



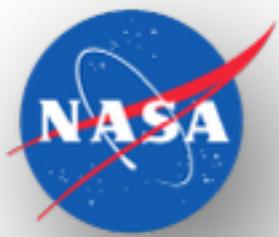
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Gravitational Wave Detection



Stephen R. Taylor

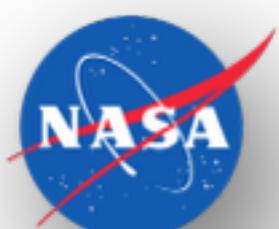
JET PROPULSION LABORATORY,
CALIFORNIA INSTITUTE OF TECHNOLOGY



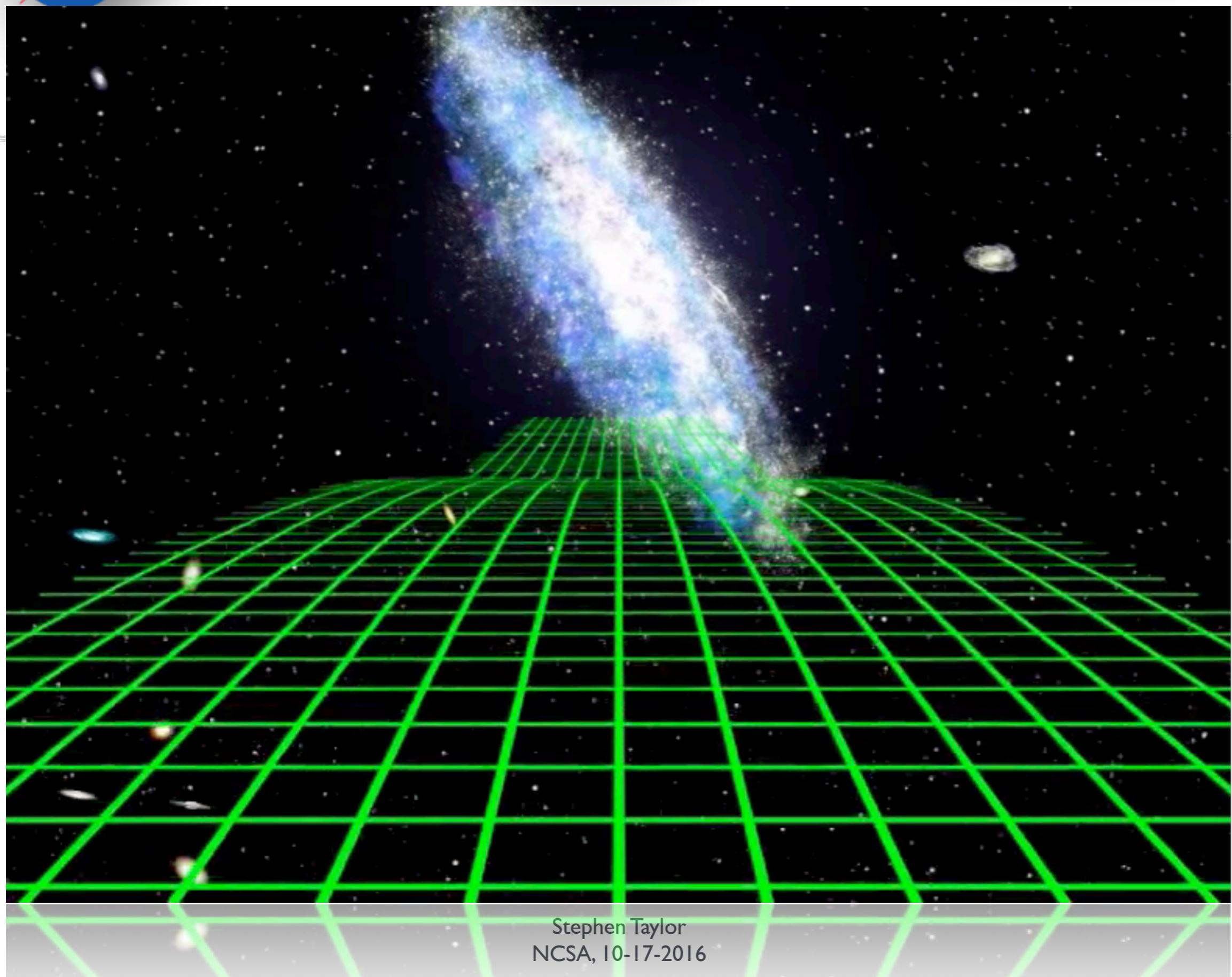
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Overview

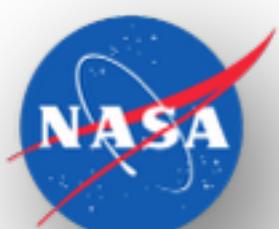
- ▶ Bayesian inference
- ▶ Search strategies for stochastic and deterministic signals
- ▶ Assessing detection significance



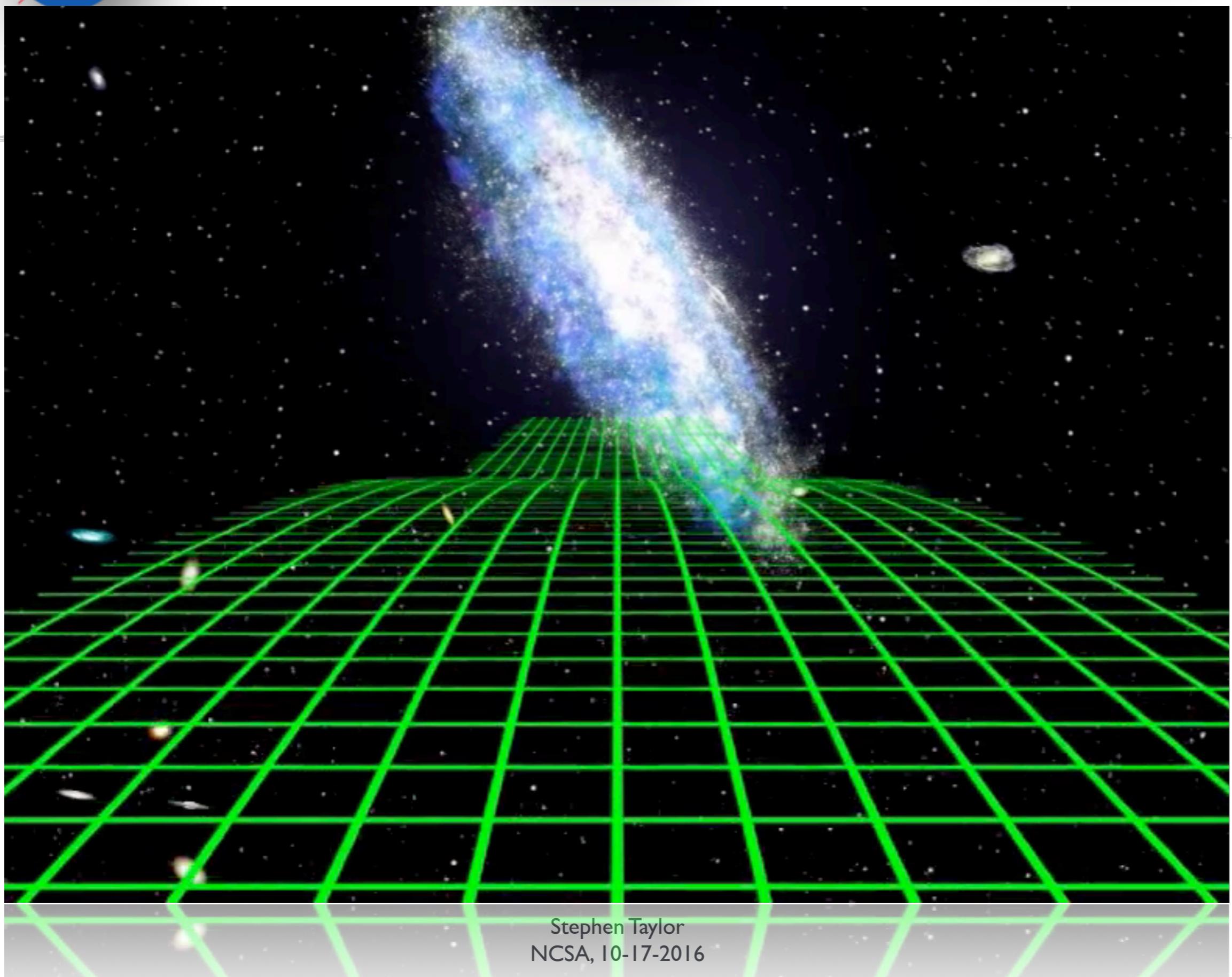
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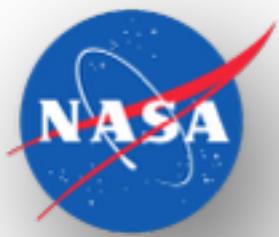
Stephen Taylor
NCSA, 10-17-2016



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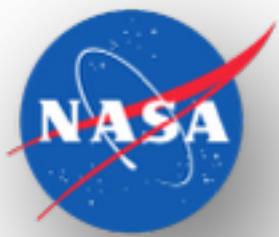


