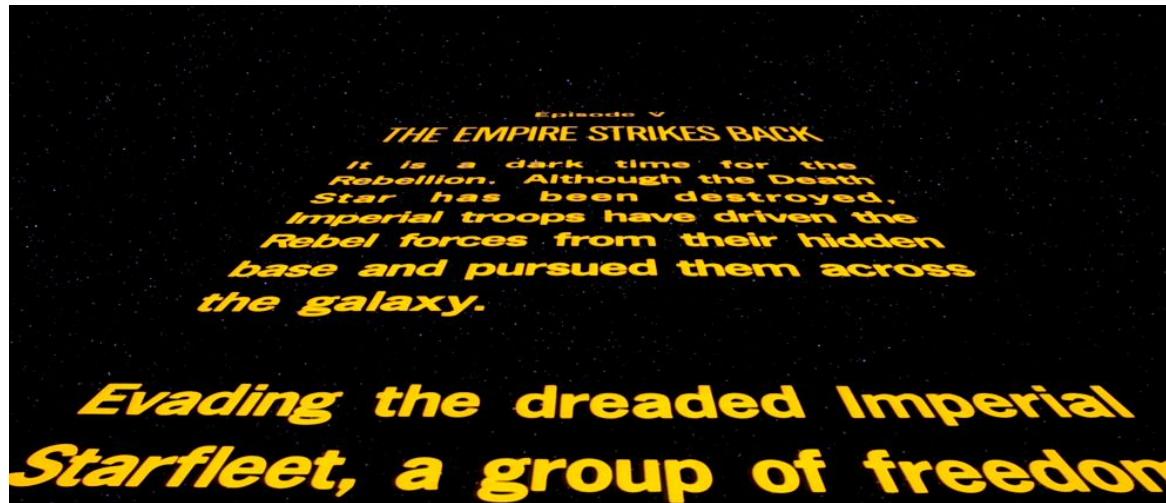


TOKENIZATION

Intro to neural networks

The need for segmentation

- Text as a stream of characters



- We need a way to understand the meaning of text
 - Break into words (assign meaning to word) ← Tokenization
 - Break into sentences (put word meanings back to sentence meaning)

Tokenization

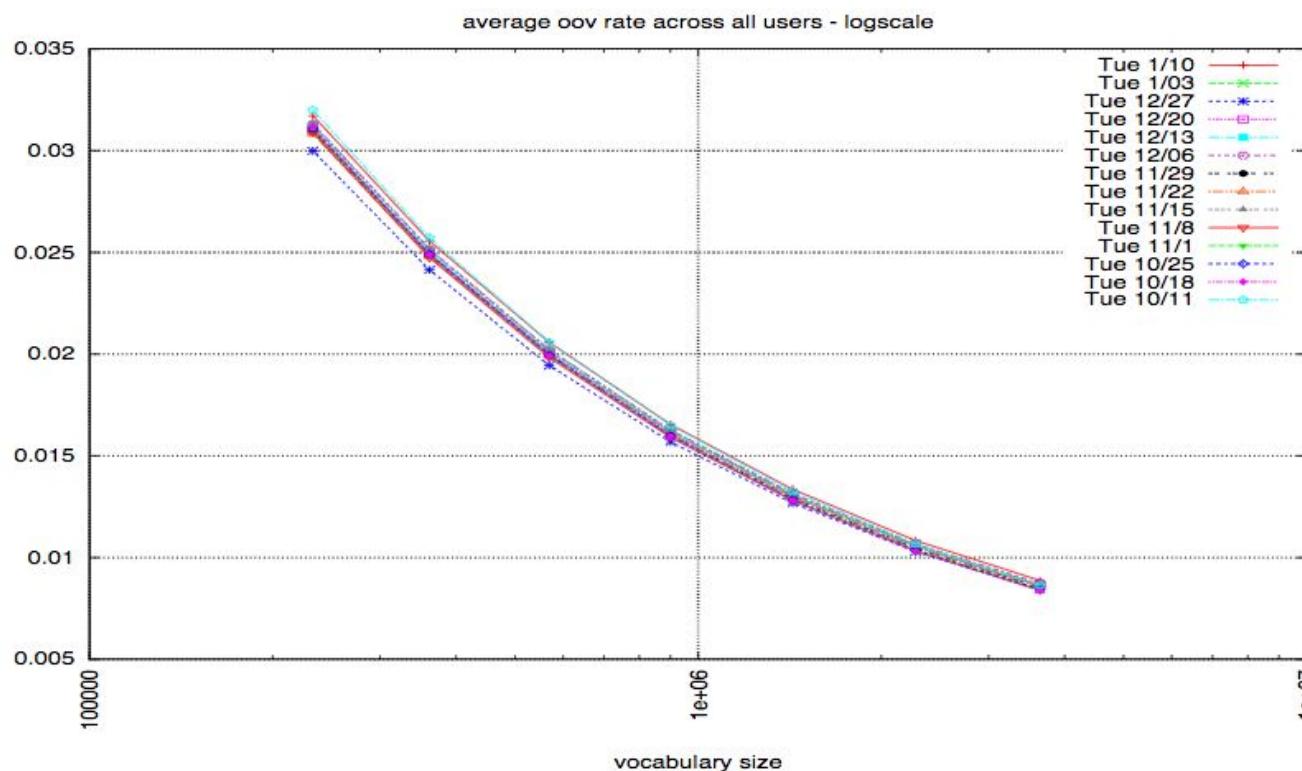
- A token should
 - 1. Linguistically significant
 - 2. Methodologically useful

Dictionary-based vs Machine-learning-based

- Dictionary-based
 - Longest matching
 - Maximal matching
- Machine-learning-based

Dictionary-based drawbacks

- Cannot handle words outside of the dictionary
(Out-of-Vocabulary, OOV words)
- Performs worse than machine-learning-based approach



NEURAL NETWORKS

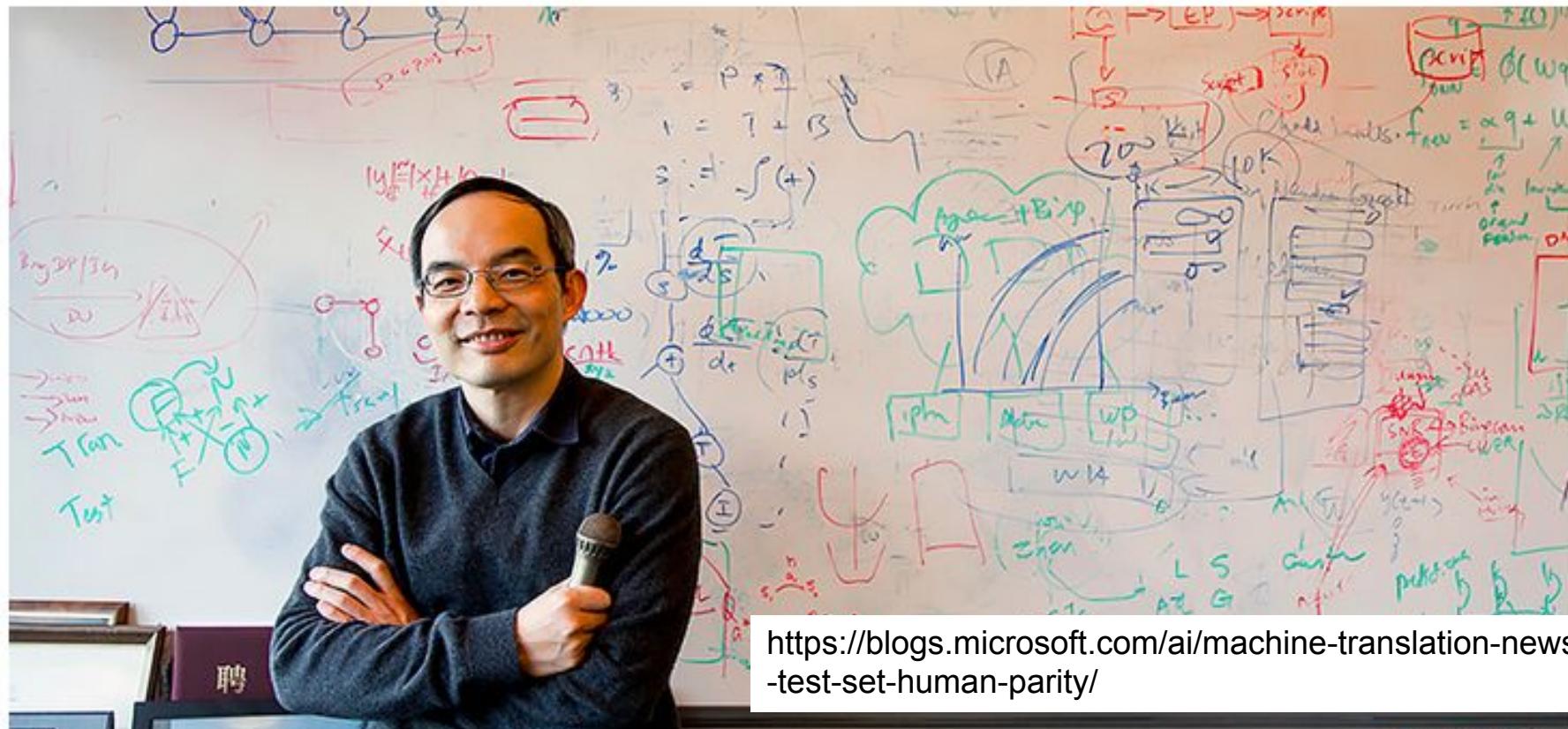
Deep learning = Deep neural networks =
neural networks

DNNs (Deep Neural Networks)

- Why deep learning?
- Greatly improved performance in ASR and other tasks (Computer Vision, Robotics, Machine Translation, NLP, etc.)
- Surpassed human performance in many tasks

Microsoft reaches a historic milestone, using AI to match human performance in translating news from Chinese to English

Mar 14, 2018 | [Allison Linn](#)



<https://blogs.microsoft.com/ai/machine-translation-news-test-set-human-parity/>

Deep learning in NLP

Easy task modest gains

	Traditional ML	Deep learning
Sentiment (th)	72%	76%
Topic classification (th)	67%	70%
PoS (th)	96%	97%

Harder task larger gains

	Traditional ML	Deep learning
QA	51%*	90%
Creating image from text	???	very good

TEXT PROMPT

an illustration of a baby daikon radish in a tutu walking a dog

AI-GENERATED IMAGES



[wangchanbert](#)

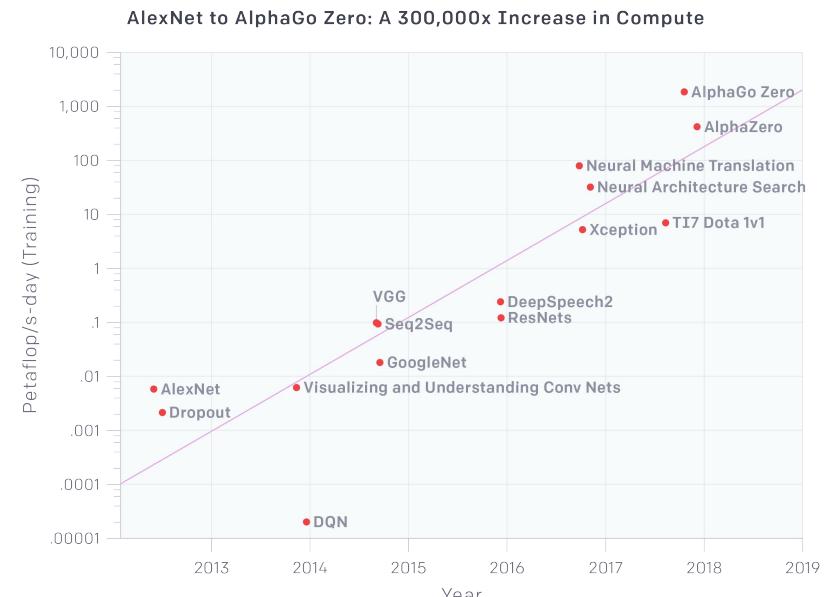
<https://www.aclweb.org/anthology/>

[D16-1264/](#)

<https://openai.com/blog/dall-e/>

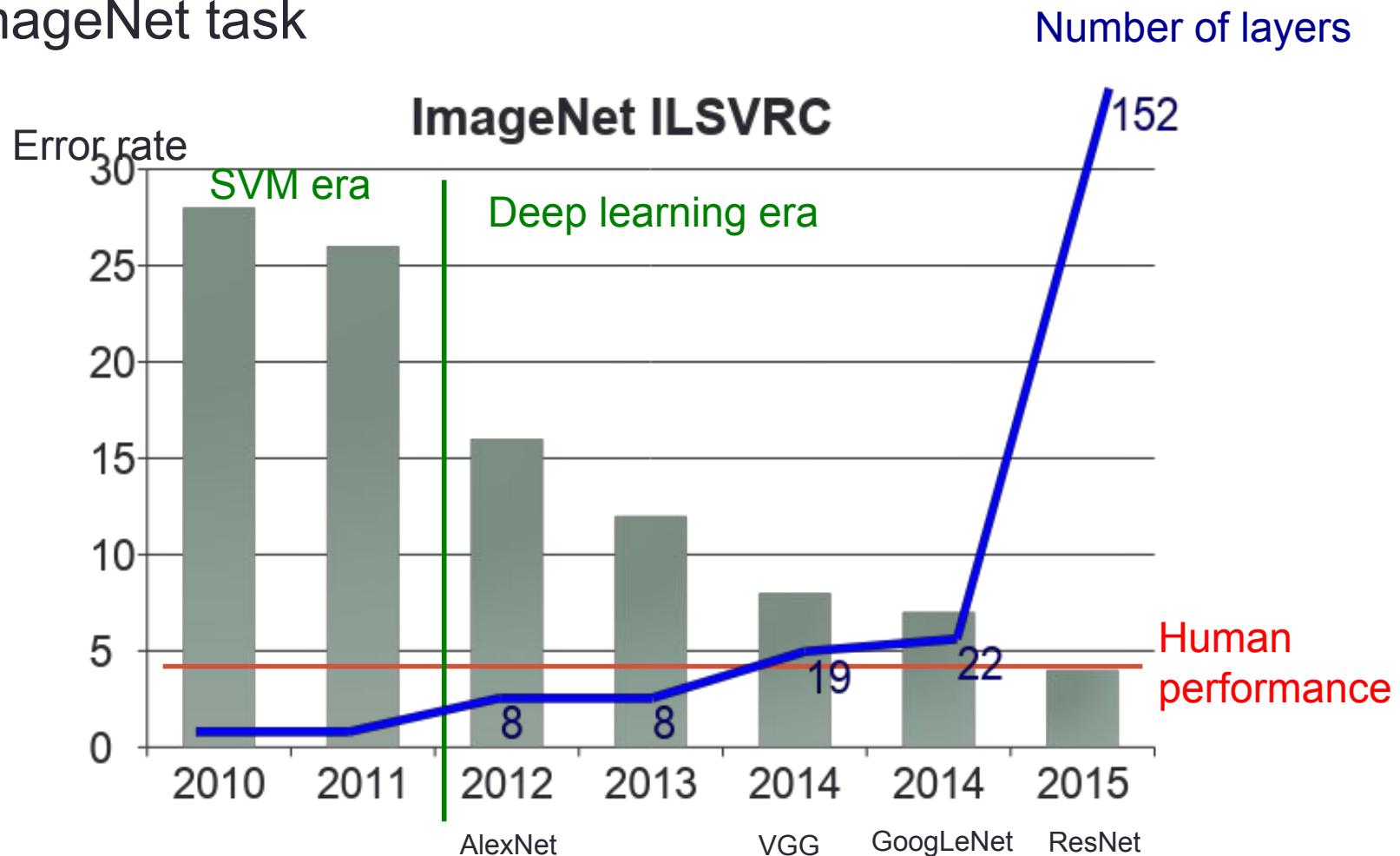
Why now

- Neural Networks has been around since 1990s
- **Big data** – DNN can take advantage of large amounts of data better than other models
- **GPU** – Enable training bigger models possible
- **Deep** – Easier to avoid bad local minima when the model is large

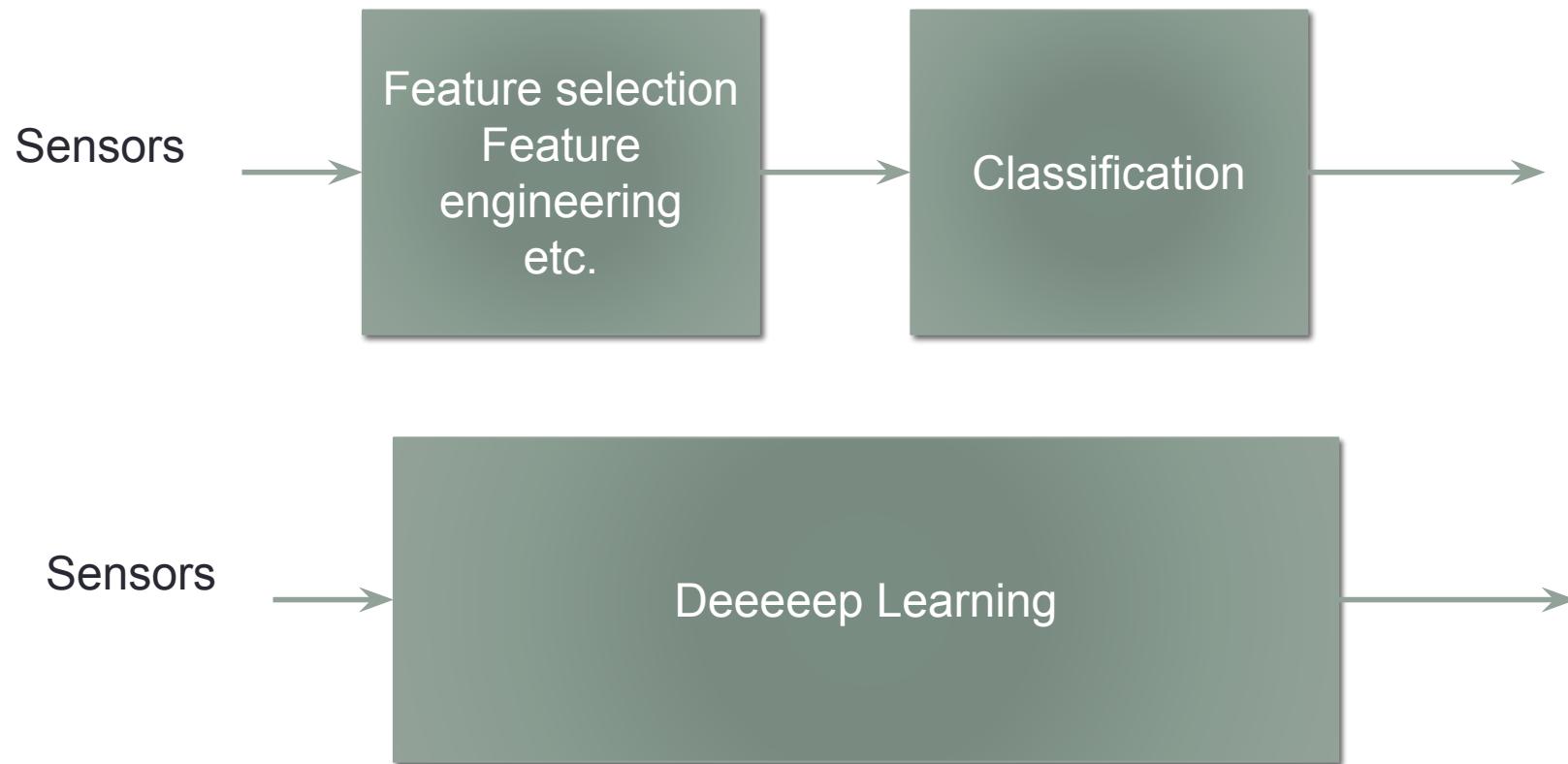


Wider and deeper networks

- ImageNet task



Traditional VS Deep learning

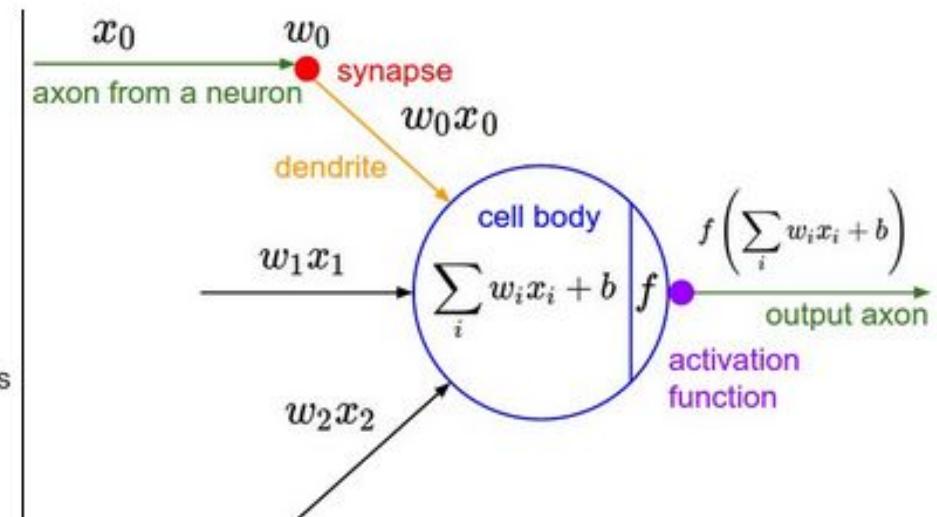
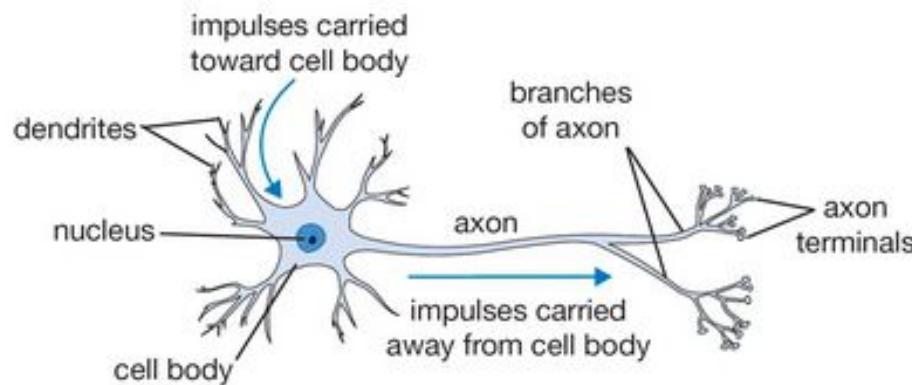


Neural networks

- Fully connected networks
 - Neuron
 - Non-linearity
 - Softmax layer
- DNN training
 - Loss function
 - SGD and backprop
 - Learning rate
 - Overfitting
- CNN, RNN, LSTM, GRU

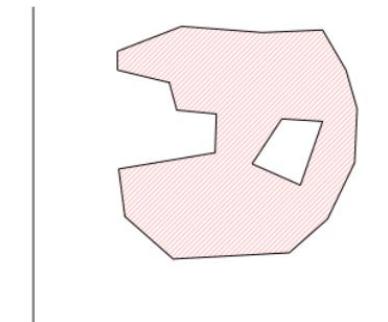
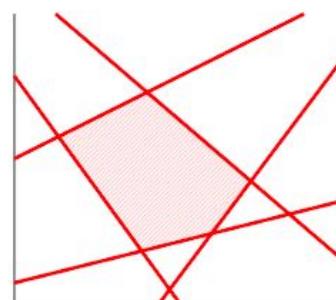
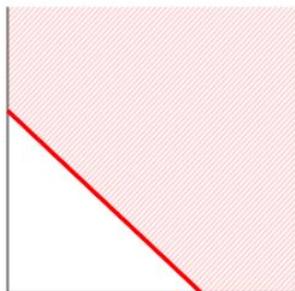
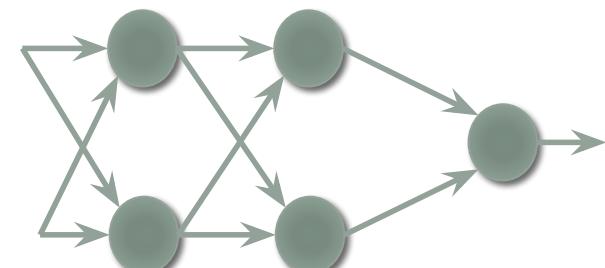
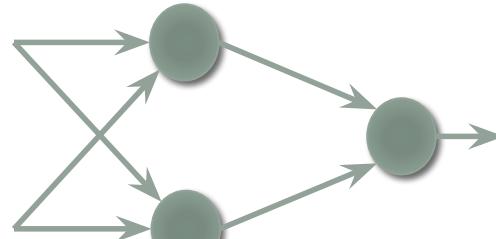
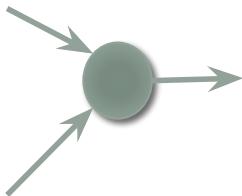
Fully connected networks

- Many names: feed forward networks or deep neural networks or multilayer perceptron or artificial neural networks
- Composed of multiple neurons



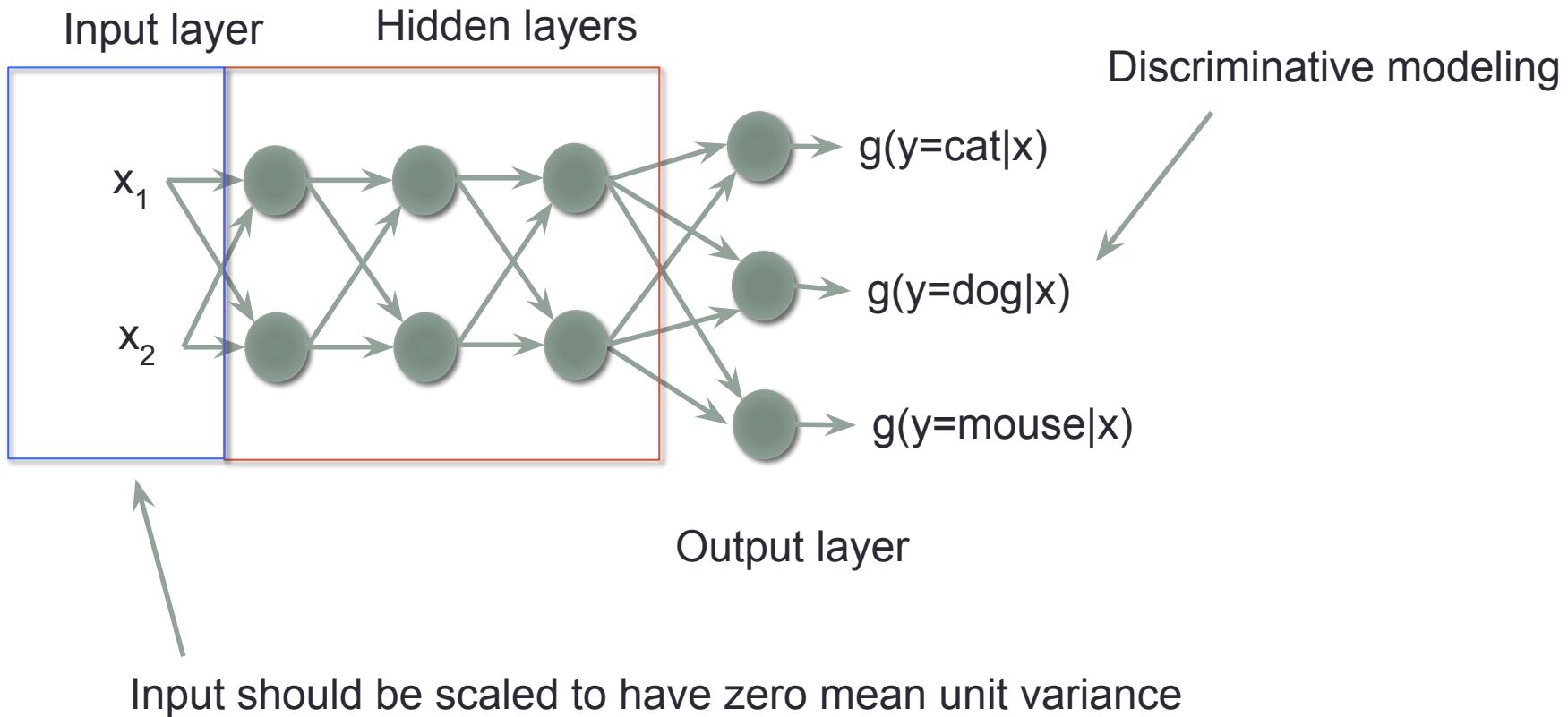
Combining neurons

- Each neuron splits the feature space with a hyperplane
- Stacking neuron creates more complicated decision boundaries
- More powerful but prone to overfitting



Terminology

Deep in Deep neural networks means many hidden layers



Matrices

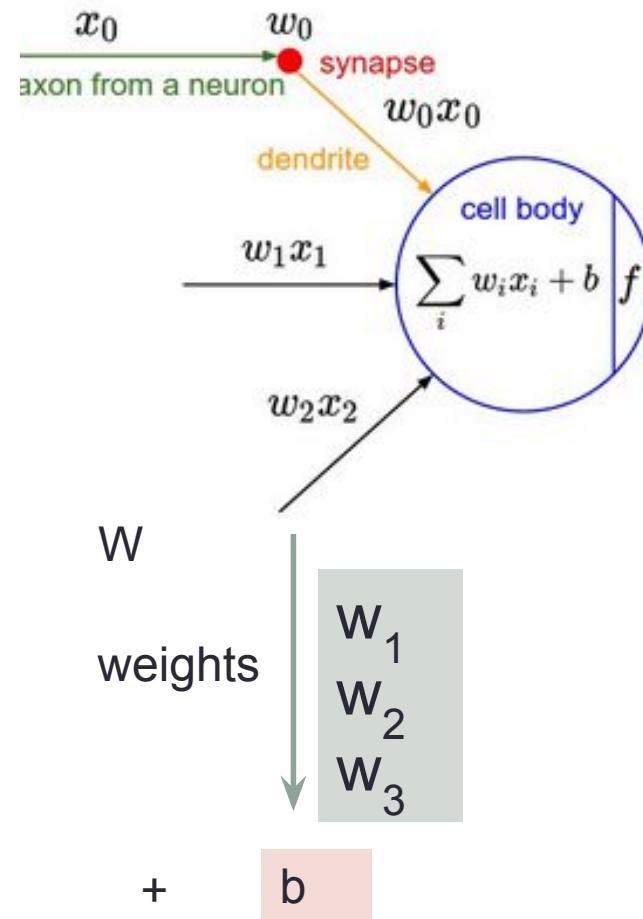
- Inputs

features ↓

$$\begin{matrix} x_1 \\ x_2 \\ x_3 \end{matrix} \quad X$$

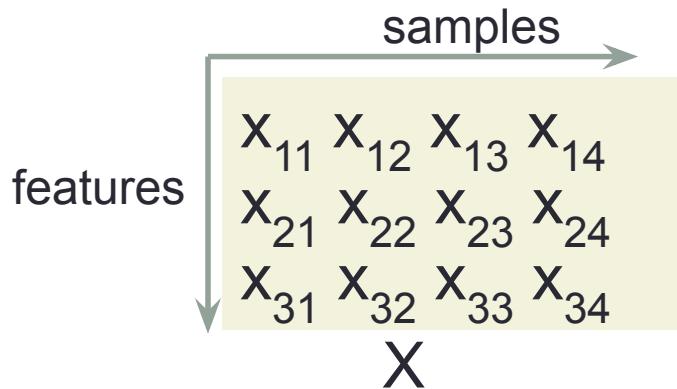
$$W^T X + b$$

$$\begin{matrix} W_1 & W_2 & W_3 \\ x_1 \\ x_2 \\ x_3 \end{matrix}$$



Matrices

- Inputs



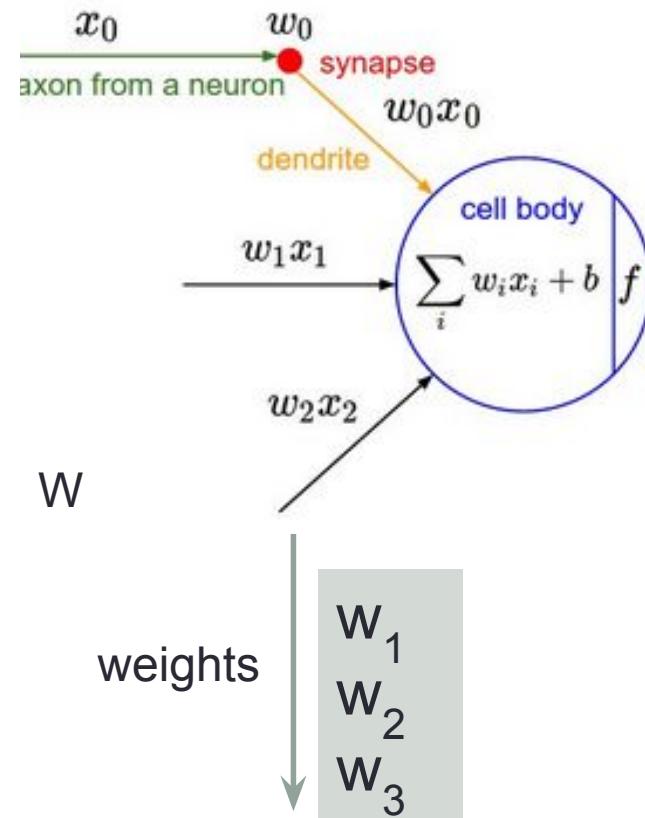
$$W^T X + b$$

$$\begin{matrix} W_1 & W_2 & W_3 \end{matrix}$$

$$\begin{matrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ x_{31} & x_{32} & x_{33} & x_{34} \end{matrix}$$

