ALBUS : Anomaly detector for Long duration BUrst Searches

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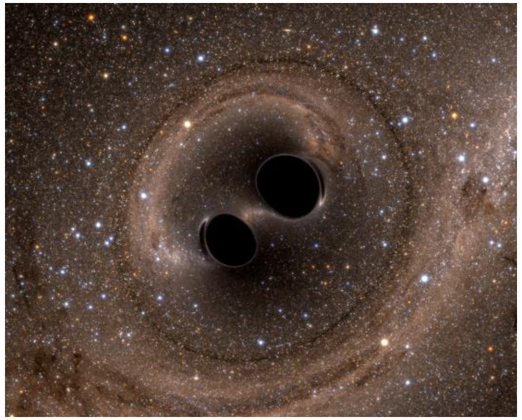
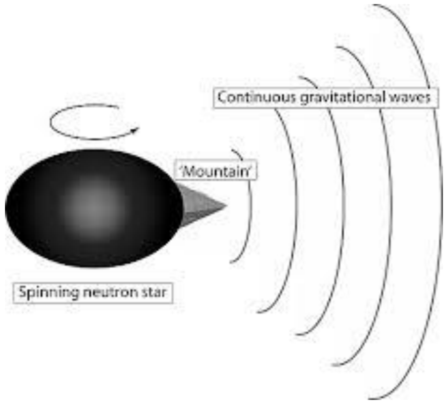
1) What are Bursts ?

- 4 main classes of events :

Compact Binary Coalescences (CBC): black hole, neutron star, white dwarfs, ...

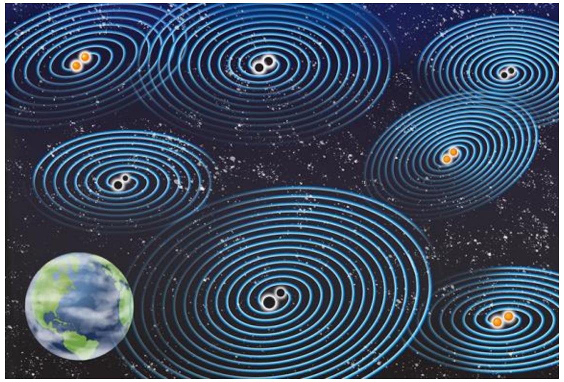


Continuous waves



Bursts : anything that is transient and not a CBC

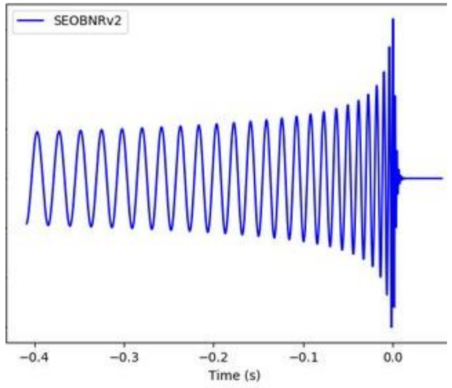
Stochastic background : superposition of a large number of events



2) How do we detect them ?

- CBC detection : general relativity => model of collision = waveform

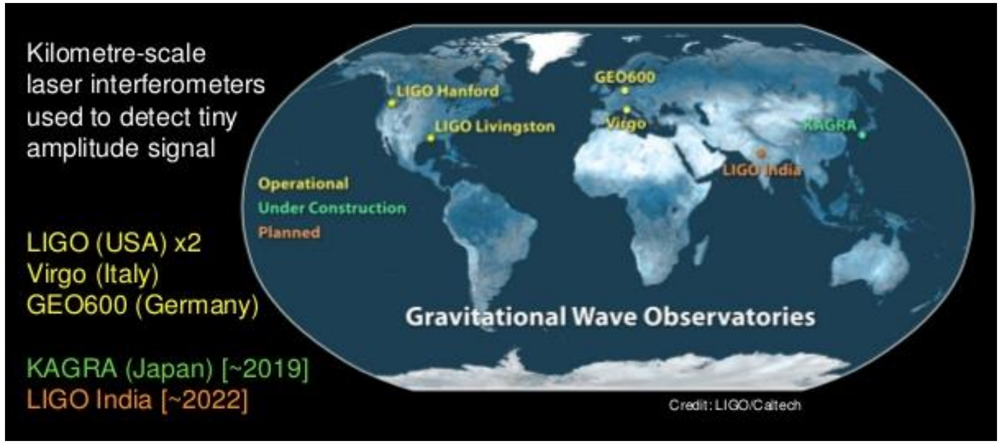
=> then try to match those models to the data (matched filtering)



- Many other phenomena can generate GWs ! But physics is sometimes poorly known...

