Cross-lingual supervised text classification

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Tutorial prepared for COMPTEXT 2022
https://github.com/haukelicht/crosslingual-supervised-text-classification-tuorial

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Overview

Today's goals

Recap

- challenges specific to *multilingual* QTA
- supervised text classification

Concepts

- approaches to *cross-lingual* supervised text classification
- input alignment approaches (machine translation, multilingual embedding)

Code (Python)

- how to machine-translate free of charge
- how to align texts using multilingual sentence embedding
- how to train supervised text classifiers using these text representations

Background

Text-as-data

Goal

- study political behavior and communication using quantitative methods
- ultimately, answer substantively interesting research questions about politics

Premise

- text generation is political $\rightsquigarrow$ text is important artifact of political behavior
- texts indicates their authors' political preferences, attitudes and beliefs, and strategies

Cross-lingual quantitative text analysis

Study political behavior and communication across languages

- multilingual institutional contexts (e.g., EP or UN)
- overcome language barriers to text-as-data applications in *comparative* research

The central challenge

> *develop an alignment between the conceptual representations of the model across languages so that we know a particular scaling, topic, or class in one language is comparable with the representation in another language.* (Lucas el al. 2015, 259)

⇝ obtain **identical measurements** for documents that indicate the **same concept**

Cross-lingual quantitative text analysis

The central challenge

obtain **identical measurements** for documents that indicate the **same concept**
⇝ even if they are written **in different languages**

Why this is challenging

Tower of Babel problem (Chan el al. 2020, Maier el al. 2021)
different vocabularies, words do not co-occur, similar words have dissimilar contexts
⇝ makes language-independent inference hard

Cross-lingual measurement equivalence
the substance of political discourses varies across polito-linguistic contexts
⇝ might necessitate to account for context

Cross-lingual supervised text classification

Text-as-data approaches and tasks

Manual content analysis

- text classification (coding/categorization)
- text scaling (through pairwise comparison)

Quantitative text analysis

Text classification

- dictionary analysis
- **supervised text classification**
- topic modeling

Text scaling

- unsupervised (*Wordfish*, *Wordshoal*)
- semi-supervised (*Wordscores*, LSA)

Cross-lingual supervised text classification

Text classification

Assign each document in a corpus to a one of several pre-defined categories

Supervised text classification

“Learn” how to assign documents to categories based on a (small) subset of documents for which you know which categories they belong to

How? apply supervised machine learning techniques

Cross-lingual supervised text classification

“Learn” to assign documents to categories when they are written in different languages

Today's running example

Lehmann and Zobel (2018) data set

- corpus of human-coded election manifestos
- quasi-sentences coded into **issue categories**: immigration, integration, "others"
- manifestos of parties from 14 countries ⇝ **8 languages**

⇝ view the data set **online**

Our goal

discriminate between the **immigration/integration** and the "others" category

Relevance

- study competition on the immigration/integration issue
- learn to extrapolate (expensive) human codings
  - to new countries (cross-lingual transfer, cf. Licht 2022)
  - to new domain (à la Osnabrügge, Ash and Morelli 2021)

Approaches

How can we apply supervised text classification to a multilingual text corpus?

Separate analysis

1. split multilingual corpus by language
2. train separate, language-specific classifiers
3. apply them to classify unlabeled documents

⇝ pool resulting measurements for cross-lingual comparison

Input alignment ← our focus today

1. transfer documents' representations to a "common denominator" (Lind et al. 2021)
2. train a single, cross-lingual classifier
3. apply it to classify unlabeled documents

⇝ use resulting measurements in cross-lingual comparison

Input alignment

A unifying idea

- transfers documents to a common denominator (i.e., “align” them)
- enable their joint analysis within a single model (Lucas et al. 2015)
  - direct cross-lingual comparison
  - information-sharing across languages
  - resource-efficient

How to achieve this

Machine translation

Translate all documents to a single **target language**

Multilingual embedding

Represent all documents in a joint, multilingual **embedding space**

Input alignment approaches

Machine translation

Idea

- overcome Babel problem by translating all documents to one target language
- the target language is the “common denominator”

Evidence

works quite very well for typical quantitative text analysis tasks

- topic modeling (Lucas el al. 2015; de Vries, Schoonvelde and Schumacher 2018; Reber 2018)
- dictionary analysis (Windsor, Cupit and Windsor 2019)
- supervised classification (Courtney el al. 2020)
- textual similarity (Düpont ant Rachuj 2021)

Implementation (I)

Machine translation

Human translators too expensive. Instead, rely on state-of-the-art **neural machine translation** (NMT) methods.

