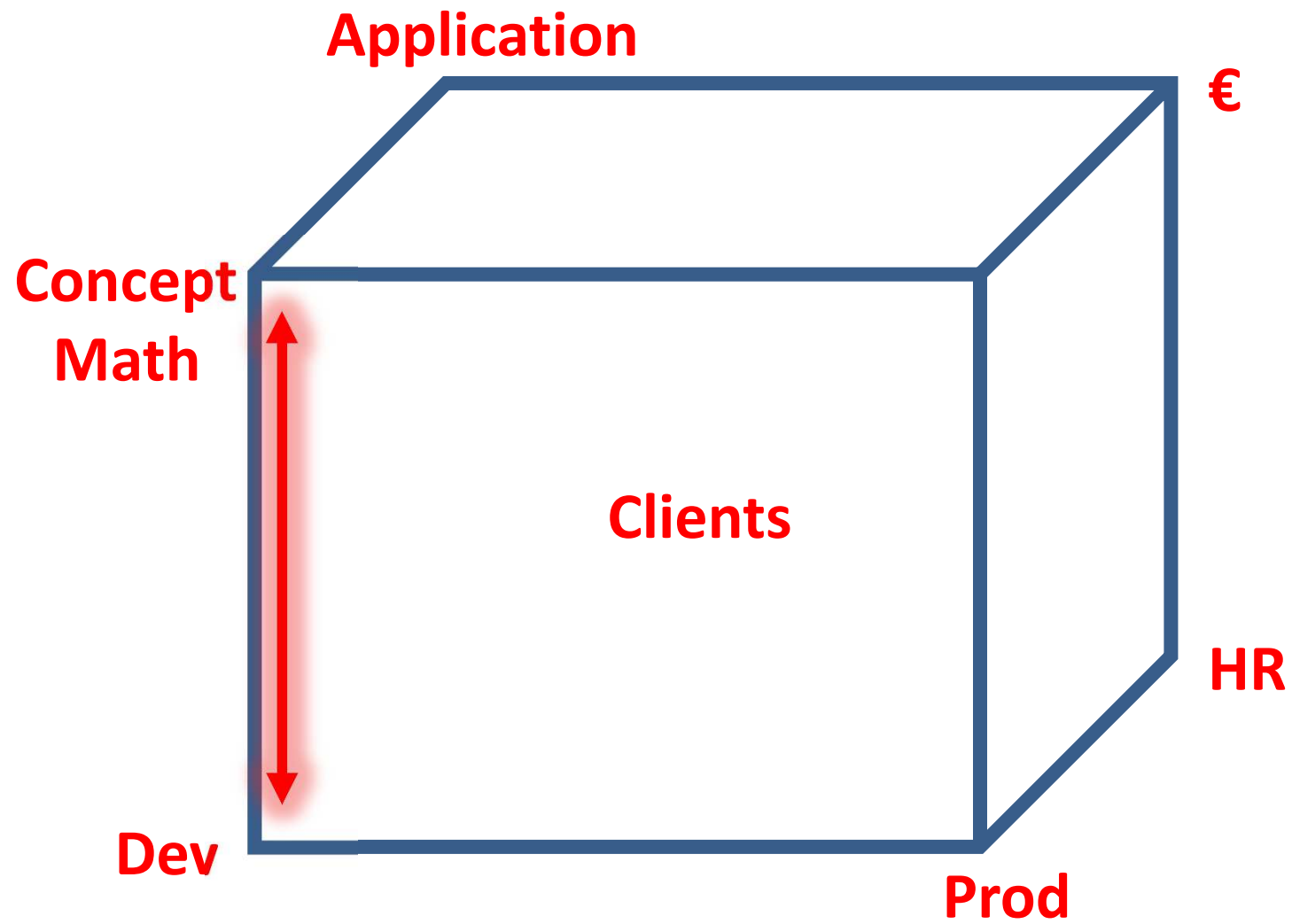


Optimisation & Machine Learning

Pr. Bijan Mohammadi
Université de Montpellier



Optimisation & Machine Learning

1. Sans contrainte

- Gradient (SD, N, QN, SGD, ADAM,...)
- Sans gradient : région de confiance
- Sans gradient : stochastique, génétique, essaim

