

# A Game Theoretic Approach to Influence Limitation Problem

Final Presentation

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# Two different problems

## [1] Virus Inoculation problem

To identify the nodes in the graph with a constraint on the number of nodes such that vaccination of those nodes would result in a minimum number of infected nodes

## [2] Limitation of Misinformation Problem

- Given:
  - Negative campaign/misinformation which starts from specified sources and detected after time delay  $d$
  - Presence of positive/counter campaign to limit the former
- To Find: Top  $k$  suitable nodes where the positive campaign is to be triggered

# Three Major Contributions

## [1] Virus Inoculation: Preventive Methods (Before Infection)

- Compare game theoretic centralities with conventional centralities
- Propose a solution in non-submodular probabilistic setting

## [2] Virus Inoculation: Reactive Methods (After Infection)

- Propose a novel reactive model for virus inoculation problem
- Propose two algorithms in the above setting
- Propose another model and proof for NP-hardness

## [3] Limitation of Misinformation

- Propose a novel characteristic function
- Proposed heuristic outperforms existing heuristics

## Virus Inoculation in Probabilistic Model

### The Probabilistic Model:

- Model assumes probabilistic infection with vaccination cost ( $C$ ) = infection cost ( $L$ )
- $f_s(T)$  be the the number of nodes that get infected by initial infected set  $S$
- $f(T) = \sum_{S \subseteq V(G)} q(S) f_s(T)$  where  $q(S)$  is the probability of set  $S$  to get infected initially and so,  $q(S) = \prod_{i \in S} q_i \prod_{i \notin S} (1 - q_i)$
- Problem: Choose set  $T$  of  $k$  nodes to minimize  $f(T)$

### Definition (Submodular Function)

For every subset  $S, T$  of  $V(G)$  where  $S \subseteq T$  and any node  $v$ ,  
 $f(S \cup \{v\}) - f(S) \geq f(T \cup \{v\}) - f(T)$  (for supermodularity the inequality is reversed)

### Lemma

$f(T)$  in the probabilistic model is not submodular.

### Reference

Zeinab Abbasi and Hoda Heidari, "Toward Optimal Vaccination Strategies for Probabilistic Models," in *Proceedings of the 20th International Conference on World wide web, WWW*; 2011, pp. 1-2.

# Game Theoretic Approach

## Key Points

- How does game theoretic centrality improve the solution?
- Game theoretic centrality vs conventional degree centrality

Characteristic Function  $\nu_1 : 2^N \rightarrow \mathbb{R}$

$$\nu_1(C) = \begin{cases} 0 & \text{if } C = \emptyset \\ \text{size}(\text{victim}(C)) & \text{else} \end{cases}$$

$\text{victim}(C)$

$\{v : v \in C \text{ or } \exists u \in C \text{ such that } (u, v) \in E(G)\}$

## Reference

JPo-An Chen, Mary David and David Kempe, "Better Vaccination Strategies for Better People," in *Proceedings of the 11th ACM Symposium on Electronic Commerce, EC*; 2010, pp. 294–301.

## Degree Centrality vs Game Theoretic Approach

### Shapley Value

$$\phi(v_i) = \sum_{w_i \in \{v_i\} \cup N_{G_o}(v_i)} \frac{1}{1 + \deg_{G_i}(w_i)}$$

where

$$N_{G_o}(v_i) = \{u \in V(G) : (v_i, u) \in E(G)\}$$

$$N_{G_i}(v_i) = \{u \in V(G') : (u, v_i) \in E(G)\}$$

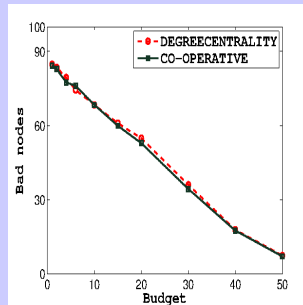
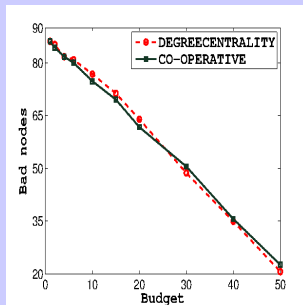
$$\deg_{G_o}(v_i) = |N_{G_o}|$$

$$\deg_{G_i}(v_i) = |N_{G_i}|$$

### Improvement

Shapley value is more for nodes with higher degree and nodes whose neighbours are weak

