Sequence Tagging with Contextual and Non-Contextual Subword Representations

A Multilingual Evaluation

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HITS

TOHOKU UNIVERSITY

AIP

ACL 2019

Multilingual Subword Representations

fastText (Bojanovski+'17) 294 languages∗

BPEmb (Heinzerling+'18) 275 languages∗

BERT  (Devlin+'19) 104 languages∗

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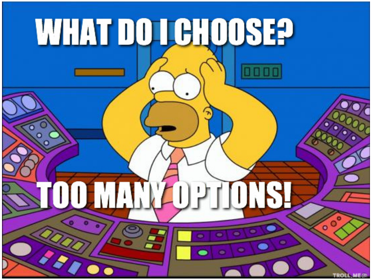

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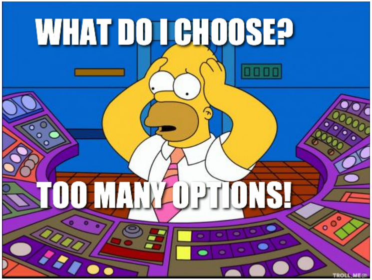

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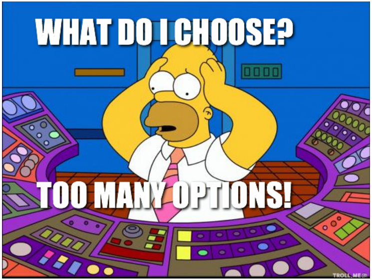

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$*$ "language" := Wikipedia edition $\leftarrow$ bad assumption for small Wikipedias

FastText (Bojanovski+'17)

Word embedding = sum of char-ngram embeddings

Magnus Carlsen played
Viswanathan Anand

$$\overrightarrow{viswanathan} = \overrightarrow{vis} + \overrightarrow{isw} + \overrightarrow{swa} + \overrightarrow{wan} + \overrightarrow{ana} + \overrightarrow{nat} + \overrightarrow{ath} + \overrightarrow{tha} + \overrightarrow{han} +$$

$$\overrightarrow{visw} + \overrightarrow{iswa} + \overrightarrow{swan} + \overrightarrow{wana} + \overrightarrow{anat} + \overrightarrow{nath} + \overrightarrow{atha} + \overrightarrow{than} + \overrightarrow{viswa} +$$

$$\overrightarrow{iswan} + \overrightarrow{swana} + \overrightarrow{wanat} + \overrightarrow{anath} + \overrightarrow{natha} + \overrightarrow{athan} + \overrightarrow{viswan} + \overrightarrow{iswana} +$$

$$\overrightarrow{swanat} + \overrightarrow{wanath} + \overrightarrow{anatha} + \overrightarrow{nathan}$$

Many char-ngrams $\rightarrow$ huge file sizes

Check out tiny FastText: "Subword-based Compact Reconstruction of Word Embeddings" (Sasaki, Suzuki, Inui, NAACL'19)

Byte-Pair Encoding (Sennrich+'16)

Iteratively merge the most frequent pair of adjacent symbols

the netherlands are neither here nor there

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BPE vocab: he, the, ther, ne, re

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With 5000 merge operations learned on Wikipedia:
the _ nether lands _ are _ ne ither _ here _ nor _ there

BPEmb (Heinzerling+'18, shameless plug)

BPE + GloVe = Byte-Pair Embeddings (http://nlp.h-its.org/bpemb)

Advantages: Easy to use, small file sizes, no tokenization required

Disadvantage: not contextual (trained with GloVe, no LM objective)

Import BPEmb:

```
>>> from bpemb import BPEmb
```

Load a BPEmb model for English:

```
>>> bpemb_en = BPEmb(lang="en")
```

Byte-pair encode text:

```
>>> bpemb_en.encode("Stratford")
['_strat', 'ford']
>>> bpemb_en.encode("This is anarchism")
['_this', '_is', '_an', 'arch', 'ism']
```

