Introduction to Deep Learning in NLP

2/2565: FRA501 Introduction to Natural Language Processing with Deep learning

Week 02

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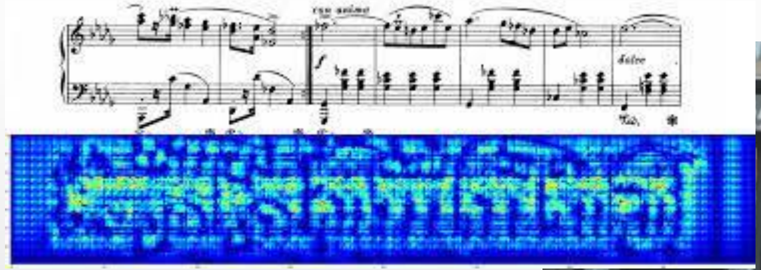
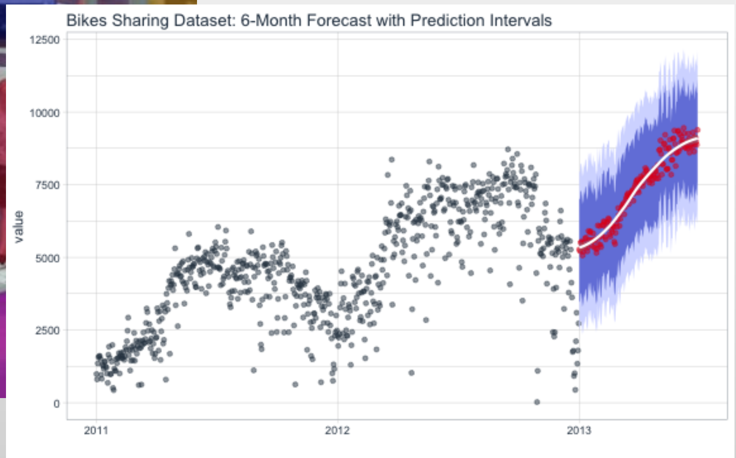
Neural Networks

Deep learning = Deep neural networks =Neural networks

Why deep learning?

- Greatly improved performance in many tasks (Computer Vision, Robotics, Time Series, NLP, etc.)
- Surpassed human performance in many tasks.





Deep learning in NLP

- Easy tasks

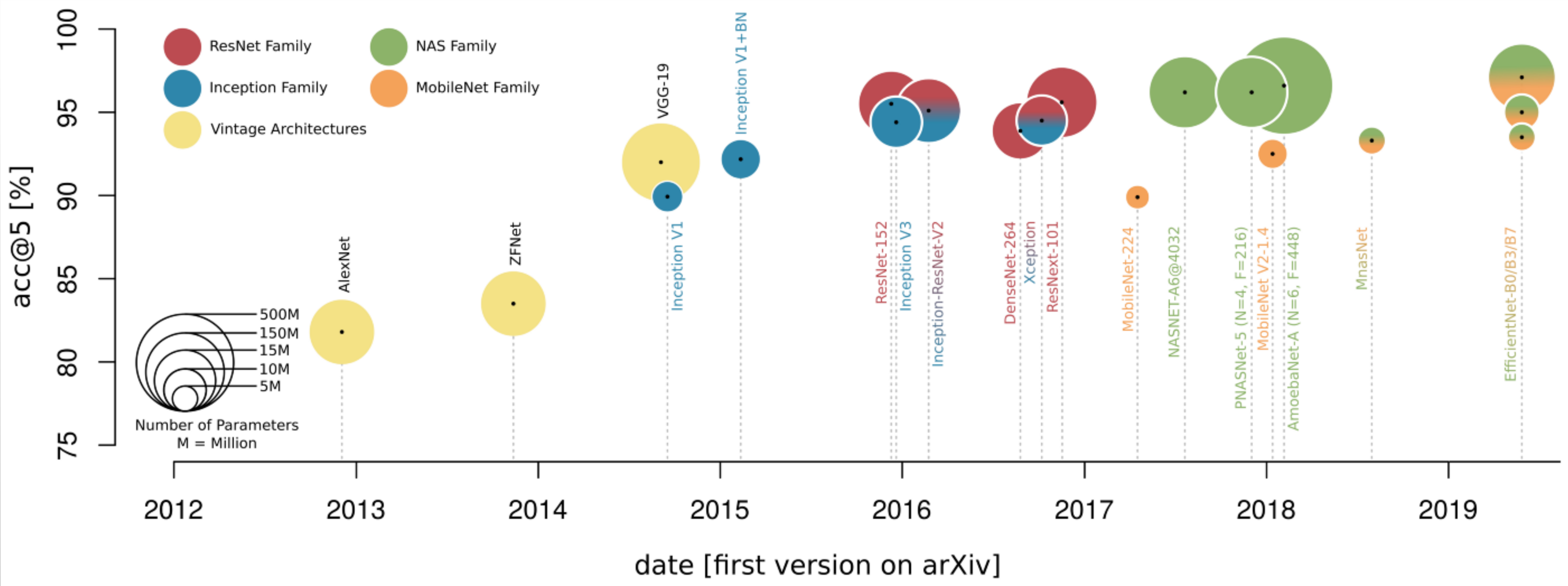
	Traditional ML	Deep learning
Sentiment	72%	76%
Topic classification	67%	70%
PoS	96%	97%

- Hard tasks

	Traditional ML	Deep learning
QA	51%	90%
Images to text or text to image	?	Done

Why deep learning? (cont.)

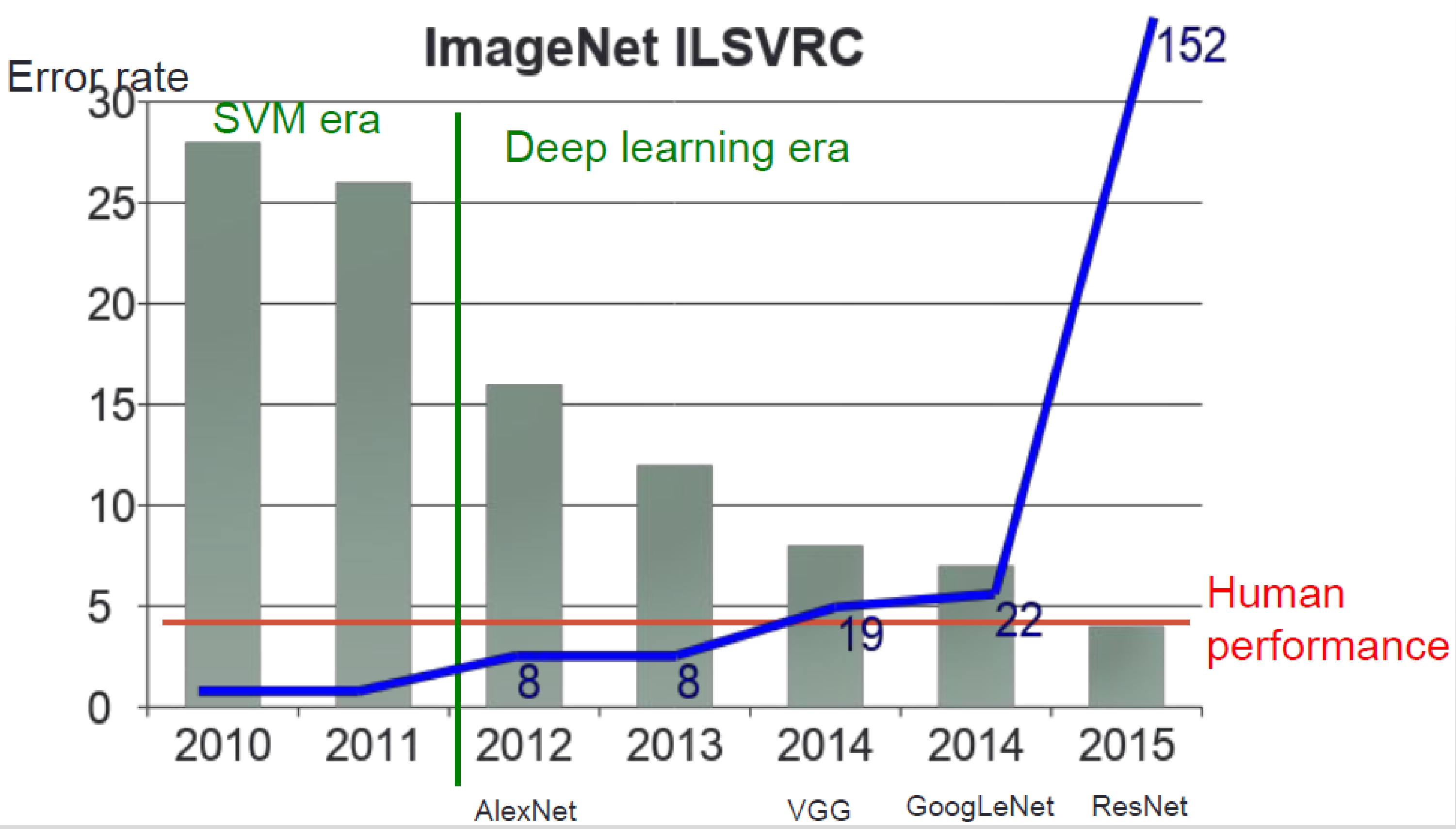
- **Big data -** Deep neural networks have the ability to utilize large amounts of data more effectively in comparison to other types of models.
- **Graphics processing unit (GPU) -** "Allows for the possibility of training larger models."
- **Deep models -** "A larger model makes it simpler to avoid bad local minimums during training."



https://towardsdatascience.com/a-reading-guide-about-deep-learning-with-cnns-3a0e0fc99b78

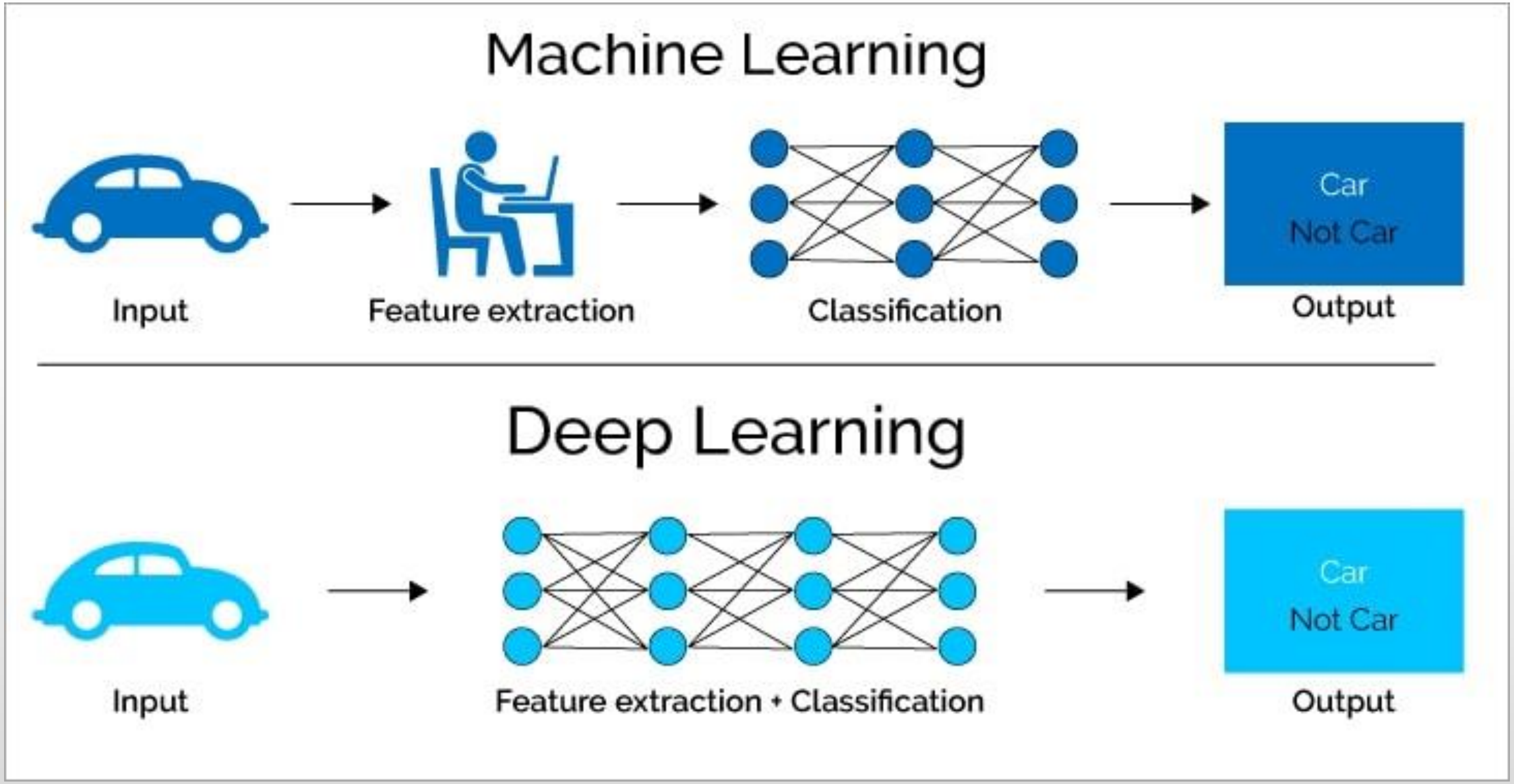
Why deep learning? (cont.)

- ImageNet task



Russakovsky, Olga, et al. "Imagenet large scale visual recognition challenge." *International journal of computer vision* 115.3 (2015): 211-252.

Machine learning vs Deep learning



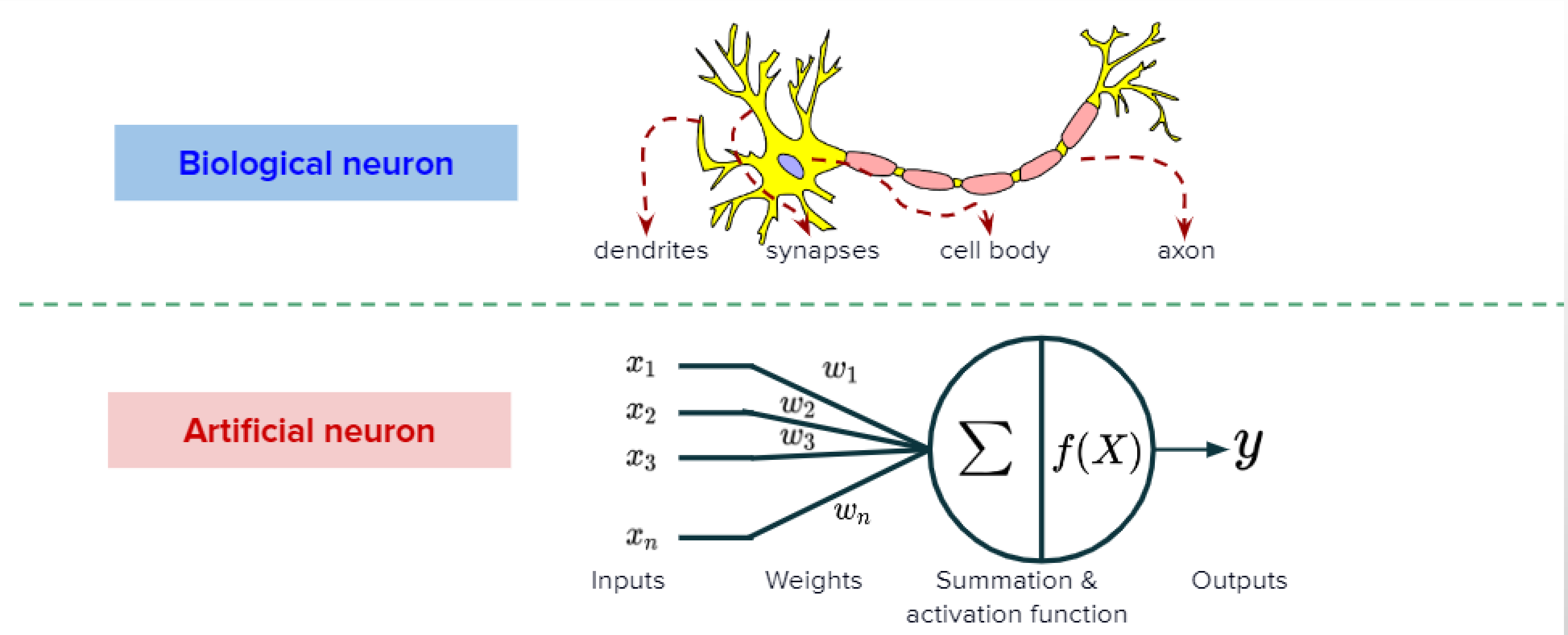
https://levity.ai/blog/difference-machine-learning-deep-learning

Basic knowledge of Neural Networks

- Fully connected networks
  - Neuron
  - Non-linearity
  - Softmax
- Deep neural network training
  - Loss function
  - Stochastic gradient descent (SGD) and backpropagation
  - Learning rate & Optimizer
  - Overfitting
- CNN, RNN, LSTM, GRU
- Deep leaning in NLP

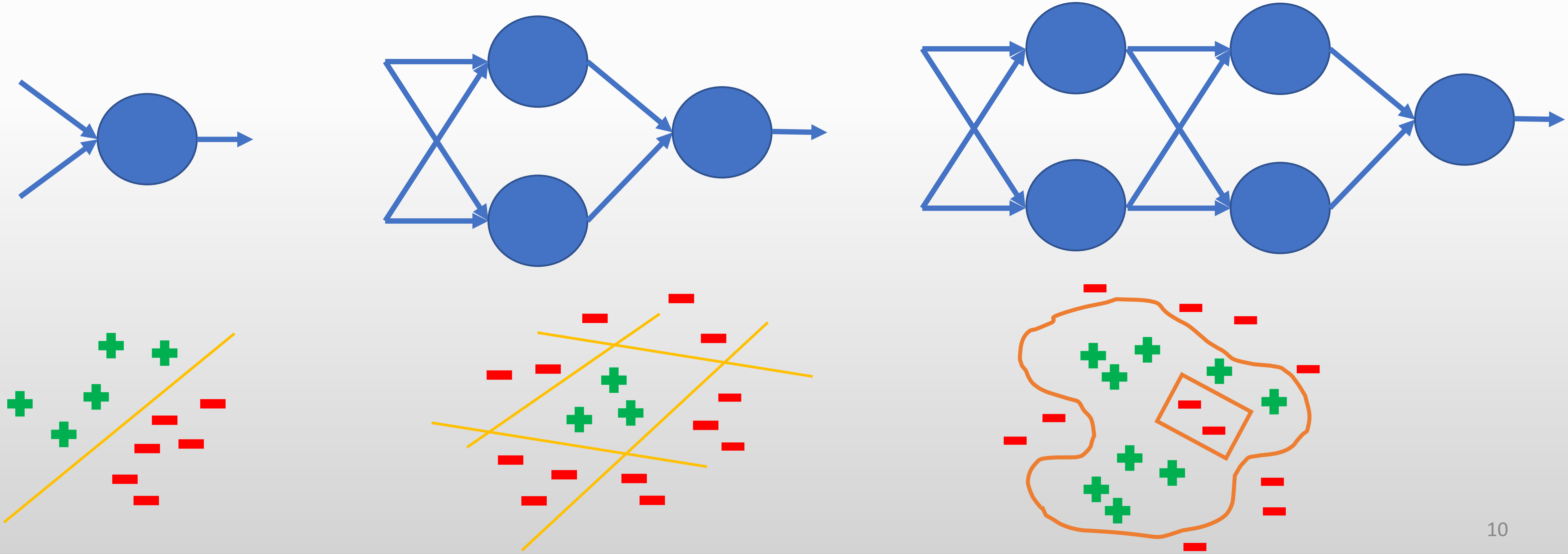
Fully connected networks

- Neural networks are sets of algorithm, modeled loosely after the human brain, that are designed to recognize patterns.

