Cross-lingual supervised text classification

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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)

$\rightsquigarrow$ 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**
$\rightsquigarrow$ 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
$\rightsquigarrow$ makes language-independent inference hard

Cross-lingual measurement equivalence
the substance of political discourses varies across polito-linguistic contexts
$\rightsquigarrow$ 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 $\rightsquigarrow$ **8 languages**

$\rightsquigarrow$ 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)
  - 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

$\leadsto$ 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

$\leadsto$ 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.

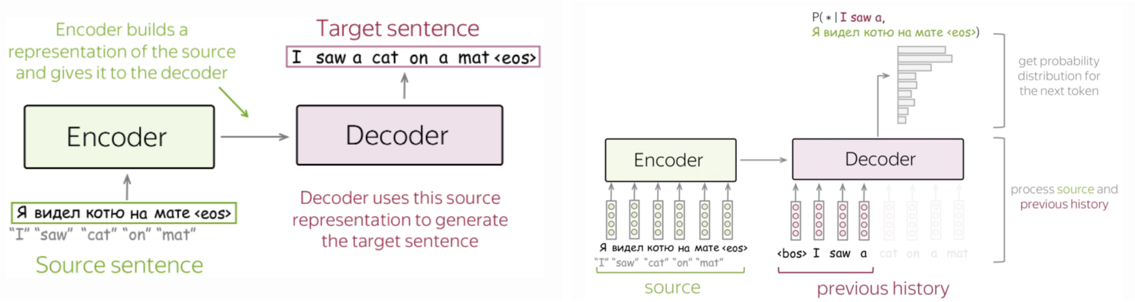


Figure 1: Translation as seq-to-seq problem. *Source:* Lena Voita's "NLP Course" (**online**)

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

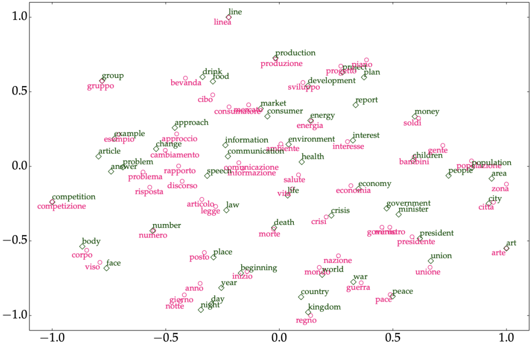


Figure 2: Low-dimensional representation of aligned English and Spanish word embeddings (Figure 1 in Ruder, Vulić and Søgaard 2019)

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

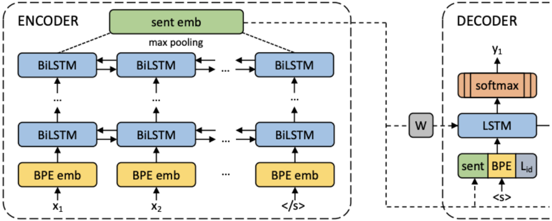


Figure 3: In Artexte and Schwenk (2019)

Knowledge distillation

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

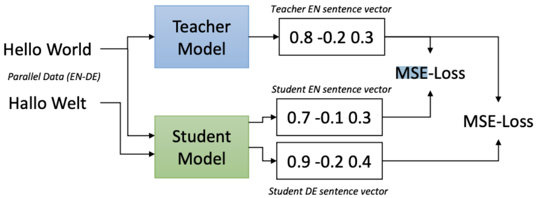


Figure 4: In Reimers and Gurevych (2020)

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
  $\rightsquigarrow$ estimate out-of-samples performance

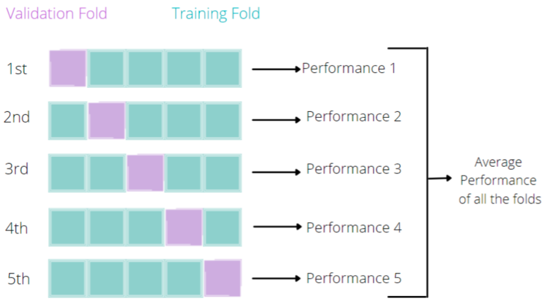


Figure 5: Cross validation procedure (source)

