Split and Rephrase: Better Evaluation and a Stronger Baseline

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NLP Lab, Bar Ilan University, Israel
ACL 2018

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B I U
N L P

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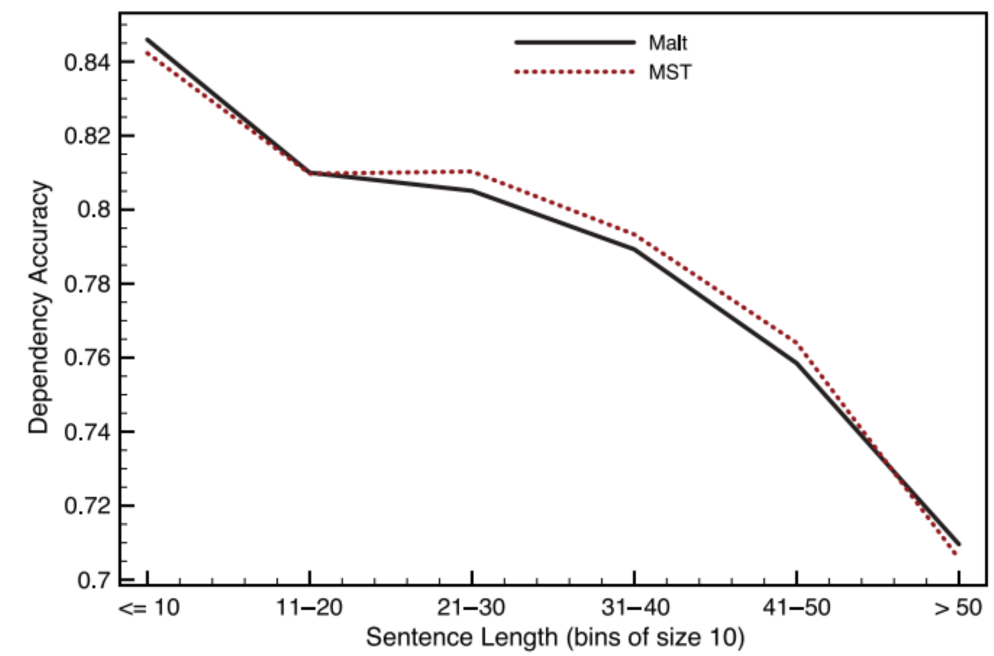

McDonald & Nivre, 2011

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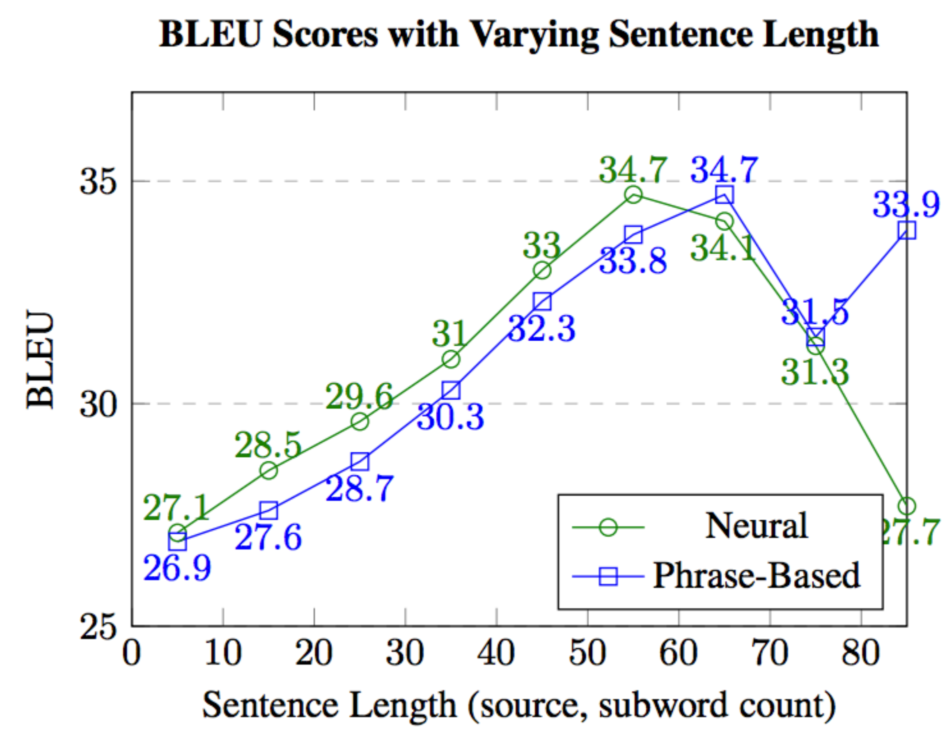

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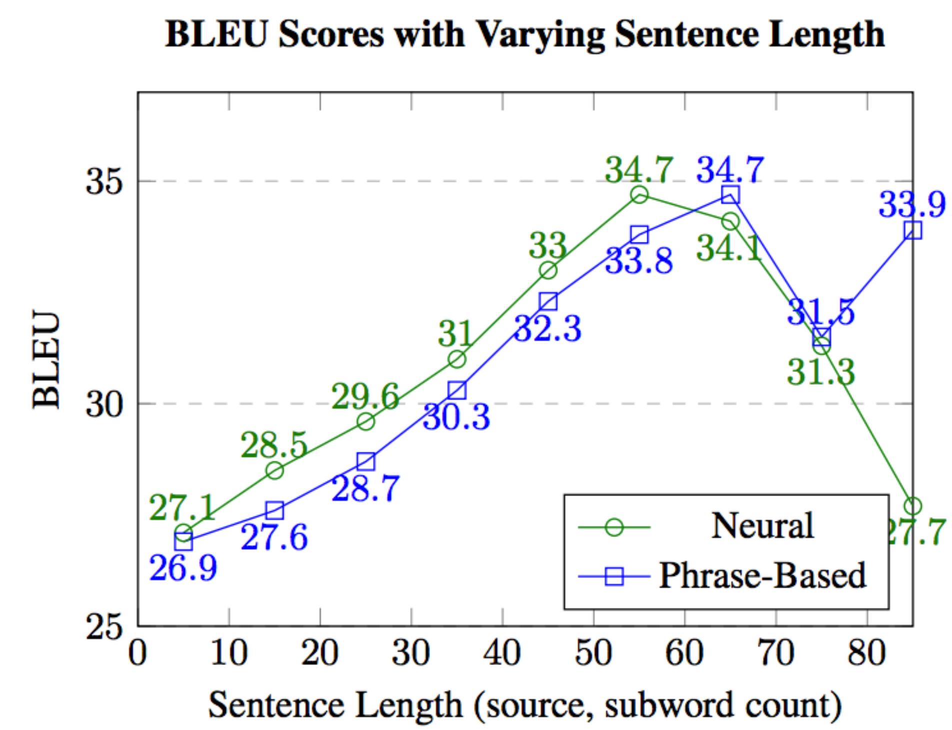
- **Can we automatically break a complex sentence into several simple ones while preserving its meaning?**



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- Dataset, evaluation method, baseline models
- Task definition: complex sentence -> several simple sentences with the same meaning
- Requires (a) **identifying** independent semantic units (b) **rephrasing** those units to single sentences

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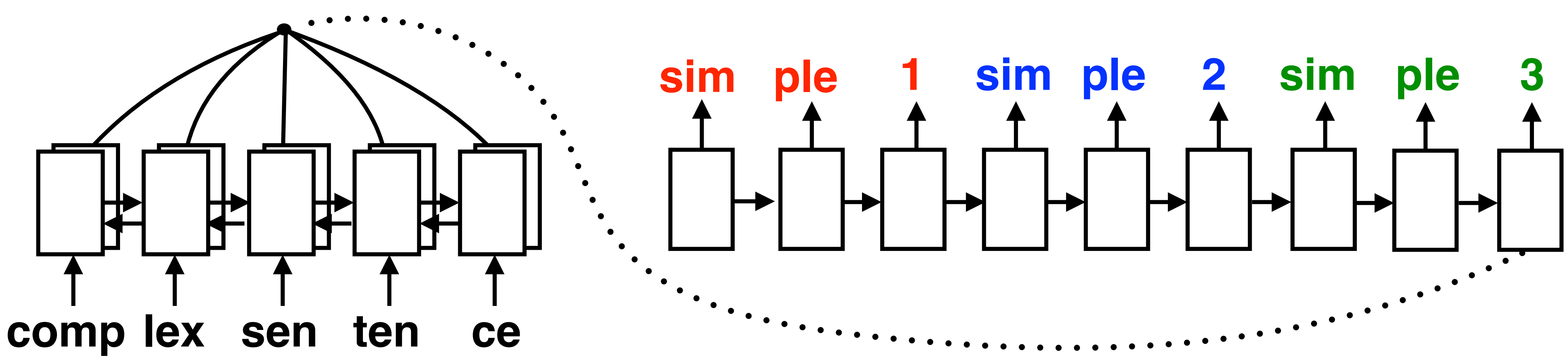

