Improving Commonsense Contingent Reasoning by Pseudo-data and its Application to the Related Tasks

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Abstract

Contingent reasoning is one of the essential abilities in natural language understanding, and many language resources annotated with contingent relations have been constructed. However, despite the recent advances in deep learning, the task of contingent reasoning is still difficult for computers. In this study, we focus on the reasoning of contingent relation between basic events. Based on the existing data construction method, we automatically generate large-scale pseudo-problems and incorporate the generated data into training. We also investigate the generality of contingent knowledge through quantitative evaluation by performing transfer learning on the related tasks: discourse relation analysis, the Japanese Winograd Schema Challenge, and the JCommonsenseQA. The experimental results show the effectiveness of utilizing pseudo-problems for both the commonsense contingent reasoning task and the related tasks, which suggests the importance of contingent reasoning.

1 Introduction

Contingency is the relation between two events, one being an action or state and the other being likely to happen after it. We humans reason contingent relation between events on a daily basis. For instance, when we read text, we unconsciously infer what happens next to deepen our understanding. In conversations, we guess the next topic from the utterance of the opponent to make a contextual and natural response. Thus, the ability to reason contingent relation between events is essential when it comes to natural language understanding (NLU).

Recently, many studies have built language resources for contingent reasoning (Roemmele et al., 2011; Mostafazadeh et al., 2016; Zellers et al., 2018; Sap et al., 2019a; Hwang et al., 2021). These resources focus on basic events and evaluate some kind of commonsense reasoning ability. Although the fundamental linguistic capabilities of computers, such as question answering, have greatly improved with progress in deep learning, several studies have empirically demonstrated they still have difficulty in commonsense reasoning (Talmor et al., 2019; Sap et al., 2019b; Talmor et al., 2021).

In this study, we aim at two objectives: to improve commonsense contingent reasoning and to investigate the effects of learning contingent knowledge on the related tasks to validate the importance of contingent reasoning. To these ends, we use the Kyoto University Commonsense Inference dataset (KUCI)\footnote{https://nlp.ist.i.kyoto-u.ac.jp/EN/?KUCI}. KUCI is a Japanese QA dataset with 104k multiple-choice questions regarding contingent relation between basic events. The correct choice is bolded.

I’m hungry, so
a. I’m gonna be absent from school.
b. I refrain from strenuous exercise.
c. I have a meal at a family restaurant.
d. I leave home.

Figure 1: Example from KUCI (English translated version). KUCI is a Japanese QA dataset containing 104k multiple-choice questions regarding contingent relation between basic events. The correct choice is bolded.
ing data and increase the coverage. However, it is not practical from a cost perspective to increase the number of training examples manyfold using crowdsourcing.

We attempt to improve the performance by omitting crowdsourcing, a bottleneck in data augmentation, and utilizing pseudo-problems generated automatically from unverified contingent pairs of basic event expressions. As a web corpus is scalable, and all of the procedures except crowdsourcing are automatic, we can generate pseudo-problems at scale. It is expected pseudo-problems complement the lack of coverage though some problems are noisy and might be unanswerable.

The second objective of this study is to investigate the effects of learning contingent knowledge on the related tasks. On the premise that contingent reasoning is essential to NLU, we can expect contingent knowledge probably helps improve the performance on other NLU tasks. While the transferability of major English datasets has been studied (Phang et al., 2018; Sap et al., 2019b; Sakaguchi et al., 2020; Pruksachatkun et al., 2020), there is room to explore this dataset in terms of the task and language. We investigate the generality of contingent knowledge through quantitative evaluation of transfer learning on the related tasks.

In summary, we improve commonsense contingent reasoning by straightforward data augmentation. We generated 862k pseudo-problems, which is about ten times as large as the training examples in KUCI (83k), and incorporated them into training. Owing to pseudo-problems, a high-performance pre-trained model has achieved near human-level performance on the commonsense contingent reasoning task. We also investigate the transferability of contingent knowledge to the related tasks. Our experiments demonstrate intermediate-task training on KUCI with pseudo-problems positively affects discourse relation analysis, the Japanese Winograd Schema Challenge, and the JCommonsenseQA, which suggests the importance of contingent reasoning

2 Approach

First, we describe our data augmentation approach to improving commonsense contingent reasoning. Our approach is to automatically generate large-scale pseudo-problems based on the construction

2The links to the pseudo-data and code are available at https://nlp.ist.i.kyoto-u.ac.jp/EN/?KUCI

method of the Kyoto University Commonsense Inference dataset (KUCI).

