CS283: Assignment 3

February 11, 2022

Due: Monday February 20th, 11:59pm
Submit by the **blakcboard system**

By turning in this assignment, I agree with the KAUST student protocol and declare that all of this is my own work.

Requirements:

- Put all files in a zip file and the file should be named LastnameFirstname_Assignment3.zip
- It is an individual assignment, independent write up, and submission in your own hand is required for credit.
- The work should be written in a **clear** way
- Late submission will receive credit penalty

1 Problem 1: Recurrent Neural Network (20 points)

Recurrent Neural Networks (RNN) are artificial neural networks that contains temporal connections among neural nodes in the same layer. Compare to normal feedforward neural networks, RNNs are good at processing sequential data with arbitrary length and can learn to model temporal dynamic behaviors. Long Short-Term memory [1] is the most famous RNN variant that are widely used in deep learning field.

a. **(10 points)** LSTM contains a forget gate to decide how many previous information need to be kept. There is a Sigmoid activation in the forget gate. Explain why we use Sigmoid here, instead of Tanh.

b. **(10 points)** In neural language processing and many other fields that process sequential data, more and more LSTM-based models are replaced by Transformer-based models [2] nowadays. Why LSTM is not as popular as before now? List at least 2 drawbacks of LSTM-compared to Transformer. Explain each of them with 1 to 3 sentences.

2 Problem 2: DCGAN (40 points)

DCGAN [3] is one of the most famous and classical GAN model in image generation task. In this question, you need to implement the discriminator of DCGAN in the file model.py and tune your model to generate MNIST numbers in GAN.ipynb. Please follow the instructions in the attached starting code.

3 Problem 3: Mode Collapse (40 points)

GANs are notoriously difficult to train. One of the famous training issues is the mode collapse. When mode collapse happen, the generator ignores the variety of the training data and produces the same output in most of the time.

a. **(5 points)** Explain the mode collapse problem happens in GANs in 2-3 sentences.

b. **(10 points)** UnRolled GAN [4] alleviates the mode collapse problem of GAN training by forecasting the future K steps of which networks? Explain your choice in 1-2 sentences.

A. Generator   **B**. Discriminator

c. **(10 points)** MAD-GAN [5] uses several generators to alleviate the mode collapse problem. Given a fake data, the discriminator needs to recognize the generator that produces it. Why this helps to alleviate the mode collapse problem?

d. **(15 points)** Wasserstein GAN [6, 7] is designed to train the generator by minimizing the Wasserstein distance (AKA earth mover's distance) between the real data distribution and generated data distribution. WGAN helps stable the training of GAN and alleviate the mode collapse issue. Explain why Wasserstein distance is better than KL/JS divergence when there is no overlap between 2 distributions? How was this notion used to develop the Wasserstein GAN Discriminator D and Generator G losses compared to standard GAN.

References

[1] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

[2] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. *arXiv preprint arXiv:1706.03762*, 2017.

[3] Alec Radford, Luke Metz, and Soumith Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv preprint arXiv:1511.06434*, 2015.

[4] Luke Metz, Ben Poole, David Pfau, and Jascha Sohl-Dickstein. Unrolled generative adversarial networks. *arXiv preprint arXiv:1611.02163*, 2016.

[5] Dan Li, Dacheng Chen, Baihong Jin, Lei Shi, Jonathan Goh, and See-Kiong Ng. Mad-gan: Multivariate anomaly detection for time series data with generative adversarial networks. In *International Conference on Artificial Neural Networks*, pages 703–716. Springer, 2019.

[6] Martin Arjovsky, Soumith Chintala, and Léon Bottou. Wasserstein generative adversarial networks. In *International conference on machine learning*, pages 214–223. PMLR, 2017.

[7] Ishaan Gulrajani, Faruk Ahmed, Martin Arjovsky, Vincent Dumoulin, and Aaron Courville. Improved training of wasserstein gans. *arXiv preprint arXiv:1704.00028*, 2017.