systems which utilize traditional linguistic processes like paraphrase in performing commonsense reasoning. The GLUE tasks are recast or included directly from other benchmark data and corpora:

- Corpus of Linguistic Acceptability (CoLA) from Warstadt, Singh, and Bowman (2018)
- Stanford Sentiment Treebank (SST-2) from Socher, Perelygin, Wu, Chuang, Manning, Ng, and Potts (2013)
- Microsoft Research Paraphrase Corpus (MRPC) from Iyer, Dandekar, and Csernai (2017) Dolan and Brockett (2005)

(A) Task 15: Basic Deduction

Sheep are afraid of wolves.
Cats are afraid of dogs.
Mice are afraid of cats.
Gertrude is a sheep.
What is Gertrude afraid of?
wolves

(B) Task 16: Basic Induction

Lily is a swan.
Lily is white.
Bernhard is green.
Greg is a swan.
What color is Greg?
white

(C) Task 17: Positional Reasoning

The triangle is to the right of the blue square.

The red square is on top of the blue square. The red sphere is to the right of the blue square.

Is the red square to the left of the triangle? **yes**

(D) Task 18: Size Reasoning

The football fits in the suitcase.
The suitcase fits in the cupboard.
The box is smaller than the football.
Will the box fit in the suitcase?
yes

Figure 8: Examples of selected logically- and physically-grounded commonsense reasoning tasks from bAbI by Weston et al. (2016). Answers in bold.

- Quora Question Pairs (QQP) from Iyer et al. (2017)
- Semantic Textual Similarity Benchmark (STS-B) from Cer, Diab, Agirre, Lopez-Gazpio, and Specia (2017)
- Multi-Genre Natural Language Inference (MNLI) from Williams et al. (2017)
- Question Natural Language Inference (QNLI) recast from SQuAD 1.1 Rajpurkar et al. (2016)
- Recognizing Textual Entailment (RTE), consisting of examples from RTE-1 (Dagan et al., 2005), RTE-2 (Bar-Haim et al., 2006), RTE-3 (Giampiccolo et al., 2007), and RTE-5 (Bentivogli et al., 2009)
- Winograd Natural Language Inference (WNLI) recast from privately shared Winograd schemas by the creators of the Winograd Schema Challenge Levesque (2011)

GLUE includes a small analysis set for diagnostic purposes, which has manual annotations of fine-grained categories pairs of sentences fall into (e.g., commonsense), and labeled reversed versions of examples. Overall, GLUE has over 1 million examples, which can be downloaded at http://gluebenchmark.com/tasks.

DNC. The Diverse Natural Language Inference Collection (DNC) by Poliak et al. (2018a) consists of 9 textual entailment tasks requiring 7 different types of reasoning. Like IIE by White et al. (2017), data for each task follows the form of the original RTE Challenge (Dagan et al., 2005). Some of the tasks within DNC cover fundamental reasoning skills which are required for any reasoning system, while others cover more challenging reasoning skills which require commonsense. Each task is recast from a previously existing dataset:

- Event Factuality, recast from UW (Lee, Artzi, Choi, & Zettlemoyer, 2015), MEANTIME (Minard, Speranza, Urizar, Altuna, van Erp, Schoen, & van Son, 2016), and (Rudinger, White, & Van Durme, 2018b)
- 2. Named Entity Recognition, recast from the Groningen Meaning Bank (Bos, Basile, Evang, Venhuizen, & Bjerva, 2017) and the ConLL-2003 shared task (Tjong Kim Sang & De Meulder, 2003)
- 3. Gendered Anaphora Resolution, recast from the Winogender dataset (Rudinger et al., 2018a)
- 4. Lexicosyntactic Inference, recast from MegaVeridicality (White & Rawlins, 2018), VerbNet (Schuler, 2005), and VerbCorner (Hartshorne, Bonial, & Palmer, 2013)
- 5. Figurative Language, recast from puns by Yang, Lavie, Dyer, and Hovy (2015) and Miller, Hempelmann, and Gurevych (2017)
- 6. Relation Extraction, partially from FACC1 (Gabrilovich, Ringgaard, & Subramanya, 2013)
- 7. Subjectivity, recast from Kotzias, Denil, De Freitas, and Smyth (2015)

The DNC benchmark consists of about 570,000 examples total, and can be downloaded at http://github.com/decompositional-semantics-initiative/DNC.

2.2 Criteria and Considerations for Creating Benchmarks

The goal of benchmarks is to support technology development and provide a platform to measure research progress in commonsense reasoning. Whether this goal can be achieved depends on the nature of the benchmark. This section identifies the successes and lessons learned from the existing benchmarks and summarizes key considerations and criteria that should guide the creation of the benchmarks, particularly in the areas of task format, evaluation schemes, balance of data, and data collection methods.

2.2.1 TASK FORMAT

In creating benchmarks, determining the formulation of the problem is an important step. Among existing benchmarks, there exist a few common task formats, and while some task formats are interchangeable, others are only suited for particular tasks. We provide a review of these formats, indicating the types of tasks they are suitable for.

Classification tasks. Most benchmark tasks are classification problems, where each response is a single choice from a finite number of options. These include textual entailment tasks, which most commonly require a binary or ternary decision about a pair of sentences, cloze tasks, which require a multiple-choice decision to fill in a blank, and traditional multiple-choice question answering tasks.

Textual entailment tasks. A highly popular format was originally introduced by the RTE Challenges, where given a pair of texts, i.e., a context and hypothesis, one must determine whether the context entails the hypothesis (Dagan et al., 2005). In the fourth and fifth RTE Challenges, this format was extended to a three-way decision problem where the hypothesis may contradict the context (Giampiccolo et al., 2008; Bentivogli et al., 2009). The JOCI benchmark further extends the problem to a five-way decision task, where the hypothesis text may range from impossible to very likely given the context (Zhang et al., 2016).

While this format is typically used for textual entailment problems like the RTE Challenges, it can be used for nearly any type of inference problem. Some multi-task benchmarks have adopted the

(A) GLUE, Question Answering NLI

Context: Who was the main performer at this year's halftime show?

Hypothesis: The Super Bowl 50 halftime show was headlined by the British rock group Coldplay with special guest performers Beyoncé and Bruno Mars, who headlined the Super Bowl XLVII and Super Bowl XLVIII halftime shows, respectively.

Label: entailed

(B) IIE, Definite Pronoun Resolution

Context: The bird ate the pie and it died.

Hypothesis: The bird ate the pie and the bird died.

Label: entailed

(C) DNC, Figurative Language

Context: Carter heard that a gardener who moved back to his home town rediscovered his roots.

Hypothesis: Carter heard a pun.

Label: entailed

Figure 9: Examples from tasks within the General Language Understanding Evaluation (GLUE) benchmark by Wang et al. (2018), Inference is Everything (IIE) by White et al. (2017), and the Diverse NLI Collection (DNC) by Poliak et al. (2018a). Each task is recast from preexisting data into classic RTE format.

format for several different reasoning tasks, for example, the Inference is Everything (White et al., 2017), GLUE (Wang et al., 2018), and DNC (Poliak et al., 2018a) benchmarks use the classic RTE format for most of their tasks by automatically recasting previously existing datasets into it. Many of these problems deal either with reasoning processes more focused than the RTE Challenges, or more advanced reasoning than the RTE Challenges demand, showing the flexibility of the format. Some such tasks include coreference resolution, recognition of puns, and question answering. Examples from these recasted tasks are listed in Figure 9.

Cloze tasks. Another popular format is the cloze task, originally conceived by Taylor (1953). Such a task typically involves the deletion of one or more words in a text, essentially requiring one to fill in the blank from a set of choices, a format suitable for language modeling problems. This format has been used in several commonsense benchmarks, including CBT (Hill et al., 2015), the Story Cloze Test for the ROCStories benchmark (Mostafazadeh et al., 2016), CLOTH (Xie et al., 2017), SWAG (Zellers et al., 2018), and ReCoRD (Rajpurkar et al., 2016). These benchmarks provide anywhere from two to ten options to fill in the blank, and range from requiring the prediction of a single word to parts of sentences and entire sentences. Examples of cloze tasks are listed in Figure 10.

Traditional multiple-choice tasks. If not in entailment or cloze form, benchmark classification tasks tend to use traditional multiple-choice questions. Benchmarks which use this format include COPA (Roemmele et al., 2011), Triangle-COPA (Gordon, 2016), the Winograd Schema Challenge (Davis, Morgenstern, & Ortiz, 2018), ARC (Clark et al., 2018), MCScript (Ostermann et al., 2018), and OpenBookQA (Mihaylov et al., 2018). Two-way and four-way decision questions are the most common among these benchmarks.

(A) CBT (Hill et al., 2015)

- 1 Mr. Cropper was opposed to our hiring you
- 2 Not, of course, that he had any personal objection to you, but he is set against female teachers, and when a Cropper is set there is nothing on earth can change him.
- 3 He says female teachers ca n't keep order.
- $4\,\,$ He 's started in with a spite at you on general principles , and the boys know it .
- 5 They know he 'll back them up in secret , no matter what they do , just to prove his opinions .
- 6 Cropper is sly and slippery, and it is hard to corner him."
- 7 "Are the boys big?"
- 8 queried Esther anxiously
- 9 "Yes.
- 10 Thirteen and fourteen and big for their age .
- 11 You can't whip 'em that is the trouble
- 12 A man might, but they 'd twist you around their fingers.
- 13 You'll have your hands full, I'm afraid.
- 14 But maybe they 'll behave all right after all . "
- $15\,\,$ Mr. Baxter privately had no hope that they would , but Esther hoped for the best .
- 16 She could not believe that Mr. Cropper would carry his prejudices into a personal application.
- 17 This conviction was strengthened when he overtook her walking from school the next day and drove her home.
- 18 He was a big , handsome man with a very suave , polite manner .
- 19 He asked interestedly about her school and her work, hoped she was getting on well, and said he had two young rascals of his own to send soon.
- 20 Esther felt relieved .
- 21 She thought that Mr. _____ had exaggerated matters a little .

 **Blank: Baxter, Cropper, Esther, course, fingers, manner, objection, opinions, right, spite

(B) ROCStories (Mostafazadeh et al., 2016)

Karen was assigned a roommate her first year of college. Her roommate asked her to go to a nearby city for a concert. Karen agreed happily. The show was absolutely exhilarating.

Ending:

- a. Karen became good friends with her roommate.
- b. Karen hated her roommate.

(C) CLOTH (Xie et al., 2017)

She pushed the door open and found nobody there. "I am the _____ to arrive." She thought and came to her desk.

- a. last
- b. second
- c. third
- d. first

(D) SWAG (Zellers et al., 2018)

On stage, a woman takes a seat at the piano. She

- a. sits on a bench as her sister plays with the doll.
- b. smiles with someone as the music plays.
- c. is in the crowd, watching the dancers.
- d. nervously sets her fingers on the keys.

(E) ReCoRD (Rajpurkar et al., 2016)

... Daniela Hantuchova knocks Venus Williams out of Eastbourne 6-2 5-7 6-2 ...

Query: Hantuchova breezed through the first set in just under 40 minutes after breaking Williams' serve twice to take it 6-2 and led the second 4-2 before _____ hit her stride.

Venus Williams

Figure 10: Examples from cloze tasks. Answers in bold.

