Natural Language Processing

Deep Learning — Units 5 & 6

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Slides available at jonkrohn.com/talks

August 4th, 2018

Outline

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Two Core Concepts

1. Deep Learning
2. Natural Language Processing (NLP)

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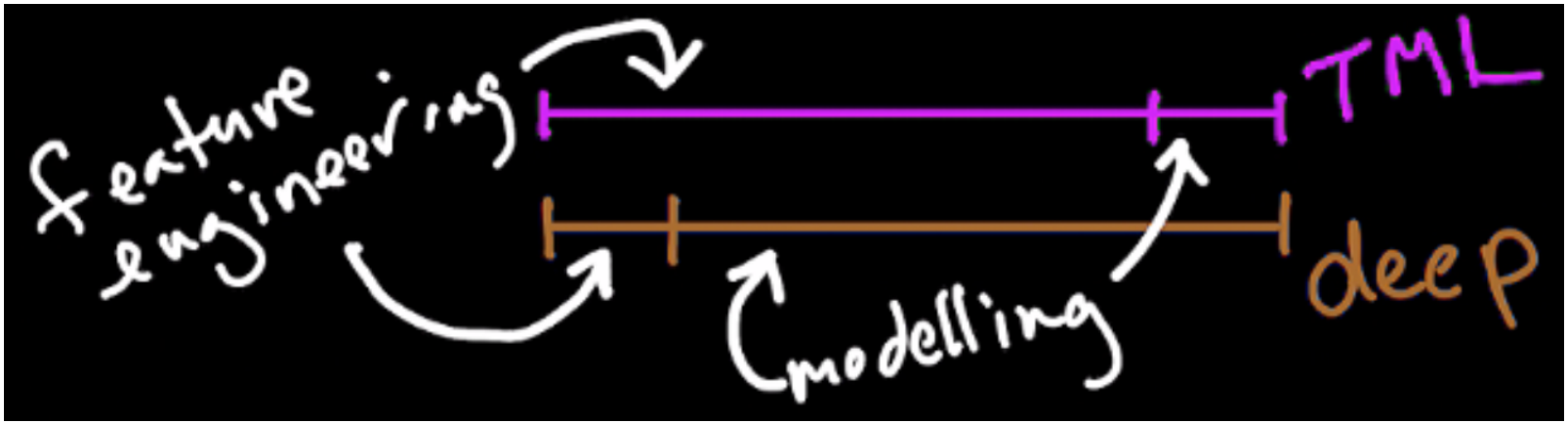
TML vs Deep Learning



