

American Astronomical Society Workshop: Exploring and Modeling Astronomical Time Series Data

Session 2: New methods for analyzing irregularly sampled time series and point data

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Friday, 8 January 11:00 – 18:00 (ET)

OUTLINE

- What are Time Series? Data Modes
- Models for Stationary Time Series

Given Arbitrarily Sampled Data, Algorithms for:

- Complex Fourier Transforms (“GLOBAL”)
 - Power Spectra
 - Phase Spectra
- Discrete Correlation (Dependence) Functions
- Bayes Blocks (“LOCAL”)
- Applications: high-energy photon and LIGO data

- What are Time Series? Data Modes
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Sample Data Modes

- Discrete Events (Individual Photons)

- * time-tags
- * energy-tags ...

- Counts in Bins

- * Predefined Time Bins
- * “Time-to-Spill” Binning

- Measurements at Points in Time

- * with measurement error distribution
- * with timing error distribution

- Categorical

Bayesian Block flexibility:

- ★ Mixtures of Data Modes
- ★ Multivariate
- ★ Higher Dimensions
- ★ Real-time versus Retrospective
- ★ Exposure Variation
- ★ Circular Domain

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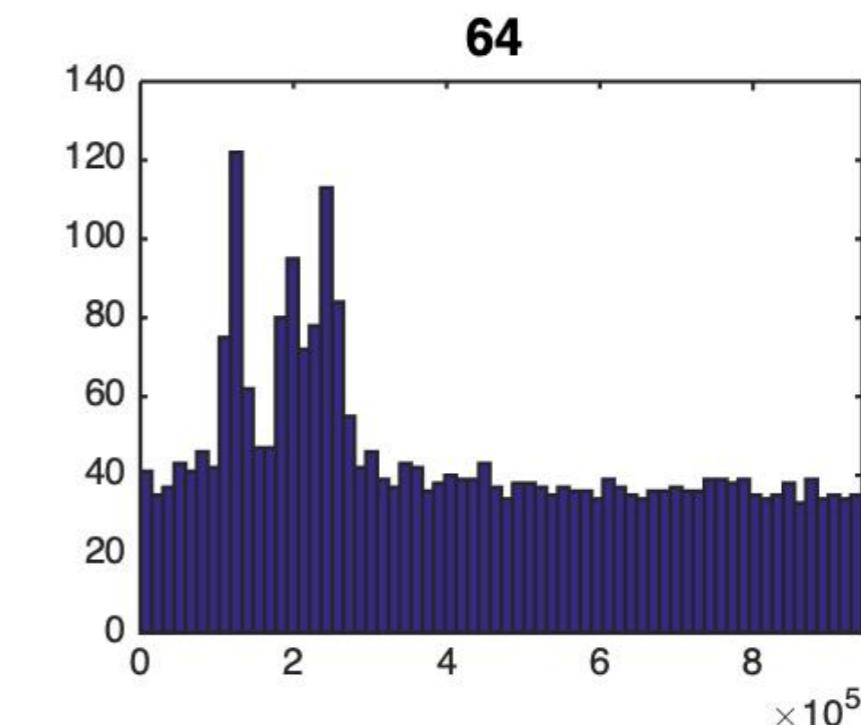
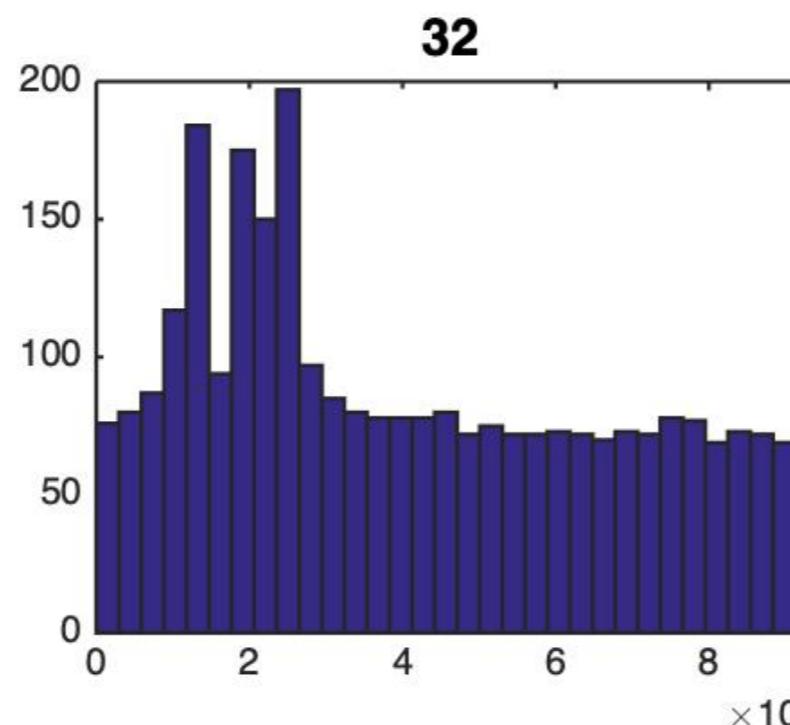
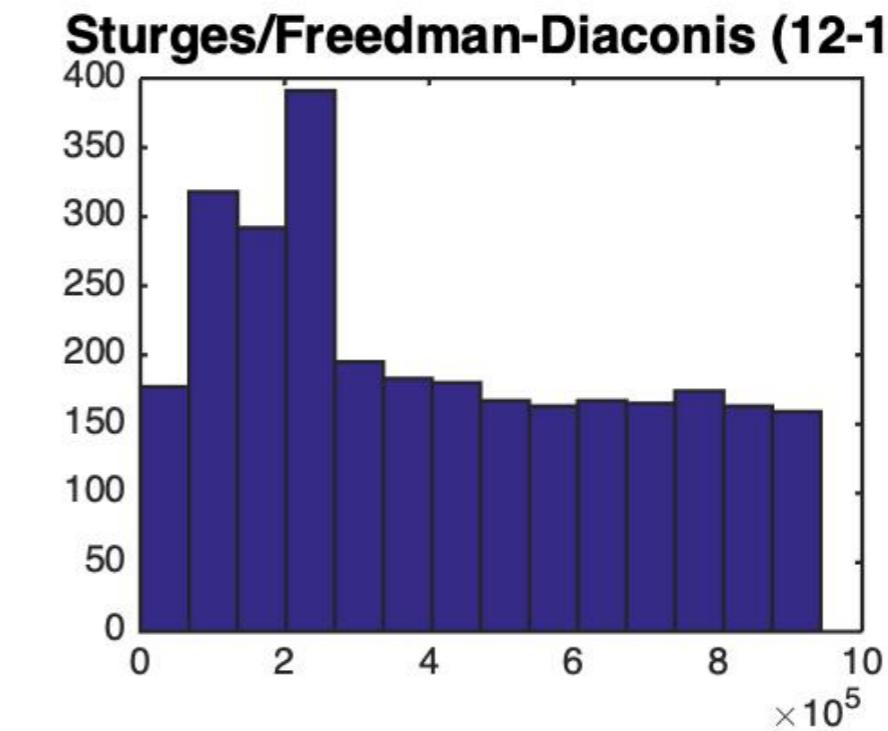
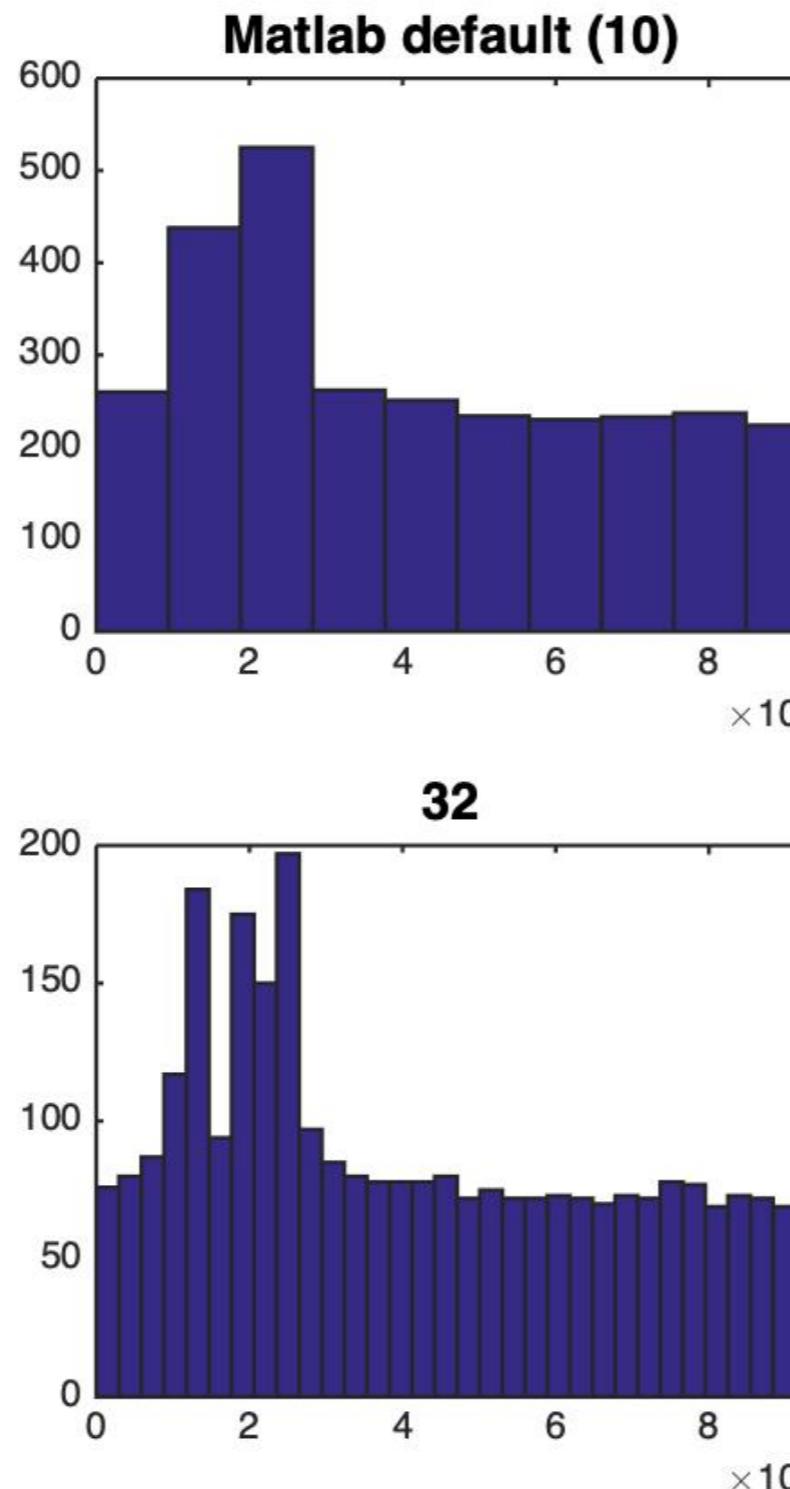
Time-Tagged Data

The errors in the times
can often be neglected.

Uncertainty information is carried by
“Poisson fluctuations” in the events themselves.

BATSE trigger 00551
N = 2894 photons

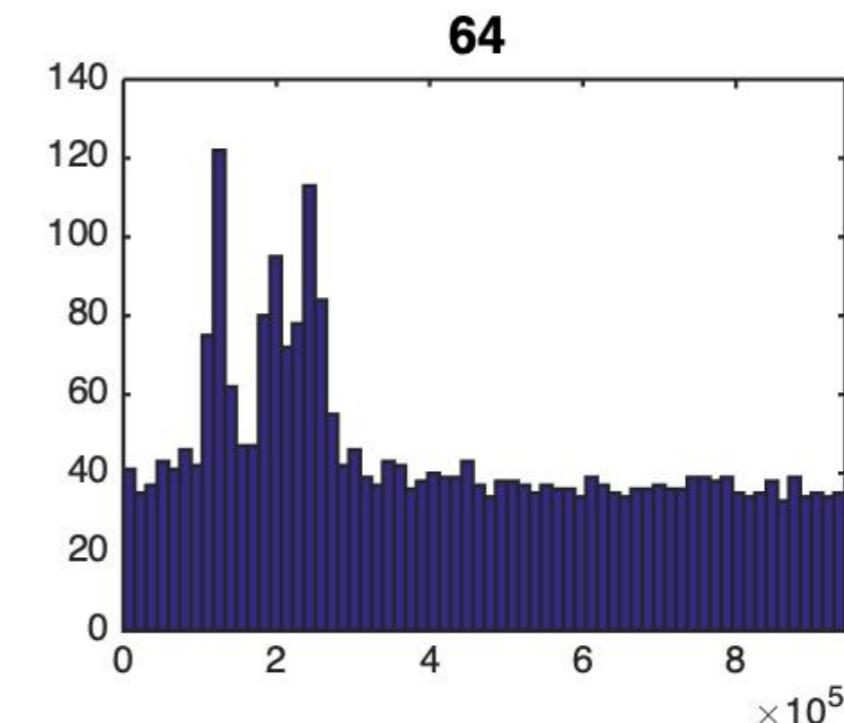
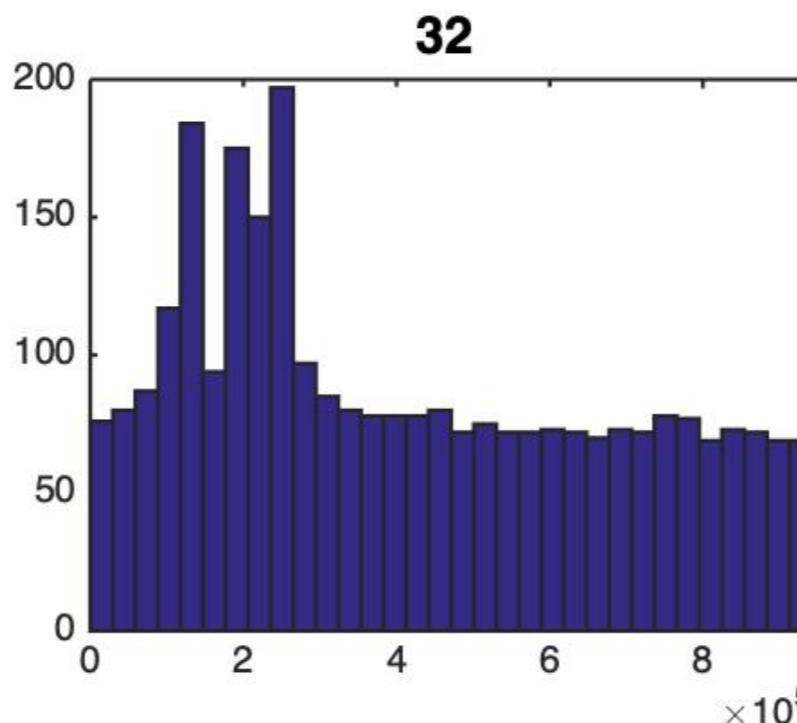
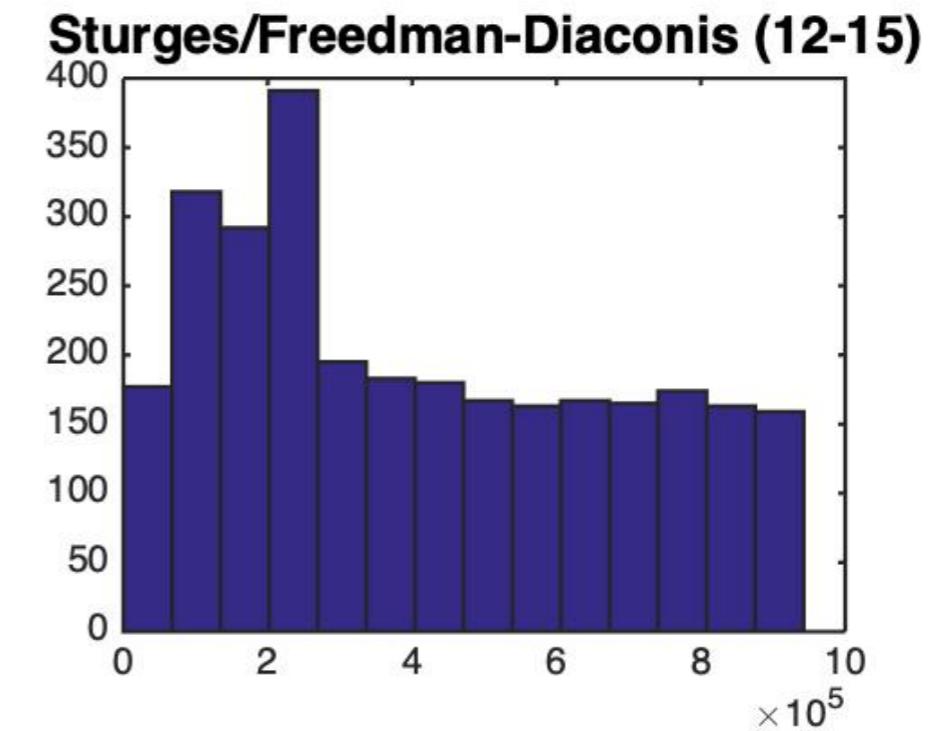
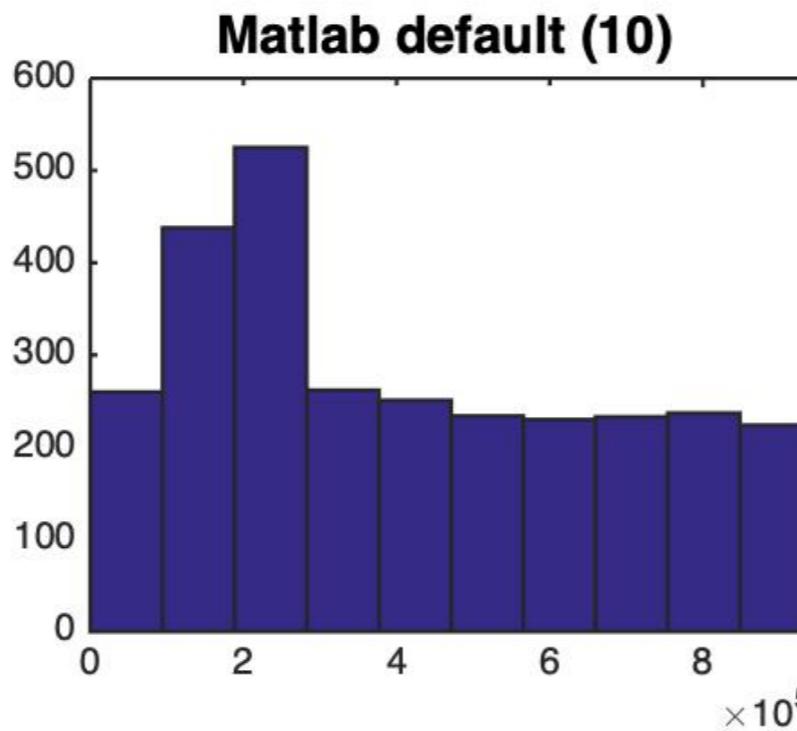
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"The problem with Sturges' rule for constructing histograms"
Rob J Hyndman (1995)

It is known that Sturges' rule leads to oversmoothed histograms,
but Sturges' derivation of his rule has never been questioned.
... the argument leading to Sturges' rule is wrong

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So what is the best number of bins?
Scott, K. Knuth, etc. ... ?