=> Models not accurate enough to apply match filtering.

=> But we can use multiple detectors to find correlation in the data



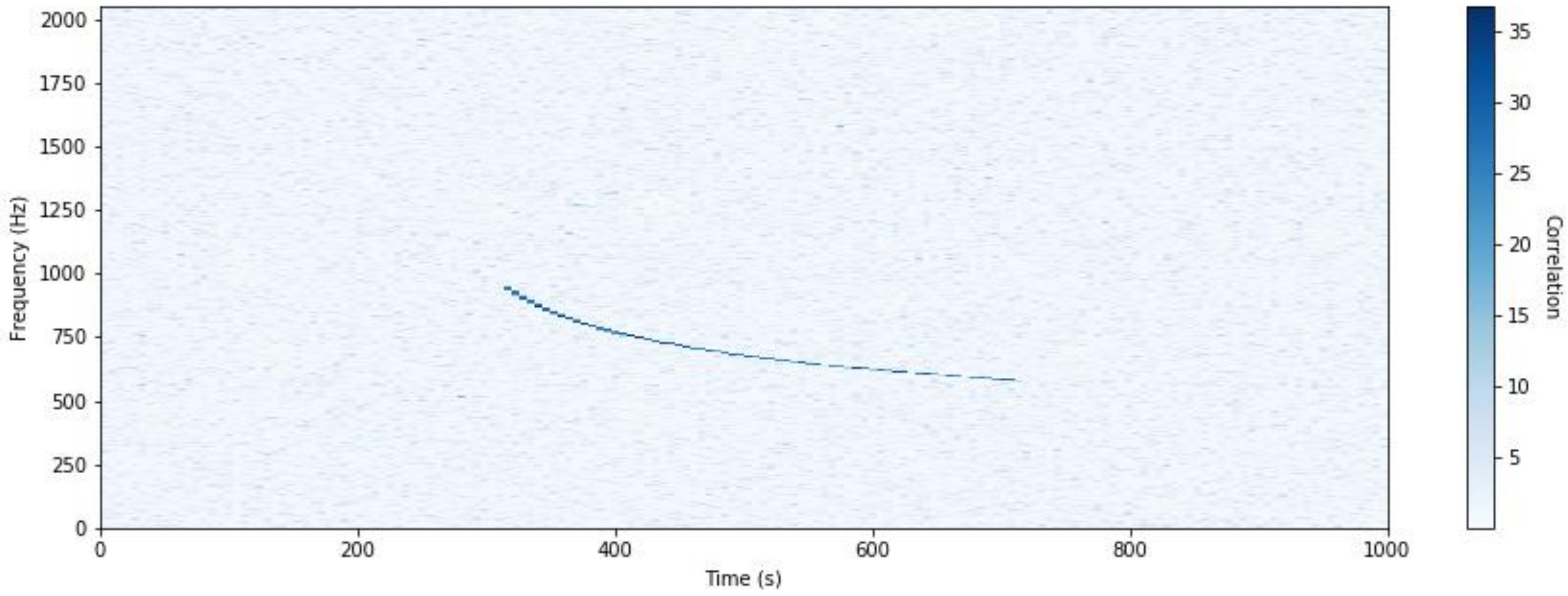
2) How do we detect them ?

