On the implementation of baselines and *Lightweight Conditional Model Extrapolation (LIMES) for class-prior shift*

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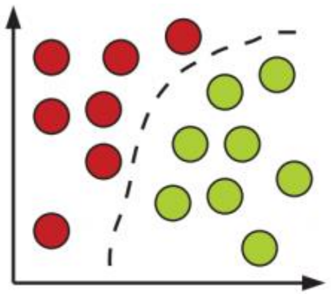
Outline

1. Overview of **LIMES** method
2. Implementation standpoint
3. Reproducibility of the results

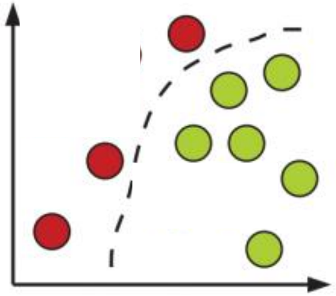
LIMES

Original data



7:8

Class-prior shift

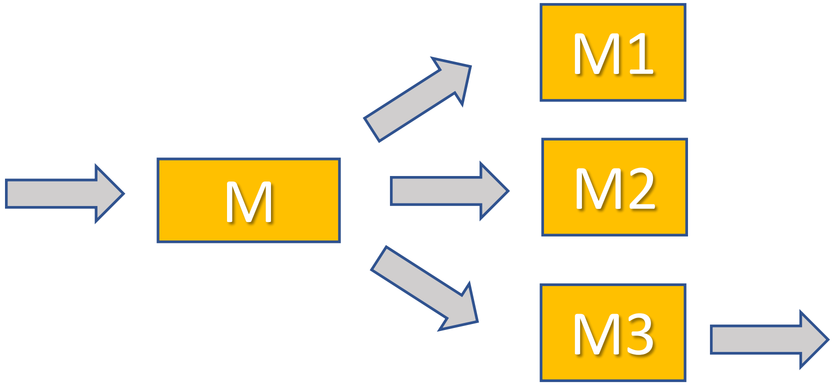


p(y) changes

3:6

one classifier that can be easily

adapted to different scenarios

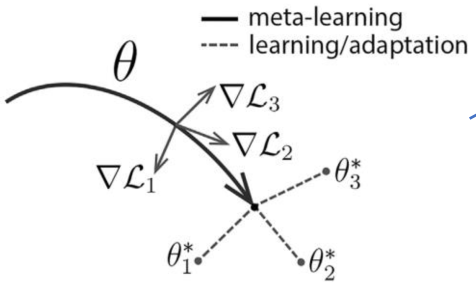


Li**ghtweight **M**odel **E**xtrapolation for **S**treaming data under Class-Prior Shift

LIMES - adaptation using analytical formula

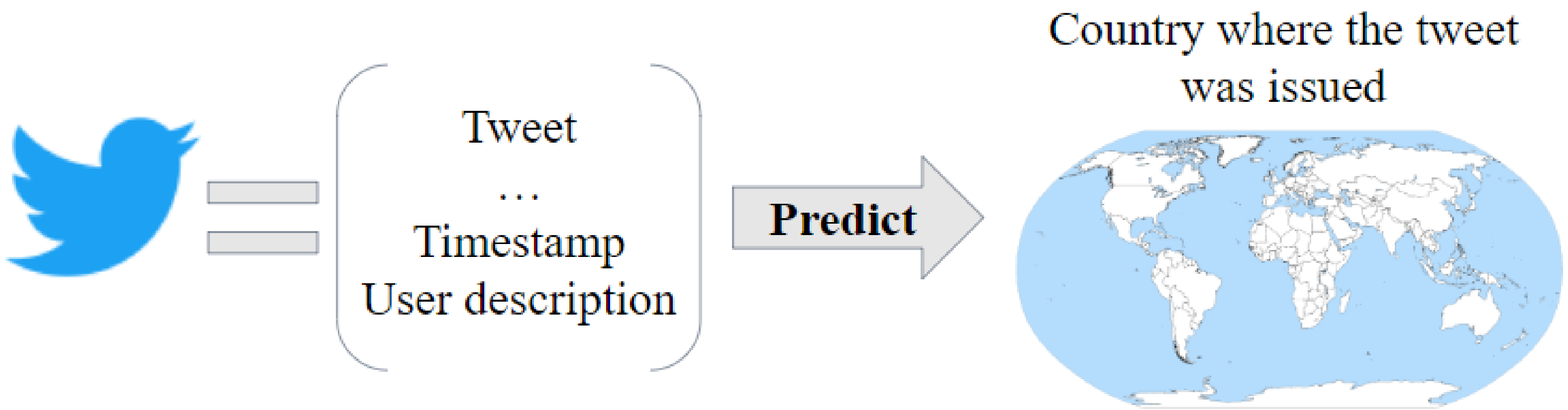
LIMES achieves superior performance to baselines especially in the most difficult scenarios

