Sparrows and Owls: Characterisation of Expert Behaviour in StackOverflow

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Abstract. Question Answering platforms are becoming an important repository of crowd-generated knowledge. In these systems a relatively small subset of users is responsible for the majority of the contributions, and ultimately, for the success of the Q/A system itself. However, due to built-in incentivization mechanisms, standard expert identification methods often misclassify very active users for knowledgable ones, and misjudge activeness for expertise. This paper contributes a novel metric for expert identification, which provides a better characterisation of users' expertise by focusing on the quality of their contributions. We identify two classes of relevant users, namely *sparrows* and *owls*, and we describe several behavioural properties in the context of the `StackOverflow` Q/A system. Our results contribute new insights to the study of expert behaviour in Q/A platforms, that are relevant to a variety of contexts and applications.

Keywords: Question answering systems. Expert modelling. Expert behaviour.

1 Introduction

Question Answering (Q/A) platforms like Yahoo! Answers or StackExchange are an important class of social Web applications. Users access such platforms: 1) to look for existing solutions to their issues; 2) to post a new question to the platform community; 3) to contribute by providing new answers; or 4) to comment or vote existing questions and answers. As a result, users jointly contribute to the creation of evolving, crowdsourced, and peer-assessed knowledge bases.

To foster participation, Q/A platforms employ effective gamification mechanisms [1] that motivate users by showing a public *reputation score* (calculated by summing the number of preferences obtained by all the posted questions and answers), and by assigning *badges* after achieving pre-defined goals (e.g. complete at least one review task, achieve a score of 100 or more for an answer).

As shown in several studies, Q/A platforms are fuelled by a set of highly active users that, alone, contributes to the vast majority of the produced content. Such users, that we call *sparrows*, are clearly an important component of a Q/A ecosystem: as their name suggests, they are numerous, highly active, and highly "social" users. However, *sparrows* are not necessarily functional to knowledge creation. Being driven by the gamification incentives, their goal might not be to provide a thorough answer to a question, but simply to "add up" reputation score. To this end, their answers, while quantitatively relevant, might be of low quality and/or low utility (i.e. having low scores from other users and/or ranked low among all the answers in a question); also, to minimise their effort, they might target simple or non-relevant questions.

Sparrows can guarantee responsive and constant feedback, thus playing an important role in keeping the community alive. However, we claim that there exists another category of users having comparable, if not greater importance. Such a category, that we call *owls*, contains users that, while being active members of the community, are driven by another motivation: to increase the overall knowledge contained in the platform. *Owls* are **experts** in the discussed topic, and they prove their expertise by providing useful answers, possibly to questions that are perceived as important or difficult by the community.

Previous studies focused on the characterisation of experts in Q/A platforms [6, 10, 11]. However, existing methods for expert identification mainly targeted *sparrows*, as they focused on quantitative properties of users' activities (e.g. reputation score, number of answers) while ignoring the inflationary effect that gamification incentives could trigger.

This paper targets `StackOverflow`, a question answering system specialised in software-related issues, and provides two main contributions: 1) a novel expertise assessment metric, called `MEC` (Mean Expertise Contribution), which helps in better discriminating *owls* from *sparrows* and normal users in Q/A platforms; and 2) a comparative study of the behaviour of *owls* and *sparrows* in `StackOverflow`. With respect to the second contribution, we address the following research questions:

- **RQ1**: How do *owls* and *sparrows* differ in terms of knowledge creation and community participation behaviours?
- **RQ2**: How do the overall activities of *owls* and *sparrows* evolve over time?

Understanding the nature of experts, their activity behaviour, and their role is of fundamental importance to drive the economy and prosperity of this class of social Web systems. Although the study specifically focused on `StackOverflow`, we believe that our results are of general interest. A better characterisation of the quality of users' contributions can also help in improving the performance of user modelling, expert retrieval, and question recommendation systems. Moreover, Q/A platforms can develop targeted motivation, engagement, and retention policies specifically addressed to different type of contributors, thus maximising their effectiveness. Finally, companies can better elicit the actual expertise of a potential employee, by exploiting a more accurate characterisation of their social reputation.

