Deep Learning for Natural Language Processing

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Overview

1. What's Deep Learning?
2. Neural Networks Recap
   - Demystifying Neural Networks
   - Forward/Backward Propagation
   - Gradient Descent & Chain Rule
3. Lego Blocks for Building NLP Deep Nets
   - Word Embedding - word2vec
   - Recurrent Neural Network - LSTM & Bidirectional
   - Recursive Neural Network
   - Convolutional Neural Network
4. Advanced Models
   - Attention Model
   - Seq2seq/End-to-end Learning

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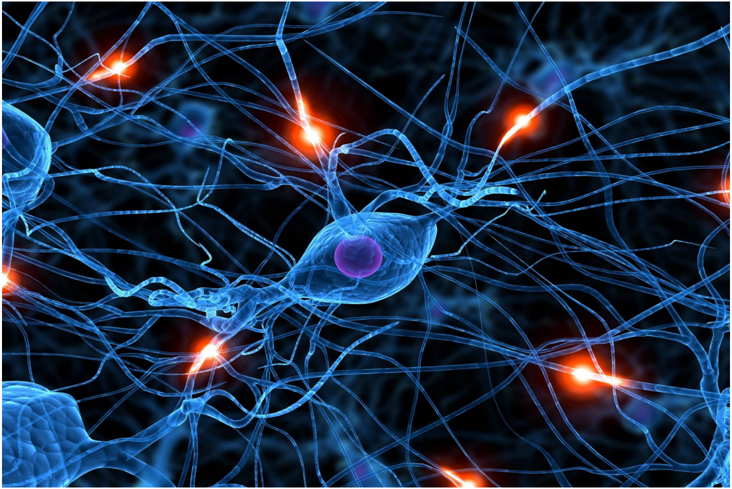

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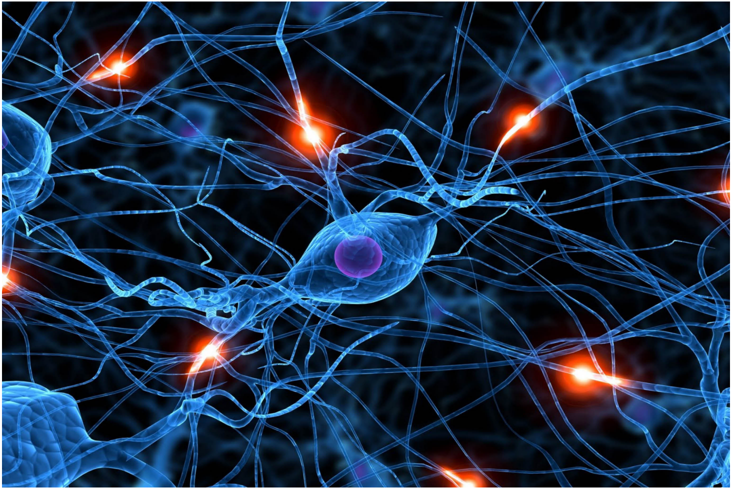
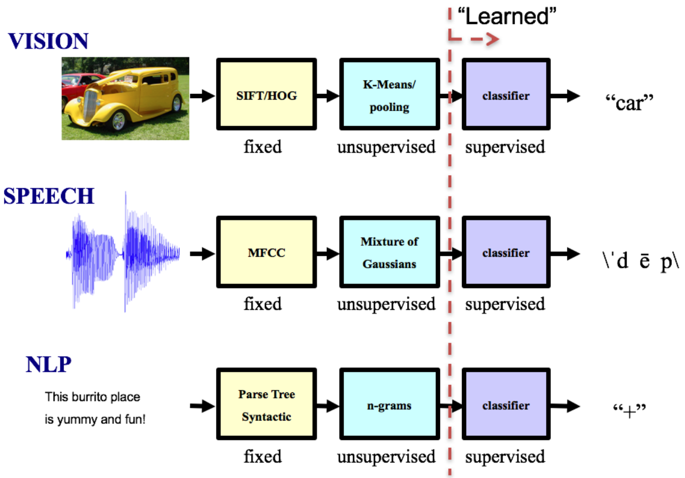


Neural nets try to mimic how humans process information.