(A) SQuAD 2.0 (Rajpurkar et al., 2018)⁶

In February 2016, over a hundred thousand people signed a petition in just twenty-four hours, calling for a boycott of Sony Music and all other Sony-affiliated businesses after rape allegations against music producer Dr. Luke were made by musical artist Kesha. Kesha asked a New York City Supreme Court to free her from her contract with Sony Music but the court denied the request, prompting widespread public and media response.

How many people signed a petition to boycott Sony Music in 2016? **over a hundred thousand**

(B) SC (Rashkin et al., 2018a)⁷

Valerie was getting ready for a formal dance. She had been preparing for hours. As she was ready to leave, her acrylic nail broke. She snapped off all of her faux nails.

Maslow: esteem, stability
Reiss: status, approval, order
Plutchik: surprise, sadness, disgust,
anger

(C) bAbI (Weston et al., 2016)

The kitchen is north of the hallway. The bathroom is west of the bedroom. The den is east of the hallway. The office is south of the bedroom. How do you go from den to kitchen? west, north

Figure 11: Examples from open-ended response tasks. Answers in bold.

Open-ended tasks. On the other hand, some benchmarks require open-ended responses rather than providing a small list of alternatives to choose from. Answers may be restricted to spans of a given text, e.g., SQuAD (Rajpurkar et al., 2016, 2018) or CoQA (Reddy et al., 2018). They may be less restricted to a subset of a large number of category labels, e.g., the Maslow, Reiss, and Plutchik tasks in Story Commonsense (Rashkin et al., 2018a). Of course, they may be purely open-ended, e.g., the motivation and emotion tasks in Story Commonsense, Event2Mind (Rashkin et al., 2018b) or bAbI (Weston et al., 2016). Examples of these open-ended formats are listed in Figure 11.

2.2.2 EVALUATION SCHEMES

The Turing Test has long been criticized by AI researchers as it does not truly evaluate machine intelligence. There is a critical need for new intelligence benchmarks to support incremental development and evaluation of AI techniques, as described by Ortiz (2016). These benchmarks should not merely provide a pass or fail grade, rather they should provide feedback on a continuous scale which enables both incremental development and comparison of approaches. One key consideration for these benchmarks is informative evaluation metrics that are objective and easy to calculate.

^{6.} Example extracted from SQuAD training data available at http://rajpurkar.github.io/SQuAD-explorer/.

^{7.} Example extracted from Story Commonsense test data available at http://uwnlp.github.io/storycommonsense/

These metrics can be used to compare different approaches and compare machine performance against human performance.

Evaluation metrics. Choice of evaluation metrics is highly dependent on the type of task, and thus so is the difficulty of calculating them. Multiple-choice tasks often use exact-match accuracy if correct answers or class labels are evenly distributed through benchmark data. If this is not the case, common practice is to additionally present F-measure as an evaluation metric (Wang et al., 2018). The precision and recall may be presented, however the F-measure (which considers both) is much more common in the recent surveyed benchmarks. Multiple-choice and classification task formats such as RTE, cloze, and traditional multiple-choice can all use these metrics.

Open-ended tasks are by nature more difficulty to evaluate, but they can still be objective and informative. Open-ended tasks like SQuAD (Rajpurkar et al., 2016) or CoQA (Reddy et al., 2018) where answers can only be spans of a provided text can be evaluated similarly to multiple-choice tasks. Exact-match accuracy and F-measure are used as evaluation metrics on both of these tasks, where the collection of tokens in the predicted and true spans (excluding punctuation and articles) are compared. Where answers are a subset of a large group of category labels, e.g., the Maslow, Reiss, and Plutchik tasks in Story Commonsense, evaluation is similar, but for these tasks particularly, precision and recall are additionally included (Rashkin et al., 2018a).

Where multiple purely open-ended responses are given, as in Event2Mind (Rashkin et al., 2018b), evaluation is more difficult. Event2Mind particularly uses the average cross-entropy and the "recall @ 10," i.e., the percentage of times human-produced ground truth labels fall within the top 10 predictions from a system. In bAbI, where a purely open-ended response is compared to a single ground truth answer, exact-match accuracy is used (Weston et al., 2016). Both Event2Mind and bAbI are able to use such exact evaluation measures because responses are short. In bAbI particularly, correct responses are limited to one word or lists of words. Such restrictions are essential for such simple and accurate evaluation. For longer generated responses, evaluation metrics like BLEU for machine translation (Papineni, Roukos, Ward, & Zhu, 2002), or the modified ROUGE for text summarization (Lin, 2004), are useful.

Comparison of approaches. Benchmarks provide common datasets and experimental setups for researchers to compare different approaches. When a new benchmark is first released, it often reports results from simple baseline approaches. Ideal baselines should lead to relatively low performance, thus leaving room for improvement from more advanced approaches. For multiple-choice problems, baseline approaches are often calculated by random choice, choosing the class appearing the most in the test data, or choosing the alternative with the highest overlap in n-grams with the question or provided text (Richardson, Burges, & Renshaw, 2013). Examples of these baseline approaches can be found in the Story Cloze Test baselines, which include most of these approaches and more (Mostafazadeh et al., 2016). For open-ended problems, shallow lexical approaches (e.g., using language models) may again be used, as in the bAbI benchmark(Weston et al., 2016). When competitive approaches are developed for existing benchmarks, they are often used as baselines in new benchmarks, thus boosting baseline performance over time and encouraging the development of new or improved models to solve problems.

Human performance measurement. To evaluate the progress of machine intelligence, human performance on benchmark tasks is often measured to provide a reference point, e.g., through crowdsourcing techniques. ROCStories (Mostafazadeh et al., 2016), SQuAD (Rajpurkar et al.,

2016), and CoQA (Reddy et al., 2018) all provide metrics for human performance. The goal of computational models is to come close to or exceed human performance.

2.2.3 DATA BIASES

When creating benchmarks, one challenge is the bias of data unintentionally introduced to the benchmark. For example, in the first release of the Visual Question Answering (VQA) benchmark (Agrawal, Lu, Antol, Mitchell, Zitnick, Parikh, & Batra, 2017), researchers found that machine learning models were learning several statistical biases in the data, and could answer up to 48% of questions in the validation set without seeing the image (Manjunatha, Saini, & Davis, 2018). This artificially high system performance is problematic, as it is not accredit to the underlying technology. Here we summarize several key dimensions of biases encountered in previous commonsense research. Some of these (e.g., class label distributions) are easier to avoid, while others (e.g., hidden correlation biases) are more difficult to address.

Label distribution bias. Class label distribution bias is the easiest to avoid. In multiple-choice problems, correct answers or class labels should be entirely randomized so that each possible choice appears in benchmark data in a uniform distribution. This way, a majority-class baseline will score as low as possible on the task. While binary-choice tasks should have a 50% majority class baseline, the MegaVeridicality task within DNC (Poliak et al., 2018a) has a 67% majority-class baseline due to unevenly distributed class labels, leaving significantly less room for incremental improvement than tasks with lower-performing baselines.

Question type bias. For benchmarks involving question answering tasks, previous work has made effort to balance the types of questions, especially if questions are generated by crowdsourcing. This will ensure a broad domain of knowledge and reasoning required to solve the task. A fairly simple method to keep a balance of question types is to calculate the distribution of the first words of each question, as the creators of CoQA (Reddy et al., 2018) and CommonsenseQA (Talmor et al., 2019) did. One could also manually label a random sample of questions with categories relating to types of knowledge or reasoning required, or have crowd workers perform this task if an expert is not essential for this process. Examples of this are shown by the creators of SQuAD 2.0 (Rajpurkar et al., 2018) and ARC (Clark et al., 2018). To entirely avoid question type biases, implementing a standard set of questions for all provided texts may be beneficial. ProPara does for all participants in its procedural paragraphs (Mishra et al., 2018), limiting questions about each entity to whether it is created, destroyed, or moved during the paragraph, and when and where this happens. Manjunatha et al. (2018) suggest that biases can further be avoided in VQA benchmarks by forcing questions to require a particular skill (e.g., telling time) to be answered, and this rule of thumb can be applicable for textual benchmarks as well.

Superficial correlation bias. The kind of biases most difficult to discern and avoid perhaps are those caused by accidental correlations between features of answers and questions. One example of this is gender bias, which commonsense reasoning systems are particularly vulnerable to when training on biased data. Rudinger et al. (2018a) highlight this problem in coreference resolution, showing that systems trained on gender-biased data perform worse in gender pronoun disambiguation tasks. For example, consider the problem from their Winogender dataset in Figure 3: "The paramedic performed CPR on the passenger even though she knew it was too late." In determining who *she* is, systems trained on gender-biased training data may be more likely, for example,

to incorrectly choose *the passenger* rather than *the paramedic* due to male gender pronouns appearing more commonly in the context of this occupation than female gender pronouns. To avoid this, gender pronouns should appear equally frequently among other words, especially those related to occupations and activities. Similar gender biases are identified in Event2Mind data, which are derived from movie scripts (Rashkin et al., 2018b).

When authoring natural language data (e.g., generating questions or hypotheses), some human stylistic artifacts such as predictable sentence structure, presence of certain linguistic phenomena, and vocabulary use can also cause these superficial correlation biases. This is particularly the case if data is authored by crowd workers. In the Story Cloze Test (Mostafazadeh et al., 2016), systems are presented a plausible and implausible ending to the story, and must choose which ending is plausible. However, previous work Schwartz, Sap, Konstas, Zilles, Choi, and Smith (2017) has shown that the Story Cloze Test can be solved with up to 75.2% accuracy by only looking at the two possible endings. They do this by exploiting human writing style biases in the possible endings rather than performing actual commonsense reasoning. For example, they find that negative language is used more commonly in the wrong ending (e.g., "hates"), and the correct ending is more likely to use enthusiastic language (e.g., "!"). An example of a biased negative ending is seen in Figure 10. Sharma, Allen, Bakhshandeh, and Mostafazadeh (2018) have begun work to update the benchmark data and remove these biases.

While generating the Story Cloze Test data was not a fast or simple task for crowd workers, Gururangan, Swayamdipta, Levy, Schwartz, Bowman, and Smith (2018) suggest that such biases can come from crowd workers' adoption of predictable annotation strategies and heuristics to quickly generate data. These strategies have been revealed for several textual entailment benchmarks which consist of pairs of short sentences. For example, on the entailment task in SemEval 2014 (Marelli, Bentivogli, Baroni, Bernardi, Menini, & Zamparelli, 2014b) as part of the SICK benchmark (Marelli et al., 2014a), Lai and Hockenmaier (2014) found that the presence of negation in an example was strongly associated with the appearance of the contradiction class label. Their trained classifier using this feature alone was able to achieve 61% accuracy. Later, Poliak, Naradowsky, Haldar, Rudinger, and Van Durme (2018b) and Gururangan et al. (2018) found the presence of particular words in the hypothesis sentence can bias the entailment prediction in several entailment benchmarks. For example, "nobody" in contradictory examples from SNLI (Bowman et al., 2015) was found to be an indicator of contradiction, while generic words like "animal" and "instrument", as well as genderneutral pronouns, were found to be indicators of entailment. Gururangan et al. further find that a high sentence length is an indicator of neutral entailment, and suggest that crowd workers often remove words from the context sentences to create entailed hypothesis sentences. Using biases like these, a baseline approach by Poliak et al. which only used the hypothesis sentence from entailment benchmarks was able to outperform a majority-class baseline in SNLI, JOCI (Zhang et al., 2016), SciTail (Khot et al., 2018), two tasks within Inference is Everything (White et al., 2017), and the MultiNLI task within GLUE (Williams et al., 2017; Wang et al., 2018).

