Annotating Event Appearance for Japanese Chess Commentary Corpus

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Abstract
In recent years, there has been a surge of interest in natural language processing related to the real world, such as symbol grounding, language generation, and non-linguistic data search by natural language queries. Researchers usually collect pairs of text and non-text data for research. However, the text and non-text data are not always a “true” pair. We focused on the shogi (Japanese chess) commentaries, which are accompanied by game states as a well-defined “real world”. For analyzing and processing texts accurately, considering only the given states is insufficient, and we must consider the relationship between texts and the real world. In this paper, we propose “Event Appearance” labels that show the relationship between events mentioned in texts and those happening in the real world. Our event appearance label set consists of temporal relation, appearance probability, and evidence of the event. Statistics of the annotated corpus and the experimental result show that there exists temporal relation which skillful annotators realize in common. However, it is hard to predict the relationship only by considering the given states.

Keywords: game commentary, modality, symbol grounding

1. Introduction
These days, the interest in the symbol grounding problems becomes larger and larger. A large number of datasets are now available in such as image and text (Young et al., 2014; Chen et al., 2015). These corpora are widely used for description generation (Vinyals et al., 2015; Xu et al., 2015), non-text information retrieval (Ushiku et al., 2017), and so on. Some of these corpora consist of pairs of non-text data and human-writing texts. We usually treat the pairs that the text and non-text data are compatible. However, the assumption is not always true if the corpora are automatically collected. For example, non-text data sometimes reminds humans of some associated things, and they mention them instead of the exactly given data. To reproduce intelligent systems which work like a human, we must analyze the gap between the text and non-text data.

We focused on commentary for extensive-form games like chess. The rules of these games are well-defined, and we can treat them with computer programs easier than the real world. With this well-defined world, computers, can access to the previous states and search the future states for predicting easily. Human players also consider the previous states and future predictions, and they often refer to these states when they comment on the game. For accurate analyzing and processing, we must analyze the relationship between texts and the real world for the first step.

In this paper, we propose “Event Appearance” label. Event appearance shows the relationship between events that are mentioned in texts and events that happen in the real world. Event appearance consists of temporal relation, appearance probability, and evidence of event. For annotation, we called annotators with high skill of shogi. In addition, we evaluated the annotated corpus with statistics and experiments.

2. Game and Commentary
2.1. Shogi: Japanese Chess
Shogi, which is known as Japanese chess, is a two-player board game similar to chess. As shown in Figure 1, each piece is presented by Japanese kanji characters. Same as chess, the goal of the shogi is to capture the opponent’s king. Each player chooses one action, called move, from legal actions alternately. The most significant difference is that the players can use the captured pieces by dropping them to the vacant cells. For more detail, please refer to (Leggett, 2009).

The rule of shogi is well-defined and more comfortable to tackle for computers than real-world tasks. Constructing strong computer players is one of the milestones of artificial intelligence, and there exist some computer AI players that defeat top human players (Silver et al., 2016). Some of them are available as applications and users can access them easily. They use these applications not only as an opponent player but also as an evaluation tool.
2.2. **Shogi and Commentary**

Some of the professional *shogi* games are broadcast with human expert commentaries. For example, in Meijin-sen and Jun’i-sen, one of the largest professional *shogi* tournament and title match, all games are broadcast via the website for a fee. These commentaries mainly explain the current game by reasoning the actions, evaluating the states, and predicting the next actions. These commentaries help spectators understand the games. On the other hand, commentators sometimes mention other games such as the players’ previous games. These commentaries are not related to the current games.

2.3. **Shogi Game Corpus**

We constructed Shogi Game Corpus (SGC) (Mori et al., 2016) by collecting the commented *shogi* records of Meijin-sen and Jun’i-sen tournament. The game record is a sequence of game states from the initial state to the end of the game. Each comment is mapped to one of the states in the sequence. We also defined *shogi* named entities (s-NEs) and annotated commentaries. We built an automatic named entity recognition (NER) tool of s-NEs by using the annotated corpus, and the experimental result showed that we could obtain high-quality NER by using our corpus. We also augmented the SGC with modality expressions and event factuality annotation (Matsuyoshi et al., 2018).

