

Artificial intelligence integration to crisis management. Part IV. Active Learning and Social Computing

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Glossary

AL Active Learning

FL Fewshot Learning

- ① Context
- ② Active Learning
- ③ Social Computing for debate and environment
- ④ Next

1 Context

Active Learning Reminder
Last Time

2 Active Learning

3 Social Computing for debate and environment

4 Next

1 Context

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Reminder

Aim reminder: *To have a model that can be quickly adapted to any crisis and new events.*

Problem: Model won't be accurate on new event during a crisis. It could be hard to improve by itself.

Introduce "Human in the loop" with Active Learning.

Query strategies are required to **reduce amount** and **identify data to annotate**.

1 Context

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Last Seminar

- **Instances selection for Active Learning annotation**
(entropy, breaking ties, dropout based) [Schröder et al., 2022].
- Event Detection
- Few results

1 Context

2 Active Learning

- Fewshot Learning
- sBERT
- Results

3 Social Computing for debate and environment

4 Next

Introduction

Since last time, we focused on new **mining methods** because of bad and too varied results. These methods were to explore many **embedding**, and **Fewshot Learning**.

① Context

② Active Learning
 Fewshot Learning
 sBERT
 Results

③ Social Computing for debate and environment

④ Next

What is FL?

Fewshot Learning

When a model is ready for inference with less than 10 labeled data per class. Compared to **zero shot learning**, when the model is able to infer on unseen labeled (but near than seen one).

① Context

② Active Learning

Fewshot Learning

sBERT

Results

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sBERT: A Powerful Model for Learning Sentence Semantics

- sBERT [Reimers and Gurevych, 2019] is a version of BERT designed specifically for learning **sentence embeddings**
- It uses unsupervised learning techniques to encode sentences into high-quality vectors
- sBERT is capable of capturing semantic and syntactic nuances of sentences more accurately than traditional models
- Same architecture as BERT, but different aim (word embedding VS sentence embedding).

Uses of sBERT

- sBERT can be used for **sentence classification**, **information retrieval**, and other natural language processing tasks
- It is often used as a benchmark for many sentence-related tasks

① Context

② Active Learning

Fewshot Learning

sBERT

Results

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Some Results

Last time context:

- French data for crisis
- French and multilang model (Flaubert [Le et al., 2019] and Bloom (BigScience))
- Only one pass

Current context:

- English data
- Light English model (distilBERT [Sanh et al., 2019])
- 100 pass for better confidence

Data

CrisisMMD [Ofli et al., 2020] [Alam et al., 2018], a benchmark dataset for crisis study

- **7 crisis** (hurricane, wildfires, earthquakes, floods)
- 8 labels (other_relevant_information, rescue_volunteering_or_donation_effort, infrastructure_and_utility_damage, not_relevant_or_cant_judge, injured_or_dead_people, affected_individuals, vehicle_damage, missing_or_found_people)
- **18.000** annotated English tweet
- from May 31 2017 to November 19 2017

AL strategy

Before: from 5% labeled dataset with 5% more each AL pass.

Now: from 1 labeled instance each class to 5 more per label each AL pass.

More current context

3 new methods:

- KNN classification + active learning selection based on Kcenter [Sener and Savarese, 2017]

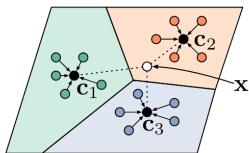


Figure 1: KNN barycenter

- distilBERT classification and active learning selection based on Kcenter
- Oracle

Fewshot vs FineTuning

score distribution for 8 label classification on harvey storm

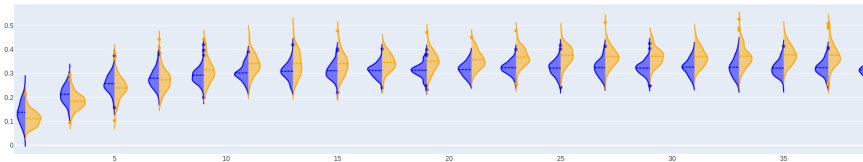


Figure 2: Fewshot Learning compared to Fine-Tuning performances

Go to wandb

go to wandb

1 Context

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Context

Methods

Limits

4 Next

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Context

Social network and big data Many debates and many biases.

- **Homophilie**: we are close to people that look like us
- Social network created amplified homophily, welcome to **echo chamber** (For eg: a no-vax person won't have any debate with a different person or debunk because in his network different points of view disappear or can't reach them)

For what use?

Social computing and big data analysis for

- detect political inference? (2017 -> alt-right creation on Twitter [Chavalarias, 2023])
- better understanding of opinion [Williams et al., 2015]
- natural disaster helps [Kozłowski et al., 2020]

- ① Context
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 - Methods**
 - Limits
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How to?

Main **methods** for those analyses are

- Graph theory
- Frequencies and statistics analyses
- NLP methods for semantics analyses

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Limits

Main **limits** to take care during social computing are

- Social network bias
- Big data annotation
- Data privacy respect

Data Annotation

There are some tricks to annotate users more easily

- AL techniques
- Keywords in description based [Brigadir et al., 2015]
- Followers based

- ① Context
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What's next?

- Improve Kcenter implementation
- Apply AL methods on various datasets and make it easier to implement
- More social computing

Thanks!

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