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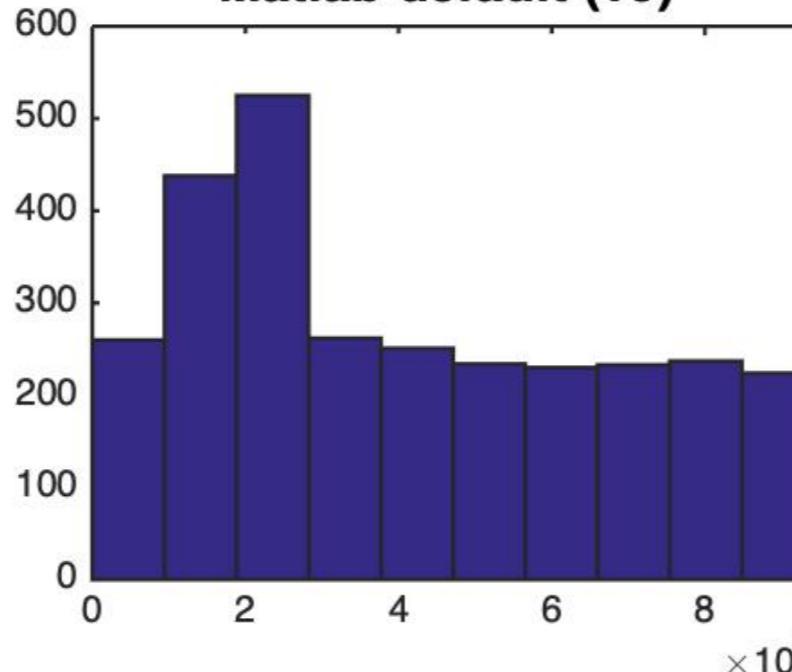
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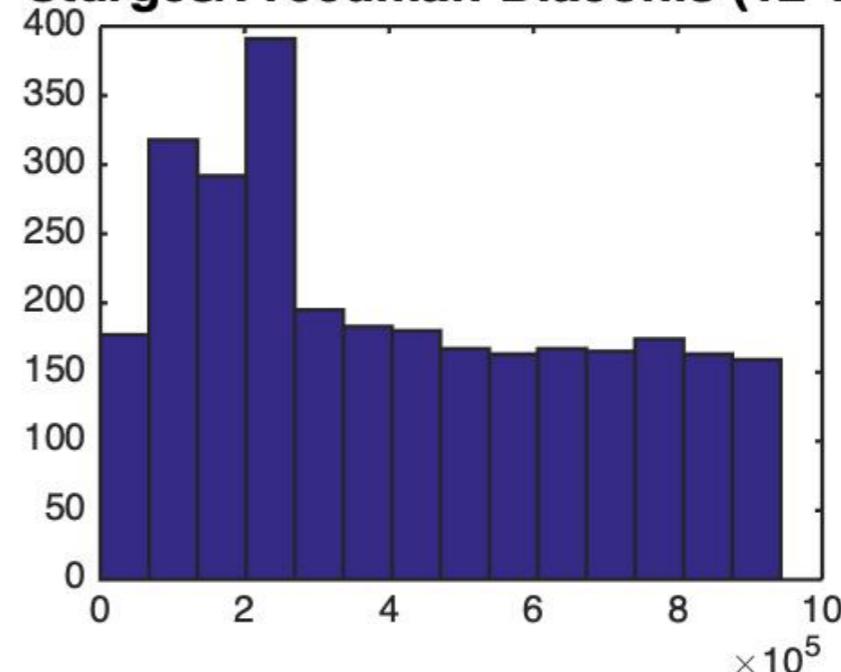
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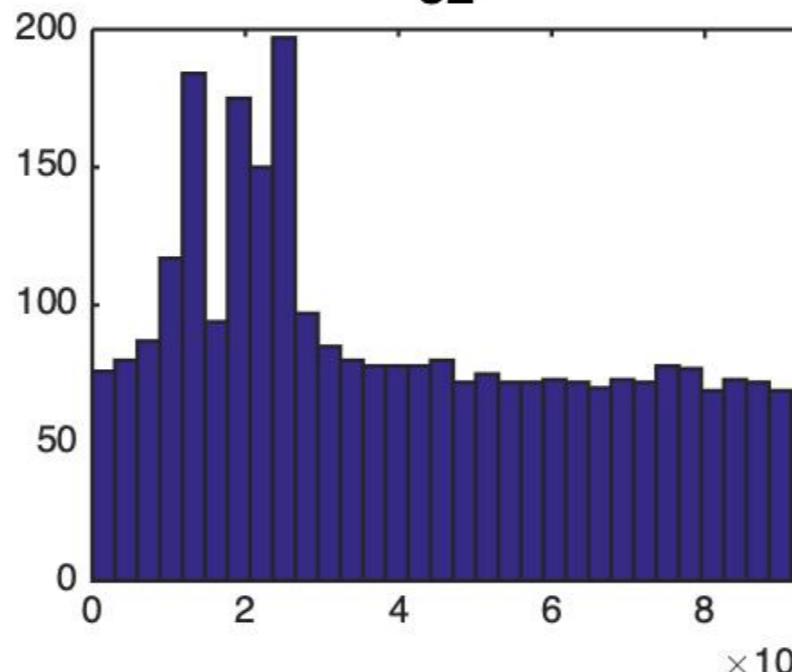
Matlab default (10)



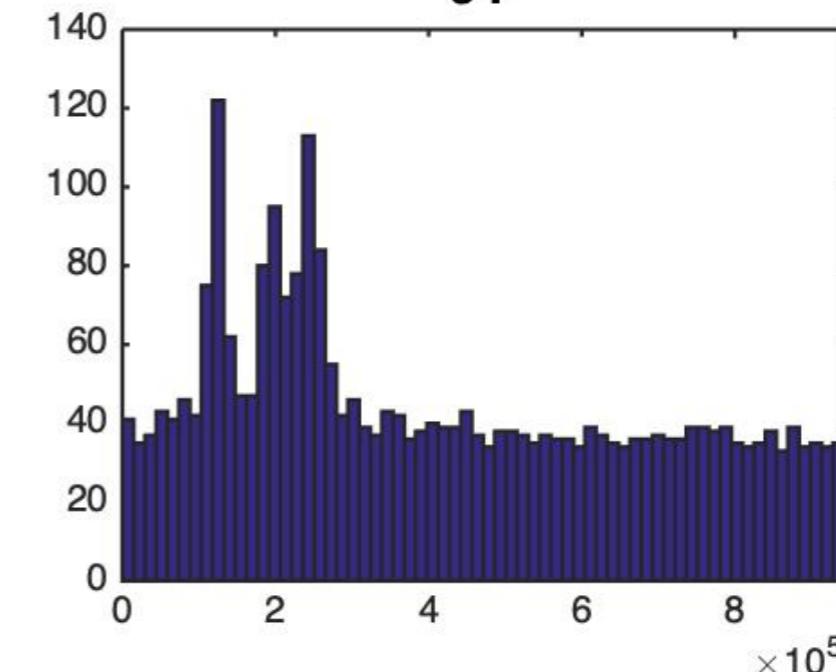
Sturges/Freedman-Diaconis (12-15)



32



64



Better yet, discard constraint of equal bins: *Bayesian Blocks*

So what is the best number of bins?
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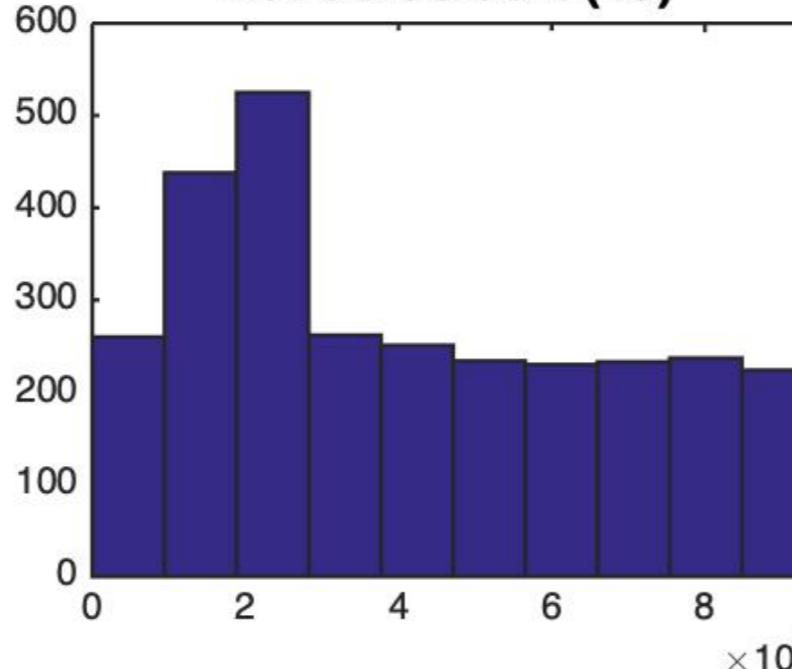
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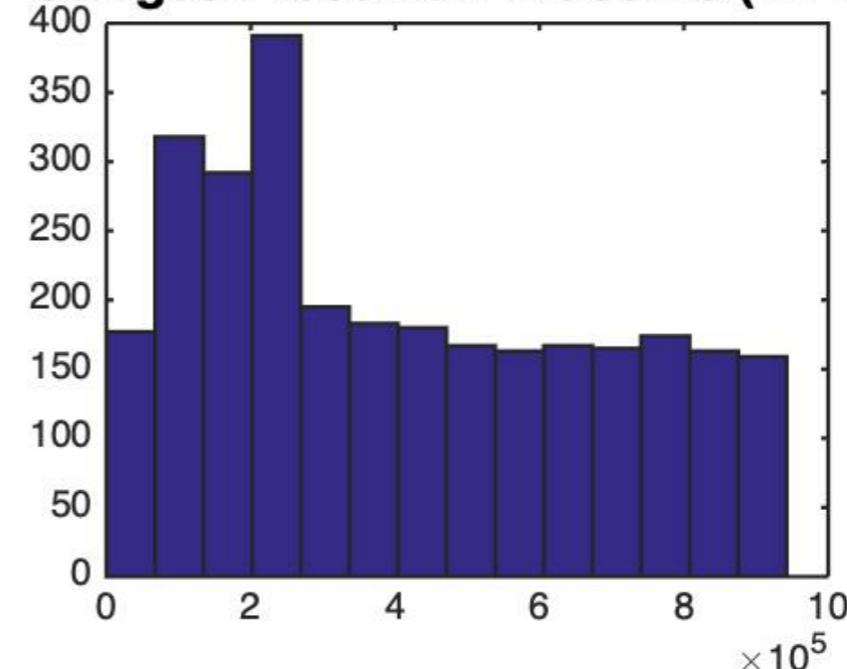
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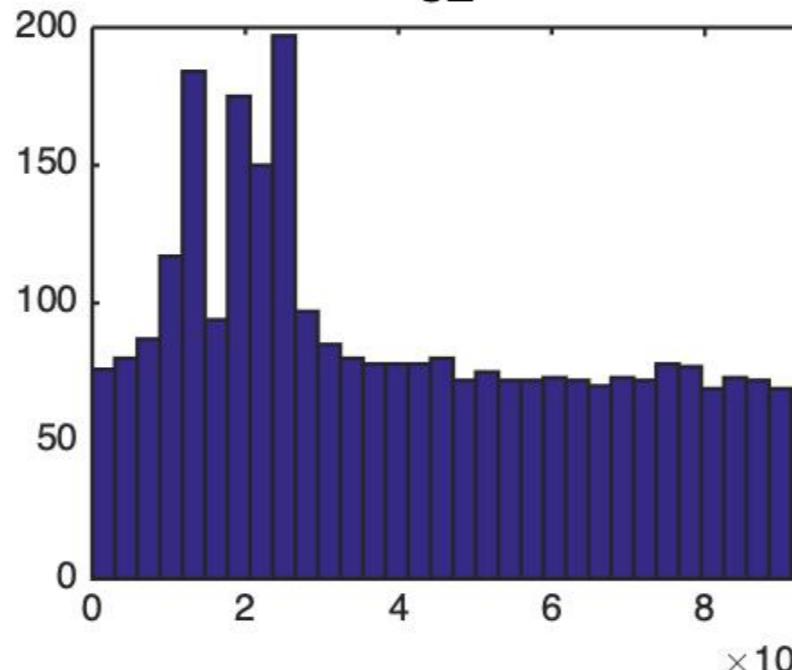
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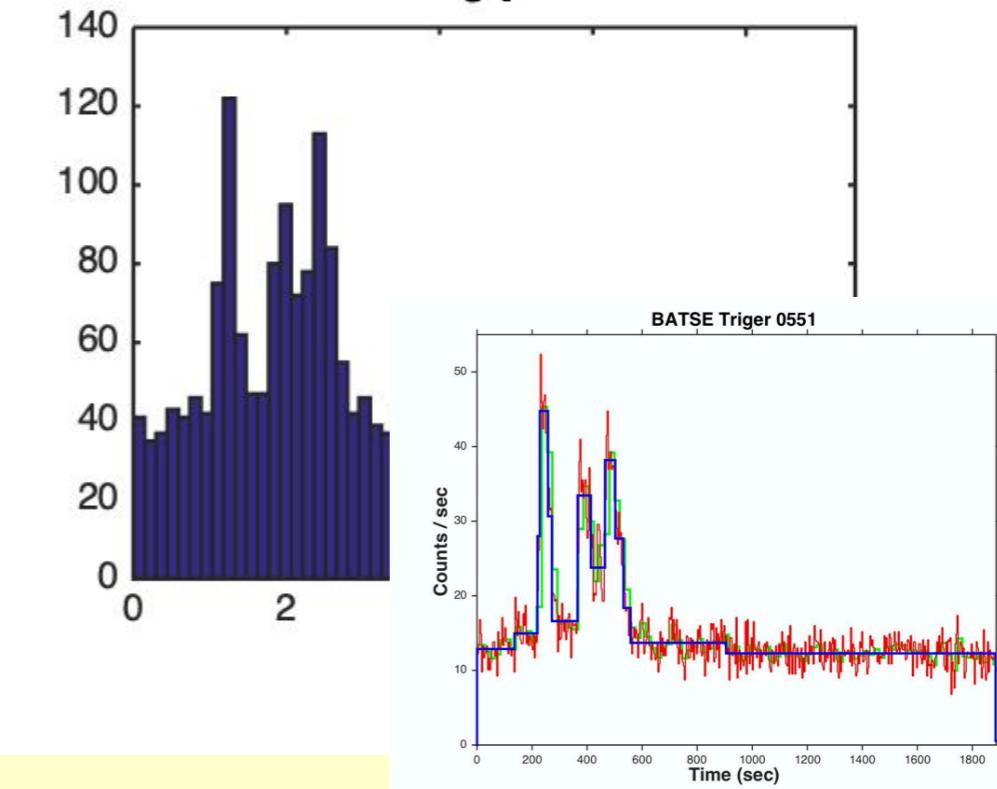
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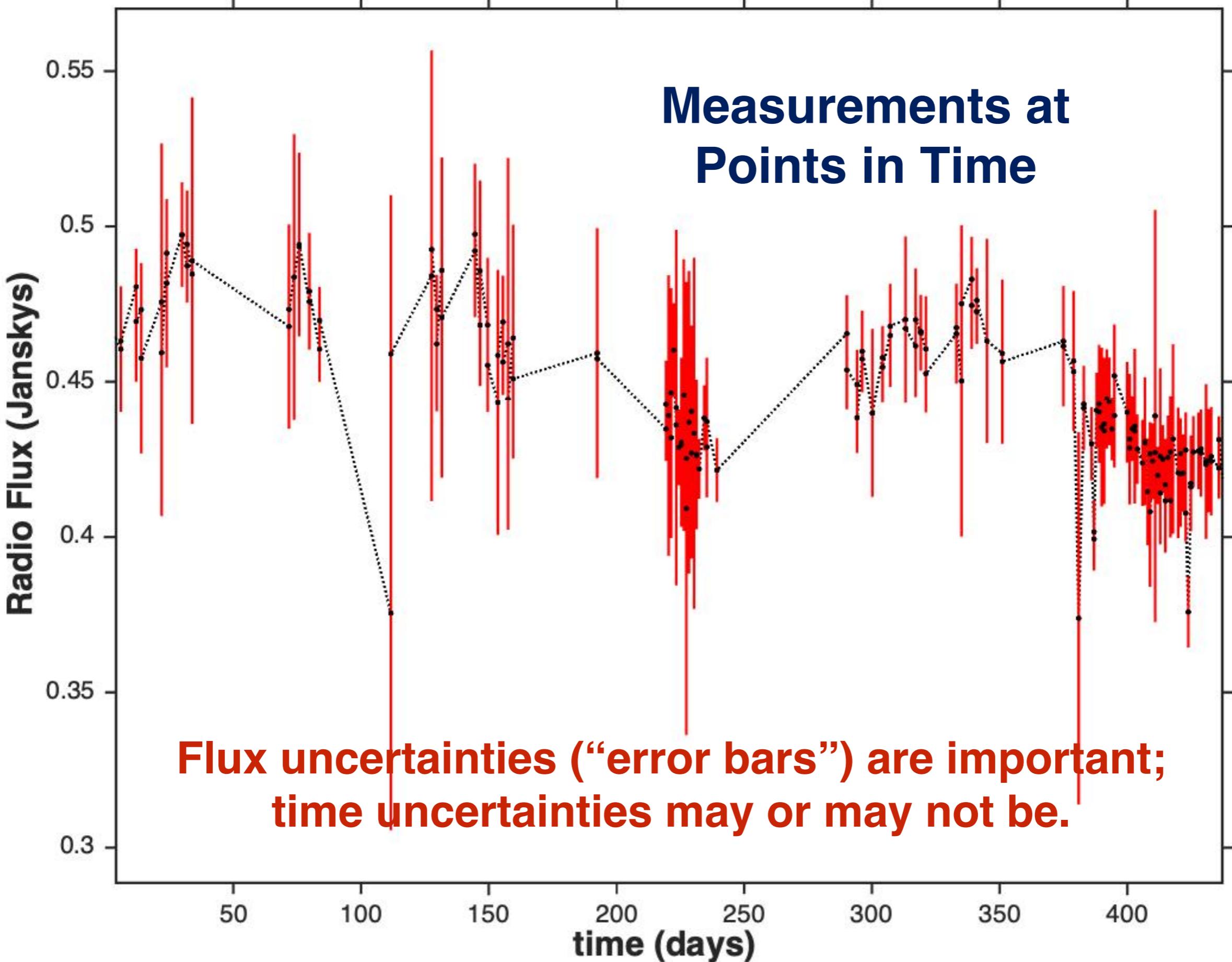


