中国科学院自动化研究所 CASIA Institute of Automation, Chinese Academy of Sciences
模式识别国家重点实验室 National Laboratory of Pattern Recognition
中国科学院大学 University of Chinese Academy of Sciences

Conditional Generative Adversarial Networks for Commonsense Machine Comprehension

Bingning Wang, Kang Liu, and Jun Zhao

National Laboratory of Pattern Recognition
Institute of Automation, Chinese Academy of Sciences
University of Chinese Academy of Sciences

Background

Recently proposed Story Cloze Test is a commonsense machine comprehension application to deal with natural language understanding problem. This dataset contains a lot of story tests which require commonsense inference ability. Unfortunately, the training data is almost unsupervised where each context document followed with only one positive sentence that can be inferred from the context. However, in the testing period, we must make inference from two candidate sentences. To tackle this problem, we employ the generative adversarial networks (GANs) to generate fake sentence. We proposed a Conditional GANs (CGANs) in which the generator is conditioned by the context. Our experiments show the advantage of the CGANs in discriminating sentence and achieve state-of-the-art results in commonsense story reading comprehension task compared with previous feature engineering and deep learning methods.

Task definition

Billy's car broke down on the highway.
He looked under the hood and realized his starter was broken.
The nearest mechanic quoted Billy 300 dollars, which was far too much.
He instead called a friend who came and fixed the starter for $100.
Billy drove away happily with a functioning engine.

Training Story

context: Maxine usually hates to shave her legs.
She doesn't like the feeling of using a razor.
One night Maxine has a big date and decides to wear a dress.
She shaves her legs for the occasion.

Candidate1: Maxine doesn't want to go on the date.
Candidate2: Maxine gets laser removal next time. ✓

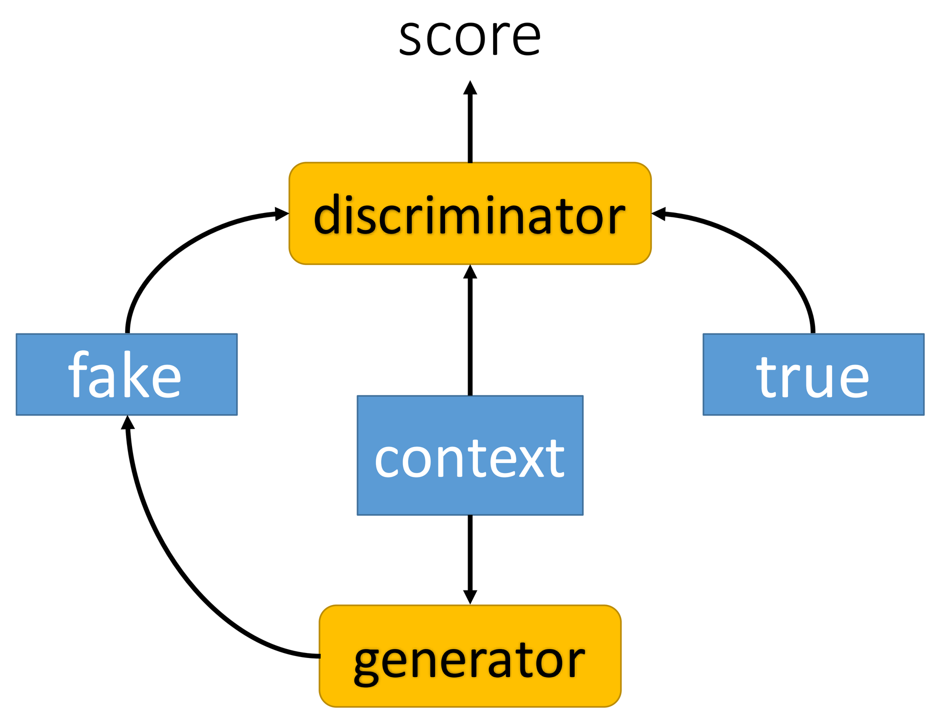
Testing Story

Key points

Generate the negative sentence(i.e. the wrong candidate)

