

COMP810 Data Warehousing and Big Data

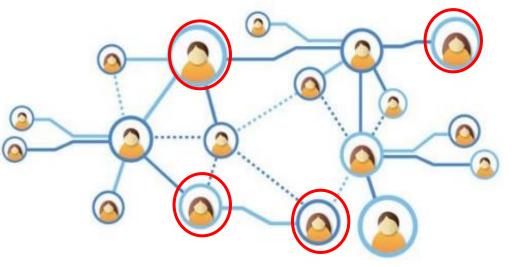
Complex Network with Big Data - Mining Large-scale and Dynamic Social Networks with Evolutionary Computation

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Outline

- Complex Network
- Social Influence Diffusion
- Classic Influence Diffusion Models
- Influence Maximization Problem
- Key Challenges
- Stigmergy-based Influencers Miner
- Experiments and Results





Complex Network

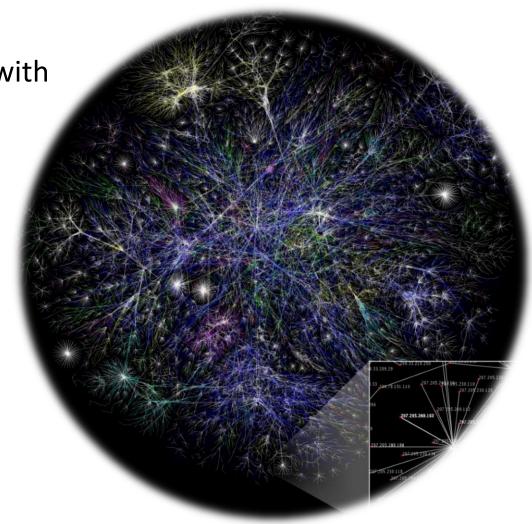
 A complex network is a graph (network) with non-trivial topological features

Node: vertex, entity

Link: edge, relationship

Key Characteristics:

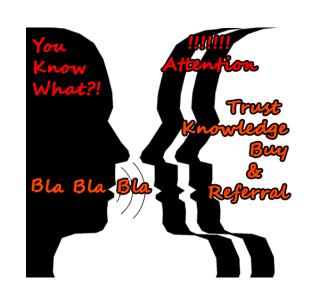
- Large scale
- Dynamic
- Heterogeneity
- Social network is a typical example of complex network.



Social Influence Diffusion

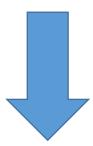


- Social influence
 - Emotions, options or behaviours are affected by others
 - Conformity, socialization, peer pressure, obedience, etc.
- Viral marketing
 - Drive network evolution direction
 - Word-of-mouth effect
- Influence propagation
 - Independent Cascade (IC) Model
 - Linear Threshold (LT) Model
 - Agent-based Influence Diffusion Model

