CS 6120/CS4120: Natural Language Processing

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Project Progress Report

- 1. What changes you have made for the task compared to the proposal, including problem/task, models, datasets, or evaluation methods? If there is any change, please explain why.
- 2. Describe data preprocessing process. This includes data cleaning, selection, feature generation or other representation you have used, etc.
- 3. What methods or models you have tried towards the project goal? And why do you choose the methods (you can including related work on similar task or relevant tasks)?
- 4. What results you have achieved up to now based on your proposed evaluation methods? What is working or What is wrong with the model?
- 5. How can you improve your models? What are the next steps?

- Grading: For 2-5, each aspect will take 25 points.
- Length: 2 page (or more if necessary). Single space if MS word is used. Or you can choose latex templates, e.g. https://www.acm.org/publications/proceedings-templateor http://icml.cc/2015/?page_id=151.
- Each group only needs to submit one copy.

Logistics

- Progress report is due at Oct 31, 11:59pm

- If you can’t finish running on a large dataset, you can try a small dataset, but notice what the effect would be

- Start with baseline models.

- Amazon Web Service credit/Google cloud credit
  - Debug models locally, learn to debug and test

Outline

- Basics about Feedforward Neural Networks
- Neural language model (word2vec)
- Recurrent Neural Network (RNN) and LSTM

[Slides borrowed from Hugo Larochelle, Raymond Mooney, Kai-wei Chang]

Neural Network Learning

- Learning approach based on modeling adaptation in biological neural systems.
- Perceptron: Initial algorithm for learning simple neural networks (single layer) developed in the 1950's.
- Backpropagation: More complex algorithm for learning multi-layer neural networks developed in the 1980's.

ARTIFICIAL NEURON

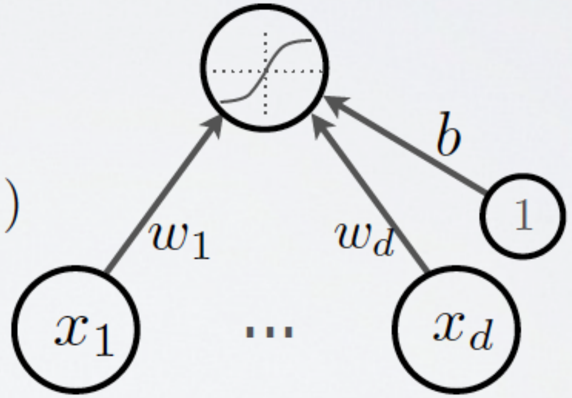
Topics: connection weights, bias, activation function

- Neuron pre-activation (or input activation):

$$a(\mathbf{x}) = b + \sum_i w_i x_i = b + \mathbf{w}^\top \mathbf{x}$$

- Neuron (output) activation

$$h(\mathbf{x}) = g(a(\mathbf{x})) = g(b + \sum_i w_i x_i)$$

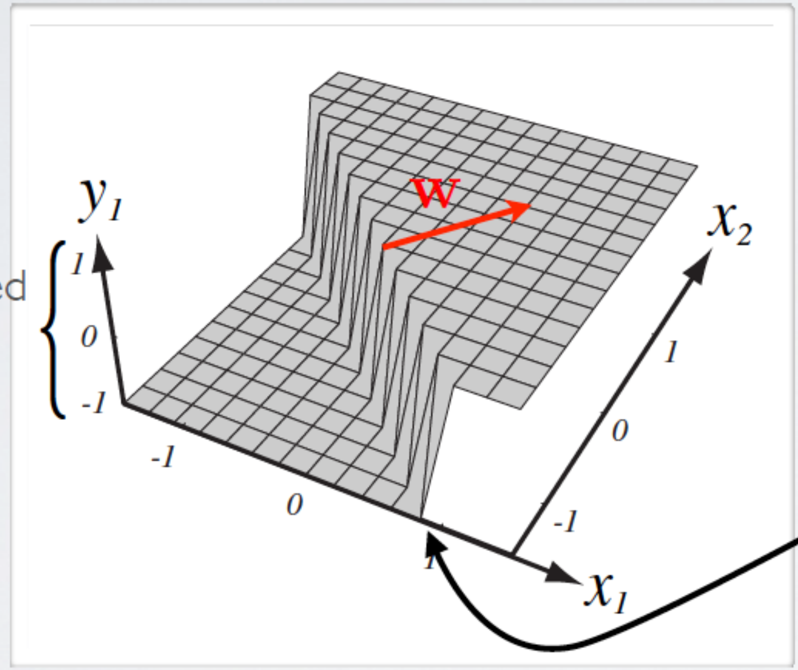


- $\mathbf{w}$ are the connection weights
- b is the neuron bias
- $g(\cdot)$ is called the activation function

ARTIFICIAL NEURON

Topics: connection weights, bias, activation function

range determined by $g(\cdot)$



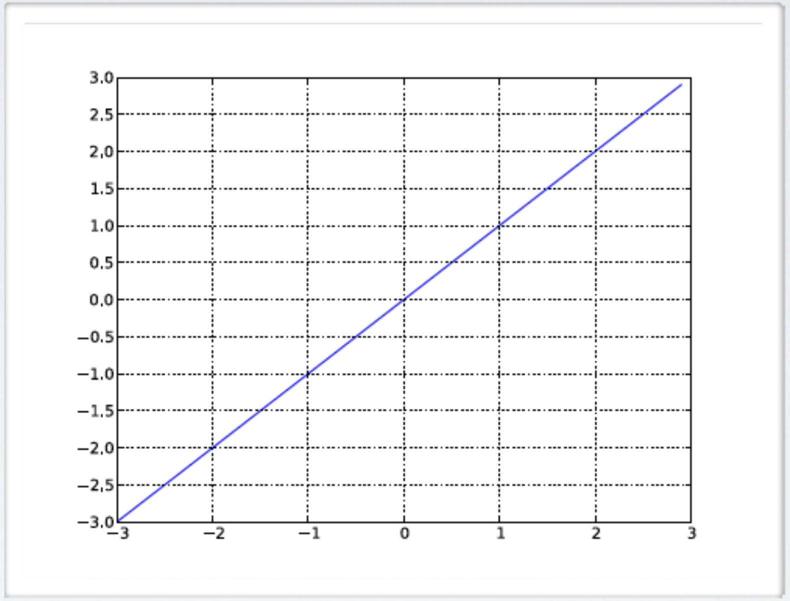
bias b only changes the position of the riff

(from Pascal Vincent's slides)

ACTIVATION FUNCTION

Topics: linear activation function

- Performs no input squashing
- Not very interesting...

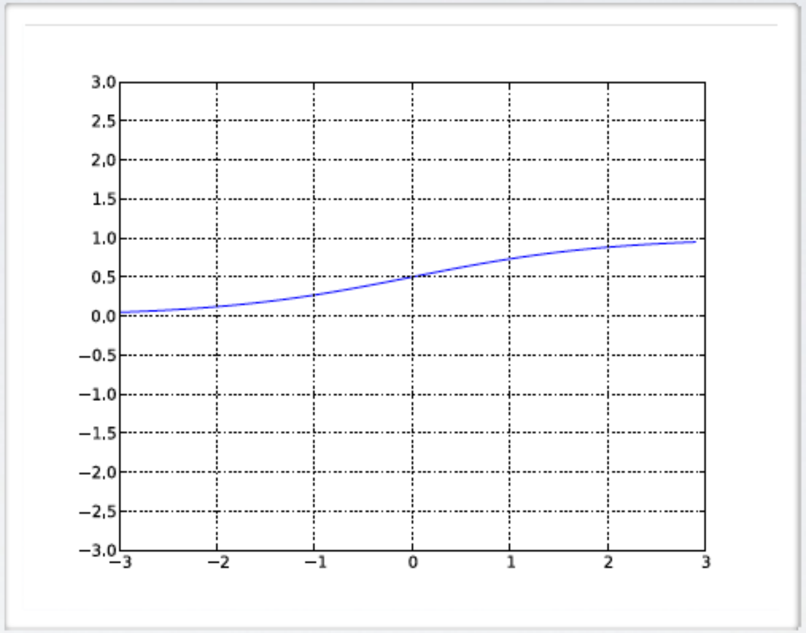


$$g(a) = a$$

ACTIVATION FUNCTION

Topics: sigmoid activation function

- Squashes the neuron's pre-activation between 0 and 1
- Always positive
- Bounded
- Strictly increasing

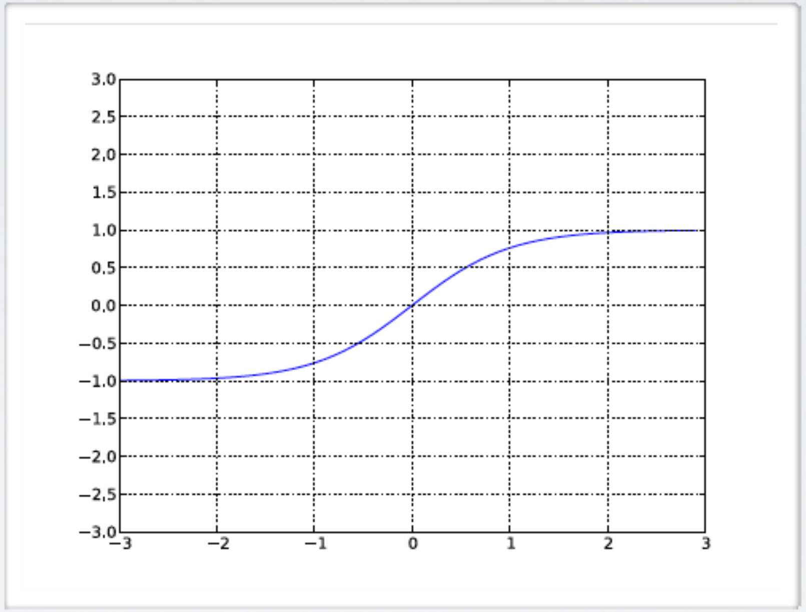


$$g(a) = \mathrm{sigm}(a) = \frac{1}{1+\exp(-a)}$$

ACTIVATION FUNCTION

Topics: hyperbolic tangent ("tanh") activation function

- Squashes the neuron's pre-activation between -1 and 1
- Can be positive or negative
- Bounded
- Strictly increasing

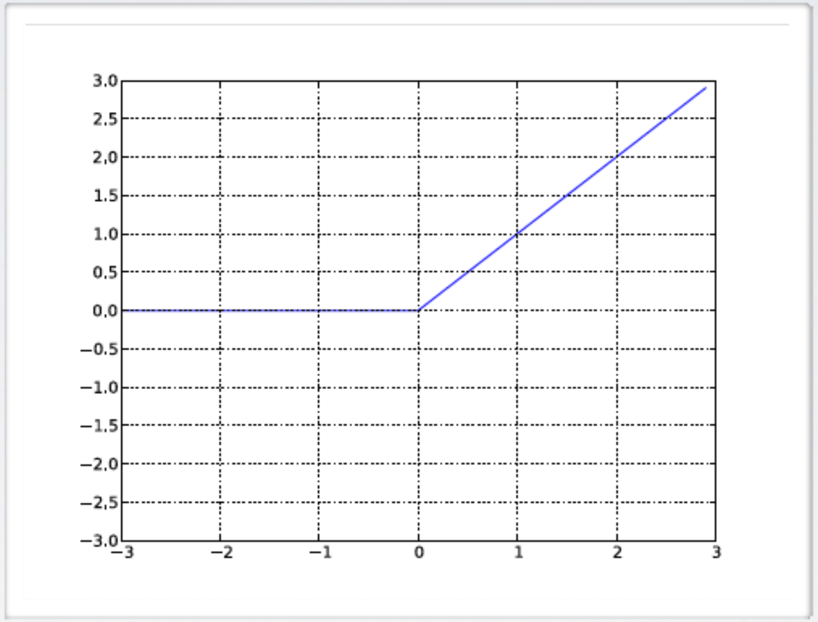


$$g(a) = \tanh(a) = \frac{\exp(a)-\exp(-a)}{\exp(a)+\exp(-a)} = \frac{\exp(2a)-1}{\exp(2a)+1}$$

ACTIVATION FUNCTION

Topics: rectified linear activation function

- Bounded below by 0 (always non-negative)
- Not upper bounded
- Strictly increasing
- Tends to give neurons with sparse activities

