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

Suguru Matsuyoshi[1], Hirotaka Kameko[2], Yugo Murawaki[3], Shinsuke Mori[4]

[1]Graduate School of Informatics and Engineering, The University of Electro-Communications
[2]Graduate School of Engineering, The University of Tokyo
[3]Graduate School of Informatics, Kyoto University
[4]Academic Center for Computing and Media Studies, Kyoto University
[1]Chofugaoka, Chofu, Tokyo, Japan   [2]Hongo, Bunkyo-ku, Tokyo, Japan
[3,4]Yoshida-honmachi, Sakyo-ku, Kyoto, Japan
[1]matuyosi@uec.ac.jp, [2]kameko@logos.t.u-tokyo.ac.jp, [3]murawaki@i.kyoto-u.ac.jp, [4]forest@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 (Tsuruoka 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., 2016; Kameko et al., 2015).
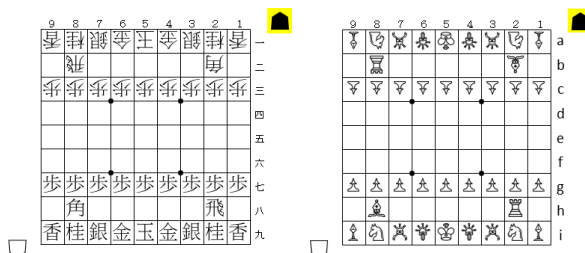

Figure 1: Starting setup of *shogi* (left: normal depiction, right: chess-like depiction).

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-

Tag	Meaning
Tu	Turn
Po	Position
Pi	Piece
Ps	Piece specifier
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

Table 1: *Shogi*-specific named entity tags.

trated in Fig 1. The goal of each player is to capture the opponent's king. Each player moves one piece alternately. The biggest difference from chess is that a player can drop a captured piece back onto the board instead of making a move. For detailed explanation of *shogi*, please refer to (Leggett, 2009).

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[1] 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.
  美濃囲いが有効だ (Black will build *Mino* castle for making it better.)

ゴキゲン中飛車との予測は外れた (I expected that white used cheerful central rook strategy, but he did not.)

- 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EVたME (White sacrificeEV-edME the pawn in the oppenent's zone.)

EX 2 この試合では居飛車を採用EV するかもしれないME (White mayME useEV rook stay strategy in the game.)

EX 3 おそらくME △１四香が良好EV (ProbablyME white's Lx1d will be goodEV.)

EX 4 ▲８五桂の跳ねEV 出しを防いME だ (The move preventedME black's Nx8e attackEV.)

EX 5 ここで△１四歩と受けEV ればME 先手はつらい (IfME white choosesEV 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 (may)" 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 "跳ね (attack)" did not happen. In EX 5, "ば (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; Izumi 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.

Layer																								
String	先手	は	美濃	囲い	が	崩れ	て	い	る	の	で	、	飛車	交換	は	後手	の	得	に	な	り	そう	だ	。
	black	TOP	Mino	castle	NOM	break	have PP			because			rook	change	TOP	white	's	good	to	be	be likely to			
POS	N	P	N	N	P	V	P	V	Sf	P	Aux	Pnc	N	N	P	N	P	N	P	V	Sf	Adj	Aux	Pnc
NE	Tu-B	O	Ca-B	Ca-I	O	Ao-B	O	O	O	O	O	O	Mn-B	Mn-I	O	Tu-B	O	Ee-B	O	Ao-B	O	O	O	O
Modality	O	O	O	O	O	MEn-B	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	MEa-B	O	O
Event class				EVe		EVe			EVf					EVi						EVe				
Factuality				FNc		FPc														FPr				

Table 2: Five annotation layers for a commentary string with a well-formatted board state.

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$_{\mathrm{EV}}$ に成功$_{\mathrm{MEy}}$ (Black succeeded$_{\mathrm{MEy}}$ in capturing$_{\mathrm{EV}}$ the silver general.)

MEa suggests the target event is possibly factual.

> 先手はこのあと居飛車に組む$_{\mathrm{EV}}$可能性が高い$_{\mathrm{MEa}}$
> (Black is likely to$_{\mathrm{MEa}}$ use$_{\mathrm{EV}}$ static rook strategy.)

ME0 suspends mentioning possibility of the target event.

> その間に先手玉に迫る$_{\mathrm{EV}}$ 手段があるかどうか$_{\mathrm{ME0}}$
> (Is there$_{\mathrm{ME0}}$ a way to attack$_{\mathrm{EV}}$ black's king before the castle is completed?)

MEm suggests the target event is possibly counterfactual.

> 後手の飛車もあまり$_{\mathrm{MEm}}$利い$_{\mathrm{EV}}$ ていない (White's rook has$_{\mathrm{EV}}$ little$_{\mathrm{MEm}}$ effect on it.)

MEn suggests the target event is counterfactual.

> △９四歩とはし$_{\mathrm{EV}}$なかつ$_{\mathrm{MEn}}$ た (He did not$_{\mathrm{MEn}}$ take$_{\mathrm{EV}}$ 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$_{\mathrm{EV}}$ に応じた$_{\mathrm{MEp}}$ (They change$_{\mathrm{EV}}$-ed$_{\mathrm{MEp}}$ each other's silver general.)

MEf suggests the target event will or will not happen in the future.