- Excess of power method

=> Search in Time-Frequency space : bursts should be clusters of high-correlation pixels

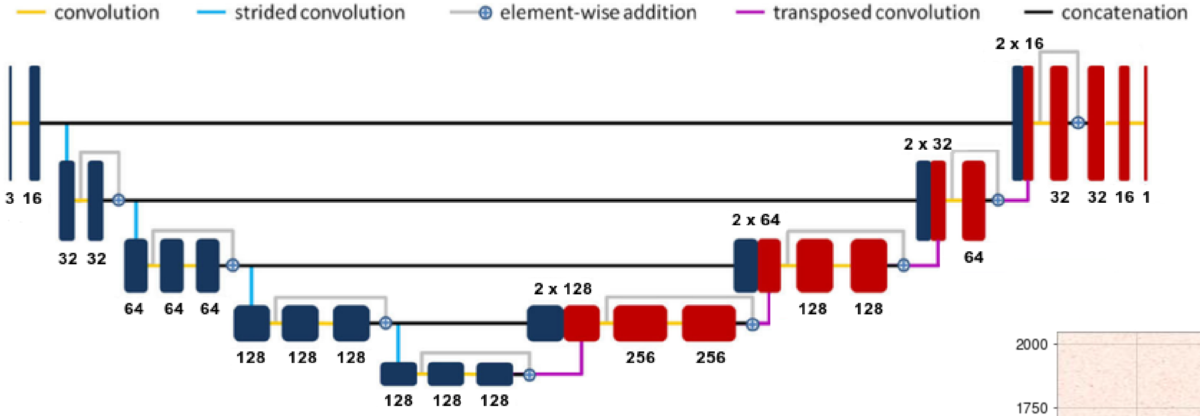
=> Many sources of noise (seismic, laser noise, suspensions, etc.)

=> Focus on long duration events (>10 seconds)



3) New approach : convolutional neural networks

- Inspired by ***Xing et al., 2019***. (https://doi.org/10.1186/s12859-019-3037-5), coded with PyTorch
- Downscaling and upscaling network + skipped connections + ELU activation

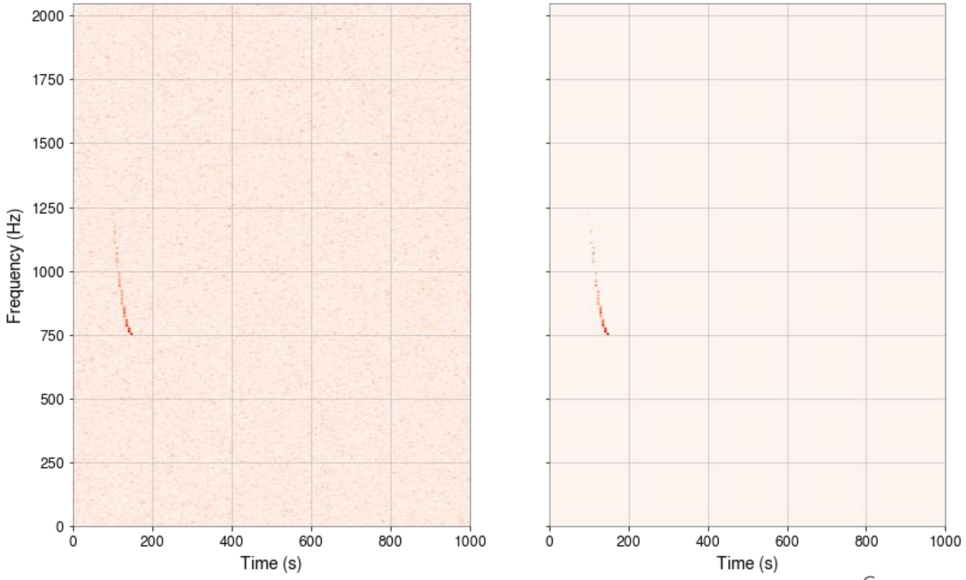


- Method :

- train the network so that : output (O) ≃ target (T)

==> our target will be injection in empty TF map

==> Empty map for noise-only images



- Loss that is being minimized : $MSE = \frac{1}{2} \sum_{i,j} (T_{ij} - O_{ij})^2$

