Experiment Results(Extended)

August 19, 2018

Due to space constraints, the version submitted for review does not include all the experiments. In this document, we present the additional experiments related to the following:

1. How do the proposed algorithms perform under the Linear Threshold (LT) diffusion model?
2. For the Independent Cascade (IC) diffusion model, with fixed probability for all the edges, what is the effect on targets influenced?
3. What is the time taken for by the Natural Greedy and MultiGreedy?

While these experiments do not reveal any new insights (compared to the ones already presented in the submitted version), they indicate the completeness of our evaluation.

Experimental Setup All experiments are conducted on Linux server (Virtual machine) with AMD Opteron 6320 CPU (8 cores andiroba 2.8 GAHz) and 64GB main memory. All the algorithms were implemented in C++.

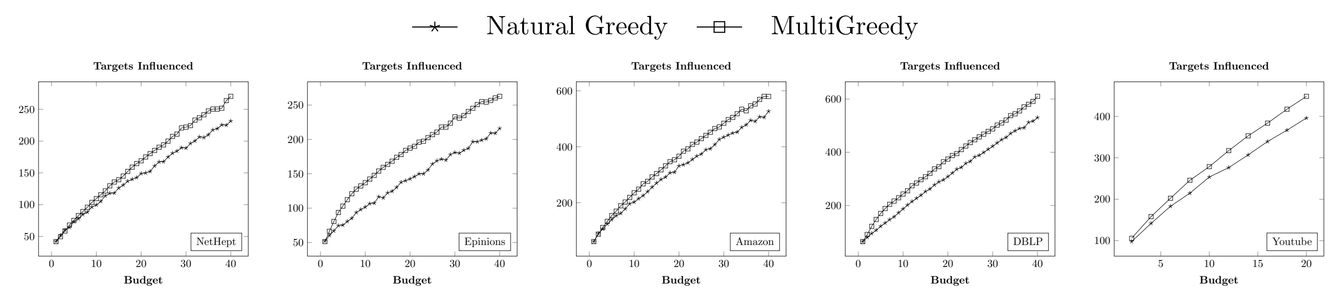

Figure 1: Budget vs Influence with $\theta = 10$ on the LT Model

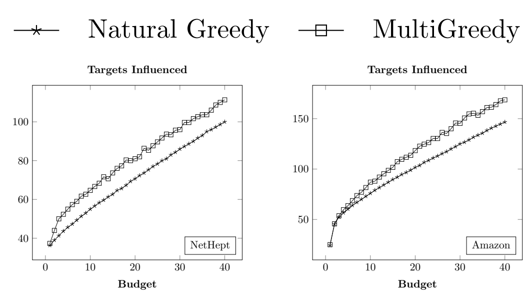

Figure 2: Budget vs Influence with $\theta = 10$ in the IC model with $p = 0.1$

Evaluation on the Linear Threshold Model In the Linear Threshold model, each node $v \in V$ is assigned a *threshold* randomly from [0,1]. Let $N^{in}(v)$ be the set of nodes such that each node in $N^{in}(v)$ has an edge going to v. For each incoming edge (u, v), a weight is assigned such that $\Sigma_{u \in N^{in}(v)} w(u, v) \leq 1$. If $N^{in}_{act}(v)$ is the activated (already influenced) neighbors of v, then v becomes active when $\Sigma_{u \in N^{in}_{act}(v)} w(u, v)$ is greater than or equal to the randomly selected *threshold* (for v). In our experiments, we have chosen the weight of an edge $w(u, v) = 1/inDeg(v)$. To generate RR sets under the LT Model, we have used the technique as presented in [1].

Figure 1 shows the influence under the LT model. In this, we have 80% Targets using the uniform labeling strategy, $\theta = 10$ for all the graphs. We see that the influence is similar to the IC Model (as presented in version under review). The MultiGreedy algorithm does outperform the Natural Greedy. Interestingly, the number of nodes influenced is marginally higher while the the difference between the MultiGreedy and Natural Greedy is comparable to the IC Model. In the IC model for example, for the Amazon graph, with budget=40, Natural Greedy and MultiGreedy influences 420 and 478 targets respectively. Under the LT Model, the algorithms influence 527 and 580 targets respectively. We observe that MultiGreedy performs better than the Natural Greedy in the LT model as well.

Influence under IC model with fix probability $p = 0.1$ Figure 2 shows the influence under the IC Model and each edge has a probability 0.1. We see that the MultiGreedy outperforms Natural Greedy under this setting as well. Note that the number of targets influenced has decreased compared to when the propagation probability is $1/inDeg(v)$. This can be explained as follows: when $p = 0.1$, the influence of a node (resulting in influencing targets and non-targets) is likely to be higher when compared to $p = 1/inDeg$. Consequently, the candidate seed nodes' influence is small as they are selected such that the non targets influenced under $\theta = 10$. In fact, as the budget increases, the targets influenced increases only by 1 or 2 with $p = 0.1$.

Figure 3: Time taken(seconds) for Phase 1

amazon	dblp	epinions	youtube	nethept
31	126	36	670	1

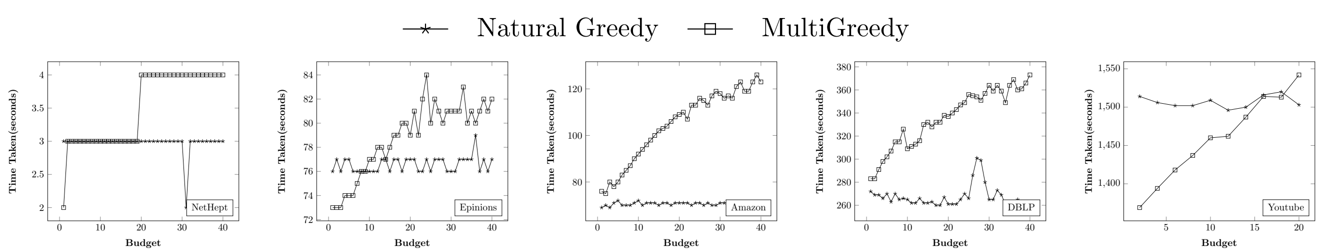

Figure 4: Overall Time Taken 80% Targets, $\theta = 10$ under the IC Model with $p = 1/inDeg$

Execution Time Under the IC Model, with propogation probability set to $1/inDeg$, we present the complete data of the time taken by the algorithms in Figures 3 and 4. The phase 1 time taken is presented in Figure 3. The overall time taken is presented in Figure 4.

References

[1] Y. Tang, X. Xiao, and Y. Shi. Influence maximization: near-optimal time complexity meets practical efficiency. In *SIGMOD*, pages 75–86, 2014.