Match the Script, Adapt if Multilingual: Analyzing the Effect of Multilingual Pretraining on Cross-lingual Transferability

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Introduction

- Situation: Traveling in a country where NLP resources are scarce.
- Pretrained multilingual language models are applicable to wide variety of languages under zero-shot transfer setting.

- What happens to languages unseen during pretraining?

Motivation

- Issues with multilingual pretraining for language models
  - Curse of multilinguality (Conneau et al., 2020)
  - Negative interference (Wang et al., 2020)

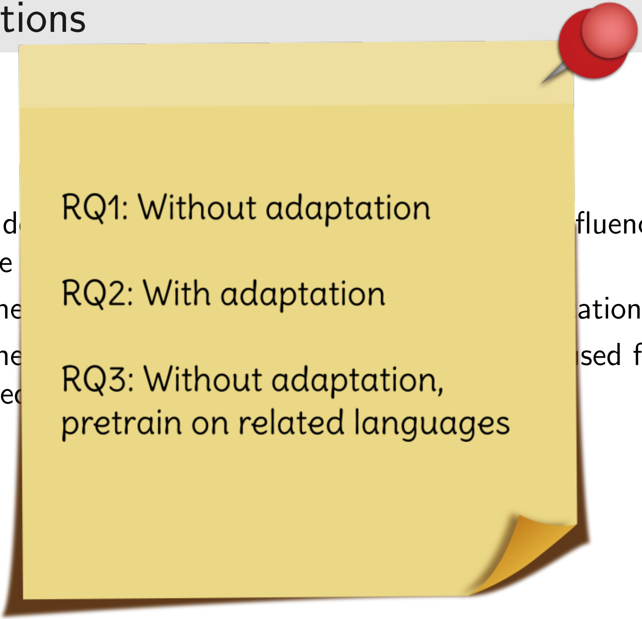
- Are the above phenomenon also an issue for languages unseen during pretraining?
- What happens if we adapt multilingual models to target languages?

Research Questions

- RQ1: How does the number of pretraining languages influence zero-shot performance on unseen target languages?
- RQ2: Do the findings of RQ1 change with model adaptation?
- RQ3: Do the findings of RQ1 change if the languages used for pretraining are all related?

Research Questions

- RQ1: How d fluence zero-shot performance
- RQ2: Do the ation?
- RQ3: Do the sed for pretraining are all relatec



Experiment Setup: Pretraining Languages

- Diverse set of languages (Div-X): up to ten languages from diverse language families for RQ1 and RQ2
- Related set of languages (Rel-X): up to five Germanic Languages for RQ3

Div-2	EN, RU
Div-3	EN, RU, ZH
Div-4	EN, RU, ZH, AR
Div-5	EN, RU, ZH, AR, HI
Div-6	EN, RU, ZH, AR, HI, ES
Div-7	EN, RU, ZH, AR, HI, ES, EL
Div-8	EN, RU, ZH, AR, HI, ES, EL, FI
Div-9	EN, RU, ZH, AR, HI, ES, EL, FI, ID
Div-10	EN, RU, ZH, AR, HI, ES, EL, FI, ID, TR

Rel-2	EN, DE
Rel-3	EN, DE, SV
Rel-4	EN, DE, SV, NL
Rel-5	EN, DE, SV, NL, DA

Experiment Setup: Model, Data and Tasks

- Transformer with the same architecture and vocabulary as XLM-R base
- Pretraining Corpus: CoNLL 2017 Wikipedia dump (Ginter et al., 2017)
  - Downsampled to $\approx$ 200MB (to the smallest pretraining language)
- Task Dataset: XTREME (Hu et al., 2020)

For RQ2 (with model adaptation):

- Continued pretraining with Masked Language Modeling (Ebrahimi and Kann, 2021).
- Adaptation Corpus: JHU Bible Corpus (McCarthy et al., 2020)

RQ1: Results Without Model Adaptation

- Cross-lingual zero-shot accuracy on using diverse set of pretraining languages
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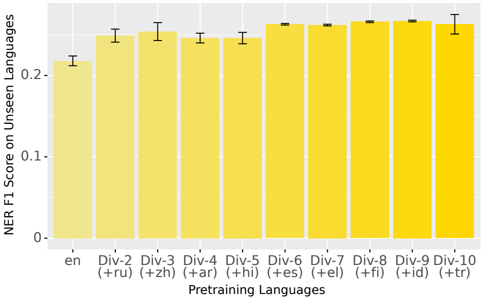
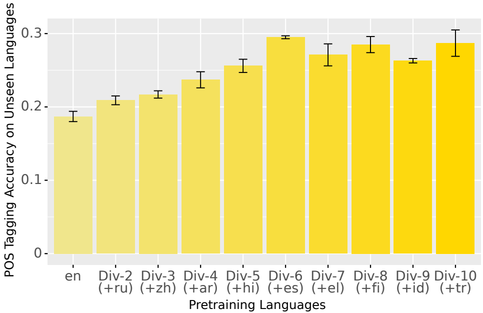