3) New approach : convolutional neural networks

- Problem : can't rely on the long-duration models

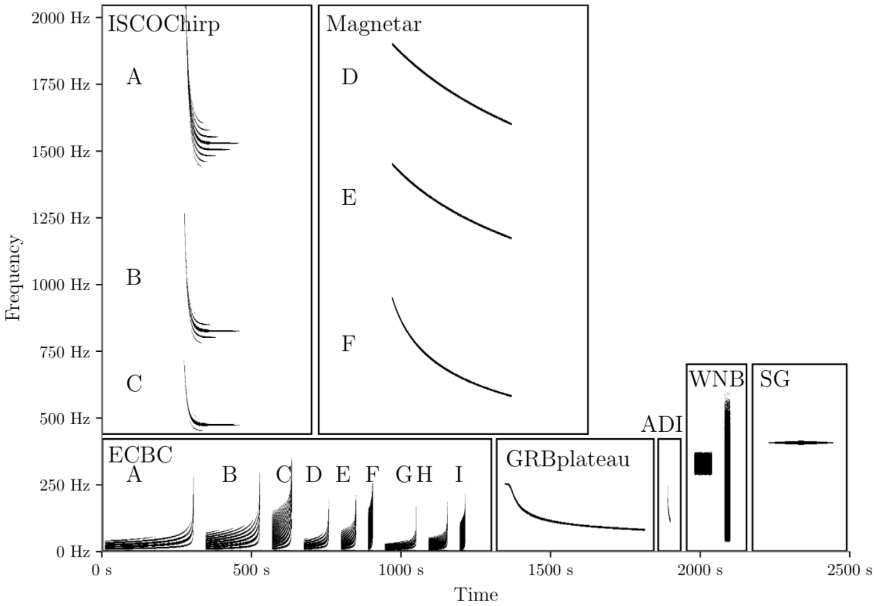
- too many uncertainties in the physical phenomena

- cannot be used as patterns to recognize

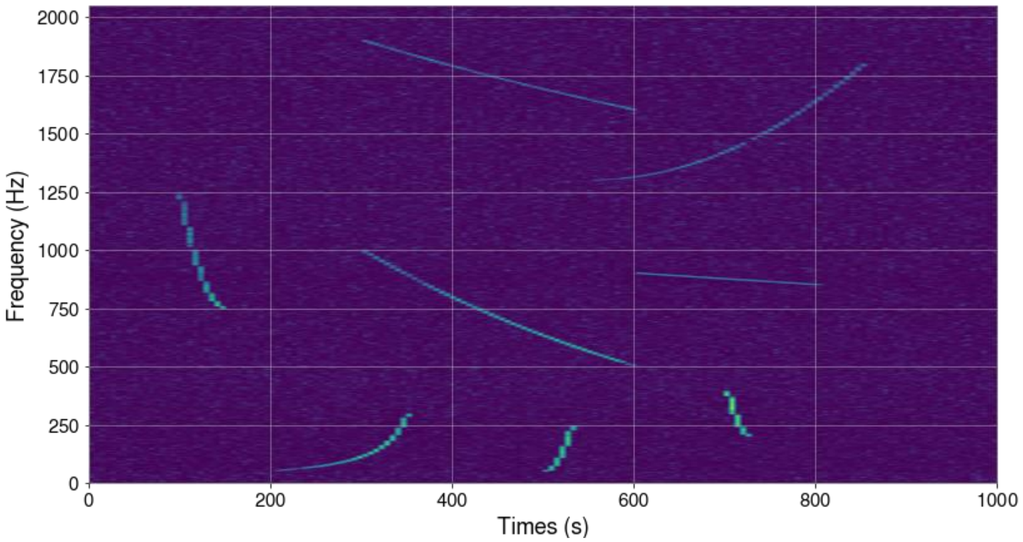
- They all show a "chirp up" or "chirp down" behavior

==> easily mimicked thanks to the *Python Scipy* library !

==> Allow to generate chirps as time series



Taken from O3 long-duration paper : https://dcc.ligo.org/public/0174/P2100078/011/o3_long_duration.pdf



