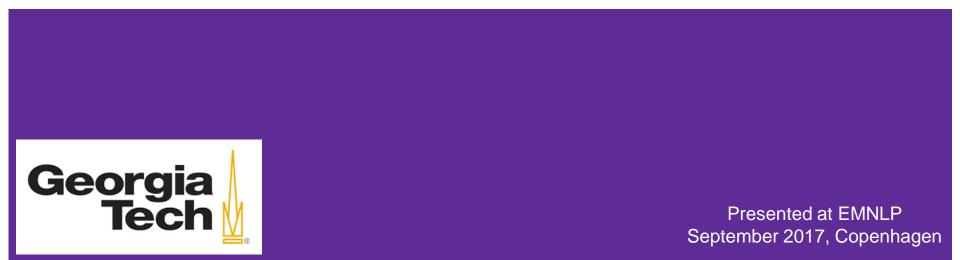
# Mimicking Word Embeddings using Subword RNNs

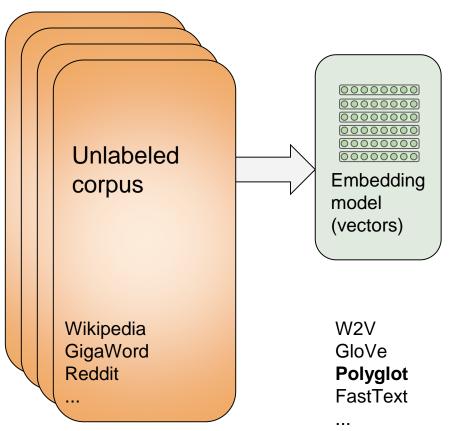
Yuval Pinter, Robert Guthrie, Jacob Eisenstein @yuvalpi

