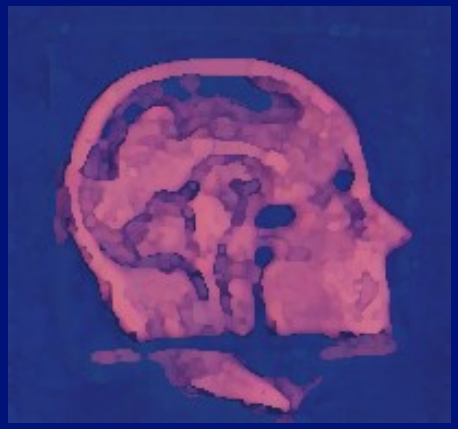
Deep Learning in Computer Vision



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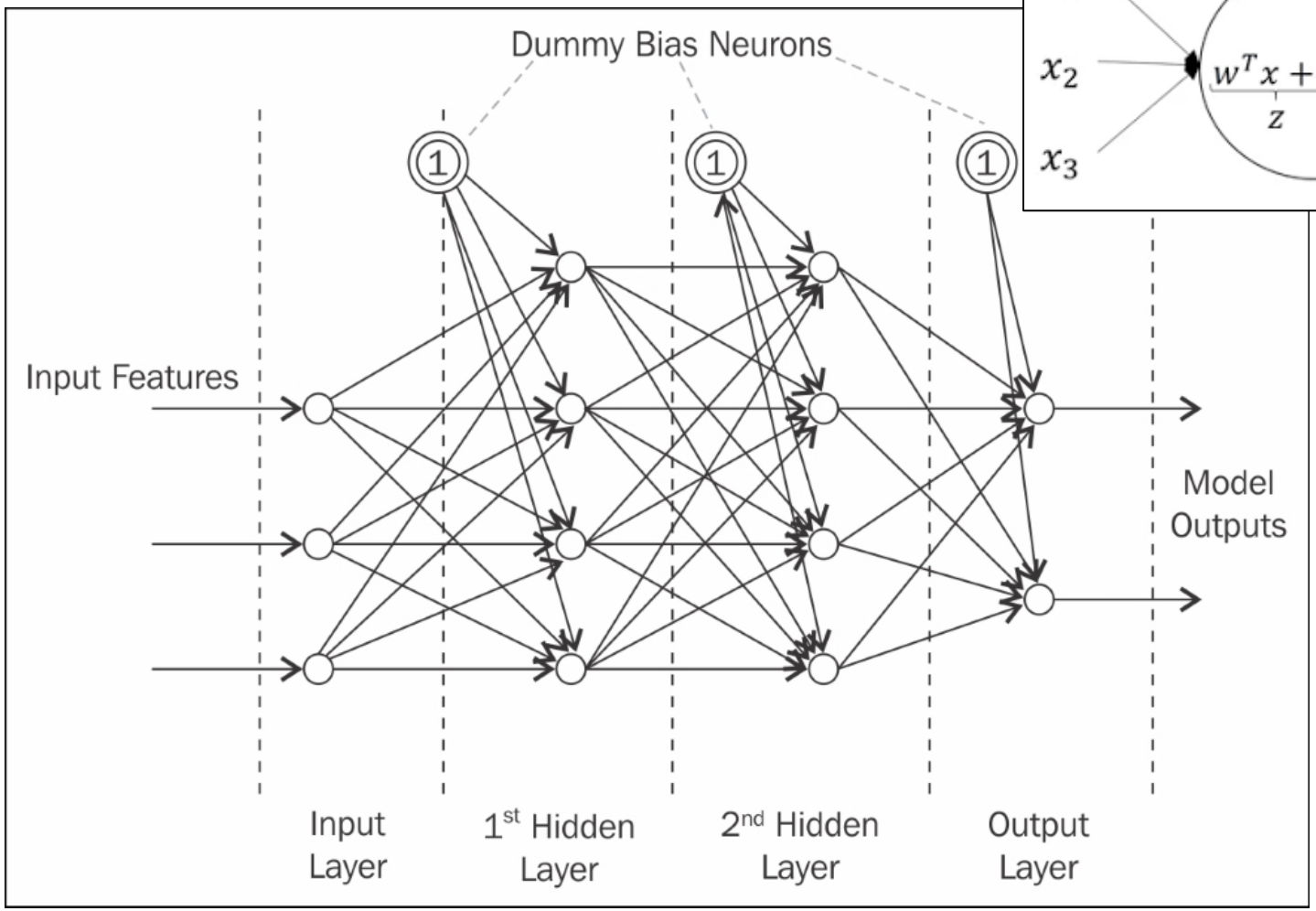
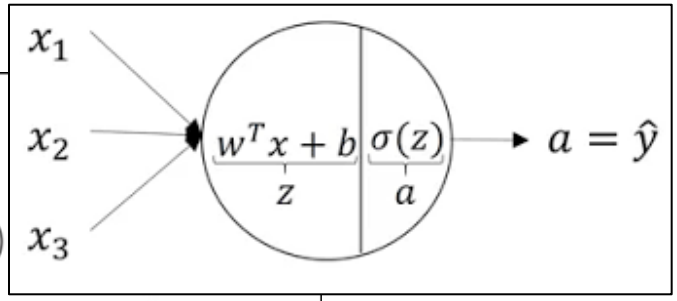
2/2020

