Effectiveness of Domain Adaptation in Japanese Predicate-Argument Structure Analysis

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Abstract
This paper proposes introducing domain adaptation into Japanese predicate-argument structure (PAS) analysis. Our investigation of a Japanese balanced-corpus revealed that the distribution of argument types is different across text media, particularly the difference is significant when the argument is exophoric. The past Japanese PAS analysis research has disregarded this tendency. We start with an RNN-based PAS analyzer as a baseline, extending it by introducing three kinds of domain-adaptation techniques and their combinations. The evaluation experiments using a Japanese balanced-corpus (BCCWJ) confirmed that the domain-adaptation is effective for improving the performance of the Japanese PAS analysis.

1 Introduction
Predicate-argument structure (PAS) analysis is the task to identify the argument for each case of the target predicate. As it is a fundamental analysis for various natural language processing (NLP) applications, the PAS analysis has been one of the most active research areas in NLP. In discourse-oriented languages like Japanese, the target language of the present study, arguments are often omitted from the sentence Kayama (2003). Those omitted arguments are considered as zero-pronouns or exophora.

(1) meiru-o kaite okuttayo. yondene.
mailACC wrotev₁ sentv₂ readv₃/imperative
I wrote a mail to you and sent it to you. Read it.

For instance, example (1) has three predicates (v₁, v₂ and v₃) and one explicit argument (mail).

| predicate \ case | NOM | ACC | DAT |
|-----------------|-----|-----|-----|
| v₁: wrote       | [writer]| mail | [reader]|
| v₂: sent        | [writer]| (mail) | [reader]|
| v₃: read        | [reader]| ((mail)) | none |

Table 1: PAS analysis result for example (1)

The PAS analysis result of example (1) looks like Table 1 where the elements enclosed with square brackets are exophoric, the round bracketed is an intra-sentential zero-anaphora and the double round bracketed is an inter-sentential zero-anaphora. The accusative argument of v₁, “meiru-o (mail)”, is explicitly marked by the case marker “o” and has a dependency relation with v₁, which is indicated by a bare noun, i.e. without any bracket.

Although the Japanese PAS analysis is similar to the semantic role labeling (SRL) (Zhou and Xu, 2015; He et al., 2017), it also involves anaphora resolution for zero-pronouns and exophora to identify the argument for every case of the predicate, which corresponds to filling the bracketed elements in Table 1. We also find omitted arguments in other pro-drop languages such as Chinese, Turkish, and some null-subject languages in the Romance languages (Iida and Poesio, 2011; Rello et al., 2012; Chen and Ng, 2016; Yin et al., 2017).

The past Japanese PAS analysis utilizes various features obtained from the morphological and syntactic analysis (Matsubayashi and Inui, 2017; Hayashibe et al., 2011; Imamura et al., 2014; Shibata et al., 2016; Ouchi et al., 2015; Yoshikawa et al., 2013; Taira et al., 2008). The recent approach includes the end-to-end approach that does not require any intermediate analysis (Ouchi et al., 2017).
The contribution of the present paper to the Japanese PAS analysis is twofold. Firstly we subcategorize the exophora into fine-grained classes, namely, the exophoric text writer (exo1), reader (exo2) and the other entity (exoX). Example (2) depicts the necessity of the subcategorization.

(2) sandoitti taberu.
sandwich eat
I eat sandwich. / Do you eat sandwich?

Both the exophoric speaker (exo1) and hearer (exo2) can be the nominative argument of the verb “eat”, and accordingly the sentence meaning is different. To distinguish these two meanings, the subcategorization of the exophora is necessary.

Secondly, we introduce domain-adaptation techniques into the Japanese PAS analysis. Surdeanu et al. (2008) and Hajic et al. (2009) reported that the SRL performance degraded when the domains were different between the training and testing data. Yang et al. (2015) tackled this problem by introducing the domain adaptation into a deep learning method. As most of the past studies of the Japanese PAS analysis targeted a mono-type of texts, i.e. newspaper articles, the domain adaptation did not matter, except for Imamura et al. (2014). They trained the PAS analyzer for dialogues by using newspaper articles. However, pairs of other media types have not been investigated yet. In contrast, we target various types of Japanese texts; we use Balanced Corpus of Contemporary Written Japanese (BCCWJ)\(^1\) (Maekawa et al., 2014) for evaluation. BCCWJ contains 100 million words that were systematically collected from several source media such as newspaper articles (PN), books (PB), magazines (PM), white papers (OW), QA texts in the Internet (OG) and blog texts (OY). We use the core data set of BCCWJ consisting of about two million words annotated with co-reference and predicate-argument relations for nominative, dative and accusative cases. As we describe in the next section, the distribution of exophoric arguments is notably different over the source media; thus consideration of the difference in the source media is necessary.

We start with a recurrent neural network (RNN)-based base model and extend it by introducing the following five kinds of domain adaptation. (1) The fine-tuning method trains the model with the entire training data and uses the learnt parameters as the initial parameter values for the second stage learning with the target-domain training data. (2) The feature augmentation method trains a shared network and domain-specific networks simultaneously (Kim et al., 2016). (3) The class probability shift method skews the output probability of the network based on the prior probability distribution of the argument types across the domains. (4) The voting method determines the output by the majority of the above three methods. (5) The mixture method combines the fine-tuning method, the feature augmentation method and the class probability shift method into a single method. We describe the details of each method in section 4.

## 2 Problem setting

### 2.1 Argument type

The past Japanese PAS analysis targeted various combinations of argument types. Table 2 summarizes the previous studies and their target argument types. The table header represents the classification of arguments from a linguistic viewpoint. Arguments are divided into endophora and exophora depending on whether they appear in the text or not. The endophoric arguments are further divided into intra- and inter-sentential arguments depending on whether they appear in the same sentence as the predicate. Some intra-sentential arguments have a dependency relation with the predicate, but this is not always the case. We call the latter case intra-sentential zero-anaphora. Since the inter-sentential arguments do not have a dependency relation with the predicate, they are also zero-anaphoric. As we described in the previous section, we divide the exophoric arguments into three subcategories: writer, reader and the other entity. In what follows, we use the labels shown in Table 2 for denoting argument types. The label none indicates that the predicate takes no argument for that case. For instance, intransitive verbs do not take an accusative argument; thus the accusative case of intransitive verbs should be filled with none.

