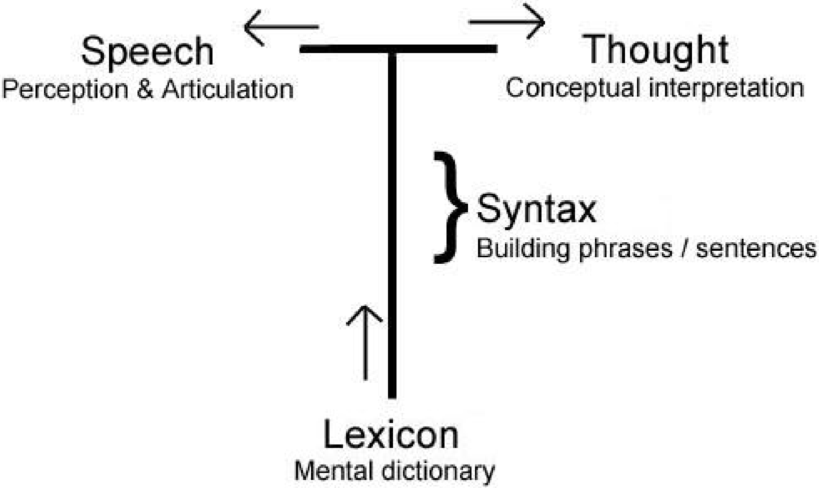
Gaël Le Godais[1,2], Tal Linzen[1,3]
and Emmanuel Dupoux[1]

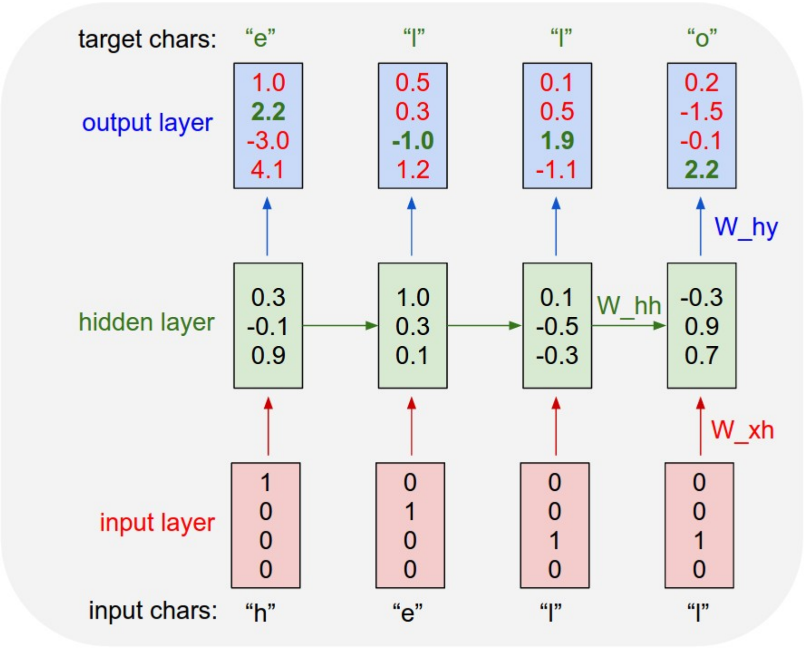
[1] LSCP & IJN, ENS Paris
[2] ENSIMAG
[3] Johns Hopkins University

Comparing Character-level Neural Language Models Using a Lexical Decision Task


Speech
Perception & Articulation
Thought
Conceptual interpretation
Syntax
Building phrases / sentences
Lexicon
Mental dictionary

Character-level Convolutional Networks for Text Classification*

Xiang Zhang **Junbo Zhao** **Yann LeCun**
Courant Institute of Mathematical Sciences, New York University
719 Broadway, 12th Floor, New York, NY 10003
{xiang, junbo.zhao, yann}@cs.nyu.edu


target chars:
“e”
“l”
“l”
“o”
output layer
1.0
2.2
-3.0
4.1
0.5
0.3
-1.0
1.2
0.1
0.5
1.9
-1.1
0.2
-1.5
-0.1
2.2
W_hy
hidden layer
0.3
-0.1
0.9
1.0
0.3
0.1
0.1
-0.5
-0.3
W_hh
-0.3
0.9
0.7
W_xh
input layer
1
0
0
0
0
1
0
0
0
0
1
0
0
0
1
0
input chars:
“h”
“e”
“l”
“l”

PANDARUS:
Alas, I think he shall be come approached and the day When little srain would be attain'd into being never fed, And who is but a chain and subjects of his death, I should not sleep.

