Programming Assignment 4:
Generating Music with LSTM Networks

CSE 253: Neural Networks
Winter 2019

Instructions

Due Saturday, March 2^{nd}:

1. Start on this assignment NOW! If you have any questions or uncertainties about the assignment instructions, please ask about them as soon as possible (preferably on Piazza, so everyone can benefit). We want to minimize any possible confusion about this assignment and have tried very hard to make it understandable and easy for you to follow.

2. Please hand in your assignment via Gradescope. We prefer a report written using LaTeXin NIPS format for each assignment. You are free to choose an alternate method (Word, etc.) if you want, but we still prefer NIPS format.

3. You should submit your code on Gradescope along with your report. For your own purposes, keep your code clean with explanatory comments, as it may be reused in the future.

4. You can use Pytorch, a Deep Learning library, for the tasks in this assignment, or you may write your own code for basic character level rnn in python.

5. Please work in teams of size 4-5. In extraordinary circumstances (e.g., you have a highly contagious disease and are afraid of infecting your teammate), we will allow you to do it on your own. Please discuss your circumstances with your TA, who will then present your case to me.

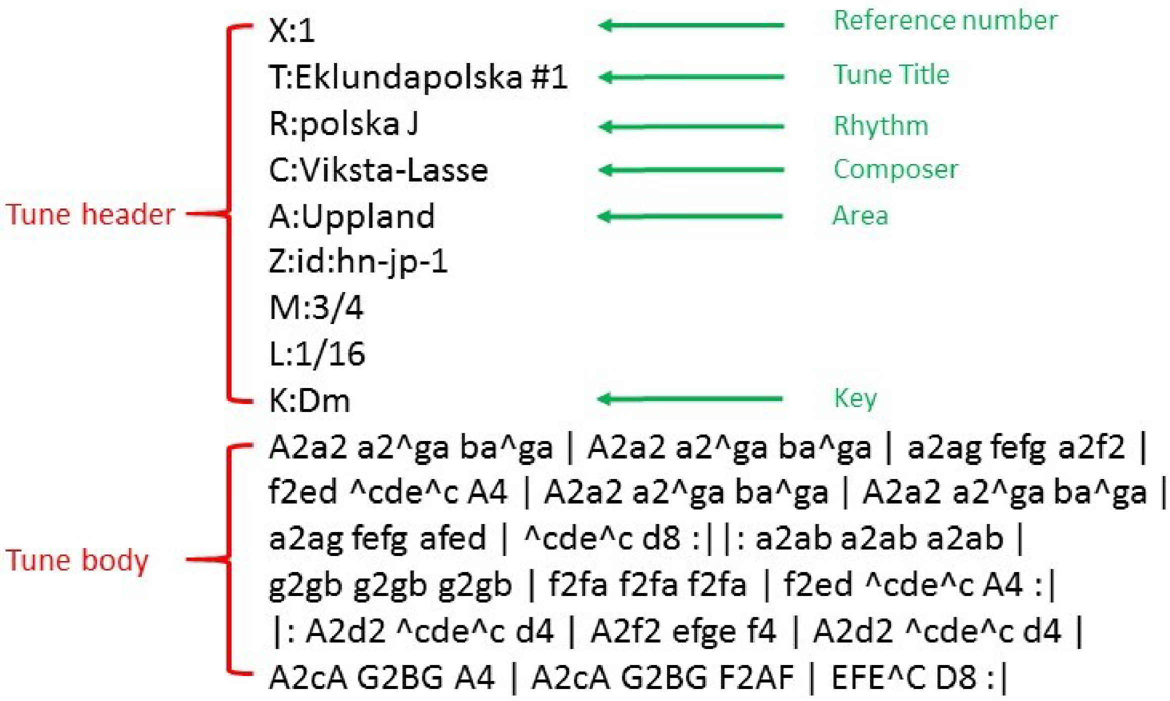
Character level LSTM for music generation (40 points)

In this assignment we will explore the power of Recurrent Neural Networks to deal with data that has temporal structure. In this problem, we will generate music in abc format. You will train an LSTM model using characters extracted from a music dataset provided to you and then run the network in generative mode to "compose" music.

