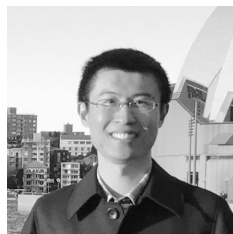




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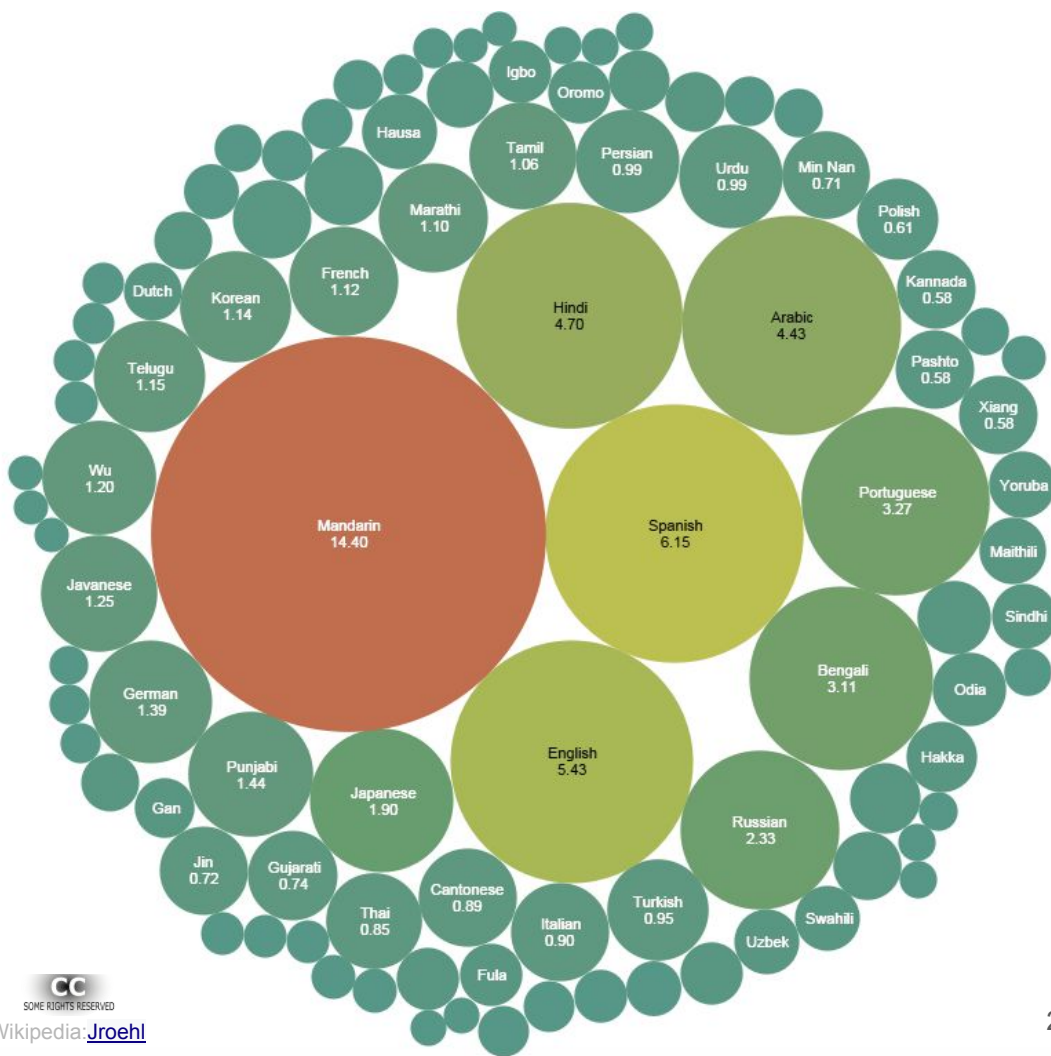
# Massively Multilingual Transfer for NER

Afshin Rahimi, Yuan Li, and Trevor Cohn  
University of Melbourne



6000+ languages

≈ 1% with annotation



Emergency Response



Named Entity Recognition

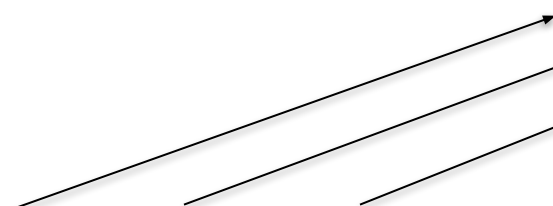


# Annotation Projection for Transfer

kailangan namin ng mas maraming dugo sa **Pagasanjan** . Tagalog



.....



**B-LOC**

we need more blood in **Pgasanjan** .

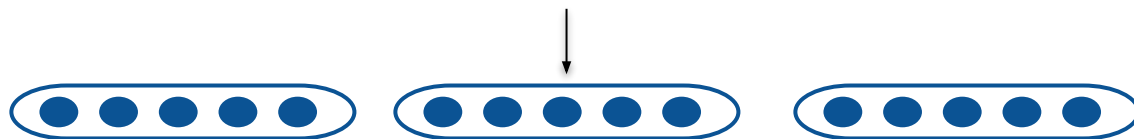
English

**O O O O O B-LOC O**

Yarowsky et al. (2001)

# Representation Projection for Transfer

kailangan namin ng mas maraming dugo sa **Pagasanjan** .



*language independent  
representation*

Cross-lingual word  
embeddings  
(Lample et al., 2018)

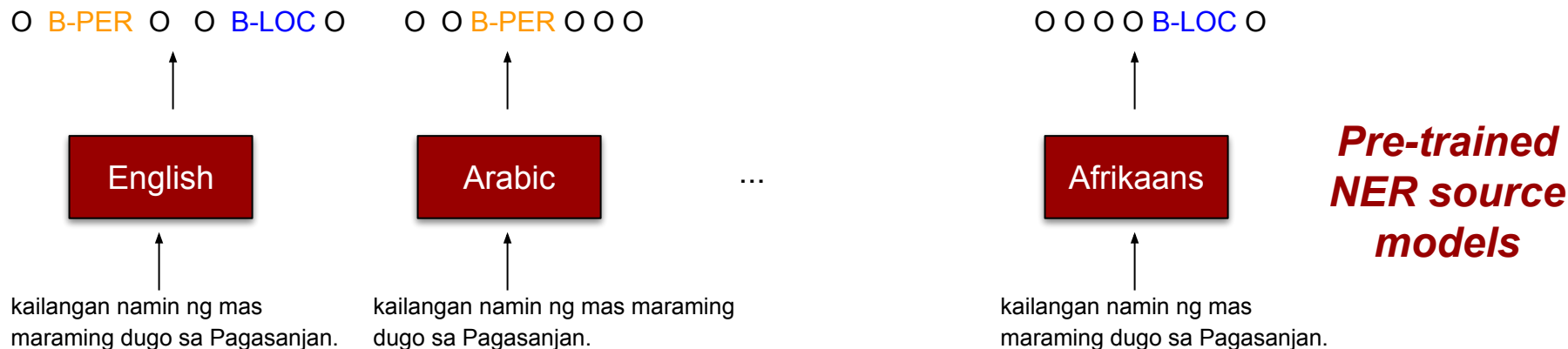
**Mis-matched  
Model**

**Ideal: source-target similar in  
word order, script, syntax**

**O O O O O B-LOC O**

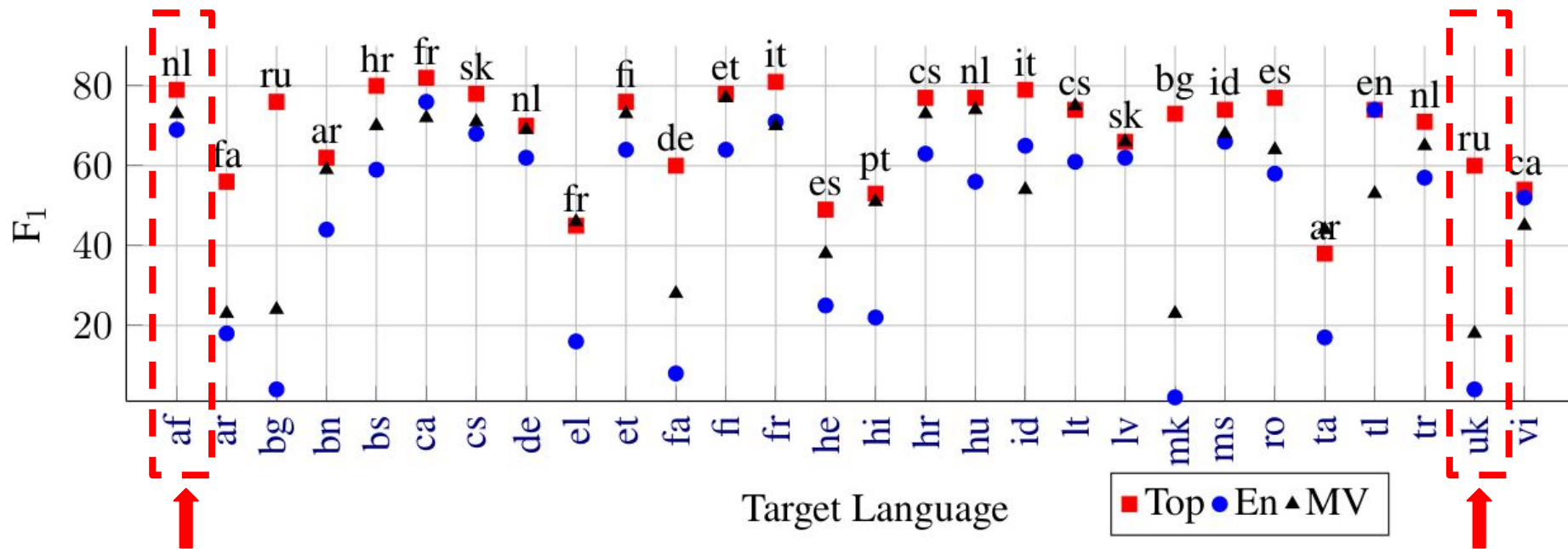
# Direct Transfer for NER

Output: Labelled sentences in the target language



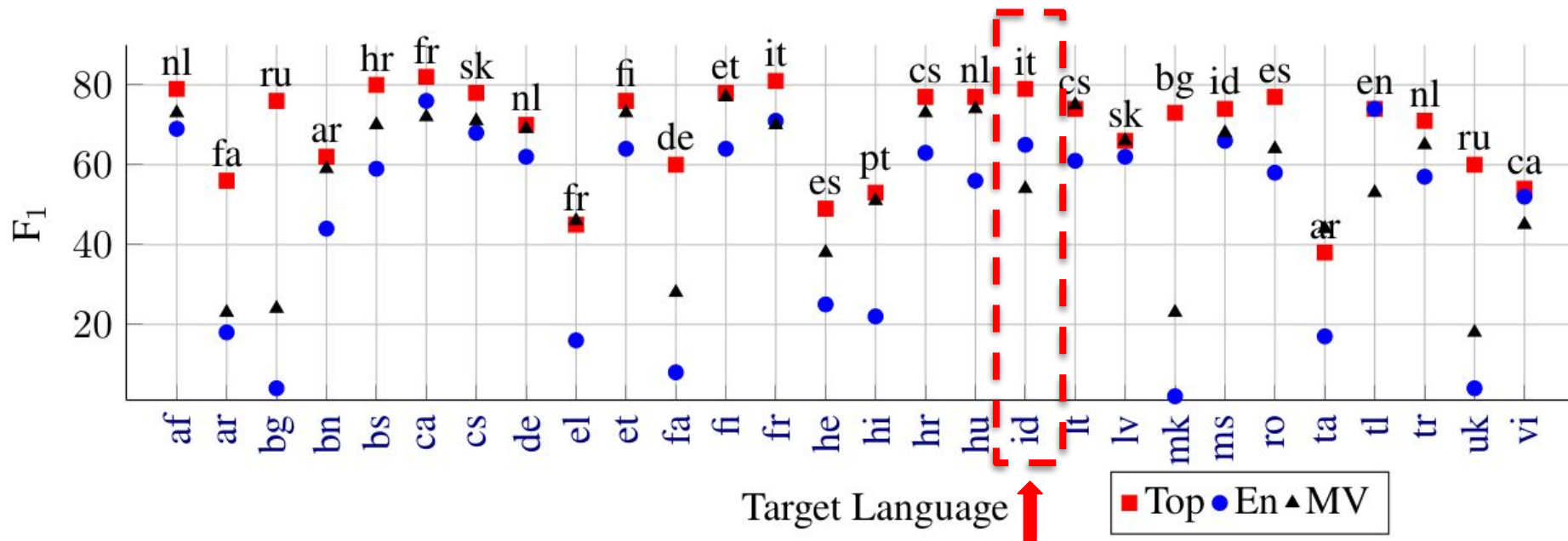
Input: Unlabelled sentences in the target language encoded with cross-lingual embeddings

