Positive Unlabeled and Transfer Learning for debris-flow Classification

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Figure 1: (A) Debris-flow in northern India’s Kadernath Valley in 2013 (Agence France-Presse/Getty Images). (B) Seismometer coverage of the Swiss CHnet (color-coded sensor types; dense station coverage in Canton Valais is circled in yellow). (C) Data volume of the Swiss Seismological Service since 2006.

1 Introduction

Sudden catastrophic mass movement events, such as landslides, debris-flows and avalanches, pose a threat to Alpine communities and critical infrastructure worldwide (see Fig. 1 (A)). Debris-flows (mixtures of sediment and water), are an important mass movement type and part of the sediment cascade: Rockfalls and landslides deposit material in steep torrent channels, which is mobilized as debris-flows moving down slopes towards the valley during and after heavy precipitation. Conventional debris-flow warning systems almost exclusively employ instrumentation within or immediately next to debris-flow torrents, limiting their ability to issue accurate early debris-flow warnings. The aim of this project is to further investigate debris-flow warning systems utilizing seismic data. Seismic instruments can be deployed further away than conventional warning systems, and hence they are easier to deploy in difficult terrain and
hard-to-reach regions.

The analysis of seismic signals in a natural hazard context is a challenging task since seismic data sets focusing on mass movement events are usually complex, imbalanced and weakly labeled. The problem is further complicated by domain-adaption/transferability issues, where we want to apply warning systems developed on well-studied, annotated data sets to data sets from less-constrained locations. Since globally, there is a steady increase in the amount of seismometer installations and available continuous seismic data, manual data analysis of debris-flows is rendered almost impossible (see Fig. 1 (B) and (C) for the seismometer coverage and data volume of the Swiss Seismological Service within Switzerland).

To tackle and potentially overcome the above-mentioned issues, this project proposes the use of machine learning techniques.

2 Details of the project

The main focus of this project will be on seismic data collected from the Illgraben region. The Illgraben data set consists of time series collected from a number of seismometers distributed over the region. For this region we have a fully labelled data set which was used by [2] to train a random forest classifier to detect debris-flows. The first task for the student is to reproduce this classifier on an updated data base. This classifier will be used to compare subsequent analysis to and also allows the student to become familiar with the data pipeline.

The second task involves applying positive unlabeled (PU) learning approaches to the Illgraben dataset. PU datasets refer to datasets where we have positive labels (in our case confirmed debris-flows) for only a small portion of the data, with the rest of the data having no labels. This is a less strict assumption that is sometimes more reasonable for monitoring networks, where negative labels have to be indentified by hand. The attractiveness of PU learning is that it can guide domain experts to identify previously undiscovered debris-flows, and also to identify negative examples that are hard to distinguish from debris-flows which can then be used in supervised learning. The results of PU learning will be compared to the random forest classifier obtained in the first task. A survey of PU learning can be found in [1].

In the third task, it is envisioned that the student will address the issue of transferability through adversarial transfer learning, an approach that has been used in the literature for time series domain adaption (see [3] for example). It is envisioned that each of the sensors distributed across the Illgraben domain will act as a different domain. The objective is to train a model that produce embeddings that is able to accurately classify debris-flows, while being agnostic towards the various domains. In the adversarial setting, we have a discriminator tasked with identifying the source domain of an embedding, and the training procedure is set-up to fool the discriminator while preserving high classification accuracy (see Figure 2). The student will also be tasked to design validation procedures for this domain adaption approach, keeping in mind the results obtained in the previous task.

3 Student Tasks

Stage 1: Getting familiar with the Data Pipeline

- Get used to the existing data pipeline and feature extraction methods
Figure 2: The Adversarial Transfer Learning pipeline involves several key steps. Firstly, the sample $x$ undergoes encoding to produce an embedding $z$. Subsequently, a classifier is trained on $z$ with the objective of accurately classifying debris-flows. At the same time, a discriminator is employed to attempt the recovery of the sample’s original location. In the desired scenario, the encoder is trained to eliminate any location-specific information from $x$ while retaining all the essential details crucial for effective debris-flow classification. This process aims to create a robust and efficient model that can generalize well to different locations, focusing solely on identifying debris-flows without being influenced by the specific geographic context of the samples.

- Create ML-ready datasets
- Train a simple Random Forest classifier to reproduce existing results

Stage 2: PU learning

- Evaluate different PU learning approaches (ERM, nnPU, per instance reweighting) on the Illgraben dataset and compare with supervised learning

Stage 3: Transfer learning

- Train a station invariant encoder using an adversarial loss
- Design a procedure to evaluate the transfer performance

Stage 4: Reporting

- Write a report
- Present the project

4 Additional information

What will you learn? Deep Learning, Positive Unlabeled (PU) learning, PyTorch, WandB, Pytorch Lightning, domain adaptation, adversarial learning

Requirements: Machine Learning fundamentals, linear algebra, good Python level, experience with Git.
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Is a publication possible? Yes, if the project goes well.

References

