Assignment 2

CS6360: Advanced Topics in Machine Learning
IIT-Hyderabad
Jan-May 2019

Max Marks: 40
Due: 30 Apr 2019 11:59 pm

This homework is intended to cover the following topics:

- Basic understanding of CNNs
- Basic understanding of RNNs

Instructions

- Please use Google Classroom to upload your submission by the deadline mentioned above. Your submission should comprise of a single file (ZIP), named <Your_Roll_No>_Assign2, with all your solutions.
- For late submissions, 10% is deducted for each day (including weekend) late after an assignment is due. Note that each student begins the course with 12 grace days for late submission of assignments (with a max of 7 per submission). Late submissions will automatically use your grace days balance, if you have any left. You can see your balance on the CS6360 Marks and Grace Days document under the course Google drive.
- You should use Python for the programming assignments.
- Please read the department plagiarism policy. Do not engage in any form of cheating or plagiarism - if we find such behavior in your submission, both receiver and giver will be imposed with severe penalties. Please talk to instructor or TAs if you have concerns.

1 Convolutional Neural Networks *(27 marks)*

In this problem, we will train a convolutional neural network for a task known as image colourization. That is, given a greyscale image, we wish to predict the colour at each pixel. This is a difficult problem for many reasons, one of which being that it is ill-posed: for a single greyscale image, there can be multiple, equally valid colourings.

We recommend you to use Colab (https://colab.research.google.com/) for this assignment. From the assignment zip file, you will find two python notebook files: `colour_regression.ipynb`, colourization.ipynb. To setup the Colab environment, you will need to upload the two notebook files using the upload tab at https://colab.research.google.com/.

We will use the CIFAR-10 data set, which consists of images of size 32×32 pixels. For most of the questions, we will use a subset of the dataset. The data loading script is included with the notebooks, and should download automatically the first time it is loaded. If you have trouble downloading the file, you can also do so manually from the provided `cifar-10-python.tar.gz`. To make the problem easier, we will only use the Horse category from this data set.

1. **Colourization as Regression *(5 marks)*:** Image colourization can be posed as a regression problem, where we build a model to predict the RGB intensities at each pixel given the greyscale input. In this case, the outputs are continuous, and so mean-squared error can be used to train the model. A set of weights for such a model is included with the assignment. In this question, you will get familar with training neural networks using cloud GPUs. Read the code in `colour_regression.py`, and answer the following questions.

   (a) Describe the model `RegressionCNN`. How many convolution layers does it have? What are the filter sizes and number of filters at each layer? Construct a table or draw a diagram.

   (b) Run all the notebook cells in `colour_regression.ipynb` on Colab (No coding involved). You will train a CNN, and generate some images showing validation outputs. How many epochs are we training the CNN model in the given setting?

   (c) Re-train a couple of new models using a different number of training epochs. You may train each new models in a new code cell by copying and modifying the code from the last notebook cell. Comment on how the results (output images, training loss) change as we increase or decrease the number of epochs.

   (d) A colour space[1] is a choice of mapping of colours into three-dimensional coordinates. Some colours could be close together in one colour space, but further apart in others. The RGBcolour space is probably the most familiar to you, but most state of the art colourization models do not use RGB colour space. The model used in `colour_regression.ipynb` computes squared error in RGB colour space. How could using the RGB colour space be problematic?

   (e) Most state-of-the-art colourization models frame colourization as a classification problem instead of a regression problem. Why? (Hint: what does minimizing squared error encourage?)

2. **Colourization as Classification *(2+2=4 marks)*:** We will select a subset of 24 colours and frame colourization as a pixel-wise classification problem, where we label each pixel with one of 24 colours. The 24 colours are selected using k-means clustering over colours, and selecting cluster centers. This has already been done for you, and cluster centers are provided in `colour/colour_kmeans*.npy` files. For simplicity, we still measure distance in RGB space. This is not ideal but reduces the dependencies for this assignment. Open the notebook `colourization.ipynb` and answer the following questions.

   (a) Complete the model `CNN` on `colourization.ipynb`. This model should have the same layers and convolutional filters as the `RegressionCNN`, with the exception of the output layer. Continue to use PyTorch layers like `nn.ReLU`, `nn.BatchNorm2d` and

[1] https://en.wikipedia.org/wiki/colour$_{s}$*pace*

nn.MaxPool2d, however we will not use nn.Conv2d. We will use our own convolution layer MyConv2d included in the file to better understand its internals.

(b) Run main training loop of CNN in colourization.ipynb on Colab. This will train a CNN for a few epochs using the cross-entropy objective. It will generate some images showing the trained result at the end. How do the results compare to the previous regression model?

3. **Skip Connections *(2+3+1=6 marks)*:** A skip connection in a neural network is a connection which skips one or more layer and connects to a later layer. We will introduce skip connections.

