# Coherent Bayesian inference on compact binary inspirals using a network of interferometric gravitational wave detectors

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# **Overview:**

- **1.** gravitational waves
- 2. measuring gravitational waves
- **3.** the binary inspiral signal
- 4. prior & model
- 5. MCMC details
- **6.** example application

# **Gravitational waves**

- general relativity: space-time curved by masses
- implication: existence of **gravitational waves** (pointed out in 1916)
- existence proven in 1979
- measurement attempted since 1960s
- no *direct* measurement yet

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# **Gravitational waves**

- very weak effect
- emitted by **rapidly** moving, **heavy** objects
- event candidates:
  - supernovae
  - big bang
  - binary star systems
  - . . .



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# Measuring gravitational waves

- laser interferometry
- output: a **time series**
- problems: signal detection, parameter estimation, ....

# **Binary inspiral events**

- binary star system, orbiting around their barycentre
- energy is radiated in the form of gravitational waves
- orbits shrink, rotation accelerates
- → "chirping" GW signal (increasing frequency and amplitude)

# The "chirp" signal



(3.5PN phase / 2.5PN amplitude approximation)

# The 9 signal parameters

- masses:  $m_1$ ,  $m_2$
- luminosity **distance**:  $d_L$
- sky location: declination  $\delta$ , right ascension  $\alpha$
- orientation: inclination  $\iota$ , polarisation  $\psi$ , coalescence phase  $\phi_0$
- coalescence time:  $t_c$

# **Prior information**

- different locations / orientations equally likely
- masses: uniform across  $[1 M_{\odot}, 10 M_{\odot}]$
- events spread uniformly across space:  $P(d_L \le x) \propto x^3$
- but: certain SNR required for detection
- cheap **SNR substitute**: signal **amplitude**  $\mathcal{A}$
- primarily dependent on masses, distance, inclination:  $\mathcal{A}(m_1, m_2, d_L, \iota)$

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• introduce sigmoid function linking **amplitude** to **detection probability**:



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# Resulting (marginal) prior density



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# Marginal prior density



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# Marginal prior densities



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# Prior

- prior 'considers' **Malmquist effect** (selection effect)
- more realistic settings once detection pipeline is set up ("selection" of signals done by the signal detection algorithm)

# Model

- data from several interferometers
- **noise** assumed **gaussian**, **coloured**; interferometer-specific spectrum
- noise independent between interferometers
  ⇒ coherent network likelihood is product of individual ones
- likelihood computation based on Fourier transforms of data and signal

# **MCMC** details

- Metropolis-algorithm
- Reparametrisation,

most importantly: chirp mass  $m_c$ , mass ratio  $\eta$ 

• Parallel Tempering<sup>1</sup>

several *tempered* MCMC chains running in parallel sampling from  $p(\theta) p(\theta|y)^{\frac{1}{T_i}}$  for 'temperatures'  $1 = T_1 \leq T_2 \leq \dots$ 

<sup>1</sup>W.R. Gilks et al.: *Markov chain Monte Carlo in practice* (Chapman & Hall / CRC, 1996).

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#### **Example application**

#### • simulated data:

 $2\,M_\odot$  -  $5\,M_\odot$  inspiral at 30 Mpc distance measurements from 3 interferometers:

SNR

LHO (Hanford)	8.4
LLO (Livingston)	10.9
Virgo (Pisa)	6.4
network	15.2

- data: 10 seconds (LHO/LLO), 20 seconds (Virgo) before coalescence, noise as expected at design sensitivities
- computation **speed**: 1–2 likelihoods / second



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# **Additional examples**

- lower (total) signal-to-noise ratio (SNR)
- 'unbalanced' SNR:

	SNR
LHO (Hanford)	9.6
LLO (Livingston)	13.9
Virgo (Pisa)	0.2
network	16.9

# Low total SNR



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#### Low SNR at one interferometer



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#### Parallel tempering MCMC

- several parallel MCMC chains
- tempering: sampling from *tempered* distributions

chain	temperature	sampling from
1	$T_1 = 1$	p( heta)  p(y  heta)
2	$T_2 = 2$	$p( heta)  p(y  heta)^{rac{1}{2}}$
3	$T_3 = 4$	$p( heta)p(y  heta)^{rac{1}{4}}$
÷	:	:
		p( heta)

• additional swap proposals between chains

# MCMC chain 1 -temperature = 1



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# MCMC chain 2 - temperature = 2



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# MCMC chain 3 -temperature = 4



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# MCMC chain 4 — temperature = 8



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# Six tempered chains over time



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