What Kind of Language Is Hard to Language-Model?

ACL 2019

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Twitter: `@sjmielke` – paper and thread pinned!

Questions and answers

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4. Is Translationese easier? *It's different, but not actually easier!*

Outline

"Difficulty"

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Models and languages

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What correlates with difficulty?

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And... is Translationese really easier?

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Europarl: 21 languages share ~40M chars

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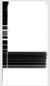
Gurobi()

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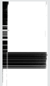
Gurobi()

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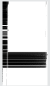
Gurobi $\Bigg($  $\Bigg)$

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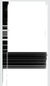
Gurobi()

Issue 2: Comparing scores

Use **total bits** of an **open-vocabulary model.**

Why?

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[note: total easily obtainable from BPC or perplexity by multiplying with total chars/words]

How to aggregate multiple intents' surprisals into "difficulties"?

For fully parallel corpora...

	en	de	bg
1	Resump- tion of the session	Wieder- aufnah- me der ...	Възобн- овяване на се- ...
2	The peace that ...	Der gestern verein- ...	Мирът, който беше ...
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$\xrightarrow[\text{model}]{\text{language}}$

LM surprisals/NLLs

$y_{1,\mathrm{en}}$	$y_{1,\mathrm{de}}$	$y_{1,\mathrm{bg}}$
$y_{2,\mathrm{en}}$	$y_{2,\mathrm{de}}$	$y_{2,\mathrm{bg}}$
$y_{3,\mathrm{en}}$	$y_{3,\mathrm{de}}$	$y_{3,\mathrm{bg}}$
$y_{4,\mathrm{en}}$	$y_{4,\mathrm{de}}$	$y_{4,\mathrm{bg}}$

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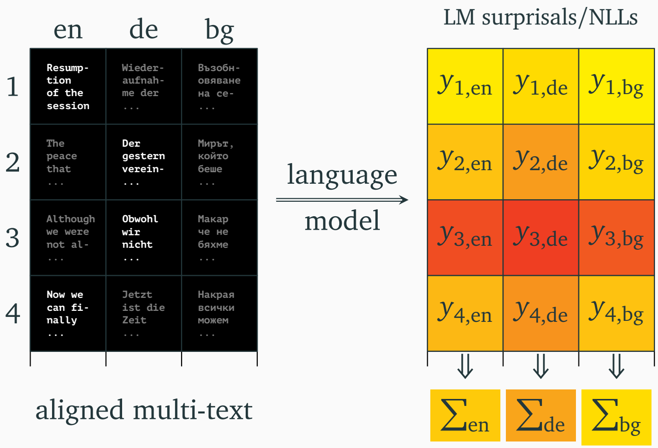
For fully parallel corpora… we can just sum everything up and compare – that is *fair*.



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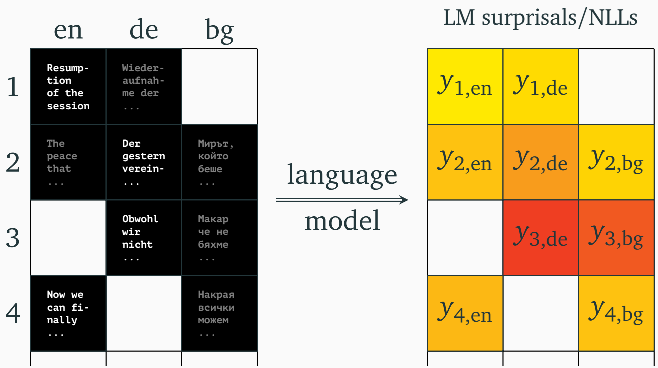

