Sparse Features for Reordering (Final Report)

Barry Haddow Lexi Birch Han Dan (Lane Schwartz)

14th September, 2013

Lexicalised Reordering Models in PBMT

Max-Likelihood [Tillmann, 2004], [Koehn et al, 2005,2007]

- Count orientations in training data
- Maybe smooth
- "Standard Model"

Maxent e.g. [Zens and Ney, 2006]

- Build a classifier to predict M, S or D
- Use lexical features, part-of-speech etc.

Lexicalised Reordering Models in PBMT

Max-Likelihood [Tillmann, 2004], [Koehn et al, 2005,2007]

- Count orientations in training data
- Maybe smooth
- "Standard Model"

Maxent e.g. [Zens and Ney, 2006]

- Build a classifier to predict M, S or D
- Use lexical features, part-of-speech etc.

Add small number of features (e.g. 6) to translation system

- We now have methods to train (i.e. tune) translation systems with thousands or even millions of features
- Normally predicates on hypotheses
- Replace maxent model (indirect objective) ...
 - ... with sparse feature model (direct objective, e.g. BLEU)
- Cherry showed improvements on large zh-en and ar-en models
 - \rightarrow Over a maxent baseline
 - $\rightarrow\,$ In addition to Tillman-style model
 - \rightarrow Lattice batch MIRA better than *k*-best batch MIRA

Sparse Features for Reordering – Example



| Template | Features |
|-------------------------------|------------|
| src.left $	imes$ orientation | sl_sie_M |
| | sl_gegen |
| src.right $	imes$ orientation | sr_wurde |
| | sr_stimm |
| tgt.left $	imes$ orientation | tl_they_ |
| | tl_again |
| tgt.right 	imes orientation | tr_would |
| | tr vou S |

sl_sie_M, sl_stimmen_D, sl_gegen_S sr_wurden_M, sr_stimmen_D, sr_sie_S tl_they_M, tl_vote_D, tl_against_S tr_would_M, tr_vote_D, tr_you_S

Lexicalised Reordering in Hiero Models

- Zens&Ney Reordering (maxent) [Huck et al, 2012]
- Tillman Reordering (max-like) [Huck et al, 2013]
- Latter shown to perform better both beat baseline

• Suppose we apply a rule:

$$X
ightarrow$$
 a X_1 b $X_2 \hspace{0.2cm} \mid \hspace{0.2cm} X_1 \hspace{0.2cm} z \hspace{0.2cm} X_2 \hspace{0.2cm} y$

- With X_1 covering c and X_2 covering de
 - \rightarrow Add features indicating that words c are *monotone* with respect to de
- Or if the rule is:

 $X \rightarrow a X_1 \ b \ X_2 \ \mid \ X_2 \ p \ X_1$

→ Add features indicating that words c are swapped with respect to de • Suppose we apply a rule:

$$X
ightarrow a X_1 \ b \ X_2 \ \mid \ X_1 \ z \ X_2 \ y$$

- With X_1 covering c and X_2 covering de
 - \rightarrow Add features indicating that words *c* are *monotone* with respect to *de*
- Or if the rule is:

 $X \rightarrow a X_1 \ b \ X_2 \ \mid \ X_2 \ p \ X_1$

 $\rightarrow\,$ Add features indicating that words c are swapped with respect to de

Sparse Reordering in Hiero Models – Example



src_left_d_mono
src_right_e_mono
src_left_f_swap
src_right_b_swap
src_left_b_swap

src_right_g_swap

 X_1 covers ef, X_2 covers g

- Small de-en model (news commentary pprox 130k sentences)
- Use src.left variant, and top 100 words.

| Model | Tune | Test |
|----------------|-------|-------|
| Baseline | 26.83 | 27.71 |
| Sparse Reorder | 27.15 | 27.90 |

(Baseline trained 25 iterations, Sparse reordering 10)

| Feature | Weights |
|-------------------------------|---------|
| $\mathtt{und}_\mathtt{swap}$ | -0.159 |
| ,_swap | -0.111 |
| ein_mono | -0.046 |
| sind_mono | -0.045 |
| : | ÷ |
| sich_mono | 0.039 |
| ,_mono | 0.057 |
| OTHER_mono | 0.062 |
| die_mono | 0.100 |