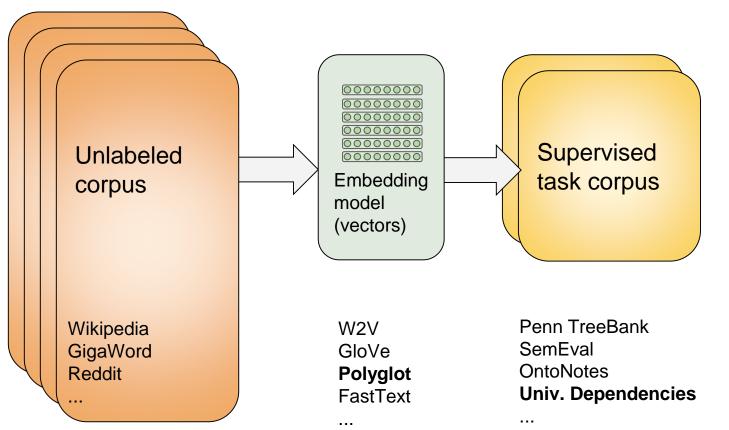


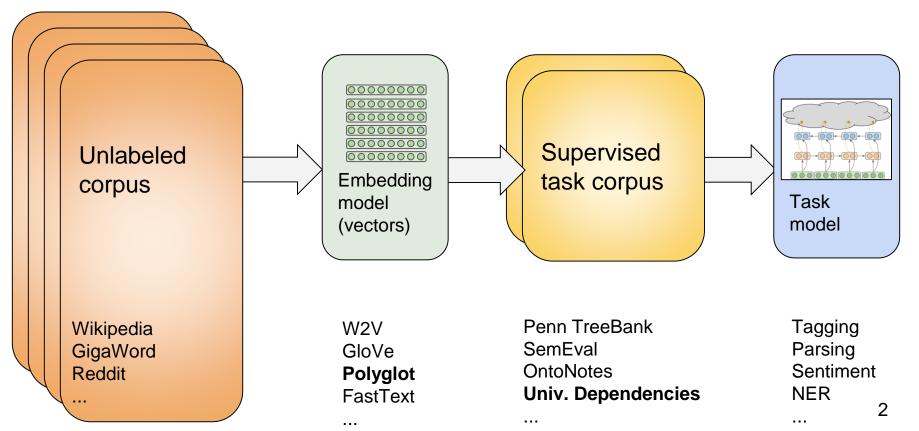
Unlabeled corpus

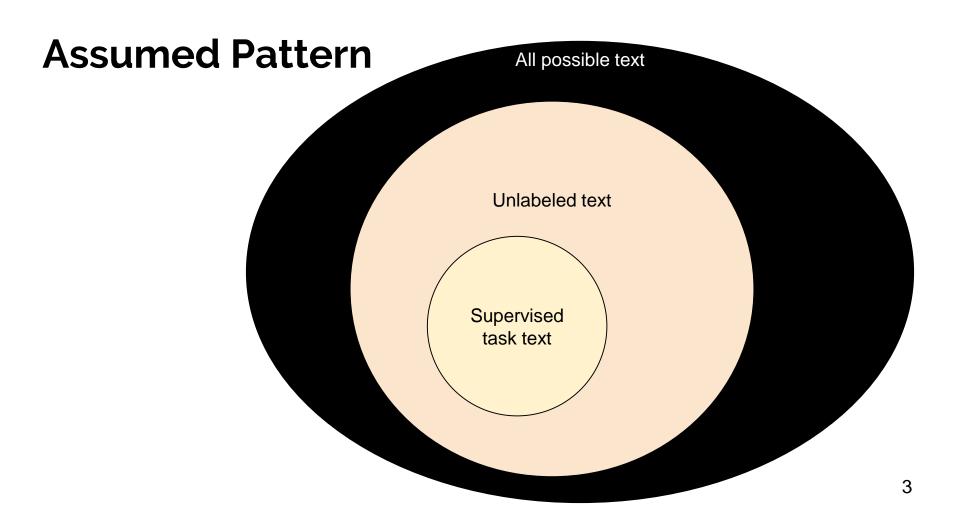
Wikipedia GigaWord Reddit

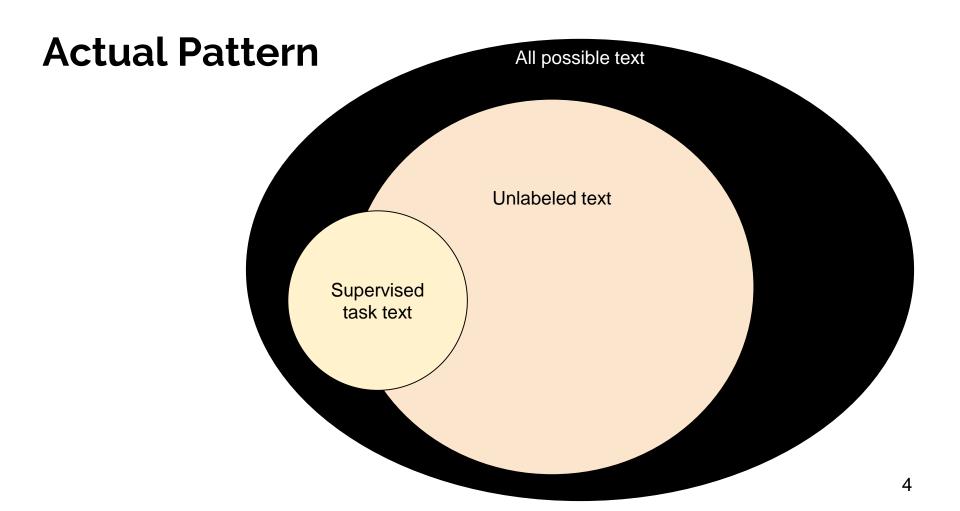
...