The remainder of the paper is organised as follows: Section 2 briefly introduces the dataset used in our study. Section 3 describes and evaluates the new `MEC` metric. Section 4 compares the behaviour of *owls* and *sparrows*. Section 5 describes related work, before Section 6 presents our conclusions.

2 Dataset Description

Launched in 2008, `StackOverflow` is one of the dominant domain-specific Q/A systems on the Web: with 2.3M users, 5.6M active questions, 10.3M answers, and 22.7M comments, `StackOverflow`[1] aims at becoming a very broad knowledge base for software developers, and it adopts a peer-reviewed moderation policy to close or remove duplicate and off-topic questions. Questions are topically classified by their submitter using one or more *tags*.

Definitions Given a topic t, we define: 1) Q_t as the set of all t-related questions. 2) A_t as the set of all t-related answers; 3) U_t as all the users that participate in discussions about t; 4) A_t^u as the set of answers provided by a user $u \in U_t$ for topic t; 5) Q_t^u as the set of questions answered by user $u \in U_t$ for topic t; 6) $A_{q,t}$ as the set of answers provided for the question $q \in Q_t$ for topic t.

A question $q \in Q_t$ is associated with an owner $u_q \in U_t$, the content c_q, the timestamp of creation ts_q, and the number of views v_q. Similarly, an answer $a \in A_t$ is described by its creator $u_a \in U_t$, content c_a, the timestamp of creation ts_a, and the number of votes it received v_a.

Table 1: Descriptive statistics about users activity for the C# topic.

Description	Characteristic
Number of questions	472,860
Number of answers	1,071,750
Number of answerers	117,113
Average voting scores $a_t \in A_t$	2.18±7.35
Average number of answers to question $q_t \in Q_t$	2.27±1.74
Average number of answers given by user $u_t \in U_t$	9.15±76.66

Table 1 reports some descriptive statistics related to the topic C#, the most discussed topic in `StackOverflow`. It clearly emerges a strongly biased distribution in the number of answers provided by each user. Fig. 1 plots on a `log-log` scale the distribution of number of answers per question, and number of answers per users in the C# topics. Both quantities resemble a power-law distribution. Fig. 2 clearly shows that there are a few users giving many answers.

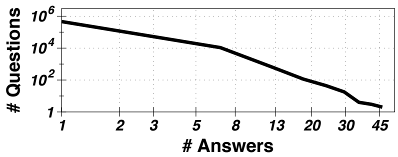


Fig. 1: C# topic: distribution of number of answers per question.

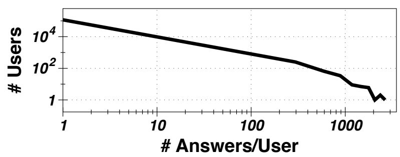


Fig. 2: C# topic: distribution of number of answers per user.

This is a property that is exhibited by the whole `StackOverflow` platform, where the most 13% active users, which provided at least $\geq$ 10 answers, are responsible for 87% of all the answers. We refer to such users as ***Sparrows***, i.e. users that, for a given topic, have $|A_{u,t}| \geq 10$.

[1] The dataset can be accessed at `https://archive.org/details/stackexchange`. Our study is based on data created up until September 2013.

3 Expertise Metric

An expert can be defined as someone who is recognised to be skilful and/or knowledgable in some specific field [4], according to the judgment of the public or his or her peers; expertise then refers to the characteristics, skills, and knowledge that distinguish experts from novices and less experienced people.

In the context of a Q/A system, social judgement is critical for expert identification. A question is usually answered by a set of users, whose answers are voted up or down by other members of the platform. On the one hand, answering questions reflects a user's capability of applying knowledge to solve problems. On the other hand, the *voting* from other users can be viewed as a cyber simulation of *social judgement* for the answerers' expertise level.

