Machine learning and physical (Earth system) modelling - course 1

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October 2021

NERSC

slides+notebook:*https://github.com/nansencenter/nersc_ml_course*

References

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  Deep Learning.
  MIT Press, 2016.
  http://www.deeplearningbook.org.
- Jake VanderPlas.
  Python Data Science Handbook: Essential Tools for Working with Data.
  O'Reilly Media, Inc., 1st edition, 2016.

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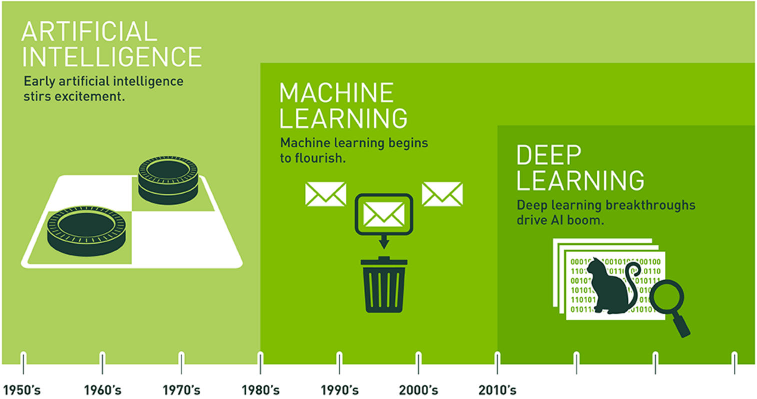
Introduction

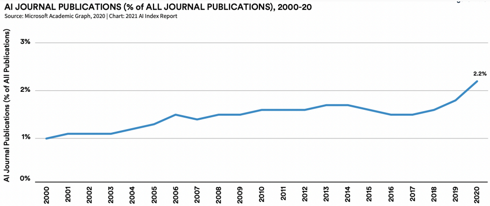
Scope of the lecture: Machine Learning

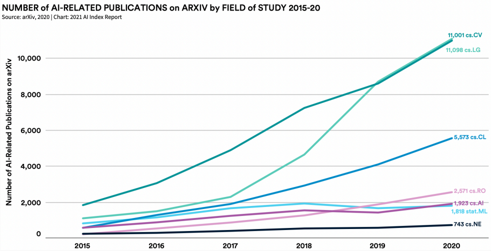


Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Source: NVidia

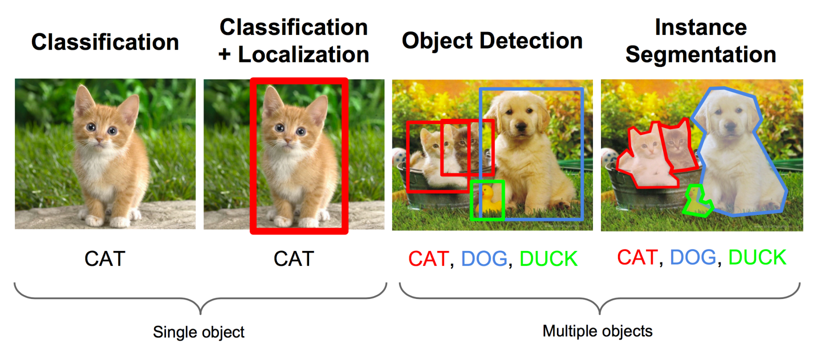
A (very) active field





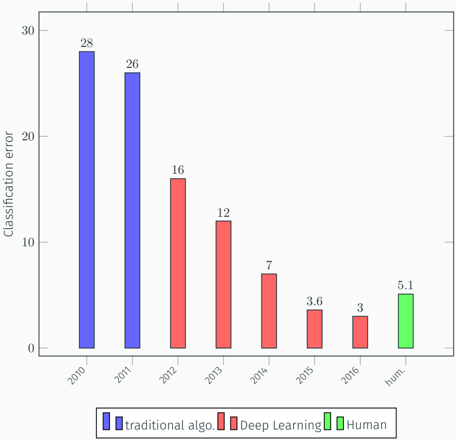
Zhang et al., “The AI Index 2021 Annual Report”

