Is neural machine translation ready for deployment?

A case study on 30 translation directions

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Introduction

- Neural Machine Translation has been widely evaluated for known shared tasks e.g. WMT, NIST, and right now IWSLT.
- Google, SYSTRAN, Microsoft announced switch to NMT for general-domain engines.
- Translation (automation) industry news sites are buzzing with articles about NMT
- But AMTA 2016: no NMT paper in the user or government sections.
- What about in-domain, in-house training data of multi-national organizations or LSPs?

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Is neural machine translation ready for deployment?

1. Is quality a problem?

2. Is translation speed a problem?

The United Nations Parallel Corpus v1.0

- United Nations Parallel Corpus v1.0 [Ziemski et al., 2016] as an example for in-domain training data used for in-house translation service;
- Human translated UN documents from 1990 to 2014;
- Arabic, Chinese, English, French, Russian, and Spanish;
- Fully aligned subcorpus across all UN languages available, 30 translation directions in total;
- Documents released in 2015 distributed as dev and test sets.

Documents	Lines	English Tokens
86,307	11,365,709	334,953,817

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Preprocessing

- Sentences longer than 100 words were discarded;
- Lowercased data as done in [Ziemski et al., 2016];
- Tokenized with the Moses tokenizer;
- Jieba[1] for Chinese segmentation;
- BPE subword units for NMT models (30,000).

[1] https://github.com/fxsjy/jieba

Phrase-based Baselines

[Ziemski et al., 2016] provided BLEU scores for Moses configurations trained on the 6-way subcorpus.

- Word alignment with MIGZA++, 5x Model1, 5x HMM;
- 5-gram language model from the target parallel data;
- Default lexical reordering model;
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Neural translation systems

- Attentional encoder-decoder [Bahdanau et al., 2014], implemented in Nematus [Sennrich et al., 2016];
- Mini-batches of size 40, maximum sentence length of 100, word embeddings of size 500, and hidden layers of size 1024.
- We clip the gradient norm to 1.0 [Pascanu et al., 2013].
- Models were trained with Adadelta [Zeiler, 2012], reshuffling the training corpus between epochs.
- Trained for 1.2M iterations, checkpoint every 30K iterations;
- Last four model checkpoints for ensembling;
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- Total time: 320 days, up to 16 GPUs (ca. 2.5 months).

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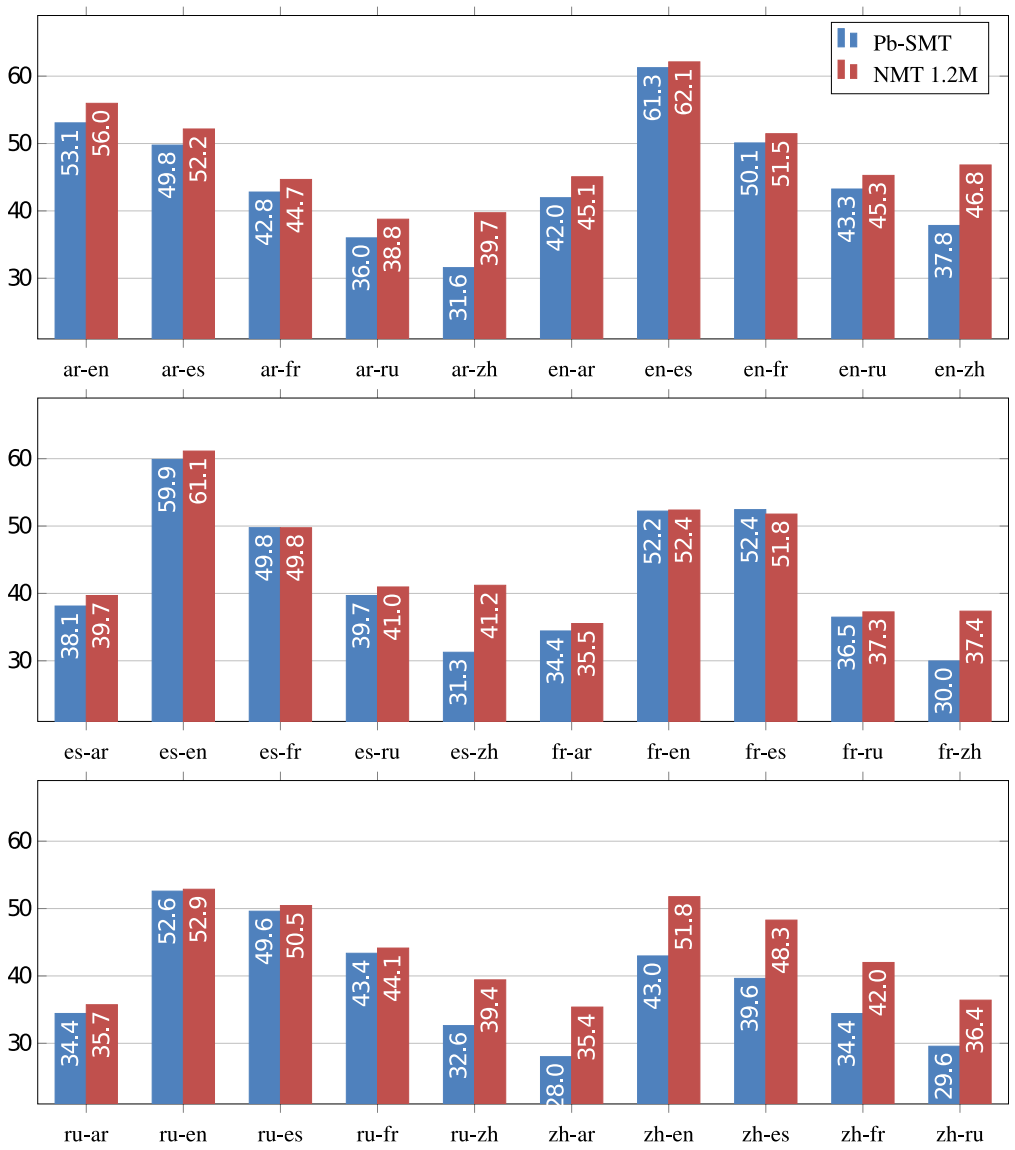
Pb-SMT
NMT 1.2M
60
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53.1 56.0
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42.8 44.7
36.0 38.8
31.6 39.7
42.0 45.1
61.3 62.1
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43.3 45.3
37.8 46.8
ar-en ar-es ar-fr ar-ru ar-zh en-ar en-es en-fr en-ru en-zh
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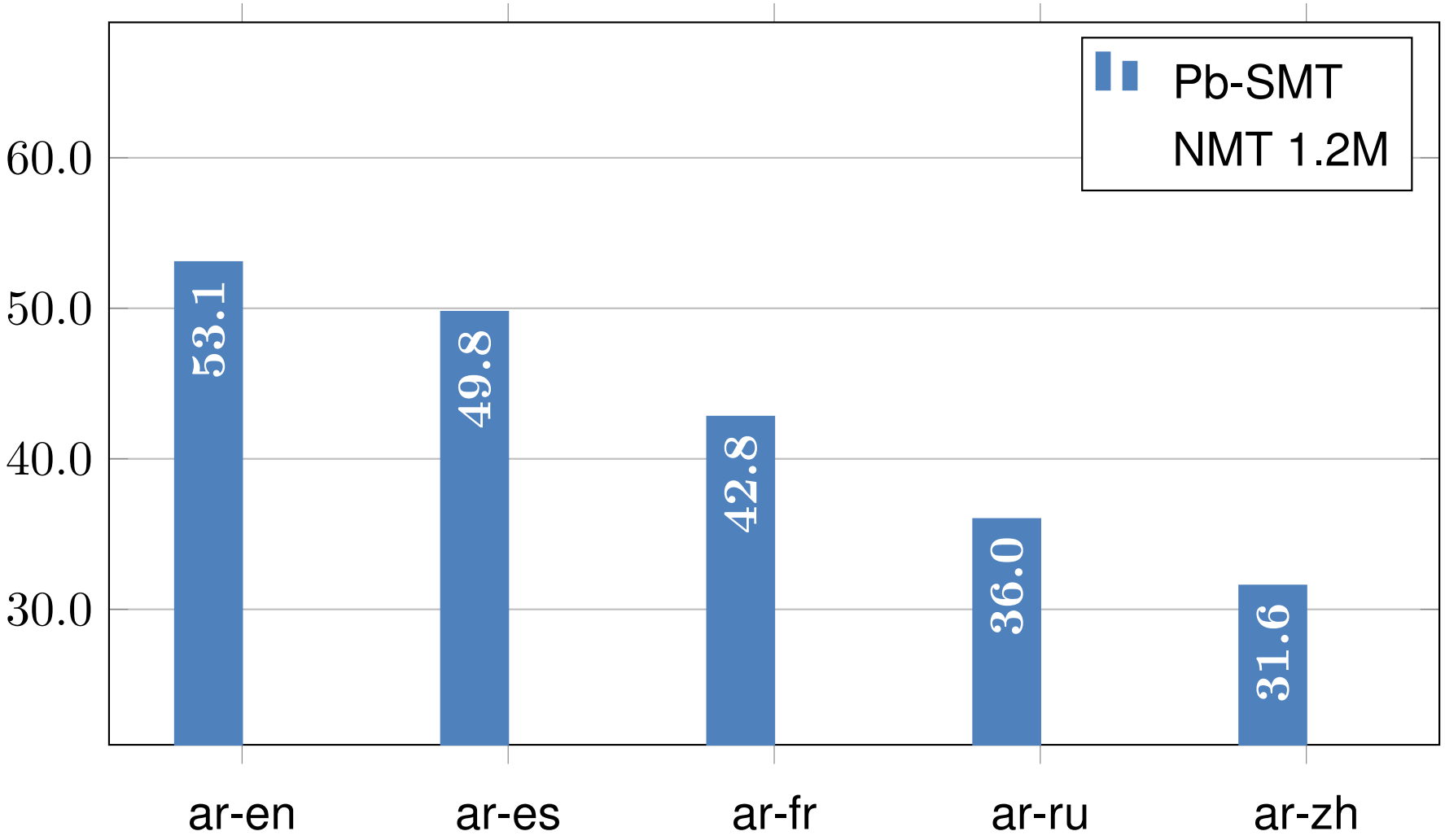
PB-SMT vs. NMT

Out of Arabic



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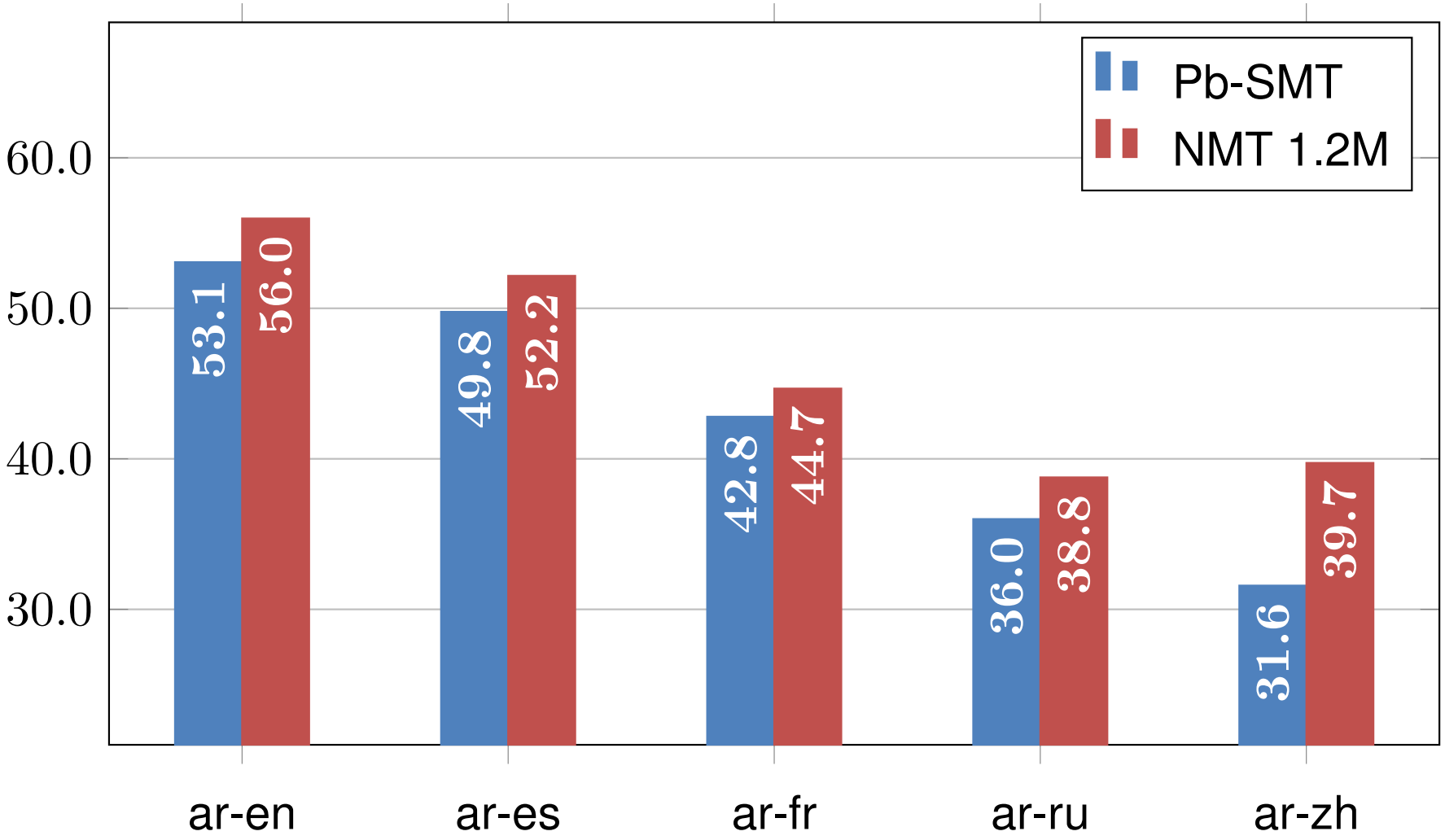
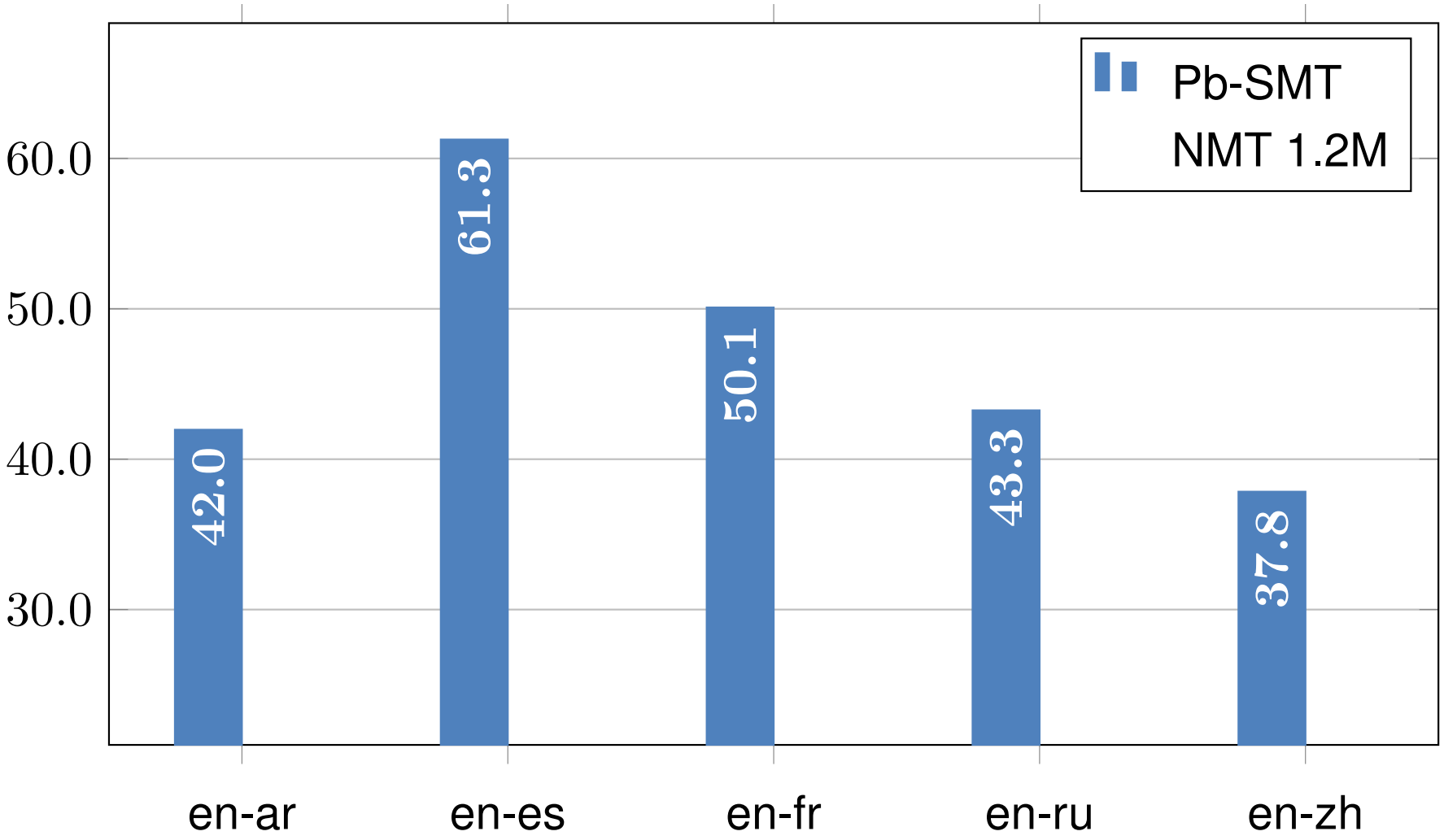