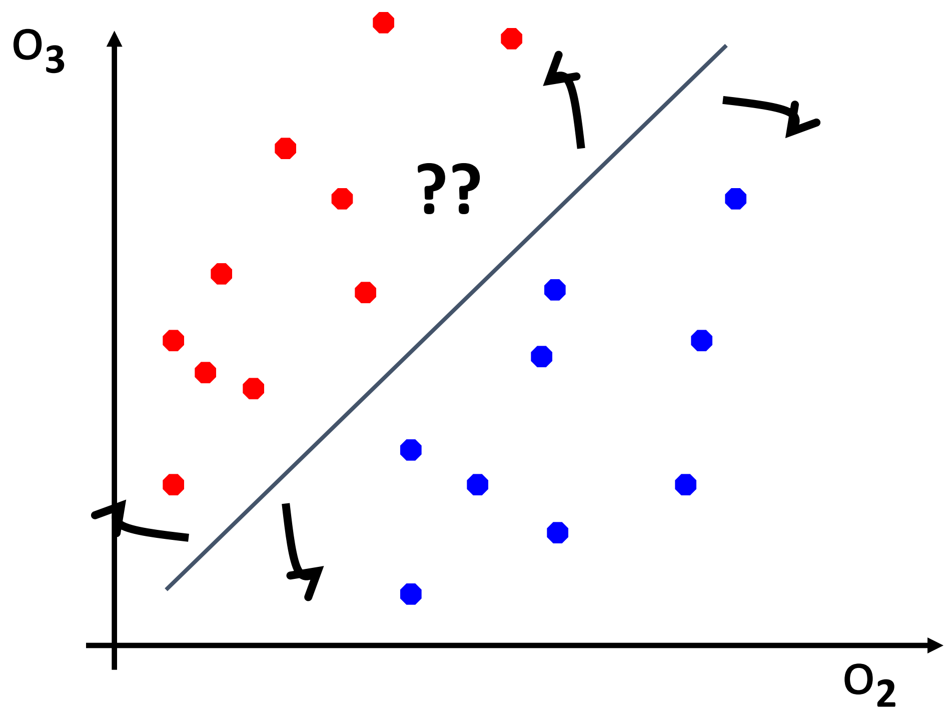


$$g(a) = \mathrm{reclin}(a) = \max(0, a)$$

```
class Neuron(object):
  # ...
  def forward(inputs):
    """ assume inputs and weights are 1-D numpy arrays and bias is a number """
    cell_body_sum = np.sum(inputs * self.weights) + self.bias
    firing_rate = 1.0 / (1.0 + math.exp(-cell_body_sum)) # sigmoid activation function
    return firing_rate
```

Linear Separator

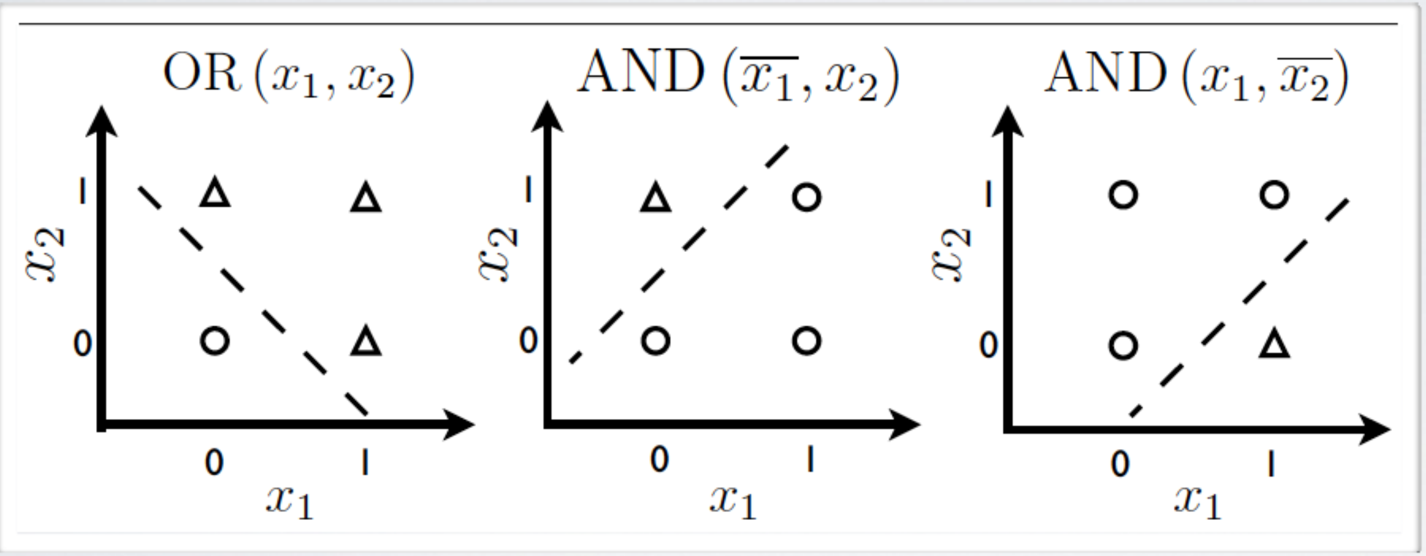
- Since one-layer neuron (aka perceptron) uses linear threshold function, it is searching for a linear separator that discriminates the classes.



ARTIFICIAL NEURON

Topics: capacity of single neuron

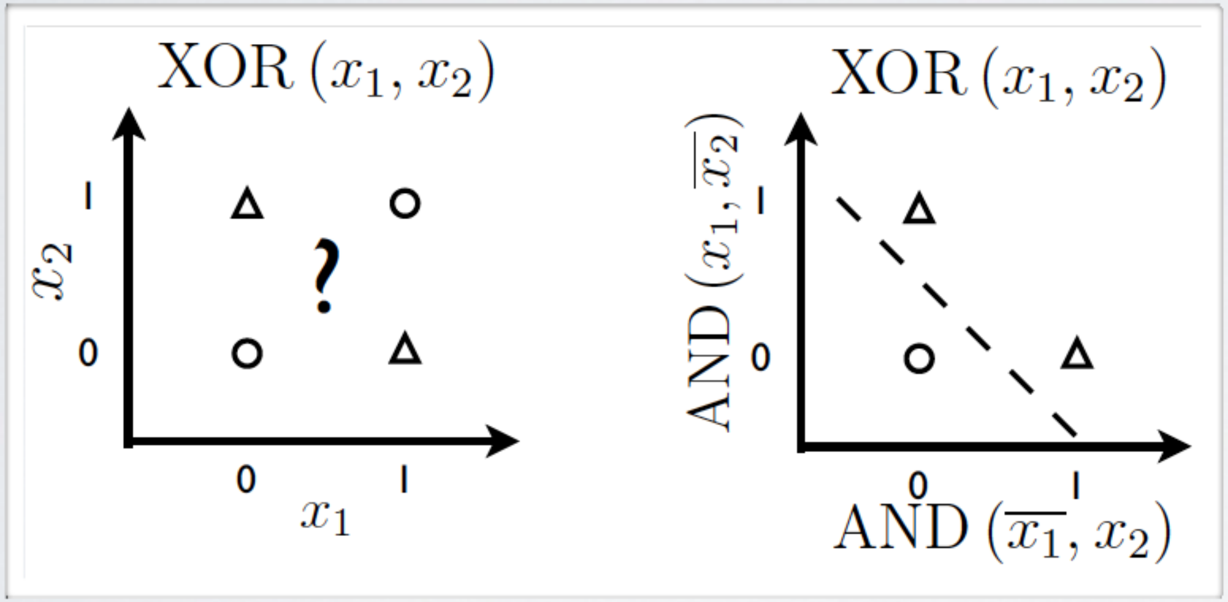
- Can solve linearly separable problems



ARTIFICIAL NEURON

Topics: capacity of single neuron

- Can't solve non linearly separable problems...



- ... unless the input is transformed in a better representation

NEURAL NETWORK

Topics: single hidden layer neural network

- Hidden layer pre-activation:

$$\mathbf{a}(\mathbf{x}) = \mathbf{b}^{(1)} + \mathbf{W}^{(1)}\mathbf{x}$$

$$\left(a(\mathbf{x})_i = b_i^{(1)} + \textstyle\sum_j W_{i,j}^{(1)} x_j\right)$$

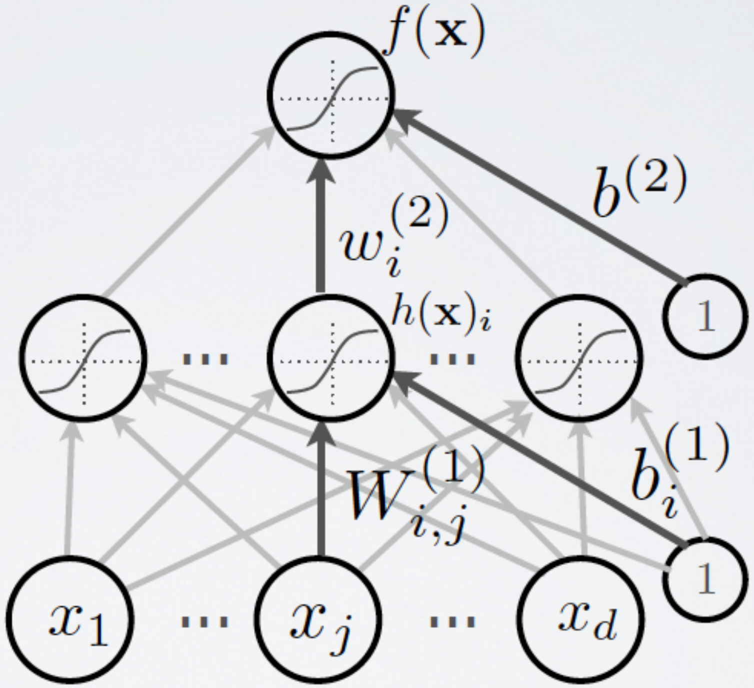
- Hidden layer activation:

$$\mathbf{h}(\mathbf{x}) = \mathbf{g}(\mathbf{a}(\mathbf{x}))$$

- Output layer activation:

$$f(\mathbf{x}) = o\left(b^{(2)} + \mathbf{w}^{(2)\top}\mathbf{h}^{(1)}\mathbf{x}\right)$$

output activation function



NEURAL NETWORK

Topics: softmax activation function

- For multi-class classification:
  - we need multiple outputs (1 output per class)
  - we would like to estimate the conditional probability $p(y = c|\mathbf{x})$
- We use the softmax activation function at the output:

$$\mathbf{o}(\mathbf{a}) = \mathrm{softmax}(\mathbf{a}) = \left[\frac{\exp(a_1)}{\sum_c \exp(a_c)} \dots \frac{\exp(a_C)}{\sum_c \exp(a_c)}\right]^\top$$

  - strictly positive
  - sums to one
- Predicted class is the one with highest estimated probability

NEURAL NETWORK

Topics: multilayer neural network

- Could have L hidden layers:
  - layer pre-activation for $k>0$ $\quad (\mathbf{h}^{(0)}(\mathbf{x}) = \mathbf{x})$

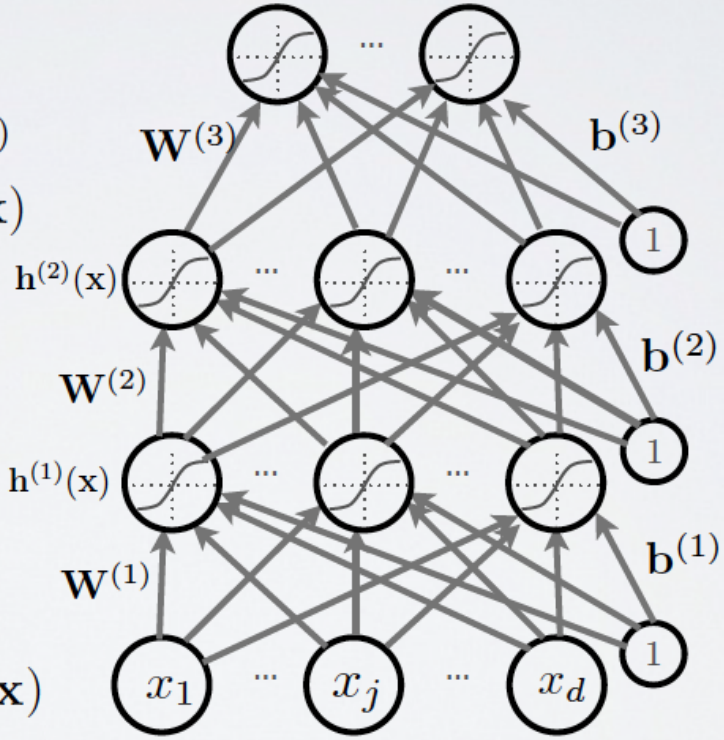
    $$\mathbf{a}^{(k)}(\mathbf{x}) = \mathbf{b}^{(k)} + \mathbf{W}^{(k)}\mathbf{h}^{(k-1)}(\mathbf{x})$$

  - hidden layer activation (k from 1 to L):

    $$\mathbf{h}^{(k)}(\mathbf{x}) = \mathbf{g}(\mathbf{a}^{(k)}(\mathbf{x}))$$

  - output layer activation ($k=L+1$):

