Using Hypothesis Selection Based Features for Confusion Network MT System Combination

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EACL 2014, Third Workshop on Hybrid Approaches to Translation

Plan

MT system combination

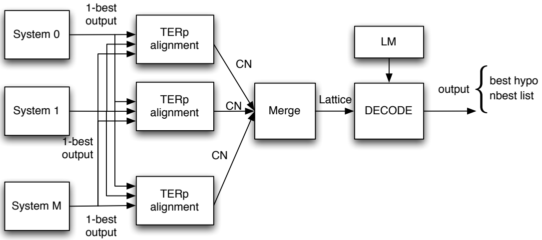
- Taken a great importance these past few years
- Resulting outputs with a better performance than any individual MT system output
- Exploit the complementarity of different MT approaches (rule-based, phrase-based, hierarchical, and syntax-based, etc...)
  $\Rightarrow$to produce consensus translations in the hope of generating better translations.

Existing Works

- Hypothesis selection using nbest list reranking based on various features [Hildebrand and Vogel, AMTA'08]
- Syscomb with SMT system, by considering source text and system outputs as bitext [Chen et al., WMT'09]
- Confusion network decoding :
  - does not require deep n-best lists
  - operates on the surface strings
  - [Rosti et al., ACL'07] [Shen et al., IWSLT'08] [Karakos et al., HLT'08] and [Matusov et al., EACL'06]

Architecture of MANY

Confusion Network (CN) based MT system combination



- Alignment of 1-best hypotheses and construction of CNs
- Construction of a lattice by merging CNs
- Decoding of the lattice
  - LM probability, Word penalty, Null-arc penalty, System weights.

Limits

- Exponential number of hypotheses $\rightsquigarrow$ n-grams do not appear in the system outputs $\rightsquigarrow$ ungrammatical
- LM score $\rightsquigarrow$ insufficient to precisely evaluate the hypotheses

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Solutions

- To boost n-grams which appear in the system outputs
- Word confidence score

Plan

Two approaches to boost *n*-grams

- *n*-gram count feature : number of *n*-grams present in input hypotheses for each combined hypothesis
  - *bi* and *tri*-grams
- Adapted language model to decode the lattice
  - enhance the training data of a language model by the systems outputs
  - modify certain n-grams probabilities

Plan

Related work

- [Quirk.2004] : presents a supervised method for training a sentence level confidence measure on translation output using a human annotated corpus
- [Ueffing and Ney.2007] : present confidence scores at word-level based on word posterior probabilities
- [Hildebrand.2008] : defines several features extracted from *n*-best lists (at the sentence level) to select the best hypothesis in a combination approach via hypothesis selection.

Related work

- [Quirk.2004] : presents a supervised method for training a sentence level confidence measure on translation output using a human annotated corpus
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- [Hildebrand.2008] : defines several features extracted from *n*-best lists (at the sentence level) to select the best hypothesis in a combination approach via hypothesis selection.

$\Rightarrow$ Exploit certain features defined by *Hildebrand* to estimate a confidence score at the *word level* and injecting it into the confusion networks.

Confidence scores

1. Word agreement score based on a window of size **t** around position **i** ($WA_k(e_{i,t})$)
   - The relative frequency
2. Position independent *n*-best List *n*-gram Agreement ($NA_k(e_i)$) :
   - The percentage
3. N-best list *n*-gram probability ($NP_k(e_i)$):
   - *n*-gram language model probability

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Word confidence score

$$SC_k(e_i) = \frac{\mathrm{WA}_k(e_i) + \sum_{j \in NG} \mathrm{NA}_k(e_i)^j + \mathrm{NP}_k(e_i)^j}{1 + 2 * |NG|} \quad (1)$$

$\Rightarrow$ NG={2-gram, 3-gram}

$\Rightarrow$ t = 2.

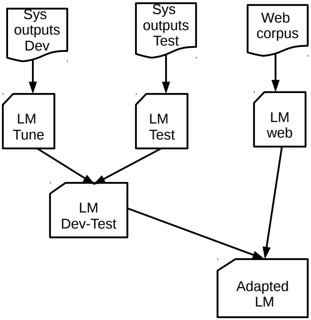
Plan

Data description

- The BOLT project on the Chinese to English translation task
- Outputs of six systems
  - 200-best lists $\Longrightarrow$ word confidence score
  - 1-best outputs $\Longrightarrow$ combination
- Corpora :

NAME	#sent.	#words.
Syscomtune	985	28671
Dev	1124	26350

Adapted language model



Language model	perplexity
LM-Web	295.43
Adapted-LM	169.923

Tests

- New features tests
  1. *n*-gram count
  2. Word confidence score
  3. *n*-gram count + Word confidence score

