

# A Machine Learning Approach to Recipe Flow Construction

Shinsuke Mori, Tetsuro Sasada,  
Yoko Yamakata, Koichiro Yoshino

Kyoto University

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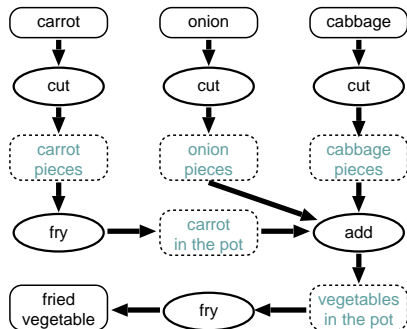
Recipe Text Analysis

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Conclusion

# What is Recipe?

- ▶ Describing the procedures for a dish
  - ▶ submitted to the Web
  - ▶ mainly written by house chefs
- ▶ One of the successful web contents
  - ▶ search, visualization, ...
- ▶ Recipe Flow [Momouchi 80, Hamada 00]



# Recipe as a Text for Natural Language Processing

- ▶ Containing general NLP problems
  - ▶ Word identification or segmentation (WS)
  - ▶ Named entity recognition (NER)
  - ▶ Syntactic analysis (SA)
  - ▶ Predicate-argument structure (PAS) analysis
  - ▶ etc.
- ▶ Simple compared with newspaper articles, etc.
  - ▶ Few modalities
  - ▶ Simple in tense and aspect
  - ▶ Mainly indicative or imperative mood
  - ▶ Only one person (Chef)

# Overall Design

1. Recipe text analysis
  - ▶ State of the art in NLP area
  - ▶ Domain adaptation to recipe texts
2. Flow construction
  - ▶ Not rule-based (hopefully)
  - ▶ Graph-based approach
3. Match with movies

# Recipe Text Analysis

Execute the following steps in this order

1. WS: Word segmentation (Including stemming)
  - ▶ Only required for languages without whitespace (ja, zh)
  - ▶ Some canonicalization required even for en, fr, ...
2. NER: Named entity recognition
  - ▶ **F**ood, **T**ool, **D**uration, **Q**uantity, **S**tate, **A**ction by the chef or foods
3. SA: Syntactic analysis
  - ▶ Grammatical relationship among NEs
4. PAS: Predicate-argument structure analysis
  - ▶ Semantic relationship among NEs

## Output

煮立て (*obj.:*水-4 0 0 -c c, *で:*鍋)

boil(*obj.:*water 400cc, *by:*pot)

## Step 1. Word Segmentation (word identification)

- ▶ Input: a sentence

水400ccを鍋で煮立て、沸騰したら中華スープの素を加えてよく溶かす。

(Heat 400 cc of water in a pot, and when it boils, add Chinese soup powder and dissolve it well.)

- ▶ Output: a word sequence

水|4-0-0|c-c|を|鍋|で|煮-立-て|、|  
沸-騰|し|た-ら|中-華|ス-ー-プ|の|素|を|  
加-え|て|よ-く|溶-か|す|。

where “|” and “-” mean existence and non-existence of a word boundary.

- ※ No dictionary form of inflectional words is needed because our standard divides them into the stem and the ending.

# Pointwise WS (KyTea) [Neubig 11]

- ▶ Binary classification problem at each point between chars

Text:  $x_{i-2}$   $x_{i-1}$   $x_i$   $x_{i+1}$   $x_{i+2}$   $x_{i+3}$   
鍋 で 煮 立 て 、 沸 騰 し た  
↑  
 $t_i$ : Decision point

Trainable from a partially annotated corpus

⇒ Flexible corpus annotation!

⇒ Easy to adapt to a specific domain!

- ▶ A partially annotated corpus allows us to focus on special terms

弱<sub>□</sub>火<sub>□</sub>で|煮-立-て|る  
こ<sub>□</sub>れ<sub>□</sub>が|煮-立|つ|ま<sub>□</sub>で





# Baseline and its Adaptation

- ▶ Baseline: BCCWJ, UniDic, etc.
- ▶ Adaptation: KWIC based partial annotation
  - ▶ 8 hours

partial\_corpus\_annotation.html  
http://corpus.ar.media.kyoto-u.ac.jp/partial\_corpus\_annotation.html

