Query Answering Efficiency in Expert Networks Under Decentralized Search

Liang Ma  
IBM T. J. Watson Research  
Yorktown, NY, USA  
maliang@us.ibm.com

Mudhakar Srivatsa  
IBM T. J. Watson Research  
Yorktown, NY, USA  
msrivats@us.ibm.com

Derya Cansever  
Army CERDEC  
Aberdeen, MD, USA  
derya.h.cansever.civ@mail.mil

Xifeng Yan  
University of California  
Santa Barbara, CA, USA  
xyan@cs.ucsb.edu

Sue Kase  
Army Research Laboratory  
Adelphi, MD, USA  
sue.e.kase.civ@mail.mil

Michelle Vanni  
Army Research Laboratory  
Adelphi, MD, USA  
michelle.t.vanni.civ@mail.mil

Abstract
Expert networks are formed by a group of expert-professionals with different specialties to collaboratively resolve specific queries. In such networks, when a query reaches an expert who does not have sufficient expertise, this query needs to be routed to other experts for further processing until it is completely solved; therefore, query answering efficiency is sensitive to the underlying query routing mechanism being used. Among all possible query routing mechanisms, decentralized search, operating purely on each expert’s local information without any knowledge of network global structure, represents the most basic and scalable routing mechanism. However, there is still a lack of fundamental understanding of the efficiency of decentralized search in expert networks. In this regard, we investigate decentralized search by quantifying its performance under a variety of network settings. Our key findings reveal the existence of network conditions, under which decentralized search can achieve significantly short query routing paths (i.e., between $O(\log n)$ and $O(\log^2 n)$ hops, $n$: total number of experts in the network). Based on such theoretical foundation, we then study how the unique properties of decentralized search in expert networks is related to the anecdotal small-world phenomenon. To the best of our knowledge, this is the first work studying fundamental behaviors of decentralized search in expert networks. The developed performance bounds, confirmed by real datasets, can assist in predicting network performance and designing complex expert networks.

Keywords
Expert Networks; Query Answering; Decentralized Search; Performance Bounds

1. INTRODUCTION
Expert networks are composed of a group of expert-professionals, who cooperate with each other to solve specific queries (e.g., reported by clients) using their professional knowledge in a variety of related subjects. The collaboration among experts is knowledge-driven, manifesting in the process of expert searching: Upon receiving a query by an expert, she first attempts to solve the problem specified in the query; if she fails, then this query is routed to another expert for further processing. This process continues until the query is resolved. Such expert networks are abundant in real life. One canonical example is the enterprise call center, where if a query ticket cannot be solved by the first responding agent, then a series of processing/forwarding attempts are triggered until qualified agents are found. The fundamental goal regarding expert networks is to route each query to experts with sufficient expertise in a timely and accurate manner. This is a challenging issue as efficient query routing mechanisms depend on the professional knowledge of each individual expert as well as the social knowledge of other experts’ specialties possessed at each expert. When the expert profiles (e.g., expertise) are not properly maintained in expert networks, finding the most knowledgeable experts with high probability while minimizing the number of routing steps is explored in [1,2]. On the other hand, even if each expert’s profile is accurately exposed to all of her contacts, this routing issue remains challenging. In particular, under the assumption that each expert has connections to only a limited number of other experts, a series of routing rules are proposed in [3,4] for improving the resolution efficiency in specific tasks (e.g., IT services). Under the same assumption, generative models [5] are developed for making global expert recommendations by estimating all possible routes to potential resolvers. The efficacy of these mechanisms, however, relies heavily on the broad knowledge of network global structure; in addition, these mechanisms, requiring non-negligible training periods, are generally complicated and sensitive to operational scenarios, thus not applicable to large-scale or dynamic networks (e.g., with experts joining/leaving the network). All these limitations, therefore, motivate us to consider if there exist simple yet efficient query routing solutions that function with only basic network information and are robust against network variations.

Among all possible query routing mechanisms, decentralized search, operating purely on each expert’s local information, represents the most basic and adaptive routing mechanism in expert networks. Specifically, under decentralized search, before reaching experts with sufficient expertise for a given query, each intermediate expert forwards this query to one of her contacts with the highest problem solving abil-
ities, which therefore forms a pure local-information-based forwarding rule. Since no historical training data or network global structure is required for routing decision making, decentralized search can be broadly adopted by any network scenarios for query routing. However, decentralized search, greedy in nature at each routing step, is generally ignored in the research community mainly for the following reason: When an expert forwards a query to one of her contacts via decentralized search, she has no clue whether this decision would successfully lead to a short path through the entire network, and thus the efficiency of decentralized search is uncertain. We note, however, without fundamental understanding of such simple decentralized search, we can never justify the value/necessity of designing other complicated query routing mechanisms for expert networks. Therefore, in this paper, we consider this unsolved fundamental problem: What is the efficiency of decentralized search in expert networks? We study this problem by quantifying the performance of decentralized search under various network settings so as to understand under what conditions decentralized search can achieve efficiency/inefficiency in query routing.

