Sentence Simplification with Deep Reinforcement Learning

Xingxing Zhang and Mirella Lapata

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What is sentence simplification

Deletion-based sentence compression:

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

A man suffered a injury after a crash .

Sentence simplification:

1. Delete elements of the original text
2. Substitute rare words with more common words or phrases
3. Make syntactically complex structures simpler

Application of sentence simplification

- Improve the performance of parsers *(Chandrasekar et al., 1996)*
- Summarizers *(Beigman Klebanov et al., 2004)*
- Semantic role labelers *(Woodsend and Lapata, 2014)*
- Benefit people with low-literacy skills such as children and non-native speakers *(Watanabe et al., 2009)*

Previous work V.S. Recent work

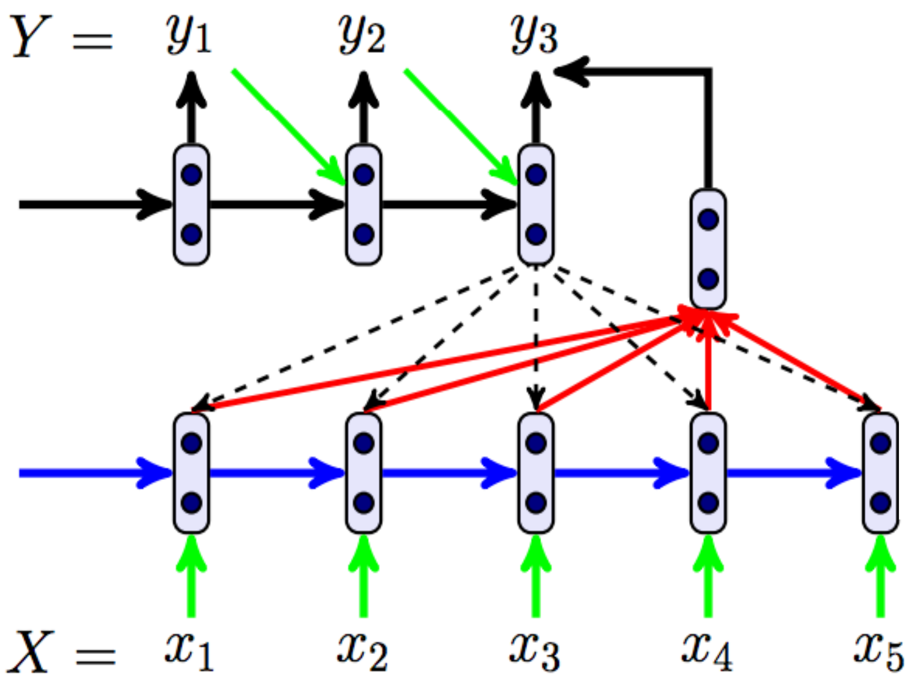
- Previous works focused on individual aspects of the simplification problem:

  (1) perform syntactic simplification only.
  (2) lexical simplification by substituting difficult words with more common WordNet synonyms or paraphrases.

- Recent works view it as a monolingual text-to-text generation task

Vanilla Encoder-Decoder with Attention Model

Given a (complex) source sentence: $X = (x_1, x_2, \dots, x_{|X|})$,
Predict its simplified target: $Y = (y_1, y_2, \dots, y_{|Y|})$.



$$P(Y|X) = \prod_{t=1}^{|Y|} P(y_t|y_{1:t-1}, X) \qquad (1)$$

- Minimizing the **negative log-likelihood** of the training source-target pairs

$$P(y_{t+1}|y_{1:t}, X) = \mathrm{softmax}(g(\mathbf{h}_t^T, \mathbf{c}_t)) \qquad (2)$$

where $g(\cdot)$ is a one-hidden-layer neural network with the following parametrization:

