Regularizing RNNs for Caption Generation by Reconstructing The Past with The Present

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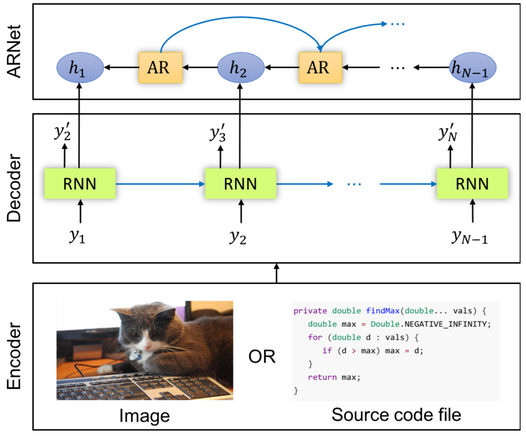
CVPR 2018 SALT LAKE CITY • JUNE 18-22

Introduction

We propose a novel architecture, namely Auto-Reconstructor Network (ARNet), which coupling with the conventional encoder-decoder framework, works in an end-to-end fashion for caption generation.

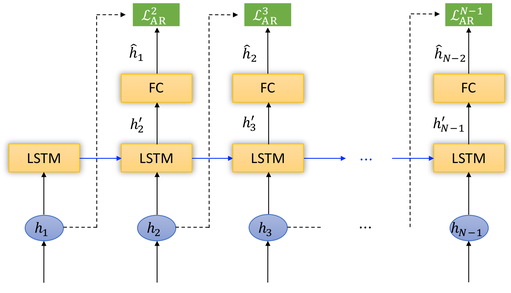


Motivation

- The latent relationships between neighbouring hidden states in RNNs are not fully exploited.
- The discrepancy problem, also named as exposure bias, in RNN between training and inference for sequence prediction tasks still exists.

Architecture

Our proposed ARNet connects two neighbouring hidden states by reconstructing the past hidden state with present one. In this paper, ARNet is realized by another LSTM.



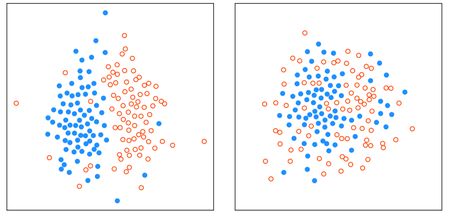
Experiments

- Image Captioning on MSCOCO

Model Name	B-1	B-2	B-3	B-4	M	R	C	S
NIC	0.666	0.451	0.304	0.203	-	-	-	-
m-RNN	0.670	0.490	0.350	0.250	-	-	-	-
Soft Attention	0.707	0.492	0.344	0.243	0.239	-	-	-
Hard Attention	0.718	0.504	0.357	0.250	0.230	-	-	-
Semantic Attention	0.709	0.537	0.402	0.304	0.243	-	-	-
ReviewNet	-	-	-	0.290	0.237	-	0.886	-
LSTM-A5	0.730	0.565	0.429	0.325	0.251	0.538	0.986	-
Encoder-Decoder	0.718	0.547	0.412	0.311	0.251	0.530	0.961	0.179
Encoder-Decoder + Zoneout	0.708	0.537	0.403	0.304	0.249	0.525	0.941	0.176
Encoder-Decoder + Scheduled Sampling	0.718	0.548	0.414	0.315	0.252	0.531	0.975	0.180
Encoder-Decoder + ARNet	0.730	0.562	0.425	0.321	0.252	0.535	0.988	0.182
Att-Encoder-Decoder	0.727	0.557	0.421	0.318	0.259	0.537	0.996	0.185
Att-Encoder-Decoder + Zoneout	0.720	0.549	0.415	0.314	0.251	0.532	0.975	0.181
Att-Encoder-Decoder + Scheduled Sampling	0.731	0.563	0.426	0.322	0.256	0.538	1.006	0.187
Att-Encoder-Decoder + ARNet	**0.740**	**0.576**	**0.440**	**0.335**	**0.261**	**0.546**	**1.034**	**0.190**

Experiments Cont.

Hidden states visualization of the attentive encoder-decoder model (a) and the attentive encoder-decoder-ARNet model (b). The filled circles in blue represent the hidden states generated in the training mode, while the open circles in red are obtained in the inference mode.



(a) (b)

We define two different distance metrics based on cosine distance to evaluate the discrepancy between the hidden states from training and inference, respectively.

1. Mean centroid distance: $d_{mc}(\mathbf{U},\mathbf{V}) = \mathrm{d}(\frac{1}{B}\sum_i^B u_{l_i}, \frac{1}{B}\sum_j^B u_{l_j})$
2. Point-wise distance: $d_{pw}(\mathbf{U},\mathbf{V}) = \frac{1}{B}(\sum_{i=1}^B d(u_{l_i}, v_{l_i}))$

Model Name	d_{mc}	d_{pw}
Encoder-Decoder	0.747	0.719
Encoder-Decoder-ARNet	0.514	0.561
Att-Encoder-Decoder	0.773	0.760
Att-Encoder-Decoder-ARNet	**0.491**	**0.595**

Experiments Cont.

- Code Captioning on HabeasCorpus

Model Name	B-1	B-2	B-3	B-4	M	R
ReviewNet	0.192	0.105	0.074	0.057	0.085	0.200
Encoder-Decoder	0.183	0.093	0.063	0.047	0.080	0.188
Encoder-Decoder + Zoneout	0.182	0.080	0.063	0.047	0.080	0.181
Encoder-Decoder + Scheduled Sampling	0.186	0.098	0.067	0.051	0.082	0.194
Encoder-Decoder + ARNet	0.196	0.107	0.075	0.058	0.089	0.213
Att-Encoder-Decoder	0.228	0.140	0.106	0.088	0.105	0.256
Att-Encoder-Decoder + Zoneout	0.227	0.140	0.105	0.086	0.090	0.220
Att-Encoder-Decoder + Scheduled Sampling	0.229	0.142	0.108	0.089	0.107	0.270
Att-Encoder-Decoder + ARNet	**0.255**	**0.173**	**0.139**	**0.120**	**0.123**	**0.289**

Model Name	d_{mc}	d_{pw}
Encoder-Decoder	0.643	0.722
Encoder-Decoder-ARNet	0.641	0.699
Att-Encoder-Decoder	0.594	0.712
Att-Encoder-Decoder-ARNet	**0.322**	**0.465**

- Permuted Sequential MNIST

Model Name	Test Accuracy
LSTM + Dropout	0.925
LSTM + Zoneout	0.931
Unregularized LSTM	0.914
LSTM + ARNet	**0.933**

Conclusions

- ARNet can regularize the transition dynamics and mitigate the discrepancy of RNN for sequence prediction tasks.
- Besides the caption generation tasks, ARNet can help model long term dependencies. Experiments on permuted sequential MNIST task demonstrate the superiority of our proposed ARNet.