Response Generation in Discrete Space Using GANs

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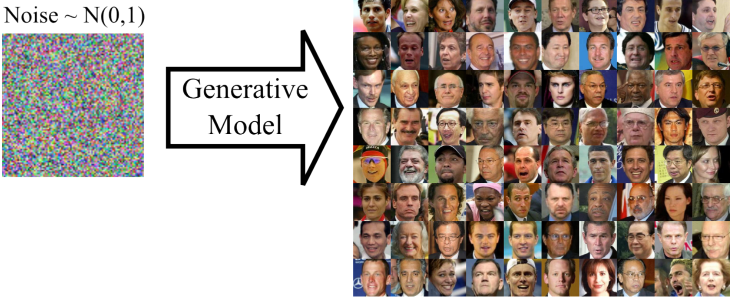
Some info about me...

- Mengjie (Joe) Zhao
- MS student from communication systems
- semester project

Overview

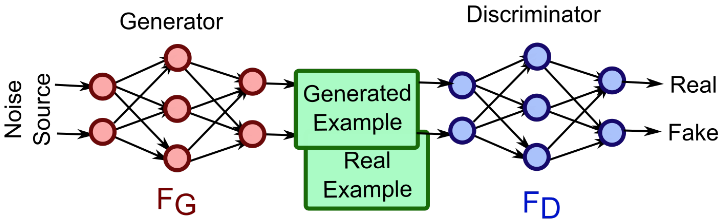
1. Generative Adversarial Networks (GANs)
2. Generating in discrete space?
3. Rate of progress
4. Conclusion

The generative model



src: http://torch.ch/blog/2015/11/13/gan.html

Generative Adversarial Networks (GANs)



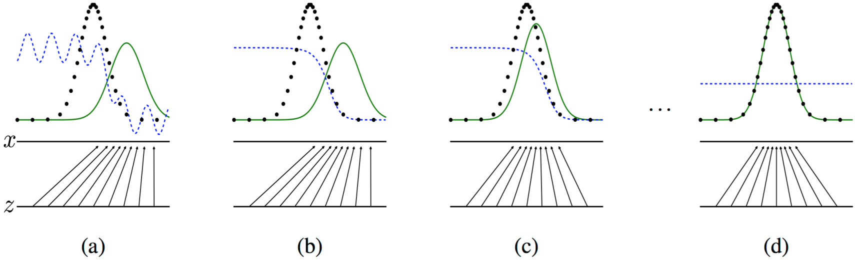
src: http://www.araya.org/archives/1183

To be more formal

- Define p_{data} as the distribution where data generated from
- Input noise $\mathbf{z}$ from noise distribution $p_z(z)$
- Generator: $G(z;\theta_g) \Rightarrow \mathbf{x}$
- Discriminator: $D(\mathbf{x};\theta_d)$
- Two-player minimax game with value function $V(G,D)$:

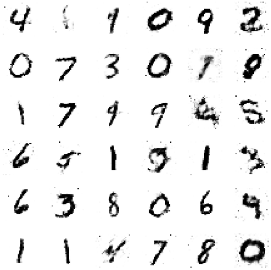
$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1-D(G(\boldsymbol{z})))]$$

To be more cartoon...

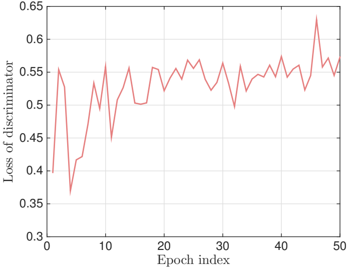


(Goodfellow et al. 2014)

Performance of a toy GAN (full connected MLPs)



Generated letters from G (50 epochs)



Loss of D (50 epochs)

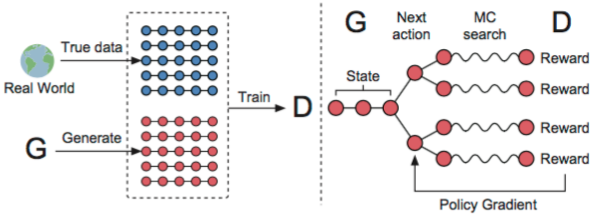
Overview

Generating in discrete space?

- Generator and discriminator have to be differentiable.
- But for text generation?
  - **policy iteration**
  - categorical reparameterisation (gumbel-softmax) ...

