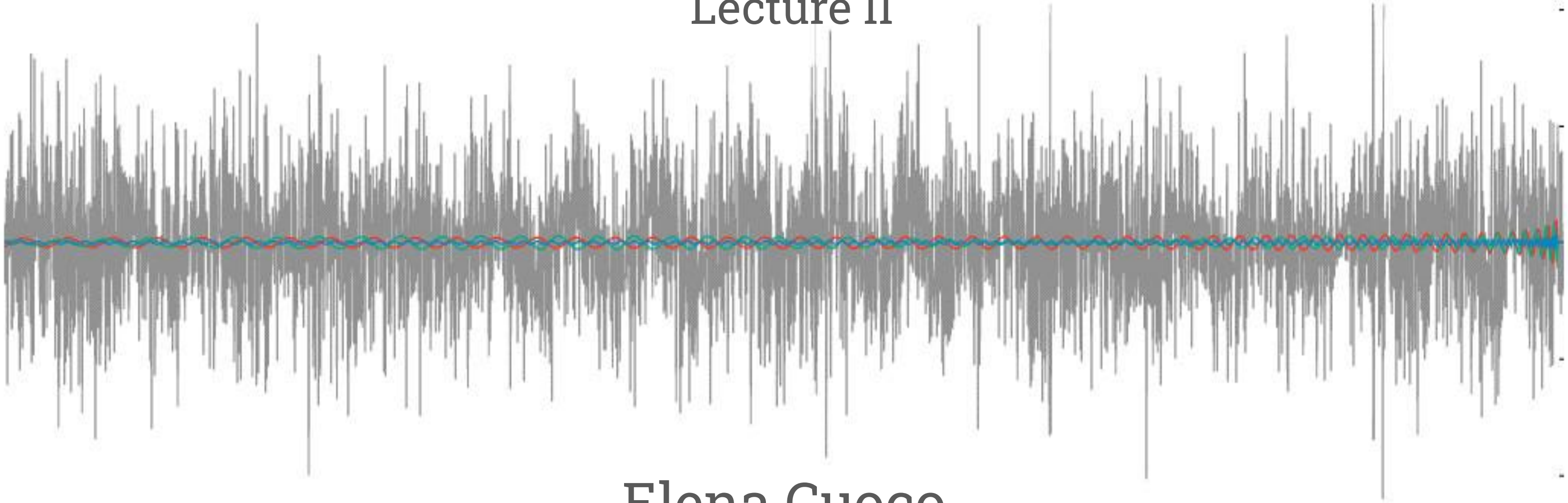
Gravitational wave data analysis and Machine Learning

Lecture II

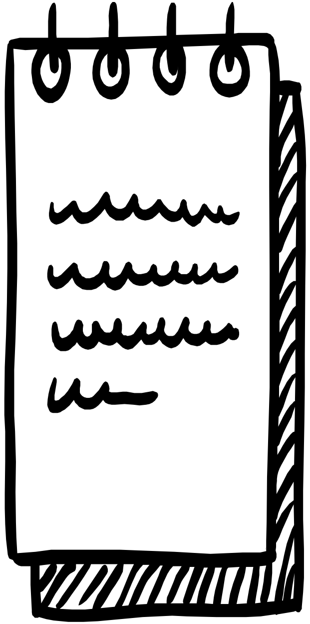


Elena Cuoco

European Gravitational Observatory

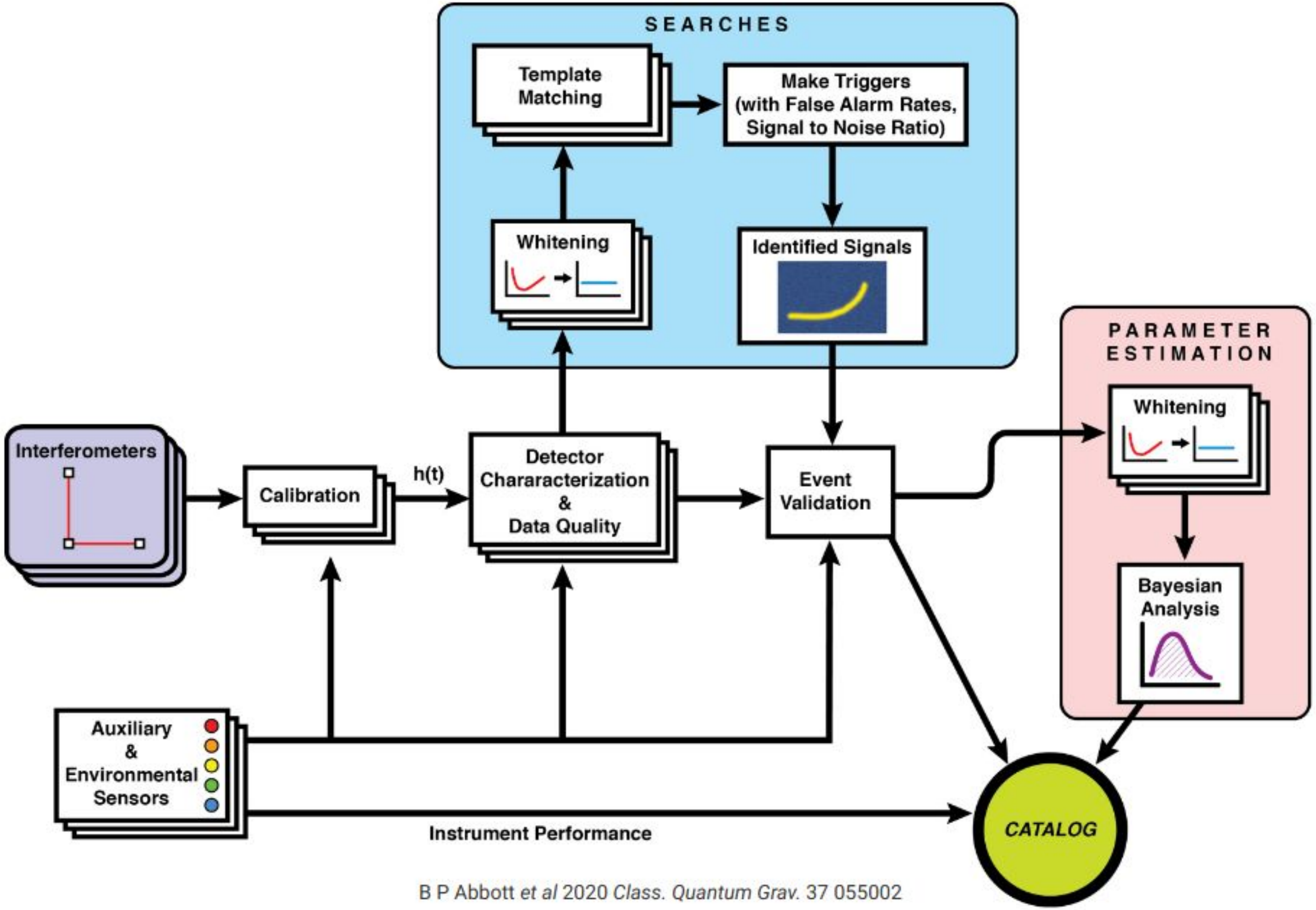
BND School 2024 - Blankenberge, Belgium 2 – 12 Sep 2024

Gravitational Waves and Machine Learning application: Outline



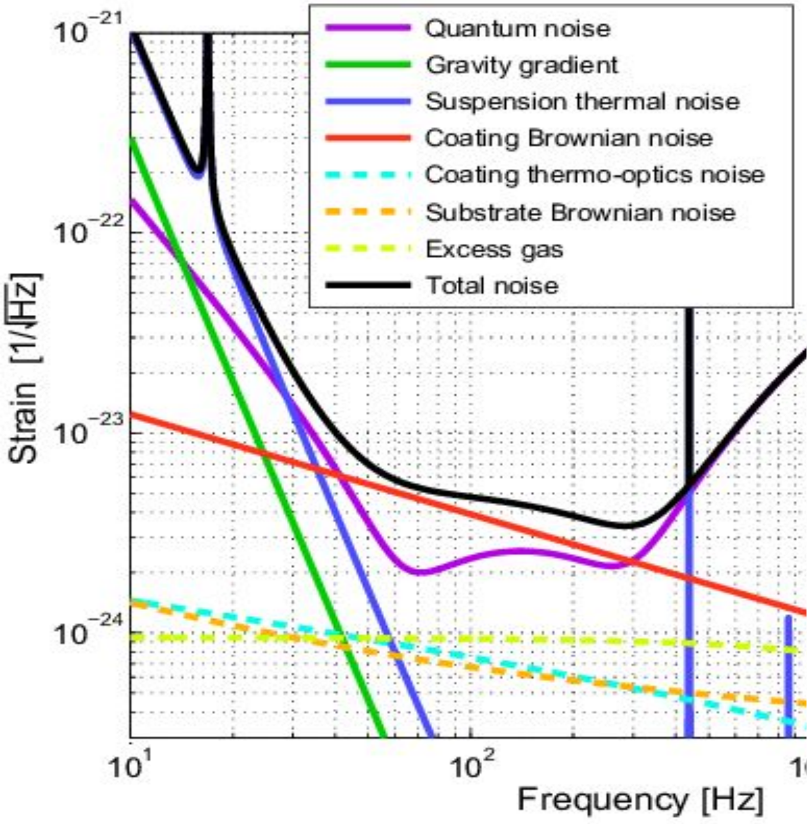
- The data analysis workflow recap
- The real data
- Machine Learning and Deep Learning
- Machine Learning for Glitch classification
- Machine Learning for GW Signal Detection and classification

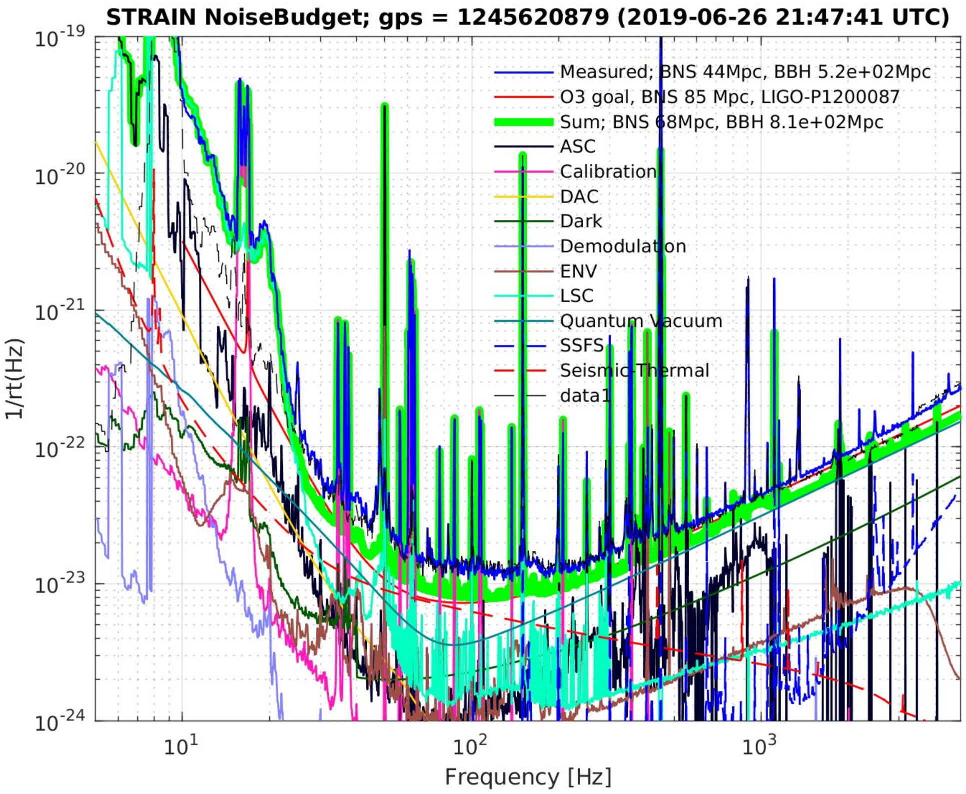
The data analysis workflow



B P Abbott *et al* 2020 *Class. Quantum Grav.* 37 055002

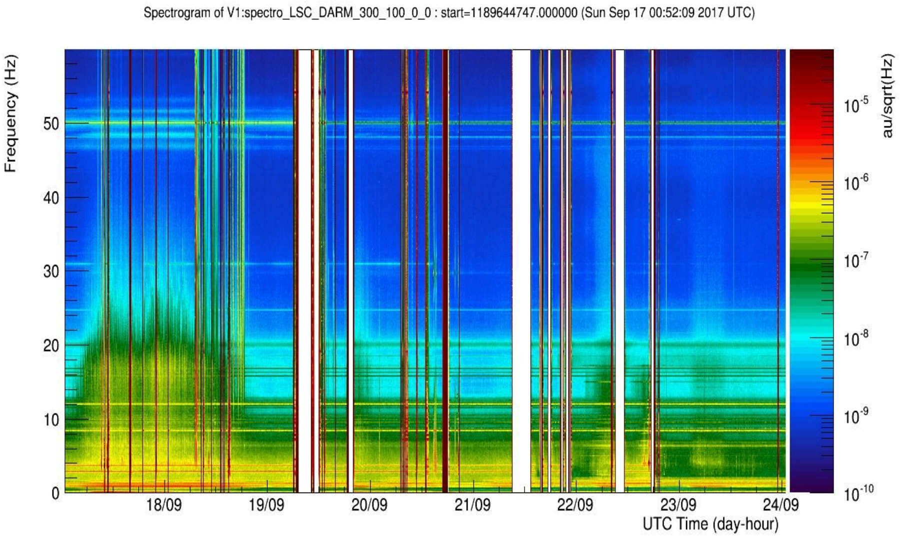
Noise budget: fundamental vs. actual



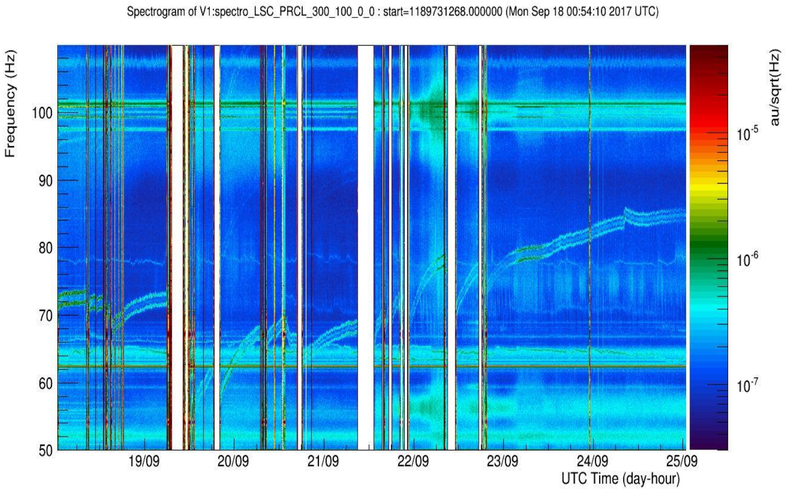


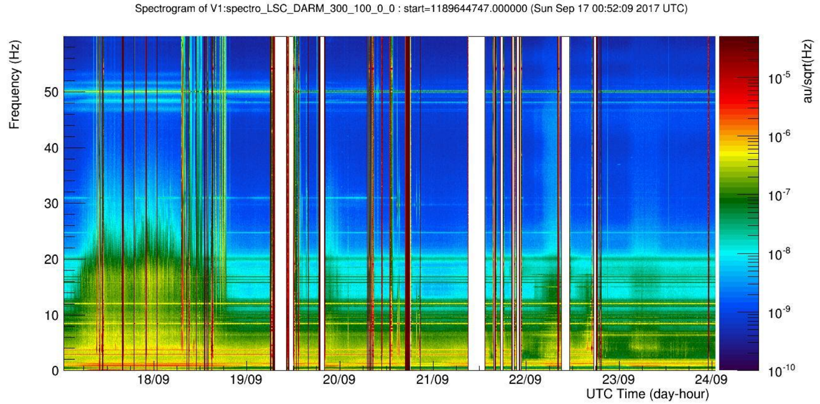
The Real Data

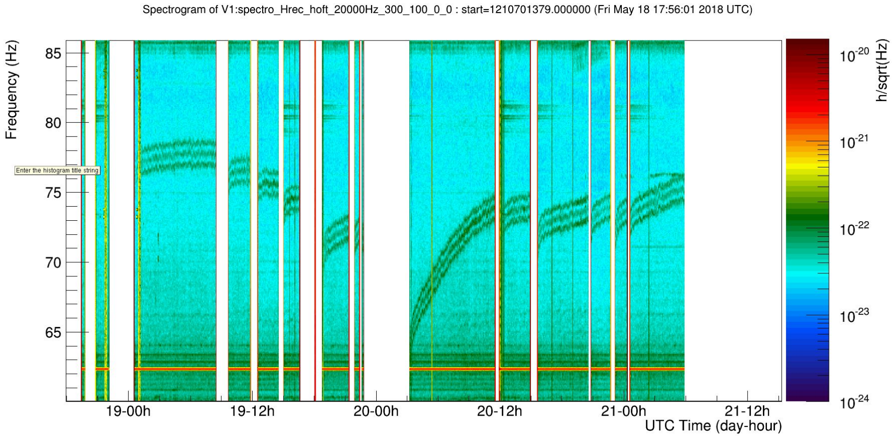
The noise it not at all ideal...



Not linear and not stationary noise

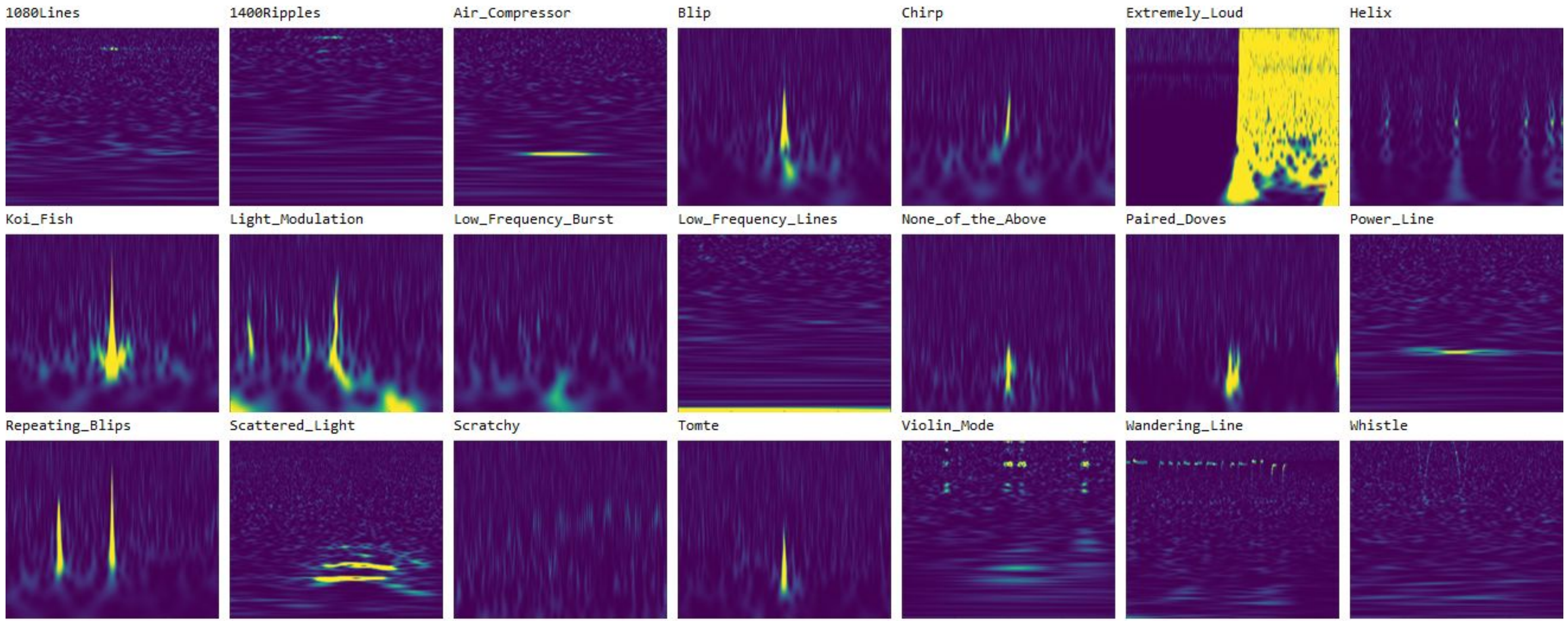






I. Fiori courtesy

Transient noise signals: Glitches

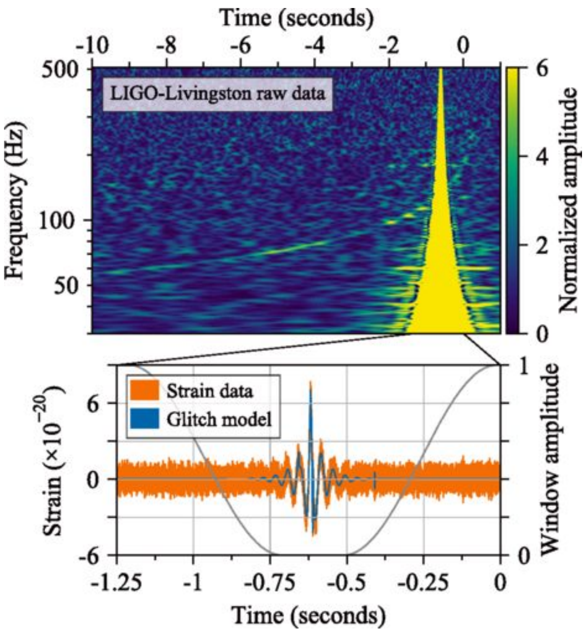


https://www.zooniverse.org/projects/zooniverse/gravity-spy

Gravity Spy, Zevin et al (2017)

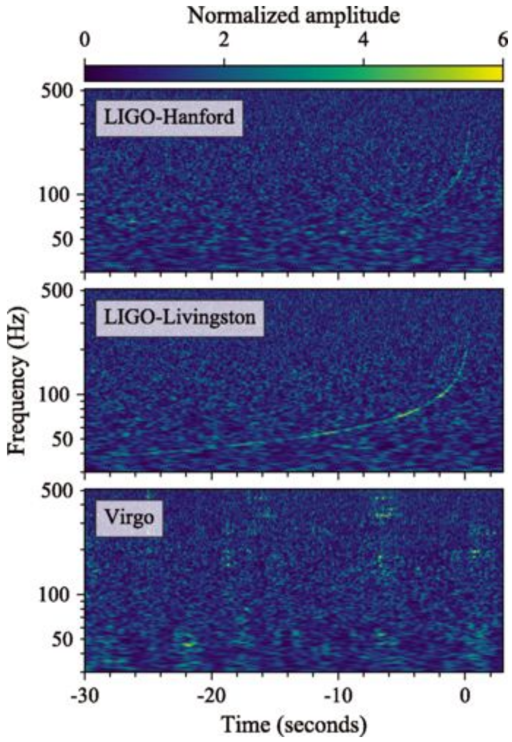
The importance of glitch analysis

Ligo Livingston



Glitch mitigation

GW 170817



Abbott et al. (2017)

https://arxiv.org/pdf/2002.11668.pdf

EGO - Virgo

Why artificial Intelligence for GW data?