Table 2 shows that the inter-sentential arguments were tackled by the fewer studies than the intra-
sentential arguments. Identifying the inter-sentential arguments requires searching in larger space compared with the intra-sentential arguments, and thus the problem becomes more difficult. Unlike the inter-sentential arguments, identifying the exophoric arguments, in particular, the $exo_1$ and $exo_2$ arguments do not drastically increase the search space. They are easy to be introduced into the PAS analyzer (Shibata et al., 2016; Hangyo et al., 2013). There are, however, variations in the $exo_X$ argument treatment. Hangyo et al. (2013) and Imamura et al. (2014) assume a single category for $exo_X$, while Sasano and Kurohashi (2011) identifies a named-entity class of the exophoric entity. Imamura et al. (2009) does not distinguish the subcategories of the exophoric arguments and the none argument. This fact is indicated by $\triangle$ in Table 2. In this present study, we target the intra-sentential arguments together with the exophoric argument. We do not distinguish the $exo_X$ and inter arguments; they are treated as a single category unknown. This is the reason for $\triangle$ at the $exo_X$ column in our work. As the target predicates, we use those which are marked as “predicate” with arguments in BCCWJ and event nouns which usually become verbs when being used with light verbs.

2.2 Domain dependency of argument type distribution

The previous studies on the Japanese PAS analysis dealt with the texts from a single “domain” in a broad sense; many of them used newspaper articles. We use BCCWJ for the evaluation of the proposed methods, considering six source media in BC-CWJ (OW, PB, PM, OW, OC, OY) as independent domains. It is probable that the characteristics of texts are different across the source media and therefore the PAS analysis performance might be affected by the domain characteristics. One of our objective in this study is to confirm that introducing domain-adaptation is effective for the Japanese PAS analysis.

The length of sentences is different across the source media. The sentence length affects the distance between the predicate and its arguments. Table 3 shows the distribution of the argument type for each case across the six source media. The OW texts have fewer inter-sentential arguments than intra-sentential arguments in contrast with the other media. We can partially explain this difference by the average sentence length. A longer sentence has more chance to include the arguments of the predicate within the sentence. The distribution of the exophoric arguments (the shaded rows) for the nominative case, in particular, that of $exo_1$ and $exo_2$ is notably different across the media. Both $exo_1$ and $exo_2$ in OC show quite high numbers compared with the other domain. The OC contains QA texts that are similar to dialogues. It is natural not to explicitly mention a questioner ($exo_1$) and responders ($exo_2$). The OY texts also show high numbers at $exo_1$ and $exo_2$ but unlike OC they are skewed toward $exo_1$, as the blog texts are monologues.

| work                  | label | intra (dep) | intra (zero) | inter | $exo_1$ | $exo_2$ | $exo_X$ | none |
|-----------------------|-------|-------------|--------------|-------|---------|---------|---------|------|
| present work          | o     | o           | o            | o     | o       | o       | o       | o    |
| Matsubayashi and Inui | 2017  | o           | o            | o     | o       | o       | o       | o    |
| Ouchi et al. (2017)   |       | o           | o            | o     | o       | o       | o       | o    |
| Shibata et al. (2016) |       | o           | o            | o     | o       | o       | o       | o    |
| Imamura et al. (2014) |       | o           | o            | o     | o       | o       | o       | o    |
| Hangyo et al. (2013)  |       | o           | o            | o     | o       | o       | o       | o    |
| Yoshikawa et al. (2013)|       | o           | o            | o     | o       | o       | o       | o    |
| Hangyo et al. (2011)  |       | o           | o            | o     | o       | o       | o       | o    |
| Sasano and Kurohashi (2011)|   | o           | o            | o     | o       | o       | o       | o    |
| Imamura et al. (2009) |       | o           | o            | o     | o       | o       | o       | o    |

Table 2: Target argument types of the past studies
Table 3: BCCWJ distribution of argument type across source media [%]

| case | arg. type\media | OC | OY | OW | PB | PM | PN | All |
|------|-----------------|----|----|----|----|----|----|-----|
| NOM  | none            | 0.06 | 0.74 | 0.19 | 0.39 | 0.76 | 1.00 | 0.58 |
|      | intra(deep)     | 37.33 | 35.86 | 35.75 | 46.20 | 43.31 | 43.06 | 41.11 |
|      | intra(zero)     | 10.50 | 13.36 | 18.20 | 18.03 | 14.62 | 19.75 | 16.81 |
|      | inter           | 18.25 | 13.21 | 8.34 | 18.46 | 21.68 | 18.35 | 16.58 |
|      | exo1            | 12.13 | 19.16 | 0.26 | 0.69 | 1.60 | 0.69 | 3.49 |
|      | exo2            | 8.26 | 2.59 | 0.03 | 0.32 | 1.33 | 0.57 | 1.46 |
|      | exoX            | 13.46 | 15.05 | 37.22 | 15.88 | 16.61 | 16.54 | 19.93 |
| ACC  | none            | 62.73 | 69.59 | 45.91 | 61.29 | 62.74 | 59.95 | 59.13 |
|      | intra(deep)     | 21.43 | 21.27 | 41.10 | 28.41 | 28.70 | 31.36 | 30.37 |
|      | intra(zero)     | 4.57 | 3.55 | 5.73 | 4.66 | 3.95 | 3.97 | 4.45 |
|      | inter           | 7.06 | 3.59 | 2.24 | 3.48 | 3.07 | 3.14 | 3.43 |
|      | exo1            | 0.17 | 0.25 | 0.00 | 0.00 | 0.03 | 0.01 | 0.05 |
|      | exo2            | 0.10 | 0.02 | 0.00 | 0.01 | 0.01 | 0.00 | 0.02 |
|      | exoX            | 3.88 | 1.68 | 4.96 | 2.12 | 1.41 | 1.44 | 2.48 |
| DAT  | none            | 80.12 | 87.37 | 87.12 | 81.43 | 85.05 | 85.71 | 84.69 |
|      | intra(deep)     | 10.78 | 9.08 | 9.03 | 13.43 | 12.42 | 11.23 | 11.19 |
|      | intra(zero)     | 4.57 | 3.55 | 5.73 | 4.66 | 3.95 | 3.97 | 4.45 |
|      | inter           | 7.06 | 3.59 | 2.24 | 3.48 | 3.07 | 3.14 | 3.43 |
|      | exo1            | 0.17 | 0.25 | 0.00 | 0.00 | 0.03 | 0.01 | 0.05 |
|      | exo2            | 0.10 | 0.02 | 0.00 | 0.01 | 0.01 | 0.00 | 0.02 |
|      | exoX            | 3.88 | 1.68 | 4.96 | 2.12 | 1.41 | 1.44 | 2.48 |

OC: QA texts, OY: blog texts, OW: white papers, PB: books, PM: magazines, PN: newspapers

3 Deep recurrent model

We implement our Japanese PAS analyzis method using a recurrent neural network (RNN) model consisting of the following three layers.

