Text Technologies for Data Science

INFR11145

Text Classification (2)

Instructor:

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Lecture Objectives

- <u>Implement</u> your first text classifier in easy steps

- Show (some) steps that often happen "under the hood" in popular libraries

- This is a practical lecture
  No equations this time ☺

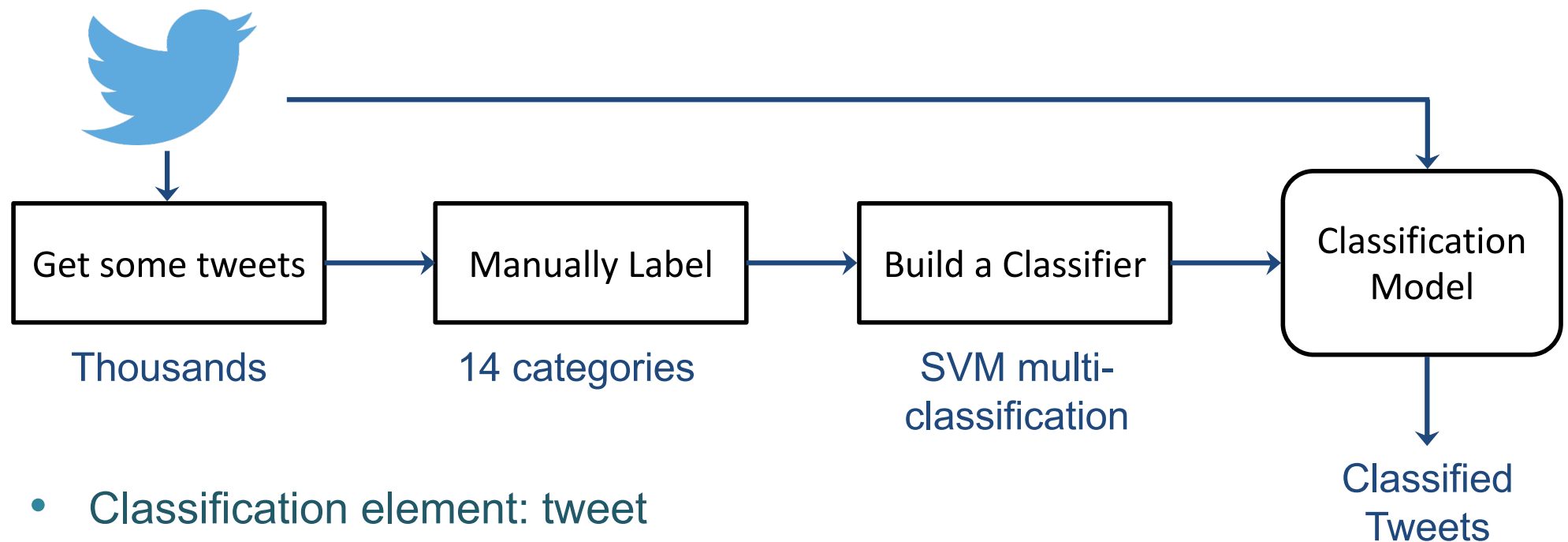THE UNIVERSITY of EDINBURGH

Building a text classifier: Ingredients

- Text elements to be classified
  - Document, paragraph, sentence

- Set of predefined classes (classification task)
  - At least two (binary)
  - Topical, spam, relevance, sentiment, …

- Training set
  - Enough samples of text elements for each class

- Test set (+ possible validation set)
  - Some samples of each class that not used in training

- Feature set
  - A set of features extracted from the text to train the classifier

- Classifier
  - The ML module that learns a classification model

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Building a text classifier: Application

- Classifying tweets into general-purpose categories

```
Get some tweets  →  Manually Label  →  Build a Classifier  →  Classification Model  →  Classified Tweets
   Thousands          14 categories       SVM multi-
                                          classification
```

- Classification element: tweet
- Classes: 14 categories: sports, politics, comedy, …
- Training/test set: 3129 tweets → 80/20% for train/test
- Features: BOW
- Classifier: SVM multiclass classifier

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Building a text classifier: Steps

1. Prepare training data
   required: piece of text (tweet) + label to class

2. Extract features

   1. Pre-process text: lowercase, tokenise, remove useless strings
   2. Create a list of all unique terms in the training data. Give each term a unique ID
   3. Convert the text into features, by replacing each term with its corresponding feature ID. Add value to the feature (simplest: value "1" if exists, or count of occurrences)

3. Prepare test file

   Convert test file text into features using the same mapping from the training data. For terms that are not in the features list, it could be neglected, or assigned to an ID representing OOV.

4. Run the learning process on the training data features to create a model

5. Run the classification on the features of the test data and get predictions

6. Evaluate performance

Examples

- ## Tweet + Label

Kobe passes Wilt for 4th on all-time scoring list	Sports

- ## Learned features (BOW) from training data

- ## After converting text to feature vectors

	0		2943	2944	2945	2946		8330	8331		10000
0	**0**	…	**0**	**1**	**0**	**0**		**1**	**0**		**0**
1	**0**	…	**1**	**0**	**0**	**1**	…	**0**	**0**	…	**0**

- ## SVM prediction output

7

Predicted Class ID

Feature ID → Corresponding word

2944	kobe
2945	rapping
..	
4525	4th
4526	trevi
..	
8330	passes
8331	ducks
..	
9929	17
9930	wilt
...	

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Practical

Possible Improvements

- Feature Extraction
  - Apply stemming & stopping
  - Duplicate hashtags words (#car → #car car)
  - Expand tweet text that has link with the page title of that link
  - Add new set of features to the terms appearing in the profile description of the author of the tweet
    - E.g. tweets terms features: ID range: 1 → 12000
      profile terms features: ID range: 12001 → 20000
    - If a term appeared in the tweet and in the profile description, these are two different features with two different IDs
  - Try non-textual features
    - Tweet length, presence of hashtags, links, emojis …

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Possible Improvements

- Feature weighting

  - Using tfidf, BM25 as the feature value instead of binary

- Learning method

  - Test other ML learning methods other than SVM

    - Random forest

    - Decision trees

    - Naive Bayesian

  - Test transformer models & LLMs

    - Google Colab: you can experiment with using GPUs for free!
      https://colab.research.google.com/

- Add more training data

  - Think about a way to create more training data

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Resources

- Magdy W., H. Sajjad, T. El-Ganainy and F. Sebastiani. (2015) Bridging Social Media via Distant Supervision. *Springer SNAM 2015 link, arXiv*

- Additional reading: Nguyen, D. P., Gravel, R., Trieschnigg, R. B., & Meder, T. How old do you think I am? A study of language and age in Twitter. *ICWSM 2013*

- *Huggingface (2024)* **Text Classification** *Link: https://huggingface.co/tasks/text-classification*

- *Sentence Transformers (2024) Link: https://www.sbert.net/*

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