Note that asking a question and posting a comment may also provide evidence of a user's expertise. However since answering a question can *directly* reflect the knowledge of a user in solving real problems – i.e., actionable knowledge – we limit our discussion of expertise judgement within the scope of answerers. Such choice is also aligned with previous studies of expert identification on Q/A systems [3, 10, 11, 14].

3.1 Characterisation of Expertise

Previous works related expertise to the overall activeness of users in the platform. A classical and often used metric of expertise is the $Z_{Score} = \frac{a-q}{\sqrt{a+q}}$ [14], which measures users according to the number of posted questions q and answers a. Alternatively, one can look at the *reputation* of the user as calculated by the platform [6, 10], a metric that is highly correlated with the number of provided answers.[2]

These two measures suffer from a common problem: they are heavily biased towards user activeness, thus favouring highly engaged users – the *sparrows* – over the ones that provide high level contributions – the *owls*. To support our claim, we performed an analysis of the distribution of the quality of users contribution for *C#*. We considered two dimensions:

1. The **debatableness** of a question, measured according to the *number of answers* it generated;
2. The **utility** of an answer, measured according to its relative *rank* in the list of answers.

Intuitively, difficult questions generate a lot of discussions, and several answers; also, the higher in the rank an answer has been voted, the more potentially useful it is to solve the related question, and the more it provides evidences about the expertise of the answerer in the topic. Table 2 contains a representative example[3] of debatable `StackOverflow` question. 13 out of 14 answers were

[2] For instance, the Spearman correlation between user reputation and total number of answers given by users in topic C# is 0.68.

[3] This question can be accessed at `http://stackoverflow.com/questions/21475723`

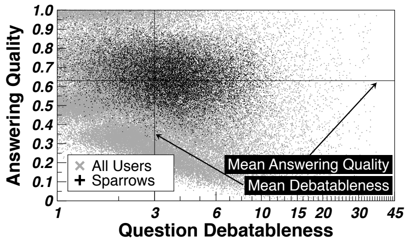


Fig. 3: Distribution of users according to the avg. debatableness of questions they answer, and the avg. answer quality. *Sparrows*: users with $|A_{u,t}| \geq 10$.

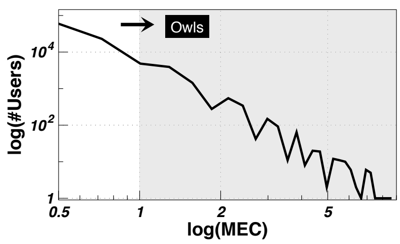


Fig. 4: Distribution of `MEC` (Mean Expertise Contribution) values in the considered user population. *Owls*: users with $\texttt{MEC} \geq 1$.

provided by very active users, but the best answer was given by a user with only 2 questions answered.

Table 2: An example question to which all answers were provided by sparrows except the best answer.

Question: *C# to C++ 'Gotchas'.*		
Rank	**Content**	**#Answered questions***
1st	*C++ has so many gotchas...*	2 answered questions
2nd	*Garbage collection!*	26 answered questions
3rd	*There are a lot of differences...*	175 answered questions
...	...	...
14th	*The following isn't meant*	24 answered questions

*This column shows the number of historical answers to C# questions by the corresponding answerer.

Such phenomenon is not rare, as shown in Fig. 3, which visualizes the entire C# dataset. Each dot represents one of the $\sim$ 117K users that provided at least one answer for the C# topics. A user is described by the average **utility** of his/her answers (a value in the $[0, 1]$, where 1 represents maximum utility), and by the average **debatableness** of the questions he/she contributed to. The $\sim$ 15K *Sparrows* are highlighted with black crosses. An evident phenomenon can be observed: the vast majority of users answers less debated questions, while only a few (approximately 10%) are able to consistently provide relevant contributions to highly debated questions. Only a fraction ($\sim$30%) of the *sparrows* belongs to the latter group, clearly showing how activeness does not suffice as a measure of expertise.

