

ACL - 2022

Dataset Geography: Mapping Language Data to Language Users

Fahim Faisal, Yinkai Wang, Antonios Anastasopoulos

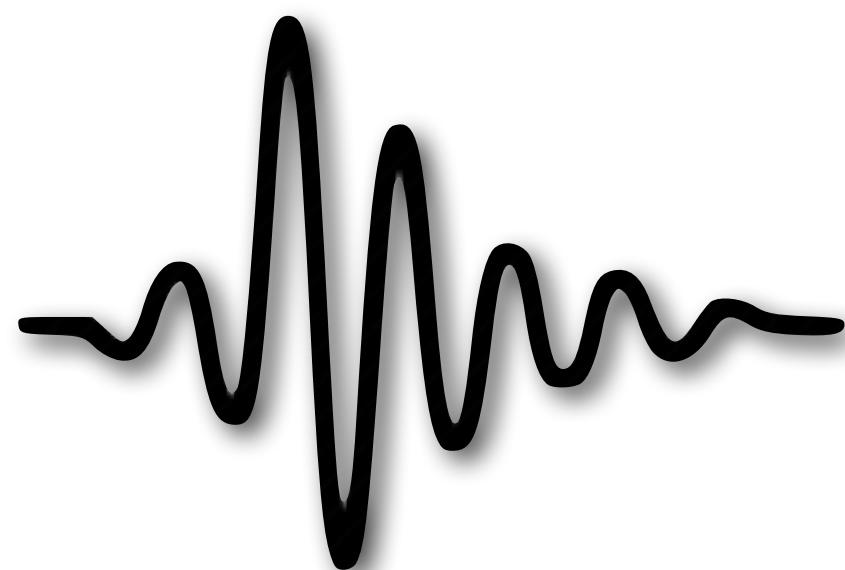
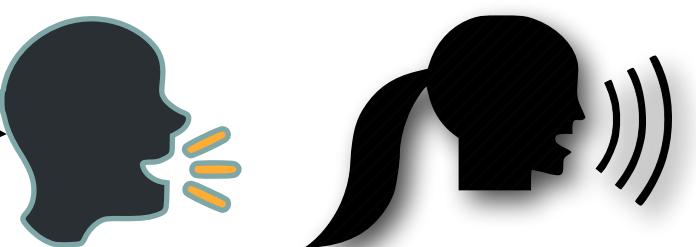
ffaisal@gmu.edu

