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Optimizing Expert Rankings with Multiple Regression Analysis

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Abstract— The primary goal of this research is to establish a methodology that gives significant weight to an expert's qualifications and experience in the expertise ranking process. This methodology aims to enhance the effectiveness of expert identification by taking into account an expert's background and credentials, thus yielding more realistic expert rankings. To achieve this, we incorporate the details of an expert's qualifications and experience into the evaluation process by assigning assumed values, which are then integrated with their expertise level. These combined factors are subsequently utilized as inputs for a multiple regression analysis to generate an optimal ranking of experts. By emphasizing the significance of experience and qualifications in the ranking process, we can significantly improve the precision of our expert ranking mechanism. Our approach employs multiple regression analysis to identify the most suitable subject expert for user query transformation.

Keywords- Expert Ranking, Expert searching, Knowledge Management, E-learning

I. INTRODUCTION

Recent years have witnessed the enormous growth of e-learning system in the education and corporate sectors. The advancement in e-learning system has begun to reshape the learning approaches from traditional learning methodology to smart learning solutions. The e-learning system plays a significant role on knowledge transformations, which includes interchanging information, opinions, experiences and perceptions. The success rate of an e-learning system can be determined by the factors: such as expert's expertization, quality of content, experts and learner connectivity, adaptability and ease of use.

The transfer of knowledge takes place from experts to learners, and externalization of the knowledge transfer is significant. Integrating the experiences and qualifications of experts as key factors in the expert ranking process paves the way for a revolutionary ranking mechanism. By emphasizing expert qualifications and experience, we can elevate the quality of expert identification, resulting in more precise solutions for the queries at hand. The utilization of multiple regression analysis is instrumental in identifying the most suitable subject specialists for user query transformations. This approach places significant importance on the expertise and qualifications of these specialists in the expert evaluation process. By applying multiple regression analysis to pinpoint subject matter experts, we obtain outcomes with a high degree of accuracy, ensuring the expertise level of the selected expert.

Furthermore, the results indicate a notable improvement in the user query transformation process and the mapping of queries to the most qualified subject experts, thereby externalizing knowledge effectively. This approach directly connects information seekers with subject experts, meeting their knowledge collection needs and facilitating the transformation of that knowledge into a usable form.

2. REVIEWS ON EXPERT RANKING TECHNIQUE.

The widespread availability of the internet and easy access to information have led many of us tobecome increasingly reliant on our internet-connected devices in our daily lives. This dependence on technology has become a common way of tackling the challenges we encounter in our work and everyday activities. This shift in behavior has had a significant impact on the world of e-learning, as it now allows students to access educational resources from virtually anywhere and at any time.

In the realm of e-learning, technological advancements have paved the way for knowledge seekers to connect with experts in various subjects, providing them with the opportunity to seek clarification and expand their understanding of specific topics. In recent years, e-learning has made substantial strides, with its applications expanding not only in education but also in corporate training.

Researchers like Zhu et al. (2014) and Zou et al. (2014) have noted a growing interest in the production of information and the harnessing of collective wisdom through knowledge-sharing networks, such as online discussions and Question Answering (Q&A) communities. One of the

major challenges in this area revolves around the identification of experts, individuals possessing specialized knowledge and skill sets in specific fields. This issue of expert ranking has gained considerable attention, highlighting the importance of effectively positioning these authorities.

The pursuit of experts is a relatively new and burgeoning area of research. In recent years, a significant number of investigators have dedicated their efforts to address this informationretrieval challenge. The process involves a user submitting a concise query that indicates a specific area of expertise, resulting in a list of individuals ranked by their skill level. Several innovative methodologies have been proposed to explore various retrieval models and sources ofevidence for evaluating an individual's skill set. Moreira et al. (2015) have pointed out that the current methods for identifying experts lack a principled approach to integrating diverse sources of information as concrete evidence for assessing their skill levels.

There are different types of data sources used to gauge an expert's level of proficiency in a given field. These sources can be broadly categorized into two groups: unfiltered and filtered data sources. Unfiltered data sources, like user recommendations, support tickets, email exchanges, publications, web content, blogs, and social media, have been employed to assess expertise without a specific ranking order. Filtered data sources, such as patents, grants, and product launches, are used to evaluate an expert's qualifications.

In this paper, a novel approach is proposed that places emphasis on an expert's qualifications and experiences as crucial factors in measuring their level of expertise. This approach has beenshown to enhance the accuracy of expert identification, ensuring that the most suitable expert is connected with to address specific problems or queries.