Deep vs. Traditional Machine Learning



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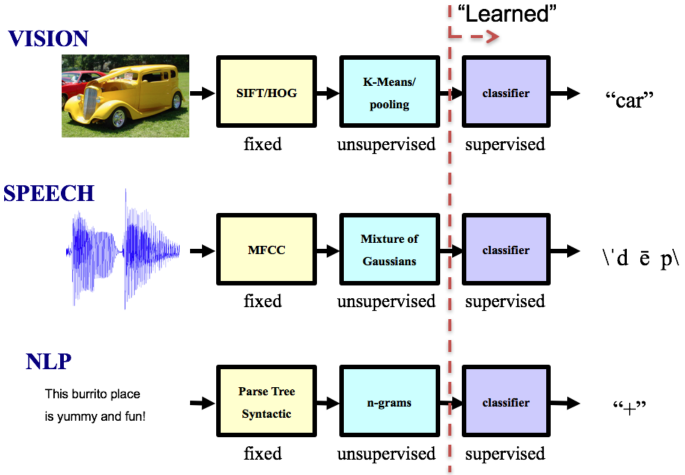

Representation Learning $\Longrightarrow$ Classifier Training

Motivations for Deep Learning

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1. Hierarchical Compositionality

- Cascade of non-linear transformations
- Multiple layers of representations

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3. End-to-end Learning

- Learning (goal-driven) representations
- Feature extraction learning

Overview

From Logistic Regression to Neural Nets

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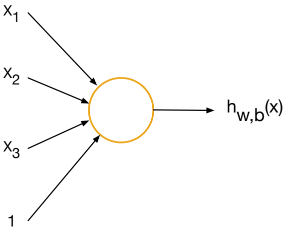
- Logistic Regression



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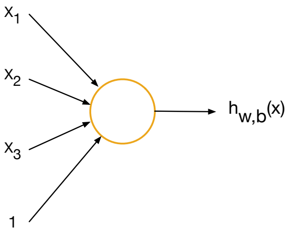

$$x = [x_1, x_2, x_3]$$
$$h_{w,b}(x) = \sigma(w^T x + b)$$
$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

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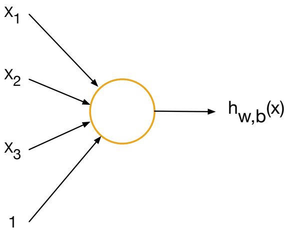

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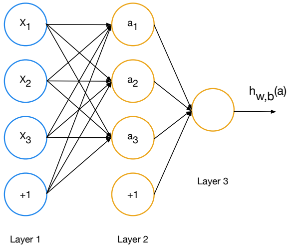

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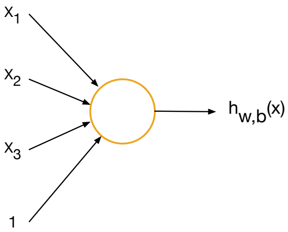

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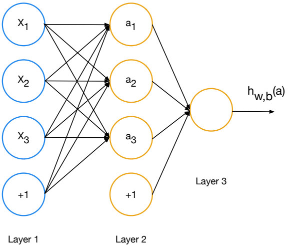

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$$z = W^T x + B$$
$$a = \sigma(z)$$
$$= [\sigma(z_1), \sigma(z_2), \sigma(z_3)]$$

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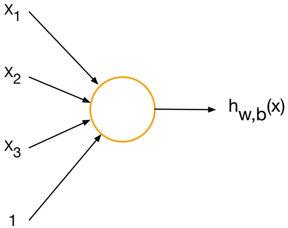

