Evaluating Disseminators for Time-critical Information Diffusion on Social Networks

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Abstract: In recent years, information diffusion in social networks has received significant attention from the Internet research community driven by many potential applications such as viral marketing and sales promotions. One of the essential problems in information diffusion process is how to select a set of influential nodes as the initial nodes to disseminate the information through their social network. Most of the existing solutions aim at how to maximize the influence effectiveness of the initially selected "influential nodes", but pay little attention on how the influential nodes selection could minimize the cost of the diffusion. Diffusion effectiveness is important for the applications such as innovation and new technology diffusion. However, many applications, such as disseminating disaster information or product promotions, have the mission to deliver messages in a minimal time. In this paper, we design and implement an efficiently k-best social sites selected mechanism in such that the total diffusion "social cost" required for each user in this social network to receive the diffusion critical time information is minimized.

1 INTRODUCTION

A social network is a social structure made of individuals or organizations that are tied by one or more specific types of inter-dependencies, such as friendship, co-authorship, collaboration, etc. On line social networking has become a very popular application in the era of Web 2.0, which enables the users to communicate, interact and share on the World Wide Web. Online social networking turns out to be part of human life. Facebook, YouTube, LinkedIn, Flickr, Orkut, are some of the prominent online social networking websites which ease the interfaces for online content sharing like photo sharing, video sharing and professional networking. Recently social networks have received a high level of attention due to their capability in improving the performance of web search, recommendations using collaborative filtering systems, new technology spreading in the market using viral marketing techniques, etc.

Generally, social networks play a vital role for the spread of an innovation or technology or information within a population of individuals. A piece of information can propagate from one node to another node through a link on the network in the form of "word-of-mouth" communication. The interpersonal relationships (or ties or links) between individuals could cause significantly change or improvement in the social system because the decisions made by individuals are influenced heavily by the behavior of their neighbors. Therefore, to enhance power of information diffusion on a social network, it is beneficial to discover the influential nodes which can strongly affect the behavior of their neighbors. It is an essential issue to find a small subset of influential individuals in a social network such that they can influence the largest number of people in the network (Wang et al., 2001).

Finding a subset of influential individuals has many applications. Recall that the motivating example given by Kempel et al. (2009). Consider a social network together with the estimates for the extent to which individuals influence one another, and the network performs as the platform for marketing. A company would like to market a new product, hoping it will be adopted by a large fraction of the network. The company plans to initially target a small number of "influential" individuals of the network by giving them free samples of the product (the product is expensive or the company has limited budge so that they can only choose a small

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number of people). The company hopes that the initially selected users will recommend the product to their friends, their friends will influence their friends' friends and so on, and thus many individuals will ultimately adopt the new product through the powerful word-of-mouth effect (or called viral marketing).

Finding influential nodes is one of the central problems in social network analysis. Thus, developing efficient and practical methods of doing this on the basis of information diffusion is an important research issue. Commonly used fundamental probabilistic models of information diffusion are the *independent cascade (IC) model* (Goldenberg et al., 2001); (Kempe et al., 2003); (Gruhl et al., 2004) and the linear threshold (LT) model (Watts, 2002); (Kempe et al., 2003). Researchers studied the problem of finding a limited number of influential nodes that are efficient for the spread of information under the above models (Kempe et al., 2003); (Kimura et al., 2007); (Kimura et al., 2010). This problem is called the *influence maximization problem*. Kempe et al. (2003) showed on large collaboration networks that the greedy algorithm can give a good approximate solution to this problem, and mathematically proved a performance guarantee of the greedy solution (i.e., the solution obtained by the greedy algorithm). The influence maximization problem has applications in sociology and "viral marketing" (Agarwal and Liu, 2008), and was also studied in a descriptive probabilistic model of interaction (Domingos and Richardson, 2001); (Richardson and Domingos, 2002). The problem has recently been extended to influence control problems such as a contamination minimization problem (Kimura et al., 2009a).

Early alert's situational awareness services enhance the command and control and decision-making process by helping users keep abreast of rapidly changing conditions, execute operational plans, and prepare for future actions.