2. Avec contraintes

- Egalité / Inégalité

Multiplicateurs de Lagrange, Lagrangien, KKT, Uzawa

3. Multicritère, Pareto

4. Optimisation robuste, sur intervalle, multipoint

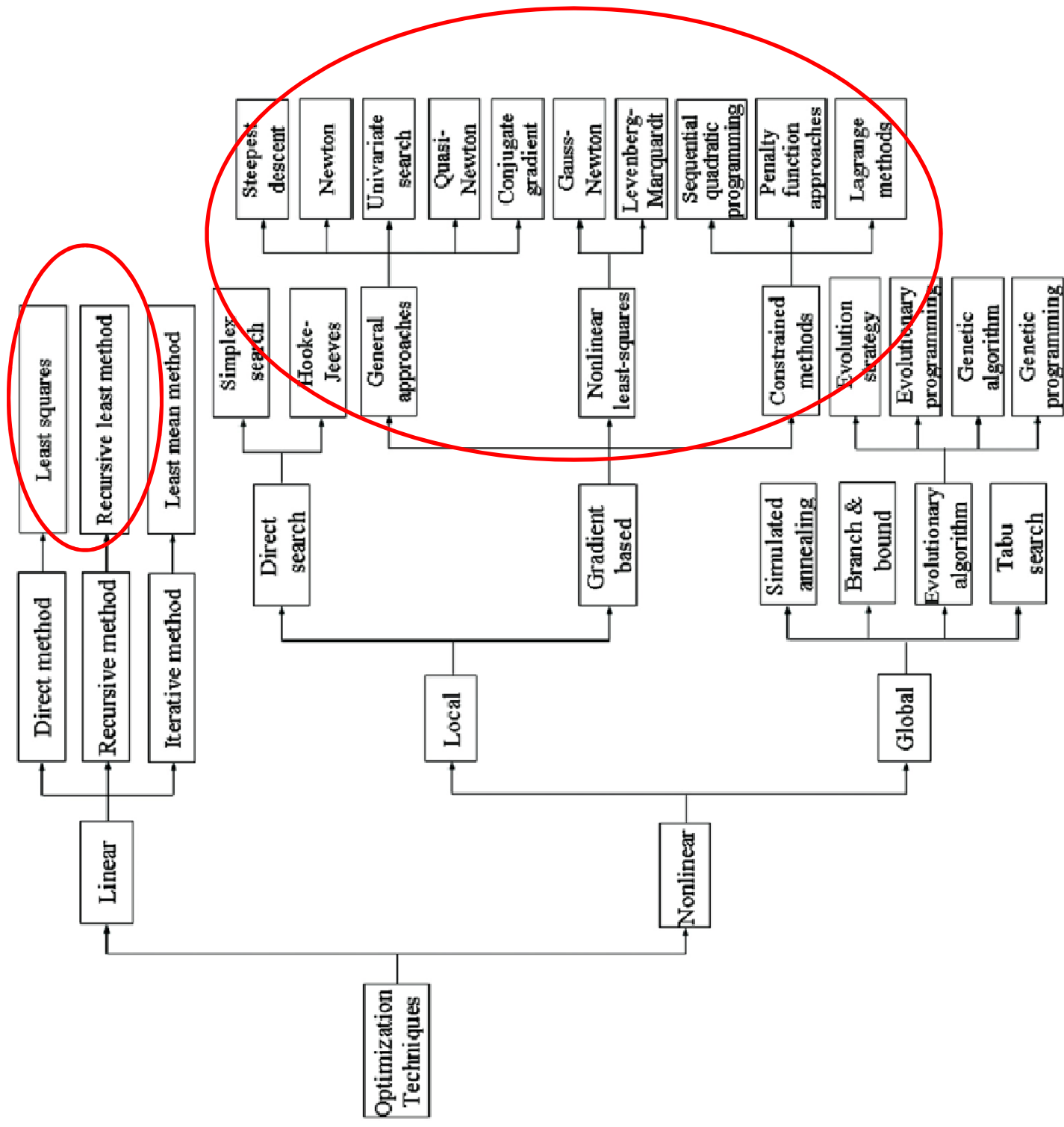
5. Optimisation globale

- Systèmes dynamiques d'ordre
- Stochastique (Génétique, recuit simulé, Tabu, Essaim, ...)

5. Apprentissage supervisé (classification / régression)

- Décomposition en Valeurs Singulières (Singular Value Decomposition)
 - Modèles linéaires (Linear Models)
 - KNN (Nearest Neighbors)
- Séparateurs à Vaste Marge (Support Vector Machines)
 - Forêts aléatoires (Random Forests)
 - réseaux de neurones (Neural Networks)

6 Apprentissage non-supervisé (clustering k-means)



Supervised Learning today in short

- Black-boxes & Requires know-how (esp. Deep NN)
- Requires lots of quality data
 - Problem when data is rare, confidential & expensive to get
 - Needs human intervention (*mechanical turks / crowdsourcing*)

Impossible for industrial regression pbs

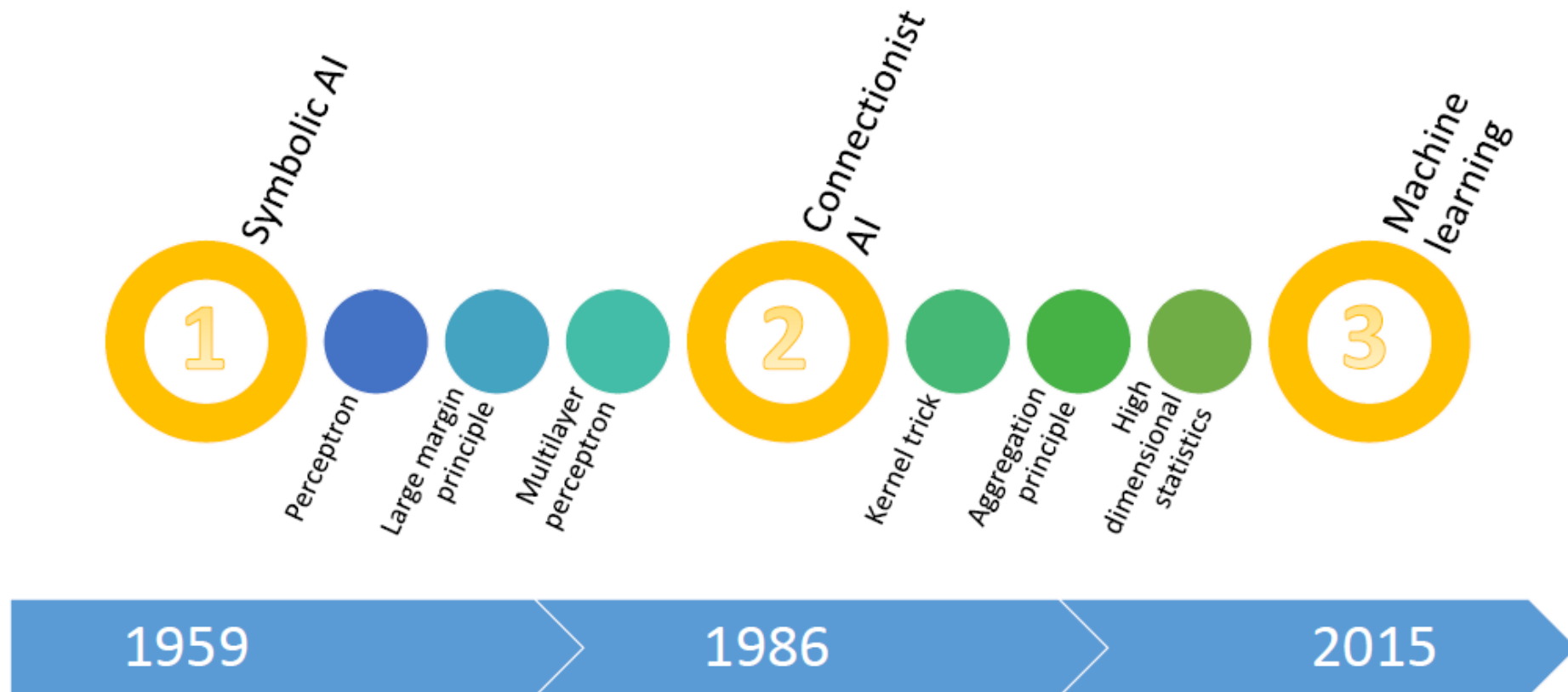
Human Intelligence Tasks (HITs)
~300K click workers in France



