Computational Intelligence

Unit # 15

NN Types

- Feedforward NNs such as the standard multilayer NN, functional link NN and product unit NN receive external signals and simply propagate these signals through all the layers to obtain the result (output) of the NN. There are no feedback connections to previous layers.
- Recurrent NNs, on the other hand, have such feedback connections to model the temporal characteristics of the problem being learned.

FF NN

- A FFNN can have more than one hidden layer.
- However, it has been proved that FFNNs with monotonically increasing differentiable functions can approximate any continuous function with one hidden layer, provided that the hidden layer has enough hidden neurons.
- A FFNN can also have direct (linear) connections between the input layer and the output layer.

Activation Function in NN

- Note that each activation function can be a different function.
- It is not necessary that all activation functions be the same. Also, each input unit can implement an activation function.
- It is usually assumed that input units have linear activation functions.

Product Unit Neural Networks

- Product unit neural networks (PUNN) have neurons that compute the weighted product of input signals, instead of a weighted sum.
- While PUNNs provide the advantage of having smaller network architectures, a major drawback of PUs is an increased number of local minima, deep ravines and valleys.
- The search space for PUs is usually extremely convoluted. Gradient descent, which works best when the search space is relatively smooth, therefore frequently gets trapped in local minima or becomes paralyzed.

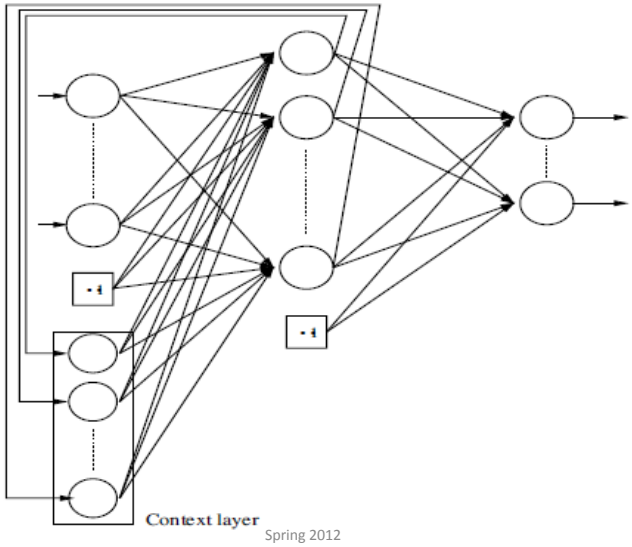
Simple Recurrent Neural Networks

- Simple recurrent neural networks (SRNN) have feedback connections which add the ability to also learn the temporal characteristics of the data set.

Elman SRNN

- The Elman SRNN, as illustrated on the next slide, makes a copy of the hidden layer, which is referred to as the *context layer.*
- *The purpose of the context layer is to* store the previous state of the hidden layer, i.e. the state of the hidden layer at the previous pattern presentation.
- The context layer serves as an extension of the input layer, feeding signals representing previous network states, to the hidden layer.

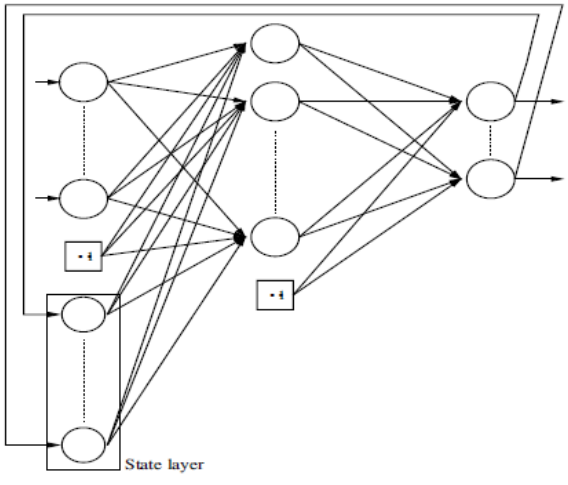
Elman SRNN (Cont'd)



Jordan SRNN

- Jordan SRNN, on the other hand, make a copy of the output layer instead of the hidden layer.
- The previous state of the output layer then also serves as input to the network.

Jordan SRNN (Cont'd)



Metaheuristics

- A metaheuristic is a general kind of solution method that orchestrates the interaction between local improvement procedures and higher level strategies to create a process that is capable of escaping from local optima and performing a robust search of a feasible region.

Sub-Tour Reversal in TSP

- A sub-tour reversal adjusts the sequence of cities visited in the current trial solution by selecting a subsequence of the cities and simply reversing the order in which that subsequences of cities is visited.
- The subsequence being reversed can consist of as few as two cities, but also can have more.
- The sub-tour reversal is an example of a local improvement procedure.

Tabu Search

- Tabu search uses common-sense ideas to enable the search process to escape from a local optimum.
- It uses a local serach procedure to find a local optimum.
- A key strategy of tabu search is that it then continues the search by allowing *non-improving moves* to the best solutions in the neighborhood of the local optimum.
- The danger with this approach is that after moving away from a local optimum, the process will cycle right back on the same local optimum.

Tabu List

- To avoid this, a tabu search temporarily forbids moves that would return to (or perhaps towards) a solution recently visited.
- A **tabu list** records these forbidden moves, which are referred to as tabu moves.
- The only exception to forbidding such a move is if it is found that a tabu move actually is better than the best feasible solution found so far.
- This use of *memory* to guide the search by using tabu lists to record some of the recent history of the search is a distinctive feature of tabu search.

