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Deep Learning Methods for Natural Language Processing

Garrett Hoffman
Director of Data Science @ StockTwits

Talk Overview

- Learning Distributed Representations of Words with Word2Vec
- Recurrent Neural Networks and their Variants
- Convolutional Neural Networks for Language Tasks
- State of the Art in NLP
- Practical Considerations for Modeling with Your Data

https://github.com/GarrettHoffman/AI_Conf_2019_DL_4_NLP

Learning Distributed Representations of Words with Word2Vec

Sparse Representation

A sparse, or one hot, representation is where we represent a word as a vector with a 1 in the position of the words index and 0 elsewhere

Sparse Representation

Let’s say we have a vocabulary of 10,000 words

V = [a, aaron, …., zulu, <UNK>]

Man (5,001) = [0 0 0 0 ... 1 ... 0 0]

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Woman (9,800) = [0 0 0 0 0 … 1 … 0]

Sparse Representation

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Man (5,001) = [0 0 0 0 … 1 … 0 0]

Woman (9,800) = [0 0 0 0 0 … 1 … 0]

King (4,914) = [0 0 0 … 1 … 0 0 0]

Queen (7,157) = [0 0 0 0 … 1 … 0 0]

Sparse Representation

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V = [a, aaron, …., zulu, <UNK>]

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King (4,914) = [0 0 0 … 1 … 0 0 0]

Queen (7,157) = [0 0 0 0 … 1 … 0 0]

Great (3,401) = [0 … 1 … 0 0 0 0 0]

Wonderful (9,805) = [0 0 0 0 0 … 1 … 0]

Sparse Representation Drawbacks

- The size of our representation increases with the size of our vocabulary

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- The representation doesn’t provide any information about how words relate to each other

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- The size of our representation increases with the size of our vocabulary
- The representation doesn't provide any information about how words relate to each other
    - E.g. "I learned so much at AI Conf and met tons of practitioners!", "Strata is a great place to learn from industry experts"

Distributed Representation

A distributed representation is where we represent a word as a prespecified number of latent features that each correspond to some semantic or syntactic concept

Distributed Representation

	Gender
Man	-1.0
Woman	1.0
King	-0.97
Queen	0.98
Great	0.02
Wonderful	0.01

Distributed Representation

	Gender	Royalty
Man	-1.0	0.01
Woman	1.0	0.02
King	-0.97	0.97
Queen	0.98	0.99
Great	0.02	0.15
Wonderful	0.01	0.05

Distributed Representation

	Gender	Royalty	...	Polarity
Man	-1.0	0.01	...	0.02
Woman	1.0	0.02	...	-0.01
King	-0.97	0.97	...	0.01
Queen	0.98	0.99	...	-0.02
Great	0.02	0.15	...	0.89
Wonderful	0.01	0.05	...	0.94

Word2Vec

One method used to learn these distributed representations of words (a.k.a. word embeddings) using the Word2Vec algorithm

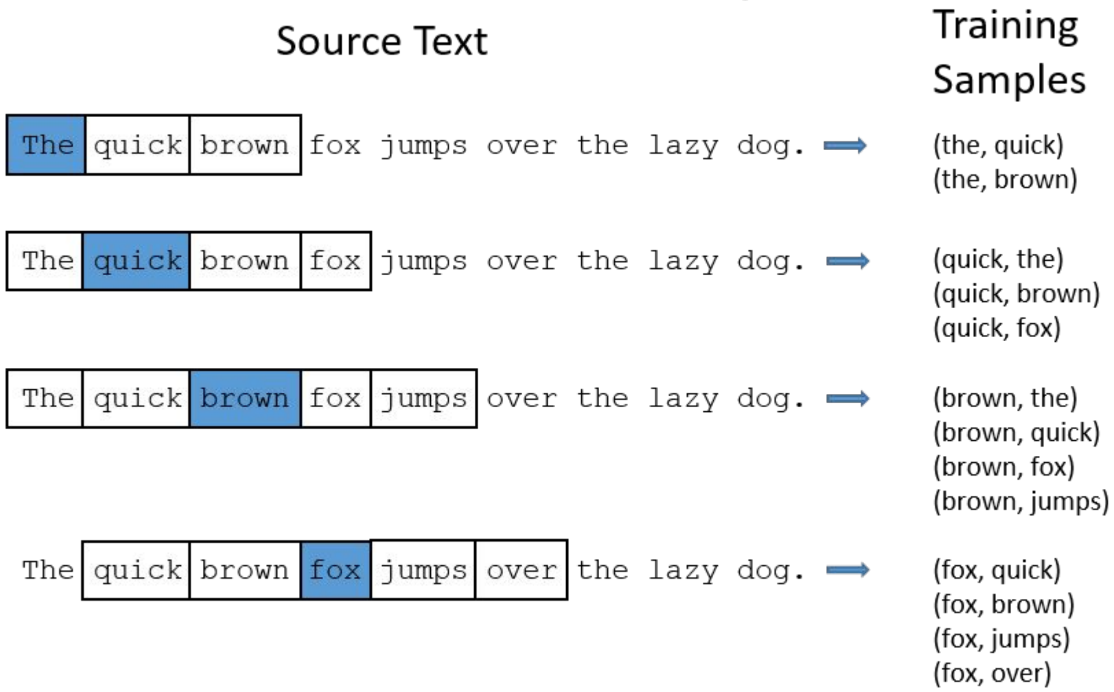
Word2Vec uses a 2-layered neural network to reconstruct the context of words

"Distributed Representations of Words and Phrases and their Compositionality", Mikolov et al. (2013)

“ *you shall know a word by the company it keeps*

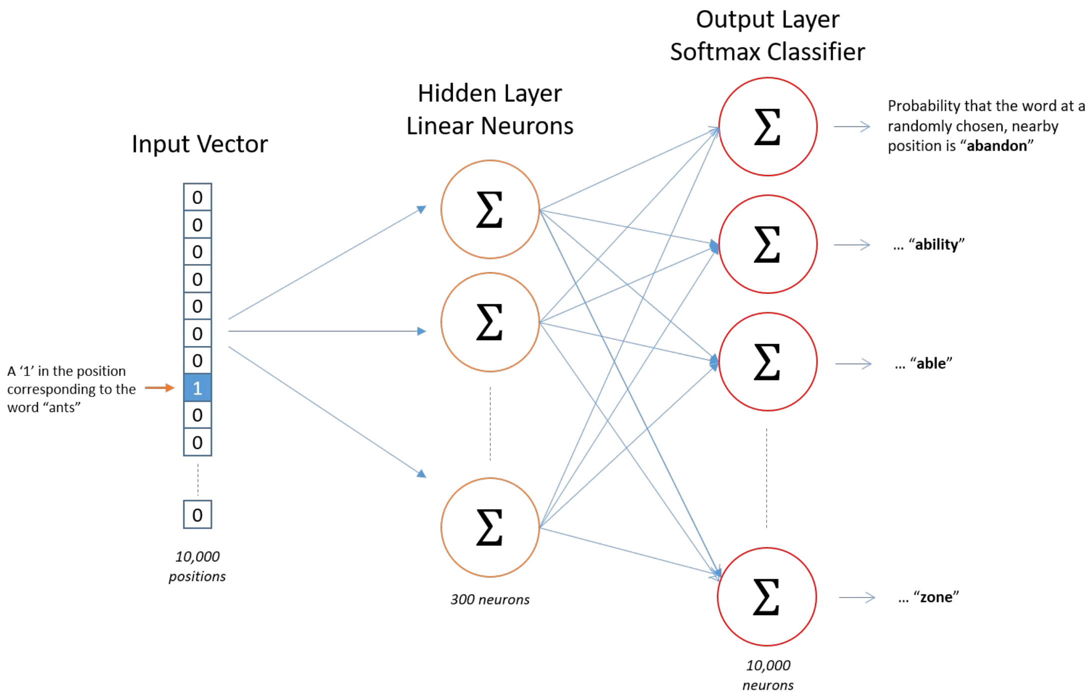
- *J.R. Firth*

Word2Vec - Generating Data



[McCormick, C. (2016, April 19). Word2Vec Tutorial - The Skip-Gram Model.]

Word2Vec - Skip-gram Network Architecture



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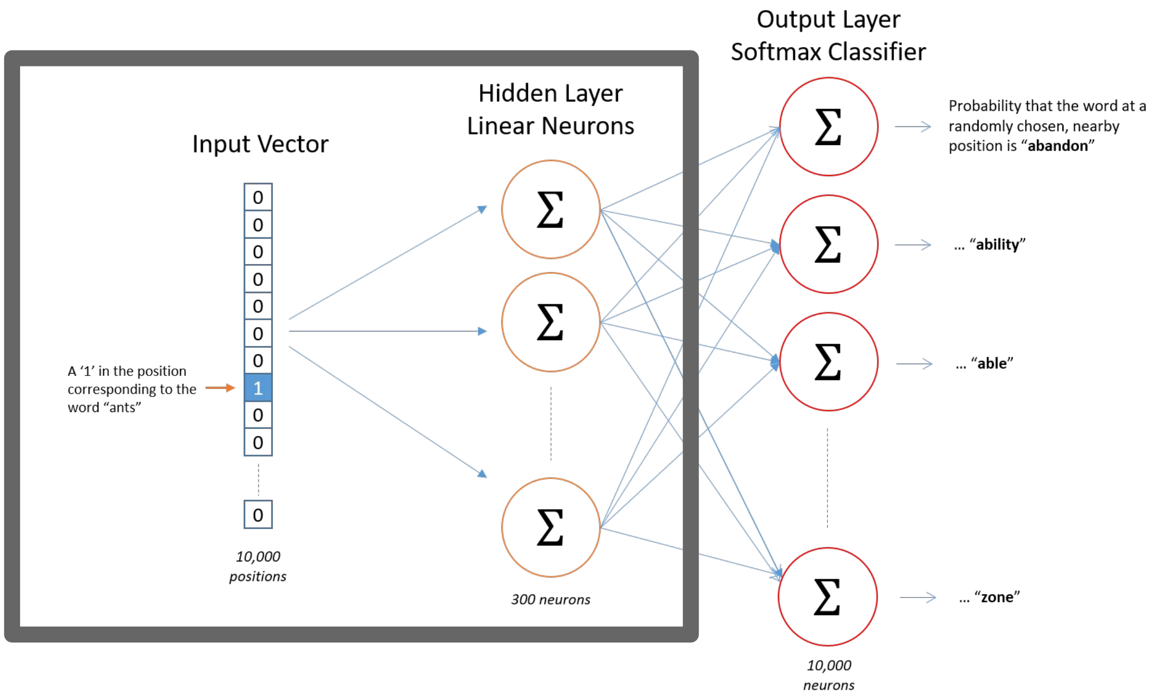
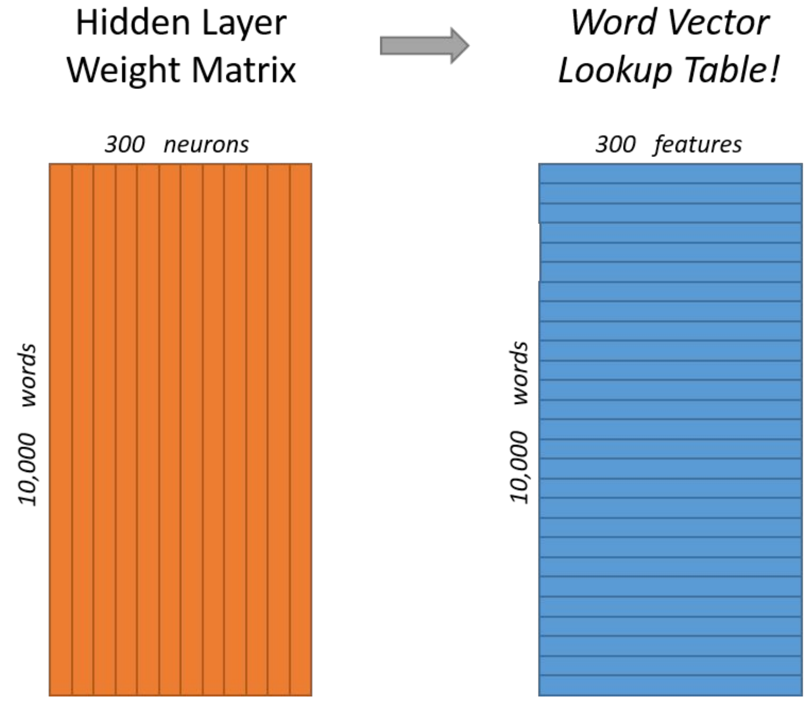


McCormick, C. (2016, April 19). Word2Vec Tutorial - The Skip-Gram Model.