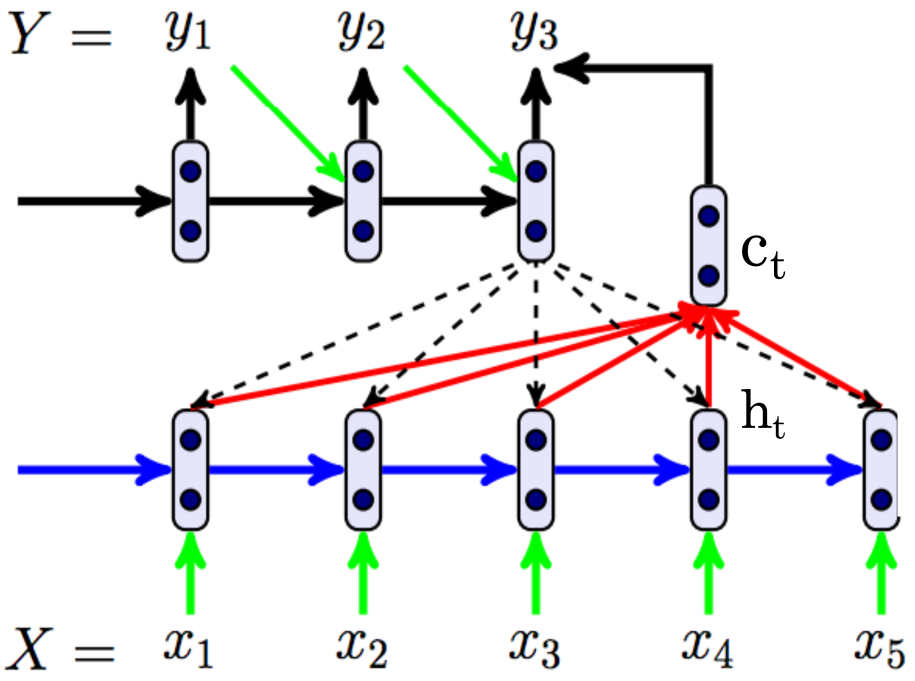
$$g(\mathbf{h}_t^T, \mathbf{c}_t) = \mathbf{W}_o \tanh(\mathbf{U}_h \mathbf{h}_t^T + \mathbf{W}_h \mathbf{c}_t) \qquad (3)$$

where $\mathbf{W}_o \in \mathbb{R}^{|V| \times d}$, $\mathbf{U}_h \in \mathbb{R}^{d \times d}$, and $\mathbf{W}_h \in \mathbb{R}^{d \times d}$; $|V|$ is the output vocabulary size and d the hidden unit size. $\mathbf{h}_t^T$ is the hidden state of the decoder LSTM which summarizes $y_{1:t}$, i.e., what has been generated so far:

$$\mathbf{h}_t^T = \mathrm{LSTM}(y_t, \mathbf{h}_{t-1}^T) \qquad (4)$$

The dynamic context vector $\mathbf{c}_t$ is the weighted sum of the hidden states of the source sentence:

$$\mathbf{c}_t = \sum_{i=1}^{|X|} \alpha_{ti} \mathbf{h}_i^S \qquad (5)$$



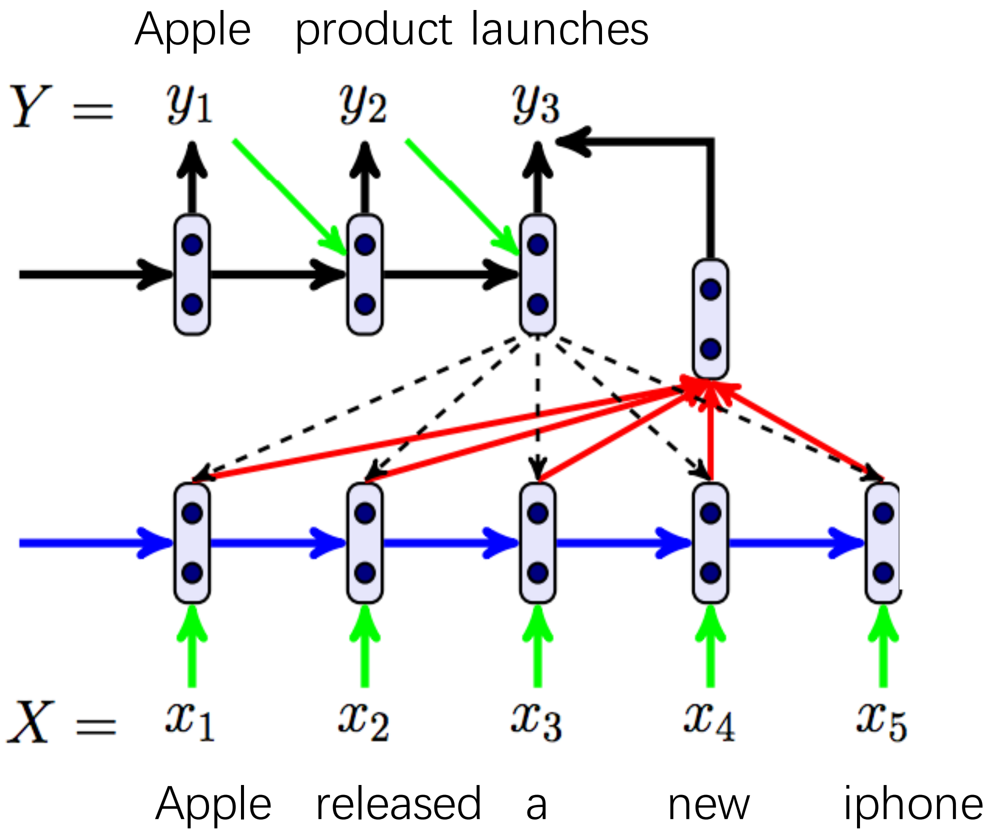
Vanilla seq2seq is not ideal for sentence simplification

