

A bit of Progress and Stronger n-gram LM Baselines

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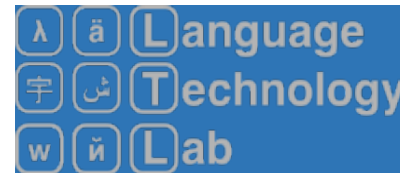
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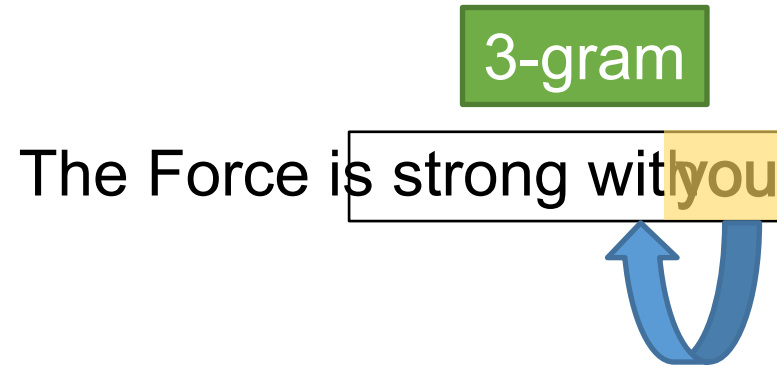


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n-gram LM

$$P(w_1^N) = \prod_{i=1}^N P(w_i | w_{i-n+1}^{i-1})$$



Questions:

- Do I know what is Kneser-Ney (KN), and what is Modified KN (MKN)?
- Has there been any progress in n-gram smoothing?
- Are NLM always superior to n-grams? When are they likely to fall short?

Smoothing in general

Donald Trump is a **X**

$$P(\text{X} = \text{politician} \mid \text{Donald Trump is a}) = \frac{\text{count}(\text{Donald Trump is a politician})}{\text{count}(\text{Donald Trump is a})}$$

$$\begin{aligned}\text{count}(\text{Donald Trump is a politician}) &= 0 \\ \text{count}(\text{Trump is a politician}) &= 100\end{aligned}$$

$$P(\text{politician} \mid \text{Donald Trump is a}) \approx P(\text{politician} \mid \text{Trump is a})$$

Smoothing- something old something new

$$\beta(w_i | w_{i-n+1}^{i-1}, \Theta) + \gamma(w_{i-n+1}^{i-1}, \Theta) P(w_i | w_{i-n+2}^{i-1}, \Theta)$$

Smoothing- something old something new

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	$\beta(w_i w_{i-n+1}^{i-1}, \Theta)$	Θ
	<hr/>	<hr/>
KN	$\frac{c(w_{i-n+1}^i) - D_n}{c(w_{i-n+1}^{i-1})}$	D_n

Smoothing- something old something new

$$\beta(w_i | w_{i-n+1}^{i-1}, \Theta) + \gamma(w_{i-n+1}^{i-1}, \Theta) P(w_i | w_{i-n+2}^{i-1}, \Theta)$$

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MKN	$\frac{c(w_{i-n+1}^i) - D_n^{c(w_{i-n+1}^i)}}{c(w_{i-n+1}^{i-1})}$	$D_n^{i \in \{1, 2, 3+\}}$