These results demonstrate a serious need for greater attention to such bias in commonsense benchmarks. To recognize biases, a simple technique is to calculate the mutual information between words and classes within benchmark examples. This was performed by researchers in *discovering* stylistic biases in entailment benchmarks (Gururangan et al., 2018), but this analysis should be performed on any new benchmark data when it is created. To *avoid* the biases, more advanced techniques may be required. For example, in creating the SWAG benchmark (Zellers et al., 2018), a novel adversarial filtering process was introduced to ensure writing styles are consistent among

ending choices, and the correct answer cannot be identified by exploitative stylistic classifiers. A continuous effort in finding techniques to avoid these kinds of biases will be important for developing future benchmarks.

2.2.4 COLLECTION METHODS

Methods to collect benchmark data ideally should be cost-efficient and should result in high-quality and unbiased data. Both manual and automatic approaches have been applied. Manual curation of data can be done by experts/researchers or through crowd-workers, which comes with its own set of considerations. Automatic approaches often involve automatically generating data by applying language models or automatically extracting or mining data from existing resources. As shown in Table 2, a benchmark is often created through a combination of these approaches. For the rest of this section, we summarize pros and cons for these different approaches.

Manual versus automatic generation. Until recently, many of the existing benchmarks were created manually by groups of experts. This may involve tedious processes like manually collecting data from other corpora or the Internet, e.g., the first RTE Challenge (Dagan et al., 2005), or authoring most data from scratch, e.g., the Winograd Schema Challenge (Levesque, 2011; Levesque et al., 2012; Morgenstern & Ortiz, 2015; Morgenstern et al., 2016). This approach ensures data is high quality and thus typically requires little validation, however it is not scalable. These datasets are often small compared to those created with other approaches.

Recent advances in NLP make it possible to automatically generate textual data (e.g., natural language statements, questions, etc.) for benchmark tasks. Although this approach is scalable and efficient, the quality of data varies, and often depends directly on the language model used. For example, in bAbI (Weston et al., 2016), as agents interacted with objects in a virtual world and with each other, examples were automatically generated. This method ensures that produced data are sensible to the constraints of the physical world. However, as the questions and answers are written with simple structure, the data is easily understood by machines. Most of the dataset is solved with 100% accuracy just by baseline systems. Consequently, the bAbI tasks are often considered as toy tasks. Further, models trained on bAbI currently cannot generalize well to real-world, naturally-generated data (Das, Munkhdalai, Yuan, Trischler, & McCallum, 2019). A more sophisticated rule-based method for probabilistically generating text data which encourages more diverse language without any added biases is presented by Manning and Hudson (2018). Though automatic natural language generation methods are improving, it is likely that such approaches will still require some manual validation.

Automatic generation versus text mining. As millions of natural language texts are publicly available on the Internet and in existing datasets, it is possible to build commonsense benchmarks from these texts by automatically mining texts and extracting sentences. This process is most successful when the information source is created by experts and highly accurate. For example, in the CLOTH (Xie et al., 2017) benchmark, data instances were mined from fill-in-the-blank English tests created by human teachers. While other automatically generated cloze tasks like CBT (Hill et al., 2015) choose missing words mostly randomly, CLOTH's cloze task is more challenging as the missing word in each example was chosen by an expert. For many other benchmarks that are built by mining less reliable or consistent sources, there's often a need for automatic or human validation or filtering, e.g., in creating SWAG (Zellers et al., 2018), which was mined in part from other corpora, such as the Large Scale Movie Description Challenge (Rohrbach, Torabi, Rohrbach, Tandon,

Pal, Larochelle, Courville, & Schiele, 2017) and the captions in ActivityNet (Heilbron, Escorcia, Ghanem, & Niebles, 2015).

Crowdsourcing considerations. Acquiring language data directly from crowd workers has become more feasible in recent years, due to the growth of crowdsourcing platforms, such as Amazon Mechanical Turk. Crowdsourcing has enabled researchers to create larger datasets than ever before, however it comes with a set of considerations relating to task complexity, worker qualification, data validation, and cost optimization.

Task complexity. When creating a crowdsourcing task, it is important to consider the difficulty level of what crowd workers will be expected to do. When given overly complicated instructions, the non-expert crowd workers may find it difficult understanding the instructions and keeping them in mind while working on the task. Easy crowdsourcing tasks typically involve quick pass/fail validation or relabeling of data, e.g., in validating SNLI (Bowman et al., 2015). Difficult crowdsourcing tasks usually require crowd workers to write large texts, e.g., in creating ROCStories (Mostafazadeh et al., 2016), where workers wrote five-sentence stories following a fairly elaborate set of restrictions on story content to ensure stories were high-quality, focused, and well-organized. Such restrictions must be explained briefly and clearly, and it may take several pilot studies to ensure workers understand and follow the instructions correctly (Mostafazadeh et al., 2016).

Worker qualification. Regardless of task difficulty, efforts should be made to avoid workers submitting invalid data, whether they are trolls or unable to follow directions. This may be done through some sort of qualification task, perhaps requiring a prospective worker to recognize examples of acceptable submissions (Mostafazadeh et al., 2016), or testing a prospective worker's grammar (Richardson et al., 2013). It may also be worthwhile to identify excellent workers, and reward them and/or recruit them for more work (Mostafazadeh et al., 2016). In our own experiences with crowd-sourcing, we have found that if a worker produces one invalid submission, all of his/her submissions will likely be invalid, and thus the worker should be rejected and potentially banned from the task. On the other hand, if a worker produces an excellent submission, all of his/her submissions will likely be excellent.

Data validation. Even though crowdsourced data is produced by non-experts, data can just as easily be validated by non-experts. In creating ROCStories, Mostafazadeh et al. (2016) employ several novel methods of crowdsourced validation of crowdsourced data. Involved validation is especially necessary for difficult crowdsourcing tasks like the authoring of ROCStories, which required crowd workers to write long texts following strict guidelines. Crowdsourced data validation typically just requires a separate group of workers to review generated data and identify any bad examples, e.g., the validation of DNC benchmark data (Poliak et al., 2018a). For labeling tasks, multiple crowd workers can label the same examples, and agreement can be measured from this to estimate data quality, e.g., in creating the JOCI benchmark (Zhang et al., 2016).

For complex writing tasks where both data authoring and validation are highly involved, it may be advantageous to present crowdsourced tasks to two interacting workers at once. Reddy et al. (2018) do this to create CoQA from actual human conversations about provided passages on Amazon Mechanical Turk, and achieve high data quality with minimal validation. In creating the data, the two interacting workers validate each others' work, and can even report workers who do not follow instructions, reducing the burden of worker qualification.

| Dataset (Reference) | Data Size | Text/ Question | Answer | Alter- natives | Anno- tation | Vali- dation |
|---|--------------|-------------------|---------|-------------------|-----------------|-----------------|
| RTE-1 (Dagan et al., 2005) | 1.37K | M | M | - | - | M |
| RTE-2 (Bar-Haim et al., 2006) | 1.60K | M | M | - | _ | M |
| RTE-3 (Giampiccolo et al., 2007) | 1.60K | M | M | _ | _ | M |
| RTE-4 (Giampiccolo et al., 2008) | 1.00K | M | M | _ | _ | М |
| RTE-5 (Bentivogli et al., 2009) | 1.20K | M | M | _ | _ | M |
| RTE-6 (Bentivogli et al., 2010) | 32.7K | T | M | - | _ | M |
| RTE-7 (Bentivogli et al., 2011) | 48.8K | T | M, T | - | _ | M |
| COPA (Roemmele et al., 2011) | 1.00K | M | M | M | _ | M |
| SICK (Marelli et al., 2014a) | 9.84K | M, T | С | _ | _ | С |
| SNLI (Bowman et al., 2015) | 570K | T, C | С | _ | С | С |
| CBT (Hill et al., 2015) | 687K | T, A | A | A | _ | _ |
| Triangle-COPA (Gordon, 2016) | 100 | M | M | M | M | M |
| ROCStories (Mostafazadeh et al., 2016) | 98.2K | С | С | С | _ | С |
| WSC (Morgenstern et al., 2016) | 60 | M | M | _ | _ | M |
| bAbI (Weston et al., 2016) | 40.0K | A | A | _ | _ | _ |
| SQuAD 1.1 (Rajpurkar et al., 2016) | 108K | T, C | С | _ | _ | С |
| JOCI (Zhang et al., 2016) | 39.1K | A, T | С | _ | _ | С |
| CLOTH (Xie et al., 2017) | 99.4K | T | T | T | С | _ |
| IIE (White et al., 2017) | 313K | T, A | T, A | - | _ | M |
| SciTail (Khot et al., 2018) | 27.0K | T, C | С | - | С | С |
| ARC (Clark et al., 2018) | 7.79K | T | T | T | _ | _ |
| MCScript (Ostermann et al., 2018) | 13.9K | M, T, C | С | С | С | С |
| SC (Rashkin et al., 2018a) | 161K | T | С | _ | С | С |
| Event2Mind (Rashkin et al., 2018b) | 57.1K | T | С | _ | _ | С |
| ProPara (Mishra et al., 2018) | 488 | С | С | _ | С | С |
| MultiRC (Khashabi et al., 2018) | 9.87K | T, C | С | С | _ | С |
| SQuAD 2.0 (Rajpurkar et al., 2018) | 151K | T, C | С | _ | _ | С |
| CoQA (Reddy et al., 2018) | 8.40K | T, C | С | _ | _ | С |
| GLUE (Wang et al., 2018) | 1.44M | T, A | T, A | _ | M | _ |
| DNC (Poliak et al., 2018a) | 570K | M, A, T | M, A, T | - | - | С |
| OpenBookQA (Mihaylov et al., 2018) | 5.96K | С | С | С | С | С |
| SWAG (Zellers et al., 2018) | 114K | T | T, A | A | С | С |
| ReCoRD (Zhang et al., 2018) | 121K | A, T | A | A | A | A, C |
| CommonsenseQA (Talmor et al., 2019) | 9.40K | С | T | T | _ | С |

Table 2: Chronological summary of methods used in creating, annotating (i.e., providing extra useful information beyond the answer which the task evaluates upon), and validating selected commonsense benchmarks and tasks, where M refers to manual approaches by experts, A to automatic approaches through language generation, T to text mining, and C to crowd-sourcing. Data size is included for comparison of methods used.

Cost optimization. Though hiring crowd workers is typically cheaper than hiring permanent workers, the cost may still be limiting, especially if the creator wishes to properly evaluate the quality of generated data through verification by even more crowd workers. For example, ROCStories (Mostafazadeh et al., 2016), consisting of about 50,000 well-evaluated five-sentence stories and 13,500 test cases, cost an average of 26 cents per story and an extra 10 cents per test case, resulting in a total cost close to 15,000 USD to generate the dataset. If the cost of such thorough validation is an issue, validating a random sample of produced data, e.g., in validating SNLI (Bowman et al., 2015), can serve as an indicator of the overall quality of benchmark data.

Ultimately, each method of data collection has its own advantages and drawbacks. While manual authoring results in high-quality, expert-verified data, it is slow and unscalable. Meanwhile, the quality of automatically authored data is highly dependent on the language model used, and though it is faster, it may require manual verification. If using text mining rather than generating from scratch, data is more likely to be representative of human language, however manual verification may still be necessary depending on the source which data are extracted from. And lastly, crowd-sourcing is a quick and convenient way to collect human-authored data following any set of criteria or restrictions, but it comes with special considerations that address the difficulty of work, qualification of workers, data validation, and cost optimization. When developing a new benchmark, the above trade-offs will need to be carefully considered.

