Annotating Modality Expressions and Event Factuality for a Japanese Chess Commentary Corpus

Suguru Matsuyoshi¹, Hirotaka Kameko², Yugo Murawaki³, Shinsuke Mori⁴

¹Graduate School of Informatics and Engineering, The University of Electro-Communications
²Graduate School of Engineering, The University of Tokyo
³Graduate School of Informatics, Kyoto University
⁴Academic Center for Computing and Media Studies, Kyoto University

Chofugaoka, Chofu, Tokyo, Japan ²Hongo, Bunkyo-ku, Tokyo, Japan ³Yoshida-honmachi, Sakyo-ku, Kyoto, Japan

¹matuyosi@uec.ac.jp, ²kameko@logos.t.u-tokyo.ac.jp, ³murawaki@i.kyoto-u.ac.jp, ⁴forest@i.kyoto-u.ac.jp

Abstract

In recent years, there has been a surge of interest in the natural language processing related to the real world, such as symbol grounding, language generation, and nonlinguistic data search by natural language queries. We argue that shogi (Japanese chess) commentaries, which are accompanied by game states, are an interesting testbed for these tasks. A commentator refers not only to the current board state but to past and future moves, and yet such references can be grounded in the game tree, possibly with the help of modern game-tree search algorithms. For this reason, we previously collected shogi commentaries together with board states and have been developing a game commentary generator. In this paper, we augment the corpus with manual annotation of modality expressions and event factuality. The annotated corpus includes 1,622 modality expressions, 5,014 event class tags and 3,092 factuality tags. It can be used to train a computer to identify words and phrases that signal factuality and to determine events with the said factuality, paving the way for grounding possible and counterfactual states.

Keywords: game commentary, modality, factuality, symbol grounding

1. Introduction

The field of natural language processing (NLP) has experienced a resurgence of interest in the symbol grounding problem (Harnad, 1990). An increasing number of datasets available align natural language expressions with real world objects in the form of images and videos (Hashimoto et al., 2014; Mori et al., 2014b; Ferraro et al., 2015), and systems built on top of such datasets typically perform image/video-to-text generation (Ushiku et al., 2011; Yang et al., 2011).

These systems are, however, more akin to great apes than to humans in the sense that “[t]heir lives are lived entirely in the present” (Donald, 1991). While there is no evidence that nonhuman animals communicate past episodes and planned future events, human language is abundant with them (Szagun, 1978). It is even suggested that the faculty of language has a close connection to the ability to image the future (Suddendorf and Corballis, 1997).

Here we argue that commentaries for an extensive-form game (e.g., chess) are an ideal testbed for developing truly intelligent systems. Specifically, we focus on shogi (Japanese chess). Unlike typical image captions, human comments on shogi games are full of references to past and future moves as we will see in Subsection 2.2. Yet, thanks to the well-definedness of the world, many of such references can be grounded in a game tree. Although ambiguities inherent in natural language remain a challenging problem, modern game-tree search algorithms (Kisuoka et al., 2002) help distinguish realistic states from unrealistic ones. For this reason, we have collected shogi commentaries together with the corresponding board states and have been developing a game commentary generator (Mori et al., 2018; Kameko et al., 2013).

A human commentator usually expresses to shogi fans the degree of confidence on the future move he is describing, which reflects his evaluation of the game-tree. Since confidence is expressed through a wide variety of words and phrases, which we call modality expressions, identifying such expressions and binding the factual statuses to events are necessary steps toward automatic generation of human-like commentaries.

To this end, we annotate a shogi corpus for a commentator’s confidence in this work. Specifically, we adopt a three-layer annotation scheme: modality expression, event class and factuality. The first layer specifies constituents of a sentence construction conveying a certain level of confidence. The second layer extracts event mentions that can be mapped into a game tree. The last layer denotes confidence level of each event mention.

