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Efficient decoding with AmuNMT

- AmuNMT[2] is a ground-up neural MT toolkit implementation, developed in C++;
- Grew out of a Moses feature function;
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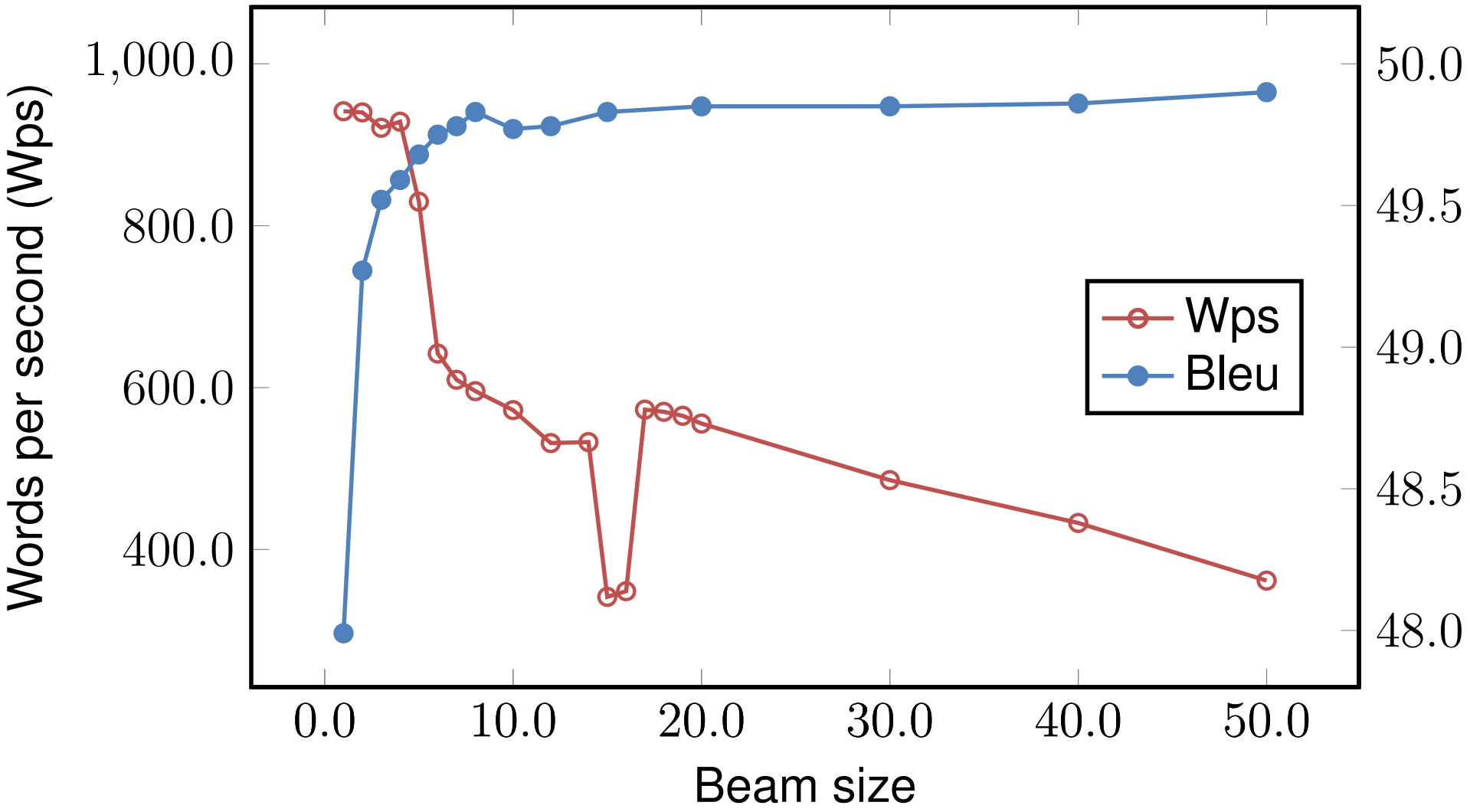
