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[2] *Bar Ilan University*
[3] *Johns Hopkins University*

Assessing the Ability of LSTMs to Learn Syntax-Sensitive Dependencies

The Unreasonable Effectiveness of Recurrent Neural Networks

May 21, 2015

There's something magical about Recurrent Neural Networks (RNNs). I still remember when I trained my first

- Machine translation (Bahdanau et al., 2015)
- Language modeling (Mikolov et al., 2010; Sundermeyer et al., 2012)
- Parsing (Vinyals et al., 2015)
- ...

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- What did the model learn?
- Linguistics and psycholinguistics can help characterize the model's strengths and weaknesses

Subject-verb agreement

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1. The station has a single platform.
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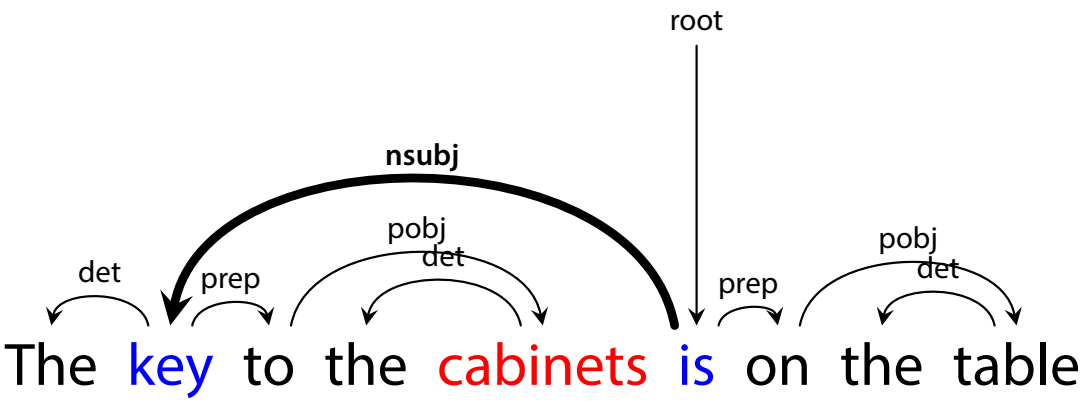
4. The professor said that the soils carried in the floodwaters add nutrients.

Why is agreement interesting?

- Straightforward with a structured representation of the sentence:



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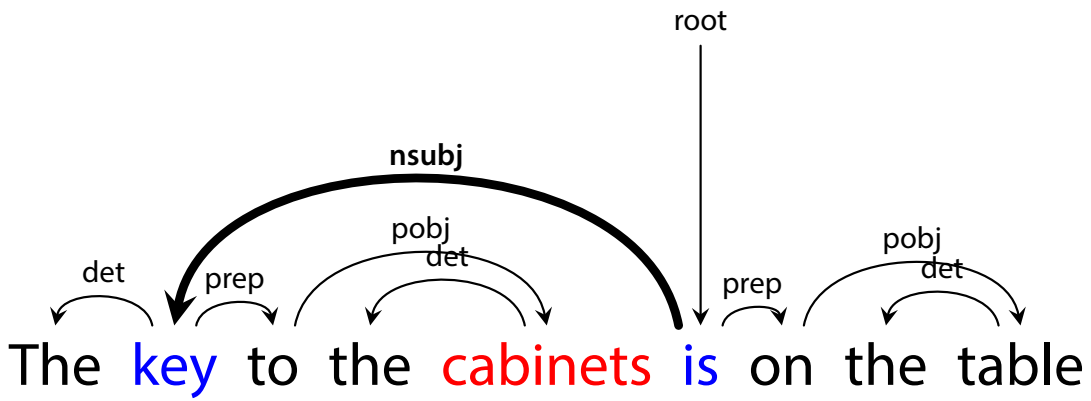

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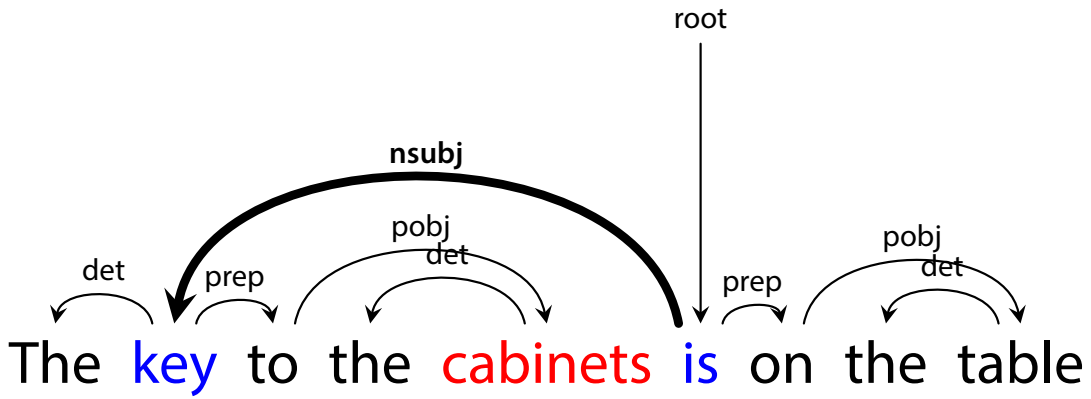

- RNNs are sequence models
- **Syntactic knowledge without explicit structure?** (Elman, 1991)

Outline

- The number prediction task

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- An RNN trained specifically to perform the task

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- Preview: LSTMs are pretty good, but only with specific supervision, and should be improved even in that setup

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Number prediction

The length of the forewings...

Number prediction

The length of the forewings... **SINGULAR**

Number prediction

The length of the forewings... **SINGULAR**

The keys to the cabinets...

Number prediction

The length of the forewings... **SINGULAR**

The keys to the cabinets... **PLURAL**

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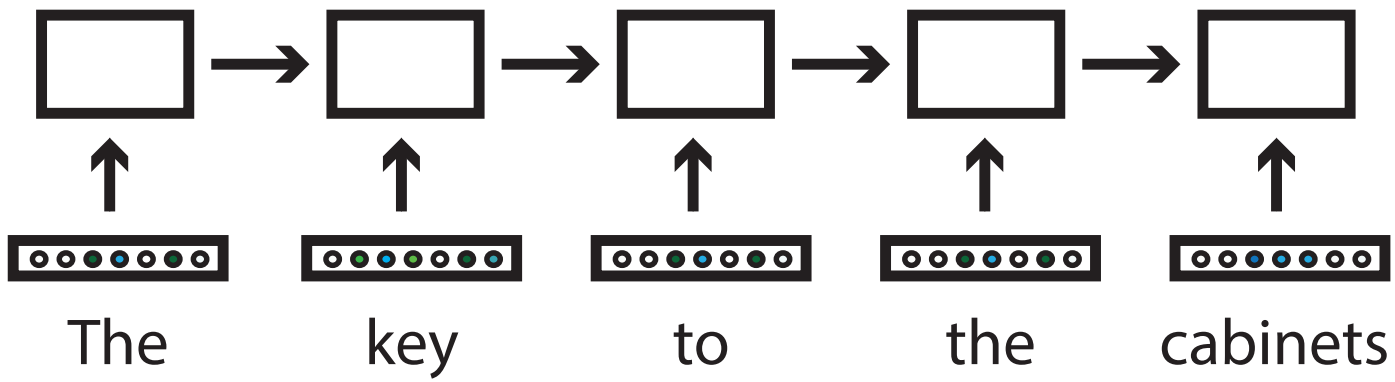
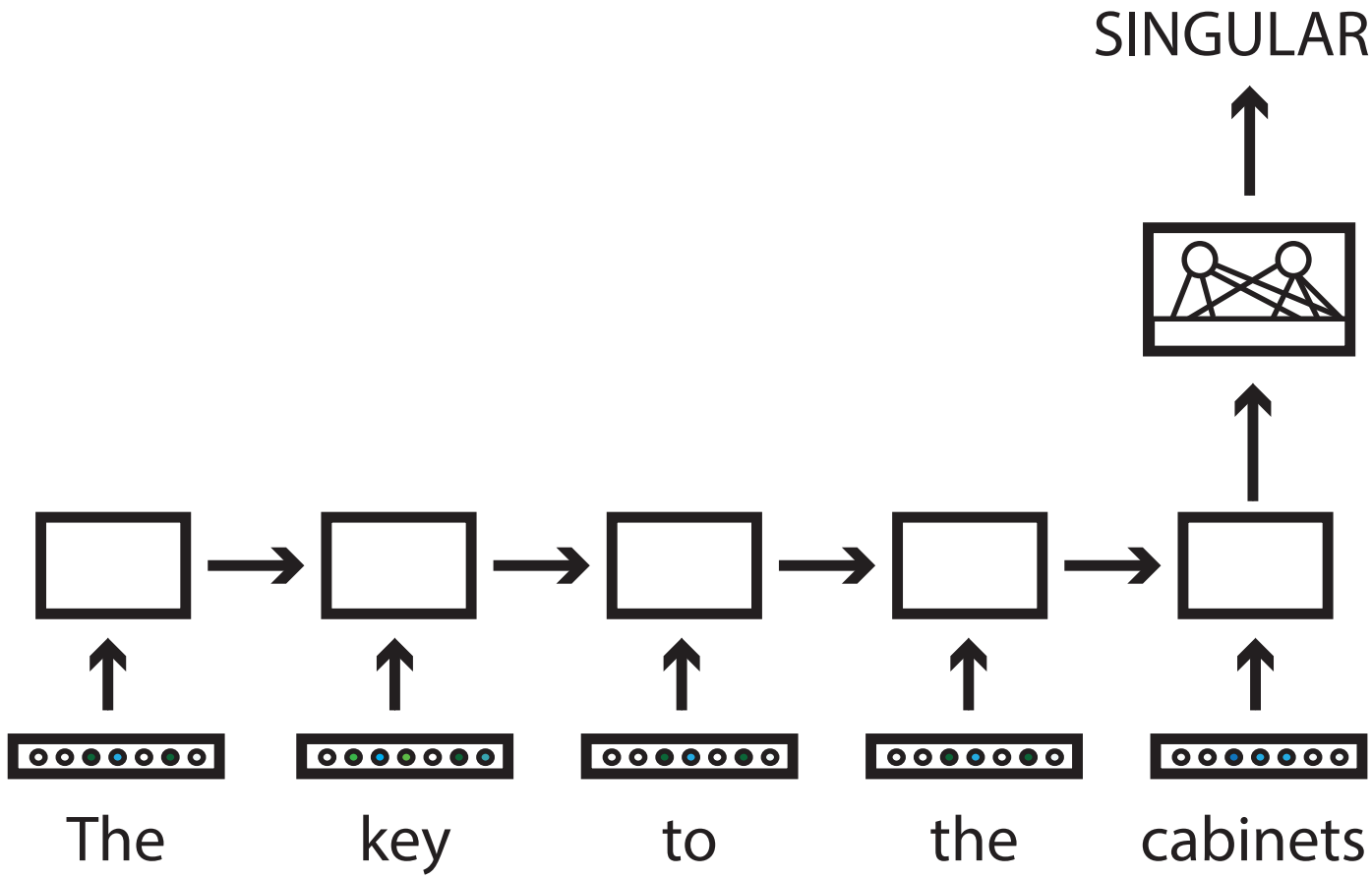
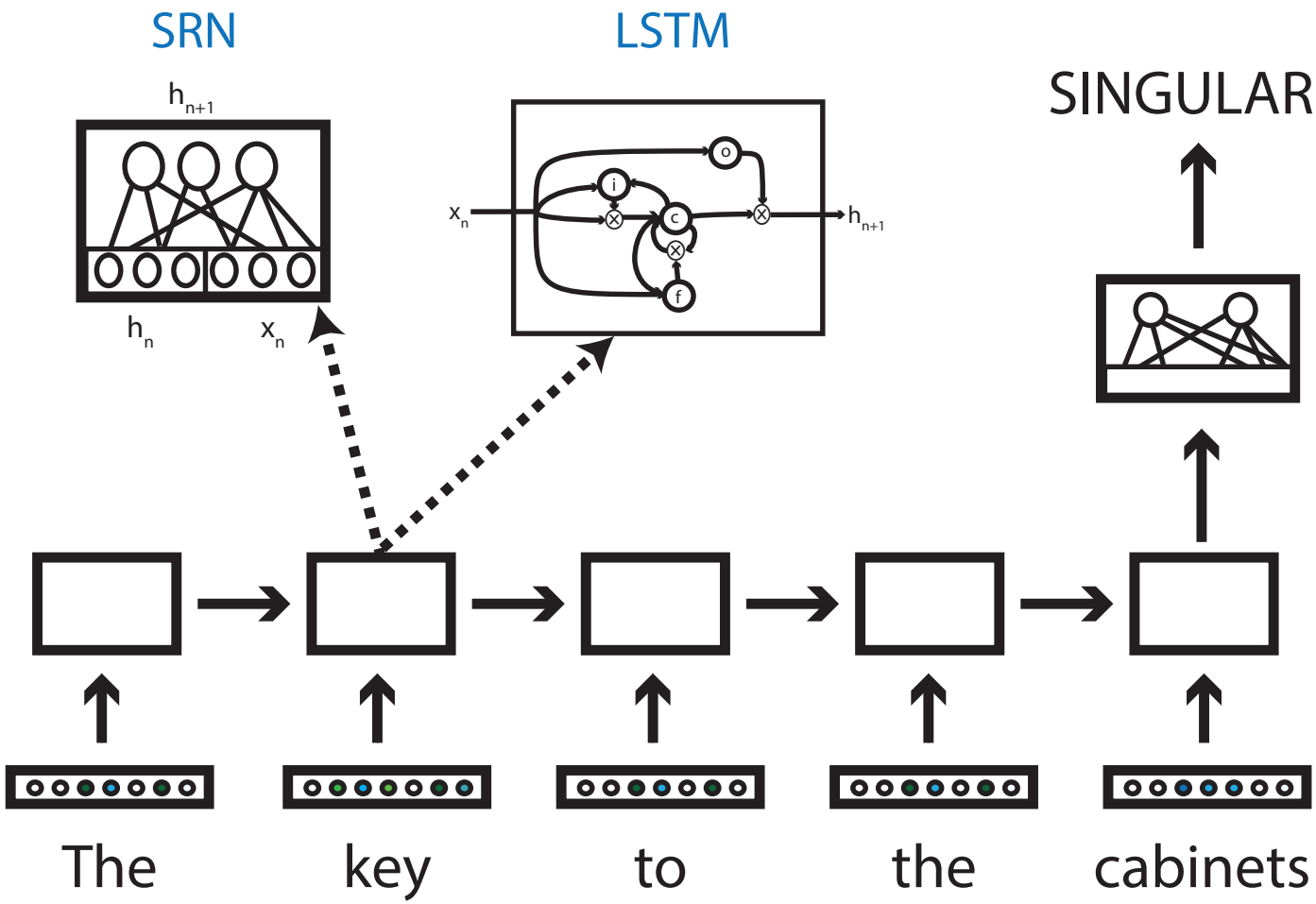
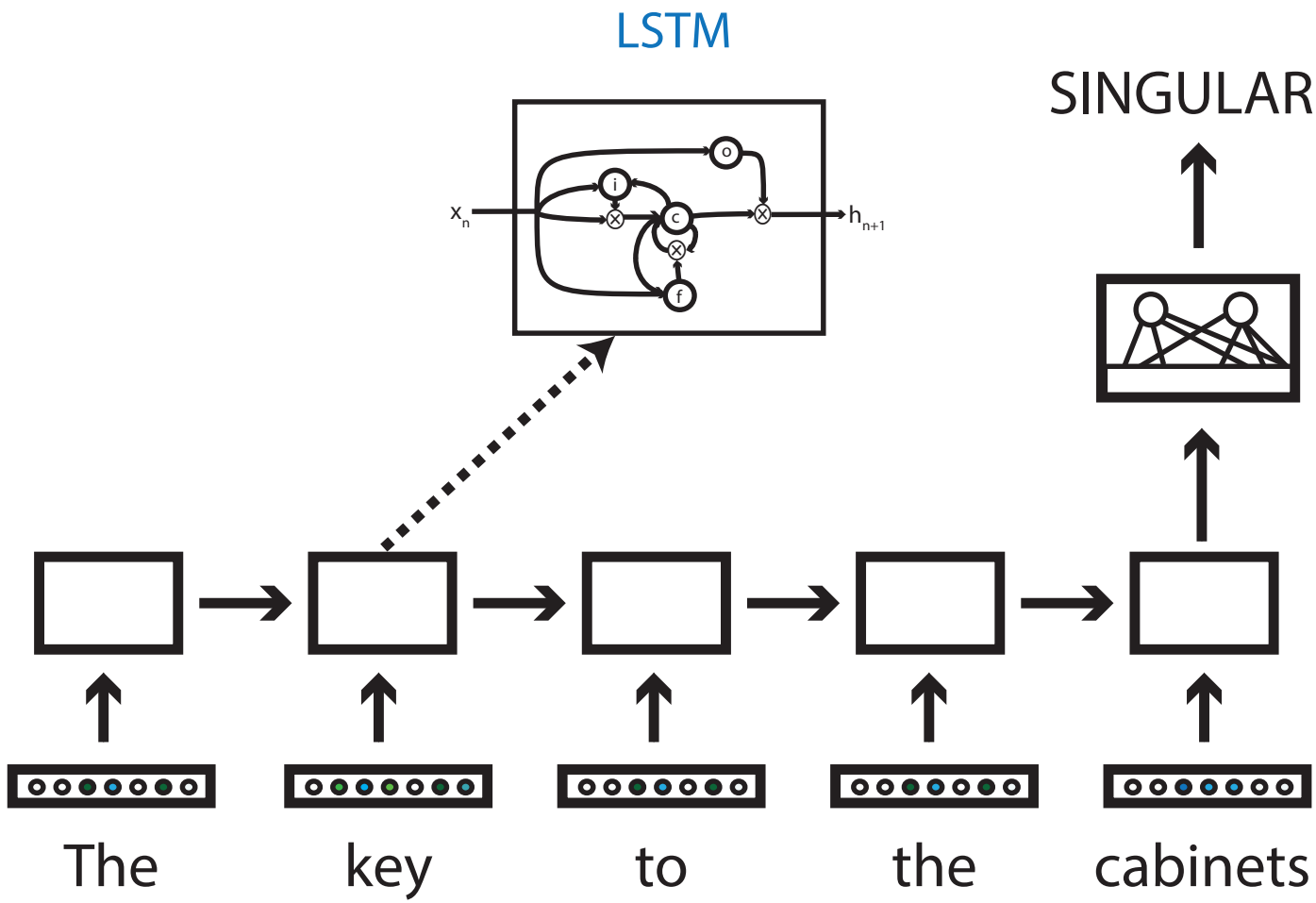