2. Game and Commentary

2.1. Shogi

Shogi is a two-player board game similar to chess as illus-
In the SGC corpus, we observed that the following con-
sists of 6,523 matches including 744,327 sentences and
11,083,669 words.

Table 1: Shogi-specific named entity tags.

| Tag | Meaning |
|-----|---------|
| Tu  | Turn    |
| Po  | Position|
| Pi  | Piece   |
| Ps  | Piece specifer |
| Mc  | Move compliment |
| Mn  | Move name |
| Me  | Move evaluation |
| St  | Strategy |
| Ca  | Castle |
| Ev  | Evaluation: entire |
| Ee  | Evaluation: part |
| Re  | Region |
| Ph  | Phase |
| Pa  | Piece attribute |
| Pq  | Piece quantity |
| Hu  | Human |
| Ti  | Time |
| Ac  | Player action |
| Ap  | Piece action |
| Ao  | Other action |
| Ot  | Other notion |

2.2. Shogi Commentary

Professional players and writers give commentaries of professional matches for shogi fans. Mori et al. (2016) collected shogi commentaries with board states described in Shogi Forsyth-Edwards notation (SFEN). The corpus consists of 6,523 matches including 744,327 sentences and 11,083,669 words. Mori et al. (2016) first segmented nine matches, or 2,041 sentences, automatically with a text analyzer KyTea and then corrected word boundaries manually. Finally they manually added to the sentences shogi-specific named entities (NEs) tags defined in Table 1. We call the annotated corpus the Shogi Game Commentary Corpus (SGC corpus).

In the SGC corpus, we observed that the following contents were mainly expressed with recollection of the past and imagination of the future:

- Reason behind moves.
  
  この桂馬打ちは飛車取りを狙ったものだ (This drop of knight aims at capturing the opponent’s rook.)
  
  角の仇ですね (The move must be a revenge for his bishop.)

- Prediction of the next moves and strategies.
  
  美濃開いが有効だ (Black will build Mino castle for making it better.)

- Mentioning future directions.
  
  △1 四香とすれば決戦 (White’s Lx1d would shift the phase to the end game.)

3. Japanese Modality Expressions

We augment the SGC corpus with annotations of modality expressions and event factuality. Table 2 shows a sample text annotated according to our annotation scheme. In this section, we describe the first layer of modality expressions. Modality expressions are words and multi-word expressions which impose a proposition in a sentence on propositional modality and event modality (Palmer, 2001). Here are some examples of Japanese modality expressions (EV denotes an event mention and ME denotes a modality expression):

| EX 1 | 後手は歩を成り捨てに (White sacrifice ed the pawn in the opponent’s zone.) |
| EX 2 | この試合では飛車を採用する (White may use rook stay strategy in the game.) |
| EX 3 | おそらく △1 四香が良好 (Probably white’s Lx1d will be good.) |
| EX 4 | 8 五桂の駒れ出しを防い (The move prevented black’s Nxa8 attack.) |
| EX 5 | ここで△1 四歩と受け入れ、先手はつらい (If white chooses Px1d, black will have a hard time.) |

In EX 1, “た (PAST)” is an auxiliary verb for past tense and indicates that the event is a fact. In EX 2, “かもしれない” is a multi-word expression functioning as an auxiliary verb and expressing the low possibility of the event. In EX 3, “おそらく (probably)” is an adverb which suggests that the event is probable. “防い (prevent)” is a verb used as a modality expression while in EX 4 it is used a main verb and can be seen as an event mention. This counterfactive verb makes it explicit that the event “防い (attack)” did not happen. In EX 5, “ぱ (if)” is a conjunctive particle that leads to a conditional construction. Factuality of event mentions in the hypothetical construction is absolutely uncertain.

In the first layer of our annotation scheme, we mark up modality expressions as described above.

