



Deep Forward Networks - Optimization

Thursday
08h00-09h00

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Machine Learning Definition

« A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P , if its performance at tasks in T , as measured by P , improves with experience E . »

Tom M. Mitchell (1997)



how well the algorithm
performs on the “walking” task

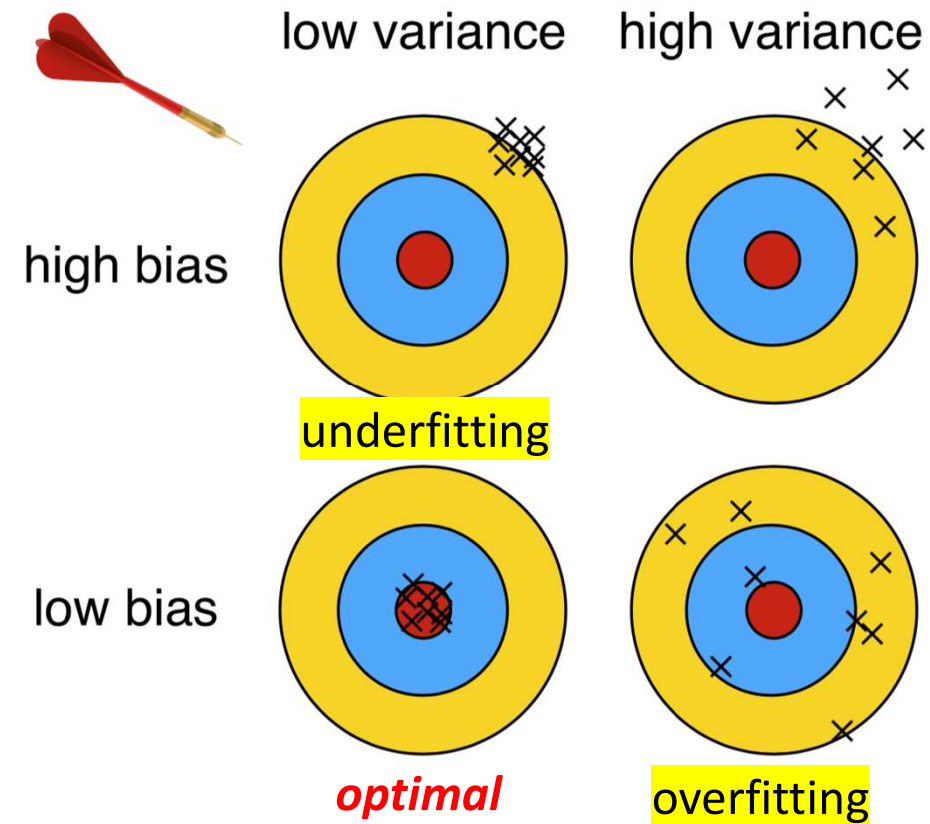
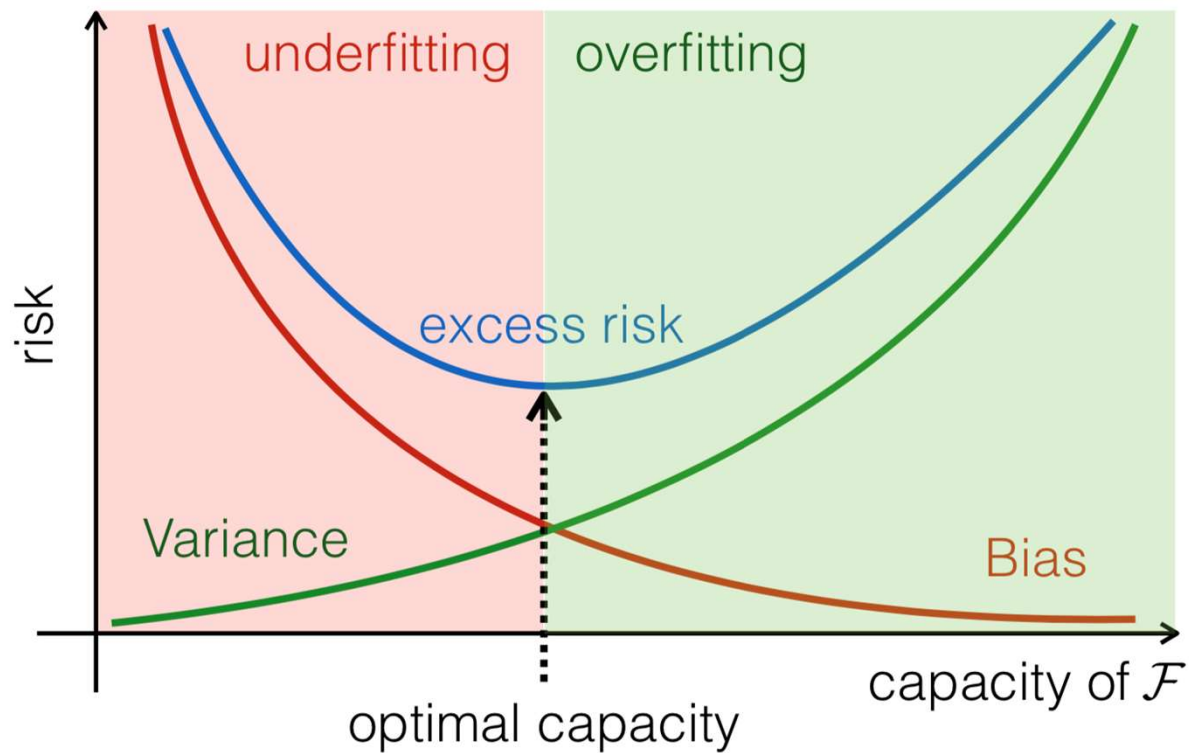
Performance Measure P

Estimate the ML algorithm performance on task T using the validation set

Introduction

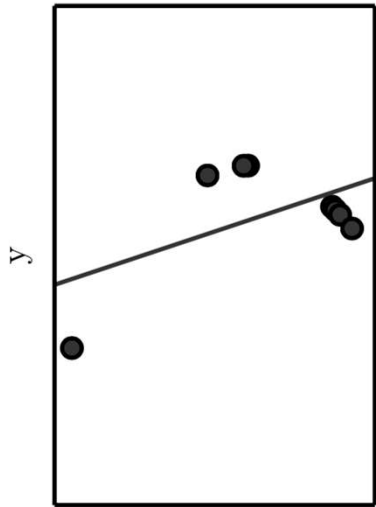
- To evaluate a ML algorithm, we need a way to measure **how well it performs on the task**
- It is measured **on a separate set** (test set) from what we use to build the function f (training set)
- **Examples :**
 - Classification accuracy (portion of correct answers)
 - Error rate (portion of incorrect answers)
 - Regression accuracy (e.g. least squares errors)