3.2 Identifying Owls

To better identify expert users, we devise a novel strategy for expertise judgement called `MEC` (Mean Expertise Contribution). Differently from existing measures, `MEC` values three expertise factors, namely: answering quality, question debatableness, and user activeness. `MEC` relates to a given topic t, and it is defined as:

$$\texttt{MEC}_{u,t} = \frac{1}{|Q_t^u|} \sum_{\forall q_i \in Q_{u,t}} \mathcal{AU}(u, q_i) * \frac{\mathcal{D}(q_i)}{\mathcal{D}_t^{avg}}$$

where:

- $\mathcal{AU}(u, q_i)$ is the **utility** of the answer provided by user u to question q_i; in our study, $\mathcal{AU}(u, q_i) = \frac{1}{Rank(a_{q_i})}$, that is the inverse of the rank of the answer provided by u for question q. The larger $\mathcal{AU}$, the higher the expertise level shown by the user in question q_i;
- $\mathcal{D}$ is the **debatableness** of the question q_i, calculated as the number of answers $|A_{q_i,t}|$ provided for question q_i;
- $\mathcal{D}_t^{avg}$ is the **average debatableness** of all the questions related to the topic t, calculated as $\frac{1}{|Q_t|} * \sum_{\forall q_j \in Q_t} |A_{q_j,t}|$.

The use of the inverse rank of a question allows to capture the quality of an answer regardless of the judgment expressed by the question provider: indeed, a requester can accept an answer as the right one, although the community, in the long run, might have a different opinion. The sum-up value of the **utility** of the provided answers acts as an indication of the expertise level of a user in a topic. By weighting in the relative debatableness questions, `MEC` accounts for the average difficulty of questions about a given topic. Note that $\mathcal{AU}(u, q_i) * \mathcal{D}(q_i)$ can be interpreted as the inversed *relative ranking* of u's answer among all answers to question q_i. To factor out user activeness, the resulting value is normalised over the total number of answers a user gave.

A value of $\texttt{MEC}_{u,t} = 1$ indicates that the user u, on average, provides the best answer to averagely debated questions, while $\texttt{MEC}_{u,t} = 0.5$ indicates that u ranks second in answering averagely debated questions, or ranks first in answering less debatable questions.

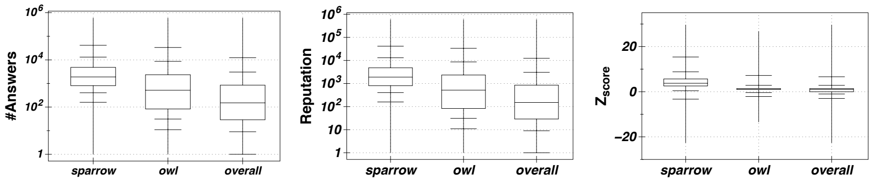
Fig. 4 depicts the log-log scale distribution of `MEC` w.r.t. the population of users involved in the C# topic. Only 11,910 users (approximately 10%) possess a $\texttt{MEC} \geq 1$: we refer to such users as ***Owls***, and observe that for the considered topic their number is significantly lower than the number of *sparrows*.

Fig. 5 shows the characterisation in terms of number of answers, reputation, and Z_{Score} of *sparrows*, *owls*, and the overall population: *sparrows* consistently obtain higher values, thus erroneously taken as experts. By conservatively considering only the *sparrows* classifying in the top 10% according to number of answers, reputation, and Z_{Score}, we observe that, respectively, only the 9.9%, 21.9% and 10.2% of them also belong to the set of *owls* (i.e. $\texttt{MEC} \geq 1$).

In the following sections we will delve into more details about the different nature of *owls* and *sparrows*, highlighting their divergent behaviours and roles in `StackOverflow`.