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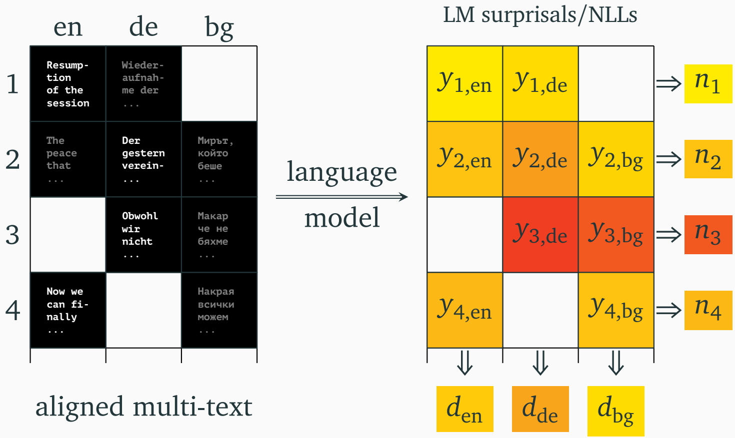

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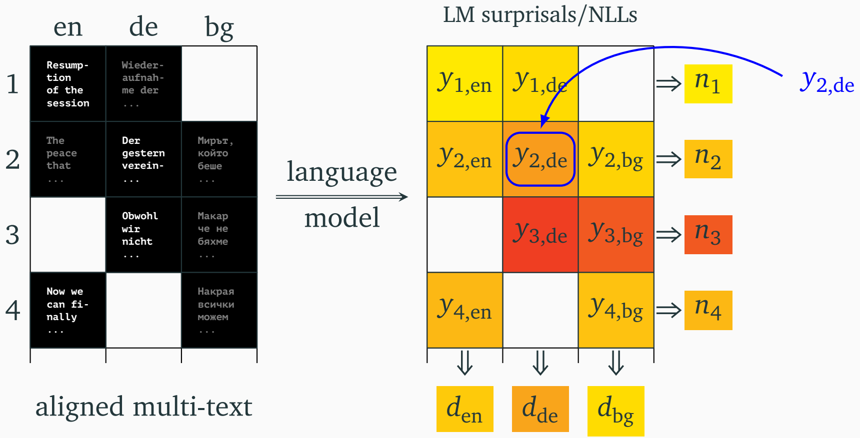

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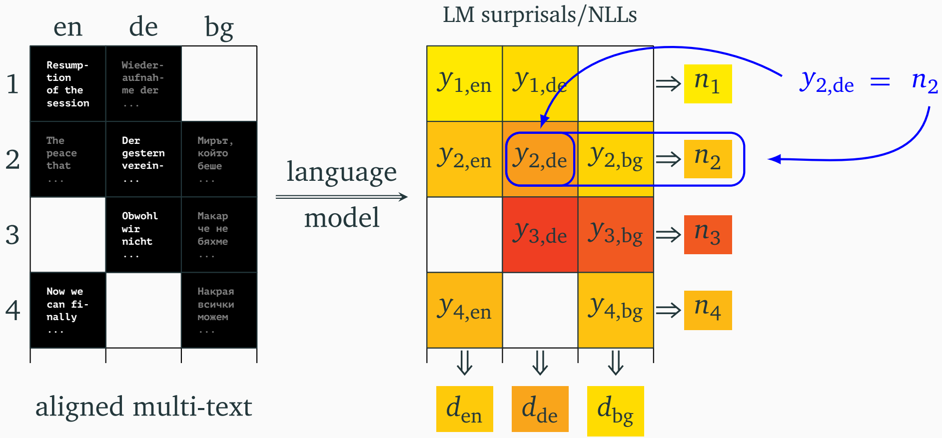