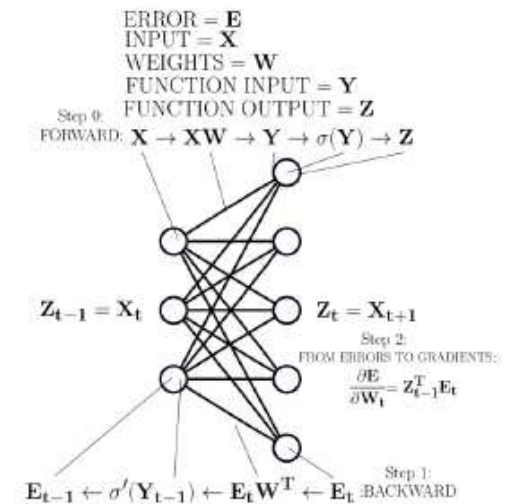
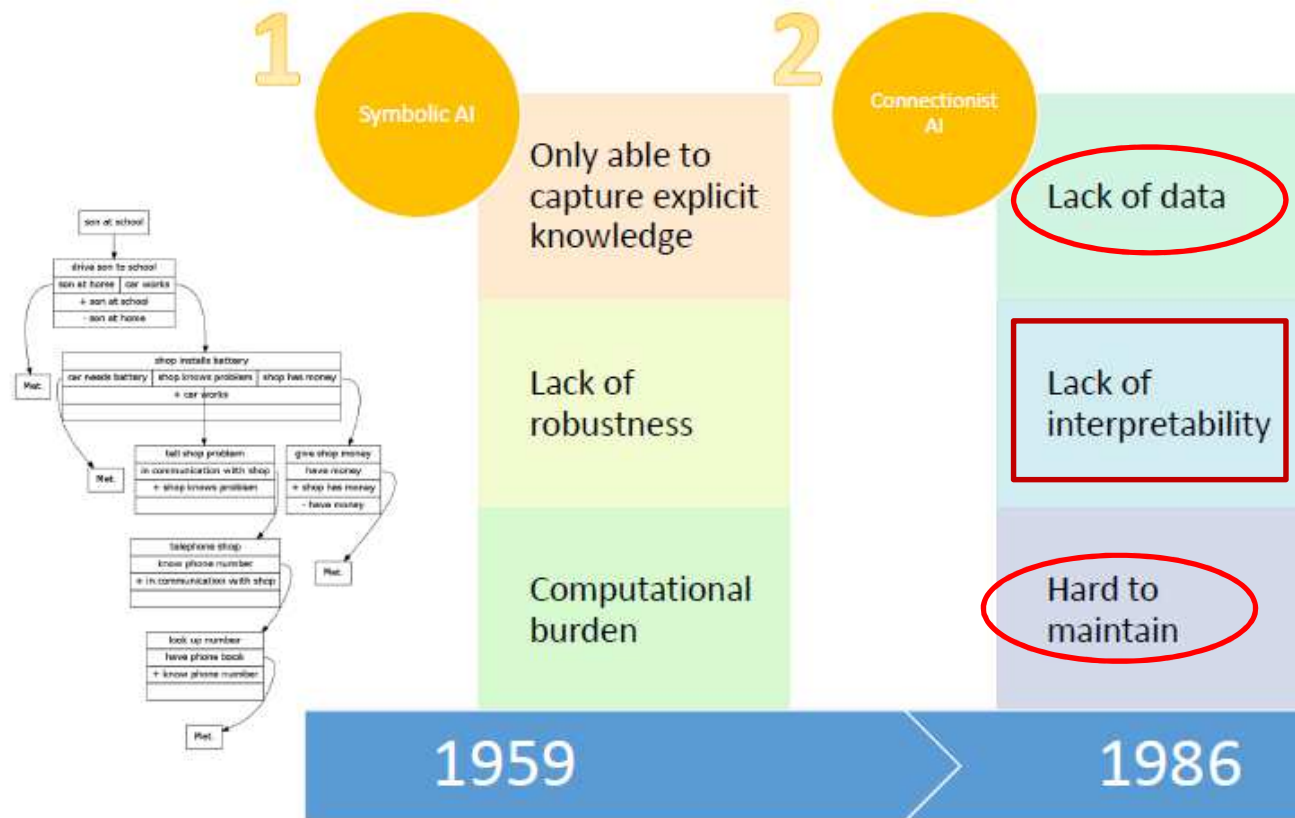
Myth of Sisyphus

