Neural Nets for NLP

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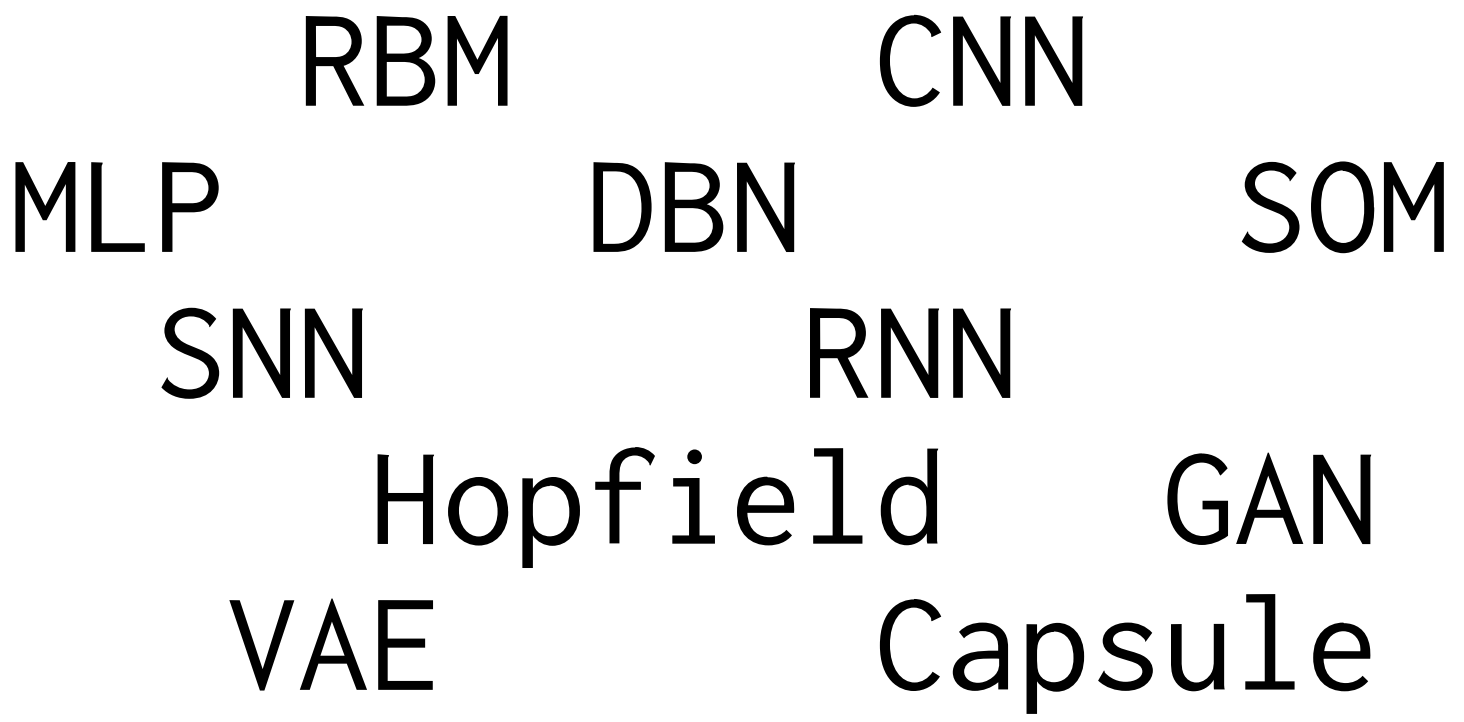
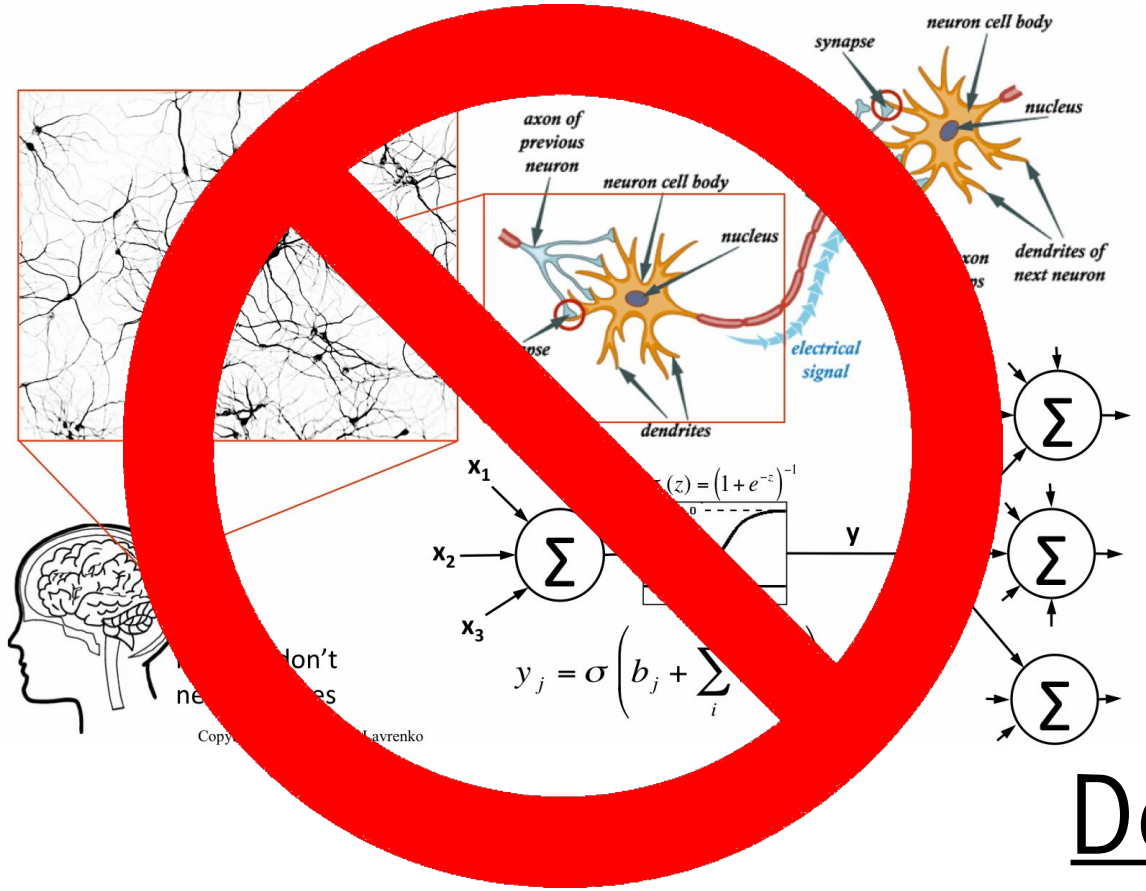
Limitations of "Classic" NLP

* categorical (1-hot) features
* extra large feature spaces
* UNK problems
* complicated feature engineering
* difficult domain adaptation
* need for markovization in sequence models
* what else?

Neural Nets to the Rescue



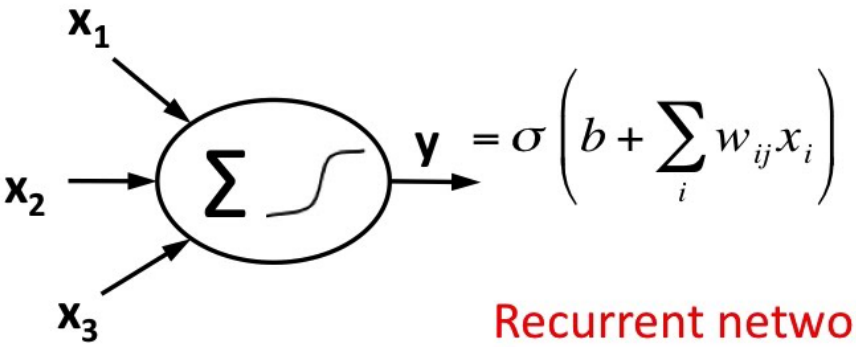
Terminology



Deep Learning?

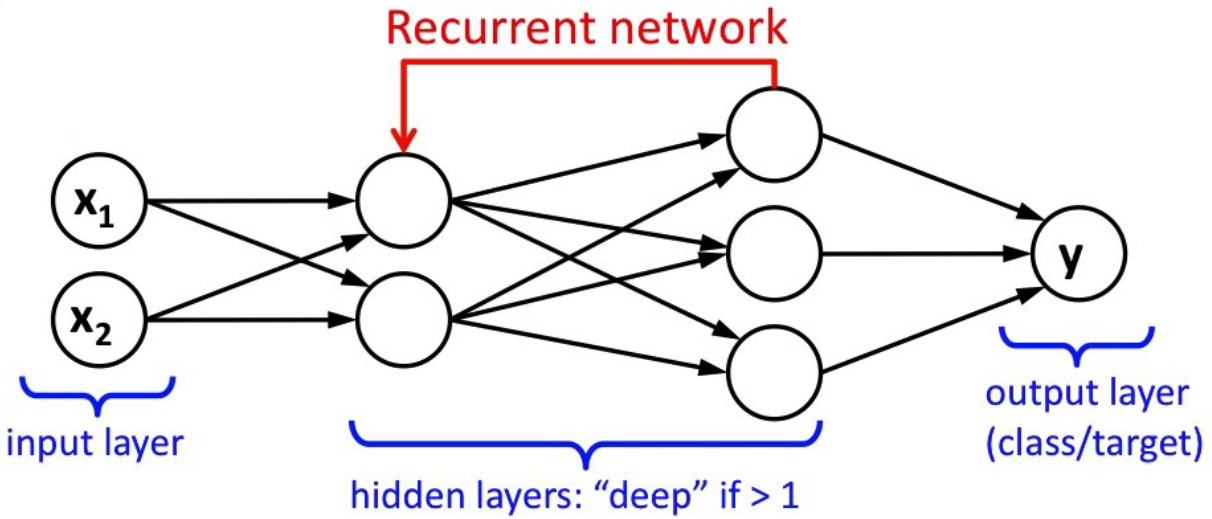
https://blog.keras.io/the-limitations-of-deep-learning.html

