Understanding Intent Arguments of Non-Canonical Directives

Won Ik Cho¹, Young Ki Moon²*, Sangwhan Moon³*, Seok Min Kim¹, Nam Soo Kim¹

¹Department of Electrical and Computer Engineering and INMC, Seoul National University
²Department of Computer Engineering, Inha University
³Department of Computer Science, Tokyo Institute of Technology

wicho@hi.snu.ac.kr, ykmoon0814@gmail.com, sangwhan@iki.fi, smkim@hi.snu.ac.kr, nkim@snu.ac.kr

Abstract

Modern dialog managers face the challenge of having to fulfill human-level conversational skills as part of common user expectations, including but not limited to discourse with no clear objective. Along with these requirements, agents are expected to extrapolate intent from the user’s dialogue even when subjected to non-canonical forms of speech. This depends on the agent’s comprehension of paraphrased forms of such utterances. In low-resource languages, the lack of data is a bottleneck that prevents advancements of the comprehension performance for these types of agents. In this paper, we demonstrate the necessity of being able to extract the intent argument of non-canonical directives, and also define guidelines for building paired corpora for this purpose. Following the guidelines, we label a dataset consisting of 30K instances of question/command-intent pairs, including annotations for a classification task for argument of non-canonical directives, and also define guidelines for building paired corpora for this purpose. Following the guidelines, we label a dataset consisting of 30K instances of question/command-intent pairs, including annotations for a classification task for predicting the utterance type. We also propose a method for mitigating class imbalance in the final dataset, and demonstrate the potential applications of the corpus generation method and dataset.

Keywords: intent argument extraction, paraphrasing, annotation, generation, non-canonical directives

1. Introduction

The advent of smart agents such as Amazon Echo and Google Home has shown relatively wide market adoption. Users have been familiarized with formulating questions and orders in a way that these agents can easily comprehend and take actions. Given this trend, particularly for cases where questions can have various forms such as yes/no, alternative, wh-, echo and embedded (Huddleston, 1994), a number of analysis techniques have been studied in the domain of semantic role labeling (Shen and Lapata, 2007) and entity recognition (Molla et al., 2006). Nowadays, various question answering tasks have been proposed (Yang et al., 2015) and have yielded systems that have demonstrated significant advances in performance. Studies on the parsing of canonical imperatives (Matuszek et al., 2013) have also been done for many household agents.

However, discerning the intent from a conversational and non-canonical sentence (question or command) and extracting its intent argument is still a challenge. Additional complexity is introduced when the target text is in a speech recognition context, as the result may not contain punctuation. For example, given an unclear declarative question (Gunlogson, 2002) such as “poppa joe you want me to go now”, a human listener can interpret the question as ‘if Joe wants the speaker to go now’, but this can be challenging to for a machine. Also, sometimes, merely the speech act can be hard to guess from the sentence form, as in informing “why don’t you just call the police” as a representation of the to-do list ‘to call the police’ (Figure 1). Although many advanced dialog managing systems may generate a plausible reaction to the input utterances, it is different from extracting the exact intent argument (a question set or a to-do-list) that should be investigated for an actual operation. Complexities like the example discussed above have not seen much exploration outside of English, especially in the context of languages with a distinguished syntax or cases which do not use Latin-like alphabets. As a more concrete example, in the Korean language, the morphology is agglutinative, the syntax is head-final, and scrambling (non-deterministic permutations of word/phrase ordering) is a common practice between native speakers. Specifically, the agglutinative property of Korean requires additional morphological analysis, which makes it challenging to identify the component of the sentence that has the strongest connection to core intent. Additionally, the head-finality characteristic introduces an additional layer of complexity, where an under-specified sentence ender incorporates a prosodic cue which requires disambiguation to comprehend the original intent (Yun, 2019; Cho et al., 2019a). Finally, considering the scrambling aspect, which frequently happens in spoken utterances, further analysis is required on top of recognizing the entities and extracting the relevant phrases. This makes it difficult for dialog managers to directly apply conventional analysis methods that have been used in Germanic or other Indo-European languages.