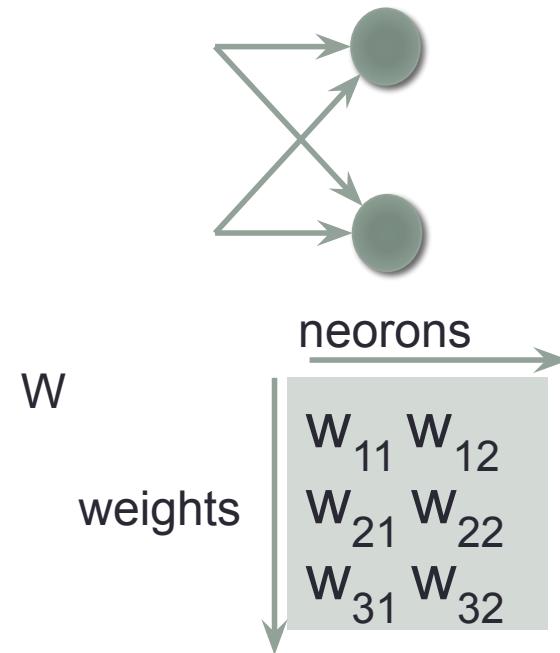
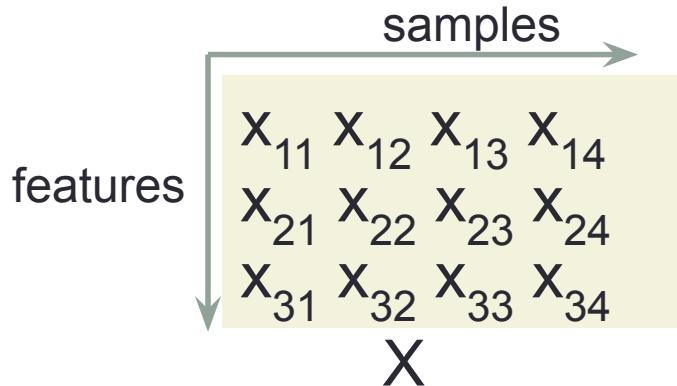
+

$$b$$



Matrices

- Inputs



$$W^T X + b$$

$$\begin{matrix} W_{11} & W_{21} & W_{31} \\ W_{21} & W_{22} & W_{23} \end{matrix}$$

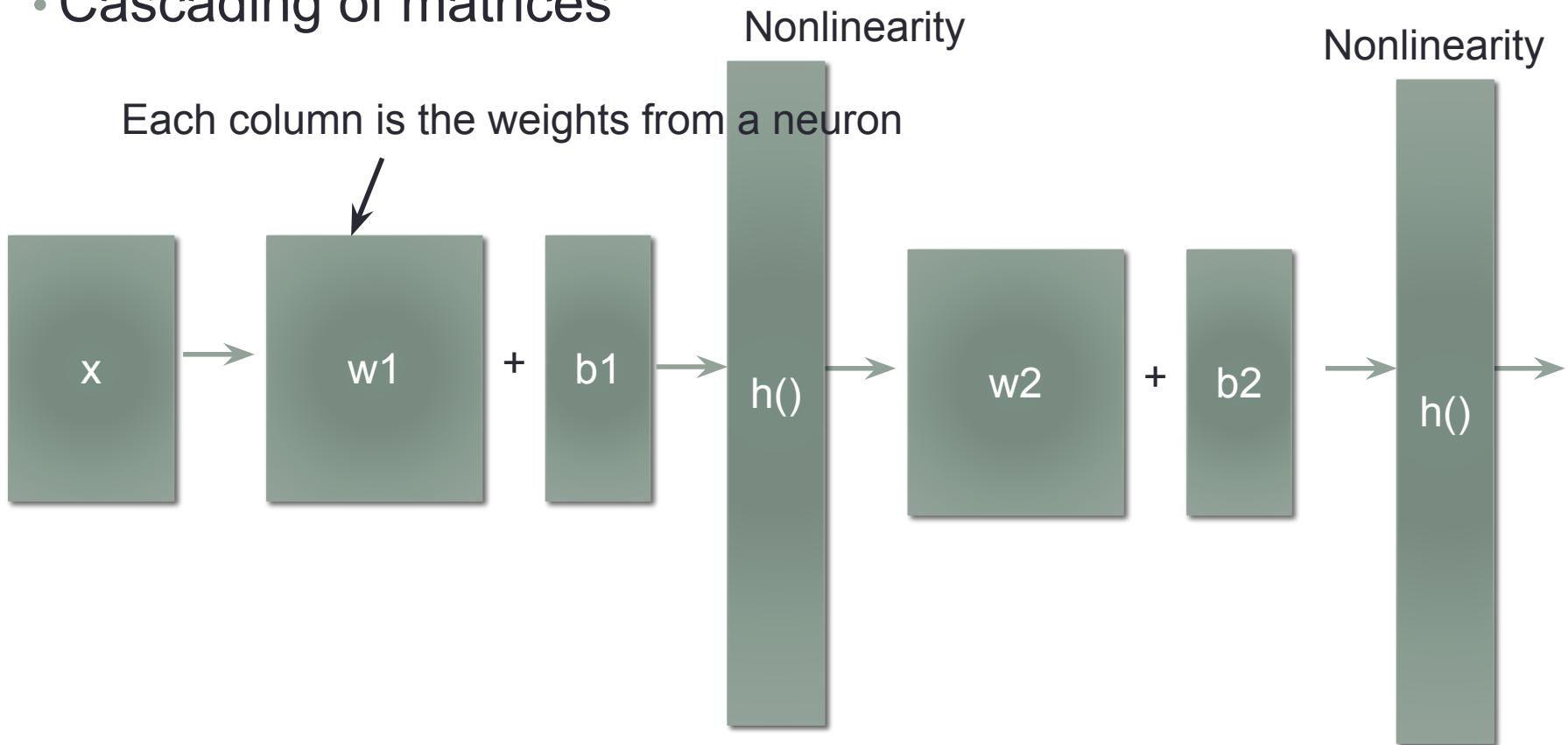
$$\begin{matrix} x_{11} & x_{12} & x_{13} & x_{14} \\ x_{21} & x_{22} & x_{23} & x_{24} \\ x_{31} & x_{32} & x_{33} & x_{34} \end{matrix}$$

+

$$\begin{matrix} b_1 \\ b_2 \end{matrix}$$

More linear algebra

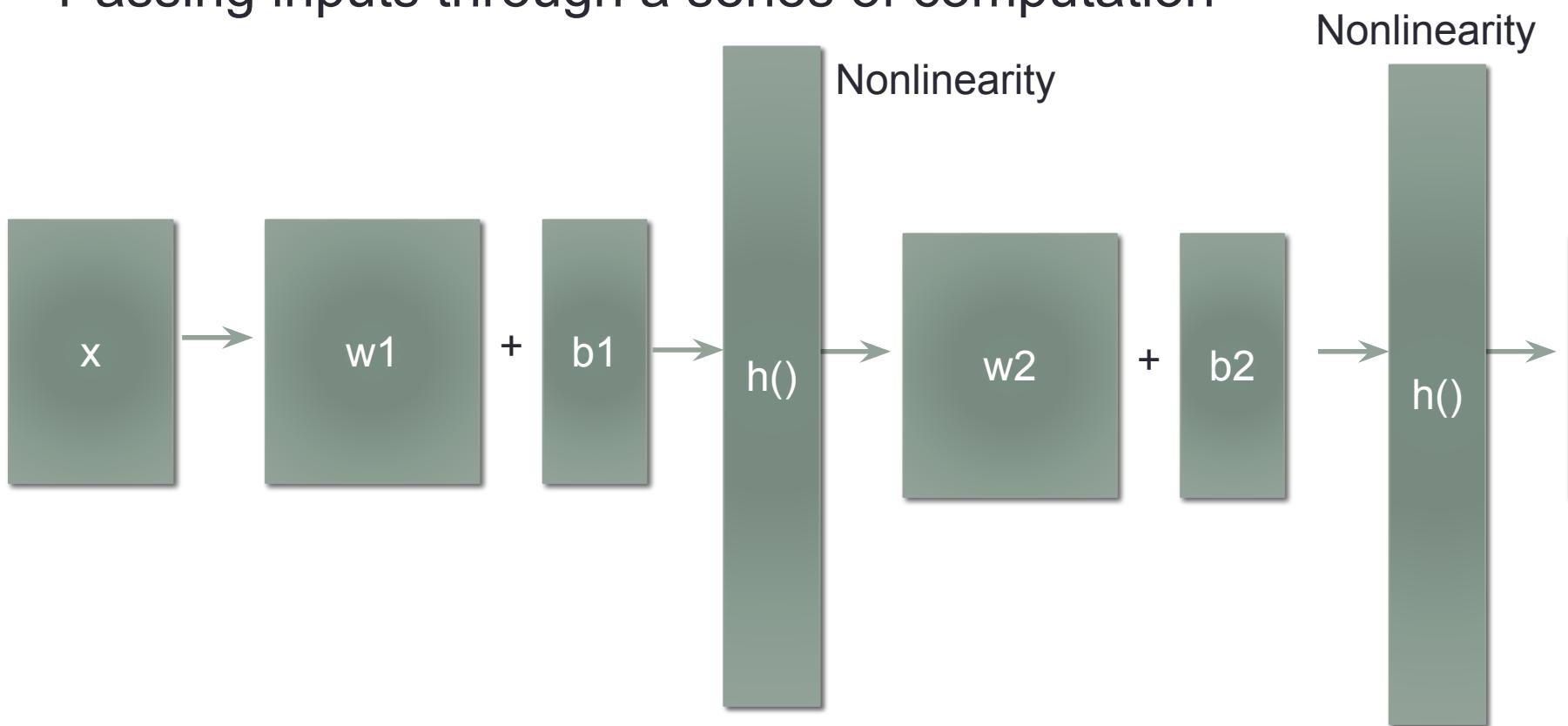
- Cascading of matrices



$$h(W_2^T h(W_1^T X + b_1) + b_2)$$

Computation graph

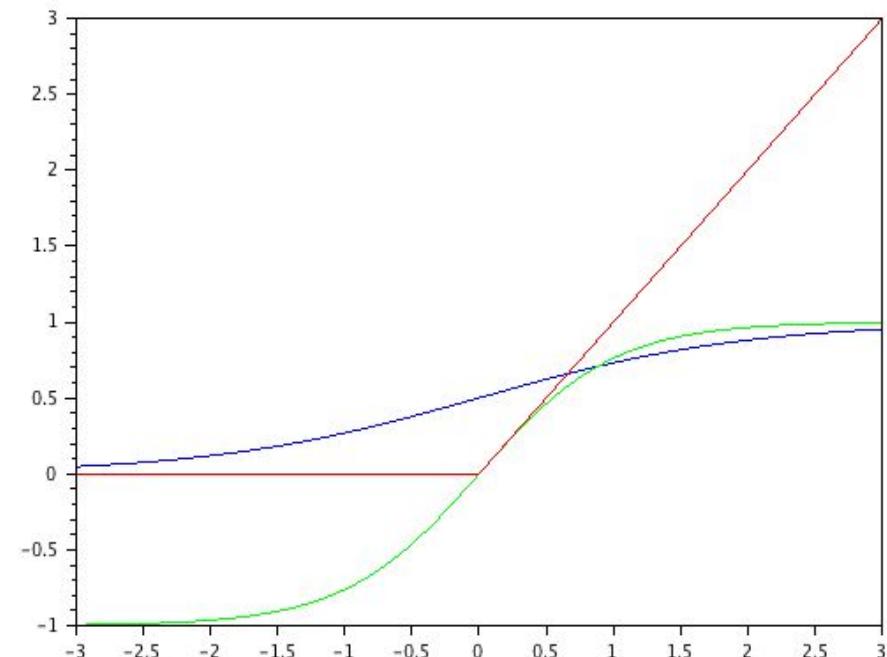
- Passing inputs through a series of computation



$$h(W_2^T h(W_1^T X + b_1) + b_2)$$

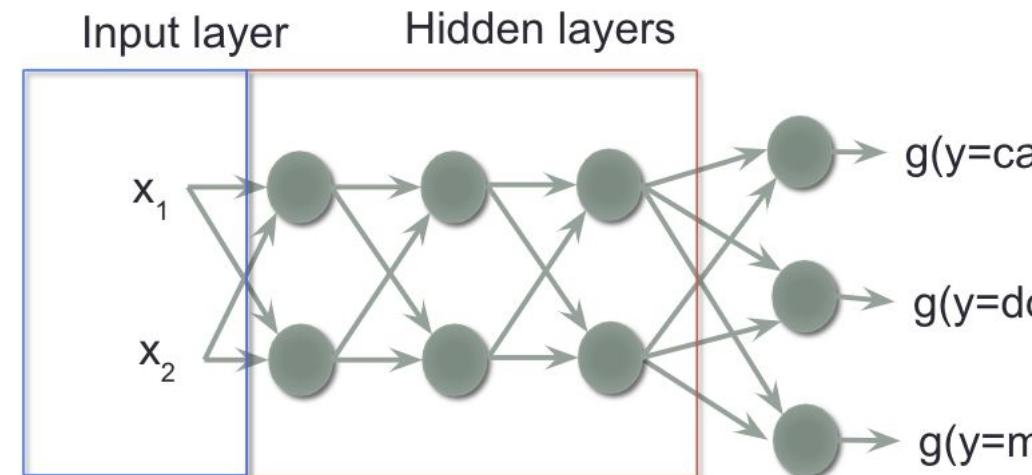
Non-linearity

- The Non-linearity is important in order to stack neurons
 - If F is linear, a multi layered network can be collapsed as a single layer (by just multiplying weights together)
- Sigmoid or logistic function
- \tanh
- Rectified Linear Unit (ReLU)
- Most popular is ReLU and its variants (Fast to train, and more stable)



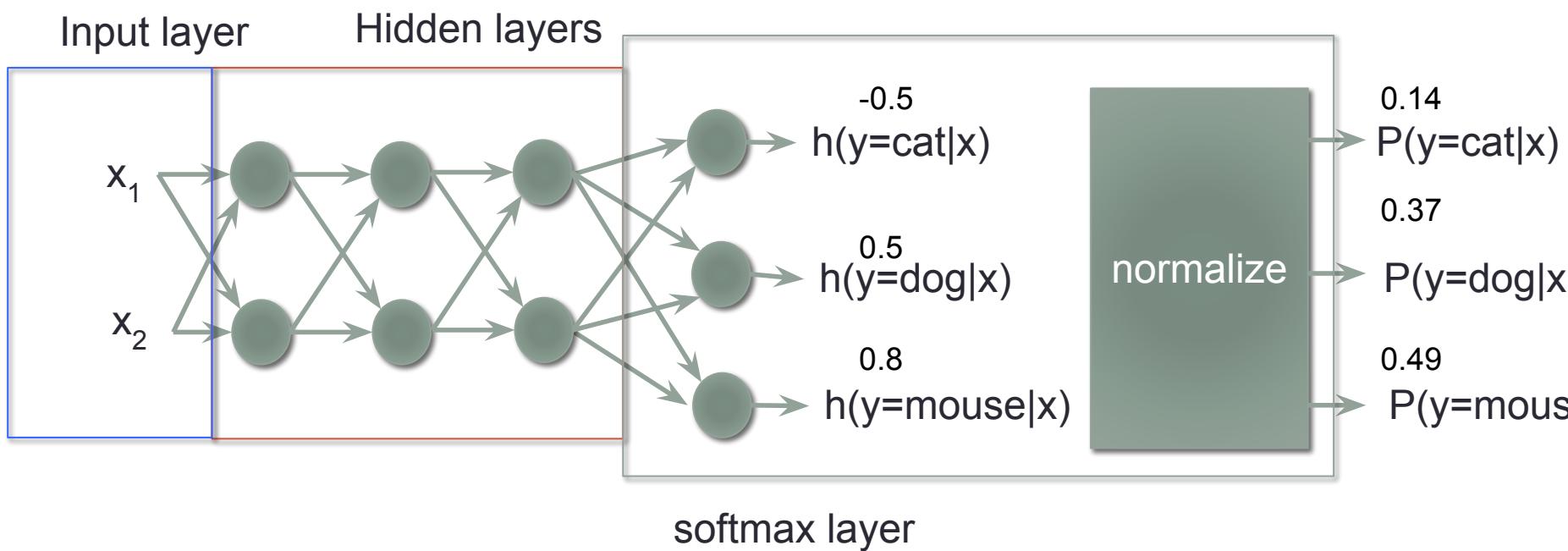
Output layer – Softmax layer

- We usually want the output to mimic a probability function ($0 \leq P \leq 1$, sums to 1)
- Current setup has no such constraint
- The current output should have highest value for the correct class.
 - Value can be positive or negative number
- Takes the exponent
- Add a normalization



Softmax layer

$$P(y = j|x) = \frac{e^{h(y=j|x)}}{\sum_y e^{h(y|x)}}$$

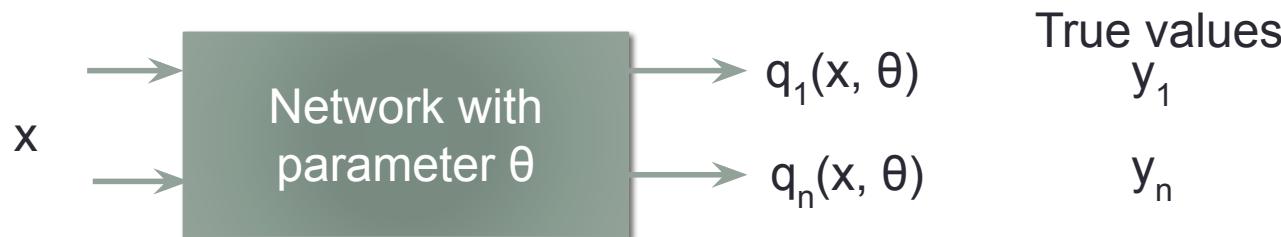


Neural networks

- Fully connected networks
 - Neuron
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 - Softmax layer
- DNN training
 - Loss function
 - SGD and backprop
 - Learning rate
 - Overfitting
- CNN, RNN, LSTM, GRU

Objective function (Loss function)

- Can be any function that summarizes the performance into a single number
- Cross entropy
- Sum of squared errors



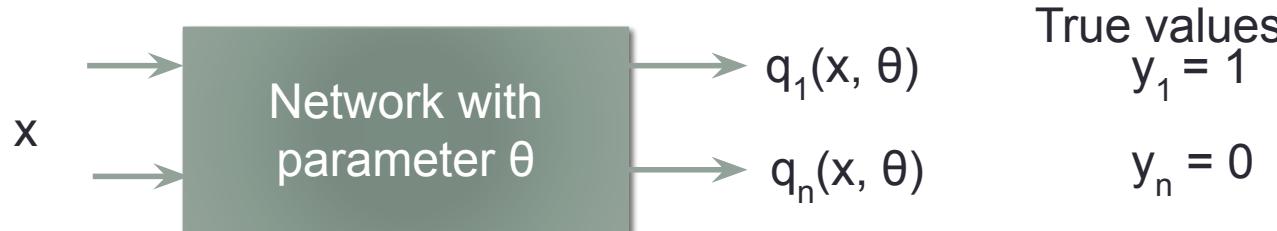
Cross entropy loss

- Used for softmax outputs (probabilities), or classification tasks

$$L = -\sum_n y_n \log q_n(x, \theta)$$

- Where y_n is 1 if data x comes from class n
0 otherwise

- L only has the term from the correct class
- L is non negative with highest value when the output matches the true values, a “loss” function

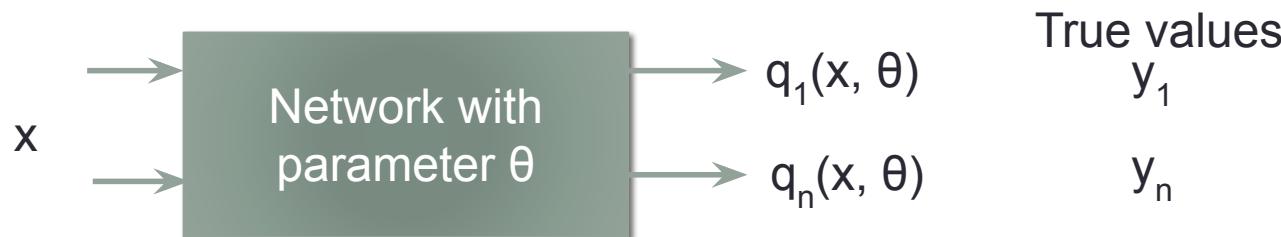


Sum of squared errors

- Used for any real valued outputs such as regression

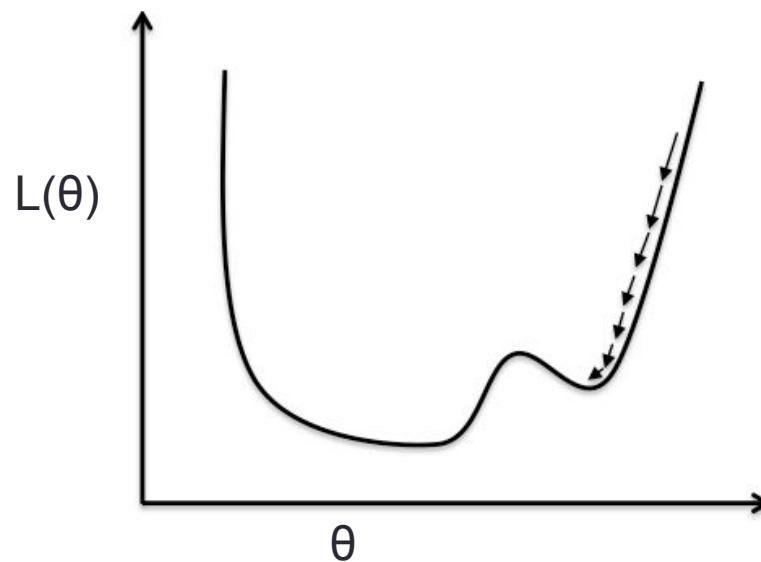
$$L = \frac{1}{2} \sum_n (y_n - q_n(x, \theta))^2$$

- Non negative, the better the lower the loss



Minimization using gradient descent

- We want to minimize L with respect to θ (weights and biases)
 - Differentiate with respect to θ
 - Gradients passes through the network by Back Propagation



Differentiating a neural network model

- We want to minimize loss by gradient descent
- A model is very complex and have many layers! How do we differentiate this!!?



Back propagation

- Forward pass
 - Pass the value of the input until the end of the network
- Backward pass
 - Compute the gradient starting from the end and passing down gradients using chain rule

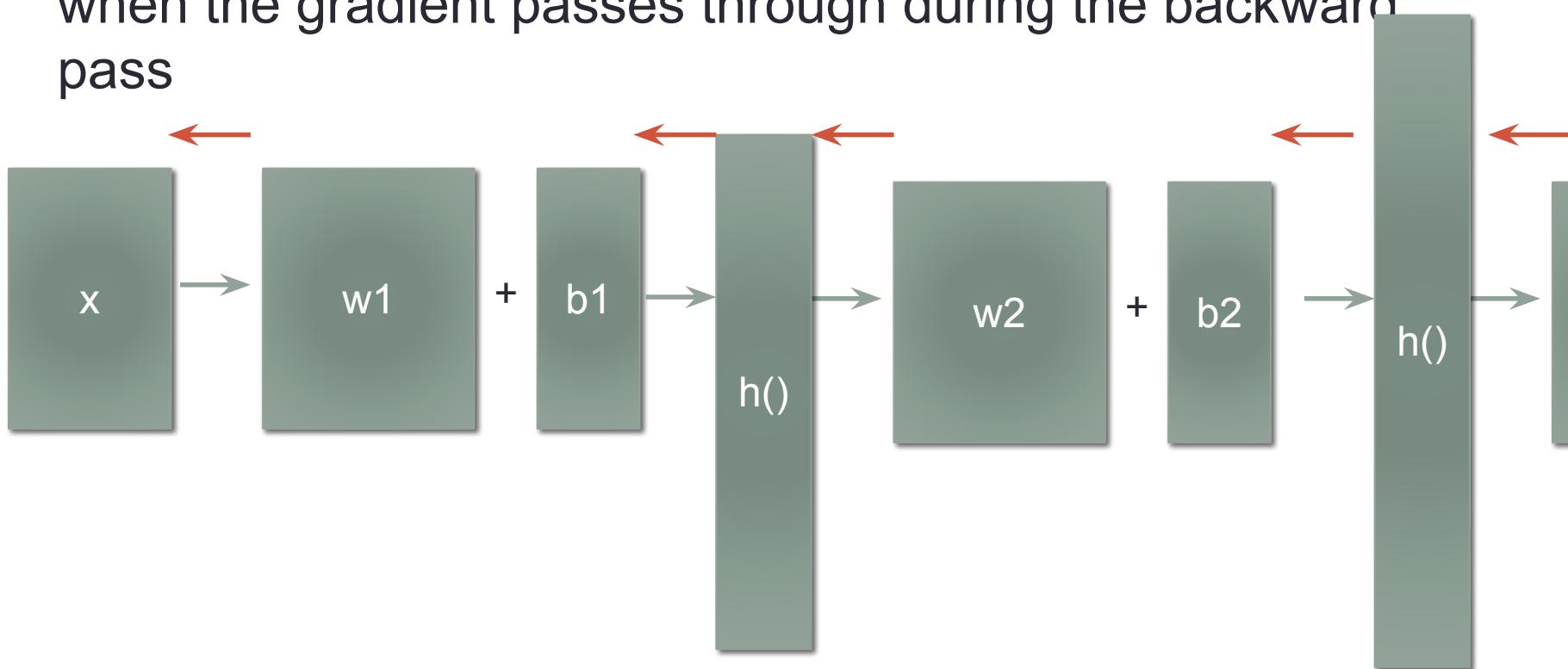
Examples to read

<https://alonalj.github.io/2016/12/10/What-is-Backpropagation/>

<https://mattmazur.com/2015/03/17/a-step-by-step-backpropagation-example/>

Backprop and computation graph

- We can also define what happens to a computing graph when the gradient passes through during the backward pass



This lets us to build any neural networks without having to redo all the derivation as long as we define a forward and backward computation for the block.

Initialization

- The starting point of your descent
- Important due to local minimas
- Not as important with large networks AND big data
- Now usually initialized randomly
 - One strategy (Xavier init)
$$\text{var}(w) = 2/(\text{fan_in} + \text{fan_out})$$
 - For ReLUs (He init)
$$\text{var}(w) = 2/\text{fan_in}$$
- Or use a pre-trained network as initialization

X. Glorot and Y. Bengio. Understanding the difficulty of training deep feedforward neural networks. 2010

Kaiming He, Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification. 2015

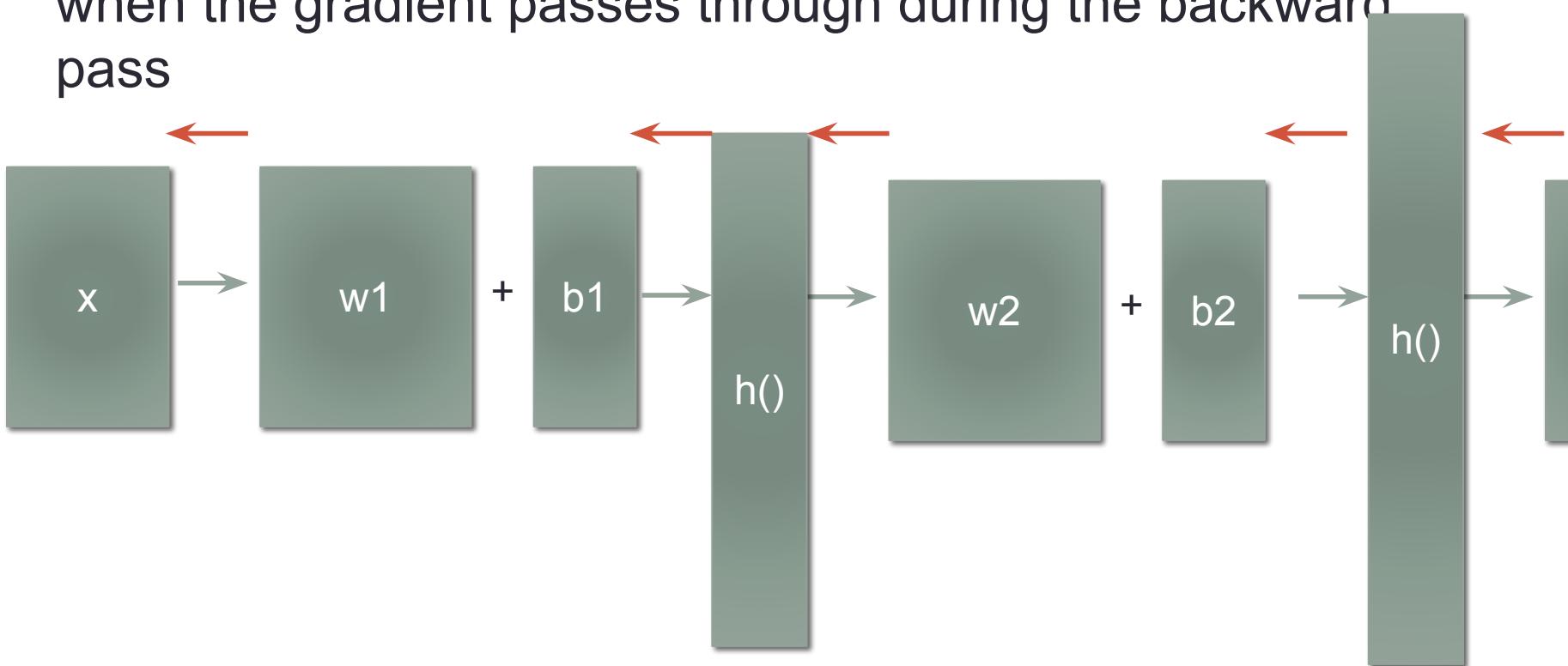
Stochastic gradient descent (SGD)

- Consider you have one million training examples
 - Gradient descent computes the objective function of **all** samples, then decide direction of descent
 - Takes too long
 - SGD computes the objective function on **subsets** of samples
 - The subset should not be biased and properly randomized to ensure no correlation between samples
- The subset is called a mini-batch
- Size of the mini-batch determines the training speed and accuracy
 - Usually somewhere between 32-1024 samples per mini-batch
- Definition: 1 batch vs 1 epoch

Note: one can read relationship between batch size and learning rate here
<https://arxiv.org/abs/1711.00489>

Backprop and computation graph

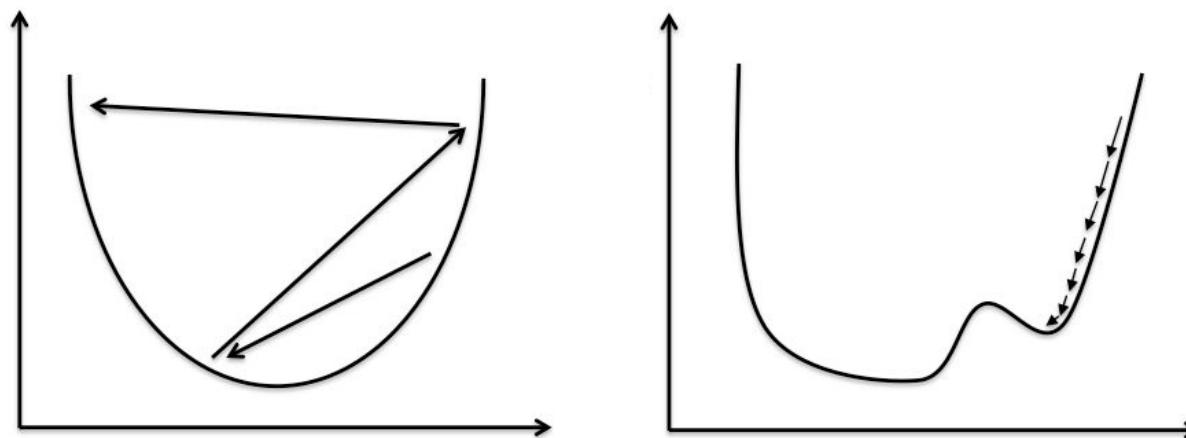
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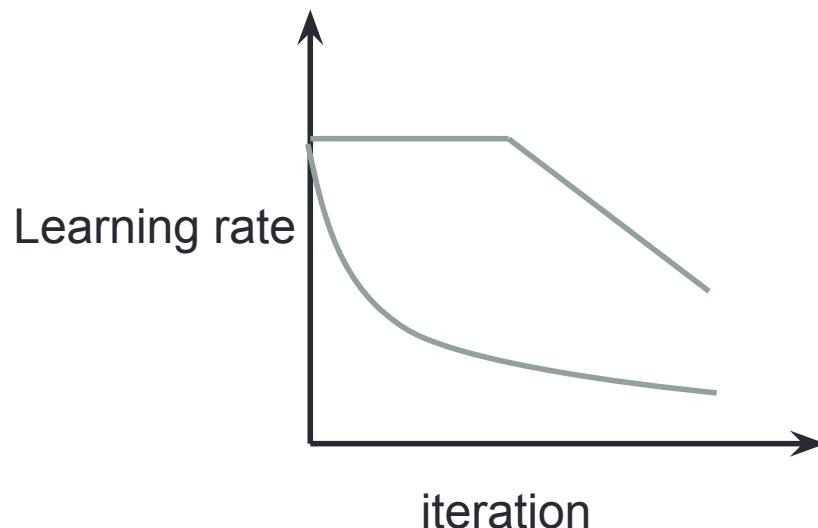
Learning rate

- How fast to go along the gradient direction is controlled by the learning rate
- Too large models diverge
- Too small the model get stuck in local minimas and takes too long to train



Learning rate scheduling

- Usually starts with a large learning rate then gets smaller later
- Depends on your task
- Automatic ways to adjust the learning rate : Adagrad, Adam, etc. (still need scheduling still)

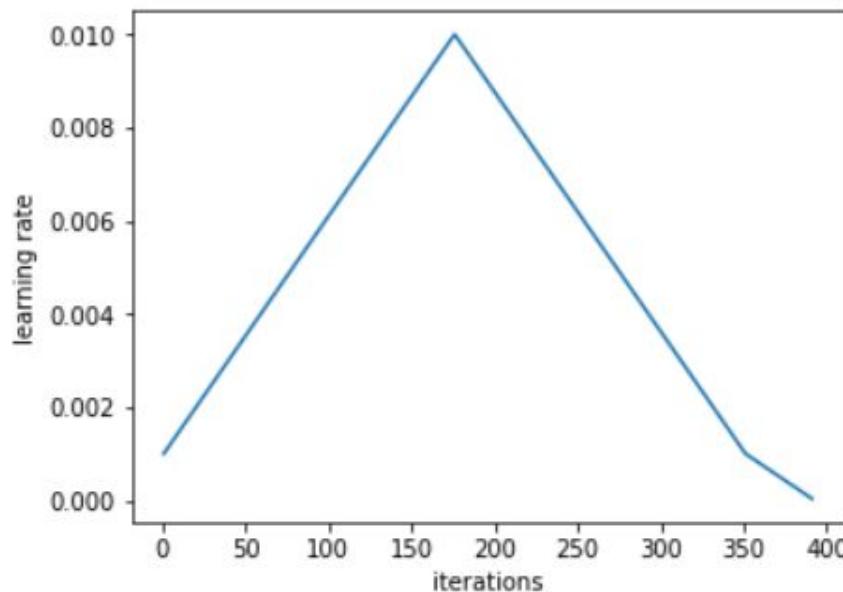


Learning rate warm up

Initial point of the network can be at a bad spot.

Try not to go to fast - has a warm up period.

