SemEval-2020 Task 4: Commonsense Validation and Explanation

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Abstract

In this paper, we present SemEval-2020 Task 4, Commonsense Validation and Explanation (ComVE), which includes three subtasks, aiming to evaluate whether a system can distinguish a natural language statement that makes sense to human from one that does not, and provide the reasons. Specifically, in our first subtask, the participating systems are required to choose from two natural language statements of similar wording the one that makes sense and the one does not. The second subtask additionally asks a system to select the key reason from three options why a given statement does not make sense. In the third subtask, a participating system needs to generate the reason automatically. The dataset used in our task can be found at https://github.com/wangcunxiang/SemEval2020-Task4-Commonsense-Validation-and-Explanation.

1 Introduction

Although in the past decades computers’ ability in processing natural language has significantly improved, the intelligence in understanding common sense expressed in language, however, is still limited. It is straightforward for humans to judge the following sentence is plausible and makes sense: “John put a turkey into a fridge”, but “John put an elephant into the fridge” does not, while it is non-trivial for a computer to tell the difference. Arguably, commonsense reasoning plays a central role in a natural language understanding system (Davis, 2017). It is an important problem to evaluate how well computers can understand whether given statements make sense. In our task, we take an operational definition of making sense by asking human subjects to generate natural language statements that obey or violate their commonsense knowledge about the world.

Many existing tasks embed the evaluation of commonsense understanding in other problems such as co-reference resolution (Levesque et al., 2012; Morgenstern and Ortiz, 2015), subsequent event prediction (Roemmele et al., 2011), ordinal common-sense inference (Zhang et al., 2017), situations with adversarial generations (Zellers et al., 2018), event validation (Wang et al., 2018), reading comprehension (Mostafazadeh et al., 2016; Ostermann et al., 2018b; Ostermann et al., 2018a), dialogue (Cui et al., 2020) and QA problems (Davis, 2016; Talmor et al., 2018; Mihaylov et al., 2018). They verify whether a system is equipped with common sense by testing whether the system can give a correct answer where the input does not contain such knowledge. The above tasks do not directly evaluate commonsense validation and they do not explicitly identify the key factor required in a commonsense validation process.

Our SemEval-2020 Task 4 includes three subtasks on testing whether a system can distinguish natural language statements that make sense from those that do not, and probe the reasons. In the first subtask, a system needs to choose from two natural language statements of similar wordings the one does not make sense and the one does, e.g., “John put an elephant into the fridge” and “John put a turkey into the fridge”, respectively. The second task aims to find the key reason from three provided options why a given nonsensical statement does not make sense. For example, for the nonsensical statement, “John put an elephant into the fridge”, the three options are “An elephant is much bigger than a fridge”, “Elephants are usually white while fridges are usually white”, and “An elephant cannot eat a fridge.” A system needs
to identify the correct reason. In addition, the third task requires the participating systems to generate
the reason automatically. We hope our task helps facilitate further research on commonsense validation
and its interpretability, other commonsense reasoning problems, as well as other related natural language
understanding and generation tasks.

2 Task Setup

2.1 Task Definition

Formally, each instance in our dataset is composed of 8 sentences: \( \{s_1, s_2, o_1, o_2, o_3, r_1, r_2, r_3\} \). \( s_1 \) and
\( s_2 \) are two similar statements that differ by only a few words; one of them makes sense while the other
does not. They are used in our Subtask A: the Validation subtask, which requires a model to identify
which makes sense. For the statement that does not make sense, we have three candidate reasons, i.e.,
three options \( o_1, o_2, \) and \( o_3; \) one of them explains why the statement does not make sense. So, in our
Subtask B, the Explanation (Multi-Choice) subtask, a model is required to find the correct reason from
the three options. For the same nonsensical statement, in Subtask C, the Explanation (Generation)
subtask, a participating system needs to generate the reason why it does not make sense. Three references,
\( r_1, r_2, \) and \( r_3, \) are used for evaluating Subtask C. Below we give an example for each subtask, in which
we introduce some notations we will used in the paper.

• Subtask A: Validation

  Question: Which statement of the two does not make sense?
  \( s_1: \) John put a turkey into a fridge.
  \( s_2: \) John put an elephant into the fridge.

  In this example, \( s_1 \) is a sensical statement, denoted as \( s_c \), while \( s_2 \) is the nonsensical statement,
  which is denoted as \( s_n \).

• Subtask B: Explanation (Multi-Choice)

  Task: Select the best reason that explains why the given statement does not make sense.
  Nonsensical statement (\( s_n \)): John put an elephant into the fridge.
  \( o_1: \) An elephant is much bigger than a fridge.
  \( o_2: \) Elephants are usually white while fridges are usually white.
  \( o_3: \) An elephant cannot eat a fridge.

  In this example, the option \( o_1 \) is the correct reason, which is denoted also as \( o_c \), while \( o_2 \) and \( o_3 \) are
  not the reason, which are also denoted as \( o_{n1} \) and \( o_{n2} \).

• Subtask C: Explanation (Generation)

  Task: Generate the reason why this statement does not make sense.
  Nonsensical statement (\( s_n \)): John put an elephant into the fridge.
  Reference reasons (used for calculating the BLEU score):
  \( r_1: \) An elephant is much bigger than a fridge.
  \( r_2: \) A fridge is much smaller than an elephant.
  \( r_3: \) Most of the fridges aren’t large enough to contain an elephant.