In this paper, we explore these aspects in the context of Ko-
Korean, a less explored, low-resource language with various non-canonical expressions. From there on, we propose a structured sentence annotation scheme which can help enrich the human-like conversation with artificial intelligence (AI). For the automation, we annotate an existing corpus and then augment the dataset to mitigate class imbalance, demonstrating the flexibility, practicality, and extensibility of the proposed methods. To further prove that the scheme is not limited to Korean, we demonstrate the methodology using English examples and supplement specific cases with Korean.

To begin with, in section 2, we present the theoretical background of this study. We then discuss the detailed procedure with examples, along with an explanation of how it fits with modern natural language understanding (NLU) systems and an evaluation framework.

2. Concept and Related Work

The foundation of this proposal is based on the studies of intent classification and slot-filling (Liu and Lane, 2016). The theoretical background builds on literature from speech act (Searle, 1976) and formal semantics (Portner, 2004). Although many task-oriented systems identify the intents as a specific action that the agent should take (Li et al., 2018), to make such intent categories generic in the aspect of sentence semantics, we hypothesized that it would be beneficial to represent them in a structured format. We believe that the closest problem we have to this task is formulating a question set (QS) or to-do-list (TDL) with multiple possible utterance permutations (Table 1) (Portner, 2004). While these concepts have stronger relations with the domain of syntactic properties, we extend on this to speech act level to reflect common patterns in a human dialog form.

| Type       | Denotations          | Discourse Component | Force     |
|------------|----------------------|---------------------|-----------|
| Declaratives| proposition (p)      | Common Ground       | Assertion |
| Interrogatives | set of propositions (q) | Question Set       | Asking    |
| Imperatives | property (p)         | To-Do List Function | Requiring |

Table 1: Clause types and their properties (Portner, 2004).

For directives which can be identified either as a question or command, conventional systems depend on slot-filling to extract the item and argument (Li et al., 2018; Haghani et al., 2018), where the number of the categories is generally restricted. Instead, for non-task-oriented dialogues, the presence of a specific domain is not assumed. Thus, we conclude that the arguments should be in natural language form rather than structured data, by, e.g., rewriting the utterances into some nominalized or simplified terms that correspond to the source text. There have been studies on paraphrasing of questions with regard to the core content (Dong et al., 2017), but little has been done on its structured formalization. Our study targets the extraction of commands, which is equivalently essential but has not been widely explored outside of the robotics domain (Matuszek et al., 2010; Matuszek et al., 2013).

The work most related to ours is likely to be semantic parsing (Berant and Liang, 2014; Su and Yan, 2017) and structured query language (SQL) generation (Zhong et al., 2017), which propose seq2seq (Sutskever et al., 2014)-like architectures to transform a natural language input into a structured format. These approaches provide the core content of the directive utterances as a sequence of queries, both utilizing it in paraphrasing (Berant and Liang, 2014) or code generation (Zhong et al., 2017). However, the proposed source sentence formats are usually canonical and mostly information-seeking, rather than being in a conversational form.

Our motivation builds on the basis that real-world utterances as input (e.g., smart speaker commands), in particular for Korean, can diverge from the expected input form, to the point that non-canonical utterances require actual comprehension on top classifying as a question or command. Moreover, as we discuss in the latter part of our work, we intend the extracted natural language terms to be reusable as building blocks for efficient paraphrasing, following the approach in Berant and Liang (2014).

Recently, in a related view, or stronger linguistic context emphasis, guidelines for identifying non-canonical natural language questions or commands have been suggested for Korean (Cho et al., 2018a). We build on top of this corpus for the initial dataset creation, and extend the dataset with additional human-annotated sentences.

3. Proposed Scheme

In this section, we describe the proposed annotation scheme along with the motivation of this work. As we discussed in the first section, our goal is to propose guidelines for annotating data which has conversational and non-canonical questions and commands as input. These forms appear a lot in everyday life, but unlike cases where the input is in a canonical form, extracting the core intent in an algorithmic manner is not straightforward. We suggest that a data-driven methodology should be introduced for this task, which can be done by creating a corpus annotated with the core content of the utterances. In this paper, all of the example sentences and the proposed structured scheme is provided in English for demonstrative purposes. Notwithstanding the actual corpus we annotate is Korean, as we demonstrate throughout the paper, the method is expected to be applicable for other languages as well.

