Finding Time-Critical Responses for Information Seeking in Social Media

Suhas Ranganath*, Suhang Wang*, Xia Hu †, Jiliang Tang ‡ and Huan Liu *
*Arizona State University, †Texas A&M University, ‡ Yahoo! Labs
Email: {suhas.ranganath, suhang.wang, huan.liu}@asu.edu, hu@cse.tamu.edu, jlt@yahoo-inc.com

***Abstract*—Social media is being increasingly used to request information and help in situations like natural disasters, where time is a critical commodity. However, generic social media platforms are not explicitly designed for timely information seeking, making it difficult for users to obtain prompt responses. Algorithms to ensure prompt responders for questions in social media have to understand the factors affecting their response time. In this paper, we draw from sociological studies on information seeking and organizational behavior to model the future availability and past response behavior of the candidate responders. We integrate these criteria with their interests to identify users who can provide timely and relevant responses to questions posted in social media. We propose a learning algorithm to derive optimal rankings of responders for a given question. We present questions posted on Twitter as a form of information seeking activity in social media. Our experiments demonstrate that the proposed framework is useful in identifying timely and relevant responders for questions in social media.**

***Keywords*-Timely Information, Q&A, Situational Awareness**

I. Introduction

The advent of social media has enabled users to request, publish and discuss information on several important events in real time. Owing to these properties of social media, it has emerged as an attractive source of real-time information during natural disasters, social unrest, and political crises, where timeliness of information is a critical requirement. There has been considerable interest in the use of social media for information seeking and providing responses during natural calamities like Hurricane Sandy, Typhoon Haiyan, and Haiti Hurricane in recent literature [1].

A few examples of requests published in the social media platform Twitter during emergency situations are illustrated in Fig 1(a). The first example illustrates the use of social media for gathering information during emergencies and the asker requests information regarding a possible tsunami in Bangladesh as a consequence of Indonesian earthquake of 2012. The second example shows a user requesting for help during emergencies and the asker seeks assistance for rehabilitation for a victim of Hurricane Sandy. The third example shows the use of social media in reaching out to calamity victims and the asker inquiries about volunteer opportunities during the recent earthquake in Nepal. These queries showcase the use of social media for information seeking during emergencies, and they require timely and relevant responses to satisfy the askers.

However, generic social media platforms like Twitter and Facebook are not designed to facilitate timely information seeking, making it difficult for users to obtain prompt responses for their requests [2]. Millions of posts are published during emergencies and information seeking posts will be buried among them making it difficult for potential responders to find them in proper time. The potential responders have to sift through many tweets in their timeline, thus delaying the response. Existing frameworks [3], [4] only identify users who can provide relevant responses and do not consider timeliness. Designing algorithmic frameworks to identify responders who can provide timely and relevant answers will provide prompt assistance to the askers. This can be used to notify potential responders to increase the chances of a quick response.

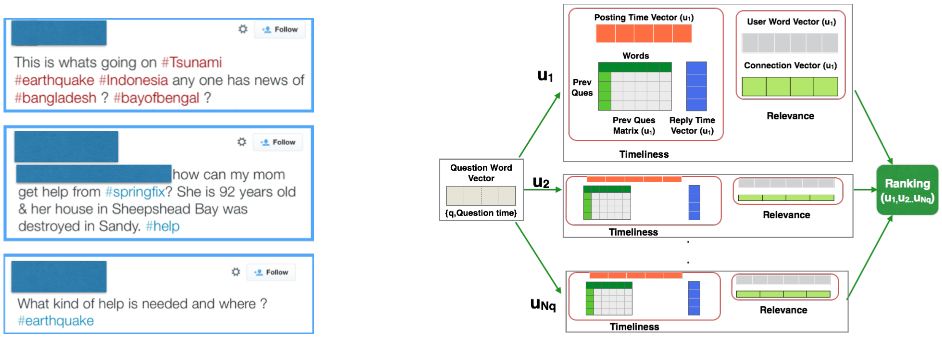
This task presents several challenges. First, it is difficult to estimate the time taken by a user to reply to a question in social media as characteristics affecting the response time are not precisely known. Second, timeliness is a distinct entity than relevance, and algorithmic frameworks need to integrate these entities to identify responders who can give timely and relevant responses to a particular question. Finally, each question can have several candidate responders, each of them having a large amount information associated with them, leading to significant issues of scalability.

