OntoRealSumm: Ontology based Real-Time Tweet Summarization

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The huge popularity of social media platforms, like Twitter, attracts a large fraction of users to share real-time information and short situational messages during disasters which belong to different topics/categories. A summary of all the messages is required by the government organizations, agencies, and volunteers for efficient and quick disaster response. Therefore, we propose an ontology based real-time tweet summarization (OntoRealSumm) for disasters which generates a summary of the tweets related to disasters with minimum human intervention. Given tweets related to a disaster, OntoRealSumm ensures fulfilment of the objectives related to disaster tweet summarization, such as identification of a category of each tweet and summarization of each category considering the category importance with respect to the disaster and ensuring information coverage of each category and diversity in summary. Comparing the performance with state-of-the-art techniques on 10 disaster datasets validates the effectiveness of OntoRealSumm.

CCS Concepts: • Information systems → Summarizations.

Additional Key Words and Phrases: Disaster tweets, Summarization, Ontology, Category summarization, Social media

1 INTRODUCTION

Recently, social media platforms, like Twitter, have been extensively used by users across the world to share opinions, promote products, spread awareness and updates on events and disasters. It has been often observed that an event is reported on social media platforms before it is covered on any mainstream media [77]. Similarly, the active participation of users on Twitter has made it an important source for continuous updates on any disaster [56]. However, due to the high volume of Twitter messages and continuous generation of real-time updates, it is very difficult to get a holistic view of an ongoing event, like disasters, which continuously generates new information. Continuous monitoring and summarization of messages related to a disaster are required by government and volunteer organizations for effective disaster response. Prior studies [28, 31, 58] show that messages during a disaster are of different categories\(^1\) [28], like infrastructure damage [55, 57], victim needs [3, 16], volunteer operations [4, 32], emotional response [37], affected population [22] and many others. An effective summary of the disaster should include all the relevant information related to all the categories while ensuring information diversity.

Therefore, there are two major steps for tweet summarization related to disasters, identification of the different groups/categories of tweets such that each group/category comprises of tweets that are related to the same topic/sub-event and further, selection of representative tweets from each group/category to form a summary [50, 58, 62, 65]. Existing disaster summarization approaches have proposed unsupervised and supervised learning based approaches for identifying the categories/groups. Existing unsupervised approaches, such as graph-based approaches [17, 19, 20] and topic-based approaches [46] utilize the content similarity of the tweets to identify different categories. However, the high vocabulary diversity, presence of inherent noise and the high number of overlapping keywords present in tweets makes automatic identification of categories and fails of the inherent semantic meaning of tweets by unsupervised approaches challenging. To address this, Rudra et al. [60, 63] proposed a supervised approach for category identification which explicitly identifies the categories of tweets by AIDR [30] and then, create a summary summarize by

\(^1\)A category consists of information related to a same topic/sub-event with respect to any disaster.
selecting appropriate tweets from each category. However, the proposed approach is dependent on AIDR \cite{30} for category identification of a tweet that requires human intervention for each dataset \cite{29}. Therefore, while unsupervised approaches fail to automatically identify categories, supervised approaches require significant human intervention, which is highly difficult to obtain.

In order to select the representative tweets from each category/group in the second step of summarization, existing research works \cite{17, 58, 62} have proposed Integer Linear Programming (ILP) \cite{61}, LUHN \cite{42}, PageRank \cite{52}, Centrality \cite{6}, maximum degree \cite{20}, maximum length \cite{19} and maximum marginal relevance \cite{8}. However, existing disaster summarization approaches consider equal importance of each category given a disaster. Moreover, all categories might not be equally important \cite{9}. Furthermore, none of these approaches considers that the information present in the same category varies across disasters (as shown in Figure 1 and Table 1). Understanding the importance of each category with respect to a disaster guide us in selecting the appropriate number of representative tweets from each category to create the summary. However, to ensure real-time summarization, we need to minimize human intervention.

Table 1. We show the presence of 5 categories in 6 disasters, like Chile Earthquake, 2010 (D$_1$), Italy Earthquake, 2016 (D$_2$), India-Pakistan Flood, 2014 (D$_3$), South Sulawesi Flood, 2019 (D$_4$), Haiyan Typhoon, 2013 (D$_5$), and Megi Typhoon, 2010 (D$_6$) based on the information from Wikipedia.

| SNo | Category         | D$_1$ | D$_2$ | D$_3$ | D$_4$ | D$_5$ | D$_6$ |
|-----|------------------|-------|-------|-------|-------|-------|-------|
| 1   | Affected Population | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| 2   | Infrastructure Damage | Yes   | Yes   | Yes   | Yes   | Yes   | Yes   |
| 3   | Aftershocks       | Yes   | Yes   | No    | No    | No    | No    |
| 4   | Donations         | No    | No    | Yes   | No    | Yes   | Yes   |
| 5   | International Aid | No    | No    | Yes   | No    | Yes   | Yes   |

In this paper, we propose an ontology based real-time tweet summarizer, OntoRealSumm to generate a summary automatically given the tweets related to a disaster with minimal human intervention. OntoRealSumm explicitly captures the importance of a category with respect to the disaster and further, ensures information coverage of each category in the final summary by a three-phase system. In the first phase, OntoRealSumm identifies the category of a tweet by ontology based
pseudo-relevance based feedback approach. It follows self-supervised learning by utilizing existing disaster ontology, namely Empathi [21] for automatic classification of tweets into categories and then, utilizes these classified tweets as feedback to determine the categories of the remaining tweets. Therefore, by using an existing ontology, it can handle both the information diversity of each category and manage the vocabulary gap by utilizing semantic similarity [78] without any human intervention. Furthermore, by integration of feedback based information from already classified tweets, it ensures it can handle the inherent issues of tweets, like short length, presence of noise and difference in vocabulary with the ontology to identify the category of a tweet given a disaster with high precision. In the second phase, we determine the specific importance of each category with respect to the disaster. For this, identify disasters which are similar on the basis of categories to automatically identify the importance of a category with respect to each type of disaster. Therefore, identifying a disaster which has similar information content in categories as that of the given disaster aids in automatic determination of the importance of each category of the disaster and thus, determining the number of tweets to be selected from each category. Finally, OntoRealSumm selects the number of tweets from each category which maximizes the information coverage of the category and ensures diversity in summary to form the disaster summary by Maximal Marginal Relevance based [8]. Therefore, it can automatically identify the category of tweets, capture category importance, ensure both information coverage of each category and diversity in summary with minimal human intervention.

