### Programming Project I – Neural Network Architectures, Optimization and Regularization Techniques

CAP 5619, Deep & Reinforcement Learning (Spring 2020), Department of Computer Science, Florida State University

Points: 100

**Maximum Team Size: 2** 

Due: Beginning of the class (11:00am) on Thursday, March 5th, 2020

**Submission:** You need to submit electronically via Canvas by uploading a) a pdf file (named "lab1-Lastnames.pdf") as your report (including analysis and experimental results), and b) the program(s) you have created (named as "lab1-prog-Lastnames.???"); if there are multiple program files, please zip them as a single archive. Here replace "Lastnames" using your last names of the group members in the file names. Only one submission is required for each group.

The main purpose of this assignment is to design (deep) neural networks and use the regularization and optimization techniques we have covered in class to improve optimization and generalization performance on a dataset. Note that the focus of this programming project is to gain a deeper understanding of these techniques and having good recognition performance itself is not sufficient.

For this assignment, we use a handwritten digit dataset, consisting of a training set (http://www.cs.fsu.edu/~liux/courses/deepRL/assignments/zip\_train.txt, 7291 samples) and a test set (http://www.cs.fsu.edu/~liux/courses/deepRL/assignments/zip\_test.txt, 2007 samples), which will be used as the validation set and there is no additional test set. In other words, the generalization performance here is the performance on the 2007 samples. A description of the entire dataset is available at <a href="http://www.cs.fsu.edu/~liux/courses/deepRL/assignments/zip\_info.txt">http://www.cs.fsu.edu/~liux/courses/deepRL/assignments/zip\_info.txt</a>. Very briefly, each row in the files is a sample, starting with the class name (0 to 9) and then 256 floating point numbers between -1 and 1. See the additional information near the end on how to visualize the digits.

# **Task I – Neural Network Design**

In the deep learning framework you have established, design three different neural networks. Each one must have at last four layers; rectified activation functions must be used at least in one of the layers (among all the three networks) and sigmoid/tanh activation functions must be used in the one of the layers as well (among all the three networks). The overall connection requirements are as follows:

- (1) **Fully** connected, where each input/neuron is connected to all the neurons in the next layer
- (2) **Locally** connected with no weights shared in the first three layers, where each input/neuron is connected to the neurons in a local neighbor in the next layer
- (3) Locally connected with weights shared in the first three layers (i.e., a **convolutional** neural network) In your report, you need to provide explanations of your design choices and describe your neural networks clearly.

### Task II - Techniques for Optimization

You need to do the required analysis and then perform experiments for each of the three networks.

- (1) Parameter initialization strategies. For each of the networks, analyze how the parameters should be initialized. Then demonstrate three cases based on your analysis: 1) learning is very slow; 2) learning is effective (i.e., fast with accurate results); and 3) the learning is too fast (i.e., the network does not give good performance).
- (2) Learning rate. Estimate a good learning rate for each of the networks. Then demonstrate three cases based on your analysis: 1) learning is very slow; 2) learning is effective; and 3) learning is too fast.
- (3) Explain how the batch size would impact the batch normalization for each of the networks. Then demonstrate an effective batch size and an ineffective batch size on each of the three networks you have.
- (4) Momentum. Commonly used momentum coefficient values are 0.5, 0.9, and 0.99. Using the best parameter initialization strategy, the best learning rate, and the best batch size you have found so far,

experiment with the three different momentum values on the three networks you have and document the results. Explain the differences you have observed on the three neural networks you have.

# Task III - Techniques for Improving Generalization

For this task, you need to do the required analysis and apply the following regularization techniques with the goal to improve the performance on the 2007 samples in zip\_test.txt.

- (1) Use an ensemble to improve the generalization performance. Here you need to use bagging of at least six neural networks to improve the performance of the individual neural networks. You need to analyze your results.
- (2) Dropout. Explain the effects of the dropout parameter (probability of keeping a neuron) on the three neural networks you have. Then demonstrate an effective case and an ineffective case on each of the three neural networks you have.
- (3)  $L_1$  regularization. Explain the effects of the  $L_1$  regularization on the three neural networks you have. Then demonstrate an effective  $L_1$  regularization case and an ineffective  $L_1$  regularization case on each of the three neural networks you have.