We take inspiration from sociological studies on information seeking and organizational behavior to identify characteristics affecting timeliness of the answers to questions in social media. A study on the motivations of information seeking behavior in social media [5] identifies free time as one of the important factors for a social media user to respond to a question. The response time of a user to a question can be related to his future availability on the platform after the question is posted. The self-consistency theory [6] states that people perform tasks in a manner consistent with their previous instances of performing related tasks. Therefore, the response time of a user for a given question can be related to his response times to previous related questions.

In this paper, we propose a framework to identify automatically responders who can provide timely and relevant responses to questions in social media by modeling and integrating their future availability, response patterns to related questions and interests. Specifically, we answer the following questions: How do we model the temporal patterns of the candidate responders to rank them according to the estimated timeliness of response? How do we integrate temporal patterns with user interests to identify users who can provide timely and relevant responses to a given question?

The primary contributions of the work are

- Formally defining the problem of identifying users who can provide timely and relevant responses to questions in social media,
- Proposing an algorithmic framework to integrate timeliness and relevance for identifying responders to ques-



(a) (b)

Figure 1. (a) Examples of questions asked in social media during emergencies (b) The proposed framework to identify responders who provide timely and relevant responses to questions in social media.

tions in social media, and

- Presenting experimental evaluations of the framework on a real-world dataset of questions in social media.

The rest of the paper is organized as follows. In Section II, we formally define the problem statement. We present the designed framework in Section III. In Section IV, we employ a real-world dataset to evaluate the framework. We describe existing literature in Section V. We conclude and explore possible future directions in Section VI.

II. Problem Statement

In this section, we present notations used in the paper, describe a few relevant terms and formally present the problem statement. Boldface uppercase letters (e.g. $\mathbf{X}$) denote matrices, boldface lowercase letters (e.g. $\mathbf{x}$) denote vectors, and calligraphic uppercase letters (e.g. $\mathcal{X}$) denote a set. The notation $\frac{1}{\mathbf{x}}$ indicates a vector whose elements are the reciprocal of each element of the vector $\mathbf{x}$. $\mathbf{X}_{ij}$ signifies the element in the i^{th} row and j^{th} column of matrix $\mathbf{X}$ and $\mathbf{x}_i$ denotes the i^{th} element of vector $\mathbf{x}$. We denote the Frebonius norm of a matrix $\mathbf{X}$ as $||\mathbf{X}||_F = \sqrt{\sum_{i,j} \mathbf{X}_{ij}^2}$.

The terms related to proposed framework are illustrated in Fig 1(b). From Fig 1(b), let $\mathbf{q} \in \mathbb{R}^{1 \times w_{\mathcal{Q}}}$ denote the question word frequency vector of q for which we want to identify responders, where $\mathcal{Q}$ is the set of questions and $w_{\mathcal{Q}}$ is the total number of words in $\mathcal{Q}$. We further denote t_q as the time when the question q is posted. Let the total set of candidate responders for each question q be $\mathcal{U}_q = \{U_1, U_2, U_3, ..., U_{n_q}\}$, where n_q is the total number of candidate responders for question q, and $\mathcal{U}$ denote the union of candidate responders of all the questions for which we want to identify the responders.

We first define the terms related to the timeliness of the response to the question q. For each user $u \in \mathcal{U}_q$, we define the posting time vector $\mathbf{t_u}$. This the vector containing the time of his previous postings with length equal to the total number of posts he made. The previous question matrix of the user u is represented as $\mathbf{P_u} \in \mathbb{R}^{o_u \times w_{\mathcal{Q}}}$, where o_u is the number of questions he answered previously. The set $\mathcal{Q}$ contains both the candidate questions for which we want to identify responders and the previous questions answered by the users in $\mathcal{U}$. Each row of $\mathbf{P_u}$ contains the question word vector of a previous question answered by the user u. We denote the time taken by the user to reply to the previous questions by the reply time vector $\mathbf{rt_u} \in \mathbb{R}^{o_u \times 1}$.

