1. Introduction to the problem and methodology

Task of simulations below is to use a LeNet-like neural network to do classification task on CIFAR-10 dataset. The network provided in example file provides an acceptable baseline for further exploration. Experiments are done on choice of hyperparameters including batch size, optimizer, activation function, percentage of neuron dropout, number of convolution kernels and structure of neural network.

* 1. Batch size choice

Common starting point of trying it out is 32, 64, 128. A power of 2 is used due to SIMD paradigm used by GPUs. This is often called Data Parallelism. Since the networks I work on are not that complex, larger batch sizes are also tried out.

* 1. Optimizer

RMSProp and Adam optimizer is experimented. RMSprop optimizer restricts the oscillations in the vertical direction. Therefore, we can increase our learning rate and our algorithm could take larger steps in the horizontal direction converging faster, being an advanced version of basic MBGD; Adam, also integrates the advantage of computing learning rates for each parameter adaptively, is an even more advanced version. Also, it has a better performance on suppressing fluctuation of loss function.

* 1. Activation function

Relu is used as baseline and more advanced elu and selu are tested to see if the problem of dead neuron brought by using relu appears in simulation of the network.

* 1. Dropout

A dropout too small will obviously hinder the ability of generalization of our model, and 0.5 is a common value in many practices, so generally values between 0.125 to 0.5 are chosen. Several value combinations of dropout are tested to see how each of it can affect final accuracy, especially to what extent can it improve validation and test accuracy, as they show generalization ability of the model. When accuracies grow more rapidly, larger value intervals are used; finetuning is done among values where higher accuracies are gained and increasing speed of accuracies start to go down.

* 1. Number of convolution kernels

Intuitively, number of convolution kernels represents the number of features we can learn. Basically, larger the number we set; somehow more complete we can represent a picture. However, when the number gets too large, almost no new features can be newly picked by extra filters but more burdens are added for training. For this lab, value between 4 and 150 are experimented, considering the input size of 32\*32.

1. Contextualization of deep learning methodologies within the state of the art of deep learning for robotics
   1. Robotics vision

deep learning is widely involved in robotics vision, and Ruiz-del-Solar et al. [1] gave a rough categorization of its application, namely Object Detection and Categorization, Object Grasping and Manipulation, Scene Representation and Classification, and Spatiotemporal Vision.

* + 1. Object Detection and Categorization

Tao et al. [2] used Mask-RCNN for target detection and instance segmentation when building their robot for VSLAM. Firstly, an ORB algorithm is used to extract image feature points. Secondly, a RANSAC algorithm is employed to eliminate mismatched points and estimate camera position-pose changes. Then, the Mask RCNN is applied to make partial adjustments to its hyper parameter.

Jia et al. [3] depends heavily on neural network in his research on detecting and segmenting overlapping fruits. ResNet combined with DenseNet can reduce input parameters and is used as a backbone network for feature extraction. Feature maps are input to the RPN for end-to-end training to generate the RoI, and finally the mask is generated by an FCN to get the region where the apple is located.

Bogun et al. [4] use LSTM to get motion aid object recognition in short videos. They implement each gate of LSTM as a convolution and show that convolutional-based LSTM models are capable of learning motion dependencies and are able to improve the recognition accuracy when more frames in a sequence are available. The whole system consists of merely the NN, 3 continuous frames are used as input and object label as output.

* + 1. Object Grasping and Manipulation

Redmon et al. [5] used CNN for predicting grasp coordinates. A five-dimensional representation for robotic grasps proposed gives the location and orientation of a parallel plate gripper before it closes on an object. Recognition and grasp detection is combined to build a task pipeline. A self-proposed NN based on Alexnet is used for the whole pipeline.

Sung et al. [6] present a novel approach to manipulation planning based on the idea that many household objects share similarly-operated object parts. They formulate the manipulation planning as a structured prediction problem and learn to transfer manipulation strategy across different objects by embedding point-cloud, natural language, and manipulation trajectory data into a shared embedding space using a deep neural network. In order to learn semantically meaningful spaces throughout our network, they introduce a method for pre-training its lower layers for multimodal feature embedding and a method for fine-tuning this embedding space using a loss-based margin.

