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

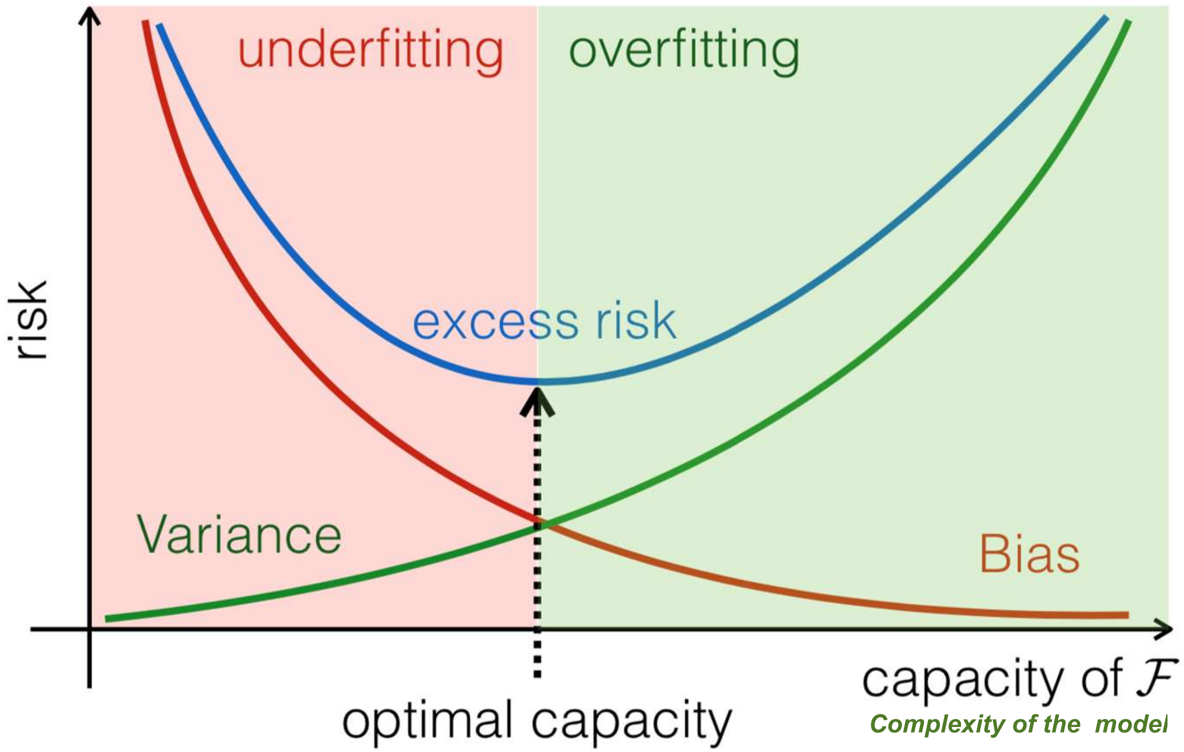
Introduction

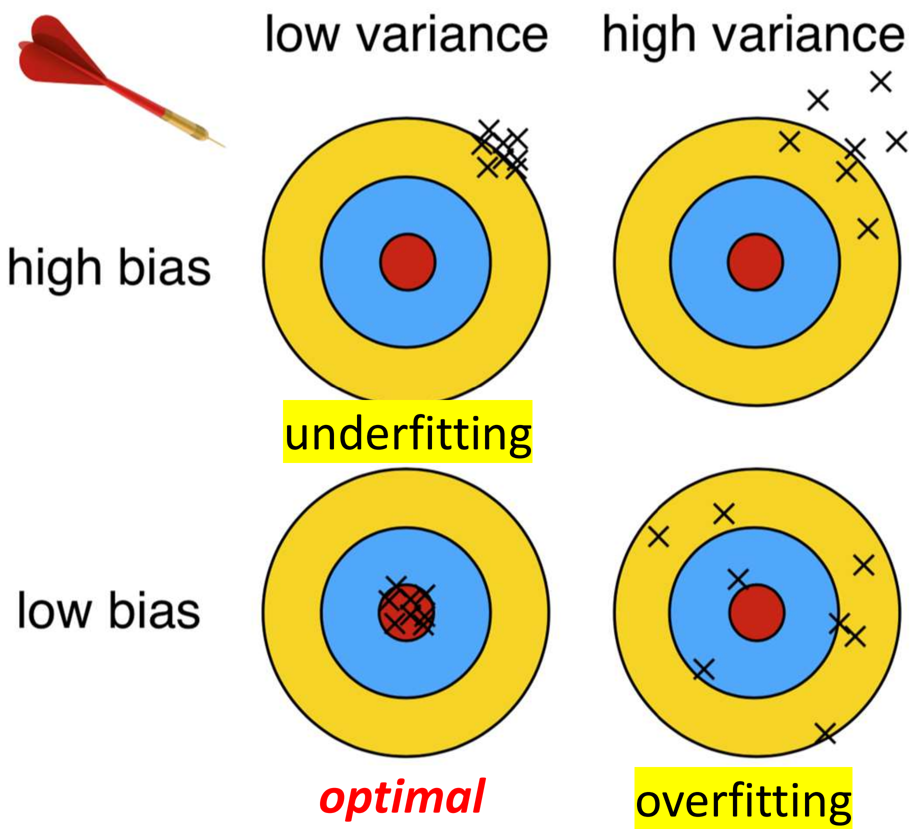
- To evaluate a ML algorithm, we need a way to measure **how well it performs on the task**

- It is measured **on a separate set** (test set) from what we use to build the function f (training set)