- Our data: a lot of noise and few GW signals (soon will be many)
- Low SNR signals (overlapping signals)
- Many transient noise disturbances (glitches)
- Not stationary/not linear noise (strange noise coupling)
- Many monitoring auxiliary channels (“big” data)
- Computational and timing efficiency (Fast alert system)

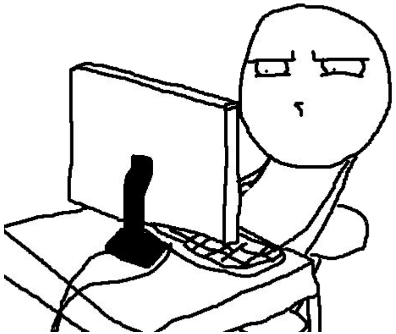
How Machine Learning can help

Data conditioning

- *Identify Non linear noise coupling*
- *Use Deep Learning to remove noise*
- *Extract useful features to clean data*

Signal Detection/Classification/PE

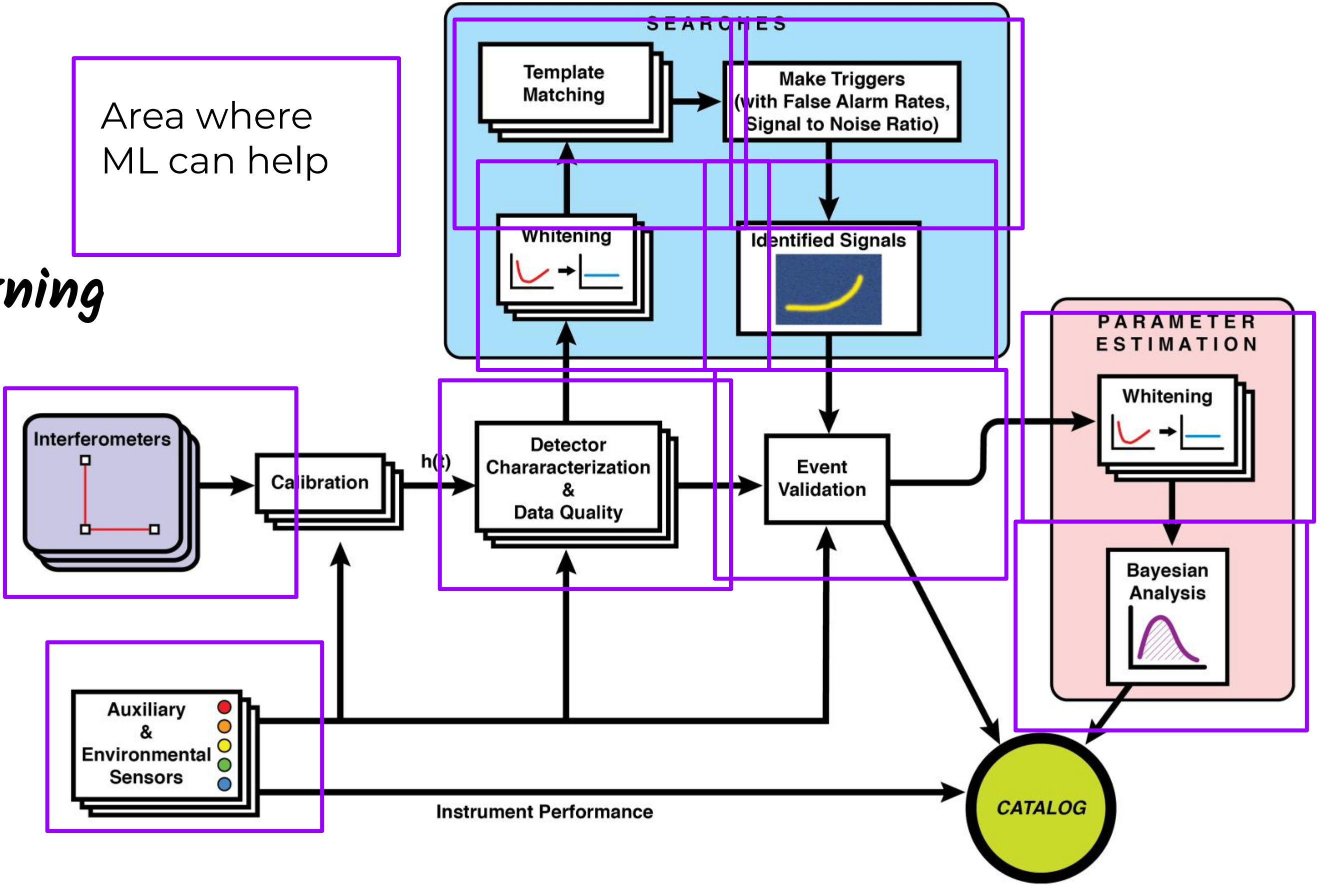
- *A lot of fake signals due to noise*
- *Fast alert system*
- *Manage parameter estimation*



The data analysis workflow and ML

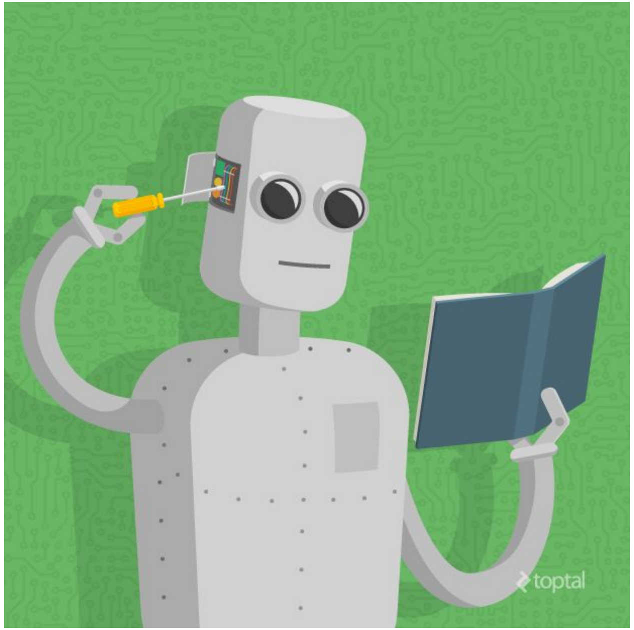
Area where ML can help

Machine Learning everywhere



Machine learning: a short overview

What is Machine Learning?



Arthur Samuel in 1959: "[Machine Learning is the] field of study that gives computers the ability to learn without being explicitly programmed."

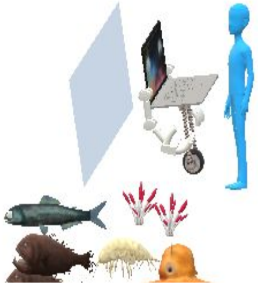
- Machine Learning is on all our day by day lives:
  - ChatGPT
  - Google search
  - Social media
  - Images recognition
  - Bank accounting
  - Shopping
  - Travels
  - ...and much more

Machine learning models

Unsupervised

No label for the data

Semi-supervised

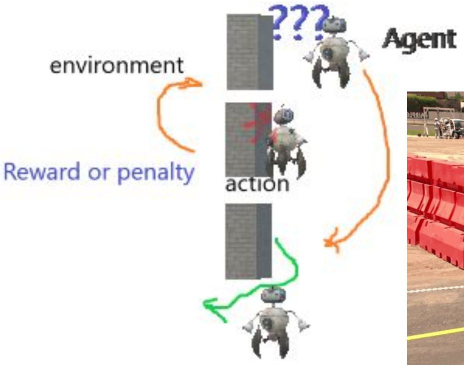


Few labeled data
A lot of not labeled data

Supervised

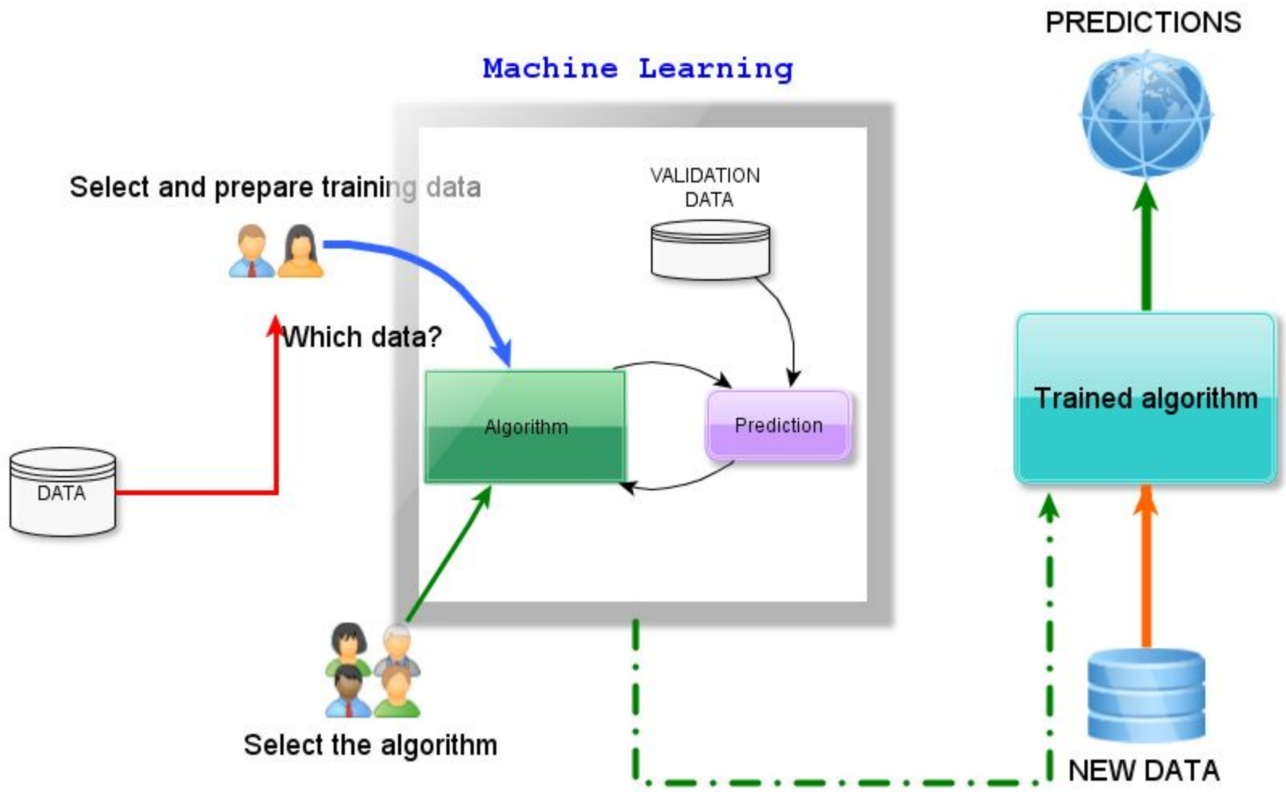
Labeled training data

Reinforcement learning



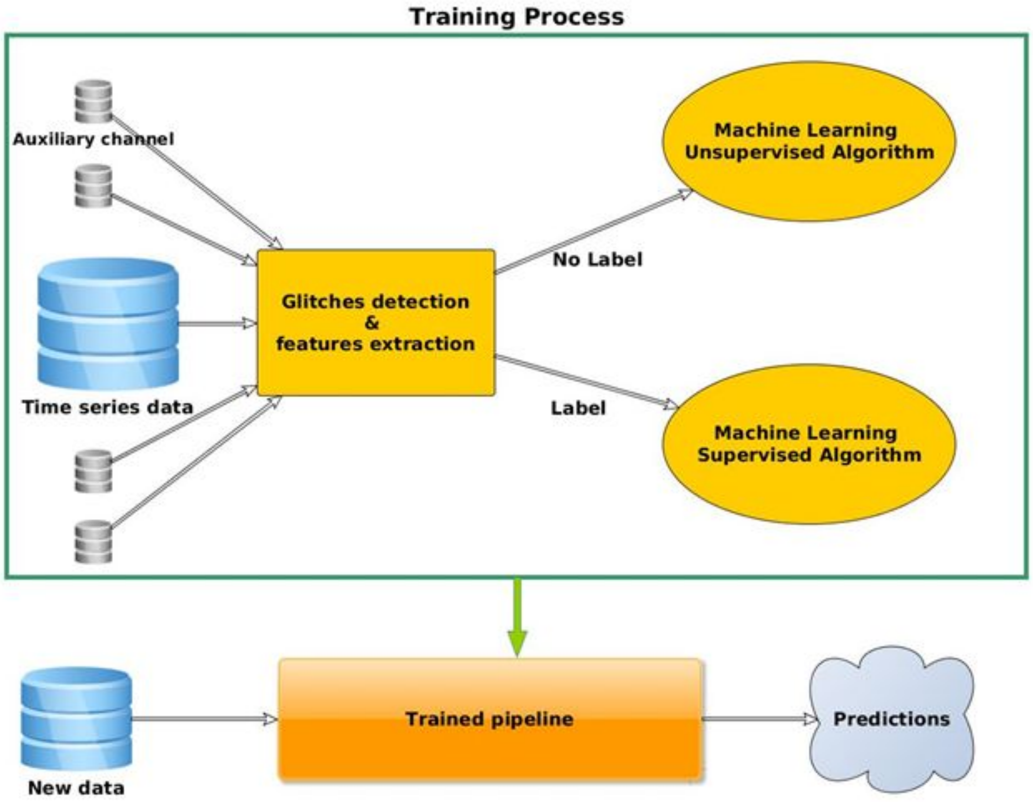
EGO - Virgo

Artificial Intelligence workflow



Training/Validation/Test data set

Classification tasks



Machine Learning in a nutshell

Data set:
x features, y target

Split the data in training, validation and test set

Algorithm and its parameter selections: what you need is to find a function which minimize an error cost function

Machine learning pipeline setup

How good is our model?

Binary Classification example

- Positive (P) : Observation is positive
- Negative (N) : Observation is not positive
- True Positive (TP) : Observation is positive, and is predicted to be positive.
- False Negative (FN) : Observation is positive, but is predicted negative.
- True Negative (TN) : Observation is negative, and is predicted to be negative.
- False Positive (FP) : Observation is negative, but is predicted positive.

Accuracy=# of correct prediction/ total # of prediction

$$\textbf{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

True Positive Rate

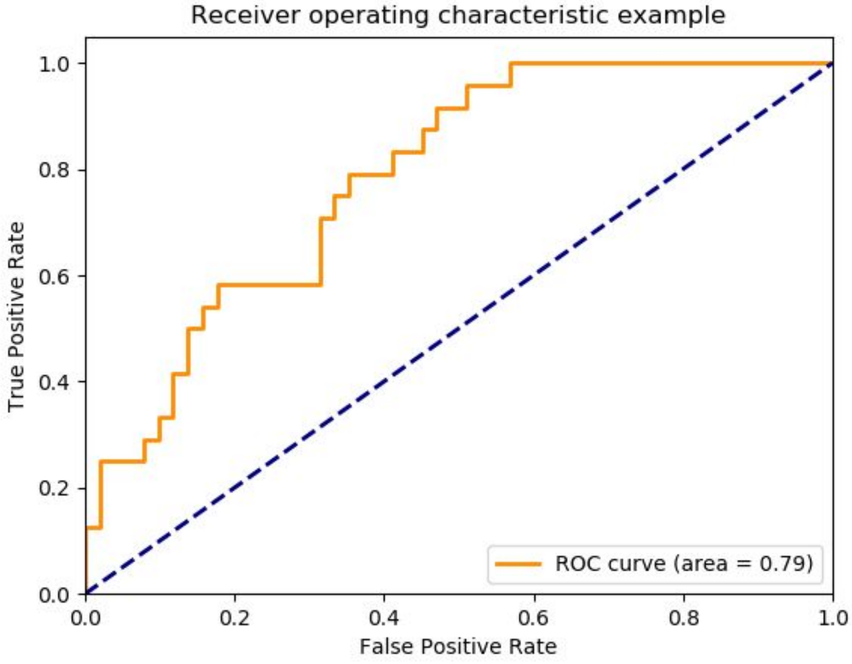
$$TPR = \frac{TP}{TP + FN}$$

False Positive Rate

$$FPR = \frac{FP}{FP + TN}$$

Receiver Operating Characteristic

A probability curve for binary classification



https://scikit-learn.org/stable/index.html

Confusion Matrix

Binary Classification

	Class A prediction	Class B prediction
Class A True value	TP	FN
Class B True value	FP	TN

- Table to show how our model performs
- It summarize the (mis)classification of our predictions
- Easy to interpret

Machine learning by example: Iris classification

Let' s try to classify Iris flower different types

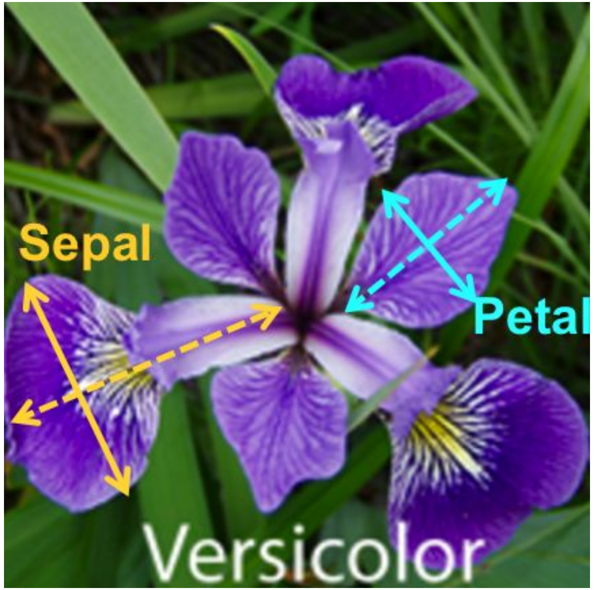
Step to do:

- Identify some features which characterize the flower
- Split the data set in training and test set
- Train classification algorithm on train set
- Verify result on test set

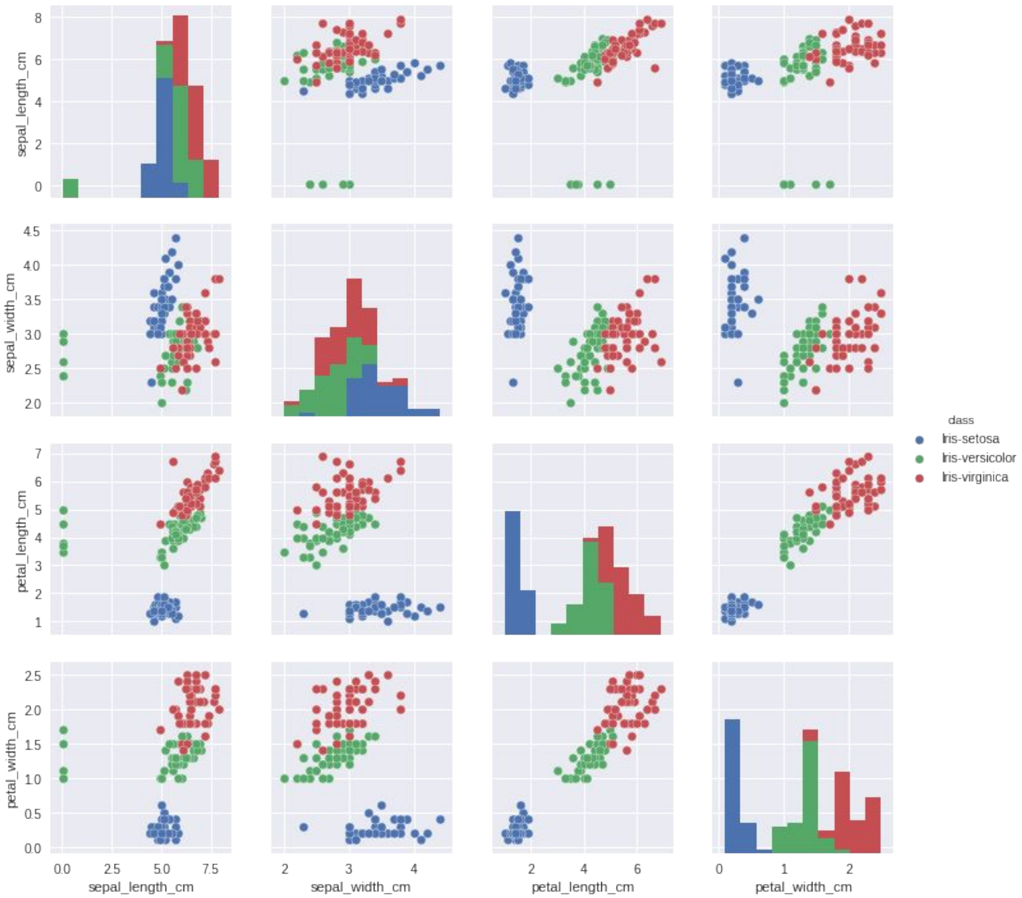
Machine learning by example: Iris features

One of the most difficult part in any Machine Learning pipeline is the extraction of correct features which can help us in classify the data

	sepal_length_cm	sepal_width_cm	petal_length_cm	petal_width_cm	class
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
5	5.4	3.9	1.7	0.4	Iris-setosa
6	4.6	3.4	1.4	0.3	Iris-setosa
7	5.0	3.4	1.5	NaN	Iris-setosa
8	4.4	2.9	1.4	NaN	Iris-setosa
9	4.9	3.1	1.5	NaN	Iris-setosa



Feature distribution

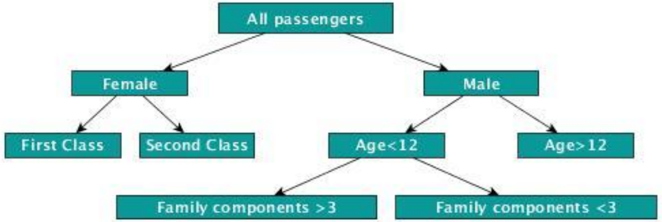


Example of classical ML algorithm

- **Decision Trees** (DTs) are a non-parametric supervised learning method used for classification and regression.

- The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features.

The sinking of the Titanic: who will survive?