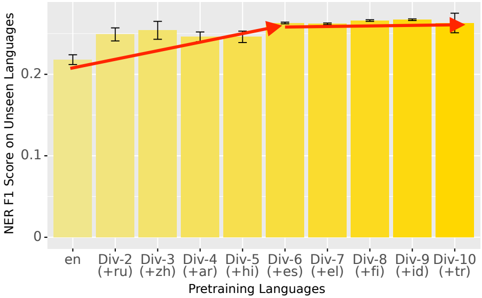
NER Results



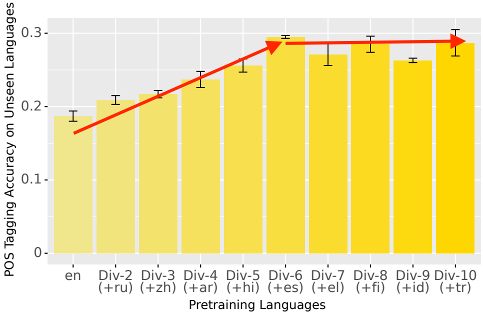
POS Tagging Results

RQ1: Results Without Model Adaptation

- Cross-lingual zero-shot accuracy on using diverse set of pretraining languages
- Average cross-lingual zero-shot accuracy increases up to a certain point



NER Results



POS Tagging Results

RQ1: Results Without Model Adaptation on Each Language

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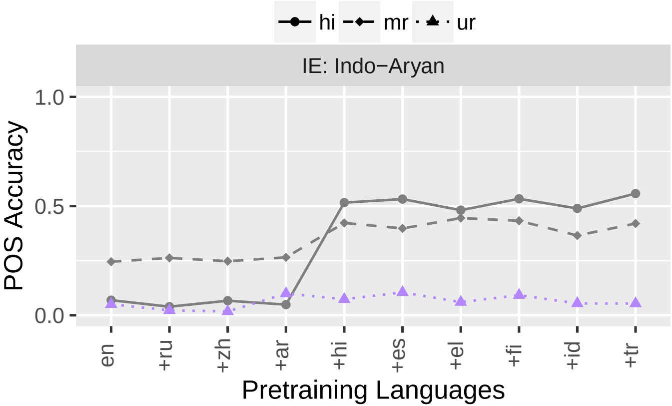

RQ1: Results Without Model Adaptation on Each Language

- Large increase if adding a pretraining language from the same language
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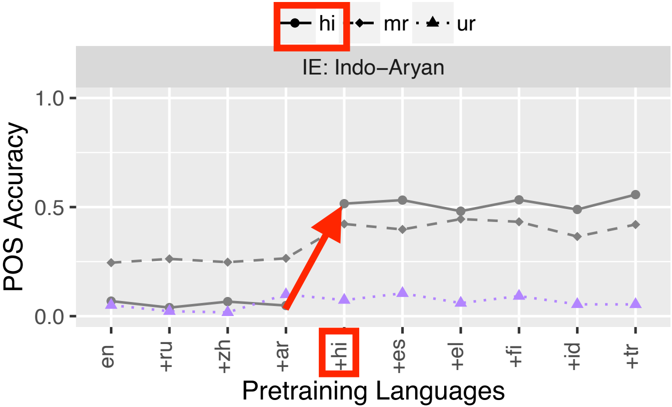
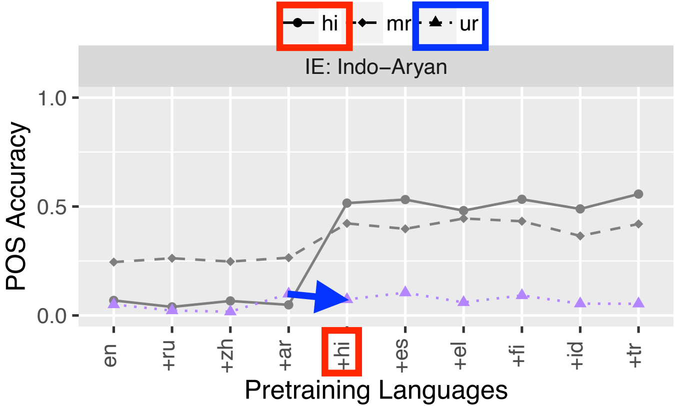


