Japanese Predicate Argument Structure Analysis Exploiting Argument Position and Type

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Predicate-Argument Structure Analysis (PASA)

#### to identify the argument for each case

Case = semantic relation between phrases

#### In short, each case corresponds to ...

Case	Semantic Role
Nominative	Agent
Accusative	Direct object
Dative	Indirect object



#### Arguments are classified into...

# 3 types

#### according to their positions relative to the predicates





intra-sentential arguments

that have direct syntactic dependency with the predicates





intra-sentential arguments that doesn't have direct syntactic dependency with the predicates



inter-sentential arguments (which are not in the same sentence)

# 3 argument types

INTRA\_Z

INTER

### The difficulty of analysis

Comparatively	
easy	

Difficult

	Nominative	Accusative	Dative
INTRA_D	75.6	88.2	89.5
INTRA_Z	30.2	11.4	3.7
INTER	23.45	9.32	11.76

F-value of PASA [Taira08]

# Why is it more difficult to identify the arguments of INTRA\_Z and INTER than INTRA\_D?

	function word , directly dependency	Arguments (e.g: nominative)
INTRA_D		57.1%
INTRA_Z		30.5%
INTER		12.4%
Poverty	of features	limited amount of training examples

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#### **Proposal1:** a novel feature with an improved similarity measure between argument positions of two predicates that take semantically similar arguments.

# Argument position

the position where the argument of a predicate may occur

#### What is the argument of nominative case of "surrender"?



# 私は( $\phi$ が) 首省した と 聞いた. I heard that $\phi$ had surrendered that beard た.

Arrest

nominative case : Police: accusative case : Hanako Surrender nominative case : ?

### Need the knowledge that an an rested person is more likely to be a person who has surrendered than an arrestee



# Arrest - accusative case

#### Surrender - nominative case





#### Large amount of Texts

# Get the knowledge using co-reference chain?

Events	Roles
A search B A arrest B B plead C D acquit B D convict B D sentence B	A = <i>Police</i> B = <i>Suspect</i> C = <i>Plea</i> D = <i>Jury</i>

[Chambers et al.09]



referring nouns)

(1)Strong dependency on co-reference chain resolutions(2)Need of many documents (does not use any non co-



# Extract large amount of triples with a <u>dependency parser</u>

Verb + case marker + noun phrase

1599	が 自首する (surrender)	5651	が 逮捕する (arrest)	82112	を 逮捕する (arrest)
136	-者 person	702	署員 PS staff	15285	人 person
117	犯人 criminal	698	警察 police	8484	-者 person
96	彼 he	376	警察官 police officer	5563	男 man
68	人 person	368	-署 police station	2804	-名 name
63	男 man	230	県警 prefectural police	1188	犯人 criminal
36	-犯 crime	177	-員 -staff	1185	男性 male
30	少年 boy	153	府警 prefectural police	763	-5-s
26	高校生 high-scool student	137	当局 authorities	671	おまえ you
			,		

か(ga):nominativecase

を(wo):accusative case

Extracted from web corpus about 5milion sentences[Kawahara et al.09]

# Similarities between argument positions calculated with WEB corpus

#### $Sim(A,B) \equiv 1$ -JenshenShanon(A,B)

	nominative case of surrender	nominative case of arrest	accusative case of arrest
nominative case of surrender	-	0.4590	0.7568
nominative case of arrest		-	0.4861
accusative case of arrest			-

### Argument position ... the position where the argument of a predicate may occur.

#### Advantages of our proposed method



In general, the accuracy of dependency parsing is higher than that of co-reference chain resolution.



This method can use all triples in documents.

#### Proposal2: Selection-and-Classification Model Considering Argument Types





Difficulty in distinguishing the marginal cases where two candidates have different argument types <sup>24</sup>





#### Experiments



#### **Experiment settings**

Case	Nominative case
Clasifier	Support Vector Machine(linear kernel)
Common features	Features proposed by [lida et al.07]
Most likely argument selection	Tournament model[lida et al.10]
Dataset	NAIST text corpus1.4β (2917 articles) source: Japanese newswire texts
Test method	5-fold cross validation
Assumption	The results of co-reference resolution and former PASA are correct.