Useful for large datasets, or adaption (transfer learning)



Potentially leads to faster convergence and better accuracy

See links below for methods to select the shape of the triangle

<https://sgugger.github.io/the-1cycle-policy.html#the-1cycle-policy>

[Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour](#)

[Cyclical Learning Rates for Training Neural Networks](#)

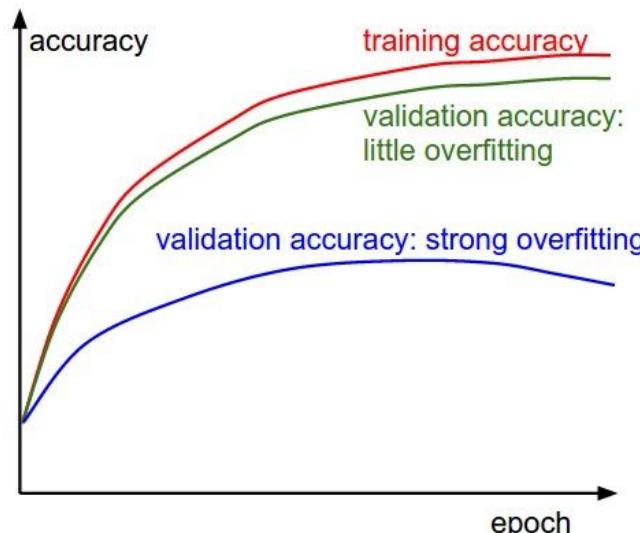
Optimizers

- Besides learning rate scheduling (coarse grain) we can do finer (and automatic) control of the learning rate
- RMSprop
 - Faster than SGD but slower than ADAM
 - More stable than ADAM
- ADAM + variants
 - Most popular for its ease of use

People find simple SGD with momentum and decay to perform better (with proper tuning)

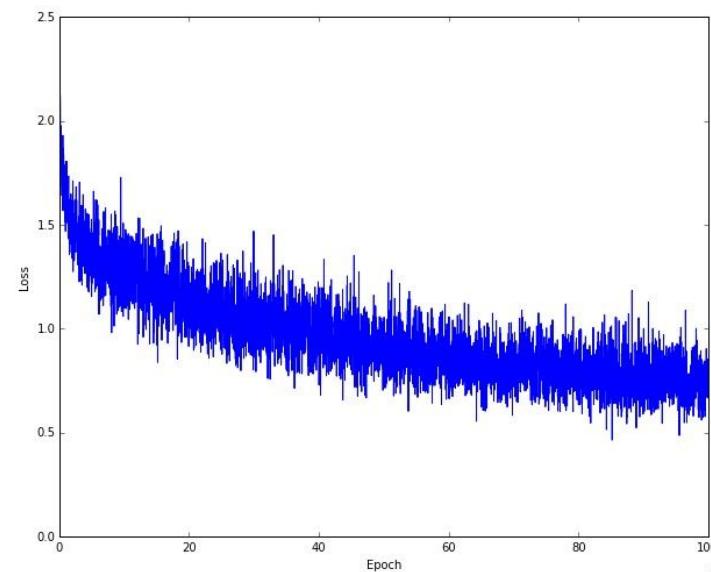
Overfitting

- You can keep doing back propagation forever!
- The training loss will always go down
- But it overfits
- Need to monitor performance on a held out set
- Stop or decrease learning rate when overfit happens



Monitoring performance

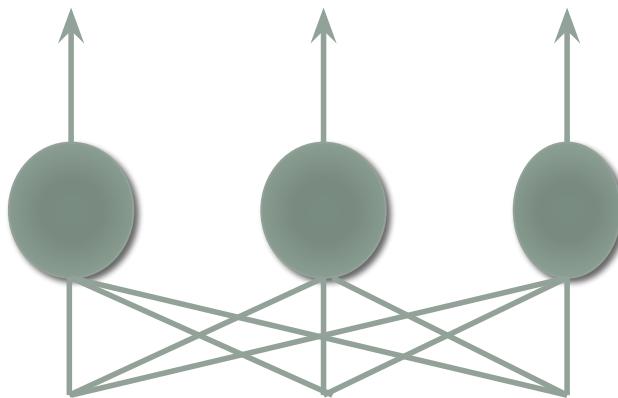
- Monitor performance on a dev/validation set
 - This is NOT the test set
- Can monitor many criterions
 - Loss function
 - Classification accuracy
- Sometimes these disagree
- Actual performance can be noisy, need to see the trend



Reducing overfitting - dropout

- A regularization technique for reducing overfitting
- Randomly turn off different subset of neurons during training
 - Network no longer depend on any particular neuron
 - Force the model to have redundancy – robust to any corruption in input data
 - A form of performing model averaging (ensemble of experts)
- Now a standard technique

Dropout visualized

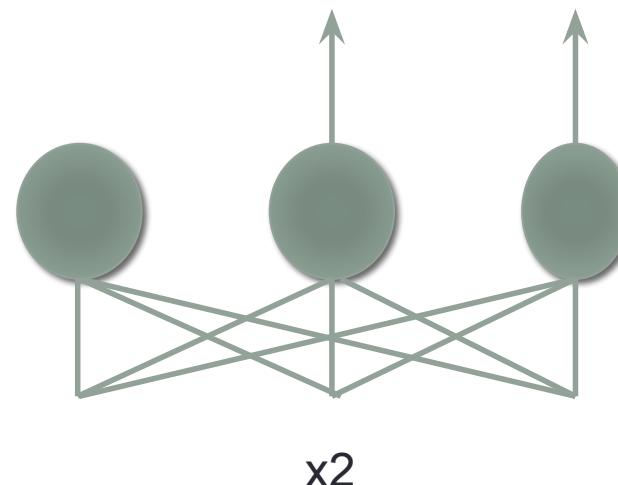
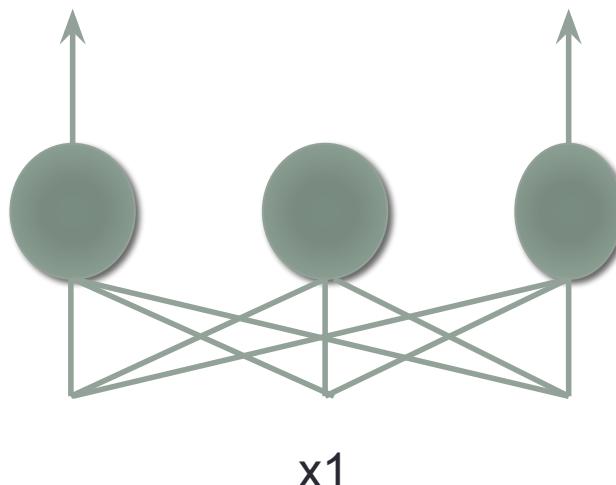


Model

Dropout training time

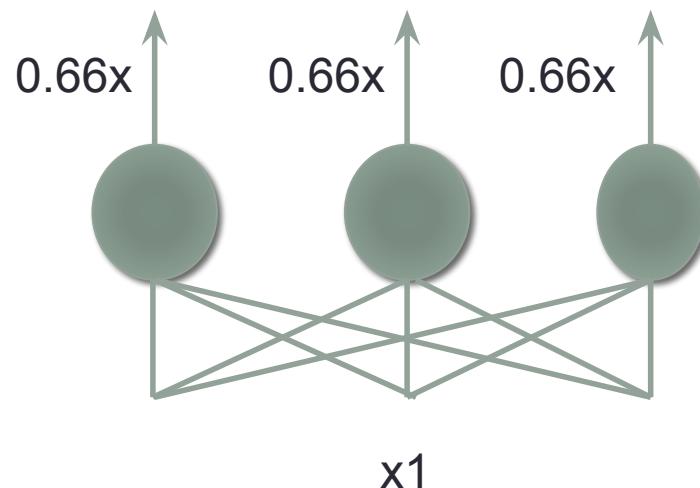
Drop out rate 0.33

Randomly removed outputs
for each training sample

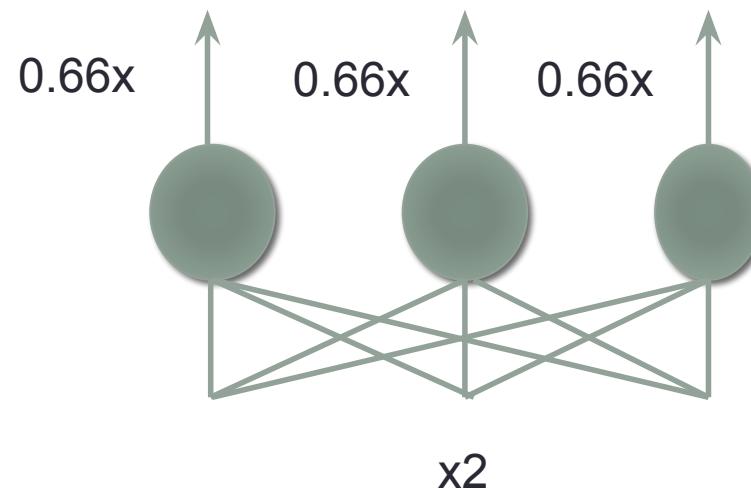


Dropout test time

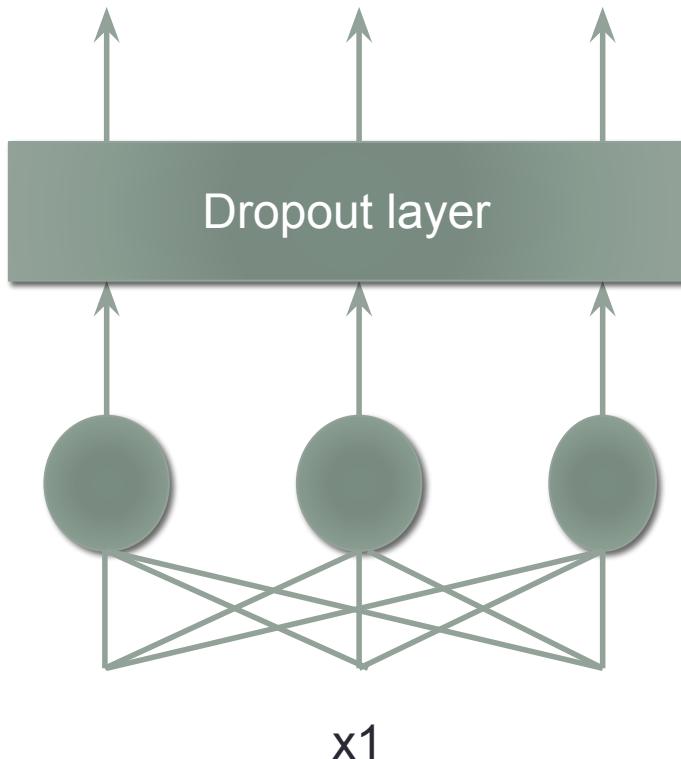
Dropout rate 0.33



Scale outputs so the output contribution is around the same



Dropout implementation



Dropout layer

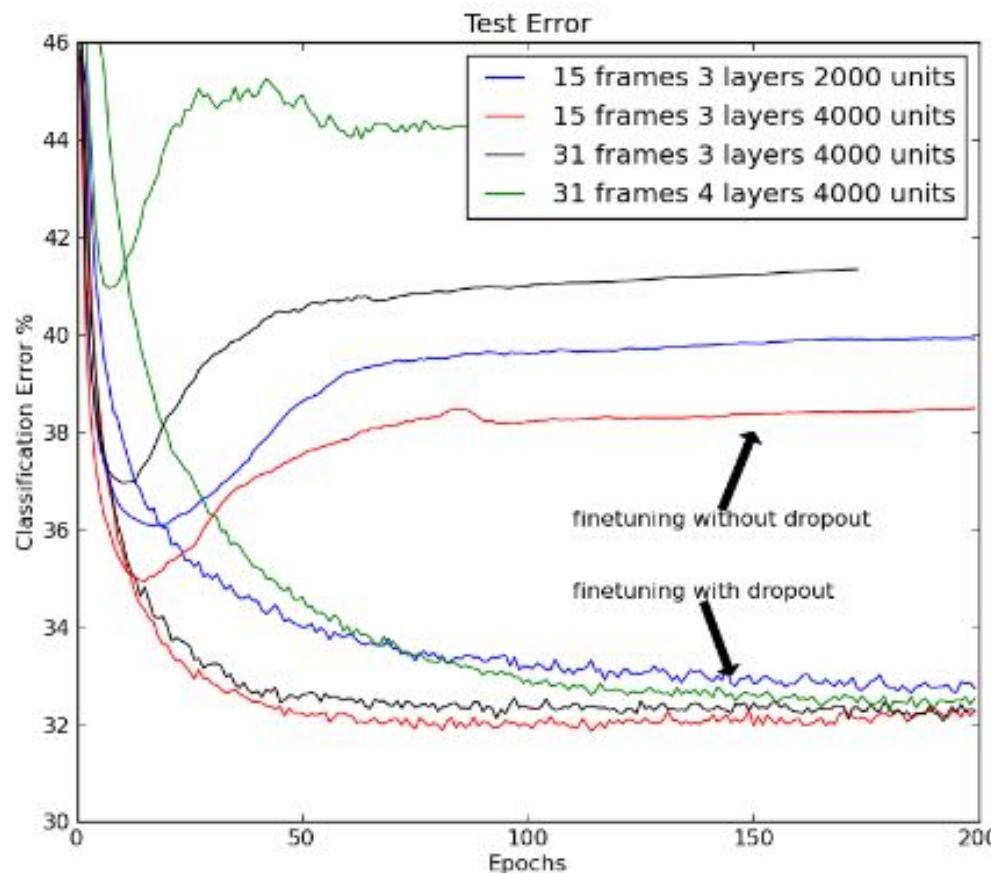
Just another layer that drops inputs

Inverted dropout

A variant of dropout that scales the dropout at training time, so that you don't have to scale at test time.

Dropout on TIMIT

- A phoneme recognition task



Batch normalization

- Recent technique for (implicit) regularization
- **Normalize every mini-batch** at various batch norm layers to standard Gaussian (different from global normalization of the inputs)
- Place batch norm layers before non-linearities
- Faster training and better generalizations

For each mini-batch that goes through
batch norm

1. Normalize by the mean and variance of the mini-batch for each dimension
2. Shift and scale by learnable parameters

$$\hat{x} = \frac{x - \mu_b}{\sigma_b}$$

$$y = \alpha \hat{x} + \beta$$

Replaces dropout in some networks

<https://arxiv.org/abs/1502.03167>

Dropout vs batchnorm

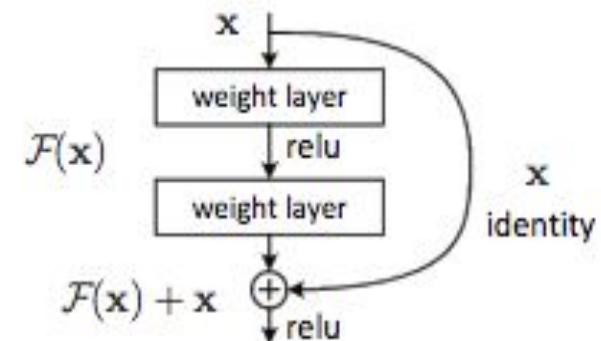
- You can add dropout in the hidden layers (0-0.5)
- Or input layers (0-0.2 is typical)
 - “Noising” the inputs, data augmentation
- Dropout in computer vision
 - use batchnorm instead
- Dropout in NLP
 - Usually works better than Batchnorm for NLP in simple architectures
 - Drop full words at the embedding
 - Recurrent dropout <http://arxiv.org/abs/1512.05287>
 - Recent works (transformers) find batchnorm to be better than dropout
 - For seq2seq models, layer norm is popular

Vanishing/Exploding gradient

- Backprop introduces many multiplications down chain
- The gradient value gets smaller and smaller
 - The deeper the network the smaller the gradient in the lower layers
 - Lower layers changes too slowly (or not at all)
 - Hard to train very deep networks (>6 layers)
- The opposite can also be true. The gradient explodes from repeated multiplication
 - Put a maximum value for the gradient (Gradient clipping)

- How to deal with this?
 - Residual connection

<https://arxiv.org/pdf/1512.03385.pdf>

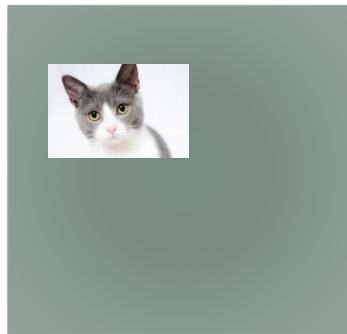
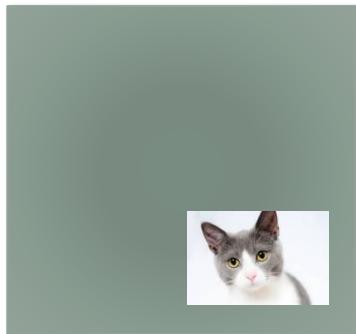


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Convolutional Neural Networks (CNNs)

- Consider an image of a cat. DNNs need different neurons to learn every possible location a cat can be

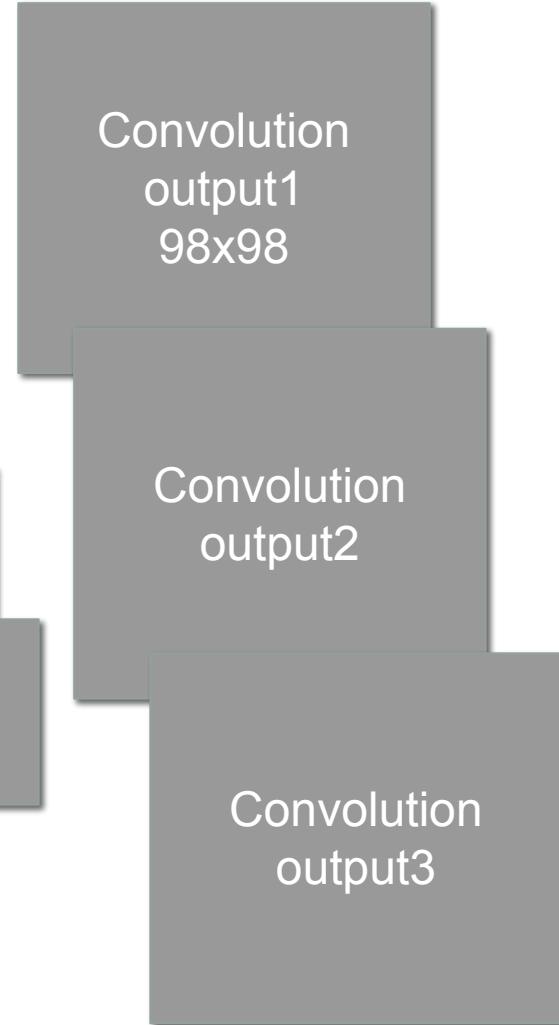
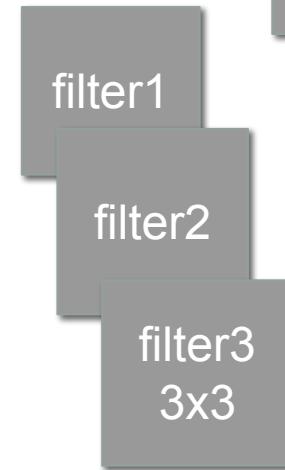
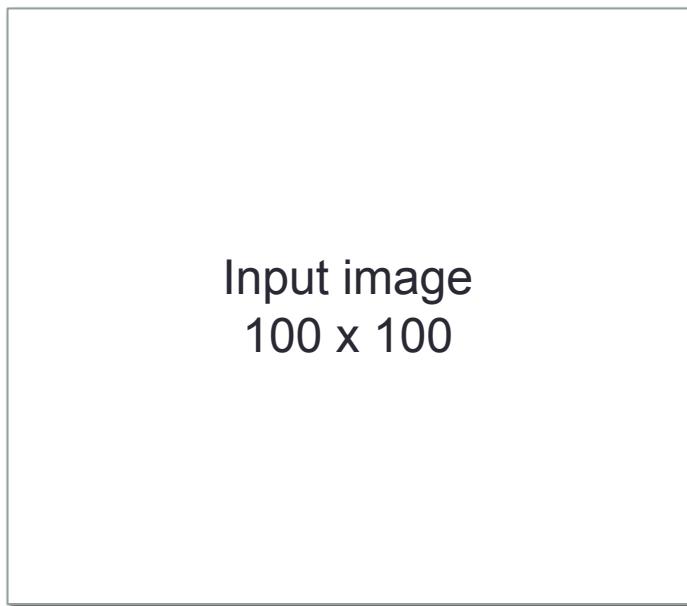


- Can we use the same parameters to learn that a cat exists regardless of location?
- 2 parts: convolutional layer and pooling layer

Convolutional filters

Multiply inputs with filter values

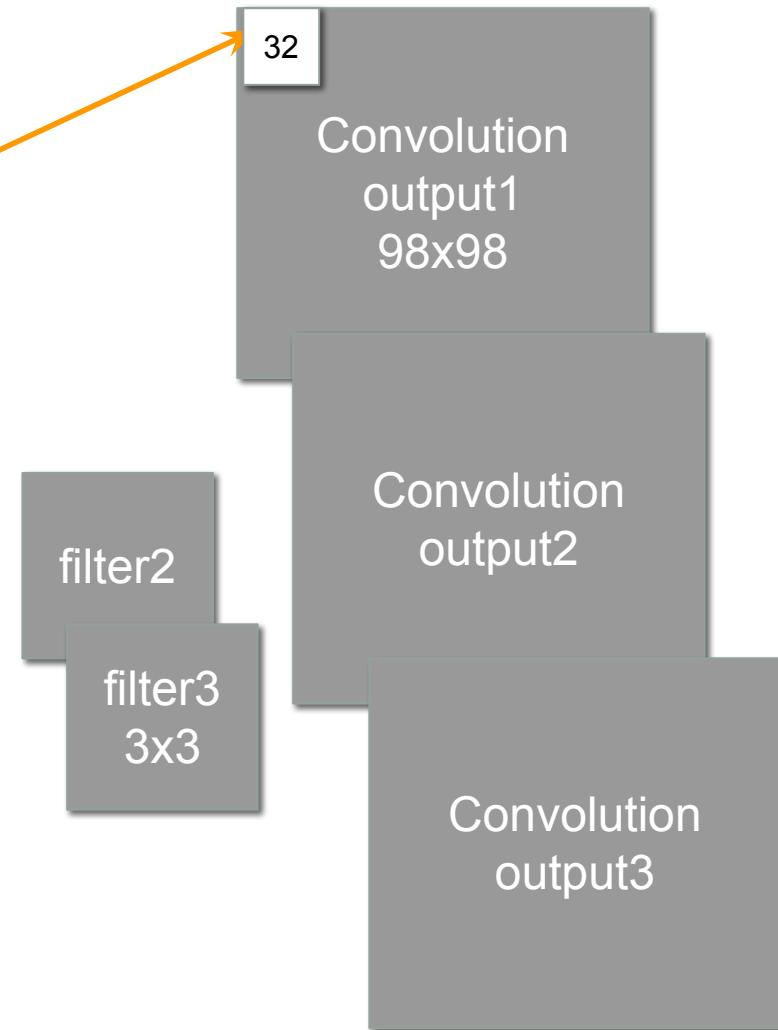
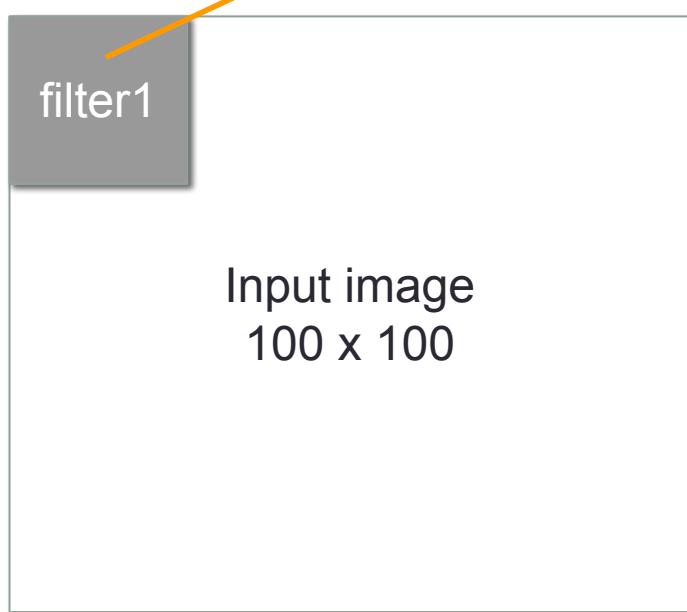
Output one feature map per filter



Convolutional filters

0	1	-1
1	0	1
1	2	0
1	2	3
4	5	6
7	8	9

$$1*2 + -1*3 + 1*4 + 1*6 + 1*7 + 2*8 = 32$$

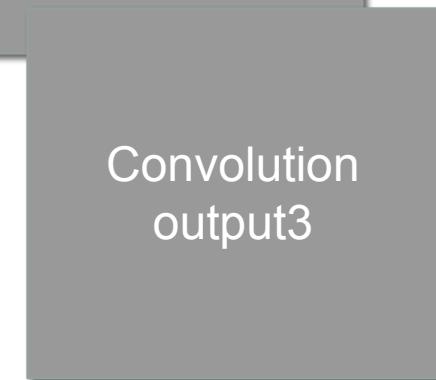
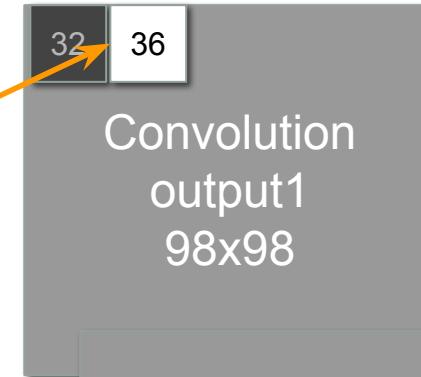
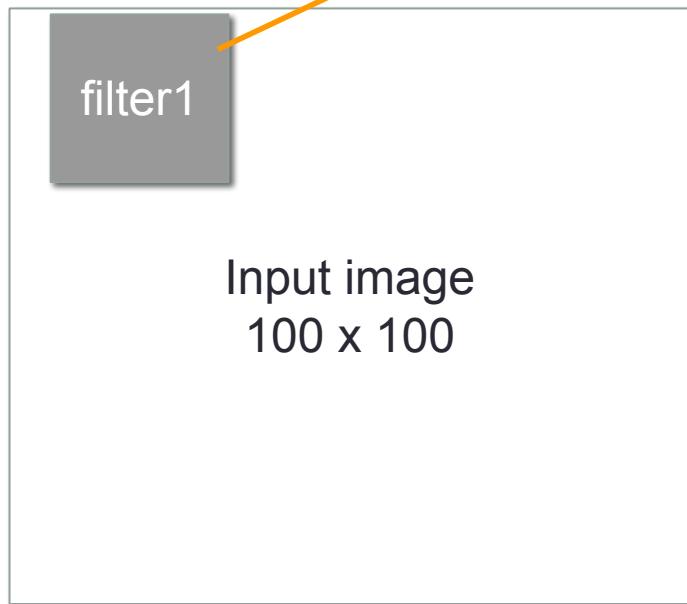


Convolutional filters

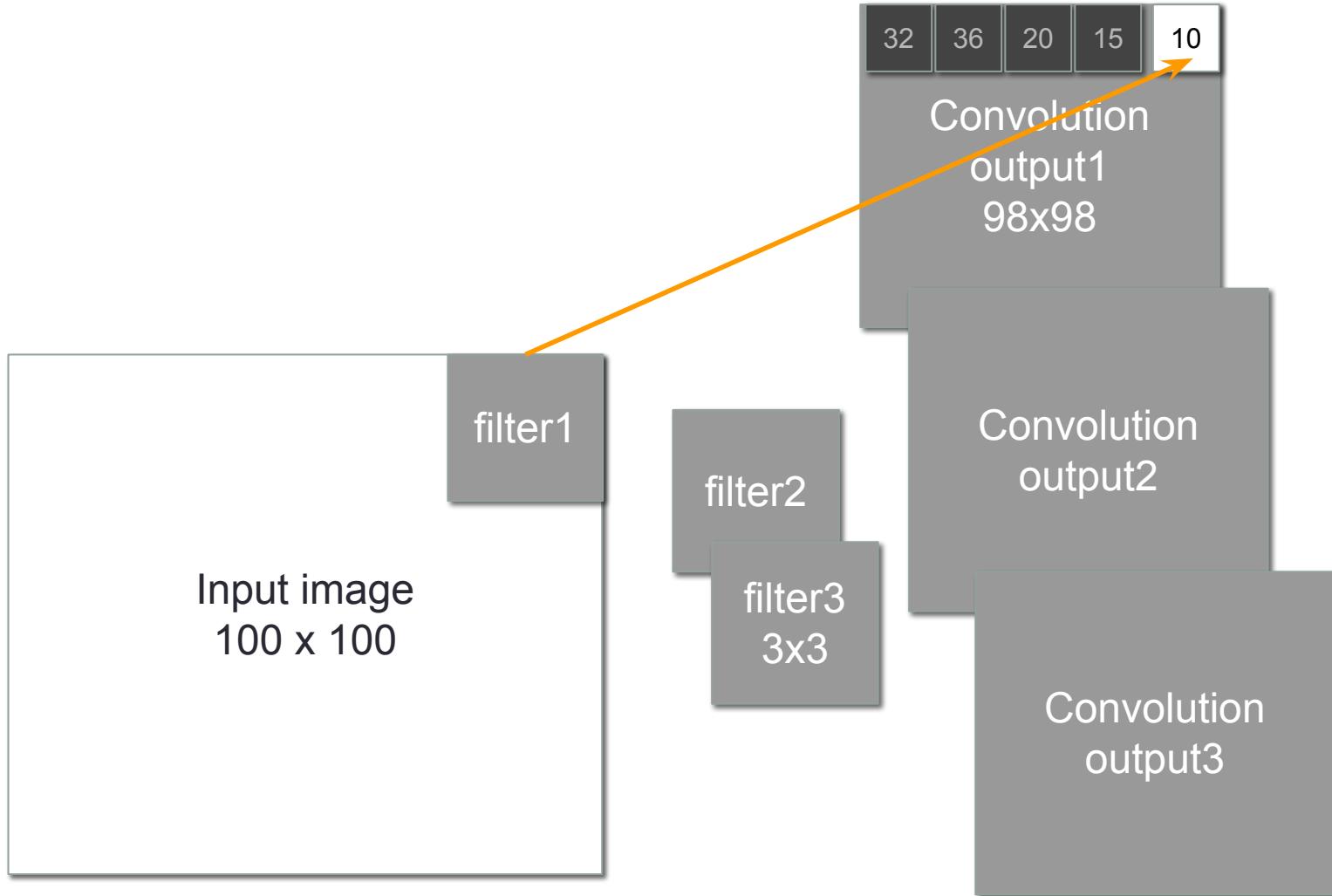
Stride of 1

0	1	-1
1	0	1
1	2	0
2	3	1
5	6	3
8	9	8

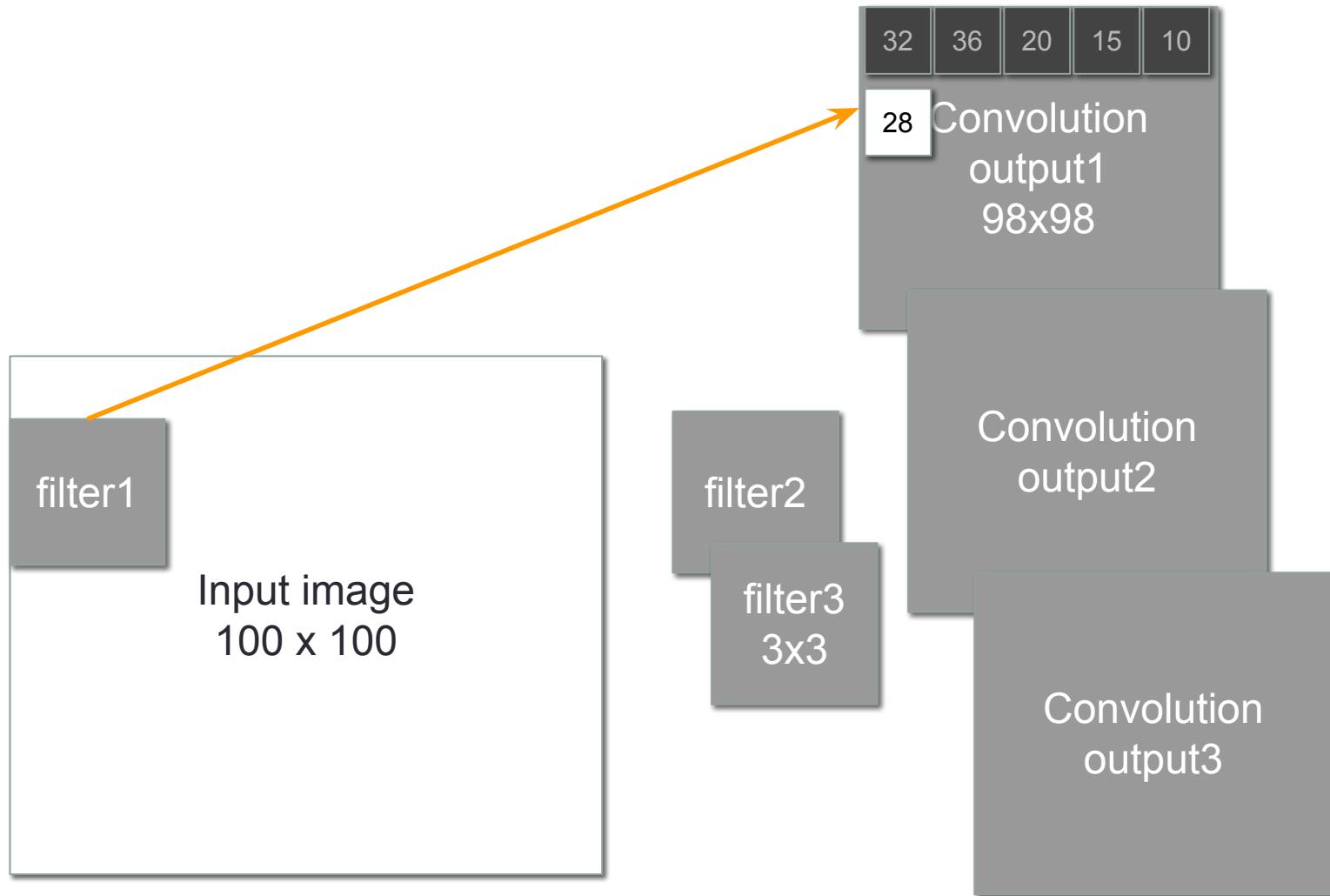
$$1*3 + -1*1 + 1*5 + 1*3 + 1*8 + 2*9 = 36$$