Problem

1. **Getting familiar with the data** In this part, we are going to see how we can convert music from ABC notation to a playable format(.midi in this case) online. Go to the website mandolintab.net/abcconverter.php. Copy the text from sample-music.txt file (found under Data.zip,which contains music in ABC notation) and hit Submit. Download the tune in midi format and play it on your computer.

   You will be generating the music in a similar format as the sample file, which is ABC format. A sample ABC file is shown in Fig 1.



```
X:1
T:Eklundapolska #1
R:polska J
C:Viksta-Lasse
A:Uppland
Z:id:hn-jp-1
M:3/4
L:1/16
K:Dm
A2a2 a2^ga ba^ga | A2a2 a2^ga ba^ga | a2ag fefg a2f2 |
f2ed ^cde^c A4 | A2a2 a2^ga ba^ga | A2a2 a2^ga ba^ga |
a2ag fefg afed | ^cde^c d8 :| |: a2ab a2ab a2ab |
g2gb g2gb g2gb | f2fa f2fa f2fa | f2ed ^cde^c A4 :|
|: A2d2 ^cde^c d4 | A2f2 efge f4 | A2d2 ^cde^c d4 |
A2cA G2BG A4 | A2cA G2BG F2AF | EFE^C D8 :|
```

Figure 1: A music file in ABC notation.

2. **Read in data**. Read in the data from the input.txt (found under Data.zip) file. This file contains multiple tunes in ABC format, with each tune delineated by <start> and <end> tags. Create a one-hot encoding of the unique characters in the text data and create data structures to efficiently get the index of a character in the encoding and vice-versa.

3. **Train a network** First, train an LSTM network to learn the structure of an ABC notation music file through **"Teacher Forcing"**. Teacher forcing works by using the actual or expected output from the training dataset at the current time step y(t) as input in the next time step x(t+1), rather than the output generated by the network. There are many ways to train the model using teacher forcing, one of them has been described below:

   - Divide the concatenated music data into chunks of fixed length (say 100 characters per chunk).
   - Pass the first chunk into your LSTM as input and pass the same chunk (left-shifted by 1) as the target. Backpropagate through time and update the weights of the RNN.
   - Pass the next chunk, but carry forward the last hidden state of the previous chunk to maintain continuity. Continue the process till you reach the last chunk (end of an epoch) and then repeat.
   - Note that it doesn't make sense here to randomize the order of the inputs!

   Implementation Guidelines

   - You should use only one hidden layer for this problem. You can either write your own code for the LSTM (not recommended) or use the available Pytorch modules to build the LSTM. You should have around 100 neurons in your hidden layer.
   - You should use a softmax output and the cross entropy loss.
   - Training, validation and test splits have been provided to you. Use the validation set for tuning your hyper-parameters (number of hidden units, optimizer learning rate, chunk-length). Report the negative log likelihood over the validation and test set. To get this metric, pass your validation/test data in the same manner as your training data, chunk by chunk carrying forward the last hidden state and average the cross-entropy error over all chunks. The only difference here is that you would not be backpropagating through time.

- Evaluate your model on the training and validation set every x iterations over the training batches. Choose x so that you evaluate every 5-10 minutes. Include the training and validation loss curves in your report.
- Write a function to generate music using the approach described below. It is a good idea to print out the generated music after every few iterations to see if the generated music makes sense.

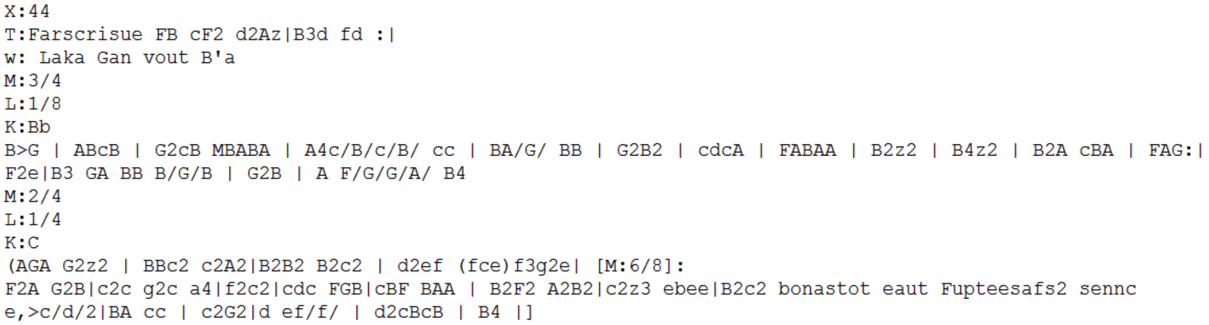
4. **Generate music** In the generation stage, the idea is to "prime" the network with a sequence, and then let the network run on its own, predicting the next character, and the using the network's output as the next input. There are at least two ways you could produce the network output. One is to take the maximum output. This is generally a bad idea, and leads to unmusical output. The right way is to flip an n-sided coin, assuming n outputs, based on the probability distribution at the softmax layer. You can make the network more or less deterministic by adjusting the Temperature parameter T in the softmax, but start with 1.