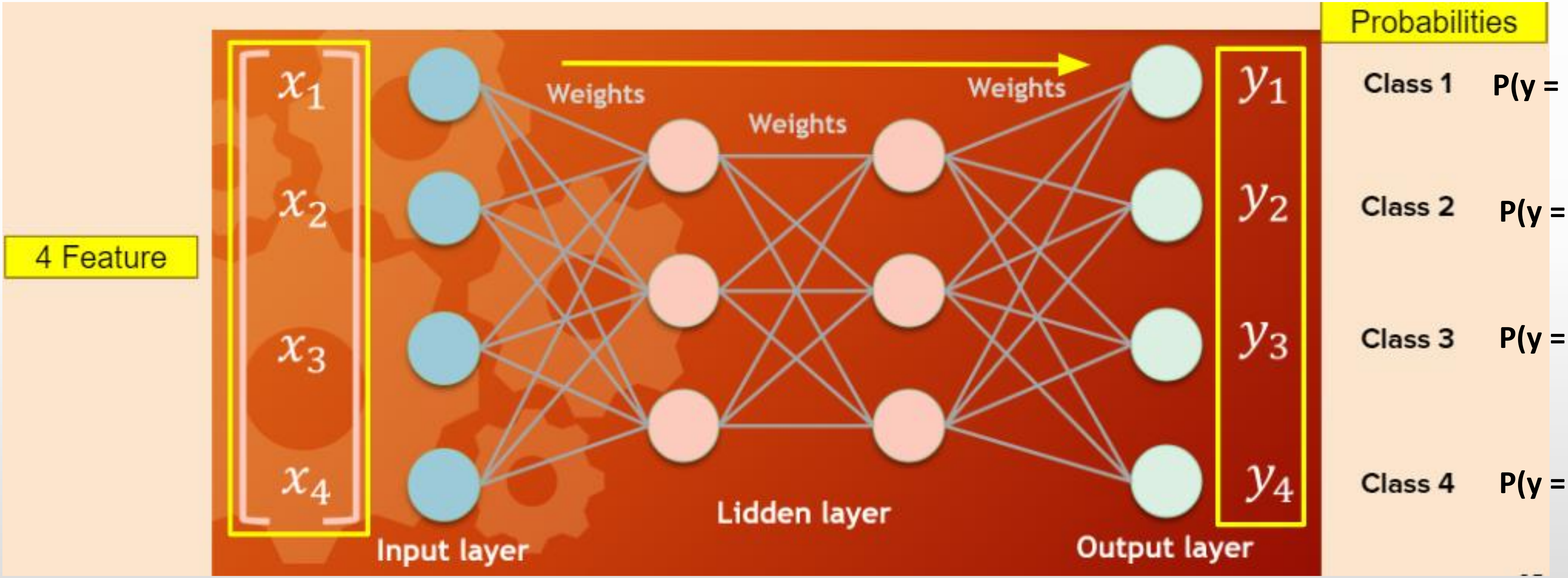


Fully connected networks (cont.)

- Each neuron in the model divides the feature space using a hyperplane. As more neurons are added, the decision boundaries become more intricate.



Fully connected networks (cont.)



P(y = dog |x)

P(y = cat |x)

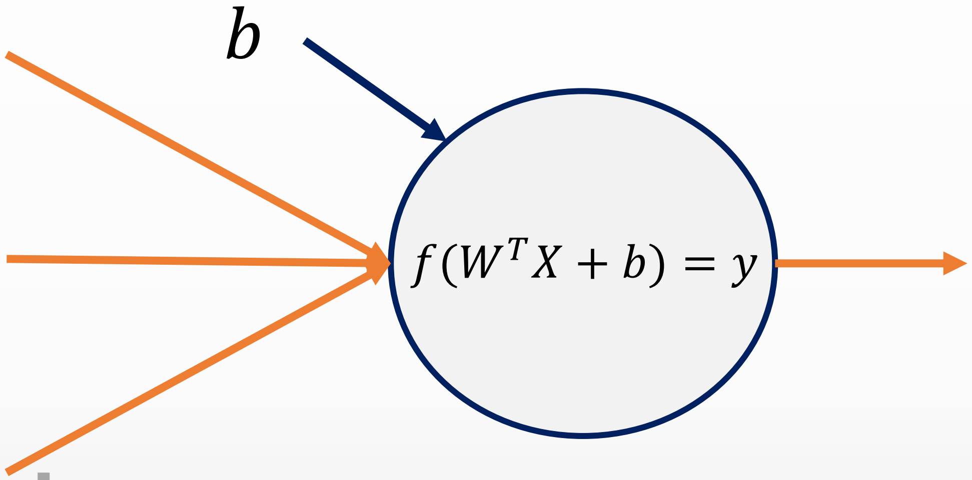
P(y = bird |x)

P(y = mouse |x)

Fully connected networks and Matrices

features

$$X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$



weights

$$W = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}$$

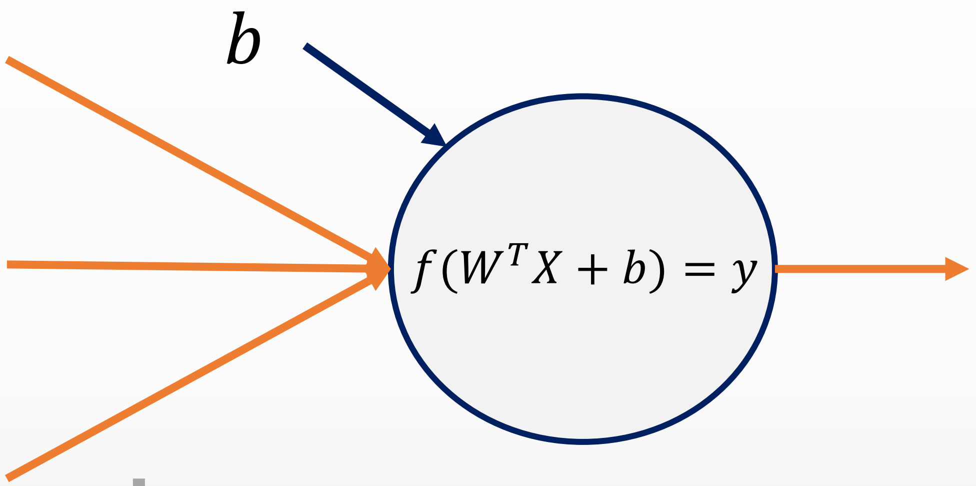
$$W^T X + b = [\mathrm{w}_1 \ \mathrm{w}_2 \ \mathrm{w}_3]_{1\times 3} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}_{3\times 1} + b$$

Fully connected networks and Matrices (cont.)

samples

features

$$X = \begin{bmatrix} x_{11} x_{12} x_{13} x_{14} \\ x_{21} x_{22} x_{23} x_{24} \\ x_{31} x_{32} x_{33} x_{34} \end{bmatrix}$$



weights

$$W = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}$$

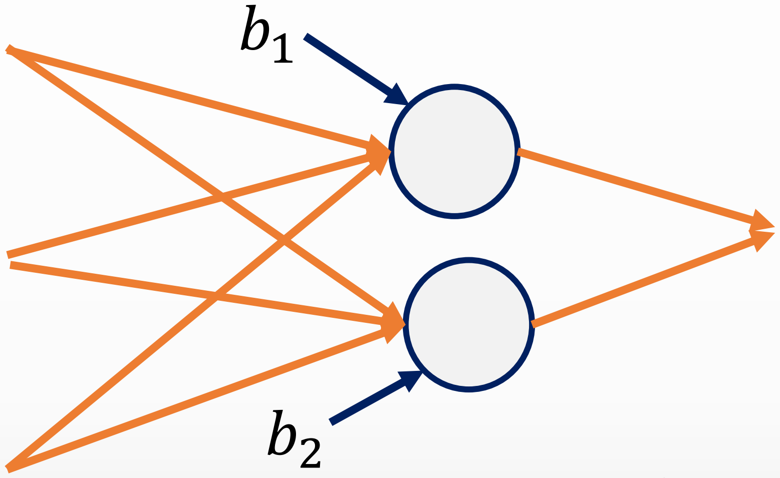
$$W^T X + b = [\mathrm{w}_1\ \mathrm{w}_2\ \mathrm{w}_3]_{1\times 3} \cdot \begin{bmatrix} x_{11} x_{12} x_{13} x_{14} \\ x_{21} x_{22} x_{23} x_{24} \\ x_{31} x_{32} x_{33} x_{34} \end{bmatrix}_{3\times 4} + [b\ b\ b\ b]$$

Fully connected networks and Matrices (cont.)

samples

features

$$X = \begin{bmatrix} x_{11} x_{12} x_{13} x_{14} \\ x_{21} x_{22} x_{23} x_{24} \\ x_{31} x_{32} x_{33} x_{34} \end{bmatrix}$$

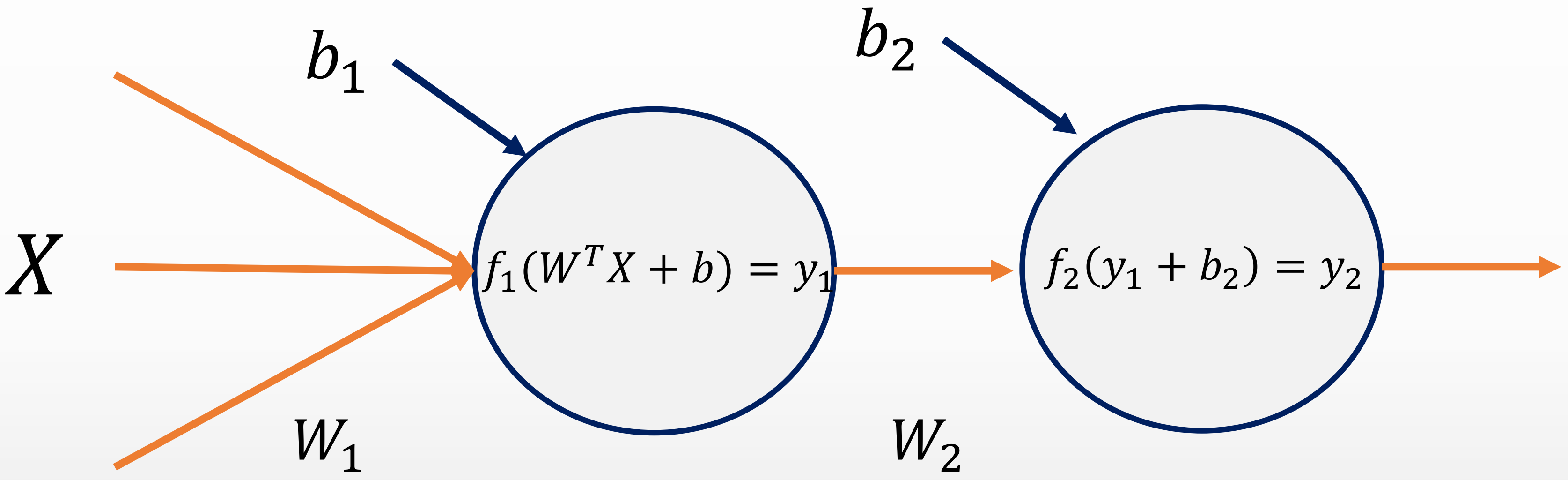


weights

$$W = \begin{bmatrix} w_{11} w_{12} \\ w_{21} w_{22} \\ w_{31} w_{32} \end{bmatrix}$$

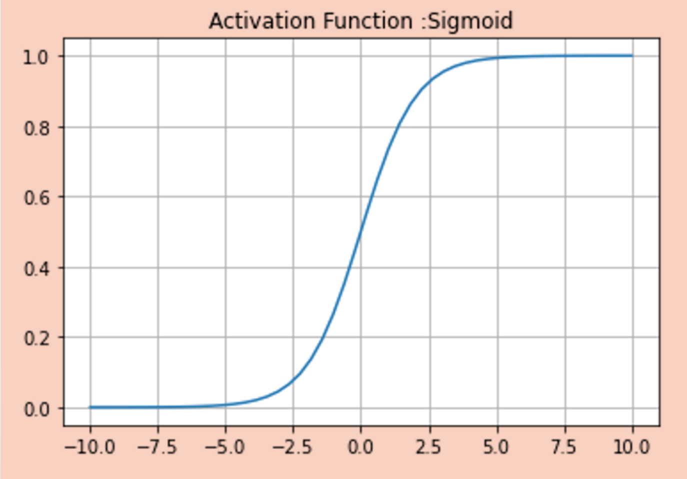
$$W^T X + b = \begin{bmatrix} \mathrm{w}_1 & \mathrm{w}_{21} & \mathrm{w}_{31} \\ \mathrm{w}_{21} & \mathrm{w}_{22} & \mathrm{w}_{23} \end{bmatrix}_{2\times 3} \cdot \begin{bmatrix} x_{11} x_{12} x_{13} x_{14} \\ x_{21} x_{22} x_{23} x_{24} \\ x_{31} x_{32} x_{33} x_{34} \end{bmatrix}_{3\times 4} + \begin{bmatrix} b_1 & b_1 & b_1 & b_1 \\ b_2 & b_2 & b_2 & b_2 \end{bmatrix}$$

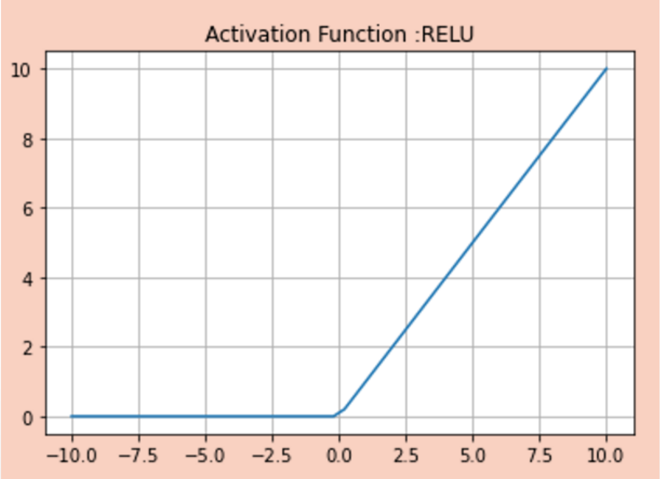
Fully connected networks and Non-linearity



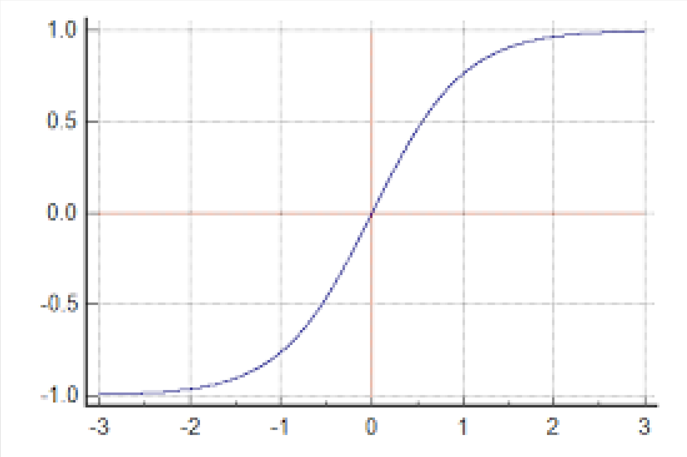
$$f_2(W_2^T f_1(W_1^T X + b_1) + b_2) = y_2$$

Fully connected networks and Non-linearity (cont.)

