Exploring Neural Text Simplification Models

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Automatic Text Simplification

- want text $\rightarrow$ simpler text
  - improve accessibility, learning, comprehension, and readibility
  - aid for hearing impaired people
  - pre-processing step for NLP
  - shorter sentences and easier words & grammar than original text

Proposed Strategy

- Strategy: To use global attention and input feeding identical to Neural Machine Translation proposed by Luong

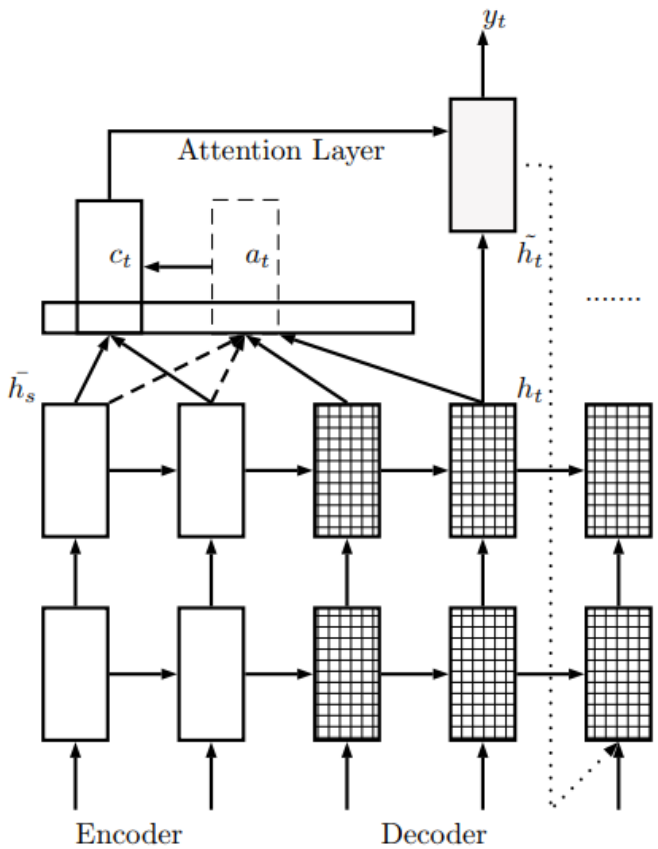

Figure 1: Architecture of the neural simplification model with global attention and input feeding.

$$a_t(s) = \frac{\exp h_t^T W_{as} \bar{h}_s}{\sum_{s'} \exp h_t^T W_{as'} \bar{h}_{s'}}$$

Model in Detail

Special Embeddings (NTS word2vec)

1. For Encoder, word2vec trained on Google News Corpus was used
2. For Decoder, combined normal data (Google News corpus) with simplified data (word2vec on training data)
   - representation for each word are concatenated
   - if word is missing in global embeddings, replace with sample from Gaussian distributino with mean 0 and std deviation 0.9

Tuning during testing - Beam search in Input Feeding

- Generate the first k hypotheses at each step ordered by the log-likelihood of the target sentence given the input sentence
- Take the first two candidate hypotheses for each beam size from $5\bar{1}2$.
- A separate tuning data set (Xu et al. (2016)) used as reference corpus in combination with BLEU and SARI to select best hypothesis for prediction reranking

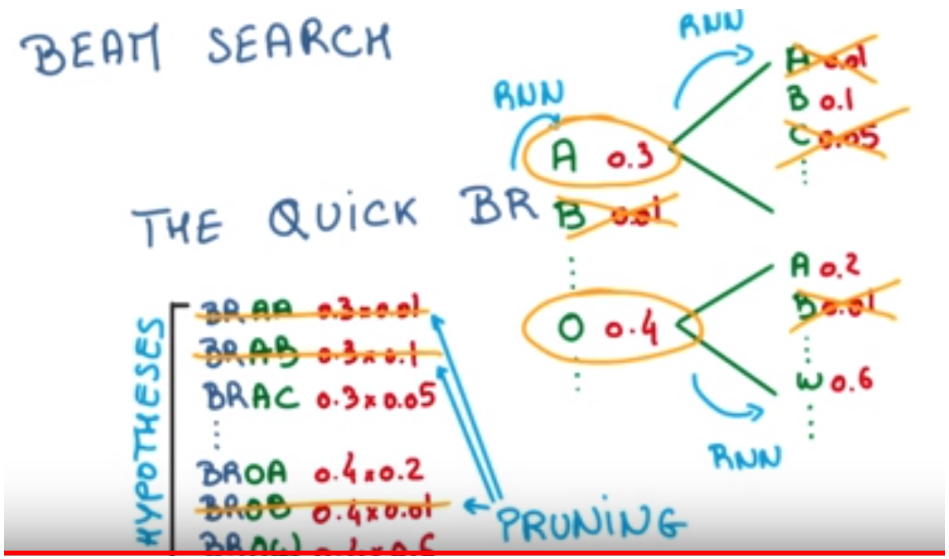

Figure: Example of beam search (This paper uses word level search instead of character level)