3.1. POS

There have been several studies of detecting Japanese modality expressions (Suzuki et al., 2012, Zum et al., 2013) (Kamioka et al., 2015). However, they focus on auxiliary verbs and functional multi-word expressions. Modal adverbs and conjunctive particles are largely out of scope of these studies. By contrast, we target all types of modality expressions for mark-up regardless of their parts-of-speech.

http://www.phontron.com/kytea/
3.2. Tags

We define the following two groups of tags: factuality and time.

3.2.1. Factuality Group

The following five tags concern possibility and polarity.

- **MEy** suggests the target event is factual.
  銀の捕獲EVに成功MEy (Black succeededMEy in capturingEV the silver general.)

- **MEA** suggests the target event is possibly factual.
  先手はこのあと居飛車に組むEV可能性が高いMEA (Black is likely toMEA useEV static rook strategy.)

- **ME0** suspends mentioning possibility of the target event.
  その間に先手玉に迫るEV手段があるかどうかME0 (Is thereME0 a way to attackEV black’s king before the castle is completed?)

- **MEn** suggests the target event is possibly counterfactual.
  後手の飛車もあまりMEn利ievでいない (White’s rook hasEV littleMEn effect on it.)

- **MEn** suggests the target event is counterfactual.
  △9四歩とはしEVかつMEnた (He did notMEn takeEV Px9d.)

3.2.2. Time Group

We introduce the following three tags from the viewpoint of timeline regardless of polarity.

- **MEp** suggests the target event was in the past.
  ここで銀交換EVに応じたMEp (They changeEV each other’s silver general.)

- **MEf** suggests the target event will or will not happen in the future.
  先手は将来MEF的に右辺に玉を勧EVこともなる (White will eventuallyMEF besiegeEV the opponent’s king at the right side of the board.)

- **MEh** suggests the target event is hypothesized or has a condition.
  ここで△1四歩と受けEVればMEh 先手はつらい (IfMEh White chooseEV Px1d, black will have a hard time.)

4. Event Classes and Factuality

In this section, we describe the second and third layers of our annotation scheme. In the second layer, we classify event mentions into event classes. The objective of the classification is to distinguish from the others event mentions that can be mapped into a game tree. In the third layer, we mark up the factual statuses of events.

4.1. Event

A sentence conveying information contains not only propositions, but also modality, polarity and the writer’s attitude. A proposition is expressed as an event mention in a sentence. Following TimeML (Sauri et al., 2006), we consider events a cover term for situations that happen or occur. Propositions describing states or circumstances are also considered as events.

4.2. Event Classes

As mentioned in the FactBank annotation guidelines (Sauri, 2008), it is not preferable to target all event mentions in a text for factuality mark-up. This is because a writer’s attitude such as wish, command, permission, question and hypothesis is expressed in a text. An event mention surrounded by such an attitude expression is not suitable for factuality mark-up because the factuality of the event is absolutely uncertain. We believe that these events should be separated from events that are free from a writer’s attitude. For this reason, we classify event mentions into several event classes from the viewpoint of attitude in advance of factuality mark-up.

Automatic extraction of event mentions in Japanese text is complicated by the existence of grammaticalized verbs and adjectives. Japanese text includes a non-negligible number of these tokens. We mark up grammaticalized tokens in advance of factuality mark-up.

We define the following two groups of class tags: attitude and grammaticalization.

4.2.1. Attitude Group

The following five classes of tags reflect a writer’s attitude.

- **EVa** With wish, request, command or obligation.
  多くのファンに楽しEVa んでもらいたい (I wish manyfans enjoyEVa this game.)

- **EVq** With interrogative.
  先手は桂を取るEVq か (Will black attackEVq white’s knight?)
With granting a permission.

EVp  With granting a permission.

Certainly the case that P.  

(EVp)  With granting a permission.

EVs  Simile or metaphor.

3 四の銀をあげ笑 EVs  うかのように玉を進行させる
(The king is proceeding as if it ridiculed EVs the silver
general of Sx3d.)

