Machine learning and gravitational-wave astronomy: a review

Eric Chassande-Mottin
AstroParticule & Cosmologie

Credits: University of Aveiro

Goal

- Intro on machine learning – landscape and terminology
- Overview of the current impact of machine learning on GW
- Identify promising progresses

High level perspective on machine learning

- Learn decision rules from examples (training data)
  - Build a model based on sample data (instead of relying on an explicit statistical model)
  - Follow automatic learning procedures (computer program) ≠ heuristics
- Main approaches
  - Supervised learning: examples (input features) with desired outputs (target)

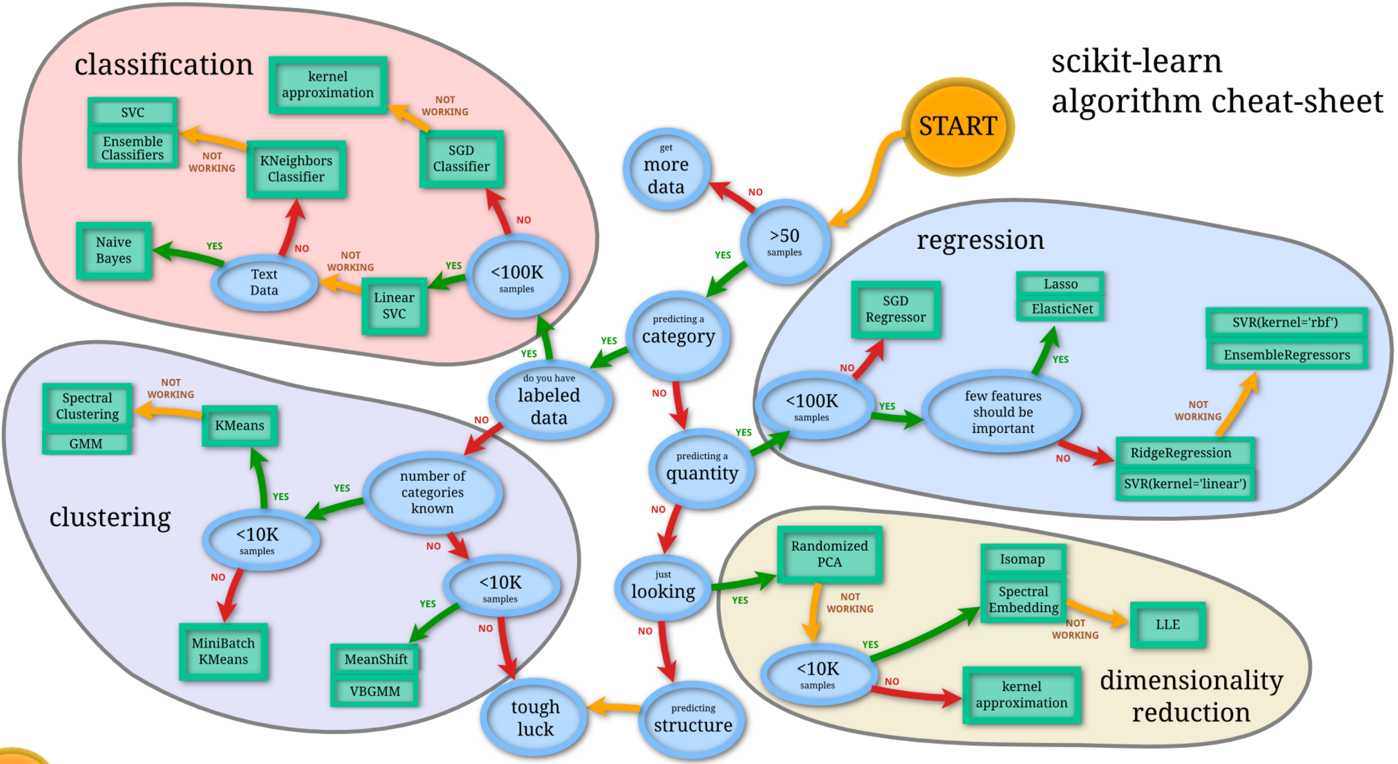
    → *classification & regression*

    Fit a function that predicts the output from new inputs
  - Unsupervised learning: only features, no target

    Data mining – Discover patterns or groupings according to similarity → *clustering*