<https://nlp.cs.gmu.edu/>

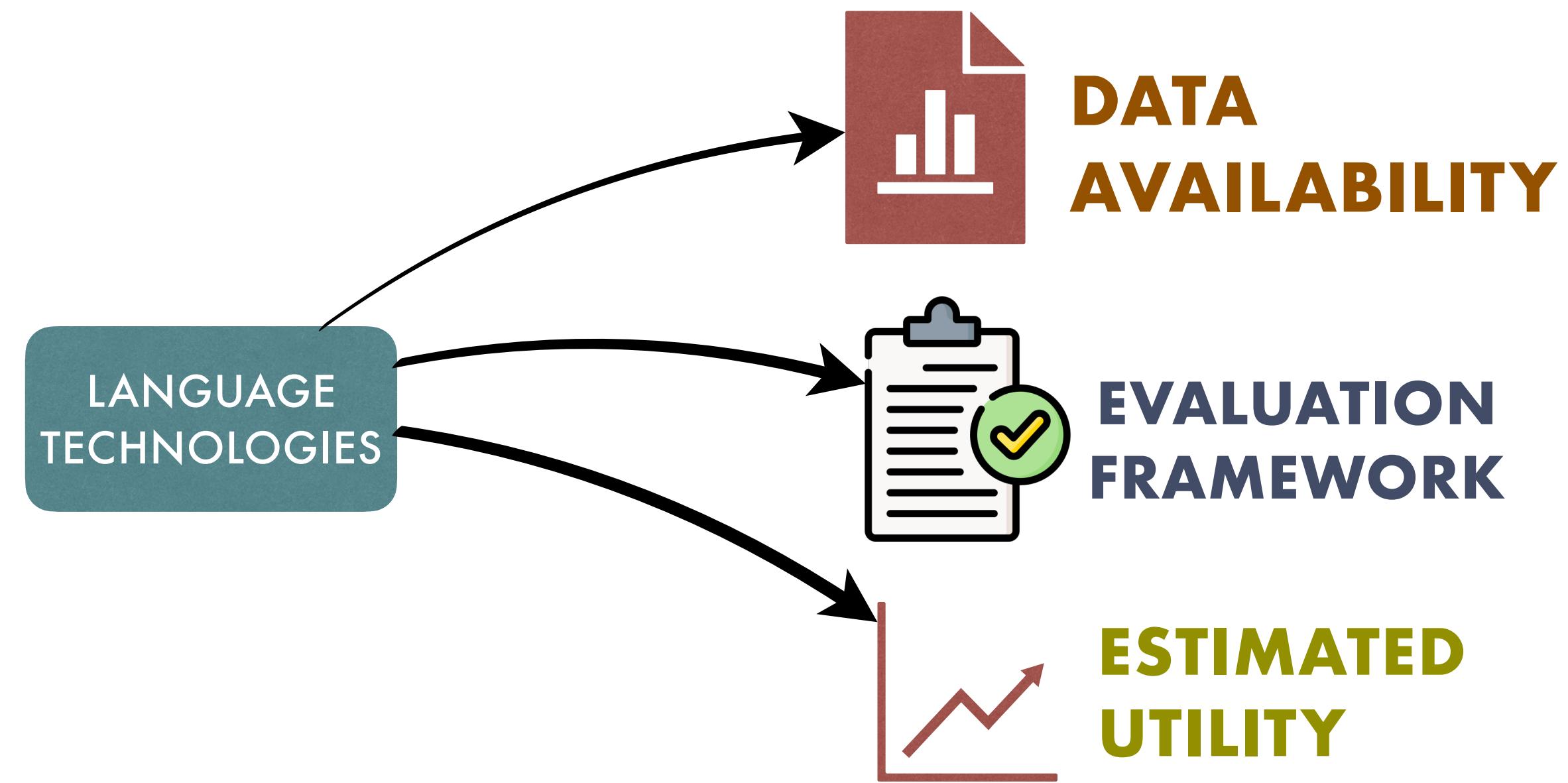




DATASET CONTENTS

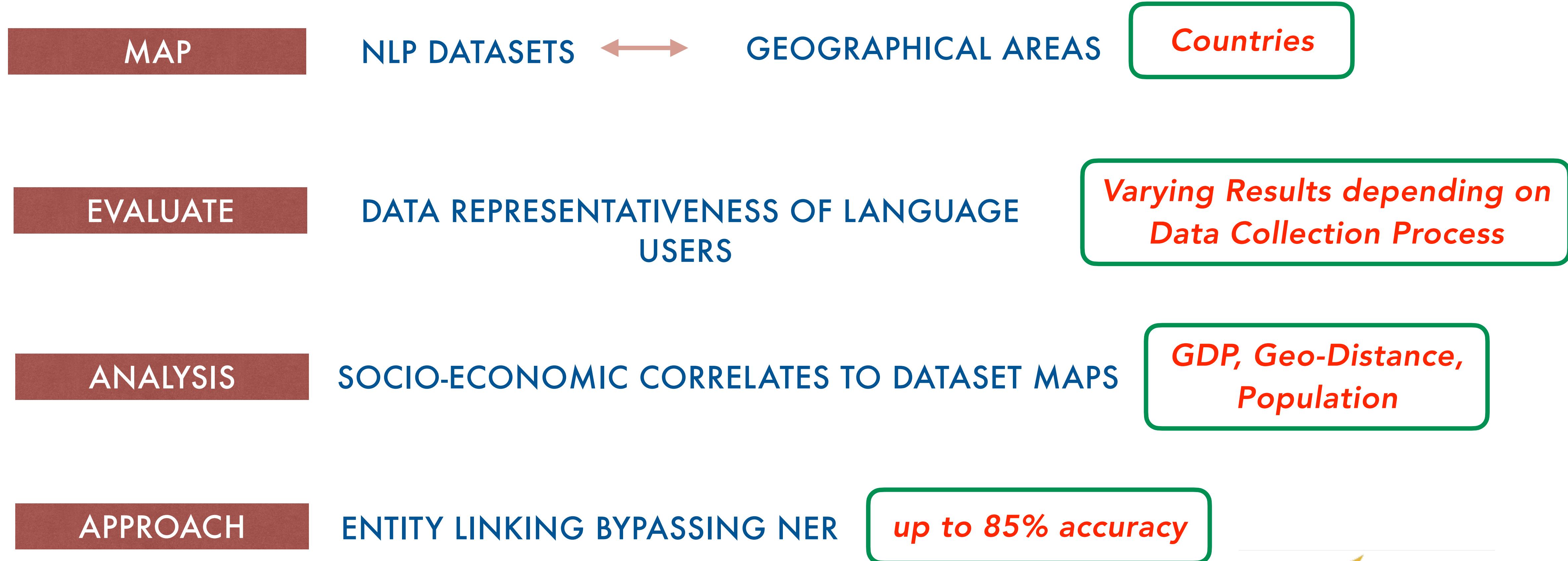


SPEAKER NEEDS



CULTURAL/GEOGRAPHICAL
REPRESENTATIVENESS

Our Contributions



Assumptions

1

Data Locality Matters

To Learn $p(L_1|text)$ (i.e. $p(L_1 = \text{Finnish}|\text{Finland})$)

Avoid Learning $p(\text{Finland}|L_1 = \text{Finnish})$

2

Capture locality by focusing on entities

English ireland irish british britain russia scotland england states american london brexit

Finnish finland finnish finns helsinki swedish finn nordic sweden sauna nokia estonian

French french france paris sarkozy macron fillon holland gaulle hamon marine valls breton