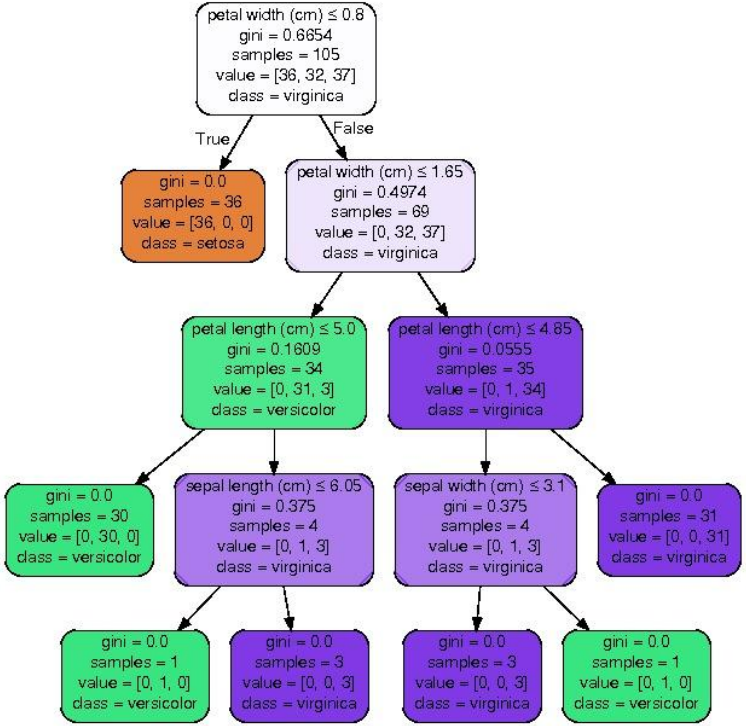
Iris classification with Decision Tree

In [9]:
```
from sklearn.model_selection import train_test_split
X=iris_data[["sepal_length_cm","sepal_width_cm","petal_length_cm","petal_width_cm"]]
Y=iris_data[["class"]]
X=X.fillna(0)
(train_inputs, test_inputs, train_classes, test_classes) = train_test_split(X, Y, train_size=0.7, random_state=1)
```

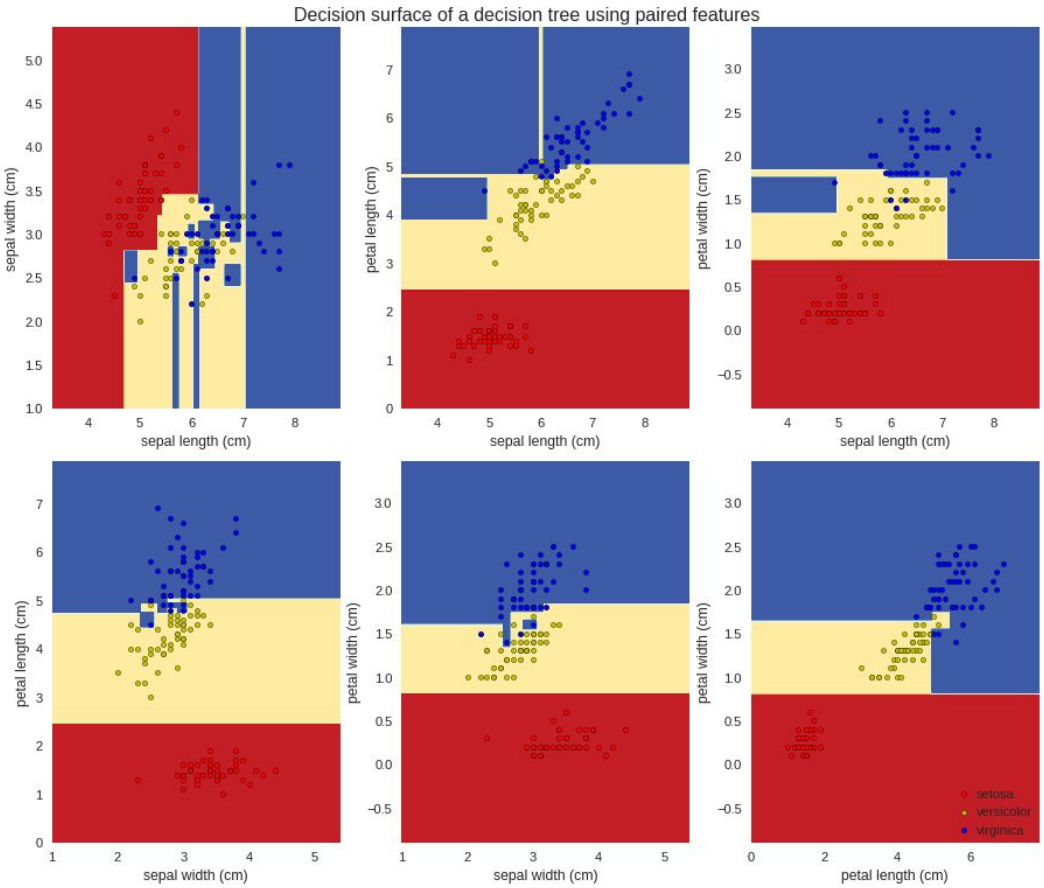
In [10]:
```
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()
model.fit(train_inputs, train_classes)
model.score(test_inputs, test_classes)
```

Out[10]: 0.9555555555555556

We were able to classify the flowers with **accuracy** of 95%

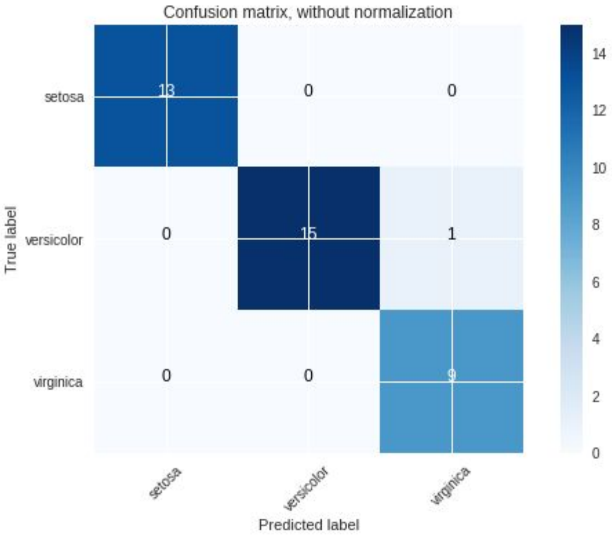


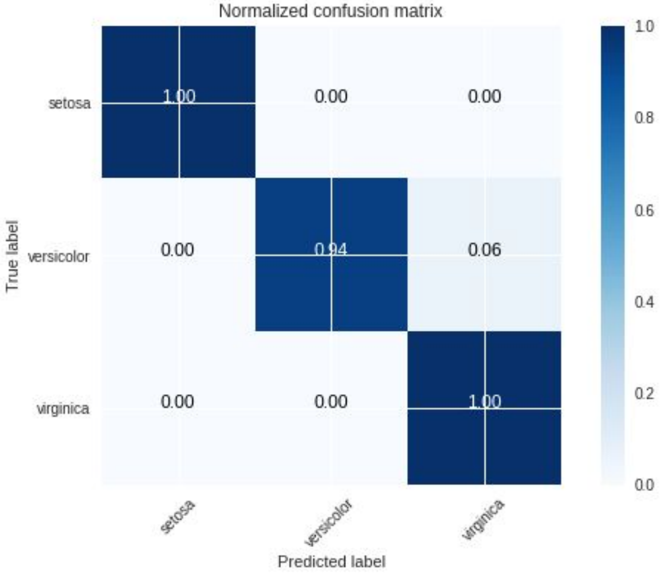
Iris Classification with Decision Tree



Confusion Matrix

It is useful to evaluate the quality of the output of a classifier on the iris data set.
The diagonal elements represent the number of points for which the predicted label is equal to the true label, while off-diagonal elements are those that are mislabeled by the classifier.

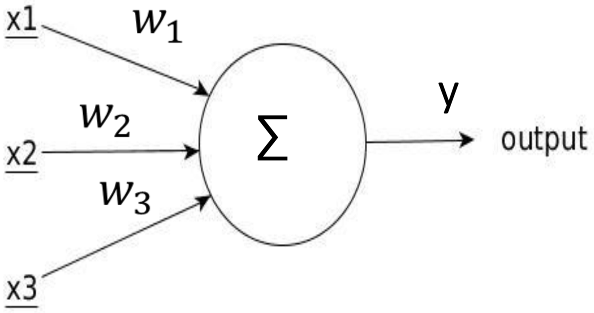




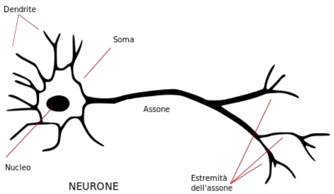
Neural Network

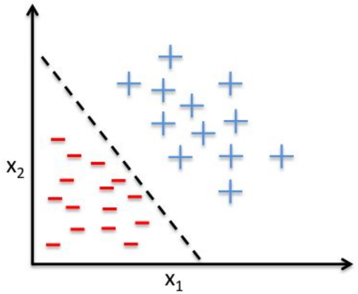
Perceptron

The algorithm find the weights w in order
To find the best y which is similar to a
Target function Y



$$y(\boldsymbol{x}) = \sum_{n=0}^{N}(w_n x_n)$$

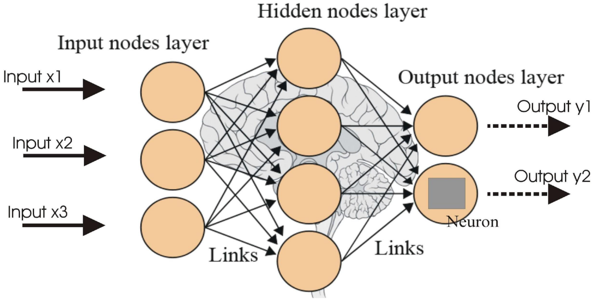


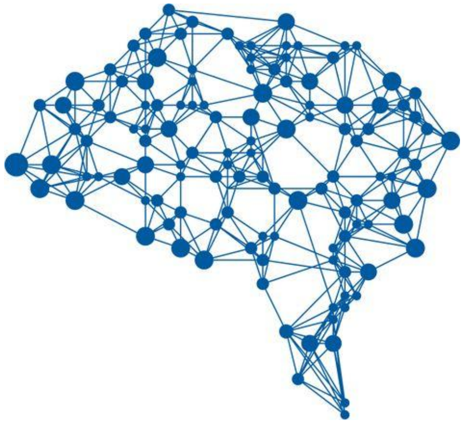


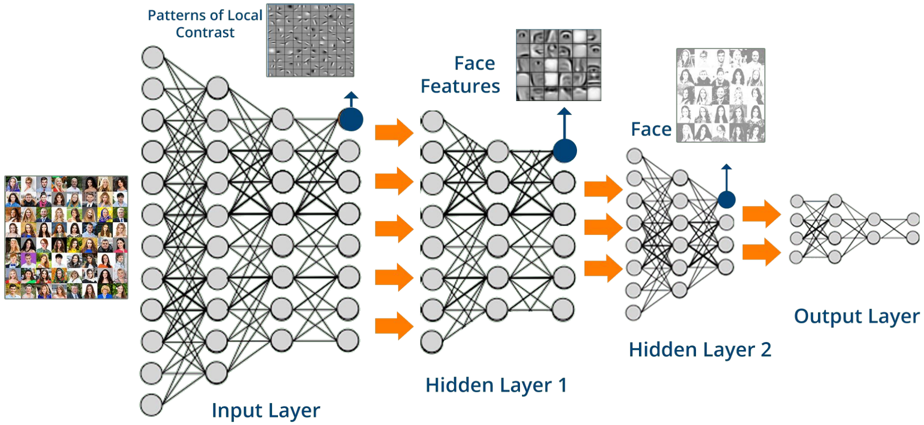
Example of a linear decision boundary for binary classification.

Frank Rosenblatt (1958)

Deep learning







https://www.edureka.co/blog/what-is-deep-learning

Cat versus dog

- We need to preprocess the images
- Define the architecture of our NN
- Verify the prediction accuracy

Dataset available at https://www.kaggle.com

We want to build a deep learning classifier able to Distinguish an image of dog from one of cat

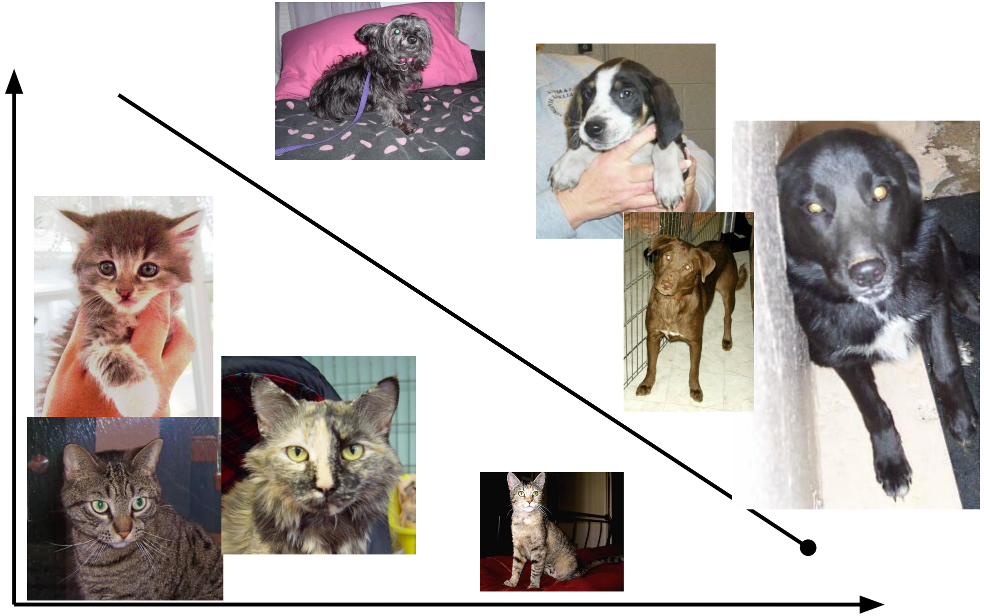
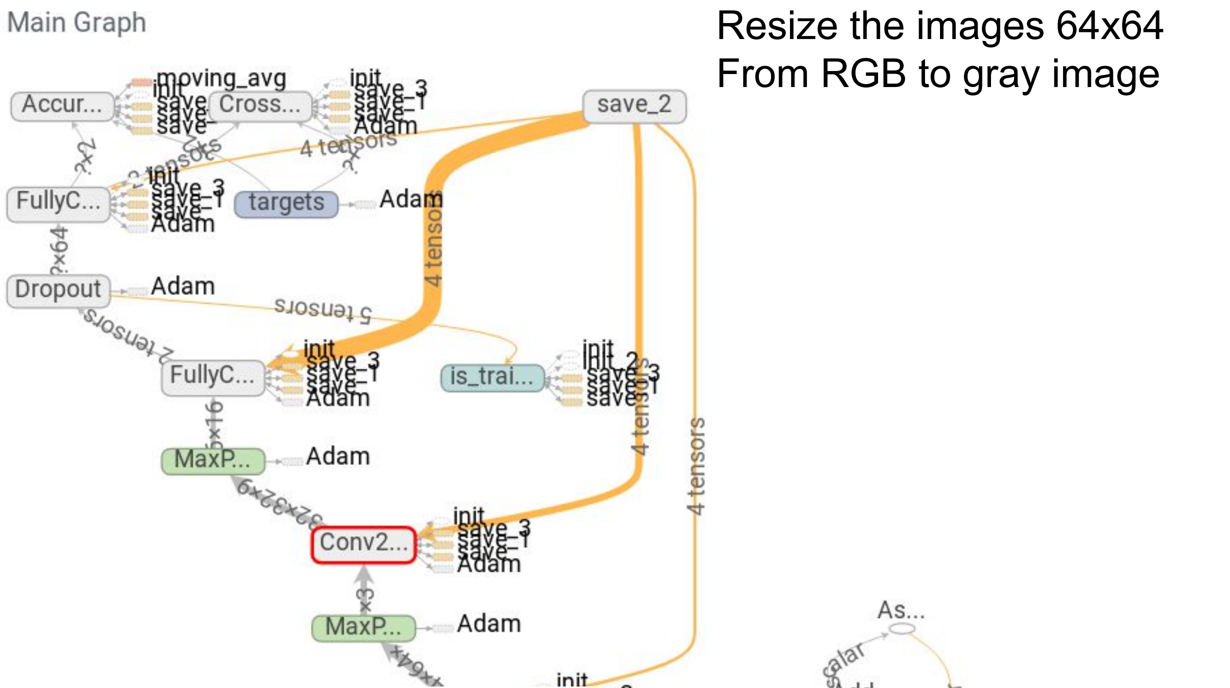
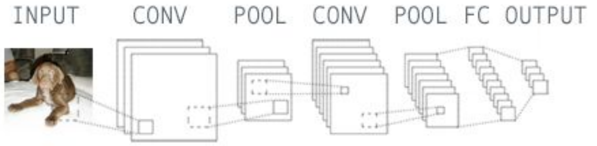
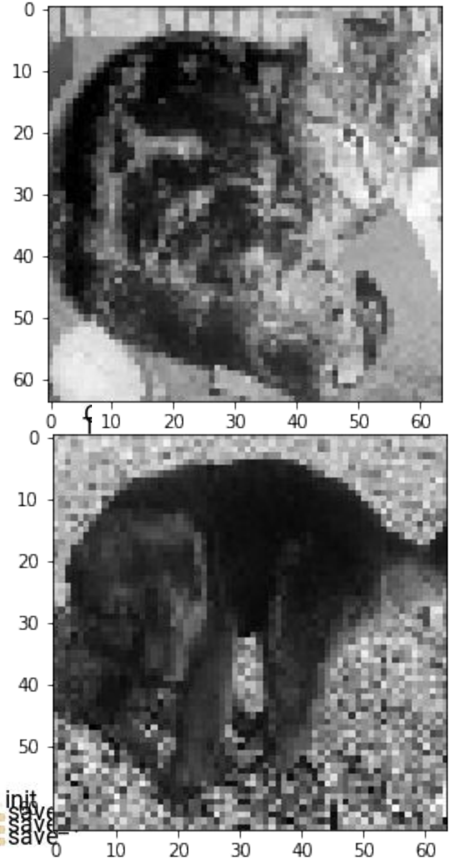


Image preparation and NN model

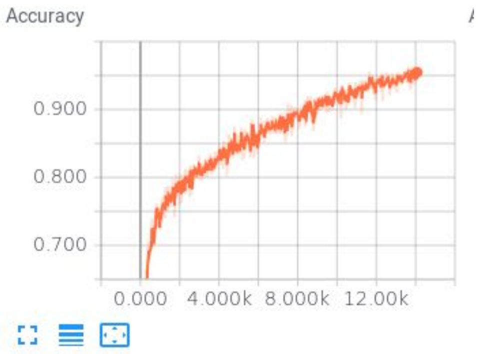


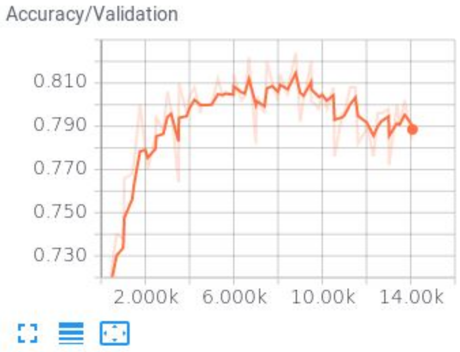


Resize the images 64x64
From RGB to gray image

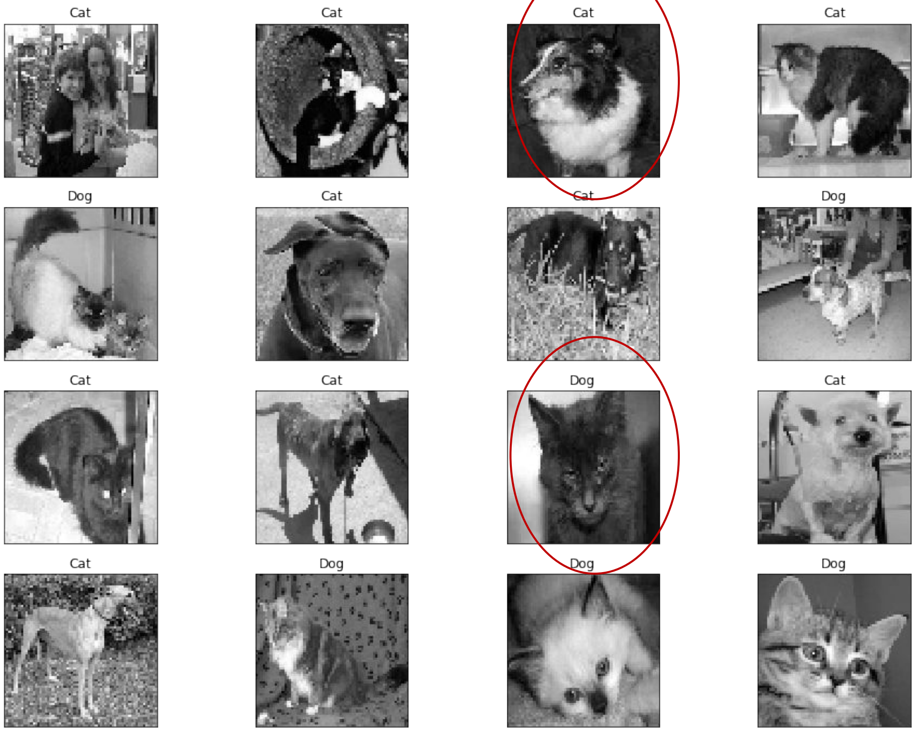


Results

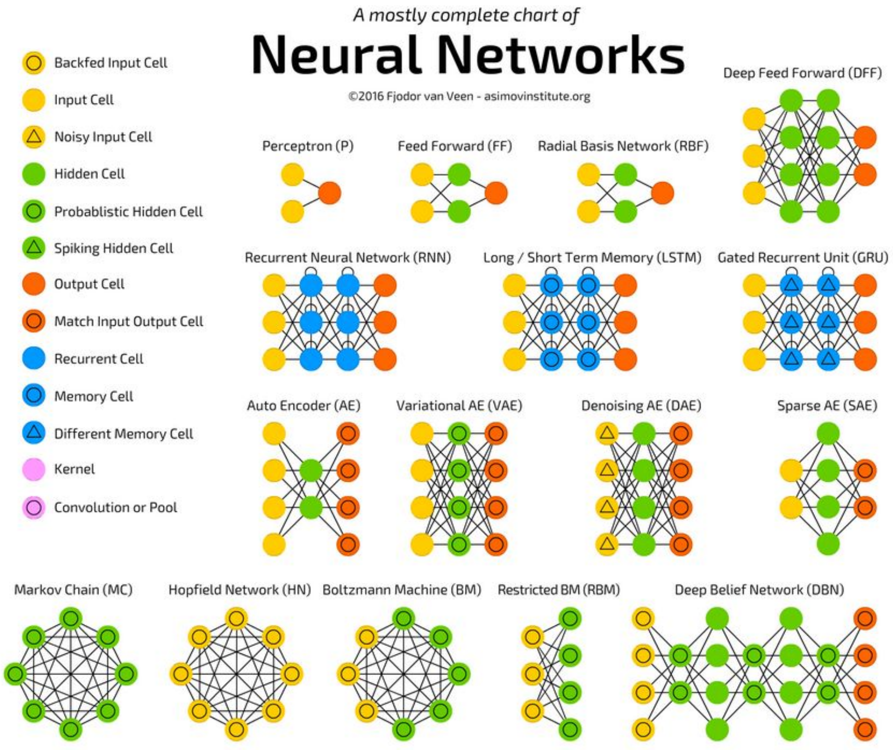




What our net will predict on a test set?



Neural network zoo

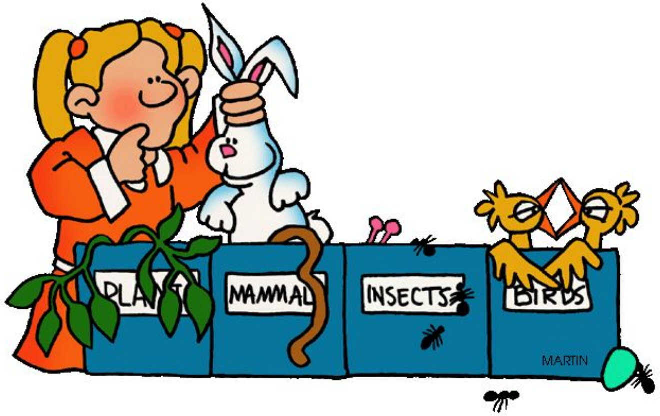


http://www.asimovinstitute.org/neural-network-zoo

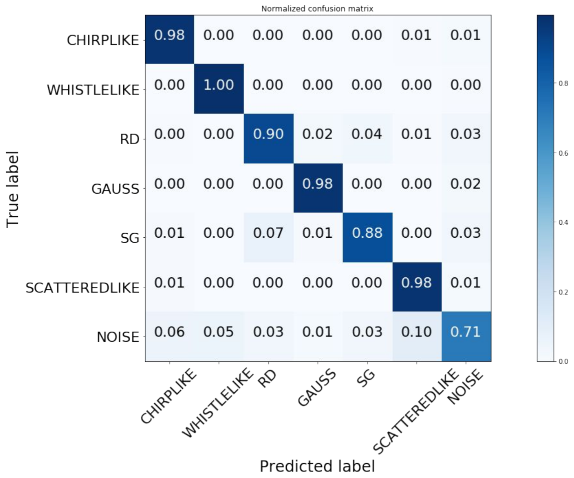
Examples of Machine learning applications to GW

Why Signal Classification?