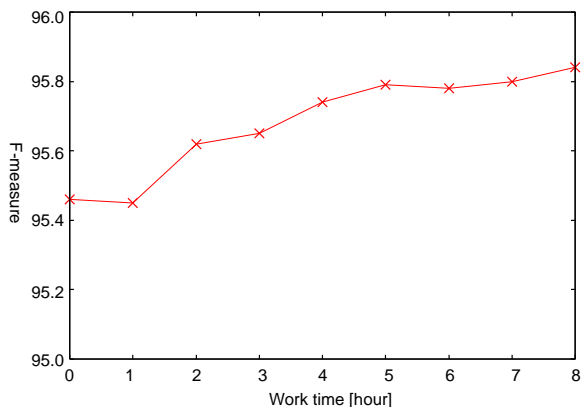
## 部分コーパス修正 2.0

前の文脈	単語候補	後の文脈	よみ(リストに無い場合は右端のボックスへ、不明確な場合は右端を空欄に)		
疲労、アレルギー、感染、角膜のこ	<input type="checkbox"/> すり傷	<input checked="" type="checkbox"/> 、角膜潰瘍、眼内の異物などが挙げ	<input type="radio"/> すりきず*	<input type="radio"/> すりしよう	<input checked="" type="radio"/>
って、皮膚が切れたり、裂けたり、	<input checked="" type="checkbox"/> すり傷	<input checked="" type="checkbox"/> 、刺し傷を負うことがあります。BT	<input checked="" type="radio"/> すりきず*	<input type="radio"/> すりしよう	<input type="radio"/>
としてあざ、やけど、みみず腫れ、	<input checked="" type="checkbox"/> すり傷	<input checked="" type="checkbox"/> などがよくみられます。BTこれらの	<input checked="" type="radio"/> すりきず*	<input type="radio"/> すりしよう	<input type="radio"/>
も尋ねられます。BT医師は切り傷や	<input type="checkbox"/> すり傷	<input type="checkbox"/> などの身体的外傷に注意して診察し	<input type="radio"/> すりきず*	<input checked="" type="radio"/> すりしよう	<input type="radio"/>
りますが、とりわけ泥まみれの深い	<input type="checkbox"/> すり傷	<input type="checkbox"/> や、皮下深くまで汚染しやすい刺し	<input type="radio"/> すりきず*	<input checked="" type="radio"/> すりしよう	<input type="radio"/>

送信

# Result

- ▶ F measure =  $\{(LCS/sysout^{-1} + LCS/corpus^{-1})/2\}^{-1}$



- ▶ WS improves as the work time increases
- ▶ More work required (about 98% in the general domain)

## Step 2. Named Entity Recognition (NER)

- ▶ Named entity
  - ▶ Word sequences corresponding to objects and actions in the real world
  - ▶ Highly domain dependent
- ▶ Named entity types for recipes:

**F**ood, **T**ool, **D**uration, **Q**uantity, **S**tate,

**A**ction by the chef, **A**ction by foods

水<sub>F</sub> 400 cc<sub>Q</sub> を鍋<sub>T</sub> で 煮立て<sub>Ac</sub>、沸騰し<sub>Af</sub> たら  
中華スープの素<sub>F</sub> を 加え<sub>Ac</sub> てよく 溶か<sub>Ac</sub> す。

Heat<sub>Ac</sub> 400 cc<sub>Q</sub> of water<sub>F</sub> in a pot<sub>T</sub>, and when it boils<sub>Af</sub>,  
add Chinese soup powder<sub>F</sub> and dissolve<sub>Ac</sub> it well.

# Pointwise NER

Trainable from a partially annotated corpus

⇒ Flexible corpus annotation!

⇒ Easy to adapt to a specific domain!

1. BIOES representation (one NE tag for a word, with **O**ther)  
水/B-F 400/B-Q cc/I-Q を/O 鍋/BT で/O  
煮立て/B-Ac 、/O 沸騰/B-Af し/I-Af たら/O
2. Train pointwise classifier (KyTea) with **logistic regression** from a tagged data including partially annotated corpus
  - ▶ No partially annotated corpus this time
  - ▶ Cf. A CRF requires a fully annotated sentences.