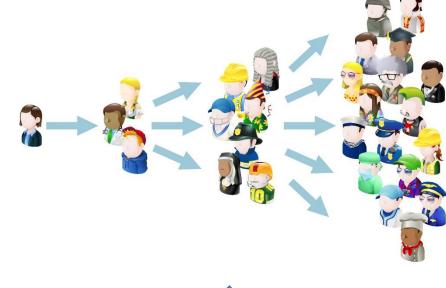


Viral Marketing

Identify influential customers



Convince them to adopt the product – Offer discount/free samples





These customers endorse the product among their friends

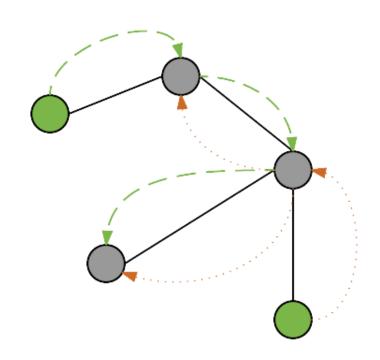


Classic Influence
Diffusion Models
and Influence
Maximization

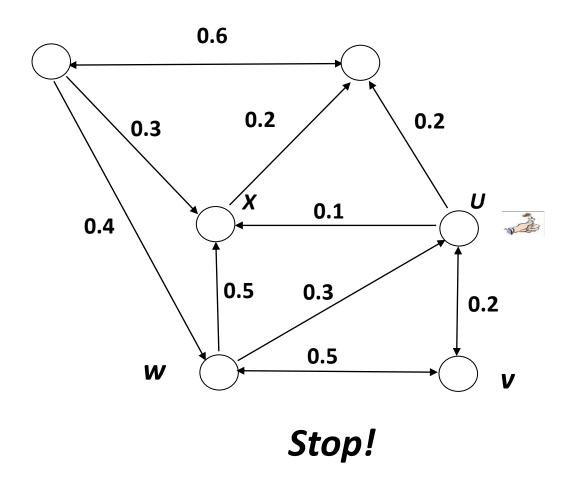
Independent Cascade (IC) Model

- When node v becomes active, it has a single chance of activating each currently inactive neighbours w.
- The activation attempt succeeds with probability p_{vw} .

- Key features
 - Propagation
 - Attenuation



IC Propagation Example



Inactive Node

Active Node

Newly active node

Successful attempt

Unsuccessful attempt

attempt

Linear Threshold (LT) Model

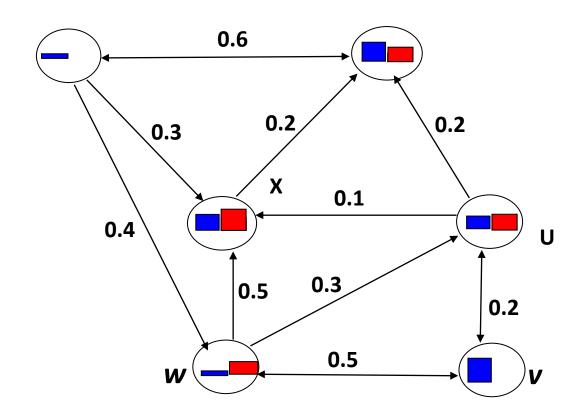
- Linear Threshold (LT) Model.
 - A node v has random threshold $\theta v \in [0, 1]$
 - A node v is influenced by each neighbour $w, w \in \Gamma(v)$, according to a weight $b_{v,w}$

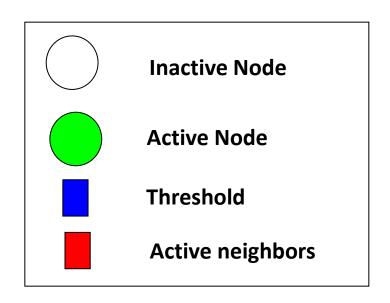
 $\sum_{w \in \Gamma(v)} b_{v,w} \le 1$

• A node v becomes active when at least (weighted) θ_v fraction of its neighbours are active

$$\sum_{w \in \Gamma(v)} b_{v,w} \ge \theta_v$$

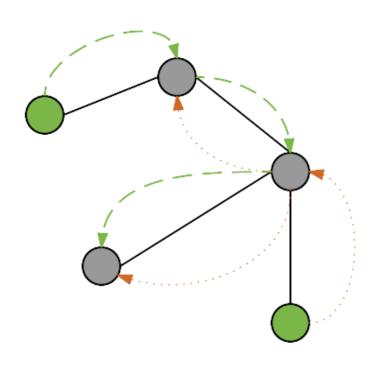
LT Propagation Example



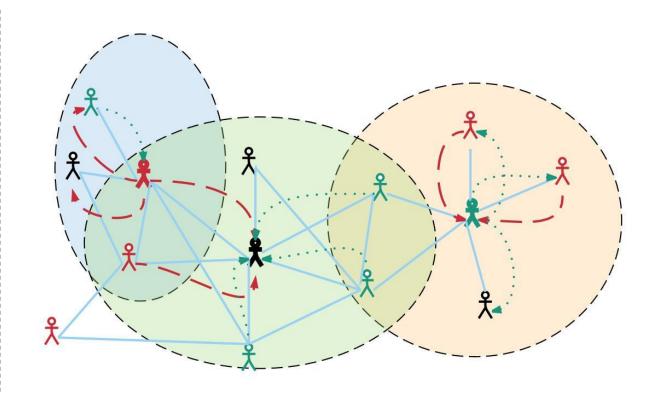


Stop!