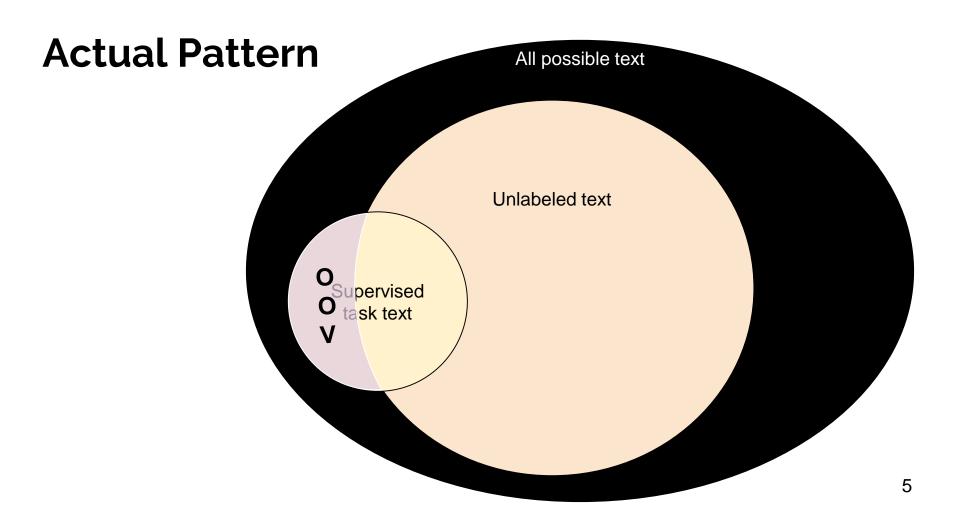


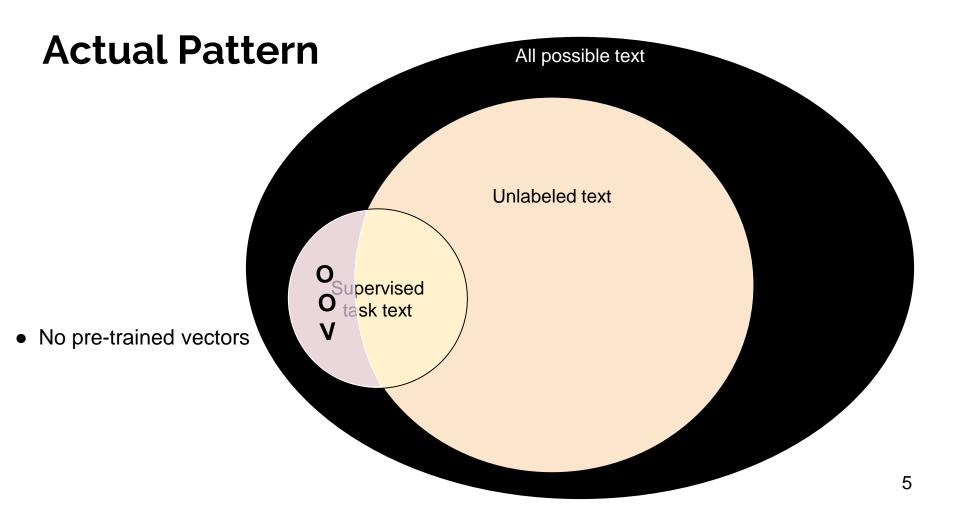


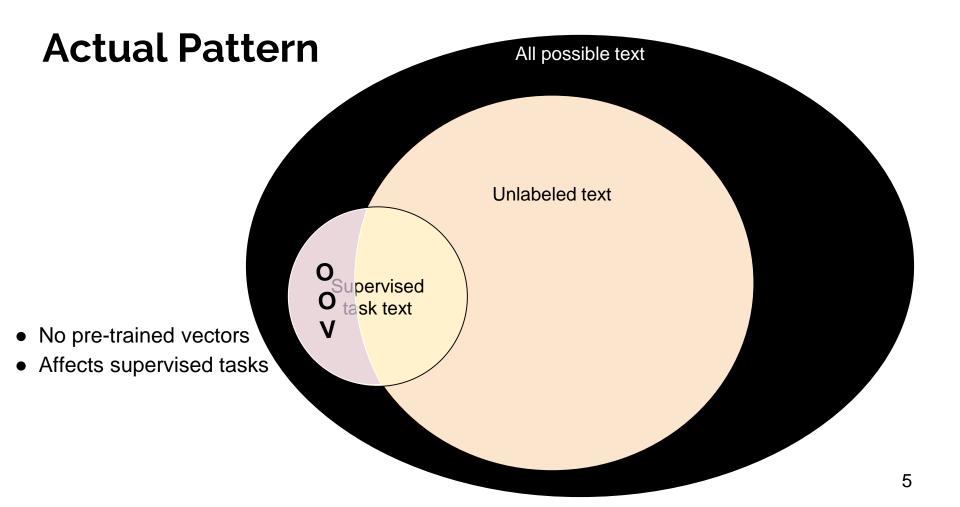


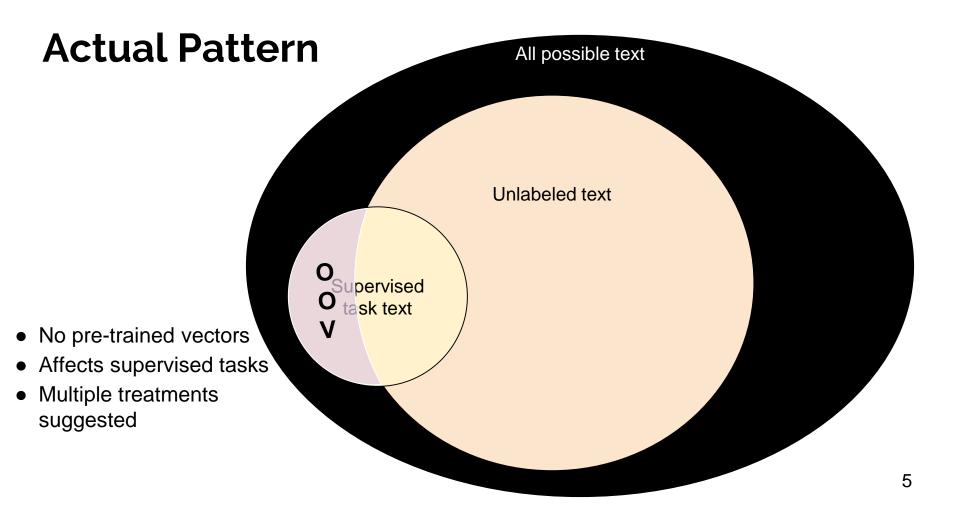


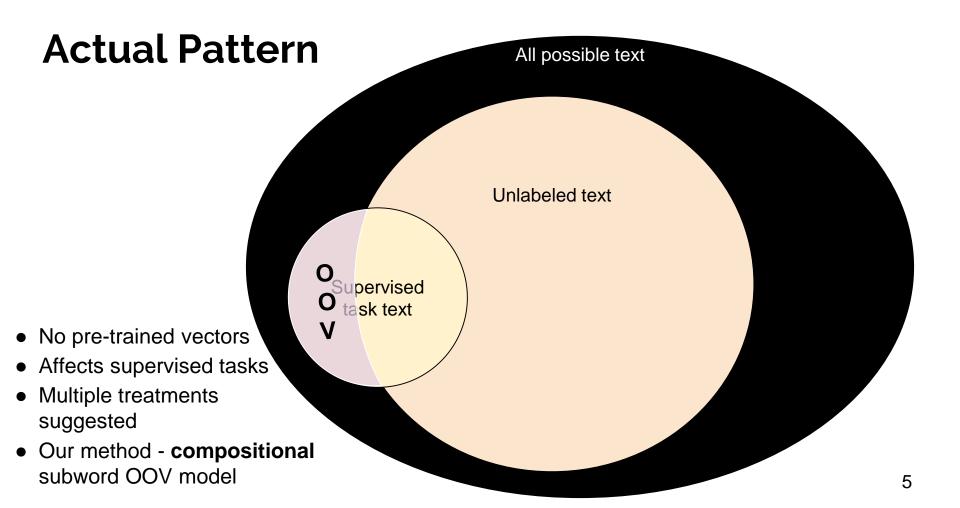












• Names

Chalabi has increasingly marginalized within Iraq, ...

- Names
- Domain-specific jargon

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Important species (...) include shrimp, (...) and some varieties of flatfish.

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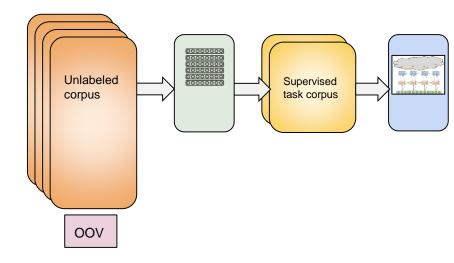
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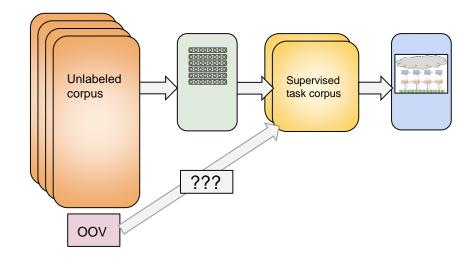
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???

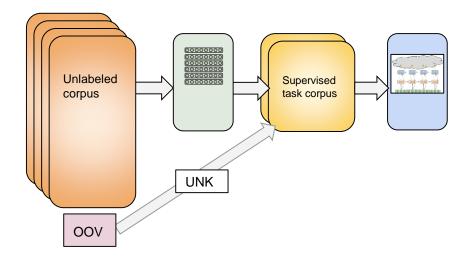
• None (random init)



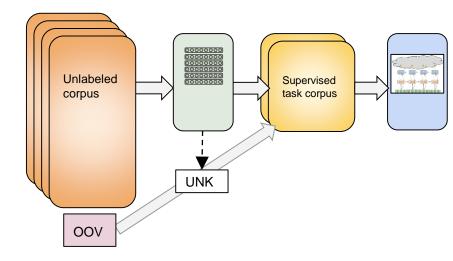
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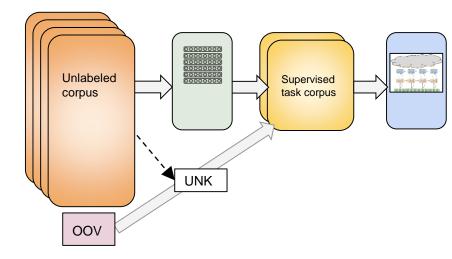
- None (random init)
- One UNK to rule them all
  - Average existing embeddings
  - Trained with embeddings (stochastic unking)



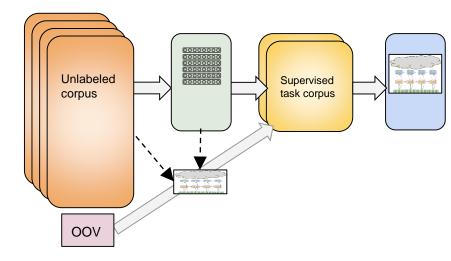
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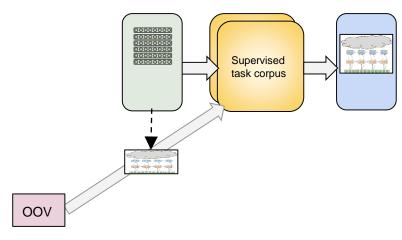
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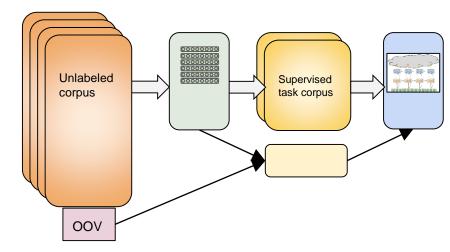