2.1 A Method of Generating Problems

The construction method of KUCI consists of the following four steps (Figure 2).

1. Acquire high-frequency predicate-argument structures (hereafter, core events\(^3\)) from case frames (Kawahara et al., 2014b).

2. Extract event pairs that are unambiguously connected by explicit discourse markers representing contingent relation and composed of a pair of core events (hereafter, contingent basic event pairs).

3. Verify by crowdsourcing whether the extracted event pairs actually have contingent relation or not.

4. Generate problems by taking one of the verified event pairs (hereafter, base\(^3\)) and selecting distractors from the latter events of other event pairs that are moderately similar to the base.

In the above procedures, it becomes possible to automatically generate pseudo-problems by omitting step 3 (Figure 2). For the parameters in the

\(^3\)We newly define these terms for clarification.
method, such as the thresholds of frequency for acquiring core events and the conditions on selecting distractors, we set them to the same values as in the construction of KUCI.

2.2 Automatic Extraction of Contingent Basic Event Pairs
We automatically extracted contingent basic event pairs following the method described in Section 2.1. We used a Japanese web corpus containing 3.3 billion sentences as the source text. It had been constructed by crawling web text from 2006 to 2015. There is no overlap of sentences between this corpus and the web corpus used in the construction of KUCI. As a result, we extracted 915k contingent basic event pairs. Omura et al. (2020) reported one-third of the extracted event pairs were removed by crowdsourcing, thus we expect about 600k event pairs to be valid.

2.3 Dealing with Data Leakage
There is a potential issue with generating training data from large-scale text, which is called "Data Contamination" (Brown et al., 2020). This issue is that text may include information about evaluation data, leading to overestimation of model performance.

We deal with this issue by heuristically excluding event pairs that are identical or remarkably similar to the bases in evaluation data. Specifically, we apply the following filters based on word order and core event pairs.

Filter by word order Exclude an event pair if the length of the overlapping word order between the event pair and any base in evaluation data exceeds 75% of the word count of the base.

Filter by core event pairs Exclude an event pair if the event pair is composed of the core event pair that also composes any base in evaluation data.

For instance, the base of the problem in Figure 1 is “I’m hungry, so → I have a meal at a family restaurant” and composed of the core event pair “be hungry → have a meal at a family restaurant”. Let us consider whether the event pair “I’m hungry, so → I have a big meal at the family restaurant” is excluded by the base or not. They have the overlapping word order, {I’m, hungry, so, I, have, a, meal, at, family, restaurant}, of which length (10) exceeds 75% of the word count of the base (11). It is also composed of the same core event pair. Thus, it will be excluded by both filters.

We expect the first filter to exclude syntactically-similar event pairs and the second to exclude those similar in content. As a result of filtering, we acquired 881k contingent basic event pairs.

2.4 Automatic Generation of Pseudo-problems
We went on performing an automatic generation of problems. As a result, we obtained 862k pseudo-problems from the 881k event pairs. The number of the pseudo-problems is about ten times as large as that of the training examples in KUCI (83k).

To analyze the quality of pseudo-problems, we randomly sampled 50 problems and manually evaluated them. As a result of manual evaluation, 36 of 50 problems were judged as answerable, which appears to be sufficient quality for pseudo-data.

3 Experiments
We conducted experiments to investigate the effects of incorporating pseudo-problems into training on the commonsense contingent reasoning task and the related tasks.

3.1 Model
We evaluated the performance of the BERT (Devlin et al., 2019) and XLM-RoBERTa (XLM-R) (Conneau et al., 2020) models.

BERT We employed the NICT BERT Japanese Pre-trained model (with BPE). It was pre-trained on the full text of Japanese Wikipedia for 1.1 million steps with a batch size of 4,096, partly referring to the pre-training configuration of RoBERTa (Liu et al., 2019). The model architecture is the same as the BERT_BASE.

