Is a 204 cm Man Tall or Small ?
Acquisition of Numerical Common Sense from the Web
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Abstract
This paper presents novel methods for modeling numerical common sense: the ability to infer whether a given number (e.g., three billion) is large, small, or normal for a given context (e.g., number of people facing a water shortage). We first discuss the necessity of numerical common sense in solving textual entailment problems. We explore two approaches for acquiring numerical common sense. Both approaches start with extracting numerical expressions and their context from the Web. One approach estimates the distribution of numbers co-occurring within a context and examines whether a given value is large, small, or normal, based on the distribution. Another approach utilizes textual patterns with which speakers explicitly expresses their judgment about the value of a numerical expression. Experimental results demonstrate the effectiveness of both approaches.

1 Introduction
Textual entailment recognition (RTE) involves a wide range of semantic inferences to determine whether the meaning of a hypothesis sentence (h) can be inferred from another text (t) (Dagan et al., 2006). Although several evaluation campaigns (e.g., PASCAL/TAC RTE challenges) have made significant progress, the RTE community recognizes the necessity of a deeper understanding of the core phenomena involved in textual inference. Such recognition comes from the ideas that crucial progress may derive from decomposing the complex RTE task into basic phenomena and from solving each basic phenomenon separately (Bentivogli et al., 2010; Sammons et al., 2010; Cabrio and Magnini, 2011; Toledo et al., 2012).

Given this background, we focus on solving one of the basic phenomena in RTE: semantic inference related to numerical expressions. The specific problem we address is acquisition of numerical common sense. For example,

(1) t : Before long, 3b people will face a water shortage in the world.

h : Before long, a serious water shortage will occur in the world.

Although recognizing the entailment relation between t and h is frustratingly difficult, we assume this inference is decomposable into three phases:

3b people face a water shortage.

⇔ 3,000,000,000 people face a water shortage.

|= many people face a water shortage.

|= a serious water shortage.

In the first phase, it is necessary to recognize 3b as a numerical expression and to resolve the expression 3b into the exact amount 3,000,000,000. The second phase is much more difficult because we need subjective but common-sense knowledge that 3,000,000,000 people is a large number.

In this paper, we address the first and second phases of inference as an initial step towards semantic processing with numerical expressions. The contributions of this paper are four-fold.

1. We examine instances in existing RTE corpora, categorize them into groups in terms of the necessary semantic inferences, and discuss the impact of this study for solving RTE problems with numerical expressions.

2. We describe a method of normalizing numerical expressions referring to the same amount in text into a unified semantic representation.

3. We present approaches for aggregating numerical common sense from examples of numerical expressions and for judging whether a given amount is large, small, or normal.
4. We demonstrate the effectiveness of this approach, reporting experimental results and analyses in detail. Although it would be ideal to evaluate the impact of this study on the overall RTE task, we evaluate each phase separately. We do this because the existing RTE data sets tend to exhibit very diverse linguistic phenomena, and it is difficult to employ such data for evaluating the real impact of this study.

2 Related work

Surprisingly, NLP research has paid little attention to semantic processing of numerical expressions. This is evident when we compare with temporal expressions, for which corpora (e.g., ACE-2005\(^1\), TimeBank\(^2\)) were developed with annotation schemes (e.g., TIMEX\(^3\), TimeML\(^4\)).

Several studies deal with numerical expressions in the context of information extraction (Bakalov et al., 2011), information retrieval (Fontoura et al., 2006; Yoshida et al., 2010), and question answering (Moriceau, 2006). Numbers such as product prices and weights have been common targets of information extraction. Fontoura et al. (2006) and Yoshida et al. (2010) presented algorithms and data structures that allow number-range queries for searching documents. However, these studies do not interpret the quantity (e.g., 3,000,000,000) of a numerical expression (e.g., 3\(b\) people), but rather treat numerical expressions as strings.

Banerjee et al. (2009) focused on quantity consensus queries, in which there is uncertainty about the quantity (e.g., weight airbus A380 pounds). Given a query, their approach retrieves documents relevant to the query and identifies the quantities of numerical expressions in the retrieved documents. They also proposed methods for enumerating and ranking the candidates for the consensus quantity intervals. Even though our study shares a similar spirit (modeling of consensus for quantities) with Banerjee et al. (2009), their goal is different: to determine ground-truth values for queries.