Load a Chinese model with vocabulary size 100,000:

```
>>> bpemb_zh = BPEmb(lang="zh", vs=100000)
>>> bpemb_zh.encode("这是一个中文句子") # "This is a Chinese sentence."
['_这是一个', '中文', '句子'] # ["This is a", "Chinese", "sentence"]
```

Multilingual BERT (Devlin+'19)

Contextual subword embeddings with shared 104-lingual vocabulary

BPE is language-agnostic$*$: can give it any character sequence

Multilingual Bert recipe:

1. Train on multilingual texts $\rightarrow$ get shared multilingual subword vocabulary (100k)
2. Subword-encode texts with this shared vocabulary
3. Train BERT on encoded texts

$*$ But not language-independent (see discussion in Appendix 1)

Overview: Subword segmentation methods

Method	Subword segmentation and token transformation					
Original text	Magnus	Carlsen	played	against	Viswanathan	Anand

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Word shape	Aa	Aa	a	a	Aa	Aa

Dataset: WikiAnn (Pan+'17)

NER annotations in 282 languages

location *location*

Così , dopo una tappa a Piacenza , si diresse verso Firenze .
[So, after a stop in Piacenza, he headed for Florence.]∗

location

Bu kişilere örnek olarak devrin ünlü Floransa'lı

person

şairi Guido Cavalcanti'yi verebiliriz .
[For example, the famous Florentine poet of the time, Guido Cavalcanti.]∗

∗Translation according to Google translate

Best (only!?) system on WikiAnn by the authors ("Pan17"):

- Crosslingual gazetters (Firenze = Floransa)
- Morphological features (Floransa'lı→ Floransa, so "lı" is a suffix)
- LSTM sequence tagger

NER Experiments: FastText vs. BPEmb vs. BERT

Which subword representation is best for multilingual NER?

Setup: Train one model for

- each subword representation
- and each language
- with crossvalidation

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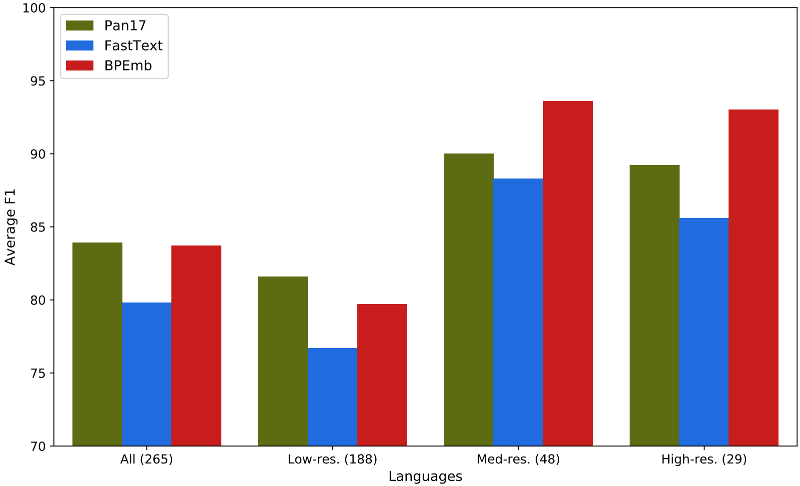
Only NER results in this talk, also did POS tagging, similar trends