We next define the terms related to the relevance of the candidate user u to the given question q. Let the user word vector of the user u be denoted as $\mathbf{k_u} \in \mathbb{R}^{1 \times w_{\mathcal{U}}}$, where $w_{\mathcal{U}}$ is the total number of words used by users in $\mathcal{U}$. Let $\mathcal{M}$ be the set of words used by all the users. Each element in the vector $\mathbf{k_u}$ contains the frequency of each word in $\mathcal{M}$ in the status messages of user u. We define the adjacency matrix $\mathbf{N} \in \mathbb{R}^{N \times N}$ of the social connections of users in $\mathcal{U}$ as

$$\mathbf{N}_{ij} = \begin{cases} 1 & \text{if } U_i \text{ connects to } U_j, i \neq j; U_i, U_j \in \mathcal{U}, \\ 0, & \text{otherwise} \end{cases}$$

where N is the total number of users in $\mathcal{U}$. The connection vector of each user is obtained from the corresponding row of the network adjacency matrix $\mathbf{N}$. Finally, the relevance of the given answer is denoted by a positive acknowledgment from the asker, like a "favorite" or a reply with "thanks". Given these notations, we formally present the problem statement as

Given a question q, the question word vector $\mathbf{q}$*, a set of candidate responders* $\mathcal{U}_q$ *for the question, the posting time vector* $\mathbf{t_u}$*, the previous question matrix* $\mathbf{P_u}$*, the reply time vector* $\mathbf{rt_u}$*, the user word vector* $\mathbf{k_u}$*, and the social connection matrix* $\mathbf{N}$*, identify people in* $\mathcal{U}_q$ *who provide timely and relevant answers.*

III. The Proposed Framework

In this section, we present a framework that identifies responders who can provide timely and relevant responses to questions in social media. We first describe the ranking criterion and present quantitative models for identifying users who provide timely and relevant responders. A learning algorithm is then proposed to learn optimally the parameters of the ranking criterion along with the time complexity analysis.

A. Modeling Timeliness

We are inspired by the sociological studies in information seeking [5] and organizational behavior [6] to model characteristics of users determining the timeliness of their responses for a given question. We are motivated by [5] to postulate that after a question is posted, the sooner a candidate responder is active on the platform, the faster can be his response to the question. We postulate from response consistency [6] that the response time of the user for the given question is proportional to his response time to questions related to it. Next, we describe these notions in detail and present ways to model them.

We first present a model to rank the candidate responders according to their future availability. For each question q posted at time t_q, we take the posting time vector $\mathbf{t_u}$ of each candidate user up to t_q, taking posting as a measure of his activity on the platform. The rank of a user is inversely proportional to the estimated time after t_q at which he is active on the platform. Therefore,

$$f_a(q, u) = \frac{1}{t_u^{est} - t_q}, \tag{1}$$

where $f_a(q, u)$ is the ranking score of candidate user u for question q and $t_\mathbf{u}^{est}$ is the time at which he posts in the platform after t_q as estimated from his posting time vector $\mathbf{t_u}$. We predict t_u^{est} with a nonlinear autoregressive neural network with a single hidden layer [7] on the posting time vector $\mathbf{t_u}$. The lower the estimated difference between estimated future availability and the question time, the higher the ranking score of candidate user u is.

We next rank the candidate responders according to their past response behavior to related questions. To represent the relationship between the given question and the previous questions answered by the user u, we transform the corresponding question word vectors into a common latent dimension space using $\mathbf{S} \in \mathbb{R}^{n \times w_\mathcal{Q}}$. Here n is the number of dimensions of the space ($n \ll w_\mathcal{Q}$). The representation of the given question q in the low dimensional space is then given by $\mathbf{qS}^T$ and the representation of the previous questions answered by the user u is given $\mathbf{P_u S}^T$. We linearly transform the question representation using $\mathbf{T_u} \in \mathbb{R}^{n \times n}$ to incorporate user specific context and represent its relationship to the previous question answered by the user as $\mathbf{qS}^T\mathbf{T_u SP_u}^T$. The ranking function can then be computed as

$$f_p(q, u) = \mathbf{qS}^T\mathbf{T_u SP_u}^T \frac{1}{\mathbf{rt_u}}, \tag{2}$$

where $\mathbf{rt_u}$ is the time taken by user u to answer the previous questions. The ranking score $f_p(q, u)$ is higher if the user u has promptly answered questions having a close relationship with question q in the past. The overall ranking criterion according to timeliness of reply is given by $f_t(q, u) = f_a(q, u) + \alpha f_p(q, u)$, where α controls the amount of contribution from the past response behavior of the user to related questions.

