CS246 Homework 3 Answers

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1 Question 1 – Latent Features for Recommendations

1.1 (a)

$\epsilon_{iu} = r_{iu} - q_i * p_u^T$

$q_i \leftarrow q_i + \eta(\epsilon_{iu} p_u - \lambda q_i)$

$p_u \leftarrow p_u + \eta(\epsilon_{iu} q_i - \lambda p_u)$

Where η is the learning rate.

1.2 (b)

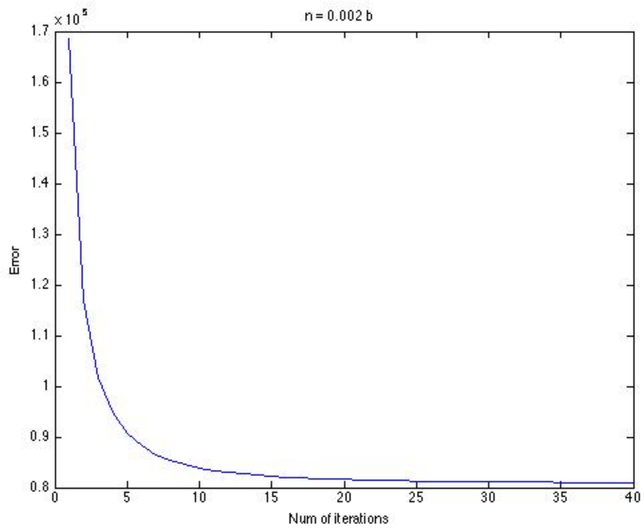

Figure 1: Error in first 40 iterations with $\eta = 0.002$:

1.3 (c)

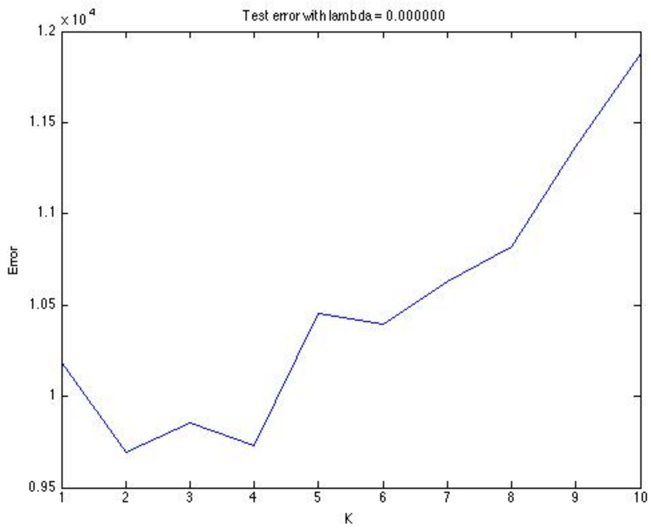

Figure 2: E_{te} as of K with $\lambda = 0.0$:

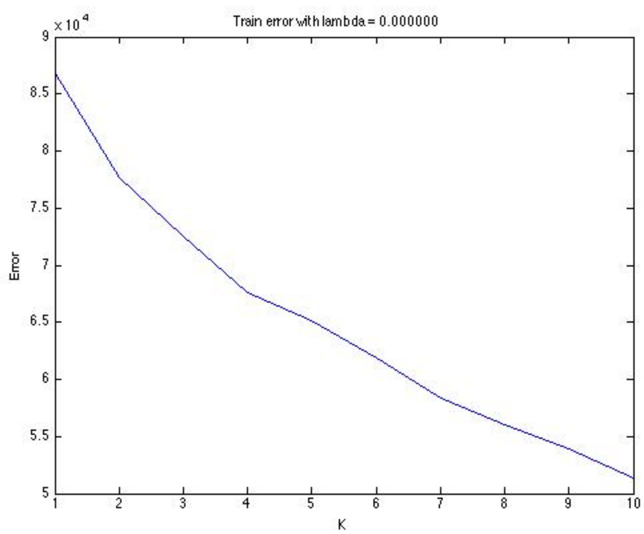

Figure 3: E_{tr} as of K with $\lambda = 0.0$:

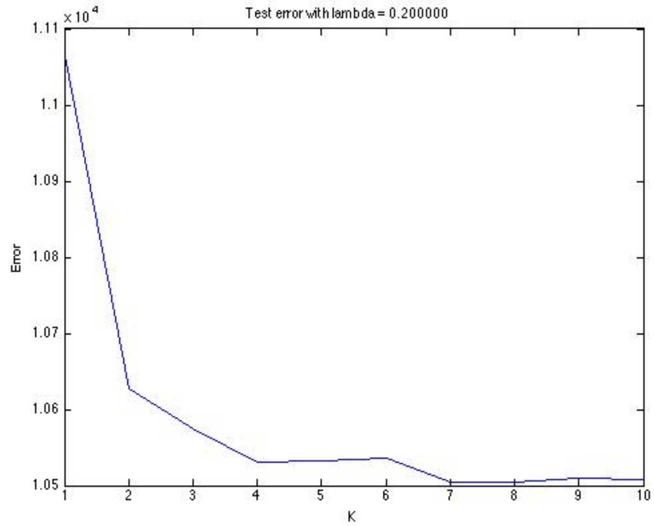

Figure 4: E_{te} as of K with $\lambda = 0.2$:

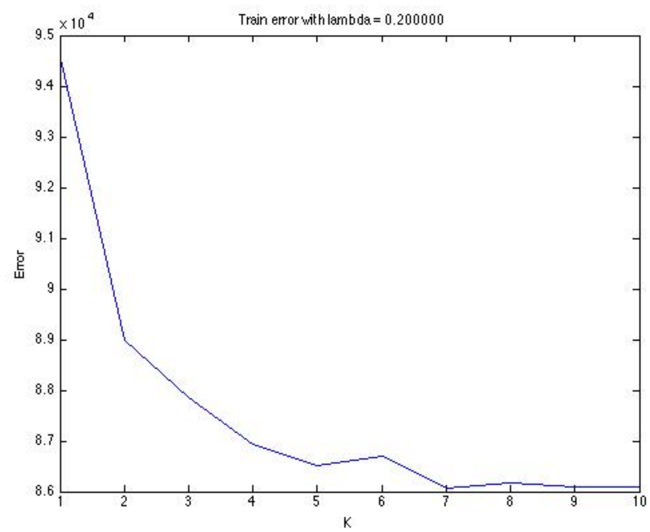

Figure 5: E_{tr} as of K with $\lambda = 0.2$:

True statements are: **B, D, H**

1.4 (d)

Update model as:

$R_{iu} = \mu + b_u + b_i + q_i \cdot p_u^T$

The update equations are:

$\epsilon_{iu} = r_{iu} - \mu - b_u - b_i - q_i * p_u^T$

$q_i \leftarrow q_i + \eta(\epsilon_{iu} p_u - \lambda q_i)$

$p_u \leftarrow p_u + \eta(\epsilon_{iu} q_i - \lambda p_u)$

$b_i \leftarrow b_i + \eta(\epsilon_{iu} - \lambda b_i)$

$b_u \leftarrow b_u + \eta(\epsilon_{iu} - \lambda b_u)$

Where η is the learning rate.

And plot the following:

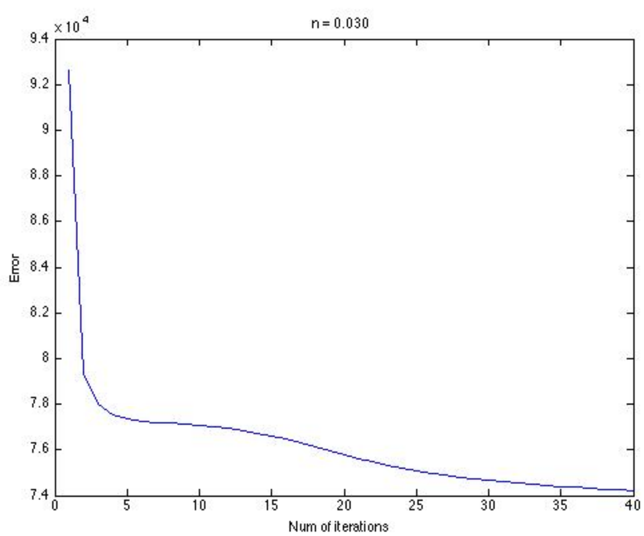

Figure 6: Error in first 40 iterations with $\eta = 0.03$:

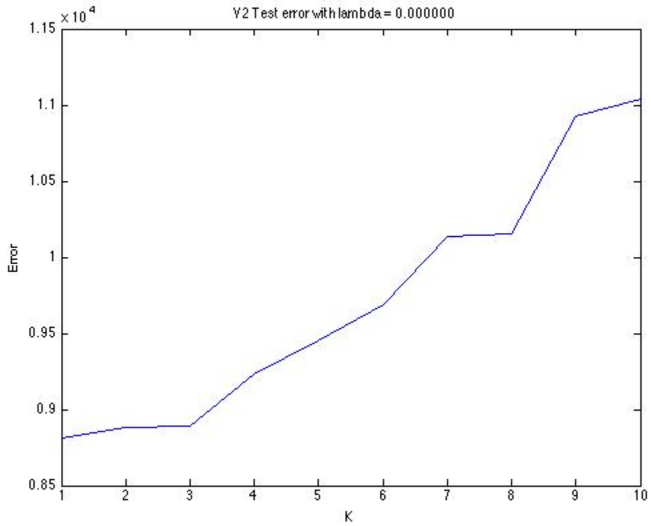

Figure 7: E_{te} as of K with $\lambda = 0.0$:

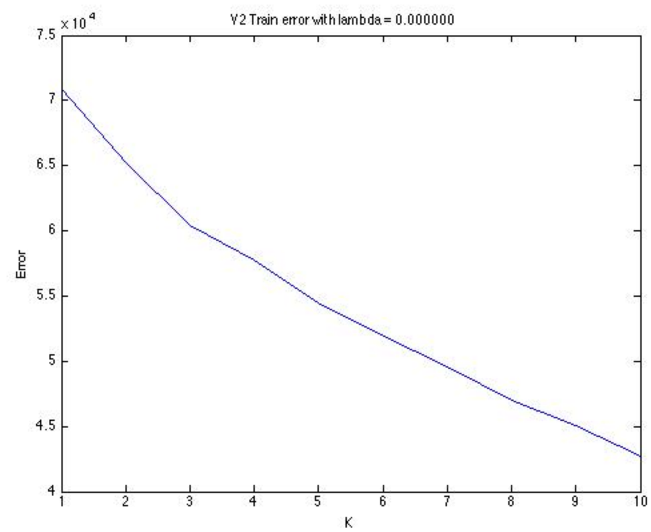

Figure 8: E_{tr} as of K with $\lambda = 0.0$:

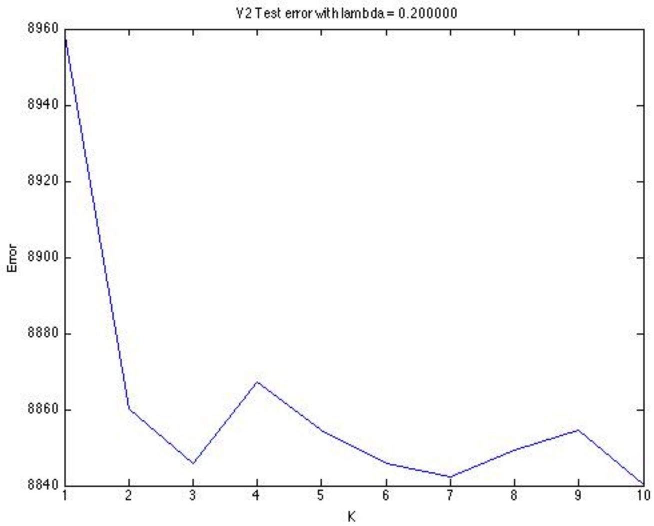

Figure 9: E_{te} as of K with $\lambda = 0.2$:

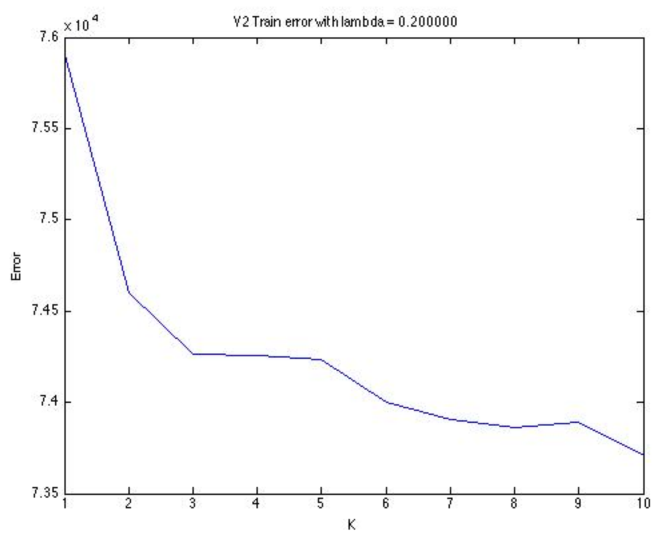

Figure 10: E_{tr} as of K with $\lambda = 0.2$:

2 Question 2 – PageRank Computation

2.1 (a)

$r - r^{(k)} = \beta M r - \beta M r^{(k-1)}$

$= \beta M(r - r^{(k-1)})$

$= \beta^2 M^2 (r - r^{(k-2)})$

$= ...$

$= \beta^k M^k (r - r^{(0)})$

M is stochastic, $\|M^k r\|_1 <= 1, \|M^k r^{(0)}\|_1 <= 1$

So $\|r - r^{(k)}\|_1 <= \|\beta^k M^k r\|_1 + \|\beta^k M^k r^{(0)}\|_1 <= 2\beta^k$

2.2 (b)

Let I be the number of iterations.

$\|r - r^{(I)}\|_1 <= 2\beta^I <= \delta$

$I >= \log_\beta(\delta/2) = \frac{\log(2/\delta)}{\log(1/\beta)}$ We need iterate through every edge one time for each iteration. So total running time is:

$Im = m\frac{\log(2/\delta)}{\log(1/\beta)} = O(\frac{m}{\log(1/\beta)})$

2.3 (c)

Let c_j be the total number of visits at node j, Then $r_j = c_j \frac{1-\beta}{nR}$

Based on the algorithm, we have: $E[c_j] = \sum_{i->j} \beta \frac{E[c_i]}{deg(i)} + R$

So, $E[\tilde{r_j}] = E[c_j]\frac{1-\beta}{nR} = \sum_{i->j} \beta \frac{E[c_i]\frac{1-\beta}{nR}}{deg(i)} + \frac{1-\beta}{n}$

$= \sum_{i->j} \beta \frac{E[c_i \frac{1-\beta}{nR}]}{deg(i)} + \frac{1-\beta}{n}$

$= \sum_{i->j} \beta \frac{E[\tilde{r_i}]}{deg(i)} + \frac{1-\beta}{n}$

Which can be re-written as: $E[\tilde{r_j}] = \frac{1-\beta}{n}\mathbf{1}^T + \beta M E[\tilde{r_j}]$

We also have: $r_j = \frac{1-\beta}{n}\mathbf{1}^T + \beta M r_j$

So $E[\tilde{r_j}] = r_j$

2.4 (d)

Expected run time of one random walker $E[w] = \sum_{i=1}^{\infty} i(1-\beta)\beta^{i-1} = \frac{1}{1-\beta}$

Expected running time of MC algorithm is: $E[w] \cdot nR = \frac{nR}{1-\beta}$

2.5 (e)

Power Iteration CPU time(40 Iterations): 13.341 ms

MC Algorithm with R=1,

CPU time: 0.701 ms

Average errors at Top 10, 30, 50, 100:

0.0028874375033

0.00381215746702

0.00337883645241

0.00257711933559

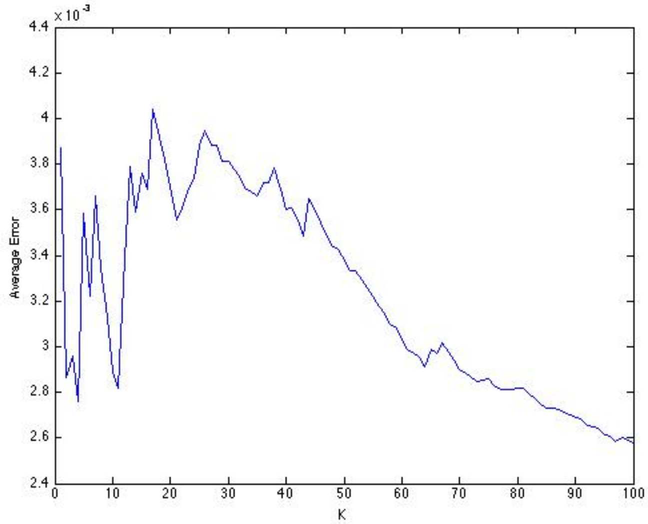

Figure 11: Error at Top K, R = 1

MC Algorithm with R=3,

CPU time: 1.800 ms

Average errors at Top 10, 30, 50, 100:

0.00258007835315

0.00231232051217

0.00199818494762

0.00149559856577

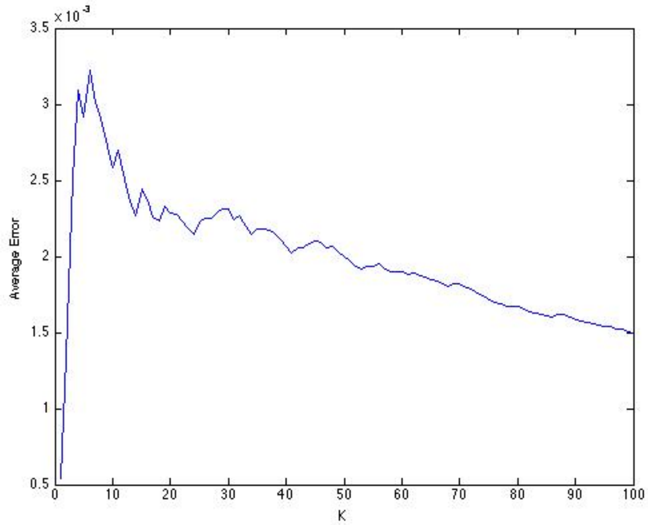

Figure 12: Error at Top K, R = 3

MC Algorithm with R=5,

CPU time: 2.577 ms

Average errors at Top 10, 30, 50, 100:

0.00299232555129

0.00228341943338

0.00180001027051

0.00131482088127

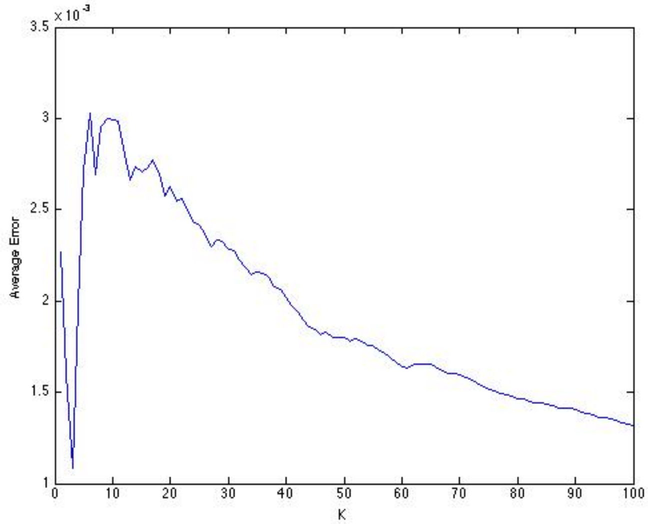

Figure 13: Error at Top K, R = 5

3 Question 3 – Similarity Ranking

3.1 (a)

$s_A(camera, phone) = 0.343$

$s_A(camera, printer) = 0.0$

In first iteration, $s_A(camera, phone) =$

$C1\frac{s_B(nokia,nokia)+s_B(nokia,apple)+s_B(kodak,nokia)+s_B(kodak,apple)+s_B(cannon,nokia)+s_B(cannon,apple)}{6} =$

$C1\frac{1+0+0+0+0+0}{6} = 0.133$

Intermediate results (Nodes are indexed based on the order in graph, e.g. 'cameras' == 1, 'phones' == 2):

Round 1:
s_A:
(1, 2): 0.133333
(1, 3): 0.000000
(3, 3): 1.000000
(2, 3): 0.000000
(2, 2): 1.000000
(1, 1): 1.000000
s_B:
(1, 2): 0.000000
(1, 3): 0.000000
(3, 3): 1.000000
(4, 5): 0.000000
(4, 4): 1.000000
(5, 5): 1.000000
(1, 4): 0.000000
(2, 4): 0.400000
(1, 5): 0.000000
(2, 3): 0.400000
(2, 2): 1.000000
(2, 5): 0.400000
(3, 4): 0.000000
(1, 1): 1.000000
(3, 5): 0.800000
Round 2:
s_A:
(1, 2): 0.293333
(1, 3): 0.000000
(3, 3): 1.000000
(2, 3): 0.000000
(2, 2): 1.000000
(1, 1): 1.000000
s_B:
(1, 2): 0.000000
(1, 3): 0.000000
(3, 3): 1.000000
(4, 5): 0.106667
(4, 4): 1.000000
(5, 5): 1.000000
(1, 4): 0.000000
(2, 4): 0.453333
(1, 5): 0.000000
(2, 3): 0.453333
(2, 2): 1.000000
(2, 5): 0.453333
(3, 4): 0.106667
(1, 1): 1.000000
(3, 5): 0.800000
Round 3:
s_A:
(1, 2): 0.343111