Types of Neural Networks



Single neuron: perceptron,

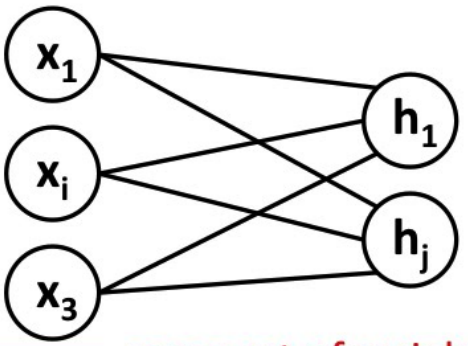
linear / logistic regression



Feed-forward network
(no cycles) -- non-linear
classification & regression

P (input | hidden)

$$\sigma\left(\beta_i + \sum_j w_{ij} h_j\right) =$$



P (hidden | input)

$$= \sigma\left(b_j + \sum_i w_{ij} x_i\right)$$

same set of weights

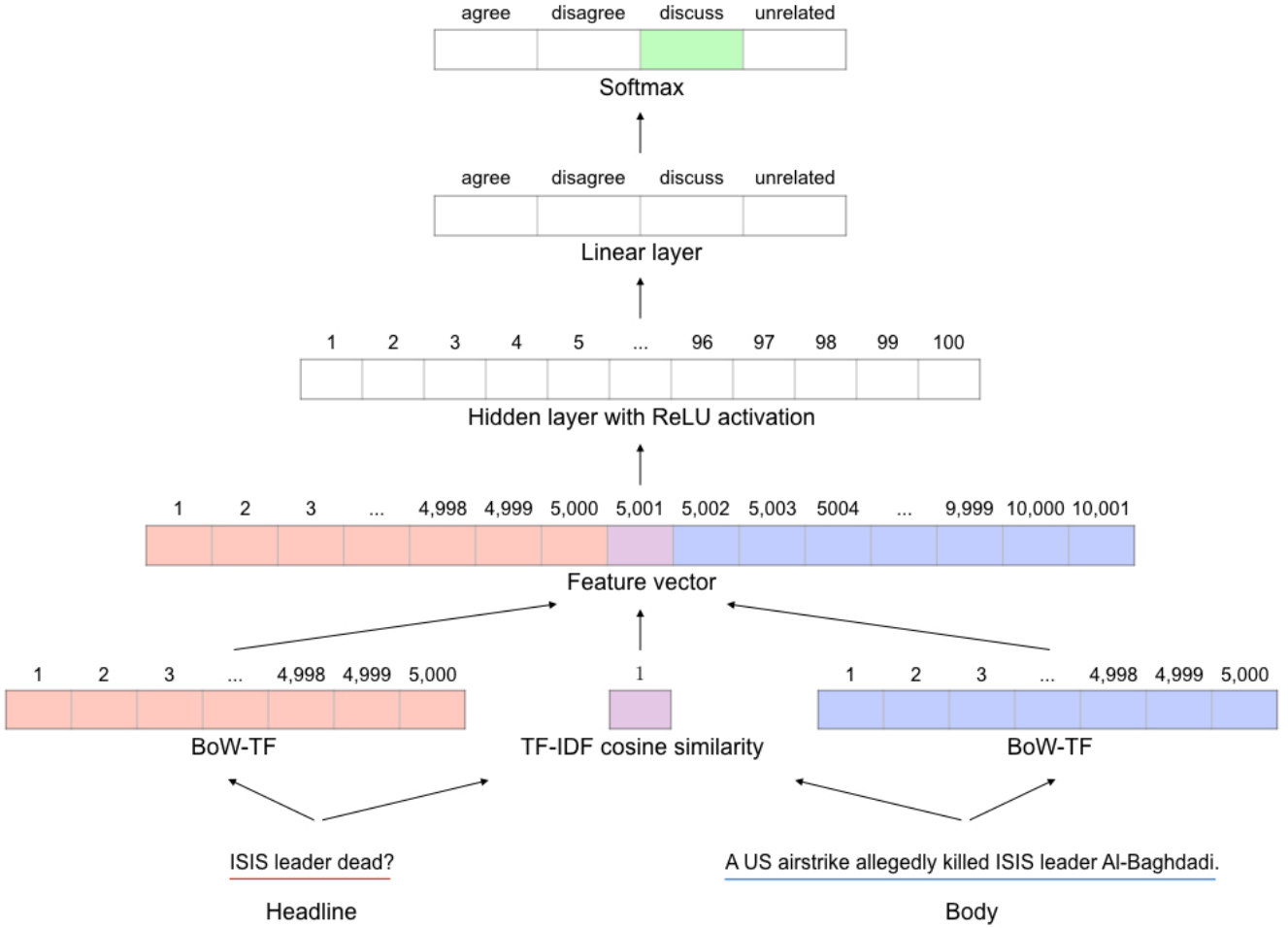
Symmetric (RBM)
unsupervised, trained
to maximize likelihood
of input data

a mixture model

~~MLPs~~ FNNs

* computational graph
* composed of various layers
* backprop for learning
* GD for optimization

Example: FNC-1



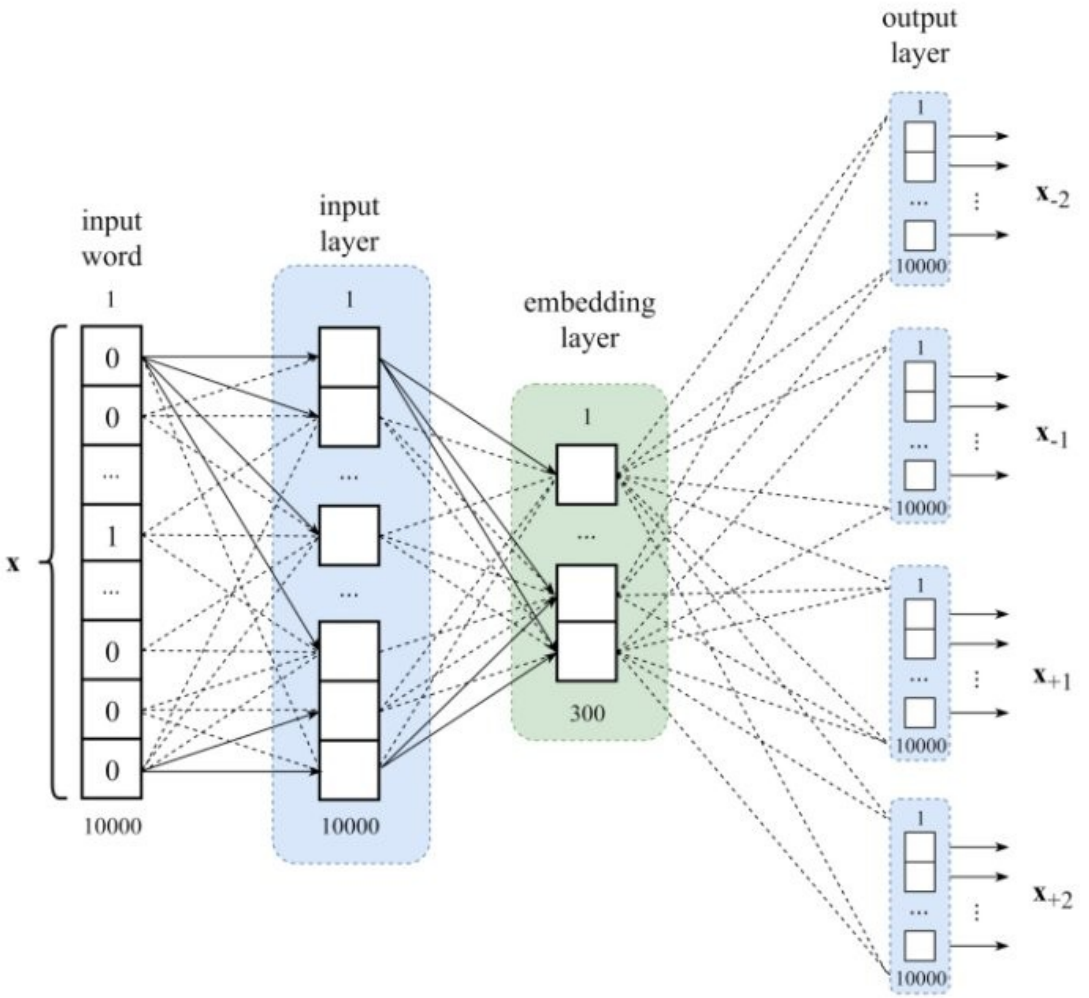
https://github.com/uclmr/fakenewschallenge

Layers

* input
* fully-connected
* convolutional
* non-linearities
* regularization
* output