PB-SMT vs. NMT

Out of English



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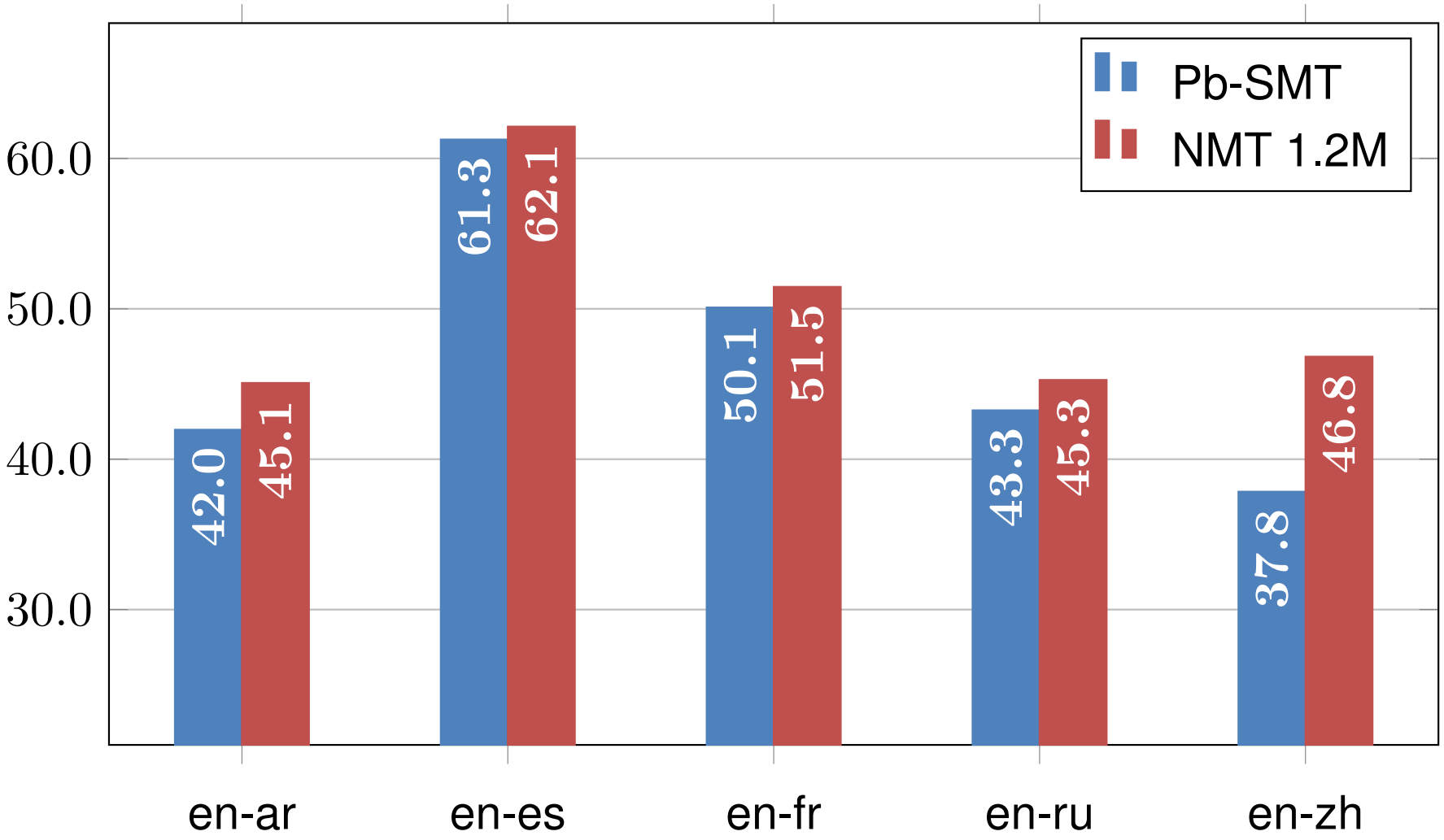
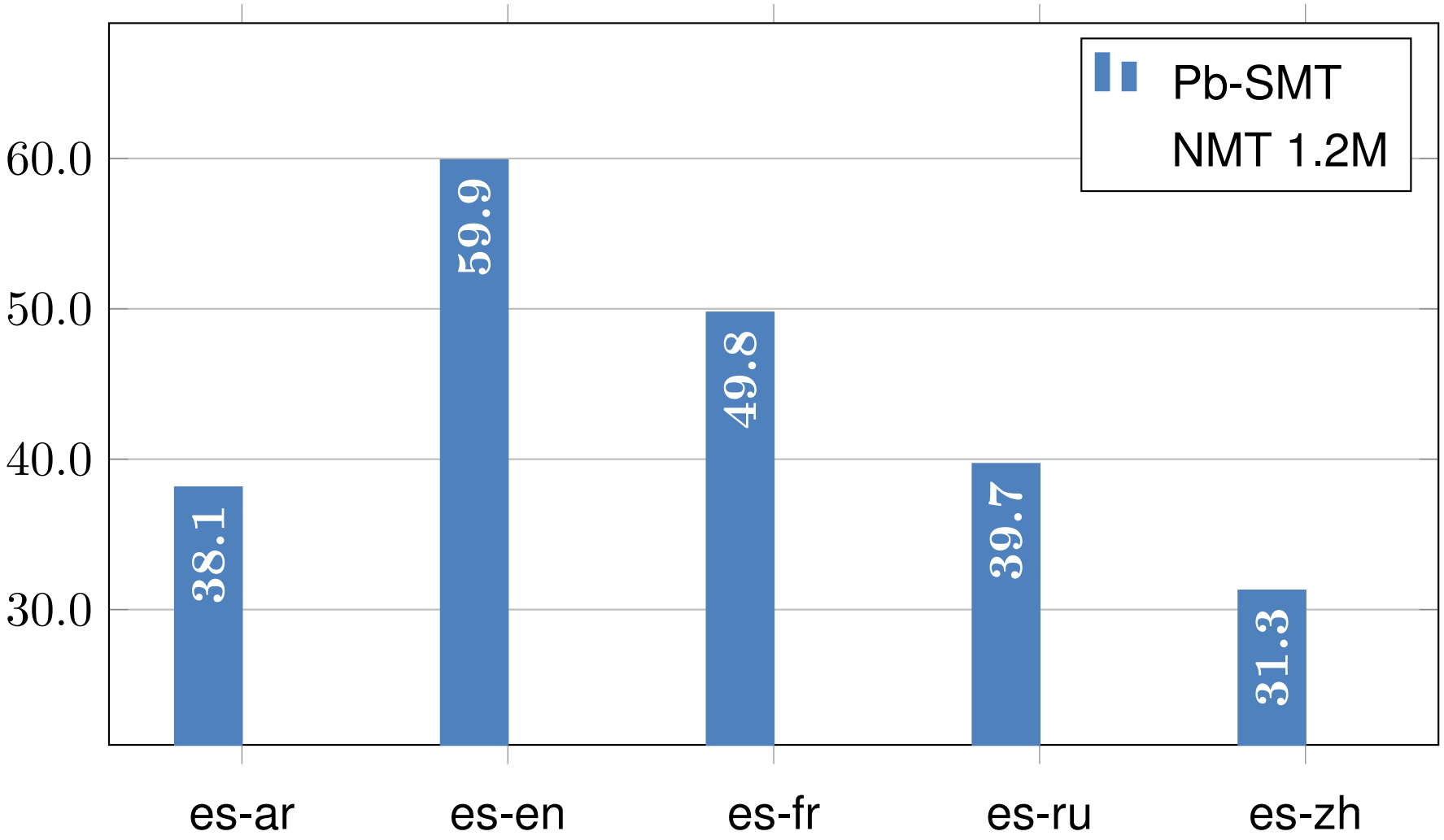


PB-SMT vs. NMT

Out of Spanish



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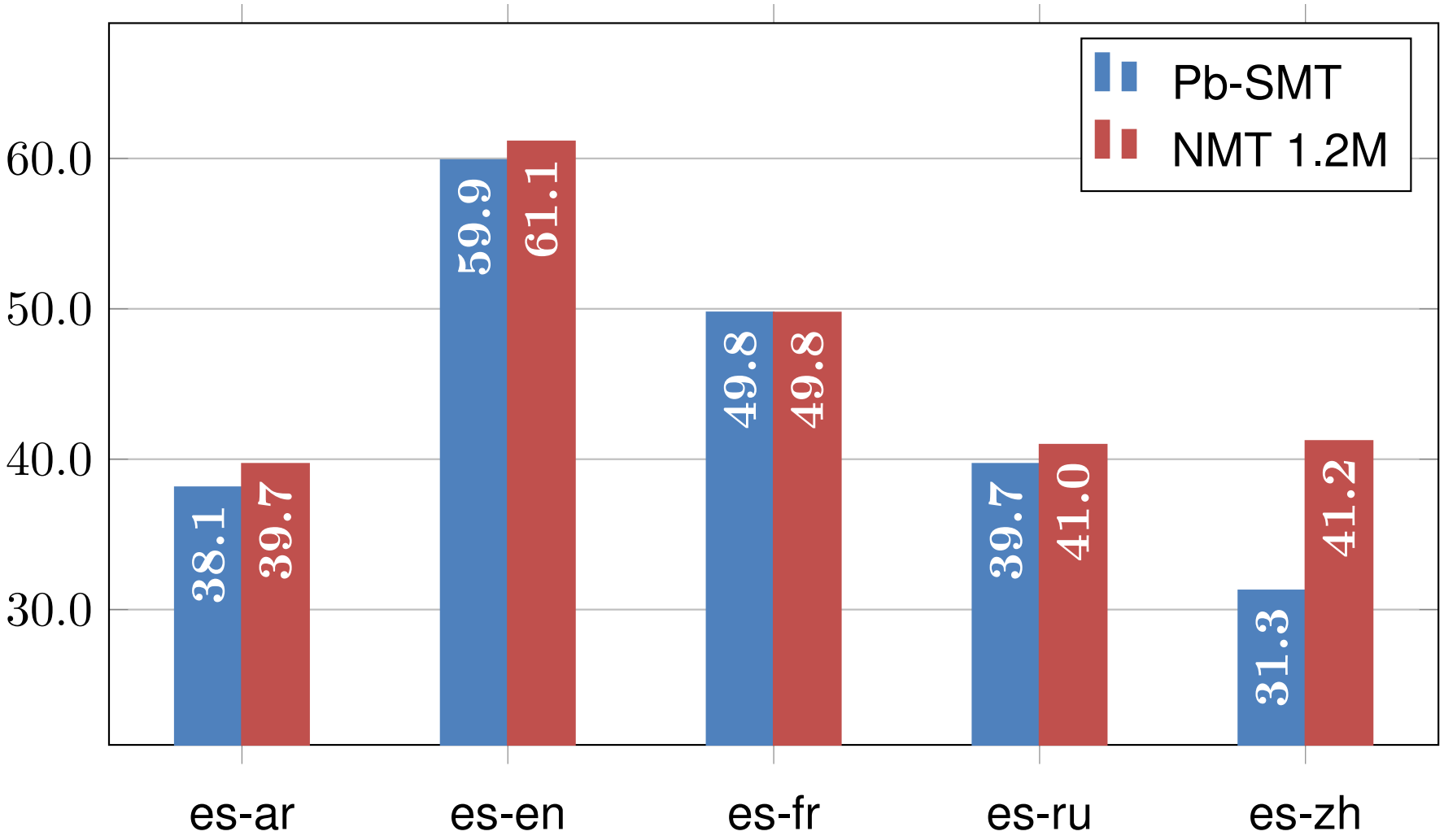
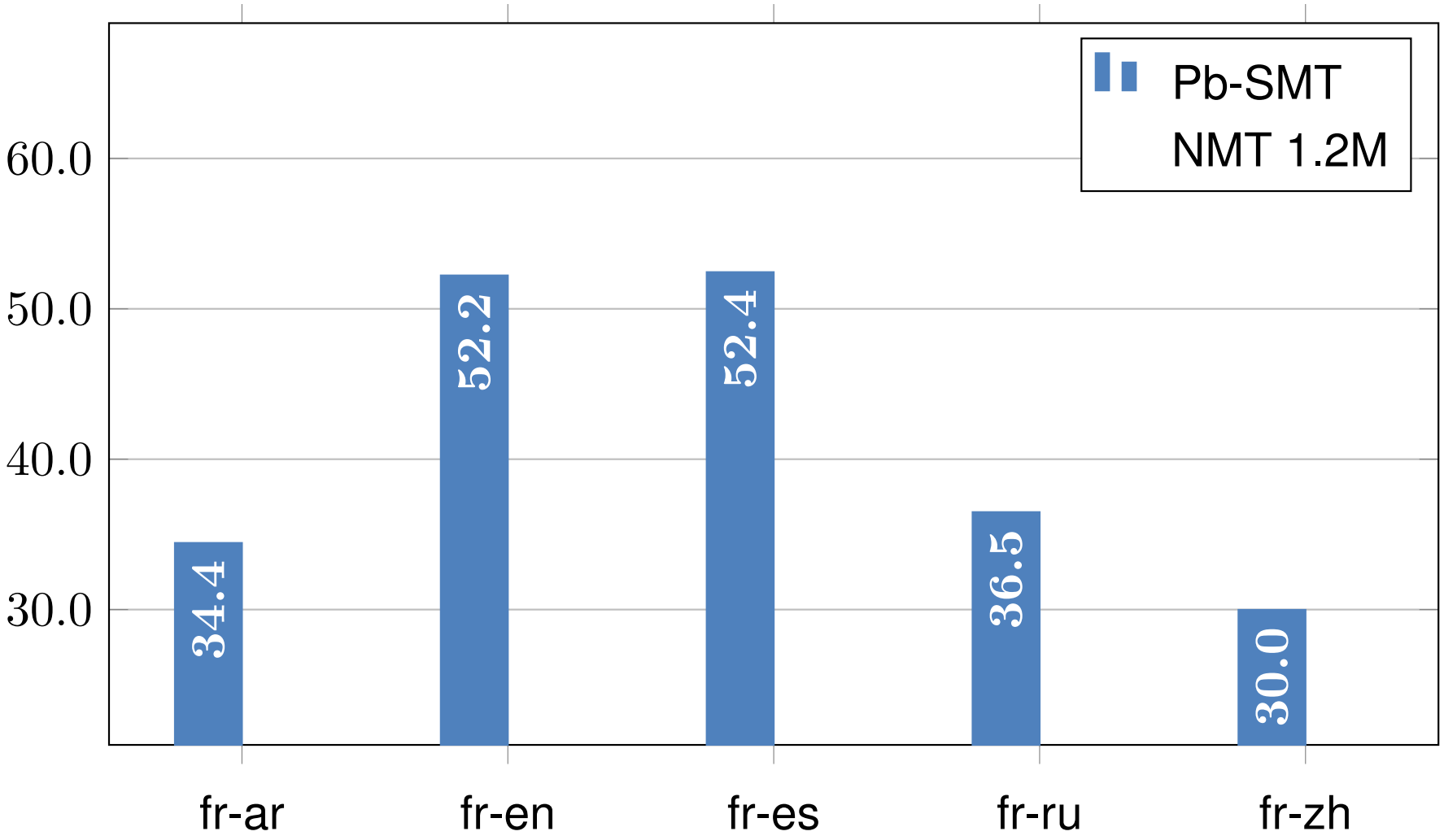


PB-SMT vs. NMT

Out of French



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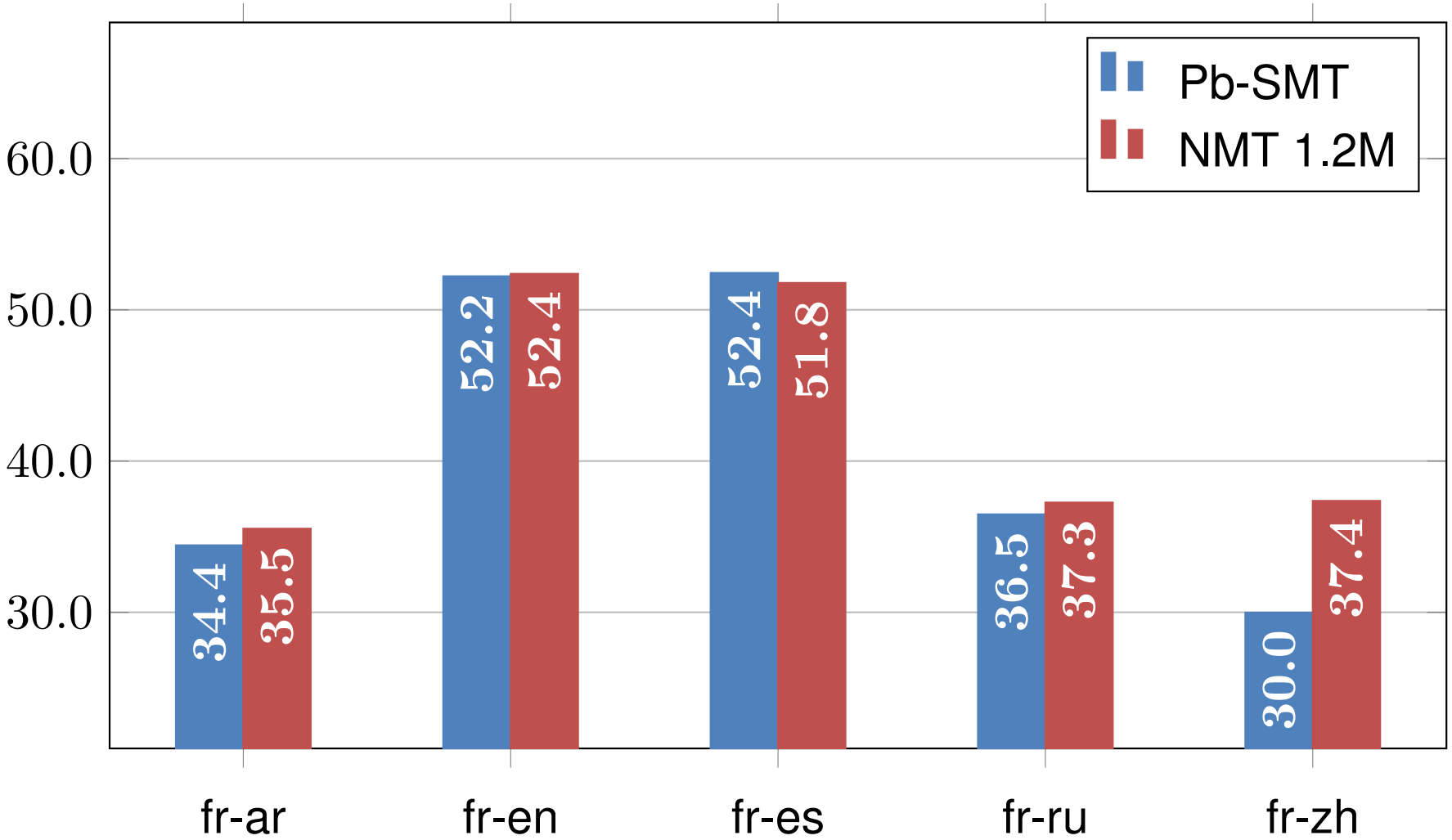