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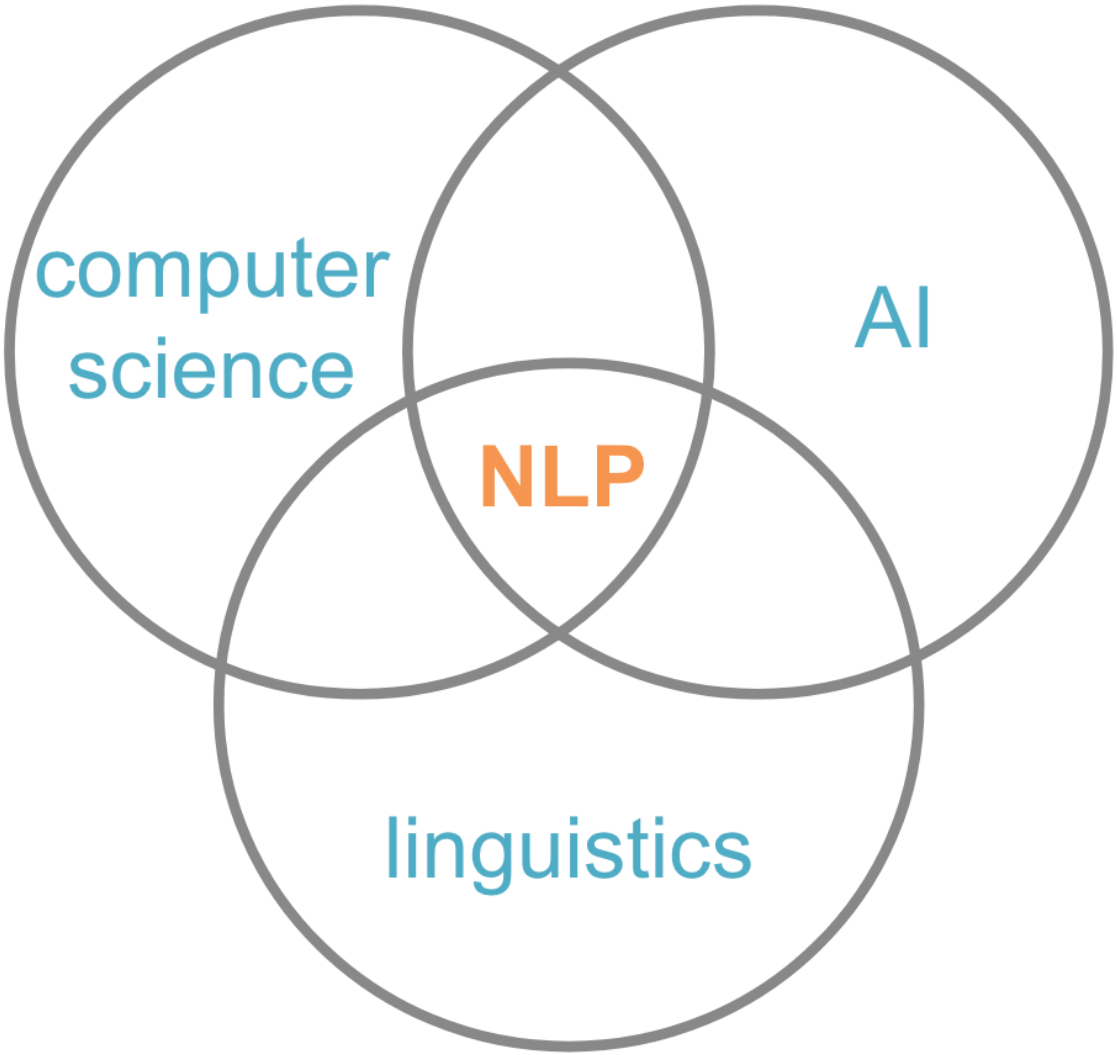
Natural Language Processing



Examples of NLP in Industry

- speech recognition (Echo, Siri, Cortana)
- search (typed into omnibox, spoken)
- classifying documents
- language translation
- chatbots

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One-Hot Word Representations

word	The	cat	sat	on	the	mat.
the	1	0	0	0	1	0
cat	0	1	0	0	0	0
on	0	0	0	1	0	0
⋮						
n_{unique_words}						

Outline

Easy

- spell checking
- synonym suggestions
- keyword search

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Intermediate

- reading level
- extracting information
- predicting next words
- classification
- sequence generation
- time-series analysis