Agent-based Influence Diffusion

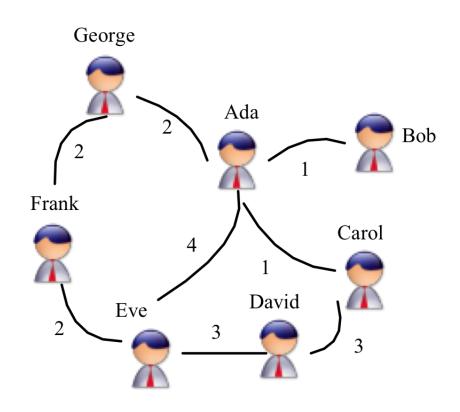


The classic influence diffusion models Independent Cascade (IC) Model / Linear Threshold (LT) Model



Agent-based Influence Diffusion Model (Li proposed in IEEE International Conference on Agents, ICA 2016)

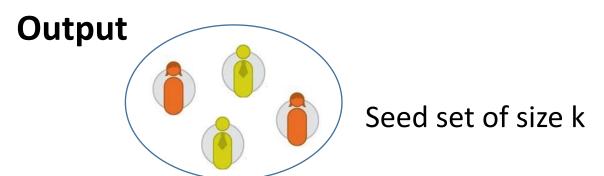
Influence Maximization Problem



Social graph with influence probabilities of edges

Problem

- Select k individuals such that by activating them, the expected spread of influence is maximized.
- The selection process is called seed selection
- The identified set of users is named as seed set



Classic Seed Selection Algorithms

Objective

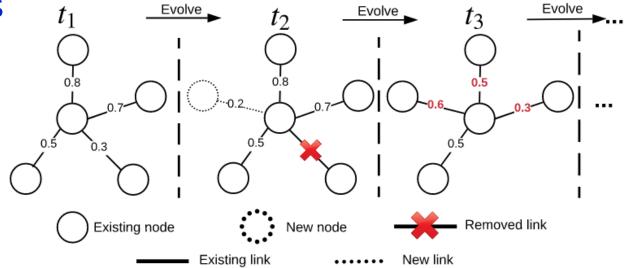
- Achieve the maximum influence by selecting a set of limited users as seed set.
- The overall influence through the network impact as many users as possible.
- The seed set is regarded as an assembled "team" and influence propagation becomes a "team work", rather than individual performance.

Traditional Seed Selection Approaches

- Random Selection: Select the users randomly.
- Ranking-based Selection: Rank the users based on the node degree and select top k users.
- Greedy Selection: Obtain the maximum influence marginal gain in selecting each seed.

Key Challenges

- Large-scale social networks
 - Huge number of nodes
 - Huge number of links
- Dynamics
 - Users join and quit
 - Links form and vanish