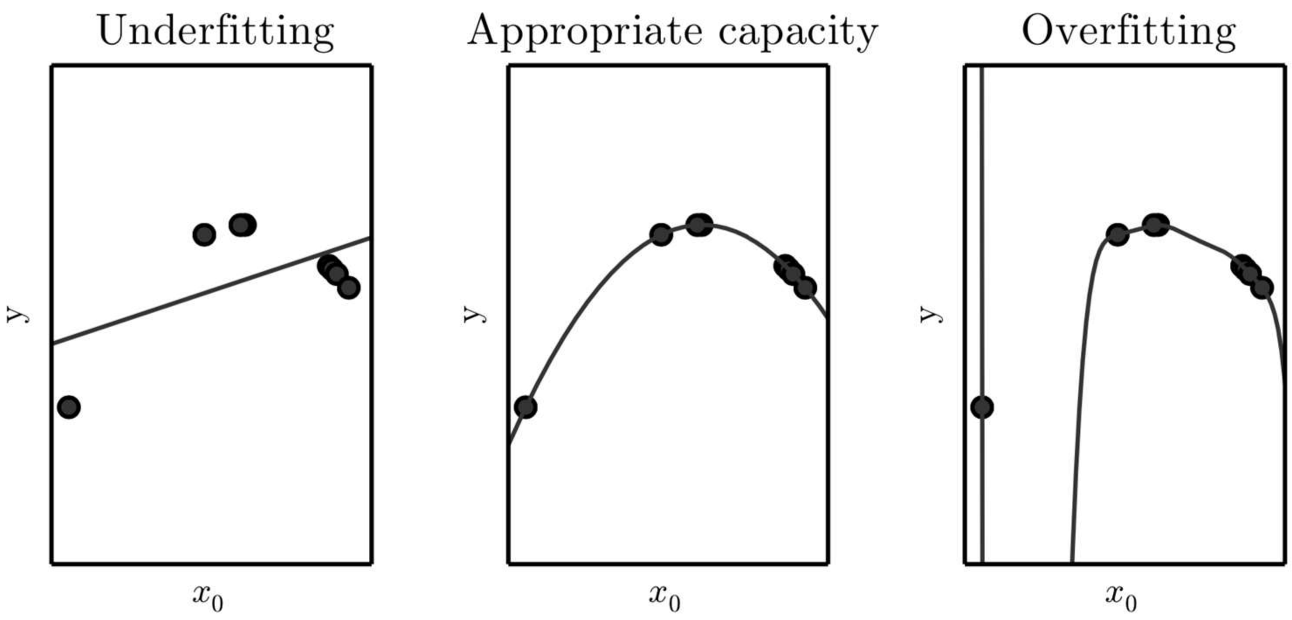
- **Examples** :
  - Classification accuracy (portion of correct answers)
  - Error rate (portion of incorrect answers)
  - Regression accuracy (e.g. least squares errors)

Bias and Variance - Overfitting and Underfitting



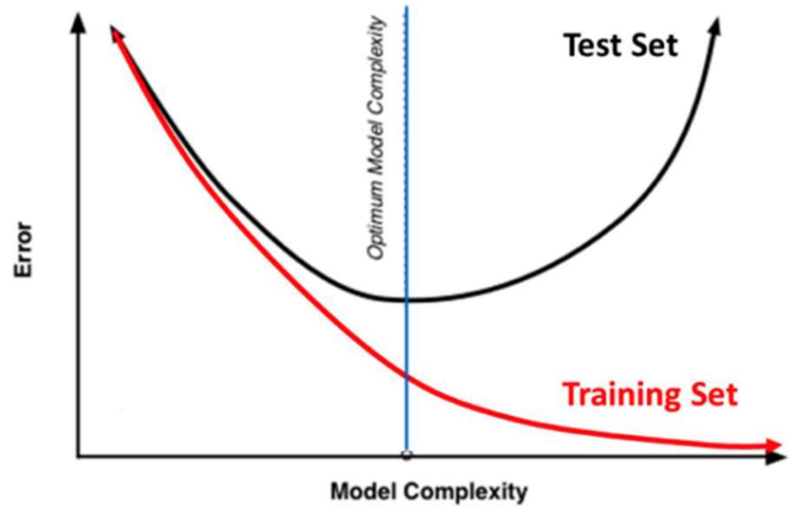


Overfitting and Underfitting



High bias

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 ?*

We can't really say with only this information

Evaluation metrics

Ground Truth

Predictions

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

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

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

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

See also Sensitivity (same as recall) and Specificity

F1-score

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

F1-score is the more precise indicator for classification

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

	Precision	Recall	F_1 Score
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 !

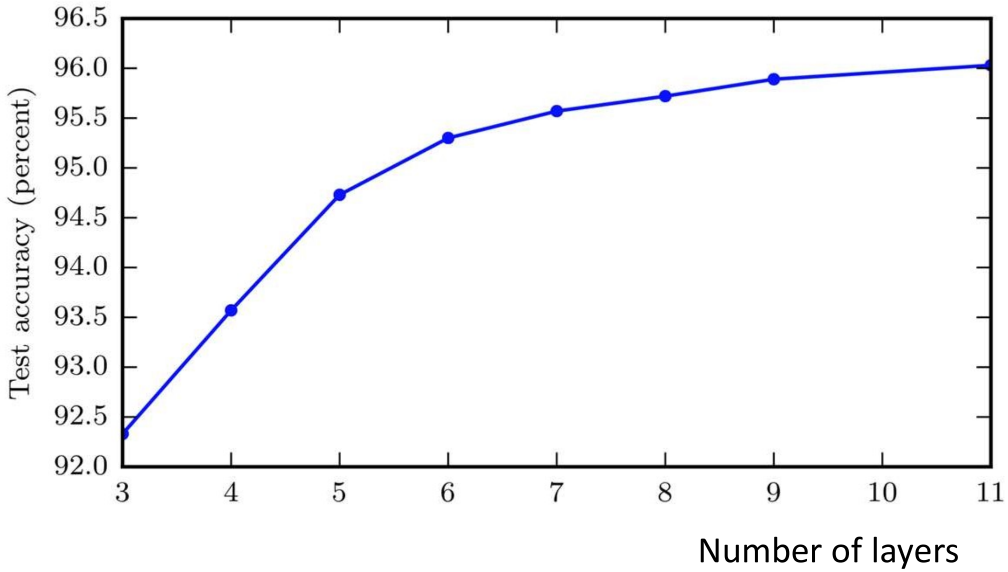
- Carry out manual error analysis
  - Look at *mislabeled development set* examples (*do not look at test set*)
  - For example : check by hand 500 pictures (incorrect labels ? Foggy pictures ? Other causes ?)
- Clean up incorrectly labeled data
  - Apply same process to your dev and test sets !

