The potential use of AI in gravitational waves research and the future Einstein Telescope

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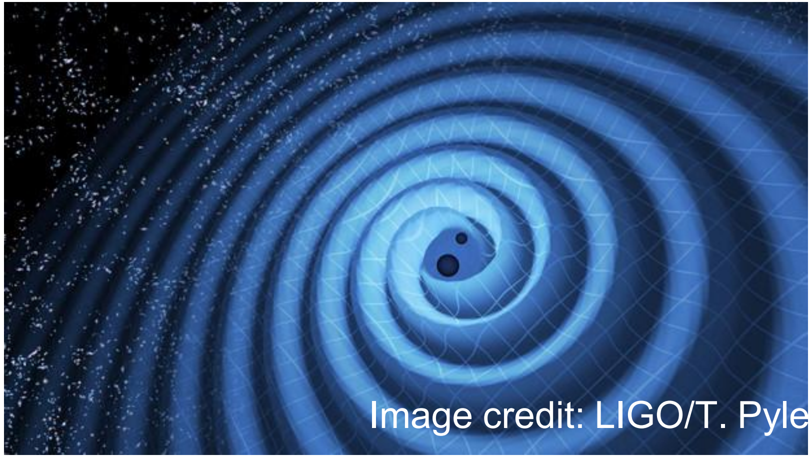
The sounds of the Universe

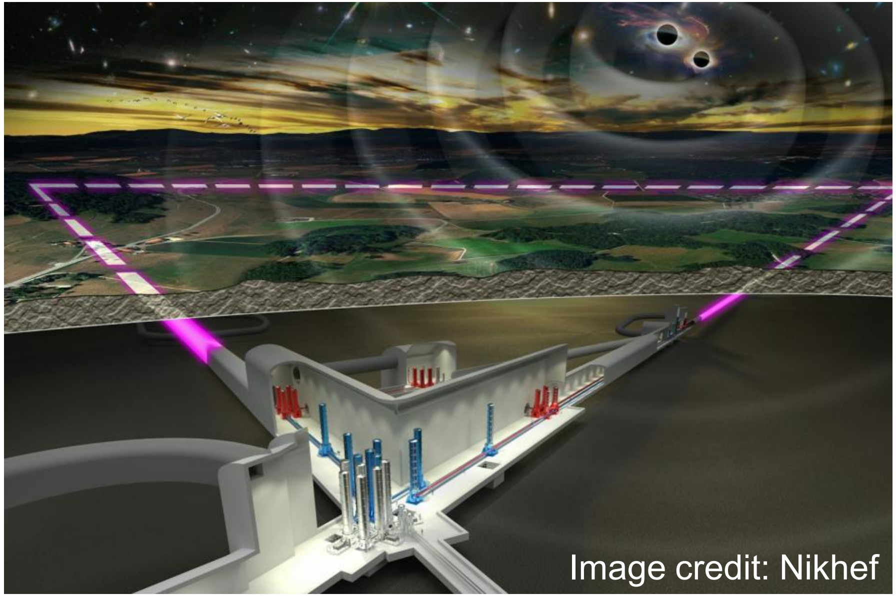
- Massive objects moving in spacetime leads to vibration of its fabric
- Since spacetime is rigid, need very dense objects to lead to detectable changes: black holes and neutron stars
- These waves travel from source to Earth for billions of years and can be detected

