

# **Global Encoding for Abstractive Summarization**

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#### Abstract

Problems in the seq2seq (repetition and semantic irrelevance);

**CNN (Inception-like structure), Self Attention and Gate** 

Concat

Self Attention

- •Our global encoding mechanism: **CNN and self attention**;
- Improved performances on the benchmark datasets;
- •Generate summaries with less repetition and higher semantic **consistency** to the source text.



$$Attention(Q,K,V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

$$\tilde{h} = h \odot \sigma(g)$$

#### **Sequence-to-Sequence** as **Baseline**

- Encoder: RNN is more popular, usually LSTM and GRU
- Decoder: RNN for sequential decoding. Usually training is with teacher forcing.
- Attention mechanism: additive attention or global attention for the relevant source-side information

## Experiments

• Datasets:

### LCSTS and Gigaword

Model	<b>R-1</b>	<b>R-2</b>	R-L
RNN	21.5	8.9	18.6
RNN-context	29.9	17.4	27.2
CopyNet	34.4	21.6	31.3
SRB	33.3	20.0	30.1
DRGD	37.0	24.2	34.2
seq2seq (Our impl.)	33.8	23.1	32.5

Model	<b>R-1</b>	R-2	R-L
ABS	29.6	11.3	26.4
ABS+	29.8	11.9	27.0
Feats	32.7	15.6	30.6
RAS-LSTM	32.6	14.7	30.0
RAS-Elman	33.8	16.0	31.2
SEASS	36.2	17.5	33.6

#### Example

Problems in the seq2seq (repetition and semantic irrelevance);

Text: the mainstream fatah movement on monday officially chose Mahmoud abbas, chairman of the Palestine liberation organization (plo), as its candidate to run for the presidential election due on jan. #, ####, the official wafa news agency reported.

seq2seq: fatah officially officially elects abbas as candidate for candidate.

Gold: fatah officially elects abbas as candidate for presidential election.

## **Problems**

•Noise in the source context.

•**Relationship** between the source and the target is different from

+CGU	39.4	26.9	36.5	DRGD
Table 2: F-Score of F	ROUGI	E on LO	CSTS.	seq2seq +CGU
				Table 3. F

DRGD	36.3	17.6	33.6
seq2seq (Our impl.)	33.6	16.3	31.3
+CGU	36.3	18.0	33.8

Table 3: F-Score of ROUGE on Gigaword.

## **Qualitative Analyses**

Source: 较早进入中国市场的星巴克, 是不少小资钟 情的品牌。相比在美国的平民形象,星巴克在中国就 显得"高端"得多。用料并无差别的一杯中杯美式咖啡,在美国仅约合人民币12元,国内要卖21元,相当 于贵了75%。第一财经日报

Starbucks, which entered Chinese market early, is a brand appealing to young people of petit bourgeoisie. Compared with its ordinary image in the United States, Starbucks seems to be of higher class in China. A Tall Americano sells about 12RMB in the United States, but 21RMB in China, which means it is 75% more expensive.

**Reference:** 媒体称星巴克美式咖啡售价中国比美国 贵75%。

Media report that the price of Starbucks Americano in China is 75% more expensive than that in the United States.

seq2seq: 星巴克中国美式咖啡在中国。 Starbucks China Americano in China.



#### Figure above demonstrates the

the alignment in machine translation, and correct alignment does not always indicate good summary.

•Source annotation at each time step lacks global information of the **context**, which may provide unnecessary information for summary.

## **Global Encoding**

- Convolutional Neural Networks over the source annotations.
- Self attention for the connections to the global context.
- Collaboratively build a **gate** for the original source annotations.

+CGU: 星巴克美式咖啡中国贵75%。 Starbucks Americano is 75% more expensive in China. percentage of duplicates of n-gram

# Conclusion

- Conventional Seq2Seq requires a mechanism to improve the source annotations so that they can provide summary-oriented information for the attention.
- Global encoding can improve the quality of generated summaries, which is reflected in both the ROUGE evaluation and the case study.
- It still requires future work to figure out what it filters and how it improves the performance of the model.