3. Knowledge Resources

It is estimated that a typical human has accrued several million different axioms of commonsense by adulthood (Chklovski, 2003). The lack of this commonsense knowledge is one of the major bottlenecks in machine intelligence. In order to remove this bottleneck, decades of efforts have been made in developing various knowledge resources in the field of AI. The acquired knowledge is often represented in various forms such as propositions, taxonomies, ontologies, and semantic networks. In this section, we start with an introduction to several existing knowledge resources, and then discuss the main issues involved in building these resources.

3.1 An Overview of Knowledge Resources for NLU

To understand human language, it is important to have *linguistic knowledge* resources that allow computers to identify syntactic and semantic structures from language. These structures often need to be augmented with *common knowledge* and *commonsense knowledge* in order to reach a full understanding.

3.1.1 LINGUISTIC KNOWLEDGE RESOURCES

Linguistic resources have been pivotal in pushing the NLP field forward in the last thirty years. Resources have been developed where annotations for syntactic, semantic, and discourse structures are provided for training machine learning models. Several knowledge bases, particularly for lexical semantics, have also been made available to facilitate semantic processing.

Annotated linguistic corpora. Widely used linguistic resources include the Penn Treebank (Marcus, Santorini, & Marcinkiewicz, 1993) and several derivatives of it. The Penn Treebank is perhaps the first annotated corpus that drove the development of earlier machine learning approaches in the 1990s. It started with POS tags and syntactic structures based on context-free grammar. The Wall

Street Journal portion of it was further augmented into PropBank (Kingsbury, Palmer, & Marcus, 2002), which provides the annotation of predicate-argument structures(Taylor, Marcus, & Santorini, 2003). The Penn Discourse Treebank (PDTB) is built upon these (Miltsakaki, Prasad, Joshi, & Webber, 2004), adding annotated discourse structures. OntoNotes revises the information in the Wall Street Journal portion of the Penn Treebank and PropBank, integrating it with word sense, proper name, coreference, and ontological annotations, as well as including some Chinese linguistic annotations (Pradhan, Hovy, Marcus, Palmer, Ramshaw, & Weischedel, 2007). The Abstract Meaning Representation (AMR) corpus extends PropBank into a sentence-level semantic formalism (Banarescu, Bonial, Cai, Georgescu, Griffitt, Hermjakob, Knight, Koehn, Palmer, & Schneider, 2013). All of these linguistic corpora can be downloaded by members of the Linguistic Data Consortium at http://www.ldc.upenn.edu/.

Lexical resources. A widely used lexical resource for commonly used nouns, verbs, adjectives and adverbs is WordNet ⁸ (Miller, 1995). Different from a traditional online dictionary, WordNet organizes words in terms of concepts (i.e., a list of synonyms) and their semantic relations to other words (e.g., antonymy, hyponymy/hypernymy, entailment, etc.). WordNet has been applied in many NLP applications which involve, for example, query expansion and similarity measures. There are also resources specifically for verbs. VerbNet ⁹ by Schuler (2005) is a hierarchical English verb lexicon that is created based on the verb classes from the English Verb Classes and Alternations (EVCA) resource by Levin (1993). VerbNet contains 280 classes of verbs and each class is described by argument structures, selectional restrictions on the arguments, and syntactic descriptions. FrameNet ¹⁰ (Fillmore, Baker, & Sato, 2002) provides a database of frame semantics for a set of verbs. It also comes with sentences that are annotated with the frame semantics. Other resources for verbs include VerbOcean ¹¹ (Chklovski & Pantel, 2004) which captures a network of 3,500 unique verbs and 22,000 fine-grained relations between the verbs, and VerbCorner ¹² (Hartshorne et al., 2013) which provides crowd-sourced validation for VerbNet.

3.1.2 COMMON KNOWLEDGE RESOURCES

Common knowledge refers to specific facts about the world that are often explicitly stated, for example, "canine distemper is a domestic animal disease." (Cambria, Song, Wang, & Hussain, 2011). Though this is not the same as commonsense knowledge, it is often required to achieve a deep understanding of both the low- and high-level concepts found in language (Cambria et al., 2011). In this section, we summarize several knowledge resources for common knowledge.

YAGO. Wikipedia is a large and open source of common knowledge. Yet Another Great Ontology (YAGO) by Suchanek, Kasneci, and Weikum (2007) augments WordNet (Miller, 1995) with common knowledge facts extracted from Wikipedia, converting WordNet from a primarily linguistic resource to a common knowledge base. YAGO originally consisted of more than 1 million entities and 5 million facts describing relationships between these entities. YAGO2 grounded entities, facts, and events in time and space, contained 446 million facts about 9.8 million entities (Hoffart, Suchanek, Berberich, & Weikum, 2012), while YAGO3 added about 1 million more entities

^{8.} http://wordnet.princeton.edu/

^{9.} http://verbs.colorado.edu/~mpalmer/projects/verbnet.html

^{10.} http://framenet.icsi.berkeley.edu/fndrupal/framenet_data

^{11.} http://demo.patrickpantel.com/demos/verbocean/

^{12.} http://archive.gameswithwords.org/VerbCorner/about.php

from non-English Wikipedia articles (Mahdisoltani, Biega, & Suchanek, 2013). YAGO is available for free download at http://www.mpi-inf.mpg.de/departments/databases-and-information-systems/research/yago-naga/yago/downloads/.

DBpedia. DBpedia by Auer, Bizer, Kobilarov, Lehmann, Cyganiak, and Ives (2007) is another Wikipedia-based knowledge base originally consisting of structured knowledge from more than 1.95 million Wikipedia articles. At its creation, DBpedia included around 103 million Resource Description Framework (RDF) triples¹³, which are triples of subjects, predicates, and objects which describe semantic relationships. These triples included descriptions of concepts within articles, information about people, links between articles, and category labels from YAGO. The latest version, available for free at http://wiki.dbpedia.org/develop/datasets, consists of 6.6 million entities, 5.5 million resources classified in the DBpedia ontology, and over 23 billion RDF triples.

WikiTaxonomy. Yet another Wikipedia-based resource is WikiTaxonomy by Ponzetto and Strube (2007) consists of about 105,000 well-evaluated semantic links between categories in Wikipedia articles. Categories and relationships are labeled using the connectivity of the conceptual network formed by the categories. The authors demonstrate that this resource can be used to calculate semantic similarity of words, which may be useful in textual entailment or inference tasks. Wiki-Taxonomy is available for free download at http://www.h-its.org/en/research/nlp/wikitaxonomy/.

Freebase. Freebase by Bollacker, Evans, Paritosh, Sturge, and Taylor (2008) was a knowledge graph which originally contained 125 million RDF triples of general human knowledge about 4,000 types of entities and 7,000 properties of entities. This resource was later absorbed into the Google Knowledge Graph for intelligent web searching, however the last release is still available for free download at http://developers.google.com/freebase/. It contains more than 1.9 billion triples.

NELL. As human knowledge is not static, it is advantageous for knowledge bases to grow over time. This is typically done through new releases, however the Never-Ending Language Learner (NELL) by Carlson, Betteridge, Kisiel, Settles, Jr, and Mitchell (2010) continually grows by automatically mining structured beliefs of varying confidence from the web daily. It originally contained 242,000 beliefs about properties of entities, but now contains over 50 million beliefs, with almost 3 million of these having high confidence. This version can be downloaded for free at http://rtw.ml.cmu.edu/rtw/.

Probase. Probase by Wu, Li, Wang, and Zhu (2011) is different from previous common knowledge taxonomies in that relationships are probabilistic rather than concrete. Probase consists of 2.7 million concepts extracted from 1.6 billion web pages. Relationships between concepts are described in 20.8 million is-a and is-instance-of pairs, and probabilistic interpretation is possible through provided similarity values between 0 and 1 for each pair of concepts in the knowledge base. Though the original resource is no longer available, the Microsoft Concept Graph which was built upon Probase can be downloaded for free at http://concept.research.microsoft.com/Home/Download.

^{13.} https://www.w3.org/TR/rdf-concepts/\#section-triples

3.1.3 Commonsense Knowledge Resources

Commonsense knowledge, on the other hand, is considered obvious to most humans, and not so likely to be explicitly stated (Cambria et al., 2011). Davis and Marcus (2015) demonstrate this fact: "if you see a six-foot-tall person holding a two-foot-tall person in his arms, and you are told they are father and son, you do not have to ask which is which." There has been a long effort in capturing and encoding commonsense knowledge. Various knowledge bases have been developed. Here, we give a brief introduction to some of the well-known commonsense knowledge bases.

Note that as there is a fine line between commonsense knowledge and common knowledge, the knowledge bases we describe here may also contain common knowledge. Learning commonsense knowledge requires generalizations over common knowledge, so it is not uncommon for these types of knowledge to appear together in knowledge bases. We present several knowledge resources which focus on commonsense knowledge, but may also include common knowledge.

Cyc. A well-known project toward encoding commonsense knowledge is Cyc by Lenat and Guha (1989), a knowledge base of rules expressing ontological relationships between objects encoded in the CycL language. The types of objects in Cyc include entities, collections, functions, and truth functions. Cyc also includes a powerful inference engine. ResearchCyc, a release of Cyc for the research community, can be licensed for free at http://www.cyc.com/researchcyc/. According to this site, the latest release of ResearchCyc contains over 7 million commonsense assertions. More recently, there have been efforts to map Cyc to Wikipedia articles in an attempt to connect it to other resources such as DBpedia and Freebase (Medelyan & Legg, 2008; Pohl, 2012).

ConceptNet Another popular knowledge base for commonsense reasoning is ConceptNet from Liu and Singh (2004), a product of the Open Mind Common Sense project by Singh (2002), which collected free text commonsense assertions from online users. This semantic network originally contained over 1.6 million assertions of commonsense knowledge represented as links between 300,000 nodes representing entities, but subsequent releases have expanded it and added more features. The latest release, ConceptNet 5.5 (Speer, Chin, & Havasi, 2017), contains over 21 million links between over 8 million nodes, having been augmented by several additional resources including Cyc (Lenat & Guha, 1989) and DBpedia (Auer et al., 2007). It includes knowledge from multilingual resources, and links to knowledge from other knowledge graphs. ConceptNet has been applied in several commonsense reasoning systems, some of which are described in Section 4.3. ConceptNet is open; information for using or downloading it can be found at http://conceptnet.io/.

AnalogySpace. Though not technically a knowledge base itself, AnalogySpace (Speer, Havasi, & Lieberman, 2008), another product of the Open Mind Common Sense project, is an algorithm for reducing the dimensionality of commonsense knowledge so that knowledge bases can be more efficiently and accurately reasoned over. Since knowledge in large knowledge bases can be noisy or subjective, it provides a way to make conclusions by analogy, i.e., through recognizing similarities and tendencies by simple vector operations. This projects concepts onto dimensions of goodness, difficulty, and so on, which may help models generalize on sparse benchmark data. AnalogySpace was originally applied to ConceptNet (Liu & Singh, 2004), and is included with the latest release of ConceptNet.

SenticNet. SenticNet by Cambria, Speer, Havasi, and Hussain (2010) was originally only a commonsense knowledge base, but later versions incorporated common knowledge as well (Cambria,

Olsher, & Rajagopal, 2014a). Though the knowledge base is intended for sentiment analysis, it may be useful in commonsense reasoning tasks which require inference about sentiment. SenticNet is available for free at http://sentic.net/downloads/.