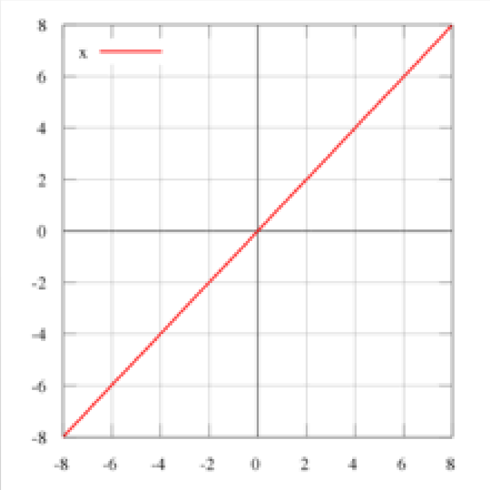




tanh



identity



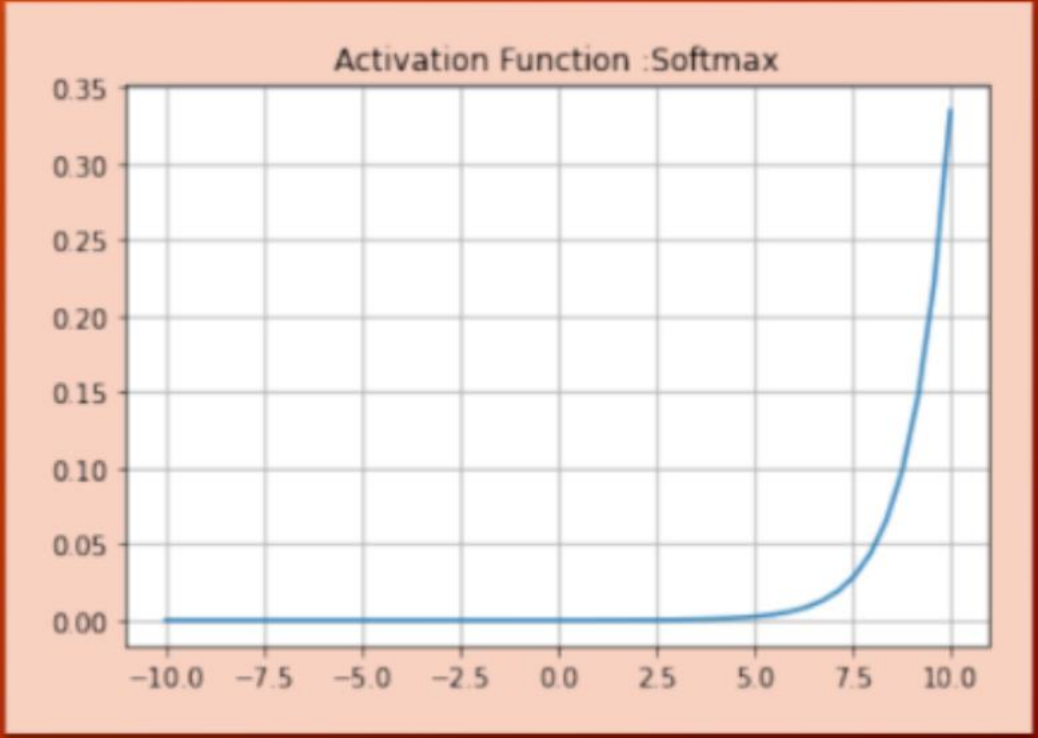
Softmax in Output Layer

$$Softmax(z_j) = \frac{e^{z_j}}{\sum_{k=1}^{n} e^{z_k}}$$

where $j = 1,2, \dots, n$

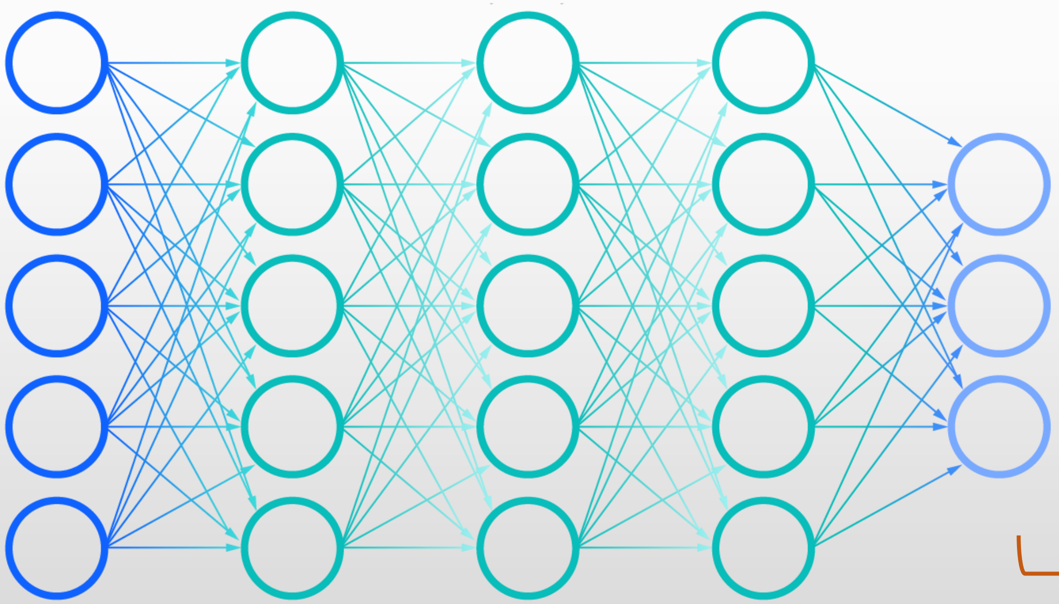
and n is the number of nodes in output layer

- *Domain*: $z_j \in \mathbb{R}$ (Real Number)
- *Range*: $Softmax(z_j) \in (0,1)$
- $z \to -\infty$ then $S(z) \to 0$
- $z \to \infty$ then $S(z) \to 1$



Softmax in Output Layer (cont.)

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



$f(y = dog|x) = -0.5$

$f(y = cat|x) = 0.8$

$f(y = bird|x) = 0.1$

Normalize to Probabilities by Softmax

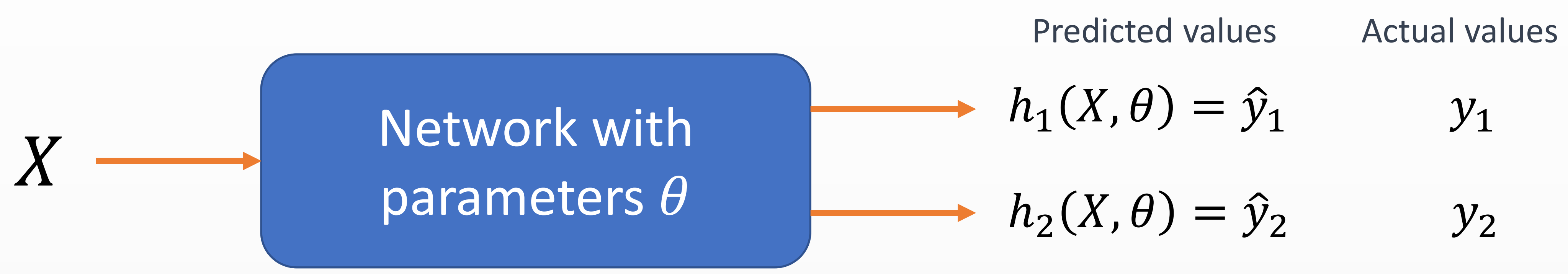
$P(y = dog|x) = 0.154$

$P(y = cat|x) = 0.565$

$P(y = bird|x) = 0.281$

Output layers

Loss function (Objective function)



- Cross entropy (Classification problems)
- Sum of square errors (Regression problems)

Loss function (cont.)

- Cross entropy (Classification problems)

$$E(W) = -\frac{1}{m}\sum_{c=1}^{k}\sum_{i=1}^{m}[y_c^i log(h_c(x^i)) + (1 - y_c^i)log(1 - h_c(x^i))]$$

where m is the number of samples and k is the number of outputs or classes

- Sum of square errors (Regression problems)

$$MSE = E(W) = \frac{1}{m}\sum_{i=1}^{m}[y^i - h(x^i)]^2$$

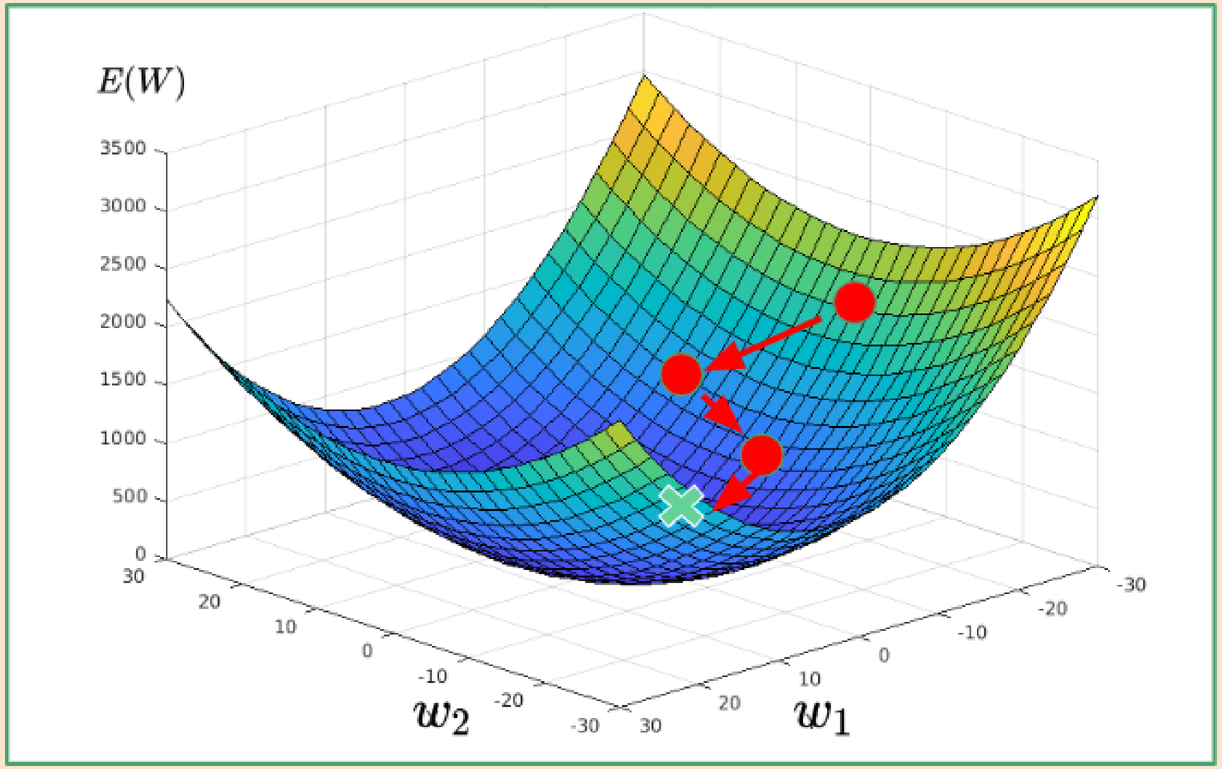
where m is the number of samples

Minimize lost function using Gradient descent

1. Randomly initialize w_1 and w_2.
2. Calculate the gradient
   ($\bigtriangledown E(w_1, w_2)$)
3. Update the algorithm with
   the following formula:

$$\begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \Longrightarrow \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} - \alpha \bigtriangledown E(w_1, w_2)$$

4. Monitor the cost function.
   Cost should be lower any
   time you update weights.
5. When cost function is low
   enough, stop updating

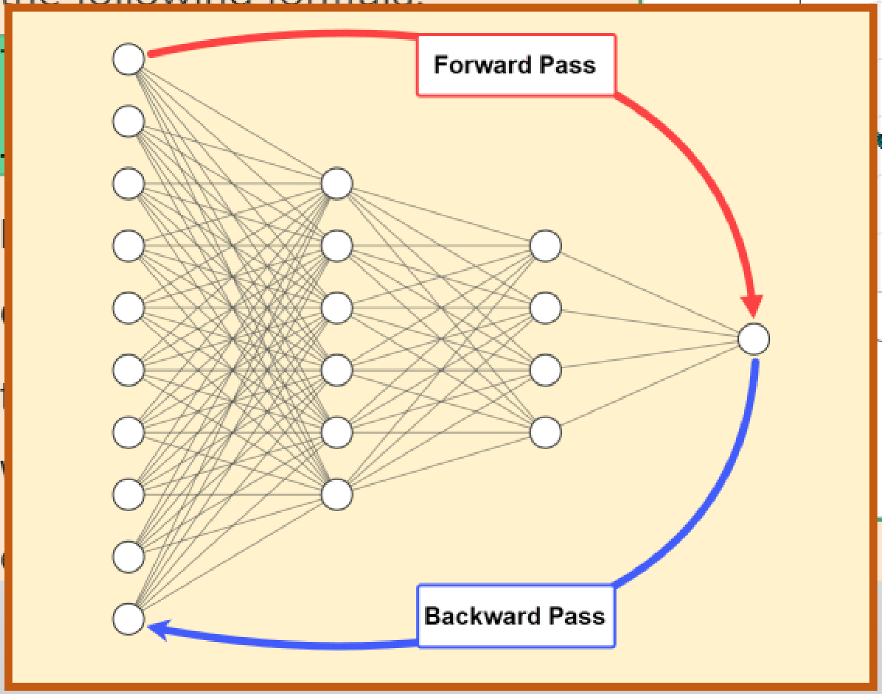


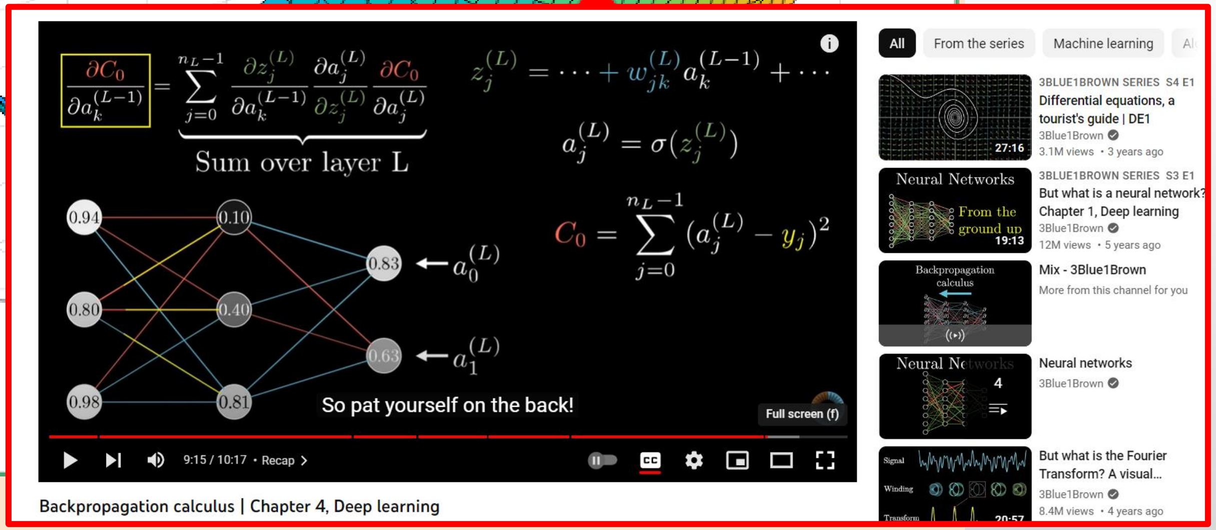
Minimize lost function using Gradient descent

Use Back propagation to compute gradient

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

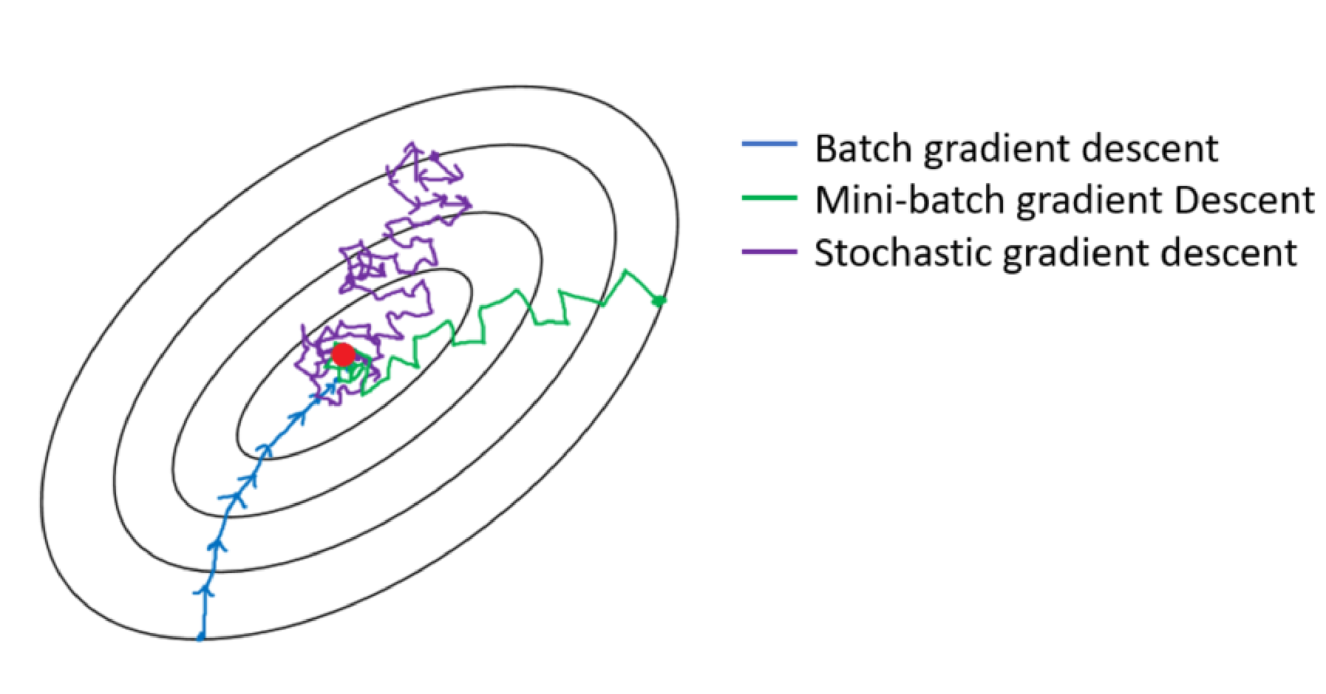




https://www.youtube.com/watch?v=tIeHLnjs5U8

Stochastic gradient descent (SGD)