2.2 Evaluation Metrics

The Subtask A and B are evaluated using accuracy. Subtask C is evaluated with the BLEU score (Papineni
et al., 2002). In addition, for Subtask C, we further perform human evaluation—we randomly select
100 instances from the test set and evaluate system outputs on Amazon Mechanical Turk. We ask three
different crowd-sourcing workers to score each generated reason with a Likert scale ranging from 0 to 3,
 inclusively, according the rubrics listed in Table 1.
| Score | Description |
|-------|-------------|
| 0     | The reason is not grammatically correct, or not comprehensible at all, or not related to the statement at all. |
| 1     | The reason is just the negation of the statement or a simple paraphrase. Obviously, a better explanation can be made. |
| 2     | The reason is relevant and appropriate, though it may contain a few grammatical errors or unnecessary parts. Or like case 1, but it’s hard to write a proper reason. |
| 3     | The reason is appropriate and is a solid explanation of why the statement does not make sense. |

Table 1: Rubrics used in human evaluation in Subtask C.

Then we calculate the average score of the three scores as our final human evaluation score. Formally, the human evaluation score of system $k$ is

$$score_k = \frac{\sum_{i=1}^{100} \sum_{j=1}^{3} score_{ijk}}{100 \times 3}$$

(1)

where $score_{ijk}$ means the score from the $j$th annotator for system $k$ on the $i$th instance.

3 Data Construction

Our data construction was mainly performed on Amazon Mechanical Turk, which consists of two steps:

- **Step 1:** In this step, we construct datasets for Subtask A and Subtask B. Specifically, we ask a crowd-sourcing worker to write a sensical statement $s_c$ and a nonsensical statement $s_n$. For the nonsensical statement $s_n$, the worker further writes three sentences, $o_1$, $o_2$, $o_3$; one of them, denoted as $o_c$, explains why the nonsensical statement does not make sense; two of them, denoted as $o_{n1}$ and $o_{n2}$, serve as the confusing choices. (Refer to Section 3.1 for details.)

- **Step 2:** We then collect three reference reasons, $r_1$, $r_2$, $r_3$, for Subtask C. We use $o_c$ as one of three references, and collect two more references in this step. We ask two different crowd-sourcing workers to write each of them. Note that instead of letting the same worker in step 1 to write these two references, we asked two more workers. The reason is to encourage diversity of the reference. (Refer to Section 3.2 for details.)

Finally, each instance of the dataset have 8 sentences: $\{s_1, s_2, o_1, o_2, o_3, r_1, r_2, r_3\}$. Note that one sentence in $o_1$, $o_2$, $o_3$ is repeated in $r_1$, $r_2$, $r_3$, but for convenience of description, we note it differently.

3.1 Step 1: Collecting Data for Subtask A and B

**Annotation Guidelines.** When writing instances, workers were asked to follow several principles: (1) Try to avoid complex knowledge and focus on daily common sense. Make the questions as understandable as possible, so that a literate person is able to give the right answers. (2) The confusing reason options, $o_{n1}$ and $o_{n2}$, should better contain more content words or information such as entities and activities in the nonsensical statements $s_n$. For example, the confusing reasons of “John put an elephant into the fridge” should better contain both “elephant” and “fridge”. (3) The confusing reasons, $o_{n1}$ and $o_{n2}$, should be related to the statements $s_n$ and the correct reason $o_c$ and not deviate from the context; otherwise it may be easily captured by pretrained models like BERT [Talmor et al., 2018]. (4) The three option reasons, $o_1$, $o_2$, and $o_3$ should only be related to the incorrect statements $s_n$ rather than the correct statements $s_c$. Because we want further studies to be able to estimate nonsensical statements $s_n$ without the correct statement $s_c$. (5) The confusing reasons, $o_{n1}$ and $o_{n2}$, should make sense themselves. Otherwise, the models may simply ignore the incorrect options $o_{n1}$, $o_{n2}$ without considering the casual semantics. This concern is raised from and motivated by the fact that models can achieve high performance in the ROC Story Cloze Task, when only looking at the alternative endings and ignoring the story content [Schwartz et al., 2017].
### Table 2: Nonsensical label distribution in Subtask A.

| Dataset | Nonsens_first | Nonsens_second | Total |
|---------|---------------|----------------|-------|
| Train   | 4,979         | 5,021          | 10,000|
| Dev     | 518           | 479            | 997   |
| Test    | 492           | 508            | 1000  |

Nonsens_first means in a \((s_1, s_2)\) pair, the first sentence is the nonsensical statement, i.e., \(s_1 = s_n\) and \(s_2 = s_c\). Nonsens_second means the second sentence is a nonsensical statement, i.e., \(s_1 = s_c\) and \(s_2 = s_n\).

### Table 3: Correct label distribution in Subtask B.

| Dataset | Option 1 correct | Option 2 correct | Option 3 correct | Label Number |
|---------|------------------|------------------|------------------|--------------|
| Training| 3,195            | 3,362            | 3,443            | 10,000       |
| Dev     | 344              | 327              | 336              | 997          |
| Test    | 320              | 355              | 325              | 1,000        |

(6) We control the length of each sentence, making the nonsensical statement \(s_n\) nearly as long as the sensical statement \(s_c\), and the correct reason \(o_c\) neither too long nor too short among the three reason options \(o_1, o_2, o_3\).

