Adaptive diffusion of sensitive information in social network

YUCHENG LU

2017.06.07

Introduction

Adaptive Diffusion

- Entropy maintenance
- Network structure(BA, informed and uninformed)

Prediction of information cascading

- Feasibility and Strategy

Reinforcement Learning

- Cascading Evaluation
- Cost Minimization

System Models

- Dynamic Routes Model
- Informed and Uninformed Network
- Multi-arm Bandit

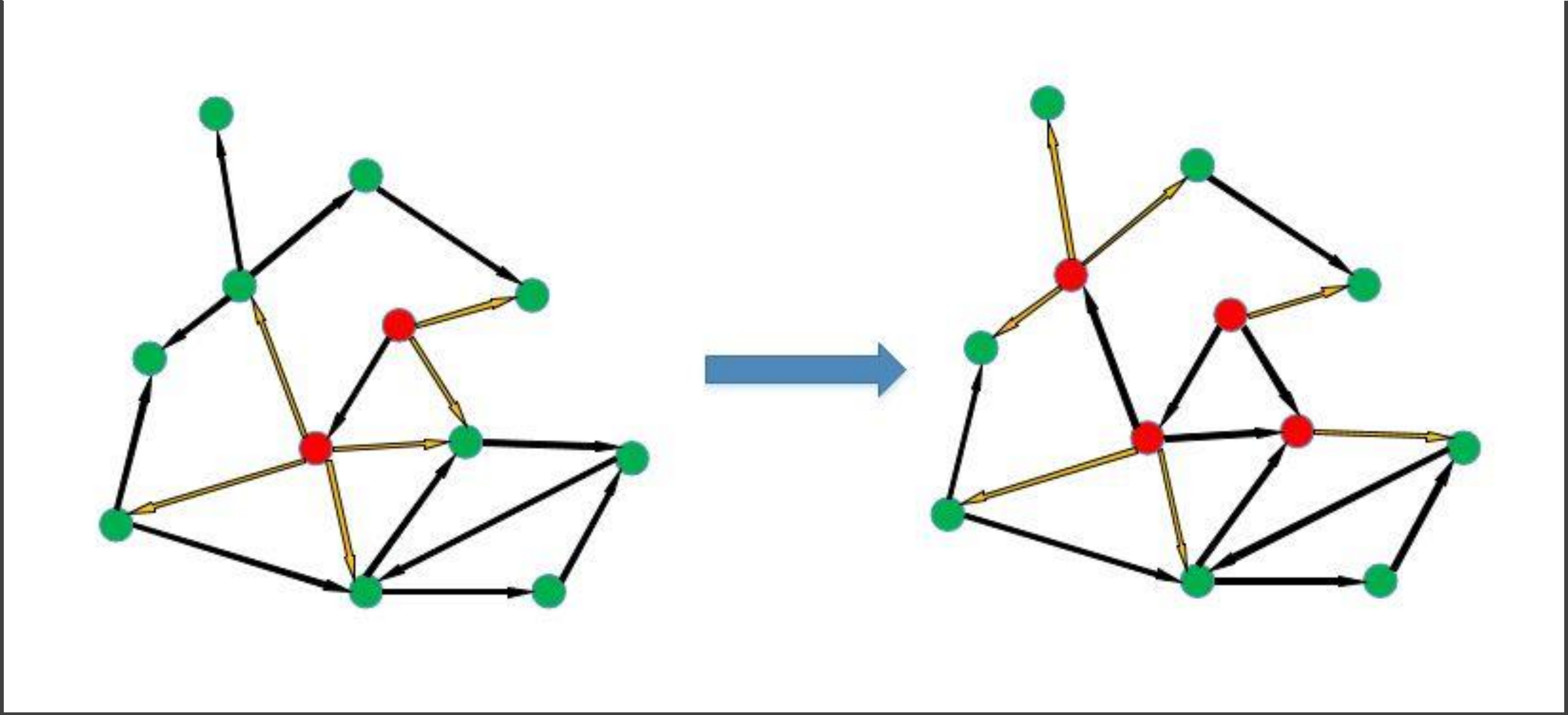
Informed Network

Question

$\mathbb{M}$ users are tolerated to receive the sensitive information at time τ

- Why
- What
- How

Dynamic Routes Model



Cascading Potential

Definition 1 : Define $\aleph_j^k$ as the set of the k-hop neighbors of node j. And node j's cascading power function $F(u,t)$ as:

$$F(u,t) = d_u + \sum_{v \in \aleph_u^1} \beta_v F(v,t)$$

Upper Bound

Lemma 1 : Given $S(0)$ and $\partial S(0)$, the total number of nodes receiving the sensitive information at time t is upped bounded by

$$|S(0)| + \frac{|\partial S(0)|}{d_{max}^2} \left[4\left(\frac{5}{4}\right)^{t-1} - 3 \right]$$