Inspiration - MAML



Finn, C., Abbeel, P., Levine, S. (2017). Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks. Proceedings of the 34th International Conference on Machine Learning

Empirical experiments - setting



Reproducibility of the results

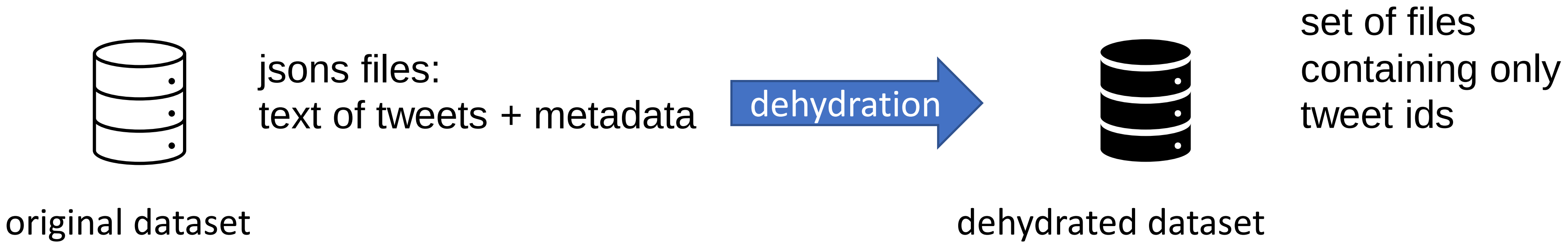
1. dataset
2. code - available at https://github.com/ptomaszewska/LIMES:
    - **LIMES**
    - baselines
    - analysis of the results (plots)

Dataset

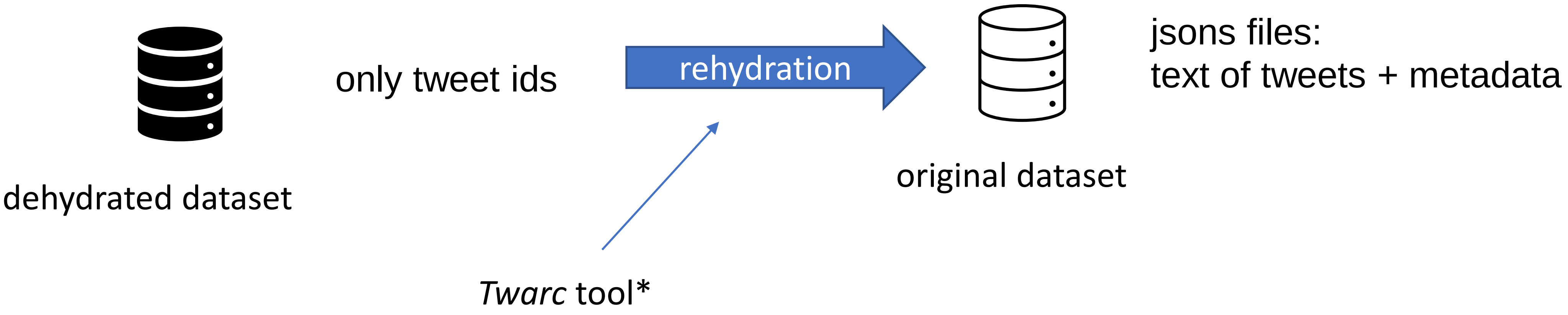
- collected using free Twitter's Streaming API*
- cannot be shared publicly in a raw version (prepared for direct use for training) due to *Terms of Service*

Solution:

- we put the *dehydrated dataset* on the website



How to restore the original data?