* + 1. Scene Representation and Classification

Maeda et al. [7] used a Time-Contrastive Network to compare current state of a task and its state of completion. This distance is represented as a metric of distance-to-go and the metric is used for describing distance towards the goal of the task.

Cadena et al. [8] explore the capabilities of Auto-Encoders to fuse the information available from cameras and depth sensors, and to reconstruct missing data, for scene understanding tasks. They seek to generate complete scene segmentations and depth maps, given images and partial and/or noisy depth and semantic data and formulate this objective of reconstructing one or more types of scene data using a Multi-modal stacked Auto-Encoder.

* + 1. Spatiotemporal Vision

Hwang et al. [9] utilized deep learning in vision part of a vision-based learning from demonstration (LfD) system to train a mimetic robot. In this system, YOLO network is used for object recognition, while multiaction recognition is carried out by an Inflated 3D ConvNet (I3D) deep learning network followed by a proposed statistically fragmented approach to enhance the action recognition results.

Yin et al. [10] presents a nonlinear time alignment method with deep autoencoder. The spatio-temporal features obtained from the neural network contain the metric information for feature comparison.

* 1. Robot tactile sensing

Melnik et al. [11] use deep reinforcement learning (DRL) for object manipulation. Tactile information from sensors on robot hands are used as input in addition to visual information. An Actor and Critic network is used as network architecture.

Lepora et al. [12] use poseNet (a CNN designed by them) to estimate pose 3D pose from optical tactile image and they see hyperparameters also as normal ones needed to be tuned, which is this first time the technique is used in tactile information.

* 1. Robot motion & navigation

Wang et al. [13] utilized deep Q-network to learn implicit control policy for robot motion planning in their research. They modeled the robot as a labeled Markov decision process (MDP) with continuous state and action spaces. Linear temporal logics (LTL) are used to specify high-level tasks. We then train deep neural networks to approximate the value function and policy using an actor-critic reinforcement learning method. The LTL specification is converted into an annotated limit-deterministic Buchi automaton (LDBA) for continuously shaping the reward ¨ so that dense reward is available during training.

Liang et al. [14] also use deep reinforcement learning in their research of collision avoidance, and their network architecture is also basically a CNN. Their simulator models realistic crowd and pedestrian behaviors, along with friction, sensor noise and delays in the simulated robot model. They also describe a technique to incrementally control the randomness and complexity of training scenarios to achieve better convergence and generalization capabilities. A novel reward function is proposed for the NN training.

3. Simulations

The method of describing NN is partially borrowed from [15]. Hyperparameters in red are those to be player around in each test, those in blue will change only within configurations that gave best results in the previous round. Green results are best ones in current test and their hyperparameter configuration will be used for the next round of simulation.

3.1 batch size & optimizer & activation function

Batch size = (batch size), Optimizer = (optimizer)

Input: 32\*32

C1: f.maps 32@32\*32 (Activation function) C2: f.maps 32@32\*32 (Activation function)

S3: f.maps 32@16\*16-Dropout=0.25

C4: f.maps 64@16\*16 (Activation function) C5: f.maps 64@16\*16 (Activation function)

S6: f.maps 64@8\*8-Dropout=0.25

F7: layers 512-Dropout=0.5

OUTPUT:10

1-Activation function = relu

|  |  |  |
| --- | --- | --- |
| Accuracy (train, val, test) Optimizer  in % @epoch num  batch size | RMSprop | Adam |
| 1024 | 96.10 78.35 76.55@120 | 95.89 78.82 78.72@100 |
| 512 | 92.10 77.86 77.36@60 | 94.67 79.49 [78.78@75](mailto:78.78@75) |
| 256 | 88.88 79.09 77.93@45 | 94.30 79.95 [79.14@65](mailto:79.14@65) |
| 128 | 82.24 72.53 78.08@50 | 93.13 80.31 79.76@60 |
| 64 | 75.20 75.07 75.19@12 | 91.97 79.02 78.72@50 |
| 32 | 68.33 70.92 70.27@6 | * 1. 78.67 78.84@50 |