# **Extra Credit Options**

- (1) **Adversarial training**. Generate adversarial examples and then use them as additional training samples to improve the generalization performance. You need to improve the performance on at least one network to receive the full credit for this option.
- (2) **Tangent prop algorithm**. You need to add a generalization term to the loss function so that the objective function is insensitive to (small) changes in translation, rotation, and scaling.
- (3) **Effective hyperparameter optimization algorithm**. You need to develop an effective algorithm to find the optimal values automatically for the hyperparameters used in Tasks II and III. At the minimum, your algorithm need to use a coarse-to-fine strategy. (Hint: Amazon AutoGluon could be a good reference, available from <a href="https://github.com/awslabs/autogluon">https://github.com/awslabs/autogluon</a>.)
- (4) **Architecture optimization algorithm**. You need to develop an effective algorithm to search through different neural network architectures to identify an optimal one for the given task. (Hint: Effective Neural Architecture Search from <a href="https://github.com/awslabs/autogluon/tree/master/autogluon/contrib/enascould">https://github.com/awslabs/autogluon/tree/master/autogluon/contrib/enascould</a> be helpful.)

### **Grading**

- **Report and analysis** 30 points
  - O Note that the focus is on understanding and you have to provide meaningful/insightful analysis for what you expect from your experiments before doing them and explain what you have observed in your experiments for each of the cases for each of the networks as explained in the tasks.
- Correct implementation and experimental results 70 points
  - $\circ$  Task I 10 points
    - Correct neural network architectures 10 points
  - $\circ$  Task II 35 points
    - **Parameter initialization strategies** 10 points
    - **Learning rate** 10 points
    - **Batch normalization** 5 points
    - **Momentum** -10 points
  - Task III 25 points
    - **Ensemble** 10 points
    - **Dropout** 10 points
    - $L_1$  regularization 5 points
- Adversarial training 10 points
- **Tangent prop algorithm** 10 points
- **Hyperparameter optimization** 10 points

### • **Architecture optimization** – 10 points

#### Additional information:

Regularization techniques are covered in Chapter 7 of the Deep Learning textbook and optimization techniques in Chapter 8. For details on how to approximate tangent vectors, see "Tangent Prop - A formalism for specifying selected invariances in an adaptive network," available from https://papers.nips.cc/paper/536tangent-prop-a-formalism-for-specifying-selected-invariances-in-an-adaptive-network.pdf. For adversarial training, you may find the paper "Explaining and Harnessing Adversarial Examples," helpful (available from https://arxiv.org/pdf/1412.6572.pdf). Various hyperparameter optimization strategies are discussed in 11.4 of the Deep Learning textbook. For architecture optimization, you may find the paper "An Empirical Exploration of Recurrent Network Architectures" (available from http://proceedings.mlr.press/v37/jozefowicz15.pdf) and "Neural Architecture Search: Survey" relevant references in Α (available https://arxiv.org/abs/1808.05377) helpful.

The following shows the hand written digits in the training set so that you know what the digits look like. If you like to show a digit, you need to scale the values from [-1 1] to [0 255] and reorganize the pixels from a 256-element vector to a 16×16 image; you may need to rotate the image.

$\Diamond$	0	O	δ	0	0	0	٥	O	ø	5	5	5	5	5	5	5	5	5	5
O	0	٥	0	٥	0	0	O	٥	ව	5	5	Ś	5	2	ও	5	5	S	3
1	1		l	t	ĺ	1	1	l	1	6	U	6	4	6	6	6	6	6	6
-	l	1	1	ι	(	1	ŧ	1	ł	6	6	L	6	6	6	6	6	6	6
2	2	Э	Q	1	ಎ	2	Ĵ	<del>,-2</del> _	2	7		1	7	7	7	7	7	7	7
2	2	R	۵	ર	2	2	2	2	Q	7	2	フ	7	7	7	7	7	7	フ
3	3	3	3	3	3	3	3	3	3	જ	\$	8	P	8	8	ջ	8	8	$\mathbf{Z}$
3	3	3	3	3	3	3	$\varepsilon$	3	3	8	8	8	ક	ક	8	$\delta$	8	£	४
4	4	4	4	Ч	4	4	4	4	4	9	9	9	9	9	9	9	9	9	9
۴	4	4	4	4	4	4	4	4	4	9	9	9	Î	9	Ĝ	9	9	9	9