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Expert recommendation for trouble ticket routing

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ABSTRACT

A trouble ticket is an important information carrier in system maintenance, which records problem symptoms, the resolving process, and resolutions. A critical challenge for the ticket management system is how to quickly assign a proper expert to deal with trouble tickets and fix problems. Thousands of tickets bouncing among multiple experts before being fixed will consume limited system maintenance resources and may also violate the service level agreement (SLA). Thus, for an incoming ticket, an expert should be recommended as quickly as possible in order to reduce the processing delay.

In this paper, to address the challenge in the expert assignment, we exploit an expert collaboration network model by combining expertise profiles and social profiles learned from problem descriptions and resolution sequences of the historical resolved tickets, and develop several two-stage expert recommendation algorithms to determine a resolver to solve the problem. To evaluate the effectiveness of expert recommendation algorithms, we conduct extensive experiments on a real ticket data set. The experimental results show that the proposed algorithms can effectively shorten the mean number of steps to resolve (MSTR) with a high recommendation precision, especially for the long routing sequences generated from manual assignments. The proposed model and algorithms have the potential of being used in a ticket routing recommendation engine to greatly reduce human intervention in the routing process.

1. Introduction

The quality of modern large-scale IT service delivery highly depends on the underlying IT infrastructure. Although powerful hardware and software tools have been used in modern IT infrastructure, it is still inevitably to suffer from system faults, even system failure, due to software aging [1], operation errors, etc. When an event (which is not part of the standard operation of a service that may cause an interruption or a reduction) happens, or when using an IT service, errors, faults, difficulties or special situations (that need attention from system management experts) occur, a trouble ticket is then generated in the ticket system. The IT infrastructure and service delivery management system is responsible for dealing with these trouble tickets in time.

In a typical IT infrastructure and service delivery management organization, each expert has the expertise to solve certain types of problems. Skilled experts need to be quickly assigned to bring an abnormal service (described in a trouble ticket) back to normal because an IT service provider typically signs up a Service Level Agreement (SLA) with their users. However, the increasing complexity of the IT infrastructure and service delivery makes the types of reported troubles diverse. Moreover, the trouble description in a ticket is often vague and may not contain the actual root cause of the trouble. Thus, it is difficult to find a right expert to solve the trouble described in the ticket.

A typical ticket routing process [5] works as shown in Fig. 1. For example, ticket t_1 is initiated by a monitoring system or a

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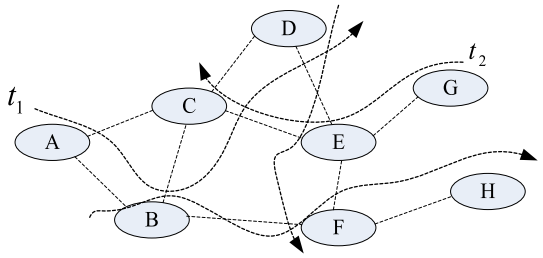

Fig. 1. Ticket routing.

customer and is subsequently routed through an expert network until it is closed. First, expert A is recommended to resolve ticket t_1, but fails to resolve it. Thus, ticket t_1 is transferred to another expert B for resolution. However, expert B still fails to resolve it. Ticket t_1 has to bounce among multiple experts before being transferred to expert D with the right expertise. As a result, the sequence $A \rightarrow B \rightarrow C \rightarrow D$ is called ticket routing sequence. Obviously, if a ticket is mistakenly transferred to an expert that cannot solve the trouble, it might not only lead to a long routing sequence and violate the SLA, but also waste limited maintenance resources. In real-world applications, the number of trouble tickets generated each day is very huge. Therefore, although manually assigning experts has a high accuracy, it suffers from a low efficiency. Rapid problem solving has to rely on the accurate expert recommendation. Expert recommendation is also known as expert finding, expert retrieval or expert search, which addresses the task of finding the right person with the appropriate skills and knowledge [2,3]. This paper focuses on the study of expert recommendation based on the expert collaboration network.

As an important carrier of the IT infrastructure and service delivery management procedure, historical trouble tickets record comprehensive information generated from automatic system monitoring, end-users, and experts in their whole life cycle. Since this information provides important clues for expert recommendation of an incoming ticket, it is necessary to further analyze these historical trouble tickets in order to address the following problems:

1) How to build an expert collaboration network model (describing both expert's professional skills and collaboration abilities) from historical tickets?
2) How to apply the expert collaboration network model to guide the expert recommendation with a high efficiency and accuracy?

Although a few studies [4–7] have been reported to deal with these problems, there are still some limitations in existing methods that need further investigation. The main limitation is that tickets and experts use different representations so as to increase the difficulty of semantic matching between ticket terms and candidate experts. Another limitation is that most previous works usually assume that a given ticket only belongs to a specific problem type. For a problem type, an expert collaboration model is built for ticket routing based on expert recommendation [4,5]. Thus, the problem type of a given ticket needs to be determined in advance by manual or automated ticket classification algorithm to narrow the expert search space. However, the accuracy of ticket classification is not high enough, which has a great impact on expert recommendation results.

To cope with these limitations, we design a vector-based distributed representation for both experts and historical tickets and develop an expert collaboration network model applicable to tickets of all problem types and the corresponding expert recommendation algorithms using different recommendation policies. Furthermore, we evaluate our algorithms on real trouble ticket datasets in terms of the effectiveness.

The main contributions are summarized as follows:

1) We employ an integrated vector-based distributed representation for both tickets and experts by transforming the ticket representation into expert profile representation using a transformation matrix, which ensures that expertise and ticket are in the same dimensional space and is easy to capture the similarity between concepts (e.g., words and candidate experts) by the closeness of their representations in vector space.
2) We develop an expert collaboration network model and the corresponding expert recommendation algorithms by connecting all experts with the learned expertise profiles and social profiles from historical ticket through the maximum likelihood estimation approach.
3) Several groups of experiments are conducted to validate the effectiveness of our recommendation algorithms. The experimental results demonstrate that the proposed algorithms can effectively shorten the average length of ticket routing sequences and works well on datasets of hybrid problem types. Moreover, our algorithms perform better than the compared standard classifiers and other popular methods in expert recommendation.

The rest of the paper is organized as follows. Section 2 discusses the related works, followed by backgrounds and notations in Section 3. Section 4 provides an expert collaboration network model. Several expert recommendation algorithms based on the expert