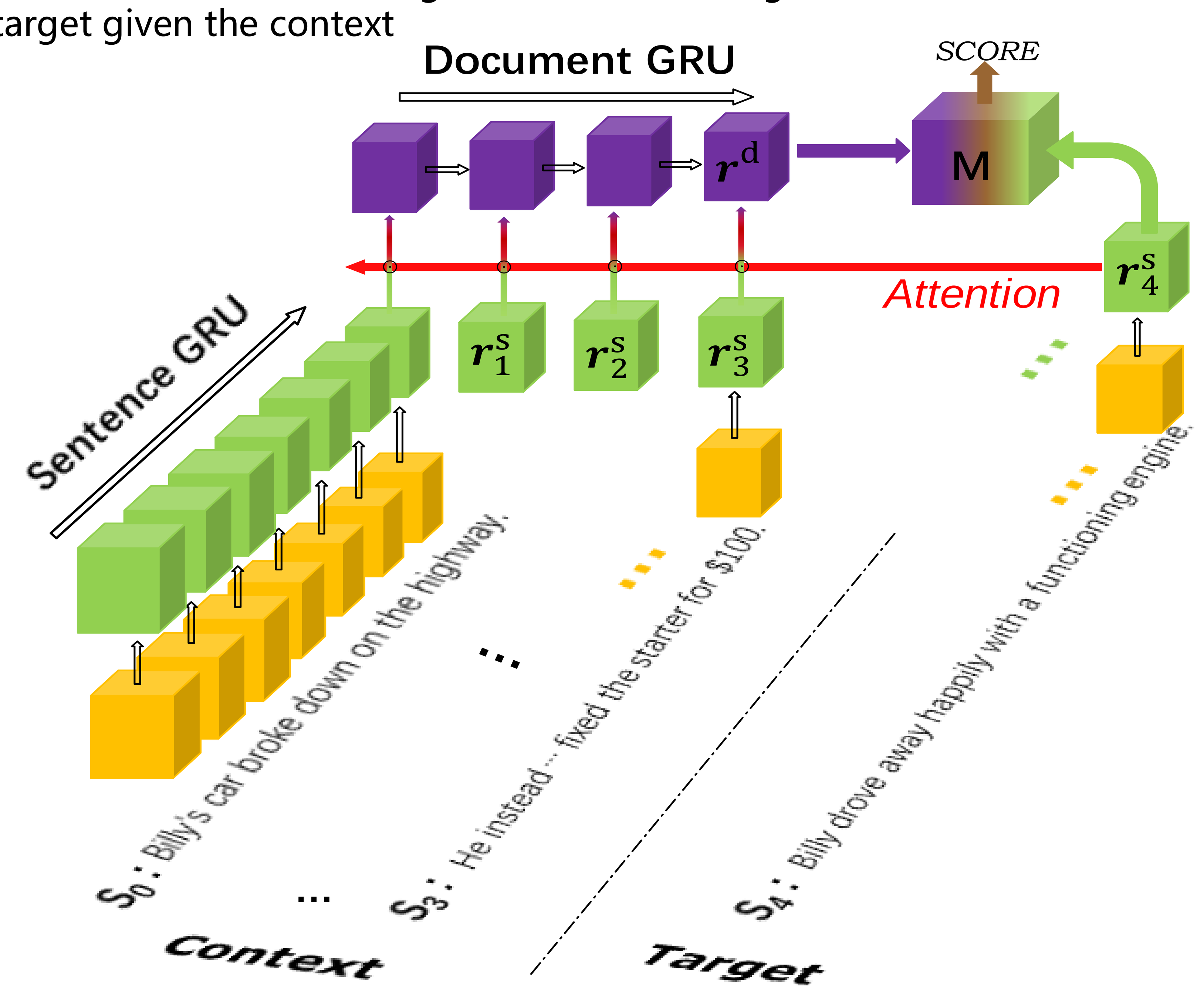
Methods

Use Generative adversarial networks(GANs) to generate the fake sentence