    Also : reinforcement learning

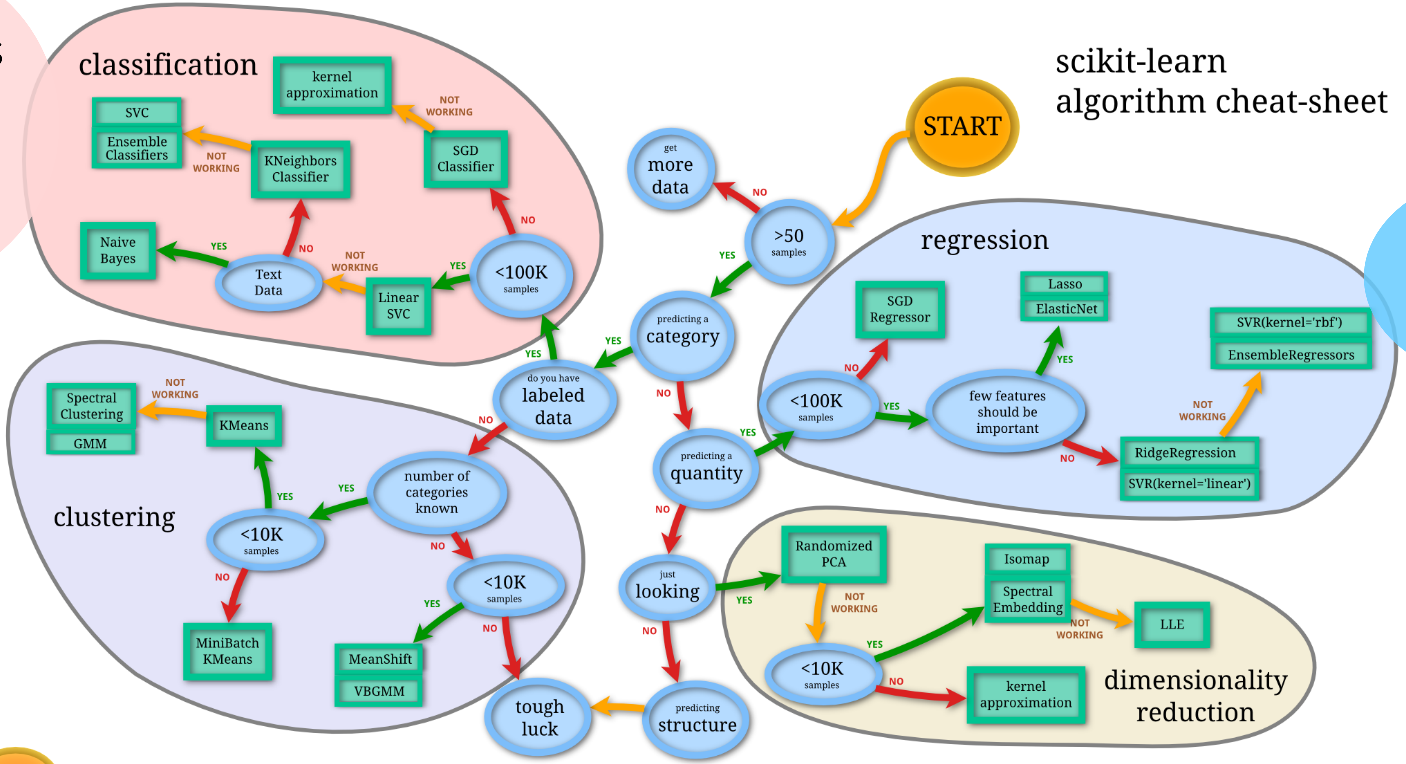
Machine learning: tasks and related algorithms



Machine learning: tasks and related algorithms

neural networks

boosted decision trees



neural networks

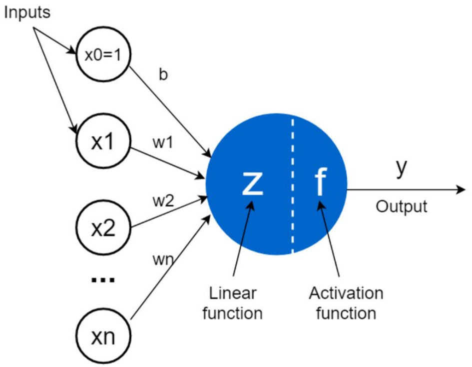
Back

Journées GdR OG Analyse des données

https://scikit-learn.org

Neural networks

Mathematical neuron

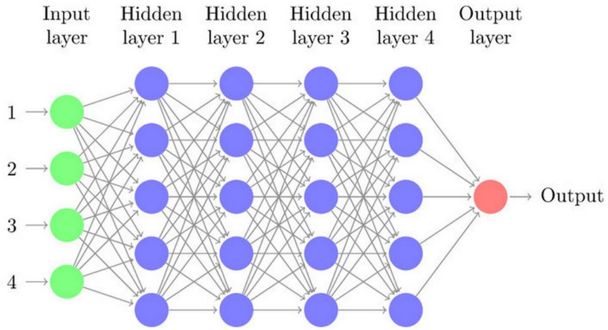


$$y = f\left(\sum_k w_k x_k + b\right)$$

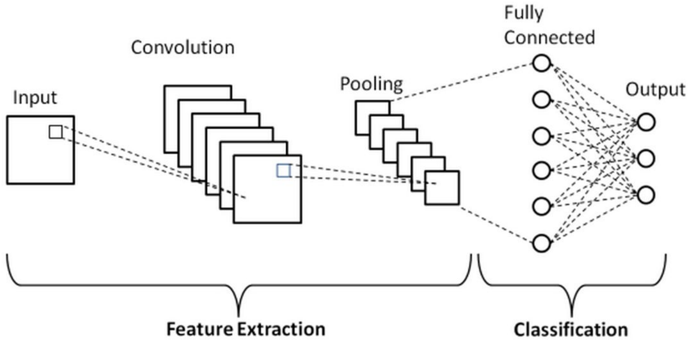
Free parameters:

***n* weights + bias**

Multi-layer perceptron



Convolutional neural network



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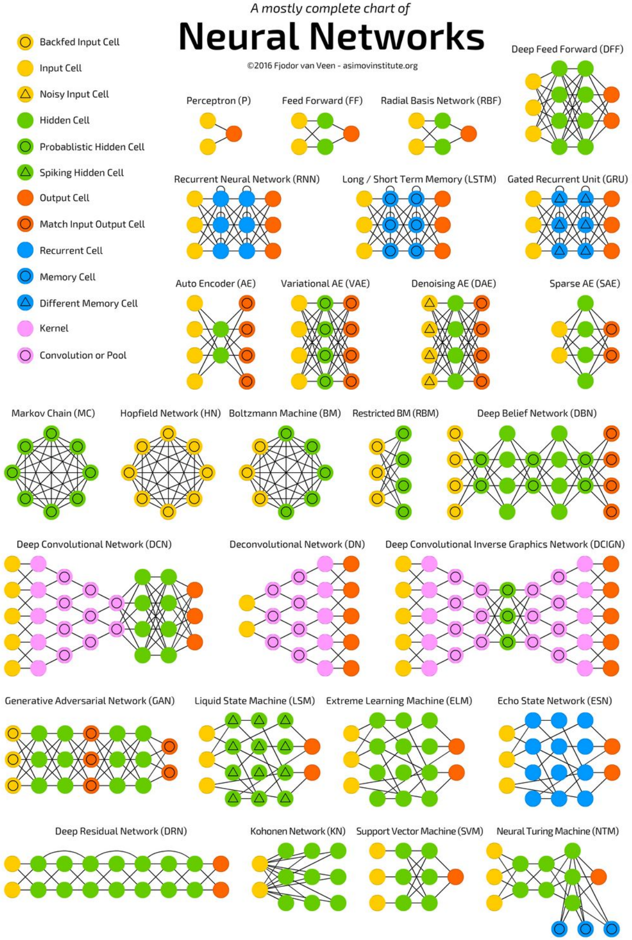

Nov 15 2022

https://towardsdatascience.com/the-mostly-complete-chart-of-neural-networks-explained-3fb6f2367464

Neural networks

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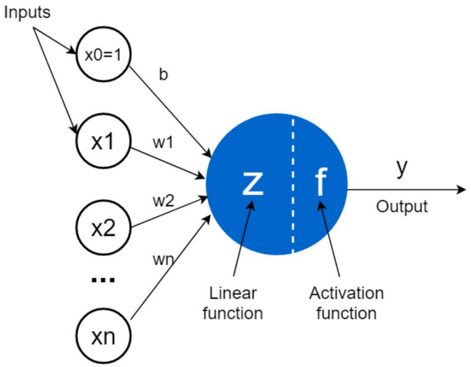

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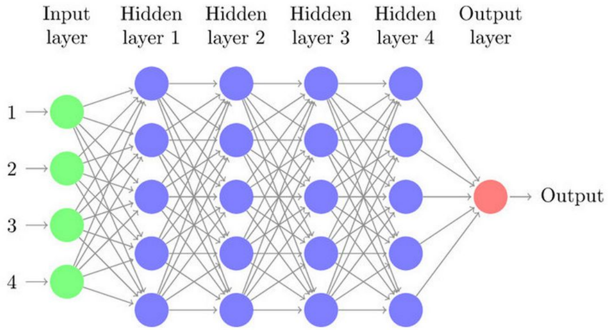

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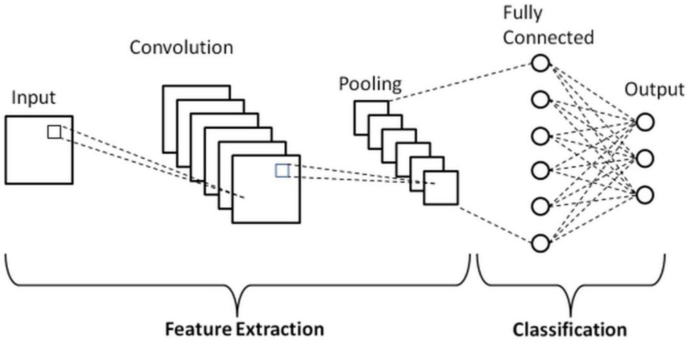


Deep NN model has billions of parameters

- Ex: GPT-3=175 billions

Training: optimization of $\{w, b\}$ to minimize classification or regression error

With **stochastic gradient descent and GPUs** it is possible to do efficiently over large training sets