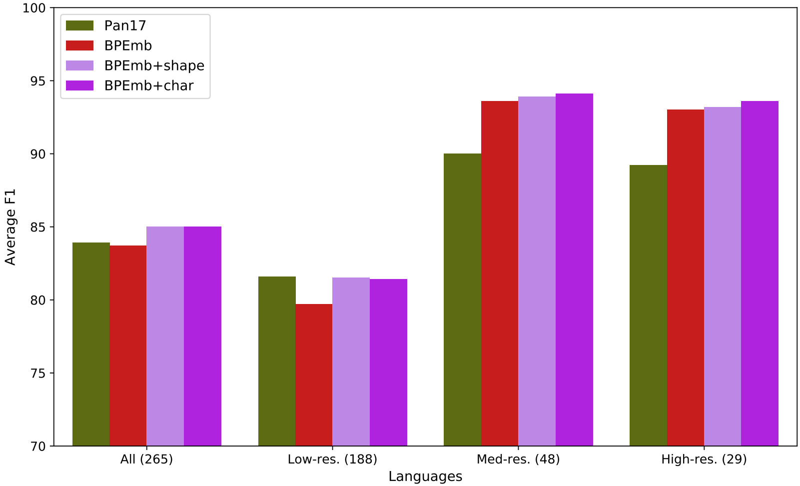
NER on 265 languages: Pan17 is best

FastText worst, BPEmb almost as good



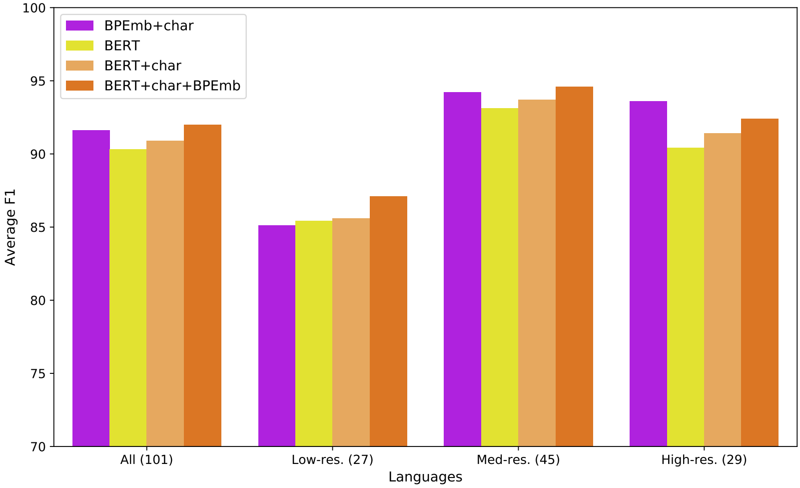
Characters are still useful with BPE

Better than word shape in high-res languages

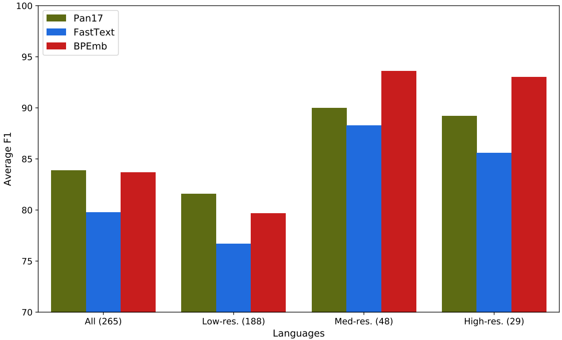


Multilingual BERT works well

Better with characters, best with BPEmb+characters



How to do better on low-res languages?



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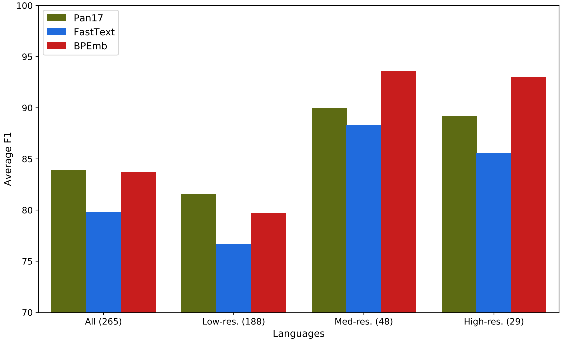

Hypothesis: Cross-lingual transfer should help

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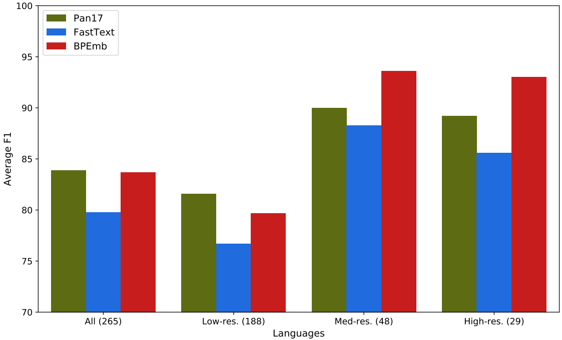

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So let's train multilingual subword embeddings!