Bias and Variance - Overfitting and Underfitting



Overfitting and Underfitting

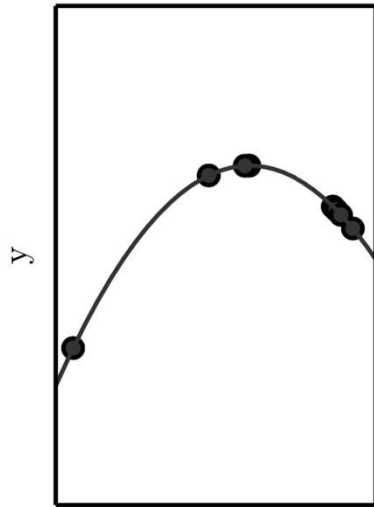
Underfitting



x_0

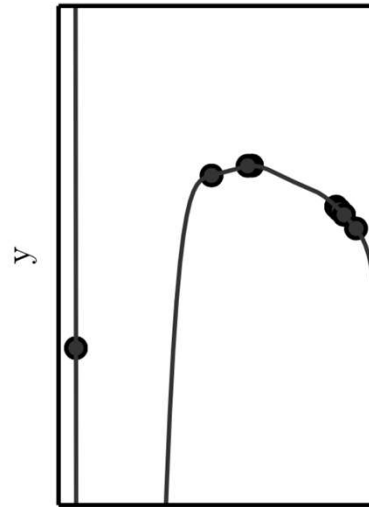
High bias

Appropriate capacity



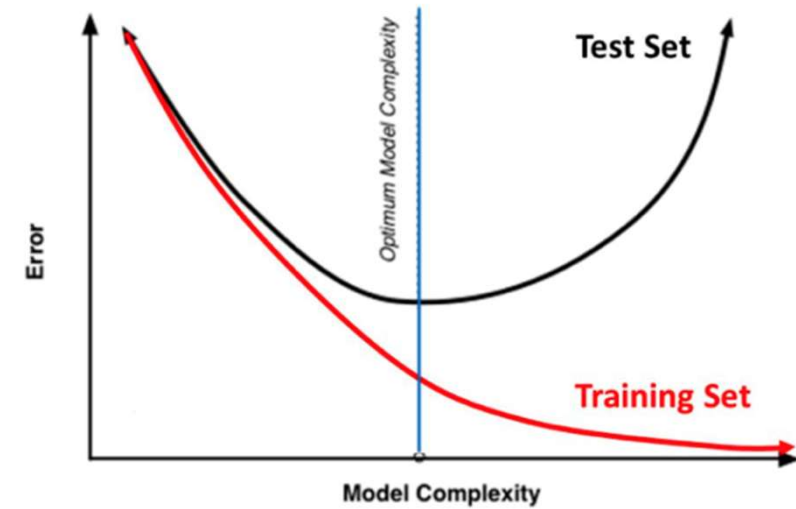
x_0

Overfitting



x_0

High variance



Optimization

In terms of performance and time





1. Performance

- Bias reduction techniques
- Variance reduction techniques

Case

- You want to find cats in images

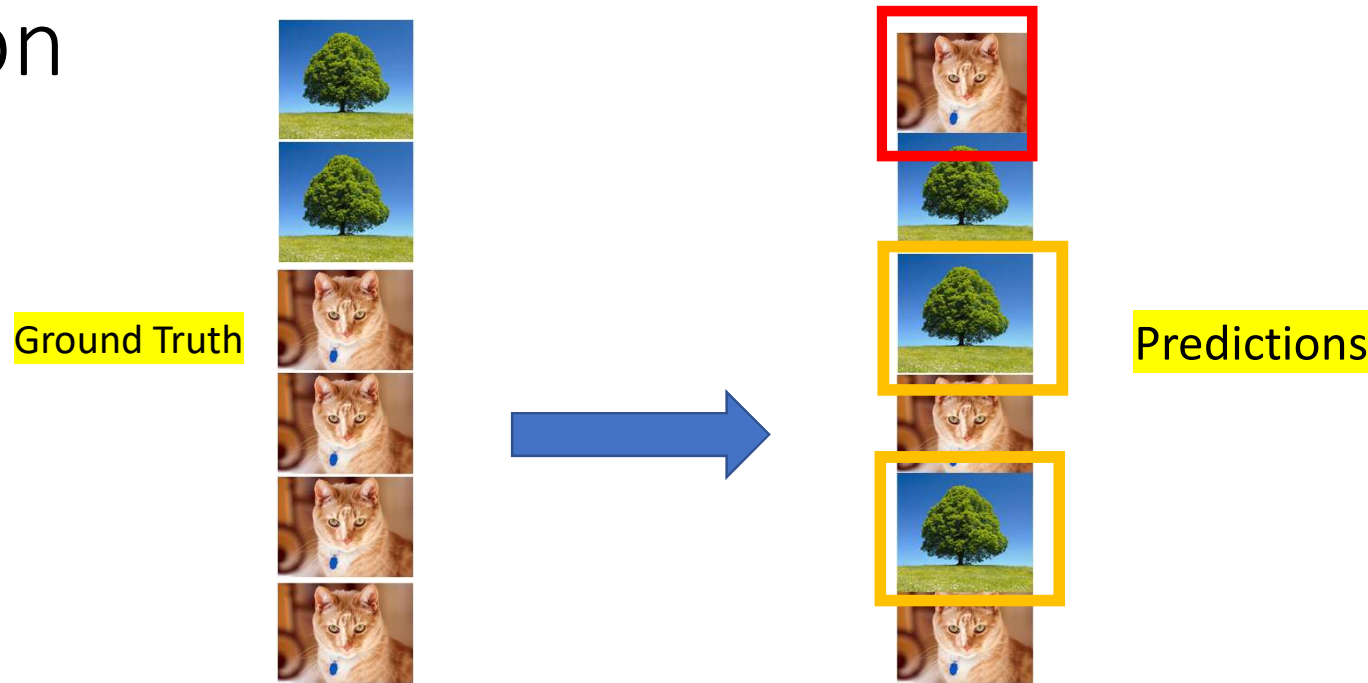


- **Classification error** (portion of wrong answers) used as an **evaluation metric**

Algorithm	Classification error (%)
A	3%
B	5%

➤ *Which one is best ?*

Evaluation metrics



$$\text{Precision (\%)} = \frac{\text{True positive}}{\text{Number of predicted positive}} \times 100 = \frac{\text{True positive}}{(\text{True positive} + \text{False positive})} \times 100$$

$$\frac{2}{2 + \boxed{1}} \times 100 = 66\%$$

$$\text{Recall (\%)} = \frac{\text{True positive}}{\text{Number of predicted actually positive}} \times 100 = \frac{\text{True positive}}{(\text{True positive} + \text{False negative})} \times 100$$

See also Sensitivity (same as recall) and Specificity

$$\frac{2}{2 + \boxed{2}} \times 100 = 50\%$$

F1-score

- F1-score is a harmonic mean combining p and r

$$\text{F1-Score} = \frac{2}{\frac{1}{p} + \frac{1}{r}}$$

	<u>Precision</u>	<u>Recall</u>	<u>F1Score</u>
Algo 1 →	0.5	0.4	0.444 ✓
Algo 2 →	0.7	0.1	0.175
Algo 3 →	0.02	1.0	0.0392

First of all, understand your data !

