Creating an Annotated Corpus for the Analysis of Causal Relations

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Abstract— **In this paper, we report the results of our investigation of the characteristics of in-text causal relations. First, we designed causal relation tags. With our designed tag set, three annotators annotated 750 newspaper articles. Then, using the annotated corpus, we investigated the causal relation instances from three viewpoints: (1) cue phrase markers, (2) part-of-speech information, and (3) position in sentences. Our quantitative study shows that causal relation instances are represented in the several types of linguistic expressions.**

I. Introduction

For many applications of natural language techniques such as question-answering systems and dialogue systems, it is one central issue to acquire knowledge about causal relations. In recent researches, some automatic acquisition methods for causal knowledge have been proposed (ex. [2], [3], [7]). They have used as knowledge resources a large amount of electric text documents: newspaper articles and Web documents.

However, while the acquisition methods have been improved by some researches, it is still unclear about the characteristics of presence of in-text causal relations: we have no empirical study about what amount of causal relation instances exist in text and where in text causal relation instances tend to appear.

In this research, aiming to resolve the above issues, we created a corpus annotated with causal relation information which is useful for investigating how many causal relation instances are present and where these instances are present in the text. Given some Japanese newspaper articles, we added several types of causal relation tags to the text segments (typically words).

Causal relation instances appear in several different ways. Some appear with a clause marked by cue phrase markers as in (1a). Some have no explicit cues for causal relation (1b). Some others are marked by a noun phrase (1c).

(1)
a. 大雨-が 降っ-た ため、 川-が 増水し-た。
heavy rain-NOM fall-PAST because river-NOM rise-PAST
b. 大雨-が 降り、 川-が 増水し-た。
heavy rain-NOM fall-PAST river-NOM rise-PAST
c. 大雨-で 川-が 増水し-た。
heavy rain-because of river-NOM rise-PAST

In this paper, we will report the details of the design of our causal relation tags. We will then describe the annotation workflow. Using the annotated corpus, we will then discuss the results for the analysis of characteristics of in-text causal relations. Hereafter, through in this paper, we denote the former (cause) part of event as e_1 and the latter (effect) part of event as e_2, where e_1 and e_2 are held in causal relation.

II. Annotated information for causal relations

A. Causal relation tags

We used three tags *head*, *mod*, and *causal_rel* to represent the basic causal relation information. We regard an event as consisting of a head element and some modifiers. The tags *head* and *mod* are used to represent an event which forms one part of the two events held in causal relation. The tag *causal_rel* is used to represent a causal relation between two annotated events.

Figure 1 shows an example of attaching causal relation information to the sentence (2a), in which a causal relation is held between two events indicated (2b) and (2c).

(2)
a. そして、遠方-からの 観光客-が
and far-from sightseer-NOM
ＧＷ-に 入って 増える。
Golden week holidays come increase
b. e_1= ＧＷに入る
Golden week holidays come.
c. e_2= 遠方からの観光客が増える
The sightseers from far increase.

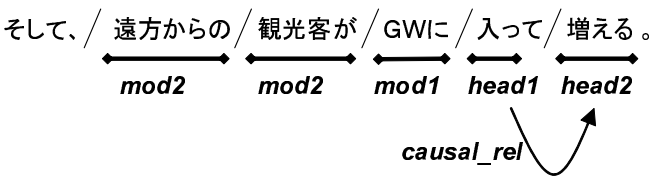

Fig. 1. An example of attaching the causal relation information

The annotation process is executed as follows. First, each sentence in the text is split to some *bunsetsu*-phrase chunks as shown in Figure 1. The *bunsetsu*-phrase is one of the fundamental units in Japanese, which consists of a content word (noun, verb, adjective, etc.) accompanied by some function words (particles, auxiliaries, etc.). Second, for each *bunsetsu*-phrase, an annotator finds the segment which represents a head element of an event, and he/she adds the *head* tag to the segment (see also *head1* and *head2* in Figure 1). If the event has any other elements in addition to head element, the annotator also adds the *mod* tags to the segments representing modifiers to the head element (*m*od1 and *m*od2 in Figure 1). The elements marked with any tags which have a common suffix number are constituents of the same event: that is, the elements marked with *head1* and *mod1* tags are constituents of e_1 and the elements marked with *head2* and *mod2* tags are constituents of e_2. Finally, the annotator adds the *causal_rel* tag between two *head* tags as link information which indicates that the corresponding two events are held in a causal relation.