In question answering, to help “sanity check” answers with numerical values that were way out of common-sense ranges, IBM’s PIQUANT (Prager et al., 2003; Chu-Carroll et al., 2003) used information in Cyc (Lenat, 1995). For example, their question-answering system rejects 200 miles as a candidate answer for the height of Mt. Everest, since Cyc knows mountains are between 1,000 and 30,000 ft. high. They also consider the problem of variations in the precision of numbers (e.g., 5 million, 5.1 million, 5,200,390) and unit conversions (e.g., square kilometers and acres).

Some recent studies delve deeper into the semantic interpretation of numerical expressions. Aramaki et al. (2007) focused on the physical size of an entity to predict the semantic relation between entities. For example, knowing that a book has a physical size of 20 cm \(\times\) 25 cm and that a library has a size of 10 m \(\times\) 10 m, we can estimate that a library contains a book (content-container relation). Their method acquires knowledge about entity size from the Web (by issuing queries like “book (*cm x *cm)”), and integrates the knowledge as features for the classification of relations.

Davidov and Rappoport (2010) presented a method for the extraction from the Web and approximation of numerical object attributes such as height and weight. Given an object-attribute pair, the study expands the object into a set of comparable objects and then approximates the numerical values even when no exact value can be found in a text. Aramaki et al. (2007) and Davidov and Rappoport (2010) rely on hand-crafted patterns (e.g., “Object is * [unit] tall”), focusing on a specific set of numerical attributes (e.g., height, weight, size). In contrast, this study can handle any kind of target and situation that is quantified by numbers, e.g., number of people facing a water shortage.

Recently, the RTE community has started to pay some attention to the appropriate processing of numerical expressions. Iftene (2010) presented an approach for matching numerical ranges expressed by a set of phrases (e.g., more than and at least). Tsuboi et al. (2011) designed hand-crafted rules for matching intervals expressed by temporal expressions. However, these studies do not necessarily focus on semantic processing of numerical expressions; thus, these studies do not normalize units of numerical expressions nor make inferences with numerical common sense.

Sammons et al. (2010) reported that most systems submitted to RTE-5 failed on examples.

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\(^1\)http://www.itl.nist.gov/iad/mig/tests/ace/ace05/  
\(^2\)http://www.timeml.org/site/timebank/timebank.html  
\(^3\)http://timex2.mitre.org/  
\(^4\)http://timeml.org/site/index.html
where numeric reasoning was necessary. They argued the importance of aligning numerical quantities and performing numerical reasoning in RTE. LoBue and Yates (2011) identified 20 categories of common-sense knowledge that are prevalent in RTE. One of the categories comprises arithmetic knowledge (including computations, comparisons, and rounding). They concluded that many kinds of the common-sense knowledge have received scarce attention from researchers even though the knowledge is essential to RTE. These studies provided a closer look at the phenomena involved in RTE, but they did not propose a solution for handling numerical expressions.

3 Investigation of textual-entailment pairs with numerical expressions

In this section, we investigate textual entailment (TE) pairs in existing corpora in order to study the core phenomena that establish an entailment relation. We used two Japanese TE corpora: RITE (Shima et al., 2011) and Odani et al. (2008). RITE is an evaluation workshop of textual entailment organized by NTCIR-9, and it targets the English, Japanese, and Chinese languages. We used the Japanese portions of the development and training data. Odani et al. (2008) is another Japanese corpus that was manually created. The total numbers of text-hypothesis (T-H) pairs are 1,880 (RITE) and 2,471 (Odani).

We manually selected sentence pairs in which one or both of the sentences contained a numerical expression. Here, we define the term numerical expression as an expression containing a number or quantity represented by a numeral and a unit. For example, 3 kilometers is a numerical expression with the numeral 3 and the unit kilometer. Note that intensity of 4 is not a numerical expression because intensity is not a unit.

We obtained 371 pairs from the 4,351 T-H pairs. We determined the inferences needed to prove entailment or contradiction of the hypotheses, and classified the 371 pairs into 11 categories. Note that we ignored T-H pairs in which numerical expressions were unnecessary to prove the entailment relation (e.g., Socrates was sentenced to death by 500 jury members and Socrates was sentenced to death). Out of 371 pairs, we identified 114 pairs in which numerical expressions played a central role in the entailment relation.