- Carry out manual **error analysis**
 - Look at *mislabeled development set* examples (*do not look at test set*)
 - For example : check by hand 500 pictures (incorrect labels ? Foggy pictures ? Other causes ?)
- Clean up **incorrectly labeled** data
 - Apply same process to your dev and test sets !



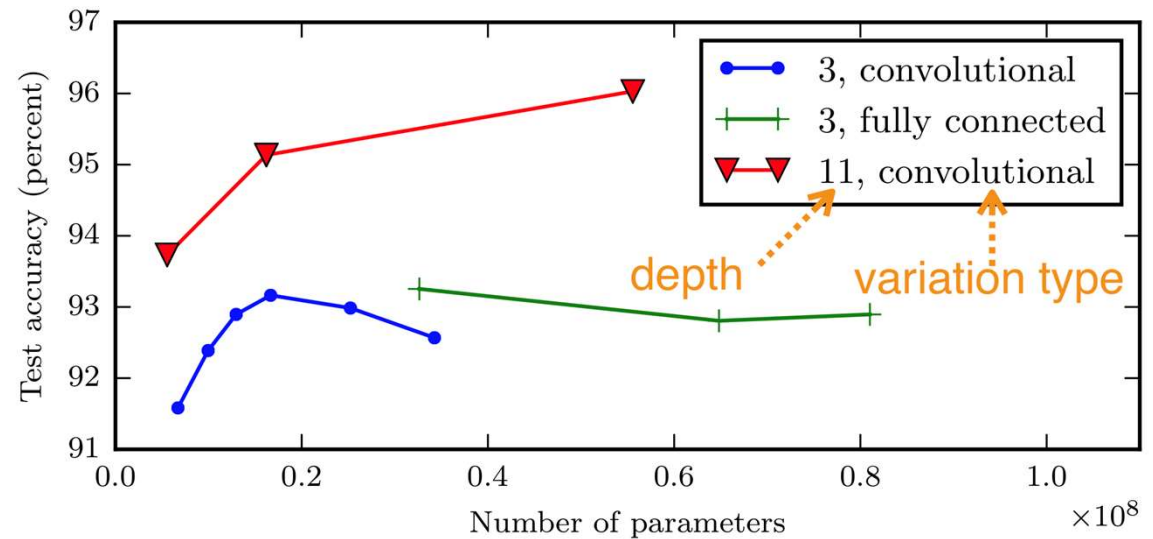
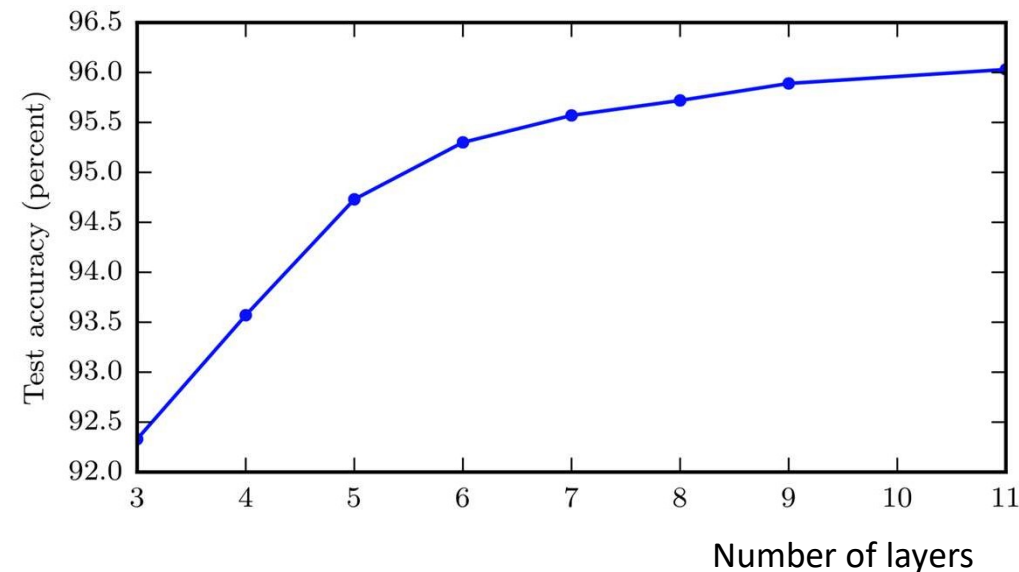


Bias Reduction techniques

- Hyperparameter tuning
- Model tuning
- Optimization algorithm

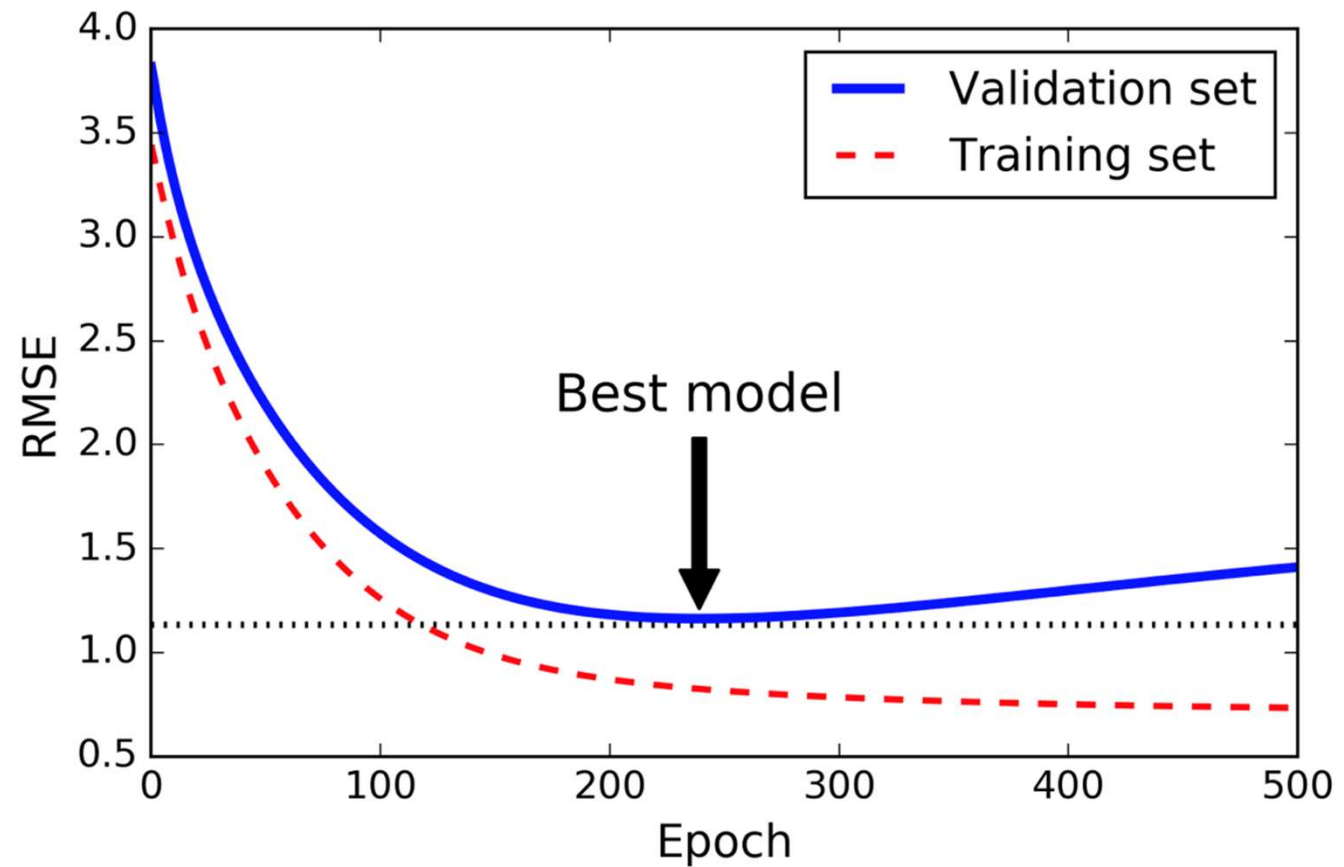
Hyperparameters : number of hidden layers/units