- Does not perform well on industrial configurations (success in B2C)
- Needs quality data (but bias is the rule in industry : machine wear, ...)
- Cannot be used in certification because stochastic/ensemble (e.g. RF, SGD)
- Most AI are for large to small dimension pbs
- Learning is on cloud (even testing)
- Energy consumption & Obesity issues

Three AI waves... and two AI winters

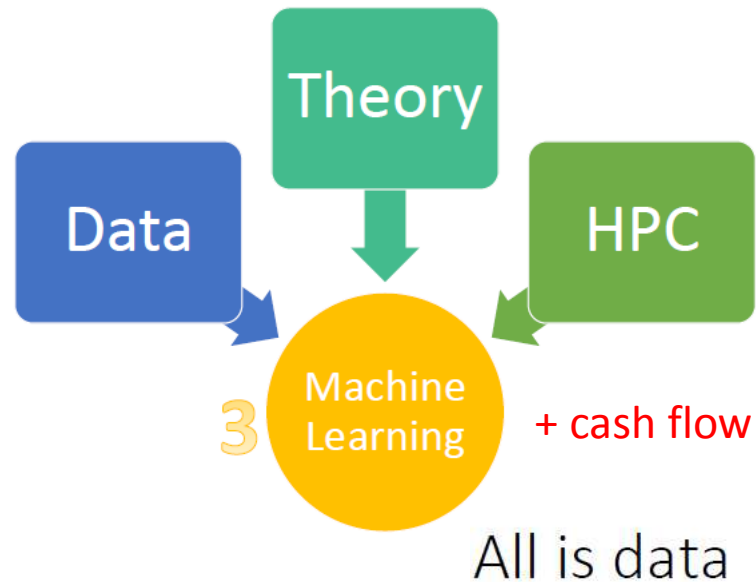


Winters explained



What is different now

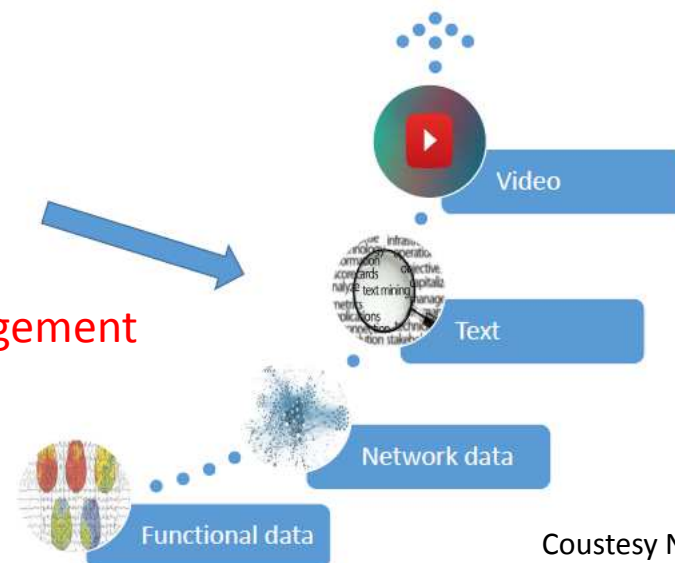
- A child recognizes a cat after seeing one → AI on small data
- Human brain consumes 10W → AI < 1W



Success mainly in B2C

Imputation
Data cleaning
Physical meanings

IT for data management



Coustesy N. Vayatis

DEEP LEARNING PLATFORMS

TensorFlow : Google

PyTorch : Facebook

Keras : Deep Learning libraries and interfaces in Python

Scikit-learn : Inria, Google, +7

Caffe : Berkeley AI Research (BAIR)

DL4j: Skymind

cuDNN: Nvidia

MatConvNet: Mathworks

...