These labels are annotated by using natural language information. The commentaries are tied up to each state, and we usually treat the pairs of comments and states as if they are correctly mapped. However, the commentaries are sometimes about the past or future states of the game, or outside of the current game. For an accurate evaluation of symbol grounding, we should construct a corpus which shows the relationship between natural language texts and non-text world states.

Table 1 shows the list of s-NEs that we defined on (Mori et al., 2016). In this work, we selected Strategy (St), Castle (Ca), and Move Name (Mn) as target s-NEs. Castle is a defensive piece formation to protect a king. These three NEs are strongly related to the states.

### 3. Event Appearance

We define “Event Appearance” (EA) and annotate SGC with it. EA consists of temporal relation, appearance probability, and evidence of event. Each s-NE has one EA label.

3.1. **Temporal Relation**

Temporal relation has four types of labels. The descriptions and examples of each label are below (underlined phrases Tag shows the target s-NEs):

- **Present** The event which the s-NE indicates appears in the current state.
  
  ex.) 対する先手は美濃囲いCaに組んだ。
  (Black player constructed Mino castle Ca.)
  
  Note that some events appear in both past and current states. In this case, we annotate the events as **Present**.

- **Past** The event which the s-NE indicates appeared in the past states.
  
  ex.) 85手目の突き捨てるMnは、この変化でも生きてくる。
  (Push Sacrifice Mn at 85th move also shows an effect on this position.)

- **Future** The event which the s-NE indicates will appear in the future states.
  
  ex.) このあと居飛車Stに組む可能性が高そうだ。
  (The probability that the player will choose Static-Rook strategy St is high.)

- **Not** The event which the s-NE indicates does not appear in the current and past states, and will not appear in the future states.
  
  ex.) (Player Name)は居飛車St党。
  ((Player Name) tends to adopt Static Rook strategy St.)

- **Undecidable** Annotators cannot decide from the four categories. This label is unexpected to be chosen.

1.http://www.meijinsen.jp/ (in Japanese).
Future temporal relation is added if the events happen on the left (Kawasaki, 2013). In this case, commentators explain the reason that they choose the s-NEs for expressions represents the sequence of actions. Annotators show one of the possible sequences, even if there are more than one sequence.

### 3.2. Appearance Probability

Future states are indefinite when the commentaries are written. We define appearance probability for s-NEs if the temporal relation is Future. Appearance probability has four types of labels:

- **High** The event which the s-NE indicates will appear with high probability.
- **One-of** There are more than one possible future state, and the state with the event which the s-NE indicates is one of those.
- **Low** There are more likely future states than that with the event which the s-NE indicates, and the future state will appear with low probability.
- **For-Comment** The event which the s-NE indicates will not appear in the proper future states because the comment is not for future prediction but for the explanation.

In shogi commentaries, experts sometimes explain bad actions that amateur players tend to choose. Professional players less likely to choose these actions, and the event will not appear in the proper future states.

We add one of the possible sequences of actions if the temporal relation is **Future**. A sequence of move expressions represents the sequence of actions. Annotators show one of the possible sequences, even if there are more than one sequence.

### 3.3. Evidence of Event

We define “Evidence of Event”. When commentators explain the reason that they choose the s-NEs for explaining the states, they will abstract the states. For example, 4th-File-Rook strategy (四間飛車) is defined as a strategy that the rook is swung to the 4th file from the left (Kawasaki, 2013). In this case, commentators may explain the evidence of 4th-File-Rook strategy that the rook is swung to the 4th file from the left even if the reason is not only the position of the rook but also the whole states.