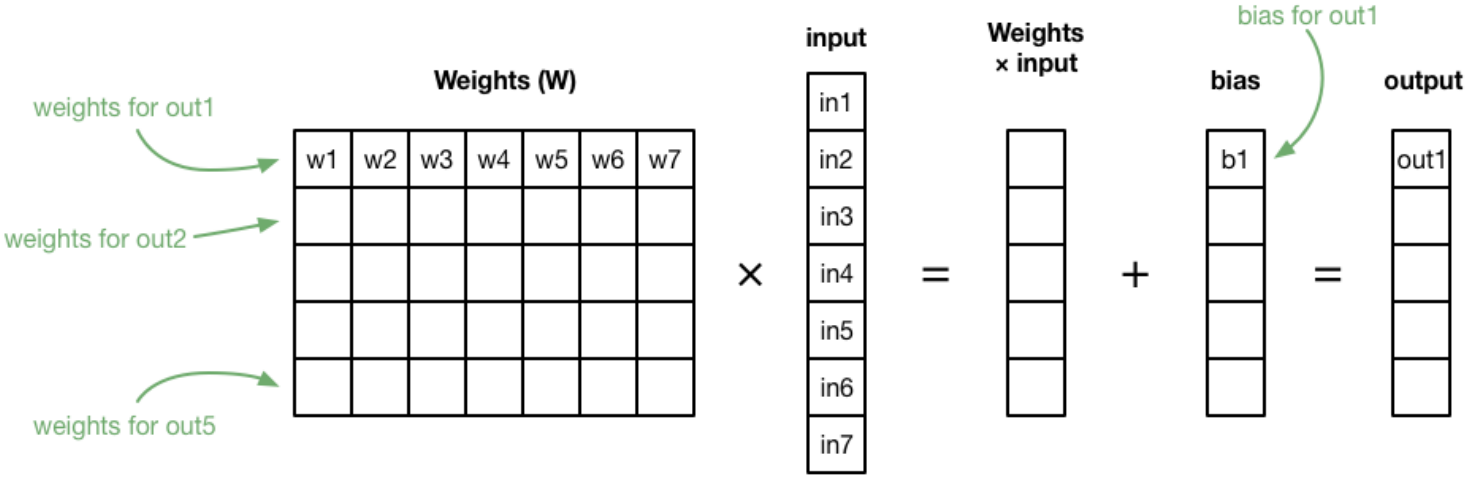
Input Layers

* 1-hot
* embedding
* mixed

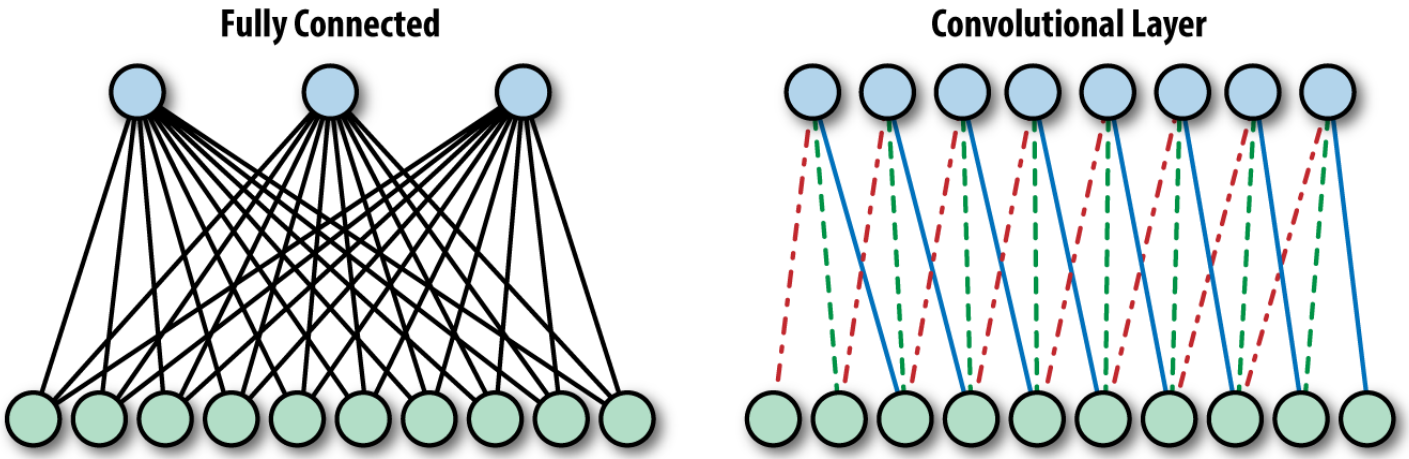


Fully-Connected Layers

* linear transformation

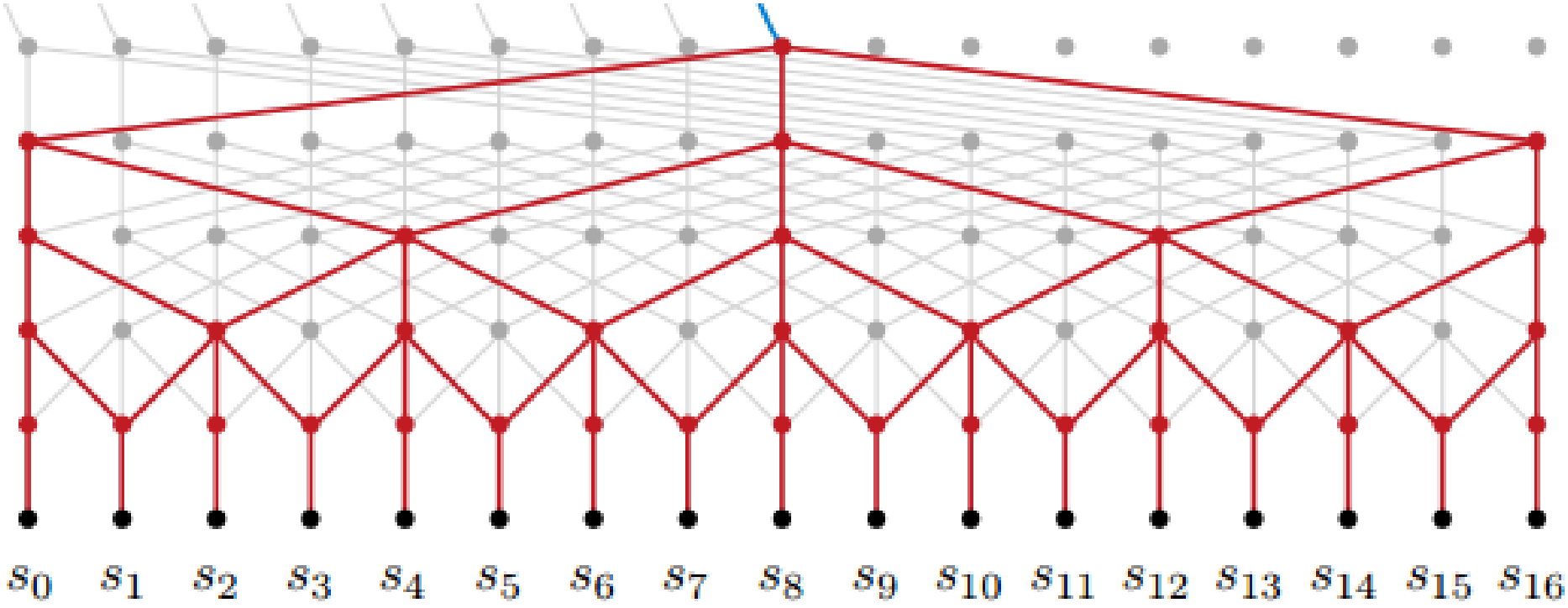


output = f(Weights × input + bias)



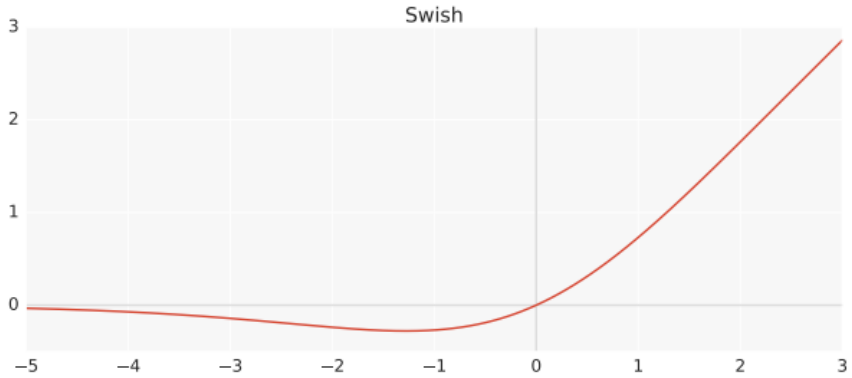
Convolutional Layers

* apply mask
+ pooling (max, mean,…)

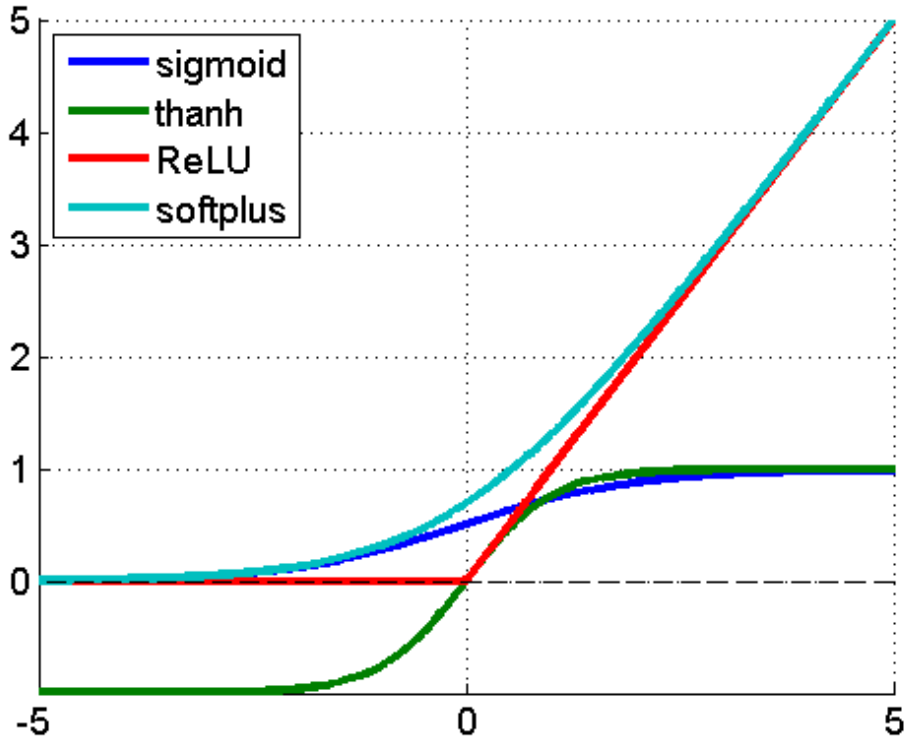


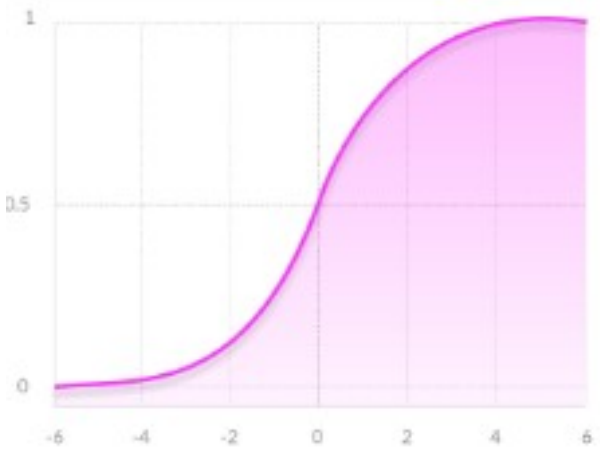
Nonlinearities

* sigmoid/logistic
* tanh
* ReLU/SeLU/ELU/leakyReLU/…
* softplus
* swish



* maxout





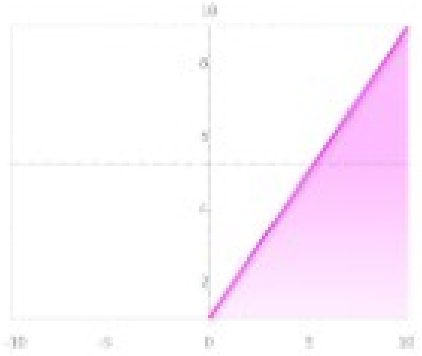
SIGMOID / LOGISTIC

ADVANTAGES

- **Smooth gradient**, preventing "jumps" in output values.
- **Output values bound** between 0 and 1, normalizing the output of each neuron.
- **Clear predictions**—For X above 2 or below -2, tends to bring the Y value (the prediction) to the edge of the curve, very close to 1 or 0. This enables clear predictions.

DISADVANTAGES

- **Vanishing gradient**—for very high or very low values of X, there is almost no change to the prediction, causing a vanishing gradient problem. This can result in the network refusing to learn further, or being too slow to reach an accurate prediction.
- **Outputs not zero centered**.
- **Computationally expensive**



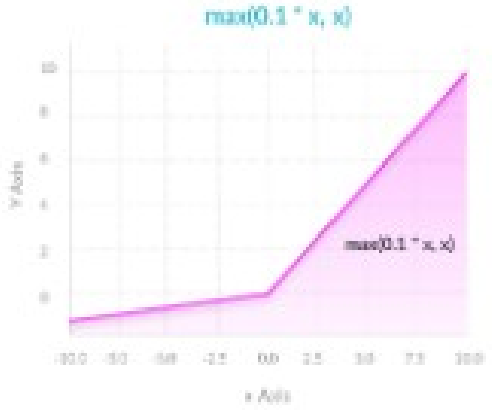
RELU (RECTIFIED LINEAR UNIT)

ADVANTAGES

- **Computationally efficient**—allows the network to converge very quickly
- **Non-linear**—although it looks like a linear function, ReLU has a derivative function and allows for backpropagation

DISADVANTAGES

- **The Dying ReLU problem**—when inputs approach zero, or are negative, the gradient of the function becomes zero, the network cannot perform backpropagation and cannot learn.



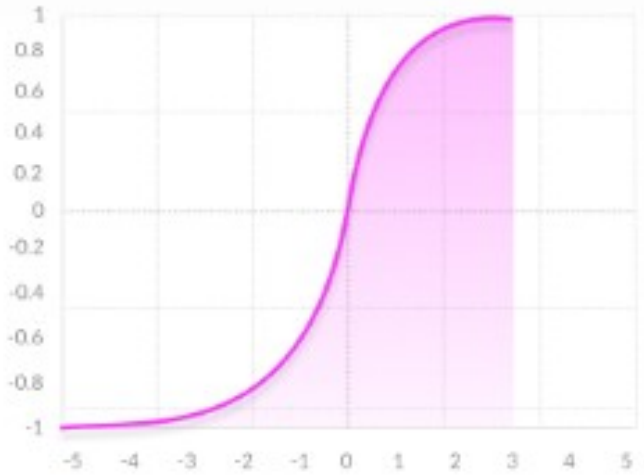
LEAKY RELU

ADVANTAGES

- **Prevents dying ReLU problem**—this variation of ReLU has a small positive slope in the negative area, so it does enable backpropagation, even for negative input values
- Otherwise like ReLU

DISADVANTAGES

- **Results not consistent**—leaky ReLU does not provide consistent predictions for negative input values.