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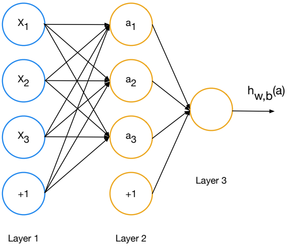

$$\begin{aligned} x &= [x_1, x_2, x_3] \\ z &= W^T x + B \\ a &= \sigma(z) \\ &= [\sigma(z_1), \sigma(z_2), \sigma(z_3)] \end{aligned}$$

Multiple Logistic Regressions

Forward/Backward Propagation

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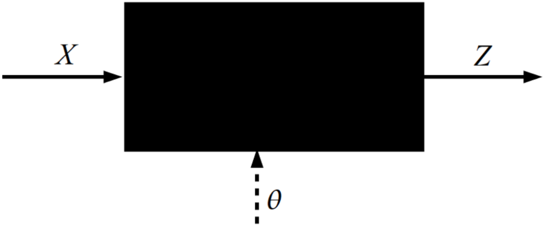
Given input, compute output:



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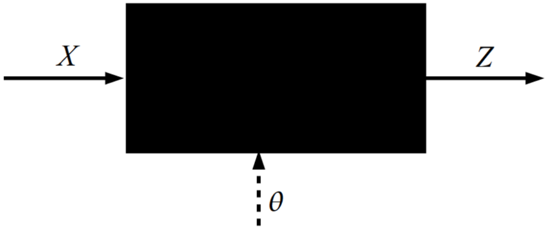
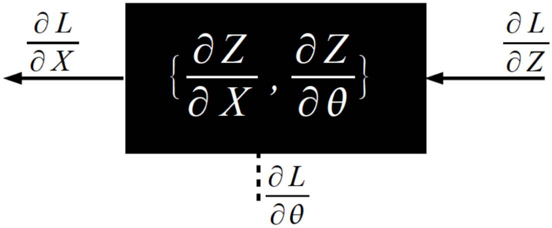


Given ground truth, backpropagate feedbacks:



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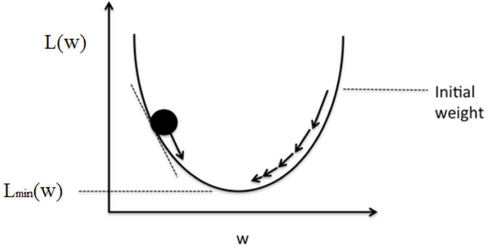

Schematic of gradient descent.

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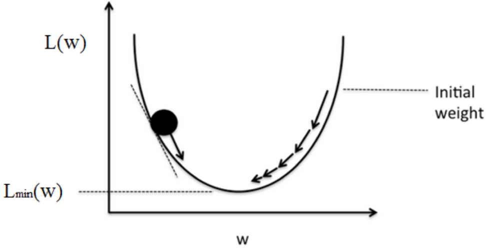

Schematic of gradient descent.

$$w = w - \eta \cdot \frac{dL}{dw}, \ \eta \text{ - step size}$$

Chain Rule

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How to get the gradients of all the parameters?

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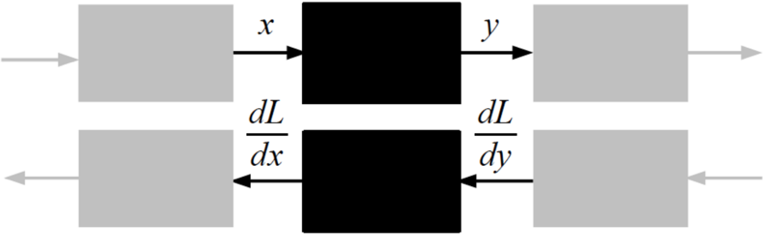

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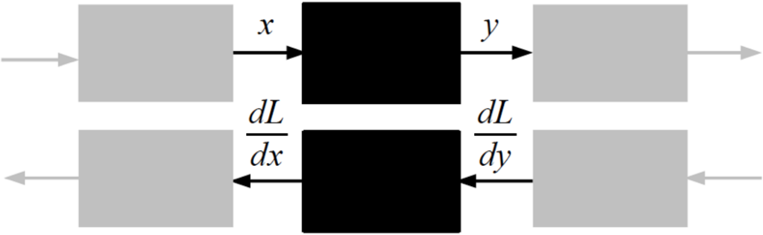