RQ1: Results Without Model Adaptation on Each Language

- Large increase if adding a pretraining language from the same language
- But no significant gain e.g., in Urdu after adding Hindi



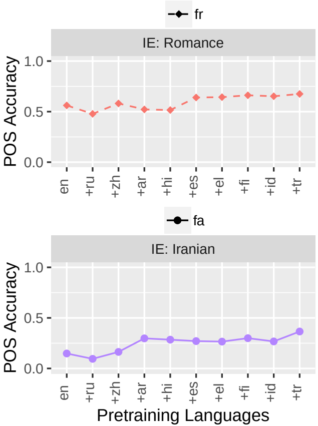
RQ1: Results Without Model Adaptation: Regression Analysis

- Predict the POS tagging accuracy Y using X which are the features of pretraining and target languages
  - Same or different script / family
  - Syntax and phonology features are from URIEL (Littell et al., 2017)
- Script match between pretraining and target languages is the most important one

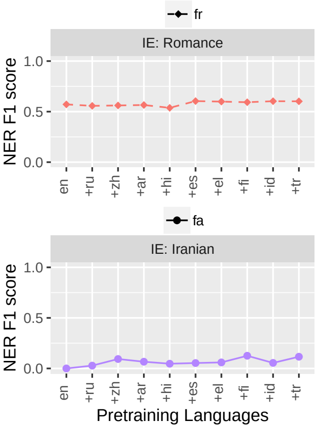
Features	**Coef.**	**p-value**	**CI**
Script	**.061**	$< .001$	[.050, .073]
Family	.022	$.004$	[.007, .036]
Syntax	.001	$.905$	[-.016, .018]
Phonology	.021	$< .001$	[.009, .033]
# pretrain langs	.011	$.044$	[.000, .022]

RQ2: Results With Model Adaptation

- Trend 1: More languages are better (French and Farsi)



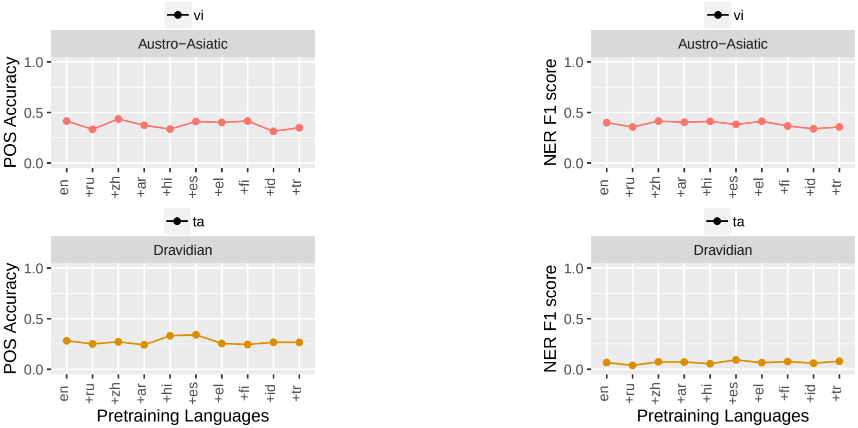
POS Tagging Results



NER Results

RQ2: Results With Model Adaptation

- Trend 2: More languages does not necessarily improve (Vietnamese and Tamil)

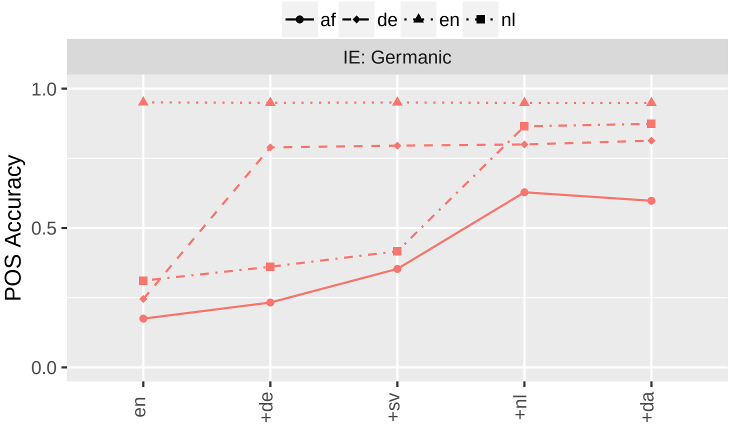


POS Tagging Results

NER Results

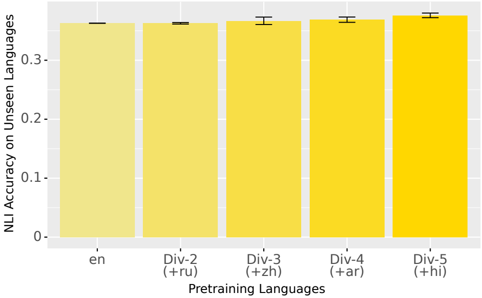
RQ3: Results w/o Adaptation, Pretrain on Related Languages