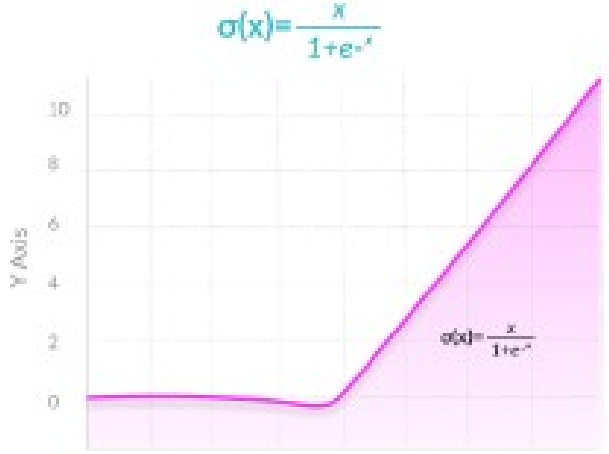
TANH / HYPERBOLIC TANGENT

ADVANTAGES

- **Zero centered**—making it easier to model inputs that have strongly negative, neutral, and strongly positive values.
- Otherwise like the Sigmoid function.

DISADVANTAGES

- Like the Sigmoid function

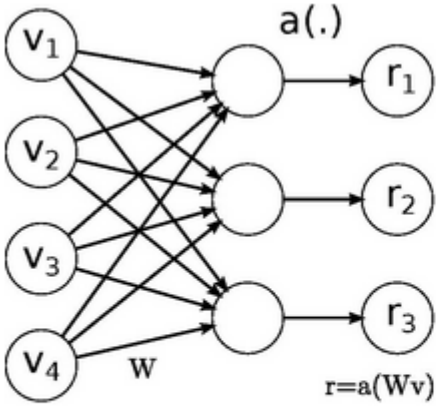


SWISH

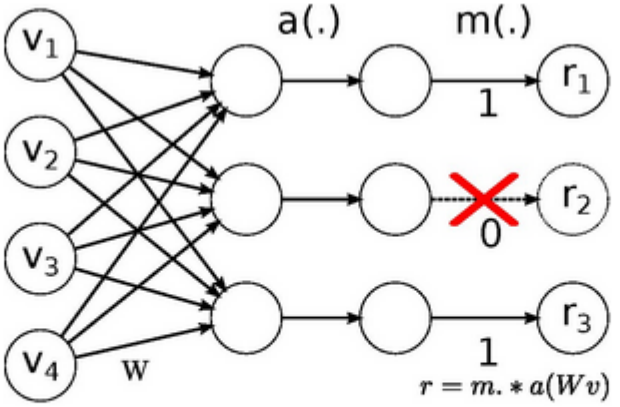
Swish is a new, self-gated activation function discovered by researchers at Google. According to their paper, it performs better than ReLU with a similar level of computational efficiency. In experiments on ImageNet with identical models running ReLU and Swish, the new function achieved top -1 classification accuracy 0.6-0.9% higher.

Regularization Layers

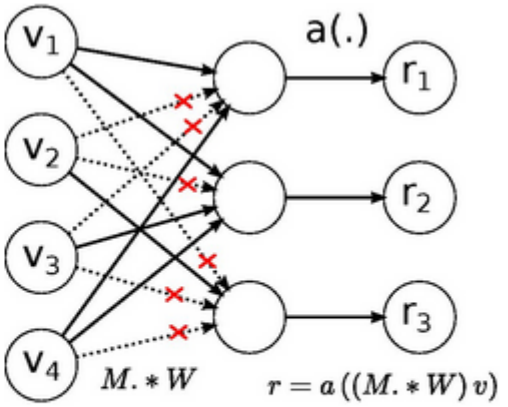
* nonlinearity regularization
* dropout
* dropconnect



No-Drop Network



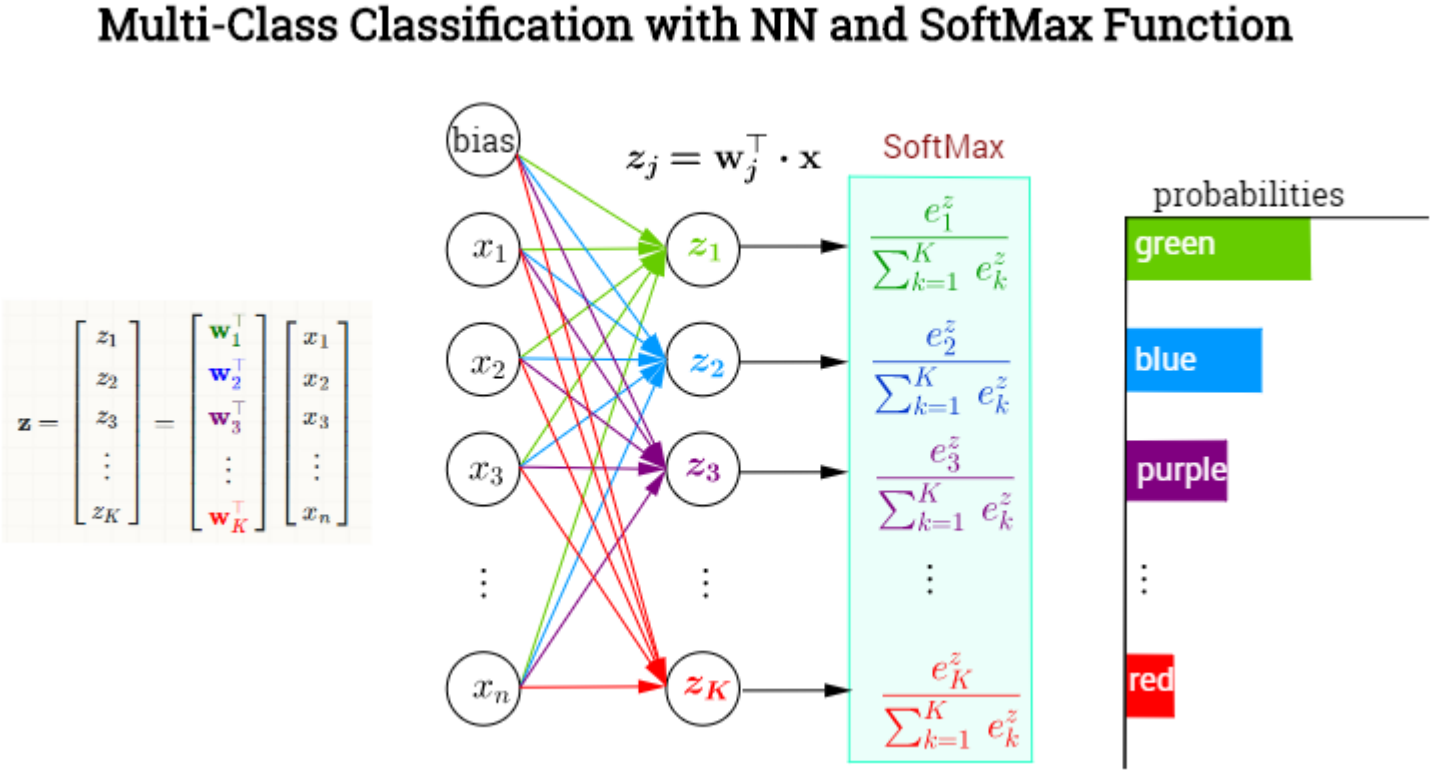
DropOut Network



DropConnect Network

Output Layers

* softmax/hierarchical softmax



Loss Functions

* maximum likelihood estimation (MLE) — Cross Entropy (Log loss)

$$CE = -\sum_{i}^{C} t_i log(s_i)$$

* max margin objective - Hinge loss

$$\mathcal{L} = \frac{1}{n}\sum_{i=1}^{n} \max(0, m - y^{(i)} \cdot \hat{y}^{(i)})$$

* KL-divergence loss

$$\begin{aligned}\mathcal{L} &= \frac{1}{n}\sum_{i=1}^{n} \mathcal{D}_{KL}(y^{(i)} || \hat{y}^{(i)}) \\ &= \frac{1}{n}\sum_{i=1}^{n} \left[y^{(i)} \cdot \log\left(\frac{y^{(i)}}{\hat{y}^{(i)}}\right)\right] \\ &= \underbrace{\frac{1}{n}\sum_{i=1}^{n} \left(y^{(i)} \cdot \log(y^{(i)})\right)}_{entropy} \underbrace{- \frac{1}{n}\sum_{i=1}^{n} \left(y^{(i)} \cdot \log(\hat{y}^{(i)})\right)}_{cross-entropy}\end{aligned}$$

https://isaacchanghau.github.io/post/loss_functions/

Backprop

* efficient way to compute derivatives (using DP)
* automatic & symbolic differentiation

https://colah.github.io/posts/2015-08-Backprop/

Optimization Algorithm

* gradient descent
* SGD (+minibatch)
* Momentum
* Adagrad/Adadelta/...
* Adam

Example: FNN for Adjective Ordering

Input: noun & 2 adjectives (embeddings)
Hidden: 4 ReLU FC-layes
Output: Sigmoid (Softmax)

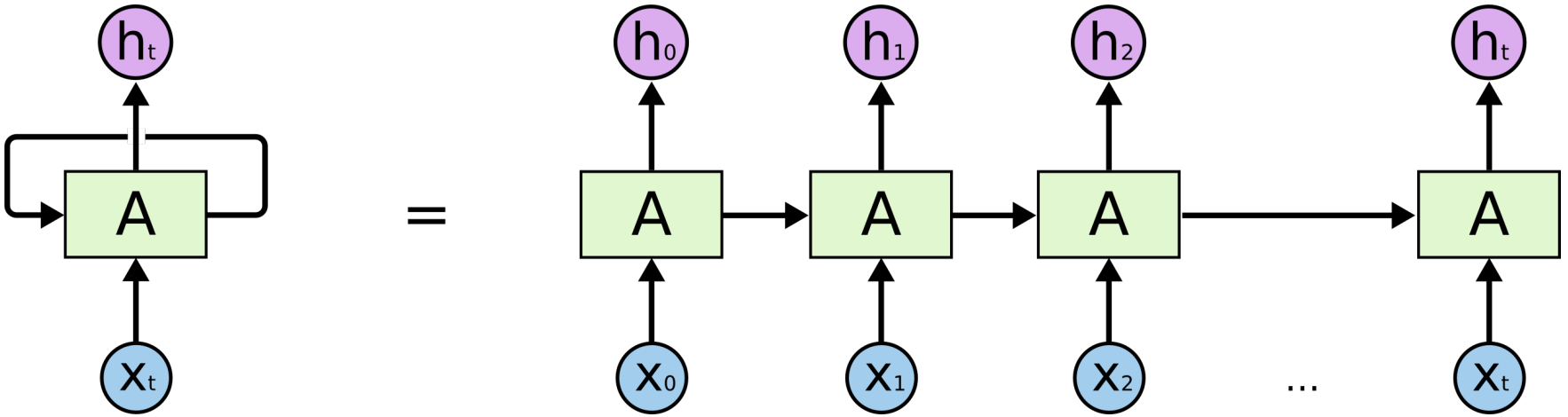
Run with both variants of order and select the better score

