

CIFAR-10 Image Recognition

EE4305 Introduction to Fuzzy/Neural Systems

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1 Introduction

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The CIFAR-10 dataset contains 60000 images bla bla.

Objectives of this project are: bla bla

Structure of the report is as follows: bla bla

2 Literature Review on Artificial Neural Networks

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This section gives a literature review on the broad topic of artificial neural networks (ANN). A more specific review on ANN designed to classify the CIFAR-10 dataset is found in Section 3. The significance and applications of ANN will be reviewed in Section 2.1 while recent trends and accomplishments are discussed in Section 2.2.

2.1 Significance and Applications of Artificial Neural Networks

This subsection will illustrate the significance and applications of ANN. Increasing computer power shifted the focus of research towards deep ANN and similar architectures which are coined under the term "deep learning". These powerful deep ANN are nowadays used in a variety of applications^{[1][2]}.

ANN are significant because they can work as a black box model. The performance can be improved by data preprocessing, augmentation and mainly by finding an appropriate network architecture and training process. No a-priori knowledge of the classification process itself is required. This makes deep ANN suited for applications where such knowledge is

difficult to obtain. Character and speech recognition are such difficult problems, as well as image classification. In speech recognition, deep ANN have been shown to outperform other methods on a variety of speech recognition benchmarks, sometimes by a large margin^[3]. In the field of image classification, the 2012 ILSVRC (ImageNet Large-Scale Visual Recognition Challenge) marks an important turning point because a convolutional neural network (CNN) architecture won the competition for the first time - by a large margin^[4]. In both fields, ANN are now widely accepted as the most powerful approach.

However, the fact that ANN do not incorporate much a-priori knowledge can also backfire. In consequence, a trained model gives little insight into its inner workings and optimal network architectures are basically found through a trial-and-error process. Most design guidelines for deep learning methods are therefore rather based on empirical knowledge than on theoretical foundations.

New methods are developed to better understand the computations deep ANN perform at each layer. The resulting visualizations reveal the process of extracting high level features out of raw input data^{[5][6]}. In general, each layer extracts higher level features of the input the previous layer provides such that the features are highly abstract after a few layers. The last layer then classifies the input into one of the output categories.

2.2 Recent Trends and Accomplishments

Recent trends and accomplishments of ANN are described in this subsection. Two recent accomplishments are looked at in detail: The AlphaGo computer program and adversarial examples. AlphaGo is a great example to illustrate the great capabilities of ANN. Adversarial examples can easily fool very different kinds of neural networks which is a good way to exemplify the limitations the present ANN still possess.

The game Go is a complex board game with the impressive number of around 10^{170} legal positions^[7]. Due to its enormous search space and difficulty to evaluate board positions, it is viewed as the most challenging of the classical games for artificial intelligence. A victory of a computer program over a professional human player has been considered to be at least a decade away. However, the computer program AlphaGo beat the European Go champion 5-0 in 2015^[8].

AlphaGo makes extensive use of ANN. It consists of a "value" and a "policy" network to separately evaluate the board position and select moves. It is trained in a combination of supervised learning from human expert games and reinforcement learning through self-play. The training of such big networks requires notable computation resources. In a recent trend, dedicated hardware to train deep ANN is developed. Besides other adaptations, it is designed to speed up matrix multiplications which are one of the main components of the training process. The most notable example is the Tensor Processing Unit which achieves a 15- to 30-fold performance compared to a contemporary GPU or CPU^[9]. It is important to note that the development of deep learning is closely connected to the ever improving available computing power^[10].

AlphaGo received considerable media coverage and is considered as one of the most impressive feats of deep learning. In a follow-up paper, a further improved version of AlphaGo is presented, AlphaZero^[11]. It uses a single neural network and trains solely through reinforcement learning with self-play, starting with random play. It is only provided with the rules of Go. After only days of training, it defeated all previous versions of AlphaGo and achieved a never seen before playing strength. It is quite intriguing that even for such a complex task, the network can achieve superhuman performance without any provided knowledge besides the rules of the game.

As a second recent trend, adversarial examples recently surprised a lot of researches

and became a hot topic of interest. To generate an adversarial example, a slight perturbation is applied to a correctly classified image. The classification process is then repeated and the perturbation is adapted such that the prediction error is *maximized*. A slight perturbation which is not recognizable by a human is already enough to let the neural network misclassify an image with a high confidence level^[12]. It has been shown that adversarial examples trained on one model are likely to be misclassified by another model as well, i.e. they possess a transferability property^[13].