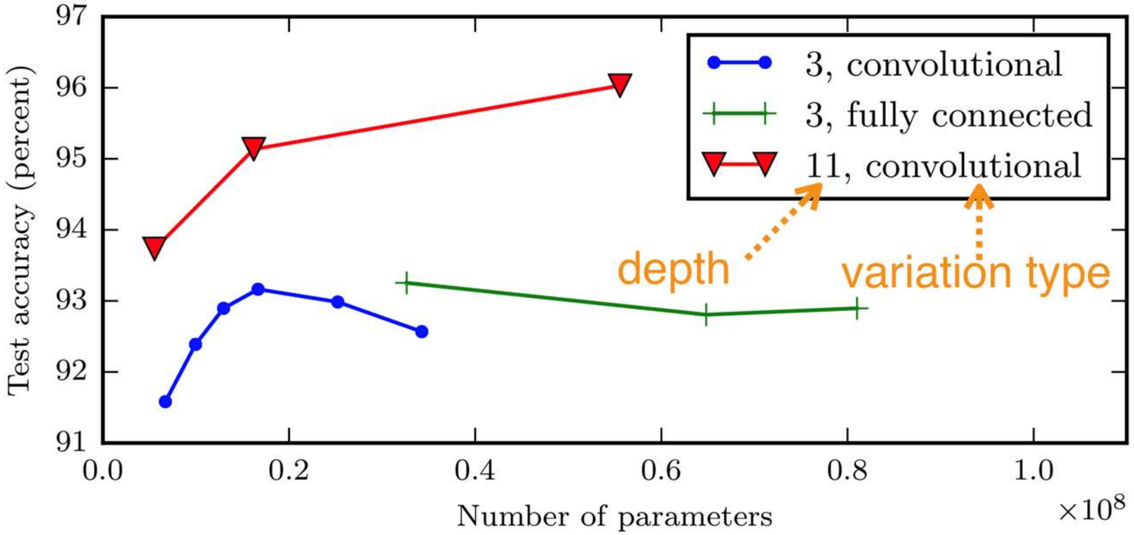
Bias Reduction techniques

- Hyperparameter tuning
- Model tuning
- Optimization algorithm

Hyperparameters : number of hidden layers/units

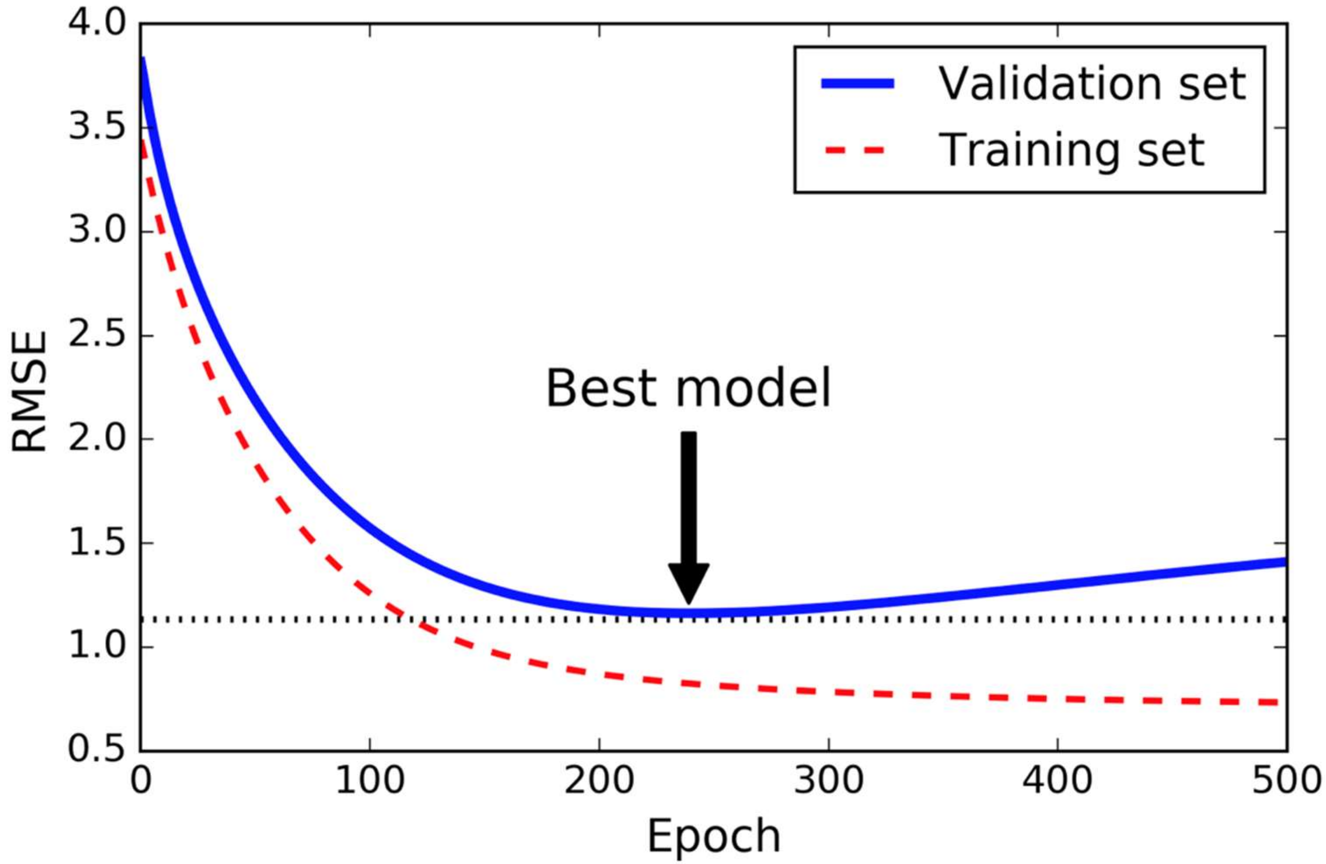
- To go deeper helps generalization (but depends on application)
- *better to have many simple layers than few highly complex ones*