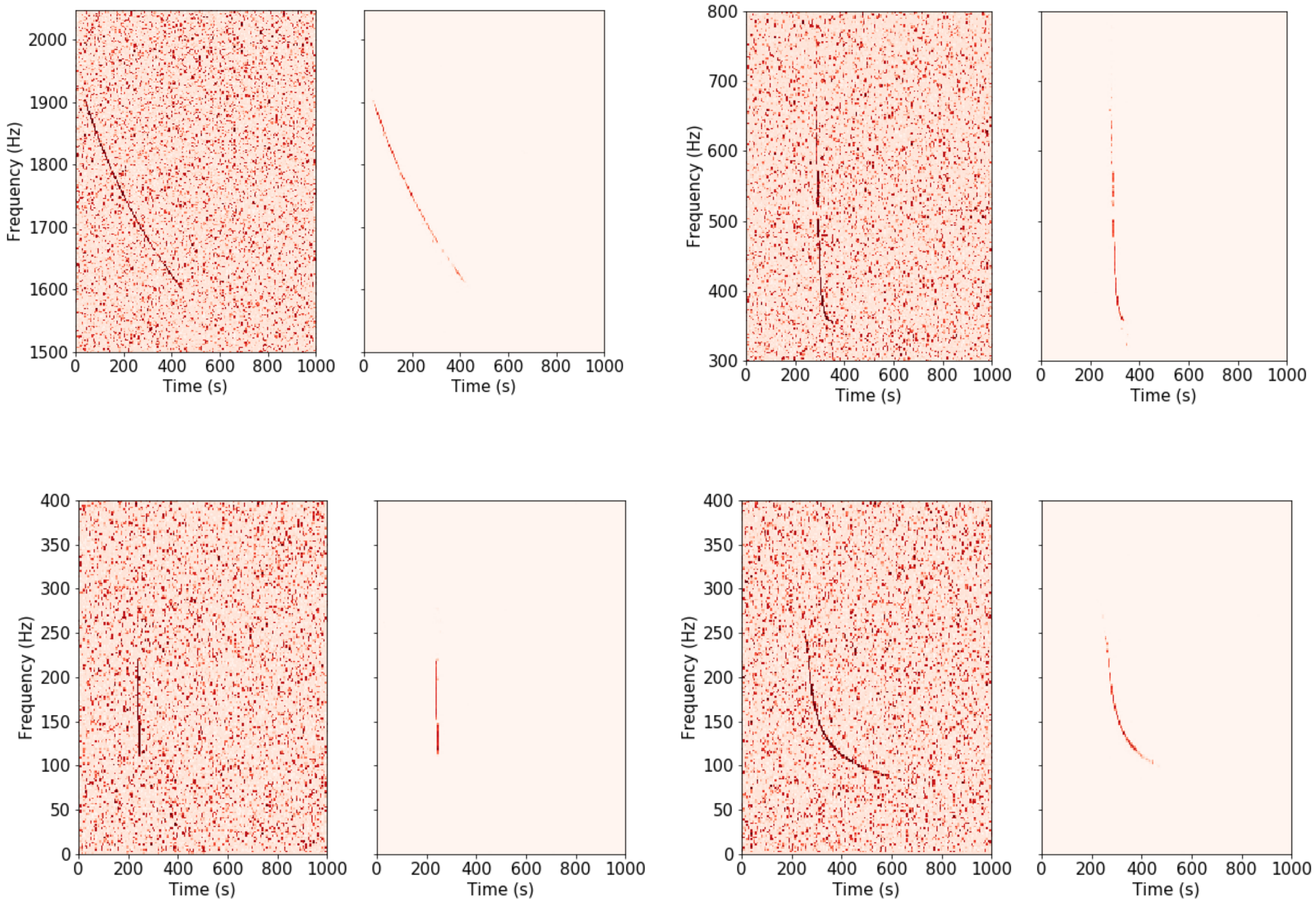
4) Early Results

- Localization : TF maps with injection

- Values > 0.5 for the detected signals

- Pixel-wise localization reached !

==> What about the time-frequency maps with only pure noise ?