- Within the same language family: Better cross-lingual transfer
- Limited cross-lingual transfer across language families (please see the paper for details)

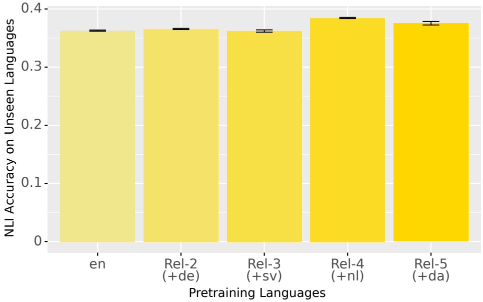


NLI Results

- Trend is less clear on NLI results
- Reason: NLI requires larger pretraining corpus (Lauscher et al., 2020)



Pretrained on Diverse Languages



Pretrained on Germanic Languages

Limitations in the Previous Experiments

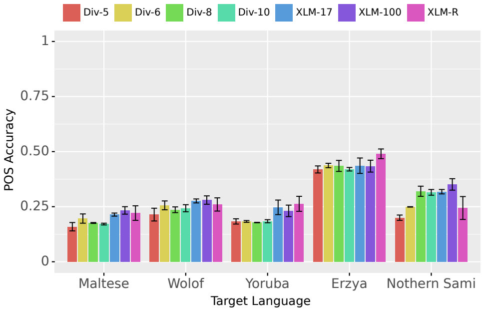
- Small scale due to pretraining being computationally intensive
  - Downsampled corpus per pretraining language ($\sim$200MB)
  - Up to 10 languages
- Using XLM-R base vocabulary are not truely unseen for the target languages

Scaling up to 100+ Languages

- Use more pretrained models in addition to the pretrained language models up to 10 languages
  - XLM-17 (Lample and Conneau, 2019)
    - 17 languages, pretrained on full Wikipedia
  - XLM-100 (Lample and Conneau, 2019)
    - 100 languages, pretrained on full Wikipedia
  - XLM-R base (Conneau et al., 2020)
    - 100 languages, pretrained on Common Crawl
- Target languages unseen when building vocabulary for XLM-17, XLM-100, or XLM-R
  - Maltese, Wolof, Yoruba, Erzya, and Northern Sami

Results up to 100 Languages

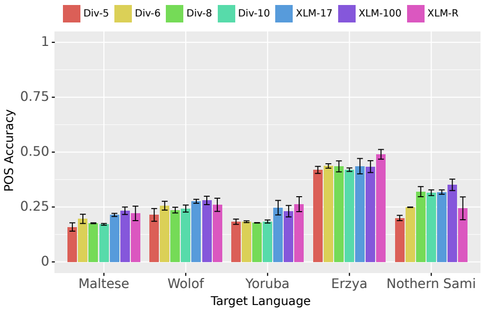
- More languages does not necessarily improve if not adapting



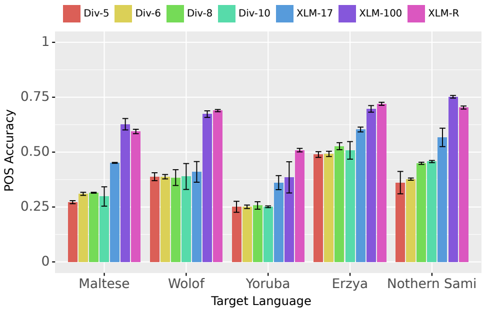
Before Adaptation

Results up to 100 Languages

- More languages does not necessarily improve if not adapting
- More languages the better when adapted



Before Adaptation



After Adaptation

Conclusion and Future Work

If pretraining a new multilingual model and applying to unseen languages:

- If not adapting, small set of diverse pretraining languages is likely sufficient
  - Match the script and family
- If adapting, at least train on 100 languages or possibly more

Future Work:

- Different vocabulary (Muller et al., 2021; Mielke et al., 2021)
- Recent models e.g., mT5 (Xue et al., 2021)
- Beyond simple NLP tasks (e.g., generation tasks)

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