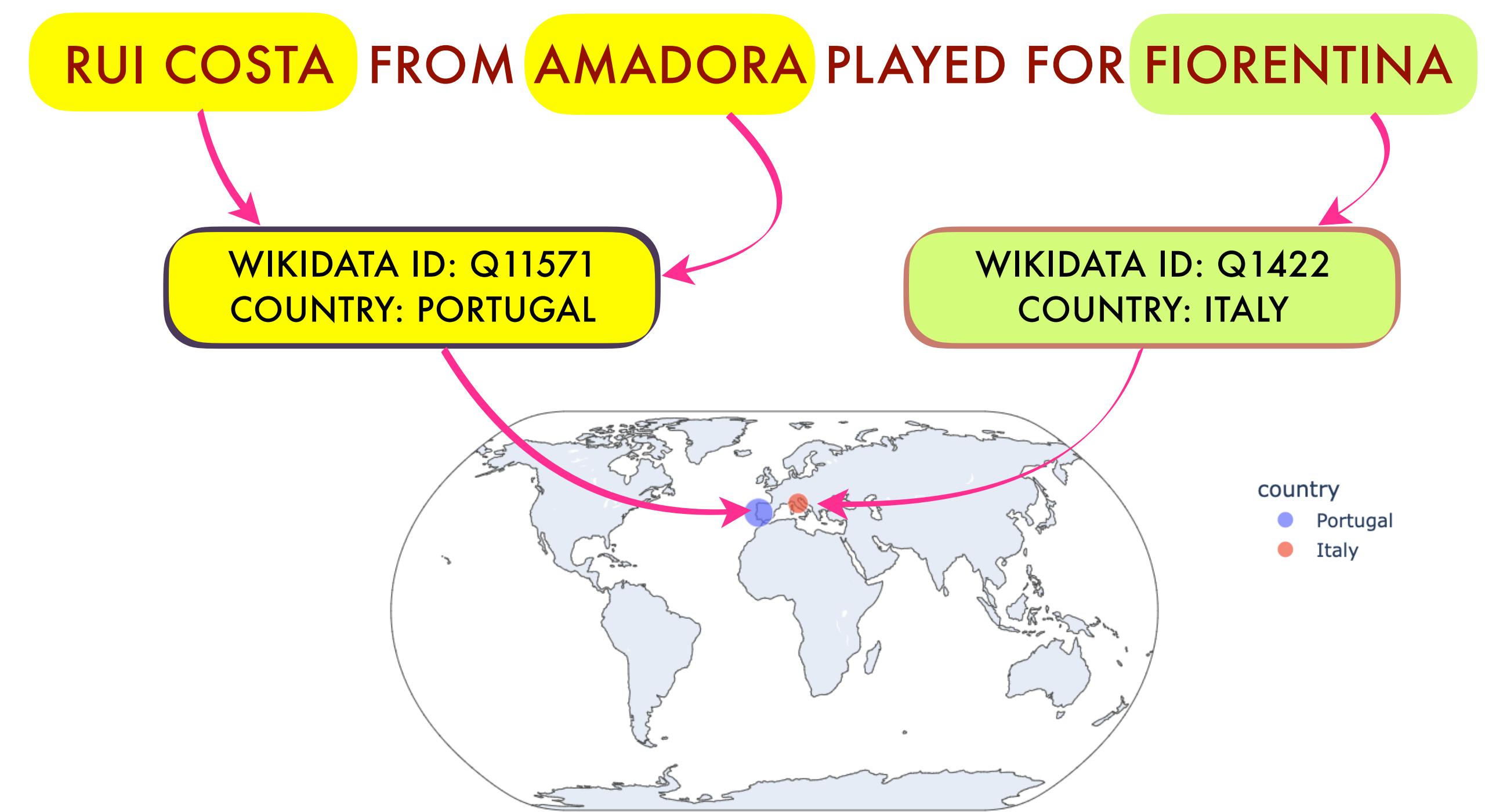
Top words based on log-odds scores for each label in the L2-Reddit dataset.

(Kumar et al. 2019)

Proposed Approach

For a given dataset

- Identify named entities
- Link entities to wikidata
- Aggregate through dataset
 - Representativeness measure
 - Fairness measure
 - Visualization



Proposed Approach

Mapping Dataset to countries

- Entity recognition-linking pipeline
- mGENRE (Cao et al. 2021): multilingual, seq2seq, auto-regressive entity linker
- Links to wikidata IDs

NER-INFORMED:

NER: [S]Rui Costa[E] from [S]AMADORA[E] played for [S]FIORENTINA[E]

NE-Link: {Rui Costa} from {AMADORA} played for {FIORENTINA}

- Bypassing NER Step to perform recognition & linking altogether

NER-RELAXED

[S]Rui Costa from AMADORA played for FIORENTINA[E]

→ {Rui, score:-1}, {Costa, score:-1}, {Rui Costa,score:2}, {AMADORA,score:3}, {FIORENTINA,score:4}