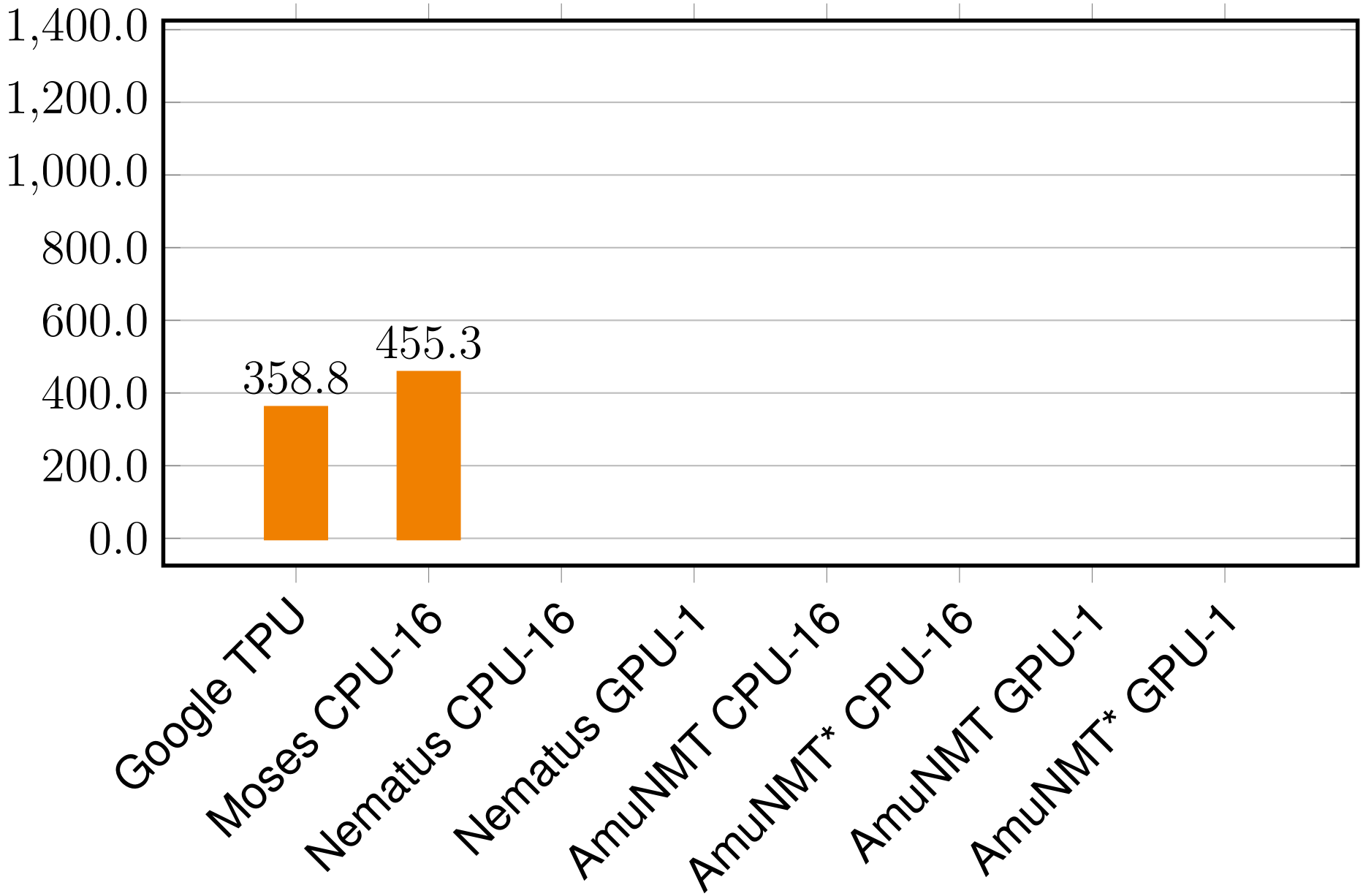
Speed and quality vs. beam size



Translation speed in words per second



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