

Models for Sequences

Sequence Modeling tasks



- Classify sequences $x_1, \dots, x_n \rightarrow y$.

x_1 x_2 x_3 x_4 x_5 x_6 x_7 x_8 x_9
 (The Idols in Madden mess are to die for?)
 $y = \text{positive}$

- Sentiment classification, question intent classification, normal versus abnormal traffic

- Next word in a sequence $x_1, \dots, x_n \rightarrow x_{\{n+1\}}$

x_1 x_2 x_3 $x_4?$
 I woke up —

- Language modelling, forecasting.

- Label per token in sequence $x_1, \dots, x_n \rightarrow y_1, \dots, y_n$

$y \in \{\text{book title, author name, None}\}$

- POS, (Named entity recognition)

- Sequence prediction tasks $x_1, \dots, x_n \rightarrow y_1, \dots, y_m$

x : Have you read Goldberg's last Conjecture?
 x_1 x_2 x_3 x_4 x_5 x_6
 None None None Book title Book title Book title

- Translation, conversation assistant, speech recognition

More examples

- Forecasting (Time Series)

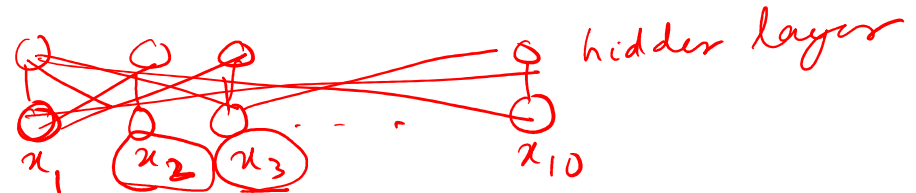
y_1, y_2, \dots, y_t outputs eg: demand for an item

x_1, x_2, \dots, x_t inputs

x_t : [day of the week, holiday?, temperature, month]

Why existing network architectures will not work

- Feed forward networks



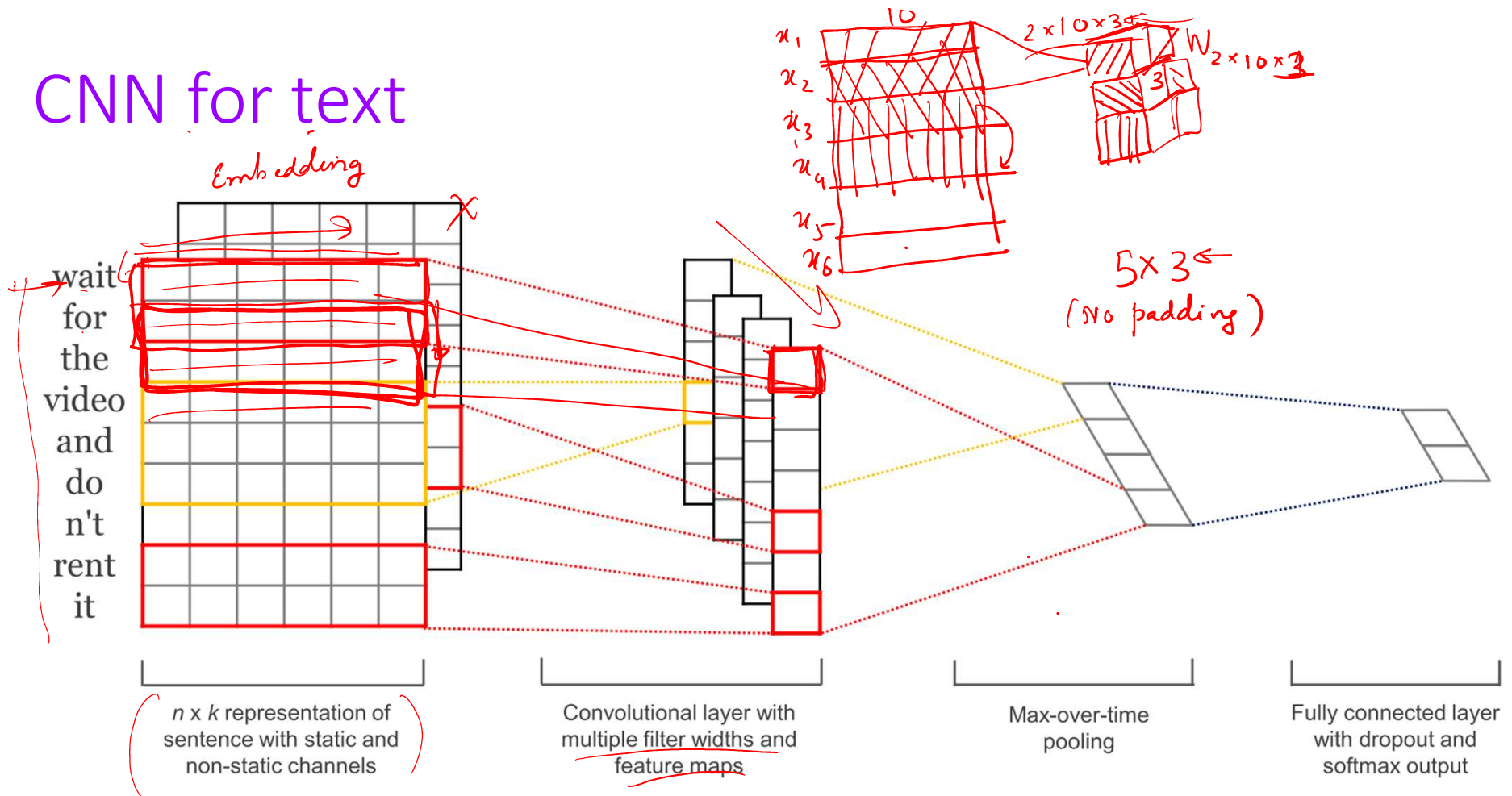
- Sequences can be of variable length. Can train only fixed number of parameters.
- Even when sequences were of fixed length, do we really need to train a parameter per input token?

