L-Università ta' Malta

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Cross-lingual transfer learning with Persian

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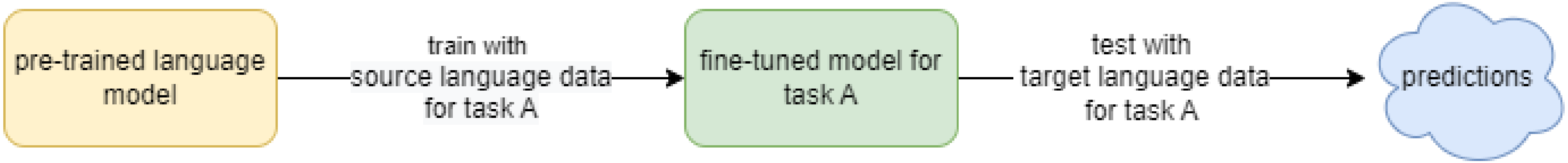
1. Introduction

Transfer Learning

- Source and target language
- English as source, why?
- Language similarity, POS tagging
- Persian can be beneficial?


pre-trained language model
train with source language data for task A
fine-tuned model for task A
test with target language data for task A
predictions

Persian

- Country, Dialect:
  - Iran, Iranian Persian (Officially Persian)
  - Afghanistan, Dari
  - Tajikistan, Tajik
- Indo-European
- Persian alphabet (32 letters)
- SOV word order
- More than 85 million people

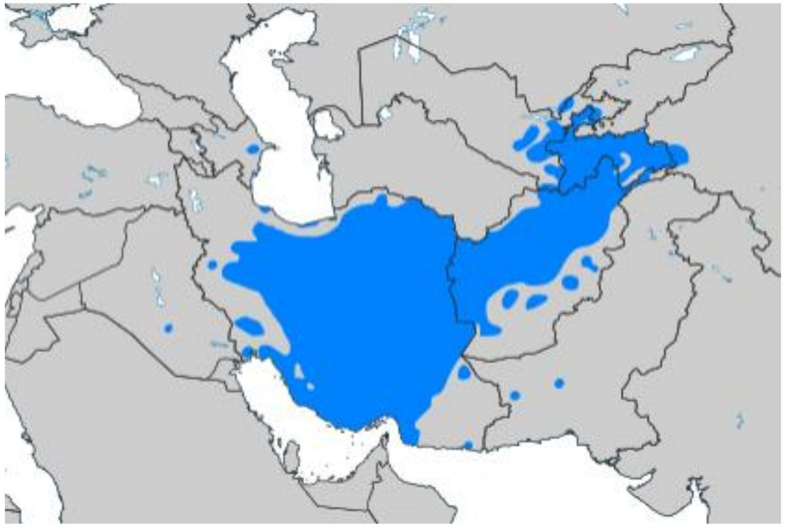


Fig2: regions where people's mother tongue is Persian (Commons, 2021b)

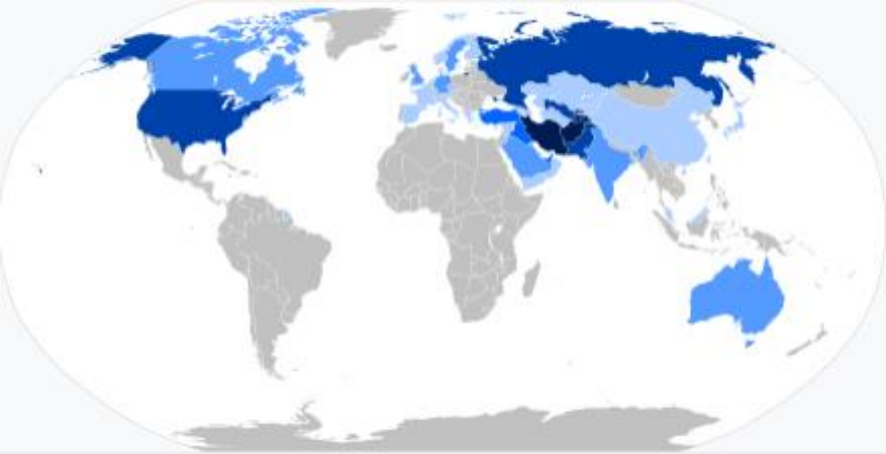


Fig3: Persian speakers around the world (Commons, 2021a)