XLM-R We adopted the XLM-RoBERTaLARGE model, which was pre-trained on a huge multilingual corpus consisting of Wikipedia and CC-100 (Wenzek et al., 2020). The model architecture is the same as the BERTLARGE, but the embedding layer is relatively large due to its multilingual vocabulary. It is one of the high-performance pre-trained models for Japanese among those publicly available.

To be specific, “evaluation data” refers to the development and test splits of KUCI.

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5https://alaginrc.nict.go.jp/nict-bert/index.html (in Japanese)
6https://huggingface.co/xlm-roberta-large
3.2 Experimental Settings

The hyper-parameters used in the experiments are included in Appendix A.

3.2.1 Commonsense Contingent Reasoning

As is mentioned in Section 1, we used KUCI for assessing commonsense contingent reasoning ability. The task is to select the most appropriate sentence following the context from 4 choices like Figure 1. The dataset contains 83,127 / 10,228 / 10,291 examples for training, development, and test split, respectively.

During the fine-tuning phase, we minimize cross-entropy loss between the scores of each choice normalized by the softmax function and a one-hot vector representing the correct answer as 1. The scores of each choice are computed by inputting pairs of a context and the choice separated by special tokens and converting the hidden representations of the first token ([CLS]) into scalars by a linear transformation. When incorporating pseudo-problems into training, we define the objective function $L$ as the weighted sum of cross-entropy losses of commonsense inference problems and pseudo-problems. The above can be expressed by the following equations.

$$H = -\frac{1}{N} \sum_{k=1}^{N} \log \frac{\exp(s_{kj})}{\sum_{i=1}^{4} \exp(s_{ki})}$$

$$L = H_{ci} + \lambda \times H_{pseudo}$$

where $N$ is a batch size, $j$ is the index of a correct choice among 1 to 4, $s_{kj}$ is the score of the $j$-th choice of $k$-th example, $H$ is the cross-entropy loss of commonsense inference problems or pseudo-problems, and $\lambda$ is the weight for pseudo-problems.

During the inference phase, the choice with the highest score is selected as an answer. We evaluated the models by accuracy.

Comparative Method To investigate the effectiveness of a multiple-choice format, we also performed additional pre-training referring to Task-Adaptive Pre-Training (Gururangan et al., 2020). Specifically, we ran an additional Masked Language Modeling (MLM) task on the 881k event pairs used for generating pseudo-problems. For convenience, we name it “AMLML”. After the additional pre-training, we fine-tuned the models on KUCI and the related tasks.

3.2.2 Intermediate-Task Transfer Learning

We performed transfer learning from the models fine-tuned on KUCI with pseudo-problems to investigate the effects of learning contingent knowledge. In this study, we employed discourse relation analysis, the Japanese Winograd Schema Challenge (JWSC) (Shibata et al., 2015), and the Japanese CommonsenseQA (JCQA) (Kurihara et al., 2022) as the related tasks.

Discourse Relation Analysis We used the Kyoto University Web Document Leads Corpus (KWDLC) (Kawahara et al., 2014a; Kishimoto et al., 2018) for this task. KWDLC has been built by collecting the first three sentences of various kinds of web documents, and its size amounts to 6,445 documents. All the documents have been annotated with discourse relations between clauses using crowdsourcing. Moreover, 500 of 6,445 documents have also been annotated by linguistic experts. In this study, we used about 37k clause pairs with crowdsourced labels as training data and evaluated the classification performance on 2,320 clause pairs with expert labels.

The task is a seven-way classification of discourse relations between clauses, including “No Relation”. We fine-tuned the models following the sentence pair classification framework proposed by Devlin et al. (2019) and ran five-fold cross validation. We used micro-averaged precision, recall, and F1 score computed without examples with the “No Relation” label as evaluation metrics.

JWSC The Winograd Schema Challenge (WSC) is the task to select the antecedent of a pronoun from two candidates (Levesque, 2011). The task itself is coreference resolution but designed to require commonsense reasoning. JWSC$^8$ is constructed by translating the Rahman and Ng (2012) version of WSC into Japanese.