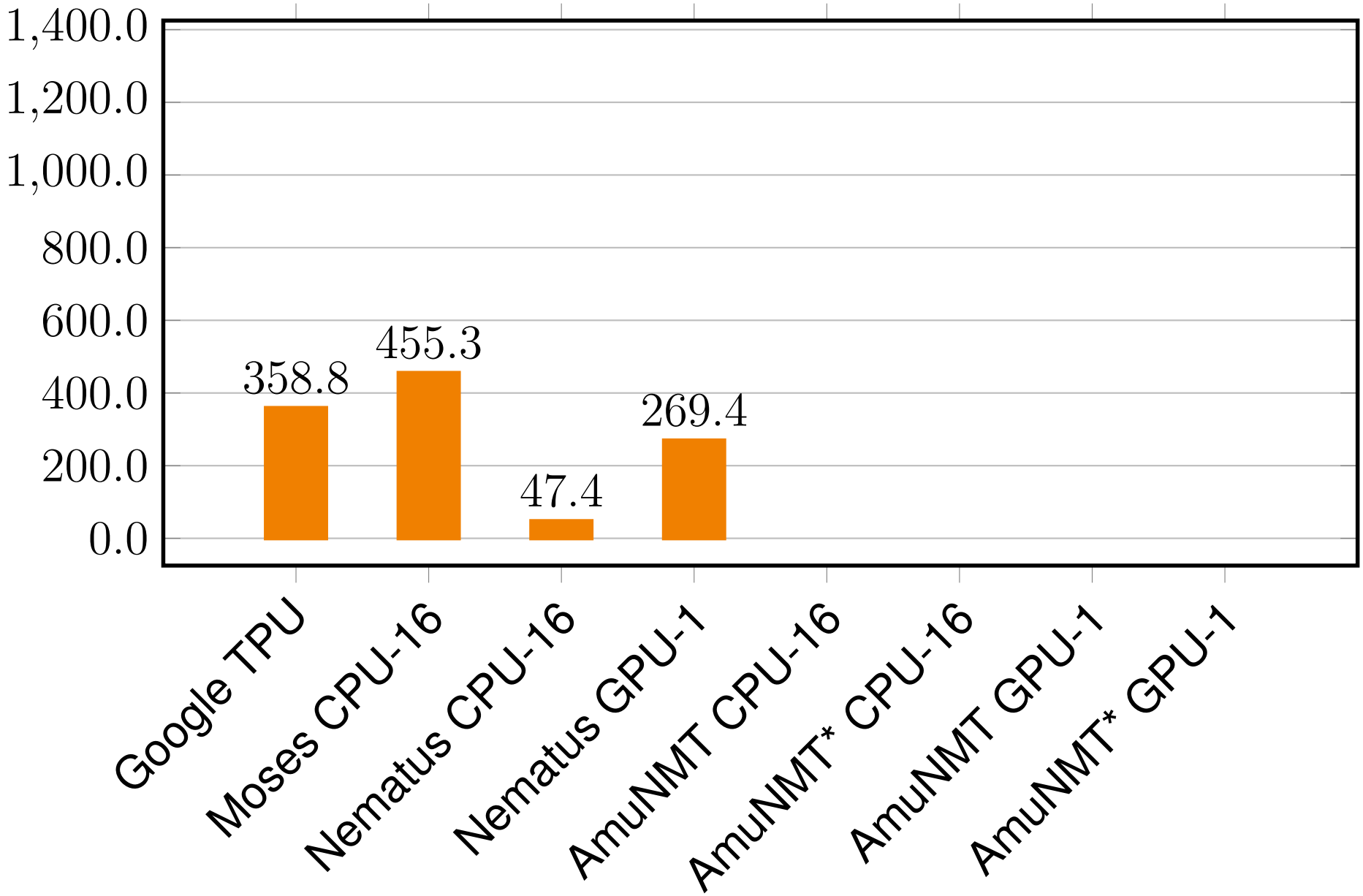

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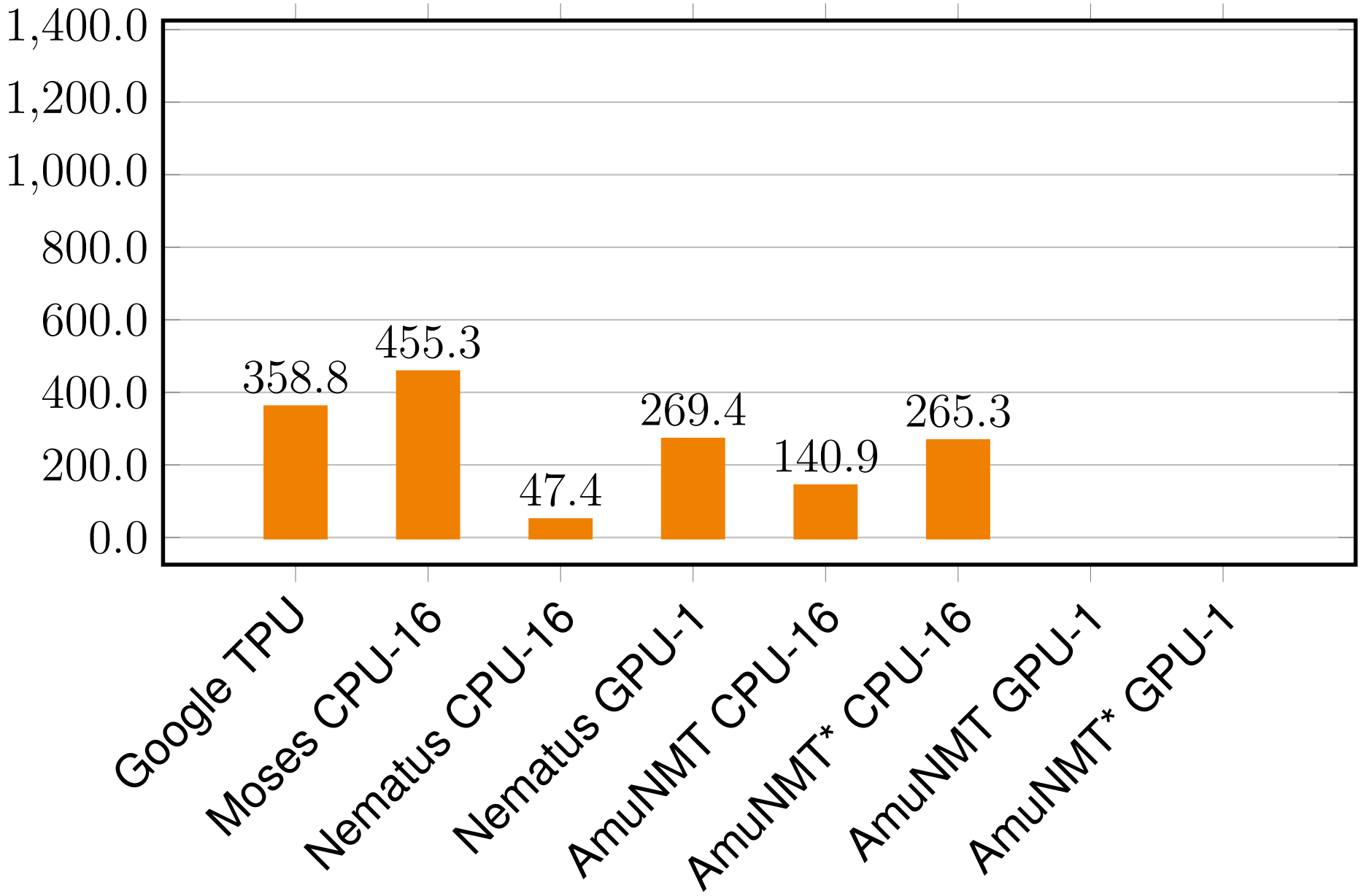