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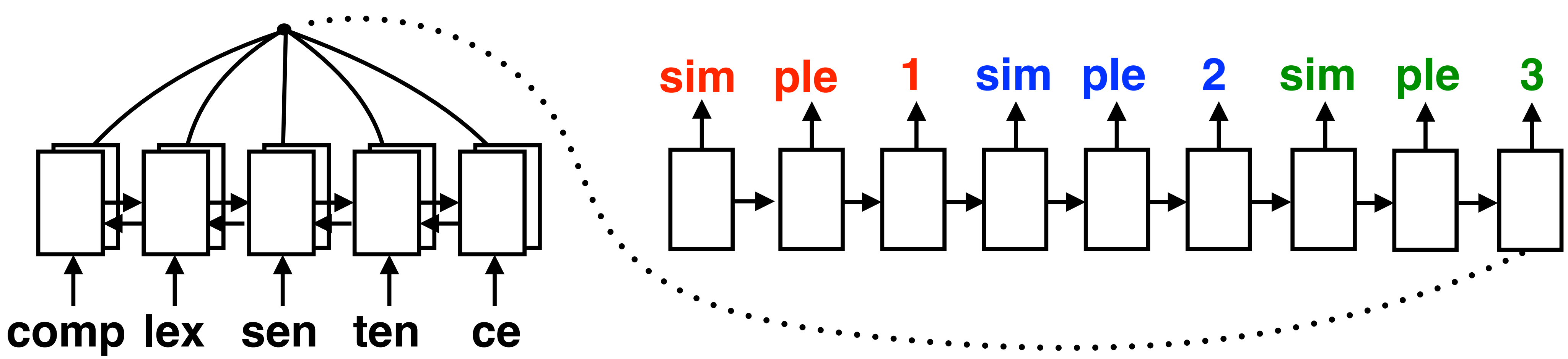

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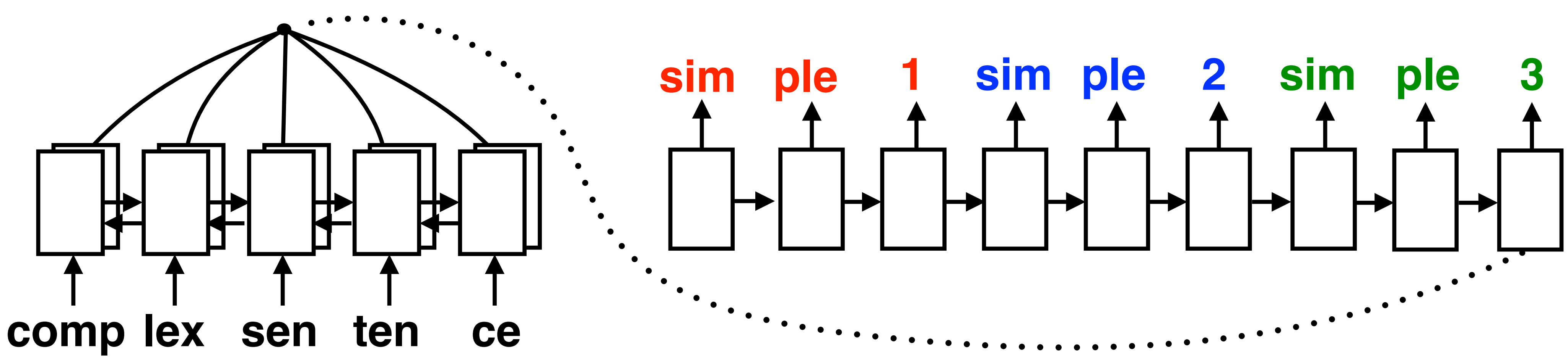

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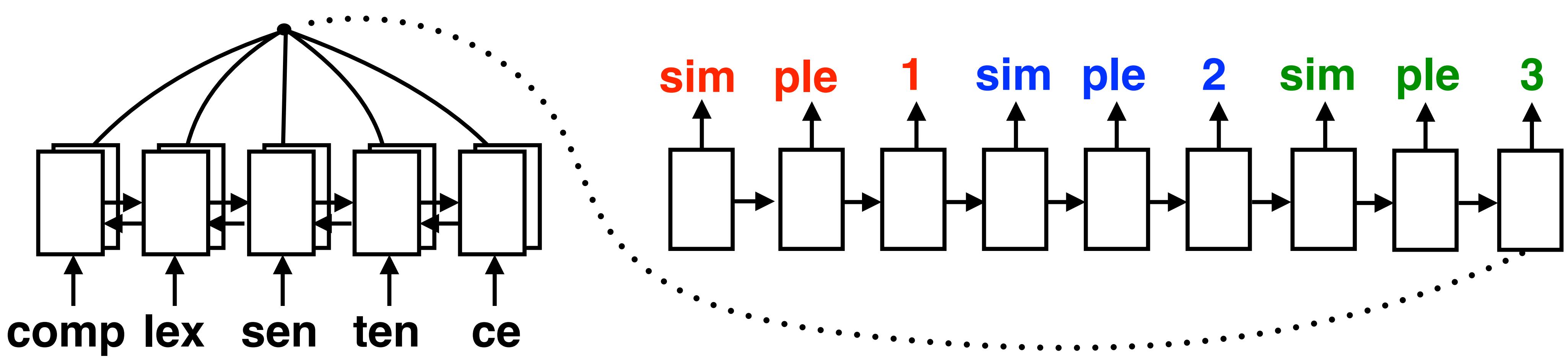

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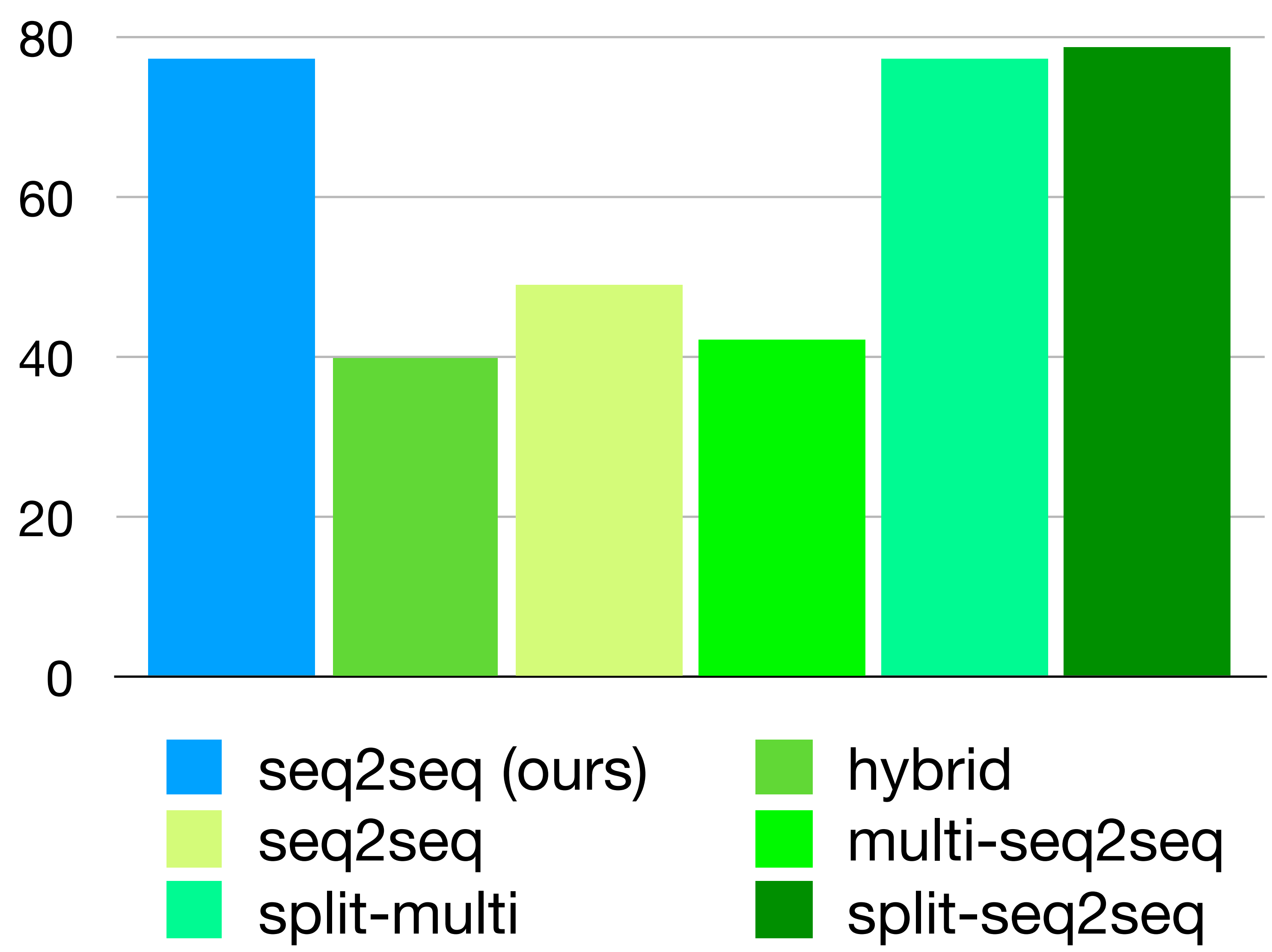

