Gravitational-wave detection with pulsar timing

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Outline

1. Pulsar Timing
   - Pulsars for GW detection?
   - Pulsar observing
   - Timing-residuals
2. Data analysis of PTAs
   - Bayesian data analysis
   - Modelling the data
   - GW Signals
3. Results so far
   - EPTA limit
   - Conclusions

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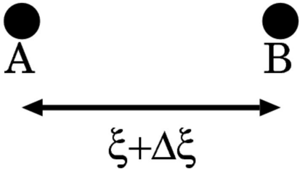
Detecting Gravitational Waves

What we are looking for are:

Changes in the metric

- Resonant mass
  - Explorer, Nautilus, miniGRAIL, . . .
- Laser interferometry
  - Geo, Ligo, Virgo, LISA, . . .



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Need precise frequency standard

- Gravitational waves are very weak
- Need very precise frequency standard/clock: e.g. LASER
- Use interferometry to detect phase change

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- Pulsar PSR B1937+21 has a rotational period of

$$T = 0.00155780644887275 \text{ sec.}$$

- Use millisecond pulsars!!! (MSPs)

Timing residuals: difference with interferometers

- Pulsar pulse times of arrival (TOA's) can be very precisely modeled.
- Timing residuals (TRs) are primary data:
- $\delta t = t_{\text{observed}} - t_{\text{expected}}$

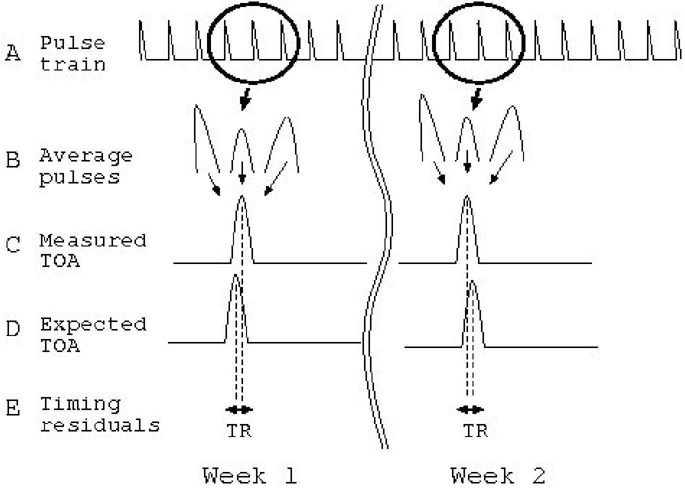
Timing residuals: difference with interferometers

- Pulsar pulse times of arrival (TOA's) can be very precisely modeled.
- Timing residuals (TRs) are primary data:
- $\delta t = t_{\mathrm{observed}} - t_{\mathrm{expected}}$

- We cannot control the setup, not possible to eliminate external systematics
- Limited to telescope time, have to share with others

- Have to do a lot of pre-processing before we have a time of arrival (TOA)

Making timing-residuals (simplified)



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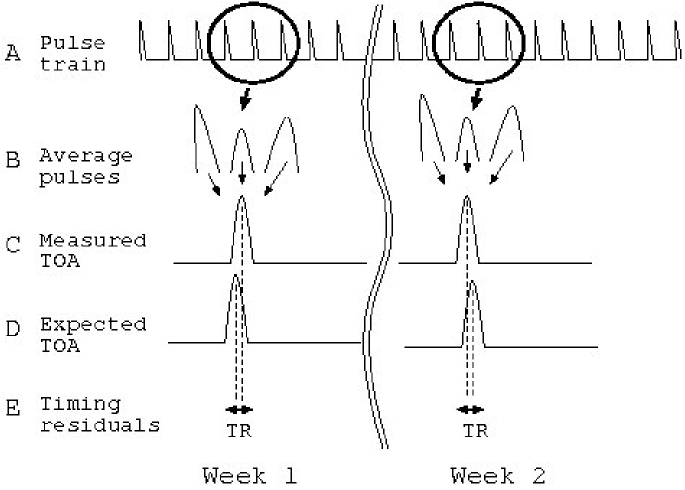
Some typical numbers

- Pulse period 5ms
- Pulse width 0.5ms
- Timing accuracy 100ns
- Distance to pulsar several kpc
- Sensitivity to distance variations to pulsar 30m (<1 part in 10^{18})
- Can account for every rotation, even when not looking at pulsar for months!