The Multi-Layer Perceptron

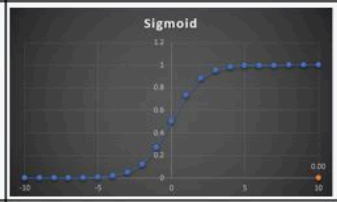
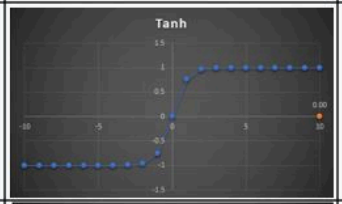
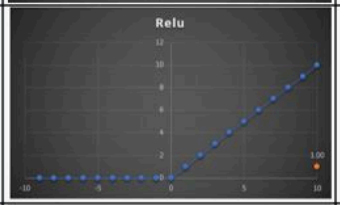




Notation

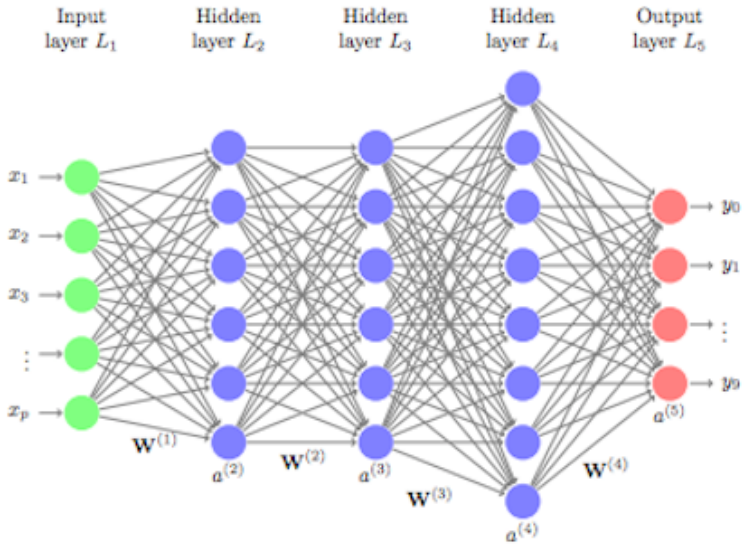
- X is the $n^{[0]}$,m data matrix of m samples
- Y is the $n^{[L]}$,m label matrix of m samples
- [l] is the layer index, l=0…L
- L is the number of layers
- $x^{(i)}$ denotes the i-th sample
- $x^{(i)}_j$ denotes the j-th variable of the i-th sample
- Each layer l has $n^{[l]}$ units
- $W^{[l]}$ is the $n^{[l]}$,$n^{[l-1]}$ weight matrix of layer l
- $b^{[l]}$ is the $n^{[l]}$ bias array in layer l
- $Z^{[l]}$ is the $n^{[l]}$,m matrix with $W^{[l]}A^{[l-1]}+b^{[l]}$
- $A^{[l]}$ is the $n^{[l]}$,m matrix with $g(Z^{[l]})$
- $X=A^{[0]}$; $Y\hat{}=A^{[L]}$

Activation Functions

Name	Plot	Equation	Derivative
Sigmoid		$f(x) = \sigma(x) = \frac{1}{1+e^{-x}}$	$f'(x) = f(x)(1-f(x))$
Tanh		$f(x) = \tanh(x) = \frac{(e^x - e^{-x})}{(e^x + e^{-x})}$	$f'(x) = 1 - f(x)^2$
Rectified Linear Unit (relu)		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Leaky Rectified Linear Unit (Leaky relu)		$f(x) = \begin{cases} 0.01x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0.01 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$

Deep MLP

- A shallow network can compute any function, but with an exponential number of hidden units
- Using more hidden layers decreases the number of units



http://uc-r.github.io/feedforward_DNN

Deep MLP Algorithm

1. Initialize parameters / Define hyperparameters
2. Loop for num_iterations:
   a. Forward propagation
   b. Compute cost function
   c. Backward propagation
   d. Update parameters (using parameters, and grads from backprop)
4. Use trained parameters to predict labels

MLP Gradient Descent – Forward/Loss

$$\mathrm{Z}^{[1]} = \mathrm{W}^{[1]}\mathrm{X} + \mathrm{b}^{[1]}$$

$$\mathrm{A}^{[1]} = g^{[1]}(\mathrm{Z}^{[1]})$$

$$\mathrm{Z}^{[l]} = \mathrm{W}^{[l]}\mathrm{A}^{[l-1]} + \mathrm{b}^{[l]}$$

$$\mathrm{A}^{[l]} = g^{[l]}(\mathrm{Z}^{[l]})$$

$$J(\mathrm{W},\mathrm{b}) = -\frac{1}{m}\sum(y \ln \hat{y} + (1-y)\ln(1-\hat{y}))$$