3.1. Identifying Directives

Identifying directive utterances is a fundamental part of this work. Thus, at this moment we demonstrate more detailed on the corpus whose guideline is for distinguishing such utterances from the non-directives such as fragments and statements (Cho et al., 2018a).

For questions, interrogatives which include do support (1a) or wh- movement (1b) were primarily considered[1]. The ones in an embedded form were also counted, possibly with the predicates such as wonder (1c). Also, a large number of the declarative questions (1d) (Gunlogson, 2002) were taken into account. Since the corpus utilized in both Cho et al. (2018a) and this annotation process does not contain punctuation marks, the final work was carried out for the

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[1] Note that this does not hold for the Korean language, which is wh-in-situ. A more complicated and audio-aided identification is required in those cases, as in Cho et al. (2019b).
clear-cut questions which were selected upon the majority voting of the annotators, at the same time removing the utterances that necessitate acoustic features. For all the types of questions, the ones in rhetorical tone (1e) were removed since their discourse component usually does not perform as an effective question set (Rohde, 2006).

(1) a. did I ever tell you about how
   b. how many points you got left on your license
   c. wonder where powell and carney are
   d. you going to attack me too
   e. why we always gotta do this

For commands, the imperatives in a covert subject (2a) and with the modal verbs such as should (2b) were primarily counted. The requests in question form were also taken into account (2c,d). All the types incorporate the prohibition (2e). Conditionalized imperatives were considered as command only if the conditional junction does not negate the to-do-list as in (2f), not as in (2g). Same as the former case, the ones in rhetorical tone or usage (2h,i) were removed despite it has an imperative structure (Han, 2000; Kaufmann, 2016). All the other types of utterances except questions and commands were considered non-directive.

(2) a. well do something about it
   b. you should contact my administration
   c. why don’t you get undressed
   d. would you stay with me while I sleep a little
   e. don’t be in such a hurry
   f. let my daughter go or I’ll take you out
   g. shoot me if you can
   h. have a pleasant evening
   i. tell me that’s not the same guy

We aim to explain the type of utterances which are also counted as non-directive in other languages, even if a 1:1 mapping might not be possible through translation. We plan to publish an expansion of this work, which is specific to English sentences accompanied by sample corpora as separate work.

3.2. Extracting Intent Arguments

The following section exhibits an example annotation of intent arguments for non-canonical directives, as shown in Figure 2. We want to note again that while we describe the procedure based on simplified English sentence examples, the actual data and process had significantly higher diversity and complexity.

3.2.1. Questions

For the three major question types, which we defined as yes/no, alternative and wh- (3a-d). We applied different annotation rules. For yes/no questions, we employ an if- clause which constraints the candidate answers to yes or no (3a). For alternative questions, we employ whether - or to - a clause accompanied by a list of possible answers (3b). For wh- questions, the extraction process starts with a lexicon which corresponds with the wh- particle that is displayed (3c,d). It is notable that some alternative questions also show the format that is close to the wh-questions, with possibly between that corresponds with whether - or to - (3e).

(3) a. did I ever tell you about how
   → if the speaker told the addressee about the procedure
   b. you hungry or thirsty or both
   → whether the addressee is hungry or thirsty
   c. how many points you got
   → the number of points that the addressee got
   d. I want to know about treadstone
   → the information about treadstone
   e. you know which is hotter in hawaii or guam
   → the place that is hotter between hawaii and guam

3.2.2. Commands

Since the main intent of the commands is analogous to a to-do-list, we annotated a list in which the addressee may take action in a structured form. All of these lists start with to indeterminate (4a), with possibly not to for the prohibitions (4b). During this process, non-content-related lexicons such

3Note that here, these are not the syntactic properties, preferably the level of speech act.
as politeness strategies (e.g., please) were not considered in the extraction (4c).

(4) a. I suggest that you ask your wife
   → to ask one’s wife
   b. yeah but don’t pick me up
   → not to pick the speaker up
   c. please don’t tell my daddy
   → not to tell the speaker’s daddy

3.2.3. Phrase Structure
As discussed above, the argument of the questions are transformed into if- clause, whether- clause or the- phrase. Following this logic, the argument of these commands is rewritten to either a to-clause or not to-clause. Except for the wh-questions and some alternative questions, all the (pseudo-)paraphrased sentences have more than one predicate, which contains at least one verb.