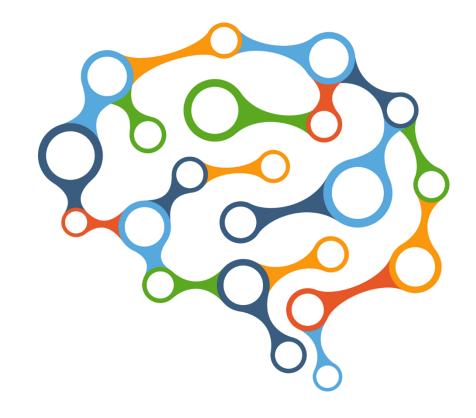


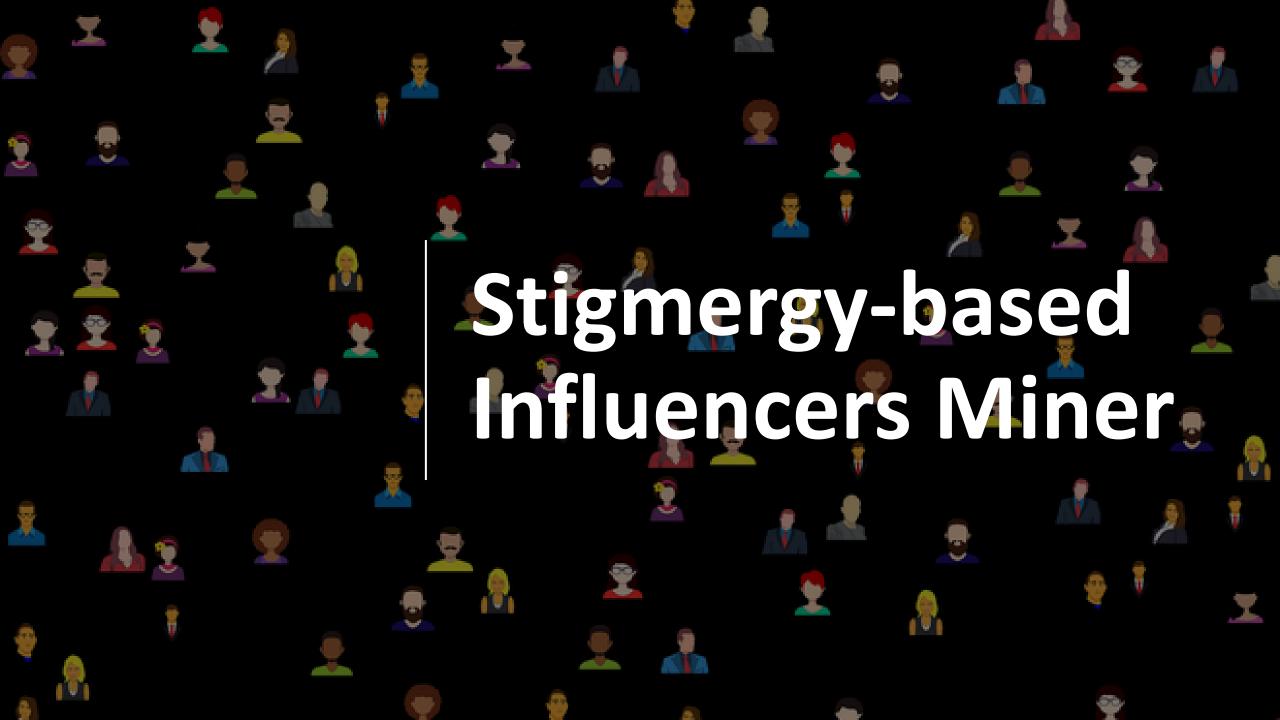
- Recalibration
 - Network evolves faster than some of the traditional seeding algorithms
 - Re-launch seeding algorithms takes time

Proposed Approach

- Decentralised agent-based modelling:
 - Share the computational cost
 - Multiple agents work in parallel

- Evolutionary computing:
 - Continuously optimise the solution and handle the dynamics of largescale social network.