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

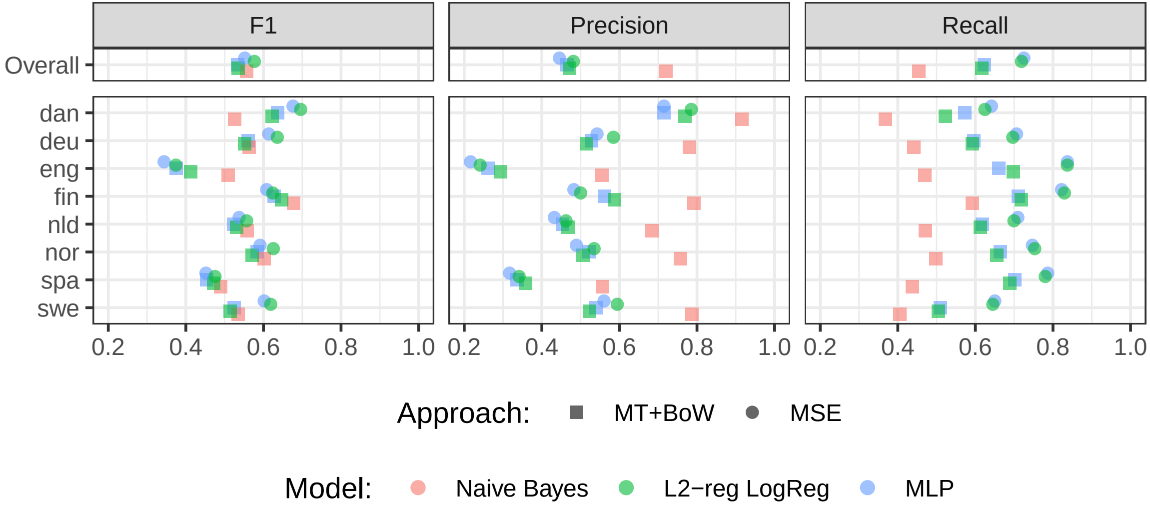
⇝ see **this notebook** for an illustration

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

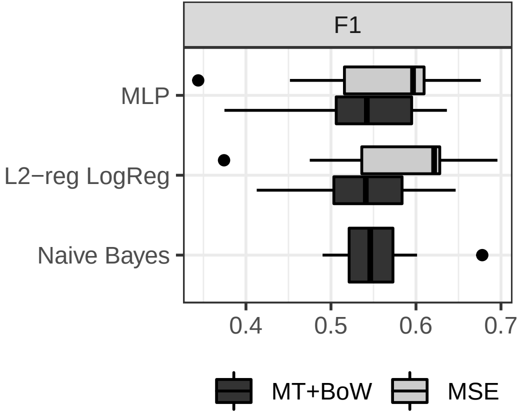
⇝ see **this notebook** for an illustration

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

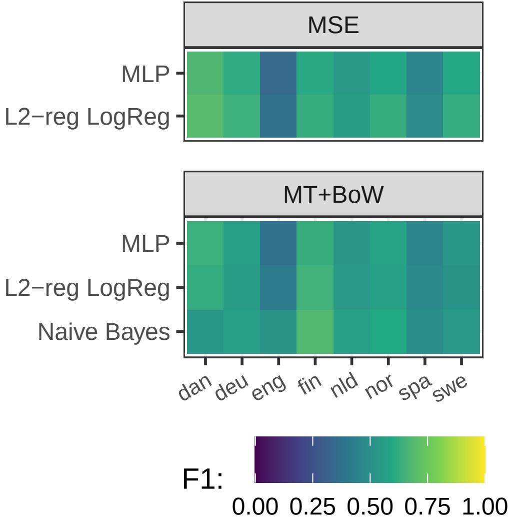
Results



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)

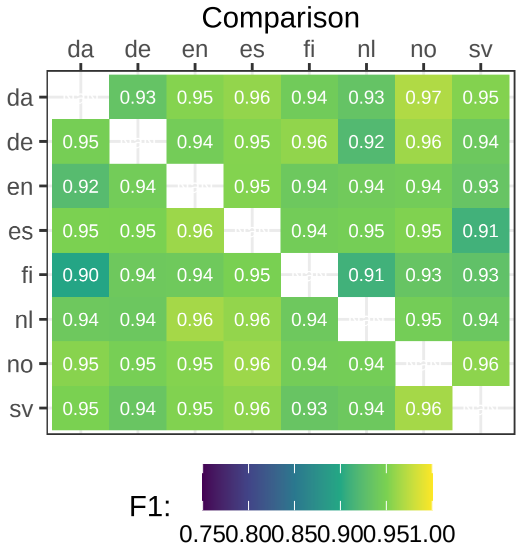
Results



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



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**)

Room for improvement

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 $\rightsquigarrow$ use **class weights**

Text representations

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

Open issues

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

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**)

Back-up slides

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