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İşaretli Sosyal Ağlarda Etki Maksimizasyonu İçin Yeni Bir Aç Gözlü Algoritma

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ÖZET

Sosyal etki insanların görüşlerini şekillendiren büyük olgulardan biridir. Bu bakımdan, Etki Maksimizasyonu (EM) problemi viral pazarlama, kamuoyu şekillendirme gibi pratik faydaları olduğu için sosyal ağ analizinde en fazla ilgili çeken araştırma alanlarından biridir. EM probleminin amacı bir sosyal ağ üzerindeki etkili kişi olarak adlandırılan az sayıdaki kişiyi kullanarak bir etkinin (bir fikir veya reklam) ağ üzerindeki yayılımını maksimize etmektir. Etkili kişilerin tespiti birçok durumda NP-Zor bir olasılıksal en iyileme problemidir. Bundan dolayı, EM problemi için birçok algoritma geliştirilmiştir ve geliştirilmeye devam etmektedir. Ne var ki, geliştirilen algoritmalar henüz çözüm kalitesi ve hız açısından istenen seviyede değildirler. Bu çalışmada, bireyler arasındaki olumlu ve olumsuz ilişkileri göz önünde bulunduran işaretli EM problemine odaklanılmıştır. Bu amaçla, en iyi k adet etkili kişiyi tespit etmek için Elitist Aç Gözlü Algoritma (EGA) olarak adlandırılan bir aç gözlü algoritma geliştirmiştir. EGA'nın performansı 2 adet açık veriseti üzerinde rasgele seçim, çıkış derecesi merkeziliği, ve bir güncel algoritma ile kıyaslanmıştır. EGA çözüm kalitesi açısından rakiplerine göre daha iyi sonuçlar vermiştir.

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A New Greedy Algorithm For Influence Maximization On Signed Social Networks

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ABSTRACT

The social influence is one of the major phenomenons that shape people's decisions. In this respect, Influence Maximization (IM) problem is one of the most attractive research topics in the social network analysis because its practical benefits in viral marketing, public opinions shaping etc. The IM problem aims to maximize the spread of an influence (e.g. an opinion, an advertisement) in a social network by using a small number of the most effective individuals, whom is called influencers. Detecting the influencers is the NP-Hard combinatorial optimization problem in most cases. Therefore, many algorithms have been and are being developed for the IM problem. However, the algorithms have not yet achieved to the desired solution quality and speed. In this study, we focused on the signed IM problem that considers both positive and negative influence between the individuals. For this purpose, we developed a greedy algorithm called the Elitist Greedy Algorithm (EGA) for detecting top-k influencers set. We compared the EGA's performance on 2 public datasets with random seed selection, out degree heuristic, and one state-of-the-art greedy algorithm. The EGA outperforms the competitors in terms of the achieved total influence.

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1. INTRODUCTION *(GİRİŞ)*

Online Social Networks (OSNs) are the digital world equivalent of real social networks. In this respect, many phenomena in real social networks are also present in OSNs. In a real social network (for example, in a friendship), people are influenced by each other's opinions and recommendations. This influence can be negative or positive. The same applies to OSNs. A person can adopt and disseminate the ideas, recommendations, and suggestions of a friend or a person he/she follows. For such a situation, OSNs have an advantage over real social networks. In OSNs, information will spread much faster than in real social networks. Actors (a product vendor or a politician) who want to benefit from this advantage may want to influence the maximum number of people in OSNs. This problem is known as Influence Maximization (IM). The key point here is to identify people who have the maximum capacity to propagate the desired influence on the OSN. Once these people have been identified, the desired influence can be initiated from these people (i.e. the influencers) and spread across the network. In a more formal description, the IM problem is the detection of top-k influencers that will maximize the propagation of a desired influence on a social network modeled as Graph G under a particular propagation model (analytical model showing how information is spread over a network) [1], [2]. The IM problem has been formulated as a combinatorial optimization problem, and its complexity is NP-Hard under many propagation models such as Independent Cascade (IC) model and Linear Threshold (LT) model [2]–[4]. Also, there are numerous the IM studies that handled on these propagation models as reviewed under the related work section.