We evaluate the effectiveness of OntoRealSumm on 10 disaster events and compare our results with the existing research works in terms of ROUGE-N [40] scores. Our results indicate that OntoRealSumm is better than existing research works by 2.69% to 31.05% ROUGE-1 F1-scores, 5.51% to 41.93% ROUGE-2 F1-scores, and 4.08% to 17.55% ROUGE-L F1-scores on an average. Additionally, we perform experiments to analyze the performance of the OntoRealSumm in identifying the category of a tweets and study the role of the different components of the OntoRealSumm. We finally perform a failure analysis of to highlight the shortcomings of OntoRealSumm. We discuss related works in Section 2 and the datasets details in Section 3. In Section 4, we present problem definition and discuss details of OntoRealSumm in Section 5. We discuss the experiment details in Section 6 and results in Section 6.2. Finally, we conclude our summary in Section 7.

2 RELATED WORKS

There is a plethora of existing tweet summarization approaches which differ based on their application, like sports events [23, 25, 27], political events [35, 53], social events [48, 69], disaster [67, 68] and news event [10, 13, 82]. Based on the application, these tweets summarization approaches utilize the temporal [76], the content diversity [2, 11, 45] or both to select the summary tweets. However, as discussed in Section 1, there is high content diversity across different categories of a disaster and further, the presence and importance of categories differ from one disaster to another. Therefore, these existing summarization approaches on different applications can not be directly applied to tweets related to a disaster.

During a disaster, a huge number of tweets that comprises of real-time and situational information is posted by eye-witnesses and affected people [81]. Therefore, to ensure immediate help, there is a requirement of automated techniques that can identify, extract, and summarize the relevant required information from this huge information overload [4, 33, 73]. Existing disaster tweet summarization approaches can be primarily categorized into abstractive [39, 59] or extractive summarization [14, 68] approaches. In this paper, we focus on developing an extractive summarization approach. Most of the existing extractive tweet summarization approaches can further be segregated based on their proposed methodology into graph based [17], content based [71], deep
learning approaches \[15, 36\], or integration of multiple approaches \[66\]. We discuss each of these approaches in details next.

Existing content based disaster summarization approaches explore the high variance in the frequency and presence of keywords related to a disaster \[61, 62\] to generate the summary. Additionally, several approaches initially classify each tweet either as relevant or non-relevant tweets and then, they summarize relevant tweets by semi-supervised learning \[12\] or supervised learning \[44, 58, 65\] on the basis of the tweet content followed by selection of representative tweets from relevant tweets by different techniques, like ILP \[61\], LSA \[24\], LUHN \[42\] or PageRank \[52\]. Additionally, recent research works utilize neural network-based techniques to utilize the tweet contents, such as Dusart et al. \[15\] propose utilization of BERT model \[41\] to identify the importance of a tweet. Li et al. \[36\] proposed the utilization of the graph convolutional neural networks on a tweet similarity graph to calculate the tweet importance and thereby, select tweets with most importance to create a summary. However, both of these approaches require huge training data. However, these summarization approaches do not consider the categories and therefore, fail to ensure the information coverage of each category in the summary \[75\].

In order to handle these challenges, several research works have proposed graph based tweet summarization approaches \[18, 19\] which initially creates the tweet similarity graph which represents tweets as nodes and an edge represent the similarity between a pair of tweets and then, groups similar tweets together by identifying communities from the tweet similarity graph. Finally, these approaches select representative tweets from each group based on the length, degree or centrality based measures to generate the summary \[6\]. Therefore, these approaches ensure integration of similar information together by the edge relationships in the graph, implicit identification of categories and further, ensure information coverage and reduction of redundancy by selecting representative tweets from each category. For example, Dutta et al. \[20\] propose a community based approach to identify the different sub-groups from the tweet similarity graph and finally, select representative tweets by centrality based measures to create a summary. However, these approaches rely on community based measures to inherently identify the categories of the disaster, which is very challenging due to high vocabulary overlap across categories in a disaster. These approaches consider only content based similarity to identify the category, which can not ensure handling of the inherent issues in tweets \[11\]. Additionally, these approaches do not consider the difference in importance of categories and their information content across different disasters.

Therefore, to cater to the different requirements, recent disaster summarization based approaches initially identify the categories from the tweets and then, create a summary from each of these categories. For example, Rudra et al. \[60, 64\] use existing category identification classifier, i.e., AIDR \[30\] to identify the categories. In \[60\], the authors create a word graph for each category and then, select representative tweets from each word graph on the basis of the presence of the most important words while ensuring information coverage in summary. Similarly, in \[64\], the authors initially identify the sub-event from each category for a disaster and then select the representative tweets from each category such that the selected tweet has the maximum number of content words of that (i.e., nouns, verbs, and numerals) to create a summary. However, AIDR requires human intervention for each new disaster event and is applicable only for real-time disaster events. Furthermore, none of these approaches considers the difference in category vocabulary and importance across disasters. Therefore, there is a need to develop a system that can automatically identify the categories of the disaster with minimum human intervention and further, capture the specific and implicit importance of each category given a disaster in the disaster summary.
However, there are several challenges in identifying the category of a tweet, like the presence of a category and high content diversity within a category vary across the different disasters. Therefore, we propose OntoRealSumm that utilizes an existing disaster ontology, Empathi [21] to effectively identify the category of a tweet irrespective of the disaster in the first phase and then, ensure category based representation and information coverage to generate the summary. We discuss datasets details next.

3 DATASET
In this Section, we discuss the datasets, pre-processing details and gold standard summary.

3.1 Dataset Details and Pre-processing
We evaluate the performance of OntoRealSumm on 10 disaster datasets which are as follows. An overview of these datasets is shown in Table 2.

1. $D_1$: This dataset is prepared based on the Sandy Hook Elementary School Shooting \(^2\) in which around 26 people, including 20 children and 6 adults were killed in December, 2012. This dataset is taken from [17].

2. $D_2$: This dataset is prepared based on the Uttarakhand Flood \(^3\) which caused dreadful floods and landslides in Uttarakhand, India in June, 2013. This dataset is taken from [17].

3. $D_3$: This dataset is prepared based on the devastating impact of the strong cyclone, Hagupit Typhoon \(^4\) on Philippines in December, 2014 which led to the death of around 18 people and evacuation of 916 people. This dataset is taken from [17].

4. $D_4$: This dataset is prepared based on the Hyderabad Blast, India \(^5\) in which two consecutive bomb blasts killed 17 people and injured 119 people in February, 2013. This dataset is taken from [17].

5. $D_5$: This dataset is prepared based on the Harda Twin Train Derailment, India \(^6\) in which 31 people died, and 100 got injured. The incident happened in August, 2015. This dataset is taken from [61].

6. $D_6$: This dataset is prepared based on the Los Angeles International Airport Shooting \(^7\) in which around 15 people were injured and 1 person was killed. The incident happened in November, 2013. This dataset is taken from [51].

7. $D_7$: This dataset is prepared based on the devastating impact of the terrible hurricane, Hurricane Matthew \(^8\) on Haiti in October, 2016 which led to the death of 603 people and evacuation of 1.5 million people. This dataset is taken from [1].