The
key
to
the
cabinets


SINGULAR
The
key
to
the
cabinets


SRN
LSTM
SINGULAR
h n+1
h n
x n
x n
i
o
c
f
h n+1
The
key
to
the
cabinets


LSTM
SINGULAR
o
i
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The
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Experimental setup

- Sentences from the English Wikipedia that have a present-tense verb
- 121K in training set, 1.21M in test set
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- 50-dimensional word embeddings
- Results averaged over 20 runs

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- **(Only) prerequisite: automatic identification of verb number**

Overall results

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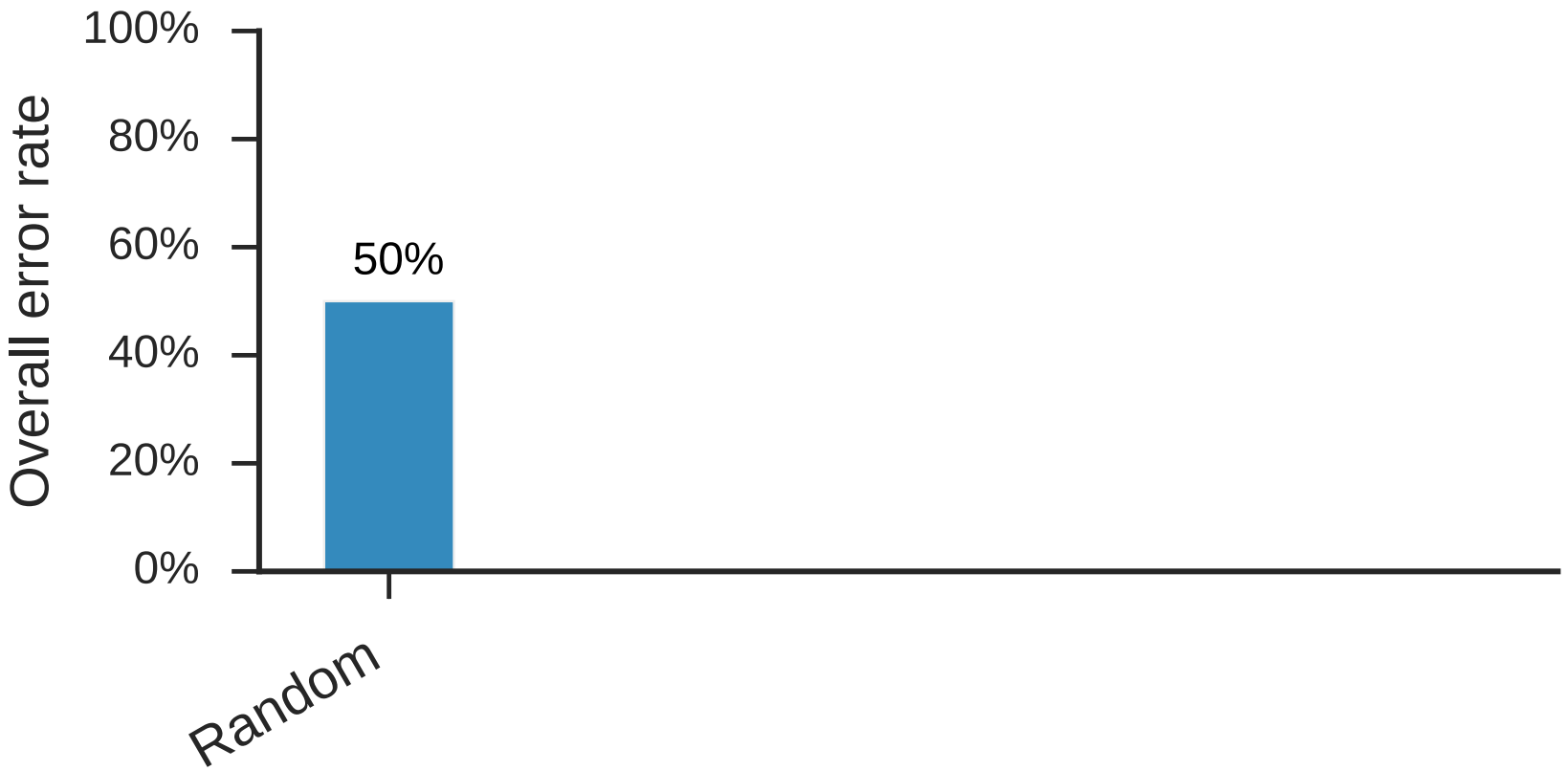
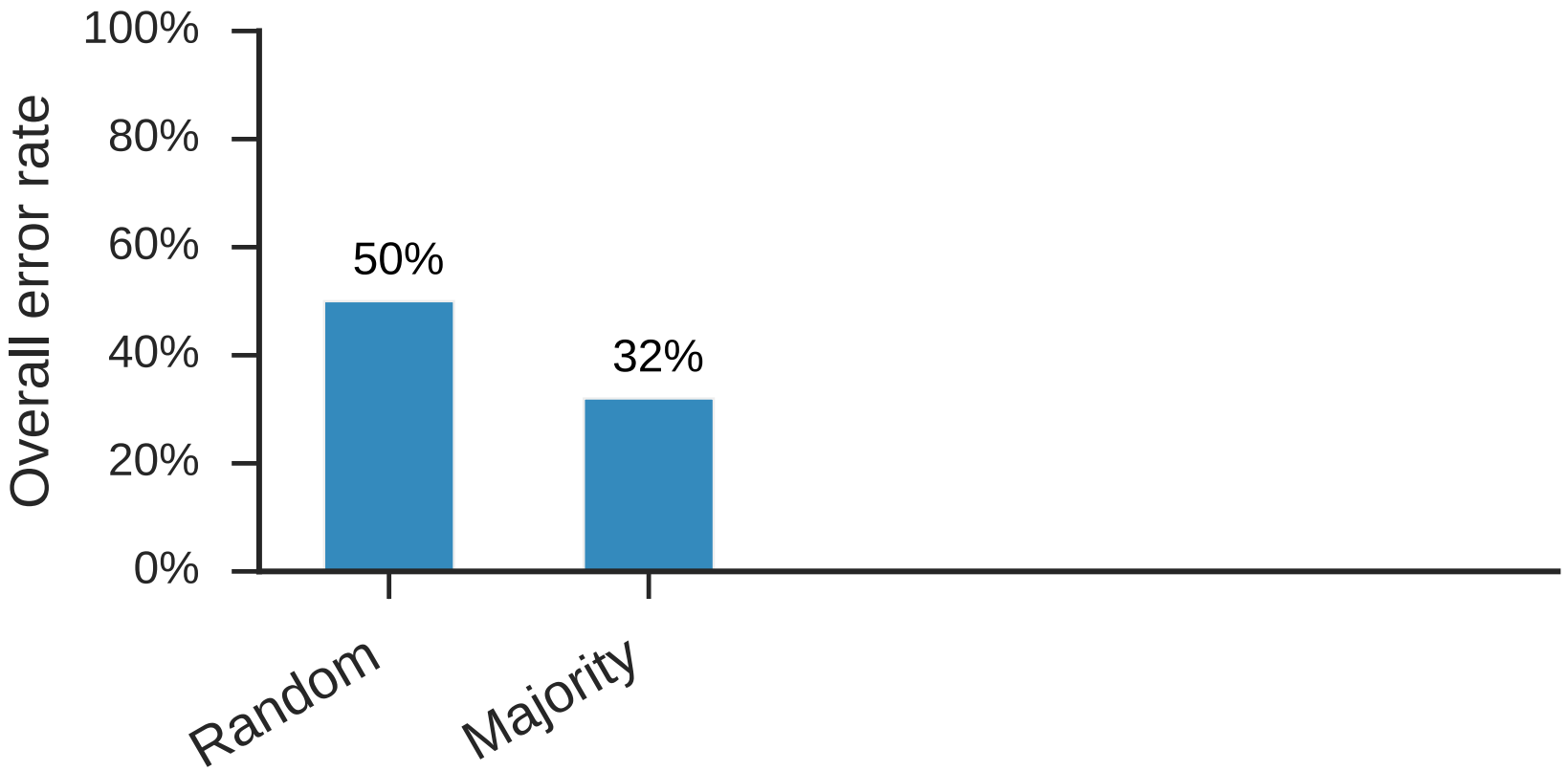


Overall results



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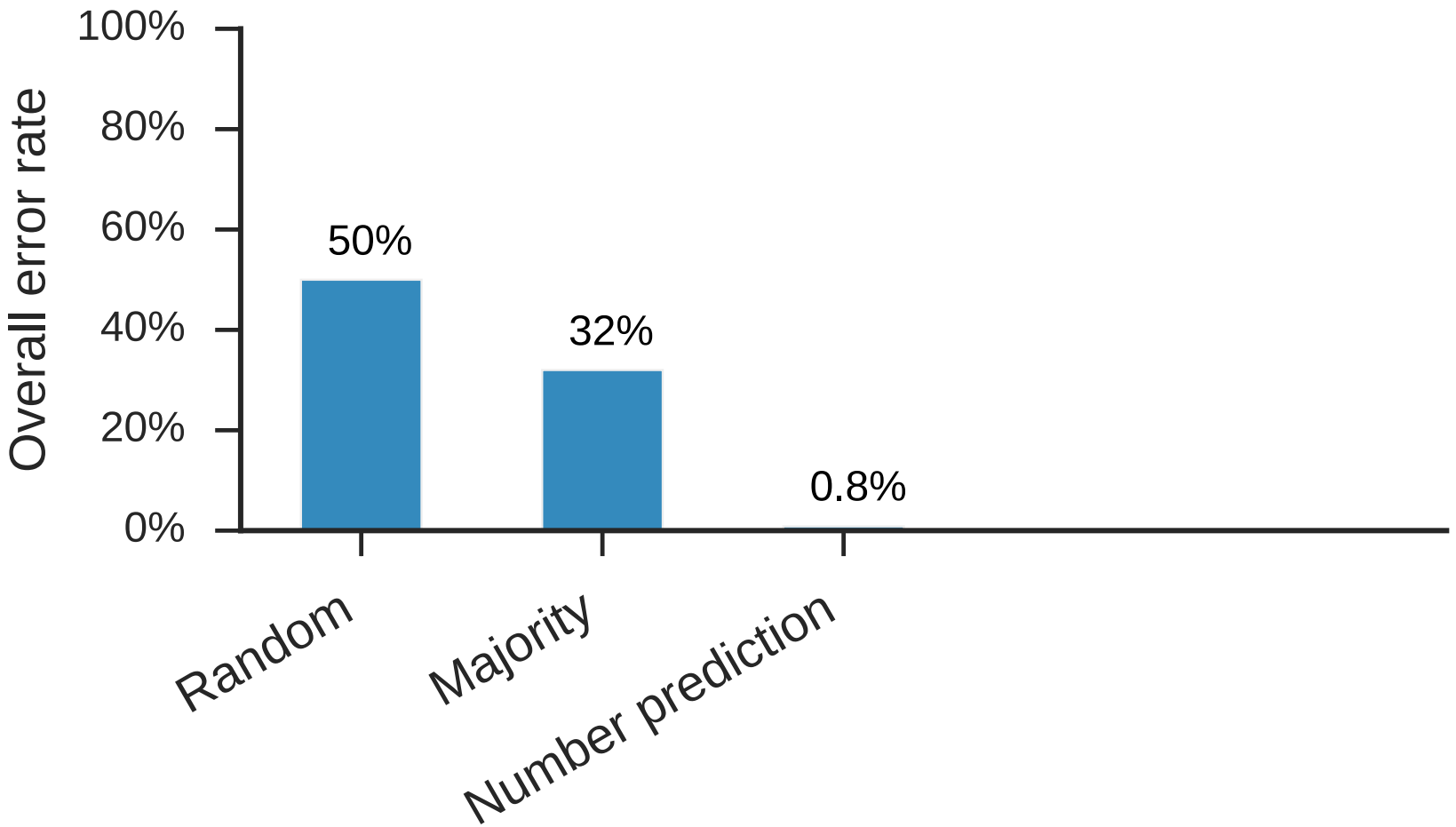
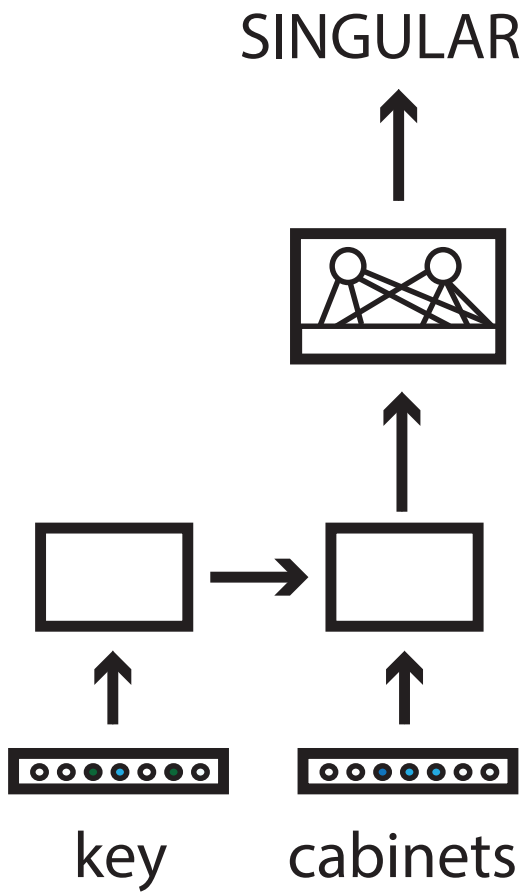


Is it just about the nouns?



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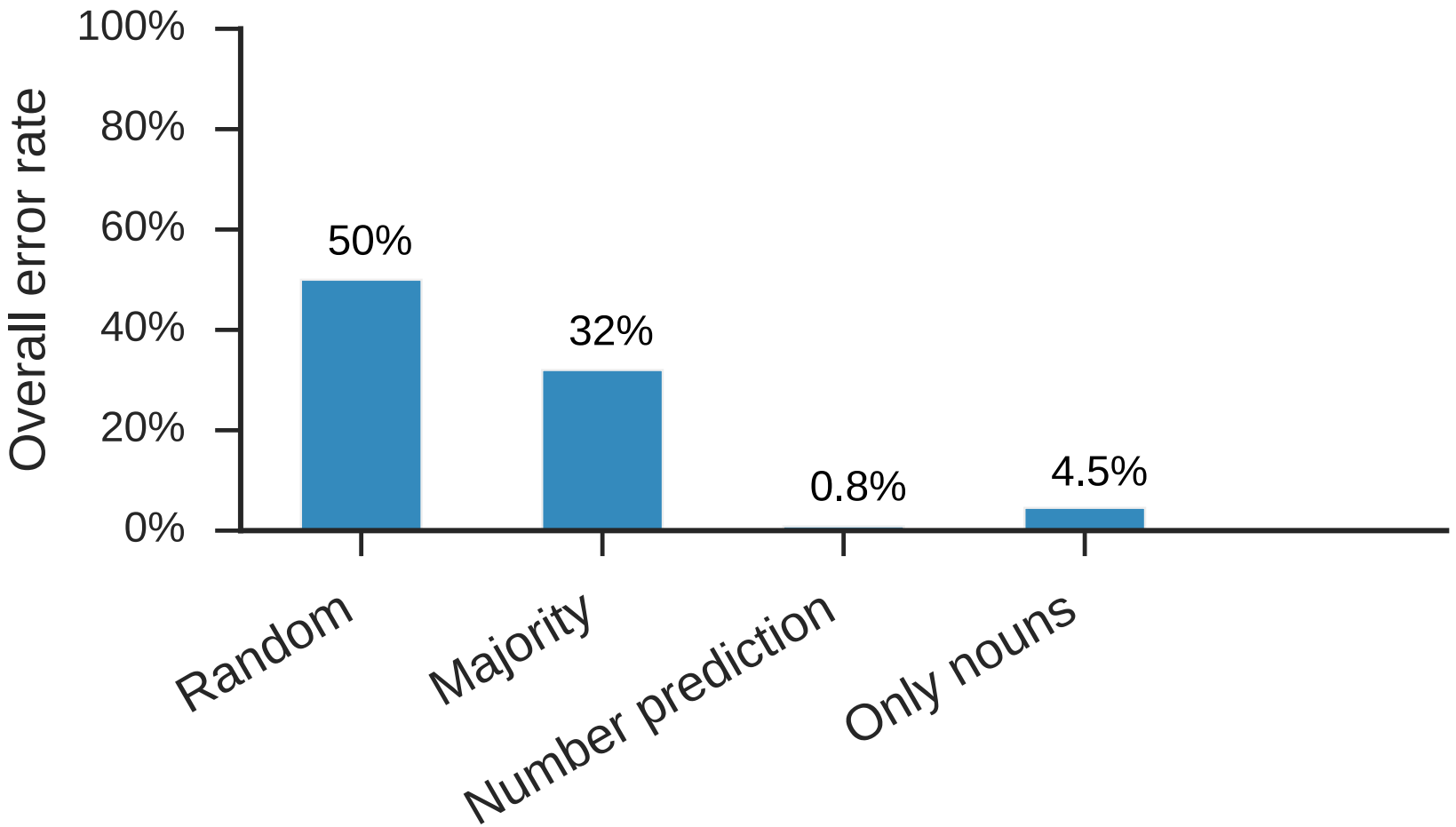