A social network, on the other hand, can have positive relationships (e.g. friend or trust), as well as negative relationships (e.g. distrust) [5], [6]. There is a difference between maximizing the influence in unsigned social networks, and in signed social networks. All the relationship (positive and negative) between people in signed networks should be modeled and a propagation model should be used to reflect this situation. In this case, the problem is named as polarity-related influence maximization (PRIM) problem which aims to maximize positive influence or maximize negative influence in signed social networks [6]. Ignoring the sign of relationship between users may lead to miss-estimation of the influence. Hence, we need a propagation model for modeling the signed relationship between users in a social network. For this purpose, some propagation models have been developed for modelling signed relationships in a social network [6]–[10]. In this study, we focused on the signed IM problem that is relatively new and challenging. We developed the Elitist Greedy Algorithm (EGA) for detecting top-k influencers set. We adopted Polarity-related Independent Cascade (IC-P) as propagation model [6]. We compared the EGA's performance on 2 public datasets with random seed selection, out degree heuristic, and the greedy algorithm (named as IC-P Greedy) that is defined in [6]. The EGA outperforms the competitors in terms of the achieved total influence.

2. RELATED WORK (*İLGİLİ ÇALIŞMALAR*)

The Influence Maximization (IM) is the problem of finding a small number of S seed individuals that affect the largest number of individuals on a network [2]. The problem can be written as a function: $f(S) = \max(|A|)$ for $S \subseteq V$. Here S is the set of seed nodes; A is the set of influenced nodes by S; V is the set of all nodes on the network. The IM problem is NP-Hard, and a lot of algorithms that adopts different approaches have been proposed for detecting influencers set. We categorize these studies into 2 titles: greedy approaches and combinatorial optimization approaches.

2.1. Greedy Approaches (*Aç Gözlü Yaklaşımlar*)

Greedy approaches mostly adopt the following strategy: rank the nodes according to a metric, and then pick the top-k nodes as seed set. This metric may be indirect indicators (heuristics) of the influence capacities of nodes such as centrality measures, or direct indicators of influence capacities of nodes. Kempe et. al's greedy algorithms one of the most well-known algorithms on the IM problem [2]. Briefly, it picks node one-by-one according to their contribution to spread influence on the network. This approach affected most of the following studies. Leskovec et. al, developed an algorithm called CELF (Cost-Effective Lazy Forward) [11]. Using the sub modularity of the influence function, it doesn't reassess the nodes' contribution to the total influence spread. This significantly reduces the computation time of the algorithm. Chen et. al, have developed an efficient greed algorithm called NewGreedyIC [12]. In each iteration, NewGreedyIC removes all the edges that placed on unsuccessful spreading path network, and creates a reduced network. In the same paper, the authors have proposed DegreeDiscount algorithm under the IC model [12]. It assumes that the propagation probability of each edge is equal. The DegreeDiscount algorithm decreases the degree of a node one by one if its neighbor is in the seed set. Lu et. al., have suggested another discount algorithm called CascadeDiscount that reduces time complexity of greedy algorithm to solve the IM problem [13]. Abbassi et al. have developed a TwoStage (TS) algorithm [14]. The TwoStage consists of 2 stages:

first choose top n nodes in the scope of influence spread. Then, pick the remaining nodes by their influence capabilities. Liu et. al., have developed a greedy algorithm for the IM problem [15]. It constructs the set of spreading paths. Then, it picks the nodes that maximize marginal gain one-by-one. Chen et. al., have developed an integrated PageRank to the signed IM problem [16]. Li et al. have developed an algorithm for the IM problem using community detecting approaches [17]. It firstly partitions the network into n communities, and then it picks the most central nodes in each community as a seed. Li et.al., have dealt with signed influence maximization problem, and suggested a more appropriate propagation model called Polarity-related Independent Cascade (IC-P) [6]. Also, they have developed a greedy algorithm called the IC-P Greedy. The IC-P Greedy selects one node on the each iteration that provides the maximum marginal gain in the total influence. The IC-P Greedy outperforms random, out-degree, and the IC-Greedy algorithm that is an adopted version of CELF to the signed IM problem. There are numerous studies in the literature on the IM problem. For a recent comprehensive survey [18] could be examined.

