**Technical Writing Week 8 HW** – annotated bibliography

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My Paper Topic : Models of Convolutional Neural Network

S. Albawi, T. A. Mohammed and S. Al-Zawi, "Understanding of a convolutional neural network," 2017 International Conference on Engineering and Technology (ICET), 2017, pp. 1-6.

This paper explains and defines all the elements and important issues related to CNN, how these elements work, and states the parameters that effect CNN efficiency. It introduces what convolution is and why using. Also, The steps of convolutional neural network is indicated in detail. And two popular CNN architectures are introduced, LeNet and ALexNet.

O'Shea, Keiron, and Ryan Nash. "An introduction to convolutional neural networks." arXiv preprint arXiv:1511.08458 (2015).

This document provides a brief introduction to CNNs, discussing recently published papers and newly formed techniques in developing these brilliantly fantastic image recognition models. It shows difference of traditional ANNs and CNNs. It outlined the basic concept of CNN, explaining the layers required to build one and detailing how best to structure the network in most image analysis tasks.

Jiuxiang Gu, Zhenhua Wang, Jason Kuen, Lianyang Ma, Amir Shahroudy, Bing Shuai, Ting Liu, Xingxing Wang, Gang Wang, Jianfei Cai, Tsuhan Chen, “Recent advances in convolutional neural networks”, Pattern Recognition, Volume 77, 2018, Pages 354-377, ISSN 0031-3203

Authors discuss the improvements of CNN on different aspects, namely, layer design, activation function, loss function, regularization, optimization, and fast computation. They introduce the applications of CNN on various tasks, including image classification, object detection, object tracking, pose estimation, text detection, visual saliency detection, action recognition, scene labeling, speech and natural language processing.

Z. Li, F. Liu, W. Yang, S. Peng and J. Zhou, "A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects," in IEEE Transactions on Neural Networks and Learning Systems, doi: 10.1109/TNNLS.2021.3084827.

They introduce history of CNN. Also, some classic and advanced CNN models are introduced. Through experimental analysis, they draw some conclusions and provide several rules of thumb for functions and hyperparameter selection. And the applications of 1-D, 2-D, and multidimensional convolution are covered. In experimental, they trained VGG-16 model with CIFAR-10 dataset.

Wu, Jianxin. "Introduction to convolutional neural networks." National Key Lab for Novel Software Technology. Nanjing University. China 5.23 (2017): 495.

The purpose of this paper is understanding how a CNN runs at the mathematical level. It is focused on image classification. It introduces how a CNN trains and predicts in the abstract level. It also introduces the convolution layer and a case study, VGG-16 net.

Guo, Tianmei, et al. "Simple convolutional neural network on image classification." 2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA). IEEE, 2017.

In this paper, they built a simple CNN on image classification. The experiments are based on benchmarking datasets mnist and cifar-10. On the basis of the CNN, they also analyzed different methods of learning rate set and different optimization algorithm of solving the optimal parameters of the influence on image classification. They verified that the shallow network has a relatively good recognition effect.

Howard, Andrew G. "Some improvements on deep convolutional neural network based image classification." arXiv preprint arXiv:1312.5402 (2013).

This paper investigates multiple techniques to improve upon the current state of the art deep convolutional neural network based on image classification pipeline. The techniques include adding more image transformations to training data, adding more transformations to generate additional predictions at test time and using complementary models applied to higher resolution images.

Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet classification with deep convolutional neural networks." Advances in neural information processing systems 25 (2012).

It is paper which introduces AlexNet. They classify the 1.2 million high-resolution images in ImageNet LSVRC-2010 contest into the 1000 different classes. To make training faster, they used non-saturating neurons and a very efficient GPU implementation of the convolution operation. And they used regularization method “dropout” to reduce overfitting in the fully-connected layers. On the test data, AlexNet achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art.

Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." arXiv preprint arXiv:1409.1556 (2014).

It is paper which introduces VGGNet. In this work they investigate the effect of the convolutional network depth on its accuracy in the large-scaled image recognition setting. Their main contribution is a thorough evaluation of networks of increasing depth using an architecture with very small (3x3) convolution filters, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth to 16-19 weight layers. They evaluated very deep convolutional networks (up to 19 weight layers) for large scale image classification. It demonstrated that the representation depth is beneficial for the classification accuracy. In terms of the single-net performance, VGGNet achieved the best result (7% test error) in ILSVRC 2014 contest, outperforming a single GoogLeNet by 0.9%.

He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

It is paper which introduces ResNet. They present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. They provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we evaluate residual nets with a depth of up to 152 layers - 8x deeper than VGG nets but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test set. This result won the 1st place on the ILSVRC 2015 classification task.