Compare C & D: Need timing model parameters



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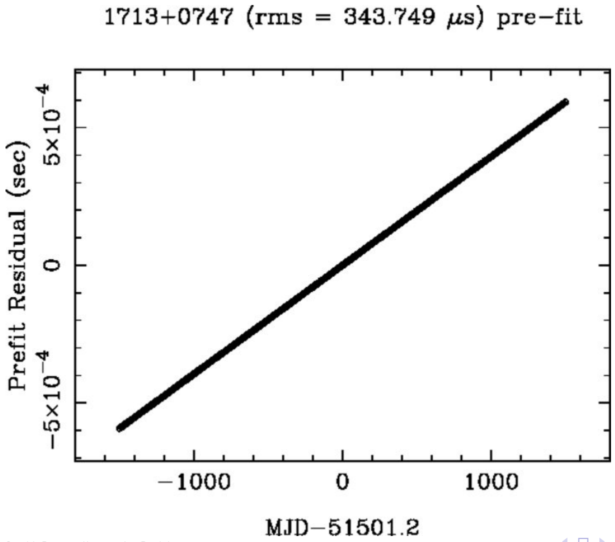
Processing TOAs: Wrong timing model. . . Re-fit!



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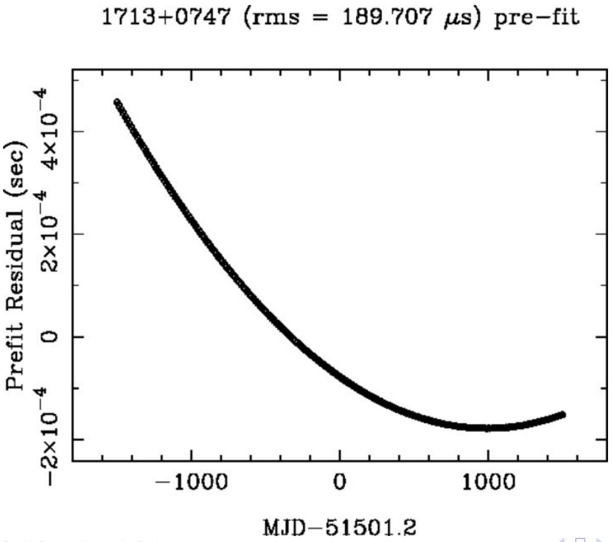
Processing TOAs - period derivative



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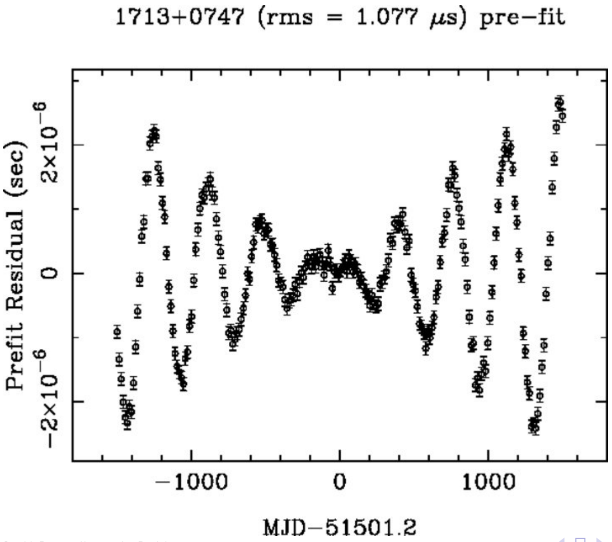
Processing TOAs - proper motion



