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Confidence Estimation for Machine Translation
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INTRODUCTION

Definition:
• Confidence Estimation (CE) is a task of judging automatically each part (e.g., word, segment, or the whole sentence) in the MT hypothesis as correct or incorrect.
• A classifier trained beforehand by a feature set calculates the confidence score for MT hypothesis, then compares it with a threshold. Those with scores exceeding this threshold are categorized in the Good label set; the rest belongs to the Bad label set.

Interesting uses of CE:
• Decide whether a given translation is good enough for publishing as is.
• Highlight words that need editing in post-editing tasks.
• Inform readers of parts of the sentence that are not reliable.
• Select the best segments among options from multiple translation systems for MT system combination.

FIRST CONTRIBUTION: WORD CONFIDENCE ESTIMATION (WCE)

1. Feature Extraction

In order to build the binary classifier, we extracted totally 25 features, including four categories:
• System-based (S),
• Lexical (L),
• Syntactic (T),
• And Semantic (M) features (see Table 1).

2. Model to train the classifier

• Conditional Random Fields (Lafferty et al., 2001).
• Training algorithm: block-wise coordinate descent (BCD) (Lavergne et al., 2010).

3. French - English SMT System Building

• Decoder: Moses (log-linear model with 14 weighted feature functions.)
• Translation model: Europarl and News parallel corpora (WMT 2010, with 1,638,440 sentences).
• Language model: SRILM, news monolingual corpus (48,653,884 sentences).

4. Corpus Preparation

• SMAT

5. Word Label Setting for Classifier:

• We tag each word of the sentence in the training set a label by comparing this sentence to its reference. This label is then used to train the classifier.
• Tool used: TERp-A (is a version of TERp).
• Type of edit: I,S,T,Y,P,E (see an example of the setting below).
• Regroup into binary category: E, T and Y = G (85%) AND S, P and I = B (15%)

FIRST EXPERIMENTS AND RESULTS

1. Preliminary experiment with all features

• We track the Precision (Pr), Recall (Rc) and F-score (F) values for G and B label along threshold variation (from 0.3 to 1.0, step 0.025).
• Compare to 2 baselines: Baseline 1 (all words in each MT hypothesis are classified as good), and Baseline 2 (assigned randomly 85%G + 15%B) (Table 2, left, below).

2. Feature Selection

• Objective: to rank our features from most to least important + to find the best performing combination.
• Strategy: “Sequential Forward Selection” algorithm. We start from the full set of N features, and in each step sequentially remove the most useless one.
• Output: The rank of each feature (also its ID in Table 1) + the system’s evolution as more and more features are removed (Figure 1, above on the right).

3. Boosting technique to improve the classifier’s performance:

• Objective: Take advantage of the sub-models’ complementarily when combined.
• How to prepare the training set for Boosting system:
  – Step 1: Starting from 25 features, we build 23 subsets, in which 1 contains all features, 1 contains top 10 in Table 1, and 21 sets of 9 randomly extracted features for each.
  – Step 2: Divide our 10K training set into 10 equal subsets (S1, S2, ..., S10).
  – Step 3: For i=1 to 10 do
    • Concatenate Sj (j=1, ..., 10, j≠i) to obtain the Boosting training set D_i.
    • Apply each above classifier to test S_i, log the “G” probability (23 in total) to form the feature classifier’s output.
  – Step 4: Concatenate D_i (i=1, ..., 10) to obtain the Boosting training set.

• Testing: Build the test set for Boosting by logging 23 scores (like Step 3) for the usual test set, coming from 23 systems built on the usual training set.

• Comparison of the performance between 2 systems in terms of averaged scores (Table 3, below) or scores along to threshold variation (Figure 2, right).

CONCLUSION AND ONGOING RESEARCH

• Experimental results show that precision and recall obtained in Good label are very promising, and Bad label reaches acceptable performance.
• A feature selection that we proposed helped to identify the most valuable features, as well as to find out the best performing subset among them.
• The protocol of applying Boosting method exploited effectively the good feature subsets for the system’s performance improvement.
• Future work will take a deeper look into the linguistic features of word; experiment the CE at segment level; and find the methodology to conclude the sentence quality reliably based on the word’s and segment’s confidence score.