### Use of Inspirational Materials.

It is not easy for all crowd-sourcing workers to write instances from scratch. To address this issue, we also provide them with external reading materials to stimulate inspiration, such as the sentences of the OMCS (Open Mind Common Sense) project (Havasi et al., 2010). For example, “he was sent to a (restaurant)/(hospital) for treatment after a car crash” can be inspired by the two sentences “restaurants provide food” and “hospitals provide medical care”. In addition, we include a small number of existing commonsense reasoning questions such as WSC (Levesque et al., 2012; Morgenstern and Ortiz, 2015), COPA (Roemmele et al., 2011), and SQUABU (Davis, 2016).

### Quality Control.

After the annotators write the instances, the first two authors of this paper check them, and if an instance containing sentences that violate the principles significantly, we will reject the instance and ask the crowd-sourcing worker to rewrite it. And if one worker writes too many low-quality instances, we will remove her or him from our annotator pool. With the quality control process, we accept between 30% and 40% submitted instances.

### 3.2 Step 2: Collecting Data for Subtask C

#### Annotation Guidelines.

To collect data for Subtask C, each worker is given a nonsensical statement \(s_n\) and a sensical statement \(s_c\) and asked to write a reason to explain why the nonsensical statement \(s_n\) does not make sense. They shall follow the following rules: (1) Do not explain why the sensical statement \(s_c\) makes sense. (2) Avoid mentioning the sensical statement \(s_c\). (3) Write the reason, rather than simply add the word “not” or “can’t” to the nonsensical statement \(s_n\) to form an explanation. (4) Write the reason, don’t use patterns like “XXX is not for YYY” to create an explanation. (5) Do not try to justify why the nonsensical statement \(s_n\) makes sense. (6) Write only one sentence, do not be overly formal. (7) Refrain from using “because” at the beginning of a sentence. (8) Do not try to correct the statement \(s_n\), but just give the reason.

#### Quality Control.

Same as in Step 1, after the annotators write the reasons in Step 2, the first two authors of the paper perform the check process again. We will reject low-quality reasons (that violate the rules significantly) and low-quality annotators (who write many low-quality reasons with the number above a threshold).
| Type of Sentences  | Training Set | Dev Set | Test Set |
|-------------------|--------------|---------|---------|
| Sensical Statements | 7.67         | 7.12    | 7.25    |
| Nonsensical Statements | 7.69         | 7.16    | 7.36    |
| Correct Reasons    | 8.13         | 7.96    | 8.09    |
| Confusing Reasons  | 7.80         | 7.14    | 7.29    |
| Referential Reasons| 8.08         | 7.92    | 8.06    |

Table 4: Average Length of different types of sentences of Training/Dev/Test set

| Types of Sentences                  | (Word, Word Frequency(‰)) |
|-------------------------------------|----------------------------|
| Sensical Statements                 | ('in', 2.928)('he', 2.754)('i', 1.88)('of', 1.408)('on', 1.403) |
| Nonsensical Statements              | ('in', 2.941)('he', 2.714)('i', 1.827)('on', 1.432)('of', 1.427) |
| Correct Reasons                     | ('not', 4.126)('in', 2.218)('and', 1.758)('cannot', 1.572)('of', 1.523) |
| Confusing Reasons                   | ('in', 2.456)('and', 2.038)('can', 1.883)('of', 1.799)('people', 1.502) |
| Referential Reasons                 | ('not', 5.164)('in', 2.2)('and', 1.691)('cannot', 1.492)('for', 1.457) |

(a) Training set

| Types of Sentences                  | (Word, Word Frequency(‰)) |
|-------------------------------------|----------------------------|
| Sensical Statements                 | ('in', 3.031)('he', 2.75)('on', 1.713)('i', 1.625)('she', 1.485) |
| Nonsensical Statements              | ('in', 3.295)('he', 2.598)('on', 1.543)('you', 1.482)('i', 1.456) |
| Correct Reasons                     | ('in', 2.429)('not', 2.107)('and', 1.785)('can', 1.549)('no', 1.462) |
| Confusing Reasons                   | ('in', 2.536)('can', 2.098)('and', 2.02)('of', 1.56)('people', 1.456) |
| Referential Reasons                 | ('not', 3.828)('in', 2.387)('and', 2.193)('for', 1.49)('of', 1.278) |

(b) Dev+Test set

Table 5: Top-5 common words and their frequencies in different types of sentences in the training and dev+test set. 1.000‰ means this word appear one time in every 1000 words. (We skip most uninformative words, including 'a', 'an', 'the', 'to', 'is', 'are' and 'be'.)

### 3.3 Data Summary and Analysis

For SemEval-2020, we created 11,997 instances (i.e., 11,997 8-sentence tuples). We further split the instances into 10,000 (the training set), 997 (the development set), and 1,000 (the test set). We conduct four more data analysis experiments to evaluate data quality, label distribution, sentence length, and common words.

**Average Length.** In Table 4, we present the average length of each type of sentence in the training/dev/test set. The sentences in the development and test set have shorter lengths than those in the training set. This is because we check the development and test more carefully and more strictly thus remove more long and incomprehensible instances, which lower the average lengths of the dev/test set. The sensible statements and nonsensical statements almost have the same average lengths in the three sets (the differences are equal or smaller than 1% ), which is balanced. However, there is an obvious gap between the correct reasons and confusing reasons in terms of the average lengths (roughly 4% in the training set and 10% in the dev/test set).