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- Add subword model during WE training
  - Bhatia et al. (2016), Wieting et al. (2016)

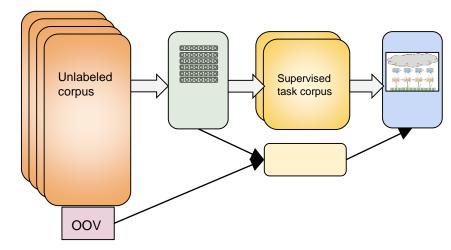


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- Add subword model during WE training
  - $\circ~$  Bhatia et al. (2016), Wieting et al. (2016)
  - What if we don't have access to the original corpus? (e.g. FastText)

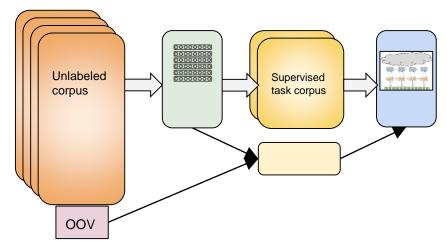




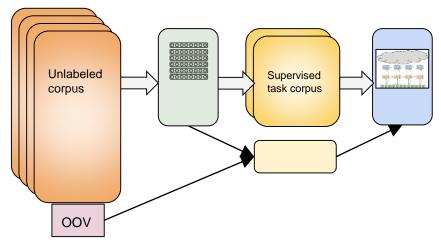
- Add subword layer to supervised task
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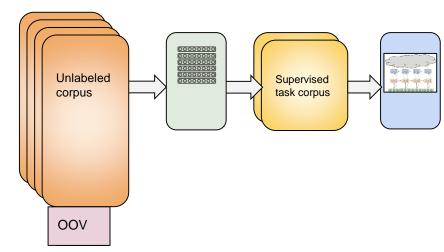


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- OOVs benefit from co-trained character model

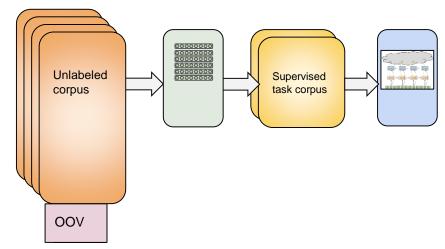


- Add subword layer to supervised task
  - Ling et al. (2015), Plank et al. (2016)
- OOVs benefit from co-trained character model
- Requires large supervised training set for efficient transfer to test set OOVs

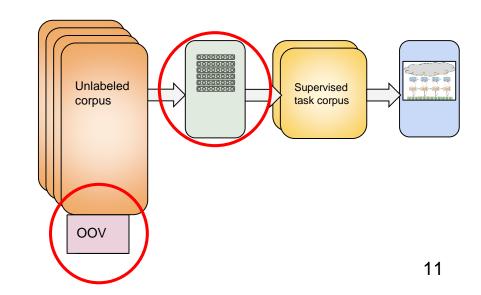




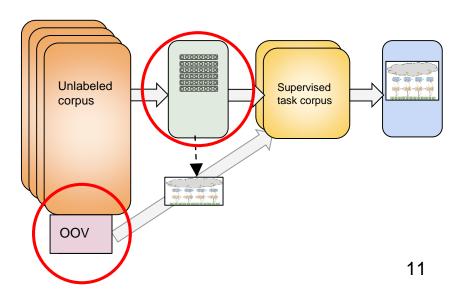
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  - Orthography (the way words are spelled)



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- Use the former as training objective, latter as input

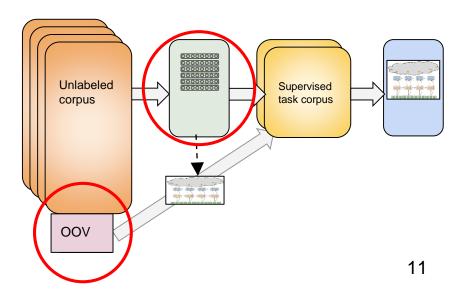


## **Enter MIMICK**

- What data do we have, post-unlabeled corpus?
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- Pre-trained vectors as target
  - No need to access original unlabeled corpus
  - Many training examples
  - (No context)

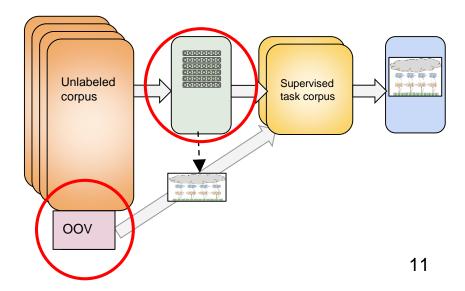


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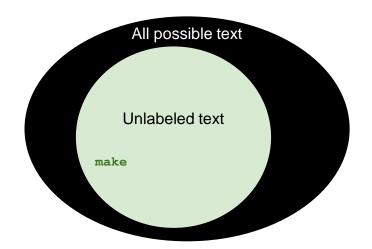
#### • Use the former as training objective, latter as input

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  - Many training examples
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- Subword units as inputs
  - Very extensible
  - (Character inventory changes?)



Pre-trained Embedding (Polyglot/FastText/etc.)







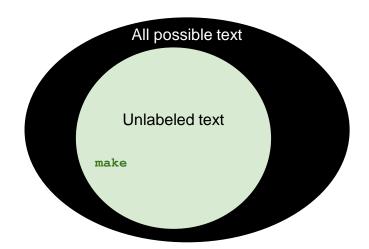
m a k

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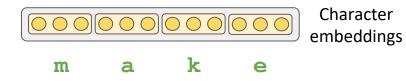


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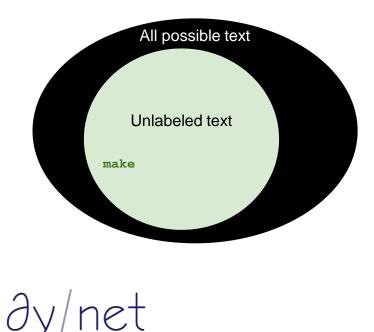


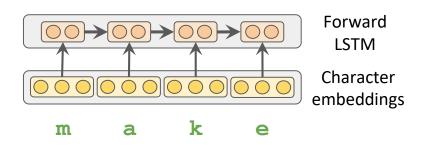
net



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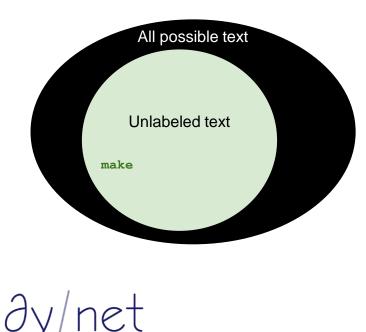