Proposed Approach

Representativeness measures from Dataset-Country Maps

Entity percentage in Language speaking countries

country [SPANISH] = {ARG, CHL, PRY, URY}

entity [SPANISH] = $(50+40+10+0)/\text{total} = 0.67$

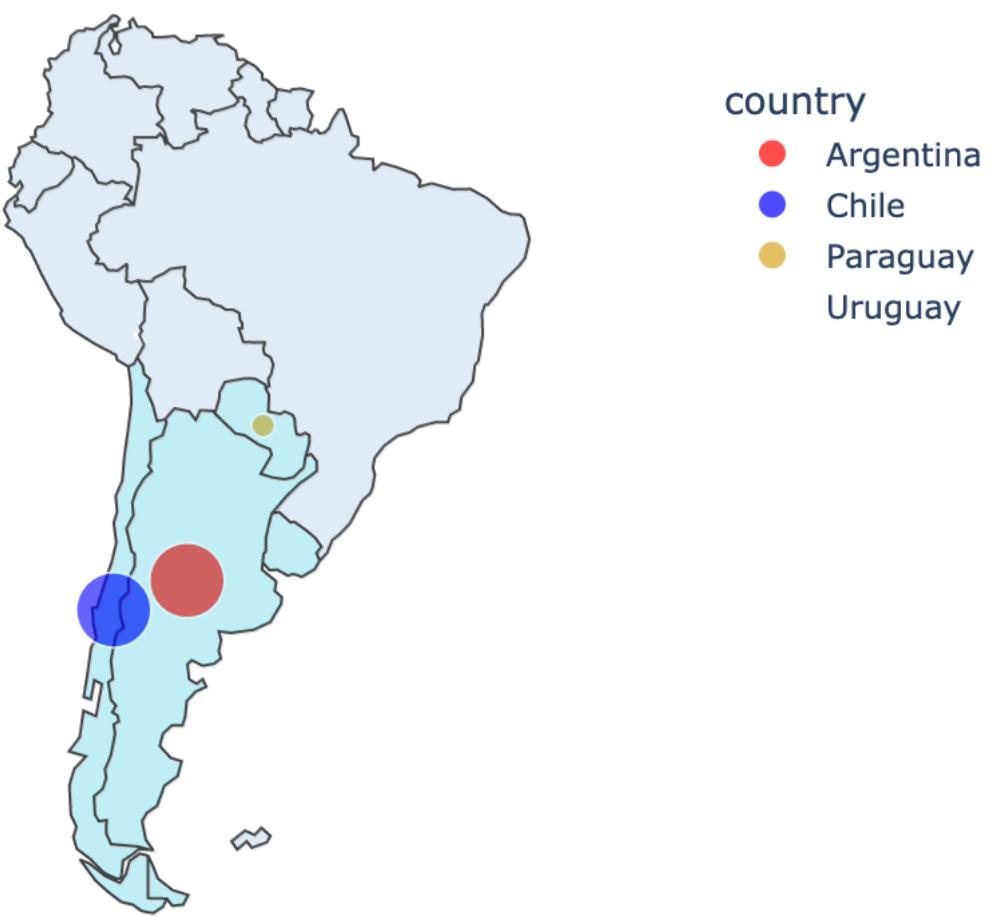
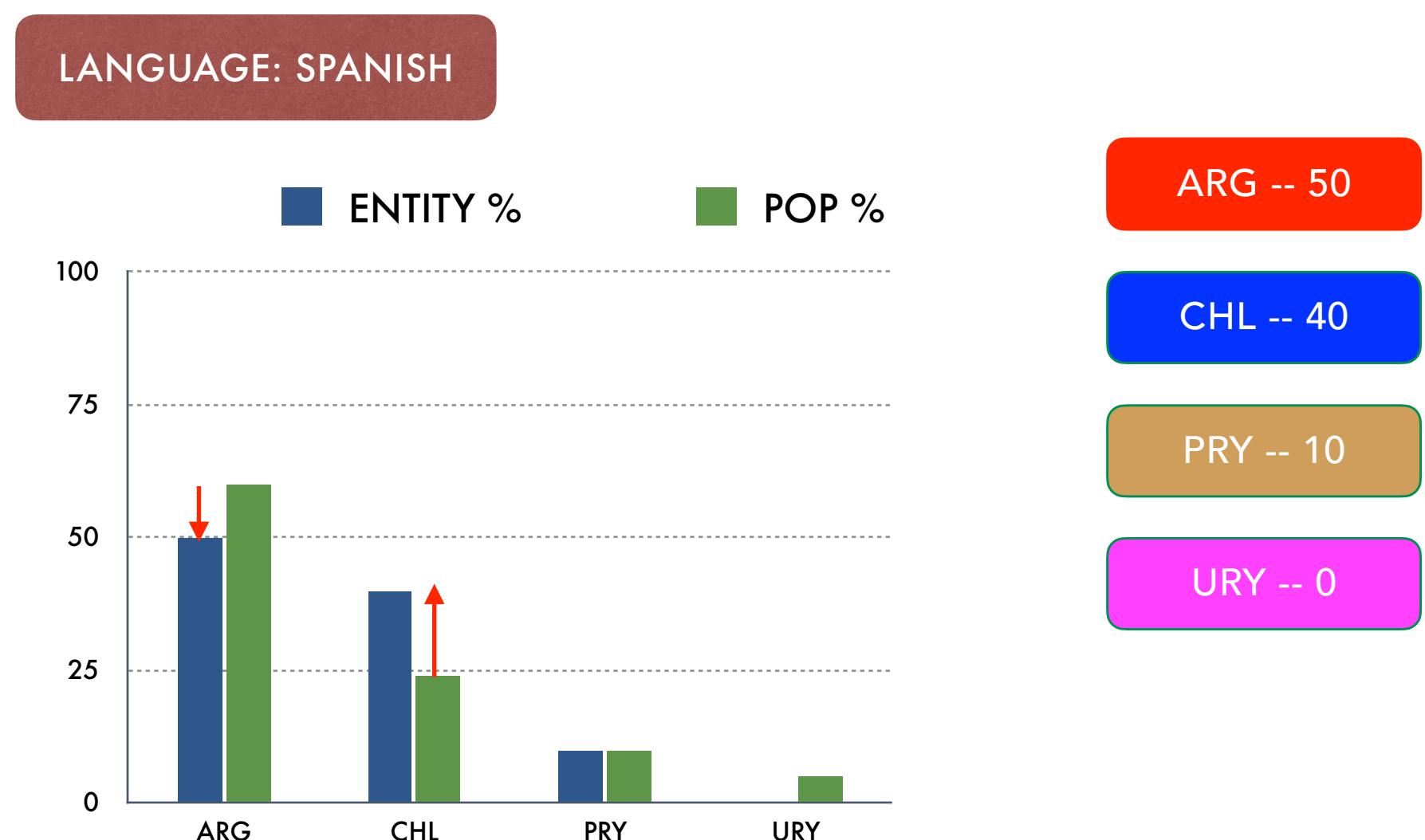
Fairness indices

