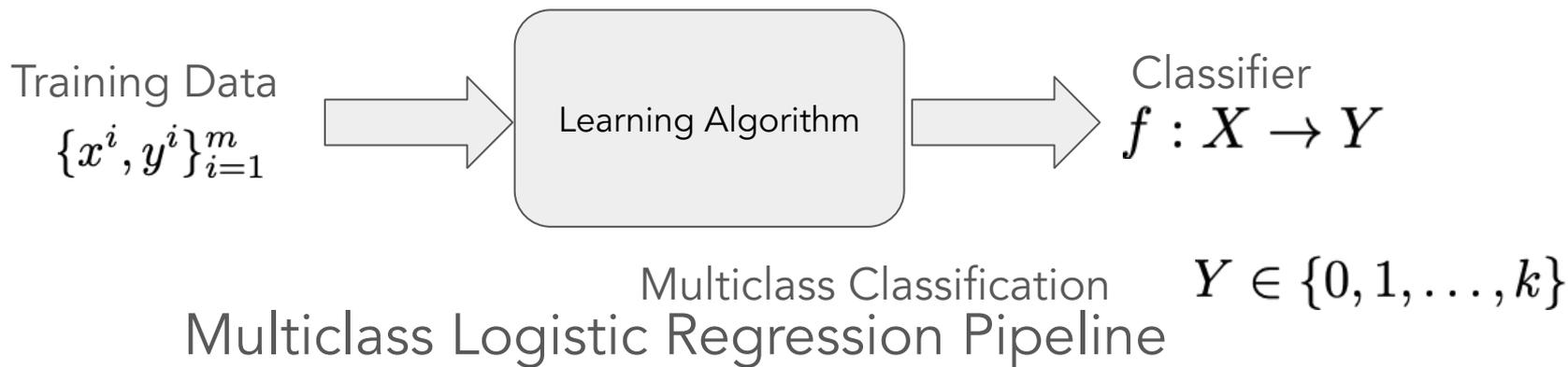


CX4240 Spring 2026

Recurrent Neural Networks

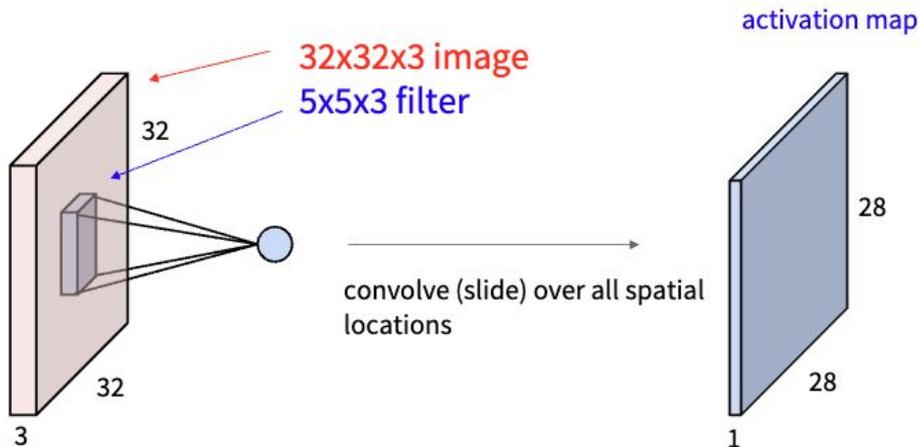
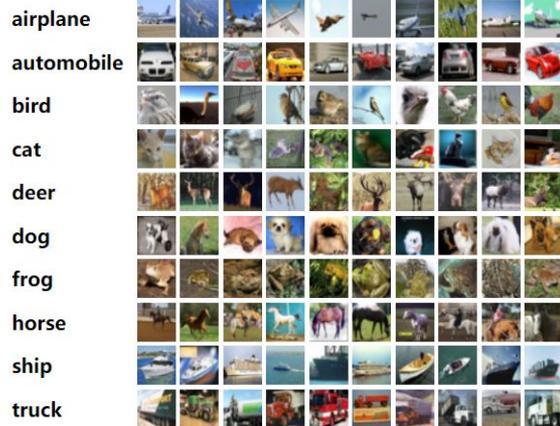
Bo Dai
School of CSE, Georgia Tech
bodai@cc.gatech.edu

Multiclass Logistic Regression Algorithms

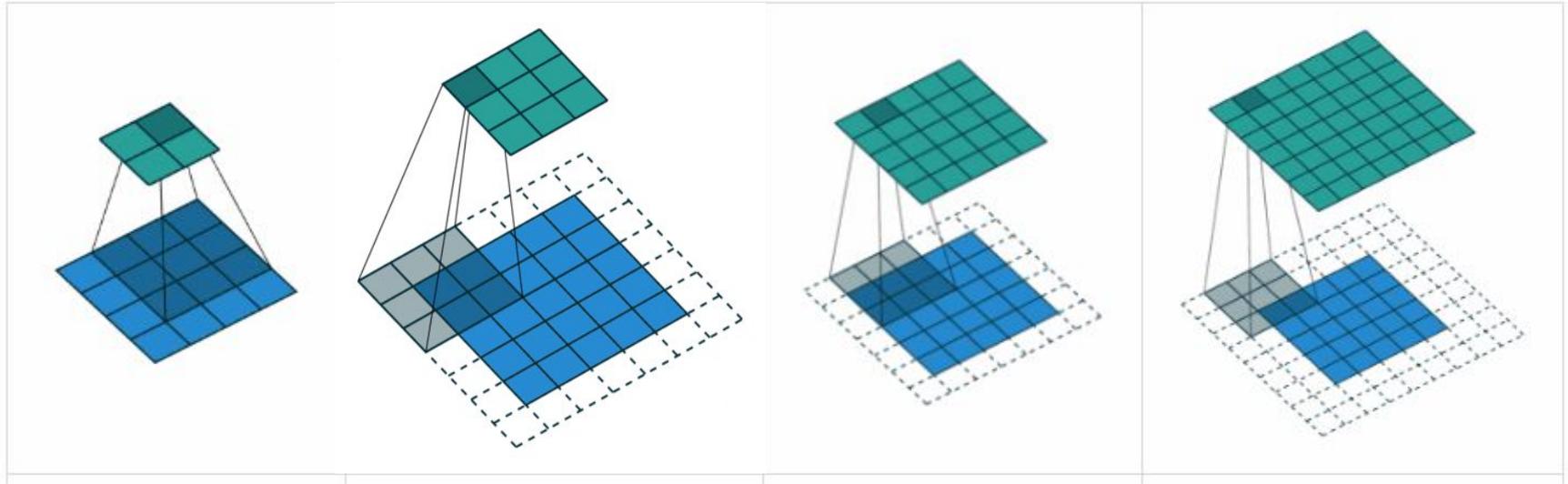


1. Build probabilistic models:
Categorical Distribution + Conv NN
2. Derive loss function: MLE and MAP
3. Select optimizer: (Stochastic) Gradient Descent

Revisit Convolution Neural Networks



Convolution for 2D Images



padding = 0, stride = 1

padding = 1, stride = 2

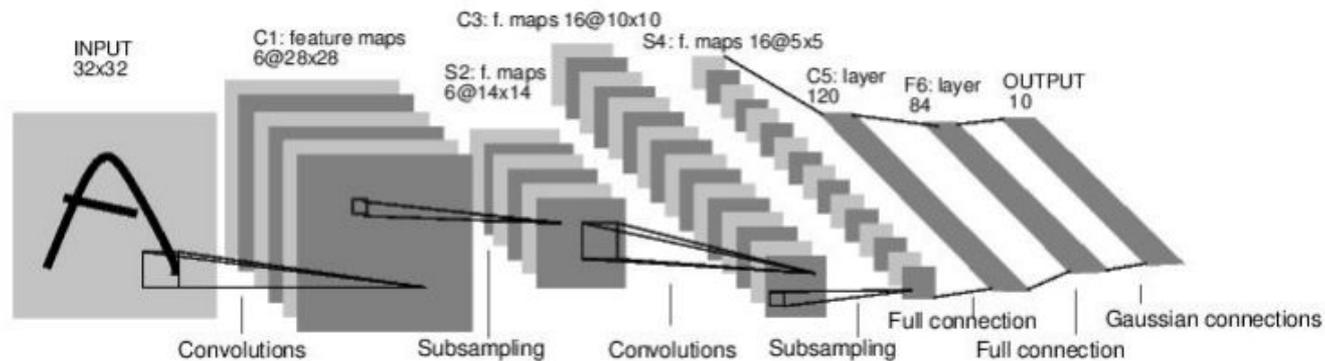
padding = 1, stride = 1

padding = 2, stride = 1

$$W_{out} = \frac{W - F + 2P}{S} + 1$$

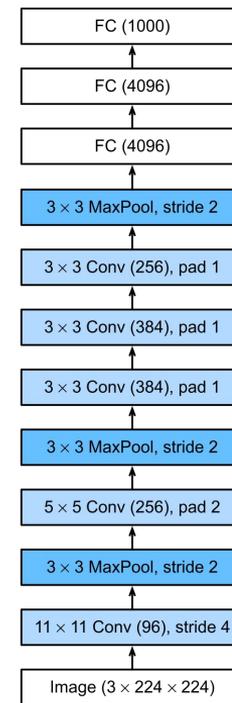
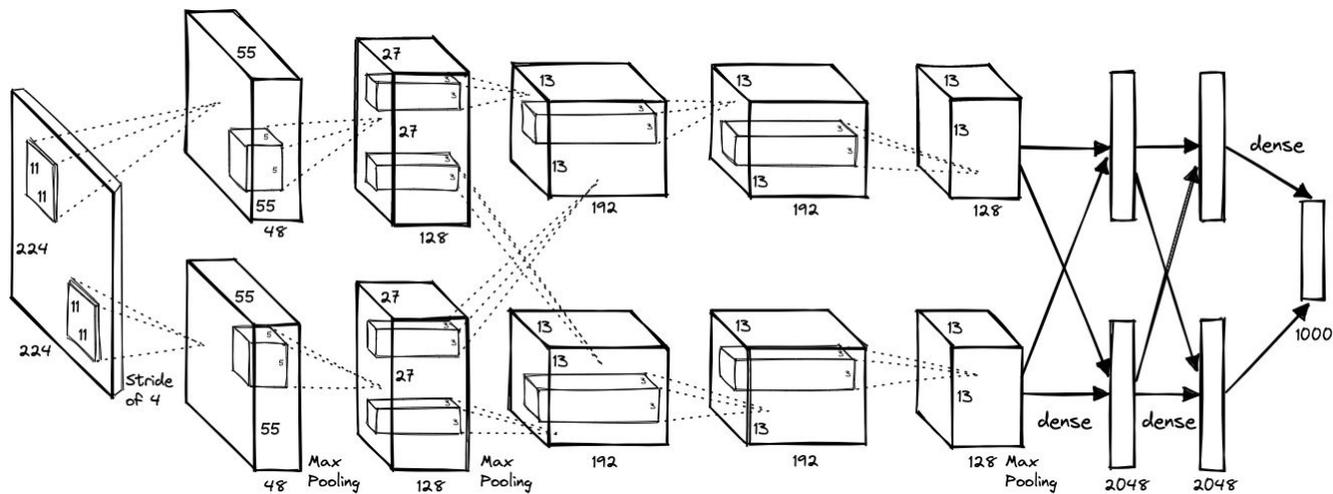
Animation from [Hochschule der Medien](https://www.hochschule-der-medien.de/)

Put Everything Together for Images



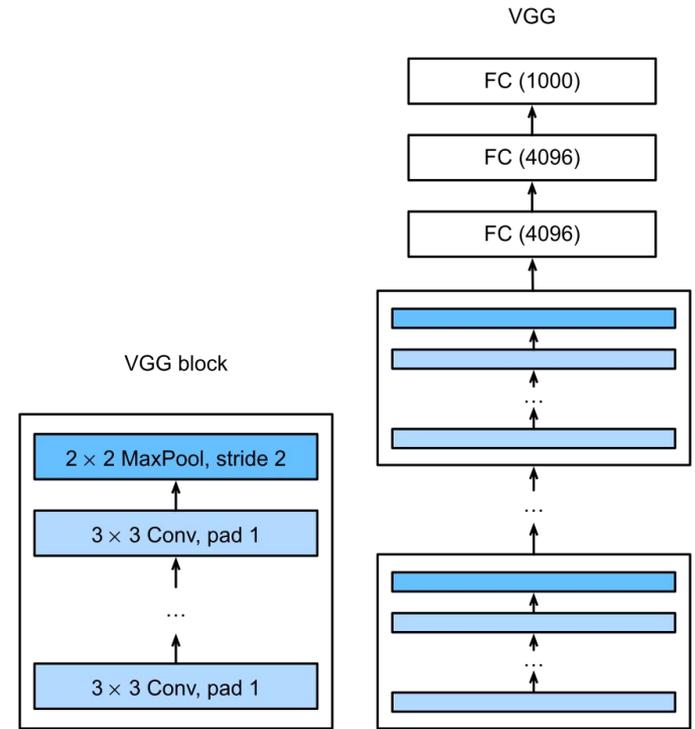
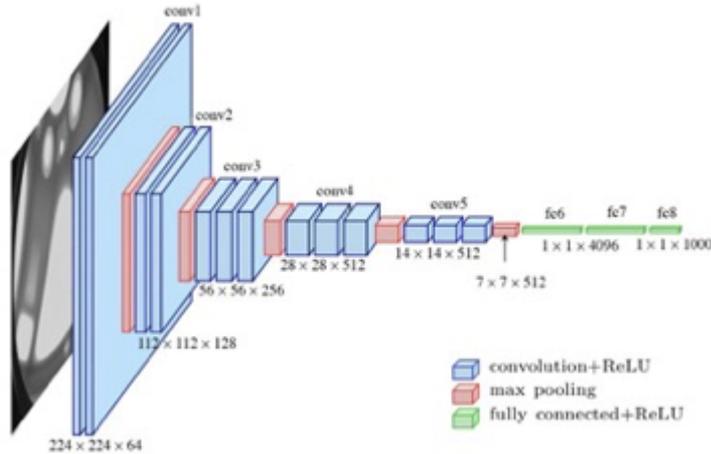
[LeNet-5, LeCun 1980]