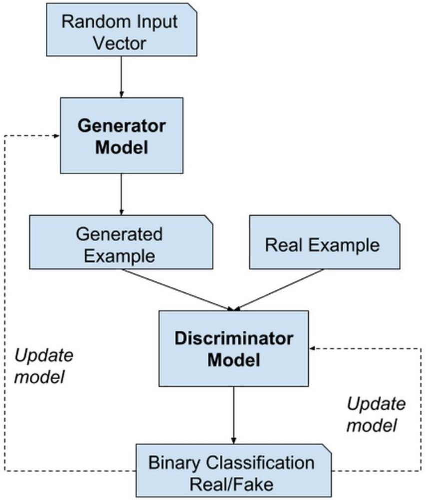
https://towardsdatascience.com/the-mostly-complete-chart-of-neural-networks-explained-3fb6f2367464

Probabilistic generative models (1)

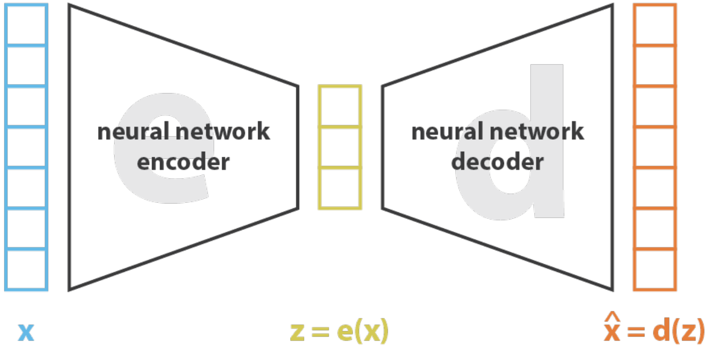
Learn probability distribution $p_X(\mathbf{x})$ of data $\mathbf{X}$ from a set of examples $\{\mathbf{x}_k\}$

→ generate samples, connection to Bayesian statistics

Generative Adversarial Networks



Variational autoencoder



$$\text{loss} = \| x - \hat{x} \|^2 = \| x - d(z) \|^2 = \| x - d(e(x)) \|^2$$

https://towardsdatascience.com

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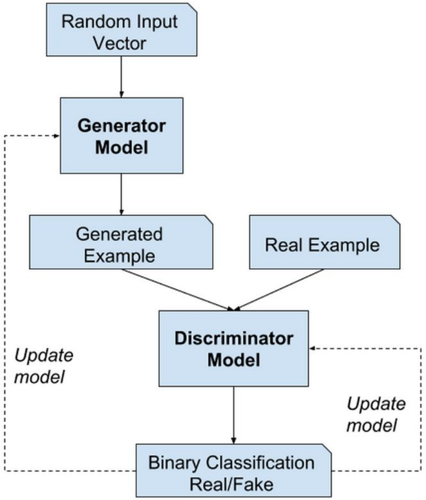

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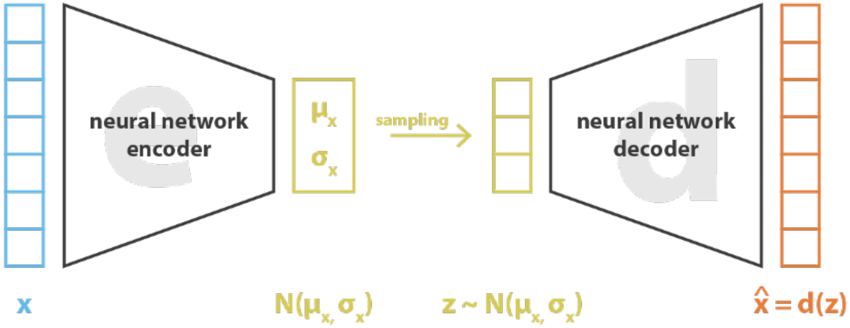


$$\text{loss} = \|x - \hat{x}\|^2 + KL[N(\mu_x, \sigma_x), N(0, I)] = \|x - d(z)\|^2 + KL[N(\mu_x, \sigma_x), N(0, I)]$$

https://towardsdatascience.com

Normalizing flows

Map from complex random variable (data)
to a Gaussian (“normal”) variable → “*normalizing*”