Tests

- New features tests
  1. *n*-gram count $\Longrightarrow$ boost-ngram
  2. Word confidence score $\Longrightarrow$ CS-ngram
  3. *n*-gram count + Word confidence score $\Longrightarrow$ Boost-ngram+CS-ngram

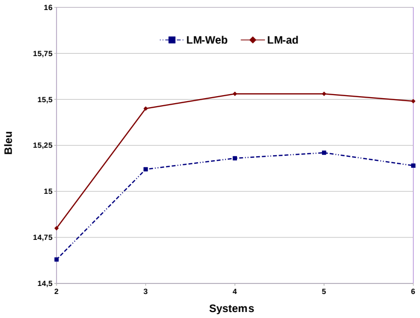
Tests

- New features tests
  1. *n*-gram count $\Longrightarrow$ boost-ngram
  2. Word confidence score $\Longrightarrow$ CS-ngram
  3. *n*-gram count + Word confidence score $\Longrightarrow$ Boost-ngram+CS-ngram

- The baseline combination system and each test are evaluated
  - *LM-Web*
  - *LM-ad*

Evaluation results

- LM-Web Vs LM-ad :

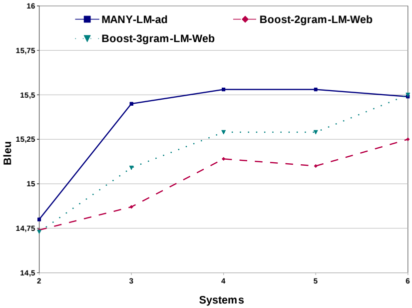


Systems	%BLEU
Sys1(Best)	**14.36**
Sys2	14.21
Sys3	13.76
Sys4	13.52
Sys5	13.36
Sys6	12.99
MANY+LM-Web	15.21
MANY+LM-ad	15.53

⇒ *0.85* and *1.17* %BLEU point relatively to the best single system
⇒ *MANY-LM-Web* is the baseline

Evaluation results

- Two approaches to boost n-grams :



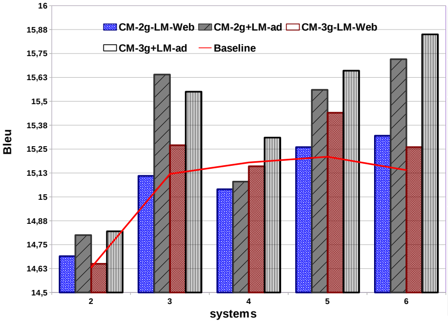
Systems	%BLEU
Sys1(Best)	14.36
MANY+LM-Web(baseline)	15.14
Boost-2gram+LM-Web	15.25
Boost-3gram+LM-Web	15.50
MANY+LM-ad	15.49
Boost-2gram+LM-ad	15.24
Boost-3gram+LM-ad	15.32

⇒ The adapted LM is better than *n*-gram count features to boost *n*-grams

⇒ LM-ad+n-gram count feature decrease results

Evaluation results

- Word confidence score :



Systems	%BLEU
Sys1(Best)	14.36
baseline	15.14
CS-2gram+LM-Web	15.25
CS-3gram+LM-Web	15.32
MANY+LM-ad	15.49
CS-2gram+LM-ad	15.72
CS-3gram+LM-ad	**15.85**

⇒ Contributes the most to the improvement of results
⇒ Performs better with the adapted LM than *LM-Web*
⇒ *1.49* and *0.71* %BLEU point over the best single system and the baseline

Evaluation results

- *n*-gram-count + word confidence score :

Systems	%BLEU
Sys1(Best)	14.36
Baseline	15.14
CS-2gram+LM-Web	15.25
CS-3gram+LM-Web	15.32
Boost+CS(2g)+LM-Web	**15.39**
Boost+CS(3g)+LM-Web	**15.78**
MANY+LM-ad	15.49
CS-2gram+LM-ad	15.72
CS-3gram+LM-ad	15.85
Boost+CS(2g)+LM-ad	**15.61**
Boost+CS(3g)+LM-ad	**15.74**

Conclusions

- MANY was run on six MT systems of different types
- An adapted LM and new features (n-gram count and confidence score) gave significant gains
- The use of an *adapted* LM in rescoring with word confidence score and the previews features improves results in term of BLEU score.
- The use of the two approaches to boost *n*-grams (*n*-gram count features and the adapted language model) together decreases results, this is mainly due to the redundancy

Perspectives

- Combine K-best hypotheses
  - complicate the search space
    $\Longrightarrow$ Reduce the number of backbones
    $\Longrightarrow$ The MBR method [Rosti et al., 2007].