Word2Vec - Embedding Layer



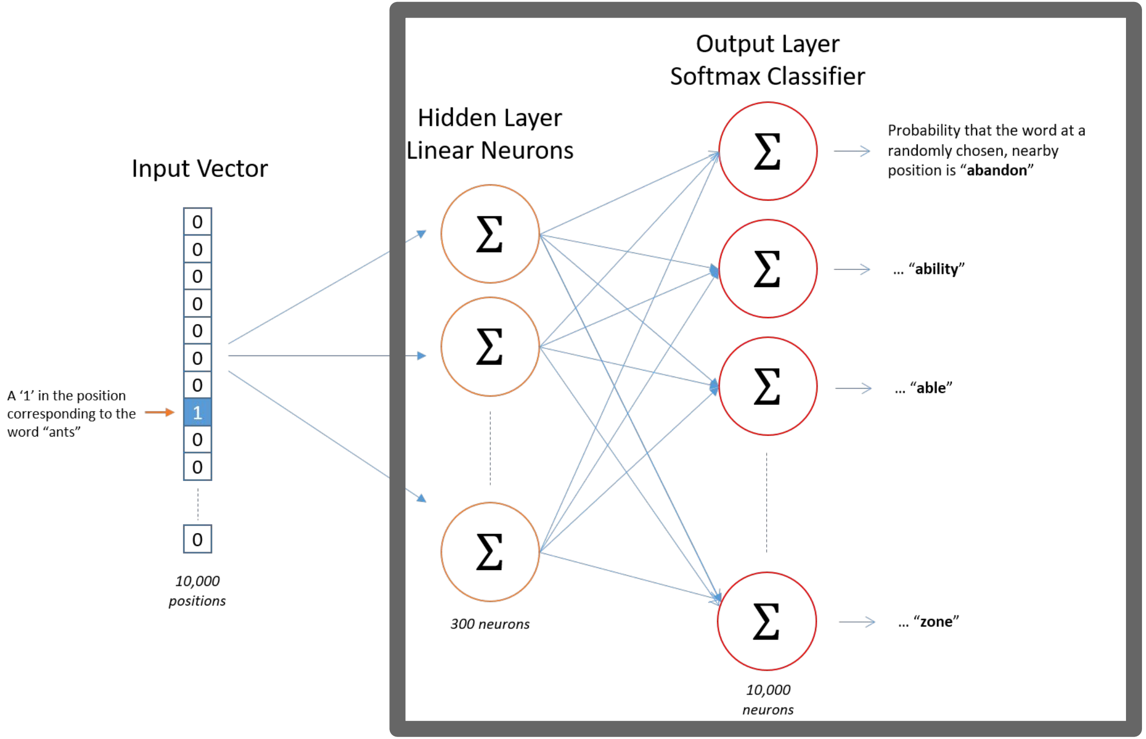
[McCormick, C. (2016, April 19). Word2Vec Tutorial - The Skip-Gram Model.]

Word2Vec - Embedding Layer

$$\begin{bmatrix} 0 & 0 & 0 & \boxed{1} & 0 \end{bmatrix} \times \begin{bmatrix} 17 & 24 & 1 \\ 23 & 5 & 7 \\ 4 & 6 & 13 \\ 10 & 12 & 19 \\ 11 & 18 & 25 \end{bmatrix} = \begin{bmatrix} 10 & 12 & 19 \end{bmatrix}$$

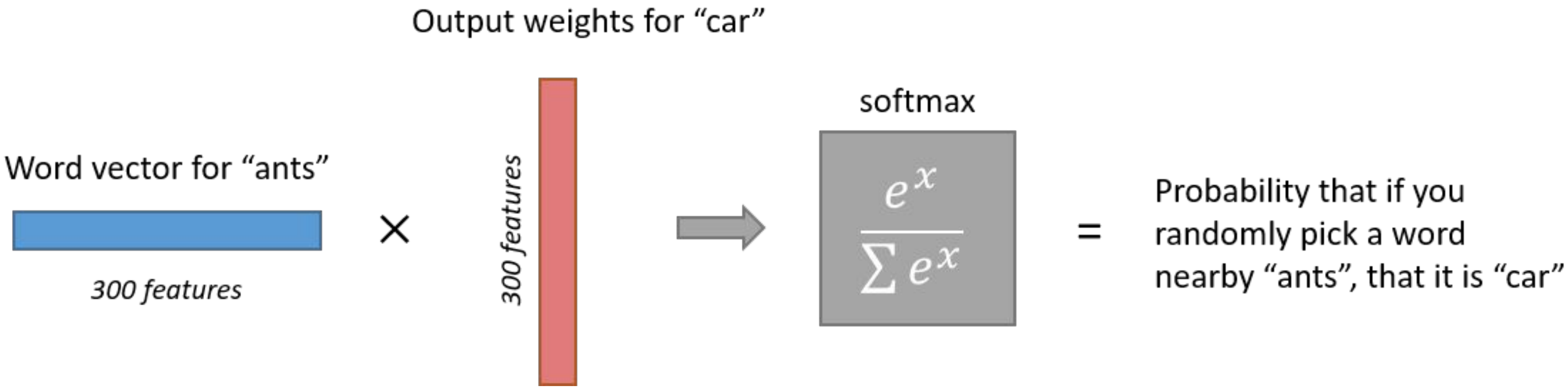
McCormick, C. (2016, April 19). Word2Vec Tutorial - The Skip-Gram Model.

Word2Vec - Skip-gram Network Architecture



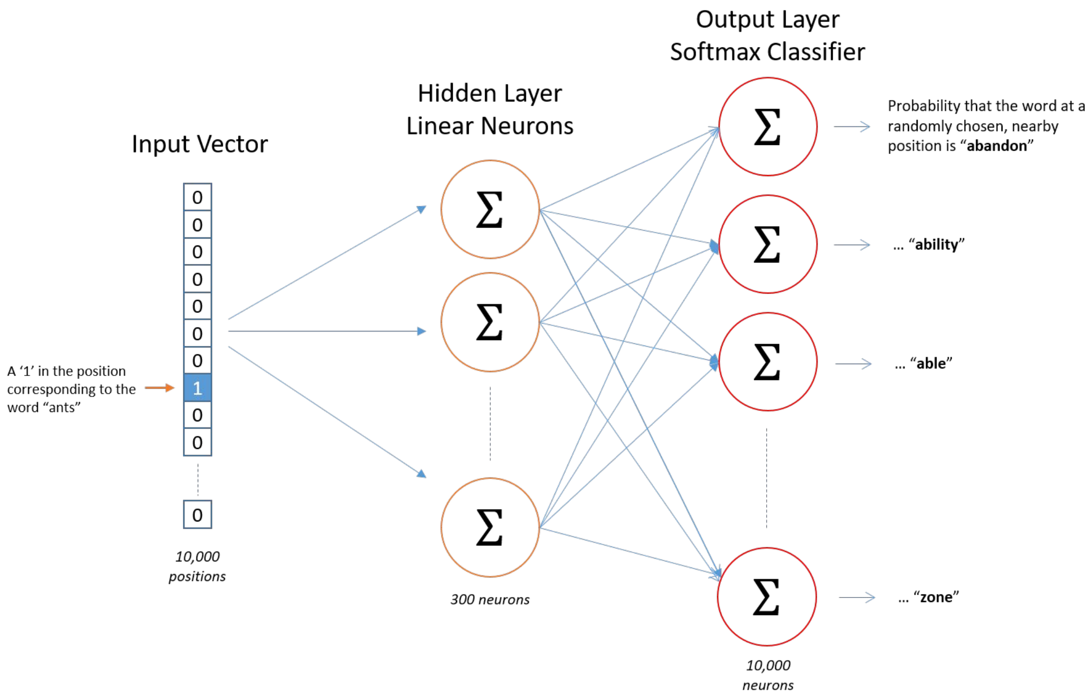
[McCormick, C. (2016, April 19). Word2Vec Tutorial - The Skip-Gram Model.]()

Word2Vec - Output Layer



[McCormick, C. (2016, April 19). Word2Vec Tutorial - The Skip-Gram Model.]

Word2Vec - Intuition



[McCormick, C. (2017, January 11). Word2Vec Tutorial Part 2 - Negative Sampling.]

Word2Vec - Negative Sampling

In our output layer we have 300 x 10,000 = 3,000,000 weights, but given that we are predicting a single word at a time we only have a single "positive" output out of 10,000 output.

McCormick, C. (2017, January 11). Word2Vec Tutorial Part 2 - Negative Sampling.

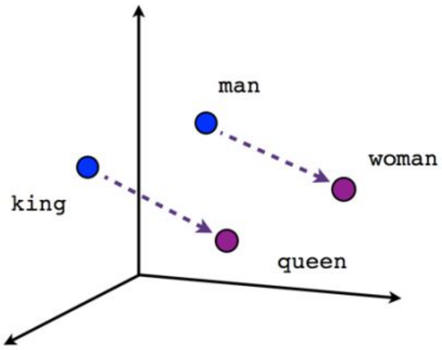
Word2Vec - Negative Sampling

In our output layer we have 300 x 10,000 = 3,000,000 weights, but given that we are predicting a single word at a time we only have a single “positive” output out of 10,000 output.

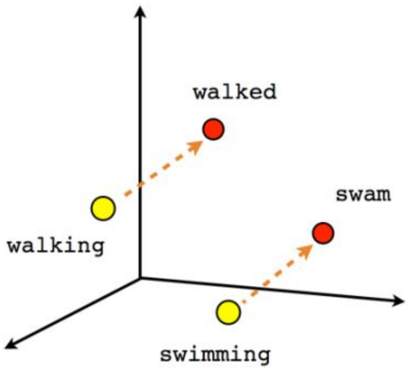
For efficiency, we will randomly update only a small sample of weights associated with “negative” examples. E.g. if we sample 5 “negative” examples to update we will only update 1,800 weights (5 “negative” + 1 “positive” * 300) weights.

[McCormick, C. (2017, January 11). Word2Vec Tutorial Part 2 - Negative Sampling.]

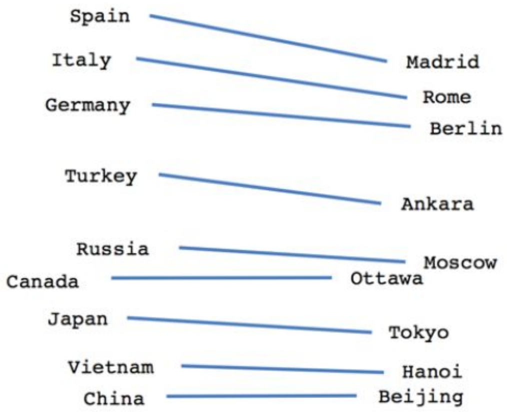
Word2Vec - Results



Male-Female



Verb tense



Country-Capital

https://www.tensorflow.org/tutorials/word2vec

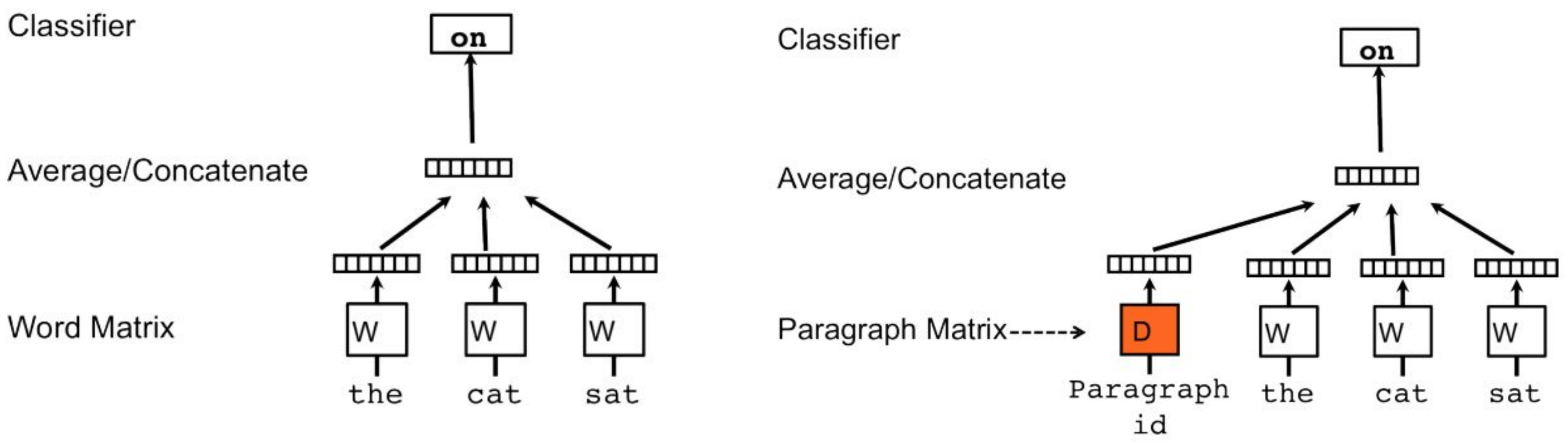
Pre-Trained Word Embedding

https://github.com/Hironsan/awesome-embedding-models

```
import gensim

# Load Google's pre-trained Word2Vec model.
model =
gensim.models.KeyedVectors.load_word2vec_format('./GoogleNew
s-vectors-negative300.bin', binary=True)
```