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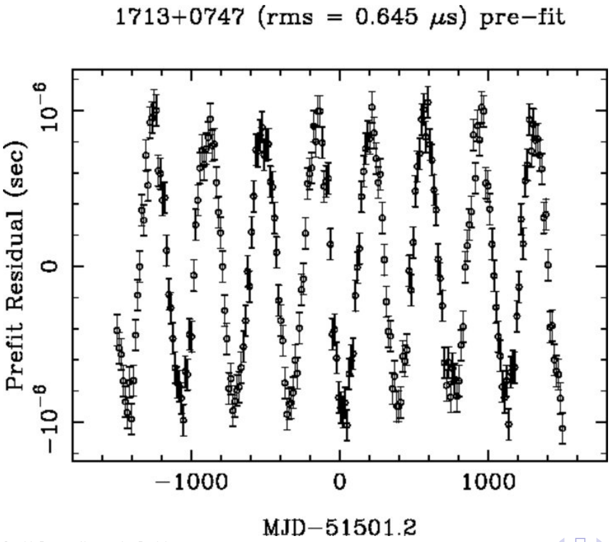
Processing TOAs - sky position



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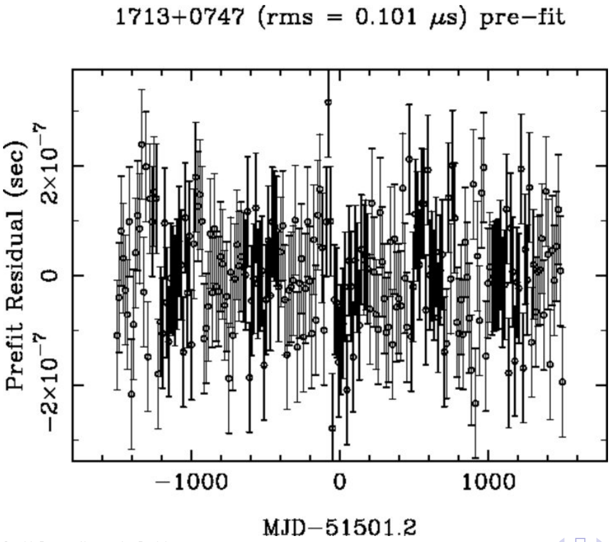
Final step: E - timing-residuals



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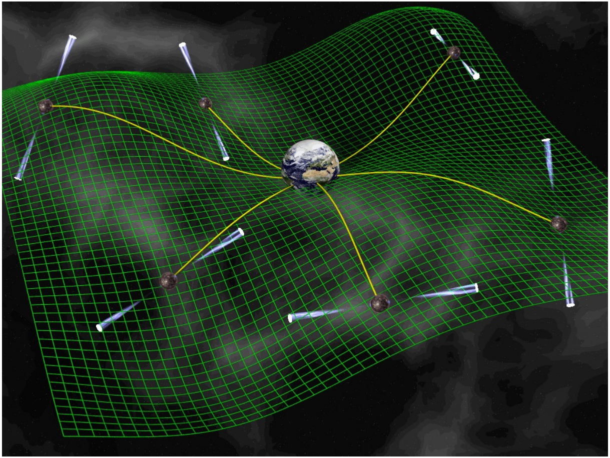
The pulsar timing array: many arms



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Sources of timing-residuals

- Noise, among others:
  - Receiver noise
  - Irregularities of pulsar beam rotation (timing-noise)
  - Imprecision of local atomic clocks
  - Variation in refractive index of interstellar medium (scintillation)
  - Polarisation calibration of the telescope
- Gravitational-waves, typically 10s of nHz, only depending on duration of experiment and observation cadence:
  - Ensemble of BH binaries at centres of galaxies (stochastic background)
  - Relic gravitational-waves (stochastic background)
  - Cusps in cosmic-string loops (stochastic background)
  - BH-BH mergers: gravitational-wave memory (burst, deterministic)
  - BH-BH orbits: single-sources (deterministic)

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Analysis: differences with controlled experiments

- No continuous data stream. Observations are taken with irregular intervals in between (typically weeks)
- Duration of the signal is comparable to the duration of the experiment.
- Very significant systematic corrections must be taken into account (e.g. quadratics): acts as a linear time-variant filter that alters low-frequency behaviour.

