Collapse All

Introduction

Required Reading

- Course Syllabus (https://yale.instructure.com/courses/68546/assignments/syllabus)
- Mathematical Notation

Optional Reading

Read the following pair of articles to get a sense of the machine learning and linguistic perspectives that we discussed in the first class. The Lasnik and Lidz paper especially provides some excellent examples of "poverty of the stimulus" arguments that motivate the need for some sort of inductive bias in language learning.

- Peter Norvig (2011). On Chomsky and the Two Cultures of Statistical Learning. (http://norvig.com/chomsky.html)
- Howard Lasnik and Jeffrey L. Lidz (2016). The Argument from the Poverty of the Stimulus. In The Oxford Handbook of Universal Grammar, Ian Roberts (ed.). (https://www.oxfordhandbooks.com/view/10.1093/oxfordhb/9780199573776.001.0001/oxfordhb-9780199573776-e-10)

The following youtube link points to an interview with Chomsky, in which he discusses his views on deep learning and what it tells us about the human language faculty. Listen especially to the part starting at 19:32 up through 28:00.

- Lex Friedman and Noam Chomsky (2019). AI Podcast: Language, Cognition, and Deep Learning. (https://www.youtube.com/watch?v=cMscNuSUy0I)

Semantics (Sep. 7–9)

Required Reading

- Course Notes Chapter 1 (last section optional)
- D2L Section 2.3
- D2L Section 14.2.1 (https://www.d2l.ai/chapter_natural-language-processing-pretraining/approx-training.html#negative-sampling)
- Anaconda, the recommended software platform for this course (https://www.anaconda.com/)

Slides

- Tuesday, Sept. 7
- Thursday, Sept. 9

- Tuesday, Sept. 14

Optional Reading

- The judge's opinion in White City Shopping Center vs. Panera (https://casetext.com/case/white-city-v-pr-restaurants)
- The WordNet ontology, official website (https://wordnet.princeton.edu/)
- Kollar et al. (2018): Technical paper on the Amazon Alexa ontology (https://www.amazon.science/publications/the-alexa-meaning-representation-language)
- NumPy Documentation (https://numpy.org/doc/stable/user/whatisnumpy.html)
- PCA in scikit-learn (https://scikit-learn.org/stable/modules/decomposition.html#pca)
- t-SNE in scikit-learn (https://scikit-learn.org/stable/modules/manifold.html#t-sne)
- Goldberg and Levy (2014): Technical paper framing SGNS as a binary classification problem (https://arxiv.org/abs/1402.3722)

Principles of Machine Learning and Neural Networks (Sep. 14–21)

Required Reading

- Course Notes Sections 2.1–2.3

- D2L Section 2.1
- D2L Section 3.1

Slides

- Thursday, Sept. 16
- Tuesday, Sept. 21

Basics of Neural Networks

You can find discussions of this material in a wide variety of sources that assume a wide range of backgrounds. Choose the one that works best for you, or look at a couple to get a variety of perspectives.

- Goldberg, chapters 2 through 4. (https://www.morganclaypool.com/doi/10.2200/S00762ED1V01Y201703HLT037)
- Michael Nielson (2019). Neural Networks and Deep Learning, chapter 1. (http://neuralnetworksanddeeplearning.com/chap1.html)
- The Deep Learning Book, sections 6.1-6.4. (http://www.deeplearningbook.org/contents/mlp.html)

The following is a nice video that gently introduces the structure of neural networks.

3Blue1Brown videos on Neural Networks: But what is a Neural Network? (https://www.youtube.com/watch?v=aircAruvnKk&list=PLZHQObOWTQDNU6R1_67000Dx_ZCJB-3pi&index=2&t=0s)

sep23.pdf

Learning as optimization and backpropogation

Readings on neural network training

Goldberg, chapter 5 (https://www.morganclaypool.com/doi/10.2200/S00762ED1V01Y201703HLT037)

Michael Nielson (2019), Neural Networks and Deep Learning, chapters 2-3. (http://neuralnetworksanddeeplearning.com/chap2.html)

Jurafsky and Martin, section 7.4 (https://web.stanford.edu/~jurafsky/slp3/7.pdf)

Deep Learning Book, section 6.5 and chapter 7. (if you really want to dig in, you can also look at chapter 8.) (http://www.deeplearningbook.org)

Lecture notes

sep28.pdf

sep30.pdf

oct5.pdf

Recurrent Neural Networks

SRNs and sequence models

Jurafsky and Martin chapter 9 through section 9.3

D2L chapter 8 (https://d2l.ai/chapter_recurrent-neural-networks/index.html)

Deep Learning Book, chapter 10

Goldberg, chapters 14-16

Jeffrey L. Elman (1991) Distributed Representations, Simple Recurrent Networks, and Grammatical Structure, Machine Learning 7.

Andrej Karpathy (2015) The Unreasonable Effectiveness of Recurrent Neural Networks, blog post.

Vanishing gradients and fancy sequence models

Jurafsky and Martin, section 9.4

Chris Olah (2015) Understanding LSTM networks, blog post.