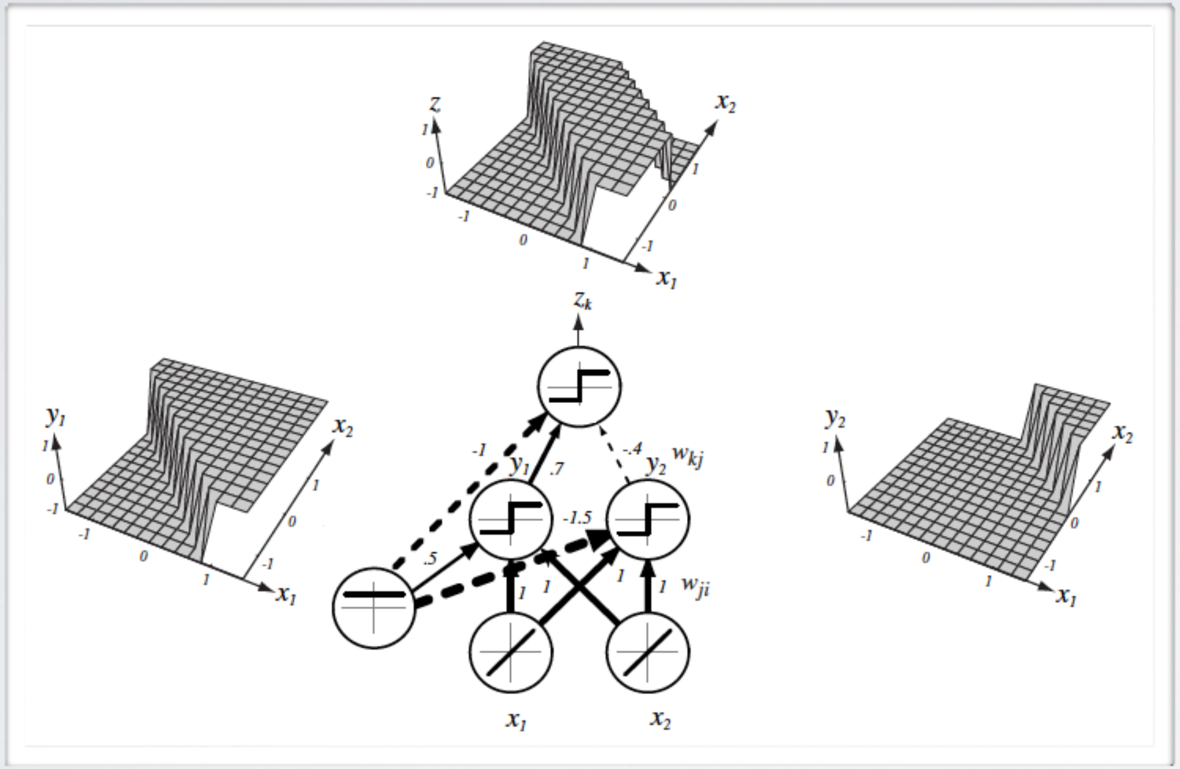
    $$\mathbf{h}^{(L+1)}(\mathbf{x}) = \mathbf{o}(\mathbf{a}^{(L+1)}(\mathbf{x})) = \mathbf{f}(\mathbf{x})$$



```python
# forward-pass of a 3-layer neural network:
f = lambda x: 1.0/(1.0 + np.exp(-x)) # activation function (use sigmoid)
x = np.random.randn(3, 1) # random input vector of three numbers (3x1)
h1 = f(np.dot(W1, x) + b1) # calculate first hidden layer activations (4x1)
h2 = f(np.dot(W2, h1) + b2) # calculate second hidden layer activations (4x1)
out = np.dot(W3, h2) + b3 # output neuron (1x1)
```

CAPACITY OF NEURAL NETWORK

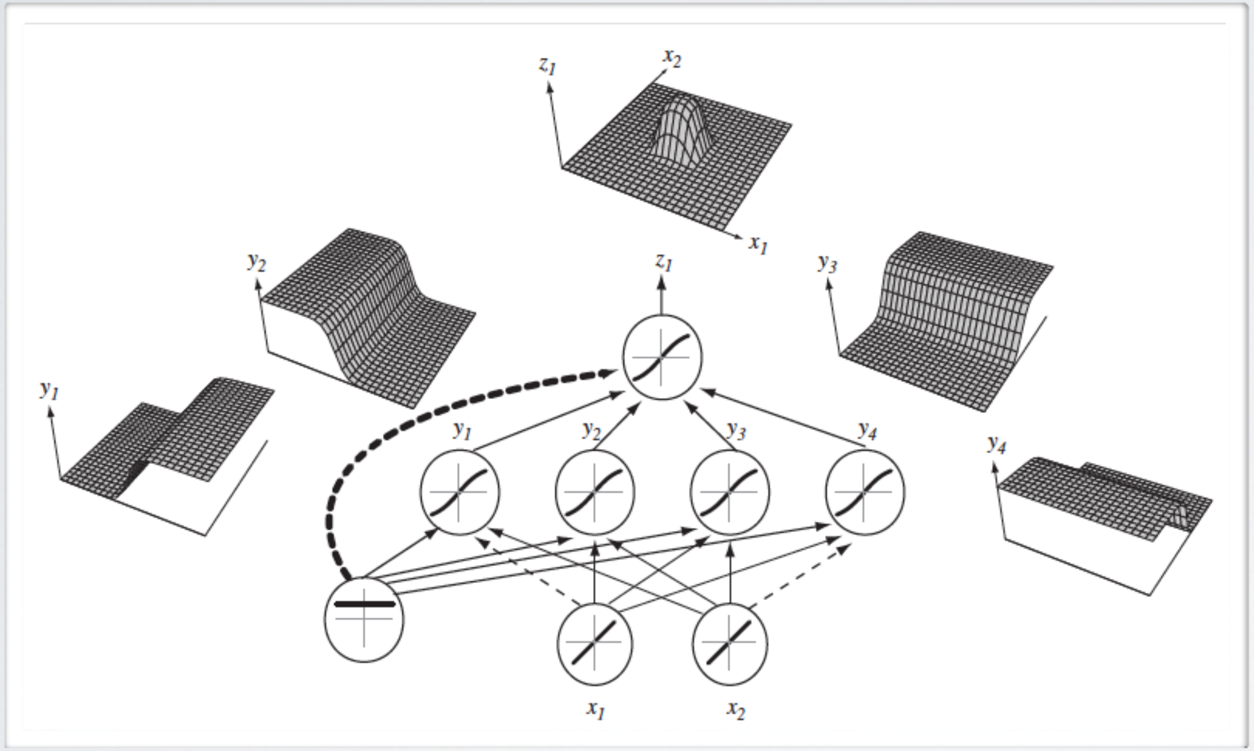
Topics: single hidden layer neural network



(from Pascal Vincent's slides)

CAPACITY OF NEURAL NETWORK

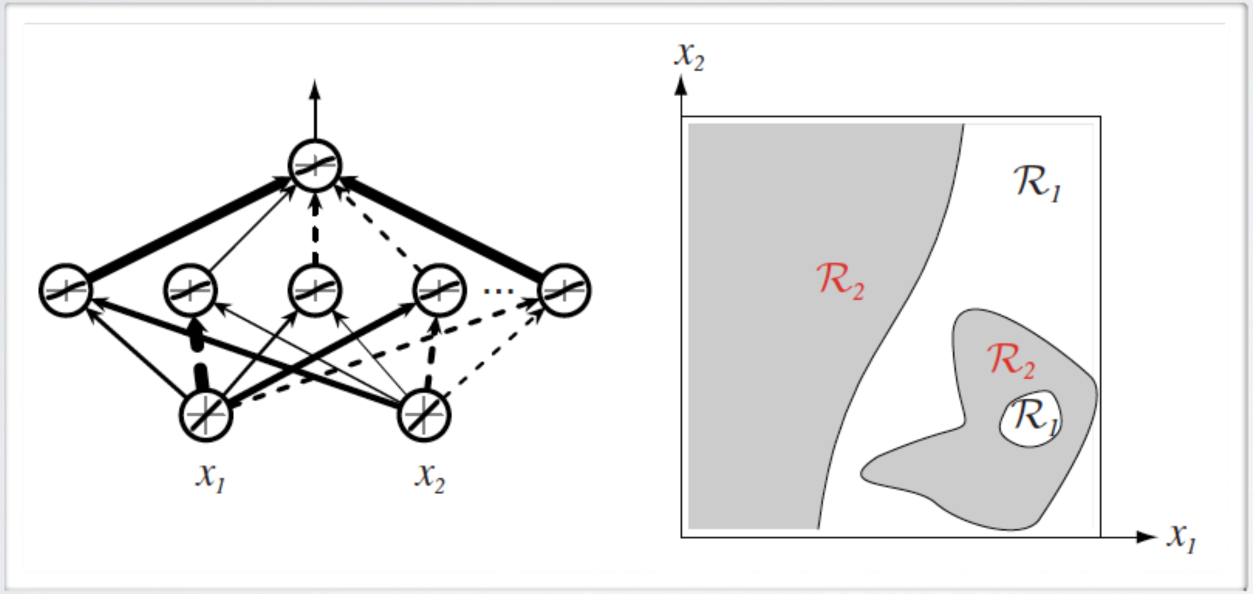
Topics: single hidden layer neural network



(from Pascal Vincent's slides)

CAPACITY OF NEURAL NETWORK

Topics: single hidden layer neural network

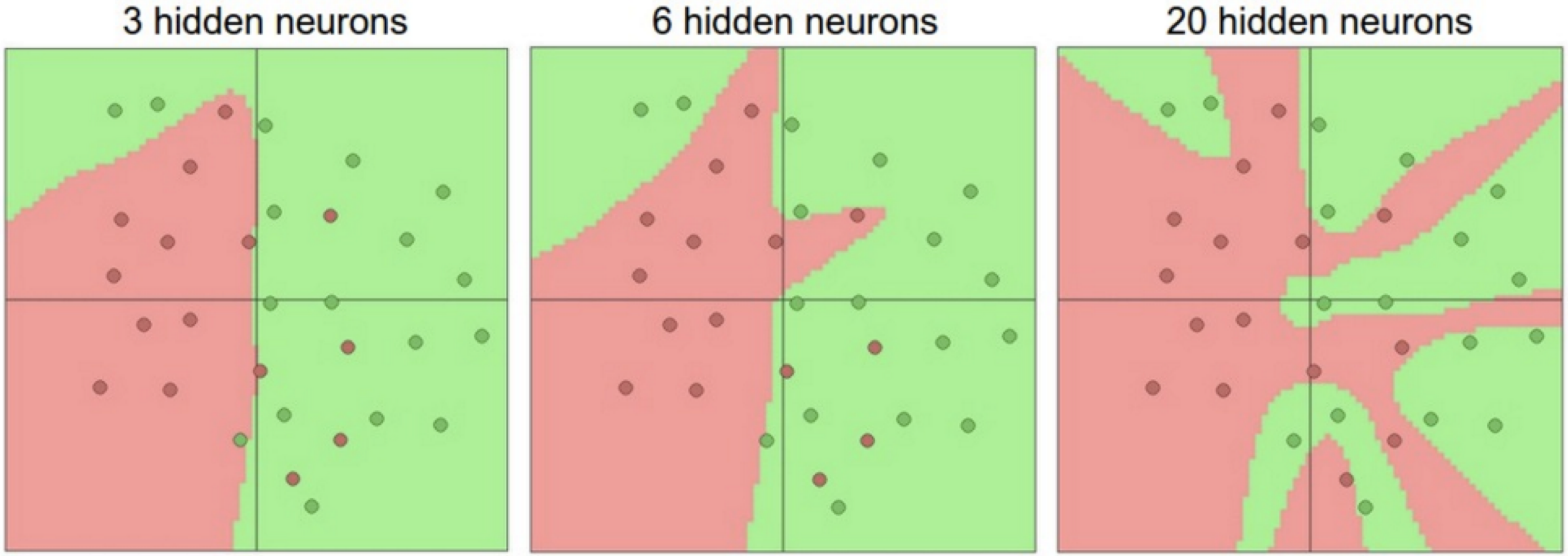


(from Pascal Vincent's slides)

CAPACITY OF NEURAL NETWORK

Topics: universal approximation

- Universal approximation theorem (Hornik, 1991):
  - "a single hidden layer neural network with a linear output unit can approximate any continuous function arbitrarily well, given enough hidden units"
- The result applies for sigmoid, tanh and many other hidden layer activation functions
- This is a good result, but it doesn't mean there is a learning algorithm that can find the necessary parameter values!


3 hidden neurons
6 hidden neurons
20 hidden neurons

How to train a neural network?