As we excluded the event pairs containing demonstrative pronouns so as not to generate problems that require more context, there is concern that intermediate-task training on KUCI with pseudo-problems might hurt performance on JWSC due to forgetting the knowledge about demonstratives. Accordingly, we recast JWSC as binary question answering by replacing a pronoun with each antecedent candidate. The resulting dataset is bal-

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7https://github.com/ku-nlp/KWDLC
8https://github.com/ku-nlp/Winograd-Schema-Challenge-Ja
| Model       | Setting                                      | Acc.    |
|------------|----------------------------------------------|---------|
| BERT       | KUCI                                         | 79.3 ± 0.2 |
|            | KUCI + Pseudo-problems (λ = 0.1)             | 84.1 ± 0.1 |
|            | KUCI + Pseudo-problems (λ = 0.5)             | **84.7 ± 0.1** |
|            | KUCI + Pseudo-problems (λ = 1.0)             | 84.6 ± 0.2 |
|            | AMLM → KUCI                                  | 83.9 ± 0.1 |
| XLM-R      | KUCI                                         | 86.0 ± 0.1 |
|            | KUCI + Pseudo-problems (λ = 0.1)             | 88.5 ± 0.1 |
|            | KUCI + Pseudo-problems (λ = 0.5)             | **88.8 ± 0.1** |
|            | KUCI + Pseudo-problems (λ = 1.0)             | 88.6 ± 0.1 |
|            | AMLM → KUCI                                  | 86.2 ± 0.2 |
| Human      | (Omura et al., 2020)                         | 88.9     |

Table 1: Accuracy on the test split of KUCI. The scores are the mean and standard deviation over three runs with different random seeds. Arrows denote multi-stage fine-tuning. For instance, “AMLM → KUCI” means fine-tuning on KUCI after additional pre-training.

Advanced and consists of 2,644 / 1,128 examples for training and test split, respectively. Since the development split is not provided, we carried out five-fold cross validation by splitting the training set into 8:2. We trained bert-based logistic regression models and evaluated them by accuracy and Area Under the ROC Curve (AUC).

**JCQA**  
JCQA⁹ is the Japanese version of CommonsenseQA (Talmor et al., 2019) and consists of 11k five-choice questions regarding a wide range of relations between basic concepts. The questions are based on subgraphs extracted from ConceptNet (Speer et al., 2017) and manually created using crowdsourcing.

Since the task is multiple-choice question answering, we fine-tuned models following the same method described in 3.2.1. We also evaluated the models by accuracy.

### 3.3 Experimental Results

**Commonsense Contingent Reasoning**  
Table 1 shows the experimental results of the commonsense contingent reasoning task. Owing to pseudo-problems, both the BERT and XLM-R models improved the accuracy by 5.4 and 2.8 points, respectively. Notably, the XLM-R model has achieved performance comparable to humans. Putting moderately low weight on pseudo-problems makes the performance slightly better.

Figure 3 shows the learning curves of the models on the development split of KUCI. The crosses representing the accuracy on the "KUCI + Pseudo-problems” setting are under the extrapolated learning curves, which implies the difference in quality between the training examples in KUCI and pseudo-problems.

**Discourse Relation Analysis**  
As for the related tasks, we can see from Table 2 that intermediate-task training on KUCI with pseudo-problems is effective in discourse relation analysis, particularly in BERT. Since the problems are based on con-