(1, 3): 0.000000
(3, 3): 1.000000
(2, 3): 0.000000
(2, 2): 1.000000
(1, 1): 1.000000
s_B:
(1, 2): 0.000000
(1, 3): 0.000000
(3, 3): 1.000000
(4, 5): 0.234667
(4, 4): 1.000000
(5, 5): 1.000000
(1, 4): 0.000000
(2, 4): 0.517333
(1, 5): 0.000000
(2, 3): 0.517333
(2, 2): 1.000000
(2, 5): 0.517333
(3, 4): 0.234667
(1, 1): 1.000000
(3, 5): 0.800000

3.2 (b)

Similarity equation incorporating link weights:

$$s_A(X,Y) = C1 \frac{\sum_{i=1}^{|O(X)|} \sum_{j=1}^{|O(Y)|} s_B(O_i(X), O_j(Y)) \cdot W_i(X) \cdot W_j(Y)}{\sum_{i=1}^{|O(X)|} \sum_{j=1}^{|O(Y)|} W_i(X) \cdot W_j(Y)}$$

Where $W_i(X)$ is the weight of the i_{th} edge originating from X. Similarly, we define s_B as following:

$$s_B(x,y) = C2 \frac{\sum_{i=1}^{|I(x)|} \sum_{j=1}^{|I(y)|} s_A(I_i(x), I_j(y)) \cdot w_i(x) \cdot w_j(y)}{\sum_{i=1}^{|I(x)|} \sum_{j=1}^{|I(y)|} w_i(x) \cdot w_j(y)}$$

Where $w_i(x)$ is the weight of the i_{th} edge originating from x.

3.3 (c)

In $K_{2,1}$, $s_A(1,2) = 0.800$

In $K_{2,2}$, $s_A(1,2) = 0.624$

For $K_{2,1}$:

If first iteration,

$s_A(1,2) =$

$C1\frac{s_B(1,1)}{1} =$

$C1\frac{1}{1} = 0.8$

$s_A(1,1) = 1$

$s_A(2,2) = 1$

$s_B(1,1) = 1$

Intermediate results:

Round 1:
s_A:
(1, 2): 0.800000
(1, 1): 1.000000
(2, 2): 1.000000
s_B:
(1, 1): 1.000000
Round 2:
s_A:
(1, 2): 0.800000
(1, 1): 1.000000
(2, 2): 1.000000
s_B:
(1, 1): 1.000000
Round 3:
s_A:
(1, 2): 0.800000
(1, 1): 1.000000
(2, 2): 1.000000
s_B:
(1, 1): 1.000000

For $K_{2,2}$:

If first iteration,

$s_A(1,2) =$

$C1\frac{s_B(1,1)+s_B(1,2)+s_B(2,1)+s_B(2,2)}{4} =$

$C1\frac{1+0+0+1}{4} = 0.4$

$s_A(1,1) = 1$

$s_A(2,2) = 1$

$s_A(2,1) = s_A(1,2) = 0.4$

$s_B(1,2) =$

$C2\frac{s_A(1,1)+s_A(1,2)+s_A(2,1)+s_A(2,2)}{4} =$

$C2\frac{1+0+0+1}{4} = 0.4$

$s_B(1,1) = 1$

$s_B(2,2) = 1$

$s_B(2,1) = s_B(1,2) = 0.4$

Intermediate results:

Round 1:
s_A:
(1, 2): 0.400000
(1, 1): 1.000000
(2, 2): 1.000000
s_B:
(1, 2): 0.400000
(1, 1): 1.000000
(2, 2): 1.000000
Round 2:
s_A:
(1, 2): 0.560000
(1, 1): 1.000000
(2, 2): 1.000000
s_B:
(1, 2): 0.560000
(1, 1): 1.000000
(2, 2): 1.000000
Round 3:
s_A:
(1, 2): 0.624000

(1, 1): 1.000000
(2, 2): 1.000000
s_B:
(1, 2): 0.624000
(1, 1): 1.000000
(2, 2): 1.000000

3.4 (d)

Update the equations as:

$N_A(X,Y) = |O(X)| * |O(Y)|$,
$s_A(X,Y) = \frac{(1-(1-C1)^{N_A(X,Y)})}{N_A(X,Y)} \sum_{i=1}^{|O(X)|} \sum_{j=1}^{|O(Y)|} s_B(O_i(X), O_j(Y))$

$N_B(x,y) = |I(x)| * |I(y)|$,
$s_B(x,y) = \frac{(1-(1-C2)^{N_B(x,y)})}{N_B(X,Y)} \sum_{i=1}^{|I(x)|} \sum_{j=1}^{|I(y)|} s_A(I_i(x), I_j(y))$

The algorithm will converge. And final values are symmetric, and between [0, 1](Replaced C1/C2 with another const $(1-(1-C1)^{N_A(X,Y)})$ and $(1-(1-C1)^{N_A(X,Y)})$ that varies depending on the number of supporting evidences. More support, higher C1/C2)

Converged value of $s_A(1,2)$ for $K_{2,1}$:

0.49107427590144004

and for $K_{2,2}$:

0.996805111821086

The algorithm assigns higher score for $s_A(1,2)$ in $K_{2,2}$ since there are more support.

