





Overlap-based Vocabulary Generation Improves Cross-lingual Transfer Among Related Languages



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E.g. theorem proving, solving reading comprehension

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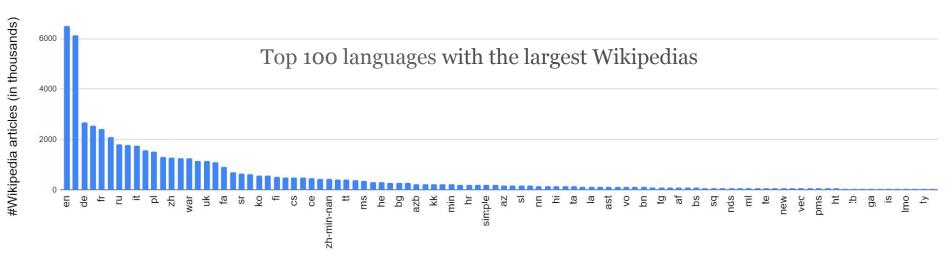
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Labeled data for such tasks is scarce

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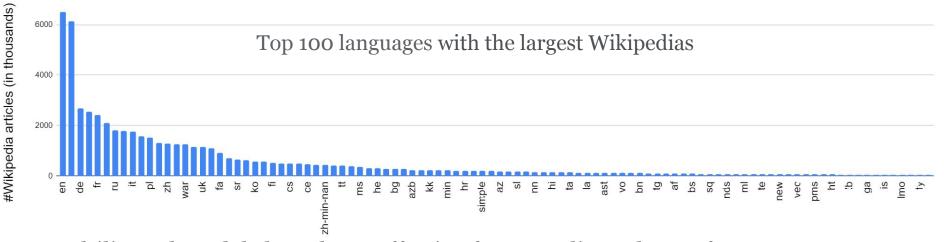
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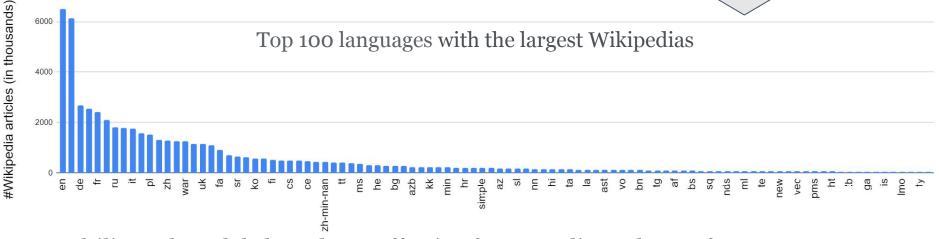
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- Multilingual models have been effective for cross-lingual transfer
 - when there is sufficient LRL unlabeled corpus (Wu and Dredze, 2020)

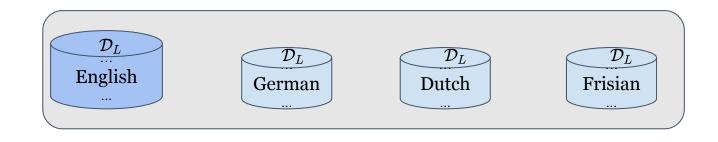
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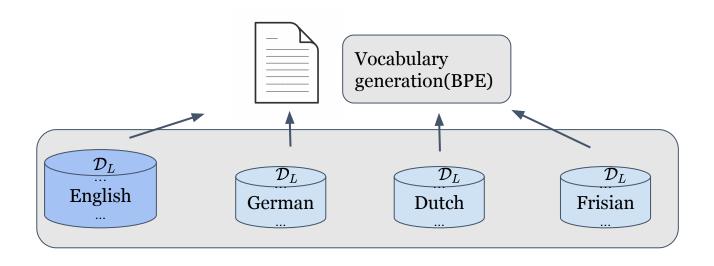
If languages belong to the same family, what more can be done to improve cross-lingual transfer?

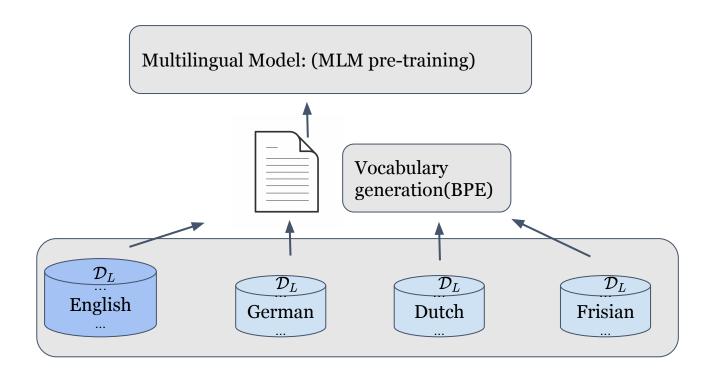


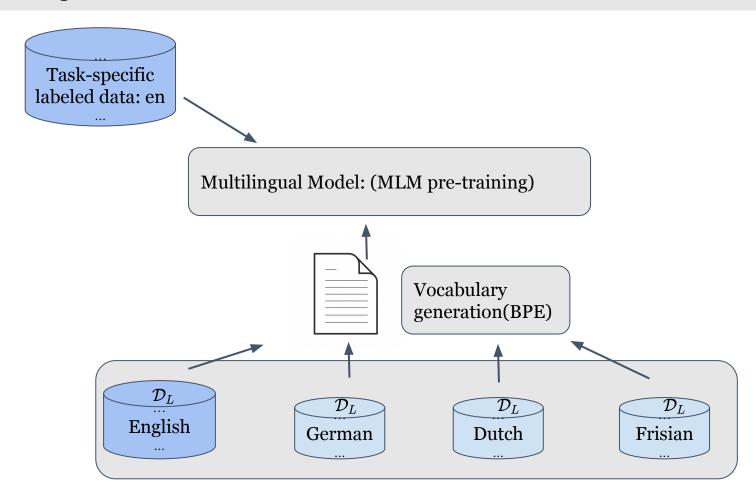
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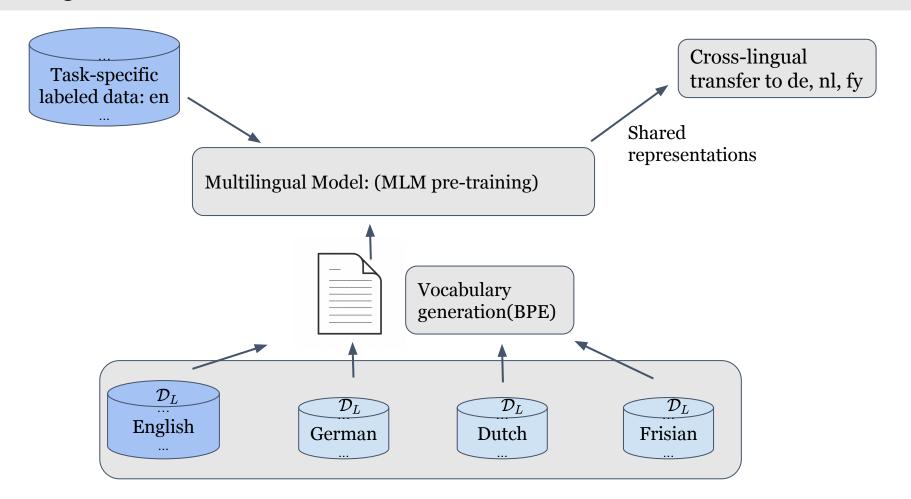