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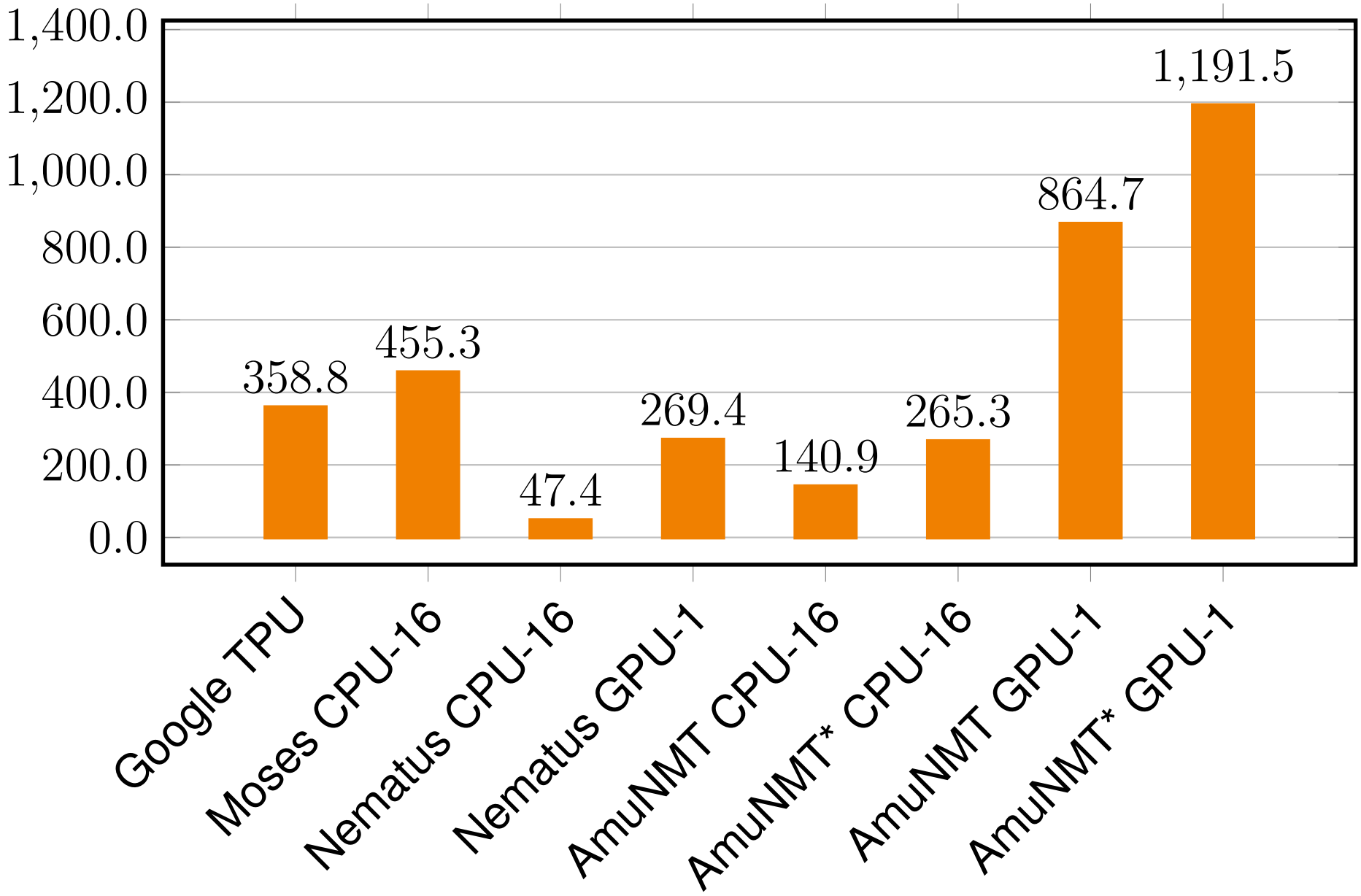
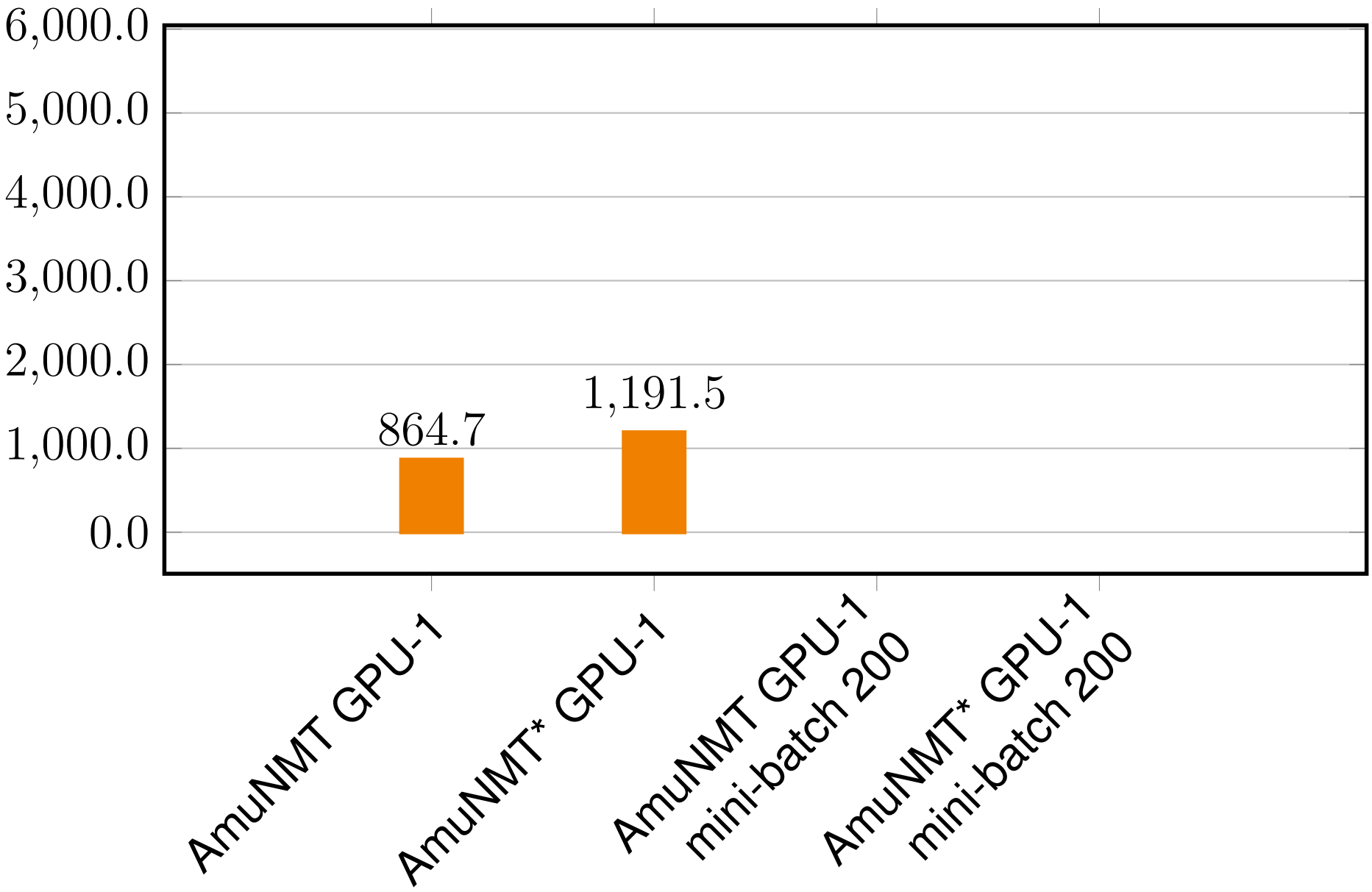