B. Modeling Relevance

To model the relevance of a user to a given question, we compute the relationship between the content of the given question and the interests of the user. The nearer the question with the interest of the user, the greater can be his relevance to the question. We obtain the interests of the user from his user word vector $\mathbf{k_u}$ and represent it in a shared low dimensional space with the question word vector $\mathbf{q}$. Let $\mathbf{V} \in \mathbb{R}^{n \times w_\mathcal{U}}$ be the latent dimension representation of the user content, where n is the number of dimensions of the space and $w_\mathcal{U}$ is the total number of words used by the set of candidate responders ($n \ll w_\mathcal{U}$). The representation of the question q in the low dimensional space is then given by $\mathbf{qS}$ and the representation of user u is given by $\mathbf{k_u V}^T$. The representation of the question q and the user u in the latent dimension space can have different contexts. Therefore, we compute their relationship after linearly transforming the question representation to the user domain by using $\mathbf{T_u} \in \mathbb{R}^{n \times n}$. The relevance of the user, u to the question q, is then computed as

$$f_r(q, u) = \mathbf{qS}^T\mathbf{T_u V k_u}^T. \tag{3}$$

The overall ranking criterion can be obtained by integrating the ranking scores $f_a(q, u)$, $f_p(q, u)$ and $f_r(q, u)$. It is therefore computed as $f(q, u) = f_a(q, u) + \alpha f_p(q, u) + \beta f_r(q, u)$, where α controls the amount of contribution from the past response behavior to related questions and β controls the amount of contribution from the relevance to the overall ranking criterion. The higher the candidate responders' estimated timeliness of response and relevance to the question, the higher is the score computed by $f(q, u)$.

C. Learning Latent Parameters

We now present a learning algorithm to compute the latent matrices $\mathbf{S}$, $\mathbf{T_u}$ and $\mathbf{V}$ for optimal ordering of the candidate responders. Let us assume we have a training set $\mathcal{X}$ of K training instances $\mathcal{X} = \{(q_i, U_i, r_{U_i})\}_{i=1,2,....,K}$ where q_i belongs to the set of training questions, $U_i \in \mathcal{U}_{q_i}$ is a user in the set of candidate responders of q_i who has responded to it and r_{U_i} is the time taken by U_i to answer the question.

We define the vector $\bar{\mathbf{f}}(\mathbf{q})$ containing the predicted scores for all the candidate responders for question q. The element of $\bar{\mathbf{f}}(\mathbf{q})$ related to U_i is denoted by $\bar{\mathbf{f}}(\mathbf{q}, U_i)$. In order to obtain an optimal ranking order for the candidate responders, we need to penalize the function when the users who have responded to the question are ranked low by the ranking criterion. The Weighted Approximate-Rank Pairwise (WARP) [8] loss is defined as $err_{WARP} = \sum_{i=1}^{K} \mathcal{L}(rank_{U_i}(\bar{\mathbf{f}}(\mathbf{q_i})))$ Here, $rank_{U_i}(\bar{\mathbf{f}}(\mathbf{q_i}))$ is a marginal ranking criterion which is be computed as $rank_{U_i}(\bar{\mathbf{f}}(\mathbf{q_i})) = \sum_{b \neq U_i} \mathbb{I}[1 + f(q_i, b) \geq f(q_i, U_i)]$ where $\mathbb{I}(x)$ is the indicator function which is 1 if x is true or 0 if it is false and $b \in \mathcal{U}_{q_i}$ is a member of the set of candidate responders of q_i who has not responded to the question.

The pair $\{U_i, b\}$ is known as the violating pair if $1 + f(q_i, b) \geq \bar{f}(q_i, U_i)$. The ranking function assigns to each pair a cost if the ranking score of b is larger or within a margin of 1 from the ranking score of U_i. The WARP loss function is therefore the penalty imposed when U_i is ranked within a certain margin or below a negative example b. $\mathcal{L}$ transforms the rank into a loss and is defined as $\mathcal{L}(k) = \sum_{i=1}^{k} a_i$. Here $a_1 \geq a_2 \geq a_3 \geq ...a_k \geq 0$, with the values of a_i determining the additional penalty for each successive reduction in rank. A choice of $a_r = 1/r$, gives a larger penalty to the top position and provides a smooth weighting over different positions [9].