In this paper, the basic approach we employ to study the performance of decentralized search is to establish its performance bounds in generic expert network models. Such models should capture two main connection properties among experts: (i) experts are rich in connections to peer experts with similar expertise; (ii) each expert also tends to connect to a few experts with fairly dissimilar expertise. Integrating these two properties that characterize expert social connections, we propose one expert network model. In this model, local expert connections (experts with similar expertise) enable the formation of the basic network structure, on top of which long-range expert connections (experts with fairly dissimilar expertise) determine to what extent the expert inter-connections do not respect such basic network structure. We prove that the natural superposition of these two properties in expert networks can lead to high efficiency of decentralized search without any centralized guidance under a range of network settings. Accordingly, if an expert network is verified to satisfy such conditions that guarantee efficient decentralized search, then there is no need to design complicated query routing mechanisms as the lightweight decentralized search will suffice. Furthermore, by a case study of real datasets, we demonstrate how commercial expert networks may take proactive actions to train their constituent experts, which equivalently approaches the efficient query routing conditions discussed in this paper.

1.1 Further Discussions on Related Work

Regarding expert networks, most existing works [1–4] seek to develop/improve query routing mechanisms, where different levels of network global knowledge are required. With network historical data, [6] develops a Markov Decision Process (MDP) model to optimize routing policies. However, the correlation between successful query answering probability and each expert’s expertise level is ignored in the proposed model. Employing game theory, [7] proposes query incentive networks to understand agent collaborations and interactions in on-line communities. In addition, routing efficiency improvement is investigated in [8] when additional expert contacts are carefully chosen. Our work belongs to a different but closely related line of work that focuses on the fundamental understanding of the most basic query routing mechanism in expert networks. Our work shares similar goals with [9] in that [9] tries to build models to understand routing behaviors in expert networks, particularly in human factors that influence routing tendencies. However, [9] does not show how the efficiency of such routing behaviors are affected by network properties. By contrast, we not only present deep insights into decentralized search in expert networks, but also show how its efficacy is related to network’s structural and social properties.

For the underlying influence of network properties on the routing efficiency, [10] show that every pair of nodes are joined by a path of length \( O(\log n) \) (\( n \): total number of nodes in the network) in a randomly generated graph. The existence of such short paths is maintained even when the network demonstrates certain structural properties [11]. Further, more complicated statistical models are considered in [12] for node inter-connections (e.g., Poisson distributions). When the number of links incident to nodes follows the power-law distribution, [13] explores how such distribution may affect routing preference. In addition, with special network properties, networks may exhibit small-world phenomenon [11, 14–18]. However, [18] proves that there exists one and only one network setting that enables efficient searching for a unique target.

1.2 Summary of Contributions

We study, for the first time, decentralized search in expert networks from the perspective of fundamental performance quantifications. Our contributions are five-fold:

1) We propose the diversified model to model expert inter-connections and expertise distributions.
2) We prove that decentralized search is highly efficient under a wide range of network settings in the diversified model; the corresponding average routing path length is between \( O(\log n) \) and \( O(\log^2 n) \) (\( n \): total number of experts).
3) We further establish conditions for the case when decentralized search is ineffective, and develop the corresponding lower bounds to quantify its performance.
4) We discuss how above theoretical results are related to the special characteristics of small-world phenomenon in expert networks.
5) We show that the theoretical bounds can also approximate the routing performance in real datasets, thus providing guidance in planning practical complex expert networks.

The remainder of the paper is organized as follows. Section 2 formulates the problem. The expert network model is proposed in Section 3. Main results of decentralized search in expert networks are presented and analyzed in Section 4. Experiments are conducted under both synthetic networks and real datasets in Section 5. Section 6 concludes the paper.

2. PROBLEM FORMULATION

In this section, we propose mathematical models to capture expert inter-connections, and then formally present decentralized search and state our research objective.