Input layer maps each word into a feature vector. Hidden layer is a bi-directional RNN. Output layer has a linear function and a softmax function for binary classification.

Since our model outputs a binary label for each word indicating whether the word is the argument of a case for the target predicate, we have to prepare a model for each case. As our preliminary experiment showed that a model solving three cases simultaneously was inferior to the models for each case, we adopt the individual model for each case in this experiment. We show our model in Figure 1, which is formalized as follow:

$$\bar{x} = w_a \oplus w_f \oplus b_f$$  
$$h^1 = \text{BiLSTM}(\bar{x})$$  
$$h^2 = \text{linear}(h^1)$$  
$$p = \text{softmax}(h^2)$$

Our model first receives a sequence of words as an input sentence. Sequence of words $\{w_i\}^T_{i=0}$ in the input sentence is mapped into corresponding sequence of feature vectors $\{\bar{x}_t\}^T_{t=0}$. Feature vector $\bar{x}$ is made by concatenating word embedding $w_a$, part-of-speech (POS) embedding $w_f$ and syntactic features $b_f$. The feature vector $\bar{x}$ is fed into a bi-directional long short-term memory recurrent network (BiLSTM) ([Schuster and Paliwal 1997] [Graves et al. 2005]). Then BiLSTM($\cdot$) computes and outputs vector $h^1$ for each word. Function linear($\cdot$) takes $h^1$ and outputs $h^2 = (h^2_0, h^2_1)$. Finally, Function softmax($\cdot$) takes $h^2$ and output probability $p$.

3.1 Input layer

We define three types of features: word embeddings, POS embeddings, and syntactic features.

Word embedding We use word embeddings developed from Japanese Wikipedia by [Suzuki et al. 2016] (Japanese Wikipedia Entity Vector [http://www.cl.ecei.tohoku.ac.jp/~m-suzuki/jawiki_vector/]).

POS embedding Each word has a hierarchical POS tag with at most six levels. We assign a five-dimensional random vector to each level of a POS tag. Thus a hierarchical POS tag is represented by

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a 30-dimensional vector that is made by concatenating six vectors of each level. A POS tag vector with less than six levels is padded by zero-vectors.

**Syntactic features**  Syntactic features include four kinds of features. (1) **Head** feature is a binary feature which indicates whether a word is the head of a base phrase or not. (2) **Position in the sentence** is an integer feature that indicates the phrase-based distance from the beginning of a sentence. We use the phrases annotated in the corpus. A word in the first phrase in the input sentence has value zero for this feature. (3) **Distance from the predicate** is an integer feature which indicates the distance from the target predicate to be analyzed. (4) **Target verb** is a binary feature which indicates whether a word is the predicate to be analyzed.

In order to allow our model to output the labels for none, exo1, exo2, and unknown, we add virtual words representing them before the first word in a sentence. We assign the feature for these virtual words as follows.

**none** We set a zero vector for none.

**exo1** We use the word embedding of “boku (I)”, commonly-used first-person singular pronoun in Japanese for exo1.

**exo2** We use the word embedding of “omae (you)” for exo2, which is commonly-used second-person singular pronoun in Japanese.

**unknown** We use the word embedding of “kore (this)” for unknown, which is commonly-used third-person singular pronoun in Japanese.

### 3.2 Hidden layer

In the hidden layer, the forward LSTM (LSTM$^f$) computes $h^f_t$ by the feature vector $\bar{x}_t$ and its state $h^f_{t-1}$ for each $t$. Conversely, the backward LSTM (LSTM$^b$) computes $h^b_t$ by the feature vector $\bar{x}_t$ and $h^b_{t+1}$ for each $t$. BiLSTM concatenates $h^f_t$ and $h^b_t$ for each $t$.

$$h^1_t = \text{BiLSTM}(\bar{x}_t) = \text{LSTM}^f(\bar{x}_t, h^f_{t-1}) \oplus \text{LSTM}^b(\bar{x}_t, h^b_{t+1})$$  \hspace{1cm} (5)

We then feed $h^1_t$ into function $\text{linear}(\cdot)$ to obtain two-dimensional vector $h^2_t$.

$$h^2_t = \text{linear}(h^1_t)$$  \hspace{1cm} (6)

### 3.3 Output layer

In the output layer, our model judges whether the word is the case argument of the target predicate. Function $\text{softmax}(\cdot)$ translates two-dimensional vector $h^2_t$ into a probability indicating to what degree the word can be the case argument of the target predicate.

$$p_t = \text{softmax}(h^2_t)$$  \hspace{1cm} (7)

$p_t$ is a probability that $t$-th word is the case argument. Our model selects the word which has the highest probability $p_y$.

$$y = \arg \max_{0 \leq t \leq T} (p_t)$$  \hspace{1cm} (8)
4 Domain adaptation

First, we prepare the following five baseline models. (1) Model Each-D is trained with the data of each media source. (2) Model All is trained with the entire data of all media sources. (3) Model Small is trained with the data reduced to an amount of 75% of all media sources, which is prepared to see the impact of the data size on accuracy. (4) Model Out-D is trained with the out-domain data. (5) Model One-H is trained with the entire. We extend each training example by adding a one-hot vector to indicate its media source. This model is a baseline for domain adaptation.

On top of these baseline models, we prepare five domain adaptation methods as follows.

(1) Fine-tuning  We train the model with the entire data of all media sources to build the All model. We then train that model with the data of the target media source.