- Rewrite operations (e.g., copying, deletion, substitution, word reordering)

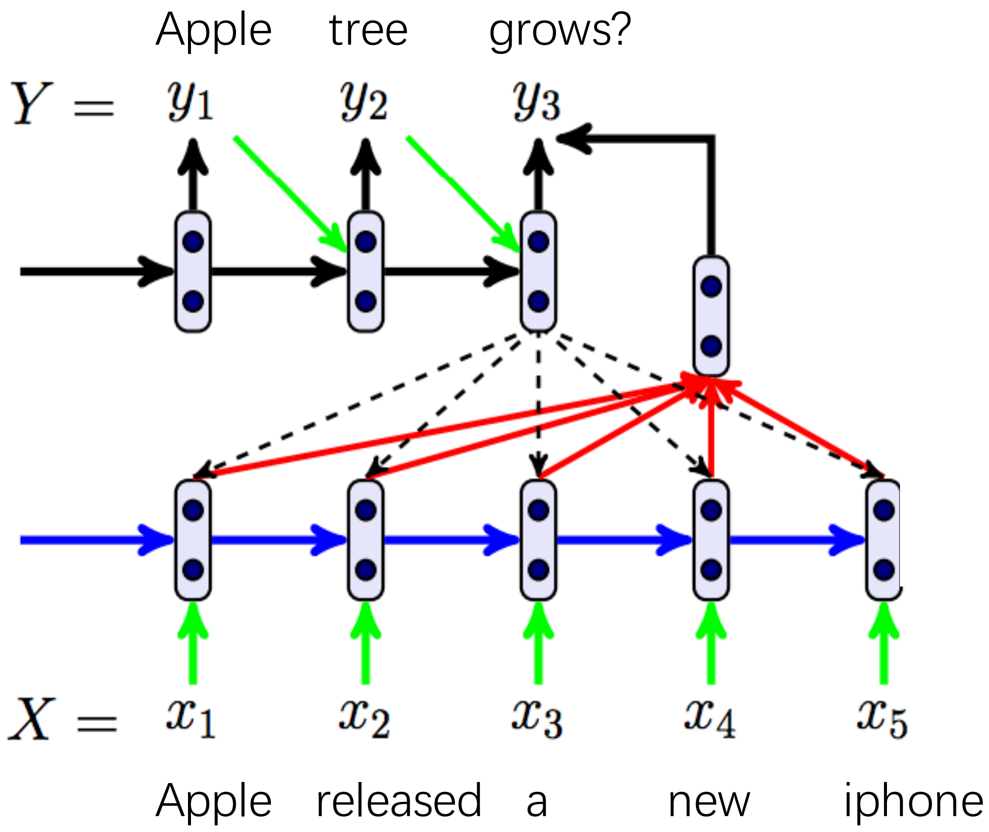
- Problem
  - Copy occupied of 73% operation in Newsela dataset, and 83% operation in Wikipedia-based dataset

Eposide

Vanilla seq2seq may not be ideal for considering the sentence as a whole



During training



During testing

Motivation

- To encourage a wider variety of rewrite operations while remaining fluent and faithful to the meaning of the source.

What leads to a good simplification - Simplicity

- Simplicity: System output Against References and against the Input sentence (SARI) which is the arithmetic average of n-gram precision and recall of three rewrite operations: addition, copying, and deletion.
  - reward the addition operations **where system output was not in the input but occurred in the references**.