- If we are able to classify the noise events, we can clean the data in a fast and clear way
- We can help commissioners
- We can identify glitch families

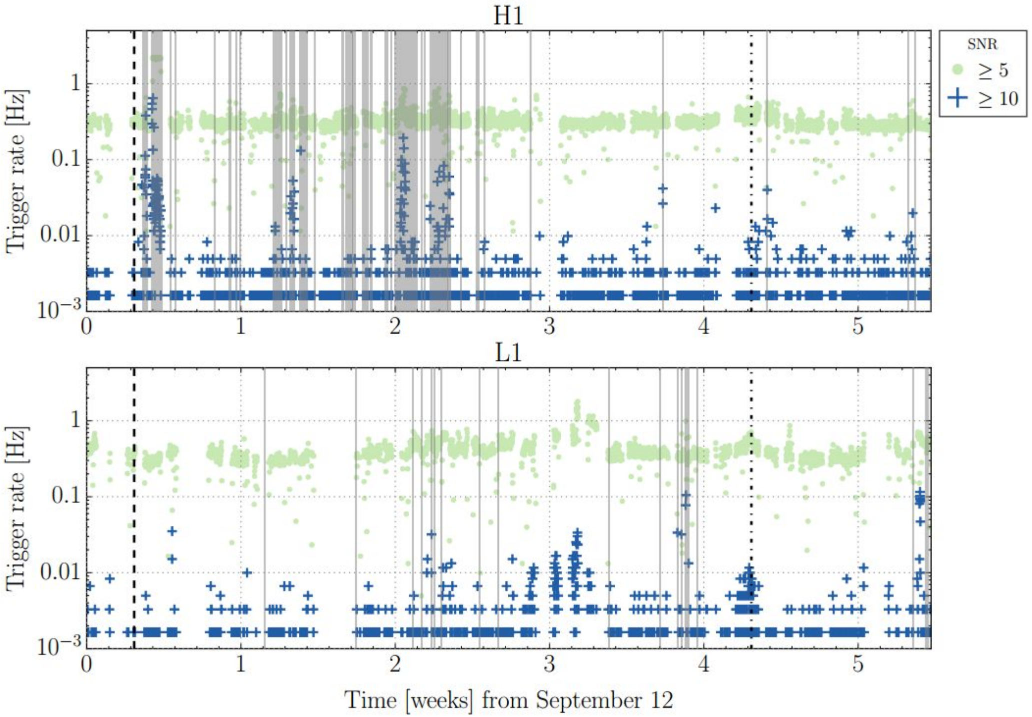


Glitch classification



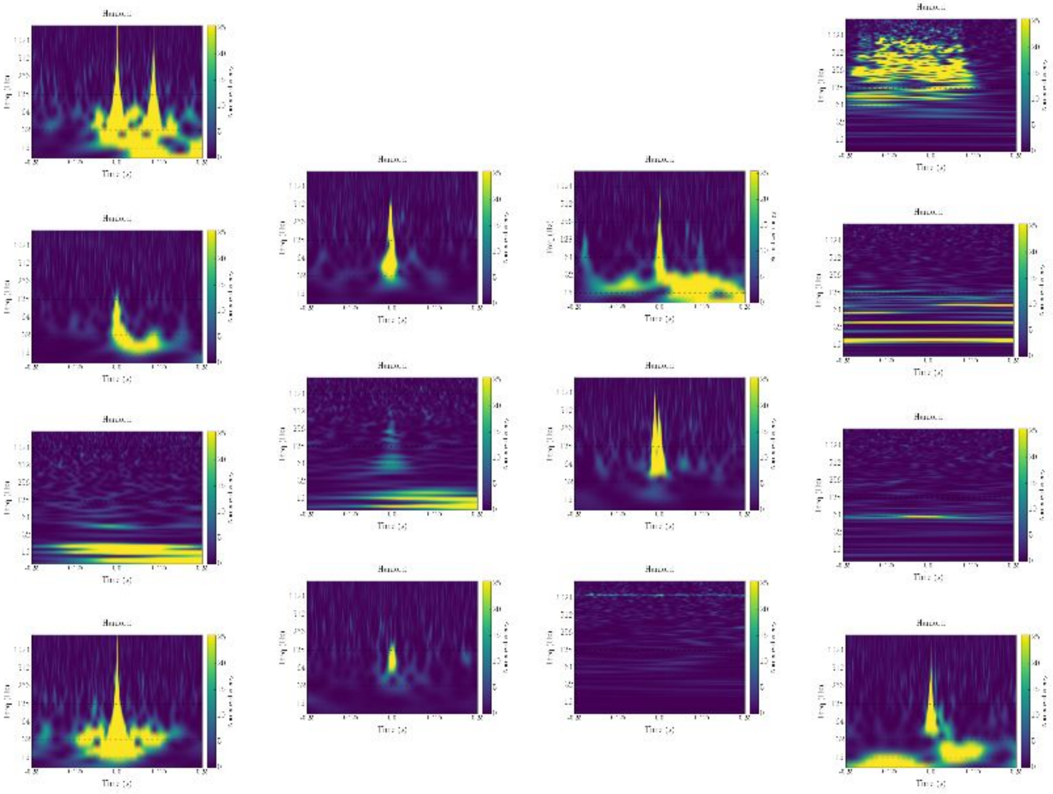
- *Unsupervised classification*
- *Time-series (Wavelet) based classification*
- *Image based classification with Deep Learning*
- *Application on Simulated data*
- *Application on Real Data*

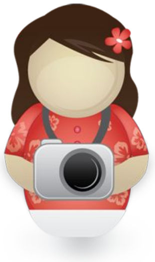
How many trash events?



LIGO L1 and H1 triggers rates

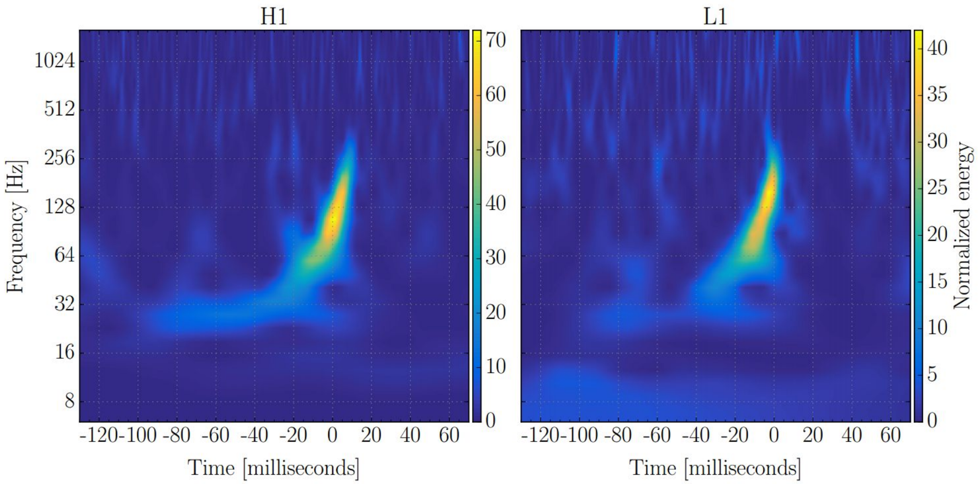
The trash is our glitch zoo





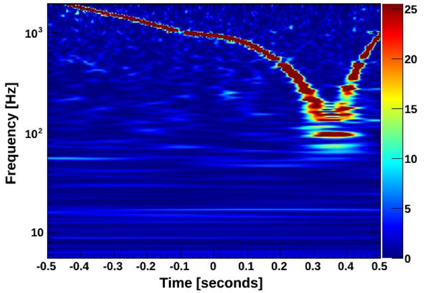
Time Frequency images

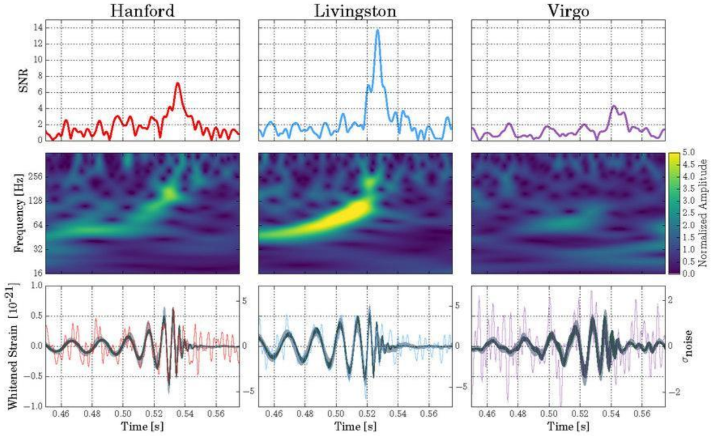
Gravitational wave signals



Signal features

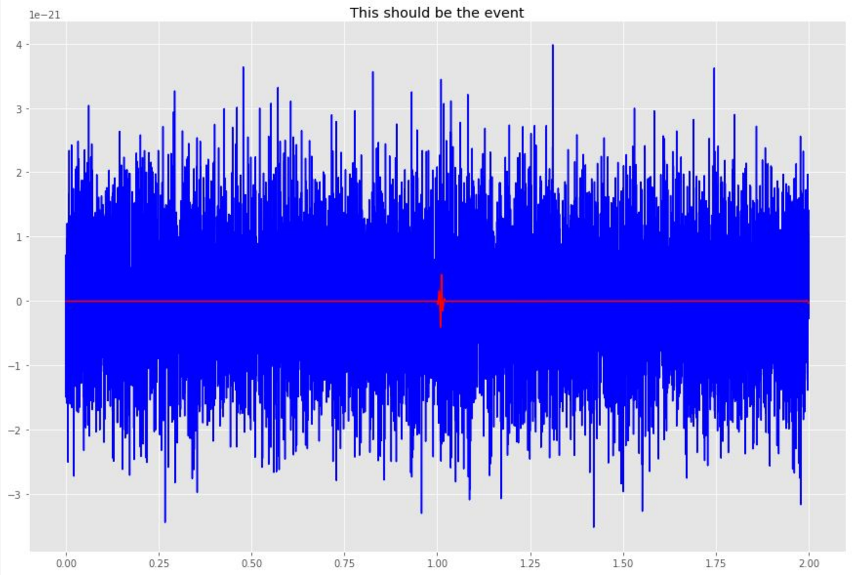
- We need to extract the features which can characterize our signals
- The detection or detector characterization save events with some meta features: SNR, Frequency, duration, etc..
- We can use also different features to identify a signals
- We can use T-F plots too!





Wavelet based classification

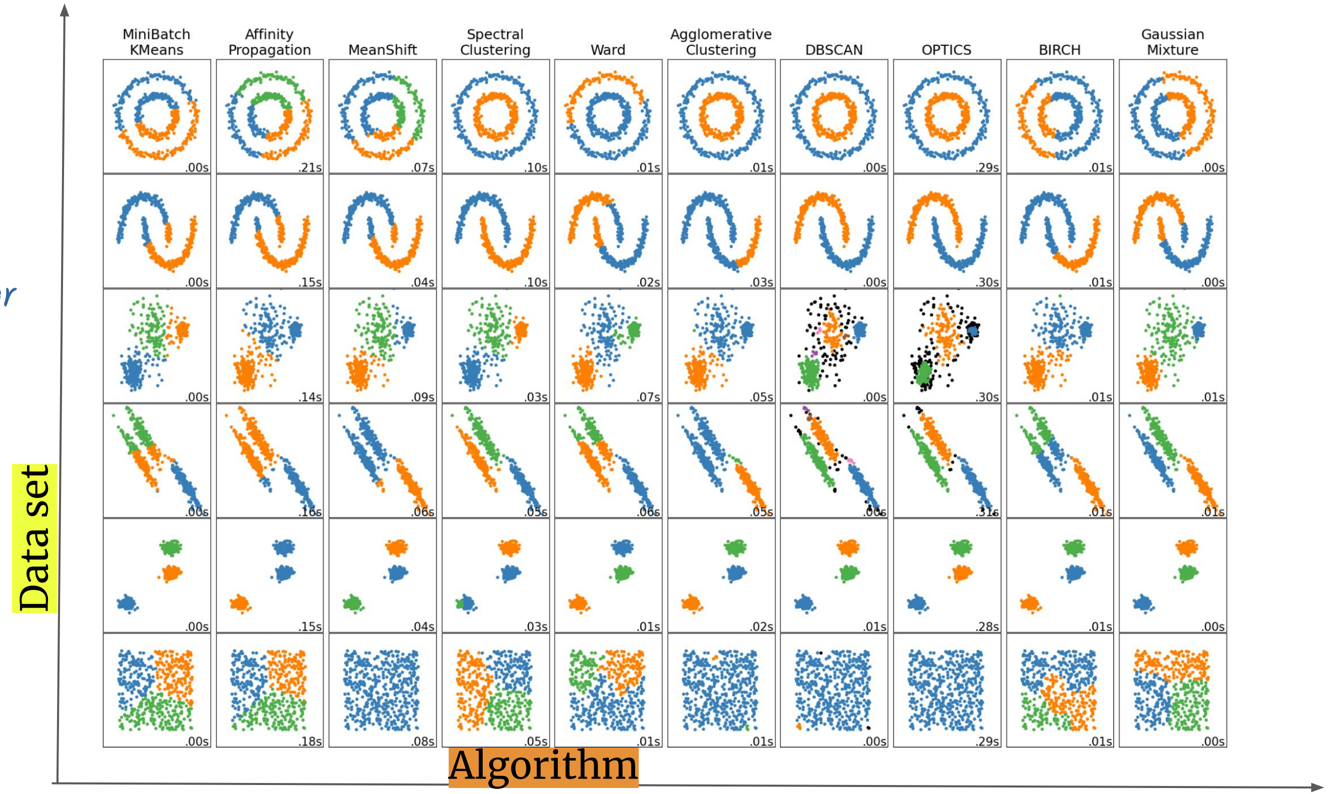
- Time series as input data



Unsupervised algorithm

The main goal is to find common pattern in the data based on criteria which make the elements of the data similar

The cluster are formed on a given metric related to the algorithm itself



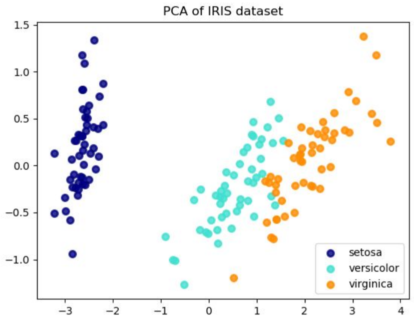
https://scikit-learn.org

Features selection and dimensionality reduction

- Cleaning features (too many missing values)
- Remove features that are correlated
- Keep the only features with high variance
- Select a model and keep only features relevant to that model

Project features in a different space, where few component keep all the information

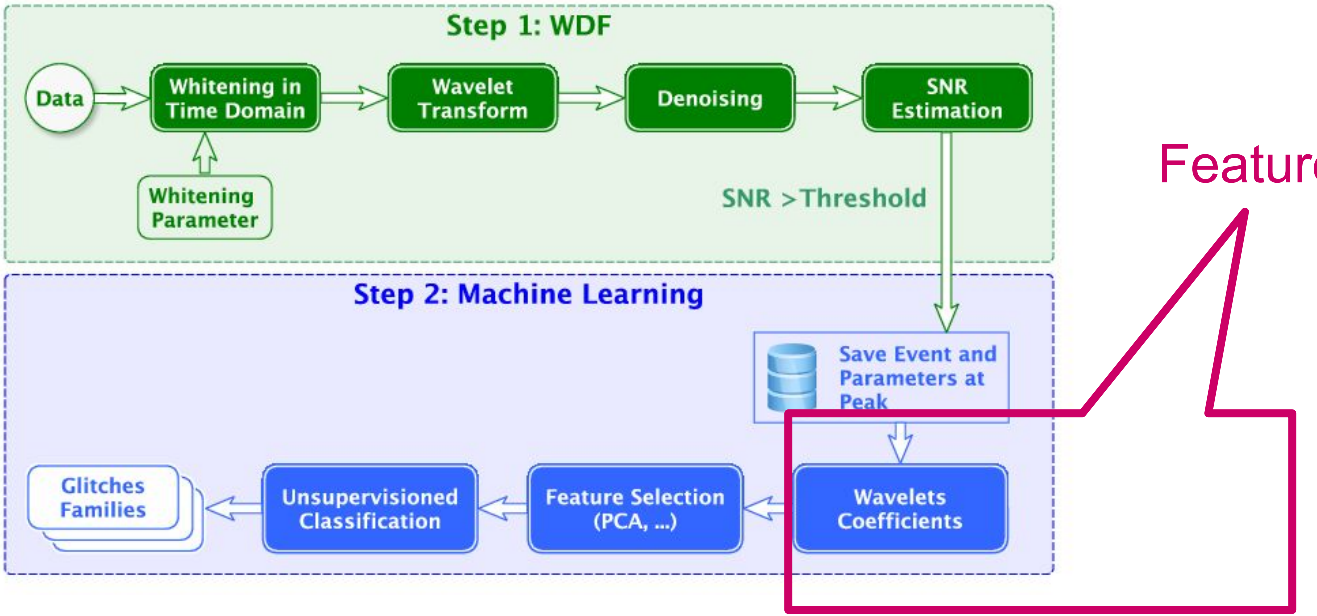
- Most used is Principal Component Analysis (PCA)



https://scikit-learn.org

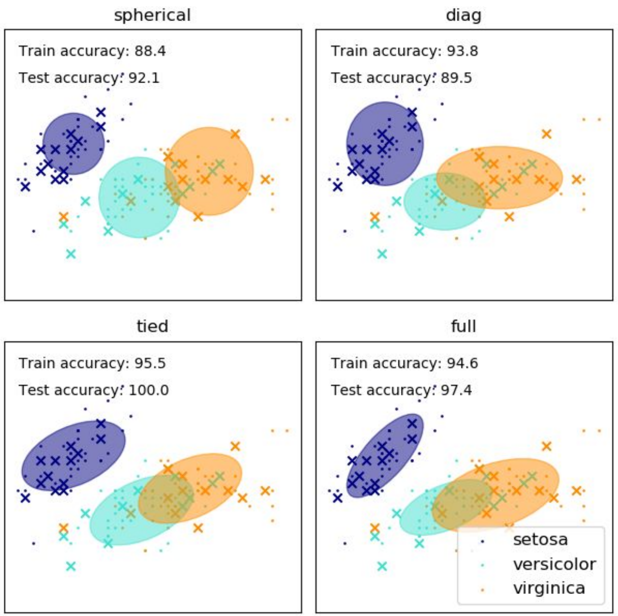
Unsupervised application

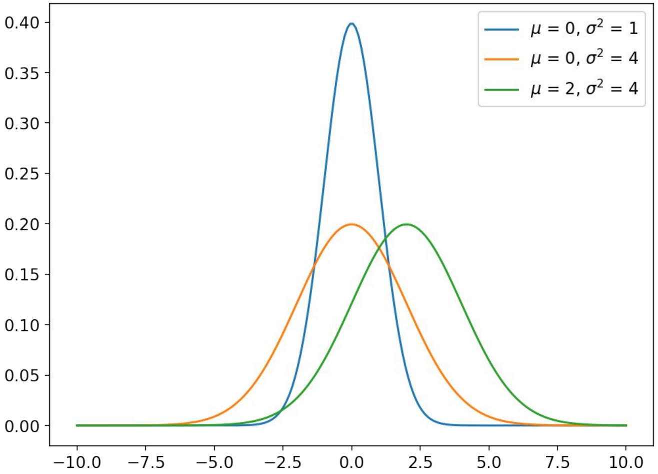
Wavelet Detection Filter and ML



Gaussian Mixture Model (GMM)

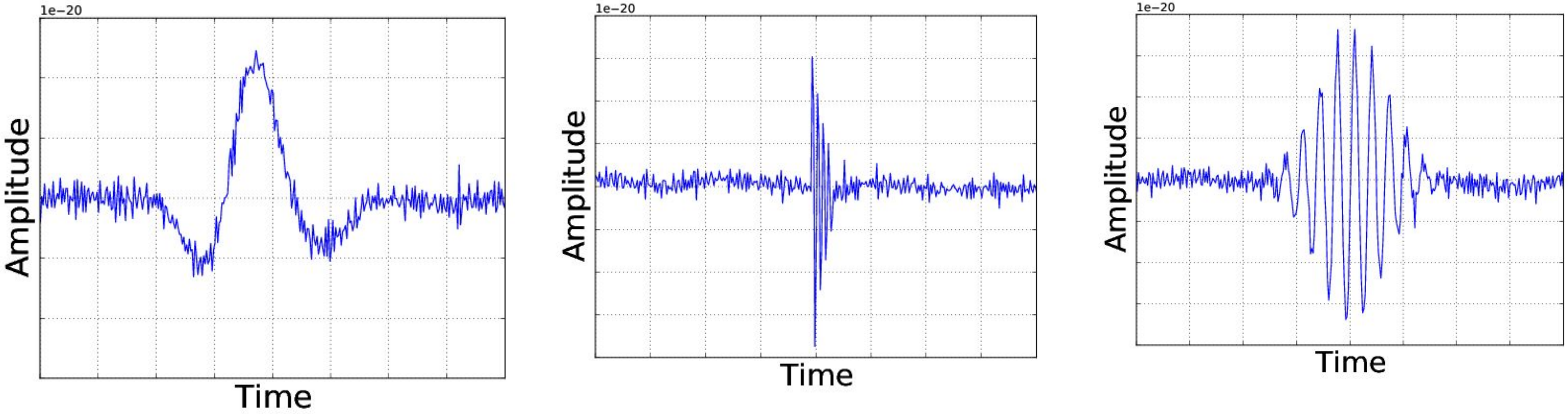
"A Gaussian mixture model is a probabilistic model that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters."