# Results



## Figure

Bad (Infected) nodes (percentage of nodes) versus budget (percentage of nodes) using Football and Celegans data set

## Proposed Preventive Method Based Algorithm: SVPM

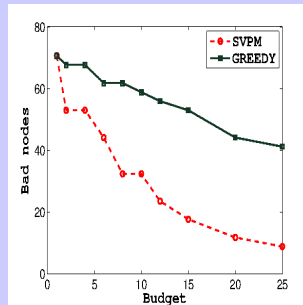
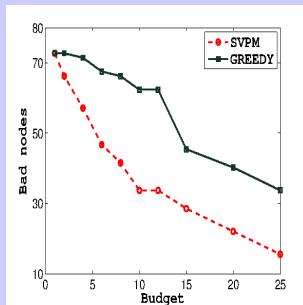
### Key Points

- Compare greedy algorithm vs SVPM
- SVPM: Greedy approach in game theoretic sense
- Solve an optimization problem using co-operative game theoretic tool
- Shapley value based concept which is agnostic to submodularity
- Characteristic Function:  $\nu_2(C) = n - f(C)$
- Running Time: Similar





# Results



Figure

Bad(Infected) nodes (percentage of nodes) versus budget (percentage of nodes) using Karate and Celegans data set

## Model to Capture Reactive Methods

### Model: General Cascade Model, GCM

- Take motivation from Independent Cascade Model(ICM)
- Infection starts at one node and spreads following ICM
- Detected at time delay  $d$
- Some nodes get vaccinated and remove from graph
- Again infection progress following ICM
- Problem: to find nodes to give vaccination

#### Reference

D. Kempe, J. Kleinberg and E. Tardos, "Maximizing the spread of influence through a social network," in *Proceedings of the 9th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, KDD*; 2003, pp. 137-146.



# Proposed Model to Capture Reactive Methods

## Issues

- No models for virus inoculation have reactive strategy
- Assume  $C = L$
- Introduce one kind of probability: Infection probability,  $p_{uv}$

## Problem Formulation:

- $g : S \rightarrow [0, n]$  where  $S = \{W | W \subset V \text{ and } |W| \leq k\}$ .
- The goal is to find a set  $W (|W| \leq k)$  of nodes to vaccinate after  $d$  to maximize  $g(\cdot)$

## Lemma

*Underlying function  $g$  in this model is not submodular.*



## Two Algorithms: SVRM and TRM

### SVRM

- Based on Global Method
- Find most powerful nodes in the network based on infection probability
- Running Time:  $O(qR(n + m) + n \log n)$  where  $q$  and  $R$  are number of permutations and iterations respectively

### TRM

- Based on Local Method
- Find most likely nodes to be infected next
- Running Time:  $O(k(n + m) + n \log n)$



## Two Algorithms: SVRM and TRM

## SVRM

$$\nu_3(C) = \sigma(C) \quad \forall C \subseteq N$$

where  $\sigma(C)$  gives the expected number of infected nodes if  $C$  is the initial infected set

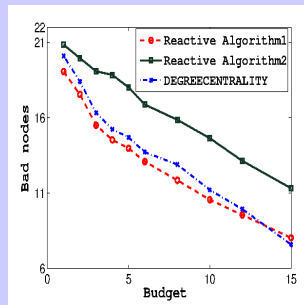
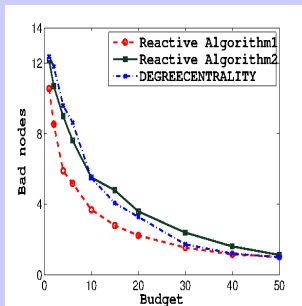
## TRM

$$f_t(\Delta_{nxt}) = \sum_{T \in \Gamma(G')} \prod_{(u,v) \in T} p_{uv}$$

where  $|\Delta_{nxt}| = k$  and  $\Gamma(G')$  is set of trees in  $G'$  with infected nodes and  $\Delta_{nxt}$