When there are any cue phrase markers such as "ため (because) " in the sentence, the annotator also adds the *marker* tag to their segments.

B. Annotation criteria

To judge whether any two events represented in text are held in causal relation or not, we conducted a linguistic test using some linguistic templates.

The linguistic test is a method for judging whether a target linguistic expression, normally a sentence or a clause, conforms to a given set of rules. In our cases, a target expression is a set of text segments representing as a whole an event which could be one of the arguments in a causal relation. The rules are realized as linguistic templates which are linguistic expressions including several slots.

『e_1』(という) 状態になれば、それに伴い、
≪adv≫『e_2』(という) 状態になる。

(『e_2』 ≪adv≫ happened as a result of
the fact that『e_1』happened.)

≪adv≫: = しばしば ("*sibasiba*", often)
| 大抵 ("*taitei*", usually)
| 常に ("*tsuneni*", always)
| φ

Fig. 2. An example of linguistic templates

In practice, a linguistic test is usually applied using the following steps:

1) Preparing the templates.
2) Embedding the target expression in the slots of the template to form a *candidate* sentence.
3) If the candidate sentence is syntactically and semantically correct, the target expression is judged to conform to the rules. If the candidate sentence is incorrect, the target is judged non-conforming.

Figure 2 shows an example of linguistic templates for causal relations. The square brackets indicate the slots and the symbol ≪adv≫ is replaced by one of four words しばしば, 大抵, 常に or φ . Here, the word φ is a quasi word introduced in order to simplify the explanation. Replacing ≪adv≫ by φ is equal to deleting ≪adv≫ from the linguistic template.

In this work, we prepared eighteen linguistic templates shown in Table I. We embed the two sets of text segments representing events in the slots of the templates to form candidate sentences. Then, if a candidate sentence is correct, the causal relation is supposed to hold between two events. If the candidate sentence is incorrect, this template is rejected, and another template is tried. If all templates are rejected, then we resort to subjective judgements. If an annotator recognizes a causal relation between two events by pure subjective judgements, he/she is allowed to annotate these text segments to get information for further refining and improving the current templates [1].

In Japanese, three adverbs in the linguistic templates

[1]Actually, we eliminated all the tags annotated just by the subjective judgements from the evaluation described in Section V and Section VI.

TABLE I

THE LINGUISTIC TEMPLATES

id	the linguistic templates
1	『e_1』(という) ことが起こるその結果として、≪adv≫『e_2』(という) ことが起こる。
2	『e_1』(という) 状態になれば、それに伴い、≪adv≫『e_2』(という) 状態になる。
3	『e_1』(という) 状態になれば、それに伴い、≪adv≫『e_2』(という) 状況になる。
4	『e_1』(という) 状態であると、≪adv≫ 『e_2』(という) 状態である。
5	『e_1』(という) 状態であると、≪adv≫ 『e_2』(という) 状況である。
6	『e_1』(という) ことをする結果、『e_2』(という) ことが ≪adv≫ 起こる。
7	『e_1』(という) ことをすると、 ≪adv≫ 『e_2』(という) 状態になる。
8	『e_1』(という) ことをすると、 ≪adv≫ 『e_2』(という) 状況になる。
9	『e_1』(という) ことをすると、≪adv≫ 『e_2』(という) 状態を保つ。
10	『e_2』(という) ことをするのは、≪adv≫ 『e_1』(という) 状態の時である。
11	『e_2』(という) ことをするのは、≪adv≫ 『e_1』(という) 状況の時である。
12	『e_1』(という) 状態になる場合、≪adv≫ 『e_2』(という) ことをする。
13	『e_1』(という) 状況になる場合、≪adv≫ 『e_2』(という) ことをする。
14	『e_1』(という) 状態では、≪adv≫ 『e_2』(という) ことをする。
15	『e_1』(という) 状況では、≪adv≫ 『e_2』(という) ことをする。
16	『e_1』(という) ことが起こらなければ、≪adv≫ 、『e_2』(という) ことができない。
17	X が『e_2』(という) ことを実現する手段として、≪adv≫ X が『e_1』(という) ことを行なう。
18	X が『e_1』(という) ことをすることによって、≪adv≫ X が『e_2』(という) ことができる。