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Bayesian Inference



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Bayesian Inference

Bayes' Theorem

$$p(A, B) = p(A)p(B|A) = p(B)p(A|B)$$

$$p(B|A) = \frac{p(A|B)p(B)}{p(A)}$$



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$$p(\vec{\theta}|\vec{d}) = \frac{p(\vec{d}|\vec{\theta})p(\vec{\theta})}{p(\vec{d})}$$



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Bayesian Inference

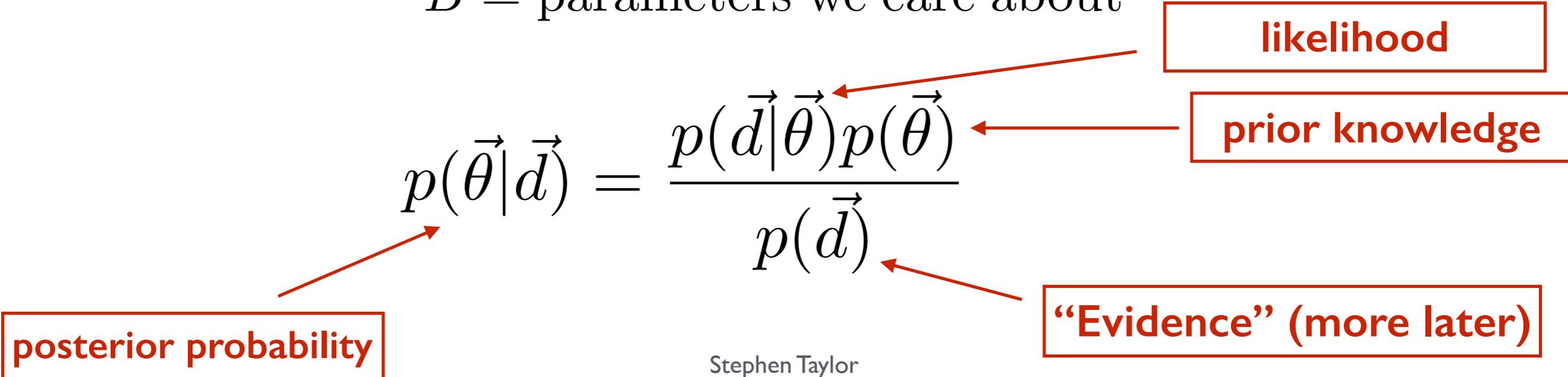
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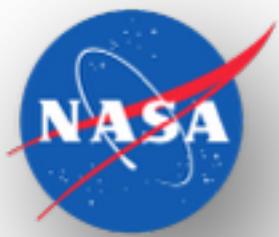
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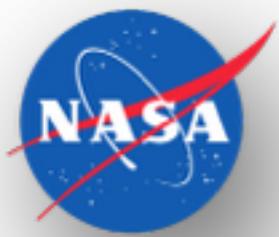
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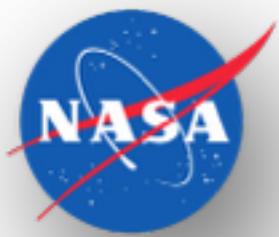
Bayesian Inference



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Bayesian Inference

- ▶ Bayesian inference recovers probability distributions — measures *the spread in our belief.*



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Bayesian Inference

- ▶ Bayesian inference recovers probability distributions — measures *the spread in our belief.*
- ▶ Frequentist inference recovers frequency distributions — measures *the long-timescale spread of experiments.*

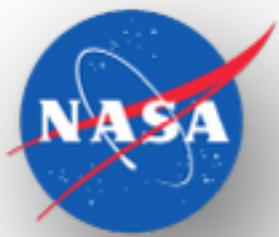


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Bayesian Inference

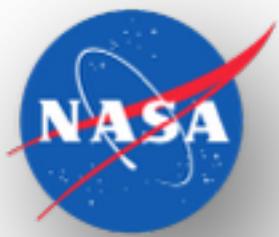
Example:

- A disease test is accurate 99% of the time.
- But the disease is quite rare: only affects 1 in 10,000 people.
- If a test comes back positive, what is the probability that you actually have the disease?
- Intuition might lead us to think that, since the test is 99% accurate, then there is a good chance we are infected!



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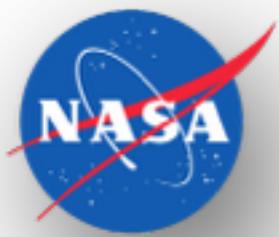
Bayesian Inference



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Bayesian Inference

$$p(\text{infected}|\text{positive test}) = \frac{p(\text{positive test}|\text{infected})p(\text{infected})}{p(\text{positive test})}$$

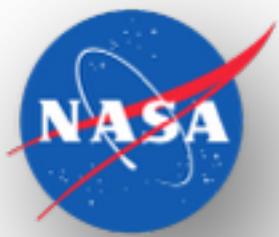


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Bayesian Inference

$$p(\text{infected}|\text{positive test}) = \frac{p(\text{positive test}|\text{infected})p(\text{infected})}{p(\text{positive test})}$$

$$p(\text{infected}|\text{positive}) = \frac{0.99 \times 0.0001}{0.99 \times 0.0001 + 0.01 \times 0.9999}$$



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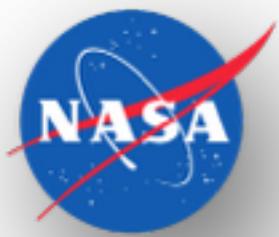
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$$\sim 0.01$$

ONLY 1% !!!

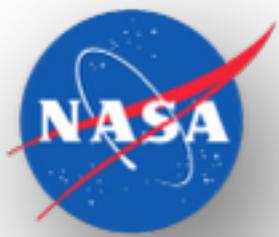


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The Pulsar-timing Likelihood

Two basic types of signals

- (1) **stochastic** — characterize through statistical properties, e.g. standard deviation
- (2) **deterministic** — characterize through amplitude, phase, etc.



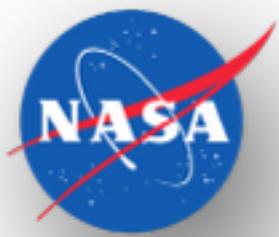
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$$p(\delta\mathbf{t}|\mathbf{n}) = \frac{\exp(-\frac{1}{2}(\delta\mathbf{t} - \mathbf{s})^T N^{-1}(\delta\mathbf{t} - \mathbf{s}))}{\sqrt{\det(2\pi N)}}$$



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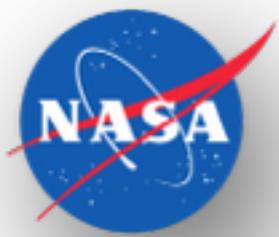
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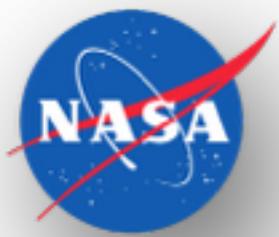
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The only difference between treating stochastic signals and deterministic signals is through our prior on \mathbf{S}



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Searching for single GW sources



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Searching for single GW sources

Deterministic signal

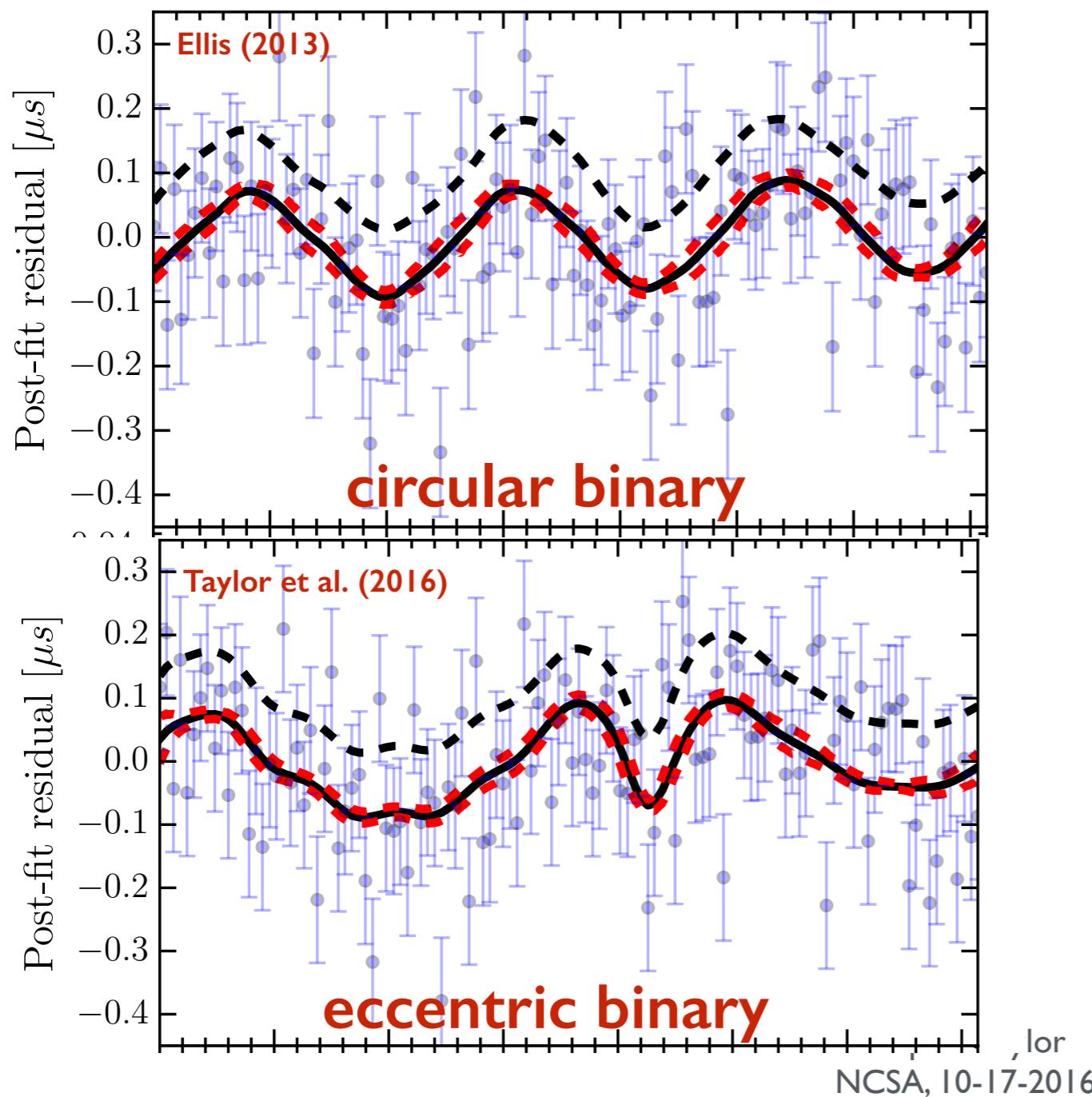
$$\delta t \rightarrow \delta t - s(t)$$



