Project IMP Report

Zhaoxu Zhang 11611308

Abstract—This is a project for CS303-Aritificial Intelligence, which is about a famous problem "Influence Maximization Problem". This project requires us to implement an algorithm to solve the IMP problem. Each student's program will be upload to an online platform and tested with multiple testeds

I. PRELIMINARIES

A. Problem Description

The problem can be divided into two subproblems: ISE, IMP.

- ISE: To estimate the maximum $\sigma(S)$ with a given seed set S in a network using a certain stochastic diffusion model.
- IMP: To find a seed set S that maximizes σ(S) in a network using a certain diffusion model, subject to S
 k.

A social network is modeled as a directed graph G=V, E with nodes in V modeling the individual in the network and each edge $u,v\in E$ is associated with a weight $w,u,v\in [0,1]$ which indicates the probability that u influences v. Let $S\subseteq V$ to be the subset of nodes selected to initiate the influence diffusion, which is called the seed set.

The stochastic diffusion models specify the random process of influence cascade from S, of which the output is a random set of nodes influenced by S. The expected number of influenced nodes $\sigma(S)$ is the influence spread of S. There are two diffusion models: Independent Cascade(IC) and Linear Threshold (LT) model.

- IC: A seed node activate its neighbors with the probability proportionally to the weight between them.
- LT: At the beginning, each node v selects a random threshold θ_V uniformly at random in range [0,1]. An inactive neighbor v for a active seed becomes activated if $\sum_{activated\ neighbors\ u} w(u,v) \ge \theta$

B. Problem Applications

This problem originates from viral marketing [1], where a company provides free samples of a product to a set of influential individuals in a social network, aiming to create a cascade of product adoptions via the word-of-mouth effect.

C. Software

This project is written by python 3.6 using IDE pycharm. The library include numpy, random, sys, time, multiprocessing, heapq, operator, math.

D. Algorithm

This project mainly use IMM[2] and CELF[3].

II. METHODOLOGY

A. Notation

- network: a n*n Graph containing the weight of each path
- invneighbors: a list with multiple length, containing nodes that have path to this node
- neighbors: a list with multiple length, containing neighbors for each node
- differential_model: 'IC' or 'LT'
- R: collection of all RR set
- RR: the collection of all node that might influence a node
- F_R(S): the fraction of RR sets in R that are covered by a node set S

B. Data and data structure

In this project, I mainly use dict, list, heap and set data structure in python. In the following, I will demonstrate how I use data structure for each objects.

- network graph: I use adjacent table as this is quich to search a weight for a path O(1).
- neighbors list and invneighbors list: I use adjacent list. There always be situations that we need to go through all neighbors for one node. Because it is a parse gragh, using adjacent list to go through is both time-efficient and space-efficient.
- RR set: I use set. It is because that in IMM when we calculate F_R(S) we need to check wether a node in a RR. Here we use set will shorten the checking time to O(1) instead of O(n) using list.
- maxmum queue: I also use heap in package 'heapq' to maintain a maximum queue in CELF.

C. Model Design

How to fomulate: First I need to understand what is ISE, IMP, IC and LT. Then I will decide to choose which algorithm. Then I need to decide which data structure to use and how to implement the algorithm. In the following, I will present how to solve IMP and ISE problem.

- ISE: For ISE problem, we need to estimate the max influence for a given seed set. I run the diffusion models for 10000 times and take the average value as the estimated value.
- IMP: For IMP problem, we need to find out a seed set with given size in order to achieve the max influence. Here I apply IMM algorithm to solve it. In the initialization process, we generate a collection of RRs which are generated by applying reverse diffusion model to a random node. Then we choosed the top k nodes that are covered most in those RRs as seed set. Here, everytime we add one node into seed set. We move all RR that contains this node and we can use CELF algorithm to accelerate this algorithm.

1

```
D. Detail of Algorithm
```

Here we represent the main algorithm for ISE and IMP.

• ISE

```
    function used to calculate ISE
```

```
1: function ISE(network,seedset)
      sum = 0
2:
3:
      result = 0
      for i from 1 to 10000 do
4:
5:
          result = IC or LT
          sum += result
6:
      end for
7:
8: return sum/N
9: end function
```

- function used for model IC to calculate estima-

```
1: function IC(network, seedset)
       activityset = seedset
2:
       count = activityset.length
3:
4:
       while activity set is not empty do
           newActivityset = \emptyset
5.
           for each seed in activitySet do
6:
               for each inactive neighbor in seed
7:
   do
                   seed activates its neighbors
8:
   according to the weight
9:
                   if neighbor is activated then
                       Refresh neighbor's state
10:
                       newActivity-
11:
   set.add(neighbor)
12:
                   end if
               end for
13:
           end for
14.
15:
           count
                   =
                        count +
                                    newActivity-
   set.length
       end while
16:
17: return count
18: end function
```