AlexNet (2012)



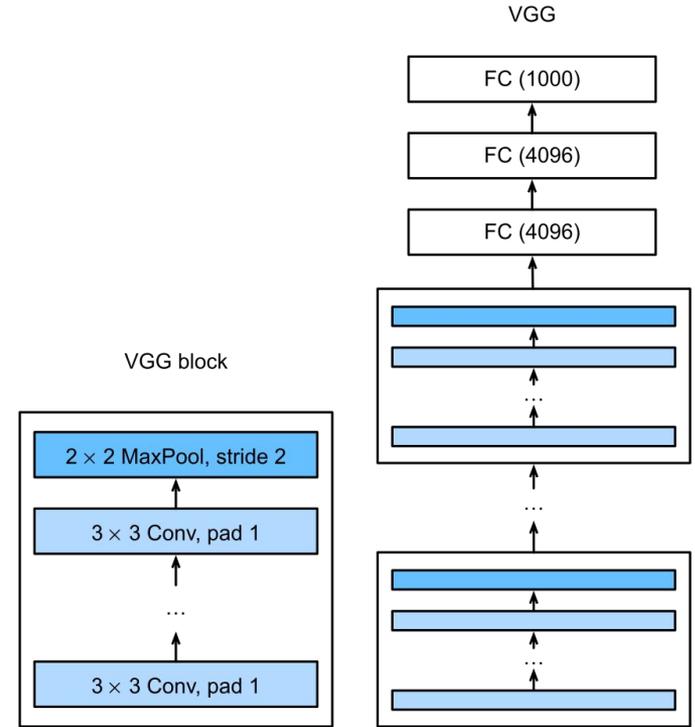
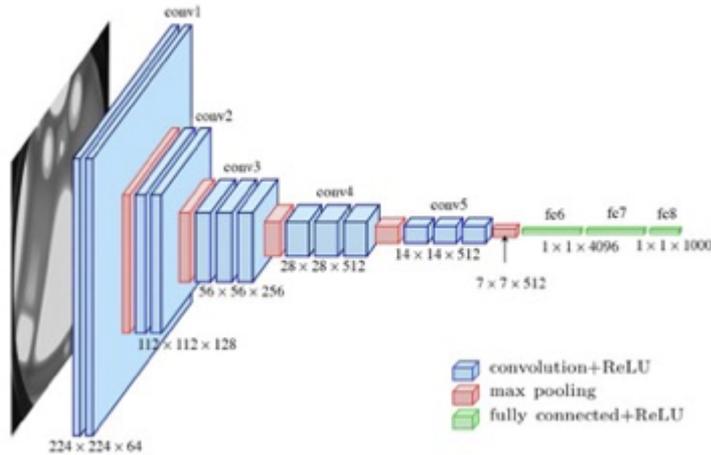
VGGNet (2014)

- Very Deep CNN
- With only 3*3 conv filters
 - Fewer parameters, deeper nonlinear layers



VGGNet (2014)

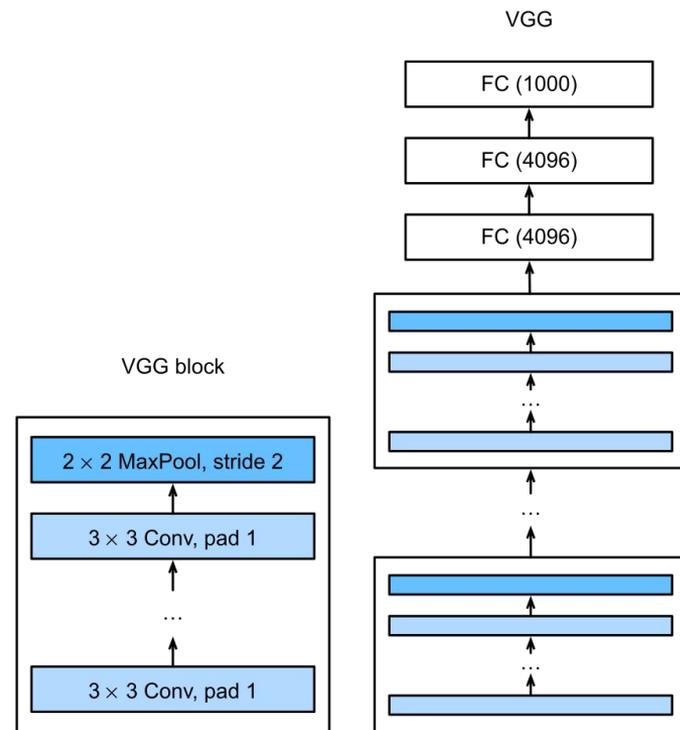
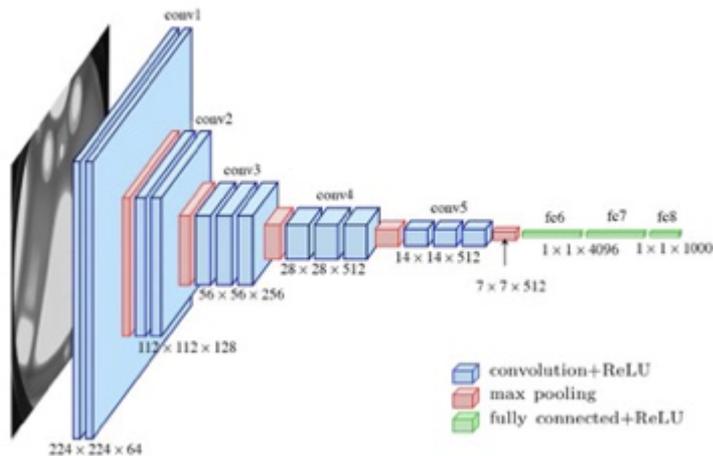
- Very Deep CNN
- With only 3*3 conv filters
 - Fewer parameters, deeper nonlinear layers



Keep increasing the depth?

VGGNet (2014)

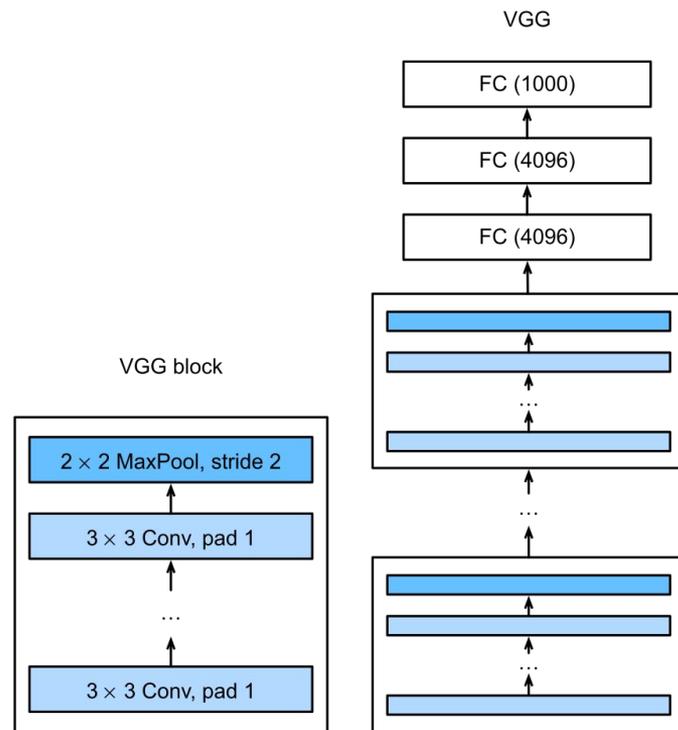
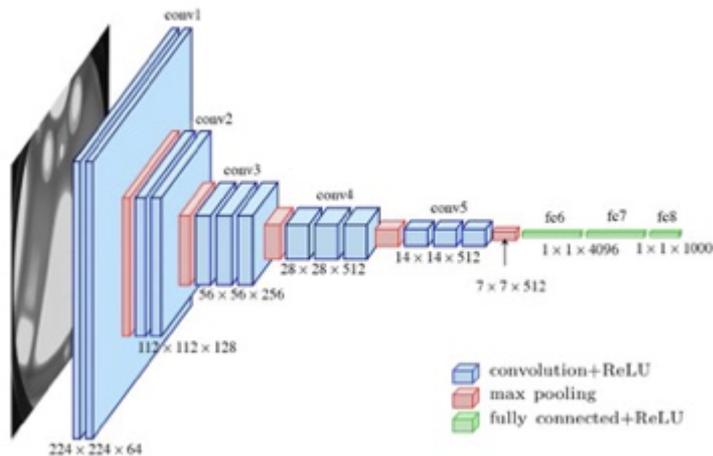
- Very Deep CNN
- With only 3*3 conv filters
 - Fewer parameters, deeper nonlinear layers



vanishing or exploding

VGGNet (2014)

- Very Deep CNN
- With only 3*3 conv filters
 - Fewer parameters, deeper nonlinear layers

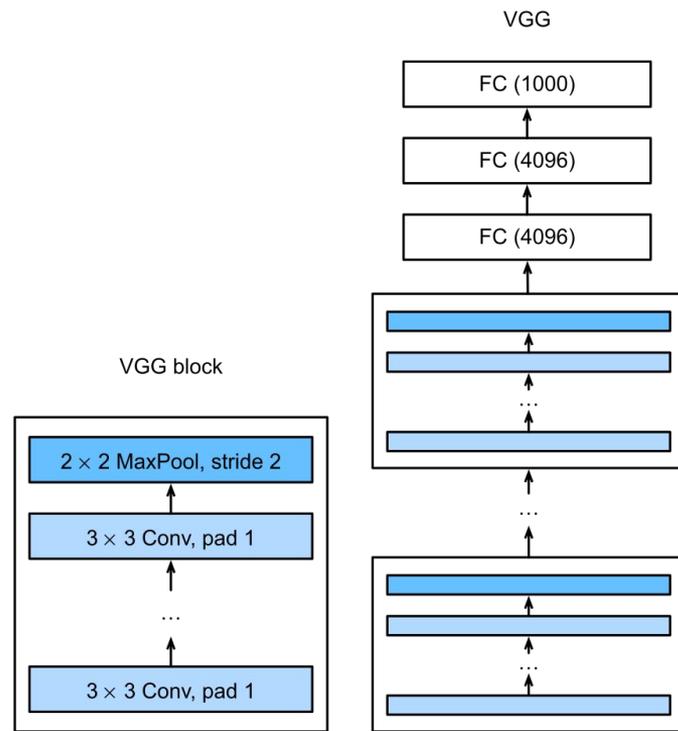
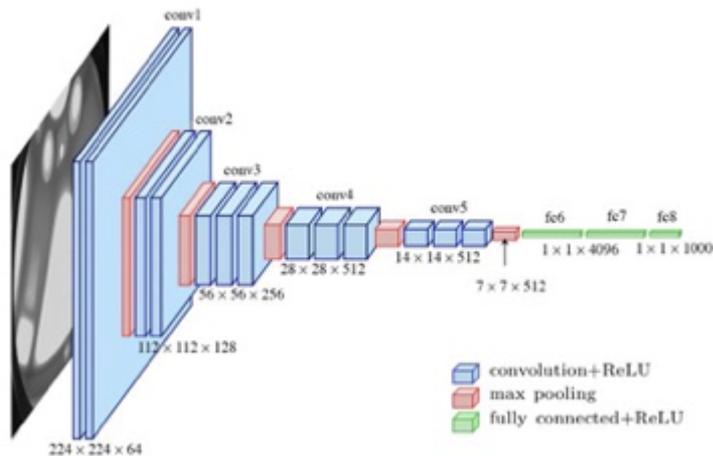


vanishing or exploding

$$\frac{\partial L}{\partial w_i} = \frac{\partial L}{\partial a_n} \cdot \frac{\partial a_n}{\partial a_{n-1}} \cdot \frac{\partial a_{n-1}}{\partial a_{n-2}} \cdot \dots \cdot \frac{\partial a_{i+1}}{\partial a_i} \cdot \frac{\partial a_i}{\partial w_i}$$

VGGNet (2014)

- Very Deep CNN
- With only 3*3 conv filters
 - Fewer parameters, deeper nonlinear layers