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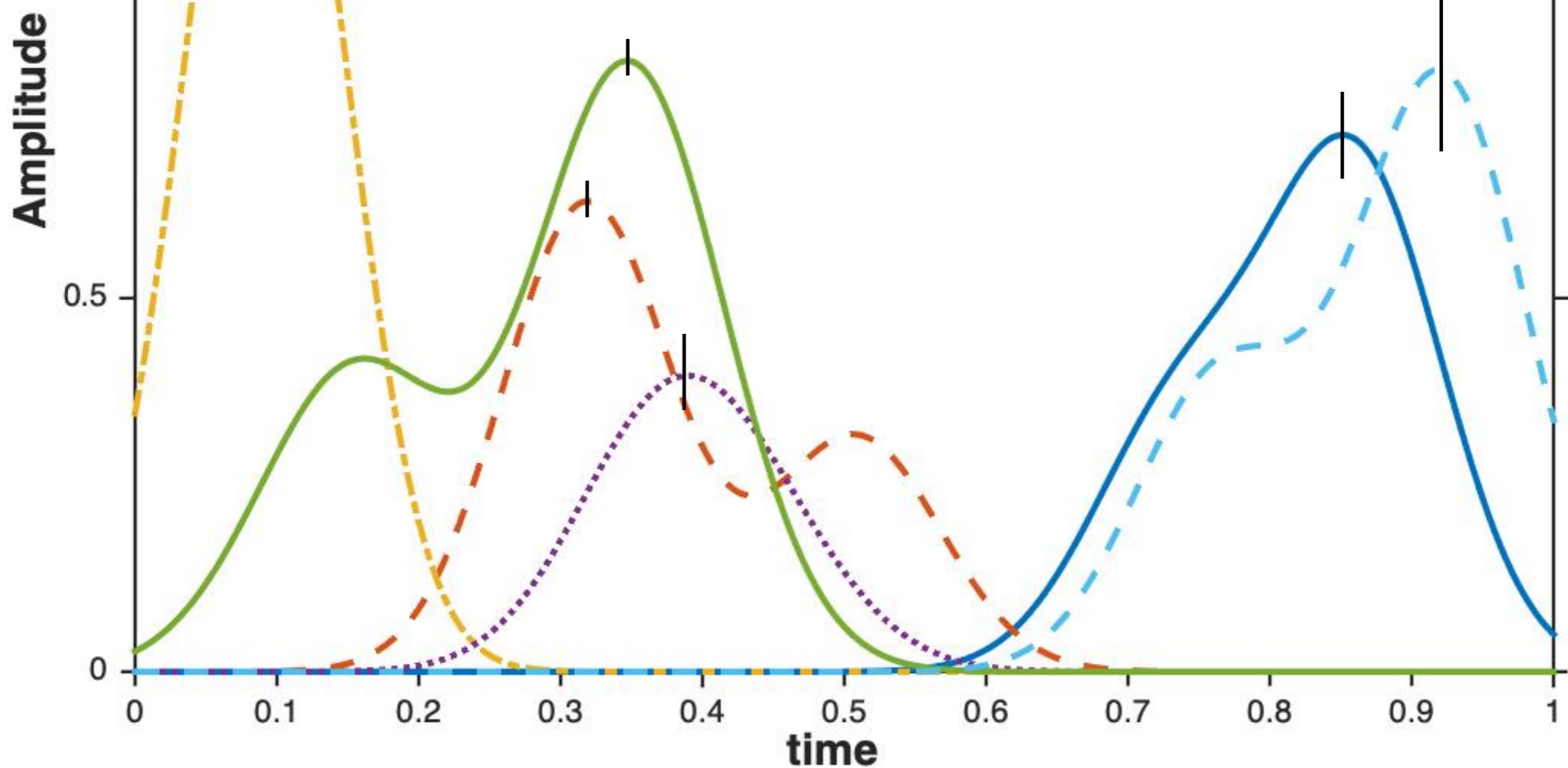
Better yet, discard constraint of equal bins: *Bayesian Blocks*

OVRO Markarian 4312



Measurements with Timing Uncertainties

(e.g., multimodal error distributions)



Measurements with Timing Uncertainties

Exercise: What is the most extreme case in the progression of timing uncertainties shown in the previous slides?

What happens to the sequential nature of the measurements?

How would you carry out time-domain analysis (e.g. Bayesian Blocks) in this case?

... Frequency domain analysis?

Amplitude

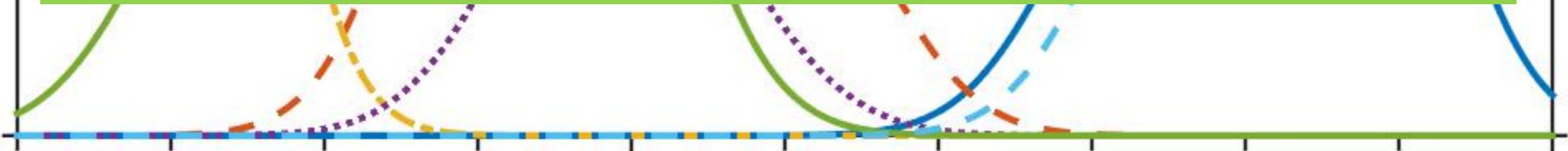
1.5

1

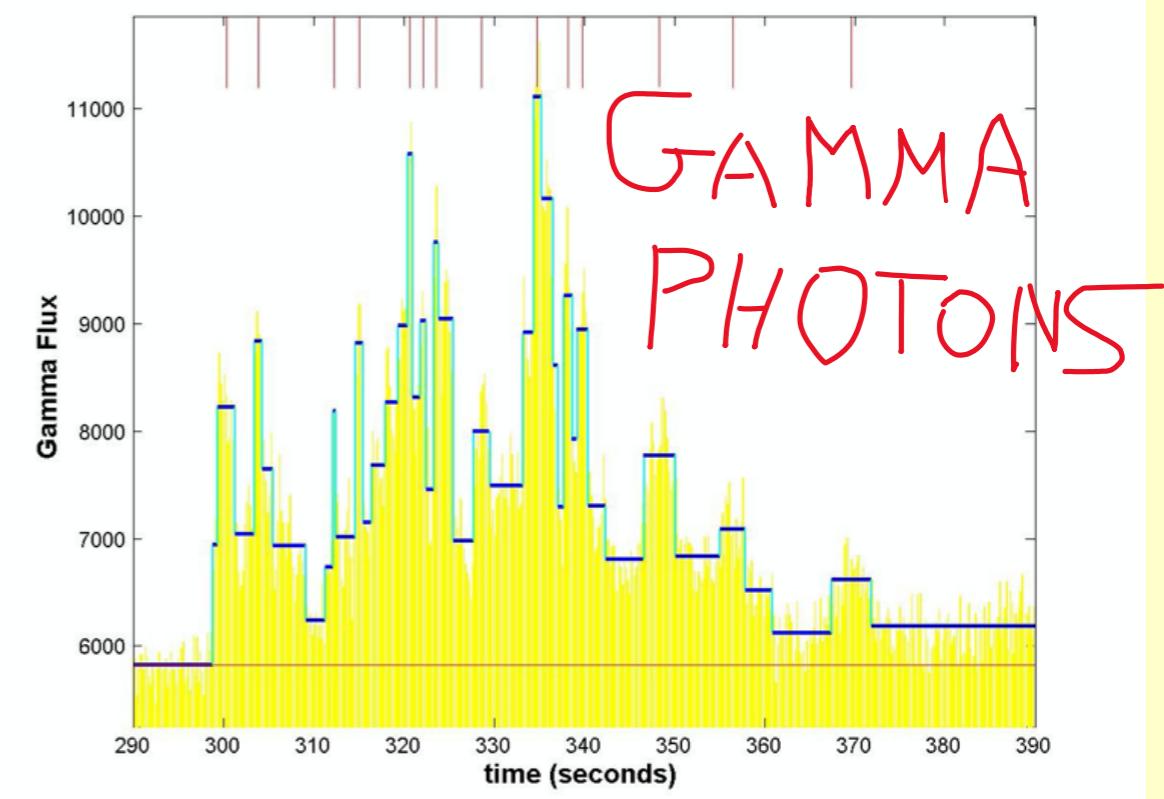
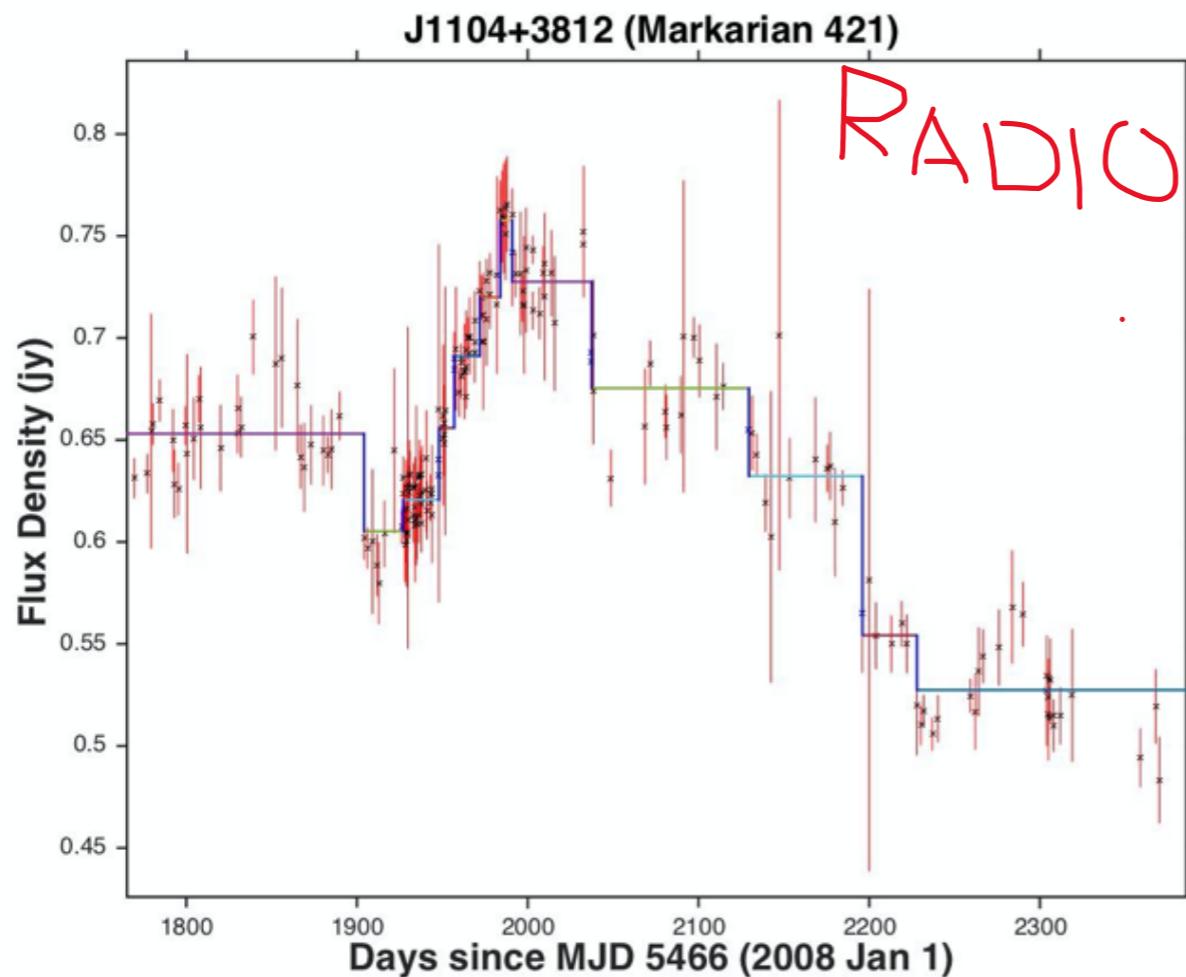
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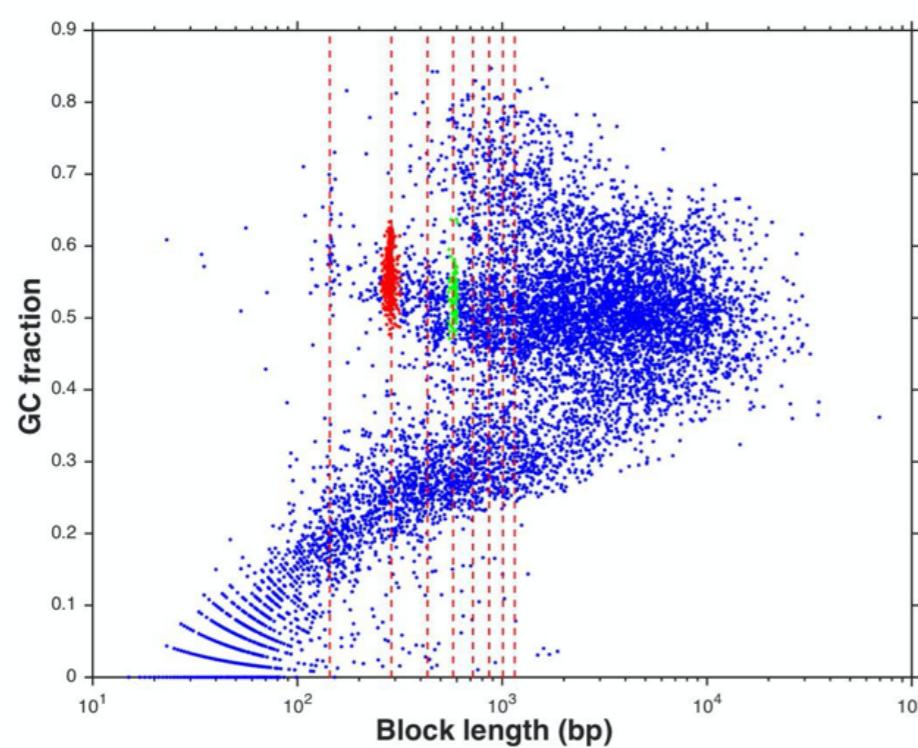
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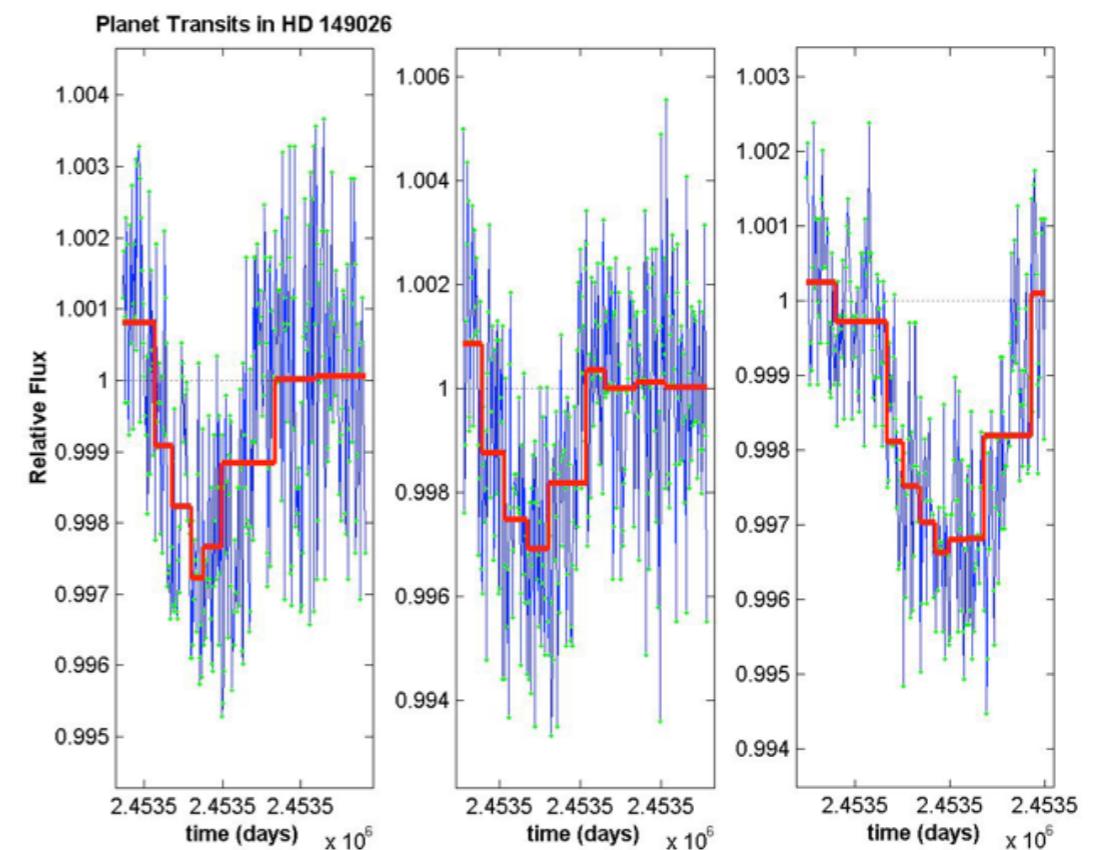
In short: lots of different kinds of sequential data!



HUMAN GENOME



OPTICAL



Interlude:

Ten (or so) Time Series Lessons I Wish I Had Been Taught*

1. Check the distribution of sample intervals: $\{t_i, X_i\} \rightarrow \text{hist}(dt_i = t_{i+1} - t_i)$
2. Check the error distribution (be alert for too large ... or too small)
3. Smoothing and binning are unnecessary and corrupt information
4. Any time series functional can be time-resolved (sliding window)
5. Removing a constraint can yield a larger but easier problem
6. Beware cherry picking, publication bias
7. ~~“non-linear” or “non-stationary” data, “characteristic time scale”~~
8. Photon rates may be correlated but photons (mostly) are not.
9. To measure relationships: correlation is weak; independence is strong
10. Remove the mean value at your own risk!
11. Errors are never the simple additive & Gaussian form often assumed.
12. Why do we sometimes get Nonsense Correlations between time series? (Yule 1926)

*After a speech by Gian-Carlo Rota <http://www.ams.org/notices/199701/comm-rota.pdf>

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Cf. Tom’s plot of sunspot period vs. time.
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Example of Data Interval Distribution

You are almost certain to learn something useful by studying the distribution of intervals between samples — even before doing any actual analysis.