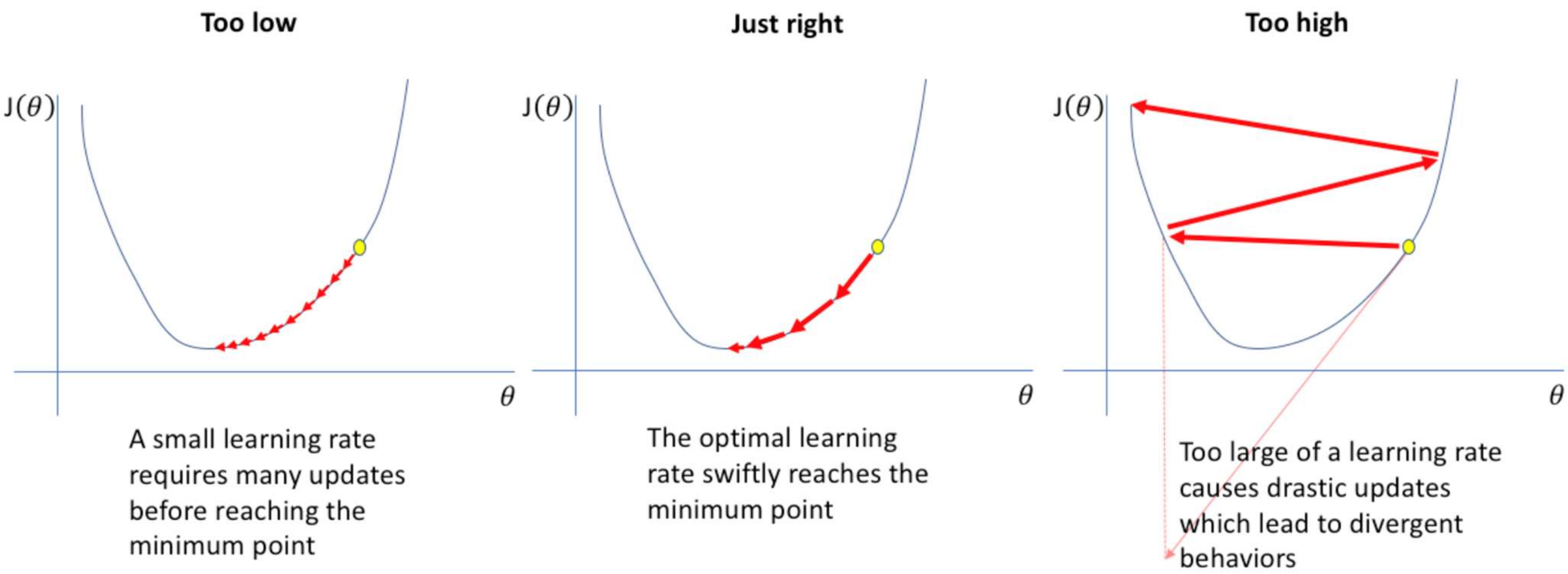
Hyperparameters : epochs

- Train *longer*



Hyperparameters : learning rate α

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

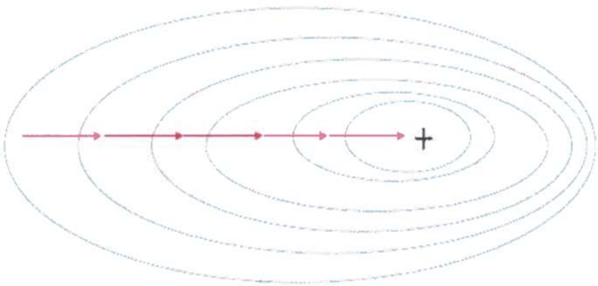


- We can also design a scheduler for the learning rate

Hyperparameters : batch size

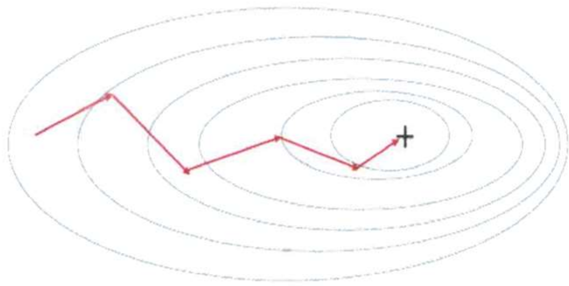
- At each iteration :

Gradient descent (GD)



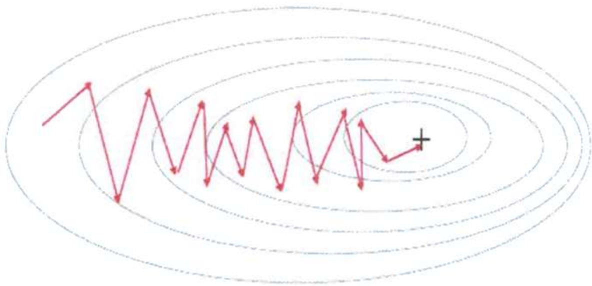
the *whole* training set

Mini-batch gradient descent



a *batch* of samples

Stochastic gradient descent (SGD)



1 sample

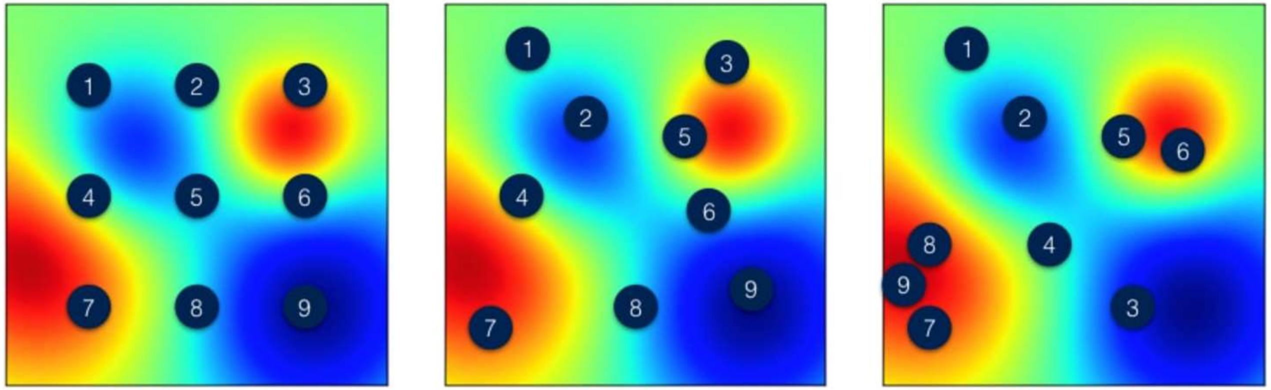
- Batch size choice *typically 32,64,128,256,512*