Research questions

- Language similarity and Persian for POS tagging
- Linguistic features of the matching languages
- Performance of ParsBERT and XLM-RoBERTa
- Matching languages with Persian for Sentiment analysis

2. Background

Language Similarity

- LDND distance measure (Wichmann et al. , 2010)
- Levenshtein distance (LD)
  - minimum number of times needed to add, delete, or substitute a character
- normalized LD (LDN)
  - dividing LD by the maximum length
  - Omit the influence of long words transformed into short words (high LD)
- LDND
  - Dividing the LDN value by the mean of all LDN values between each two words

Language similarity and transfer learning

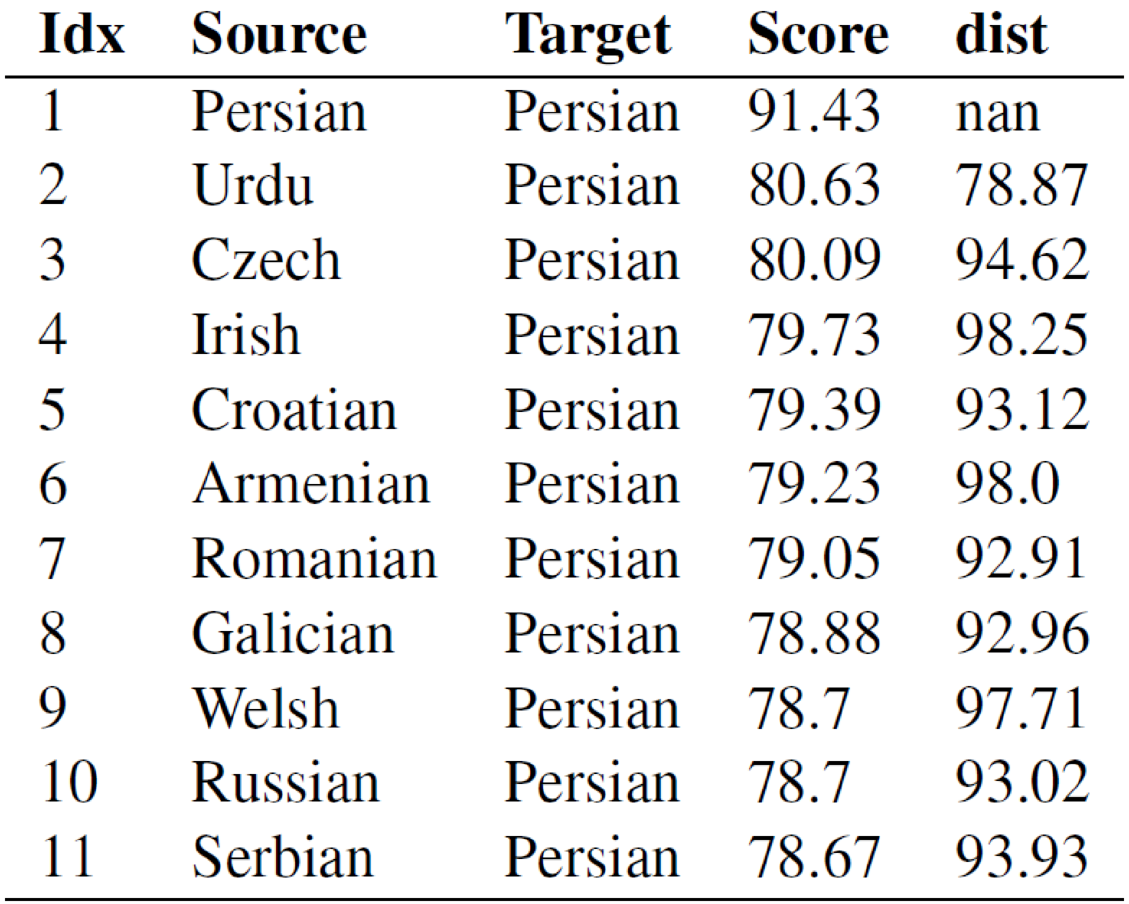
- de Vries et al. (2022)
  - POS tagging task
  - Search for good pairs and success factors
  - pre-trained multilingual language model XLM-RoBERTa (Conneau et al., 2019)
  - No global source languages
  - Success factors:
    - target in pre-training
    - LDND distance