# Direct Transfer Results (NER F1 score, WikiANN)



unsurprising

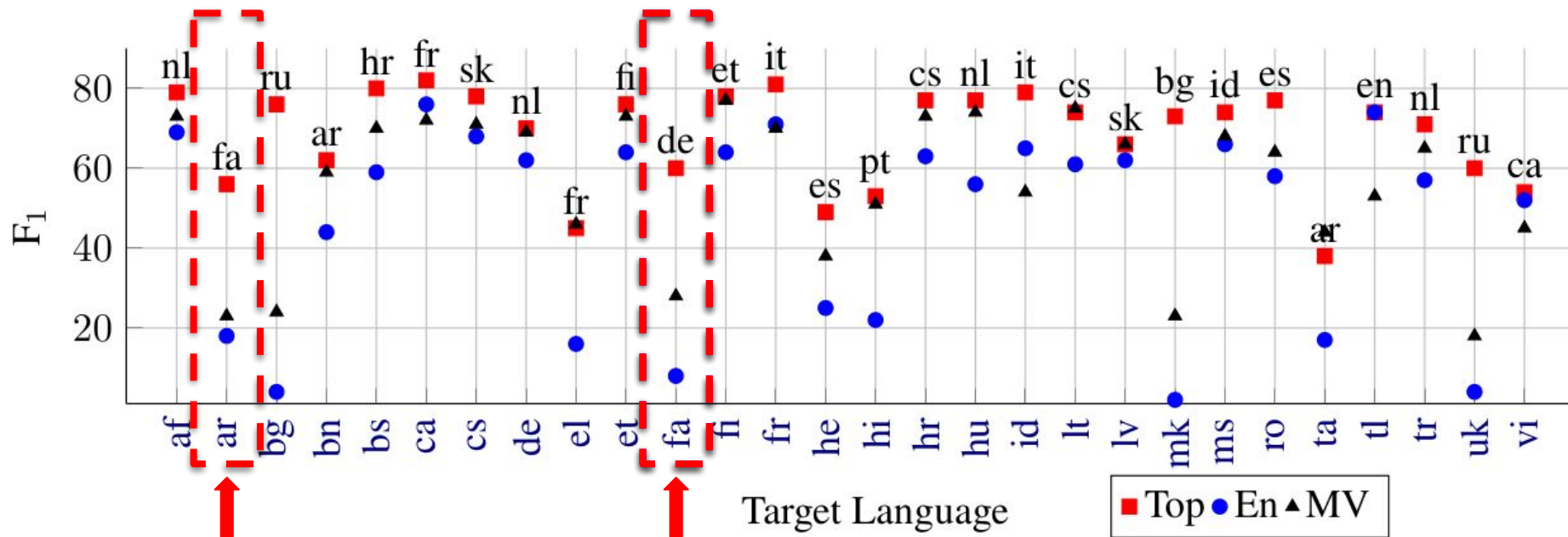
# Direct Transfer Results (NER F1 score, WikiANN)



unrelated

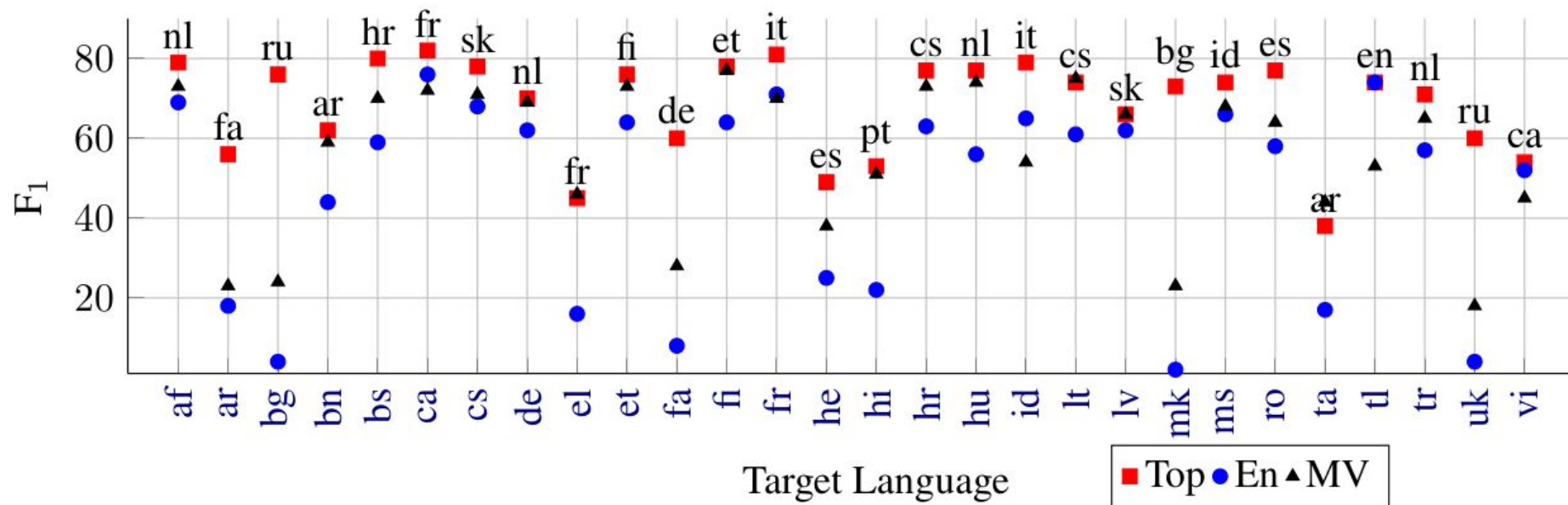


# Direct Transfer Results (NER F1 score, WikiANN)



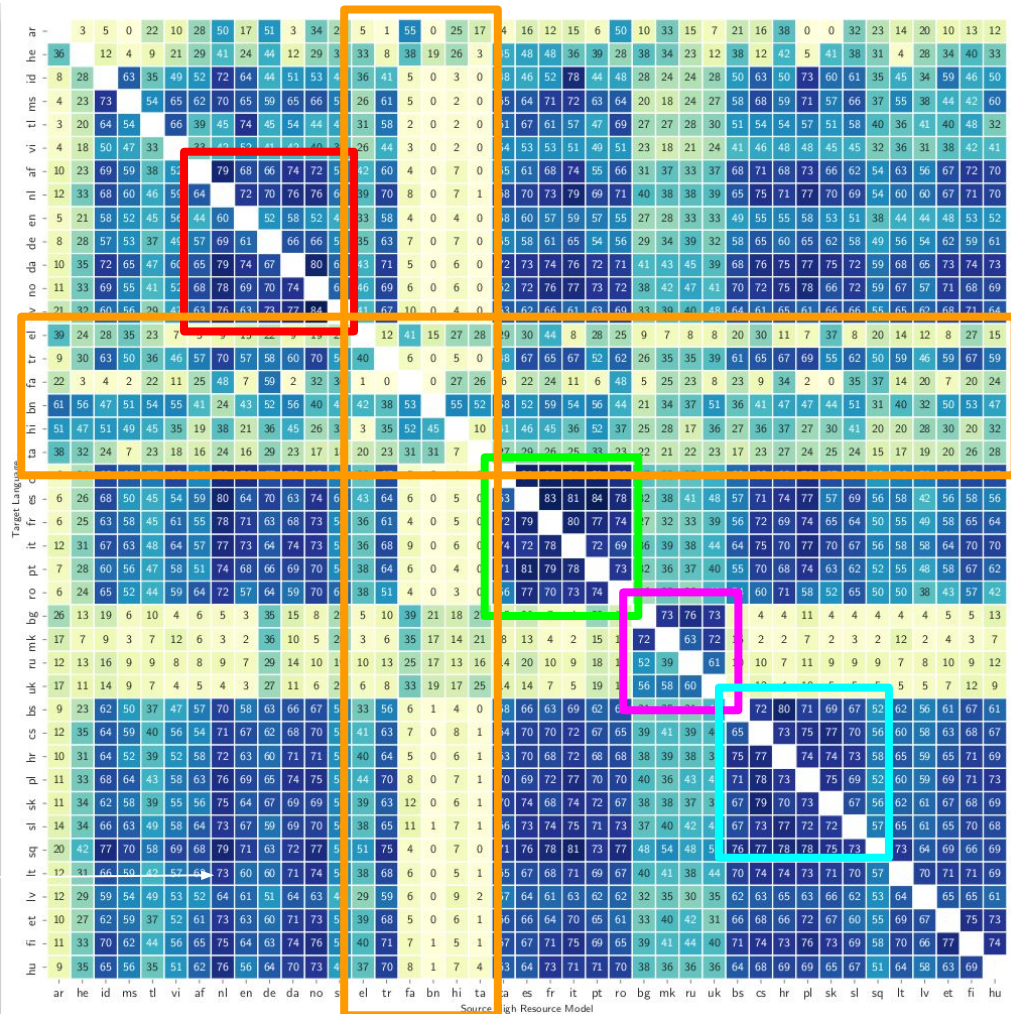
asymmetry

# Voting & English are often poor!



# General findings

- Transfer strongest within language family  
(**Germanic**, **Roman**, **Slavic-Cyr**, **Slavic-Latin**)
- Asymmetry between use as source vs target language (**Slavic-Cyr**, **Greek/Turkish/...**)
- But lots of odd results & overall highly noisy



# Problem Statement

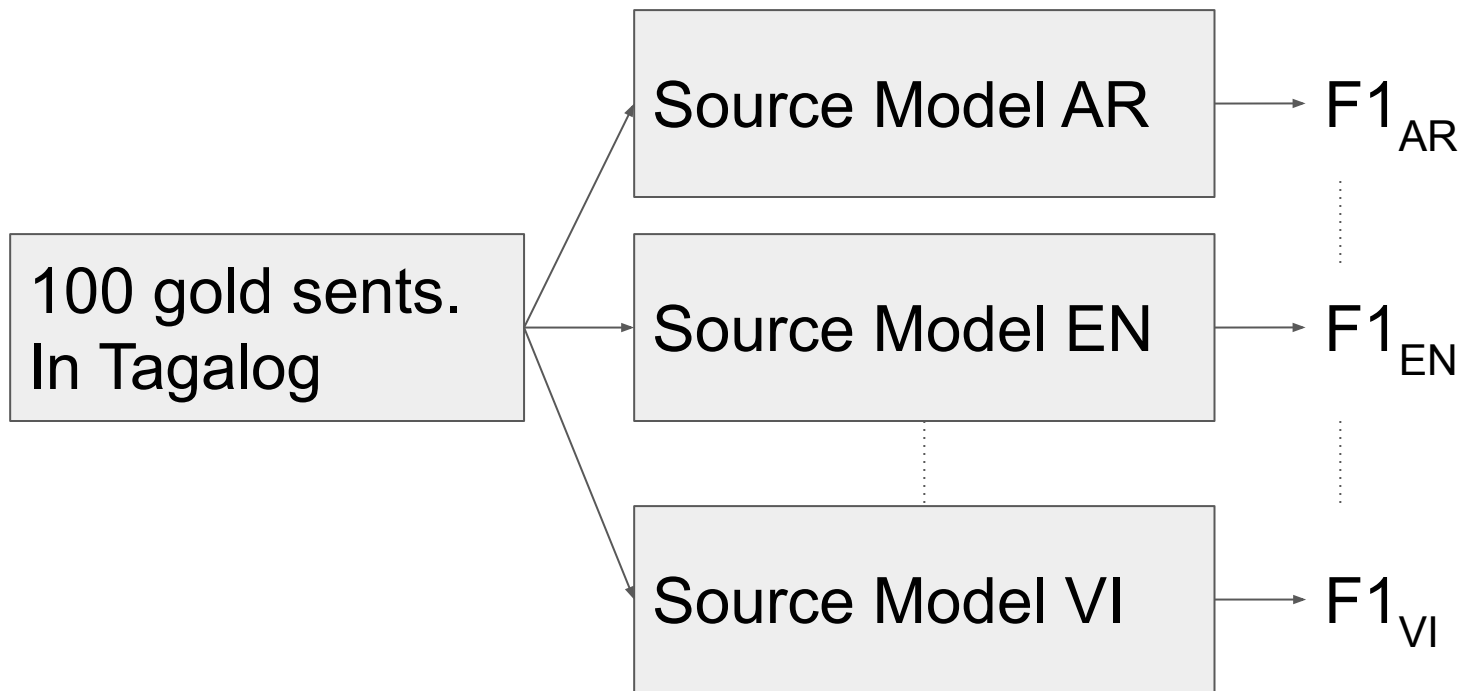
## Input:

- N black-box source models
- Unlabelled data in target language
- Little or no labelled data (few shot and zero shot)

## Output:

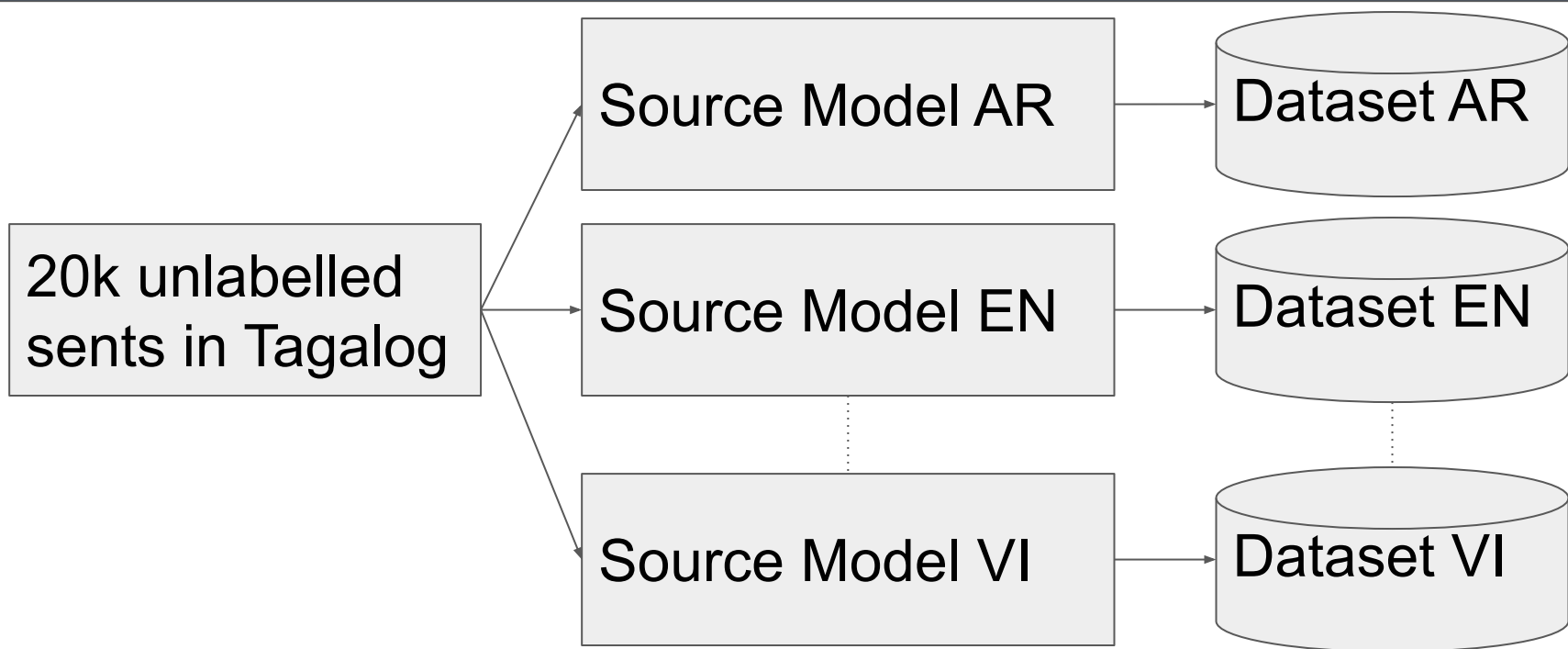
- Good predictions in the target language

# Model 1: Few Shot Ranking and Retraining (RaRe)



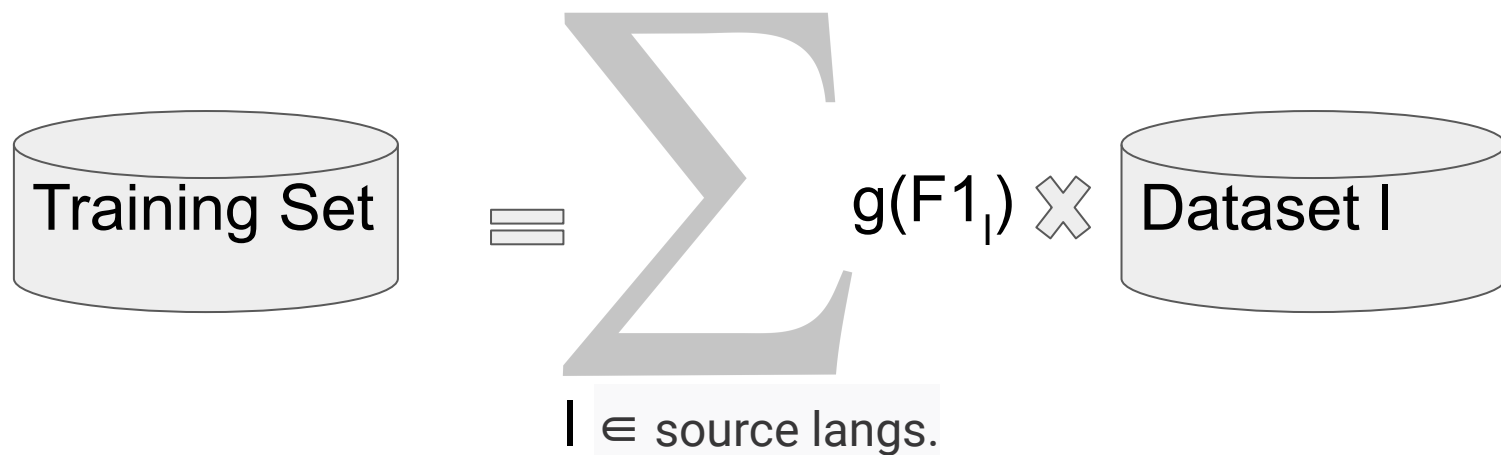
**Source model qualities**

# Model 1: Few Shot Ranking and Retraining (RaRe)



**N training sets in Tagalog**

# Model 1: Few Shot Ranking and Retraining (RaRe)



**Final training set, a mixture of distilled knowledge**

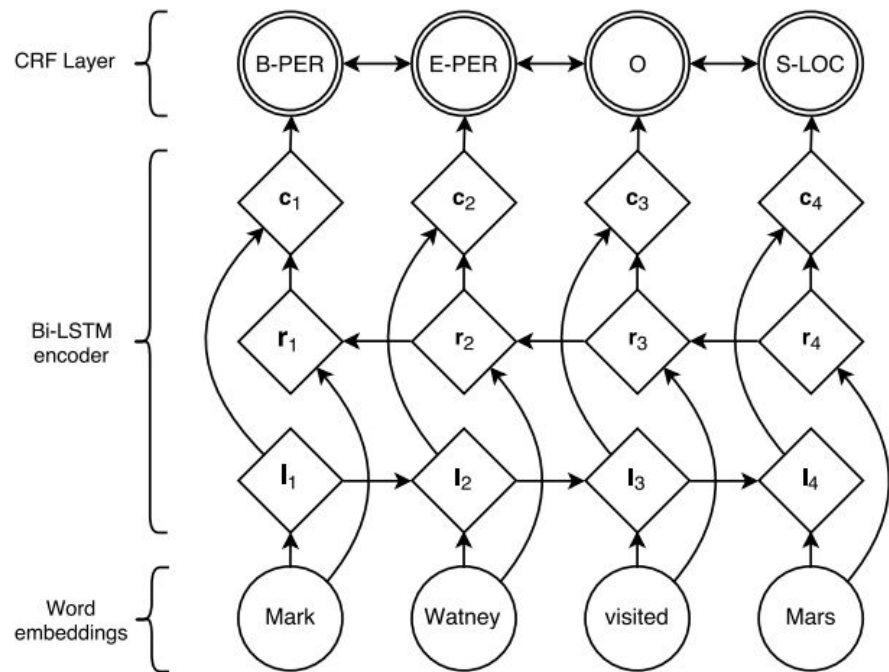
# Model 1: Few Shot Ranking and Retraining (RaRe)

1. Train an NER model on the mixture datasets.
2. Fine-tune on 100 gold samples.

Zero-shot variant: uniform sampling without fine-tuning  
(**RaRe<sub>uns</sub>**)



# Hierarchical BiLSTM-CRF as model



Our method is **independent** of model choice.

Lample et al., (2016)

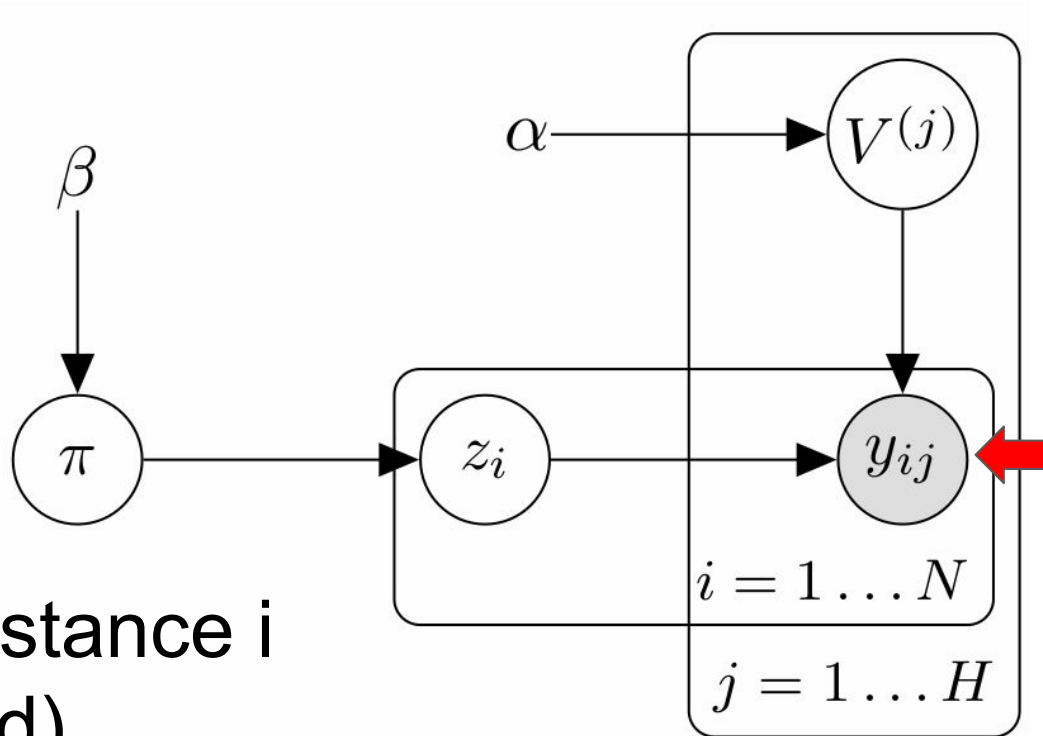
## Model 2: Zero Shot Transfer (BEA)

What if no gold labels are available?