MLP Gradient Descent – Backward/ Update

$$dA^{[L]} = -Y / A^{[L]} - (1 - Y)/(1\text{-}A^{[L]})$$

$$dZ^{[L]} = A^{[L]} - Y$$

$$dA^{[L-1]} = W^{[L]T} dZ^{[L]}$$

$$dW^{[L]} = \frac{1}{m} dZ^{[L]} A^{[L-1]T}$$

$$db^{[L]} = \frac{1}{m} \sum dZ^{[L]}$$

$$dZ^{[l]} = dA^{[l]} * g^{[l]'}(Z^{[l]})$$

$$dA^{[l-1]} = W^{[l]T} dZ^{[l]}$$

$$dW^{[l]} = \frac{1}{m} dZ^{[l]} A^{[l-1]T}$$

$$db^{[l]} = \frac{1}{m} \sum dZ^{[l]}$$

$$dZ^{[1]} = dA^{[1]} * g^{[1]'}(Z^{[1]})$$

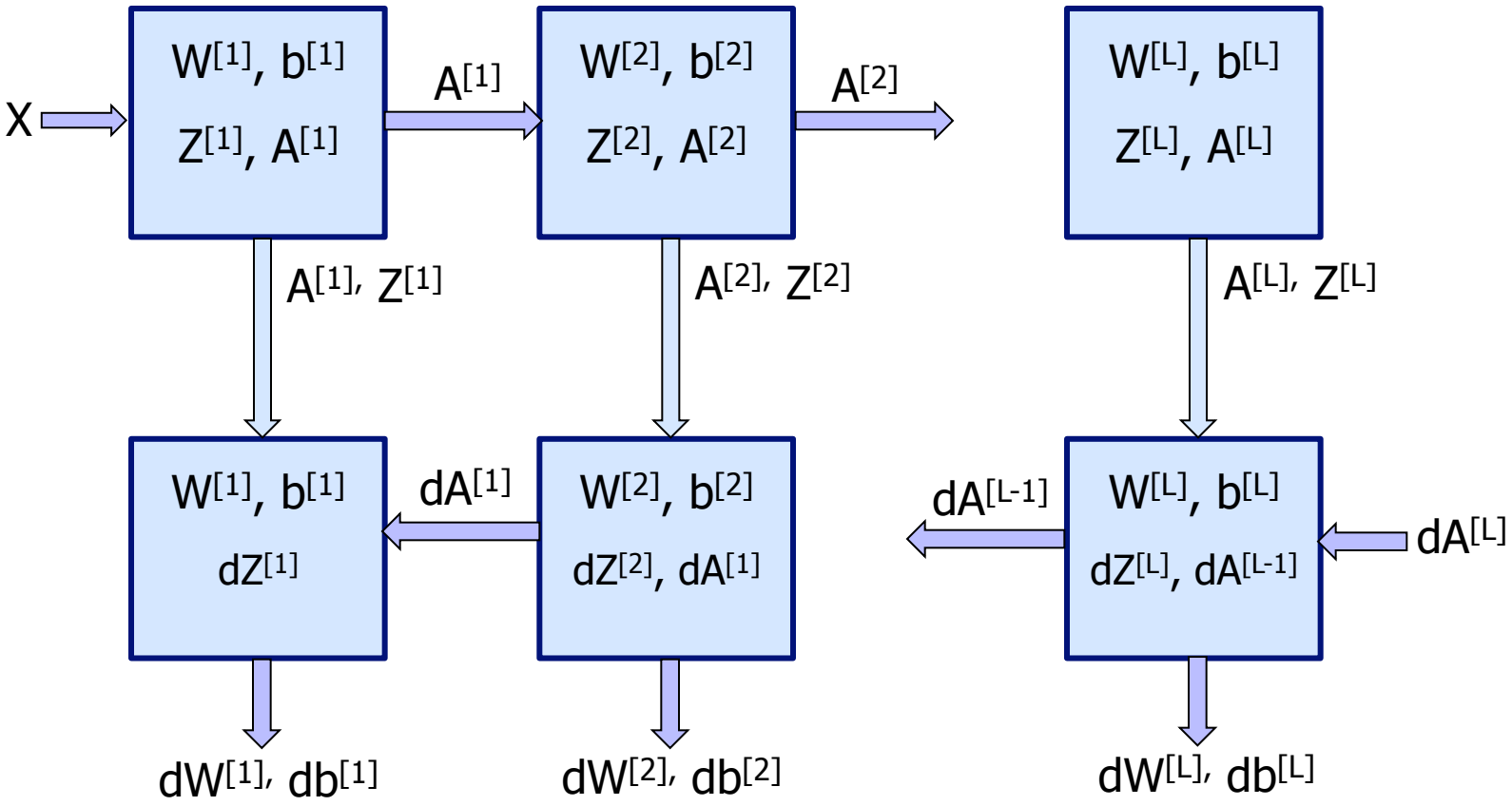
$$dW^{[1]} = \frac{1}{m} dZ^{[1]} X^{T}$$