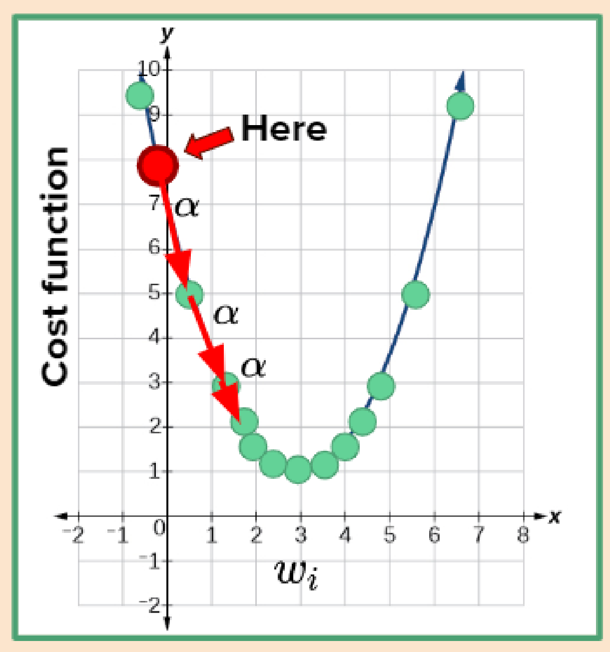
- We have one million training examples
  - Gradient descent compute the loss function of all samples, the decide the direction of the descent
  - ---> Take too long!!!
  - SGD compute the loss function on sub subset of samples
    - ---> The subset should not be biased and properly randomized to ensure no correlation between samples.
    - The subset is called a mini-batch
    - Size of the mini-batch determines the speed and accuracy

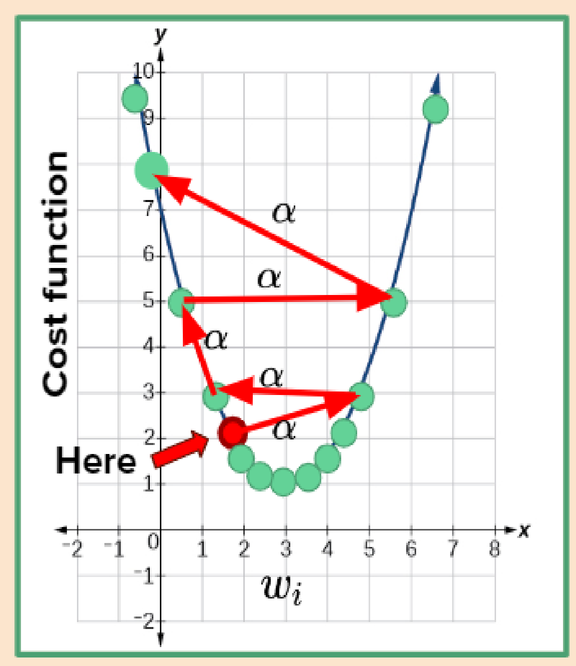


https://medium.com/analytics-vidhya/gradient-descent-vs-stochastic-gd-vs-mini-batch-sgd-fbd3a2cb4ba4

Learning rate (α) & Optimizer

- Learning rate is usually between 0 and 1.
- Large alpha: big step downhill.
- Small alpha: small step.
- You do not want too big or too small alpha



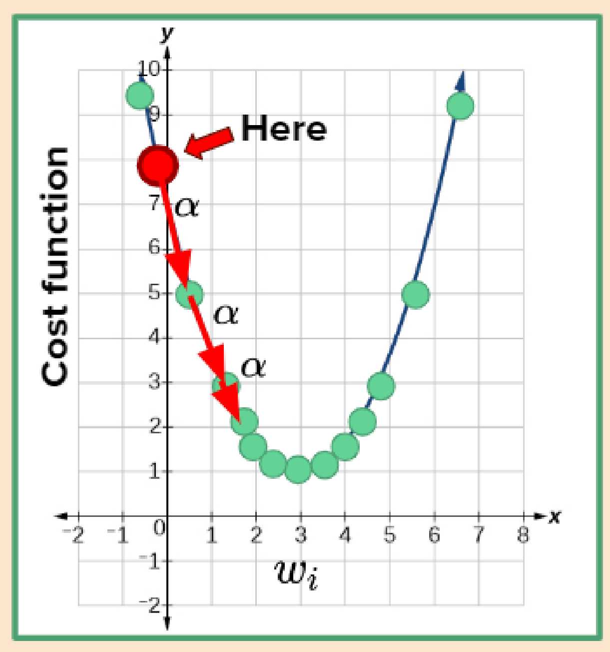


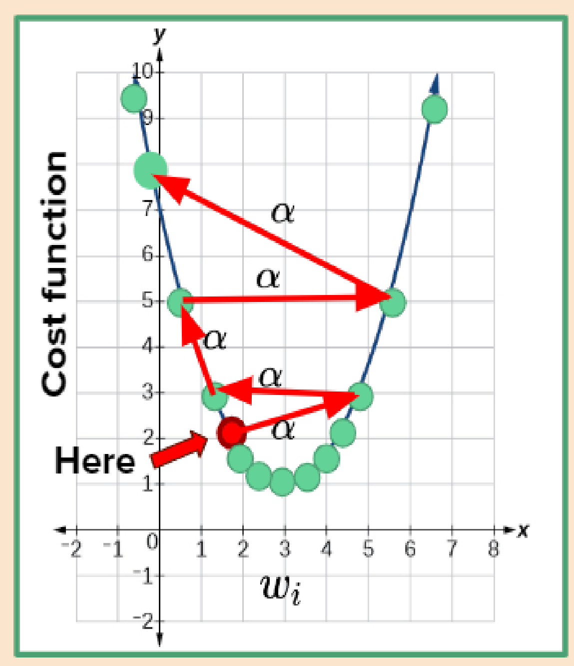
Learning rate (α) & Optimizer (cont.)

- Learning rate is usually between 0 and 1.
- Large alpha: big step downhill.
- Small alpha: small step.
- You do not want too big or too small alpha

Learning rate scheduling

Usually starts with a large learning rate then gets smaller later





Learning rate (α) & Optimizer (cont.)

- Besides learning rate scheduling (coarse grain) we can do finer (and automatic) control of the learning rate
- People find simple SGD with momentum and decay to perform better (with proper tuning)
- ADAM

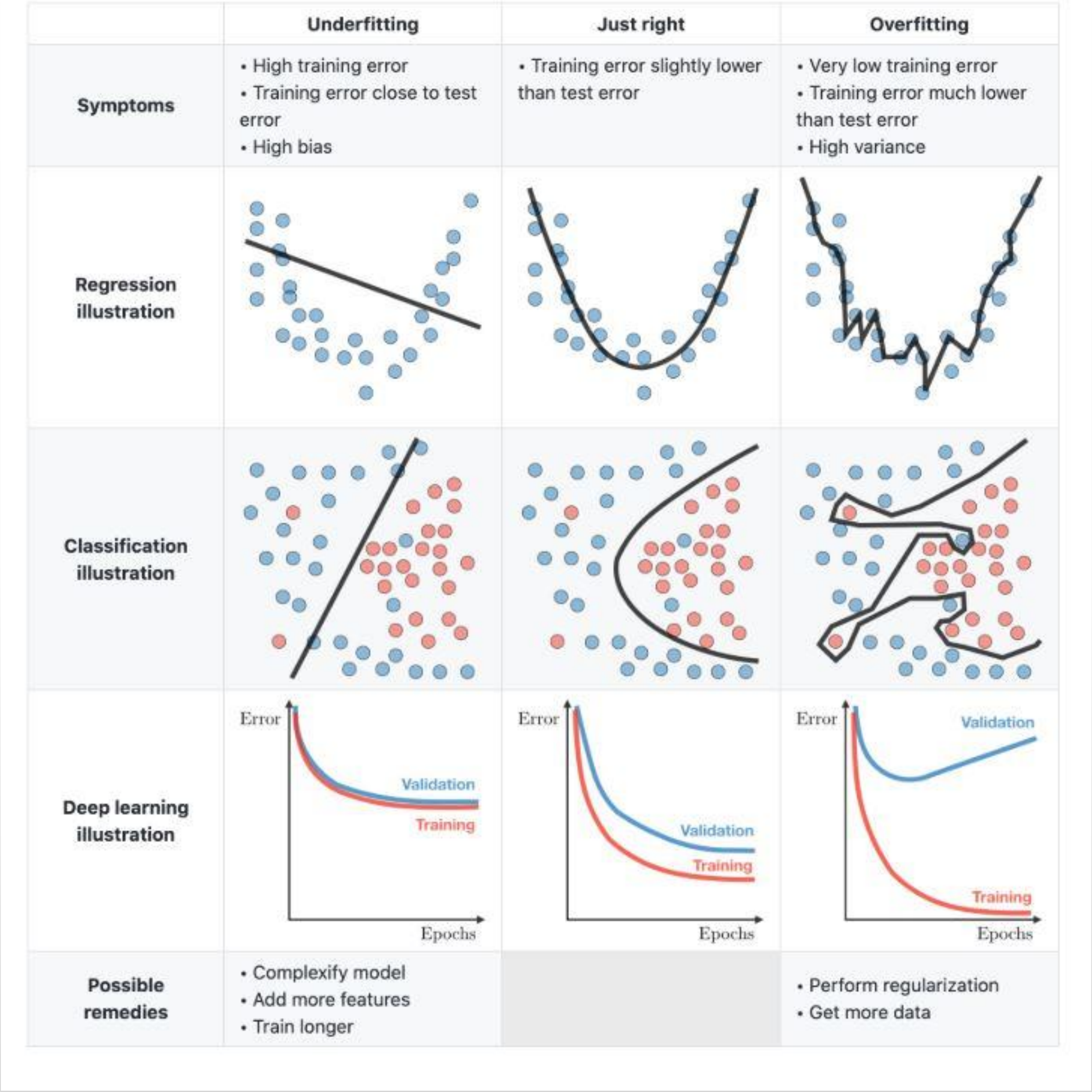
  Most popular for its ease of use
- RMSprop

  Faster than SGD but slower than ADAM

  More stable than ADAM

Overfitting

- 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



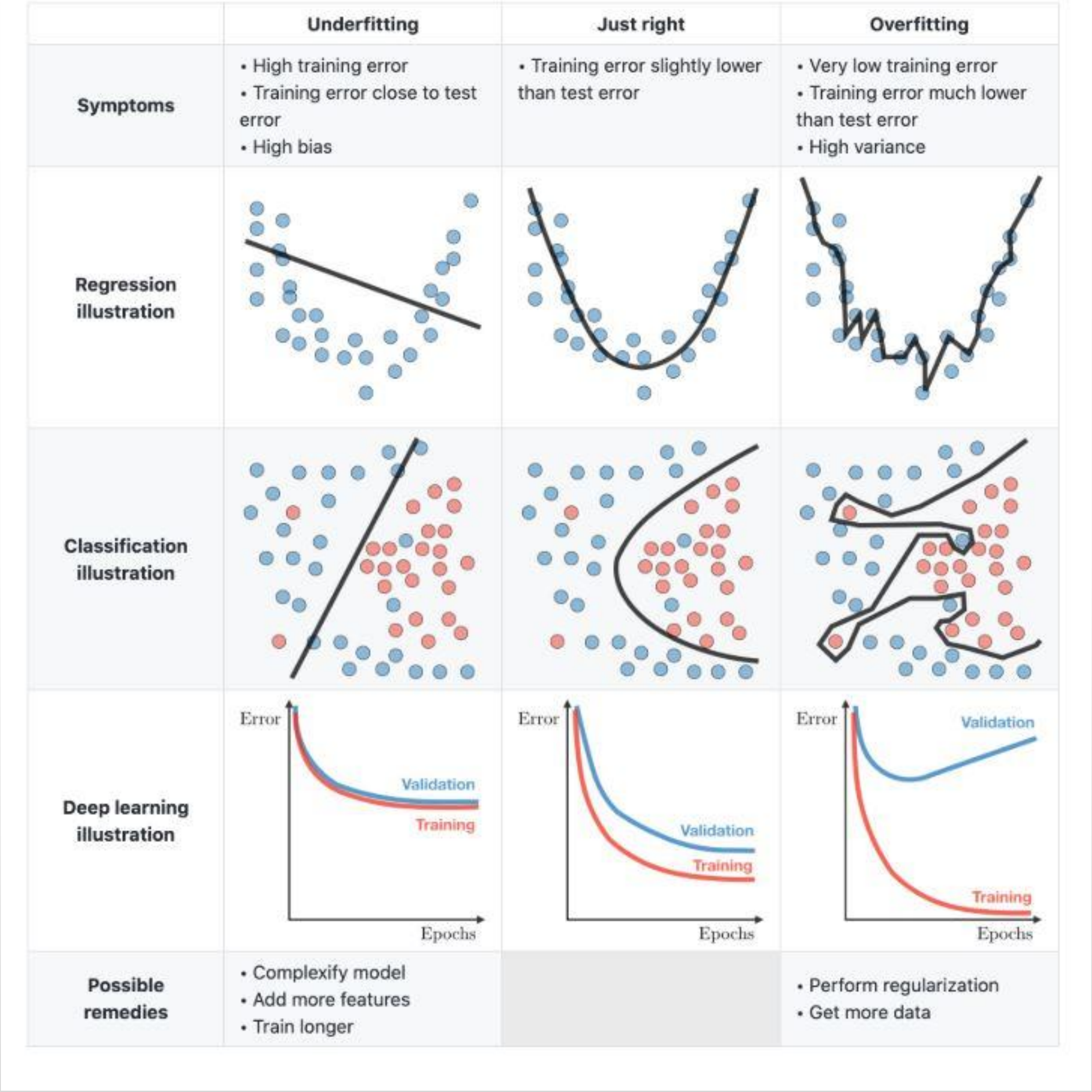
	Underfitting	Just right	Overfitting
Symptoms	• High training error • Training error close to test error • High bias	• Training error slightly lower than test error	• Very low training error • Training error much lower than test error • High variance
Regression illustration			
Classification illustration			
Deep learning illustration	Error, Validation, Training, Epochs	Error, Validation, Training, Epochs	Error, Validation, Training, Epochs
Possible remedies	• Complexify model • Add more features • Train longer		• Perform regularization • Get more data

https://www.kaggle.com/getting-started/166897

Overfitting (cont.)

- 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

- Dropout
- Regularization
- Batch normalization



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Possible remedies	• Complexify model • Add more features • Train longer		• Perform regularization • Get more data

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Convolutional Neural Networks (CNNs)

How we identify things ?

Let's identify key features in each image category

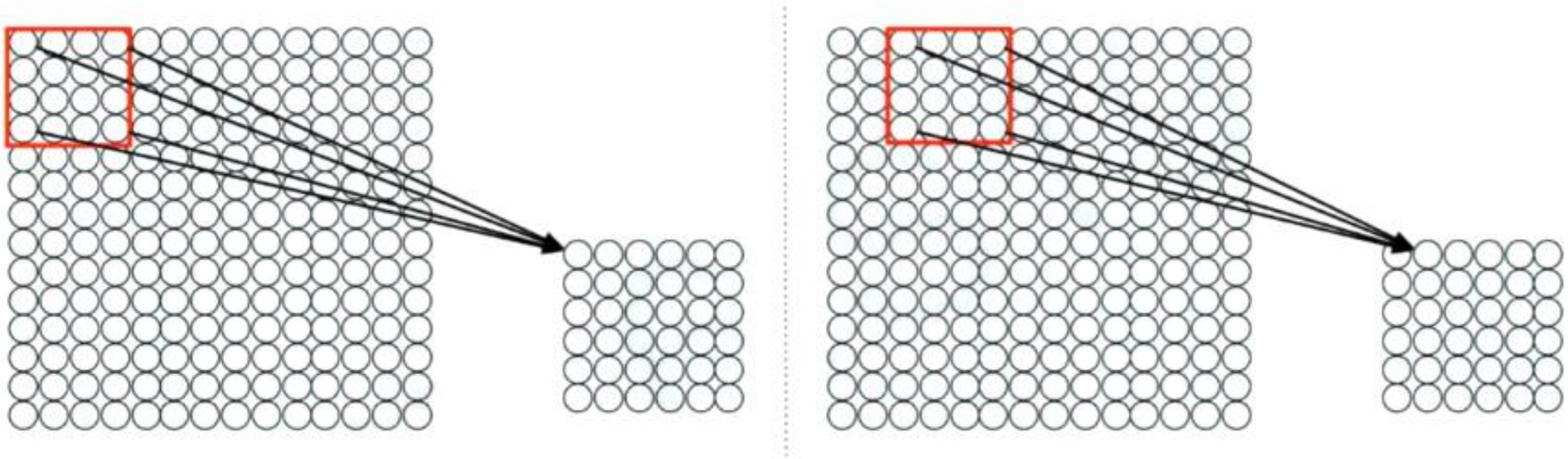
Nose, Eyes, Mouth

Wheels, License Plate, Headlight

Door, Windows, Steps

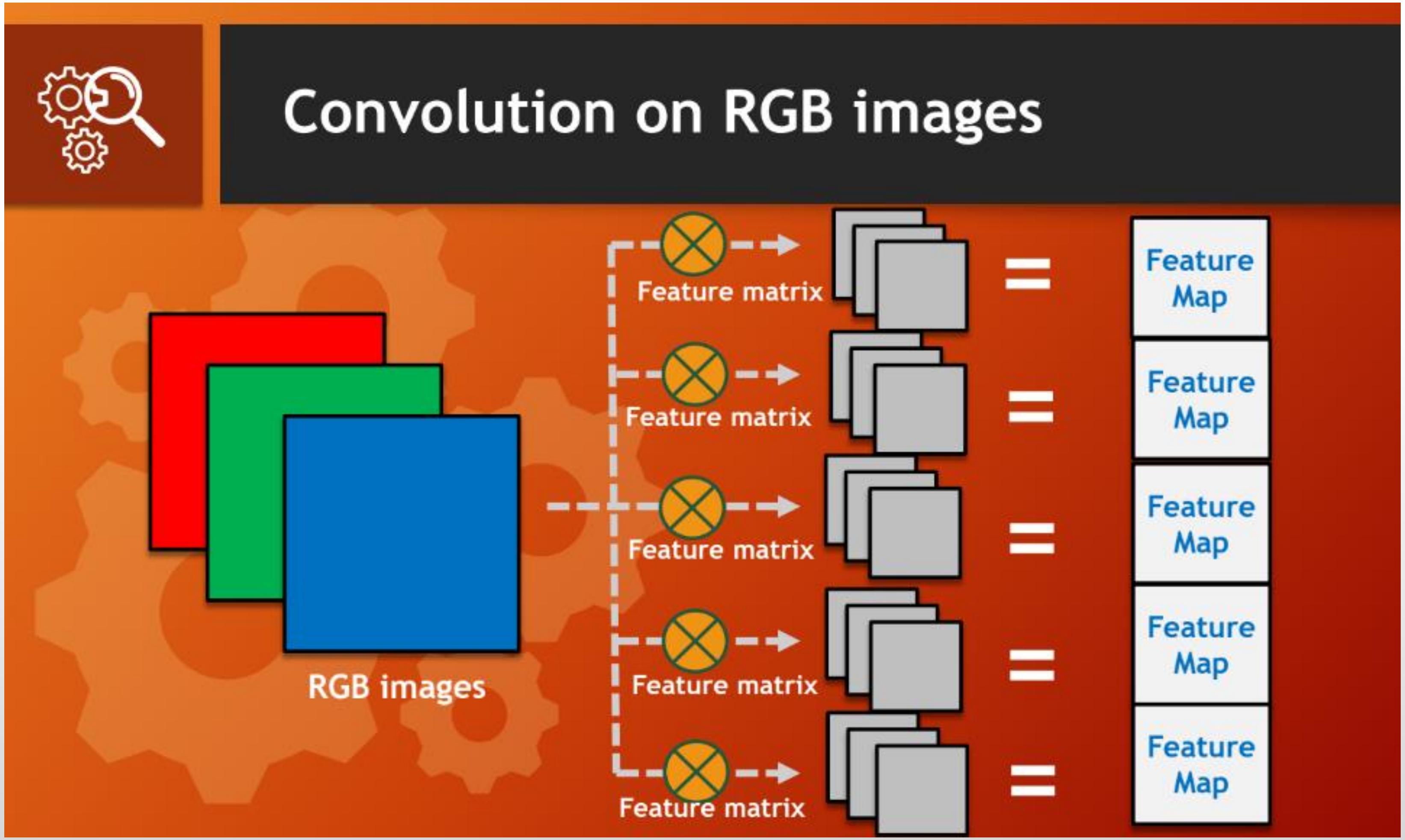
Convolutional Neural Networks (CNNs) (cont.)