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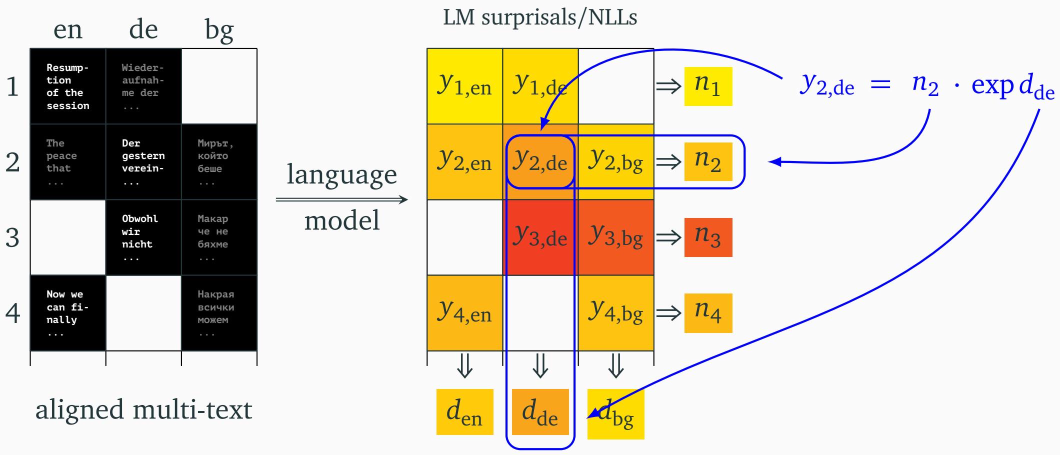

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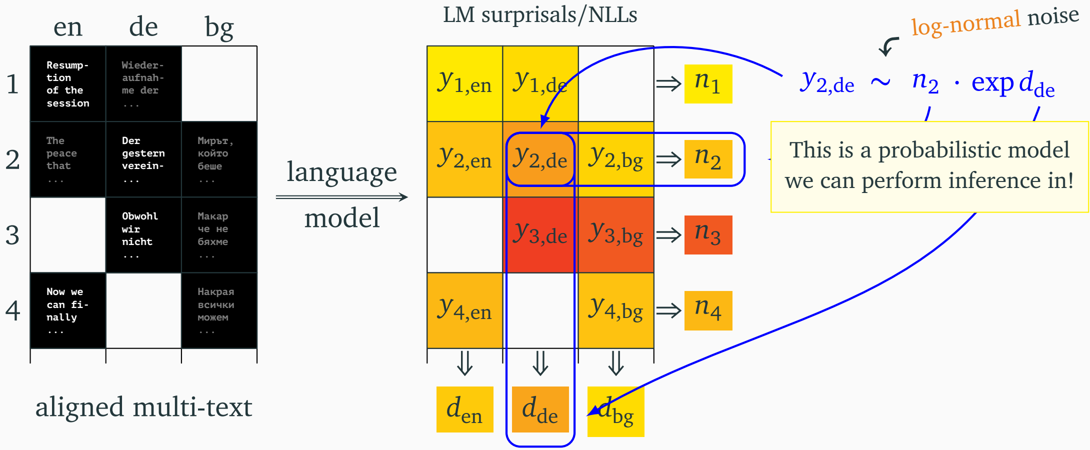

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language model

LM surprisals/NLLs

log-normal noise

$y_{2,\mathrm{de}} \sim n_2 \cdot \exp d_{\mathrm{de}}$

d_{en} d_{de} d_{bg}

not quite, our actual model is

H E T E R O S C E D A S T I C

$$y_{ij} = n_i \cdot \exp(d_j) \cdot \exp(\epsilon_{ij})$$
$$\sigma_i^2 = \ln\left(1 + \frac{\exp(\sigma^2)-1}{n_i}\right)$$
$$\epsilon_{ij} \sim \mathcal{N}\left(\frac{\sigma^2-\sigma_i^2}{2}, \sigma_i^2\right)$$

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“Difficulty” ✓

Models and languages

What correlates with difficulty?

And… is Translationese really easier?

