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► **To cite this version:**

Ngoc Quang Luong, Laurent Besacier, Benjamin Lecouteux. Word Confidence Estimation for Machine Translation. Journées du LIG, 2013, Grenoble, France. hal-02094767

**HAL Id: hal-02094767**

**<https://hal.science/hal-02094767>**

Submitted on 9 Apr 2019

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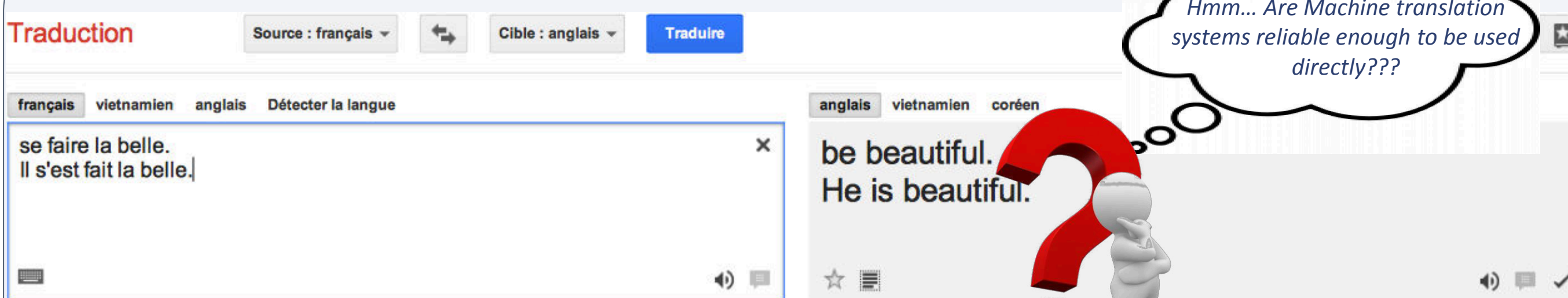
# Confidence Estimation for Machine Translation

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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 portions 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)

Table 1: The various types of features used to train the classifier.

| ID  | Feature name         | ID  | Feature name          |
|-----|----------------------|-----|-----------------------|
| 1L  | Source POS           | 14S | Left source context   |
| 2S  | Source word          | 15M | Polysemy count        |
| 3S  | Target Word          | 16S | Source Language Model |
| 4S  | Backoff Behavior     | 17S | Number of Occurrences |
| 5S  | WPP <i>any</i>       | 18L | Numeric               |
| 6L  | Target POS           | 19L | Proper name           |
| 7T  | Null Link            | 20S | Left target context   |
| 8L  | Stop word            | 21S | Min                   |
| 9S  | Nodes                | 22S | Target Language Model |
| 10T | Constituent Label    | 23S | Right source context  |
| 11S | Right target context | 24T | Distance to Root      |
| 12S | Max                  | 25S | WPP <i>exact</i>      |
| 13L | Punctuation          |     |                       |