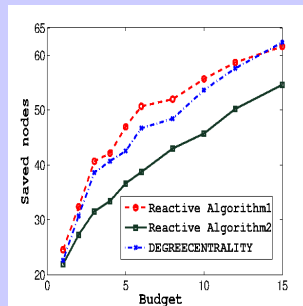
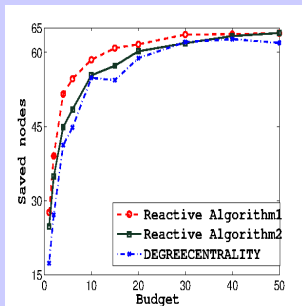
# Results



Figure

Bad nodes (percentage of nodes) versus budget (percentage of nodes) using Football and Jazz data set

# Results



Figure

Saved nodes (percentage of nodes) versus budget (percentage of nodes) using Football and Jazz data set

## Model to Capture Reactive Methods

### Model: Modified General Cascade Model, MGCM

- Assumption on GCM
- Neighbours of vaccinated nodes are also saved
- Problem: to find nodes to give vaccination

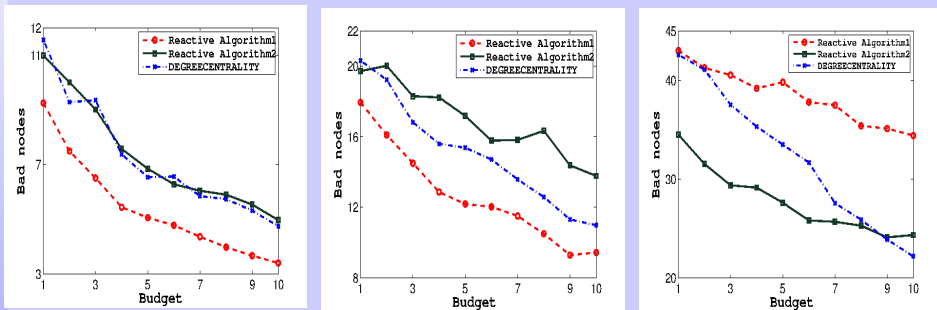
### Lemma

*Virus inoculation problem under MGCM is NP-hard*





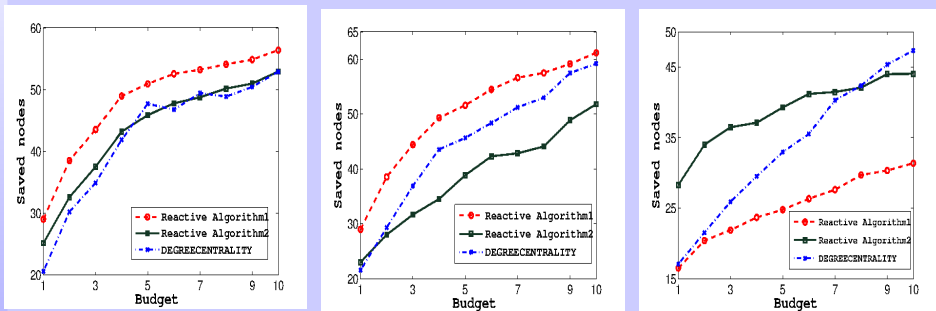
# Results



Figure

Bad nodes (percentage of nodes) versus budget (percentage of nodes) using Football, Jazz and elegans data set

# Results



**Figure**  
 Saved nodes (percentage of nodes) versus budget (percentage of nodes) using Football, Jazz and elegans data set

## Model

### Limiting Misinformation Problem

- The problem is first proposed by Budak, Agarwal and Abbadi
- More generalized version is proposed and solved by Prem Raj

### Limiting Misinformation vs Virus Inoculation

- Limiting rumour does not involve costs
- No question of preventive methods, only involves reactive methods
- Unlike virus inoculation problem, positive influence is used to limit misinformation

### Reference

- [1] Ceren Budak and Divyakant Agrawal and Amr El Abbadi, "Limiting the Spread of Misinformation in Social Networks," in *Proceedings of the 20th International conference on World Wide Web, WWW*; 2011, pp. 665–674.
- [2] H Prem Raj and Y. Narahari, "Influence Limitation in Multi-Campaign Social Networks with Non-Submodular Influence Functions: A Shapley Value Based Approach," in *Proceedings of IEEE conference on Automation Science and Engineering (CASE)*; 2012