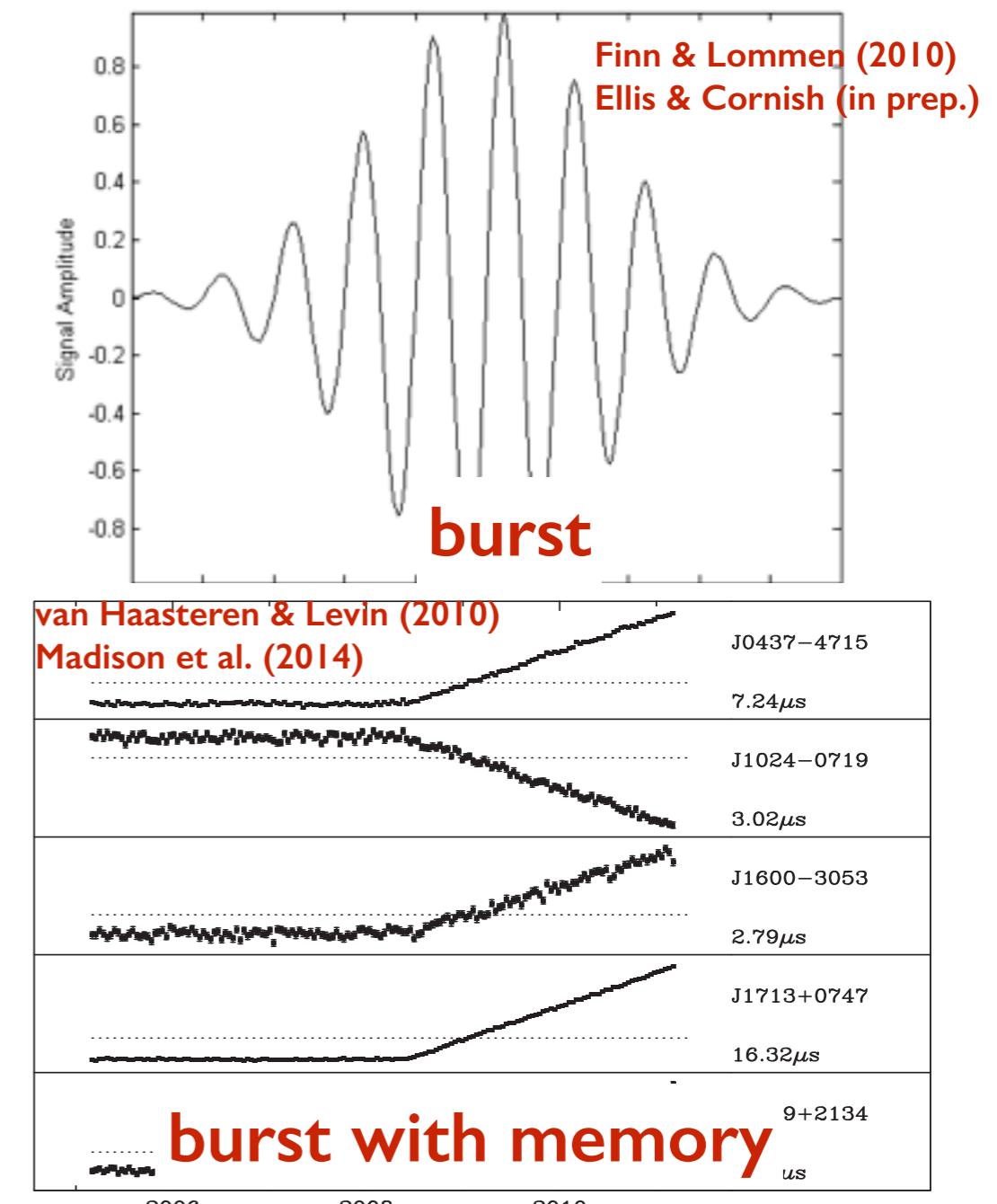
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Searching for single GW sources

Deterministic signal



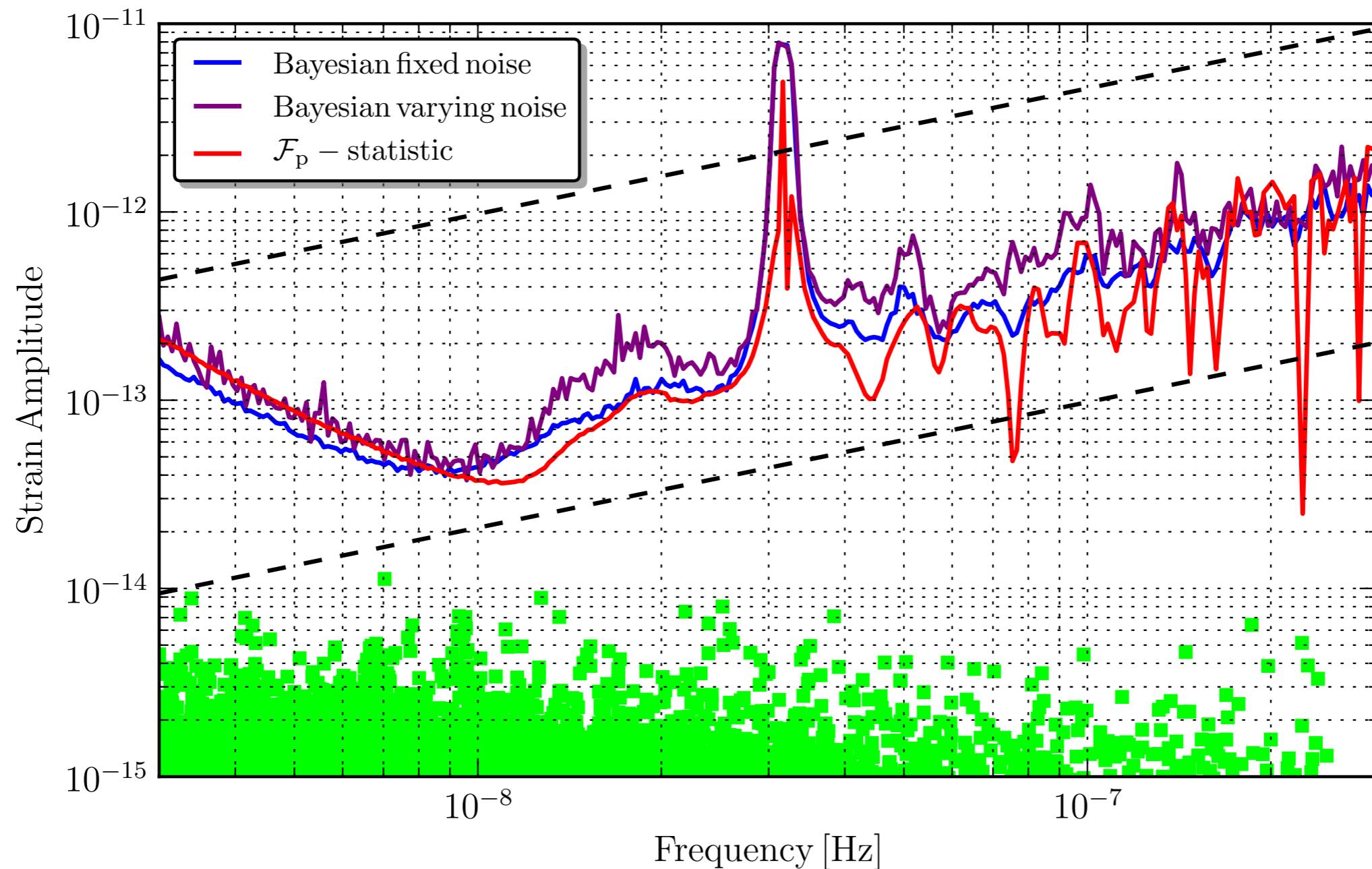
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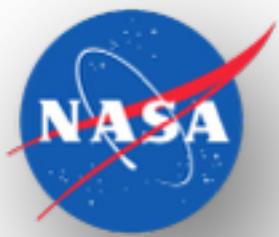




