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Introduction

Flooding is one of the most harmful natural disasters, so it's important to monitor it to define prevention strategies. We propose to use data from social media for detecting flooding events.



Figure 1: Examples of non-flood (left) and flood data (right).

Datasets

The dataset used in this work was the Disaster Image Retrieval from Social Media, used in the MediaEval 2017 competition.

- 6,600 Flickr images with metadata;
- 9 image descriptors: ACC, EH, CEDD, CL, FCTH, JCD, Gabor, SC, and Tamura;
- 1 text descriptor: **2GRAMS_TF (PCA)**



Figure 4: Representation of the Bag of Graphs approach.

GRAPH-BASED EARLY-FUSION FOR FLOOD DETECTION

Rafael de O. Werneck, Icaro C. Dourado, Samuel G. Fadel, Salvatore Tabbone, Ricardo da S. Torres rafael.werneck@ic.unicamp.br



Graph-based Methods

We present two graph-based early-fusion methods to combine features and/or modalities in the representation of the data.



Figure 2: Bag of KNN Graphs first builds a graph, where a vertex represents the object and edges connect their multiple representations associated with different feature spaces. Then, this graph is enriched by connecting each object with its k-nearest neighbors according to each representation.



Figure 3: Bag of Cluster Graphs. In this graph, objects represented within the same feature space are first clustered into n clusters, whose centroids represent the vertices of the final graph. Next, for each object in the collection, we find the clusters in the different spaces for which the object is assigned. Later, we connect the centroids of clusters to which the same object belongs.



Figure 5: Comparison in terms of accuracy between the four methods using the best features (EH and 2GRAMS_TF (PCA)).

Conclusions

We present two new approaches to create a joint representation of multiples modalities: **Bag of KNN Graphs** and **Bag of Cluster Graphs**. In the scenario of flood detection, we show that:

- network (RN).

In our future work, we propose to:

- well as other deep learning approaches;

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• Our early-fusion approach outperforms the traditional concatenation fusion when dealing with multiple modalities;

• Our approach has better performance than a deep neural

• Compare our methods with other early-fusion methods, as

• Include deep features as input of our approaches.