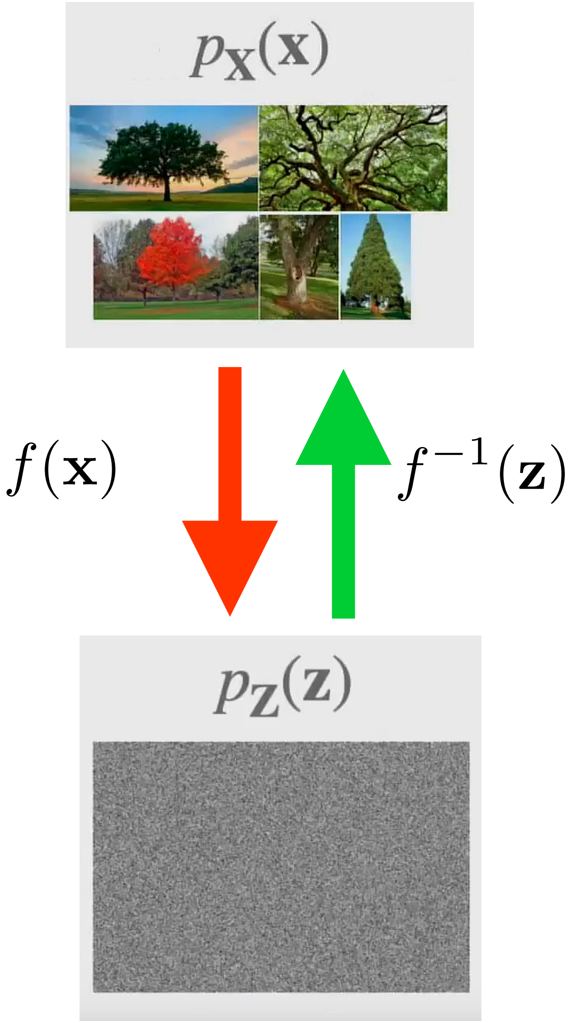
$$p_X(\mathbf{x}) = p_Z(f(\mathbf{x}))|\det Df(\mathbf{x})|$$

Z=*f*(**X**) is an **invertible and differentiable** mapping → “*flow*”

can easily do density evaluation and sampling of **X**

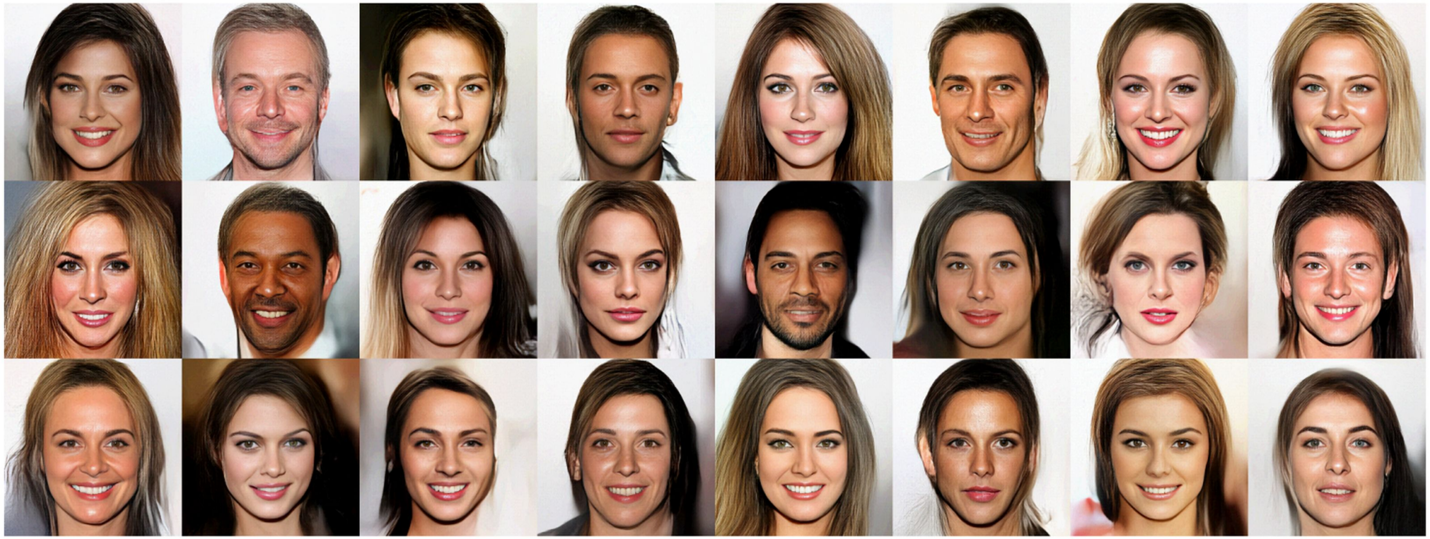
How to choose *f* ?

[More with Konstantin → next talk]



https://youtu.be/u3vVyFVU_lI

Normalizing flows



Depth of flow K = 32

Kingma & Dhariwal, NeurIPS 2018

Application to gravitational wave astronomy

- **Data analysis**
  - Searches
  - Detchar/denoising
  - Parameter estimation
- **Waveform modelling**
  - Rapid generation
- **Instrument science**
  - Design R&D
  - Control
  - Other

"GW and machine learning" → 75 papers on Inspire HEP for 2021 and 2022

"GW and deep learning" → 45 papers

Detection	→	classification
Simulation	→	generative models
Inversion	→	regression

Application to gravitational wave astronomy (1)