Briefly, we categorize the greedy approaches into 2 sub-categories: pure greedy and heuristic-based greedy. Pure greedy algorithms use simulated influence capabilities of nodes for ranking nodes. Heuristic-based greedy algorithms use centrality measures of nodes such as degree, PageRank etc for ranking nodes. Pure greedy algorithms need costly Monte Carlo simulations; however, they give an approximation guaranty. Heuristic-greedy algorithms use centrality measures as proxies (heuristics) to estimate the nodes' influence capabilities. So, they are much faster that the first category; however, their solution quality are very sensitive to the measure and the network structure.

2.2. Combinatorial Optimization Approaches (*Kombinasyonal En İyileme Yaklaşımları*)

Borgatti deals the IM problem as an combinatorial optimization problem [19]. So, seed nodes should be picked at same time. The influence power of a node when it is selected alone is not same with the influence power of the same node when it is in a seed set. This is the main reason of that the IM problem is an NP-Hard problem. In this case, the desired number of seed nodes should be selected at the same. For this purpose, the researches have utilized many optimization algorithms such as simulated annealing (SA), genetic algorithm (GA), particle swarm optimization (PSA), memetic algorithm etc. [5], [20]–[24]. In general, optimization algorithms work much slower than the greedy algorithms that use heuristics (centrality measures). On the other hand, their solution qualities are competitive. For further reading [24] could be examined.

In this study, we focused on development of a pure greedy algorithm because they give more robust and guaranteed quality. To eliminate their running time disadvantage, our algorithm (namely EGA) creates an elite group of nodes by using their individual influence capabilities, and picks the seeds among the elites one-by-one by using a discount strategy.

3. MATERIALS AND METHODS (MATERYAL VE YÖNTEMLER)

3.1. Modelling The Social Network (*Sosyal Ağların Modellenmesi*)

An unsigned social network can be defined as a directed and weighted graph $\mathrm{G} = \{\mathrm{V}, \mathrm{E}, \mathrm{W}\}$. Here, V is the set of nodes (individuals), E is the set of edges (relations), and W is the weighted adjacency matrix that defines influence diffusion probabilities between neighbor nodes. For arbitrary u and v nodes in V, the following proposition must be fulfilled: $\forall(\mathrm{u}, \mathrm{v}) \in \mathrm{E} \leftrightarrow \mathrm{W}_{\mathrm{u,v}} > 0$. A signed social network also can be defined as a directed and weighted graph, too; however, we need one more property: Polarity. So, the definition will be $\mathbb{G} = \{\mathrm{V}, \mathrm{E}, \mathrm{W}, \mathbb{P}\}$. Here V, E and W are same with in G; $\mathbb{P}$ is the sign matrix of edges. Each value in $\mathbb{P}$ is determined by (1). Please note that, $\mathbb{P}_{\mathrm{u,v}} \neq \mathbb{P}_{\mathrm{v,u}}$. For more detailed explanation of signed social networks see [6].

$$\mathbb{P}_{u,v} = \begin{cases} +1, & v\ is\ positively\ influenced\ by\ u \\ -1, & v\ is\ negatively\ influenced\ by\ u \\ 0, & v\ is\ not\ influenced\ by\ u \end{cases} \quad (1)$$

3.2. Problem Statement (*Problem Tanımı*)

Influence Maximization is defined as the problem of selecting a small number of S seed individuals to influence the largest number of individuals in a social network. Positive influence maximization is the problem of finding a small number of S seed individuals that positively affect the largest number of individuals in the network. The problem can be written as a function: $\mathrm{f}^{+}(\mathrm{S}) = \max(|\mathrm{A}^{+}|)$ for $\mathrm{S} \subseteq \mathrm{V}$. Here, S is the set of seed nodes; A^{+} is the set of positively influenced nodes by S; f^{+} is the positive influence function that returns the positive influence of S.