In addition to the WARP loss, we increase the error penalty in proportion to the timeliness and relevance of the response given by U_i in the violating pair. We weigh the

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Algorithm 1: Finding Time Critical Responses in Social Media
Input: Training examples X = {(q_i, U_i, r_{U_i})}_{i=1,2,..,N}, U_{q_i} q_i ∈ Q
Output: Trained values of latent matrices S, V and T_u
Initialize S, V, T_U randomly
do
    Pick a random labeled example (q_i, U_i, r_{U_i})
    Compute f(q, U_i)
    k=0
    do
        Randomly pick a negative example b ,b ∈ U_q
        Compute f(q, b)
        k=k+1
    while 1 + f(q, b) < f(q, U_i) or k ≤ size(U_{q_i}) − 1
    Minimize f by updating S, V, T_{U_i}, T_b
    Substitute update matrices in f
while err_weighted does not converge
```

WARP loss as

$$\mathrm{err_{weighted}} = \sum_{i=1}^{N}(1+\frac{1}{\mathrm{r_{U_i}}})(\mathrm{rel_{U_i}})\mathcal{L}(\mathrm{rank_{U_i}}(\overline{\mathbf{f}}(\mathbf{q_i}))), \quad (4)$$

where $\mathrm{r_{U_i}}$ is the response time of $\mathrm{U_i}$ and $\mathrm{rel_{U_i}}$ is 1 if the reply given by the positive example is accepted as relevant by the asker of $\mathrm{q_i}$ and 0 otherwise.

Calculating the exact rank is computationally expensive [10] and we therefore approximate by sampling. We compute the stochastic gradient approach to minimize the error, choosing at each iteration a single training instance randomly from the training set $\mathcal{X}$. We compute the ranking score of $\mathrm{U_i}$, $f(q_i, U_i)$. We then randomly select users from $\mathcal{U}_{\mathrm{q_i}}$ who have not replied to the question $\mathrm{q_i}$ and compute the ranking score for each of them until we find a violating pair i.e. $1 + \mathrm{f}(q_i, b) \geq \mathrm{f}(q_i, U_i)$, $\mathrm{b} \in \mathcal{U}_{\mathrm{q_i}}$. If L steps are required to find a pairwise violation, then the approximate value of the term $\mathrm{rank_{U_i}}(\overline{\mathbf{f}}(\mathbf{q_i}))$ is given by

$$\mathrm{rank_{U_i}}(\overline{\mathbf{f}}(\mathbf{q_i})) = \lfloor \frac{|\mathcal{U}_{\mathrm{q_i}}| - 1}{\mathrm{L}} \rfloor, \quad (5)$$

where $|\mathcal{U}_{\mathrm{q_i}}|$ indicates the size of the candidate set $\mathcal{U}_{\mathrm{q_i}}$ and $\lfloor . \rfloor$ denotes the floor function. The single instance objective becomes [10]

$$\mathrm{f_r} = (1+\frac{1}{\mathrm{r_{U_i}}})(\mathrm{rel_{U_i}})\mathcal{L}(\lfloor \frac{|\mathcal{U}_{\mathrm{q_i}}| - 1}{\mathrm{L}} \rfloor).|1 - \mathrm{f}(\mathrm{q_i}, \mathrm{U_i}) + \mathrm{f}(\mathrm{q_i}, \mathrm{b})|. \quad (6)$$

We introduce regularization terms that consider social connections and overfitting. The theory of network homogeneity [11] suggests that people connected to each other display similar interests and affiliations. Therefore, we have the following regularization error

$$\mathrm{f_{socreg}} = \sum_{\mathrm{j}:\mathbf{N}_{\mathrm{ij}}=1} ||\sigma(\mathbf{k}_{\mathbf{U_i}}\mathbf{V}^{\mathrm{T}}\mathbf{V}\mathbf{k}_{\mathbf{U_j}}^{\mathrm{T}}) - 1||^2. \quad (7)$$

We constrain the magnitude of the elements of matrices $\mathbf{S}$,$\mathbf{V}$,and $\mathbf{T}_{\mathbf{U_i}}$ to reduce overfitting. The final objective function is then defined as follows

$$f = \mathrm{f_r} + \mathrm{w_s}\mathrm{f_{socreg}} + \gamma_1||\mathbf{S}||_{\mathrm{F}}^2 + \gamma_2||\mathbf{V}||_{\mathrm{F}}^2 + \gamma_3||\mathbf{T}_{\mathbf{U_i}}||_{\mathrm{F}}^2. \quad (8)$$

We optimize the objective function through gradient descent to obtain the update values for the latent matrices $\mathbf{S}$,$\mathbf{V}$, $\mathbf{T}_{\mathbf{U_i}}$ and $\mathbf{T_b}$. We repeat the procedure by randomly selecting a training instance until the error converges which we test using a validation set. We summarize the learning algorithm in **Algorithm 1**. We substitute the values of the latent matrices and compute the scores for the questions in the test set. For each question q, we order the set of candidate responders $\mathcal{U}_{\mathrm{q}}$ according to the scores and return the ranked list.

Parameter	Statistics
# of Candidate Questions	1191
# of Askers	1158
# of Respondents	2877
# of Negative Examples	40177
# of Candidate Respondents	43064
# of Tweets by Candidate Respondents	26911778
# of Network Connections	812817
# of Previous Questions Answered	572202

Table I
DATASET CONTAINING QUESTIONS POSTED IN TWITTER.

IV. EXPERIMENTS

In this section, we describe the dataset and experiments. We aim to answer the following questions: How effective is the framework for identifying the users who provide timely answers to questions in social media? How effective is it in integrating timeliness and relevance in identifying responders for questions in social media? We next describe the dataset and then proceed to answer these questions later.

A. Dataset