しばしば ("*sibasiba*", often), 大抵 ("*taitei*", usually) and 常に ("*tsuneni*", always) indicate a pragmatic constraint on the necessity of the relationship between any two events: that is, the relations indicated by these words usually have a high degree of neccesity. With this pragmatic constraint, we introduce an attribute to the *causal_rel* tags about the degree of neccesity. For each of eighteen templates, if one judges the text segments as holding causal relation by using the template with one of three adverbs, the *necessity* attribute value is added to the relation instance. If one judges the text segments as holding causal relation by using the template with φ , the *chance* attribute value is added.

If a head element of text segments representing an event is conjugated, it is replaced by its base form before embedded to the slot. If a head element is represented by a noun phrase (np), the following rewriting rules are also applied before embedded to the slot.

Rewriting rules

- np → np + する
  (ex. 停電 → 停電する)
  (ex. blackout → a blackout happens)
- np → np + が-起こる
  (ex. 地震→地震が起こる)
  (ex. earthquake → an earthquake happens)
- np → np + に-なる
  (ex. 大雨→大雨になる)
  (ex. heavy rain → it rains heavily)
- nominalized verb → verb
  (ex. 疲れ→疲れる)
  (ex. tiredness → someone gets tired)

C. Annotation ranges and preferences

There are some pieces of previous work on analysis of in-text causal relations. However, although causal relation instances appear in several different ways, just a few forms have been treated in the previous studies, mainly treated verb phrase form with cue phrase markers such as (1a) in Section I. In this work, to realize the further analysis with wide coverage, we treated not only those mentioned in previous work but also those without explicit cues for causal relation as in (1b) , and those formed by noun phrases as in (1c) .

Ideally, we should try to judge for tagging of causal relation tags over all any event pairs in text. However, it seems that the more the distance between two events represented in text, the smaller the probability of holding causal relation between them. Thus, in this work, we set a constraint on the ranges of judgements; if both two events are represented in the same sentence or two sentences which are adjacent to each other, we try judgements, if not, skip judgements. This constraint is applied only when tagging the *head* tag. A modifier and its head element are sometimes located in different sentences when anophora or ellipsis phenomenon occurs in the text. In such cases, we tagged *mod* tags to the text segments anywhere in the text.

In practice, it is observed that there are some complex behaviors with respect to causal relations. For example, a former event e_1 has sometimes more than two latter relevant events, and the several causal relation instances

could be interconnected with each other. In this work, however, we consider only one-to-one event pairs, that is, the former event e_1 has only one latter event e_2, to facilitate annotators' judgements and to reduce annotation costs. To choose an e_1- e_2 pair, we used the following two preference rules.

Annotation preference rules

1) prefer an event pair which is lied the nearest position in the text,
2) prefer an event pair which is held in a causal relation which has the *necessity* attribute value.

III. Data

We selected as text for annotation Mainichi Shimbun newspaper articles from 1995 [6]. In particular, we used articles included on the social aspect domain. When adding our causal relation tags to the text, it is preferable that each annotator can understand the whole contents of the articles. This requirement is related to the reason why we picked the social aspect domain articles. We consider that the contents of social aspect domain articles are familiar to everybody and are easier for annotators to understand than the contents of articles included on politics, economy domain, etc.