1. Treat gold labels  $Z$  as hidden variables
2. Estimate  $Z$  that best explains all the observed predictions
3. Re-estimate the quality of source models

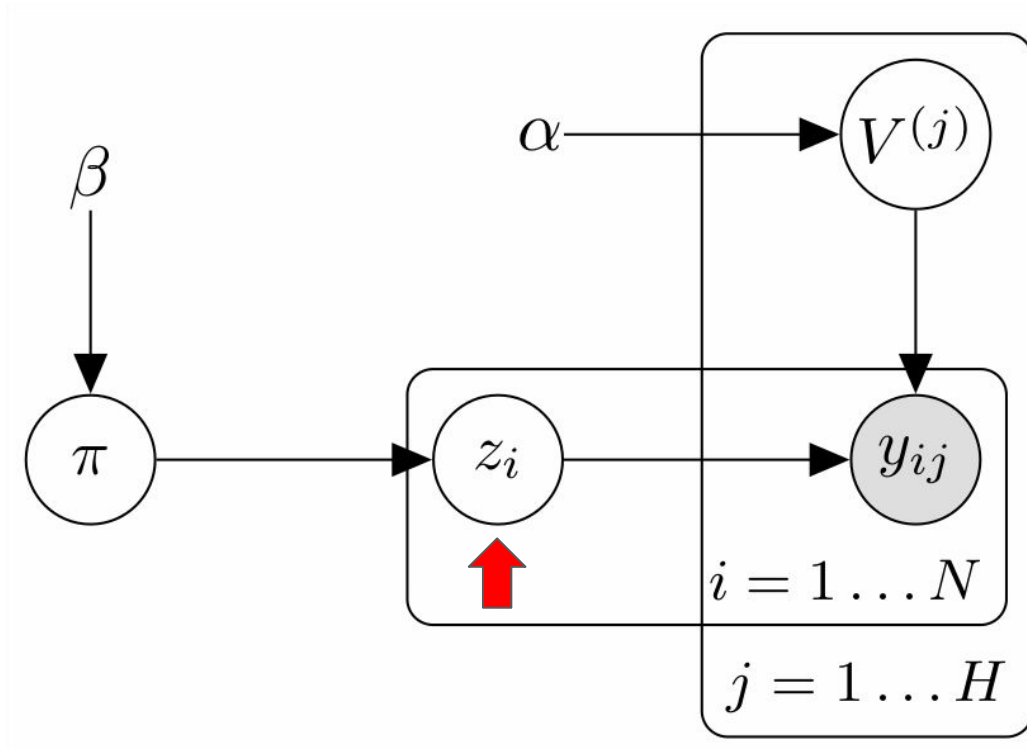
Inspired by Kim and Ghahramani (2012)

## Model 2: Zero Shot Transfer (BEA)



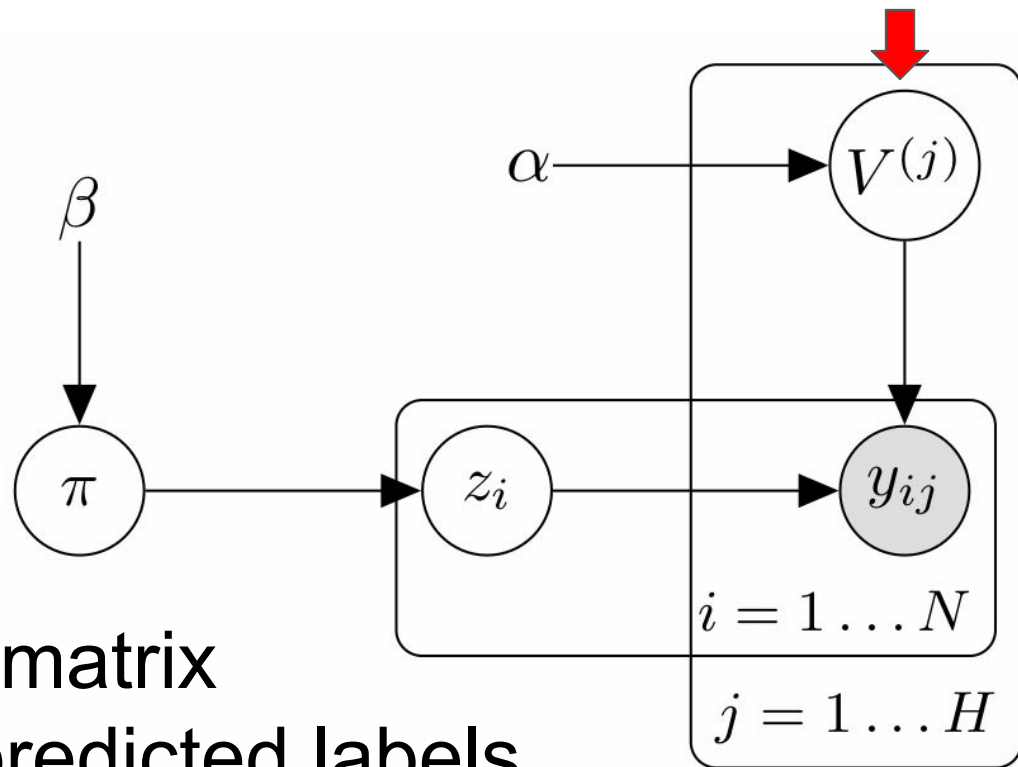
Predicted label of instance  $i$   
by model  $j$  (observed)

## Model 2: Zero Shot Transfer (BEA)



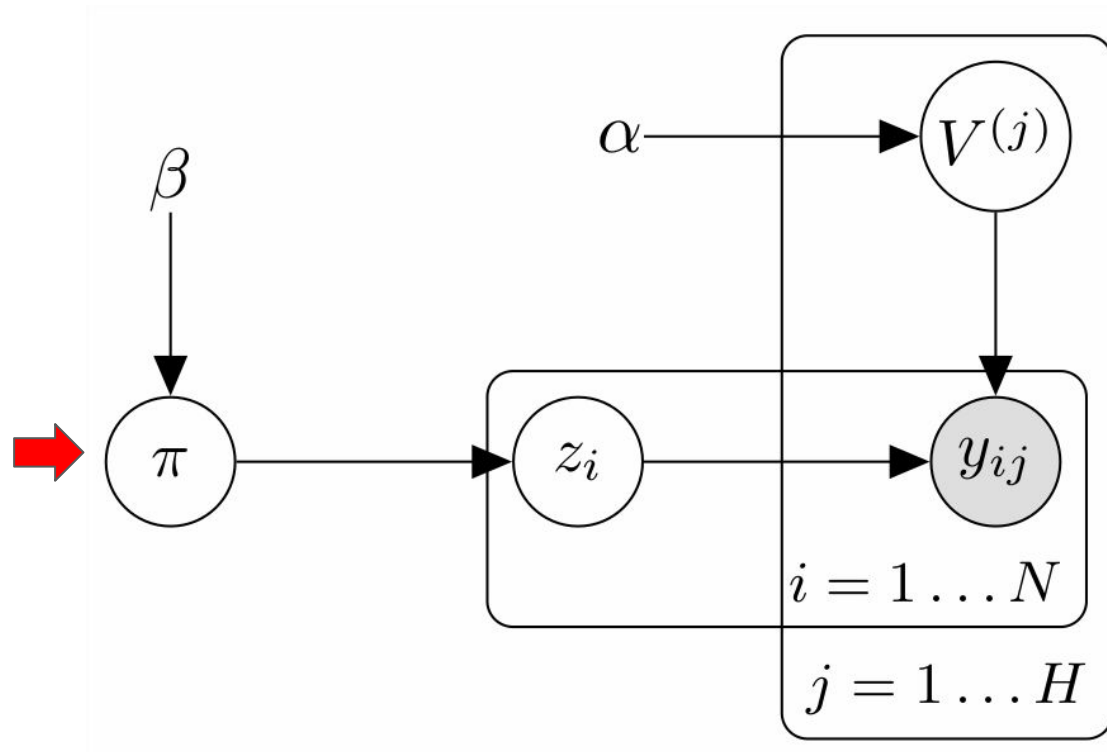
True label of  
instance  $i$

## Model 2: Zero Shot Transfer (BEA)



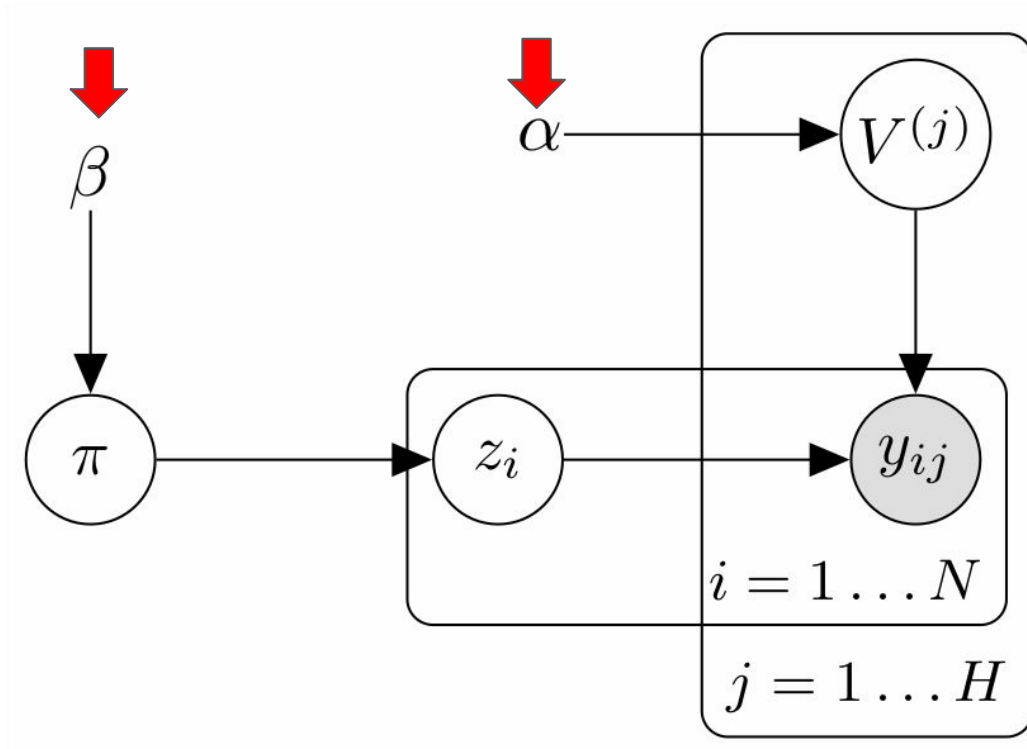
Model  $j$ 's confusion matrix  
between True and predicted labels.

## Model 2: Zero Shot Transfer (BEA)



Categorical  
Distribution

## Model 2: Zero Shot Transfer (BEA)

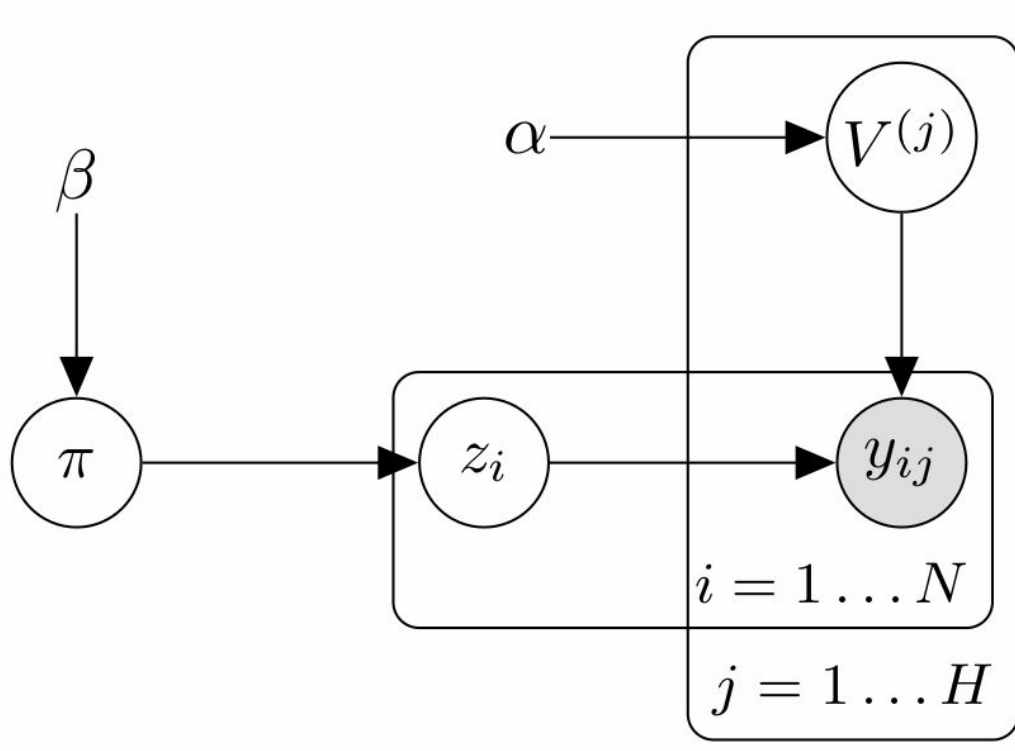


Uninformative  
Dirichlet Priors

## Model 2: Zero Shot Transfer (BEA)

Find  $Z$  to maximises  $P(Z|Y, \alpha, \beta)$ , using variational mean-field approx.