  The use of a power of 2 comes from GPU architecture

Hyperparameters : Global Search

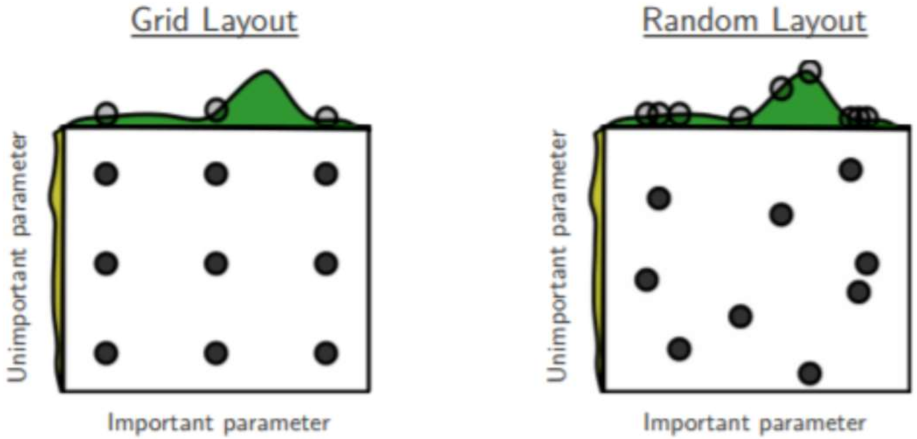
Used to test different parameters

- 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**



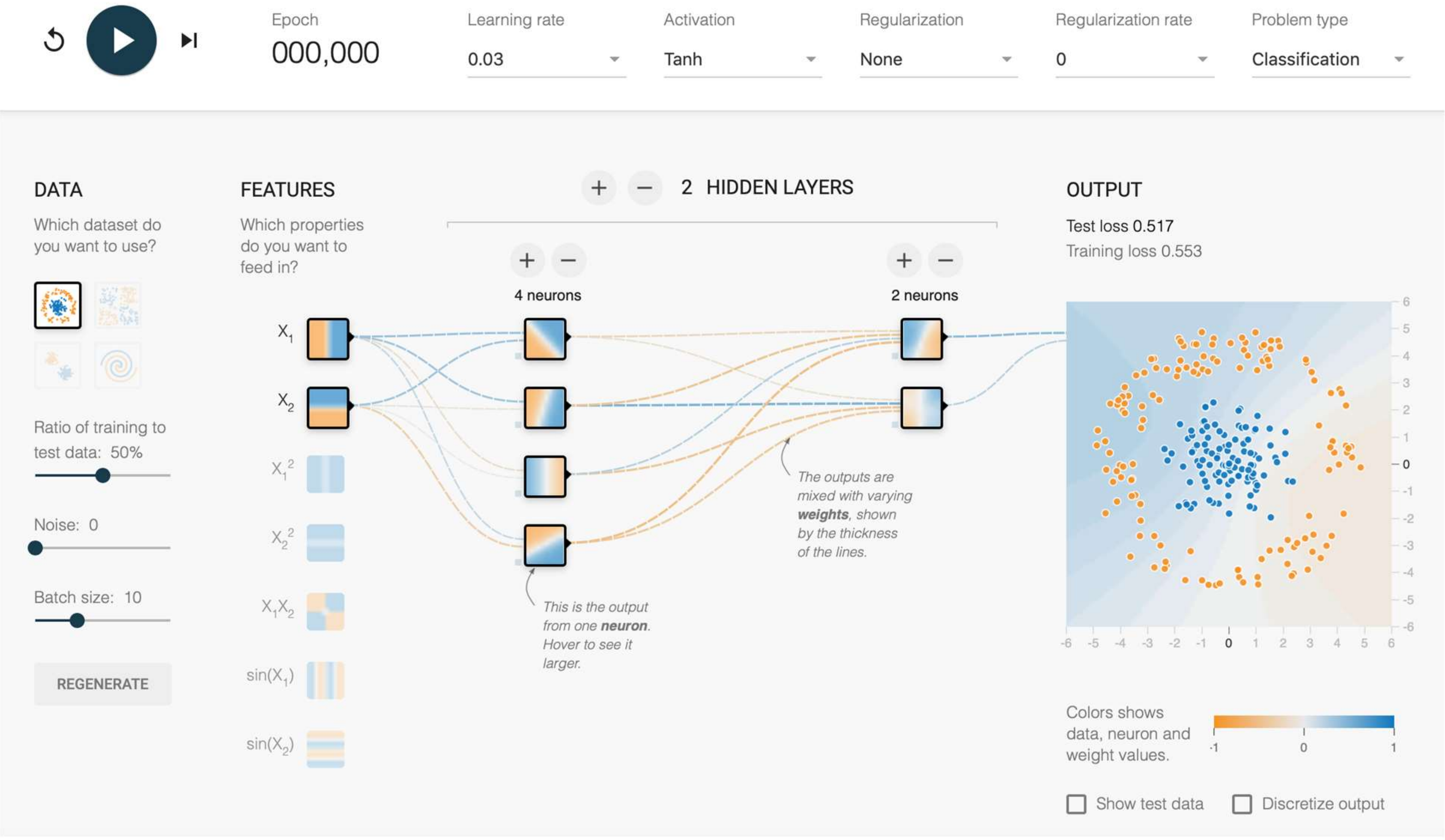
Grid Search Random Search Adaptive Selection

In practice , we usually used one after the other. First to find a good region and then to test in more details



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*   ***By defaulkt use He weights***

- Another strategy is to initialize weights by transferring weights learnt via an unsupervised learning method (method also called fine-tuning)

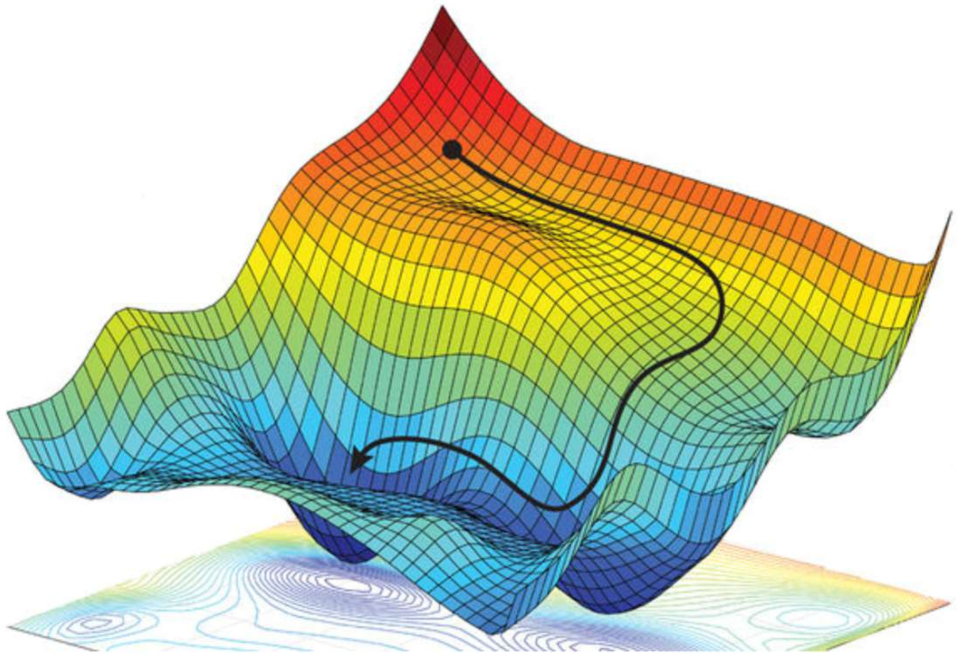
Optimization algorithm

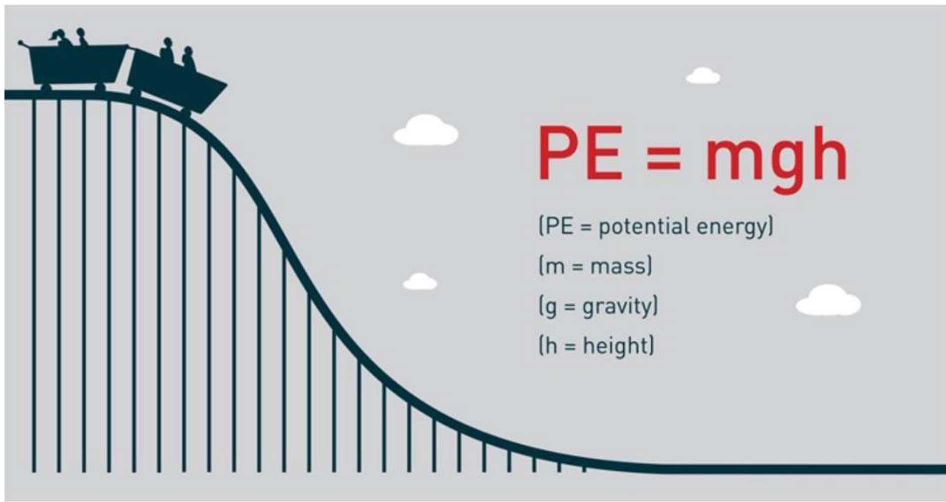
- No consensus on what algorithm performs best

