

Active Opinion Maximization in Social Networks

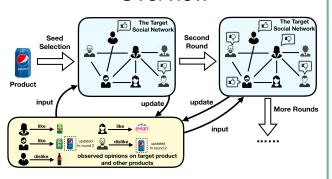




Xinyue Liu, Xiangnan Kong Worcester Polytechnic Institute

Philip S. Yu University of Illinois at Chicago

Overview



Objective: finding the optimal seed selection for each round under the given budget that maximizes the total opinion spread.

Diffusion Model: Linear Threshold (LT), we extend it to multiround setting (MLT). It could be changed to Independent Cascade (LT) effortlessly.

Opinion Model: We assume that each user has inherent opinion towards product/item, which does not affected by his/her neighbors.

Side Information: We use the observed opinions on other products expressed by users (the yellow box in the figure) to help modeling the user profile. The profile of target item (Pepsi in the figure) is learned gradually and actively from round to round.

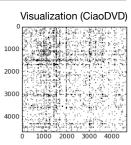
Applications: Online marketing campaign, brand reputation building, market segmentation, etc.

Dataset

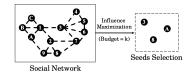
	# Nodes	# Edges	# Items	# Ratings	Linkage
Flixster	5,372	58k	3,470	110k	undirected
CiaoDVD	4,658	40k	16k	72.6k	directed

- · Threshold: randomly assign to users in the network via a uniform distribution.
- · Weights: quantify using Jaccard Coefficient

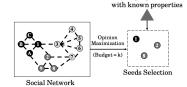
$$w_{ij} = \frac{|\Gamma_{\rm in}(u_i) \cap \Gamma_{\rm out}(u_j)|}{|\Gamma_{\rm in}(u_i) \cup \Gamma_{\rm out}(u_j)|}$$



Influence Maximization

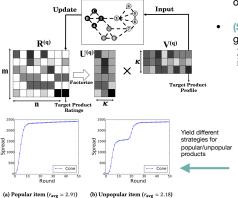


Opinion Maximization Target product

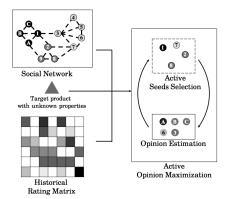


- (Q1) How to fuse opinion maximization with information diffusion?
- (Q2) How to perform opinion maximization while users' opinions are mostly unknown?
- (Q3) How to minimize negative opinions spread?
- (Q4) How to tackle the hardness (NP-hard) of the proposed problem?

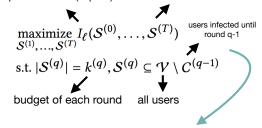
• (S2) Active Learning on Target Product



Active Opinion Maximization



opinion function(implicit) seeds of each round



(S1) We employ multi-round linear threshold (MLT) as the diffusion model, and we adjust the objective function for maximizing opinion instead of influence spread.

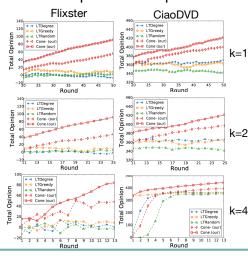
(S3, S4) CONE wisely avoid negative user groups by using greedy search:

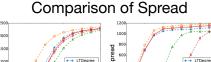
```
Algorithm 1 Greedy Algorithm for Opinion Maximization
Require: social network G = (V, \mathcal{E}), target product p_t, estimated
       ratings vector \hat{\mathbf{r}}^{(q)}, seed user size for current round k^{(q)}, the
       set of active users C^{(q-1)}
  1: initialize S^{(q)} \leftarrow \emptyset
  2: while V \setminus (C^{(q-1)} \cup S^{(q)}) \neq \emptyset \land |S^{(q)}| \neq k^{(q)} do
           for each u in \mathcal{V} \setminus (C^{(q-1)} \cup \mathcal{S}^{(q)}) do
                 S \leftarrow C^{(q-1)} \cup S^{(q)} \cup \{u\}
                 propagate influence up to \ell\text{-layer} with seeds \mathcal S to obtain
       the set of activated users C
                 O \leftarrow \sum_{u_i \in C} (\hat{r}_i^{(q)} - r_{\text{neutral}})
                 if O > O_{\text{max}} then
                       O_{\text{max}} \leftarrow O, u_{\text{hart}} \leftarrow u, C_{\text{hart}} \leftarrow C
           S^{(q)} \leftarrow S^{(q)} \cup \{u_{\text{best}}\}, C^{(q)} \leftarrow C_{\text{best}}
 13: end while
 14: Return S(q)
```

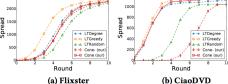
Number of +/- Opinions

Methods	# pos. (↑)	# neg. (↓)	# pos # neg. (↑)	rank		
	Flixster					
LTrandom	1278.00 (4)	1146.92 (4)	170.67(4)	4.00		
LTdegree	1274.00 (5)	1109.00 (3)	165.00(5)	4.33		
LTGREEDY	1363.08 (1)	1277.30 (5)	216.15(2)	2.67		
Cone-	1283.16 (3)	1082.50 (1)	200.63(3)	2.33		
Cone	1328.00 (2)	1098.88 (2)	229.13(1)	1.67		
	DVD					
LTrandom	648.09 (5)	451.40 (2)	196.61 (5)	4.00		
LTDEGREE	749.66 (2)	544.46 (4)	205.22 (3)	3.00		
LTGREEDY	788.85 (1)	588.27 (5)	200.65 (4)	3.33		
Cone-	658.44 (4)	430.84 (1)	227.61 (2)	2.33		
Cone	743.01 (3)	490.61 (3)	252.47 (1)	2.33		

Comparison of Opinion







Acknowledgements: This work is supported in part by National Science Foundation through grant IIS-1718310, MRI-1626236, IIS-1526499, IIS-1763325, and CNS-1626432.