Smoothing- something old something new

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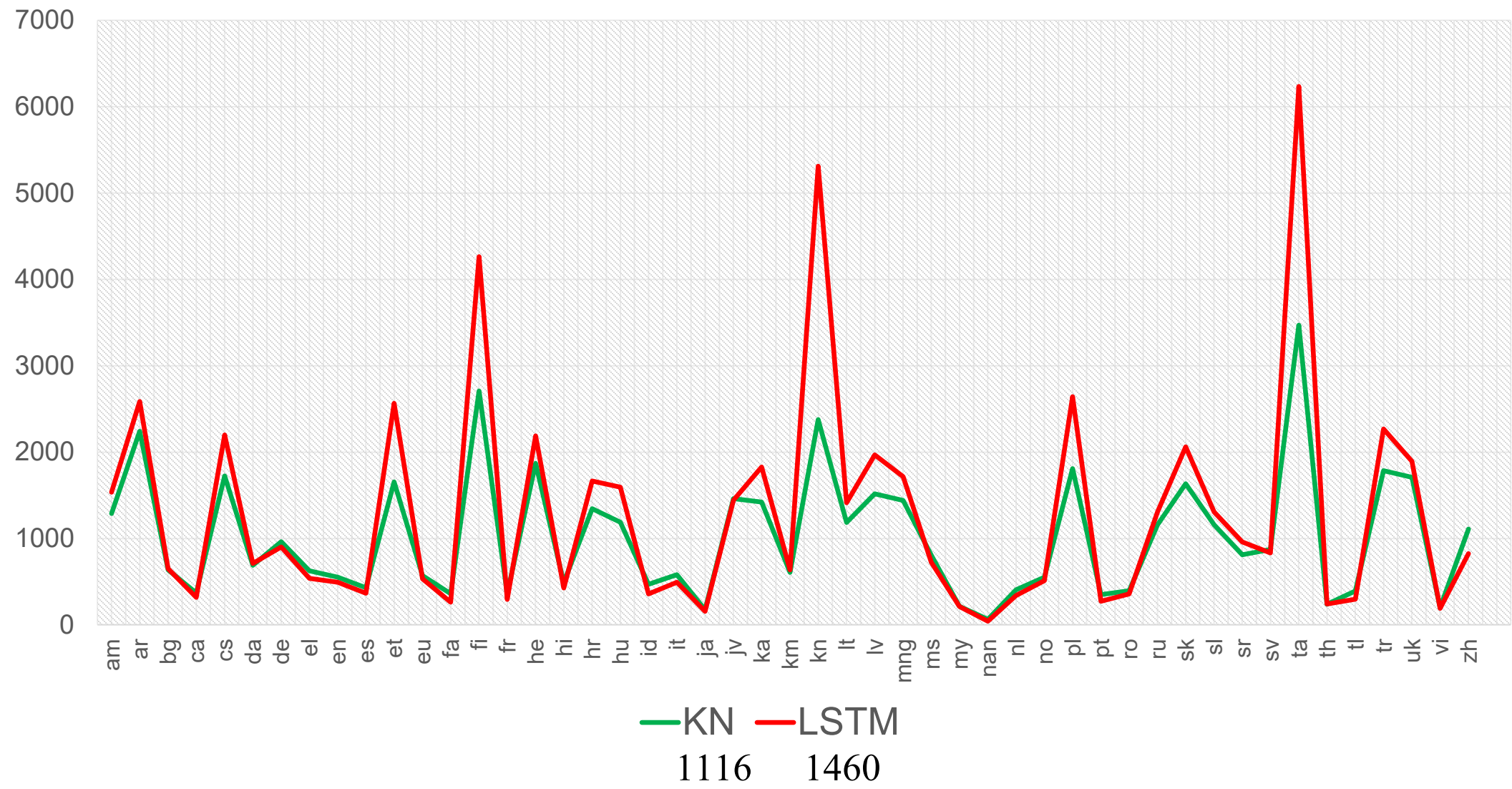
	$\beta(w_i w_{i-n+1}^{i-1}, \Theta)$	Θ
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GKN	$\frac{c(w_{i-n+1}^i) - D_n^{c(w_{i-n+1}^i)}}{c(w_{i-n+1}^{i-1})}$	$D_n^{i \in \{1, \dots, 10+\}}$