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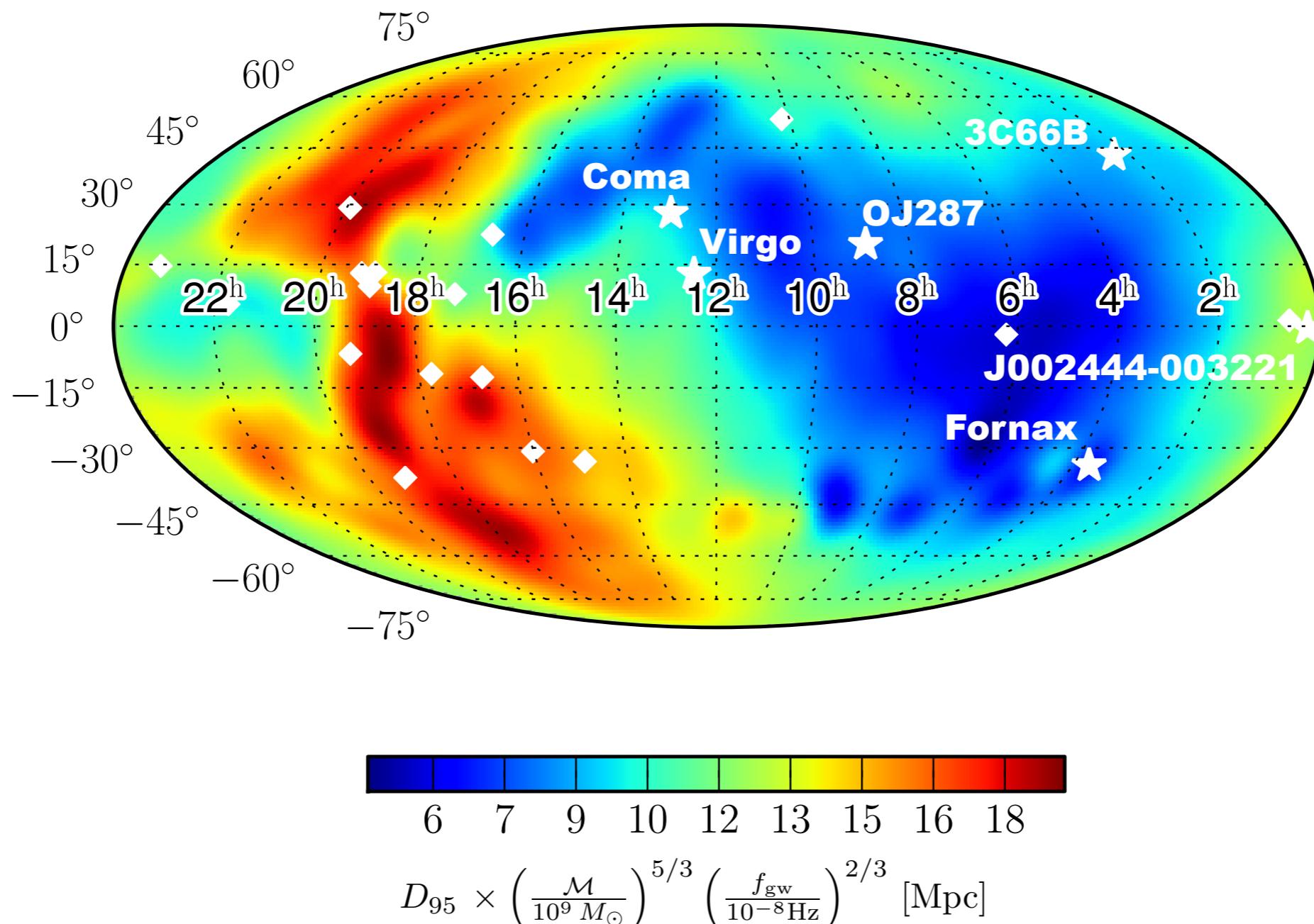
Searching for single GW sources

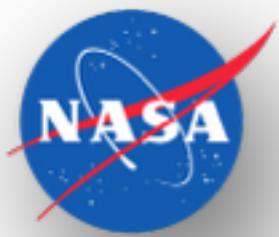




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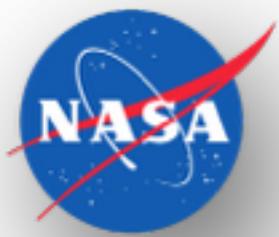
Searching for single GW sources





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Searching for a GW background



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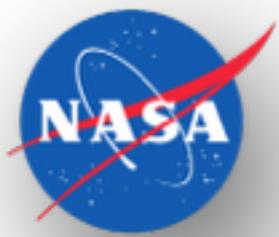
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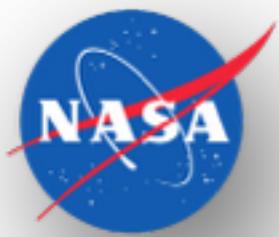
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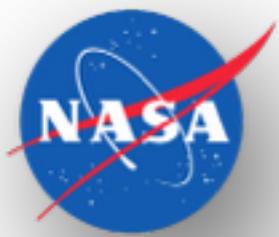
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- *Let's do a simple Fourier analysis of the background.*



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$$\mathbf{s} = T\mathbf{b}$$



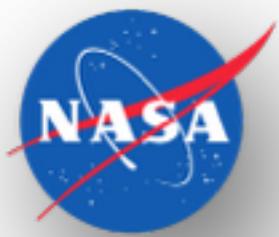
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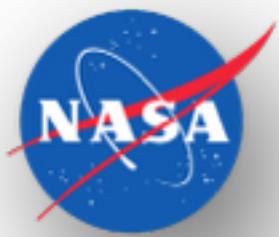
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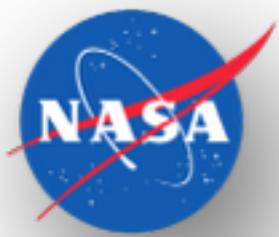
- *Put a Gaussian prior on the signal amplitude coefficients.*



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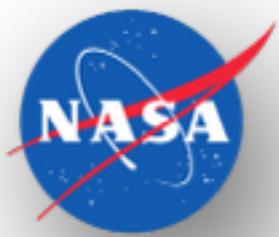
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Searching for a GW background

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- *We can parameterize that power spectrum whichever way we want...*

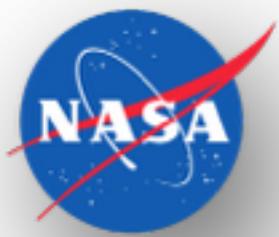


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$$p(\mathbf{b}|\boldsymbol{\eta}) = \frac{\exp\left(-\frac{1}{2}\mathbf{b}^T B^{-1} \mathbf{b}\right)}{\sqrt{\det(2\pi B)}}$$



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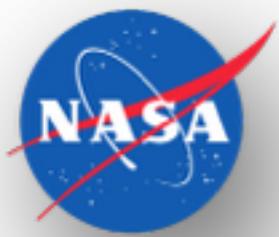
Searching for a GW background

$$p(\eta, \mathbf{b} | \delta \mathbf{t}) \propto p(\delta \mathbf{t} | \mathbf{b}) p(\mathbf{b} | \eta) p(\eta)$$

hierarchical modelling

$$p(\eta | \delta \mathbf{t}) = \int p(\eta, \mathbf{b} | \delta \mathbf{t}) d\mathbf{b}$$

**(analytically!) marginalize
over coefficients**



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Searching for a GW background

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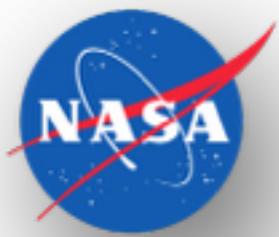
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marginalized likelihood

$$p(\boldsymbol{\eta} | \delta \mathbf{t}) \propto \frac{\exp\left(-\frac{1}{2}\delta \mathbf{t}^T C^{-1} \delta \mathbf{t}\right)}{\sqrt{\det(2\pi C)}} p(\boldsymbol{\eta})$$

$$\mathbf{C} = \mathbf{N} + \mathbf{T} \mathbf{B} \mathbf{T}^T$$



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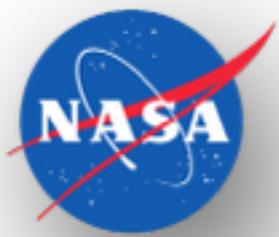
Searching for a GW background

$$C = N + TBT^T$$

what are we actually doing here?

$$[F\phi F^T]_{ij} \simeq \int df S(f) \cos(2\pi f |t_i - t_j|)$$

this is just the Wiener-Kinchin theorem!