2.1 Expert Inter-Connections

We assume that in an expert network with \( n \) experts, experts can collectively solve problems in up to \( m \) different areas. For all experts, we assume that their expertise in different areas are quantifiable to non-negative integers, and thereby each expert is associated with an expertise vector defined as follows: The expertise vector of expert \( u \), denoted by \( \mathbf{e}^{(u)} \), is an \( m \times 1 \) column vector with the value in entry \( i \) (i.e., \( e^{(u)}_i \)) indicating \( u \)'s skill in area \( i \) (larger value corresponds to superior skill); \( e^{(u)}_i = 0 \) if \( u \) does not have any skill in area \( j \). We call \( ||\mathbf{e}^{(u)}|| = \sum_i e^{(u)}_i \) the total ability of expert \( u \). Using this concept, we can compare the expertise
levels in different areas for one individual expert or in the same area across multiple experts. Furthermore, we define the expertise distance from expert u to expert w as d(u → w) := \sum \max(e_i(w) - e_i(u), 0). Intuitively, expertise distance characterizes the superior skills of one expert against another, and it implies that generally d(u → w) \neq d(w → u). With all these concepts, we are ready to model homophily and heterophily of expert inter-connections.

Homophily refers to the tendency that each expert is rich in connections to peer experts with similar expertise. To characterize such expertise similarity, both inferior and superior skills should be considered when comparing two experts, i.e., expertise difference in all areas between two experts relate to the efficiency of decentralized search. In this paper, we study how these parameters relate to the efficiency of decentralized search.

Heterophily refers to the phenomenon that each expert has a few connections to experts with fairly dissimilar expertise. These dissimilar experts are called long-range contacts of u. When experts are connected by the homophily rule (adding local contacts for each constant parameter), they are called local contact. Therefore, we use a statistical model to capture long-range contacts for each individual expert. In particular, when r = 0, all experts in the candidate set C_u are equally likely to be long-range contacts of u, which corresponds to a purely random case; when r increases, long-range contacts of an expert tend to only exist within her vicinity (measured by the expertise distance); when r approaches +\infty, all long-range contacts disappear, i.e., there is no heterophily in the expert network. In this paper, we study how these parameters relate to the efficiency of decentralized search.

Algorithm 1: Decentralized Search

input: Expert network, query (i, τ), first query holder u
output: Routing path P for resolving query (i, τ)
1 P ← u; // "←": assignment operation
2 while \( e_i(u) - τ < 0 \) do
3 \( u = \arg \max_{w \in N(u)} (\min(e_i(w) - τ, 0)) ; // N(u): set of all (local and long-range) contacts of u
4 P ← P + u; // append u to P
5 end

2.2 Decentralized Search

We now formally present decentralized search for query routing. In an expert network, its constituent experts can generally resolve queries in more than one problem area; however, for the queries posted to the network, the most frequent case is that each of them belongs to one and only one problem area. In this regard, we model each query as a 2-tuple \((i, τ)\), where i is the problem area to which this query belongs (τ > 0) indicates the corresponding difficulty level, i.e., query \((i, τ)\) is solvable by experts with expertise level in area i being at least τ. We assume that there is no ambiguity in determining the problem areas of queries, and there exist qualified experts in the network to solve each query, i.e., for any query \((i, τ)\), \exists expert w with expertise in area i and \( e_i(w) \geq τ \). In this paper, the most crucial assumption is that for each query holder, besides knowing the expertise vector and (local and long-range) contacts of herself, she also knows the expertise vectors of all her (local and long-range) contacts; however, she does not have knowledge of expertise vectors or contacts of other experts, i.e., no experts have the global view of the network. Under these assumptions, decentralized search is detailed in Algorithm 1. In Algorithm 1, for a given query, if the current query holder u cannot solve this query, then line 3 searches for the best expert from all u’s contacts (with ties broken arbitrarily) as the next routing step. This process continues until a qualified expert is found.

Remark: In decentralized search, if a query holder’s contacts cannot solve the received query, then this query holder has no knowledge of where the qualified experts are. Therefore, one may concern that the condition in line 2 may never be satisfied for some queries, thus resulting in endless loops. We will show in Section 3 that the structural properties of the network model abstracted from real networks ensure that at least one expert satisfying the condition in line 2 can be found by Algorithm 1 (although the resulting routing path may be long).

2.3 Objective

Suppose that the problem area and the difficulty level in each query are independently and uniformly distributed (subject to the maximum problem solving ability in the network) and the first query holder is also randomly chosen. Our goal is to understand decentralized search in expert networks by computing its upper/lower bound of the average routing path length (measured by the number of hops) under different network structures and expert inter-connections.