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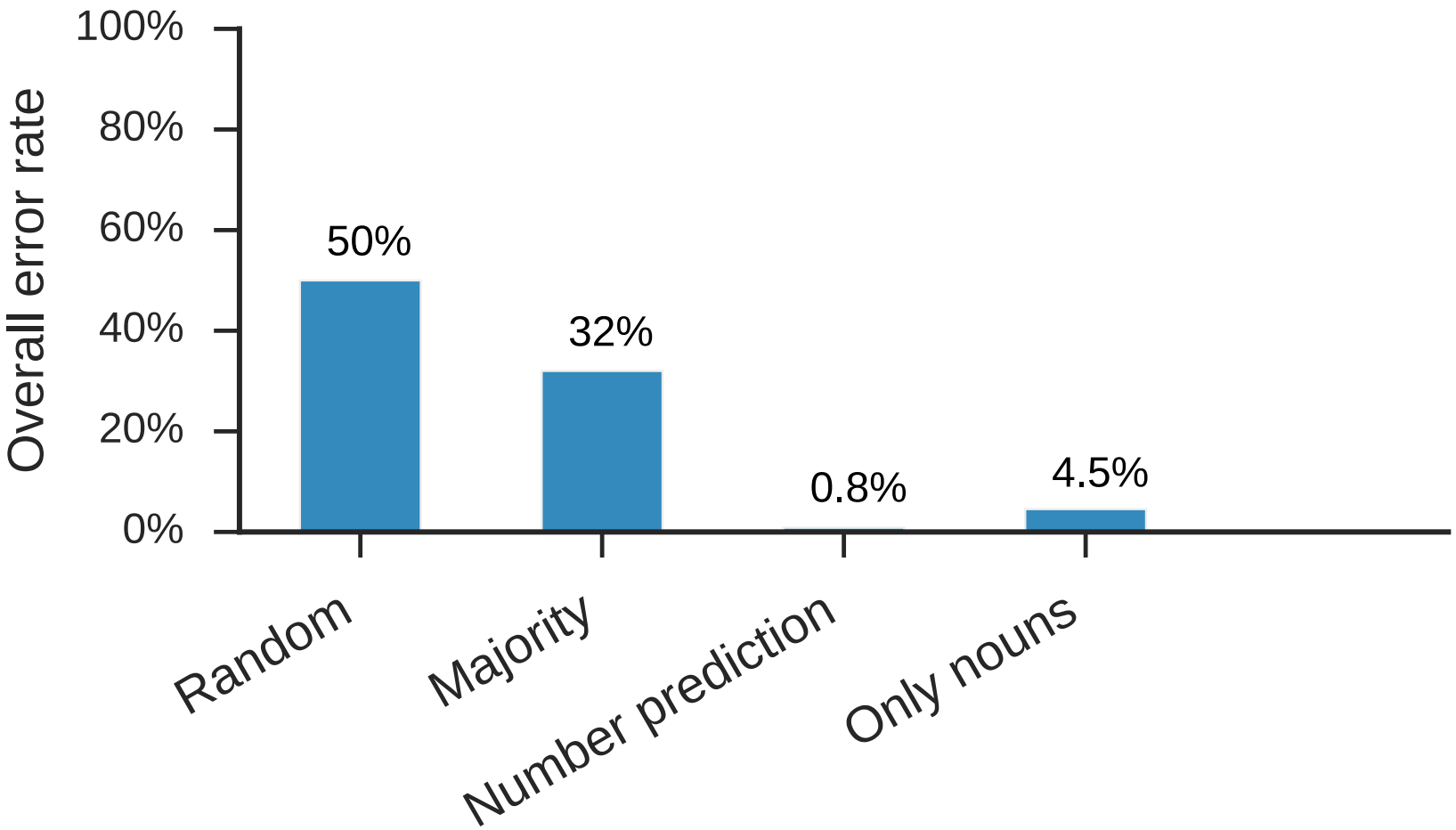

- Other parts of speech are essential: more than five times as many errors without them

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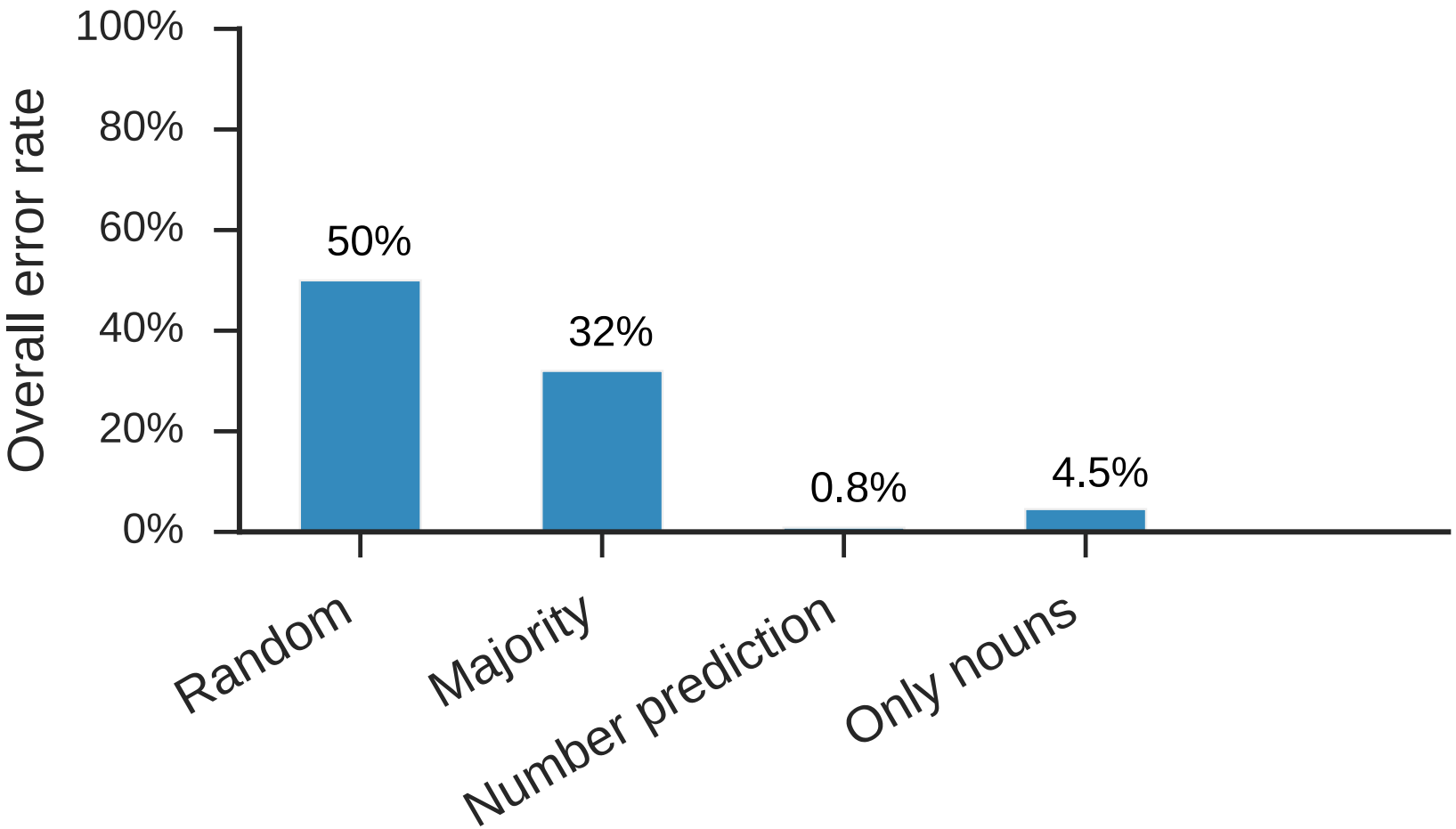

- Other parts of speech are essential: more than five times as many errors without them
- On average the task isn't very hard...

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Attractors
(Bock & Miller, 1991)

1. The keys are on the table.

Attractors

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4. The ratio of men to women is not clear.

Attractors

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5. The ratio of men to women and children is not clear.

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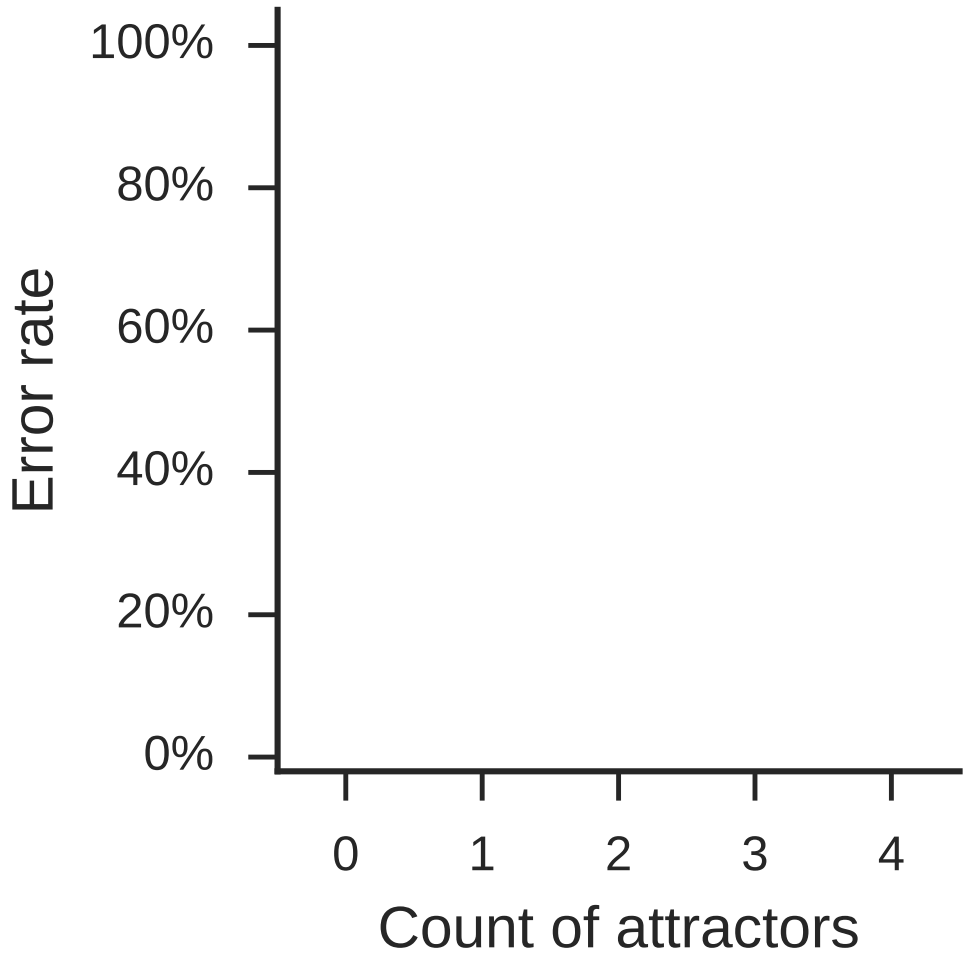
- **Prerequisite: a dependency parse of the test sentences**
  (Goldberg & Nivre, 2012)

Attractors



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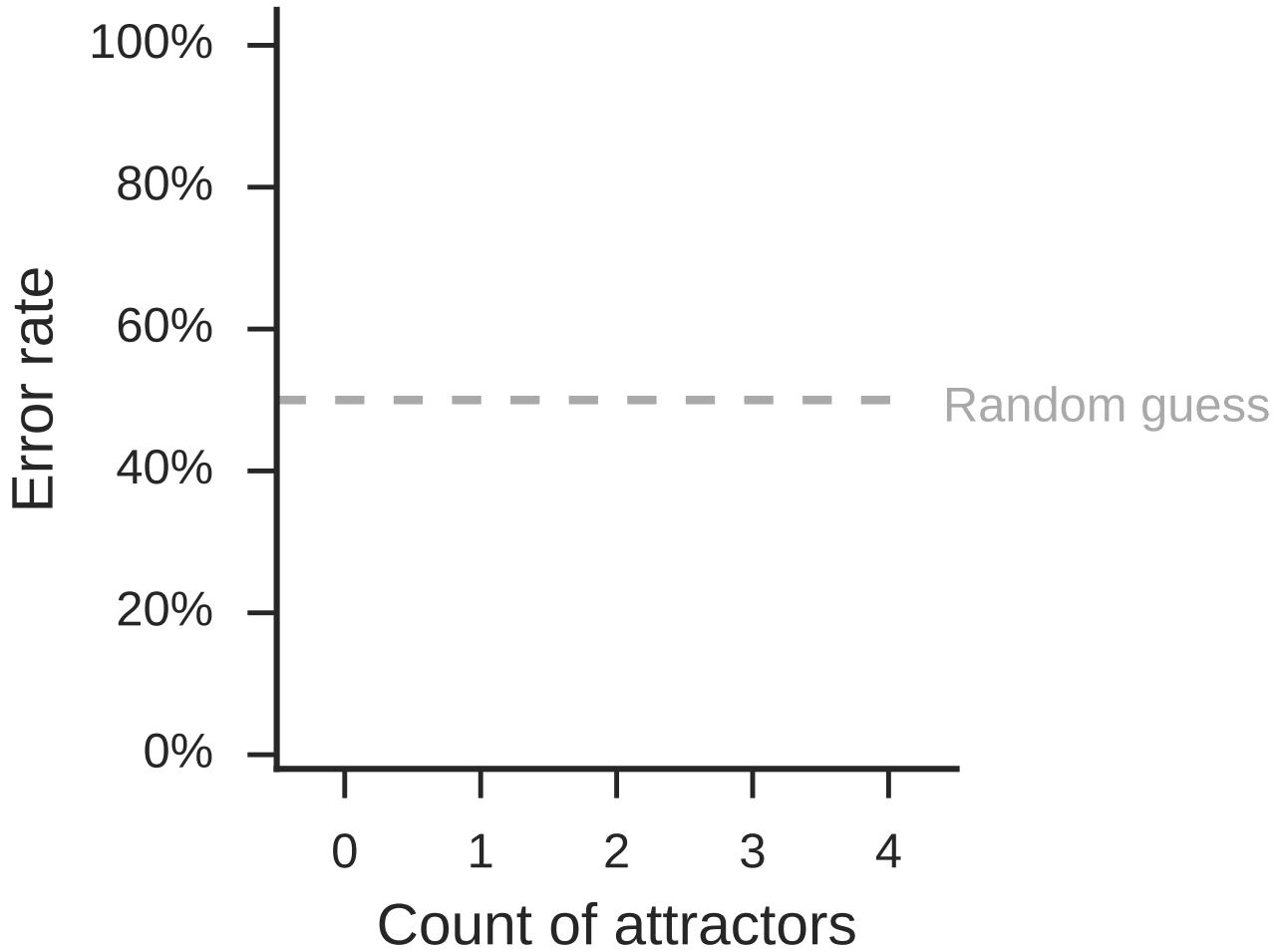
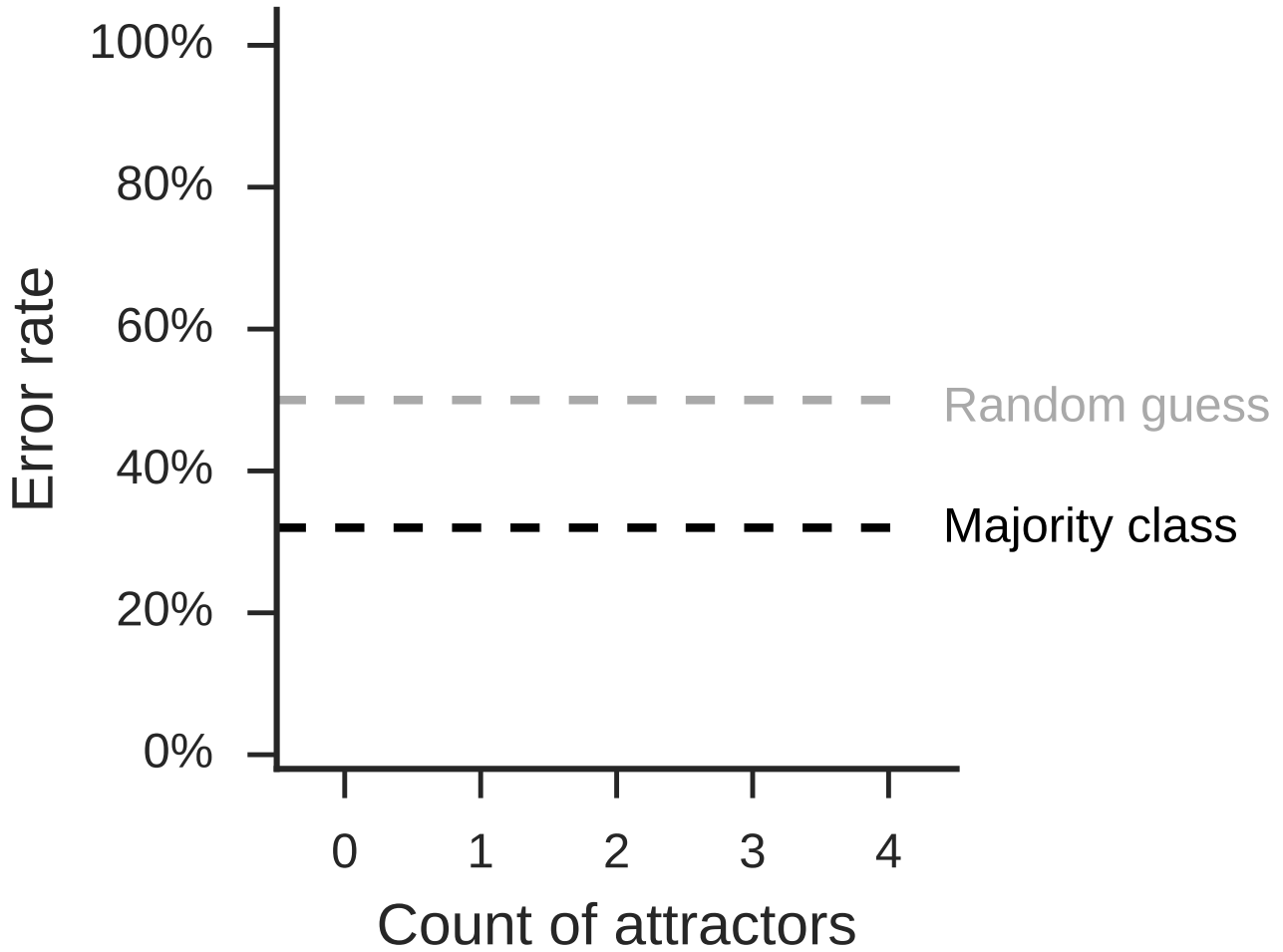