   Save the sequence to a file, and then use e http://mandolintab.net/abcconverter.php to convert back to midi format, and play what is generated.

   For your report, provide:

   (a) Generate 6 sample music pieces, two at $T = 1$, two at $T = 2$, and two at $T = 0.5$. They should be of reasonable length. Pick ones that sound the best to you for your report. Provide their ABC notation and music representation generated from http://mandolintab.net/abcconverter.php. Also upload the tunes in midi format on vocareum. Discuss your results. Also report all your hyperparameters.*(15 points)*

   A sample output would look like the example shown in Figure 2. Note that this music was one of the best examples generated by our character level rnn in 2 hours; your tune can be shorter than this. Figure 3 shows the music in Figure 2 in standard musical notation.



```
X:44
T:Farscrisue FB cF2 d2Az|B3d fd :|
w: Laka Gan vout B'a
M:3/4
L:1/8
K:Bb
B>G | ABcB | G2cB MBABA | A4c/B/c/B/ cc | BA/G/ BB | G2B2 | cdcA | FABAA | B2z2 | B4z2 | B2A cBA | FAG:|
F2e|B3 GA BB B/G/B | G2B | A F/G/G/A/ B4
M:2/4
L:1/4
K:C
(AGA G2z2 | BBc2 c2A2|B2B2 B2c2 | d2ef (fce)f3g2e| [M:6/8]:
F2A G2B|c2c g2c a4|f2c2|cdc FGB|cBF BAA | B2F2 A2B2|c2z3 ebee|B2c2 bonastot eaut Fupteesafs2 sennc
e,>c/d/2|BA cc | c2G2|d ef/f/ | d2cBcB | B4 |]
```

Figure 2: Generated Music

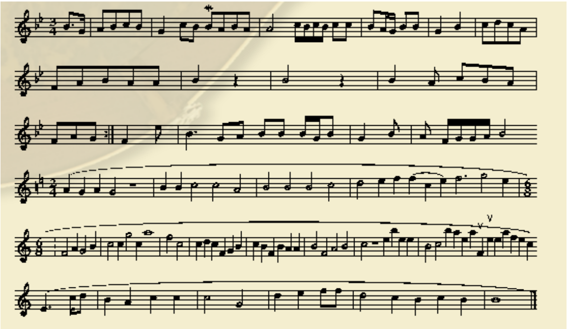


Figure 3: Music from Figure 2 in standard music notation.

   (b) Plot your training loss and validation loss vs number of epochs on data. Discuss your findings. Report the results of your best model on the test set. *(5 points)*

(c) Try changing the number of neurons in your hidden layer for at least 3 different numbers, for ex. 50, 75 and 150. Now, again plot your training loss and validation loss vs number of epochs on data. What do you observe? Discuss your findings. *(5 points)*

(d) Instead of the temperature based sampling (use T = 0.7), use arg-max sampling at each time-step. Qualitatively compare and comment on the generation quality for the same initial seed for the 2 sampling techniques. *(5 points)*

(e) Replace the LSTM module with a vanilla RNN implementation. Compare the training/validation curves for the 2 implementations (LSTM and vanilla RNN) for the same set of hyper-parameters (100 hidden units, same optimizer, same learning rate) . Discuss your findings. *(5 points)*

(f) **Feature Evaluation -** For one of your generated music samples, do forward propagation through the network and note the activation of each neuron for each of the characters. Plot each of these activations as a heatmap and report the heatmap for at least 1 neuron whose activation pattern you can interpret as signaling some feature of the music.*(5 points)*.