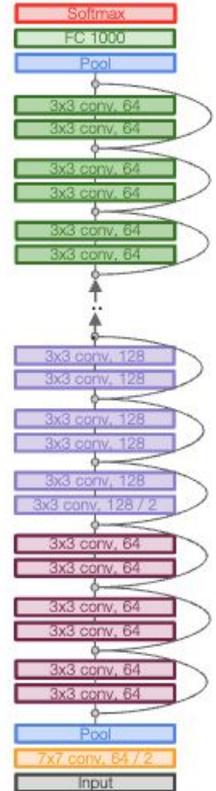
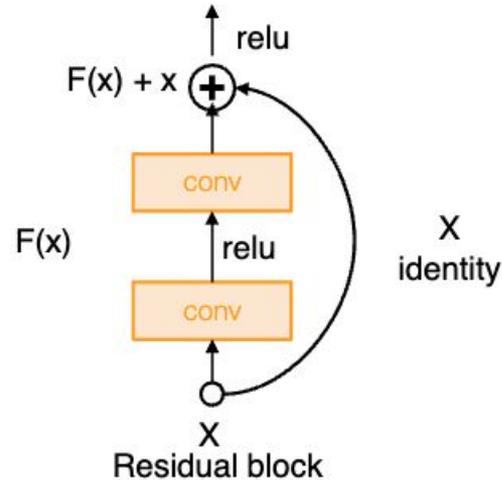


vanishing or exploding

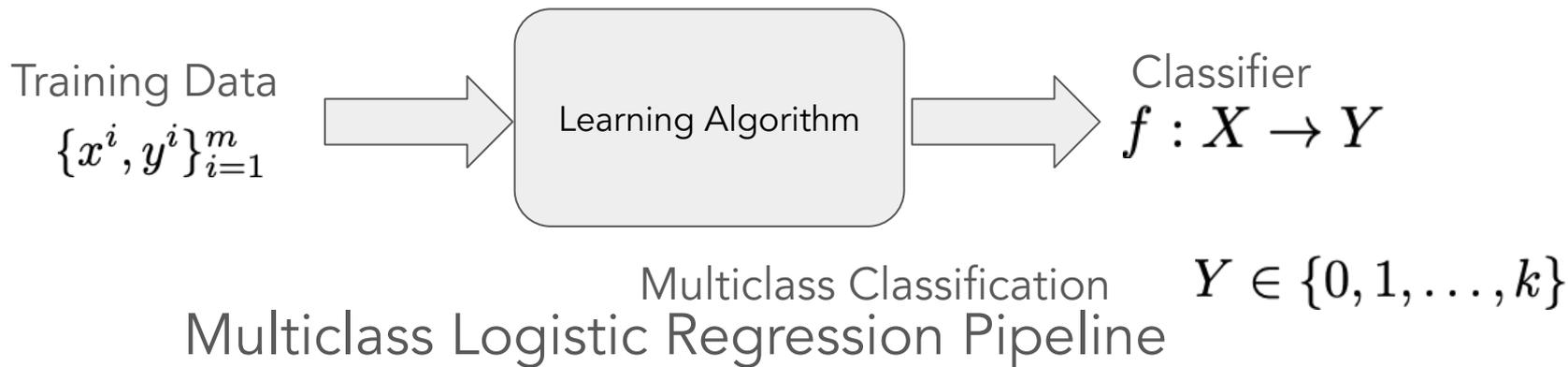
$$\frac{\partial L}{\partial w_i} = \frac{\partial L}{\partial a_n} \cdot \frac{\partial a_n}{\partial a_{n-1}} \cdot \frac{\partial a_{n-1}}{\partial a_{n-2}} \cdot \dots \cdot \frac{\partial a_{i+1}}{\partial a_i} \cdot \frac{\partial a_i}{\partial w_i} \quad \frac{\partial L}{\partial w_i} = \frac{\partial L}{\partial a_n} \cdot \prod_{j=i}^n \frac{\partial a_j}{\partial a_{j-1}}$$

ResNet (2015)

- Very Deep CNN with residual connections
 - **152-layer** model for ImageNet
 - ILSVRC'15 classification winner (3.57% top 5 error)
 - Swept all classification and detection competitions in ILSVRC'15 and COCO'15!



Multiclass Logistic Regression Algorithms



1. Build probabilistic models:
Categorical Distribution + Conv NN
2. Derive loss function: MLE and MAP
3. Select optimizer: (Stochastic) Gradient Descent

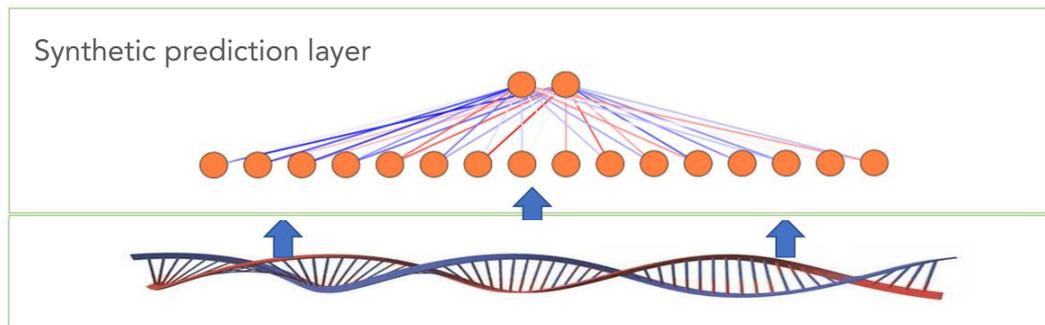
Sequence Prediction



texts[0]

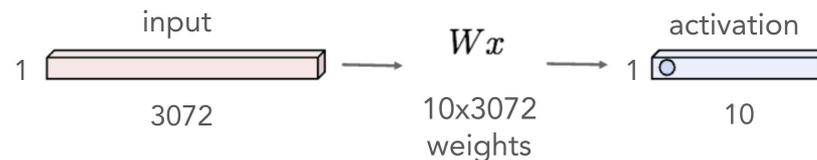
For a movie that gets no respect there sure are a lot of memorable quotes listed for this gem. Imagine a movie where Joe Piscopo is actually funny! Maureen Stapleton is a scene stealer. The Moroni character is an absolute scream. Watch for Alan "The Skipper" Hale jr. as a police Sgt.

Sequence Prediction

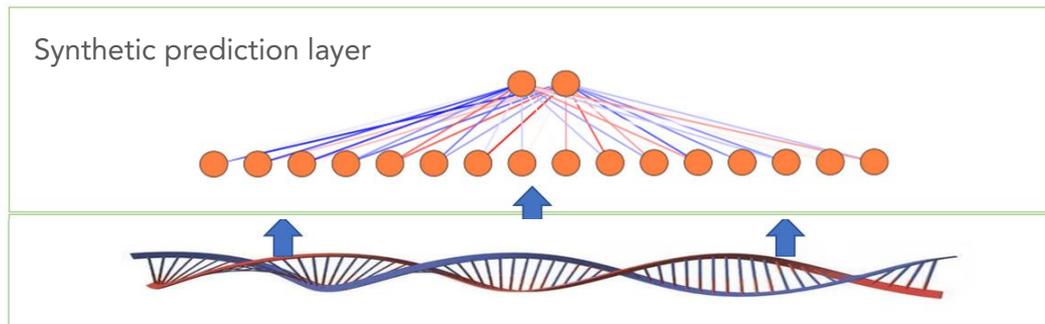


texts[0]

For a movie that gets no respect there sure are a lot of memorable quotes listed for this gem. Imagine a movie where Joe Piscopo is actually funny! Maureen Stapleton is a scene stealer. The Moroni character is an absolute scream. Watch for Alan "The Skipper" Hale jr. as a police Sgt.

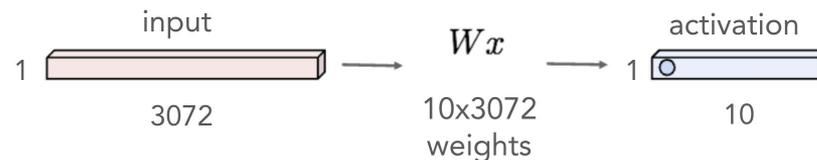


Sequence Prediction



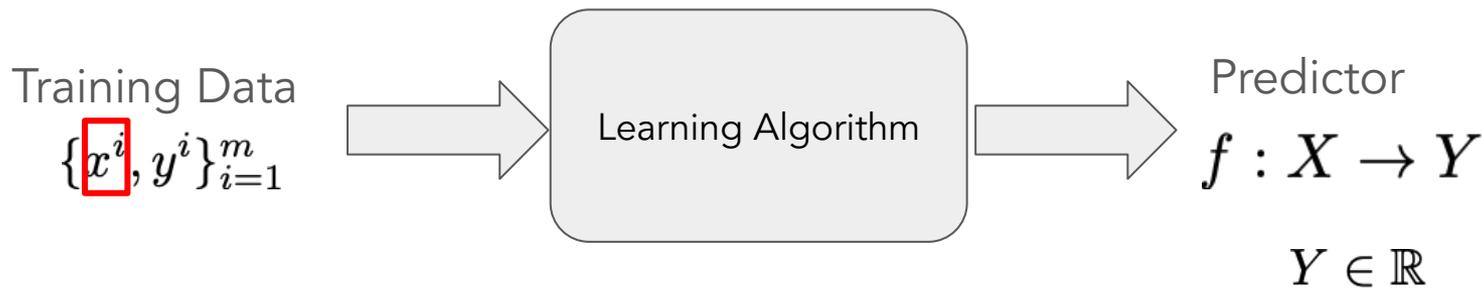
I saw the movie with two grown children. Although it was not as clever as Shrek, I thought it was rather good. In a movie theatre surrounded by children who were on spring break, there was not a sound so I know the children all liked it. There parents also seemed engaged. The death and apparent death of characters brought about the appropriate gasps and comments. Hopefully people realize this movie was made for kids.

For a movie that gets no respect there sure are a lot of memorable quotes listed for this gem. Imagine a movie where Joe Piscopo is actually funny! Maureen Stapleton is a scene stealer. The Moroni character is an absolute scream. Watch for Alan "The Skipper" Hale jr. as a police Sgt.



What if the length of sequences varies?

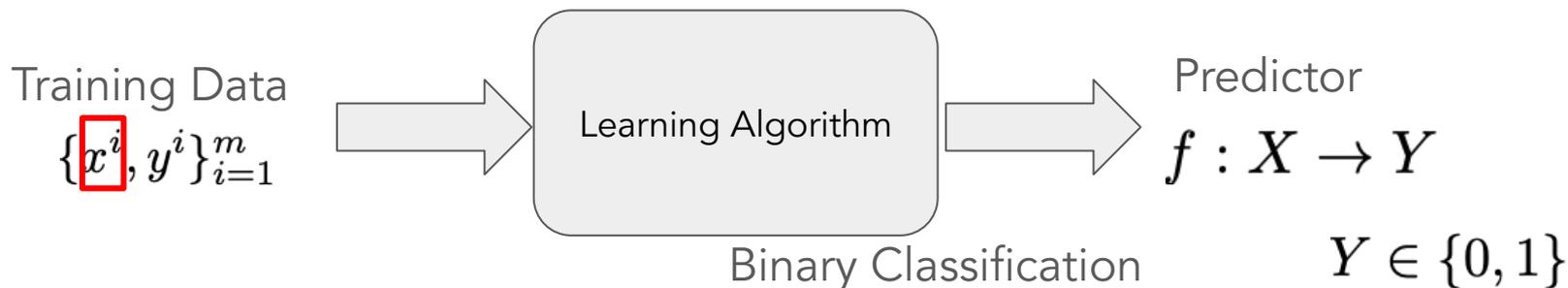
Sequential Regression Algorithms



Linear Regression Pipeline

1. Build probabilistic models:
Gaussian Distribution + RNN
2. Derive loss function: MLE and MAP
3. Select optimizer: (Stochastic) Gradient Descent

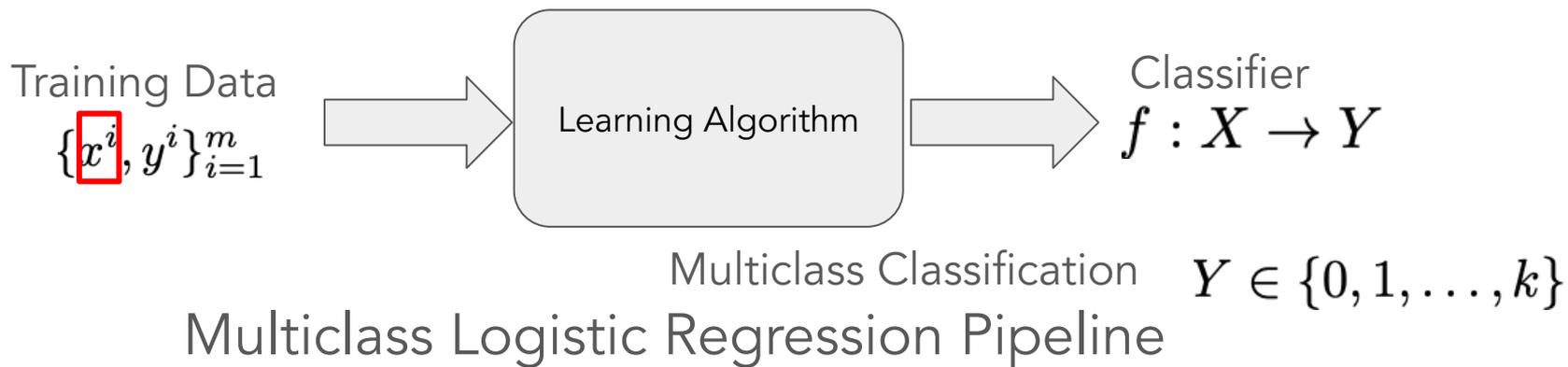
Sequential Binary Classification Algorithms



Binary Logistic Regression Pipeline

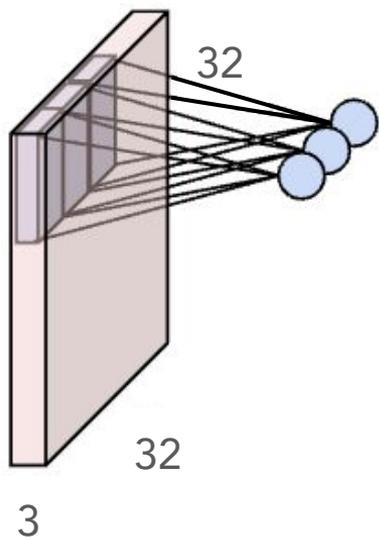
1. Build probabilistic models:
Bernoulli Distribution + RNN
2. Derive loss function: MLE and MAP
3. Select optimizer: (Stochastic) Gradient Descent

Sequential Multiclass Logistic Regression Algorithms



1. Build probabilistic models:
Categorical Distribution + RNN
2. Derive loss function: MLE and MAP
3. Select optimizer: (Stochastic) Gradient Descent