MultiBPEmb

Non-contextual $\rightarrow$ large vocab size, `https://nlp.h-its.org/bpemb/multi/`

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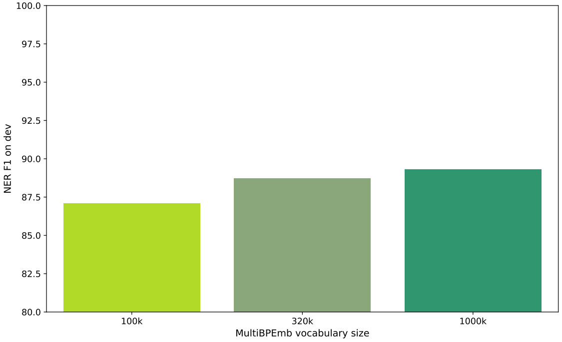
You can use MultiBPEmb in Python like this:

```
>>> from bpemb import BPEmb
>>> multibpemb = BPEmb(lang="multi", vs=1000000, dim=300)
>>> text = 'John F. Kennedy said "Ich bin ein Pfannkuchen". 这是一个中文句子.日本語の文章です。'
>>> subwords = multibpemb.encode(text)
>>> print(" ".join(subwords))
_john _f . _kennedy _said _" ich _bin _ein _pfann kuchen ". _这 是一个 中文 句子 . _日本 語の 文章 です 。
```

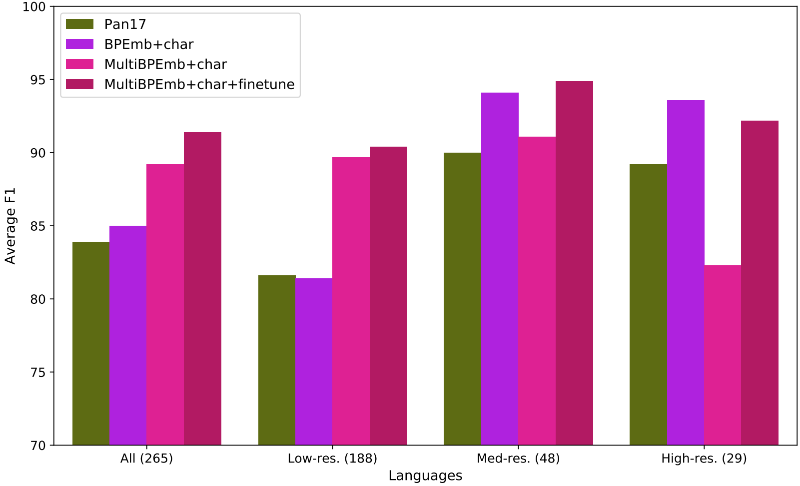
Bigger multilingual subword vocab is better

Two percent higher average NER F1 score on dev of all languages



Multilingual training allows crosslingual transfer

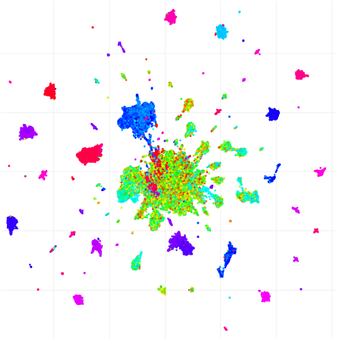
Train one model on concatentation of NER training data in all languages



finetune: multilingual pretraining, then train on one language only

265-lingual semantic space? No.

