LSTM Neural Reordering Model for Statistical Machine Translation

Yiming Cui, Shijin Wang, Jianfeng Li

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OUTLINE

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- LSTM Neural Reordering Model
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LEXICALIZED RM

- Lexicalized Reordering Model
  - The most widely used RM
  - Given source and target sentence **f,e** and phrase alignment **a**

$$p(\boldsymbol{o}|\boldsymbol{e},\boldsymbol{f}) = \prod_{i=1}^{n} P(o_i|e_i, f_{a_i}, a_{i-1}, a_i)$$

LEXICALIZED RM

- Lexicalized Reordering Model
  - orientation type **o**: LR, MSD, MSLR
  - Take MSD type for e.g., it can be defined as

$$o_i = \begin{cases} M, if\ a_i - a_{i-1} = 1 \\ S, if\ a_i - a_{i-1} = -1 \\ D, if\ |a_i - a_{i-1}| \neq 1 \end{cases}$$

Lexicalized RM

- Lexicalized Reordering Model
  - Some researcher also suggested that by including both current and previous phrase pairs into condition, can improve accuracy (Li et al., 2014)

$$P(\mathbf{o}|\mathbf{f},\mathbf{e},\mathbf{a}) \approx \prod_{i=1}^{n} P(o_i|\tilde{f}_{a_i},\tilde{e}_i,a_{i-1},a_i)$$

$$\Downarrow$$

$$P(\mathbf{o}|\mathbf{f},\mathbf{e},\mathbf{a}) \approx \prod_{i=1}^{n} P(o_i|\tilde{f}_{a_i},\tilde{e}_i,\tilde{f}_{a_{i-1}},\tilde{e}_{i-1},a_{i-1},a_i)$$

LSTM Neural RM

- Why RNN?
  - RNNs are capable to learn sequential problems
  - It is natural to use RNNs to include much more history to predict next word's orientation (reordering)
  - Further by utilizing LSTM, RNNs are able to capture long-time dependency, and solve "Gradient Vanishing" problem (Bengio, 1997)

LSTM Neural RM

- Training data processing
  - Given source and target sentence pair and alignment

(1) If current target word is one-to-one alignment, then we can directly induce its orientations (left or right).

(2) If current source/target word is one-to-many alignment, then we judge its orientation by considering its first aligned target/source word, and the other aligned target/source words are annotated as “<follow>” reordering type, which means this word pair inherent orientation of previous word pair.

(3) If current source/target word is not aligned to any target/source words, we introduce a “<NULL>” token in the opposite side, and annotate this word pair as “<follow>” reordering type.

LSTM Neural RM

- Training Data Processing: Example

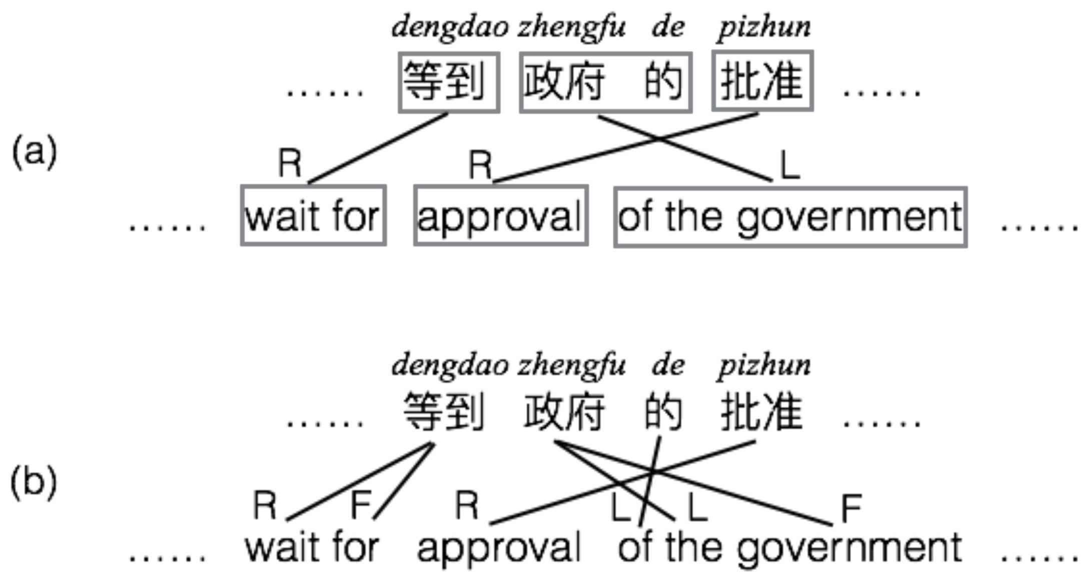


Figure 1: Illustration of data processing. (a) Original reordering (omit the alignment inside phrase); (b) processed reordering, "R"-right, "L"-left, "F"-follow.