Convolutional filters

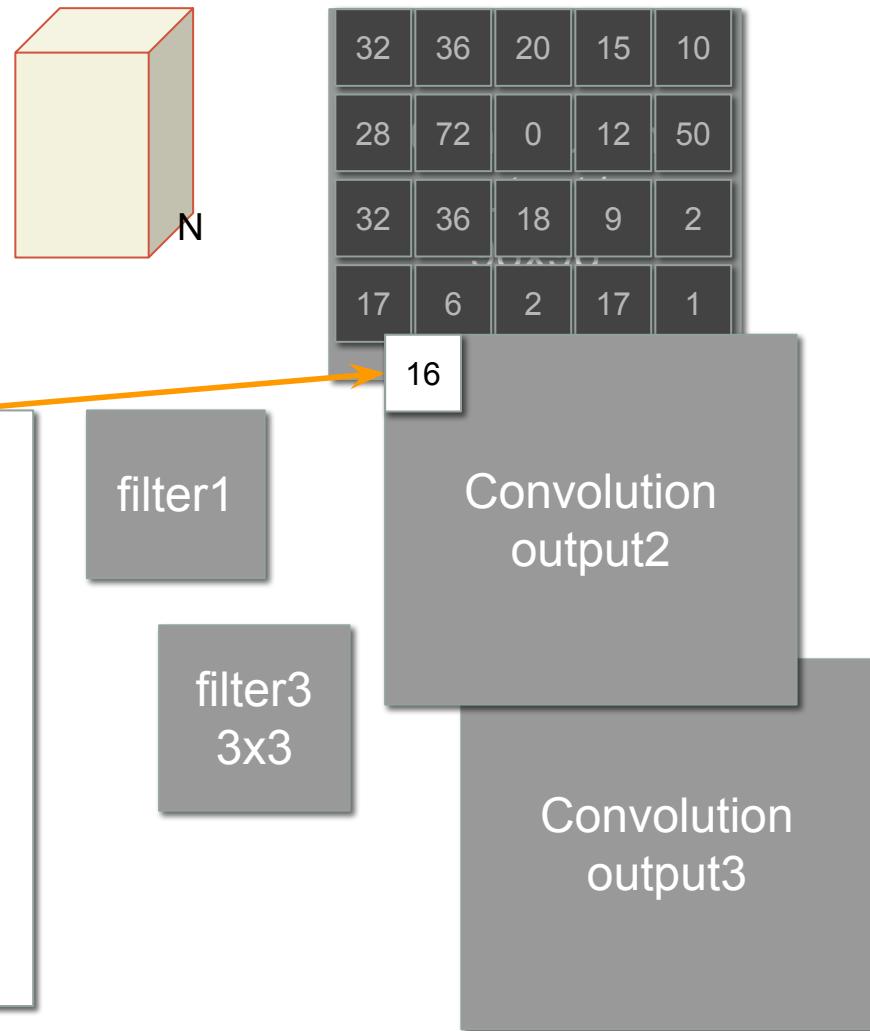


Convolutional filters



Convolutional filters

N filters means N feature maps
You get a 3 dimensional output

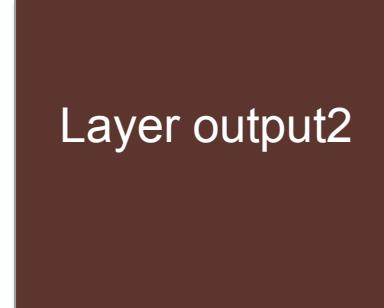


Pooling/subsampling

Reduce dimension of the feature maps



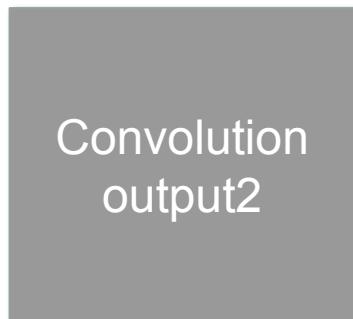
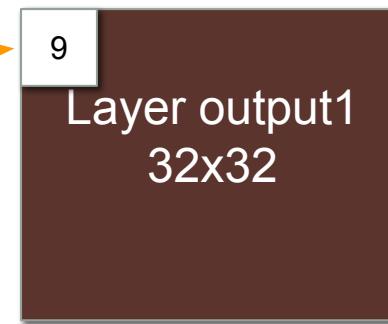
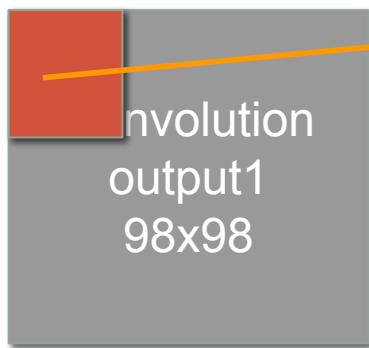
3x3 Max filter
with no overlap



Pooling/subsampling

1	2	3
4	5	6
7	8	9

Max = 9

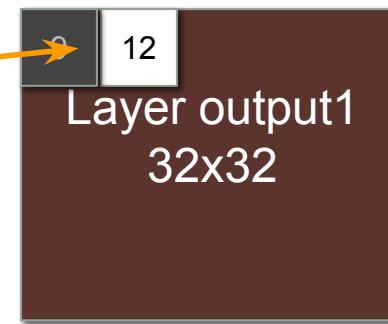
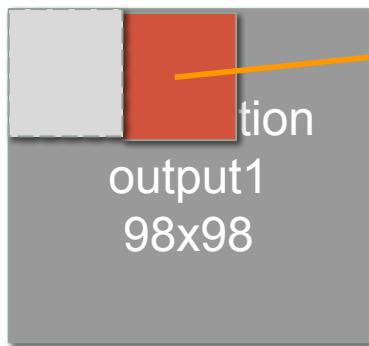


Pooling/subsampling

5	2	1
5	7	1
9	5	12

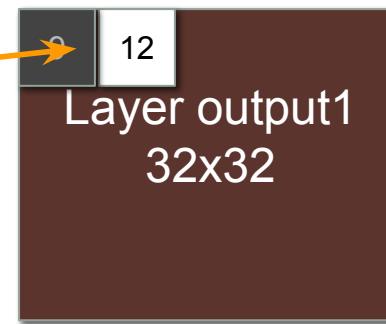
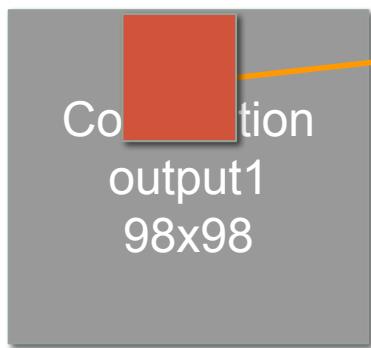
Max = 12

Stride = 3



Pooling/subsampling

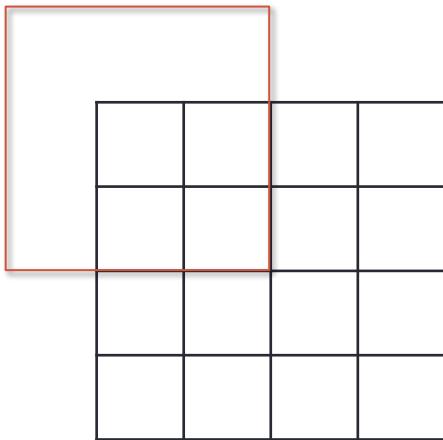
Can use other functions besides max
Example, average



Convolution puzzle

5 filters 3x3 filter pad, stride 1, pad 1

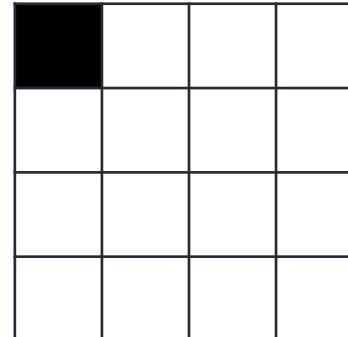
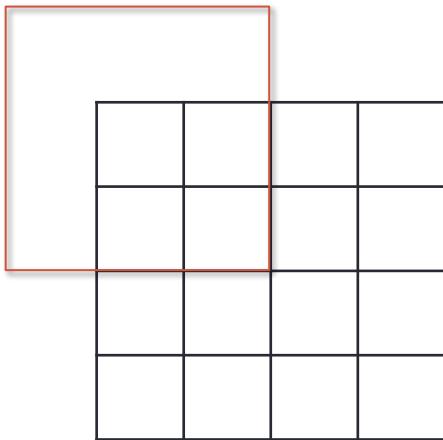
What is the output size?



Convolution puzzle

5 filters 3x3 filter pad, stride 1, pad 1

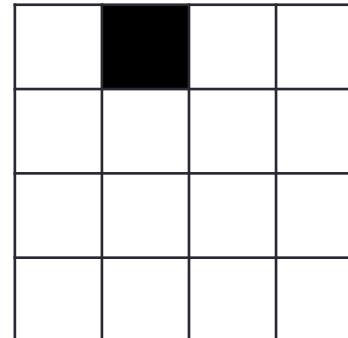
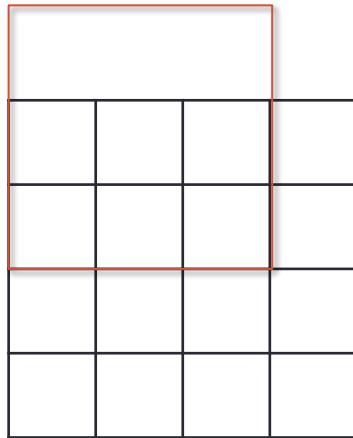
What is the output size?



Convolution puzzle

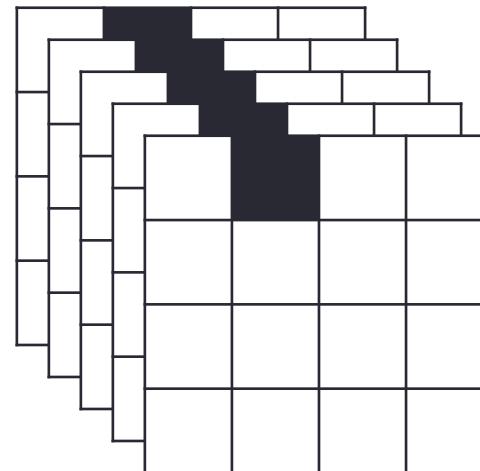
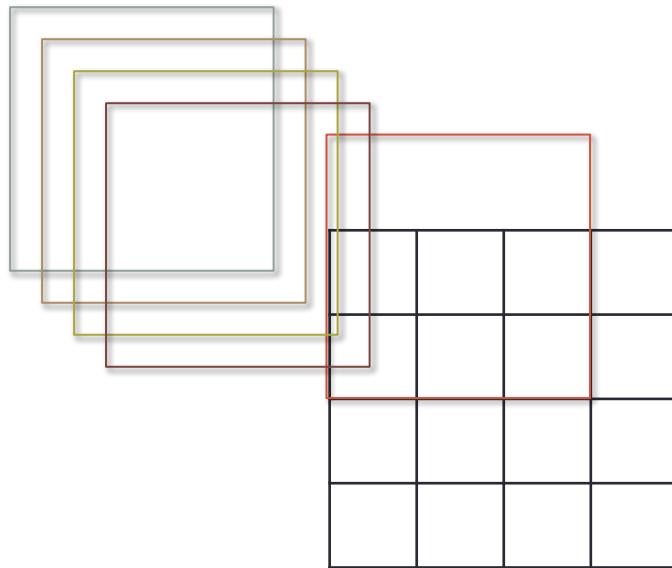
5 filters 3x3 filter pad, stride 1, pad 1

What is the output size?



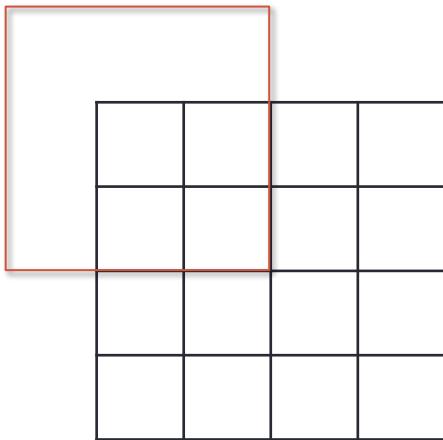
Convolution puzzle

5 filters 3x3 filter pad, stride 1, pad 1



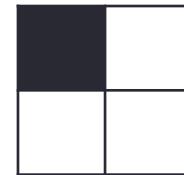
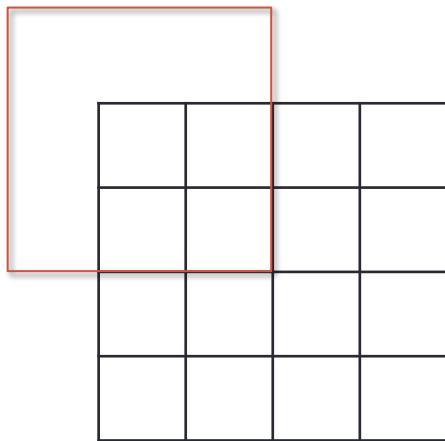
Convolution puzzle

3x3 filter pad, stride 2, pad 1



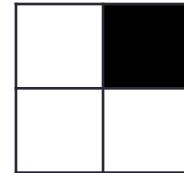
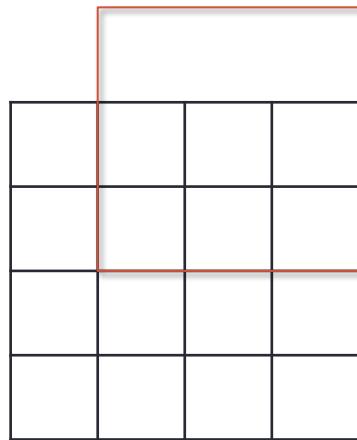
Convolution puzzle

3x3 filter pad, stride 2, pad 1



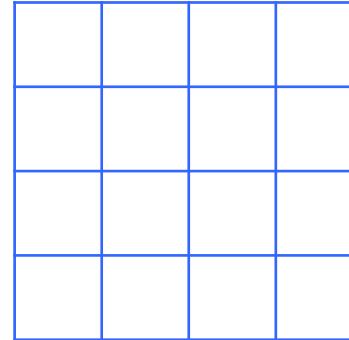
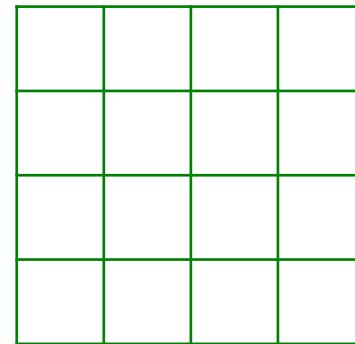
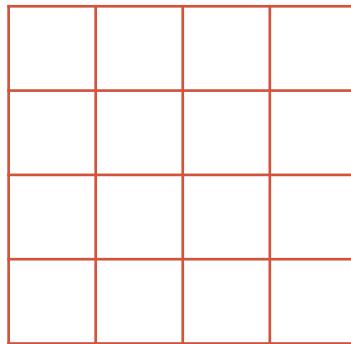
Convolution puzzle

3x3 filter pad, stride 2, pad 1



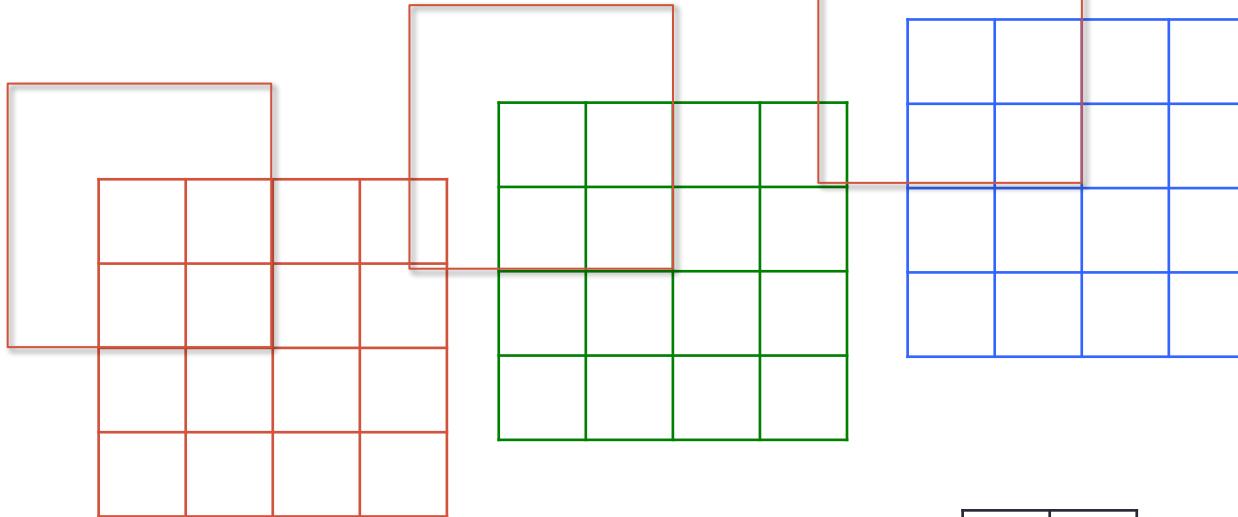
Convolution puzzle

RGB input (3 channels) 5 filters 3x3 filter pad, stride 2, pad 1

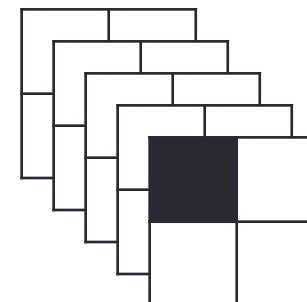


Convolution puzzle

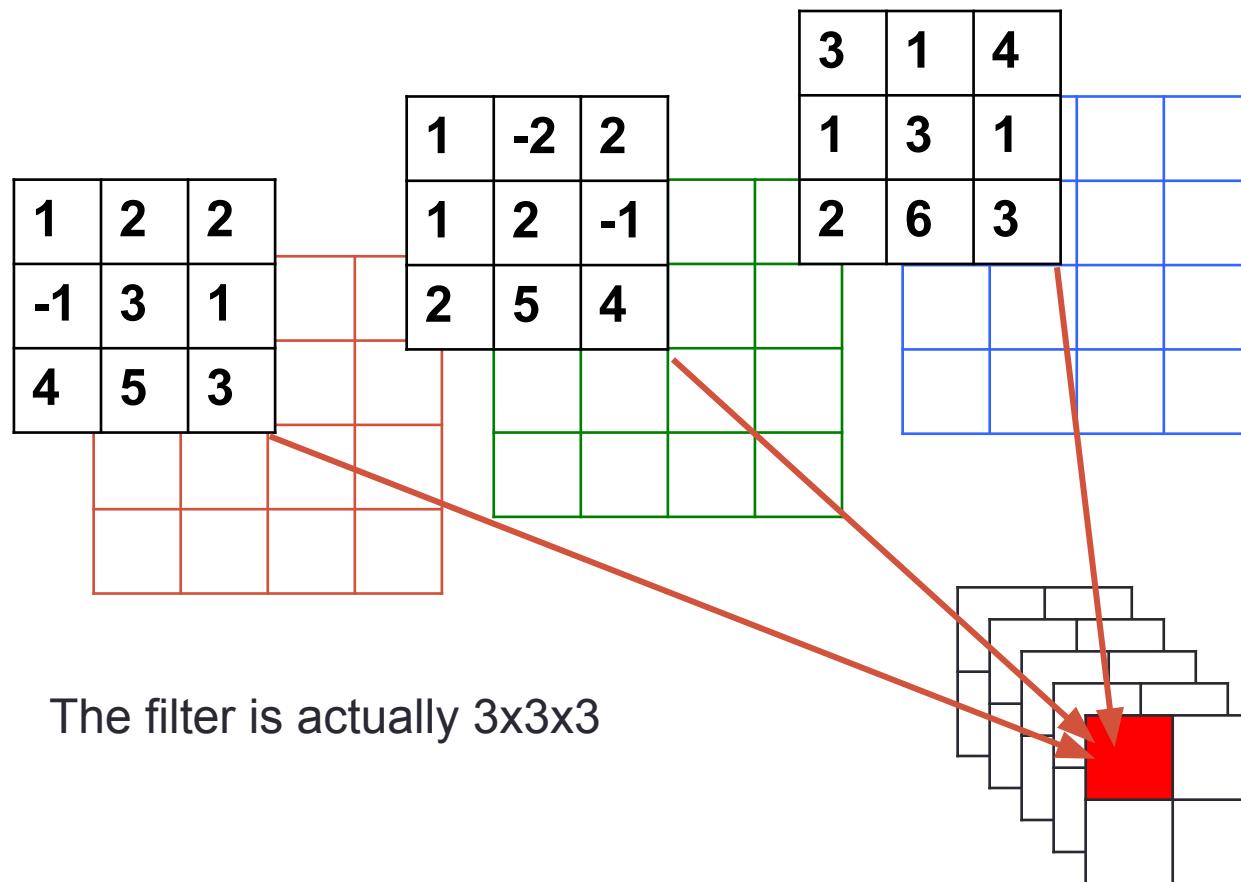
RGB input (3 channels) 5 filters 3x3 filter pad, stride 2, pad 1



The filter is actually 3x3x3

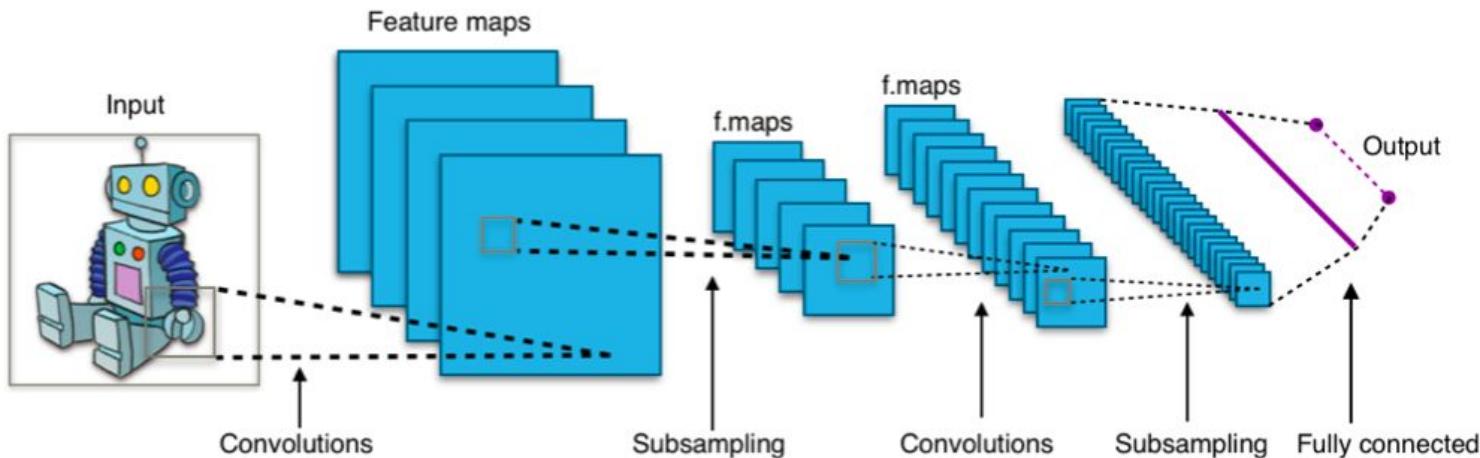


Convolution puzzle



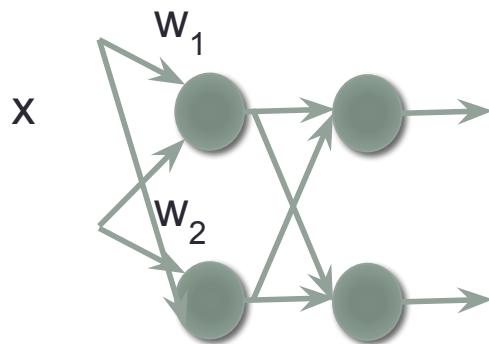
CNN overview

- Filter size, number of filters, filter shifts, and pooling rate are all parameters
- Usually followed by a fully connected network at the end
 - CNN is good at learning low level features
 - DNN combines the features into high level features and classify

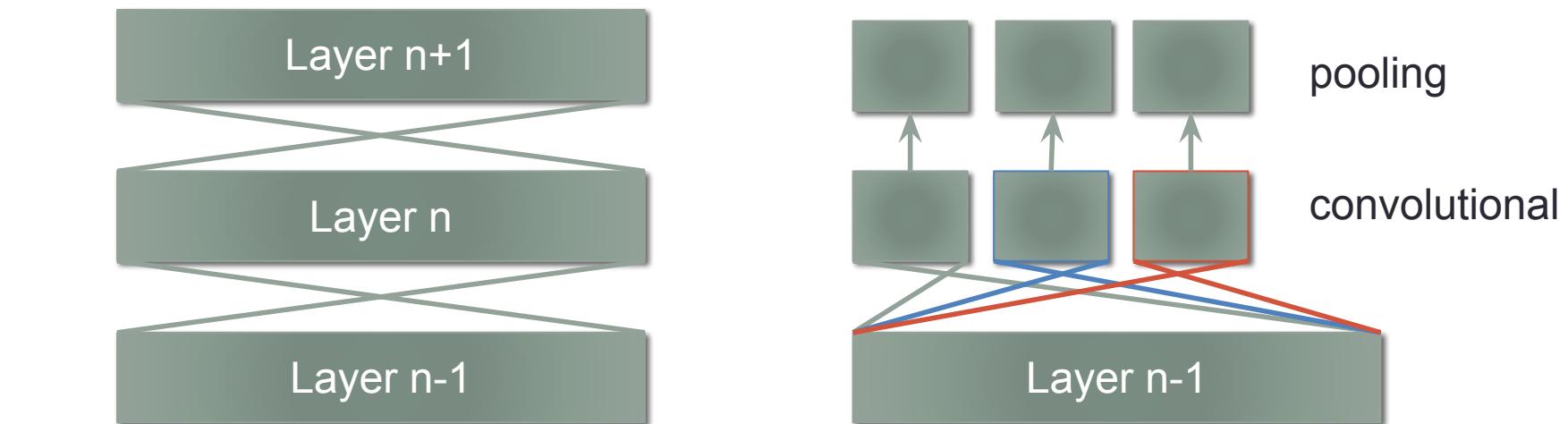


Parameter sharing in convolution neural networks

- $W^T x$

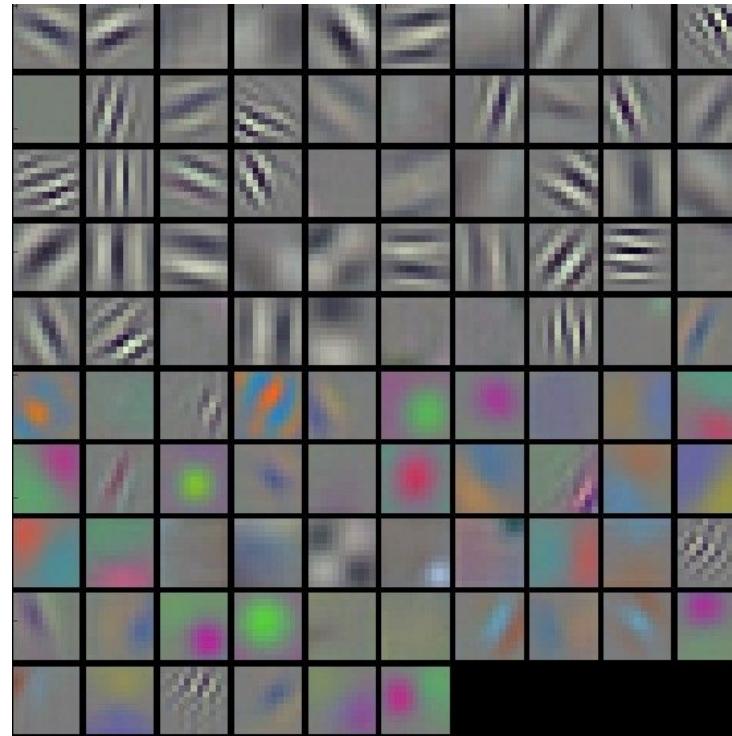


- Cats at different location might need two neurons for different locations in fully connect NNs.
- CNN shares the parameters in 1 filter
- The network is no longer fully connected



Visualizing convolutional layers

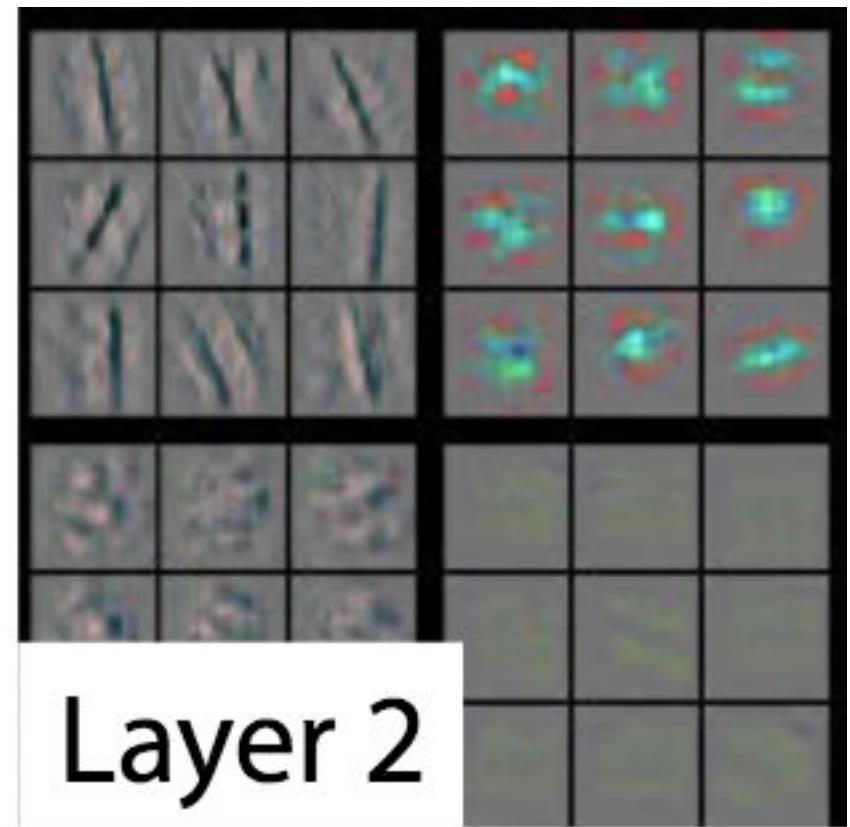
- We can visualize the weights of the filter
- “Matched filters”

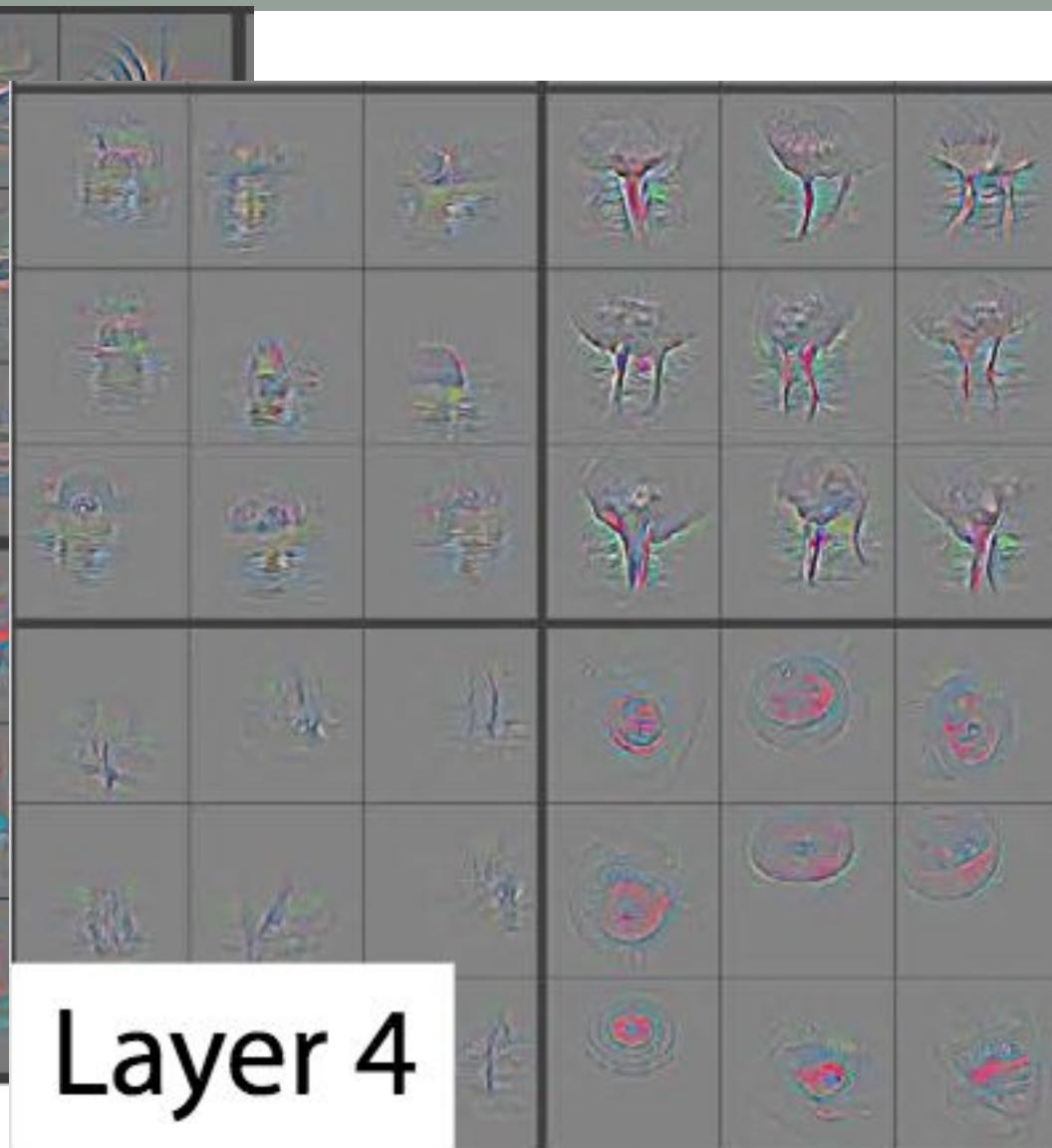


Higher layer captures higher-level concepts



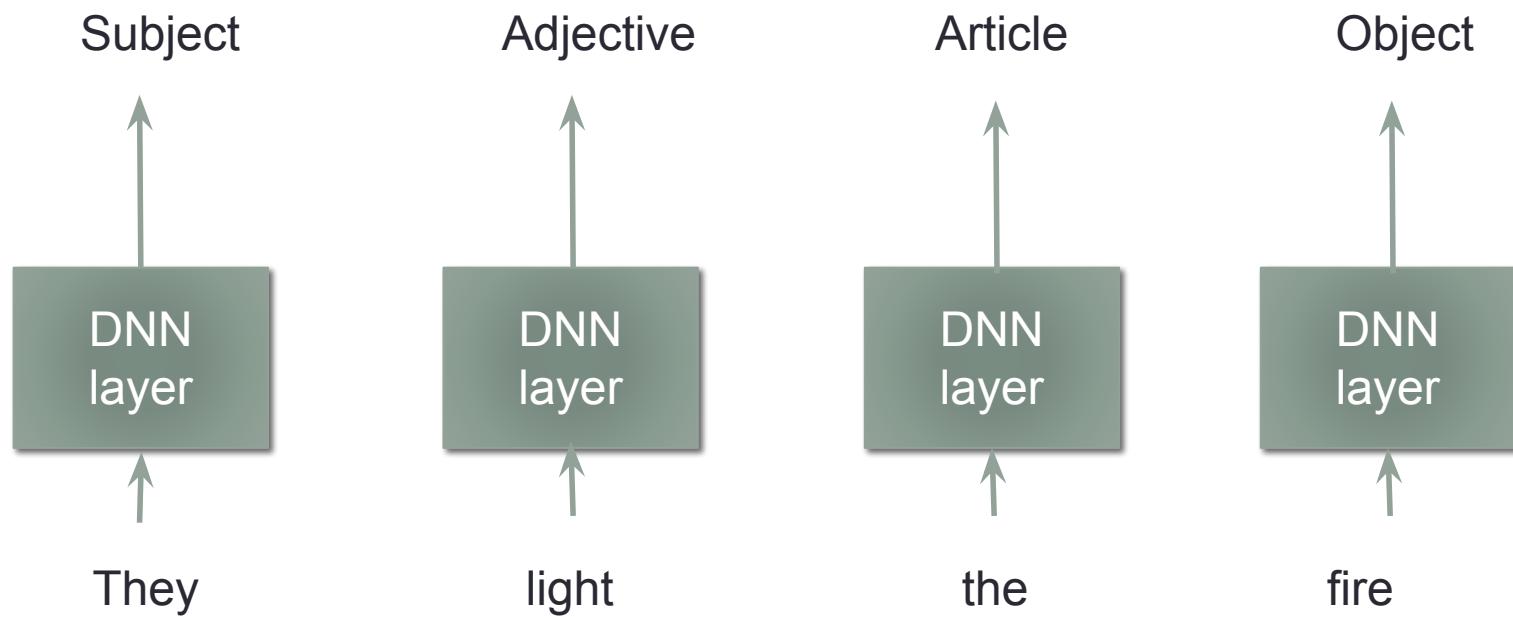
Layer 1





Recurrent neural network (RNN)