IsaCore. Isanette by Cambria et al. (2011) was a semantic network of both common and commonsense knowledge created by combining ProBase (Wu et al., 2011) and ConceptNet 3 (Havasi, Speer, & Alonso, 2007) into a set of "is a" relationships and confidences. This work was later cleaned and optimized into IsaCore (Cambria, Song, Wang, & Howard, 2014b), and demonstrated to be effective for sentiment analysis. IsaCore may also be a useful resource for commonsense reasoning. It is available for free download at http://sentic.net/downloads/.

COGBASE. COGBASE by Olsher (2014) uses a novel formalism to represent 2.7 million concepts and 10 million commonsense facts about them. It makes up the core of SenticNet 3 (Cambria et al., 2014a). Data from COGBASE can currently be accessed via an online interface and a demo API available at http://cogview.com/cogbase/.

WebChild. WebChild by Tandon, de Melo, Suchanek, and Weikum (2014) was originally a commonsense knowledge base of general noun-adjective relations extracted from Web content and other resources, consisting of about 78,000 distinct noun senses, 5,600 distinct adjective senses, and 4.6 million assertions between them. These assertions captured fine-grained relations among the noun and adjective senses. Unlike other resources collected from the Web, WebChild consists primarily of commonsense knowledge, as it consists of generalized, fine-grained relationships between nouns and adjectives collected from various corpora rather than structured common knowledge taken directly from a single open source like Wikipedia. WebChild 2.0 (Tandon, de Melo, & Weikum, 2017) was later released to include over 2 million concepts and activities, and over 18 million such assertions. Data from WebChild can be browsed and downloaded online at http://www.mpi-inf.mpg.de/departments/databases-and-information-systems/research/yago-naga/webchild/.

LocatedNear. Xu, Lin, and Zhu (2018a) claim that objects which tend to be near each other (e.g., silverware, a plate, and a glass) is a type of commonsense knowledge lacking in previous knowledge bases like ConceptNet 5.5 (Speer et al., 2017). They refer to this property as LocatedNear, and to address this issue, they create two datasets which we refer to jointly as LocatedNear. The first consists of 5,000 sentences describing scenes of two objects labeled for whether the objects tend to occur near each other, which can serve as a commonsense task similar to those introduced in Section 2. The second consists of 500 pairs of objects with human-produced confidence scores for how likely the objects are to appear near each other. These resources can be downloaded from https://github.com/adapt-sjtu/commonsense-locatednear.

ATOMIC. The Atlas of Machine Commonsense (ATOMIC) by Sap, LeBras, Allaway, Bhagavatula, Lourie, Rashkin, Roof, Smith, and Choi (2019) is a knowledge graph consisting of about 300,000 nodes corresponding to short textual descriptions of events, and about 877,000 "if-event-then" triples representing if-then relationships between everyday events. Rather than taxonomic or ontological knowledge, this graph contains easily-accessed inferential knowledge. Sap et al. demonstrate that neural models can learn simple commonsense reasoning skills from ATOMIC which can be used to make inferences about previously unseen events. ATOMIC can be browsed and downloaded for free at http://homes.cs.washington.edu/~msap/atomic/.

3.2 Approaches to Creating Knowledge Resources

Similar to creating commonsense reasoning benchmarks described in Section 2, various approaches have been applied to create knowledge resources. These approaches range from manual encoding by experts, to text mining from web documents, and to collection through crowdsourcing. A detailed description of these approaches is provided by Davis and Marcus (2015). Here, we give a brief discussion about pros and cons of these approaches.

Manual encoding. Early knowledge bases were often manually created. The classic example of this is Cyc, which is produced by knowledge engineers who hand-code commonsense knowledge into the CycL formalism (Lenat & Guha, 1989). Since its first release in 1984, Cyc has been going through continuous development over the last 35 years. The cost of this manual encoding is high, with a total estimated cost of \$120M (Paulheim, 2018). As a consequence, Cyc is small relative to other resources, and growing very slowly. On the other hand, this expert-based approach ensures high quality of data.

Text mining. Text mining and information extraction tools such as TextRunner (Etzioni, Banko, Soderland, & Weld, 2008) and KnowItAll (Etzioni, Cafarella, Downey, Popescu, Shaked, Soderland, Weld, & Yates, 2005) are applied to automatically generate knowledge graphs and taxonomies from information sources. One popular information source is Wikipedia, which was drawn from in creating common knowledge bases such as YAGO (Suchanek et al., 2007), DBpedia (Auer et al., 2007), WikiTaxonomy (Ponzetto & Strube, 2007). Other knowledge bases are generated from crawling the Web, e.g., NELL (Carlson et al., 2010), or even from other knowledge bases, e.g., IsaCore (Cambria et al., 2014b). One key advantage of text mining approaches is cost efficiency. According to Paulheim (2018), creating a statement in the Wikipedia-extracted DBpedia and YAGO costs 1.85¢and 0.83¢respectively (USD), which are hundreds of folds less than the cost of manually encoding a statement in Cyc (which was estimated at about \$5.71 per statement). This makes text mining approaches easily scale up to create large knowledge bases. However, the drawback is that the acquired knowledge can be noisy and inconsistent, and may often need human validation.

Crowdsourcing. Another highly popular approach to creating knowledge bases is crowdsourcing. The Open Mind Common Sense project responsible for producing ConceptNet (Liu & Singh, 2004) used a competitive online game to accept statements from humans in free text (Singh, 2002). Later, researchers converted the knowledge within collected statements into a knowledge graph by automatic processes. This method of using games to attract users to perform human intelligence tasks for free has been applied in creating other knowledge resources such as VerbCorner (Hartshorne et al., 2013) and the Robot Trainer knowledge base by Rodosthenous and Michael (2016), where players must teach a virtual robot human knowledge. The cost of crowdsourcing effort is difficult to assess. It ranges from literally getting it for free (e.g., the Open Mind Common Sense platform where users who submitted data were unpaid) to an estimate of \$2.25 per statement (Paulheim, 2018). Though the gaming approach may be cheaper in the long run, developing such a game platform is inevitably more time-consuming. Another challenge of the crowdsourcing approach, as pointed out by Davis and Marcus (2015), is that naive crowd workers may not be able to follow the theories and representations of knowledge that engineers have worked out. As a result, knowledge acquired by crowdsourcing can be somewhat messy, which again often needs human expert validation.

Each of these methods has its own advantages and drawbacks in terms of the trade-offs between the cost and the quality of the acquired knowledge. Most of these knowledge resources are developed from a bottom-up fashion. The goal is to create general knowledge bases to provide inductive bias for a variety of learning and reasoning tasks. Nevertheless, it is not clear whether such a goal is met and to what extent these knowledge resources are applied to commonsense reasoning in practice. A systematic study, as suggested by Davis and Marcus (2015), for Cyc and other resources would be useful.

4. Learning and Inference Approaches

To solve the benchmark tasks described in Section 2, a variety of approaches have been developed. These range from earlier symbolic and statistical approaches to recent approaches that apply deep learning and neural networks. This section gives a brief overview to some representative approaches.

4.1 Symbolic and Statistical Approaches

Manually authored logic rules and formalisms have been demonstrated to perform well for various reasoning tasks. Davis (2017) provides a more detailed review of these approaches in commonsense reasoning, but we introduce a few which have been applied to the surveyed commonsense benchmarks. Manually authored logical rules were applied, for example, in systems for the earlier RTE Challenges (Raina, Ng, & Manning, 2005). They were also applied in more recent work such as the baseline approach to the Triangle-COPA benchmark which achieved 91% accuracy (Gordon, 2016). The highest-performing system (Iftene, 2008) in the 3-way task of the fourth RTE challenge (Giampiccolo et al., 2008) used both manually authored logical rules and outside knowledge from Wikipedia, WordNet (Miller, 1995), and VerbOcean (Chklovski & Pantel, 2004). While manually authored logical rules have been demonstrated to be highly effective in some tasks (Gordon, 2016), this approach is not scalable for more complex tasks and reasoning.

Statistical approaches often rely on engineered features to train statistical models for various tasks. Lexical features, for example, based on bag of words and word matching were commonly used in the earlier RTE Challenges (Dagan et al., 2005; Bar-Haim et al., 2006), but often achieved results only slightly better than random guessing (Bar-Haim et al., 2006). More competitive systems have used more linguistic features to make predictions, such as semantic dependencies and paraphrases (Hickl, Bensley, Williams, Roberts, Rink, & Shi, 2006), synonym, antonym, and hypernym relationships derived from training data, and hidden correlation biases in benchmark data Lai and Hockenmaier (2014).

External knowledge and the Web are often used to complement features derived from the training data. For example, the best system in the first RTE Challenge (Dagan et al., 2005) used a naïve Bayes classifier with features from the co-occurrences of word from an online search engine (Glickman, 2006). A similar approach was also applied in the top system from the seventh RTE Challenge (Bentivogli et al., 2011), which utilized knowledge resources from Section 3, acronyms extracted from the training data, and linguistic knowledge to calculate a statistical measure of entailment between sentences (Tsuchida & Ishikawa, 2011). While the use of some external knowledge provides an advantage over models which only use linguistic features extracted from training data, statistical models have still not been competitive in recent benchmarks of large data size. Nonetheless, such models may serve as useful baselines for new benchmarks, as demonstrated for JOCI (Zhang et al., 2016).

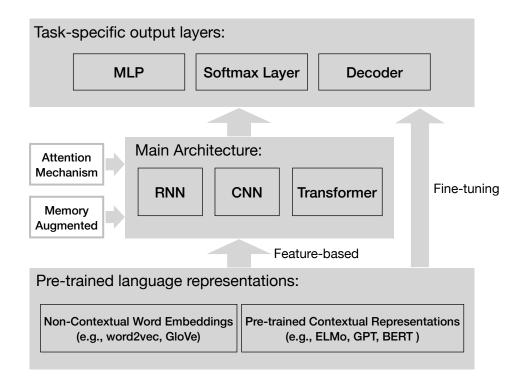


Figure 12: Common components in neural approaches to language-based commonsense tasks.

4.2 Neural Approaches

The increasingly large amount of data available for recent benchmarks make it possible to train neural models. These approaches often top various leaderboards. Figure 12 shows some common components in neural models. First of all, distributional representation of words is fundamental where word vectors or embeddings are usually trained using neural networks on large-scale text corpora. In traditional word embedding models like word2vec (Mikolov, Chen, Corrado, & Dean, 2013) or GloVe (Pennington, Socher, & Manning, 2014), the embedding vectors are context independent. No matter what context the target word appears in, once trained, its embedding vector is always the same. Consequently, these embeddings lack the capability of modeling different word senses in different context, although this phenomena is prevalent in language. To address this problem, recent work has developed contextual word representation models, e.g., Embeddings from Language Models (ELMo) by Peters, Neumann, Iyyer, Gardner, Clark, Lee, and Zettlemoyer (2018) and Bidirectional Encoder Representations from Transformers (BERT) by Devlin et al. (2018). These models give words different embedding vectors based on the context in which they appear. These pre-trained word representations can be used as features or fine-tuned for downstream tasks. For example, the Generative Pre-trained Transformer (GPT) by Radford, Narasimhan, Salimans, and Sutskever (2018) and BERT (Devlin et al., 2018) introduce minimal task-specific parameters, and can be easily fine-tuned on the downstream tasks with modified final layers and loss functions.