Furthermore, in our previous examination, it is found that as the length of articles gets longer, it is getting hard to judge which segments represent causal relation instances. Because the text areas in which annotators should consider in order to annotate for any causal relation instances are also long according to the length of articles. Therefore, we focus on social aspect domain articles which consists of less than 10 sentences.

After all, we extracted 750 articles (3912 sentences) for our annotation work with above conditions.

IV. Annotation workflow

After training phase for annotators, we spent approximately one month to create a corpus annotated with causal relation information. We call works accomplished by a series of the annotation flow, *main work*. The flow of the main work is as follows.

The flow of main work

- A document article is displayed to each annotator independently. The sentences in the document article are automatically split to *bunsetsu*-phrases by preprocessing. Some kinds of words such as connective markers and verbs are highlighted to draw annotators' attention to the text segments which could represent elements in causal relation instances. The annotator finds text segments which represent causal relation instances from the document article, and then he/she adds causal relation tags to their segments as described in Section II. The annotation process is executed efficiently using an annotation interface. Using the interface, all of annotators can add tags through only simple keyboard and mouse operations.
- After each annotator finished the annotation process for a fixed number of document articles (in this work, 30 document articles), he/she moves to a modification process. In this process, first, only the segments with causal relation tags are extracted from the documents, such as the instances in Table II. Then, the same annotator who adds tags to the extracted segments, checks their extracted causal relation instances with attention. When wrong tagged instances are found, they are corrected on the moment. After checking and correcting for all the extracted instances, the annotator moves back to the above-mentioned annotation process in order to annotate a new 30 document articles set.

In this work, three annotators have been employed. Each annotator has added our designed causal relation tags independently. Two annotators of the three are linguists, and the last one is the author of this paper. We denote each annotator under anonymity, *A*, *B* and *C*, hereafter. Since it seems that the notion of causal relation in itself strongly depends on human subjectivity, we have had much time for training before moving on to the main annotation work; including primary trials for the designing of the causal relation tag set, we have spent actually two or three months on training.

After three annotators finished annotating all 750 document articles, we ran an automatic post-processing. With this process, we intend to modify or delete some instances which are tagged in a wrong manner. For example, we deleted the instances which have e_1 and e_2 but no *causal_rel* tag. Only the instances that passed the post-processing are evaluated in Section V and Section VI.

In some work on the corpus creation, the meta-annotator is sometimes employed and he/she checks and corrects the corpus which has been previously annotated. In this work, however, we did not introduce the meta-annotation process because our annotation criteria described in Section II have a room of getting into some subjective aspects.

TABLE II

EXAMPLES OF TAGGED INSTANCES

id	*mod1*	*head1*	*mod2*	*head2*
1	中学校舎-から (school building-from)	転落する (tumble)		死亡 (dead)
2	6 階-から (sixth floor-from)	転落する (tumble)		意識不明 (lie unconscious)
3	川-に (river-to)	転落 (tumble)		助け上げ (help out)
4	二階屋根-から (roof-from)	転落 (tumble)	頭-など-を (head-ACC)	打つ (hit)
5		転落 (tumble)	胸-など-を (breast-ACC)	打つ (hit)
6	屋根-から (roof-from)	転落 (tumble)		死亡 (dead)
7		殴る (beat)	けが-を (injury-ACC)	負う (suffer)
8	軽乗用車-と (minivan-to)	衝突 (crash)	打撲傷-を (bruise-ACC)	負う (suffer)
9	郵便物-が (postal matter-NOM)	爆発する (burst)	重傷-を (heavy injury-ACC)	負う (suffer)
10	けん銃-で (handgun-with)	撃つ (shoot)	重傷-を (heavy injury-ACC)	負う (suffer)
11	顔-に 火傷-を (head-DAT) (burn-ACC)	負う (suffer)		重傷 (heavy injury)
12	重傷-を (heavy injury-ACC)	負う (suffer)		休職する (take a sabbatical leave)

V. RESULTS

A. Total number of tagged instances

Table II shows some examples of tagged instances. Table III shows the total number of tagged instances for each annotator. The numbers within the round brackets are average numbers of instances per document article. In Table III, we see that the total numbers of tagged instances of the annotators are quite different. Although all annotators tagged under the same annotation criteria, the annotator *A* tagged to text segments twice as large as the annotator *C* did. This result suggests that recognizing causal relations is strongly dependent on human subjectivity.