Smoothing- something old something new

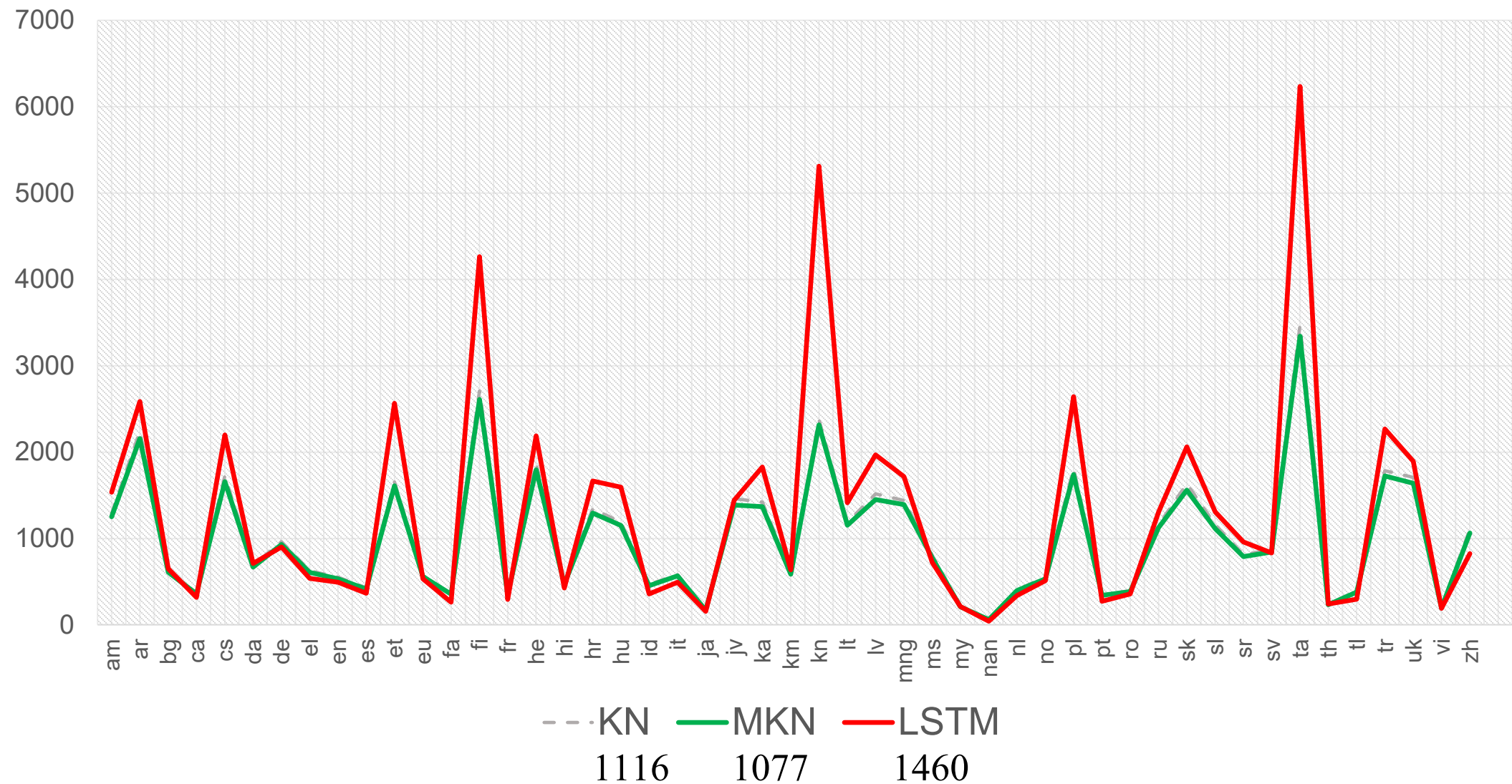
$$\beta(w_i | w_{i-n+1}^{i-1}, \Theta) + \gamma(w_{i-n+1}^{i-1}, \Theta) P(w_i | w_{i-n+2}^{i-1}, \Theta)$$

	$\beta(w_i w_{i-n+1}^{i-1}, \Theta)$	Θ
KN	$\frac{c(w_{i-n+1}^i) - D_n}{c(w_{i-n+1}^{i-1})}$	D_n
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BKN	$\frac{c(w_{i-n+1}^i) - D_{w_{i-n+1}}^{w_i} t_{w_{i-n+1}}^{w_i}}{c(w_{i-n+1}^{i-1}) + \theta_{w_{i-n+1}}}$	$D_{w_{i-n+1}}, \theta_{w_{i-n+1}}, t_{w_{i-n+1}}^{w_i}$