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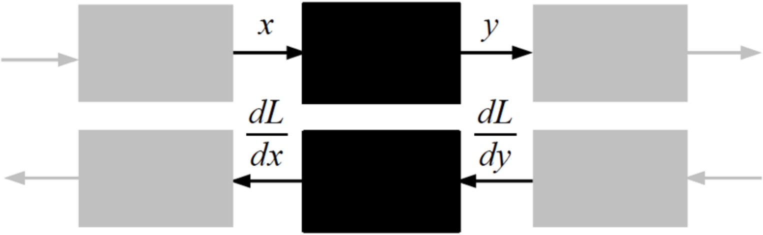

Given $y(x)$ and $\frac{dL}{dy}$, what is $\frac{dL}{dx}$? $\implies \frac{dL}{dx} = \frac{dL}{dy} \cdot \frac{dy}{dx}$

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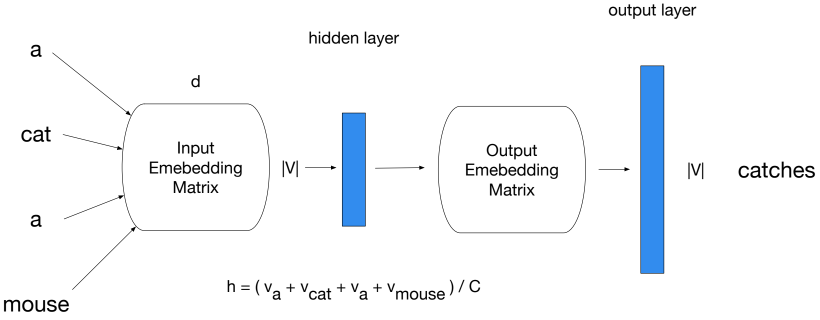

Continuous Bag-of-word (CBOW)

Mikolov, Tomas, et al. "Efficient estimation of word representations in vector space." arXiv, 2013

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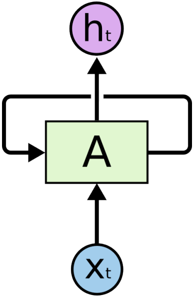

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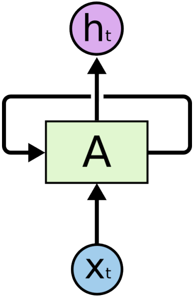

$$a^t = W_x^T x^t + W_h^T h^{t-1}$$
$$h^t = \theta(a^t)$$
$$\theta : \sigma, \text{tanh}, \text{ReLU}, \ldots$$

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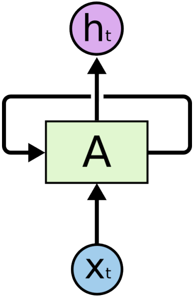

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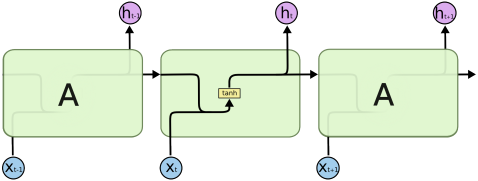

Unrolled version of vanilla RNN

Problem of Long Term Dependencies

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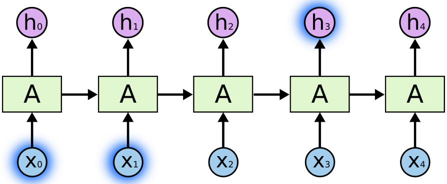

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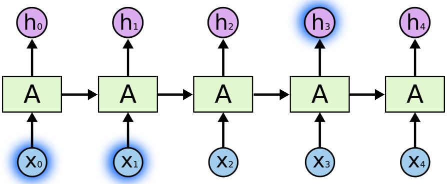