$$db^{[1]} = \frac{1}{m} \sum dZ^{[1]}$$

$$W^{[l]}_{new} = W^{[l]} - \alpha dW^{[l]}$$

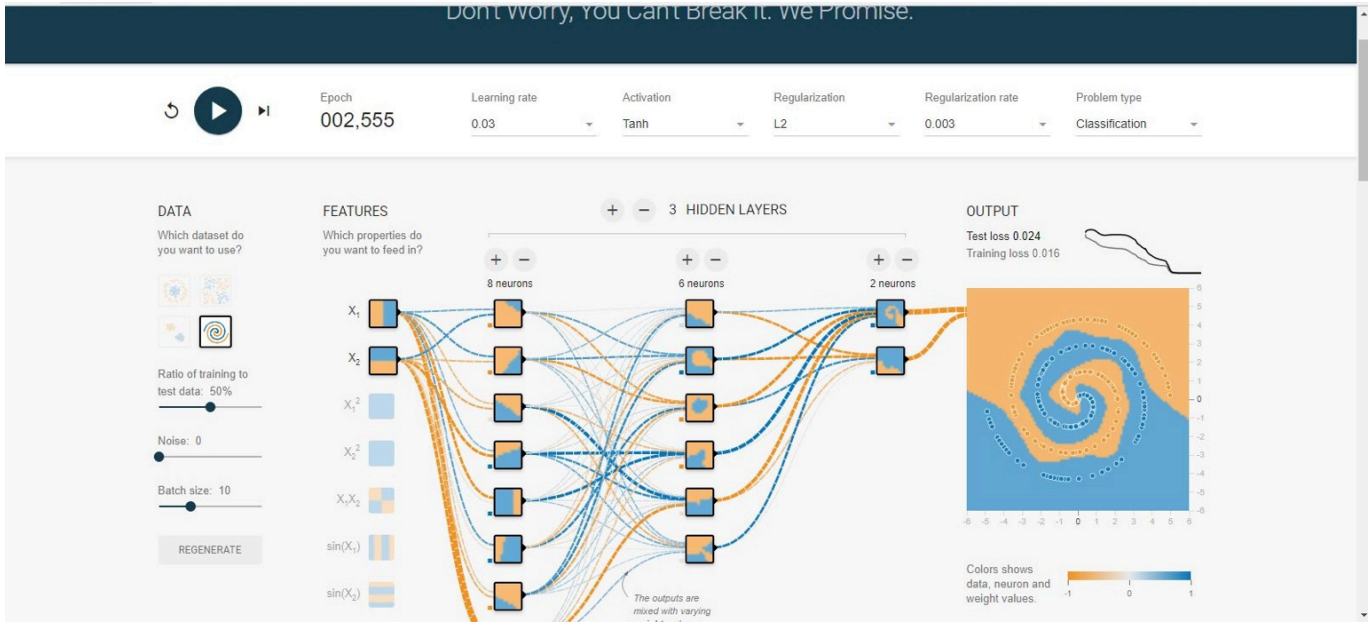
$$b^{[l]}_{new} = b^{[l]} - \alpha db^{[l]}$$