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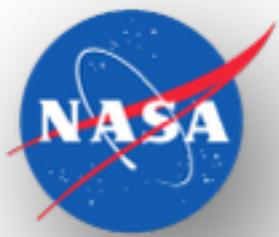
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Woodbury lemma

$$C^{-1} = (N + TBT^T)^{-1}$$

$$= N^{-1} - N^{-1}T(B^{-1} + T^T N^{-1} T)^{-1} T^T N^{-1}$$



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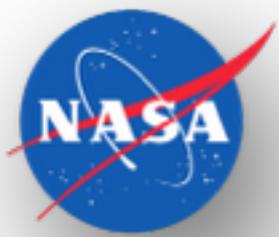
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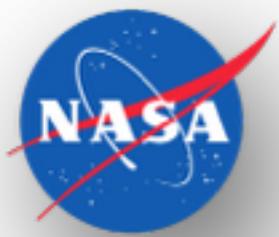
easy!



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The Pulsar-timing Likelihood

- ▶ Without cross-pulsar correlations [\sim ms]
- ▶ With cross-pulsar correlations [\sim 0.1s]

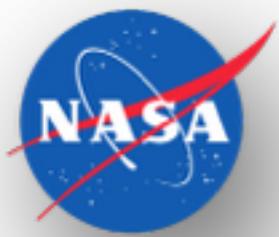


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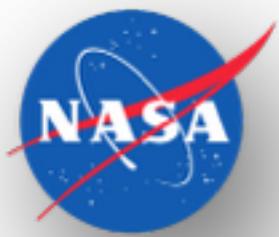




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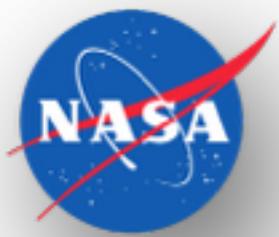


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The Pulsar-timing Likelihood

$$[F\phi F^T]_{ij} \simeq \int df S(f) \cos(2\pi f |t_i - t_j|)$$

$$[\phi]_{(ak),(bl)} = \Gamma_{ab}\rho_k\delta_{kl} + \kappa_{ak}\delta_{ab}\delta_{kl}$$

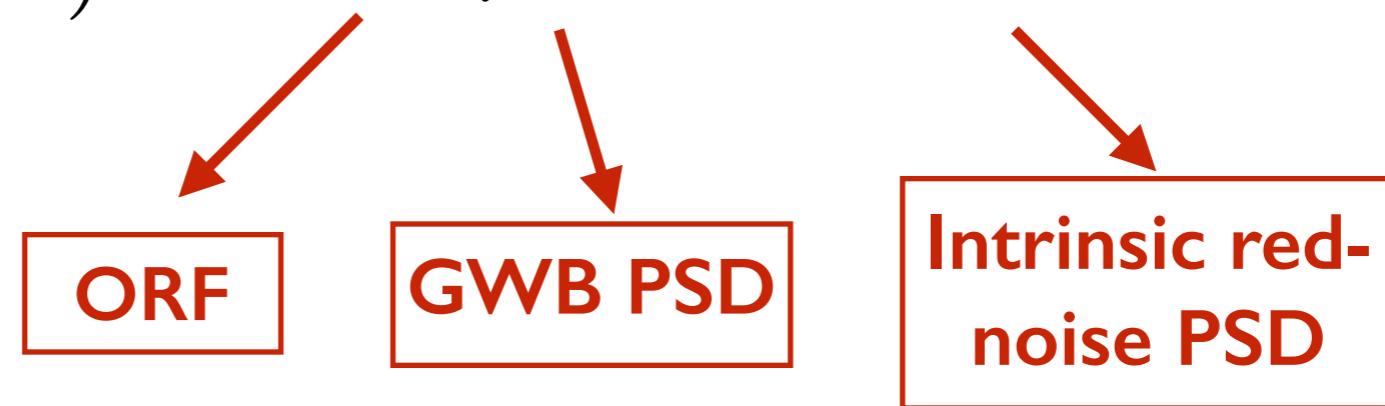


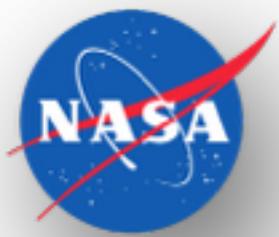
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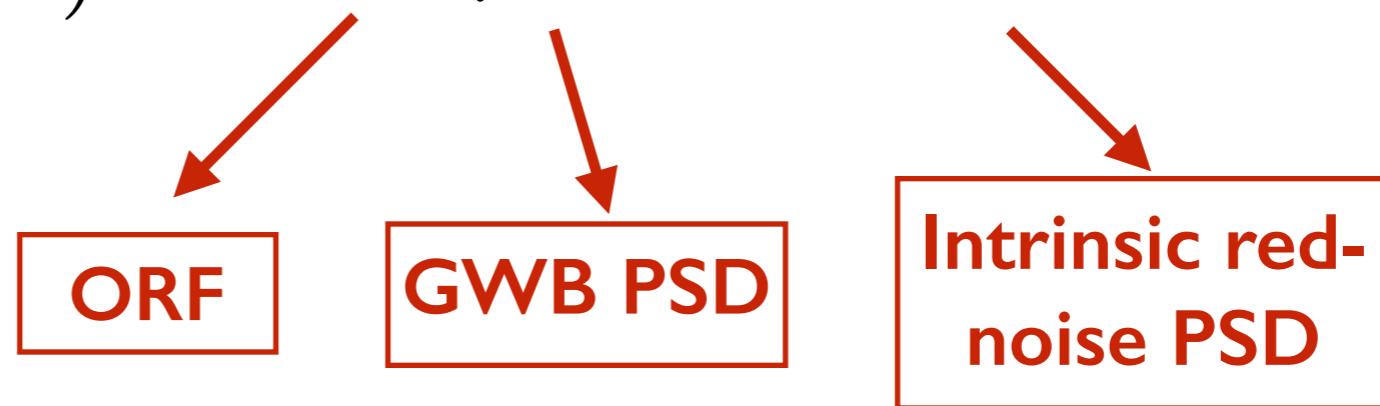


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$$\begin{aligned} \rho_k &= S(f_k)\Delta f \\ &\rightarrow \frac{A_{\text{gwb}}^2}{12\pi^2 T_{\text{obs}}} \left(\frac{f_k}{\text{yr}^{-1}}\right)^{-\gamma} \text{yr}^2 \end{aligned}$$



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Lentati, Taylor et al. (2015)

- ▶ Simultaneously fit for stochastic GW background, correlated clock-noise, dipole process due to imprecise solar-system ephemerides, and intrinsic low-frequency pulsar noise.
- ▶ Investigated consistency of constraints with astrophysical predictions from Sesana (2013). Upper limit cuts out 5% of plausible amplitude distribution.
- ▶ Detailed analysis of constraints on possible cosmic-string network and primordial GWs



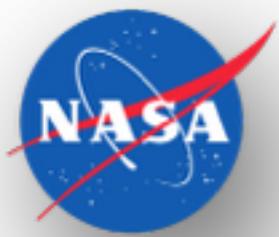
Shannon et al. (2015)

- ▶ Best published constraints to date.
- ▶ Used 4 pulsars, but limit dominated by J1909-3744 which is exceptionally well-timed with no measured low-frequency noise.
- ▶ Limit is in tension with our basic astrophysical predictions. Excludes 91 - 99.7% of range of basic predictions.



Arzoumanian et al. (2016)

- ▶ Detailed investigations of consistency of upper limits with Sesana (2013) and McWilliams, Ostriker, Pretorius (2014) predictions.
- ▶ Searched with a **generalized turnover model** to investigate “final-parsec” processes.
- ▶ Detailed analysis of constraints on possible cosmic-string network and primordial GWs



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Parametrizing the GWB angular power

$$\Gamma_{ab} \propto (1 + \delta_{ab}) \int d^2\hat{\Omega} P(\hat{\Omega}) \left[F(\hat{\Omega})_a^+ F(\hat{\Omega})_b^+ + F(\hat{\Omega})_a^\times F(\hat{\Omega})_b^\times \right]$$



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Parametrizing the GWB angular power

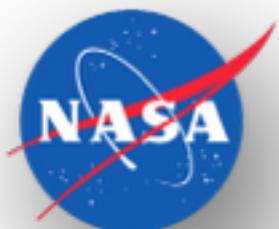
$$\Gamma_{ab} \propto (1 + \delta_{ab}) \int d^2\hat{\Omega} P(\hat{\Omega}) \left[F(\hat{\Omega})_a^+ F(\hat{\Omega})_b^+ + F(\hat{\Omega})_a^\times F(\hat{\Omega})_b^\times \right]$$

$$\Gamma = R \cdot P \cdot R^T$$

$\Gamma \rightarrow [N_{\text{psr}} \times N_{\text{psr}}]$ $R \rightarrow [N_{\text{psr}} \times 2N_{\text{pix}}]$ $P \rightarrow \text{diag}(2N_{\text{pix}})$