FNNs Recap

+ nonlinear, flexible
+ efficient training
+ allows to use embeddings
- fixed input
- limited context

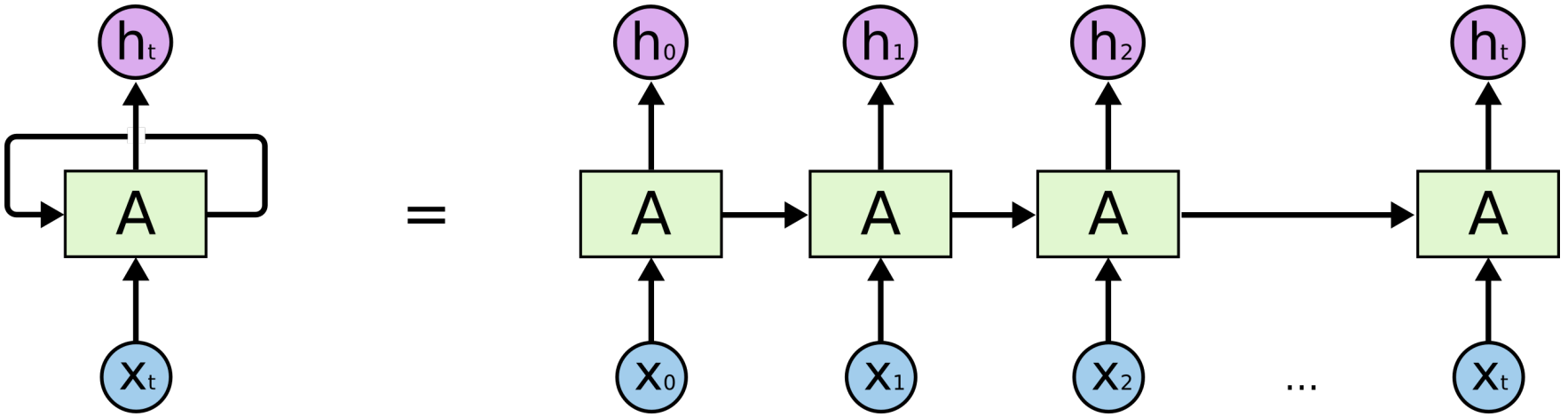
RNNs to the Rescue

* add previous state to input
* backpropagate through time (truncated - BPTT)



RNNs to the Rescue

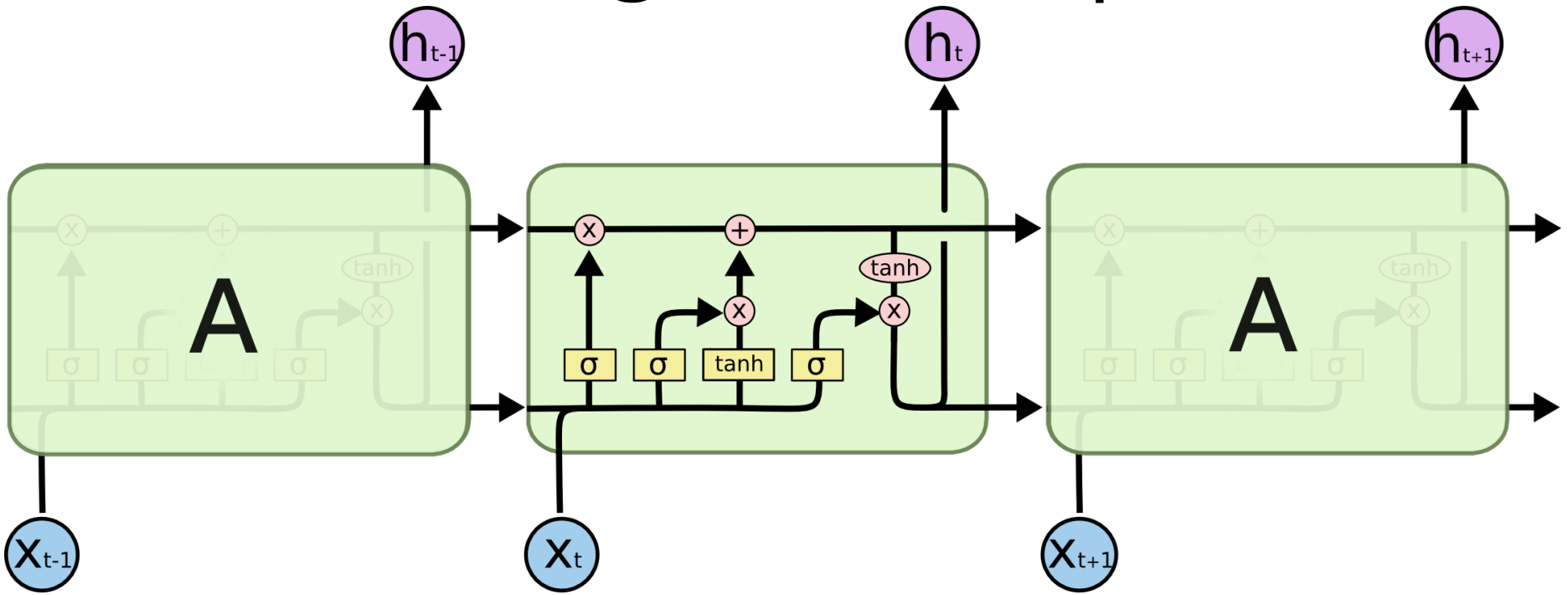
* add previous state to input
* backpropagate through time