Here, note that unlike the English examples displayed above, in the Korean samples the components that decide the phrase structure are all placed at the end of the sentence, with regard to head-finality. To be discussed in the experiment analysis, but sometimes this property seems to help the automatic inference in an autoregressive setting positively.

3.2.4. Coreference
Coreference is a critical issue when extracting the information from the text. This appears a lot in conversational utterances, in the form of pronouns or anaphora. In the annotation process, we decided to preserve such lexicons with the exception of I/we and you since they are participants in the dialog. The concepts which correspond with the two were replaced with either the speaker(s) or the addressee as shown in (3a-c) and (4b,c); and in some cases with one(self) to make it sound more natural (4a).

3.2.5. Spatial-Temporal and Subjective Factors
Unlike other question or command corpora, the proposed scheme includes content which requires an understanding of spatial (5a) and temporal (5b) dependencies. These factors are related to the coreference in the previous section, in particular, involving lexicons such as there and then. Also, the dialog being non-task-oriented results in the content unintentionally incorporating the subjective information, such as current thoughts of the speaker or the addressee. The proposed scheme does not ignore such factors in the intent argument (5c,d), to ensure that the core content is preserved.

(5) a. put your right foot there
   → to put the right foot there
   b. i don’t want to see you tomorrow
   → not to meet tomorrow
   c. any ideas about the colour
   → the idea about the colour
   d. i think you ought to know what our chances are
   → to be aware about the speaker’s chances

### Table 2: Structured annotation scheme for the Korean language

| Types          | Correspondings                   |
|----------------|----------------------------------|
| Yes/no         | whether or not -(in)ji, yepwu     |
| Alternative    | what is/to do between -lang-cwung -han/hal kes |
| Who            | person, identity sa-lam, ceng-chey |
| What           | meaning uy-mi                     |
| Where          | location, place wi-chi, cang-so   |
| When           | time, period, hour si-kan, ki-kan, si-kak |
| Why            | reason i-yu                       |
| How            | method, measure pang-pep, tay-chayk |
| Prohibitions   | Requirement: to -(-ci anh-ki)     |
| Requirements   | Requirement: to -(-hak-ki)        |
| Strong Requirements | Requirement: to -(-hak-ki)    |

4. Dataset Construction

4.1. Corpus Annotation
During the labeling and annotating process, we referred to the corpus constructed in Cho et al. (2018a), a Korean single utterance corpus for identifying directives/non-directives that contains a wide variety of non-canonical directives. The tagging of questions and commands was performed with three native speakers for the process, which eventually resulted in an inter-annotator agreement (IAA) of \( \kappa = 0.85 \) (Fleiss, 1971).

More related to this paper, in our previous work (Cho et al., 2018b), an annotation guideline for the Korean language was proposed. The dataset that was created and verified contains about 30K directive utterances and their intent arguments. We want to emphasize here that our work is not precisely an annotation task, but closer to a story generation or summarization task with lax constraints on the expected answer. Although the written natural language argument may not be identical for all the addressees, we hypothesize that there is a plausible semantic boundary for each utterance.

In the Korean language, due to the head-finality, all of the structured expressions which are used to construct the phrase structure (Section 3.2.3.) goes to the end of the intent arguments (Table 2). However, in a cross-linguistic perspective, this does not necessarily change the role of the intent arguments. For example, in the Korean sentence SENT = “mwe ha-ko siph-ni (what do you want to do)”, which has an intent argument ARG = ‘cheng-ca-ka ha-ko siph-uns kes (the thing that the addressee wants to do)’, the original SENT can be rewritten as SENT* = “ARG-i mnu-ess-ip-ni-kka”.