Adaptive Function

Definition 2 : Define the adaptive function $\mathcal{A}(t)$ as:

$$\mathcal{A}(t) = \sum_{u \epsilon \partial S(t)} \Delta\beta_u |\partial(S(t), u)| \, \mathrm{F(u)}$$

Lower Bound

Lemma 3 : Adaptive diffusion is subjected to optimal substructure properties.

Lemma 4 : (τ, M) requirement is achievable if and only if output of **Adaptive Cascading Algorithm** is able to satisfy the requirement.

Adaptive Cascading Algorithm

Adaptive Cascading Algorithm

Input $l, G, \tau, M, \mathrm{S(t)}, \partial\mathrm{S(t)}$

For $t \leftarrow 1$ **to** τ

$\Delta\boldsymbol{\beta}(\boldsymbol{t}) \leftarrow argmax\{A(l,t)\}$

$\boldsymbol{\beta}'(\boldsymbol{t}) \leftarrow \boldsymbol{\beta}(\boldsymbol{t}) + \Delta\boldsymbol{\beta}(\boldsymbol{t})$

$\mathrm{S(t)} \leftarrow \mathrm{S(t-1)} + \mathrm{cascading(G, t)}$

End

Output $\mathrm{S}(\tau)$

Limitations and Target

Limitations:

$$\left|\Delta\beta_j - \beta_c\right| \leq 0\,, j \in \partial S(t)$$

$$\sum_{j=1}^{|\partial S(t)|} \Delta\beta_j = 0$$

Target:

$$\delta = \sum_{j=1}^{|\partial S(t)|} \Delta\beta_j^2$$

Transition

$$\sum_{j=1}^{|\partial S(t)|} (\beta_j + \Delta\beta_j) d_j^2 = C(\gamma + \Delta\gamma)$$

where:

$$C \triangleq \frac{\sum_{i\in S(t)} \frac{d_i}{\sum_1^N d_m} \left(1 - \sum_{i\in S(t)} \frac{d_i}{\sum_1^N d_m}\right)}{\left(\sum_{i\in S(t)} \frac{d_i}{\sum_1^N d_m} - \sum_{i\in N\setminus S(t)} \frac{d_i}{\sum_1^N d_m}\right) D}$$

Convex Optimization Problem

Minimize:

$$\delta = \sum_{j=1}^{|\partial S(t)|} \Delta\beta_j^2$$

Subject to:

$$\sum_{j=1}^{|\partial S(t)|} \Delta\beta_j d_j^2 = C\Delta\gamma$$

$$\sum_{j=1}^{|\partial S(t)|} \Delta\beta_j = 0$$

$$\left|\Delta\beta_j - \beta_c\right| \leq 0\;, j \in \partial S(t)$$

Steepest Descent Algorithm

Steepest Descent Algorithm

Initiate $\lambda_0,\ \Delta\beta_0$

$k \leftarrow 0$

$d_0 \leftarrow argmin\{\nabla\delta(\Delta\beta_0)^T d\}$

While

    If $bounded$ or $d_k = 0$

        Break

    Else

        $k \leftarrow k+1$

        $d_k \leftarrow argmin\{\nabla\delta(\Delta\beta_{k-1})^T d\}$

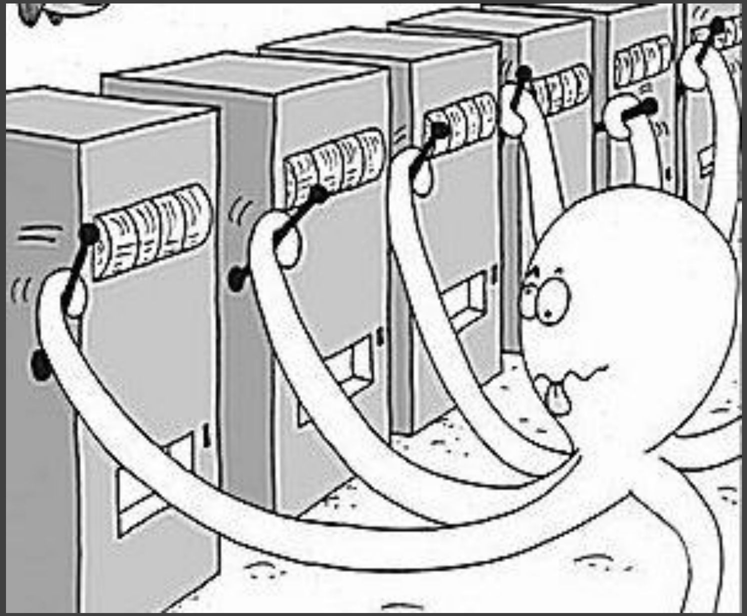
        $\lambda_k \leftarrow argmin\{\delta(\Delta\beta_{k-1} + \lambda_{k-1} d_{k-1})\}$