## Pointwise NER (cont'd)

3. Output all the possible pairs of tag and probability to fill the Viterbi table:

$P(y w)$	$w$				
	水	4 0 0	c c	を	...
<b>F-B</b>	0.62	0.00	0.00	0.00	...
<b>F-I</b>	0.37	0.00	0.00	0.00	...
<b>Q-B</b>	0.00	0.82	0.01	0.00	...
<b>Q-I</b>	0.00	0.17	0.99	0.00	...
<b>T-B</b>	0.00	0.00	0.00	0.00	...
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$
<b>O</b>	0.01	0.01	0.00	1.00	...

4. Search for the best sequence satisfying the constraints
- ▶ Ex. “**F-I Q-I**” is invalid
  - ▶ In future work we change this part into CRFs

# Baseline and its Adaptation

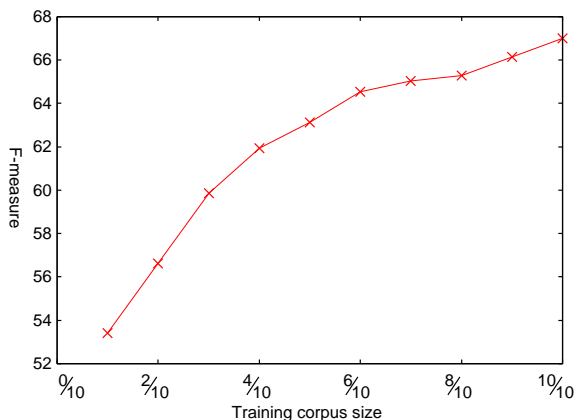
- ▶ Baseline: 1/10 of *Meet-potato* recipe text (24 sent.)
- ▶ Annotation: from 1/10 to 10/10 (about 5 hours, 242 sent.)  
*Not randomly selected recipes ... (bad setting)*



Meet potato

# Result

## ► F measure

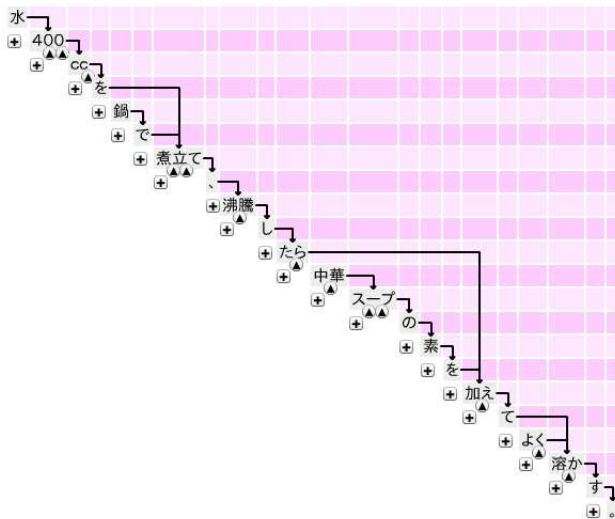


- Very low F measure compared with the general domain (around 80%)
- NER improves rapidly as the work time increases



# Step 3. Syntactic Analysis

- ▶ Dependency among the words (and NEs) in a sentence



# Pointwise SA

- ▶ Pointwise MST (EDA) [Flannery 11]

Trainable from a partially annotated corpus

⇒ Flexible corpus annotation!

⇒ Easy to adapt to a specific domain!

1. Estimate dependency scores of all the possible pairs in a sentence

$$\sigma(\langle \mathbf{i}, \mathbf{d}_i \rangle, \vec{\mathbf{w}}), \quad \text{where } \mathbf{w}_i \text{ depends on } \mathbf{w}_{\mathbf{d}_i}$$

2. Select the Spanning Tree which Maximizes the total score (MST)

$$\hat{\mathbf{d}} = \operatorname{argmax}_{\mathbf{d} \in \mathbf{D}} \sum_{i=1}^n \sigma(\langle \mathbf{i}, \mathbf{d}_i \rangle, \vec{\mathbf{w}})$$

# Pointwise SA (cont'd)

- Features for dependency score of a word pair

		oyster	<i>obj.</i>	Hiroshima	to	<i>eat</i>	to	<i>go</i>	<i>infl.</i>	
		牡蠣	を	広島島	に	食べ	に	行	く	
$w_{i-3}$	$w_{i-2}$	$w_{i-1}$	$w_i$	$w_{i+1}$	$w_{i+2}$	$w_{i+3}$				
				$w_{d_i-3}$	$w_{d_i-2}$	$w_{d_i-1}$	$w_{d_i}$	$w_{d_i+1}$	$w_{d_i+2}$	$w_{d_i+3}$