Country population

Country missing(1) or underrepresented
(eg. URY~25%)

In-country representativeness for widely spoken languages

Distribution Difference in speaker population & Observed entity



Datasets and Settings

NER DATASETS

- WikiANN (Pan et al. 2017)
- Masakhaner (Adelani et al. 2021)

QA DATASETS

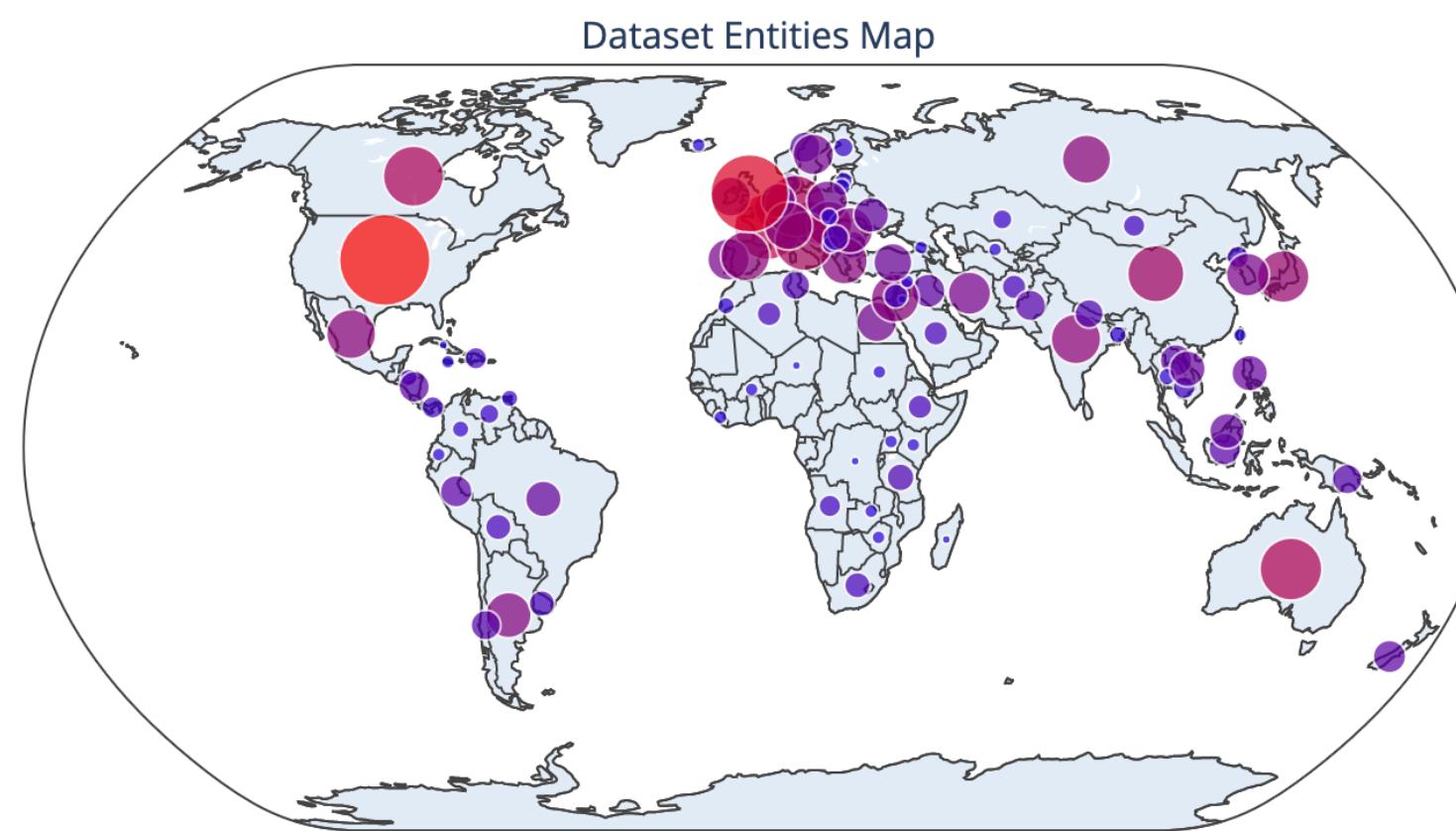
- SQuAD (Rajpurkar et al. 2016)
- MLQA (Lewis et al. 2020)
- TyDi-QA (Clark et al. 2020)
- Natural Questions (Kwiatkowski et al. 2020)