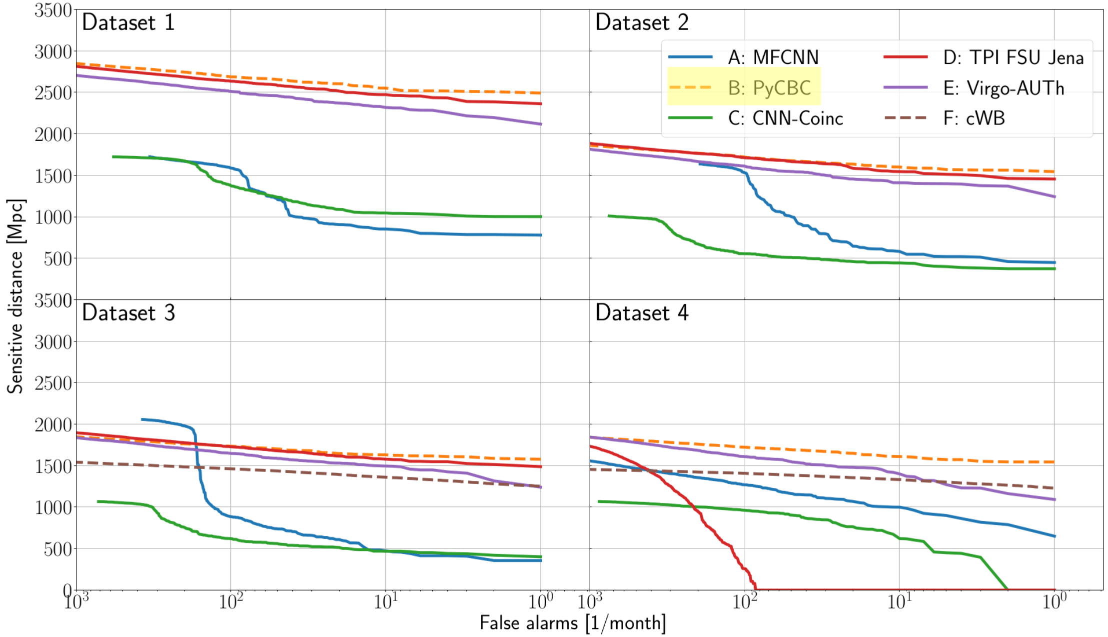
- Data analysis
  - Searches
  - Detchar/denoising
  - Parameter estimation

- **Compact binaries**
  - First prototypes: Gabbard *et al*, 2017 and others
  - Kaggle challenge
  - Many recent papers
    - Schaefer et al, 2021 achieve FAR > 1/month
  - *State of the art (next slide)*
- **Bursts**
  - Skliris et al, 2022 Mly pipeline in development
  - Lopez et al, 2021 – Prototype search for SN
  - Long bursts – Boudart et al, 2022 ALBUS pipeline
  - Xgboost clustering in pystampas (ARTEMIS)
- **Continuous waves**
  - Dreissigacker et al, 2019 et 2020
    - CNN achieves state-of-the-art on "easy" short search

State of the art – MLGWSC-1 challenge

Easy: Non-spinning BBH (10-50 Msun, 1s) in Gaussian noise – No lines

Medium: Spin-aligned BBH (7-50 Msun, 20s) in Gaussian noise with lines



Difficult: Precessing BBH with HM (7-50 Msun, 20s) in Gaussian noise with evolving PSD

Real case: Iso-spinning BBH (7-50 Msun, 20s) in real det noise O3a

Main conclusions

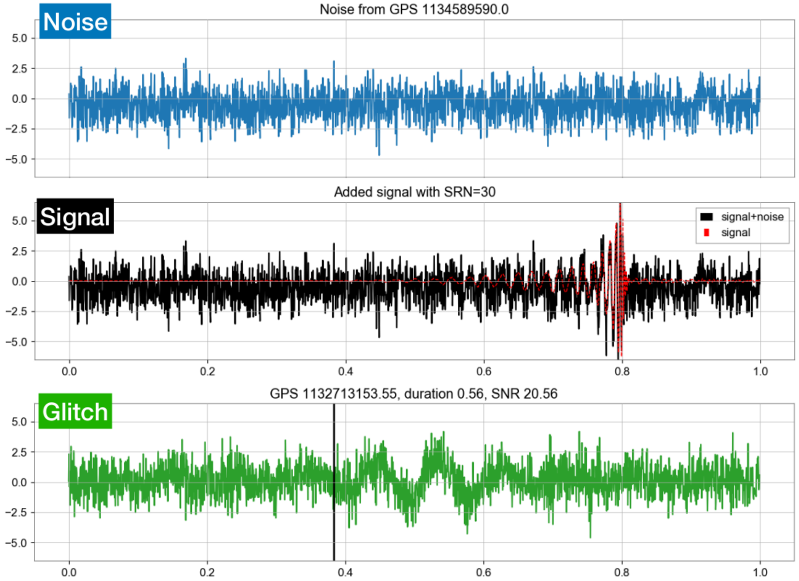
- ML competitive in sensitivity on simulated data and the limited parameter space
- ML struggles with real noise
- ML fails at lower FARs
- ML struggles with long duration signals