3. POS tagging

POS tagging analysis

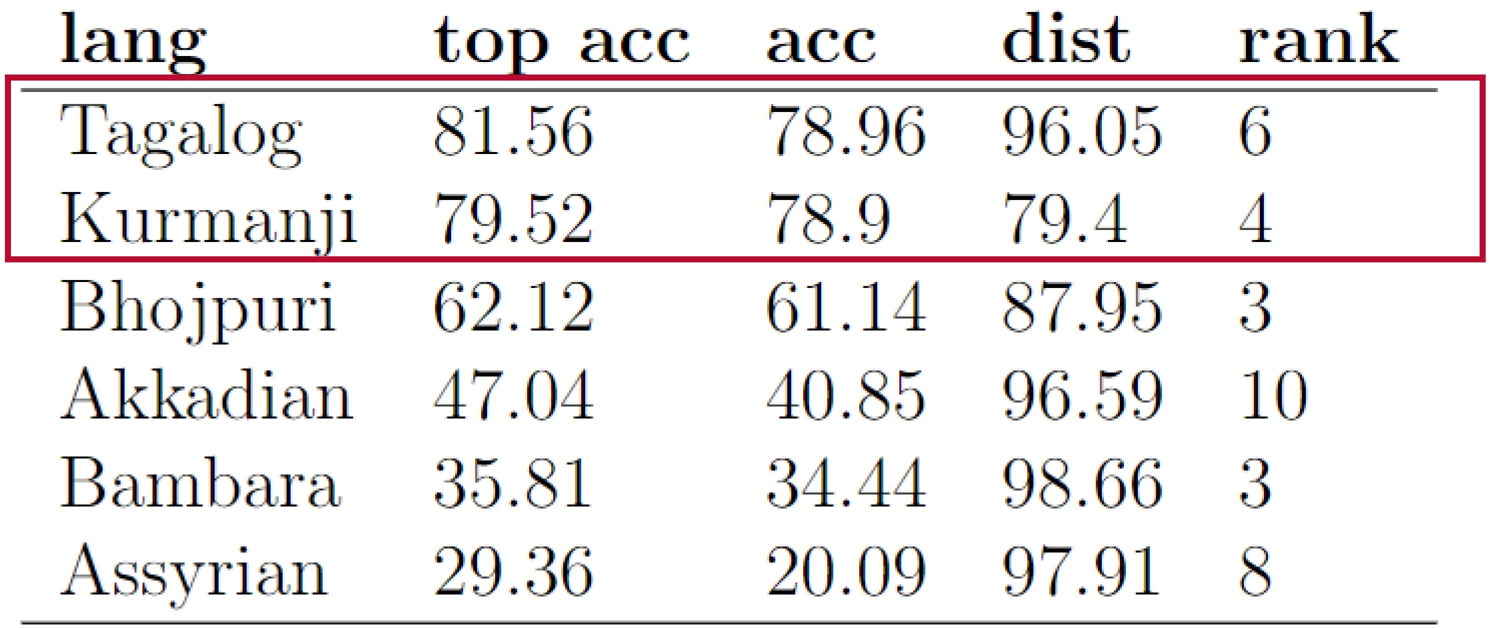
- UD dataset, 17 tags
- 65 source and 105 target
- Pre-trained (CommonCrawl data) XLM-RoBERTa language model
- Fine-tune and test with source-target combinations
- Accuracy score
- LDND distance

Persian as target



Idx	Source	Target	Score	dist
1	Persian	Persian	91.43	nan
2	Urdu	Persian	80.63	78.87
3	Czech	Persian	80.09	94.62
4	Irish	Persian	79.73	98.25
5	Croatian	Persian	79.39	93.12
6	Armenian	Persian	79.23	98.0
7	Romanian	Persian	79.05	92.91
8	Galician	Persian	78.88	92.96
9	Welsh	Persian	78.7	97.71
10	Russian	Persian	78.7	93.02
11	Serbian	Persian	78.67	93.93