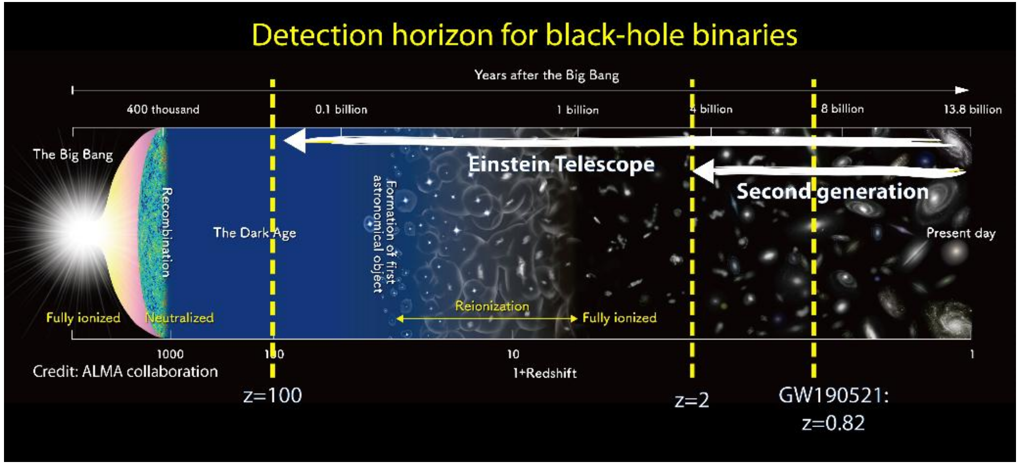


A bit like the behavior of a pound when one throws a stone into it

Listening to the Universe

Ground-based detectors are our ears to the Universe and will measure these small ripples in spacetime. They are based on interferometry.
Einstein Telescope is a planned future detector.
These instruments need to be **super sensitive** to detect signals (sensitive to changes in lengths smaller than the size of a proton).
Currently, we detect about 1 event every 3 days.
Einstein Telescope will detect a signal every few minutes.





Solving the cosmic puzzle

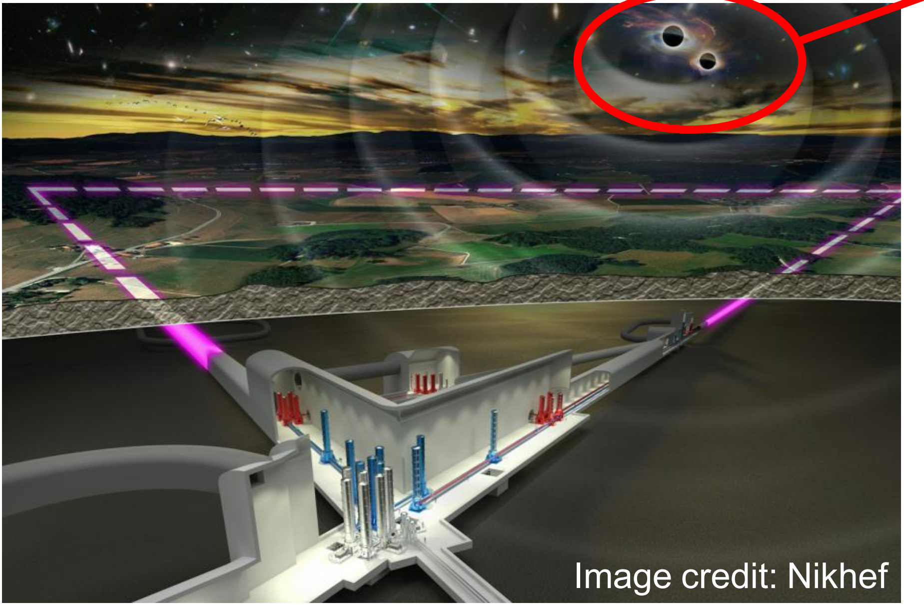
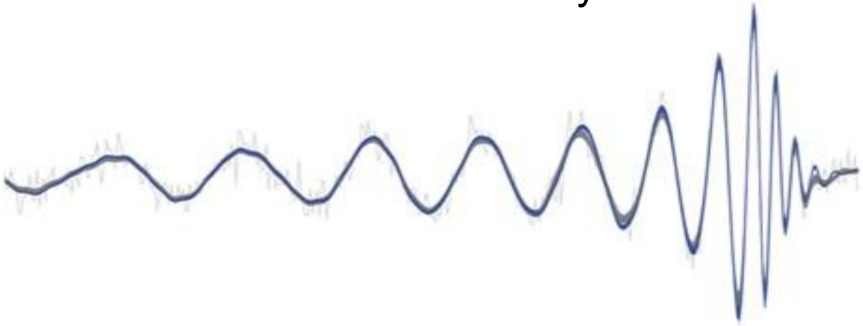


Image credit: Nikhef

Gravitational wave recorded by the detector



What are these objects?