On top of the word embedding layers, task-specific network architectures are designed for different downstream applications. These architectures often adopt recurrent neural networks (RNNs, e.g., LSTM and GRU), convolutional neural networks (CNNs), or more recently, transformers to solve specific tasks. And the output layers of networks are chosen based on the task formulation, e.g., linear layer plus softmax for classifications, language decoder for language generations. Because of the sequential nature of language, RNN-based architectures are widely applied and are often implemented in both baseline approaches (Bowman et al., 2015; Rashkin et al., 2018b) and the current state-of-the-art approaches (Kim, Hong, Kang, & Kwak, 2019; Chen, Cui, Ma, Wang, Liu, & Hu, 2018; Henaff, Weston, Szlam, Bordes, & LeCun, 2017). Given different architectures, neural models also benefit from techniques like memory augmentation and attention mechanisms. For tasks that require reasoning based on multiple supporting facts, e.g., bAbI (Weston et al., 2016), memory-augmented networks like memory networks (Weston, Chopra, & Bordes, 2015) and recurrent entity networks (Henaff et al., 2017) have been shown effective. And for tasks that require alignment between input and output, e.g., textual entailment tasks like SNLI (Bowman et al., 2015), or capturing long-term dependencies, it is often beneficial to adopt attention mechanisms to models.

Next, we give examples of current state-of-the-art systems, particularly focusing on three aspects: memory augmentation, attention mechanism, and pre-trained models and representations.

4.2.1 MEMORY AUGMENTATION

Mentioned earlier, a popular type of approach for tasks which require comprehending passages with several state changes or supporting facts, such as bAbI (Weston et al., 2016) or ProPara (Mishra et al., 2018), involves augmenting systems with a dynamic memory which may be maintained over time to represent the changing state of the world. We discuss memory networks (Weston et al., 2015), recurrent entity networks (Henaff et al., 2017), and the recent Knowledge Graph-Machine Reading Comprehension (KG-MRC) system (Das et al., 2019) to highlight key characteristics of such an approach.

Memory networks. Memory networks by Weston et al. (2015), introduced as high-performing baseline approaches to both bAbI (Weston et al., 2016) and CBT (Hill et al., 2015), track the world state by adding a long-term memory component to the typical network architecture. A memory network consists of a memory array, an input feature map, a generalization module which updates the memory array given new input, an output feature map, and a response module which converts output to the appropriate response or action. The networks can take characters, words, or sentences as input. Each component of the network can take different forms, but a common implementation is for them to be neural networks, in which case the network is called a MEMNN.

The ability to maintain a long-term memory provides more involved tracking of the world state and context. On the CBT cloze task (Hill et al., 2015), it is demonstrated that memory networks can outperform primarily RNN- and LSTM-based approaches in predicting missing named entities and common nouns, and this is because memory networks can efficiently leverage a wider context than these approaches in making inferences. When tested on bAbI, MEMNNs also achieved high performance and outperformed LSTM baselines, and on some tasks were able to achieve high performance with fewer training examples than provided (Weston et al., 2016).

Recurrent entity networks. The recurrent entity network (ENTNET) by Henaff et al. (2017) is composed of several dynamic memory cells, where each cell learns to represent the state or properties concerning entities mentioned in the input. Each cell is a gated RNN which only updates its content when new information relevant to the particular entity is received. Further, ENTNET's memory cells run in parallel, allowing multiple locations of memory to be updated at the same time.

ENTNET is, to our knowledge, the first model to pass all twenty tasks in bAbI (Weston et al., 2016), and achieves impressive results on CBT (Hill et al., 2015), outperforming memory network baselines on both benchmarks. ENTNET is also used as a baseline in the Story Commonsense benchmark (Rashkin et al., 2018a) in an attempt to track the motivations and emotions of characters in stories from ROCStories (Mostafazadeh et al., 2016) with some success. An advantage of ENTNET is that it maintains and updates the state of the world as it reads the text, unlike memory networks, which can only preform reasoning when the entire supporting text and the question are processed and loaded to the memory. For example, given a supporting text with multiple questions, ENTNET does not need to process the input text multiple times to answer these questions, while memory networks need to re-process the whole input for each question.

While ENTNET achieves state-of-the-art performance on bAbI, it does not perform so well on ProPara (Mishra et al., 2018), another benchmark which requires tracking the world state. According to Das et al. (2019), a drawback of ENTNET is that while it maintains memory registers for entities, it has no separate embedding for individual states of entities over time. They further explain that ENTNET does not explicitly update coreferences in memory, which can certainly cause errors when reading human-authored text which is rich in coreference, as opposed to the simply-structured, automatically-generated bAbI data.

KG-MRC. A more recent model, the Knowledge Graph-Machine Reading Comprehension (KG-MRC) system from Das et al. (2019), maintains a dynamic memory similar to memory networks. However, this memory is in the form of knowledge graphs generated after every sentence of procedural text, leveraging research efforts from the area of information extraction. Generated knowledge graphs are bipartite, connecting entities in the paragraph with their locations (currently, it only captures the location relation). Connections between entities and locations are updated to generate a new graph after each sentence.

According to the official ProPara leaderboard¹⁴, the Knowledge Graph-Machine Reading Comprehension (KG-MRC) system from Das et al. (2019) achieves the highest accuracy on the benchmark, reported as 47.0% in the paper. It provides advantages over PROSTRUCT, the previous state of the art for ProPara (Tandon, Mishra, Grus, Yih, Bosselut, & Clark, 2018). While PROSTRUCT manually enforces hard and soft commonsense constraints, further investigation shows that KG-MRC learns these constraints automatically, violating them less often than PROSTRUCT Das et al. (2019). This shows that the use of the recurrent graph representation helps the model learn these constraints, perhaps better than can be manually enforced. Further, since KG-MRC includes a trained reading comprehension model, it can likely better track changes in coreference which often occur in these texts.

4.2.2 ATTENTION MECHANISM

Since the first application of attention mechanism for neural machine translation (Bahdanau, Cho, & Bengio, 2015), attention has been used widely in NLP tasks, especially to capture the alignment between an input (encoder) and an output (decoder). Modeling attention has several advantages. It allows the decoder to directly go to and focus on certain parts of the input. It alleviates the vanishing gradient problem by providing a way to account for states far away in the input sequence. Another advantage is that the attention distribution learned by the model automatically provides an alignment between inputs and outputs which allows some understanding of their relations. Be-

^{14.} https://leaderboard.allenai.org/propara/submissions/public

cause of these advantages, attention mechanisms have been successfully applied to commonsense benchmark tasks.

Attention in RNN/CNN. Adding an attention mechanism to RNNs, LSTMs, CNNs, and more has been shown to improve performance on various tasks compared to their vanilla models (Kim et al., 2019). It is particularly successful for tasks which require alignment between input and output, such as various RTE tasks which require the modeling of context and hypothesis, and reading comprehension questions which refer directly to an accompanying passage, like MCScript (Ostermann et al., 2018).

For example, the official leaderboard¹⁵ for the SNLI task (Bowman et al., 2015) reports that the best performing system (Kim et al., 2019), partly inspired by DENSENET (Huang, Liu, van der Maaten, & Weinberger, 2016), uses a densely connected RNN while concatenating features from an attention mechanism to recurrent features in the network. As discussed by Kim et al. (2019), the attentive weights resulting from this alignment help the system make accurate entailment and contradiction decisions for highly similar pairs of sentences. One such example given is the context sentence "Several men in front of a white building" compared to the hypothesis sentence "Several people in front of a gray building." For the MCScript task Ostermann et al. (2018) used in SemEval 2018, online results¹⁶ indicate that the best performer (Chen et al., 2018) achieved an accuracy of 84.13% using a bidirectional LSTM-based approach with an attention layer.

RNNs with attention also have limitations particularly when the alignment between inputs and outputs is not straightforward. For example, Chen et al. (2018) found that yes/no questions were particularly challenging in MCScript, as they require a special handling of negation and deeper understanding of the question. Further, since the multiple choices to answer questions in MCScript are human-authored instead of extracted directly from the accompanying passage like other QA benchmarks, this caused some difficulties in connecting words back to the passage that stemming alone could not fix.

Self-attention in transformers. In lieu of adding attention mechanisms to a typical neural model such as an RNN, LSTM, or CNN, the recently proposed transformer architecture is composed entirely of attention mechanisms (Vaswani, Shazeer, Parmar, Uszkoreit, Jones, Gomez, Kaiser, & Polosukhin, 2017). ¹⁷ One key difference is the self-attention layer in both the encoder and the decoder. For each word position in an input sequence, self-attention allows it to attend to all positions in the sequence to better encode the word. It provides a method to potentially capture long-range dependencies between words, such as syntactic, semantic, and coreference relations. Furthermore, instead of performing a single attention function, the transformer performs multi-head attention in the sense that it applies the attention function multiple times with different linear projections, and therefore allows the model to jointly capture different attentions from different subspaces, e.g., jointly attend to information that might indicate both coreference and syntactic relations.

Another big benefit of the transformer is its suitability for parallel computing. The sequence models such as RNN and LSTM by their sequential nature make it difficult for parallelization. The transformer, which uses attention to capture global dependencies between inputs and outputs, maximizes the amount of parallelizable computations. Empirical results on NLP tasks such as machine

^{15.} http://nlp.stanford.edu/projects/snli/

^{16.} http://competitions.codalab.org/competitions/17184\#results

^{17.} An excellent post on the implementation of the transformer can be found at http://nlp.seas.harvard.edu/2018/04/03/attention.html.

translation and constituency parsing have shown impressive performance gains with a significant reduction in training costs (Vaswani et al., 2017). Transformers have recently been used in pre-trained contextual models like GPT (Radford et al., 2018) and BERT (Devlin et al., 2018) to achieve state-of-the-art performance on many commonsense benchmarks.

4.2.3 PRE-TRAINED MODELS AND REPRESENTATIONS

One of the most exciting recent advances in NLP is the development of pre-trained models and embeddings that can be used as features or further fine-tuned for downstream tasks. These models are often trained based on a large amount of unsupervised textual data. The earlier pre-trained word embedding models such as word2vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014) have been widely applied. However, these models are context independent, meaning the same embedding is used in different contexts, and they therefore cannot capture different word senses. More recent work has addressed this problem by pre-training models that can provide a word embedding based on context. The most representative models are ELMO, GPT, and BERT. Next, we give a brief overview of these models and summarize their performance on the selected benchmark tasks.

ELMo. ELMo's characteristic contribution is its contextual word embeddings, which each rely on the entire input sentence they belong to Peters et al. (2018). These embeddings are calculated from learned weights in a bidirectional LSTM which is pre-trained on the supervised One Billion Word language modeling benchmark (Chelba, Mikolov, Schuster, Ge, Brants, Koehn, & Robinson, 2014). Simply adding these embeddings to the input features of previous state-of-the-art systems improved performance, suggesting that they are indeed successful in representing word context. An investigation by the authors shows that ELMo embeddings make it possible to identify word sense and POS, further supporting this.

When the ELMo embedding system was originally released, it helped exceed the state of the art on several benchmarks in the areas of question answering, textual entailment, and sentiment analysis. These included SQuAD (Rajpurkar et al., 2018) and SNLI (Bowman et al., 2015). All of these approaches have since been exceeded. ELMo still commonly appears in baseline approaches to benchmarks, e.g., to SWAG (Zellers et al., 2018) and CommonsenseQA (Talmor et al., 2019). It is often combined with the enhanced LSTM-based models such as the ESIM model (Chen, Zhu, Ling, Wei, Jiang, & Inkpen, 2017), or the CNN- and bidirectional GRU-based models such as the DocQA model (Clark & Gardner, 2018).