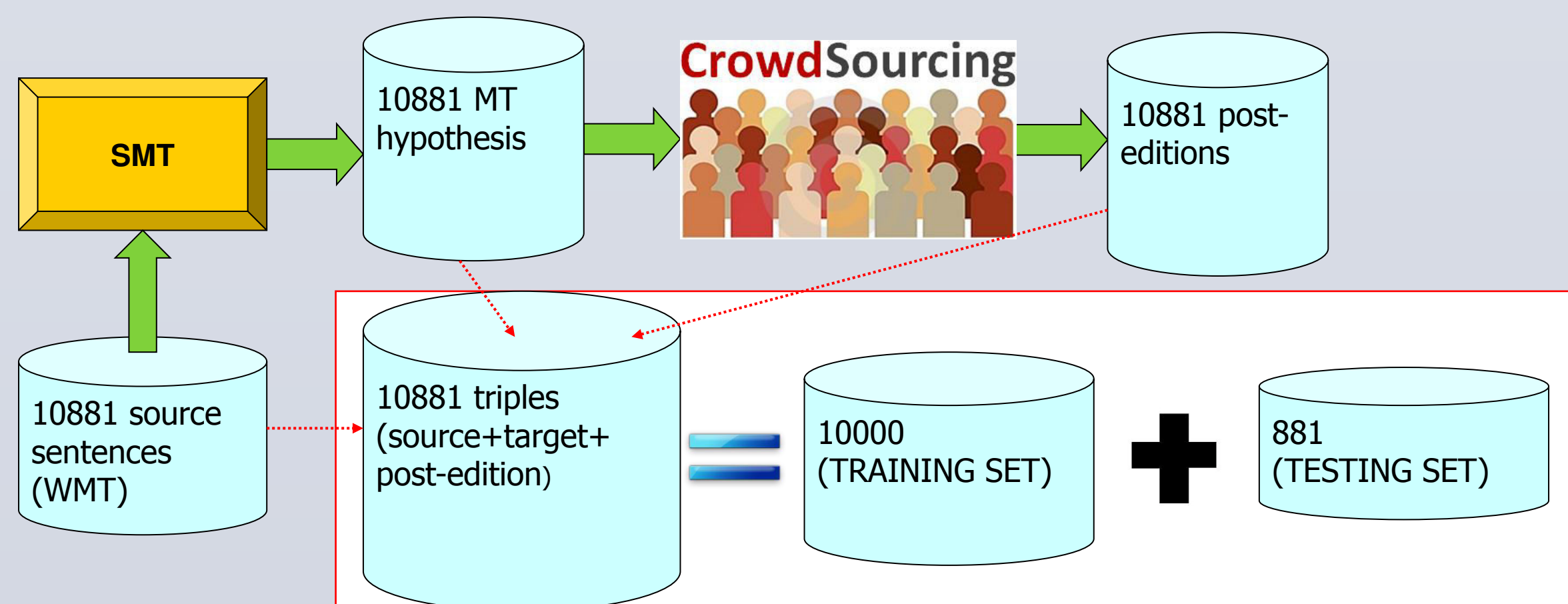
### 2. Model to train the classifier

- 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



### 5. Word Label Setting for Classifier:

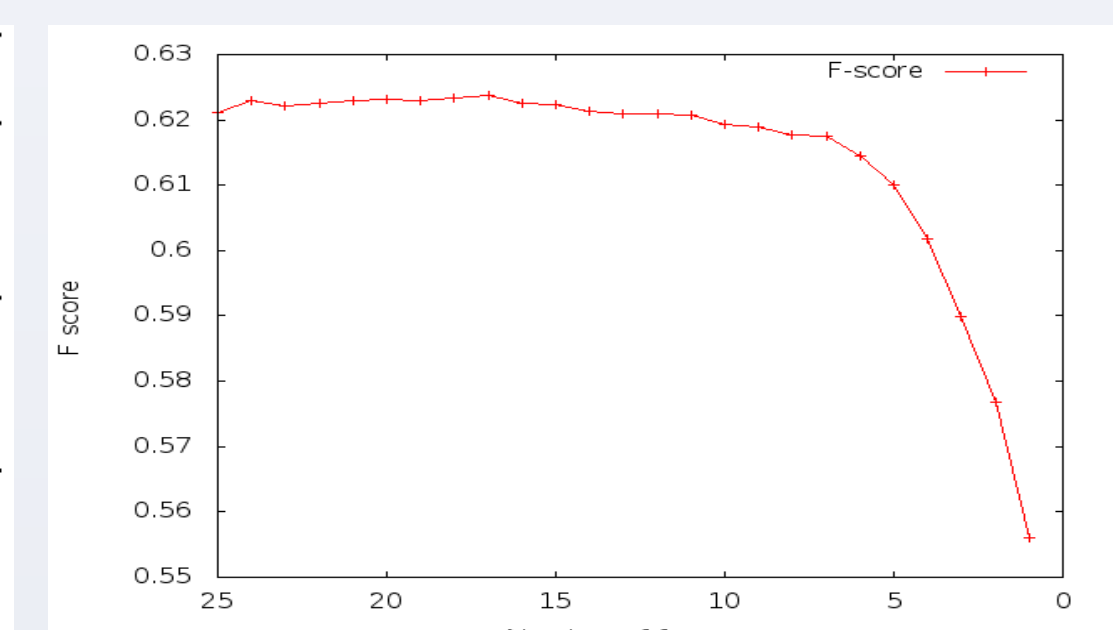
- We tag each word of the sentence in the training set a label by comparing this sentence to its reference. This label is then used to train the classifier.
- Tool used: TERp-A (is a version of TERp)
- Type of edit: I,S,T,Y,P,E (see an example of the setting below).
- Regroup into binary category: E,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

| System       | Label | Pr(%) | Rc(%)  | F(%)  |
|--------------|-------|-------|--------|-------|
| All features | Good  | 86.02 | 88.07  | 87.04 |
|              | Bad   | 39.11 | 35.41  | 37.17 |
| Baseline 1   | Good  | 81.78 | 100.00 | 89.98 |
|              | Bad   | -     | 0      | -     |
| Baseline 2   | Good  | 81.77 | 85.20  | 83.45 |
|              | Bad   | 18.14 | 14.73  | 16.26 |