- Vocabulary is generated using
 - Byte Pair Encoding (BPE) (Sennrich et al., 2016).
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If languages belong to the same family, what more can be done while **generating vocabulary** for supervision transfer from HRL to LRL?

Lexical Overlap

	Hindi: Vaapariyo, Marathi: Vaapartat , Punjabi: Vaaparan,
Indo-Aryan	Gujarati: <mark>Vaapar</mark> vana
	English: Category, German:Kategorie, Dutch:Categorie, Western
West-Germanic	Frisian:K <mark>ategor</mark> y
	French: Association, Spanish: Associacion, Portuguese:
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Lexically overlapping tokens with similar meanings across four languages in each of three families

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How can relatedness help improve cross-lingual transfer?

Main takeaways

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- Token overlap matters (unlike K et al., 2020) under two settings:
 - Languages are sufficiently related
 - LRL is resource-poor even in the amount of unlabeled data

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OPPORTUNITY: Relatedness between Languages

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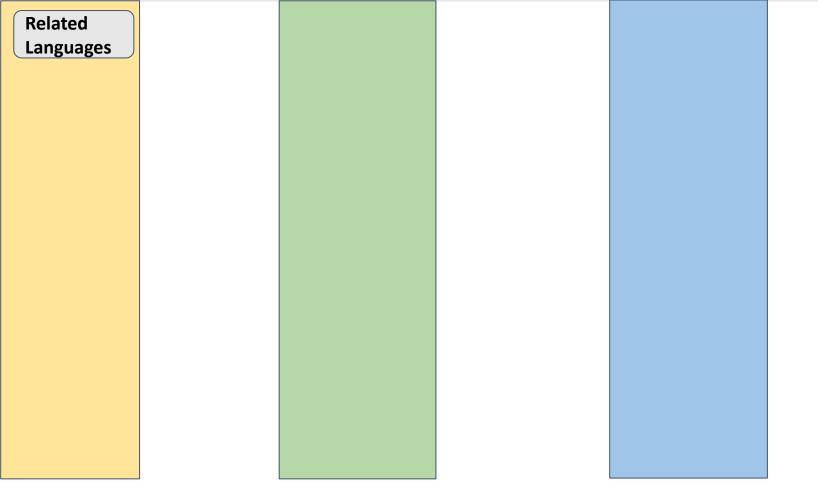
- Many languages are part of the same language family (e.g. Indo-Aryan, Germanic, Romance etc)
- Languages of same family have lexically overlapping words with similar meanings even when languages are of different scripts

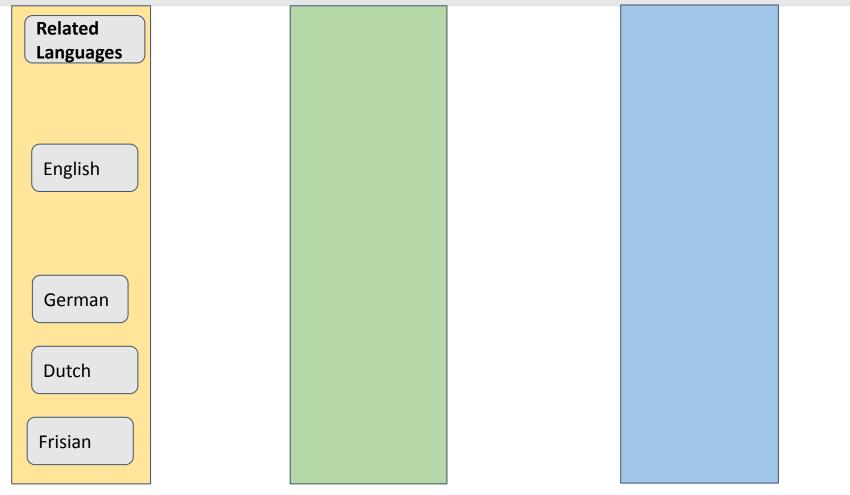
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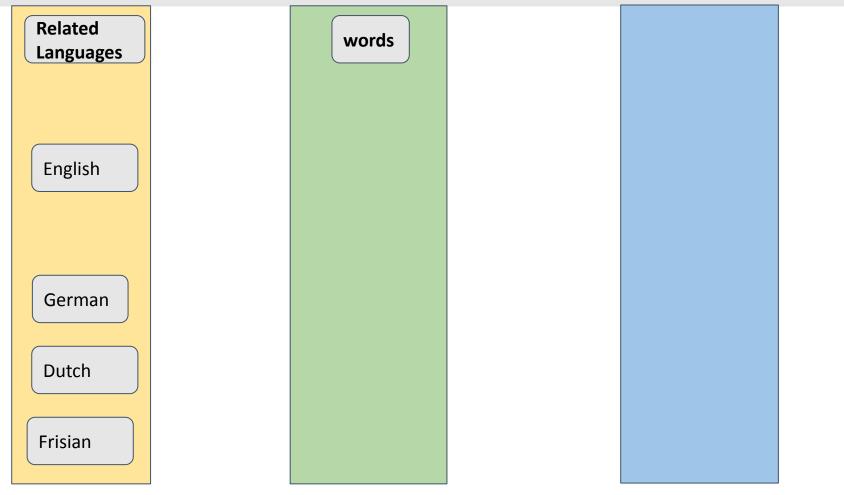
Can we take advantage of this *relatedness* to overcome the barriers of resource scarcity?