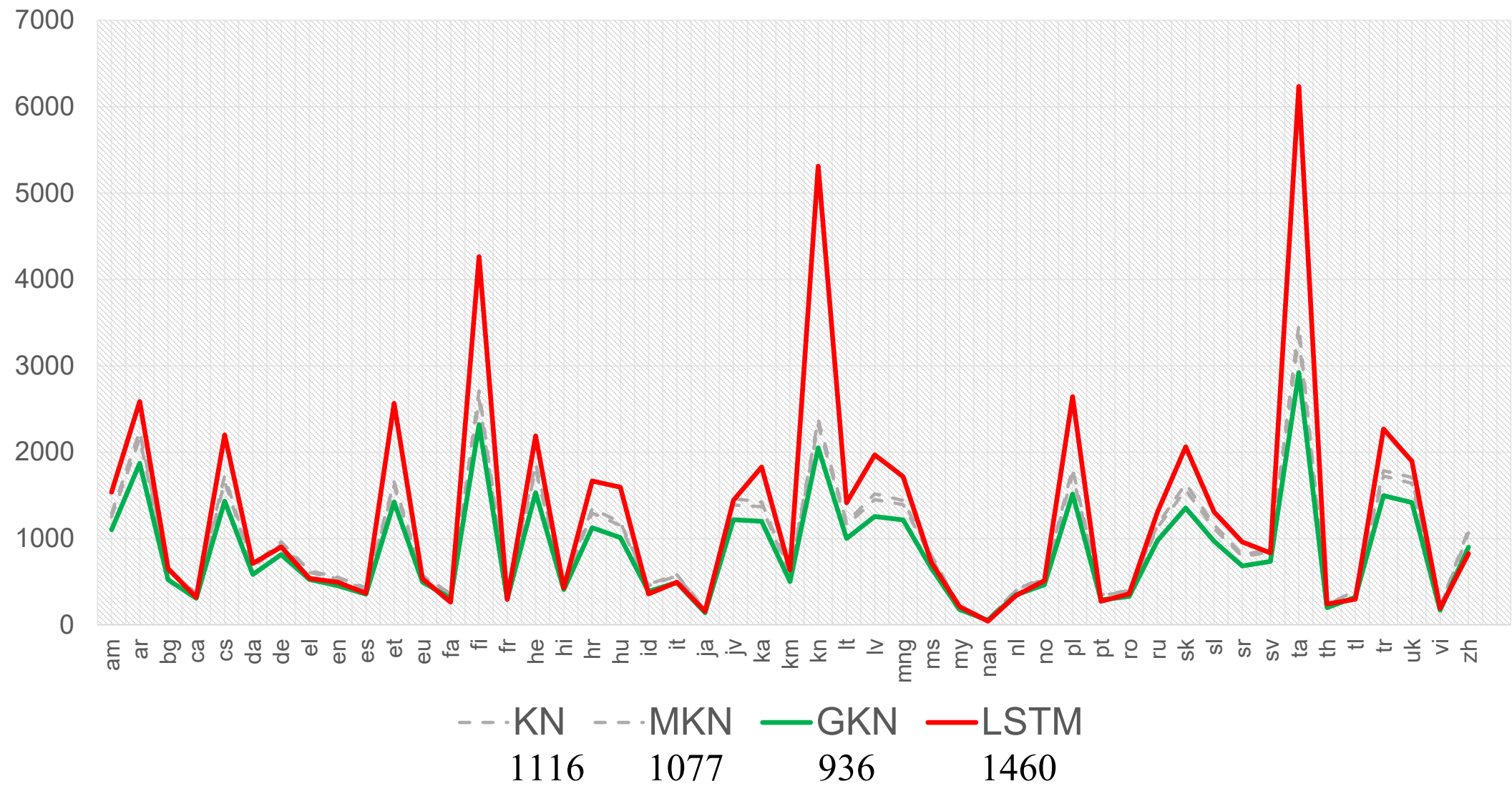
Perplexity



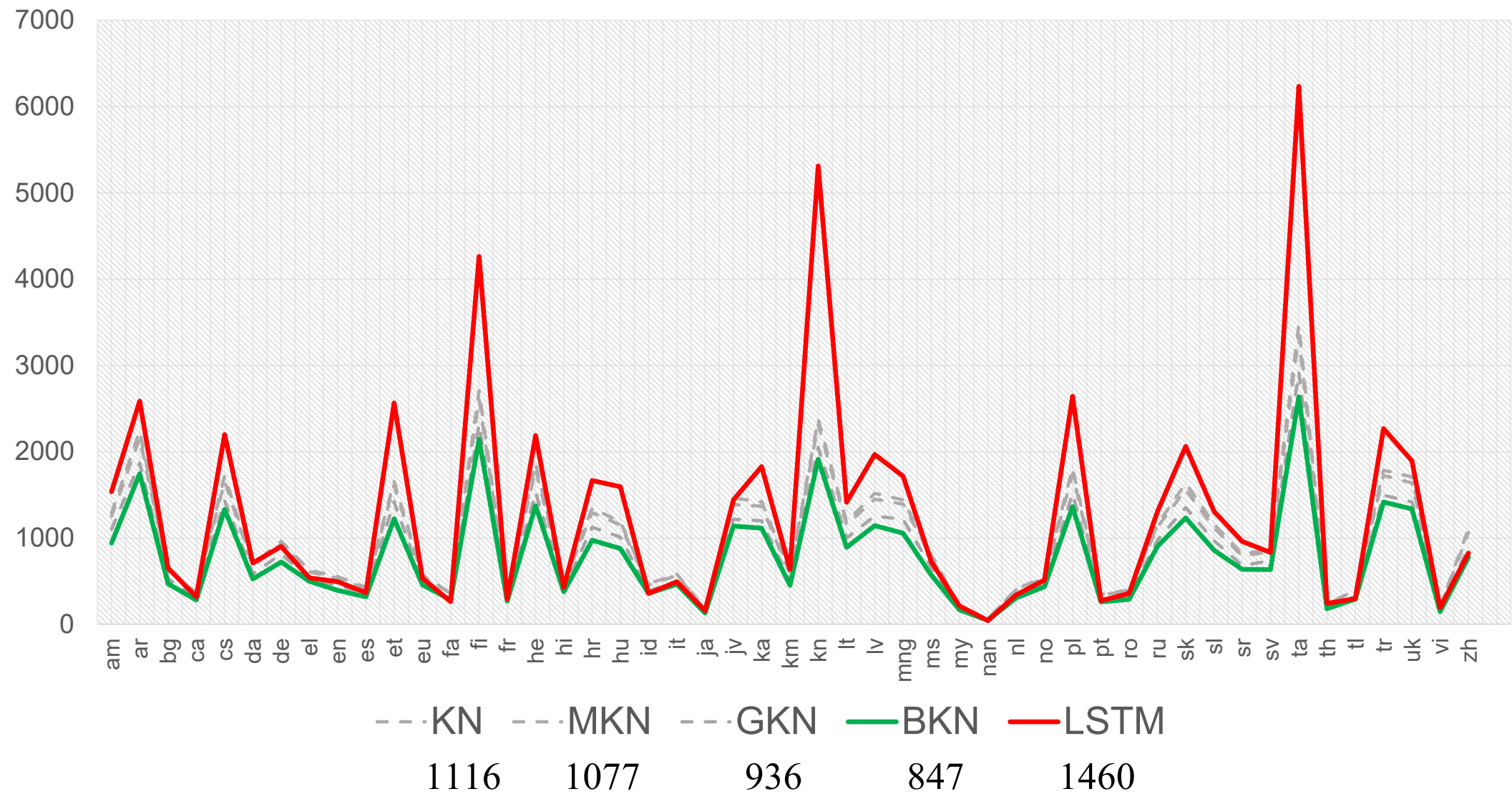