(Karpathy et al., 2016)

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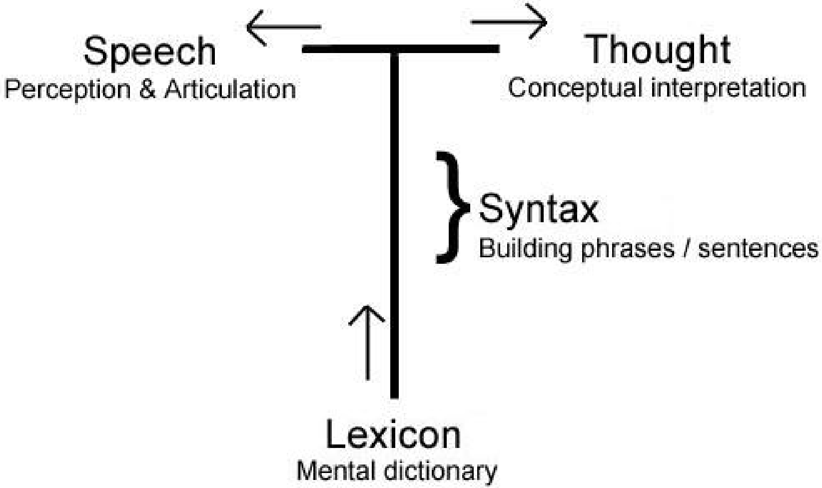
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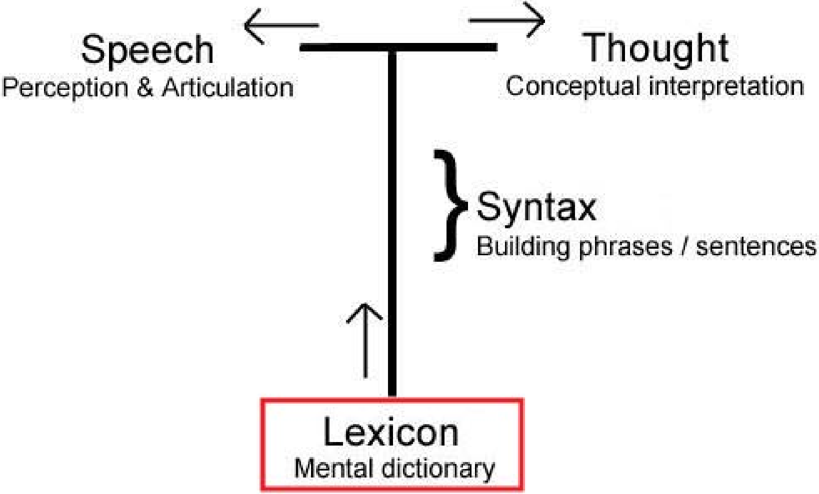
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Lexical decision
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Lexical decision
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plurb

Lexical decision
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NONWORD

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WORD

Lexical decision using a language model

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(Lau et al., 2016)

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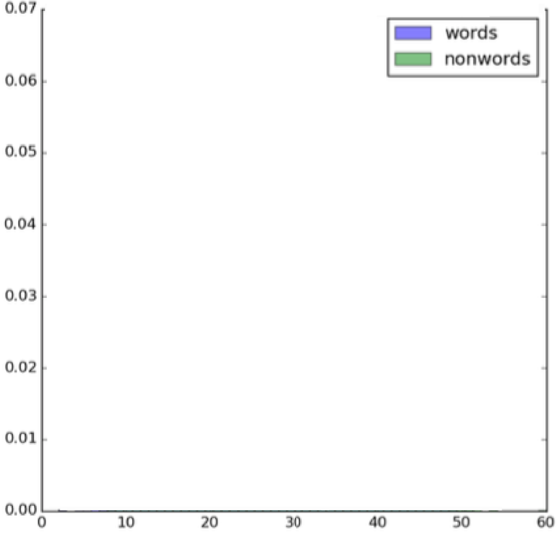
(Balota et al., 2007)



