Table 13: Comparison of ROUGE-1 F-scores for SCC (the proposed methodology) and its three variations on the same tweet stream for each dataset, for each day

Datasets	Day	SCC	SCC (uniform)	SCC (proportion)	SCC (whole)
NEQuake	25/04/2015	**0.4117**	0.2598	0.3058	0.3095
	26/04/2015	**0.3055**	0.3033	0.2758	0.2809
	27/04/2015	**0.3853**	0.3687	0.3613	0.3416
Hagupit	06/12/2014	**0.3223**	0.3108	0.3080	0.3176
	07/12/2014	**0.4124**	0.3172	0.3046	0.3064
	08/12/2014	**0.3475**	0.2849	0.2608	0.3475
PFlood	07/09/2014	**0.4524**	0.4173	0.3886	0.4365
	08/09/2014	**0.4145**	0.3197	0.3529	0.3621

(ii). some of the overlapping information is present in more than one class (e.g., information about airport, flight is present in both 'infrastructure' and 'shelter' class) and independent consideration of the classes fails to capture this phenomenon. Note that SCC can dynamically adjust the proportion of each class as per 'real' content and hence provides superior summaries.

7 CONCLUSION

After interacting with several responders, we realized that summarization of information in the tweets from various perspectives and producing a summary focusing on sub-events is a pressing need in the real world. Accordingly, we have proposed a simple summarization approach, which can generate summaries across various scenarios. Specifically, in this paper, we have considered summaries : (i) of the overall situation, and (ii) of different humanitarian classes. We proposed DEPSUB, a sub-event identification algorithm. A crowdsourced evaluation of DEPSUB showed it to be superior in terms of relevance, usefulness as well as expressiveness. Summaries generated by DEPSUB were rated to be in the top two among five competing algorithms; this observation was confirmed by a quantitative evaluation using ROUGE-1 scores. Our proposed summarization algorithm, SCC - was rated to be superior in terms of diversity, coverage and understandability. Highlighting of sub-events also made the summary more understandable. SCC outperformed baseline algorithms between 6-30%; specifically, we show that the improvement resulted from the inclusion of sub-events. The importance of the different humanitarian classes (infrastructure, missing, shelter etc.) varies over days. SCC nicely captures and adjusts to the changing need. To the best of our knowledge, our work is the first to propose a comprehensive multi-faceted summarization approach; the framework developed can be applied to several important specialized situations (e.g. summarizing missing people information, geography-centric information etc.) - some of which will be our immediate future work.

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