Perplexity



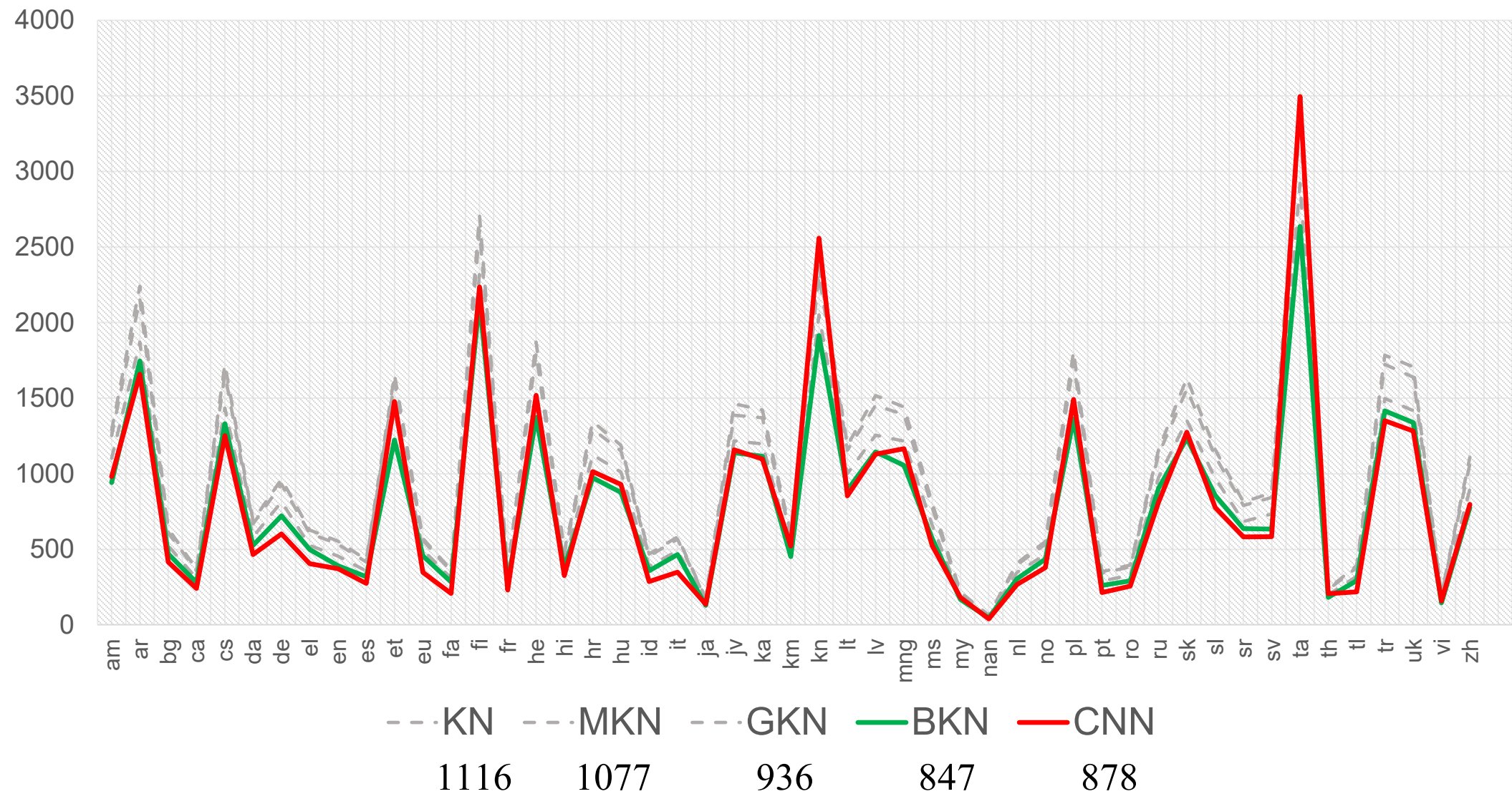
