You Can Have Your Data and Balance It Too: Towards Balanced and Efficient Multilingual Models

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Multilingual Language Models are go to solution for cross-lingual transfer. However, the performance on some languages of interest is hindered by their underrepresentation in training data.

Motivation!

Multilingual Language Models are go to solution for cross-lingual transfer. However, the performance on some languages of interest is hindered by their underrepresentation in training data.

How do we improve performance on low-resource, while preserving the good performance on high-resource?

Motivation!

>> Approach

- We train multilingual language model performing well on languages with small digital footprint (low-resource)
- Preserve good performance on highresource languages

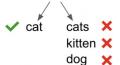
Unbalanced training data





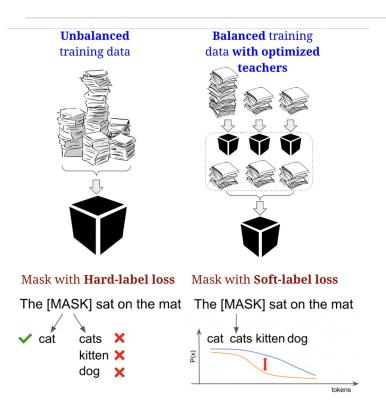
Mask with Hard-label loss

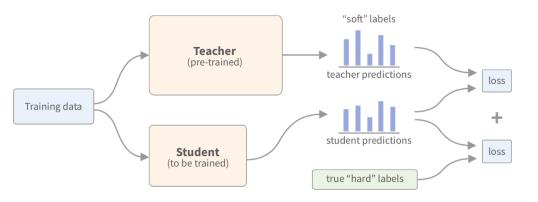
The [MASK] sat on the mat



Approach

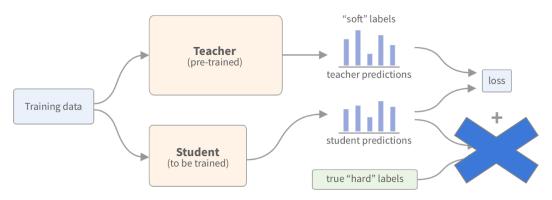
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- Preserve good performance on highresource languages





Soft-target distillation used e.g. in DistilledBERT Sanh et al. 2019



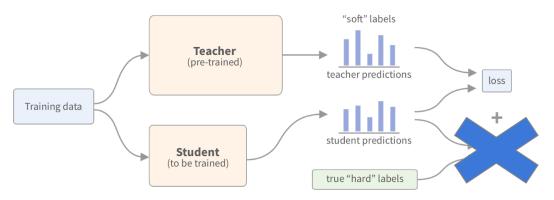


Soft-target distillation used e.g. in DistilledBERT Sanh et al. 2019

Our Approach:

• Use only "soft" labels for student



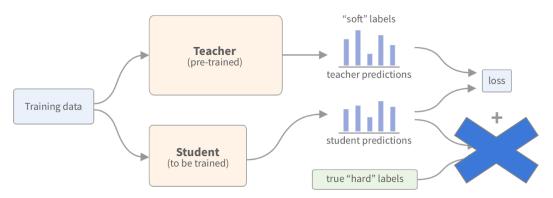


Soft-target distillation used e.g. in DistilledBERT Sanh et al. 2019

Our Approach:

- Use only "soft" labels for student
- Use many monolingual teachers





Soft-target distillation used e.g. in DistilledBERT Sanh et al. 2019

Our Approach:

- Use only "soft" labels for student
- Use many monolingual teachers
- Scale down data not model size