States are sometimes in the events over a long sequence of states. However, annotating all over the states may cost huge annotation efforts. Thus, in this paper, we define the evidence of event that a set of elements on exactly one state. We are mainly interested in “when the event happens” and “when the event ends”. To acquire that information, we define the states of evidence for **Present** and **Past** as follows. If the temporal relation is **Present**, the state of evidence is the state in which the event happens and there is no state which is not in the event between the evidence state and the current state. For example, if the sequence of states is “XXOXXOXX” where “O” and “X” are the states with and without the event, respectively, the state of evidence is the 7th one. If the temporal relation is **Past**, the state of evidence is the state just before the
state in which the event ends. For example, if the sequence of states is “XXOOOXOOOXXX”, the state of evidence is the 9th one. Annotators choose evidence from the following elements on states:

- Last action,
- Captured pieces, and
- Cells on the board.

4. Annotated Corpus

4.1. Annotation Process

First, we prepared nine games and commentaries for the games which are written in human experts. These commentaries are already annotated with s-NEs.

Four annotators annotated the same corpus. The annotators are native Japanese speakers as well as amateur shogi players. Table 2 shows the player ranks (dan) of annotators (Anttr.). Shogi club 24 and shogi wars are online shogi game servers and all players are rated by the results of games. Values in parentheses show that the rank is in the top X percentile provided by http://shoginaka.com/cgi-bin/24_ranking_checker.cgi and https://nandemoplus.com/shogiwars_occupancy/ (in Japanese). dan is a name of higher rank and higher number shows higher rank. kyu is a name of lower rank and lower number shows higher rank similar to negative numbers.

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Table 3: Statistics of the corpus: the number of shogi NEs of each type.

4.2. Statistics

Tables 3 and 4 show the statistics of the corpus. No annotator chose Undecidable as temporal relation. There are few events with Future label. It shows that commentators rarely mention to St, Ca, or Mn on future states.

Table 5 shows Cohen’s kappa score (Cohen, 1960) of temporal relation labels between each pair of two annotators. It shows that the agreement between annotators is high. It suggests that annotation by annotators with high domain skills is important to analyze the texts. Fleiss’ kappa score (Fleiss, 1971) of four annotators (except for the first author) is 0.74. These results show that the agreement of temporal relation is substantial.

We calculated the F-score of evidence of event by the following step:

- If the annotators chose different states, F-score = 0.
- If both annotators chose the same states but 0 elements, F-score = 1.
- Otherwise, calculate F-score by using the sets of elements of evidence.

Table 6 shows the F-score of evidence of event between each pair of two annotators. The F-scores seem a little bit low, considering the high agreement of temporal relation. There are two possible reasons. One is that the annotators have their decision process, and the evidence of the decisions is different. The other is that making the evidence of the decisions is hard, and there exists some error. We are confident that collecting the evidence of decisions is important for analyzing the humans’ decision-making process.

4.3. Experiments

We evaluated the Temporal Relation labels by comparing them and predicted s-NEs from states.

First, we trained an s-NE prediction model that predicts s-NEs that will appear in the comments for given

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2https://www.shogidojo.net/
3https://shogiwars.herokuapp.jp/
Figure 3: Web Interface of Annotation. The web page is written in Japanese.

states. Note that we used unlabeled comments as a training corpus, so we treated comments as positive examples if the comments include the phrases of s-NEs. We used the positions of all the pieces on the board and the captured pieces as the features of a state. We trained binary classifiers for each s-NE by using linear support vector machines, which are implemented by (Fan et al., 2008).
Table 5: Cohen Kappa score of each pair of annotators. “A” means first author.

|       | 1   | 2   | 3   | 4   | A   |
|-------|-----|-----|-----|-----|-----|
| Antr. 1 | 0.70 | 0.71 | 0.68 | 0.70 |     |
| Antr. 2 | 0.78 | 0.78 | 0.72 |     |     |
| Antr. 3 | 0.79 | 0.66 |     |     |     |
| Antr. 4 |     |     |     |     | 0.68|
| 1st author |     |     |     |     |     |

Table 6: Pairwise F-score of evidence of event between each annotator. “A” means the first author.