In this paper, we study the problem for disseminating the emergence information (ex, storm surge, inland flooding, winter and severe weather, earthquakes and tsunamis and critical time promotion) through a social network. These problems are usually significant in practice, especially for cases where the influence is meaningful only in a short period time. Our goal is to minimize the total social cost for all users in a social network to receive such information. The major contributions of this paper as summarized as follows.

- We present a minimize "*social cost*" information dissemination, namely the K Best *Disseminators*, which is indeed an important type of social network influence diffusion with many real applications.
- We propose a naïve approach to process the *KBDD* and also analyze the processing cost required for this approach.
- An efficient algorithm, name the K Best *Disseminators (KBDD)* algorithm, operates by the support of R-tree and Voronoi diagram to improve the performance of KBDD.

The remaining area of the paper is structured as follows. Section 2 reviews the related literature in the area of viral marketing and social networks. Section 3 meant for the materials and methods used and formulate research problem (K-Best *Disseminators-KBDD*). Disseminator's model with social cost is presented in Section 4. In Section 5, a naïve approach and its cost analysis are presented. Section 6 describes the KBDD algorithm with the used indexes. Performance evaluation is presented in Section 7. Finally, we conclude the paper along with future research direction as mentioned in Section 8.

2 RELATED LITERATURE

2.1 Viral Marketing and Influential Users

Word of mouth (WOM), one of the most ancient mechanisms in the history of human society, is being given new significance by this unique property of the Internet. Recently WOM communication has received scholarly attention in the research areas of opinion leadership, interpersonal influence, and diffusion of innovation. WOM play a vital role in influencing attitudes and behaviors, especially with regard to the diffusion of innovations (Kardes and Kim, 1991). Diffusion studies have provided useful information in identifying the role of communication channels, characteristics of potential adopters (e.g., innovators and early adopters), and major stages in the adoption process.

Online WOM (i.e., viral marketing) has become a common topic of research in the area of computer-mediated communication, particularly in the context of consumer-to-consumer interactions. Powered by such tools as email, instant messenger, chat rooms, weblogs, and bulletin boards, online WOM communication has helped give rise to different types of online communities. Viral marketing is a new marketing method, which uses electronic communications to trigger brand messages throughout a widespread network of buyers.

Regarding the study of viral marketing, Dobele et al. (2005) studied several real marketing cases and analyze why they need viral marketing, and how to use it successfully. Dobele et al. (2007) showed that emotion has more impact than the expectation of recipient in the successful message passing. They also stated that marketing to several influential people will perform better than sending message to everyone and that is what we want to achieve. Richardson and Domingos (2002) utilized probabilistic models and data from knowledge-sharing sites to design the best viral marketing plan.

2.2 Social Networks and Social Analysis

A social network is a social structure made up of individuals (or organizations) called "nodes", which are tied (connected) by one or more specific types of interdependency, such as friendship, kinship, common interest, financial exchange, dislike, sexual relationships, or relationships of beliefs, knowledge or prestige. There are three important elements included in a social network: actors, ties, and relationships. Actors are the essential elements in the social network to define the people, events or objects. Ties are used to construct the relationship between actors by using a mean of path to establish the relationship directly or indirectly. Ties can also be divided into strong and weak tie according to the strength of the relationships; they are also useful for discovering subgroups of the social network. Relationships are used to illustrate the interactions and relationships between two actors. Furthermore, different relationships may cause the network to reflect different characteristics (Easley and Kleinberg, 2010).

Social networks are usually modeled by graphs, where nodes represent individuals and edges represent the relationships between pairs of individuals (Easley and Kleinberg, 2010). Such graphs are either "directed" or "undirected", and "weighted" or "unweighted". In weighted graphs, the weights of edges represent the level of relationship or influence between individuals. Several diffusion models have been proposed to analyze the diffusion of innovation in social networks. The widely studied models can be generalized into the categories of threshold models and cascade models (Easley and Kleinberg, 2010).