Doc2Vec



[Distributed Representations of Sentences and Documents]

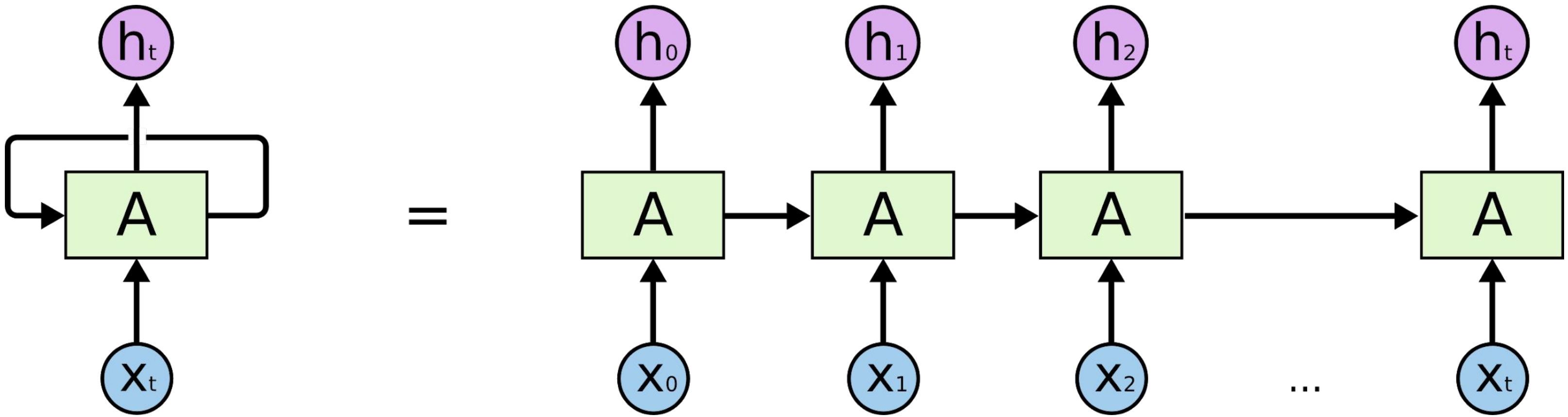
Recurrent Neural Networks and their Variants

Sequence Models

When dealing with text classification models, we are working with sequential data, i.e. data with some aspect of temporal change

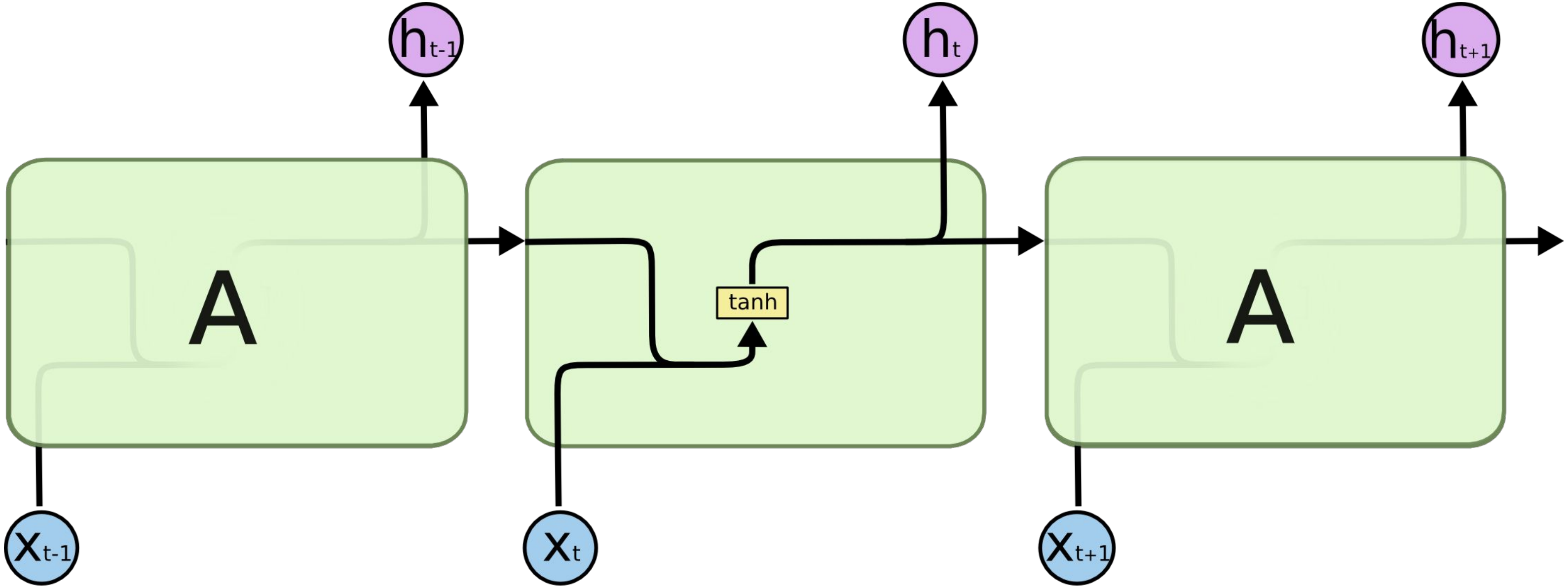
We are typically analyzing a sequence of words and our output can be a single value (e.g. sentiment classification) or another sequence (e.g. text summarization, language translation, entity recognition)

Recurrent Neural Networks (RNNs)



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Recurrent Neural Networks (RNNs)



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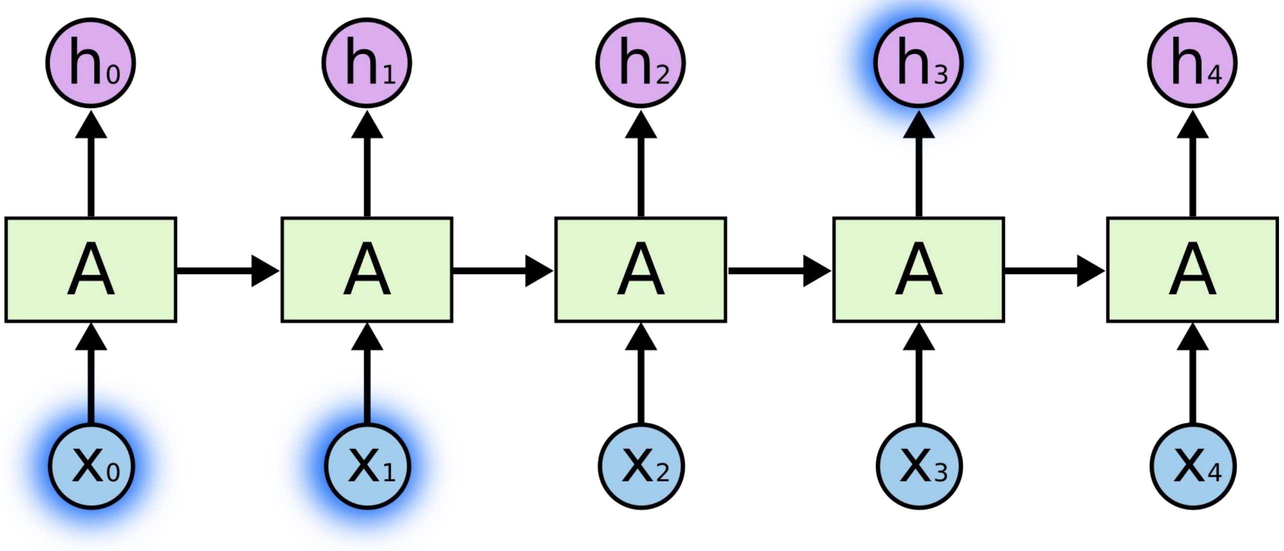
Recurrent Neural Networks (RNNs)



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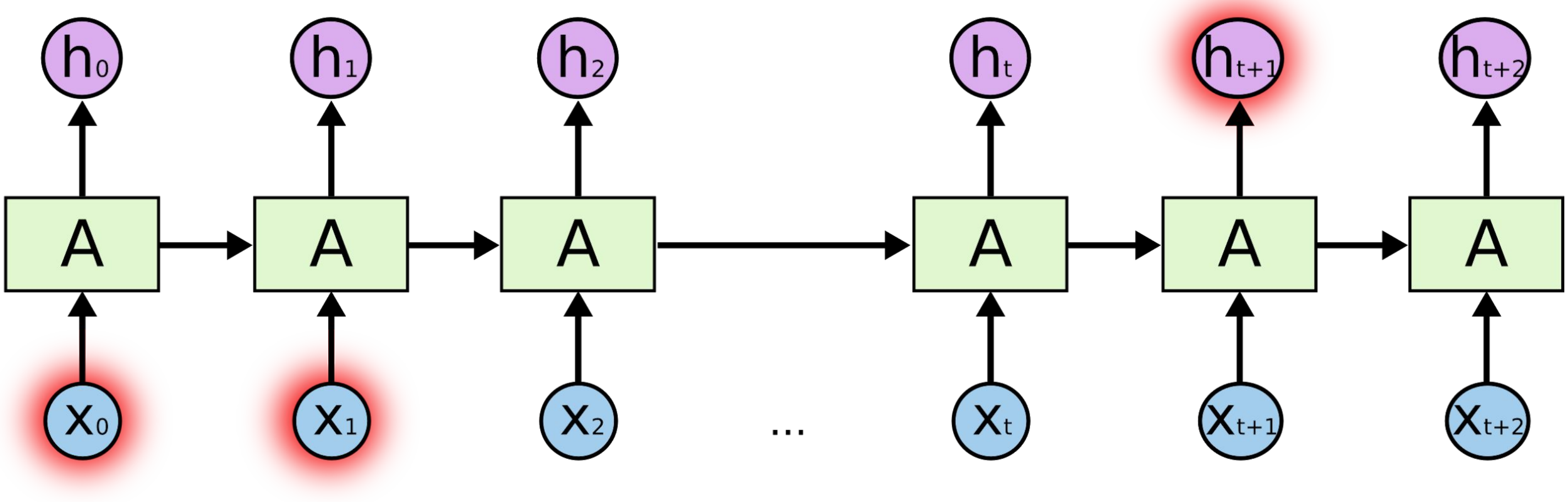
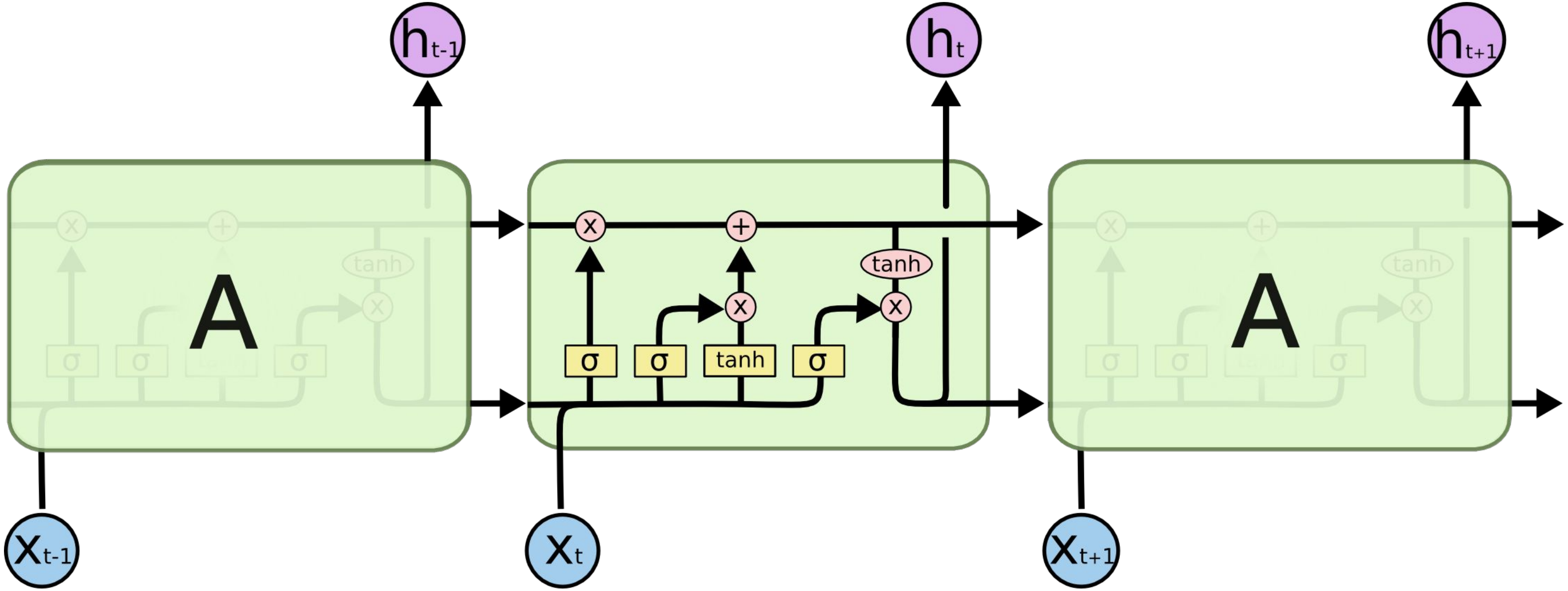
Long Term Dependency Problem