Table 1 summarizes the categories of TE phenomena we found in the data set. The largest category is numerical matching (32 pairs). We can infer an entailment relation in this category by aligning two numerical expressions, e.g., 2.2 million = over 800 thousand. This is the most fundamental task in numerical reasoning, interpreting the amount (number, unit, and range) in a numerical expression. We address this task in Section 4.1. The second largest category requires common sense about numerical amounts. In order to recognize textual entailment of pairs in this category, we need common-sense knowledge about humans’ subjective judgment of numbers. We consider this problem in Section 5.

To summarize, this study covers 37.9% of the instances in Table 1, focusing on the first and second categories. Due to space limitations, we omit the explanations for the other phenomena, which require such things as lexical knowledge, arithmetic operations, and counting. The coverage of this study might seem small, but it is difficult to handle varied phenomena with a unified approach. We believe that this study forms the basis for investigating other phenomena of numerical expressions in the future.

4 Collecting numerical expressions from the Web

In this paper, we explore two approaches to acquiring numerical common sense. Both approaches start with extracting numerical expressions and their context from the Web. We define a context as the verb and its arguments that appear around a numerical expression.

For instance, the context of 3b people in the sentence 3b people face a water shortage is ‘face’ and “water shortage.” In order to extract and aggregate numerical expressions in various documents, we converted the numerical expressions into semantic representations (to be described in Section 4.1), and extracted their context (to be described in Section 4.2).

The first approach for acquiring numerical common sense estimates the distribution of numbers that co-occur within a context, and examines whether a given value is large, small, or normal based on that distribution (to be described in Section 5.1). The second approach utilizes textual patterns with which speakers explicitly expresses their judgment about the value of a numerical ex-
Numerical matching
Aligning numerical expressions in T and H, considering differences in unit, range, etc.
- It is said that there are about 2.2 million alcoholics in the whole country.
- It is estimated that there are over 800 thousand people who are alcoholics.

Numerical common sense
Inferring by interpreting the numerical amount (large or small).
- In the middle of the 21st century, 7 billion people, corresponding to 70% of the global population, will face a water shortage.
- It is concerning that a serious water shortage will spread around the world in the near future.

Lexical knowledge
Inferring by using numerical aspects of word meanings.
- Mr. and Ms. Sato celebrated their 25th wedding anniversary.
- Mr. and Ms. Sato celebrated their silver wedding anniversary.

Arithmetic
Arithmetic operations including addition and subtraction.
- The number of 2,000-yen bills in circulation has increased to 490 million, in contrast with 440 million 5,000-yen bills.
- The number of 2,000-yen bills in circulation exceeds the number of 5,000-yen bills by 10 million bills.

Temporal expression
Temporal expression consists of three fields: the value or range, as in Table 1.

| Category              | Definition                                                                 | Example                                                                                     | #     |
|-----------------------|---------------------------------------------------------------------------|---------------------------------------------------------------------------------------------|-------|
| Numerical matching    | Aligning numerical expressions in T and H, considering differences in unit, range, etc. | It is said that there are about 2.2 million alcoholics in the whole country.                | 32    |
|                       |                                                                           | It is estimated that there are over 800 thousand people who are alcoholics.                  |       |
| Numerical common sense| Inferring by interpreting the numerical amount (large or small).           | In the middle of the 21st century, 7 billion people, corresponding to 70% of the global population, will face a water shortage. | 12    |
|                       |                                                                           | It is concerning that a serious water shortage will spread around the world in the near future. |       |
| Lexical knowledge     | Inferring by using numerical aspects of word meanings.                     | Mr. and Ms. Sato celebrated their 25th wedding anniversary.                                 | 12    |
|                       |                                                                           | Mr. and Ms. Sato celebrated their silver wedding anniversary.                               |       |
| Arithmetic            | Arithmetic operations including addition and subtraction.                 |                                                                                             |       |
|                       |                                                                           |                                                                                             |       |
| Temporal expression   | Temporal expression consists of three fields: the value or range, as in Table 1. |                                                                                             |       |

In this study, we acquired numerical common sense from a collection of 8 billion sentences in 100 million Japanese Web pages (Shinzato et al., 2012). For this reason, we originally designed text patterns specialized for Japanese dependency trees. For the sake of the readers’ understanding, this paper uses examples with English translations for explaining language-independent concepts, and both Japanese and English translations for explaining language-dependent concepts.