- To go **deeper** helps generalization (but depends on application)
- *better to have many simple layers than few highly complex ones*



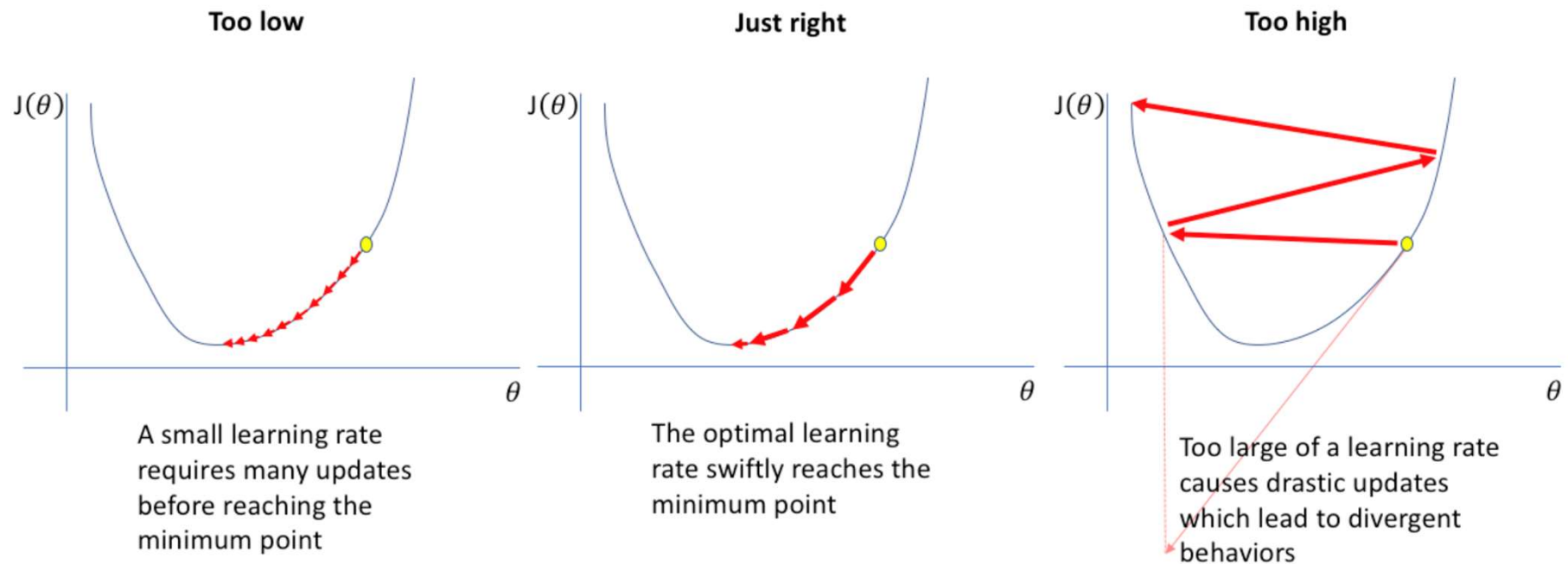
Hyperparameters : epochs

- Train *longer*



Hyperparameters : learning rate α

- Has a significant impact on the model performance, while being **one of the most difficult parameters** to set

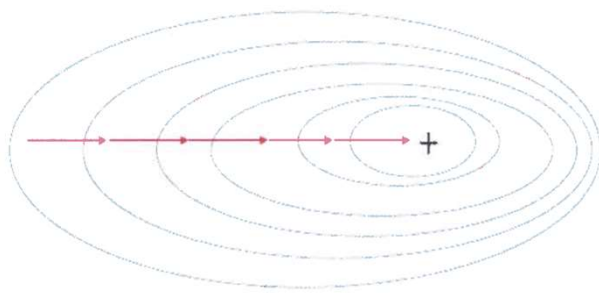


- We can also design a scheduler for the learning rate

Hyperparameters : batch size

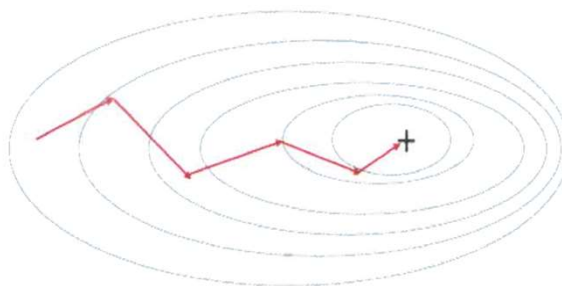
- At each iteration :

Gradient descent (GD)



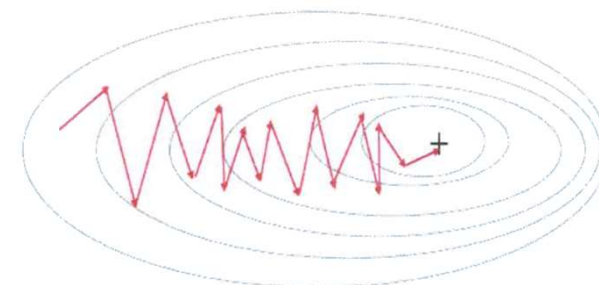
the *whole* training set

Mini-batch gradient descent



a *batch* of samples

Stochastic gradient descent (SGD)

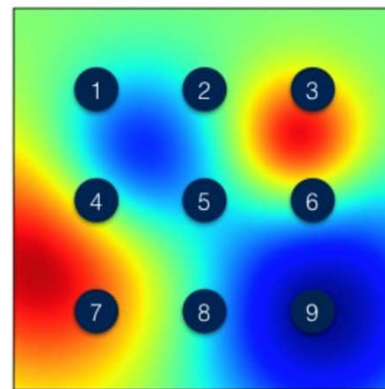


1 sample

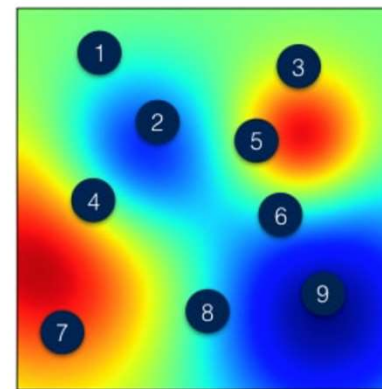
- Batch size choice *typically 32,64,128,256,512*