Example 1: Computer Vision



Li, Karpathy and Johnson, 2016, Stanford CS231n course

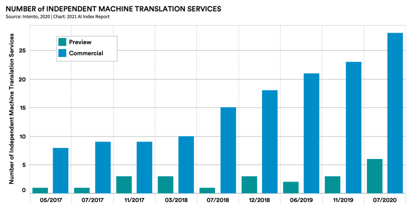
Example 1: Computer Vision



Deep learning architectures were based on Convolutional Neural Networks (CNN).

Example 2: Machine Translation

Objective : translate a text from a language to another.



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- **Oct. 2013**: Pionneering scientic paper (Kalchbrenner, N., and Blunsom, P).
- **2016**: Neural machine translation outperform traditional approaches on public benchmarks
- **2017**: Major systems switch to neural machine translation (using deep recurrent neural networks)

Example 3: Playing Games

- **1997**: Deep Blue defeats Kasparov at Chess.
- **2016**: AlphaGo's victory again Lee Sedol at Go.
- **2017**: AphaGo Zero learns how to play Go only by playing against itself. It outperformed previous AlphaGo version (Reinforcement learning)
- **2017**: DeepStack beats professional human poker players.

Example 4: Protein folding

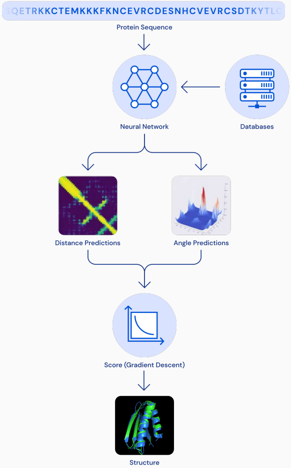


Diagram of Alpha Fold (source: Deepmind)

Senior et al. 2020

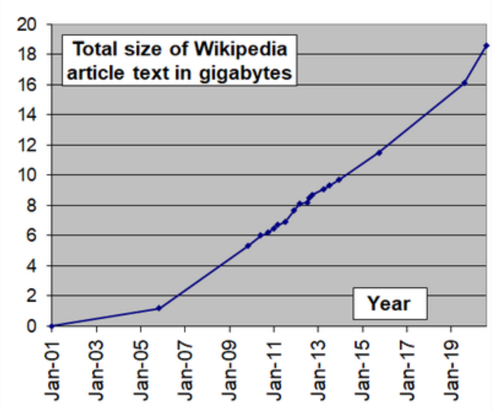
AI Art?

Edmond de Bellamy by Obvious(collective)

Generated using a Generative Adversarial Network.
Selling prince (Oct. 2018): $432,000

Reasons for these recent achievements?

- Increasing of the datasets in size and quality



source: Wikipedia

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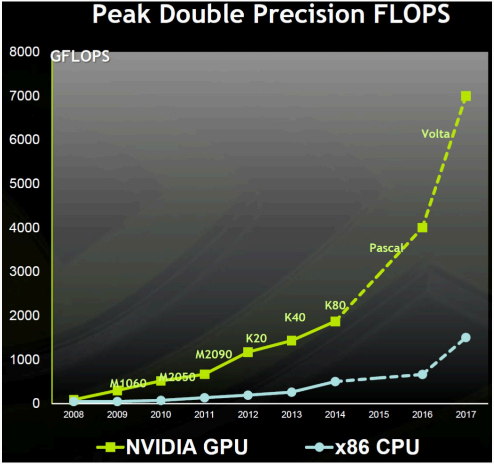

source: NVDIA

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- Scientific research on new algorithms (e.g adapted to image processing)

source: Deep Dream Generator

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- Very efficient software (GPU, cloud computing, automatic differentiation, ...)