Outline of a Basic Tabu Search Algorithm

- Initialization
  - Start with a feasible initial trial solution.
- Iteration
  - Use an appropriate local search procedure to define the feasible moves into the local neighborhood of the current trial solution.
  - Eliminate from consideration any move on the current tabu list unless that move would result in a better solution than the best trial solution found so far.
  - Determine which of the remaining moves provides the best solution and adapt it regardless of whether it is better or worse than the current trial solution.
  - Update the tabu list. If the tabu list is already full, delete the oldest member of the tabu list.
- Stopping Rule
  - Same as used for other algorithms discussed in this course

Example Revisited

	A	B	C	D	E	F	G
A	0	12	10				12
B	12		8	12			
C	10	8		11	3		9
D		12	11		11	10	
E			3	11		6	7
F				10	6		9
G	12		9		7	9	

A – B – C – D – E – F – G - A : 12 + 8 + 11 + 11 + 6 + 9 + 12 = 69

Working of Tabu Search

- Initial solution
  - A – B – C – D – E – F – G – A : Distance = 69
  - Tabu list: Blank at this point
- Iteration 1: Reverse C – D
  - Deleted Links: B – C, D – E
  - Added Links: B – D, C – E
  - Tabu List: B – D, C – E
  - A – B – D – C – E – F – G – A : Distance = 65
- Iteration 2: Reverse C – E – F
  - Deleted Links: D – C, F – G
  - Added Links: D – F, C – G
  - Tabu List: B – D, C – E, D – F, C – G
  - A – B – D – F – E – C – G – A : Distance = 64

Working of Tabu Search (Cont'd)

- Iteration 3: Reverse C – G
  - Deleted Links: E – C, G – A
  - Added Links: E – G, C – A
  - Tabu List: ~~B – D, C – E~~, D – F, C – G, E – G, C – A
  - A – B – D – F – E – C – G – A : Distance = 66
- The process continues in a similar fashion until one of the stopping condition is satisfied.

Simulated Annealing

- Developed in 1983, SA is another widely used metaheuristic that enables the search process to escape from a local optimum.
- The name and inspiration come from annealing in metallurgy, a technique involving heating and controlled cooling of a material to increase the size of its crystals and reduce their defects.
- The heat causes the atoms to become unstuck from their initial positions (a local minimum of the internal energy) and wander randomly through states of higher energy; the slow cooling gives them more chances of finding configurations with lower internal energy than the initial one.

Analogy

- By analogy with this physical process, each step of the SA algorithm replaces the current solution by a random "nearby" solution, chosen with a probability that depends both on the difference between the corresponding function values and also on a global parameter *T* (called the *temperature*), that is gradually decreased during the process. The dependency is such that the current solution changes almost randomly when *T* is large, but increasingly "downhill" as *T* goes to zero.

Working of the Algorithm

- At each step, the SA heuristic considers some neighboring state *s′* of the current state *s*, and probabilistically decides between moving the system to state *s′* or staying in state *s*.
- These probabilities ultimately lead the system to move to states of lower energy.
- Typically this step is repeated until the system reaches a state that is good enough for the application, or until a given computation budget has been exhausted.

Method

- SA's major advantage over other methods is its ability to avoid becoming trapped in local minima.
- The algorithm employs a random search which not only accepts changes that decrease the objective function f, but also some changes that increase it.
- The latter are accepted with a probability
  - $P = \exp(\Delta f/T)$
  - Where Δf is the increase in f and T is a control parameter "temperate".

Outline of Simulated Annealing Algorithm

- Initialization
  - Start with a feasible initial trial solution
- Iteration
  - Use the *selection rule* to select the next trial solution.
  - If none of the immediate neighbors of the current trial solution are accepted, the algorithm is terminated.
- Check the temperature schedule
  - When the desired number of iterations have been performed at the current value of T, decrease T to the next value in the temperature schedule and resume performing iterations at this next value.
- Stopping Rule
  - Same as used for other algorithms discussed in this course

TSP Example: Temperature Schedule

- Five iterations are performed at each of the five values of T (T_1, T_2, T_3, T_4, T_5) in turn, where
  - $T_1 = 0.2Z_c$ when Z_c is the objective function value for the initial trial solution
  - $T_2 = 0.5T_1$
  - $T_3 = 0.5T_2$
  - $T_4 = 0.5T_3$
  - $T_5 = 0.5T_4$

TSP Example: Working

- Initial Trial
  - A – B – C – D – E – F – G – A, Zc = 69, T1=0.2xZc = 13.8
- Second Iteration
  - Pick two random numbers to find the swapping slots. Suppose the sub-tour of cities C – D is reversed.
  - A – B – D – C – E – F – G – A, Zn = 65
- Third Iteration
  - Reverse C – E – F
  - A – B – D – F – E – C – G – A, Zn = 64
- Fourth Iteration
  - Reverse C – G
  - A – B – D – F – E – G – C – A, Zn = 66 and Zc = 64 implies $\Delta f = -2$
  - Prob {acceptance} = exp (-2/13.8) = 0.865
  - If the next random number generated is less than 0.865, this candidate solution will be accepted as the next trial solution. Otherwise it will be rejected.