* not so easy:
  - vanishing gradients
  - exploding gradients

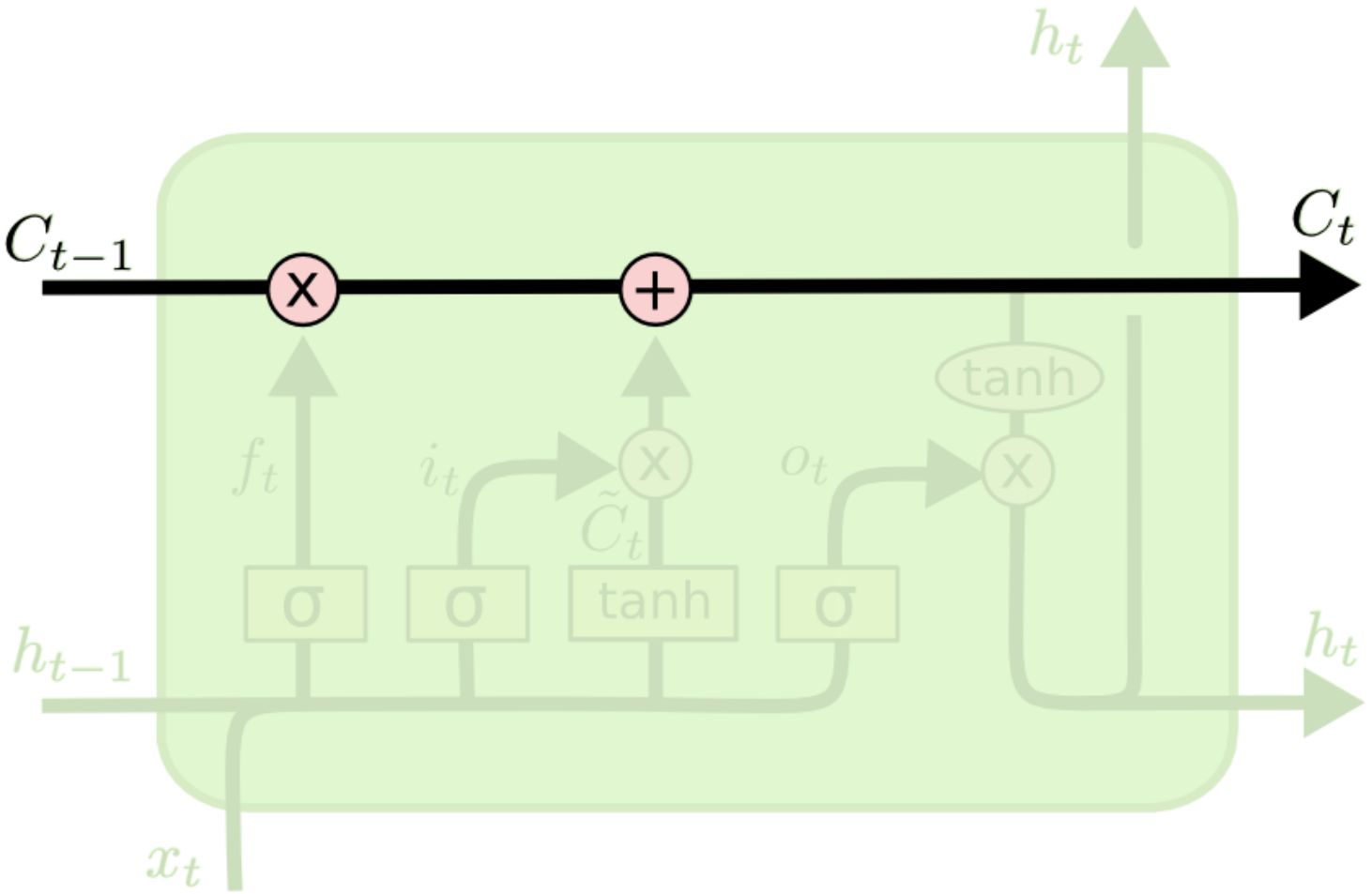
LSTM

specifically designed to remember long-term dependencies

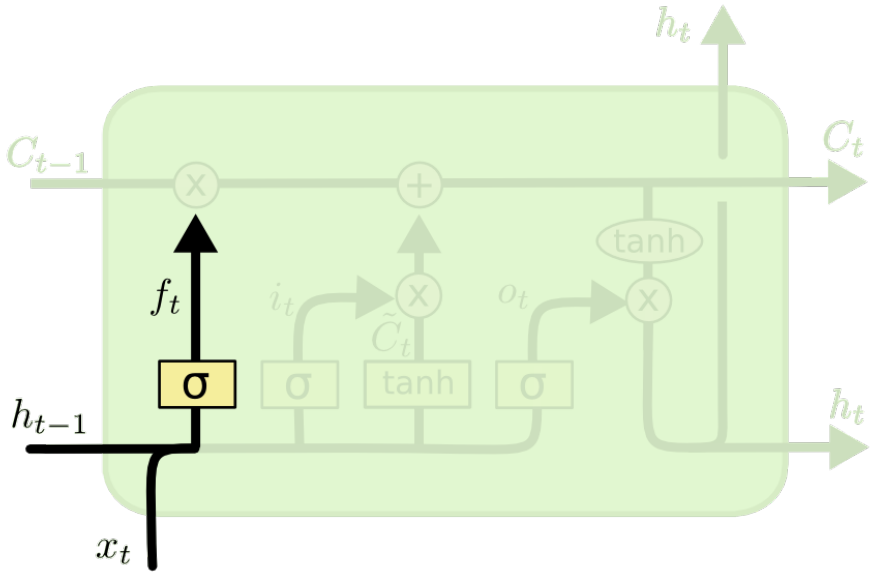


https://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM Cell State

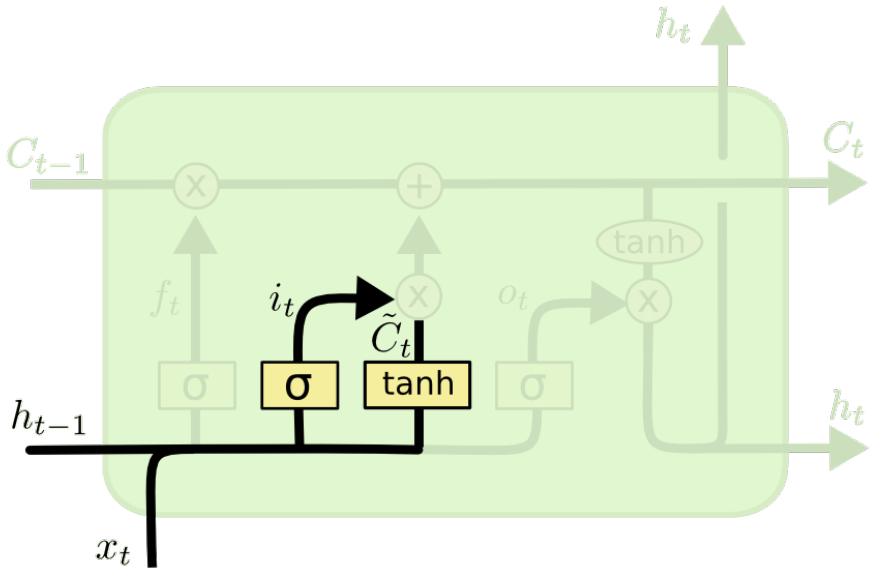


LSTM Forget Gate



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

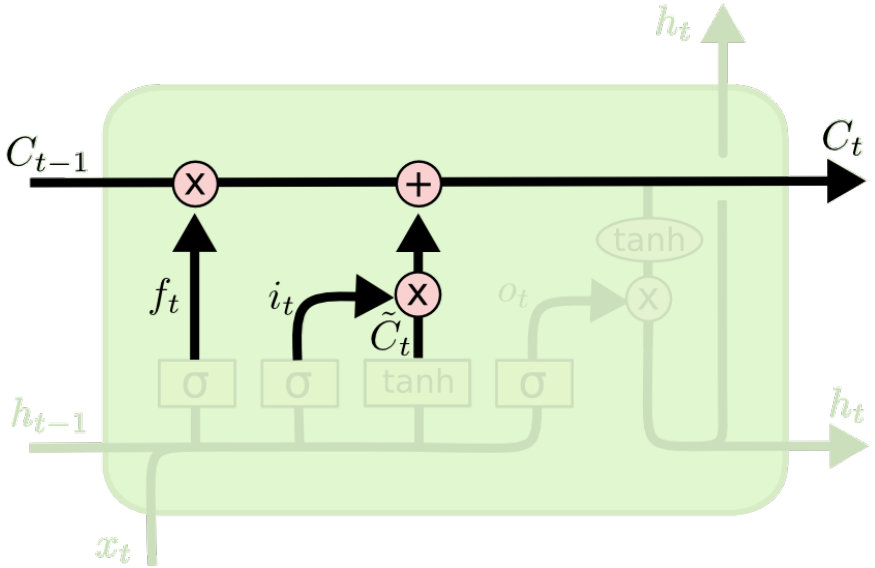
LSTM Remember Gate



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

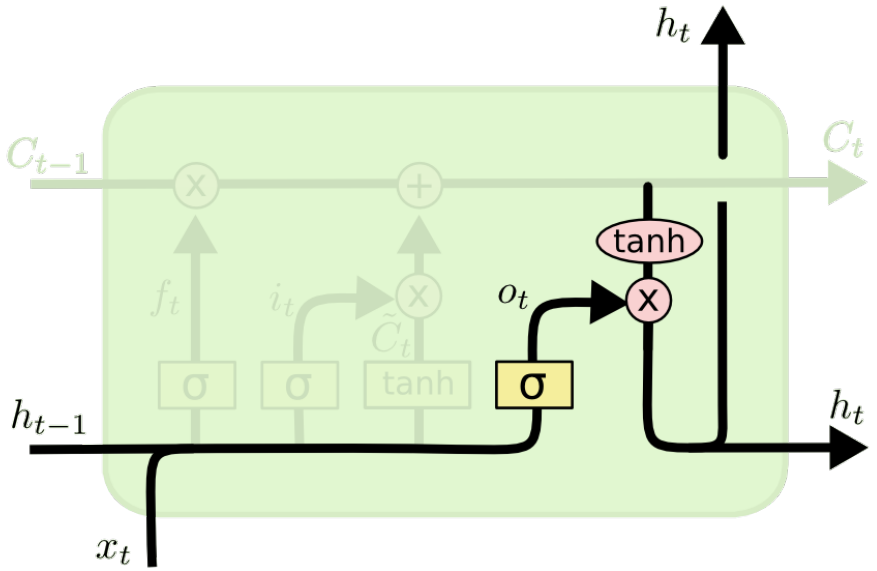
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

LSTM State Update



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

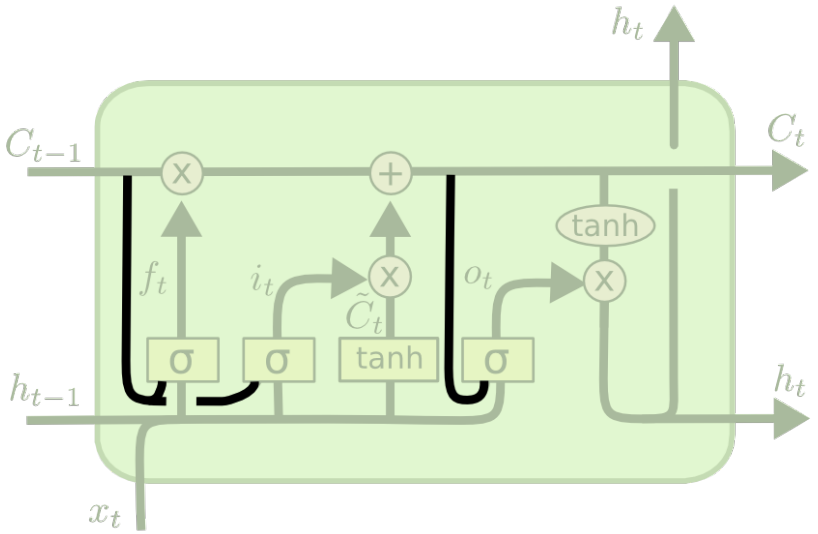
LSTM Output



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

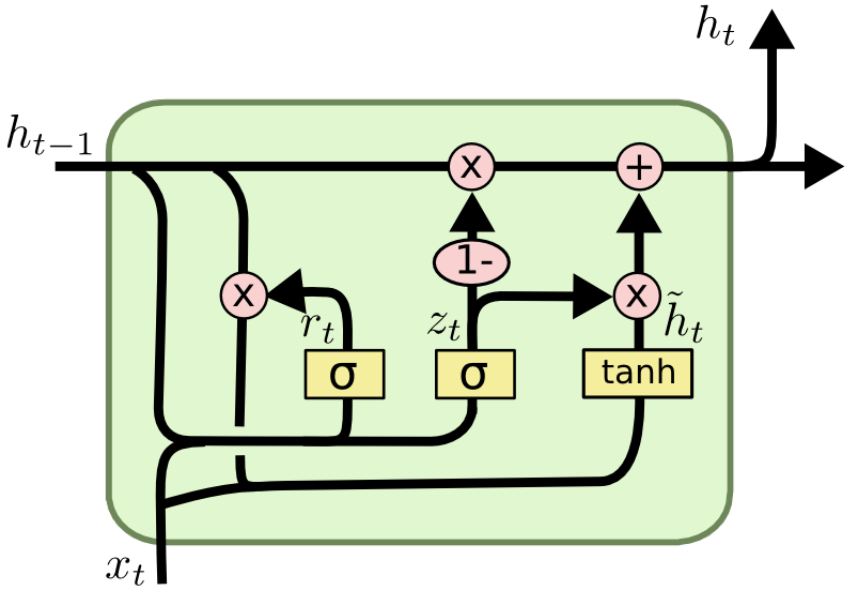
$$h_t = o_t * \tanh\left(C_t\right)$$

LSTM Peephole Connections



$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \; + \; b_o\right)$$

Gated Recurrent Unit (GRU)



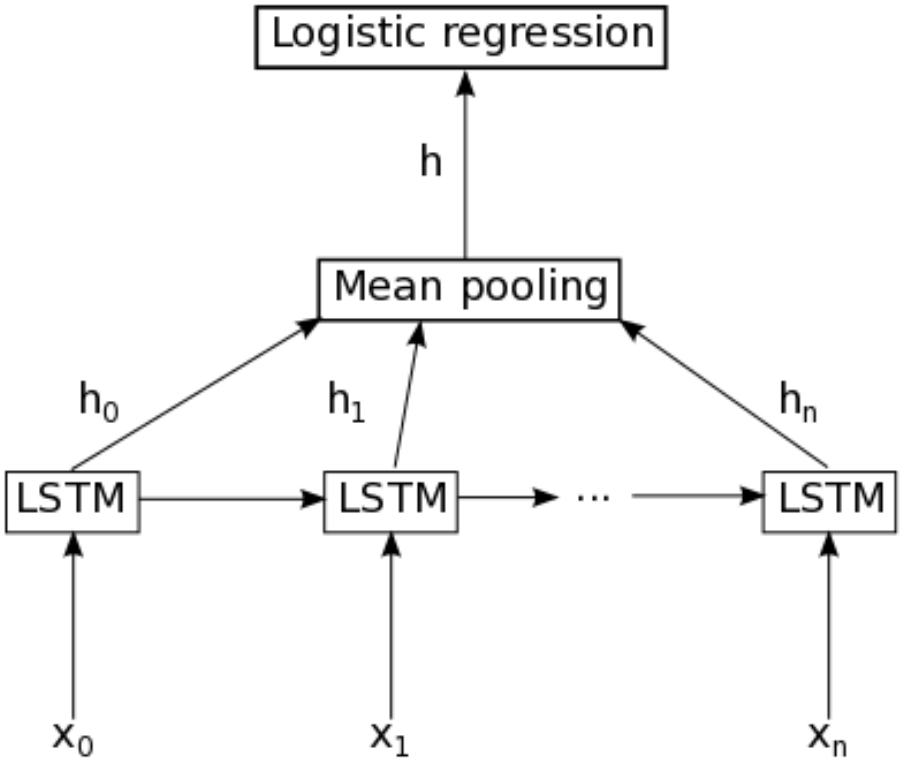
$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