Using caches



MLP Visualization

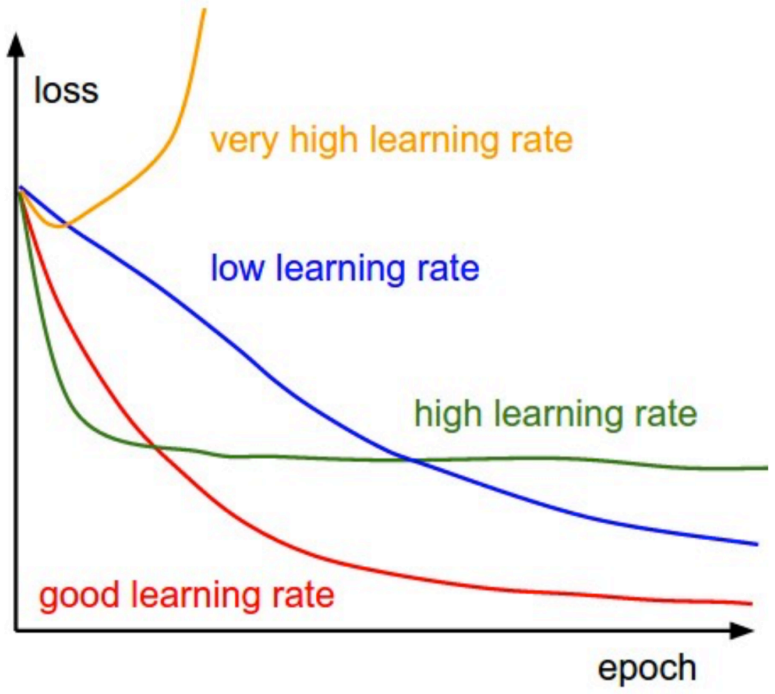
https://playground.tensorflow.org



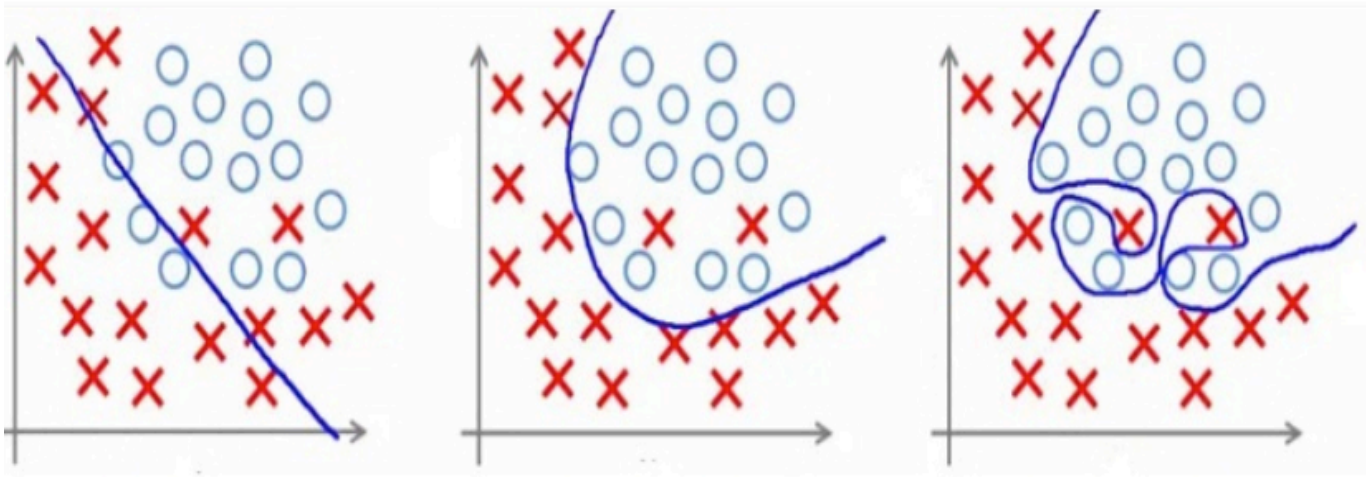
MLP Hyperparameters

- Learning rate
- Number of iterations
- Number of Layers
- Number of units per layer
- Activation functions

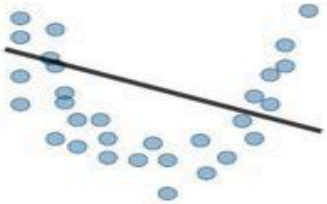
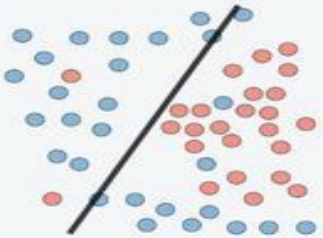
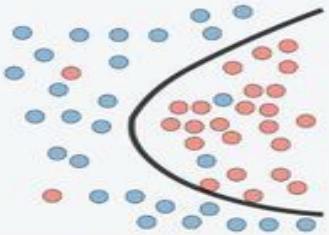
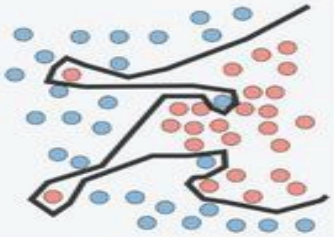
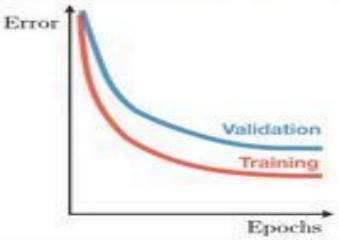
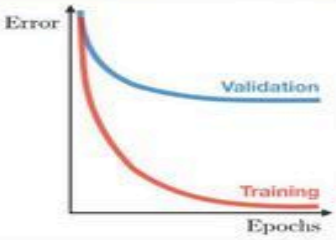
Learning Rate



Overfiting


Under-fitting
(too simple to explain the variance)
Appropriate-fitting
Over-fitting
(forcefitting -- too good to be true)