3. EXPERT NETWORK MODEL

1 If a query contains problems in \( p \) (\( p > 1 \)) areas, then this query can be treated as \( p \) separate queries.
2 If the global picture of the network is fully known to each expert, then simple breadth-first search will suffice to find the shortest query routing path, which is not of interest to this paper.
Based on expert inter-connection models in Section 2, we now present an expert network model, called diversified model. In this model, both the total abilities and specialties may vary for different experts. Moreover, this model naturally captures the Gaussian-like distribution of expert total abilities in real expert networks. Suppose that up to $m$ ($m \geq 1$) specific areas can be solved in the expert network. Let $\lambda$ denote the maximum expertise level in each area (i.e., the maximum value for every entry in any expertise vector), then the diversified model is structured as follows:

1. Suppose for any expertise vector $e$, $\forall i$, $e_i$ is an integer between 1 and $\lambda$ (i.e., $[1, 1, ..., 1]$) such that $\sum_{i=1}^{m} e_i \leq [\lambda, \lambda, ..., \lambda]^T$, and each possible value of $e$ corresponds to one expert. Hence, the total number of experts is $n = \lambda^m$;

2. Each expert only has the most similar experts (i.e., similarity degree $\delta = 1$) as local contacts, thus forming an $m$-dimensional grid (Fig. 1 illustrates a sample $2$-dimensional grid). As Fig. 1 shows, if an expert is not at the boundary, she has $2m$ local contacts; otherwise, the number of local contacts is between $m$ and $2m$.

Then based on the above network substrate, long-range contacts are constructed following the inverse $r$-th power distribution for each expert (see the example in Fig. 1).

**Discussions:** In this model, the number of experts with the total ability $\phi$ is $\sum_{q=0}^{\min(m, \lceil 1-q \cdot \lambda \rceil)} \frac{\phi^{-q}}{(\phi^{-q-1} - \phi^{-1} \cdot q)}$, and the expected value of total ability is $(m + m \sqrt{\lambda})/2$. By these numerical expressions, the distribution of total abilities is reported in Fig. 2 under different values of $m$. The most important property of the diversified model revealed by Fig. 2 is that the expert total ability follows a Gaussian-like distribution as $m$ increases. Therefore, the diversified model ($m > 2$) represents a real expert network that is abundant in experts with average problem solving abilities, while lacks experts with significantly superior/inferior total abilities.

**Remark:** The theoretical results in this paper are based on the network model proposed in this section, where specific expertise distributions over experts are required. Nevertheless, we point out that even if such requirement is not strictly satisfied, our theoretical results still demonstrate high accuracy in predicting query routing performance (see the case study of real datasets in Section 5), thus making contributions from both theoretical and practical perspectives.

### 4. Efficiency of Decentralized Search in Expert Networks

Recall that we assume (in Section 2) that the problem area and the difficulty level in queries are generated uniformly (up to the maximum problem solving ability per area in the expert network) at random, and the first query holder is also arbitrarily chosen. We now present the corresponding quantitative performance bounds and analysis of decentralized search under the diversified model. We then discuss how the small-world phenomenon is related to decentralized search in expert networks.

#### 4.1 Statement of Main Results

Under the diversified model, we have the performance bounds of decentralized search stated as below, where $\ln(\cdot)$ denotes natural logarithm. In these results, we assume that $n$ is sufficiently large such that $\sqrt{\ln n} > 8$ and $n >> k$. Complete theoretical proofs are presented in [19].

**Theorem 1.** The average routing path length generated by decentralized search is monotonically increasing with $r$.

**Theorem 2.** The average routing path length generated by decentralized search is upper bounded by

$$O \left( \frac{1}{m^r} \cdot (\ln n)^{r+1} \right)$$

for $0 \leq r \leq 1$.

**Theorem 3.** The average routing path length generated by decentralized search is lower bounded by

$$\Omega \left( \frac{1}{k^{1/r} \cdot n^{r/2m}} \right)$$

for $r > 1$.