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short Term Memory (LSTMs)



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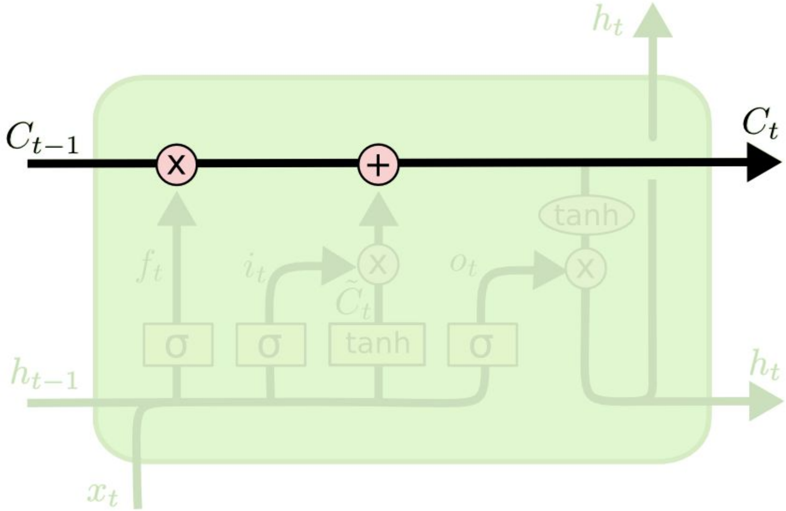

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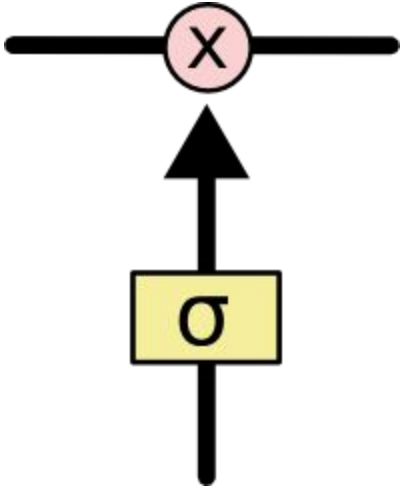
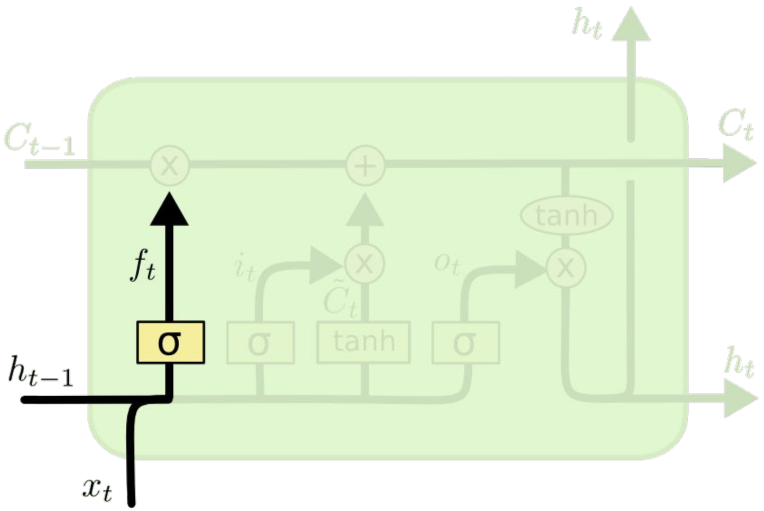


http://colah.github.io/posts/2015-08-Understanding-LSTMs/

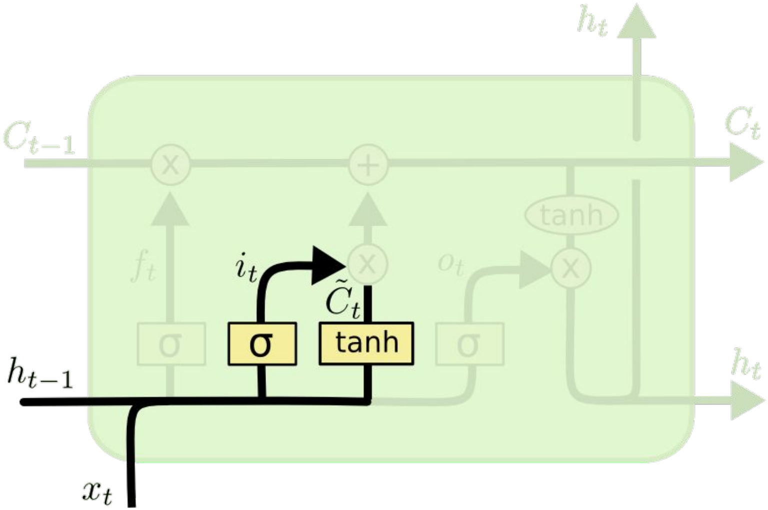
LSTM - Forget Gate



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM - Learn Gate

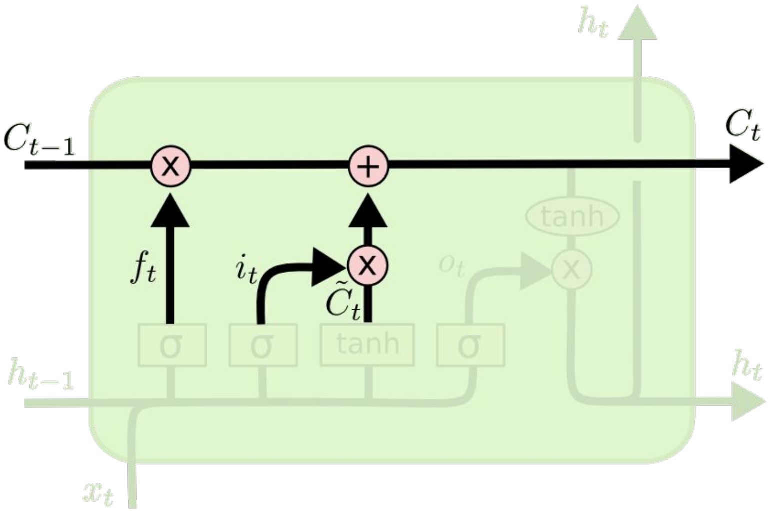


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

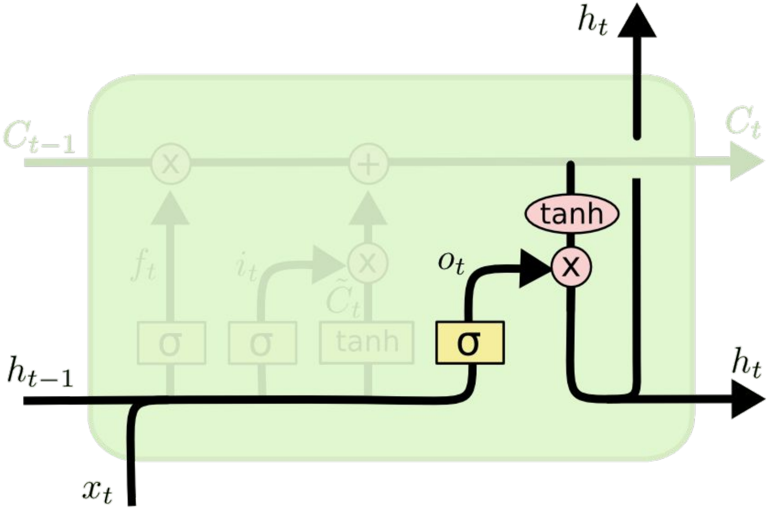
LSTM - Update Gate



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM - Output Gate

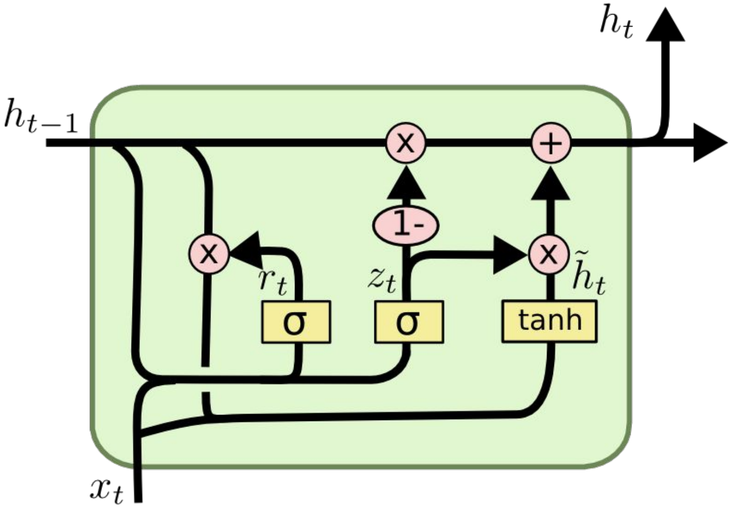


$$o_t = \sigma\left(W_o \left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Gated Recurrent Unit (GRU)



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

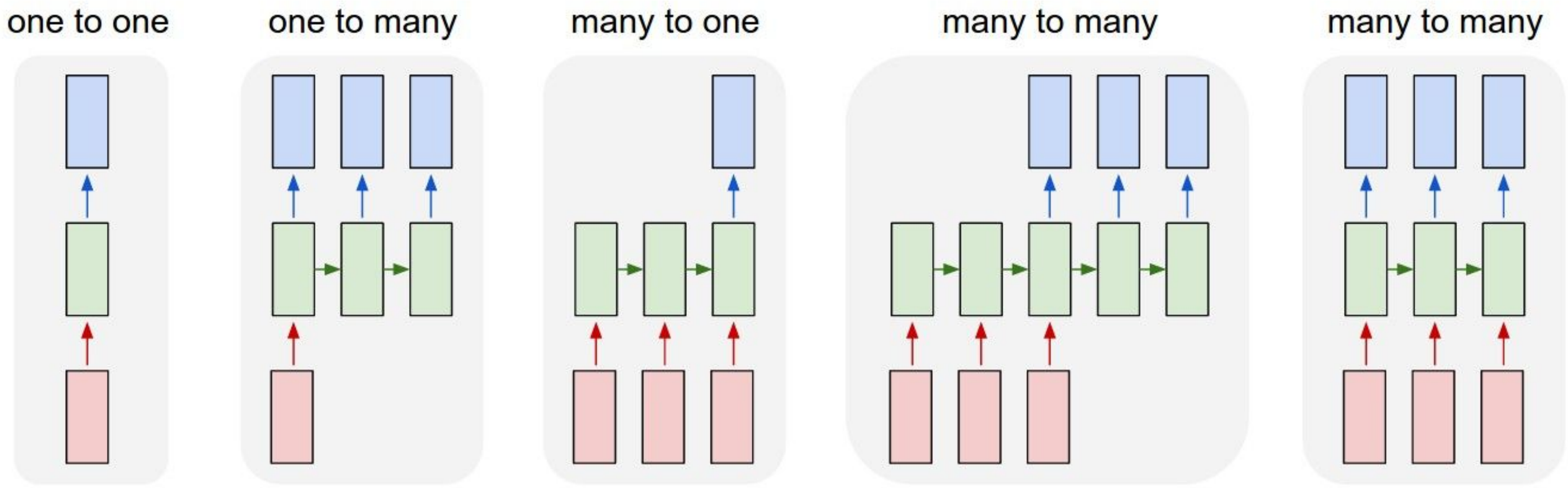
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