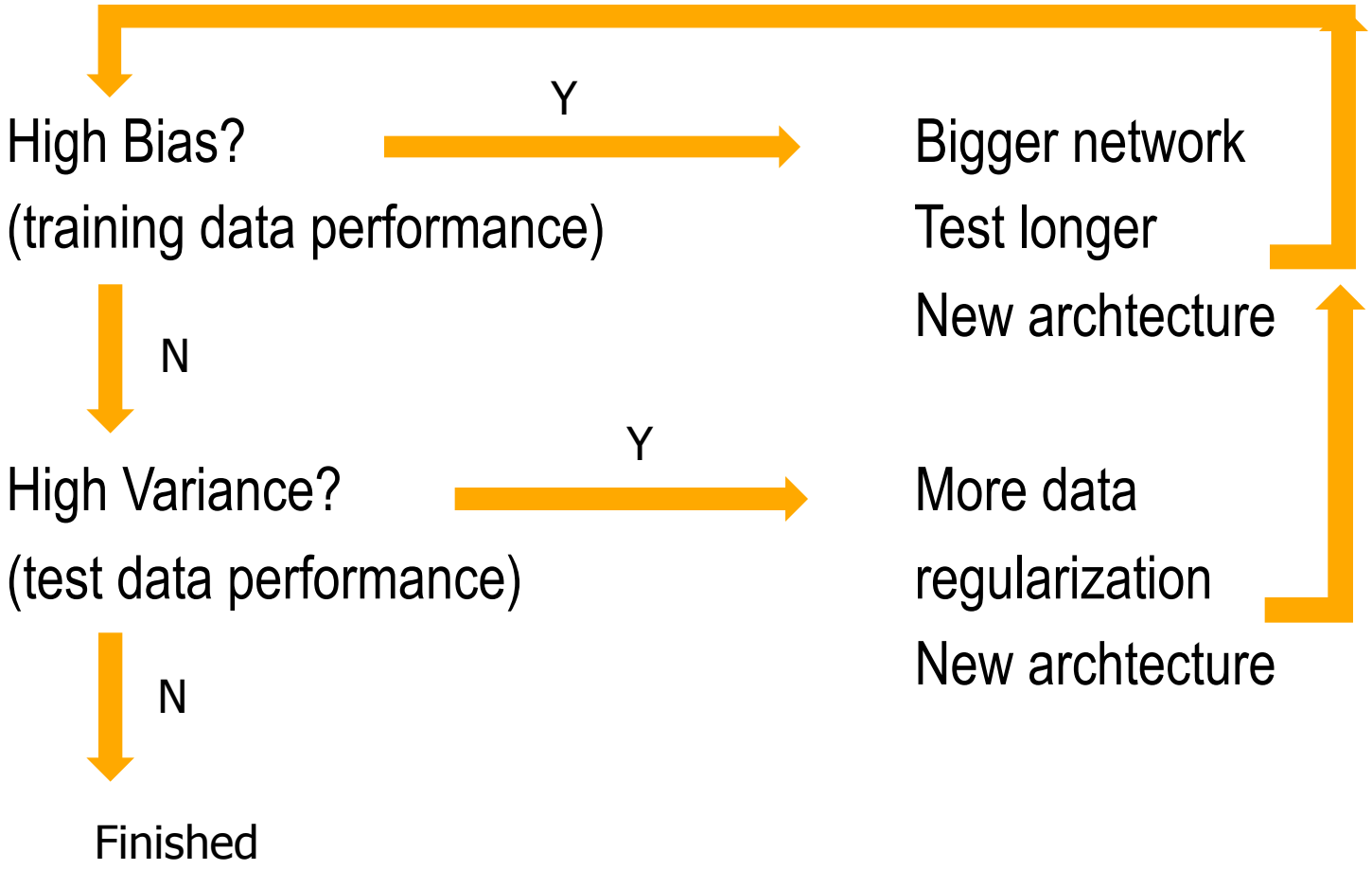
Bias and Variance

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

Bias and Variance

- If your model presents high bias:
  - Try a larger NN (> hidden layers, > units)
  - Try a different architecture that better fits your problem
  - Run longer
  - Try different optimization algorithms
- If your model presents high variance:
  - Get more data
  - Try regularization
  - Try a different architecture that better fits your problem

Guidelines for a ML algorithm



Techniques to reduce overfitting

- Regularization
- Data augmentation
- Early stopping (stop iterating if the dev error starts to increase). May result in underfitting.

L2 Regularization

- Include a term in the cost function in order to keep NN weights small. Some will be close to 0, reducing the number of active hidden units (simpler networks)
- W influences the value of z. The activation function of small z has a more linear behavior (less overfitting)

$$J(\mathrm{W},\mathrm{b}) = -\frac{1}{m}\sum L(y,\hat{y}) + \frac{\lambda}{2m}\sum_{l}\sum_{i}\sum_{j}(w_{ji}^{[l]})^2$$

