

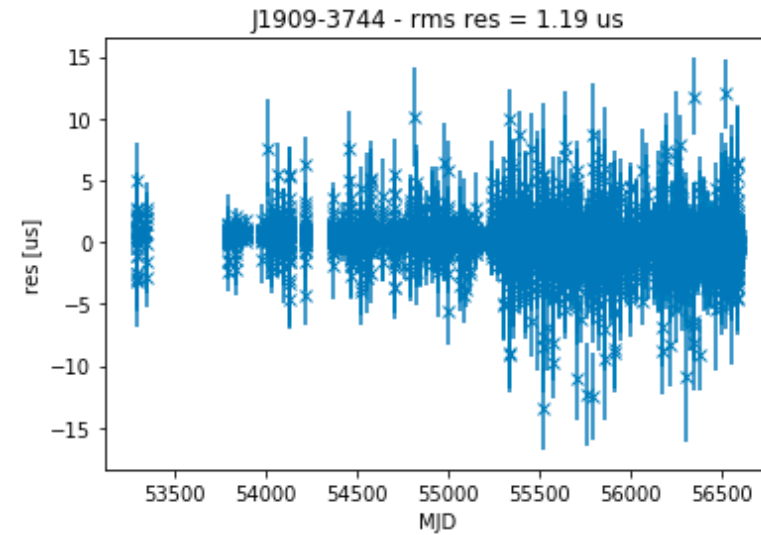
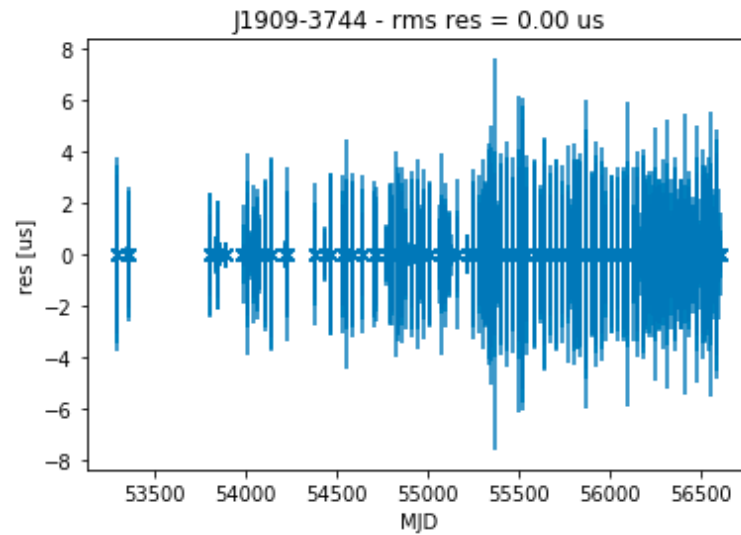
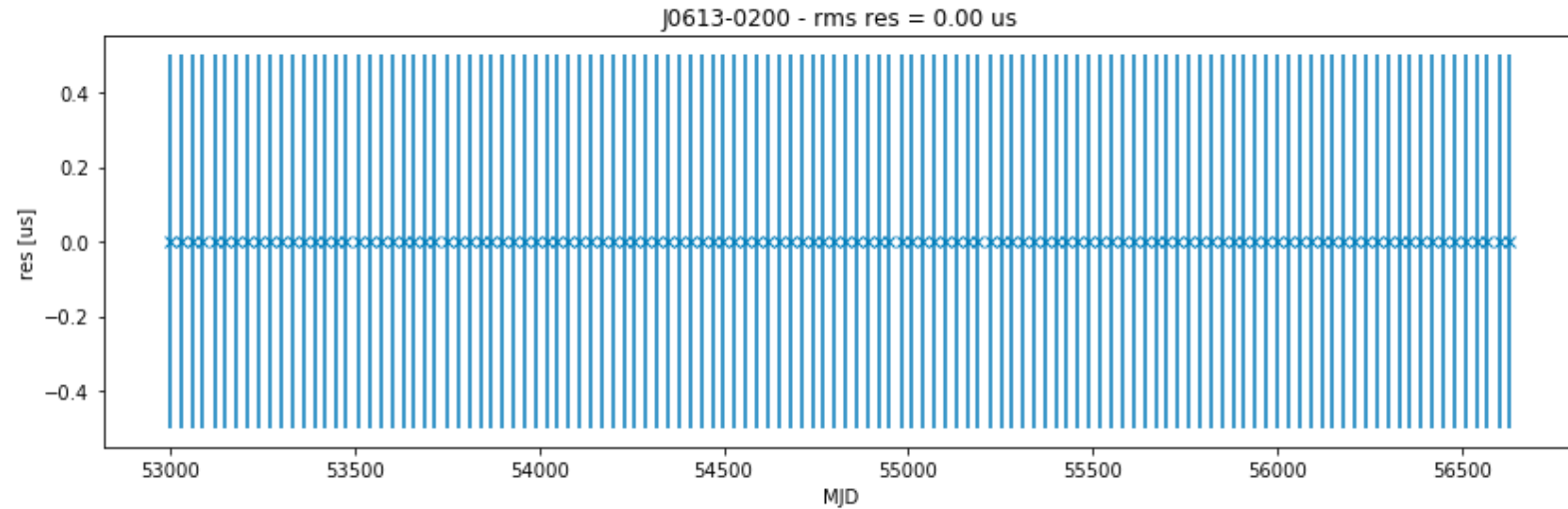
# Introduction to inference in pulsar timing

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# Measurement in pulsar timing