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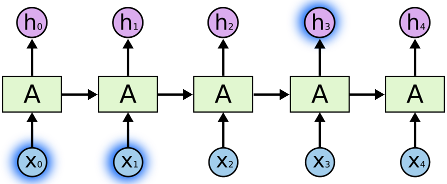

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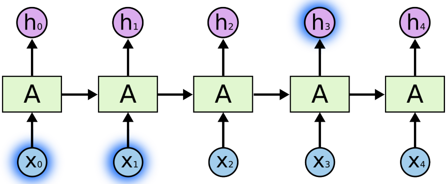

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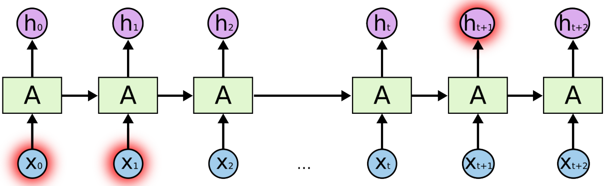

Long and Short Term Memory networks

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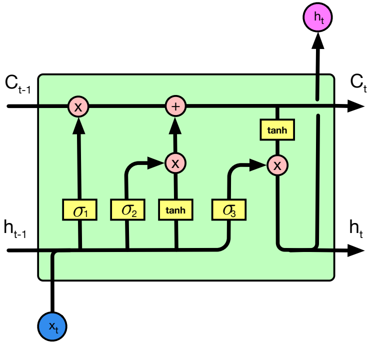

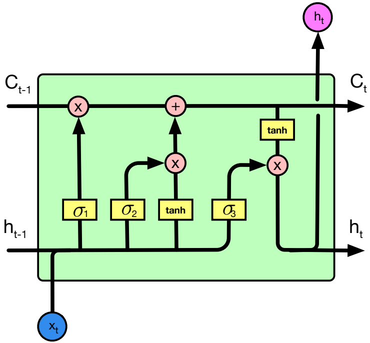

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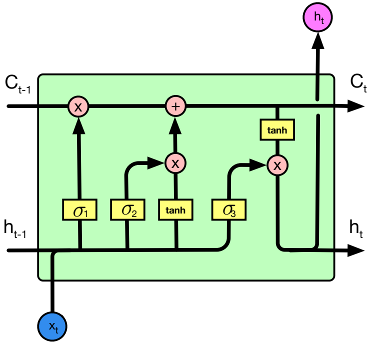

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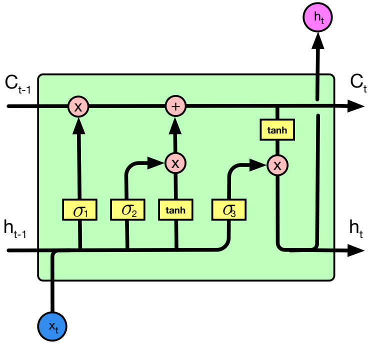

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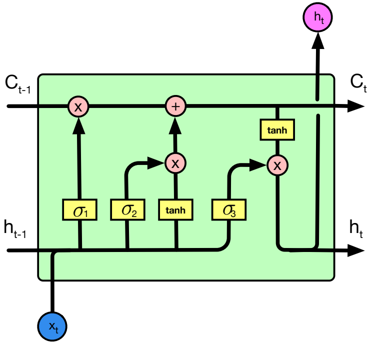

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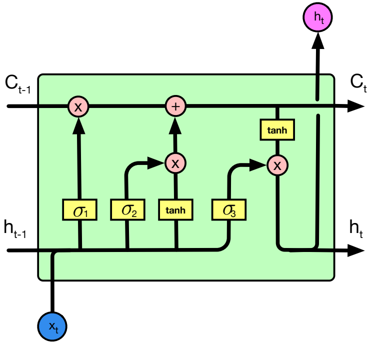

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Ideas behind LSTM

- The cell states on top memorizes long term information
- Update strengths are controlled by gates, i.e., σ function

Bidirectional RNN

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The semantics at some step not only depends on previous words, but also future ones.