Using Spatial Structure



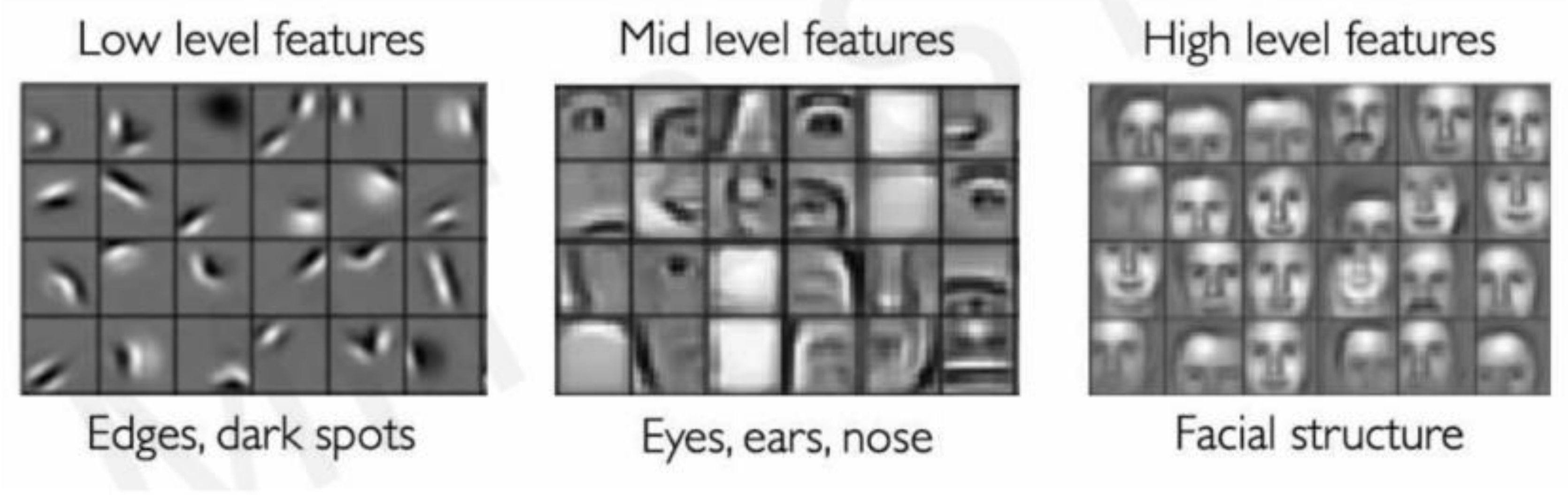
Connect patch in input layer to a single neuron in subsequent layer.
Use a sliding window to define connections.
How can we ***weight*** *the patch to detect particular features?*

Convolutional Neural Networks (CNNs) (cont.)



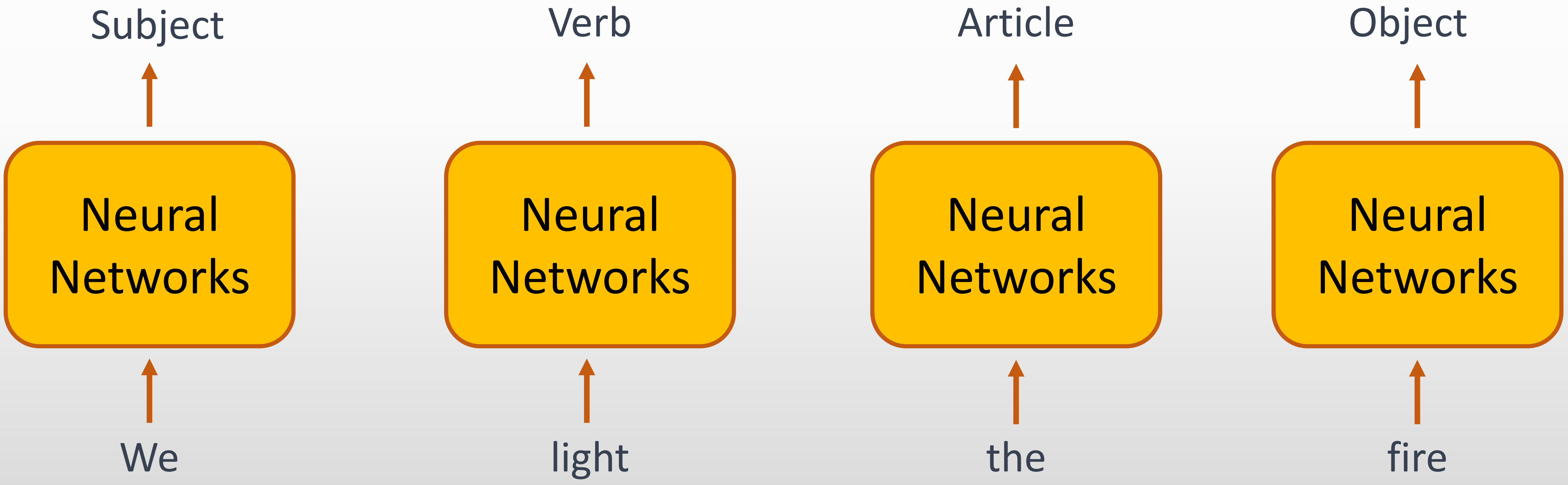
Convolutional Neural Networks (CNNs) (cont.)

Can we learn a hierarchy of features directly from the data instead of hand engineering?



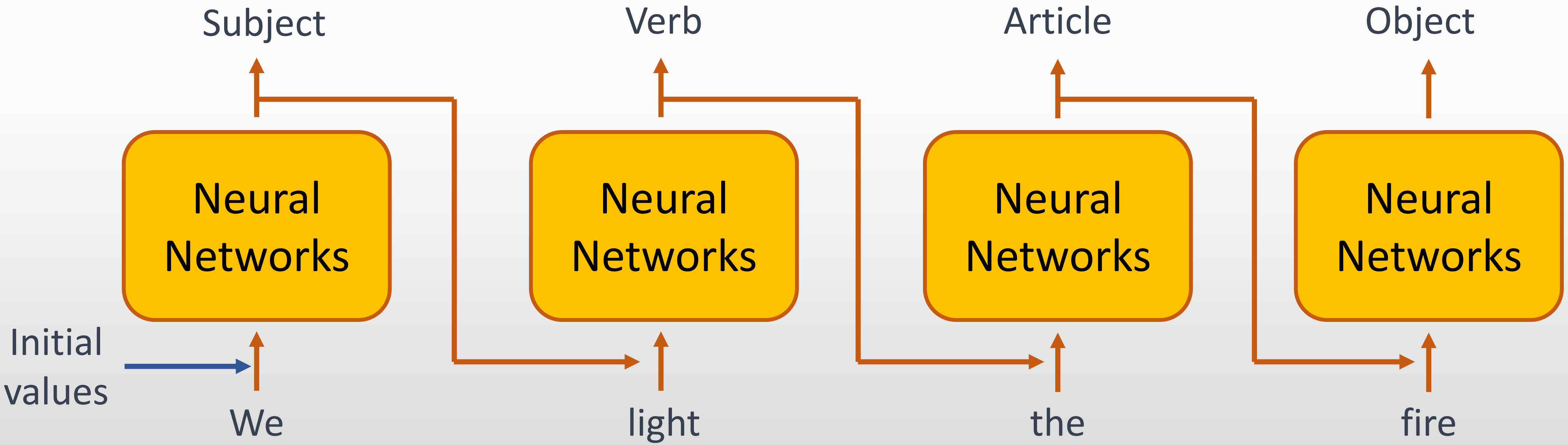
Recurrent Neural Networks (RNNs)

- Neural network concept



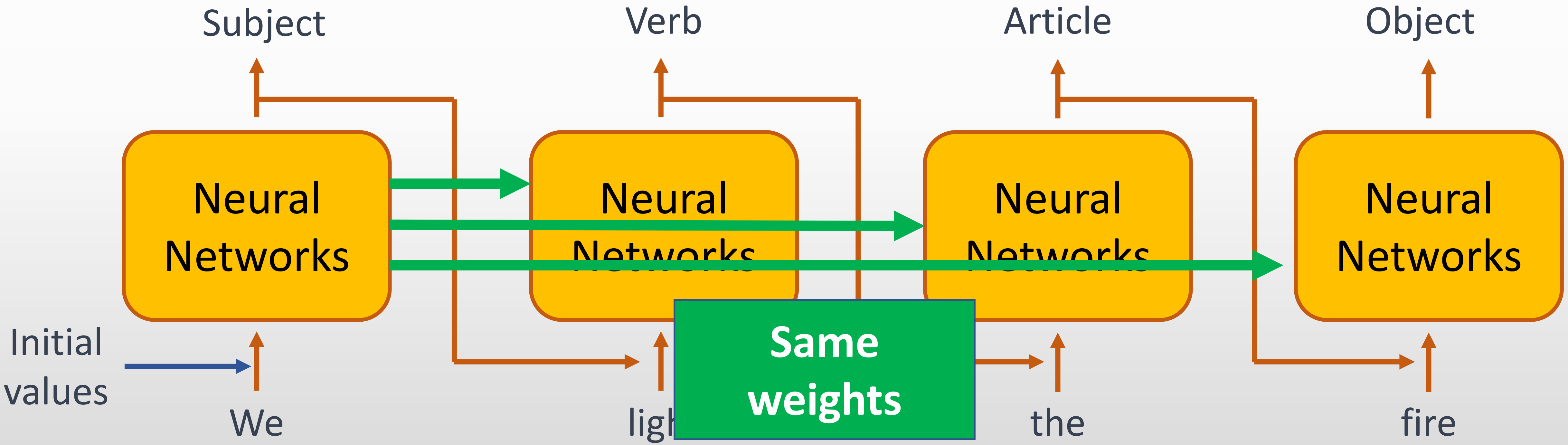
Recurrent Neural Networks (RNNs) (cont.)

- Recurrent Neural network concept

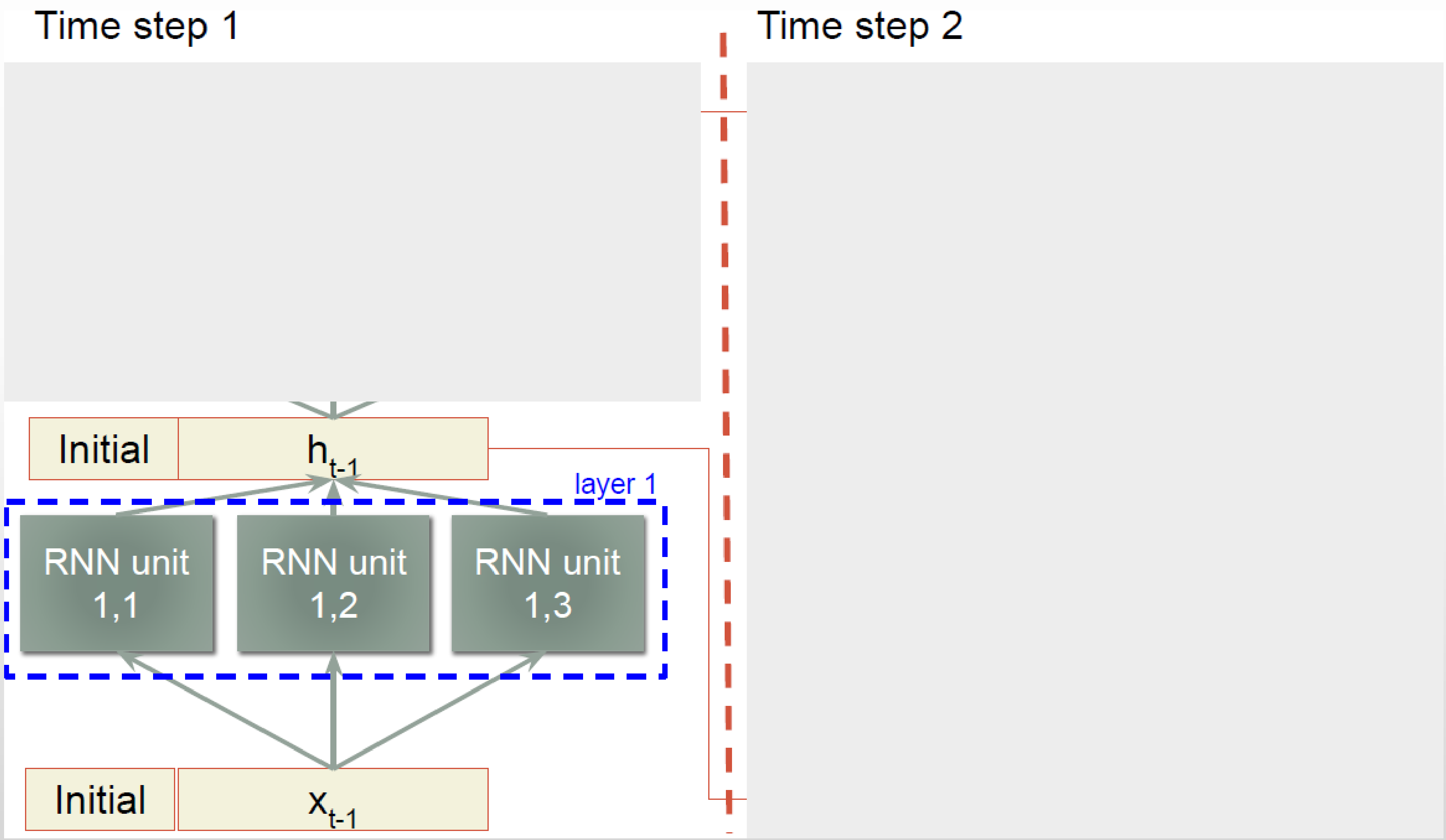


Recurrent Neural Networks (RNNs) (cont.)