- Most popular choices :
  - SGD (mini-batch gradient descent)
  - SGD + Momentum
  - RMSProp
  - RMSProp + Momentum
  - Adam

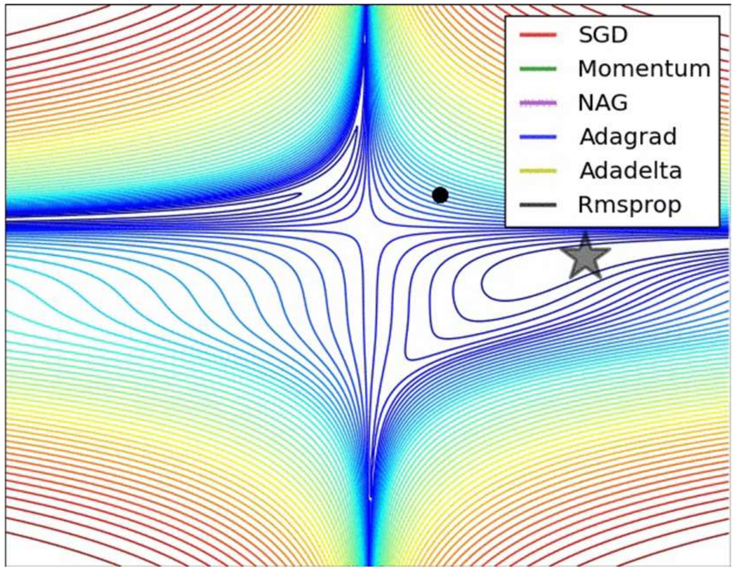
    In practice, everyone use Adam

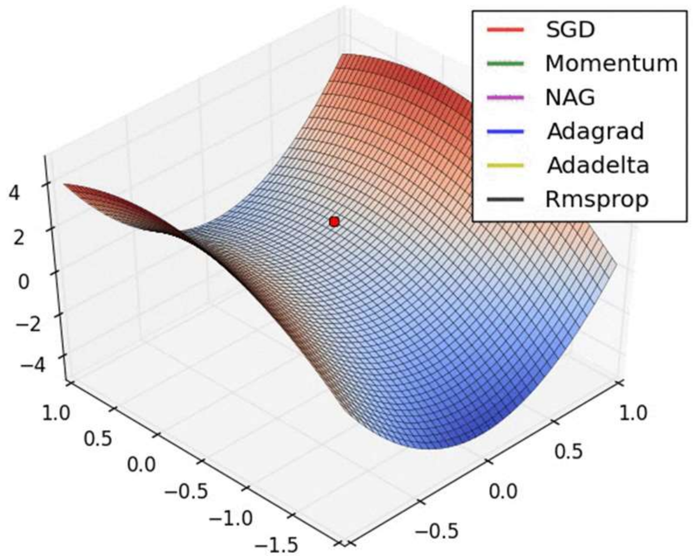
- Strategy : *pick one and get familiar* with the tuning





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)

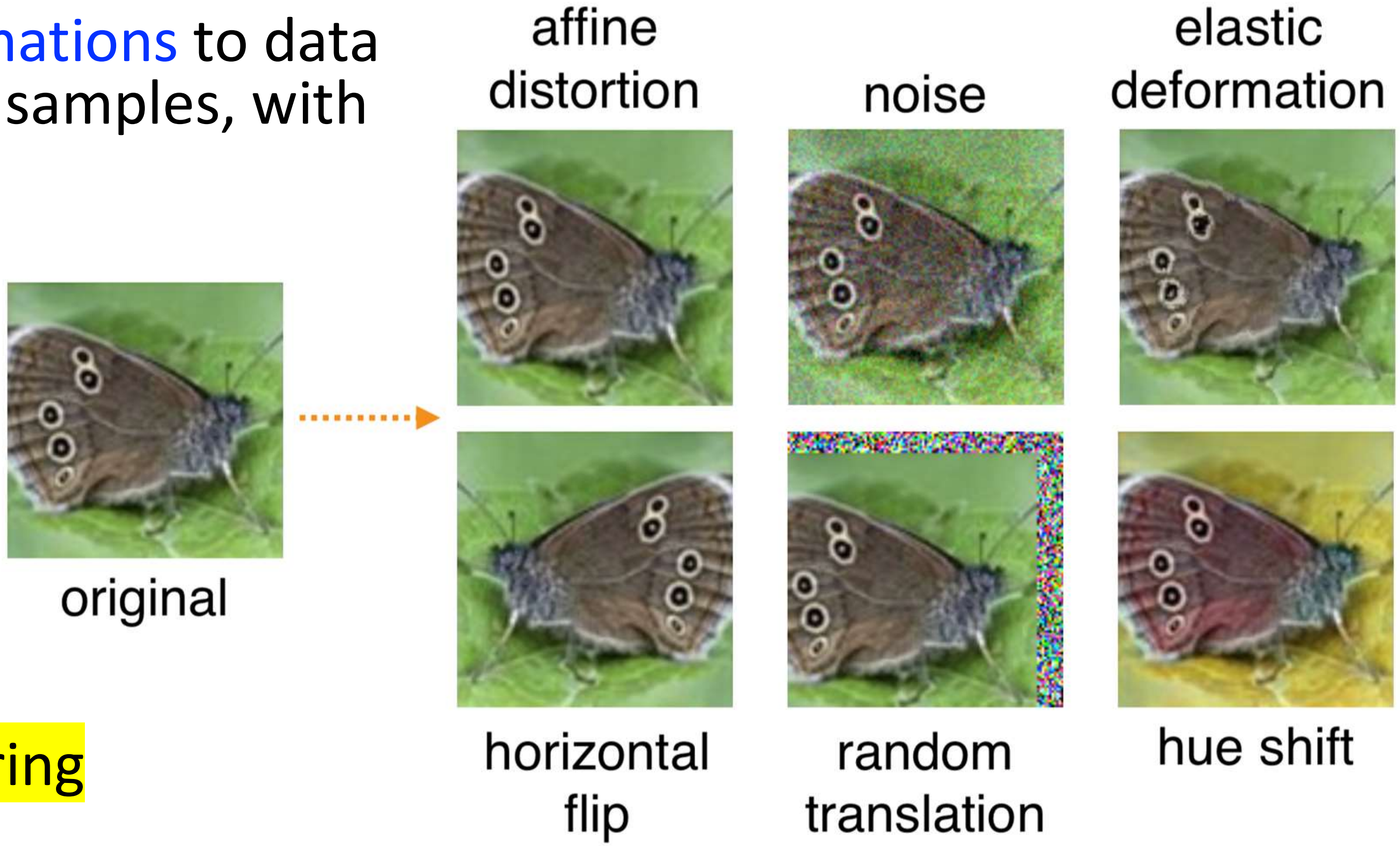
Regularization (*Dataset*) : Division

- 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

The ratio depends of the number of data we have
With 200 datas it could be 60/40% and with 10000 95/5%

