Deletion-based Sentence Compression with Deep Reinforcement Learning

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Overview

- Introduction
- Sentence compression with reinforcement learning
- Experiment
- Result

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What is Sentence Compression

- Sentence compression aims to
  - use fewer words than the source sentence,
  - retain the most important information from the source sentence,
  - remain grammatical.

- Example:

S: A man suffered a serious head injury after a morning car crash today .

C: A man suffered a injury after a car crash .

Applications of Sentence Compression

1. Compress text to be displayed on small screens like cellphone. *[Corston-Oliver, 2001]*

2. Generate subtitle for high-rate speech. *[Vandeghinste and Pan, 2004]*

3. Compress lengthy product titles for E-commerce. *[Wang et al., 2018]*

Points of Sentence Compression

- Sentence compression aims to
  - use fewer words than the source sentence,
  - retain the most important information,
  - remain grammatical.

- Length Constrains
- Informativeness
- Readability

S: A man suffered a serious head injury after a morning car crash today .

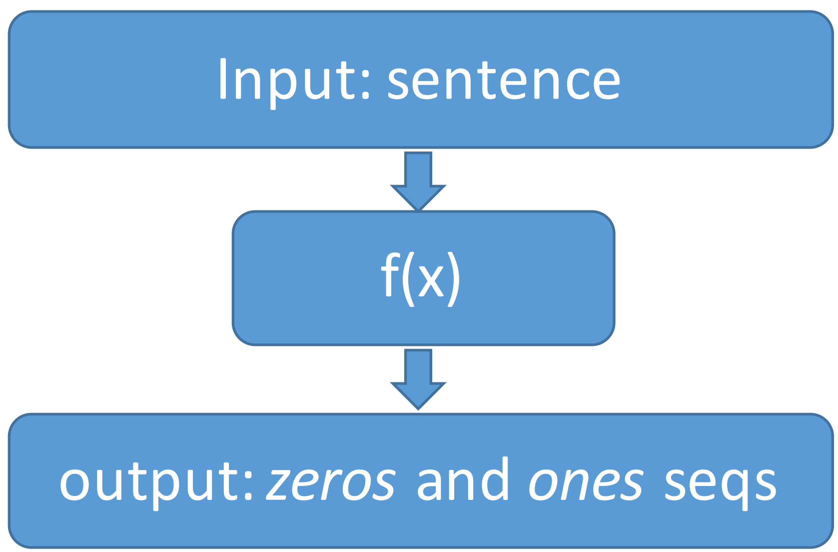
C: A man suffered a injury after a car crash .

Problem formulation

S: A man suffered a serious head injury after a morning car crash today .

1 1 1 1 0 0 1 1 1 0 1 1 0

- Sequence labeling problem



Previous works on sentence compression

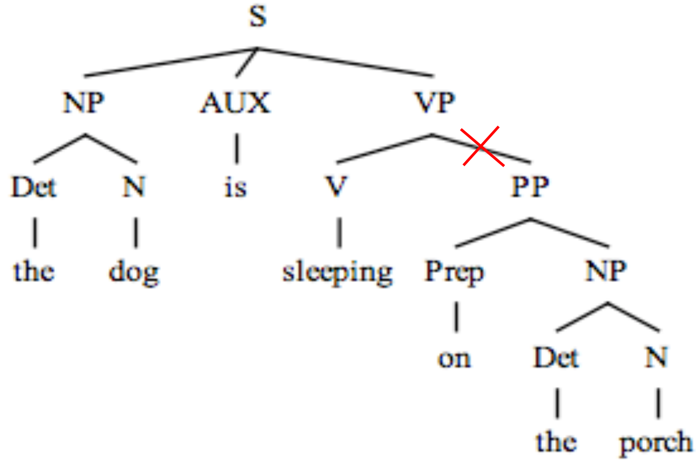
- Tree-pruning based approaches
  - Dependency tree pruning