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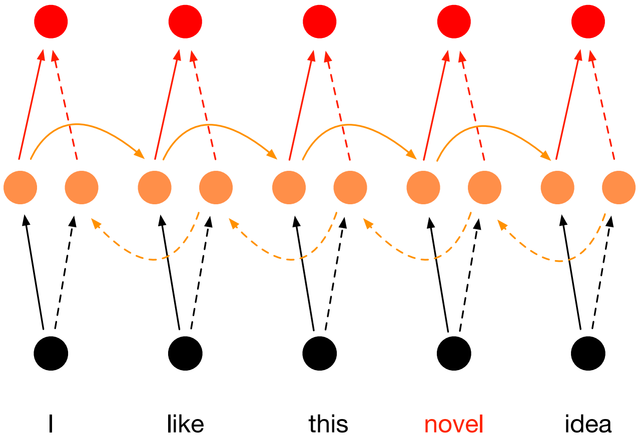

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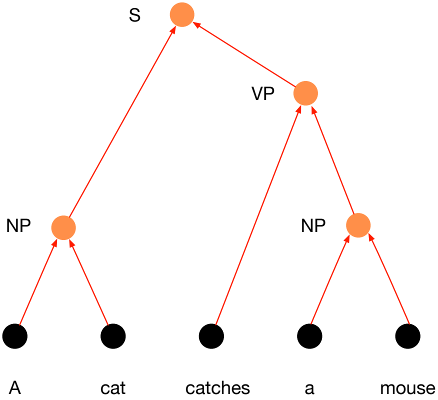

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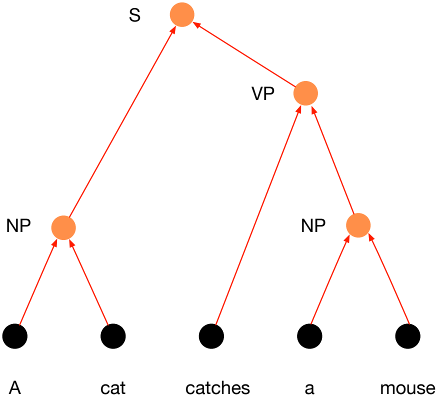

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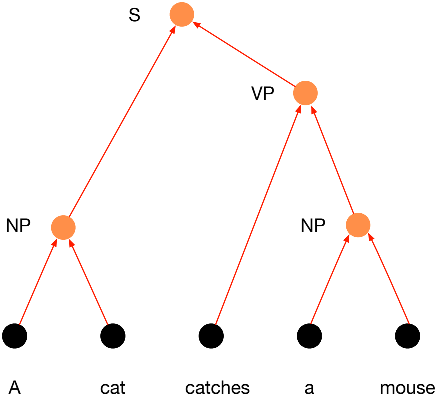

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$$s = U^T p$$

Training objective:

$$s(x_i, y_i) = \sum s$$

$$W, U = \arg\max \sum_i s(x_i, y_i)$$

Fixed W and U at all nodes

Socher, et al. "Learning continuous phrase representations and syntactic parsing with recursive neural networks." NIPS, 2010.

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Convolution

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Mathematical Definition

$$(I * K)(\mu) = \int I(t) \cdot K(\mu - t)dt$$

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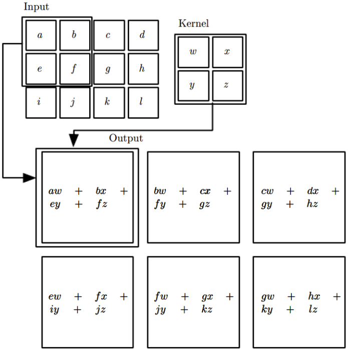

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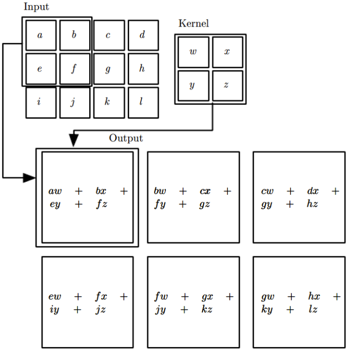