3. METHODOLOGY

Expert finding techniques offer various strategies to assess an expert's level of expertise and determine their ranking. In this particular approach, emphasis is placed on an expert's experience and qualifications as primary factors in the expert ranking process, complementing considerations of the relevance of internet data and the expertise mapping model. This approach prioritizes the following processes to implement the proposed technique:

- Unsupervised BME K-Mean clustering Algorithm.
- Assumed values for qualification and experience.
- Association of Multiple Regression Analysis.

3.1 UNSUPERVISED BME K-MEAN CLUSTERING ALGORITHM.

We formed three clusters of experts, namely, those with beginner-level skills, those with moderate skill sets, and those with advanced expertise. These clusters were created by following the steps outlined below.

Cluster:
BME K-Mean Cluster:

- K= 3 (Beginner, Moderate, Expert).
  - (K1, K2, K3)
  - Centroid = C1, C2, C3.
    - C1 (Mid point from Min to c2)
    - C2 (Mid Point Min and Max)
    - C3 (Mid point c2 to Max)
  - Formula Centroid
    - Mi = Min Value.
    - MX = Max Value.
    - C2 = value (Avg (Min , Max))
    - C1 = value (Avg(Min, C2))
    - C3 = value (Avg(C2,Max))
  - Cluster
    - Beginners = (Min Value, , Avg(C1,C2))

o Moderate = ((Avg(C1,C2)+0.1) Avg(C2,C3))

o Expertise = ((Avg(C2,C3)+0.1), Max Value)

The variable "K" determines the number of clusters to be generated. In this algorithm, we set K=3 to create three distinct cluster groups: Beginners, Moderates, and Experts. The centroid values, denoted as C1, C2, and C3, are employed to establish a central or mean value for each of these groups.

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C2 represents the midpoint between the minimum and maximum expertization levels. C1 is calculated as the midpoint between the minimum expertization level and C2, while C3 is the midpoint between C2 and the minimum expertization level. This methodology results in the formation of three clusters for each expert domain within the system. This algorithm serves to create expert clusters for each domain.

In the realm of expert finding techniques, various strategies are available for assessing an expert's level of expertise and determining their ranking. In this particular approach, the emphasis is placed on an expert's experience and qualifications as primary factors in the expert ranking process.

3.2 ASSUMED VALUES FOR QUALIFICATION AND EXPERIENCE

In this approach, we have made an effort to incorporate an expert's qualifications and experiences as crucial parameters in the expert ranking process. However, integrating these parameters into the system posed certain challenges. The qualification parameter, for instance, accepts only alphabetical input values, while the experience parameter exclusively allows numerical input values.

To address this issue and achieve a balanced integration of input values for both qualification and experience parameters, we have chosen to assign assumed values to these parameters. These assumed values are then integrated as outlined in Tables 3.1 and 3.2.

Table 3.1 Assumed values for qualification parameters

EDUCATIONAL QUALIFICATION	**VALUES FOR DEGREES**
POST DOCTORATE (PDF)	100
DOCTOR OF PHILOSOPHY	80
MASTER OF PHILOSOPHY (M. PHIL)	60
POST GRADUATE (P.G) M.SC /M.TECH/MCA/MBA/M.E/OTHER S	40
POST GRADUATE (U.G) B.SC/B.C.A/B.COM/B.E/OTHERS	20
DIPLOMA/OTHERS	10

When an expert registers their qualifications within the system, including designations such as Post Doctorate (or PDF), Doctorate of Philosophy (or Ph.D.), Master of Philosophy (or M.Phil), Post Graduate (or M.Tech/M.Sc/MCA/MBA/ME/Others), Under Graduate (or B.Sc / B.C.A / B.Com / B.E / Others), Diploma, or other credentials, assumed values of 100, 80, 60, 40, 20, and 10 are assigned accordingly.

Table 3.1 Assumed values for qualification parameters

EXPERIENCE	**Values for Experience**
>= 50	100
< 50 AND >=40	80
< 40 AND >=30	60
< 30 AND >=20	40
< 20 AND > =10	20
< 10 AND > =1	10

When an expert enters their years of experience into the system, the following assumed values are integrated based on the range of experience:

- For experience ranging from 1 to 9 years, an assumed value of 10 is assigned.
- If the expert reports 10 to 19 years of experience, an assumed value of 20 is integrated.
- Experience within the range of 20 to 29 years corresponds to an assumed value of 40.
- When an expert has 30 to 39 years of experience, an assumed value of 60 is applied.
- Experience spanning 40 to 49 years leads to an assumed value of 80.
- If an expert declares their experience as 50 years or more, an assumed value of 100 is integrated.
- These integrated values serve the purpose of balancing the relationship between qualifications and experience.

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3.3 ASSOCIATION OF MULTIPLE REGRESSION ANALYSIS

The method employed here is multiple regression analysis, which involves consolidating various values to identify the most suitable subject expert. Multiple regression, an extension of simple linear regression, is applied to predict variable values by considering more than two variables. Consequently, multiple regression analysis plays a key role in forecasting the subject expert using data from multiple variables.