The statistics of the dataset is described in Table I. We collected the questions posted on the social networking platform Twitter during Hurricane Sandy using keywords and hashtags related to the events collected using [12]. The earliest question in the dataset is posted on October 24th, 2012 and the latest question is posted on November 27th, 2012. For each question, we collected the text, user information and the timestamp of its replies and assigned the users who replied as the positive examples. We assigned the users who are posting on the same keywords and hashtags related to Hurricane Sandy within a day of the question being posted but have not replied to the questions as negative examples. We use up to 1000 negative examples per question, and each negative example can be used for multiple questions. The positive and negative examples for each question q are jointly considered as the set of candidate responders $\mathcal{U}_{\mathrm{q}}$. We collected the tweets, times of tweets posted, network connections and previous questions answered by the candidate responders to construct $\mathbf{q}$, $\mathbf{k_u}$, $\mathbf{t_u}$, $\mathbf{P}$, $\mathbf{rt_u}$ and $\mathbf{N}$ as defined in Section II.

B. Experiment Settings

We evaluate the proposed framework and the baselines with Mean Reciprocal Rank (MRR), Mean Average of Precision (MAP), Non-Discounted Cumulative Gain (NDCG). We present some alternative baselines to compare our framework with related methods.

- **Random Selection**: We randomly order the candidate responders for each question and aggregate the rankings obtained by repeating over 100 iterations.

Method	MAP@10	MRR	NDCG@10
Random	0.12%	1.39%	0.60%
Nandi et al [13]	1.01%	2.20%	2.29%
Future Availability	3.21%	4.23%	5.40%
Mahmud et al [14]	3.76%	6.06%	6.07%
Past Response	4.45%	8.01%	8.92%
Our Model	6.76%	10.53%	14.66%

Table II
PERFORMANCE OF THE PROPOSED FRAMEWORK IN RANKING TIMELY RESPONDERS.

Method	MRR	MAP@10	NDCG@10
Random	0.14%	0.38%	0.30%
Nandi et al [13]	3.67%	1.13%	2.29%
Mahmud et al [14]	4.86%	3.61%	3.75%
Relevance	7.24%	4.78%	8.52%
Our Model	11.85%	5.42%	11.47%

Table III
PERFORMANCE OF THE FRAMEWORK IN RANKING RESPONDERS PROVIDING TIMELY AND RELEVANT RESPONSES

- **Future Availability**: This computes ranking scores considering only the future availability of the responder ($\alpha = 0$ and $\beta = 0$).
- **Nandi et al. [13]**: The authors built a probabilistic model to combine temporal features and content metrics to rank candidate responders.
- **Mahmud et al. [14]**: It proposes a supervised learning approach by learning features on the users' posting times and replying time to previous questions.
- **Past Response**: This baseline computes ranking scores only considering information related only to the past response behavior to the previous questions.
- **Relevance**: This baseline computes ranking scores from information related to relevance of the user to the candidate questions.

C. Identifying Timely Responders

We first evaluate the effectiveness of the framework in identifying users providing timely responses. We select 60% of the questions in the dataset presented in Table I for training and the rest for testing. As we are concentrating on identifying timely responders in this experiment, we choose $\beta = 0$ and $\mathrm{w_i} = 1 + \frac{1}{\mathrm{r_{U_i}}}$. We illustrate the results of the evaluation in Table II and make the following observations.

The random ordering of users gives a weak performance of less than 1% precision demonstrating the difficulty of the problem. The probabilistic model by Nandi et al. [13] captures the daily and weekly temporal variations in the posting of the candidate responders performs better than random, showing the potential of temporal patterns in identifying timely responders. The improvement of "Future Availability" demonstrates the utility of estimating future user behavior in identifying timely responders to questions in social media.

The improved performance of [14] indicates the utility of response times from previous questions and supervised models for our task. "Past Response", which models the relationship between the given question and the previous questions answered by the candidate user, considerably outperforms the baseline methods. This demonstrates the utility of giving greater prominence to previous related questions and the effectiveness of the framework in learning the relationships between them. Finally, integrating future availability significantly improves the performance demonstrating its additional utility in identifying timely responders for a given question. We performed a paired t-test to compare with the baselines and the results showed the improvements are significant.

In summary, from the results in Table II, we can say that our framework is effective in identifying timely responders for a given question in social media. The results also demonstrate the effectiveness of the proposed ranking criterion and the learning framework for modeling and integrating the crucial information required for the problem.

D. Timely and Relevant Responders

