An Architectural Framework for Expert Identification Based on Social Network Analysis

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Abstract. *This work proposes a solution for syntactic and semantic analysis in social networks in the Global Software Development context. We conducted three case studies using data extracted from GitHub to evaluate the proposed approach. The case studies provide evidence that our proposed method can identify specialists, highlighting their expertise and importance to the evolution of the social network.*

Resumo. *Este trabalho propõe uma solução para a análise sintática e semântica em redes sociais no contexto do Desenvolvimento Global de Software. Conduzimos três estudos de caso utilizando dados extraídos de GitHub para avaliar a abordagem proposta. Os estudos de caso fornecem indícios de que o nosso método proposto pode identificar especialistas, destacando a sua especialidade e importância para a evolução da rede social.*

1. Introduction

The world is evolving fast, and a large volume of information is becoming increasingly available. The growing complexity of software development processes and demand for fast software delivery bring challenges associated with the need for efficient methods to extract knowledge from data. In this sense, data analysis is valuable as it aims to transform datasets into valuable information, converting them into insights for decision-making [Androniki et al 2018].

Global Software Development (GSD) has arisen driven by the growing importance of software as a vital component in almost every business. The complexity, effort required, and unpredictability in large-scale software development [Bosh et al 2010] raise challenges associated with finding qualified professionals to assist with specific tasks. Experts are essential individuals in GSD, as they are often responsible for most of the relevant contributions in software development [Lopes et al 2020]. However, identifying those suitable to assist with project needs is difficult, especially considering that various characteristics, such as technical knowledge, previous experiences, collaborative skills, and availability, may influence the search for the right person [Rubin et al 2016].

Recommendation Systems (RS) can be valuable in GSD as they allow for reducing the human effort of finding suitable developers by providing suggestions based on the analysis of developers' past behavior and interpersonal relationships [Lopes et al

2021]. However, there are challenges in designing recommendation systems when analyzing social structures in GSD: **Temporal information**: Taking the time dimension into account is essential as people's interests are constantly changing, impacting how they interact with each other and their ranking in recommendations [Singh et al 2020]. Not considering temporal information may result in giving greater importance to individuals who were but are no longer involved in a particular subject, e.g., a developer who has contributed to a specific topic in the past but has lost interest in that topic over time; **Work overload**: Traditional approaches often lead to the design of analytical models that recommend the same group of popular developers [Xie et al 2021]. Such a naive system could drastically increase the requests for assistance from these individuals, who could end up overloaded with numerous tasks to solve [Das et al 2017]. Moreover, the excessive workload faced by some developers promotes a stagnant collaboration scenario with low knowledge dissemination, reduced productivity, and increasing software defects [Mirsaeedi et al 2017]. Thus, identifying developers who are not obvious but have similar skills to those considered experts expands the diversity of recommendations by identifying additional potential individuals who could contribute to project needs [Asthanaet al 2019]. **Semantic Analysis**: Various studies support algorithms that improve automatically through experience and data usage [Ali al 2021]. However, learning from data is more than just analyzing data. Some authors [Scheider al 2017] suggest that there is no meaningful knowledge discovery without exploring the context information in which data is generated. Thus, including semantic analysis into data analysis systems can increase the flexibility and quality of the study by bridging semantic gaps between data [Dou al 2015,LSI 2010].

Considering the three research challenges related to analyzing social structures in GSD, we present a new expert recommendation system. First, we seek to identify and classify experts by investigating the evolution of their communities in social networks. Furthermore, our approach combines syntactic and semantic analysis techniques to explore distinct aspects of the network, helping us identify those with specific knowledge. Figure 1 highlights the contributions of our work along with the proposed analytics process. First, we model the data as a social network, representing the relationship between individuals that best aligns with the goals we seek to solve. Then we consider temporal information and model the network over sequential time periods to analyze how its structure evolves. Finally, we analyze the evolution of the network formed among developers who collaborate to achieve project goals.

Syntactic and semantic analyses are implemented separately to explore the data more comprehensively. In the syntactic analysis step, we characterize the network and use a clustering algorithm to investigate how the influence of developers changes over time. We work to identify the individuals considered essential for network evolution and the development of projects. Furthermore, we seek to identify less obvious developers with similar skills to those considered influential using both clustering and classification approaches. To that end, we propose and integrate a diversity-based study focused on reducing the work overload faced by highly requested individuals.