## Our Algorithm

### Key Points

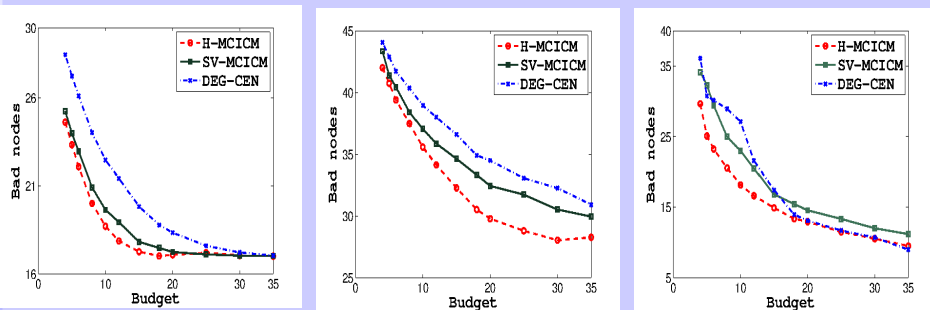
- Work with MCICM
- Algorithm uses Shapley value
- Novel characteristic function
- To stop the powerful nodes of negative campaign
- To trigger positive influence to the powerful nodes of positive campaign

### H-MCICM

$$\nu_4(C) = \sigma_R(C) + \sigma_G(C) \quad \forall C \subseteq N$$

where  $\sigma_R(C)$  and  $\sigma_G(C)$  give the expected number of nodes misinformed and influenced by positive campaign respectively

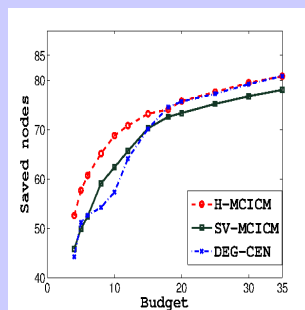
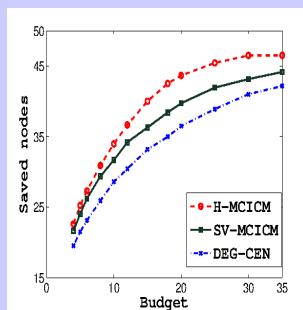
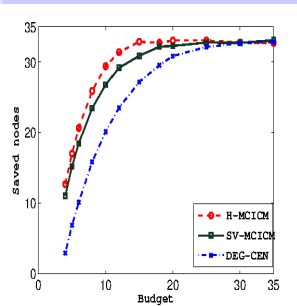
# Results



Figure

Bad nodes (percentage of nodes) versus budget (percentage of nodes) using Football, Jazz and elegans data set

# Results



## Figure

Saved nodes (percentage of nodes) versus budget (percentage of nodes) using Football, Jazz and elegans data set

# The Whole Picture

- Preventive Method for virus inoculation:
  - Work with probabilistic model
  - Minimization problem
  - Underlying function is not submodular
  - Any tool which does not depend on submodularity will work well
- Reactive Method for virus inoculation:
  - No model captures reactive strategies
  - Maximization problem
  - Underlying function is not submodular
  - Propose two methods to solve the problem



# The Whole Picture

- Reactive Method for virus inoculation:
  - Modify the model with extra assumption
  - The problem under this model is NP-hard
- Modified Algorithm for Limiting Misinformation
  - Maximization problem
  - Underlying function is not submodular
  - Propose novel characteristic function





# The Path Ahead: 1 of 2

## Game Theoretic Aspects

- Incorporating Costs and Game: Does Nash Equilibrium exist?
  - If yes, how far is it from social optimum?
  - If no, what will be the social optimum?
- Network Formation: Developing a network of suitable characteristics which makes vaccination more effective.



# The Path Ahead: 2 of 2

## Algorithmic Aspects

- Special Structures:
  - Submodular functions can be well approximated by constant factor
  - In both cases underlying functions are non-submodular
  - Designing some algorithms which can well approximate certain kinds of network with some special graphical structures
- Agnostic Approximation Algorithm: Designing a good approximation algorithm which is agnostic towards underlying nature of the function



THANK YOU !!