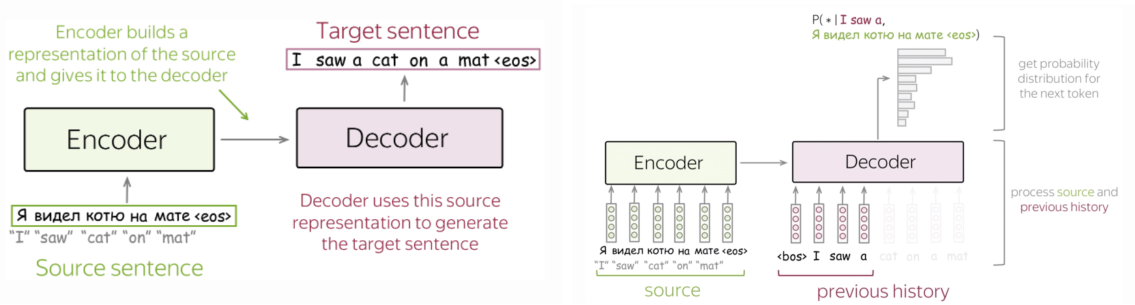

Encoder builds a representation of the source and gives it to the decoder
Target sentence
I saw a cat on a mat <eos>
Encoder
Decoder
Я видел котю на мате <eos>
"I" "saw" "cat" "on" "mat"
Source sentence
Decoder uses this source representation to generate the target sentence
P(* | I saw a,
Я видел котю на мате <eos>)
get probability distribution for the next token
Encoder
Decoder
process source and previous history
Я видел котю на мате <eos>
"I" "saw" "cat" "on" "mat"
source
<bos> I saw a cat on a mat
previous history

Figure 1: Translation as seq-to-seq problem. *Source:* Lena Voita's "NLP Course" (**online**)

Implementation (II)

Machine translation

Human translators too expensive. Instead, rely on state-of-the-art **neural machine translation** (NMT) methods.

Approaches

Using commercial service

- state-of-the-art NMT technology (e.g., *Google Translate* or *DeepL*)
- extensively evaluated in PolSci/CommSci literature
- “black box” (cf. Chan el al. 2020)
- quite expensive

Use open-source NMT model ← our approach today

- open-source ⇝ reproducible and free of charge
- massively pre-trained (e.g., Fan et al.'s M2M)

Free machine translation

pip install easynmt

The easyNMT python package provides a simple interface to download and use several large pre-trained NMT models:

```
from easynmt import easyNMT

# download and instantiate a pre-trained M2M model
model = easyNMT("m2m_100_418M")

# translate a single sentence
model.translate("Guten Tag liebe Freunde!", target_lang="en")
```

⇝ see **this** Colab Notebook for an illustration

Multilingual embedding

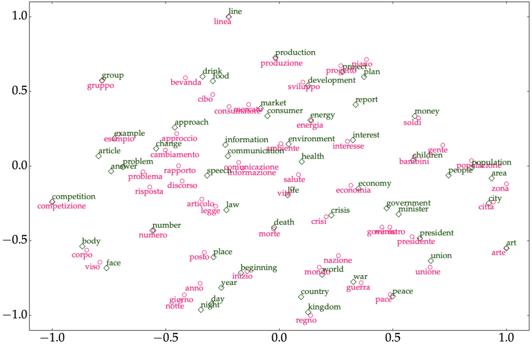


Figure 2: Low-dimensional representation of aligned English and Spanish word embeddings (Figure 1 in Ruder, Vulić and Søgaard 2019)