Hyperparameters : Global Search

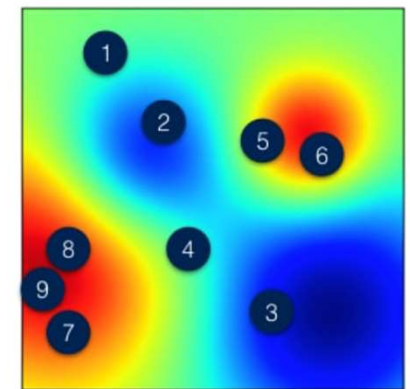
- List :
 - α (**0.0001 – 1**)
 - number of hidden layers
 - number of hidden units
 - learning rate decay
 - mini-batch size
 - ...
- Advice is to use **random values**



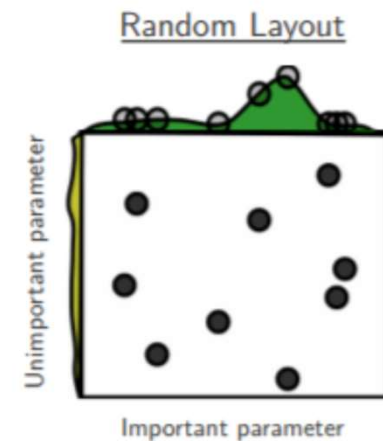
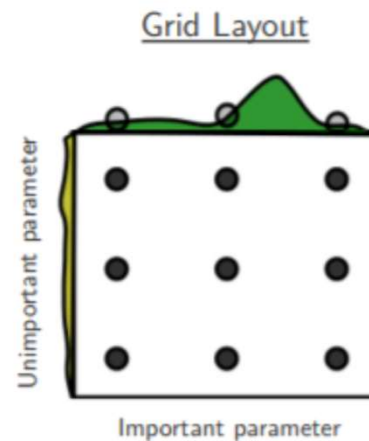
Grid Search