The following Equation (3.1) has been utilized to acquire the actual result.

$$Y=X1W1+X2W2+X3W3+\ldots\ldots+XNWN \quad (3.1)$$

In this context, the following variables are defined: Y represents the expert's name, X1 corresponds to the expertise value obtained through the ranking mechanism, X2 stands for the integrated assumed qualification value, and X3 represents the integrated assumed experience value. Additionally, we have W1 as the weightage assigned to X1, W2 as the weightage for X2, and W3 as the weightage for X3.

Regression analysis is a statistical method used for estimating relationships between variables. It encompasses various techniques for modeling and analyzing multiple variables, with a primary focus on understanding the connection between a dependent variable and one or more independent variables.

The assumed qualification and experience values, as well as the expertise level, can be found in Table 3.3, which serves as an input for the multiple regression analysis process. This process employs Equation 3.1 to generate the most suitable expert ranking.

TABLE 3.3 EXPERT RATING GENERATED USING INTERNET CLASSIFICATION AND QUALIFICATION & EXPERIENCE.

KEYWORD	**EXPERTLIST**	**EXPERTISE LEVEL**	**QUALIFICATION**	**EXPERIENCE**	**EXPERT RATING**
ONTOLOGY	Expert 1	7	20	2.5	29.5
ONTOLOGY	Expert 2	9.5	20	10	39.5
ONTOLOGY	Expert 3	11.5	15	5	31.5
ONTOLOGY	Expert 4	6	10	2.5	18.5
ONTOLOGY	Expert 5	12	15	5	32
ONTOLOGY	Expert 6	14	20	15	49
ONTOLOGY	Expert 7	2.5	10	10	22.5
ONTOLOGY	Expert 8	8.5	15	5	28.5
ONTOLOGY	Expert 9	13	20	15	48
ONTOLOGY	Expert 10	18.5	20	10	48.5
ONTOLOGY	Expert 11	17	20	2.5	39.5
ONTOLOGY	Expert 12	28.5	10	2.5	41
ONTOLOGY	Expert 13	9	20	5	34
ONTOLOGY	Expert 14	32	10	2.5	44.5
ONTOLOGY	Expert 15	27.5	10	2.5	40
ONTOLOGY	Expert 16	34	15	10	59
ONTOLOGY	Expert 17	36	20	5	61
ONTOLOGY	Expert 18	17.5	20	5	42.5
ONTOLOGY	Expert 19	18	20	2.5	40.5
ONTOLOGY	Expert 20	18	20	10	48

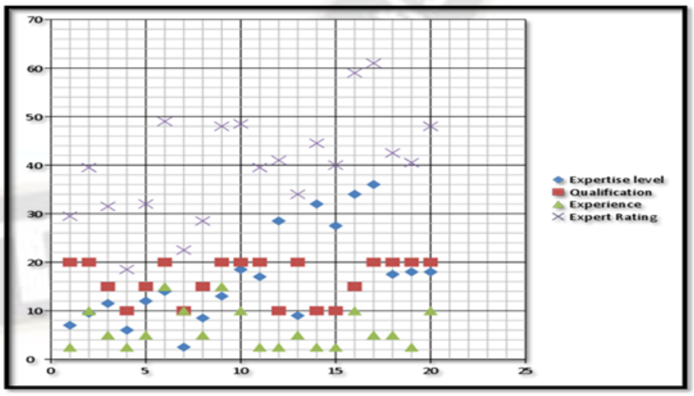

Fig 3.1 Expert rating graph

Table 3.3 provides a clear representation of the top expert in the Ontology experts group, where Expert 17 stands out with the highest expert rating value of 61. Figure 3.1 further illustrates that Expert 17 possesses a commendable expertise level value of 36, coupled with a reasonable qualification value of 20 and an acceptable experience value of 5 in the field of Ontology. These results demonstrate a significant enhancement in the approach to finding experts for specific topics and effectively connecting user queries with the most qualified experts to externalize knowledge.

4. CONCLUSION

Experts provide their qualifications and experiences, which are harmonized with assumed values to ensure consistent input formatting. These assumed qualification and experience values, along with expertise levels, are then utilized as inputs for the multiple regression analysis process. The multiple regression modules process these inputs and produce the most optimal expert ranking. Using multiple regression analysis to emphasize the significance of an expert's qualifications and experiences in expert ranking allows for the selection of the best subject experts to facilitate the transformation of user queries. This approach effectively connects knowledge seekers with domain experts, enabling the extraction of expert tacit knowledge and its conversion into externalized knowledge. These improvements have been tested, and the results have consistently demonstrated their practicality and effectiveness.

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