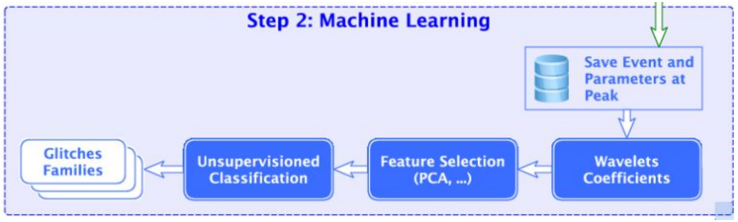


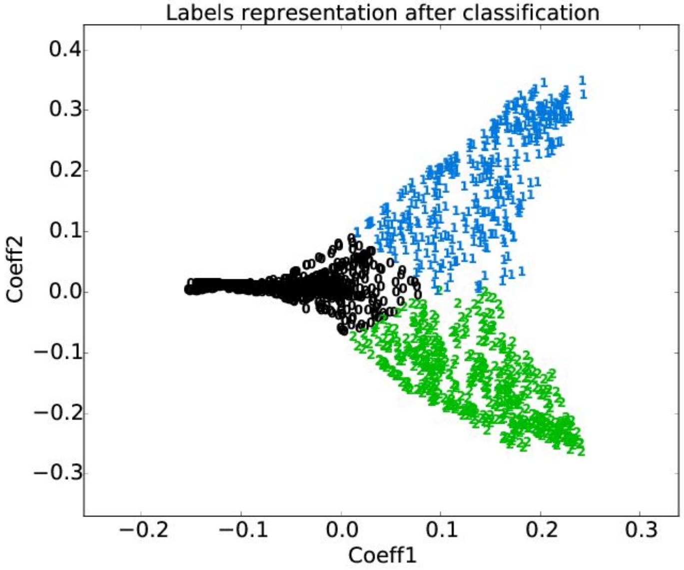
Simulated Signal

aLIGO-like simulated noise with transient signals injected

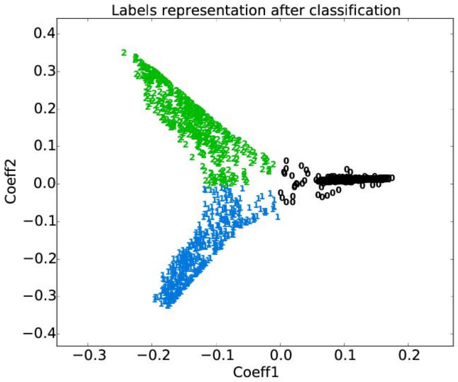


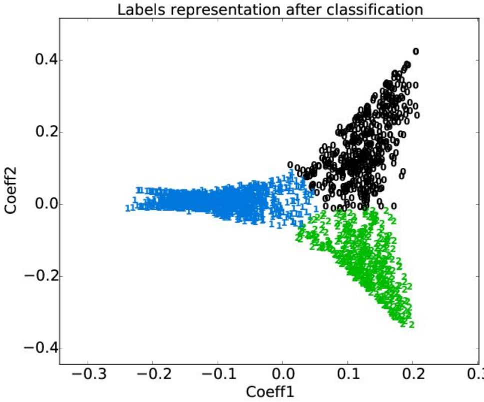
GMM clustering





Reduced features projections after labeling





Comparison: WDF-GMM, PCA and PC LIB

	SG	G
PCAT Type 1	99%	0%
PCAT Type 2	1%	100%
LIB Type 1	99.9%	5%
LIB Type 2	0.1%	95%
WDF Type 0	99.5%	2.4%
WDF Type 1	0.3%	46.1%
WDF Type 2	0.2%	51.5%

	SG	RD
PCAT Type 1	1.1%	97.4%
PCAT Type 2	98.9%	2.5%
LIB Type 1	97.8%	4.8%
LIB Type 2	2.2%	95.2%
WDF-ML Type 0	8.7%	100%
WDF-ML Type 1	48.0%	0%
WDF-ML Type 2	43.3%	0%

	SG	G	RD
PCAT Type 1	15.5%	0%	13.6%
PCAT Type 2	36.8%	0%	41.4%
PCAT Type 3	14.2%	0%	13.0%
PCAT Type 4	9.1%	0%	13.0%
PCAT Type 5	0.8%	0%	0.3%
PCAT Type 6	21.8%	0%	17.2%
PCAT Type 7	1.8%	100%	1.5%
LIB Type 1	39.5%	4.9%	23.8%
LIB Type 2	17.3%	88.3%	23.2%
LIB Type 3	43.3%	6.8%	53.0%
WDF-ML Type 0	89.5%	9.6%	86.9%
WDF-ML Type 1	5.9%	49.7%	7.0%
WDF-ML Type 2	4.6%	40.7%	6.1%

- PCAT: PCA and ML prediction
- PC-LIB: PCA and Bayesian model prediction

Classification methods for noise transients in advanced gravitational-wave detectors

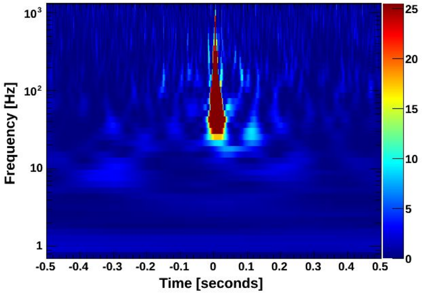
Class. Quant. Grav., 32 (21), pp. 215012, 2015

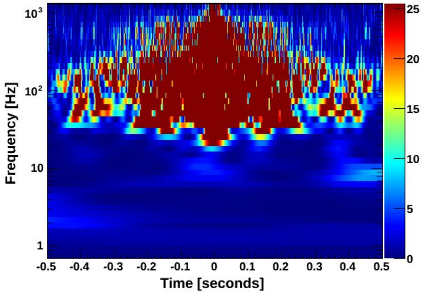
Application on real data

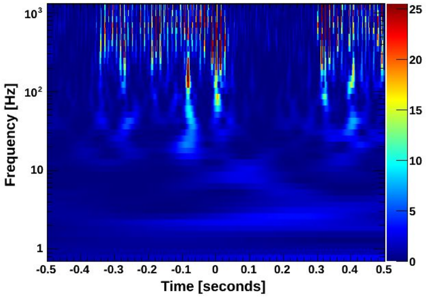
ER7 LIGO engineering run

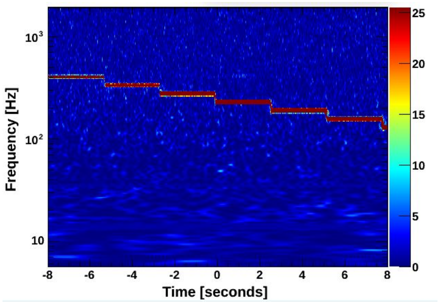
- Data from the 7th aLIGO engineering run (ER7), which began on the 3rd of June 2015 and finished on the 14th of June 2015. The average binary neutron star inspiral range for both Hanford and Livingston detectors in data analysis mode during ER7 was 50-60 Mpc.
- The total length of Livingston data analysed is about 87 hours.
- The total length of Hanford data analysed is about 141 hours.

LIGO Hanford glitches

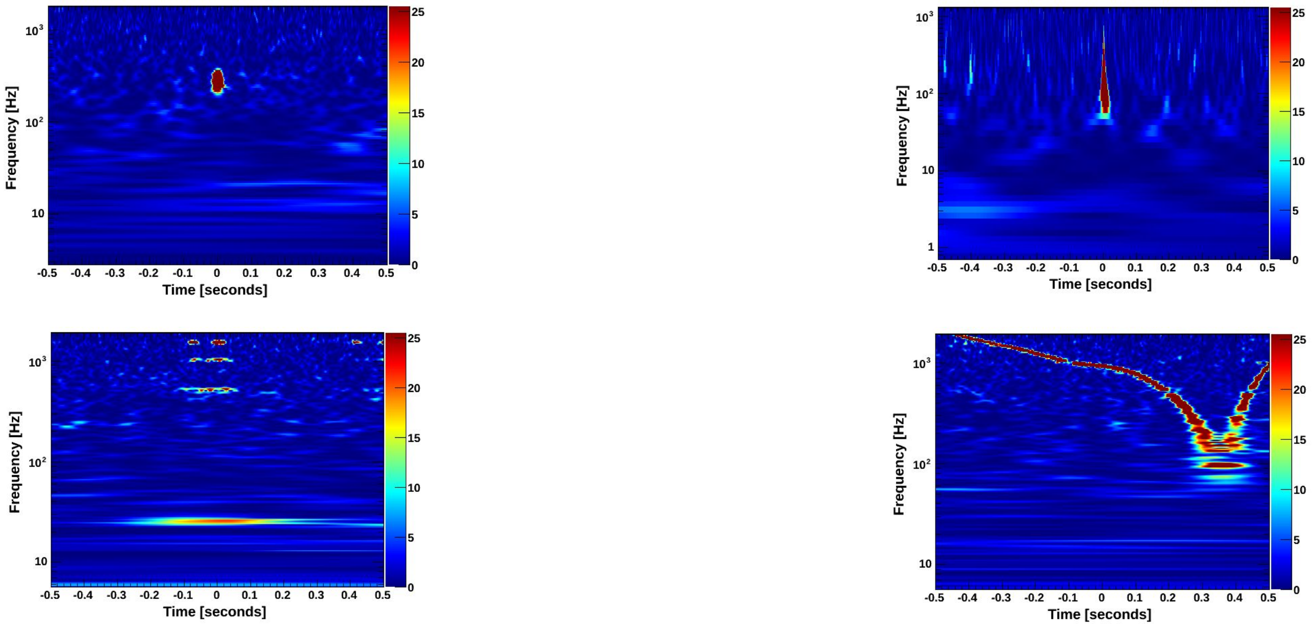








LIGO Livingston Glitches



Application on real data

LIGO Hanford		
Pipeline	Correct classification	Missed triggers
PCAT	99%	120
PC-LIB	95%	6
WDF-ML	92%	0

LIGO Livingston		
Pipeline	Correct classification	Missed triggers
PCAT	95%	90
PC-LIB	98%	33
WDF-ML	97%	0

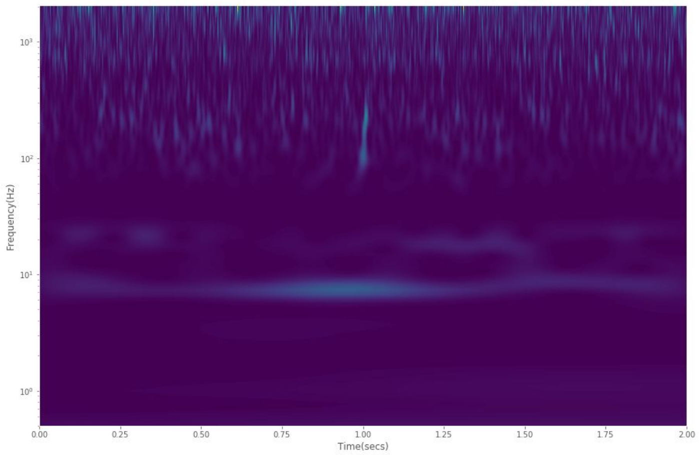
We conclude that our methods have a high efficiency in real non-stationary and non-Gaussian detector noise

Classification methods for noise transients in advanced gravitational-wave detectors II: performance tests on Advanced LIGO data Class. and Quant. Grav, 34 (3) 2017

How did we know correct classification??
JADE-Classifier

Supervised classification: Different approaches

- Images
- Time series



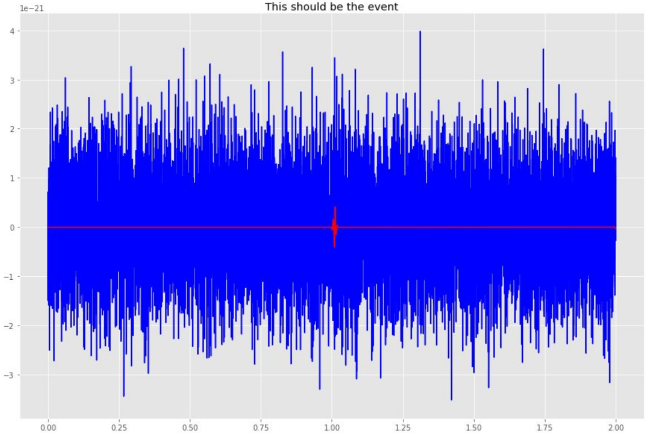
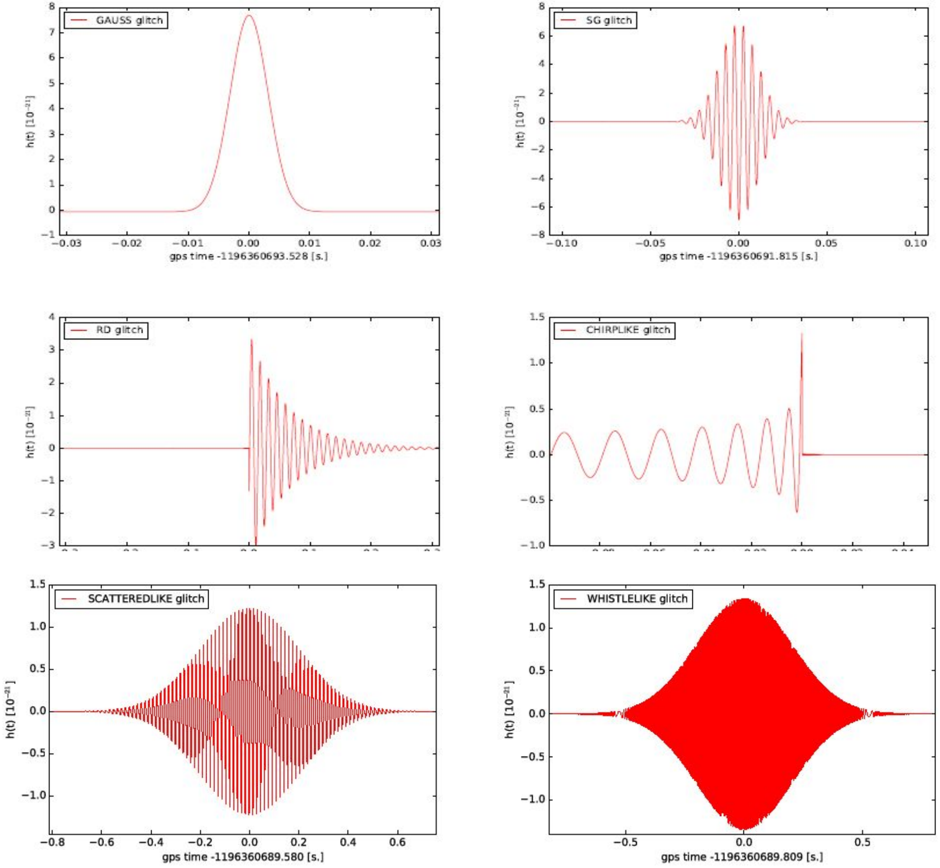


Image-based deep learning for classification of noise transients in gravitational wave detectors, Massimiliano Razzano**, Elena Cuoco**, Class.Quant.Grav. 35 (2018) no.9, 095016

Wavelet-based Classification of Transient Signals for Gravitational Wave Detectors**, Elena Cuoco**, Massimiliano Razzano and Andrei Utina, #1570436751 accepted reviewed paper at EUSIPCO2018

Data simulation: signal families and noise

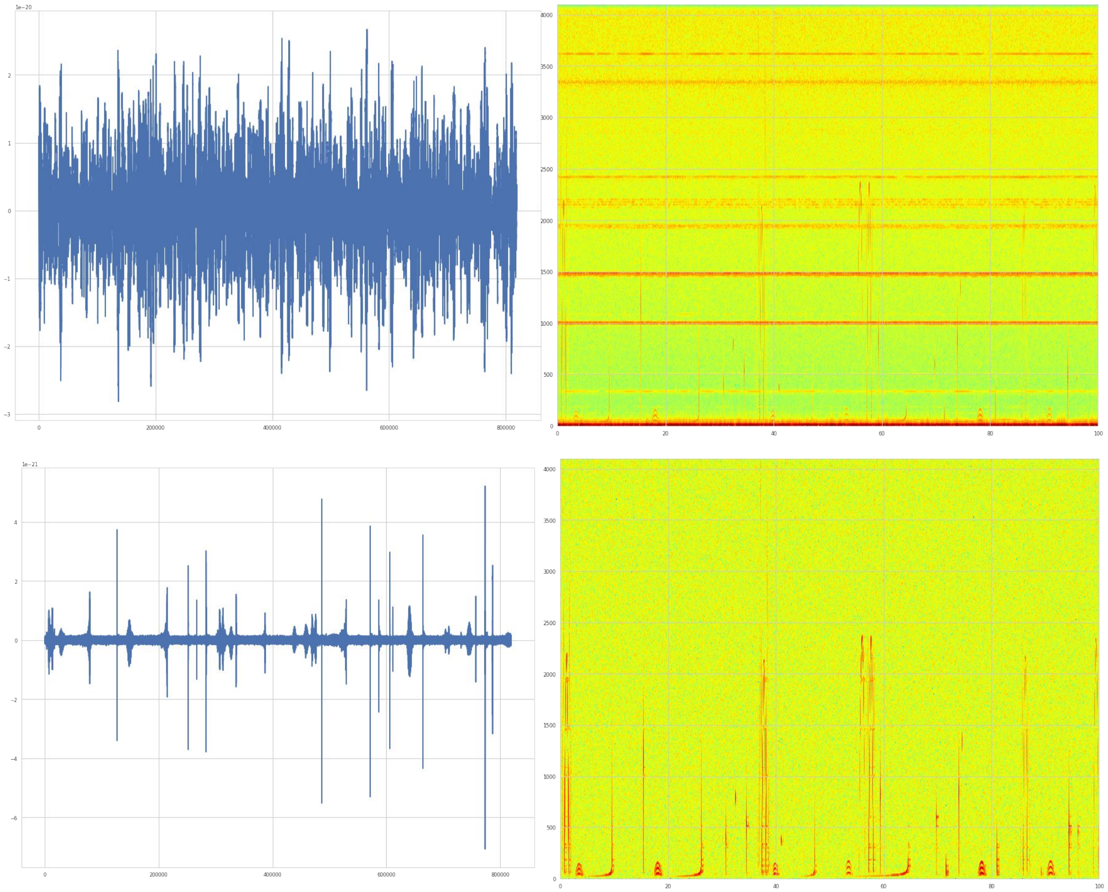


Waveform
Gaussian
Sine-Gaussian
Ring-Down
Chirp-like
Scattered-like
Whistle-like
NOISE (random)

To show the glitch time-series here we don't show the noise contribution

Razzano M., Cuoco E. CQG-104381.R3

Signals in whitened data

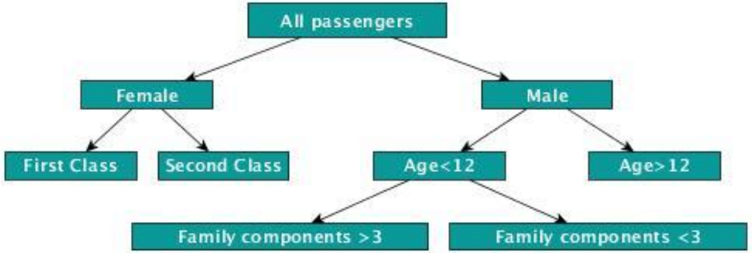


Not Whitened

Whitened

Supervised Classification:
eXtreme Gradient Boosting

- https://github.com/dmlc/xgboost
- Tianqi Chen and Carlos Guestrin. XGBoost: A Scalable Tree Boosting System. In 22nd SIGKDD Conference on Knowledge Discovery and Data Mining, 2016
- XGBoost originates from research project at University of Washington, see also the Project Page at UW.



Tree Ensemble

$$y_n = \sum_{k=1}^{K} f_k\left(x_n\right)$$

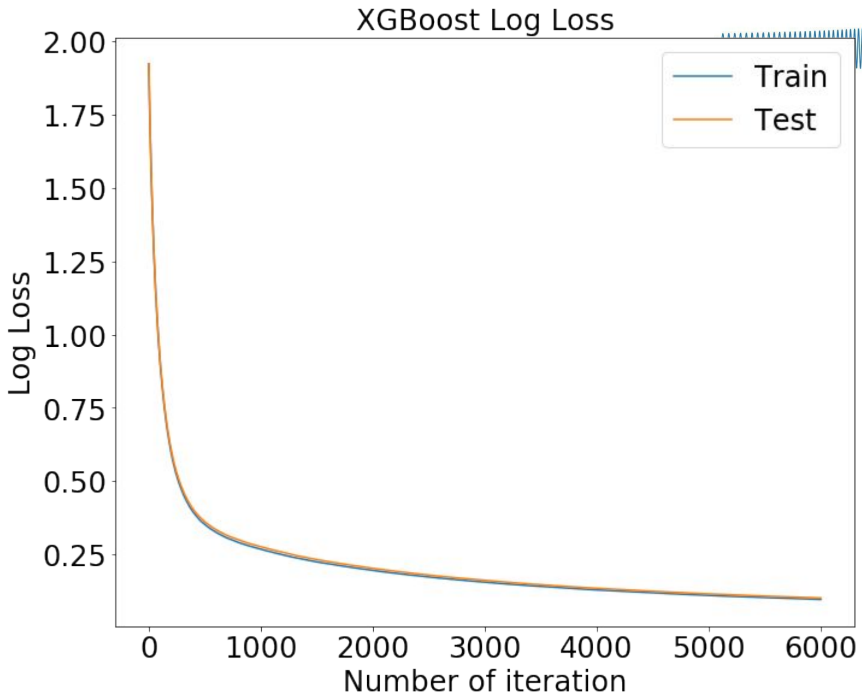
dmlc XGBoost

Xgboost performance

$$L = -\frac{1}{N}\sum_{1}^{N}((y_i \log(p_i) + (1 - y_i)(log(1 - p_i)) + \Omega$$

Cost function

Train/validation/test set: 70/15/15



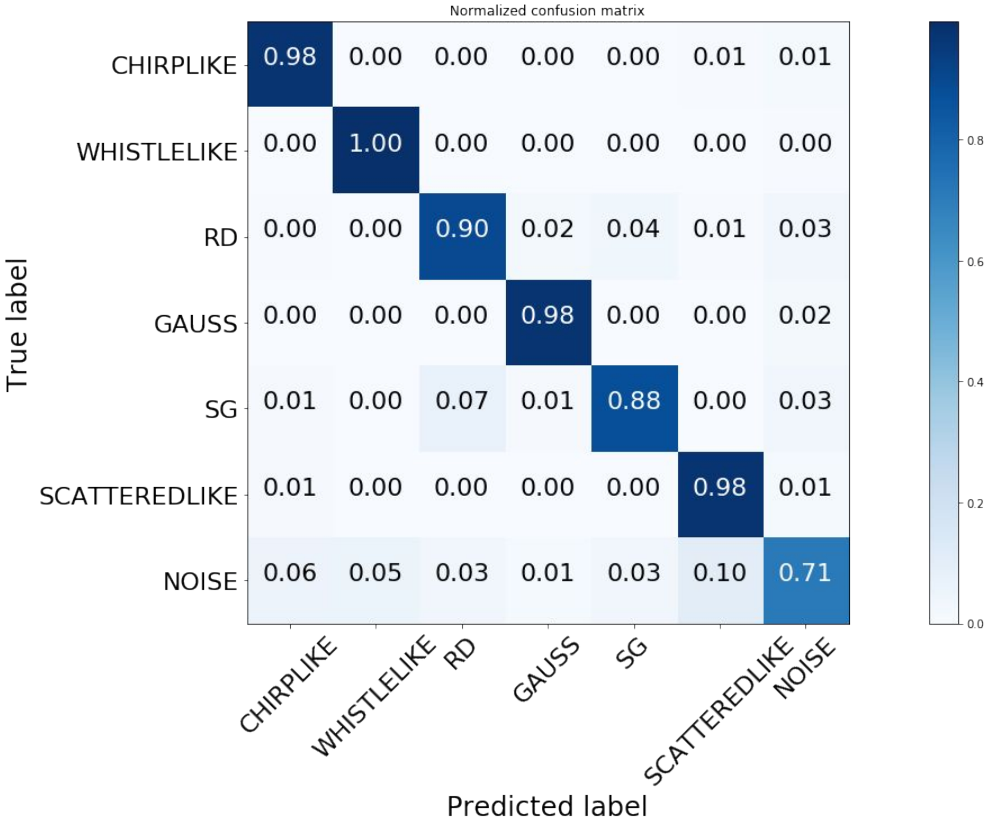
Data set Features: Wavelet coefficients

task	Classes	Learning-rate	Max_depth	estimators
Binary	2	0.01	7	5000
Multi-label	7	0.01	10	6000

WDFX Results: Multi-Label Classification

Overall accuracy
>93%

Cuoco et al.
[10.23919/EUSIPCO.2018.8553393](https://doi.org/10.23919/EUSIPCO.2018.8553393)
2018 26th European Signal Processing Conference (EUSIPCO)



WDFX: Binary Classification Results

Chirp-like signals

OR

Noise

Cuoco et al.