- As part of the EPTA, a public toolkit/library is being implemented that can be used when developing new algorithms for PTA data analysis. Stochastic GWB, single-source, F-statistic, correlations. . .

PTA Bayesian analysis in a nutshell

- Model the stochastic signals (timing-noise and GWB) as a random Gaussian process with a certain power spectral density: construct likelihood.
- Analytically marginalise over all the deterministic timing model parameters.
- Use MCMC / Affine invariant sampler to marginalise over all the other model parameters

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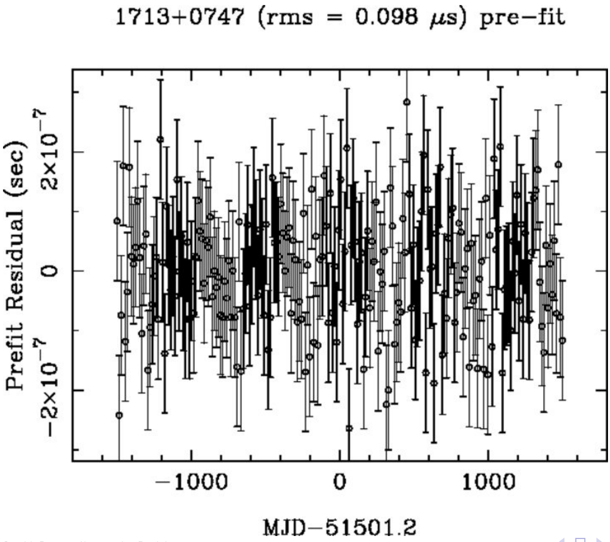
- Computational cost goes as n^3, with n number of observations. Need a lot of computational time.
- For recent EPTA limit we used 1000 cpu hours, but real datasets are already over 5 times larger.

Simulated residuals without a signal



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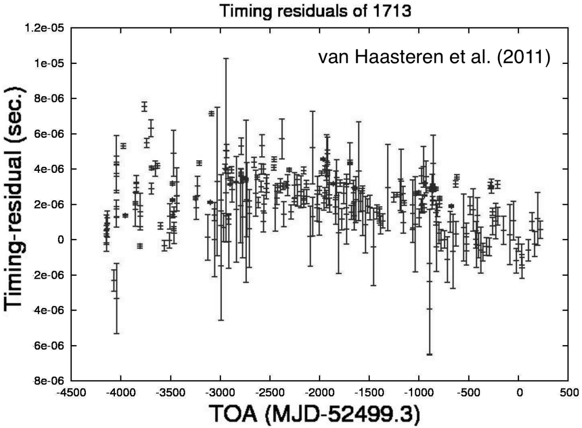
Example of J1713 (Effelsberg)



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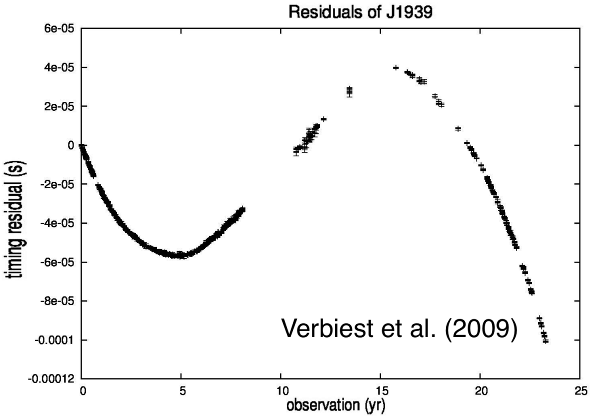
Example of J1939 (Parkes)