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Complex

- machine translation
- question-answering
- chatbots

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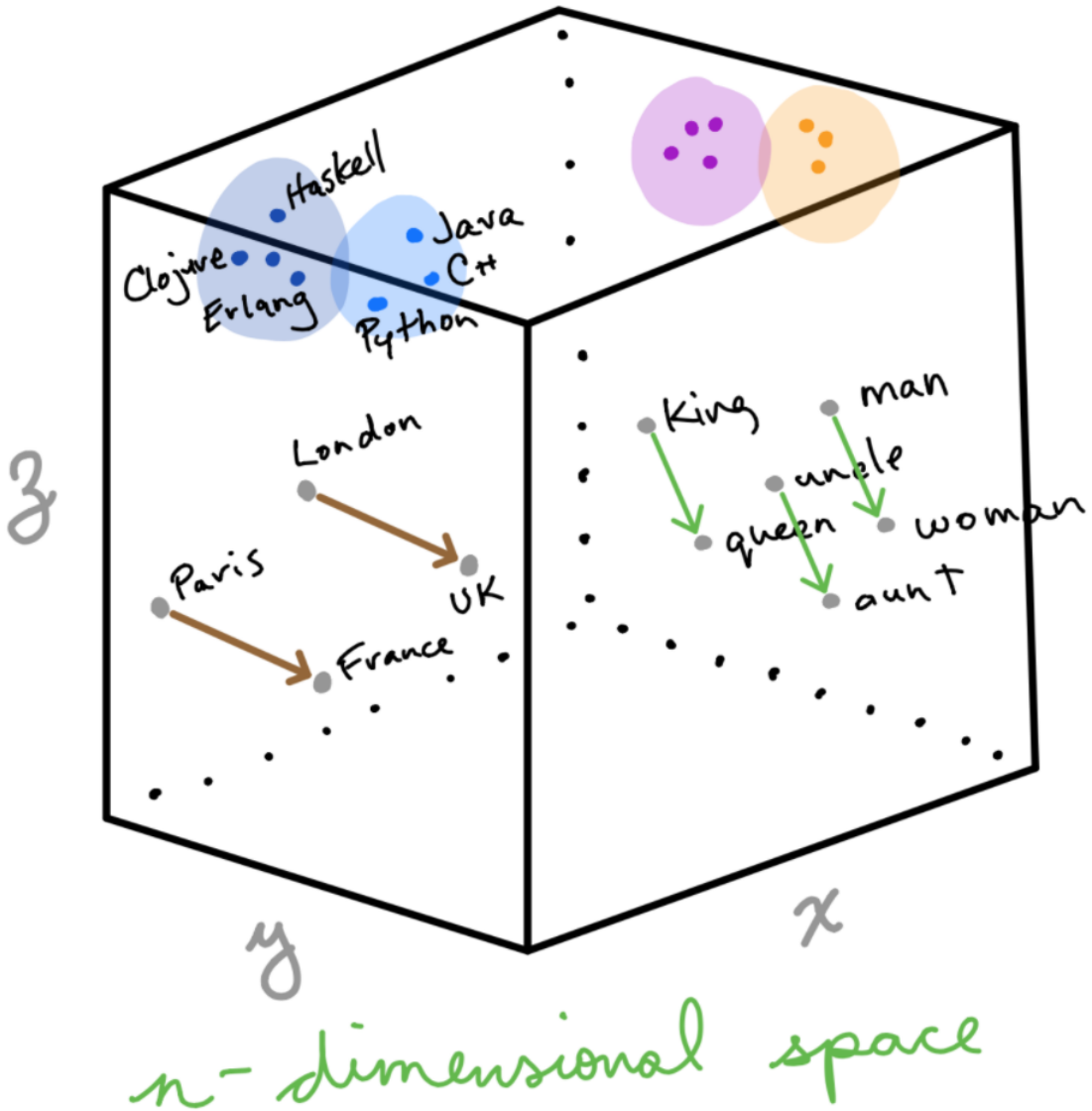
JR Firth (1957)

"You shall know a word by the company it keeps"

Vector Representations of Words



Word Vector Arithmetic

$$v_{king} - v_{man} + v_{woman} = v_{?}$$

$$v_{jeff\_bezos} - v_{amazon} + v_{facebook} = v_{?}$$

$$v_{windows} - v_{microsoft} + v_{google} = v_{?}$$

$$v_{cu} - v_{copper} + v_{gold} = v_{?}$$

[word2viz demo]

Word Representations

One-Hot	Vector-Based
lack nuance	extremely **nuanced**
handle new words poorly	seamlessly incorporate **new words**
subjective	**driven by** natural language **data**
laborious, manual taxonomies	fully-**automatic**
word similarity ignored	**word similarity** = closeness in space
unwieldy with large vocabulary	accommodate **large vocabularies**

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Word Representations

	predicts	**relative strengths**
Skip-Gram (SG)	context given target	• small data set • rare words
CBOW	target given context	• many times faster • slightly better for frequent words

Evaluating Word Vectors

1. intrinsic
2. extrinsic

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1. intrinsic
2. extrinsic

word2vec Hyperparameters

1. *n* dimensions
2. window size (SG ~10, CBOW ~5)
3. *n* iterations
4. data set size

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[*creating word vectors* notebook]

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Best Practices for Preprocessing NLP Data

[*NL preprocessing best practices* notebook]

