Lecture 3

Multilingual modelling

Today's topics

- Introduction
  - What are multilingual models?
  - Why do we need them?
- Earlier methods
  - Language transfer and joint learning
  - Word embeddings
- SOTA models and their limitations
- Promising directions

INTRO: What are multilingual models?

A language model is called ‘multilingual’ when it can understand many (4+) different languages

Goal: Create a single model that captures **universal language structures** such that it can reason across all known languages

INTRO: In theory..

According to Noam Chomsky's universal grammar theory:

Linguistic universals are patterns that occur systematically across natural languages. For example, (almost) all languages make a distinction between *nouns* and *verb*s and distinguish *function words* from *content words*.

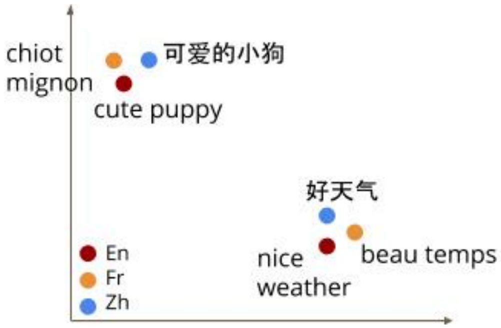
Multilingual models can automatically find such commonalities between languages (on the lexical, syntactic and semantic level) and exploit them i.e. capturing language-agnostic information

INTRO: In practice..

Goal: phrases with similar meaning should obtain similar representations (distributional hypothesis)

Constraints:

- This should be done irrespective of the language



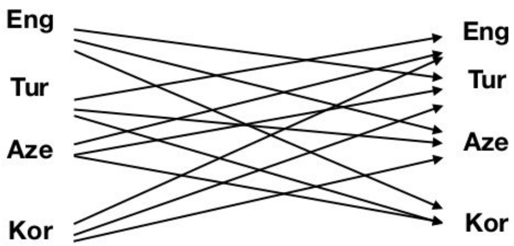
- And without affecting the monolingual semantic relations between the phrases within a language

  Example: the word *'table'* should appear close to its Italian translation *'tavola'* without losing the proximity to *'desk'* which should in turn be close to the Italian translation *'scrittoio'*. (Beinborn et al., 2020)

INTRO: Why do we need multilingual models?

Practical:

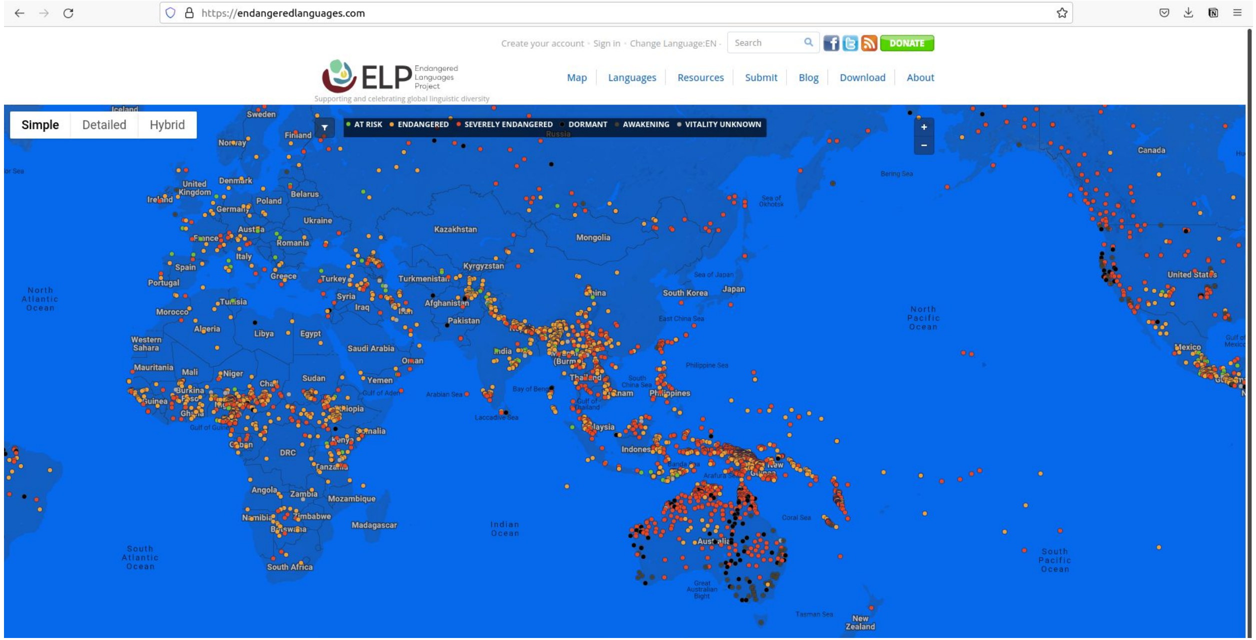
There are over 7K languages spoken in the world today, we don't want to train a model for each one..



- Supporting translation across just 4 languages requires 4*3=12 models
- Across all languages requires us to build .. ~ 49 million models

Social:

We want to extend the benefits of NLP technology to more language communities + capture endangered languages



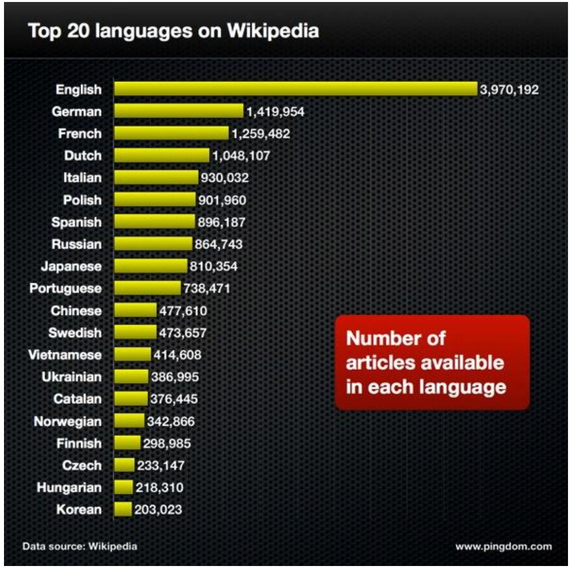
Technical:

SOTA methods are data hungry!

For many languages there's simply too little data to train a monolingual model successfully

Transformer based models:

- BERT: 13GB (3.4 billion word text corpora)
- GPT2: 40GB…
- RoBERTa: 160GB…
- GPT-3: 45 TB…



Many languages are left behind!

INTRO: Some terminology

In the NLP community we talk about:

- **High resource**: languages for which we have *'much'* data available

  -> we can generally train good monolingual models

- **Low resource**: languages for which we have *'too little'* data available (most languages)

Pay attention: each paper can use a different threshold to determine the categorisation!