Log N

3

2.5

2

1.5

1

0.5

0

0

10

20

30

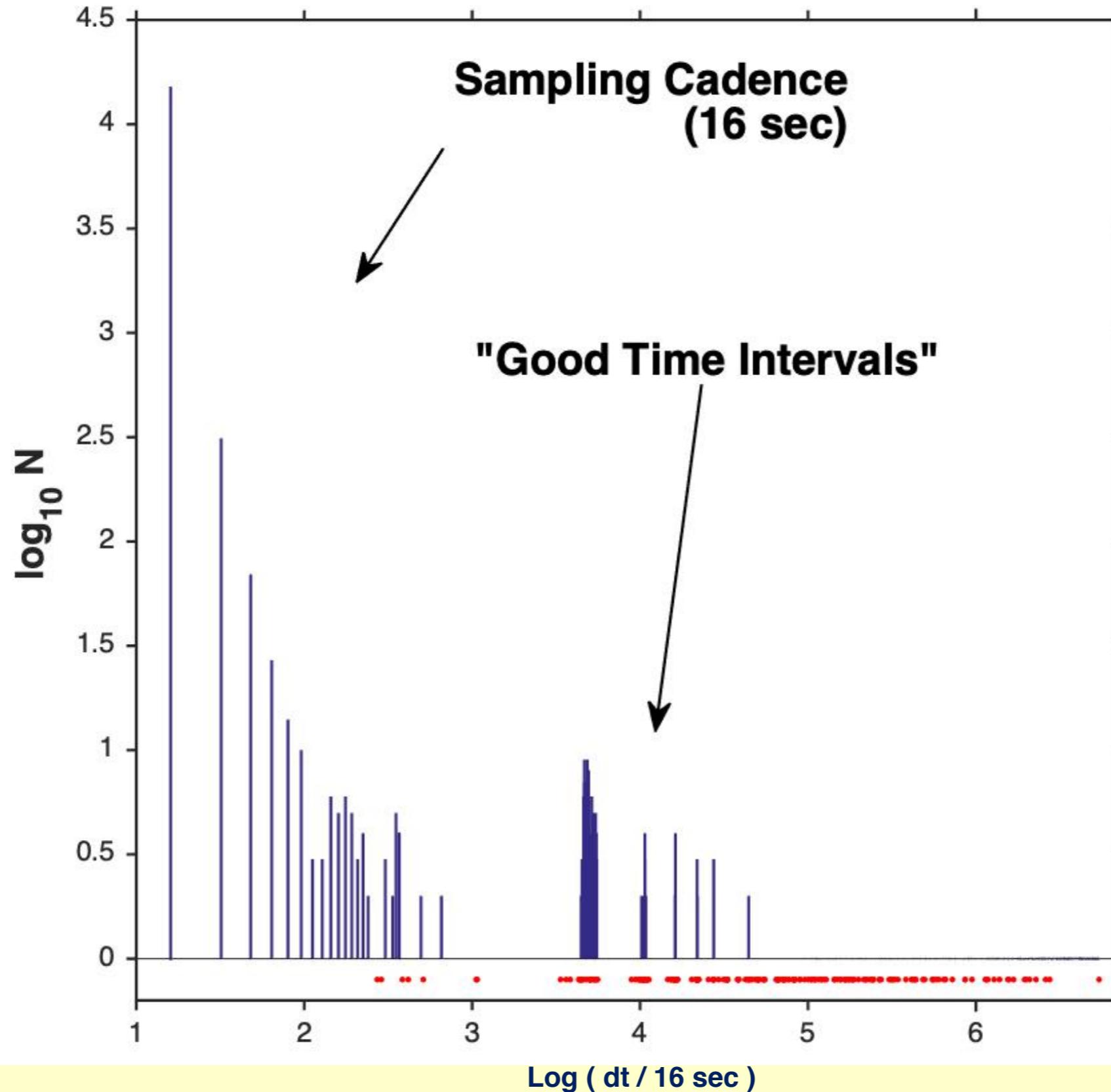
40

50

Interval size (days)

A few more

Distribution of Intervals between Nicer Observations



KIC 9650712 Krista Lynne Smith

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Given Arbitrarily Sampled Data, Algorithms for:

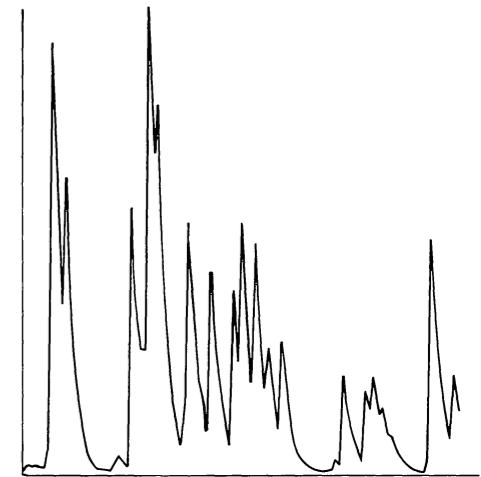
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The Wold Theorem: Any Stationary Process has an exact Moving Average (and/or Auto-regressive) Representation



$$X = C * R + D$$

(random + deterministic)



Gaussian R \rightarrow AR = Gauss-Markov = OU

Auto-regressive (AR): $X(n) = \sum_{k=1}^{\infty} A(k)X(n-k) + R(n)$

Memory Random Driver

Moving Average (MA): $X(n) = \sum_{k=0}^{\infty} C(k)R(n-k)$

Shot (Filtered) Noise

AR/MA Equivalence: $\sum A(k)X(n-k) \Leftarrow \sum C(k)R(n-k)$

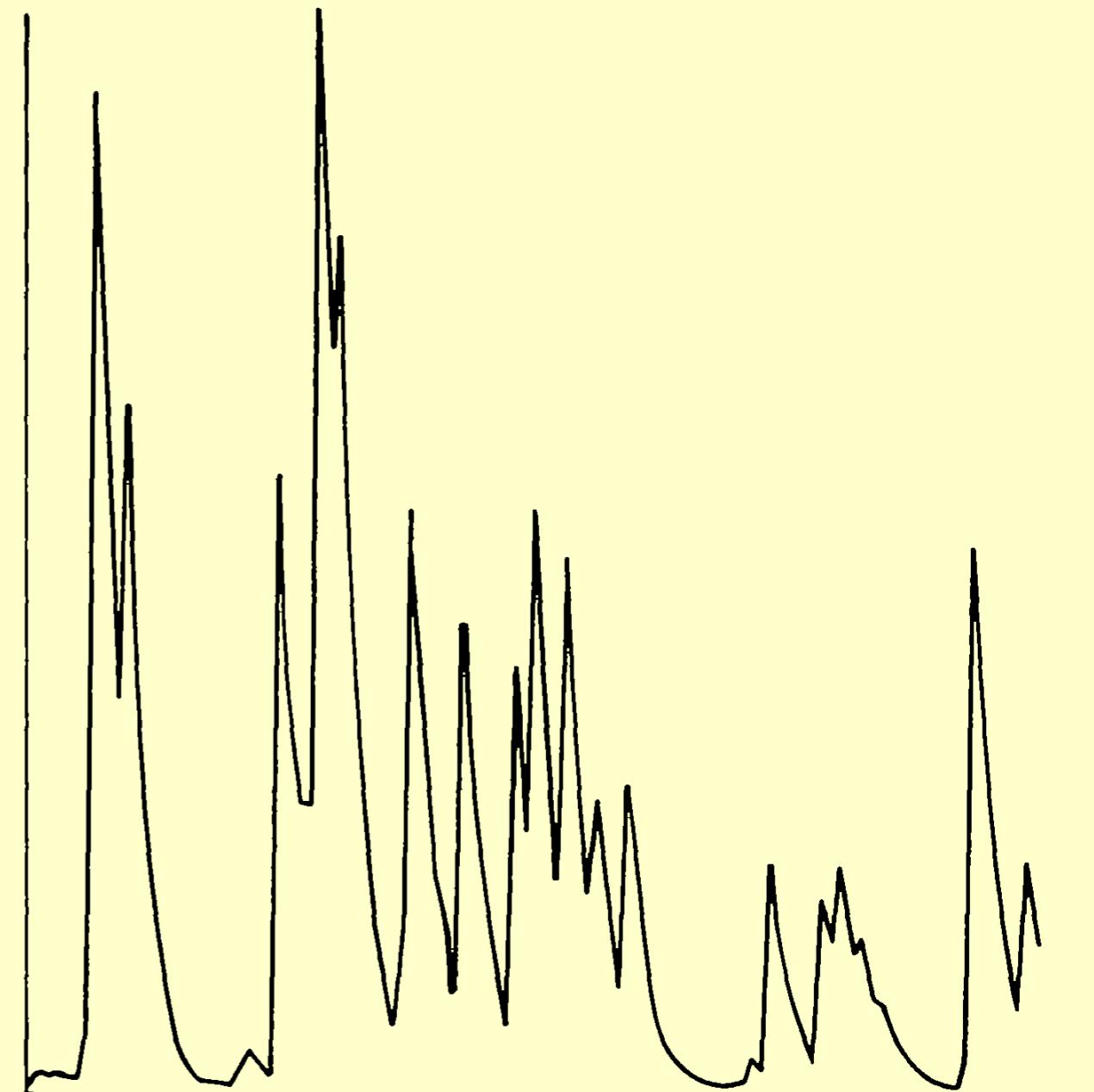
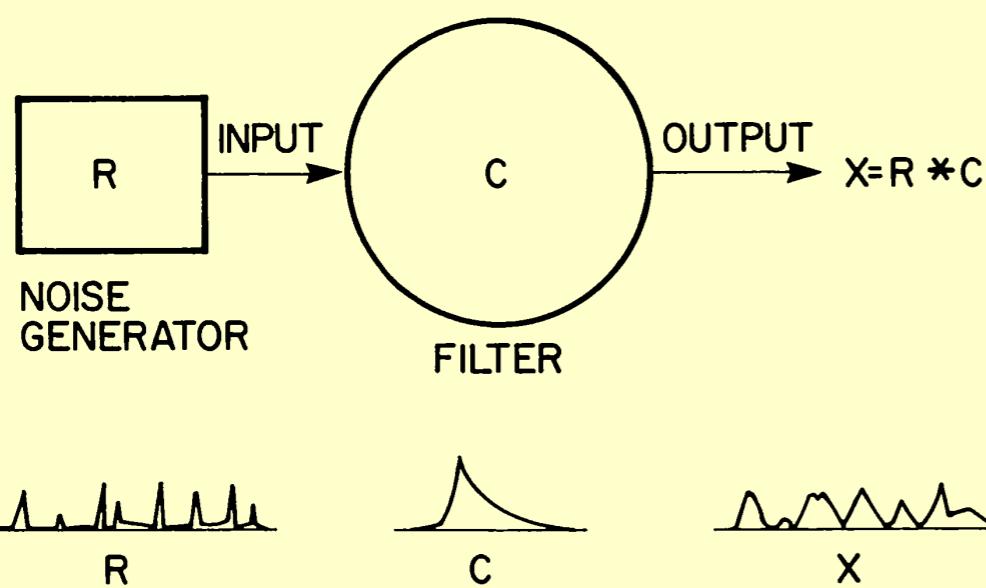
A moving average (MA) is a process X which can be written in the form:

$$X_n = \sum_{i=-\infty}^{\infty} C_i R_{n-i} \quad (X = C * R), \quad (15)$$

where R is an *uncorrelated* white noise process, possibly with nonzero mean:

$$\langle (R_n - \bar{R})(R_m - \bar{R}) \rangle = \sigma^2 \delta_{n,m} \quad (\bar{R} = \langle R_n \rangle) \quad (16)$$

and the C_i are constants satisfying $\sum_{-\infty}^{\infty} C_i^2 < \infty$ (called *stability* of the filter C). If the C_i are zero for all negative (positive) values of i this is a *causal* (*purely acausal*) moving average. If neither is true, it is called a two-sided, or acausal MA. A MA is said to be of order (p, q) if the range of i for which C_i is nonzero is from $-q$ to p .



The *Wold Decomposition Theorem*: Given any stationary process, X , there exist:

1. a purely deterministic process D ,
2. an uncorrelated zero-mean noise process R , and
3. a moving average filter C ,

such that $X = R * C + D$.

The *Extended Decomposition Theorem*: Given any stationary process X , there exist:

1. a purely deterministic process D ,
2. a family of uncorrelated, zero-mean noise processes, $\{R^{(i)}\}$, and
3. a family of two-sided moving average filters, $\{C^{(i)}\}$,

such that $X = D + C^{(i)} * R^{(i)}$. The filter family is the set of all filters which have the same autocorrelation function as X ; one of them is minimum delay, and one maximum delay, and the rest are mixed delay.

Generalized Wold Theorem: Any Stationary Process has a family of equivalent, exact AR and/or MA Representations

Family of MA representations: $X(n) = \sum_{k=-\infty}^{\infty} C^m(k) R^m(n-k)$

If the Moving Average has M coefficients
there are 2^M C's (with different, but white, R's)
that yield *exactly equivalent representations of X.*

One minimum delay, one maximum delay; others mixed delay.

Conjecture: *the unique R of the “correct” MA is IID.*
→ *minimum dependence blind deconvolution!*

Two Possible Solutions to the Arrow of Time:

- (1) two-sided (acausal) models + new fitness measures
- (2) “local” models, such as Bayesian Blocks

All this, and more, in JS, Studies in Astronomical Time Series Analysis:
I. Modeling Random Processes in the Time Domain, ApJS. 1981, 45, 1-71

Three Representations of a given stationary process:

$$X = C * R$$

MA



$$A * X = C * R$$

ARMA



$$A * X = R$$

AR

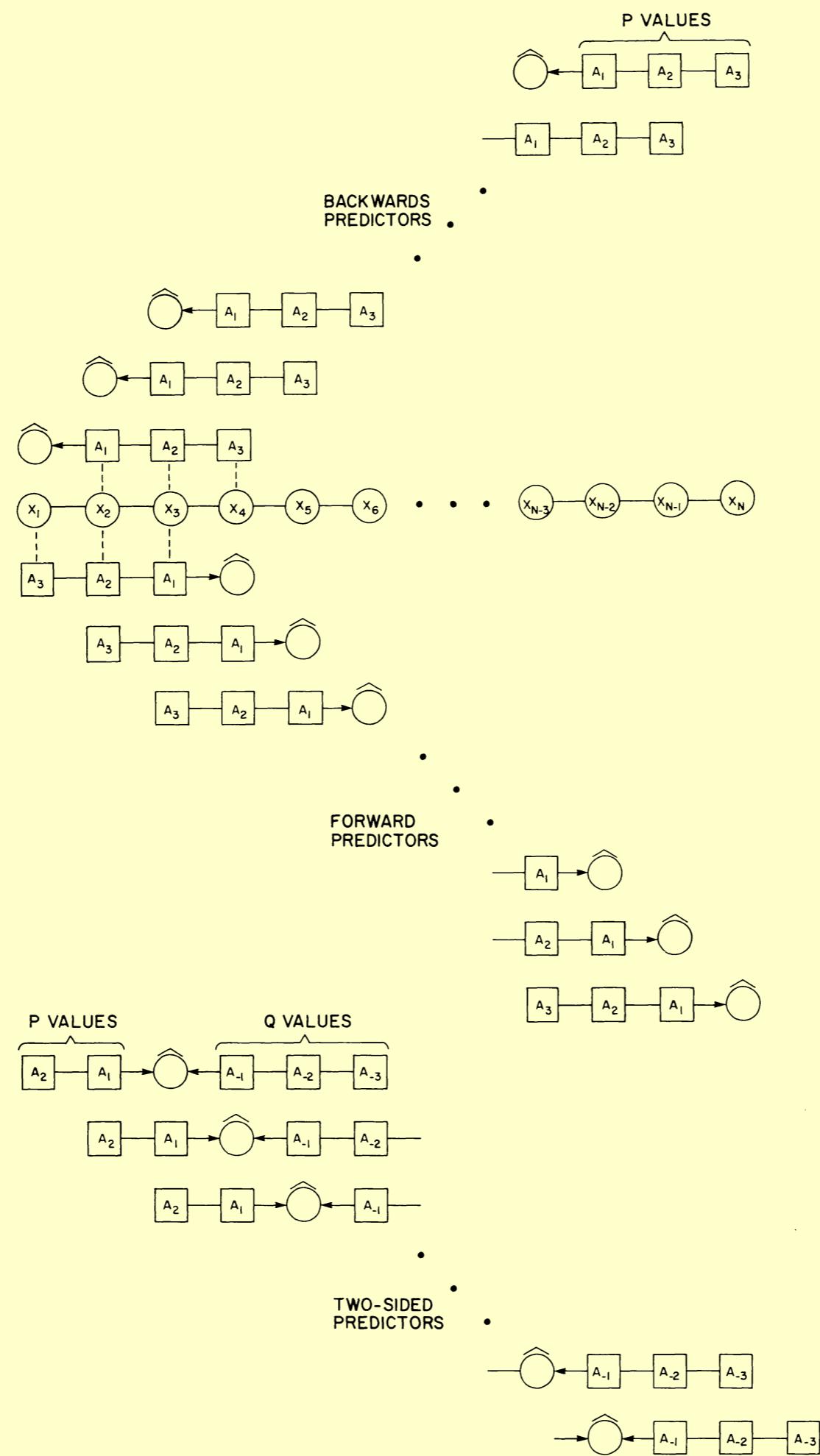
$$C = A^{-1}$$

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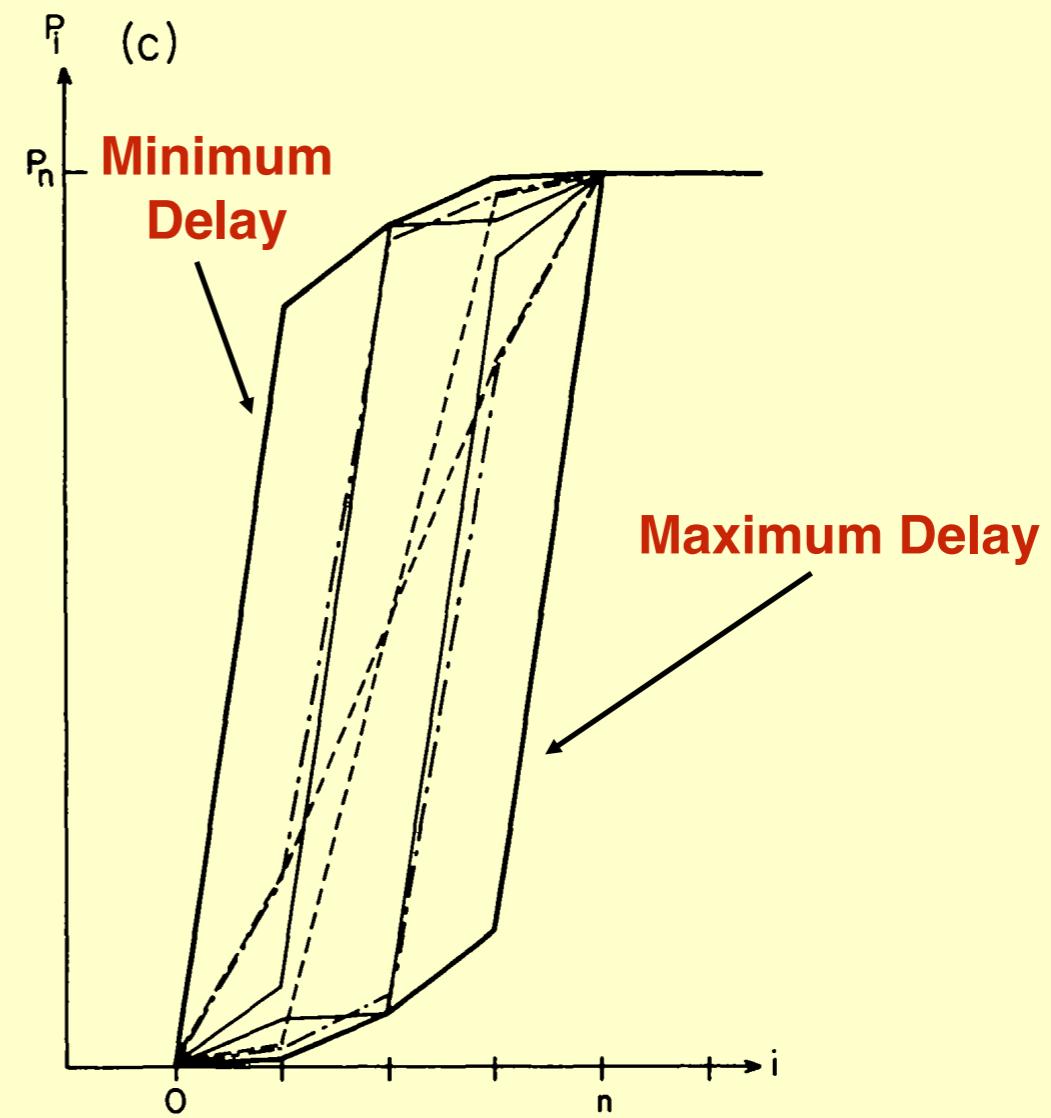
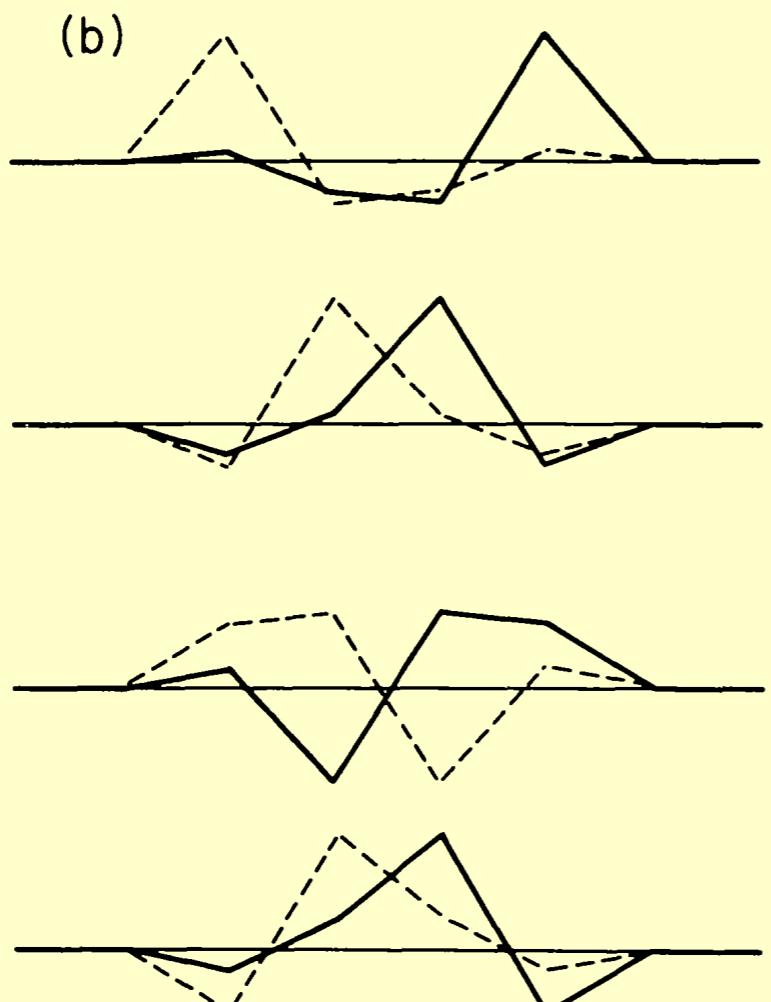
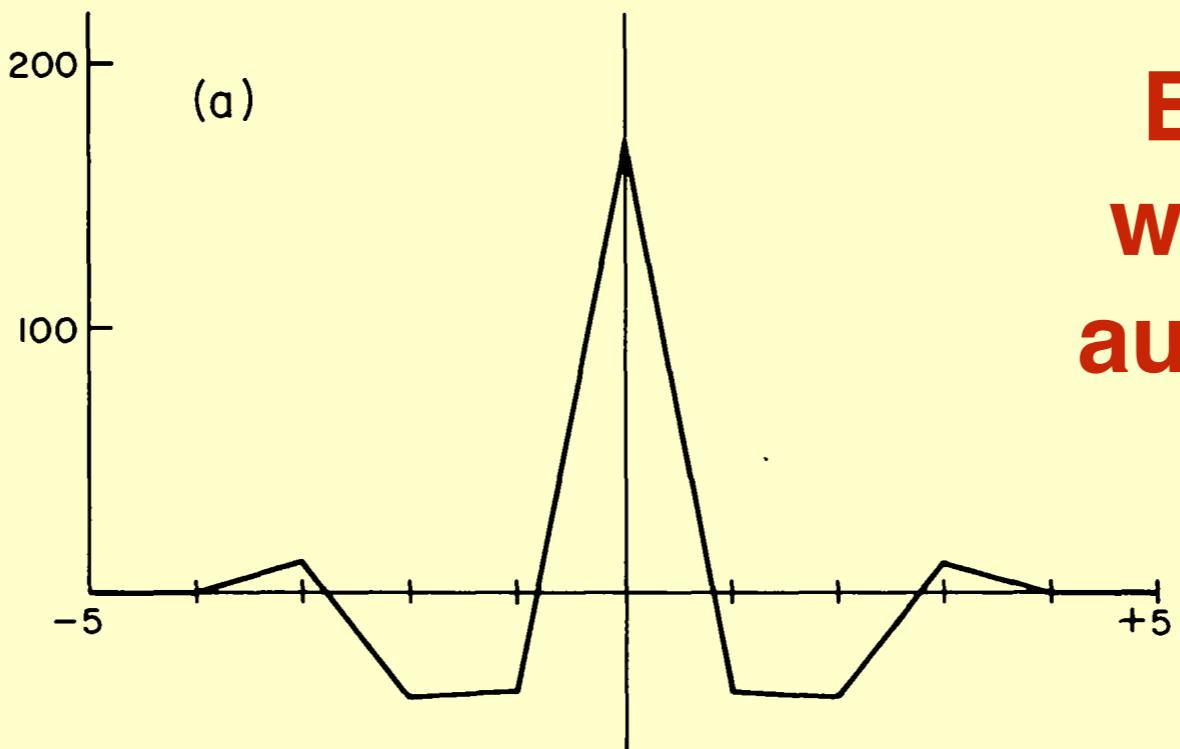
Similarly for certain types of Nonstationarities

Autoregressive / Integrated / Moving Average

ARIMA

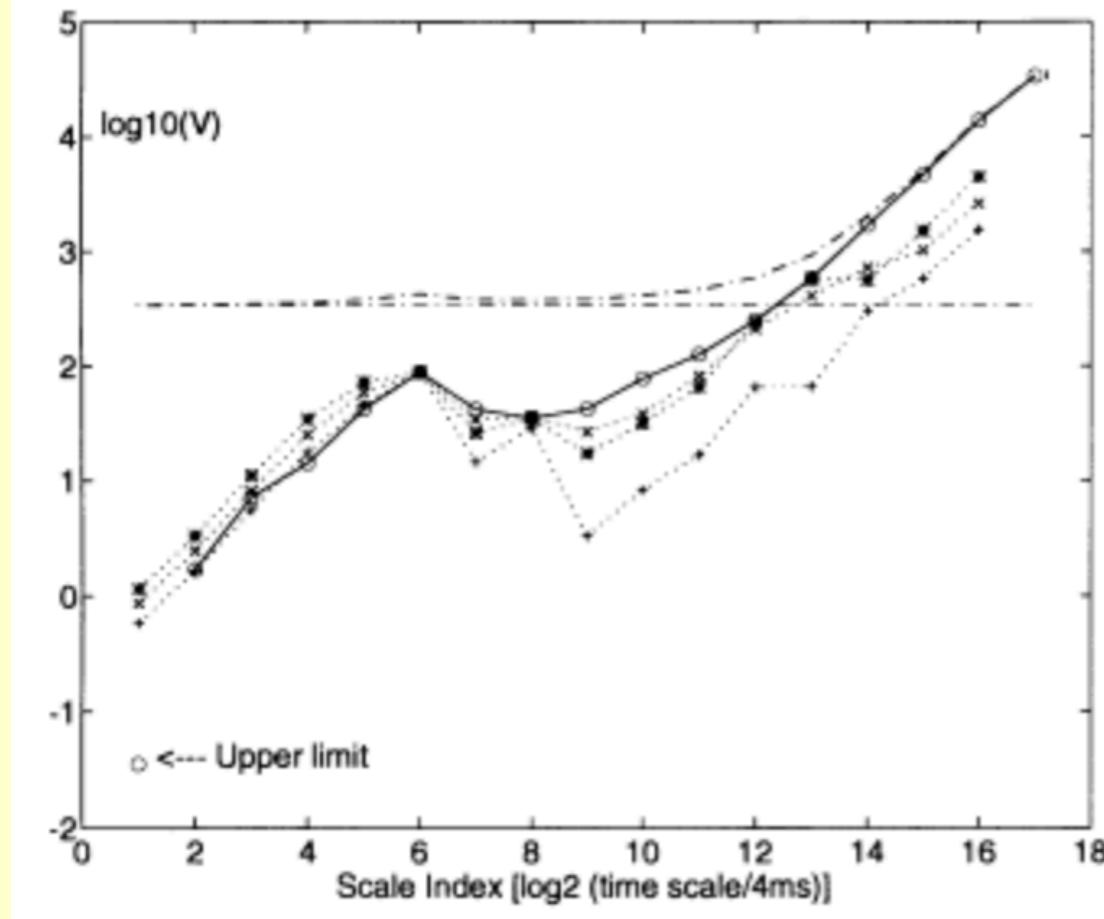


Eight pulses with the same autocorrelation



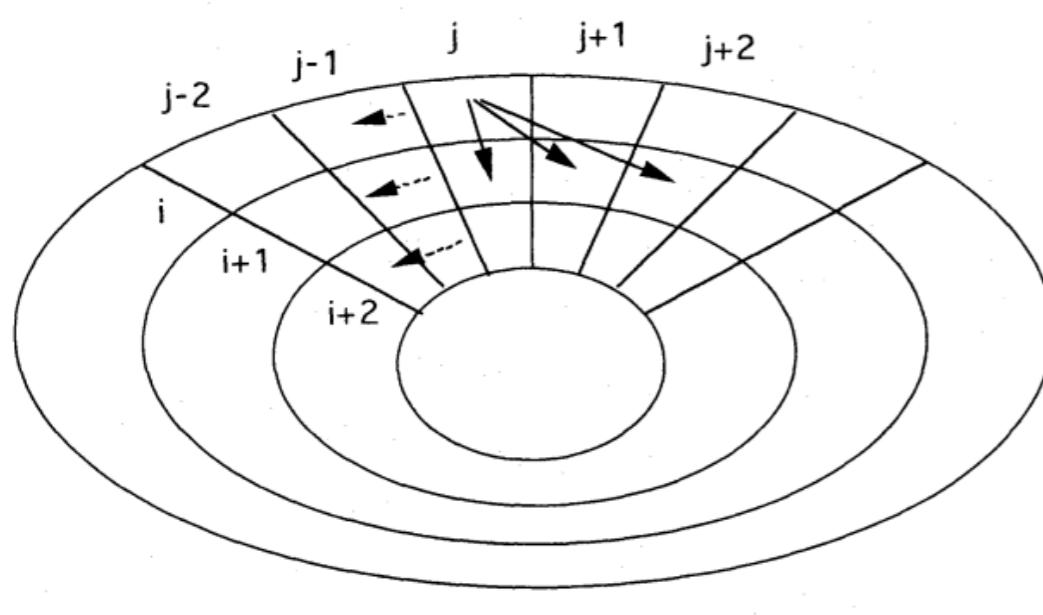
Physical Models

THE QUASI-PERIODIC OSCILLATIONS AND VERY LOW FREQUENCY NOISE OF SCORPIUS X-1 AS TRANSIENT CHAOS: A DРИPPING HANDRAIL?



$$\frac{\partial \rho}{\partial t} = D \frac{\partial^2 \rho}{\partial x^2} + \omega_A ,$$

with the threshold a condition imposed on the solution. 1



On the Generation of 1/f Fluctuations
in X-Rays from Black-Hole Objects

Shin MINESHIGE,¹ N. Bob OUCHI,² and Hiraku NISHIMORI³

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Fourier Transform of Unevenly Spaced Time Series

weights (extensive) (intensive) amplitudes time tags

The Measurable Quantities of Physics
Tolman, 1917, Phys. Rev. 9, 237–253

frequencies
(arbitrary)

$$FT_X(\omega) = F_0 \left\{ \frac{\sum_n w_n x_n \cos \omega(t_n - \tau(\omega))}{[\sum_m w_m \cos^2 \omega(t_m - \tau(\omega))]^{1/2}} + i \frac{\sum_n w_n x_n \sin \omega(t_n - \tau(\omega))}{[\sum_m w_m \sin^2 \omega(t_m - \tau(\omega))]^{1/2}} \right\} \quad (1)$$

where

$$\tau(\omega) = \frac{1}{2\omega} \arctan [(\sum w_n \sin 2\omega t_n) / (\sum w_m \cos 2\omega t_m)] \quad (2)$$

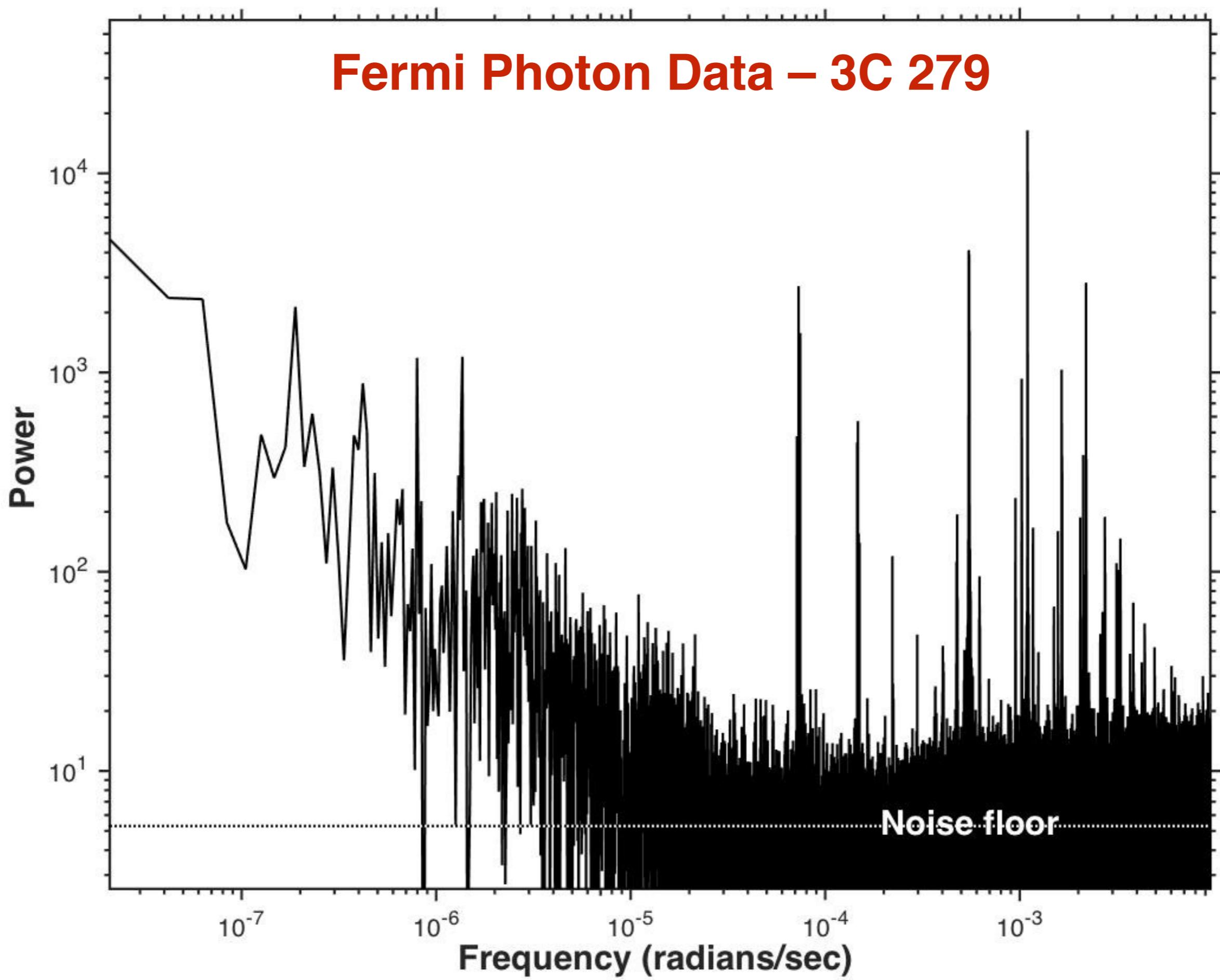
where all sums are over $n = 1, 2, \dots, N$.