$$dw^{[l]} = (from\_bp) + \frac{\lambda}{m}w^{[l]}$$

$$w^{[l]} = w^{[l]} - \alpha dw^{[l]}$$

Dropout Regularization

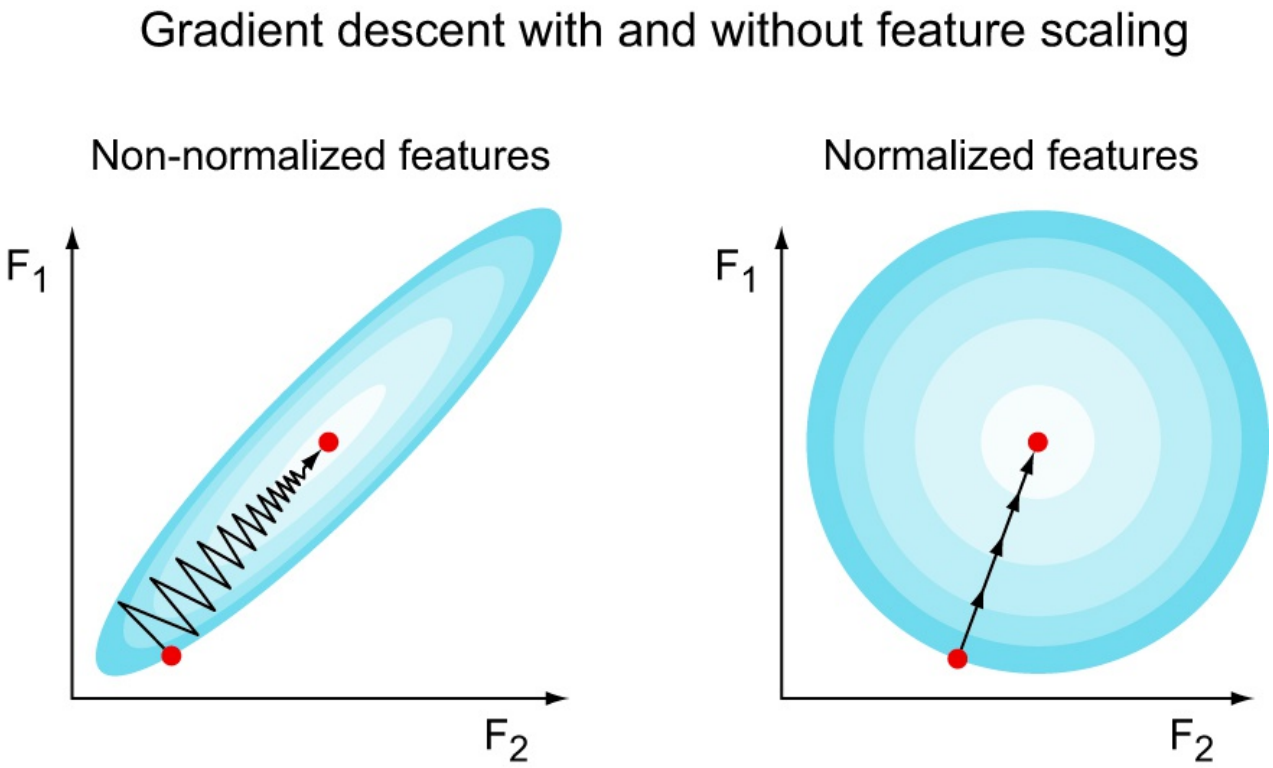
- Inverted dropout: Randomly block a fraction *p* of units from each hidden layer (make a=0), at each iteration of the training process (no dropout to test!)
- Normalize the remaining by dividing *a/(1-p)*
- As any unit can be blocked, the network tends to get more balanced weights
- Larger layers may have larger dropout fractions
- Input layer usually has no dropout

Techniques to speedup convergence

- Normalization
- Momentum
- Mini-batch descent
- Initialization

Normalization

- Bring input variables into same scale: (x-mean)/stdev.
- Training mayspeed up.



Momentum

- Use momentum to smooth the gradients and speed up convergence. Momentum considers the history of gradients

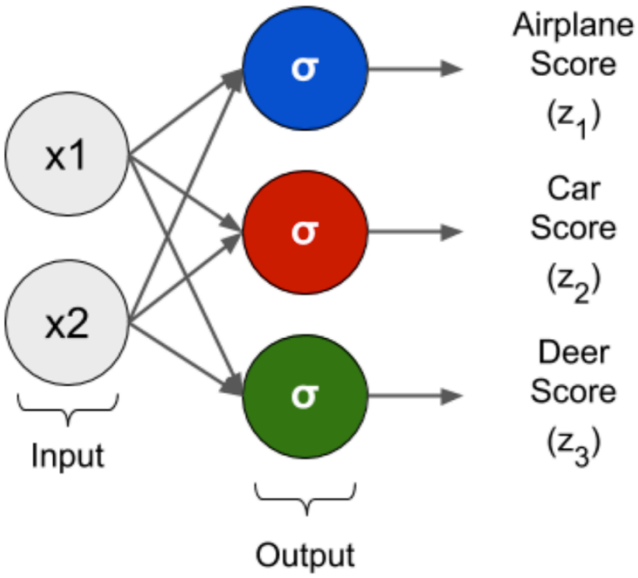
$$v_{dW} = \beta v_{dW} + (1 - \beta) dW$$
$$v_{db} = \beta v_{db} + (1 - \beta) db$$
$$W = W - \alpha v_{dW}, \quad b = b - \alpha v_{db}$$