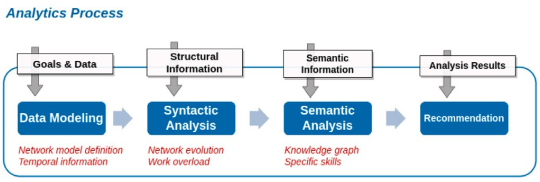

Figure. 1. Outlining the recommendation system's analytics process. Research challenges we address are in red italics.

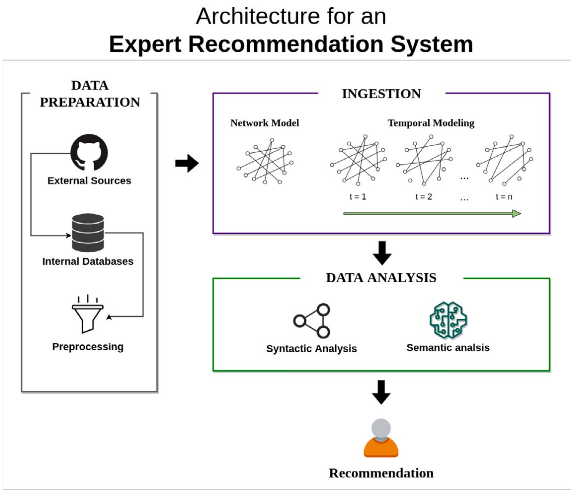

Fig. 2. Architecture for an expert recommendation system.

On the other hand, semantic analysis is the process of drawing meaning from data. When combined with syntactic analysis, semantic-based methods allow us to delve deeper into the analysis context, extracting knowledge from semantic structures. In this sense, we create an ontology to categorize relations between the entities in the network. Ontologies are logic models that explicitly represent concepts' meaning (semantics) and relationships. We use the model to create a knowledge graph by inferring implicit connections between objects. Finally, we focus on finding individuals with advanced knowledge or skills in the network by analyzing the semantic structure. Thus, we summarize the main contributions of our approach: (1) We perform a temporal characterization of the network to explore how its structure evolves; (2) We introduce a diversity-based analysis to address the problem of potential work overload of certain experts; (3) We create a semantic model using an ontology to explore implicit aspects of the network; (4) We propose a recommendation system combining syntactic and semantic analysis techniques to identify experts in GSD. As future work, we intend to explore multiaspect graphs [wehmuth et al., 2016] to improve the temporal analysis. Regarding the analyzed data, extracted from the Github platform, no type of sensitive data that could lead to bias related to prejudice or similar was considered. For space restrictions, we could not detail the results of the analyzes carried out. However, the dissertation text provides a detailed discussion on this topic. We highlight the application of the work encompassing Recommender Systems, Mining Software Repositories and Software Project Management areas, emphasizing the practical implications that software PMs will be able to take in the formation and monitoring of their teams, in particular in the formation of geographically distributed teams mainly considering OSS projects, co-located and outsourcing.

2. Related Works

In research focused on multiple dimensions, social networks are analyzed concerning the big data paradigm dimensions [Riche al 1979,Sanderson et al 2012]. A multiple-dimensional analysis, including spatial, social, temporal, and semantic perspectives, is conducted in [Pérez-Marcos et al 2020] in order to understand Twitter users' discussion.

Most graph analytics methods suffer the high computation and space costs [Reddy et al 2020]. [Camacho et al 2020] introduce a new setting for graph embedding, and social network analysis has also been explored in [Ianni et al 2021,Kitchin et al 2016]. In this sense, analyzing social networks in search of specialists can be carried out from the investigation of structural data [Ye et al 2019], and content data [Cai et al 2018]. In recent works [Cavallari et al 2019,20], collaborative models are used to identify communities' specialists. Few works aim to find appropriate individuals to help with GSD issues. Instead, they recommend individuals to help with code reviews based on their historical contributions [Cavallari et al 2019] or previously explored code [Meng et al 2016]. These approaches are considered static algorithms in community discovery, as they refer to methods that do not consider the evolution of social networks. Dynamic community finding algorithms [Cai et al 2018] refer to those approaches that incorporate the variable time into the model. Temporal analysis was used to identify patterns of user contributions [Dakiche et al 2019] and show that analyzing the evolution of their activities can be used to describe changes in the network structure [Rossetti et al 2018]. The evolution of social networks can be described by analyzing them based on some aspects over time, e.g., shared activities, members' associations, the similarity between individuals' attributes, and the closure of network cycles [Yang et al 2016]. When using machine learning models on evolutionary data, the authors in [Medeiros et al 2022] demonstrated that identifying experts by observing their temporal activity outperforms models that use static data snap- shots. In [Horta et al 2019], a temporal analysis performed on overlapping communities showed that overlapping nodes might be associated with either multidisciplinary developers collaborating on different technologies simultaneously or changing their interests. In [Ianni et al 2021], the authors consider that light knowledge in other areas allows them to collaborate on different aspects of the project. Finally, [Kitchin et al 2016] presents the TTEA model that simultaneously uncovers the topics, activities, expertise, and temporal dynamics to study the user behaviors and topics dynamics.