# Likelihood function

$$L(\theta, \xi | \delta t) = \frac{1}{\sqrt{(2\pi)^k \det(C)}} \times \exp \left( -\frac{1}{2} (\delta t - s - M\xi)^T C^{-1} (\delta t - s - M\xi) \right)$$

- $C$  – covariance matrix, **stochastic signals**, dimensions:  $n \times n$
- $\delta t$  – vector of timing residuals
- $(-s - M\xi)$  – **deterministic signal** vector that has a known functional form for time-evolution
- $M\xi$  – timing model signal vector
- $M$  – design matrix, dimensions:  $n \times m$  [ToA x timing model parameters]
- $\xi$  – timing model parameters
- $s$  – other deterministic signals, i.e. from perturbation in Solar System Ephemeris parameters

# Likelihood marginalization over timing model parameters

In order not to sample timing model parameters  $\xi$ , we can assume a uniform prior and marginalize our likelihood over these parameters:

$$L(\theta|\delta t) = \frac{\sqrt{\det(M^T C^{-1} M)^{-1}}}{\sqrt{(2\pi)^{n-m} \det(C)}} \times \exp\left(-\frac{1}{2}(\delta t - s)^T C' (\delta t - s)\right)$$

$$C' = C^{-1} - C^{-1} M (M^T C^{-1} M)^{-1} M^T C^{-1}$$

# Correlations in pulsar timing

- No correlations, white noise
- Between measurements
  - Red noise
  - DM variations
- Between pulsars
  - Clock error (monopole)
  - Error in Solar System Ephemeris (dipole)
  - Stochastic gravitational-wave background (quadrupole)

**Dominant computational cost:  $C^{-1}$**

# Likelihood

- We can further reduce computational cost by rewriting our likelihood:

$$L(\theta|\delta t) = \frac{1}{\sqrt{(2\pi)^{n-m} \det(G^T C G)}} \times \exp \left( -\frac{1}{2} (\delta t - s)^T G (G^T C G)^{-1} G^T (\delta t - s) \right)$$

Where G obtained through the singular value decomposition of design matrix M:

$$M = U S V^*$$

S – singular values of M

U, V – unitary matrices

# Covariance matrix – stochastic signals

- White noise: diagonal covariance matrix, the inverse of elements:

$$\sigma_s^2 = T^2 E F A C^2 (\sigma^2 + T^2 E Q U A D^2)$$

$$\sigma_s^2 = (E F A C \sigma)^2 + E Q U A D^2$$

- Red noise: off-diagonal terms are non zero
  - We model PSD of a stochastic process,  $P(f)$ , and construct a covariance matrix, given parameters of that PSD model. For example:

$$C(\tau) = \int_0^\infty P(f) \cos \tau f df \quad - \text{Weiner-Khinchin theorem}$$

- $\tau$  – time delay between measurements of timing residuals

# Red noise modelling

$$P(f) = \frac{P_0}{\left[1 + \left(\frac{f}{f_c}\right)^2\right]^{\alpha/2}}, \quad \text{Lorentzian power-law}$$

$$P(f) = \frac{A^2}{12\pi^2} \text{yr}^3 \left(\frac{f}{\text{yr}^{-1}}\right)^{-\gamma} \quad \text{Power-law}$$

In our analysis represented in covariance matrix  $C$ ,  
as a component:

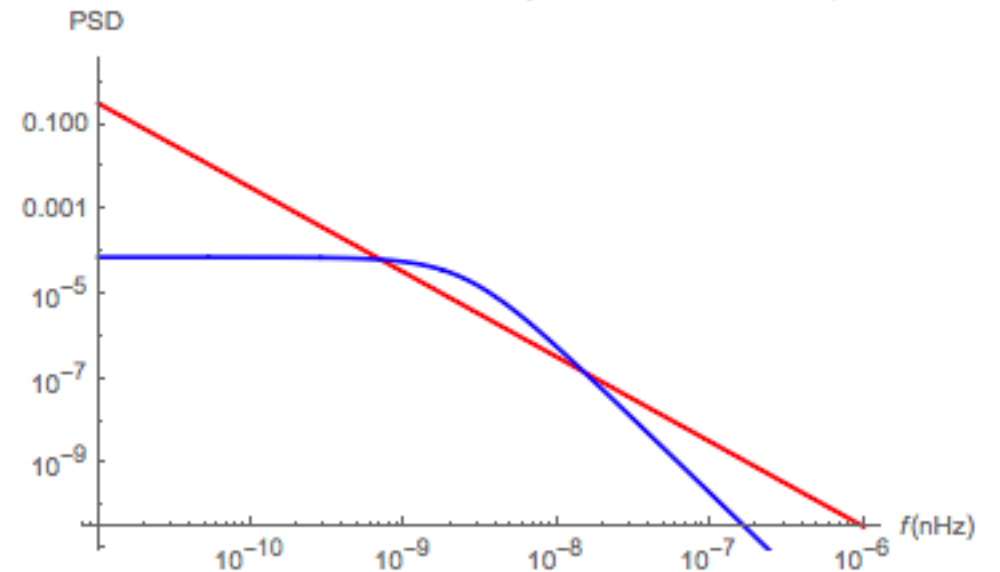
$$K = F \Phi F^T$$

Where  $\Phi$  – defines a power-law  
 $F$  – Fourier transformation matrix  
(Fourier design matrix)

Then we can do a faster inversion of  $C$ :

$$(N + F\Phi F^T)^{-1} = N^{-1} - N^{-1}F(\Phi^{-1} + F^T N^{-1}F)^{-1}F^T N^{-1}$$

J0437–4715 red noise. Red line: Bayesian. Blue line: Frequentist.





# Red noise process example (DM noise)