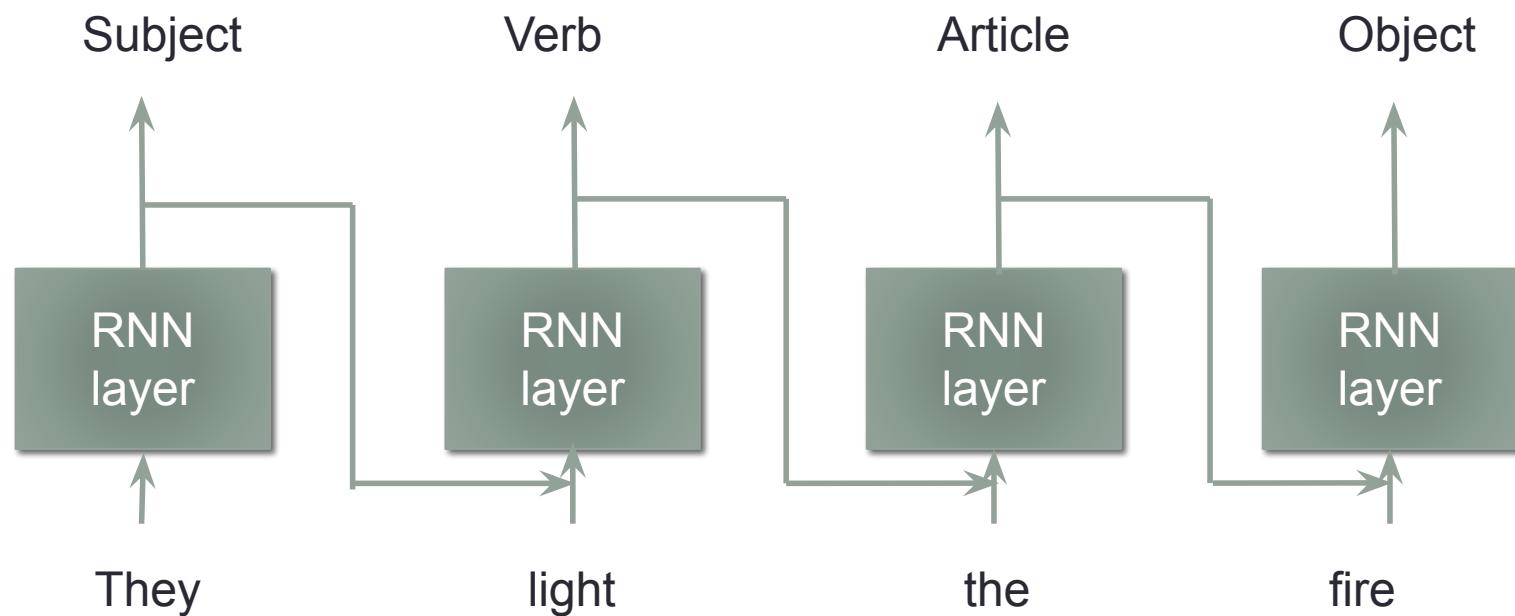
- DNN framework



Problem1: need a way to remember the past

Recurrent neural network (RNN)

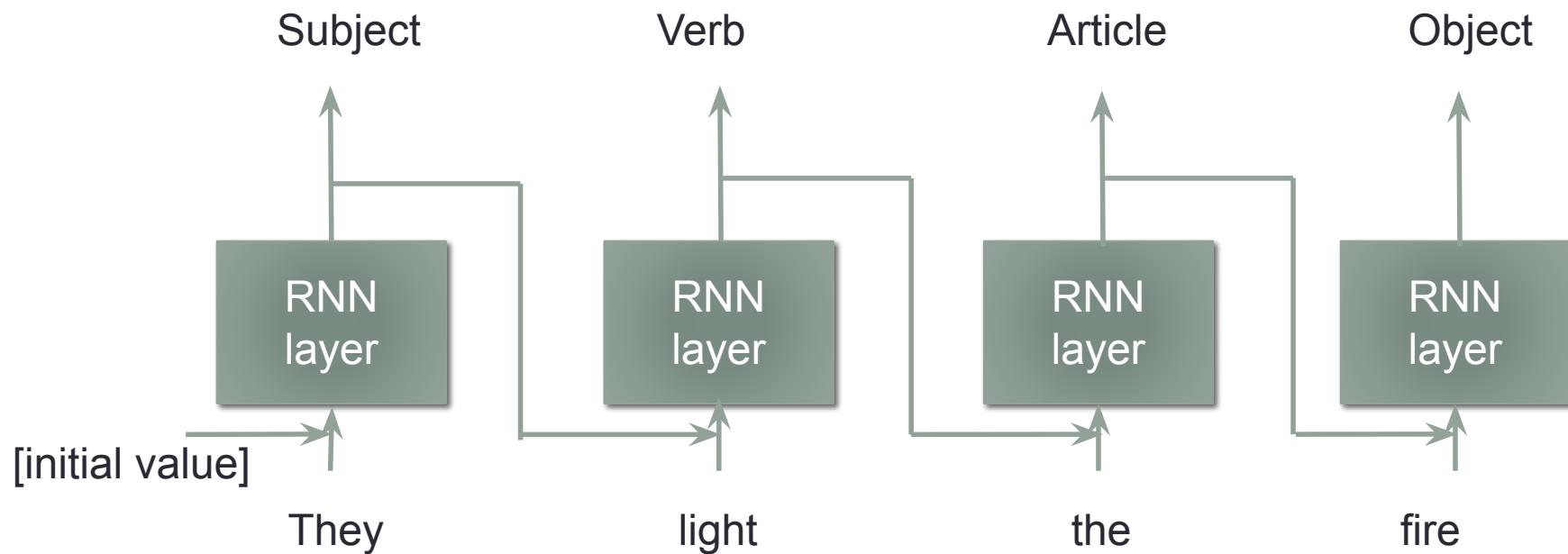
- RNN framework



Output of the layer encodes something meaningful about the past

Recurrent neural network (RNN)

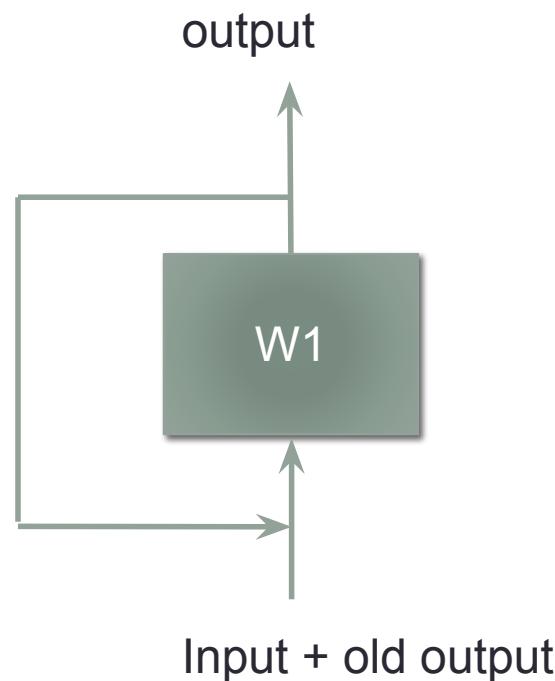
- RNN framework



New input feature = [original input feature, output of the layer at previous time step]

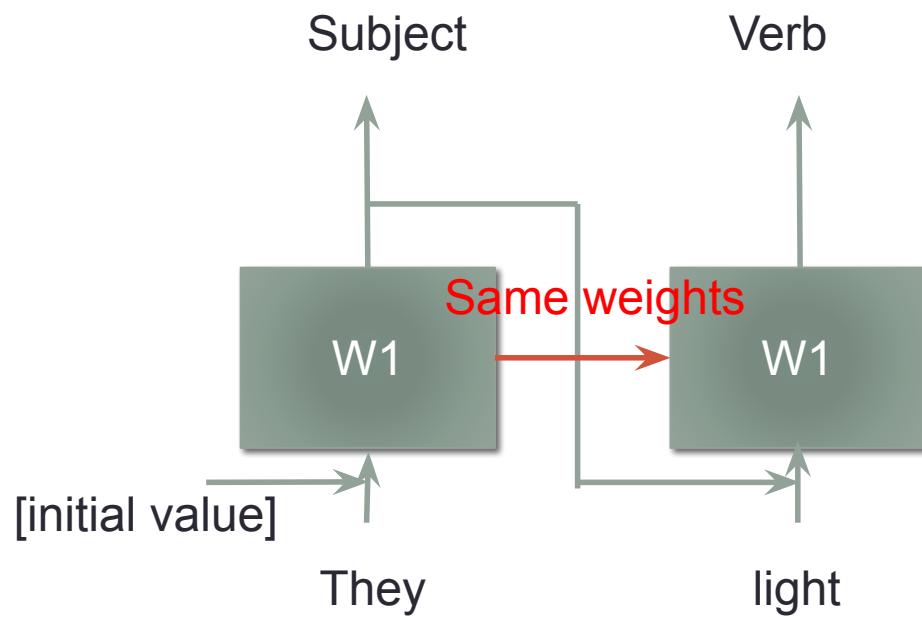
Recurrent neural network (RNN)

- Unrolling of a recurrent layer.



Recurrent neural network (RNN)

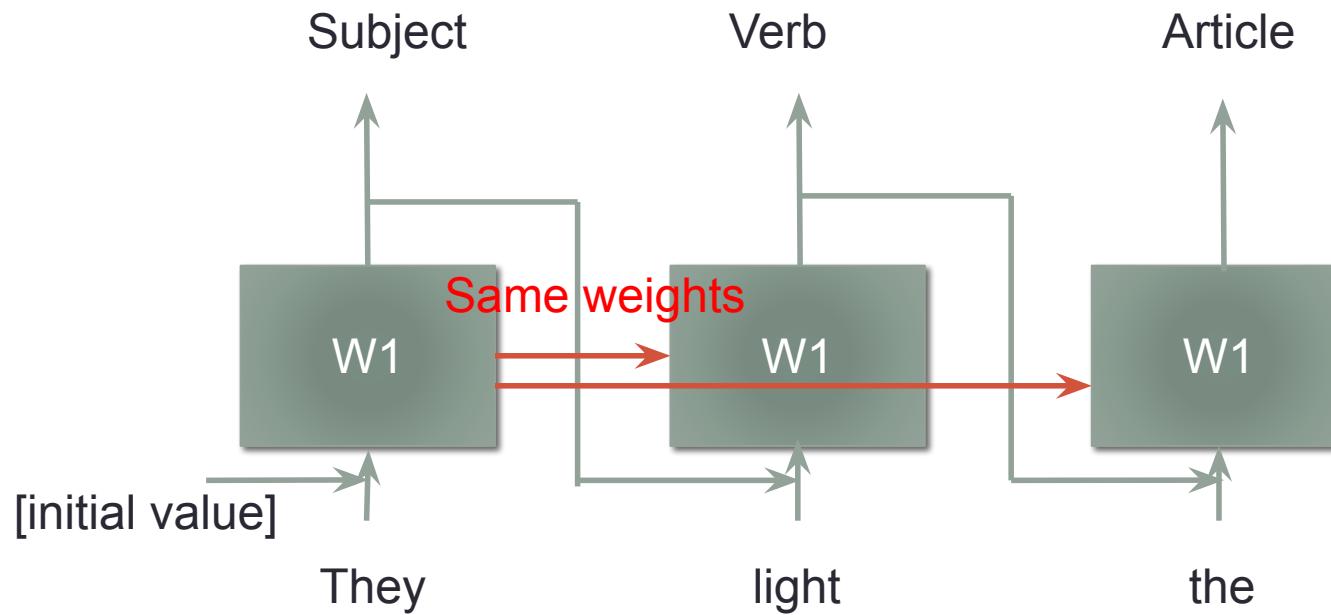
- Unrolling of a recurrent layer.



Parameter sharing

Recurrent neural network (RNN)

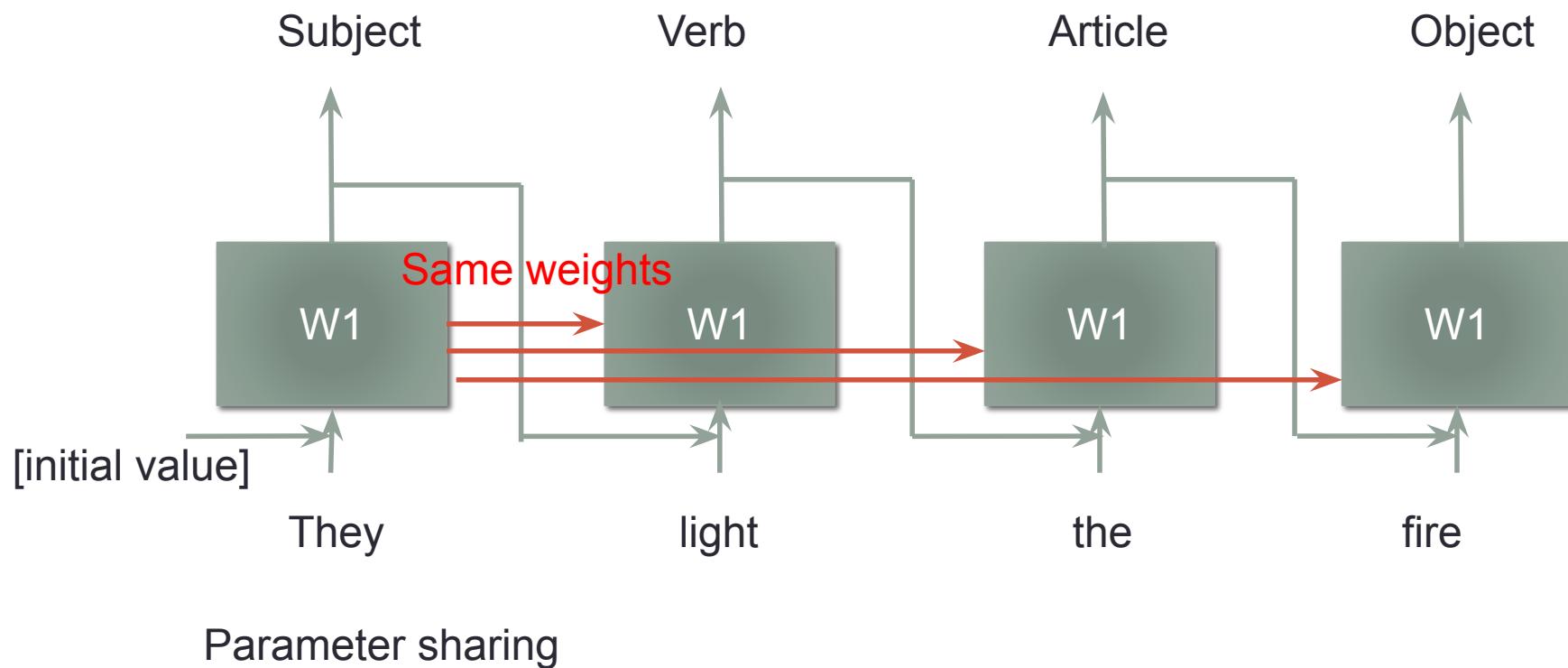
- Unrolling of a recurrent layer.



Parameter sharing

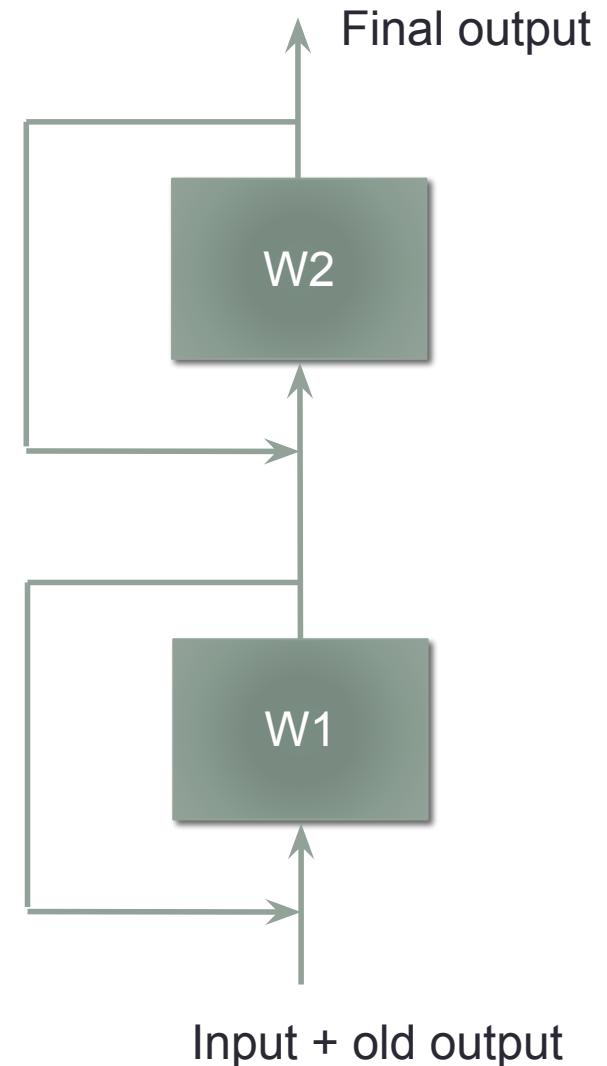
Recurrent neural network (RNN)

- Unrolling of a recurrent layer.



Recurrent neural network (RNN)

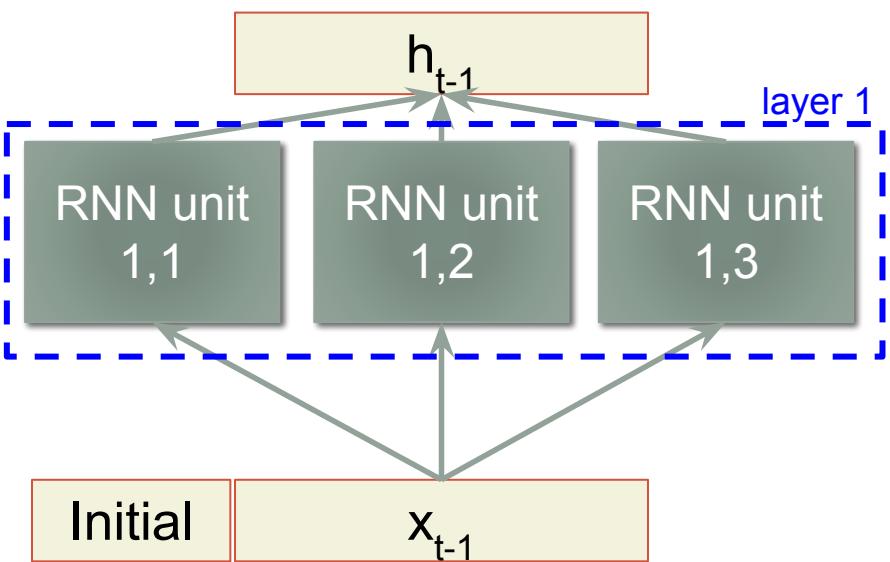
- Stacks of recurrent layer



RNN layers (expanded in time)

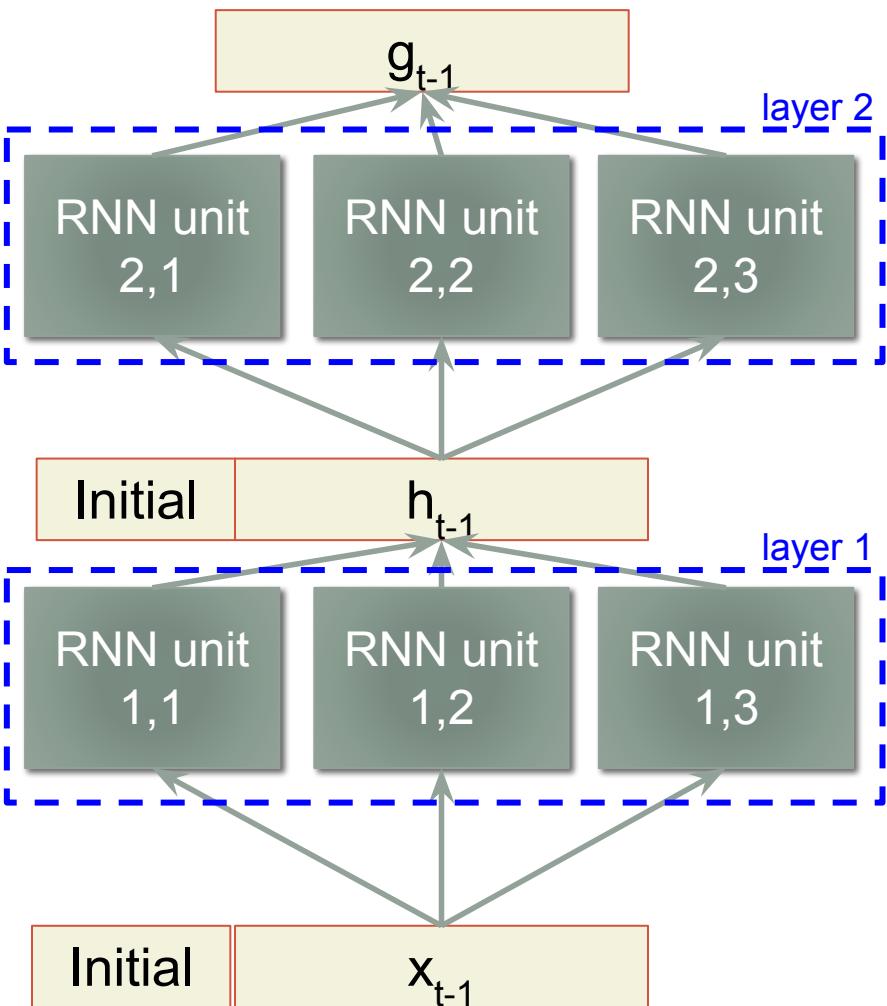
Time step 1

Time step 2



RNN layers (expanded in time)

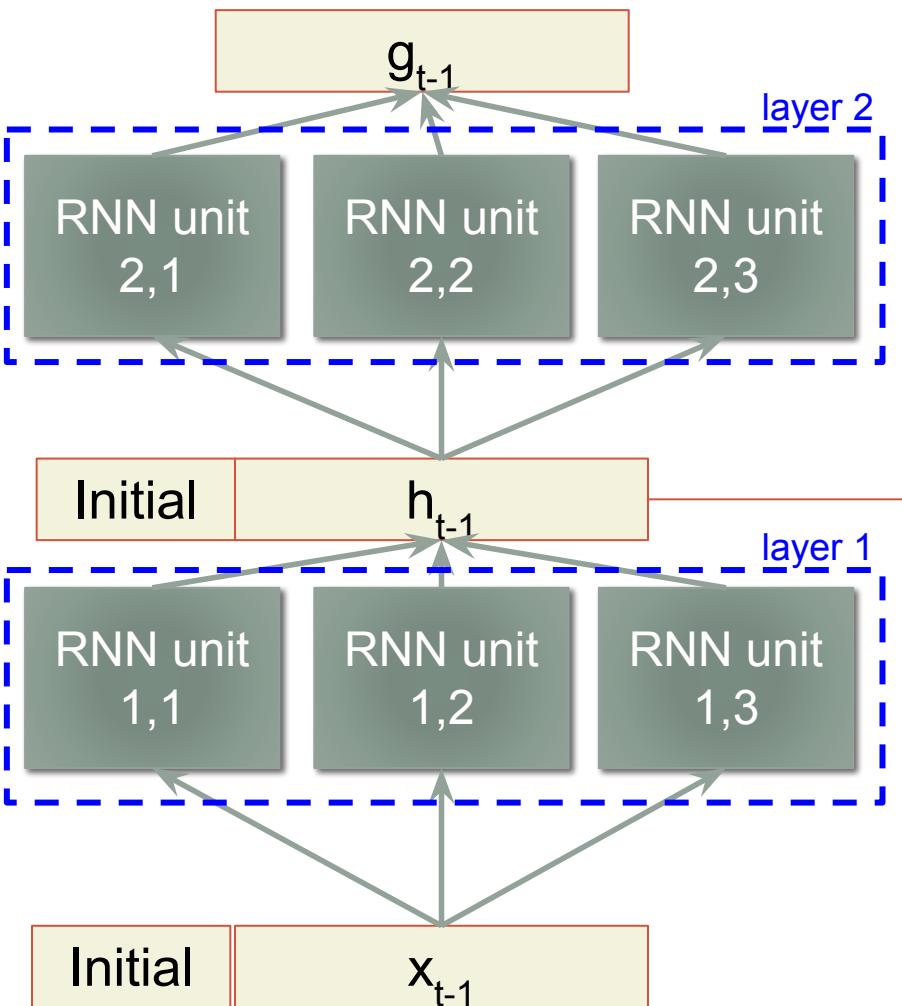
Time step 1



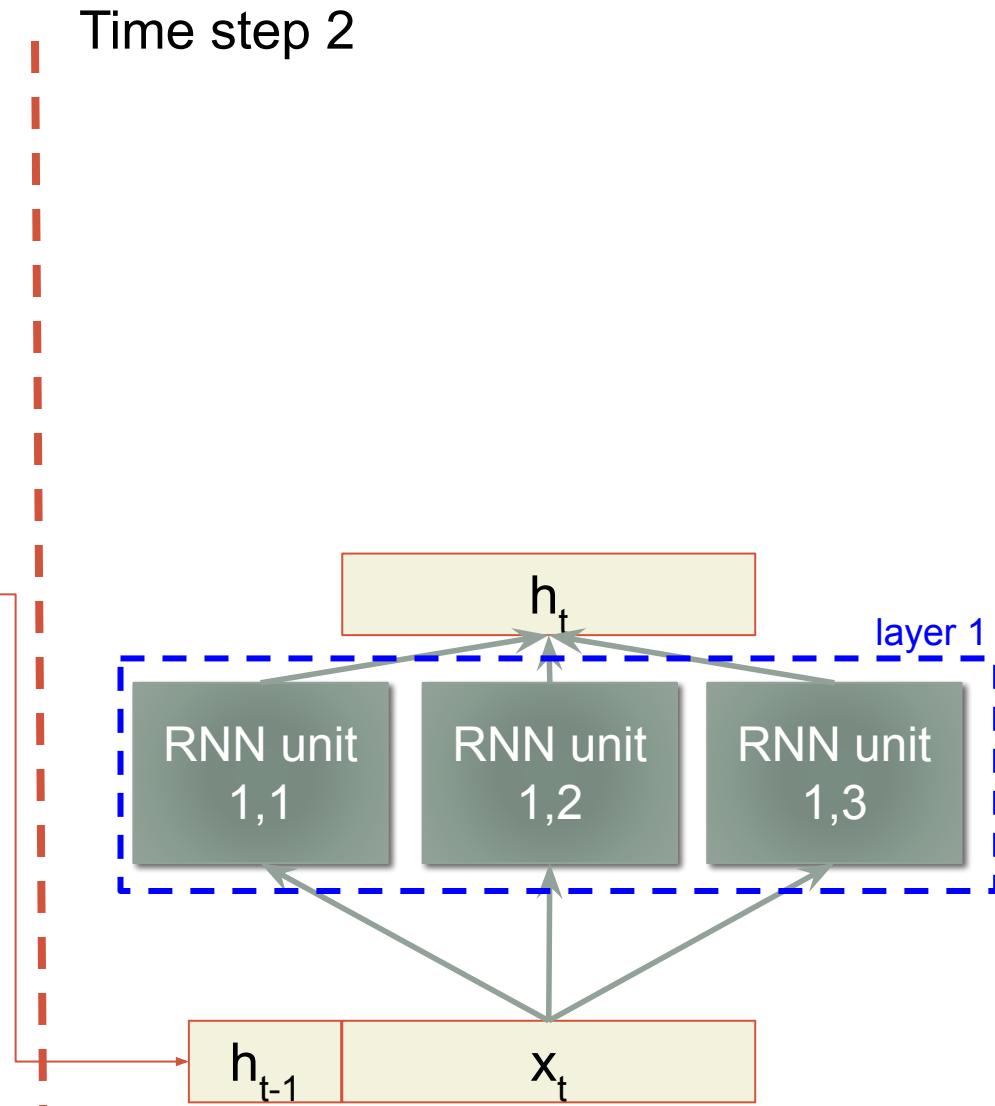
Time step 2

RNN layers (expanded in time)

Time step 1

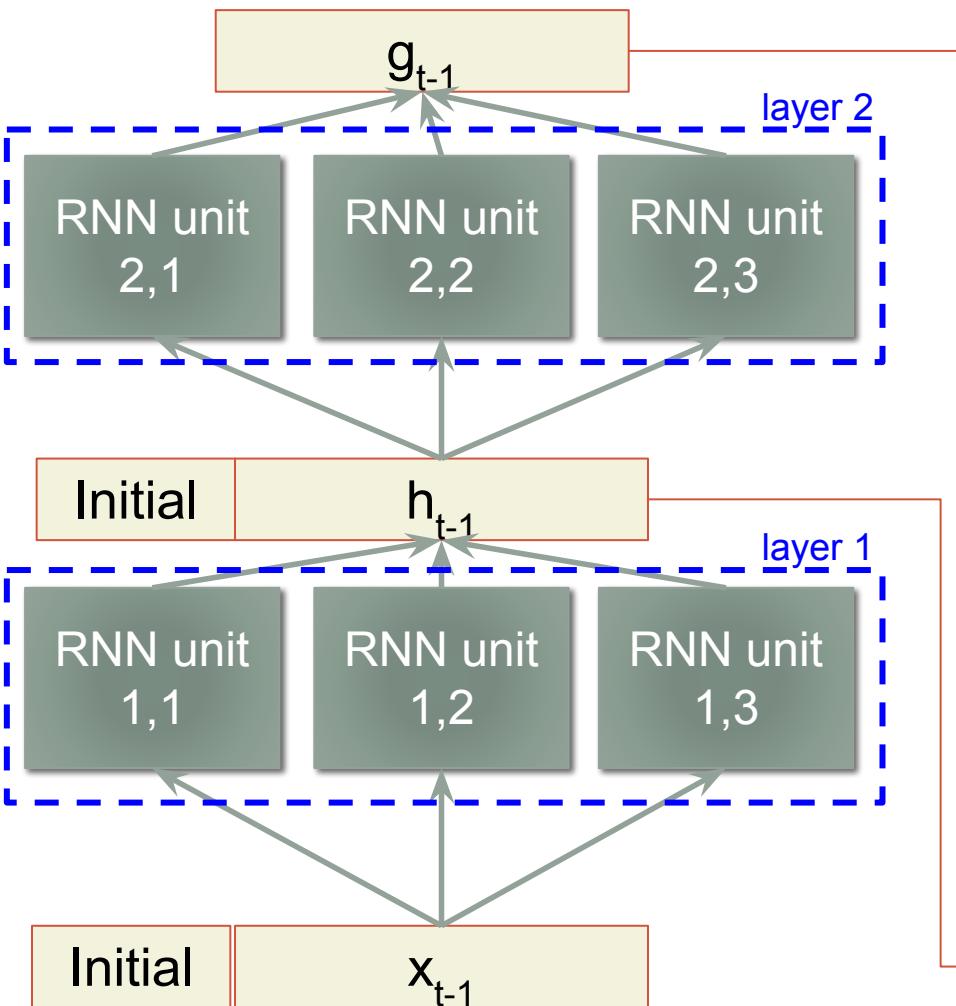


Time step 2

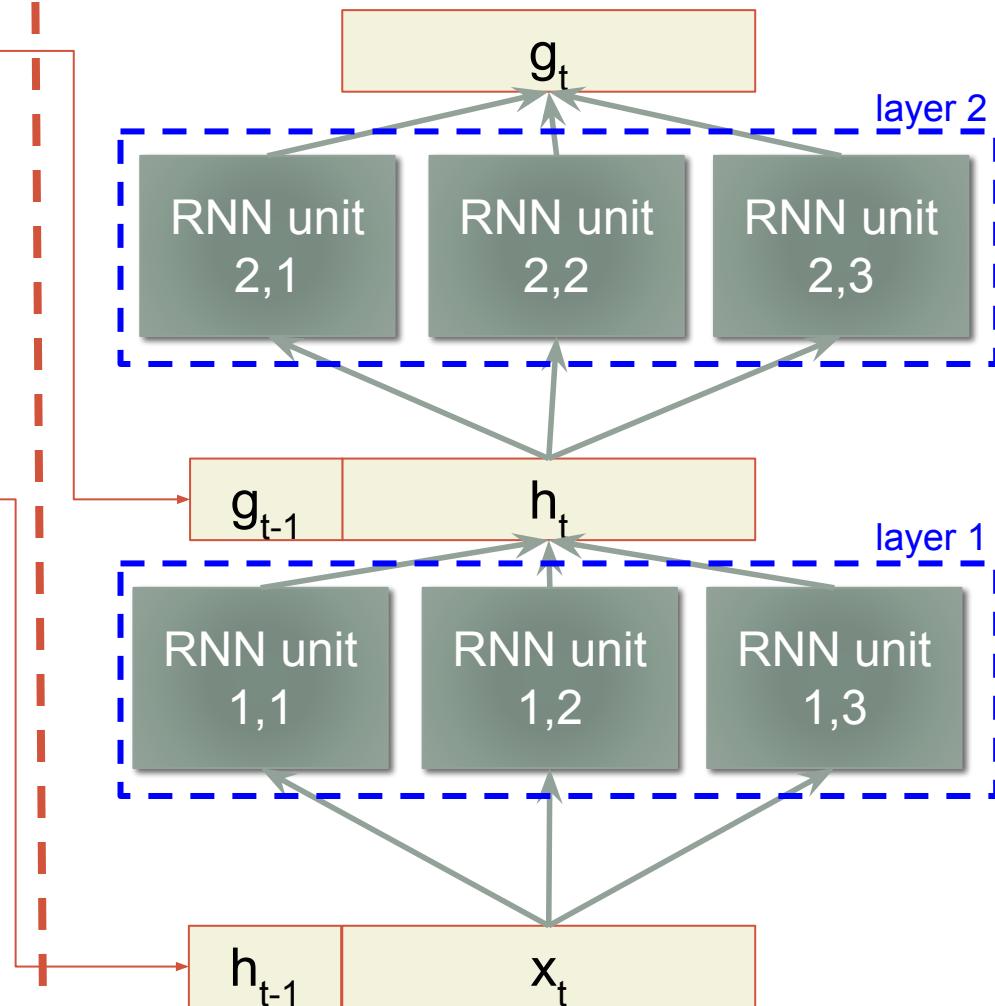


RNN layers (expanded in time)