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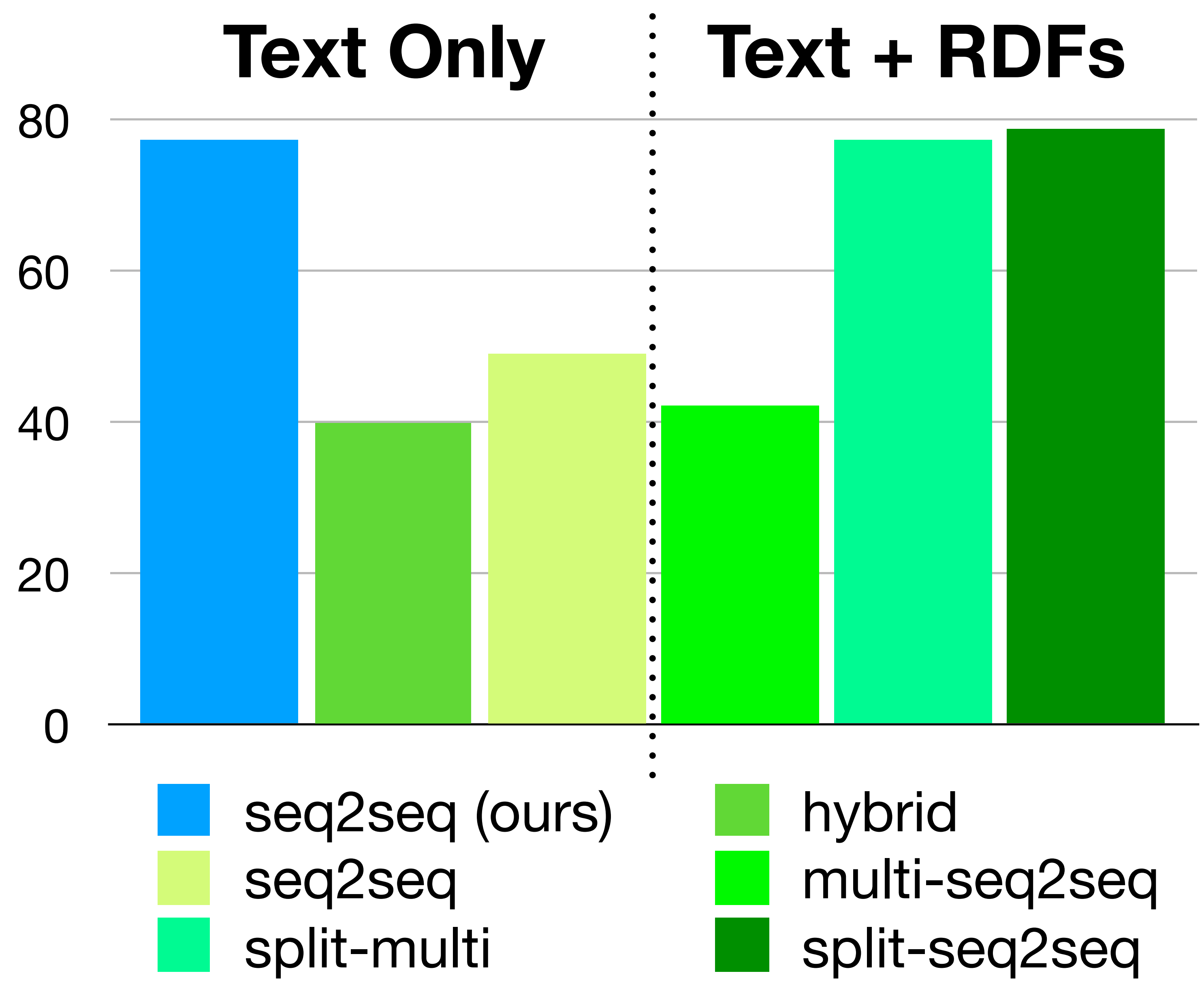

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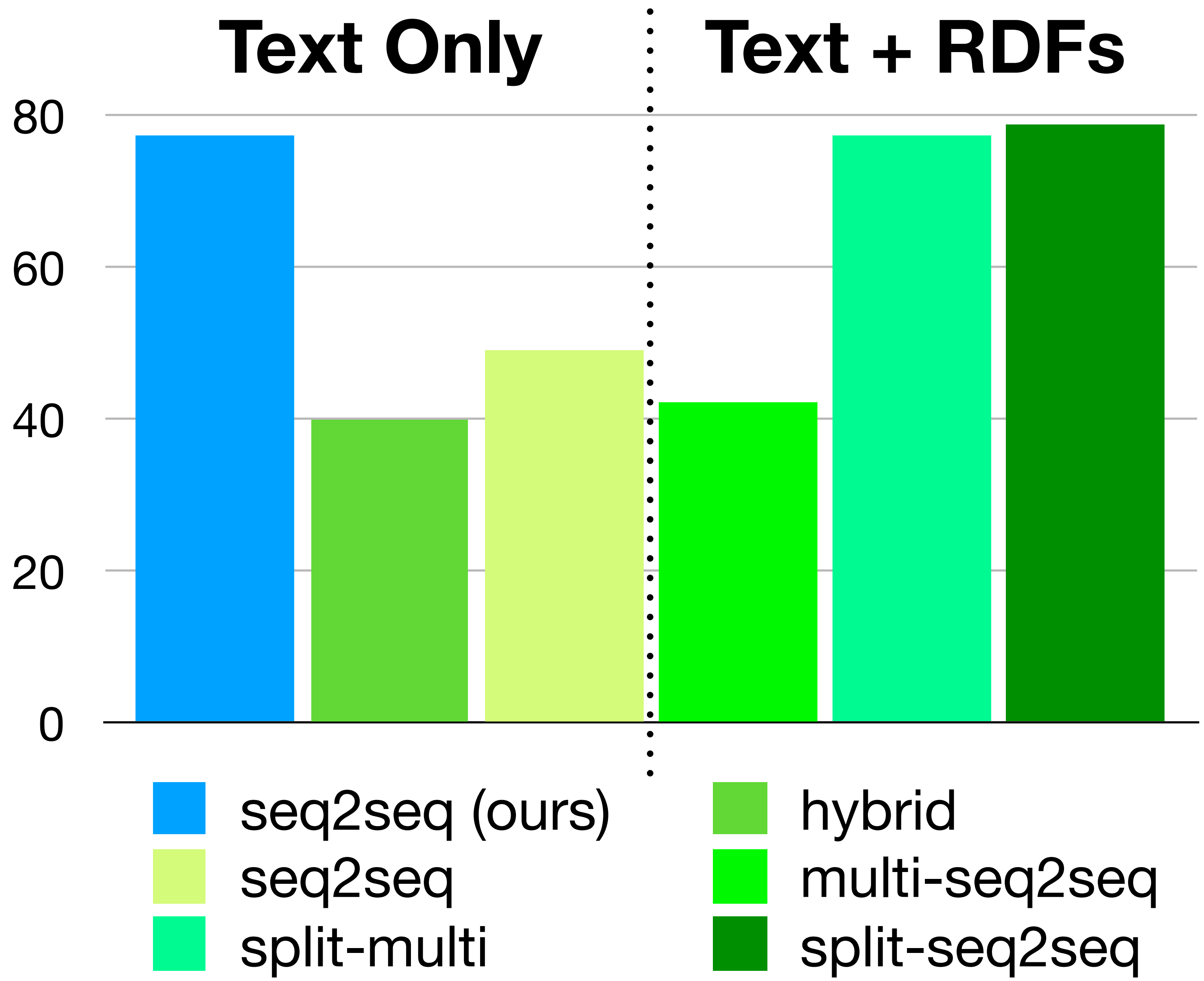
- **Do the simple seq2seq model really performs so well?**



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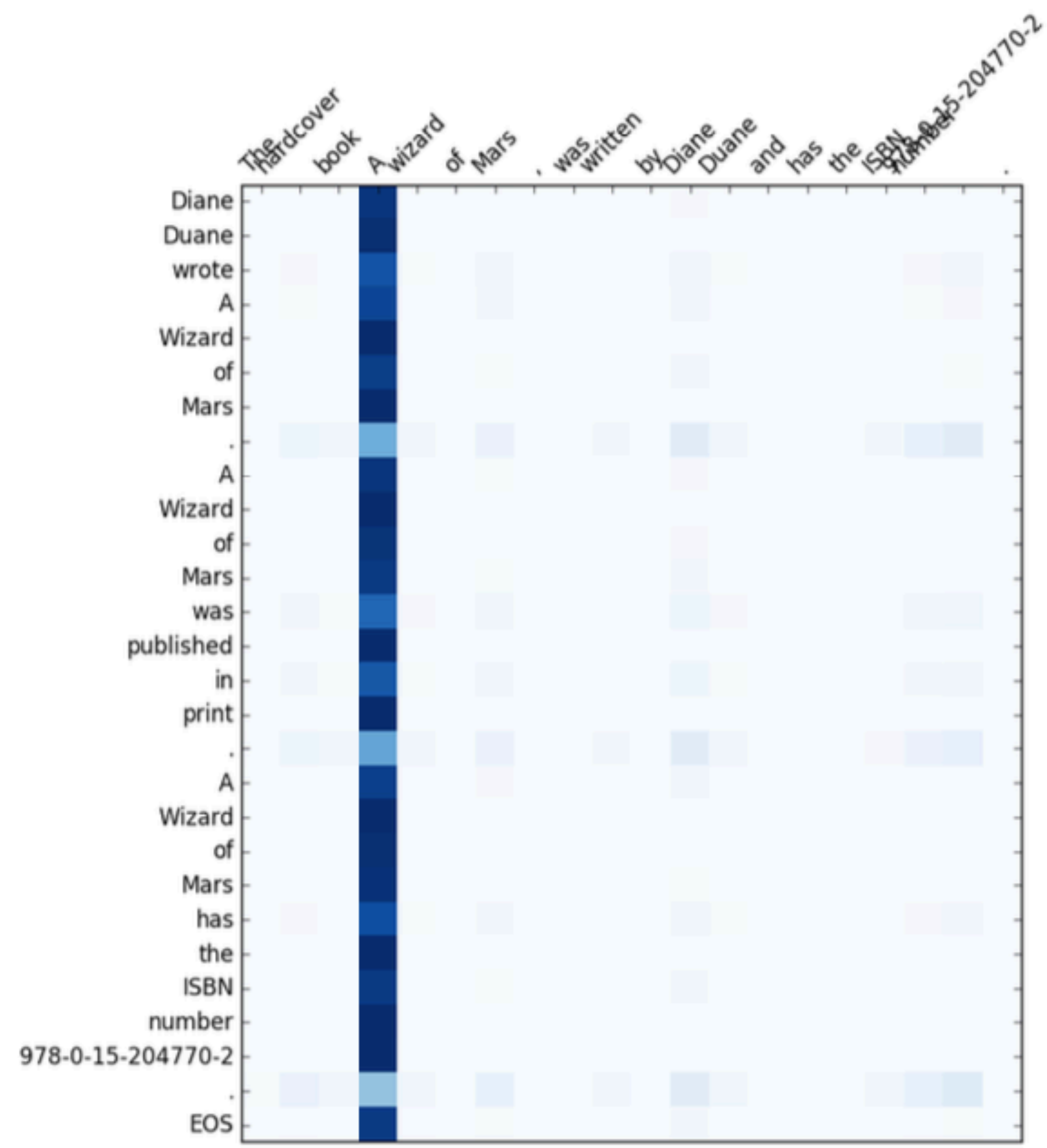