Good open-vocabulary language models

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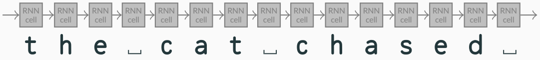
char-RNNLM:



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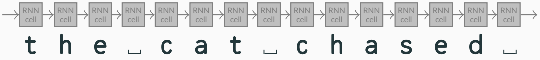
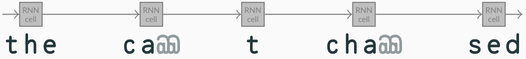


BPE-RNNLM, few merges:



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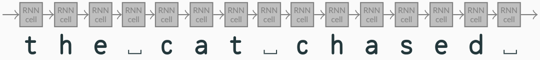

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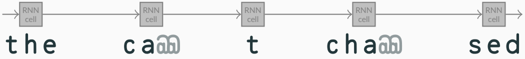

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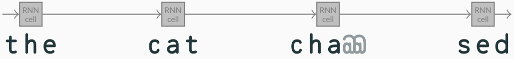

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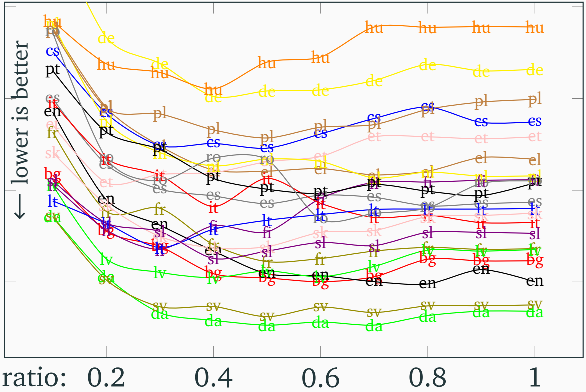
It depends on the language (total surprisal, given merges as a ratio of the vocabulary):



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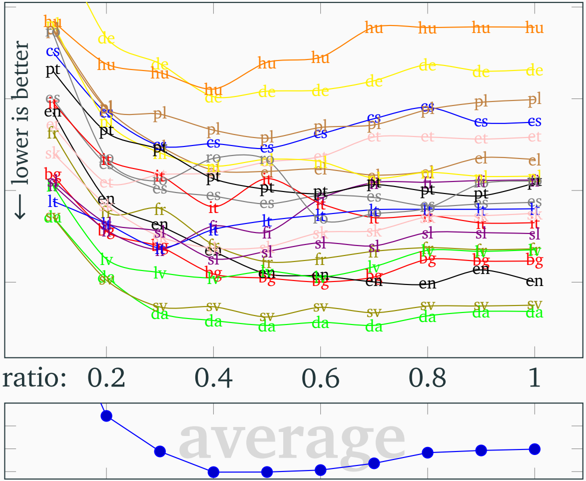

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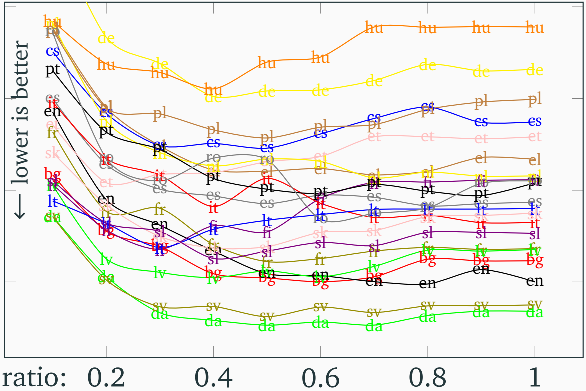

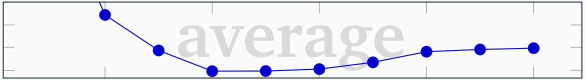

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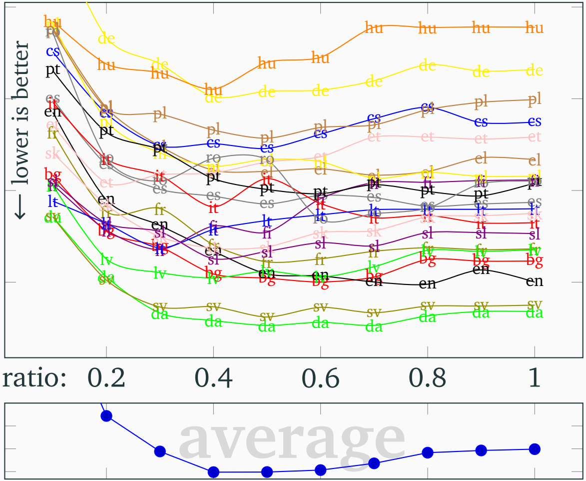