Idea

align documents by representing them in a multilingual embedding space

Existing applications

- topic modeling (Chan el al. 2020)
- text scaling (Glavaš, Nanni and Ponzetto 2017b; Goist 2021)
- textual semantic similarity (Radford, Dai and Golder 2021)
- supervised classification (Glavaš, Nanni and Ponzetto 2017a; Dai and Radford 2019; Licht 2022)

Approaches

Multilingual *word* embedding

- many different approaches (see Ruder, Vulić and Søgaard 2019)
- currently most common among ME-based contributions (e.g. Chan el al. 2020; Goist 2021)

Multilingual *sentence* embedding ← our focus today

- again different approaches (next slide)
- well-suited for applications when documents have sentence-like lengths

  ⇝ **supervised text classification** (Licht 2022)

Multilingual sentence embedding (I)

LASER

encoder–decoder model learns fixed-size embedding layer (Artexte and Schwenk 2019)
⇝ essentially like NMT architecture

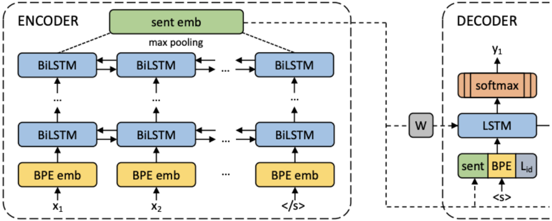


Figure 3: In Artexte and Schwenk (2019)

Knowledge distillation

extend pre-trained monolingual sentence embedding model to new languages (Reimers and Gurevych 2020)

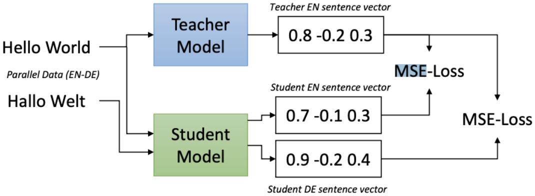


Figure 4: In Reimers and Gurevych (2020)

Multilingual sentence embedding (II)

`pip install sentence-transformers`

The sentence-transformers python package provides a simple interface to download and use several large pre-trained MSE models:

```
from sentence_transformers import SentenceTransformer

# download and instantiate a knowledge-distilled XLM-R model
model = SentenceTransformer("paraphrase-xlm-r-multilingual-v1")

# translate a single sentence
model.encode("Guten Tag liebe Freunde!")
```

⇝ see **this** Colab Notebook for an illustration

Application in cross-lingual supervised text classification

Supervised classification: recap (I)

Terminology

- **classes**: the set of outcome categories
- **label**: the class a document belongs to
- **sample**: a single document and its label
- **data set**: a collection of samples

```
   | label | text                                       |
   |-------|--------------------------------------------|
-> |   +   | "Our government is doing a great job!"     | <-- a sample
   |   -   | "Those crooks in power are super corrupt!" |
   |  ...  |                                            |
```

Supervised classification: recap (II)

Training & Evaluation

- **training**: fit a model to a data set to optimize its classification accuracy
- **held-out samples**: samples not used to train a classifier
- **evaluation**: see how a classifier performs in held-out samples (“out of sample”)
- ***k*-fold cross validation** (CV): train and evaluate a classifier on *k* partitions of a training data set
  ⇝ estimate out-of-samples performance

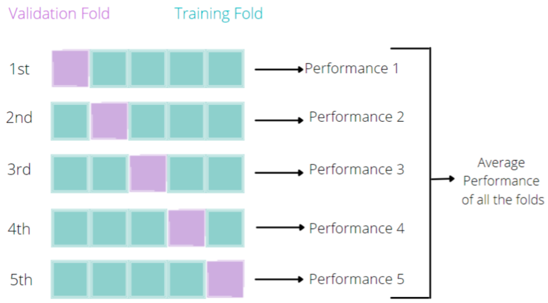


Figure 5: Cross validation procedure (source)

Cross-lingual supervised text classification

MT approach

1. **machine-translate** all documents into the target language
2. train classifier using **documents' target-language representations**
3. evaluate classifier on held-out documents