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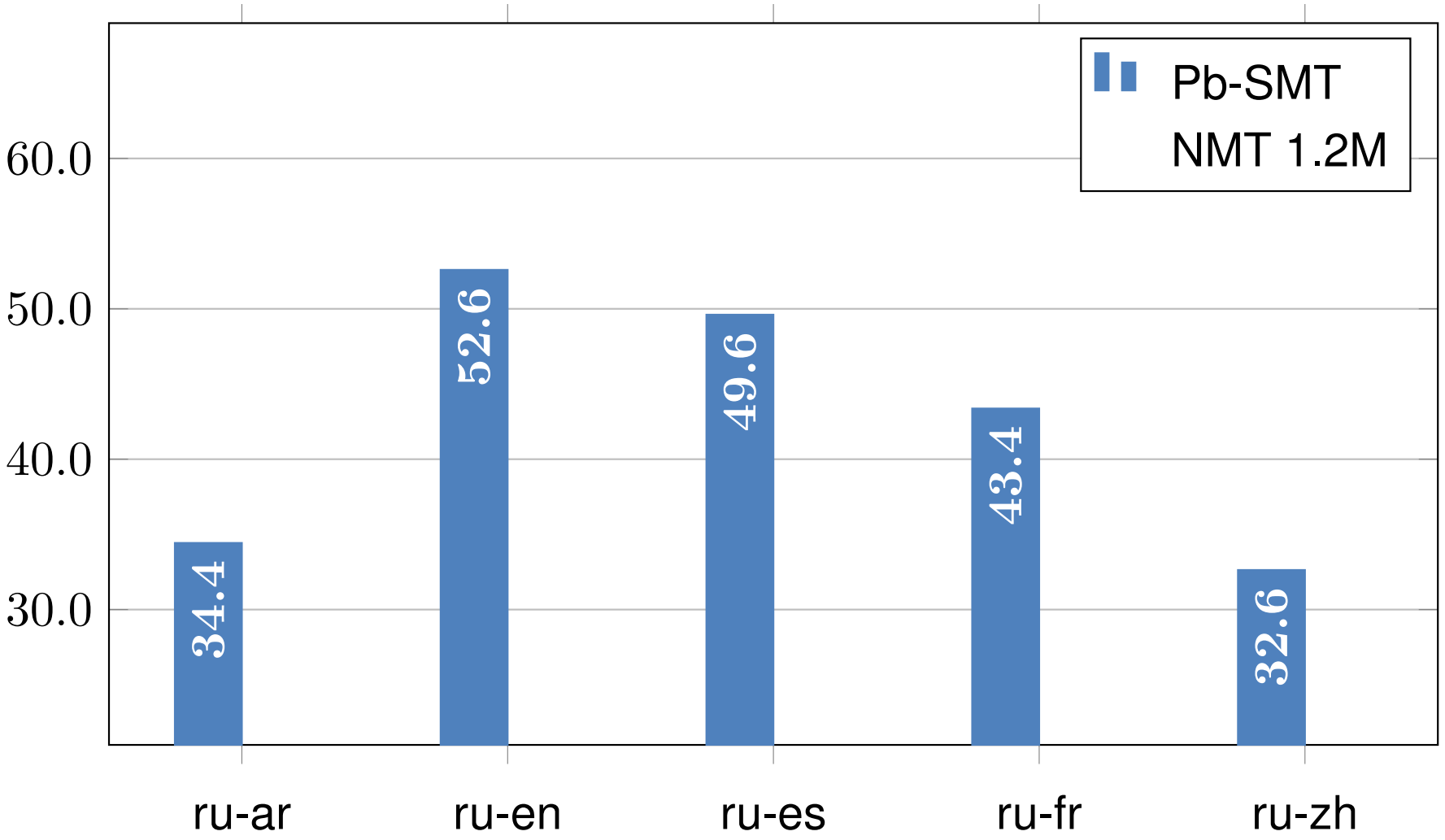

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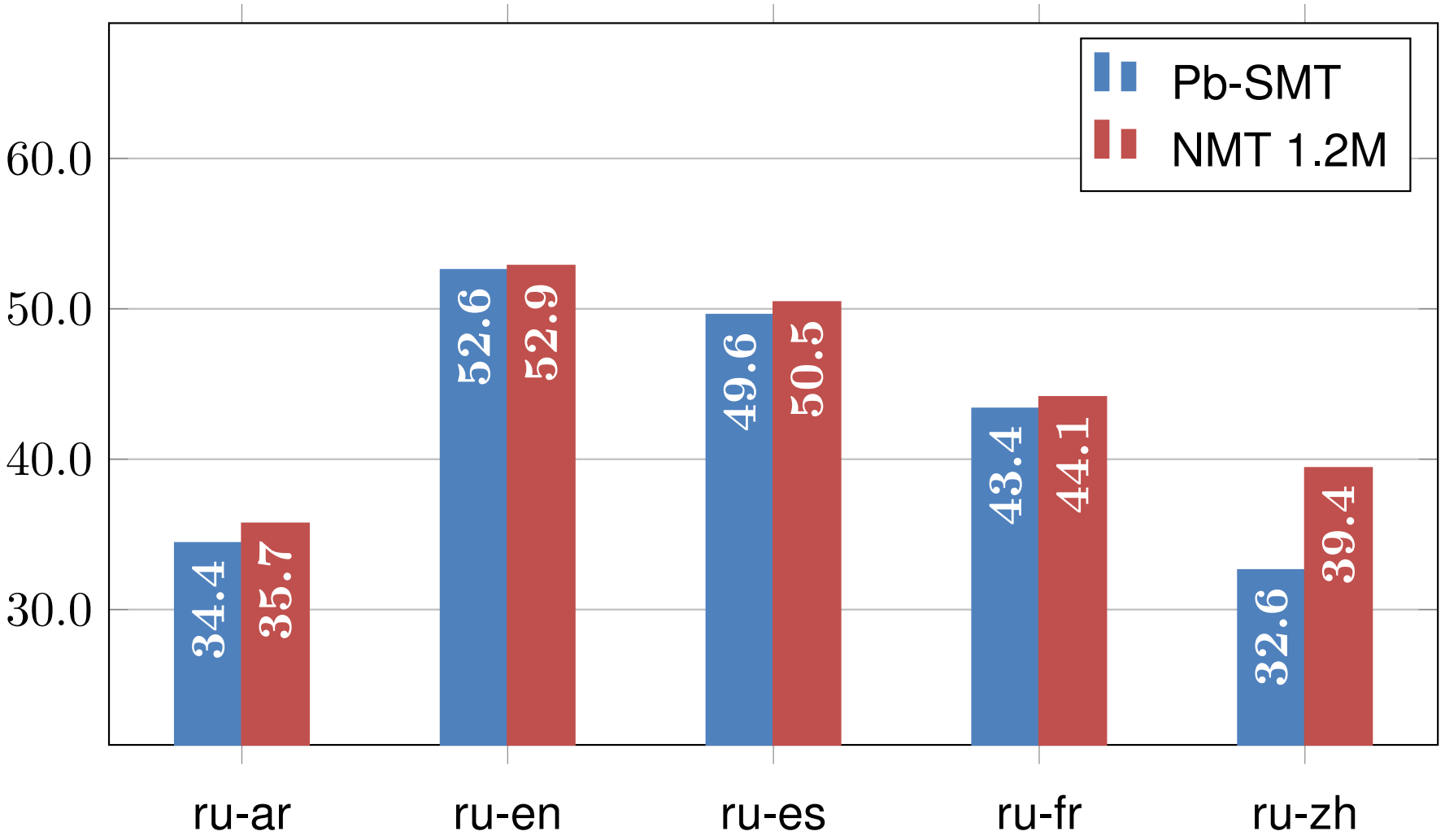

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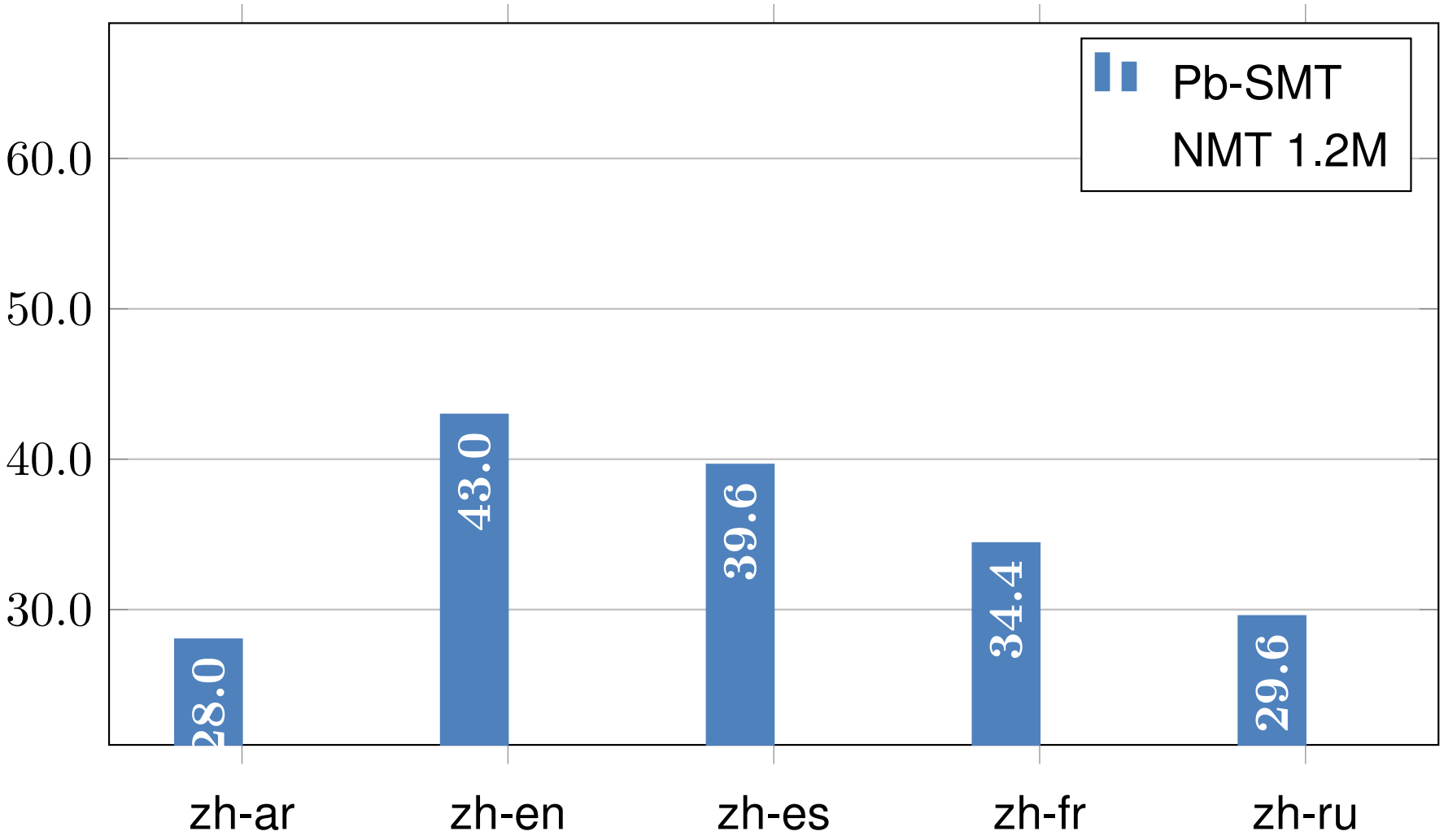

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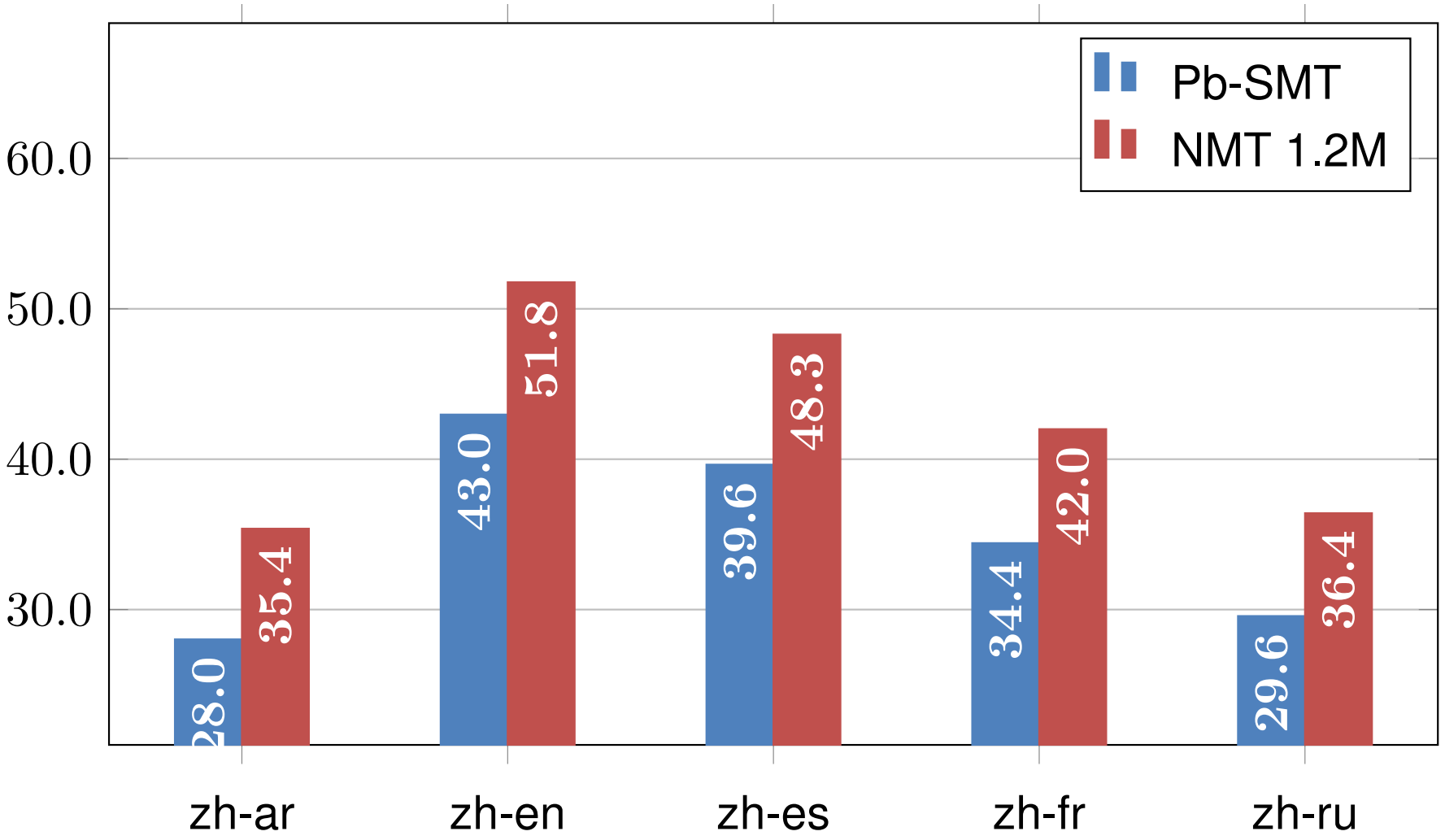