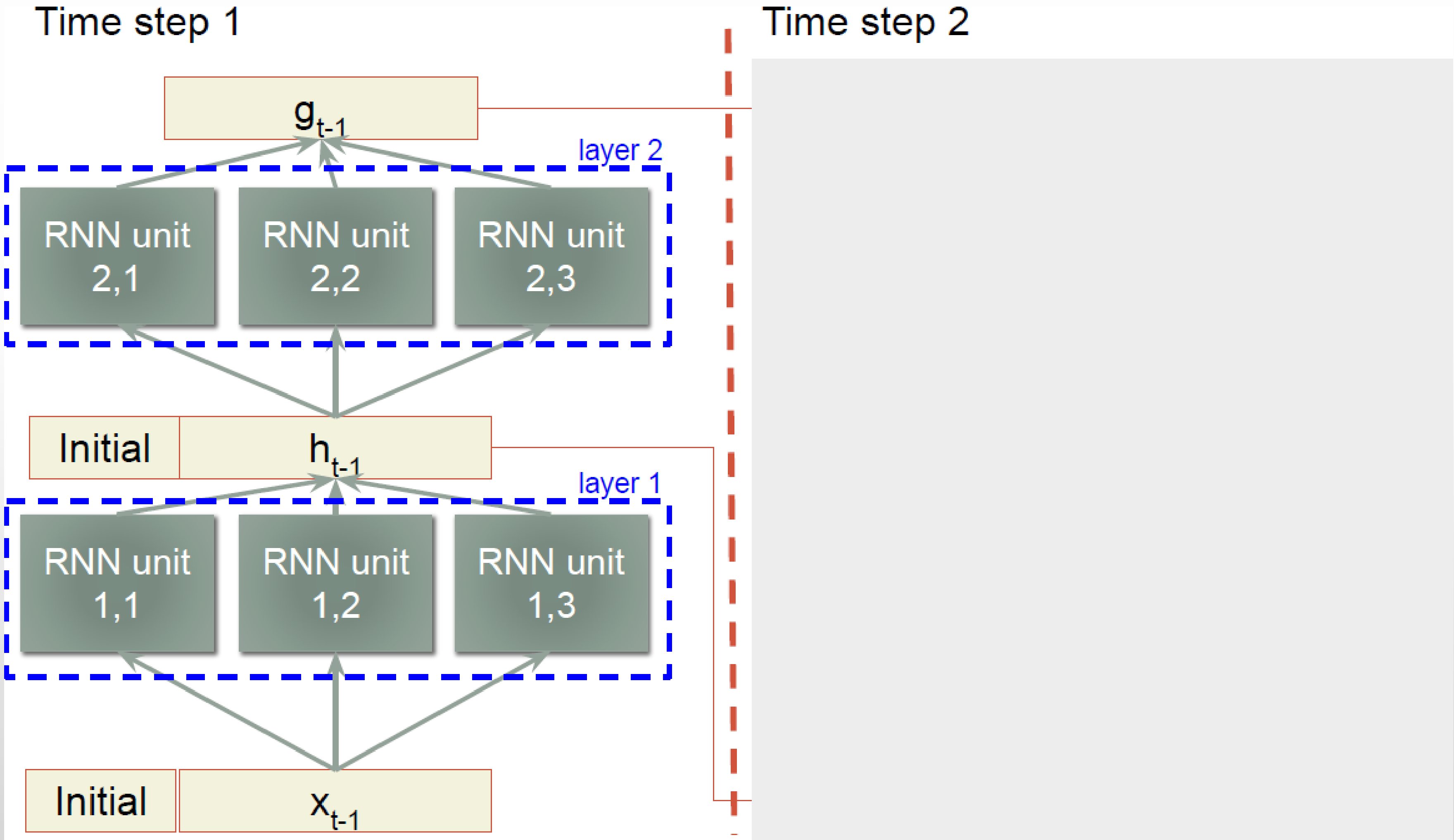
- Recurrent Neural network concept



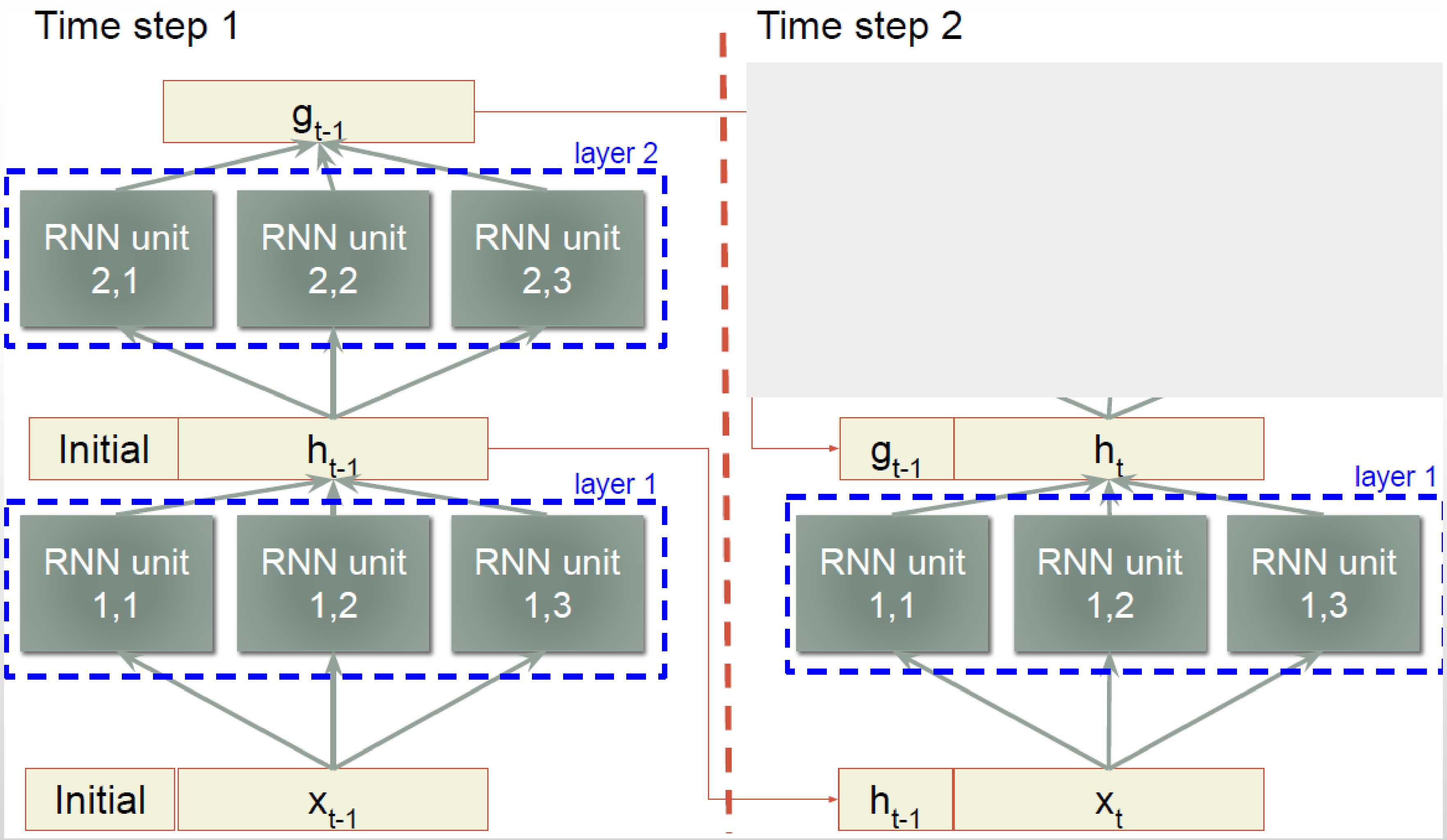
Recurrent Neural Networks (RNNs) (cont.)



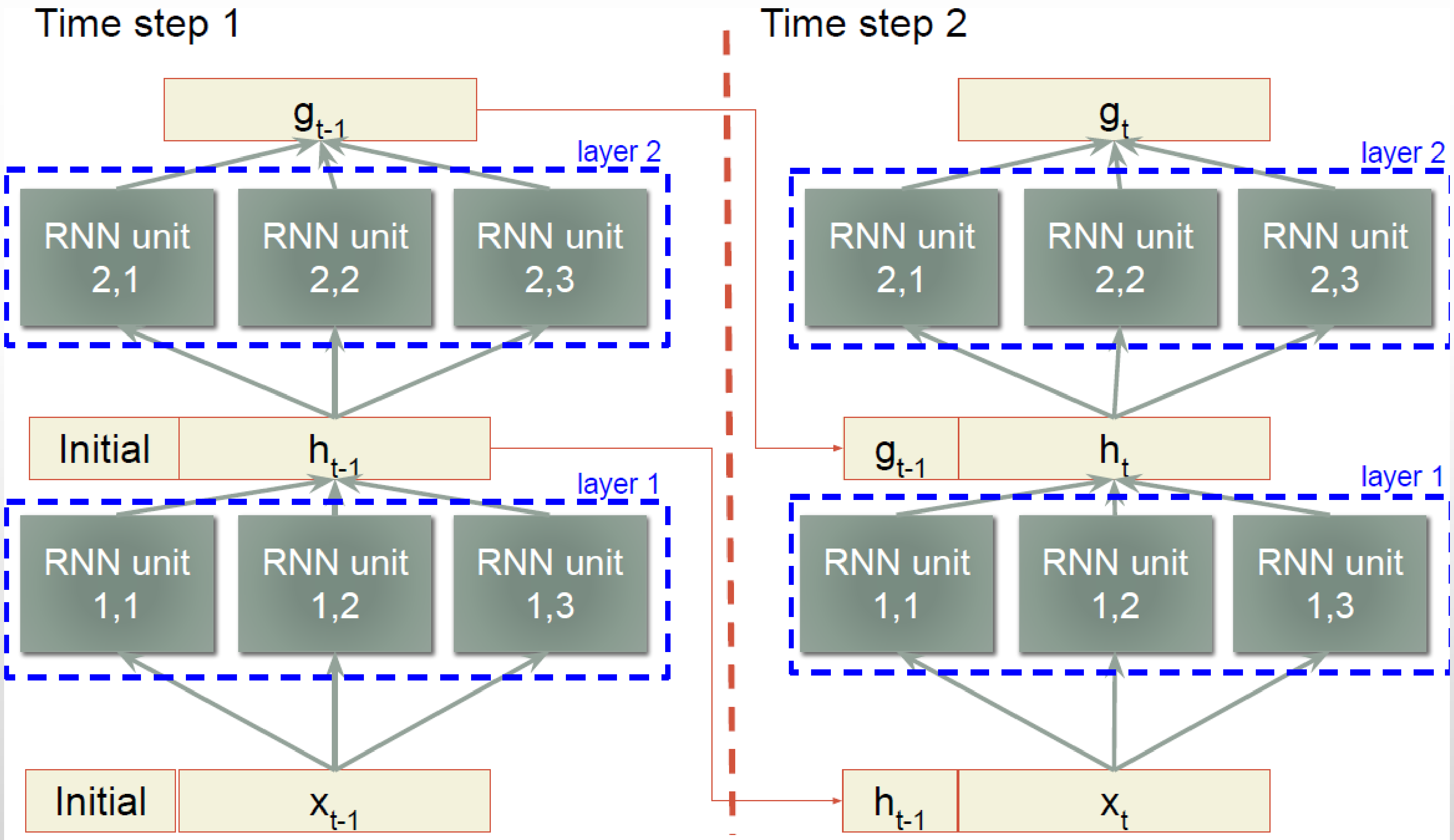
Recurrent Neural Networks (RNNs) (cont.)



Recurrent Neural Networks (RNNs) (cont.)

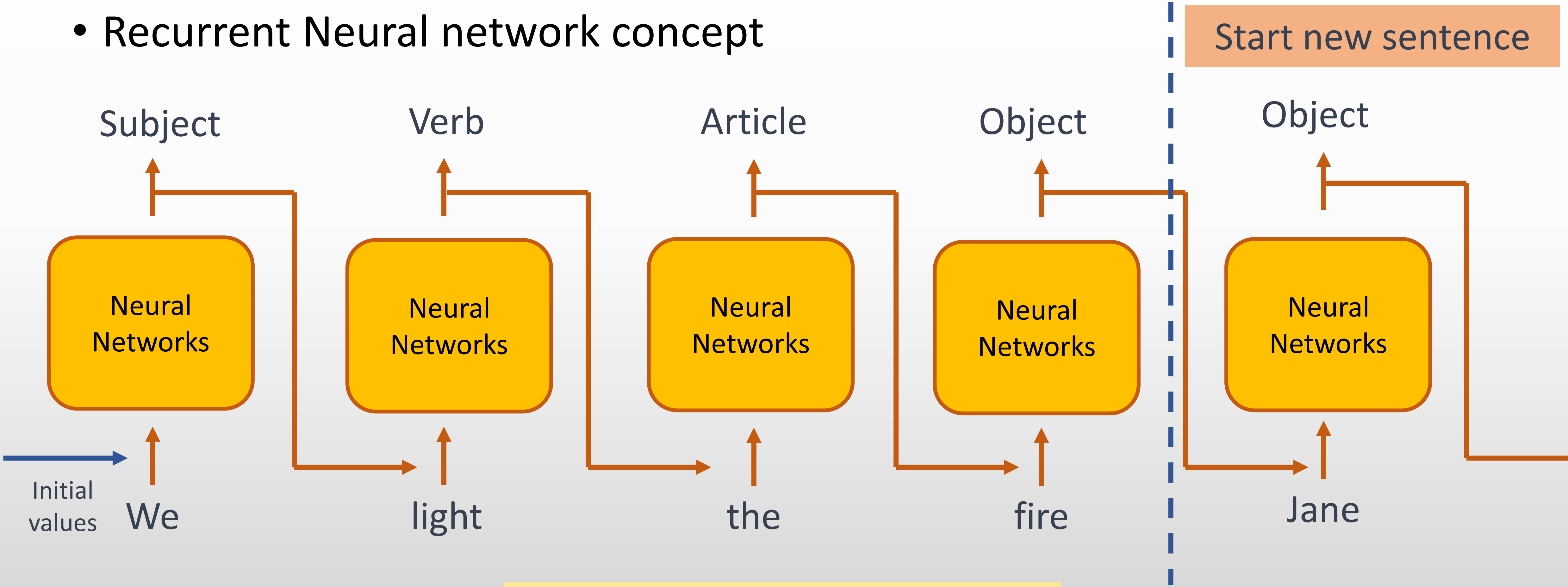


Recurrent Neural Networks (RNNs) (cont.)



Recurrent Neural Networks (RNNs) (cont.)

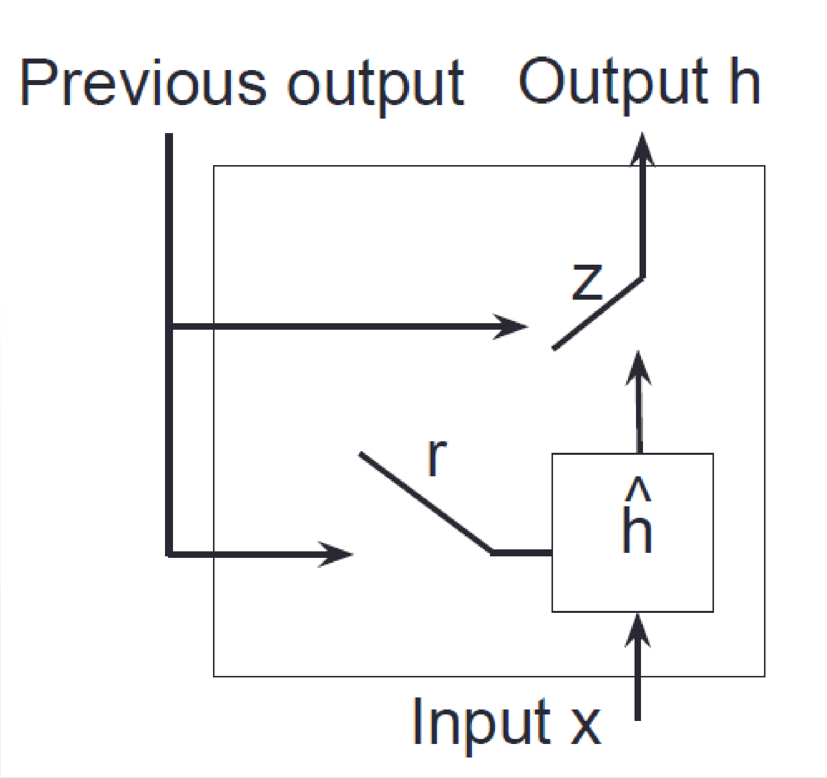
- Recurrent Neural network concept



How can we stop remembering

Gated Recurrent Unit (GRU)

- Add gates that can choose to reset (r) or update (z)



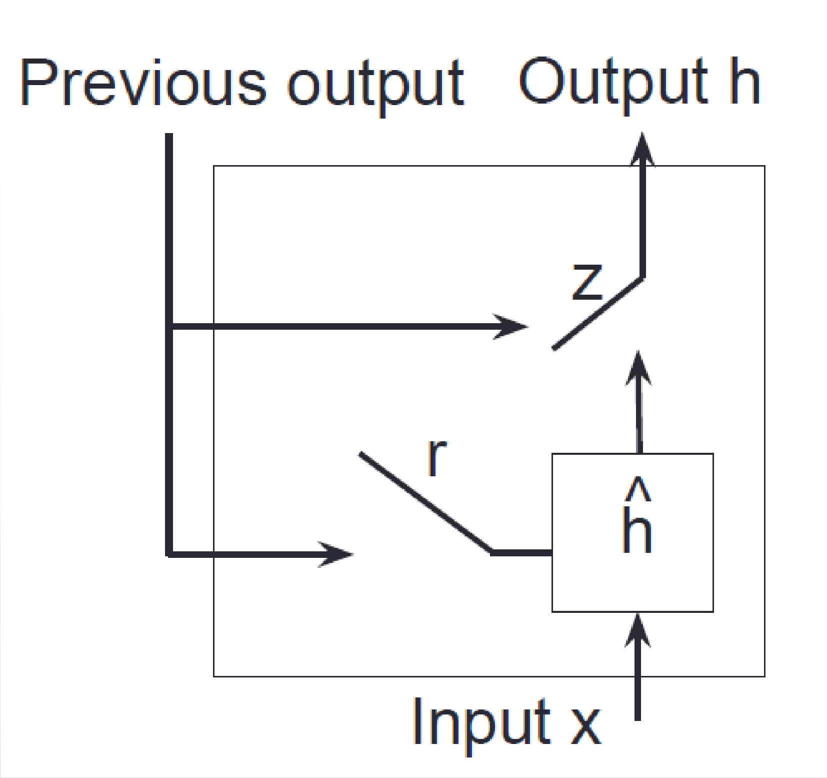
Neuron index

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

time index

Gated Recurrent Unit (GRU)

- Add gates that can choose to reset (r) or update (z)

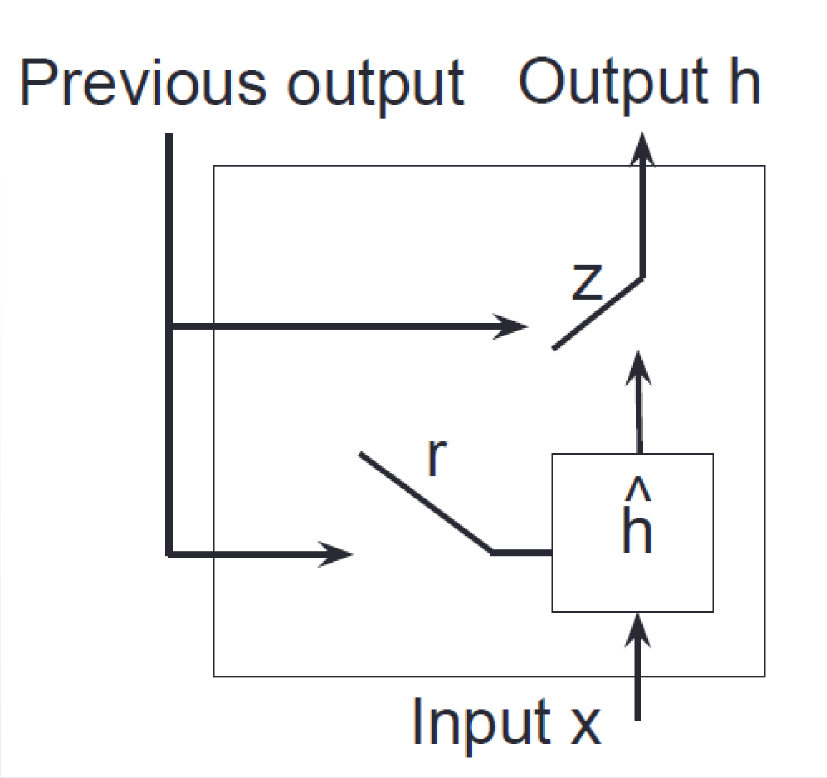


$$\boxed{h_t^j} = (1 - z_t^j) h_{t-1}^j + z_t^j \hat{h}_t^j$$

One GRU neuron output (scalar)

Gated Recurrent Unit (GRU) (cont.)