8. $D_8$: This dataset is prepared based on the Puebla Mexico Earthquake \(^9\) in which 370 people died, and 6011 got injured. The incident happened in September, 2017. This dataset is taken from [1].

9. $D_9$: This dataset is prepared based on the Pakistan Earthquake \(^10\) in which 40 people died, and 850 got injured. The incident happened in September, 2019. This dataset is taken from [1].

\(^2\)https://en.wikipedia.org/wiki/Sandy_Hook_Elementary_School_shooting
\(^3\)https://en.wikipedia.org/wiki/2013_North_India_floods
\(^4\)https://en.wikipedia.org/wiki/Typhoon_Hagupit_(2014)
\(^5\)https://en.wikipedia.org/wiki/2013_Hyderabad_blasts
\(^6\)https://en.wikipedia.org/wiki/Harda_twin_train_derailment
\(^7\)https://en.wikipedia.org/wiki/2013_Los_Angeles_International_Airport_shooting
\(^8\)https://en.wikipedia.org/wiki/Hurricane_Matthew
\(^9\)https://en.wikipedia.org/wiki/2017_Puebla_earthquake
\(^10\)https://en.wikipedia.org/wiki/2019_Kashmir_earthquake
(10) \( D_{10} \): This dataset is prepared based on the *Midwestern U.S. Floods* \(^{11}\) which caused dreadful floods and massive damages in Midwestern United States in March 2019 to December 2019. This dataset is taken from [1].

Table 2. We show the details of the 10 datasets, including dataset number, year, number of tweets, type of disaster, country, and continent.

| SNo | Dataset | Year | Number of tweets | Type of disaster | Country     | Continent |
|-----|---------|------|------------------|-----------------|-------------|------------|
| 1   | \( D_1 \) | 2012 | 2080             | Man-made        | United States | USA        |
| 2   | \( D_2 \) | 2013 | 2069             | Natural         | India        | Asian      |
| 3   | \( D_3 \) | 2014 | 1461             | Natural         | Philippines  | Asian      |
| 4   | \( D_4 \) | 2013 | 1413             | Man-made        | India        | Asian      |
| 5   | \( D_5 \) | 2015 | 1676             | Man-made        | India        | Asian      |
| 6   | \( D_6 \) | 2013 | 1409             | Man-made        | United States | USA        |
| 7   | \( D_7 \) | 2016 | 1654             | Natural         | Haiti        | USA        |
| 8   | \( D_8 \) | 2017 | 2015             | Natural         | Mexico       | USA        |
| 9   | \( D_9 \) | 2019 | 1958             | Natural         | Pakistan     | Asian      |
| 10  | \( D_{10} \) | 2019 | 1880             | Natural         | United States | USA        |

Pre-processing and Gold Standard Summary: As we consider only the tweet text in the OntoRealSumm, we perform pre-processing to remove URLs, usernames, emoticons, punctuation marks, and noise from the tweet text. We use gold standard summary provided by Dutta et al. [17] for \( D_1-D_4 \) and by Rudra et al. [61] for \( D_5 \). For \( D_6-D_{10} \), we ask 3 annotators to prepare a summary of 40 tweets for each dataset. We follow the procedure by Dutta et al. [17] to combine the individual summaries to prepare the final gold standard summary.

4 PROBLEM STATEMENT

Given a disaster event, \( D \), that comprises of \( n \) tweets, \( \mathcal{T} = \{T_1, T_2, \ldots, T_n \} \), we intend to create a summary, \( S \) of \( \mathcal{T} \). As in most summarization applications, we assume that the length of the summary, \( m \), is provided. We previously discussed in Section 1 that a disaster tweet summarization approach must ensure information coverage of all the categories present in \( \mathcal{T} \) where information coverage of a category refers to representation of all the important aspects of that category in \( S \) [80]. As there are many different mechanisms, such as topics, keywords, a combination of content and context based information, to represent aspects [59], we do not provide any specific method to calculate information coverage and only provide an intuition of information coverage next. We refer to information of \( C_i \) as \( \text{In}(C_i) \) which refers to the aspects present in \( C_i \) and measure the information coverage provided by a tweet, \( T_j \), of \( C_i \) as \( \text{ICov}(T_j, \text{In}(C_i)) \). Therefore, \( \text{ICov}(T_j, \text{In}(C_i)) \) measures the number of aspects that are present in \( C_i \) which are covered by \( T_j \). We show all the used notations and corresponding descriptions for OntoRealSumm in Table 3.

As previously highlighted by existing summarization approaches, the tweets selected in summary, \( S \), must be diverse among each other, i.e., no two tweets selected in \( S \) convey same information and every tweet in \( S \) adds novel information [8, 80]. Therefore, diversity ensures to minimize redundancy \( S \). In order to ensure diversity in \( S \), it is required to select that tweet into \( S \) such that it maximizes the novelty of information and reduces redundancy in \( S \). Existing research

\(^{11}\)https://en.wikipedia.org/wiki/2019_Midwestern_U.S._floods
Table 3. We show notations and their corresponding description used in OntoRealSumm.

| Notation | Description |
|----------|-------------|
| D        | Given a disaster event dataset |
| n        | Number of tweets in D |
| T        | Set of tweets in D |
| T_j      | j^{th} indexed tweet |
| m        | Desired length summary (number of tweets) |
| K        | Total number of categories |
| S        | Generated summary |
| C_i      | i^{th} category in D |
| I(C_i)   | Importance of a category C_i |
| ICov(T_j, In(C_i)) | Information coverage provided by tweet, T_j of C_i |
| D(T_j, S) | Diversity if tweet T_j added to S |
| SemSIM(T_j, C_i) | Semantic Similarity score between T_j and C_i |
| ConSIM(T_j, C_i) | Content based similarity between T_j and C_i |
| W(C_i)   | Weight score of C_i |
| Kw(T_j)  | Keywords of T_j, such as nouns, verbs, and adjectives |
| Kw(C_i)  | Comprise keywords of C_i |
| MaxSIM(T_j) | Highest Semantic Similarity score among all C_i for T_j |

works measure diversity, i.e., the novelty of information, by the presence of keywords, aspects, content or contextual information that has not been covered by the tweets already selected in summary [62, 64]. We use $D(T_j, S)$ to measure the diversity provided by selecting $T_j$ into $S$. Therefore, to create $S$, we need to select tweets iteratively that can maximize both information coverage of each $C_i$, $ICov(T_j, In(C_i))$, and diversity of the summary, $D(T_j, S)$ simultaneously.