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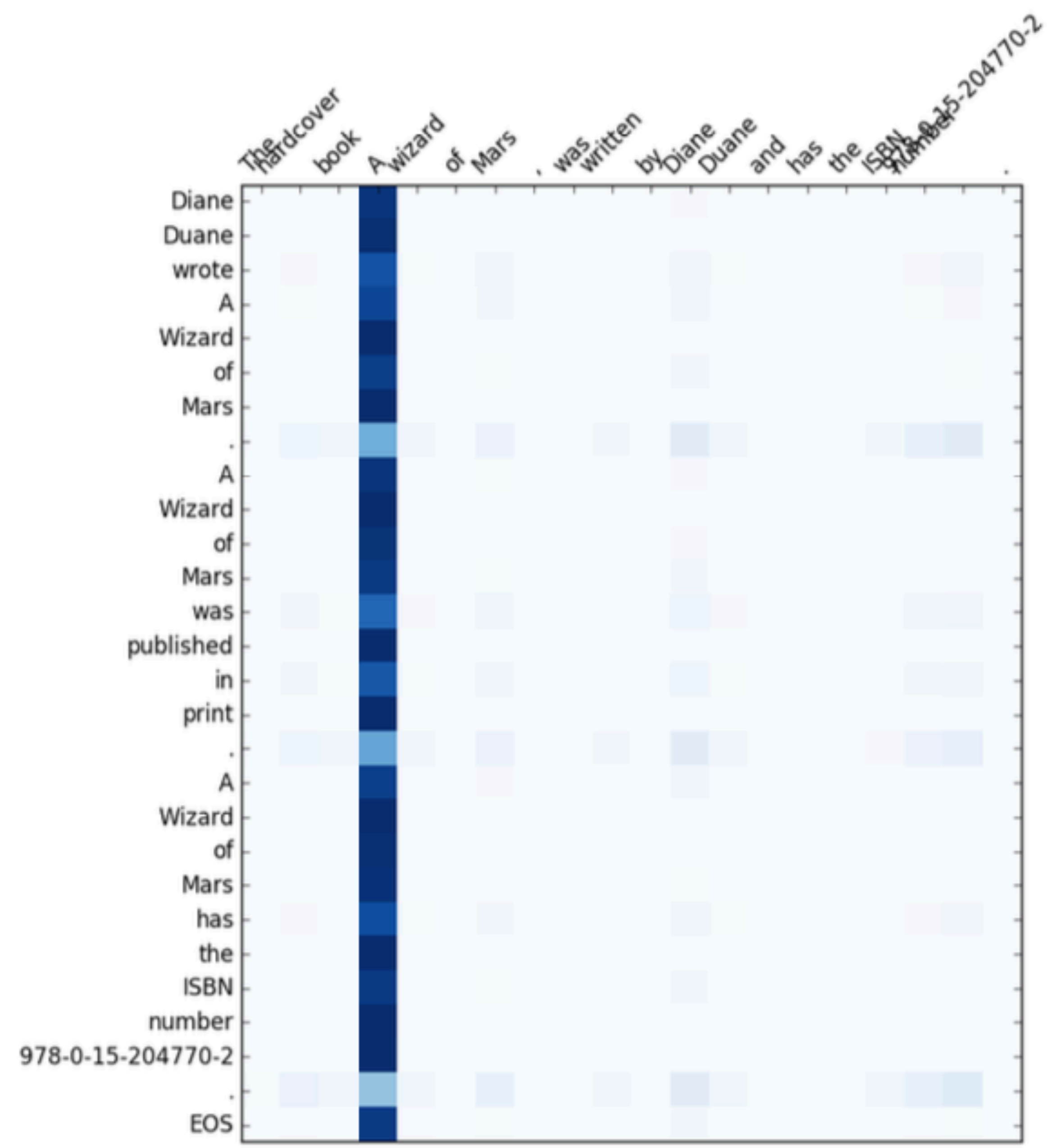

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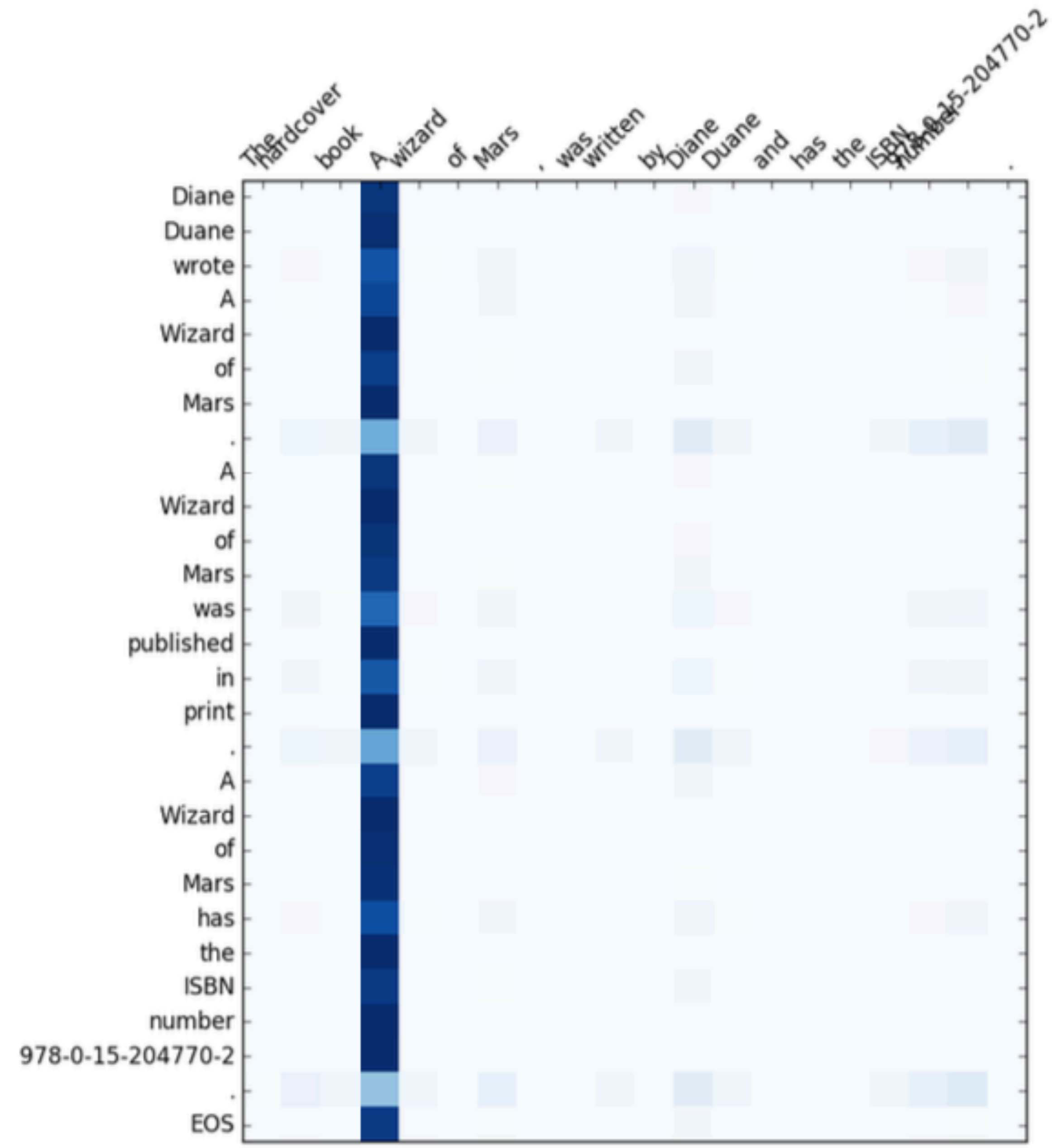