2-Activation function = elu

|  |  |  |
| --- | --- | --- |
| Accuracy (train, val, test) Optimizer  in % @epoch num  batch size | RMSprop | Adam |
| 1024 | 95.95 78.77 78.58@110 | 96.02 78.96 78.56@120 |
| 512 | 95.51 78.55 [78.69@90](mailto:78.69@90) | 95.36 79.01 [78.36@90](mailto:78.36@90) |
| 256 | 94.92 77.55 77.53@90 | 94.99 78.31 [77.81@90](mailto:77.81@90) |
| 128 | 93.50 77.45 76.68@85 | 93.85 77.37 77.21@90 |
| 64 | 91.11 76.58 75.61@85 | 92.19 76.28 76.84@90 |
| 32 | 85.41 75.14 74.68@85 | 88.50 75.41 74.52@50 |

3- Activation function = selu

|  |  |  |
| --- | --- | --- |
| Accuracy (train, val, test) Optimizer  in % @epoch num  batch size | RMSprop | Adam |
| 1024 | 93.02 70.30 70.75@120 | 94.17 75.80 74.96@250 |
| 512 | 94.24 75.57 [75.13@115](mailto:78.69@90) | 95.26 76.43 76.06@210 |
| 256 | 93.00 75.02 74.31@90 | 94.50 76.13 75.11@160 |
| 128 | 91.40 74.56 74.63@85 | 92.49 76.34 74.99@145 |
| 64 | 88.10 74.67 74.03@100 | 89.67 74.63 74.29@90 |
| 32 | 81.20 72.74 71.89@100 | 84.37 72.85 71.99@50 |

3.2 dropout

Batch size = (batch size), Optimizer = Adam

Input: 32\*32

C1: f.maps 32@32\*32 (Activation function=relu) C2: f.maps 32@32\*32 (Activation function=relu)

S3: f.maps 32@16\*16-Dropout=a

C4: f.maps 64@16\*16 (Activation function=relu) C5: f.maps 64@16\*16 (Activation function=relu)

S6: f.maps 64@8\*8-Dropout=b

F7: layers 512-Dropout=c

4- Testing on different dropout values

|  |  |  |  |
| --- | --- | --- | --- |
| Accuracy batch  (train, val, test) size  in % @epoch num  val of a,b,c | 128 | 256 | 512 |
| 0.0625, 0.0625, 0.125 | 99.11 76.08 [75.43@80](mailto:75.43@80) |  |  |
| 0.125, 0.125, 0.25 | 98.08 75.88 74.98@70 |  |  |
| 0.375, 0.375, 0.5 | 91.38 81.16 [79.66@70](mailto:79.66@70) |  |  |
| 0.4, 0.4, 0.4 | 93.26 81.43 80.35@110 | 94.25 81.46 [79.99@110](mailto:79.99@110) | 94.24 80.75 79.67@105 |
| 0.4, 0.4, 0.5 | 91.42 81.82 80.30@110 | 91.71 81.67 [80.59@110](mailto:80.59@110) | 92.77 81.80 81.33@120 |
| 0.45, 0.45, 0.45 | 91.87 82.16 80.94@110 | 90.12 82.26 [80.90@105](mailto:80.9@105) | 92.63 81.88 80.67@115 |
| 0.45, 0.45, 0.5 | 90.33 81.77 81.29@120 | 90.55 81.85 81.23@120 | 91.67 81.55 80.59@115 |
| 0.5, 0.5, 0.5 | 87.13 81.20 80.63@120 | 88.48 81.84 81.63@115 | 88.82 81.93 80.23@115 |
| 0.6, 0.6, 0.6 | 69.41 67.61 [66.79@120](mailto:66.79@120) |  |  |

3.3 number of convolution filters

Batch size = (batch size), Optimizer = Adam

Input: 32\*32

C1: f.maps w@32\*32 (Activation function=relu) C2: f.maps 32@32\*32 (Activation function=relu)

S3: f.maps x@16\*16-Dropout=a

C4: f.maps y@16\*16 (Activation function=relu) C5: f.maps 64@16\*16 (Activation function=relu)