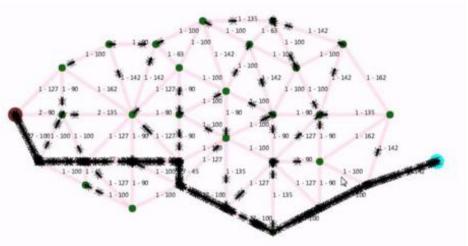




Preliminary – Ant and Stigmergy Algorithms

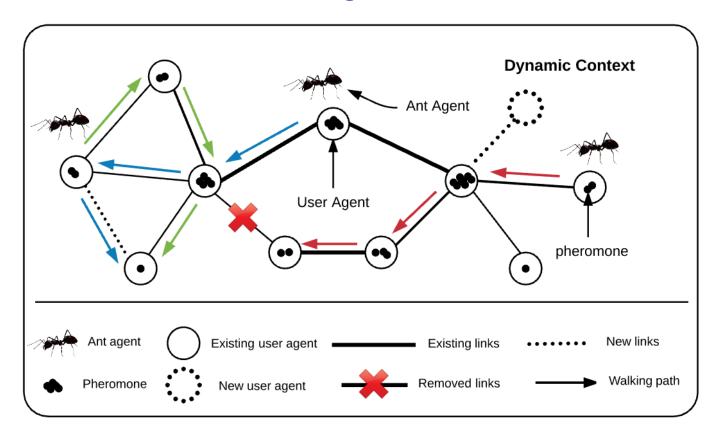
- Multi-Agent System (MAS)
- Indirect communications stigmergic interactions
- The individuals of the species conduct communications and pass signals to others via a chemical substance, i.e., pheromone





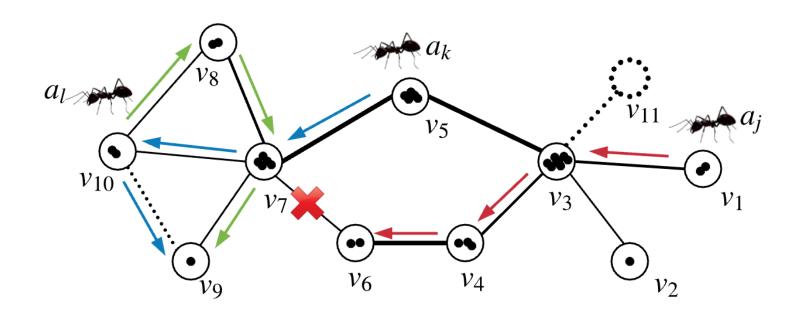
SIMiner – Stigmergy-based Influencers Miner

- Social network is modelled as the environment of ant agents.
- Influence diffusion process is modelled as ants' crawling behaviours.
- The objective of an ant is to explore the potential influential nodes from the network.
- Ants leave the pheromone on the nodes as messages, which can be referred by their peers.

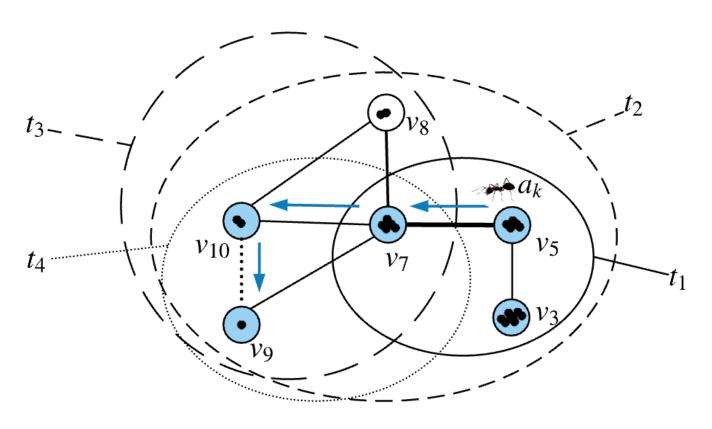


An Annotated Dynamic Social Network

- Numerous ant agents crawl simultaneously and update the shared environment by allocating pheromones on the nodes
- The pheromone amount distributed by an ant to a node is proportional to the contribution of the node in the tour.



SIMiner – Agent's Local View



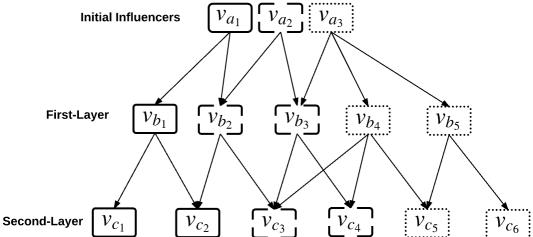
- Each ant agent has a local view, which keeps changing over time.
- The local view only cover the node and its corresponding neighbours.
- Ants keeps walking until reach the "end" of the network.