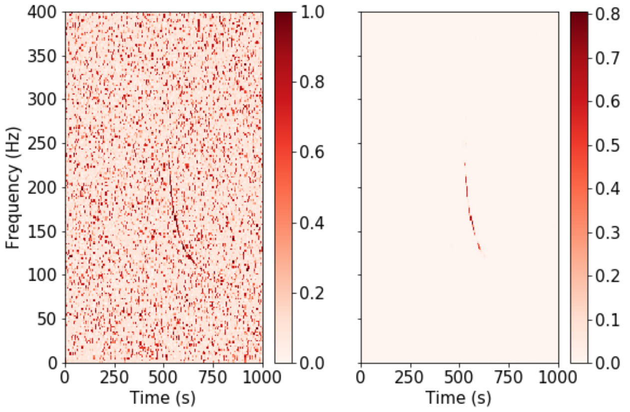


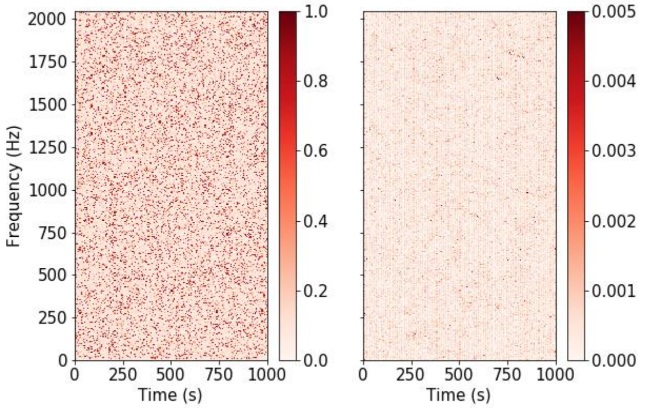
4) Early Results

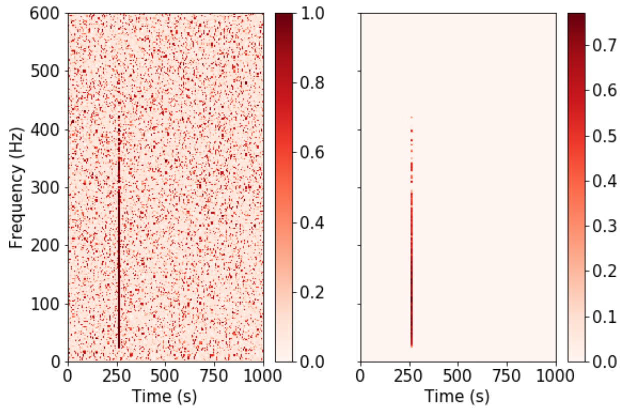
- Localization : TF maps with pure noise

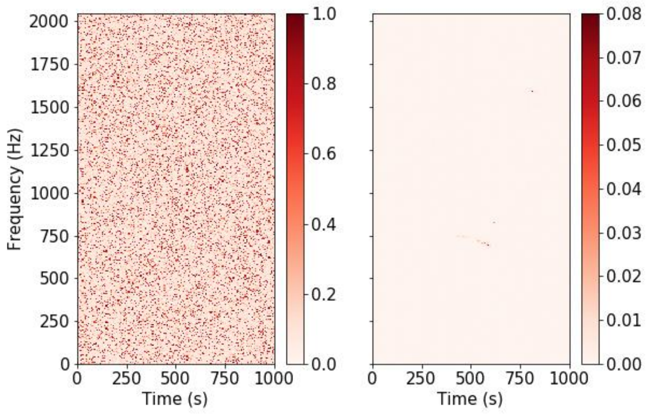
- Empty map when nothing is seen

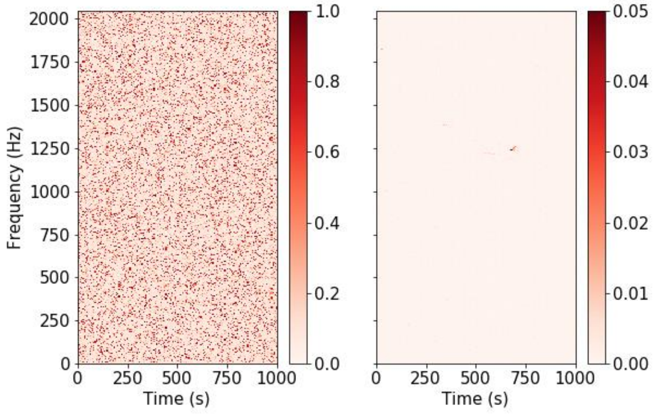
- Instrumental/environmental noise transients (glitches) are detected !