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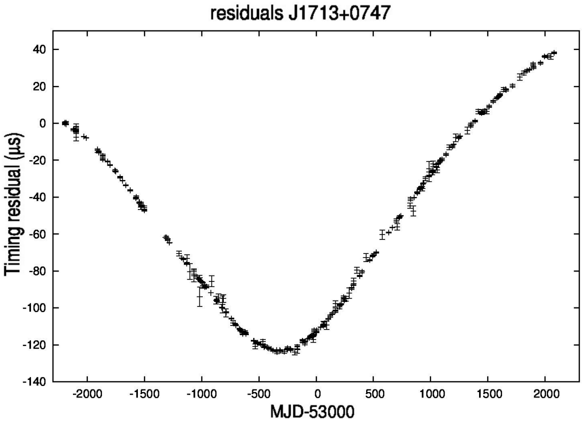
Simulated data: red noise - power-law PSD



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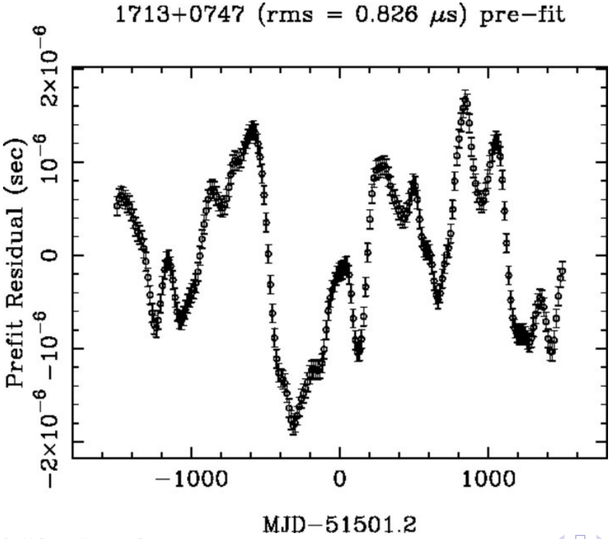
Simulated data: red noise - exponential PSD



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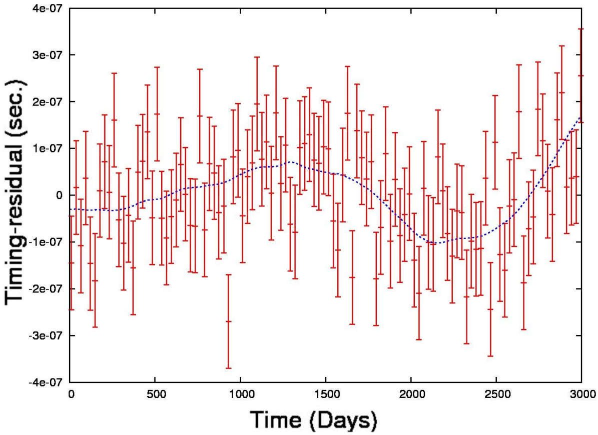
Stochastic background



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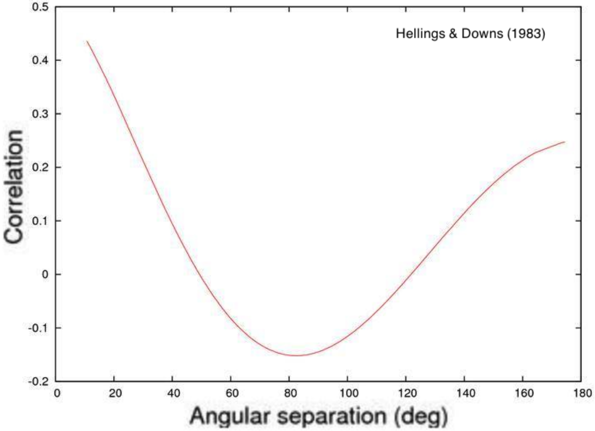
Overlap reduction function (H&D Curve)