Different researchers carried out various aspects in different dimensions of datasets using social network analysis. In order to examine how friends affect one's decision to get vaccinated against the flu, 2007 Neel combine information on social networks with medical records and survey data. Domingos and Richardson (2001) study the influence maximization problem and propose a probabilistic solution. Kempe et al. (2009a) formulate the problem of finding a set of influential individuals as an optimization problem.

Different definitions of influential nodes lead to different computational challenges. In the blogosphere, there is significant research in the identification of influential blogs (Gruhl et al., 2004) and bloggers (Agarwal and Liu, 2008); (Mathioudakis and Koudas, 2009). For example, Gruhl et al. (2004) study information diffusion of various topics in the blogosphere. Their focus is on studying how the topics propagate or how "sticky" the topics are. In these cases, the authors define a metric that determines the influence potential of a blogger. Similarly, for marketing surveys, the problem of identifying the set of early buyers has been addressed. The focus is on developing efficient algorithms for identifying the top-k influential nodes. Information propagation models have been considered in the context of influence maximization (Kimura et al., 2010).

The focus of those works is on identifying the set of nodes in the network that need to be targeted, so that the propagation of a product or an idea spreads as much as possible. In influence maximization, the goal is to identify the nodes that will cause the most propagation effect in the network. Finding the set of the most influential nodes is a well-known problem in social networks analysis (Kimura et al., 2010). Different from the above works, we consider the problem of minimizing the total time delay of all users in a social network getting the emergent information.

3 PROBLEM DEFINITION

Figure 1 gives an illustration to present our problem. The social network includes totally N+S nodes, S of them are people with sufficient capability as serving as diffusion seeds these sites are predefined, registered or contracted. Given a set of social nodes *O*, a set of sites *S*, and a user-given value K, a

KBDD retrieves the K sites s_1, s_2, ..., s_K from S such that $sc(o_i,s_j)$ $o_i \in O$ is minimized, where $sc(o_i,s_j)$ refers the social cost to successfully distribute the time-critical information between nodes o_i and its closest site $s_j \in \{s_1, s_2, ..., s_K\}$. We term the sites retrieved by executing KBDD the *best diffusion disseminators* (or *bdd* for short).

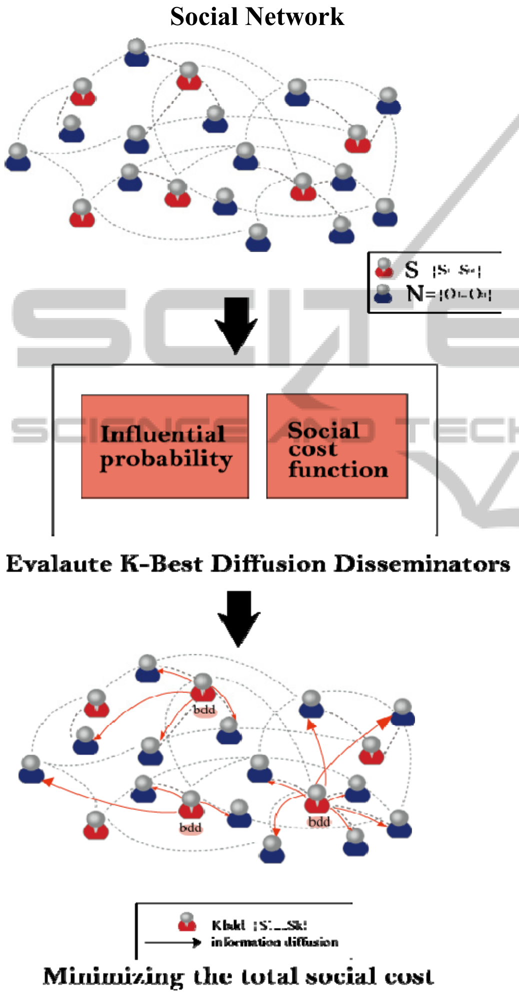


Figure 1: K-best diffusion disseminators problem.