3.5 (e)

Suppose we have two random walkers, one starting at $x \in A$, one starting at $y \in A$, in each iteration, if the walkers are in A, the process terminates with probability of (1 - C1), otherwise they walk to one of their neighbor nodes in B with uniform probability respectively. If the walkers are in B, the process terminates with probability of (1 - C2), otherwise they walk to one of their neighbor nodes in A with uniform probability respectively. Then $s_A(x, y)$ is the probability that the two random walkers from x, y meet each other at some time, (at any round of the iteration).

4 Question 4 – Dense Communities in Networks

4.1 (a)

4.1.1 (i)

Suppose $|A(S)| < \frac{\epsilon}{1+\epsilon}|S|$,

We denote $S \backslash A(S)$ as $B(S)$

Then $|B(S)| = |\{i \in S | deg_s(i) > 2(1+\epsilon)\rho(S)\}| > \frac{1}{1+\epsilon}|S|$

$|E[B(S)]| \geq |B(S)| \cdot 2(1+\epsilon)\rho(S)/2 > \frac{1}{1+\epsilon}|S| \cdot (1+\epsilon)\frac{|E[S]|}{|S|} = |E[S]|$, which is impossible.

So $|A(S)| \geq \frac{\epsilon}{1+\epsilon}|S|$

4.1.2 (ii)

We denote S in the i_{th} iteration as S_i

Based on the proof in **i**, we have: $|S_{i+1}| < \frac{1}{1+\epsilon}|S|$

$|S_k| < \frac{1}{(1+\epsilon)^k}|S| = \frac{1}{(1+\epsilon)^k}n$

$S_k \neq \emptyset$, So $|S_k| \geq 1$, $k < log_{1+\epsilon}(n)$

4.2 (b)

4.2.1 (i)

If $\exists v \in S^*|deg_{S^*}(v) < \rho^*(G)$

We can remove v from S^*, let the resulting set be $S' = S^* \backslash \{v\}$

$\rho(S') = \frac{|E[S']|}{|S'|} = \frac{|E[S^*]| - deg_{S^*}(v)}{|S^*|-1}$

Since $deg_{S^*}(v) < \rho^*(G) = \frac{|E[S^*]|}{|S^*|}$,

$\rho(S') = \frac{|E[S^*]| - deg_{S^*}(v)}{|S^*|-1} > \frac{|E[S^*]|}{|S^*|}$

S' is 'denser' than S^*. Which is contrary to the statement that S^* is the densest subgrapgh of G.

So such v doesn't exist.

4.2.2 (ii)

In the first iteration of the while loop in which there exists a node $v \in S^* \cap A(S)$, Since $v \in S^*$, base on proof in **i**, we have $deg_{S^*}(v) \geq \rho^*(G)$

Since $v \in A(S)$, we have $deg_S(v) \leq 2(1+\epsilon)\rho(S)$

$A(S) \in S$, So $S^* \cap A(S) \in S$, So $deg_{S^*}(v) \leq deg_S(v)$

$2(1+\epsilon)\rho(S) \geq deg_S(v) \geq deg_{S^*}(v) \geq \rho^*(G)$

In conclusion, $2(1+\epsilon)\rho(S) \geq \rho^*(G)$

4.2.3 (iii)

There should be at least 1 iteration (Assume in j_{th} iteration) in which there exist node v such that $v \in S^* \cap A(S)$.

Then $2(1+\epsilon)\rho(S_j) \geq \rho^*(G)$

$\rho(\bar{S}) = \max_{i=1}^{NumIter}\{\rho(S_i)\} \geq \rho(S_j) \geq \frac{1}{2(1+\epsilon)}\rho^*(G)$

4.3 (c)

4.3.1 (i)

Number of iterations when $\epsilon = \{0.1, 0.5, 1, 2\}$ are:

{7, 5, 4, 3} Corresponding theoretical bounds are:

{137, 32, 18, 11}

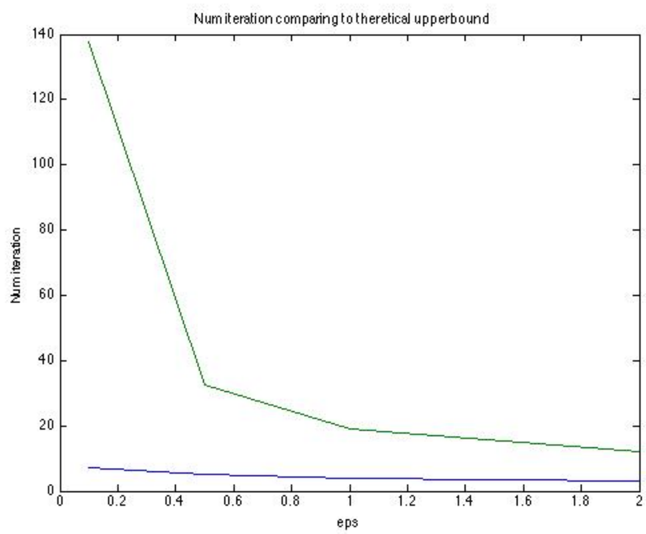

Figure 14: Num iterations and bounds

4.3.2 (ii)