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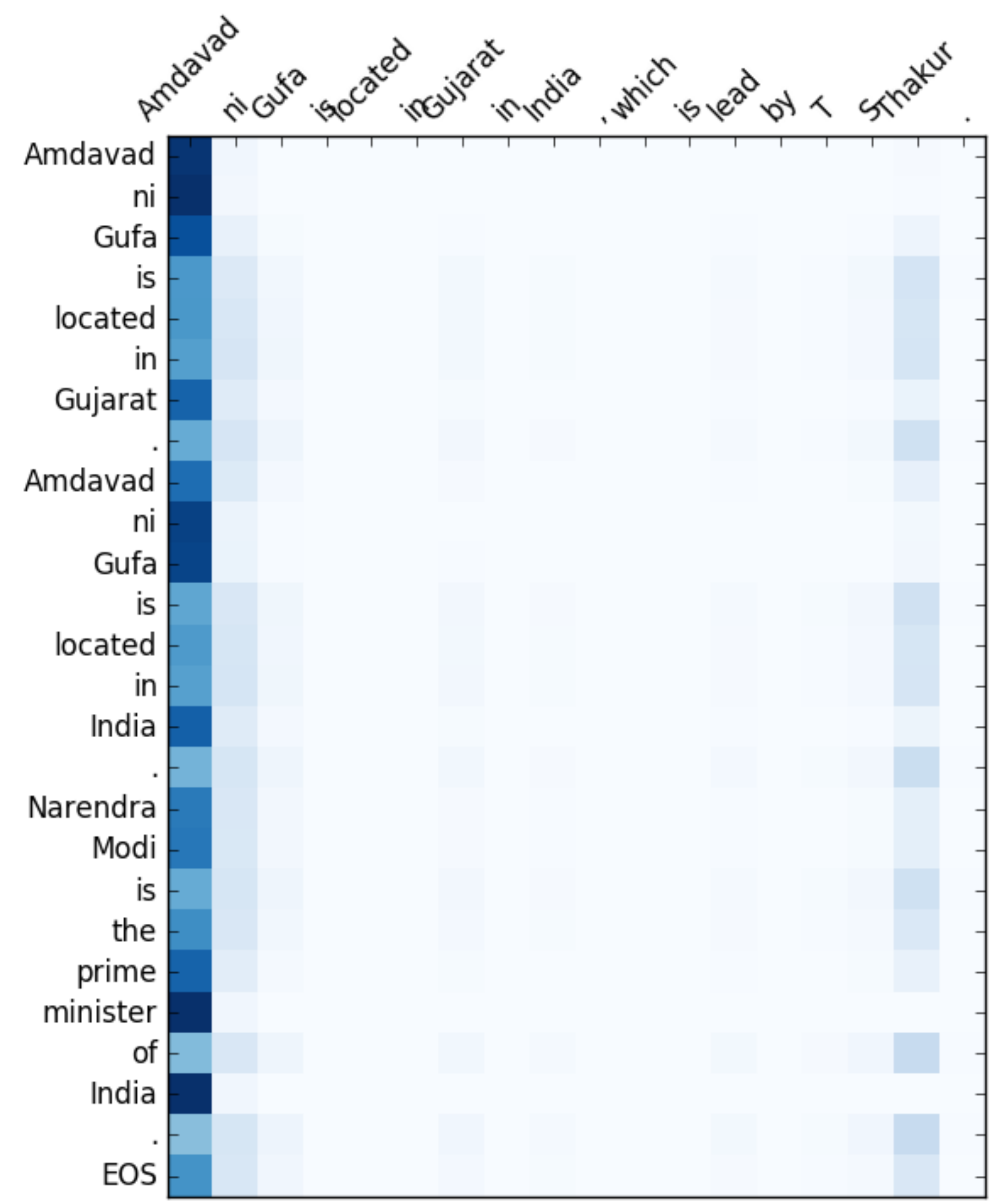

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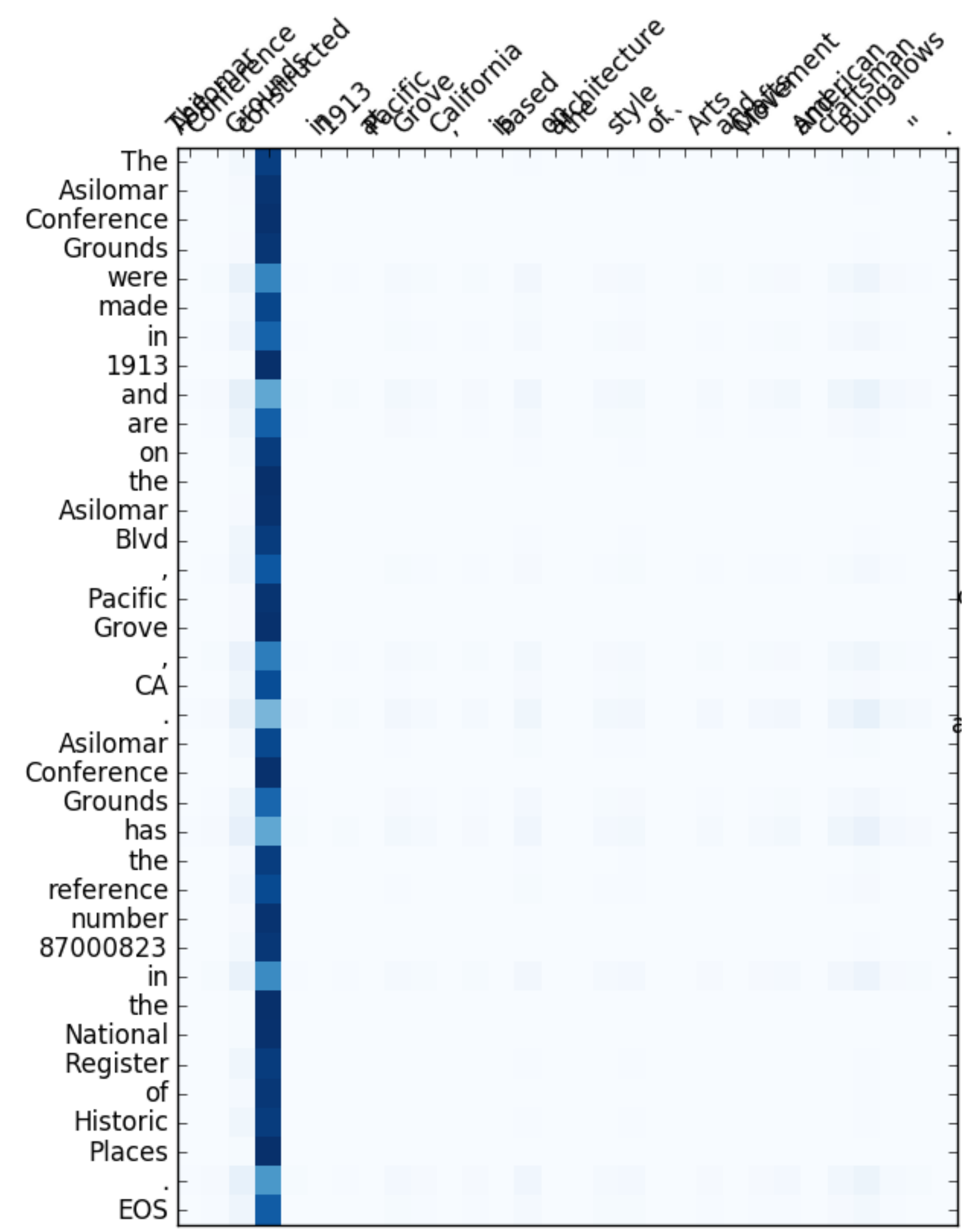

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AFC Ajax AFC Ajax AFC Ajax	AFC Ajax 's manager is Jong Ajax . AFC Ajax N.V. own Sportpark De Toekomst .