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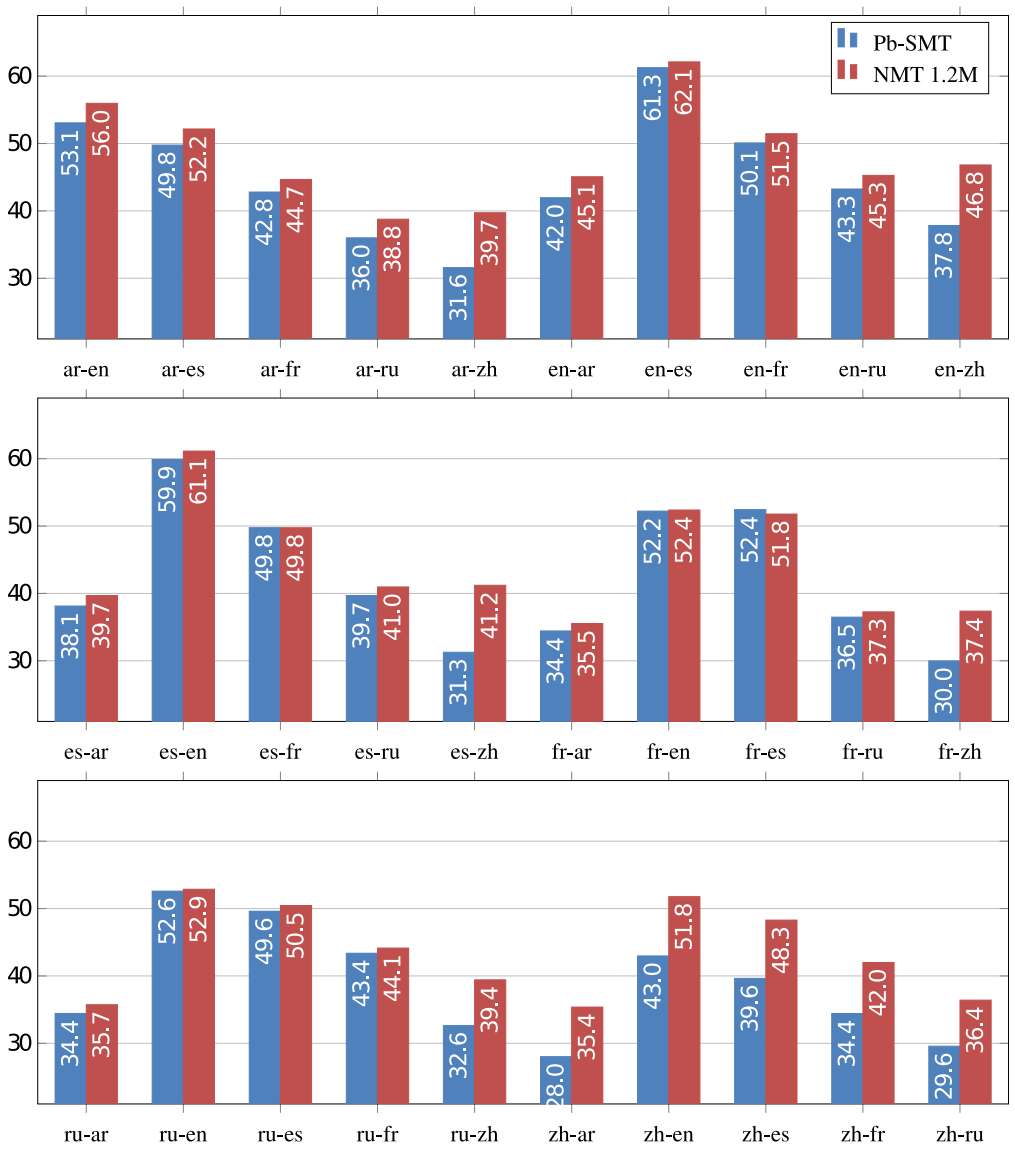
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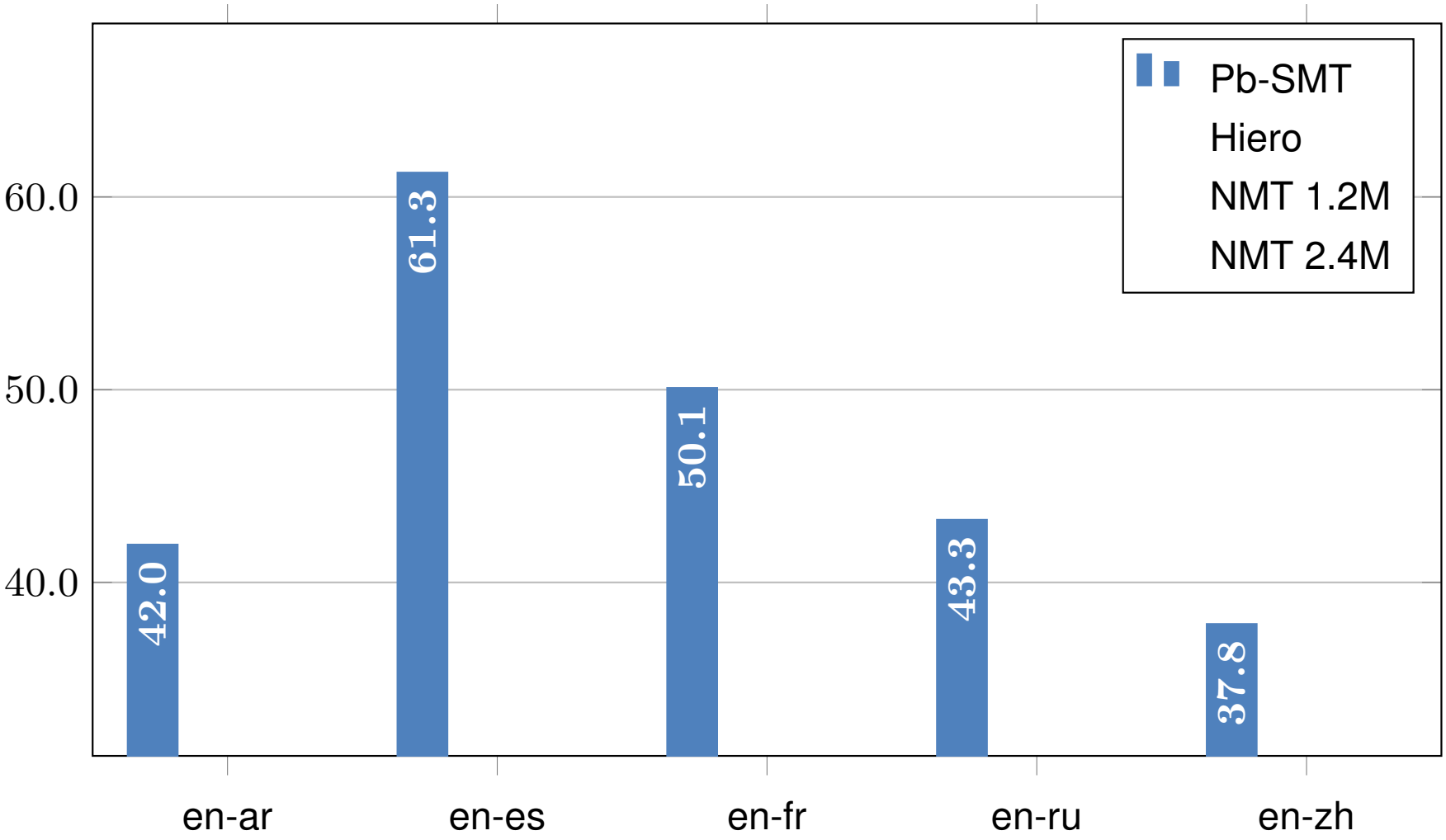

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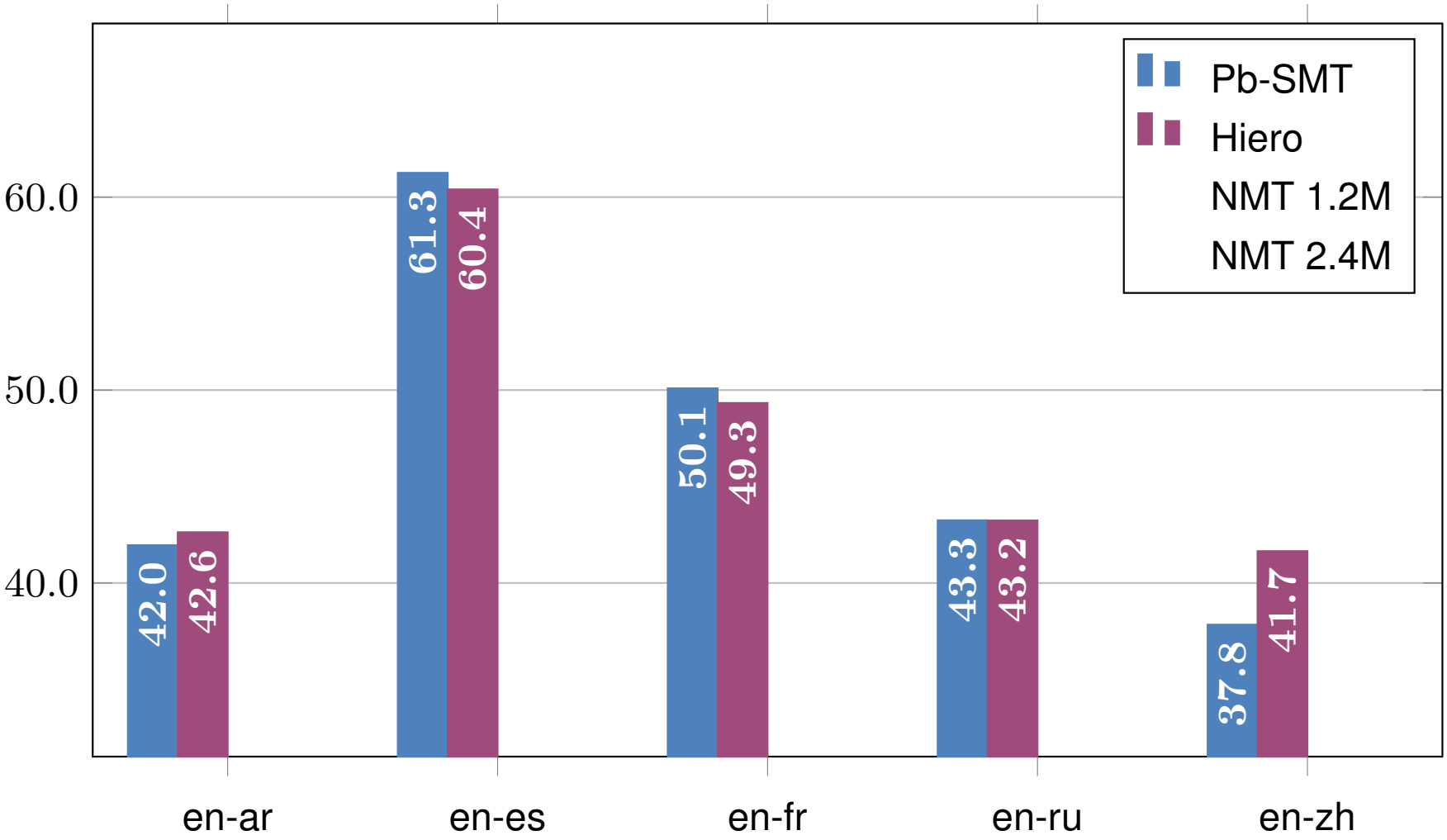

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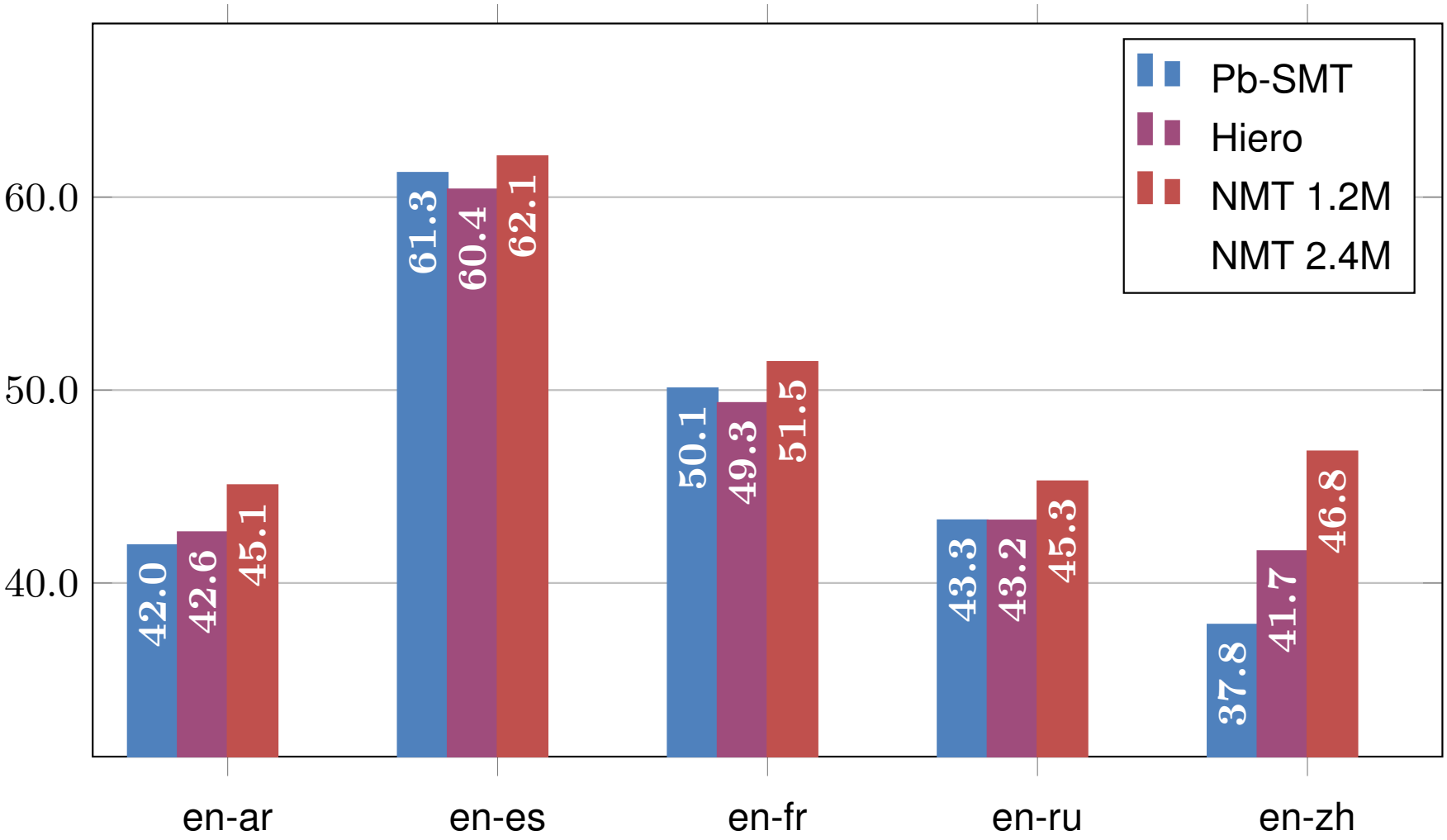

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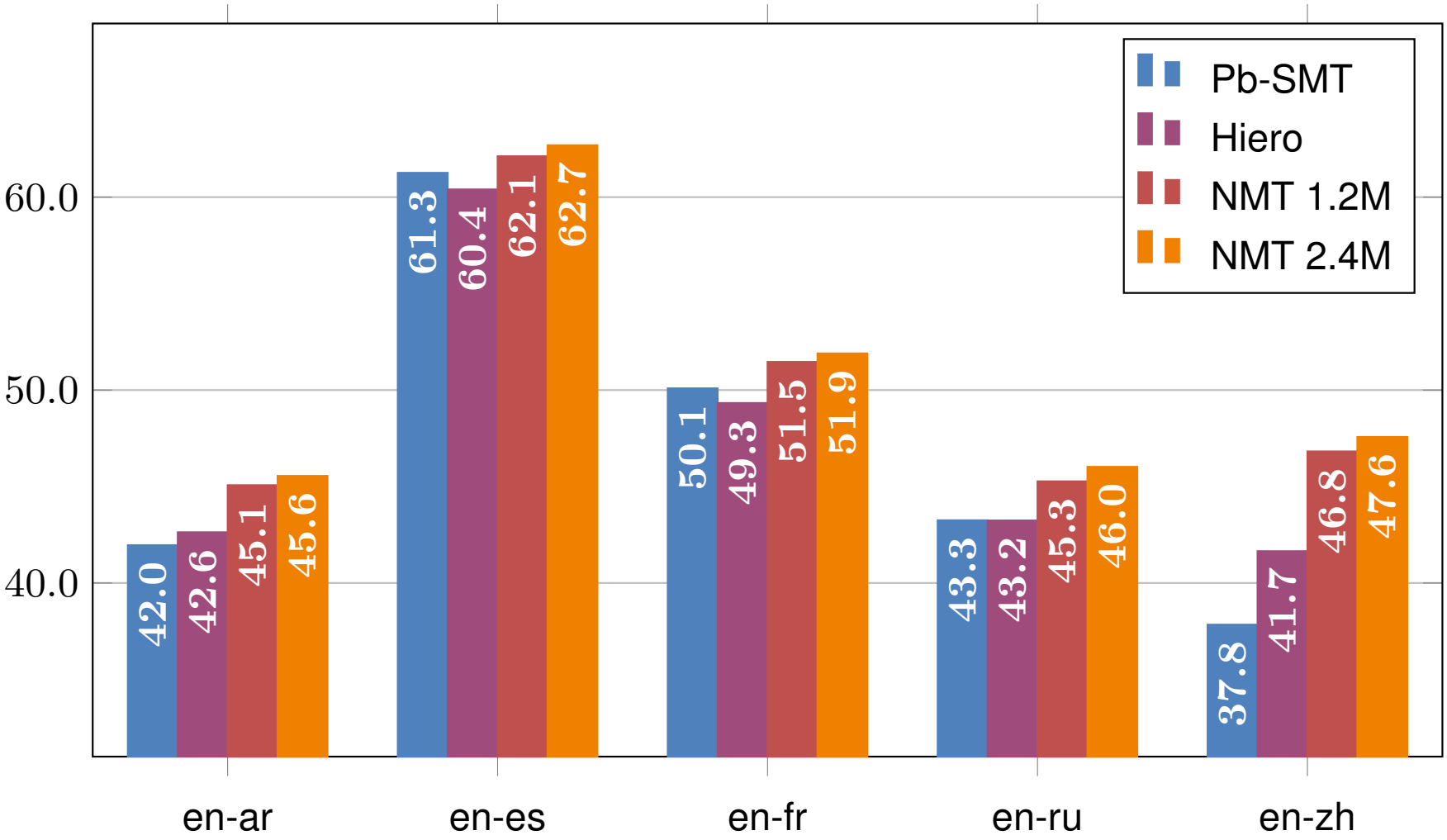