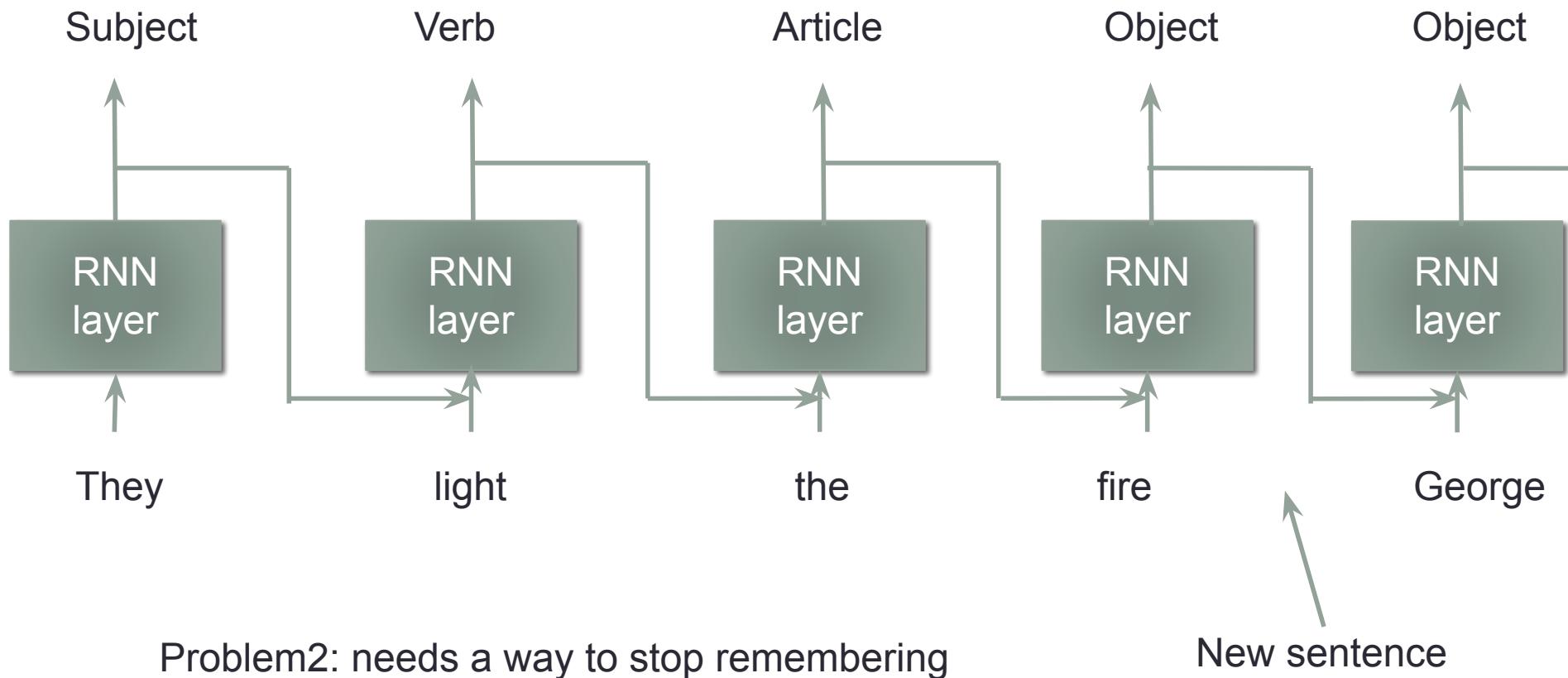
Time step 1



Time step 2



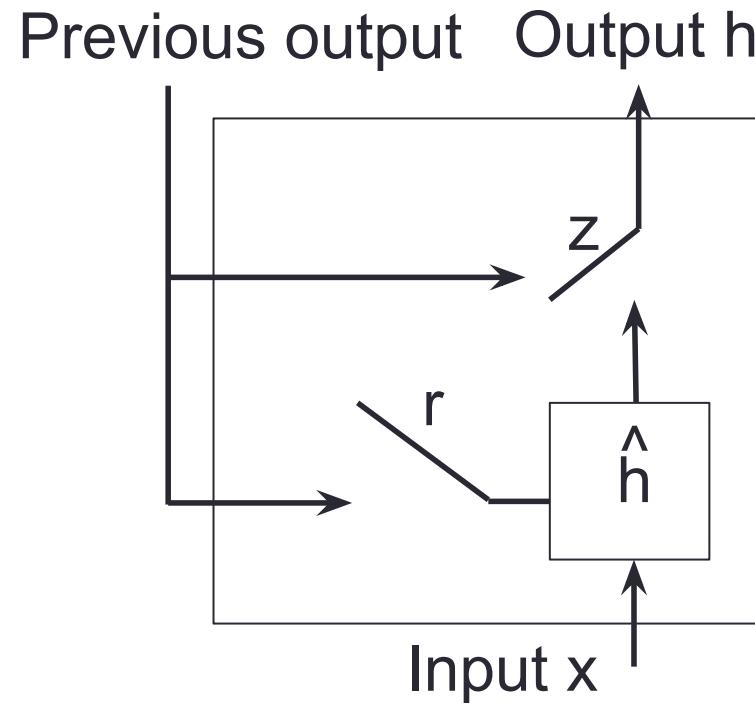
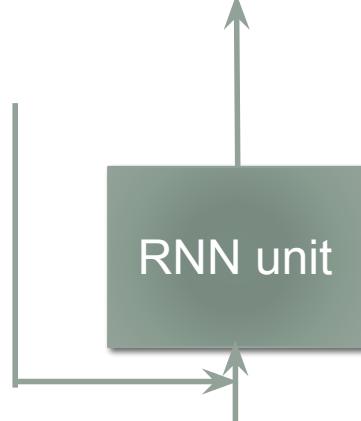
Recurrent neural network (RNN)



Can the network learn when to start and stop remembering things?

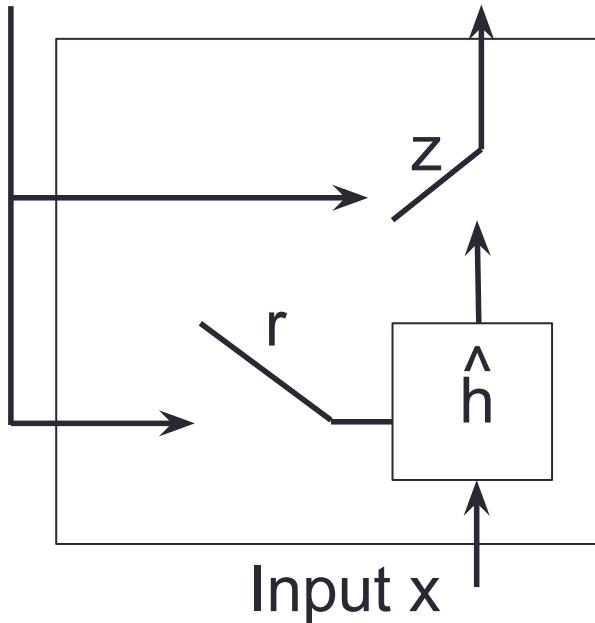
Gated Recurrent Unit (GRU)

- Forms a Gated Recurrent Neural Networks (GRNN)
- Add gates that can choose to reset (r) or update (z)



Gated Recurrent Unit (GRU)

Previous output Output h

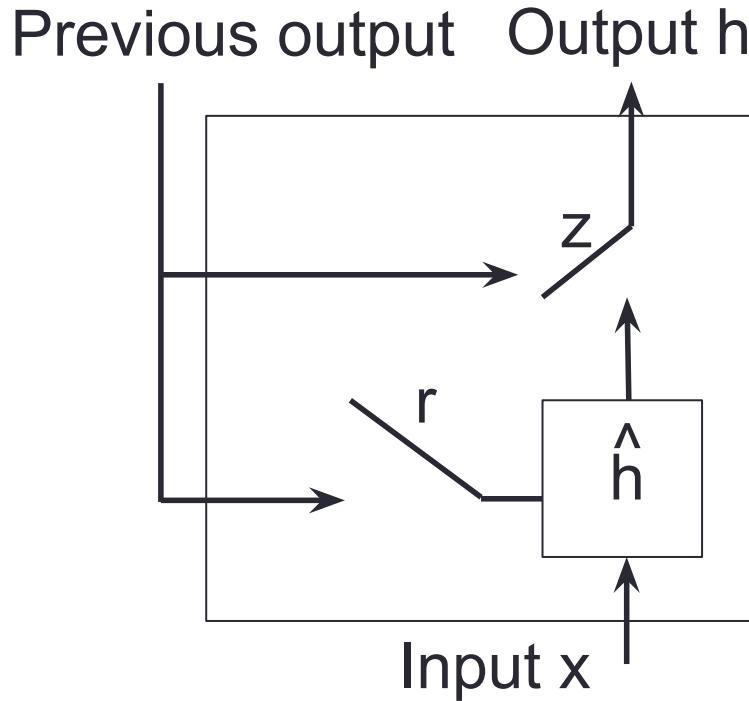


Neuron index

$$h_t^j = (1 - z_t^j)h_{t-1}^j + z_t^j \hat{h}_t^j$$

time index

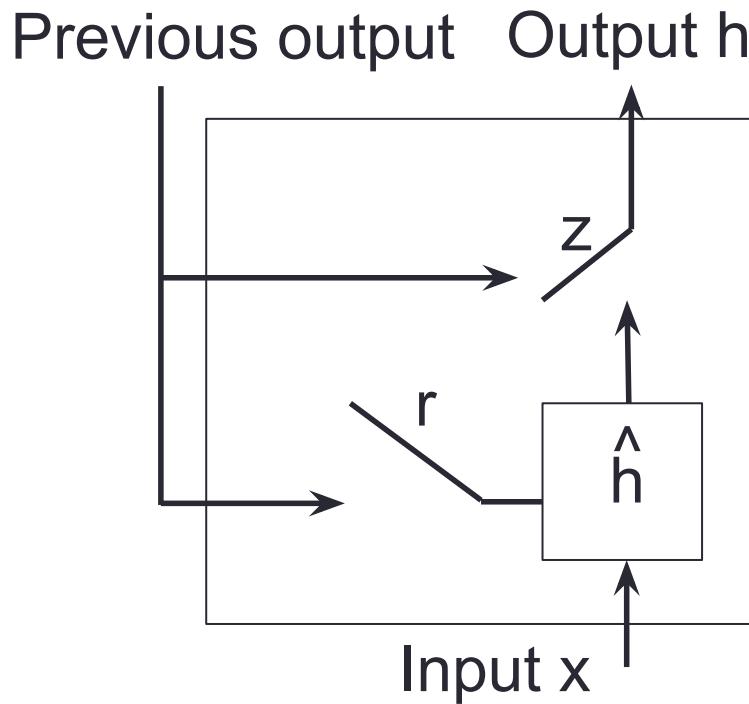
Gated Recurrent Unit (GRU)



$$h_t^j = (1 - z_t^j)h_{t-1}^j + z_t^j \hat{h}_t^j$$

One GRU neuron output (scalar)

Gated Recurrent Unit (GRU)



$$h_t^j = (1 - z_t^j)h_{t-1}^j + z_t^j \hat{h}_t^j$$

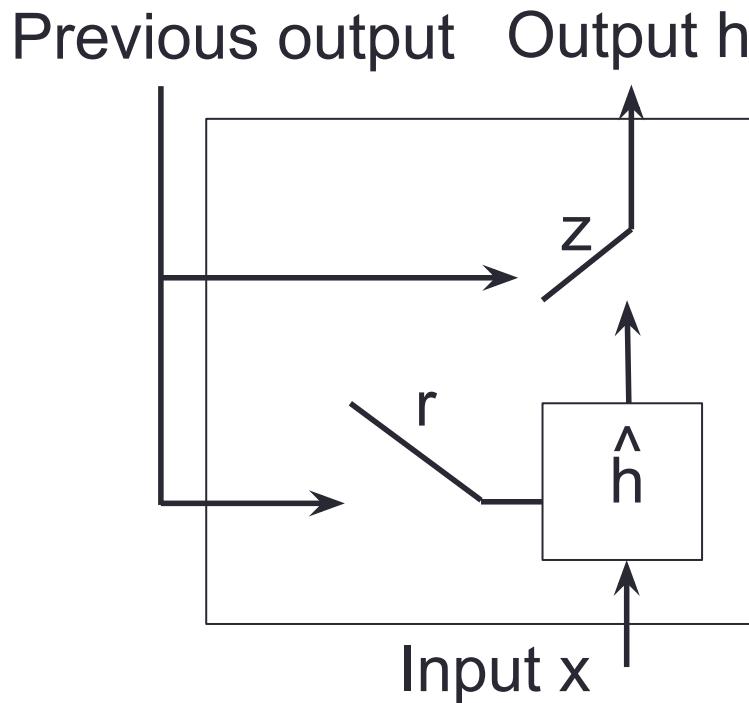
$$\hat{h}_t^j = \tanh^j (W \boxed{\mathbf{x}_t} + U (\boxed{\mathbf{r}_t} \odot \underline{\mathbf{h}_{t-1}}))$$

Linear transform with matrix multiply

Vector (each value from each GRU unit in the previous layer)

$$\mathbf{x}_t^j = \mathbf{h}_t^j$$

Gated Recurrent Unit (GRU)



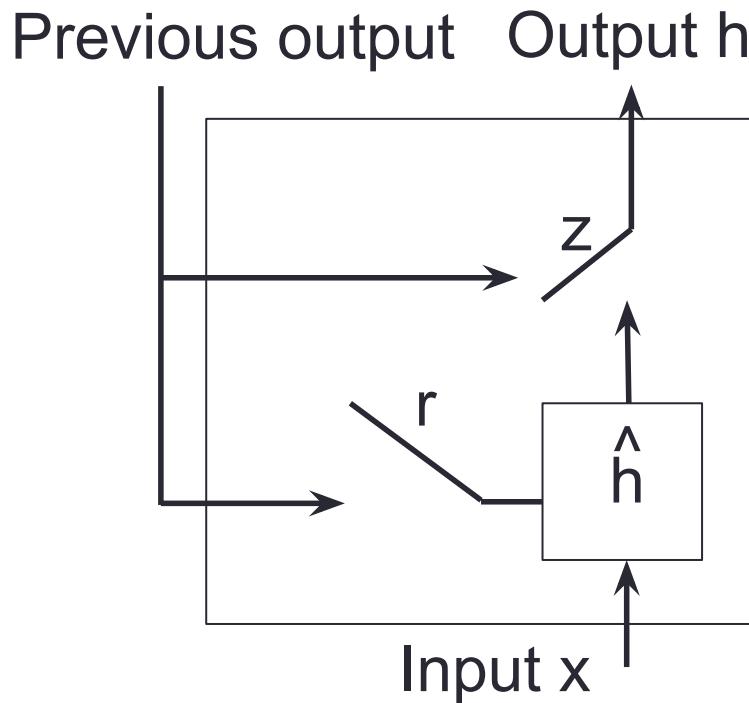
$$h_t^j = (1 - z_t^j)h_{t-1}^j + z_t^j \hat{h}_t^j$$

$$\hat{h}_t^j = \underline{\tanh^j}(W\mathbf{x}_t + U(\mathbf{r}_t \odot \mathbf{h}_{t-1}))$$

Takes the j-th element

Bounds the output

Gated Recurrent Unit (GRU)



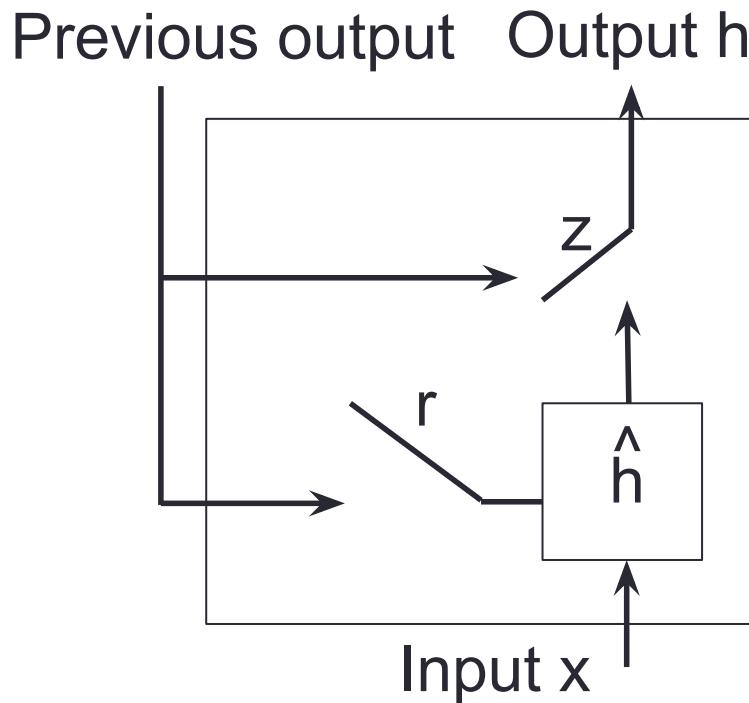
$$h_t^j = (1 - z_t^j)h_{t-1}^j + z_t^j \hat{h}_t^j$$

$$\hat{h}_t^j = \tanh^j(W\mathbf{x}_t + U(\mathbf{r}_t \odot \mathbf{h}_{t-1}))$$

$$z_t^j = \text{sigmoid}^j(W_z \mathbf{x}_t + U_z \mathbf{h}_{t-1})$$

Indicates a different set of weights

Gated Recurrent Unit (GRU)



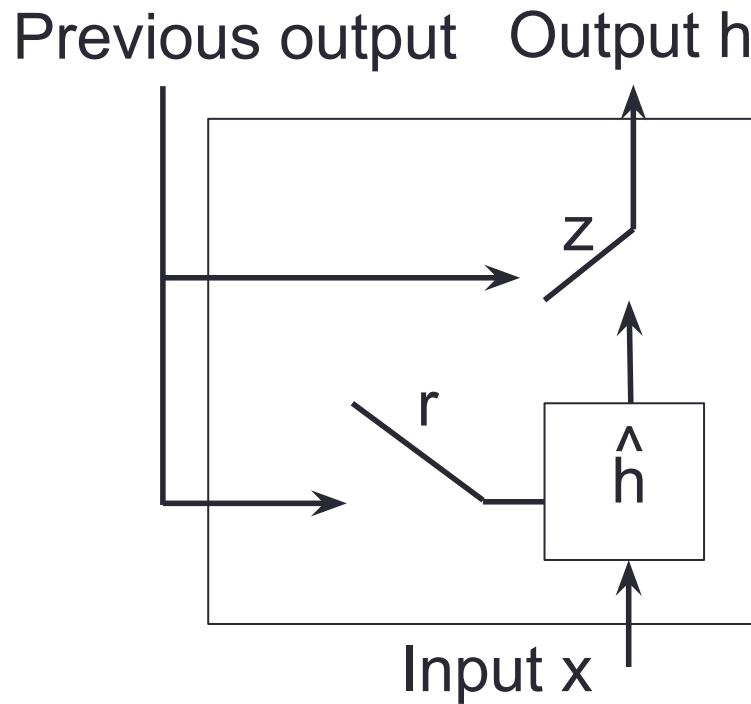
$$h_t^j = (1 - z_t^j)h_{t-1}^j + z_t^j \hat{h}_t^j$$

$$\hat{h}_t^j = \tanh^j(W\mathbf{x}_t + U(\mathbf{r}_t \odot \mathbf{h}_{t-1}))$$

$$z_t^j = \text{sigmoid}^j(W_z \mathbf{x}_t + U_z \mathbf{h}_{t-1})$$

Bounds the output to 0 to 1 for interpolation

Gated Recurrent Unit (GRU)



$$h_t^j = (1 - z_t^j)h_{t-1}^j + z_t^j \hat{h}_t^j$$

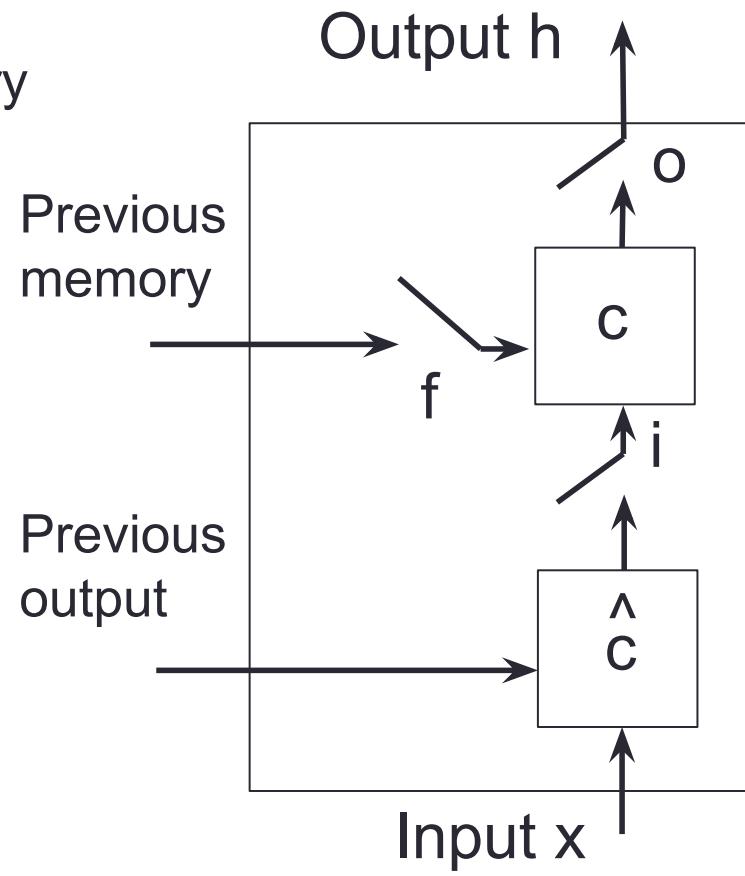
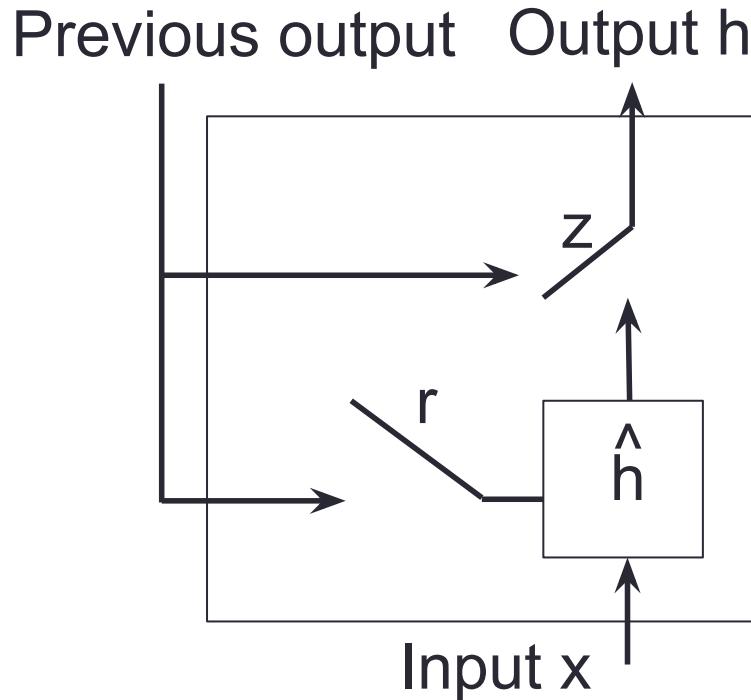
$$\hat{h}_t^j = \tanh^j(W\mathbf{x}_t + U(\mathbf{r}_t \odot \mathbf{h}_{t-1}))$$

$$z_t^j = \text{sigmoid}^j(W_z\mathbf{x}_t + U_z\mathbf{h}_{t-1})$$

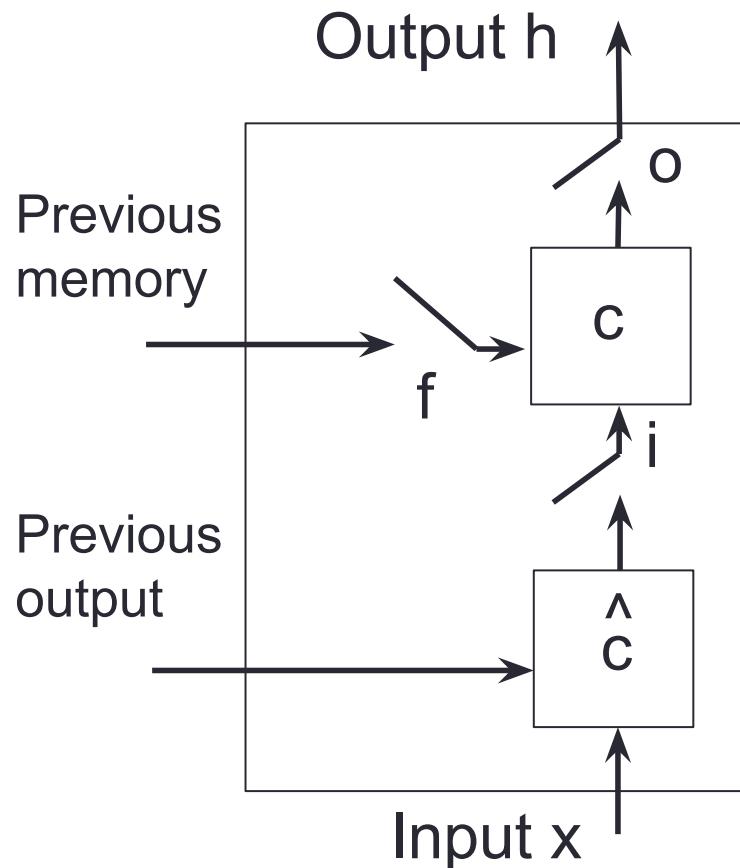
$$r_t^j = \text{sigmoid}^j(W_r\mathbf{x}_t + U_r\mathbf{h}_{t-1})$$

Long Short-Term Memory (LSTM)

- Have 3 gates, forget (f), input (i), output (o)
- Has an **explicit memory cell** (c)
 - Does not have to output the memory



Long Short-Term Memory (LSTM)

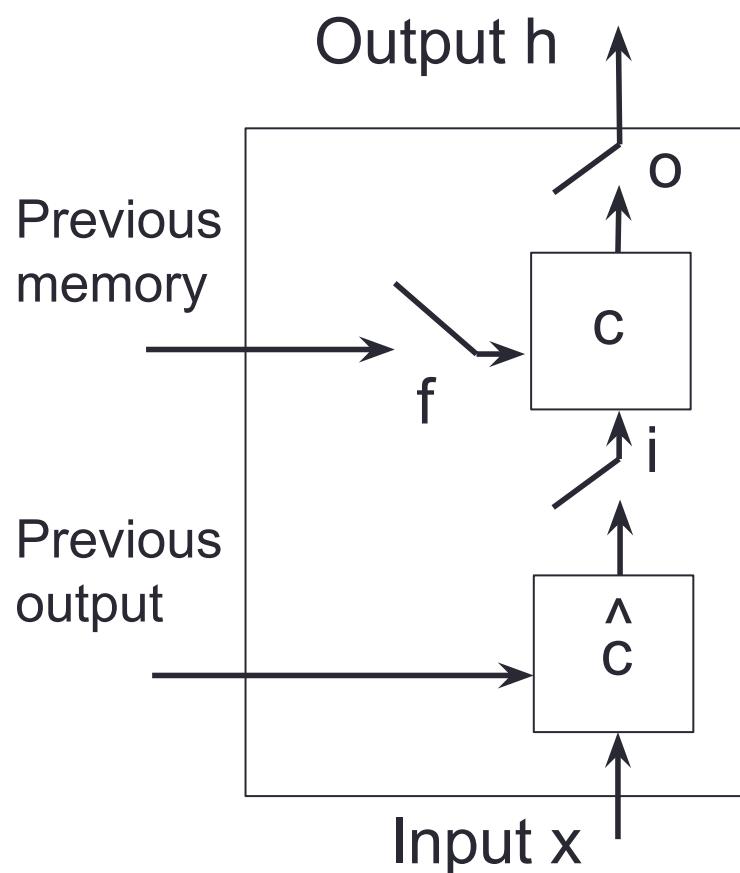


$$i_t^j = F^j(W_i \mathbf{x}_t + U_i \mathbf{h}_{t-1} + V_i \mathbf{c}_{t-1})$$
$$o_t^j = F^j(W_o \mathbf{x}_t + U_o \mathbf{h}_{t-1} + V_o \mathbf{c}_t)$$
$$f_t^j = F^j(W_f \mathbf{x}_t + U_f \mathbf{h}_{t-1} + V_j \mathbf{c}_{t-1})$$

Contribution from memory “Peephole connection”

Vs are diagonal matrices(Each cell can only see its own memory)

Long Short-Term Memory (LSTM)



$$i_t^j = F^j(W_i \mathbf{x}_t + U_i \mathbf{h}_{t-1} + V_i \mathbf{c}_{t-1})$$

$$o_t^j = F^j(W_o \mathbf{x}_t + U_o \mathbf{h}_{t-1} + V_o \mathbf{c}_t)$$

$$f_t^j = F^j(W_f \mathbf{x}_t + U_f \mathbf{h}_{t-1} + V_j \mathbf{c}_{t-1})$$

$$h_t^j = o_t^j \tanh(c_t^j)$$

$$c_t^j = f_t^j c_{t-1}^j + i_t^j \hat{c}_t^j$$

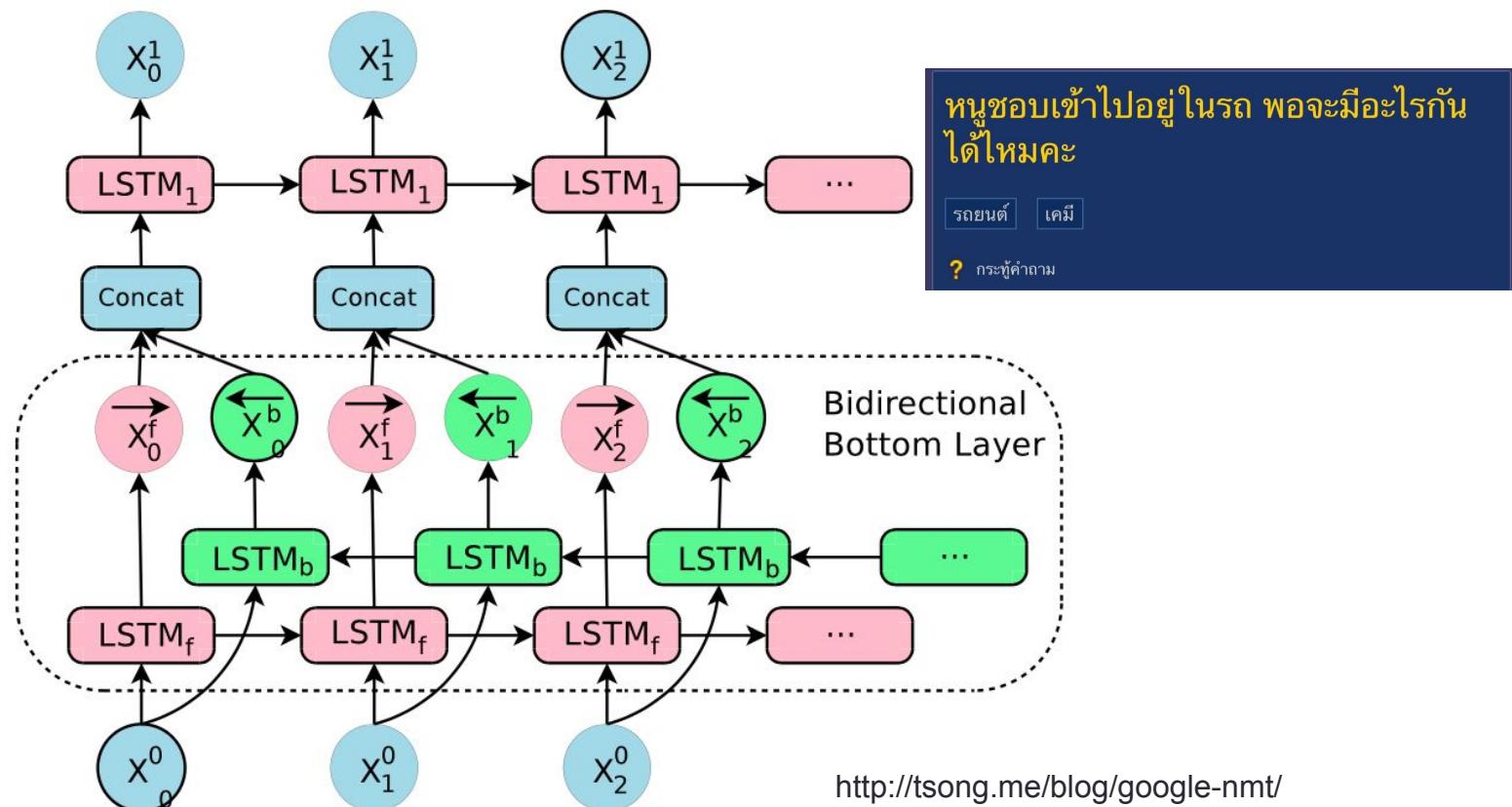
$$\hat{c}_t^j = \tanh^j(W_c \mathbf{x}_t + U_c \mathbf{h}_{t-1})$$

GRU vs LSTM

- GRU and LSTM offers the same performance with large dataset
 - GRU better for smaller dataset (less parameters)
 - GRU faster to train and faster runtime (smaller model)
- Use GRUs!