(2) Feature augmentation  The second method follows [Kim et al. (2016)] in which BiLSTM\textsuperscript{m} is prepared for each media source \( m \) in addition to a common BiLSTM\textsuperscript{c} covering all media sources. This method is summarized as follows.

\[ \begin{align*}
\bar{x} &= w_a \oplus w_f \oplus b_f \\
\bar{h}^1 &= \text{BiLSTM}^m(\bar{x}) \oplus \text{BiLSTM}^c(\bar{x}) \\
\bar{h}^2 &= \text{linear}^m(\bar{h}^1) \\
p &= \text{softmax}(\bar{h}^2)
\end{align*} \] (9) (10) (11) (12)

We expect that the media-specific BiLSTM\textsuperscript{m} learns media-specific characteristics and the common BiLSTM\textsuperscript{c} learns general characteristics of the PAS analysis. We train this model with randomly selected batches from all media sources.

(3) Class probability shift  The third method leverages the distribution of argument types for each case in each media source. Given a target case, we use probability \( p_{tp}^m \) that argument type \( tp \) appears in the training examples of media source \( m \) for the target case. Since this probability distribution is different among media sources, we use the difference in this distribution as follows. We define two functions \( f^m(h) \) and \( g^m(h) \) for each media source \( m \).

\[ \begin{align*}
f^m(h) &= \frac{p_{tp}^m}{p_{tp}^c} \cdot h \\
g^m(h) &= \frac{100 - p_{tp}^m}{100 - p_{tp}^c} \cdot h,
\end{align*} \] (13) (14)

Where \( tp \) is one of none, exo1, exo2, unknown and intra. Label intra includes both dependent and zero intra-sentential arguments.

\[ h^2 = (h^2_0, h^2_1) \] is a two-dimensional vector where \( h^2_0 \) is a probability that a word is the argument of the predicate and \( h^2_1 \) is a probability that a word is not the argument of the predicate.

\[ \begin{align*}
\bar{x} &= w_a \oplus w_f \oplus b_f \\
h^1 &= \text{BiLSTM}(\bar{x}) \\
h^2 &= \text{linear}(h^1) \\
h^3 &= (f^m(h^2_0), g^m(h^2_1)) \\
p &= \text{softmax}(h^3)
\end{align*} \] (15) (16) (17) (18) (19)

Equation (18) shifts the output probability by conditioning the distribution of argument types across the media sources.

(4) Voting  This method determines its output based on the majority of the above three methods. When the decisions split, we select the decision with the highest probability.

(5) Mixture  The last method combines the above three methods: Fine-tuning, Feature augmentation and Class probability shift into a single model.

5 Experiment

5.1 Setting

We evaluated our models on a Japanese balanced-corpus (BCCWJ). We divided the corpus into three portions: 70% for training, 10% for development, and 20% for testing. We trained each model for 10 epochs and used the best model in terms of accuracy in the test data for evaluation.

Hyper parameter  The number of dimensions of word embeddings and POS embedding are 200 and 30, respectively. The dropout rate of BiLSTM is 0.2. The batch size is 32. Our models were optimized with Adam [Kingma and Ba 2014] in which
### Table 4: NOM accuracy

| arg. type \ target | OC \ # of predicates | Each-D | All | Vote | Mix | Each-D | All | Vote | Mix | Each-D | All | Vote | Mix | Each-D | All | Vote | Mix |
|---------------------|----------------------|--------|-----|------|-----|--------|-----|------|-----|--------|-----|------|-----|--------|-----|------|-----|
| intra(dep)          |                     | 73.5   | 85.5| 86.0| 84.1| 62.0   | 78.0| 79.5| 76.2| 79.2   | 83.7| 82.6| 81.7| 33.9   | 33.1| 34.4|    |
| intra(zero)         |                     | 32.3   | 46.3| 46.5| 45.8| 33.7   | 41.7| 46.1| 43.1| 33.9   | 40.7| 33.1| 34.4| 33.9   | 33.1| 34.4|    |
| exo1                |                     | 50.4   | 36.3| 45.5| 47.8| 58.4   | 24.9| 37.5| 60.1| 0.0    | 0.0  | 0.0  | 0.0  | 3.2    | 0.0  | 1.2  |    |
| exo2                |                     | 40.5   | 40.1| 46.4| 36.1| 9.1    | 27.3| 13.6| 20.5| 0.0    | 0.0  | 0.0  | 0.0  | 3.2    | 0.0  | 1.2  |    |
| unknown             |                     | 66.3   | 75.4| 73.5| 69.8| 53.7   | 76.1| 76.3| 60.7| 86.3   | 85.0| 90.9| 90.4| 86.3   | 85.0| 90.4|    |

### Table 5: NOM accuracy details

\(\alpha\) is 0.001, \(\beta\) is 0.9 and weight decay is 0. For fine-tuning, weight decay is 0.0001.

#### 5.2 Result

Table 4 shows the result of each model for the nominative case. Due to the page limitation, we show only brief results of the nominative case. Appendix includes the detailed results of all cases.

For the Each-D models, the media source of the training data affected the accuracy. In general, the model worked better when the training examples and the test examples came from the same media source, i.e. the training data is in-domain.

The All model performed better than the Small model in all media sources. This reveals that the total amount of training examples is vital to improve the accuracy. These facts show that both the total amount of examples and the media source should be taken into consideration.

The All model performed better than the Each-D models in all media sources. This implies that on top of the in-domain data, more training examples are effective even though they are out-domain.

However, removing the in-domain data from the training data degrades the performance even using large data. Although the training data of all Out-D models except for PN is larger than that of the Small model, the Small model worked better than the Out-D models. When the training data lacks the data from the target media source, the data size does not always compensate the discrepancy in domains between the training and test data.

The All model and the One-H model showed no significant difference in accuracy. It indicates that a one-hot vector about media does not work well.

The right-hand side in Table 4 shows the result of the domain adaptation methods: the Fine-tuning method (F-t), the Feature augmentation method (F-a), the Class probability shift method (C-p),

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5 The total amount of training examples in the Out-D model for PN is 123, 564 – 33, 327 = 90, 237.
Please tell me a good way to recover my eyesight.

I will watch a lot and try English hard.