Warm-start with MV.





# Extensions to BEA

## 1. Spammer removal:

After running BEA, estimate source model qualities and remove bottom k, run BEA again (**BEA<sub>unsx2</sub>**)

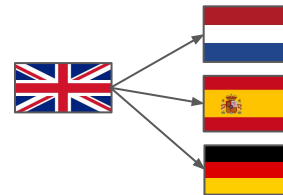
## 2. Few shot scenario:

Given 100 gold sentences, estimate source model confusion matrices, then run BEA (**BEA<sub>sup</sub>**)

## 3. Token vs Entity application

# Benchmark: BWET (Xie et al., 2018)

Single source annotation projection with bilingual dictionaries from cross-lingual word embeddings



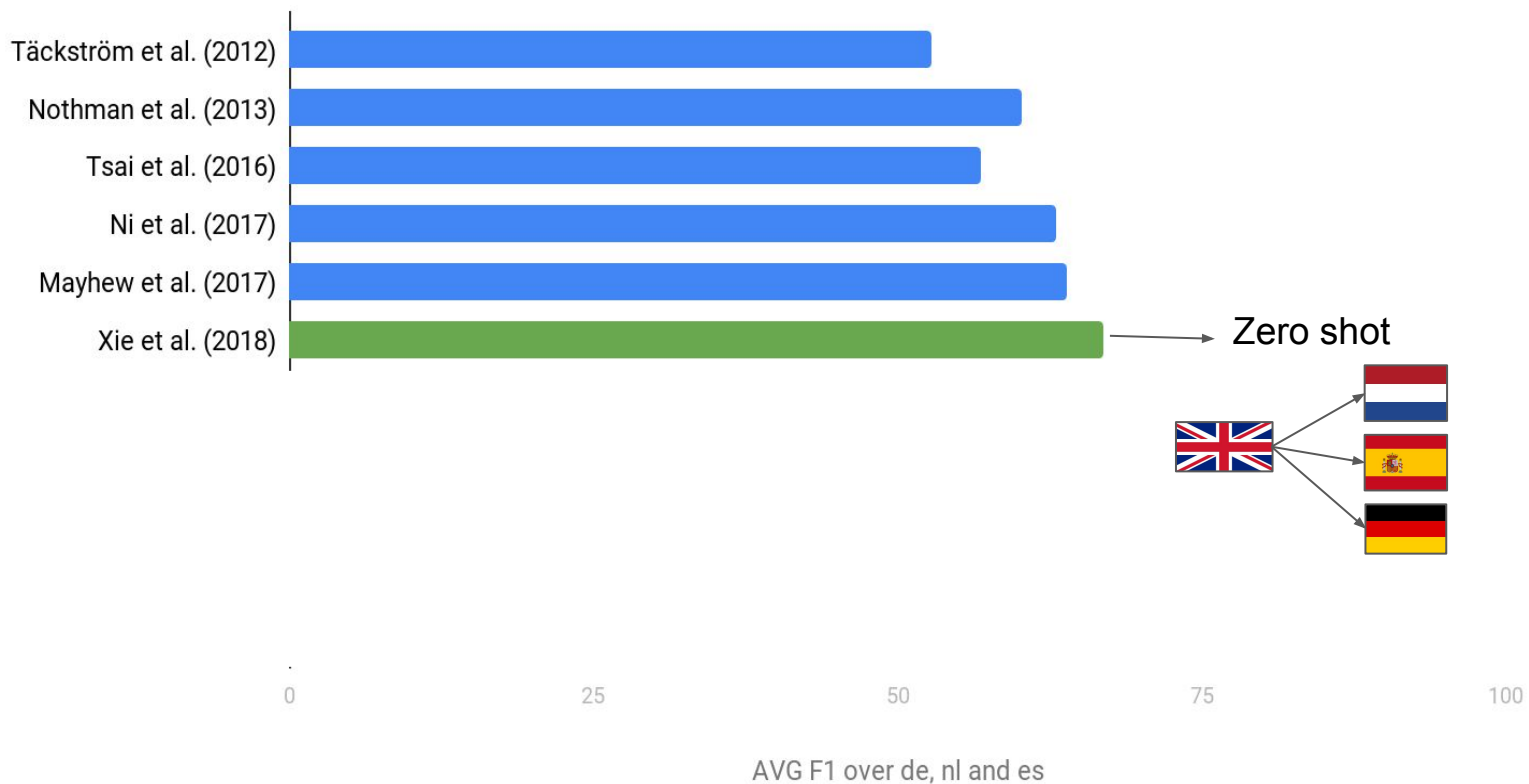
- Transfer english training data to German, Dutch, and Spanish.
- Train a transformer NER on the projected training data.

State-of-the-art on **zero-shot** NER transfer (orthogonal to this)

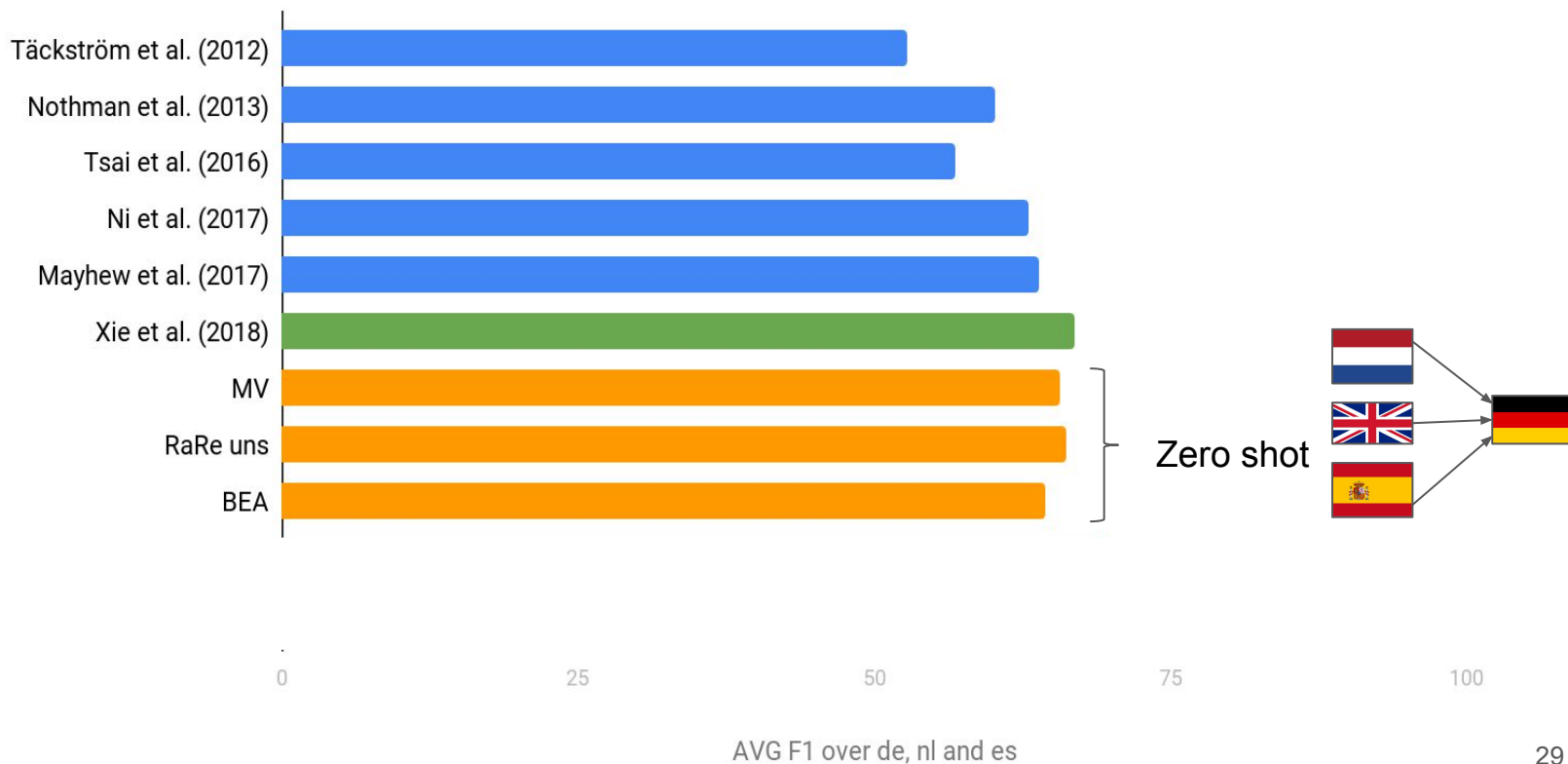
# CoNLL Results (avg F1 over de, nl, es)



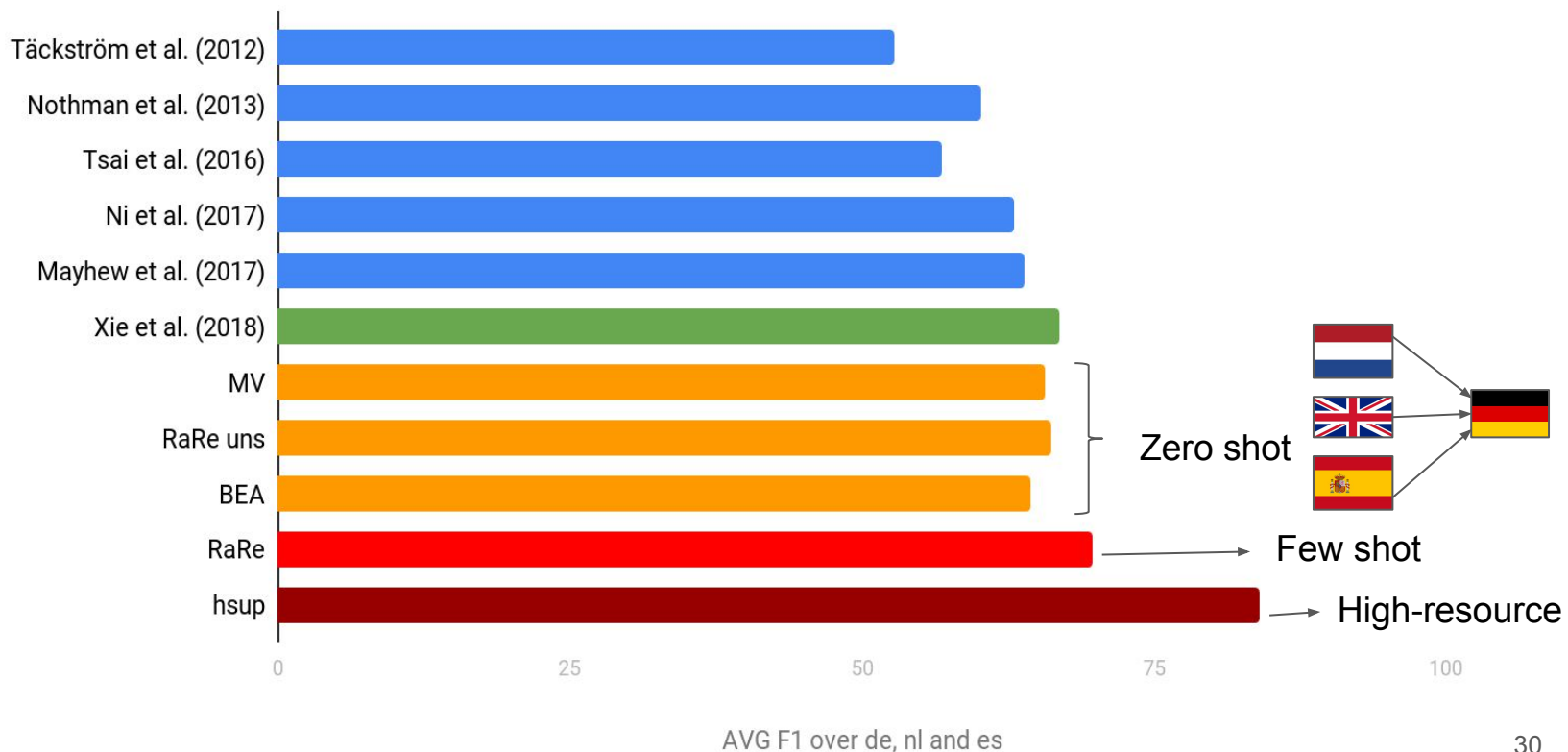
# CoNLL Results (avg F1 over de, nl, es)