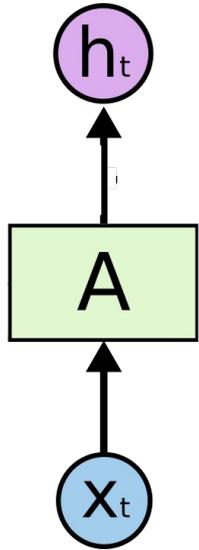
Inspiration from Convolution Layer



one computation cell is shared



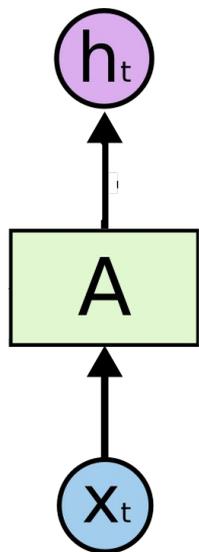
Recurrent Neural Network



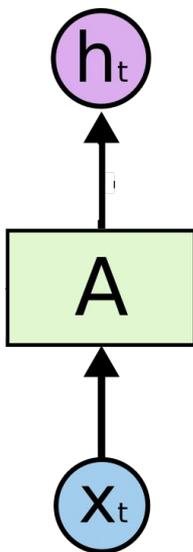
For

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Recurrent Neural Network



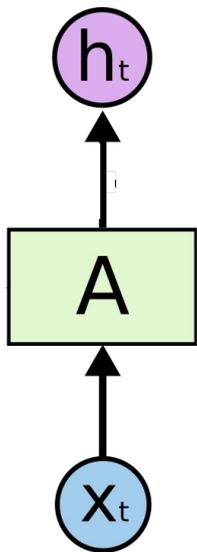
For



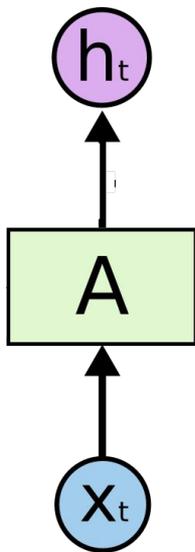
a

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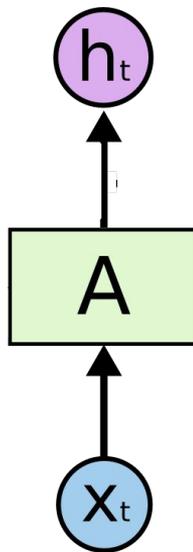
Recurrent Neural Network



For



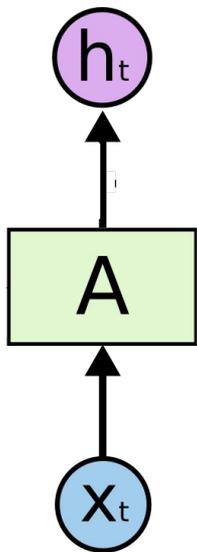
a



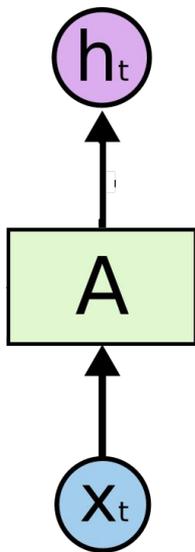
movie

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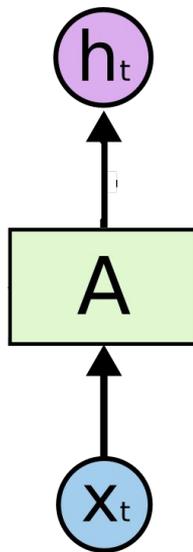
Recurrent Neural Network



For



a

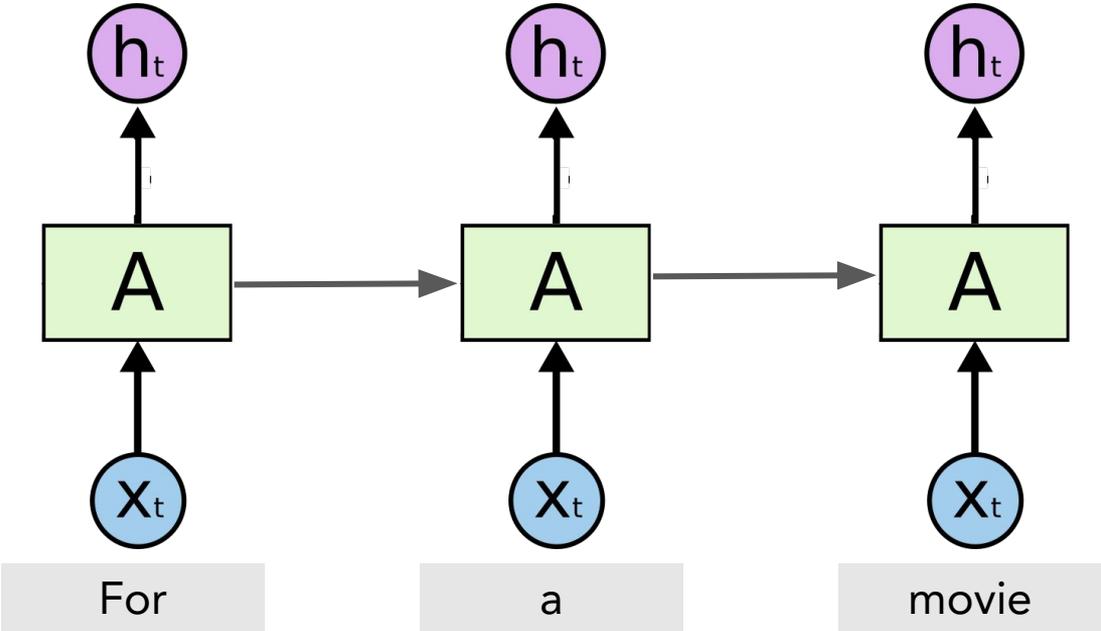


movie

Order Matters!

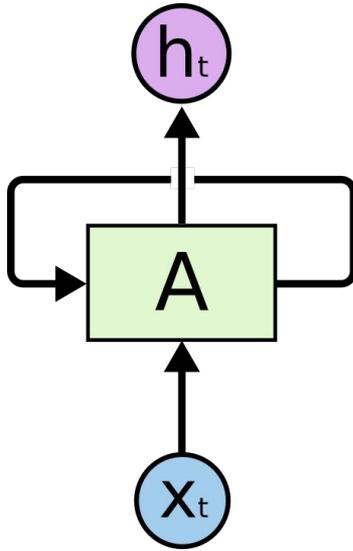
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Recurrent Neural Network



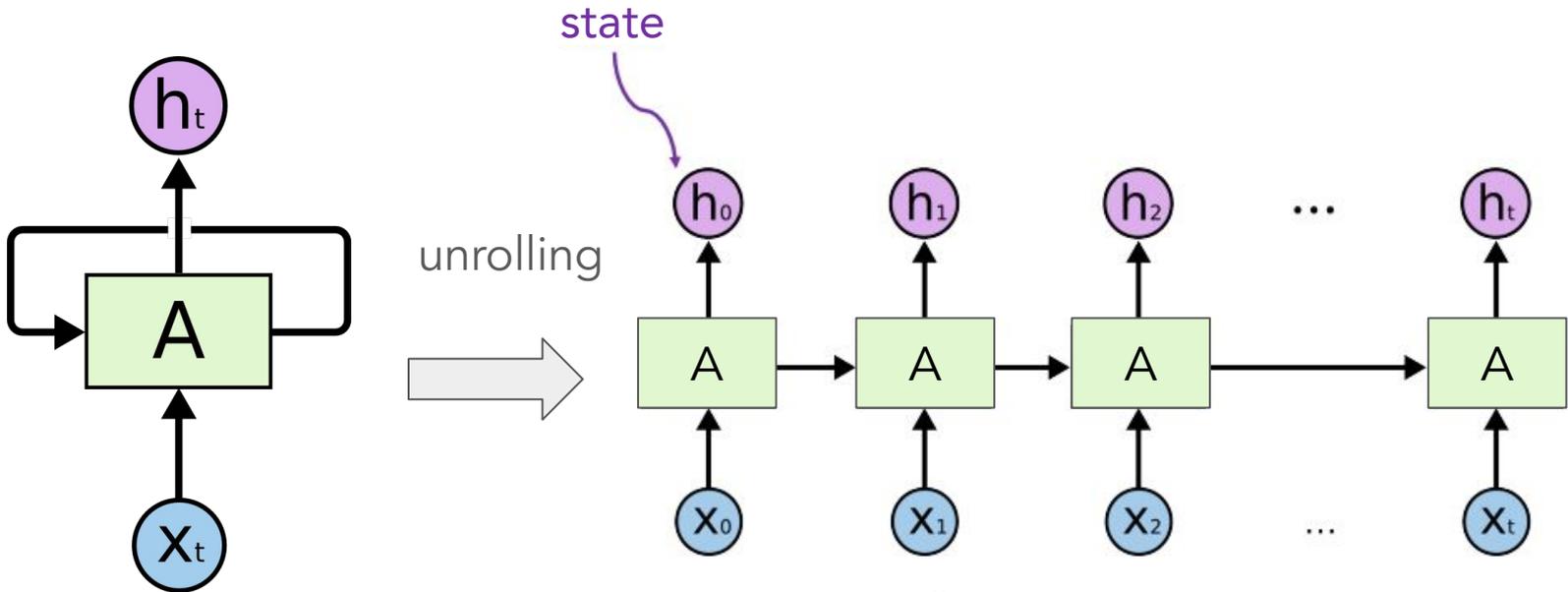
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Recurrent Neural Network



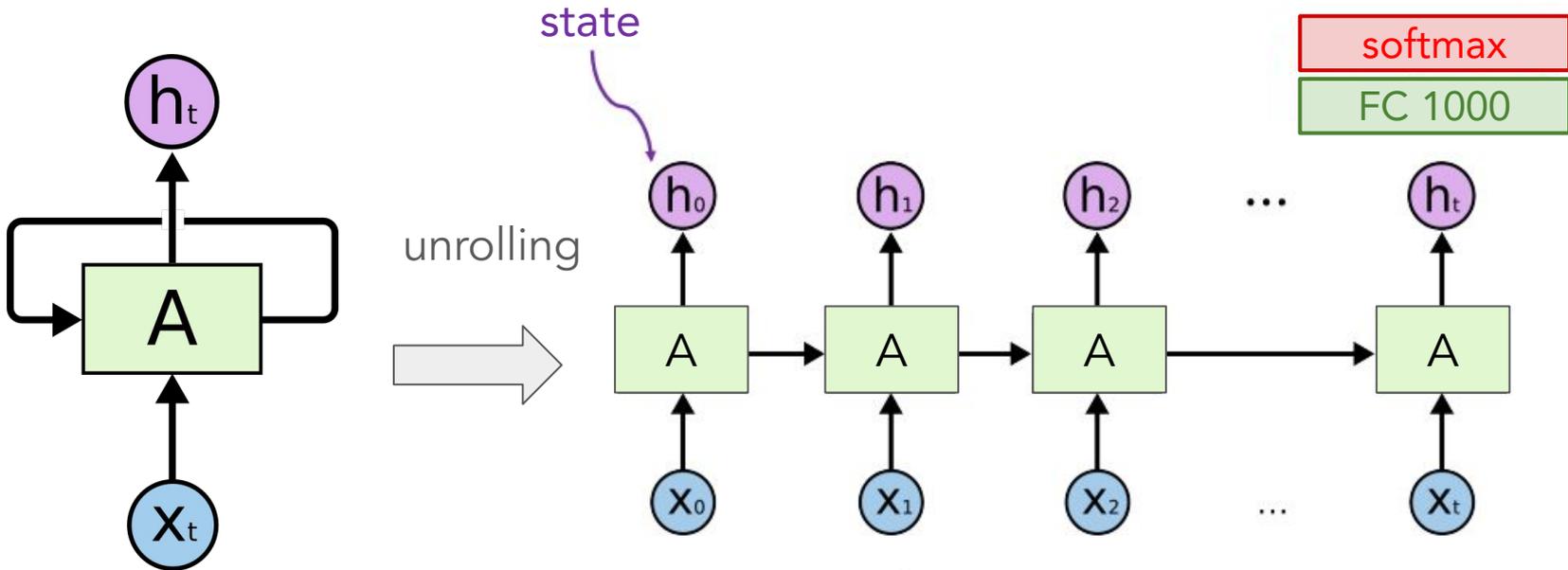
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Recurrent Neural Network



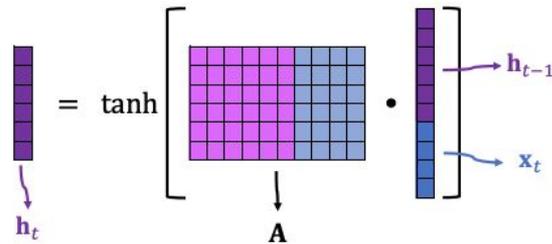
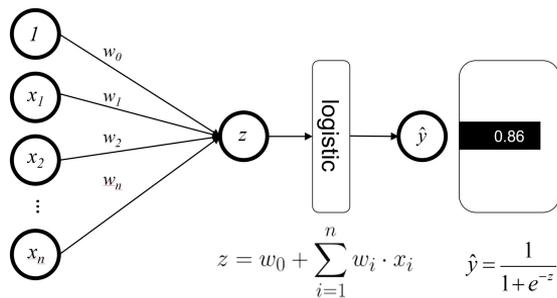
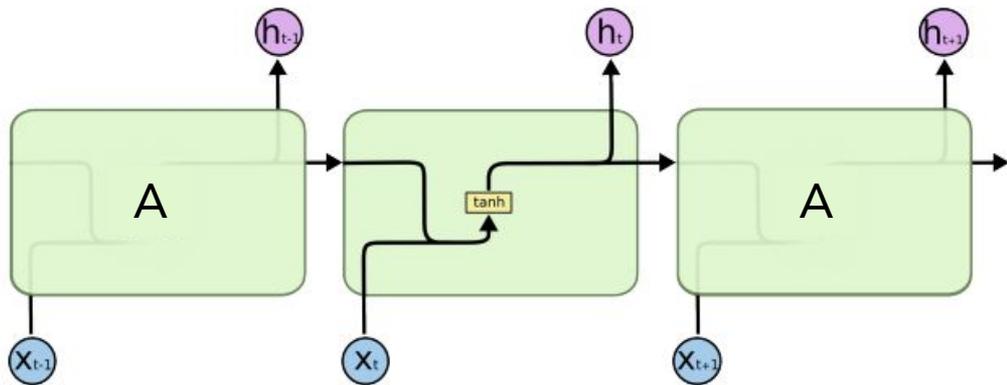
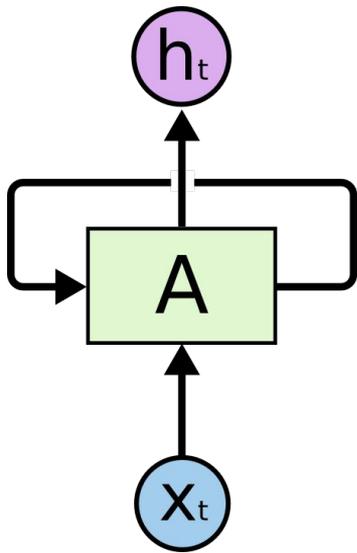
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Recurrent Neural Network