|       | 1   | 2   | 3   | 4   | A   |
|-------|-----|-----|-----|-----|-----|
| Antr. 1 | 0.48 | 0.50 | 0.39 | 0.38 |     |
| Antr. 2 | 0.50 | 0.44 | 0.44 |     |     |
| Antr. 3 | 0.53 | 0.37 |     |     |     |
| Antr. 4 |     |     |     |     | 0.66|
| 1st author |     |     |     |     |     |

Table 7: Relationship between annotators’ labels and probabilities by trained shogi NE predictor. mean: Mean value of probabilities which the trained predictor outputs for each class. AUC: Area under the curve of one-versus-the-rest classification.

|       | Present | mean | AUC |
|-------|---------|------|-----|
| Antr. 1 | 0.055  | 0.61 |
| Antr. 2 | 0.031  | 0.53 |
| Antr. 3 | 0.020  | 0.57 |
| Antr. 4 | 0.026  | 0.61 |

We evaluated the relationship between temporal relation labels and the prediction of the trained model in two ways. One is to compare the mean of the probabilities that are calculated by the model for each label. The other is the area under the curve (AUC). We calculated AUC for each label by the following steps:

- Convert the labels into binary labels (1 if the label is focused else 0).
- Calculate AUC score by the converted labels and the probabilities that are calculated by the model.
- If AUC score < 0.5, output 1.0 − AUC score.

Table 7 shows the result of the experiment. The mean value of the probabilities for Present is higher than the other labels. It suggests that there is a stronger relationship between the current states and the event with Present labels than those with other labels. Present label means that the events are in the current states, so the result is expected. However, the AUC scores are about 0.5, and it shows that it is hard to classify the temporal relation by the probabilities. It suggests that considering only the current states is insufficient for analyzing the commentary.

4.4. Availability

We plan to distribute our corpus except for text data on our website http://www.ar.media.kyoto-u.ac.jp/data/game/home-e.html. For detailed explanations, readers may visit it.

4The game records and the commentary sentences are distributed on the website: http://www.meijinsen.jp (in Japanese) for a fee. We provide a helper script to download the records and the text at https://github.com/hkmk/shogi-comment-tools.

5. Applications

5.1. Module Evaluation of Symbol Grounding

Some multimodal models are trained by end-to-end architecture to reproduce the outputs by humans. A large amount of data improves these systems with the advance of technologies such as deep neural networks. However, when the performance of trained models is low, specifying the problems is sometimes hard. Our high-quality corpus, which is annotated by annotators with high skill of target domain, may help to evaluate the module evaluation of symbol grounding.

5.2. Symbol Grounding to Search Tree

For describing the machine thought, symbol grounding to the searching tree is an important factor. Searching trees is one of the results of intelligent machine thought, but it is too hard for humans to understand the huge searching tree of computer game players. Hence there is a demand for the representing system of searching trees in human-readable media such as natural language texts. The temporal relation and appearance probability, including the path to the future states, are the positive examples for symbol grounding.

5.3. Evaluation of Explainable AI

These days, Explainable AI is one of the hot topics (Costabello et al., 2019). One goal is to explain the reason for the decisions of AI by natural language since natural language is one of the easiest protocols for humans to understand. We built an automatic game commentary system (Kameko et al., 2015). This system outputs comments for given states. For more detailed explanation, to show the evidence of the decision is a good way.
We consider that we can use our proposed corpus to evaluate such explainable abilities of the system.

6. Conclusion

In this paper, we proposed event appearance labels and augmented the SGC corpus by annotating the labels. We called annotators with high skill of the target domain shogi. In addition, we evaluated the hardness of predicting the temporal relation. The experimental result suggests that considering only the current states is insufficient for analyzing. Expanding the target for event appearance labels is one of the future work. In this paper, we focused on strategy, castle, and move name because we expected that they are strongly related to states and easy for annotating and evaluating. The agreement of the labels shows that we can annotate meaningful event appearance labels.

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