        $\Delta\beta_k \leftarrow \Delta\beta_{k-1} + \lambda_k d_k$

End

Uninformed Network

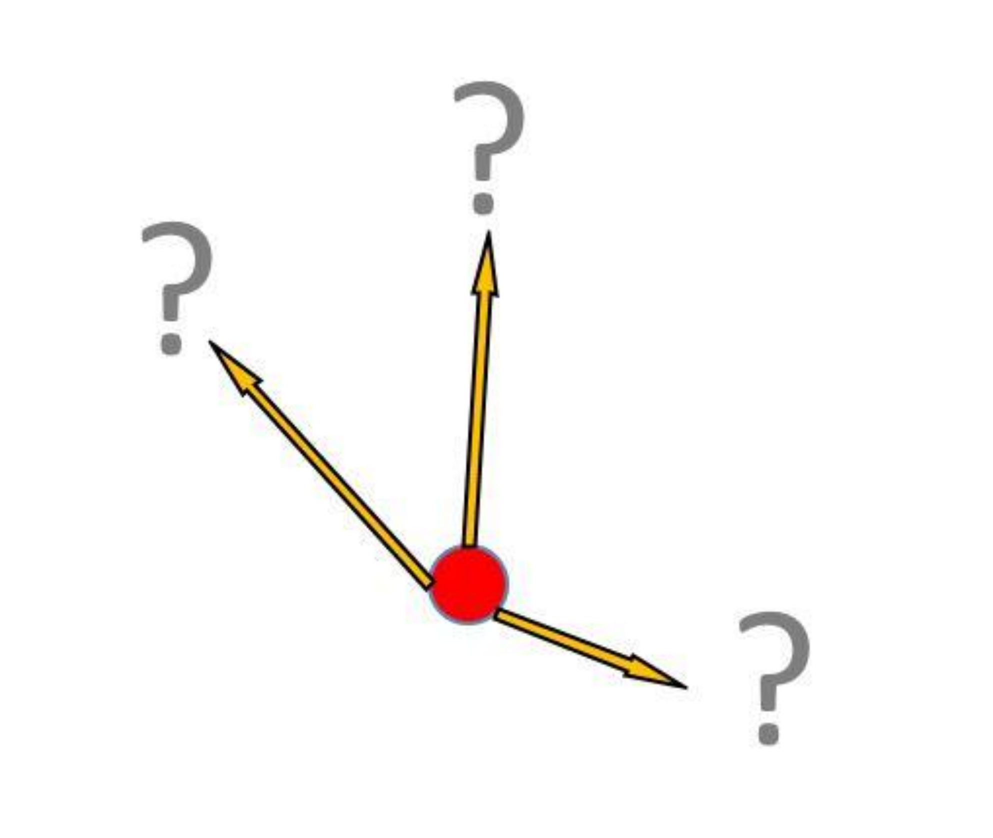
Multi-arm Bandit



Get the most out of your experiment

Get to know your neighbors

Explore and Exploit



K.Y.N. Algorithm

$A \leftarrow \{\}$
$R \leftarrow \mathbf{0}^{|A|}$
$T \leftarrow time$
For $i \in \partial S(t)$
  For $j \in \partial S(t) \backslash \{i\} \cap \{k \mid p(k) < p(i)\}$
    If $\frac{p(i)+p(j)}{2} > \frac{\beta_{min}+\beta_{max}}{2}$
      $p'(i) \leftarrow \beta_{max}$
      $p'(j) \leftarrow p(i) + p(j) - \beta_{max}$
      action $\leftarrow \{p'(i), p'(j)\}$
    Else
      $p'(i) \leftarrow p(i) + p(j) - \beta_{min}$
      $p'(j) \leftarrow \beta_{min}$
      action $\leftarrow \{p'(i), p'(j)\}$
    $A \leftarrow$ action
  End
End
While True
  If $t \leq threshold$
    If $random(0,1) < \varepsilon$
      $action \leftarrow random(A)$
    Else
      $action \leftarrow argmax_a[Q_t(a) + c\sqrt{\frac{\ln(t)}{N_t(a)}}]$
    $R \leftarrow influence(action)$
    $Q_{t+1} \leftarrow (1-\alpha)^n Q_1 + \sum_{i=1}^{t} \alpha(1-\alpha)^{t-i} R_t$
  Else
    $action \leftarrow argmax_a[Q_t(a)]$
End

Experiment: $\varepsilon - greedy$

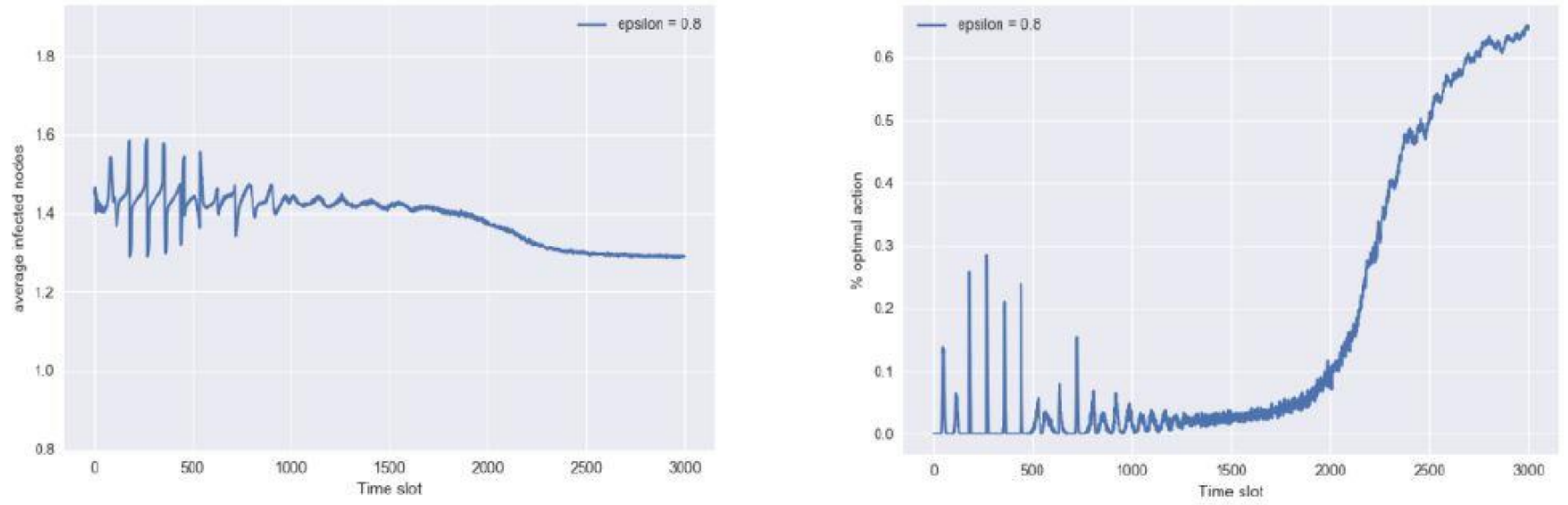


Fig 5. $\varepsilon - greedy$ method for Power-Law graph(ε = 0.8)