The *KBDD* (K-best *Disseminators*) problem arises in many fields and application domains. As an example of real-world scenario, consider a company has a time-limited deal for a special group. In order to propagate this message to this special group as soon as possible; the company may want to choose the K influential users from this group to propagate this message. To achieve the fastest diffusion information, the sum of diffusion time delay from each group member to its closest influential node should be minimized.

Another real-world example is that an earthquake or a tsunami occurs in a city. In order to reduce the damage of earthquake or tsunami, how to quickly propagate the emergency alert to people is the most import thing. In this case, the top-k opinion leaders of the organization should be chosen to propagate information so that people can obtain information immediately.

Let us use an example in Figure 2 to illustrate the *KBDD* problem, where six nodes o_1, o_2, ..., o_6 and four sites s_1, s_2, ..., s_4 are depicted as circles and rectangles, respectively. Assume that two best *Disseminators* (i.e., 2*bdd*) are to be found in this example. There are six combinations (s_1, s_2), (s_1, s_3), ... , (s_3, s_4), and one combination would be the result of *KBDD*. As we can see, the sum of diffusion social cost from objects o_1, o_2, o_3 to their closest site s_3 is equal to 9, and the sum of social cost between objects o_4, o_5, o_6 and site s_1 is equal to 12. Because combination (s_1, s_3) leads to the minimum total social cost (i.e., 9 + 12 = 21), the two sites s_1 and s_3 are the 2*bdd*.

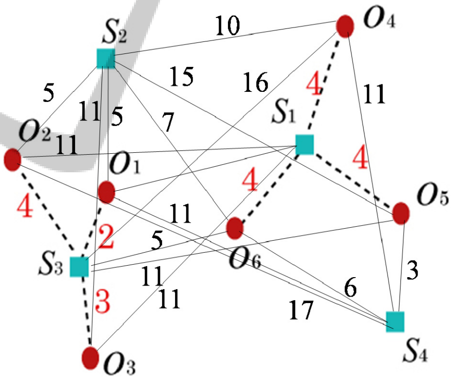
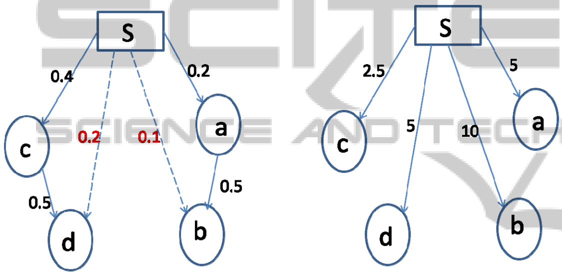


Figure 2: An example of *KBDD*.

4 THE MODEL

4.1 Mapping Influence Probability to Diffusion Social Cost

Goyal et al. (2010) present the concept of user influential probability and action influential probability. The assumption is that if user v_i performs an action y at time t and later ($t' > t$) his friend v_j also perform the action, then there is an influence from v_i on v_j. The goal of learning influence probabilities (Goyal et al, 2010) is to find a model (static representation of dynamic system) to best capture the information of user influence and action influence using the network of information diffusion social cost (*sc*). A node with a high value of influential probability (IP) to other social nodes reveals it is easier for him/her to affect other nodes in propagating an idea or an advertisement across the network. It takes less social cost for a node to receive the message from a node with higher IP than from a node with low IP. Hence, we define the social cost is inversely proportional to the IP. Figure 3(a) illustrates a general influential probability network. The influential probability can be interpreted as the successful rate of information propagated from disseminator to social nodes directly or indirectly. Indirect influential probability is depicted by a dotted line, which is derived based on the production rule. Figure 3(b) shows a diffusion social cost network, which is transferred from Figure 3(a).



(a) Influential Probability (b) Diffusion Social Cost

Figure 3: Transfer diffusion probability network to diffusion social cost network.

5 NAÏVE APPROACH

In this section, we first suggest a straightforward approach to solve the *KBDD* problem, and then study the processing cost required for this approach. Assume that there are *n* nodes and *m* sites, and the *K bdd* would be chosen from the *m* sites. The straightforward approach basically includes three steps.