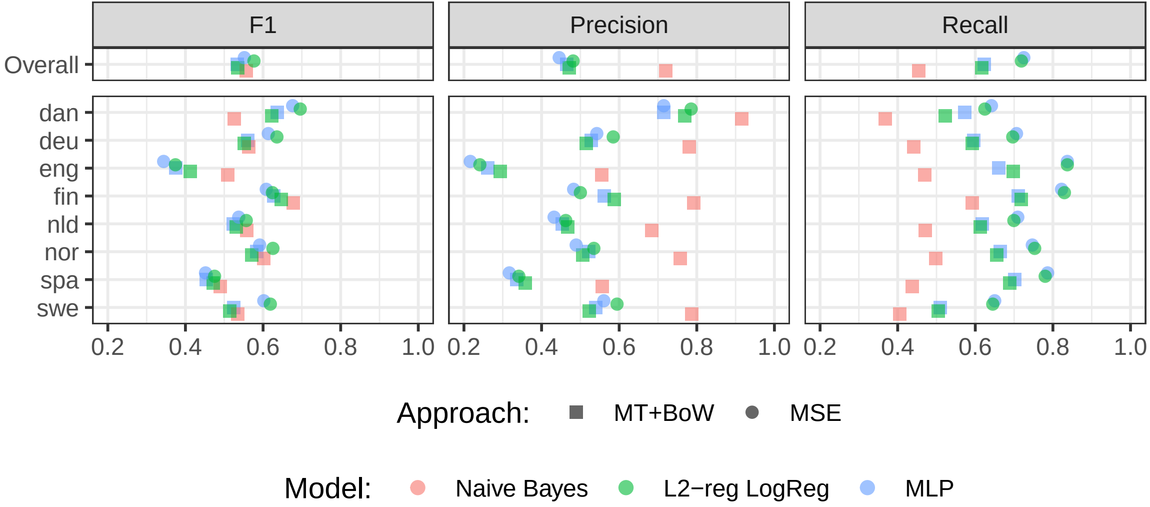
⇝ see **this notebook** for an illustration

MSE approach

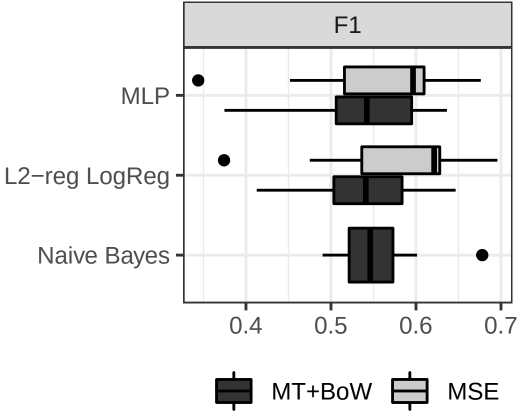
1. **embed** all documents using a pre-trained MSE model
2. train classifier on **documents' embeddings**
3. evaluate classifier on held-out documents

⇝ see **this notebook** for an illustration

Results


F1
Precision
Recall
Overall
dan
deu
eng
fin
nld
nor
spa
swe
0.2
0.4
0.6
0.8
1.0
Approach:
■ MT+BoW
● MSE
Model:
● Naive Bayes
● L2−reg LogReg
● MLP

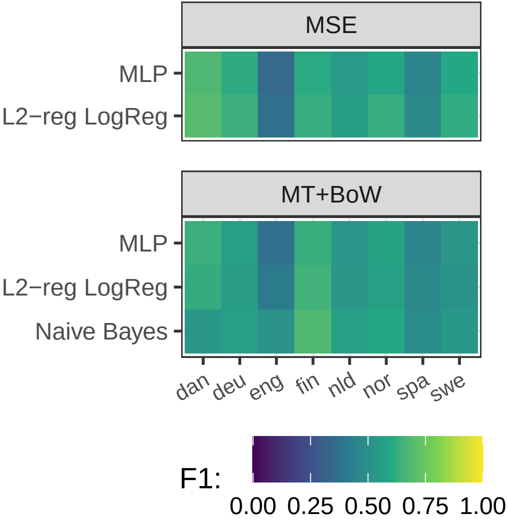
Results



Language-specific F1 scores

- MSE approach “better” overall
- much variation in F1 scores for all classifiers but the Naive Bayes
- but the Naive Bayes classifier massively overshoots (see prev. slide)