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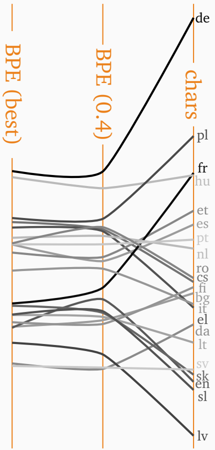
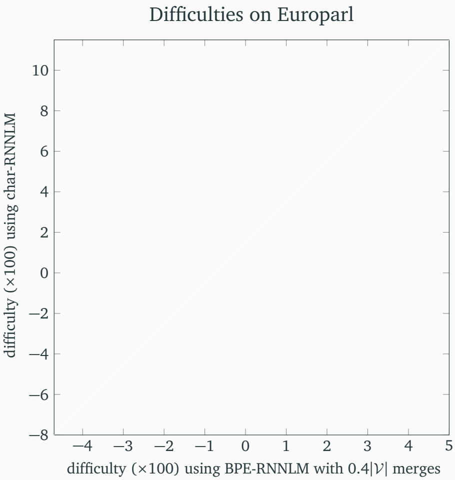
Yeah:

it doesn't matter that much.



Difficulties for char-/BPE-RNNLM: 21 Europarl languages



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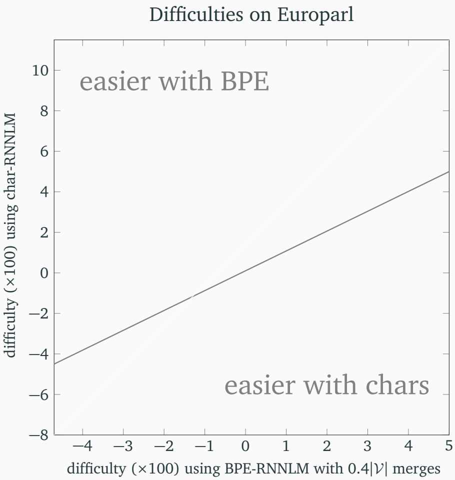

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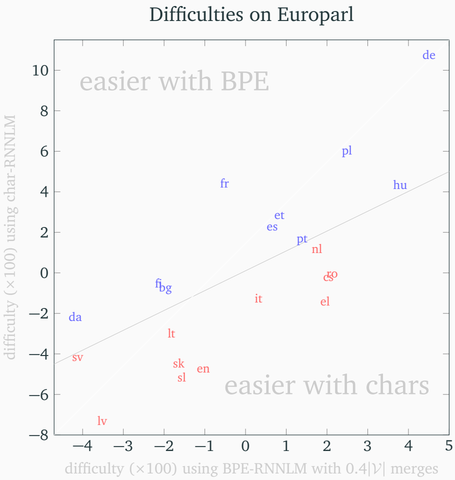

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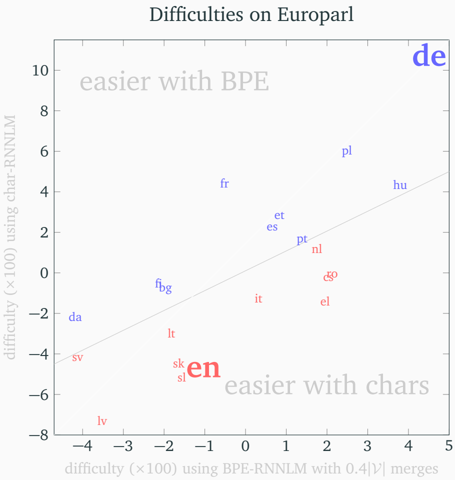