MultiBPEmb embedding space before (l) and after (r) NER training



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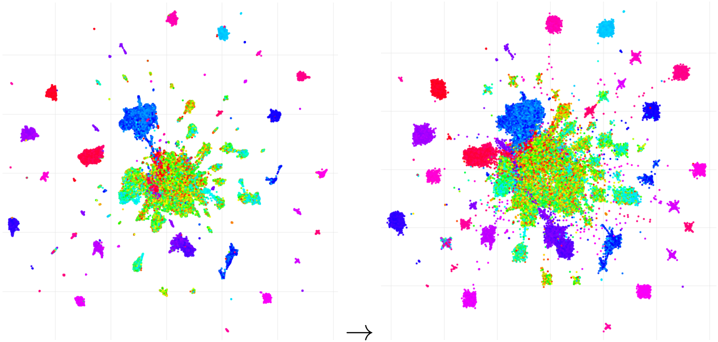

Color = unicode codepoint (≈ language families)

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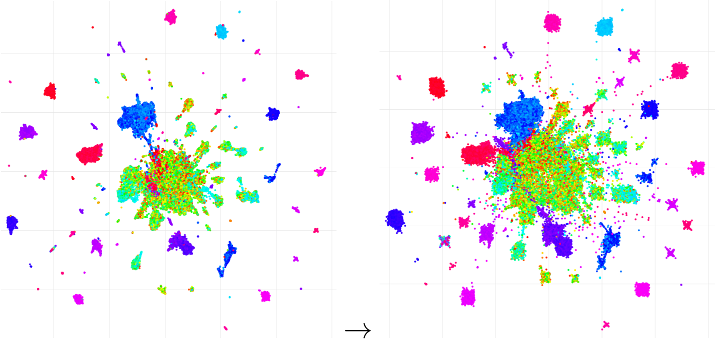

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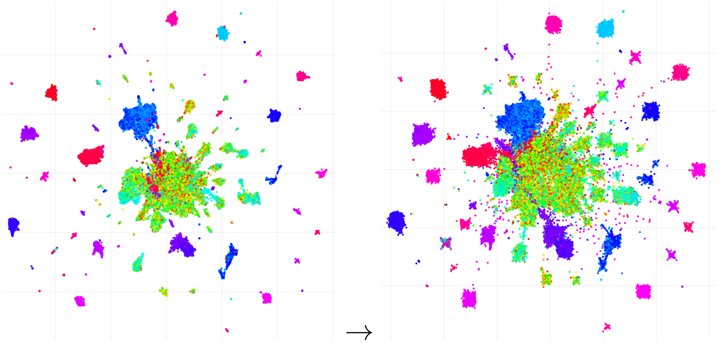
- Does not suggest crosslingual transfer

265-lingual semantic space? No.

MultiBPEmb embedding space before (l) and after (r) NER training



Color = unicode codepoint (≈ language families)

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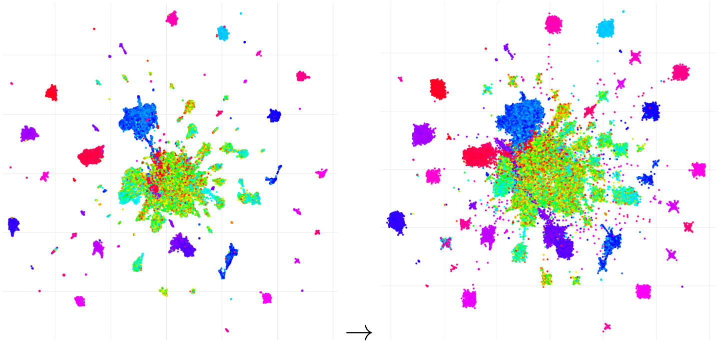

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- Improvements more likely due to the multilingual setting: enables the model to better learn BIO constraints, tag distributions

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Thank You!