# CoNLL Results (avg F1 over de, nl, es)

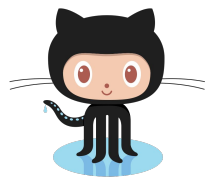


# CoNLL Results (avg F1 over de, nl, es)



# WIKIANN NER Datasets (Pan et al., 2017)

- Silver annotations from Wikipedia for **282** languages.
- We picked **41** languages based on availability of bilingual dictionaries.
- Created balanced training/dev/test partitions (varying size of training according to data availability)



[github.com/afshinrahimi/mmner](https://github.com/afshinrahimi/mmner)

# L.O.O. over 41 languages





# L.O.O. over 41 languages



Transfer from 40 source languages



Tagalog

L.O.O. over 41 languages



# L.O.O. over 41 languages



Transfer from 40 source languages

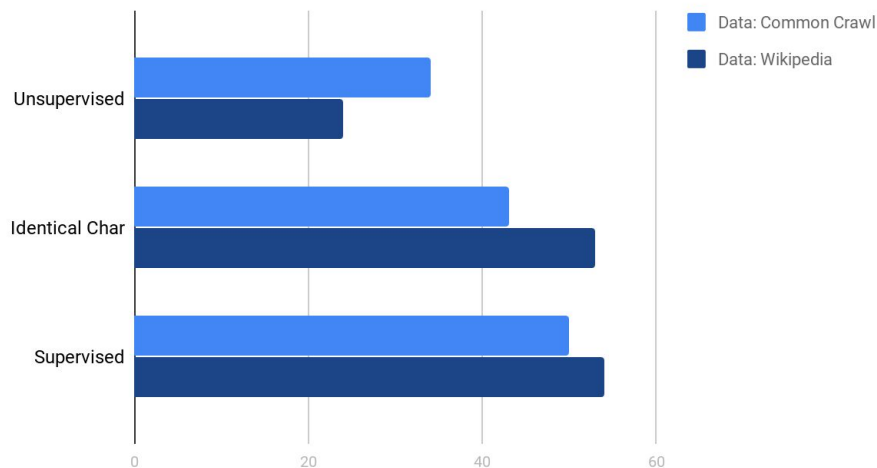


Tamil

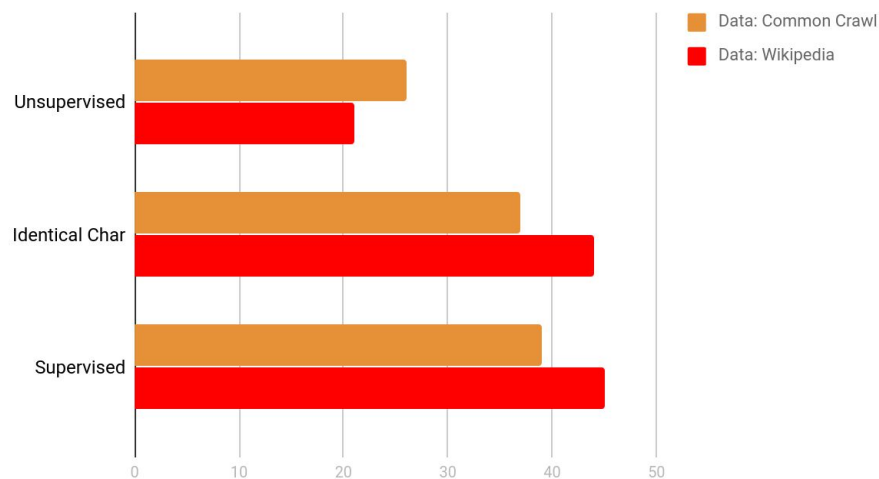
# Word representation: FastText/MUSE

Use **fasttext** monolingual **wiki** embeddings mapped to English space using **Identical Character Strings**.

