# **Combining Remote Sensing with Webdata and Machine Learning to Support** Humanitarian Relief Work

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- situ data
- Webdata and social media potentially adds value in monitoring natural and man-made disasters [2,3,4]
- General issues: Limited resources, data overload and bias, missing or uncertain location information, trustworthiness, ....

### Addressed questions (Fig. 1):

- What are the current information gaps and user needs?
- How can these gaps be complemented by webdata and corresponding ML methods?
- What are the potentials, benefits and weaknesses, especially for social media data?

### **Scenarios and Data**

- <u>Focus Area:</u> Mozambique, Africa (Fig. 2) Incident types:
- Natural disasters: Cyclones Idai & Kenneth, March-May 2019
- Conflicts, humanitarian crises & securityrelated incidents

#### Data sources:

### 1) GEDELT [5]:

- Live, global event database
- Broadcast, print, online news
- 60+ languages

Fig. 1: Main question of this work: How to complement, enrich and fill gaps of existing workflows?



- 2) Twitter:
  - Worldwide & immediate platform
  - 1 % live stream + full history archive



Fig. 2: Map and AOI of the study area Mozambique.

## **Needs Assessment Results**

• Natural disasters already well covered, but information gaps possible • Desired: A better description of conflicts and human behavior

- Embeddings-based text representation
- Merging and linking of clusters
- Topic detection and tracking
- Topic and stream summarization



<u>Collected data (March 15 – May 15, 2019):</u>

- ~2.3 GB/day (1% worldwide Twitter stream)
- ~200k news articles/day (GDELT)

### 1) Twitter

- Filtering by geolocation (Fig. 2)
- F1-score  $\sim$  0.83, but expected to be lower in case of new event types not yet covered in training data [6]
- After overload reduction (binary classification): ~7,000 potentially relevant Tweets identified  $\rightarrow$  to be investigated

### 2) GDELT

- Filtering by keywords & locations (Fig. 2)
- Web-scaping of news articles
- Application of binary ML model to identify potentially relevant news articles
- F1-score ~ 0.83
- Result products: daily/weekly maps (Fig. 4)
- Despite data sparsity, Twitter tends to add

Fig. 4: Interactive example map representing four crisis-related news articles (GDELT) published March 15, 2019, Beira, Mozambique.

## **Conclusions and Outlook**

- Current ML models are well suited to analyze the content of microblogs and news articles
- Each NGO addresses different questions  $\rightarrow$  flexible methods required
- Adaptive stream analysis, clustering and summarization is required, in order to better understand single information snippets
- $\rightarrow$  noise reduction and validation
- Future work will focus on tweet classification and Twitter stream analysis (quantitative experiments)
- A prototypical workflow according to Fig. 3 will be implemented in order to analyze historical and live stream data

### References

[1] https://reliefweb.int/report/world/data4human-aid-organisations-gethelping-hand-german-aerospace-center

[2] Wiegmann, et al.: Opportunities and Risks of Disaster Data from Social Media: A Systematic Review of Incident Information, Nat. Hazards Earth Syst. Sci. Discuss., in press, 2020.

[3] Kruspe et al.: Review article: Detection of informative tweets in crisis events, Nat. Hazards Earth Syst. Sci. Discuss., in review, 2020.

- <u>Relevant and helpful</u>: Local information
  - Impact, needs & damage assessment
  - Health-related content
  - Information on injuries and death toll
  - Detection and monitoring of securityrelated incidents, social domino effects, armed clashes, .....

more value (impact assessment)

- Information overload reduction is definitely required, but just the starting point for further in depth-analyses that allow to gain valid and localized information from unstructured stream data
- Besides the type of information contained in a tweet (e.g. help needed), also the source type (e.g. first party observation or governmental) is crucial

[4] Kersten and Klan: What happens where during disasters? A Workflow for the multifaceted characterization of crisis events based on Twitter data. JCCM, 28(3), 2020.

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