Toyota announces its new structure.
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## Appendix: Experimental results

### Table 7: Result for nominative case (NOM) (accuracy)

| \\model \ | OC   | OY   | OW   | PB   | PM   | PN   | F-t | F-a | C-p | Vote | Mix |
|-----------|------|------|------|------|------|------|-----|-----|-----|------|-----|
| **target** size | 11,777 | 10,929 | 23,471 | 22,773 | 21,287 | 33,327 | 92,674 | 123,564 | -   | -    | -   |
| OC        | 61.2  | 53.6 | 51.6 | 58.6 | 58.3 | 66.9 | 68.5 | 62.4 | 66.9 | 67.7 | 65.6 | 61.4 | 69.6 | 67.2 |
| OY        | 51.7  | 54.1 | 47.5 | 52.3 | 52.5 | 61.1 | 60.4 | 58.4 | 63.2 | 63.2 | 61.5 | 65.6 | 64.0 | 62.8 |
| OW        | 54.4  | 57.2 | 74.3 | 66.1 | 64.9 | 74.5 | 76.5 | 70.6 | 76.8 | 73.0 | 76.1 | 70.2 | **77.6** | 77.2 |
| PB        | 61.6  | 57.2 | 66.1 | 74.0 | 71.4 | 76.8 | 78.8 | 75.1 | 79.2 | 73.8 | 77.6 | 78.3 | 79.3 | 78.0 |
| PM        | 55.0  | 52.3 | 66.2 | 75.5 | 74.5 | 76.3 | 76.4 | 75.1 | 78.8 | 74.4 | 78.7 | 78.0 | 74.4 | 77.4 |
| PN        | 54.1  | 54.0 | 63.2 | 64.3 | 65.1 | 72.1 | 74.0 | 71.1 | 73.6 | 70.7 | 72.5 | 73.9 | **74.4** | 73.0 |

OC: QA tests, OY: blog texts, OW: white papers, PB: books, PM: magazines, PN: newspapers

### Table 8: Result for accusative case (ACC) (accuracy)

| \\model \ | OC   | OY   | OW   | PB   | PM   | PN   | F-t | F-a | C-p | Vote | Mix |
|-----------|------|------|------|------|------|------|-----|-----|-----|------|-----|
| **target** size | 11,777 | 10,929 | 23,471 | 22,773 | 21,287 | 33,327 | 92,674 | 123,564 | -   | -    | -   |
| OC        | 83.4  | 79.0 | 78.2 | 81.7 | 80.1 | 80.1 | 83.9 | 85.3 | 83.6 | 85.9 | 85.3 | 84.8 | 84.4 | **86.1** | 85.9 |
| OY        | 81.0  | 82.4 | 77.6 | 80.3 | 84.0 | 82.9 | 84.9 | 85.8 | 83.9 | 86.2 | 83.8 | 84.7 | 85.8 | 85.8 | 84.7 |
| OW        | 65.4  | 64.9 | 79.8 | 73.1 | 72.4 | 74.3 | 81.1 | 82.1 | 78.4 | 81.7 | 77.9 | 81.8 | 76.2 | **82.9** | 80.6 |
| PB        | 84.8  | 83.7 | 83.9 | 86.5 | 85.8 | 86.1 | 88.1 | 88.6 | 88.0 | 89.0 | 86.6 | 87.8 | 88.6 | 88.3 | 88.8 |
| PM        | 80.9  | 81.2 | 80.3 | 82.9 | 84.2 | 83.8 | 85.8 | 86.4 | 86.2 | 85.8 | 83.7 | 86.0 | 85.7 | **86.3** | 85.4 |
| PN        | 77.5  | 78.1 | 80.1 | 79.9 | 81.6 | 83.8 | 85.1 | 85.8 | 84.4 | 85.8 | 83.8 | 85.3 | 85.5 | **85.9** | 85.2 |

OC: QA tests, OY: blog texts, OW: white papers, PB: books, PM: magazines, PN: newspapers

### Table 9: Result for dative case (DAT) (accuracy)

| \\model \ | OC   | OY   | OW   | PB   | PM   | PN   | F-t | F-a | C-p | Vote | Mix |
|-----------|------|------|------|------|------|------|-----|-----|-----|------|-----|
| **target** size | 11,777 | 10,929 | 23,471 | 22,773 | 21,287 | 33,327 | 92,674 | 123,564 | -   | -    | -   |
| OC        | 86.8  | 84.6 | 84.0 | 85.9 | 85.9 | 85.6 | 88.7 | 87.3 | 88.9 | 87.5 | 87.9 | 87.8 | **89.5** | 88.7 |
| OY        | 90.7  | 91.8 | 91.5 | 91.0 | 92.3 | 91.8 | 92.4 | **92.9** | 91.7 | 92.3 | 92.0 | 92.2 | 92.4 | 92.5 | 92.2 |
| OW        | 87.6  | 87.5 | 90.5 | 88.8 | 88.7 | 89.2 | 90.7 | **91.2** | 90.4 | 90.9 | 89.6 | 90.8 | 88.6 | 91.0 | 90.1 |
| PB        | 88.3  | 88.1 | 87.6 | 90.3 | 89.8 | 89.2 | 91.0 | **91.2** | 90.6 | 90.8 | 90.1 | 90.4 | 91.0 | 91.1 | **91.2** |
| PM        | 88.3  | 88.2 | 87.6 | 89.0 | 90.6 | 90.0 | **91.4** | 91.3 | 91.3 | 90.8 | 90.0 | 90.4 | 91.1 | 91.2 | 91.3 |
| PN        | 89.5  | 90.3 | 90.6 | 89.7 | 91.4 | 91.7 | 92.1 | **92.5** | 91.8 | 92.4 | 91.7 | 91.9 | 92.3 | 92.3 | 92.4 |