TensorFlow Keras PyTorch

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- Scientific research on new algorithms (e.g adapted to image processing)
- Very efficient software (GPU, cloud computing, automatic differentiation, ...)
- Free software and open data culture.

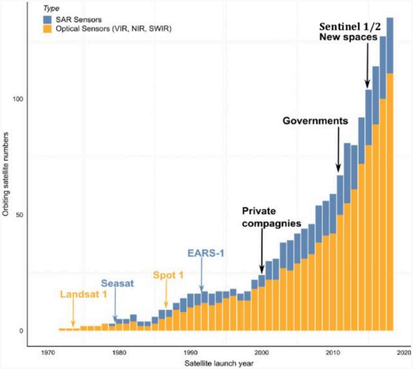
arXiv.org

GitHub

Apply Machine-Learning to physical (Earth-system) modelling?

Why is it a good idea?

- A increasing number of geophysical data (one spatial mission: 24 TB/day)



Earth System observavtion satellites

source: Tonneau et al. (2020)

Apply Machine-Learning to physical (Earth-system) modelling?

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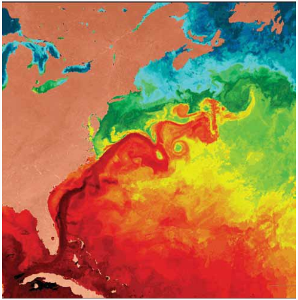
- A increasing number of geophysical data (one spatial mission: 24 TB/day)
- Data with highly significant spatial patterns



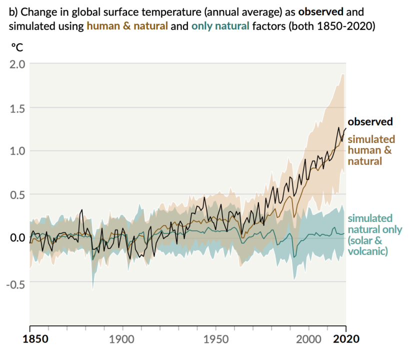
Sea Surface temperature of the gulf stream

source: Talley (2000)

Why is physical modelling specific?

NASDAQ Composite sock market index over the last 10 years

Figure 1: IPCC, AR6, WG1



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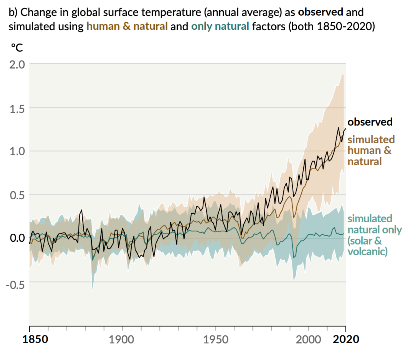
Mostly unknown dynamical processes

Figure 1: IPCC, AR6, WG1



Mostly known dynamical processes (based on physical principles)

What about data assimilation?

Machine learning and data assimilation are closely linked.

Some references:

- Geer, A.J., 2021. Learning earth system models from observations: machine learning or data assimilation?. *Philosophical Transactions of the Royal Society A*, 379(2194)
- Brajard et al. 2019. Connections between data assimilation and machine learning to emulate a numerical model. *Proceedings of the 9th International Workshop on Climate informatics*
- Bocquet et al. 2019. Data assimilation as a learning tool to infer ordinary differential equation representations of dynamical models. *Nonlinear processes in geophysics.* 26(3).
- Abarbanel, H.D., Rozdeba, P.J. and Shirman, S., 2018. Machine learning: Deepest learning as statistical data assimilation problems. *Neural computation, 30(8)*.

Generalities on Machine Learning

What is this about ?

Can we extract knowledge, make some predictions, determine a "model" using this large amount of data ?