GPT. GPT by Radford et al. (2018) uses the transformer architecture originally proposed by Vaswani et al. (2017), in particular the decoder. This system is pre-trained on a large amount of open online data unsupervised, then fine-tuned to various benchmark datasets. Unlike ELMO, GPT learns its contextual embeddings in an unsupervised setting, which allows it to learn features of language without restrictions. The creators found that this technique produced more discriminative features than supervised pre-training when applied to a large magnitude of clean data. The transformer architecture itself can then be easily fine-tuned in a supervised setting for downstream tasks, which ELMO is not as suitable for, and instead should be used for input features to a separate task-specific model.

When GPT was first released, it pushed the state of the art forward on 12 benchmarks in textual entailment, semantic similarity, sentiment analysis, commonsense reasoning, and more. These included SNLI (Bowman et al., 2015), MultiNLI (Williams et al., 2017), SciTail (Khot et al., 2018),

the Story Cloze Test (Mostafazadeh et al., 2016), COPA (Roemmele et al., 2011), and GLUE (Wang et al., 2018). To our knowledge, GPT is still the highest-performing documented system for the Story Cloze Test and COPA, achieving 86.5% and 78.6% accuracy, respectively. GPT holds high positions on several other commonsense benchmark leaderboards as well. It is often commonly used as a baseline for new benchmarks, e.g., CommonsenseQA (Talmor et al., 2019).

Radford et al. (2018) identify several limitations of the model. First, the model has high computational requirements, which is undesirable for obvious reasons. Second, data from the Internet, which the model is pre-trained on, are incomplete and sometimes inaccurate. Lastly, like many deep learning NLP models, GPT shows some issues with generalizing over data with high lexical variation.

To improve the generalization ability and develop upon the use of unsupervised training settings, the larger GPT 2.0 was recently released (Radford, Wu, Child, Luan, Amodei, & Sutskever, 2019), which is highly similar to the original implementation, but with significantly more parameters and formulated as a language model. The expanded model has achieved new state-of-the-art results on several language modeling tasks, including CBT (Hill et al., 2015) and the 2016 Winograd Schema Challenge (Davis et al., 2017). Further, it exceeds three out of four baseline approaches to CoQA (Reddy et al., 2018) in an unsupervised setting, i.e., trained only on documents and questions, not answers. In a supervised training setting, the model would be fed the answers directly with the questions so that model parameters could be updated based upon correlations between them. The model instead learns to perform tasks by observing natural language demonstrations of them without being told where the questions and answers are. This way, it is ensured that the model is not overfitting to superficial correlations between questions and answers. A qualitative investigation into model predictions suggests that some heuristics are indeed being learned to answer questions. For example, if asked a "who" question, the model has learned to return the name of a person mentioned in the passage that the question is posed on. This provides some evidence of the model performing reasoning processes similar to what the benchmarks intend.

BERT. Recently, the BERT model (Devlin et al., 2018) exceeded the state-of-the-art accuracy on several benchmarks including GLUE (Wang et al., 2018), SQuAD 1.1 (Rajpurkar et al., 2016), and SWAG (Zellers et al., 2018) benchmarks. According to the GLUE leaderboard¹⁸, BERT originally achieved an overall accuracy of 80.4% on the multi-task benchmark. Meanwhile, according to the SQuAD leaderboard, BERT solved SQuAD 1.1 with 87.433% exact-match accuracy, exceeding human performance by 5.13%, and it solved SWAG with 86.28% accuracy according to the SWAG leaderboard, ²⁰ greatly exceeding the previous state of the art set by GPT (Radford et al., 2018).

After its initial release, BERT further topped several new leaderboards such as OpenBookQA (Mihaylov et al., 2018), CLOTH (Xie et al., 2017), SQuAD 2.0 (Rajpurkar et al., 2018), CoQA (Reddy et al., 2018), ReCoRD (Zhang et al., 2018), and SciTail (Khot et al., 2018). The deeper BERT_{LARGE} model introduced alongside the base model topped the leaderboards of OpenBookQA²¹ (Mihaylov et al., 2018) and CLOTH²² (Xie et al., 2017), achieving accuracies of 60.40% and 86.0%, respectively. According to the SQuAD leaderboard, various implementations of BERT had beaten the state of the art performance on SQuAD 2.0 more than a dozen times at the time of writing,

^{18.} https://gluebenchmark.com/leaderboard

^{19.} http://rajpurkar.github.io/SQuAD-explorer/

^{20.} http://leaderboard.allenai.org/swag/submissions/public

^{21.} http://leaderboard.allenai.org/open\ book\ ga/submissions/public

^{22.} http://www.qizhexie.com/data/CLOTH_leaderboard

| Benchmark | Simple Baseline | Best Baseline | ELMo | GPT | BERT | BIGBIRD | Human |
|------------|--------------------|------------------|------|------|------|---------|-------|
| SQuAD 1.1 | 1.3 | 40.4 | 81.0 | _ | 87.4 | _ | 82.3 |
| SWAG | 25.0 | 59.2 | | 78.0 | 86.3 | _ | 88.0 |
| SciTail | 60.4 | 79.6 | _ | 88.3 | _ | 94.1 | _ |
| ReCoRD | 18.6 | 45.4 | | _ | 73.0 | _ | 91.3 |
| OpenBookQA | 25.0 | 50.2 | _ | _ | 60.4 | _ | 91.7 |
| CLOTH | 25.0 | 70.7 | _ | _ | 86.0 | _ | 85.9 |
| GLUE | _ | 60.3 | | 72.8 | 83.3 | 83.1 | 87.1 |
| SQuAD 2.0 | 48.9 | 63.4 | | _ | 86.7 | _ | 86.9 |
| CoQA | 1.3 | 65.1 | _ | _ | 86.8 | _ | 88.8 |
| SNLI | 33.3 | 77.8 | 89.3 | 89.9 | _ | 91.1 | _ |

Table 3: Comparison of exact-match accuracy achieved on various benchmarks by a random or majority-choice baseline, the best-performing baseline presented in the original paper for each benchmark, ELMO, GPT, BERT, BIGBIRD, and humans. ELMO refers to the highest-performing listed approach using ELMO embeddings. Best system performance on each benchmark in bold. Information extracted from leaderboards linked to in Section 4.2 at time of writing (March 2019), and original papers for benchmarks introduced in Section 2.

the highest performance coming from an updated implementation which achieved an F-measure of 89.147. A modified ensemble implementation of BERT tops the CoQA leaderboard²³ with an accuracy of 86.8%, and a single-model implementation tops the ReCoRD leaderboard²⁴ with an accuracy of 74.76%. Most recently, a new implementation of BERT with updated loss functions is topping the GLUE leaderboard with 83.3% accuracy, beating the original implementation. Most of this progress comes in a span of just a few months.

BERT provides several advantages over past state-of-the-art systems with pre-trained contextual embeddings. First, it is pre-trained on larger data than previous competitive systems like GPT (Radford et al., 2018). Where GPT is pre-trained with a large text corpus, BERT is trained with two larger corpora of passages on two tasks: a cloze task where input tokens are randomly masked, and a sentence ordering task where given two sentences, the system must predict whether the second sentence could come directly after the first. This sort of transfer learning from large-scale supervised tasks has been demonstrated several times to be effective in NLP problems. Similar to GPT, BERT was further fine-tuned for each of the 11 commonsense benchmark tasks it originally attempted.

^{23.} http://stanfordnlp.github.io/coga/

^{24.} http://sheng-z.github.io/ReCoRD-explorer/

Second, BERT uses a bidirectional form of the transformer architecture (Vaswani et al., 2017) for pre-training contextual embeddings. This better captures context, an advantage that previous competitive approaches like GPT (Radford et al., 2018) and ELMo (Peters et al., 2018) do not have. Instead, GPT uses a left-to-right transformer, while ELMo uses a concatenation of left-to-right and right-to-left LSTMs.

Lastly, BERT's input embeddings are superior at representing context, which besides a traditional embedding for tokens, also capture a learned embedding for each sentence (i.e., if a pair of sentences is the input) applied to each token, and learned positional embeddings for tokens. Consequently, its embedding can capture each unique word and its context, perhaps in a more sophisticated way than previous systems. Further, it can uniquely represent a sentence or pair of sentences, advantageous for solving a wide variety of language processing tasks in question answering, textual entailment, and more.

Recently, another BERT-based system called BIGBIRD or the Multi-Task Deep Neural Network (MT-DNN) by Liu, He, Chen, and Gao (2019) is achieving competitive performance on several leaderboards such as for SciTail ²⁵ with an accuracy of 94.07%, SNLI (Bowman et al., 2015) ²⁶ with an accuracy of 91.1%, and GLUE with an accuracy of 83.1%, beating the original implementation of BERT. It appears that the performance gain from the BIGBIRD model can mostly be attributed to adding multi-task learning during fine-tuning procedures. This is done through task-specific layers which generate representations for specific tasks, e.g., text similarity and sentence pair classification. While pre-training the bi-directional transformer helps BERT learn universal word representations which are applicable across several tasks, multi-task learning prevents the model from overfitting to particular tasks during fine-tuning, thus allowing it to leverage more cross-task data.

BERT and its variations are currently the state of the art on nearly all commonsense benchmark tasks, even exceeding human performance in some cases. According to Devlin et al. (2018), a goal of future work will be to determine whether BERT truly captures the intended semantic phenomena in benchmark datasets. Further, as the BIGBIRD model was able to improve performance on several benchmarks by adding task-specific layers and enabling multi-task learning, BERT may be a bit too task-invariant, and potentially missing helpful information that comes from differentiating between specific tasks. It could likely benefit from further investigation into multi-task learning approaches such as BIGBIRD. Figure 3 compares performance from ELMO, GPT, BERT, and BIGBIRD on various benchmarks.

When to fine-tune. These new pre-trained contextual models are applied to benchmark tasks in different ways. Particularly, while ELMo has been traditionally used to generate input features for a separate task-specific model, BERT-based models are typically fine-tuned on various tasks and applied to them directly. Understanding why these choices were made are important for the further development of these models. Peters et al. (2018) investigate this difference in training the two models and compare their performance both when just extracting their output as features for another model, against when fine-tuning them to be used directly on various tasks. Their results show that ELMo's LSTM architecture can actually be fine-tuned and applied directly to downstream tasks like BERT can with some success, although it is more difficult to perform this fine-tuning on ELMo. Further, performance on sentence pair classification tasks like MultiNLI (Williams et al., 2017) and SICK (Marelli et al., 2014a) is shown to be better when the contextual embeddings generated by

^{25.} http://leaderboard.allenai.org/scitail/submissions/public

^{26.} https://nlp.stanford.edu/projects/snli/

ELMo are instead used as input features to a separate task-specific architecture. They infer that this may be because the LSTM architecture of ELMo must consider tokens sequentially, rather than being able to compare all tokens to each other across sentence pairs like BERT's transformer architecture can. BERT's output can also be used as features for a task-specific model with some success, and it actually outperforms ELMo in most of the studied tasks when used in this way, likely for the same reason. It is important to note, however, that performance on sentence similarity tasks like the Microsoft Research Paraphrase Corpus (Dolan & Brockett, 2005) is significantly better when the model is fine-tuned to the task.