S6: f.maps z@8\*8-Dropout=b

F7: layers 512-Dropout=c

5- Testing on different numbers of convolution filters (part 1)

|  |  |  |  |
| --- | --- | --- | --- |
| Accuracy other  (train, val, test) config  in % @epoch num  val of w,x,y,z | batch size=128  a=0.45, b=0.45, c=0.45 | batch size=128  a=0.45, b=0.45, c=0.5 | batch size=512  a=0.4, b=0.4, c=0.5 |
| 4, 4, 4, 4 |  | 53.05 57.00 [56.98@55](mailto:56.98@55) |  |
| 8, 8, 8, 8 |  | 62.73 66.97 [66.43@85](mailto:66.43@85) |  |
| 16, 16, 16, 16 |  | 63.14 69.37 [68.46@70](mailto:68.46@70) |  |
| 32, 32, 32, 32 |  | 85.18 80.01 [79.36@110](mailto:79.36@110) |  |
| 64, 64, 64, 64 |  | 91.77 82.40 [81.37@135](mailto:81.37@135) |  |
| 80, 80, 80, 80 |  | 92.61 82.53 81.95@120 |  |
| 100, 100, 100, 100 | 93.44 82.53 82.23@120 | 93.27 82.93 82.38@130 | 95.52 82.65 81.68@125 |
| 128, 128, 128, 128 | 95.08 82.78 [81.93@140](mailto:81.93@140) | 94.86 83.07 82.73@135 | 96.32 83.27 81.78@125 |
| 150, 150, 150, 150 | 95.24 83.31 82.78@120 | 94.42 83.23 [82.29@120](mailto:82.29@120) | 95.24 83.03 82.00@110 |

6- Testing on different numbers of convolution filters (part 2)

|  |  |  |  |
| --- | --- | --- | --- |
| Accuracy other  (train, val, test) config  in % @epoch num  val of w,x,y,z | batch size=256  a=0.45, b=0.45, c=0.45 | batch size=256  a=0.45, b=0.45, c=0.5 | batch size=256  a=0.5, b=0.5, c=0.5 |
| 100, 100, 100, 100 | 95.48 82.82 82.39@125 | 94.09 83.17 82.76@130 | 93.42 83.64 82.93@140 |
| 128, 128, 128, 128 | 95.24 83.22 82.18@105 | 95.19 83.38 82.63@120 | 94.77 83.97 82.99@140 |
| 150, 150, 150, 150 | 96.11 83.56 [82.86@120](mailto:82.86@120) | 94.96 84.04 83.50@150 | 94.47 83.87 [83.02@140](mailto:83.02@140) |

4. Description, interpretation and assessment of the results

Initial accuracy of lab example is train-82.24%, validation-79.14%, test-78.95%, after parameter tuning, they improved to train-94.96%, validation-84.04%, test-83.50% respectively, on average around 4%~5% of accuracy improvement is gained, proving that hyperparameter tuning is indeed meaningful in improving results.

For this network architecture, Adam optimizer always gain a better result than RMSprop regarding validation and testing accuracy, this can give A primary conclusion that Adam optimizer is more suitable for the network (or other similar networks), yet the conclusion cannot be generalized. The pre-knowledge that Adam and RMSprop integrate more techniques when doing back propagation neither can give reference like “of course Adam and RMSprop can outperform primitive MBGD on evert network” so further tests still need to be done with MBGD and other optimizers selected.

When batch size increases, accuracy will first increase and training time of each epoch goes down. For this network the best values are 128, 256 and 512 as they give highest results. Furthering increase it will no longer benefit the result obviously r cause accuracy to drop-as the network worked with selu. The tendency of “first increase then decrease” of accuracy when increasing batch size needs to be validated under other network configurations.

For activation function, relu works better than elu and selu for this network. Elu and selu are originally proposed to solve the problem of dead neurons, yet in this network this problem did not occurred, and it can be inferred that linear activation works better than nonlinear ones here (elu and selu has non-linear shape when x>0). Sigmoid, tanh and softsign can still be used with batch normalization in CNN and this is also further possible experiments to do.

Increasing dropout value will give better results on validation and testing accuracy while decrease training accuracy, or to say, prevent overfitting. However, when dropout value gets too large (maybe especially when dropout value near input layer gets too large, as too few information is passed into the network), all 3 accuracies starts to decrease. Further experiments are expected to validate the guess.