- CNNs

- Designed to capture local patterns whereas in sequences interaction may be non-local. E.g.

■ He, after a vigorous workout, is enjoying a delicious breakfast with his friends.

CNN for text



RNN: Recurrent Neural Network

- A model to process variable length 1-D input
- In CNN, each hidden output is a function of corresponding input and some immediate neighbors.
- In RNN, each output is a function of a 'state' summarizing all previous inputs and current input. State summary computed recursively.
- RNN allows deeper, longer range interaction among ~~parameters~~ *input tokens* than CNNs for the same cost.

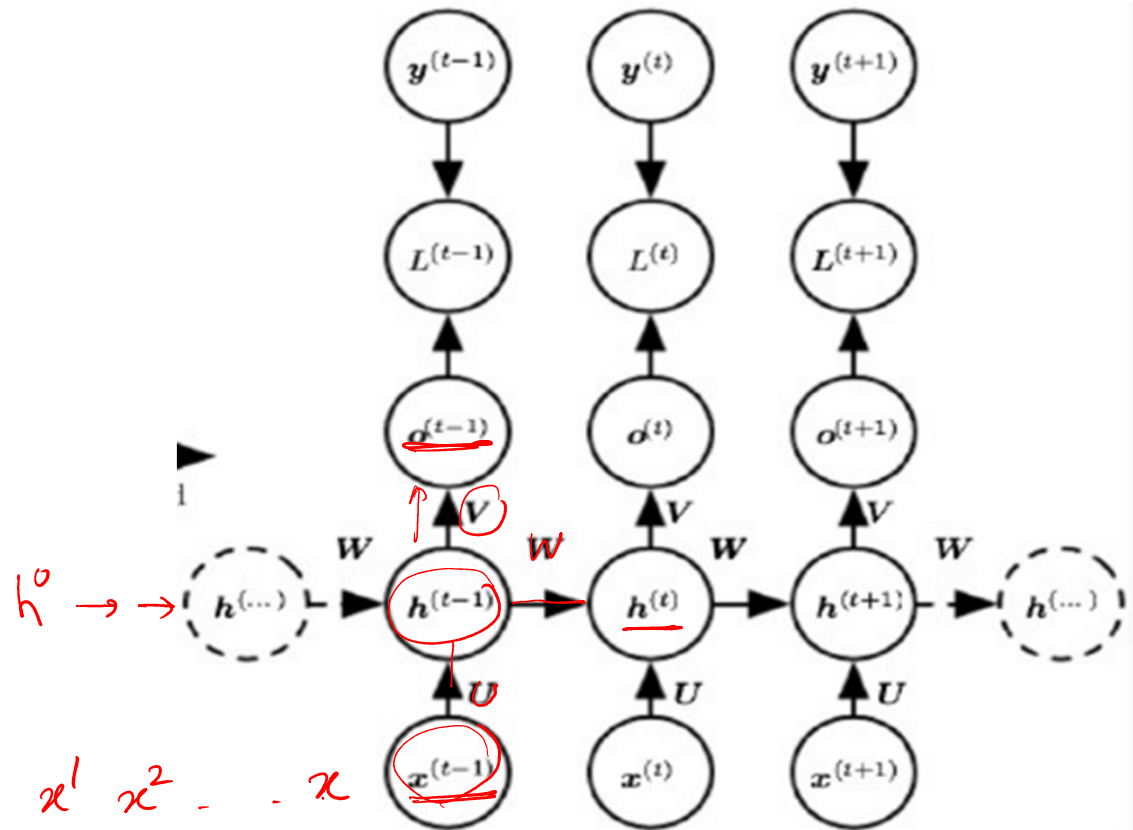
RNNs: Basic type

Notation:

- State to be denoted as $\underline{h_t}$ or $\underline{z_t}$
- Input to RNN can be x_t or y_t

$$\underline{h^t} = \sigma(\underline{b} + \underline{W}h^{t-1} + \underline{U}x^t)$$

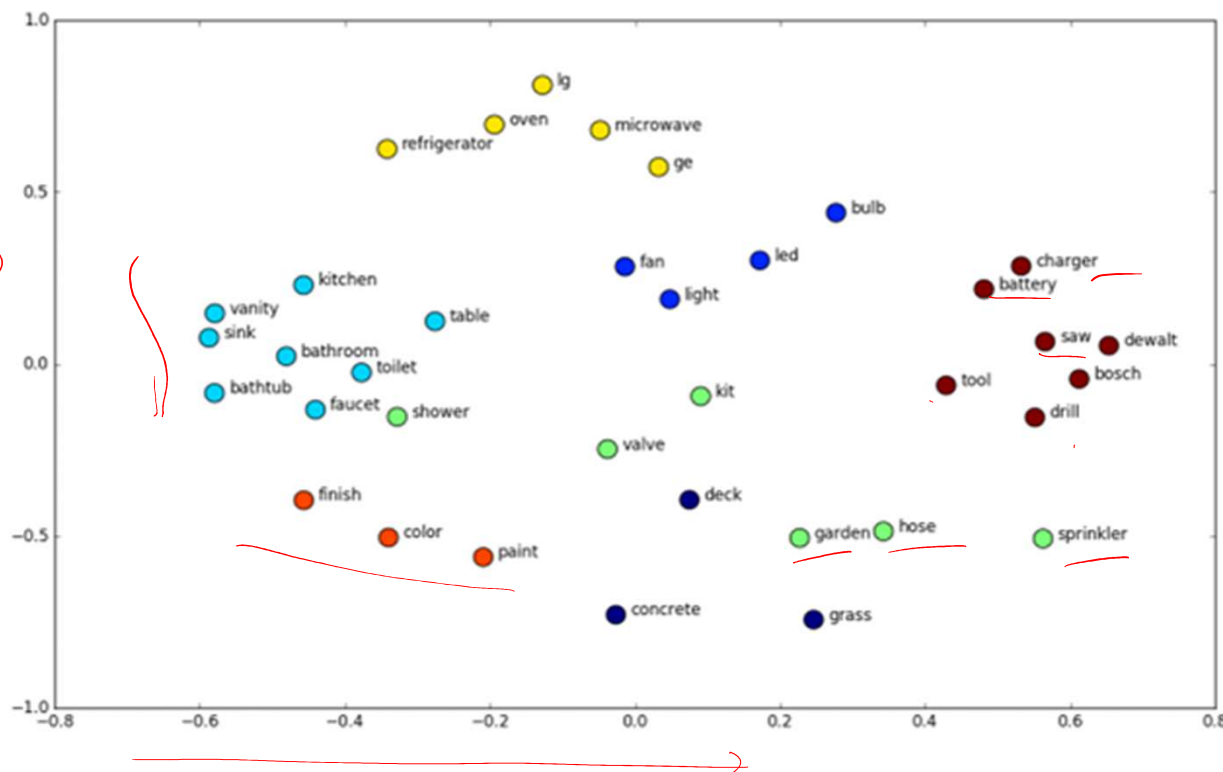
$$\underline{o^t} = \underline{c} + \underline{V}h^t,$$



