

# Cross-lingual supervised text classification

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- 1 Background
- 2 Cross-lingual supervised text classification
- 3 Input alignment approaches
- 4 Application in cross-lingual supervised text classification
- 5 Back-up slides

# Background

## 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 et 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 et al. 2020, Maier et 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 politico-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  $\rightsquigarrow$  **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
- ~> 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

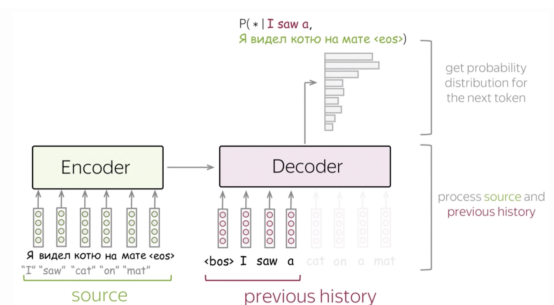
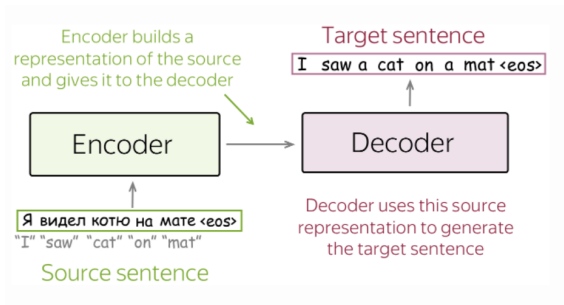
works quite very well for typical quantitative text analysis tasks

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

### *Use open-source NMT model* ← our approach today

- open-source  $\rightsquigarrow$  reproducible and free of charge
- massively pre-trained (e.g., Fan et al.’s M2M)



# Free machine translation

```
pip install easynt
```

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

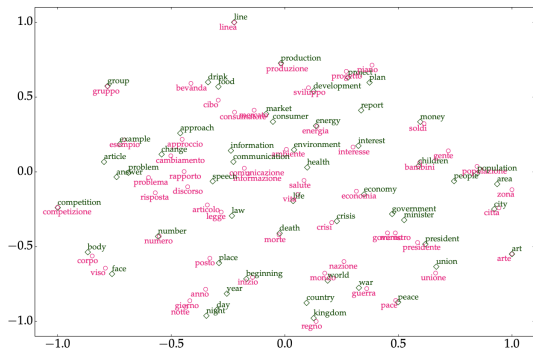
```
from easynt import easyNMT

# 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 et 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 et al. 2020; Goist 2021)

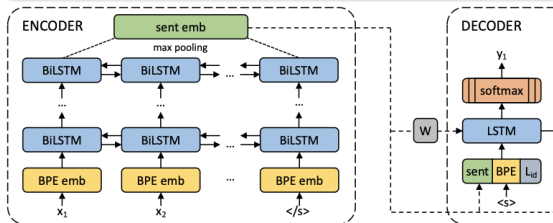
## Multilingual *sentence* embedding ← our focus today

- 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

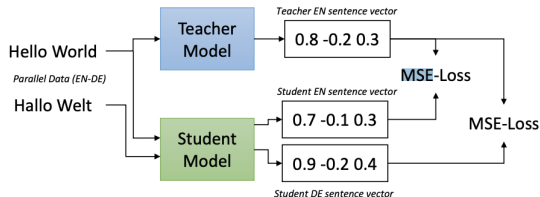
encoder-decoder model learns fixed-size embedding layer (Artexte and Schwenk 2019)  
~> essentially like NMT architecture



**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

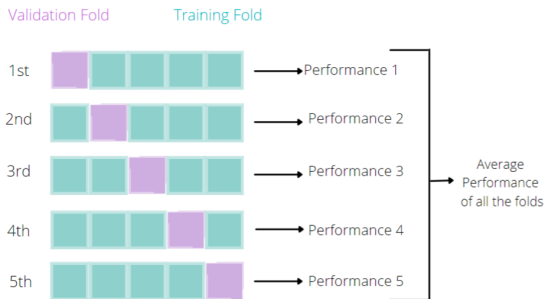
- **classes**: the set of outcome categories
- **label**: the class a document belongs to
- **sample**: a single document and its label
- **data set**: a collection of samples

```
-> | label | text | <-- a sample
    |-----|-----|
    | +     | "Our government is doing a great job!" |
    | -     | "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