Key research topics

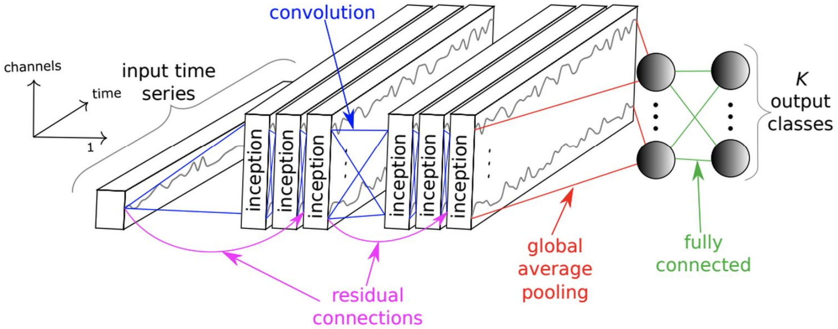
- Improve **consistency check between detectors** and **noise rejection**
- Expand the computation large amounts of **background**
- Tune searches for **longer duration** of data

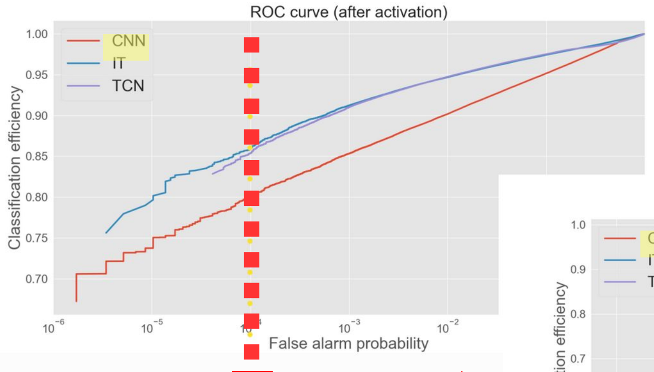
https://arxiv.org/abs/2209.11146

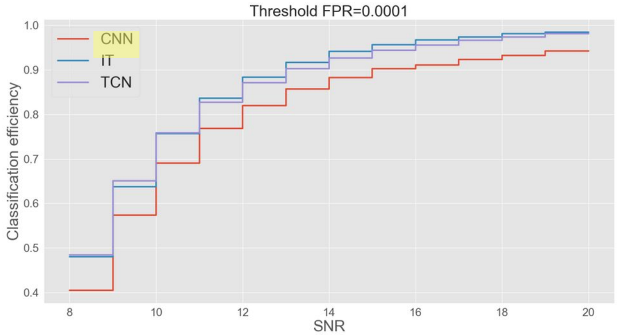
DL based searches for single detector periods



- 1 detector operating
  - 14 % of the observation time during O3 (1.6 month)
- Training set from O1 data and injections
- Use NN specialized for time-series







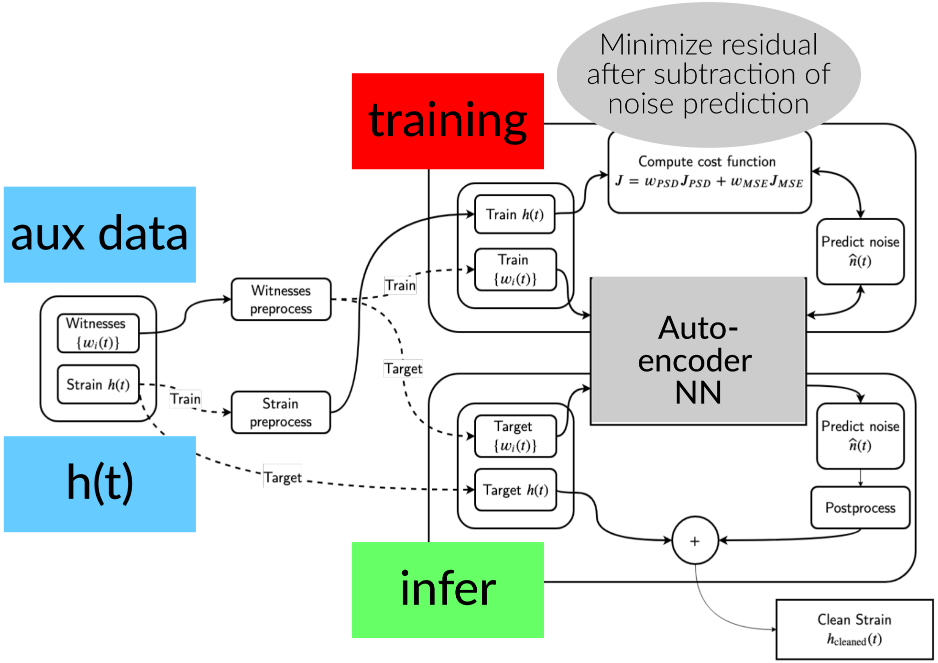
Trovato, Bejger, Courty, Flamary, Marchand, in progress

Application to gravitational wave astronomy (2)

