Prior Knowledge Integration for Neural Machine Translation using Posterior Regularization

Andrew Drozdov

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Background

- Neural Machine Translation
- Posterior Regularization

Background: Neural Machine Translation

- Standard Seq2seq.

$$\mathcal{L}(\theta) = \Sigma_n \log P(y^n | x^n; \theta)$$

- It's difficult to incorporate linguistic prior knowledge in discrete symbolic forms (like phrase tables).
  - There are other ways to incorporate linguistic priors. [1]
- Coverage constraint.
- Existing approaches are not scalable.
  - Only works for simple constraints.
  - Not flexible.

[1] Eriguchi et al. 2017 Learning to Parse and Translate Improves Neural Machine Translation

Background: Posterior Regularization

- Posterior regularized likelihood:

$$F(\theta, q) = \lambda_1 \mathcal{L}(\theta) - \lambda_2 \Sigma_n \min_{q \in \mathcal{Q}} KL\big(q(y) || P(y|x^n; \theta)\big)$$

- $\mathcal{Q}$ is a constrained posterior set.

$$\mathcal{Q} = \{q(y) : \mathbb{E}_q[\phi(x, y)] \leq b\}$$

- The q is on the left side of KL because...

Model

- Use a log-linear model rather than a constrained posterior set.

$$\mathcal{J}(\theta, \gamma) = \lambda_1 \mathcal{L}(\theta) - \lambda_2 \Sigma_n KL\big(Q(y|x^n; \gamma) || P(y|x^n; \theta)\big)$$

$$Q(y|x^n; \gamma) = \frac{\exp(\gamma \cdot \phi(x, y))}{\Sigma_{y'} \exp(\gamma \cdot \phi(x, y'))}$$

Feature Design

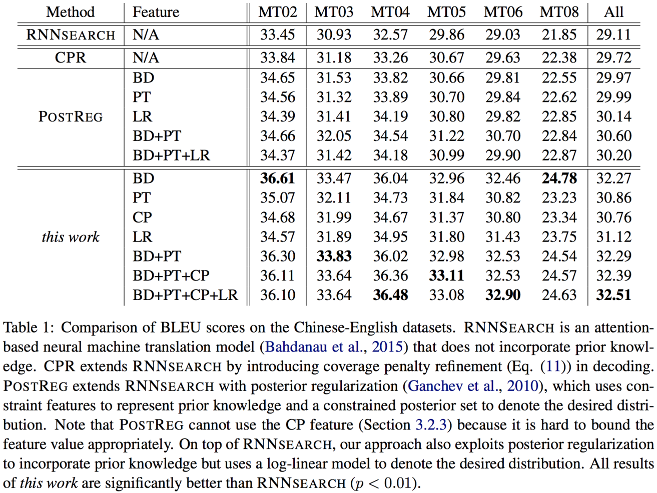
- Bilingual Dictionary $\phi \in \{0, 1\}$
- Phrase Table $\phi \in \{0, 1\}$
- Coverage Constraint $\phi_{CP}(x, y) = \Sigma_{i \in |x|} \log \left(\min(1.0, \Sigma_{j \in |y|} a_{i,j}) \right)$
  - Dependent on sentence lengths.
- Length Ratio $\phi_{LR}(x, y) = \frac{\beta|x|}{|y|}$ if $\beta|x| < |y|$ otherwise $\frac{|y|}{\beta|x|}$

Training and Inference

- During training, subsample predicted target sentences.
- During inference, generate a candidate list using maximum likelihood only, then rerank by incorporating prior knowledge.

$$\hat{y} = arg \max_{y \in \mathcal{C}(x)} \{\log P(y|x;\theta) + \gamma \cdot \phi(x,y)\}$$