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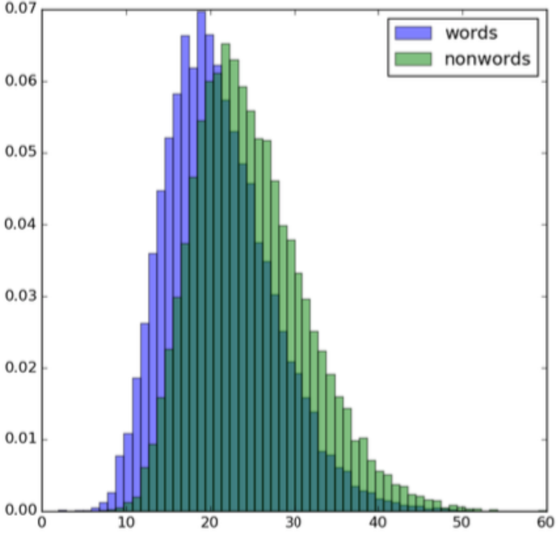

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- Alternative: matching (Linzen et al., 2016)

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- Trained on 10M words (50M characters) from the movie/book corpus (Zhu et al., 2015)

Nonword generation

- Nonwords matched for length and bigram probability (respecting position and syllable structure) using Wuggy (Keuleers & Brysbaert, 2010):