However, this requires knowledge about the category of $T$ which is not known apriori as discussed in Section 1. Additionally, the importance of a category, i.e., the number of tweets to be selected from a category in $S$ is required to create $S$. However, we have previously shown that the importance of a category varies from disaster to disaster and therefore, requires an automated system that can determine the importance of each category. We refer to the list of categories as $C = \{C_1, C_2, \ldots, C_K\}$ such that there are $K$ categories present in $T$ and the importance of a category, $C_i$ as $I(C_i)$ which measures the number of tweets to be selected from $C_i$. Thus, we intend to select $m$ tweets from $T$ such that it maximizes the information coverage present in each category, $In(C_i)$ in $C$ and diversity in $S$ on the basis of $I(C_i)$. We formally define the problem as

$$S = \bigcup_{i=1}^{K} \bigcup_{j=1}^{I_i} \max_{T_j \in C_i, 1 \leq j \leq n} (\alpha \cdot ICov(T_j, In(C_i)) + \beta \cdot D(T_j, S))$$

s.t. $\sum_{i=1}^{K} I_i = m$  \hspace{1cm} (1)

where, $I = \{I_1, I_2, I_3, \ldots, I_K\}$ represents the importance of each category/ number of tweets to be selected from each category, $\alpha$ and $\beta$ are tunable parameters that consider the importance of
information coverage and diversity respectively [8]. Therefore, we intend to propose an automatic tweet summarization approach that fulfils all these objectives.

- **Identification of the category of each tweet, Phase-I**: We propose a self-supervised approach to identify the category, \( C_i \) of a tweet, \( T_j \). The approach identifies the category of \( T_j \) on the basis of semantic similarity of \( T_j \) with an existing ontology and then, uses the relevant knowledge of the identified tweets as feedback to identify the category of tweets which could not be resolved directly by semantic similarity.
- **Determination of importance of each category, Phase-II**: We determine the importance of each \( C_i \), \( I(C_i) \), with respect to \( D \) using a Linear Regression model. On the basis of \( I(C_i) \), we select the number of tweets from \( C_i \) in \( S \).
- **Representative tweets selection from \( C_i \), Phase-III**: We select the representative tweets from \( C_i \) to ensure information coverage of each category while maintaining the importance of the category and diversity in summary. For Phase-I, we propose an ontology based pseudo-relevance feedback approach to identify the category of a tweet. For Phase-II, we proposed a metric to compare the similarity between two disaster events considering content and probability distribution of tweets across categories. By identifying a similar disaster, we predict the number of tweets to be selected from each category in the final summary. Finally, in Phase-III, we select the number of tweets as predicted in Phase-II from each category which ensures information coverage and diversity of each category in the final summary.

5 PROPOSED APPROACH

In this Section, we discuss proposed approach in details.

5.1 Overview

The proposed approach, OntoRealSumm comprises of three phases, Phase-I where we identify the category of \( T \), Phase-II where we compute the importance of \( C_i \) for \( D \), and finally, Phase-III in which we select representative tweets from \( C_i \) that ensures information coverage of each category while maintaining the importance of the category and diversity in summary. For Phase-I, we propose an ontology based pseudo-relevance feedback approach to identify the category of a tweet. For Phase-II, we proposed a metric to compare the similarity between two disaster events considering content and probability distribution of tweets across categories. By identifying a similar disaster, we predict the number of tweets to be selected from each category in the final summary. Finally, in Phase-III, we select the number of tweets as predicted in Phase-II from each category which ensures information coverage and diversity of each category in the final summary.

Although in this sequential process of summarizing, we require some data pre-processing and knowledge base in the form of ontology, it does not require human intervention to get an effective summary in real-time. We show the overview of OntoRealSumm in Figure 2. We next describe each of these steps of the OntoRealSumm in detail.

5.2 Phase-I

To identify the category of a tweet, we propose an ontology based pseudo-relevance feedback approach. Although there are several different disasters specific ontology available [38, 47, 70, 79], we choose Empathi [21] as it provides the maximum number of categories and covers information related to different types of disasters compared to others. The Empathi disaster ontology comprises of 70 categories and the vocabulary of these categories. We identify the category of those tweets which have high similarity with Empathi by Semantic Similarity score [78], \( \text{SemSIM}(T_j, C_i) \) of a category, \( C_i \) with the tweet, \( T_j \) as shown in Equation 2.

\[
\text{SemSIM}(T_j, C_i) = \text{ConSIM}(T_j, C_i) \ast W(C_i)
\]  

(2)

\( \text{SemSIM}(T_j, C_i) \) is the product of content based similarity of the tweet with the category, \( \text{ConSIM}(T_j, C_i) \), and the weight of the category, \( W(C_i) \) that represents the number of keywords in \( C_i \). We calculate \( \text{ConSIM}(T_j, C_i) \) as the overlap of the tweet keywords, \( \text{Kw}(T_j) \), with the category keywords,
Fig. 2. An overview of OntoRealSumm is shown

Kw(Ci). We consider only nouns, verbs, and adjectives of Tj as Kw(Tj) [34] and W(Ci) as the normalised number of keywords in Ci as shown in Equation 3.

\[ W(C_i) = \frac{Kw(C_i)}{\sum_{i \in k} Kw(C_i)} \]  

where, K is the total number of categories. On the basis of SemSIM(Tj, Ci), we assign the category of Tj which has the highest Semantic Similarity score, MaxSIM(Tj) among all categories.

\[ MaxSIM(T_j) = \arg \max_{i \in K}(SemSIM(T_j, C_i)) \]  

Our observations indicate that around 10 – 30% of the total tweets remain unclassified as they have no overlap with any of the category keywords. The reason being the high vocabulary diversity in tweets [26, 54]. Therefore, we use the information from the classified tweets of the category as feedback to increase the existing vocabulary of the disaster category. We create an extended vocabulary of the category by including only those keywords with frequencies greater than 3 of the already classified tweets [72]. We use this extended vocabulary to determine the category of the unclassified tweets. Although we can not ensure the classification of all the tweets, we observe only a small number of tweets, i.e., around 1 – 10% of the total tweets remain unclassified after this step. We show in Table 4 the fraction of tweets classified in each of the steps and the fraction of tweets that are unclassified for 10 disaster events. We do not consider the tweets whose category could not be determined in Phase-I.