10.23919/EUSIPCO.2018.8553393
2018 26th European Signal Processing Conference (EUSIPCO)

Overall accuracy >98%

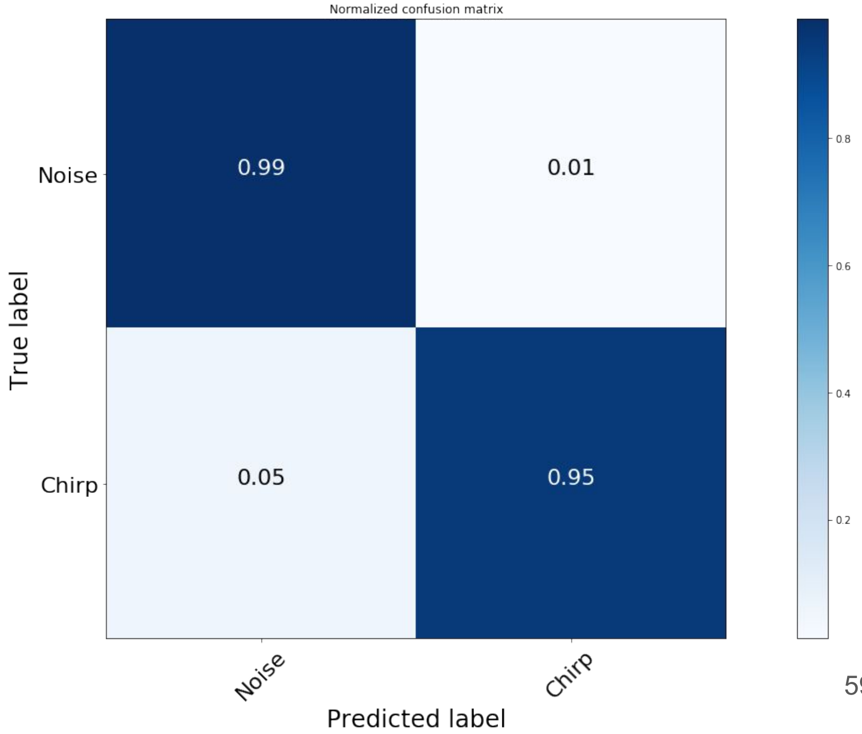
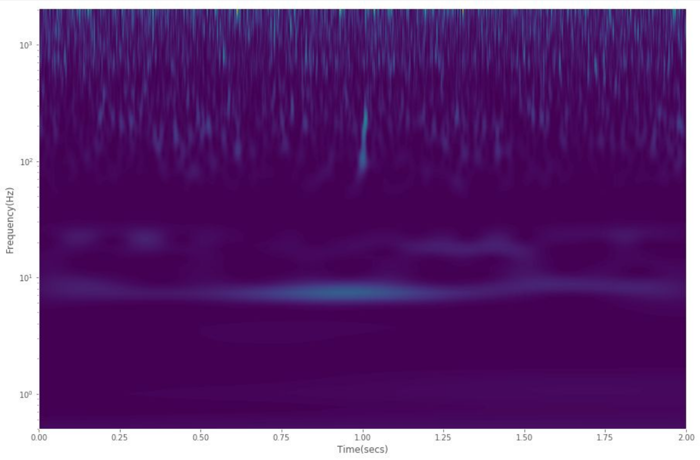


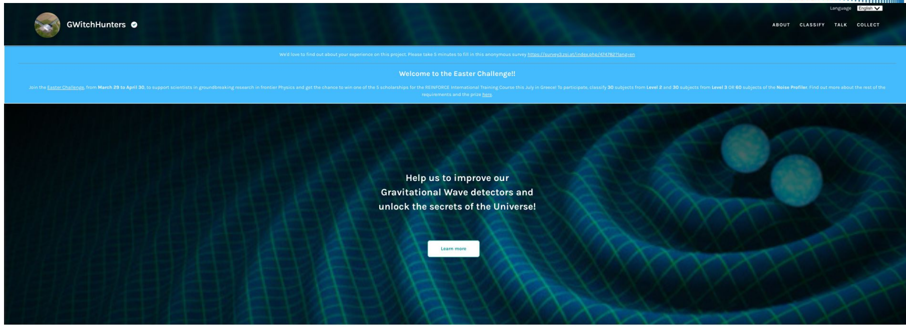
Image-based classification

- Images as input data

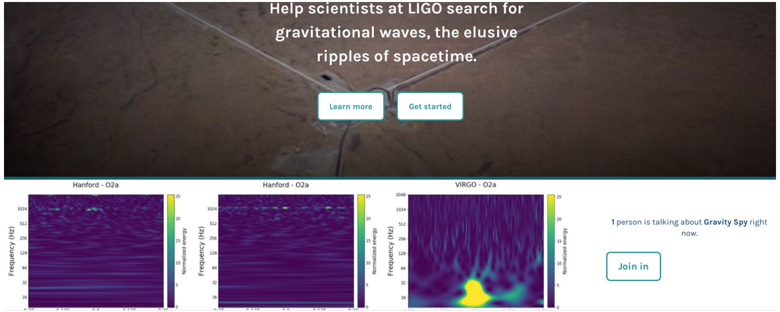


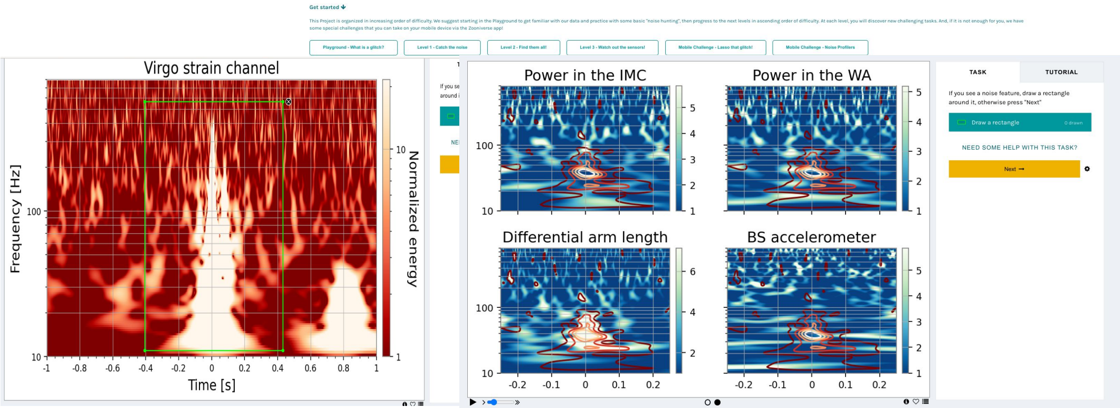
Citizen science for GW-AI

GWitchHunters



Gravity Spy





Citizen scientists contribute to classify glitches

More details in Zevin+17 [10.1088/1361-6382/aa5cea](10.1088/1361-6382/aa5cea)

- *Team: M. Razzano, F. Di Renzo, F. Fidecaro (@Unipi), G. Hemming, S. Katsanevas (@EGO)*
- *Launched @ Nov 2019 – REINFORCE Project H2020-SWAFS (2019-2022)*

https://www.zooniverse.org/projects/reinforce/gwitchhunters

Building the images

Spectrogram for each image

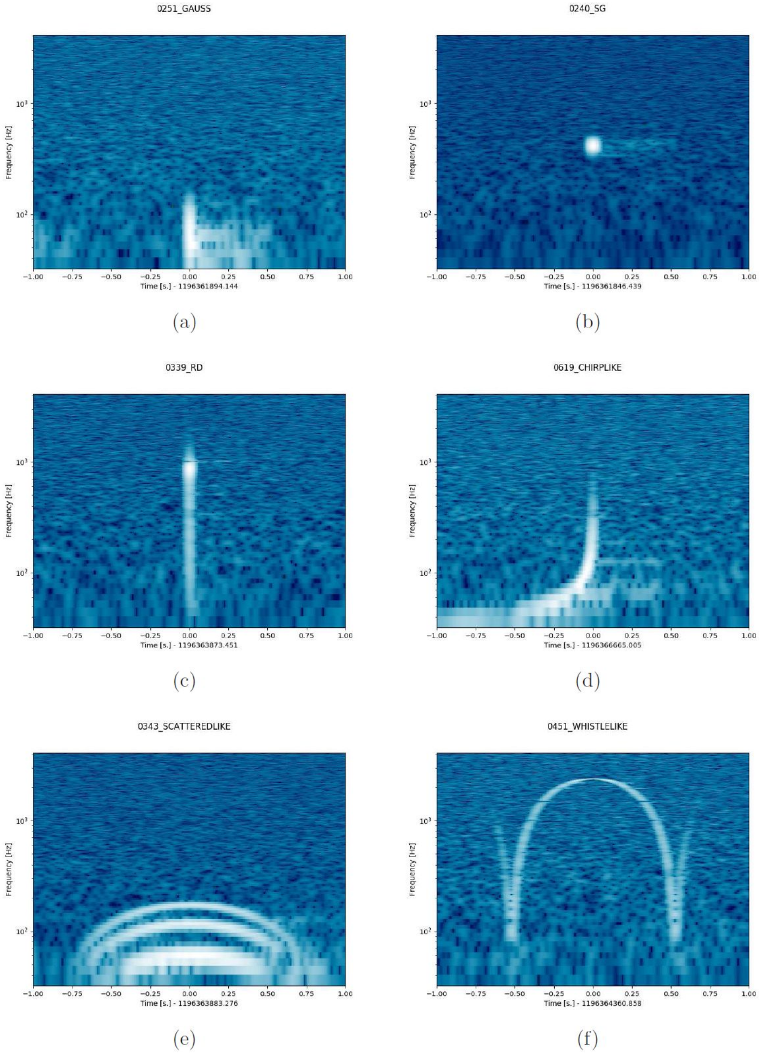
2-seconds time window to highlight features in long glitches

Data is whitened

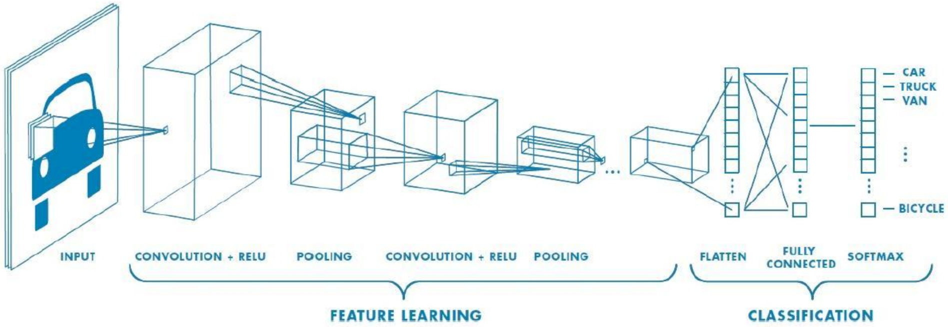
Optional contrast stretch

Simulations now available on FigShare

Razzano, Massimiliano; Cuoco, Elena (2018): Simulated image data for testing machine learning classification of noise transients in gravitational wave detectors (Razzano & Cuoco 2018). figshare. Collection. [*https://doi.org/10.6084/m9.figshare.c.4254017.v1*](https://doi.org/10.6084/m9.figshare.c.4254017.v1)



Deep learning: Convolutional Neural Network



0	0	0	0	0	0	0
0	60	113	56	139	85	0
0	73	121	54	84	128	0
0	131	99	70	129	127	0
0	80	57	115	69	134	0
0	104	126	123	95	130	0
0	0	0	0	0	0	0

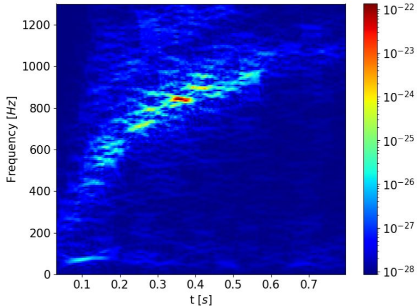
Kernel

0	-1	0
-1	5	-1
0	-1	0

114				

2-D CNN

Spectrogram images



Alberto Iess courtesy

Pipeline structure

Input GW data

- ❖ Image processing
- ❖ Time series whitening
- ❖ Image creation from time series (FFT spectrograms)
- ❖ Image equalization & contrast enhancement

Classification

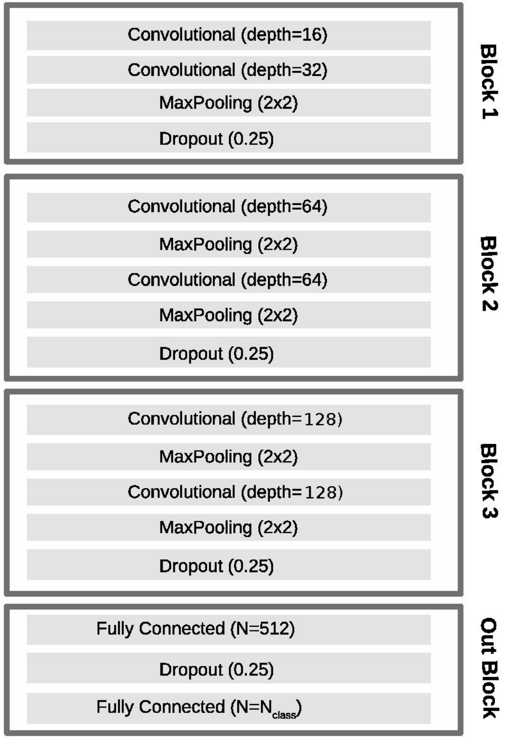
- A probability for each class, take the max
- Add a NOISE class to crosscheck glitch detection

Network layout

- Tested various networks, including a 4-block layers

Run on GPU Nvidia GeForce GTX 780

- 2.8k cores, 3 Gb RAM)
- Developed in Python + CUDA-optimized libraries



EGO - Virgo

Classification Results

We compared classification performances with simpler architectures

Metric	Accuracy	Precision	Recall	F1 score	Log loss
SVM	0.971	0.972	0.971	0.971	0.08
Shallow CNN	0.986	0.986	0.986	0.986	0.04
1 CNN block	0.991	0.991	0.991	0.991	0.02
3 CNN blocks	0.998	0.998	0.998	0.998	0.008

Linear Support Vector Machine

CNN with 1 hidden layer

CNN with one block
(2 CNNs+Pooling&Dropout)

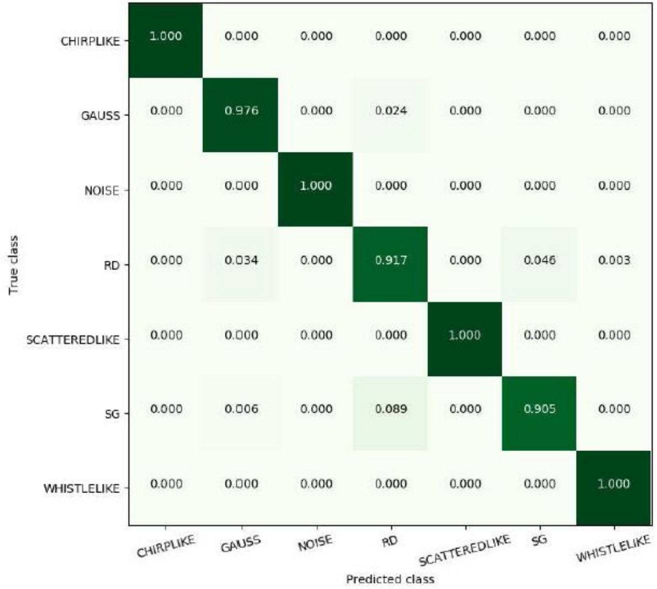
Deep 4-blocks CNNs

Razzano M., Cuoco E. CQG-104381.R3

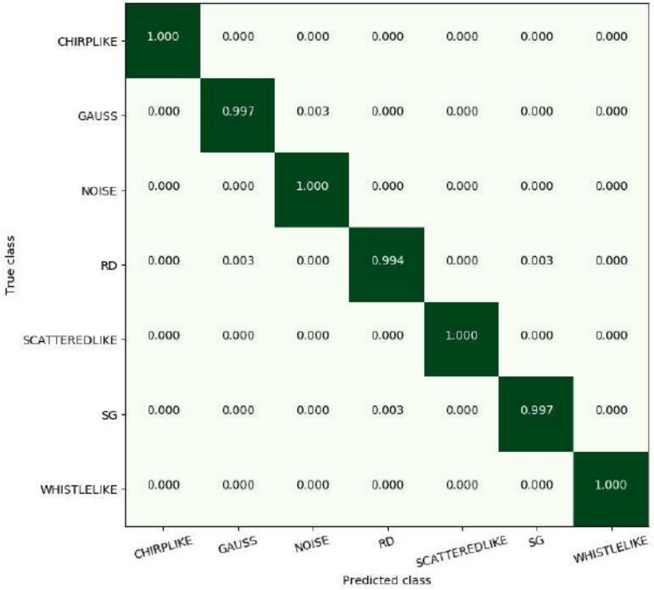
Classification accuracy

Normalized Confusion Matrix

SVM



Deep CNN



Deep CNN better at distinguishing similar morphologies

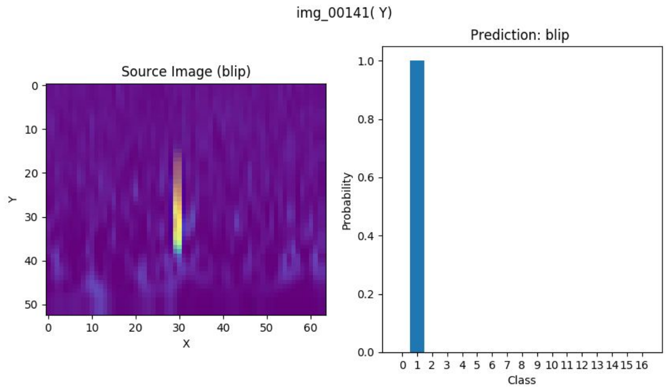
Razzano M., Cuoco E. CQG-104381.R3

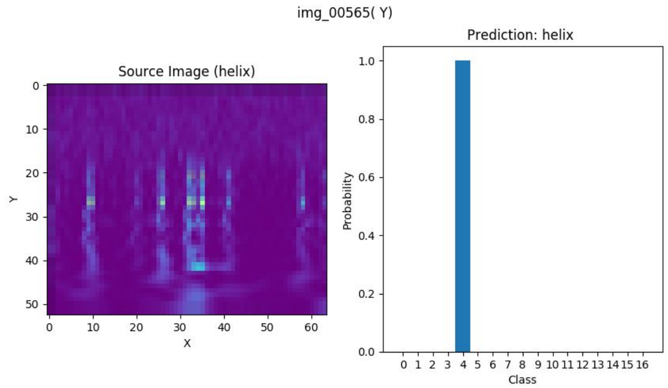
Real data: O1 run

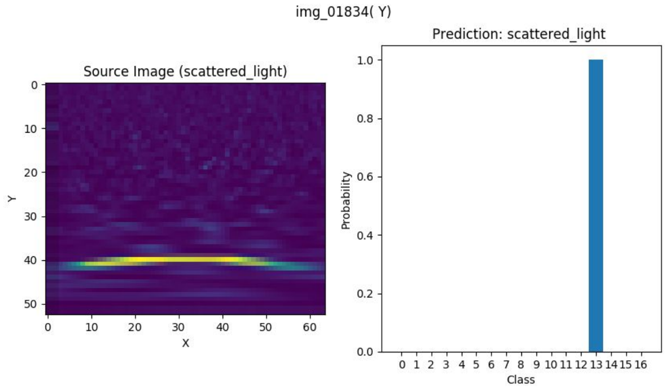
Dataset from GravitySpy images

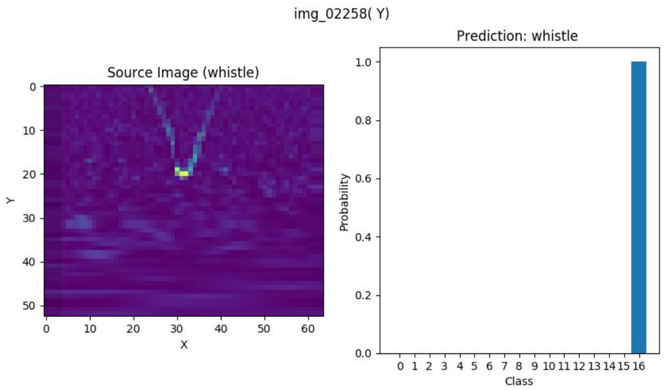
Glitch name	# in H1	# in L1
Air compressor	55	3
Blip	1495	374
Chirp	34	32
Extremely Loud	266	188
Helix	3	276
Koi fish	580	250
Light Modulation	568	5
Low_frequency_burst	184	473
Low_frequency_lines	82	371
No_Glitch	117	64
None_of_the_above	57	31
Paired doves	27	-
Power_line	274	179
Repeating blips	249	36
Scattered_light	393	66
Scratchy	95	259
Tomte	70	46
Violin_mode	179	-
Wandering_line	44	-
Whistle	2	303

Examples of classification

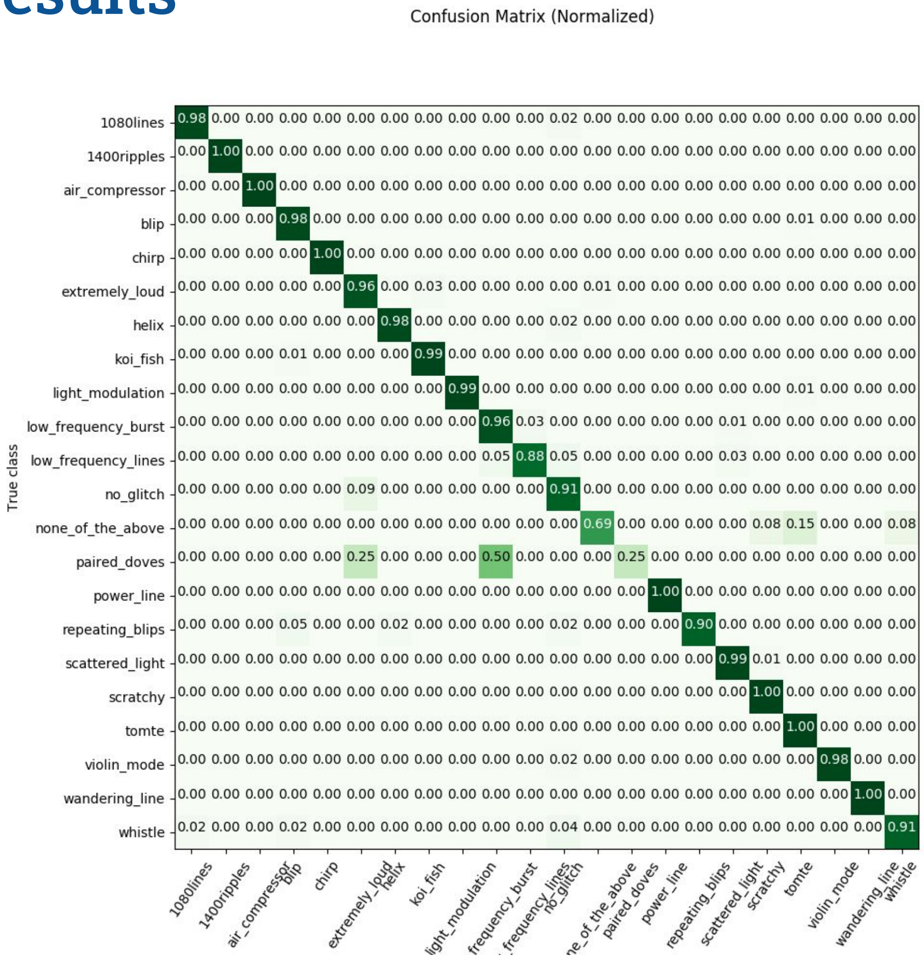








Results

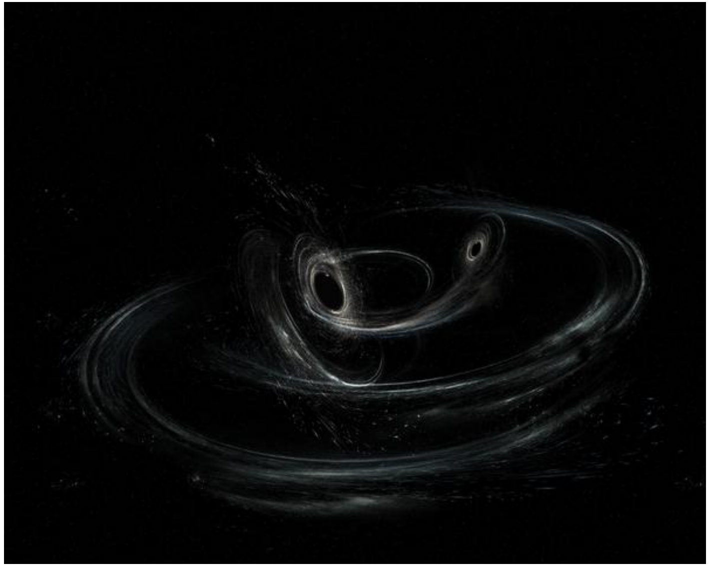


Full CNN stack

Consistent with Zevin+2017

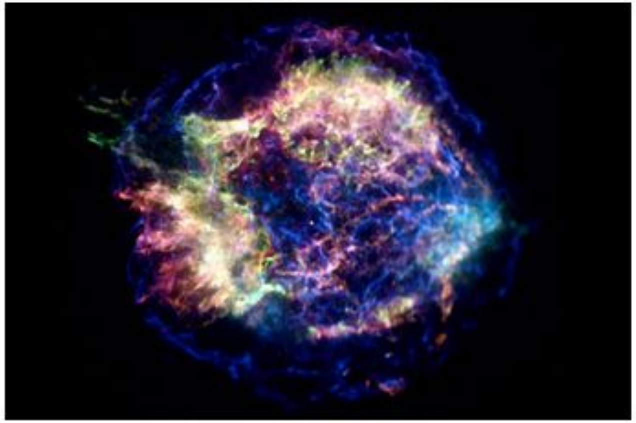
GW Astrophysical signal classification

Compact Binary Coalescences



Credit
LIGO/Caltech/MIT/Sonoma State (Aurore Simonnet)

Core Collapse Supernovae



This is Cassiopeia A, a core collapse supernova remnant with a neutron star in its center. Located in the Milky Way only some 11,000 light-years away from Earth, it originally exploded about 330 years ago.

