



Chinese Overt Pronoun Resolution: A Bilingual Approach

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Task: Chinese Overt Pronoun Resolution (PR)

Find an antecedent for each anaphoric overt pronoun in a Chinese text

An Illustrative Example



Resolve pronouns 她(**she**) and 他(**him**) to their antecedents, which are 玛丽(**Mary**) and 约翰(**John**) respectively.

Why is it more Challenging than English PR?

- Less coreference-annotated data available for training resolvers in Chinese than in English
- Lack of publicly-available linguistic resources in Chinese that are essential for overt PR, such as **Gender** and **Number** wordlists

Goal: Improve Chinese PR

Address the two challenges above by exploiting

- English coreference-annotated data, and
 - English Gender and Number wordlists
- in addition to Chinese coreference-annotated data

How?

- Idea 1: Feature augmentation**
 - Machine-translate Chinese text to English text
 - Align the Chinese and English mentions
 - Train a Chinese pronoun resolver on Chinese data, where instances are represented by features derived from Chinese mentions and those derived from the mapped English mentions
 - Pros:** use Chinese training data; use English wordlists
 - Cons:** does not use English training data
- Idea 2: Annotation projection**
 - Train an English pronoun resolver on English data
 - Apply resolver on English text machine-translated from Chinese
 - Pros:** use English training data; use English wordlists
 - Cons:** does not use Chinese training data
- Idea 3: Our bilingual approach**
 - Combine ideas 1 and 2 via an ensemble approach

Related Work

- All existing approaches to Chinese overt PR or coreference resolution are **monolingual**, training models on either
 - Chinese** data (e.g., Luo and Zitouni (2005); Wang and Ngai (2006); Kong and Zhou (2012); Kong and Ng (2013)); or
 - English** data (by adopting Idea 2) (Rahman and Ng, 2012), but none of them exploits resources in both languages

Bilingual Approach: Implementation Details

Document preprocessing

Step 1: Machine-translate each training and test document from Chinese to English using Google Translate

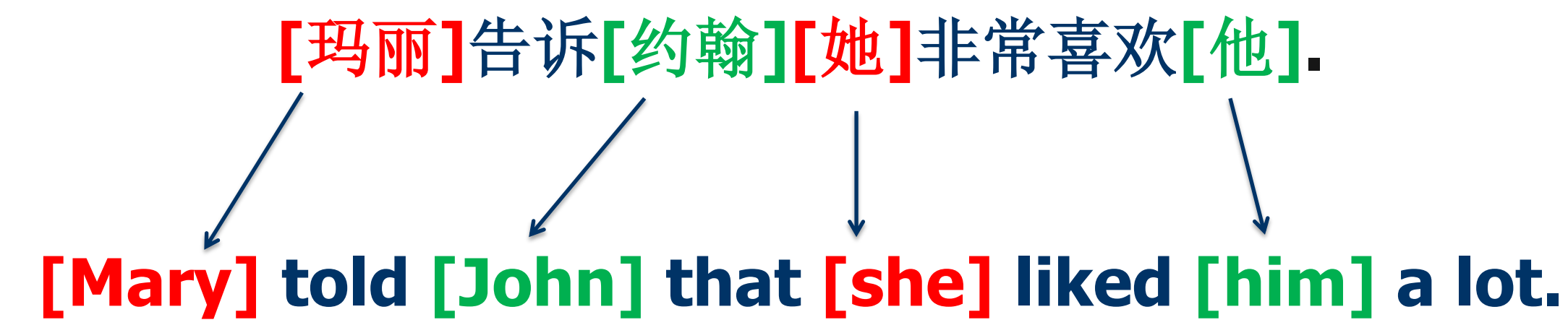
玛丽告诉约翰她非常喜欢他。



Mary told John that she liked him a lot.