Random Search

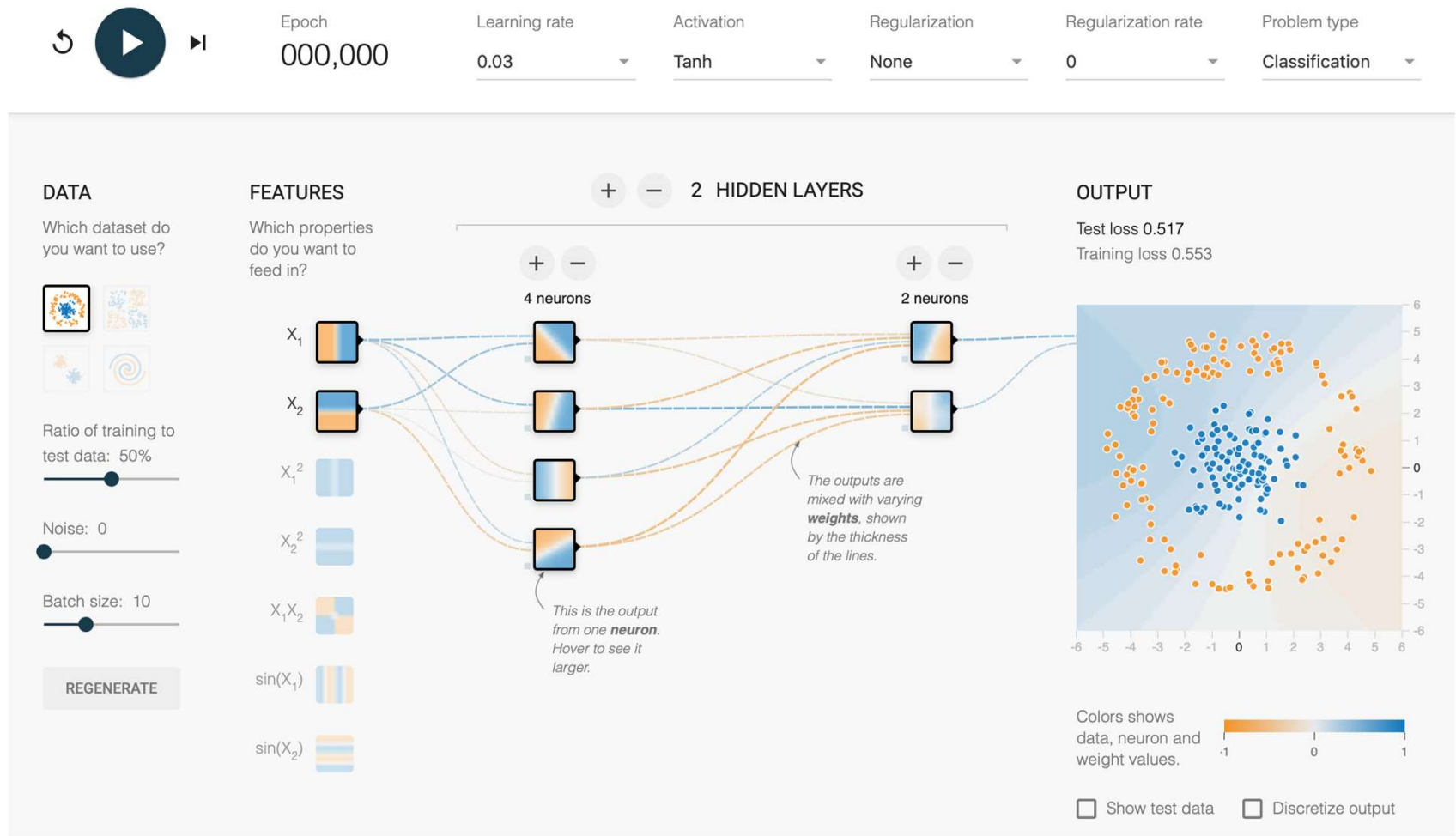


Adaptive Selection



Hyperparameters : Global Search

Demo



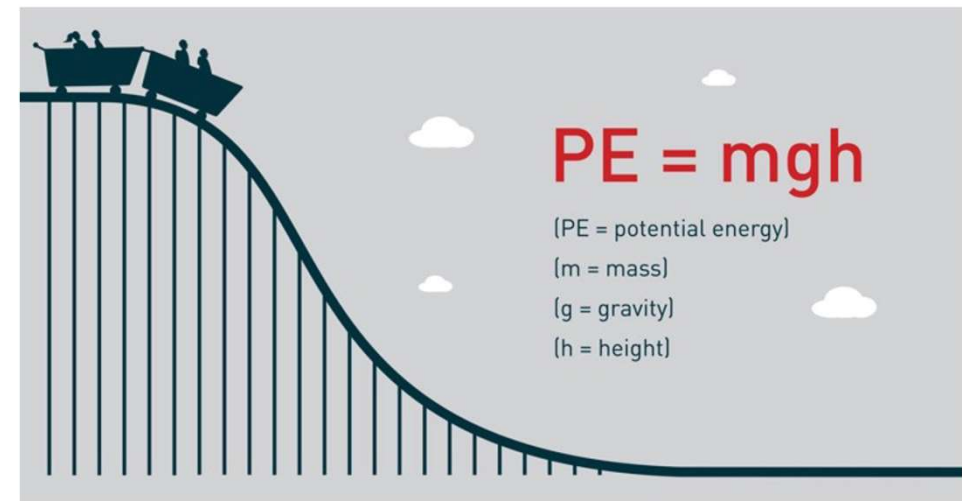
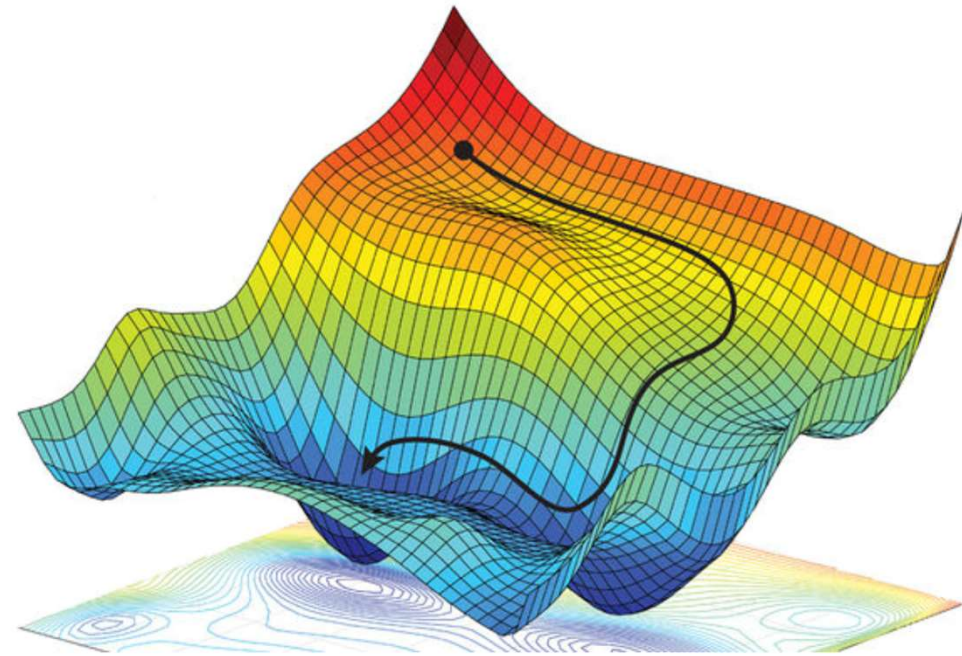
Model : Weight initialization

- The initial parameters need to **break the symmetry** between different units
- Use *random weights* from a Gaussian or Uniform distribution. Alternatively, use *He* or *Xavier weights*
- Another strategy is to initialize weights by **transferring weights** learnt via an unsupervised learning method (method also called **fine-tuning**)

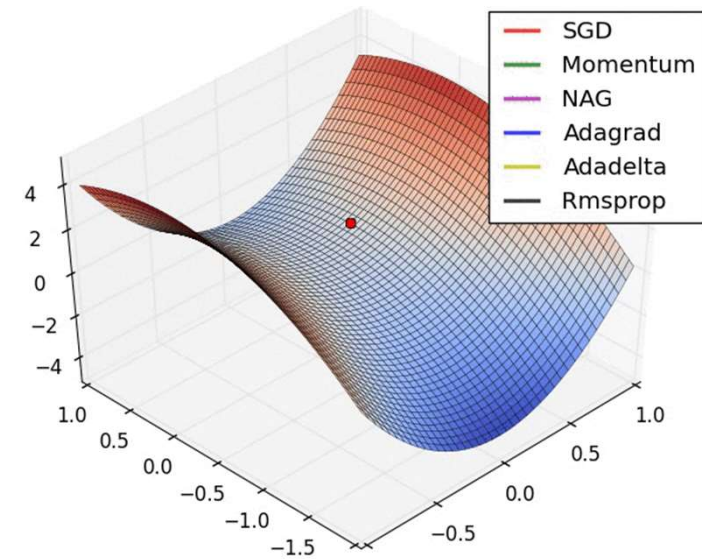
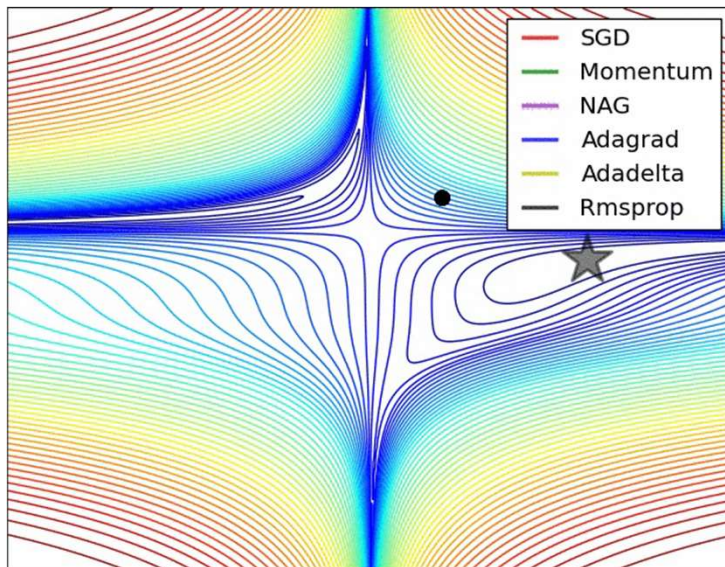


Optimization algorithm

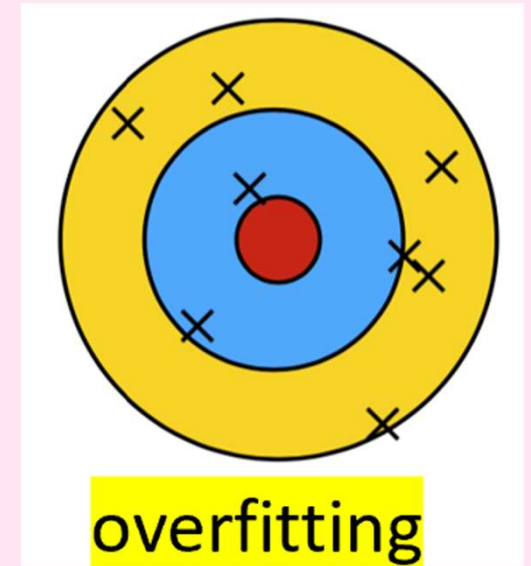
- No consensus on what algorithm performs best
- Most popular choices :
 - SGD (mini-batch gradient descent)
 - SGD + Momentum
 - RMSProp
 - RMSProp + Momentum
 - Adam
- Strategy : *pick one and get familiar* with the tuning