Table IV shows the frequency distributions of the degree of necessity on causal relations. The relation instances without attribute value are categorized as "no value".

In Table IV, we see that each annotator tagged approximately the same rate of instances for the degree of necessity. In this work, approximately 60% of instances are judged as relation instances with *necessity* attribute value. This result suggests that over 60% of relation instances extracted from text are applicable to the stages of automatic causal knowledge acquisition.

TABLE III

THE TOTAL NUMBER OF TAGGED INSTANCES

A	2014	(2.7)
B	1587	(2.1)
C	1048	(1.4)

TABLE IV

FREQUENCY DISTRIBUTION OF THE DEGREE OF NECESSITY

A	*necessity*	1224
	chance	766
	no value	24
B	*necessity*	1094
	chance	492
	no value	1
C	*necessity*	603
	chance	431
	no value	14

B. Inter-annotator agreement

We examined inter-annotator agreement. Here, let x and y be causal relation instances. x consists of e_{1x} and e_{2x}, and y consists of e_{1y} and e_{2y}. e_{1x} has $head_{1x}$ as its head element. Similarly, $head_{2x}$, $head_{1y}$ and $head_{2y}$ are

TABLE V

INTER-ANNOTATOR AGREEMENT

A	*B*	*C*	$\mathcal{S}_{mixed}$	$\mathcal{S}_n$	$\mathcal{S}_c$
1	0	0	1222	632	535
0	1	0	602	487	255
0	0	1	218	134	207
1	1	0	567	230	90
1	0	1	167	92	77
0	1	1	182	107	83
1	1	1	689	270	64

the head elements corresponding respectively to events e_{2x}, e_{1y} and e_{2y}. Then, we regard two instances x and y as the same instance, when $head_{1x}$ and $head_{1y}$ are located in the same *bunsetsu*-phrase and $head_{2x}$ and $head_{2y}$ are also located in the same *bunsetsu*-phrase. Using the above defined agreement measure, we counted the number of instances tagged by the different annotators

Table V shows the results. The symbol "1" in the left-hand side of Table V indicates that the corresponding annotator tagged to an instance, and the "0" indicates not tagged. For example, the fourth row ("110") indicates the instances to which both *A* and *B* tagged but *C* did not.

Let a set of all tagged instances denote $\mathcal{S}_{mixed}$, a set of all tagged instances with the *neccesity* attribute value $\mathcal{S}_n$, and a set of all tagged instances with the *chance* attribute value $\mathcal{S}_c$.

First, we focus on the relation instances in the set $\mathcal{S}_{mixed}$. The 1605 ($= 567 + 167 + 182 + 689$) instances are tagged by more than two annotators, and the 689 instances are tagged by all three annotators. The 40% of instances within a set of instances tagged by *A* are also tagged by *B* or *C*. The 62% of instances for *B* are tagged by the other annotators. The 80% of instances for *C* are also tagged by the other annotators.

Next, we focus on the two different contrastive sets of instances, $\mathcal{S}_n$ and $\mathcal{S}_c$. The ratio of the instances tagged by more than two annotators is small in $\mathcal{S}_c$. This becomes clear when comparing phenomenon between $\mathcal{S}_n$ and $\mathcal{S}_c$. While the 270 instances tagged by all three annotators in $\mathcal{S}_n$, only the 64 instances in $\mathcal{S}_c$.

VI. DISCUSSION

To discuss some characteristics of causal relations, in this chapter, we focus on the 699 ($= 230 + 92 + 107 + 270$) instances marked by more than two annotators with the *necessity* attribute value. We examined the following three parts: (1) cue phrase markers, (2) the part-of-speech of the head element, and (3) the position of the head element.

