CS272 Assignment 2

Deadline 2022/4/13 23:59:59

Notes:

30 points for question 1, 30 points for question 2, 30 points for question 3, 10 points for question 4, a total of 100 points. Please try to achieve the bestperformance as you can. Discussions are encouraged and plagiarism is strictly prohibited, source code should not be shared in any form. Please submit your assignment (report in .pdf format, your codes and **trained model** with *readme*). to blackboard with both subject and file named in this format. (CS272+ID+name+hw2) example, CS272_2019123321_张三_hw2. Do not upload the datasets in submission. Late Policy please refer to the course slides. Do not forget to submit your report to gradescope. Template will be given in the attachment.

Overview:

In this assignment we will explore to solve Unsupervised Domain Adaptation (UDA) Problem in four steps with knowledge you have learnt on class.

UDA demands us to predict target domain testing data on the basis of learning over labeled source domain data and unlabeled target domain training data. You can refer to thesis we listed in appendix to further explore this problem. **Feel free to read and refer to other relevant theses**. Don't forget to specify referred paper in your report. In this assignment you should first download Office-31 dataset and each domain should be used.

So briefly, this assignment consists of Four subsections:

- Implement CNN directly to UDA problems
- Introduce MMD loss and show performance improvement
- Introduce GAN with adversarial loss to further improve model performance
- Compare the above three methods and visualize domain adaptation with the help of **TSNE**

Question 1 Preparing Image Data and Choose one typical CNN to solve UDA

Tasks:

Download the Office-31 dataset, understand its format and show some instances per domain. Select one classic CNN model(ResNet, VGG and etc) to solve UDA problem. Here, you can make full use of labeled training set. There is no specific demand over usage of unlabeled target training data, maybe pseudo label can help if you want to try. Show your design and accuracy. Performance should excess 50%.

Checkpoints:

Show images in each domain of Office-31, give a whole picture over the UDA problem including setting and few introductions. Show your model and according Results. (30 pts)

Question 2 MMD loss

Tasks:

Maximum Mean Discrepancy (MMD) loss is a conventional tool to make two domain features aligned. In this question, you should add MMD loss to the model you run in Q1. Performance here should excess 60%.

Checkpoints:

Specify how MMD help in DA from your view, show the results. (30 pts)

Question 3 Adversarial loss

Tasks:

GAN has shown huge success in image generation and can be seen as another potent tool to help model align domain features. Add GAN module with Adversarial loss and show your results. We expect your model to achieve accuracy above 70%.

Checkpoints:

Specify how GAN works and introduce your design. Show the testing performance. (30 pts)

Question 4 Comparison and Visualization

Tasks:

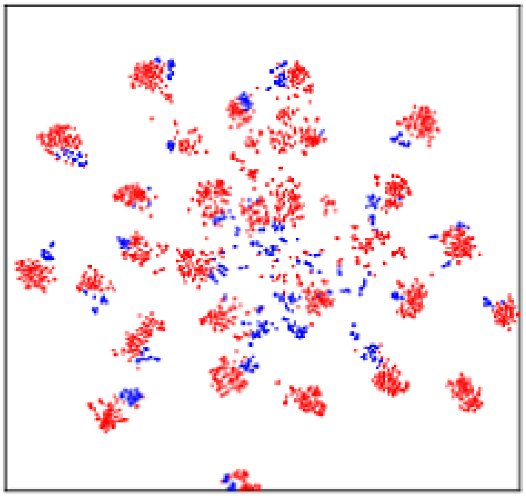
Compare four different models' performance (Q1's model. Q1's model with MMD, Q1's model with GAN, Q1's model with MMD and GAN). Use TSNE to visualize domain adaptation effects and give some concrete analyses. TSNE help you to check whether the same class of two different domains has been aligned.

Checkpoints:

Visualize four model's domain adaptation effects on testing set. Write down your analyses and give one possible method to further improve UDA problems. (10 pts)

Appendix:

Example of TSNE visualization:



Each color represents one domain

Reference list:

·Long, Mingsheng, et al. "Learning transferable features with deep adaptation networks." International conference on machine learning. PMLR, 2015.

·Sener, Ozan, et al. "Learning transferrable representations for unsupervised domain adaptation." Advances in neural information processing systems 29 (2016).

·Gan, Zhe, et al. "Triangle generative adversarial networks." Advances in neural information processing systems 30 (2017).

·Csurka, Gabriela, et al. "Discrepancy-based networks for unsupervised domain adaptation: a comparative study." Proceedings of the IEEE International Conference on Computer Vision Workshops. 2017.

·Hemanth Venkateswara, Jose Eusebio, Shayok Chakraborty, and Sethuraman Panchanathan. Deep hashing network for unsupervised domain adaptation. In Proceedings of the IEEE

·Xingchao Peng, Ben Usman, Neela Kaushik, Judy Hoffman, Dequan Wang, and Kate Saenko. Visda: The visual domain adaptation challenge, 2017 Conference on Computer Vision and Pattern Recognition, pages 5018–5027, 2017

·Kate Saenko Trevor Darrell Eric Tzeng, Judy Hoffman. Adversarial discriminative domain adaptation. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 7167–7176, 2017

·Guoliang Kang, Lu Jiang, Yi Yang, and Alexander G Hauptmann. Contrastive adaptation network for unsupervised domain adaptation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 4893–4902, 2019.

·Ganin, Yaroslav, et al. "Domain-adversarial training of neural networks." The journal of machine learning research 17.1 (2016): 2096-2030.