5.3 Phase-II

After identifying the category of the tweets related to a disaster, we determine the importance of a category with respect to a disaster (say Di). The importance of a category, Ij, is needed to
Table 4. We show the % of classified tweets using ontology vocabulary (Pass-I), extended vocabulary (Pass-II), and remaining tweets after Pass-I and Pass-II for 10 datasets.

| Event | Pass-I | Pass-II | Remaining tweets | Event | Pass-I | Pass-II | Remaining tweets |
|-------|--------|---------|------------------|-------|--------|---------|------------------|
| $D_1$ | 72.64  | 27.15   | 0.19             | $D_6$ | 80.57  | 14.41   | 5.01             |
| $D_2$ | 89.72  | 7.43    | 2.84             | $D_7$ | 99.51  | 0.36    | 0.12             |
| $D_3$ | 67.22  | 22.35   | 10.41            | $D_8$ | 99.20  | 0.44    | 0.29             |
| $D_4$ | 73.58  | 17.55   | 8.85             | $D_9$ | 98.05  | 1.38    | 0.56             |
| $D_5$ | 76.95  | 11.29   | 11.75            | $D_{10}$ | 97.17  | 2.34    | 0.47             |

determine the number of tweets to be selected from each category in the final disaster summary. Therefore, $I_j$ of $C_j$ represents the total number of tweets to be selected from $C_j$ given $D_i$. We use a linear regression model to predict the number of tweets to be included in the final summary. This regression model is trained with a disaster dataset (say $D_j$), which is very similar to $D_i$ in terms of content and tweet distribution across categories. To identify $D_j$ for a given $D_i$, we propose a metric disaster similarity score.

**Disaster Similarity Score** : Content of the tweets across the categories and the distributions of the tweets across categories vary with disasters. We propose a disaster similarity score, $DisSIM(D_i, D_j)$ to compute the similarity between any pair of disasters, $D_i$ and $D_j$. We define $DisSIM(D_i, D_j)$ as the weighted score of information content of the categories, $C_{IC}$ and similarity in probability distribution between categories $C_p$. We compute $C_p$ as $(1-C_{ds})$ where $C_{ds}$ is the Jensen Shannon Divergence of two events. $DisSIM(D_i, D_j)$ is calculated as:

$$DisSIM(D_i, D_j) = w_1 * C_{IC} + w_2 * C_p$$

(5)

subject to

$$w_1 + w_2 = 1$$

(6)

$$w_1, w_2 \in (0, 1)$$

(7)

where, $w_1$ and $w_2$ are the weights of $C_{IC}$ and $C_p$ respectively. We calculate $C_{IC}^i$ as the cosine similarity [49] of the most frequent occurring keywords between $D_i$ and $D_j$ for a category, $i$ and $C_{IC}$ as the average cosine similarity over all categories as shown in Equation 8.

$$C_{IC} = \frac{1}{K} \sum_{i=1}^{K} C_{IC}^i$$

(8)

where $K$ is the total number of categories. We calculate $C_p$ by the Jensen-Shannon divergence [12] of a disaster pair $D_i$ and $D_j$. $C_p$ measures the similarity of the probability distributions of the categories between $D_i$ and $D_j$. We select $D_q$ as the disaster which has maximum similarity with $D_i$ on the basis of $DisSIM(D_i, D_q)$ where, $e \in 0, 1, \ldots, Q$ and $Q$ is the total number of disasters we have. We discuss this experiment and our observations in detail in Subsection 6.5.

5.4 Phase-III

We finally select $I_j$ from each category using a representative tweet selection approach that can captures the maximum information coverage and ensures diversity in summary. Based on the experiment where we compare different selection approaches, such as **Semantic similarity score**

[12]https://en.wikipedia.org/wiki/Jensen%E2%80%93Shannon_divergence
Eigenvector centrality based [5], PageRank based [7], K-mean clustering based [43], and Maximal Marginal Relevance based selection [8], we select MMR in OntoRealSumm. We show the experiment and our observations in details in Subsection 6.6. MMR uses an incremental approach, comparing each tweet to the current summary tweet to determine its inclusion in summary. We discuss the experiments next.

6 EXPERIMENTS

In this Section, we initially discuss the details of the existing research works related to disaster summarization which we use as baseline methods for comparison. Then we provide a performance comparison of baseline methods with the proposed approach OntoRealSumm.

6.1 Baselines

We compare OntoRealSumm with following state-of-the-art summarization approaches:

1. B1: Rudra et al. [63] propose a summarization framework that initially identifies the tweets, which comprises of most important disaster-specific keywords, such as numerals, nouns, verbs, and location. Then, the authors create a graph where the nodes represent all the words of the identified tweets, and an edge is created between two words if they had occurred as a bigram in any of the tweets. Finally, they select those paths from the graph, which can ensure maximum information coverage to generate the summary.

2. B2: Dutta et al. [17] propose an ensemble graph based summarization approach which initially generates summary by 9 existing text summarization algorithms. The authors create a tweet similarity graph where the nodes represent the tweets present in the summary of anyone of the 9 existing text summarization algorithms and the edges represent their content and context similarity. Finally, the authors follow a community detection algorithm to automatically identify the categories and then select representative tweets from each category on the basis of length, informativeness and centrality scores to create the summary.

3. B3: Rudra et al. [64] propose a sub-event based summarization approach that initially identifies the sub-events and then, they generate a summary by selecting representative tweets by Integer Linear Programming based selection such that it ensures maximum information coverage of sub-events.