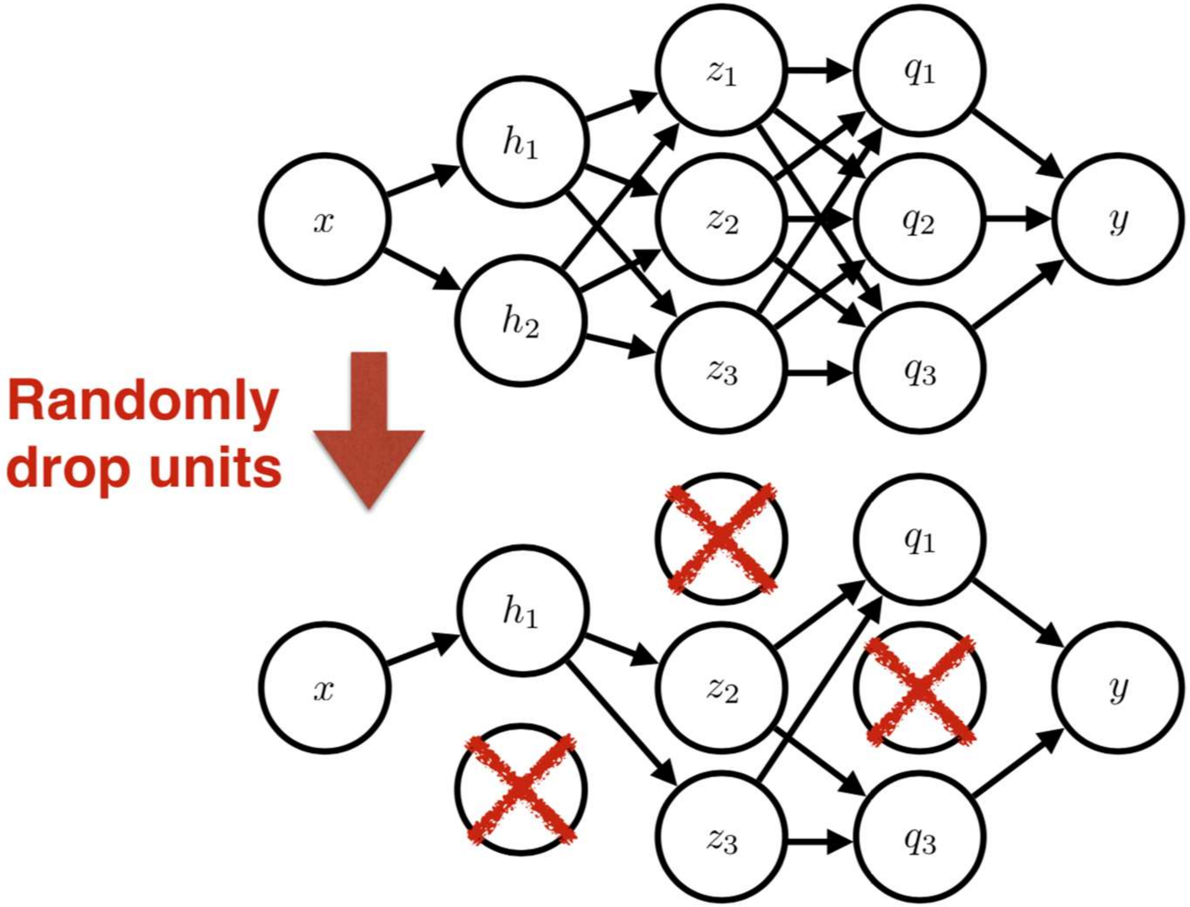
Regularization (*Dataset*) : Augmentation

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



- Process also called jittering

Regularization (*Model*) : Dropout



- Apply it both in forward and backward propagations

- *BUT* use it only in the *training phase !*

  Used to simplify the model to try to reduce overfitting

Regularization (*Model*) : L2-regularization

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

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

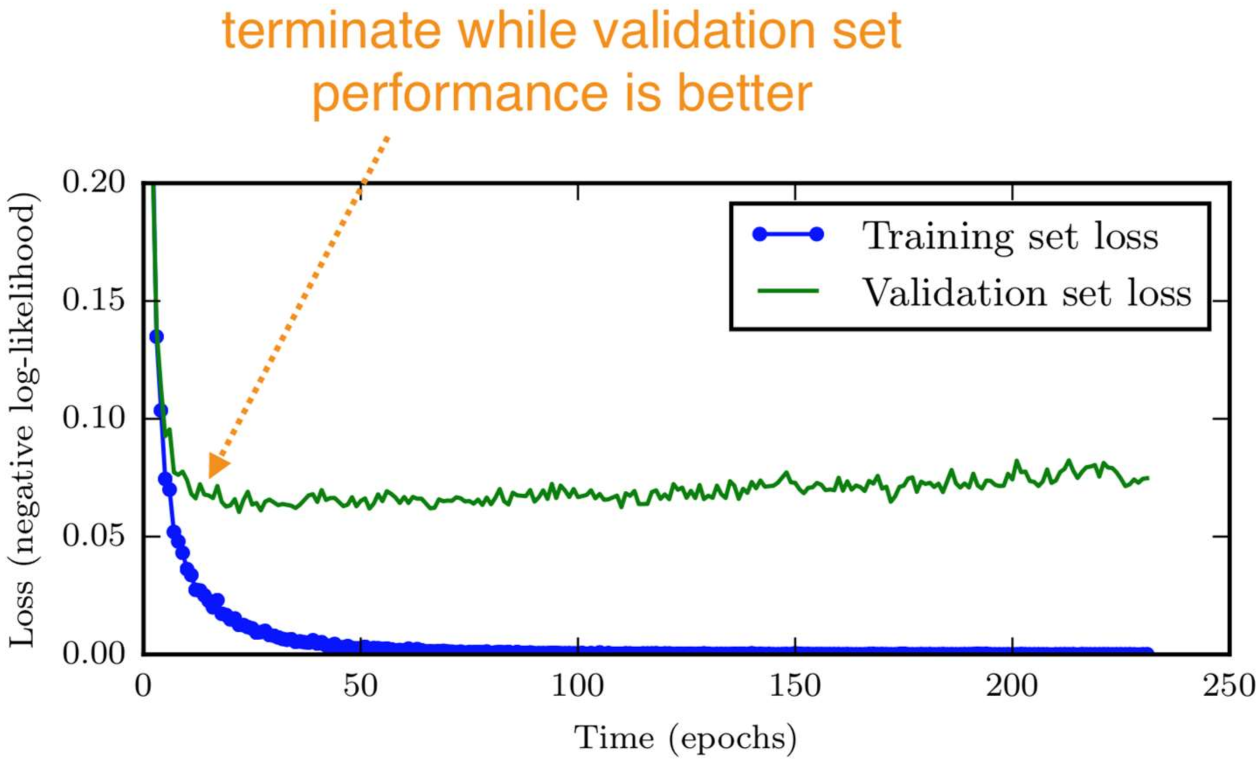
- λ regulates the complexity/capacity of the predictors. It smoothens the decision boundary