**Common Word Analysis** The most common words are important for showing the differences between sentences. Instead of using a standard stopword list, we manually created one for our task here, which we called uninformative words and are listed in the caption of Table 5. After removing those words, we can list the top-5 common words in each type of sentence in the training/dev+test sets. For sensible sentences $s_c$ and nonsensical statements $s_n$, there are no significant differences between the training, dev, and test set. However, there is an obvious gap in the correct reasons $o_c$ and confusing reasons $o_n$ in negative words such as “not”, “no”, and “cannot”. In the training data, negative words are about 3 times more common in the correct option $o_c$ than in the confusing options $o_n$. In the dev+test data, the gap is about 40%, which indicates that the dev+test data has a higher quality than the training data. However, as discussed in (Niven and Kao, 2019), the Spurious Statistical Cues can affect BERT’s results. We suppose that the negative words are also spurious effective clues, which make the Subtask B potentially easier.

**Repetition.** The dev+test set have 12 instances (0.6%) that repeat the same nonsensical statements in the training data and 36 instances (1.8%) that repeat the same correct reasons with the training data.
Figure 1: The most commonly used model architectures used in the three subtasks. This figure is mostly based on Solomon’s system. For Subtask B and C, the connector can be simply “No, ”, to help in constraining the model to learn a choice that explains the unreasonability of the statement. For Subtask A and B, the pretrained models are finetuned on the task-specific data with MLM-objective, and then trained as a binary classification task to score each input. For Subtask C, the cross-entropy loss of next-token-prediction is used to train the model, and beam search is used at inference.

3.4 Cautions of using the data

The following advice is given to the participants: (1) Feel free to use whatever additional data they deem appropriate for the tasks to train their model. (2) Do not use the input of Subtask B/C to help Subtask A and do not use the option o of Subtask B to help Subtask C. Otherwise the task will be artificially easy. This is because of two reasons: a) The nonsensical statements \( s_n \) of Subtask B and Subtask C is exactly the nonsensical statements \( s_c \) of Subtask A and, participants can use the input of the Subtask B/C to directly obtain the answer of Subtask A and the option answers \( o \) of Subtask B will also reduce the difficulty of Subtask A; b) the correct reason \( o_c \) of Subtask B is also one of the reference reason \( o \) in Subtask C.

4 Systems and Results

In this section, we show the evaluation results of all the submitted systems for the three subtasks. Since most systems share similar model architecture for subtasks A and B, we discuss the two subtasks together.

4.1 Subtask A and Subtask B

The formal evaluation results of Subtask A and B are shown in Table 6 and 7. There are in total 39 valid submissions for Subtask A and 27 valid submissions for Subtask B. Most top-performing submissions adopted the pretrained language models such as BERT (Devlin et al., 2018), RoBERTa (Liu et al., 2019c), XLNET (Yang et al., 2019) and ALBERT (Lan et al., 2019) as the encoder of the model, and then finetune on the training set of the task. See Figure 1 for the most commonly-used model architectures for...
| Team Name       | Accuracy | Team Name       | Accuracy | Team Name       | Accuracy |
|-----------------|----------|-----------------|----------|-----------------|----------|
| CN-HIT-IT.NLP   | 97.0     | JinaLi*         | 92.5     | LiJunyi*        | 83.0     |
| ECNU-SenseMaker | 96.7     | ZhengxianFan*   | 92.4     | ehsantaher*     | 82.5     |
| IIE-NLP-NUT     | 96.4     | LMVE            | 90.4     | TakeLab*        | 81.2     |
| nlpx*           | 96.4     | Warren*         | 90.4     | Vicki*          | 79.8     |
| Solomon         | 96.0     | TMLab*          | 89.2     | TR              | 79.7     |
| Qiaoning        | 95.9     | UAICS           | 89.1     | KDE SenseForce  | 79.6     |
| BUT-FIT         | 95.8     | JUST            | 89.1     | Hitachi*        | 78.4     |
| olenet*         | 95.5     | eggy*           | 89.0     | paramitamirza*  | 69.2     |
| KaLM            | 95.3     | UI              | 88.2     | UoR             | 67.6     |
| CS-NET          | 94.8     | Armins*         | 87.1     | UoR             | 67.6     |
| tkerey*         | 94.4     | DEEPYANG        | 85.1     | chengguang*     | 62.3     |
| JUSTers         | 92.9     | WUY*            | 84.2     | praveenjoshi007*| 55.9     |
| CS-NLP          | 92.7     | YNU-oxz         | 83.6     | dania*          | 21.6     |

Table 6: Subtask A results of all the submitted systems. Those marked with * did not submit system description paper.

| Team Name       | Accuracy | Team Name       | Accuracy | Team Name       | Accuracy |
|-----------------|----------|-----------------|----------|-----------------|----------|
| ECNU-SenseMaker | 95.0     | JBU          | 91.4     | Masked Reasoner | 73.5     |
| CN-HIT-IT.NLP   | 94.8     | Qiaoning      | 90.8     | KDE SenseForce  | 72.8     |
| IIE-NLP-NUT     | 94.3     | CS-NET        | 89.0     | SSN-NLP         | 68.3     |
| Solomon         | 94.0     | WUY*          | 85.3     | TakeLab*        | 66.8     |
| LMVE            | 93.8     | SWAGex        | 84.6     | UoR             | 65.9     |
| CS-NLP          | 93.7     | TMLab*        | 82.0     | dania*          | 55.5     |
| KaLM            | 93.2     | UI            | 80.5     | CUHK            | 51.2     |
| BUT-FIT         | 93.1     | ehsantaher*   | 79.3     | bhuv*           | 36.4     |
| JUSTers         | 92.3     | uzhi*         | 75.8     | praveenjoshi007*| 32.6     |

Table 7: Subtask B results of all the submitted systems. Those marked with * did not submit system description paper.