6.2 Comparison with Existing Research Works

To evaluate the performance of the OntoRealSumm, we compare the summary generated by the OntoRealSumm and the existing research works with the ground truth summary on the basis of ROUGE-N score [40]. ROUGE-N score computes the overlapping words in the generated summary with a set of ground truth summary. We calculate precision, recall and F1-score for 3 different variants of ROUGE-N score, i.e., N=1, 2 and L, respectively. Our observations from Table 5 indicate that OntoRealSumm ensure better ROUGE-N precision, recall and F1-scores in comparison with baselines. The improvement in summary scores of ROUGE-1 F1-score ranges from 1.96% to 62.74%, ROUGE-2 F1-score ranges from 4.34% to 73.33% and ROUGE-L F1-score ranges from 3.57% to 20.68% respectively. The improvement is highest over the B3 baseline and lowest with the B2 baseline. The performance of the OntoRealSumm is the best for D3 baseline and lowest with the B2 baseline. The performance of the OntoRealSumm is the best for D5 with 0.58 – 0.29 and worst for D4 with 0.47 – 0.28 in Rouge-1, Rouge-2 and Rouge-L F1-scores.
| Dataset | Approaches | ROUGE-1 | | | ROUGE-2 | | | | | ROUGE-L | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Precision | Recall | F1-score | Precision | Recall | F1-score | Precision | Recall | F1-score |
| $D_1$ | OntoRealSumm | 0.56 | 0.48 | 0.51 | 0.21 | 0.18 | 0.20 | 0.31 | 0.27 | 0.29 |
| | $B_1$ | 0.49 | 0.58 | 0.53 | 0.24 | 0.29 | 0.26 | 0.31 | 0.36 | 0.33 |
| | $B_2$ | 0.59 | 0.47 | 0.52 | 0.25 | 0.20 | 0.22 | 0.32 | 0.27 | 0.29 |
| | $B_3$ | 0.44 | 0.53 | 0.48 | 0.18 | 0.22 | 0.20 | 0.25 | 0.29 | 0.27 |
| $D_2$ | OntoRealSumm | 0.46 | 0.45 | 0.46 | 0.17 | 0.17 | 0.17 | 0.27 | 0.26 | 0.27 |
| | $B_1$ | 0.32 | 0.35 | 0.33 | 0.14 | 0.15 | 0.14 | 0.23 | 0.25 | 0.24 |
| | $B_2$ | 0.44 | 0.32 | 0.37 | 0.18 | 0.14 | 0.16 | 0.28 | 0.22 | 0.25 |
| | $B_3$ | 0.39 | 0.44 | 0.41 | 0.11 | 0.13 | 0.12 | 0.23 | 0.26 | 0.24 |
| $D_3$ | OntoRealSumm | 0.50 | 0.48 | 0.49 | 0.19 | 0.18 | 0.19 | 0.28 | 0.27 | 0.28 |
| | $B_1$ | 0.36 | 0.36 | 0.36 | 0.14 | 0.14 | 0.14 | 0.29 | 0.29 | 0.29 |
| | $B_2$ | 0.50 | 0.34 | 0.40 | 0.23 | 0.15 | 0.18 | 0.32 | 0.23 | 0.27 |
| | $B_3$ | 0.42 | 0.47 | 0.44 | 0.17 | 0.18 | 0.17 | 0.23 | 0.25 | 0.24 |
| $D_4$ | OntoRealSumm | 0.49 | 0.44 | 0.47 | 0.19 | 0.17 | 0.18 | 0.29 | 0.27 | 0.28 |
| | $B_1$ | 0.29 | 0.36 | 0.32 | 0.12 | 0.14 | 0.13 | 0.22 | 0.27 | 0.24 |
| | $B_2$ | 0.48 | 0.35 | 0.41 | 0.19 | 0.18 | 0.16 | 0.29 | 0.23 | 0.26 |
| | $B_3$ | 0.43 | 0.48 | 0.45 | 0.16 | 0.18 | 0.17 | 0.24 | 0.26 | 0.25 |
| $D_5$ | OntoRealSumm | 0.58 | 0.58 | 0.58 | 0.29 | 0.29 | 0.29 | 0.31 | 0.30 | 0.31 |
| | $B_1$ | 0.35 | 0.62 | 0.44 | 0.18 | 0.32 | 0.23 | 0.24 | 0.40 | 0.29 |
| | $B_2$ | 0.48 | 0.34 | 0.51 | 0.22 | 0.25 | 0.23 | 0.26 | 0.29 | 0.28 |
| | $B_3$ | 0.48 | 0.58 | 0.53 | 0.23 | 0.28 | 0.25 | 0.25 | 0.29 | 0.27 |
| $D_6$ | OntoRealSumm | 0.57 | 0.56 | 0.56 | 0.23 | 0.23 | 0.23 | 0.29 | 0.28 | 0.29 |
| | $B_1$ | 0.50 | 0.47 | 0.49 | 0.23 | 0.22 | 0.22 | 0.29 | 0.28 | 0.29 |
| | $B_2$ | 0.37 | 0.41 | 0.48 | 0.21 | 0.15 | 0.18 | 0.29 | 0.22 | 0.25 |
| | $B_3$ | 0.50 | 0.55 | 0.52 | 0.20 | 0.22 | 0.21 | 0.25 | 0.27 | 0.23 |
| $D_7$ | OntoRealSumm | 0.54 | 0.45 | 0.49 | 0.17 | 0.14 | 0.15 | 0.25 | 0.22 | 0.23 |
| | $B_1$ | 0.45 | 0.51 | 0.48 | 0.12 | 0.14 | 0.13 | 0.24 | 0.21 | 0.22 |
| | $B_2$ | 0.57 | 0.40 | 0.47 | 0.17 | 0.13 | 0.14 | 0.27 | 0.21 | 0.22 |
| | $B_3$ | 0.49 | 0.40 | 0.44 | 0.14 | 0.11 | 0.12 | 0.24 | 0.20 | 0.22 |
| $D_8$ | OntoRealSumm | 0.48 | 0.49 | 0.48 | 0.15 | 0.16 | 0.16 | 0.25 | 0.24 | 0.25 |
| | $B_1$ | 0.43 | 0.48 | 0.45 | 0.13 | 0.14 | 0.13 | 0.22 | 0.24 | 0.23 |
| | $B_2$ | 0.51 | 0.43 | 0.46 | 0.15 | 0.13 | 0.14 | 0.26 | 0.22 | 0.24 |
| | $B_3$ | 0.43 | 0.46 | 0.44 | 0.13 | 0.14 | 0.14 | 0.22 | 0.24 | 0.23 |
| $D_9$ | OntoRealSumm | 0.56 | 0.45 | 0.50 | 0.17 | 0.14 | 0.15 | 0.25 | 0.21 | 0.23 |
| | $B_1$ | 0.26 | 0.16 | 0.20 | 0.05 | 0.03 | 0.04 | 0.25 | 0.17 | 0.20 |
| | $B_2$ | 0.50 | 0.44 | 0.47 | 0.15 | 0.13 | 0.14 | 0.22 | 0.20 | 0.21 |
| | $B_3$ | 0.45 | 0.45 | 0.45 | 0.11 | 0.11 | 0.11 | 0.21 | 0.21 | 0.21 |
| $D_{10}$ | OntoRealSumm | 0.51 | 0.50 | 0.51 | 0.13 | 0.12 | 0.13 | 0.22 | 0.22 | 0.22 |
| | $B_1$ | 0.46 | 0.15 | 0.19 | 0.06 | 0.03 | 0.04 | 0.22 | 0.15 | 0.18 |
| | $B_2$ | 0.51 | 0.45 | 0.48 | 0.10 | 0.09 | 0.10 | 0.22 | 0.19 | 0.20 |
| | $B_3$ | 0.50 | 0.49 | 0.50 | 0.12 | 0.12 | 0.12 | 0.22 | 0.22 | 0.22 |

### 6.3 Identification of Category of a Tweet

In this Subsection, we evaluate the effectiveness of Phase-I of *OntoRealSumm*, proposed self-supervised tweet category identification approach with an existing unsupervised approach (*UnSuA*). We select the approach followed by Dutta et al. [19] for identifying categories to summarize disaster tweets as *UnSuA*. Although there are several existing unsupervised approaches, we found [19] to be most successful. In [19], the authors propose utilization of Louvain community detection algorithm [74] to identify communities which inherently represents categories related to the disaster. For an experiment, we select 20% tweets randomly from each category for Phase-I of *OntoRealSumm* and *UnSuA* from 3 disaster events, such as, $D_2$, $D_3$ and $D_9$. We ask 3 volunteers who had a good knowledge of English and provide them with these tweets for annotation. On comparing the performance of Phase-I of *OntoRealSumm* with *UnSuA* as shown in Table 6, we observe that...
Phase-I of OntoRealSumm has better performance of at least 43% in F1-score. Based on our observations, we found that unsupervised approaches can not directly segregate the tweets into different categories due to the high vocabulary overlap across different categories and immense vocabulary diversity in each category on the basis of information related to tweet text. Utilization of the semantic information from ontology in Phase-I helps in categorization of tweets and therefore, increases the performance.