While traditional expert recommendation approaches ignore semantic-based information, in [Yang et al 2016] is proposed a novel Temporal-Expert-Topic (TET) approach based on Semantics and Temporal Information for temporal expert finding. We can see expertise-oriented [Horta et al 2019] and topic-oriented [Guo et al 2009] approaches used as the basis for such semantic search models.Some strategies are used to analyze semantically constructed graphs [Bidoki et al 2019,Li et al 2010]. The authors in [Pal et al 2012] propose a novel expert-finding method in CQA based on multi-granularity semantic analysis and interest drift. A new deep model for expert findings based on convolutional neural networks is proposed in [Yeniterzi et al 2015]. Also, [Akter et al 2021] seeks to verify the level of influence among researchers by analyzing a bidirectional graph-based model. Furthermore, diversity-based methods aim to recommend non-common people [Brochier et al 2018] rather than follow traditional strategies that lead to the same group of individuals [Bader et al 2007]. The lack of diversity may bring situations where experts begin ignoring their expertise and follow the crowd due to social pressure or the information cascade effect [Dehghan et al 2020]. In [Oliveira et al., 2020] is presented the JExpert, an automated tool that identifies library experts from source code. This tool is designed to identify experts in specific libraries based on source code activities from GitHub projects.

Comparatively, we are different in that: (i) we performed the analysis of social networks by exploring structural and semantic aspects. We performed a temporal characterization of the network, searching for communities and identifying essential members for the evolution of the network. Many studies identify individuals that are somehow relevant but not crucial to the evolution of the network structure. (ii) We employ machine learning models and apply centrality metrics to classify developers according to their contribution to the network. With this, we further explored the study of the term diversity, showing that the lack of diversity can inhibit the performance of some specialists, bringing situations in which other specialists are overloaded with tasks to solve. (iii) We address the use of the term expert in GSD, and for that, we propose a taxonomy categorizing keywords in GSD projects, which extends to future related work. Thus, we propose an ontology to explore implicit aspects of the network through a semantic perspective and use ontological terms and rules to identify experts and expertise. Some stud- ies focus on identifying experts according to their expertise but not on identifying them by linking developers with implicit semantic expertise and their change of interest over time. (iv) Finally, while graphical metrics, machine learning algorithms, and semantic approaches are becoming more common in recommender systems, they are barely seen together in the approach. Thus, we put together all the approaches above to compose an architecture to identify experts in GSD by performing enriched data analysis. Some studies combine the analysis of different network dimensions to analyze its structure but do not focus on improving the detection of communities.

3. Architecture

Figure 2 presents the proposed conceptual architecture, which is defined in four layers. Initially, fundamental actions, such as data scraping and storage, are employed in the Data Preparation layer. This step collects data from code hosting and version control platforms like GitHub, focusing on repositories for software development projects. Information captured includes developers' data and elements describing how they collaborate to achieve project goals. Still, the data is pre-processed in this stage, going through cleaning, integration, reduction, and transformation steps until it is ready to be ingested by the data modeling layer. These steps consist of ETL (Extract, Transform, and Load) [Bradley et al 2001], responsible for extracting data from different sources, transforming the data into a usable and trusted resource, and loading that data into the systems so end-users can access and make use downstream to solve problems.

Next, in the Data Modeling layer, social network structures are generated according to the network model that best represents the relationships in the investigation context of the problem. This is done by defining the graph structure [McGinty et al 2003], a mathematical representation composed of objects (nodes) connected by pairs of edges (connections). Once the graph model is established, the modeling process is extended using a temporal approach to represent the network in specific periods. Including time information in the modeling process allows us to generate and analyze time frames in order to understand how the network evolves. With the network structures in hand, we can use several methods separately or together to compose analysis strategies. We divided them into two groups: syntactic and semantic analysis approaches, as illustrated in the Data Analysis layer. Syntactic analysis approaches include methods focused on exploring the structural aspects of networks. In this sense, machine learning algorithms and centrality analysis measures are examples of approaches for this purpose. In addition, semantic analysis approaches focus on representing and interpreting the meaning of data in a specific context. Therefore, knowledge graphs are defined and formalized using ontologies to infer implicit connections between objects. Finally, regardless of the approach adopted, the results are gathered and analyzed in order to identify and recommend specialists according to the required expertise.