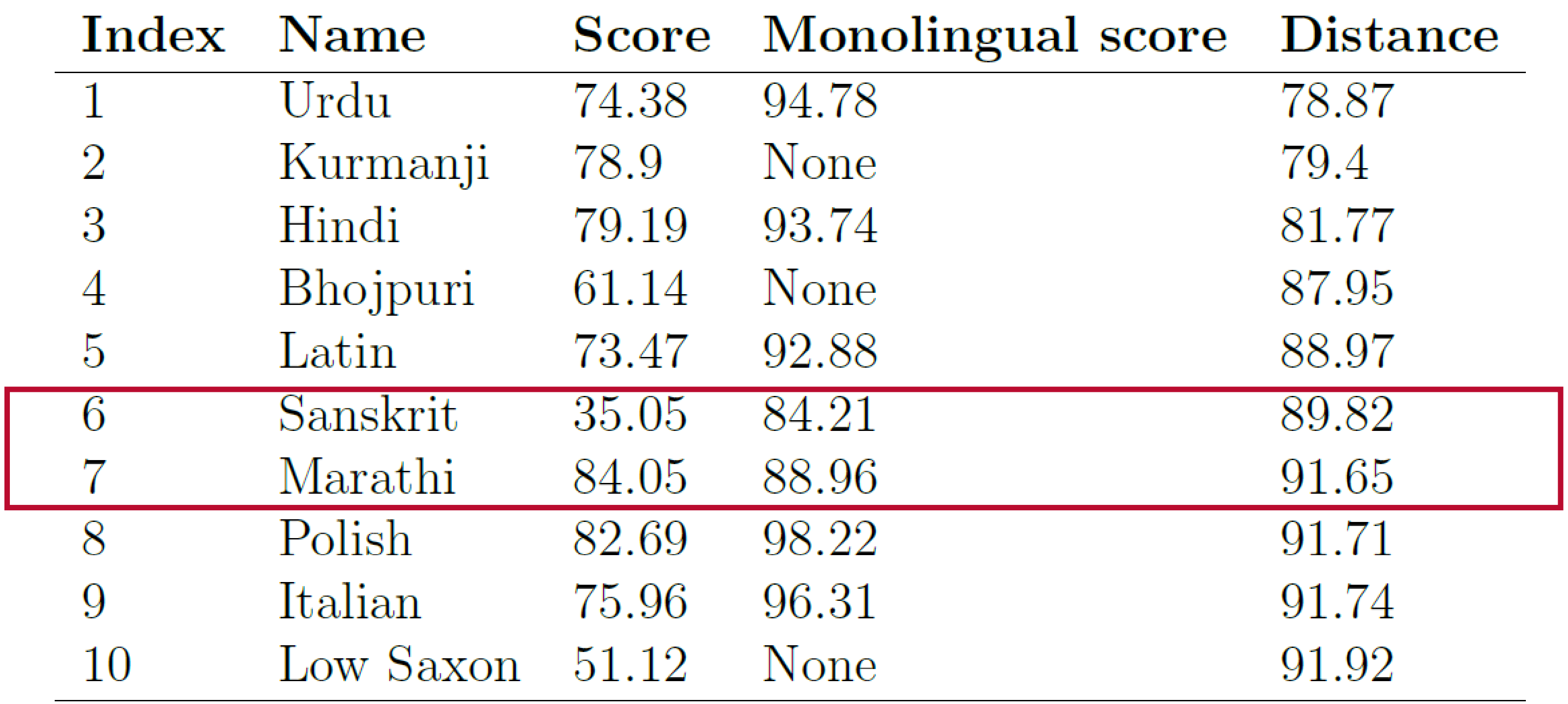
Persian source, low-resource target



lang	top acc	acc	dist	rank
Tagalog	81.56	78.96	96.05	6
Kurmanji	79.52	78.9	79.4	4
Bhojpuri	62.12	61.14	87.95	3
Akkadian	47.04	40.85	96.59	10
Bambara	35.81	34.44	98.66	3
Assyrian	29.36	20.09	97.91	8