Regarding number of convolution filters, increasing the number can improve accuracy, as more information from the input is extracted. However, when it reaches a certain value (it may depend on input size, information complexity of the picture and target of the task), further increase will give no extra improvement to the result. Further experiments shall be done on different input size to check if the guess is correct.

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Raw data:

RMSProp, batch\_size=1024 96.10 78.35 76.55

512 92.10 77.86 [77.36@60](mailto:77.36@60)

256 88.88 79.09 7793@45

128: train\_acc=82.24 val\_acc=72.53 test\_acc=78.08 @epoch=50

=64 75.20 75.07 75.19 @12

32 68.33 70.92 70.27@6

Adam 1024 9589 7882 7872@100

512 94.67 79.49 [78.78@75](mailto:78.78@75)

256 94.30 79.95 [79.14@65](mailto:79.14@65)

128 93.13 80.31 7976@60

64 9197 7902 7872@50

32 8841 7867 7884@50

Activation function: all elu

RMSProp, batch\_size=1024 9595 7877 7858@110

512 9551 7855 [7869@90](mailto:77.36@60)

256 9492 7755 7753@90

128: train\_acc=9350 val\_acc=7745 test\_acc=7668 @epoch=85

=64 9111 7658 7561 @85

32 8541 7514 7468@85

Adam 1024 9602 7896 7856@120

512 9536 7901 [7836@90](mailto:78.78@75)

256 9499 7831 [7781@90](mailto:79.14@65)

128 9385 7737 7721@90

64 9219 7628 7684@90

32 8850 7541 7452@50

Activation function: all selu

RMSProp, batch\_size=1024 9595 7877 7858@110

512 9551 7855 [7869@90](mailto:77.36@60)

256 9492 7755 7753@90

128: train\_acc=9350 val\_acc=7745 test\_acc=7668 @epoch=85

=64 9111 7658 7561 @85

32 8541 7514 7468@85

Adam 1024 9602 7896 7856@120

512 9536 7901 [7836@90](mailto:78.78@75)

256 9499 7831 [7781@90](mailto:79.14@65)

128 9385 7737 7721@90

64 9219 7628 7684@90

32 8850 7541 7452@50

Input: 32\*32 C1:f.maps 32@32\*32 C2:f.maps 32@32\*32 S3:f.maps 32@16\*16

C4:f.maps 64@16\*16 C5:f.maps 64@16\*16 S6: f.maps 64@8\*8

F7: layers 512 OUTPUT:10

Activation function: all relu optimizer: Adam

batch\_size=128

S3-Dropout=0.0625 S6- Dropout=0.0625 F7-Dropout=0.125 99.11 76.08 [75.43@80](mailto:75.43@80)

S3-Dropout=0.125 S6- Dropout=0.125 F7-Dropout=0.25 98.08 75.88 7498@70

S3-Dropout=0.375 S6- Dropout=0.375 F7-Dropout=0.5 91.38 81.16 [79.66@70](mailto:79.66@70)

S3-Dropout=0.4 S6- Dropout=0.4 F7-Dropout=0.4 93.26 81.43 80.35@110

S3-Dropout=0.4 S6- Dropout=0.4 F7-Dropout=0.5 91.42 81.82 80.3 @110

S3-Dropout=0.45 S6- Dropout=0.45 F7-Dropout=0.45 91.87 82.16 80.94 @110

S3-Dropout=0.45 S6- Dropout=0.45 F7-Dropout=0.5 90.33 81.77 81.29 @120

S3-Dropout=0.5 S6- Dropout=0.5 F7-Dropout=0.5 87.13 81.20 80.63 @120

S3-Dropout=.0.6 S6- Dropout=0.6 F7-Dropout=0.6 69.41 67.61 [66.79 @120](mailto:66.79@120)

batch\_size=256

S3-Dropout=0.4 S6- Dropout=0.4 F7-Dropout=0.4 94.25 81.46 [79.99@110](mailto:79.99@110)