**Corollary 4.** Any routing path length generated by decentralized search is upper bounded by $\sqrt{\ln}$.

#### 4.2 Performance of Decentralized Search in Expert Networks

1) $0 \leq r \leq 1$. Theorem 2 shows that when $0 \leq r \leq 1$, the average routing path length using decentralized search is upper bounded by a polylogarithmic function, i.e., a polynomial function of $\ln n$. Therefore, decentralized search is highly efficient in expert searching when $0 \leq r \leq 1$. Such high efficiency occurs mainly for the following two reasons:

(i) In expert networks, experts exhibit a certain level of randomness in inter-connections, which causes the formation of a network gradient that drives the query to the destination via decentralized search. (ii) Qualified experts for a given query may not be unique, i.e., query routing terminates at any expert who is capable of resolving this query; therefore, the query routing problem in expert networks is an anycast problem. Hence, if a query is routed to an over-qualified expert, then this query does not need to be further routed to the expert with the exact required knowledge level as the
problem is already solvable. Another significant insight revealed by Theorem 2 is that decentralized search is most effective when \( r = 0 \) (i.e., long-range contacts are randomly selected) as the number of experts \( n \) is sufficiently large according to our assumption; the corresponding routing path length is only logarithmic in the network size.

2) \( r > 1 \). When \( r \) increases, Theorem 1 shows that the average routing path length also rises. When \( r > 1 \), as shown in Theorem 3, the average routing path length can no longer be expressed as a polylogarithmic function, which indicates the ineffectiveness of decentralized search. Nevertheless, Corollary 4 proves that for any values of \( r \), there is always an upper bound, which is determined by the network size. Therefore, the worst performance of decentralized search happens when \( r \) approaches \( +\infty \), for which the lower bound is \( \Omega(\sqrt{n}) \). Comparing to Corollary 4, this result suggests that the performance bound in Theorems 3 is tight when \( r \) is large. On the other hand, Theorem 3 also shows that although a larger \( k \) may increase the probability of connecting to qualified experts, the impact of \( k \) in reducing the average routing path length is weakened when \( r > 1 \). This is because when \( r \) is large, long-range contacts tend to only exist in the vicinity of each expert or even overlap with local contacts, and thus the contribution of a large \( k \) diminishes.

4.3 Uniqueness of Small-World Phenomenon in Expert Networks

As shown in [10,20], the basic standard for justifying networks with the small-world phenomenon is that the associated network diameters can be expressed as a polylogarithmic function of \( n \). Thus, by Theorem 2, we conclude that not only does the small-world phenomenon exist when \( 0 \leq r \leq 1 \), but also decentralized search is able to find these short paths. This is in sharp contrast with the unicast problem in prior works on the small-world phenomenon. Specifically, assuming that individual connections also follow the inverse \( r \)-th power distribution (constructed based on their lattice distances) in the unicast problem, [18] shows that though the small-world phenomenon is pervasive for a range of \( r \), decentralized search is only efficient under a unique value of \( r \). This is because in a unicast problem with the destination being \( t \) along the way from the current message holder to \( t \), if each intermediate node routes this message to a long-distance node (corresponding to one over-qualified expert in expert networks) that is beyond \( t \), then this message needs to be routed back to \( t \), thus resulting in long routing paths.

5. EXPERIMENTS

In this section, we evaluate the performance of decentralized search by computing its average routing path length under the diversified model and explaining the corresponding observations using the performance bounds in Section 4. Then, we compare the predicted query routing time using the performance bounds to the actual routing time in a case study of real datasets for justifying the applicability of the performance bounds to real networks.

Performance Under the Diversified Model: To evaluate the performance of decentralized search, we select \( n = 729 \) and \( m = 1, 2, 3 \) for the diversified model under \( k = 1, 2, 3 \). We generate queries by randomly selecting the corresponding problem area and the required expertise level; moreover, the first query holders are also randomly chosen. For each network parameter setting, 100 random network realizations are generated, and 500 Monte Carlo runs (each run corresponds to a newly generated query) are conducted on each network realization. Using decentralized search, the resulting routing path length averaged over all network realizations and Monte Carlo runs are reported in Fig. 3.

In Fig. 3, as expected, we first observe that the average routing path length increases with \( r \) (supported by Theorem 1). The most significant conclusion we can draw from Fig. 3 is that they confirm the high efficiency of decentralized search when \( 0 \leq r \leq 1 \) (as proved in Theorem 2). Specifically, compared to the network size (729 experts), decentralized search achieves extremely small routing path length, i.e., between 2 to 4 when \( r = 0 \). When \( r \) increases (\( r > 1 \)), the performance under different parameters begins to depart, and the performance under small \( m \) degrades significantly; for which Theorem 3 provides a quantitative bound to capture such performance deterioration. Nevertheless, such performance degradation converges when \( r \) is large, because all routing path lengths are constrained by the upper bound (independent of \( r \) ) established in Corollary 4.