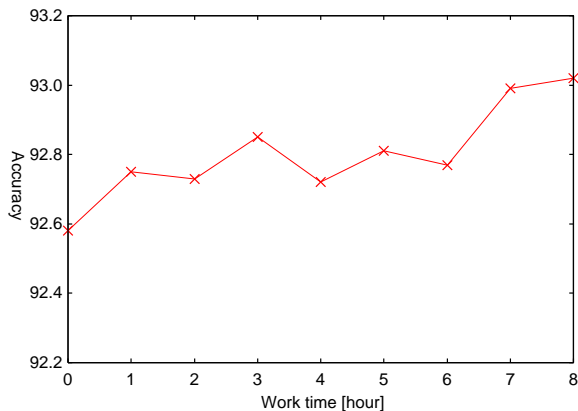
- F1 The distance between a dependent word  $w_i$  and its candidate head  $w_{d_i}$ .
- F2 The surface forms of  $w_i$  and  $w_{d_i}$ .
- F3 The parts-of-speech of  $w_i$  and  $w_{d_i}$ .
- F4 The surface forms of up to three words to the left of  $w_i$  and  $w_{d_i}$ .
- F5 The surface forms of up to three words to the right of  $w_i$  and  $w_{d_i}$ .
- F6 The parts-of-speech of the words selected for F4.
- F7 The parts-of-speech of the words selected for F5.

# Baseline and its Adaptation

- ▶ Baseline: about 20k sent.
  - ▶ EHJ (Dictionary example sentences):  
11,700 sentences, 145,925 words
  - ▶ NKN (*Nikkei* newspaper articles):  
9,023 sentences, 263,425 words
- ▶ Adaptation: Annotate new pairs of a noun and a postposition with the dependency
  1. Find a pair of a noun and a postposition not appearing in the training corpus
  2. Annotate the dependencies from the noun to its head  
verb            *obj.*  
c c → を → ( ... **boil**  
   煮立て )
  3. 8 hours

# Result

## ► Accuracy

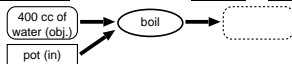


- Low accuracy compared with the in-domain data (96.83%)
- SA improves slowly as the work time increases

# Step 4. Predicate-argument structure analysis

- ▶ Rule-based (as far as it is)
  - ▶ Should be based on a machine learning
  - ▶ Have to guess zero-pronouns
- ▶ Correspond to the smallest units in the recipe flow

1. <sup>boil</sup>煮立<sub>Ac</sub> (Chef, <sup>water</sup>水<sub>F</sub> 400 cc <sub>Q</sub> <sup>obj.</sup>を, <sup>pot</sup>鍋<sub>T</sub> <sup>in</sup>で)



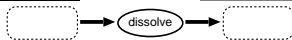
2. <sup>boils</sup>沸騰<sub>Af</sub> (Food)



3. <sup>add</sup>加え<sub>Ac</sub> (Chef, <sup>Chinese soup powder</sup>中華 スープ の 素<sub>F</sub> <sup>obj.</sup>を, <sup>water</sup>水<sub>F</sub> に)



4. <sup>dissolve</sup>溶か<sub>Ac</sub> (Chef, <sup>Chinese soup powder</sup>中華 スープ の 素<sub>F</sub> を)



# Experimental Setting

1. Test data: randomly selected 100 recipes in Japanese

#recipes	#sent.	#words	#NEs
100	724	13,150	3,797

2. Training data

- ▶ WS: (BCCWJ + etc.) + partial annotation
- ▶ NER: *Meet-potato* 1/10 + 9/10 (bad setting ...)
- ▶ SA: (EHJ + NKN) + partial annotation
- ▶ PAS: on going
- ▶ Recipe Flow: on going

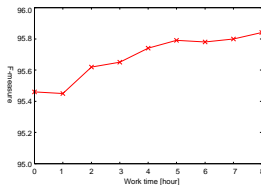
# Evaluation 1: Each Step (summary)

Step 1. WS: Word segmentation

Baseline: 95.46%

↓ (8 hours)

Adaptation: 95.84%

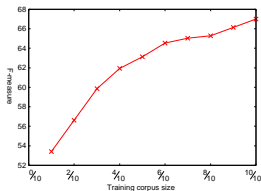


Step 2. NER: Named entity recognition

Baseline: 53.42%

↓ (5 hours)