Dataset

- manual and automatic alignments between standard English Wikipedia and Simple English Wikipedia (EWSEW)
- one of the largest freely available resources for text simplification
- replaced with UNK symbols during training
  - At prediction time, we replace the unknown words with the highest probability score from the attention layer

Evaluation

- Used human evaluation criteria to assess output
- grammatically (G) 1-5 scale of the simplification regardless of original sentence
- meaning preservation (M) amount of content preserved on 1-5 scale
- simplicity (S) outputs +2, +1, 0, -1, -2 ranging from much simpler to much more difficult
- correct number of changes, assessed by native or non-native highly fluent English speakers

Results

Compared against:

1. the PBSMT system with reranking of n-best outputs (Wubben et al., 2012), which represent the best PBSMT approach to ATS, trained and tuned over the same datasets as our systems;
2. the state-of-the-art SBMT system (Xu et al., 2016) with modified tuning function (using SARI) and using PPDB paraphrase database (Ganitkevitch et al., 2013)
3. one of the state-of-theart unsupervised lexical simplification (LS) systems that leverages word-embeddings (Glavas and Stajner, 2015).

Results

Approach	Changes		Scores		Rank	SARI	BLEU
	Total	Correct	G	M	S		
NTS default (beam 5, hypothesis 1)	36	72.2%	**4.92**	**4.31**	+0.46	30.65	84.51
NTS SARI (beam 5, hypothesis 2)	72	51.6%	4.19	3.62	+0.38	37.25	80.69
NTS BLEU (beam 12, hypothesis 1)	44	73.7%	4.77	4.15	+**0.92**	30.77	84.70
NTS-w2v default (beam 5, hypothesis 1)	31	54.8%	4.79	4.17	+0.21	31.11	**87.50**
NTS-w2v SARI (beam 12, hypothesis 2)	110	68.1%	4.53	3.83	+**0.63**	36.10	79.38
NTS-w2v BLEU (beam 12, hypothesis 1)	61	**76.9%**	4.67	4.00	+0.40	30.67	85.03
PBSMT-R (Wubben et al., 2012)	**171**	41.0%	3.10	2.71	−0.55	34.07	67.79
SBMT (SARI+PPDB) (Xu et al., 2016)	143	34.3%	4.28	3.57	+0.03	**38.59**	73.62
LightLS (Unsupervised) (Glavaš and Štajner, 2015)	132	26.6%	4.47	2.67	−0.01	34.96	83.54

Table 2: Human evaluation results (the highest scores by each evaluation criterion are shown in bold).

Results

System	Output
NTS-w2v default	Perry Saturn (with terri) defeated Eddie Guerrero (with chyna) to win the WWF European Championship (8:10); Saturn pinned Guerrero after a diving elbow drop.
NTS-w2v SARI	Perry Saturn **pinned Guerrero to win the WWF European Championship.**
NTS-w2v BLEU	Perry Saturn pinned Guerrero after a diving **drop** drop.
NTS default	**He** (with terri) defeated Eddie Guerrero (with chyna) to win the WWF European Championship (8:10); Saturn pinned Guerrero after a diving elbow drop.
NTS BLEU/SARI	**He** defeated Eddie Guerrero (with Chyna) to win the WWF European Championship (8:10); Saturn pinned Guerrero after a diving elbow drop.
LightLS (Glavaš and Štajner, 2015)	Perry Saturn (with terri) defeated Eddie Guerrero (with chyna) to win the WWF European Championship (8:10); Saturn pinned Guerrero after a **swimming shoulder fall**.
SBMT (Xu et al., 2016)	Perry Saturn (with terri) **beat** Eddie Guerrero (with chyna) to win the WWF European **League** (8:10); Saturn pinned Guerrero after a diving elbow drop.
PBSMT-R (Wubben et al., 2012)	Perry Saturn with terri **and** Eddie Guerrero **,** chyna **,** to win the European Championship **then-wwf** 8:10); **he** pinned Guerrero after a diving elbow drop.
Original	Perry Saturn (with terri) defeated Eddie Guerrero (with chyna) to win the WWF European Championship (8:10); Saturn pinned Guerrero after a diving elbow drop.

Table 4: Output examples, differences to the original sentence are shown in bold.