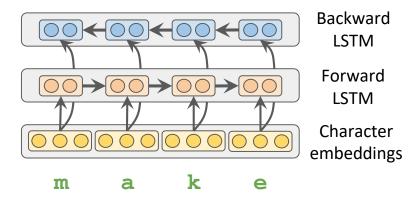




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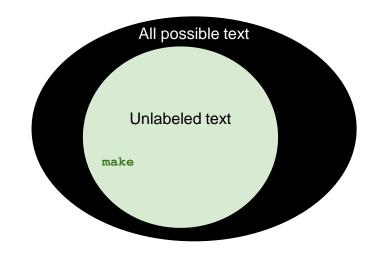




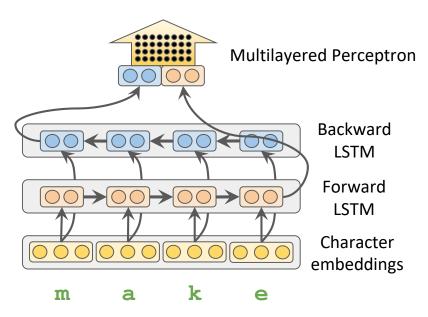


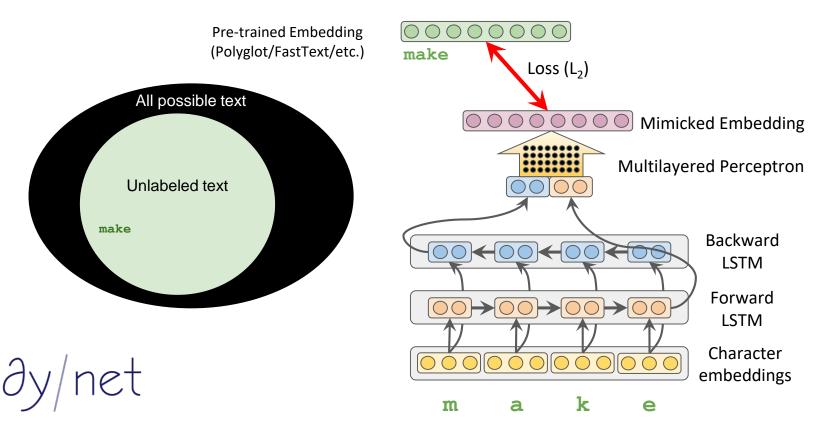
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 $\bigcirc \bigcirc$ 

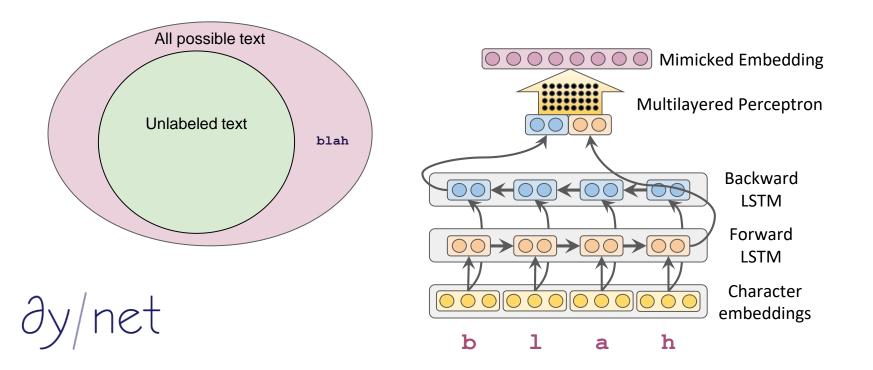


net





### **MIMICK Inference**



• English (OOV → Nearest in-vocab words)

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  - $\circ$  MCT  $\rightarrow$  AWS, OTA, APT, PDM

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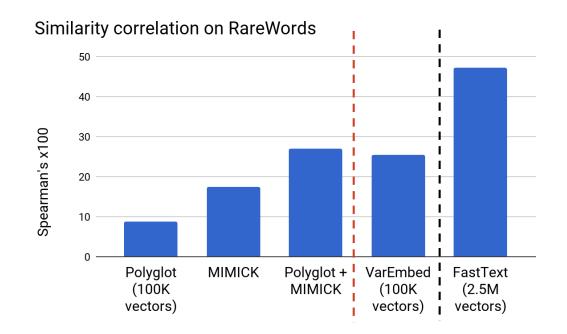
• ✓ Surface form

✓ Syntactic properties

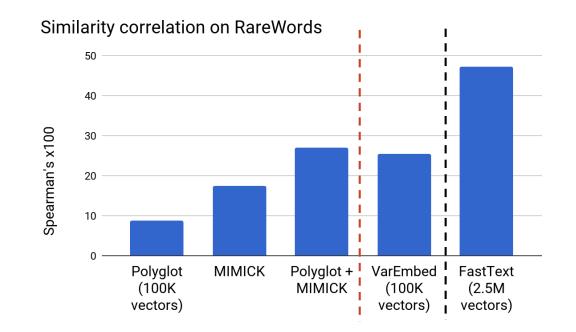
#### X Semantics

• <u>RareWords</u> similarity task: morphologically-complex, mostly unseen words

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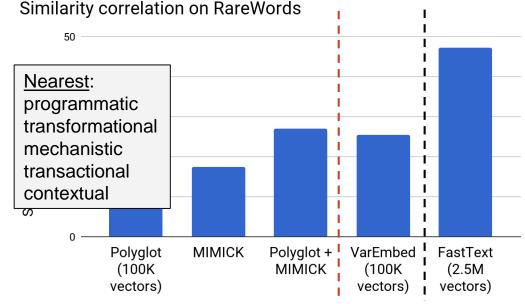
- Names
- Domain-specific jargon
- Foreign words
- Rare(-ish) morphological derivations
- Nonce words
- Nonstandard orthography
- Typos and other errors

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• <u>RareWords</u> similarity task: morphologically-complex, mostly unseen words



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- UD is annotated for POS and morphosyntactic attributes
  - Eng: his **stated** goals
- Tense=Past|VerbForm=Part
- Cze: osoby v **pokročilém** věku people of **advanced** age
- $\label{eq:animacy} Animacy = Inan | Case = Loc | Degree = Pos | Gender = Masc | Negative = Pos | Number = Sing | Number = Si$