Slides

oct7.pdf

oct12.pdf

oct14.pdf

Encoder-Decoder Networks

Jurafsky and Martin, chapter 10 draft: Encoder-Decoder Models, Attention, and Contextual Embeddings (http://web.stanford.edu/~jurafsky/slp3/10.pdf)

Goldberg, chapter 17 (https://www.morganclaypool.com/doi/abs/10.2200/S00762ED1V01Y201703HLT037)

slides

oct19.pdf

Transformer Networks

D2L chapter 10

The Illustrated Transformer (blog post)

The Annotated Transformer (paper annotations + code)

Slides

oct26.pdf

Oct. 26 Lecture Recording

oct28.pdf

nov2.pdf

Structured Neural Networks

nov4.pdf

Neural Networks and Grammar

Student paper presentation spreadsheet

Tal Linzen, Emmanuel Dupoux and Yoav Goldberg (2016). Assessing the ability of LSTMs to learn syntax-sensitive dependencies. Transactions of the Association for Computational Linguistics. (https://www.mitpressjournals.org/doi/abs/10.1162/tacl_a_00115)

nov9.pdf

- Lakretz et al. 2019
- Lin et al. 2019
- Slides: OpenSesame-YL&MC&ZM.pdf
- Williams et al. 2019
- Slides: A Broad-Coverage Challenge Corpus for Sentence Understanding through Inference.pdf
- McCoy et al. 2019
- Slides: Right for the Wrong Reasons_ Diagnosing Syntactic Heuristics in Natural Language Inference.pdf

▾ Neural Networks, Language Acquisition and Universal Grammar

- nov16.pdf
- McCoy, Frank and Linzen (2018) Revisiting the poverty of the stimulus: hierarchical generalization without a hierarchical bias in recurrent neural networks (https://yale.zoom.us/j/175558514)
- Slides: McCoyEtAl2018-YL&JM&WX.pdf
- White and Cotterell 2021
- Slides: Examining the Inductive Bias of Neural Language Models with Artificial Languages.pdf

- Ethan Wilcox, Roger Levy, Takashi Morita and Richard Futrell (2018). What do RNN language models learn about filler-gap dependencies? BlackboxNLP 2018. (https://www.aclweb.org/anthology/W18-5423/)
- Kim and Linzen 2020
- Christo Kirov and Ryan Cotterell (2018) Recurrent Neural Networks in Linguistic Theory: Revisiting Pinker and Prince (1988) and the Past Tense Debate (https://www.mitpressjournals.org/doi/abs/10.1162/tacl_a_00247)

Topic	Paper Authors	Paper Title and Link
Neural Networks and Grammar	Linzen et al. (2016)	Assessing the ability of LSTMs to learn syntax-sensitive dependencies
	Lakretz et al. (2019)	The Emergence of Number and Syntax Units in LSTM Language Models
	Lin et al. (2019)	Open Sesame: Getting Inside BERT's Linguistic Knowledge
	Williams et al. (2019)	A Broad-Coverage Challenge Corpus for Sentence Understanding through Inference
	McCoy et al. (2019)	Right for the Wrong Reasons: Diagnosing Syntactic Heuristics in Natural Language Inference
	McCoy et al. (2020)	Revisiting the poverty of the stimulus: hierarchical generalization without a hierarchical bias in recurrent neural networks
Neural Networks, Language Acquisition, and Universal Grammar	White and Cotterell (2021)	Examining the Inductive Bias of Neural Language Models with Artificial Languages
	Wilcox et al. (2018)	What do RNN language models learn about filler-gap dependencies?
	Kim and Linzen (2020)	COGS: A Compositional Generalization Challenge Based on Semantic Interpretation
	Kirov and Cotterell (2018)	Recurrent Neural Networks in Linguistic Theory: Revisiting Pinker and Prince (1988) and the Past Tense Debate
	Misra et al. (2020)	Exploring BERT's Sensitivity to Lexical Cues using Tests from Semantic Priming
Neural Networks, Language, and Cognition	Abnar et al. (2019)	Blackbox Meets Blackbox: Representational Similarity & Stability Analysis of Neural Language Models and Brains
	Hao et al. (2020)	Probabilistic Predictions of People Perusing: Evaluating Metrics of Language Model Performance for Psycholinguistic Modeling
	Wehbe et al. (2014)	Aligning context-based statistical models of language with brain activity during reading
	Schwartz and Mitchell (2019)	Understanding language-elicited EEG data by predicting it from a fine-tuned language model
	Strubell et al. (2019)	Energy and Policy Considerations for Deep Learning in NLP
Neural Networks, Society, and the Ethics of Language Technology	Bender and Koller (2020)	Climbing towards NLU: On Meaning, Form, and Understanding in the Age of Data
	Caliskan et al. (2017)	Semantics derived automatically from language corpora contain human-like biases
	Bolukbasi et al. (2016)	Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings
	Gonen and Goldberg (2019)	Lipstick on a Pig: Debiasing Methods Cover up Systematic Gender Biases in Word Embeddings But do not Remove Them