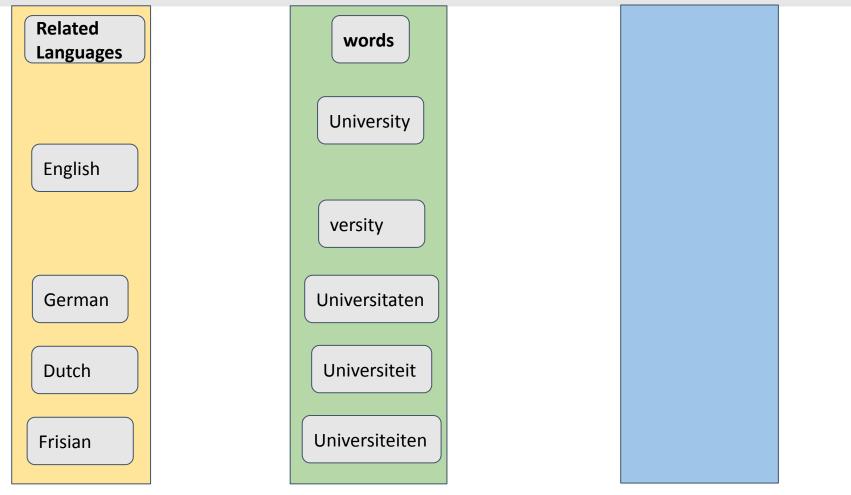
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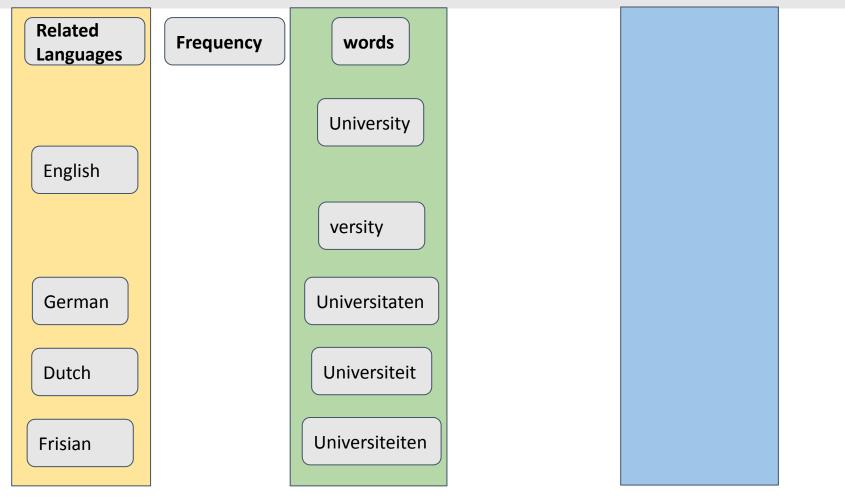
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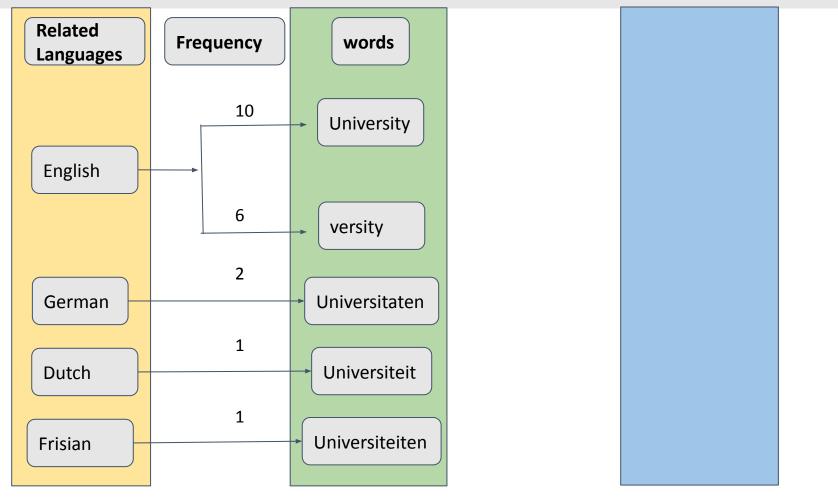