Approaches: Two solutions to data-scarcity

- Language transfer (cross-lingual transfer):

  Transfer from **high-resource** to **low-resource** languages, hence leveraging information across languages

- Multilingual joint learning:

  Jointly learn from annotations in multiple languages to leverage language interdependencies

For further reading see Ponti et al., 2019

Approaches: Language transfer methods

To leverage useful information from a source language, it typically needs to be manipulated to better suit the properties of the target language first (Ponti et al., 2019)

Earlier methods include:

- **Data transfer** -> facilitate homogeneous use of data

  Annotation projection (Hwa et al., 2002)

  Machine translation (Tiedemann et al., 2014)

- **Model transfer** -> directly transfer trained model

  Delexicalization (Zeman and Resnik, 2008)

Annotation projection

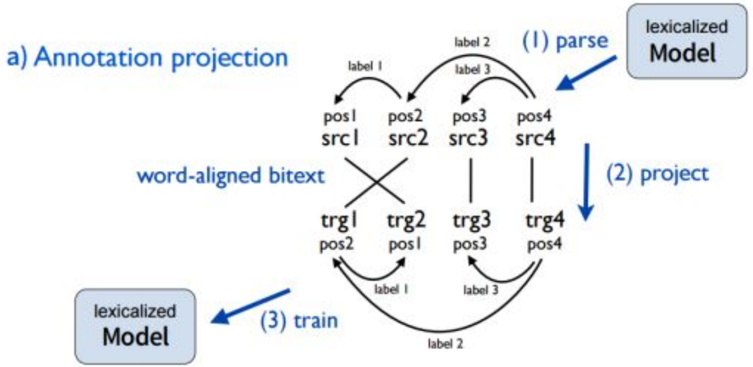
1. Parse high resource language

2. Extract word-alignments from parallel corpora:

   ‘I can speak two languages’

   ‘Ik kan twee talen spreken’

3. Use created data in the target language for supervised training (Ganchev et al., 2009; Hwa et al., 2005; Yarowsky et al., 2001)



Drawback: noise coming from two sources – parser and word-alignment method
Quite successful: 70% accuracy between English and Spanish

Image taken from Ponti et al., 2019

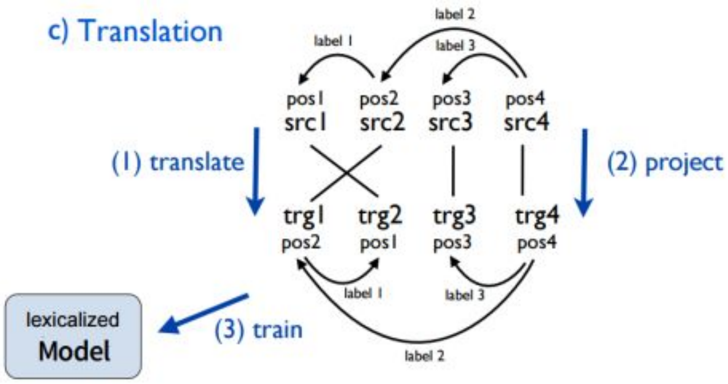
Translation

1. Retrieve gold annotations in the source language

2. Translate source input to target language

3. Align words

4. Train a model on the synthetic target data



Benefits:

- Reduces noise by using gold annotations
- Machine translations more similar to input than manual translations

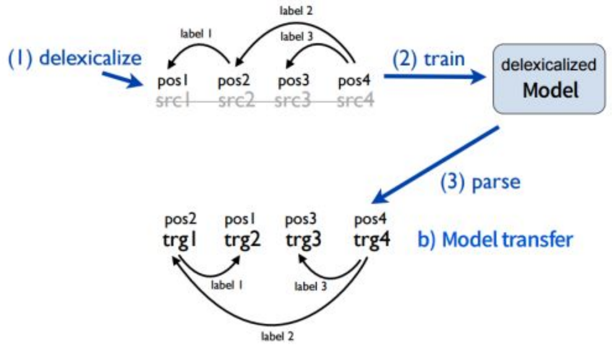
Image taken from Ponti et al 2019

Model transfer

1. Delexicalize data to solve for incompatible vocabularies

2. Train model on delexicalized model

3. Directly apply this model to the target language



Delexicalization: replace the words in a language by the corresponding POS tags

-> performance relies on the ability to find robust universal features

Image taken from Ponti et al 2019

Approaches: Limitations

- Doesn't solve the practical problem -> methods remain inherently bilingual
- Doesn't solve the social problem -> methods rely on the assumption that high quality resources exist at least for the source language.

  Suppose you want to transfer between:
  English -> Dutch
  ? -> Filipino

  Most languages do not have a suitable high-resource language for transfer

Approaches: Joint learning methods

Learn information from **multiple languages simultaneously** such that they can learn to support each other and thereby jointly enhance each others quality

Key strategy: **Parameter sharing**-> share (otherwise private) representations

This is still used in SOTA methods today as you will see in a bit!

Parameter sharing

Share (otherwise private) representations e.g., word embeddings (Guo et al., 2016), hidden layers (Duong et al., 2015) or attention mechanisms (Pappas and Popescu-Belis, 2017) across languages

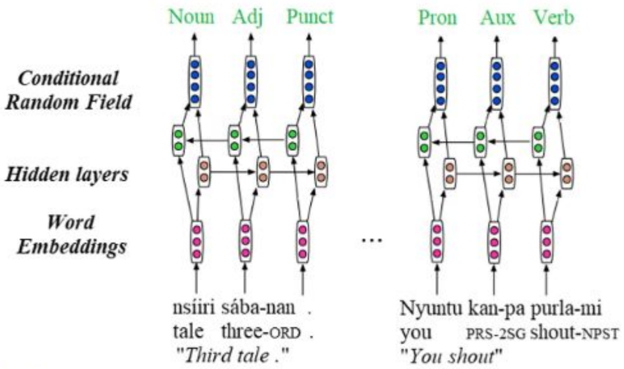


Figure 2
In multilingual joint learning, representations can be private or shared across languages. Tied parameters are shown as neurons with identical color. Image adapted from Fang and Cohn (2017), representing multilingual PoS tagging for Bambara (left) and Warlpiri (right).

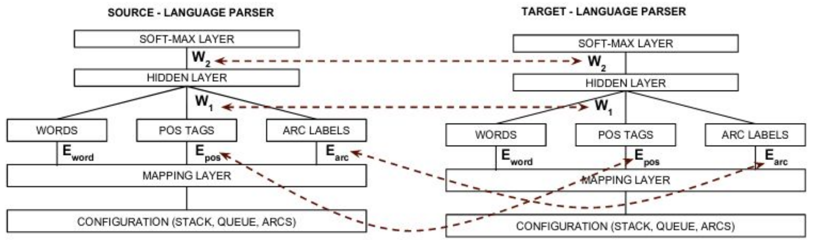


Figure 1: Neural Network Parser Architecture from Chen and Manning (2014) (left). Our model (left and right) with soft parameter sharing between the source and target language shown with dashed lines.

Full parameter sharing: parameter values are identical across languages

Soft parameter sharing: distance between parameters from different language-specific models is minimized

Left image from Ponti et al., 2019; right from Duong et al., 2015

Word embeddings: Different methods

1. **Monolingual mapping**:

   Learn linear mapping between monolingual representations in different languages

2. **Pseudo-cross-lingual**:

   Train a model on a corpus created by mixing contexts of different languages

3. **Cross-lingual training**:

   Optimize a cross-lingual constraint between embeddings of different languages

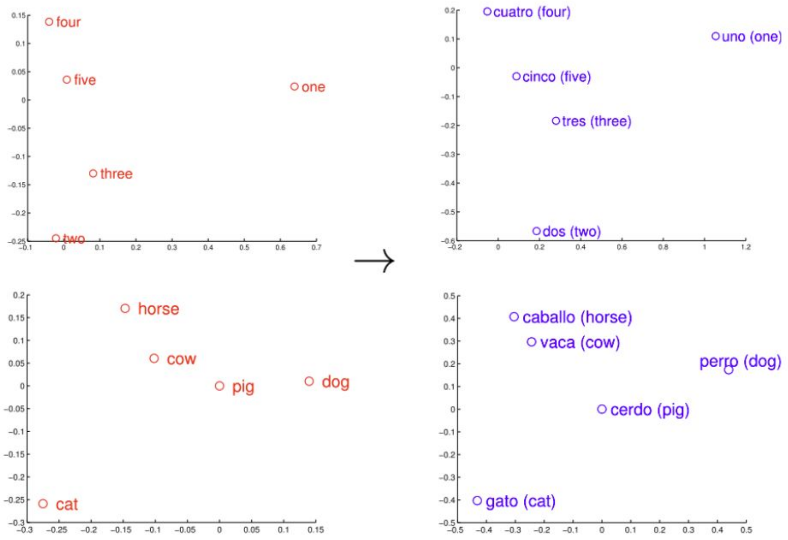
4. **Joint optimization**:

   Jointly optimise a combination of monolingual and cross-lingual losses

For further reading see Ruder et al., 2019a

Word embeddings: Mapping models

Linear projection



Learn a transformation between languages? (Mikolov et al., 2013):

- Use 5K translations as bilingual dictionary
- Learn transformation matrix W using SGD by minimising:

$$\min_{W} \sum_{i=1}^{n} |Wx_i - z_i|^2$$

Xi = monolingual representation of the source word wi

zi = monolingual representation of translation of wi

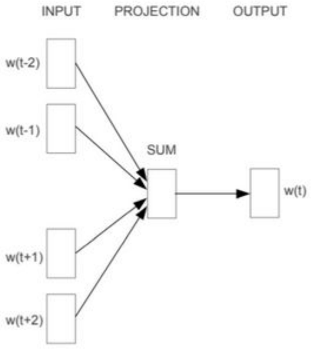
Word embeddings: Pseudo-cross-lingual

Random translation replacement (Gouws et al., 2015):

- Google Translate pairs of words in the source and target language
- Concatenate + shuffle source and target corpus
- Replace each word with its translation with a probability of 50% e.g.:

  'build the house' -> construire the house, build la maison etc.

- Train CBOW on this corpus



CBOW

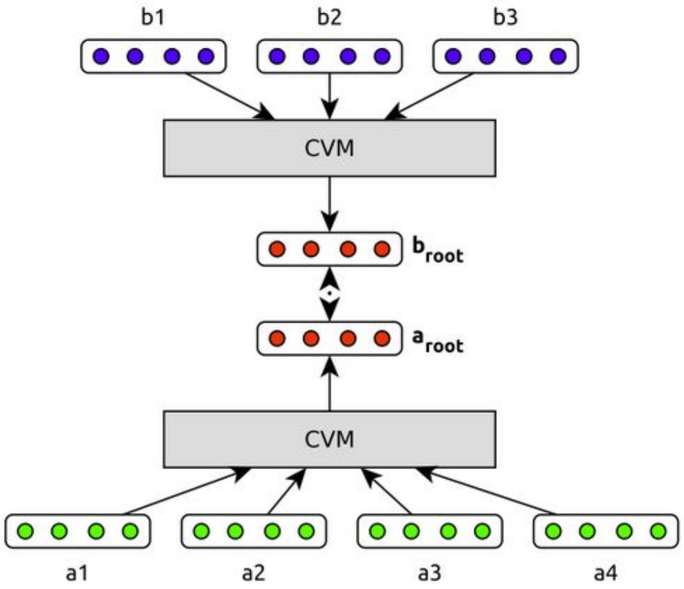
Word embeddings: Cross-lingual training

Bilingual compositional sentence model (Hermann et al., 2013):

- Train two models to produce sentence representations of parallel sentences in two languages
- Use the distance between the two sentence representations as objective
- Minimise the following loss:

$$E_{dist}(a, b) = |a_{\text{root}} - b_{\text{root}}|^2$$

where a_{root} and b_{root} are the representations of two aligned sentences from different languages

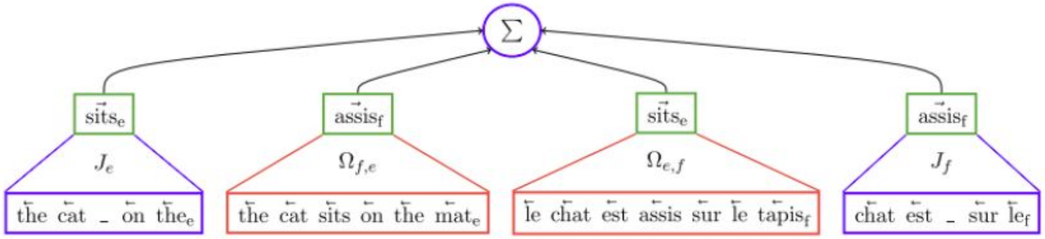


Word embeddings: Joint optimization

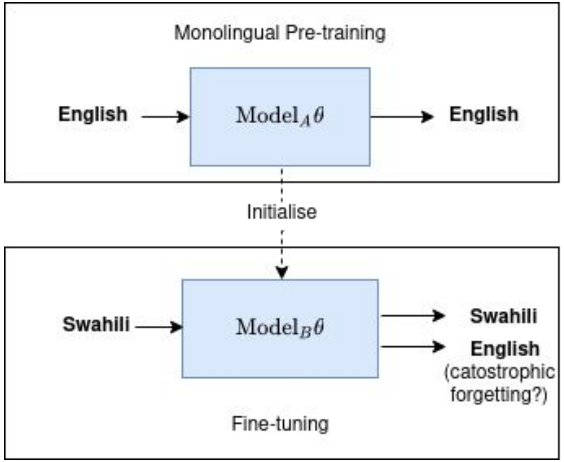
Trans-gram (Coulmance et al., 2015):

Train on a combination of monolingual and cross-lingual objectives

- 2 monolingual skip-gram losses: J_e (English) and J_f (French)
- and 2 cross-lingual trans-gram losses: $\Omega_{f,e}$ (French->English) and $\Omega_{e,f}$ (English->French)



SOTA approaches: Cross-lingual Transfer



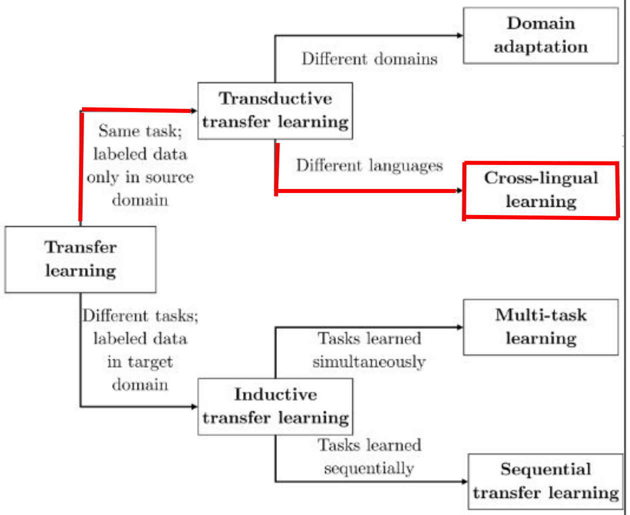
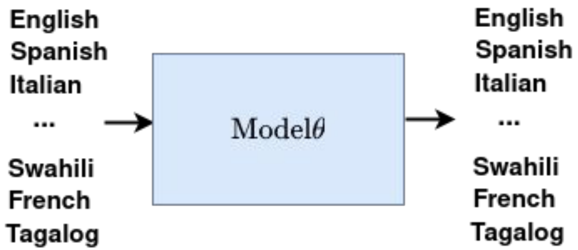


Image adapted from Ruder 2019b

Different options:

- Pre-training on large dataset and Fine-tuning on large dataset (regular)
- Pre-training on large dataset and Fine-tuning on small dataset (**few-shot**)
- Pre-training on large dataset no Fine-tuning on the test language (**zero-shot**)

SOTA approaches: Multilingual joint learning



Train one single model on a mixture of data from multiple languages

- Full parameter sharing
- Code switching!:

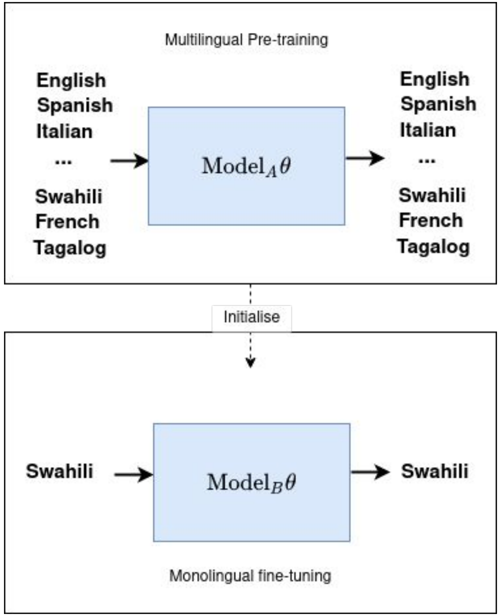
Spanglish Word/Phrase	English Meaning	Example Sentence
chilear	to chill out	*Chilé!* I'll be there in a second!
cojelo con take it easy/cojelo suave	don't worry	*Cojelo con take it easy*. You'll get the job.
conflei	cereal (from "Cornflakes," but refers to all cereal)	I'll just have some *conflei* for breakfast.

SOTA approaches: Best practice

SOTA sentence encoders commonly use:

A combination of **cross-lingual transfer** and **multilingual joint learning**

A **monolingual** or **cross-lingual training objective** in combination with **different architectures** (e.g. LSTMs or Transformers)



SOTA approaches: Pre-training objectives

- Monolingual: Masked Language Modelling (MLM) and Next Sentence Prediction (NSP)

  -> Inexpensive, easier to expand the number of train languages

  -> No cross-lingual signal

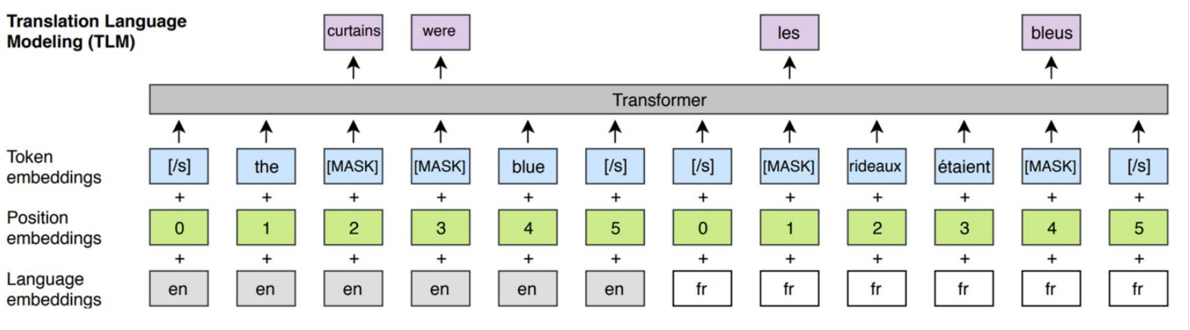
- Cross-lingual: Machine Translation (MT) and Translation Masked Modelling (TLM)

  -> Tasks designed to force the model to understand patterns across languages

  -> Requires parallel corpora

SOTA approaches: Translation Language Modelling (TLM)

The model can leverage information from the context in either language to predict the words, thereby encouraging the alignment of representations in both languages.



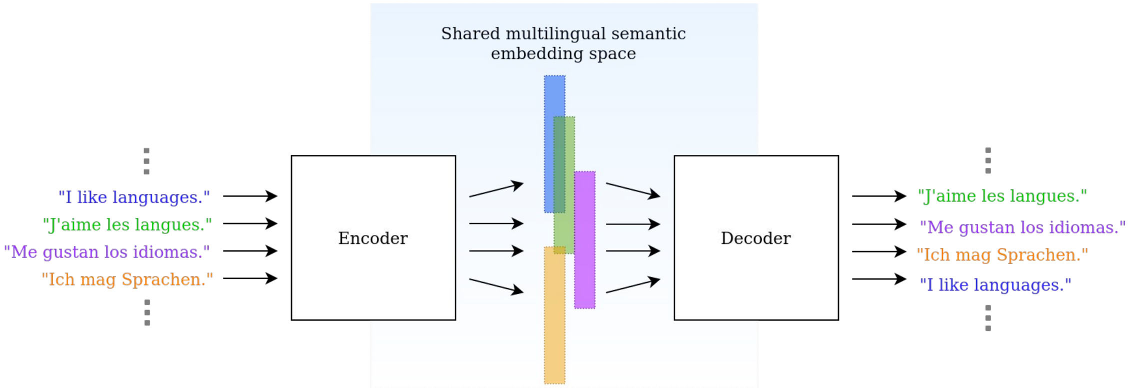
‘build the house’ -> construire the house, build la maison etc.

Image taken from Conneau et al., 2019

SOTA models: LASER

The first multilingual sentence encoder! (93 languages - 30 families, 28 scripts) (Artexte et al., 2019)

- Training objective: Machine translation
- Encoder/decoder type: BiLSTM
- Key: Encoder and decoder are jointly trained on parallel corpora (end-to-end)



The decoder functions as a feedback generator to the encoder

When training stabilizes, the decoder is discarded and the encoder can be used as multilingual model

SOTA models: BERT-based models

Model	tokenization	L	dim	H	params	V	task	languages
LASER	BPE	5	1024	-	52M	50K	MT	93
M-BERT	WordPiece	12	768	12	172M	110K	MLM+NSP	104
XLM	BPE	12	1024	8	250M	95K	MLM+TLM	15
XLM-R	SentencePiece	12	768	12	270M	250K	MLM	100

Table 1: Summary statistics of the model architectures: tokenization method, number of layers L, dimensionality of sentence representations dim, number of attention heads H, number of model parameters, vocabulary size V and pretraining tasks used.

- M-BERT = BERT + more diverse data (Devlin et al., 2018)
- XLM = BERT-based architecture - NSP + TLM + data from 15 languages (Conneau et al., 2019)
- XLM-R = RoBERTa - NSP + more diverse data (Conneau et al,. 2020)

SOTA models: Data collection

How to add data from e.g. 104 languages?

Exponentially smoothed weighting:

- P(en) -> 21% of data is English
- Exponentiate each prob by factor *S* -> re-normalize -> sample from new distribution

Under-sampled English, Oversample Icelandic:

Old: English sampled 1000x more than Icelandic

After smoothing it's ***only*** sampled 100x more!

In practice: data is still very skewed!

Shouldn’t this result in an exploding vocabulary size?
1 language BERT: ~30K Vocab -> 100 languages: ~3M vocab?

SOTA: Subword Tokenization

Split rare words into frequent subwords: e.g. “*reconstructing*” -> “re” - “construct” - “ing”

BERT: ~30K Vocab - 1 language -> M-BERT: **only** ~110K Vocab - 104 languages!