100%
80%
60%
40%
20%
0%
Error rate
Random guess
0
1
2
3
4
Count of attractors

Attractors


100%
80%
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Error rate
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Majority class
0
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2
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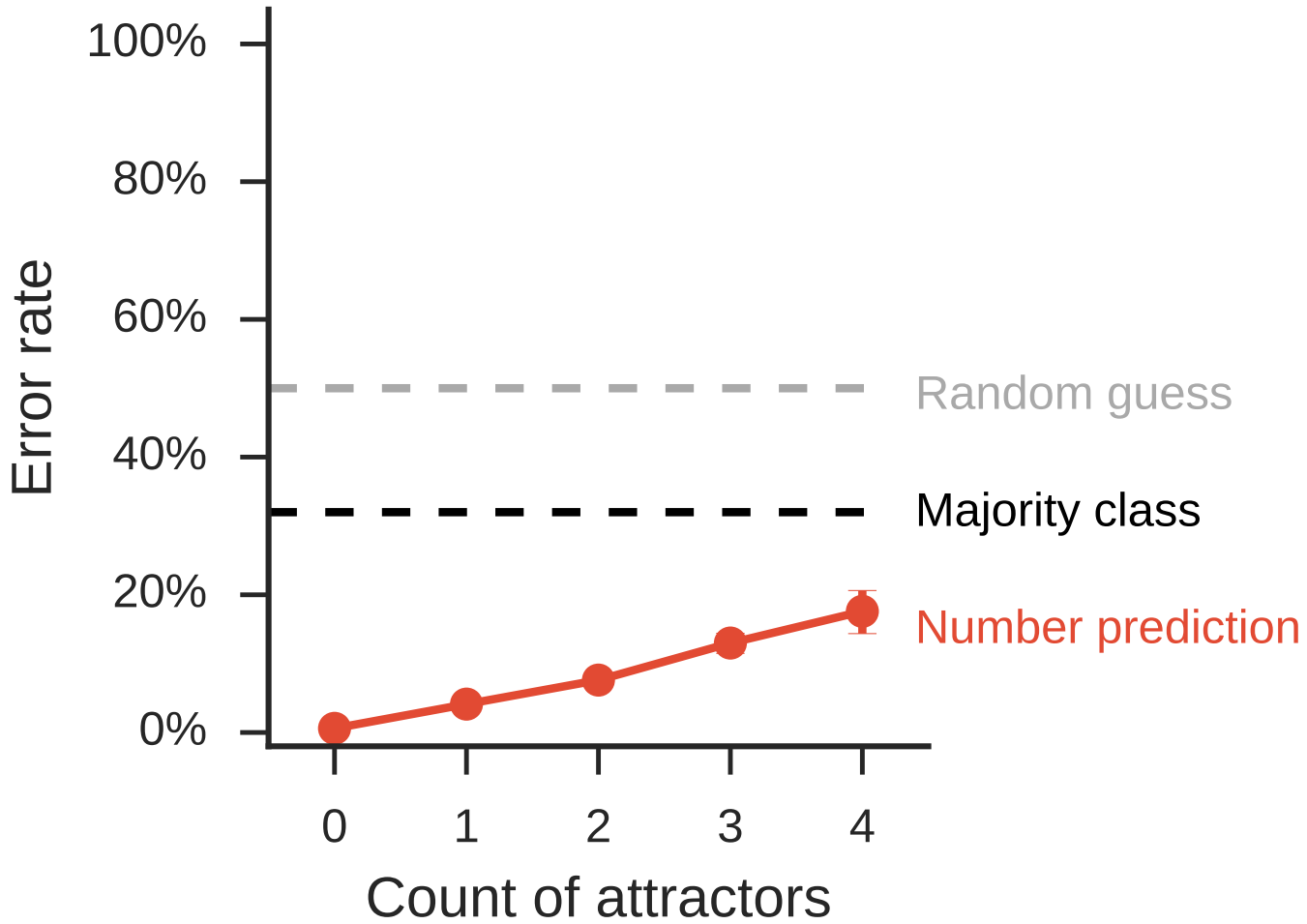
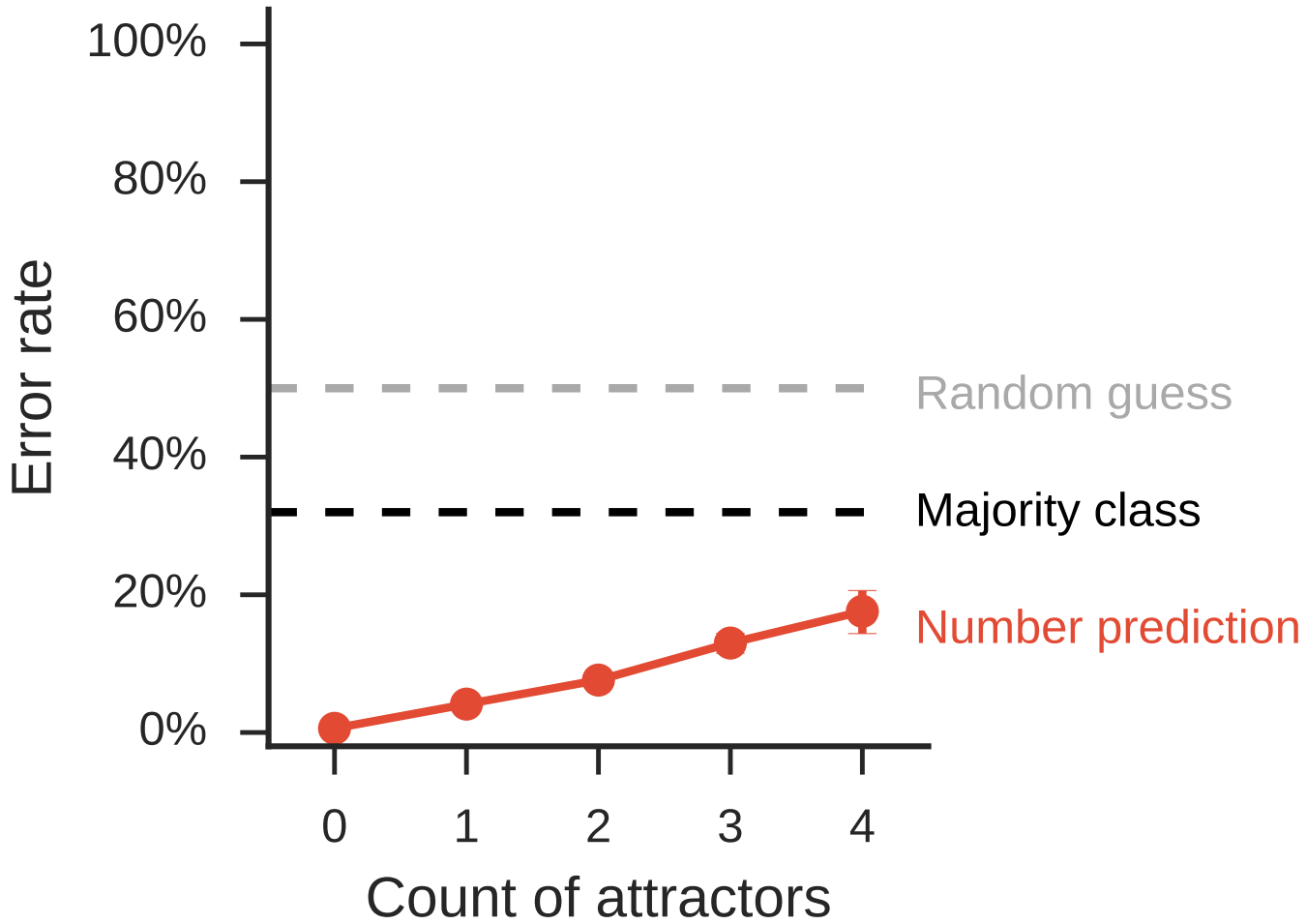
Attractors


100%
80%
60%
40%
20%
0%
Error rate
0
1
2
3
4
Count of attractors
Random guess
Majority class
Number prediction

Attractors



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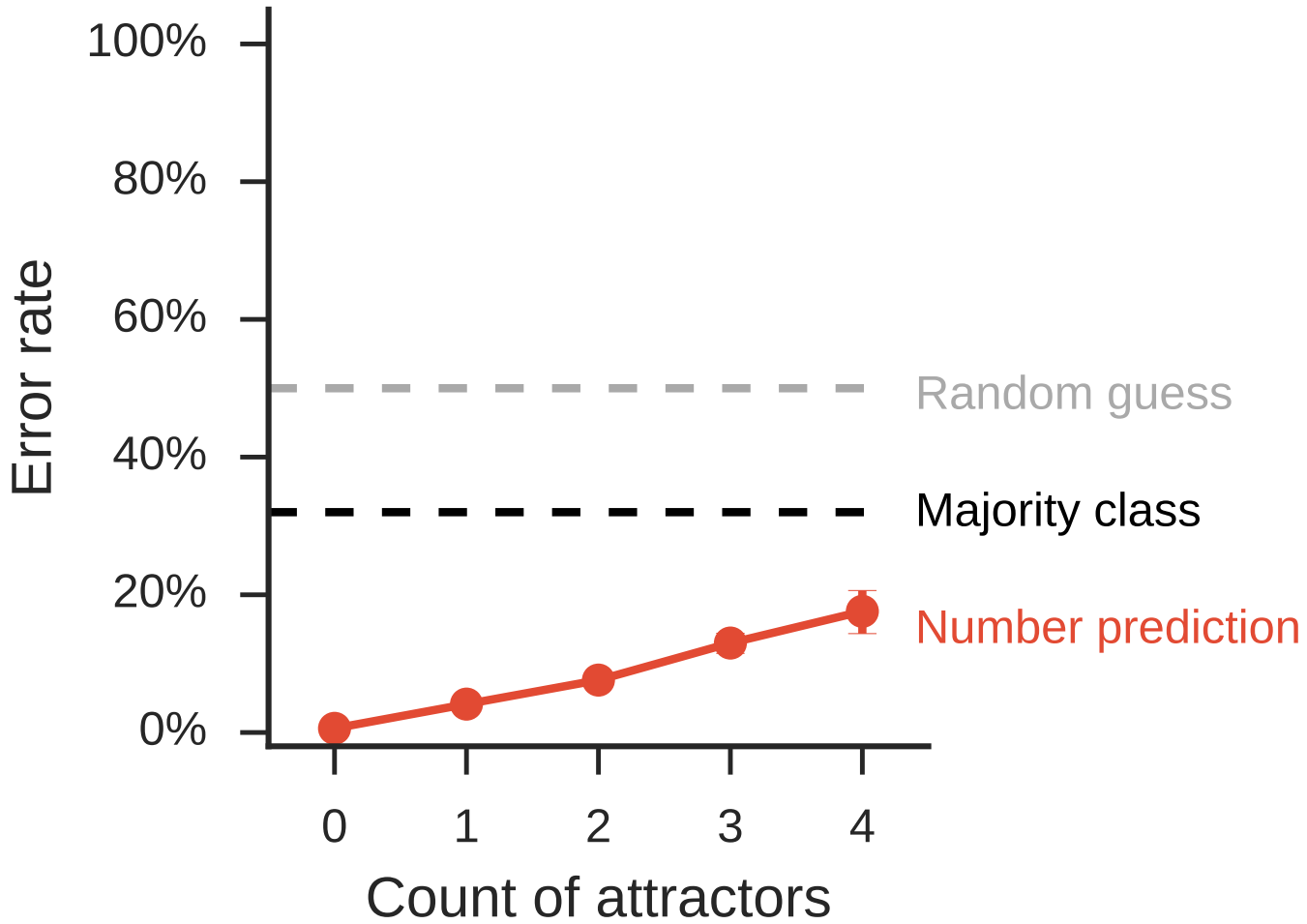

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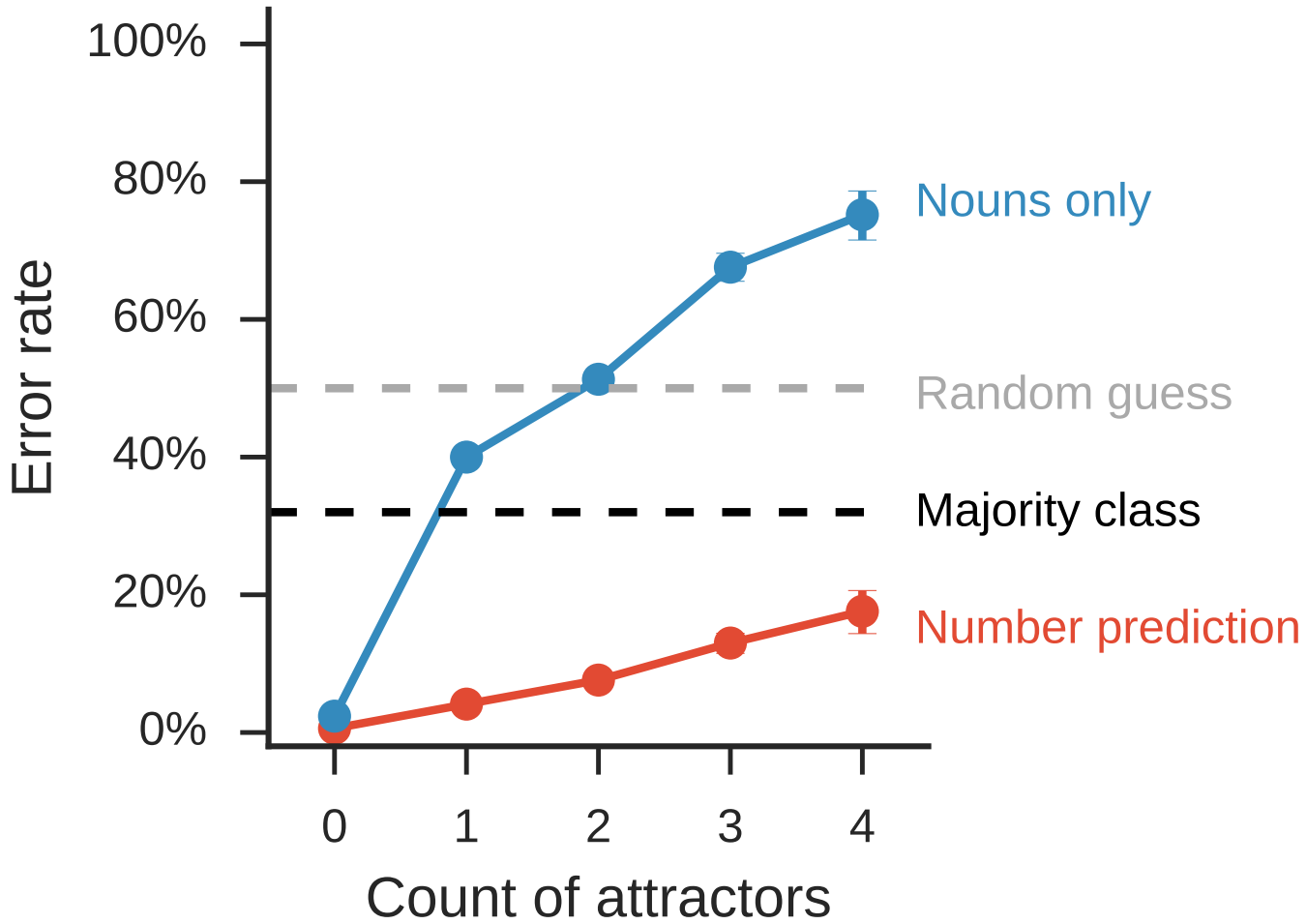

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Relative clauses

1. The landmarks **from** this article are not notable.
2. The landmarks **that** this article lists are not notable.
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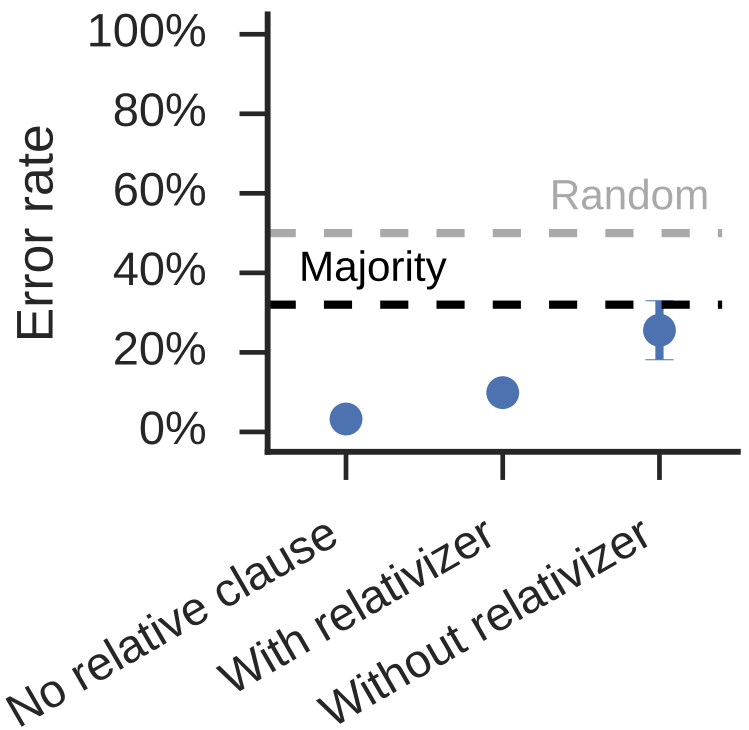

Leaky representation of structure

1. **PP:** The houses of the man from the office across the street...

Leaky representation of structure

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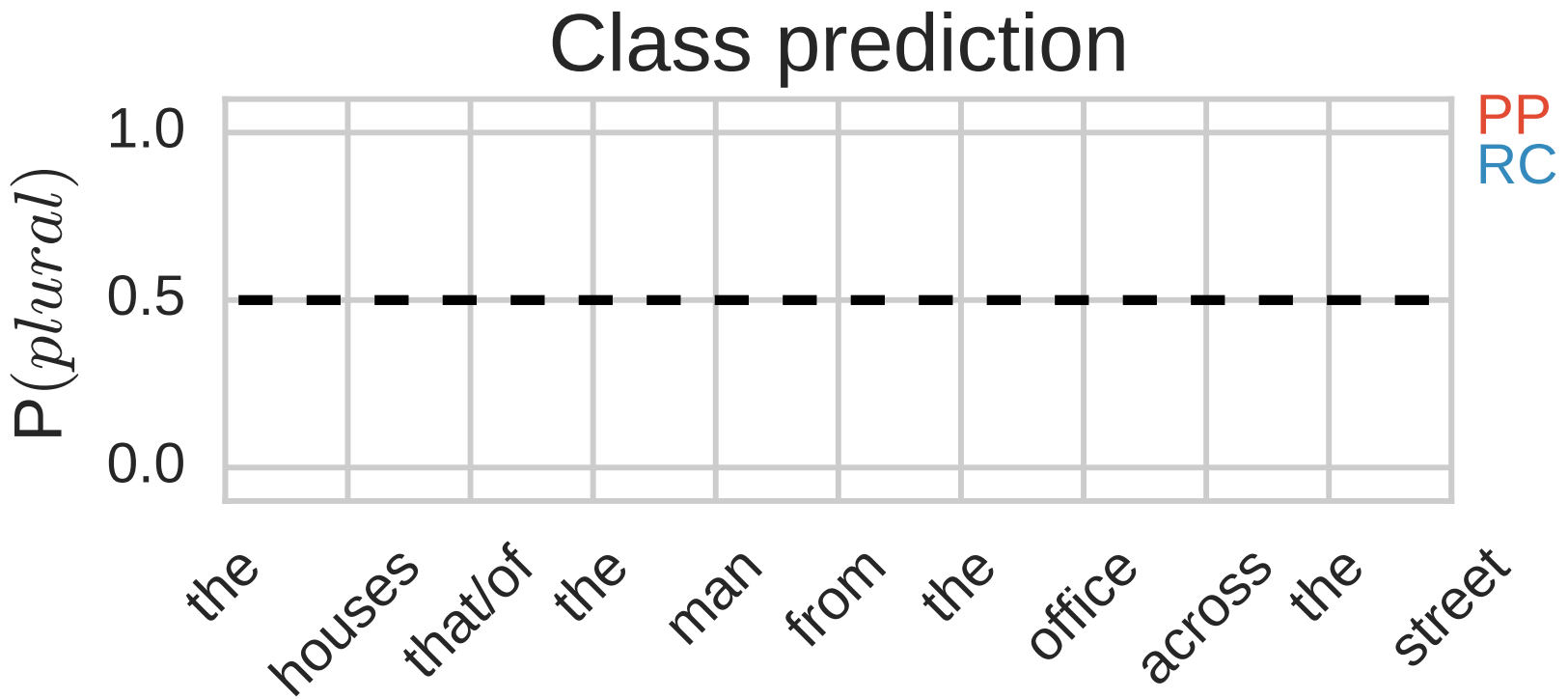