Here, SENT* can be interpreted as “what is ARG” or “tell me about ARG”, where the core content ARG is not necessarily damaged in the translation process. Though displayed merely for a pair of languages, this kind of rewriting...
Table 3: The final composition of the dataset.

| Intention   | Types | Original | Augmented | Sum |
|-------------|-------|----------|-----------|-----|
| Question    | Yes/no Q | 5,715    | -         | 5,715 |
|             | Alternative Q | 229     | 4,000    | 4,229 |
|             | Wh- Q    | 11,988   | 8,000     | 19,988 |
| Command     | Prohibition | 478     | 4,000     | 4,478 |
|             | Requirement | 12,302  | -         | 12,302 |
|             | Strong REQ. | 125     | 4,000     | 4,125 |
|             | Total     | 30,837   | 20,000    | 50,837 |

supports that the natural language-formatted intent argument can be robust in preserving the purpose of input directives. We claim that the constraints of our method guarantees this, as it utilizes the nominalized and structured terms. While it is difficult to prove that this holds for all possible languages or language pairs, we at least expect this assumption holds for head-first and head-final languages. Specific constraints when creating a Korean dataset are discussed in the two following sections.

4.1.1. Strong Requirements

The term strong requirement is not an official academic term, but was coined and proposed in (Cho et al., 2018) for their existence in the corpus. Simply explained, this can be described as a co-existence of a prohibitive (PH) expression and the canonical requirement (REQ), as we can see in the sentence “don’t go outside, just stay in the house”. Although the prohibitive expression comes immediately before the requirement, it does not have any guarantee that such forbidding expressions will be part of the core content in the final sentence. In these cases, simply expressing it as “just stay in the house” can be considered a more concise form better suited for argument extraction, which in turn results in the ideal final form: ‘to stay in the house’. In Korean, scrambling is common, so both [PH+REQ] and [REQ+PH] can be valid expressions. In our work, we did not encounter cases where scrambling resulted in the interpretation of the utterance to be a prohibition.

4.1.2. Speaker/Addressee Notation

We consider the notation of coreference significant in this work. A subject omission is a common pattern that can be observed in casual spoken Korean. This is different from English, where the agent and the experiencer are explicit. The intent arguments in Korean can be vague or implicit when denoting the speaker/addressee. For these reasons, to minimize the ambiguity, we created two separate corpora; one with the speaker/addressee notation, and the other without this information. In the former corpus, we classify all possible cases into one of five categories: only the speaker (hwa-ca), only the addressee (cheng-ca), both (hwa-ca-wa cheng-ca), none, and unknown. We believe this kind of information will be beneficial for both the disambiguation in the context of analysis and further research. As for the latter, while the orientation must be inferred from the context, the expression will be closer to what one would encounter in everyday life. We also believe that ambiguity, which introduces stronger context dependencies, is a crucial piece of future advancements in natural language understanding of high-context languages.

4.2. Corpus Augmentation

In the above, we used an existing dataset to annotate intent arguments for questions and command utterances. During our work, we concluded that there was an imbalance in the dataset - specifically not having enough data for some utterance types. Additionally, we concluded that the amount of parallel data was not large enough for wh-questions to be useful in real life, also taking into account that the extraction of arguments from wh-questions involves the abstraction of the wh-related concept. To mitigate the issues, we increased the dataset size by obtaining various types of sentences from intent arguments, specifically via human-aided sentence rewriting.

First, alternative questions, prohibitions, and strong requirements were needed to ensure that we had class balance for each utterance type, or at least a sufficient number for the automation. To do this, we manually wrote 400 intent arguments for each of the three types. In the process of deciding intent arguments, the topic of sentences to be generated was also carefully considered. Specifically, sentences were created at a 1:1:1:4 ratio for mail, schedule, house control, weather, and other free topics. This reflects the topic characteristics of the dataset used in Section 4.1, and its purpose is to build a corpus oriented to the future advancement of smart agents.

To enforce the second goal - wh-questions, 800 intent arguments were constructed. Topics of each sentence considered in this process are identical to the above. However, the use of wh-particles that can assist with natural transformations between wh-particles and wh-related terms was not allowed, which can occur in wh-questions. This means that the intent arguments were created in the way in which they only expose the nominalized format, and not the wh-particles, e.g., the weather of tomorrow rather than what the weather is like tomorrow. This trend was also applied when constructing additional phrases for the alternative questions above.