Experiment: $\varepsilon - greedy$

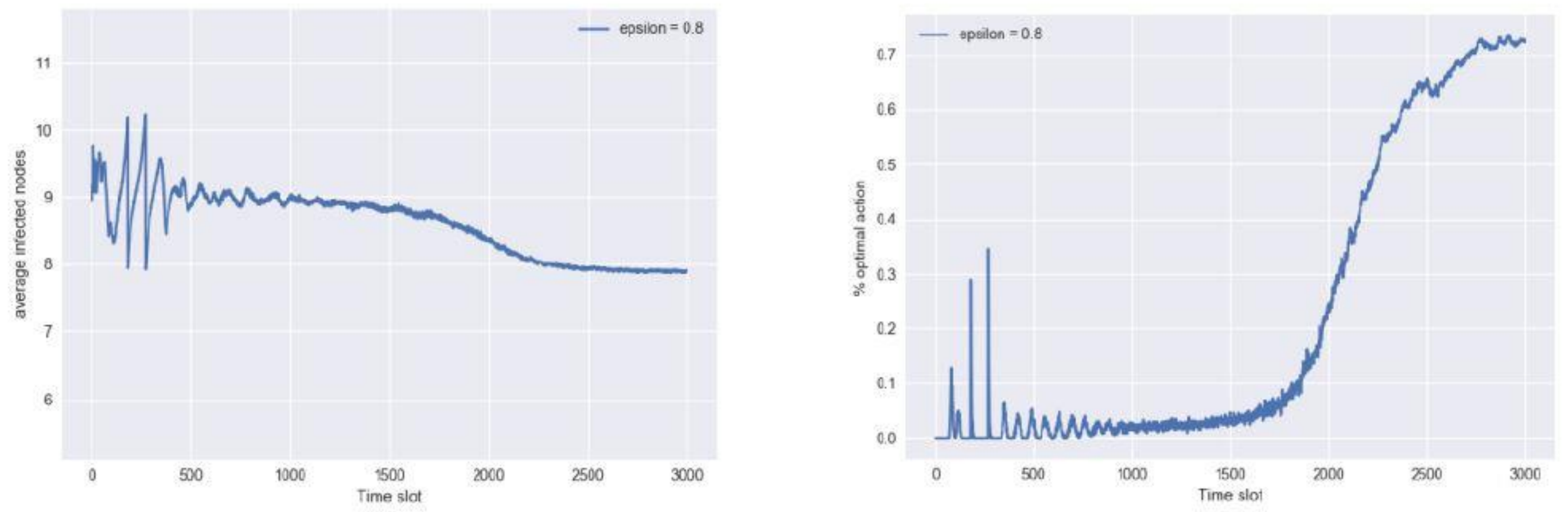


Fig 6. $\varepsilon - greedy$ method for random graph($\varepsilon = 0.8$)