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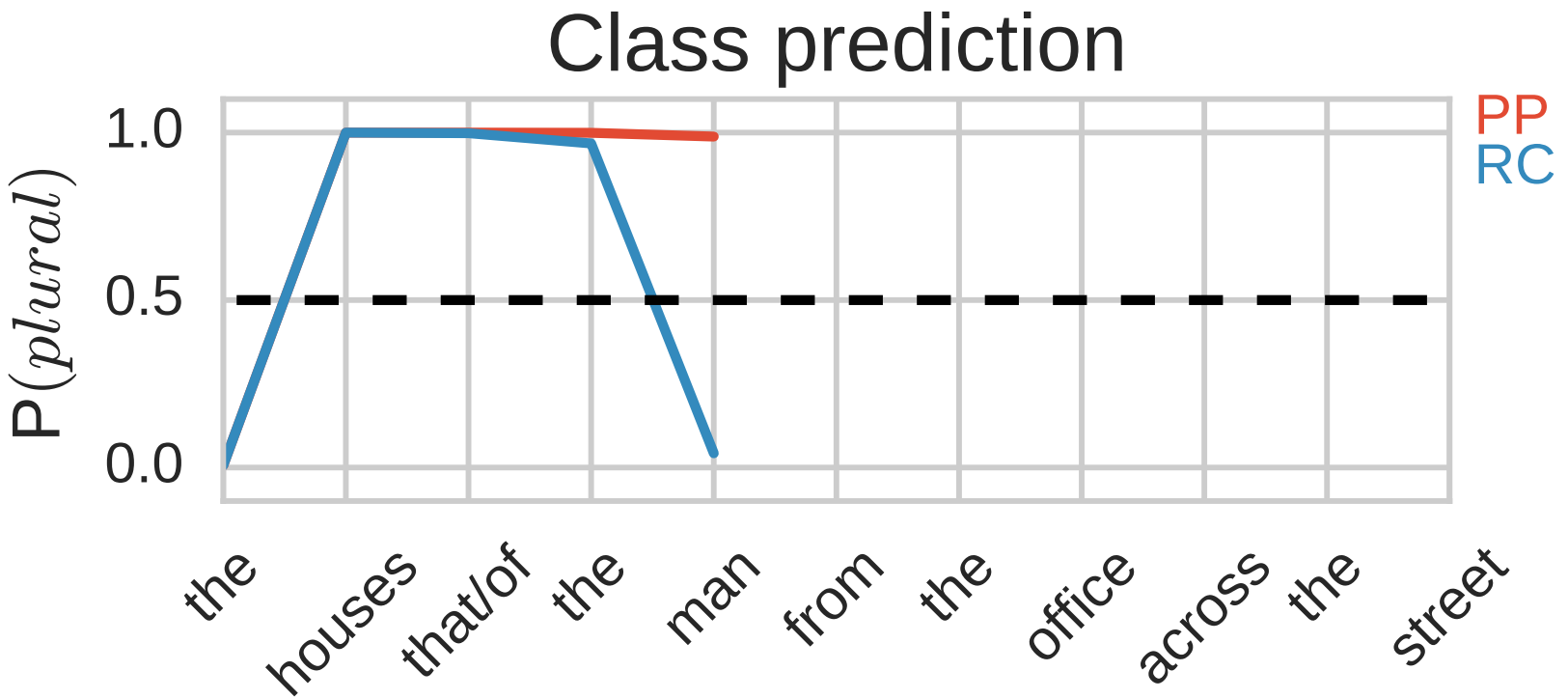

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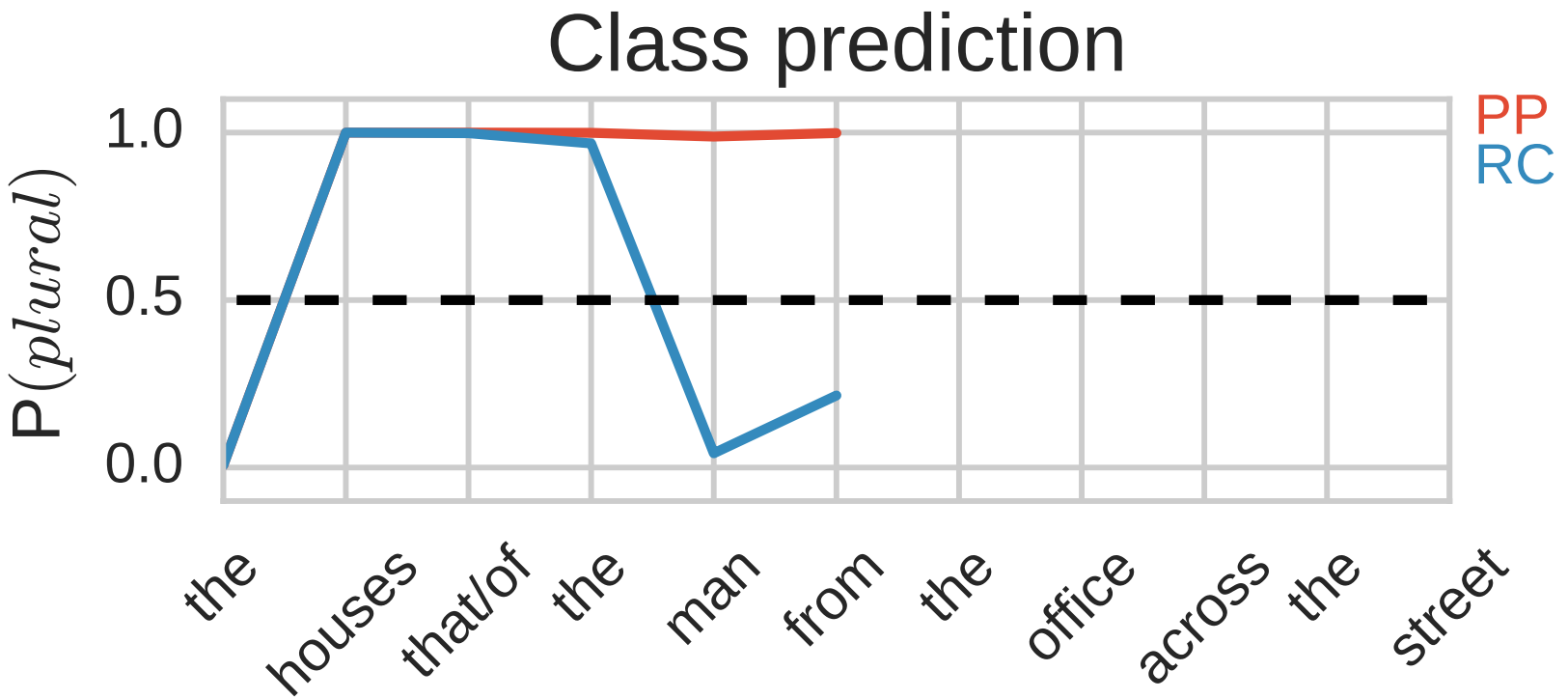

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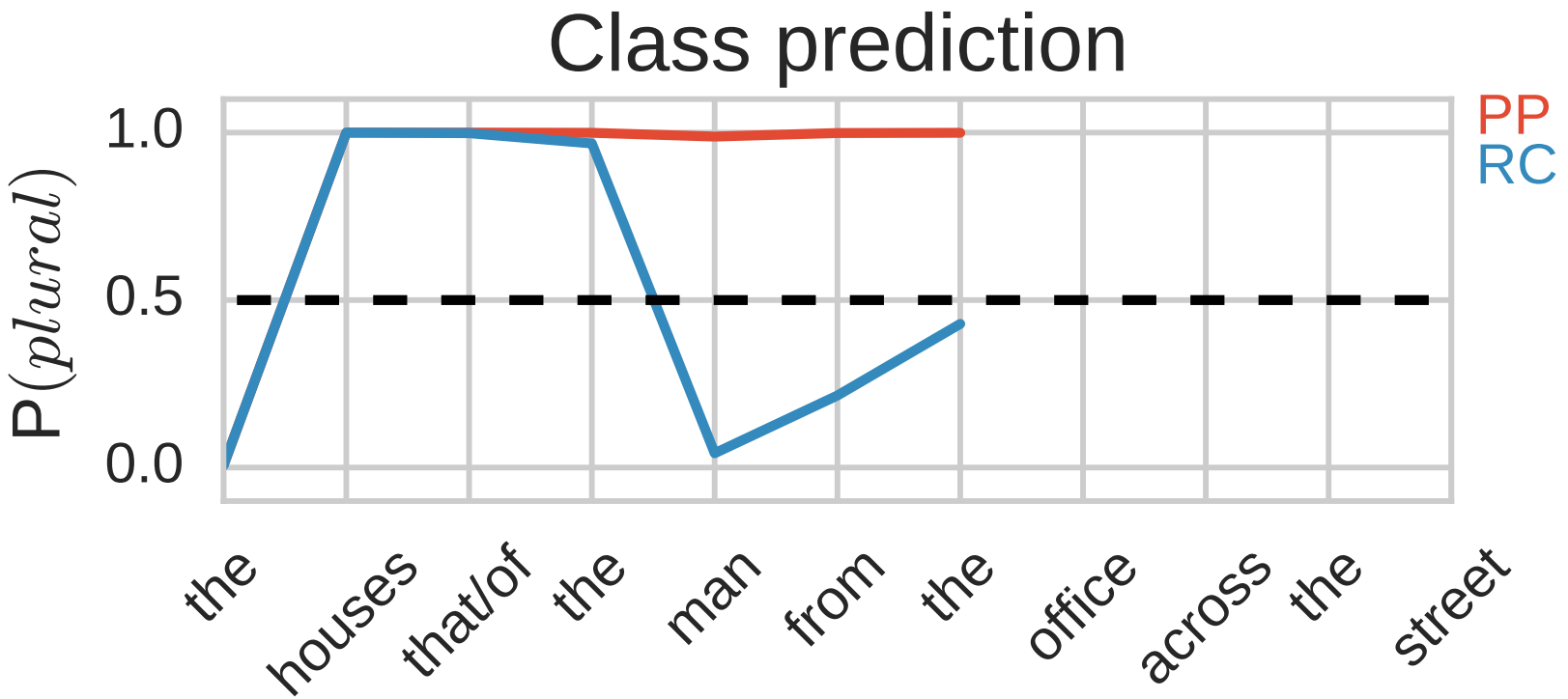

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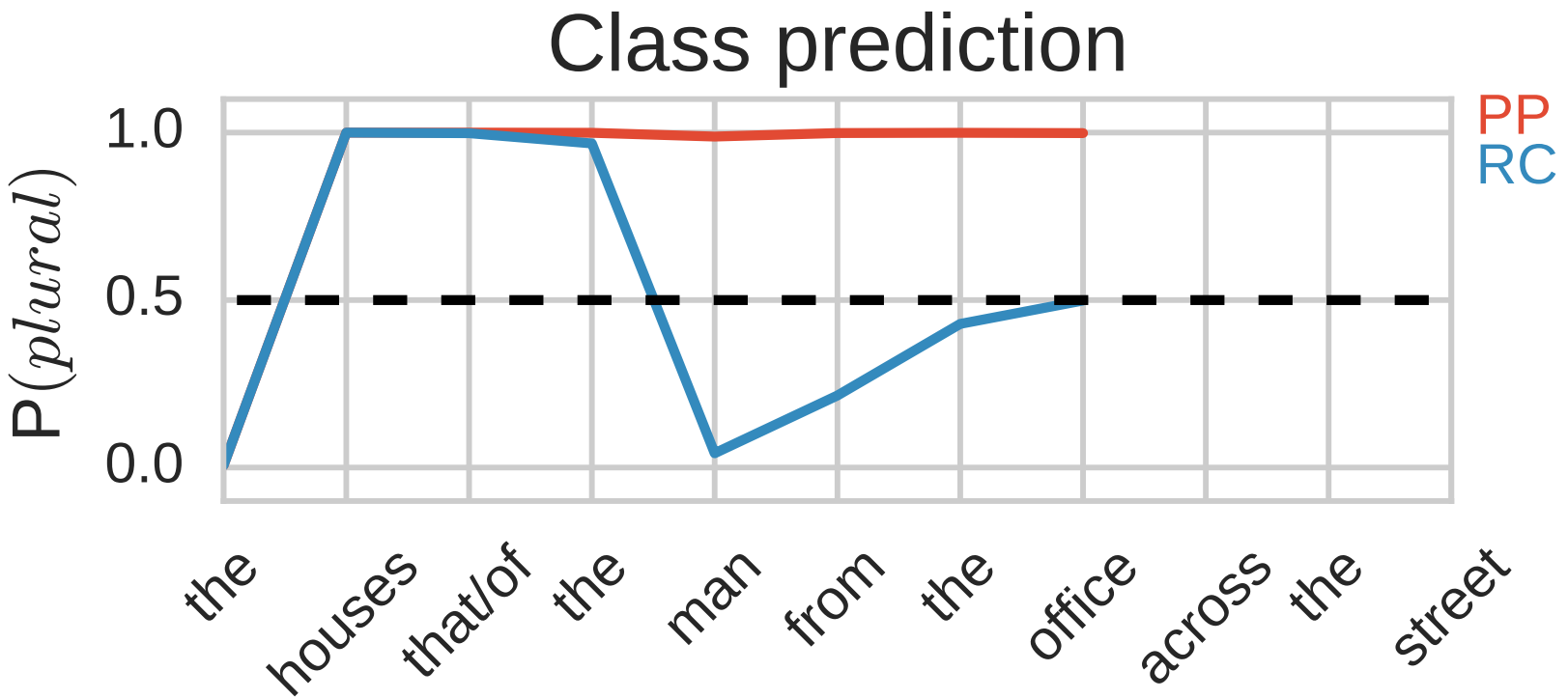

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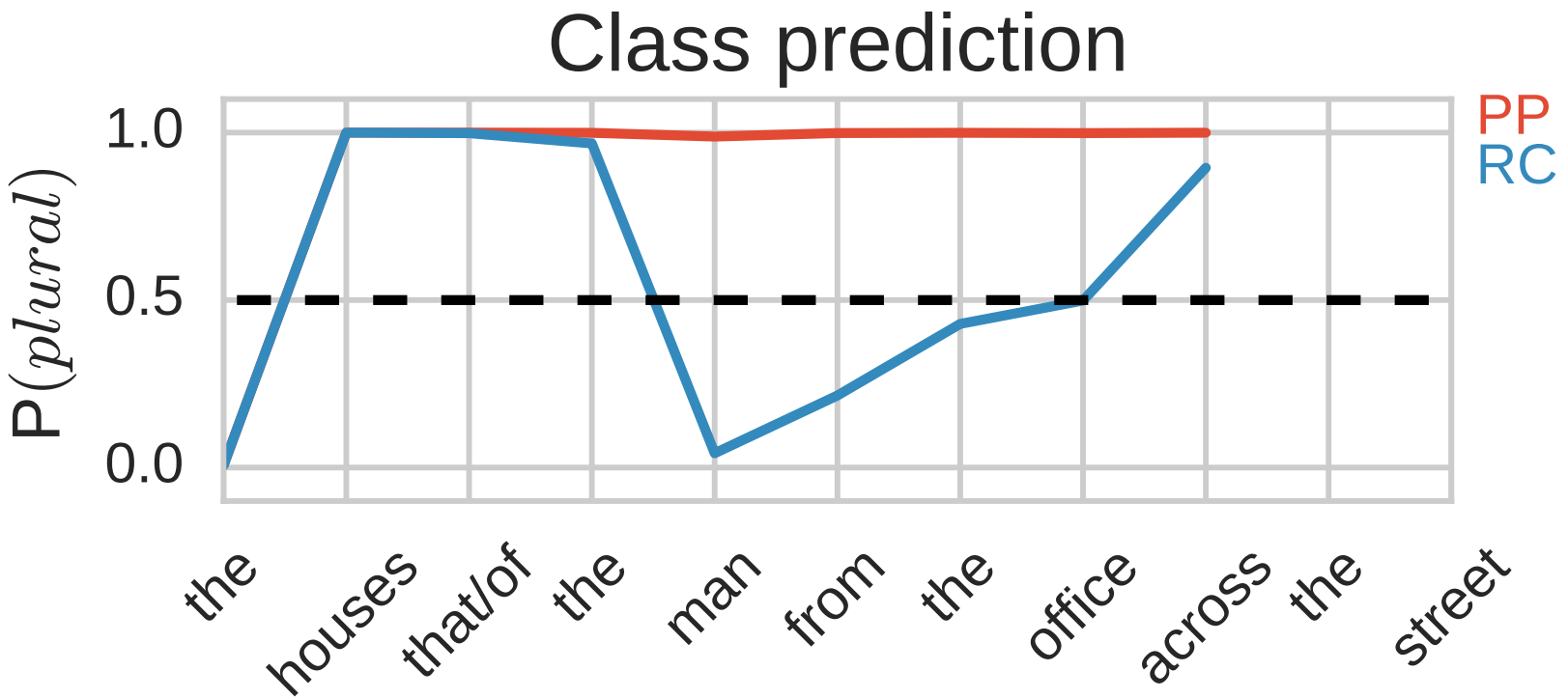