We now evaluate the performance of the framework in identifying responders who can provide both timely and relevant answers to questions in social media. We employ the procedure described in **Algorithm 1** for training and substitute the obtained latent matrices for scoring the questions and the candidate responders in the test set. For each question, we rank the candidate responders and evaluate the position of the relevant responders in the rank list. The results of the experiment is presented in Table III, and we make the following observations.

From the table, we can see that the performance of random ordering is low demonstrating the difficulty of the problem. The performance of [13] improves upon the random performance show the utility of modeling relevance for identifying responders for our task. The difference between the supervised framework in [14] and [13] and is considerably lesser than in Table II. This low difference might be because [14] models only the temporal behavior of candidate responders and does not model their relevance to the question. The performance of "Relevance", which considers only the relevance terms described in Section III-B improves the performance of baselines. Our framework considerably outperforms existing baselines with a significant margin demonstrating its effectiveness in integrating information related to future availability, previous response patterns and relevance in identifying responders who provide timely and relevant answers. We performed a paired t-test to compare the results with the baselines that showed the improvement is significant. We vary the values of α and β with different values between 0 and 1 and find that the framework is robust to parameter variation.

In summary, we can say from Table II and III that our framework is effective in identifying responders who provide timely and relevant answers. The results also demonstrate the ability of the framework to integrate effectively information crucial for the problem.

V. RELATED WORK

Information seeking in social media has received considerable attention in research communities. An analytical study of the primary motivations for information seeking and replying in Twitter is presented in [5]. The factors affecting the quantity and speed of the responses [15] are studied and these mainly related this to question characteristics such as phrasing and posting time. The ability of users to evaluate useful information in social media is explored in [16], [17]. We use the insights in these works to collect the ground truth for helpful answers. These papers give interesting information to the question answering process in social media, but here we focus on identifying responders to these questions.

Recently, systems have been proposed to identify responders for questions in social media. Search architectures with empirical models to route questions to responders using social information are discussed in [3]. A system for recommending users who can answer questions in social media [14] models temporal, behavioral and content related factors to identify suitable users. Our framework is different from these in that we can identify users who can provide both timely and relevant responses to a given question posted in social media.

A related line of research is the study of community Q&A systems like Yahoo! Answers [18]. Methods for identifying suitable responders for a question use link structure and topic sensitive page rank [19]. The temporal behavior of users of community Q&A platforms, such as factors affecting response time [20], have been recently studied. However, these papers do not explicitly identify users who provide timely and relevant responses to a given question.

VI. Conclusions and Future Work

Online social media provides a new platform for people seeking information during emergencies and natural disasters in real time. Questions in social media represent a form of information seeking behavior of users. However, these questions are buried among other posts, impeding social media users from getting timely responses to their questions. We propose a novel framework to identify responders who can provide timely and relevant answers to questions in social media by integrating information related to their future availability, past response behavior and interests. We evaluate the framework on questions in Twitter and demonstrate its effectiveness in identifying users who can provide timely and relevant responses to questions in social media.

This work paves way to many interesting future directions of research. Identifying users who are providing misinformation/answers to questions will help to increase the effectiveness of social media as a quality information source. Study the interactions between people requesting for help and the first responder of the request will help understand how people collaborate on social media platforms,.

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