- What the paper used is: SARI score(e.x. 0.7594)

What leads to a good simplification - Relevance

- **Relevance**: while encouraging changes, generated sentence should preserve the meaning of the source.

  - Cosine similarity between original one and simply one.

$$r^R = \cos(\mathbf{q}_X, \mathbf{q}_{\hat{Y}}) = \frac{\mathbf{q}_X \cdot \mathbf{q}_{\hat{Y}}}{||\mathbf{q}_X||\,||\mathbf{q}_{\hat{Y}}||}$$

- q_x and q_y are vector representation of source and target.

What leads to a good simplification - Fluency

- Fluency: be readable & be grammatical

  - LSTM language model trained on simple sentences

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

We take the exponential of Y's perplexity to ensure that $r^F \in [0,1]$

Put them together

simplicity, relevance, and fluency:

$$r(\hat{Y}) = \lambda^S r^S + \lambda^R r^R + \lambda^F r^F$$

where $\lambda^S, \lambda^R, \lambda^F \in [0,1]$; $r(\hat{Y})$ is a shorthand for $r(X, Y, \hat{Y})$ where X is the source, Y the reference (or target), and $\hat{Y}$ the system output.

The reward r(Yˆ) for system output Yˆ is the weighted sum of the three components

Put them together

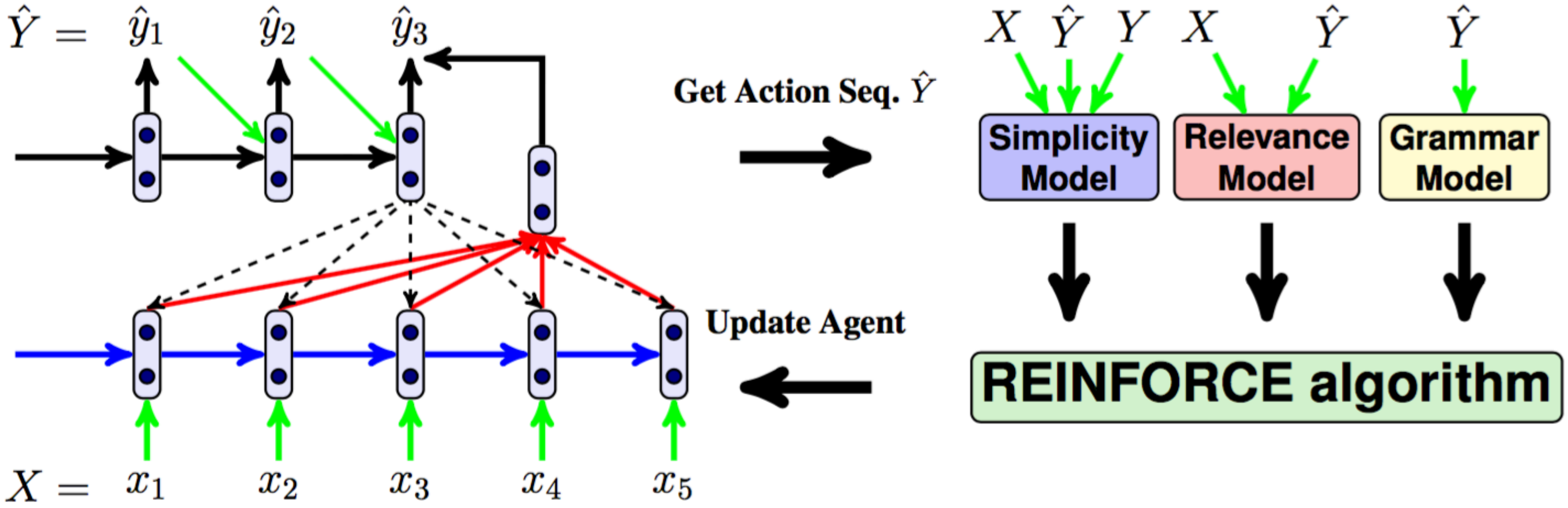


Figure 1: Deep reinforcement learning simplification model. X is the complex sentence, Y the reference (simple) sentence and $\hat{Y}$ the action sequence (simplification) produced by the encoder-decoder model.