Input: Text, Task: Text classification

- Input sequence: x_1, x_2, \dots, x_n
- Each x_t instead of a real-valued vector is a discrete word.
- The task is to predict a label for this text
 - Example: Spam or Not-spam
 - Sentiment or star rating of a review
 - Topic of a document
 - Intent of a query
- How to convert a discrete word into a real-value for input into a RNN?
- How to convert a variable length sentence as a fixed-dimensional vector

Word-embeddings: Represent each word as a point in a multi-dimensional space..

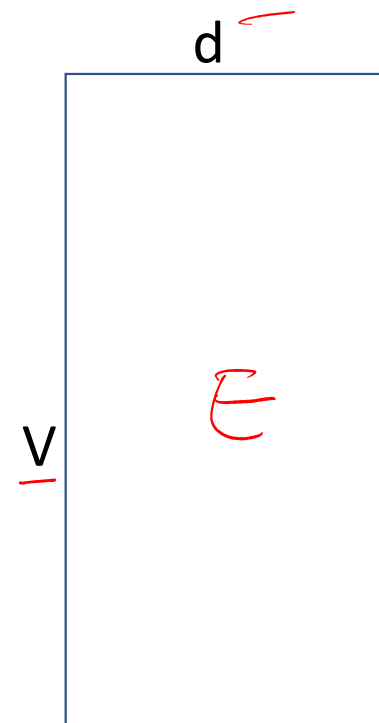


Similar words are close together in that space.

Src: <http://suriyadeepan.github.io/>

Word embeddings

- Choose the embedding size: d
 - Typical value for words: 128
- Choose the vocabulary size: V
 - Typical size: 30 thousand.
 - Rest are broken into subwords or UNKs.
- Embedding matrix: E
- If an input word x_t is a one-hot vector of size V , then embedding is obtained as $E^T x_t$