4.3. Factuality Tags

In the third layer of our annotation scheme, we mark up a factuality tag for an event mention whose class is EVe in
the previous phase.

As factuality tags, we use factuality values proposed in FactBank (Sauri, 2008). However, the value Uu is the sole
exception. It is not adopted in our scheme because a predicate which would have Uu has been annotated with an EVq
or EVi tag in the previous phase. Consequently, we use the following six tags for factuality mark-up. (P stands for the
proposition mentioned in a target event. The corresponding values in FactBank are shown in brackets):

FPC  Certainly the case that P.  

FPC  Certainly the case that P.  

(FPC)  Certainly the case that P.

FPR  Probably the case that P.  

FPR  Probably the case that P.  

(FPR)  Probably the case that P.

Table 3: Frequency and ratio of each tag of the three-layer annotation.

| Tag  | Freq. | Ratio |
|------|-------|-------|
| MEx-B | 49 | 3% |
| MEA-B | 224 | 14% |
| ME0-B | 158 | 10% |
| MEm-B | 21 | 1% |
| MEn-B | 269 | 16% |
| MEp-B | 692 | 43% |
| MEf-B | 59 | 4% |
| MEh-B | 150 | 9% |
| Total | 1,622 | 100% |

EVa  39 | 1% |
EVq  111 | 2% |
EVi  707 | 14% |
EVP  14 | 0% |
EVS  4 | 0% |
EVe  3,092 | 62% |
Evc  293 | 6% |
EVI  761 | 15% |
Total | 5,014 | 100% |

| Tag  | Freq. | Ratio |
|------|-------|-------|
| FPc  | 2,646 | 86% |
| FPr  | 233 | 7% |
| FPs  | 35 | 1% |
| FNs  | 34 | 1% |
| Total | 3,092 | 100% |

Table 5: Annotated Corpus

5.1. Annotation Process

In annotation process, we annotated the SGC corpus with modality expressions, event classes and factuality in this
or-
annotation was performed by a single annotator. To prepare concise guidelines for annotating our tags for other annotators and examine inter-annotator agreement are future work.

5.2. Some Statistics
Table 4 shows the frequency and ratio of each tag in our three-layer annotation. Our corpus contains 1,622 modality expressions and 3,092 lexical event mentions (EVE). Among them, 2,646 are labeled with FPC (factual), while 140 are labeled with FNC (counterfactual). The remaining are judged as being in hedge contexts.

5.3. Experiments
To give a glimpse of how difficult the tasks of modality expression detection and event factuality analysis are, we ran on the corpus a simple tagger with a basic set of features. As described in Subsection 5.2.1, the SGC corpus consists of nine matches. We used the latest match among them as test data and the others as training data in experiments. The numbers of the sentences in the training and the test data are 968 and 1,072, respectively.

For both of modality expression detection and event factuality analysis, we adopt sequential labeling of tags in sequence by using conditional random fields referring to the tag-confidence pairs. Tables 4 and 5 show the results of modality expression detection and event factuality analysis, respectively. In the tables, “Freq.” indicates the number of a target tag in the test data. From Table 4, we can see that the F-measures of the modality expression tags whose frequencies are more than 100 are high although the training data is small in size.

We expect that increasing the size of the corpus can lead to higher performance of modality expression detection for shogi commentaries. In the event factuality analysis task, we obtained the F-measure of 0.64 for the FPC (factual) tag while the F-measures for the other tags are low, as shown in Table 5. This suggests that event factuality analysis for shogi commentaries is a difficult task, although increasing the size of the corpus might be effective. Given the obvious dependency of event factuality analysis on modality expressions, we expect to improve performance of event factuality analysis by incorporating the results of modality expression detection as features.

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

6. Application
The most important applications of our corpus are text analysis such as modality expression detection and factuality analysis as employed in Subsection 5.2.3. Below we discuss several future research directions.