One is interested not only in the detection but also in characteristics of the objects at the origin of the detections, such as:

- Nature of the objects (black hole v.s. Neutron star)
- Masses of the objects
- Distance at which this took place

⇒ The process of reconstructing this information is called **parameter estimation**

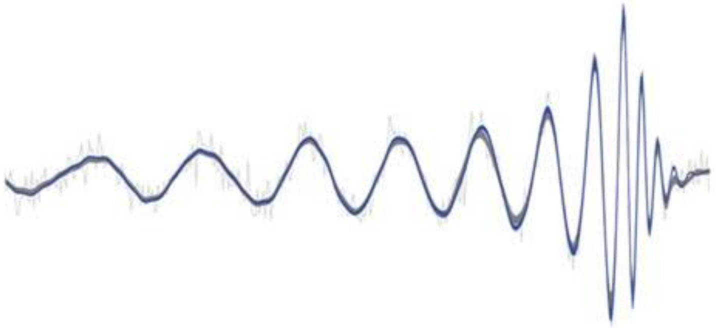
Analogy

SPLASH:

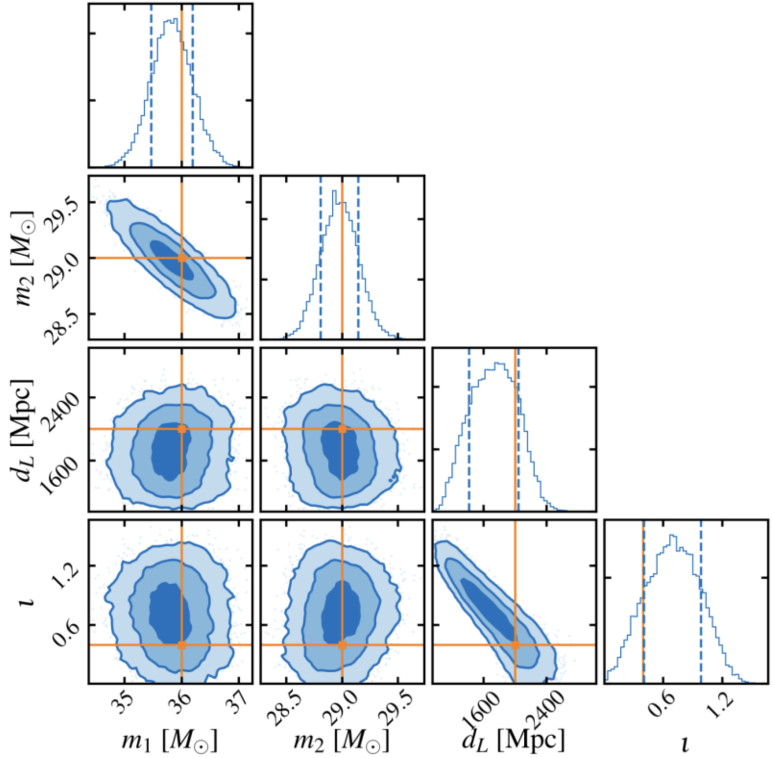
- Mass of the stone
- Distance one threw it

Solving the cosmic puzzle

Currently, parameter estimation is done with Bayesian approaches (nested sampling or MCMC)