The first step is to compute the information diffusion social cost $sc(o_i,s_j)$ from each social node o_i $(1 \le i \le n)$ to each site s_j $(1 \le j \le m)$. Since the *K* best sites needed to be retrieved, there are totally C_K^m possible combinations and each of the combinations has *K* sites.

The second step is to consider all of the combinations. For each combination, the diffusion social cost from each node to its closest site is determined so as to compute the total diffusion social cost.

In the last step, the combination of *K* sites having the minimum total diffusion social cost is chosen to be the diffusion strategy of *KBDD*. The procedure of the straightforward approach is detailed in Algorithm 1.

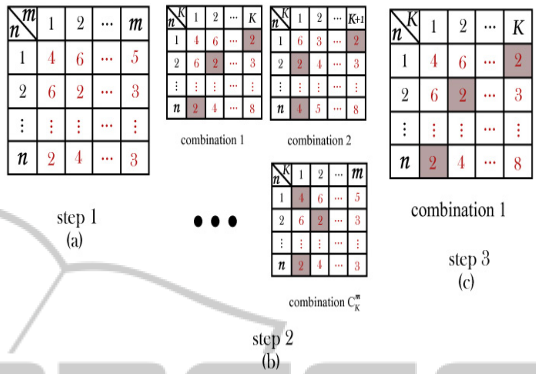


Figure 4: Naïve approach.

Figure 4 illustrates the three steps of the naive approach. As shown in Figure 4(a), the diffusion social cost between social nodes and sites are computed and stored in a table, in which a tuple represents the diffusion social cost from a social node to all sites. Then, the C_K^m combinations of K sites are considered so that C_K^mtables are generated (shown in Figure 4(b)). For each table, the minimum attribute value of each tuple (marketed with gray box) refers to the diffusion social cost between a social node and its closest site. As such, the total diffusion social cost for each combination can be computed by summing up the minimum attribute value of each tuple. Finally, in Figure 4(c) the combination 1 of K sites can be the K *bdd* because its total diffusion social cost is minimum among all combinations.

As the naive approach includes three steps, we consider the three steps individually to analyze the processing cost. Let *m* and *n* be the numbers of sites and nodes, respectively. Then, the time complexity of the first step is $m \times n$ because the diffusion social cost between all nodes and sites has to be computed. In the second step, C_K^mcombinations are considered and thus the complexity is $C_K^m \times n \times$ K. Finally, the combination having the minimum total diffusion social cost is determined among all combinations so that the complexity of the last step is C_K^m. The processing cost of the straightforward approach is represented as $m \times n + C_K^m \times n \times K + C_K^m$.

Algorithm 1: The Naïve approach.

Input: A number K, a set of n social nodes with influential probability, and a set of m sites.
Output : The K best *Disseminators bdd*

/* Step 1

for each node o_i ***do***

  for each site s_j ***do***

   compute the diffusion social cost $sc(o_i,s_j)$ diffusion information from o_i to s_j;

/* Step 2

for each combination $c \in C_K^m$ ***do***

  for each node o_i **do**

   compute the diffusion social cost $sc\ (o_i,s_j)$ from o_i to its closet site s_j;

   compute the total diffusion social cost sc_c for combination c as $\sum_{o_i} sc(o_i, s_j)$

/* Step 3

return the combination c having the minimum total diffusion social cost;

6 KBDD ALGORITHM

The above approach is performed without any index support, which is a major weakness in dealing with large datasets. In this section, we propose the *KBDD* algorithm combined with the existing indexes R-tree (Guttman, 1984) and Voronoi diagram (Franz Aurenhammer, 1991) to efficiently process the *KBDD*. In order to apply the proposed algorithm, the nodes in the diffusion social cost network should be transformed to points in a 2-dimensional Euclidean space. Some dimensionality reduction methods (e.g.; Multi-Dimensional Scaling (MDS) can be used for converting distance information into coordinate information (Asano et al., 2009). Besides, we need to find the closest site s for each object *o* (that is, finding the RNN o of site s). Since the Voronoi diagram can be used to effectively determine the RNN of each site (Zhang et al., 2003), we divide the data space so that each site has its own Voronoi cell. For example, in Figure 5(b), the four sites s_1, s_2, s_3, and s_4 have their corresponding Voronoi cells V_1, V_2, V_3, and V_4, respectively.

