Model Adaptation in Statistical Machine Translation for Synchronous Context-Free Grammars

Manaal Faruqui   Baskaran Sankaran   Anoop Sarkar

Statistical Machine Translation (SMT)

- The process of translating one human language to another human language by the computer using probabilistic models.

Let x be a source language sentence

y be a target language sentence

Our work is to maximize the probability of 'x' translating into 'y'

$$\hat{y} = \arg max_y \log P(\, y \mid x \,)$$

Context Free Grammar

- A grammar in theoretical computer science is a re-writing system
  - It consists of some terminal (think of values) and non-terminals (think of variables)
  - It has some production rules: LHS $\longrightarrow$ RHS
  - It means we can replace/re-write the LHS with RHS

- A CFG is a grammar in which every production rule is of the form :-

Non-terminal $\longrightarrow$ A combination of Terminals and Non-terminals

For example:-

$$X \longrightarrow Y\,a\,Z$$
$$Y \longrightarrow b$$
$$Z \longrightarrow c$$

where,

$$X, Y, Z \in \{\text{Non-terminals}\}$$
$$a, b, c \in \{\text{Terminals}\}$$

- A synchronous CFG combines two CFG together .

Using SCFG to do Machine Translation

- Suppose we have the following rules ,

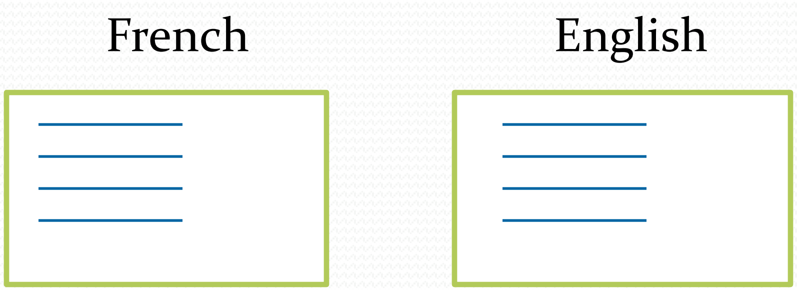
$$
\begin{array}{ll}
S \longrightarrow (X_1 , X_1) & \log P_1 = -8.0 \\
X \longrightarrow (\text{Je } X_1 , \text{I } X_1) & \log P_2 = -3.0 \\
X \longrightarrow (X_1 \text{ étudiante} , X_1 \text{ student}) & \log P_3 = -5.2 \\
X \longrightarrow (\text{suis} , \text{am a}) & \log P_4 = -2.6
\end{array}
$$

We can derive a translation using these rules,

$$
\begin{array}{lll}
S & \longrightarrow (X_1 , X_1) & \log P = -8.0 \\
 & \longrightarrow (X_1 \text{ étudiante} , X_1 \text{ student}) & \log P = -13.2 \\
 & \longrightarrow (\text{Je } X_1 \text{ étudiante} , \text{I } X_1 \text{ étudiante}) & \log P = -16.2 \\
 & \longrightarrow (\text{Je suis étudiante} , \text{I am a student}) & \log P = -18.8
\end{array}
$$

Where do the rules come from?

- In training phase of our SCFG translation model, we extract the rules from a big parallel corpus .
- In a parallel corpus we have all the sentences in the source language corpus translated into the target language corpus . The source language corpus is translated by humans into the target language.



- The parallel corpus used in our experiments was Europarl-v3 French-English corpus which is freely available.

  It had 1.27 M sentences of both French and English language .

- We derive translation rules from this corpus using phrase alignments for each sentence.

Model Adaptation

- Consider the situation where we have lots of parallel text to train our SMT system ; but all the text comes from one source, e.g. Parliamentary proceedings (the Europarl Corpus) .

- We actually would like to translate newswire text or blogs -- we need to adapt to the new domain

- We use a log-linear model for domain adaptation .