Experiments

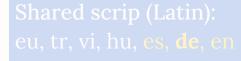
Baselines

Hard-Labels: all data

Hard-Labels: balanced

Ours: Soft-Labels all data → balanced

Languages



te, ur, hi, el, ko, ru, de

Evaluation

Language modeling

Part of Speech

Named Entity Recognition



Experiments

Baselines

Hard-Labels: all data

Hard-Labels: balanced

Ours: Soft-Labels all data⇒ balanced

Languages

Shared scrip (Latin): eu, tr, vi, hu, es, de, en

Diverse script: te, ur, hi, el, ko, ru, de

Evaluation

Language modeling

Part of Speech

Named Entity Recognition



Experiments

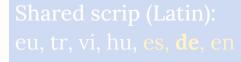
Baselines

Hard-**L**abels: all data

Hard-Labels: balanced

Ours: Soft-**L**abels all data**⇒** balanced

Languages



te, ur, hi, el, ko, ru, **de**

Evaluation

Language modeling

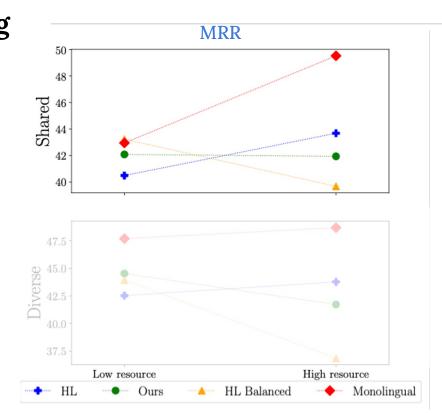
Part of Speech

Named Entity Recognition



Results: Language Modeling

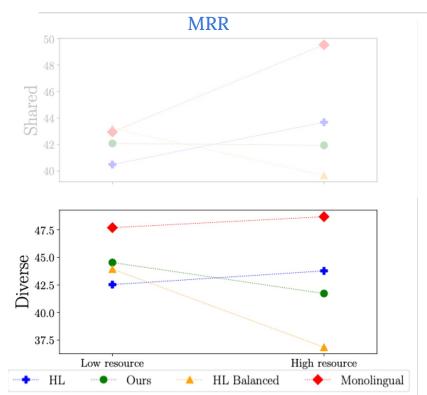
- Our approach achieves good balance of scores between low- and highresource languages.
- For low-resource naive balancing significantly improves results but it hinders performance for highresource languages.





Results: Language Modeling

- Our approach achieves good balance of scores between low- and highresource languages.
- For low-resource naive balancing significantly improves results but it hinders performance for highresource languages.





Results: Zero Shot

Our approach performs best in POS

	Lang. set	HL		HL b	HL balanced		ırs
		I-L	Z- S	I-L	Z- S	I-L	Z- S
75	Low-Res	35.2	33.4	35.5	34.3	36.6	34.5
Shared	High-Res	83.3	33.7	81.2	32.4	84.3	33.8
ha	$\{de\}$	87.1	32.3	84.1	32.2	86.8	33.0
$\mathbf{\alpha}$	All	55.8	33.5	55.1	33.5	57.0	34.2
ē	Low-Res	53.1	35.8	54.6	34.9	55.7	35.9
\mathbf{sre}	High-Res	76.8	36.2	73.4	34.7	77.3	36.8
Diverse	$\{de\}$	87.7	36.8	83.3	35.3	87.4	38.1
Ω	All	63.3	36.0	62.7	34.8	64.9	36.3



Results: Zero Shot

 Our approach performs best in POS and the most cases of NER zero-shot transfers.

	Lang. set	\mathbf{n}		nt balanced		Ours	
		I-L	Z- S	I-L	Z- S	I-L	Z- S
	Low-Res	35.2	33.4	35.5	34.3	36.6	34.5
ĕ	High-Res	83.3	33.7	81.2	32.4	84.3	33.8
\mathbf{Shared}	$\{de\}$	87.1	32.3	84.1	32.2	86.8	33.0
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	<u> </u>	All	63.3	36.0	62.7	34.8	64.9	36.3	-
		Lang. set	H I-L	L Z-S	HL ba	alanced Z-S	Oı I-L	ırs Z-S	-
NER	Shared	Low-Res High-Res {de} All	26.5 34.2 31.4 29.8	23.7 24.9 27.4 24.2	27.9 34.7 32.1 30.8	24.3 24.7 25.7 24.5	29.8 37.6 32.0 33.1	23.9 26.0 23.9 24.8	-
	Diverse	Low-Res High-Res {de} All	25.7 32.8 32.5 28.7	12.8 14.9 14.8 13.7	28.0 29.9 31.5 28.8	13.8 15.1 15.7 14.4	29.9 37.2 35.3 33.0	12.9 17.1 17.2 14.7	17



Results: In Language

- Our approach performs best in POS and the most cases of NER zero-shot transfers.
- We also overperform in in-language probing results.