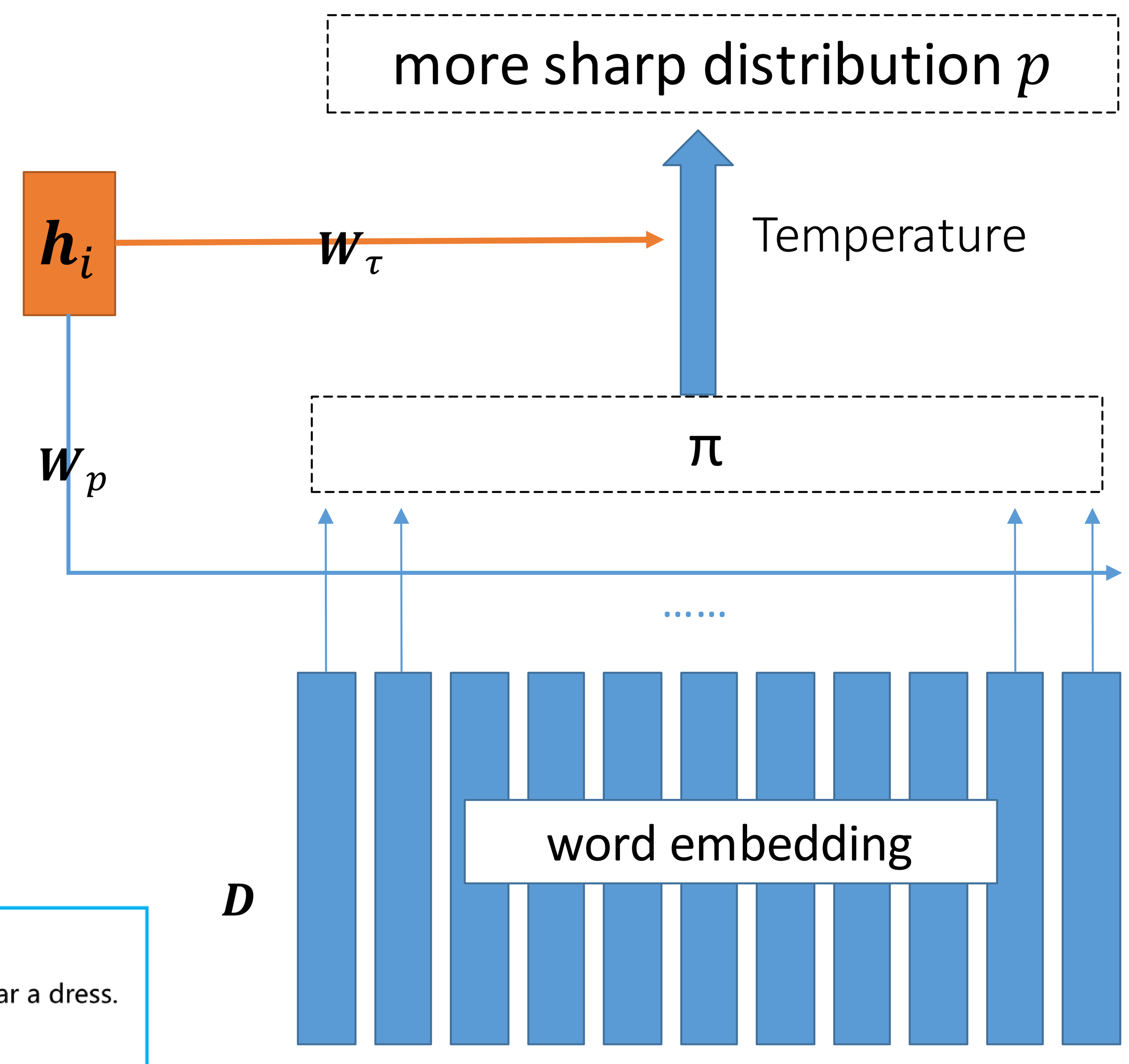


Discriminator

A Hierarchical context-target GRU network to give the score of a target given the context