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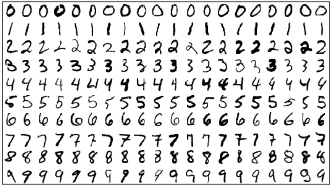

Base of images

$\longrightarrow$ Digit$\in \{0, \ldots, 9\}$

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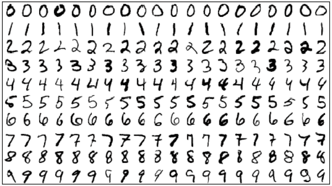

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- From high dimensional data (thousands to millions dimensions) to reduced dimensional data (less than 100)
- From disorganized data to comprehensive information
- Can we teach a machine how to do that ?

Two classes of Machine Learning problems

1. Regression: Determination of a quantitative variable from a set of data
   - The price of a building from various predictors (Surface, ...)
   - A physical value (Temperature, humidity, ...) in the future knowing the past
   - ...

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1. Regression: Determination of a quantitative variable from a set of data
    - The price of a building from various predictors (Surface, ...)
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    - ...
2. Classification: Determination of a class
    - A digit from a image
    - Identification of the content of an image
    - ...

Two types of objectives

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    - Playing a chess game.

Formally

A Machine

$$y = \mathcal{M}(x, \theta)$$

- x: input
- y: output
- $\mathcal{M}$: a model (named ”machine”)
- θ : parameters of the model $\mathcal{M}$.

Machine learning consists in optimizing θ using a set of data. This is the training process.

The Machine Learning recipe

A Machine

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  - linear
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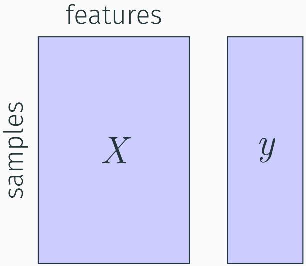
- A learning process
  - Estimation of θ

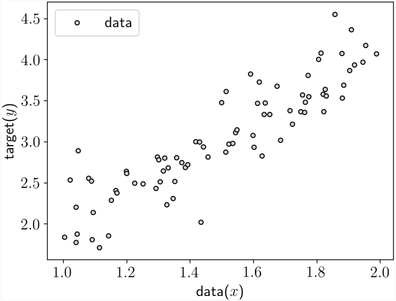
Multidimensional data

Generally, we have multidimensional data X and a one-dimensional target y.



An illustration

- Some Data



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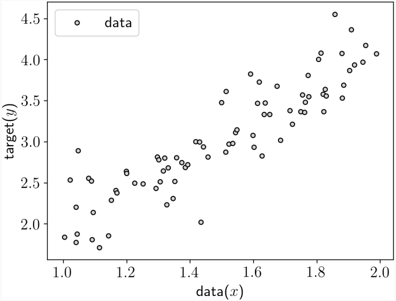

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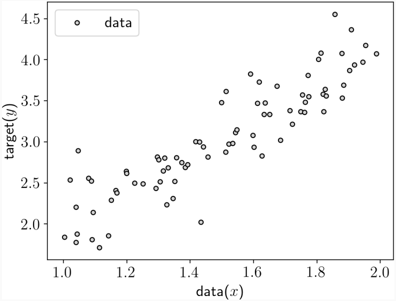

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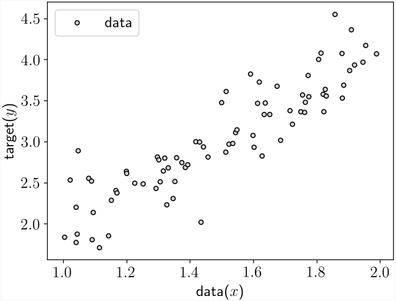

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- A learning process: $\theta = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T y$

An illustration

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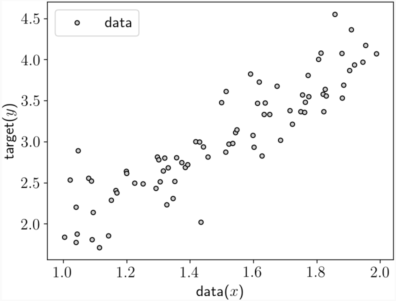

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Result