<u>Byte Pair Encoding (BPE)</u> (Sennrich et al., 2016):

1. Init *base_vocab* using unique symbols and characters + set vocab size *V* (hyperparameter)
2. Split each word into the base vocabulary characters e.g.: **[(‘c’,’a’,’r’ , 5), (‘c’,’a’,’b’,’l’,’e’, 3), (‘w’,’a’,’t’,’c’,’h’, 2), (‘c’,’h’,’a’,’i’,’r’, 5)]**
3. While len(*base_vocab*) < *V*:
   a. Count the occurrence of every symbol pair and pick the one with the highest frequency
   b. Add symbol pair to *base_vocab* + merge all occurences of the symbol pair

   E.g.: The pair “*ca*” occurs 5 x in *car* + 3 x in *cable* = 8 occurrences

   -> *base_vocab* += [“ca”] + **[(‘ca’,’r’ , 5), (‘ca’,’b’,’l’,’e’, 3), (‘w’,’a’,’t’,’c’,’h’, 2), (‘c’,’h’,’a’,’i’,’r’, 5)]**

   The pair “ch” is occurs 2 x in *watch* and 5 x in *chair* = 7 occurrences

   -> *base_vocab* += [“ch”] + **[(‘ca’,’r’ , 5), (‘ca’,’b’,’l’,’e’, 3), (‘w’,’a’,’t’,’ch’, 2), (‘ch’,’a’,’i’,’r’, 5)]**

SOTA: Subword Tokenization

WordPiece (Schuster et al., 2012):

1. Init *base_vocab* using unique symbols and characters + set vocab size *V* (hyperparameter)
2. Train language model *M* on *base_vocab*
3. While len(*base_vocab*) < *V*:
    a. Pick the pair that maximizes the likelihood of the train data
    b. Add symbol pair to *base_vocab* + merge all occurences of the symbol pair

E.g.: Pick "*ca*" if p(ca)/p(c)p(a) > any other symbol pair in vocab

SOTA: Subword Tokenization

BPE and WordPiece are created for English-> Some languages do not split words by spaces (e.g. Chinese)!!

Solutions:

- WordPiece: add white space around characters and perform character tokenization for corner cases – Quick fix
- SentencePiece (Kudo et al., 2018): does not treat space as a separator, it takes the string as input in its original raw format, i.e. along with all spaces. It then uses e.g. BPE as its tokenizer to construct the vocabulary (size has grown to 250K)

```
In [20]: from transformers import AutoTokenizer

         WordPiece = AutoTokenizer.from_pretrained('bert-base-multilingual-cased')
         SentencePiece = AutoTokenizer.from_pretrained('xlm-roberta-base')

         zh = "你好！这是一个例句。"
         ja = "こんにちは！これは例文です。"
         ko = "안녕하세요! 나는 예시 문장이다."

         for lang, tokenizer in itertools.product([zh, ja, ko], [WordPiece, SentencePiece]):
             print(tokenizer.tokenize(lang))
```

Chinese

```
['你', '好', '!', '这', '是', '一', '个', '例', '句', '。'] -> WP
['_', '你好', '!', '这是一个', '例', '句', '。'] -> SP
```

Japanese

```
['こ', '##ん', '##に', '##ち', '##は', '!', 'これは', '例', '文', 'で', '##す', '。'] -> WP
['_', 'こんにちは', '!', 'これは', '例', '文', 'です', '。'] -> SP
```

Korean

```
['안', '##녕', '##하', '##세', '##요', '!', '나는', '예', '##시', '문', '##장이', '##다', '.'] -> WP
['_안녕하세요', '!', '_나는', '_예', '시', '_문', '장', '이다', '.'] -> SP
```

There is no language detection, in the multilingual setting the tokenizer can mix up languages

SOTA: Subword Tokenization

Tokenization gets little attention but:

1. It prevents the vocab and model size from exploding
2. OOV words are rare
3. Better equipped to handle minor misspellings

   -> reconstuctin = re - construct - in

4. It allows for easy adaption of models to the multilingual setting

SOTA: Subword Tokenization

Linguistic pitfalls:

- Still not suitable for some languages that do not rely on word splitting e.g. Arabic:

كتب	k-t-b	"write" (root form)
كَتَبَ	**kataba**	"he wrote"
كَتَّبَ	**kattaba**	"he made (someone) write"
إِكْتَتَبَ	**iktataba**	"he signed up"

Table 1: Non-concatenative morphology in Arabic.[3] When conjugating, letters are interleaved *within* the root. The root is therefore not separable from its inflection via any contiguous split.

- Difficult pre-processing trade-offs: Lowercase? Remove punctuation? Remove diacritics?

DIACRITICS					
´	(é)	acute accent	˘	(ŭ)	breve
`	(è)	grave accent	ˇ	(č)	haček
ˆ	(ô)	circumflex	¨	(naïve)	diaeresis
˜	(ñ)	tilde	¨	(glögg)	umlaut
¯	(ō)	macron	¸	(ç)	cedilla

Left example from Clark et al., 2022, also good source for further reading

SOTA: Successful or not?

(RECAP) Approach:

1. **Pretrain** multilingual BERT (M-BERT) -> yields multilingual general-purpose representations
2. **Fine-tune** the general purpose model on a high-resource language for e.g. the task of Part-of-speech tagging -> yields a task-specific model
3. Test the task-specific model on a different language -> **zero-shot transfer**

Test: does the model learn truly universal structures?

Results from Pires et al. 2020

SOTA: Successful or not?

Surprisingly good zero-shot results!

Fine-tuning \ Eval	EN	DE	ES	IT
EN	**96.82**	89.40	85.91	91.60
DE	83.99	**93.99**	86.32	88.39
ES	81.64	88.87	**96.71**	93.71
IT	86.79	87.82	91.28	**98.11**

Table 2: POS accuracy on a subset of UD languages.

Fine-tuning \ Eval	EN	DE	NL	ES
EN	**90.70**	69.74	77.36	73.59
DE	73.83	**82.00**	76.25	70.03
NL	65.46	65.68	**89.86**	72.10
ES	65.38	59.40	64.39	**87.18**

Table 1: NER F1 results on the CoNLL data.

vs

Fine-tuning \ Eval	EN	DE	ES	IT
EN	**96.94**	38.31	50.38	46.07
DE	28.62	**92.63**	30.23	25.59
ES	28.78	46.15	**94.36**	71.50
IT	52.48	48.08	76.51	**96.41**

Table 8: POS accuracy on the UD test sets for a subset of European languages using EN-BERT.

Fine-tuning \ Eval	EN	DE	NL	ES
EN	**91.07**	24.38	40.62	49.99
DE	55.36	**73.32**	54.84	50.80
NL	59.36	27.57	**84.23**	53.15
ES	55.09	26.13	48.75	**81.84**

Table 7: NER results on the CoNLL test sets for EN-BERT.

SOTA: Successful or not?

WOW!

	HI	UR
HI	**97.1**	85.9
UR	91.1	**93.8**

	EN	BG	JA
EN	**96.8**	87.1	49.4
BG	82.2	**98.9**	51.6
JA	57.4	67.2	**96.5**

Table 4: POS accuracy on the UD test set for languages with different scripts. Row=fine-tuning, column=eval.

It gets more difficult when transferring between ‘less similar’ languages

But how can we define similarity?