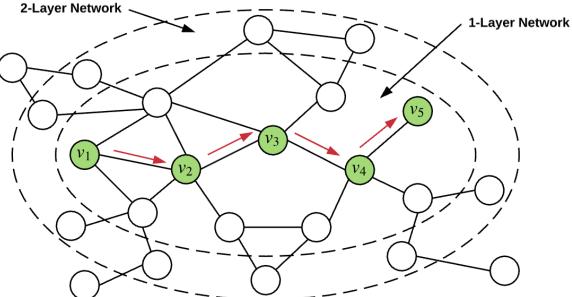
SIMiner - Sub-networks Generation

 Each ant agent captures a N-layer subgraph after completing a tour.

Simulate the number of influence cascade levels

 We use the following diffusion model to estimate the contribution of each node





SIMiner – Operations

Tour Formation

 Path Selection. Probability of an ant clawing from node i to node j is affected by both the edge weight and pheromone amount

$$q_{ij} = \begin{cases} \frac{(e_{ij}.w)^{\alpha} \cdot (v_{j}.p)^{\beta}}{\sum_{v_x \in \Gamma(v_i) \setminus T} (e_{ix}.w)^{\alpha} \cdot (v_x.p)^{\beta}}, & e_{ij} \in v_i.E \\ 0, & e_{ij} \notin v_i.E, \end{cases}$$

 Skip. Many central nodes are clustered together and it is not necessarily to target all of them. Skip the node is common neighbour ratio is greater than a threshold

$$\eta_{ij} = \frac{|(v_i) \cap (v_j)|}{|(v_j)|}.$$

SIMiner – Operations (cont.)

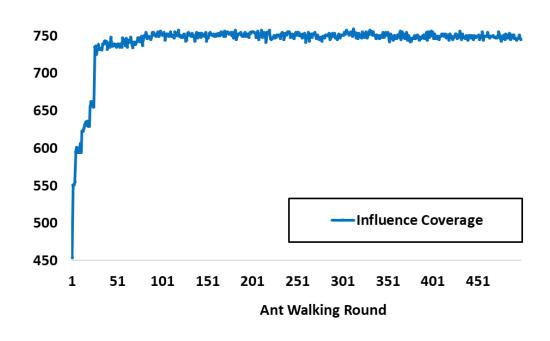
Pheromone Evaporation

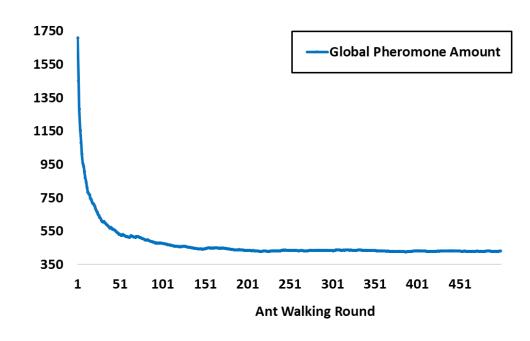
- Amount of allocated pheromone decreases over time
- Delay the faster convergence
- Avoid to converge to a locally optimal solution