S3-Dropout=0.4 S6- Dropout=0.4 F7-Dropout=0.5 91.71 81.67 [80.59@110](mailto:80.59@110)

S3-Dropout=0.45 S6- Dropout=0.45 F7-Dropout=0.45 90.12 82.26 [80.9@105](mailto:80.9@105)

S3-Dropout=0.45 S6- Dropout=0.45 F7-Dropout=0.5 90.55 81.85 81.23@120

S3-Dropout=0.5 S6- Dropout=0.5 F7-Dropout=0.5 88.48 81.84 81.63@115

batch\_size=512

S3-Dropout=0.4 S6- Dropout=0.4 F7-Dropout=0.4 94.24 80.75 79.67@105

S3-Dropout=0.4 S6- Dropout=0.4 F7-Dropout=0.5 92.77 81.80 81.33@120

S3-Dropout=0.45 S6- Dropout=0.45 F7-Dropout=0.45 92.63 81.88 80.67@115

S3-Dropout=0.45 S6- Dropout=0.45 F7-Dropout=0.5 91.67 81.55 80.59@115

S3-Dropout=0.5 S6- Dropout=0.5 F7-Dropout=0.5 88.82 81.93 80.23@115

Input: 32\*32 C1:f.maps a@32\*32 C2:f.maps b@32\*32 S3:f.maps b@16\*16

C4:f.maps c@16\*16 C5:f.maps d@16\*16 S6: f.maps d@8\*8

F7: layers 512 OUTPUT:10

Activation function: all relu optimizer: Adam batch\_size=128

S3-Dropout=0.45 S6- Dropout=0.45 F7-Dropout=0.45

a=100, b=100, c=100, d=100 93.44 82.53 82.23@120

a=128, b=128, c=128, d=128 95.08 82.78 [81.93@140](mailto:81.93@140)

a=150, b=150, c=150, d=150 95.24 83.31 82.78@120

S3-Dropout=0.45 S6- Dropout=0.45 F7-Dropout=0.5

a=4, b=4, c=4, d=4 53.05 57.00 [56.98@55](mailto:56.98@55)

a=8, b=8, c=8, d=8 62.73 66.97 [66.43@85](mailto:66.43@85)

a=16, b=16, c=16, d=16 63.14 69.37 [68.46@70](mailto:68.46@70)

a=32, b=32, c=32, d=32 85.18 80.01 [79.36@110](mailto:79.36@110)

a=64, b=64, c=64, d=64 91.77 82.40 [81.37@135](mailto:81.37@135)

a=80, b=80, c=80, d=80 92.61 82.53 81.95@120

a=100, b=100, c=100, d=100 93.27 82.93 82.38@130

a=128, b=128, c=128, d=128 94.86 83.07 82.73@135

a=150, b=150, c=150, d=150 94.42 83.23 [82.29@120](mailto:82.29@120)

batch\_size=256

S3-Dropout=0.45 S6- Dropout=0.45 F7-Dropout=0.45

a=100, b=100, c=100, d=100 95.48 82.82 82.39@125

a=128, b=128, c=128, d=128 95.24 83.22 82.18@105

a=150, b=150, c=150, d=150 96.11 83.56 [82.86@120](mailto:82.86@120)

S3-Dropout=0.45 S6- Dropout=0.45 F7-Dropout=0.5

a=100, b=100, c=100, d=100 94.09 83.17 82.76@130

a=128, b=128, c=128, d=128 95.19 83.38 82.63@120

a=150, b=150, c=150, d=150 94.96 84.04 83.50@150

S3-Dropout=0.5 S6- Dropout=0.5 F7-Dropout=0.5

a=100, b=100, c=100, d=100 93.42 83.64 82.93@140

a=128, b=128, c=128, d=128 94.77 83.97 82.99@140

a=150, b=150, c=150, d=150 94.47 83.87 [83.02@140](mailto:83.02@140)

batch\_size=512

S3-Dropout=0.4 S6- Dropout=0.4 F7-Dropout=0.5

a=100, b=100, c=100, d=100 95.52 82.65 81.68@125

a=128, b=128, c=128, d=128 96.32 83.27 81.78@125

a=150, b=150, c=150, d=150 95.24 83.03 82.00@110