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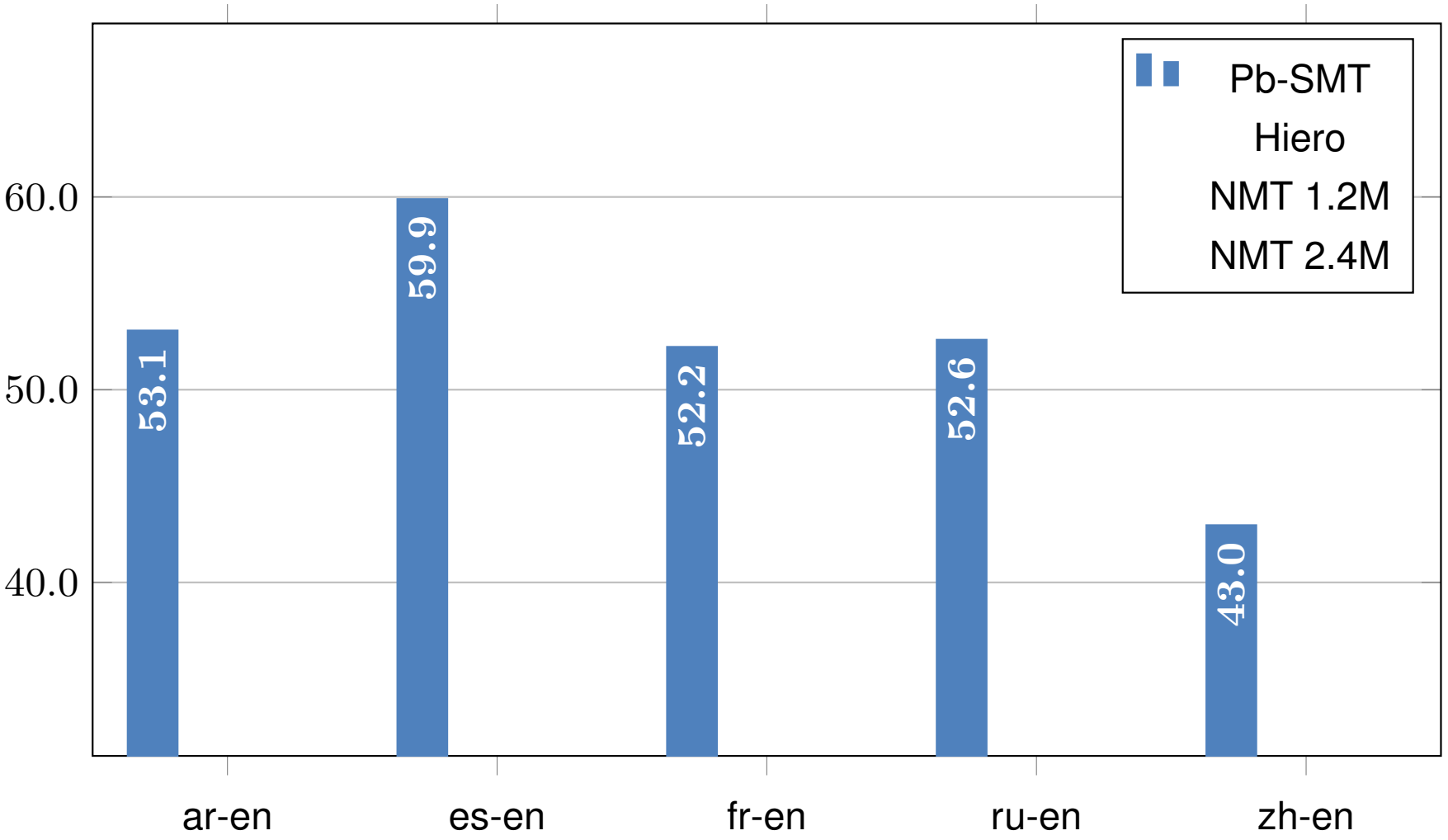

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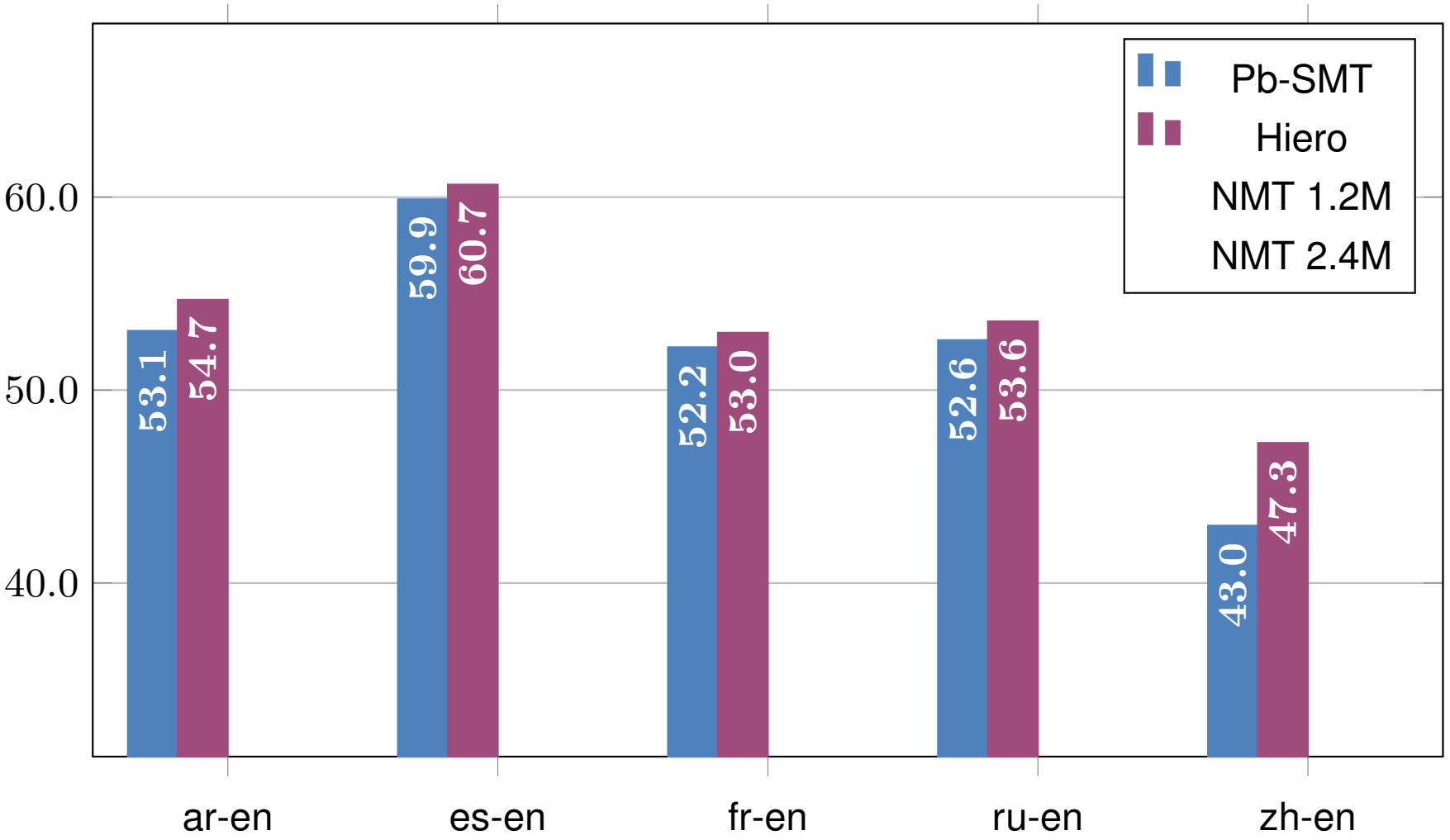

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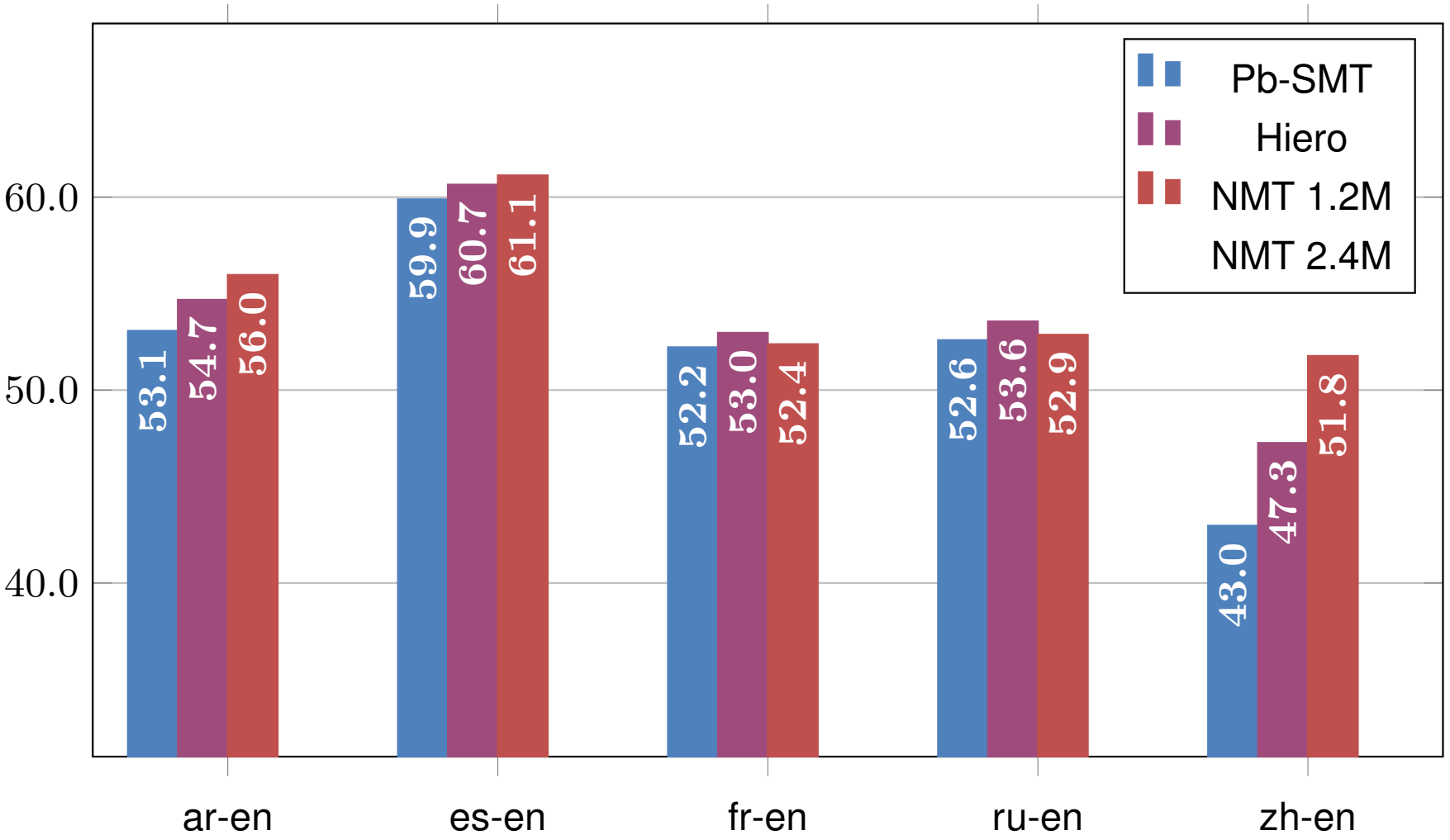

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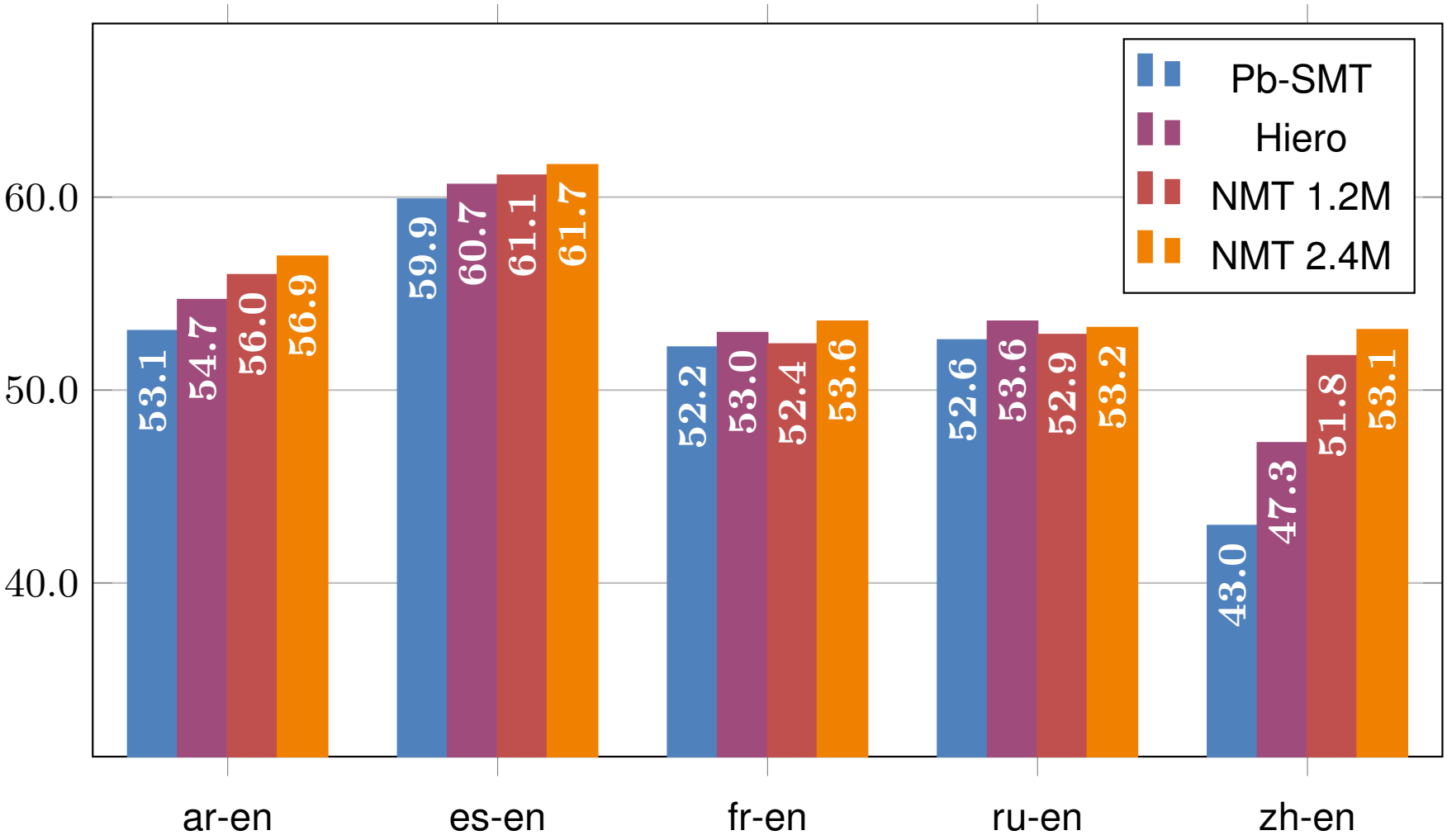

Is neural machine translation ready for deployment?

1. Is quality a problem?

2. Is translation speed a problem?

Efficient decoding with AmuNMT

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- Grew out of a Moses feature function;
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Checkpoint ensembling and averaging

System	BLEU	Wps	Memory
Single best	49.68	ca. 860	301M
Last-4 ensemble	51.38	ca. 200	1.2G
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Table: Example for en-fr system

- Averaging models from different training runs does not work!

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- Decoding time on CPU is dominated by the final output layer (30,000 vocabulary items);
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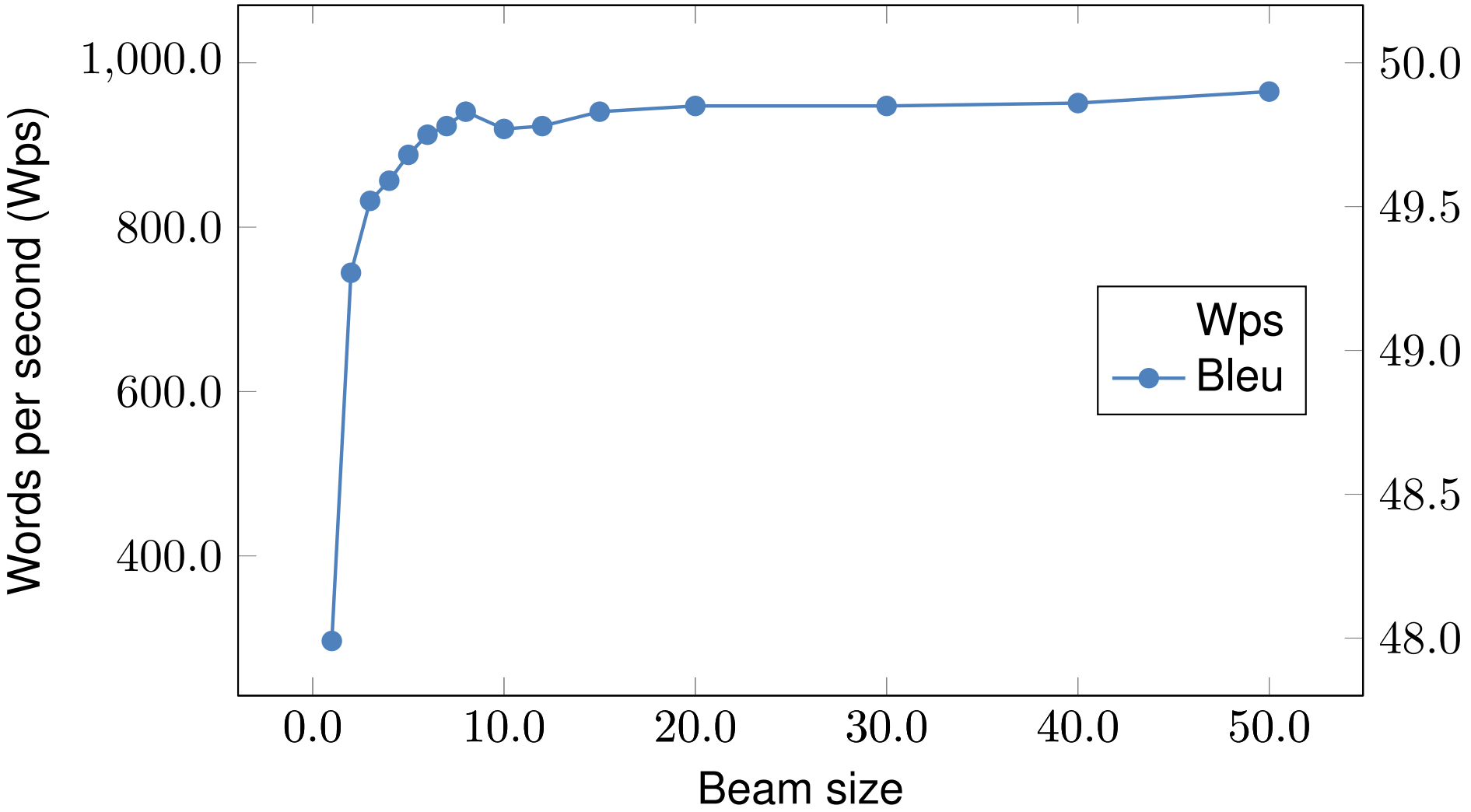
Speed and quality vs. beam size