3.3. Propagation Model (*Yayılım Modeli*)

One of the most popular information propagation models in the literature is the Independent Cascade (IC) model [2]. Briefly, in the IC model a node can be found only in one state: active or inactive. Initially, all the nodes are inactive. If a node is influenced by another node, it becomes active. An activated node can influence other nodes and cannot return to inactive state again. It is assumed that the nodes selected as seeds are already active. In the IC model, every edge on the graph has a propagation probability between 0 and 1, $P(e) = [0,1]$ [25].

In [6], a new propagation model called as the IC-P (Polarity related IC Model) has been developed for signed social networks based on the IC Model. The IC-P model is an extension of the IC Model. In the IC-P model, if a person is activated as positively or negatively, it can influence other persons. How one person will affect another person depends on the current state of the person and the polarity of the relationship between them. Let A^{+} be the positively influenced persons set; A^{-} be the negatively influenced persons set; u and v are the neighbor nodes and u is previously activated. The state of node v is determined by (2) in the IC-P model. If node v is affected positively, it is included to A^{+}; if node v is affected negatively, it is included to A^{-}; otherwise nothing is done.

$$Activation\ state\ of\ v = \begin{cases} A^{+} = A^{+} \cup \{v\}, \mathbb{P}_{u,v} = +1\ and\ u \in A^{+} \\ A^{-} = A^{-} \cup \{v\}, \mathbb{P}_{u,v} = +1\ and\ u \in A^{-} \\ A^{-} = A^{-} \cup \{v\}, \mathbb{P}_{u,v} = -1\ and\ u \in A^{+} \\ A^{+} = A^{+} \cup \{v\}, \mathbb{P}_{u,v} = -1\ and\ u \in A^{-} \\ \quad -, \mathbb{P}_{u,v} = 0 \end{cases} \quad (2)$$

3.4. Diffusion Probability Model (*Yayılım Olasılığı Modeli*)

If we already know that the probability of influence diffusion from one node to another, we can use this information. If have no idea about this, we use existed influence diffusion probability models. In this study, we adopted the following model.

Weighted Cascade Setting (wcs): In this model, $W_{u,v} = 1/\deg^{-}(v)$, where $\deg^{-}(v)$ is the in-degree of the node v.

3.5. Developed Greedy Algorithm: Elitist Greedy Algorithm (EGA) (*Geliştirilen Aç Gözlü Algoritma: Elitist Aç Gözlü Algoritma (EGA)*)

There are very few influencers in a social network. Thus, it is not necessary to assume that all the nodes are influencer candidates in a social network graph [26]. The EGA eliminates the weak nodes, and then applies greedy approach and discount strategy for selecting seed set. The EGA picks all the nodes one-by-one as seed node, and repeats the propagation 20.000 times in each iteration [1]. Only one node is selected as the seed in one iteration. Thus, an average expected influence value is calculated for all nodes in each iteration. After that, the EGA gives a decision of a node's state when creating the set of the influenced nodes. Let u and v be arbitrary nodes. Let pick the node u as seed. After 20.000 times propagation simulation, node v's average probability of being influenced by u is p. If $p \geq 0{,}5$, we assume that v is influenced by u. So, the EGA adds the node v into the node u's set of the influenced nodes. As a result, it keeps set of the influenced nodes for all nodes. Namely, each node has one separate set. Then, if the size of a node's set of the influenced nodes is greater than $\text{average} + \text{standard deviation}$ of all nodes' sets, the EGA adds this node to a list called as elites. After that, it passes to picking and discounting stage. The EGA picks the most influential node from the list; excludes the selected node and (if any) all influenced nodes by this node from the list. More formal definition:

Let I_u be the set of the positively influenced nodes by the selected seed node u . The average of all nodes' influence capabilities (number of influenced nodes by the node) are calculated as in (3).

$$\mu = \left(\sum\nolimits_{u \in V} |I_u|\right) / |V| \quad (3)$$

Here, we calculate the standard deviation as in (4).