NASA/CXC/UNAM/IOFFE/D. PAGE, P. SHTERNIN ET AL

Core Collapse Supernovae

Waveform depends on progenitor star

Different emission mechanisms (Proto-neutron star oscillation, Standing Accretion Shock Instability (SASI)..)

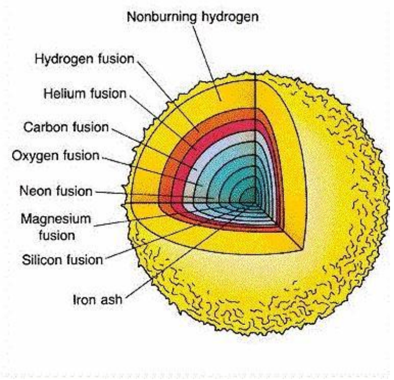
Rare (~100 yrs in Milky Way)

Largely Stochastic

Different simulation models

Best waveform models from computationally expensive 3D simulations

Need an alternative to matched filter approach



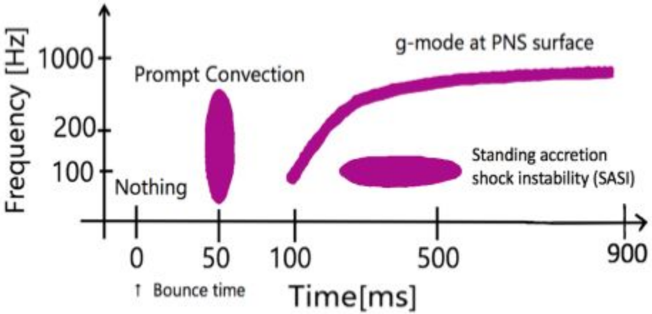
Ott et al. (2017)

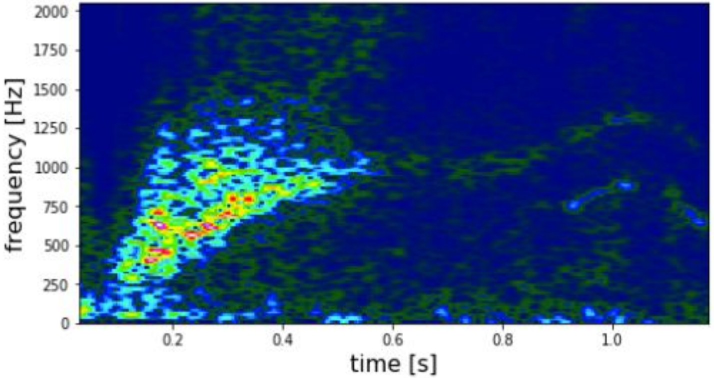
GW emission Process	Potential explosion mechanism: MHD mechanism (rapid rotation)	Neutrino mechanism (slow/no rotation)	Acoustic mechanism (slow/no rotation)
Rotating collapse and Bounce	Strong	None/weak	None/weak
3D rotational instabilities	Strong	None	None
Convection & SASI	None/weak	Weak	Weak
PNS g-modes	None/weak	None/weak	Strong

EGO - Virgo

Supernovae search

- Some burst searches are for targeted sources like supernovae.
- There is not enough supernova waveforms to match filter search but some supernova waveform features are known.
- The known features from supernova simulations can be incorporated into supernova searches using machine learning.

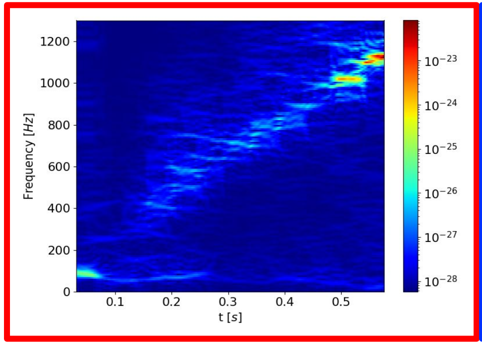


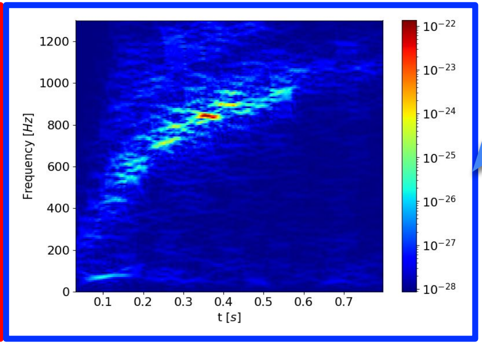


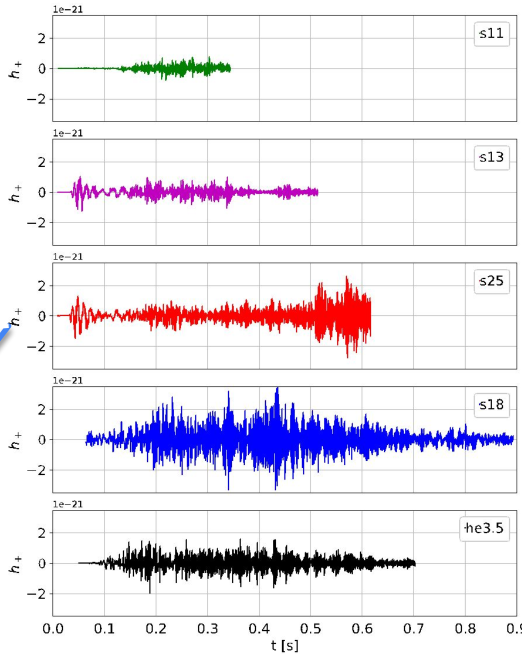
J. Powell courtesy

Core Collapse Supernova models

- Andresen s11: Low amplitude, non-exploding, peak emission at lower frequencies
- Radice s13: Non-exploding, lower amplitudes
- Radice s25: Late explosion time, standing accretion shock instability (SASI), high peak frequency
- Powell s18: High peak frequency, exploding model
- Powell He3.5: ultra-stripped helium star, high peak frequency, exploding model







Iess, Cuoco, Morawski, Powell,
https://doi.org/10.1088/2632-2153/ab7d31

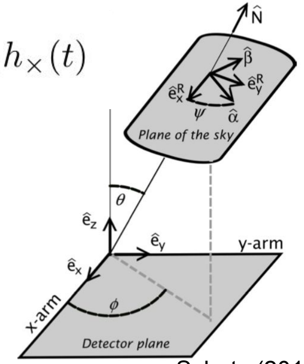
MDC and CCSN simulation

$$h(t) = F_+ h_+(t) + F_\times h_\times(t)$$

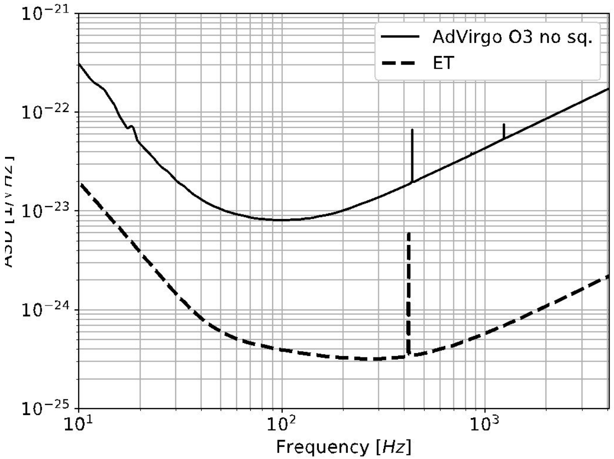
Distances:
VO3 0.01 kpc to 10 kpc
ET 0.1 kpc to 1000 kpc

Random sky localization

Large SNR range



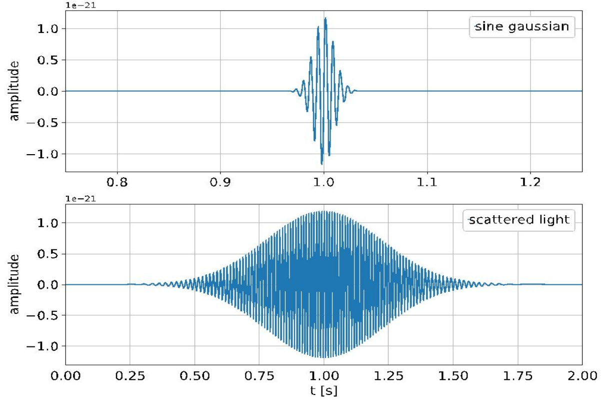
Schutz (2011)



SINE GAUSSIAN & SCATTERED LIGHT GLITCHES

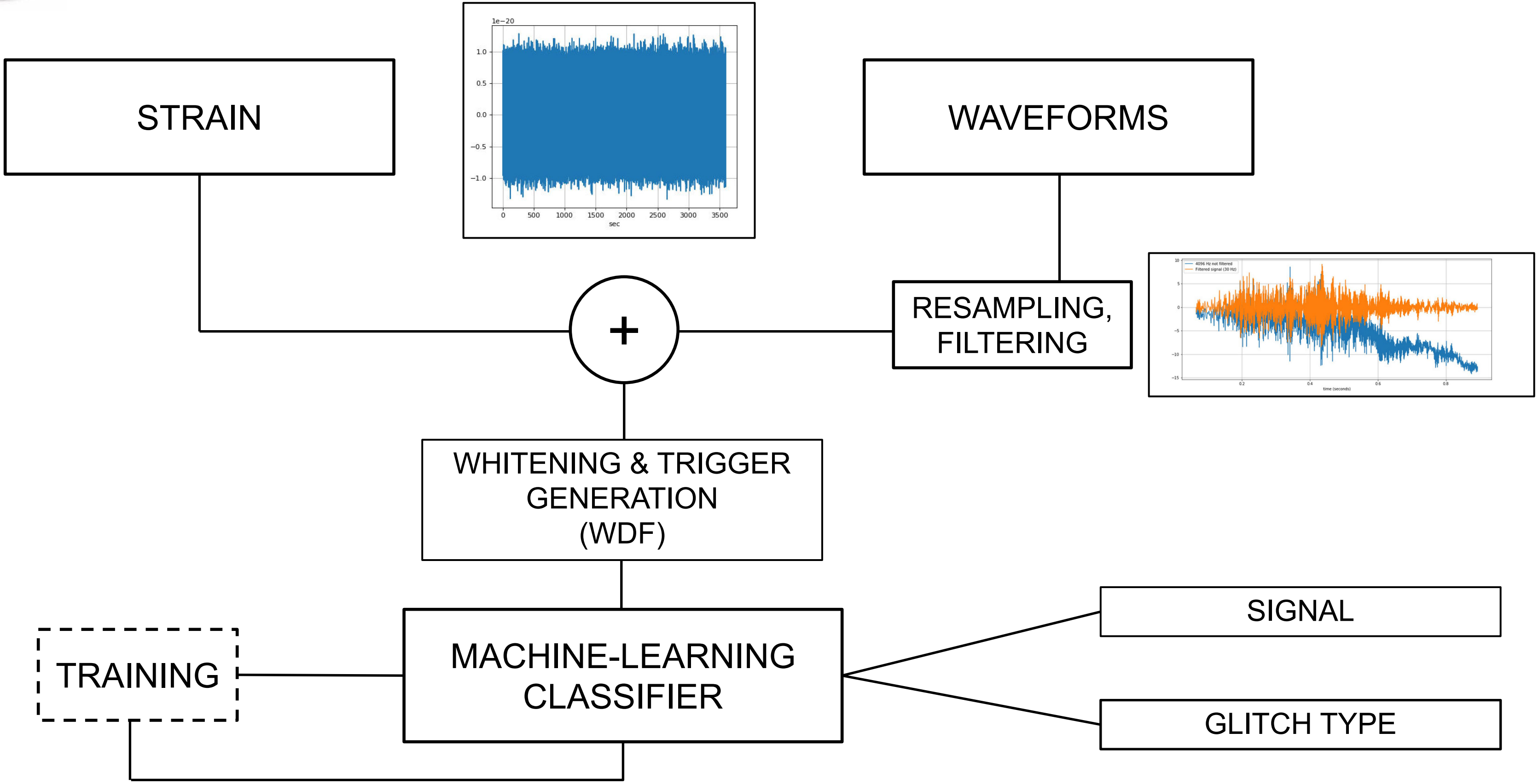
$$h_{SG}(t) = h_0 \sin(2\pi f_0 (t - t_0)) e^{-\frac{(t-t_0)^2}{2\tau^2}}$$

$$h_{SL}(t) = h_0 \sin(\phi_{SL}) e^{-\frac{(t-t_0)^2}{2\tau}} \qquad \phi_{SL} = 2\pi f_0 (t - t_0)[1 - K(t - t_0)^2]$$



BACKGROUND STRAIN : simulated data sampled at 4096 Hz built from VO3 and ET projected sensitivities

Pipeline Workflow

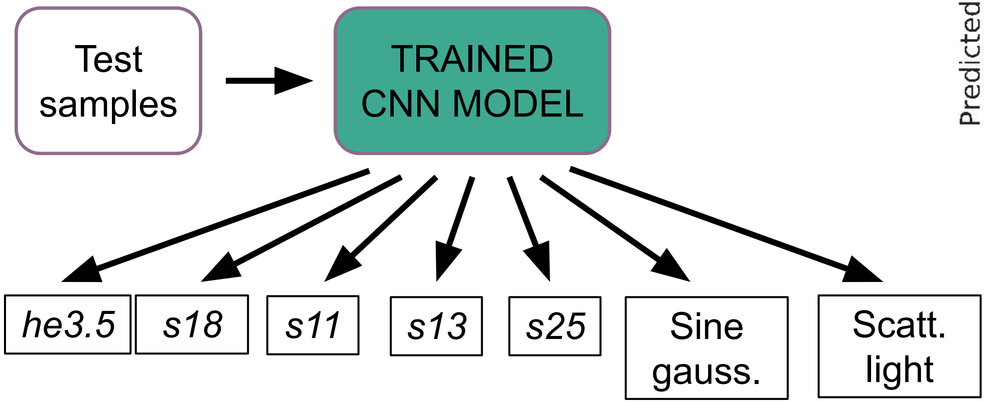


Alberto Iess courtesy

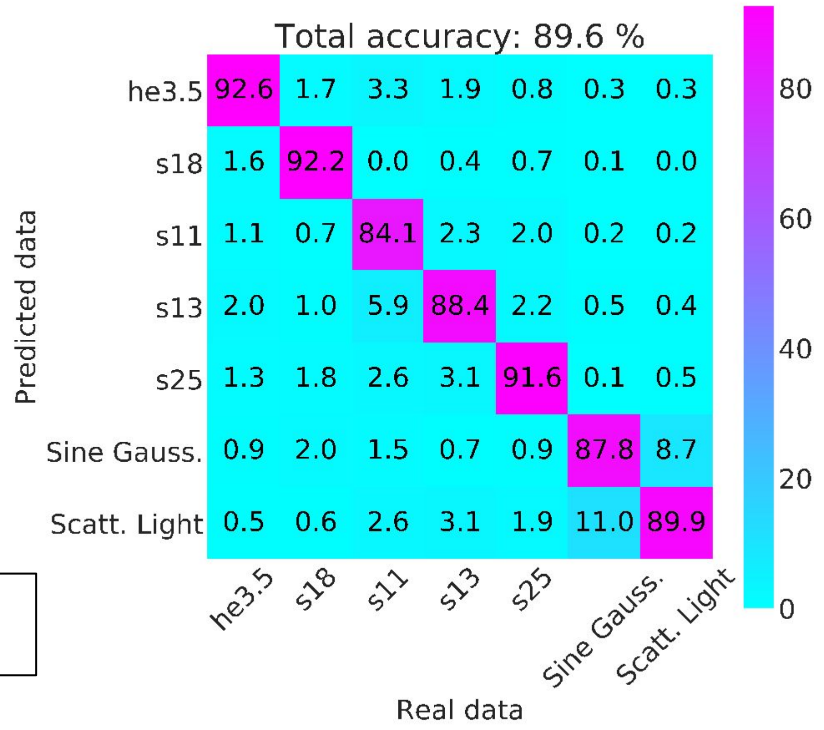
Multilabel classification

Train on **all** (4 CCSNe waveform models + glitches).

Test on **all.**



ET, MERGED 1D & 2D CNN



COMPLEX TASK ➡ LONGER TRAINING (> 1 hr)

Test on real data

44 segments (4096s per segment) from O2 science run.

Added m39, y20, s18np models (Powell, Mueller 2020).

<u>Fixed distance of 1 kpc</u>.

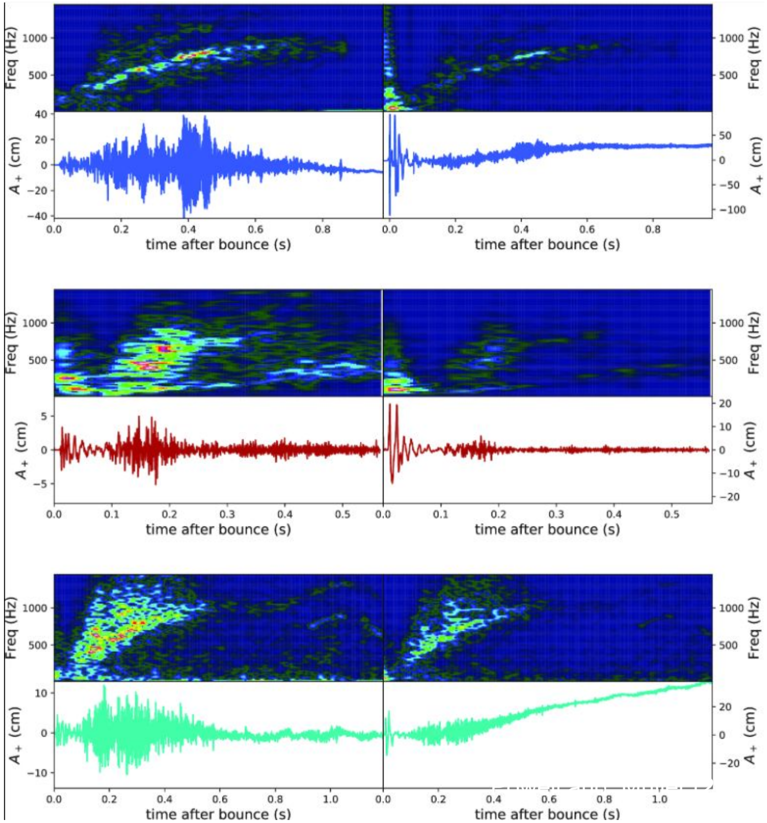
Added LSTM Networks, suited for time series data.

Added Three ITF classification.

Powell s18np: differs from s18 since simulation does not include perturbations from the convective oxygen shell. As a result, this model develops strong SASI after collapse.

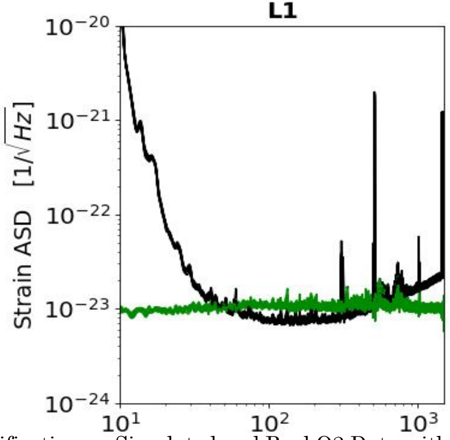
Powell y20: non-rotating, 20 solar mass Wolf-Rayet star with solar metallicity.

Powell m39: rapidly rotating Wolf-Rayet star with an initial helium star mass of 39 solar masses

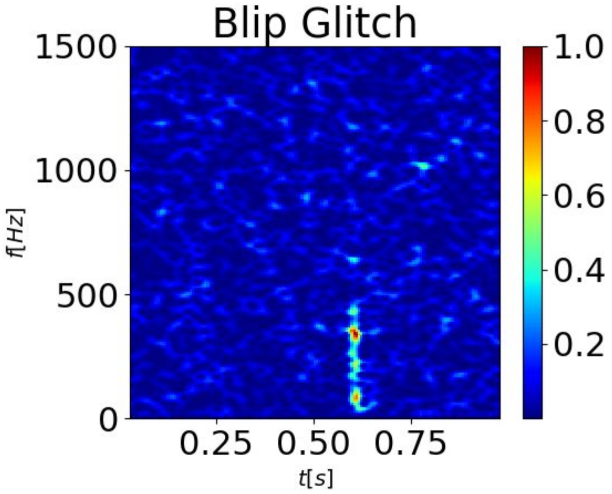


Real noise from O2 run

- Noise PSD is non stationary.
- Multiple Glitch Families.
- SNR distribution is affected by ITF antenna pattern.
- Dataset: ~15000 samples.
- Imbalanced Dataset due to different model amplitudes.