Results from Pires et al. 2020

Defining language similarity

Different approaches e.g. lexical overlap: writing systems, vocabulary overlap (e.g. shared WordPieces)

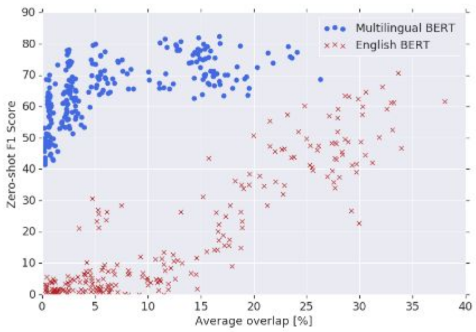


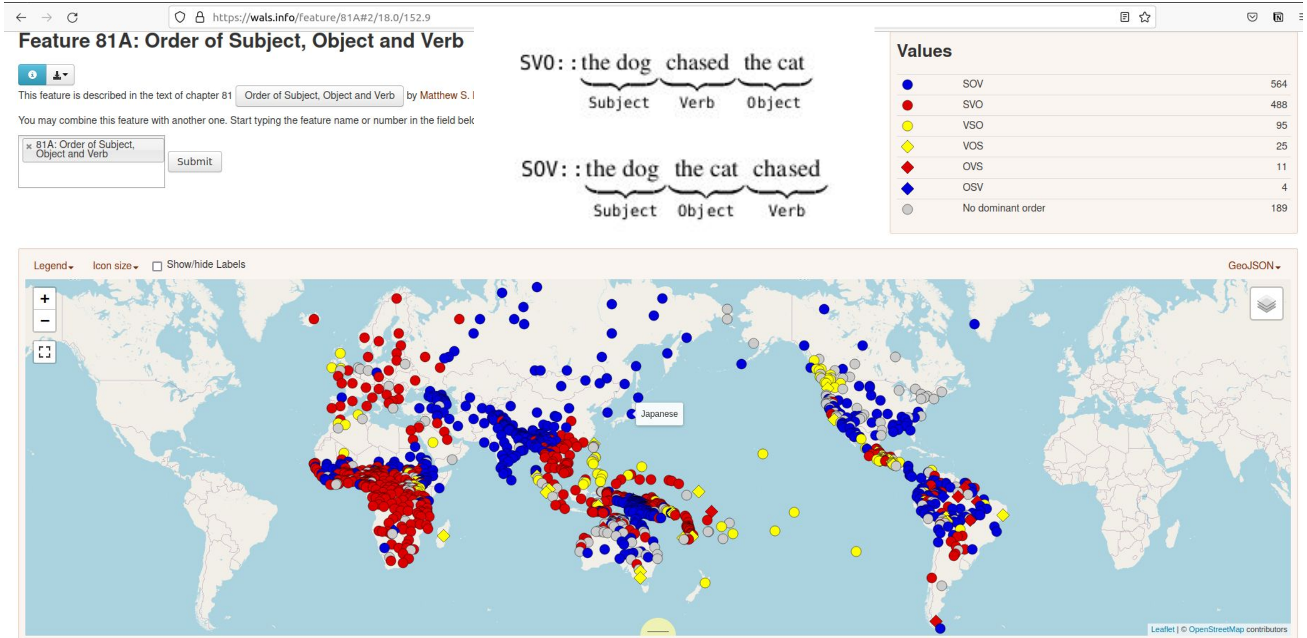
Figure 1: Zero-shot NER F1 score versus entity word piece overlap among 16 languages. While performance using EN-BERT depends directly on word piece overlap, M-BERT's performance is largely independent of overlap, indicating that it learns multilingual representations deeper than simple vocabulary memorization.

Transferability not dependent on lexical overlap.
Other possible explanations?

Results from Pires et al. 2020

Defining language similarity

Linguistic Typology studies, categorizes and documents the variation in the world's languages through systematic cross-linguistic comparisons (Croft, 2002)

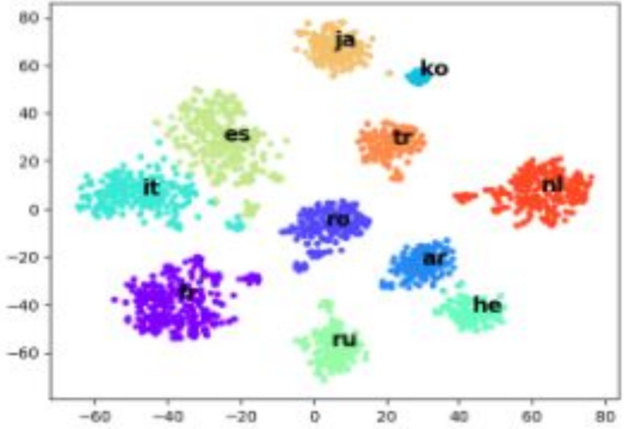


Japanese is a SOV language, Bulgarian and English are SVO -> maybe that's why transfer is easier between the latter?

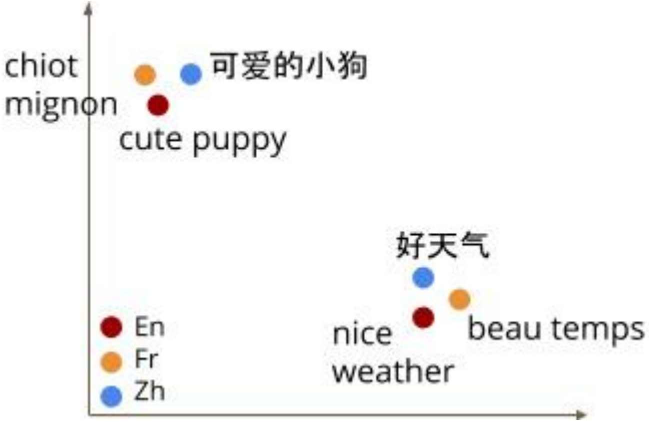
SOTA: Successful or not?

Surprisingly good results!

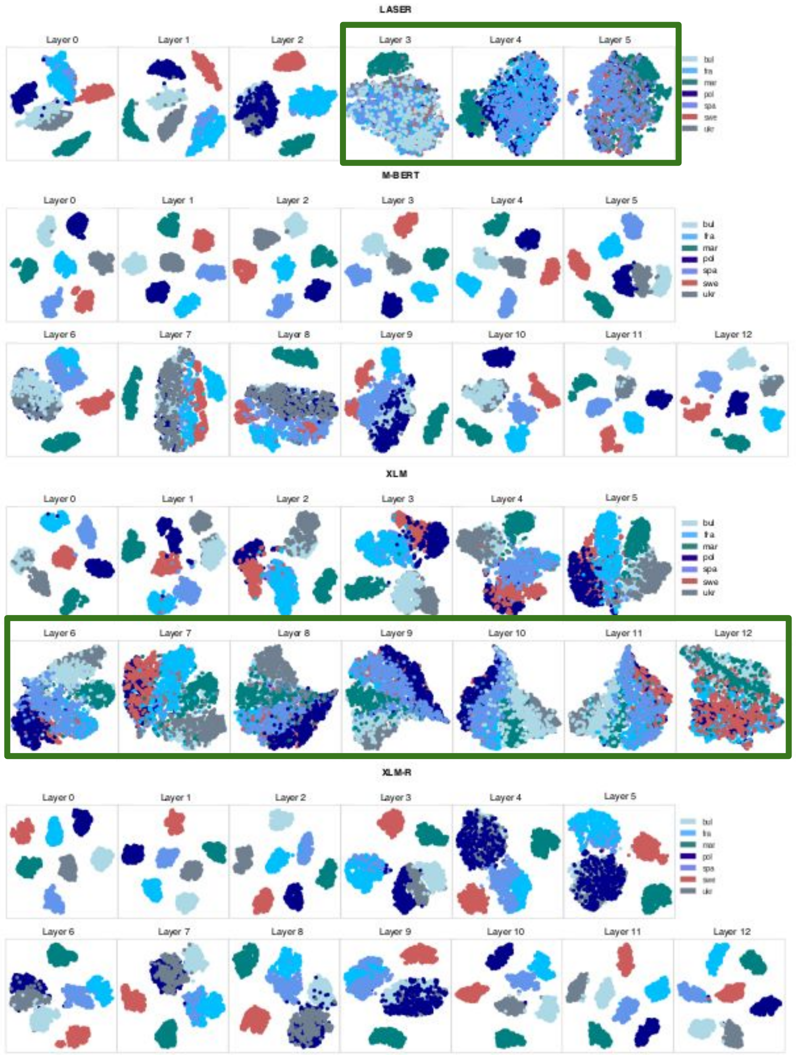
… but does it really create universal representations?