Annotation: 67.02%

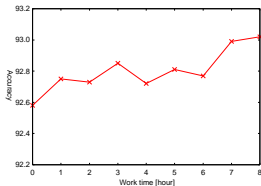


Step 3. SA: Syntactic analysis

Baseline: 92.58%

↓ (8 hours)

Adaptation: 93.02%





# Evaluation 2: Overall

## 1. Predicate-argument structure

- ▶ PA pair as an evaluation unit
  - ▶  $\langle \text{煮立て, obj.:水-4 0 0-c c} \rangle$   
 $\langle \text{boil, obj.:400 cc of water} \rangle$
  - ▶  $\langle \text{煮立て, で:鍋} \rangle$   
 $\langle \text{boil, by:pot} \rangle$
- ▶ F measure  
Baseline 42.01%  
↓ (8 + 5 + 8 hours) **28.0% error elimination!**  
Adaptation 58.27%
- ▶ F measure is still low
  - ▶ Because of NER? (67.02%  $\ll$  90%)
  - ▶ More annotation required (21 hours  $\ll$   $\infty$ )
  - ▶ Strict criterion (word boundary incl., etc.)

## 2. Flow Accuracy

# Conclusion

- ▶ Recipe Text Analysis
  - ▶ Word segmentation, Named entity recognition
  - ▶ Syntactic analysis, Predicate-argument structure analysis
- ▶ A Machine Learning Approach
  - ▶ Systematic domain adaptation
  - ▶ Easily trainable to achieve the required accuracy
- ▶ Future work
  - ▶ Improvement<sup>3</sup>
  - ▶ Recipe flow construction (search, visualization, ...)
  - ▶ Matching with movies to understand the real world
  - ▶ Spoken dialog system to help a chef (Smart kitchen)
    - ▶ equipped with the recipe flow as the database

# PNAT: Pointwise NLP Annotation Tool

- ▶ Word segmentation
- ▶ Part-of-speech tag
- ▶ Pronunciation
- ▶ Named entity tag
- ▶ Syntactic structure

FILE SELECT SAVE PREV NEXT UNDO REDO /home/mori/tmp/sample/corpus\_tr CloseList ヘルプ

No1:  
玉ねぎを薄切りにして水にさらしておく。

次の文とマージ

品記	品詞	読み	埋め表	ラ	係り受け表示
玉ねぎ	名詞	たまねぎ	F-B		玉ねぎ
を	助詞	を			を
薄切り		うすぎり	0		薄切り
に	助詞	に	0		に
し	動詞	し	Ac-B		し
で	助詞	で	0		で
水	名詞	みず	F-B		水
に	助詞	に	0		に
さら	動詞	さら	Ac-B		さら
し	語尾	し	0		し
て	助詞	て	0		て
お	動詞	お	0		お
く	語尾?	く	0		く
,	補助記号	,	0		,

表示/非表示

No1: 玉ねぎを薄切りにして水にさらしておく。  
No2: 油揚げはオープンで焼く。  
No3: サウとさせる。  
No4: きゅうり はら センチ にきって 半分 にして  
No5: レタスを食べやすい大きさに切る。  
No6: 焼いた油揚げを食べやすい大きさにする  
No7: 梅を種を取って白でこまかくする。  
No8: 酒、砂糖、酢、醤油、ごま、梅干しを  
No9: 塩見して 調節する。  
No10: 器にすべて盛り付ける。

Navigation icons: back, forward, search, etc.

## References

-  Flannery, D., Miyao, Y., Neubig, G., and Mori, S.: Training Dependency Parsers from Partially Annotated Corpora, in *Proceedings of the Fifth International Joint Conference on Natural Language Processing* (2011)
-  Hamada, R., Ide, I., Sakai, S., and Tanaka, H.: Structural Analysis of Cooking Preparation Steps in Japanese, in *Proceedings of the fifth international workshop on Information retrieval with Asian languages*, No. 8 in IRAL '00, pp. 157–164 (2000)
-  Momouchi, Y.: Control Structures for Actions in Procedural Texts and PT-Chart, in *Proceedings of the Eighth International Conference on Computational Linguistics*, pp. 108–114 (1980)



Neubig, G., Nakata, Y., and Mori, S.: Pointwise Prediction for Robust, Adaptable Japanese Morphological Analysis, in *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics* (2011)