- Machine-learning based approaches
  - CRF v.s. Recurrent neural network

Previous works

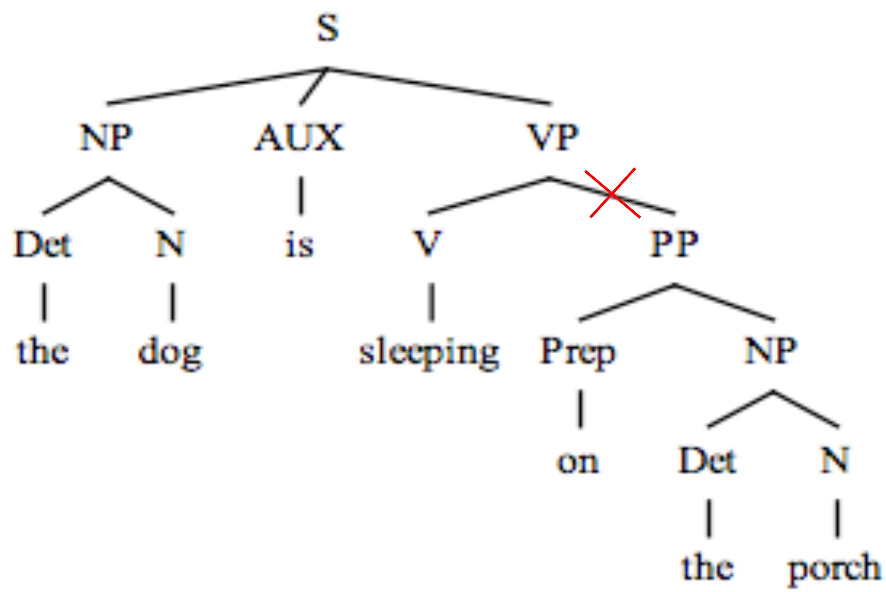
- Previous approaches for sentence compression are mainly rule-based or data-driven.

    -Directly prune syntactic trees to generate compression
    (Knight and Marcu, 2000; Kirkpatrick et al., 2011; Filippova and Altun, 2013; …)



The dog is sleeping on the porch.

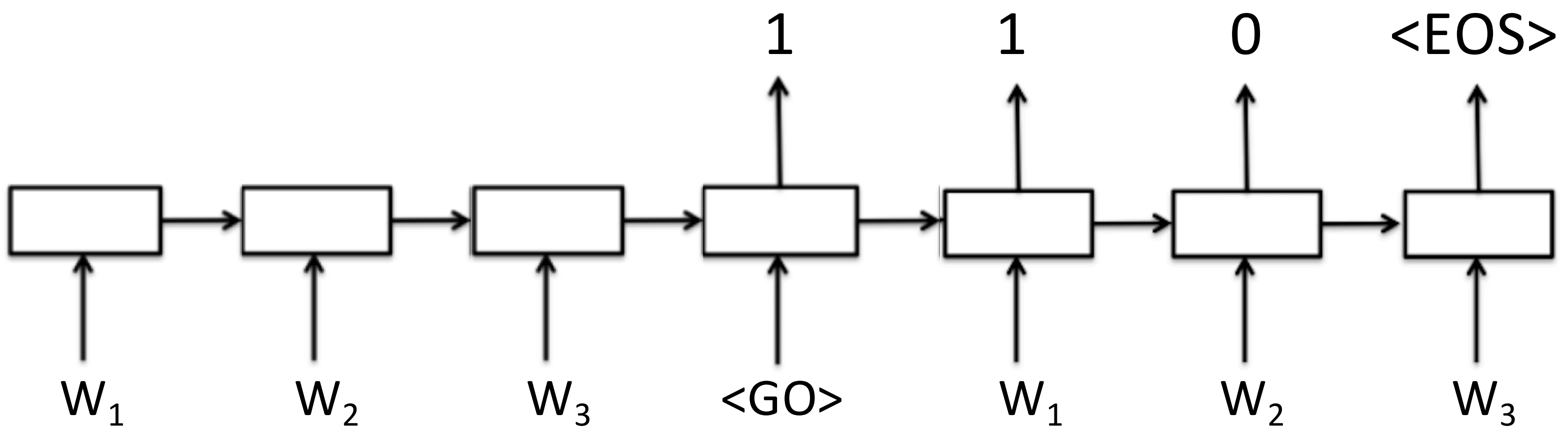
Problem with rule-based compression



- If syntactic parse trees are incorrect, deleting sub-trees could yield wrong compression.