OC: QA tests, OY: blog texts, OW: white papers, PB: books, PM: magazines, PN: newspapers
| arg. type \ target | none | intra(dep) | intra(zero) | exo1 | exo2 | unknown |
|-------------------|------|------------|------------|------|------|---------|
| Each-D | Small | All | Out-D | One-H | | | |
| F-t | F-a | C-p | Vote | Mix |
| | | | | | |
| OC | |
| 73.5 | 82.5 | 85.5 | 82.9 | 85.4 | 83.6 | 84.0 | 80.8 | 86.0 | 84.1 |
| 32.3 | 45.8 | 46.3 | 39.8 | 45.8 | 43.8 | 44.3 | 32.8 | 46.5 | 45.8 |
| 50.4 | 40.2 | 36.3 | 24.0 | 41.4 | 44.3 | 36.6 | 0.0 | 45.5 | 47.8 |
| 40.5 | 25.8 | 40.1 | 21.8 | 42.5 | 42.5 | 50.8 | 14.3 | 46.4 | 36.1 |
| 66.3 | 75.9 | 75.4 | 70.5 | 68.5 | 72.6 | 66.3 | 83.2 | 73.5 | 69.8 |
| OY | |
| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 62.0 | 77.6 | 78.0 | 77.1 | 78.3 | 79.7 | 76.7 | 79.1 | 79.5 | 76.2 |
| 33.7 | 41.4 | 41.7 | 42.9 | 45.4 | 43.9 | 47.4 | 44.4 | 46.1 | 43.1 |
| 58.4 | 27.0 | 24.9 | 10.1 | 57.8 | 49.4 | 56.8 | 63.6 | 37.5 | 60.1 |
| 9.1 | 11.4 | 27.3 | 15.9 | 22.7 | 6.8 | 27.3 | 22.7 | 13.6 | 20.5 |
| 53.7 | 78.3 | 76.1 | 81.0 | 60.2 | 66.2 | 56.1 | 63.8 | 76.3 | 60.7 |
| OW | |
| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 79.2 | 77.8 | 83.7 | 77.3 | 81.5 | 73.2 | 80.3 | 80.2 | 82.6 | 81.7 |
| 33.9 | 32.2 | 40.7 | 22.9 | 34.1 | 33.2 | 32.1 | 26.6 | 33.1 | 34.4 |
| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 | 0.0 |
| 86.3 | 88.1 | 85.0 | 83.9 | 89.8 | 88.0 | 89.9 | 79.5 | 90.9 | 90.4 |
| PB | |
| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 79.7 | 84.7 | 86.2 | 85.5 | 87.1 | 77.5 | 86.0 | 86.1 | 86.8 | 85.6 |
| 45.0 | 51.1 | 55.9 | 51.3 | 54.4 | 45.2 | 52.8 | 54.5 | 53.8 | 52.9 |
| 0.0 | 14.3 | 0.0 | 14.3 | 0.0 | 0.0 | 0.0 | 20.0 | 0.0 | 0.0 |
| 0.0 | 16.0 | 56.0 | 24.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 |
| 83.2 | 80.8 | 81.6 | 74.1 | 83.4 | 85.6 | 80.4 | 81.3 | 84.0 | 82.2 |
| PM | |
| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 77.6 | 84.2 | 86.2 | 85.1 | 86.6 | 75.1 | 85.1 | 86.4 | 85.5 | 82.7 |
| 47.1 | 51.3 | 53.6 | 51.0 | 52.9 | 44.2 | 53.6 | 51.6 | 52.1 | 44.7 |
| 2.4 | 2.4 | 3.2 | 5.5 | 0.8 | 1.6 | 0.8 | 0.0 | 0.0 | 1.6 |
| 0.0 | 9.7 | 9.7 | 9.7 | 3.2 | 12.9 | 12.9 | 12.9 | 6.5 | 0.0 |
| 81.4 | 82.0 | 79.7 | 78.5 | 85.0 | 87.7 | 85.8 | 83.9 | 88.9 | 87.8 |
| PN | |
| 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 76.3 | 81.0 | 84.0 | 82.5 | 83.7 | 78.3 | 80.6 | 83.5 | 83.3 | 81.5 |
| 45.7 | 46.1 | 51.0 | 47.9 | 47.9 | 43.1 | 45.7 | 49.7 | 47.7 | 48.0 |
| 0.0 | 6.1 | 2.4 | 7.3 | 1.2 | 0.0 | 8.5 | 0.0 | 0.0 | 1.2 |
| 5.4 | 27.4 | 24.3 | 2.7 | 5.4 | 0.0 | 21.6 | 13.5 | 5.4 | 13.5 |
| 79.5 | 79.8 | 78.9 | 74.2 | 80.0 | 81.2 | 81.4 | 79.8 | 82.9 | 80.7 |

Table 10: Detailed result for nominative case (NOM) (accuracy)
| arg. type | target  | # of predicates | model  | OC | F-t | F-a | C-p | Vote | Mix |
|-----------|---------|----------------|--------|----|-----|-----|-----|------|-----|
|           | Each-D | Small | All | Out-D | One-H |       |
| none      | 95.8   | 96.8  | 96.4 | 96.7  | 95.8  | 94.4 | 95.4 | 96.8  | 96.0 | 95.2 |
| intra(dep)| 73.1   | 76.7  | 80.7 | 79.7  | 82.6  | 79.3 | 79.3 | 82.8  | 81.1 | 82.1 |
| intra(zero)| 27.7  | 27.0  | 34.0 | 28.3  | 23.9  | 30.8 | 28.3 | 39.0  | 27.7 | 30.2 |
| exo1      | 0.0    | 0.0   | 0.0  | 0.0   | 0.0   | 0.0  | 0.0  | 0.0   | 0.0  | 20.0 |
| exo2      | 0.0    | 0.0   | 0.0  | 0.0   | 0.0   | 0.0  | 0.0  | 0.0   | 0.0  | 25.0 |
| unknown   | 58.4   | 50.3  | 55.7 | 41.9  | 64.1  | 70.9 | 61.7 | 38.6  | 66.6 | 65.5 |

| arg. type | target  | # of predicates | model  | OY | F-t | F-a | C-p | Vote | Mix |
|-----------|---------|----------------|--------|----|-----|-----|-----|------|-----|
|           | Each-D | Small | All | Out-D | One-H |       |
| none      | 93.5   | 93.5  | 92.4 | 91.7  | 94.0  | 93.2 | 94.4 | 93.0  | 93.6 | 93.4 |
| intra(dep)| 70.3   | 76.9  | 82.4 | 76.5  | 81.3  | 73.6 | 74.5 | 82.3  | 79.7 | 77.8 |
| intra(zero)| 22.6  | 23.3  | 32.3 | 28.3  | 21.1  | 21.1 | 27.1 | 32.3  | 29.3 | 27.1 |
| exo1      | 0.0    | 0.0   | 0.0  | 0.0   | 16.7  | 0.0  | 33.3 | 0.0   | 0.0  | 0.0  |
| exo2      | 0.0    | 0.0   | 0.0  | 0.0   | 0.0   | 20.0 | 0.0  | 0.0   | 0.0  | 0.0  |
| unknown   | 39.0   | 57.9  | 59.8 | 57.2  | 57.9  | 57.2 | 48.4 | 50.9  | 57.2 | 48.4 |