LSTM NEURAL RM

- History Extended Reordering Model

$$P(\mathbf{o}|\mathbf{f},\mathbf{e},\mathbf{a}) \approx \prod_{i=1}^{n} P(o_i|\tilde{f}_{a_i}, \tilde{e}_i, a_{i-1}, a_i)$$

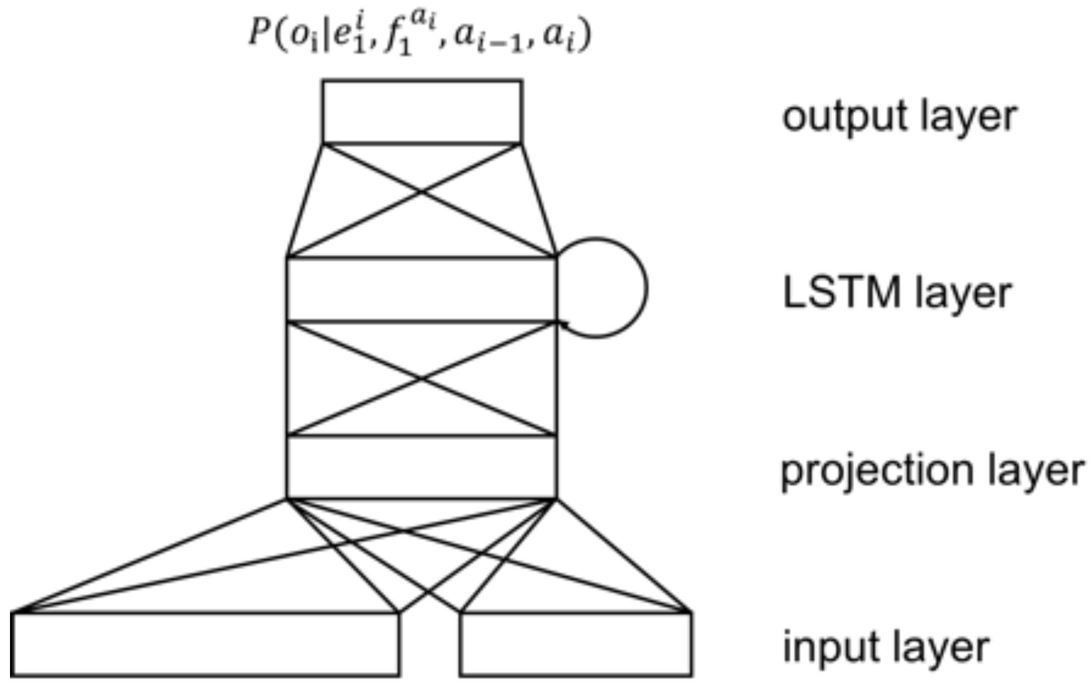
$$P(\mathbf{o}|\mathbf{f},\mathbf{e},\mathbf{a}) \approx \prod_{i=1}^{n} P(o_i|\tilde{f}_{a_i}, \tilde{e}_i, \tilde{f}_{a_{i-1}}, \tilde{e}_{i-1}, a_{i-1}, a_i)$$

Proposed model

$$p(\boldsymbol{o}|\boldsymbol{e},\boldsymbol{f}) = \prod_{i=1}^{n} P(o_i|e_1^i, f_1^{a_i}, a_{i-1}, a_i)$$

LSTM NEURAL RM

- LSTM NRM Architecture



$$y_i = W_1 * f_{a_i} + W_2 * e_i$$
$$z_i = LSTM(y_i, W_3, y_1^{i-1})$$
$$P\left(o_i \middle| e_1^i, f_1^{a_i}, a_{i-1}, a_i\right) = softm(W_4 * z_i)$$

Experiment

- Setups
  - NIST OpenMT12 ZH-EN and AR-EN Task
  - Apply RNNRM into N-best rescoring step
  - Results are average with 5 runs (Clark et al., 2011)
  - Neural params: hidden units 100, SGD(alpha=0.01), source-vocab 100k, target-vocab 50k

EXPERIMENT

- Results on different orientation types
- All results are significantly better than each baseline, using paired bootstrap resampling method (Koehn, 2004)

System	Dev	Test1	Test2
Baseline	43.87	39.84	42.05
+LR	44.43	40.53	**42.84**
+MSD	44.29	40.41	42.62
+MSLR	**44.52**	**40.59**	42.78

Table 2: LSTM reordering model with different orientation types for Arabic-English system.

System	Dev	Test1	Test2
Baseline	27.18	26.17	24.04
+LR	**27.90**	26.58	**24.59**
+MSD	27.49	26.51	24.39
+MSLR	27.82	**26.78**	24.53

Table 3: LSTM reordering model with different orientation types for Chinese-English system.

EXPERIMENT

- Results on different reordering baselines

Ar-En System	Dev	Test1	Test2
Baseline_wbe	43.87	39.84	42.05
+NRM_MSLR	44.52	40.59	42.78
Baseline_phr	44.11	40.09	42.21
+NRM_MSLR	44.52	40.73	42.89
Baseline_hier	44.30	40.23	42.38
+NRM_MSLR	44.61	40.82	42.86

Zh-En System	Dev	Test1	Test2
Baseline_wbe	27.18	26.17	24.04
+NRM_MSLR	27.90	26.58	24.70
Baseline_phr	27.33	26.05	24.13
+NRM_MSLR	27.86	26.46	24.73
Baseline_hier	27.56	26.29	24.38
+NRM_MSLR	28.02	26.49	24.67

Related Work

- Neural network based approach has been widely applied into SMT field
  - LM: NNLM(Bengio et al., 2003), RNNLM(Mikolov et al., 2011)
  - TM: NNJM(Devlin et al., 2014), RNNTM(Sundermeyer et al., 2014)
  - RM: RAE classification method (Li et al., 2014)

CONCLUSION & FUTURE WORK

- Conclusion
  - propose a purely lexicalized neural reordering model
  - support different orientation types: LR/MSD/MSLR
  - Easily integrate into rescoring & outperform baseline systems
- Future Work
  - Dissolve much more ambiguities and improve reordering accuracy by introducing phrase-based
  - Apply NRM into NMT

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Thank You !