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

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

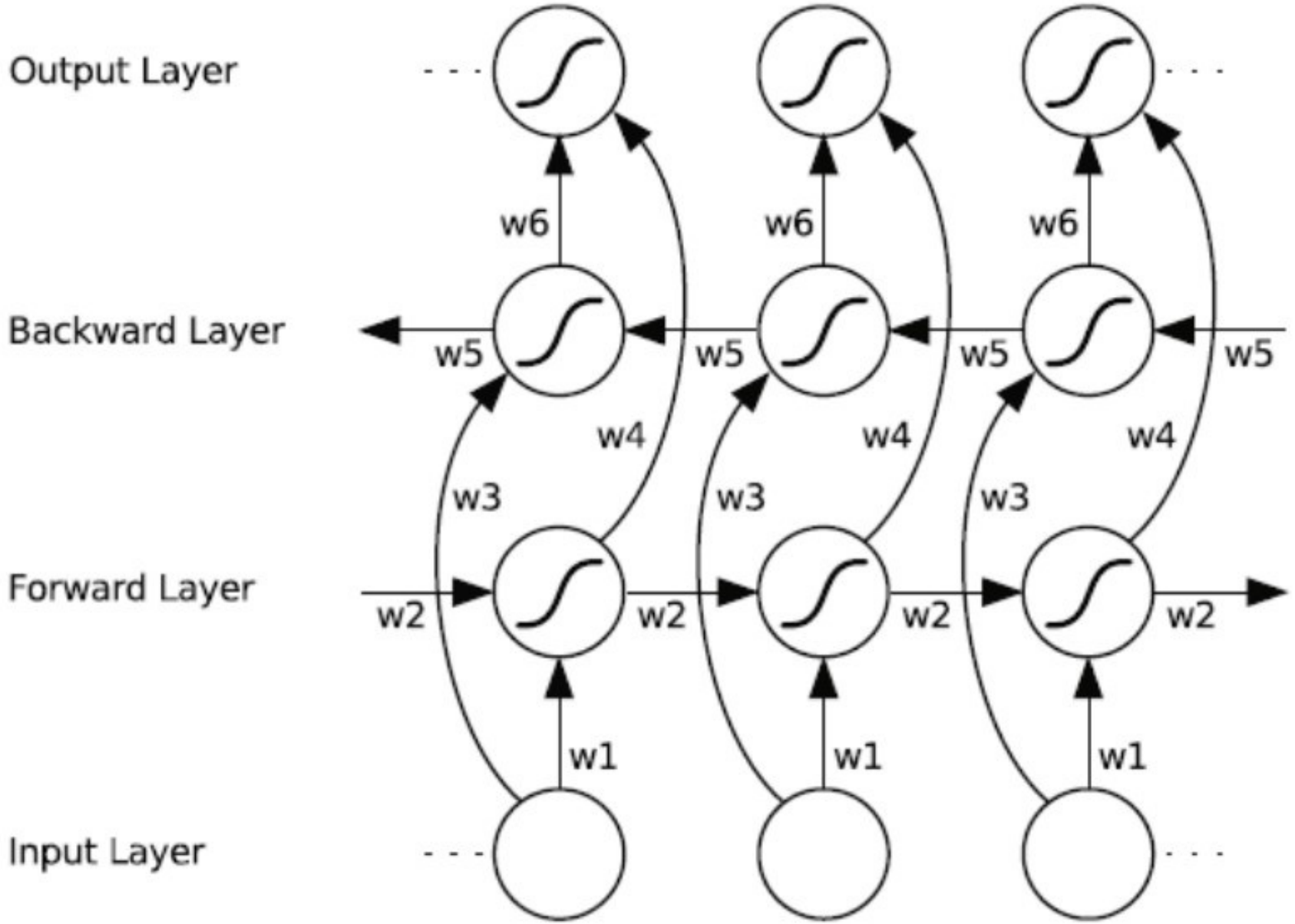
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

LSTM Example: Sentiment Analysis

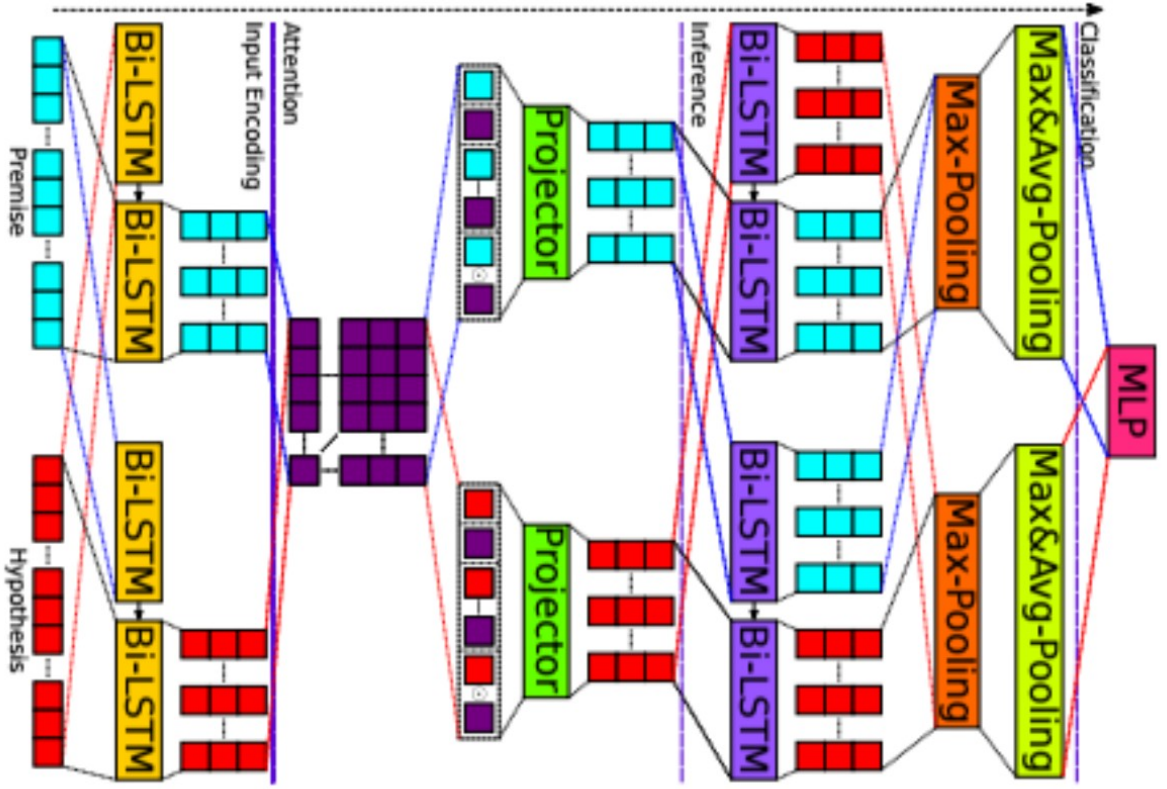


http://deeplearning.net/tutorial/lstm.html

BiLSTM


Output Layer
Backward Layer
Forward Layer
Input Layer
w1
w2
w3
w4
w5
w6

BiLSTM Example: Machine Reading

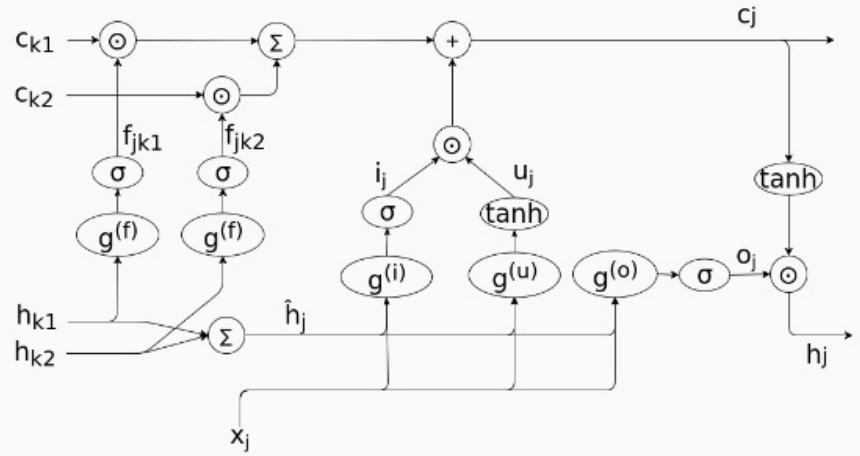


https://arxiv.org/pdf/1802.05577.pdf

TreeLSTM

Child-sum tree LSTM

Children outputs and memory cells are summed



Child-sum tree LSTM at node j with children k_1 and k_2

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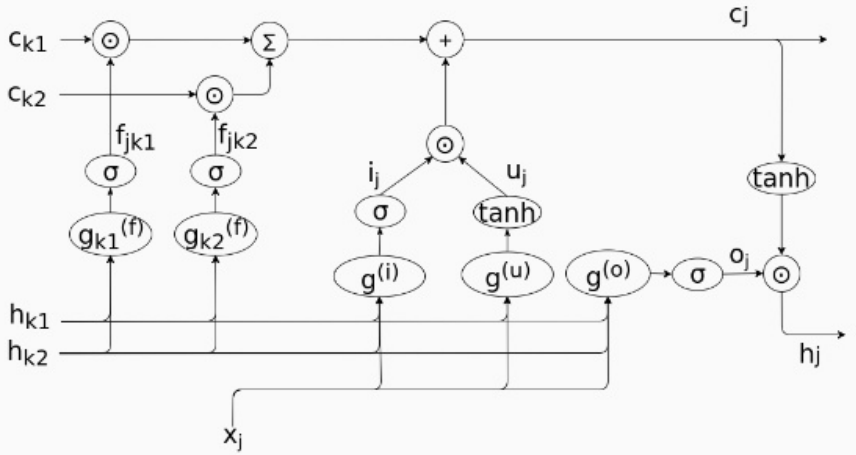
N-ary tree LSTM

Given $g_k^{(n)}(x_t, h_{l_1}, \cdots, h_{l_N}) = W^{(n)}x_t + \sum_{l=1}^{N} U_{kl}^{(n)} h_{jl} + b^{(n)}$



Binary tree LSTM at node j with children k_1 and k_2

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https://www.slideshare.net/tuvistavie/tree-lstm

TreeLSTM Example

Semantic relatedness

Task

Predict similarity score in $[1, K]$ between two sentences

Method

Similarity between sentences L and R annotated with score $\in [1, 5]$

- Produce representations h_L and h_R
- Compute distance h_+ and angle $h_\times$ between h_L and h_R
- Compute score using fully connected NN

$$h_s = \sigma\left(W^{(\times)} h_\times + W^{(+)} h_+ + b^{(h)}\right)$$

$$\hat{p}_\theta = \text{softmax}\left(W^{(p)} h_s + b^{(p)}\right)$$

$$\hat{y} = r^T \hat{p}_\theta \qquad r = [1, 2, 3, 4, 5]$$

- Error is computed using KL-divergence

LSTM Deficiencies

* computation not parallelizable
* neuron interpretability

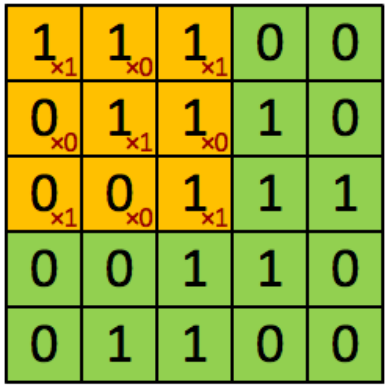
Improvements/alternatives:
* RAN (Recurrent Additive Network)
  https://arxiv.org/pdf/1705.07393.pdf
* Janet (just the forget gate)
  https://arxiv.org/pdf/1804.04849.pdf
* QRNN (Quasi-recurrent Neural Network)
  https://goo.gl/NUx7VC