Sequence GAN (SeqGAN) for text generation

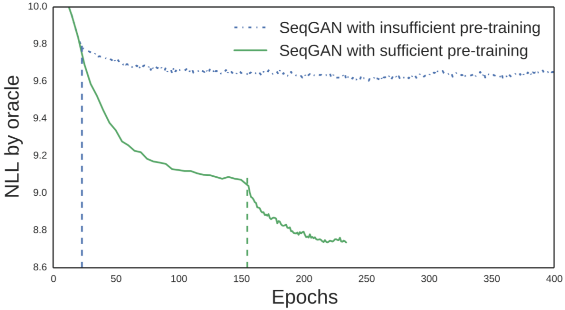
- Treat generator as an agent in reinforcement learning
  - State: generated tokens so far
  - Action: next token to be generated
  - Reward: evaluation of the sequence from D
  - **Policy iteration**
- Structure of SeqGAN:



(Yu et al. 2017)

Sequence GAN (SeqGAN) for text generation

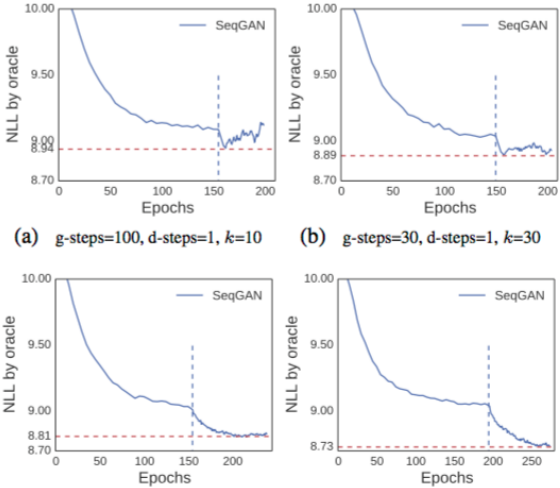
- Performance and the importance of pre-training:



(Yu et al. 2017)

Sequence GAN (SeqGAN) for text generation

- Coordinating pre-trainings for G and D:



(a) g-steps=100, d-steps=1, k=10

(b) g-steps=30, d-steps=1, k=30

(c) g-steps=1, d-steps=1, k=10

(d) g-steps=1, d-steps=5, k=3

(Yu et al. 2017)

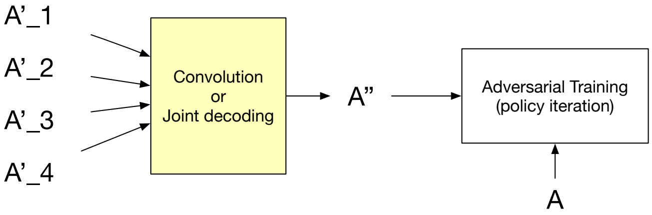
Generated sentences by SeqGAN

- Applying SeqGAN over the Big Bang Theory subtitle dataset
- Some generated sentences:
  - how was that , but that doesn ‘t come that waitress kisses me stop
  - you were my chicken ? no hello
  - penny you ‘re just never been decided you put it ‘s nice to talk
  - [Howard] sheldon i should just do that ?
- Reinforcement training is increasingly used for text generation

Dialog generation (Li et al. 2017)

- Use *seq2seq* model as a generator to generate dialog
- Discriminator decides the source of the dialog
- Policy iteration

For QA problem - a tentative framework



B x **4** x **T** x **D** **==>** **B** x **1** x **T** x **D**

B: batch size

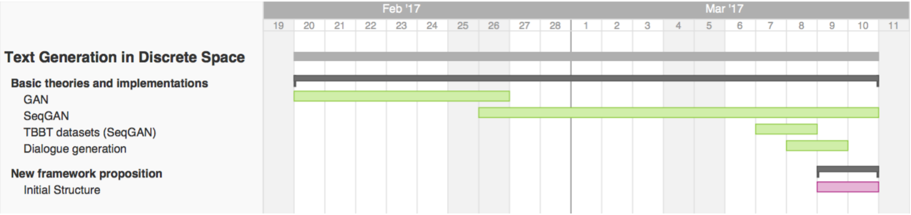
T: time dependency

S: number of candidates

E: embedding dim (word-wise)

Overview

Rate of progress



Conclusion

- In GANs, differentiable G and D are required
- Policy iteration in text generation
- Applying GANs in the QA problem is to be considered

That's it!

References

Goodfellow et al. (2014)
Generative Adversarial Networks
NIPS 2014

Yu et al. (2017)
SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient
AAAI 17

Li et al. (2017)
Adversarial Learning for Neural Dialogue Generation
arXiv:1701.06547

Jang et al. (2016)
Categorical Reparameterization with Gumbel-Softmax
arXiv:1611.01144

Appendix

- BLEU (bilingual evaluation understudy):
  - the closer a machine translation is to a professional human translation, the better it is
  - evaluating the quality of text which has been machine-translated from one natural language to another.
- GitHub: @joemzhao
- Likelihood:

$$f(y_1, \ldots, y_n; \theta) = \prod_{i=1}^{n} f(y_i; \theta) = L(\theta; y)$$

Appendix

- SeqGAN
  - Generator LSTM maximize the expected rewards
  - Discriminator TextCNN minimize cross entropy