Bilingual Induction Accuracy

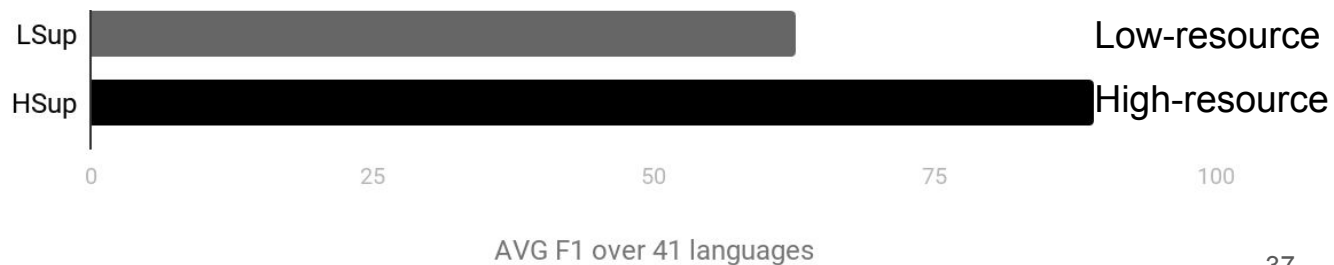


Direct Transfer F1 averaged over 41 languages



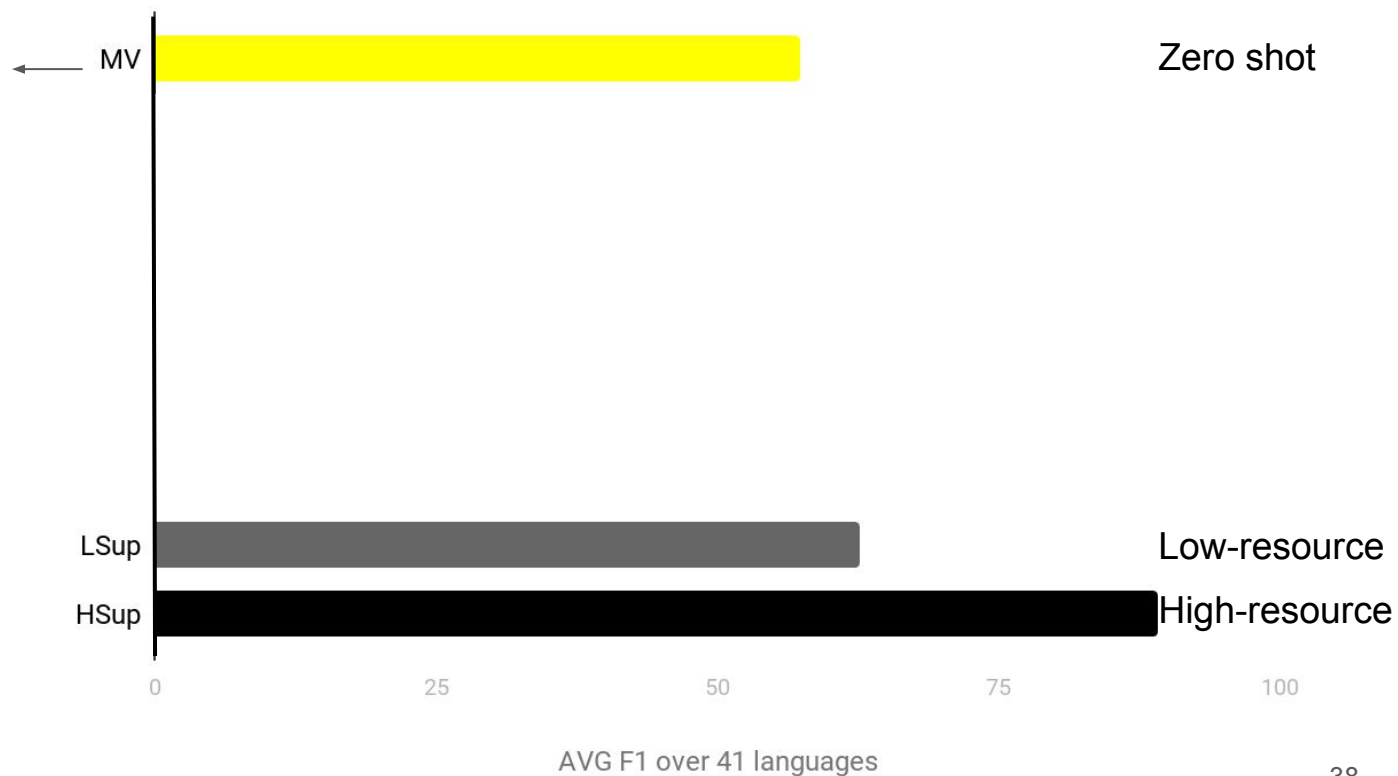
# Results: WikiANN

Supervised: no transfer



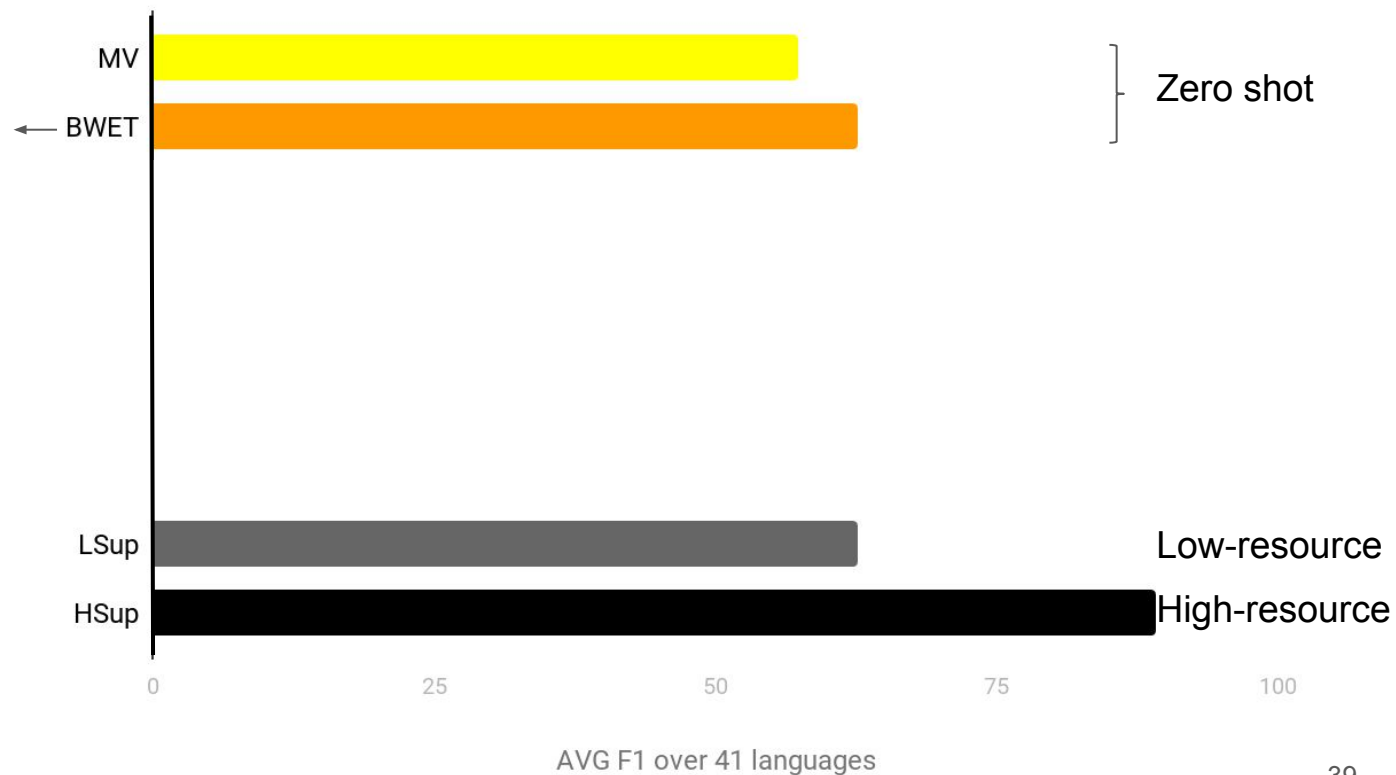
# Results: WikiANN

Many low quality source models



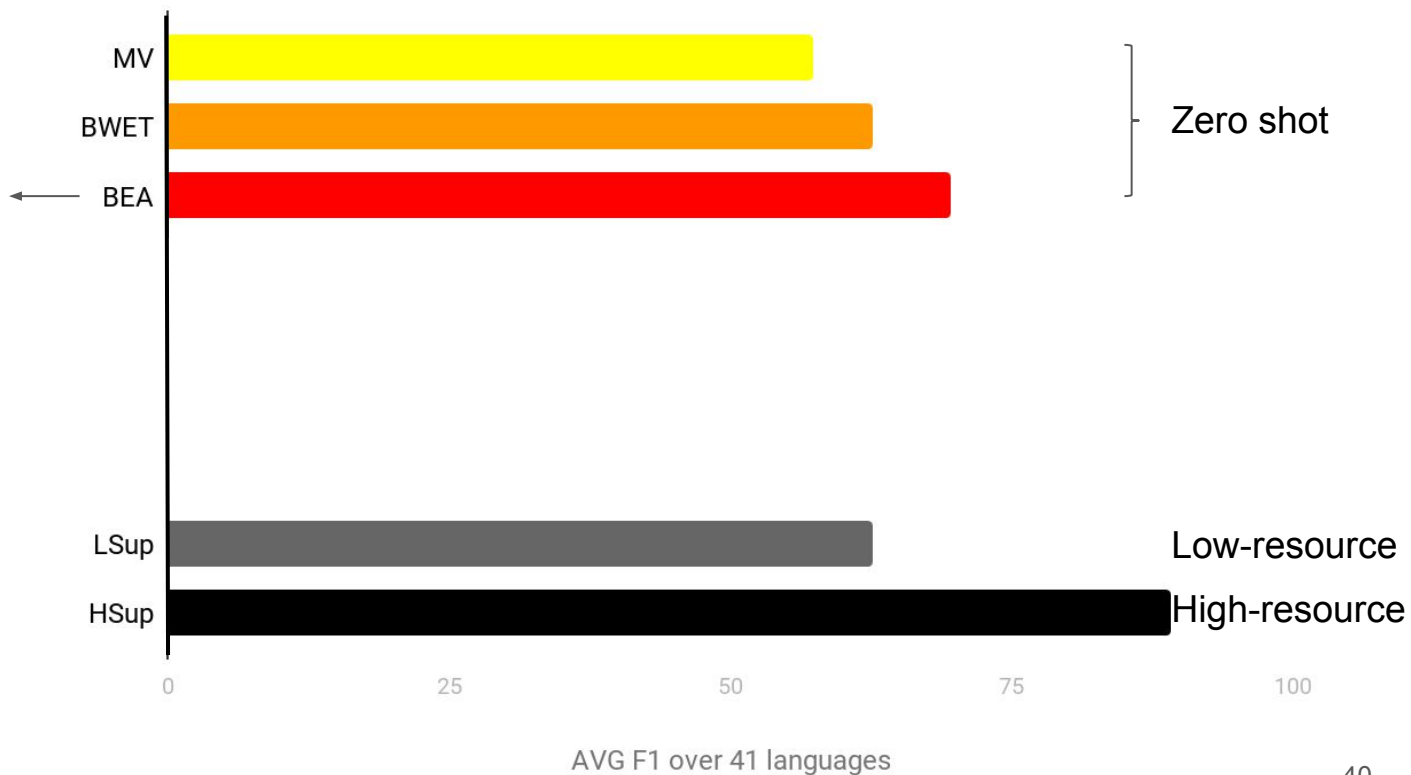
# Results: WikiANN

Single source  
(en)