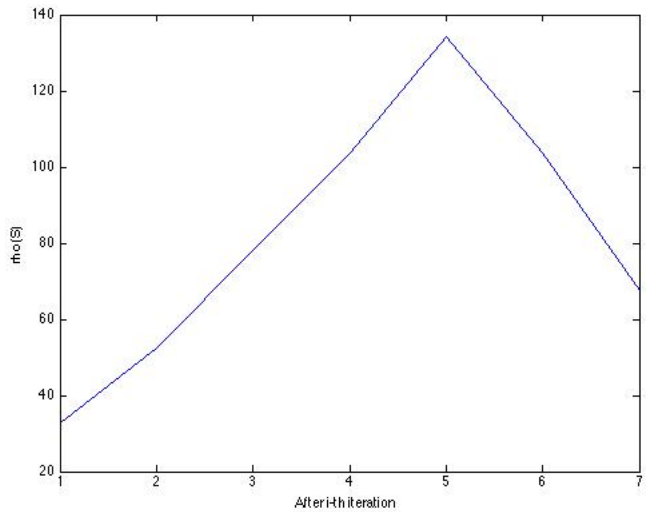

Figure 15: $\rho(S_i)$ as of i

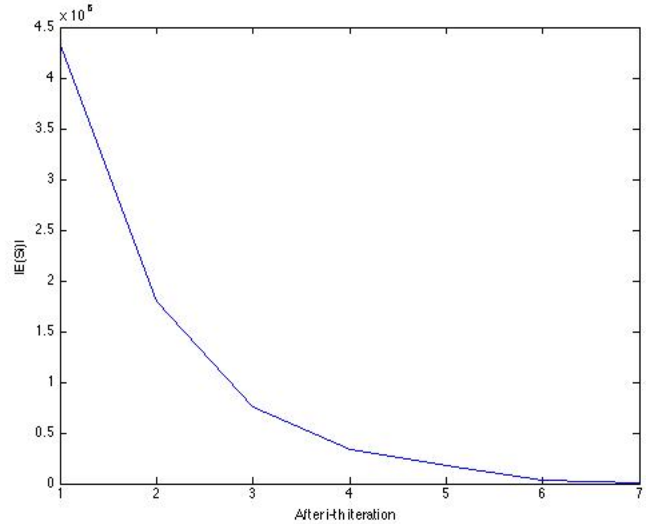

Figure 16: $|E(S_i)|$ as of i

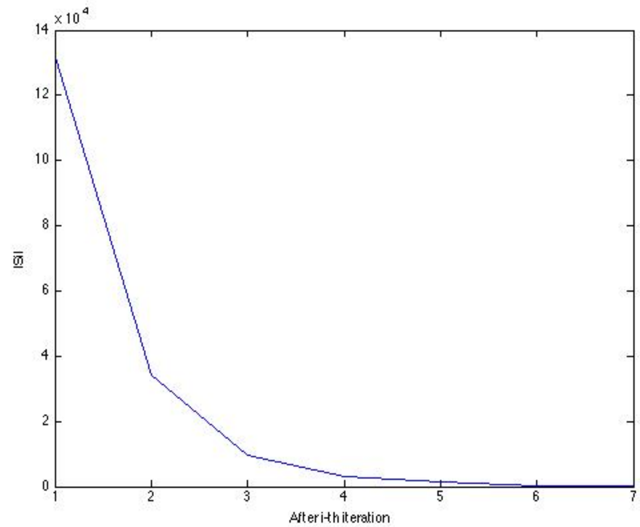

Figure 17: $|S_i|$ as of i

4.3.3 (iii)

The plot of $\rho(\bar{S}_j), |E[\bar{S}_j]|$ and $|\bar{S}_j|$:

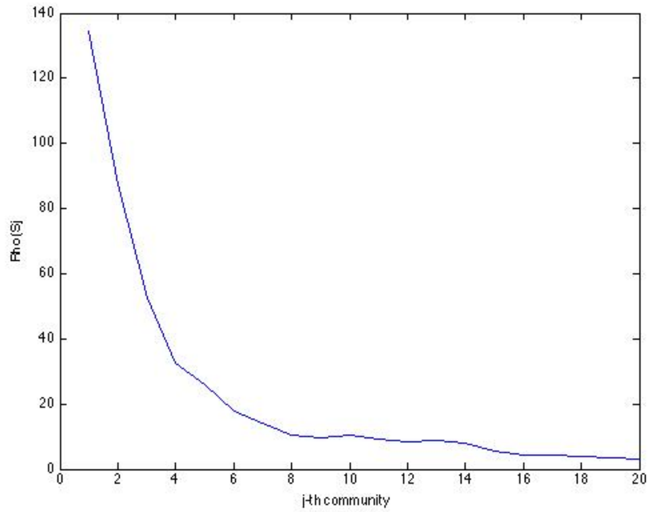

Figure 18: $\rho(\bar{S}_j)$ as of j

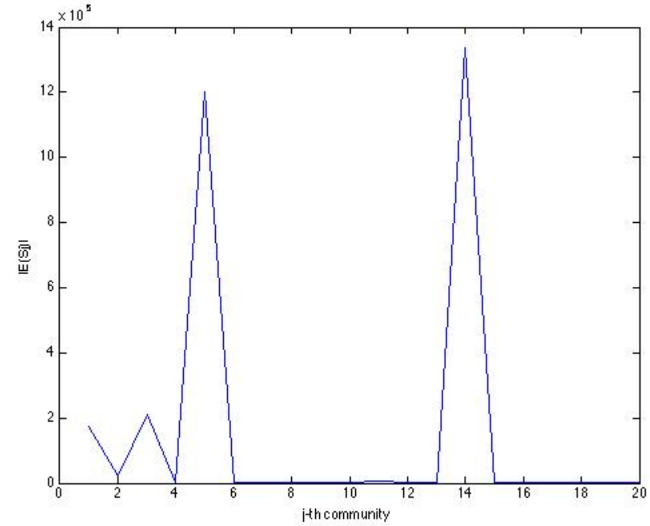

Figure 19: $|E[\bar{S}_j]|$ as of j

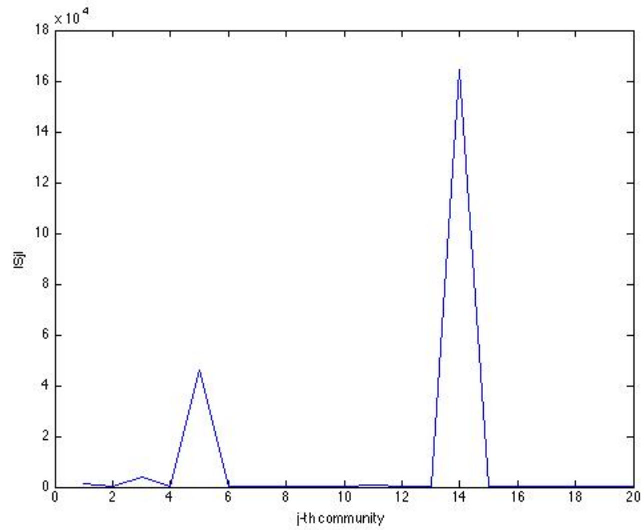

Figure 20: $|\bar{S}_j|$ as of j

The code:

```
from collections import defaultdict
import copy
import itertools
from optparse import OptionParser
import random
import sets
import sys
import time

def preprocess(graph_file, removed):
  f = open(graph_file)
  V = sets.Set()
  num_edge = 0
  for line in f:
    a, b = line.strip().split('\t')
    if removed and ((a in removed) or (b in removed)):
      continue
    if a not in V:
      V.add(a)
    if b not in V:
      V.add(b)
    num_edge += 1
  f.close()
  return V, num_edge

def count_edge(graph_file, S):
  f = open(graph_file)
  count = 0
```

```
  for line in f:
    a, b = line.strip().split('\t')
    if (a in S) and (b in S):
      count += 1
  f.close()
  return count

def find_dense(graph_file, eps, removed=None):
  V, e = preprocess(graph_file, removed)
  if len(V) == 0:
    return None, None, None, None, None
  S_bar = copy.copy(V)
  rho_S_bar = float(e) / len(V)
  S = copy.copy(V)
  num_iter = 0
  list_rho = []
  list_num_edge = []
  list_size_s = []
  while len(S) > 0:
    num_iter += 1
    deg = defaultdict(int)
    num_edge = 0
    f = open(graph_file)
    for line in f:
      a, b = line.strip().split('\t')
      if removed and ((a in removed) or (b in removed)):
        continue
      if (a not in S) or (b not in S):
        continue
      deg[a] += 1
      deg[b] += 1
      num_edge += 1
    f.close()
    rho_S = float(num_edge) / len(S)

    A = sets.Set()
    for v in S:
      if deg[v] <= 2 * (1 + eps) * rho_S:
        A.add(v)
    S.difference_update(A)
    num_edge = count_edge(graph_file, S)
    if len(S) == 0:
      break
    rho_S = float(num_edge) / len(S)
    if rho_S > rho_S_bar:
      rho_S_bar = rho_S
      S_bar = copy.copy(S)

    list_rho.append(rho_S)
    list_num_edge.append(num_edge)
    list_size_s.append(len(S))
  return S_bar, num_iter, list_rho, list_num_edge, list_size_s

def main():
  parser = OptionParser()
  parser.add_option("-f", "--file", dest="file", type="string",
                    help="File containing the graph.")
```

```
  (options, args) = parser.parse_args()

  for eps in [0.05, 0.1, 0.5, 1, 2]:
    S_bar, num_iter, list_rho, list_num_edge, list_size_s = find_dense(options.file, eps)
    print "Eps: %f, num iteration: %d" % (eps, num_iter)
    print list_rho
    print list_num_edge
    print list_size_s

  removed = sets.Set()
  eps = 0.05
  list_rho = []
  list_num_edge = []
  list_size_s = []
  for j in xrange(1, 21):
    print "%d-th iter" % j
    S_bar, t1, t2, t3, t4 = find_dense(options.file, eps, removed)
    if not S_bar:
      print "Remaining graph is empty"
      break
    num_edge = count_edge(options.file, S_bar)
    print "rho: %f" % (float(num_edge) / len(S_bar))
    list_rho.append(float(num_edge) / len(S_bar))
    print "num_edge: %d" % num_edge
    list_num_edge.append(num_edge)
    print "size_S_bar: %d" % len(S_bar)
    list_size_s.append(len(S_bar))
    removed = removed.union(S_bar)
    print S_bar
  print list_rho
  print list_num_edge
  print list_size_s

if __name__ == '__main__':
  main()
```