Stochastic sampling



Credits: Ashton et al, 2018

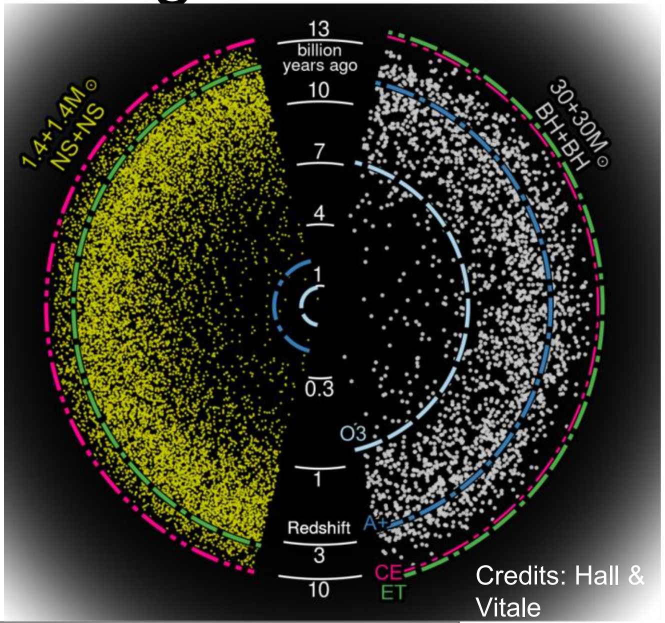
Need to find at least 15 parameters describing each detected gravitational wave event

Solving the cosmic puzzle—The Challenge

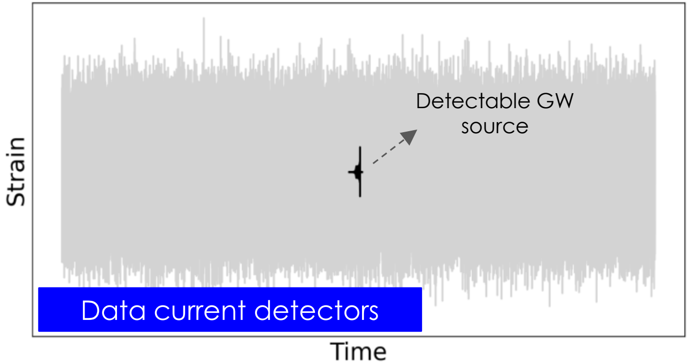
Currently, parameter estimation takes 3 days on average (16 CPUs). This is tractable when we have 1 detection every few days.

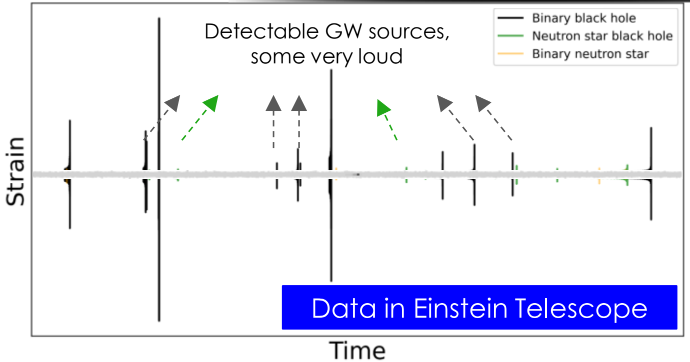
For Einstein Telescope, we would need **~33000 CPU years**. Using a computer clusters, we could bring this down to **about 10 years to analyze 1 year of Einstein Telescope data.**

This does not account for source diversity and particular conditions in Einstein Telescope (e.g. overlapping signals)



Credits: Hall & Vitale





Solving the cosmic puzzle—A solution: machine learning

Disclaimer: Various solutions have been proposed. Here, I focus on one.

Use machine learning to go from data to information about the cosmic event.

