



RESEARCH ARTICLE

NEAREST NEIGHBOUR SEARCH ON GEOGRAPHICAL LOCATION WITH SOCIAL NETWORKS

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ABSTRACT

Although kNN search on a road network Gr(graph of mobile network), i.e., finding k nearest objects to letter of the alphabetuery a question user q on Gr, has been extensively studied, existing works neglected the very fact that the q's social data will play a very important role during this kNN query. Several real-world applications, like location-based social networking services, need such a question. During this paper we tend to study a brand new problem: kNN search on road networks by incorporating social influence (RSkNN). Specifically, the progressive Independent Cascade (IC) model in social network is applied to outline social influence. One vital challenge of the matter is to speed up the computation of the social influence over massive road and social networks. To handle this challenge, we propose three economical index-based search algorithms, i.e., road network-based (RN-based), social network-based (SN-based) and hybrid indexing algorithms. Within the RN-based algorithmic rule, we tend to use a filtering-and-verification framework for grappling the laborious downside of computing social influence. Within the SN-based algorithmic rule, we tend to infix social cuts into the index, in order that we tend to speed up the question. In the hybrid algorithmic rule, we tend to propose associate degree index, summarizing the road and social networks, supported that we are able to get question answers efficiently. Finally, we tend to use real road and social network information to through empirical observation verify the potency and efficaciousness of our solutions.

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INTRODUCTION

With the ever-growing quality of mobile devices (e.g., smartphones), location-based service (LBS) systems (e.g., Google Maps for Mobile) are wide deployed and accepted by mobile users. The k-nearest neighbor (kNN) search on road networks may be a basic downside in LBS. Given a question location and a collection of static objects (e.g., restaurant) on the road network, the kNN search downside finds k nearest objects to the question location. Alone with the popular usage of LBS, the past few years have witnessed a vast boom in location-based social networking services like Foursquare, Yelp, Loopt, Geomium and Facebook Places. Altogether these services, social network users are typically related to some locations (e.g., home/office addresses and visiting places). Such location info, bridging the gap between the physical world and therefore the virtual world of social networks, presents new opportunities for the kNN search on road networks. The aforesaid example motivates United States to think about the social influence to a user once process the kNN search on road networks. Specifically, a question user q would love not solely retrieving k geographically nearest objects, however get an outsized social influence from q's friends UN

agency are to. Therefore, during this paper, we have a tendency to study a completely unique query: kNN search on a road-social network (RSkNN), and propose economical question process algorithms. Specifically, Given Gs(graph of social media), Gr and q, the RSkNN search finds k nearest objects (Aq = ) to question q's location on Gr, such the social influence SI(or) to Q through q's friends, UN agency are to or, is a minimum of a threshold.

Problem statement

We can rummage around for some reviews of the places in specific class on social media network, the other user from our friend list UN agency had denote the reviews for same class of places are shown because the result however, this result contains random location of knowledge thus, it's troublesome to filter that result for specific location. In Google API we will offer location and search the places with reviews. But, we tend to cannot realize those reviews from folks that square measure renowned to USA. So, we want a system that mix on top of mentioned each system and should offer expected result.

Literature survey

Title: Fast probabilistic algorithms for hamiltonian circuits and matchings.

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**Author:** D. Angluin and L. G. Valiant

**Year:** 1977

To relinquish techniques for analysing the probabilistic performance of sure forms of algorithms, and then to recommend some quick algorithms with demonstrably fascinating probabilistic behaviour. The actual issues we tend to think about are: finding Hamiltonian circuits in directed graphs (DHC), finding Hamiltonian circuits in directionless graphs (UHC), and finding excellent matchings in directionless graphs (PM). We tend to show that for every downside there's associate rule that's extraordinarily quick ( $O(n(\log n)^2)$  for DHC and UHC, and  $O(n \log n)$  for PM), and that with likelihood tending to 1 finds an answer in at random chosen graphs of sufficient density. These results distinction with the renowned NP-completeness of the primary 2 issues and also the best worst-case edge renowned of  $O(n^{2.5})$  for the last.