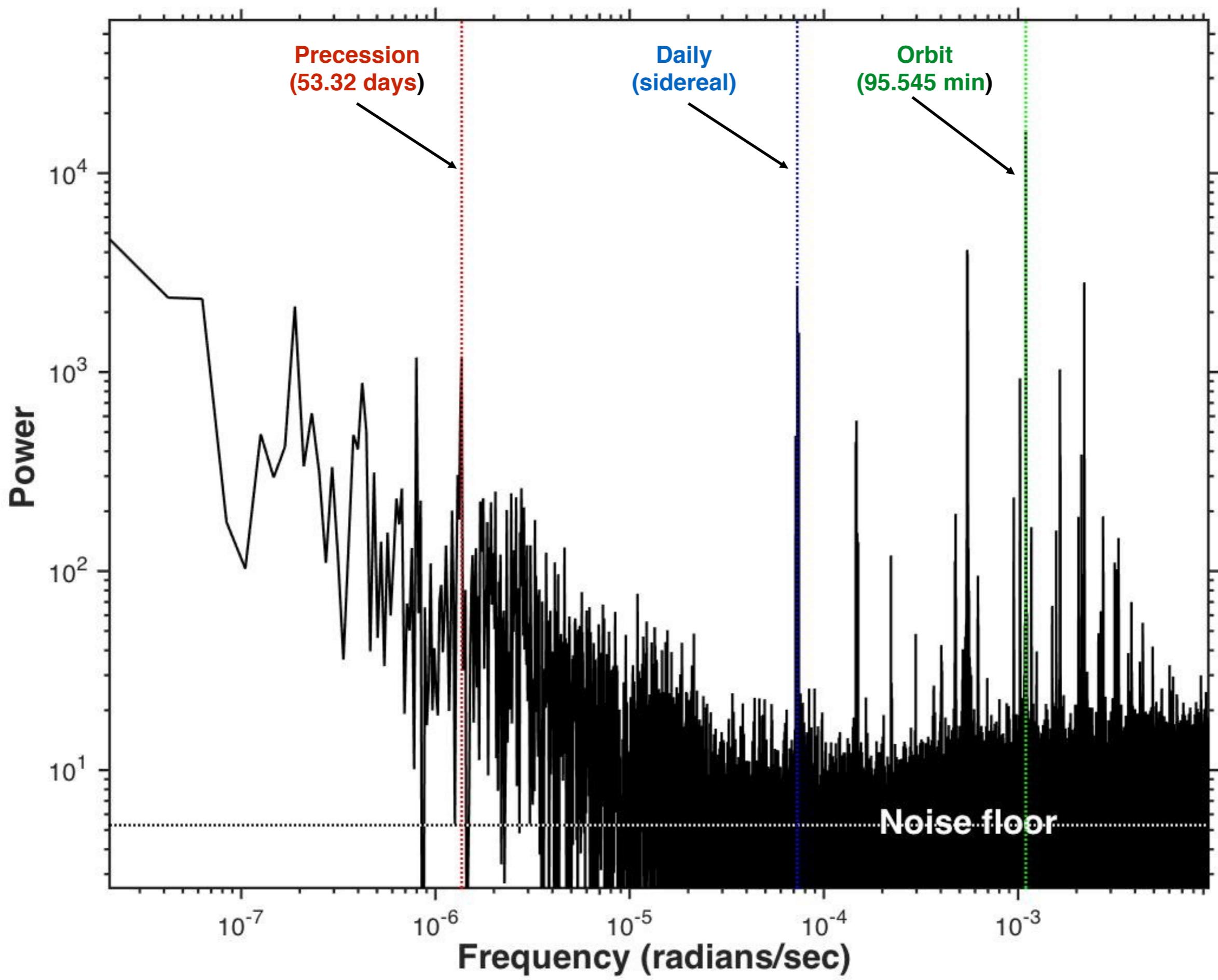
Many applications:

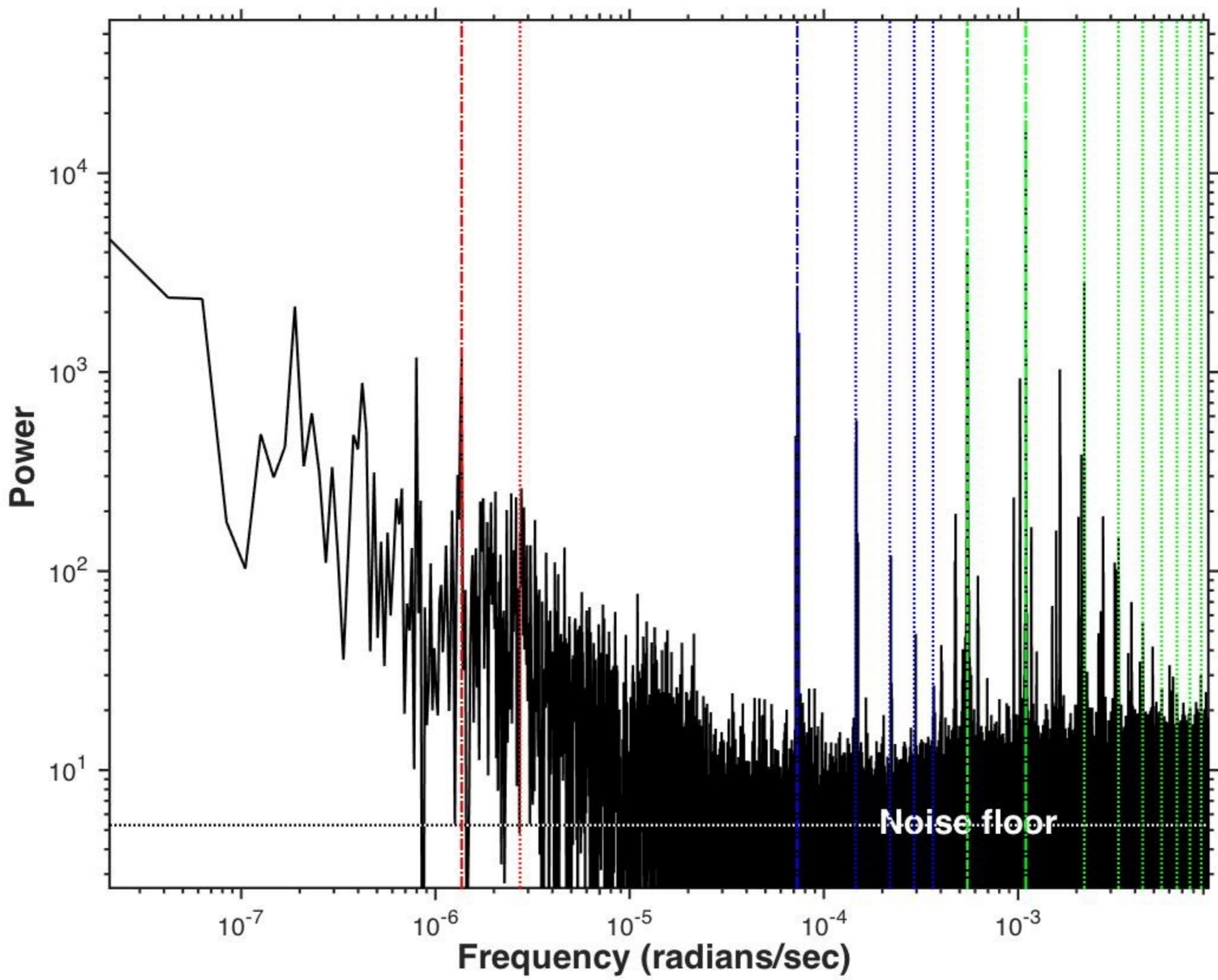
individual photons $x_n = \delta(t - t_n)$

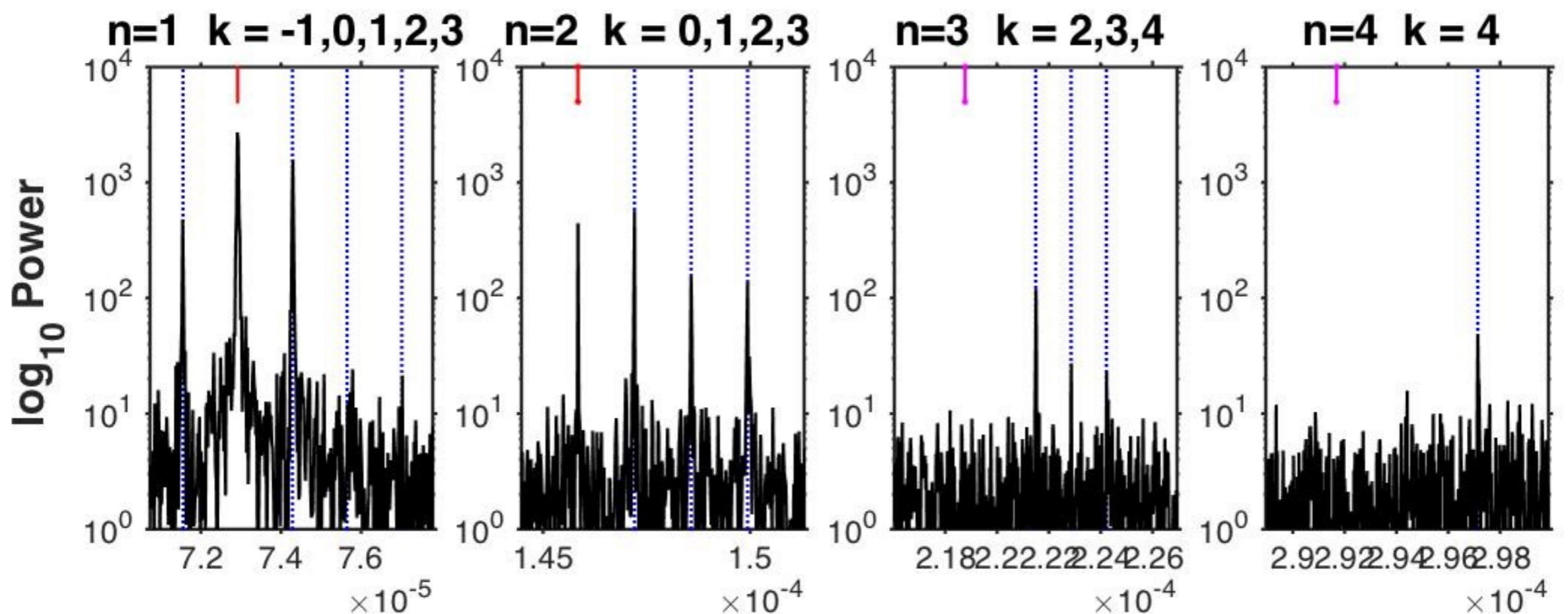
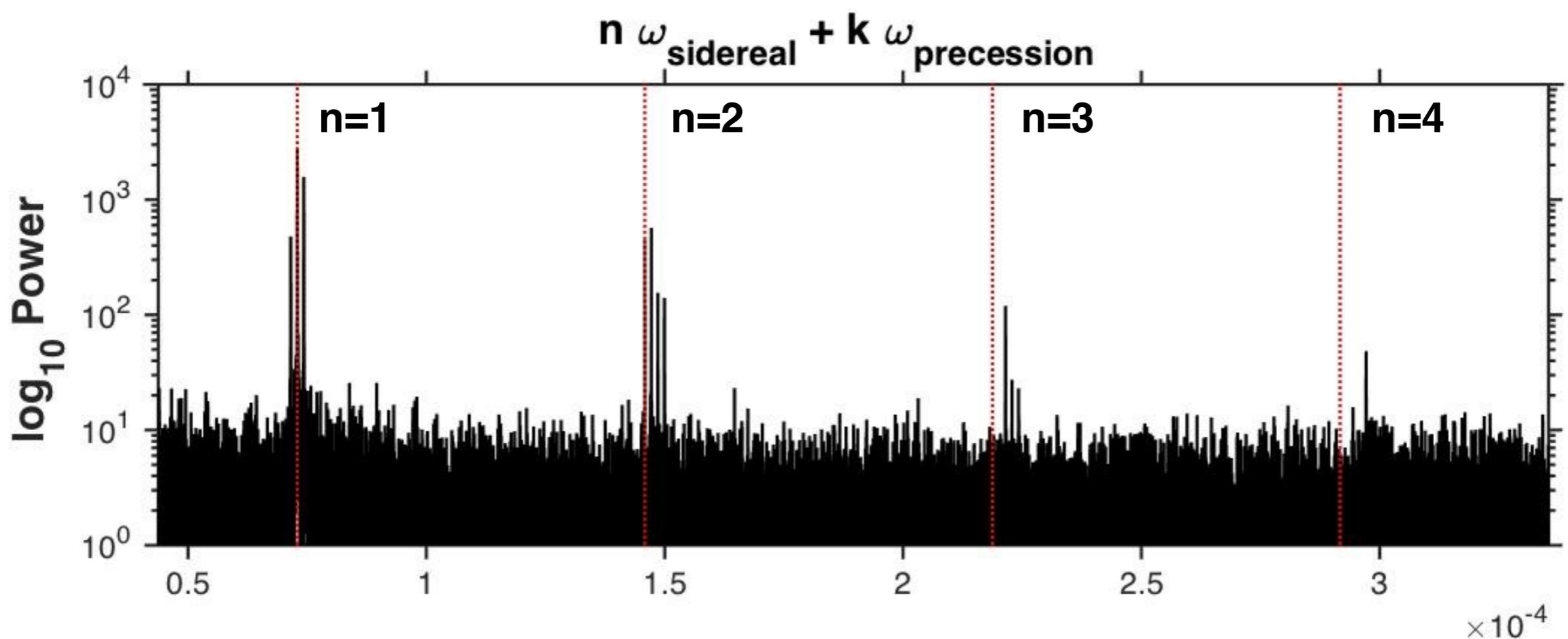
cross-spectra: $FT_X FT_Y^*$ [cf. Daniela's presentation]

Fermi Photon Data – 3C 279

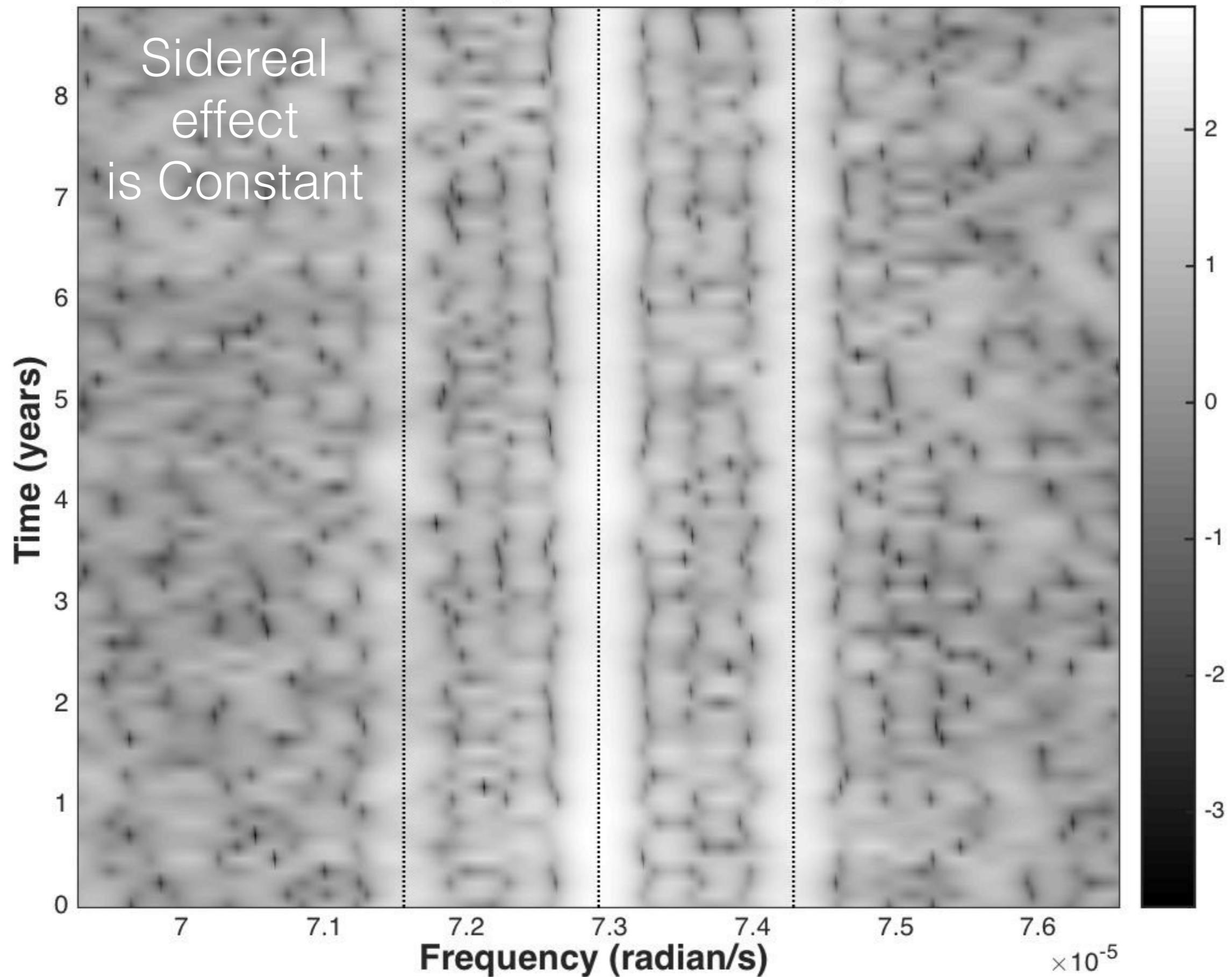




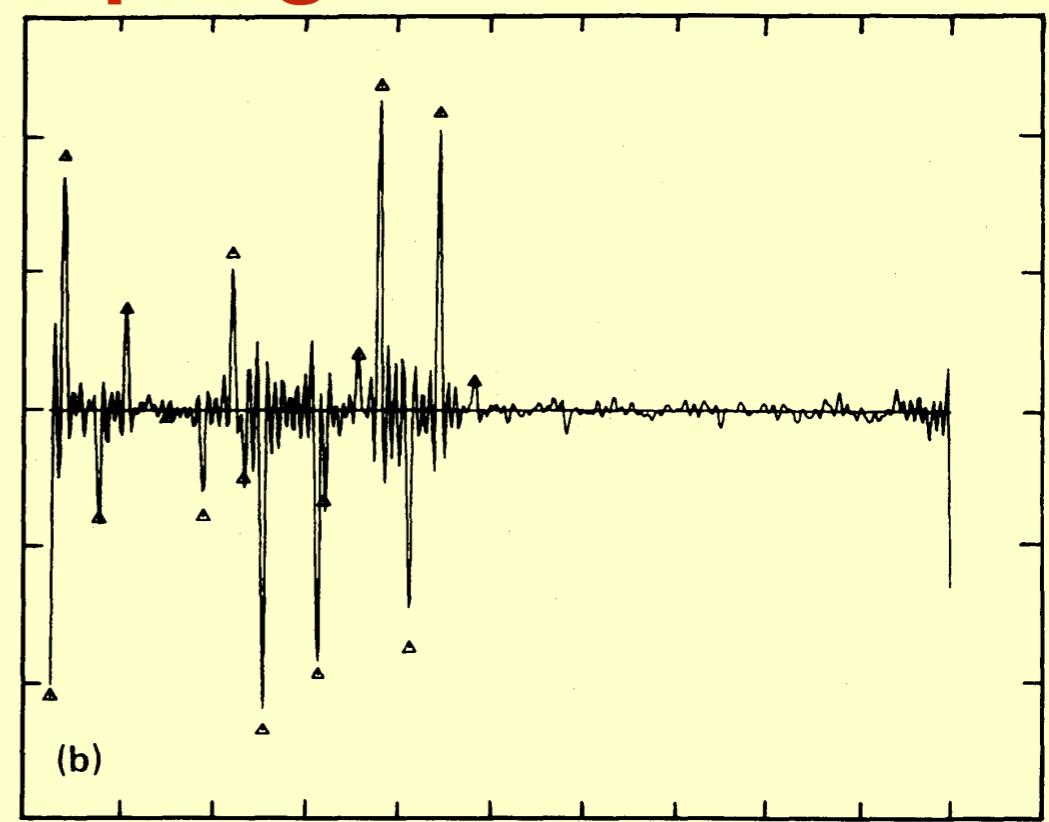
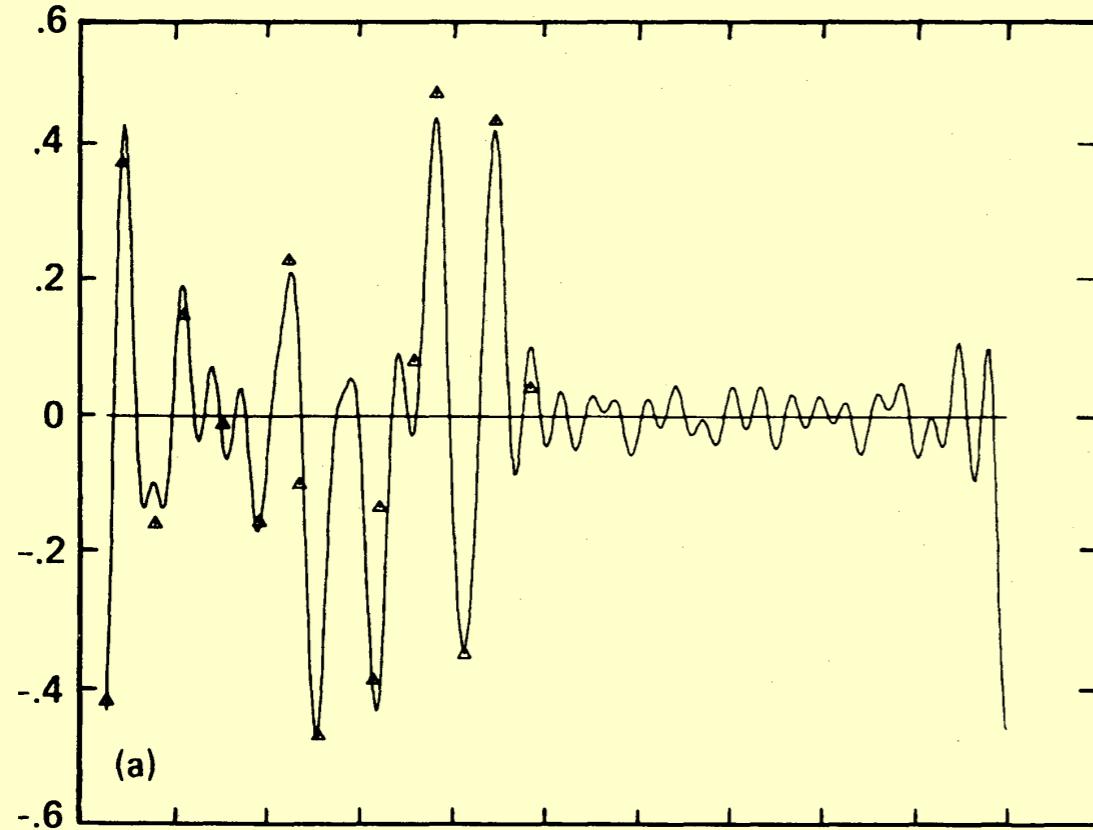




