ISEN 621: Homework 4

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Problem 1: Graph Bisection Problem with the Neural Network Approach

From any graph G=(V,E) such that |V|=2n, we intend to from 2 disjoint subgraphs V_1 and V_2 such that $V_1 \cup V_2 = V$, $V_1 \cap V_2 = \emptyset$ and $|V_1| = |V_2| = n$ while minimizing the total number of edges between the subgraphs.

In other words, we wish to minimize $f(x) = -\frac{1}{2}x^TA_Gx$ where each element in x is defined as $x_i = -1$ if $i \in V_1$ and $x_i = 1$ if $i \in V_2$; A_G represents the adjacency matrix for graph G. However this needs to be penalized to ensure equal number of vertices in both subgraphs. This results in a final Energy function given by:

$$E(x) = -\frac{1}{2}x^{T}A_{G}x + \frac{1}{2}\alpha \left(\left(\sum_{i=1}^{2n} x_{i} \right)^{2} - \left(\sum_{i=1}^{2n} x_{i}^{2} \right) \right)$$
 (1)

This also reduces to:

$$E(x) = -\frac{1}{2}x^T A_G x + \frac{1}{2}\alpha \left(2\sum_{i \neq j} x_i x_j\right)$$

$$\tag{2}$$

Thus the Neural Network transfer function can be constructed as:

$$x_i(k+1) = \tanh\left(\frac{1}{T}\sum_{i\neq j=1}^{2n} (a_{ij} - 2\alpha)x_j\right) = \tanh\left(\frac{1}{T}\sum_{i\neq j=1}^{2n} w_{ij}x_j\right) \ \forall i = 1,\dots, 2n$$
 (3)

Where α represents the LaGrange multiplier. The first term in the penalty terms of Equation ?? calculates difference in the sizes of the subgraphs while the second term which has a constant value of 2n only regularrizes the augumented matrix W. A function value f(x) which is maximized in the Minimum Bisection algorithm can also constructed as:

$$f(x)) = \frac{1}{2} \sum_{i < j} a_{ij} (1 - x_i x_j) = \frac{1}{4} \left(\sum_{i,j} a_{ij} - x^T A_G x \right)$$
 (4)

A MATLAB code shown in ?? was written to implement this algorithm an apply to the graph shown in ??. Figure ?? shows the behavior of the energy function E(x) and the objective f(x). As expected, E(x) is minimized while f(x) is maximized. For this run, the following optimal bisection subgraphs were obtained: $V_1 = \{1, 2, 4, 6, 9\}$ and $V_2 = \{3, 5, 7, 8, 10\}$; with the corresponding energy and objective function values of E(x) = -93 and f(x) = 17 respectively.

Figure 1: MATLAB code for Problem 1

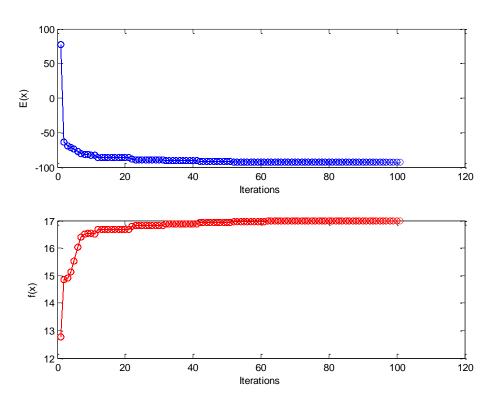


Figure 2: Results for the Neural Network Algorithm

Problem 2: Maximum Clique Problem with the Replicator Dynamics Approach

(a) We consider a maximum clique problem of some graph G = (V, E) of size n and adjacency matrix A_G . This is reduced to a form for which we perform the Motzkin-Straus quadratic program regularization:

maximize
$$f(x) = x^T (A_G + \frac{1}{2}I_n)x$$

subject to $e^T x = 1; x \ge 0$

Defining the characteristic vector of a set of vertices $C \in V$ as a feasible point $x = x^C$ given as:

$$x_i^C = \begin{cases} 1/|C|, & \text{if } i \in C\\ 0, & \text{otherwise} \end{cases}$$

Bomze(1997) showed that x^* maximizes f(x) over the feasible region if and only if x^* is the characteristic vector of the maximum clique in G. It is required to prove that the size of this clique is given by $\frac{1}{2(1-f(x^*))}$.

Proof. Let $m = |C^*|$ represent the maximum clique size so that each element of the corresponding characteristic vector is defined as:

$$x_i^* = \begin{cases} 1/|C^*|, & \text{if } i \in C^* \\ 0, & \text{otherwise} \end{cases}$$

Writing the augumeneted adjacency matrix in the regularized QP formulation as

$$\widehat{A_G} = A_G + \frac{1}{2}I_n \tag{5}$$

where I_n represents a $n \times n$ identity matrix, the objective function becomes $f(x) = x^T \widehat{A_G} x$ which can be written as:

$$x^{T} \widehat{A_{G}} x = \sum_{i,j}^{n} a_{ij} x_{i} x_{j} = \sum_{i=j}^{n} a_{ij} x_{i} x_{j} + \sum_{i \neq j}^{n} a_{ij} x_{i} x_{j}$$
 (6)

Knowing that $[a]_{ij} = 1/2 \ \forall i = j \in [1, n]$; going by the deinition for x^* given above and for a clique size of $|C^*| = m$, the first term of v becomes:

$$\sum_{i=j}^{n} a_{ij} x_i x_j = \sum_{i \in C^*} a_{ii} x_i^2 = \sum_{i \in C^*} \frac{1}{2} \frac{1}{m^2} = \frac{1}{m^2} \frac{m}{2}$$
 (7)