Subtask A and B. Also, the top-performing systems take advantage of external knowledge graphs such as ConceptNet (Speer et al., 2017), or unstructured text containing commonsense knowledge. Below we introduce in detail several top-performing systems and their main features.

- **CN-HIT-IT.NLP** ranks top in Subtask A. They use a variant of K-BERT (Liu et al., 2019a) as the encoder to enhance language representations through knowledge graphs. K-BERT is a Transformer-based model, which enhances the language representations of the text by injecting relevant triples from a KG to form a knowledge-rich sentence tree, and then use a mask-Transformer to make the triples visible only to the corresponding entity. They use ConceptNet as the commonsense repository to extract the triples for the statements.

- **ECNU-SenseMaker** ranks top in Subtask B. It uses Knowledge-enhanced Graph Attention Network to leverage heterogeneous knowledge from both the structured knowledge base (i.e. ConceptNet) and the unstructured text to better improve the commonsense understanding. Like **CN-HIT-IT.NLP**, their model is also based on K-BERT. In addition, they use unstructured text from ConceptNet and Subtask C to pretrain the language model.

- **IIE-NLP-NUT** uses RoBERTa as the encoder, and conduct a second pretraining on the original RoBERTa model with the textual corpus from Open Mind Common Sense (Singh et al., 2002). They also explore several prompt templates to constructs as the inputs to the model.

- **Solomon, KaLM, CS-NET, JUSTers, CS-NLP, UI, TR UoR, Masked Reasoner** have similar model architecture, with RoBERTa as the encoder. In addition, UoR finetunes the pretrained language model on NLI and STS dataset, and UI finetunes on MNLI data. TR combines RoBERTa features with additional features from text-to-image generation using Gradient Boosted Decision Tree, and give better results in post-evaluation.

- **Qiaoning** and **JUST** use several ensembles of BERT, ALBERT, XLNet and RoBERTa.
Table 8: Subtask C results of all the submitted systems. Those marked with * did not submit system description paper, and those marked with + means they do not include Subtask C in their system description paper.

| Team       | BLEU | Human Eval | Team               | BLEU | Human Eval |
|------------|------|------------|--------------------|------|------------|
| BUT-FIT    | 22.4 | 1.84       | CN-HIT-IT+NLP+     | 9.7  | 1.74       |
| Solomon    | 19.3 | 1.84       | SWAGEx             | 7.1  | 1.75       |
| KaLM       | 18.5 | 2.08       | UI                 | 5.5  | 0.73       |
| panaali*   | 17.2 | 1.22       | TMLab*             | 5.4  | 1.05       |
| JUSTers    | 16.1 | 1.94       | CUHK               | 4.3  | 0.58       |
| cdjhz*     | 16.0 | 1.75       | SSN-NLP            | 2.2  | 0.59       |
| JBNU       | 15.9 | 1.80       | UoR+               | 0.9  | 0.53       |
| ANA        | 15.7 | 2.10       | Masked Reasoner+   | 0.6  | 0.81       |
| LMVE+      | 12.9 | 1.78       |                    |      |            |

- **BUT-FIT, LMVE, Lijunyi** use ALBERT as the encoder. **BUT-FIT** uses back-translation from Czech for data augmentation, and **LMVE** uses hint sentence, back-translation from French and intra-subtask transfer learning between Subtask A and B to enhance their system.

- **UAICS, DEEPYANG, YNU-oxz, KDE-SenseForce, CUHK, JBNU, SWAGex** are BERT-based. **JBNU** put an BiLSTM on top of BERT, and **SWAGex** finetunes BERT with SWAG data. **CUHK** uses a Multitask Learning framework MTDNN (Liu et al., 2019b), adopting the "Explain, Reason and Predict" system.

It can be seen from the results that pretrained language models such as RoBERTa can achieve rather high performance; (e.g., the team Solomon achieves 96.0% and 94.0% on Subtask A and Subtask B, respectively, without using further resources). This shows that large-scale pretrained language models do contain commonsense knowledge to deal with the Subtask A and B in this challenge. Additionally finetuning the pretrained language models on commonsense-related text such as OMCS, which we use as inspirational materials, can push the results even higher. The best-performing teams on Subtask A and Subtask B both adopt K-BERT, which incorporates the external knowledge base (i.e. ConceptNet) to complement the pretrained language models with knowledge triples. This shows that KG-enhanced approaches, such as K-BERT can effectively incorporate external knowledge. However, the high number may also indicate data leaking to some extent, since in the data creation stage, both ConceptNet and OMCS are used as references for the annotator to write the data instances.

### 4.2 Subtask C

The results for Subtask C is shown in Table 8. There are in total 17 valid submissions for Subtask C. There are generally two approaches: (1) sequence-to-sequence approach, where the source side is the non-sensical statement, and the reason is the target sequence. (2) language model generation approach, which uses large-scale pretrained auto-regressive language models such as GPT-2 (Radford et al., 2019) for reason generation, where the non-sensical sentence acts as prompt. An example of the language model generation approach is shown in Figure I which is most commonly used and achieves relatively good results. Below we describe in detail the systems and their main features.

- **BUT-FIT** experiments with both the sequence-to-sequence approach and the language generation approach. For the sequence-to-sequence approach, they use BART (Lewis et al., 2019) with beam-search decoding to achieve the highest BLEU among all the teams. For the language generation approach, the nonsensical statement is used as a prompt. At the training stage, the statement and the explanation are concatenated together, and a GPT-2 is trained on these sequences with a next token prediction objective. At the test time, based on the statement, the model generates the reason tokens until the end-of-sentence token is generated.