6.1. Factuality Analysis
Every sentence in our corpus has the corresponding board state (the state history if necessary) and NE labels. They can assist in event factuality analysis. Automatic simultaneous tagging of NE and factuality might work well.

6.2. Automatic Commentary Generation
With our corpus, we can improve automatic commentary generation (Kaneko, 2012; Kameko et al., 2015). The previous work proposed a two-step approach where identification of characteristic words for the given game state is followed by language model-based generation. With consideration for event factuality in addition to characteristic words, the generator is expected to choose appropriate modality expressions. We can try generation using automatically generated templates (Reiter, 1995; Mori et al., 2014) or deep learning with NEs in place of dialog acts (Wen et al., 2015).
6.3. Game State Retrieval
We can also create a system for game state search by natural language queries. A previous study proposed search for game states by piece positions (Ganguly et al., 2014). NE recognition enables a user to search by strategy names and move evaluation (Ushiku et al., 2017). Factuality analysis allows for fine grained retrieval of game states, for example, the one in which the given strategy was judged good by a commentator, and the one where the strategy was mentioned as an option but was not adopted by the player.

6.4. Symbol Grounding
One of the most interesting research directions is symbol grounding. While symbol grounding of a content word to the world is a straight concept, grounding of a modality expression such as “must” and “may” to images, videos, many other forms of media is an open question. An application of modal logic (Kripke, 1963) to shogi game tree as a set of possible worlds can be a solution to grounding of some modality expressions.

We believe that there are many other novel applications including bilingual lexicon acquisition for function words and modality expressions based on symbol grounding (Kiela et al., 2015).

7. Conclusion
In this paper, we described our annotation scheme of modality expressions, event classes, and factuality. We annotated the text of a shogi commentary corpus with these tags. The annotated corpus includes 1,622 modality expressions, 5,014 event class tags and 3,092 factuality tags. As illustrated in the example sentences at Subsection 6.4. Symbol Grounding, human language, which is different from great ape communication, is abundant with recollection of the past and imagination of the future. Our work leads to the tasks of automatically identifying modality expressions and binding the factual statuses to events in a text. They are necessary steps toward automatic analysis and generation of human commentaries.

The most interesting characteristics of our corpus is that every commentary is associated with a game state (real world). This will enable NLP and AI researchers to tackle various new problems such as commentary generation, intelligent game state search, and symbol grounding.