Datasets

Automatic alignment

professional editors

- Parallel corpus$_1$ *WikiSmall*
  - It contains automatically aligned complex and simple sentences from the ordinary and simple English Wikipedias.
  - train/val/test 89,042/205/100
- Parallel corpus$_2$ *WikiLarge*
  - It contains 8 (reference) simplifications for 2,359 sentences partitioned into 2,000 for development and 359 for testing.
  - train/val/test 296,402/2,000/359
- Parallel corpus$_3$ Newsela
  - It consists of 1,130 news articles, each rewritten four times by professional editors for children at different grade levels
  - train/val/test 94,208/1,129/1,076

Automatic Evaluation

1. Bilingual Evaluation Understudy BLEU[blɛ：]
   - To assess the degree to which generated simplifications differed from gold standard references

2. Flesch-Kincaid Grade Level (FKGL) score
   - To measure the simplicity of the output (lower FKGL implies simpler output)

3. System output Against References and against the Input sentence (SARI)
   - To evaluate the quality of the output by comparing it against the source and reference simplifications

Human Evaluation

Native English speakers were asked to rate simplifications on three dimensions:

- *Fluency* (is the output grammatical and well formed?),
- *Adequacy* (to what extent is the meaning expressed in the original sentence preserved in the output?)
- *Simplicity* (is the output simpler than the original sentence?)

All ratings were obtained using a five point Likert scale.

Results

Newsela	BLEU	FKGL	SARI
PBMT-R	18.19	7.59	15.77
Hybrid	14.46	**4.01**	**30.00**
EncDecA	21.70	5.11	24.12
DRESS	23.21	4.13	27.37
DRESS-LS	**24.30**	4.21	26.63

WikiSmall	BLEU	FKGL	SARI
PBMT-R	46.31	11.42	15.97
Hybrid	**53.94**	9.20	**30.46**
EncDecA	47.93	11.35	13.61
DRESS	34.53	**7.48**	27.48
DRESS-LS	36.32	7.55	27.24

WikiLarge	BLEU	FKGL	SARI
PBMT-R	81.11	8.33	38.56
Hybrid	48.97	**4.56**	31.40
SBMT-SARI	73.08	7.29	**39.96**
EncDecA	**88.85**	8.41	35.66
DRESS	77.18	6.58	37.08
DRESS-LS	80.12	6.62	37.27

Table 1: Automatic evaluation on Newsela, WikiSmall, and WikiLarge test sets.

Newsela	Fluency	Adequacy	Simplicity	All
PBMT-R	3.56	**3.58****	2.09**	3.08**
Hybrid	2.70**	2.51**	2.99	2.73**
EncDecA	3.63	2.99	2.56**	3.06**
DRESS	3.65	2.94	**3.10**	3.23
DRESS-LS	**3.71**	3.07	3.04	**3.28**
Reference	3.90	2.81**	3.42**	3.38

WikiSmall	Fluency	Adequacy	Simplicity	All
PBMT-R	3.91	**3.74****	2.80**	3.48*
Hybrid	3.26**	3.42	2.82**	3.17**
DRESS-LS	**3.92**	3.36	**3.55**	**3.61**
Reference	3.74*	3.34	3.13**	3.41**

WikiLarge	Fluency	Adequacy	Simplicity	All
PBMT-R	3.68	**3.63***	2.70**	3.34*
Hybrid	2.60**	2.42**	**3.52**	2.85**
SBMT-SARI	3.34**	3.51*	2.77**	3.21**
DRESS-LS	**3.70**	3.28	3.42	**3.46**
Reference	3.79	3.72**	2.86**	3.46

Table 2: Mean ratings elicited by humans on Newsela, WikiSmall, and WkiLarge test sets. Ratings significantly different from DRESS-LS are marked with * ($p < 0.05$) and ** ($p < 0.01$). Significance tests were performed using a student t-test.

System output for example sentence

Complex	There's just one major hitch: the primary purpose of education is to develop citizens with a wide variety of skills.
Reference	The purpose of education is to develop a wide range of skills.
PBMT-R	It's just one major hitch: the purpose of education is to **make people** with a wide variety of skills.
Hybrid	one hitch the purpose is to develop citizens.
EncDecA	The **key** of education is to develop **people** with a wide variety of skills.
DRESS	There's just one major hitch: the **main goal** of education is to develop **people** with **lots of** skills.
DRESS-LS	There's just one major hitch: the **main goal** of education is to develop citizens with **lots of** skills.

Substitutions are shown in bold.

Conclusion

- Definition of the reward function is the key.

- Take the evaluation metric itself as optimization objective (like SARI score)
  - evaluation is thus important

- …