Bi-directional LSTM

- The previous GRU/LSTM only goes backward in time (uni-directional)
- Most of the time information from the future is useful for predicting the current output



LSTM remembers meaningful things

Cell sensitive to position in line:

```
The sole importance of the crossing of the Berezina lies in the fact  
that it plainly and indubitably proved the fallacy of all the plans for  
cutting off the enemy's retreat and the soundness of the only possible  
line of action--the one Kutuzov and the general mass of the army  
demanded--namely, simply to follow the enemy up. The French crowd fled  
at a continually increasing speed and all its energy was directed to  
reaching its goal. It fled like a wounded animal and it was impossible  
to block its path. This was shown not so much by the arrangements it  
made for crossing as by what took place at the bridges. When the bridges  
broke down, unarmed soldiers, people from Moscow and women with children  
who were with the French transport, all--carried on by vis inertiae--  
pressed forward into boats and into the ice-covered water and did not,  
surrender.
```

Cell that turns on inside quotes:

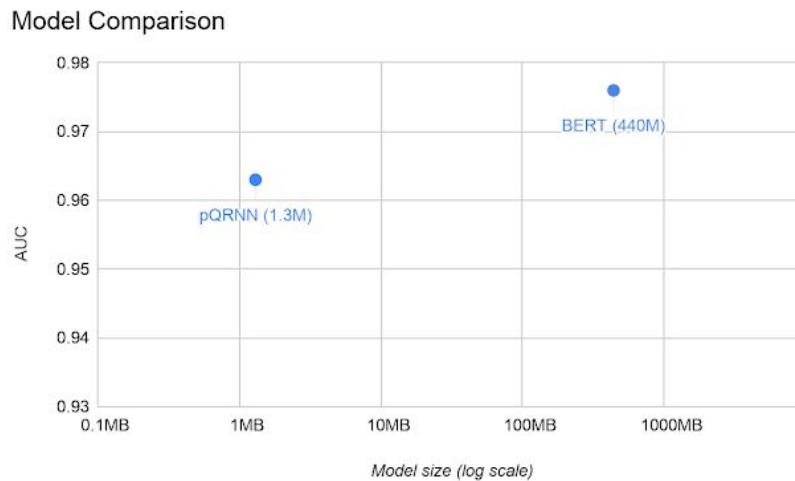
```
"You mean to imply that I have nothing to eat out of.... On the  
contrary, I can supply you with everything even if you want to give  
dinner parties," warmly replied Chichagov, who tried by every word he  
spoke to prove his own rectitude and therefore imagined Kutuzov to be  
animated by the same desire.
```

```
Kutuzov, shrugging his shoulders, replied with his subtle penetrating  
smile: "I meant merely to say what I said."
```

Notes on RNNs

Considered obsolete by some due to speed and performance

- Improved speed using QRNN <https://arxiv.org/abs/1611.01576>
- Can be as good as BERTs on simple tasks



<https://ai.googleblog.com/2020/09/advancing-nlp-with-efficient-projection.html>

Easier to train than attention-based models (easier to tune and faster convergence). Less memory requirements.

Embeddings

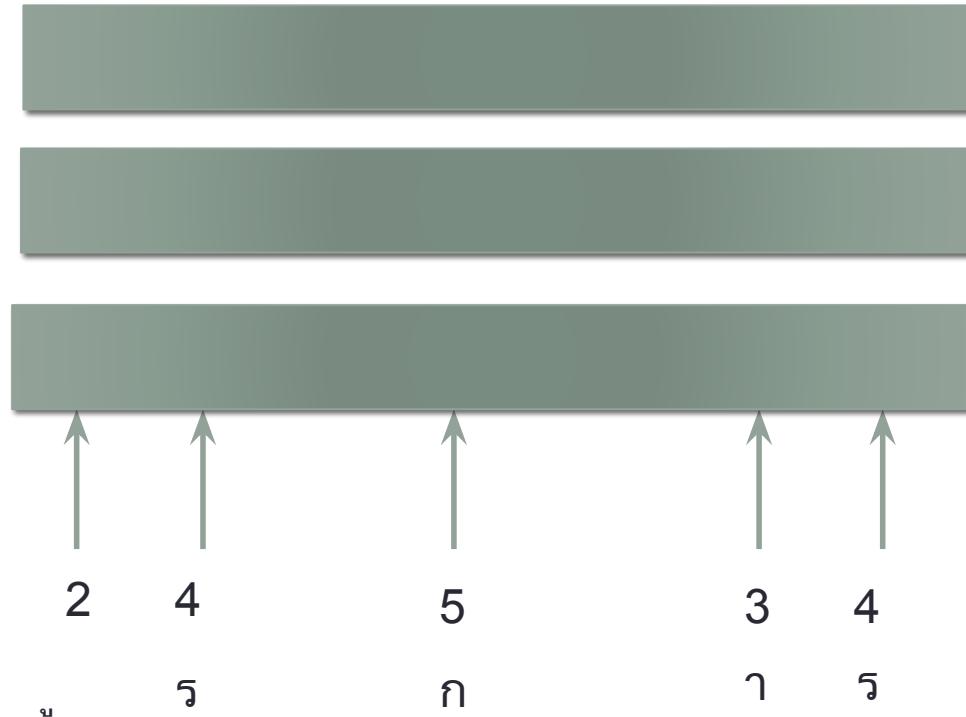
- A way to encode information to a lower dimensional space
 - PCA
 - We learn about this lower dimensional space through data

Word segmentation with fully connected networks

1 = word beginning, 0 = word middle



Logistic function



One hot encoding

- Categorical representation is usually represented by **one hot encoding**
- Categorical representations examples:
 - Words in a vocabulary, characters in Thai language

Apple -> 1 -> [1, 0, 0, 0, ...]

Bird -> 2 -> [0, 1, 0, 0, ...]

Cat -> 3 -> [0, 0, 1, 0, ...]

- **Sparse** representation
 - Spare means most dimension are zero

One hot encoding

- Sparse – but lots of dimension
 - Curse of dimensionality
- Does not represent meaning.

Apple -> 1 -> [1, 0, 0, 0, ...]

Bird -> 2 -> [0, 1, 0, 0, ...]

Cat -> 3 -> [0, 0, 1, 0, ...]

$$|\text{Apple} - \text{Bird}| = |\text{Bird} - \text{Cat}|$$

Getting meaning into the feature vectors

- You can add back meanings by hand-crafted rules
- Old-school NLP is all about feature engineering
- Word segmentation example:
 - Cluster Numbers
 - Cluster letters
- Concatenate them
- 1 = [0 0 0 0 1 0 0 0, 1, 0]
- n = [0 0 0 1 0 0 0 0, 0, 1]
- γ = [1 0 0 0 0 0 0 0, 0, 2]
- Which rules to use?
 - Try as many as you can think of, and do feature selection or use models that can do feature selection

Dense representation

- We can encode sparse representation into a lower dimensional space
 - $F: \mathbb{R}^N \rightarrow \mathbb{R}^M$, where $N > M$

Apple -> 1 -> [1, 0, 0, 0, ...] -> [2.3, 1.2]

Bird -> 2 -> [0, 1, 0, 0, ...] -> [-1.0, 2.4]

Cat -> 3 -> [0, 0, 1, 0, ...] -> [-3.0, 4.0]

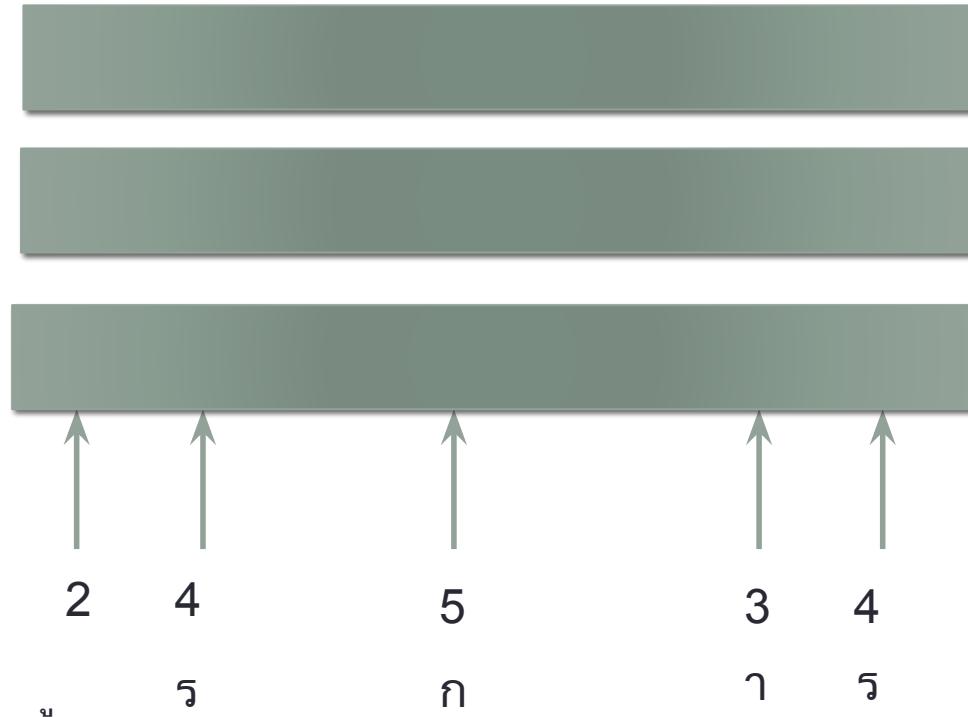
- We can do this by using an embedding layer

Word segmentation with fully connected networks

1 = word beginning, 0 = word middle



Logistic function



Adding embedding layer



Embedding layer
shares the same
weights



Parameter sharing!



[1, -1] [3, -2] [5.3, -2.1] [5.3, -3.1] [3, -2]



More on embeddings
in the next two
lectures!

2

4

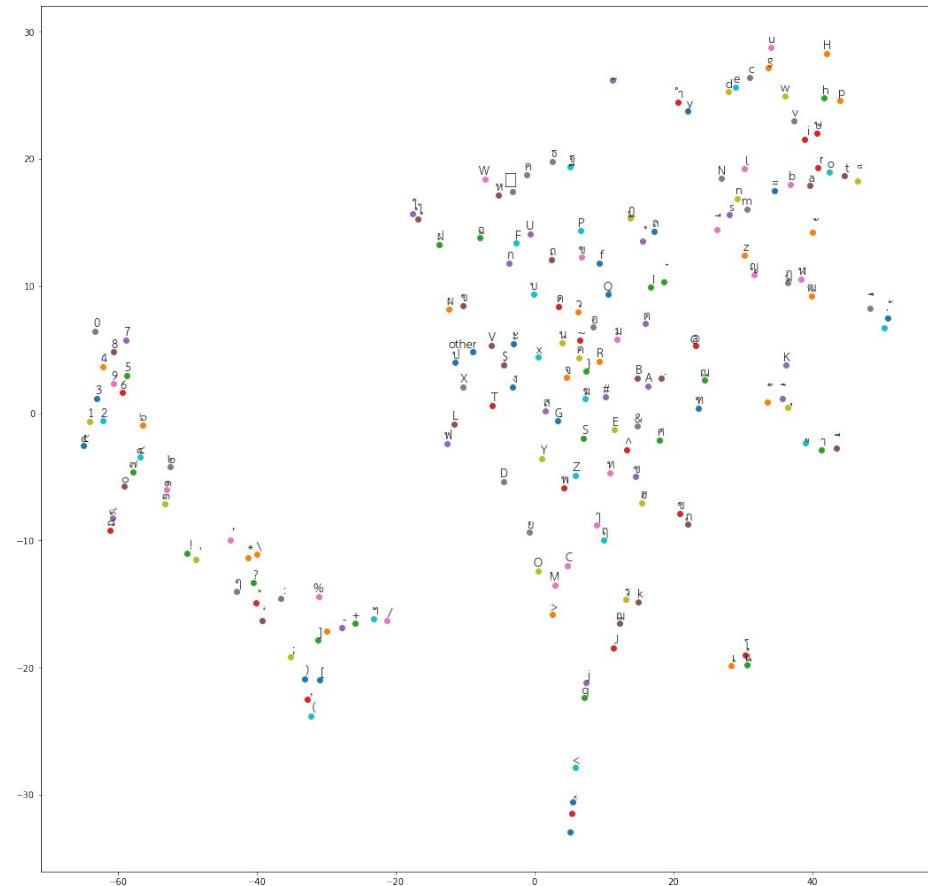
5

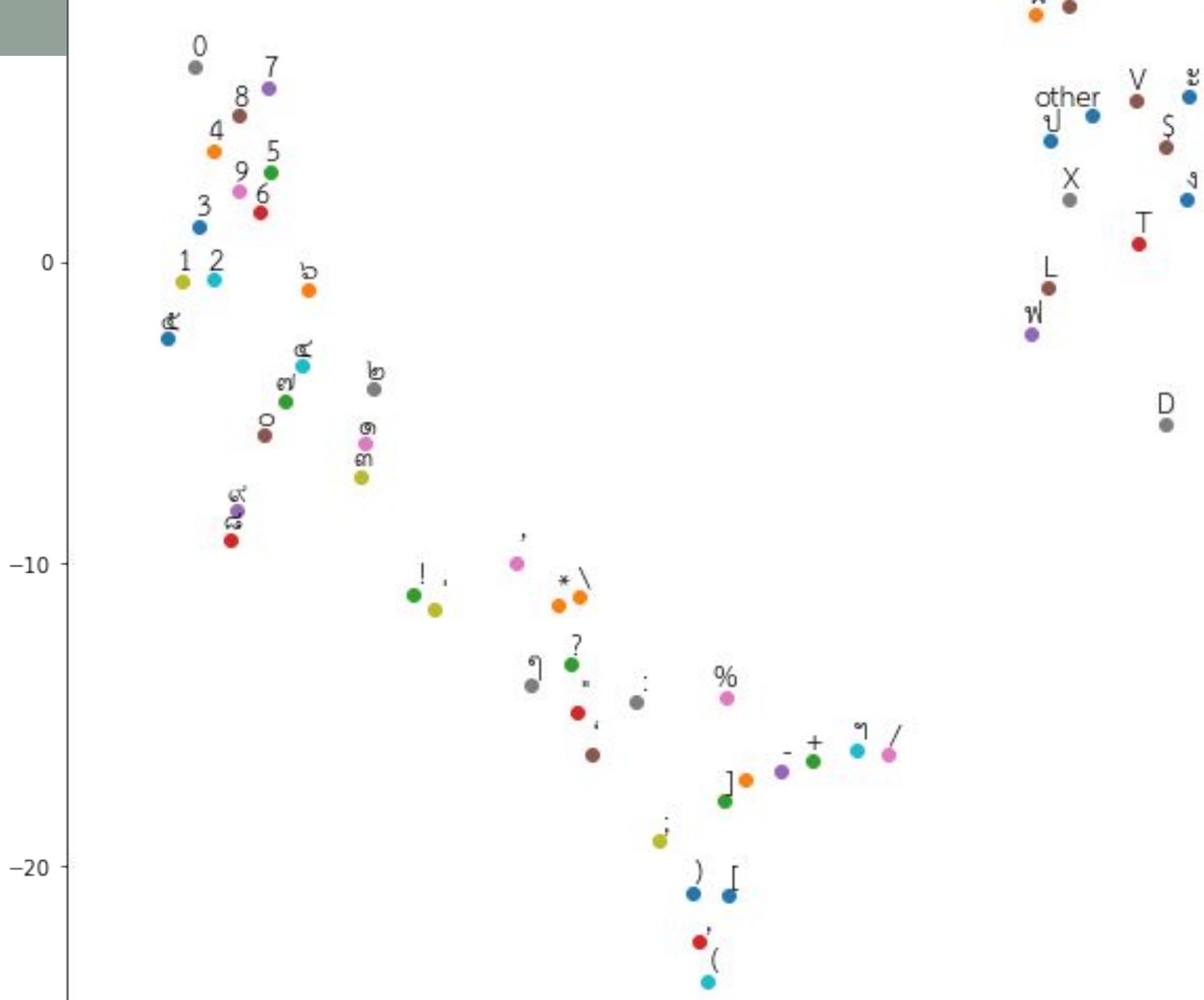
3

4

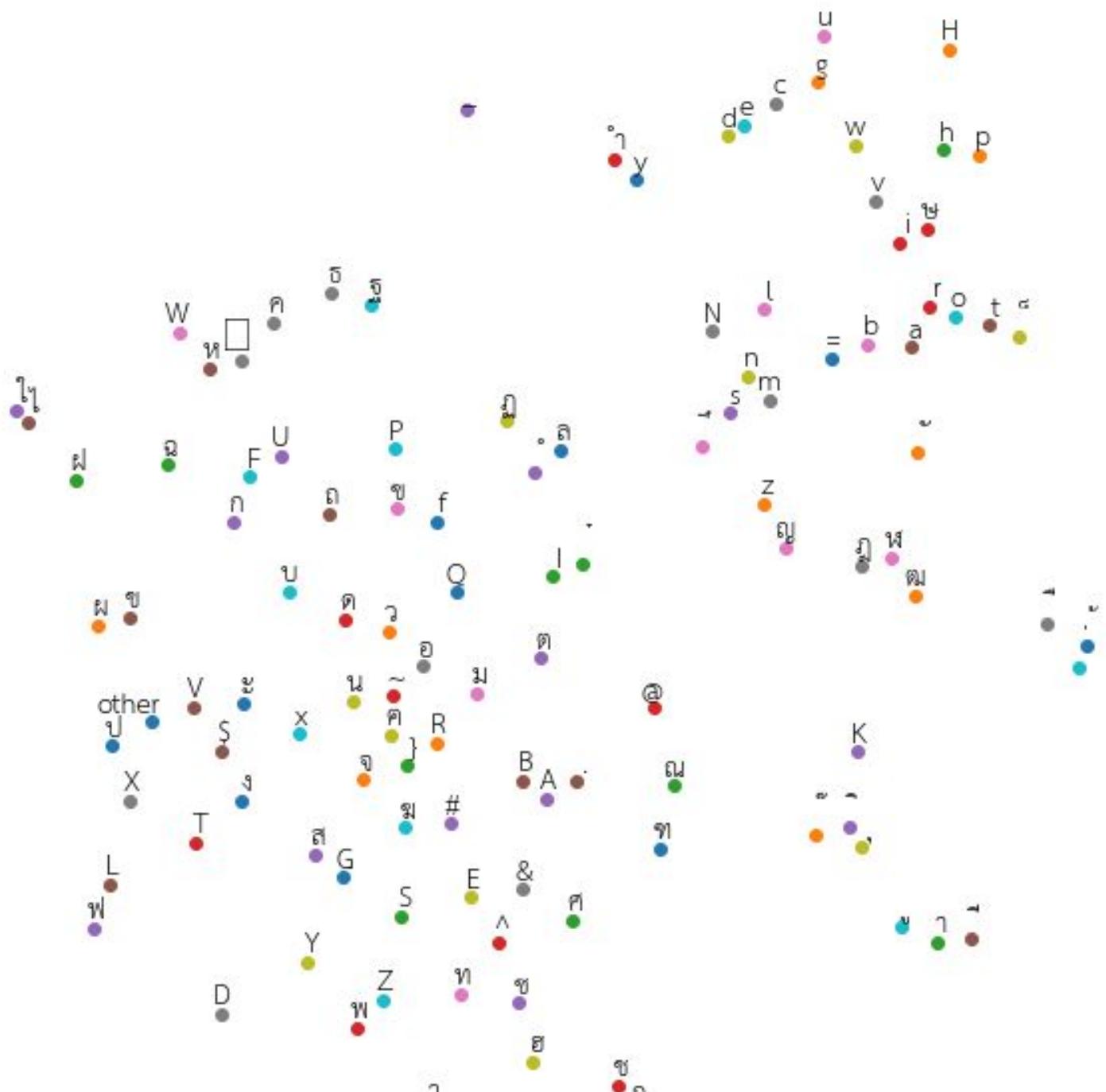
Embedding and meaning (semantics)

- Meaning is inferred from the task
- Embedding of 32 dimensions -> t-SNE into 2 dimension for visualization
- Automatically!



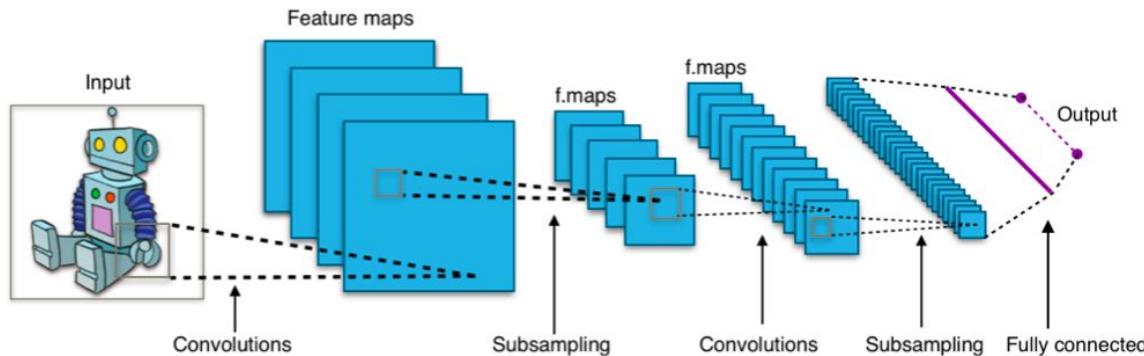
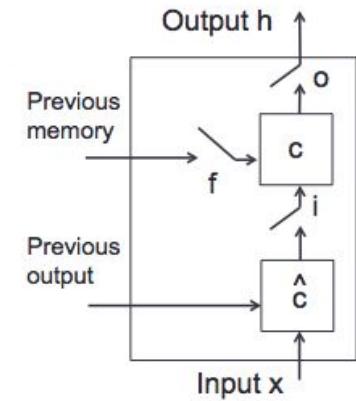
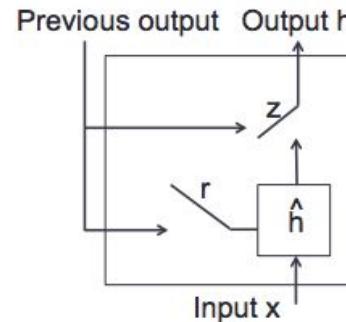






Neural networks

- Fully connected networks
 - SGD, backprop
- CNN
- RNN, LSTM, GRU

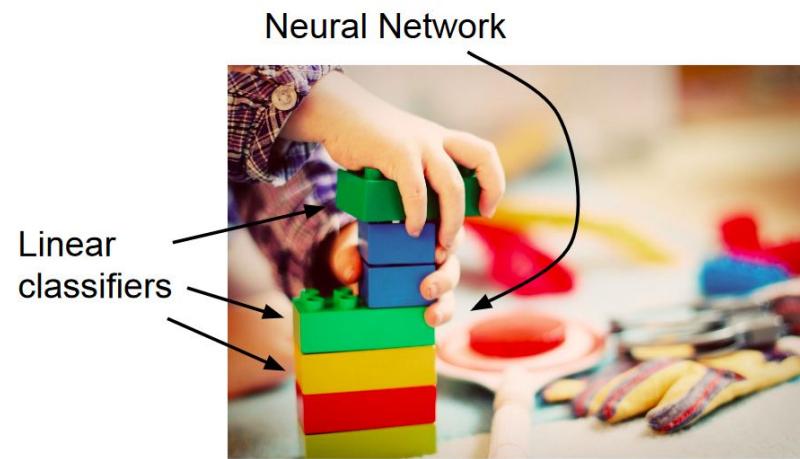
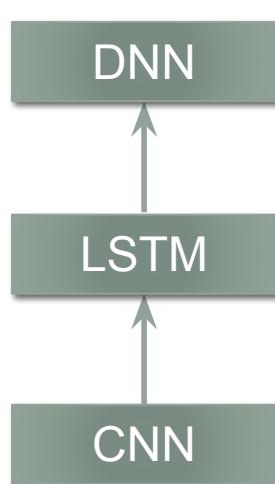


Attention modeling
Recursive neural networks

← Future lectures

DNN Legos

- Typical models now consists of all 3 types
 - CNN: local structure in the feature. Used for feature learning.
 - LSTM: remembering longer term structure or across time
 - DNN: Good for mapping features for classification. Usually used in final layers



Back to tokenization...

TABLE II
RESULTS OF THE SIX BEST TEAMS

Type of participants	F-Measure (%)	Time (mm:ss)
<i>Non-Students^a</i>	97.94937	00:47
<i>Non-Students</i>	97.84097	02:46
<i>Non-Students</i>	97.18822	00:26
<i>Bachelor Students^b</i>	95.78162	01:08
<i>Master Students</i>	95.56670	12:14
<i>PhD+Master Students</i>	92.02067	02:28

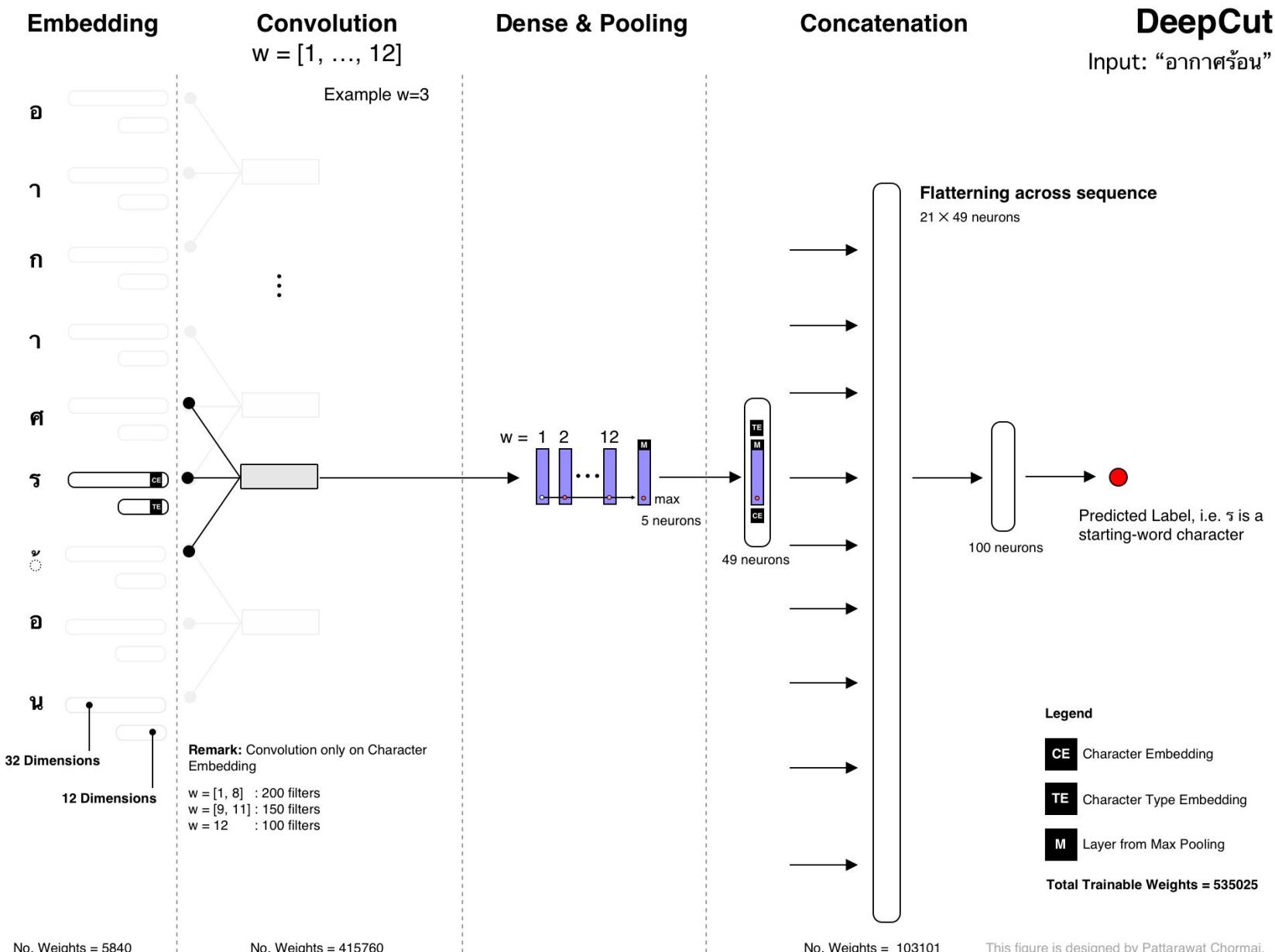
^aBest of the BEST 2009 Award Winner

^bBEST Student 2009 Award Winner

BEST 2009 : Thai word segmentation software contest

<http://ieeexplore.ieee.org/document/5340941/>

https://sertiscorp.com/thai-word-segmentation-with-bi-directional_rnn/

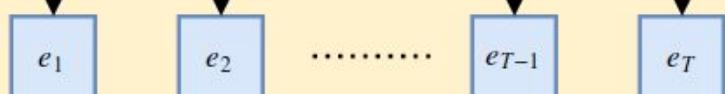


Input sequence



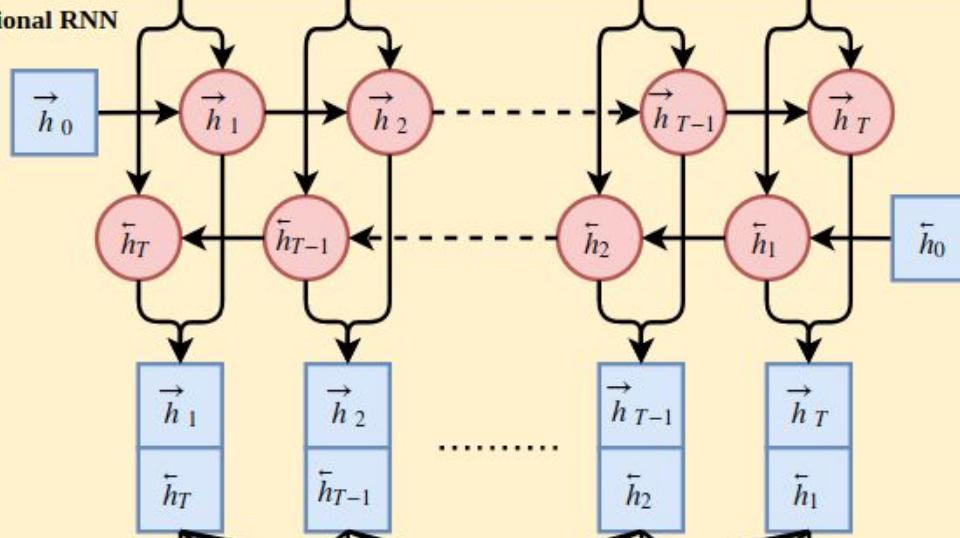
<https://www.sertiscorp.com/november-20-2017>