4. Social network data, model, and case studies description

GSD is supported by many platforms that enable collaboration between developers. GitHub [Hoang et al 2019] is one of the biggest code hosting platforms. It offers Git functionality, such as distributed version control and source code management. GitHub offers collaborative features supported by pull-based methods [Vassiliadis 2009], which works with *Issues*, and *Pull requests*. Issues are trackers of bugs, enhancements, requests, and ideas, while Pull requests are a mechanism for developers to notify team members that a feature or fix is ready. With this kind of system, a developer can let everyone know that they can review the code, providing a forum to discuss the implementation of the proposed feature. Therefore, in order to evaluate our approach in a real-world scenario, we analyzed some of the most starred (⋆) projects on GitHub: **Node.js** (86,445 ⋆), **Kubernetes** (86,761 ⋆), and **Symfony** (26,626⋆). These are popular projects with new features being continuously developed and supported by a large community with various active developers worldwide.

The projects are briefly described below: **Node.js** is an open-source, cross-platform JavaScript runtime environment that lets developers use JavaScript to write command-line tools. **Kubernetes** is an open-source container orchestration system for automating computer application deployment, scaling, and management. **Symfony** is an open-source PHP web application framework that aims to speed up the creation and maintenance of full-featured web applications. All data used in this research were obtained through the GitHub RESTful API. However, as the work progressed, new data were obtained and used in our analysis- from January 2014 to June 2018. Table 1 shows the different tables used in the experiments, as well as the number of records in each table: (i) *User*: table with data about distinct developers contributing to the projects; (ii) *Pull request* : table with data about pull requests that were opened in projects; (iii) *Review comments*: table with data of comments related to proposed changes in pull requests; (iv) *Discussion comments*: table with data of comments in discussions forums; (v) *Label*: table with distinct tags used to categorize pull requests.

Table 1

Dataset's tables and number of records.

Table	Value
Users	15,762
Pull Requests	79,375
Review Comments	265,714
Discussion Comments	226,628
Labels	425

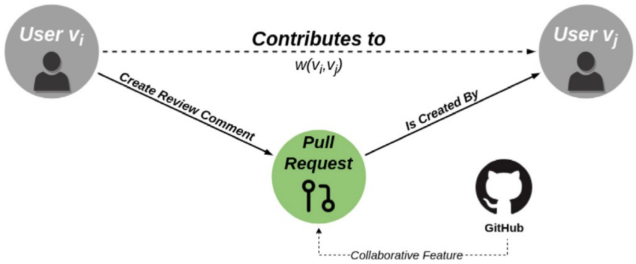

Figure 3. Collaboration network model.

Seeking to explore the collaboration context in GSD projects, we propose a collaboration network model created from implicit contribution relationships between developers. As illustrated in Figure 3, a contribution relationship is created from User vi to User vj when user vi creates a review comment on a pull request created by user vj. Review comments were chosen as they can be seen as contributions that involve specific knowledge since, they are comments related to code changes proposed in pull requests. For space restrictions, details of the modelling are discussed in the published author´s papers and the dissertation text.

The data and the social network model presented in this section were used in the case studies that evaluate the proposal of this article. Considering the three pillars of the proposed solution, we divided the evaluation into three case studies. Case Study 1 was conducted to verify the proposal's feasibility regarding the temporal characterization of the social network. In Case Study 1, a clustering algorithm was used to identify experts, and a temporal analysis was conducted to analyze the evolution of the network over time. We also use domain knowledge to understand which experts are responsible for the evolution of the network. Case Study 2 verifies the proposal's feasibility to identify alternative specialists, i.e., to reduce the workload of some developers who are widely requested at certain times. We used clustering and classification algorithms in this case study to identify alternative specialists. The results were analyzed to see if the identified developers could be considered alternative experts. In Case Studies 1 and 2, we used information about the social network structure for the analyses carried out. In Case Study 3, a semantic analysis is conducted to enrich the data through the proposal of an ontology. This ontology was instantiated using GitHub data and the network structure. For space restrictions, the case studies were not presented. The complete description is available at dissertation text and in the published articles.

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