8. Bibliographical References
Donald, M. (1991). Origins of the Modern Mind: Three Stages in the Evolution of Culture and Cognition. Harvard University Press.
Ferraro, F., Mostafazadeh, N., Huang, T.-H., Vanderwende, L., Devlin, J., Galley, M., and Mitchell, M. (2015). A survey of current datasets for vision and language research. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 207–213.
Ganguly, D., Leveling, J., and Jones, G. J. (2014). Retrieval of similar chess positions. In Proceedings of the 37th annual international ACM SIGIR conference, pages 687–696. ACM.
Harnad, S. (1990). The symbol grounding problem. Physica D, 42:335–346.
Hashimoto, A., Sasada, T., Yamakata, Y., Mori, S., and Minoh, M. (2014). KUSK dataset: Toward a direct understanding of recipe text and human cooking activity. In Proceedings of the Sixth International Workshop on Cooking and Eating Activities.
Izumi, T., Imamura, K., Asami, T., Saito, K., Kikui, G., and Sato, S. (2013). Normalizing complex functional expressions in Japanese predicates: Linguistically-directed rule-based paraphrasing and its application. ACM Transactions on Asian Language Information Processing, 12(3):1–20.
Kameko, H., Mori, S., and Tsuruoka, Y. (2015). Learning a game commentary generator with grounded move expressions. In Proceedings of the 2015 IEEE Conference on Computational Intelligence and Games.
Kaneko, T. (2012). Real time commentary system for shogi. In First Workshop on Games and NLP.
Kiela, D., Vulić, I., and Clark, S. (2015). Visual bilingual lexicon induction with transferred convnet features. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 148–158.
Kripke, S. A. (1963). Semantical considerations on modal logic. Acta Philosophica Fennica, 16:83–94.
Leggett, T. (2009). Japanese chess : the game of shogi. Tuttle Publishing.
Mori, S., Maeta, H., Sasada, T., Yoshino, K., Hashimoto, A., Funatomi, T., and Yamakata, Y. (2014a). Flowgraph2text: Automatic sentence skeleton compilation for procedural text generation. In Proceedings of the Eighth International Conference on Natural Language Generation, pages 118–122.
Mori, S., Maeta, H., Yamakata, Y., and Sasada, T. (2014b). Flow graph corpus from recipe texts. In Proceedings of the Ninth International Conference on Language Resources and Evaluation, pages 2370–2377.
Mori, S., Richardson, J., Ushiku, A., Sasada, T., Kameko, H., and Tsuruoka, Y. (2016). A japanese chess commentary corpus. In Proceedings of the Tenth International Conference on Language Resources and Evaluation.
Palmer, F. (2001). Mood and Modality Second edition. Cambridge University Press.
Reiter, E. (1995). Nlg vs. templates. In Proceedings of the the Fifth European Workshop on Natural Language Generation, pages 147–151.
Sang, E. F. T. K. and Meulder, F. D. (2003). Introduction to the conll-2003 shared task: Language-independent named entity recognition. In Proceedings of the Seventh Conference on Computational Natural Language Learning, pages 142–147.
Sasada, T., Mori, S., Kawahara, T., and Yamakata, Y. (2015). Named entity recognizer trainable from partially annotated data. In Proceedings of the Eleventh International Conference Pacific Association for Computational Linguistics.
Suddendorf, T. and Corballis, M. C. (1997). Mental time travel and the evolution of the human mind. Genetic, So-
Suzuki, T., Abe, Y., Toyota, I., Utsuro, T., Matsuyoshi, S., and Tsuchiya, M. (2012). Detecting Japanese compound functional expressions using canonical/derivational relation. In International Conference on Language Resources and Evaluation.

Szagun, G. (1978). On the frequency of use of tenses in English and German children’s spontaneous speech. Child Development, 49(3):898–901.

Tsuruoka, Y., Yokoyama, D., and Chikayama, T. (2002). Game-tree search algorithm based on realization probability. ICGA Journal, 25(3):145–152.

Ushiku, Y., Harada, T., and Kuniyoshi, Y. (2011). Automatic sentence generation from images. In Proceedings of the 19th Annual ACM International Conference on Multimedia, pages 1533–1536.

Ushiku, A., Mori, S., Kameko, H., and Tsuruoka, Y. (2017). Game state retrieval with keyword queries. In Annual International ACM SIGIR conference.

Wen, T.-H., Gasic, M., Mrksic, N., Su, P.-H., Vandyke, D., and Young, S. (2015). Semantically conditioned LSTM-based natural language generation for spoken dialogue systems. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 207–213.

Yang, Y., Teo, C. L., III, H. D., and Aloimonos, Y. (2011). Corpus-guided sentence generation of natural images. In Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing.

9. Language Resource References

Kamioka, Y., Narita, K., Mizuno, J., Kanno, M., and Inui, K. (2015). Semantic annotation of Japanese functional expressions and its impact on factuality analysis. In Proceedings of The 9th Linguistic Annotation Workshop, pages 52–61.

Sauri, R., Littman, J., Knippen, B., Gaizauskas, R., Setzer, A., and Pustejovsky, J., (2006). TimeML Annotation Guidelines Version 1.2.1. https://catalog.ldc.upenn.edu/docs/LDC2006T08/timeml_annguide_1.2.1.pdf

Sauri, R., (2008). FactBank 1.0 Annotation Guidelines. https://catalog.ldc.upenn.edu/docs/LDC2009T23/annotationGuidelines.pdf