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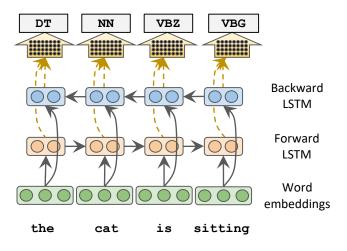
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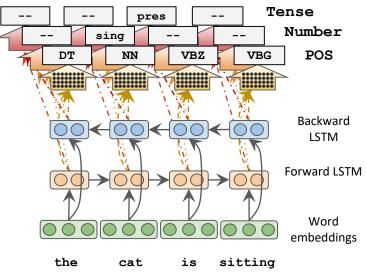
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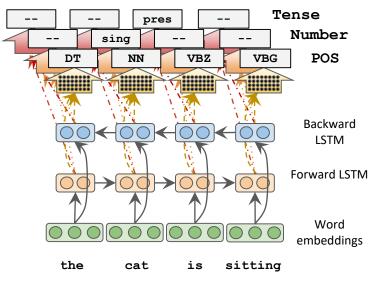
Animacy=Inan|Case=Loc|Degree=Pos|Gender=Masc|Negative=Pos|Number=Sing

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- Negative effect on POS

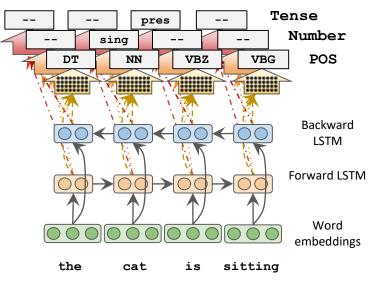
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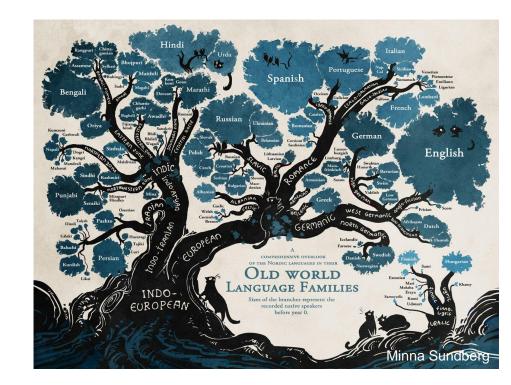
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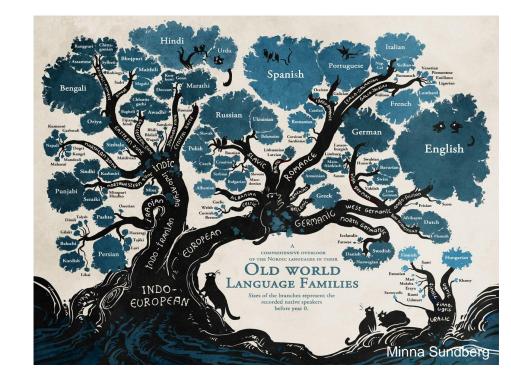
- Cze: osoby v **pokročilém** věku people of **advanced** age
- POS model from Ling et al. (2015)
- Attributes same as POS layer
- Negative effect on POS
- Attribute evaluation metric
  - Micro F1



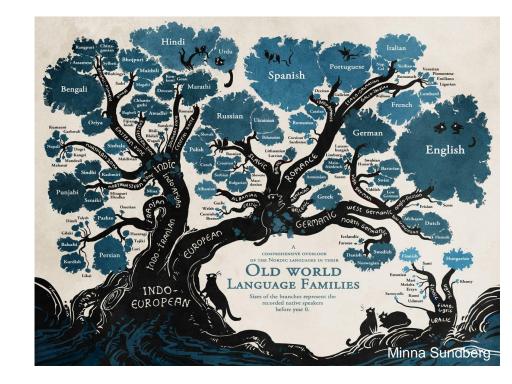
Animacy=Inan|Case=Loc|Degree=Pos|Gender=Masc|Negative=Pos|Number=Sing



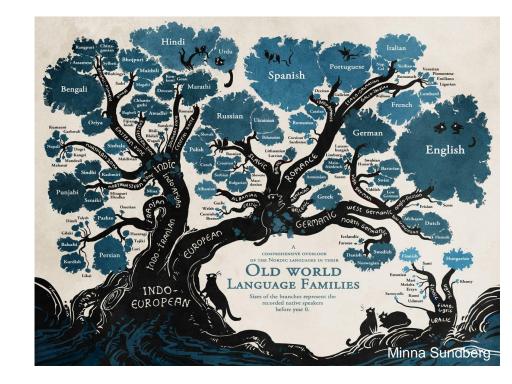
•  $|UD \cap Polyglot| = 44$ , we took 23



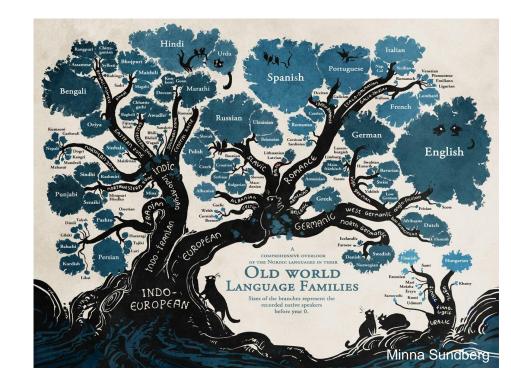
- $|UD \cap Polyglot| = 44$ , we took 23
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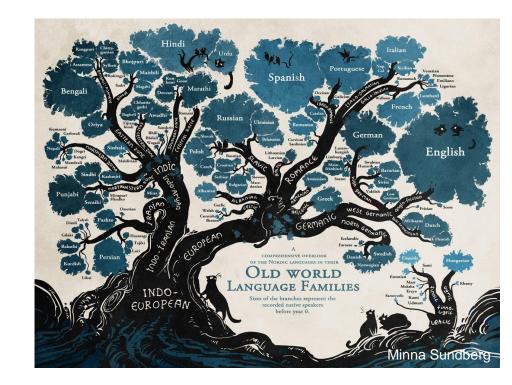
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  - $\circ$  12 fusional