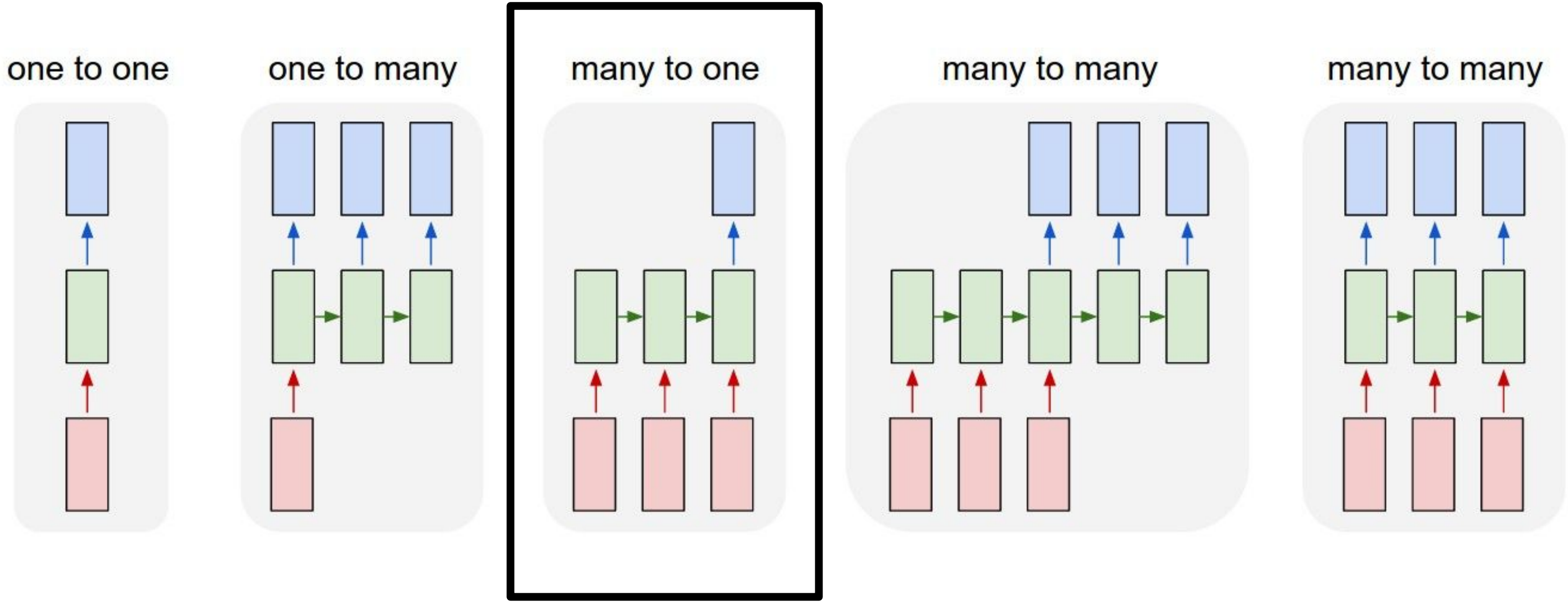
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Types of RNNs



http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Types of RNNs



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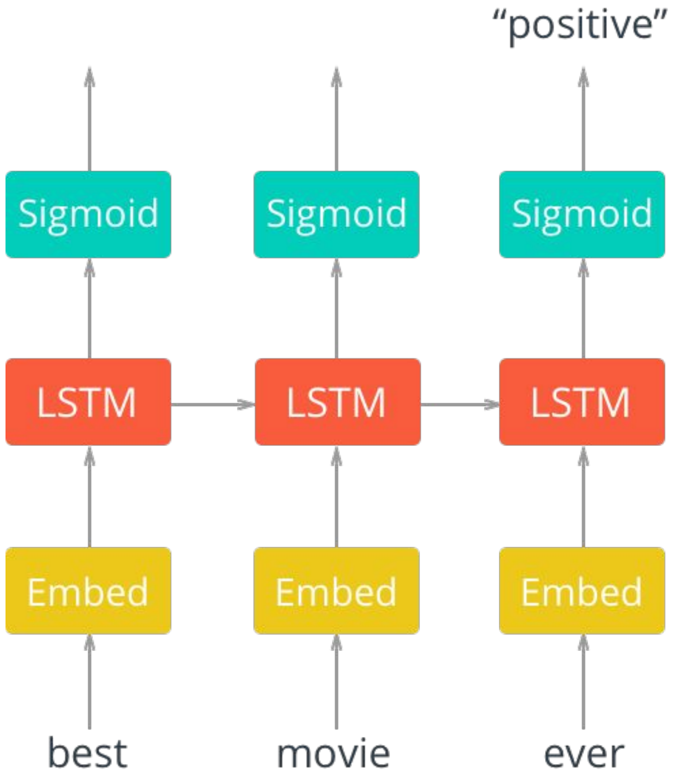
LSTM Network Architecture

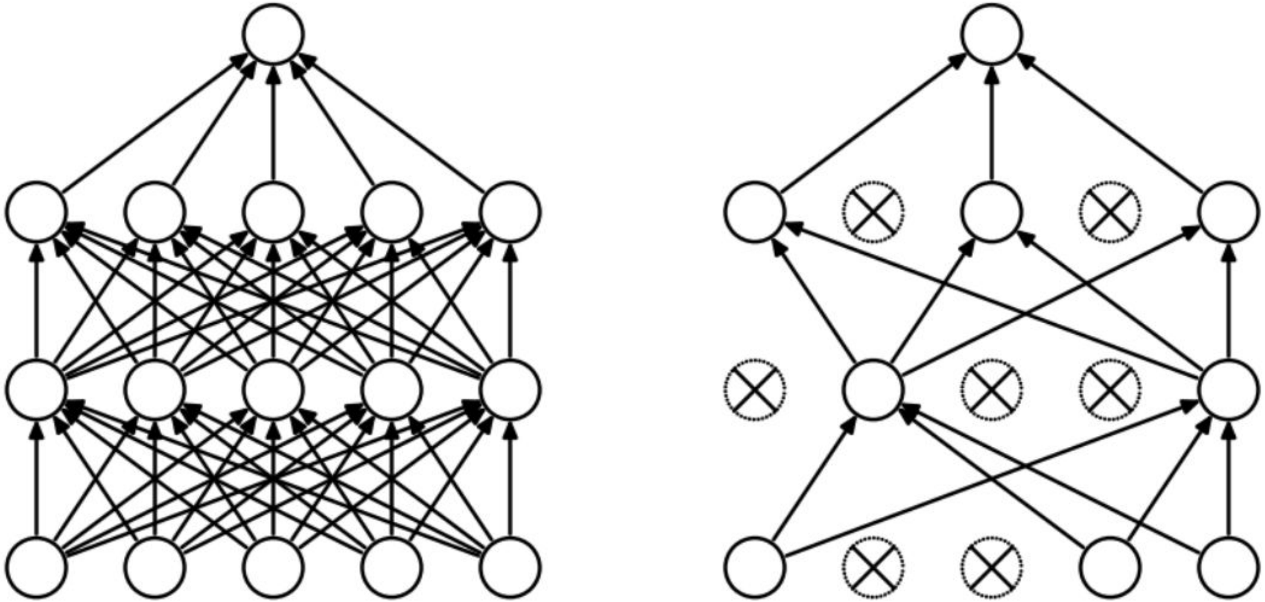


Learning Embeddings End-to-End

Distributed representations can also be learned in an end-to-end fashion as part of the model training process for an arbitrary task.

Trained under this paradigm, distributed representations will specifically learn to represent items as they relate to the learning task.

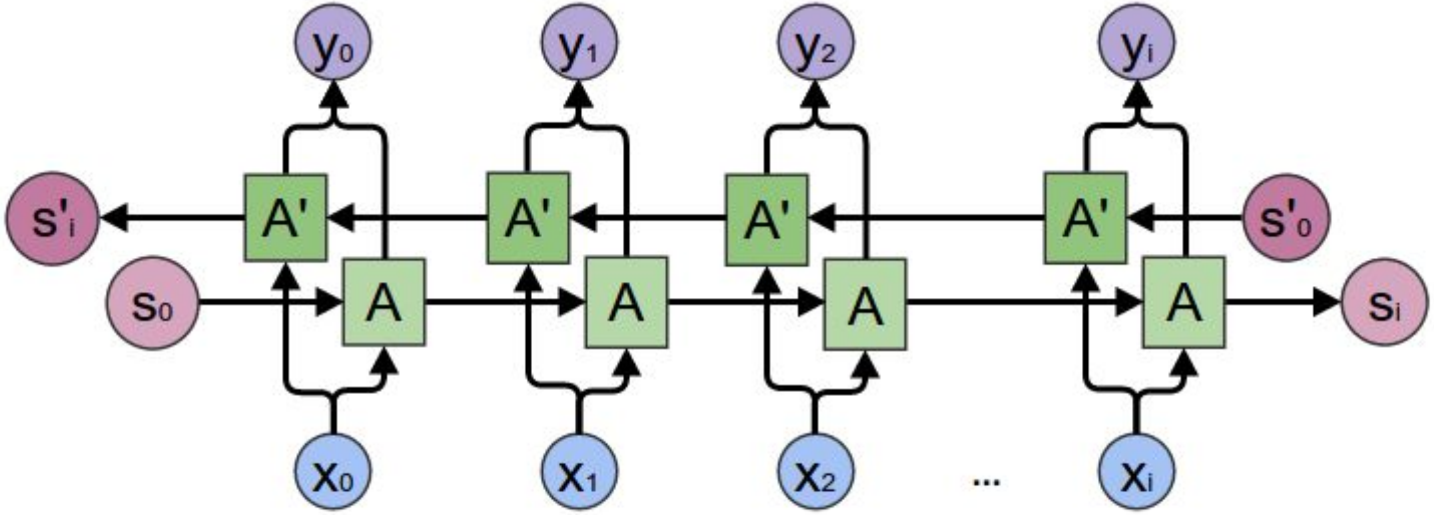
Dropout



(a) Standard Neural Net

(b) After applying dropout.

Bidirectional LSTM



http://colah.github.io/posts/2015-09-NN-Types-FP/

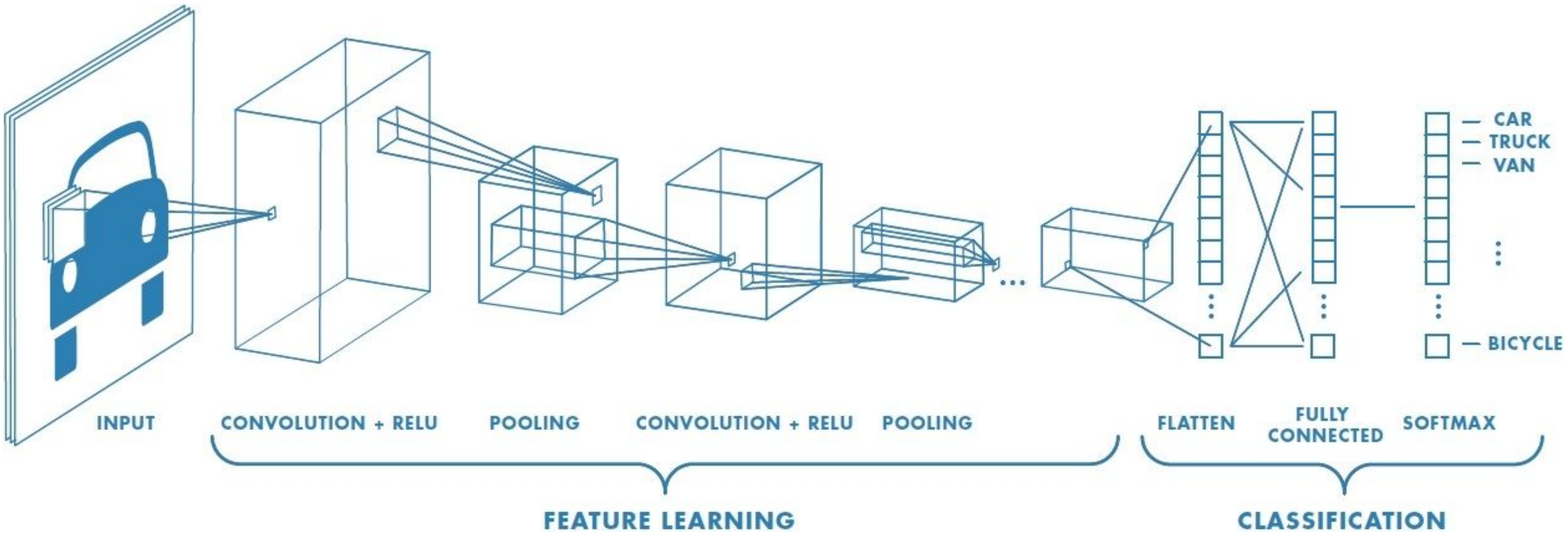
Convolutional Neural Networks for Language Tasks