Result: sentence representations from M-BERT are clustered by language



Original goal: cluster sentences with similar meaning together irrespective of language



Model	tokenization	L	dim	H	params	V	task	languages
LASER	BPE	5	1024	-	52M	50K	$\boxed{\text{MT}}$	93
M-BERT	WordPiece	12	768	12	172M	110K	MLM+NSP	104
XLM	BPE	12	1024	8	250M	95K	MLM+$\boxed{\text{TLM}}$	15
XLM-R	SentencePiece	12	768	12	270M	250K	MLM	100

Table 1: Summary statistics of the model architectures: tokenization method, number of layers L, dimensionality of sentence representations dim, number of attention heads H, number of model parameters, vocabulary size V and pretraining tasks used.

Cross-lingual pre-training seems to result in more universal representations?

For further reading see Choenni & Shutova 2022

Cross-lingual pre-training seems to result in more universal representations?

Zero-shot performance on XNLI

Model	en	ar	bg	de	el	es	fr	hi	ru	sw	th	tr	ur	vi	zh	avg
Cross-lingual zero-shot transfer (models fine-tune on English data only)																
mBERT	80.8	64.3	68.0	70.0	65.3	73.5	73.4	58.9	67.8	49.7	54.1	60.9	57.2	69.3	67.8	65.4
XLM	82.8	66.0	71.9	72.7	70.4	75.5	74.3	62.5	69.9	58.1	65.5	66.4	59.8	70.7	70.2	69.1
XLM-R	88.7	77.2	83.0	82.5	80.8	83.7	82.2	75.6	79.1	71.2	77.4	78.0	71.7	79.3	78.2	79.2

… but in practice not worth the extra cost?

Results taken from Xue et al. 2021

SOTA: Successful or not?

How multilingual is Multilingual BERT?

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Abstract

In this paper, we show that Multilingual BERT (M-BERT), released by Devlin et al. (2019) as a single language model pre-trained from monolingual corpora in 104 languages, is surprisingly good at zero-shot cross-lingual model transfer, in which task-specific annotations in one language are used to fine-tune the model for evaluation in another language. To understand why, we present a large number of probing experiments, showing that transfer is possible even to languages in different scripts, that transfer works best between typologically similar languages, that monolingual corpora can train models for code-switching, and that the model can find translation pairs. From these results, we can conclude that M-BERT

...this paper, we e...

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CROSS-LINGUAL ABILITY OF MULTILINGUAL BERT: AN EMPIRICAL STUDY

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Are All Languages Created Equal in Multilingual BERT?

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Abstract

Multilingual BERT (mBERT) (Devlin, 2018) trained on 104 languages has shown surprisingly good cross-lingual performance on several NLP tasks, even without explicit cross-lingual signals (Wu and Dredze, 2019; Pires et al., 2019). However, these evaluations have focused on cross-lingual transfer with high-resource languages, covering only a third of the languages covered by mBERT. We explore how mBERT performs on a much wider set of languages, focusing on the quality of representation for low-resource languages, measured by within-language performance. We consider three tasks: Named Entity Recognition (99 languages), Part-of-speech Tagging, and Dependency Parsing (54 languages each). mBERT does better than or comparable to baselines on high resource languages but does much worse for low resource languages. Furthermore, monolingual BERT models for these

shot cross-lingual transfer performance (Wu and Dredze, 2019; Pires et al., 2019). However, evaluations have focused on high resource languages, with cross-lingual transfer using English as a source language or within language performance. As Wu and Dredze (2019) evaluated mBERT on 39 languages, this leaves the majority of mBERT's 104 languages, most of which are low resource languages, untested.

Does mBERT learn equally high-quality representation for its 104 languages? If not, which languages are hurt by its massively multilingual style pretraining? While it has been observed that for high resource languages like English, mBERT performs worse than monolingual BERT on English with the same capacity (Devlin, 2018). It is unclear that for low resource languages (in terms of monolingual corpus size), how does mBERT compare to a monolingual BERT? And, does multilingual joint

How Language-Neutral is Multilingual BERT?

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Abstract

...ilingual BERT (mBERT) provides sen... representations for 104 languages, which ...eful for many multi-lingual tasks. Pre... work probed the cross-linguality of ... using zero-shot transfer learning on ...logical and syntactic tasks. We instead ... the semantic properties of mBERT. ... that mBERT representations can ...nto a language-specific component ...guage-neutral component, and that ...e-neutral component is sufficiently ...erms of modeling semantics to al... ...curacy word-alignment and sen...

methodological issues with zero-shot transfer (possible language overfitting, hyper-parameter tuning), we selected tasks that only involve a direct comparison of the representations: cross-lingual sentence retrieval, word alignment, and machine translation quality estimation (MT QE). Additionally, we explore how the language is represented in the embeddings by training language identification classifiers and assessing how the representation similarity corresponds to phylogenetic language families.

Our results show that the mBERT representations, even after language-agnostic fine-tuning, are

Problems: Balance

Multilingual models need to:

1. To generalize over many different languages by finding ‘universal’ representations *(language-agnostic information)*
2. Yet at the same time still capture enough subtle nuances of each individual language *(language-specific information)*

Finding a perfect balance is hard!

Problems: Conflict of interests

The curse of multilinguality: Languages will start fighting for model capacity

-> When performance improves for some languages others start to suffer

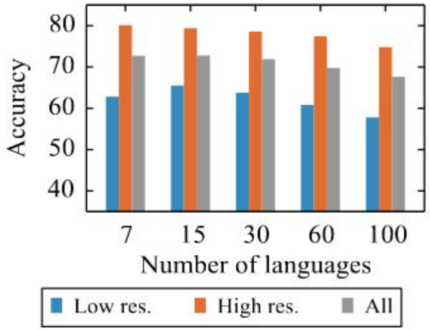


Figure 2: The transfer-interference trade-off: Low-resource languages benefit from scaling to more languages, until dilution (interference) kicks in and degrades overall performance.

Figure from Conneau et al. 2020

Problems: Conflict of interests

Negative interference: Performance on high resource languages for which we normally obtain good results deteriorate

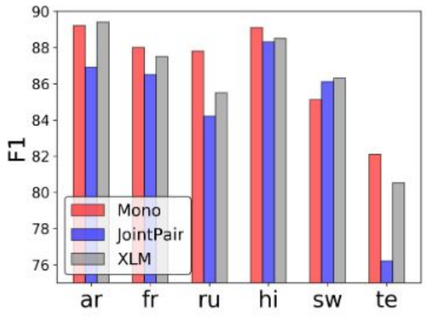


Figure 1: Comparing monolingual vs multilingual models on NER. Lower performance of multilingual models is likely an indicator of negative interference.

Figure from Wang et al. 2020

New directions: Modular deep learning

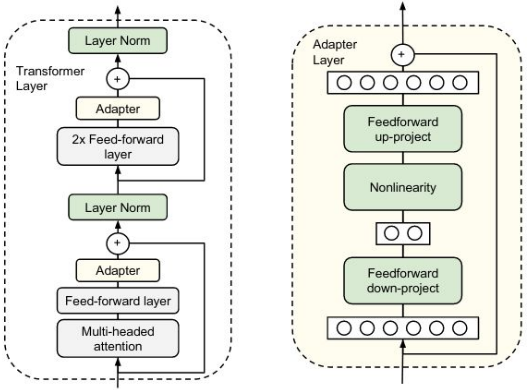
- Modularity definition:

  The correspondence between strongly interconnected components of a system (i.e., modules) and the functions they perform (Baldwin & Clark, 2000; Ulrich, 1995).