Topics: multilayer neural network

- Could have L hidden layers:
  - layer input activation for $k>0$ $\quad (\mathbf{h}^{(0)}(\mathbf{x}) = \mathbf{x})$

$$\mathbf{a}^{(k)}(\mathbf{x}) = \mathbf{b}^{(k)} + \mathbf{W}^{(k)}\mathbf{h}^{(k-1)}(\mathbf{x})$$

  - hidden layer activation (k from 1 to L):

$$\mathbf{h}^{(k)}(\mathbf{x}) = \mathbf{g}(\mathbf{a}^{(k)}(\mathbf{x}))$$

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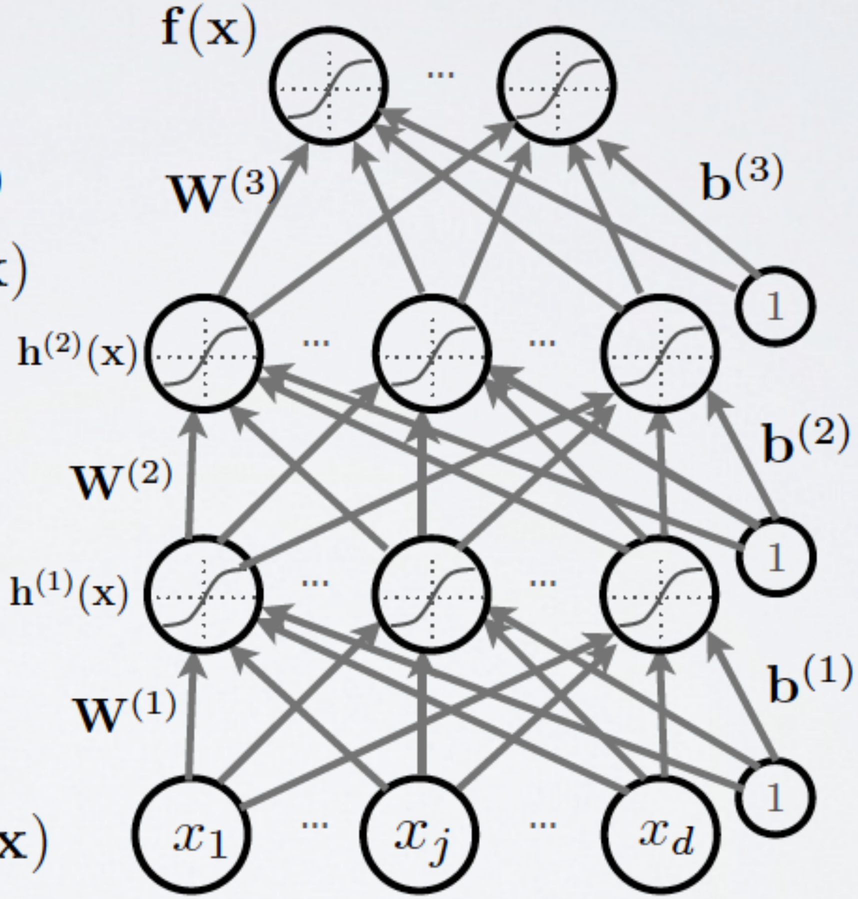
$$\mathbf{h}^{(L+1)}(\mathbf{x}) = \mathbf{o}(\mathbf{a}^{(L+1)}(\mathbf{x})) = \mathbf{f}(\mathbf{x})$$



Empirical Risk Minimization

Topics: empirical risk minimization, regularization

- Empirical risk minimization
  - framework to design learning algorithms

$$\arg\min_{\boldsymbol{\theta}} \frac{1}{T} \sum_t l(f(\mathbf{x}^{(t)}; \boldsymbol{\theta}), y^{(t)}) + \lambda \Omega(\boldsymbol{\theta})$$

  - $l(f(\mathbf{x}^{(t)}; \boldsymbol{\theta}), y^{(t)})$ is a loss function
  - $\Omega(\boldsymbol{\theta})$ is a regularizer (penalizes certain values of $\boldsymbol{\theta}$)
- Learning is cast as optimization
  - ideally, we'd optimize classification error, but it's not smooth
  - loss function is a surrogate for what we truly should optimize (e.g. upper bound)

LOSS FUNCTION

Topics: loss function for classification

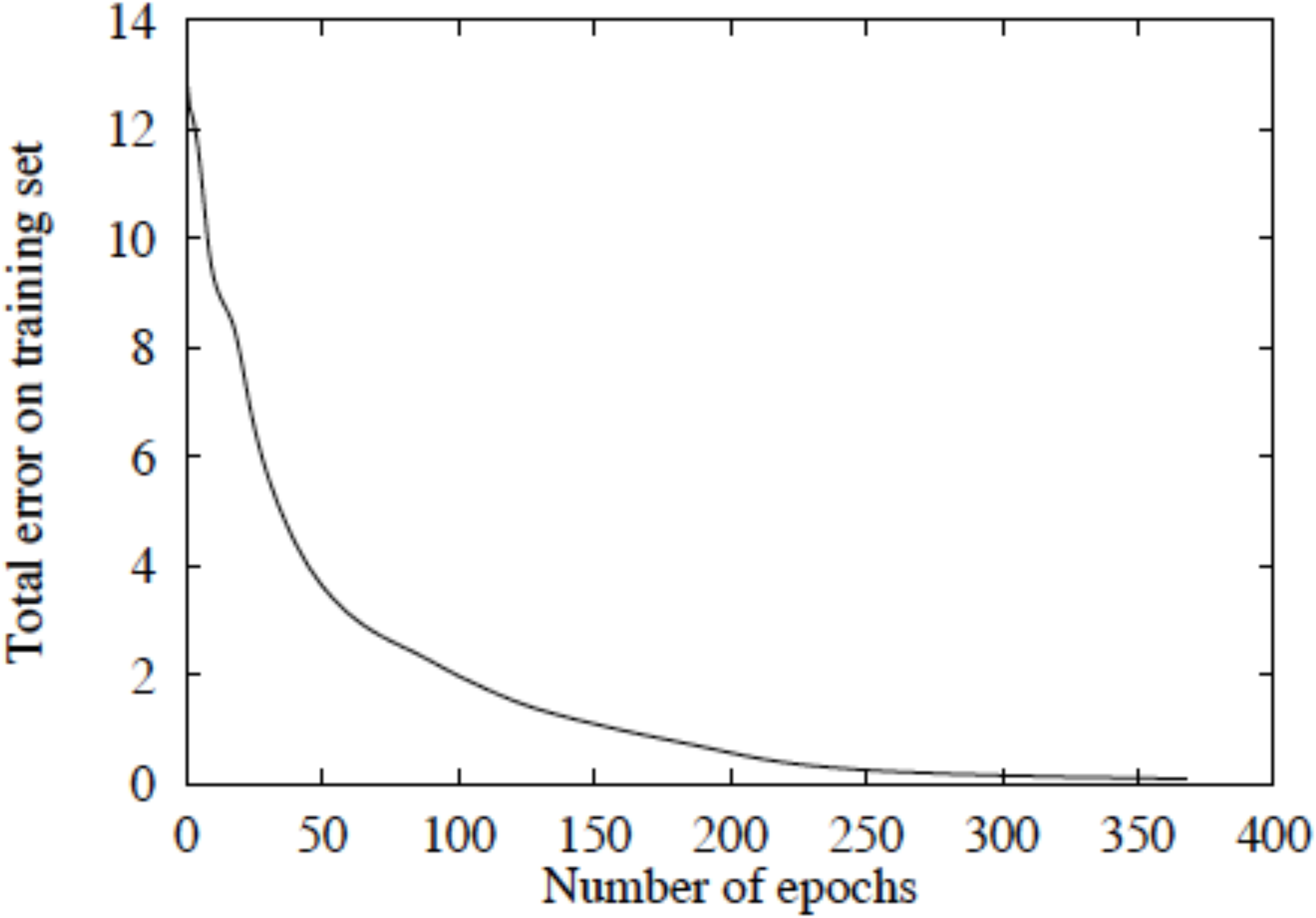
- Neural network estimates $f(\mathbf{x})_c = p(y = c|\mathbf{x})$
  - we could maximize the probabilities of $y^{(t)}$ given $\mathbf{x}^{(t)}$ in the training set

- To frame as minimization, we minimize the negative log-likelihood

natural log (ln)

$$l(\mathbf{f}(\mathbf{x}), y) = -\sum_c 1_{(y=c)} \log f(\mathbf{x})_c = -\log f(\mathbf{x})_y$$

  - we take the log to simplify for numerical stability and math simplicity
  - sometimes referred to as cross-entropy



[figure from Greg Mori's slides]

REGULARIZATION

Topics: L2 regularization

$$\Omega(\boldsymbol{\theta}) = \sum_k \sum_i \sum_j \left(W_{i,j}^{(k)}\right)^2 = \sum_k ||\mathbf{W}^{(k)}||_F^2$$

Empirical Risk Minimization

Topics: empirical risk minimization, regularization

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$$\arg\min_{\boldsymbol{\theta}} \frac{1}{T} \sum_t l(f(\mathbf{x}^{(t)}; \boldsymbol{\theta}), y^{(t)}) + \lambda \Omega(\boldsymbol{\theta})$$

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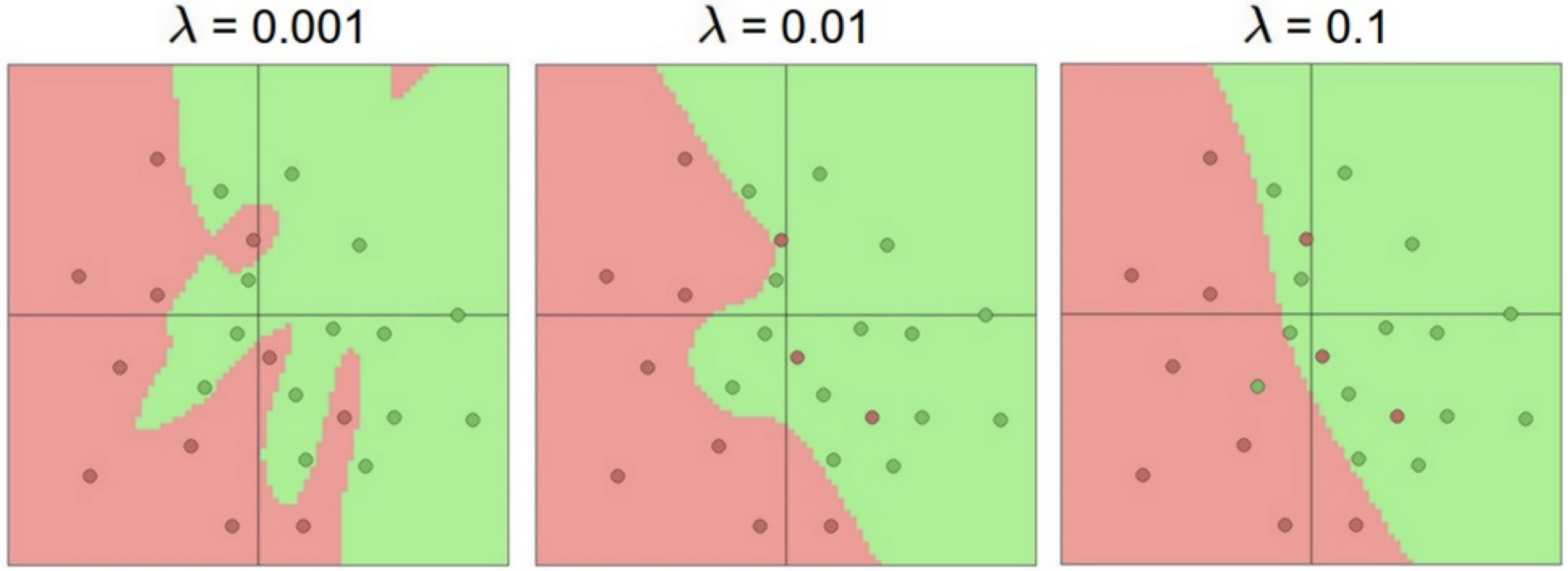


[http://cs231n.github.io/neural-networks-1/]

INITIALIZATION

Topics: initialization

- For biases
  - initialize all to 0
- For weights
  - Can't initialize weights to 0 with tanh activation
    - we can show that all gradients would then be 0 (saddle point)
  - Can't initialize all weights to the same value
    - we can show that all hidden units in a layer will always behave the same
    - need to break symmetry
  - Recipe: sample $\mathbf{W}^{(k)}_{i,j}$ from $U\left[-b, b\right]$ where $b = \frac{\sqrt{6}}{\sqrt{H_k + H_{k-1}}}$

    size of $\mathbf{h}^{(k)}(\mathbf{x})$
    - the idea is to sample around 0 but break symmetry
    - other values of b could work well (not an exact science) (see Glorot & Bengio, 2010)

Model Learning

- Backpropagation algorithm (not covered in the lecture)

Toolkits

- TensorFlow
  - https://www.tensorflow.org/
- Theano (not maintained any more)
  - http://deeplearning.net/software/theano/
- PyTorch
  - http://pytorch.org/

Neural language models

- Skip-grams
- Continuous Bag of Words (CBOW)
    - More details can be found at https://cs224d.stanford.edu/lecture_notes/notes1.pdf

Prediction-based models: An alternative way to get dense vectors

- **Skip-gram** (Mikolov et al. 2013a), **CBOW** (Mikolov et al. 2013b)
- Learn embeddings as part of the process of word prediction.
- Train a neural network to predict neighboring words
- Advantages:
  - Fast, easy to train (much faster than SVD)
  - Available online in the `word2vec` package
  - Including sets of pretrained embeddings!