Approach

- Recall that we find the best translation as :-

$$\hat{y} = \arg max_y \log P(y \mid x)$$

- We compute the best translation using a log-linear model :-

$$\log P(y \mid x) = (\lambda_1 * feature_1 + \lambda_2 * feature_2 + \ldots - \lambda_n * feature_n) - \log Z$$

Where,

$feature_i$ ϵ Various components of our translation model

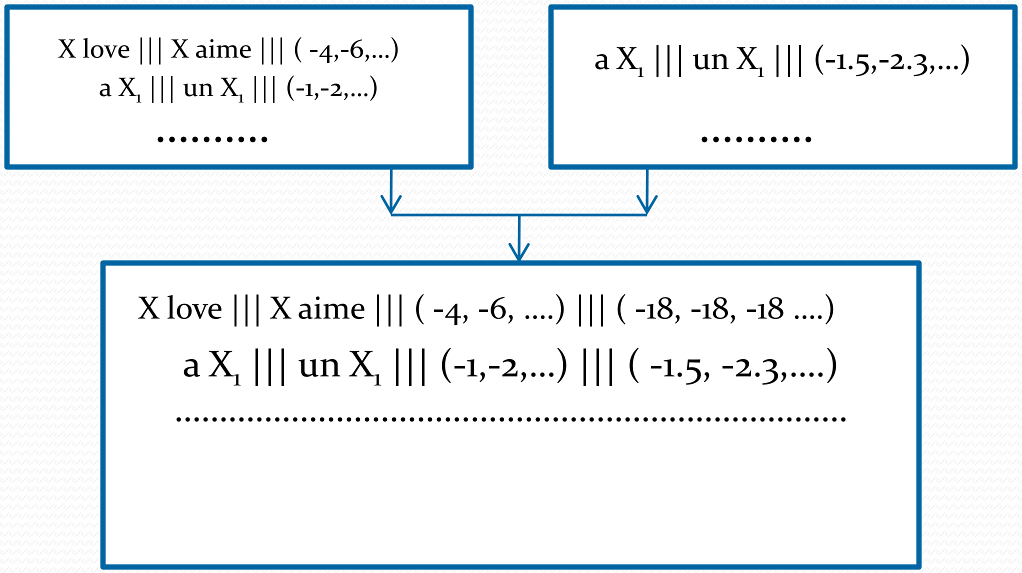
λ_i ϵ Respective feature weights

- We add new components for our new domain and they get new feature weights λ

The new λ `s are set to set to values that allow the specific in-domain information to be combined with the general out of domain information

Merging Rule Tables

- We merge the rule tables in such a way that the new table contains all the rules present in both tables .



- So every rule in the merged table has the following form :-

  source ||| target ||| probset_1 ||| probset_2

- This ensures that every candidate translation proposed by our system obtains a score from the log-linear model for domain adaptation

Filtering Rules

Rule Tables	Number of Rules
Rules from in-domain corpus	8.54 M
Rules from the merged data	321.76 M
Rules from the merged Rule-Tables	320.48M

Due to the large size of the rule-tables , I also worked on filtering rules to improve translation speed.

Rule filtering according to the sentence structure in the given data-set

- The filtering was done according to sentence structure in the given data-set.

X est belle . $\longrightarrow$ X is beautiful .

-If the word "belle" is not present in the set of given sentences then the above rules can't be used .

je X étudiante . $\longrightarrow$ I X student .

-Even if "je" and "étudiante" occur in the data-set, but if in no sentence "je" occurs before "étudiante" then the above rule can't be used.

Individual Rule-Filtering

- We did not allow a target phrase to have more than “n” number of translations .
- For our experiments, we fixed n = 10 .
- The translations having the highest target side counts were chosen as the top 10 translations .
- This filtering reduced the existing rule table to 1/3 of its original cardinality .

After Rule-Filtering

Rule-Tables	No. of Rules before filtering	No. of Rules after filtering
Rules from the in-domain corpus	8.54 M	0.45 M
Rules from the merged data	321.76 M	2.60 M
Rules from the merged Rule-Tables	320.48M	2.67 M

Evaluation Metrics

- Each evaluation metric compares the system output to a set of reference translations. There is no such thing as one correct translation -- there are many
- Bilingual Evaluation Understudy (BLEU) : BLEU is the geometric mean of the number of phrase matches of different lengths combined with a penalty for being too short compared to the input .
- Multi-Reference Word Error Rate (mWER) : The minimum number of substitutions, insertions and deletions required to transform the hypothesis into the reference translation .
- Multi-Reference Position Independent Error Rate (mPER) : The minimum number of substitutions, insertions and deletions required to transform the unordered set of words into the reference translation .

Results

Rules obtained from	BLEU	m-WER	m-PER
In-domain corpus	11.31	64.67	80.25
Merged data	14.67	59.22	78.57
Merged Tables	15.30	57.66	76.22

- BLEU (Higher the better)
- m-WER & m-PER (Lower the better)

Future Work

- The system has been developed to handle any number of phrase tables together .

- Experiments can be carried out with more than two translation tables and results can be analyzed and generalized for ‘n’ number of translation tables.