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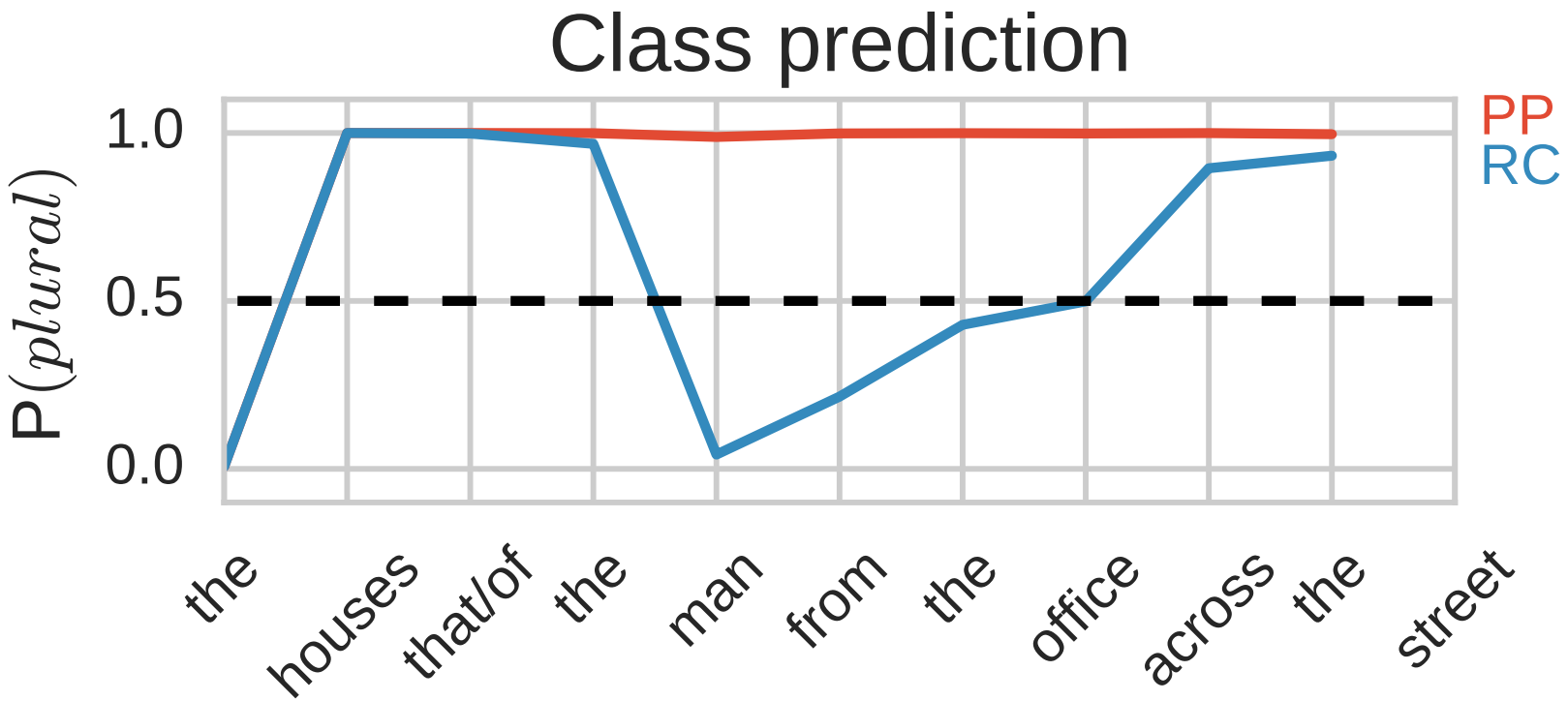

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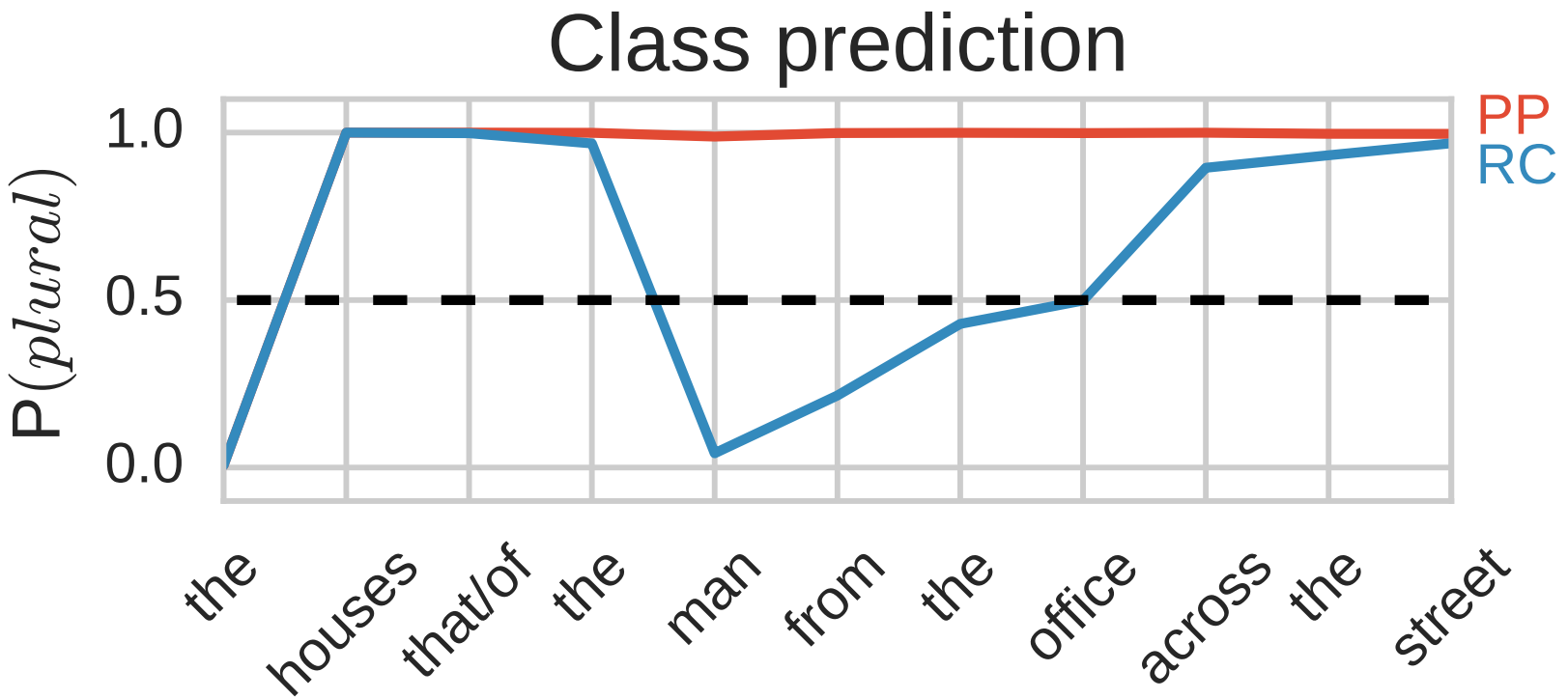

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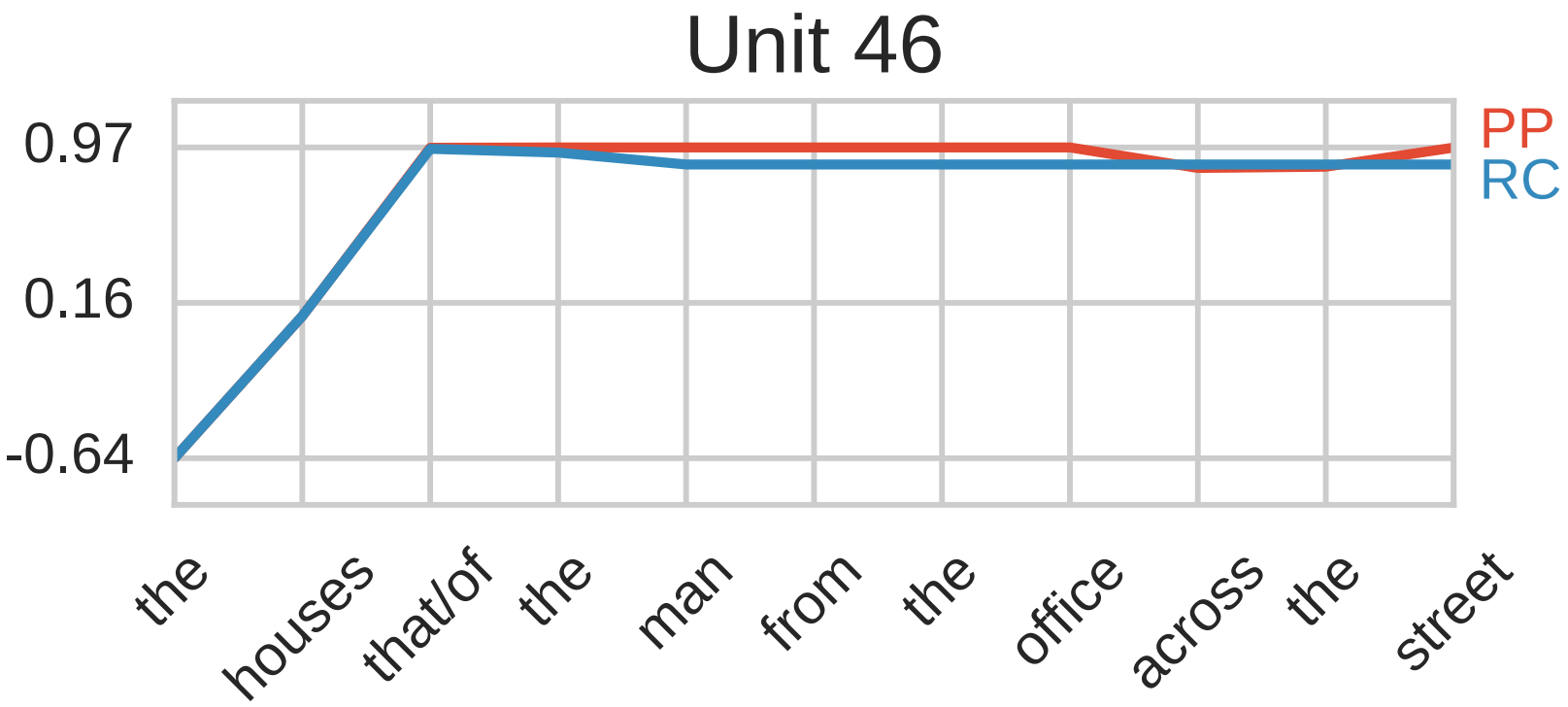
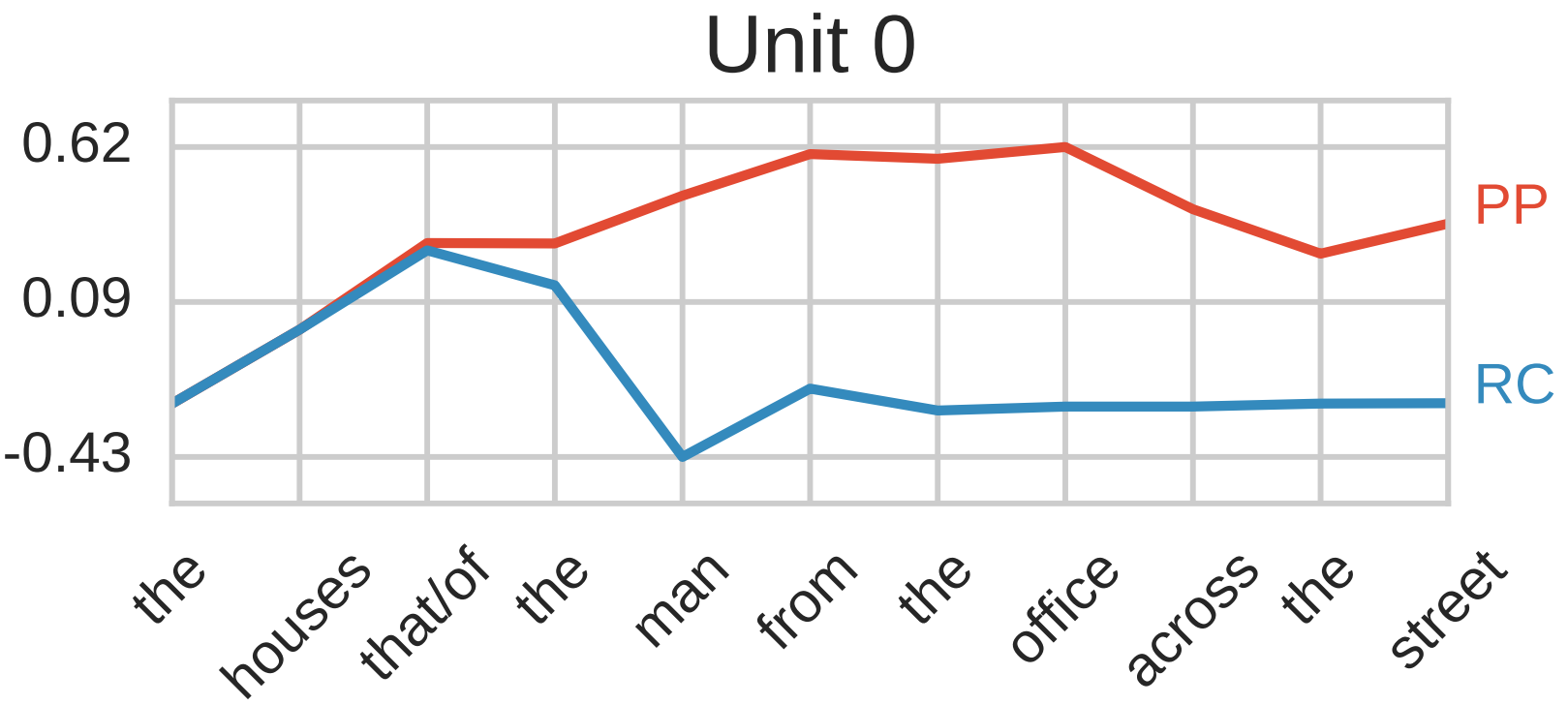


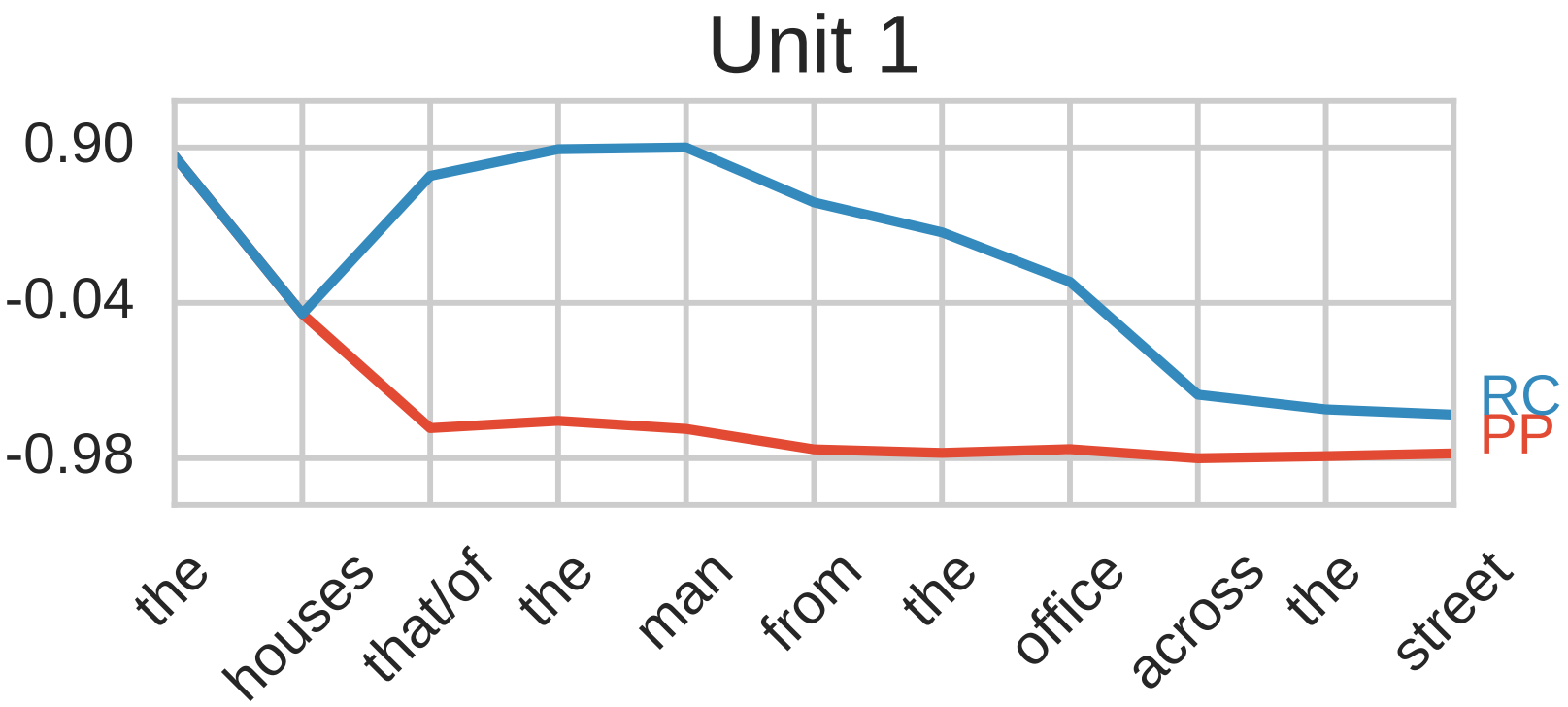
A unit that represents the number of the main clause subject!

Leaky representation of structure



A unit that represents the number of the embedded subject!

Leaky representation of structure



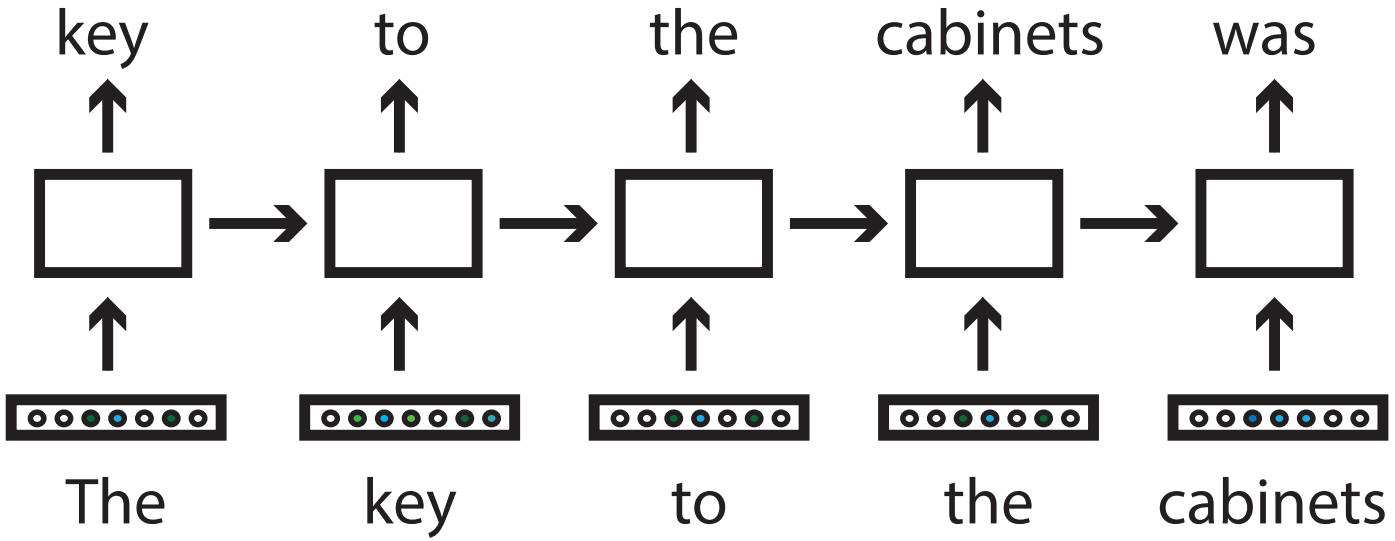
A unit that, uh...

