7.11 Meet Agenda

进展：

1.模型采用seq2seq、NMT初步完成

2.故事的生成长度存在问题

2.seq2seq: exposure bias的问题

解决方法：

每个词的生成会基于 groud-truth 生成，而不是根据模型自己之前生成的词。

Paper: Professor Forcing: A New Algorithm for Training Recurrent Networks

Link: http://papers.nips.cc/paper/6099-professor-forcing-a-new-algorithm-for-training-recurrent-networks.pdf

Paper: Scheduled Sampling for Sequence Prediction with Recurrent Neural Networks

讲 exposure bias 的解决方法的 Schedule Sampling

Link: https://papers.nips.cc/paper/5956-scheduled-sampling-for-sequence-prediction-with-recurrent-neural-networks.pdf

Paper: How (not) to Train your Generative Model: Scheduled Sampling, Likelihood, Adversary?

说这个 Schedule Sampling 有问题 不是无偏估计

Link: https://arxiv.org/pdf/1511.05101.pdf

逐字的 loss 是不是不太符合我们的习惯，一般都是以句子这个粒度来评估生成的质量

MLE -> Professor Forcing -> Scheduled Sampling

3.关于temperature：
完成了利用temperature去做softmax概率后的工作，对句子的最初生成的句子多样性进行控制,之后的句子趋近于argmax
Paper: GANS for Sequences of Discrete Elements with the Gumbel-softmax Distribution

Then

$$\mathbf{p} = \text{softmax}(\mathbf{h}) \tag{1}$$

where softmax$(\cdot)$ returns here a d-dimensional vector with the output of the softmax function:

$$[\text{softmax}(\mathbf{h})]_i = \frac{\exp(\mathbf{h}_i)}{\sum_{j=1}^{K}\exp(\mathbf{h}_j)}, \quad \text{for} \quad i = 1, \ldots, d. \tag{2}$$

It can be shown that sampling $\mathbf{y}$ according to the previous multinomial distribution with probability vector given by (1) is the same as sampling $\mathbf{y}$ according to

$$\mathbf{y} = \text{one\_hot}(\arg\max_i(h_i + g_i)), \tag{3}$$

where the g_i are independent and follow a Gumbel distribution with zero location and unit scale.

The sample generated in (3) has gradient zero with respect to $\mathbf{h}$ because the one_hot$(\arg\max(\cdot))$ operator is not differentiable. We propose to approximate this operator with a differentiable function based on the soft-max transformation [8]. In particular, we approximate $\mathbf{y}$ with

$$\mathbf{y} = \text{softmax}(1/\tau(\mathbf{h} + \mathbf{g}))), \tag{4}$$

where τ is an inverse temperature parameter. When $\tau \to 0$, the samples generated by (4) have the same distribution as those generated by (3) and when $\tau \to \infty$, the samples are always the uniform probability vector. For positive and finite values of τ the samples generated by (4) are smooth and differentiable with respect to $\mathbf{h}$.

The probability distribution for (4), which is parameterized by τ and $\mathbf{h}$, is called the Gumbel-softmax distribution [8]. A GAN on discrete data can then be trained by using (4), starting with some relatively large τ and then anealing it to zero during training.

Link:
https://arxiv.org/pdf/1611.04051.pdf

问题：
1. SeqGAN 等一系列 GAN + RL 做 Generation 可行性
2.提高inputs的context的方向？该从哪里出发

计划：
1.可控制的文本生成
2.在inference阶段：Discriminator，Generator 负责生成,生成完给Discriminator 打分,根据打分改进自己的生成.