It is very likely that a randomly selected input to a neural network built from linear parts is processed incorrectly and the models only behave reasonably on a very thin manifold encompassing the training data^[14]. This result questions the generalization abilities of ANN. Furthermore, the transferability property allows potential attacks on systems using ANN^{[15][16]}. For example, stop signs could be slightly modified with stickers such that they are misclassified by autonomous vehicles which then behave unexpectedly. Further research is required to develop defense strategies against such attacks. Only then, ANN can be deployed in safety critical applications.

3 Literature Review on the CIFAR-10 dataset

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4 MLP Classifier

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This section should contain:

a) on the selection of the inputs and outputs of the MLP b) on the size of the training data c) on the training of the MLP d) on the performance of the MLP with different objective functions and optimization methods e) any other interesting observation that you think are pertinent (e.g. effect of learning rate on convergence speed).

4.1 Data Preprocessing and Augmentation

- Normalization

The input data is normalized to lie within the range $[0,1]$.

- Mean subtraction

To further normalize the data, the mean is subtracted on a per-pixel basis.

- Data augmentation

Experience shows that a larger training data set increases network performance

4.2 Network Structure

- Basic structure

Since this is a classification problem, parts of the network structure are fixed. The last layer consists of 10 nodes and is in a "softmax" configuration. PICTURE of basic structure.

- Number of hidden layers/nodes
Parameter search over 1-3 hidden layers, 1-500 neurons

4.3 Optimization of Further Network Parameters

- Different learning rates
- Different optimization methods

5 CNN network

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6 Conclusion

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Long story short: we completely aced our project BOOM

Bibliography

- [1] Li Deng, Dong Yu, et al. Deep learning: methods and applications. *Foundations and Trends® in Signal Processing*, 7(3–4):197–387, 2014.
- [2] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. *Nature*, 521(7553):436–444, 2015.
- [3] Geoffrey Hinton, Li Deng, Dong Yu, George E Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara N Sainath, et al. Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. *IEEE Signal Processing Magazine*, 29(6):82–97, 2012.
- [4] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012.
- [5] Alexander Mordvintsev, Christopher Olah, and Mike Tyka. Inceptionism: Going Deeper into Neural Networks, June 2015. URL <http://googleresearch.blogspot.com/2015/06/inceptionism-going-deeper-into-neural.html>.
- [6] Jason Yosinski, Jeff Clune, Anh Nguyen, Thomas Fuchs, and Hod Lipson. Understanding neural networks through deep visualization. *arXiv preprint arXiv:1506.06579*, 2015.
- [7] John Tromp and Gunnar Farnebäck. Combinatorics of go. In *International Conference on Computers and Games*, pages 84–99. Springer, 2006.
- [8] David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. *Nature*, 529(7587):484–489, 2016.

- [9] Norman P Jouppi, Cliff Young, Nishant Patil, David Patterson, Gaurav Agrawal, Ramin-der Bajwa, Sarah Bates, Suresh Bhatia, Nan Boden, Al Borchers, et al. In-datacenter performance analysis of a tensor processing unit. *arXiv preprint arXiv:1704.04760*, 2017.
- [10] Jim X Chen. The evolution of computing: Alphago. *Computing in Science & Engineering*, 18(4):4–7, 2016.
- [11] David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, et al. Mastering the game of go without human knowledge. *Nature*, 550(7676):354–359, 2017.
- [12] Anh Nguyen, Jason Yosinski, and Jeff Clune. Deep neural networks are easily fooled: High confidence predictions for unrecognizable images. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2015.
- [13] Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus. Intriguing properties of neural networks. *arXiv preprint arXiv:1312.6199*, 2013.
- [14] Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. *arXiv preprint arXiv:1412.6572*, 2014.
- [15] Alexey Kurakin, Ian Goodfellow, and Samy Bengio. Adversarial examples in the physical world. *arXiv preprint arXiv:1607.02533*, 2016.
- [16] Nicolas Papernot, Patrick McDaniel, Ian Goodfellow, Somesh Jha, Z Berkay Celik, and Ananthram Swami. Practical black-box attacks against machine learning. In *Proceedings of the 2017 ACM on Asia Conference on Computer and Communications Security*, pages 506–519. ACM, 2017.