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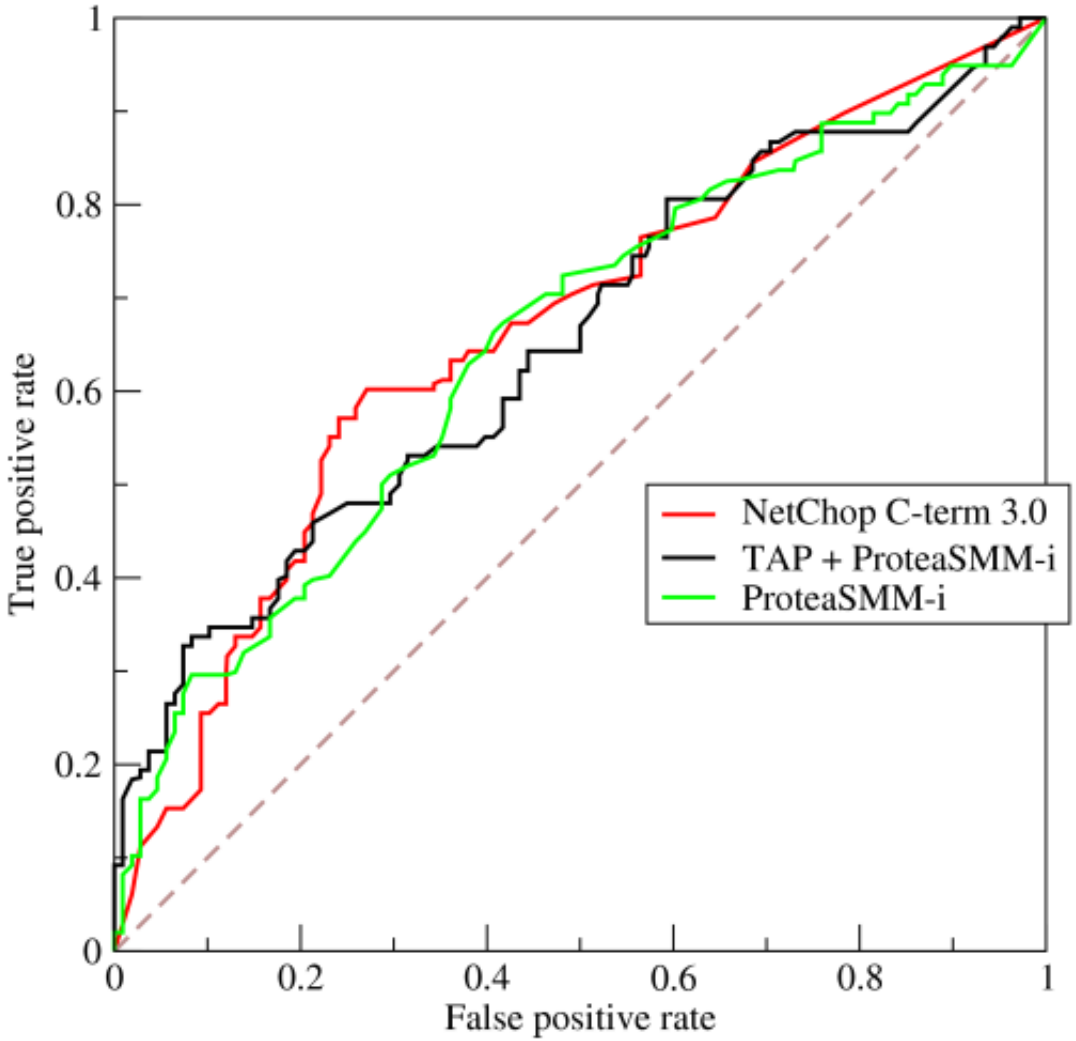
The Area Under the ROC Curve



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Dense Net Classification

[*dense sentiment classifier* notebook]

ConvNet Classification

[*convolutional sentiment classifier* notebook]