TABLE VI

THE NUMBER OF INSTANCES WITH/WITHOUT CUE PHRASE MARKERS

with marker	219
without marker	480

TABLE VII

CUE PHRASE MARKERS MARKED BY ANNOTATORS

marker		frequency
ため	(because)	120
で	(by)	35
結果	(result of)	5
ので	(because)	5
と	(when)	5
場合	(when)	4
ば	(if)	4
ことから	(from)	4
から	(from)	3
理由で	(reason)	2
目的で	(purpose)	2
影響で	(effect)	2
より	(by)	2
ように	(in order to)	2
よう	(in order to)	2
として	(as)	2
ところ	(when)	2
が	(but)	2
背景には 続いて 事故で 事件で 取り入れようと 際に 際 限り れると み による ており せようと ことで うとした ことによって		1

A. Cue phrase markers

While annotating the document articles with our causal relation tags, *head*, *mod*, and *causal_rel*, the annotators also marked the cue phrase markers for causal relations with the *marker* tag at the same time. We investigated a proportion of instances attached with the *marker* tag.

The result is shown in Table VI. Table VII shows the cue phrase markers actually marked by at least one annotator.

It has been supposed that causal relation instances are sometimes represented with no explicit cue phrase marker (see for example [1]). We empirically confirmed the supposition. In our case, only 30% of our 699 instances have one of cue phrase markers shown in

TABLE VIII
DISTRIBUTION OF SYNTACTIC TYPES

		e_1	e_2
vp	(verb) (adjective)	365	412
np	(verbal noun) (general noun)	322	269
others		12	18

Table VII, though this value can be dependent of the data.

This result suggests that in order to develop knowledge acquisition methods for causal relations with high coverage, we must deal with linguistic expressions with no explicit cue phrase markers as well as those with cue phrase markers.

B. The part-of-speech of head element

Next, we classified the events included in the 699 instances into two categories: the verb phrase (vp) and the noun phrase (np) To do this, we used morphological information of their head elements. If the part-of-speech of a head is verb or adjective, the event is classified as a verb phrase. If the part-of-speech of a head is noun (including general noun and verbal noun), the event is classified as a noun phrase. We used *ChaSen* [5] to get part-of-speech information.

The result is shown in Table VIII. The events classified as a verb phrase are major part. This matches our intuition. However, the number of events classified as a noun phrase is comparable to the number of events classified a verb phrase; 322 events of e_1 are represented as a noun phrase, and 269 events of e_2 are also represented as a noun phrase. This result is quite suggestive. To promote the current methods for knowledge acquisition to further stage, we should develop a knowledge acquisition framework applicable both to the verb phrases and to the noun phrases.

C. The position of head element

For each e_1 and e_2 included in the 699 instances, we examined the positions of their head elements in the sentences.

We consider a dependency structure between *bunsetsu*-phrases in the original sentences from which causal relation instances are extracted. The dependency structure forms a tree structure. The *bunsetsu*-phrase located in the end of the sentence is the root node of the tree. We focus on the depth of the head element from the root node. We used *CaboCha* [4] to get dependency structure information between *bunsetsu*-phrases.

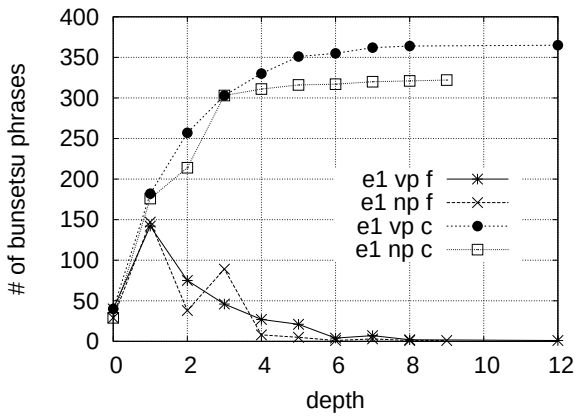

Fig. 3. Absolute position of head elements (e_1)