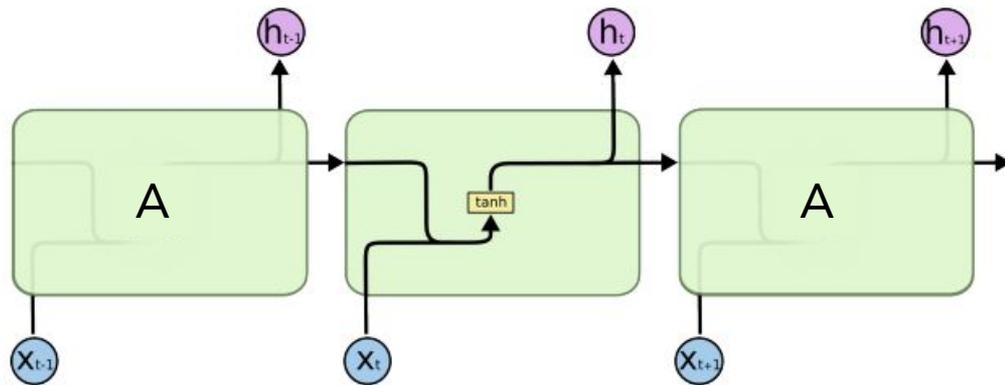
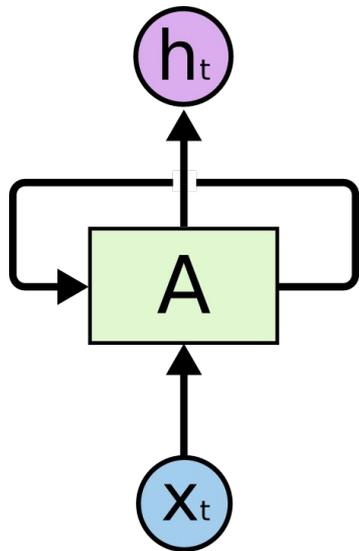


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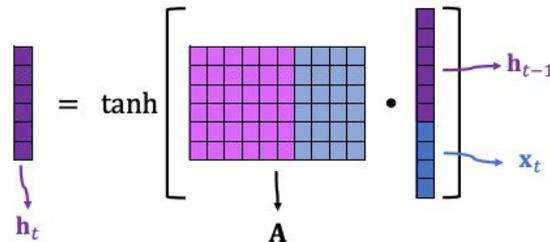
Simple RNN Cell



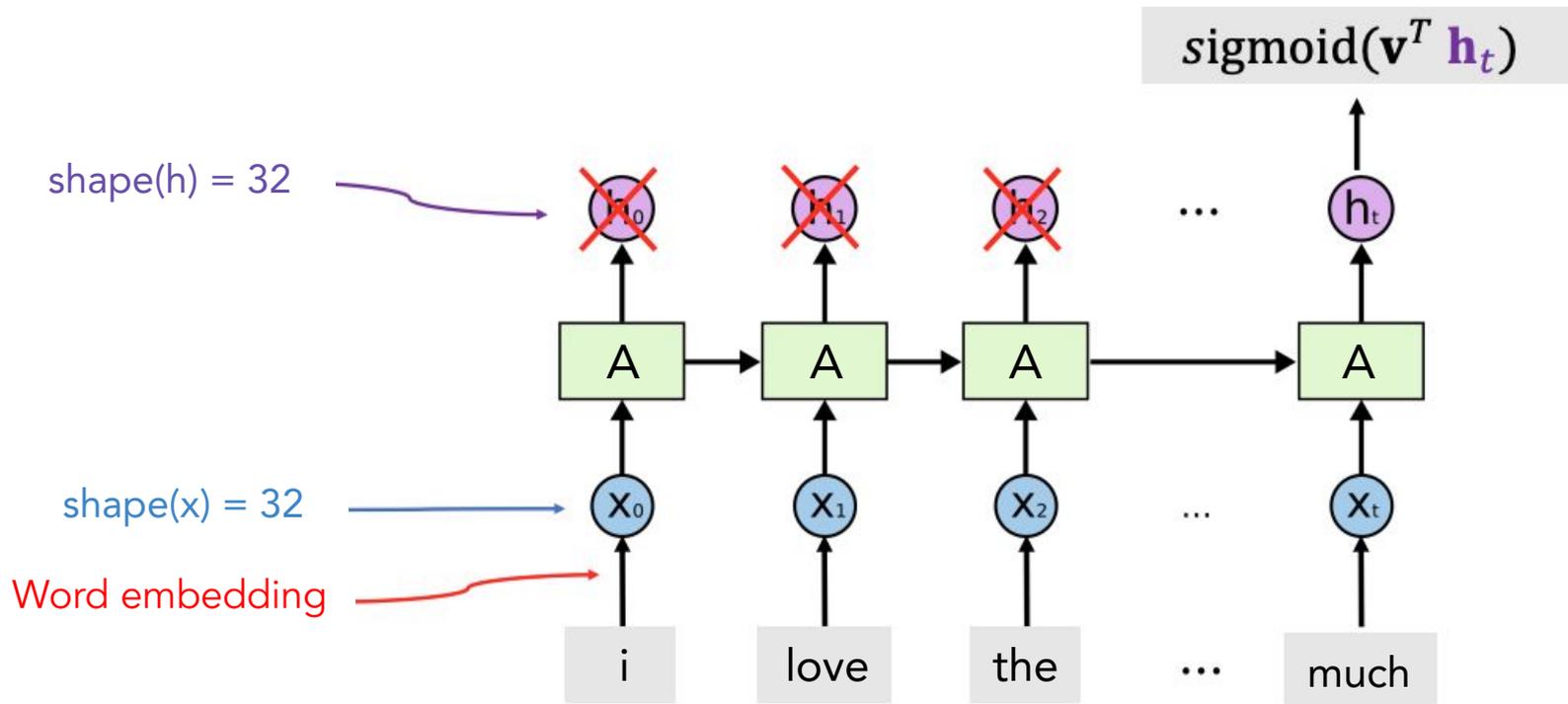
Simple RNN Cell



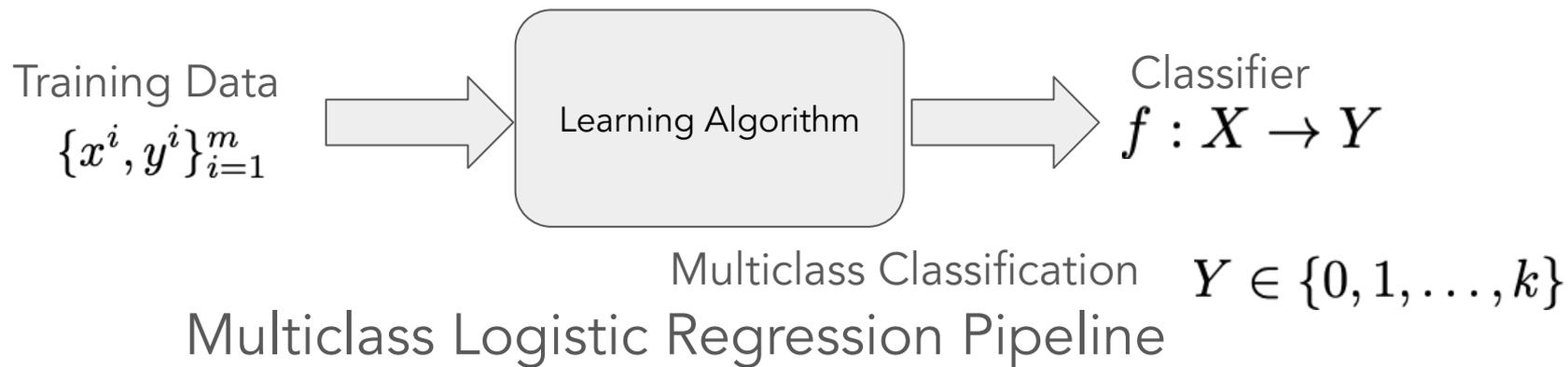
Binary step		$\begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{if } x \geq 0 \end{cases}$
Logistic, sigmoid, or soft step		$\sigma(x) \doteq \frac{1}{1 + e^{-x}}$
Hyperbolic tangent (tanh)		$\tanh(x) \doteq \frac{e^x - e^{-x}}{e^x + e^{-x}}$
Rectified linear unit (ReLU) ^[13]		$(x)^+ \doteq \begin{cases} 0 & \text{if } x \leq 0 \\ x & \text{if } x > 0 \end{cases} \\ = \max(0, x) = x \mathbf{1}_{x>0}$
Gaussian Error Linear Unit (GELU) ^[5]		$\frac{1}{2}x \left(1 + \operatorname{erf} \left(\frac{x}{\sqrt{2}} \right) \right)$ where erf is the gaussian error function.
Softplus ^[14]		$\ln(1 + e^x)$
Exponential linear unit (ELU) ^[15]		$\begin{cases} \alpha (e^x - 1) & \text{if } x \leq 0 \\ x & \text{if } x > 0 \end{cases}$ with parameter α



Simple RNN for IMDB Review

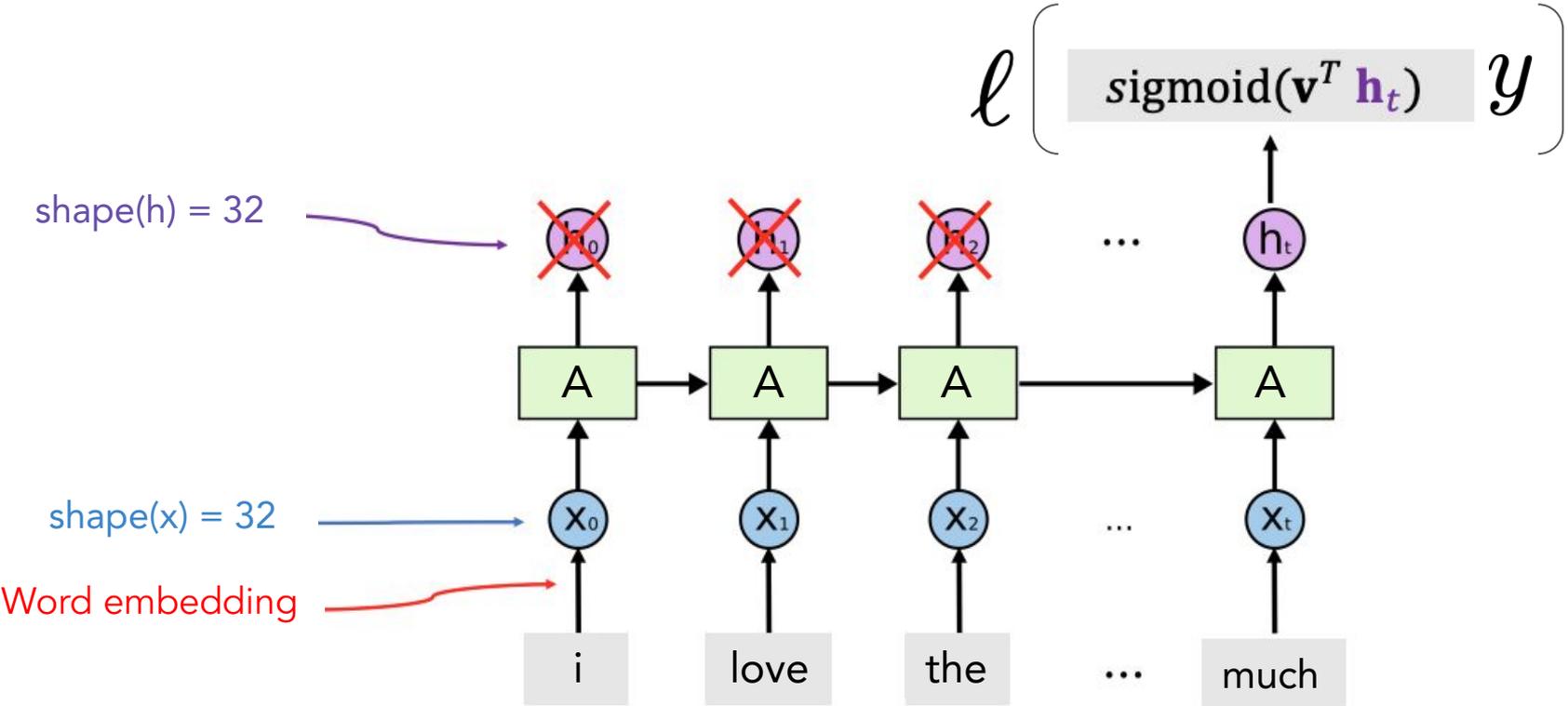


Sequential Multiclass Logistic Regression Algorithms



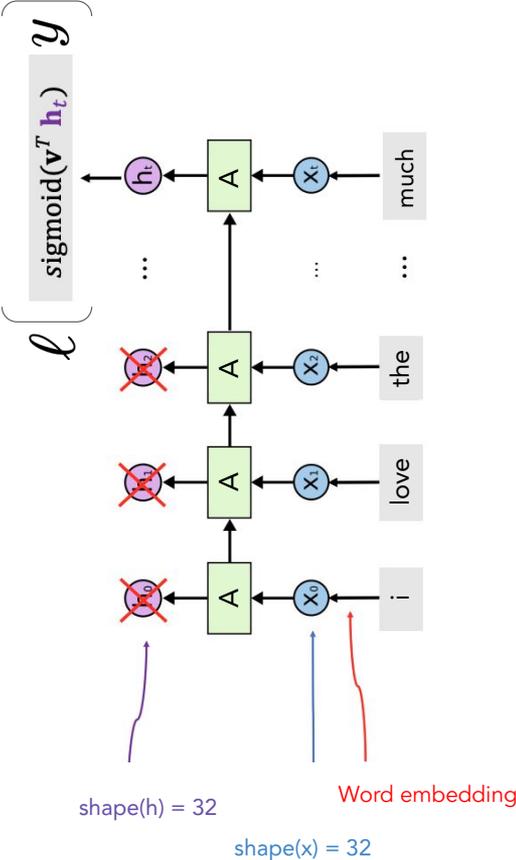
1. Build probabilistic models:
Categorical Distribution + RNN
2. Derive loss function: MLE and MAP
3. Select optimizer: (Stochastic) Gradient Descent