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⁹https://github.com/yahoojapan/JGLUE
| Model          | Setting                      | Prec.   | Rec.    | F1     |
|----------------|------------------------------|---------|---------|--------|
| BERT           | KWDLC                        | 55.2 ± 2.9 | 38.4 ± 1.0 | 45.1 ± 1.1 |
|                | KUCI → KWDLC                 | 58.1 ± 2.4 | 38.3 ± 1.3 | 45.7 ± 0.8 |
|                | KUCI + Pseudo-problems (λ = 0.5) → KWDLC | 55.9 ± 1.1 | 41.0 ± 2.9 | 47.0 ± 2.4 |
|                | AMLM → KUCI → KWDLC          | 51.8 ± 3.7 | 38.4 ± 1.3 | 43.7 ± 0.7 |
| XLM-R          | KWDLC                        | 57.4 ± 1.7 | 45.5 ± 2.8 | 50.3 ± 1.3 |
|                | KUCI → KWDLC                 | 57.8 ± 2.3 | 48.2 ± 0.3 | 51.9 ± 0.2 |
|                | KUCI + Pseudo-problems (λ = 0.5) → KWDLC | 57.2 ± 1.0 | 47.4 ± 1.8 | 51.5 ± 0.7 |
|                | AMLM → KUCI → KWDLC          | 55.2 ± 1.6 | 34.5 ± 0.6 | 40.9 ± 1.0 |
| Human (Crowdworker) (Kishimoto et al., 2020) |                          | 54.7     | 48.6    | 51.5   |

Table 2: Performance of discourse relation analysis on KWDLC. The scores are the mean and standard deviation over three runs of five-fold cross-validation with different random seeds. As with Table 1, arrows denote multi-stage fine-tuning. Note that we performed additional Masked Language Modeling (AMLM) on the 881k event pairs used for generating pseudo-problems, not the training examples in KWDLC, to compare the methods of utilizing pseudo-data.

| Model          | Setting                      | Ca./Re. | Cond. | Purp. | Justif. | Cont. | Conc. | F1     |
|----------------|------------------------------|---------|-------|-------|---------|-------|-------|--------|
| BERT (ensemble)| KWDLC                        | 76 / 138 | 32 / 43 | 18 / 37 | 0 / 6   | 2 / 19 | 54 / 84 | 46.7   |
|                | KUCI → KWDLC                 | 81 / 132 | 32 / 43 | 18 / 31 | 1 / 6   | 2 / 17 | 47 / 72 | 48.0   |
|                | KUCI + Pseudo-problems → KWDLC | 81 / 139 | 33 / 49 | 17 / 29 | 0 / 4   | 1 / 12 | 56 / 85 | 48.8   |
| XLM-R (ensemble)| KWDLC                        | 98 / 159 | 33 / 46 | 16 / 34 | 2 / 4   | 0 / 18 | 60 / 88 | 52.1   |
|                | KUCI → KWDLC                 | 109 / 201 | 34 / 53 | 18 / 32 | 3 / 7   | 0 / 26 | 56 / 85 | 51.3   |
|                | KUCI + Pseudo-problems → KWDLC | 99 / 168 | 33 / 50 | 18 / 28 | 1 / 2   | 0 / 22 | 64 / 98 | 52.4   |
| Human (Crowdworker) (Kishimoto et al., 2020) |                          | 100 / 175 | 37 / 54 | 19 / 44 | 6 / 32  | 4 / 30 | 54 / 67 | 51.5   |
| Total number of true positives and false negatives |                                 | 242     | 54     | 36     | 15     | 6     | 100 —  |

Table 3: Detailed results of discourse relation analysis by the ensemble models. The third to eighth columns stand for the discourse relations, “Cause or Reason”, “Condition”, “Purpose”, “Justification”, “Contrast”, and “Concession”, respectively. The values on the left side are the numbers of true positives for the discourse relation, and those on the right side are total numbers of true positives and false positives.

tingent basic event pairs, which are connected by explicit discourse markers representing causal or conditional relation\(^{10}\), we presume the knowledge about these discourse relations is successfully transferred.

We also describe the detailed results of discourse relation analysis in Table 3. The models transferred from KUCI with pseudo-problems perform better on classifying causal and purpose relations. Compared with crowdworkers, there is room for improvement in precision of concession and infrequent relations.

**JWSC** The experimental results of JWSC are shown in Table 4. We observed a few degenerate runs\(^{11}\) (Phang et al., 2018; Pruksachatkun et al., 2020) on the “JWSC” setting despite fine-tuning for 50 epochs. This phenomenon often occurs when training large models on a small dataset, and several studies have reported intermediate-task training can alleviate it (Phang et al., 2018; Pruksachatkun et al., 2020). We also confirmed the same result in this experiment.