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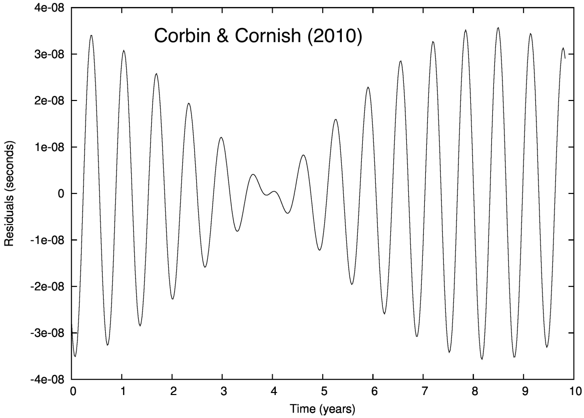
Quadrupolar correlations: the GW fingerprint

Single sources: massive BHB



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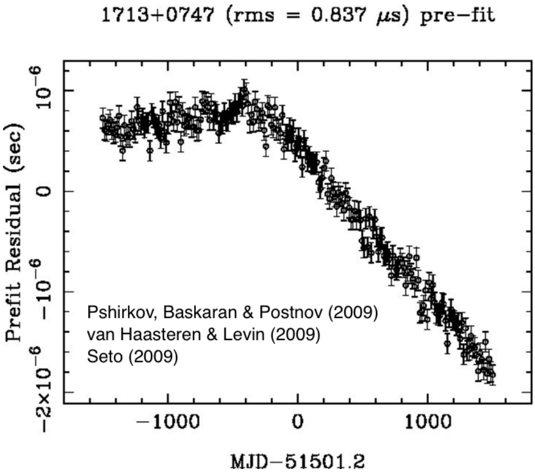
Single sources: GW Memory



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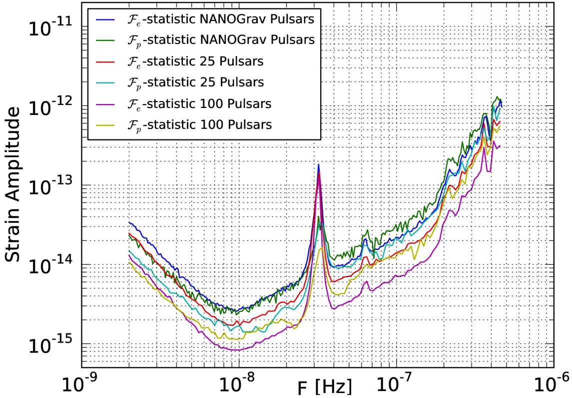
Correlated between pulsars

Sensitivity



Ellis, Siemens & Creighton (2012)

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The International Pulsar Timing Array

EPTA

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PPTA

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NANOGrav

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The European Pulsar Timing Array

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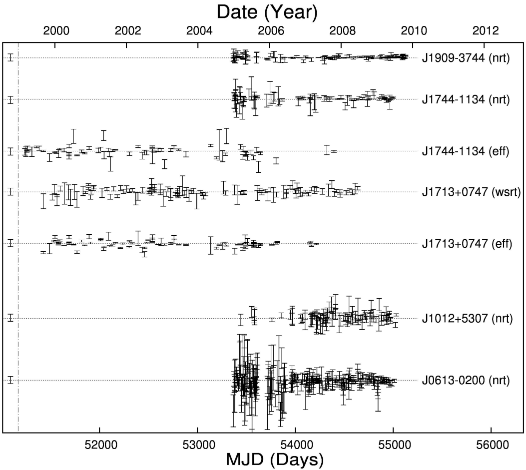
All the timing residuals