4 Comparison of Sparrows and Owls

RQ1: How do *sparrows* and *owls* differ in terms of participation and quality of contribution? To answer this question we first compared the mean numbers of



(a) # Answers **(b)** Reputation **(c)** Z_{Score}

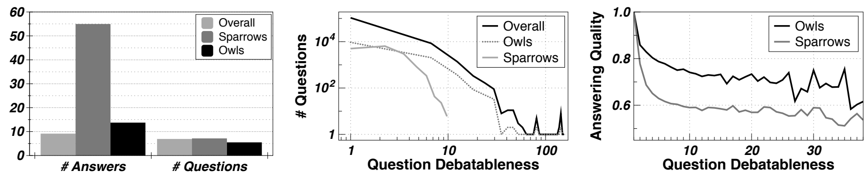
Fig. 5: Comparison of expertise metrics.

questions and answers posted by the two groups of users. As depicted in Fig. 6a, the ratio between answered and submitted questions is significantly higher for *sparrows*. *Owls*, on the other hand, show a behaviour more similar to average users, thus further highlighting the distinctive "hunger" for answers of *sparrows*.

Such a distinction is evident not only in absolute terms, but also with respect to the type of questions and overall utility of answers.

Fig. 6b shows the distribution of questions answered by *sparrows* and *owls* with respect to the their debatableness: *sparrows* are more focused on questions in a smaller range (and value) of debatableness, while *owls* exhibit a broader range of participation, and a distribution very similar to the one of average users.

Fig. 6c compares the quality of the answers provided by *sparrows* and *owls* with respect to the debatableness of the answered question. To provide a fair comparison, we just consider questions answered by at least one user in each group. Vertical axis depicts the value of $1-$ *relative ranking* (i.e., $1-1/(\mathcal{AU}(u, q_i) * \mathcal{D}(q_i)))$. As question debatableness is same for *owls* and *sparrows*, the answering quaity is only determined by utility: a higher value in this figure indicates higher answering quality. We observe that *Owls* consistently provide answers with higher utility, thus showing their grater value for the platform in terms of knowledge creation. The results shown in Fig. 6c indicate the ability of `MEC` to identify highly valuable users that, even if not driven by the need for higher reputation in the platform, are able to provide relevant and useful answers.



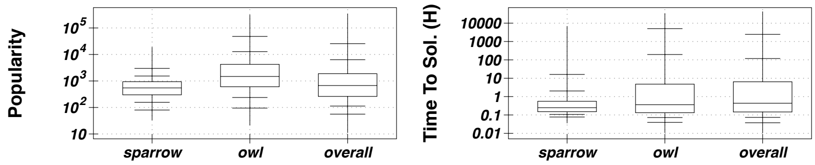
(a) **(b)** **(c)**

Fig. 6: Comparison of activity profiles of *sparrows* and *owls*: a) distribution of number of questions and answers; b) distribution of preferences for question debatableness; c) distribution of quality of contribution for question debatableness.

4.1 Preferences in Knowledge Creation

This section describes the different behaviours of *sparrow* and *owls* in terms of knowledge creation. We focus on the properties of the questions answered and posted by the two group of users.

Finding 1: *Owls* answer questions that are more difficult, and more popular. We consider two dimensions: **question popularity**, measured in terms of the number of times a question has been viewed in `StackOverflow`; and **time to solution** [6], measured in terms of the number of hours needed for the question creator to accept an answer as satisfactory. Time to solution can also be an indicator of the difficulty of a question: intuitively, the longer the time to accept an answer, the more difficult is the question.



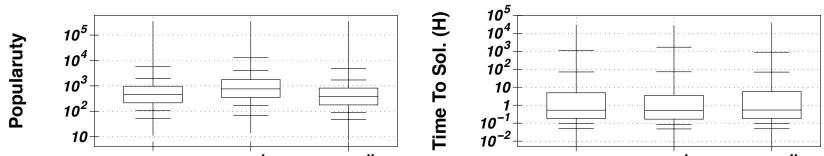
(a) Popularity **(b)** Time To Solution (Hours)

Fig. 7: Comparison of question preferences of *sparrows* and *owls*.

Fig. 7a shows that questions answered by *sparrows* are, on average, significantly less popular than the ones picked by *owls*. Such difference is even more evident when considering the time required to close a questions – Fig. 7b.