Illustration

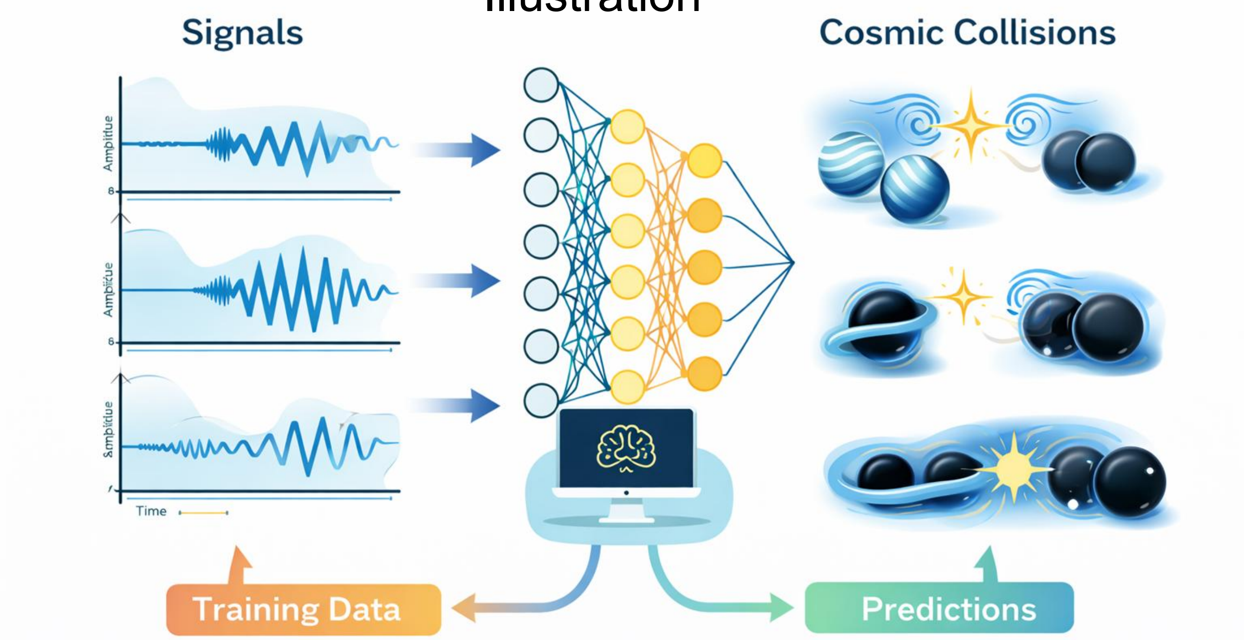


Image generated with ChatGPT

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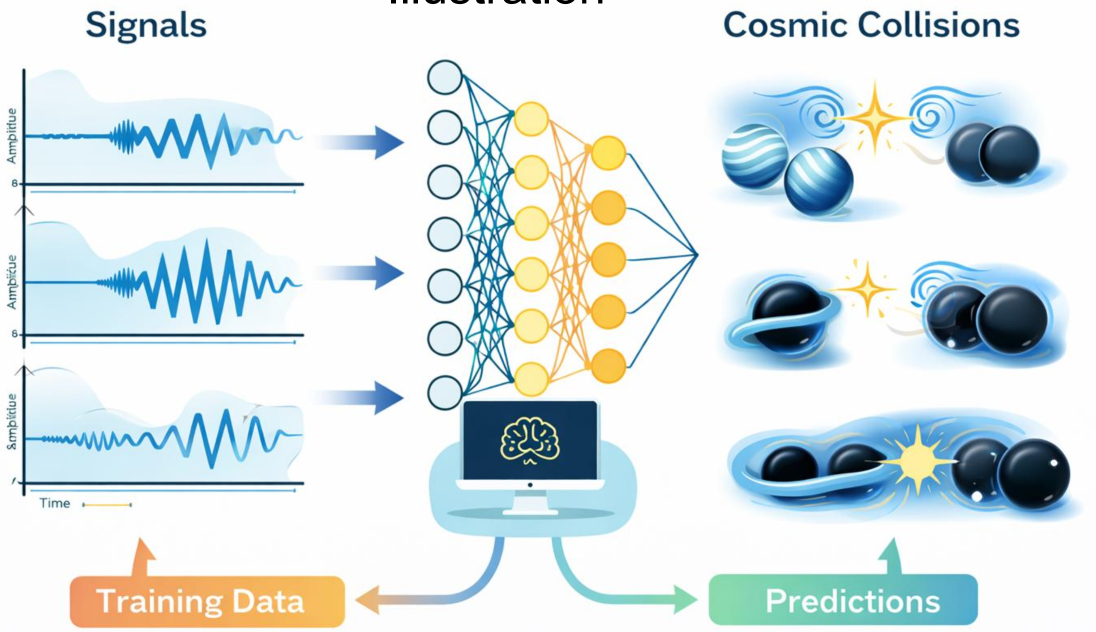