Lowest dist among others

LDND distance with Persian

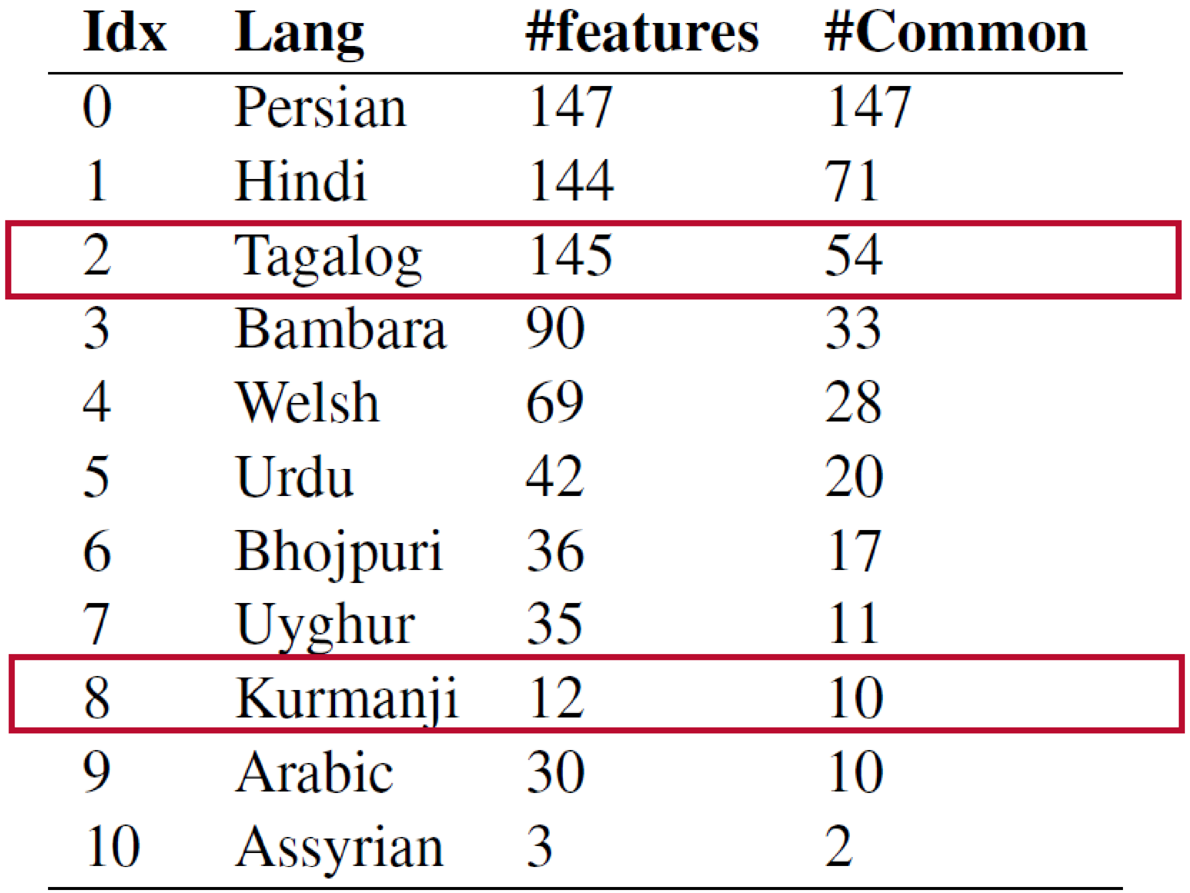


Index	Name	Score	Monolingual score	Distance
1	Urdu	74.38	94.78	78.87
2	Kurmanji	78.9	None	79.4
3	Hindi	79.19	93.74	81.77
4	Bhojpuri	61.14	None	87.95
5	Latin	73.47	92.88	88.97
6	Sanskrit	35.05	84.21	89.82
7	Marathi	84.05	88.96	91.65
8	Polish	82.69	98.22	91.71
9	Italian	75.96	96.31	91.74
10	Low Saxon	51.12	None	91.92

LDND not a good measure

WALS linguistic features

- (Dryer & Haspelmath, 2013)
- Help to explain neural network performance
- Language similarity measure based on number of common features
- Potential ground for Tagalog high score