- Add gates that can choose to reset (r) or update (z)



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

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

Element-wise product

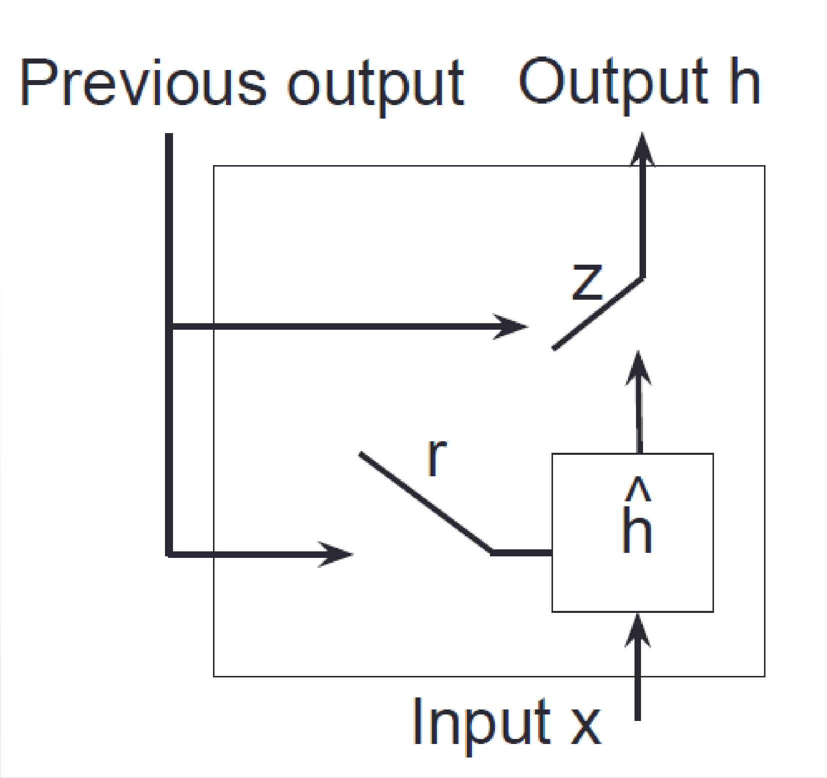
Linear transform with matrix multiply

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

$x_t^j = h_t^j$

Gated Recurrent Unit (GRU) (cont.)

- Add gates that can choose to reset (r) or update (z)



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

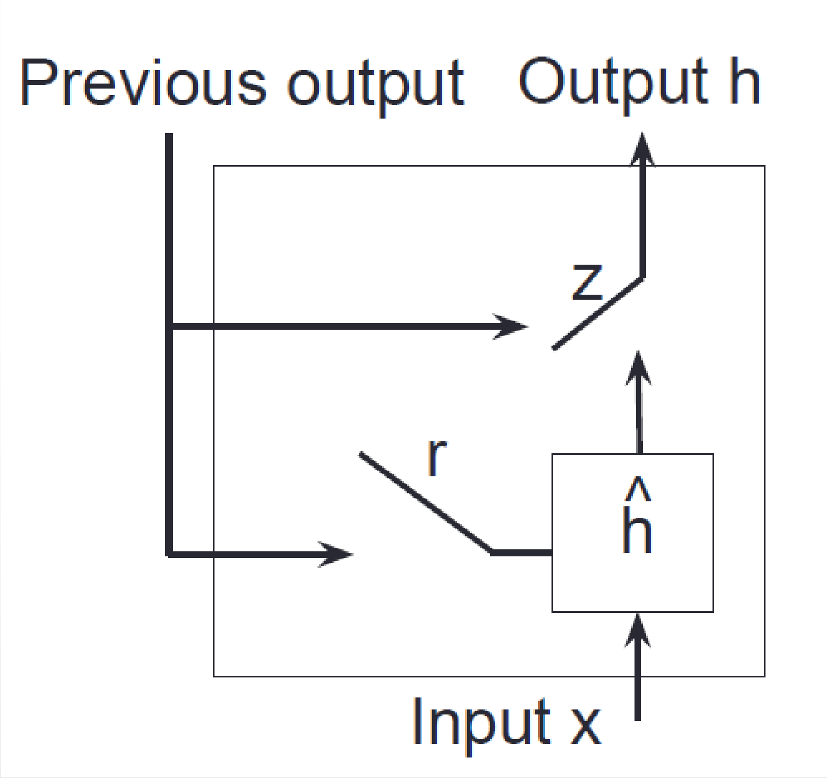
$$\hat{h}_t^j = tanh^j(W\mathbf{x}_t + U(\mathbf{r}_t \odot \mathbf{h}_{t-1}))$$

$$z_t^j = sigmoid^j(W_{\boxed{z}}\mathbf{x}_t + U_{\boxed{z}}\mathbf{h}_{t-1})$$

Indicates a different set of weights

Gated Recurrent Unit (GRU) (cont.)

- Add gates that can choose to reset (r) or update (z)



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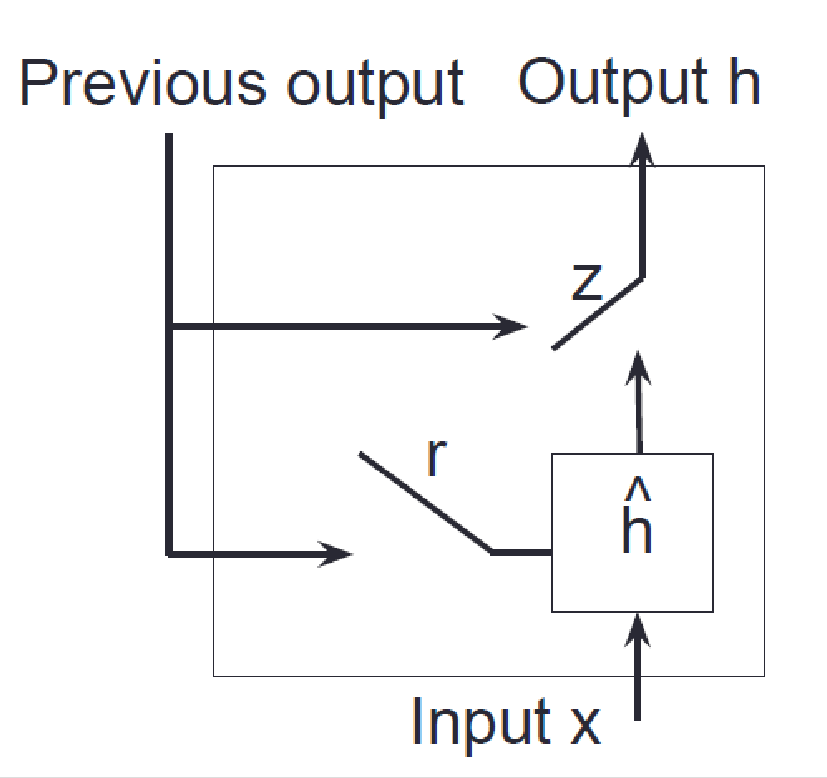
$$z_t^j = \underline{sigmoid}^j(W_z\mathbf{x}_t + U_z\mathbf{h}_{t-1})$$

Bounds the output to 0 to 1 for interpolation

Gated Recurrent Unit (GRU) (cont.)

- Add gates that can choose to reset (r) or update (z)



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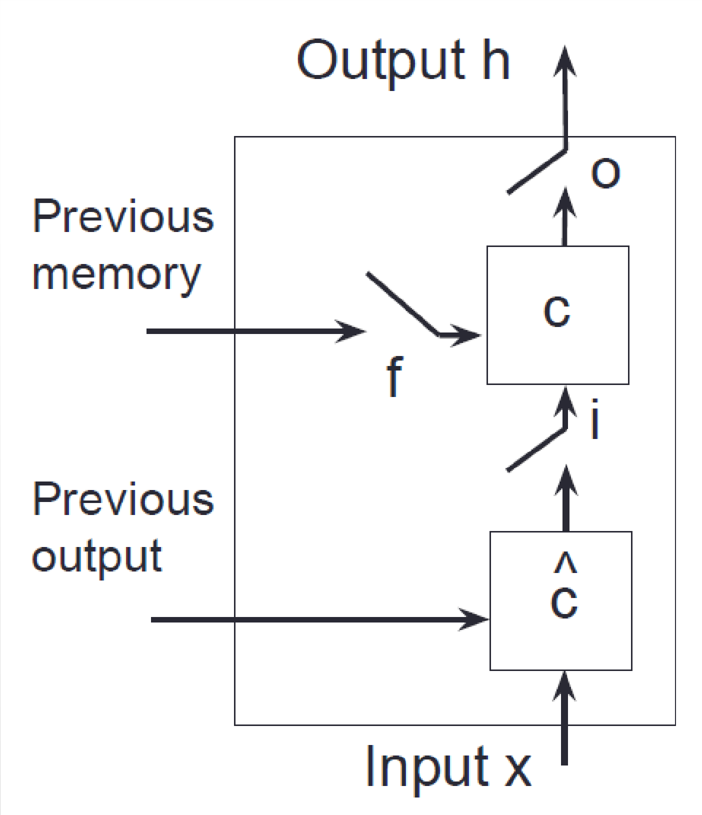
$$r_t^j = sigmoid^j(W_r\mathbf{x}_t + U_r\mathbf{h}_{t-1})$$

Long Short-Term Memory (LSTM)

- Have 3 gates, forget (f), input (i), output (o)
- Has an explicit memory cell (c)



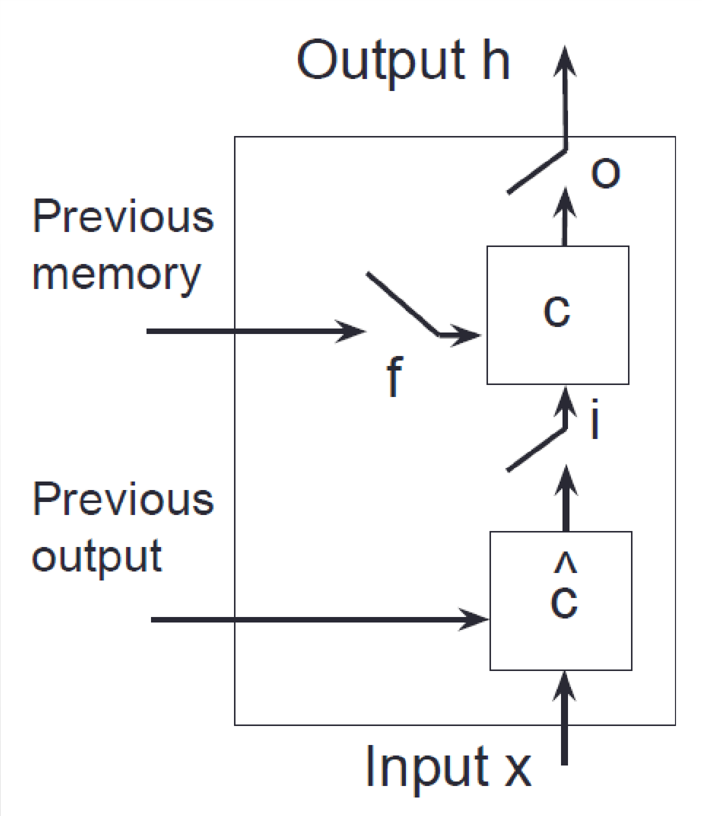
$$i_t^j = F^j(W_i \mathbf{x}_t + U_i \mathbf{h}_{t-1} + V_i \mathbf{c_{t-1}})$$
$$o_t^j = F^j(W_o \mathbf{x}_t + U_o \mathbf{h}_{t-1} + V_o \mathbf{c_t})$$
$$f_t^j = F^j(W_f \mathbf{x}_t + U_f \mathbf{h}_{t-1} + V_f \mathbf{c_{t-1}})$$

Contribution from memory "Peephole connection"

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

Long Short-Term Memory (LSTM) (cont.)

- Have 3 gates, forget (f), input (i), output (o)
- Has an explicit memory cell (c)