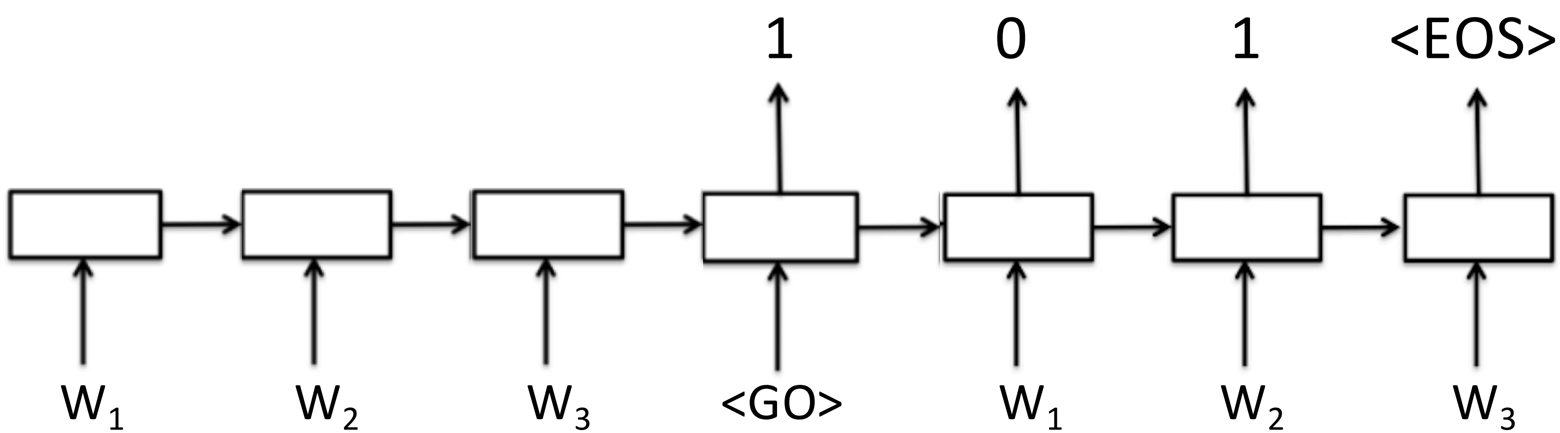
Previous works

Input: The dog is sleeping on the porch
Output: 1 1 1 1 0 0 0



- Treat sentence compression as a sequence labeling problem (label “1”: kept; label “0”: removed) *(Filippova et al., 2015; Klerke et al., 2016; …)*

Problem with data-driven compression



Problem: it is not able to consider the whole predicted compression as a whole

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What the RL brings

- Previous models are optimized to maximize the likelihood of training data, which may not well match the evaluation metrics that actually quantify the compression quality.

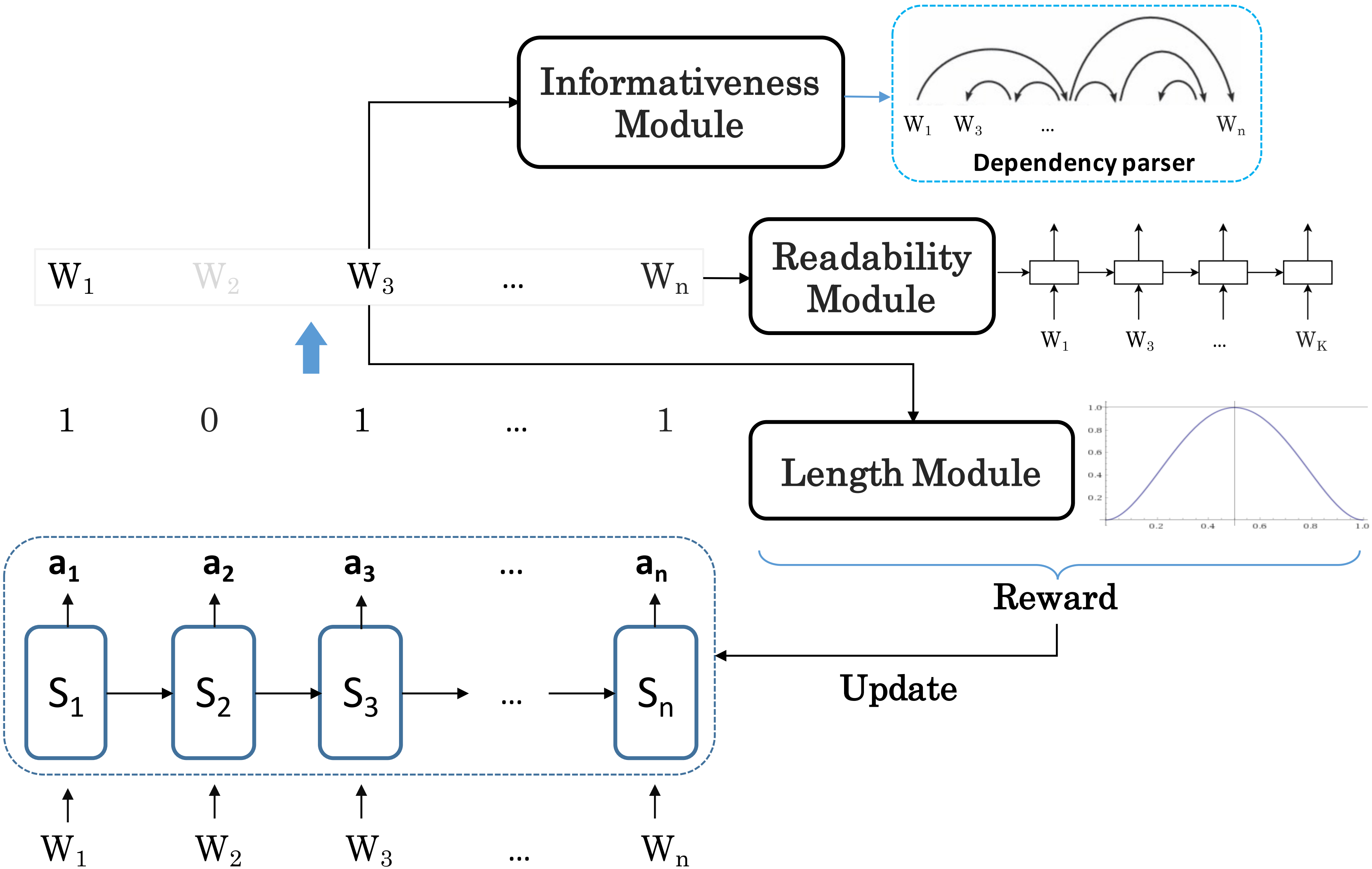
- Automatic evaluations in Sentence compression