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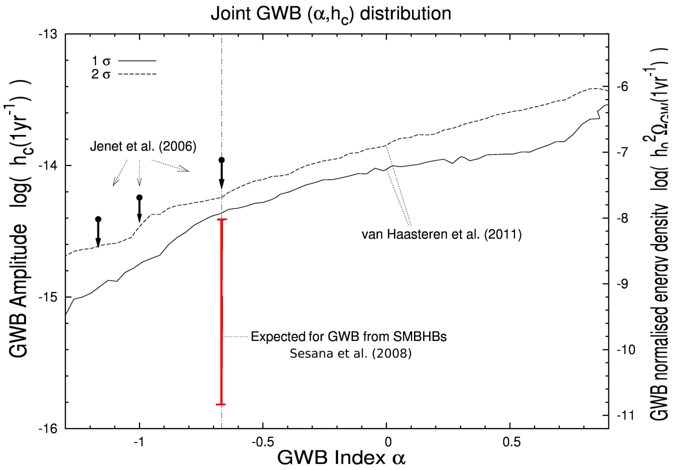
GWB limit



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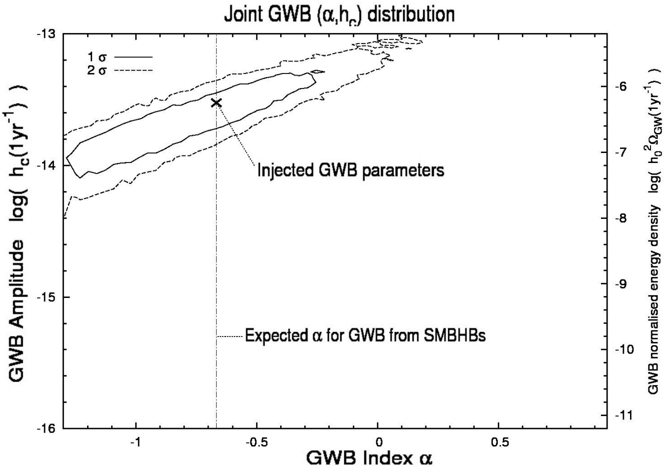
GWB detection of injected signal



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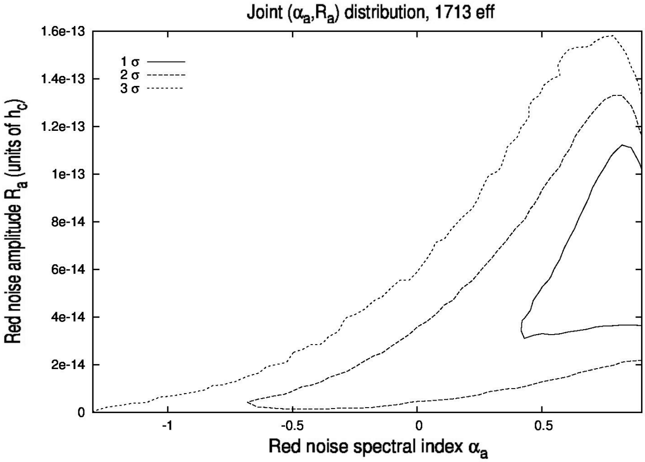
Red noise



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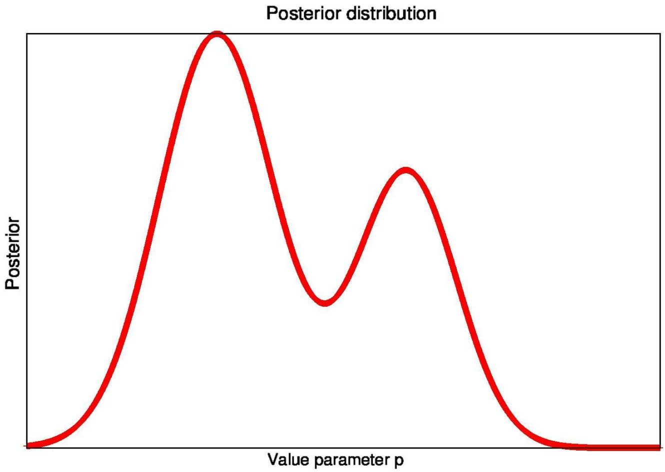
Conclusions and remarks