Skip-grams

- Predict each neighboring word
  - in a context window of 2*C* words
  - from the current word.
- So for C=2, we are given word w_t and predicting these 4 words:

$$\left[w_{t-2}, w_{t-1}, w_{t+1}, w_{t+2}\right]$$

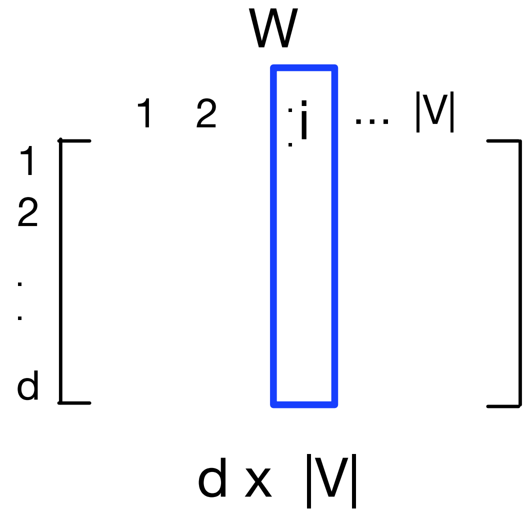
Skip-grams

- Predict each neighboring word
  - in a context window of 2*C* words
  - from the current word.
- So for C=2, we are given word w_t and predicting these 4 words:

$$\left[w_{t-2}, w_{t-1}, w_{t+1}, w_{t+2}\right]$$

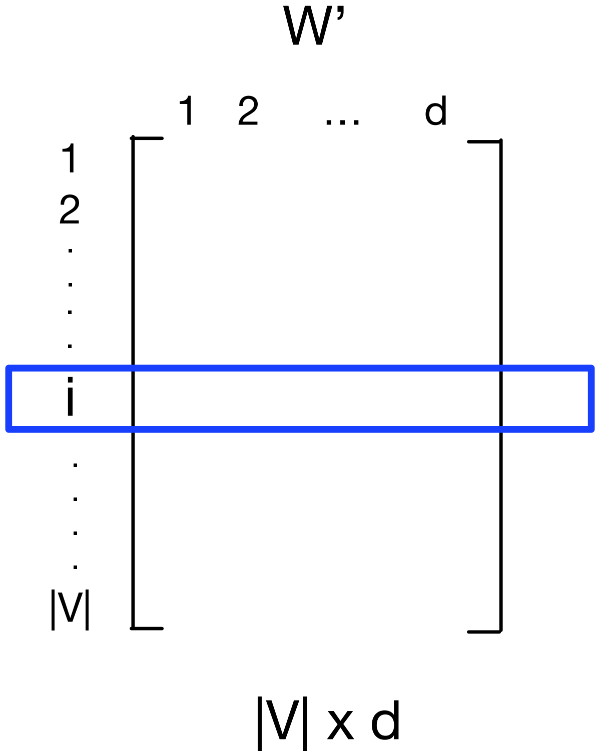
Example: Natural language processing is a subarea of artificial intelligence.

Skip-grams learn 2 embeddings for each w



input embedding *v,* in the input matrix *W*

- Column *i* of the input matrix *W* is the 1×*d* embedding v_i for word *i* in the vocabulary.



output embedding *v*′, in output matrix W'

- Row *i* of the output matrix *W*′ is a *d* × 1 vector embedding v'_i for word *i* in the vocabulary.

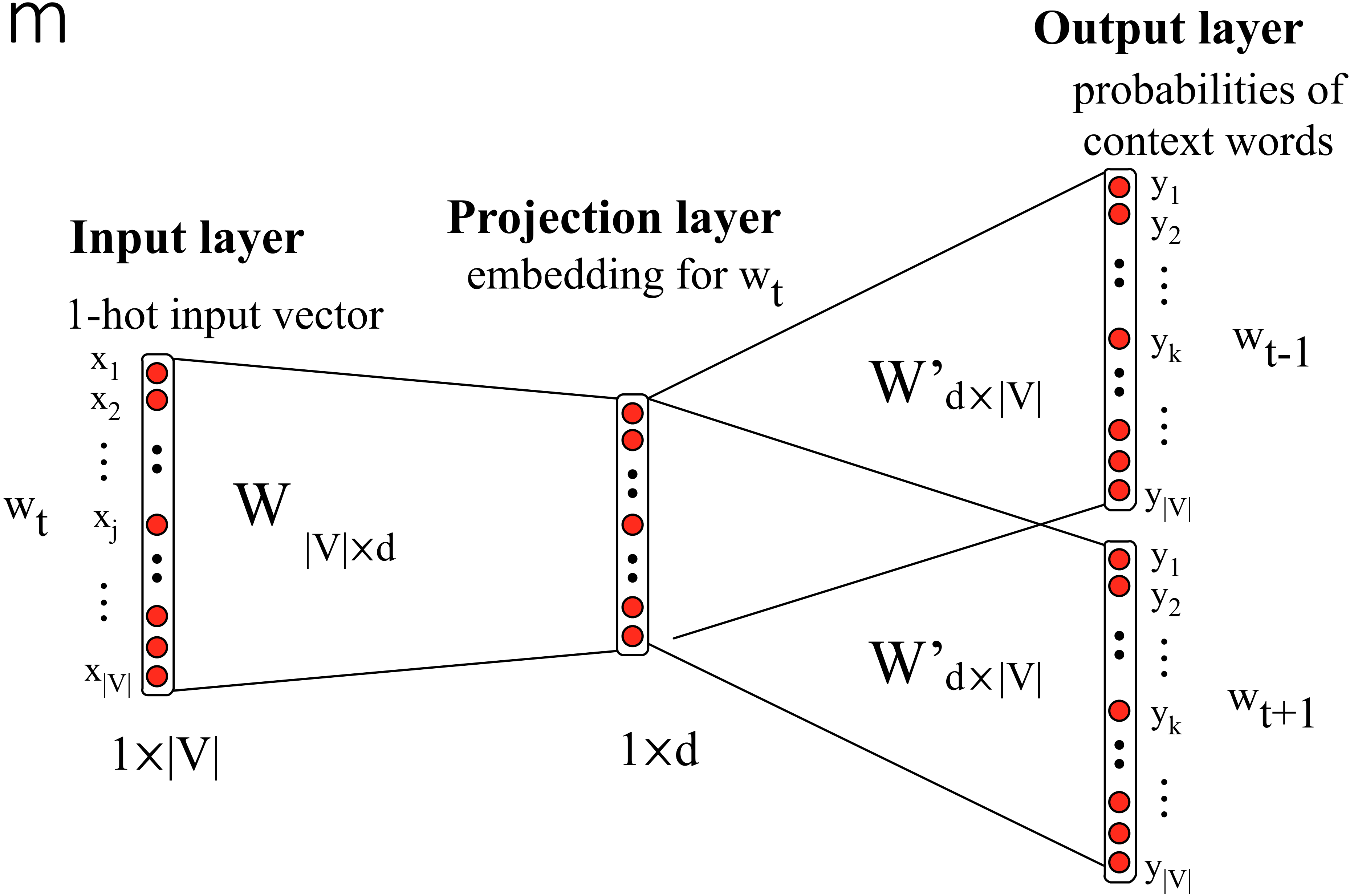
Setup

- Walking through corpus pointing at word w_t, whose index in the vocabulary is j, so we'll call it $\boldsymbol{w_j}$ ($1 < j < |V|$).
- Let's predict w_{t+1} , whose index in the vocabulary is k ($1 < k < |V|$). Hence our task is to compute $P(\boldsymbol{w_k}|\boldsymbol{w_j})$.

One-hot vectors

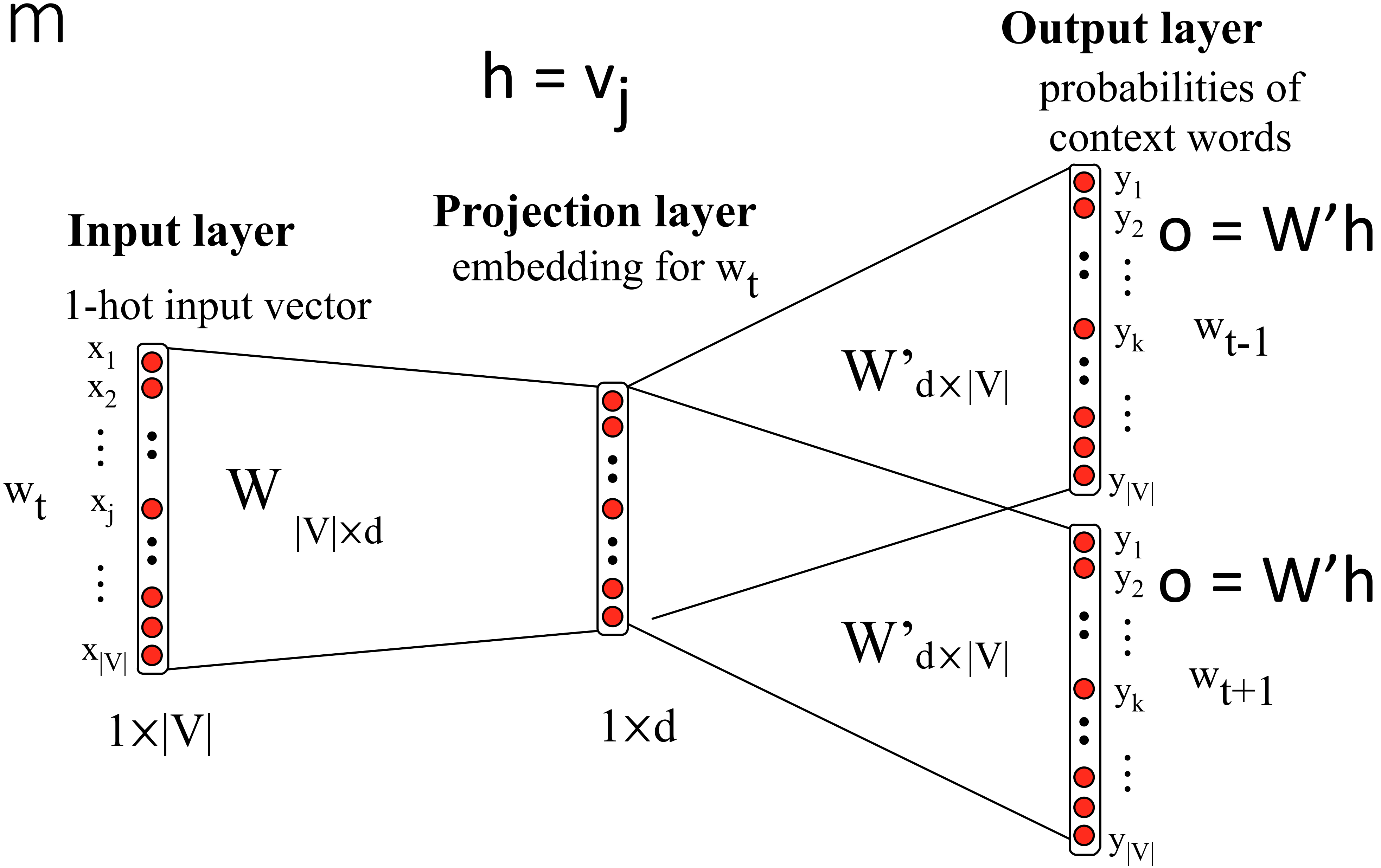
- A vector of length |V|
- 1 for the target word and 0 for other words
- So if “popsicle” is vocabulary word 5
- The **one-hot vector** is
- [0,0,0,0,1,0,0,0,0…….0]

Skip-gram

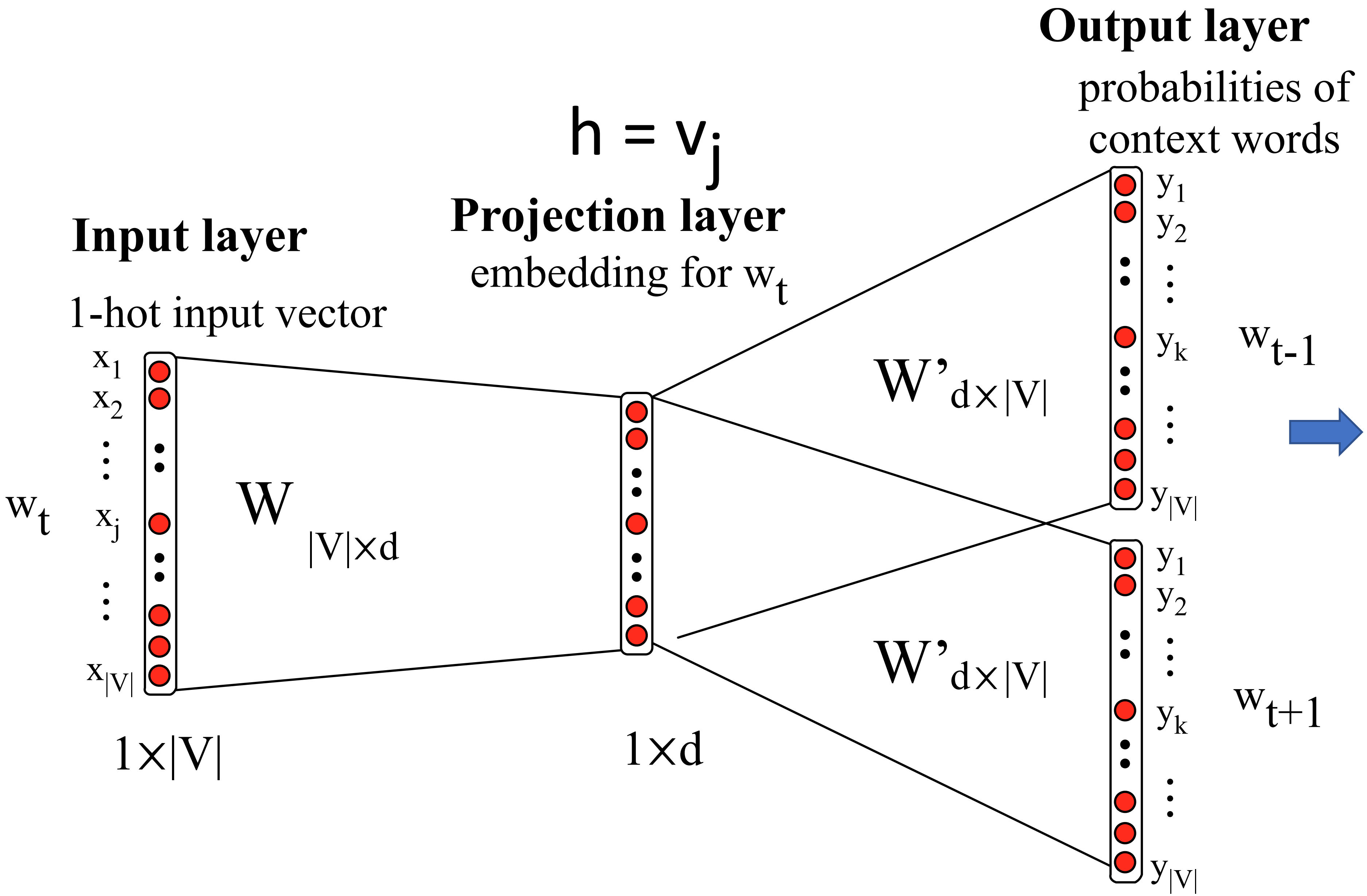

Output layer
probabilities of
context words
Input layer
Projection layer
embedding for w_t
1-hot input vector
x_1
x_2
w_t
x_j
x_|V|
W |V|×d
1×|V|
1×d
W'd×|V|
y_1
y_2
y_k
y_|V|
w_t-1
W'd×|V|
y_1
y_2
y_k
y_|V|
w_t+1