**Title:** A general framework for geo-social query processing.

**Author:** N. Armenatzoglou, S. Papadopoulos, and D. Papadias

**Year:** 2013

The proliferation of GPS-enabled mobile devices and also the quality of social networking have recently light-emitting diode to the ascent of Geo-Social Networks (GeoSNs). GeoSNs have created a fertile ground for novel location-based social interactions and advertising. These will be expedited by GeoSN queries, which extract helpful info combining each the social relationships and also the current location of the users. This paper constitutes the primary systematic work on GeoSN question process. We tend to propose a general framework that provides versatile knowledge management and algorithmic style. Every GeoSN question is processed via a clear combination of primitive queries issued to the social and geographical modules. We tend to demonstrate the facility of our framework by introducing many "basic" and "advanced" question varieties and production numerous solutions for every sort. Finally, we tend to perform associate degree complete experimental analysis with real and artificial datasets, supported realistic implementations with each business computer code (such as MongoDB) and progressive analysis strategies. Our results make sure the viability of our framework in typical large-scale GeoSNs.

**Title:** Scalable influence maximization for prevalent viral marketing in large-scale social networks.

**Author:** W. Chen, C. Wang, and Y. Wang

**Year:** 2010

The measurability of influence maximization may be a key issue for enabling prevailing infective agent selling in large-scale on-line social networks. A previous solution, similar to the greedy algorithmic rule of Kempe et al. (2003) and its enhancements area unit slow and not ascendible, whereas alternative heuristic algorithms don't give systematically smart performance on influence spreads. During this paper, we tend to style a brand new heuristic algorithmic rule that's simply ascendible to many nodes and edges in our experiments. Our algorithmic rule incorporates an easy tunable parameter for users to regulate the balance between the periods of time and

therefore the influence unfolds of the algorithmic rule. Our results from intensive simulations on many real-world and artificial networks demonstrate that our algorithmic rule is presently the most effective ascendible resolution to the influence maximization problem: (a) our algorithmic rule scales on the far side million-sized graphs wherever the greedy algorithmic rule becomes unfeasible, and (b) altogether size ranges, our algorithmic rule performs systematically well in influence unfold --- it's invariably among the most effective algorithms, and in most cases it considerably outperforms all alternative ascendible heuristics to the maximum amount as 100%--260% increase in influence unfold.

**Title:** Scalable influence maximization in social networks under the linear threshold model.

**Author:** W. Chen, Y. Yuan, and L. Zhang

**Year:** 2010

Influence maximization is that the drawback of finding a little set of most authoritative nodes during a social network in order that their aggregate influence within the network is maximized. During this paper, we tend to study influence maximization within the linear threshold model, one amongst the necessary models formalizing the behavior of influence propagation in social networks. As a distinction, we tend to show that computing influence in directed a cyclic graphs (DAGs) is tired time linear to the dimensions of the graphs. Supported the quick computation in DAGs, we tend to propose the primary ascendible influence maximization rule tailored for the linear threshold model. we tend to conduct intensive simulations to indicate that our rule is ascendible to networks with variant nodes and edges, is orders of magnitude quicker than the greedy approximation rule projected by Kempe et al. and its optimized versions, and performs systematically among the simplest algorithms whereas alternative heuristic algorithms not style specifically for the linear threshold model have unstable performances on totally different real-world networks.

**Title:** Approximation algorithms for NP-Hard problems.

**Author:** D. H. (ed.).

**Year:** 1997

Approximation algorithms have developed in response to the impossibility of resolution a good type of necessary optimisation issues. Too oftentimes, once making an attempt to urge an answer for a haul, one is confronted with the actual fact that the matter is NP-hard. This, within the words of Garey and Johnson, suggests that "I cannot notice associate economical algorithmic rule, however neither will all of those notable folks." whereas this is often a big theoretical step, it hardly qualifies as a cheering piece of stories. If the best answer is impossible then it's affordable to sacrifice optimality and accept a "good" possible answer that may be computed expeditiously. Of course, we might prefer to sacrifice as very little optimality as attainable, whereas gaining the maximum amount as attainable in potency. Trading-off optimality in favor of flexibility is that the paradigm of approximation algorithms. The main themes of this book revolve round the style of such algorithms and also the "closeness" to optimum that's possible in polynomial time. To judge the boundaries of approximability, it's necessary to derive lower bounds or inapproximability results.

In some cases, approximation algorithms should satisfy further structural necessities like being on-line, or operating inside restricted area. This book reviews the planning techniques for such algorithms and also the developments during this space since its beginning concerning 3 decades past.