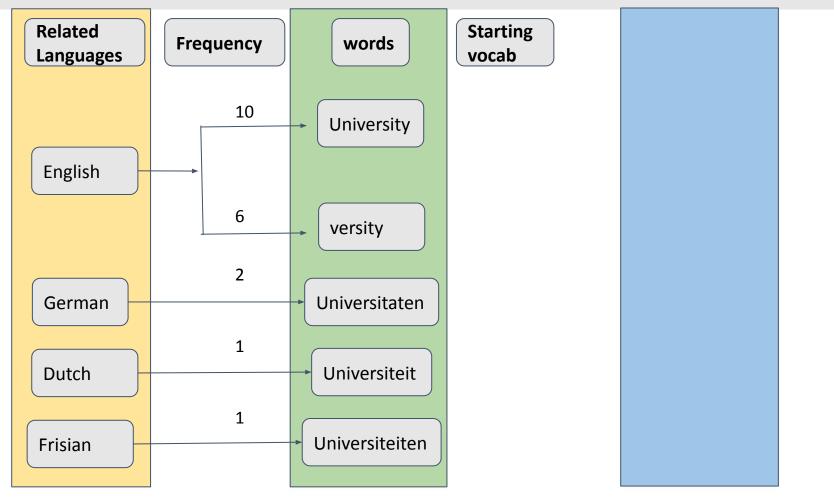


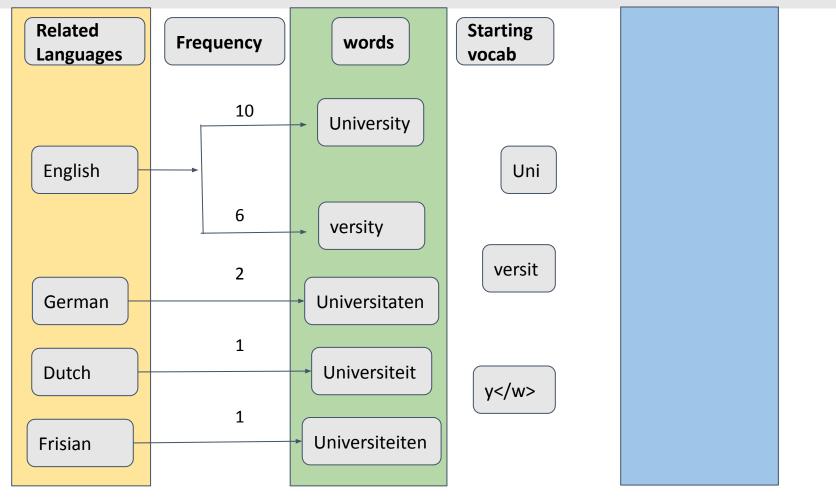


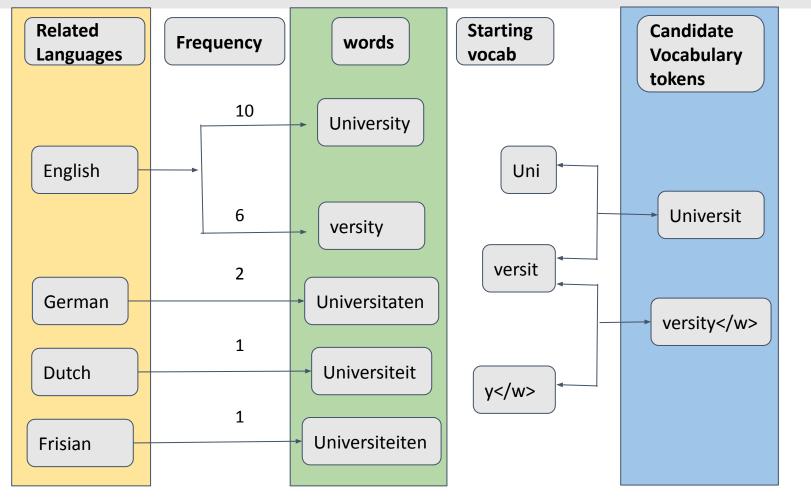


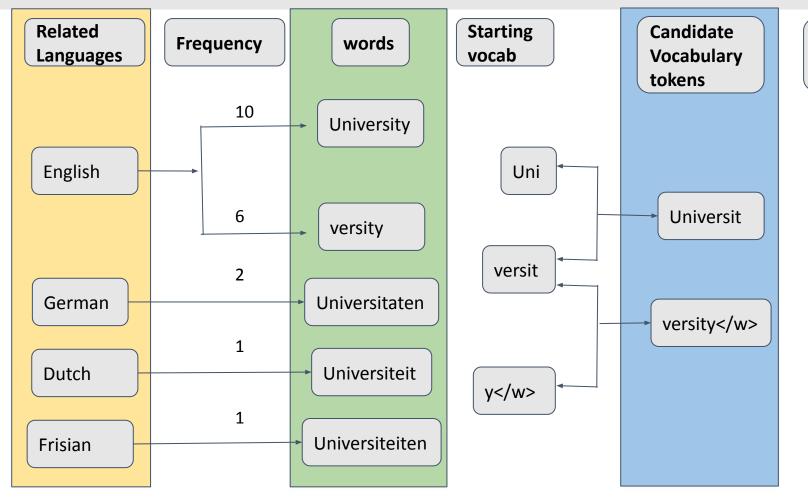




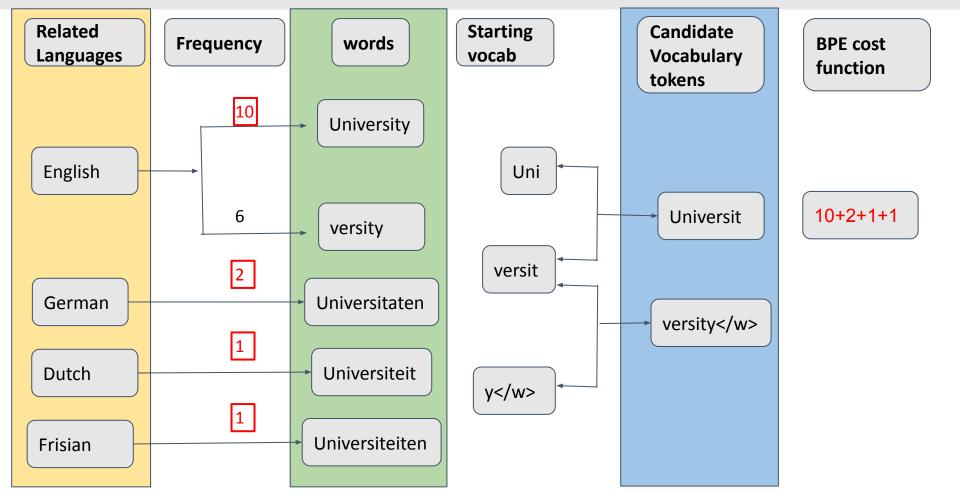


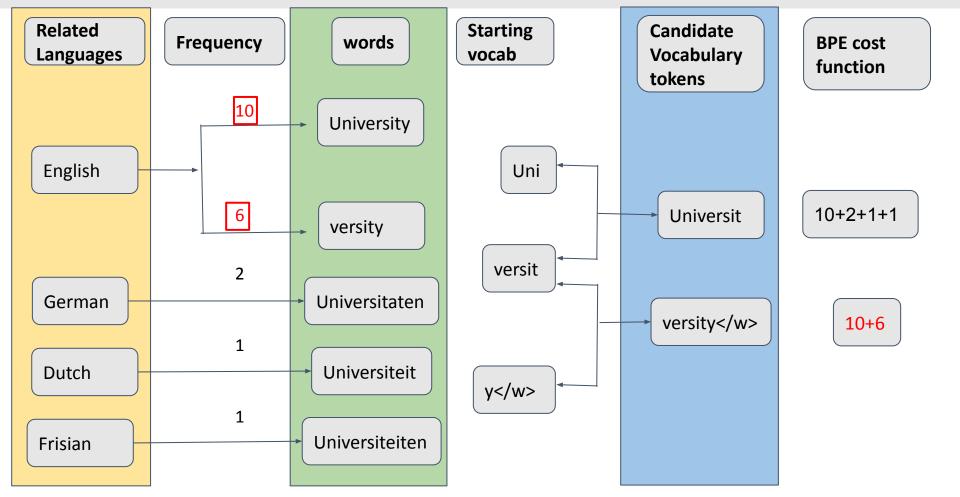


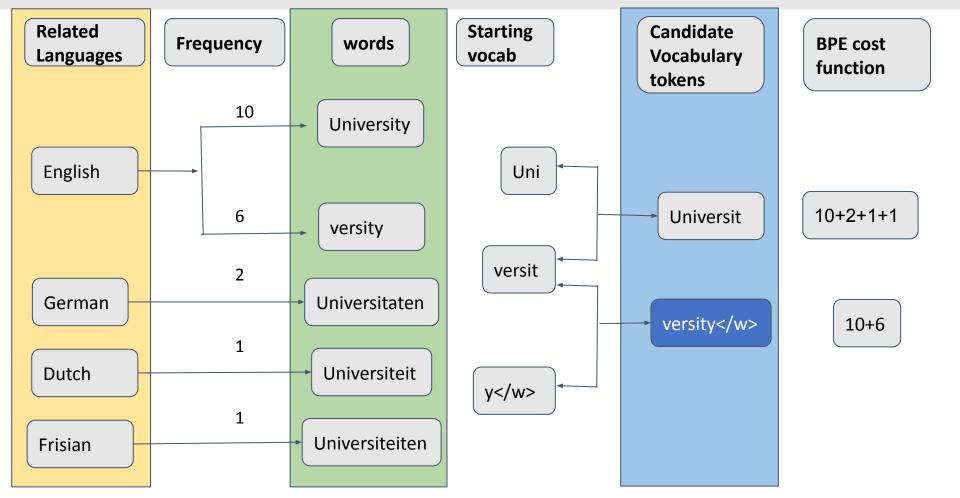




BPE cost function







- o prefers vocabulary units which are shared across multiple languages
- o encodes the input corpora compactly

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- The objective function that governs the candidate token to be added to the vocabulary at every iteration comprises of two terms:
 - The first term compactly represents the total corpus, as in BPE