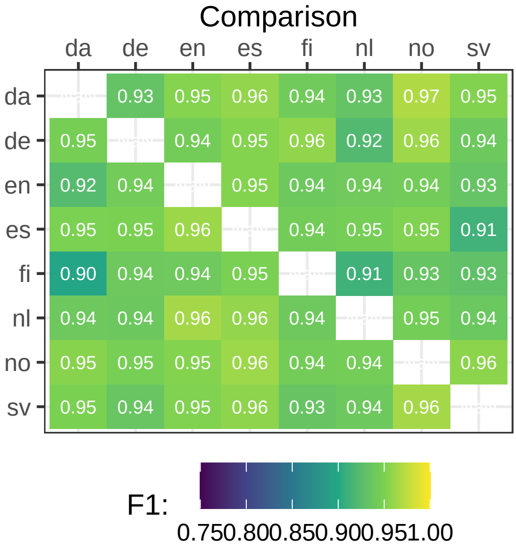
Results



Language-specific F1 scores

- both approaches systematically under-perform in English and perform rel. well in Finnish
  - Naive Bayes classifier is exception
- compare to prevalence of positive samples in corpus (overall 0.039):
  - English: 0.014 (lowest)
  - Spanish: 0.024 (2nd lowest)
  - Finnish: 0.034
  - Danish: 0.094 (highest)

Results



	da	de	en	es	fi	nl	no	sv
da		0.93	0.95	0.96	0.94	0.93	0.97	0.95
de	0.95		0.94	0.95	0.96	0.92	0.96	0.94
en	0.92	0.94		0.95	0.94	0.94	0.94	0.93
es	0.95	0.95	0.96		0.94	0.95	0.95	0.91
fi	0.90	0.94	0.94	0.95		0.91	0.93	0.93
nl	0.94	0.94	0.96	0.96	0.94		0.95	0.94
no	0.95	0.95	0.95	0.96	0.94	0.94		0.96
sv	0.95	0.94	0.95	0.96	0.93	0.94	0.96	

Language-independent measurement?

One potential way to assess language-independence:

1. take set of *parallel* texts
2. translate/embed them
3. predict their labels
4. compare consistency

Example: Figure shows results for MSE-based classifier (**code**)

Discussion

Class imbalance

- we have artificially down-sampled negative samples
  - label distribution in training and test data differs
  - discards relevant info
- maybe better: make misclassifying positive samples more costly ⇝ use **class weights**

Text representations

- BoW representations are very sparse ⇝ use pre-trained (English) word embeddings
- MSEs are "frozen" (not specialized for the classification task)
  ⇝ fine-tune multilingual Transformer (e.g., mBERT, XLM-R)

Discussion

Alternative input alignment approaches

- train neural net classifier using multilingual/aligned word embeddings as inputs (e.g., Glavaš et al. 2017a)
- fine-tune multilingual transformers (e.g., mBERT) (panels 1A, 2A, 3A, and 7C)

Open issues

- How to account for fact that prevalence varies across countries?
- How to asses cross-lingual measurement equivalence?

References and resources

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Resources

Links to Google Colab notebooks

- inspect the Lehmann and Zobel (2019) data set (**link**)
- *input alignment*
  - how to machine-translate with the `easyNMT` package (**link**)
  - how to sentence-embed with the `sentence-transformers` package (**link**)
- *supervised classification*
  - sample the train, CV, and test indices (**link**)
  - train MT+BoW classifiers (**link**)
  - train MSE-based classifiers (**link**)

Data

- the cleaned Lehmann and Zobel data set (incl. machine-translated texts, **link**)
  - XLM-R sentence embeddings (**link**)
- the train, CV, and test indeces configuration JSON (**link**)