$$v_j.p(n+1) = v_j.p(n) \cdot \rho_n$$

$$\rho_n = 1 - \sqrt{\frac{n}{n+a}}.$$

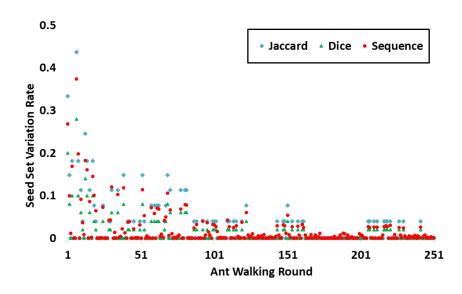
Experiment 1 - Convergence Analysis



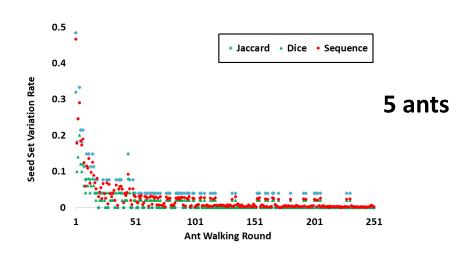


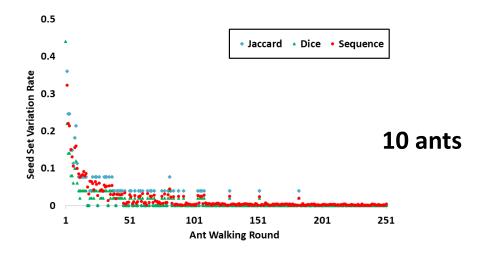
Experiment 1 - Convergence Analysis

Seed set (solution) variation

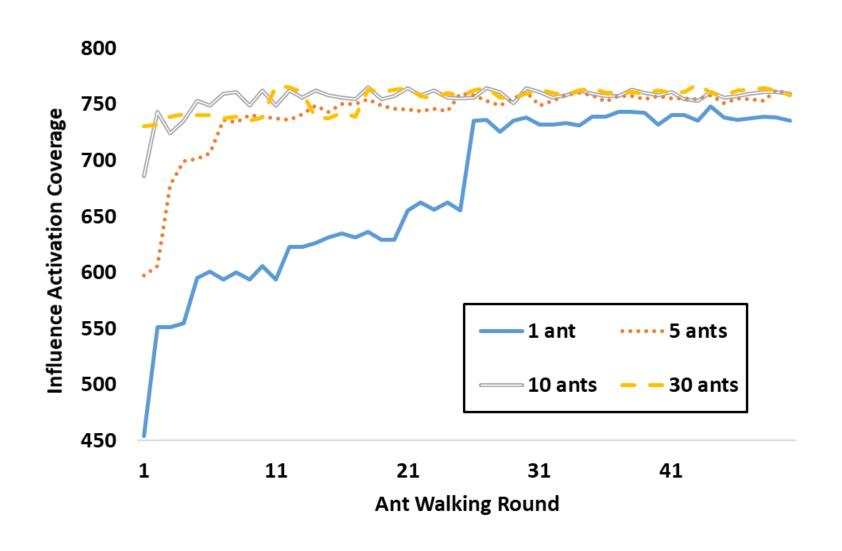


Single ant

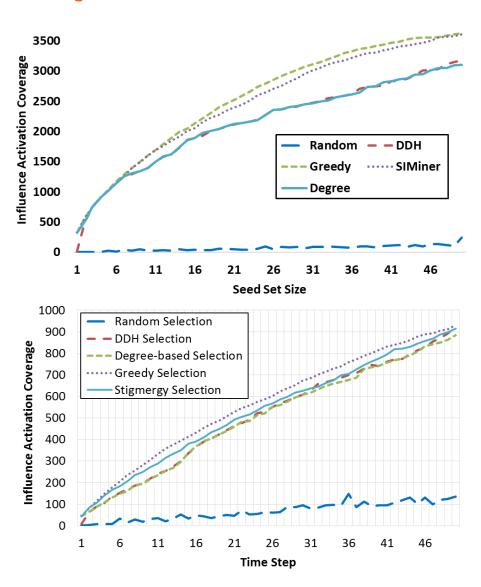


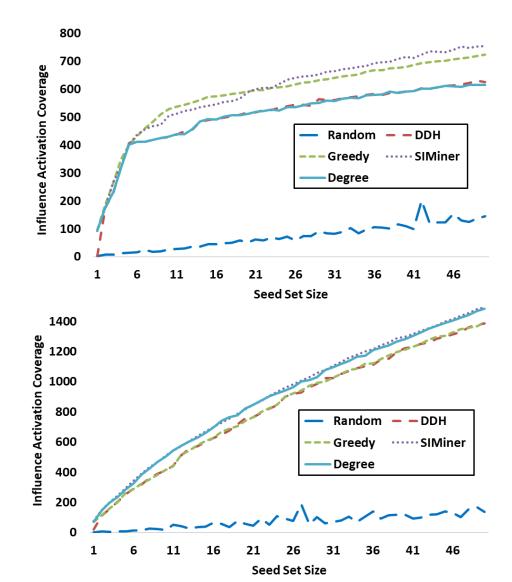


Experiment 2 – Time to Converge

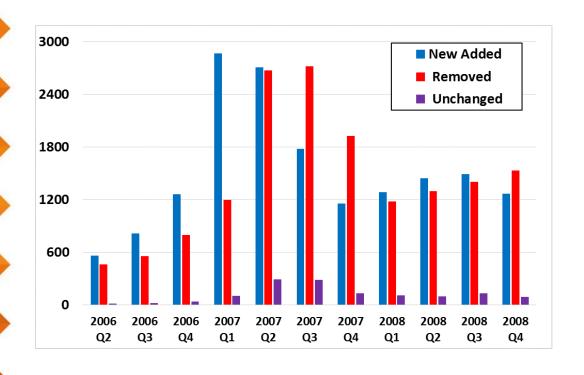


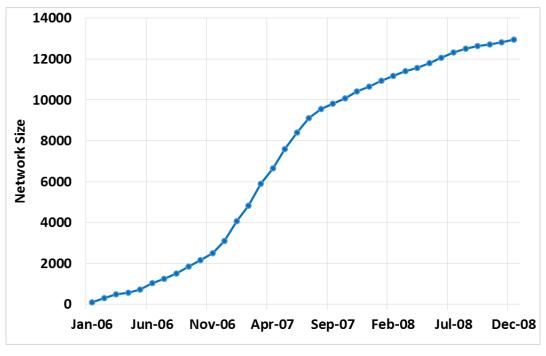
Experiment 3 – SIMiner in Static Networks



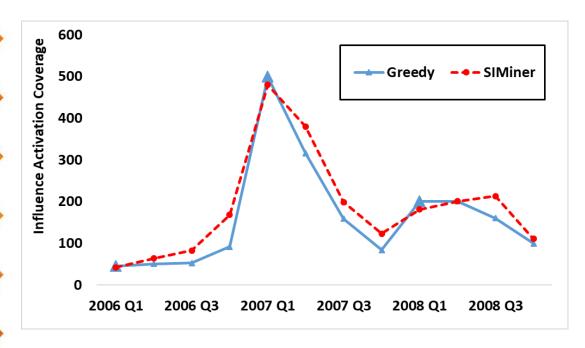


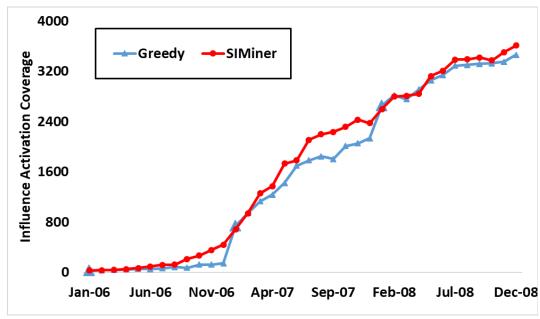
Experiment 4 – Datasets





Experiment 4 – SIMiner in Dynamic Networks





Quarterly changes

Monthly changes

Conclusion

- Continuously adapt to the dynamic environment (social networks)
- Multiple ants work together
- Distribute the computational cost and handle dynamics
- Identification of influencers based on the pheromone amount
- Better performance
- More efficient handle Big Data

Reference

- Li, W., Bai, Q., & Zhang, M. (2019). SIMiner: a stigmergy-based model for mining influential nodes in dynamic social networks. *IEEE Transactions on Big Data*, 5(2), 223-237.
- Li, W., Bai, Q., & Zhang, M. (2019). A multi-agent system for modelling preference-based complex influence diffusion in social networks. *The Computer Journal*, 62(3), 430-447.
- Li, W. (2018). Comprehensive modelling of influence diffusion in complex social networks, an agent-based perspective. (Auckland University of Technology, New Zealand). Retrieved from http://156.62.60.45/handle/10292/11904