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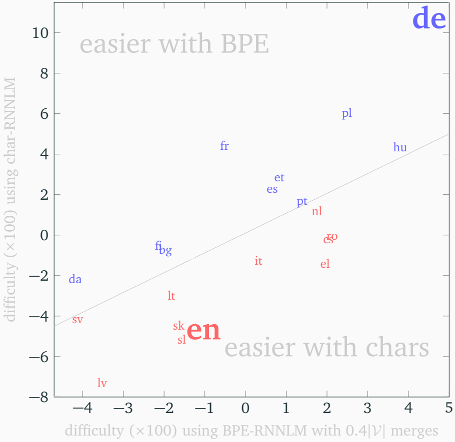
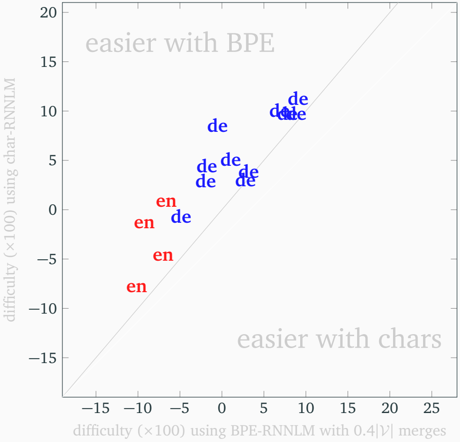
Difficulties on Europarl



vs.

Difficulties on Bibles



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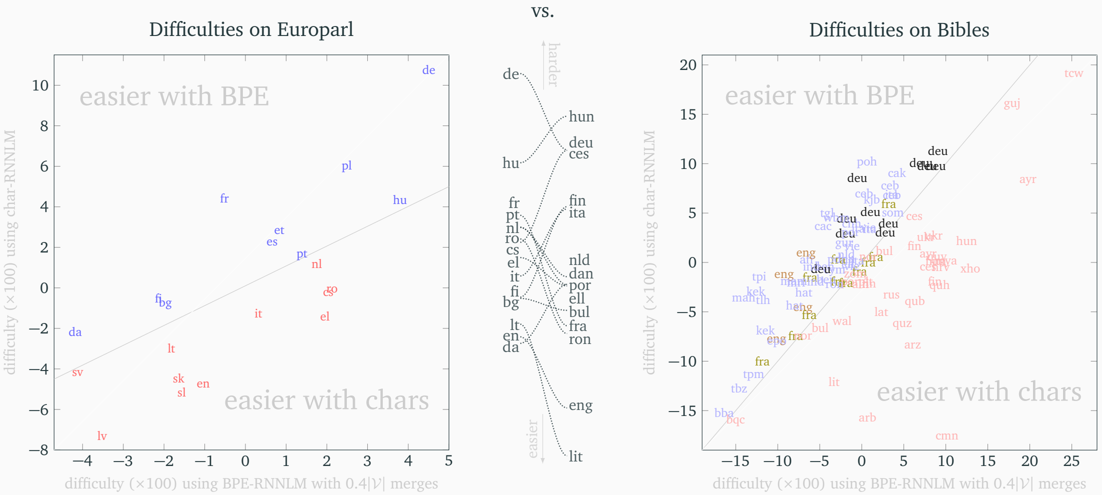

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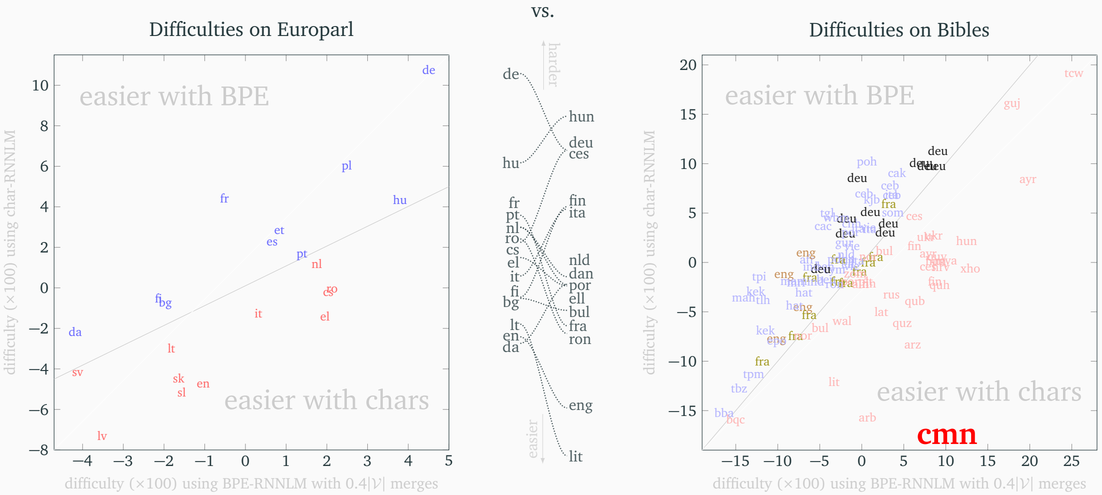