These results might be interpreted as a clear indication of the different motivation and expertise level of the two group of users. *Sparrows* appear focused in building their reputation, which they increase by consistently answering to a lot of easy and non-interesting questions. Their behaviour is however providing important contribution to the community, as they can guarantee fast answers to many questions. On the other hand, *owls* intervene when their expertise is needed the most, i.e. in difficult question. Notice that such questions are not necessarily the most debated ones, as shown in Fig. 6b.

Finding 2: *Owls* post questions that are more difficult, and more popular. An analysis performed on the popularity of question posted by *sparrows* and *owls* show another difference between the two groups: questions submitted by *sparrows* are less popular than those posted by the *owls*. On the other hand, the time to completion for such questions is comparable. These results also suggest a difference in the expertise level of the two groups of users, as more popular questions might be a sign of the better understanding that *owls* possess on the subject. However, the higher (on average) difficulty and popularity of *sparrows*'s answers w.r.t. the average of users, also suggests that *sparrows* are good contributors in terms of new problems to be addressed by the community.



(a) Popularity **(b)** Time To Solution (Hours)

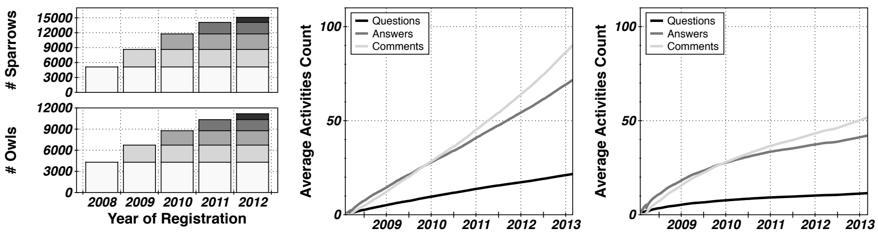
Fig. 8: Comparison of question posted by *sparrows* and *owls*.

4.2 Temporal Evolution of Activities

RQ2: How do the overall activities of *sparrows* and *owls* evolve over time?

Fig. 9a shows, cumulatively, the number of *sparrows* and *owls* active with the C# topic that registered in `StackOverflow`. Interestingly, only half of the users in those two categories registered in the first half of `StackOverflow`'s lifetime. A decline can be observed in the number of new registration starting from 2012.

Fig. 9b and Fig. 9c describe the temporal evolution of the activities of *sparrows* and *owls*. For each type of users, we extract the number of actions including posting questions, answers and comments, which we refer to the *activity counts*, together with the corresponding timestamp. For each action and for each user group, we averaged the overall amount of activities in the reference timeframe with respect to the number of *sparrows* and *owls* registered up to that time, plotting the resulting value over the time axis.

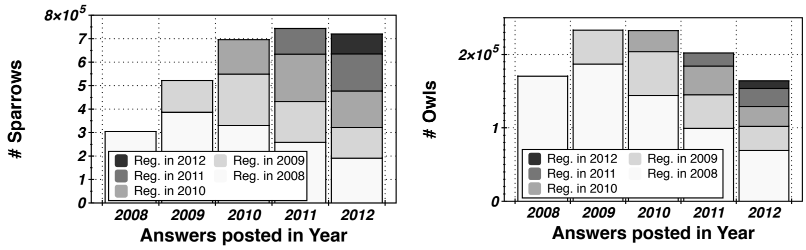


(a) **(b)** Sparrows **(c)** Owls

Fig. 9: Activity evolution of the *sparrows* and *owls*: a) registration date distribution; b) and c) answers, questions and comments.

Finding 3: gamification incentives can more effectively retain *sparrows* than *owls*. Despite the increasing number of *sparrows* and *owls* over time, the average number of questions per user remains roughly the same, as shown by the black curve in Fig. 9b and Fig. 9c. This result indicates a relatively stable question posting behaviour, which can be explained in two ways: on one hand, posting questions is not as rewarding (in terms of increased reputation) as providing answers; therefore, what we observe is the result of a genuine question for new information. On the other hand, one can argue that such stable behaviour can be due to a turnover in the number of active users for the topic.