ADDITIONAL DATASETS

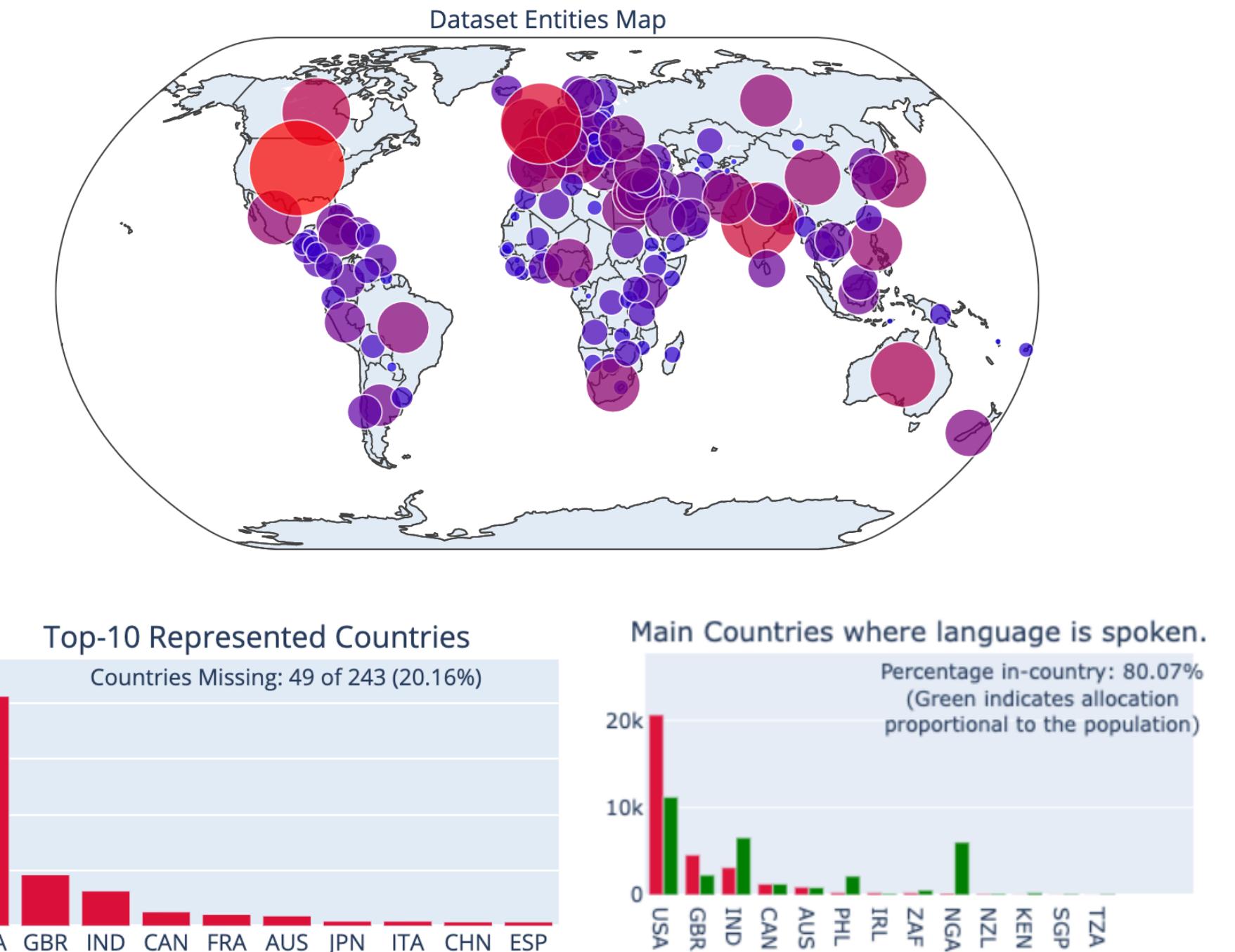
- Visualizations (X-FACTR benchmark~Jiang et al. 2020, WMT datasets) available in project webpage