- Pulsar timing very similar to interferometers with respect to GW detection: different frequency band
- GWs are unambiguously detect by their uniquely correlated signal across
- Most stringent GWB upper limit to date from European PTA data.
- Currently working on International PTA (IPTA) data analysis: worldwide collaboration
- Public and universal data analysis library/tookit in production as part of the EPTA. Includes an implementation of the Bayesian PTA analysis pipeline. Language: Python (and C)
- IPTA mock data challenge has just been released. Everyone invited to participate

Posterior distribution



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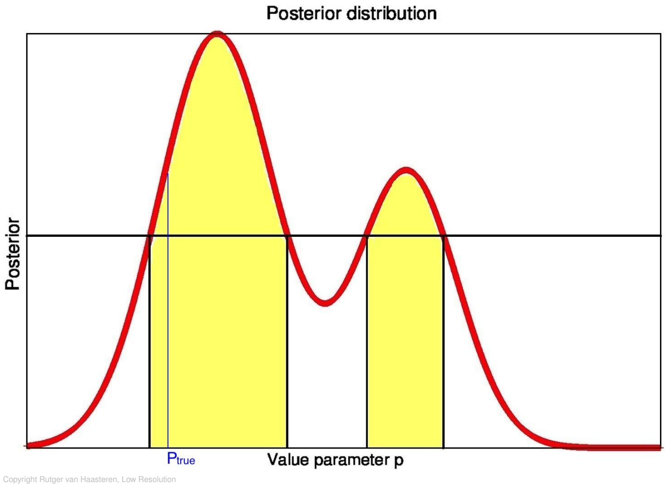
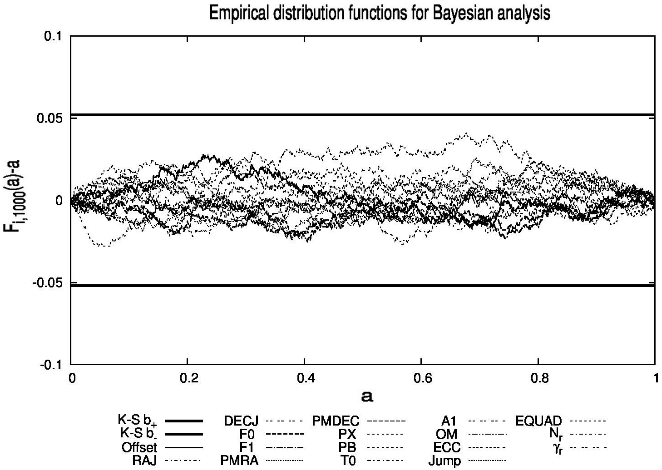
Posterior distribution



Emperical distribution function (Bayesian)



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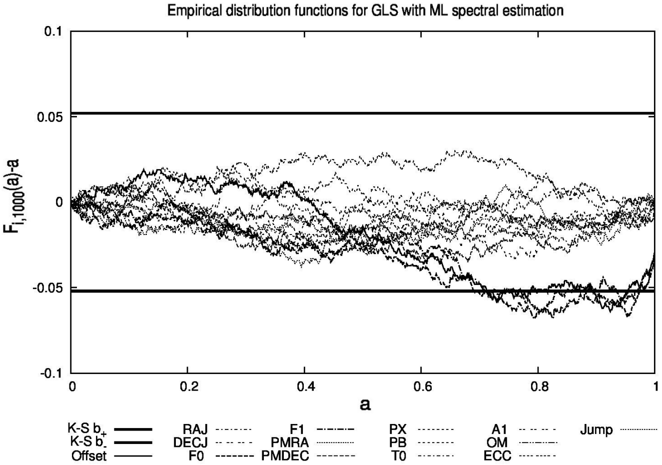
Posterior distribution (ML)



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