 - The second term additionally biases towards vocabulary with greater overlap of each LRL to one HRL

• OBPE quantifies overlap between two languages'

encoding as a generalized mean function

$$\operatorname{overlap}(L_i, L_h, S) = \sum_{k \in S} \left(\frac{f_{ki}^p + f_{kh}^p}{2} \right)^{\frac{1}{p}}, \quad p \le 1$$

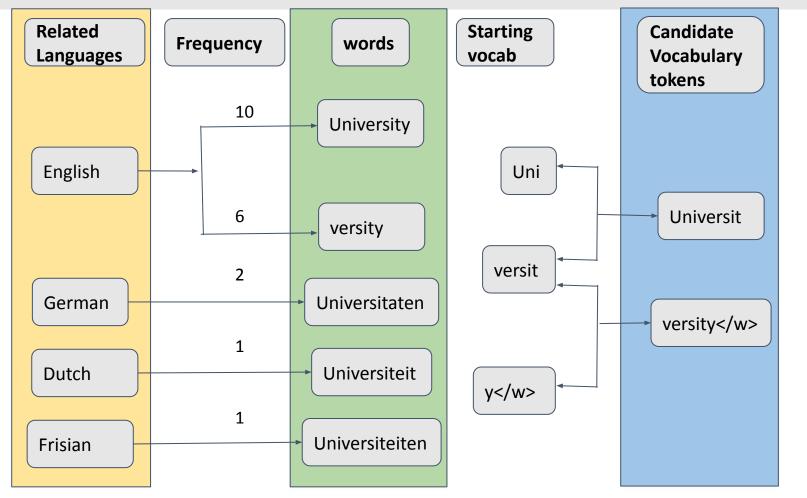
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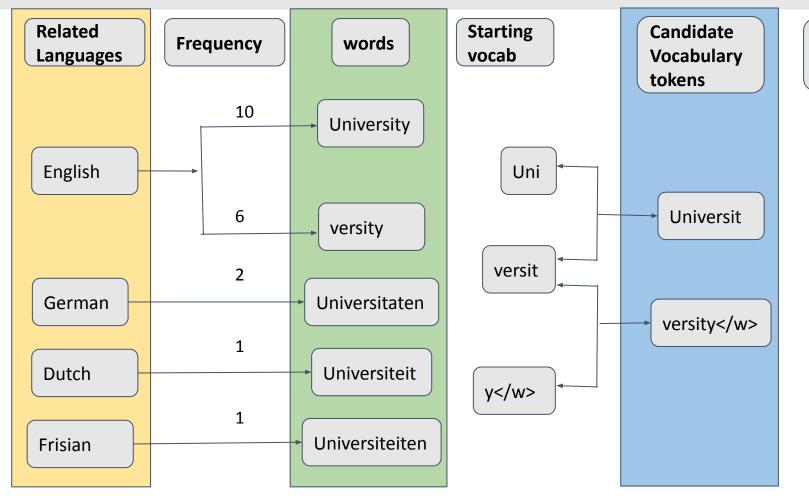
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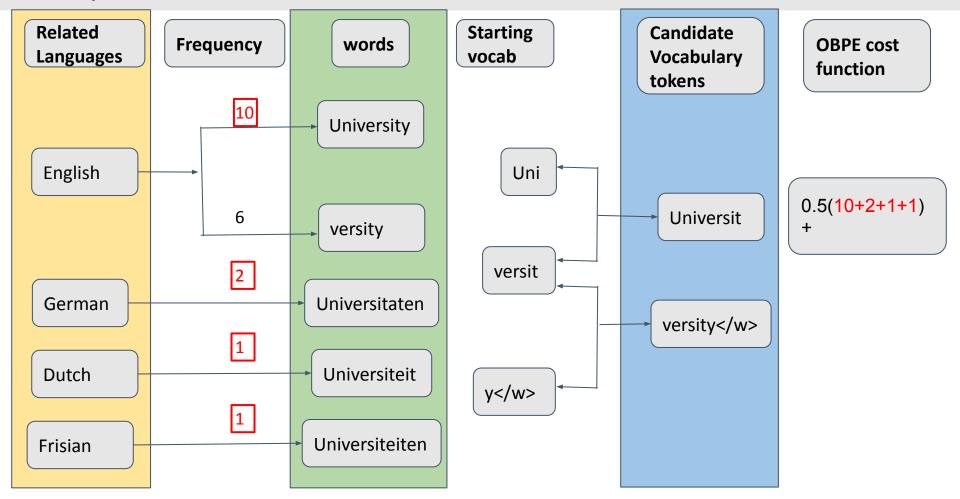
 The greedy version of the objective that controls the candidate vocabulary item to be inducted in each iteration of OBPE