- Each module is specialised for a unique purpose, for which it is reused consistently
- Solution to the curse of multilinguality: disentangle fully shared models using specialised modules for individual languages
- Common approaches: adapter modules and sparse fine-tuning with subnetworks

New directions: Adapters

- Introduced by Houlsby et al. 2019 for more efficient transfer
- Instead of updating all weights during fine-tuning a *few* trainable parameters are added per task
- Traditional fine-tuning: add a new layer to fit the targets specified in the downstream task, and train the new layer together with the pretrained weights
- Adapter tuning strategy: inject new layers (randomly initialized) into the original network. Parameter sharing between tasks is supported by keeping the pretrained model parameters frozen

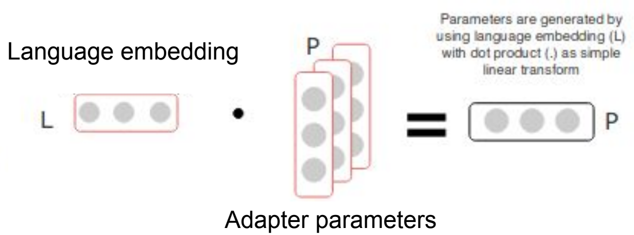


New directions: UDapter

- Uses adapter modules for truly language universal dependency parsing (Ustun et al. 2020)
- The adapters are now used to capture both task-specific and language-specific information
- Original model parameters serve as memory for the languages
- How to scale to 100+ languages?

-> Generate adapter weights by a Contextual Parameter Generator (CPG) (Platanios et al., 2018)

- CPG is implemented as a function of language embedding



->Enables our model to modify its parsing decisions depending on a language embedding

- Defining language embeddings as a function of a large set of Linguistic typological features (Remember WALS and URIEL?)
- 289 linguistic features are fed into an MLP to learn a 32 dim language embedding

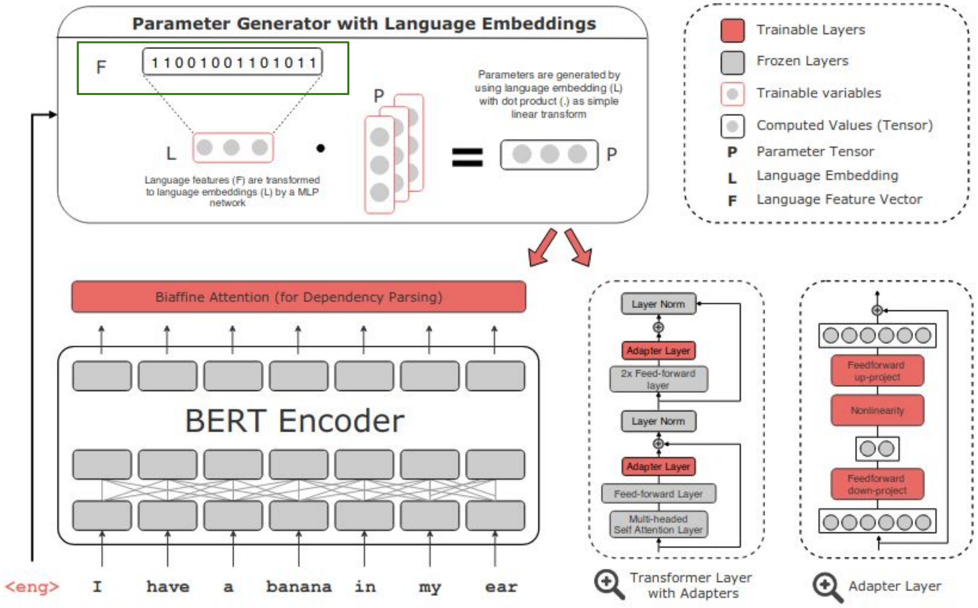
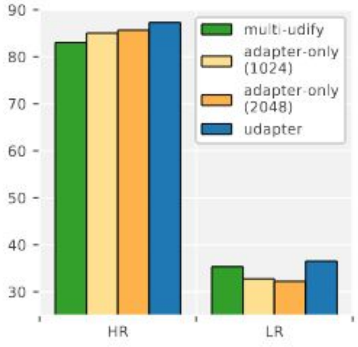
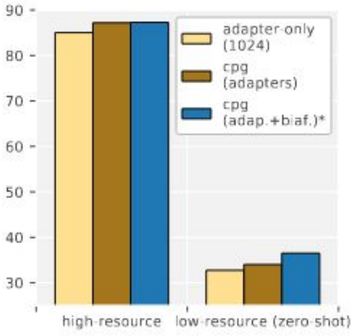


Figure 1: UDapter architecture with contextual parameter generator (CPG) and adapter layers. CPG takes languages embeddings projected from typological features as input and generates parameters of adapter layers and biaffine attention.

New directions: UDapter

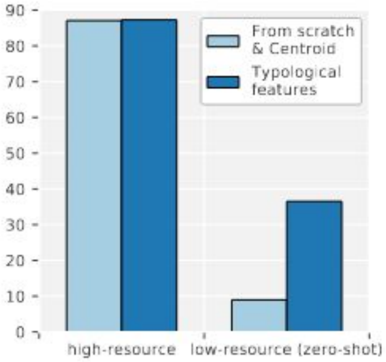


(a)

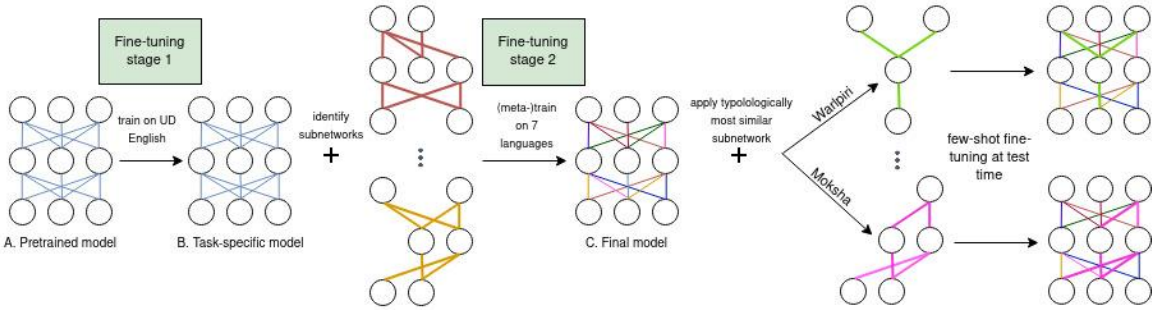


(b)

Figure 3: Impact of different UDapter components on parsing performance (LAS): (a) adapters and adapter layer size, (b) application of contextual parameter generation to different portions of the network. In (b) the model named 'cpg (adap.+biaf.)' coincides with the full UDapter.



New directions: Subnetworks



- This framework relies on the notion that the knowledge for different languages is somehow localizable in specific sets of model parameters
- , and that those parameters can individually be fine-tuned in an autonomous and parameter-efficient manner

Questions?

Further reading:

Overview papers:

- Survey on cross-lingual word embedding models
- Survey on the use of Linguistic Typology in NLP

SOTA models:

- LASER
- MBERT , Github documentation
- XLM
- XLM-R
- Unicoder
- MT5

Analysis papers:

- Cross-lingual ability of M-BERT
- On the language-neutrality of M-BERT
- Language equality in M-BERT
- Probing for typological properties
- Negative interference in multilingual models

Promising directions:

- Meta-learning for cross-lingual zero-shot transfer
- Newest UDapter
- CANINE: A tokenization-free encoder

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