$$\sigma = \sqrt{\frac{1}{|V|} \sum\nolimits_{u \in V} (|I_u| - \mu)^2} \quad (4)$$

Let $f^{+}(\cdot)$ is the positive influence function that returns the positively influenced nodes set by node u. Let $\mathbb{E}$ be list of elites, and $L(\cdot)$ be the function that adds the nodes that have number of influenced nodes is greater than $\text{average} + \text{standard deviation}$ to a list of elites. We write $L(\cdot)$ as in (5).

$$L(u) = \begin{cases} \mathbb{E} \cup \{u\}, & f^{+}(u) \geq (\mu + \sigma) \\ -, & f^{+}(u) < (\mu + \sigma) \end{cases} \quad (5)$$

EGA's algorithm is shown in Algorithm 1.

ALGORITHM 1: EGA($\mathbb{G} = \{V, E, W, \mathbb{P}\}, k$) // k is number of seeds
// S is the set of seed nodes
$I \longleftarrow \emptyset; \mathbb{E} \longleftarrow \emptyset; S \longleftarrow \emptyset;$
foreach $u \in V$
$I_u \longleftarrow \emptyset;$
$I_u \longleftarrow f^+(u)$ // *set of influenced individuals by u*
End foreach
calculate μ *by using (3)*
calculate σ *by using (4)*
foreach $u \in V$
$L(u)$ // this calls the function in (5), and it creates the list of elites $\mathbb{E}$
End foreach
for *1* **to** k **do**
$s^* \longleftarrow \underset{u \in \mathbb{E}}{\text{argmax}}|I_u|$ // pick most influential elite individual
$S \cup \{s^*\}$ // add most influential elite individual to the seed set
$\mathbb{E} \longleftarrow \mathbb{E} \setminus (\{s^*\} \cup I_{s^*})$ // exclude s^* and (if any) all influenced individuals by s^* from $\mathbb{E}$
End for
Output S
End

Here, k is the desired number of seeds; S is the set of seed nodes.

4. EXPERIMENTS (*DENEYLER*)

In this section we give the brief information about the used datasets, and the competitors. Then, we present the experimental results.

4.1. Datasets (*Veri Setleri*)

In the experiments, we used Stanford Large Network Dataset Collection – SNAP's (http://snap.stanford.edu/data/index.html) large signed social network datasets Epinions and Slashdot [27]. Epinions is a product review web site. The users vote to trust or distrust someone based on their reviews of products. It has 131.828 nodes and 841.372 edges. Slashdot is a technology news web site. The users can rate each other as friend or foe. It has 81.871 nodes and 545.671 edges.

4.2. The competitors (*Rakipler*)

We compared the EGA with the IC-P Greedy, out-degree heuristic, and random selection method. The IC-P greedy is a recent algorithm for the IM problem [6]. Out-degree heuristic and random selection method are often used for benchmarking. We give the details of the algorithms below.

IC-P Greedy The IC-P Greedy picks one node on the each iteration that provides the maximum marginal gain in the total influence. Its algorithm is shown in Algorithm 2.

ALGORITHM 2: IC-P Greedy $\left(k, f^+(\cdot)\right)$ // k is the number of seeds
// S is set of seed nodes
$S \longleftarrow \emptyset;$
for *1* **to** k **do**
Select $u \longleftarrow \underset{u \in V \setminus S}{\text{argmax}}\left(f^+(S \cup \{v\}) - f^+(S)\right)$
$S = S \cup \{u\}$
End for
Output S
End

Here, k is the desired number of seeds; $f^+(\cdot)$ is the positive influence function that returns the positive influence of S.

Out-Degree — This heuristic picks the top − k nodes, which have the highest out degree.

Random — This method randomly selects seed nodes from network.

4.3. Experimental Results (*Deneysel Sonuçlar*)

We used Polarity related IC Model (IC-P) as propagation model, and weighted cascade setting for determining the edge weights on the graph datasets. Achieved positive influence values on Epinions and Slashdot datasets are shown in Fig. 1 and Fig. 2, respectively.