   (a) Add a skip connection from the first layer to the last, second layer to the second last, etc. That is, the final convolution should have both the output of the previous layer and the initial greyscale input as input. This type of skip-connection results in a UNet model[2]. Following the CNN class that you have completed, complete the `__init__` and `forward` methods of the `UNet` class. (*Hint:* You will need to use the function `torch.cat`.)

   (b) Train the UNet model for the same amount of epochs as the previous CNN and plot the training curve using a batch size of 100. How does the result compare to the previous model? Did skip connections improve the validation loss and accuracy? Did the skip connections improve the output qualitatively? How? Give at least two reasons why skip connections might improve the performance of our CNN models.

   (c) Re-train a few more UNet models using different mini batch sizes with a fixed number of epochs. Describe the effect of batch sizes on the training/validation loss, and the final image output.

4. **Super-resolution *(1+3=4 marks)*:** Many classic image processing problems are to transform the input images into an output image via a transformation pipeline, e.g. colourization, denoising, and super-resolution. These image processing tasks share many similarities, where the inputs are lower quality images and the outputs are the restored high-quality images. Instead of hand-designing the transformations, one approach is to learn the transformation pipeline from a training dataset using supervised learning. Previously, you have trained conv nets for colourization. In this question, you will use the same conv net models to solve super-resolution tasks. In the super-resolution task, we aim to recover a high-resolution image from a low-resolution input.

   (a) Take a look at the data process function `process`. What is the resolution difference between the downsized input image and output image?

   (b) Bilinear interpolation[3] is one of the basic but widely used resampling techniques in image processing. Run super-resolution with both CNN and UNet. Are there any difference in the model outputs? Also, comment on how the neural network results (images from the third row) differ from the bilinear interpolation results (images from the fourth row). Give at least two reasons why conv nets are better than bilinear interpolation.

5. **Visualizing Intermediate Activations *(3 marks)*:** We will visualize the intermediate activations for several inputs. Run the visualization block in the `colourization.ipynb` that

[2]Ronneberger et al, U-net: Convolutional networks for biomedical image segmentation, MICCAI 2015

[3]https://en.wikipedia.org/wiki/Bilinear_interpolation

has already been written for you. For each model, a list of images will be generated and be stored in `cs6360/a2/outputs/model_name/act0/` folder in the Colab environment. You will need to use the left side panel (the Table of contents panel) to find these images under the Files tab.

(a) Visualize the activations of the CNN for a few test examples. How are the activation in the first few layers different from the later layers? You do not need to attach the output images to your writeup, only descriptions of what you see.

(b) Visualize the activations of the colourization UNet for a few test examples. How do the activations differ from the CNN activations?

(c) Visualize the activations of the super-resolution UNet for a few test examples. Describe how the activations differ from the colourization models.

6. **Some Conceptual Questions** ***(2+1+1+1=5 marks)*****:**

(a) We did not tune any hyperparameters for this assignment other than the number of epochs and batch size. What are some hyperparameters that could be tuned? List five. Try any one and report what you observe for the colourization problem.

(b) In the `RegressionCNN` model, `nn.MaxPool2d` layers are applied after `nn.ReLU` activations. Comment on how the output of CNN changes if we switch the order of the max-pooling and ReLU.

(c) The loss functions and the evaluation metrics in this assignment are defined at pixel-level. In general, these pixel-level measures correlate poorly with human assessment of visual quality. How can we improve the evaluation to match with human assessment better? (*Hint:* You may find this paper useful for answering this question.)

(d) In `colourization.ipynb`, we trained a few different image processing convolutional neural networks on input and output image size of 32×32. In the test time, the desired output size is often different than the one used in training. Describe how we can modify the trained models in this assignment to colourize test images that are larger than 32×32.

2 Recurrent Neural Networks *(13 marks)*

In this problem, you will work on extending `min-char-rnn.py`, the vanilla RNN language model written by Andrej Karpathy[4]. You will experiment with the Shakespeare dataset, provided with this assignment.

1. *(2+2=4 marks)* The RNN language model uses a softmax activation function for its output distribution at each time step. It's possible to modify the distribution by multiplying the logits by a constant α:

$$\mathbf{y} = \mathrm{softmax}(\alpha \mathbf{z})$$

Here, $1/\alpha$ can be thought of as a temperature, i.e. lower values of correspond to a hotter distribution. (This terminology comes from an algorithm called simulated annealing.) Write a function to sample text from the model using different temperatures (i.e., $1/\alpha$ values). Try different temperatures, and, in your report, include examples of texts generated using

[4]https://gist.github.com/karpathy/d4dee566867f8291f086

different temperatures. Briefly discuss what difference the temperature makes. Include the source code of the function you wrote/modified to accomplish the task in the report. You should either train the RNN yourself, or use the weights from Part 3 (later here) - up to you.

2. *(2+2=4 marks)* Write a function that uses an RNN to complete a string. That is, the RNN should generate text that is a plausible continuation of a given starter string. In order to do that, you will need to compute the hidden activity $\mathbf{h}$ at the end of the starter string, and then to start generating new text. Include 5 interesting examples of outputs that your network generated using a starter string. (This part need not be easily reproducible). Include the source code of the function you wrote in the report. You should either train the RNN yourself, or use the weights from Part 3 - up to you.