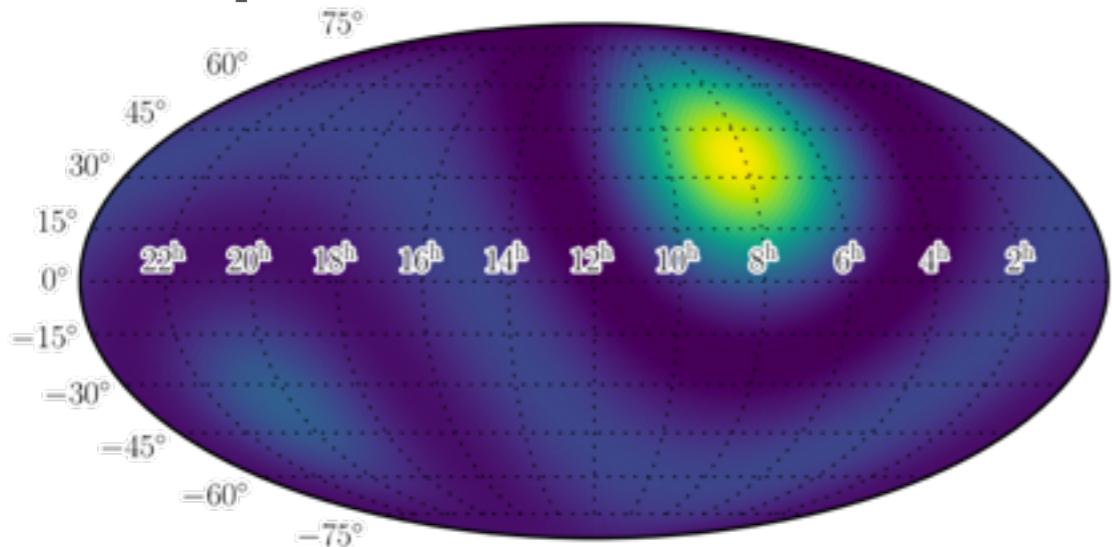
- \mathbf{R} = pulsar response matrix [fixed]
- \mathbf{P} = power in each pixel [parametrize]



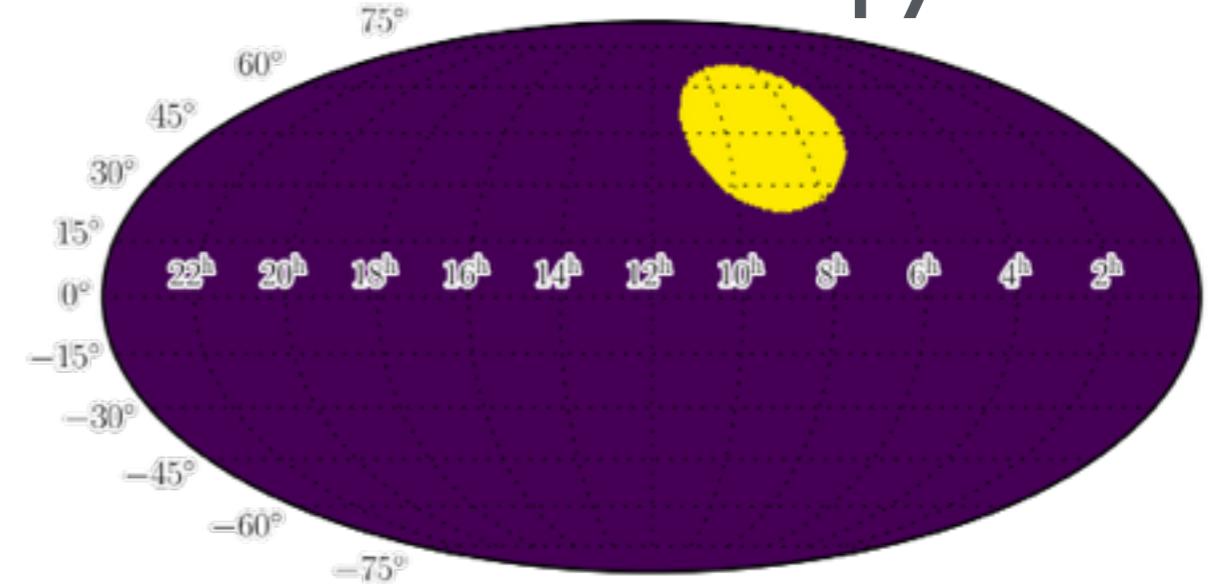
Caltech

Parametrizing the GWB angular power

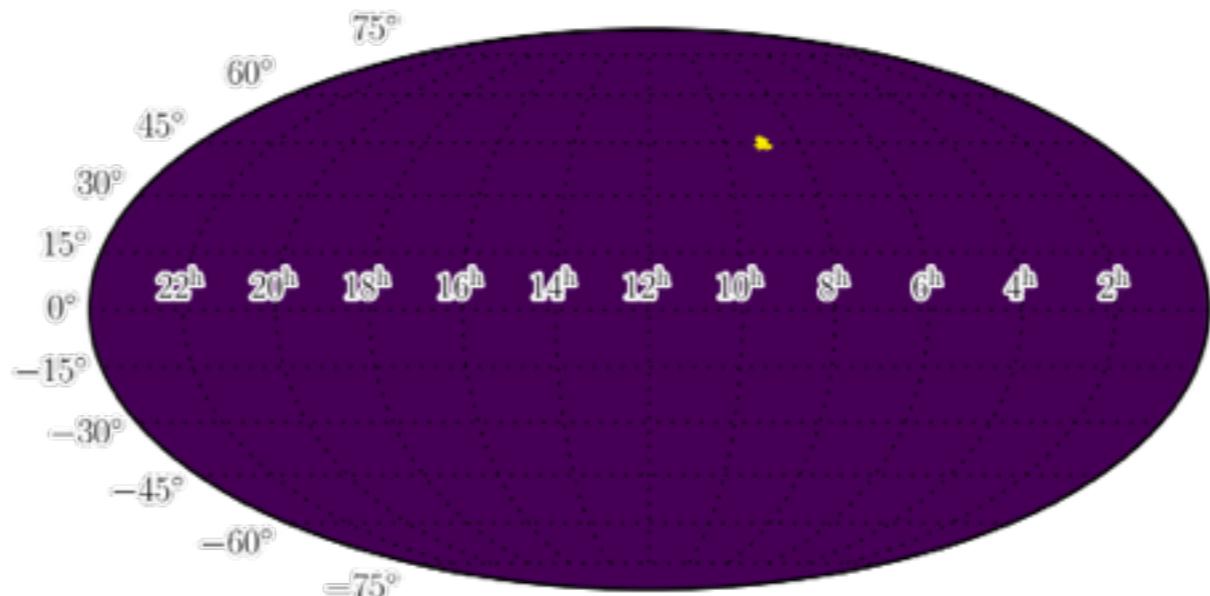
Spherical harmonics

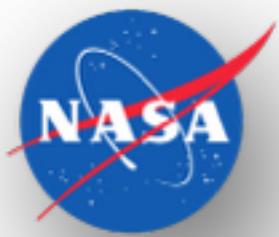


Disk anisotropy



Point source





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Detection

- ▶ Detection is a model-selection problem.
- ▶ We need to prove the presence of spatial correlations between pulsars.
- ▶ ***Compare Bayesian evidence for a model with Hellings and Downs correlations versus no correlations.***



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$$\mathcal{P}_{12} = \frac{p(\mathcal{H}_1 | \mathbf{d})}{p(\mathcal{H}_2 | \mathbf{d})} = \frac{p(\mathbf{d} | \mathcal{H}_1)}{p(\mathbf{d} | \mathcal{H}_2)} \frac{p(\mathcal{H}_1)}{p(\mathcal{H}_2)}$$

Posterior odds ratio

Bayes factor

Prior odds ratio



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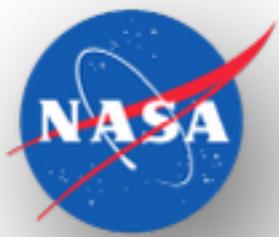
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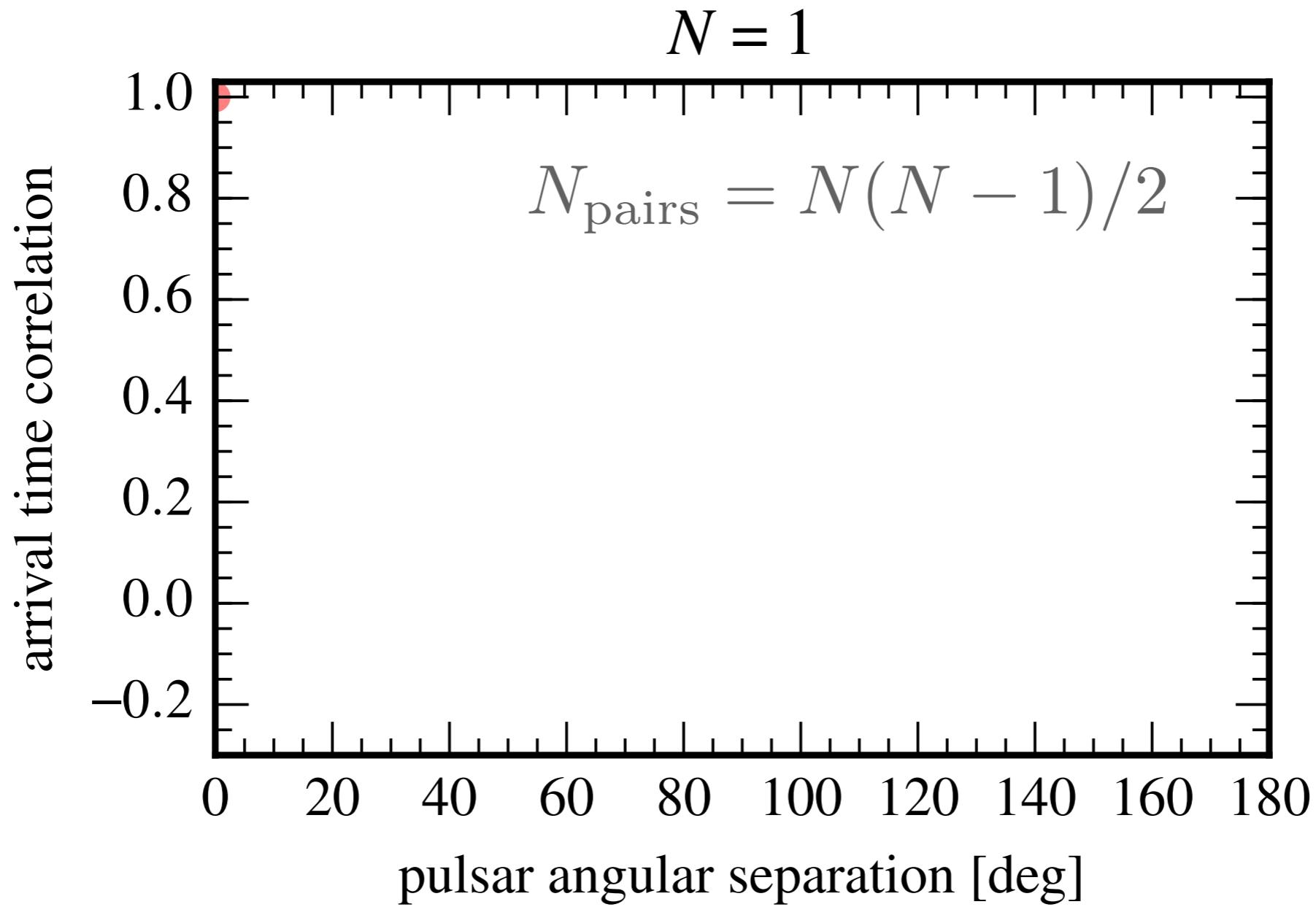