Backpropagation SGD



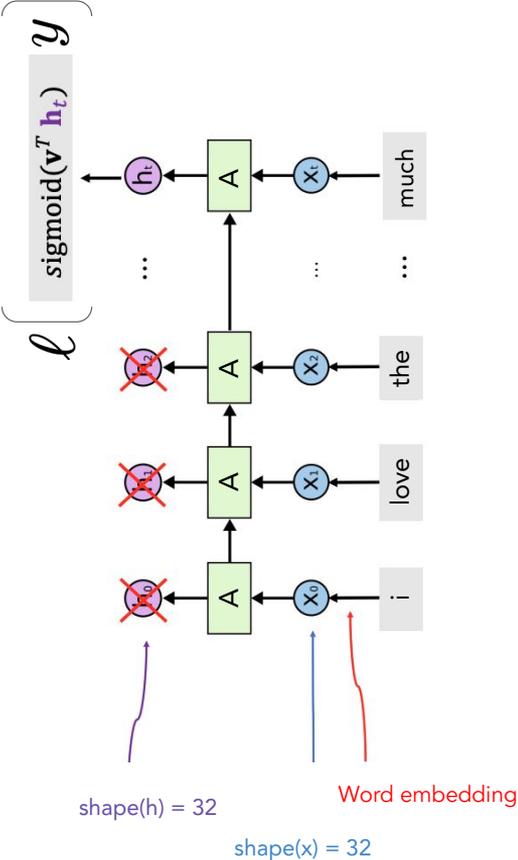
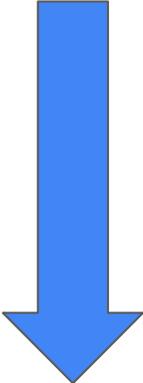
Backpropagation SGD

Layer \longleftrightarrow Time-step

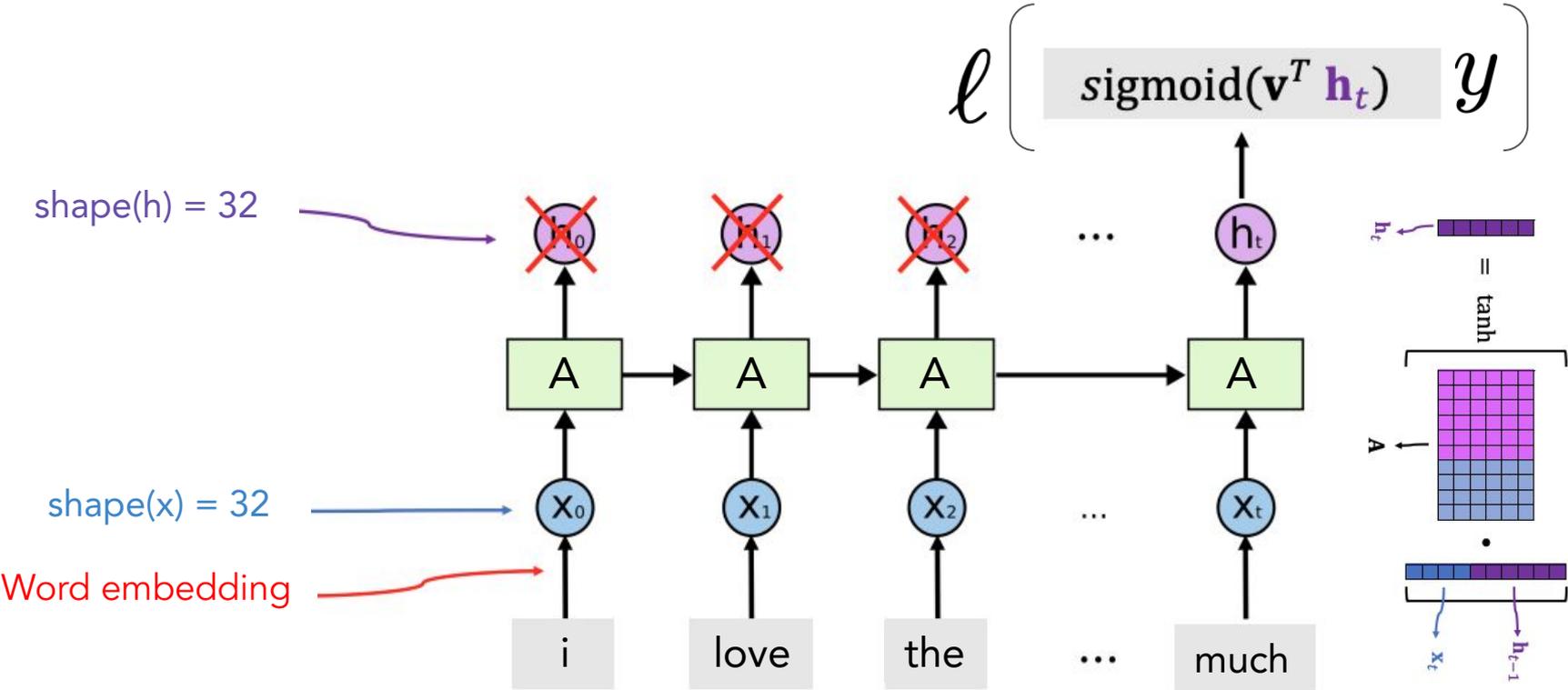


Backpropagation SGD

Backpropagation through Time (BPTT)

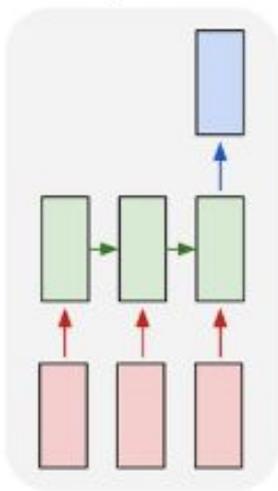


Backpropagation SGD



More Usages of RNNs

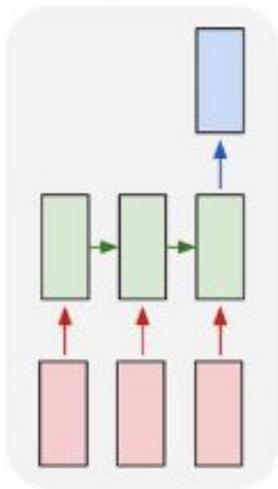
many to one



IMDB text review classification

More Usages of RNNs

many to one



one to many

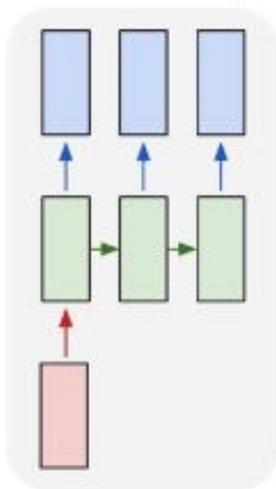
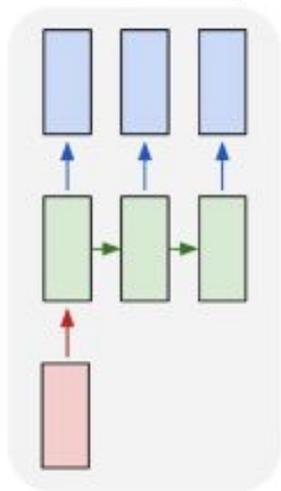


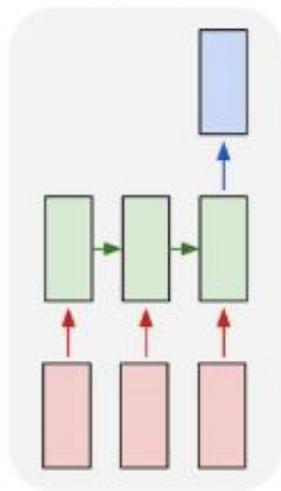
Image Captioning
image -> sequence of words