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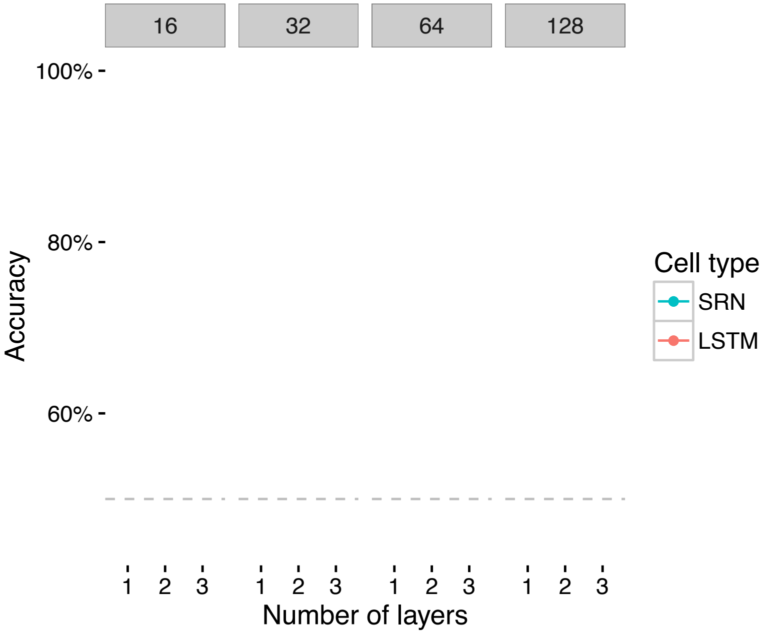
16
32
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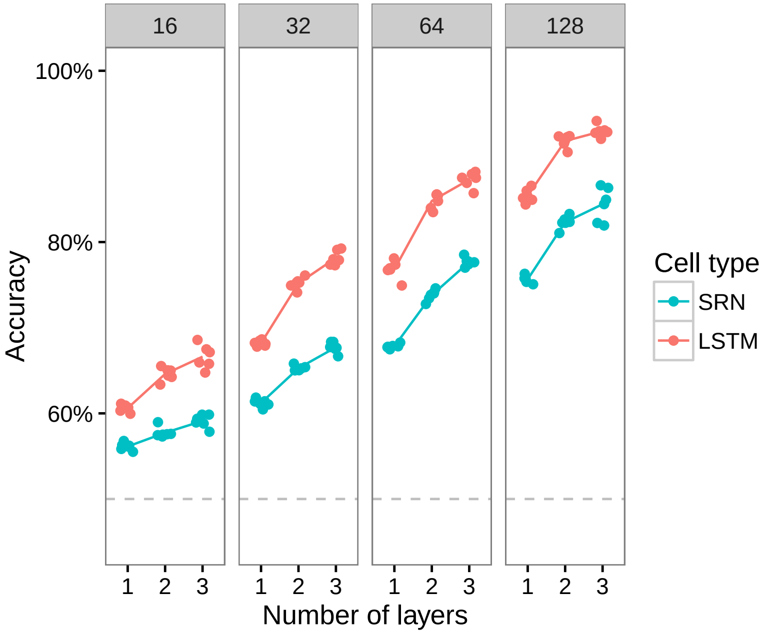
128
100%
80%
60%
Accuracy
1 2 3 1 2 3 1 2 3 1 2 3
Number of layers
Cell type
SRN
LSTM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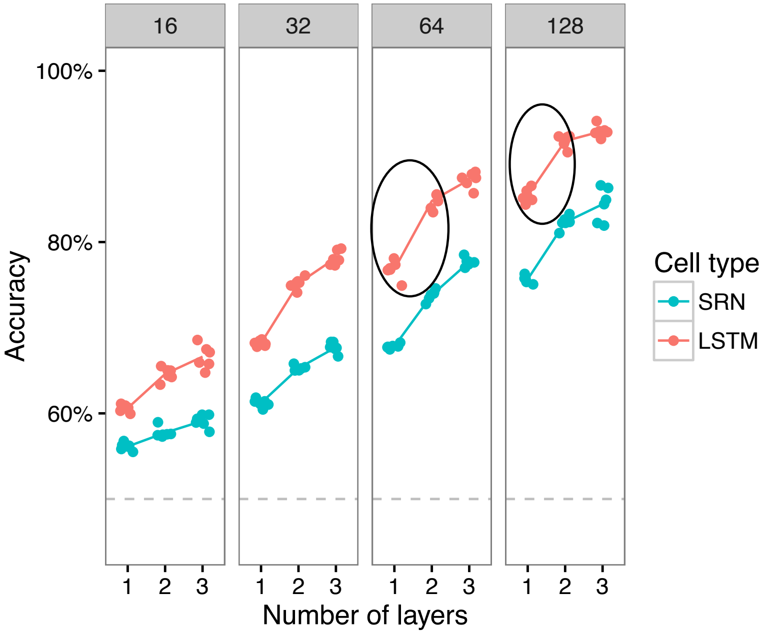
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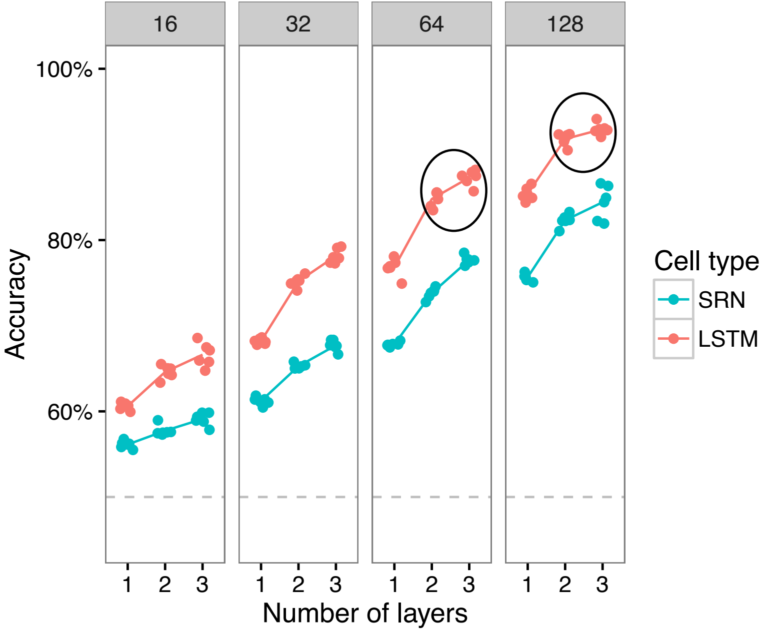