- ▶ MultiNest
- ▶ Thermodynamic integration
- ▶ RJMCMC
- ▶ Savage-Dickey ratio
- ▶ **Product space**



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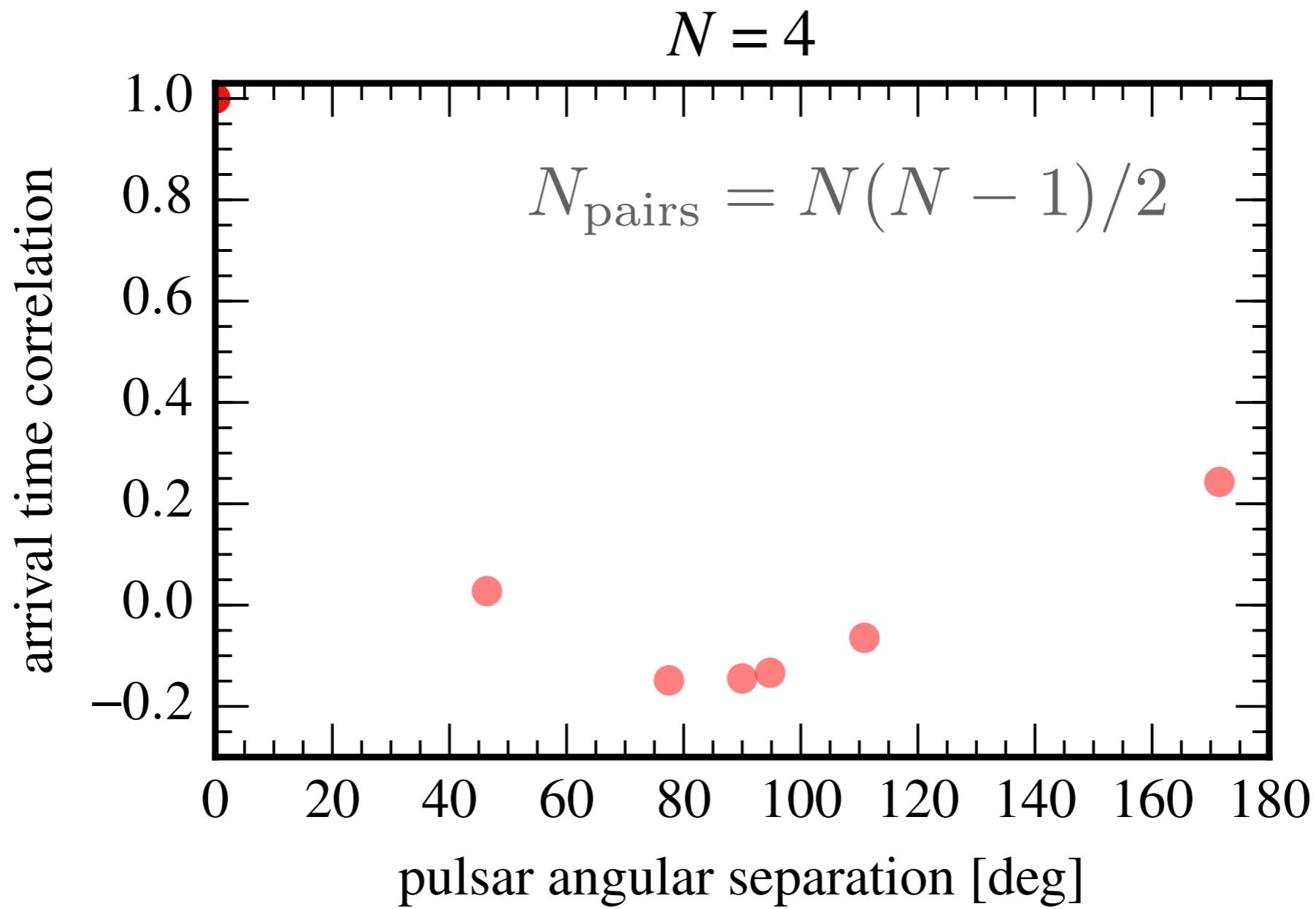
Detection

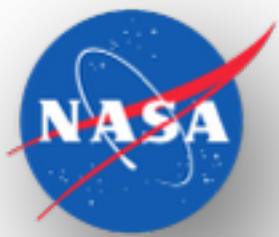




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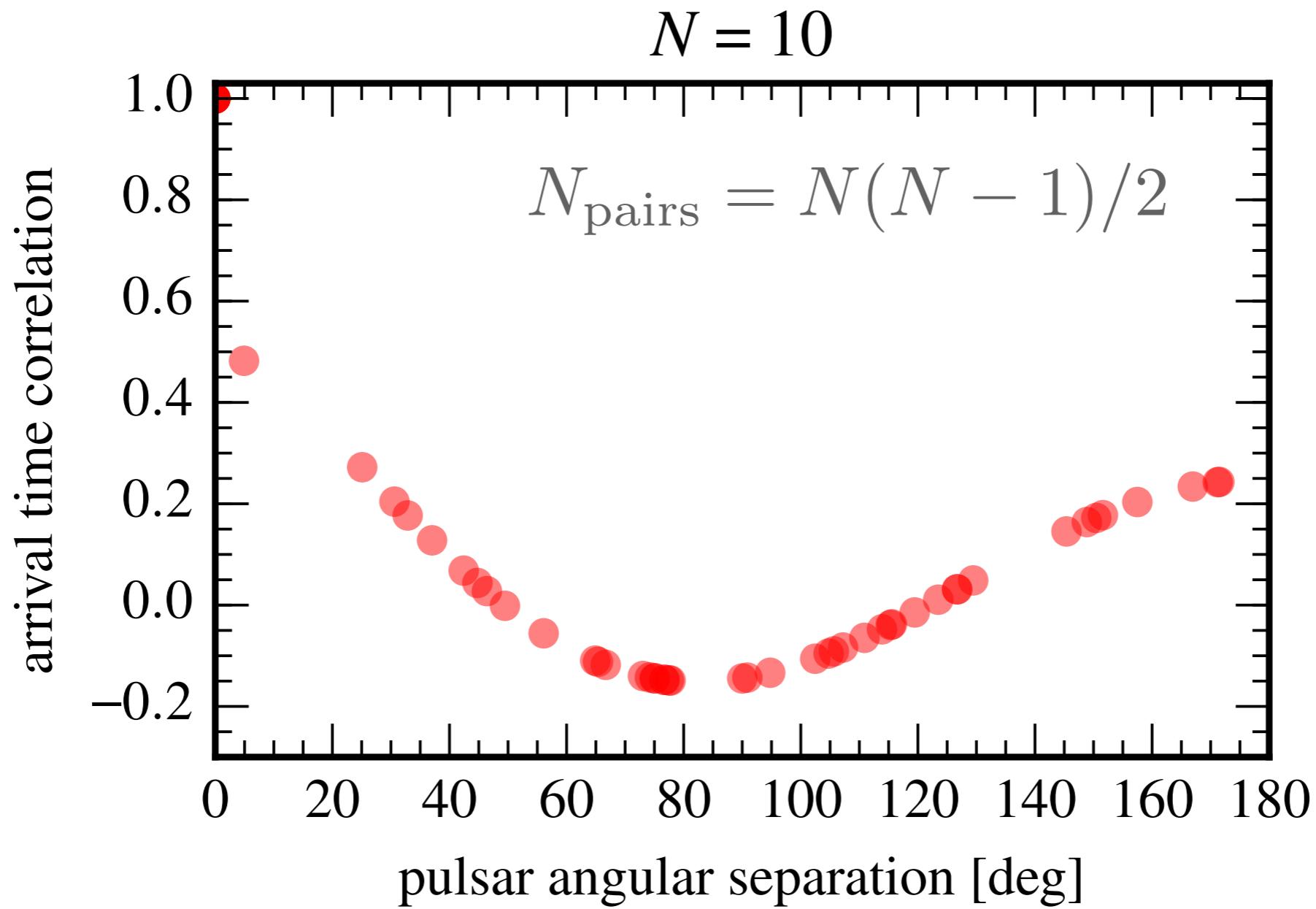
Detection