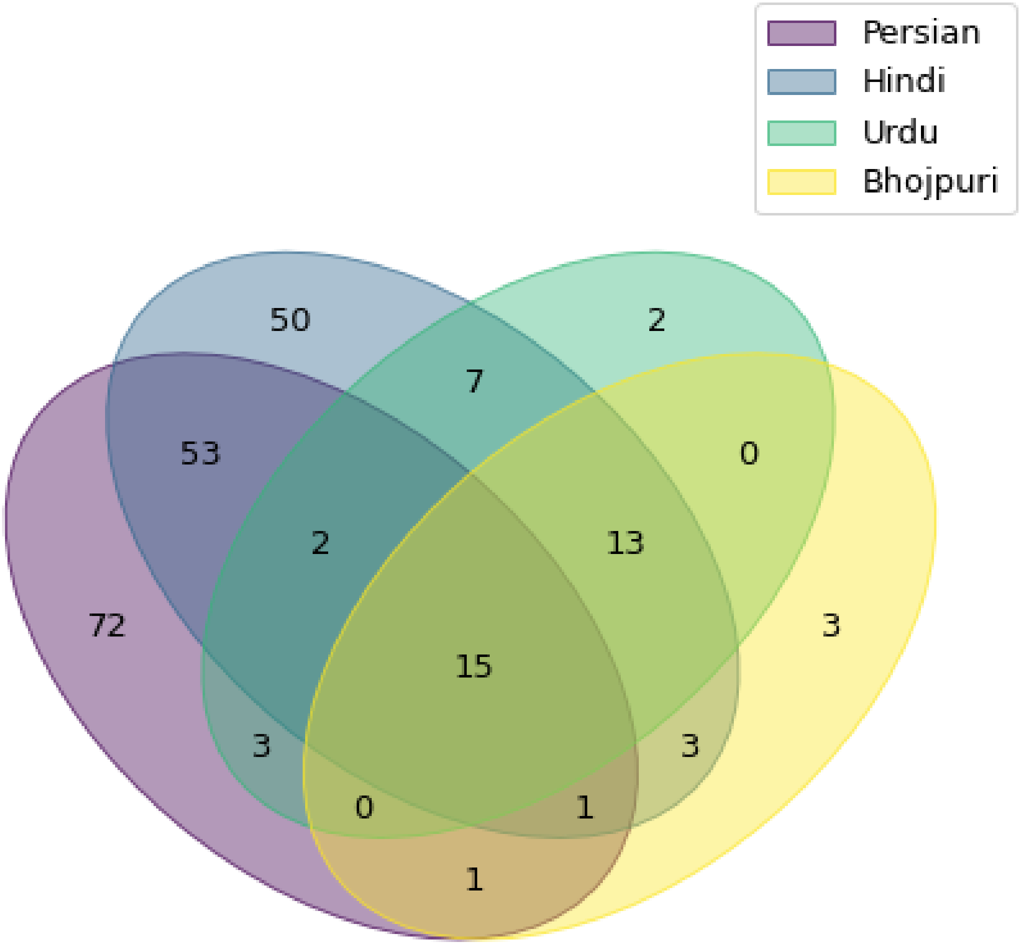


Idx	Lang	#features	#Common
0	Persian	147	147
1	Hindi	144	71
2	Tagalog	145	54
3	Bambara	90	33
4	Welsh	69	28
5	Urdu	42	20
6	Bhojpuri	36	17
7	Uyghur	35	11
8	Kurmanji	12	10
9	Arabic	30	10
10	Assyrian	3	2