Embedding lookup



$$e_t = W_c c_t$$

Bi-directional RNN



$$z_t = \text{sigmoid}(W_z e_t + U_z h_{t-1} + b_z)$$

$$r_t = \text{sigmoid}(W_r e_t + U_r h_{t-1} + b_r)$$

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tanh(W_h e_t + U_h (r_t \odot h_{t-1}) + b_h)$$

$$H_t = [\vec{h}_t, \tilde{h}_{T-t+1}]$$

Output score

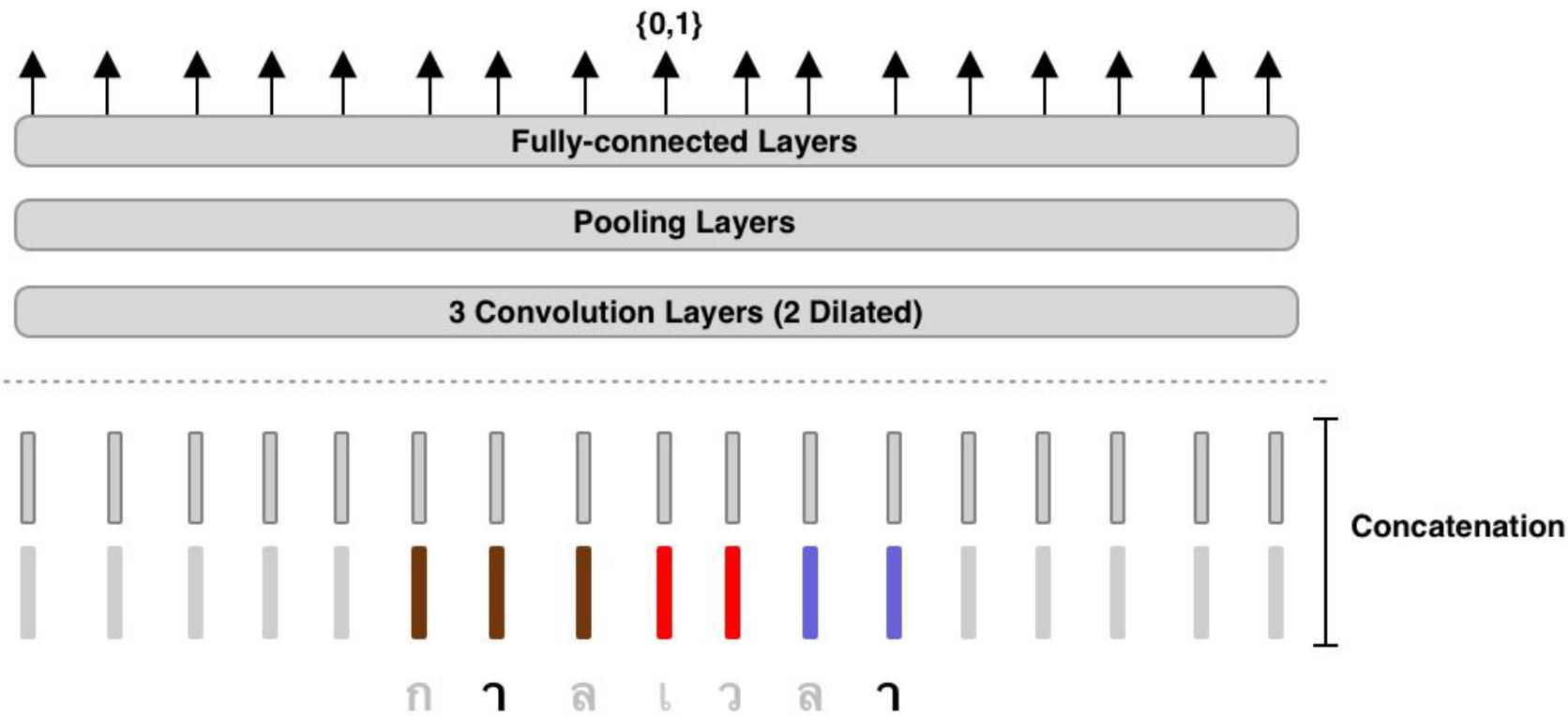


$$s_t = H_t W_s + b_s^\top$$

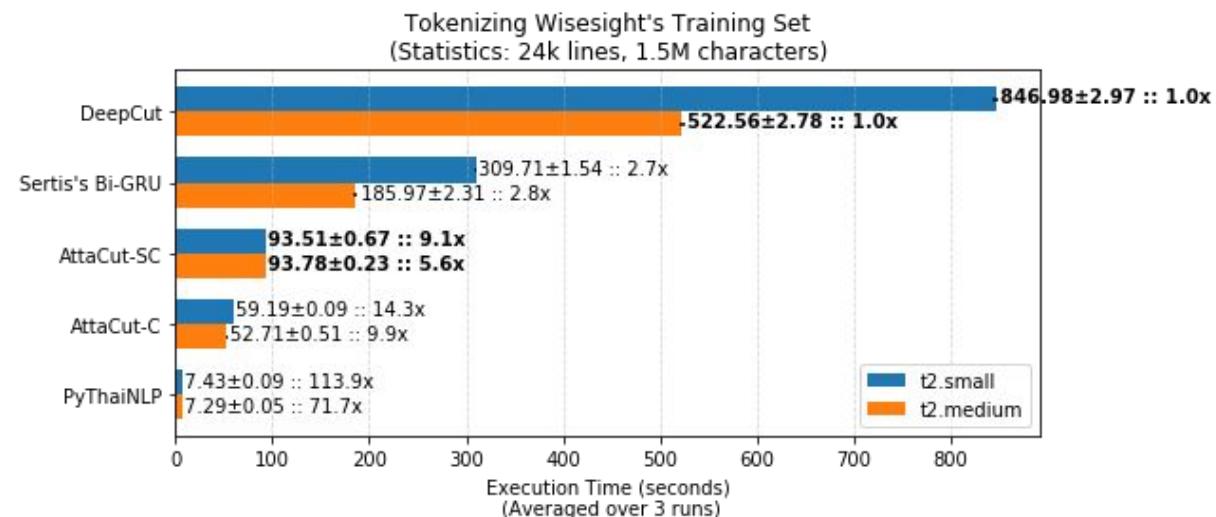
Softmax output



$$p_t = \frac{\exp(s_t)}{\exp(s_{t1}) + \exp(s_{t2})}$$



		Others			Ours	
Last Updated: 29/08/2019		PyThaiNLP newmm	Sertis Bi-GRU	DeepCut	<u>AttaCut-C</u>	<u>AttaCut-SC</u>
BEST Validation Set						
Character-Level	precision	0.94±0.11	0.95±0.10	0.99±0.05	0.97±0.07	0.98±0.05
	recall	0.83±0.09	0.99±0.02	0.99±0.03	0.98±0.04	0.99±0.03
	f1	0.88±0.08	0.97±0.07	0.99±0.04	0.98±0.05	0.99±0.04
Word-Level	precision	0.73±0.16	0.91±0.14	0.97±0.07	0.94±0.10	0.96±0.08
	recall	0.65±0.16	0.94±0.10	0.97±0.07	0.94±0.09	0.97±0.08
	f1	0.68±0.15	0.93±0.12	0.97±0.07	0.94±0.10	0.97±0.08
BEST Test Set						
Character-Level	precision	0.91±0.15	0.92±0.11	0.96±0.08	0.94±0.10	0.95±0.09
	recall	0.85±0.09	0.98±0.04	0.98±0.04	0.98±0.04	0.98±0.04
	f1	0.86±0.11	0.95±0.08	0.97±0.06	0.96±0.07	0.96±0.07
Word-Level	precision	0.70±0.19	0.85±0.18	0.92±0.14	0.88±0.17	0.91±0.15
	recall	0.64±0.18	0.90±0.14	0.93±0.12	0.91±0.14	0.92±0.13
	f1	0.67±0.19	0.87±0.16	0.93±0.13	0.89±0.16	0.91±0.14



ผมเห็นคนวางแผนการนี้เมื่อ 20-30 ปีที่แล้วทำเรื่องตัดคำ วงการ
นี้มันไม่ไปไหนเลยใช่ไหมเนี่ย

มิตรสหาย Business Development ท่านนึง



Words of caution

Statistical tokenizers fail on mismatched data

A tokenizer trained on social text might not be able to cut simple words like

มะม่วง มะละกอ

<https://www.aclweb.org/anthology/2020.emnlp-main.315/>

	WS160	TNHC
Deepcut	93.8	93.5
Attacut	93.5	80.8

Statistical tokenizers fails unpredictably

หมูกรอบ => |หมู|กรอบ|

ข้าวผัดกะหล่ำหมูกรอบหนึ่งจาน => |ข้าวผัด|กะหล่ำ|หมูกรอบ|หนึ่ง|จาน|

Might need rule-based override (Deepcut has this)

For speed, maximal matching (newmm) is reliable.

- drawbacks?

Words of caution

Tokenization performance effects downstream task performance

Can be small (1%) or large (10%)

Specialized tokenizer can help your downstream task

Example: ecommerce search |หู|ฟัง| |ต่าง|หู|

Ekapol Chuangsuwanich
October 25, 2020 ·

Month 1 in ตัดคำ: the best solution is deep learning
Month 6 in ตัดคำ: the best solution is no segmentation
Month 24 in ตัดคำ: the best solution is sentencepiece
Month 36 in ตัดคำ: the best solution is dict-based
Month infinity in ตัดคำ: the best solution is a new language 😊
The thing I find the most fascinating is that for *all* the changes in Thai NLP in the last 3 years, this problem still causes other shit to break.

#ThaiNLP #WordSegmentation

Tokenization - English

- Even English has tokenization issues!
 - Space is usually not enough
 - aren't
 - are + n't
 - aren't
 - arent
 - aren t
 - are + not
 - San Francisco
- Usually includes the text normalization step
- Again depends on application
 - “aren't” might be different from “are not” for sentiment analysis

Other English issues - hyphens

- “*the New York-based co-operative was fine-tuning forty-two K-9-like models.* “
- Lexical vs Sentential hyphens

Tokenization of non-standard text

- Twitter

@SentimentSymp: can't wait for the Nov 9 #Sentiment talks! YAAAAAAAY!!! >:-D [http://sentimentsymposium.com/.](http://sentimentsymposium.com/)

Needs to correctly tokenize

Emoticons

Twitter markup (# and @)

Capitalization (and html tags for bold, etc.)

Lengthening

Dates

Hand-crafted for tweets

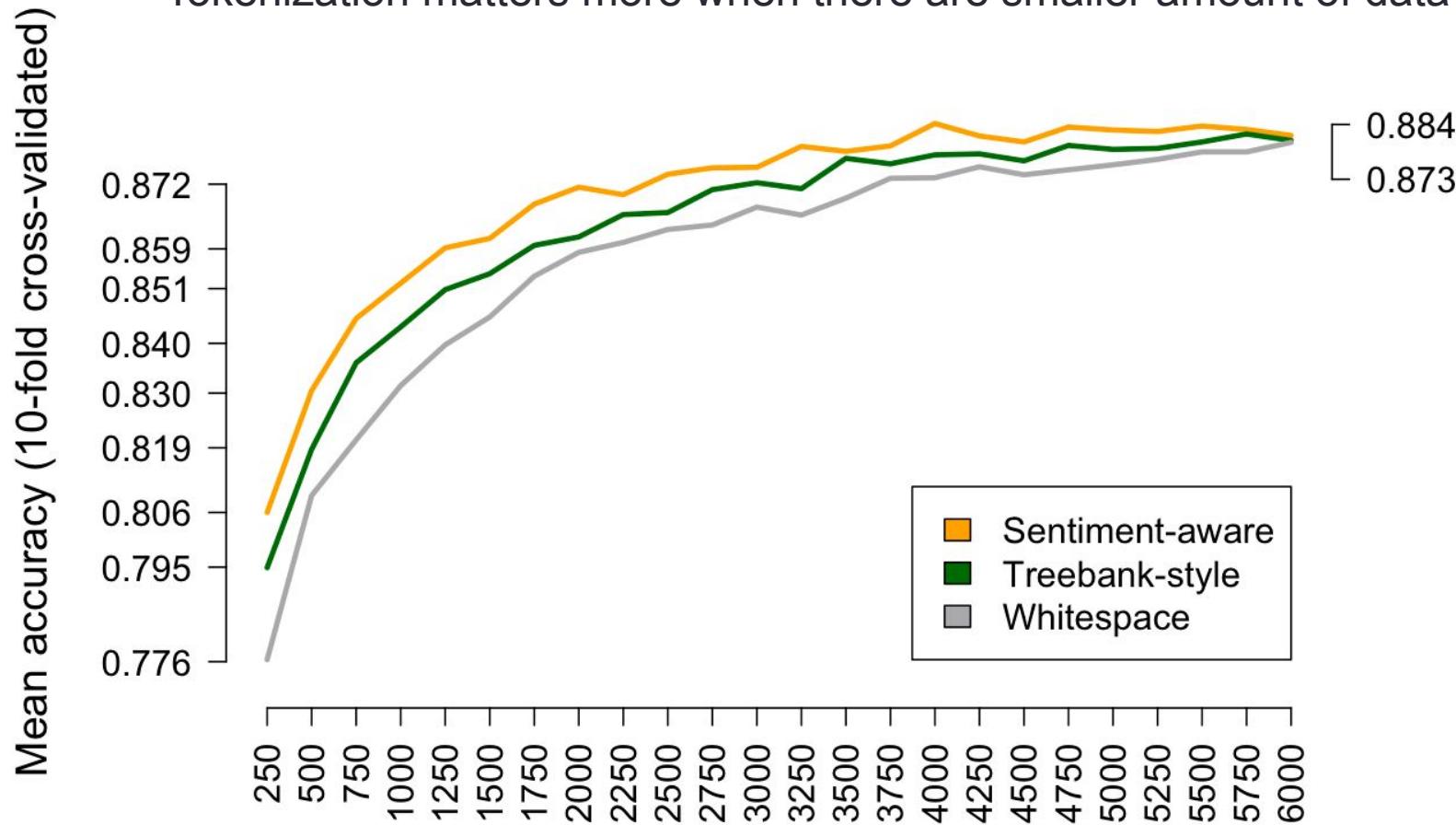
```
@sentimentsymp
:
can't
wait
for
the
Nov_09
#sentiment
talks
!
YAAAAAY
!
!
!
>:-D
http://sentimentsymposium.com/
.
```

@
SentimentSymp
:
ca
n't Standard tokenizer
wait (Stanford tokenizer)
for
the
Nov
9

Sentiment
talks
!
YAAAAAY
!
!
!
>
;
:
-D
http
:
//sentimentsymposium.com/
.

Sentiment analysis (in-domain)

Tokenization matters more when there are smaller amount of data



Sentiment analysis (out-of-domain)

Better tokenizer gives better portability



End-to-end models

- Classical machine learning systems usually break the problem into smaller subtasks
 - Self-driving:
 - Image -> objects detection -> path finding -> steering
 - Speech2speech translation:
 - Speech A -> text A -> text B -> Speech B
- End-to-end models use one large neural networks process the input and generate the desired output
 - Image -> steering
 - Speech A -> Speech B

End-to-end NLP?

Discourse

Semantics

CommunicationEvent(e)
Agent(e, Alice)
Recipient(e, Bob)
SpeakerContext(s)
TemporalBefore(e, s)

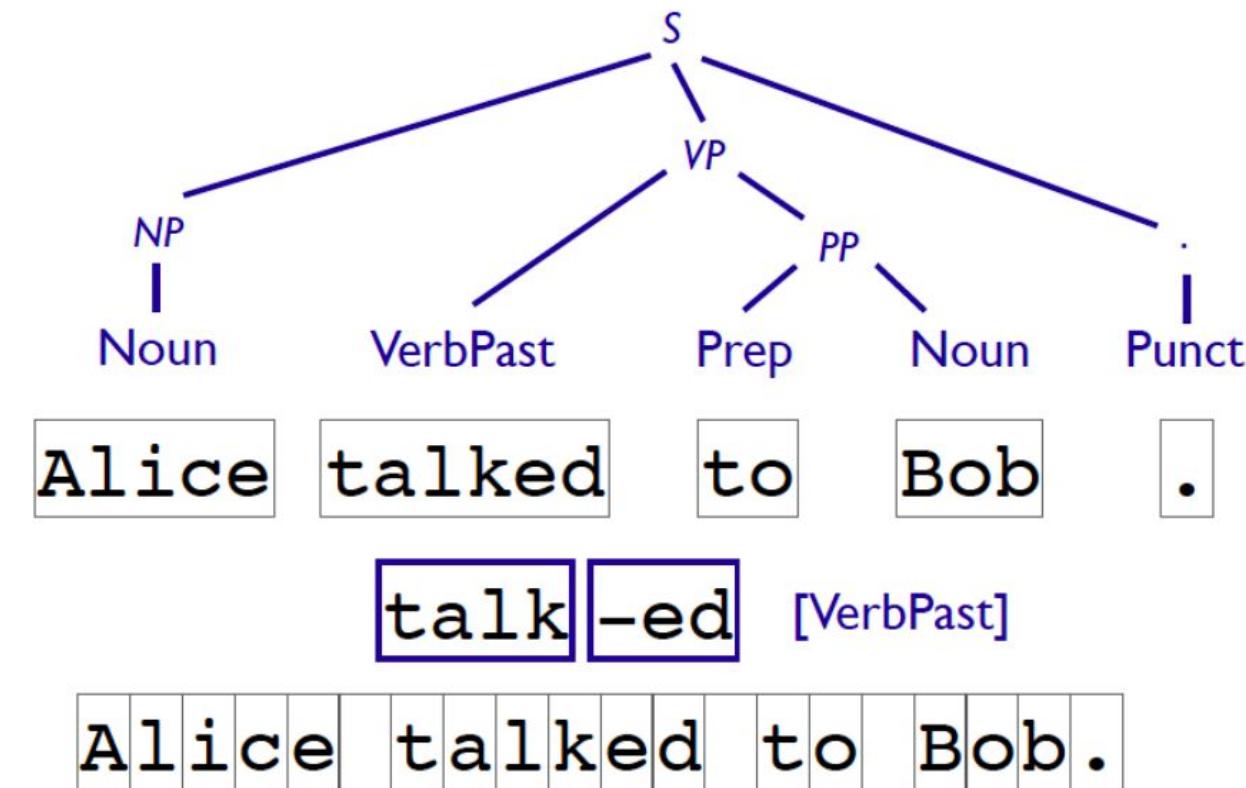
Syntax: Constituents

Syntax: Part of Speech

Words

Morphology

Characters



Towards no tokenization? :Character-aware neural language models

- Input: previous characters
- Output: next word

CNN over characters capture character sequence patterns

Fully connected

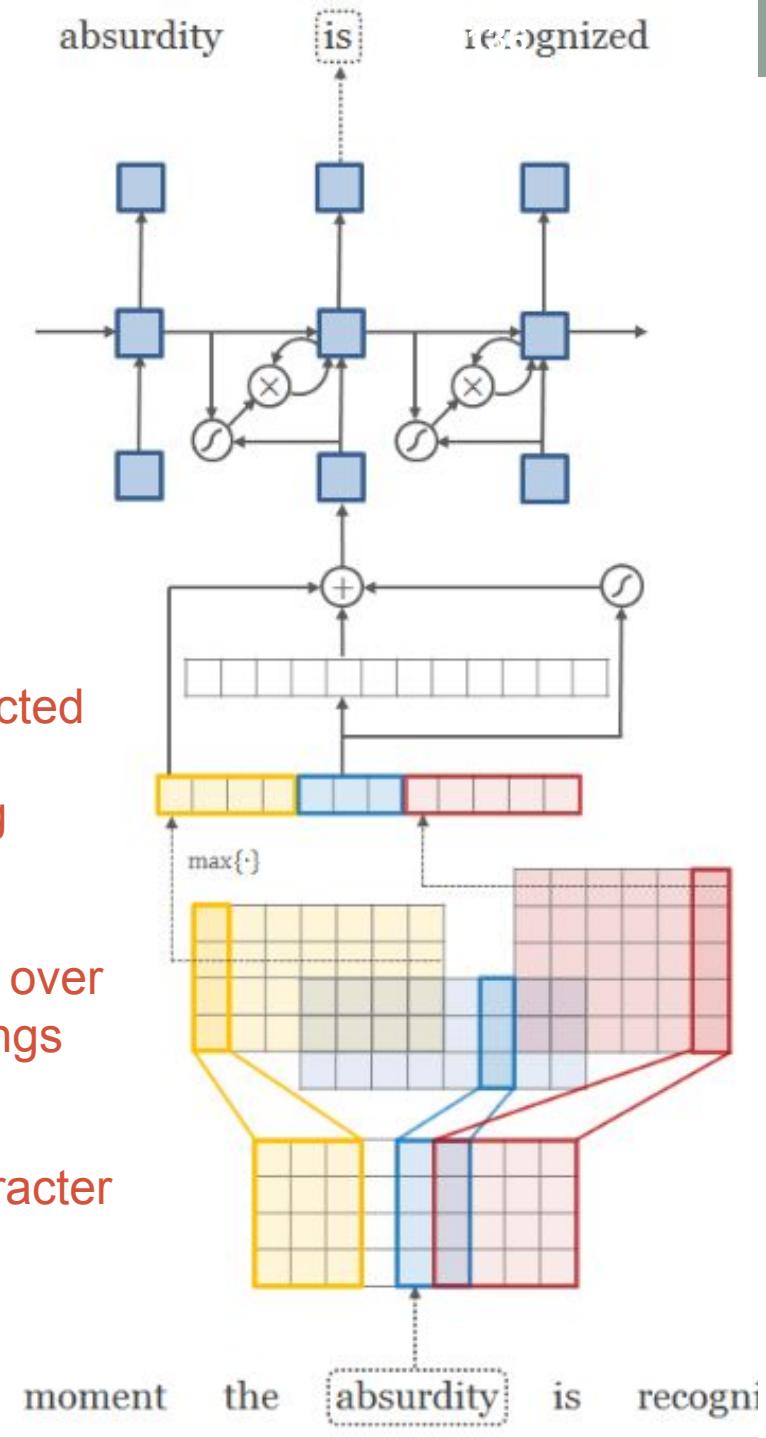
LSTM

Fully connected

Max pooling

Convolutional layer over character embeddings

Character to character embeddings

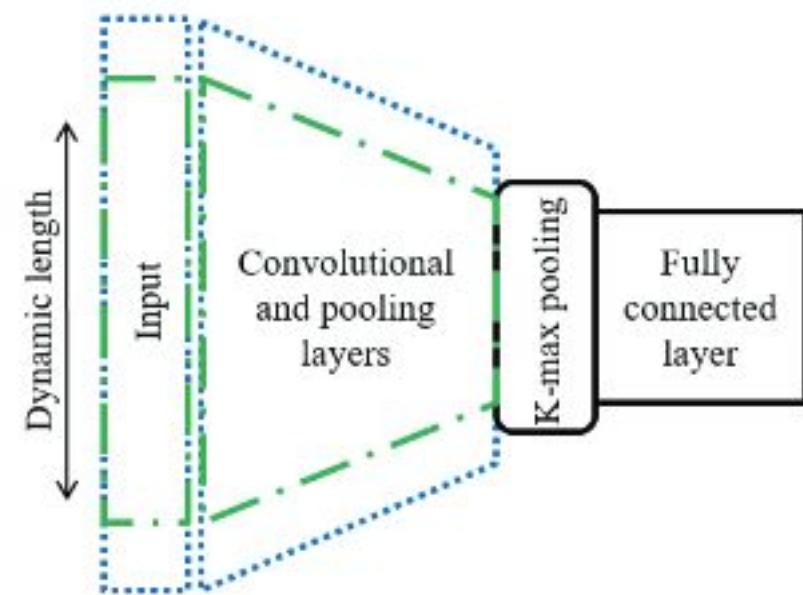


Towards no tokenization

- Text classification using charCNN on Thai

Method	Accuracy (%)	F_1 (%)
Naïve Bayes, BoW	87.2	87.1
Naïve Bayes, TF-IDF	89.0	88.9
Logistic Regression, BoW	94.8	94.8
Logistic Regression, TF-IDF	94.7	94.7
SVM, BoW	93.7	93.7
SVM, TF-IDF	95.2	95.2
DCNN (Kalchbrenner et al., 2014)	95.9	95.9
Proposed Char-CNN	95.4	95.4

Word-based methods



A character-level convolutional neural network with dynamic input length for Thai text categorization
<http://ieeexplore.ieee.org/document/7886102/>

Caveats of end-to-end models

- Requires lots of data for the specific task
- Hard to fix specific mistakes by the model

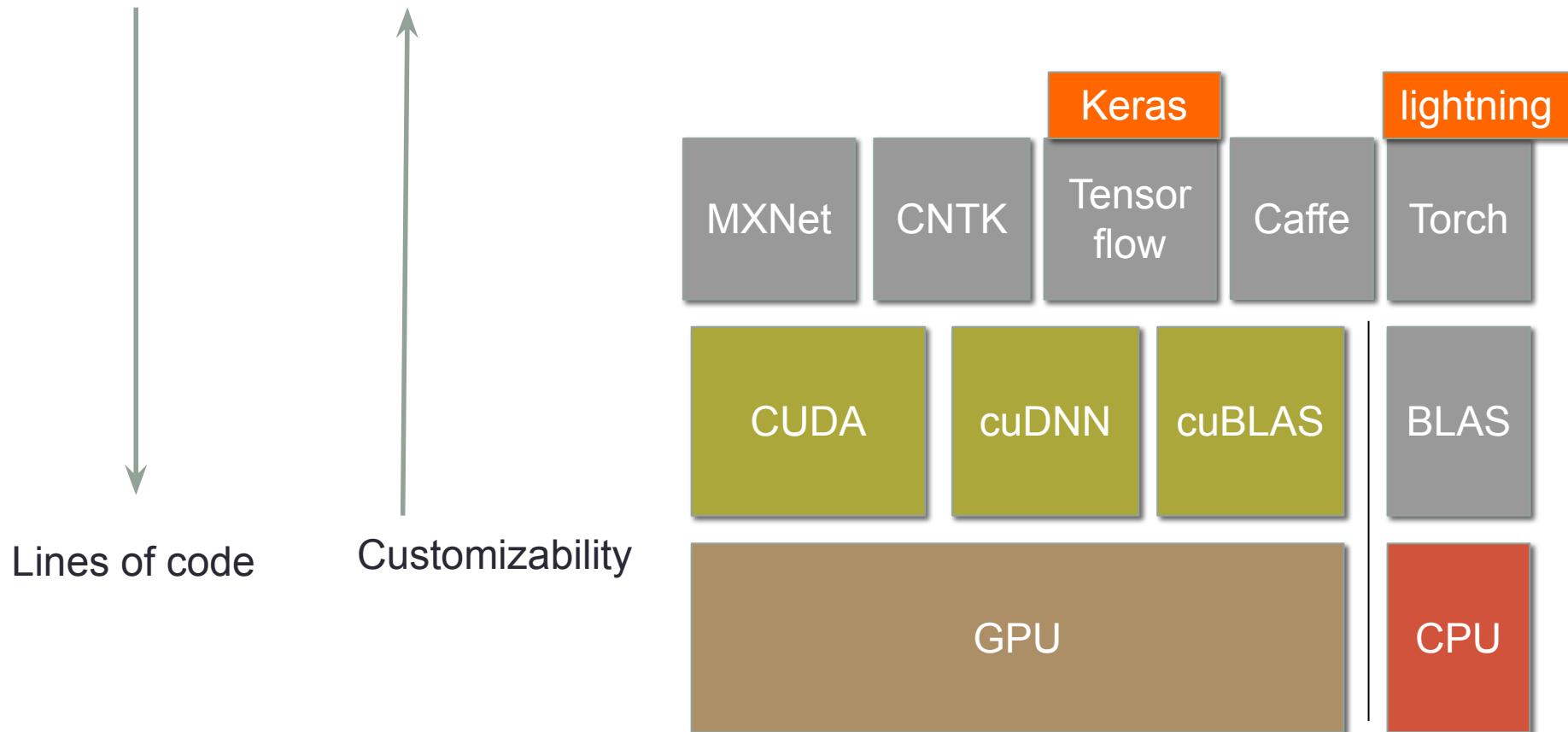
Things to consider when thinking about tokenization

Know your use cases

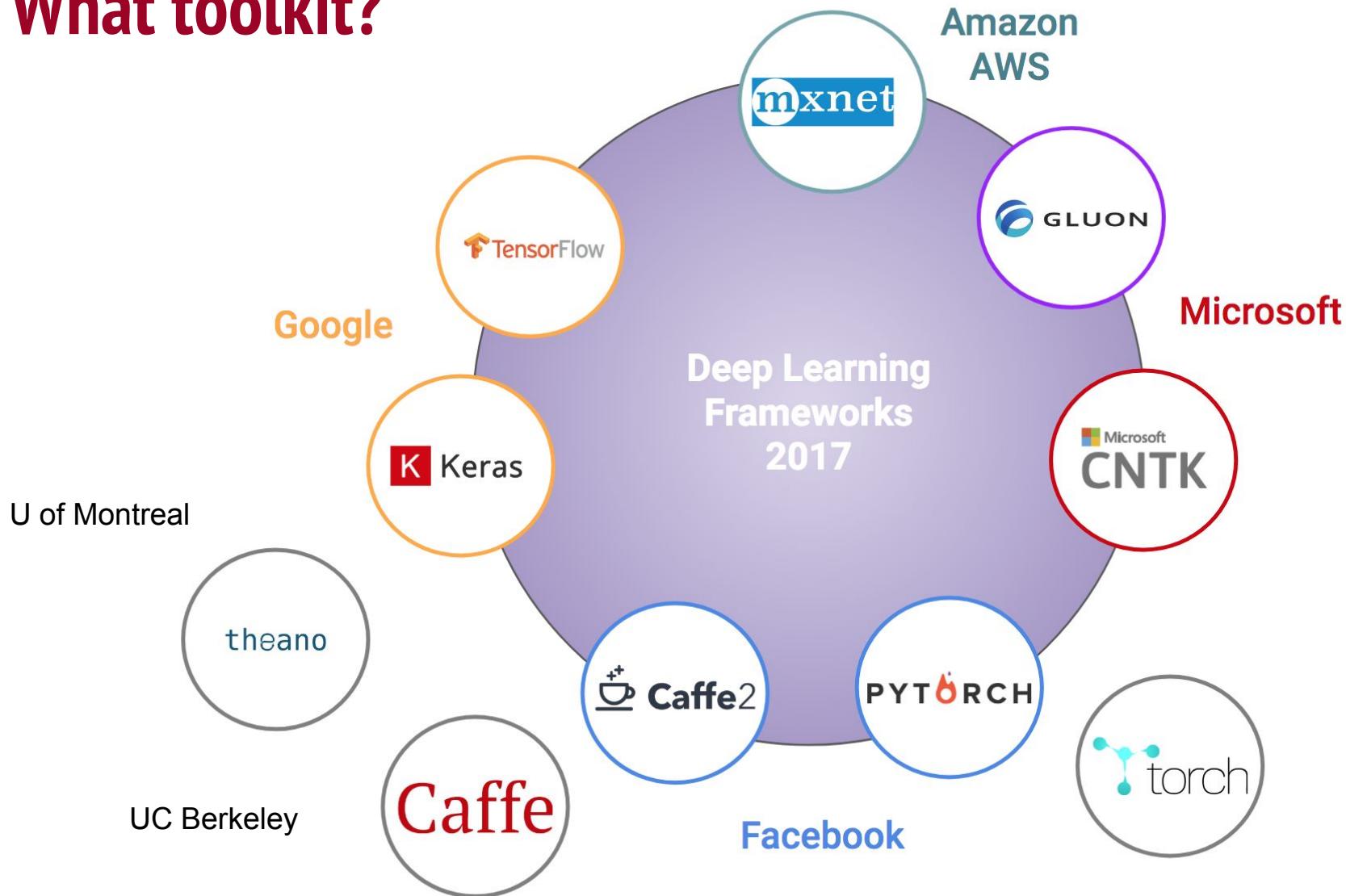
Segment text into characters	Segment text into word-pieces	Segment text into words
<ul style="list-style-type: none">→ Small embedding table→ Needs a powerful model to learn very long range influences→ Individual tokens are not very meaningful	<ul style="list-style-type: none">→ Medium-sized embedding table→ Needs a model that can learn long range dependencies→ Individual tokens are partially meaningful	<ul style="list-style-type: none">→ Very large embedding table→ Smaller number of segments means the model need not learn long range influences→ Individual tokens are meaningful

What toolkit

Tradeoff between customizability and ease of use

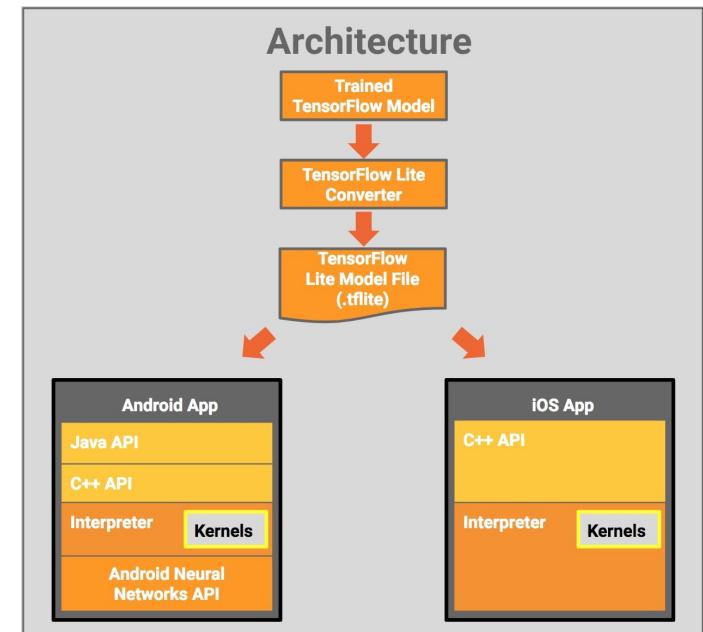


What toolkit?



Which?

- Easiest to use and play with deep learning: Keras
- Easiest to use and tweak: pytorch
- Easiest to deploy: tensorflow
 - Tensorflow lite for mobile
 - TensorRT support
 - tf-serving
 - Kubeflow



Which?

- Easiest to use and play with deep learning: Keras
- Easiest to use and tweak: pytorch
- Easiest to deploy:
 - Tensorflow lite for mobile
 - TensorRT support
 - tf-serving
 - Kubeflow
- Community: TensorFlow?

Demos

- Keras
- You should read before doing the homework
 - https://keras.io/guides/functional_api/

Keras steps

- Define the network
 - Compile the network
 - Fit the network

```
def get_feedforward_nn():
    input1 = Input(shape=(21,))
    x = Dense(100, activation='relu')(input1)
    x = Dense(100, activation='relu')(x)
    x = Dense(100, activation='relu')(x)
    out = Dense(1, activation='sigmoid')(x)

    model = Model(inputs=input1, outputs=out)
    model.compile(optimizer=Adam(),
                  loss='binary_crossentropy',
                  metrics=['acc'])

    return model
```

Keras is easy!

Dense layer

Dense class

```
tf.keras.layers.Dense(  
    units,  
    activation=None,  
    use_bias=True,  
    kernel_initializer="glorot_uniform",  
    bias_initializer="zeros",  
    kernel_regularizer=None,  
    bias_regularizer=None,  
    activity_regularizer=None,  
    kernel_constraint=None,  
    bias_constraint=None,  
    **kwargs  
)
```

Just your regular densely-connected NN layer.

`Dense` implements the operation: `output = activation(dot(input, kernel) + bias)` where `activation` is the element-wise activation function passed as the `activation` argument, `kernel` is a weights matrix created by the layer, and `bias` is a bias vector created by the layer (only applicable if `use_bias` is `True`).

Dropout layer

Dropout class

```
tf.keras.layers.Dropout(rate, noise_shape=None, seed=None, **kwargs)
```

Applies Dropout to the input.

The Dropout layer randomly sets input units to 0 with a frequency of `rate` at each step during training time, which helps prevent overfitting. Inputs not set to 0 are scaled up by $1/(1 - \text{rate})$ such that the sum over all inputs is unchanged.

Note that the Dropout layer only applies when `training` is set to True such that no values are dropped during inference. When using `model.fit`, `training` will be appropriately set to True automatically, and in other contexts, you can set the kwarg explicitly to True when calling the layer.

(This is in contrast to setting `trainable=False` for a Dropout layer. `trainable` does not affect the layer's behavior, as Dropout does not have any variables/weights that can be frozen during training.)

Conv2D layer

Conv2D class

```
tf.keras.layers.Conv2D(  
    filters,  
    kernel_size,  
    strides=(1, 1),  
    padding="valid",  
    data_format=None,  
    dilation_rate=(1, 1),  
    groups=1,  
    activation=None,  
    use_bias=True,  
    kernel_initializer="glorot_uniform",  
    bias_initializer="zeros",  
    kernel_regularizer=None,  
    bias_regularizer=None,  
    activity_regularizer=None,  
    kernel_constraint=None,  
    bias_constraint=None,  
    **kwargs  
)
```

2D convolution layer (e.g. spatial convolution over images).

Deep learning demo

Red boundaries Indicate output and input tensors