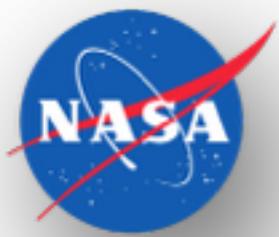




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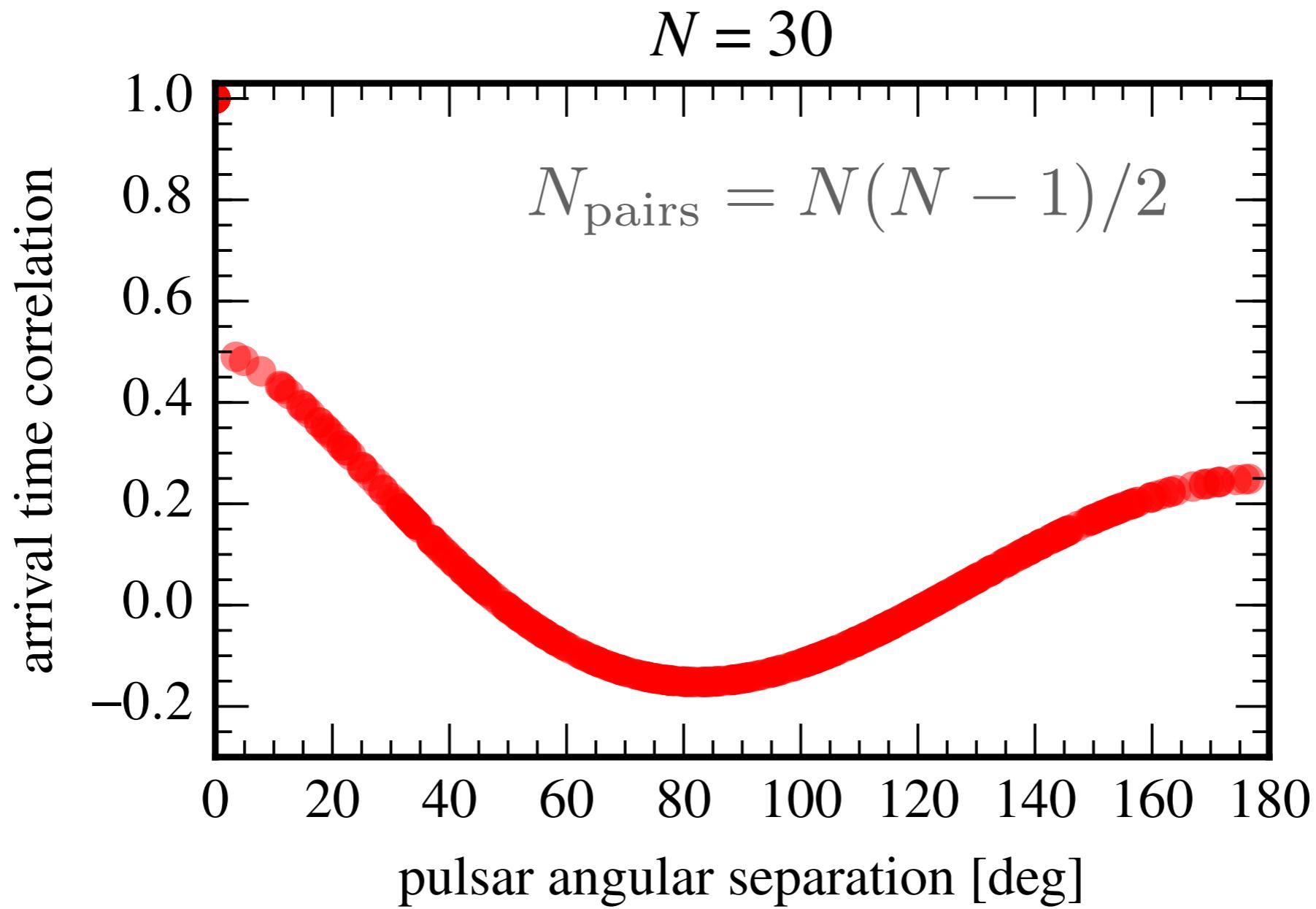
Detection

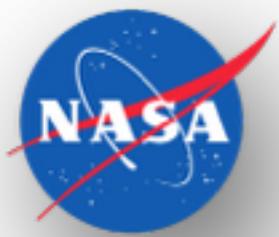




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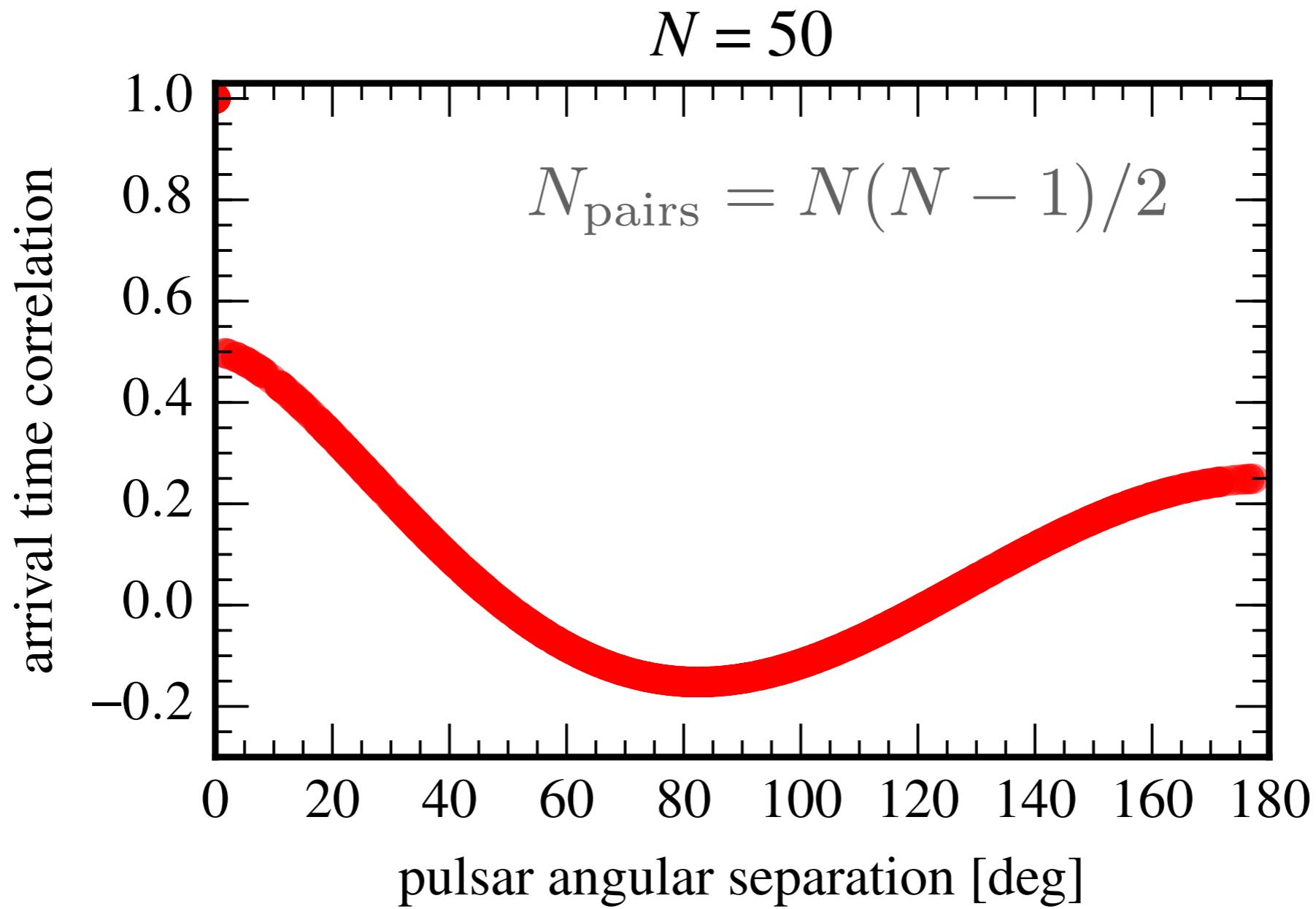
Detection





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Detection





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Summary

- ▶ We can do single-source searches and stochastic background searches all together in our pipelines.
- ▶ Current limits are cutting into astrophysically interesting territory.
- ▶ We can probe the dynamics and environments of supermassive black-holes binaries.
- ▶ Within the next 10 years, we should have convincing signs of nanohertz GWs with pulsar-timing arrays.