Perplexity



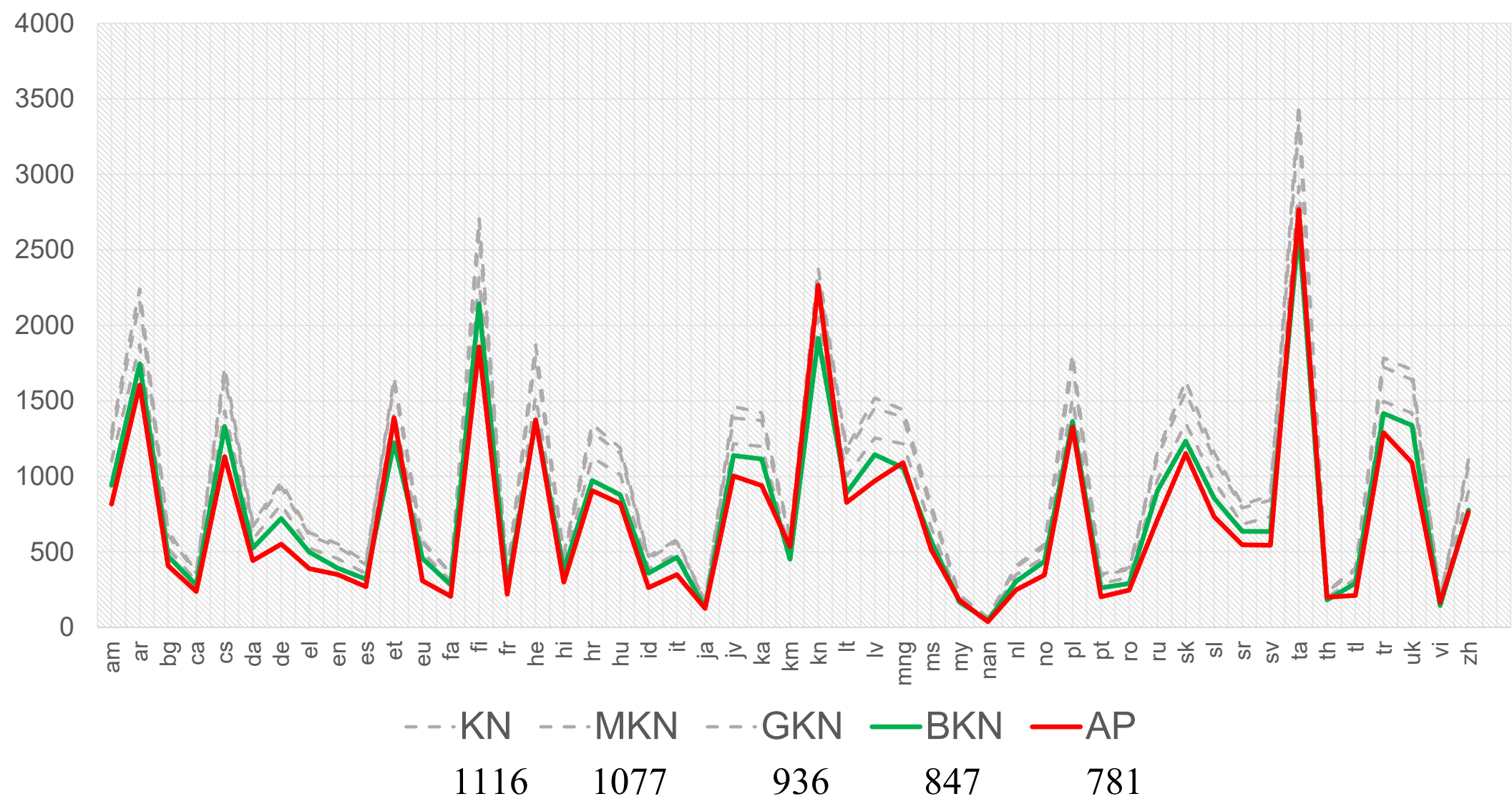