**Existing system**

The k-nearest neighbor (kNN) search on road networks is a fundamental problem in LBS. Given a query location and a set of static objects (e.g., restaurant) on the road network, the kNN search problem finds k nearest objects to the query location. Along with the popular usage of LBS, the past few years have witnessed a massive boom in location-based social networking services like Foursquare, Yelp, Loopt, Geomium and Facebook Places. In all these services, social network users are often associated with some locations (e.g., home/office addresses and visiting places). Such location information, bridging the gap between the physical world and the virtual world of social networks, presents new opportunities for the kNN search on road networks. kNN search (k=1) over the road-social network, where the road- social network is split into a social layer ( $G_s$ ) and a road layer ( $G_r$ ) for clear presentation.

The integer on an edge (u, v) of  $G_r$  represents the shortest-path distance between vertices u and v on the road network  $G_r$ . The visited relation gives a mapping that a user  $v_s \in G_s$  has been to a location  $v_r \in G_r$ . Suppose that a user named John Smith ( $s_3$  in  $G_s$ ) wants to find a French restaurant closest to his current location, i.e.,  $r_3$  in  $G_r$ . In this example, assume that  $r_1$  and  $r_4$  are both French restaurants. In  $G_r$ , the restaurant  $r_1$  is the nearest one, and the restaurant  $r_4$  is a little farther than  $r_1$  to  $r_3$ . A traditional kNN search will return  $r_1$  to John. However, as observed in the social layer, two one-hop friends of John ( $s_3$ ),  $s_1$  and  $s_2$ , have visited  $r_4$ , while only one two-hop friend of John,  $s_7$  has visited  $r_1$ . Obviously, John will be influenced by many friends to choose  $r_4$  instead of  $r_1$ , since  $r_4$  may have much more tasty food to John and is not far from  $r_3$ .

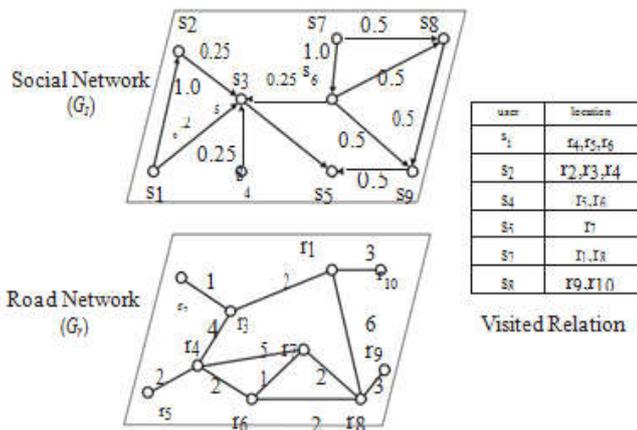


Fig. 1. Example of road-social network. The visited relation gives a mapping that users have visited the locations

**Disadvantages of existing system**

- Social network user location information, bridging the gap between the physical world and the virtual world of social networks, presents new opportunities for the kNN search on road networks.
- It is quite challengeable to answer the RSkNN query efficiently over large road-social networks.

**Proposed system**

For an implementation of a system we use three efficient index-based search algorithms, i.e., road network-based (RN-based), social network-based (SN-based) and hybrid indexing algorithms. RN-based algorithm, defines filtering-and-verification framework for tackling the hard problem of computing social influence. SN-based algorithm, embedded social cuts into the index, so that we speed up the query. And hybrid algorithm, an index summarizing the road and social networks, based on which we can obtain query answers efficiently. Finally, we use real road and social network data to empirically verify the efficiency and efficacy of our solutions.