4.1 Extracting and normalizing numerical expressions

The first step for collecting numerical expressions is to recognize when a numerical expression is mentioned and then to normalize it into a semantic representation. This is the most fundamental step in numerical reasoning and has a number of applications. For example, this step handles cases of numerical matching, as in Table 1.

The semantic representation of a numerical expression consists of three fields: the value or range of the real number(s)\(^5\), the unit (a string), and the optional modifiers. Table 2 shows some examples of numerical expressions and their semantic representations. During normalization, we identified spelling variants (e.g., kilometer and km) and transformed auxiliary units into their corresponding canonical units (e.g., 2 tons and 2,000 kg to 2,000,000 grams). When a numerical expression is accompanied by a modifier such as over, about, or more than, we updated the value and modifier fields appropriately.

3 Internally, all values are represented by ranges (e.g., 75 is represented by the range [75, 75]).
We developed an extractor and a normalizer for Japanese numerical expressions⁶. We will outline the algorithm used in the normalizer with an example sentence: “Roughly three thousand kilograms of meats have been provided every day.”

1. Find numbers in the text by using regular expressions and convert the non-Arabic numbers into their corresponding Arabic numbers. For example, we find *three thousand⁷* and represent it as 3,000.

2. Check whether the words that precede or follow the number are units that are registered in the dictionary. Transform any auxiliary units. In the example, we find that *kilograms⁸* is a unit. We multiply the value 3,000 by 1,000, and obtain the value 3,000,000 with the unit *g*.

3. Check whether the words that precede or follow the number have a modifier that is registered in the dictionary. Update the value and modifier fields if necessary. In the example, we find *roughly* and set *about* in the modifier field.

We used a dictionary⁹ to perform procedures 2 and 3 (Table 3). If the words that precede or follow an extracted number match an entry in the dictionary, we change the semantic representation as described in the operation.

The modifiers ‘large’ and ‘small’ require elaboration because the method in Section 5.2 relies heavily on these modifiers. We activated the modifier ‘large’ when a numerical expression occurred with the Japanese word *mo*, which roughly corresponds to *as many as*, *as large as*, or *as heavy as* in English¹⁰. Similarly, we activated the modifier ‘small’ when a numerical expression occurred with the word *shika*, which roughly corresponds to *as little as*, *as small as*, or *as light as¹¹*. These modifiers are important for this study, reflecting the writer’s judgment about the amount.

⁶The software is available at http://www.cl.ecei.tohoku.ac.jp/~katsuma/software/normalizeNumexp/
⁷In Japanese 3,000 is denoted by the Chinese symbols “三千”.
⁸We write kilograms as “キログラム” in Japanese.
⁹The dictionary is bundled with the tool. See Footnote 6.
¹⁰In Japanese, we can use the word *mo* with a numerical expression to state that the amount is ‘large’ regardless of how large it is (e.g., large, big, many, heavy).
¹¹Similarly, we can use the word *shika* with any adjective.

![Figure 1: Example of context extraction](image)

### 4.2 Extraction of context

The next step in acquiring numerical common sense is to capture the context of numerical expressions. Later, we will aggregate numbers that share the same context (see Section 5). The context of a numerical expression should provide sufficient information to determine what it measures. For example, given the sentence, “He gave $300 to a friend at the bank,” it would be better if we could generalize the context to *someone gives money to a friend* for the numerical expression $300. However, it is a nontrivial task to design an appropriate representation of varying contexts. For this reason, we employ a simple rule to capture the context of numerical expressions: we represent the context with the verb that governs the numerical expression and its typed arguments.

Figure 1 illustrates the procedure for extracting the context of a numerical expression¹². The component in Section 4.1 recognizes $300 as a numerical expression, then normalizes it into a semantic representation. Because the numerical expression is a dependent of the verb *gave*, we extract the verb and its arguments (except for the numerical expression itself) as the context. After removing inflections and function words from the arguments, we obtain the context representation of Figure 1.