Generator



$$\pi_j = softmax(\mathbf{D}_j^T \mathbf{W}_p \mathbf{h}_i^d)$$

$$p_j = softmax(\frac{\pi_j}{\tau})$$

$$\mathbf{y} = \sum_{j=1}^{|V|} p_j \mathbf{D}_j$$

$$\tau = Relu(\mathbf{w}_\tau^T \mathbf{h}_i^d) + \varepsilon$$

Tricks to train GANs

- Pre-training the generator with MLE
- Adding small noise to the inputs of the discriminator in each step
- Instead of training the generator and discriminator with fixed ratio, we monitor the score of the real and fake example and tuning the training step for D and G thereof.

Algorithm 1 Conditional Generative Adversarial Networks

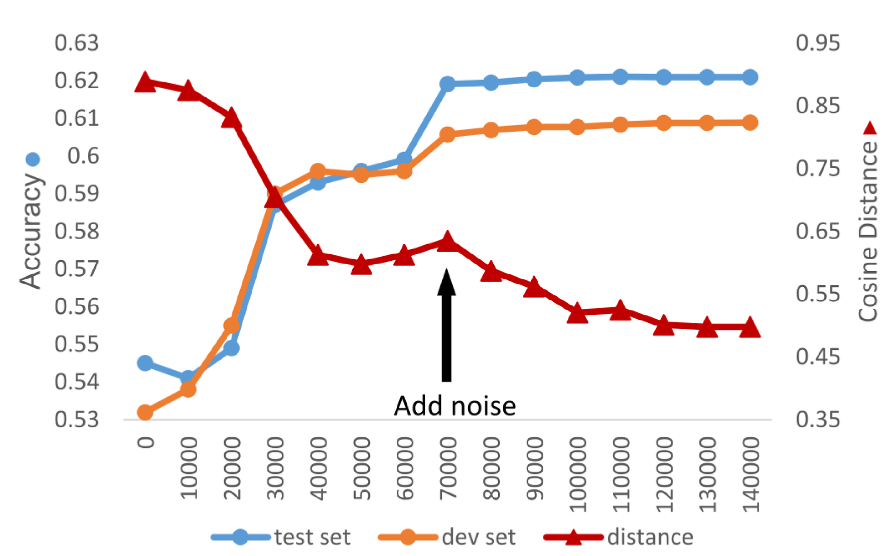
Require: $Threashold$: # of iteration to add noise. k_d=k_g=1 .

Pre-training G by maximizing target sentence likelihood.
for number of training iterations **do**
  for number steps k_d **do**
    sample a context document $\{s_0, ..., s_3\}$ and the real target s_4, then use G to generate fake sentence $\bar{s}$
    if iteration $> Threashold$ **then** sample $\mathbf{z}_d$ from $\mathcal{N}(\mathbf{0}, \mathbf{1})$, add $\mathbf{z}_d$ to the embedding of s_4 or $\bar{s}$.
    Calculate $SCORE$ from Equation 4.
    $\mathcal{L}_D = -\log SCORE(s_4) - \log(1 - SCORE(\bar{s}))$
    ▷ Update the discriminator:
    $\nabla_{\theta_D} = \frac{d\mathcal{L}_D}{d\theta_D}$ $\quad \theta_D = \theta_D + \lambda \nabla_{\theta_D}$
  for number steps k_g **do**
    sample a context document $\{s_0, ..., s_3\}$ and get the generated sentence $\bar{s}$ from generator G
    $\mathcal{L}_G = -\log SCORE(\bar{s})$+$similarity(s_4, \bar{s})$
    ▷ Update the generator:
    $\nabla_{\theta_G} = \frac{d\mathcal{L}_G}{d\theta_G}$ $\quad \theta_G = \theta_G + \lambda \nabla_{\theta_G}$
  ▷ Update k_g and k_d based on $\mathcal{L}_G$ and $\mathcal{L}_D$