WALS linguistic features

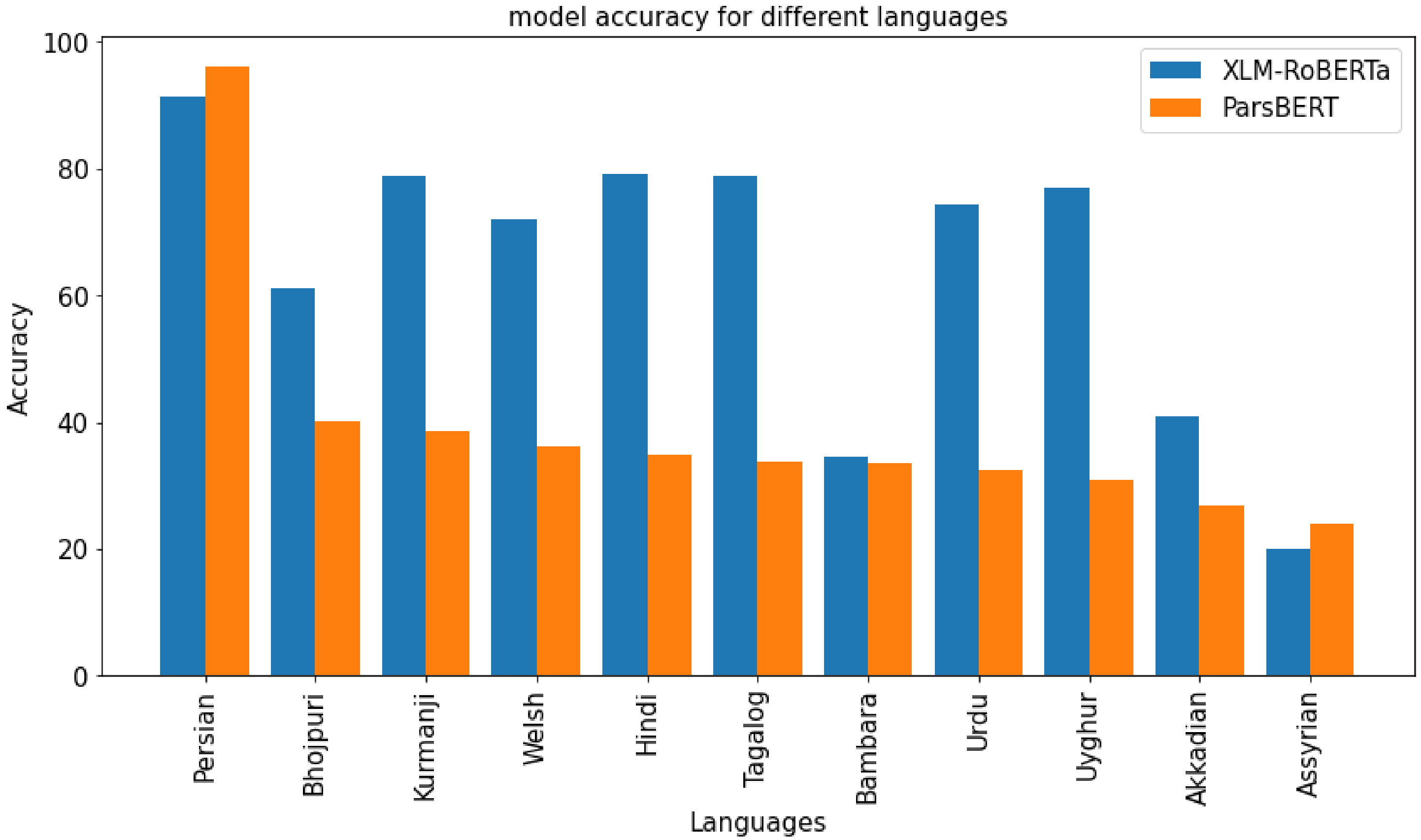
Mostly syntactic features:

- SOV
- Demonstrative-Noun
- Numeral-Noun
- initial position of Polar Question Particles