### 5 Acquiring numerical common sense

In this section, we present two approaches for acquiring numerical common sense from a collection of numerical expressions and their contexts. Both approaches start with collecting the numbers (in semantic representation) and contexts of numerical expressions from a large number of sentences (Shinzato et al., 2012), and storing them

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¹²The English dependency tree might look peculiar because it is translated from the Japanese dependency tree.
in a database. When a context and a value are given for a prediction (hereinafter called the query context and query value, respectively), these approaches judge whether the query value is large, small, or normal.

5.1 Distribution-based approach

Given a query context and query value, this approach retrieves numbers associated with the query context and draws a distribution of normalized numbers. This approach considers the distribution estimated for the query context and determines if the value is within the top 5 percent (large), within the bottom 5 percent (small), or is located in between these regions (normal).

The underlying assumption of this approach is that the real distribution of a query (e.g., money given to a friend) can be approximated by the distribution of numbers co-occurring with the context (e.g., give and friend) on the Web. However, the context space generated in Section 4.2 may be too sparse to find numbers in the database, especially when a query context is fine-grained. Therefore, when no item is retrieved for the query context, we employ a backoff strategy to drop some of the uninformative elements in the query context: elements are dropped from the context based on the type of argument, in this order: he (prep_to), kara (prep_from), ha (nsubj), yori (prep_from), made (prep_to), nite (prep_at), de (prep_at, prep_by), ni (prep_at), wo (dobj), ga (nsubj), and verb.

5.2 Clue-based approach

This approach utilizes textual clues with which a speaker explicitly expresses his or her judgment about the amount of a numerical expression. We utilize large and small modifiers (described in Section 4.1), which correspond to textual clues mo (as many as, as large as) and shika (only, as few as), respectively, for detecting humans’ judgments. For example, we can guess that $300 is large if we find an evidential sentence13. He gave as much as $100 to a friend.

Similarly to the distribution-based approach, this approach retrieves numbers associated with the query context. This approach computes the largeness $L(x)$ of a value $x$:

$$L(x) = \frac{p_l(x)}{p_s(x) + p_l(x)},$$

(1)

$$p_l(x) = \frac{|\{r | r_v < x \land r_m \ni large\}|}{|\{r | r_m \ni large\}|},$$

(2)

$$p_s(x) = \frac{|\{r | r_v > x \land r_m \ni small\}|}{|\{r | r_m \ni small\}|}.$$  

(3)

In these equations, $r$ denotes a retrieved item for the query context, and $r_v$ and $r_m$ represent the normalized value and modifier flags, respectively, of the item $r$. The numerator of Equation 2 counts the number of numerical expressions that support the judgment that $x$ is large14, and its denominator counts the total number of numerical expressions with large as a modifier. Therefore, $p_l(x)$ computes the ratio of times there is textual evidence that says that $x$ is large, to the total number of times there is evidence with large as a modifier. In an analogous way, $p_s(x)$ is defined to be the ratio for evidence that says $x$ is small. Hence, $L(x)$ approaches 1 if everyone on the Web claims that $x$ is large, and approaches 0 if everyone claims that $x$ is small. This approach predicts large if $L(x) > 0.95$, small if $L(x) < 0.05$, and normal otherwise.

6 Experiments

6.1 Normalizing numerical expressions

We evaluated the method that we described in Section 4.1 for extracting and normalizing numerical expressions. In order to prepare a gold-standard data set, we obtained 1,041 sentences by randomly sampling about 1% of the sentences containing numbers (Arabic digits and/or Chinese numerical characters) in a Japanese Web corpus (100 million pages) (Shinzato et al., 2012). For every numerical expression in these sentences, we manually determined a tuple of the normalized value, unit, and modifier. Here, non-numerical expressions such as temporal expressions, telephone numbers, and postal addresses, which were very common, were beyond the scope of the project15. We obtained 329 numerical expressions from the 1,041 sentences.

We evaluated the correctness of the extraction and normalization by measuring the precision and

13. Although the sentence states a judgment about $100, we can infer that $300 is also large because $300 > $100.

14. This corresponds to the events where we find an evidence expression “as many as $r_v$,” where $r_v < x$.

15. If a tuple was extracted from a non-numerical expression, we regarded this as a false positive.
recall using the gold-standard data set\textsuperscript{16}. Our method performed with a precision of 0.78 and a recall of 0.92. Most of the false negatives were caused by the incompleteness of the unit dictionary. For example, the proposed method could not identify \textit{1Ghz} as a numerical expression because the unit dictionary did not register \textit{Ghz} but \textit{GHz}. It is trivial to improve the recall of the method by enriching the unit dictionary.