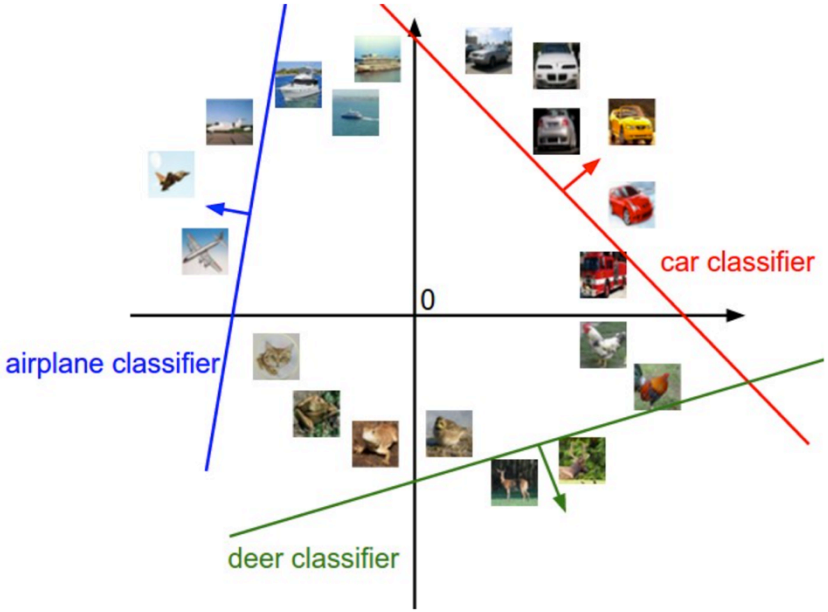
- Other methods to update parameters: RMSprop, Adam, Adaptative learning rate...

Other useful techniques

- Vanishing/exploding gradients may occur in deep NN, slowing down training. Initializing the weights properly may avoid some of these problems:
  - $W^{[l]}$=random*sqrt(2/$n^{[l-1]}$) for ReLU
  - $W^{[l]}$=random*sqrt(1/$n^{[l-1]}$) for tanh
- Use mini-batch gradient descent: partition training set into small batches and do many forward-backward loops for each epoch
- Size of batches is a hyperparameter: size=m is the batch version; size=1 is the stochastic gradient descent. Size must fit in memory

Multiple classes





Multiple classes

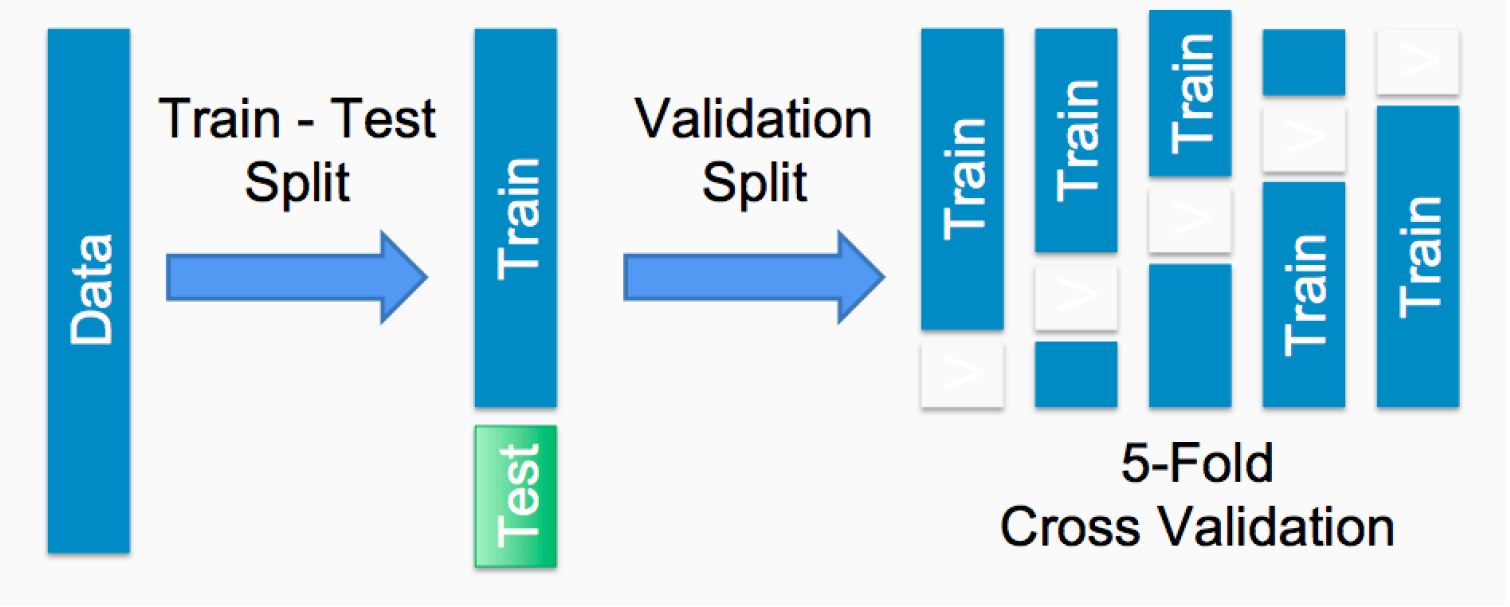
- In order to classify into n classe, use a n-unit output layer
- Each unit's output should reflect the probability of the input being each class
- Use the softmax activation function:

$$a_i = \hat{y}_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

and the Loss Function (Maximum Likelihood Estimator):

$$L(y, \hat{y}) = -\sum_{j=1}^{n} y_j \log \hat{y}_j ; dz = \hat{y} - y$$

Data Split Strategies



References and acknowledgements

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Reference courses include Machine Learning and Deep Learning CS230 and CS231 from Stanford University, Deep Learning from UFMG, Deep Learning CS498 from Un. Of Illinois.