Skip-gram

$h = v_j$



Skip-gram



$o_k = v'_k h$ $(h = v_j)$

$\Rightarrow o_k = v'_k \cdot v_j$

Turning outputs into probabilities

- $o_k = v'_k \cdot v_j$
- We use softmax to turn into probabilities

$$p(w_k|w_j) = \frac{exp(v'_k \cdot v_j)}{\sum_{w' \in |V|} exp(v'_w \cdot v_j)}$$

Embeddings from W and W'

- Since we have two embeddings, v_j and v'_j for each word w_j
- We can either:
  - Just use v_j
  - Sum them
  - Concatenate them to make a double-length embedding

But wait; how do we learn the embeddings?

$$\underset{\theta}{\operatorname{argmax}} \ \log \ p(\text{Text})$$

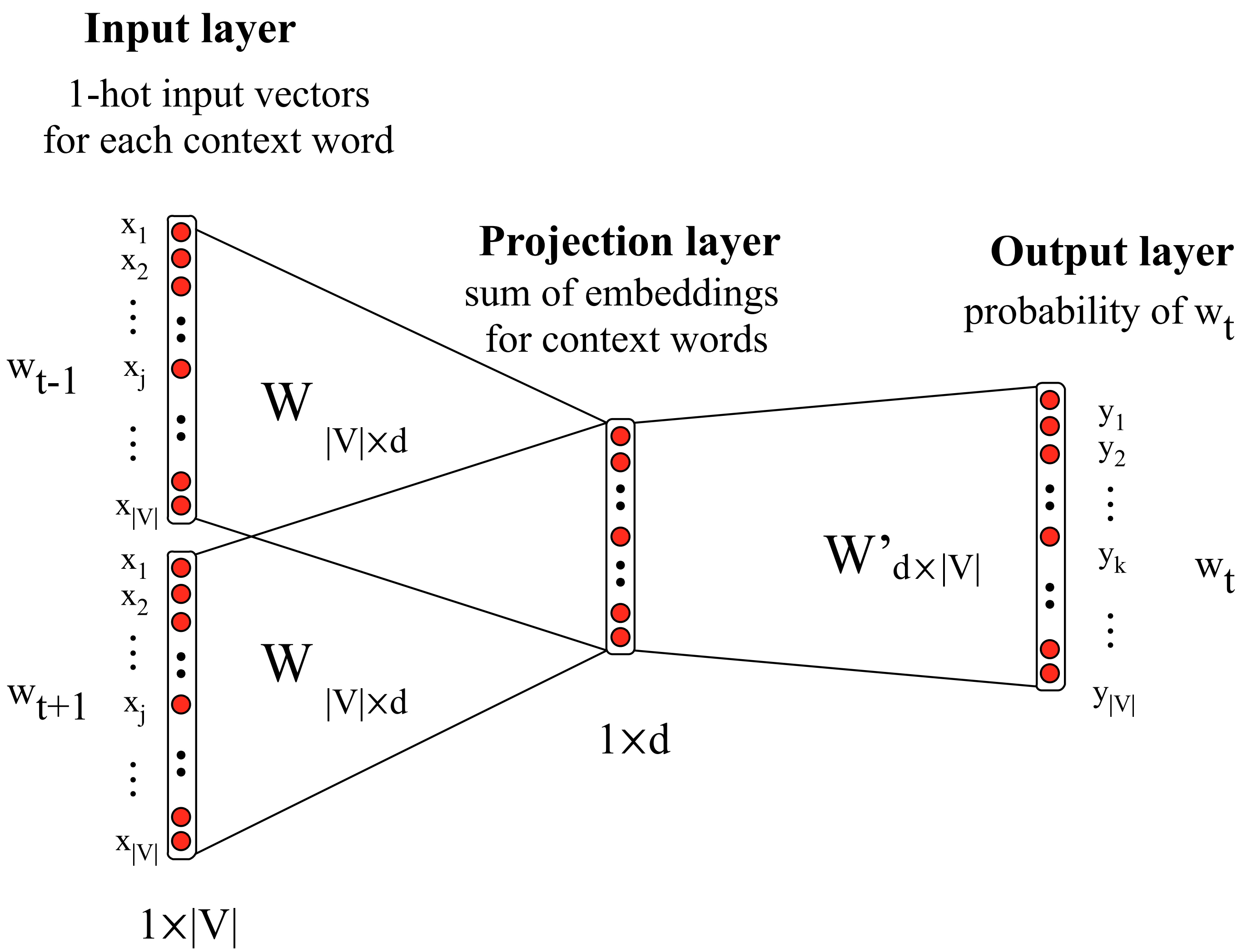
But wait; how do we learn the embeddings?

$$\underset{\theta}{\operatorname{argmax}} \ \log \ p(\text{Text})$$

$$= \underset{\theta}{\operatorname{argmax}} \sum_{t=1}^{T} \sum_{-c \leq j \leq c, j \neq 0} \log \frac{exp(v'^{(t+j)} \cdot v^{(t)})}{\sum_{w \in |V|} exp(v'_w \cdot v^{(t)})}$$

$$= \underset{\theta}{\operatorname{argmax}} \sum_{t=1}^{T} \sum_{-c \leq j \leq c, j \neq 0} \left[v'^{(t+j)} \cdot v^{(t)} - \log \sum_{w \in |V|} exp(v'_w \cdot v^{(t)}) \right]$$

CBOW (Continuous Bag of Words)



Properties of embeddings

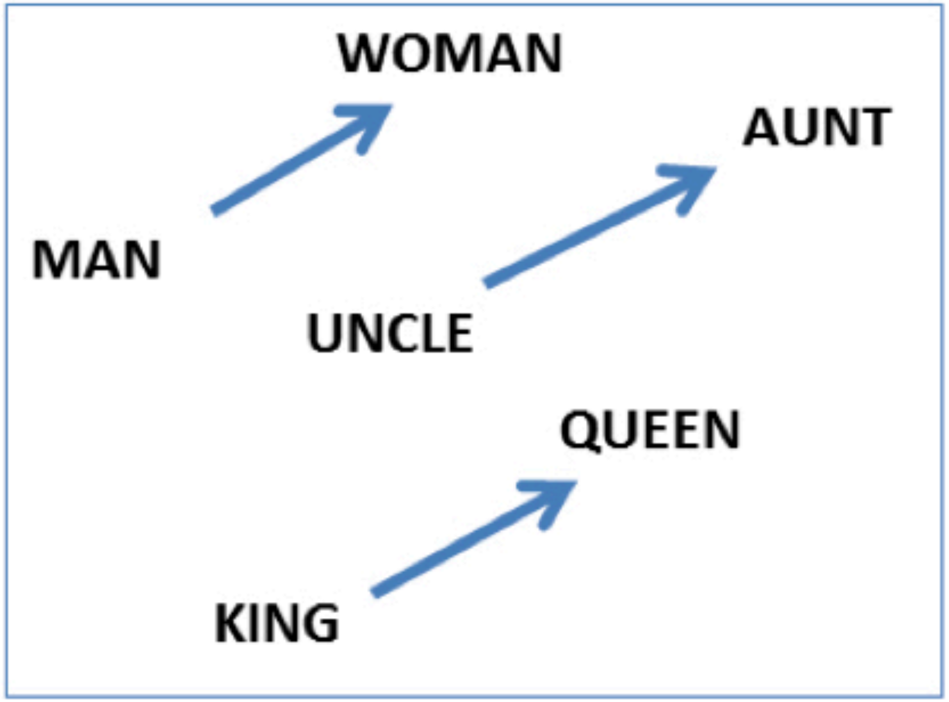
- Nearest words to some embeddings (Mikolov et al. 20131)

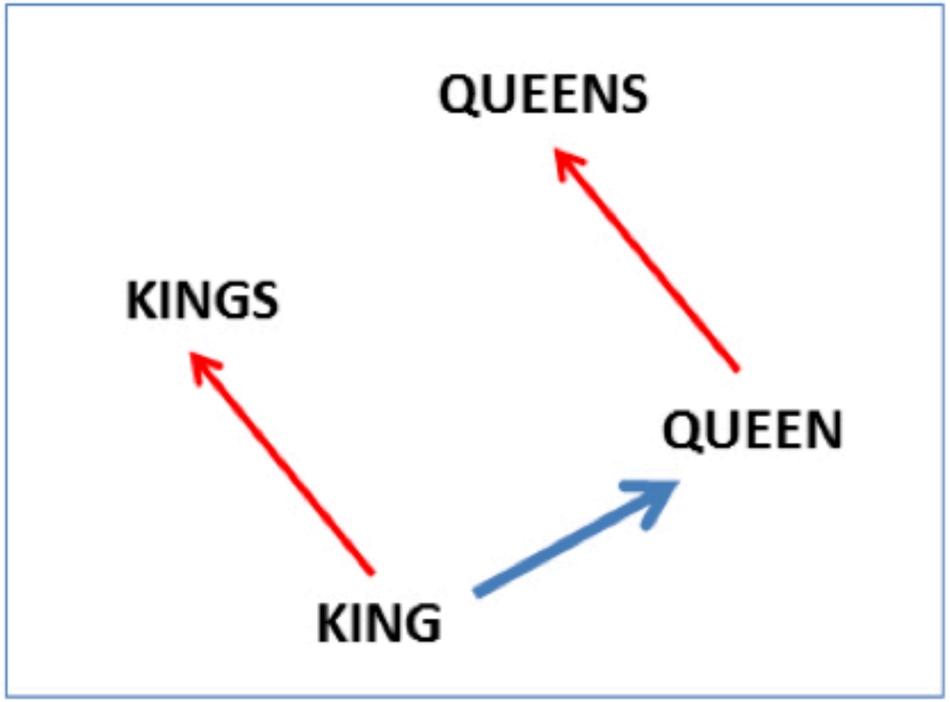
target:	Redmond	Havel	ninjutsu	graffiti	capitulate
	Redmond Wash.	Vaclav Havel	ninja	spray paint	capitulation
	Redmond Washington	president Vaclav Havel	martial arts	grafitti	capitulated
	Microsoft	Velvet Revolution	swordsmanship	taggers	capitulating

Embeddings capture relational meaning!

vector(*'king'*) - vector(*'man'*) + vector(*'woman'*) ≈ vector('queen')

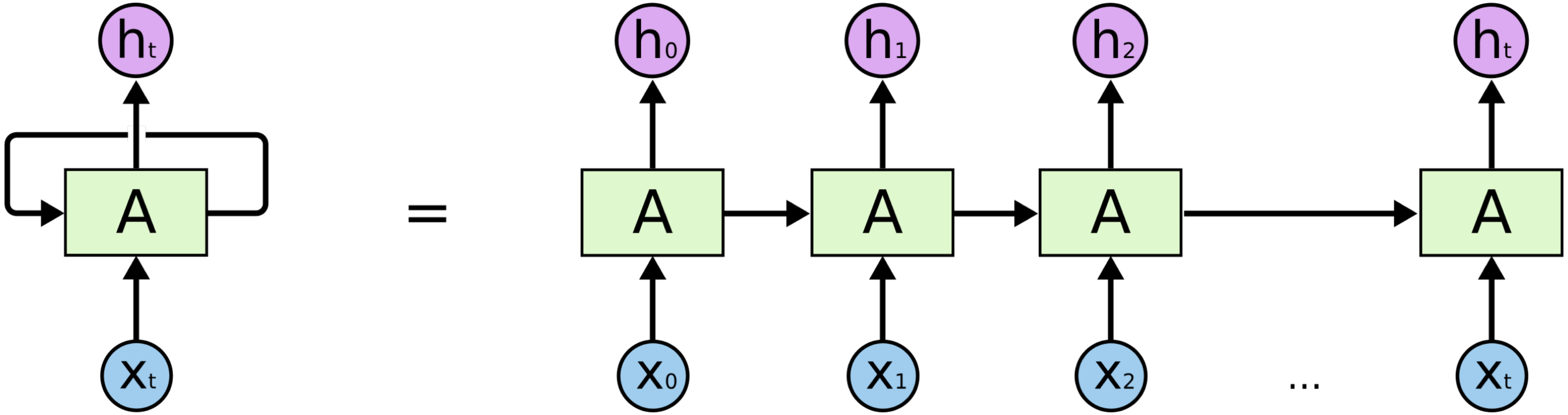
vector(*'Paris'*) - vector(*'France'*) + vector(*'Italy'*) ≈ vector('Rome')