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

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

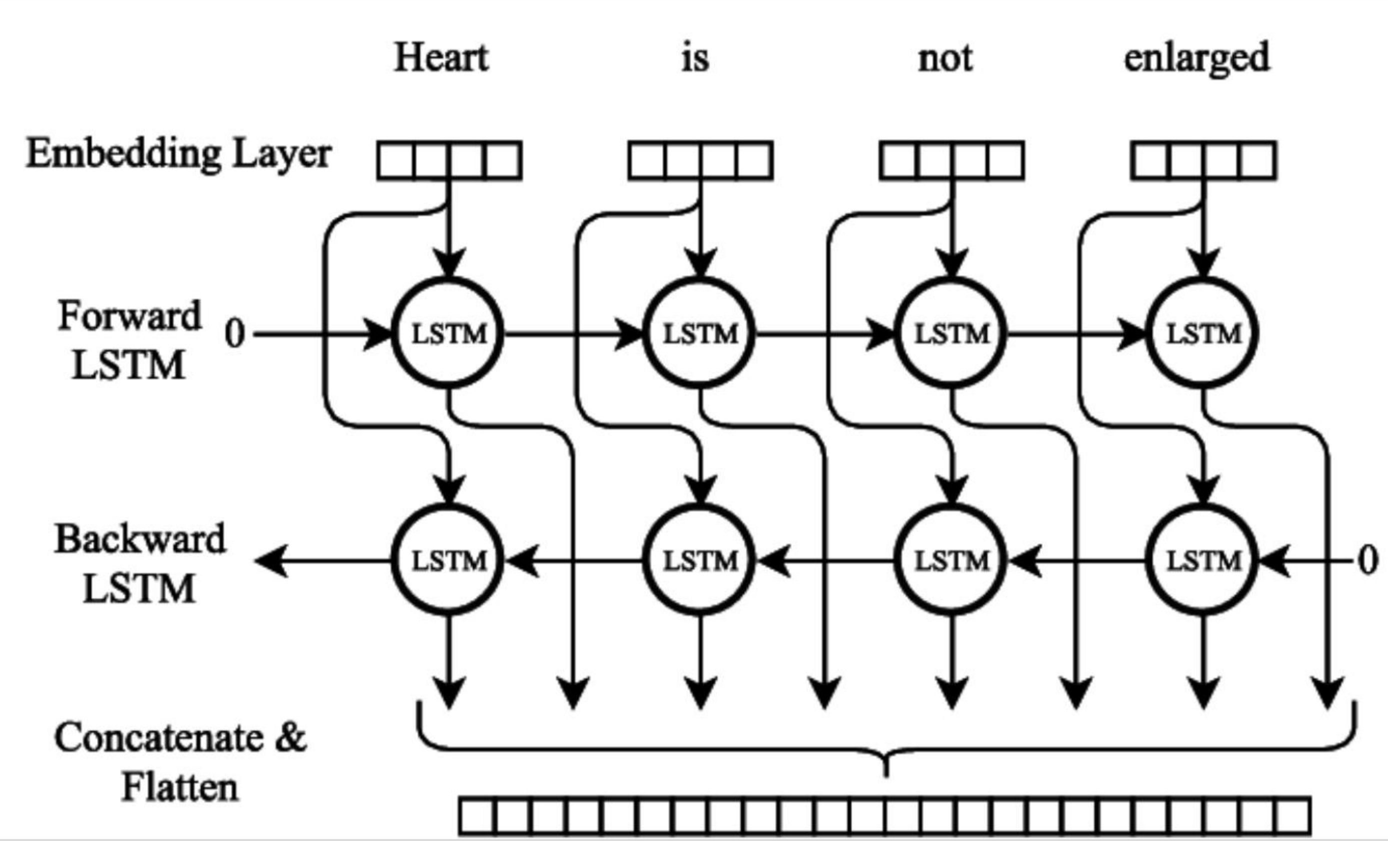
$$h_t^j = o_t^j tanh(c_t^j)$$

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

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

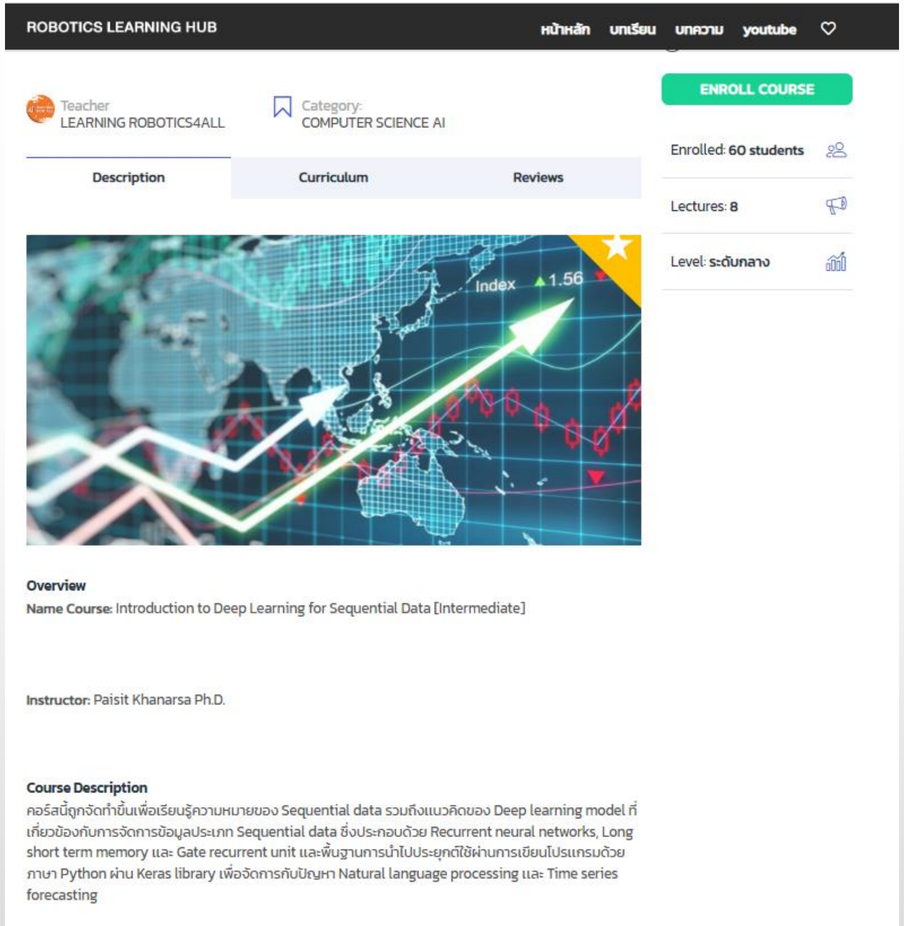
Bi-directional LSTM

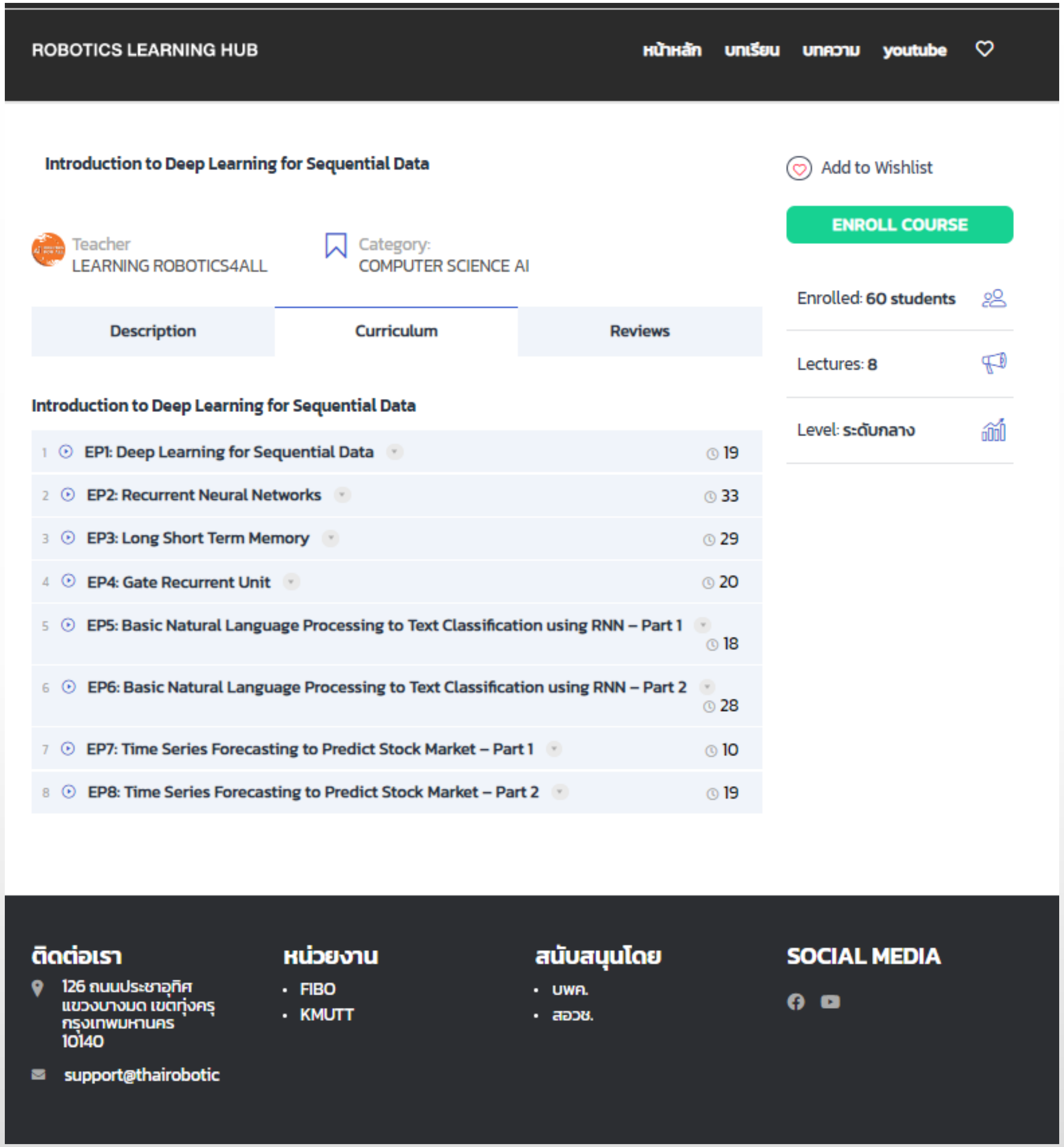
- Most of the time information from the future is useful for predicting the current output



https://paperswithcode.com/method/bilstm

External sources

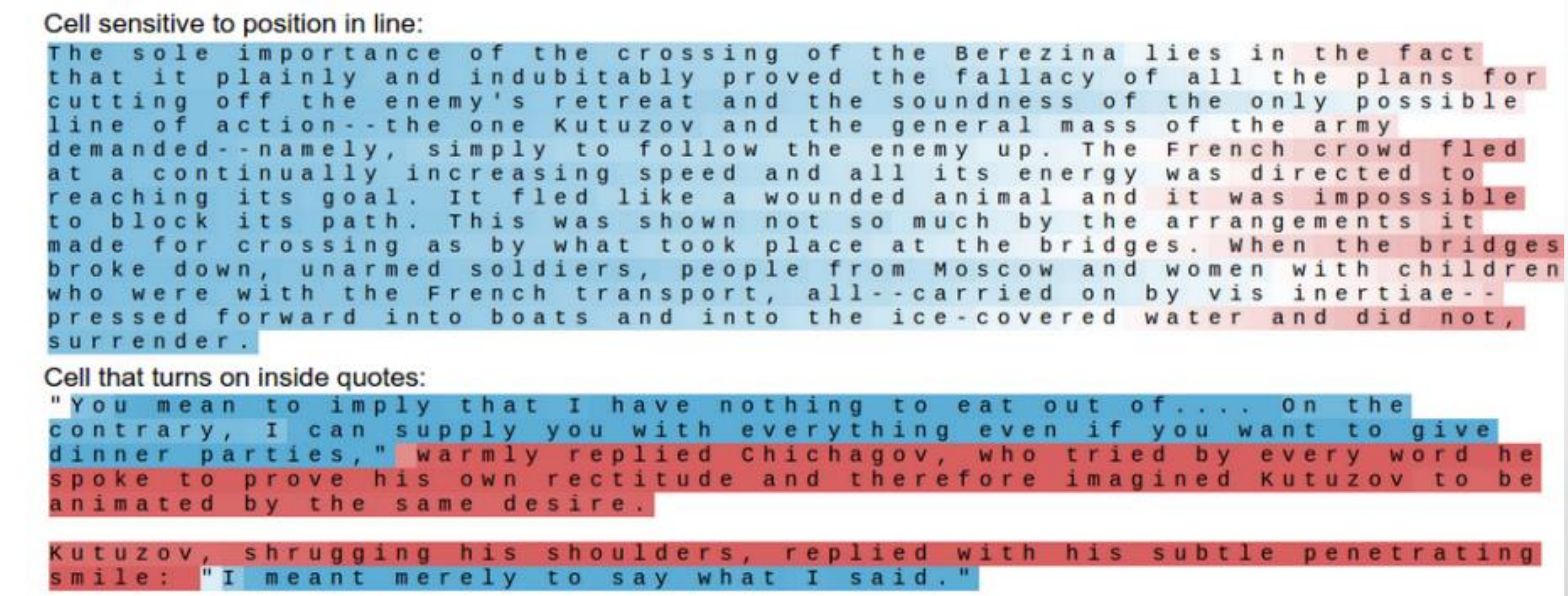




https://learn.thairobotics.org/courses/introduction-to-deep-learning-for-sequential-data-intermediate/

Deep Learning in NLP

- LSTM remembers meaningful thinks



Karpathy, Andrej, Justin Johnson, and Li Fei-Fei. "Visualizing and understanding recurrent networks." *arXiv preprint arXiv:1506.02078* (2015).

Adding meaning in NLP

- One hot encoding
- Dense representation (embedding)

Adding meaning in NLP

- One hot encoding
  - Categorical representation example:
    - Apple ---> 1 ---> [1,0,0,0,…]
    - Bird ---> 2 ---> [0,1,0,0,…]
    - Cat ---> 3 ---> [0,0,1,0,…]
    - Car ---> 5 ----> [0,0,0,0,1,…]

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  - Sparse representation: most values are zero
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  - Solve by Getting meaning into the feature vectors (Concatenate)
    - Apple ---> 1 ---> [1,0,0,0,..., 1,0]
    - Bird ---> 2 ---> [0,1,0,0,..., 0,1]
    - Cat ---> 3 ---> [0,0,1,0,..., 0,1]
    - Car ---> 5 ----> [0,0,0,0,1,...,1,0]

Feature vectors

Adding meaning in NLP

- Dense representation (embedding)
  - Encode sparse representation into a lower dimensional space
    - Apple ---> 1 ---> [1,0,0,0,…] ---> [1.2,2.5]
    - Bird ---> 2 ---> [0,1,0,0,…] ---> [0.3,0.6]
    - Cat ---> 3 ---> [0,0,1,0,…] ---> [0.25,0.71]
    - Car ---> 5 ----> [0,0,0,0,1,…] ---> [1.6,2.1]

Adding meaning in NLP

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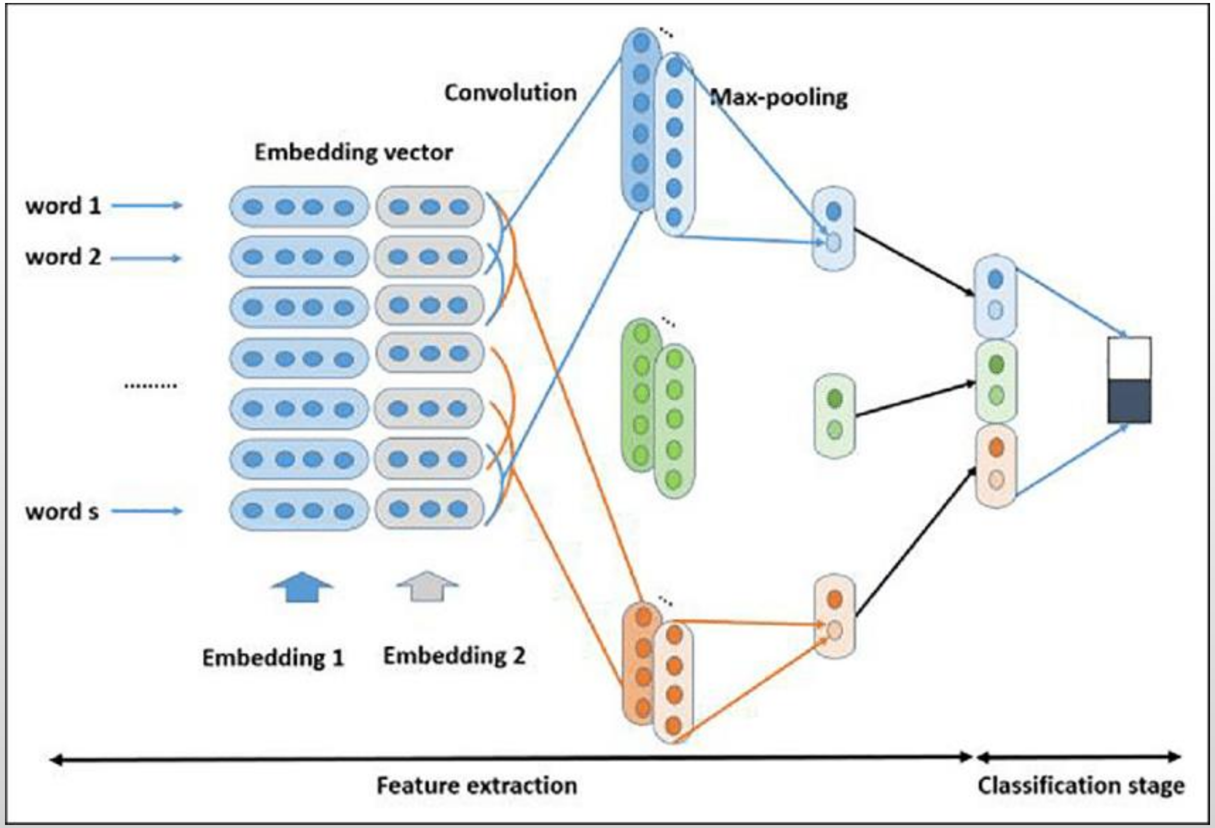
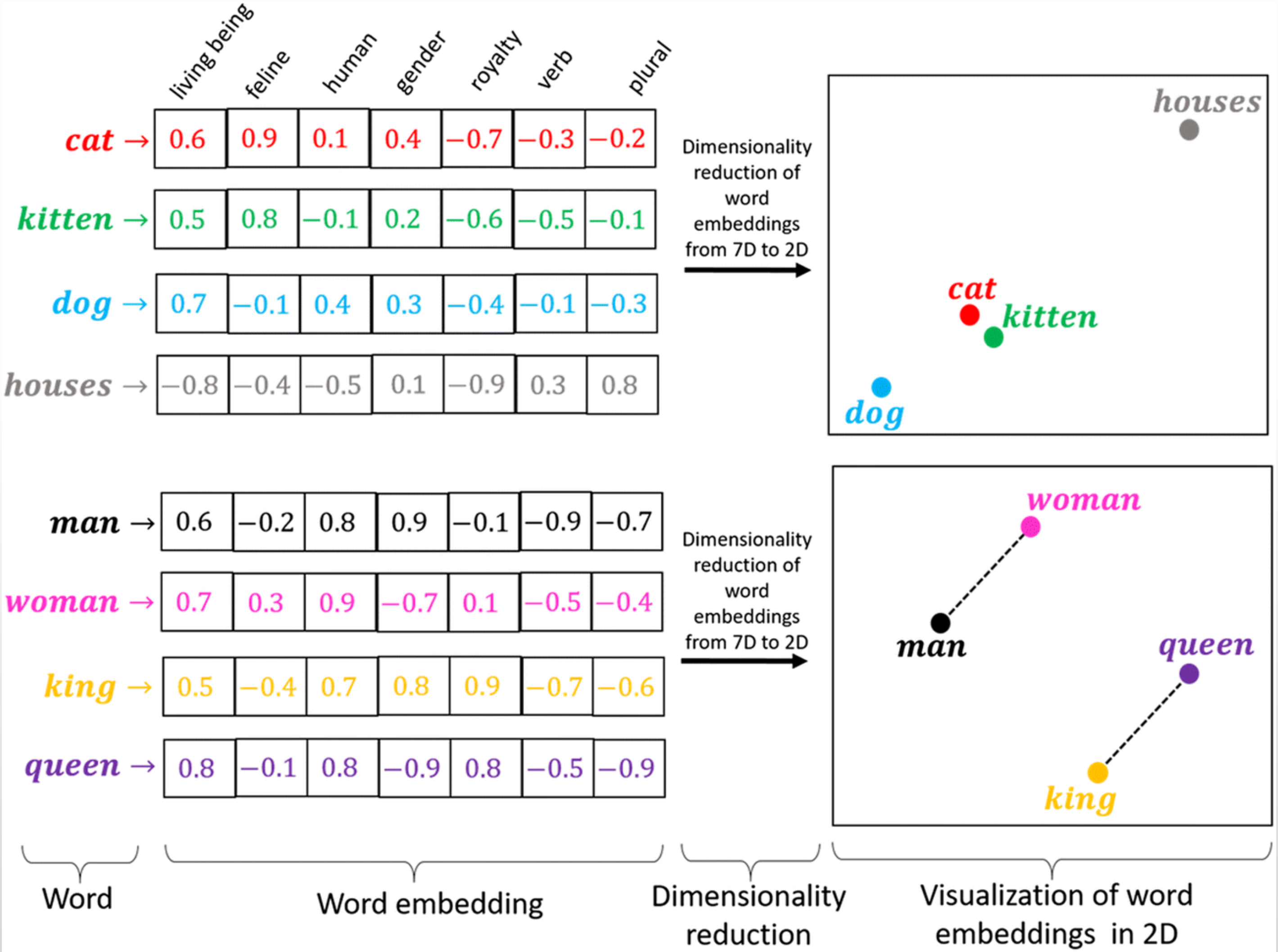
  - Encode sparse representation into a lower dimensional space
    - Apple ---> 1 ---> [1,0,0,0,…] ---> [1.2,2.5]



https://www.researchgate.net/figure/Proposed-CNN-on-multiple-word-embeddings-concatenated-at-embedding-layer_fig3_333752473

Embeddings



https://medium.com/@hari4om/word-embedding-d816f643140

Embeddings and meaning (semantic)

- Character Embedding of 32 dims to 2 dims for visualization