The major cause of false positives was the semantic ambiguity of expressions. For example, the proposed method identified \textit{Seven Hills} as a numerical expression although it denotes a location name. In order to reduce false positives, it may be necessary to utilize broader contexts when locating numerical expressions; this could be done by using, for example, a named entity recognizer. This is the next step to pursue in future work.

However, these errors do not have a large effect on the estimation of the distribution of the numerical values that occur with specific named entities and idiomatic phrases. Moreover, as explained in Section 5, we draw distributions for fine-grained contexts of numerical expressions. For these reasons, we think that the current performance is sufficient for acquiring numerical common sense.

6.2 Acquisition of numerical common sense

6.2.1 Preparing an evaluation set

We built a gold-standard data set for numerical common sense. We applied the method in Section 4.1 to sentences sampled at random from the Japanese Web corpus (Shinzato et al., 2012), and we extracted 2,000 numerical expressions. We asked three human judges to annotate every numerical expression with one of six labels, \textit{small}, \textit{relatively small}, \textit{normal}, \textit{relatively large}, \textit{large}, and \textit{unsure}. The label \textit{relatively small} could be applied to a numerical expression when the judge felt that the amount was rather small (below the normal) but hesitated to label it \textit{small}. The label \textit{relatively large} was defined analogously. We gave the following criteria for labeling an item as \textit{unsure}: when the judgment was highly dependent on the context; when the sentence was incomprehensible; and when it was a non-numerical expressions (false positives of the method are discussed in Section 4.1).

Table 4 reports the inter-annotator agreement.

\textbf{Table 4: Inter-annotator agreement}

| Agreement     | \# expressions |
|---------------|----------------|
| 3 annotators  | 733 (36.7%)    |
| 2 annotators  | 963 (48.2%)    |
| no agreement  | 302 (15.1%)    |
| Total         | 2000 (100.0%)  |

For the evaluation of numerical expressions in the data set, we used those for which at least two annotators assigned the same label. After removing the \textit{unsure} instances, we obtained 640 numerical expressions (20 \textit{small}, 35 \textit{relatively small}, 152 \textit{normal}, 263 \textit{relatively large}, and 170 \textit{large}) as the evaluation set.

6.2.2 Results

The proposed method extracted about 23 million pairs of numerical expressions and their context from the corpus (with 100 million Web pages). About 15\% of the extracted pairs were accompanied by either a large or small modifier. Figure 2 depicts the distributions of the context human’s height produced by the distribution-based and clue-based approaches. These distributions are quite reasonable as common-sense knowledge: we can interpret that numbers under 150 cm are perceived as small and those above 180 cm as large.

We measured the correctness of the proposed methods on the gold-standard data. For this evaluation, we employed two criteria for correctness: strict and lenient. With the strict criterion, the method must predict a label identical to that in the gold-standard. With the lenient criterion, the method was also allowed to predict either \textit{large/small} or \textit{normal} when the gold-standard label was \textit{relatively large/small}.

Table 5 reports the precision (P), recall (R), F1 (F1), and accuracy (Acc) of the proposed methods.

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\textsuperscript{16}All fields (value, unit, modifier) of the extracted tuple must match the gold-standard data set.
| No. | System | Gold | Sentence | Remark |
|-----|--------|------|----------|--------|
| 1   | small  | small| I think that three men can create such a great thing in the world. | Correct |
| 2   | normal | normal| I have two cats. | Correct |
| 3   | large  | large| It’s above 32 centigrade. | Correct |
| 4   | large  | large| I earned 10 million yen from horse racing. | Correct |
| 5   | small  | normal| There are 2 reasons. | Difficulty in judging small. Since a few people say, “There are only 2 reasons,” our approach predicted a small label. |
| 6   | small  | large| Ten or more people came, and my eight-mat room was packed. | Difficulty in modeling the context because this sentence omits the locational argument for the verb came. We should extract the context as the number of people who came to my eight-mat room instead of the number of people who came. |
| 7   | small  | normal| I have two friends who have broken up with their boyfriends recently. | Difficulty in modeling the context. We should extract context as the number of friends who have broken up with their boyfriends recently instead of the number of friends. |
| 8   | small  | large| Lack of knowledge. We extract the context as the number of heads of a turtle, but no corresponding information was found on the Web. |