We found KUCI is beneficial to JWSC, but pseudo-problems are not necessarily. JWSC contains a non-negligible number of questions regarding concession relation (e.g. “James asked Robert a favor. However, James/Robert declined.”), thus we consider putting much emphasis on contingent relation would rather worsen performance. Learning various discourse relations is a promising solution.

\(^{10}\)These discourse relations are corresponding to “CONTINGENCY:Cause” and “CONTINGENCY:Condition” in the Penn Discourse Treebank (Prasad et al., 2008) and automatically analyzed by the Japanese parser, KNP (Kurohashi and Nagao, 1994).

\(^{11}\)The training runs that models result in around chance performance. Specifically, we regard less than 0.55 accuracy or AUC as the degenerate runs.
Table 4: Accuracy and AUC on the test split of JWSC. The scores are the mean and standard deviation over three runs of five-fold cross-validation with different random seeds. † denotes the results include a few degenerate runs. We also report the results excluding the degenerate runs in parentheses for reference. As for the “AMLM → KUCI → JWSC” setting of XLM-R, the models failed to learn.

| Model Setting               | Acc.       | AUC        |
|-----------------------------|------------|------------|
| BERT JWSC                   | 66.0 ± 3.4†| 71.4 ± 4.5†|
| KUCI → JWSC                 | 69.9 ± 0.3 | 77.0 ± 0.6 |
| KUCI + Pseudo-problems (λ = 0.5) → JWSC | 68.8 ± 1.1 | 75.0 ± 2.0 |
| AMLM → KUCI → JWSC          | 58.1 ± 1.0 | 61.9 ± 1.1 |
| XLM-R JWSC                  | 78.7 ± 3.2†| 85.6 ± 4.0†|
| KUCI → JWSC                 | 81.2 ± 0.1 | 88.7 ± 0.2 |
| KUCI + Pseudo-problems (λ = 0.5) → JWSC | 80.0 ± 0.2 | 88.7 ± 0.0 |
| AMLM → KUCI → JWSC          | 50.8 ± 0.5 | 51.7 ± 0.8 |

which we leave for future work.

JCQA  Referring to Table 5, we can see performance gain regarding XLM-R. We speculate it is thanks to the domain match between pseudo-problems and JCQA, considering the report by Kurihara et al. (2022) that pre-training on CC-100 is more effective in JCQA than Wikipedia. Pseudo-problems alone are somewhat insufficient for adapting to the web domain, but they complement some knowledge.

Comparison to AMLM  Although AMLM is somewhat effective in KUCI, it is poor at transferring the knowledge\(^\text{12}\). It can be inferred the models learn task-specific knowledge.

3.4 Qualitative Analysis

Figure 4 shows the example problems that BERT got to answer correctly by incorporating pseudo-problems into training. We can see the improvement in accuracy of the problems regarding quite basic contingent relation like Figure 4. The model sometimes gave low scores to all the choices and appeared to choose by elimination, but we observed it became less frequent. We speculate pseudo-problems complement the lack of coverage of the training examples in KUCI. For further information, we include the confusion matrix in Table 6. The improvement is greater though the model got to make a wrong prediction to some problems.

4 Related Work

Owing to large-scale pre-training, the pre-trained models have achieved unprecedented performance on a variety of NLU tasks, including commonsense reasoning (Wang et al., 2019). Besides such improvement in general language understanding, there have been many approaches to improving the performance on commonsense reasoning tasks.

One group of approaches is to utilize automatically created data, to which our approach belongs. For instance, Ye et al. (2019) performed additional pre-training on 16 million fill-in-the-blank multiple-choice questions generated from Wikipedia and ConceptNet (Speer et al., 2017). They improved the performance on two benchmarks for entity-level commonsense reasoning, CommonsenseQA (Talmor et al., 2019) and Winograd Schema Challenge (WSC) (Levesque, 2011), though their method requires the manually constructed resource (ConceptNet). Staliunaite et al. (2021) proposed a data augmentation method for the Choice of Plausible Alternatives (COPA) and its extension (Roemmele et al., 2011; Kavumba et al., 2019), which consists of roughly three steps: filtering web text by several conditions, extracting causal pairs of clauses with the clue of discourse connectives, and generating distractors using language models. They have not investigated the application to the related tasks, focusing on improving commonsense causal reasoning. Shen et al. (2021) improved unsupervised pronoun resolution and commonsense reasoning by pre-training on