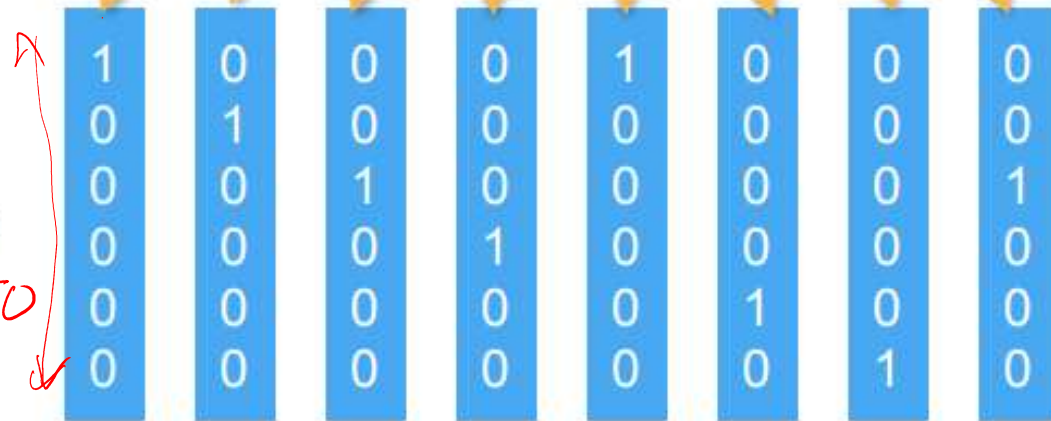


Input Encoding

T H E - T I M E

Canonical Vectors \mathbf{v}

$|V| = 50$
26 + 10 + punctual.



Embedding Matrix $\mathbf{W} \xrightarrow{E}$

10 = d

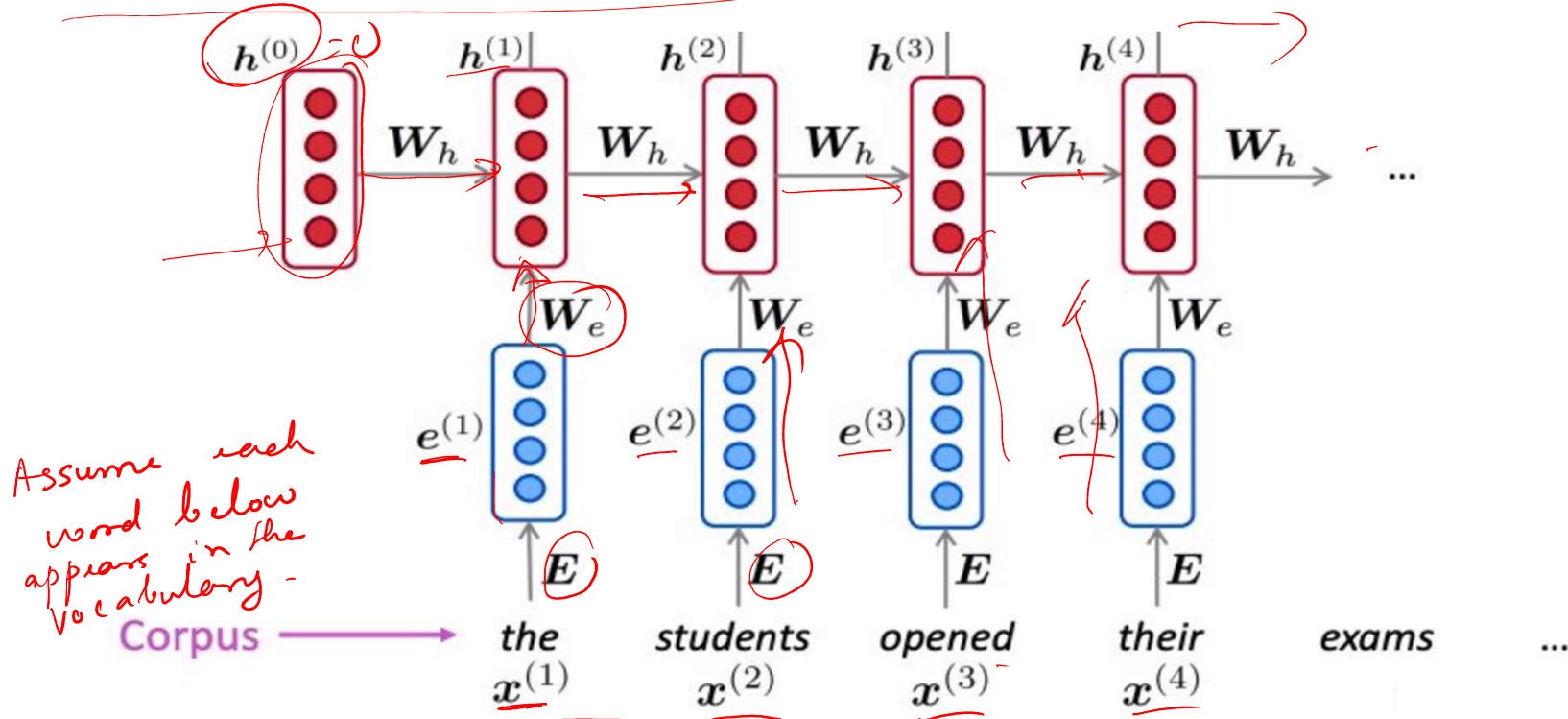
A B C D - ✓ 2 0 ... 9 - , ?