With 2,000 arguments constructed through the approach discussed above, we requested participants to write ten utterances per phrase as diversely as possible. The paraphrasing process resulted in a total of 20,000 argument-directive pairs, constructed from 2,000 arguments. Examples of various question and command expressions for phrases obtained in this process include, e.g.,

**Argument:** The most important concept in algebra

**Topic:** Free, Type: wh-question

→ just pick me one the most important concept in algebra
→ what do you think the core concept in algebra is
→ which concept is the most important in algebra
→ what should i remember among various concepts in algebra ··· (various versions in Korean)

The composition of the entire dataset and data created by augmenting the original data is shown in Table 3. We ensured the ratio between the utterance types is balanced so that common utterances which were not statistically well-represented in the corpus had enough training samples. Additionally, we increased the absolute count of utterances for

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4The detailed guideline is to be published as a separate article.
wh-questions where our approach can be proven most effective. As a result, the class imbalance which was problematic for at the initial point, has been partially resolved.

5. Experiments

5.1. Format

The final format of the corpus is as follows:

| Utterance # | Label | Sentence | Argument |
|-------------|-------|----------|----------|

Here, the label denotes the six utterance types as in Section 4.1., and the utterance and intent argument are in raw text form. As stated in Section 4.1.2, there are two versions of the corpus: with and without the speaker/addressee notation. Both are to be distributed on-line, but only the latter is utilized in the experiment and is available on-line currently.\(^5\)

In the experiment utilizing seq2seq approach (Sutskever et al., 2014), we aim to infer the intent argument directly rather than identifying the label, by giving sentence as an input and argument as output. Moreover, the correct inference of the intent argument is not independent with the identification of the exact utterance type. Thus, here we need both the metric related to classification and generation, respectively, which is to be discussed in the Evaluation section.

5.2. Automation

Although the volume may not be significant for the automation, we experimented with the corpus to observe how the proposed scheme works. The implementation was done for recurrent neural network (RNN)-based seq2seq with attention (Cho et al., 2014) [Luong et al., 2015] and Transformer (Vaswani et al., 2017). Due to the agglutinative nature of the Korean language, the morpheme-level tokenization was done with Mecab\(^6\) via KoNLPy (Park and Cho, 2014) python wrapper.

For the RNN seq2seq with attention, which utilized the morpheme sequence of maximum length 25, hidden layer width and dropout rate \(^7\) (Srivastava et al., 2014) was set to 256 and 0.1, respectively. The training stopped after 100,000 iterations, just before the increase of training loss took place.

For the Transformer, which adopts a much more concise model compared to the original paper (Vaswani et al., 2017), the maximum length of the morpheme sequence was set to also 25, with hidden layer width 512 and dropout rate 0.5. Additionally, multi-head attention heads were set to 4, and a total of two layers were stacked, considering the size of the training data.

5.3. Evaluation

The most controversial part of the implementation is probably the evaluation measure, as in many other translation or generation tasks. Taking into account that the paraphrasing is a monolingual translation, there exist several candidates of an answer that can be considered felicitous for an input utterance. That means the same phrase can be expressed in various similar ways, without harming the core content. Ironically, such flexibility makes up the different viewpoints between translation/paraphrasing/summarization and generation. There is no exact answer for both kind of tasks, but for the former types, at least there exists a rough boundary regarding how tolerable the output is. In our task, which is close to the former ones, the answer have to be some formatted expression. However, if we utilize only BLEU (Papineni et al., 2002) or ROUGE (Lin, 2004) as a measure, there is a chance that the diversity of the expression can bring a lousy evaluation result, although it is semantically tolerable. Also, in the corpus construction, we have explicitly set the formats for different utterance types, which requires the correct identification of the speech act and thus can largely influence the accurate inference of an argument.

In this regard, we first surveyed a proper evaluation for the automatic and quantitative analysis of the result, respectively. A part of the conclusion is that the automatic analysis of semantic similarity can be executed utilizing and modifying the recent BERT-based scoring system\(^7\) (Zhang et al., 2019). Such an approach can be adopted regardlessly the label is correctly inferred, and also well reflects the common sense inherited in the pre-trained language models. Moreover, in the case that the label is correct that some format-related tokens (e.g., the method, whether, not to) in the output overlap with the ones in the gold data, the lexical similarity can also be taken into account, probably as an extra point. It can be further represented by ROUGE compared to the gold standard.

