Learning Cascaded Influence under Partial Monitoring

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ASONAM, 2016

Outline

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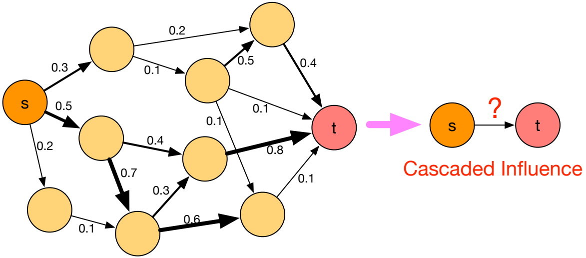
Social Influence

- Social influence is the phenomenon that people's opinions, emotions or behaviors are affected by others
- Application: viral marketing, propaganda, advertising promotion...

Outline

Cascaded Indirect Influence

- Social influence between non-adjacent users in the social network



Direct Influence Network

- Application: friend recommendation, link prediction, ...

Challenges

- Information about non-adjacent users is rare
- The number of potential paths between two users is exponentially large
- Most of the previous works infer the direct influence from the cascade data – **partial, sparse and dynamic**

Cascaded Indirect Influence

Given a dynamic influence network $G_t = (V, E, W_t)$

- Direct influence

$$w_{e,t} = \sum_i e^{-(t-\tau_i)/\delta}$$

- Influence path from u to v

$$I_t(p_i) = \prod_{e \in p_i} w_{e,t}$$

- Influence probability v is activated by u indirectly

$$I_t = 1 - \prod_{i=0}^{N} (1 - I_t(p_i)) = \sum_{i=0}^{N} I_t(p_i) + o(I_t(p_i))$$

Omit the high-order terms of $I_t(p_i)$ and take the top-k terms of the first-order $I_t(p_i)$

Cascaded Indirect Influence

Definition

Cascaded Indirect Influence. The cascaded indirect influence from u to v is defined as the sum of the top k influence score among all the paths in $\mathcal{P}$,

$$I_t = \max_{Q \subset \mathcal{P}} \sum_{p_i \in Q} I_t(p_i)$$
$$\text{s.t. } |Q| = k$$

Partial Monitoring Setting

- The number of the intermediate paths are exponentially large – Intractable to learn indirect influence from all the paths
- Partial Monitoring Setting & Online Learning

Problem

$$\min_{decision} \frac{1}{T}\left(\max_{Q \subset \mathcal{P}} \sum_{p_i \in Q} \sum_{t=1}^{T} I_t(p_i) - \sum_{t=1}^{T} \hat{I}_t(\mathcal{D}_t)\right)$$

$$s.t.\ |Q| = k$$

Partial Monitoring Setting

Problem

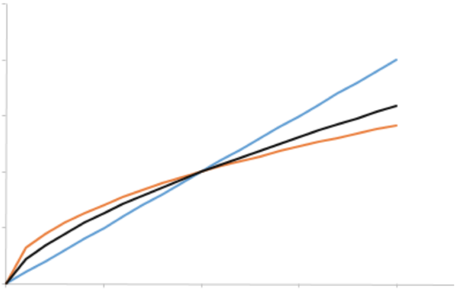
$$\min_{decision} \frac{1}{T}(\max_{Q \subset \mathcal{P}} \sum_{p_i \in Q} \sum_{t=1}^{T} I_t(p_i) - \sum_{t=1}^{T} \hat{I}_t(\mathcal{D}_t))$$

$$s.t. \ |Q| = k$$

- **Regret**
- **Normalized Regret**

Regret

- Growth rate of the Regret



- Our Goal

Algorithm – E-EXP3

Algorithm 1: E-EXP3

Input : The edge set E, The path set $\mathcal{P}$, initialize $w_{e,0} = 1$ for each $e \in E$, $\overline{w}_{i,0} = 1$ for each $i \in \mathcal{P}$, normalization factor $\overline{W}_0 = |\mathcal{P}|$, mixing coefficient $\gamma > 0$, learning rate $\eta > 0$

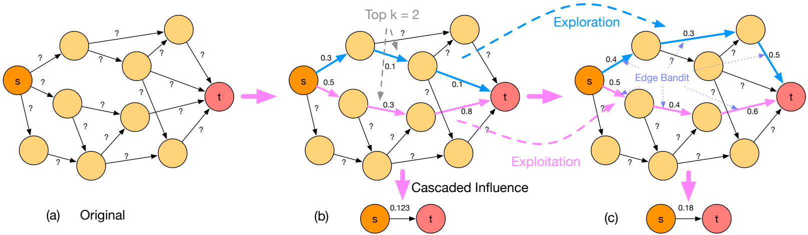
Output: The set of k paths $\mathcal{D}_T$ chosen at the time T

$t \leftarrow 1$
while $t \leq T$ **do**
  foreach $i \in \mathcal{P}$ **do**
    if $i \in \mathcal{C}$ **then**
      $p_{i,t} \leftarrow (1-\gamma)\frac{\overline{w}_{i,t-1}}{\overline{W}_{t-1}} + \frac{\gamma}{|\mathcal{C}|}$
    else
      $p_{i,t} \leftarrow (1-\gamma)\frac{\overline{w}_{i,t-1}}{\overline{W}_{t-1}}$
  foreach $e \in E$ **do**
    $q_{e,t} \leftarrow \sum_{i:e\in i} p_{i,t}$