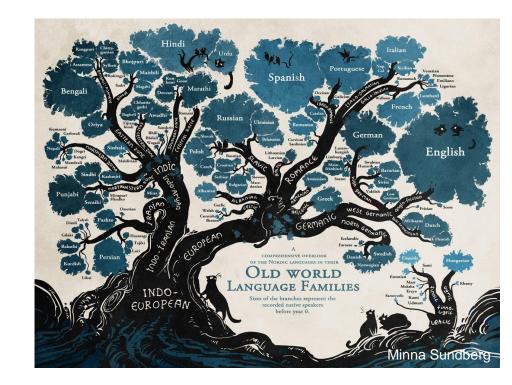
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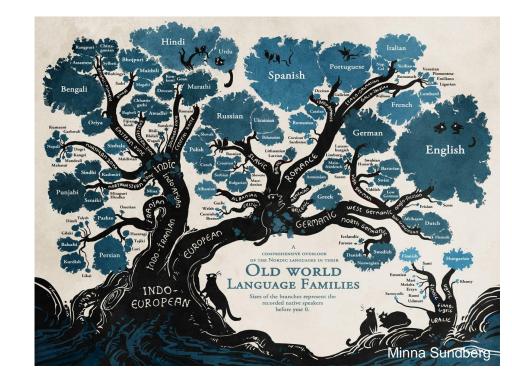
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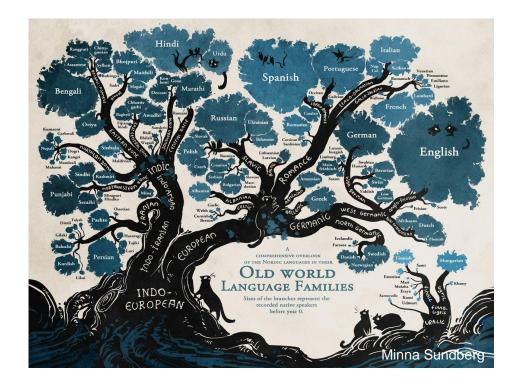
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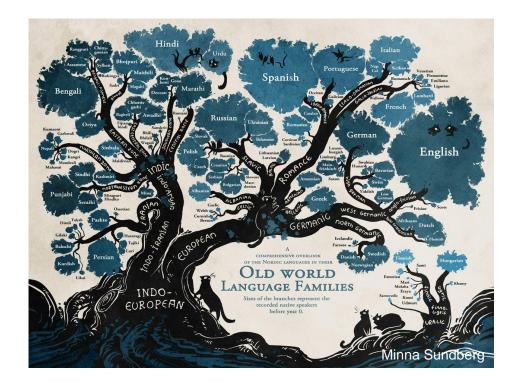
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- Geneological diversity



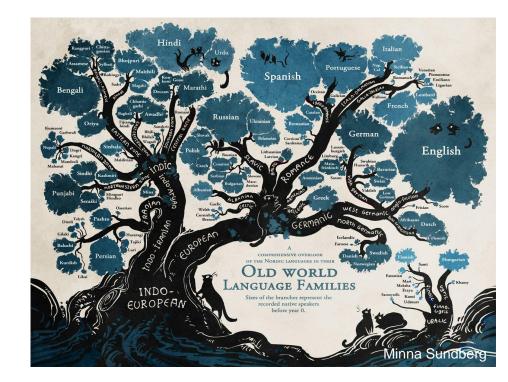
- $|UD \cap Polyglot| = 44$ , we took 23
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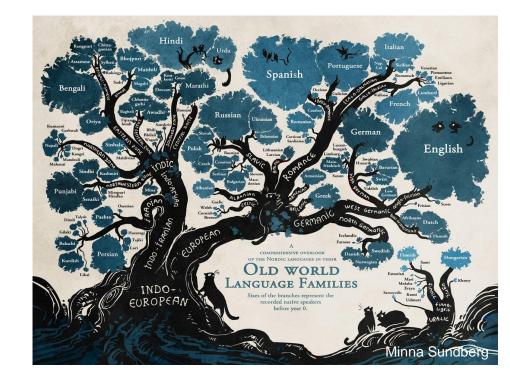
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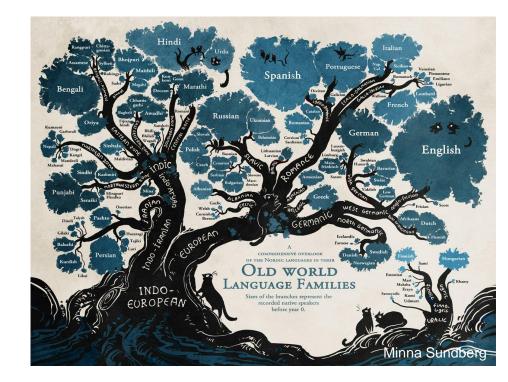
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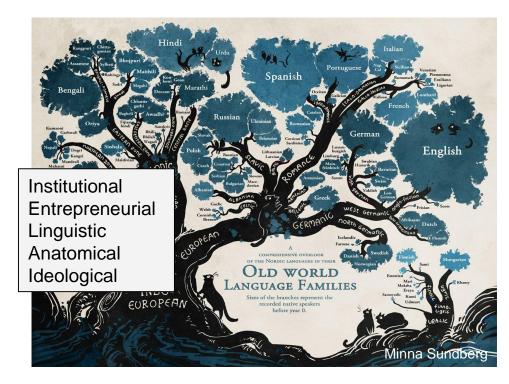
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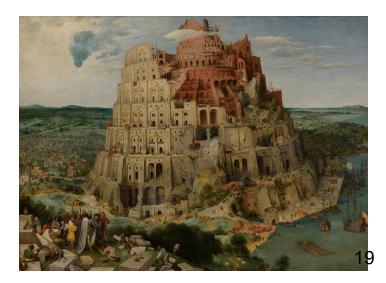
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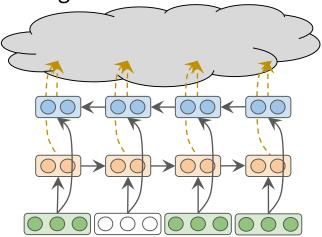
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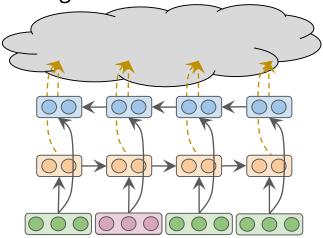


• NONE: Polyglot's default UNK embedding



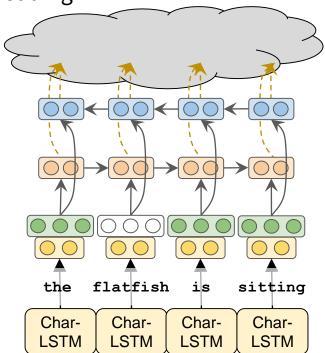
the flatfish is sitting

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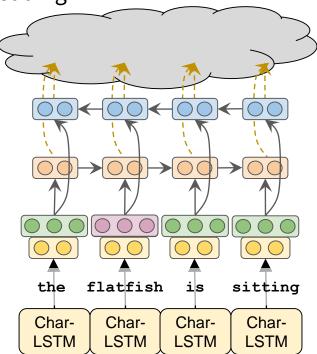