Outline

- The number prediction task
- An RNN trained specifically to perform the task
- A focus on structurally interesting sentences
- RNN trained on a language modeling objective

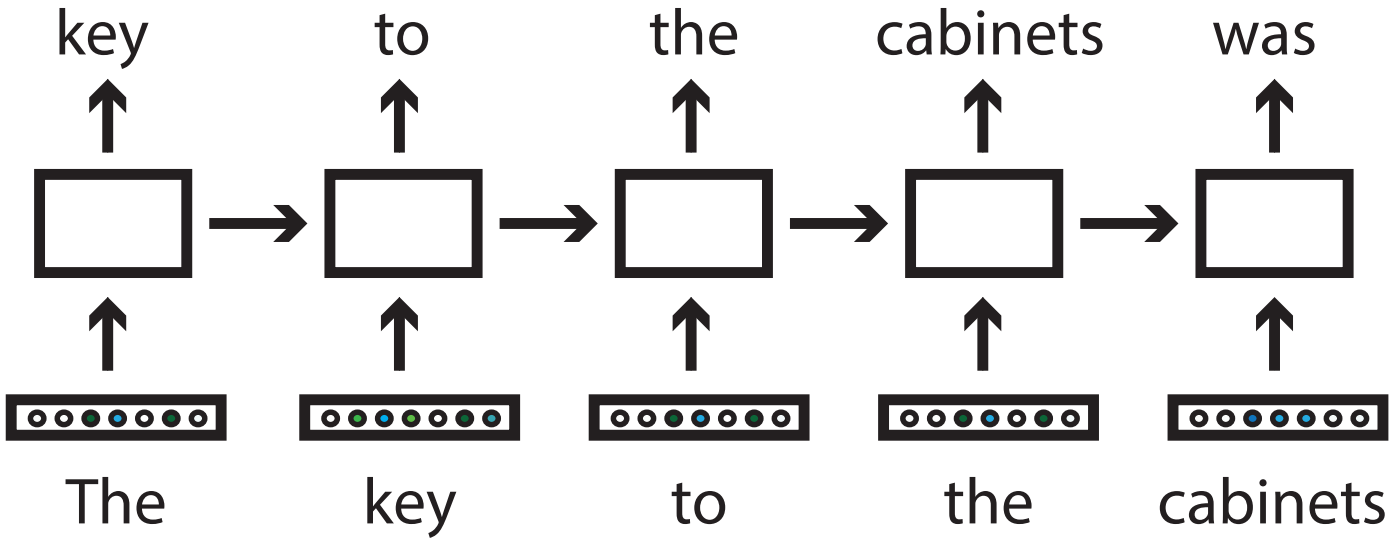
Language model

Training:



Language model

Training:

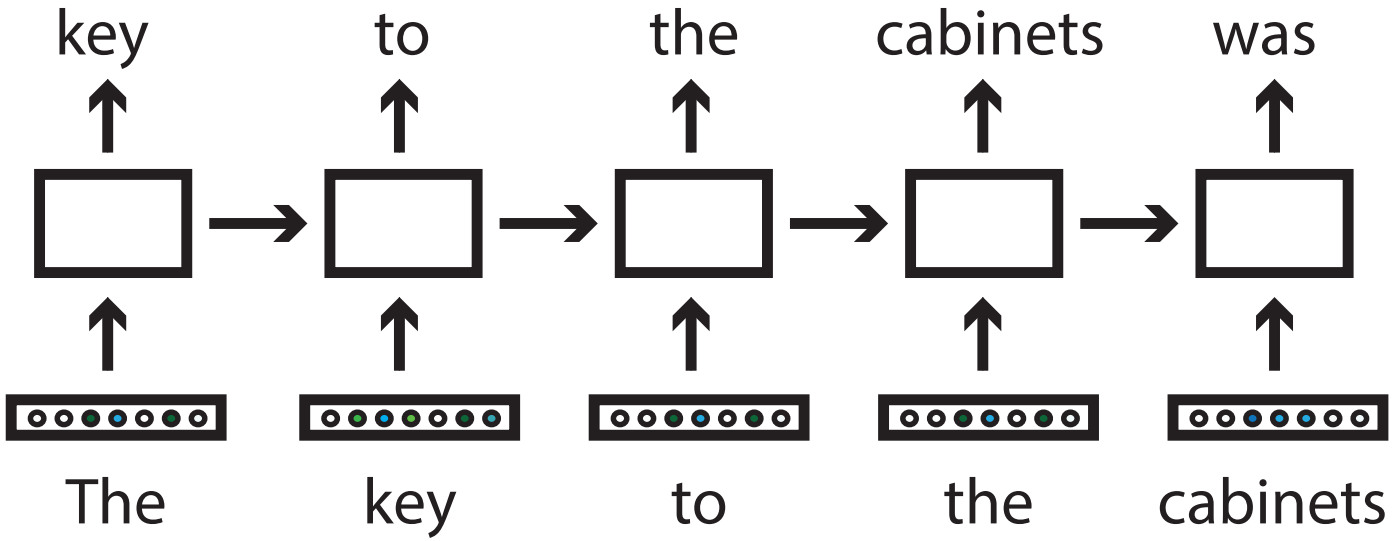


Evaluation:

The length of the forewings...

Language model

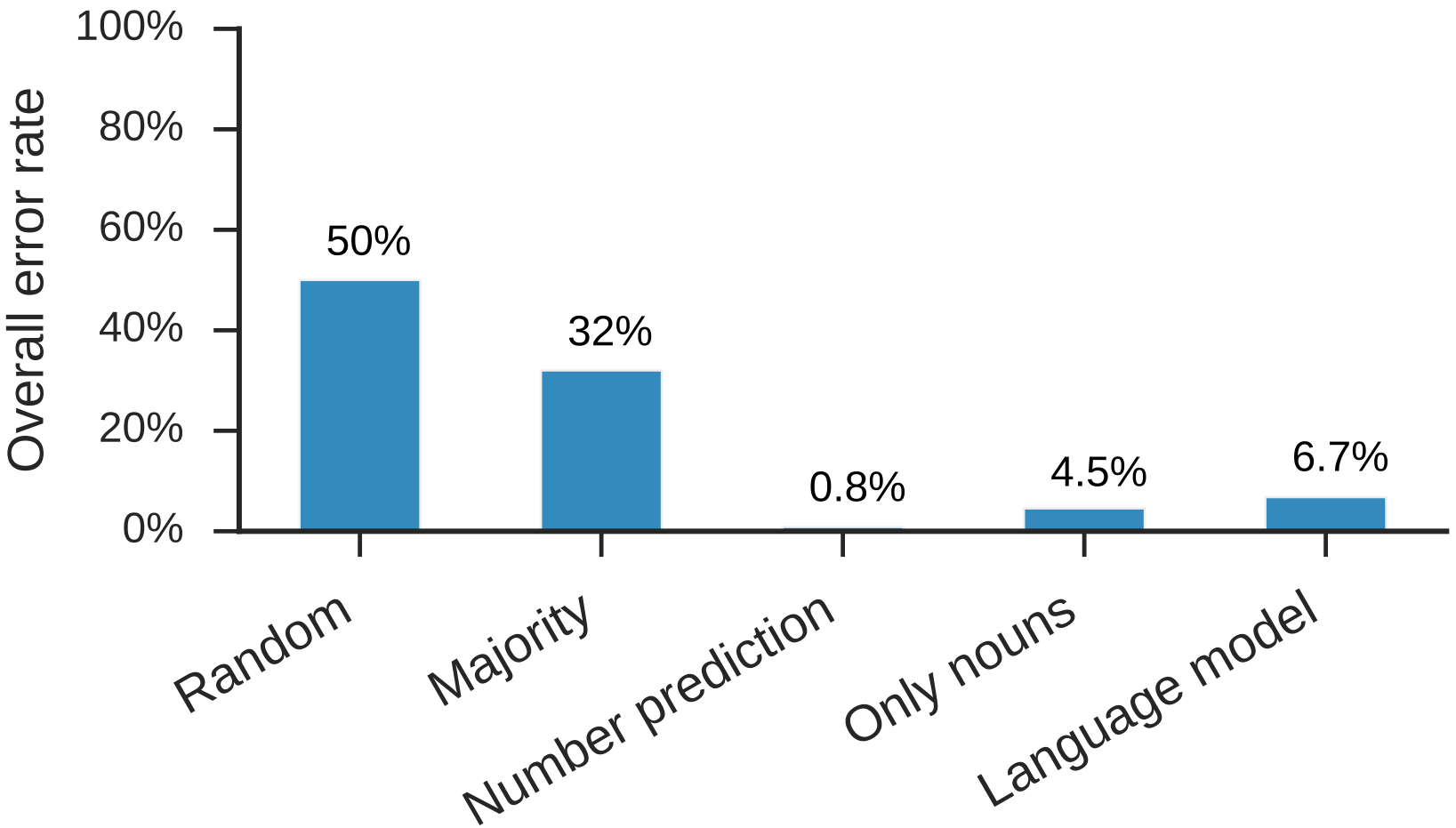
Training:



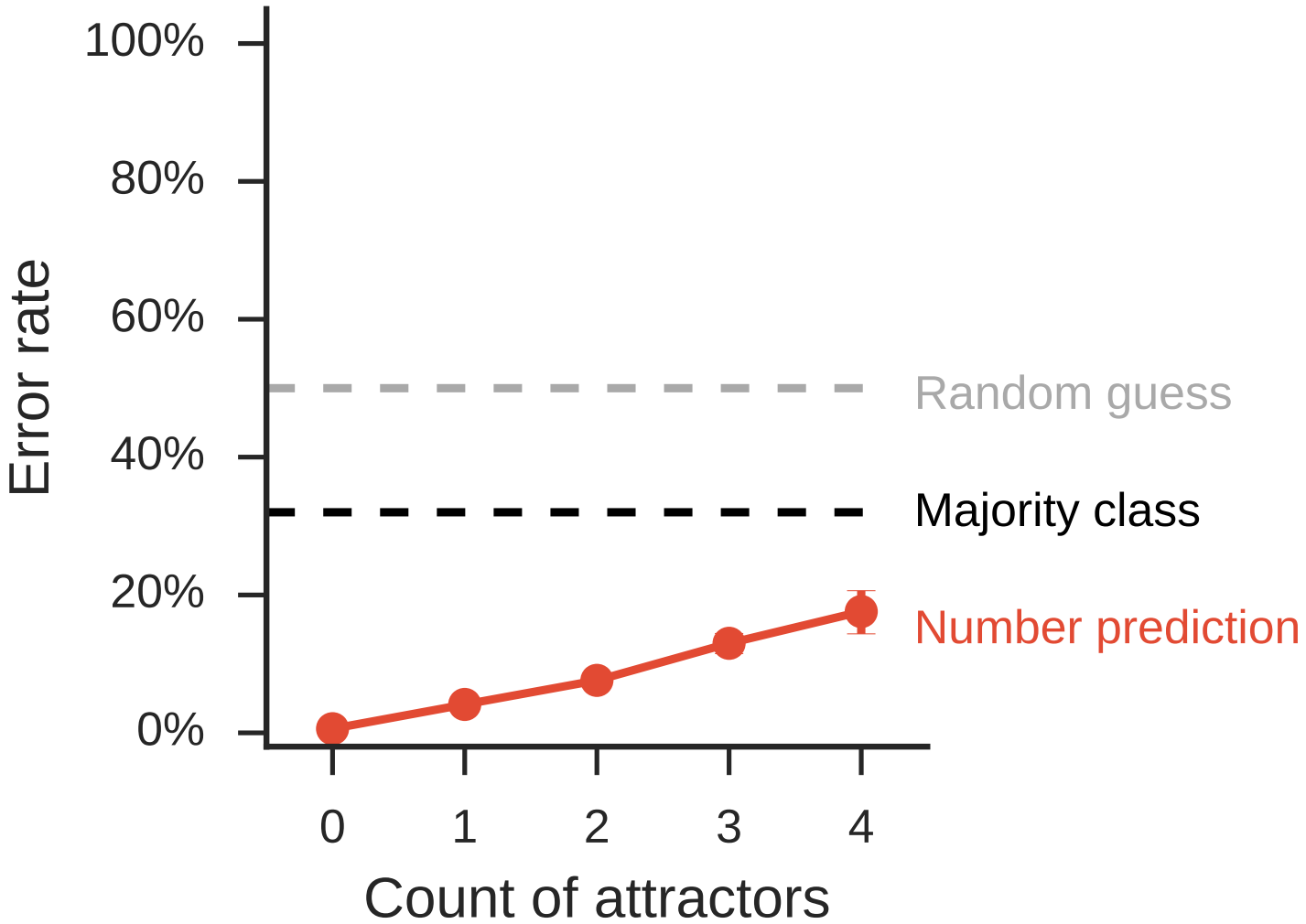
Evaluation:

The length of the forewings... $P(\text{is}) > P(\text{are})$?