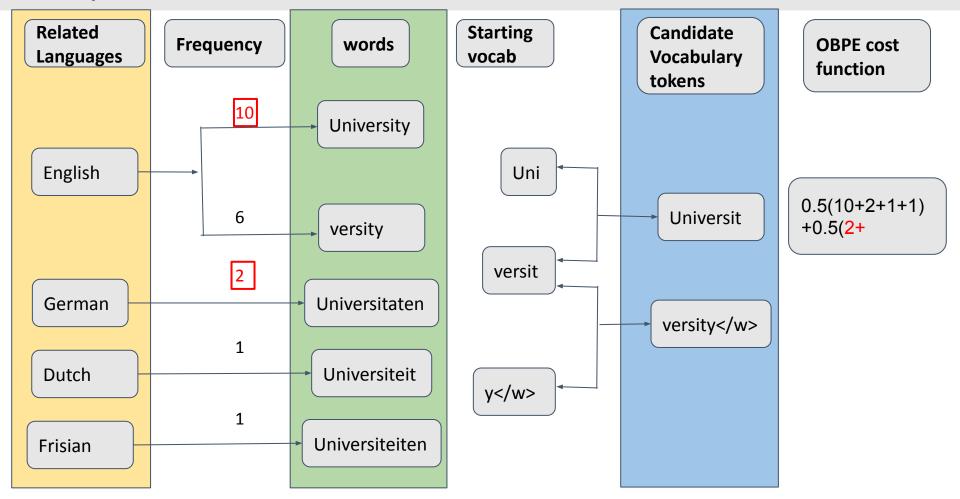
$$\mathcal{V} = \mathcal{V} \cup \underset{k=[u,v]:u,v \in \mathcal{V}}{\operatorname{argmax}} (1-\alpha) \sum_{j} f_{kj}$$
$$+\alpha \sum_{i \in \mathcal{L}_{\mathsf{IRL}}} \max_{h \in \mathcal{L}_{\mathsf{HRL}}} \left(\frac{f_{ki}^p + f_{kh}^p}{2} \right)^{\frac{1}{p}}$$