5) Improvements and future plans

- State of the work : draft finished

- Combine the training procedure with Curriculum Learning (train with the easiest samples at first)

=> should increase the performances particularly at low visibility

- Add a classifier to remove glitches

=> see the work of Melissa Lopez and myself (paper out soon)

- Improve the detection statistic

=> Look at the "connection" between the N-largest values

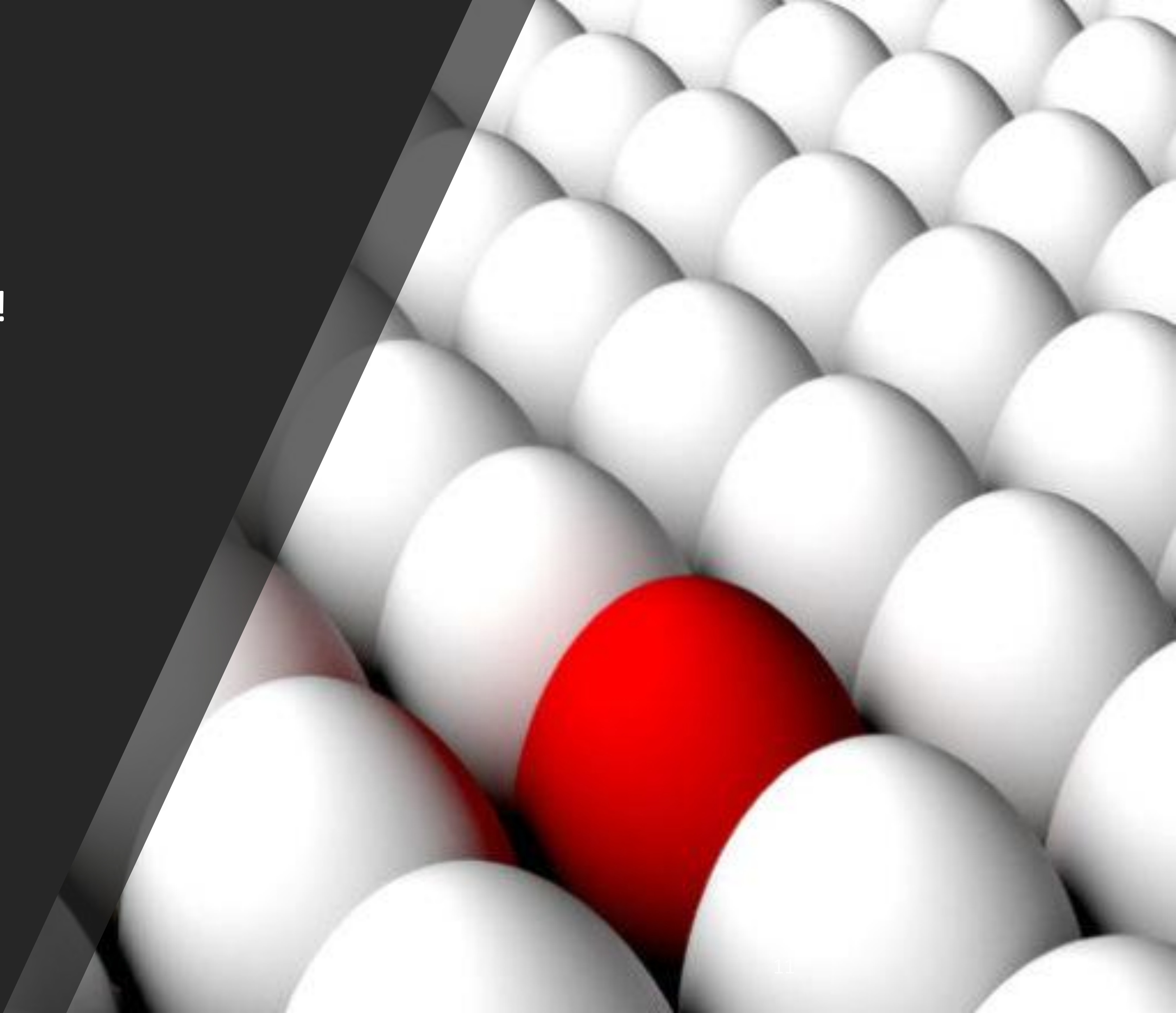
- Test on new problems (can be adapted to any image shape !)

=> CBC detection, supernovae, ...

THE END

Thank you for your attention !

Questions ?



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