Caffe



DL4J
Deeplearning4j



Microsoft
CNTK

MatConvNet

MINERVA

mxnet



theano



Energy consumption distribution in cloud-based embedded AI

IoT
 $1/3$

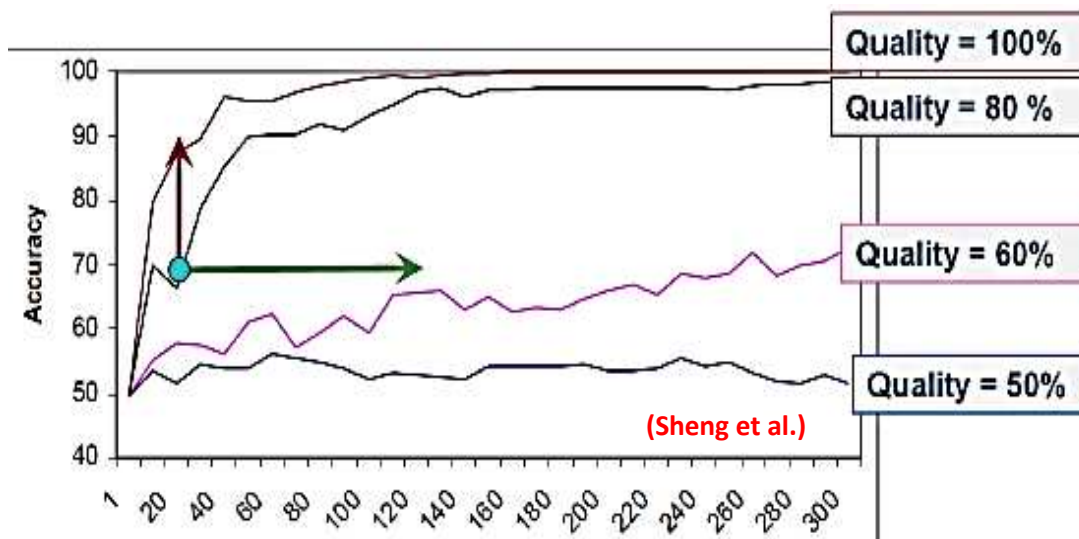
Edge

Network
 $1/3$

Cloud

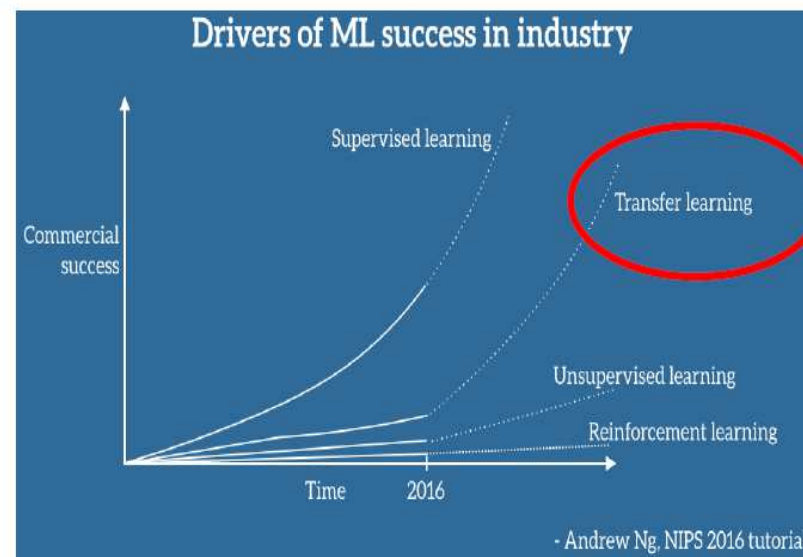
Servers
 $1/3$

**Learning accuracy bounded by learning database
quality rather than size**



**This is a limit to transfer learning as
flaws in data is common when using
data from one field in another**

Sampling bias is the rule in industry



Efficient reinforcement learning will require embedded learning

Methods:

-10-15 Y : SVM, KNN

-5-10 Y : RF, XGBoost

-Today : CNN

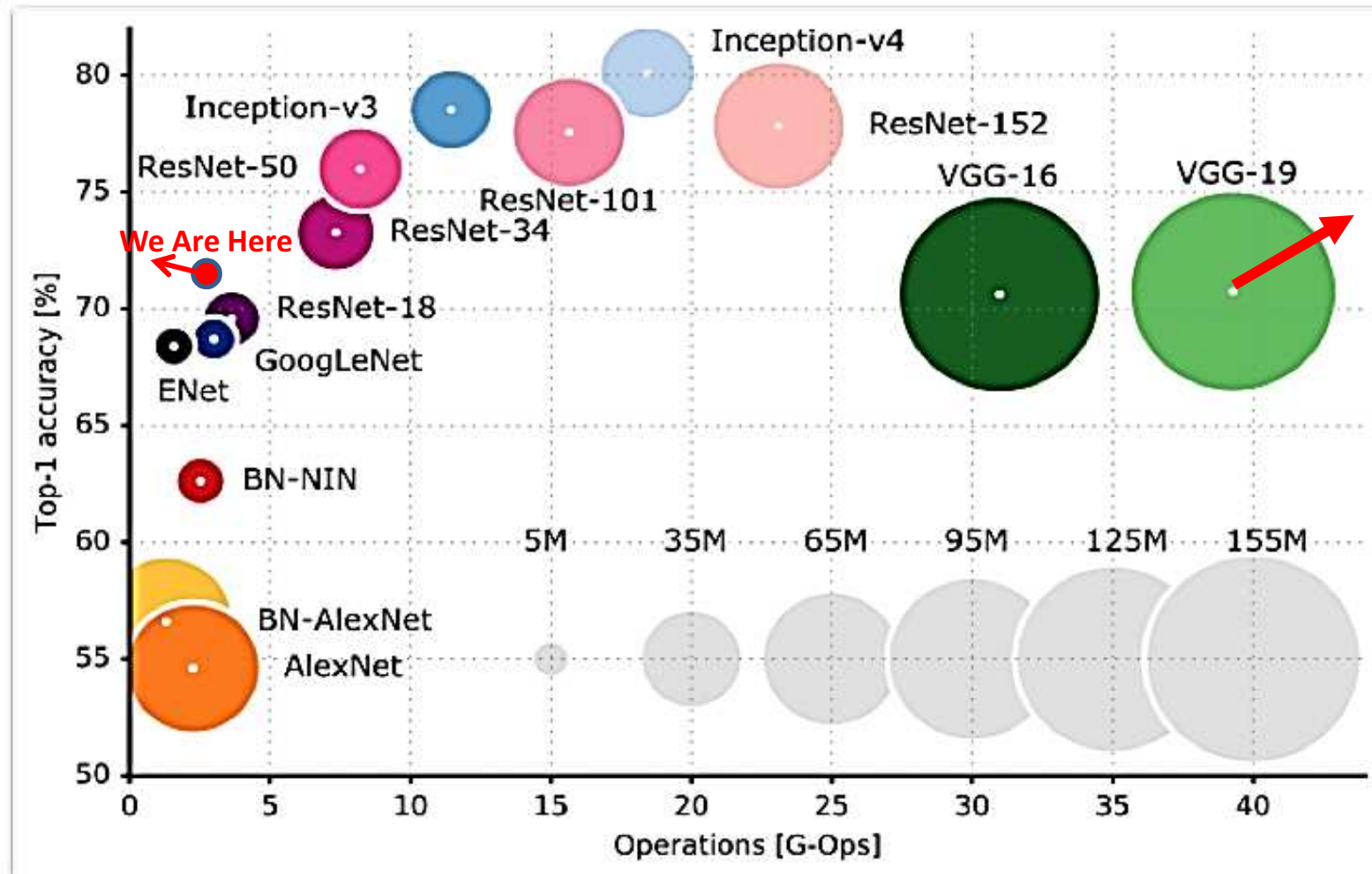
Ref: Simon Knowles, graphcore, 2018

Limitations:

-Large output dimension impossible with RF, SVM

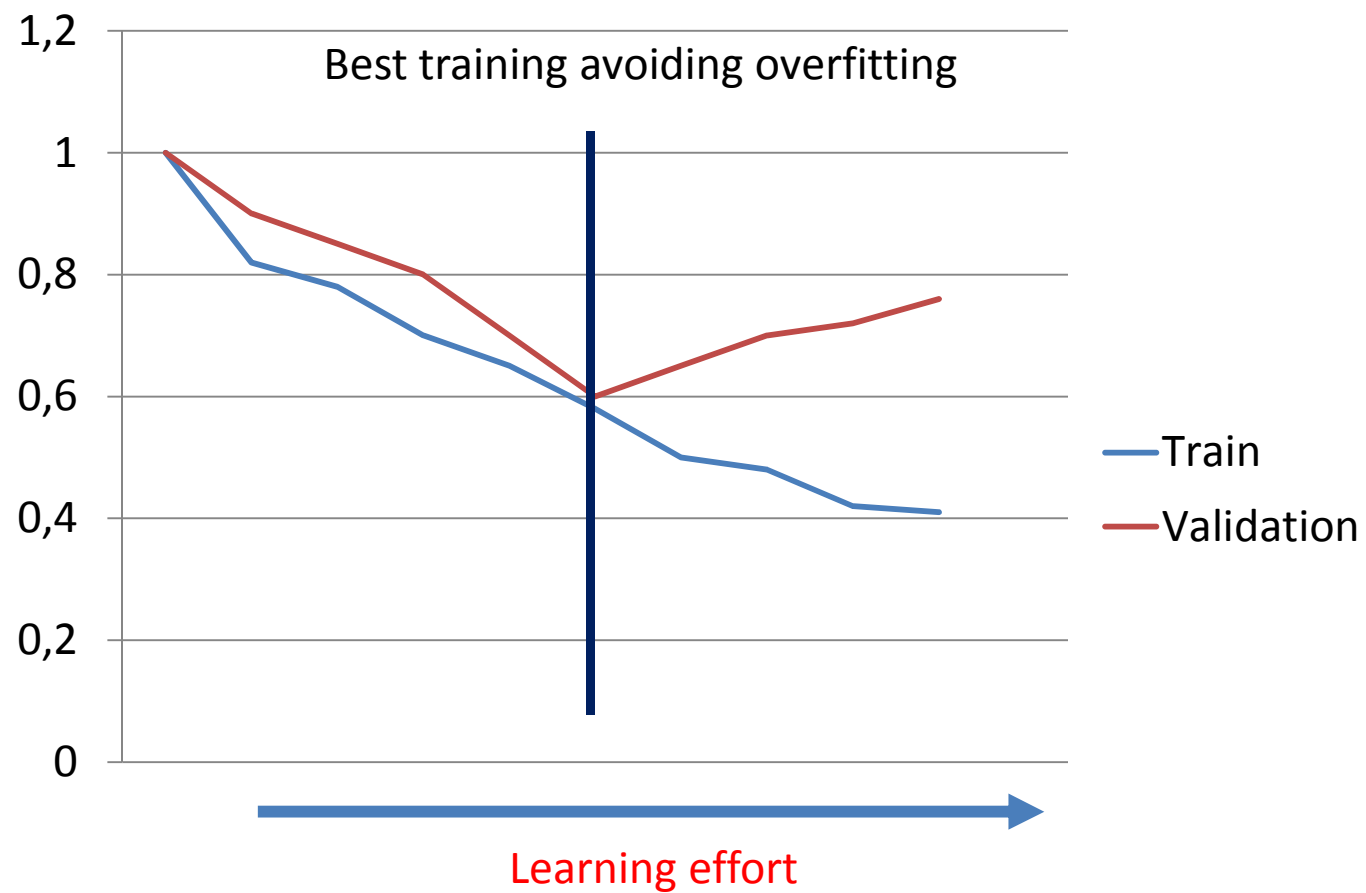
-CNN difficult to build (know-how)

-CNN Obesity issue (VGG-19 : 0.55GB)



Pic source: Eugenio Culurciello, topbots.com

Avoid **overfitting** monitoring **validation error**



https://en.wikipedia.org/wiki/Comparison_of_deep_learning_software

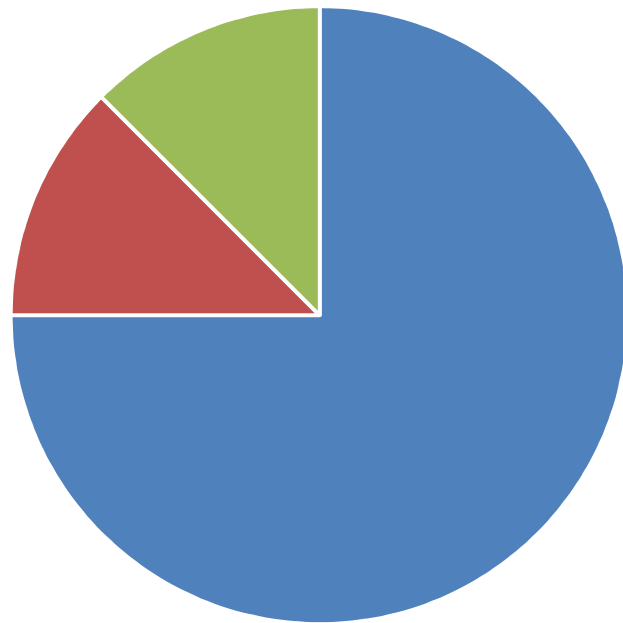
roNNie.aig	Kevin Lok	MIT license
BigDL	Jason Dai	Apache 2.0
Caffe	Berkeley Vision and Learning Center	BSD
Deeplearning4j	Skyrim engineering team; Deeplearning4j community; originally Adam Gibson	Apache 2.0
Chainer	Preferred Networks	MIT license
Darknet	Joseph Redmon	Public Domain
Dlib	Davis King	Boost Software License
DataMelt (DMelt)	S.Chekanov	Freemium
DyNet	Carnegie Mellon University	Apache 2.0
Intel Data Analytics Acceleration Library	Intel	Apache License 2.0
Intel Math Kernel Library	Intel	Proprietary
Keras	François Chollet	MIT license
MATLAB + Neural Network Toolbox	MathWorks	Proprietary
Microsoft Cognitive Toolkit	Microsoft Research	MIT license ^[25]
Apache MXNet	Apache Software Foundation	Apache 2.0