Gold	**Aaron donald won the 2013 bronko nagurski trophy .**
1	(ncsubj, win+*ed* : 3_VVD, donald: 2_NP1)
2	(dobj, win+*ed* : 3_VVD, trophy: 8_NN1)
3	(det, trophy: 8_NN1, the: 4_AT)
4	(ncmod, trophy: 8_NN1, 2013: 5_MC)
5	(ncmod, trophy: 8_NN1, bronko: 6_JJ)
6	(ncmod, trophy: 8_NN1, nagurski: 7_JJ)
7	(ncmod, donald: 2_NP1, Aaron: 1_NP1)
System	**Aaron donald won .**
1	(ncsubj, win+*ed* : 3_VVD, *donald* : 2_NP1)
2	(ncmod, donald: 2_NP1, *Aaron* : 1_NP1)

Grammatical relations yielded by dependency parser

- G = a set of grammatical relations in ground truth
- S = a set of grammatical relations in system output
- $F_1 = \frac{2|G \cap S|}{|G|+|S|}$

Model Overview



Key Modules of the Model

- Informativeness Module
- Readability Module
- Length Module

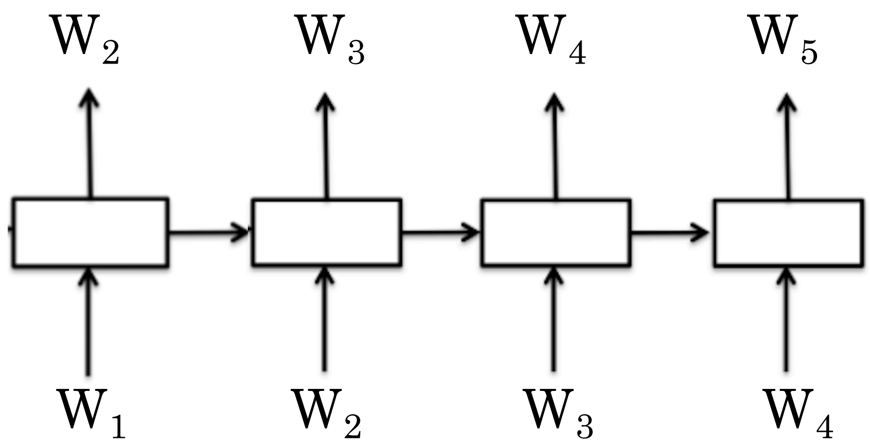
Informativeness Module

- During training, when we apply dependency parser to both compressed sentence (S) and ground truth (G), two sets of grammatical relations would be yielded respectively