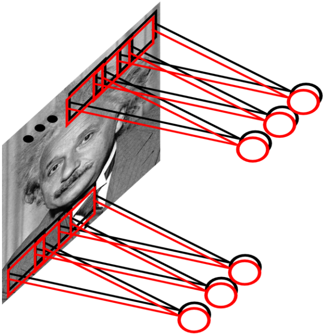

CNN Text Classifier

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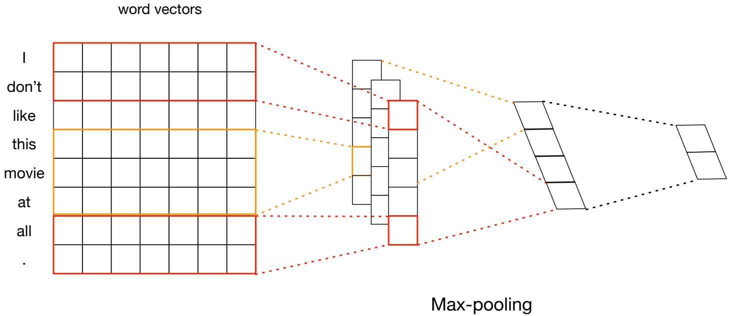
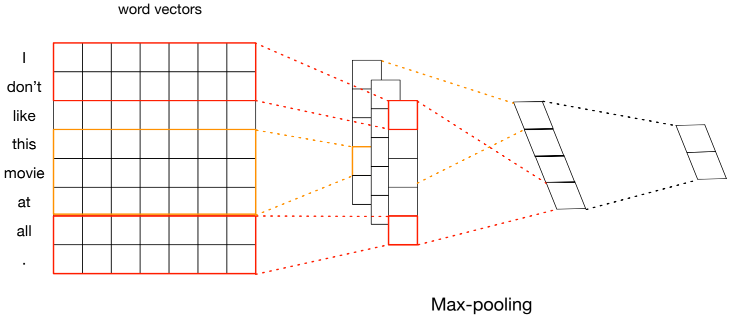
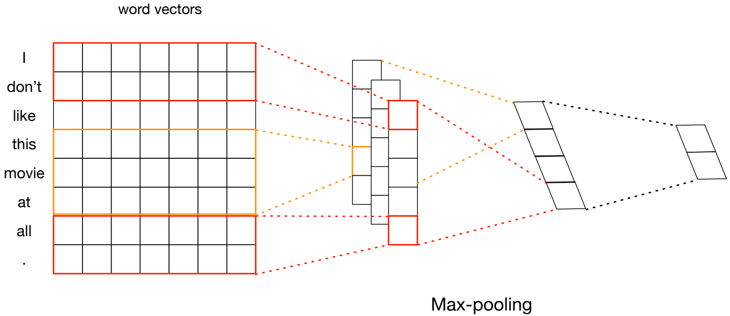


CNN Text Classifier



Motivations

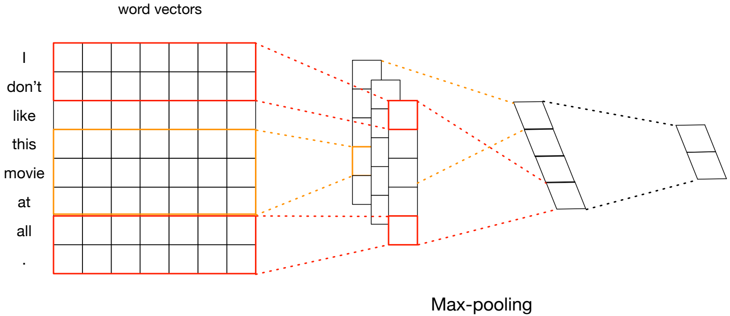
CNN Text Classifier



Motivations

- Convolution with different size learns n-grams.