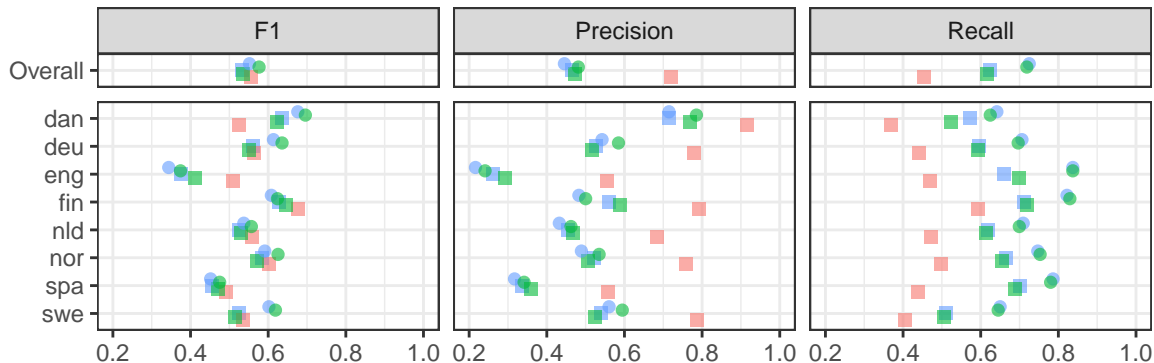
↪ see **this notebook** for an illustration

## 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

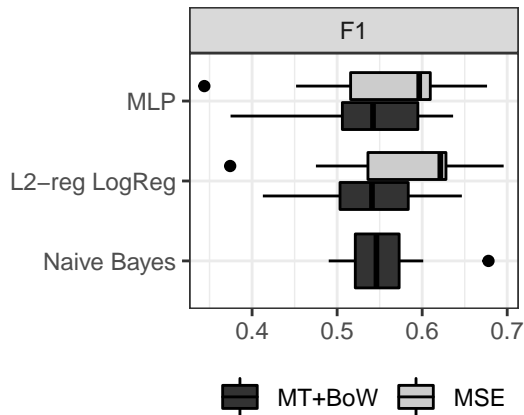
# Results



Approach: ■ MT+BoW ● MSE

Model: ● Naive Bayes ● L2-reg LogReg ● MLP

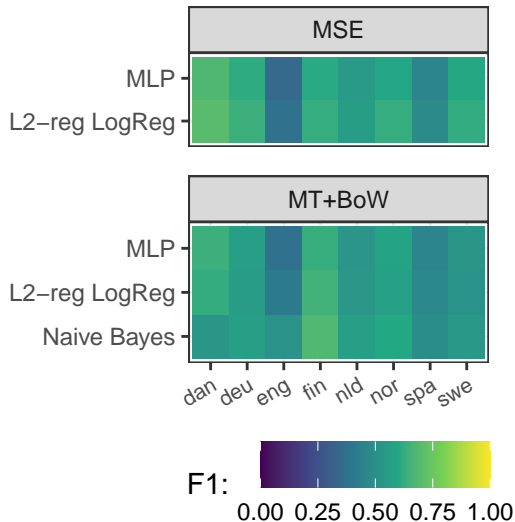
# Results



## 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)

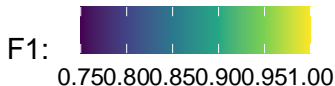
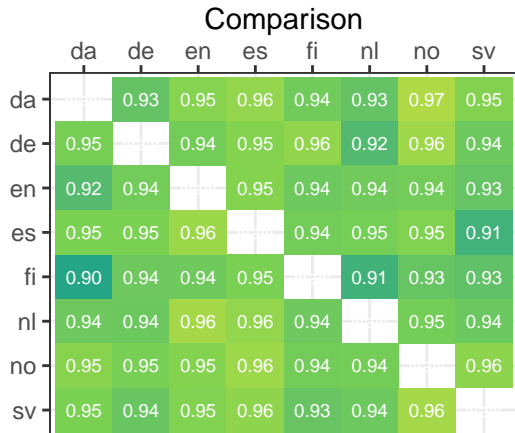
# Results



## 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 assess 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



# References I

- Artetxe, Mikel and Holger Schwenk (2019). “Massively Multilingual Sentence Embeddings for Zero-Shot Cross-Lingual Transfer and Beyond”. In: *Transactions of the Association for Computational Linguistics* 7, pp. 597–610. DOI: 10.1162/tacl\_a\_00288.
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