More Usages of RNNs

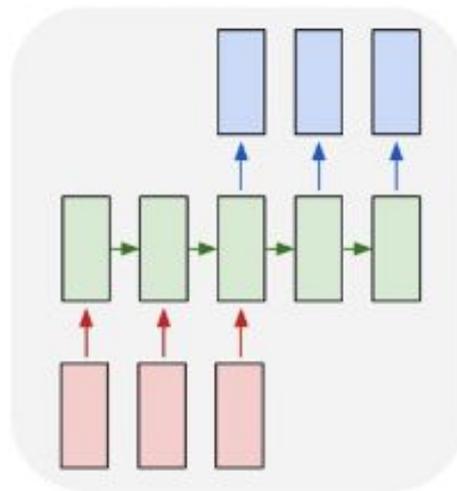
one to many



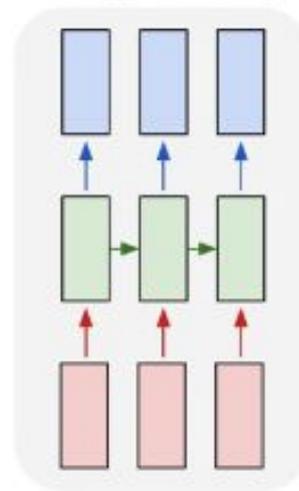
many to one



many to many

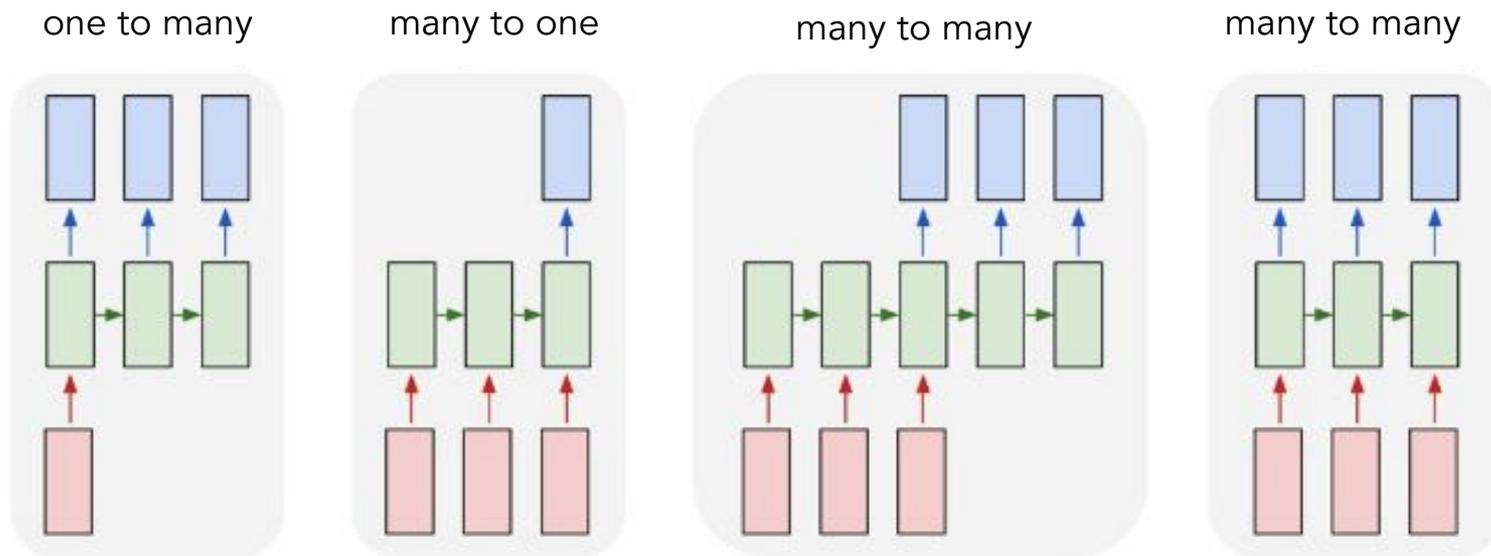


many to many



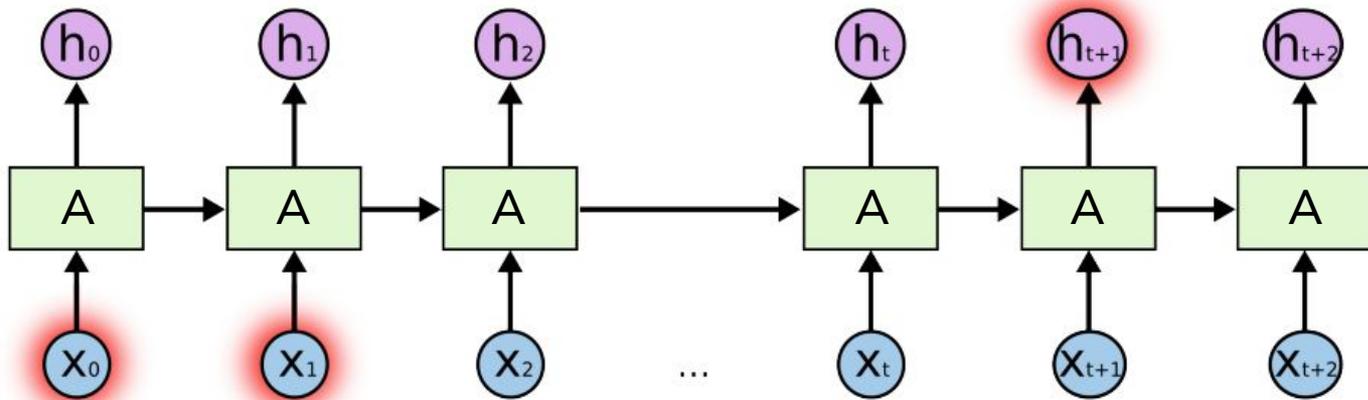
Translation

Training of RNNs



Backpropagation Through Unrolling Steps

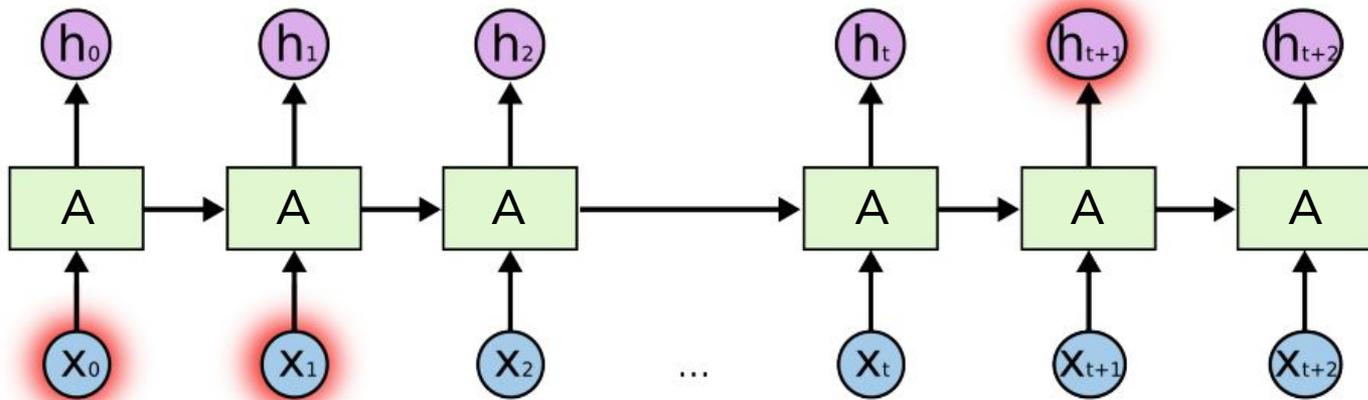
Simple RNN is not good at long-term dependence



h_{100} is almost irrelevant to x_1 : $\frac{\partial h_{100}}{\partial x_1}$ is near zero or exploding.

Gradient Vanishing Again!

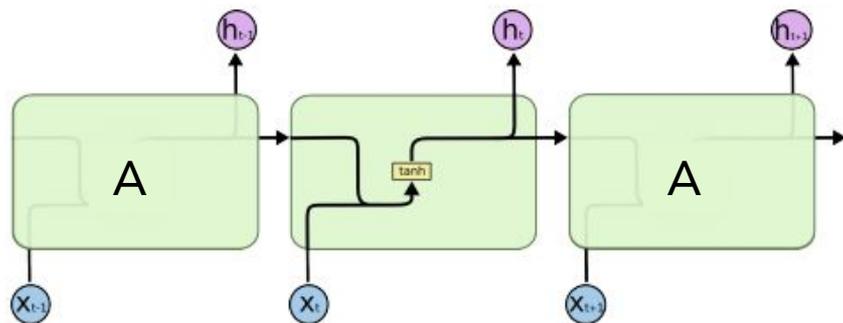
Simple RNN is not good at long-term dependence



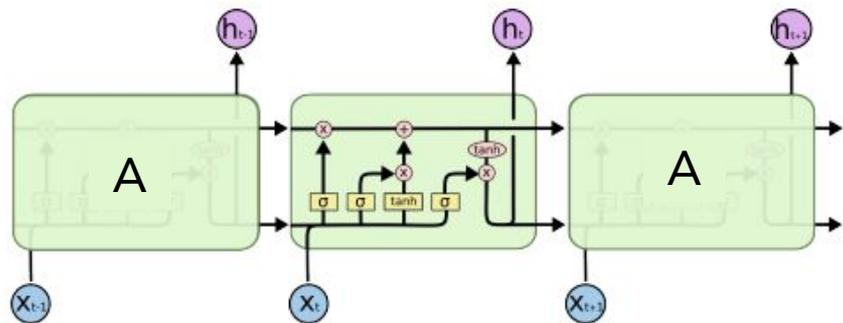
h_{100} is almost irrelevant to x_1 : $\frac{\partial h_{100}}{\partial x_1}$ is near zero or exploding.

Gradient Vanishing Again! -> ShortCut connection

Long Short Term Memory (LSTM)



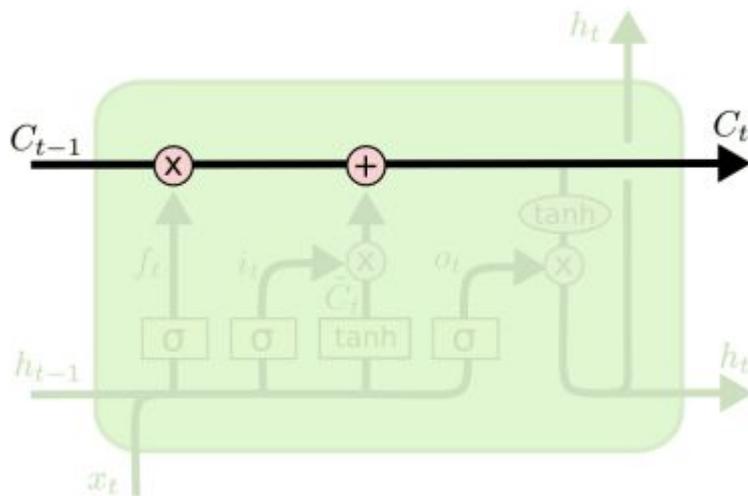
Simple RNN



LSTM

LSTM Cell: Conveyor Belt

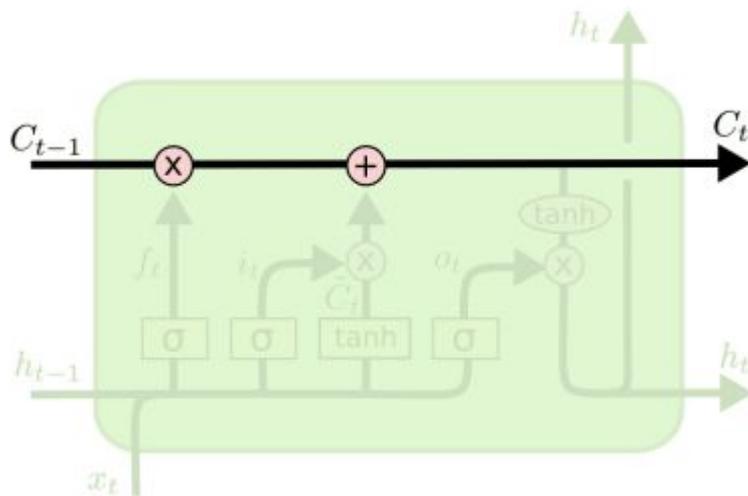
The past information directly flows to the future.



$$C_t = C_{t-1} \circ f_t + \hat{C}_t \circ i_t$$

LSTM Cell: Conveyor Belt

The past information directly flows to the future. ([ShortCut connection](#))

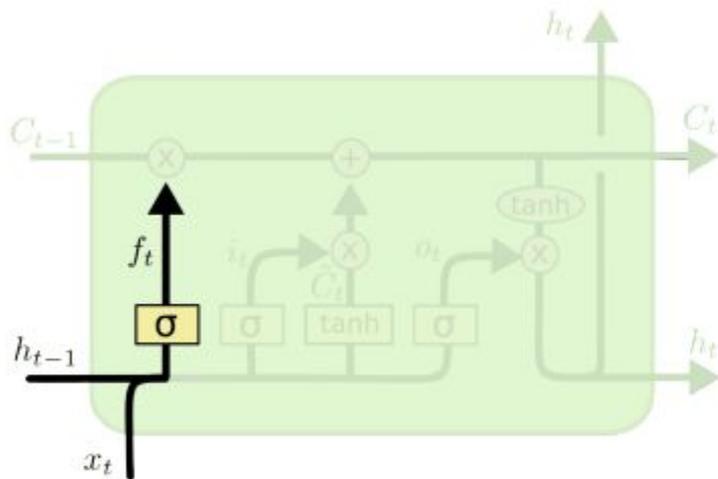


$$C_t = C_{t-1} \circ f_t + \hat{C}_t \circ i_t$$

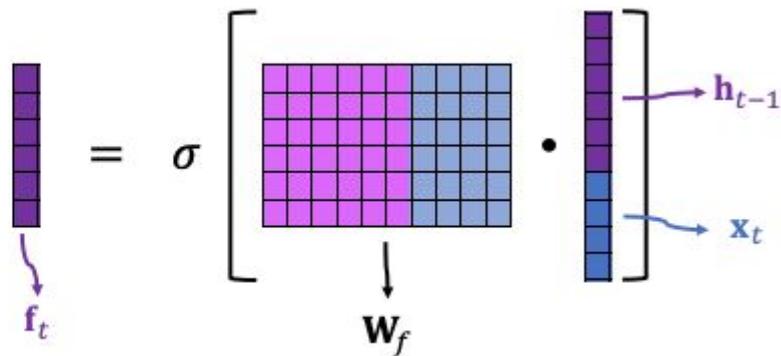
LSTM Cell: Forget Gate

A value of zero means "let *nothing* through."

A value of *one* means "let *everything* through!"



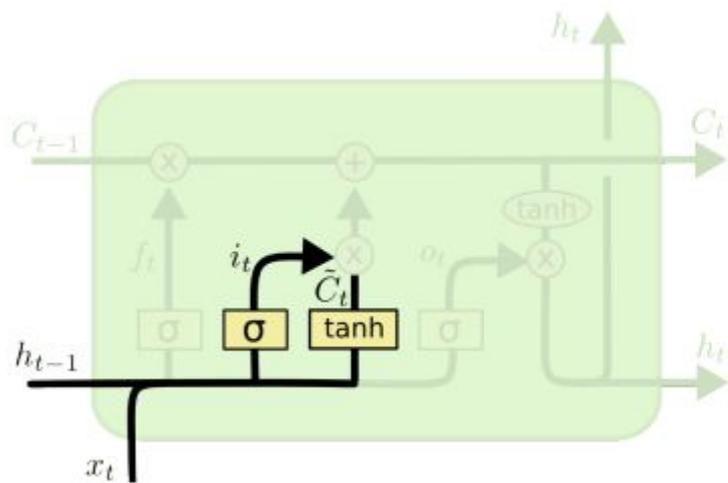
$$f_t = \sigma(W_f x_t + U_f h_{t-1})$$



$$C_t = C_{t-1} \circ f_t + \hat{C}_t \circ i_t$$

LSTM Cell: Input Gate

How much information current context provided.



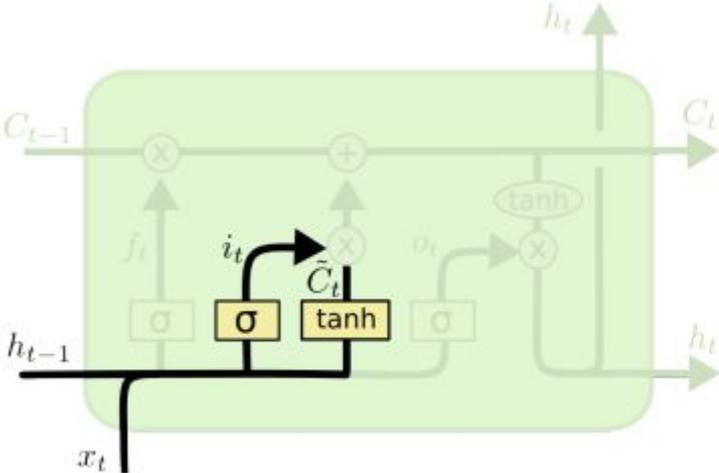
$$i_t = \sigma(W_i x_t + U_i h_{t-1})$$

The matrix representation of the input gate equation shows a vertical vector i_t (purple) equal to the sigmoid function σ applied to the product of a weight matrix W_i (a grid with a purple left half and blue right half) and a vertical vector $\begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix}$ (purple and blue). The vector $\begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix}$ is shown as a vertical stack of two vectors, with h_{t-1} in purple and x_t in blue.