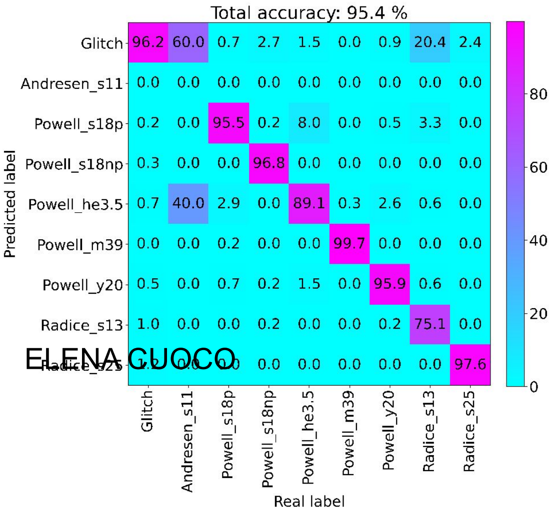
	Triggers		
Detector	*Signal*	*Noise*	*Total*
Virgo V1	9273	47901	57174
Ligo L1	10480	3810	14290
Ligo H1	10984	4103	15087
L1, H1, V1	5647	675	6322



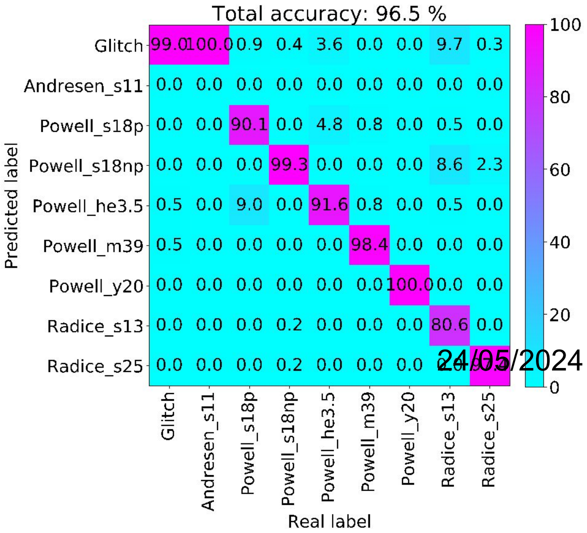
CCSN Classification on Simulated and Real O2 Data with CNNs and LSTMs
***A. Iess**, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, A&A 669, A42 (2023)*

Multilabel classification task

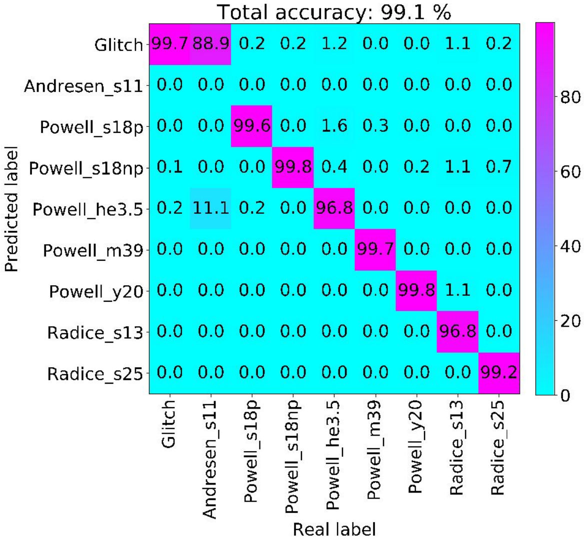
- **Bi-LSTM**, 2 recurrent layers
- ~10 ms/sample
- Best weights over 100 epochs



- **1D-CNN**, 4 convolutional layers
- ~2 ms/sample
- Best weights over 20 epochs



- **2D-CNN**, 4 convolutional layers
- ~3 ms/sample
- Best weights over 20 epochs

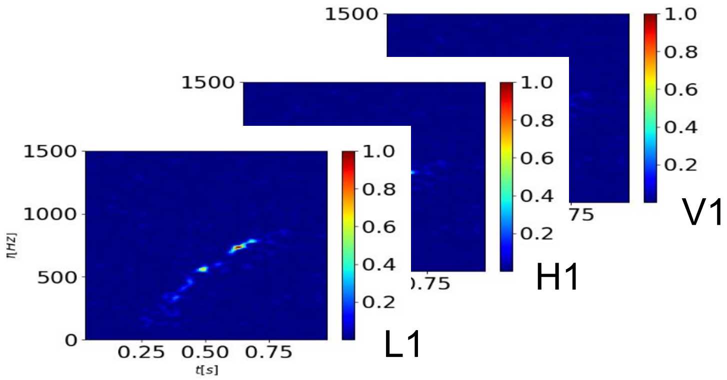


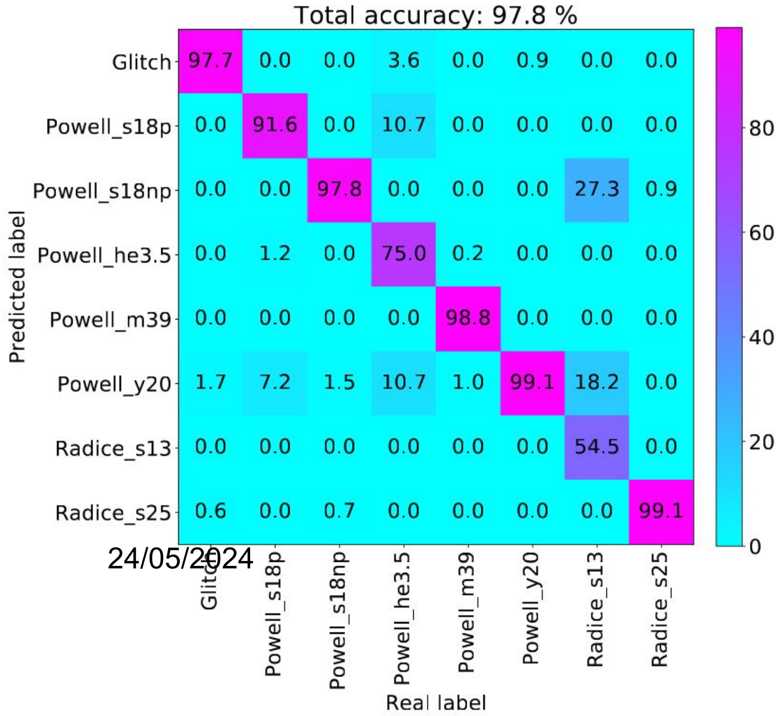
A. Iess, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, A&A 669, A42 (2023)

Result merger on 3 ITFs

Dataset breakdown: 675 noise, 329 s18p, 491 s18np, 115 he3.5, 1940 m39, 1139 y20, 76 s13, 1557 s25.

Input to NNs have additional dimension (ITF)

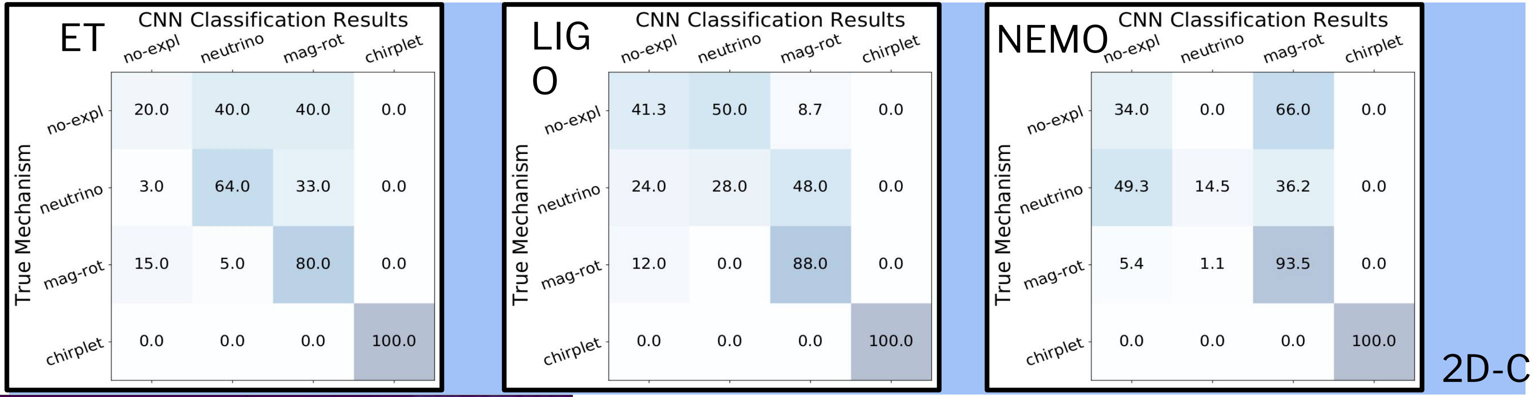




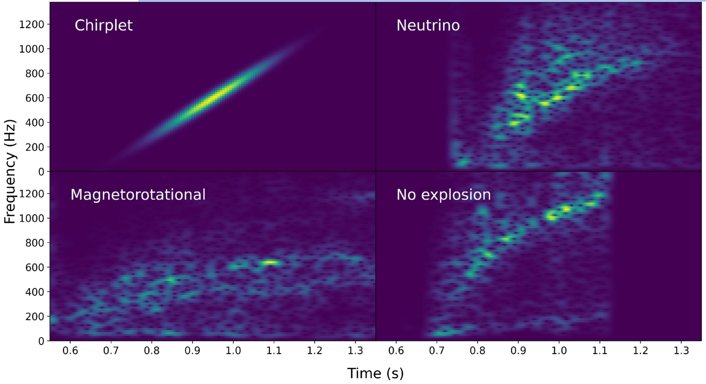
24/05/2024

A. Iess, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, A&A 669, A42 (2023)

Determining CCSN mechanism



2D-CNN



Jade Powell, Alberto Iess, Miquel Llorens-Monteagudo, Martin Obergaulinger, Bernhard Muller, Alejandro TorresFornè, Elena Cuoco, and Josè A. Font. *Determining the core-collapse supernova explosion mechanism with current and future gravitational-wave observatories*. 11 2023, 2311.18221, accepted for publication on PRD

EGO - Virgo

Gravitational Wave science and AI

NOISE
- Data cleaning
- Glitch classification
- Nonlinear noise
- ITF anomaly detection
- Glitch simulation

BURST
- ML-based method for detection
- CCSN waveform classification

CBC
- Detection
- Early warning
- Anomaly detection

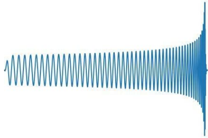
CW
- Clustering in the parameter space
- Computing efficiency

SWBG
- Noise correlation

PARAMETER ESTIMATION
- Faster and efficient methods

ALERT SYSTEM
- Ad hoc hardware/software solution?

E. Cuoco, M. Cavaglià, Ik. S. Heng, D. Keitel. C. Messenger,
Living Review in Relativity, submitted



Thank you

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Extra examples

Anomaly Detection in Gravitational Waves data using Convolutional AutoEncoders for CBC signals

https://doi.org/10.1088/2632-2153/abf3d0

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cost
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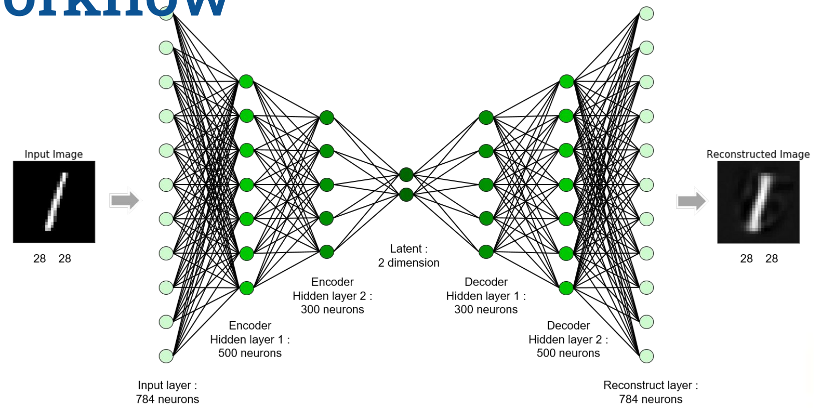
Example for detection/classification for CBC signals

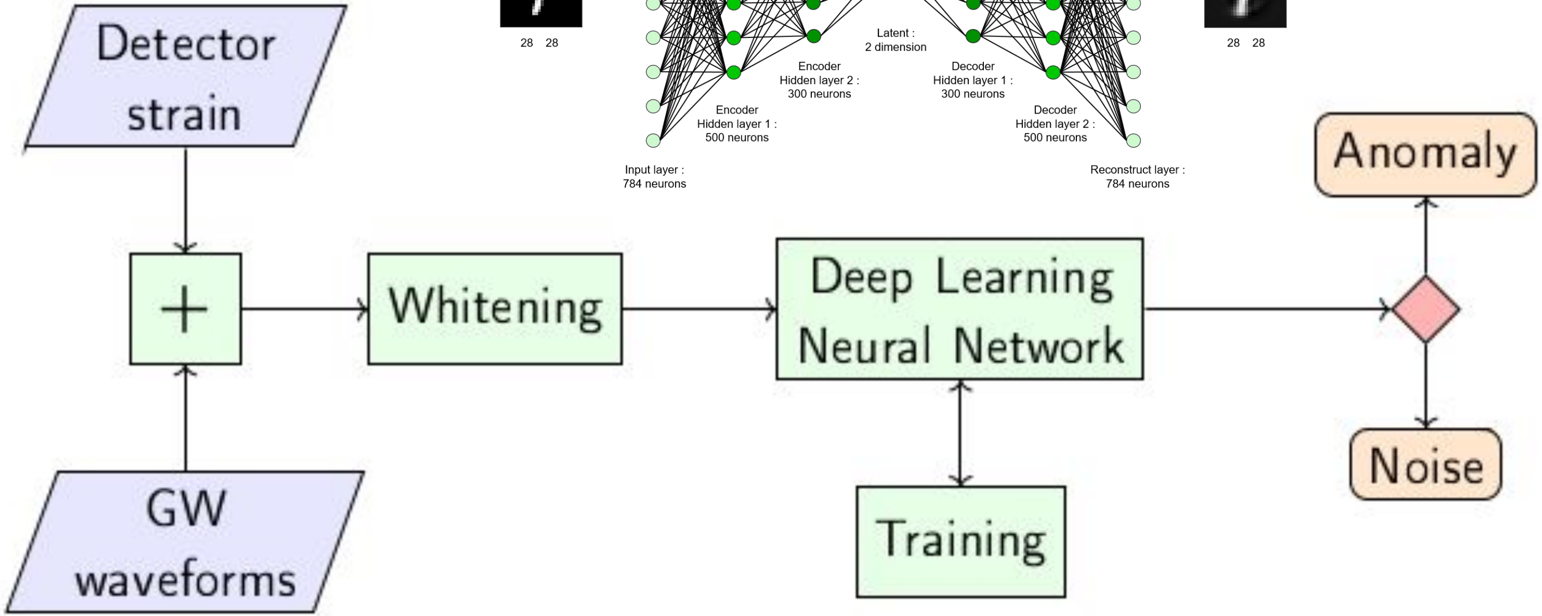
Create a deep learning pipeline allowing detection of anomalies defined in terms of **transient signals**: gravitational waves as well as glitches.

Additionally: Consider **reconstruction of the signal** for the found anomalies.

Filip Morawski*, Michał Bejger, Elena Cuoco, Luigia Petre, https://iopscience.iop.org/article/10.1088/2632-2153/abf3d0*

Auto-Encoder workflow



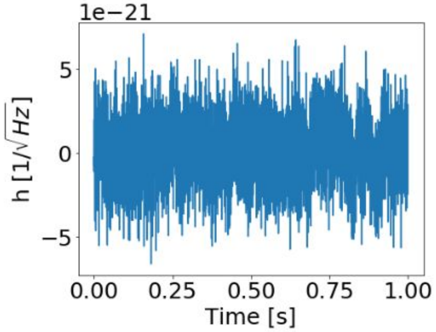


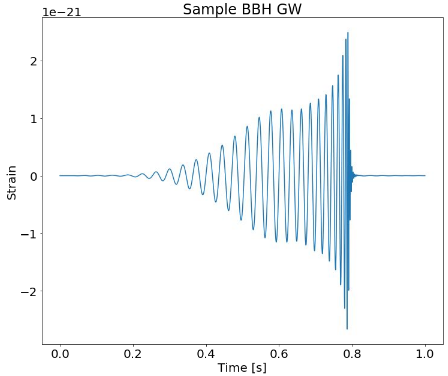
Filip Morawski, *Michał Bejger, Elena Cuoco, Luigia Petre, https://iopscience.iop.org/article/10.1088/2632-2153/abf3d0*

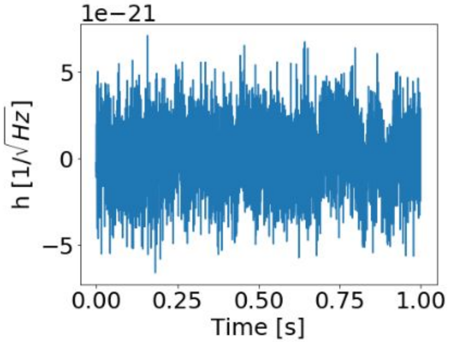
Auto-encoder workflow

Model input

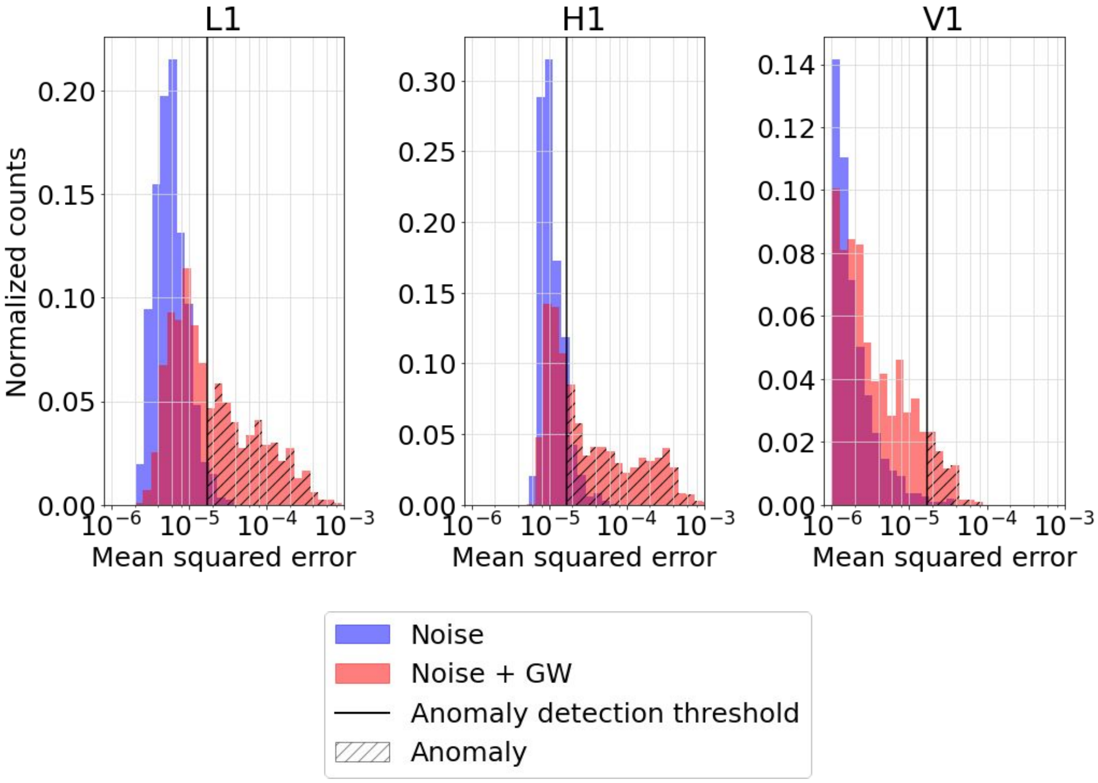
Model prediction







O2 data - MSE Distributions



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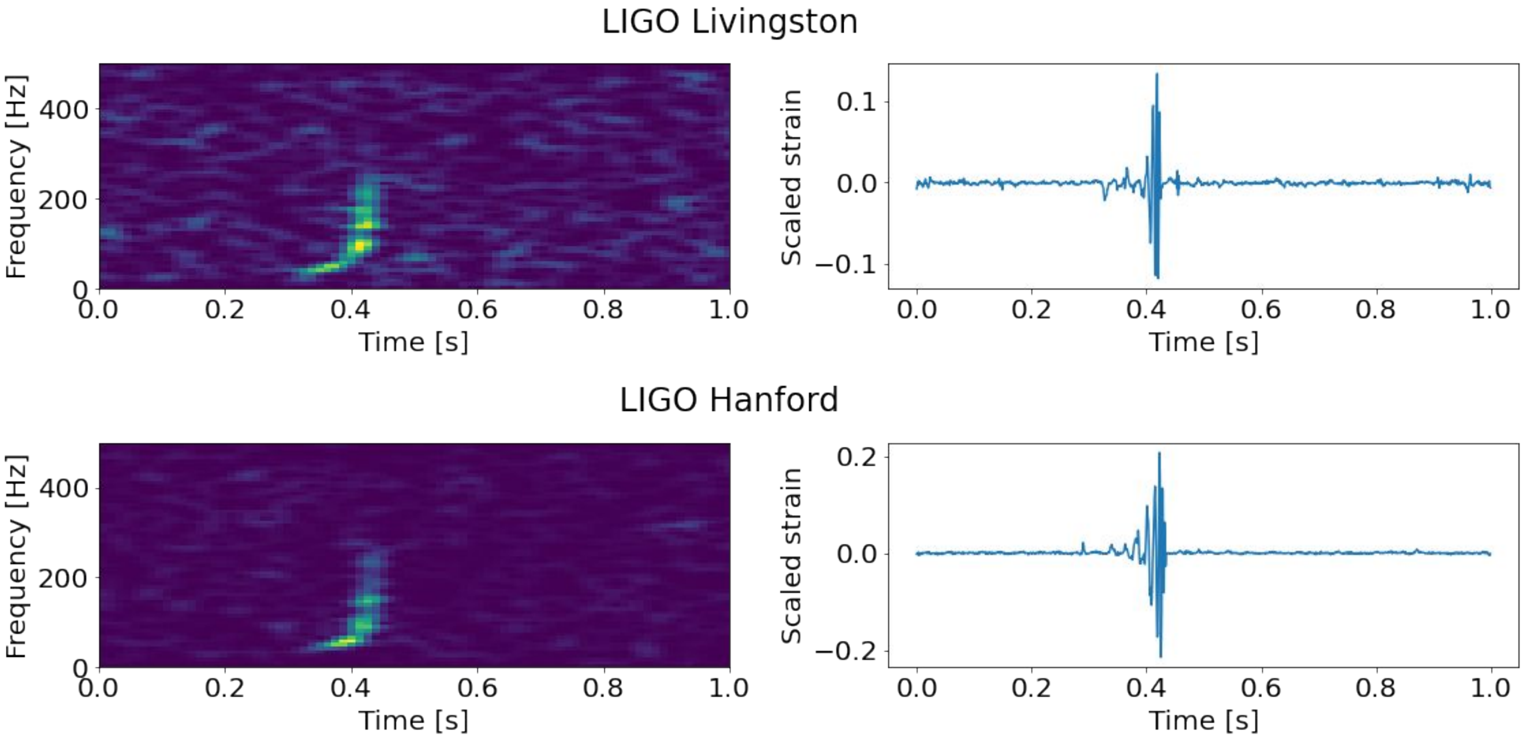

Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,
https://iopscience.iop.org/article/10.1088/2632-2153/abf3d0