Gradient Descent Variations



<https://ruder.io/optimizing-gradient-descent/>



Variance Reduction techniques

- Bigger training set
- Regularization

Regularization

- Different strategies :
 - Dataset (division, augmentation,...)
 - Model (dropout, L2-, ...)
 - Training (early stopping)
- Use cases : if few data or if model has more than 50 layers (CNN)

Regularization (*Dataset*) : Division

- Divide the data into a **training**, **validation** and **test** sets
 - **Training set** to define the optimal predictor
 - **Validation set** to choose the capacity
 - **Test set** to evaluate the performance



Regularization (*Dataset*) : Augmentation

- Apply **realistic transformations** to data to create new synthetic samples, with same label



original



affine
distortion



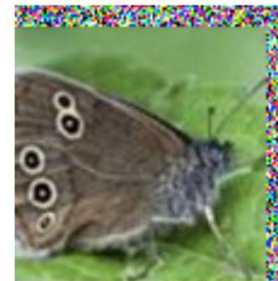
noise



elastic
deformation



horizontal
flip



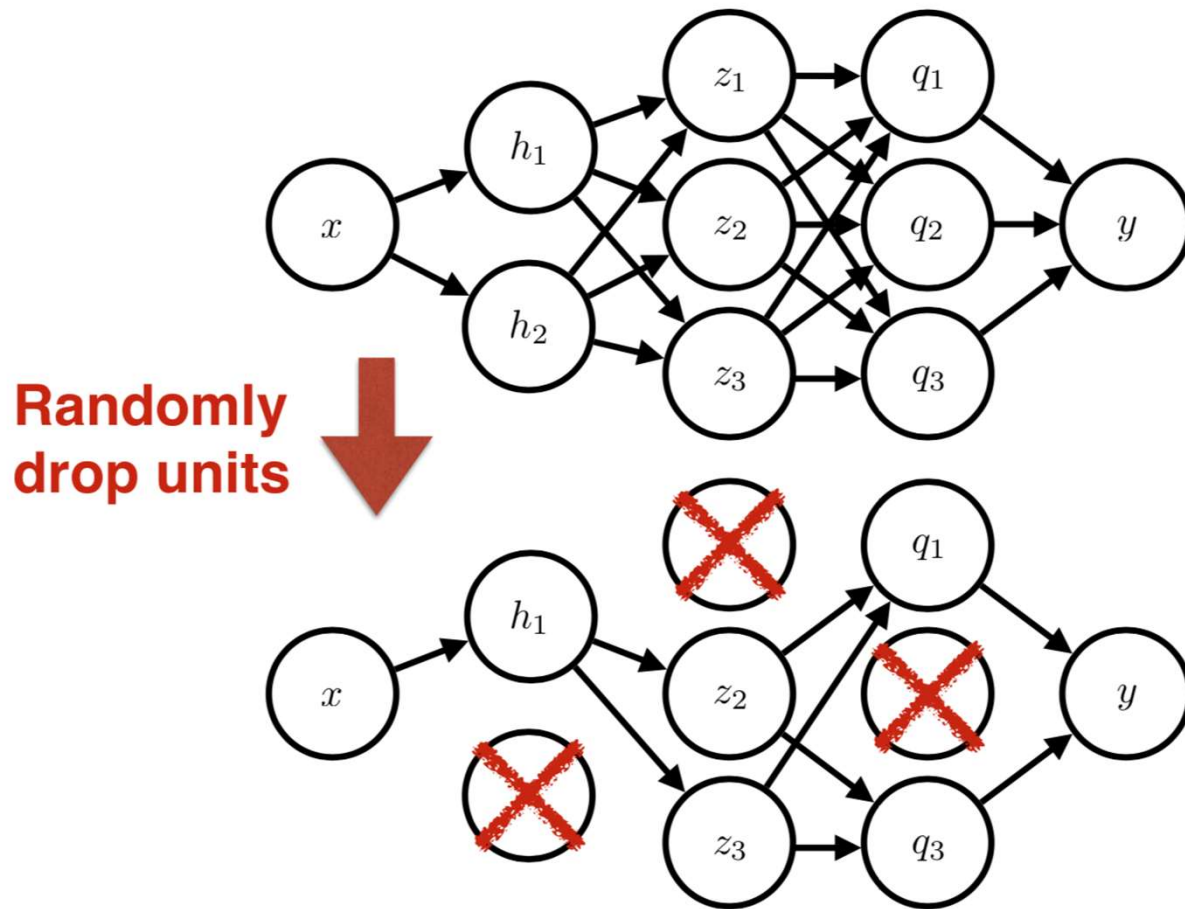
random
translation



hue shift

- Process also called **jittering**

Regularization (*Model*) : Dropout



- Apply it both in forward and backward propagations
- *BUT* use it only in the training phase !

Regularization (*Model*) : L2-regularization

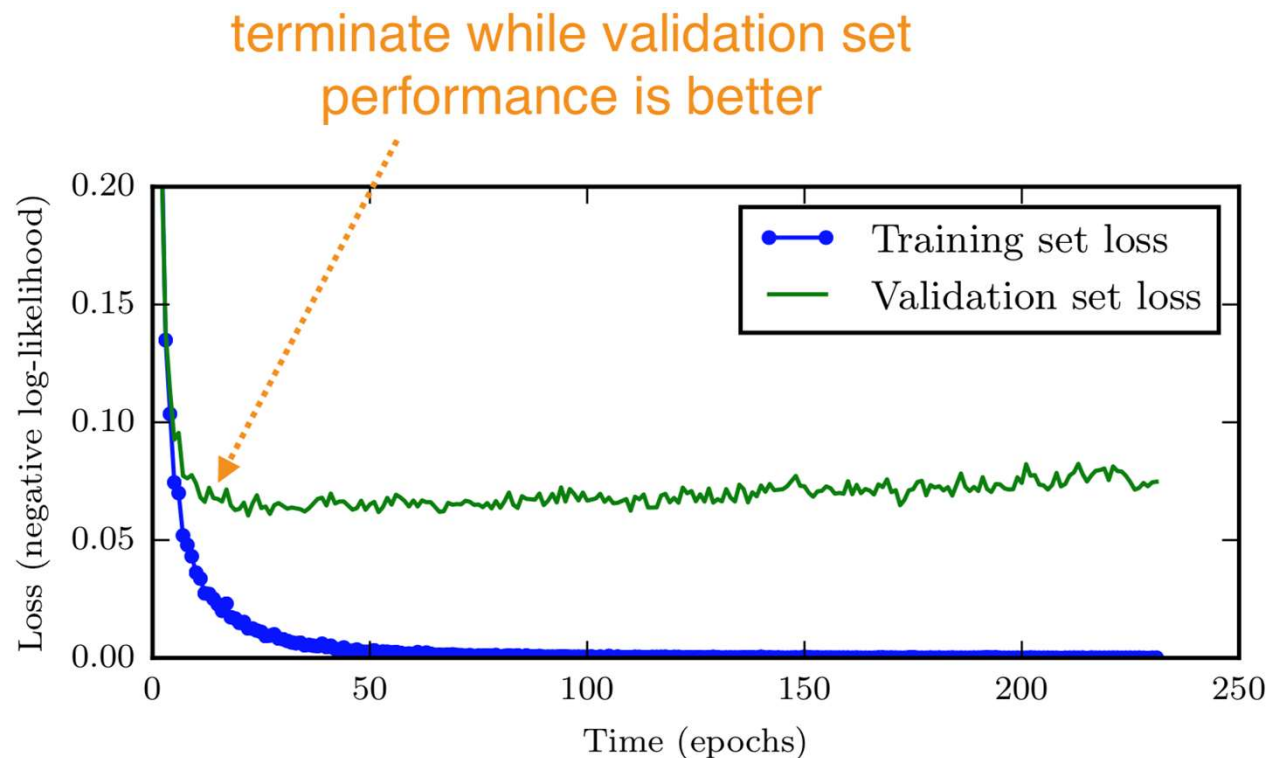
- Modify the cost function (add **soft constraint**) :
 - L2-regularization cost = $\lambda * \sum(w^2)$