Taking the cell V_1 as an example. If node o lies in V_1, then o must be the RNN of site s_1. Based on this characteristic, node o needs not be considered in finding the RNNs for the other sites. With Voronoi diagram, the following pruning criteria can be used to greatly reduce the number of social nodes consider in query processing.

Pruning Nodes. Given an node o and the K sites s_1, s_2, ..., s_K, if o lies in the Voronoi cell V_i of one site s_i $\in$ {s_1, s_2 , ..., s_K }, then the diffusion social cost between node o and the other K − 1 sites need not be computed so as to reduce the processing cost. With Voronoi diagram index approach, the processing is represented as (log *m*)×*n*+ C_K^m ×*n*×*K*+ C_K^m.

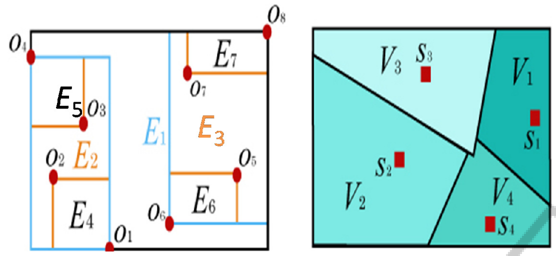
The R-tree was proposed by Antonin Guttman in 1984 and has found significant use in both research and real-world application. The key idea of the data structure is to group nearby objects and represent them with their minimum bounding rectangle in the next higher level of the tree; the "R" in R-tree is for rectangle. Since all objects lie within this bounding rectangle, a query that does not intersect the bounding rectangle also cannot intersect any of the contained objects. At the leaf level, each rectangle describes a single object; at higher levels the aggregation of an increasing number of objects. Therefore, we use the R-tree, which is a height-balanced indexing structure, to index the social nodes.

In a R-tree, nodes are recursively grouped in a bottom-up manner according to their locations. For instance, in Figure 5(a), eight objects o_1, o_2, ..., o_8 are grouped into four leaf nodes E_4 to E_7 (i.e., the minimum bounding rectangle (MBR) enclosing the objects). Then, nodes E_4 to E_7 are recursively grouped into nodes E_2 and E_3, which become the entries of the root node E_1.

Combined with the R-tree and Voronoi diagram, we design the following pruning criteria to greatly reduce the number of social nodes considered in query processing.

Pruning Nodes. Given a node o and the *K* sites s_1, s_2, ..., s_K, if *o* lies in the Voronoi cell V_i of one site s_i $\in$ {s_1, s_2 , ..., s_K }, then the diffusion social cost between node *o* and the other *K* − 1 sites need not be computed so as to reduce the processing cost.

Pruning MBRs. Given a MBR *E* enclosing a number of nodes and the *K* sites s_1, s_2, ..., s_K, if *E* is fully contained in the cell V_i of one site $s_i \in \{s_1, s_2, ..., s_K\}$, then the diffusion social cost from all nodes enclosed in E to the other $K - 1$ sites would not be computed.



(a) (b)

Figure 5: R-tree and Voronoi diagram.

To find the K_{bdd} for the *KBDD*, we need to consider C_K^m combinations of K sites. For each combination of K sites s_1, s_2, ..., s_K with their corresponding Voronoi cells V_1, V_2, ..., V_K, the processing procedure begins with the R-tree root node and proceeds down the tree. When an internal node E (i.e., MBR E) of the R-tree is visited, the pruning criterion 2 is utilized to determine which site is the closest site of the nodes enclosed in E. If the MBR E is not fully contained in any of the K Voronoi cells, then the child nodes of E need to be further visited. When a leaf node of the R-tree is checked, the pruning criterion 1 is imposed on the entries (i.e., nodes) of this leaf node. After the traversal of the R-tree, the total diffusion social cost for the combination of K sites s_1, s_2, ..., s_K can be computed. By taking into account the total combinations, the combination of K sites whose total diffusion social cost is minimum would be the diffusion strategy of the *KBDD*. Algorithm 2 gives the details for the *KBDD* algorithm.