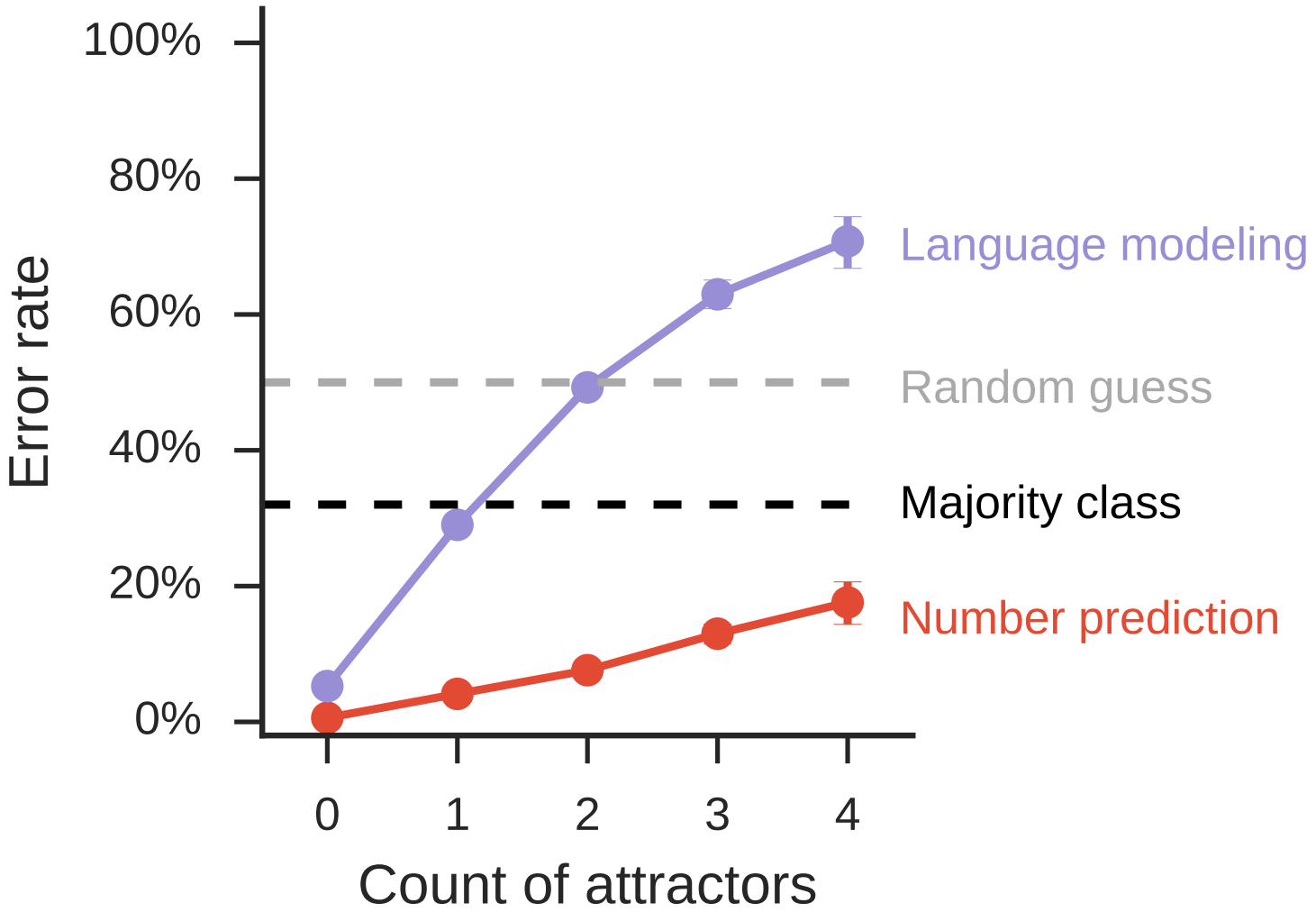
Overall results



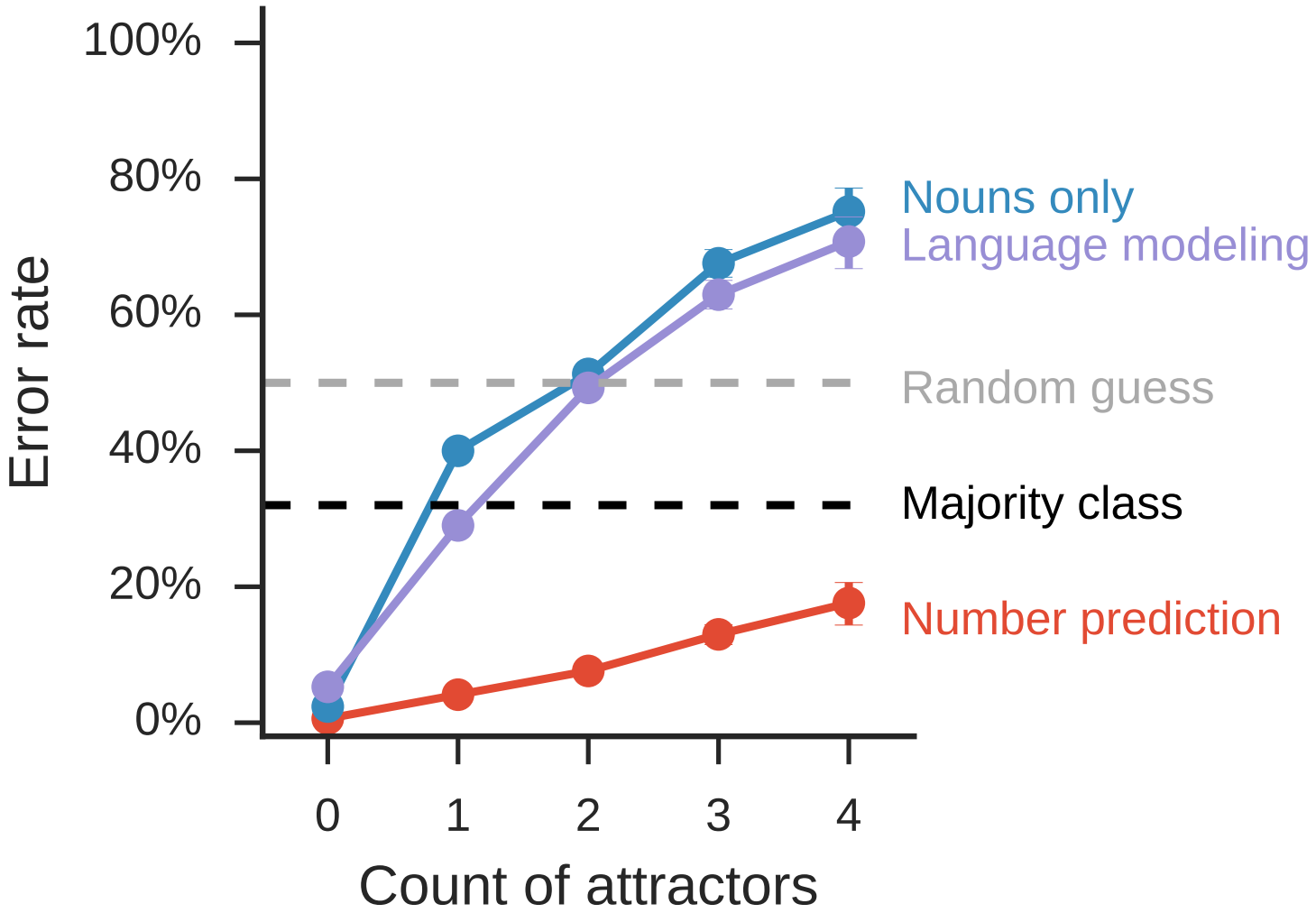
Attraction errors



Attraction errors



Attraction errors



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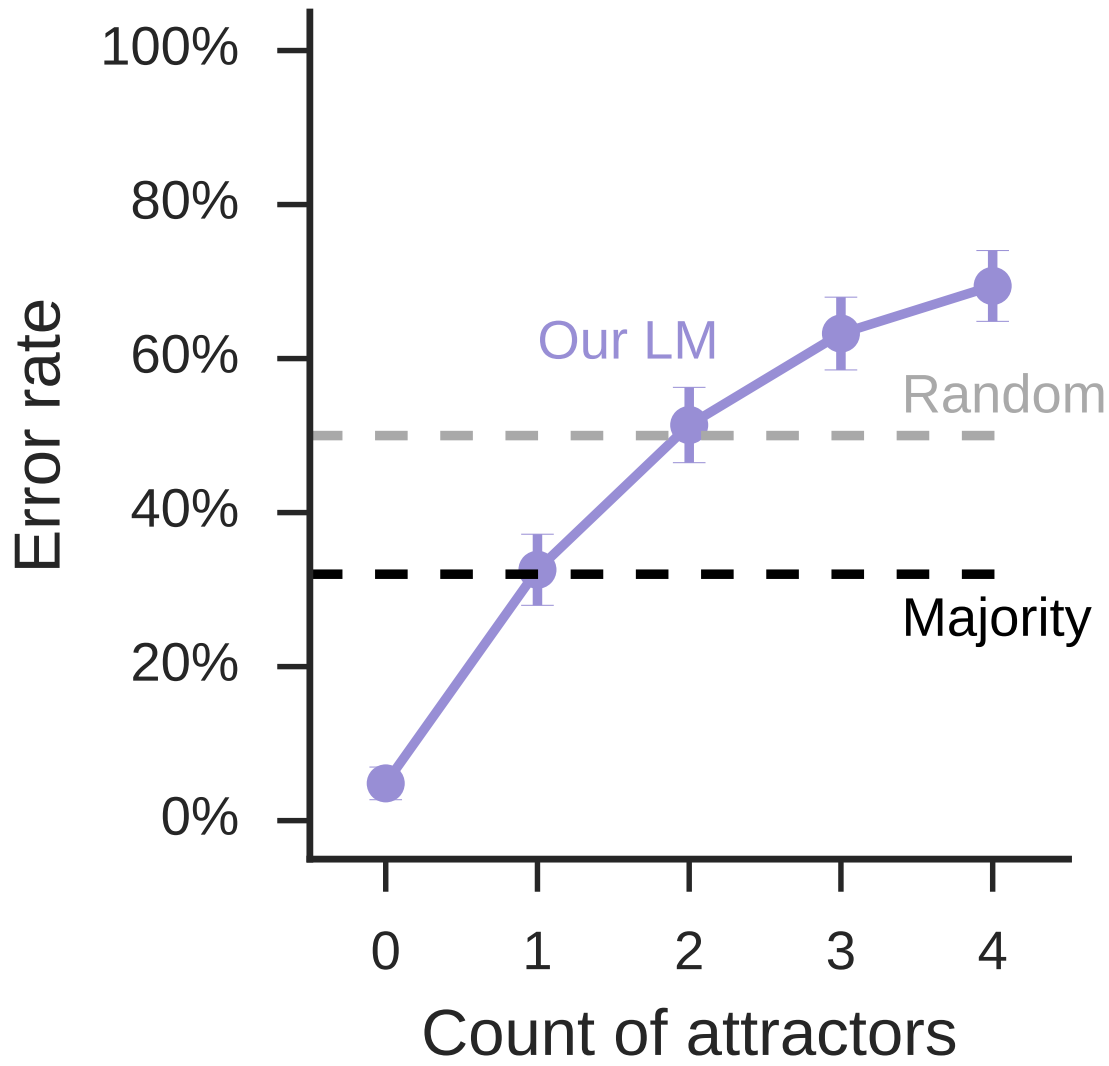
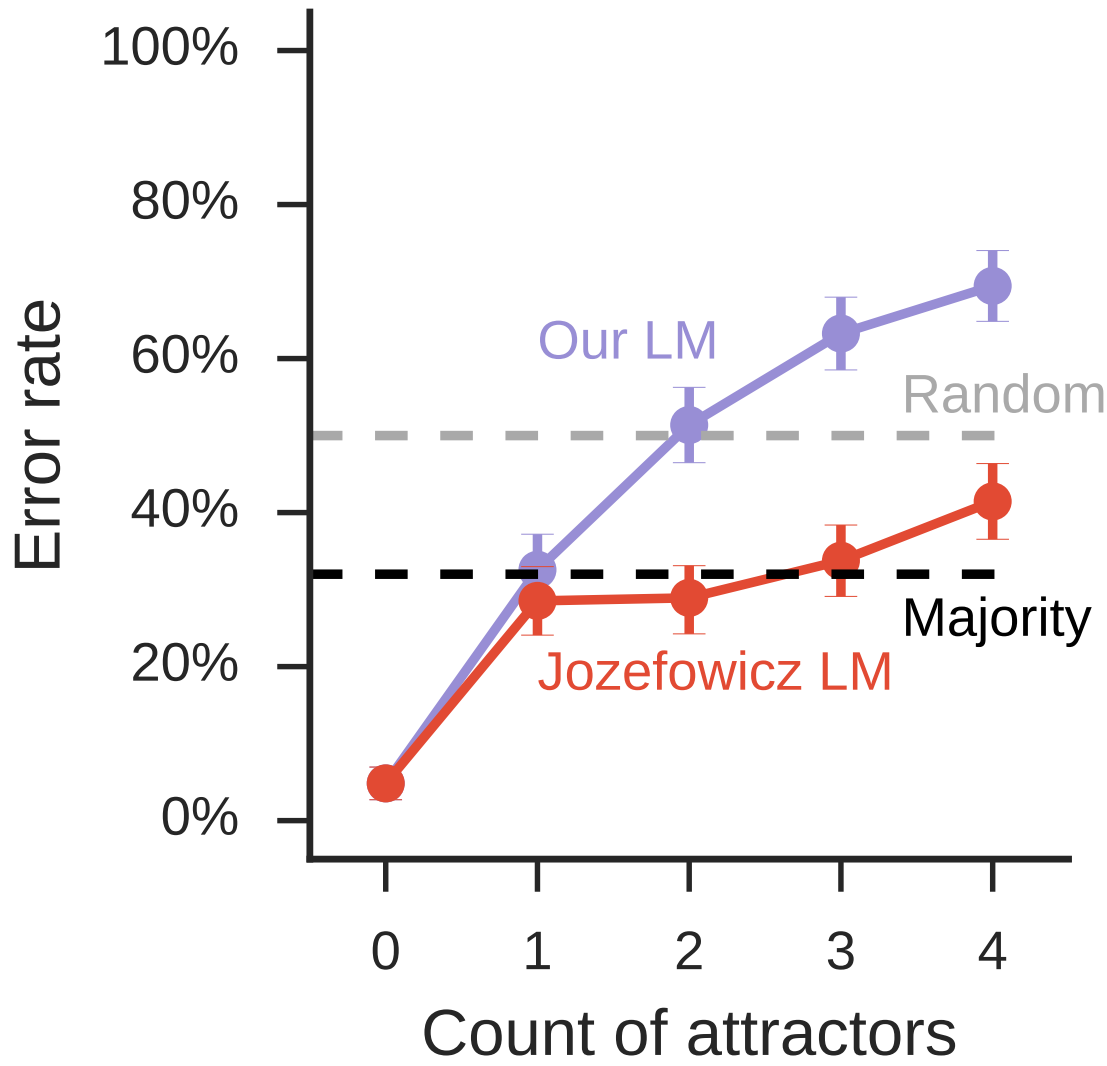
- Test with the Jozefowicz et al. (2016) language model (2 layers of 8192 LSTM units each)


100%
80%
60%
40%
20%
0%
Error rate
Our LM
Random
Majority
0
1
2
3
4
Count of attractors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Error rate
Our LM
Random
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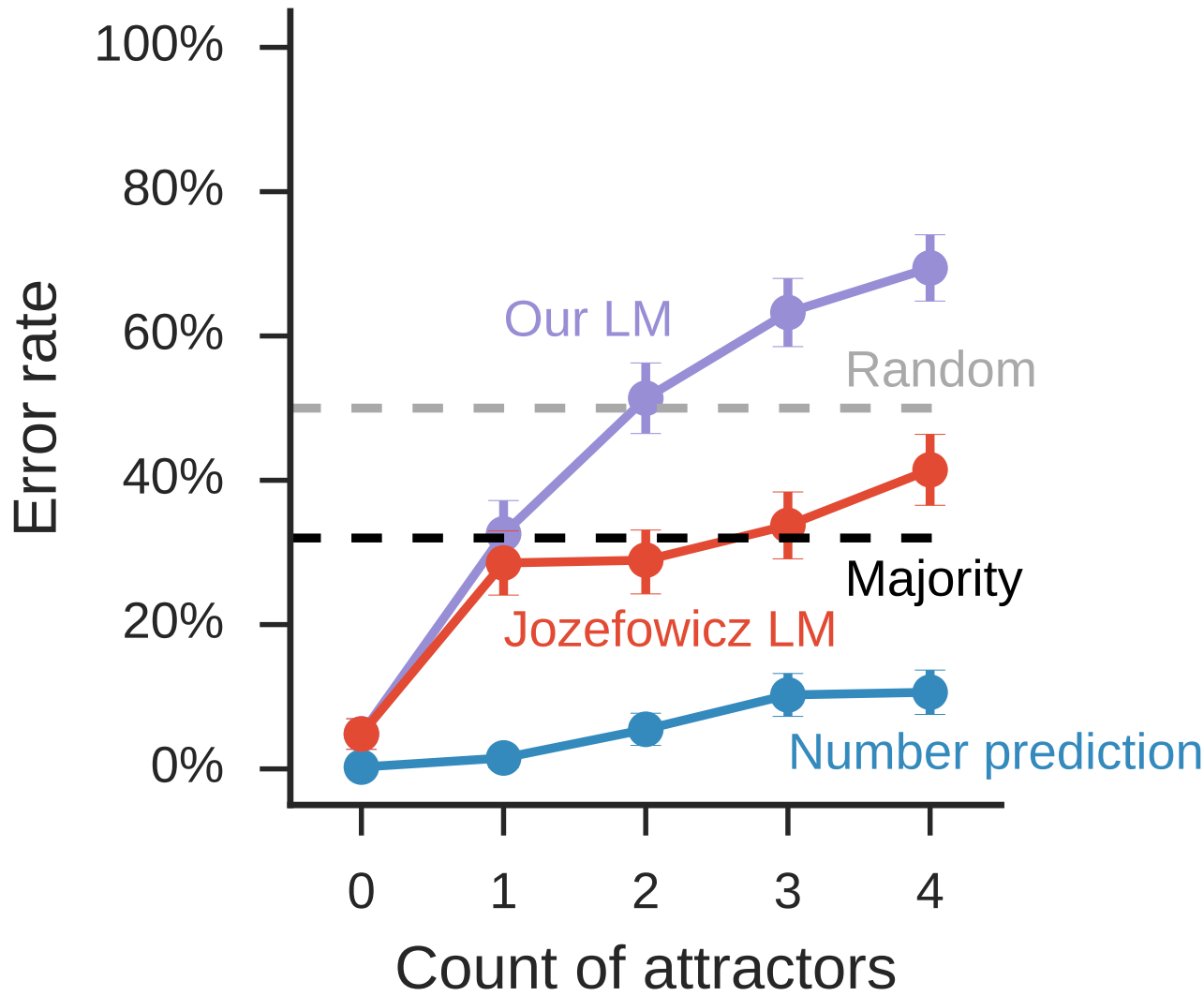
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Error rate
Our LM
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Jozefowicz LM
Number prediction
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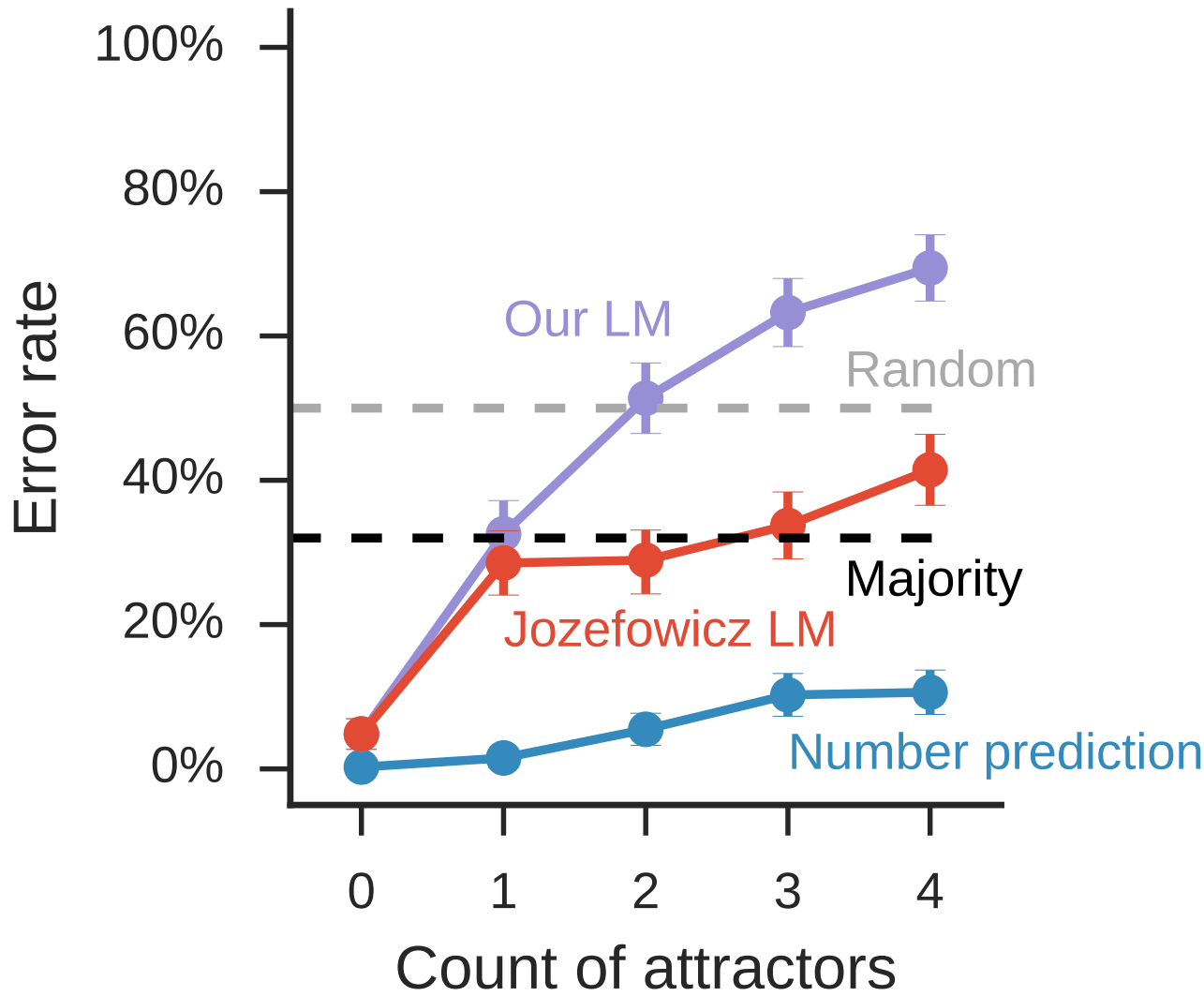
Count of attractors



A very large LSTM LM is only somewhat better

Summary of findings

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- But were still tripped up by difficult cases (e.g., long relative clauses): representations of structure are leaky
- Dramatic decline in performance on difficult cases with language modeling objective (even with SOTA LM)
- Many more experiments in the paper and in ongoing work

Conclusions

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Conclusions

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- **Evaluate your LMs on this task rather than just perplexity!**
- Linguistics and psycholinguistics can help characterize a learner's strengths and weaknesses

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- Grzegorz Chrupała
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Bahdanau, D., Cho, K., & Bengio, Y. (2015). Neural machine translation by jointly learning to align and translate. In *International conference for learning representations*.

Bock, K., & Miller, C. A. (1991). Broken agreement. *Cognitive Psychology*, *23*(1), 45–93.

Elman, J. L. (1991). Distributed representations, simple recurrent networks, and grammatical structure. *Machine Learning*, *7*(2-3), 195–225.

Goldberg, Y., & Nivre, J. (2012, December). A dynamic oracle for arc-eager dependency parsing. In *Proceedings of COLING 2012* (pp. 959–976).

Jozefowicz, R., Vinyals, O., Schuster, M., Shazeer, N., & Wu, Y. (2016). Exploring the limits of language modeling. *arXiv preprint arXiv:1602.02410*.

Mikolov, T., Karafiát, M., Burget, L., Cernockỳ, J., & Khudanpur, S. (2010). Recurrent neural network based language model. In *Proceedings of the 11th Annual Conference of the International Speech Communication Association (INTERSPEECH 2010)* (pp. 1045–1048). Makuhari, Chiba, Japan.

Sundermeyer, M., Schlüter, R., & Ney, H. (2012). LSTM neural networks for language modeling. In *Proceedings of the 13th Annual Conference of the International Speech Communication Association (INTERSPEECH)* (pp. 194–197).

Vinyals, O., Kaiser, Ł., Koo, T., Petrov, S., Sutskever, I., & Hinton, G. (2015). Grammar as a foreign language. In *Advances in neural information processing systems* (pp. 2755–2763).