	Lang. set	\mathbf{HL}		HL b	alanced	Ours	
		I-L	Z-S	I-L	Z-S	I-L	Z-S
Shared	Low-Res	35.2	33.4	35.5	34.3	36.6	34.5
	High-Res	83.3	33.7	81.2	32.4	84.3	33.8
	$\{de\}$	87.1	32.3	84.1	32.2	86.8	33.0
	All	55.8	33.5	55.1	33.5	57.0	34.2
Diverse	Low-Res	53.1	35.8	54.6	34.9	55.7	35.9
	High-Res	76.8	36.2	73.4	34.7	77.3	36.8
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	Lang. set	HL		HL ba	alanced	Ours	
	J	I-L	Z-S	I-L	Z-S	I-L	Z-S
7	Low-Res	26.5	23.7	27.9	24.3	29.8	23.9
\mathbf{Shared}	High-Res	34.2	24.9	34.7	24.7	37.6	26.0
	$\{de\}$	31.4	27.4	32.1	25.7	32.0	23.9
	All	29.8	24.2	30.8	24.5	33.1	24.8
Diverse	Low-Res	25.7	12.8	28.0	13.8	29.9	12.9
	High-Res	32.8	14.9	29.9	15.1	37.2	17.1
	$\{de\}$	32.5	14.8	31.5	15.7	35.3	17.2
	All	28.7	13.7	28.8	14.4	33.0	14.7



Results: Script Groups

- Our approach performs best in POS and the most cases of NER zero-shot transfers.
- We also overperform in in-language probing results.
- Interestingly, in the set of languages with diverse scripts transfer is worse for NER and better for POS, in comparison to same script set.

	Lang. set	\mathbf{HL}		HL b	alanced	Ours	
		I-L	Z- S	I-L	Z- S	I-L	Z- S
7	Low-Res	35.2	33.4	35.5	34.3	36.6	34.5
\mathbf{Shared}	High-Res	83.3	33.7	81.2	32.4	84.3	33.8
	$\{de\}$	87.1	32.3	84.1	32.2	86.8	33.0
	All	55.8	33.5	55.1	33.5	57.0	34.2
е	Low-Res	53.1	35.8	54.6	34.9	55.7	35.9
Diverse	High-Res	76.8	36.2	73.4	34.7	77.3	36.8
	$\{de\}$	87.7	36.8	83.3	35.3	87.4	38.1
	All	63.3	36.0	62.7	34.8	64.9	36.3

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	Lang. set	\mathbf{H}	${f IL}$	HL b	alanced	Οι	ırs
	o .	I-L	Z- S	I-L	Z- S	I-L	Z- S
7	Low-Res	26.5	23.7	27.9	24.3	29.8	23.9
rec	High-Res	34.2	24.9	34.7	24.7	37.6	26.0
\mathbf{Shared}	$\{de\}$	31.4	27.4	32.1	25.7	32.0	23.9
∞	All	29.8	24.2	30.8	24.5	33.1	24.8
е	Low-Res	25.7	12.8	28.0	13.8	29.9	12.9
\mathbf{r}	High-Res	32.8	14.9	29.9	15.1	37.2	17.1
Diverse	$\{de\}$	32.5	14.8	31.5	15.7	35.3	17.2
D	All	28.7	13.7	28.8	14.4	33.0	14.7

Summary:

- 1. Better low-res performance, while high-resource results are preserved.
- 2. Diverse script can be beneficial for cross-lingual transfer.
- 3. Future work needed to validate the method on larger models.

Thank You

For your Attention!