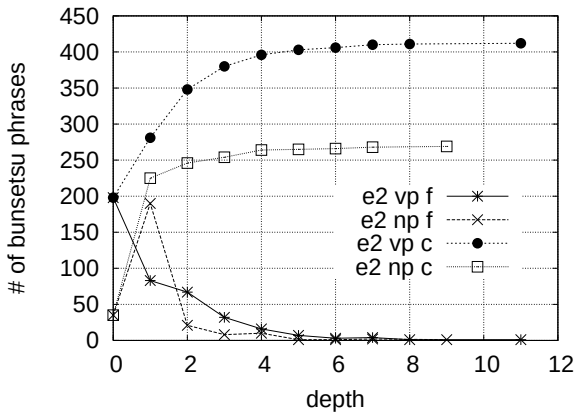

Fig. 4. Absolute position of head elements (e_2)

The results are shown in Figure 3 and Figure 4. Figure 3 is the result for the head elements of e_1, and Figure 4 is the result for the head elements of e_2. The letter "f" in Figure 3 and Figure 4 indicates frequency. Similarly, the letter "c" indicates cumulative frequency.

In Figure 4, the 198 head elements of the events represented as a verb phrase are located in the end of the sentences, namely depth $= 0$. The 190 of the 269 events represented as a noun phrase are located in depth $= 1$. For events represented as either a verb phrase or a noun phrase, over 80% of head elements of the events are located within depth < 3. In Figure 3, similarly, over 80% of head elements of the events are located within depth < 4. From these findings, we can suppose that the most of the events are able to be found simply by searching the *bunsetsu*-phrases located in the shallow position at the phase of causal knowledge acquisition.

TABLE IX
RELATIVE POSITION OF TWO HEAD ELEMENTS

		e1 ⇒ e2	e1 ⇐ e2
intra	$d = 1$	259	15
	$= 2$	152	23
	> 2	33	4
	no dep	72	
inter		141	

D. Relative position of two head elements

We next examined relative positions between head elements of e_1 and e_2 where these two events are held in a causal relation. In the previous section, we discussed each absolute position for e_1 and e_2 by means of the notion of depth in sentences. Here, we focus on the difference of the depth values between e_1 and e_2.

The result is shown in Table IX. The symbol "⇒" in Table IX indicates the case where the head element of e_1 is located nearer to the beginning of the sentence than that of e_2. The "⇐" indicates the opposite case. The symbol "no dep" indicates the case where neither the condition *a* nor *b* is satisfied:

a. the head element of e_2 is an ancestor of the head element of e_1.
b. the head element of e_2 is a descendant of the head element of e_1.

"inter" indicates the case where two head elements appear in different sentences.

The most instances (259 instances) are categorized into $d = 1$ on $e_1 \Rightarrow e_2$, that is, the head element of e_1 directly depends on the head element of e_2. This result matches our intuition. However, there are several other cases. For example, 152 instances are categorized into $d = 2$ on $e_1 \Rightarrow e_2$, 72 instances are categorized into "no dep", and 141 instances are categorized into "inter". If an instance is represented as the form that a head element of e_1 depends on a modifier of e_2, the instance tends to be categorized into $d = 2$. Most of the instances extracted from sentences including any parallel relations are categorized into "no dep". In this study, we consider causal relation instances as binary relation. To deal with instances categorized into "no dep" adequately, we should extend our framework to the more complex structure.

VII. CONCLUSION

In this paper, we first reported our causal relation tags, and described the annotation workflow. Using the annotated corpus, we examined the causal relation instances from three viewpoints: (1) cue phrase markers, (2) the part-of-speech of the head element, and (3) the position of the head element.

From our investigation, it became clear that causal relation instances are represented in the several types of linguistic expressions. Based on these findings, we plan to develop an automatic knowledge acquisition method for causal relations.

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