Table 6. F1-score of Phase-I of OntoRealSumm and unsupervised tweet category identification approach (UnSuA) on comparing the volunteers annotations for 3 disasters, such as, $D_2$, $D_3$, and $D_6$ is shown.

| Dataset | Approach                  | F1-score |
|---------|---------------------------|----------|
| $D_2$   | Phase-I of OntoRealSumm   | 67.07    |
|         | UnSuA                     | 38.72    |
| $D_3$   | Phase-I of OntoRealSumm   | 64.58    |
|         | UnSuA                     | 23.37    |
| $D_6$   | Phase-I of OntoRealSumm   | 62.99    |
|         | UnSuA                     | 29.93    |

6.4 Determining Relevance of Category Importance

In Phase-II of OntoRealSumm, we propose a linear regression based model to calculate the importance of each category given a disaster based on the assumption that the importance of the category varies across disasters. Although we discuss this assumption by intuition in Section 1, we show this through an experiment next. For our experiments, we compare the summaries generated by OntoRealSumm and summaries generated by an approach when each category is given equal importance, EqCatSumm on 6 datasets, such as, $D_2$, $D_3$, $D_4$, $D_5$, $D_6$, and $D_9$. To generate the summary by EqCatSumm, we follow Phase-III of OntoRealSumm for selection of tweets from each category. We show the precision, recall, and F1-score for 3 different variants of the ROUGE-N score, i.e., $N=1$, 2, and L, in Table 7 which indicates that OntoRealSumm performs consistently better than EqCatSumm. Therefore, we have empirically shown how identifying the importance of each category given a disaster is essential for effective disaster tweet summarization.

6.5 Comparing Disaster Similarity

On comparing $\text{DisSIM}(D_i, D_j)$ for every disaster pair, we observe that any disaster has the most similarity score with a disaster that belongs to the same continent, such as USA or ASIA and is of the same type, i.e., man-made or natural. For example, Uttarakhand Flood ($D_2$) has the highest score with disaster Pakistan Earthquake ($D_9$) among all the disasters. Similarly, Sandy Hook Elementary School Shooting ($D_1$) has the highest score with Los Angeles International Airport Shooting ($D_6$) among all the disasters. Therefore, we term $D_i$ and $D_j$ as homogeneous disasters if they belong to the same continent and is of the same type. Subsequently, we term $D_i$ and $D_j$ as heterogeneous disasters if they do not satisfy either of these two conditions. We validate next the impact of training on a homogeneous disaster or a heterogeneous disaster on the summary quality. We show the results in Table 8.

For each disaster $D_i$, we predict the number of tweets to be selected from each category as predicted by the linear regression model if it was trained on homogeneous disaster or heterogeneous disaster. We, then, select the representative tweets from each category based on the predicted number of tweets to create the summary and finally, compare the generated summary with the ground-truth summary on the basis of ROUGE-N scores. For the experiments, we randomly select
Table 7. F1-score of ROUGE-1, ROUGE-2 and ROUGE-L score on comparing OntoRealSumm which identifies the importance of each category with an approach when each category gives equal importance, EqCatSumm is shown.

| Dataset | Approach   | ROUGE-1 F1-score | ROUGE-2 F1-score | ROUGE-L F1-score |
|---------|------------|------------------|------------------|------------------|
| D2      | OntoRealSumm | 0.46             | 0.17             | 0.27             |
|         | EqCatSumm   | 0.42             | 0.14             | 0.24             |
| D3      | OntoRealSumm | 0.49             | 0.19             | 0.28             |
|         | EqCatSumm   | 0.47             | 0.17             | 0.27             |
| D4      | OntoRealSumm | 0.47             | 0.18             | 0.28             |
|         | EqCatSumm   | 0.42             | 0.13             | 0.24             |
| D5      | OntoRealSumm | 0.58             | 0.29             | 0.31             |
|         | EqCatSumm   | 0.50             | 0.20             | 0.26             |
| D6      | OntoRealSumm | 0.56             | 0.23             | 0.29             |
|         | EqCatSumm   | 0.53             | 0.19             | 0.25             |
| D9      | OntoRealSumm | 0.50             | 0.15             | 0.23             |
|         | EqCatSumm   | 0.48             | 0.14             | 0.21             |

5 disasters, such as, D2, D4, D5, D7, and D8. We show the precision, recall, and F1-score for 3 different variants of the ROUGE-N score, i.e., N=1, 2, and L, respectively, in Table 9. Our observations indicate that there is around 7 – 21% and 6 – 9% increase in ROUGE-2 F1-score for any disaster in Asia and USA, respectively, for both man-made and natural disasters. Therefore, our observations indicate that an effective summary for $D_i$ can be ensured if we identify the importance of categories from a $D_j$ which is of the same type and from the same continent as $D_j$.

Table 8. We show the disaster similarity scores for every disaster pair. The first row and first column of this Table represent the various disasters.

|     | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 | D9 | D10 |
|-----|----|----|----|----|----|----|----|----|----|-----|
| D1  |    | 0.4| 0.43| 0.44| 0.52| 0.43| 0.39| 0.45| 0.4 |
| D2  | 0.4|    | 0.54| 0.48| 0.44| 0.4 | 0.45| 0.48| 0.45| 0.4 |
| D3  | 0.43| 0.54|    | 0.44| 0.4 | 0.47| 0.46| 0.48| 0.46 | 0.44|
| D4  | 0.44| 0.5 | 0.44|    | 0.51| 0.45| 0.43| 0.48| 0.45 | 0.45|
| D5  | 0.44| 0.48| 0.4 | 0.51|    | 0.45| 0.46| 0.45| 0.48 | 0.47|
| D6  | 0.52| 0.44| 0.47| 0.45| 0.45|    | 0.44| 0.45| 0.48 | 0.43|
| D7  | 0.43| 0.5 | 0.46| 0.47| 0.46| 0.44|    | 0.52| 0.48 | 0.55|
| D8  | 0.39| 0.5 | 0.46| 0.45| 0.45| 0.45| 0.52|    | 0.49 | 0.52|
| D9  | 0.45| 0.55| 0.51| 0.48| 0.48| 0.48| 0.49| 0.49|    | 0.46|
| D10 | 0.4 | 0.5 | 0.44| 0.45| 0.47| 0.43| 0.55| 0.52| 0.46|    |