Long Distance Dependencies

- It is very difficult to train NNs to retain information over many time steps
- This make is very difficult to handle long-distance dependencies, such as subject-verb agreement.
- E.g. Jane walked into the room. John walked in too. It was late in the day. Jane said hi to _?_

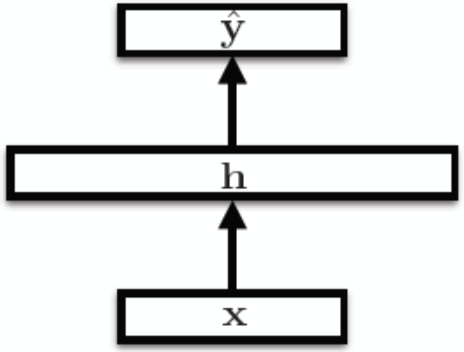


Recurrent Neural Networks

Feed-forward NN

$$\mathbf{h} = g(\mathbf{V}\mathbf{x} + \mathbf{c})$$

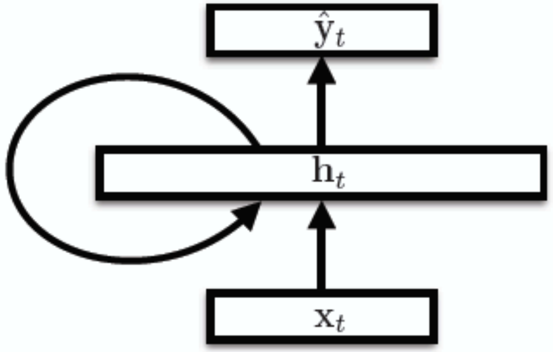
$$\hat{\mathbf{y}} = \mathbf{W}\mathbf{h} + \mathbf{b}$$



Recurrent NN

$$\mathbf{h}_t = g(\mathbf{V}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{c})$$

$$\hat{\mathbf{y}}_t = \mathbf{W}\mathbf{h}_t + \mathbf{b}$$



Recurrent Neural Networks

Feed-forward NN

$$\mathbf{h} = g(\mathbf{V}\mathbf{x} + \mathbf{c})$$

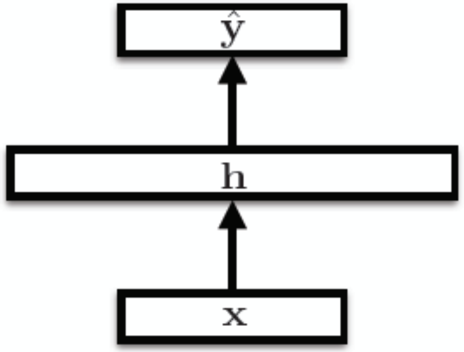
$$\hat{\mathbf{y}} = \mathbf{W}\mathbf{h} + \mathbf{b}$$

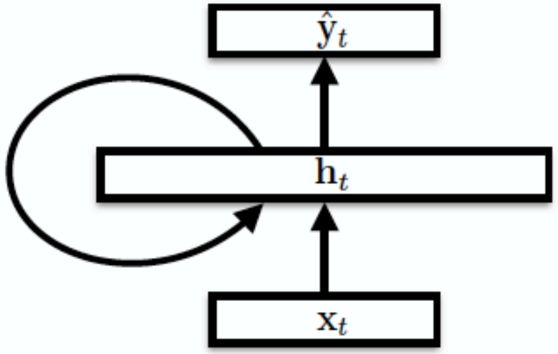
Recurrent NN

$$\cancel{\mathbf{h}_t = g(\mathbf{V}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{c})}$$

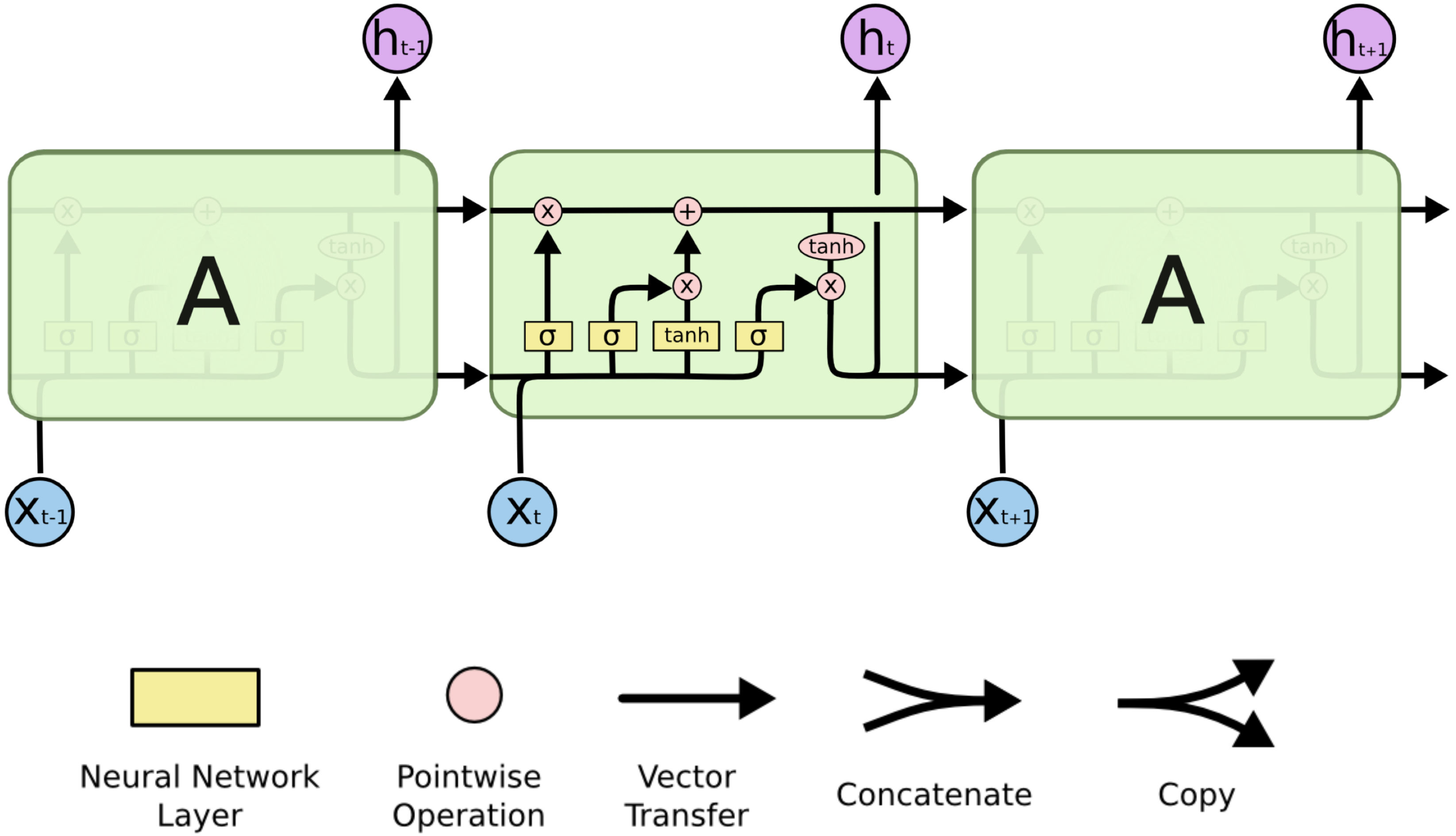
$$\mathbf{h}_t = g(\mathbf{V}[\mathbf{x}_t; \mathbf{h}_{t-1}] + \mathbf{c})$$

$$\hat{\mathbf{y}}_t = \mathbf{W}\mathbf{h}_t + \mathbf{b}$$

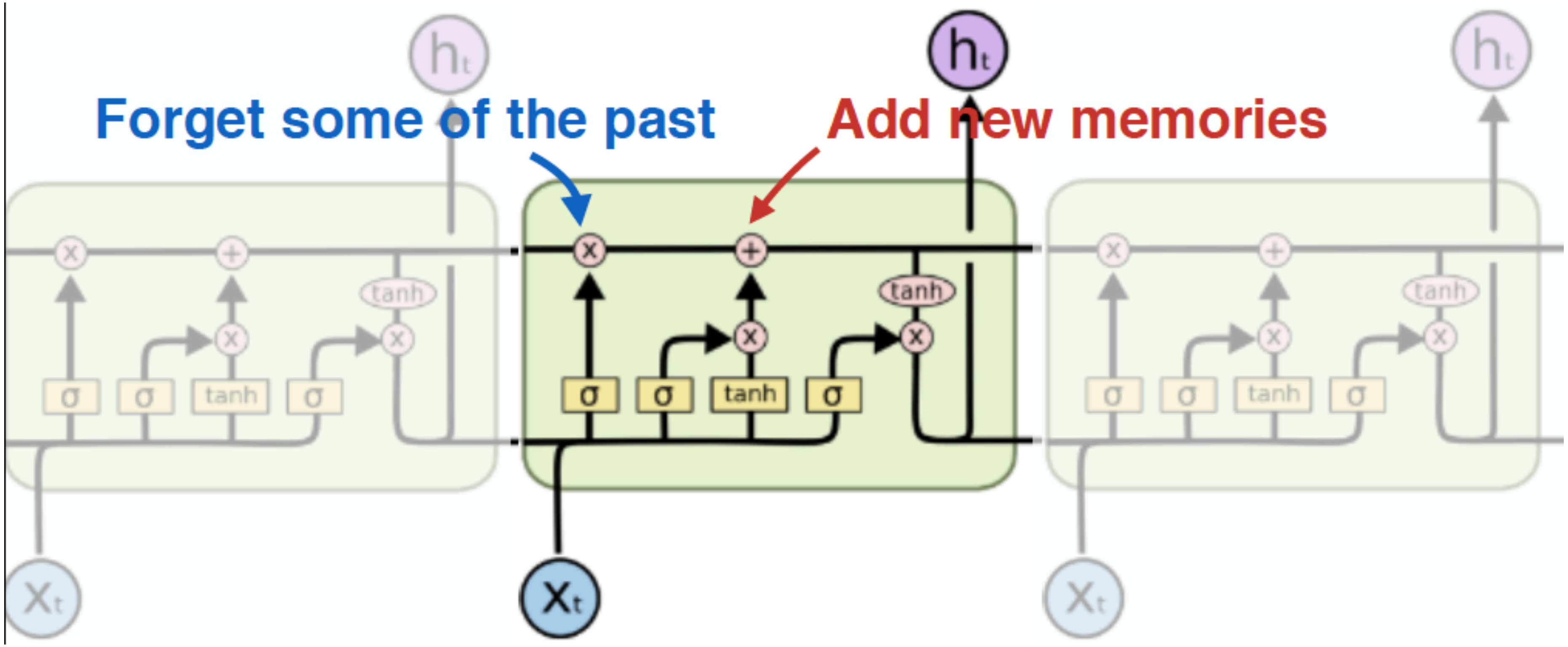




Long-Short Term Memory Networks (LSTMs)



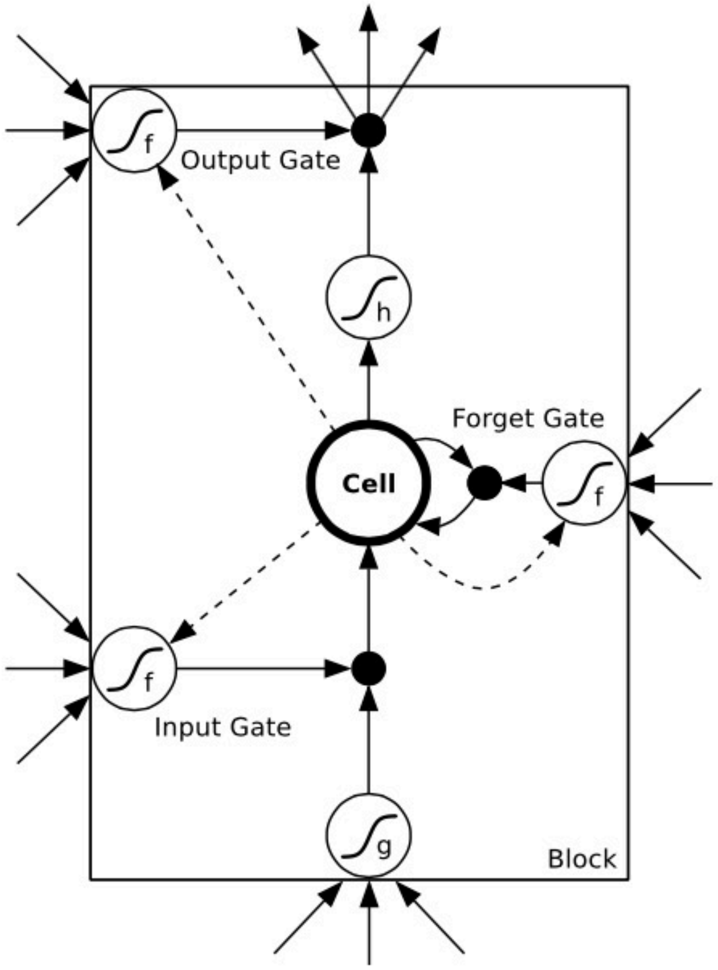
Another Visualization



Capable of modeling long-distant dependencies between states.