Case Study of Real Datasets: Next, using our theoretical results, we analyze real-world query routing data collected from the IBM IT service department throughout 2006. Depending on query contents, these datasets are categorized into four independent classes: Operating System 1 (OS-1), Operating System 2 (OS-2), Database, and Web Service. Table 1 lists the network parameters in these datasets. For these datasets, we first observe that their network structures can be characterized by the diversified model\(^3\) for the case of \( m = 2 \) and \( k = 1 \). In Table 1, two values of \( r \) (i.e., \( r_1 \) and \( r_2 \)) are derived from these datasets based on expert inter-connections, where \( r_2 \) corresponds to new connections after applying a mentoring program to the original expert networks (associated with \( r_1 \)). In this mentoring program, some less-skilled experts are mentored by experienced experts, which equivalently reduces the value of \( r \). In order to justify application of our theoretical results in Section 4, we still need to determine whether or not the query routing behaviors in these real datasets share any similarities with decentralized search. To this end, we define relative expertise difference as \( ||e^{(w)} - e^{(u)}||_1/||e^{(w)}||_1 \), where \( w \) is the next hop expert selected by expert \( u \). The query forwarding probability versus relative expertise difference averaged over all queries received in the four networks of the datasets is shown in Fig. 4(a). As comparison, we also compute the same metric based on decentralized search in the diversified model as reported in Fig. 4(b), where three networks of similar network sizes and similar values of \( r_1 \) and \( r_2 \) as those in the real datasets are evaluated. We note that Fig. 4(a) and (b) have similar shapes, i.e., the expert

\(^3\)Note that in Table 1, the expert network associated with each dataset is not as strictly structured as that in Fig. 1, i.e., some experts in Fig. 1 may be missing; however, the performance prediction remains accurate.
Table 1: Performance in Real Expert Networks

<table>
<thead>
<tr>
<th>Datasets</th>
<th>n</th>
<th>r1</th>
<th>r2</th>
<th>real $\frac{T_1}{T_2}$</th>
<th>predicted $\frac{T_1}{T_2}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>OS-1</td>
<td>184</td>
<td>1.98</td>
<td>1.44</td>
<td>1.44</td>
<td>1.63</td>
</tr>
<tr>
<td>OS-2</td>
<td>122</td>
<td>1.24</td>
<td>1.04</td>
<td>1.31</td>
<td>1.45</td>
</tr>
<tr>
<td>Database</td>
<td>305</td>
<td>1.61</td>
<td>1.01</td>
<td>2.37</td>
<td>2.87</td>
</tr>
<tr>
<td>Web Service</td>
<td>266</td>
<td>1.14</td>
<td>1.04</td>
<td>1.19</td>
<td>1.26</td>
</tr>
</tbody>
</table>

with neither too similar nor too different expertise is selected with high probability as the next hop; therefore, the routing behaviors in these datasets do exhibit a certain level of decentralized search. Hence, we can use our results in Section 4 on decentralized search to predict the routing performance in these real datasets. Let $T_i$ denote the average query routing path length under $r_i$ ($i = 1, 2$). We compare the real $T_1/T_2$ with the predicted $T_1/T_2$ using Theorem 3 (as $r_1, r_2 > 1$ for all datasets). The comparison in Table 1 shows that using the theoretical performance bounds, the predicted routing path length is accurate (the error is 21.1% for Database, and 5.9% ~ 13.2% for other datasets); therefore, the theoretical results in this paper can naturally serve as an efficient tool for analyzing/predicting behaviors in real expert networks. Moreover, these datasets also suggest that to achieve high routing efficiency, network owners can take proactive actions to adjust the expert connections such that the resulting network condition ($r_2 > 1$) approaches the high efficiency region (i.e., $0 \leq r \leq 1$).

6. CONCLUSION

We investigated the efficiency of local-information-based decentralized search for query answering in expert networks, focusing on quantifying the performance of decentralized search under various network settings. Under the proposed network model, we established fundamental theories demonstrating when decentralized search is exceptionally effective in finding short query routing paths. In cases where decentralized search is ineffective, we also quantified how the performance deterioration is correlated to network structures. Evaluations and comparisons of these theoretical results in both synthetic networks and real datasets confirm the efficiency of decentralized search in expert networks as well as the significance of the developed performance bounds in guiding real network design.

7. ACKNOWLEDGEMENTS

Research was sponsored by the Army Research Laboratory and was accomplished under Cooperative Agreement Number W911NF-09-2-0053 (the ARL Network Science CTA). The views and conclusions contained in this document are those of the Army Research Laboratory or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation here on.

8. REFERENCES