- Data analysis
  - Searches
  - Detchar/denoising
  - Parameter estimation

- Detchar
  - GravitySpy & GwitchHunters : citizen science → labelled data
  - iDQ – Essick et al, 2020: rely on a variety of classifiers
  - Powell et al, 2022: glitch simulation using GAN
- Denoising
  - Ormiston et a, 2020 : Deepclean
- Parameter estimation
  - Dax et al, 2021 : Dingo – Normalizing flows
  - Williams et al, 2021 : nessai – Normalizing flows
- Population studies and cosmology
  - Mould et al, 2022
  - Interest and initial studies at APC and L2IT

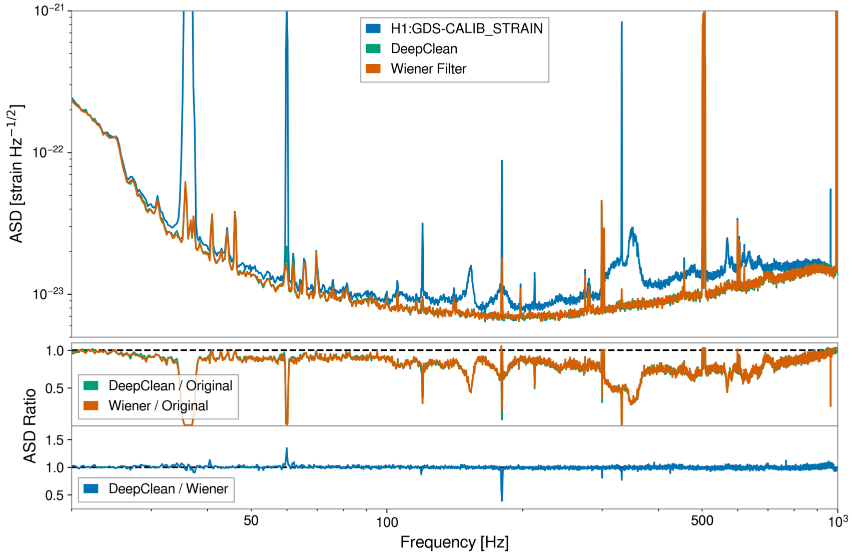
Deepclean



Subtraction of linear, non-linear and non-stationary noise couplings

Learn the transfer function that minimize residual after noise subtraction

Re-training every few hours (takes ~8 minutes for 600s segment)



https://arxiv.org/abs/2005.06534

Application to gravitational wave astronomy (3)

- Waveform modelling
  - Rapid generation

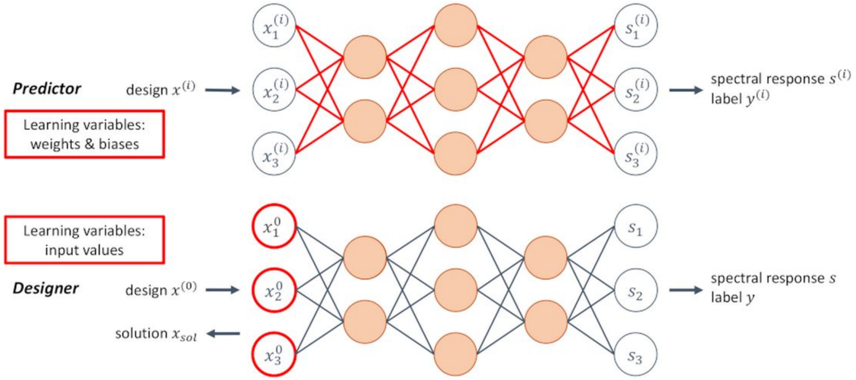
- Compact binaries – Waveform regression
  - Reduced order models (Puerrer et al) – Splines
    Schmidt et al 2021, Cano et al, 2022 – ML based regressor
  - Setyawati, Y et al 2020 – Regression methods in waveform modeling: a comparative study
  - L Thomas et al, 2022 SEOBNN_v4PHM_4dq2 (SEOBNRv4PHM) – precessing BBH, higher-order modes
    - Achieves mismatch ~ few 10^{-3}, ~18 msec (speedup x 100 on GPU)
- Bursts – Supernovae
  - ML for resolution of EDP for SN simulation

Application to gravitational wave astronomy (4)

- Instrument science
  - Design R&D
  - Control

- Instrument control

Experiments on the 40 m for beam spot position control and lock acquisition



Design of multilayer optical thin-films based on light scattering properties

Inversion of the numerical optical response computation

Fouchier et al, Optics Express, 2021 (*Fresnel Inst.*)

Conclusions

- Statistical learning expanding very rapidly
  - 12,000 submissions at NeurIPS 2021 (+40 %/yr)
  - Natural language processing makes large progresses
- Applying ML to GW is a very active area of research
  - ~50 papers / year
- First ML based algorithms reaching production
  - Recent breakthrough: neural posterior estimation
- Ressources
  - Machine learning at IN2P3 MACHINE-LEARNING-L@in2p3.fr
    (D Rousseau, A Boucaud, V Gautard)

    Workshop : https://indico.in2p3.fr/event/27507/
  - Biblio – Hastie, Tibshirani, and Friedman, Intro to Stat learning

    Cuoco et al, Enhancing Gravitational-Wave Science with Machine Learning