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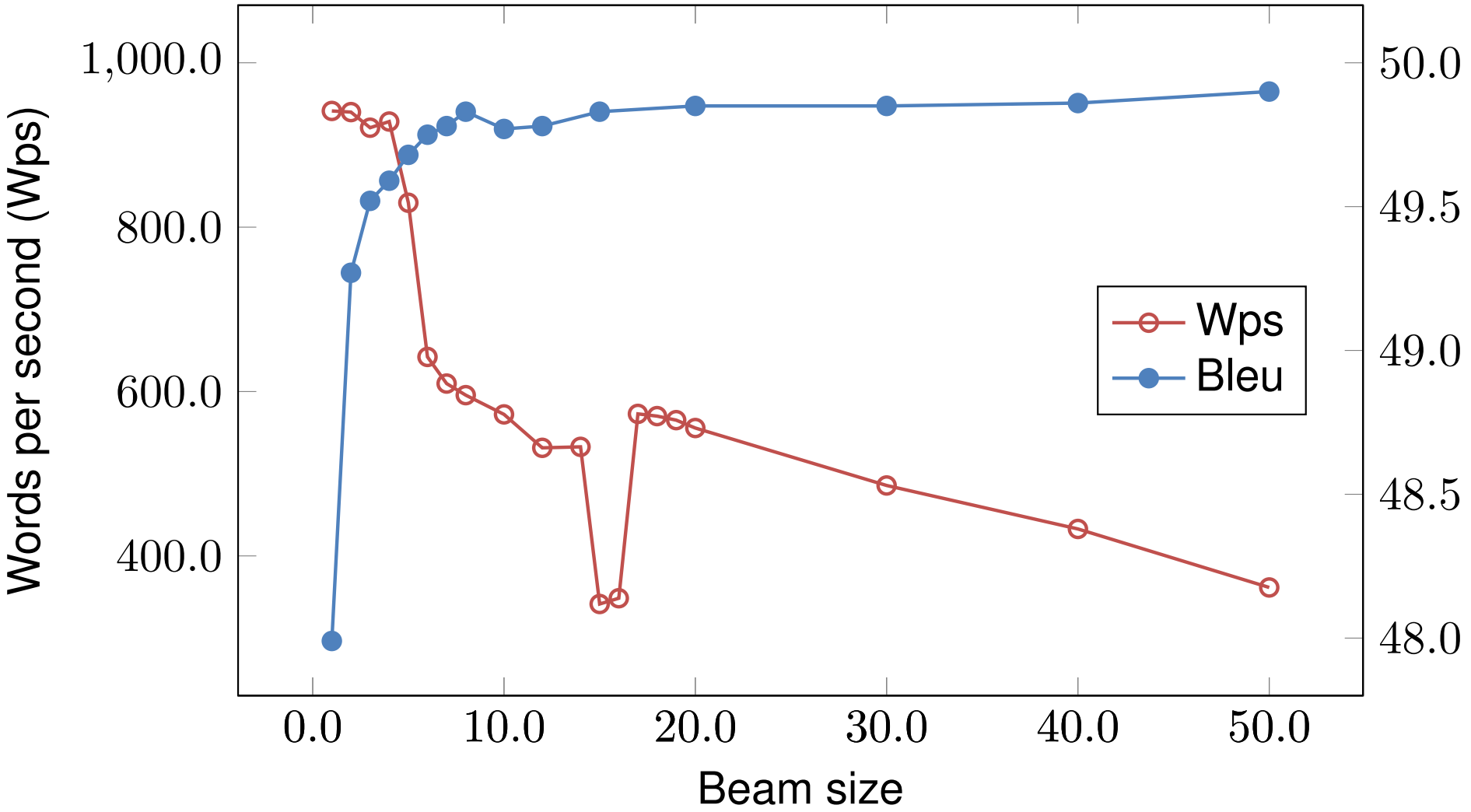
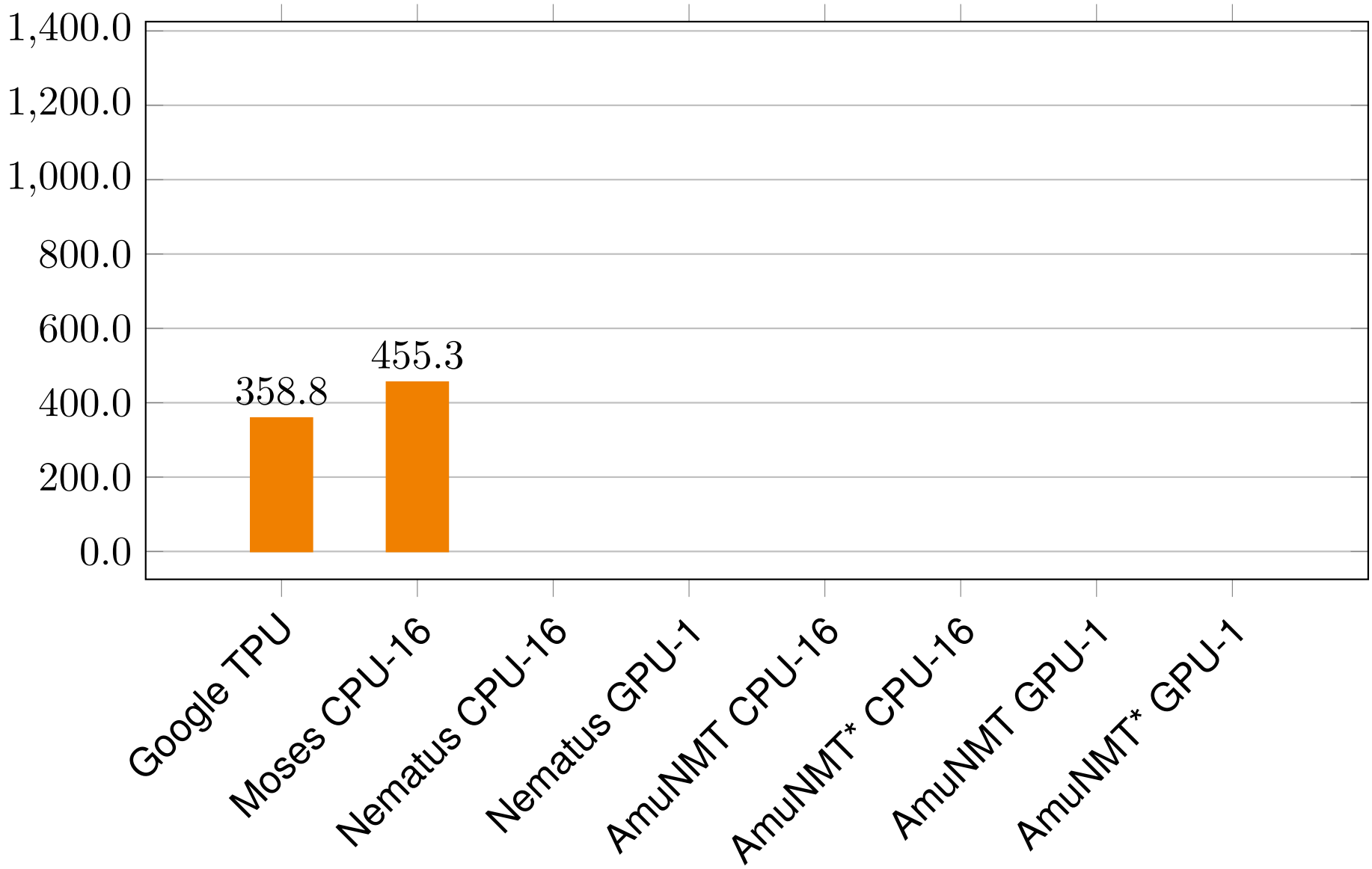


Translation speed in words per second



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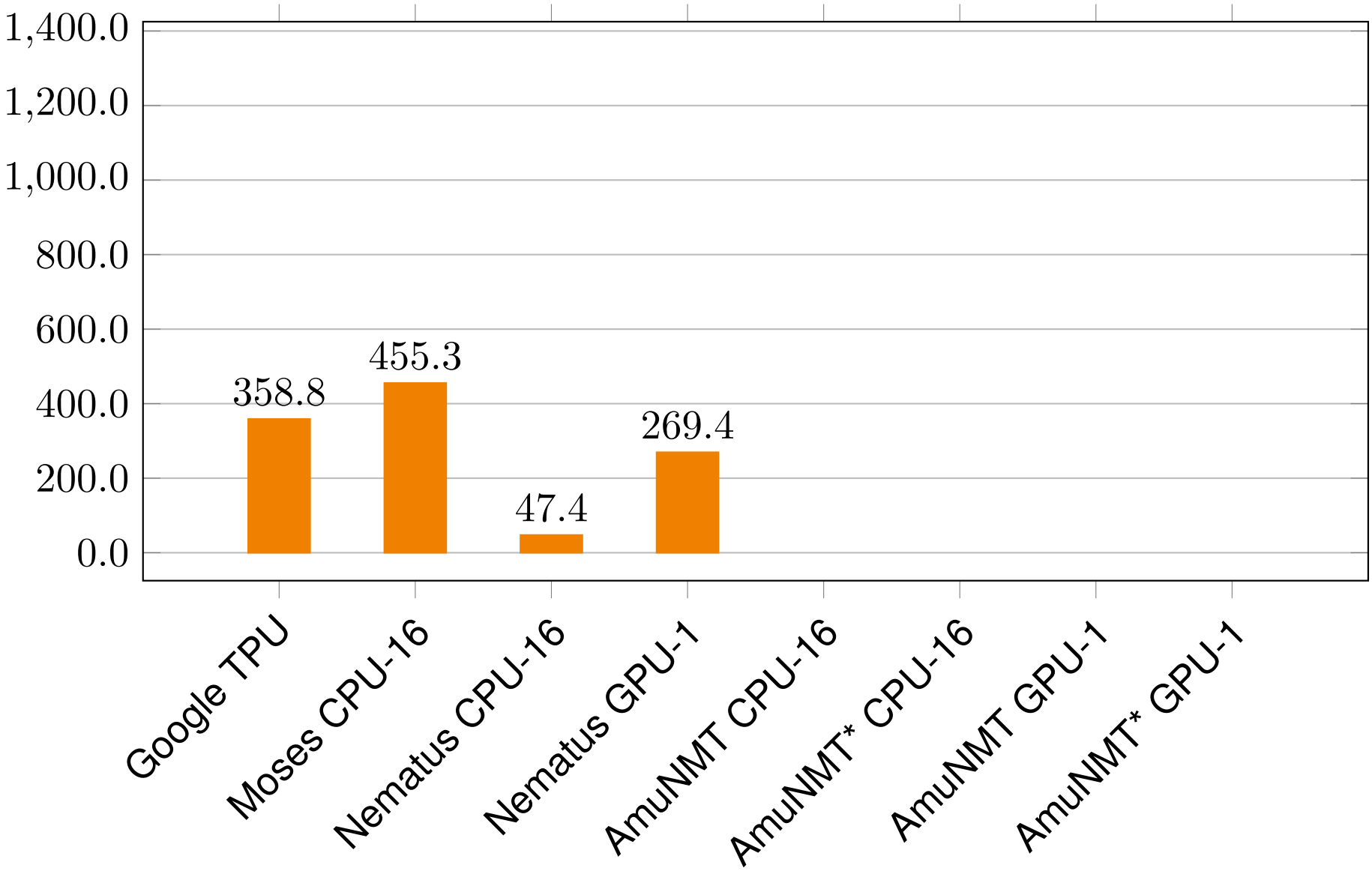

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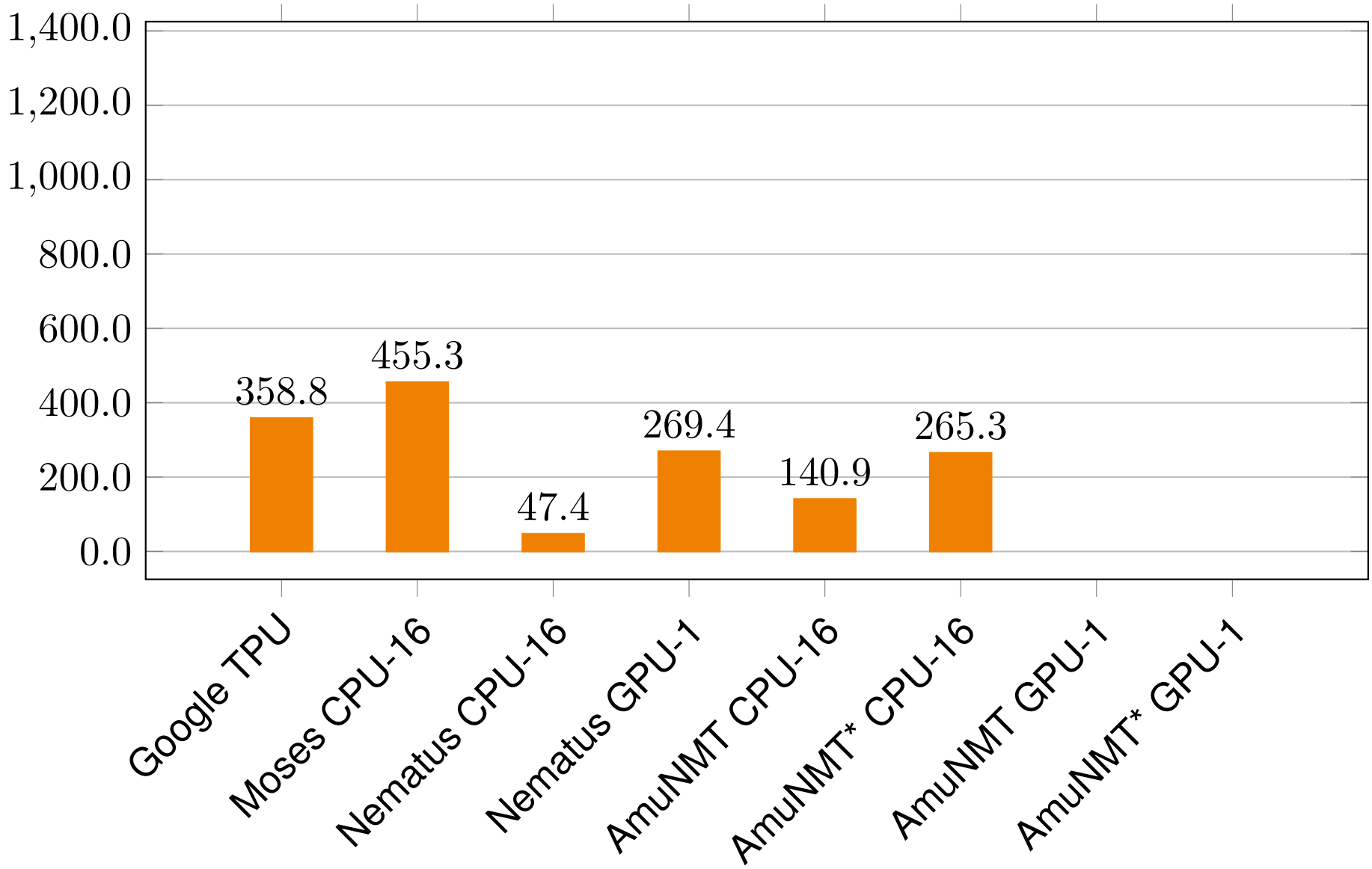