Computer Vision Models

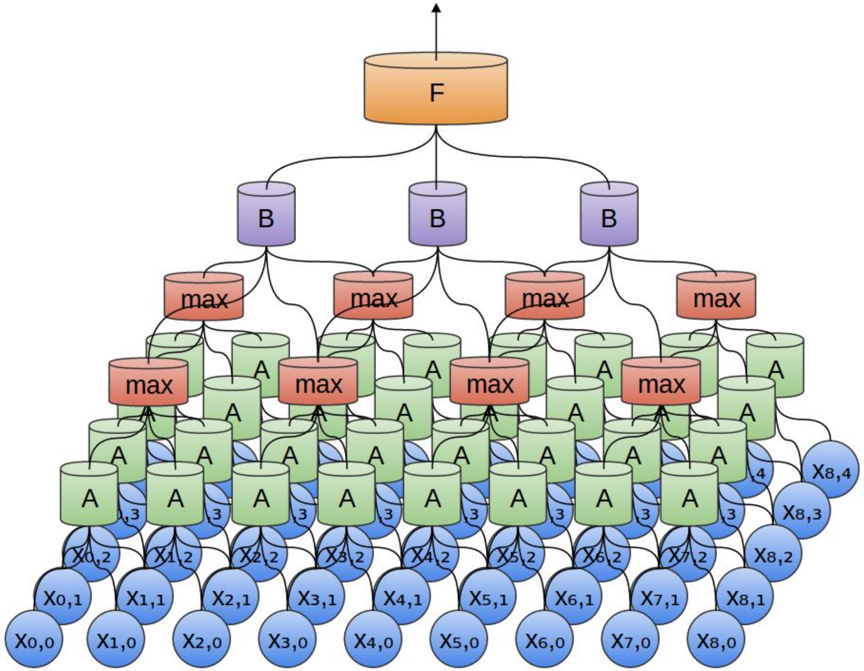
Computer Vision (CV) models are used for problems that involve working with image or video data - this typically involves image classification or object detection.

The CV research community has seen a lot of progress and creativity over the last few year - ultimately inspiring the application of CV models to other domains.

Convolutional Neural Networks (CNNs)



Convolutional Neural Networks (CNNs)



http://colah.github.io/posts/2014-07-Conv-Nets-Modular/

CNNs - Convolution Function

Input Vector

0	0	0	0	0	0
0	1	2	1	1	2
0	1	1	1	1	1
1	0	0	0	0	0
0	0	1	1	1	0
0	1	1	1	1	1

Kernel / Filter

0	0	2
1	2	0
1	2	2

CNNs - Convolution Function

Input Vector

0	0	0	0	0	0
0	1	2	1	1	2
0	1	1	1	1	1
1	0	0	0	0	0
0	0	1	1	1	0
0	1	1	1	1	1

Kernel / Filter

0	0	2
1	2	0
1	2	2

CNNs - Convolution Function

Input Vector

0	0	0	0	0	0
0	1	2	1	1	2
0	1	1	1	1	1
1	0	0	0	0	0
0	0	1	1	1	0
0	1	1	1	1	1

Kernel / Filter

0	0	0
1	0	0
0	2	0

Output Vector

2			

CNNs - Convolution Function

Input Vector

0	0	0	0	0	0
0	1	2	1	1	2
0	1	1	1	1	1
1	0	0	0	0	0
0	0	1	1	1	0
0	1	1	1	1	1

Kernel / Filter

0	0	0
1	0	0
0	2	0

Output Vector

2	3		

CNNs – Convolution Function

Input Vector

0	0	0	0	0	0
0	1	2	1	1	2
0	1	1	1	1	1
1	0	0	0	0	0
0	0	1	1	1	0
0	1	1	1	1	1

Kernel / Filter

0	0	0
1	0	0
0	2	0

Output Vector

2	3	4	

CNNs - Convolution Function

Input Vector

0	0	0	0	0	0
0	1	2	1	1	2
0	1	1	1	1	1
1	0	0	0	0	0
0	0	1	1	1	0
0	1	1	1	1	1

Kernel / Filter

0	0	0
1	0	0
0	2	0

Output Vector

2	3	4	3

CNNs - Convolution Function

Input Vector

0	0	0	0	0	0
0	1	2	1	1	2
0	1	1	1	1	1
1	0	0	0	0	0
0	0	1	1	1	0
0	1	1	1	1	1

Kernel / Filter

0	0	0
1	0	0
0	2	0

Output Vector

2	3	4	3
0			

CNNs - Convolution Function

Input Vector

0	0	0	0	0	0
0	1	2	1	1	2
0	1	1	1	1	1
1	0	0	0	0	0
0	0	1	1	1	0
0	1	1	1	1	1

Kernel / Filter

0	0	0
1	0	0
0	2	0

Output Vector

2	3	4	3
0	1		

CNNs – Convolution Function

Input Vector

0	0	0	0	0	0
0	1	2	1	1	2
0	1	1	1	1	1
1	0	0	0	0	0
0	0	1	1	1	0
0	1	1	1	1	1

Kernel / Filter

0	0	0
1	0	0
0	2	0

Output Vector

2	3	4	3
0	1	1	1
1	2	2	2
2	2	3	3

CNNs - Max Pooling Function

Input Vector

2	3	4	3
0	1	1	1
1	2	2	2
2	2	3	3

Output Vector

3	

CNNs - Max Pooling Function

Input Vector

2	3	4	3
0	1	1	1
1	2	2	2
2	2	3	3

Output Vector

3	4

CNNs - Max Pooling Function

Input Vector

2	3	4	3
0	1	1	1
1	2	2	2
2	2	3	3

Output Vector

3	4
2	

CNNs - Max Pooling Function

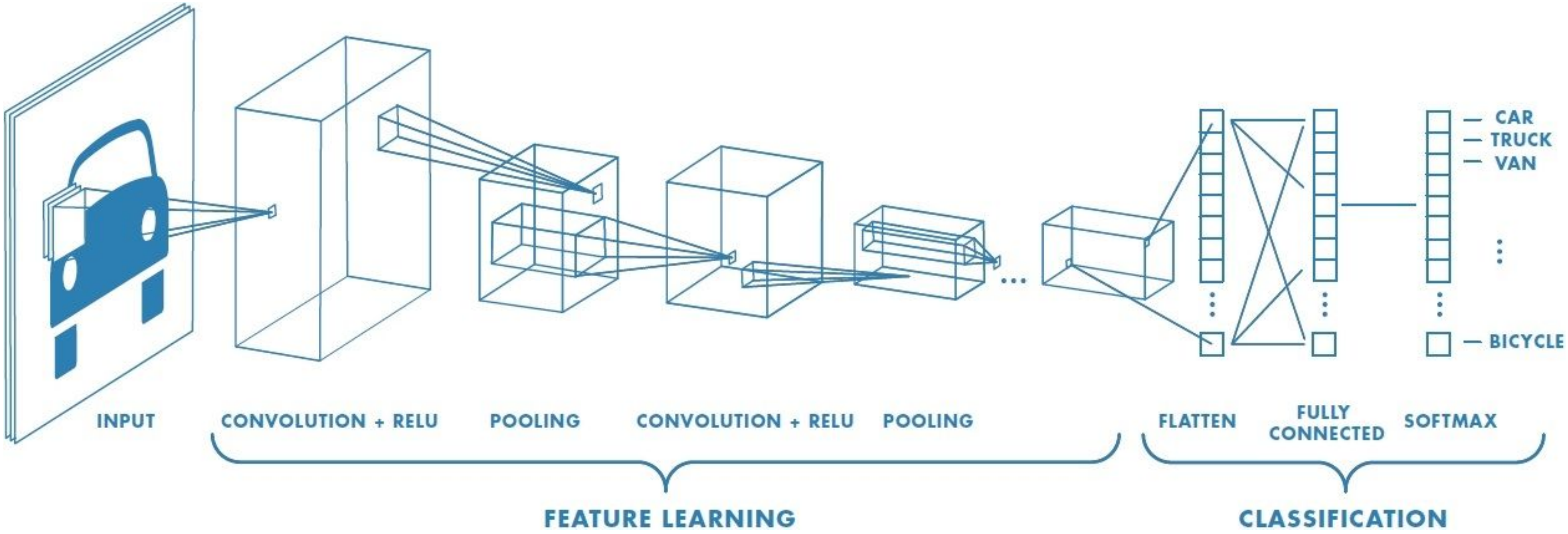
Input Vector

2	3	4	3
0	1	1	1
1	2	2	2
2	2	3	3

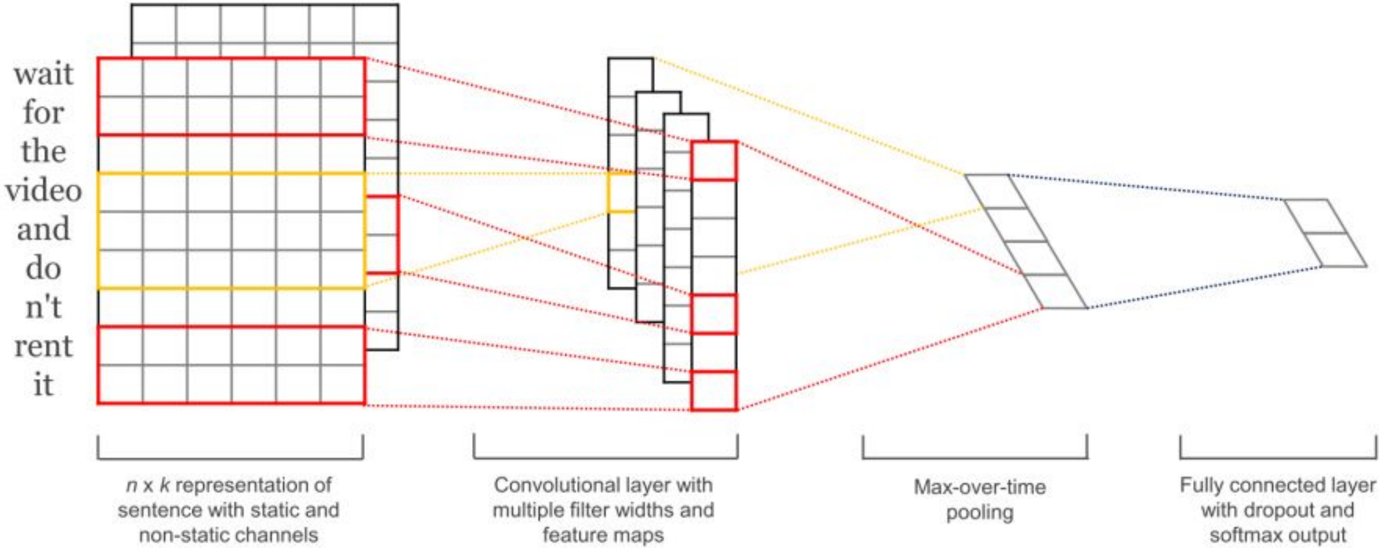
Output Vector

3	4
2	3

Convolutional Neural Networks (CNNs)