> 先手は将来$_{\mathrm{MEf}}$ 的に右辺に玉を囲う$_{\mathrm{EV}}$ ことになる (White will eventually$_{\mathrm{MEf}}$ besiege$_{\mathrm{EV}}$ 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$_{\mathrm{EV}}$ れば$_{\mathrm{MEh}}$ 先手はつらい (If$_{\mathrm{MEh}}$ white chooses$_{\mathrm{EV}}$ 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$_{\mathrm{EVa}}$んでもらいたい (I wish many fans enjoy$_{\mathrm{EVa}}$ this game.)

EVq With interrogative.

> 先手は桂を取る$_{\mathrm{EVq}}$ か (Will black attack$_{\mathrm{EVq}}$ white's knight?)

EVi Imaginary event, i.e., in conditional construction or not instantiated.

ここで△１四歩と受け$_{EVi}$ れば先手はつらい$_{EVi}$

(If white chooses$_{EVi}$ Px1d, black will have$_{EVi}$ a hard time.)

EVp With granting a permission.

サイン会だけの参加$_{EVp}$ も可能です (You can participate$_{EVp}$ only in an autograph session.)

EVs Simile or metaphor.

３四の銀をあざ笑$_{EVs}$ 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.)

4.2.2. Grammaticalization Group

We introduce the following three classes of tags from the viewpoint of lexical/grammatical usage.

EVe Event mention whose core is a lexical predicate with some arguments.

後手は歩を成り捨て$_{EVe}$ た (White sacrifice$_{EVe}$-ed the pawn in the oppenent's zone.)

EVc Constituent of a named entity or a verb phrase whose role is a modifier. While it is not a normal event mention, it can be interpreted as an event mention if required in some tasks such as recognizing textual entailment and information extraction.

遊び$_{EVc}$ 駒を竜にぶつけた (He made an idle$_{EVc}$ piece invade a path of the opponent's promoted rook.)

EVf Grammaticalized function word or a constituent of a functional multi-word expression.

封じ手につい$_{EVf}$ て検討が進んでいる (Examination of [= について (*lit.* be attached$_{EVf}$ to)] the next move has been progressing.)

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 propositon mentioned in a target event. The corresponding values in FactBank are shown in brackets):

FPc Certainly the case that P. <CT+>

後手は歩を成り捨て$_{FPc}$ た (White sacrifice$_{FPc}$-ed the pawn in the oppenent's zone.)

FPr Probably the case that P. <PR+>

おそらく△１四香が良好$_{FPr}$ (Probably white's Lx1d will be good$_{FPr}$.)

Tag	Freq.	Ratio
MEy-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	7	0%
EVs	4	0%
EVe	3,092	62%
EVc	293	6%
EVf	761	15%
Total	5,014	100%
FPc	2,646	86%
FPr	233	7%
FPs	35	1%
FNc	140	5%
FNr	34	1%
FNs	4	0%
Total	3,092	100%

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

FPs Possibly the case that P. <PS+>

この試合では居飛車を採用$_{FPs}$ するかもしれない

(White may use$_{FPs}$ rook stay strategy in the game.)

FNc Certainly not the case that P. <CT−>

角交換$_{FNc}$ には応じなかった (He was not tempted to change$_{FNc}$ each other's bishop.)

FNr Probably not the case that P. <PR−>

穴熊に組む$_{FNr}$ つもりはないだろう (I don't think white will use$_{FNr}$ *anaguma* castle.)

FNs Possibly not the case that P. <PS−>

△９四歩は指し$_{FNs}$ づらいかもしれません (Maybe it is hard to take$_{FNs}$ Px9d.)

5. Annotated Corpus

We explain our annotation process and show some statistics on our annotated corpus. We also report preliminary experiments on modality expression detection and event factuality analysis using it.

5.1. Annotation Process

In annotation process, we annotated the SGC corpus with modality expressions, event classes and factuality in this order. Because a modality expression can be made of more than one word, we adopt the IOB2 tagging style (Sang and Meulder, 2003) for our modality expression layer. The

Tag	Freq.	Precision	Recall	F-measure
MEy	21	0.00	0.00	0.00
MEa	103	0.63	0.68	0.65
ME0	105	0.63	0.60	0.62
MEm	7	1.00	0.14	0.25
MEn	140	0.75	0.71	0.73
MEp	370	0.91	0.92	0.92
MEf	32	0.92	0.34	0.50
MEh	66	0.69	0.47	0.56

Table 4: Results of modality expression detection.

Tag	Freq.	Precision	Recall	F-measure
FPc	1,349	0.64	0.63	0.64
FPr	116	0.34	0.14	0.20
FPs	21	0.00	0.00	0.00
FNc	67	0.50	0.15	0.23
FNr	16	0.00	0.00	0.00
FNs	3	0.00	0.00	0.00

Table 5: Results of event factuality analysis.

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 3 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 2.2., the SGC corpus consists of nine matches. We used the latest match[2] 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 including the O ("not the case") tag. In the experiments, we used PWNER[3] (Sasada et al., 2015) as a tool for sequential labeling. PWNER is a named entity recognizer, which is composed of two modules. The first module enumerates IOB2 tags with confidences for each word independently from the tags for other words. It uses character strings and character types (Chinese character, *hiragana*, Arabic numeral, and so on) of words surrounding the target word as

features. The second module searches for the best tag 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,[4] 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 5.3. 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., 2014a) or deep learning with NEs in place of dialog acts (Wen et al., 2015).

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[2] This is a title match called "*Meijinsen*," which causes longer text than a usual match.

[3] http://www.ar.media.kyoto-u.ac.jp/tool/PWNER/home.html

[4] The game records and the commentary sentences are distributed in 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.

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 2.2., 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.

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