- **KaLM** uses the sequence-to-sequence architecture BART. To enhance the source side statement, they extract keywords from the statement and search for evidence from Wiktionary[1] After that, they...

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[1] Wiktionary version: enwiktionary-20200220
concatenate the evidence along with the original statement as the source sentence for the generation. This approach proves effective and makes their system second-best for human evaluations.

• **ANA** has the highest human evaluation score with a multitask learning framework. Specifically, they use a decoder-only transformer based on GPT-2 as the backbone model, and train the model with two heads: one for language model and another for classification. They then use data from both task B and task C to calculate language model loss and classification loss. Furthermore, they use OMCS at the pretraining stage and use CoS-E [Rajani et al., 2019] and OpenBook [Mihaylov et al., 2018] at the task-specific training stage.

• **Solomon, JUSTers, SWAGex, UI, CUHK** use GPT or GPT-2 finetuned on the task training data. **JBNU** uses UniLM, which incorporates three LM tasks: unidirectional LM, bidirectional LM and sequence-to-sequence prediction LM, and only use one of the reference correct reasons. **UI** does not use the training data and treats the generation as a Cloze task. **SSN-NLP** uses the seq2seq NMT framework without a pretrained LM.

Large-scale pretrained language models such as BART and GPT-2 dominates the submissions. The two systems with the highest human evaluations, namely **ANA** and **KaLM**, use additional resources such as Wiktionary, OMCS, and other commonsense datasets. This again shows that additional knowledge from structured databases can help with the generation of the reasons. From Table 8, we can see that BLEU does not correlate well with Human Evaluations, especially for the top-performed systems. According to a further experiment of BUT-FIT, the naive baseline of “copying source sentence as the reason” can get BLEU of 17.23, which can rank No. 4 among all the submissions. This indicates that BLEU, which focuses on the surface token overlap, has difficulty in evaluating the generated text reliably. The top-performed system achieves the human evaluation score of 2.1, showing the power of pretrained language models, but considering the full score 3.0, we still have a long way to go to generate human acceptable reasons.

## 5 Related Work

Commonsense reasoning in natural language has been studied in different forms of tasks and has recently attracted extensive attention. In the Winograd Schema Challenge (WSC) [Levesque et al., 2012; Morgenstern and Ortiz, 2015], a model needs to solve hard co-reference resolution problems based on commonsense knowledge. For example, “The trophy would not fit in the brown suitcase because it was too big. What was too big (trophy or suitcase)?” The Choice of Plausible Alternatives (COPA) [Roemmele et al., 2011] emphasizes on events and consequences. Each question in COPA aims to find the suitable cause or result of the premise from two given alternatives. All premises and alternatives are simple sentences. For example, the premise can be “The man broke his toe. What was the CAUSE of this?” and the two candidate answers are “(1) He got a hole in his sock.” and “(2) He dropped a hammer on his foot.” Several subsequent datasets are inspired by COPA. The JHU Ordinal Common-sense Inference (JOCI) [Zhang et al., 2017] aims to label the plausibility from 5 (very likely) to 1 (impossible) of human response after a particular situation. Situations with Adversarial Generations (SWAG) [Zellers et al., 2018] request a system to choose the most likely-to-happen alternative after a specific situation. Those datasets emphasize the pre-situations and/or the after-situations of certain situations, but not on the reasons why they occur or are caused.

Some datasets are inspired by reading comprehension. The Story Cloze Test and ROCStories Corpora [Mostafazadeh et al., 2016; Sharma et al., 2018] aim to figure out the right ending from two candidate sentences after a four-sentence story. For a narrative text, MCScript [Ostermann et al., 2018a] gives various types of questions and pairs of answer candidates for each question. Most questions require knowledge beyond the facts mentioned in the text. Compared to those reading comprehension tasks, our benchmark encourages people to use any external resources they want.

Some other datasets evolved from QA problems and care more about factual commonsense knowledge. SQUABU [Davis, 2016] provides a small hand-constructed test of commonsense and scientific questions.
CommonsenseQA (Talmor et al., 2018) asks crowd workers to create questions from ConceptNet (Speer et al., 2017), which is a large graph of commonsense knowledge, where each question discriminates its answer candidates between three target concepts that all share the same relationship to a single source drawn from ConceptNet. OpenBookQA (Mihaylov et al., 2018) provides questions and answer candidates, as well as thousands of diverse facts about elementary level science that are related to the questions. The AI2 Reasoning Challenge (ARC) (Clark et al., 2018) gives thousands of questions with different knowledge types, as well as a relevant 14M-sentence corpus, mixed with science facts and other narrative sentences. MuTual provides a dataset for Multi-Turn dialogue reasoning in the commonsense area (Cui et al., 2020). Those questions are not easy to answer without specializing certain knowledge, while our questions are based on common sense.

Some datasets focus on physical knowledge validation (Wang et al., 2018; Porada et al., 2019), or only limited attributes or actions of world knowledge (Forbes and Choi, 2017). In contrast, our dataset concerns general commonsense knowledge beyond just the physical world. For example, the sentence in our task “Tom’s mom become (happy)/(upset) when Tom gets high grades in the exam” is about social and emotional common sense. Besides, our dataset is based on statements which includes events, descriptions, assertion etc, not merely events.