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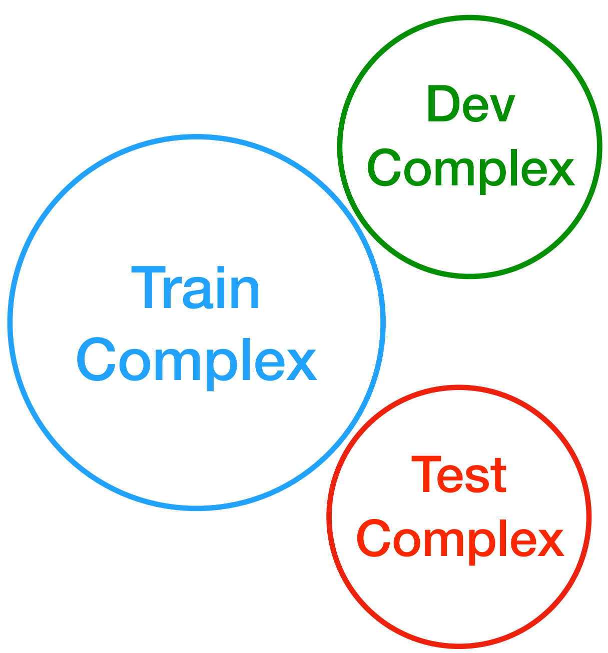

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- When looking at the complex sentences side, there is no overlap
- On the other hand, **most of the simple sentences** did overlap (~90%)
- Makes memorization very effective - “leakage” from train on the target side

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- Has more unknown symbols in dev/test - **need better models!**

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unique test simple sentences in train	89.8%	**0%**
% dev vocabulary in train	97.2%	**63%**
% test vocabulary in train	96.3%	**61.7%**

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- Uses a “copy switch” - feed-forward NN component with a sigmoid-activated scalar output
- Controls the **interpolation** of the softmax probabilities and the copy probabilities over the input tokens in each decoder step

$$p(w) = \underbrace{p(z=1)}^{\text{copy switch}}\overbrace{p_{copy}(w)}^{\text{attention weights (copy)}} + \overbrace{p(z=0)}^{\text{1 - copy switch}}\overbrace{p_{softmax}(w)}^{\text{softmax output}}$$

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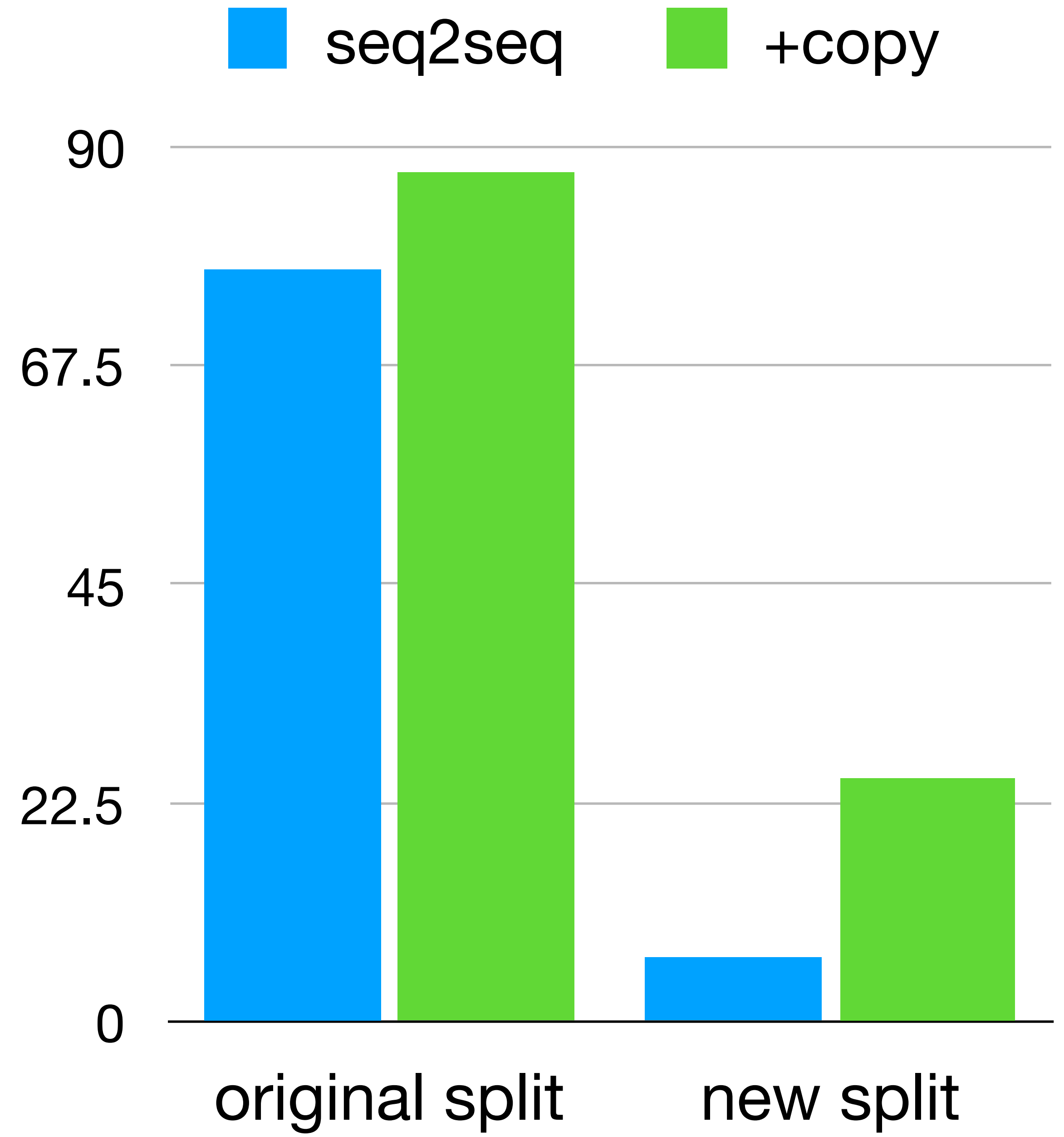

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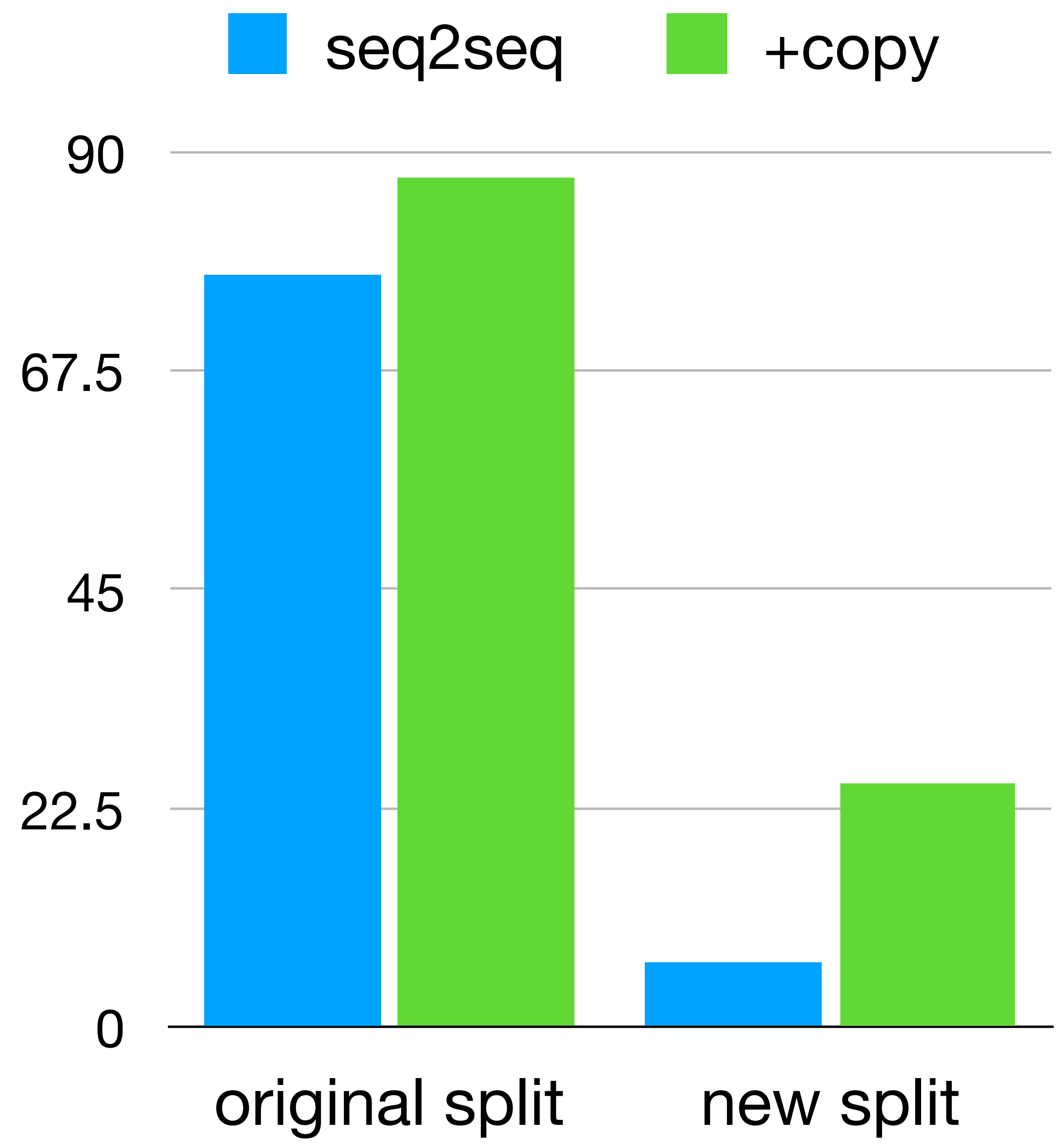