\(^{12}\)We also tried the “AMLM → related task” setting, but the performance is generally worse than those on the “AMLM → KUCI → related task” setting.
| Model     | Setting                                                                 | Acc.       |
|-----------|------------------------------------------------------------------------|------------|
| JCQA      |                                                                        | 81.8 ± 0.1 |
|           | (82.3)                                                                |            |
| BERT      | KUCI → JCQA                                                           | 82.0 ± 0.3 |
|           | KUCI + Pseudo-problems (λ = 0.5) → JCQA                               | 81.9 ± 0.2 |
|           | AMLM → KUCI → JCQA                                                   | 68.1 ± 0.4 |
|           |                                                                        |            |
| XLM-R     | KUCI → JCQA                                                           | 85.0 ± 0.4 |
|           | KUCI + Pseudo-problems (λ = 0.5) → JCQA                               | 85.3 ± 0.6 |
|           | AMLM → KUCI → JCQA                                                   | 75.2 ± 0.5 |
|           |                                                                        |            |
| Human     | (Kurihara et al., 2022)                                               | 98.6       |

Table 5: Accuracy on the development split of JCQA. The scores are the mean and standard deviation over three runs with different random seeds. We also include the reported values in the original paper (the numbers in the parentheses) for reference.

| Sentence 1 | Sentence 2 | Sentence 3 |
|------------|------------|------------|
| 霧が晴れると、 | 嫌な夢を見ると、 | 午後から病院へいくので |
| (When a fog clears,) | (If I have a bad dream,) | (I’m going to see a doctor this afternoon, so) |
| a. 景色が素晴らしい | a. とりあえず寝る | a. 満に病院に行かない |
| (the scenery is amazing) | (I’ll go to bed for now) | (I rarely see a doctor) |
| b. 川の音がすごい | b. もう寝ます | b. 土日は勉強に動きます |
| (the sound of river is loud) | (I’m going to go to bed now) | (I’ll study hard on weekends) |
| c. 雪遊びも楽しそうだ | c. さっさと寝ることにする | c. 今日は休暇をとる |
| (playing in the snow sounds nice) | (I’ll go to bed quickly) | (I take a vacation today) |
| d. 写真写りがいまいちだ | d. 目を覚ます | d. 火曜日は眠い |
| (it’s not photogenic) | (I’ll wake up) | (I’m sleepy on Tuesday) |

Figure 4: Example problems that the BERT model got to answer correctly by incorporating pseudo-problems into training. The correct choice is bolded, and the choice that BERT previously selected is highlighted in red.

| KUCI                  | correct | incorrect |
|-----------------------|---------|-----------|
| KUCI + Pseudo-problems |         |           |
| (λ = 0.5)             |         |           |
| correct               | 7,891   | 1,028     |
| incorrect             | 401     | 908       |

Table 6: Confusion matrix organizing the numbers of correct and incorrect answers on the development split of KUCI. The matrix shows the results of the BERT model (ensemble).

For the second objective of this study, there are several studies about the transferability of commonsense knowledge from existing language resources. For instance, it has been reported intermediate-task training on two benchmarks for commonsense reasoning, Social IQA (Sap et al., 2019b) and WinoGrande (Sakaguchi et al., 2020), helps improve the performance on WSC and COPA. Pruksachatkun et al. (2020) showed the datasets that require complex commonsense reasoning, such as CosmosQA (Huang et al., 2019) and HellaSwag (Zellers et al., 2019), are beneficial to several target tasks. Lourie et al. (2021) ran multi-task learning on multiple resources for commonsense reasoning to examine their interactions. Since they have used the datasets that require complex reasoning, they have not focused on a specific type of commonsense reasoning. We focus on commonsense contingent reasoning and investigate the transferability in the language other than English.