New: Batched decoding on the GPU



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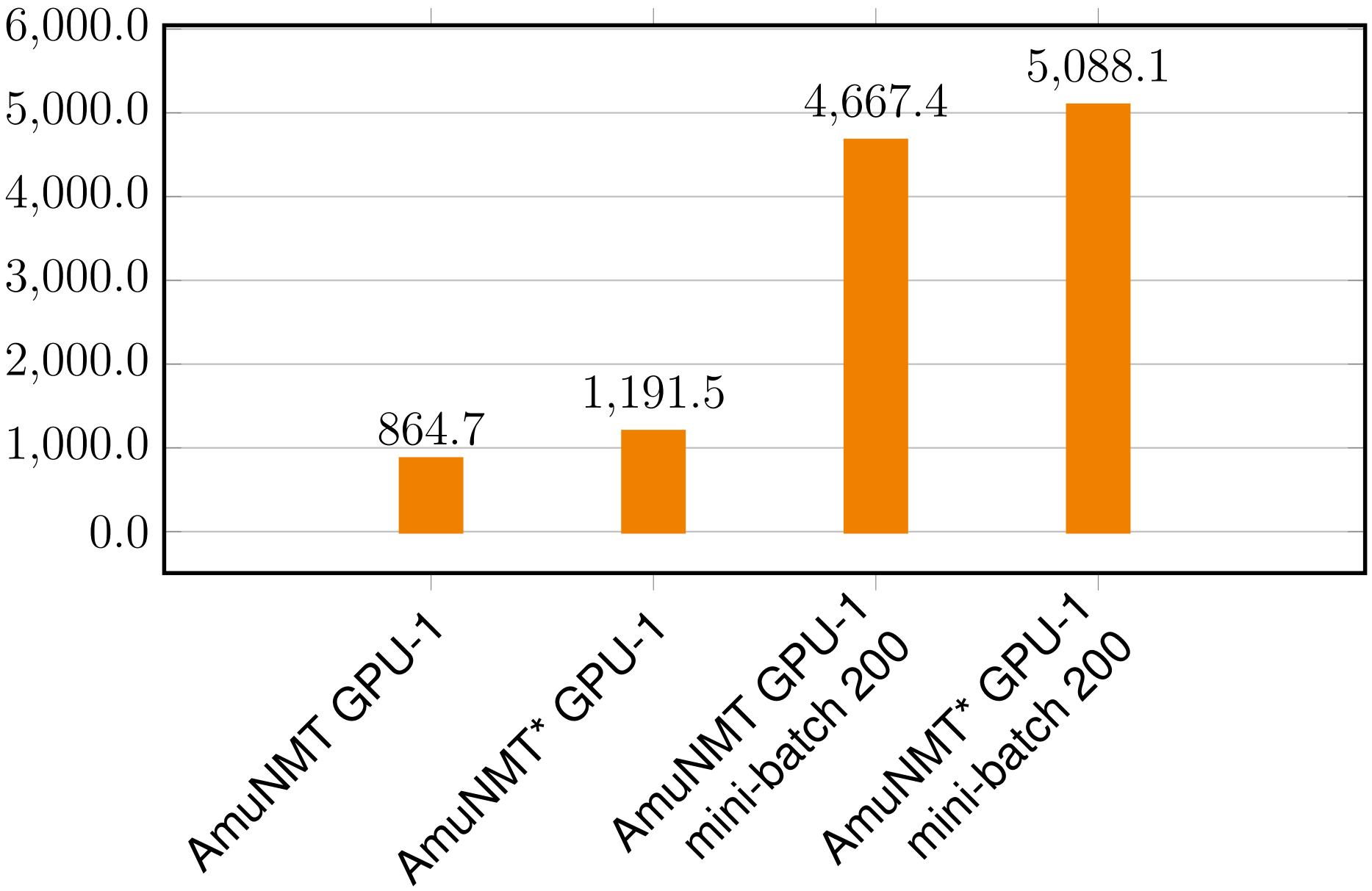
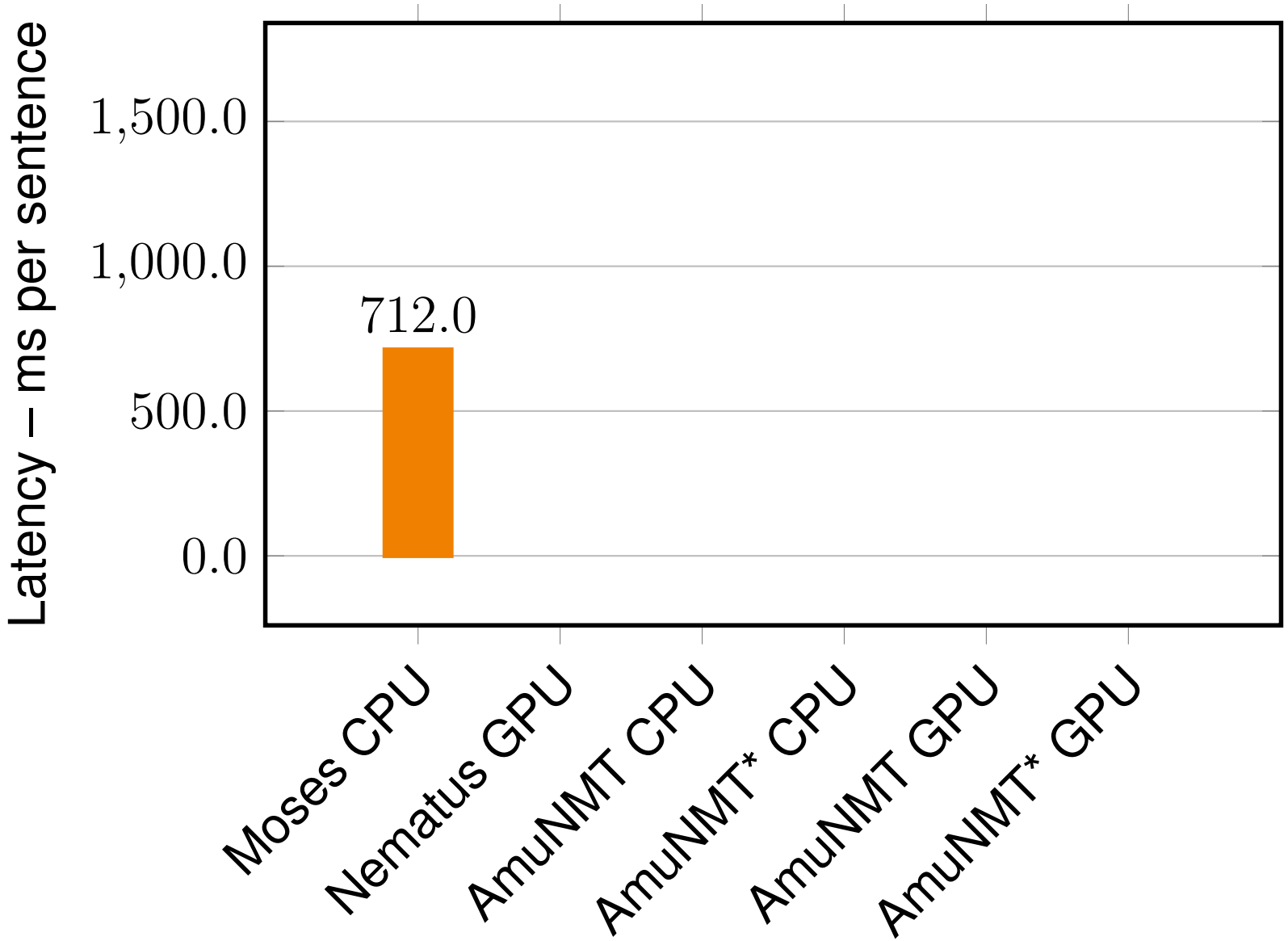