For a fair evaluation, we determined to aggregate both kinds of evaluation values. The final score was obtained by averaging those two results, namely ROUGE-1 and BERTScore. With this, we prevent the case that the format difference caused by the wrong label leads to the wrong judgment on lexical features.

5.4. Result

The validation result is in Table 4. For clarity, we recorded both BERTScore and ROUGE-1. Note that for ROUGE-1, the character-level comparison was utilized, regardless of the tokenizer that was adopted in the training and inference.

The result shows the advantage coming from (a) adopting the Transformer (Vaswani et al., 2017), and (b) setting aside a larger volume of data for the training phase. (a) is evident here, comparing both ROUGE-1 and BERTScore, where the Transformer model has better performance with the same split model, and even with the 7:3 split model and

\(^5\)https://github.com/warnikchow/sae4k
\(^6\)https://bitbucket.org/eunjeon/mecab-ko-dic/src/master/
\(^7\)https://github.com/Tiiiger/bert_score

Table 4: Validation result with the test set.
(7) “수영을 온천에서는 하면 안됩니다” / “it is prohibited to swim in an onsen”
→ 온천에서 수영하지 않기 / not to swim in an onsen

(8) “박사 졸업과 결혼 준비비를 비교한다면 어떤게 더 저축 같아” / “which is more hell if you compare your phd with your wedding preparation”
→ 박사 졸업과 결혼 준비 비 중 더 힘들 었던 것 / the tougher process (for the addressee) between getting phd and preparing wedding

(9) “오늘 눈이 얼마나 오니” / “how much does it snow today”
→ 오늘 강설량 / the amount of today’s snowfall

(10) “몇 도 기준으로 열대야라고 해” / “from what temperature is it called a tropical night”
→ 열대야 기준 온도 / the reference temperature of tropical night

We expect the formalization as (7) can be useful for a real-life command to the social robots, and (8) meaningful if smart agents more become human-like beings, though far future. Also, as in the case of two wh-questions (9-10), the nominalization of wh-related features may help the NLU modules to efficiently get the answer of information-seeking questions that are not in a canonical form. Not all the results were nice, especially regarding some intonation-dependent utterances (11) and the most challenging ones that incorporate various OOV/loanwords (12).

(11) “목 목 대학원을 가야겠어” / “should you go to grad school”
→ 대학원 진학 하기 / to go to grad school

(12) “인터넷 파크 스팸차단했니” / “did you ban the mails from interpark”
→ 인터파크 편지 차단 여부 / if the addressee banned the tickets from interpark

Built on these preliminary results, we aim to make up a more reliable extracting system, of which the main feature is the utilization of a pre-trained language model that can compensate for the deficit of the training data and appearance of OOVs. Also, content-preserving and controllable sentence generation are to be great strategies that fit the core of our task.

6. Application

Since the proposed approach regards the formal semantics and the task domain is not specified, we expect our study to be meaningful for a general AI that talks with human beings without making the users feel isolated. Recalling that for also humans, the reaction towards the directive and the non-directive utterance differs, our two-way approach makes sense. Along with the non-task-oriented dialog, our scheme may be useful for avoiding inadvertent ignorance of the users’ will.

Beyond the application to the spoken language understanding (SLU) modules within the smart agents, our approach
can be utilized in making up the paraphrase corpus or supporting the semantic web search. Along with the boosted performance of recent text generation and reconstruction algorithms, we expect a large size of the dataset is furthermore constructed and be utilized with the real-life personal agents.

7. Conclusion
The significance of this research is to establish a creation and augmentation methodology for summarization and paraphrasing of less explored sentence units, and distribute them. In this paper, only dataset acquisition and application for directive utterances are presented, but the implementation of automatic question/command generation and sentence similarity test using this concept is also possible. Besides, we have shown a baseline system that automatically extracts intent arguments from the non-canonical Korean question/command by utilizing the constructed dataset and some up-to-date architectures, implying that the methodology to be practically meaningful. Our next work plans to extend this more typologically by showing that the annotation/generation scheme is applicable to other languages. We hope that research on automatic keyphrase/argument extraction is to be active among Korean natural language processing (NLP), and other low-resourced languages, via released annotation scheme and datasets.

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