CNN Architecture for Text

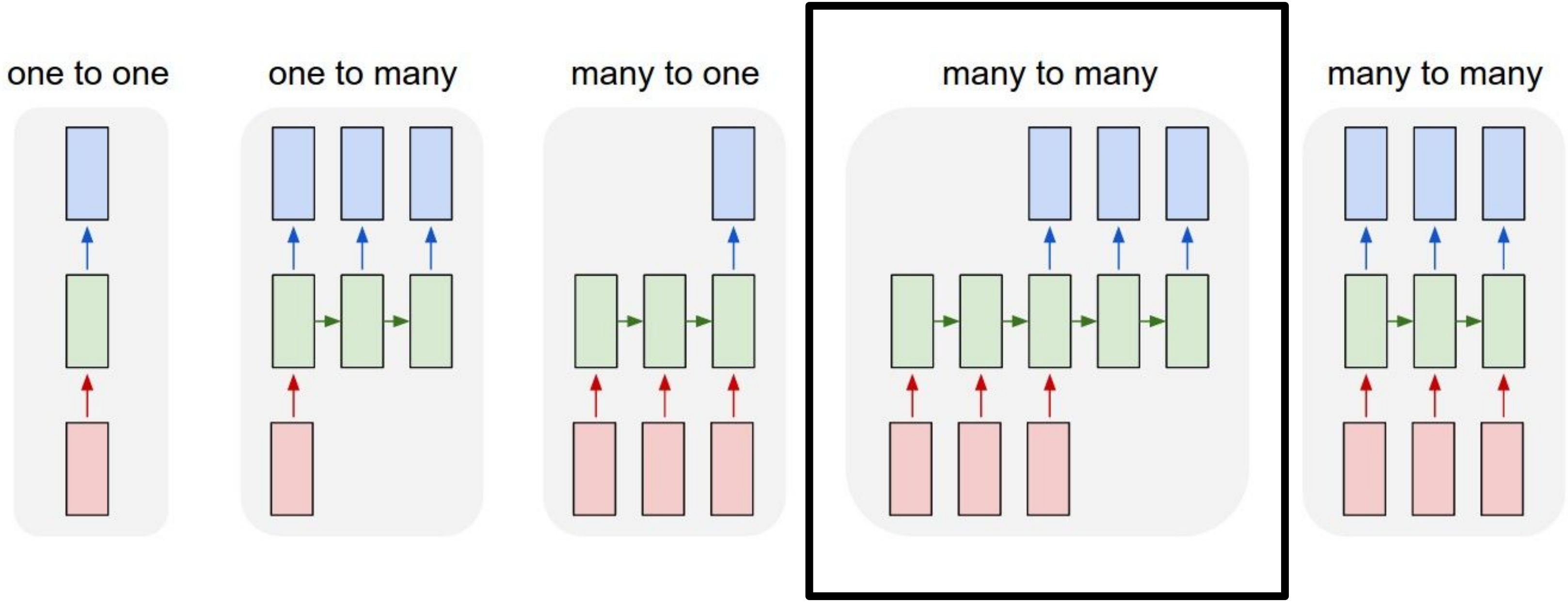


State of the Art in NLP - Generalized Language Models

Generalized Language Modeling

Model that predicts the next word in a sentence. This is a model that is literally trying to learn the nuances of a language.

Types of RNNs



http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Generalized Language Modeling

$P(S)$

$=P(w_1,\ldots,w_n)$

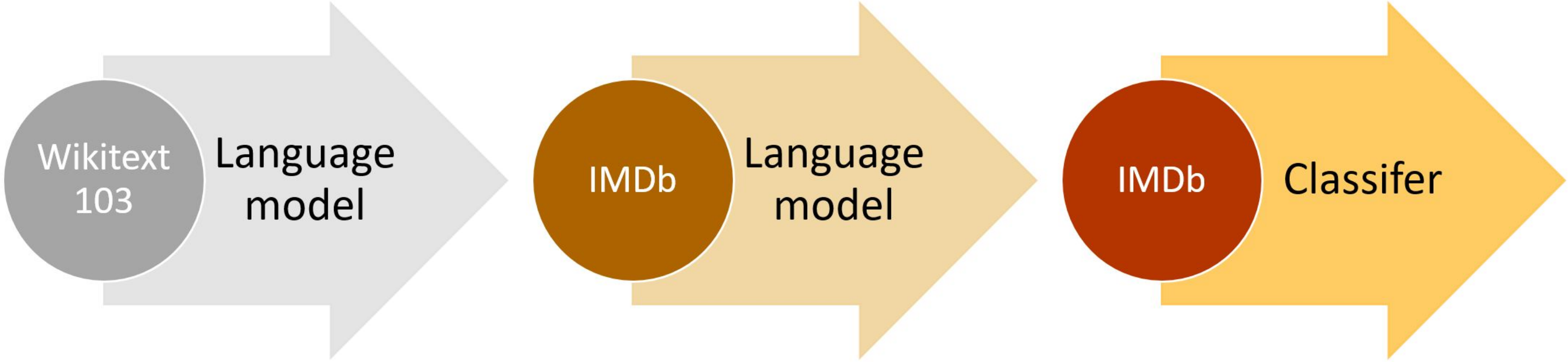
$=\prod_i P(w_i|w_1,\ldots w_{i-1})$

$=P(w_1)*P(w_2|w_1)*P(w_3)*P(w_1,w_2)*\ldots*\mathbf{P(w_n|w_1,\ldots w_{n-1})}$

Current SOTA

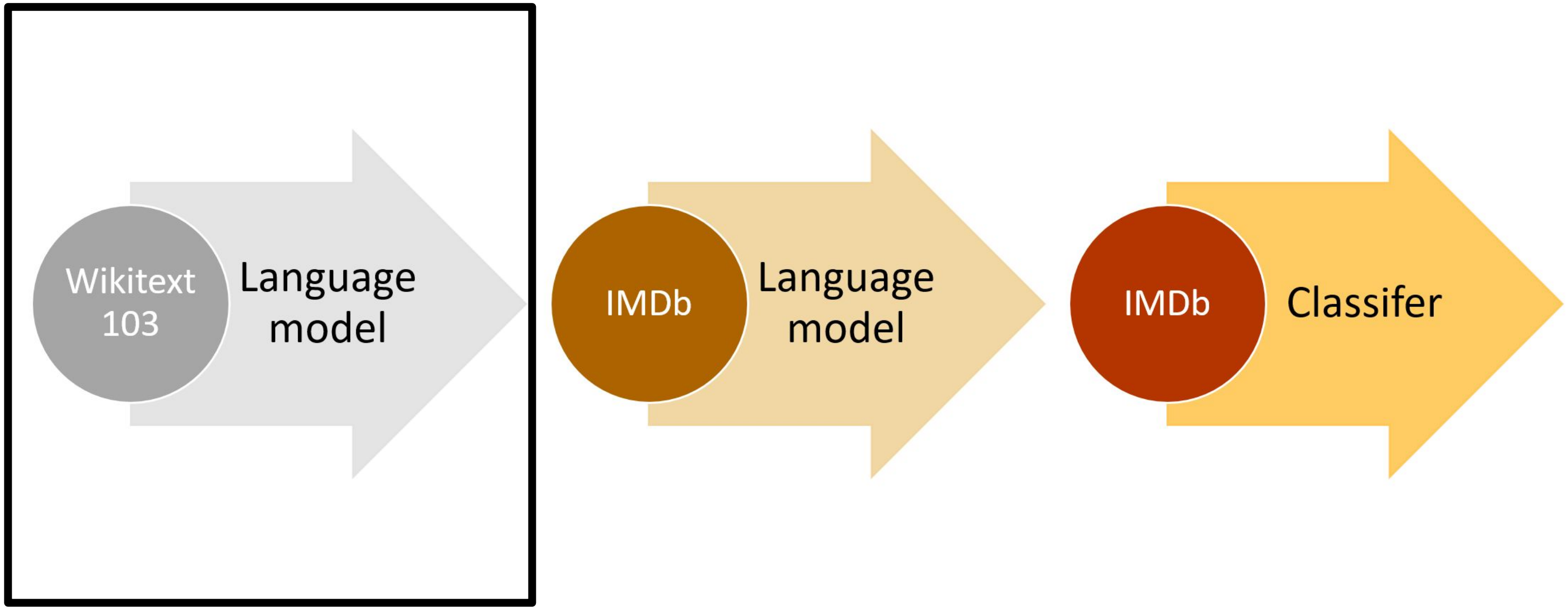
- ELMo — Universal Language Model Fine-tuning for Text Classification, Allen AI / UW (March 2018)
- ULMFiT — Universal Language Model Fine-tuning for Text Classification, fast.ai (May 2018)
- BERT — Bidirectional Encoder Representations from Transformers, GoogleAI (Nov 2018)
- GPT / GPT-2 — Generative Pre-training Transformer, OpenAI (June 2018, Feb 2019)

ULMFiT



http://nlp.fast.ai/classification/2018/05/15/introducting-ulmfit.html

ULMFiT



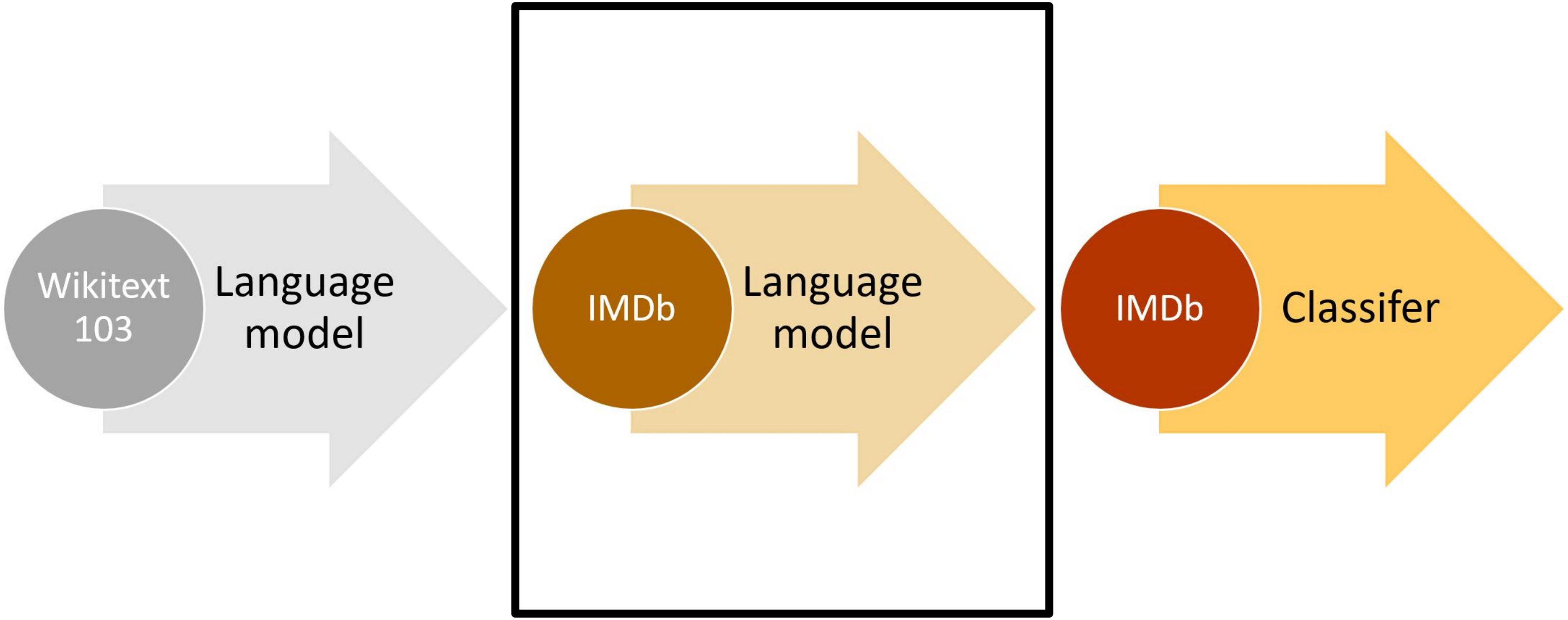
http://nlp.fast.ai/classification/2018/05/15/introducting-ulmfit.html

ULMFiT - GLM Pre Training

- Train Generalized Language Model using an ***AWD-LSTM*** on Wikipedia text

- AWD-LSTM is like a regular LSTM but is super regularized (lot's of dropout!) and uses some optimization tricks