Dataset Comparison (QA)

TyDi-QA(EN)



Natural Questions



Under-represented English Speakers in TyDi-QA(EN): Global South
(eg. Kenya, South Africa, Nigeria)

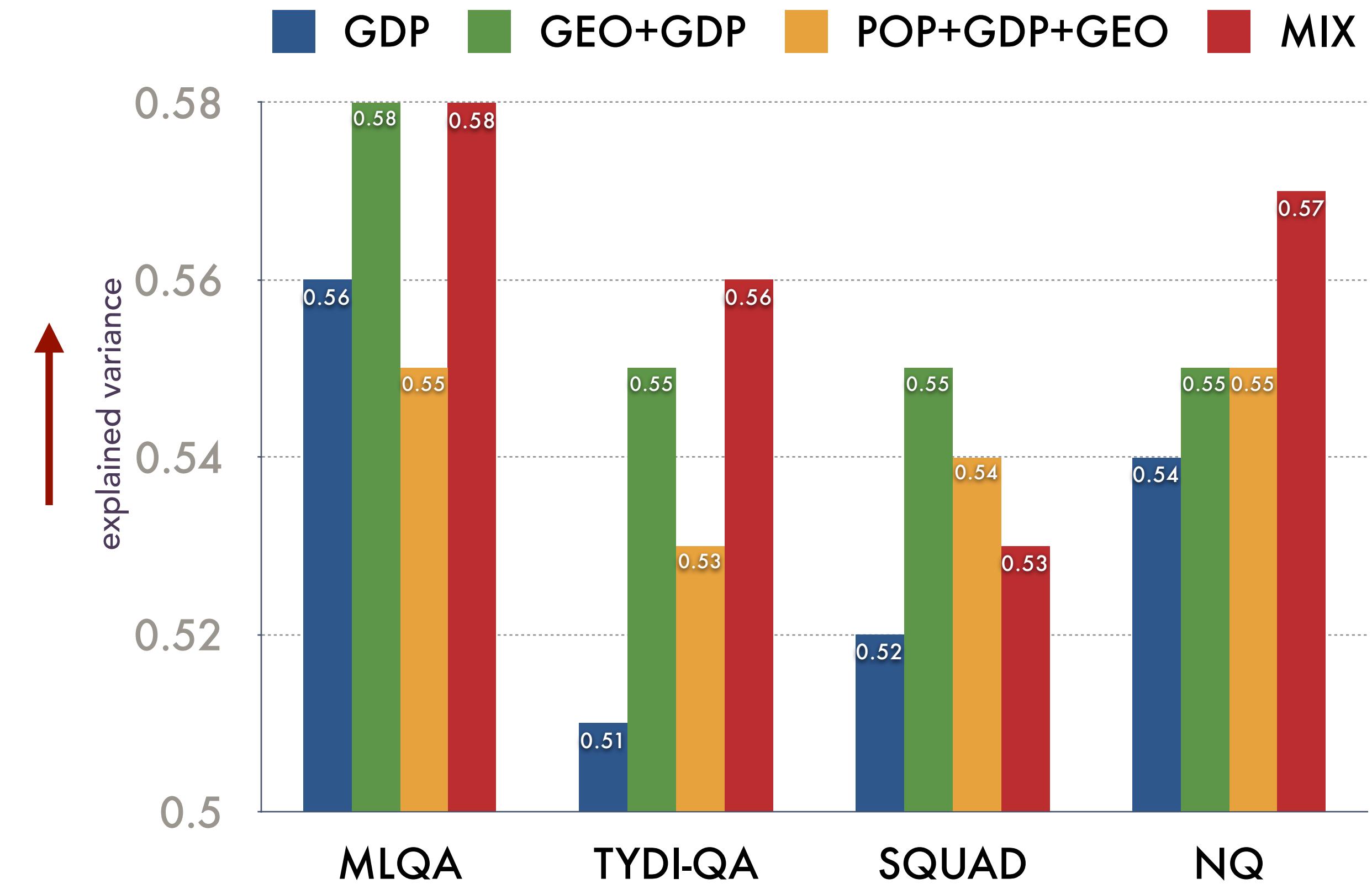
Socioeconomic correlates

Single best predictor: GDP (all dataset over-representing wealthy countries)