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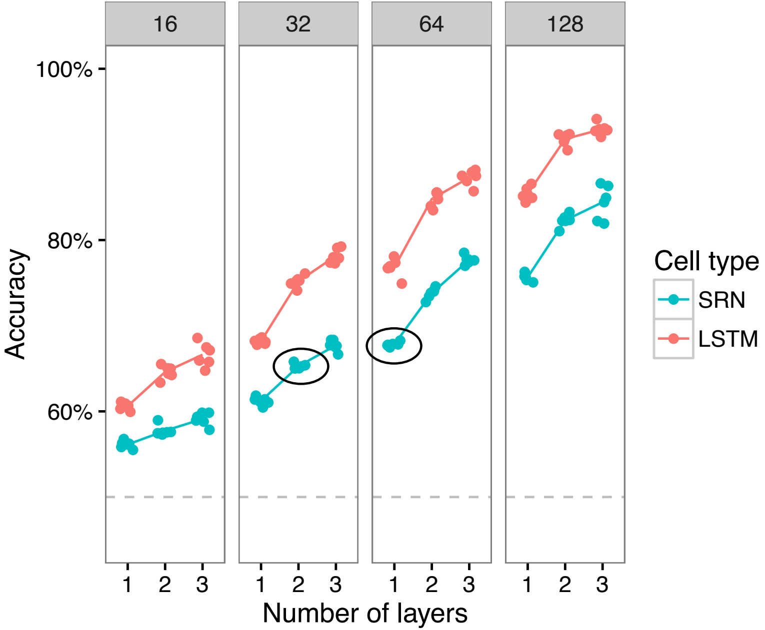
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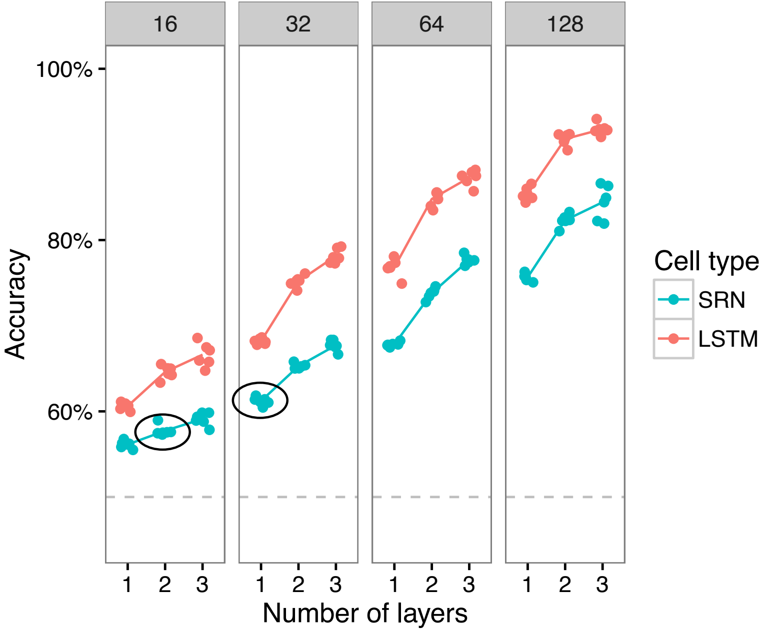
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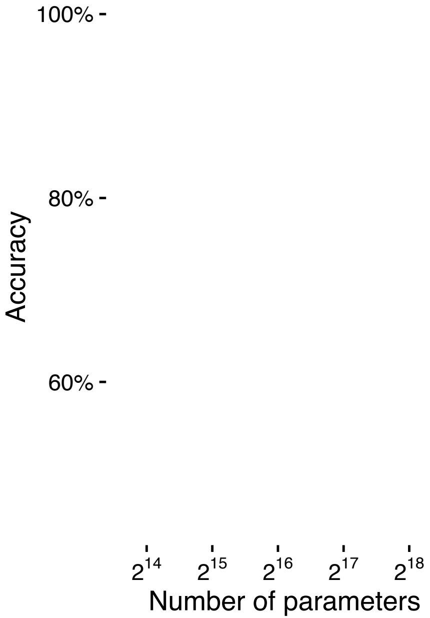
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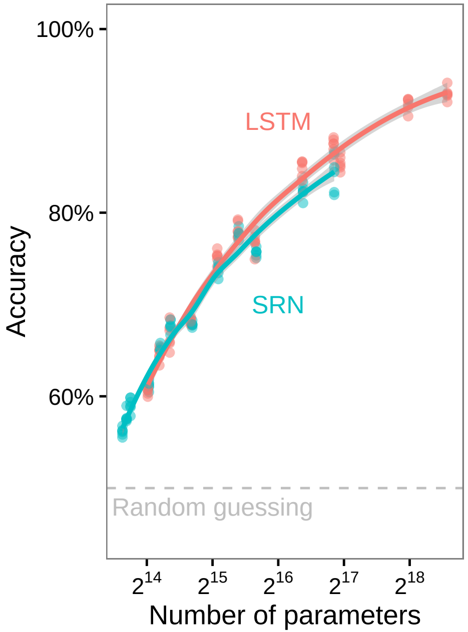