### Result



#### We investigate from 3 standpoints

#### (1) Effect of our proposed S&C model

# (2) Effect of our proposed similarity based similarity feature(3) Effect of In and Out-of-domain

#### **Baseline** Not Considering argument types

S&C model Considering argument types





#### Our proposed model is superior to others

	INTRA_D			INTRA_Z			INTER			ALL
	Ρ	R	F	Ρ	R	F	Р	R	F	F
Baseline model	80.51	56.86	66.63	27.97	54.91	37.06	19.05	17.70	16.60	50.72
Proposed S&C model	80.71	85.35	82.96	47.57	75.74	46.64	23.79	15.93	19.07	67.46
[Taira et al. 08]	-	-	75.53	-	-	30.15	-	-	23.45	57.40

All use standard features

We investigate from 3 standpoints

(1) Effect of our proposed S&C model

(2) Effect of our proposed similarity based similarity feature

(3) Effect of In and Out-of-domain

#### **Co-reference based feature**

Events	Roles
A search B A arrest B B plead C D acquit B D convict B D sentence B	A = <i>Police</i> B = <i>Suspect</i> C = <i>Plea</i> D = <i>Jury</i>

[Chambers et al.09]

#### similarity based feature

1599	<sup>続</sup> 自首する (surrender)	5651	<sup>読</sup> 逮捕する (arrest)	82112	<sup>w</sup> を逮捕する (arrest)
136	-者 person	702	署員 PS staff	15285	人 person
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#### Our proposed similarity based feature is effective

	INTRA_D			INTRA_Z			INTER			ALL
	Р	R	F	Р	R	F	Р	R	F	F
standart features	80.71	85.35	82.96	47.57	75.74	46.64	23.79	15.93	19.07	67.46
+COREF	86.82	88.90	87.85	54.07	52.89	53.47	25.83	20.08	22.58	71.99
+SIM	88.42	91.10	89.74	59.05	58.12	58.58	24.81	19.91	22.08	74.17

All use S&C model

COREF : co-reference based feature calculated from Web Texts SIM: similarity based feature calculated from Web Texts We investigate from 3 standpoints

(1) Effect of our proposed S&C model

(2) Effect of our proposed similarity based similarity feature

(3) Effect of In and Out-of-domain

# Use these sources to calculate similarity between events

#### Web text Newswire text





#### Our proposed feature is effective

	INTRA_D			INTRA_Z			INTER			ALL
	Р	R	F	Р	R	F	Р	R	F	F
standart features	80.71	85.35	82.96	47.57	75.74	46.64	23.79	15.93	19.07	67.46
+SIM_WEB	88.42	91.10	89.74	59.05	58.12	58.58	24.81	19.91	22.08	74.17
+SIM_NEWS	87.00	90.44	88.69	64.76	60.27	62.43	25.63	21.32	23.27	74.45
+SIM_WEB &SIM_NEWS	89.70	91.55	90.62	65.08	61.37	63.17	24.86	21.57	23.08	75.61

All use S&C model

SIM\_WEB : similarity based feature calculated from Web Texts SIM\_NEWS: similarity based feature calculated from Newswire texts

## Result

(1) Our proposed model is effective

(2) Similarity based feature is more effective than co-reference based feature

(3) Measures with In-and-Out-ofdomain data work complementary

# **Error Analysis**

#### **Predicate Sense Ambiguity**

### Light Verb Construction

It's difficult to calculate similarity when the predicate has Sense Ambiguity

#### (φが) 数字を早急に<mark>詰める(tsumeru)</mark>必要性 を強調した。

They emphasized that  $\phi$  should be brought to an conclusion as soon as possible.

詰める 1. to pack tsumeru 2. to bring to a conclusion

# Ambiguous verbs tend to have a mixture of several distributions of arguments



more difficult when the predicate is more essential verb...



## **Error Analysis**

### **Predicate Sense Ambiguity**

### **Light Verb Construction**

#### **Light Verb Construction** Particle Verb Noun affection get WO 受ける 影響 な [eikyou] [wo] [ukeru] carries the main doesn't play a central role

meaning of this phrase

## Future work

(1) to combine internal argument to take semantic argument into consideration, if the verb is in light verb construction

(2) to perform word sense disambiguation before calculating similarity

(3) to conduct experiments not only on nominative case but also on other cases

### Conclusion

Proposal1: A similarity feature between argument positions using distribution similarity

#### Proposal2:

Selection-and-Classification Model Considering Argument Types

#### Proposal1:

# A similarity feature between argument positions using distribution similarity

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