3. *(3 marks)* The weights for a trained RNN are included as `char-rnn-snapshot.npz`. Some samples from the RNN (at temperature $1/\alpha = 1$) are included as `samples.txt`, and code to read in the weights is included as `read_in_npz.py` (if this doesnt work, try the pickle file, and get it using `import cPickle as pickle; a = pickle.load(open("char-rnn-snapshot.pkl"))`.)

   In the samples that the RNN generated, it seems that a newline or a space usually follows the colon (i.e., :) character. In the weight data provided, identify the specific weights that are responsible for this behavior by the RNN. In your report, specify the coordinates and values of the weights you identified, and explain how those weights make the RNN generate newlines and spaces after colons.

4. *(2 marks)* Identify another interesting behaviour of the RNN, identify the weights that are responsible for it. Specify the coordinates and the values of the weights, and explain how those weights lead to the behavior that you identified.

Practice Exercises

NO SUBMISSION REQUIRED; PLEASE USE THIS FOR PRACTICE AND LEARNING.

1. **Steerable Filters:** Let $G^0(x, y)$ be some 2-D filter, a function of the Cartesian coordinates x and y. Let $G^\theta(x, y)$ be a rotation of $G^0(x, y)$ by q radians about the origin in the counterclockwise direction, i.e.:

$$G^\theta(x, y) = G^\theta(r \cos\phi, r \sin\phi) = G^0(r \cos\phi - \theta, r \sin\phi - \theta)$$

   where $r = \sqrt{(x^2 + y^2)}$ and $\tan\theta = y/x$. In this problem, you may give your answers in Cartesian or polar coordinates, whichever is more convenient.

   (a) Suppose $G^0(x, y) = -2xe^{-(x^2+y^2)}$. Find $G^\theta(x, y)$.

   (b) Show that:

$$G^\theta(x, y) = \cos\theta G^0(x, y) + \sin\theta G^{\pi/2}(x, y)$$

   and that the output image $F(x, y) = I(x, y) * G^\theta(x, y)$ is equal to:

$$\cos\theta\{I(x, y) * G^0(x, y)\} + \sin\theta\{I(x, y) * G^{\pi/2}(x, y)\}$$

   where $*$ denotes convolution.

(c) Find the direction and magnitude of maximum response at a point (x, y) of the image $I(x, y)$ to the steerable filter $G^{\theta}(x, y)$. The direction of maximum response is the q, such that $F^{\theta}(x, y)$ has the biggest magnitude. Give your answer in terms of the image $I(x, y)$ and the responses $F^{0}(x, y)$, $F^{\pi/2}(x, y)$ to the two steerable basis filters $G^{0}(x, y)$, $G^{\pi/2}(x, y)$. Note that other steerable filters could require more basis filters than two.

2. **SIFT:**

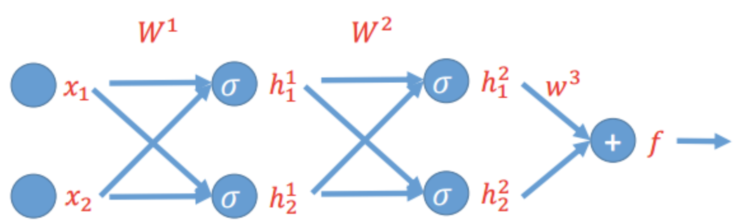
   (a) Given that the dimensions of the SIFT keypoint descriptor is 128, what exactly does the value recorded in a single dimension of a SIFT keypoint descriptor signify? (Dont just describe how it is obtained, think and explain what aspect of the keypoint it is capturing.)

   (b) Give any one idea to extend SIFT to find spatio-temporal keypoints in videos (3-dimensions, considering space and time).

3. **Backpropagation:** Consider a 3-layer network:

$$h^1 = \sigma(W^1 x), h^2 = \sigma(W^2 h^1), f(x) = < w^3, h^2 >$$

. Compute $\frac{\partial f}{\partial W^1_{i,j}}$.



4. L_2**-Weight decay:** Show that L_2-weight decay is equivalent to adding Gaussian noise with zero mean and unit variance to the data.

5. **The Bias:** We generally initialize the bias to random numbers larger than 0. Why? What happens if we initialize it to a value below zero? Does this affect our ability to train?

6. **Cross-entropy Loss:** How does the cross-entropy loss function avoid the saturation issues of the sigmoid neuron? Derive your answer mathematically.

7. For a neural network with one hidden layer and `tanh(s)` as the activation functions on all neurons (including the output neuron), prove that for the backprop algorithm (with gradient descent), when all the initial weights w^l_{ij} are set to 1 (for all layers l), then $w^{(1)}_{ij} = w^{(1)}_{i(j+1)}$ for all i and $1 \le j \le d^{(1)}$.