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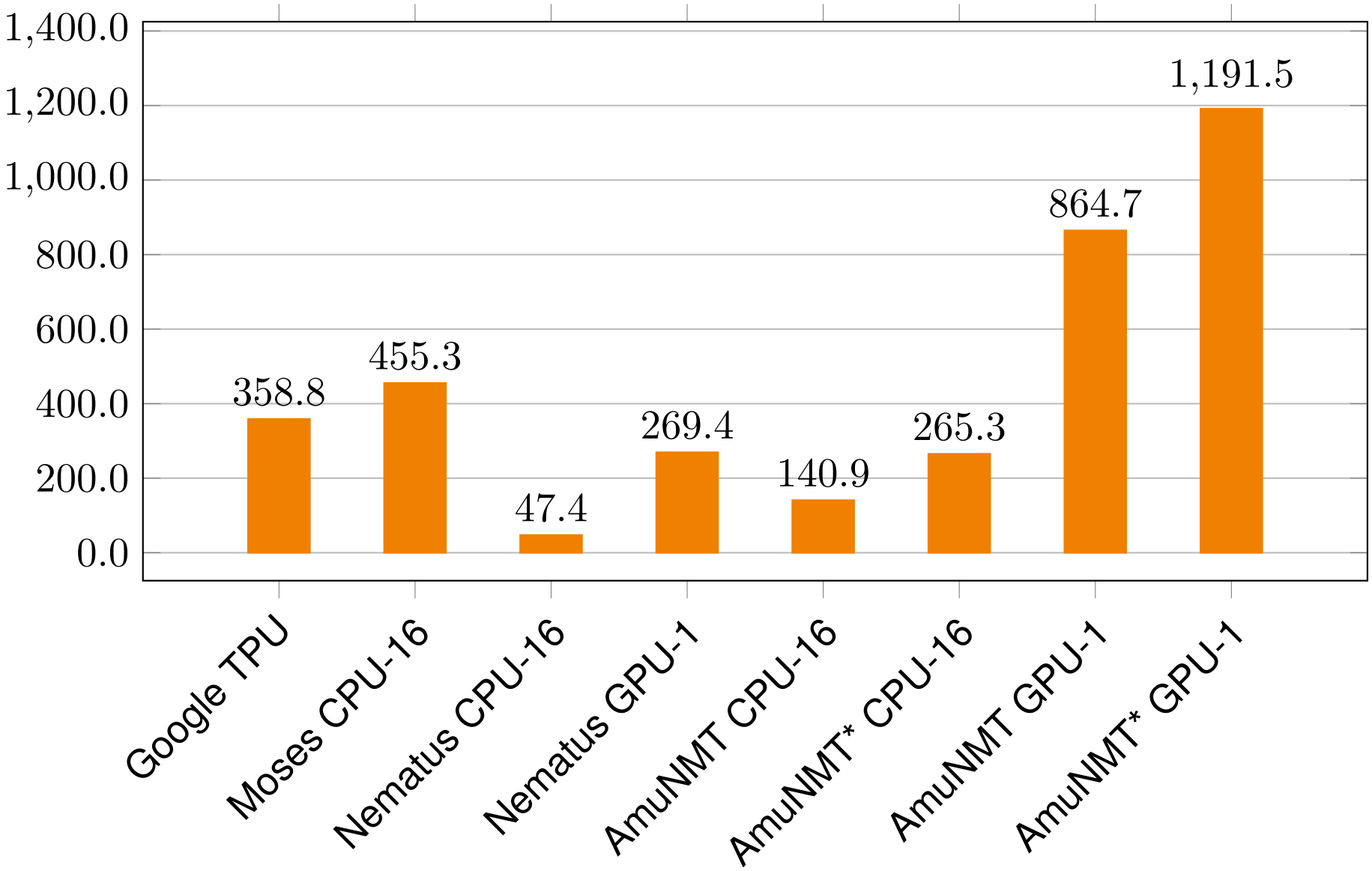
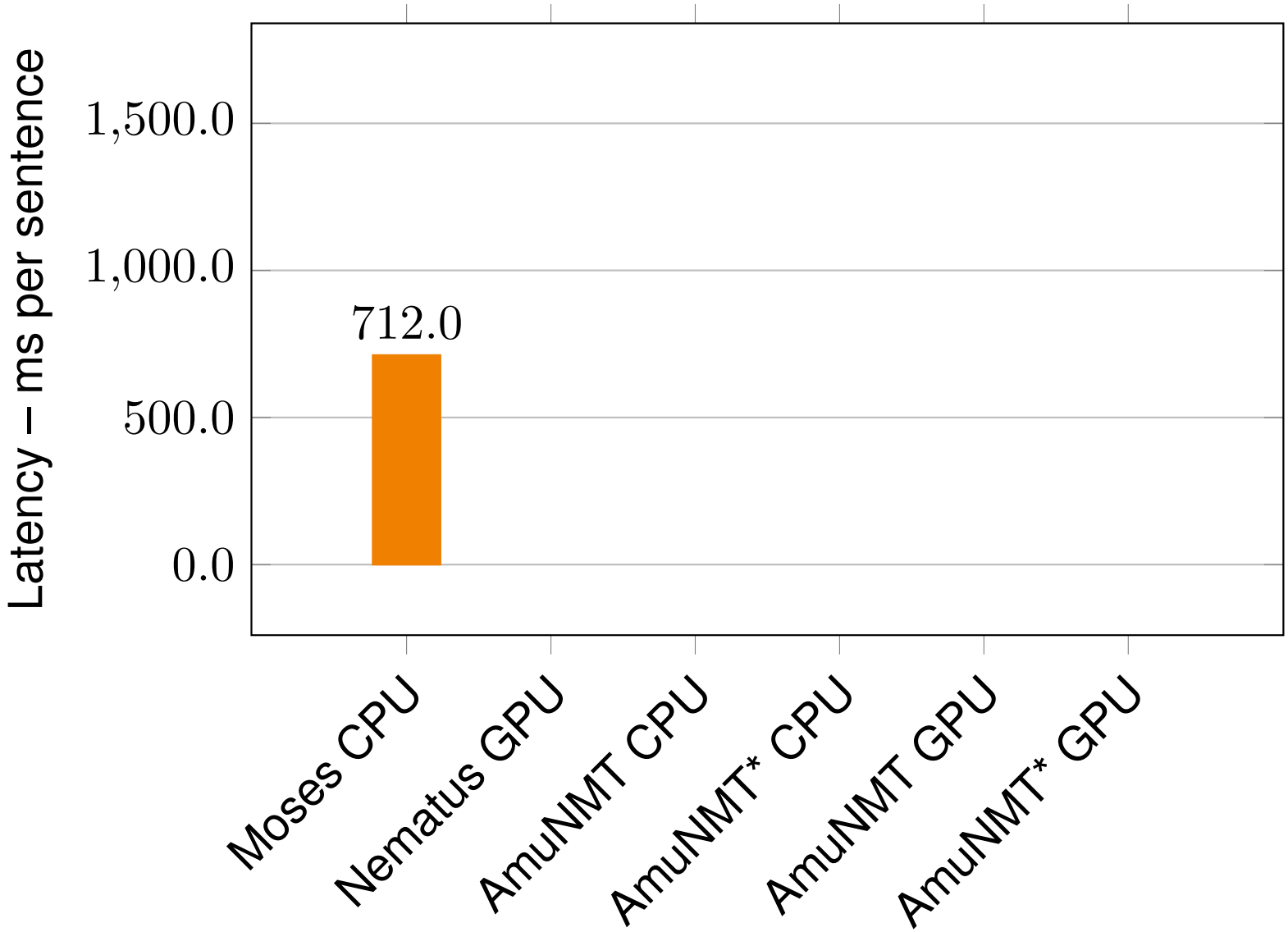


Latency in ms per sentence

Lower is better



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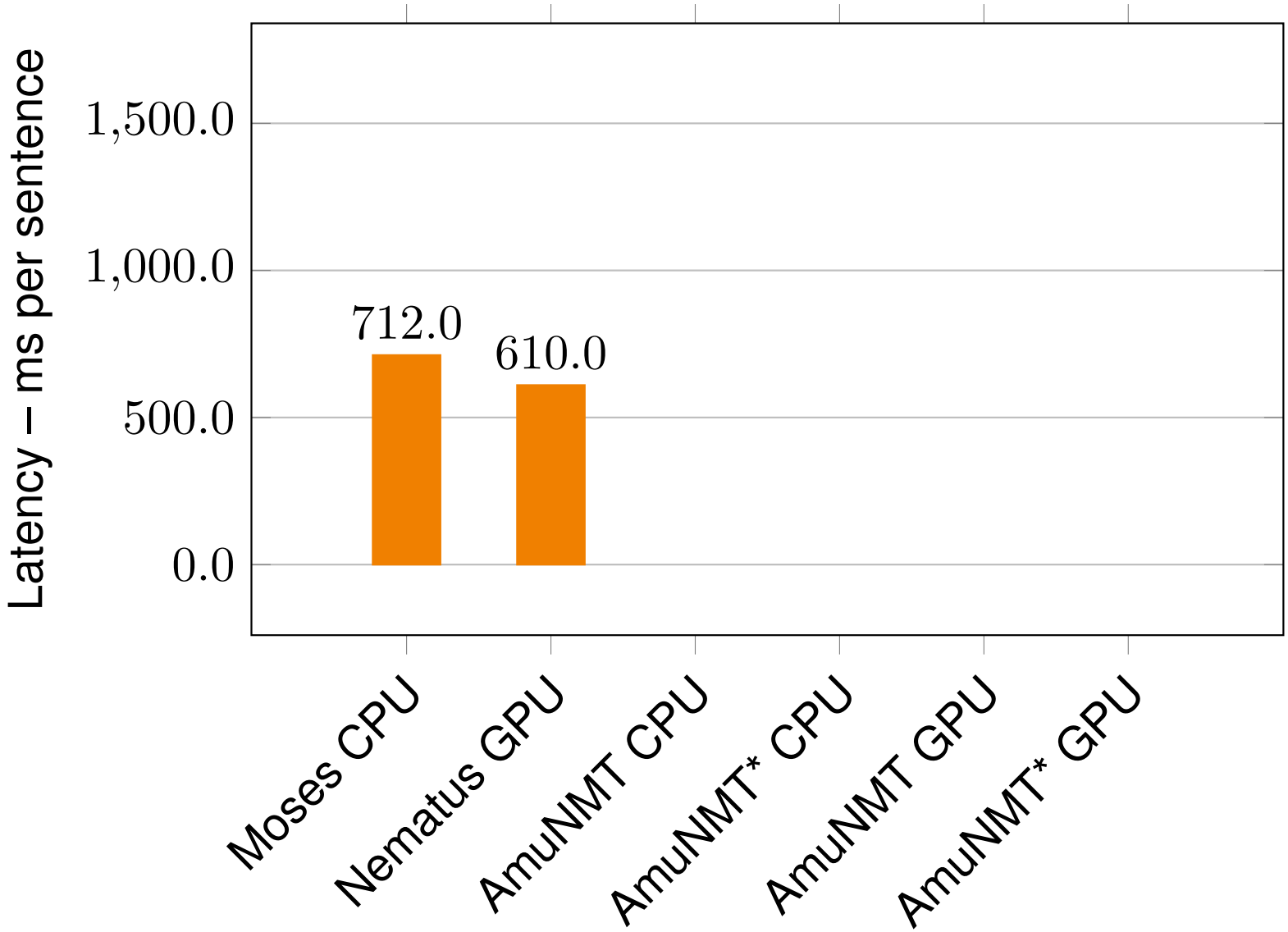

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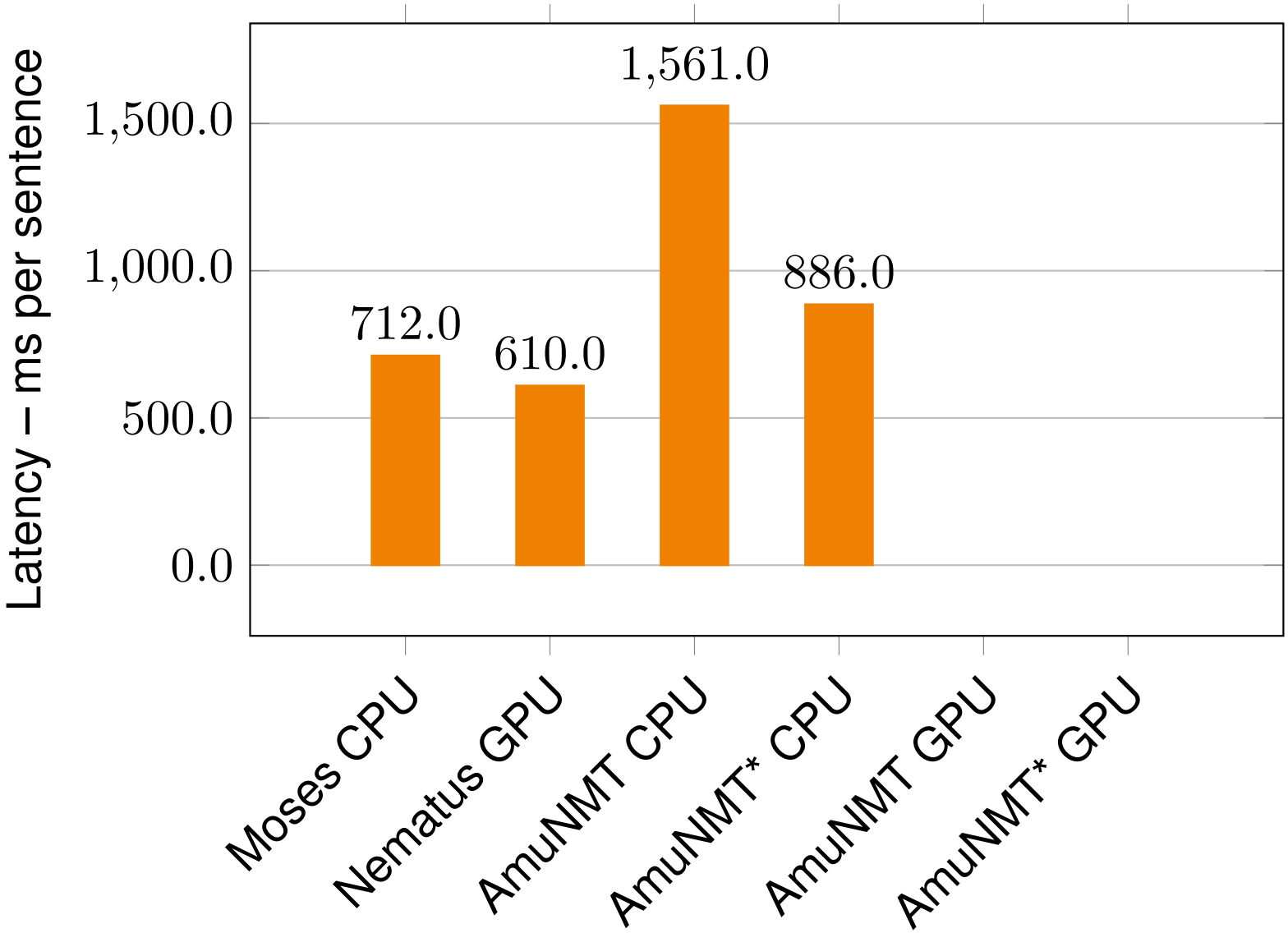

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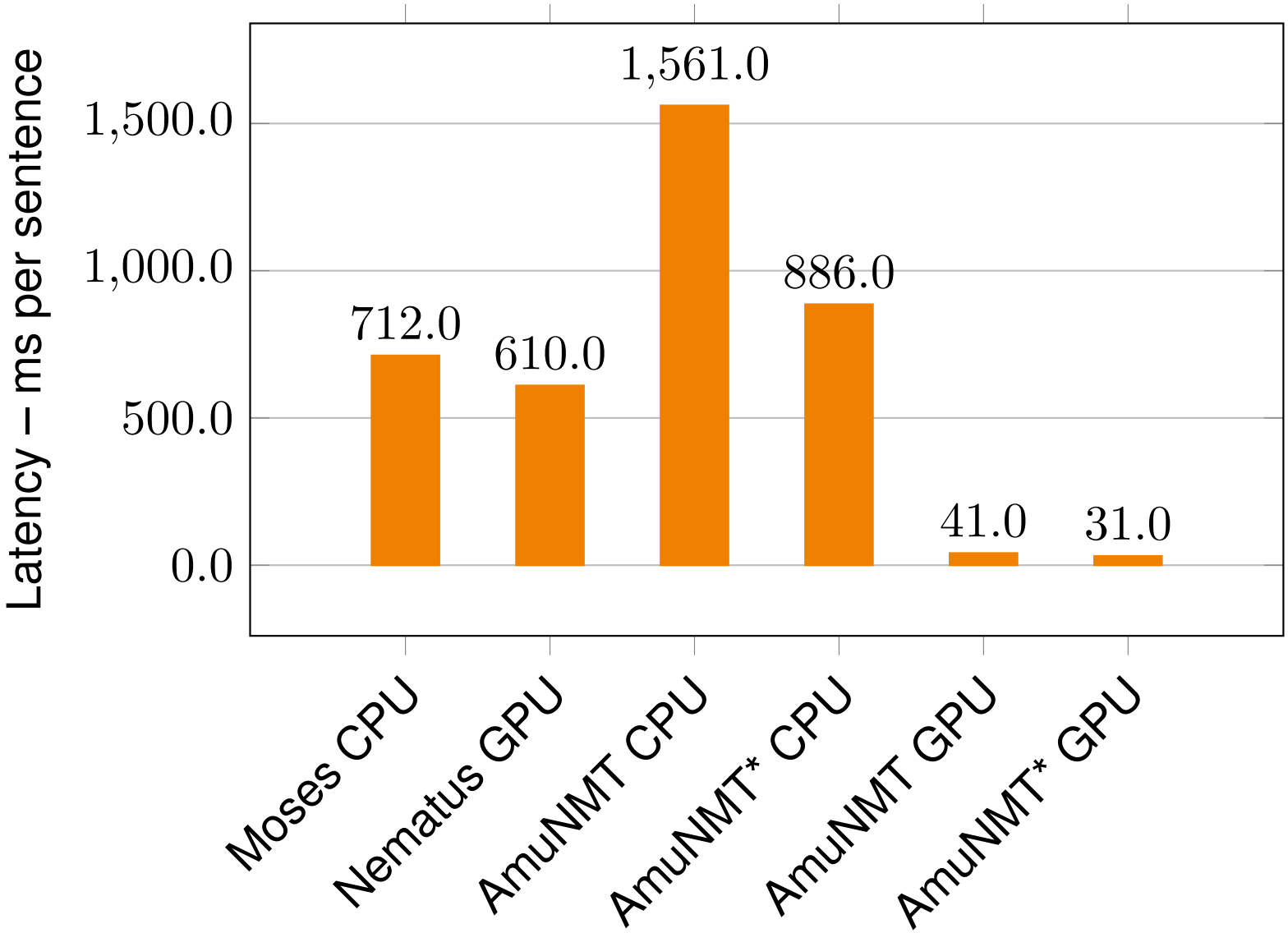

Conclusions

- Replacing PB-SMT with NMT seems to incurs no quality loss in terms of BLEU, in most cases improvements;
- Here: quality after 10 days of training mostly converged, small gains still possible;
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Bonus slide I

Deployment at WIPO (World Intellectual Property Organization)

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Language Industry Intelligence

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Technology

Neural Conquers Patent Translation in Major WIPO Roll-out

by Marion Marking on November 18, 2016

Barely two years after it was first proposed, machine translation technology based on neural networks is going mainstream. After Google, Systran, and Microsoft, the World Intellectual Property Organization (WIPO) announced on October 31, 2016 the roll-out of neural machine translation (NMT) on its publicly