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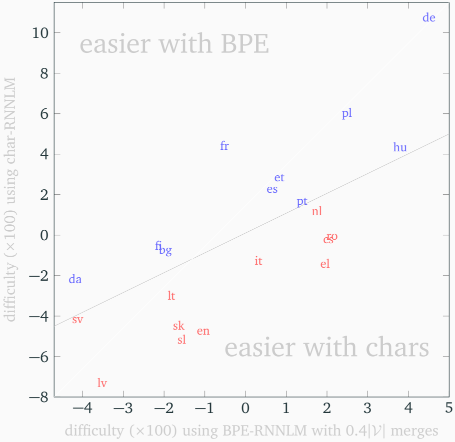

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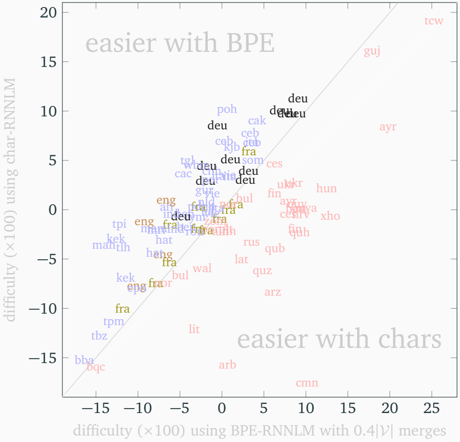

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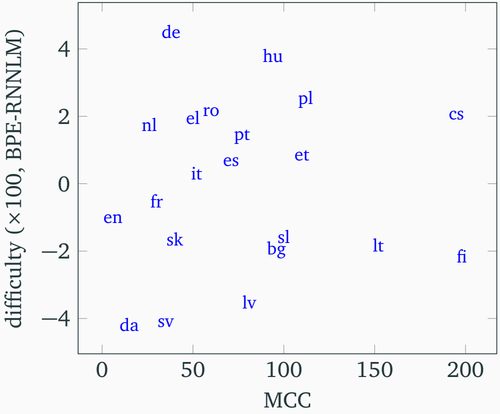
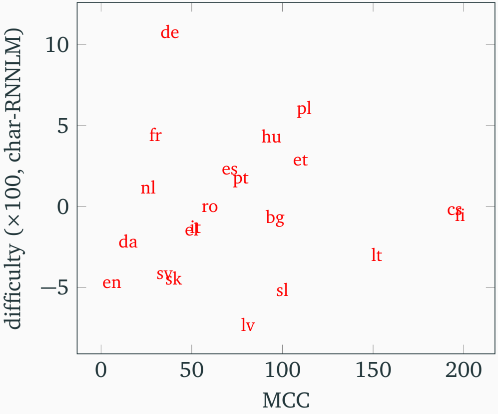
How about: morphological counting complexity (Sagot, 2013)





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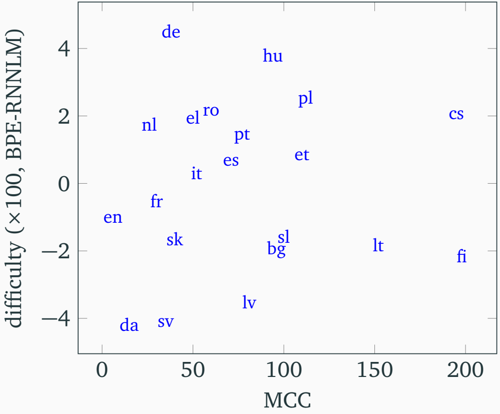