Embedded Vectors \mathbf{v}'

10



RNNs on sentences

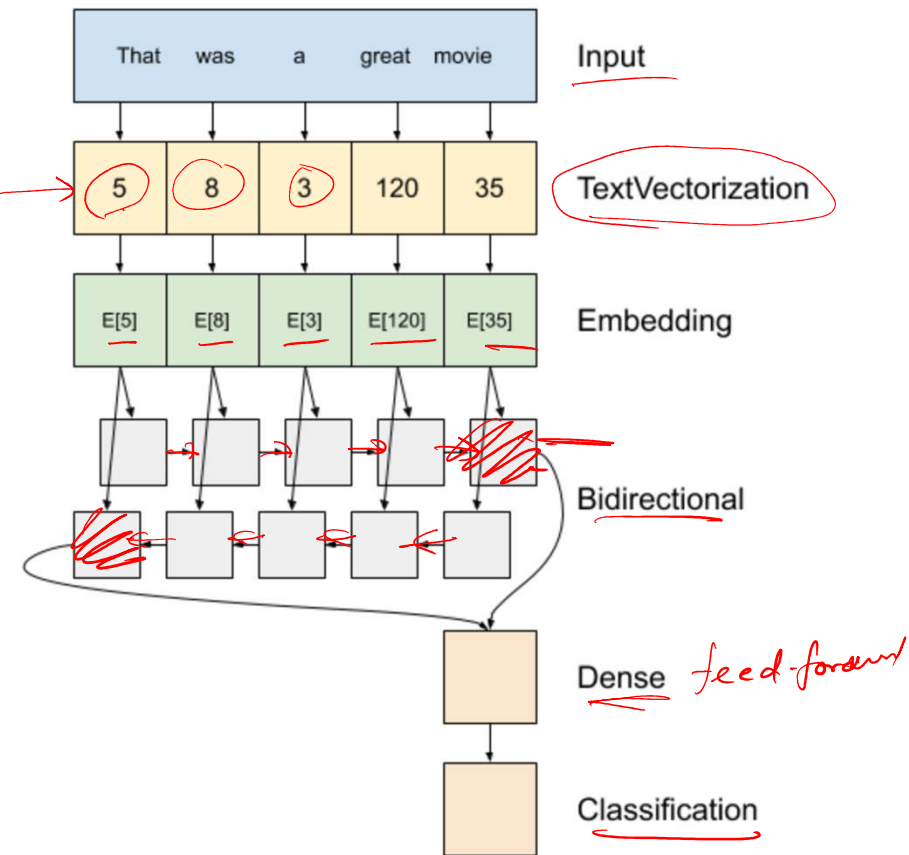


The last state (h) is the sentence encoding that converts variable length sentences into a fixed dimensional vector

Text classification with a bidirectional RNN.

All parameters including the word embeddings are trained end-to-end.

Token-id in the vocabulary



https://www.tensorflow.org/tutorials/text/text_classification_rnn

Gated RNNs

- Gates control which part of the long past is used for current prediction
- Gates also allow forgetting of part of the state
- LSTM: Long Short Term Memory, one of the most successful gated RNNs
[Not in syllabus]
- Gated Recurrent Units (GRU)
 - [Not in syllabus]
- An excellent introductions here:
 - <http://colah.github.io/posts/2015-08-Understanding-LSTMs/>
 - <http://blog.echen.me/2017/05/30/exploring-lstms/>
 - https://www.tensorflow.org/tutorials/text/text_generation