CNN Text Classifier



Motivations

- Convolution with different size learns n-grams.
- Max-pooling learns the most salient features (phrases).

Kim, Yoon. "Convolutional neural networks for sentence classification." EMNLP, 2014

Overview

1. What's Deep Learning?
2. Neural Networks Recap
   - Demystifying Neural Networks
   - Forward/Backward Propagation
   - Gradient Descent & Chain Rule
3. Lego Blocks for Building NLP Deep Nets
   - Word Embedding - word2vec
   - Recurrent Neural Network - LSTM & Bidirectional
   - Recursive Neural Network
   - Convolutional Neural Network
4. Advanced Models
   - Attention Model
   - Seq2seq/End-to-end Learning

Attention Model

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Words at different steps should have different effects.

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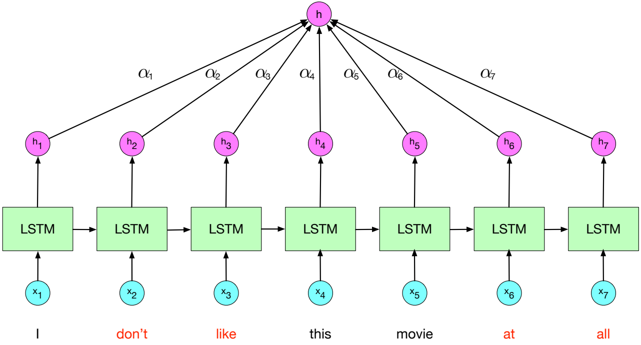

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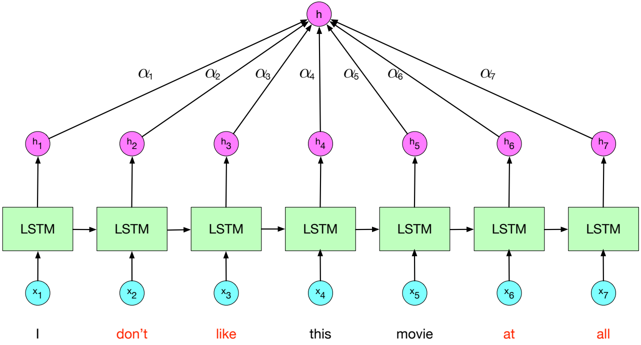

$$h_c = [h_1, \ldots, h_7], \; S = \tanh(W h_c)$$

$$\alpha = \mathrm{softmax}(w^T S), \; h = \sum_{i=1}^{7} \alpha_i h_i$$

Seq2seq/End-to-end Learning

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Suppose we want to do machine translation.

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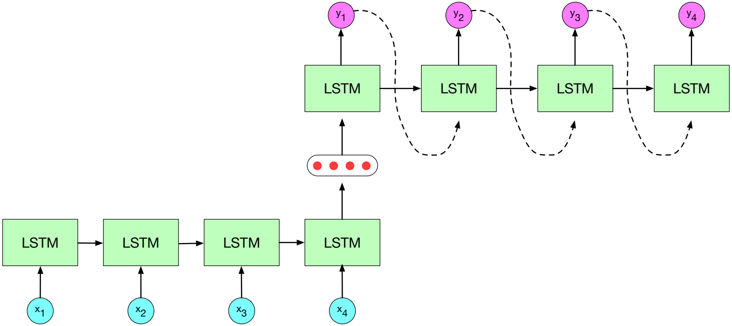

Sutskever, Ilya, et al. "Sequence to sequence learning with neural networks." NIPS, 2014

Questions?

Activity - Get familiar with neural networks

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Go to http://playground.tensorflow.org

1. Select dataset and split them into training and test;
2. Choose input features you want to feed into the network;
3. Determine number of layers and neurons in each layer;
4. Tune hyperparameter:
   - Learning rate - start with intermediate ones like 0.03;
   - Nonlinear activation function - ReLU is recommended;
   - Regularization: L1 or L2 norm, and its strength rate;
5. Start training and see how your model fits the data;

Activity - Get familiar with neural networks