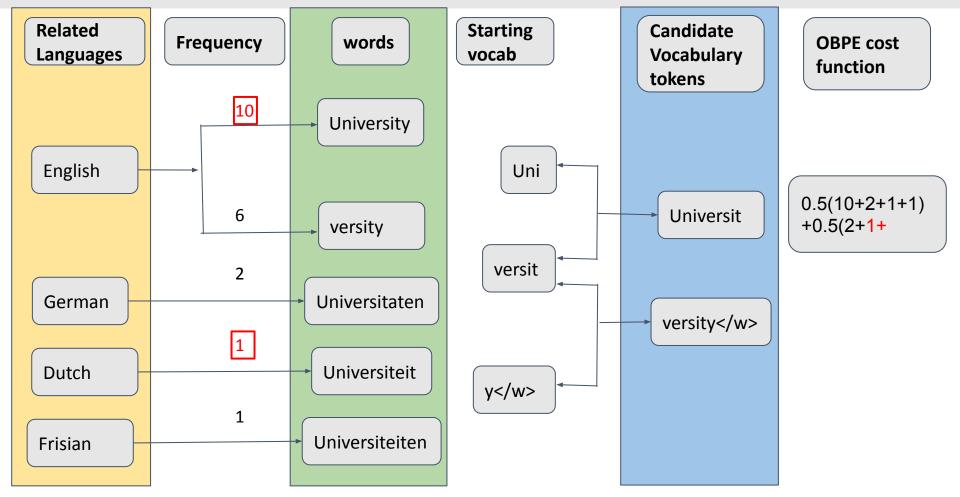


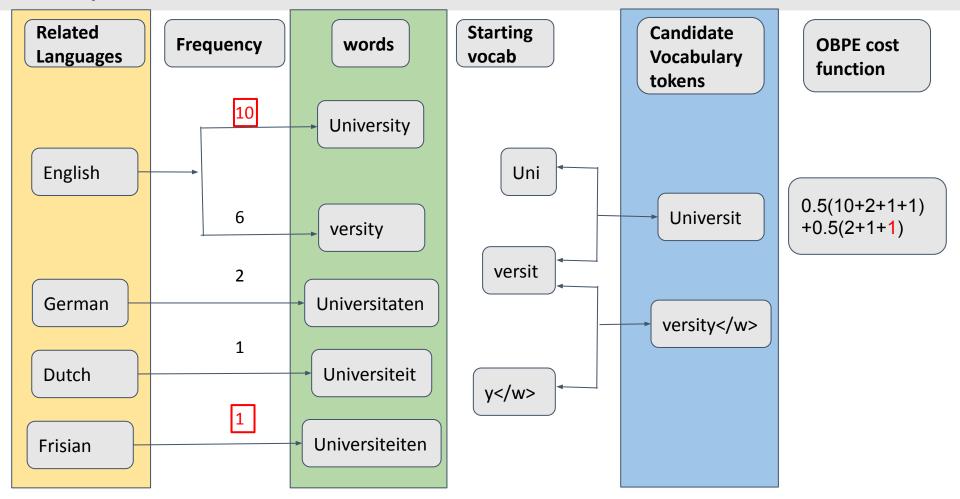


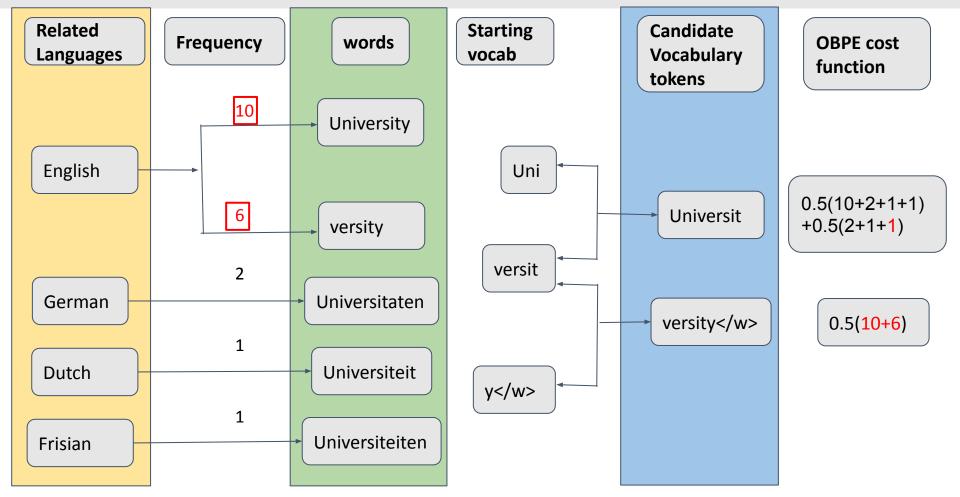
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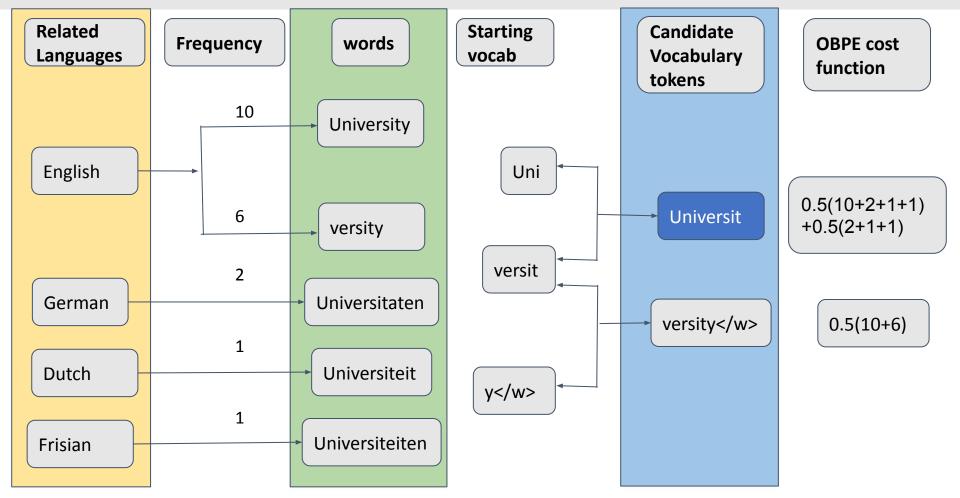












Experimental Setup

Family	HRL	LRLs	Number of	HRL Docs
			Balanced	Skewed
West		German (de), Dutch (nl),		
Germanic	English (en)	Western Frisian (fy)	0.16M	1.00M
		Spanish (es), Portuguese (pt),		
Romance	French (fr)	Italian (it)	0.16M	0.50M
		Marathi (mr), Punjabi (pa),		
Indo-Aryan	Hindi (hi)	Gujarati (gu)	0.16M	0.16M

Twelve Languages simulated as HRLs and LRLs across with two different corpus distribution: Balanced and Skewed
Number of documents in languages simulated as LRLs is 20K

Balanced setting

Method	LF	RL Perfo	rmance((†)	HRL Performance(↑)			
	NER	TC	XNLI	POS	NER	TC	XNLI	POS
BPE	64.48	65.52	52.07	84.64	83.26	82.07	62.71	95.20
BPE-dp	63.92	64.15	52.66	84.75	81.73	81.07	63.74	94.61
CV	59.58	61.91	49.30	81.68	81.15	80.93	64.51	94.47
TokComp	63.79	65.77	53.94	85.49	82.43	80.93	66.10	94.86
OBPE	65.72	68.02	54.03	85.26	83.98	81.91	66.27	95.09

Zero-shot LRL accuracy improves compared to the baselines across all four tasks

Skewed setting

Method	LF	RL Perfo	rmance((†)	HRL Performance(↑)				
	NER	TC	XNLI	POS	NER	TC	XNLI	POS	
BPE	52.91	51.68	48.57	74.79	81.78	80.04	64.96	95.03	
CV	52.73	54.40	44.28	76.70	79.84	77.74	57.18	94.60	
OBPE	55.09	55.3 7	50.01	75.05	82.94	80.31	65.57	95.09	

Zero-shot LRL accuracy improves compared to the baselines across all four tasks

Balanced setting

Method	LRL Performance(↑)				HRL Performance(↑)			
	NER	TC	XNLI	POS	NER	TC	XNLI	POS
BPE	64.5	65.5	52.1	84.6	83.3	82.1	62.7	95.2
+overSample	64.4	67.6	52.1	84.6	82.4	82.0	62.0	95.2
OBPE	65.7	68.0	54.0	85.3	84.0	81.9	66.3	95.1
+overSample	64.6	67.9	53.5	85.1	82.7	81.7	65.7	94.8

Even though BPE_overSamp improves LRL performance somewhat, it causes HRL performance to drop

Balanced setting

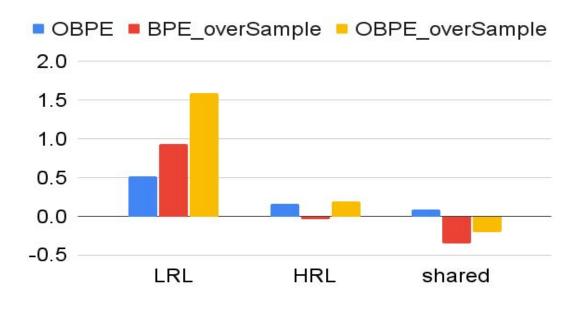
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OBPE	65. 7	68.0	54.0	85.3	84.0	81.9	66.3	95.1
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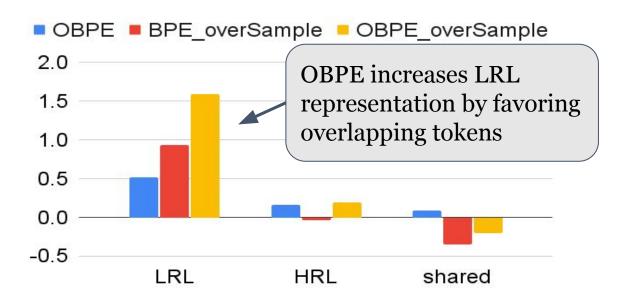
OBPE with default sampling is best for both LRLs and HRLs