Neural Designer	Artelnics	Proprietary
OpenNN	Artelnics	GNU LGPL
PaddlePaddle	Baidu	Apache License
PlaidML	Vertex.AI	AGPL3
PyTorch	Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan	BSD
Apache SINGA	Apache Incubator	Apache 2.0
TensorFlow	Google Brain team	Apache 2.0
TensorLayer	Hao Dong	Apache 2.0
Theano	Université de Montréal	BSD
Torch	Ronan Collobert, Koray Kavukcuoglu, Clement Farabet	BSD
Wolfram Mathematica	Wolfram Research	Proprietary
VerAI	VerAI	Proprietary

Data format and destination

Train/validation/test

Data Base splitting



■ Learning ■ Overfitting test ■ A posteriori test

N scenarii of ($\#n \rightarrow \#m$)

$\{X_1^1, \dots, X_n^1\}$

...

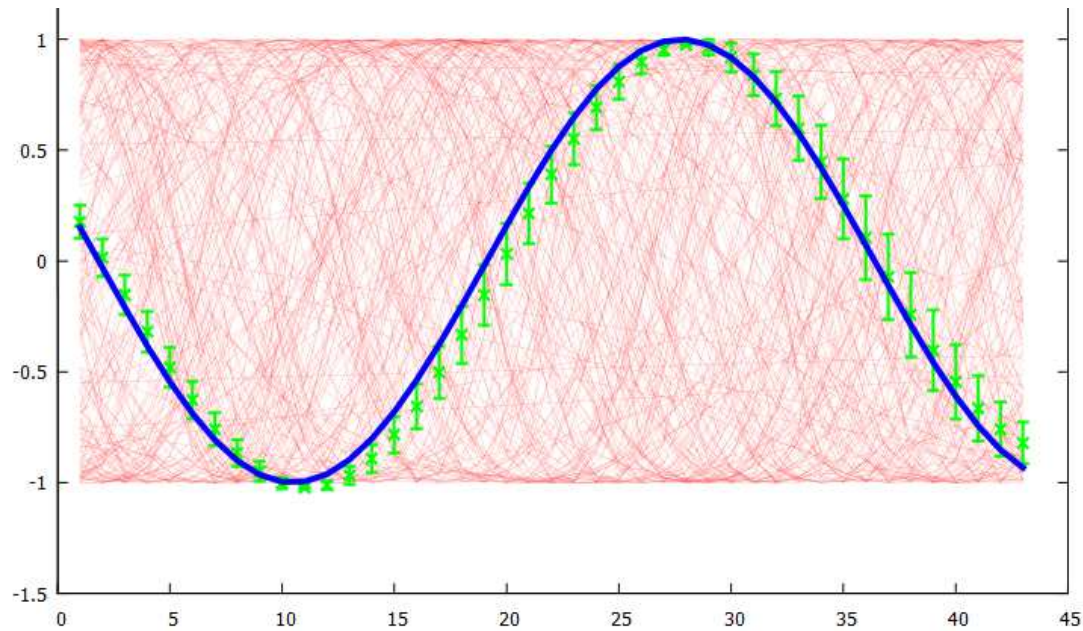
$\{X_1^N, \dots, X_n^N\}$

$\{Y_1^1, \dots, Y_m^1\}$

...