| arg. type | target  | # of predicates | model  | OW | F-t | F-a | C-p | Vote | Mix |
|-----------|---------|----------------|--------|----|-----|-----|-----|------|-----|
|           | Each-D | Small | All | Out-D | One-H |       |
| none      | 90.8   | 91.2  | 90.4 | 92.5  | 91.6  | 93.3 | 90.9 | 90.3  | 92.4 | 90.2 |
| intra(dep)| 86.9   | 88.9  | 89.1 | 83.1  | 88.5  | 81.2 | 88.0 | 83.6  | 89.3 | 88.3 |
| intra(zero)| 27.6  | 26.5  | 28.9 | 18.9  | 24.7  | 25.0 | 27.8 | 17.4  | 29.3 | 32.3 |
| exo1      | -      | -     | -   | -     | -     | -    | -    | -     | -    | -    |
| exo2      | -      | -     | -   | -     | -     | -    | -    | -     | -    | -    |
| unknown   | 34.8   | 39.2  | 51.8 | 36.8  | 46.5  | 31.6 | 51.8 | 20.9  | 49.7 | 37.3 |

| arg. type | target  | # of predicates | model  | PB | F-t | F-a | C-p | Vote | Mix |
|-----------|---------|----------------|--------|----|-----|-----|-----|------|-----|
|           | Each-D | Small | All | Out-D | One-H |       |
| none      | 96.5   | 96.9  | 96.9 | 97.4  | 96.3  | 96.8 | 95.4 | 96.7  | 96.9 | 97.2 |
| intra(dep)| 80.6   | 86.9  | 87.5 | 84.5  | 88.1  | 80.0 | 87.3 | 88.2  | 86.6 | 86.4 |
| intra(zero)| 26.0  | 23.0  | 25.3 | 21.3  | 28.3  | 23.3 | 32.0 | 28.3  | 29.7 | 26.7 |
| exo1      | -      | -     | -   | -     | -     | -    | -    | -     | -    | -    |
| exo2      | -      | -     | -   | -     | -     | -    | -    | -     | -    | -    |
| unknown   | 41.8   | 39.3  | 44.7 | 44.0  | 54.4  | 46.5 | 42.8 | 39.0  | 39.3 | 49.1 |

| arg. type | target  | # of predicates | model  | PM | F-t | F-a | C-p | Vote | Mix |
|-----------|---------|----------------|--------|----|-----|-----|-----|------|-----|
|           | Each-D | Small | All | Out-D | One-H |       |
| none      | 95.2   | 94.4  | 94.5 | 93.2  | 94.2  | 95.8 | 95.7 | 93.2  | 96.0 | 94.4 |
| intra(dep)| 84.9   | 88.8  | 90.0 | 90.3  | 88.7  | 81.8 | 87.7 | 90.3  | 88.4 | 89.0 |
| intra(zero)| 27.2  | 24.1  | 31.3 | 33.8  | 26.0  | 23.3 | 35.7 | 27.4  | 30.2 | 27.7 |
| exo1      | 0.0    | 0.0   | 0.0  | 0.0   | 0.0   | 0.0  | 0.0  | 0.0   | 0.0  | 0.0  |
| exo2      | -      | -     | -   | -     | -     | -    | -    | -     | -    | -    |
| unknown   | 29.6   | 47.8  | 43.9 | 51.1  | 48.6  | 34.9 | 32.4 | 48.6  | 36.9 | 37.2 |

| arg. type | target  | # of predicates | model  | PN | F-t | F-a | C-p | Vote | Mix |
|-----------|---------|----------------|--------|----|-----|-----|-----|------|-----|
|           | Each-D | Small | All | Out-D | One-H |       |
| none      | 90.9   | 91.7  | 91.7 | 91.3  | 93.3  | 93.1 | 93.0 | 91.8  | 93.0 | 91.4 |
| intra(dep)| 84.4   | 86.2  | 87.2 | 84.7  | 86.5  | 82.7 | 85.6 | 87.4  | 87.0 | 86.4 |
| intra(zero)| 23.1  | 22.3  | 25.2 | 21.2  | 19.1  | 19.1 | 23.6 | 25.2  | 24.1 | 21.2 |
| exo1      | 0.0    | 0.0   | 0.0  | 0.0   | 0.0   | 0.0  | 0.0  | 0.0   | 0.0  | 0.0  |
| exo2      | -      | -     | -   | -     | -     | -    | -    | -     | -    | -    |
| unknown   | 37.7   | 45.8  | 50.2 | 47.4  | 44.7  | 24.9 | 35.1 | 41.4  | 37.7 | 51.6 |

OC: QA tests, OY: blog texts, OW: white papers, PB: books, PM: magazines, PN: newspapers

Table 11: Detailed result for accusative case (ACC) (accuracy)
| arg. type \ target | OC | # of predicates \ model | Each-D | Small | All | Out-D | One-H | F-t | F-a | C-p | Vote | Mix |
|---------------------|----|-------------------------|--------|-------|-----|-------|-------|-----|-----|-----|------|-----|
| none                |    |                         | 97.3   | 98.2  | 98.8 | 99.3  | 98.8  | 98.2| 96.6| 99.2| 98.2 | 97.0|
| intra(dep)          |    |                         | 65.9   | 75.8  | 71.7 | 67.9  | 73.9  | 72.8| 75.0| 74.7| 78.0 | 77.5|
| intra(zero)         |    |                         | 16.7   | 16.7  | 15.3 | 11.1  | 12.5  | 16.7| 15.3| 15.3| 16.7 | 19.4|
| exo1                |    |                         | 54.9   | 51.0  | 54.9 | 0.0   | 58.8  | 60.8| 54.9| 0.0 | 60.8 | 64.7|
| exo2                |    |                         | 68.2   | 9.1   | 36.4 | 22.7  | 50.0  | 45.5| 0.0 | 31.8| 63.6 | 63.6|
| unknown             |    |                         | 15.8   | 26.3  | 22.1 | 14.7  | 20.5  | 4.2 | 37.9| 11.1| 26.3 | 29.5|