Step 2: Align the words in each pair of sentences using BerkeleyAligner

Step 3: Align Chinese mentions to English mentions heuristically



Classifier training (3 classifiers, all mention-pair models)

- English pronoun resolver (PR^E)**
 - Trained on English training data
 - Training instances created from English anaphoric pronouns
 - Employs the English features from Björkelund and Farkas (2012)
- Chinese pronoun resolver (PR^C)**
 - Trained on Chinese training data
 - Training instances created from Chinese anaphoric pronouns
 - Employs the Chinese features from Björkelund and Farkas (2012)
- Mixed pronoun resolver (PR^M)**
 - Trained on Chinese training data and translated English data
 - Training instances created from the subset of Chinese anaphoric pronouns that have been aligned to some English pronouns
 - Employs the features used in both PR^E and PR^C

Resolution methods

- Method 1**
 - Resolve pronoun m_k to the closest preceding mention m_j whose coreference probability with m_k according to PR^E is at least 0.5
 - If m_k is not aligned to any English pronoun or PR^E does not resolve m_k , apply PR^C to resolve m_k
- Method 2**
 - Same as method 1 except that PR^E is replaced with PR^M
- Method 3**
 - Same as method 1, except that the coreference probability between m_k and m_j is computed as the unweighted average of the probabilities returned by PR^E , PR^M and PR^C (which we will refer to as P^E , P^M , and P^C respectively)
- Method 4**
 - Resolve m_k to the closest preceding mention if at least one of four conditions is satisfied: (1) $P^C > t_C$; (2) $P^M > t_M$; (3) $P^E > t_E$ and $P^{norm} \geq 0.5$

$$P_{jk}^{norm} = \frac{P_{jk}^C + P_{jk}^E w_e (P_a)^{w_{ae}} + P_{jk}^M w_m (P_a)^{w_{am}}}{1 + w_e (P_a)^{w_{ae}} + w_m (P_a)^{w_{am}}}$$

Note: P_a is the mention alignment probability, and t_C , t_M , t_E , w_e , w_m , w_{am} are parameters tuned using the development set

Evaluation

Corpus: CoNLL-2012 shared task data

- Training set:** 1,391 Chinese docs (750K words); 1,940 English docs (1.3M words)
- Development set:** 172 Chinese docs (110K words)
- Test set:** 166 Chinese docs (90K words)

Baseline systems

- Monolingual approach**
 - Supervised mention-pair model trained only on Chinese data
- Best Chinese coreference system in the CoNLL-2012 shared task**
 - Hybrid model combining rules and machine learning (Chen and Ng, 2012)
- Rahman and Ng's (2012) approach**
 - Annotation projection approach (method 1 without using PR^C as backoff)

Evaluation metrics

- Recall (**R**), precision (**P**), and F-score (**F**) on resolving anaphoric pronouns
- Accuracies: **A^a** is the percentage of anaphoric pronouns correctly resolved; **A^{na}** is the percentage of non-anaphoric pronouns not resolved; **A^o** is overall accuracy

Results on CoNLL-2012 shared task test set

Resolution Method	R	P	F	A ^a	A ^{na}	A ^o
Monolingual Approach (Closest-first)	71.7	65.3	68.4	71.7	59.3	67.4
Monolingual Approach (Best-first)	72.0	65.6	68.7	72.0	59.3	67.6
Best Shared Task System	63.8	67.5	65.6	63.8	76.7	68.2
Rahman and Ng's (2012) Approach	64.3	65.2	64.7	64.3	68.5	65.8
Method 1	65.6	64.4	65.0	65.6	66.0	65.8
Method 2	73.0	65.1	68.8	73.0	56.7	67.4
Method 3	71.5	70.5	71.0	71.5	67.6	70.2
Method 4	71.1	71.5	71.3	71.1	70.4	70.8

Methods 3 and 4 significantly outperform the baselines w.r.t. both F-score and accuracy.

Impact of Machine Translation Quality

5-fold cross-validation results on a 400-document parallel corpus

	Machine Translation (MT)			Human Translation (HT)		
Resolution Method	R	P	F	R	P	F
Monolingual Approach (Closest-first)	63.0	62.7	62.8	63.0	62.7	62.8
Monolingual Approach (Best-first)	62.3	62.0	62.2	62.3	62.0	62.2
Best Shared Task System	55.2	65.8	60.1	55.2	65.8	60.1
Rahman and Ng's (2012) Approach	54.7	58.1	56.4	46.1	59.9	52.1
Method 1	55.6	57.4	56.5	56.3	59.8	58.0
Method 2	65.6	59.8	62.5	65.7	61.7	63.7
Method 3	61.7	66.9	64.2	63.6	66.7	65.1
Method 4	63.8	65.3	64.5	64.5	67.0	65.7

When MT is replaced with HT, the F-scores of all four methods increase significantly by 0.9-1.5%, but their relative performance does not change.