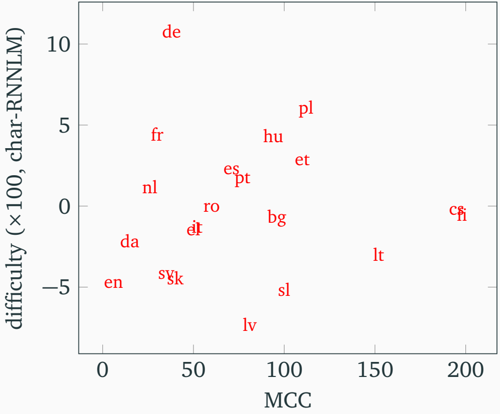

...not particularly striking. Perhaps Finnish was an outlier in Cotterell et al. (2018)?

Other linguistically motivated regressors

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This is **disappointing**.

Very simple heuristics are very predictive

Raw sequence length / # predictions
$\longrightarrow$ **char-RNNLM difficulty**

Significant on:

- Europarl at $p < .01$
- Bibles at $p < .001$

i.e., for the char-RNNLM
puč$_{\text{cz}}$ is easier than Putsch$_{\text{de}}$!

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Wow! What is happening here? We have many conjectures...

Outline

"Difficulty" ✓

Models and languages ✓

What correlates with difficulty? ✓

And... is Translationese really easier?

Translationese: translations as a separate language?

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$\mathbf{en}_{\mathbf{original}}$	$\mathbf{en}_{\mathbf{translated}}$	$\mathbf{de}_{\mathbf{original}}$	$\mathbf{de}_{\mathbf{translated}}$	$\mathbf{nl}_{\mathbf{original}}$	$\mathbf{nl}_{\mathbf{translated}}$	…
Resumption...			Wiederauf-...		Hervatten...	…
The German...			Der deutsche...		De Duitse...	…
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...and indeed the original languages **seem** harder.

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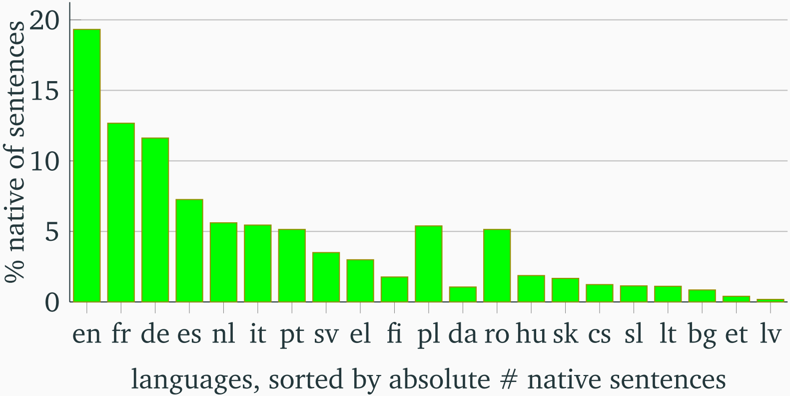
...and indeed the original languages seem harder. **But we missed something!**

We trained on mostly translationese!



Of course we will then find it easier...

Repeat the experiment with fairly balancing training data

Change the training sets!

We can **rebalance a single language**, leaving the others merged, i.e.:

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Resumption...		Wiederauf-...	Hervatten...	...
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And the result: the **difficulties are now the same**!

(more precisely, "native" is 0.004 ± 0.02 *easier*)

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1. Make sure your training data is comparable and fair.
2. Make sure your metrics are comparable and fair.
3. Make sure your stats are fair (no p-hacking!).
4. Work on more NLP resources for more languages!

What Kind of Language Is Hard to Language-Model?

ACL 2019

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