Latency in ms per sentence

Lower is better



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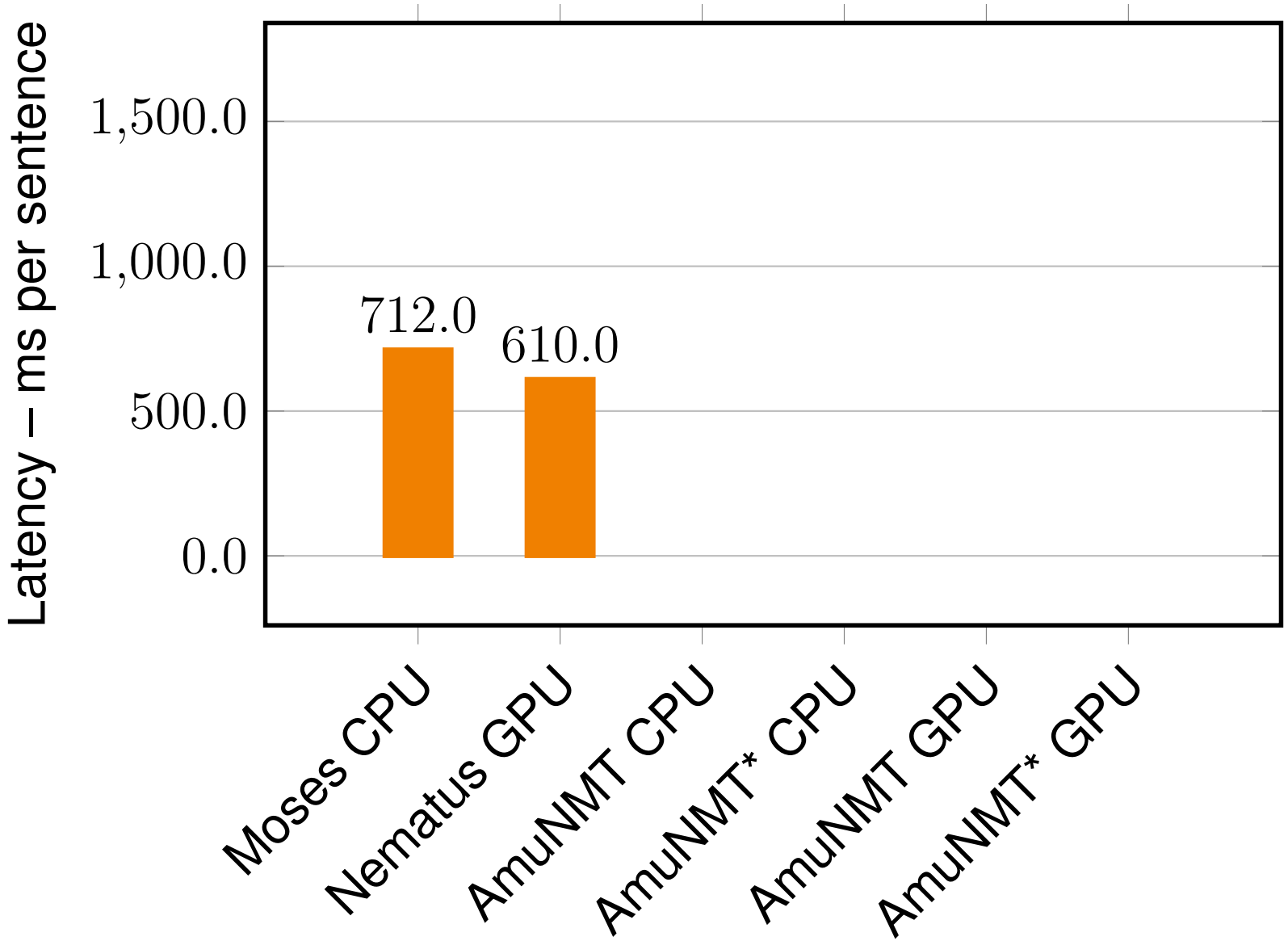