Figure: Christopher Olah

Long-Short Term Memory Networks (LSTMs)



$$\begin{pmatrix} \boldsymbol{i}_t \\ \boldsymbol{f}_t \\ \boldsymbol{o}_t \\ \boldsymbol{g}_t \end{pmatrix} = \begin{pmatrix} \sigma(\boldsymbol{W}_i[\mathbf{x}_t, \boldsymbol{h}_t] + \boldsymbol{b}_i) \\ \sigma(\boldsymbol{W}_f[\mathbf{x}_t, \boldsymbol{h}_t] + \boldsymbol{b}_f) \\ \sigma(\boldsymbol{W}_o[\mathbf{x}_t, \boldsymbol{h}_t] + \boldsymbol{b}_o) \\ f(\boldsymbol{W}_g[\mathbf{x}_t, \boldsymbol{h}_t] + \boldsymbol{b}_g) \end{pmatrix}$$

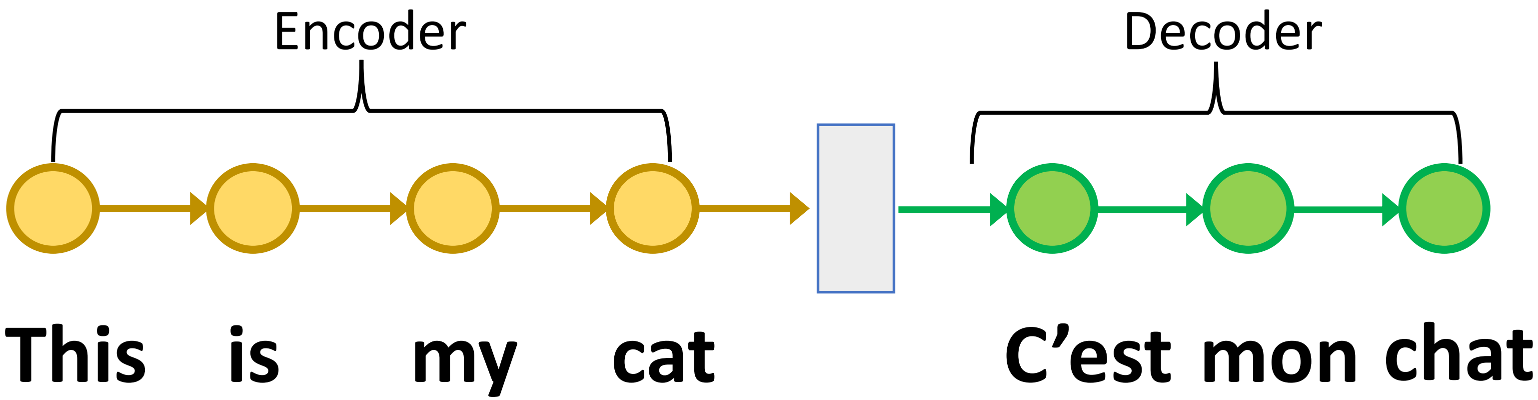
$$\boldsymbol{c}_t = \boldsymbol{f}_t * \boldsymbol{c}_{t-1} + \boldsymbol{i}_t * \boldsymbol{g}_t$$

$$\boldsymbol{h}_t = \boldsymbol{o}_t * f(\boldsymbol{c}_t)$$

Use gates to control the information to be added from the input, forgot from the previous memories, and outputted.
σ and f are *sigmoid* and *tanh* function respectively, to map the value to [-1, 1]

Sequence to Sequence

- Encoder/Decoder framework maps one sequence to a "deep vector" then another LSTM maps this vector to an output sequence.



Summary of LSTM Application Architectures

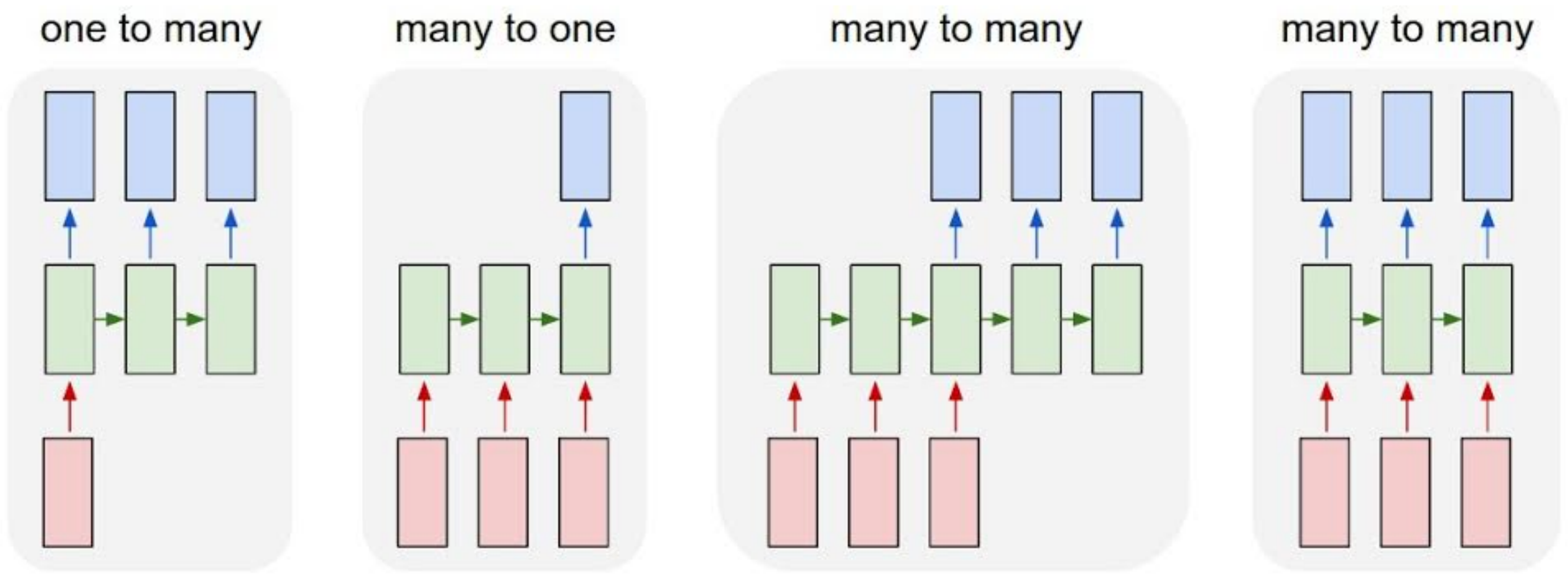


Image Captioning

Video Activity Recog
Text Classification

Video Captioning
Machine Translation

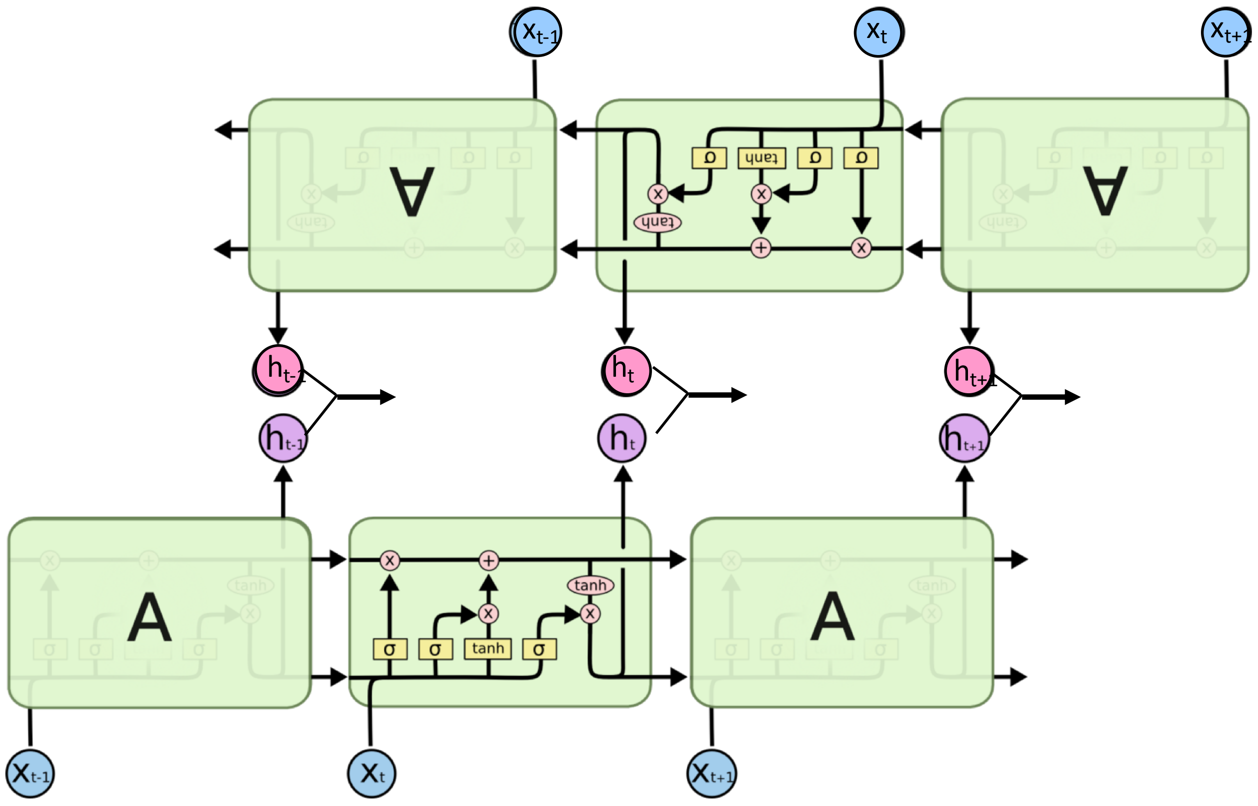
POS Tagging
Language Modeling

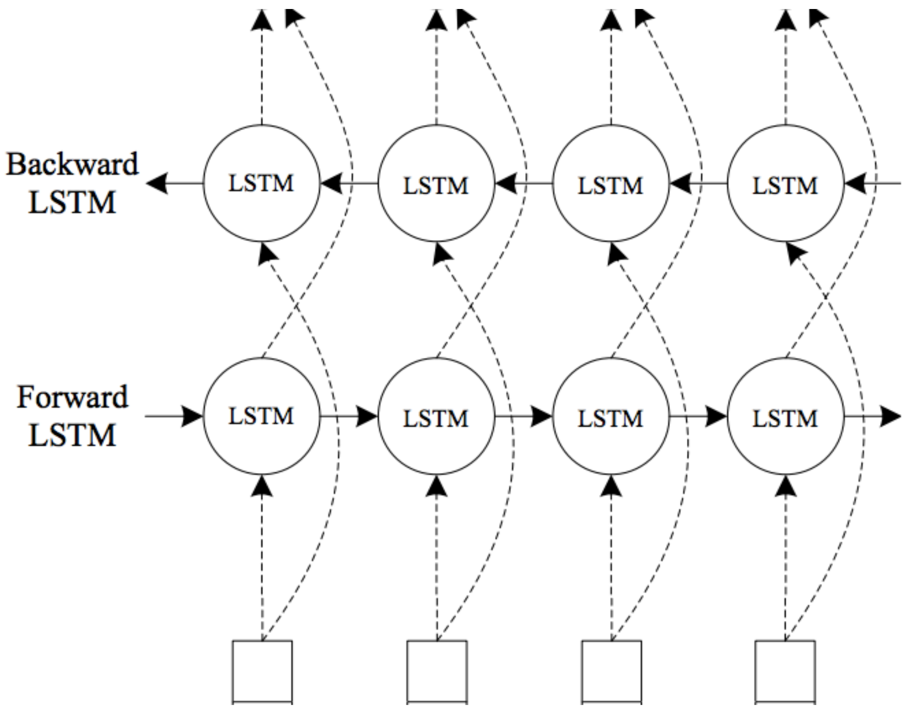
Successful Applications of LSTMs

- Speech recognition: Language and acoustic modeling
- Sequence labeling
  - POS Tagging
  - NER
  - Phrase Chunking
- Neural syntactic and semantic parsing
- Image captioning
- Sequence to Sequence
  - Machine Translation (Sustkever, Vinyals, & Le, 2014)
  - Video Captioning (input sequence of CNN frame outputs)

Bi-directional LSTM (Bi-LSTM)

- Separate LSTMs process sequence forward and backward and hidden layers at each time step are concatenated to form the cell output.





Homework

- Neural language models: https://web.stanford.edu/~jurafsky/slp3/7.pdf, 3rd ed
- Project progress report is due on Oct 31.