Algorithm – E-EXP3

$\mathcal{D}_t \leftarrow Sample(p_t, k)$
Observe $g_{e,t}$ of the edges included in $\mathcal{D}_t$
foreach $e \in i \in \mathcal{D}_t$ **do**
  $w_{e,t} \leftarrow w_{e,t-1} e^{\eta g_{e,t}/q_{e,t}}$
foreach $i \in \mathcal{P}$ **do**
  $\overline{w}_{i,t} \leftarrow \prod_{e \in i} e^{\eta g_{e,t}/q_{e,t}}$
$\overline{W}_t \leftarrow \sum_{i \in \mathcal{P}} \overline{w}_{i,t}$
$t \leftarrow t + 1$

Algorithm – E-EXP3 Example



(a) Original (b) (c)

- **Exploration & Exploitation**

Algorithm Theory Analysis

- Parameter

$$mixing\ \ coefficient:\ \ \gamma=\sqrt{\frac{|\mathcal{C}|\ln N}{(e-1)T}}$$

$$learning\ \ rate:\ \ \eta=\frac{1}{K}\sqrt{\frac{\ln N}{(e-1)|\mathcal{C}|T}}$$

- Regret Upper Bound

$$2K\sqrt{(e-1)T|\mathcal{C}|\ln N}$$

- More Proof Details: http://www.jiaqima.me/papers/learning-cascaded-influence.pdf

Algorithm – RE-EXP3

Algorithm 1: Preprocessing Schedule of RE-EXP3

Input : Preprocessing Round T_p γ, K, $|\mathcal{C}|$

Output: η

$\eta \leftarrow \gamma / K|\mathcal{C}|$

$\mathcal{G} \leftarrow \emptyset$

foreach t *in range*(T_p) **do**

  Choose $\mathcal{D}_t$ with E-EXP3

  $\mathcal{G} \leftarrow \mathcal{G} \cup \{g'_{i,t} : i \in \mathcal{D}_t\}$

$\eta \leftarrow \eta \times \min\{\frac{1}{mean(\mathcal{G})+3var(\mathcal{G})}, 1\}$

Outline

Experiments: Datasets

- Synthetic Networks
  - 2000 vertexes
  - edge generation probability 0.01
  - edge weight U[0, 0.3] or U[0.6, 1]
  - 60,000 times
- WeiBo
  - 1,776,950 users
  - 308,739,489 following relationships
  - 23,755,810 retweets
  - 100 time stamps
- Aminer
  - 231,728 papers
  - 269,508 authors
  - 347,735 citation relationships
  - 44 time stamps

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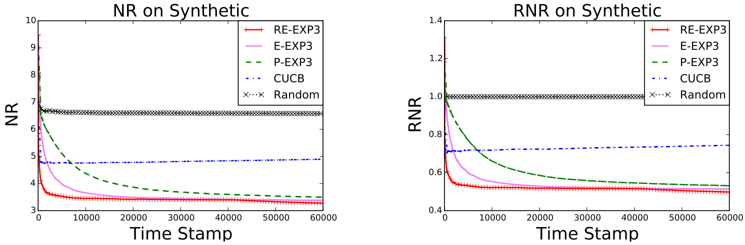
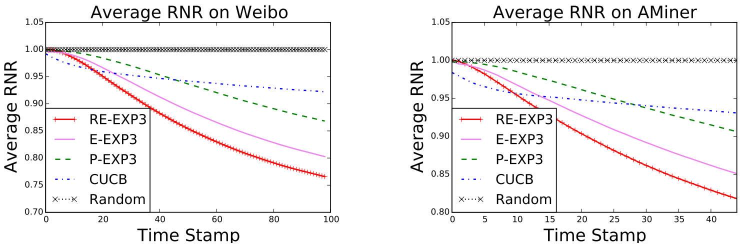
Experiments on Normalized Regrets(Synthetic)



(a) NR (b) RNR

Figure: Normalized Regret on Synthetic Data

Experiments on Normalized Regrets(Weibo & Aminer)



(a) Average RNR on Weibo (b) Average RNR on AMiner

Figure: Average Normalized Regret on real social networks (1500 pairs of users)

Outline

Experiments on Application Improvement(Weibo)

Table: Application Improvement - Logistic Regression

Methods	Accuracy	Precision	Recall	F1 score
PF	0.55	0.58	0.45	0.51
P-EXP3	0.57	0.58	0.55	0.57
E-EXP3	0.59	0.61	0.55	0.58
RE-EXP3	**0.64**	**0.65**	**0.63**	**0.64**
FO	*0.70*	*0.77*	*0.60*	*0.68*

Table: Application Improvement - SVM

Methods	Accuracy	Precision	Recall	F1 score
PF	0.58	0.57	**0.72**	**0.63**
P-EXP3	0.56	0.58	0.53	0.55
E-EXP3	0.58	0.60	0.55	0.57
RE-EXP3	**0.63**	**0.65**	0.61	**0.63**
FO	*0.70*	*0.77*	*0.57*	*0.66*

Conclusion

- Formalized a novel problem of cascade indirect influence based on IC model
- Proposed two online learning algorithms (E-EXP3 and RE-EXP3) in the partial monitoring setting
- Theoretically proved that E-EXP3 has a cumulative regret bound of $O(\sqrt{T})$.
- Compared the algorithms with three baseline methods on both synthetic and real networks (Weibo and AMiner).
- Applied the learned cascaded influence to help behavior prediction