ParsBERT

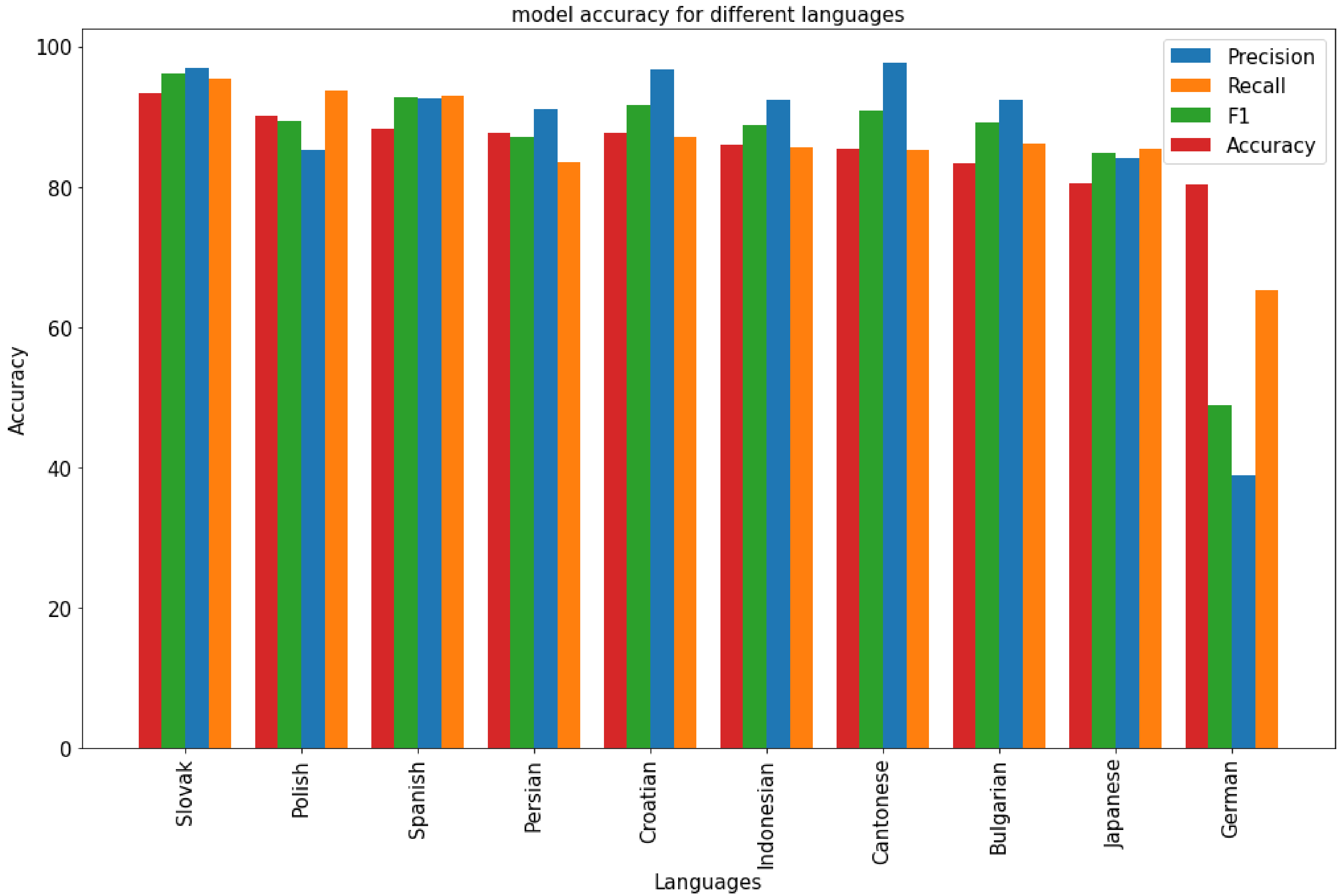
- (Farahani et al, 2021)
- Pre-trained monolingual Persian language model:
    - MLM
    - next sentence prediction
- Fine-tune with Persian
- Inference with others



4. Sentiment Analysis

Data Collection

- Binary dataset
- 23 languages from Martinez-Garcia et al. (2021):
  - Algerian, Arabic, Basque, Bulgarian, Cantonese, Chinese, Croatian, English, Finnish, German, Greek, Hebrew, Indonesian, Japanese, Korean, Maltese, Norwegian, Russian, Slovak, Spanish, Thai, Turkish, and Vietnamese
- 8 languages from various sources gathered
- Identical structure
- Public access at https://huggingface.co/sepidmnorozy


model accuracy for different languages
Accuracy
100
80
60
40
20
0
Precision
Recall
F1
Accuracy
Slovak
Polish
Spanish
Persian
Croatian
Indonesian
Cantonese
Bulgarian
Japanese
German
Languages

5. Conclusion

Conclusion

- Monolingual Persian 91.43% POS tagging! Persian best case for itself!
- Persian a potential good source for Kurmanji and Tagalog for other tasks
- ParsBERT outperforms XLM-RoBETa only for monolingual Persian 96%
- Monolingual Persian is not the best for sentiment analysis
- Task-dependent

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Thanks for your attention!

Any questions?

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