  - G = a set of grammatical relations in ground truth
  - S = a set of grammatical relations in system output
  - $F_1 = \frac{2|G \cap S|}{|G|+|S|}$

F_1 as a reward is to feed into policy network during training

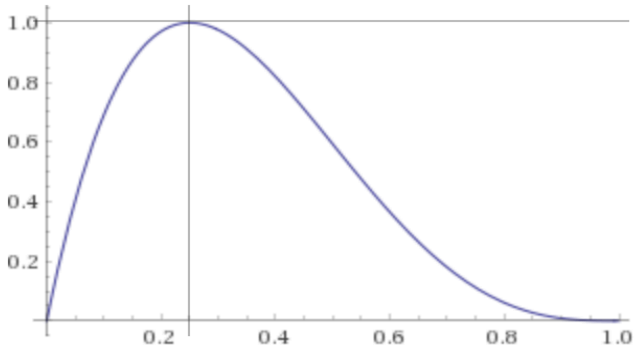
Readability Module

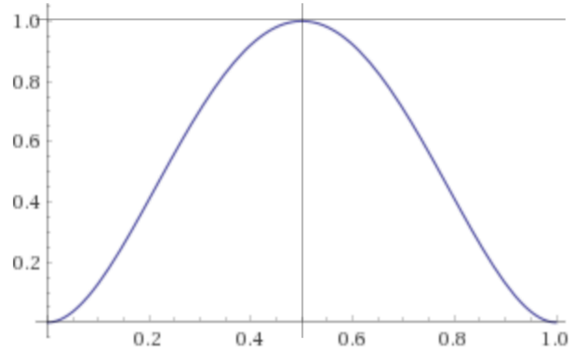


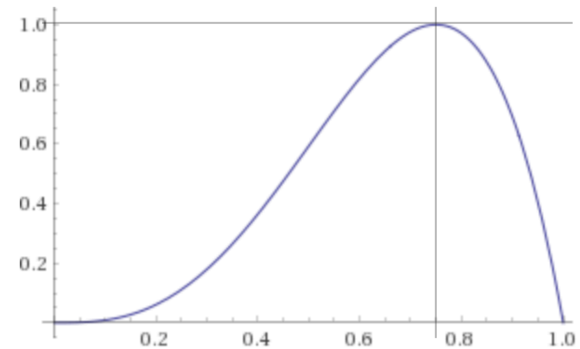
$$R_{LM} = \exp\left(\frac{1}{|\hat{Y}|}\sum_{i=1}^{|\hat{Y}|}\log P_{LM}(\hat{y}_i|\hat{y}_{0:i-1})\right)$$

- It is the normalized sentence probability assigned by an LSTM language model trained on sentence compression corpus

Length module - Compression Rate Reward Inspired by Beta Function







0.25	0.5	0.75
$f(x)=\frac{2^8}{3^3}x^1(1-x)^3$	$f(x)=16x^2(1-x)^2$	$f(x)=\frac{2^8}{3^3}x^3(1-x)^1$

- Experimental results show that model can get to our specifying compression rate very quickly.

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Dataset

GOOGLE News Dataset	
Domain	NEWS
size	10,000 sentence compression pairs
training/dev/test	8,000/1,000/1,000

Training details

- Policy network is a two-layer bi-directional LSTM followed by a binary Softmax layer.
- Embedding size is 128.
- Hidden size is 128.
- Since the converge takes time, pre-training is used to speed up the training.

Baselines

- Integer linear programming (ILP) (Clarke & Lapata, 2008)
- Long short-term memory network (LSTM) (Filippova et. al, 2015)
- ILP+LSTM (Wang et al., 2017)

Preliminary Result

Google News Dataset	F_1	Stanford-parser-F_1	compression rate
Original ILP (Clarke Lapata, 08)	56.0	-	0.50
LSTMs (Filippova et al.,15)	80.1	78.4	0.49
LSTMs+ILP(Wang et al., 17)	75.2	56.7	0.47
Our model	81.6	81.1	0.47

Table 1: F_1 results based on ground-truth (F_1) and grammatical relations ($Stanf - F_1$).

Next Step

- Conduct experiments on other datasets
- Replace the sequential language model with syntactic language model
- …

Thank you!