Figure 6 continues the previous example in Figure 5 to illustrate the processing procedure, where there are eight nodes o_1 to o_8 and four sites s_1 to s_4 in social network. Assume that the combination (s_2,s_3) is considered and the Voronoi cells of sites s_2 and s_3 are shown in Figure 6(a). As the MBR E2 is not fully contained in the Voronoi cell V_2 of site s_2, the MBRs E_4 and E_5 still need to be visited. When the MBR E_4 is checked, based on the pruning criterion 2 the distances from nodes o_1 and o_2 to site s_3 would not be computed because their closest site is s_2. Similarly, the closest site of the nodes o_7 and o_8 enclosed in MBR E_7 is determined as site s_3.

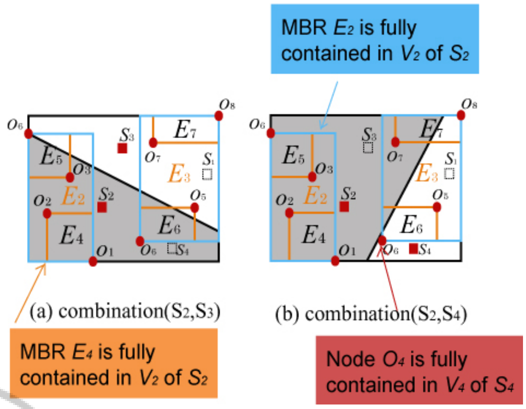


Figure 6: KBDD algorithm.

Algorithm 2: The KBDD algorithm.

Input: A number K, a set of *n* nodes indexed by R-tree, and a set of *m* sites index by Voronoi diagram.
Output: The K best *Disseminators bdd*
create an empty queue *Q*;
for each combination $c \in C_K^m$ ***do***
  insert the root node of R-tree into *Q*;
  while Q is not empty do
    de-queue *q*;
    if *q* corresponds to an internal node E_i ***then***
      if E_i is fully contained in a voronoi cell V_j ***then***
        for each node o_i enclosed in E_i ***do***
          compute the diffusion social cost $sc(o_i, s_j)$ from o_i to site s_j;
      else
        insert child nodes of E_i into *Q*;
    else
      if o_i is enclosed by a voronoi cell V_j ***then***
        compute the diffusion social cost $sc(o_i, s_j)$ from o_i to site s_j;
    compute the total diffusion social cost sc_c for combination *c* as $\sum_{o_i} sc(o_i, s_j)$;
return the combination *c* having the minimum total diffusion social cost;

As for nodes o_3 to o_6, their closest sites can be found based on the pruning criterion 1. Having determined the closest site of each node, the total distance for combination (s_2, s_3) is obtained. Consider another combination (s_2, s_4) shown in Figure 6(b). The closest site s_2 of four nodes o_1 to o_4 enclosed in MBR E_2 can be found when E_2 is visited. Also, we can compute the total distance for the combination (s_2, s_4) after finding the closest sites for nodes o_5 to o_8. By comparing the diffusion social cost for all combinations, the 2_{bdd} are retrieved.

We use an example to illustrate how the *KBDD* algorithm works. For the combination (s_2, s_3), when the MBR E_4 is visited, because E_4 is fully contained in site s_2's V_2, the closest site of objects o_1 and o_2 enclosed in E_4 is site s_2. Therefore, the distances form objects o_1 and o_2 to site s_3 need not be computed. Similarly, for the combination (s_2, s_4), MBR E_2 is fully contained in site s_2's V_2 so that the distances from objects o_1, o_2, o_3, and o_4, to site s_4 need not be computed. Based on the proposed pruning criterion, the performance of *KBDD* can be improved because many unnecessary distance computations are reduced. With Voronoi diagram + R-tree index approach, the processing is represented as $(\log m)\times(\log n)+C_K^m \times n\times K+C_K^m$.