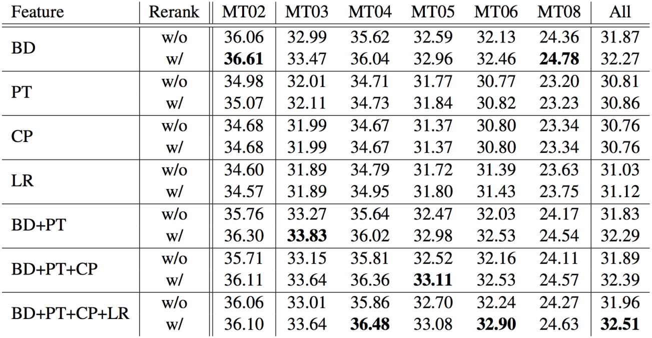
Results



Method	Feature	MT02	MT03	MT04	MT05	MT06	MT08	All
RNNSEARCH	N/A	33.45	30.93	32.57	29.86	29.03	21.85	29.11
CPR	N/A	33.84	31.18	33.26	30.67	29.63	22.38	29.72
POSTREG	BD	34.65	31.53	33.82	30.66	29.81	22.55	29.97
	PT	34.56	31.32	33.89	30.70	29.84	22.62	29.99
	LR	34.39	31.41	34.19	30.80	29.82	22.85	30.14
	BD+PT	34.66	32.05	34.54	31.22	30.70	22.84	30.60
	BD+PT+LR	34.37	31.42	34.18	30.99	29.90	22.87	30.20
this work	BD	**36.61**	33.47	36.04	32.96	32.46	**24.78**	32.27
	PT	35.07	32.11	34.73	31.84	30.82	23.23	30.86
	CP	34.68	31.99	34.67	31.37	30.80	23.34	30.76
	LR	34.57	31.89	34.95	31.80	31.43	23.75	31.12
	BD+PT	36.30	**33.83**	36.02	32.98	32.53	24.54	32.29
	BD+PT+CP	36.11	33.64	36.36	**33.11**	32.53	24.57	32.39
	BD+PT+CP+LR	36.10	33.64	**36.48**	33.08	**32.90**	24.63	**32.51**

Table 1: Comparison of BLEU scores on the Chinese-English datasets. RNNSEARCH is an attention-based neural machine translation model (Bahdanau et al., 2015) that does not incorporate prior knowledge. CPR extends RNNSEARCH by introducing coverage penalty refinement (Eq. (11)) in decoding. POSTREG extends RNNSEARCH with posterior regularization (Ganchev et al., 2010), which uses constraint features to represent prior knowledge and a constrained posterior set to denote the desired distribution. Note that POSTREG cannot use the CP feature (Section 3.2.3) because it is hard to bound the feature value appropriately. On top of RNNSEARCH, our approach also exploits posterior regularization to incorporate prior knowledge but uses a log-linear model to denote the desired distribution. All results of *this work* are significantly better than RNNSEARCH ($p < 0.01$).

Ablation



Feature	Rerank	MT02	MT03	MT04	MT05	MT06	MT08	All
BD	w/o	36.06	32.99	35.62	32.59	32.13	24.36	31.87
	w/	**36.61**	33.47	36.04	32.96	32.46	**24.78**	32.27
PT	w/o	34.98	32.01	34.71	31.77	30.77	23.20	30.81
	w/	35.07	32.11	34.73	31.84	30.82	23.23	30.86
CP	w/o	34.68	31.99	34.67	31.37	30.80	23.34	30.76
	w/	34.68	31.99	34.67	31.37	30.80	23.34	30.76
LR	w/o	34.60	31.89	34.79	31.72	31.39	23.63	31.03
	w/	34.57	31.89	34.95	31.80	31.43	23.75	31.12
BD+PT	w/o	35.76	33.27	35.64	32.47	32.03	24.17	31.83
	w/	36.30	**33.83**	36.02	32.98	32.53	24.54	32.29
BD+PT+CP	w/o	35.71	33.15	35.81	32.52	32.16	24.11	31.89
	w/	36.11	33.64	36.36	**33.11**	32.53	24.57	32.39
BD+PT+CP+LR	w/o	36.06	33.01	35.86	32.70	32.24	24.27	31.96
	w/	36.10	33.64	**36.48**	33.08	**32.90**	24.63	**32.51**

Table 2: Effect of reranking on translation quality.