Also, knowing that $[a]_{ij} = 1 \ \forall i = j \in [1, m]$ the second term of equation ?? can be expressed as:

$$\sum_{i \neq j}^{n} a_{ij} x_i x_j = \sum_{i=1; i \in C^*}^{m-1} \sum_{j=i+1}^{m} 2a_{ij} x_i x_j = 2 \sum_{i=1}^{m-1} x_i \sum_{j=i+1}^{m} x_j = \frac{2}{m^2} \sum_{i=1}^{m-1} (m-i)$$

But

$$2\sum_{i=1}^{m-1}(m-i) = 2\left(\sum_{i=1}^{m-1}m - \sum_{i=1}^{m-1}i\right) = 2\left(m(m-1) - \frac{m(m-1)}{2}\right) = m(m-1)$$
 (8)

Thus The objective function at the maximum clique, $m = |C^*|$ becomes:

$$f(x^*) = x^T \widehat{A_G} x = \frac{1}{m^2} \left(\frac{m}{2} + m(m-1) \right) = 1 - \frac{1}{2m}$$
 (9)

Therefore

$$m = |C^*| = \frac{1}{2(1 - f(x^*))} \quad \Box$$
 (10)

(b) Solving the Motzkin-Straus QP results in an approximate solution of the maximum clique problem for some graph G = (V, E). Bomze (1997) proposed a recurvive algorithm, called the replicator dynamics, to solve the problem. In this algorithm, starting from a random vector of size |V| for x, the $(k+1)^{th}$ value of x_i for vertex i is calculated from the k^{th} value as follows:

$$x_i(k+1) = x_i^k \frac{(A_G x(k))_i}{x(k)^T A_G x(k)}; \ \forall i \in V$$
 (11)

A MATLAB code shown in Figure ?? was written to implement the replicator dynamics algorithm. This was applied to a graph of size 10 shown in Figure ??. The stopping criteria was set for some small $\epsilon > 0$ as follows:

$$\max_{i \in 1, \dots, n} |x_i(k+1) - x_i(k)| < 2\epsilon \tag{12}$$

The augumented adjacency matrix corresponding the graph in Figure ?? is given as:

$$A_G = \begin{bmatrix} \frac{1}{2} & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & \frac{1}{2} & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 \\ 1 & 1 & \frac{1}{2} & 1 & 0 & 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & \frac{1}{2} & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & \frac{1}{2} & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 & \frac{1}{2} & 1 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 & 1 & 1 & \frac{1}{2} & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & \frac{1}{2} & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 0 & 0 & 1 & \frac{1}{2} & 1 \\ 1 & 0 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & \frac{1}{2} \end{bmatrix}$$

The algorithm was run 10 times, each time with a completely random intial starting vector for x such that $x_i \in [0,1] \ \forall i \in V$. Figure ?? shows the objective function values with iteration for the 10 trials. As can be noticed, the maximum objective function, $f(x^*) = 0.900$, was obtained for all but one trails. The maximum clique obtained was $C^* = \{1, 3, 4, 9, 10\}$, that is $|C^*| = 5$. The deviant trail, on the other hand gave a $C^* = \{2, 3, 4, 9\}$, that is $|C^*| = 4$.

```
function [Results, Obj, maxClique, maxObj] = ReplicatorDyn(AG,N)
%Initialize & parameters
n = size(AG, 1);
Results = zeros(n,N);
Initial = zeros(n,N);
myeps = 1e-6;
Obj = zeros(1000,N);
% Begin Algorithm for i = 1:N
     x0 = rand(n,1); x0 = x0/sum(x0);
     Initial(:,i) = x0;
itr = 1; notConverged = 1;
     while notConverged
   Obj(itr,i) = (x0'*AG*x0);
   x = x0.*(AG*x0)/Obj(itr,i);
          notConverged = max(abs(x-x0)) > myeps;
           x0 = x;
           itr = itr+1;
     end
     Results(:,i) = x0;
end
Results(Results<myeps) = 0;
% Visualize
maxObj = 0; imax = 0;
figure(1); hold on for i = 1:N
    stopind = find(Obj(:,i)<eps,1,'first')-1;
plot(Obj(1:stopind,i),'linewidth',2);
if Obj(stopind) > maxObj; maxObj = Obj(stopind); imax = i; end
maxClique = find(Results(:,imax)~=0);
grid on;
xlabel('Iterations'); ylabel('Objective Function')
```

Figure 3: MATLAB code for Problem 2

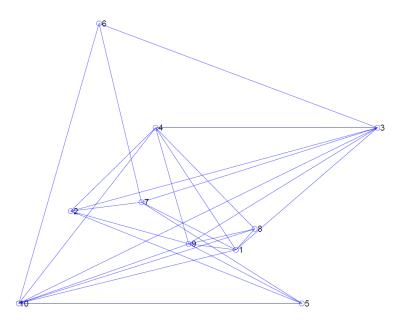


Figure 4: Graph Example

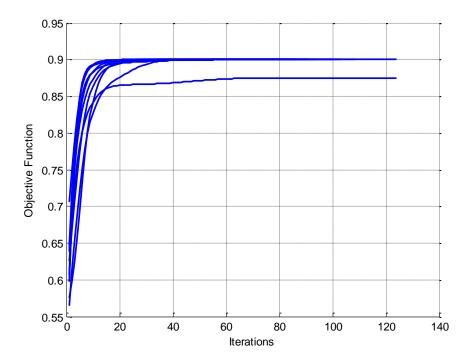


Figure 5: Plot of Objective Function for 10 Trials