ULMFiT

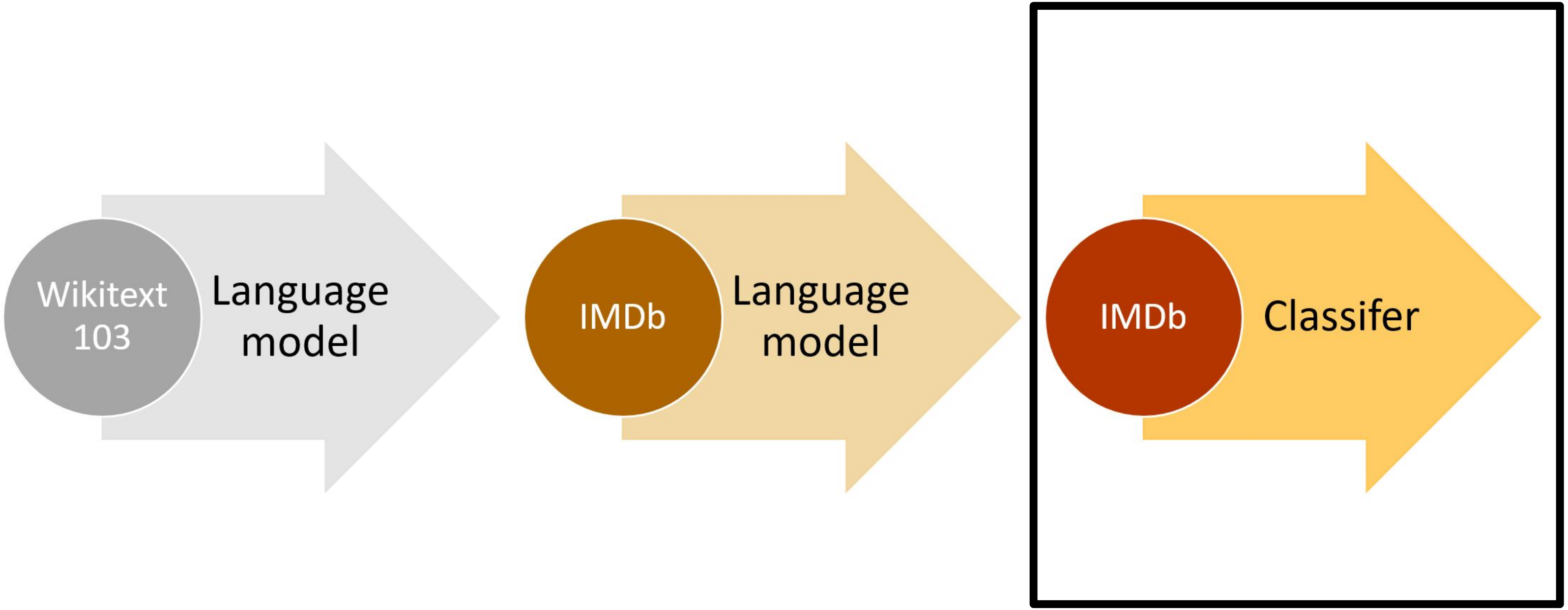


http://nlp.fast.ai/classification/2018/05/15/introducting-ulmfit.html

ULMFiT - Refine GLM for Target Task

- Start with pre-trained model and train on corpus / vocabulary for specific task
- Uses **Discriminative Fine-Tuning** — different learning rates are used for different layers since layers capture different information
- Users **Slanted Triangular Learning Rates (STLR)** — learning rates first increased, then decreased slightly

ULMFiT



http://nlp.fast.ai/classification/2018/05/15/introducting-ulmfit.html

ULMFiT - Target Task Classification Training

- Append two feed forward layers and a softmax output layer to predict target labels

- Uses **Concat Pooling** — extracts max and mean pooling over history of hidden states and appends to final state

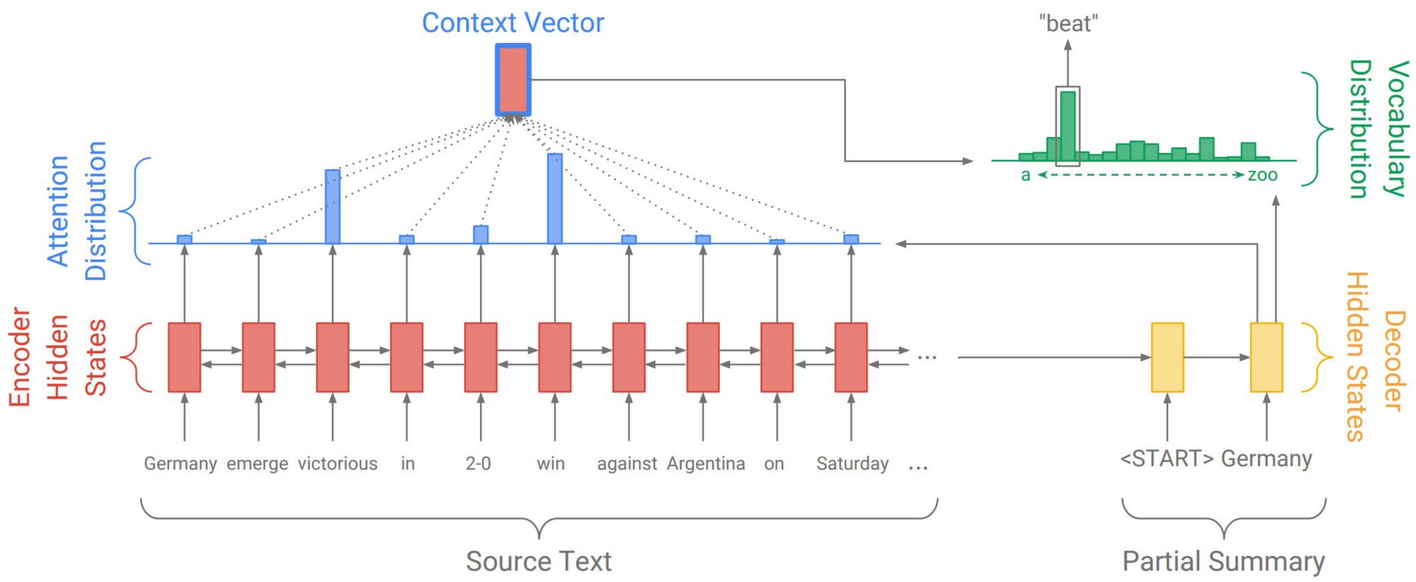
- Users **Gradual Unfreeze** — during training update only a single GLM layer on each epoch

BERT / GPT-2 - Transformer Model

- BERT and GPT-2 use a similar approach of learning a Generalized Language Model and uses supervised fine tuning

- These models use a **Transformer Model** instead of an RNN

Attention Mechanism



http://www.abigailsee.com/2017/04/16/taming-rnns-for-better-summarization.html

Transformer Model

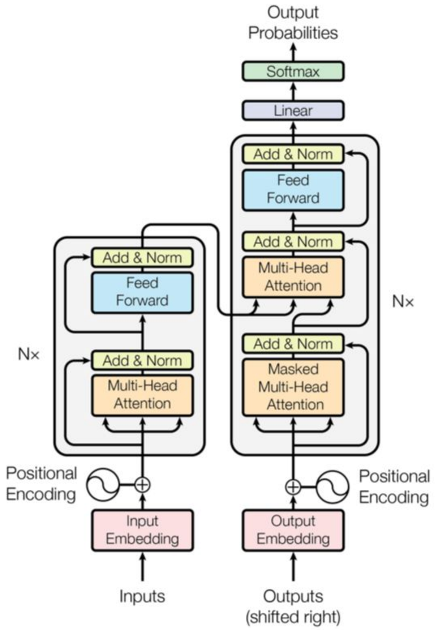


Figure 1: The Transformer - model architecture.

[Attention Is All You Need]

Transformer Model

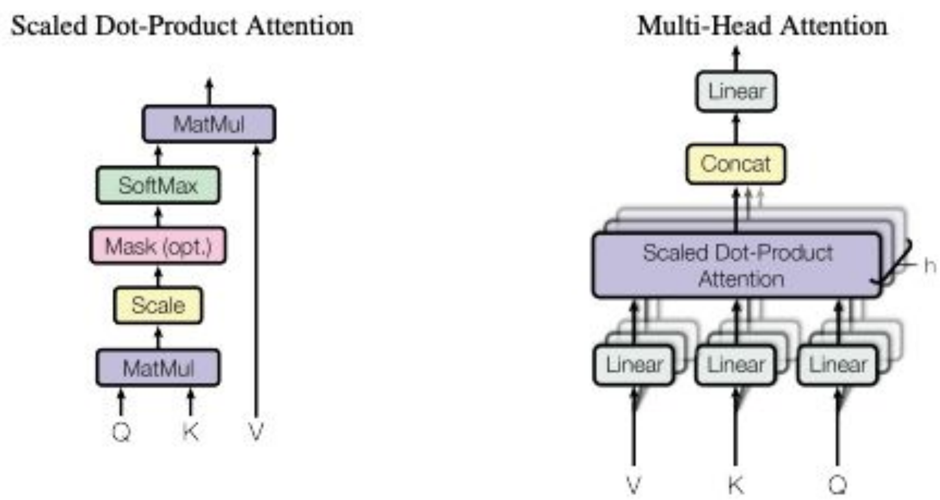
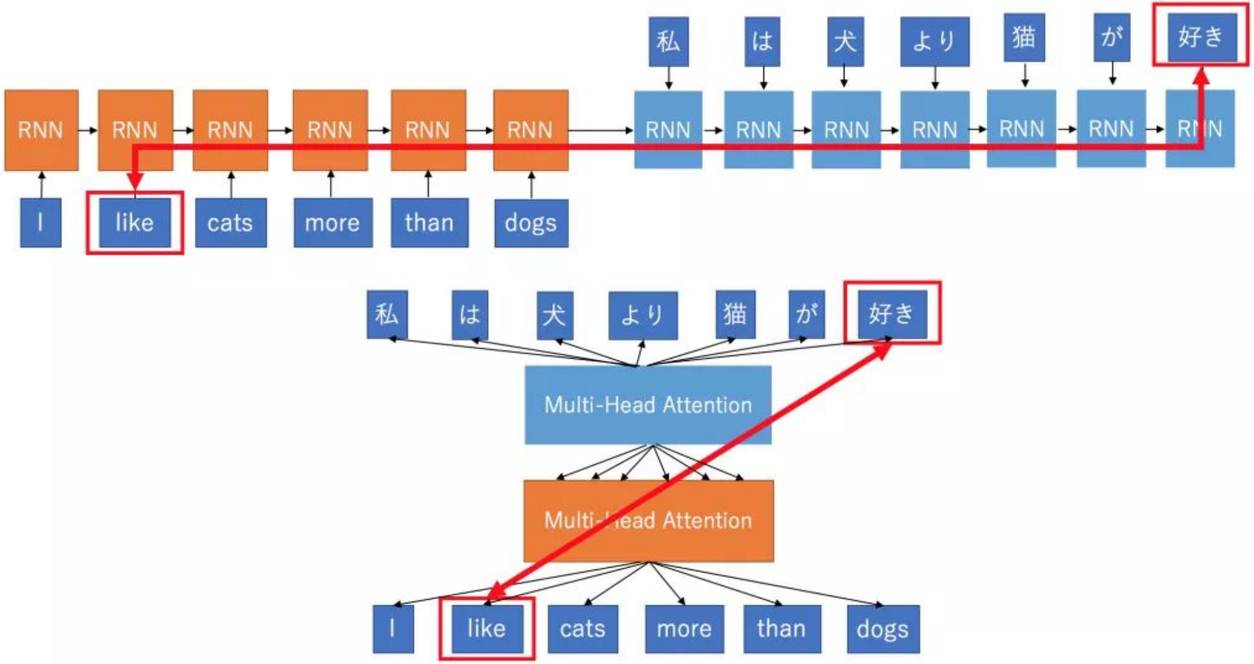


Figure 2: (left) Scaled Dot-Product Attention. (right) Multi-Head Attention consists of several attention layers running in parallel.

[Attention Is All You Need]

Transformer Model



http://mlexplained.com/2017/12/29/attention-is-all-you-need-explained/

Practical Considerations for Modeling with Your Data

Practical Considerations

- Data, data, data — but now maybe a little bit less data with transfer learning

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- Subject Matter and Domain Specific Lexicon — be cognisant of how you embeddings are created and tune them to your domain!

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- Data, data, data — but now maybe a little bit less data with transfer learning
- Subject Matter and Domain Specific Lexicon — be cognisant of how you embeddings are created and tune them to your domain
- Changing Lexicon over Time — retrain / re-tune as necessary

Thanks!

Any questions?

You can find me at

- @garrettleeh (Twitter and StockTwits)
- garrett@stocktwits.com

and related resources at

- https://github.com/GarrettHoffman/talks-and-tutorials
- https://www.oreilly.com/ideas/introduction-to-lstms-with-tensorflow

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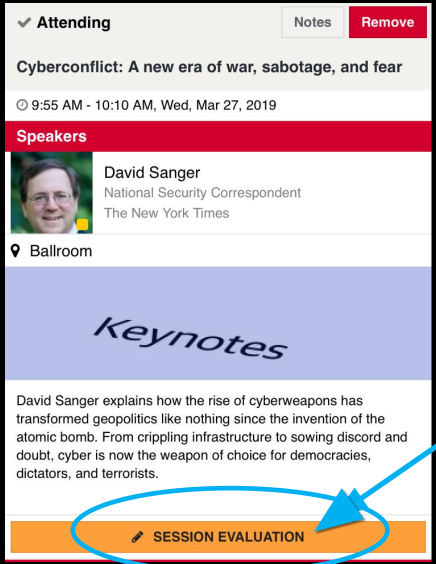

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