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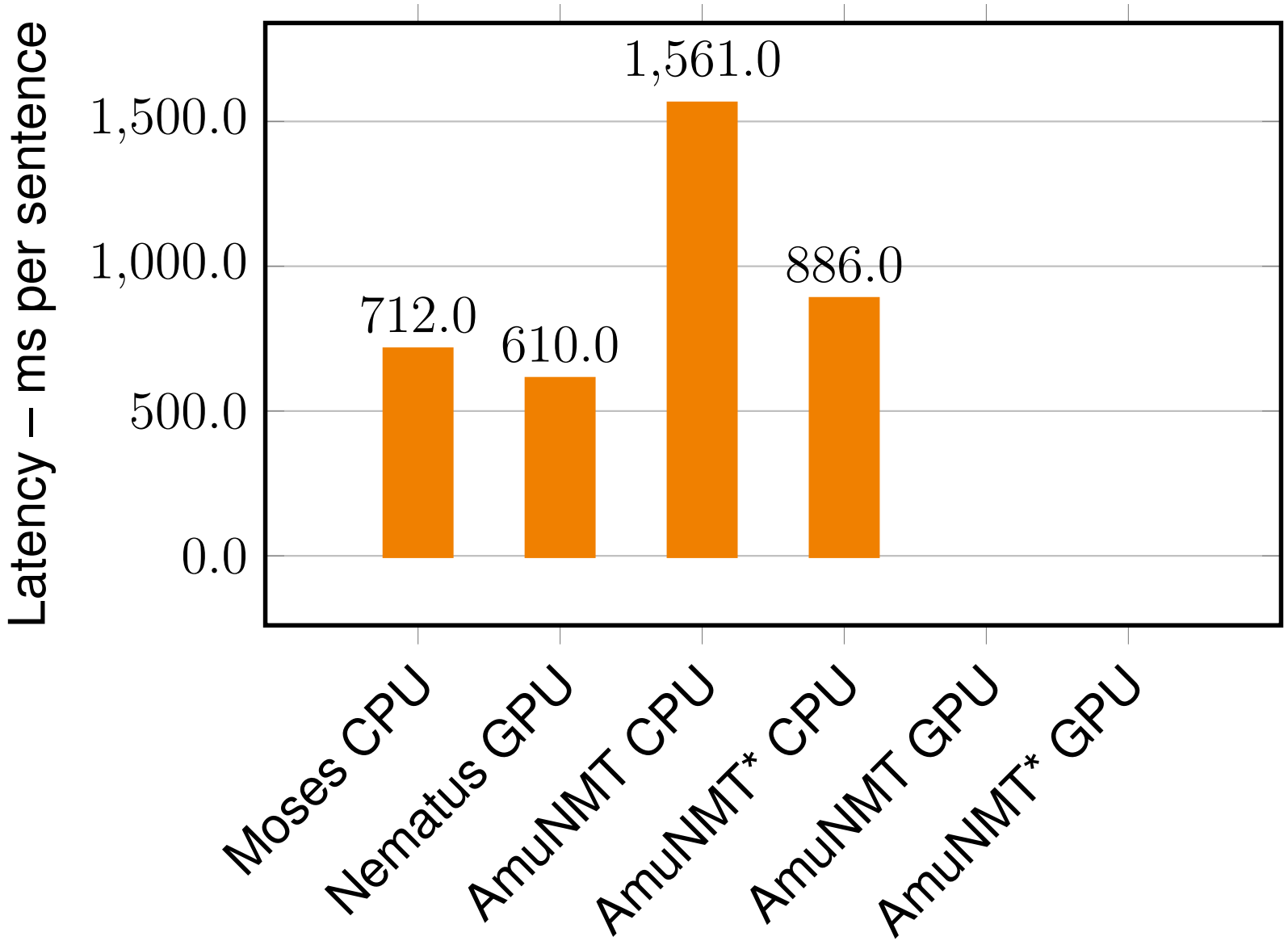

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