6.6 Comparing different Regression Models
In this Subsection, we compare 3 different types of regression models, such as, Linear regression model ($R_1$), Ridge regression ($R_2$) model, and Bayesian regression model ($R_3$) to understand which model should be selected to predict the number of tweets from each category into summary given $D_i$. In order to understand this, given any similar disaster to $D_i$, say $D_j$, we train $R_1$, $R_2$ and $R_3$
Table 9. F1-score of ROUGE-1, ROUGE-2 and ROUGE-L score of OntoRealSumm for training a linear regression model on a dataset from homogeneous and heterogeneous disasters on 5 datasets is shown.

| Dataset | Training disaster | ROUGE-1 | ROUGE-2 | ROUGE-L |
|---------|-------------------|---------|---------|---------|
| D1      | D5                | 0.50    | 0.19    | 0.29    |
|         | D6                | 0.51    | 0.20    | 0.30    |
|         | D9                | 0.49    | 0.18    | 0.28    |
|         | D10               | 0.49    | 0.19    | 0.28    |
| D2      | D1                | 0.43    | 0.14    | 0.25    |
|         | D5                | 0.43    | 0.15    | 0.25    |
|         | D8                | 0.44    | 0.15    | 0.25    |
|         | D9                | 0.46    | 0.17    | 0.27    |
| D3      | D4                | 0.58    | 0.29    | 0.30    |
|         | D6                | 0.56    | 0.27    | 0.28    |
|         | D7                | 0.56    | 0.27    | 0.29    |
|         | D9                | 0.53    | 0.23    | 0.28    |
| D4      | D1                | 0.47    | 0.12    | 0.21    |
|         | D5                | 0.46    | 0.11    | 0.21    |
|         | D9                | 0.47    | 0.13    | 0.22    |
|         | D10               | 0.49    | 0.15    | 0.23    |
| D5      | D1                | 0.45    | 0.12    | 0.23    |
|         | D2                | 0.46    | 0.15    | 0.24    |
|         | D4                | 0.46    | 0.14    | 0.24    |
|         | D7                | 0.48    | 0.16    | 0.25    |

respectively on the categories of $D_j$ and predict the number of tweets from each category for $D_i$. We evaluate the performance of $R_1$, $R_2$ and $R_3$ through mean squared error as shown in Equation 9.

$$MSE(R_i) = \frac{1}{K} \sum_{s=1}^{K} (N_g - N_r)^2$$

where $N_g$ and $N_r$ are the number of tweets from each category in ground truth summary and predicted by the regression model respectively. $K$ is the number of categories in $D_i$ and $i$ could be 1, 2 or 3. Therefore, lower the value of $MSE(R_i)$, better is the performance of $R_i$. For the experiments, we randomly select 5 different disasters, such as, $D_1$, $D_4$, $D_5$, $D_6$, and $D_9$ and compare the performance of $R_1$, $R_2$ or $R_3$ on the basis of $MSE(R_i)$. We show our observations in Table 10 which indicate that $R_1$ performs the best followed by $R_2$ and $R_2$. Therefore, based on these observations, we select $R_1$, i.e., Linear regression model in OntoRealSumm to automatically identify the number of tweets to be selected from a category given a disaster.

6.7 Identifying Representative Tweets from a Category

In this Subsection, we compare the performance of Semantic similarity score based [78] ($S_1$), Eigenvector centrality based [5] ($S_2$), PageRank based [7] ($S_3$), K-mean clustering based [43] ($S_4$), and Maximal Marginal Relevance based selection [8] ($S_5$) for Phase-III. For the experiments, we randomly select 4 different disasters, such as $D_2$, $D_3$, $D_5$, and $D_6$. We compute the F1-scores for 3 different variants of ROUGE-N score, i.e., N=1, 2, and L respectively. Our observation from Figure 3 indicate
Table 10. We compare Mean Square Error (MSE) of 3 different regression models, i.e, Linear, Ridge, and Bayesian models.

| Dataset | Linear | Ridge | Bayesian |
|---------|--------|-------|----------|
| D_1     | 2.84   | 2.93  | 3.22     |
| D_2     | 1.12   | 1.14  | 1.15     |
| D_3     | 1.37   | 2.19  | 2.28     |
| D_4     | 1.66   | 1.85  | 2.88     |
| D_5     | 4.13   | 4.13  | 4.40     |

Fig. 3. F1-score of ROUGE-1 in Figure 3(a), ROUGE-2 in Figure 3(b) and ROUGE-L score in Figure 3(c) of OntoRealSumm for 5 different representative tweets selection methods, i.e., Semantic similarity score based (S_1), Eigenvector centrality based (S_2), PageRank based (S_3), k-mean clustering based (S_4), and Maximal Marginal Relevance (MMR) based (S_5) on 4 disasters is shown.

that S_5 consistently performs the best followed by S_1 and S_2. S_3 performs the worst irrespective of the dataset. Therefore, based on our observations, we select S_5, i.e., MMR based selection approach in OntoRealSumm.
6.8 Limitations of OntoRealSumm

We discuss the limitations of OntoRealSumm that we have observed next.

1. Dependence on Existing Ontology: As OntoRealSumm relies on an existing ontology to identify the categories of a tweet, it is not directly applicable for other summarization applications, like news events, user opinions regarding products, etc., unless an existing ontology for that application is available. We are working towards developing an ontology automatically from publicly available resources for any application as a future direction so that OntoRealSumm is not dependent on an existing ontology.

2. Identification of category of a Tweet: OntoRealSumm can not identify the categories of all tweets. For example, we found among all the disasters, OntoRealSumm performs the worst for D5, where it could not identify the category for around 12% of the tweets. Therefore, we believe Phase-I of OntoRealSumm could be further improved such that the category of more number of tweets could be identified.

3. Generalizability of OntoRealSumm: As we currently do not have any dataset from other continents except Asia and USA, we can not ensure the generalizability of OntoRealSumm irrespective of location. To resolve this, we are working towards collection of tweets related to disasters from different locations and preparation of ground truth summaries for them such that we can validate the performance of OntoRealSumm as one of our future directions.

7 CONCLUSIONS AND FUTURE WORKS

In this paper, we propose OntoRealSumm which can generate a real-time tweet summary for a disaster with minimal human intervention. OntoRealSumm utilizes a three-phase approach to explicitly handles multiple challenges, like improving categorization quality, finding the importance of each category, ensuring information coverage and information diversity of each category in the final summary. Our experimental analysis shows that OntoRealSumm can ensure 6 – 42% increase in Rouge-N F1-scores over existing research works. Through experiments, we show the effectiveness of each Phase of OntoRealSumm in generating a summary with minimum human intervention.

As a future goal, we plan to extend OntoRealSumm such that it is not dependent on an ontology by automatically creating the ontology as well as we are working towards improvement in the categorization of Phase-I.

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