4.3 Incorporating External Knowledge

Most of recent approaches have relied on the benchmark datasets (e.g., training data) to build models for reasoning and inference. Despite the availability of knowledge resources discussed in Section 3, few of them were actually applied to solve the benchmark tasks. WordNet (Miller, 1995) is perhaps the mostly applied lexical resource, and its word relations are particularly useful for textual entailment problems. WordNet has made an appearance in earlier approaches all throughout the RTE Challenges (Dagan et al., 2005; Hickl et al., 2006; Giampiccolo et al., 2008; Iftene, 2008; Bentivogli et al., 2011; Tsuchida & Ishikawa, 2011), and more recently used by a competitive approach to the 2016 Winograd Schema Challenge (Davis et al., 2018; Trinh & Le, 2018). The well-known and popular common knowledge resources such as DBpedia (Auer et al., 2007) and YAGO (Suchanek et al., 2007) have been used in creating benchmarks (Morgenstern et al., 2016; Choi et al., 2018), however, have not been directly applied to solve the benchmark tasks.

ConceptNet (Liu & Singh, 2004) and Cyc (Lenat & Guha, 1989) are by far the most talked-about commonsense knowledge resources available. However, Cyc does not seem to appear in any of our surveyed approaches, while ConceptNet has been occasionally applied. For example, OpenBookQA (Mihaylov et al., 2018) uses ConceptNet in a neural baseline approach, which often retrieves additional common and commonsense knowledge facts not included in benchmark data. ConceptNet is most often used to create knowledge-enhanced word embeddings. A neural model applied to COPA leverages commonsense knowledge from ConceptNet (Roemmele & Gordon, 2018) through ConceptNet-based embeddings which were generated by applying the word2vec skip-gram model (Mikolov et al., 2013) to commonsense knowledge tuples in ConceptNet (Li, Lee-Urban, Johnston, & Riedl, 2013). A recent approach to the Winograd Schema Challenge from (Liu, Jiang, Ling, Zhu, Wei, & Hu, 2017) uses a similar technique, as well as a baseline approach to SWAG (Zellers et al., 2018). Though ConceptNet is demonstrated to be useful for such purposes, still very few stateof-the-art approaches actually use it, rather they gain commonsense knowledge relations through benchmark training data only. This brings up some important questions as to how to incorporate external knowledge in modern neural approaches and how to acquire relevant external knowledge for the tasks at hand.

5. Other Related Benchmarks

While this paper intends to cover language understanding tasks for which some external knowledge or advanced reasoning beyond linguistic context is required, many related benchmarks have not been covered. First of all, nearly all language understanding benchmarks developed throughout the last couple decades could benefit from commonsense knowledge and reasoning. Second, as

language communication is integral to other perception and reasoning systems, recent years have also seen an increasing number of benchmark tasks that combine language and vision.

Language-related tasks. Many early corpora for classical NLP tasks such as semantic role labeling, relation extraction, and paraphrase may also require commonsense knowledge and reasoning, though this was not emphasized or investigated at the time. For example, in creating the Microsoft Research Paraphrase Corpus, Dolan and Brockett (2005) found that the task of annotating text pairs was difficult to streamline because this often required commonsense, suggesting that the paraphrases within the corpus require commonsense knowledge and reasoning to identify. Some such tasks are actually included in the multi-task benchmarks like Inference is Everything (White et al., 2017), GLUE (Wang et al., 2018), and DNC (Poliak et al., 2018a). Other examples of related textual benchmarks include QuAC (Choi et al., 2018), which relies on conversation discourse for robust contextual question answering, but does not require commonsense in the way that the similar CoQA benchmark does (Choi et al., 2018), and a conversation dataset created by Xu, Zhou, Young, Zhao, Huang, and Zhu (2018b) which explores the use of commonsense knowledge from ConceptNet in producing higher quality and more relevant responses for chatbots.

Besides English, there are also benchmarks in other languages. For example, there have been RTE datasets created in Italian²⁷ and Portuguese²⁸, and cross-lingual RTE datasets have appeared in several SemEval shared tasks over the years (Negri, Marchetti, Mehdad, Bentivogli, & Giampiccolo, 2012, 2013; Cer et al., 2017) to encourage progress in machine translation and content synchronization. There also exist various cross-lingual knowledge resources, including the latest version of ConceptNet (Speer et al., 2017), which contains relations from several multilingual resources.

Visual benchmarks. Commonsense plays an important role in integrating language and vision, for example, grounding language to perception (Gao, Doering, Yang, & Chai, 2016), languagebased justification for action recognition (Yang, Gao, Sadiya, & Chai, 2018), and visual question answering (Kafle & Kanan, 2017). Visual commonsense benchmarks include VQA benchmarks like the original VQA (Agrawal, Lu, Antol, Mitchell, Zitnick, Batra, & Parikh, 2015), other similar VQA datasets like Visual7W (Zhu, Groth, Bernstein, & Fei-Fei, 2016), and similar datasets with synthetic images, such as CLEVR (Johnson, Hariharan, van der Maaten, Fei-Fei, Zitnick, & Girshick, 2017) and the work by Suhr, Lewis, Yeh, and Artzi (2017). They also include the tasks of commonsense action recognition and justification, which are found in the dataset by Fouhey, Kuo, Efros, and Malik (2018), and Visual Commonsense Reasoning (VCR) by Zellers, Bisk, Farhadi, and Choi (2019). These are all image-based, but we are also beginning to see similar video-based datasets, such as Something Something (Goyal, Kahou, Michalski, Materzyńska, Westphal, Kim, Haenel, Fruend, Yianilos, Mueller-Freitag, Hoppe, Thurau, Bax, & Memisevic, 2017), which aims to evaluate visual commonsense through over 100,000 videos portraying everyday actions. We have also seen the vision-and-language navigation (VLN) task such as Room-to-Room (R2R) by Anderson, Wu, Teney, Bruce, Johnson, Sünderhauf, Reid, Gould, and van den Hengel (2018). Such benchmarks are important to promote progress in physically grounded commonsense knowledge and reasoning.

^{27.} See http://www.evalita.it/2009/tasks/te.

^{28.} See http://nilc.icmc.usp.br/assin/.

6. Discussion and Conclusion

The availability of data and computing resources and the rise of new learning and inference methods make this an unprecedentedly exciting time for research on commonsense reasoning and natural language understanding. As the research field moves forward, here are a few things we think are important to pursue in the future.

Among different kinds of knowledge, two types of commonsense knowledge are considered fundamental for human reasoning and decision making: intuitive psychology and intuitive physics. Several benchmarks are geared towards intuitive psychology, e.g., Triangle-COPA (Gordon, 2016), Story Commonsense (Rashkin et al., 2018a), and Event2Mind (Rashkin et al., 2018b). Reasoning with intuitive physics is scattered in different benchmarks such as bAbI (Weston et al., 2016) and SWAG (Zellers et al., 2018). Understanding how such commonsense knowledge is developed and acquired in humans and how they are related to human language production and comprehension may shed light on computational models for language processing.

In addition, besides benchmark tasks in a written language form as discussed in this paper, it may be worthwhile to also explore new tasks that involve artificial agents (in either a simulated world or the real physical world) which can use language to communication, to perceive, and to act. Some examples can be interactive task learning (Chai, Gao, She, Yang, Saba-Sadiya, & Xu, 2018) or embodied question answering (Das, Datta, Gkioxari, Lee, Parikh, & Batra, 2018). As commonsense knowledge is so intuitive for humans, it would be difficult even for researchers to identify and formalize such kind of knowledge. Working with agents and observing their abilities and limitations in understanding language and grounding language to their own sensorimotor skills will allow researchers to better understand the space of commonsense knowledge and tackle the problem of knowledge acquisition accordingly.

One challenge of the current trend of work is the disconnect between commonsense knowledge resources and approaches taken to tackle those benchmark tasks. Most approaches, particularly neural approaches, only accrue knowledge or learn models from training data, a method that critics are unsure can result in comparable reasoning ability on the level of humans (Cambria et al., 2011). Although there exist many knowledge bases designed for commonsense reasoning, most of them are not used directly to solve the benchmark tasks, except for very few. One likely reason is that these knowledge bases do not cover the kind of knowledge that is required to solve those tasks. This was discovered, for example, of ConceptNet (Liu & Singh, 2004) in creating the Event2Mind benchmark (Rashkin et al., 2018b). To address this problem, several methods have been proposed for leveraging incomplete knowledge bases. One method mentioned in Section 3 is AnalogySpace (Speer et al., 2008), which uses principle component analysis to make analogies to smooth missing commonsense axioms. Another example is memory comparison networks (Andrade, Bai, Rajendran, & Watanabe, 2018), which allow machines to generalize over existing temporal relations in knowledge resources in order to acquire new relations. Future work will need to come up with more solutions to handle the long-tail phenomenon (Davis & Marcus, 2015).

Another potential avenue to address the disconnection is to jointly develop benchmark tasks and construct knowledge bases. Recently, we are seeing the creation of knowledge graphs geared toward particular tasks, like the ATOMIC knowledge graph by Sap et al. (2019) which expands upon data in the Event2Mind benchmark, and ideally provides the required relations that Concept-Net does not. We are also seeing the creation of benchmarks geared toward particular knowledge graphs, like CommonsenseQA (Talmor et al., 2019), where questions were drawn from subgraphs

of ConceptNet, thus encouraging the use of ConceptNet in approaching the benchmark tasks. A tighter coupling of benchmark tasks and knowledge resources will help understand and formalize the scope of knowledge needed, and facilitate the development and evaluation of approaches that can incorporate external knowledge.

As more benchmark tasks become available and performance on these tasks keeps growing, one central question is whether the technologies developed are in fact pushing the state-of-the-art or only learning superficial artifacts from the dataset. Better understanding of the behaviors of these models, especially deep learning models that achieve high performance, is critical. For example, when applied to DNC (Poliak et al., 2018a), the multi-task two-way entailment benchmark, In-FERSENT achieves high accuracy on many of the benchmark's tasks (sometimes over 90%) just by training and testing on only the hypothesis texts from the benchmark rather than both the context and hypothesis sentences. Since humans require both the context and hypothesis to perform textual entailment, this suggests that the model is learning obscure statistical biases in the data rather than performing actual reasoning. For another example, Jia and Liang (2017) propose an adversarial evaluation scheme for SQuAD (Rajpurkar et al., 2016) which randomly inserts distractor sentences into passages which do not change the meaning of the passage, and shows that high-performing models on the benchmark drop significantly. Marasović (2018) also highlights several more models which have been shown to be spurious, identifying several recent works which show that highperforming modern NLP systems can break down due to small, inconsequential changes in inputs. BERT may suffer from a similar issue, as its deep, bidirectional architecture makes its reasoning processes highly unexplainable, and thus it is quite opaque why certain conclusions are made by the model. It is unclear if BERT is capturing semantic phenomena or again learning statistical biases. According to the creators of BERT, this will be a subject of future research.

Lastly, like most deep learning applications, a significant amount of effort has been spent on tuning parameters to improve the performance. We have also recently seen in other AI subfields that more sophisticated models may lead to better performance on a particular benchmark, but simpler models with better parameter tuning may later lead to comparable results. For example, in image classification, a study by Brendel and Bethge (2019) shows that nearly all improvements of recent deep neural networks over earlier bag-of-features classifiers come from better fine-tuning rather than improvements in decision processes. NLP models may be similarly vulnerable to this. More efforts on theoretical understanding and motivation for model design and parameter tuning would be beneficial.

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