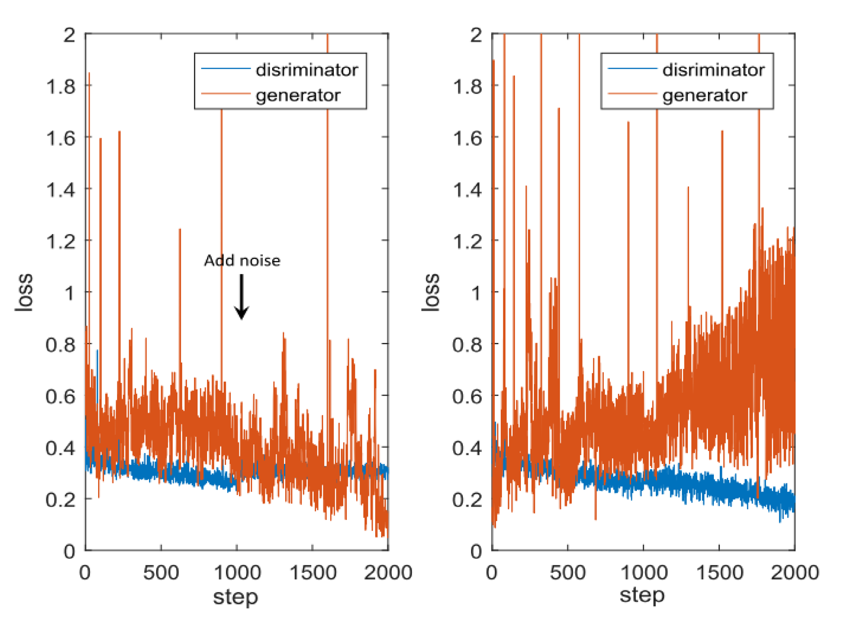
Experiments

	Random	Frequency	N-gram-overlap	Gensim	Sentiment-Full	Sentiment-Last	Skip-thoughts	Narrative-Chains-AP	Narrative-Chains-Stories	DSSM	GRU	w/o CGAN&Attention	w/o Attention	w/o CGAN	CGAN
Validation Set	0.514	0.506	0.477	0.545	0.489	0.514	0.536	0.472	0.510	0.604	0.573	0.589	0.603	0.593	**0.625**
Test Set	0.513	0.520	0.494	0.539	0.492	0.522	0.552	0.478	0.494	0.585	0.561	0.580	0.595	0.578	**0.609**

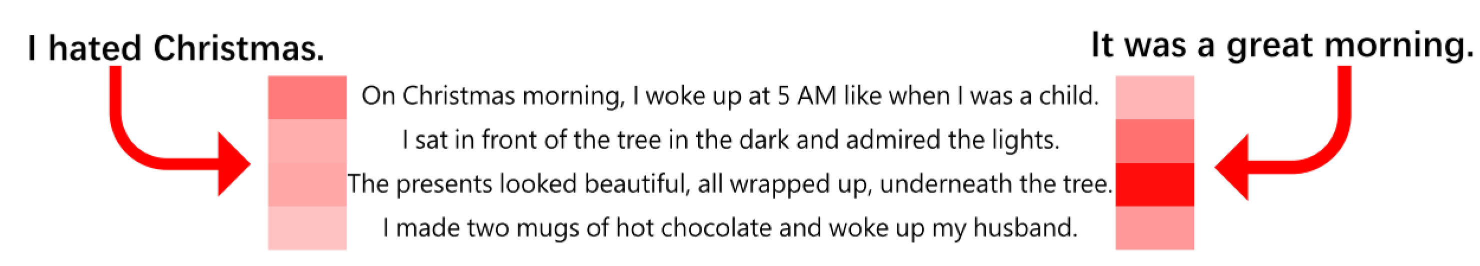
Results



Performance with respect to the training process. X-axis is the training examples that had been fed to the discriminator. The red line is the normalized Euclidian distance between true target sentence and generated fake sentence.



The training loss w.r.t. discriminator and generator. The right model is not fed with noise. We add noise to the from step 1000 to the end, one step equals to 8 batches.



An example drawn from the validation set. The red rectangle denotes the attention weight. Deeper color means more attention.