More importantly, compared with our work, the above tasks do not directly estimate general common sense or ask the logical reasons behind the correct answers and questions. In recent years, some large-scale commonsense inference knowledge resources have been developed, which may be helpful in commonsense reasoning tasks. Atomic (Sap et al., 2018) presents a large-scale everyday commonsense knowledge graph, which has nine if-then relations with variables, including causes, effects, and so on. Event2Mind (Rashkin et al., 2018) proposes a new corpus and task, aiming to find out the mentioned/unmentioned people’s intents and reactions under various daily circumstances. These datasets are not directly useful for our benchmark since they focus only on a small domain. ConceptNet is a seminal knowledge graph that has been upgraded over time (Liu and Singh, 2004; Havasi et al., 2007; Speer and Havasi, 2013; Speer et al., 2017). ConceptNet constructs triples using labeled edges as relations and various words and/or phrases as entities. It also has the sentences describing the corresponding triples. In contrast to these resources, we investigate the evaluation of common sense, rather than building a resource.

A pilot study (Wang et al., 2019) has been performed, showing that there is still a significant gap between human and machine performance when no training data is provided, despite that the models have already been pretrained with over 100 million natural language sentences. In our task here, we also provide training data with human annotations.

6 Summary

This paper summarizes SemEval2020-Task4: Commonsense Validation and Explanation. In this task, we constructed a dataset that consists of 11,997 instances and 83,986 sentences. The task attracted over forty participating teams, out of which 31 teams submit their system papers. Participants show that the pretrained models are very effective in Subtask A and Subtask B, but there is still significant room to improve model performance in Subtask C.

We attribute the high performance on Subtask A and B to several main reasons: 1) Subtask A is a relatively easy question by definition: a model needs only to detect less plausible content from two sentences; 2) Pretrained models are trained on billion-words large corpora such as Wikipedia data, which seem to contain adequate commonsense knowledge (Zhou et al., 2019) 3) As described in the annotation process, we use sentences of OMCS to inspire crowd-sourcing workers. The top-3 systems also use OMCS, which possibly leads to overfitting in our task; 4) for Subtask B, as discussed in our data analysis section, the data has some flaws in the average length and common words, which reduces the difficulty. 5) Some instances have obvious patterns. For example, there are tens of instances that contain 'put XXX into YYY', and 'XXX is bigger than YYY', making the problems simper. 6) Hundreds of crowd-sourcing workers write instances and it is likely for workers to think about the same commonsense knowledge, such as ‘XXX is bigger/shorter/quicker/slower than YYY’. We can classify the reasons into three categories: A. Task Design (reason 1); B. Overfitting by External Resources (reason 2/3) B. Overfitting by Data/Quality
We consider future works in four directions: 1) There is still some gap between machine performance and human performance in Subtask C, and the reason generation task still needs further investigation. 2) The dataset can be fixed in length, cut instances with repeated commonsense knowledge, balance in common words, and remove the common patterns. 3) Subtask A can be turned into a difficult form. Instead of comparing which statement makes more sense, we can form it into a classification task, which directly validates whether one statement makes sense or not. 4) We notice that the BLEU score does not align with human evaluation in systems with high performance, so that is need to develop an auto-metric for comparing the semantic correlation between two reasons.

Acknowledgements

This work is supported by the National Science Foundation of China (Grant No. 61976180), the Westlake University, and the Bright Dream Joint Institute for Intelligent Robotics. Yue Zhang is the corresponding author.

References

Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. 2018. Think you have solved question answering? try arc, the AI2 reasoning challenge. CoRR, abs/1803.05457.

Leyang Cui, Yu Wu, Shujie Liu, Yue Zhang, and Ming Zhou. 2020. Mutual: A dataset for multi-turn dialogue reasoning. In Proceedings of the 58th Conference of the Association for Computational Linguistics. Association for Computational Linguistics.

Ernest Davis. 2016. How to write science questions that are easy for people and hard for computers. AI Magazine, 37:13–22, 04.

Ernest Davis. 2017. Logical formalizations of commonsense reasoning: a survey. Journal of Artificial Intelligence Research, 59:651–723.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Maxwell Forbes and Yejin Choi. 2017. Verb physics: Relative physical knowledge of actions and objects. In ACL.

Catherine Havasi, Robert Speer, and Jason Alonso. 2007. Conceptnet 3: a flexible, multilingual semantic network for common sense knowledge. In Recent advances in natural language processing, pages 27–29. Citeseer.

Catherine Havasi, Robert Speer, Kenneth Arnold, Henry Lieberman, Jason Alonso, and Jesse Moeller. 2010. Open mind common sense: Crowd-sourcing for common sense. In Workshops at the Twenty-Fourth AAAI Conference on Artificial Intelligence.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2019. Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942.

Hector J. Levesque, Ernest Davis, and Leora Morgenstern. 2012. The winograd schema challenge. In Proceedings of the Thirteenth International Conference on Principles of Knowledge Representation and Reasoning, KR’12, pages 552–561. AAAI Press.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461.

Hugo Liu and Push Singh. 2004. Conceptneta practical commonsense reasoning tool-kit. BT technology journal, 22(4):211–226.

Weijie Liu, Peng Zhou, Zhe Zhao, Zhiruo Wang, Qi Ju, Haotang Deng, and Ping Wang. 2019a. K-bert: Enabling language representation with knowledge graph. arXiv preprint arXiv:1909.07606.

Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. 2019b. Multi-task deep neural networks for natural language understanding. arXiv preprint arXiv:1901.11504.
Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019c. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv*:1907.11692.