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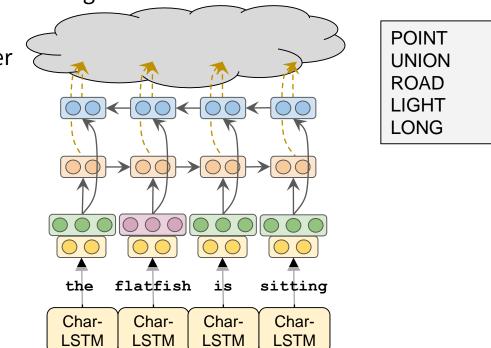
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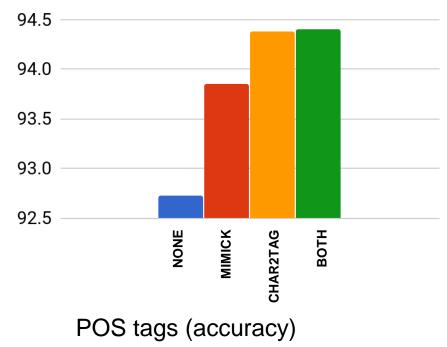


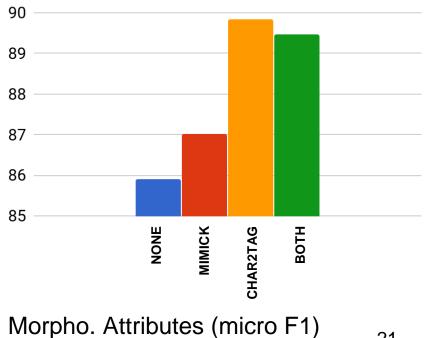
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## **Results - Full Data**

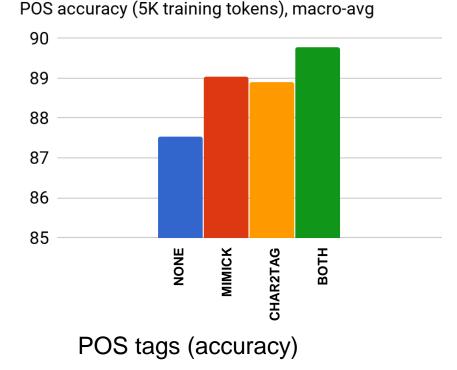
#### POS accuracy (Full data), macro-avg

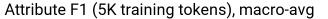


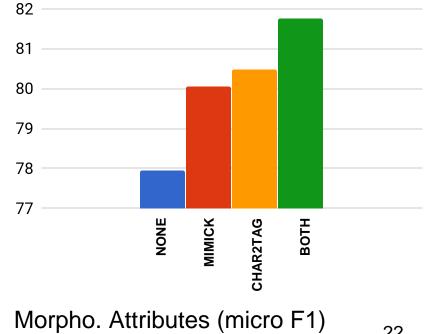


#### Attribute F1 (full data), macro-avg

## **Results - 5,000 training tokens**



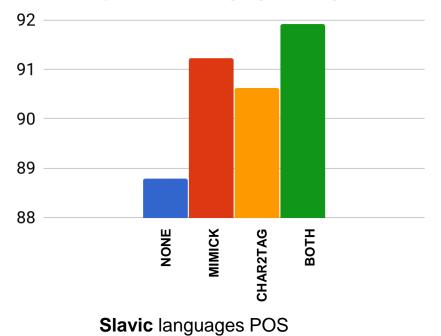




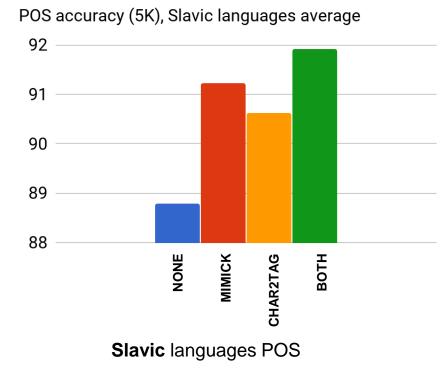
22

# Results - Language Types (5,000 tokens)

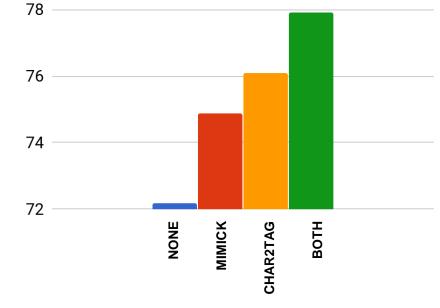
#### POS accuracy (5K), Slavic languages average



# Results - Language Types (5,000 tokens)



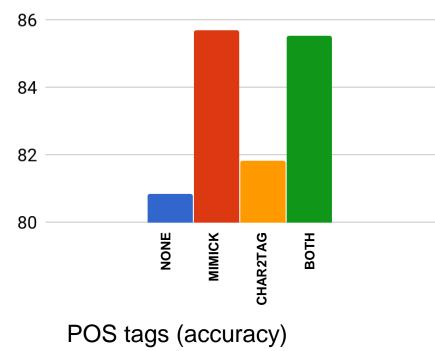
Attribute F1 (5K), agglutinative languages average



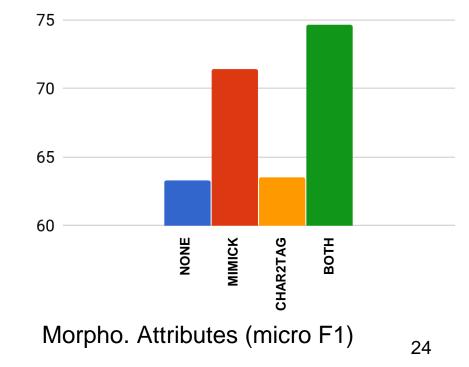
**Agglutinative** languages morpho. attribute F1

## **Results - Chinese**

#### POS accuracy (5K training tokens), Chinese



#### Attribute F1 (5K training tokens), Chinese



Code & models:

https://github.com/yuvalpinter/Mimick

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# Questions?

Neglect Satisfaction Illness Espionage Bullying

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