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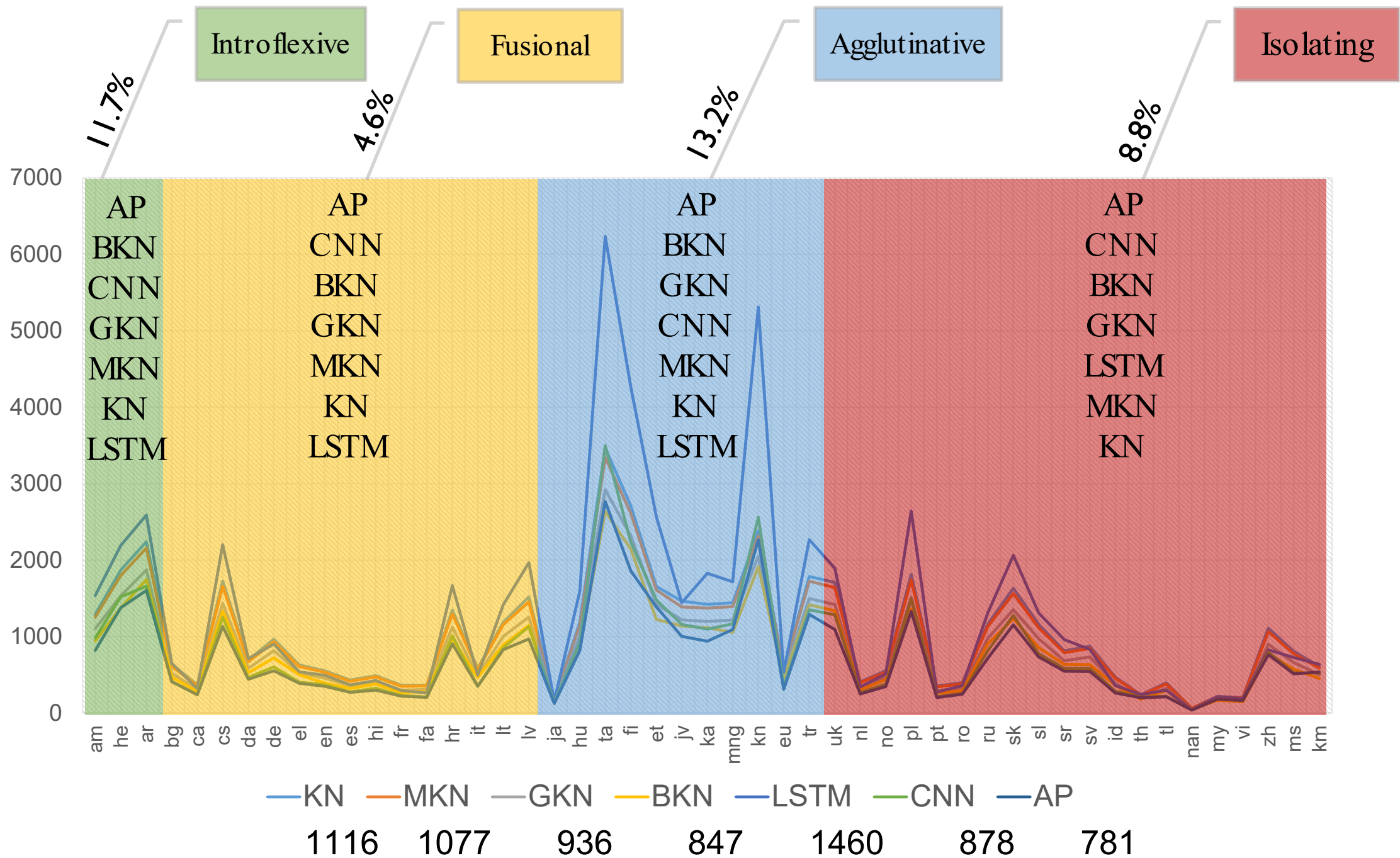