Cost function (regularized) = cost function + L2-regularization cost

- λ regulates the complexity/capacity of the predictors. It **smoothens the decision boundary**
 - weights pushed to **smaller values**, preventing any weight from becoming too large and dominating the learning process
- Typical values : logarithmic scale between 0 and 0.1, such as **0.1, 0.001, 0.0001** (tuned using validation set)
 - If λ is too large, it can “oversmooth”, resulting in a model with high bias

Regularization (*Training*) : Early stopping

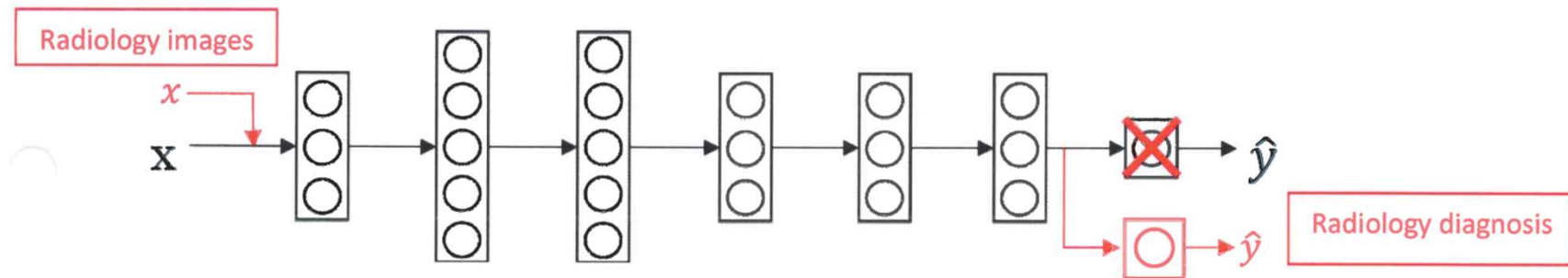
- Limit the number of iterations



Stop the training when dev set error starts increasing again

Transfer Learning

- Use weights that **have been previously trained for another task**
- **Use cases :**
 - Tasks A and B have the same input X
 - A lot more data for Task A than Task B
 - Low level features from Task A could be helpful for Task B



Pre-training : training on cat images

Fine-tuning : update the weights for radiology

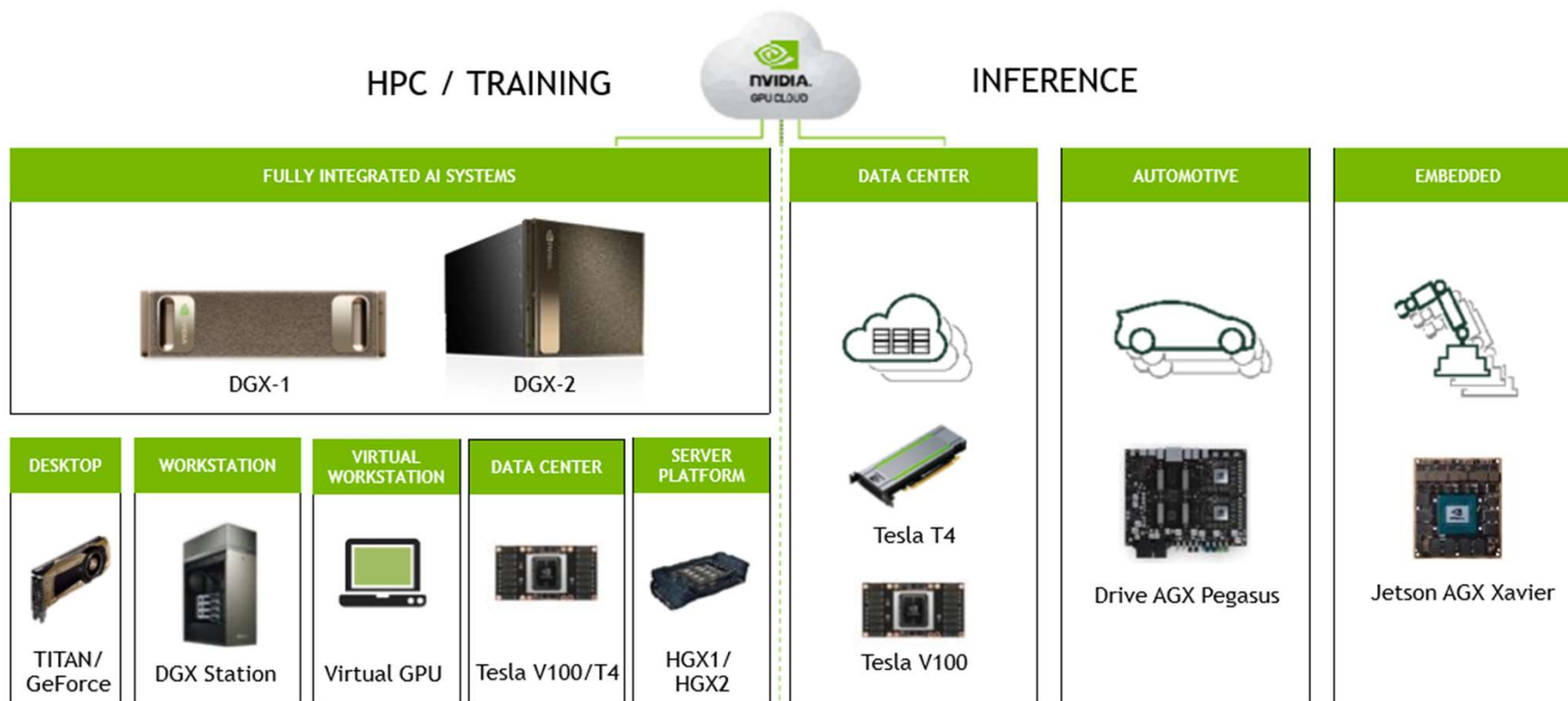
2. Time

How to improve time consumption when critical to get results



Material Acceleration (GPUs)

END-TO-END PRODUCT FAMILY



Tutorial / Practical