| arg. type \ target | OY | # of predicates \ model | Each-D | Small | All | Out-D | One-H | F-t | F-a | C-p | Vote | Mix |
|---------------------|----|-------------------------|--------|-------|-----|-------|-------|-----|-----|-----|------|-----|
| none                |    |                         | 98.1   | 97.0  | 98.0 | 96.1  | 97.8  | 98.2| 97.2| 97.5| 97.6 | 97.5|
| intra(dep)          |    |                         | 60.9   | 78.2  | 73.6 | 74.7  | 70.9  | 62.8| 74.7| 73.6| 75.1 | 69.4|
| intra(zero)         |    |                         | 7.4    | 22.2  | 11.1 | 18.5  | 11.1  | 14.8| 18.5| 18.5| 18.5 | 22.2|
| exo1                |    |                         | 0.0    | 7.1   | 0.0  | 7.1   | 7.1   | 0.0 | 7.1 | 0.0 | 7.1  | 14.3|
| exo2                |    |                         | 0.0    | 0.0   | 0.0  | 0.0   | 0.0   | 0.0 | 0.0 | 0.0 | 0.0  | 0.0 |
| unknown             |    |                         | 6.4    | 7.9   | 11.1 | 27.0  | 0.0   | 0.0 | 1.6 | 3.2 | 0.0  | 7.9 |

| arg. type \ target | OW | # of predicates \ model | Each-D | Small | All | Out-D | One-H | F-t | F-a | C-p | Vote | Mix |
|---------------------|----|-------------------------|--------|-------|-----|-------|-------|-----|-----|-----|------|-----|
| none                |    |                         | 98.7   | 98.1  | 98.8 | 98.5  | 98.4  | 99.3| 98.0| 95.3| 98.7 | 96.3|
| intra(dep)          |    |                         | 59.4   | 64.1  | 64.8 | 59.9  | 64.1  | 47.4| 68.0| 67.7| 63.6 | 68.8|
| intra(zero)         |    |                         | 7.8    | 10.3  | 8.6  | 8.6   | 11.2  | 5.2 | 9.5 | 11.2| 8.6  | 12.9|
| exo1                |    |                         | -      | -     | -   | -     | -     | -   | -   | -   | -    | -   |
| exo2                |    |                         | -      | -     | -   | -     | -     | -   | -   | -   | -    | -   |
| unknown             |    |                         | 2.9    | 11.2  | 5.9  | 2.4   | 4.7   | 0.0 | 2.4 | 4.1 | 2.9  | 21.8|

| arg. type \ target | PB | # of predicates \ model | Each-D | Small | All | Out-D | One-H | F-t | F-a | C-p | Vote | Mix |
|---------------------|----|-------------------------|--------|-------|-----|-------|-------|-----|-----|-----|------|-----|
| none                |    |                         | 97.2   | 97.4  | 98.4 | 98.1  | 98.1  | 97.7| 96.7| 97.1| 97.6 | 97.3|
| intra(dep)          |    |                         | 76.3   | 81.4  | 76.5 | 75.8  | 78.3  | 79.0| 82.6| 82.1| 81.3 | 80.2|
| intra(zero)         |    |                         | 7.8    | 11.4  | 10.6 | 9.6   | 11.2  | 13.5| 10.6| 13.5| 13.5 | 12.8|
| exo1                |    |                         | -      | -     | -   | -     | -     | -   | -   | -   | -    | -   |
| exo2                |    |                         | 0.0    | 0.0   | 0.0  | 0.0   | 0.0   | 0.0 | 0.0 | 0.0 | 0.0  | 0.0 |
| unknown             |    |                         | 14.2   | 8.5   | 6.3  | 3.4   | 6.3   | 15.9| 2.8 | 11.4| 5.1  | 20.5|

| arg. type \ target | PM | # of predicates \ model | Each-D | Small | All | Out-D | One-H | F-t | F-a | C-p | Vote | Mix |
|---------------------|----|-------------------------|--------|-------|-----|-------|-------|-----|-----|-----|------|-----|
| none                |    |                         | 97.2   | 96.6  | 97.5 | 97.0  | 97.2  | 98.3| 96.5| 96.0| 97.6 | 96.8|
| intra(dep)          |    |                         | 74.7   | 83.4  | 77.8 | 79.4  | 77.0  | 65.7| 78.1| 81.5| 78.0 | 79.8|
| intra(zero)         |    |                         | 15.7   | 16.5  | 9.6  | 20.0  | 10.4  | 4.4 | 12.2| 13.9| 7.8  | 17.4|
| exo1                |    |                         | 0.0    | 0.0   | 25.0 | 25.0  | 25.0  | 0.0 | 0.0 | 25.0| 0.0  | 0.0 |
| exo2                |    |                         | 0.0    | 0.0   | 0.0  | 0.0   | 0.0   | 0.0 | 0.0 | 0.0 | 0.0  | 0.0 |
| unknown             |    |                         | 3.2    | 8.9   | 11.3 | 6.5   | 0.8   | 0.0 | 2.4 | 31.5| 0.8  | 19.4|

| arg. type \ target | PN | # of predicates \ model | Each-D | Small | All | Out-D | One-H | F-t | F-a | C-p | Vote | Mix |
|---------------------|----|-------------------------|--------|-------|-----|-------|-------|-----|-----|-----|------|-----|
| none                |    |                         | 97.9   | 96.8  | 97.9 | 96.9  | 97.9  | 98.4| 97.2| 96.9| 97.7 | 97.1|
| intra(dep)          |    |                         | 67.0   | 77.9  | 73.3 | 75.8  | 73.0  | 63.3| 73.5| 78.5| 73.5 | 77.7|
| intra(zero)         |    |                         | 7.5    | 9.0   | 7.5  | 6.0   | 6.7   | 3.7 | 9.0 | 9.7 | 6.7  | 9.0 |
| exo1                |    |                         | -      | -     | -   | -     | -     | -   | -   | -   | -    | -   |
| exo2                |    |                         | 0.0    | 0.0   | 0.0  | 0.0   | 0.0   | 0.0 | 0.0 | 0.0 | 0.0  | 0.0 |
| unknown             |    |                         | 4.4    | 8.1   | 9.6  | 2.9   | 1.5   | 2.2 | 1.5 | 8.8 | 4.4  | 9.6 |

OC: QA tests, OY: blog texts, OW: white papers, PB: books, PM: magazines, PN: newspapers

Table 12: Detailed result for dative case (DAT) (accuracy)