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However, interested in probability distribution of parameters → Need an adapted approach

Solving the cosmic puzzle—A solution: Normalizing flows

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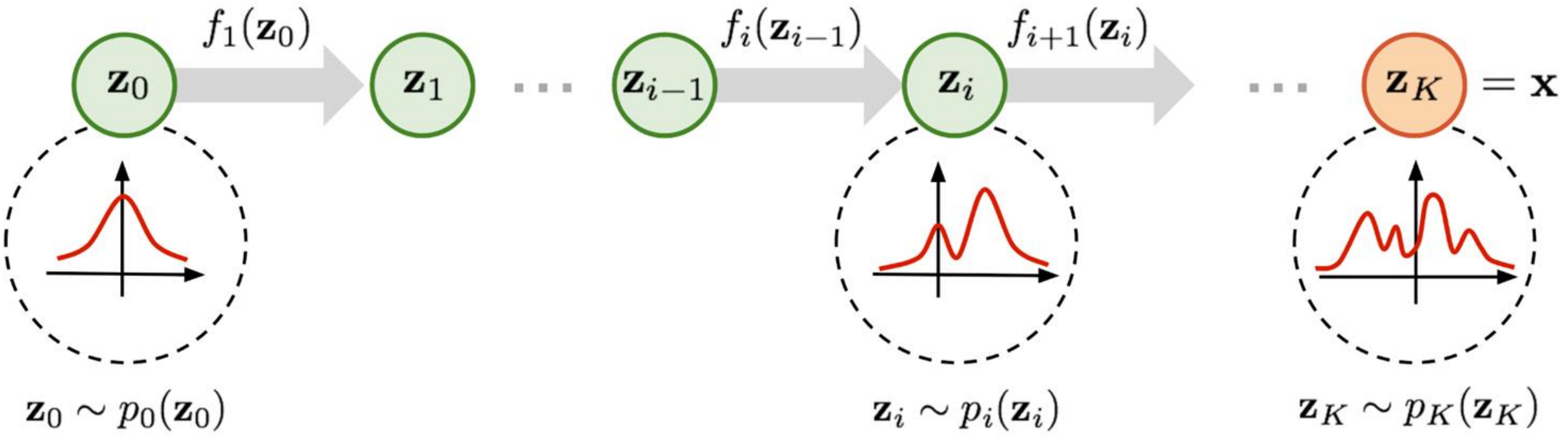
Learn the transformation from a simple distribution to a target distribution by having a series of learnable transformation shaping the initial distribution into the one we want to obtain