BiLSTM+attention as SOTA

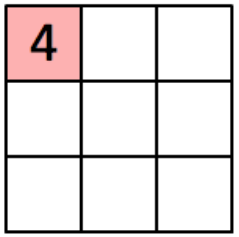
“Basically, if you want to do an NLP task, no matter what it is, what you should do is throw your data into a Bi-directional long-short term memory network, and augment its information flow with the attention mechanism.”
— Chris Manning

https://twitter.com/mayurbhangale/status/988332845708886016

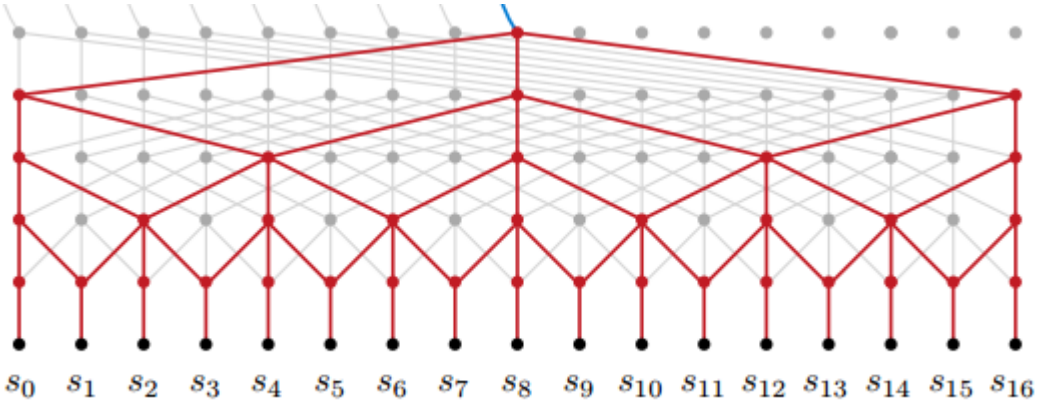
Convolutional Neural Networks (CNNs)



Image

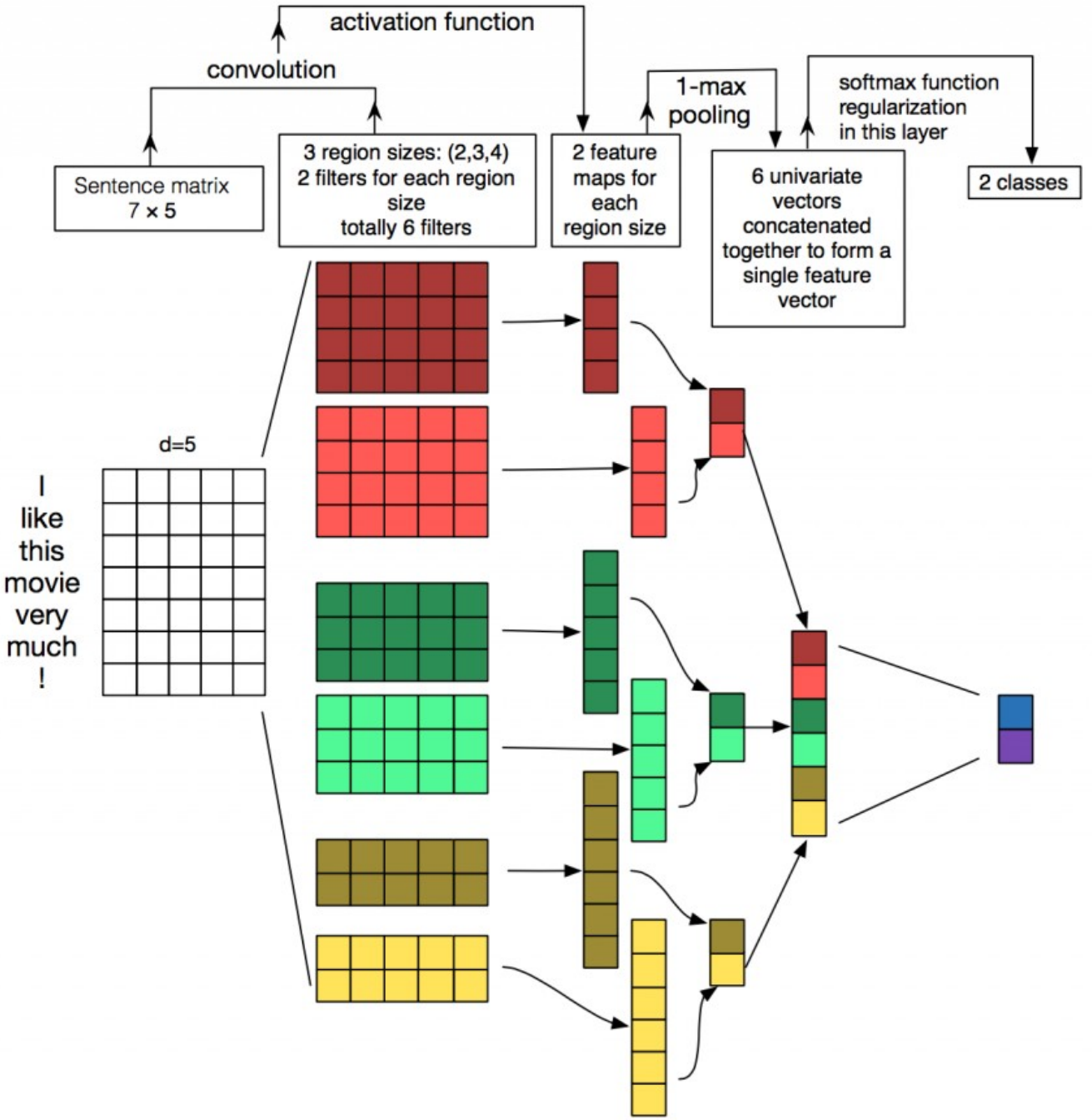


Convolved Feature



* convolutions can do the same as RNNs but faster
* any part of a sentence can influence the semantics of a word
  So we want our network to see the entire input at once
* getting that big a receptive can make gradients vanish
  and our networks fail
* we can solve the vanishing gradient problem
  with DenseNets or Dilated Convolutions
* use “deconvolutions” to generate arbitrarily long outputs

https://medium.com/@TalPerry/convolutional-methods-for-text-d5260fd5675f

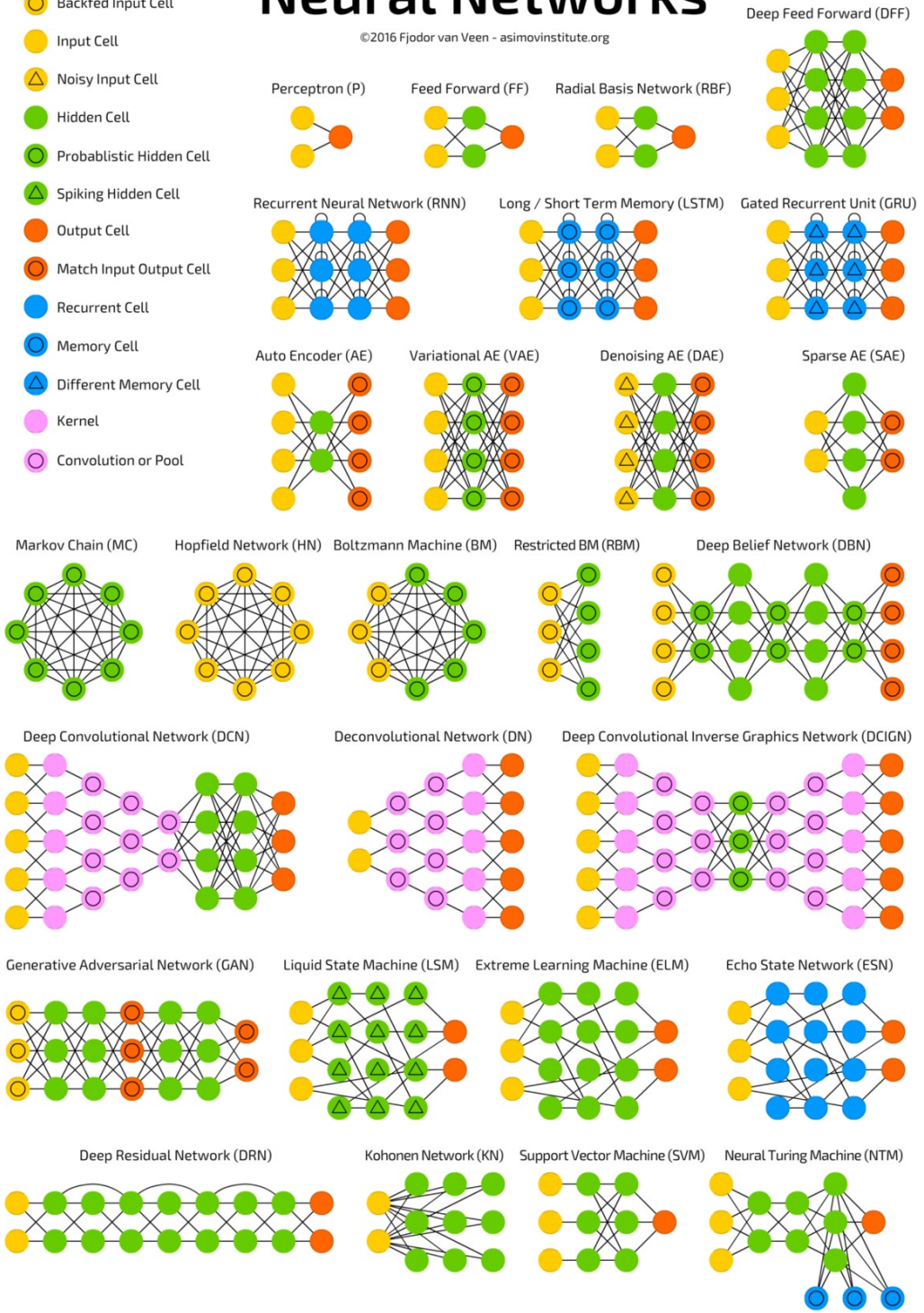


http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/

A mostly complete chart of

Neural Networks

- Backfed Input Cell
- Input Cell
- Noisy Input Cell
- Hidden Cell
- Probablistic Hidden Cell
- Spiking Hidden Cell
- Output Cell
- Match Input Output Cell
- Recurrent Cell
- Memory Cell
- Different Memory Cell
- Kernel
- Convolution or Pool



Read More

Neural Nets for NLP:
http://cs231n.github.io
https://hackernoon.com/the-unreasonable-ineffectiveness-of-deep-learning-in-nlu-e4b4ce3a0da0
https://colah.github.io/posts/2014-03-NN-Manifolds-Topology/
https://blackboxnlp.github.io/

Nonlinearities:
https://towardsdatascience.com/selu-make-fnns-great-again-snn-8d61526802a9
https://medium.com/@jaiyamsharma/experiments-with-swish-activation-function-on-mnist-dataset-fc89a8c79ff7
https://towardsdatascience.com/the-mostly-complete-chart-of-neural-networks-explained-3fb6f2367464
http://building-babylon.net/2017/08/01/hierarchical-softmax/

Read More x2

Backprop & gradient descent:
https://medium.com/@karpathy/yes-you-should-understand-backprop-e2f06eab496b
http://ruder.io/optimizing-gradient-descent/
https://openreview.net/pdf?id=ryQu7f-RZ
https://fosterelli.co/executing-gradient-descent-on-the-earth

RNN & LSTM:
https://deeplearning4j.org/lstm.html
http://karpathy.github.io/2015/05/21/rnn-effectiveness/
https://medium.com/@aidangomez/let-s-do-this-f9b699de31d9