Todor Mihaylov, Peter Clark, Tushar Khot, and Ashish Sabharwal. 2018. Can a suit of armor conduct electricity? a new dataset for open book question answering. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2381–2391. Association for Computational Linguistics.

Leora Morgenstern and Charles L. Ortiz. 2015. The winograd schema challenge: Evaluating progress in commonsense reasoning. In *Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence*, AAAI’15, pages 4024–4025. AAAI Press.

Nasrin Mostafazadeh, Nathanael Chambers, Xiaodong He, Devi Parikh, Dhruv Batra, Lucy Vanderwende, Pushmeet Kohli, and James F. Allen. 2016. A corpus and cloze evaluation for deeper evaluation of commonsense stories. In *HLT-NAACL*.

Timothy Niven and Hung-Yu Kao. 2019. Probing neural network comprehension of natural language arguments. *CoRR*, abs/1907.07355.

Simon Ostermann, Ashutosh Modi, Michael Roth, Stefan Thater, and Manfred Pinkal. 2018a. Mscript: A novel dataset for assessing machine comprehension using script knowledge. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC-2018)*. European Language Resource Association.

Simon Ostermann, Michael Roth, Ashutosh Modi, Stefan Thater, and Manfred Pinkal. 2018b. Semeval-2018 task 11: Machine comprehension using commonsense knowledge. In *Proceedings of The 12th International Workshop on Semantic Evaluation*, pages 747–757. Association for Computational Linguistics.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA, July. Association for Computational Linguistics.

Ian Porada, Kaheer Suleman, and Jackie Chi Kit Cheung. 2019. Can a gorilla ride a camel? learning semantic plausibility from text. *arXiv preprint arXiv*:1911.05689.

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. *Technical report*.

Nazneen Fatema Rajani, Bryan McCann, Caiming Xiong, and Richard Socher. 2019. Explain yourself! leveraging language models for commonsense reasoning. *arXiv preprint arXiv*:1906.02361.

Hannah Rashkin, Maarten Sap, Emily Allaway, Noah A. Smith, and Yejin Choi. 2018. Event2mind: Commonsense inference on events, intents, and reactions. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 463–473. Association for Computational Linguistics.

Melissa Roemmele, Cosmin Adrian Bejan, and Andrew S. Gordon. 2011. Choice of Plausible Alternatives: An Evaluation of Commonsense Causal Reasoning. In *AAAI Spring Symposium on Logical Formalizations of Commonsense Reasoning*, Stanford University, March.

Maarten Sap, Ronan Le Bras, Emily Allaway, Chandra Bhagavatula, Nicholas Lourie, Hannah Rashkin, Brendan Roof, Noah A. Smith, and Yejin Choi. 2018. ATOMIC: an atlas of machine commonsense for if-then reasoning. *CoRR*, abs/1811.00146.

Roy Schwartz, Maarten Sap, Ioannis Konstas, Leila Zilles, Yejin Choi, and Noah A. Smith. 2017. The effect of different writing tasks on linguistic style: A case study of the roc story cloze task. In *Proceedings of the 21st Conference on Computational Natural Language Learning (CoNLL 2017)*, pages 15–25. Association for Computational Linguistics.

Rishi Sharma, James Allen, Omid Bakhshandeh, and Nasrin Mostafazadeh. 2018. Tackling the story ending biases in the story cloze test. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 752–757. Association for Computational Linguistics.

Push Singh, Thomas Lin, Erik T Mueller, Grace Lim, Travell Perkins, and Wan Li Zhu. 2002. Open mind common sense: Knowledge acquisition from the general public. In *OTM Confederated International Conferences” On the Move to Meaningful Internet Systems”*, pages 1223–1237. Springer.
Robert Speer and Catherine Havasi. 2013. Conceptnet 5: A large semantic network for relational knowledge. In *The Peoples Web Meets NLP*, pages 161–176. Springer.

Robyn Speer, Joshua Chin, and Catherine Havasi. 2017. Conceptnet 5.5: An open multilingual graph of general knowledge. In *Thirty-First AAAI Conference on Artificial Intelligence*.

Alon Talmor, Jonathan Herzig, Nicholas Lourie, and Jonathan Berant. 2018. Commonsenseqa: A question answering challenge targeting commonsense knowledge. *CoRR*, abs/1811.00937.

Su Wang, Greg Durrett, and Katrin Erk. 2018. Modeling semantic plausibility by injecting world knowledge. *arXiv preprint arXiv:1804.00619*.

Cunxiang Wang, Shuailong Liang, Yue Zhang, Xiaonan Li, and Tian Gao. 2019. Does it make sense? and why? a pilot study for sense making and explanation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4020–4026, Florence, Italy, July. Association for Computational Linguistics.

Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Russ R Salakhutdinov, and Quoc V Le. 2019. Xlnet: Generalized autoregressive pretraining for language understanding. In *Advances in neural information processing systems*, pages 5754–5764.

Rowan Zellers, Yonatan Bisk, Roy Schwartz, and Yejin Choi. 2018. Swag: A large-scale adversarial dataset for grounded commonsense inference. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP)*.

Sheng Zhang, Rachel Rudinger, Kevin Duh, and Benjamin Van Durme. 2017. Ordinal common-sense inference. *Transactions of the Association for Computational Linguistics*, 5:379–395.

Xuhui Zhou, Yue Zhang, Leyang Cui, and Dandan Huang. 2019. Evaluating commonsense in pre-trained language models. *arXiv preprint arXiv:1911.11931*.