| Source                    | r    | opération | "      | n'    | était  | pas          | hémorragique | et | ne        | nécessitait | donc | pas |
|---------------------------|------|-----------|--------|-------|--------|--------------|--------------|----|-----------|-------------|------|-----|
| Alignment                 |      |           |        |       |        |              |              |    |           |             |      |     |
| Target                    | the  | operation | "      | was   | not    | hémorragique | and          | is | therefore | not         |      |     |
| Labels (by TERp-A)        | G    | G         | G      | G     | G      | B            | G            | B  | G         | B           |      |     |
| Labels (by our CE System) | G    | G         | G      | G     | B      | B            | G            | B  | G         | G           |      |     |
| Source                    | pose | d'        | un     | drain | "      | a-t-il       | ajoute       |    |           |             |      |     |
| Alignment                 |      |           |        |       |        |              |              |    |           |             |      |     |
| Target                    | have | a         | combat | "     | a-t-il | added        |              |    |           |             |      |     |
| Labels (by TERp-A)        | B    | G         | B      | G     | G      | B            | G            | G  |           |             |      |     |
| Labels (by our CE System) | B    | B         | G      | G     | G      | B            | G            | G  |           |             |      |     |

Table 3: Example of all-feature classifier's output

### 2. Feature Selection

- Objective: to rank our features from most to least important + to find the best performing combination.
- Strategy: "Sequential Backward 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).

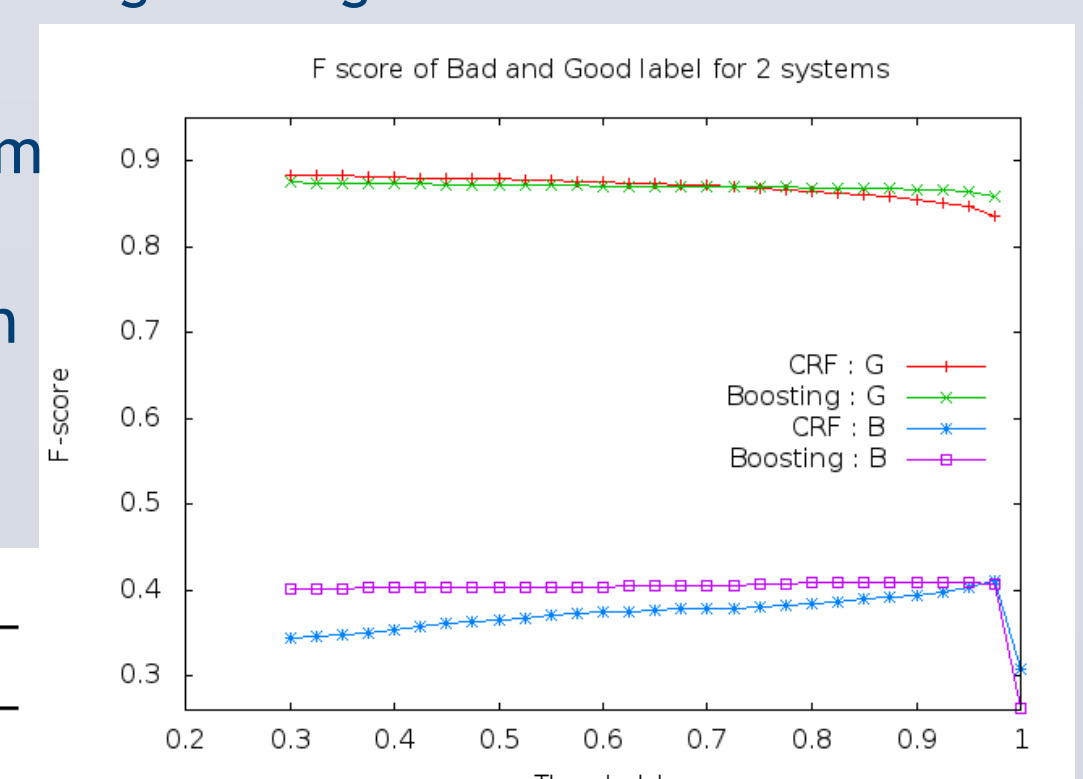
### 3. Boosting technique to improve the classifier's performance:

- 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 S<sub>j</sub> (j=1..10, j≠i)
    - Train this set by 23 feature above sets (sequentially) => 23 different classifiers.
    - Apply each above classifier to test S<sub>i</sub>, log the "G" probability (23 in total) to form the training set D<sub>i</sub>.
  - Step 4: Concatenate D<sub>i</sub> (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).

| System   | Pr(G) | Rc(G) | F(G)  | Pr(B) | Rc(B) | F(B)  |
|----------|-------|-------|-------|-------|-------|-------|
| Boosting | 90.10 | 84.13 | 87.01 | 34.33 | 49.83 | 40.03 |
| CRF      | 86.02 | 88.07 | 87.04 | 39.11 | 35.41 | 37.17 |



## CONCLUSION AND ONGOING RESEARCH

- Experimental results show that precision and recall obtained in Good label are very promising, and Bad label reaches precision 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 relied on the word's and segment's confidence score.