7 PERFORMANCE EVALUATION

7.1 Experimental Setting

All experiments are performed on a PC with Intel Pentium 4 3.0 GHZ CPU and 4 GB RAM. The algorithm is implemented in JAVA 2 (j2sdk-1.4.0.01). One synthetic social network consisting of 1K social nodes is used in our simulation. The performance is measured by the total running time in k-best social sites selected from *m* candidate *Disseminators* for initial influence diffusion such that all the total diffuse social cost which all social nodes in this social network may get the diffusion critical time information is minimize.

The performance is measured by total running time of process KBDD query. To exploit the efficiency of the proposed k-best diffusion site algorithm, we compare the performance of our approach with the Naive approach (that operates without the support of index). Table 1 summarizes the parameters under investigation, along with their ranges and default values. The number (*#social nodes*) of the metric social nodes in a social network varies from 1,000 to 10,000. The candidate social node for initial influence diffusion metric *S* is 25. The user gives the best influence *Disseminators K* is 5. The final statistic result is an average value of 100 experiments. The program used for experiment is modified with the Voronoi diagram code of Fortune's algorithm (http://www.cs.sunysb.edu/~algorith/implement/fortune/implement.shtml) and the R-tree codes of R-tree Portal (http://www.rtreeportal.org/).

Table 1: System parameters.

Parameter	Default	Range
Number of social nodes (*N*)	1K	1K, 5K, 10K
Diffusion site candidates (*S*)	25	
Number of best diffusion site (*K*)	5	

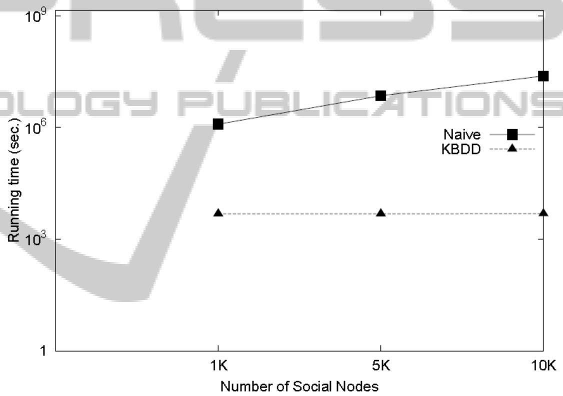


Figure 7: Influence of the number of considered social nodes on performance.

Figure 7 studies the effect of various numbers of considered social nodes (varying n from 1k to 10k) on the performance of processing K *bdd* queries. Note that Fig. 7 uses a logarithmic scale for the y-axis. As we can see in Figure 7, the running time (i.e., the CPU time required to find the K *bdd*) of naïve approach increases with the increasing *N*. The reason is that as *N* becomes greater, the amounts of social cost that need to be computed increases so that more cost spent on for finding their corresponding K *bdd* is required. However, the experimental result shows that the running time of the KBDD approach is basically a constant for various numbers of social nodes. This indicates that for most of the cases the system's running time is acceptable. Even when the number of social nodes increases up to more than 10K, the running time still increases with a slow rate within a fairly acceptable range. This result indicates that the performance of the KBDD algorithm is insensitive to the numbers of considered social nodes. This is mainly because Voronoi Diagram index approach largely reduces the amount of social cost computation between the social nodes and *Disseminators* and hence the effect of the increase social nodes can be alleviated. With the R-tree index, the KBDD algorithm decreases the amount of the search of social nodes is nearest to which diffusion site hence the running time can be improved. From the experimental results, we find that KBDD approach is more suitable for the highly dynamic environments in which the social network changes its scale of network size frequently.

8 CONCLUSIONS

In this paper, we study the problem for diffusing the emergence information through social network. Our goal is to minimize the "social cost" to reach (successfully distribute the time-critical information) "all" the users in the social network. To solve the *KBDD* problem, we first proposed a straightforward approach and then analyzed its processing cost. In order to improve the performance of processing the KBDD, we further proposed a KBDD algorithm combined with the R-tree and Voronoi diagram to greatly reduce the costs. Our next step is to process the KBDD for social nodes with dynamic influential probability.

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