How to use the *Twarc?*

1. *Configuration:*
    - provide Twitter application API keys
    - grant access to Twitter account
2. *Rehydration:*
    - use command *twarc hydrate*

*https://twarc-project.readthedocs.io/en/latest/

After *rehydration*, the dataset size increases 200x.

Implementation

Tools

python™ Keras TensorFlow backend

- python libraries specified in `requirements.txt`
- cluster with SLURM queuing system

  (to ensure increased efficiency in case of large size of dataset)

Pipeline - scripts

Generating embeddings

- pretrained `distiluse-base-multilingual-cased-v1` multilingual sentence embedding network[1]

  (suitable for social media texts)

- results saved to `.npy` files → smaller file size and more efficient data loading

[1]https://github.com/UKPLab/sentence-transformers

Model training

- custom training loop and layer definition (incorporating non-trainable
- bias correction term)
- streaming data is simulated = each sample is processed only once in a chronological order
- the training step is wrapped using `tensorflow.function` decorator

  → model is treated as static graph

  → global performance optimization enabled

Note: the default mode in Tensoflow 2 is eager execution

which can slow down training but can be useful for the debugging

Model training

- script for model training can be directly used to reproduce results of experiements on Twitter data
    - for other use (replication), the code can be easily adjusted (thanks to modularity)

- baseline methods can be specified as an argument – they are implemented using `if` conditions

Large scale training

- it is recommended to run experiments on cluster
- it can be done efficiently using two bash scripts from the repository
    1. scheduling training within loops iterating over different parameters of experiments (subset, realization, data source, model)
    2. the experiments are sent to the SLURM queue and run

Towards high level reproducibility[1]

- source code available at github repository
- permissive MIT license (very limited restriction on reuse)
- `requirements.txt`
- configuration scripts to run the experiments on SLURM queuing system
- detailed instructions on how to get the data and run the code

[1]Tatman, R., Vanderplas, J., Dane, S.: A practical taxonomy of reproducibility for machine learning research. In: Reproducibility in Machine Learning – Workshop at ICML (2018)

Towards high level reproducibility[1] – regarding code

- good code writing practices:
  - modularity
  - informative variable names
  - comments
- fixed random seed (for train/validation split, weight initialization)
- code for results analysis and figure generation provided

Facilitating reproducibility

Good practice is to provide Google Colaboratory notebooks

BUT we didn't

Why?

- data cannot be publicly shared in an original form and rehydration requires personal keys to configure the `Twarc` tool
- dataset is of significant size
- computations take significant time so cluster would be helpful

Credibility of results

Common problems:

- selective reporting of results
- drawing conclusions from insufficient number of experiments

How did we mitigate these risks?

1. We generated many dataset subsets:
    - 2 different time subsets
        - from 1st to 5th day of each month – *"early"*
        - from 11th to 15th day – *"lately"*
    - 10 different realizations of data
    - 3 different data sources ("tweet", "location" and concatenation of both)

→ to analyze whether there is correlation between the task difficulty and the performance boost of the proposed method

Credibility of results – measures taken:

2. We compute 2 metrics: *avg-of-avg* and *avg-of-min accuracy*

   → to reduce bias that could be introduced by the choice of the metric and show the broader spectrum of advantages and limitations of **LIMES**

3. We report mean and std of metric values across runs
4. We provide in code the exact way in which the metrics are computed
5. We applied the Wilcoxon statistical test to validate the performance of the proposed method over the baseline
6. We combined statistical analysis with the results visualization

Supplement

Reproducibility vs. students

- Reproducibility is a great topic for student projects:
  1. Taking the github repository and checking whether the code works and comparing results
  2. Implementing the solution from the paper (when code is not provided) and verifying if the results match
- Both raise awareness and can be adjusted to students' skills
- The students work from my teaching group:
  https://mi2-education.github.io/2021L-WB-Book/ (chapter 4)

- analogy: ReproducedPapers.org

Thank you very much!

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