Experiment: *Upper Confidence Bound*

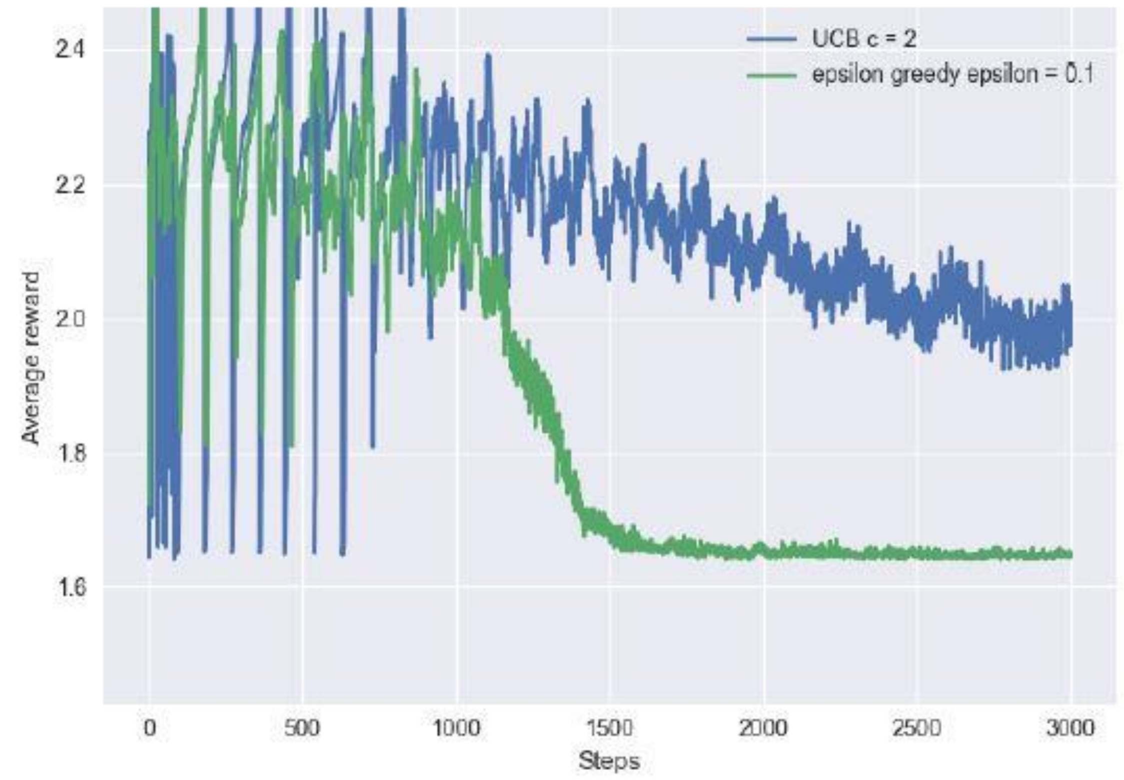


Fig 10. Comparison using UCB strategy

Experiment: Initial Value Adjustment

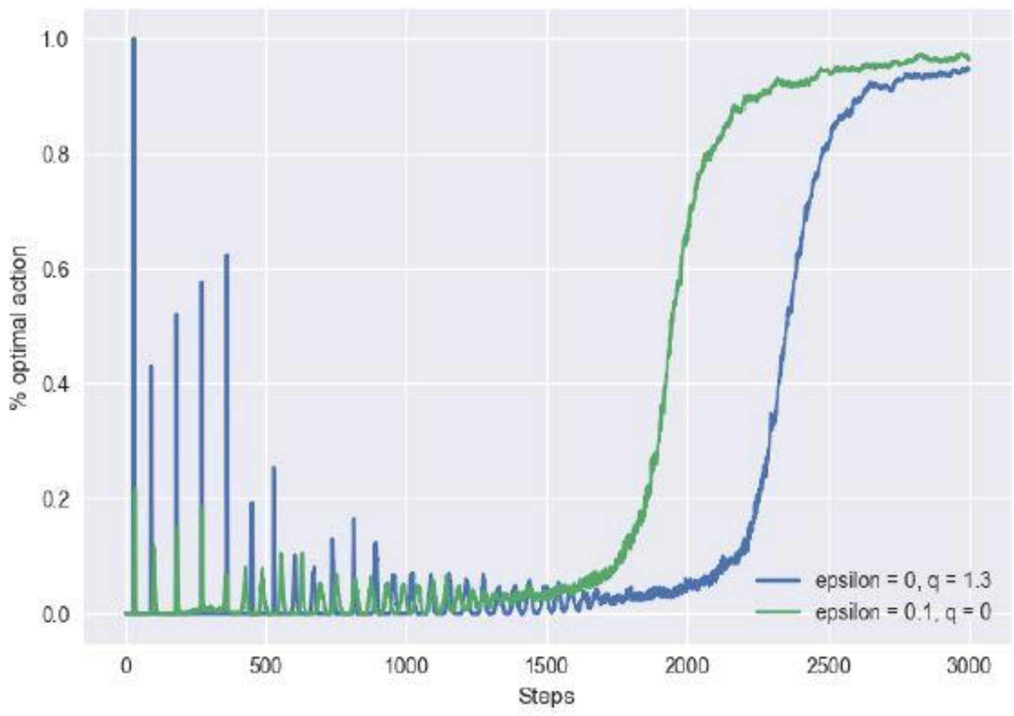


Fig 9. Initial value setting comparison

Conclusion

In this paper, I analyze the how the probability adjustment between nodes in the social network influences the cascading of sensitive information. I propose Dynamic Routes Model and Multi arm bandit Model to analyze the situation in informed network and uninformed network, respectively. Besides, I also design Steepest Descent Algorithm and K.Y.N Algorithm to propose optimal solution of protecting sensitive information via probability transmission between nodes.

Future Work

In the future, I plan to discuss the dynamic network and do more research on threshold phenomenon in the multi arm bandit model.

Q&A