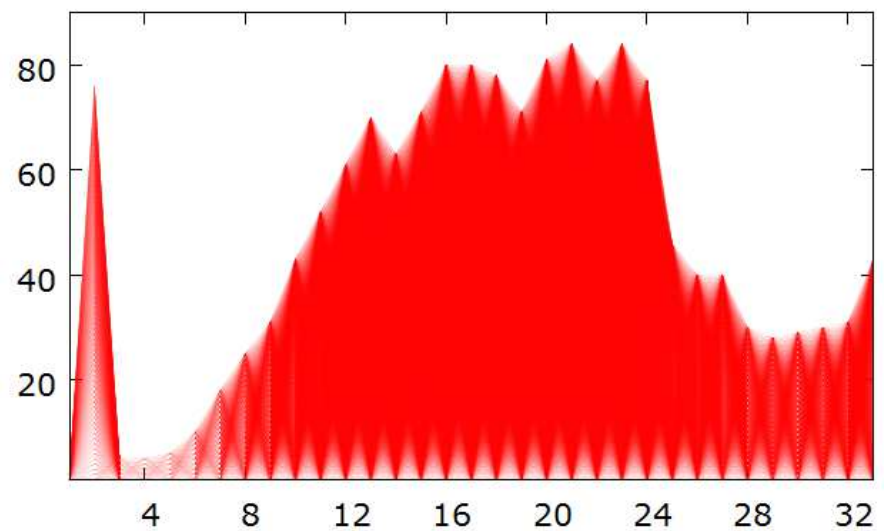
$\{Y_1^N, \dots, Y_m^N\}$

Learning ODE solutions
 $ndim_{in}=2, ndim_{out}=43, nb_{obs}=200$



$$y' = x_1 \cos(x_1 t + x_2)$$
$$y(0) = \sin(x_2)$$

**33 layers with up to
80 variables / layer**

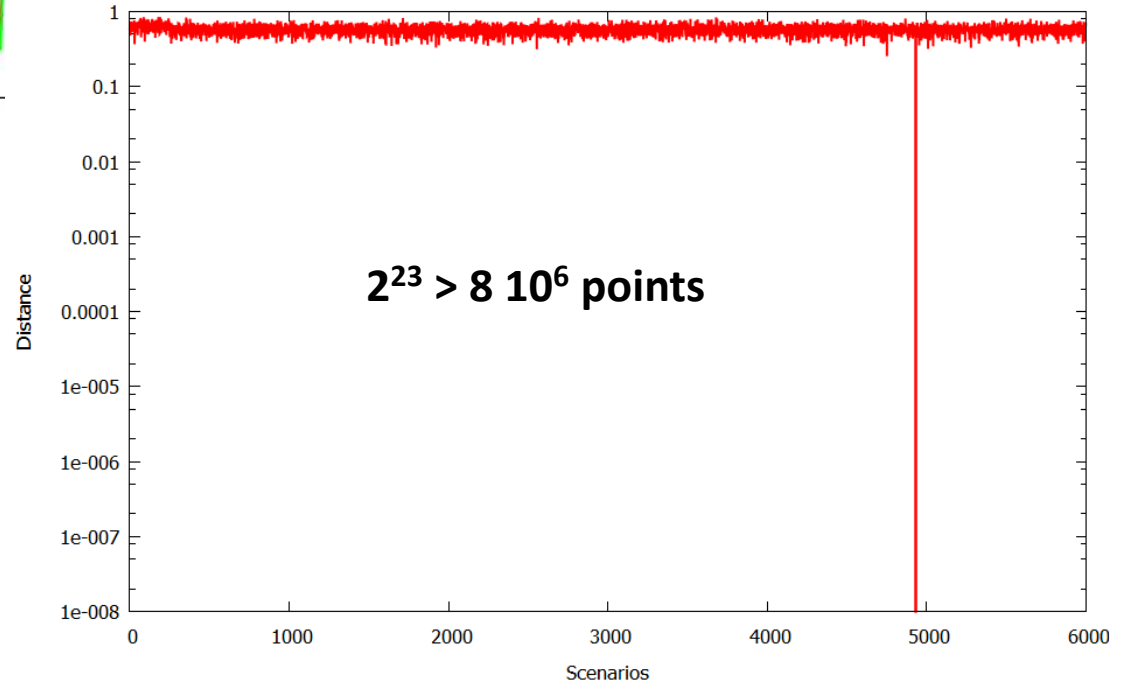
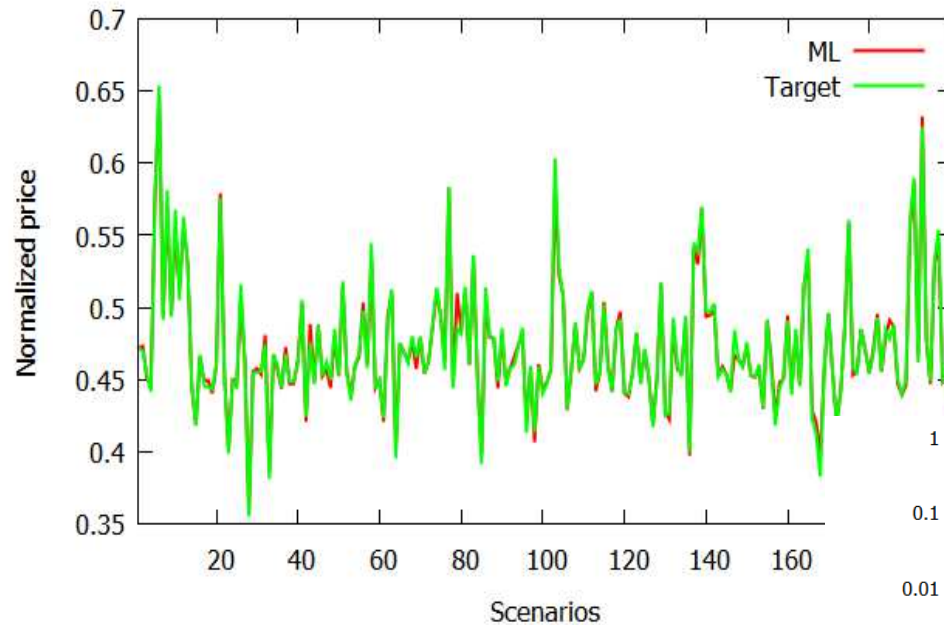


Challenges

<https://www.kaggle.com/> ---- <https://challengedata.ens.fr/>

Exotic pricing with multidimensional non-linear interpolation by Natixis

Training set of 1 million prices to learn how to price a specific type of instruments described by 23 parameters by nonlinear interpolation on these prices. Testing set of 400K scenarios.



Variables

ML works on real variables

Real

Integer

Characters $\rightarrow$ integer

Categorical $\rightarrow$ integer or One-hot-encoding

One-Hot-Encoding for both input & output variables

Classification in 10 classes (MNIST) $\rightarrow$ dimension 10

0 $\rightarrow$ (1,0,...,0)

2 $\rightarrow$ (0,0,1,0...,0)

9 $\rightarrow$ (0,...,0,1)

Also permits to have a probability distribution of belonging to given class

Missing data $\rightarrow$ Imputation

Median...

Gradients

- Finite differences
- Complex variables
- Adjoint variables
- Automatic differentiation