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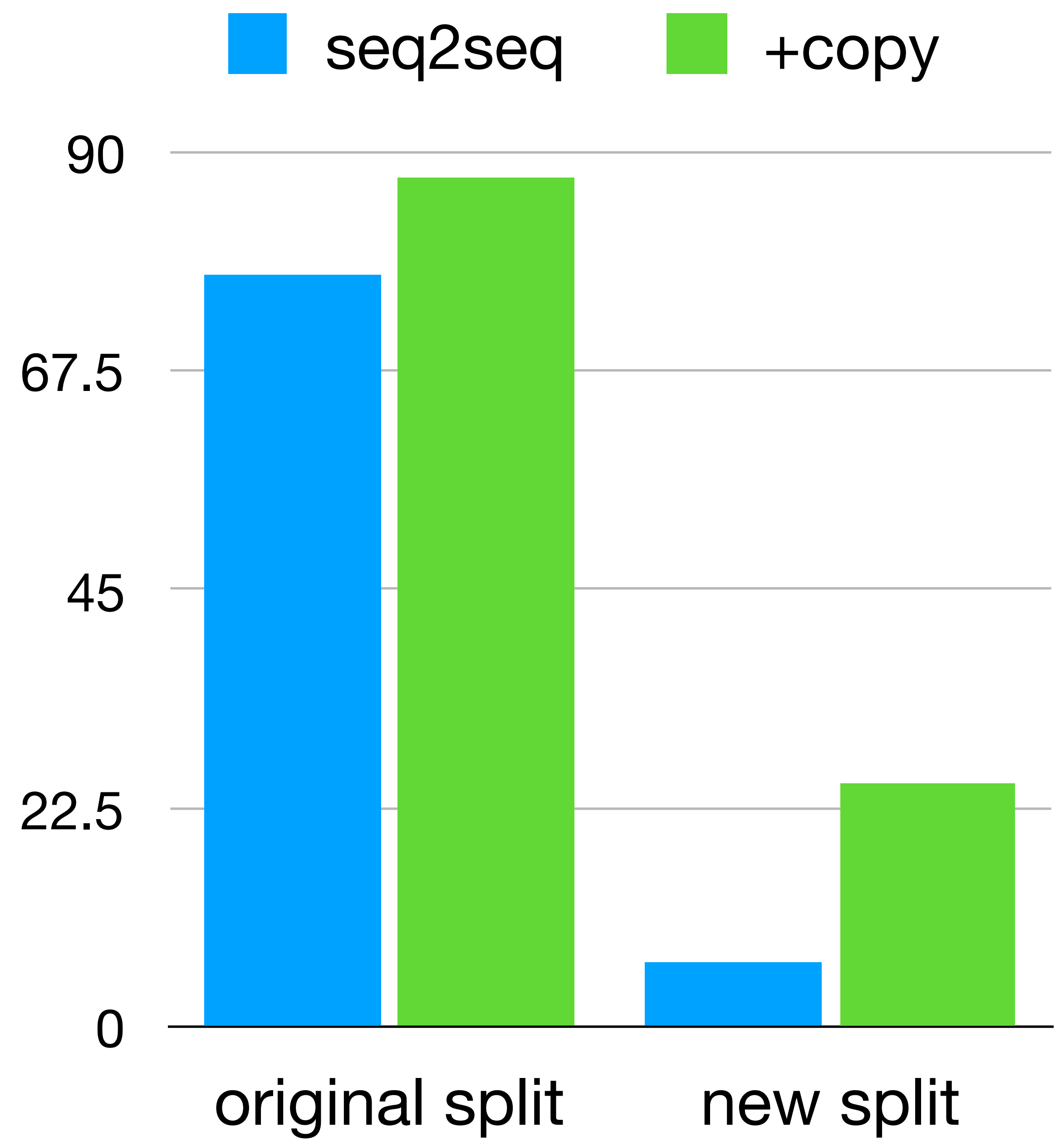
- Much lower than the original benchmark - memorization was crucial for the high BLEU



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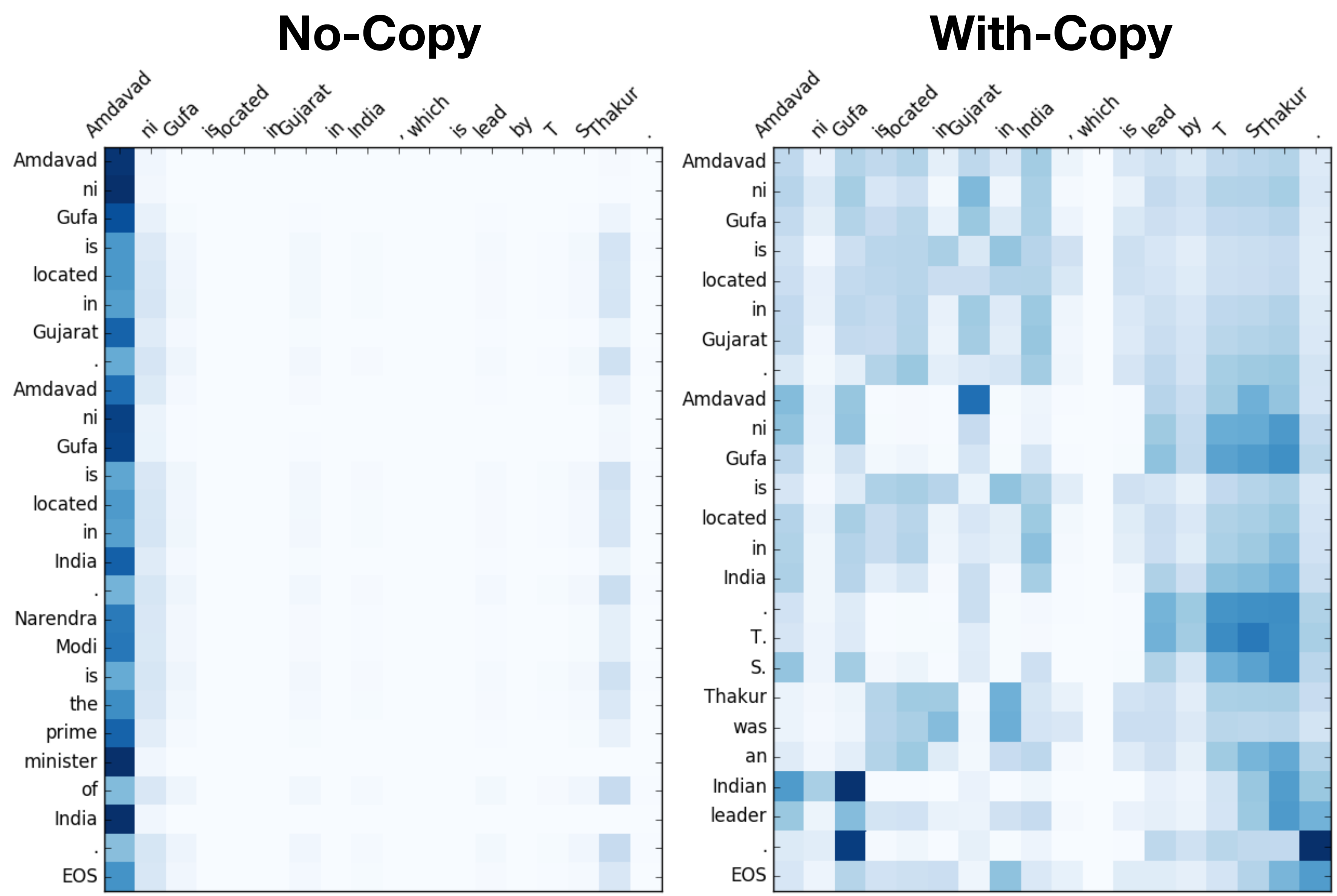
The copy-enhanced models spread the attention across the input tokens while improving results



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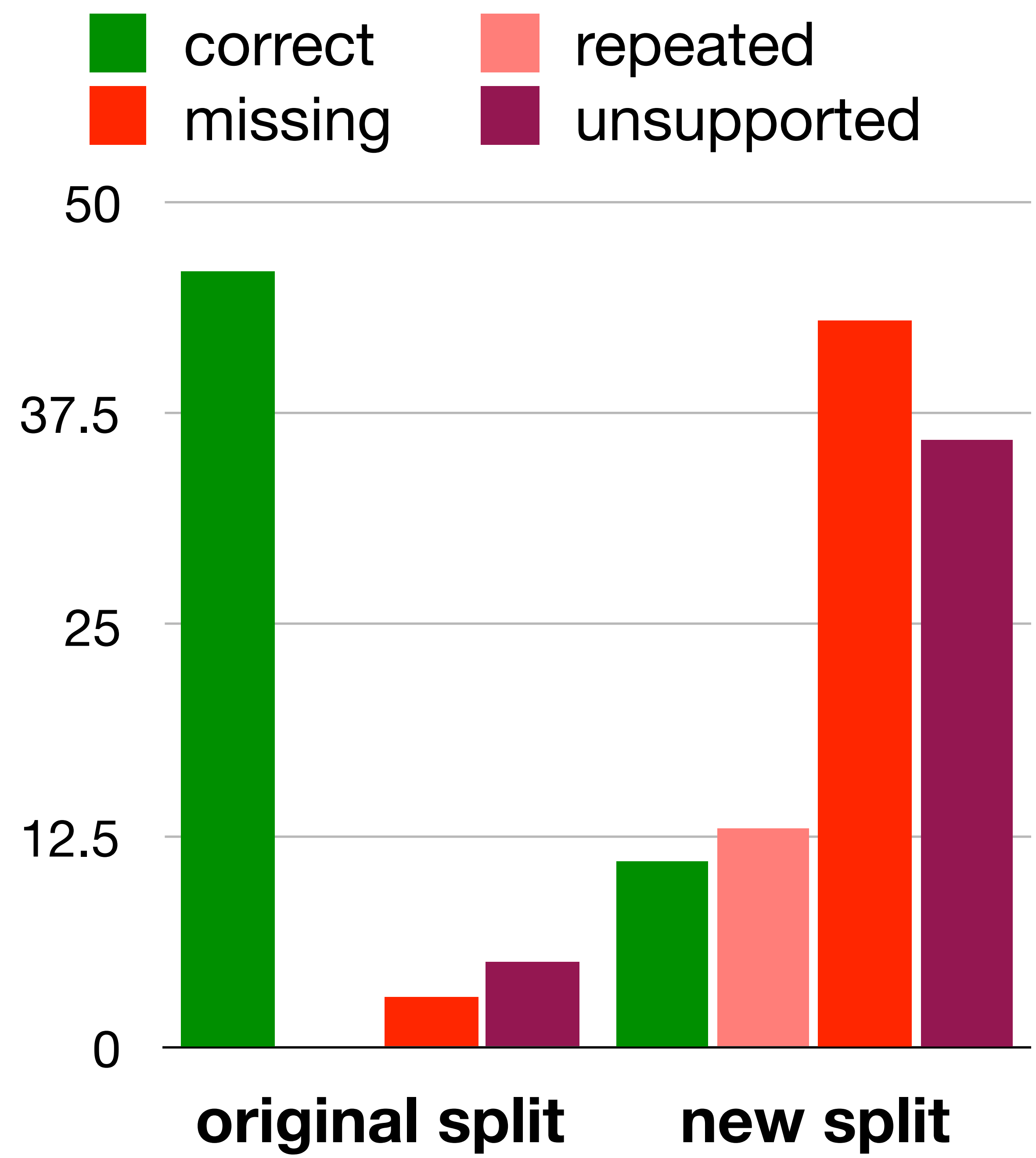