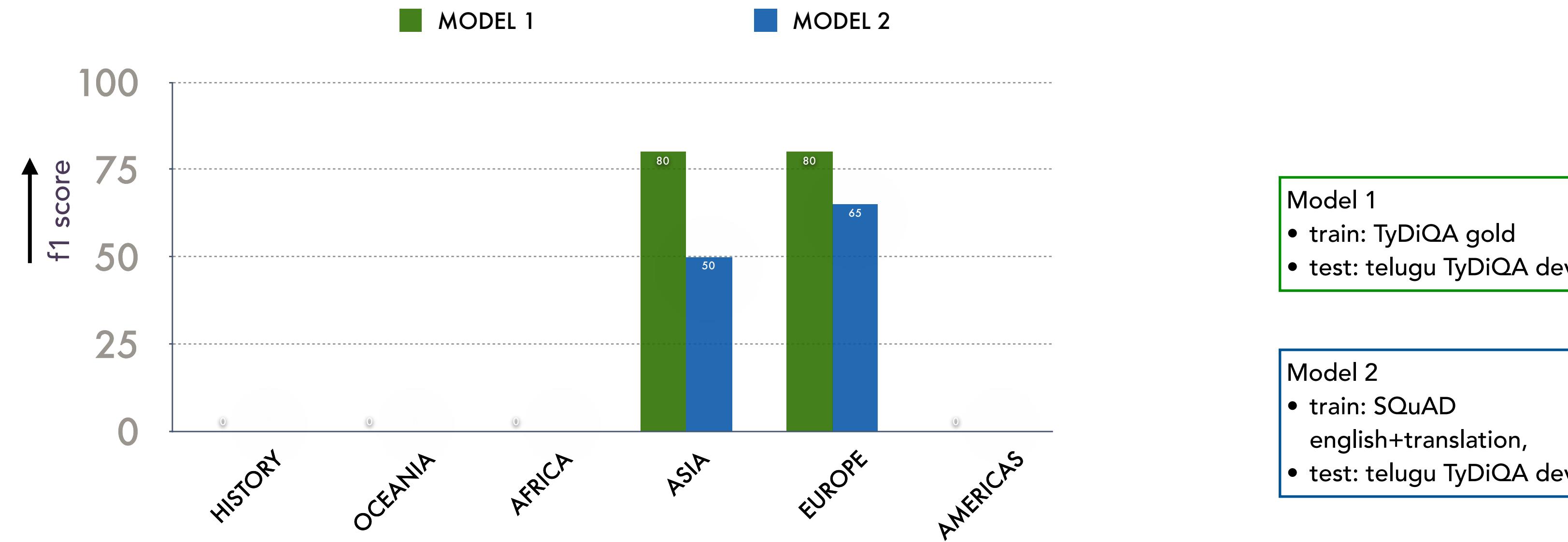
Including population statistics impact negatively except NQ (exemplar of representativeness)

Mix of factors explain variance well.

- GEO: Distance from Language Spoken Country
- POP: population average
- MIX: combination of GDP, GDP/CAPITA, GEO, POP and Land-Mass



Geographical Breakdown (QA)



Model 2 performs worse on Asia-related data than Europe-related ones, unlike Model 1



A recipe for representativeness visualization for NLP datasets



- Country-language mapping: inherently lossy
- Granularity level smaller than country: higher cultural relevance
- Wikidata: western country bias
- Ideal combination of socioeconomic factors: subjective



- Robustness of NER/EL model
- Expansion of dataset and task coverage
- Inspect other granularity level



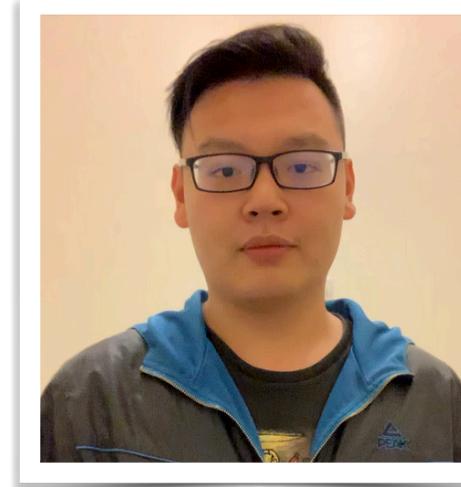
Code & Dataset



https://github.com/ffaisal93/dataset_geography



FAHIM FAISAL (ffaisal@gmu.edu)

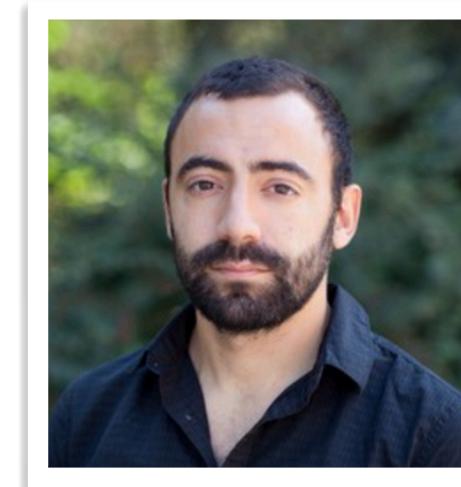


Yinkai Wang (ywang88@gmu.edu)

Project Webpage & Additional Visualizations



<https://nlp.cs.gmu.edu/project/datasetmaps>



Antonios Anastopoulos (antonis@gmu.edu)