A different behaviours can be observed with answers and comments. The average activity level of *sparrows* increases over time: this is expected, given the important role that reputation incentives play for these users. *Owls*, however, are, on average, less and less active, especially with respect to the number of answers. This result calls for a more detailed analysis of the evolution of *sparrows* and *owls* activities over time.



(a) Sparrows **(b)** Owls

Fig. 10: Distribution of answers for according to registration date.

Fig. 10 depicts the temporal distribution of answers given by *sparrows* and *owls* (Figure 10b) partitioned by the registration date of the answerer. Fig. 10b shows how "older" *owls* always contribute for the larger portions of the provided answers. However, *owls* consistently tend to decrease their activity in time, especially for more recently registered users. On the other hand, new *sparrows* significantly contribute to a share of answers produced by their group and, although in the long term a decrease in the overall activities of the older member can be seen, the effect is less important. These results suggest that the gamification incentives put in place by `StackOverflow` are really effective to retain the activity of sparrows.

5 Related Work

Collectively edited Q/A systems have been emerging as important collective intelligence platforms. A specialised Q/A system such as `StackOverflow` is reforming the way people are communicating and accessing opinions and knowledge [13]. Given such background, matching expertise to the right answerer in Q&A system has recently been a relevant research stream [11, 14, 15]. We introduce the related work by focusing on two aspects: 1) expert finding, and ii) expert modelling in Q/A systems.

Expert finding, a classic problem in information retrieval, has been recently re-investigated in the case of Q/A systems. An early work [14] focused on the Java developer platform, where it emerged that such expertise network shows a few different characteristics with traditional social networks. In particular, it was found that a simple expertise metric called Z_{Score} (introduced in Section 3) outperforms graph-based metric such as the expertise propagation method (adapted from PageRank). Graph-based methods were then explored for Yahoo! Answers, a much larger Q/A platform [7]. A similar topic was also studied in [3], where the author proposed to use the number of best answerers for user expertise estimation. They employed Bayesian Information Criterion and Expectation-Maximization to automatically select the right number of users as experts.

A more recent work [11] adapted Z_{Score} for expert finding in `StackOverflow`, by using the number of answers a user posted as the ground truth for expertise identification. A similar expertise metric *reputation*, which is highly correlated with the number of answers, was also used for expert identification in the most recent studies of StackOverflow [6, 10]. However, both metrics are biased to user activeness, therefore partially suitable for `StackOverflow` due to its gamification design, given that users activities are largely influenced by the reputation and badge rewarding [1]. An important difference between our method for expertise judgement and existing methods is that we take into account the user activeness and eliminate its effect on expertise judgement.

From the point of view of expert modelling, previous works were mostly investigated in the area of software engineering, through analyzing source code [9], version history [8], and developers' interaction history with development environment [5]. Specific to Q/A systems, expert modelling focused on modelling the property of questions and answers. In Yahoo! Answers [2], it was found that considering the mutual reinforcing effect between Q/A quality and user reputation can improve the effectiveness of expert modelling. Question selection preferences of active users were studied in `StackOverflow` [11, 12]. While these studies are biased to active user, we target modeling user expertise directly. Our study address the difference between active users and the experts, although the application of our findings is left to future work.

6 Conclusions

As Q/A systems grow in popularity and adoption, identifying and motivating the users that effectively contribute to their success is becoming more and more crucial. This paper contributes a novel metric for the characterisation of experts in Q/A systems, showing its resilience to bias introduced by gamification incentives. Using `StackOverflow` as reference platform, we investigated differences in the behaviour of most active users (the *sparrows*) and most savvy users (the *owls*), showing how the two groups exhibit very distinct fingerprints in terms of knowledge creation, community participation, and temporal evolution of activities. Although targeted at a single topic, investigations show that similar results can be observed for other topics of similar overall amount of participation.

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