**Implementation**

**Modules Description**

The Modules are:

1.Influence Maximization Module

2.Influential Node Tracking Module

3.Upper bounds comparison Module

4.Upper Bound of Node Replacement Gain Module

**Influence Maximization Module**

Marketing campaign is usually not a one-time deal, instead enterprises carry out a sustaining campaign to promote their products by seeding influential nodes continuously. Often, a marketing campaign may last for months or years, where the company periodically allocates budgets to the selected influential users to utilize the power of the word-of-mouth effect. Under this situation, it is natural and important to realize that social or information networks are always dynamics, and their topology evolves constantly over time. For example, links appear and disappear when users follow/unfollow others in Twitter or friend/unfriend others in Facebook. Moreover, the strength of influence also keeps changing, as you are more influenced by your friends who you contact frequently, while the influence from a friend usually dies down as time elapses if you do not contact with each other. As a result, a set of nodes influential at one time may lead to poor influence coverage after the evolution of social network, which suggests that using one static set as seeds across time could lead to unsatisfactory performance.

**Influential Node Tracking Module**

The traditional Influence Maximization problem aims at finding influential nodes for only one static social network. However, real-world social networks are seldom static. Both the structure and also the influence strength associated with the edges change constantly. As a result, the seed set that maximizes the influence coverage should be constantly updated according to the evolution of the network structure and the influence strength. In this work, we model the dynamic social network as a series of snapshot graphs, G1,. . . , GT . We assume that the nodes remain the same while the edges in each snapshot graph change across different time intervals. Each snapshot graph is modeled as a directed network, Gt = (V;Et), which includes edges appearing during the periods under consideration. Moreover, a set of propagation probabilities Pt u;v is associated with each snapshot graph Gt. Our goal is to track a series of seed sets, denoted as St; t = 1; : : : ; T, that maximizes the influence function t() at each of the snapshot Gt.

**Upper bounds comparison Module**

Upper bound termed as active nodes’ path excluded upper bound (AB), is theoretically tighter than the upper bound proposed , which we call it the naive upper bound (NB). In order to validate our theory, we run empirical experiments to compare our bound AB with the naive upper bound. We first extract a series of snapshot graphs from Mobile datasets by setting both time window and time difference to one hour. We run equivalent number of iterations in computing both AB and NB on the same node set with size k = 30 where propagation probabilities are set according to DWA model. The seed set is selected by Greedy algorithm that maximizes the influence under each snapshot. As is shown in Figure 9, our bound is consistently tighter than the naive bound proposed in as suggested by our theory. It should be noticed that the poor performance of NB under DWA model is due to the fact that sometimes NB fails to converge in Mobile network.

**Upper Bound of Node Replacement Gain Module**

In this section, we illustrate the only mysterious part in our UBI algorithm, namely the computation of the upper bound of the replacement gain u;vs (S). Zhou et al. first use the upper bound on influence function to accelerate the greedy algorithm in influential seeds selection . we propose a tighter upper bound on the replacement gain by excluding the influence along paths, which include incoming edges to the seed set. We have shown previously how to compute a tighter bound on the replacement gain for one static network with a fixed seed set S. However, as network changes constantly, we need to update the upper bound according to the changes in propagation probability. Moreover, as we include new node into the seed set S, we also need to update the upper bound as the propagation probability matrix PG(S+T) also changes.