Solving the cosmic puzzle—A solution: Normalizing flows

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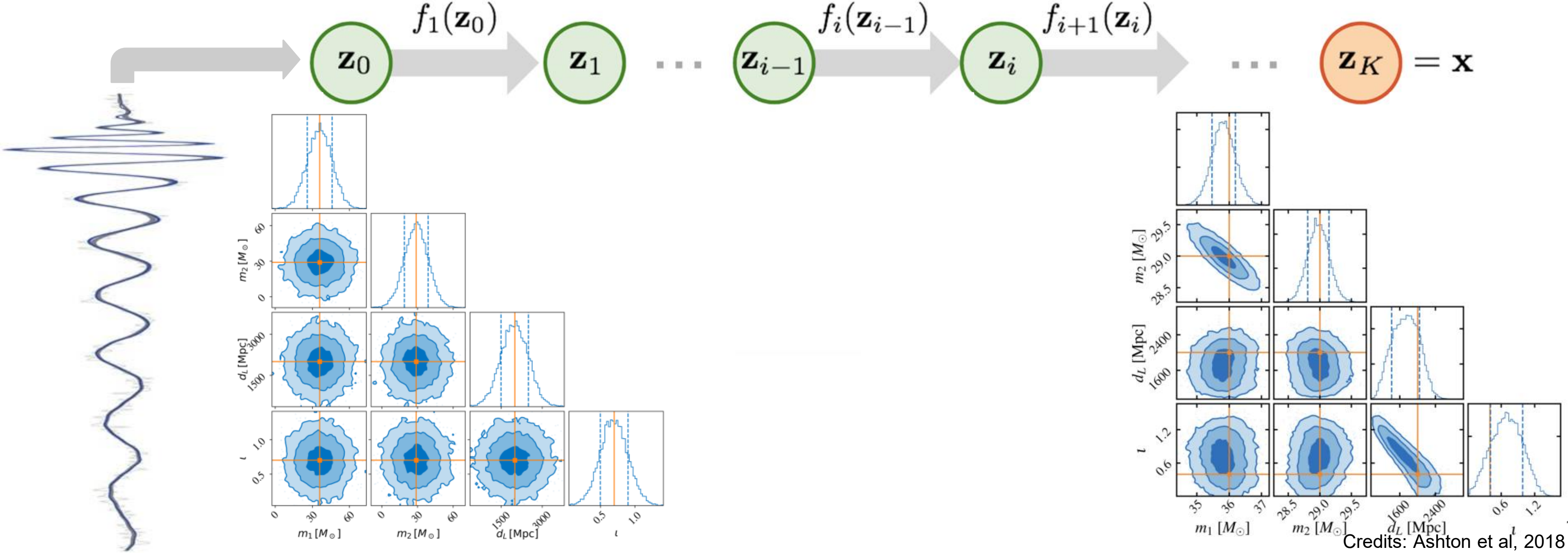
Learn the transformation from a simple distribution to a target distribution by having a series of learnable transformation shaping ~~the initial distribution~~ a Gaussian into the ~~one we want to obtain~~ parameter probability distribution conditional on the observed data.



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Solving the cosmic puzzle—A solution: Normalizing flows

Learn the transformation from a simple distribution to a target distribution by having a series of learnable transformation shaping a Gaussian into the parameter probability distribution conditional on the observed data.

Why is this important?

After training, **analyzing a signal takes a few seconds** (compared to several days), regardless of the duration of the signal.

Parameter estimation being the first step in many scientific goals of gravitational wave detectors, being able to do this step swiftly **opens many avenues**.

If the goal of future detectors is to hear the entire Universe, one also needs to be capable of analyzing all these whispers to understand the symphony. **Machine learning approaches can help enabling this.**

Why is this not routinely deployed?

Some **stability** issues and **sensitivity to changing conditions** (offline detectors, non-idealized noise, …), but growing usage.

Final words & Conclusion

Other approaches for parameter estimation are envisaged and tested. **Different methods have different strengths and weaknesses**.

There are also **other aspects of gravitational wave science** for which machine learning methods are being developed and tested (e.g. noise characterization, detector control, workflow management). Case, for example, of the ETCETERA initiative.

One main problem is accuracy and reliability: many applications are satisfied with 99.9% accuracy, science and new discoveries require 99.99997% accuracy, which is a challenging task. Currently, is obtained only in certain cases when **combining machine learning and traditional approaches** to gain some time.

However, entering an era of big data science for gravitational waves, machine learning is a valuable tool helping scientists and pushed further by scientists.

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