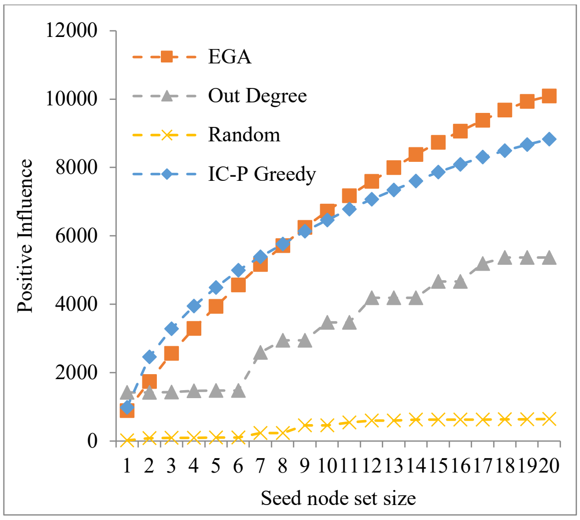

Fig. 1. Results for Epinions dataset *(Epinions veri seti için sonuçlar)*

4.3. Experimental Results (*Deneysel Sonuçlar*)

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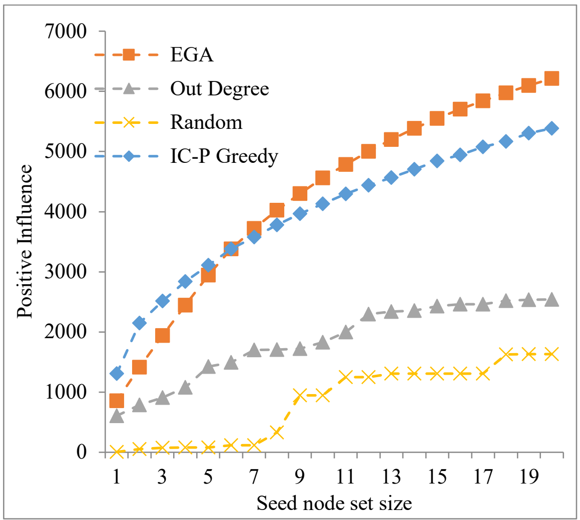

Fig. 2. Results on Slashdot dataset *(Slashdot veri seti için sonuçlar)*

Random and out-degree heuristic have given the worst results. The IC-P Greedy outperforms the EGA for relatively low seed node set size, especially less than 9. For higher sizes, the EGA outperforms the IC-P Greedy. Please note that, the IM problem is getting harder to solve with the increase of seed node set size. As a result, the EGA gives competitor performance in terms of solution quality.
Additionally, we compared the EGA and the IC-P Greedy in terms of running times. The EGA has generated the list of elites by picking ~21.000 nodes among 131.828 nodes in Epinions dataset; generated the list of elites by picking ~16.500 nodes among 81.871 nodes in Slashdot dataset. These are the 16% of total nodes, and 20% of total nodes respectively. Main time consuming part of the algorithms is the computing a node's marginal gain to the total influence. The EGA has reduced the number of nodes that need to be calculated to approximately one fifth. Thus, the EGA's running time is 5 time faster than the IC-P.

5. DISCUSSION AND CONCLUSION (*TARTIŞMA VE SONUÇ*)

The IM problem is one of the most attractive research topics in the social network analysis because its practical benefits in viral marketing, public opinions shaping etc. In this study, we dealt the signed IM problem, which considers positive and negative relations between social network users, and we developed a new fast greedy algorithm called EGA. The EGA gives better results than state-of-the-art the IC-P Greedy algorithm in the most experiments in terms of solution quality and the time efficiency. Even if the EGA adopts pure greedy approach, its strategy could be applied to heuristic-based approaches. The nodes can be easily qualified by their centrality measure values during the creation of the list of elites. This improves the time efficiency of the algorithm significantly because the centrality measures bypass heavy Monte Carlo propagation simulations. For this purpose, robust centrality measures that have good ranking capabilities should be developed.

CONFLICT OF INTEREST

No conflict of interest was declared by the author.

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