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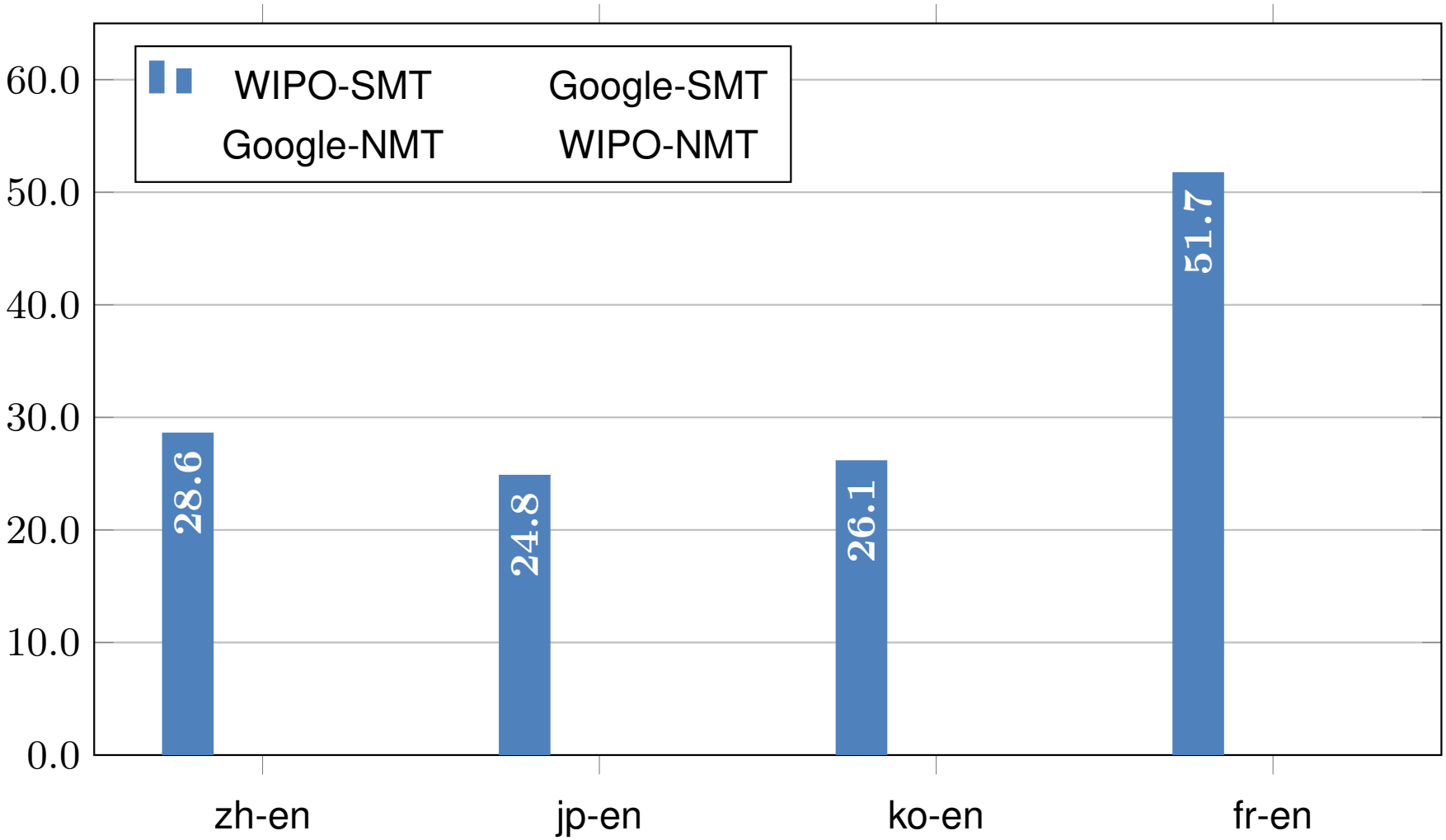
Bonus slide II

Deployment at WIPO (World Intellectual Property Organization)

- Large corpora of in-domain patent data (30M-100M segments).



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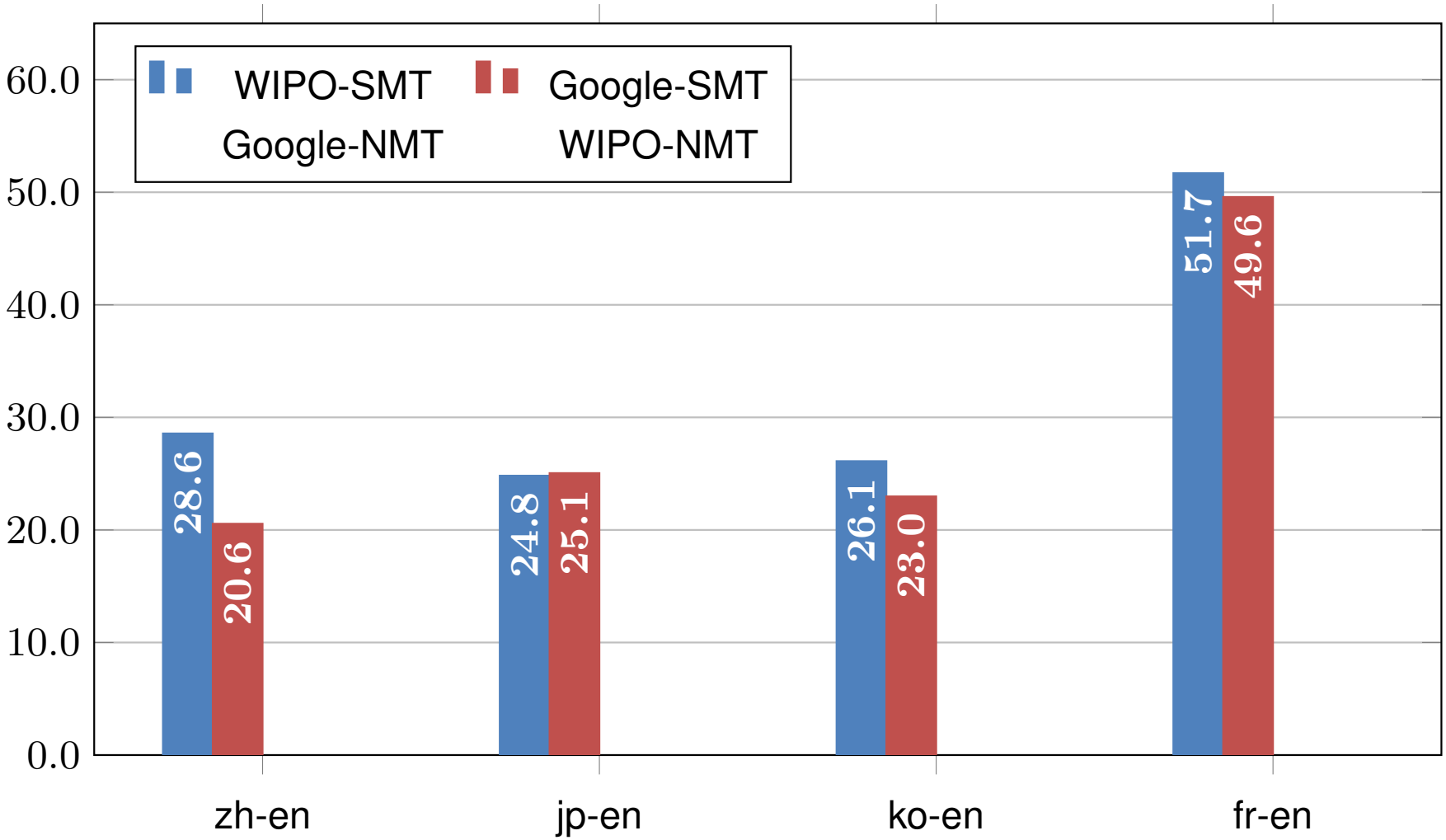

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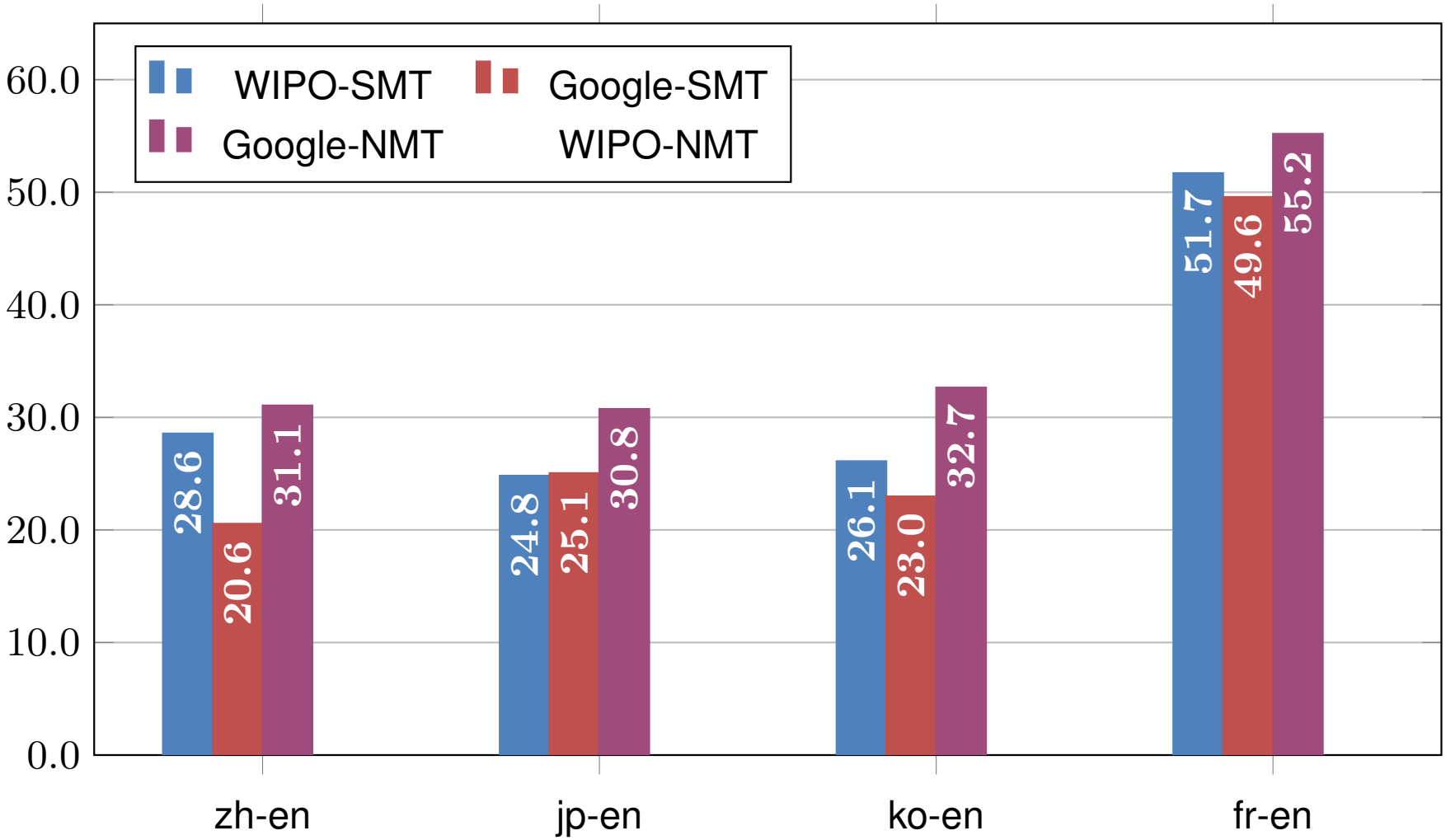

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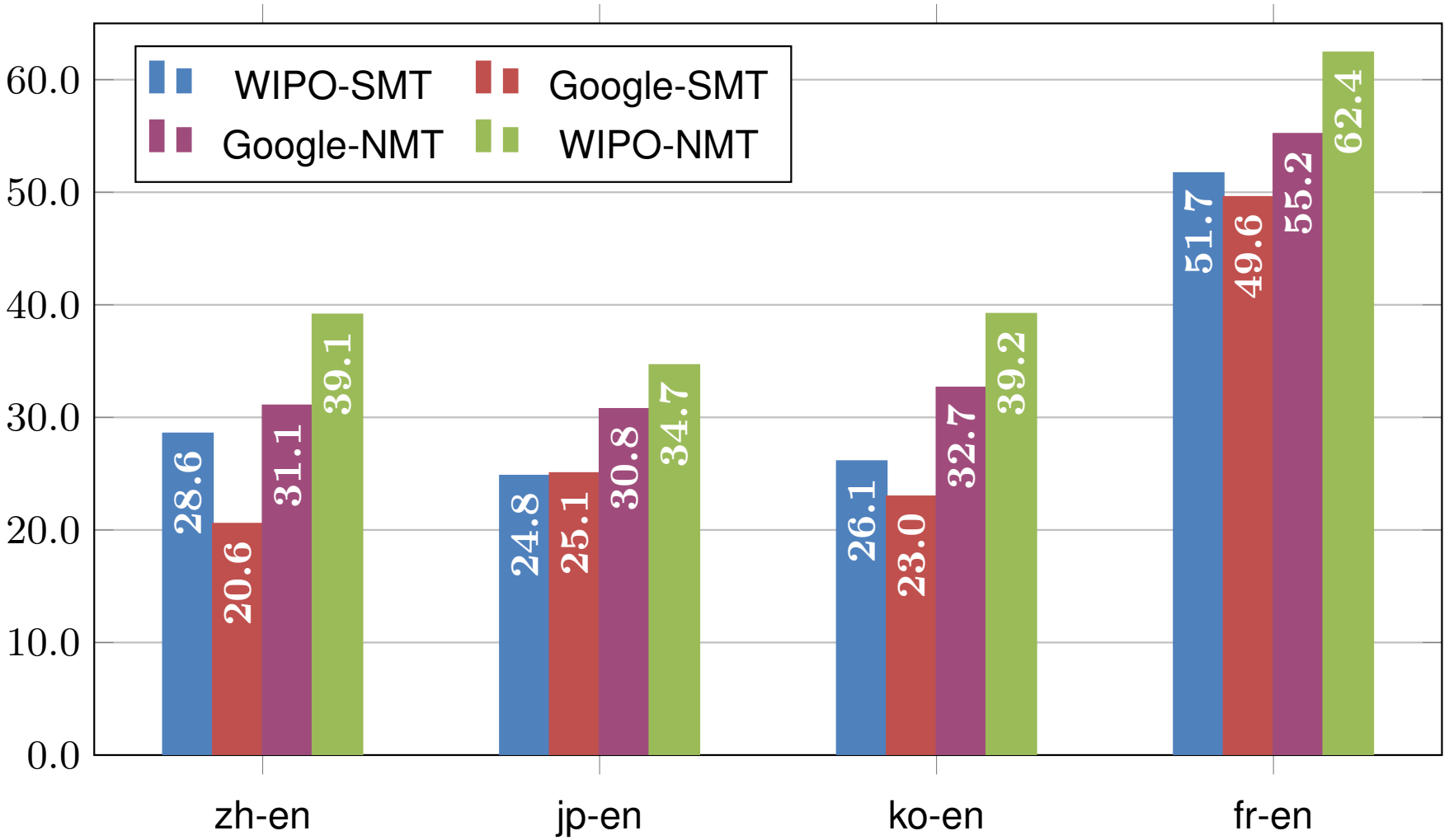
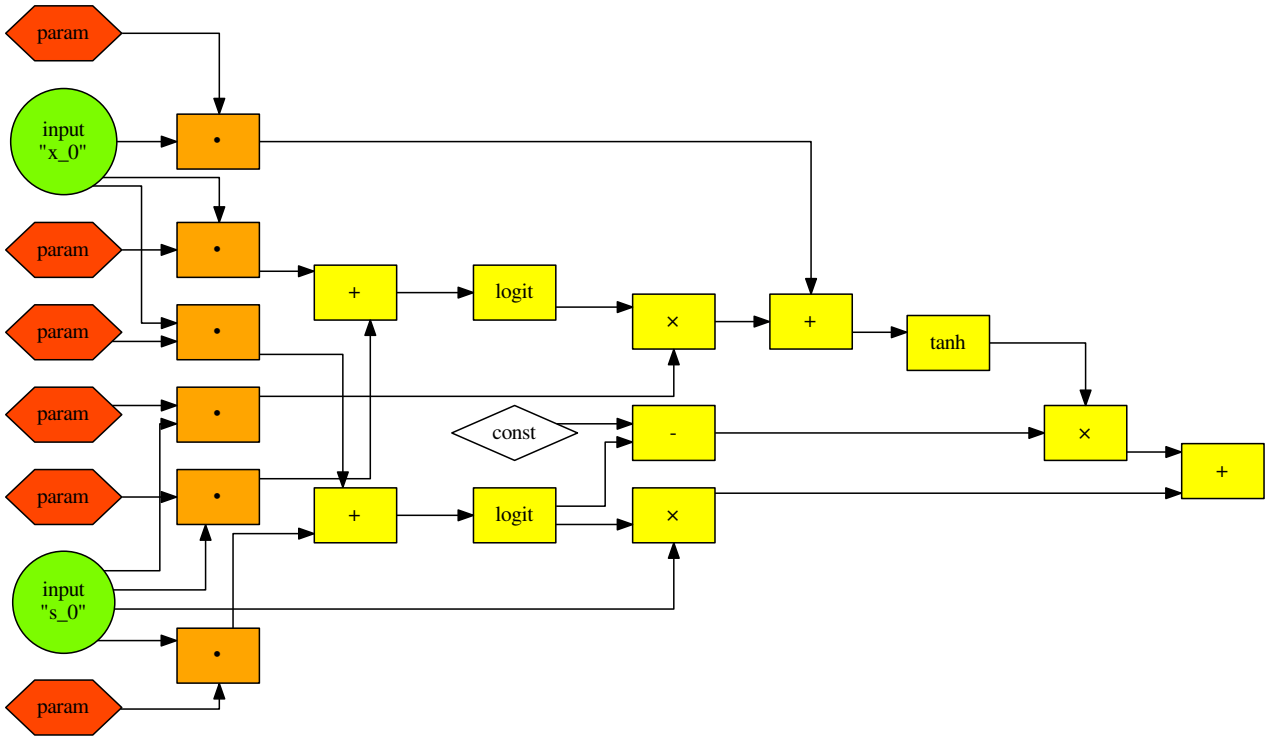


Bonus slide III

Custom C++ training framework

- Working on faster Nematus-compatible training framework;
- Toy models 2-3x faster than Theano or Tensorflow.



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