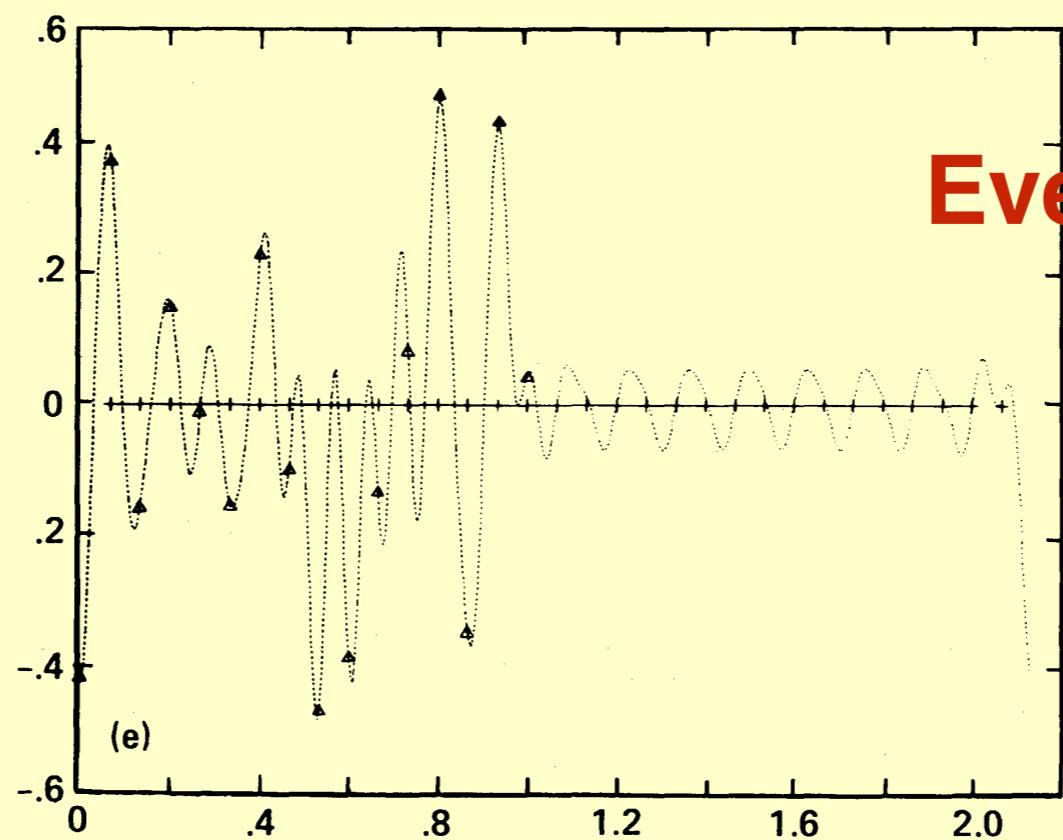
Time-Frequency Distribution of Log Power



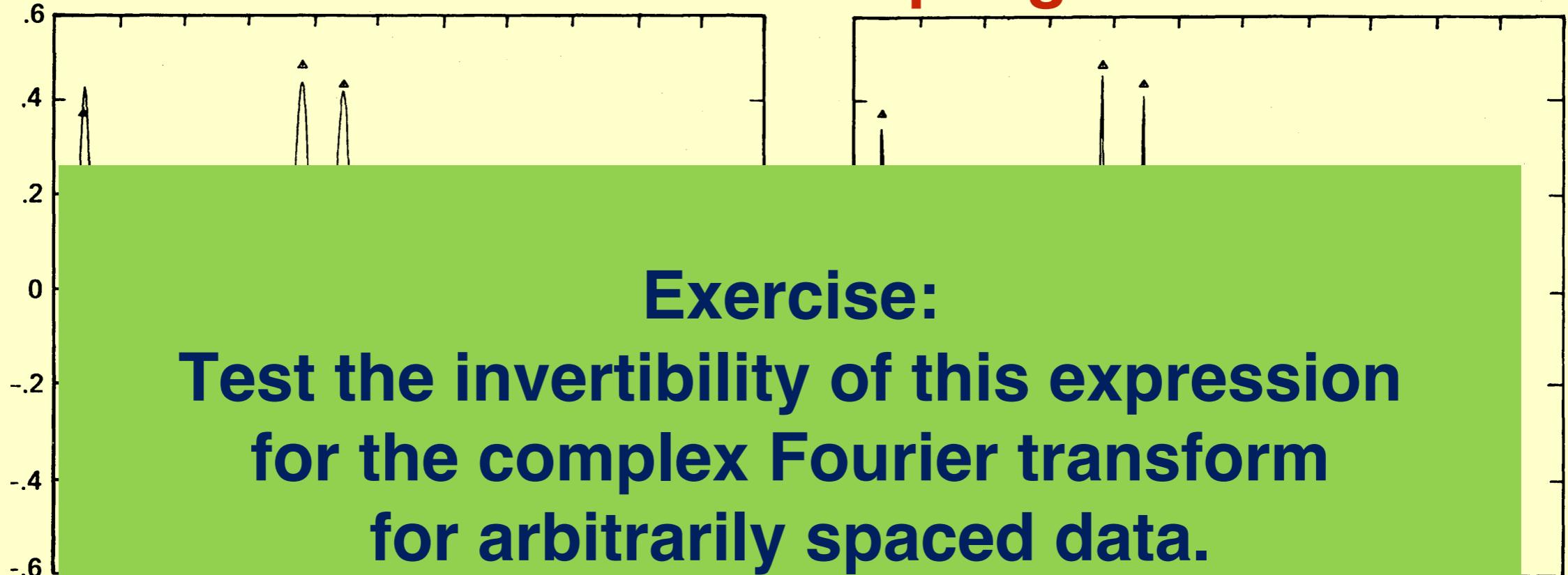
Random Sampling



Test Invertibility of Fourier Transform

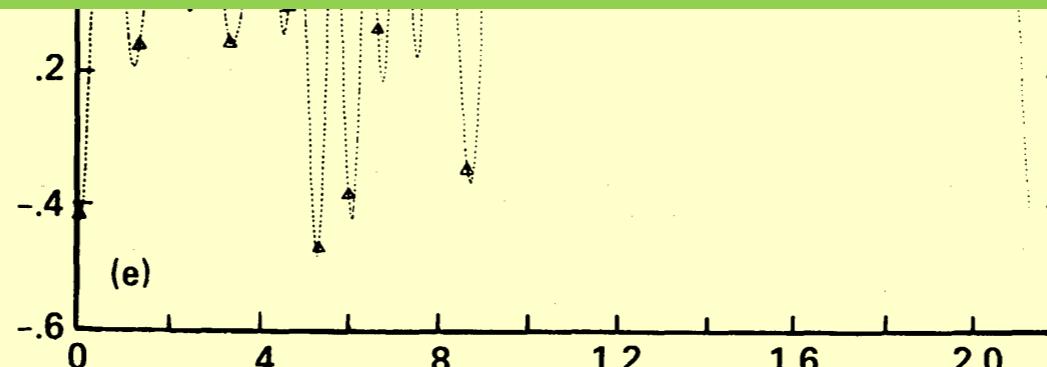


Random Sampling



Explore the frequency grid needed.

**What happens between the samples
and outside of the sampling interval?**



OUTLINE

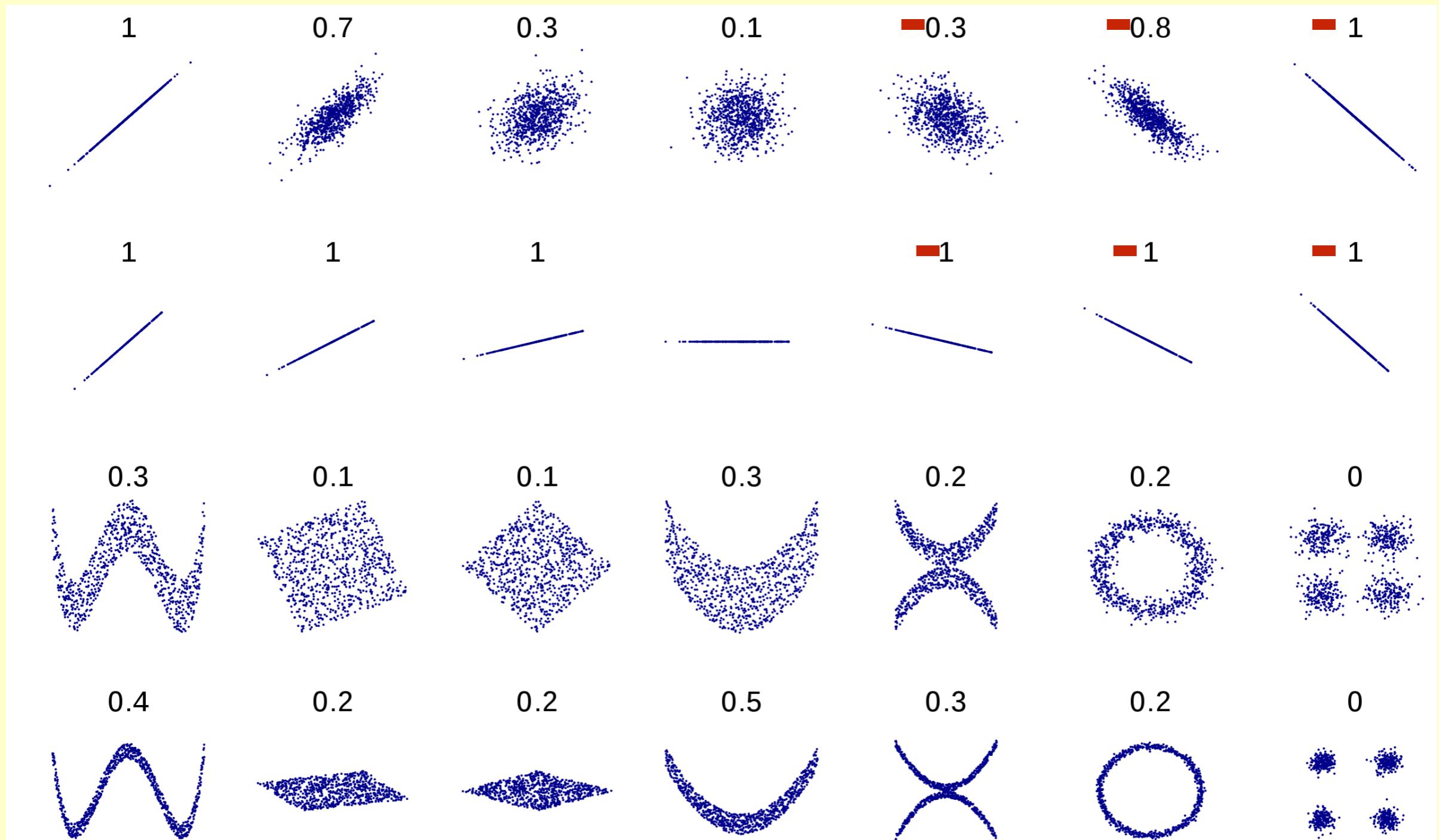
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How related are two given time series?

The ubiquitous **correlation coefficient** characterizes linear relations, but is insensitive to non-linear ones.

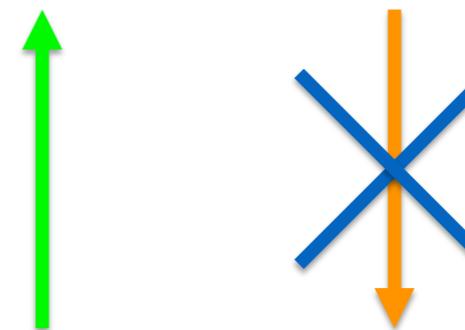


Hierarchy of Degrees of Relationship between two processes X and Y

(Inner Product)

Uncorrelated:

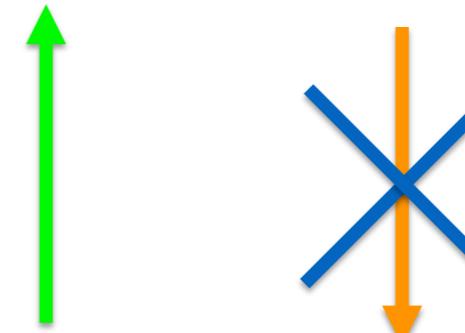
$$E [X(t) Y(t)] = 0$$



(Expectations)

Martingale Property: $E [X(t) | Y(t)] = E [X(t)]$

$E [Y(t) | X(t)] = E [Y(t)]$

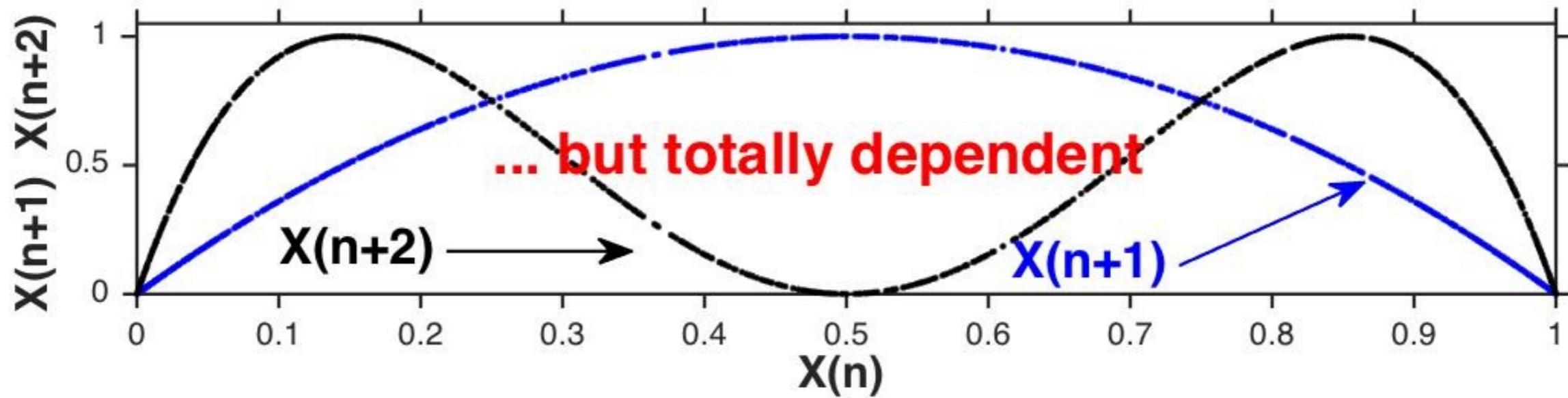
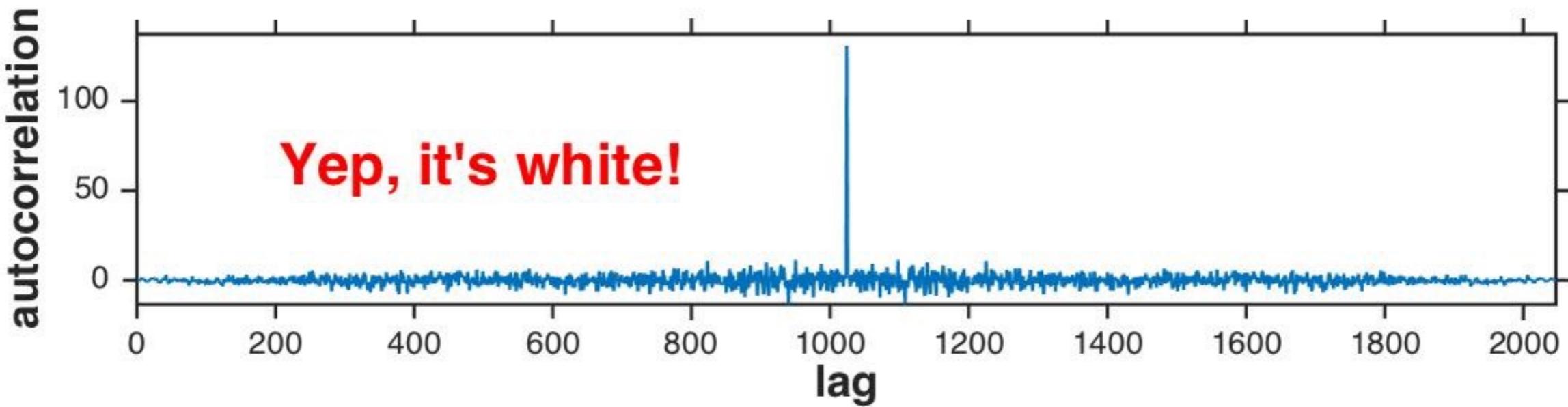
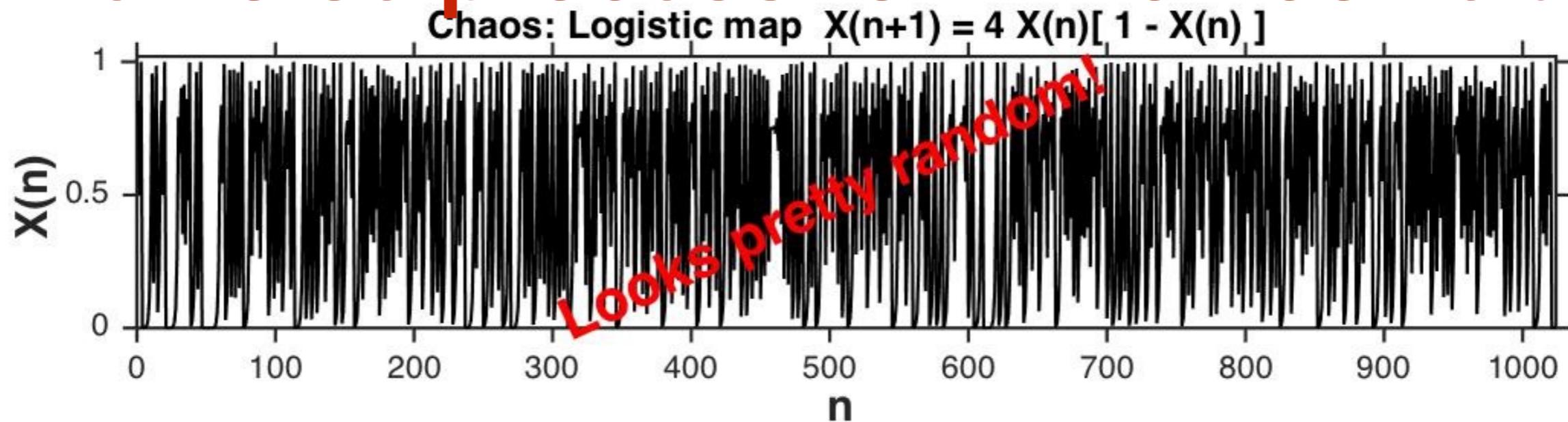


(Distributions)

Independent:

$$F(X, Y) = F(X) F(Y)$$

white noise process for which correlation



Measure (in)dependence between two time series

$$D(X, Y) == \langle F(X, Y), F(X) F(Y) \rangle$$

F can be:

- Differential Probability Distribution
- Cumulative Probability Distribution
- Characteristic Function ...