# Results: WikiANN

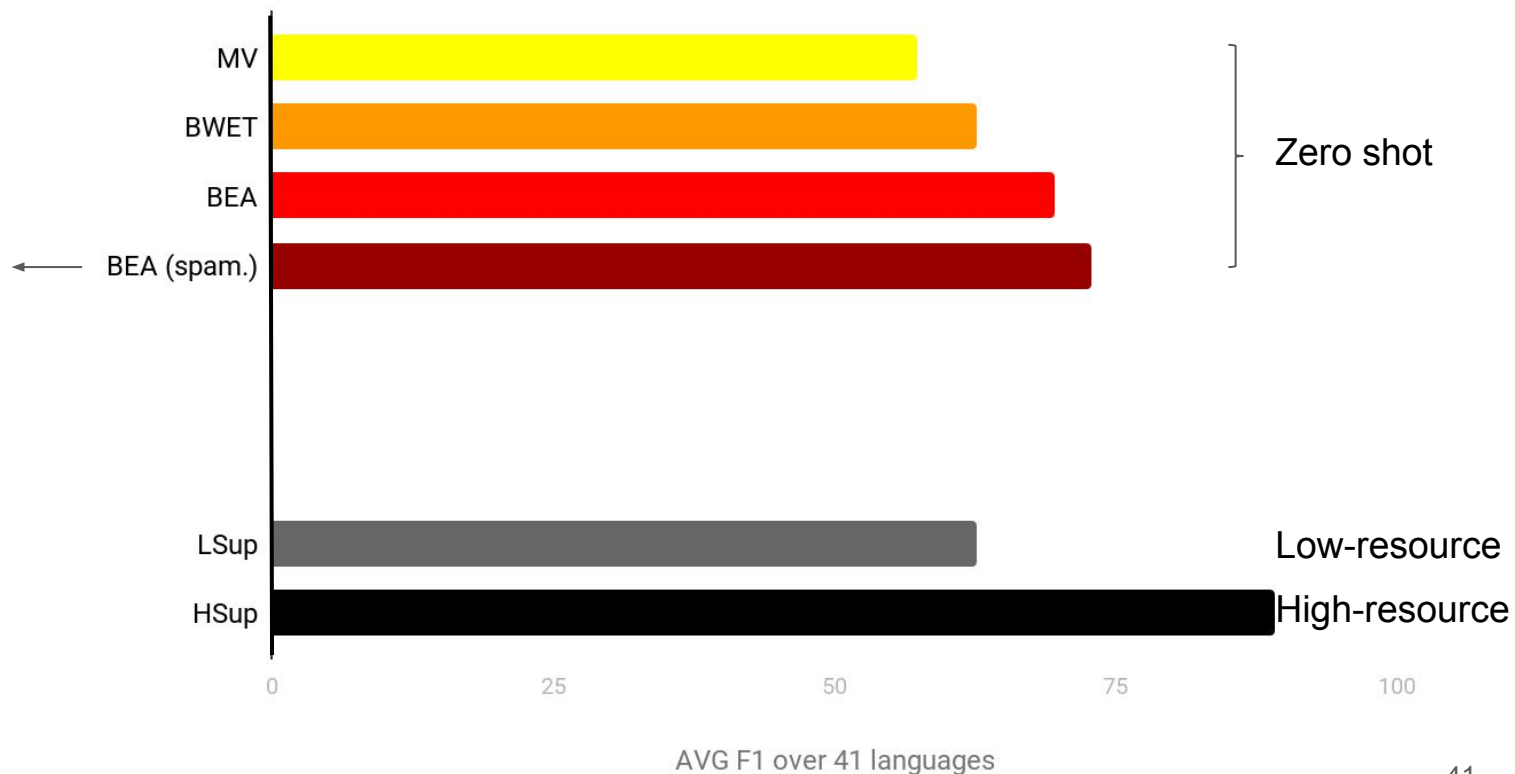
Bayesian  
ensembling





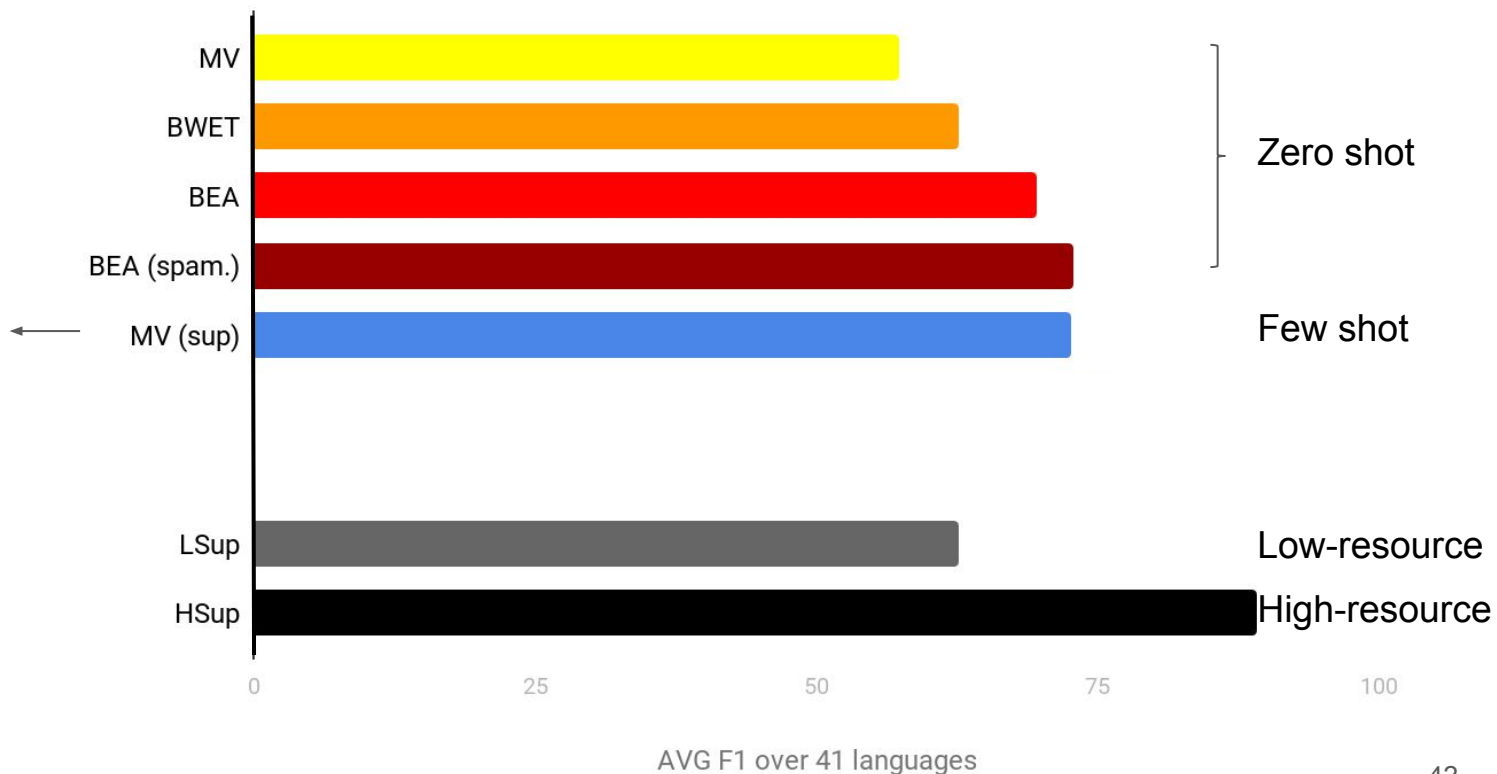
# Results: WikiANN

+spammer  
removal



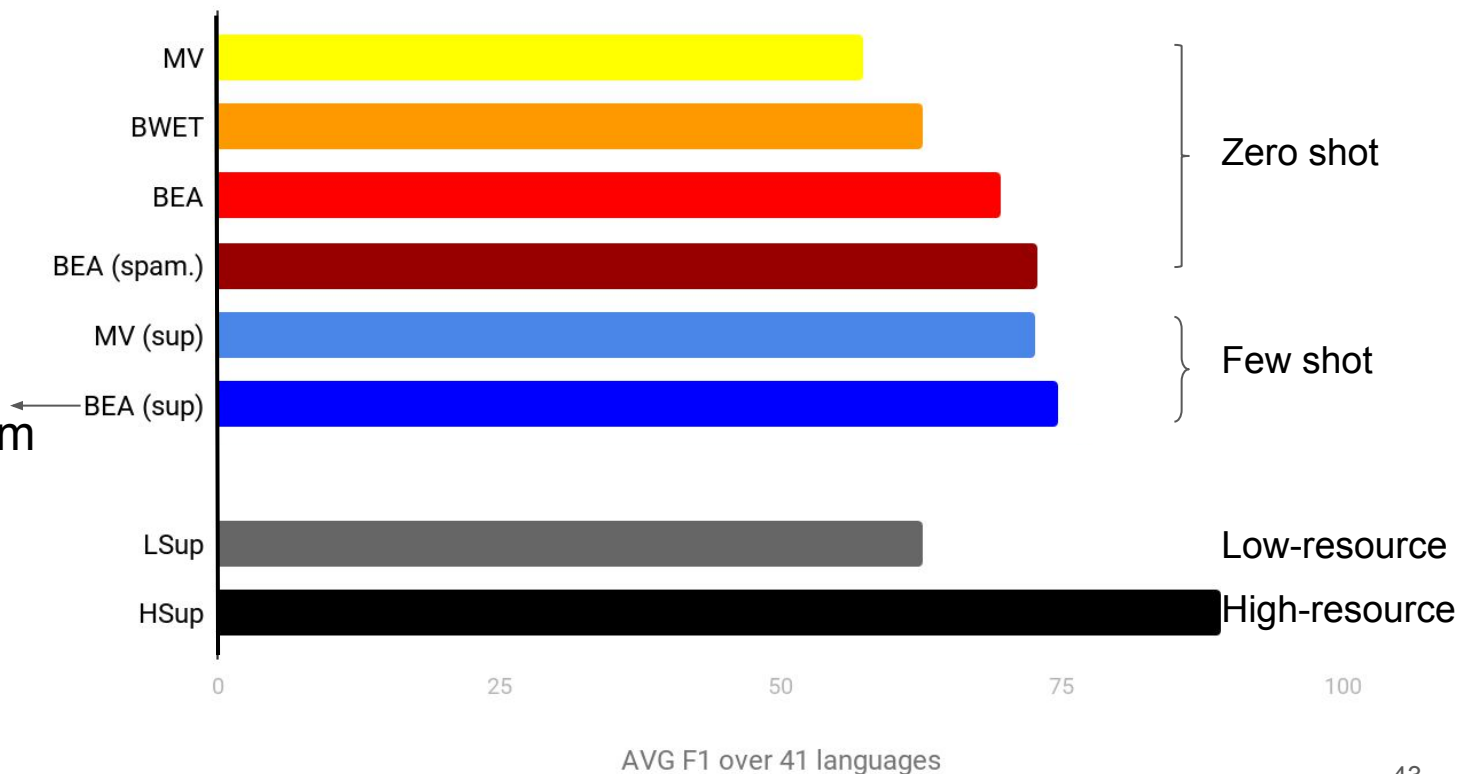
# Results: WikiANN

MV between  
top 3 sources



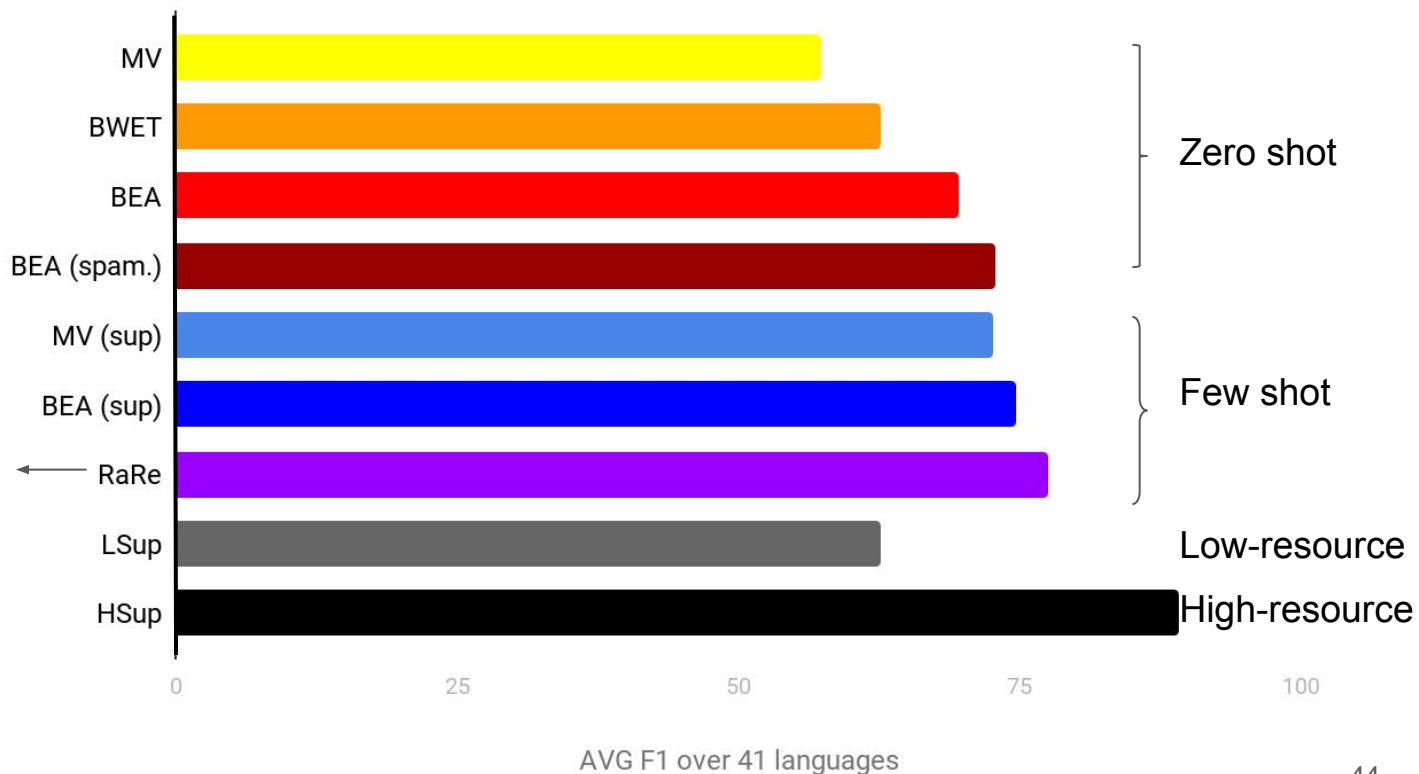
# Results: WikiANN

Estimate BEA  
confusion & prior from  
annotations



# Results: WikiANN

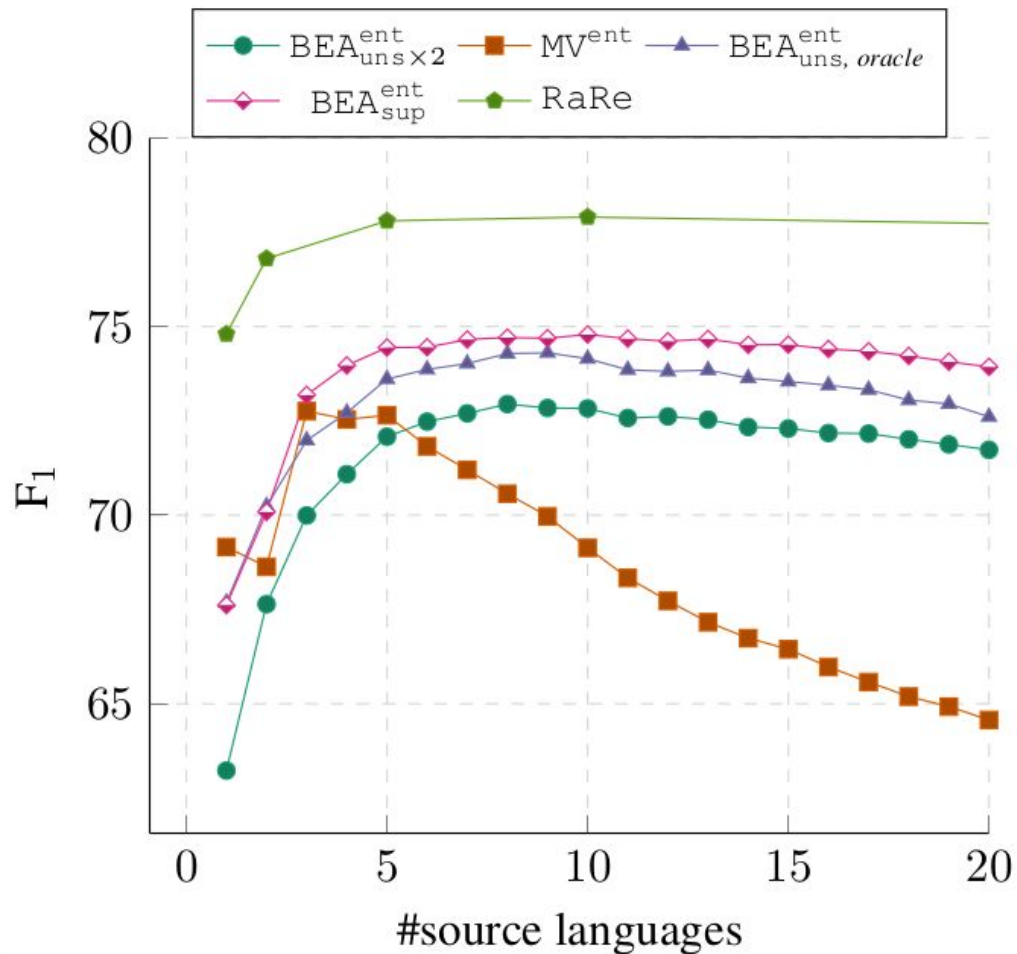
Ranking Retraining  
Method (using  
character info)



# Effect of increasing #source languages

Methods robust to many varying quality source languages.

Even better with few-shot supervision.



# Takeaways I



Transfer from **multiple source languages** helps because for many languages we don't know the best source language.

# Takeaways II



With multiple source languages, you need to **estimate their qualities** because uniform voting doesn't perform well.

## Takeaways III



**A **small training set** in target language helps, and can be done cheaply and quickly (Garrette and Baldrige, 2013).**



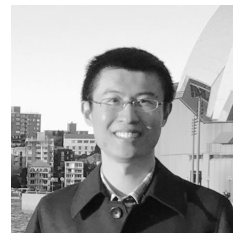


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# Thank you!



Datasets  
& code



[github.com/afshinrahimi/mmner](https://github.com/afshinrahimi/mmner)



# Future Work

- Map all scripts to IPA or Roman alphabet (good for shared embeddings and character-level transfer)
  - uroman: Hermjakob et al. (2018)
  - epitran: Mortensen et al. (2018)
- Can we estimate the quality of source models/languages for a specific target language based on language characteristics (Littell et al., 2017)?
- Technique should apply beyond NER to other tasks.