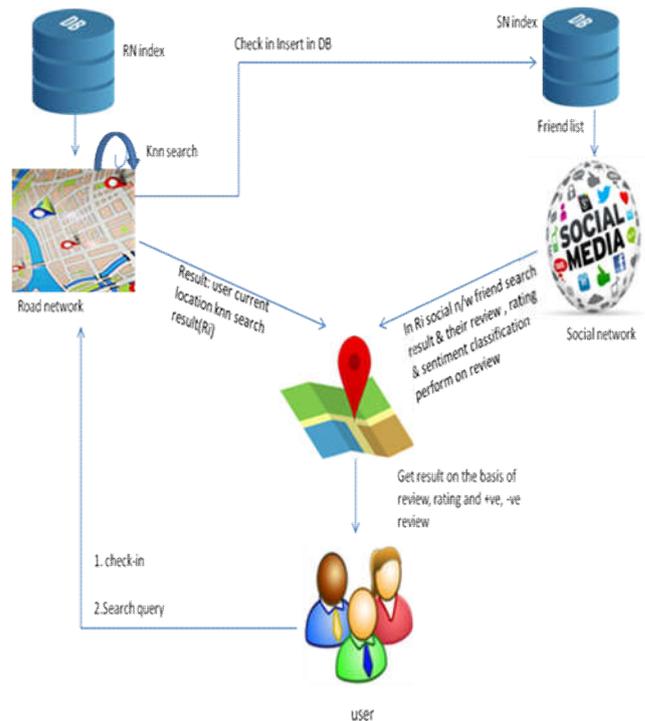


Figure 4.2. Architecture diagram

**Mathematical model**

Input-I  
 $I = \{Cu_{11}, Cu_{22}, Cu_{33}, \dots, Cu_{nn}\}$   
 $C_s$  - Category  
 $H_L$  - Check-in hotel location  
 $L_q$  - Location near by  $H_L$   
 Query - Q  
 User - u  
 Friend list -  $F_L = \{A, B, C, D\}$   
 $R_A$  - Review for  $H_L$  from user A & for check in  
 $R_B$  - Review for  $H_L$  from user B  
 Sentiment analysis on ( $R_A, R_B$ ) performed and save in database.  
 User U submits query Q - on location  $L_A$  for searching of category  $C_s$   
 $RN_s$  - perform RN Index with  $L_A$  for category  $C_s$   
 If K is user defined distance  
 D is distance of search place P and current location  
 if ( $D < K$ )  
 R is the result set  
 Add P in R  
 $P_{(RN)}$  - perform knn to select nearest places of category  $C_s$  on ( $RN_s$ )  
 $S_{(Pr)}$  - perform SN Index search on ( $P_r$ )

R is the review for place P from user A  
 if  $A \in f_r$  of current user on social media.  
 Then add(r,p) into Result set R  
 $S_{(Pr)} = \{ R_A, R_B \}$   
 Sentiment level classification  
 Remove stop words from r  
 Then K is the set of meaningful keywords ( $K = K_1, K_2, K_3, \dots, K_n$ )  
 Detect positive keywords set count p for positive words count n for negative words  
 for each k  
 if (k= positive)  
 count p = count p + 1  
 elseif (k = negative)  
 count n = count - 1  
 calculate positive review rating = count p / ( count p + count n)  
 calculate negative review rating = count n / ( count p + count n)  
 Final Result –  
 $F_R = \{ R_A, R_B \}$   
 Calculate average result for review rating and start rating.

### Algorithm

#### Algorithm: Knn

- To verify parameter K = range of nearest neighbors
- Calculate the gap between the query-instance and every one the coaching samples
- Kind the gap and verify nearest neighbors supported the K-th minimum distance
- Gather the class Y of the closest neighbors
- Use straightforward majority of the class of nearest neighbors because the prediction price of the question instance

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I would like to take this opportunity to express my profound gratitude and deep regard to my Project Guide, Prof. A.L. Golande (Faculty of Computer Engineering Department), for his exemplary guidance, valuable feedback and constant encouragement throughout the duration of the project. I also want to thanks Prof. J.P. Kshirsagar (Project Coordinator) and Prof. Kedar (HOD )for her valuable suggestions were of immense help throughout my project work. His perceptive criticism kept me working to make this project in a much better way. Working under both of them was an extremely knowledgeable experience for me.

### Conclusion and future scope

To realize high potency, we have a tendency to 1st propose a road network-based assortment algorithmic rule. During this algorithmic rule, we have a tendency to use a filtering and verification framework to answer the RSkNN question. Next, to boost the question performance, we have a tendency to style social network-based and hybrid assortment algorithms, specifically ISN and IH.

Our most effective algorithmic rule depends on the hybrid index, IH, that gives tight bounds for the road-social search house. A direction for future work is to use the techniques in to hurry up question. Another future work is joint social and road process on networks hold on in a very distributed manner.

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