

**EECS 484 Computational Intelligence, Fall 2011**  
**Problem Set 8: Recurrent Neural Nets and Back-Propagation Through Time**

Assigned: 11/20/11

Due: 12/1/11

We have seen recurrent neural nets (including MaxNet, Content-Addressable Memory and Hopfield nets) that are capable of producing more sophisticated outputs than feedforward nets. Recurrent neural nets are also useful for interpreting or for producing time sequences.

In the present assignment, you should construct and train a neural net that receives a “pacemaker” input (a regular “beat”, which is high once every four time steps) and produces a target output beat. Example code is provided. You will need to complete the functions: `compute_F_o()`, `compute_F_u()` and `compute_F_wji()`, consistent with Werbos’ derivation.

Note the following definitions in the starter code. Neuron 1 is assumed to be a bias terms, which always outputs unity. The  $u$ -value (net input) and all synapses leading into this neuron for all time steps are irrelevant. Similarly, neuron 2 is assumed to be the external stimulus (the sync beat). Thus, the  $u$ -values for this neuron as well as all synapses leading into this neuron are also irrelevant for all time steps. Neuron 3 is assumed to be the output neuron (without loss of generalization). The output of this neuron is defined for time 1 to match the target output value at time 1. For all time steps greater than 1, this output should try to match the target outputs at the respective time steps. This code is specialized for consideration of a single output. For all nodes greater than index 3, these nodes are “interneurons”—neither bias nor sensory nor output. You should select the number of interneurons to use. Note that the initial conditions for the interneurons may be set to random outputs, but these are presumably not optimal. In addition to learning improved synaptic weights, one can also learn more useful initial conditions for the interneurons.

Also, note that the starter code assumes that the time delay from input to output is inserted as follows. All neuronal outputs (sigmas) are defined for time 1. These lead to computations of net inputs ( $u$ -values) at time 2. ( $U$  values at time 1 are irrelevant). The  $u$ -values at time 2 lead to both  $g$ primes and sigmas at time 2 (using the `logsig()` activation function). That is, the activation function is assumed to have no time delay; there is only a time delay from sigmas at time  $t$  implying  $u$ -values at time  $t+1$ . It will be important to compute both  $u$ -values and sigma values up through time  $T_{\text{final}}$ .

Once you have completed the necessary 3 functions for this program, test your result using the function `test_dEsqd_dwji()`. This function computes  $dE/dw_{ji}$  using perturbations of each weight individually and performing a recomputation of error for each weight change, thus computing the derivatives  $dE/dw_{ji}$  numerically. These should compare favorably (exact at least to 4 decimal places) with the analytic derivatives from your ordered derivative computations. (If not, look for bugs in your code). Once you have  $dE/dw_{ji}$  debugged, be sure to comment out future calls to `test_dEsqd_dwji()`, as this function is slow.

Once your code is working, train recurrent nets on two example target sets: beats.dat and beats2.dat. This data corresponds to a single input and a single output. The inputs consist of a regular “heartbeat”, and the outputs are a responsive pattern. For beats.dat, the input is (1,0,0,0) in a repeating pattern and the desired output is (0,0,1,1), in a repeating pattern. For beats2.dat, the input is the same, but the desired output repeats the pattern: (0,0,1,1,0,0,1,0).

Beats.dat can be trained using a single interneuron (total number of neurons=4, including bias, input, output and 1 hidden neuron). For Beats2.dat, you will need more hidden neurons. Report on how many are needed and plot out your results vs. the target outputs.

Note: in performing training, you may want to tune the value for the learning factor used in the gradient descent, or apply an adaptive learning factor. Report on your convergence rates (how many iterations were required) and on what learning factors you recommend.