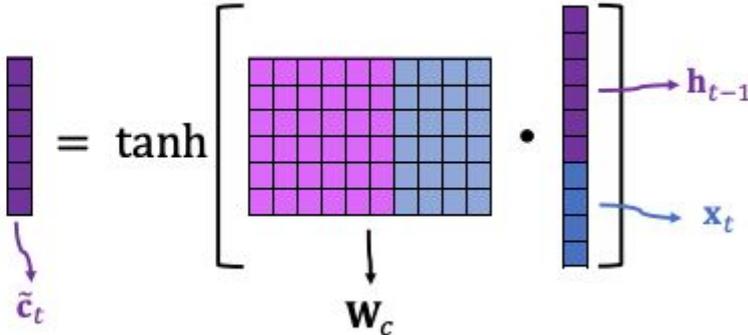
$$C_t = C_{t-1} \circ f_t + \hat{C}_t \circ i_t$$

LSTM Cell: New Value

“local” context, only up to immediately preceding state

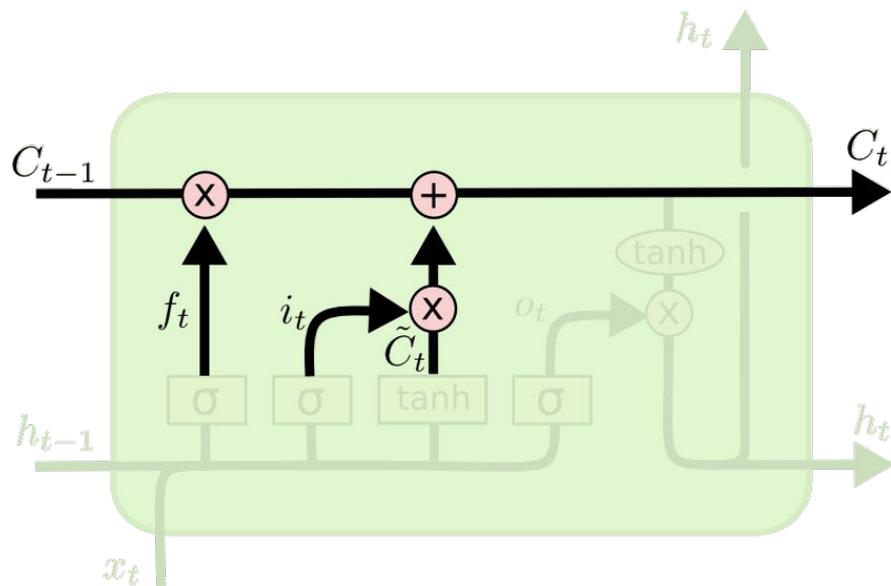


$$\hat{C}_t = \sigma(W_c x_t + U_c h_{t-1})$$



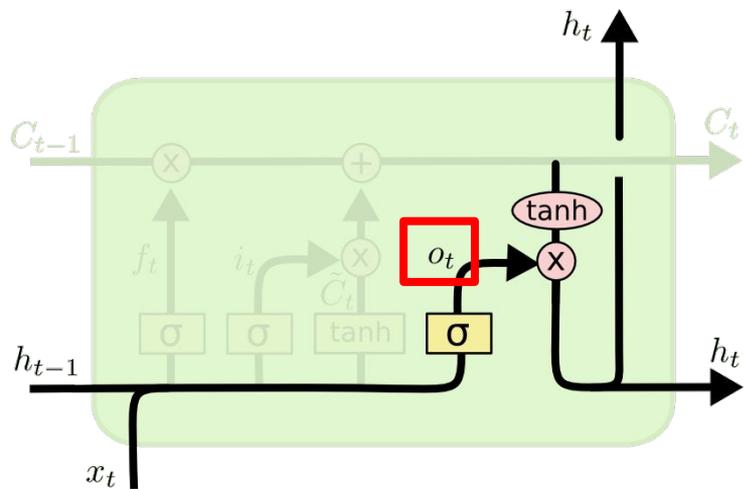
$$C_t = C_{t-1} \otimes f_t + \hat{C}_t \otimes i_t$$

LSTM Cell: Update Conveyor Belt

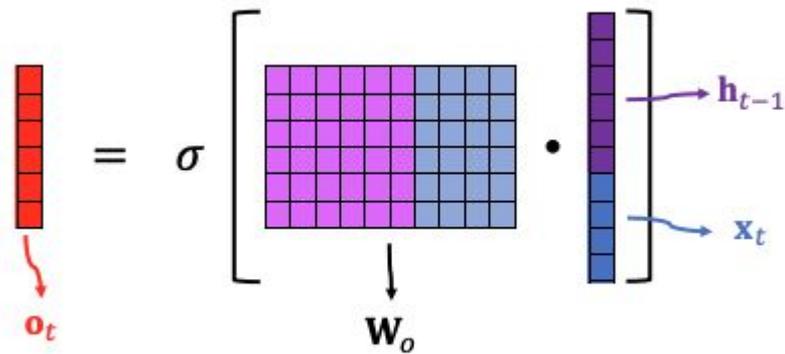


$$C_t = C_{t-1} \circ f_t + \hat{C}_t \circ i_t$$

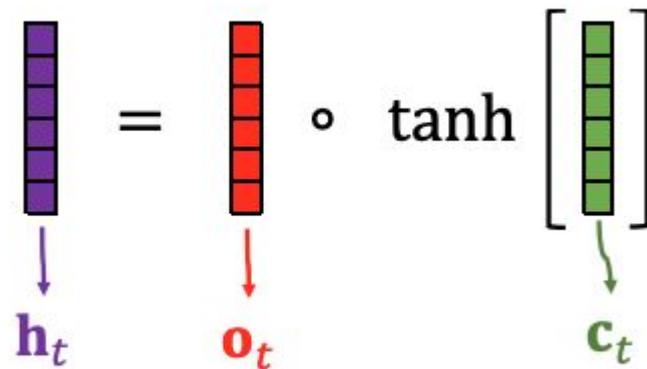
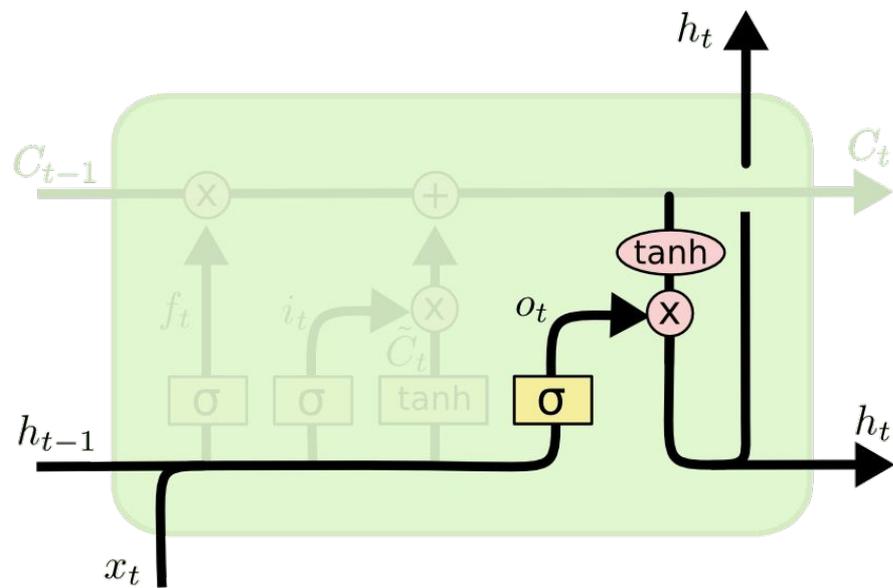
LSTM Cell: Output Gate



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

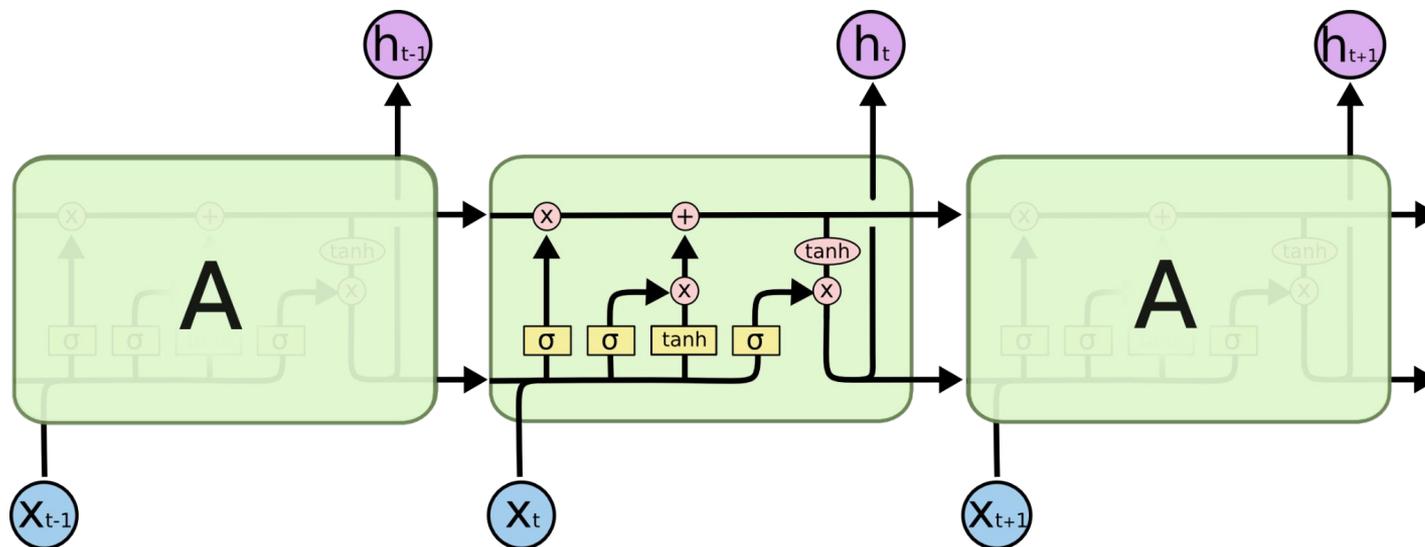


LSTM Cell: Update State



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

LSTM Cell

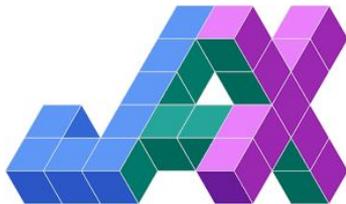


Auto-differentiation Packages

PyTorch



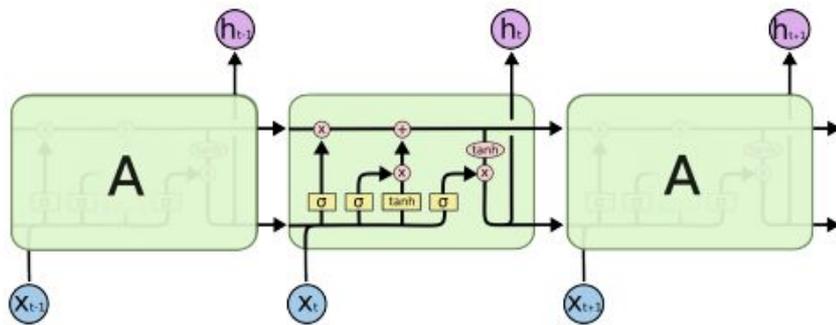
JAX



Tensorflow

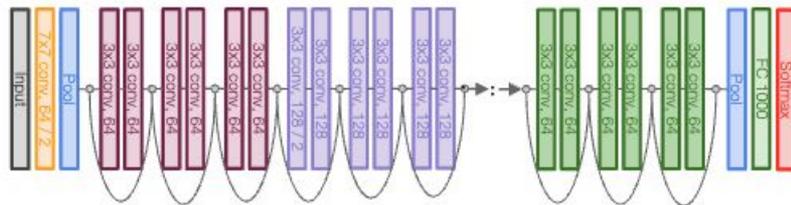


LSTM vs. ResNet



$$C_t = C_{t-1} \circ f_t + \hat{C}_t \circ i_t$$

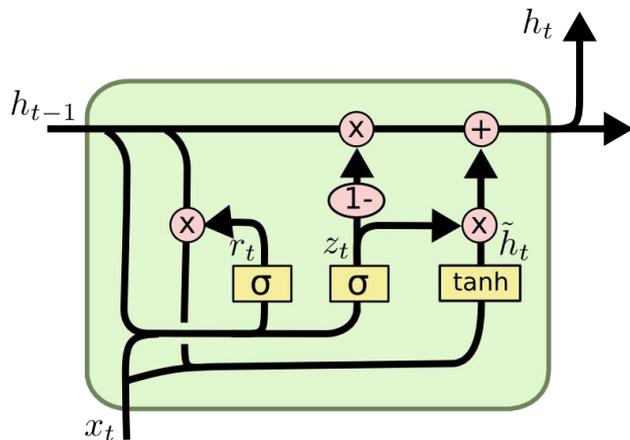
LSTM



Similar to ResNet

Other Variants of RNN

Gated Recurrent Unit



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

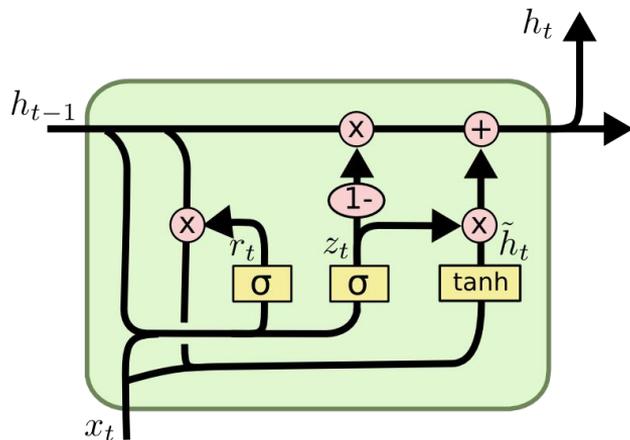
$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$

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

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

Other Variants of RNN

Gated Recurrent Unit



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- RNNs allow a lot of flexibility in architecture design
- Vanilla RNNs are simple but don't work very well
- Backward flow of gradients in RNN can explode or vanish. Exploding is controlled with gradient clipping. Vanishing is controlled with additive interactions (LSTM)

PyTorch session will be online
next Monday

Q&A