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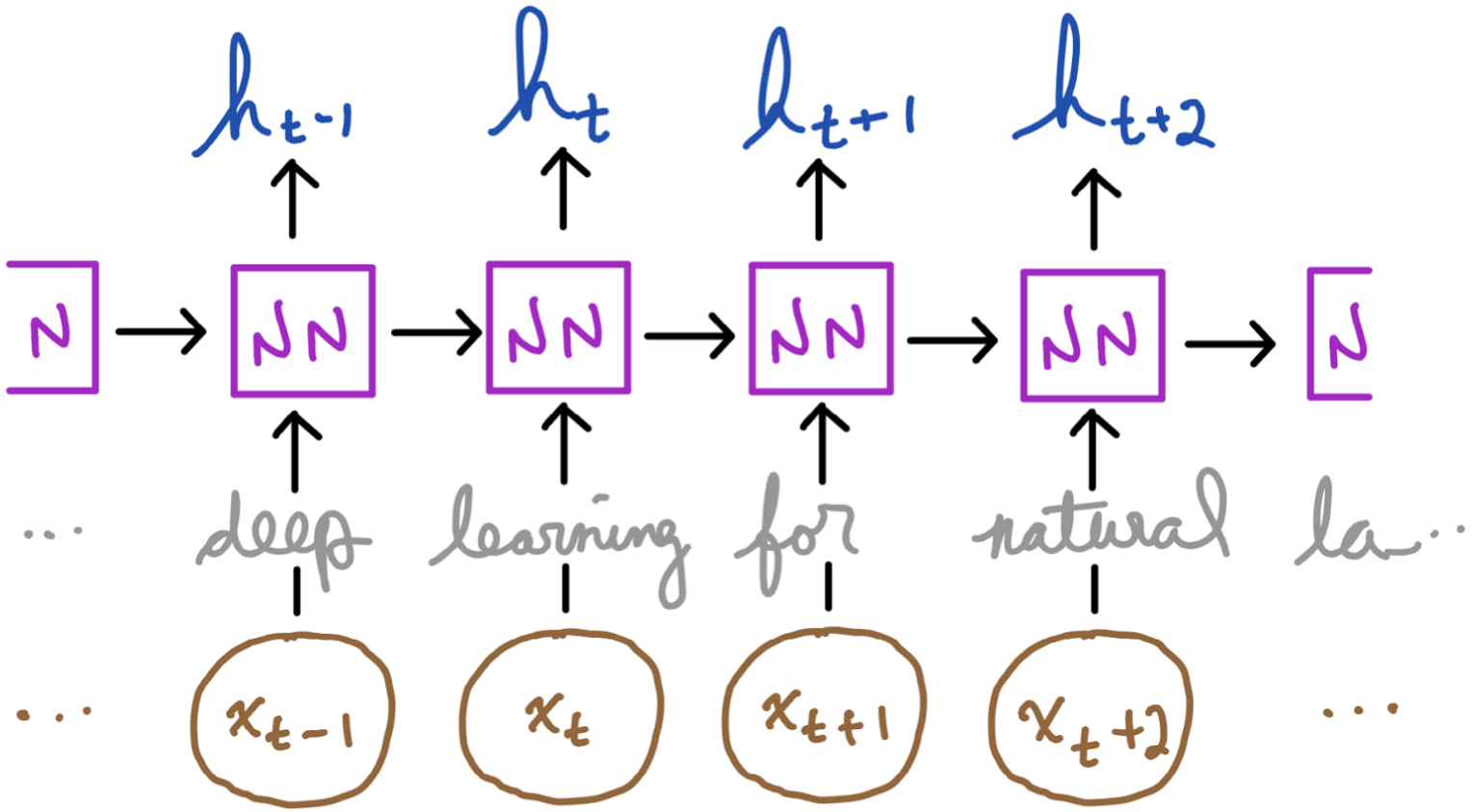
RNN Theory