A example of one of these heatmaps is given in Figure 4.It basically shows some generated text from our trained network and shows how a neuron behaves for each of the character in that. In this case, the neuron had low activation for body of the music and high activation for header, which shows that it is able to recognize header of music in ABC format. *(5 points)*

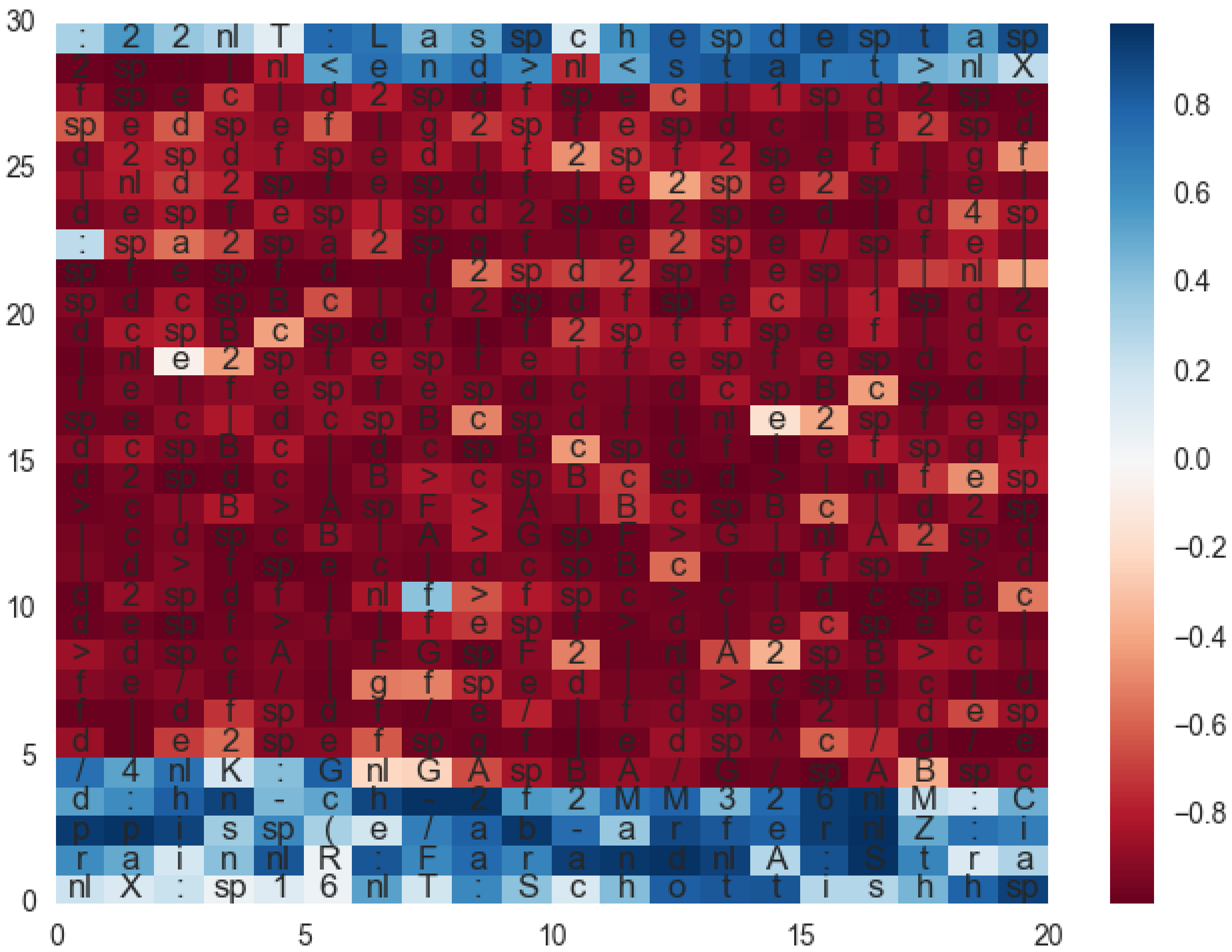


Figure 4: Heatmap showing that this particular neuron fires for the header.

Note- The above heatmap has been generated using an LSTM network that was trained for a whole day. So your heatmap might not be that effective. But a heatmap giving some kind of insight would be good enough for this task. Also note that this “heatmap” is backwards, with hot colors representing low values. Yours should be the other way around.