Accuracy
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Random guessing
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  - Run humans on the spot-the-word task

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- The number of parameters is by far the most important determinant of performance: depth isn't useful

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- Our code is available at `https://github.com/bootphon/char_rnn_lexical_decision`

Acknowledgements

- European Research Council (grant ERC-2011-AdG 295810 BOOTPHON)
- Agence Nationale pour la Recherche (grants ANR-10-IDEX-0001-02 PSL and ANR-10-LABX-0087 IEC)

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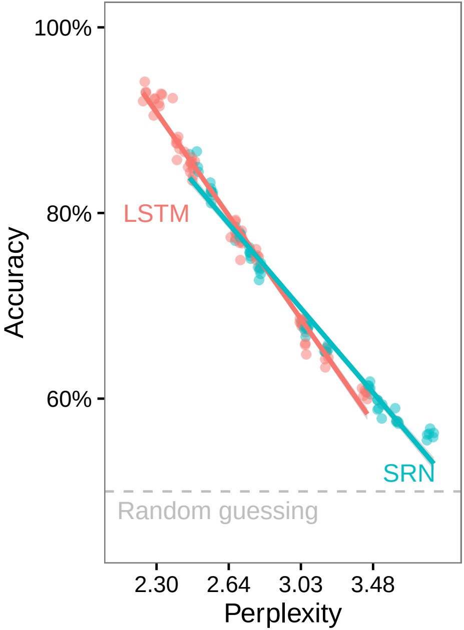
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Balota, D. A., Yap, M. J., Cortese, M. J., Hutchison, K. A., Kessler, B., Loftis, B., … Treiman, R. (2007). The English lexicon project. *Behavior Research Methods*, *39*(3), 445–459.

Berg-Kirkpatrick, T., Burkett, D., & Klein, D. (2012). An empirical investigation of statistical significance in nlp. In *Proceedings of the 2012 joint conference on empirical methods in natural language processing and computational natural language learning* (pp. 995–1005).

Karpathy, A., Johnson, J., & Li, F.-F. (2016). Visualizing and understanding recurrent networks. In *Proceedings of international conference on learning representations.*

Keuleers, E., & Brysbaert, M. (2010). Wuggy: A multilingual pseudoword generator. *Behavior Research Methods*, *42*(3), 627–633. Retrieved from `http://dx.doi.org/10.3758/BRM.42.3.627` doi: 10.3758/BRM.42.3.627

Lau, J. H., Clark, A., & Lappin, S. (2016). Grammaticality, acceptability, and probability: A probabilistic view of linguistic knowledge. *Cognitive Science*.

Linzen, T., Dupoux, E., & Goldberg, Y. (2016). Assessing the ability of LSTMs to learn syntax-sensitive dependencies. *Transactions of the Association for Computational Linguistics*, *4*, 521–535.