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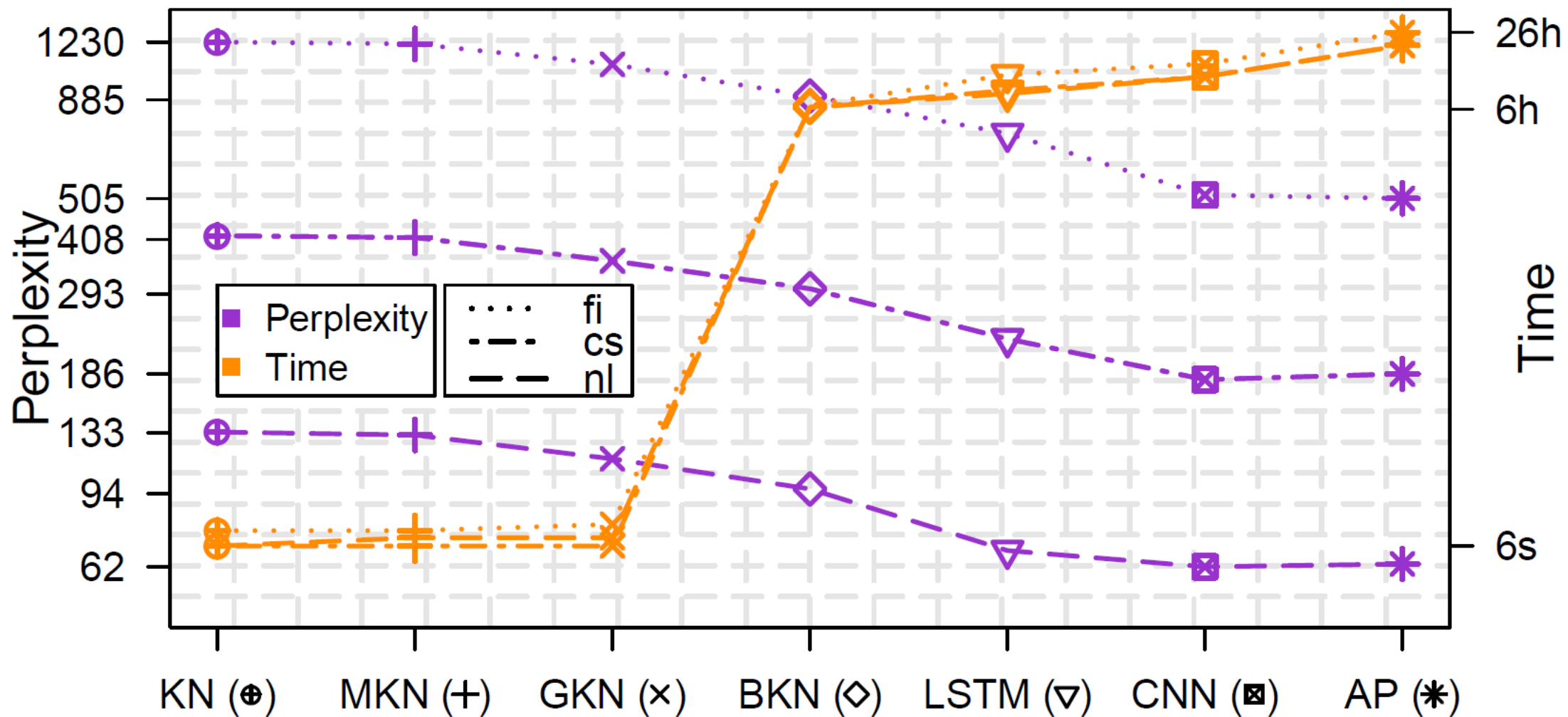


Perplexity





Training Time



Wrapping up ...

- n-grams are highly competitive with neural LMs for low-resource setting, high OOV ratio, or for languages with high type-token ratio
- Recent developments in n-gram models permit to lift the finite-order Markov assumption, hence in theory models should be capable of capturing long range dependencies
- The gap between neural and stand-alone n-gram models could be reduced by (somehow) incorporating continuous word representations into n-gram models
- n-gram models have far more attractive computational properties (Memory/Time usage) for both training and inference steps. So invest in improving neural models computational shortcomings.

Thanks! 😊

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