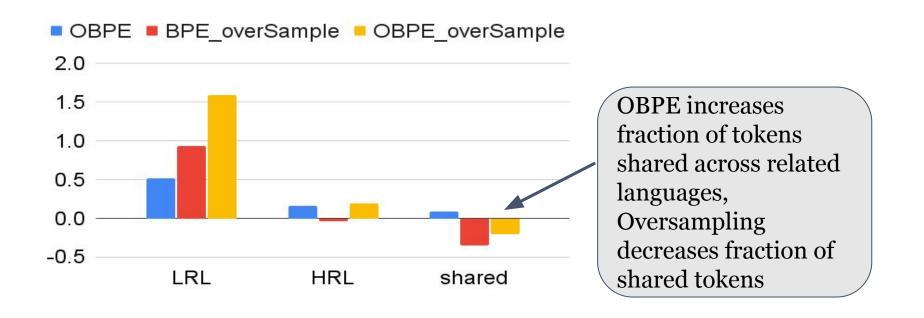
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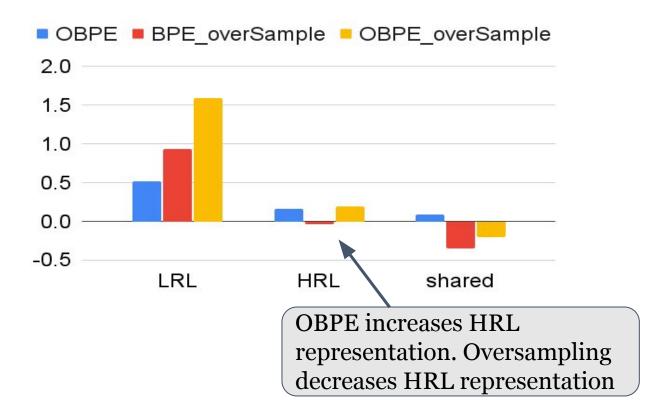
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OBPE_overSampled is better than BPE_overSampled

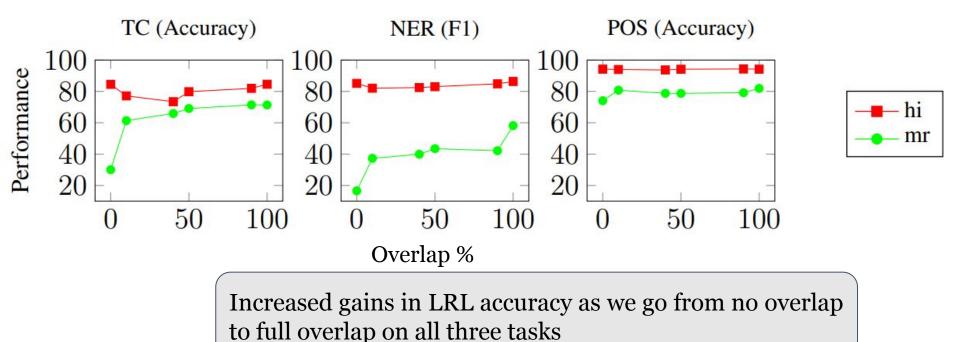




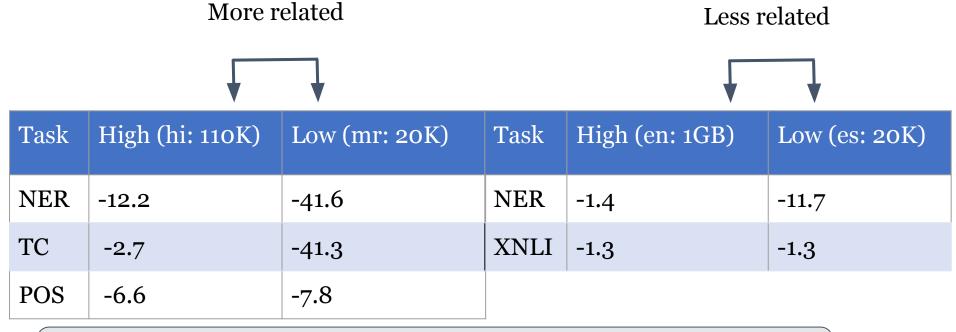




What is the effect of token overlap on overall accuracy?

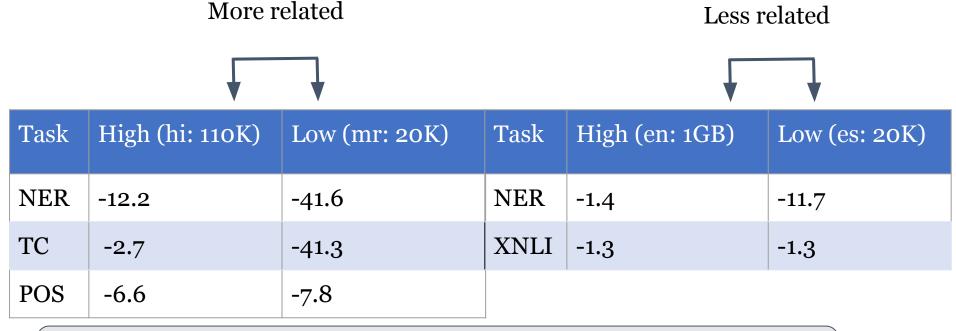


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Drop in Accuracy of Zero-shot transfer when we synthetically reduce token overlap to zero

What is the effect of token overlap on overall accuracy?



Token overlap is important for related languages and its benefit is higher in the low resource setting

• OBPE exploits language relatedness along lexical overlap

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- Exploiting language relatedness results in an overall more effective vocabulary compared to oversampling
- Token overlap is important in a low resource, related-language setting



Thank You

Paper: https://arxiv.org/abs/2203.01976

Github: https://github.com/Vaidehi99/OBPE

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