- function used for model LT to calcualte estima-

```
1: function LT(network,invneightbors)
```

Initialize each node with a threshold, if the threshold is 0, add this node into activityset

count = activityset.length 3:

while activityset is not empty do newactivityset = \emptyset

for each seed in Activity do

for each inactive neighbors in 6: seed do

w total = sum of all weight 7: for all activited neighbors of this node

if w_total≤neighbors.thresh 8:

then

14:

5:

Refresh neighbor's state 9: newActivity-10:

set.add(neighbor)

end if 11: end for 12: end for 13:

count = count+newactivityset.length

```
activityset = newactivityset
15:
16:
       end while
17: return count
18: end function
```

IMP

```
- IMM method
```

```
1: function IMM(graph,k,\varepsilon,l)
       l = l * (1 + log2/logn)
       R = Sampling(G,k,\varepsilon,l)
       S_k^* = \text{NodeSelection}(R,k)
5: return S_k^*
6: end function
```

- functions used to generate R

```
1: function SAMPLING(graph,k,\varepsilon,l)
          Initialize a set R = \emptyset and LB = 1
  3:
  4:
          for i = 1 to log_2 n - 1 do
               x = n/2^i
  5:
               \lambda 1 = \frac{(2+\frac{2}{3}*\varepsilon')(\log\binom{n}{k}+\log(1/\sigma_3))}{2}*\frac{n}{2}
  6:
               \theta_i = \lambda 1/x
  7:
               while |R| \leq \theta_i do
  8:
  9:
                   Select a node v from G uniformly
     at Random
                   Generate an RR set for v, and
10:
     insert it into R
               end while
11:
               S_i = NodeSelection(R)
12:
               if n*F_R(S_i) \ge (1 + \varepsilon 1) * x then
13:
                   LB = n*F_R(S_i)/(1 + \varepsilon 1)
14
15:
                   break;
               end if
16:
17:
               \alpha = \sqrt{l * log n + log 2}
18:
         (1 - 1/e)(\log\binom{n}{k} + l * \log n + \log 2)
               \lambda^* = 2n * ((1 - 1/e) * \alpha + \beta)^2 * \varepsilon^{-2}
19:
               \theta = \lambda^* / LB
20:
21:
               while |R| < \theta do
                   Select a node v from G uniformly
22:
     at random
                   Generate an RR set for v and
23:
     insert it into R
               end while
24:
          end for
25:
26: return R
27: end function
function used to select k seed set using collection
```

```
1: function NodeSelection(R,k)
      for i = 1 to k do Identify the node v that
  maximizes F_R(S_k^*) - F_R(S_k^*) Insert v into
      end for
5: return S_k^*
6: end function
```

III. EMPIRICAL VERIFICATION

A. Dataset

Here I use Gnutella30 dataset to test my program. In this dataset there is 36682 nodes and 88328 edges.

B. Performance Measurement

- Test envirment: MacOS Mojave version 10.14; Processor 2.3 GHz Intel Core i5 4 cores; Memory 8 GB 2133 MHz LPDDR3.
- How to measure: For ISE, I use the total time and the accuracy of the estimation to evaluate(however without a reference answer, I can't judge wether my answer is correct). For IMP, I use total time and the estimation influence of the output seed set to measure the performance.

C. Hyperparameters

For ISE, the parameters is the the size of iterations. This parameter decide the number of iteration which also connect with the speed. For IMP, the parameters is the input for IMM algorithm, which decide the size of R set. With a larger size ,we need spend more time to construct it

In the paper, the author assigns following values to them:

ε	1	size
0.1	1	10000

I try to make these parameter to be smaller in order to maket the program faster. However, after being modified, the output is extramely unaccurate. At the same time, I added multiprocess in my program which accelerate it dramatically. Therefore, I decided not to modify the parameters.

D. Experimental Results

Here is the result on the dataset Gnutella30

IMP(k=5)	time/s	grade
IC IC	668.9	35632
LT	1.32	35589

ISE(seedsize=5)	time/s	grade
IC	80	35632
LT	213.6	35589

E. Conclusion

As a state-of-art algorithm, the IMM algorithm perform quite well.

In my point of view, such a great performance have strong connection with the data structure that we use. For example, using adjacent list is much better than adjacent matrix. It is also due to how we implement the algorithm. For example, in the NodeSelection method, after find out one point, we need to remove all RRs that contains that node. Here we can't immediately delete it. Instead, we can label it. However, there are also some disadvantage in this algorithm. For example, for 'IC' model, it's performance is not so good compared with 'LT' model, for which I don't know why.

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