Table 6: Output example and error analysis. We present translations of the sentences, which were originally in Japanese.

| Approach | Label | P    | R    | F1   | Acc  |
|----------|-------|------|------|------|------|
| Distribution | large | 0.892 | 0.498 | 0.695 | 0.760 |
|           | normal | 0.793 | 0.935 | 0.844 |      |
|           | small  | 0.273 | 0.250 | 0.262 |      |
| Distribution | large | 0.861 | 0.365 | 0.613 | 0.590 |
|           | normal | 0.529 | 0.908 | 0.719 |      |
|           | small  | 0.222 | 0.100 | 0.161 |      |
| Clue     | large  | 0.923 | 0.778 | 0.854 | 0.770 |
|           | normal | 0.814 | 0.765 | 0.790 |      |
|           | small  | 0.228 | 0.700 | 0.464 |      |
| Clue     | large  | 0.896 | 0.659 | 0.778 | 0.620 |
|           | normal | 0.593 | 0.586 | 0.590 |      |
|           | small  | 0.164 | 0.550 | 0.357 |      |

Table 5: Precision (P), recall (R), F1 score (F1), and accuracy (Acc) of the acquisition of numerical common sense.

Labels with the suffix ‘+’ correspond to the lenient criterion. The clue-based approach achieved 0.851 F1 (for large), 0.790 F1 (for normal), and 0.464 (for small) with the lenient criterion. The performance is surprisingly good, considering the subjective nature of this task.

The clue-based approach was slightly better than the distribution-based approach. In particular, the clue-based approach is good at predicting large and small labels, whereas the distribution-based approach is good at predicting normal labels. We found some targets for which the distribution on the Web is skewed from the ‘real’ distribution. For example, let us consider the distribution of the context "the amount of money that a person wins in a lottery". We can find a number of sentences like if you won the 10-million-dollar lottery, .... In other words, people talk about a large amount of money even if they did not win any money at all. In order to remedy this problem, we may need to enrich the context representation by introducing, for example, the factuality of an event.

6.2.3 Discussion

Table 6 shows some examples of predictions from the clue-based approach. Because of space limitations, we mention only the false instances of this approach.

The clue-based approach tends to predict small even if the gold-standard label is normal. About half of the errors of the clue-based approach were of this type; this is why the precision for small and the recall for normal are low. The cause of this error is exemplified by the sentence, “there are two reasons.” Human judges label normal to the numerical expression two reasons, but the method predicts small. This is because a few people say there are only two reasons, but no one says there are as many as two reasons. In order to handle these cases, we may need to incorporate the distribution information with the clue-based approach.

We found a number of examples for which modeling the context is difficult. Our approach represents the context of a numerical expression with the verb that governs the numerical expression and its typed arguments. However, this approach sometimes misses important information, especially when an argument of the verb is omitted (Example 6). The approach also suffers from the relative clause in Example 7, which conveys an essential context of the number. These are similar to the scope-ambiguity problem such as encoun-

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tered with negation and quantification; it is difficult to model the scope when a numerical expression refers to a situation.

Furthermore, we encountered some false examples even when we were able to precisely model the context. In Example 8, the proposed method was unable to predict the label correctly because no corresponding information was found on the Web. The proposed method might more easily predict a label if we could generalize the word turtle as animal. It may be worth considering using language resources (e.g., WordNet) to generalize the context.

7 Conclusions

We proposed novel approaches for acquiring numerical common sense from a collection of texts. The approaches collect numerical expressions and their contexts from the Web, and acquire numerical common sense by considering the distributions of normalized numbers and textual clues such as mo (as many as) and shika (only, as few as). The experimental results showed that our approaches can successfully judge whether a given amount is large, small, or normal. The implementations and data sets used in this study are available on the Web17. We believe that acquisition of numerical common sense is an important step towards a deeper understanding of inferences with numbers.

There are three important future directions for this research. One is to explore a more sophisticated approach for precisely modeling the contexts of numbers. Because we confirmed in this paper that these two approaches have different characteristics, it would be interesting to incorporate textual clues into the distribution-based approach by using, for example, machine learning techniques. Finally, we are planning to address the ‘third phase’ of the example explained in Section 1: associating many people face a water shortage with a serious water shortage.

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