5 Conclusion

In this study, we improved commonsense contingent reasoning by incorporating large-scale pseudo-problems into training. We automatically generated 862k pseudo-problems from a Japanese web corpus of 3.3 billion sentences using the existing data.
construction method with modification. Owing to pseudo-problems, a high-performance pre-trained model has achieved near human-level performance on the commonsense contingent reasoning task.

We also investigated the effects of learning contingent knowledge on the related tasks: discourse relation analysis, the Japanese Winograd Schema Challenge, and the JCommonsenseQA. Our experiments demonstrated intermediate-task training on KUCI with pseudo-problems has a positive impact on the related tasks, which indicates the importance of contingent reasoning.

We will further analyze what kind of problems current models still answer incorrectly. From the qualitative analysis, we consider building a language resource for evaluating deeper language understanding. As another research direction, it is also tempting to pursue the improvement in NLU by learning various discourse relations between entities or events in documents.

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A Hyper-parameters

Table 7, 8, 9, 10, and 11 show the hyper-parameters used in the experiments. We found lower learning rate makes the training of the XLM-R model more stable, thus we set the learning rate of the XLM-R model lower than that of BERT.

| Name                        | BERT     | XLM-R    |
|-----------------------------|----------|----------|
| Epoch                       | 3        |          |
| Batch size                  | 32       |          |
| Max sequence length         | 128      |          |
| Optimizer                   | AdamW    |          |
| Learning rate               | 2e-5     | 5e-6     |
| Weight decay                | 0.01     | 0.1      |
| Adam’s betas params         | (0.9, 0.999) | (0.9, 0.98) |
| Scheduler                   | Linear decay with linear warmup | Linear decay with linear warmup |
| Warmup proportion           | 0.1      |          |
| Seed                        | [0, 1, 2] |          |

Table 7: Hyper-parameters for fine-tuning on KUCI and pseudo-problems.

| Name                        | Value     |
|-----------------------------|-----------|
| Epoch                       | 100       |
| Batch size                  | 256       |
| Max sequence length         | 128       |
| Optimizer                   | AdamW     |
| Learning rate               | 1e-4      |
| Weight decay                | 0.01      |
| Adam’s betas params         | (0.9, 0.999) | (0.9, 0.98) |
| Scheduler                   | Linear decay with linear warmup |
| Warmup proportion           | 0.06      |
| gradient clipping value     | -0.25     |
| Seed                        | 0         |

Table 8: Hyper-parameters for AMLM. Almost all of the hyper-parameters are referred to Gururangan et al. (2020).

| Name                        | BERT     | XLM-R    |
|-----------------------------|----------|----------|
| Epoch                       | 10       |          |
| Patience for early stopping | 3        |          |
| Batch size                  | 32       |          |
| Max sequence length         | 128      |          |
| Optimizer                   | AdamW    |          |
| Learning rate               | 2e-5     | 5e-6     |
| Weight decay                | 0.01     | 0.1      |
| Adam’s betas params         | (0.9, 0.999) | (0.9, 0.98) |
| Scheduler                   | Linear decay with linear warmup |
| Warmup proportion           | 0.1      |          |
| Seed                        | [0, 1, 2] |          |

Table 9: Hyper-parameters for fine-tuning on KWDLC.
| Name               | Value  |
|--------------------|--------|
| Epoch              | 50     |
| Batch size         | 32     |
| Max sequence length| 128    |
| Optimizer          | AdamW  |
| Learning rate      | 2e-5   |
| Weight decay       | 0.01   |
| Adam’s betas params| (0.9, 0.999) |
| Scheduler          | Linear decay with linear warmup |
| Seed               | {0, 1, 2} |

Table 10: Hyper-parameters for fine-tuning on JWSC. We set the number of epochs to a large value referring to Mosbach et al. (2021).

| Name               | Value  |
|--------------------|--------|
| Epoch              | 4      |
| Batch size         | 32     |
| Max sequence length| 128    |
| Optimizer          | AdamW  |
| Learning rate      | 2e-5   |
| Weight decay       | 0.01   |
| Adam’s betas params| (0.9, 0.999) |
| Scheduler          | Linear decay with linear warmup |
| Seed               | {0, 1, 2} |

Table 11: Hyper-parameters for fine-tuning on JCQA.