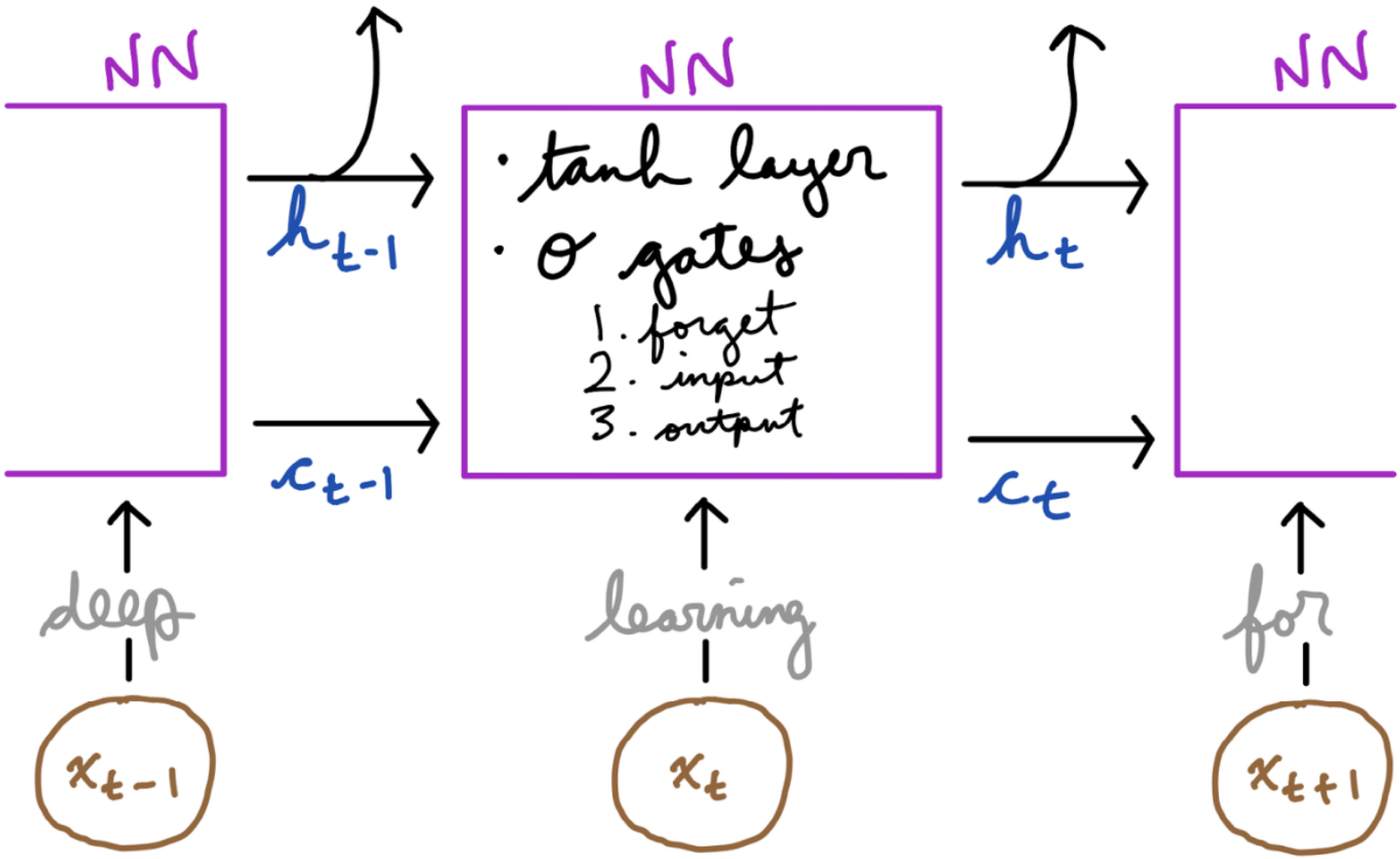


RNNs in Practice

[*rnn* notebook]

Outline

LSTM Theory



LSTMs in Practice

[*vanilla LSTM* and *GRU* notebooks]

Bi-Directional LSTMs

[*Bi-LSTM* notebook]

Stacked LSTMs

[*stacked LSTM* and *ye olde stackeroo* notebooks]

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Parallel Network Architectures

[*multi-ConvNet* notebook]

Assessing

Your Deep Learning Project III

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1. split your data
   - training set (80% — for optimizing parameters)
   - validation set (10% — for hyperparameters)
   - test set (10% — don't touch yet!)
2. build and assess architecture
   - get above chance (simplifying problem, if necessary)
   - do existing performance benchmarks exist?
   - if not, use a simple architecture as benchmark
3. "teamwork makes the dream work" (?)

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Up Next: TensorFlow

March 24trh