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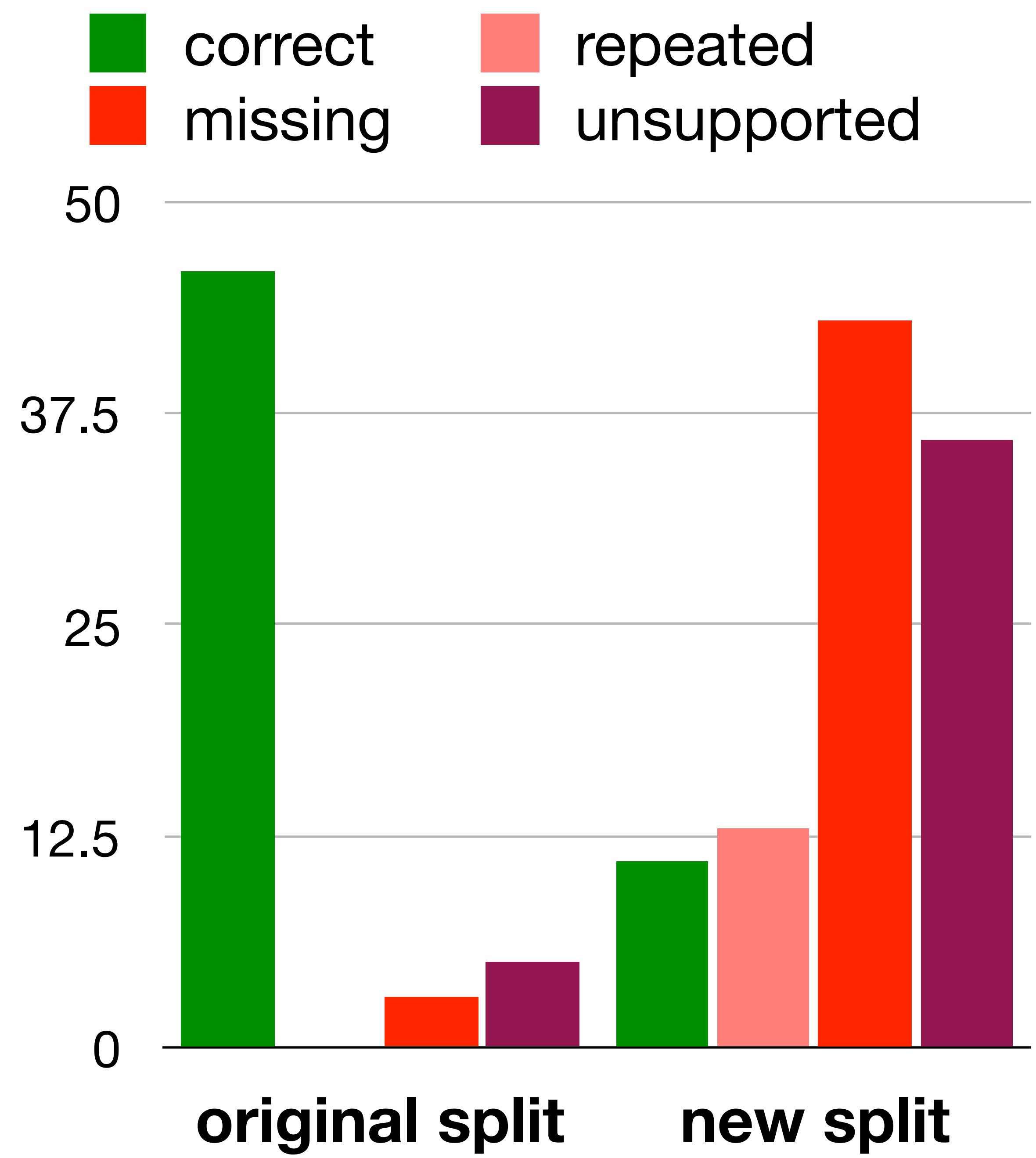

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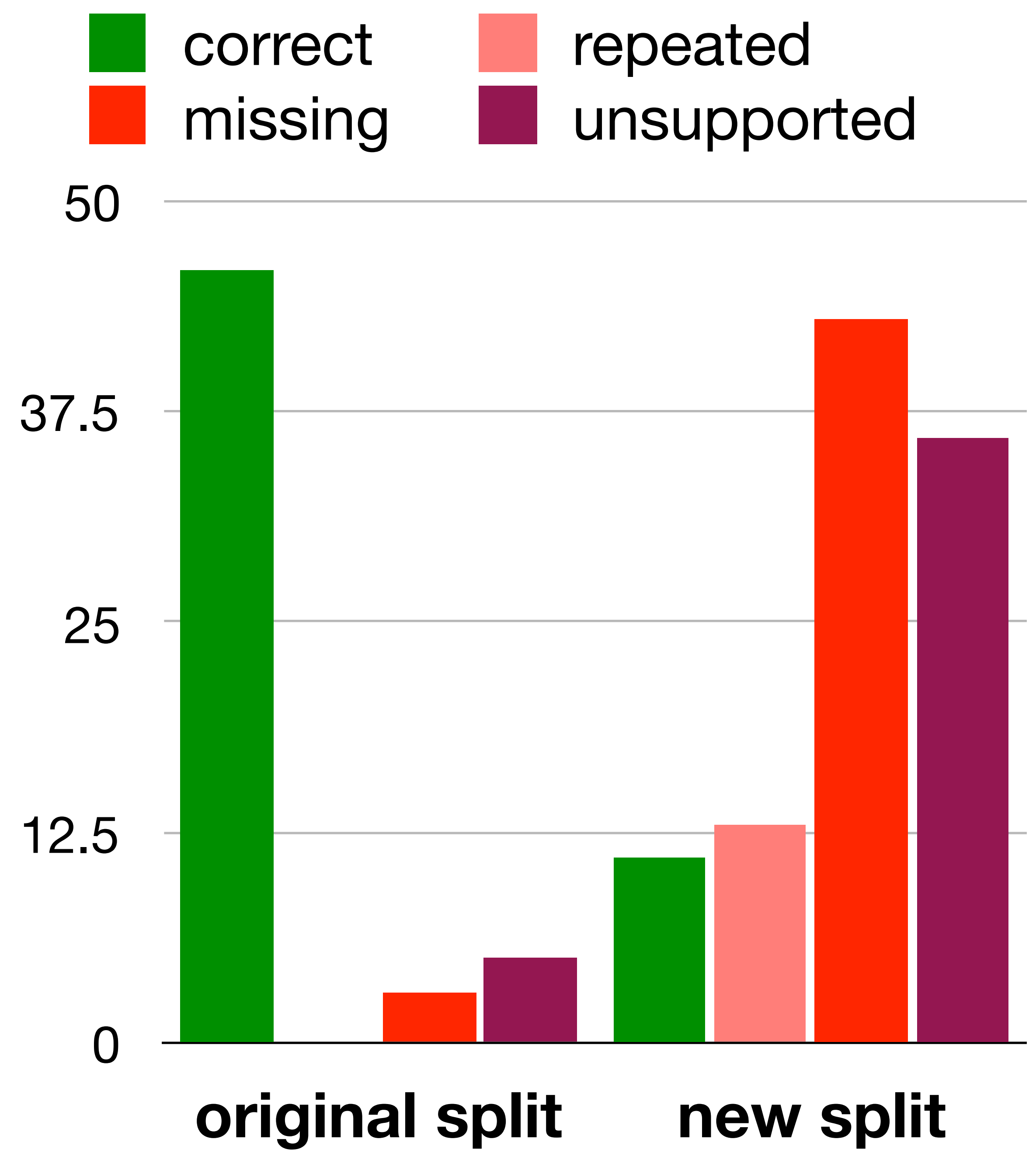

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Thank You!

Link to code and data is available in the paper :)