  → 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

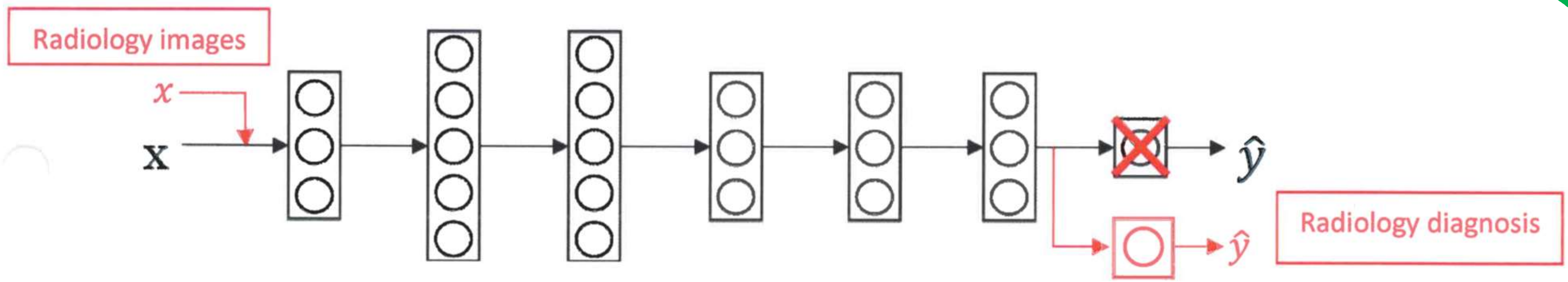


Stop the training when dev set error starts increasing again

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

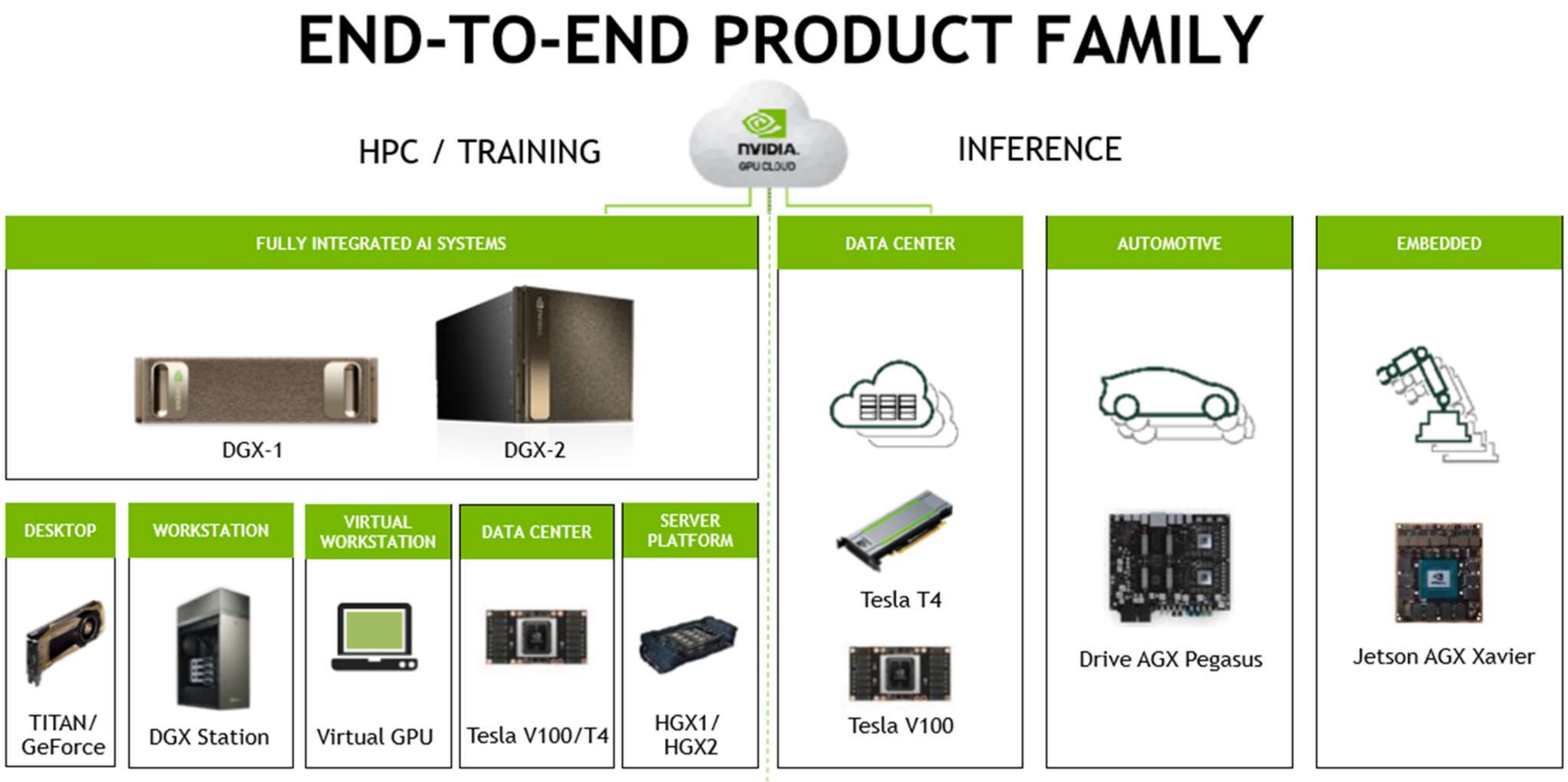


Pre-training : training on cat images
Fine-tuning : update the weights for radiology

2. Time

How to improve time consumption when critical to get results

Material Acceleration (GPUs)



Tutorial / Practical