\langle , \rangle can be:

- Mean Square Difference
- Mutual Information
- Bayesian Histogram Comparator (D.Wolpert)
- Earth-Mover's Distance
- Copula, etc., etc., etc.

Why are Dependence Measures not Used as much as Correlations?

Correlations (and Correlation Functions)

- Bi-Linear in the Data
- Directly computable from the time series
- Widely used standard tool (the Lemming effect)
- Easily computable

Dependence Measures (and Functions)

- Not Bi-Linear in the Data
- Require estimates of probability distributions
(But bin-free estimates are straightforward)
- Many ways to measure $F(X, Y)$ vs. $F(X)F(Y)$
- Theoretical analysis difficult

Dependence in the Statistics Literature

Goodman (1997)

Statistical Methods ... the Midway View of Nonindependence

The Practice of Data Analysis, Essays in Honor of John W. Tukey, Princeton U. Press,

Szekely, Rizzo and Bakirov (2007)

Measuring and Testing Dependence by Correlation of Distances

Annals of Statistics, 35, 2769-2794.

Ding and Li (2015)

Copula Correlation: An Equitable Dependence Measure and Extension of Pearson's Correlation 1312.7214

Yakir et al (2016)

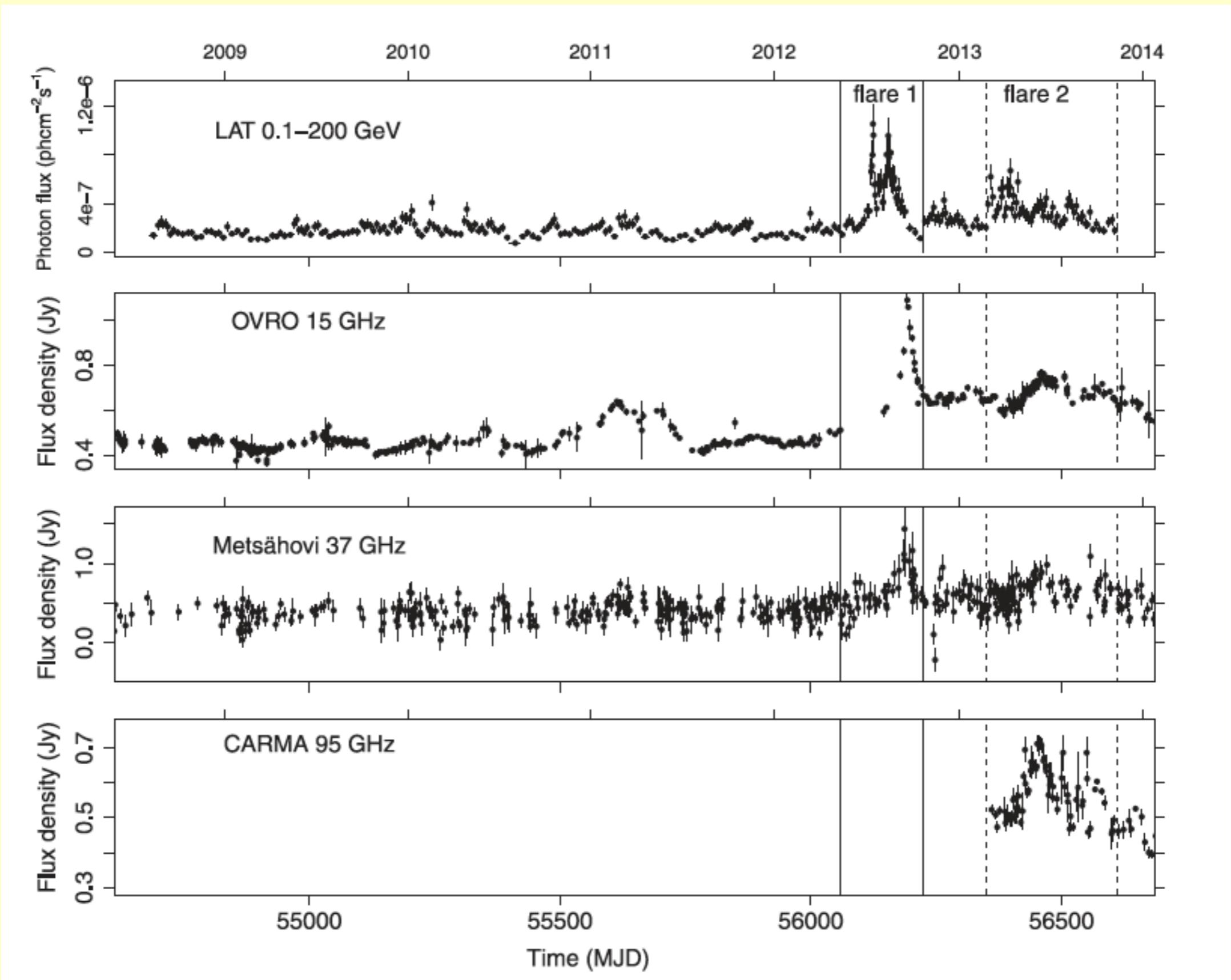
Measuring Dependence Powerfully and Equitably 1505.02213

Richards (2017)

Distance Correlation: A New Tool for Detecting Association and Measuring Correlation Between Data Sets 1709.06400

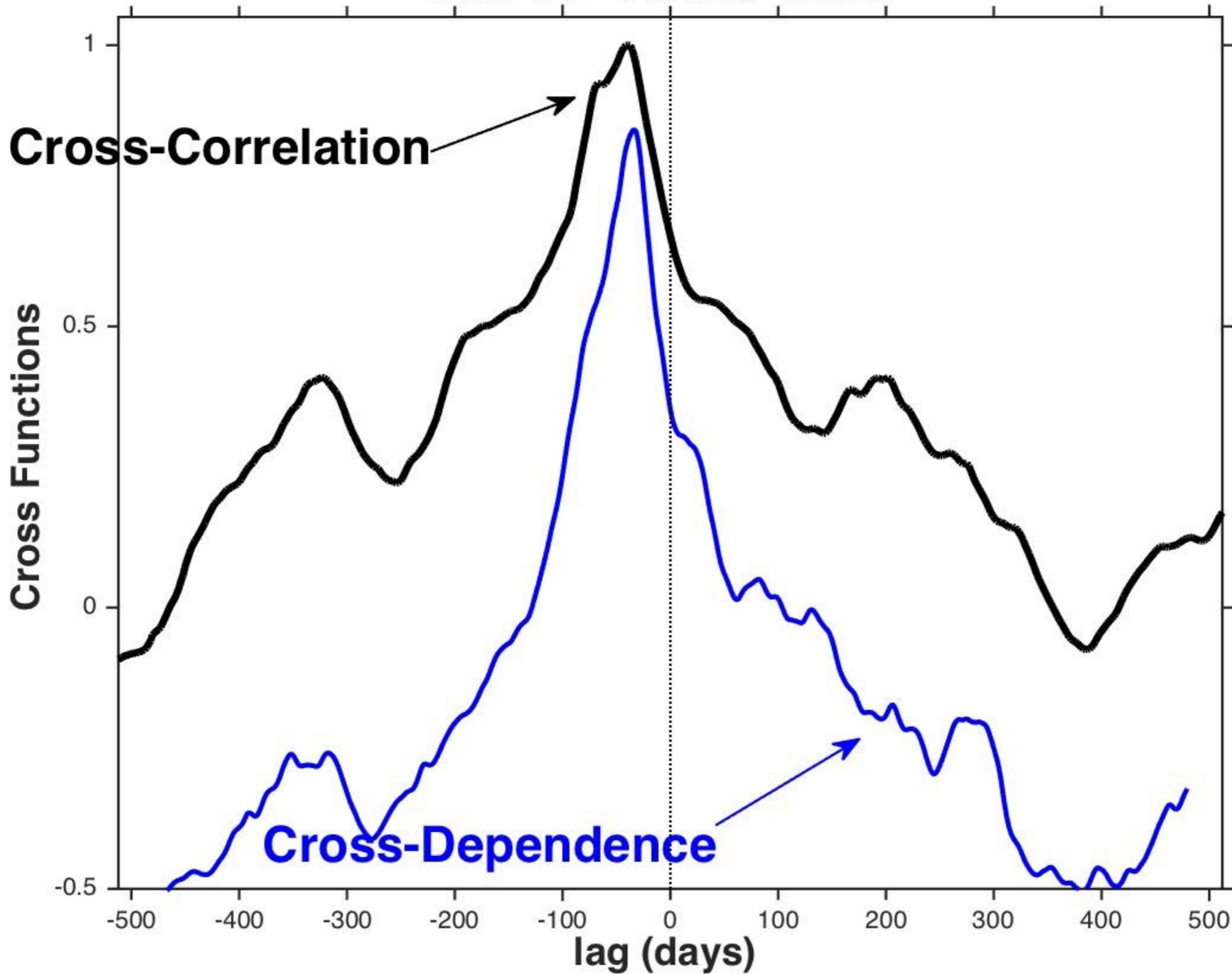
Kagan and Szekely (2019)

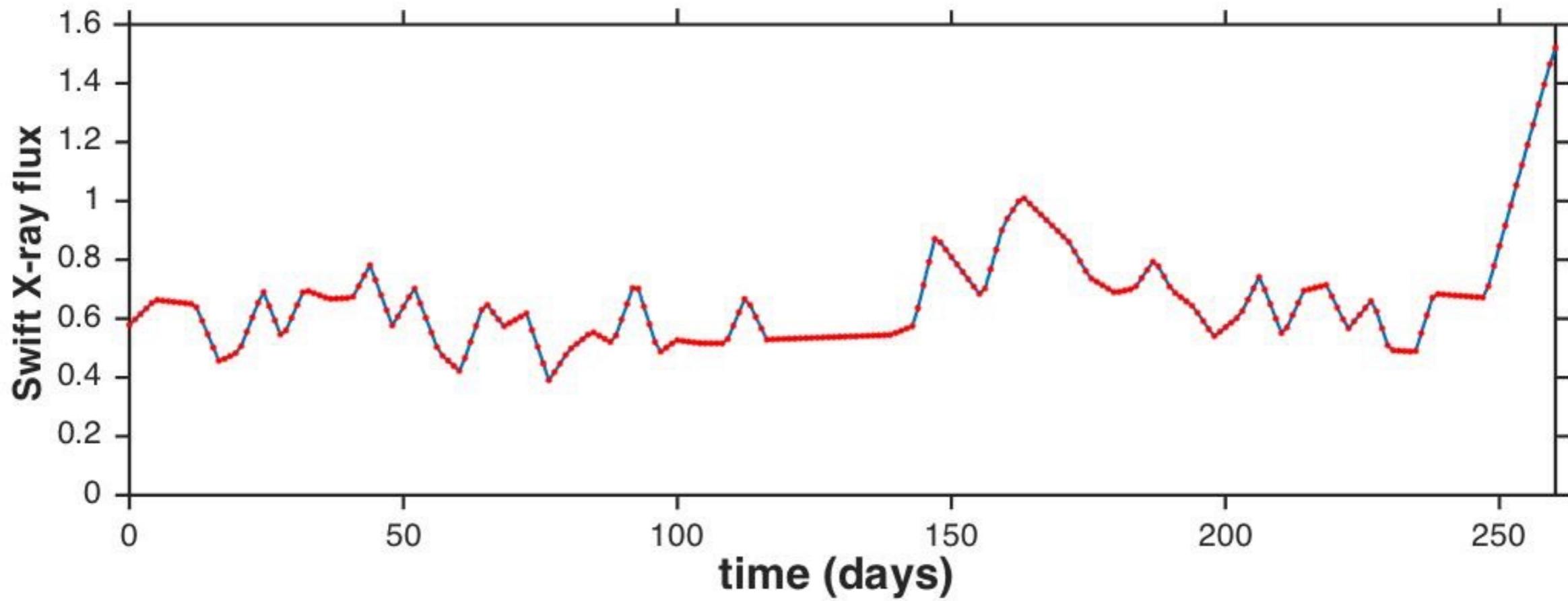
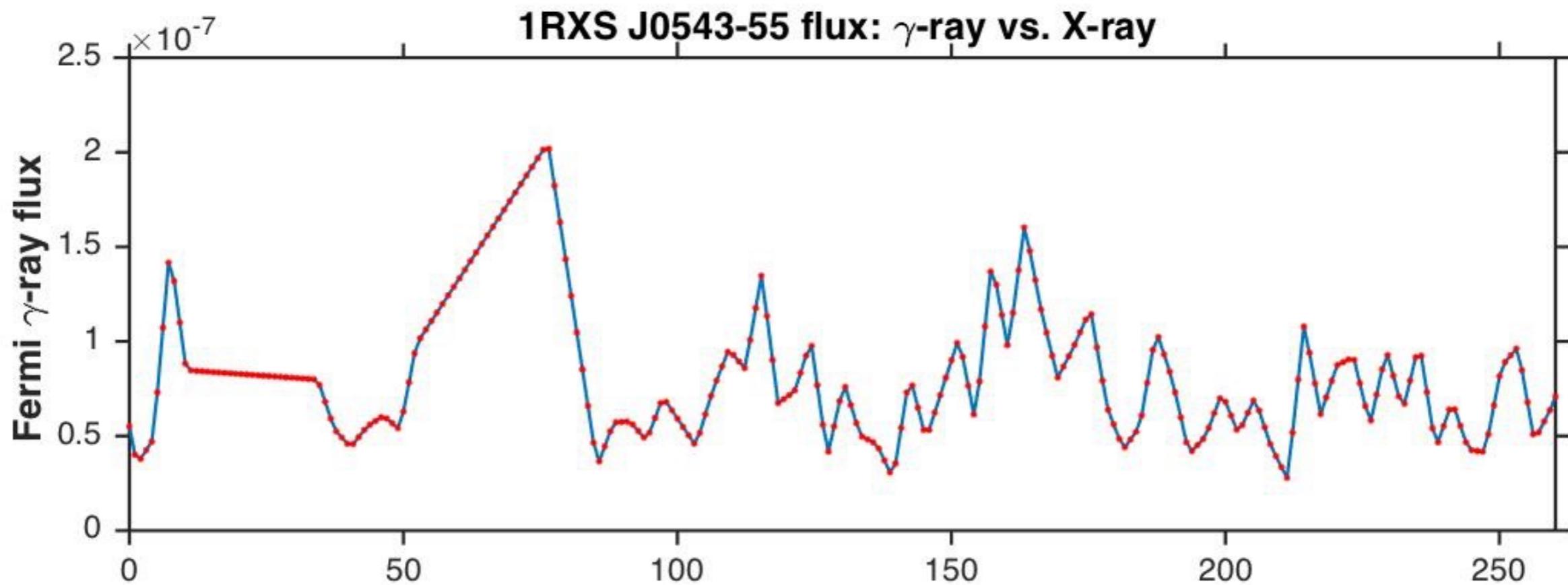
Calibrating Dependence between Random Elements 1903.04663



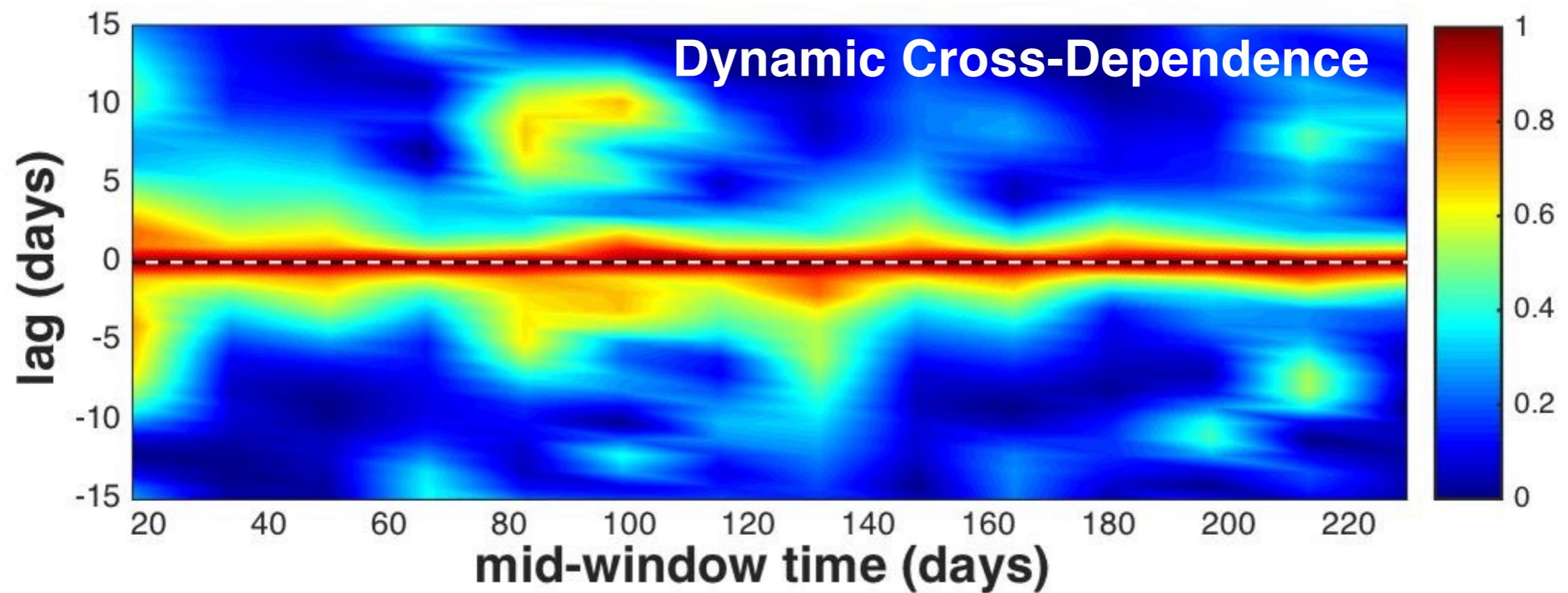
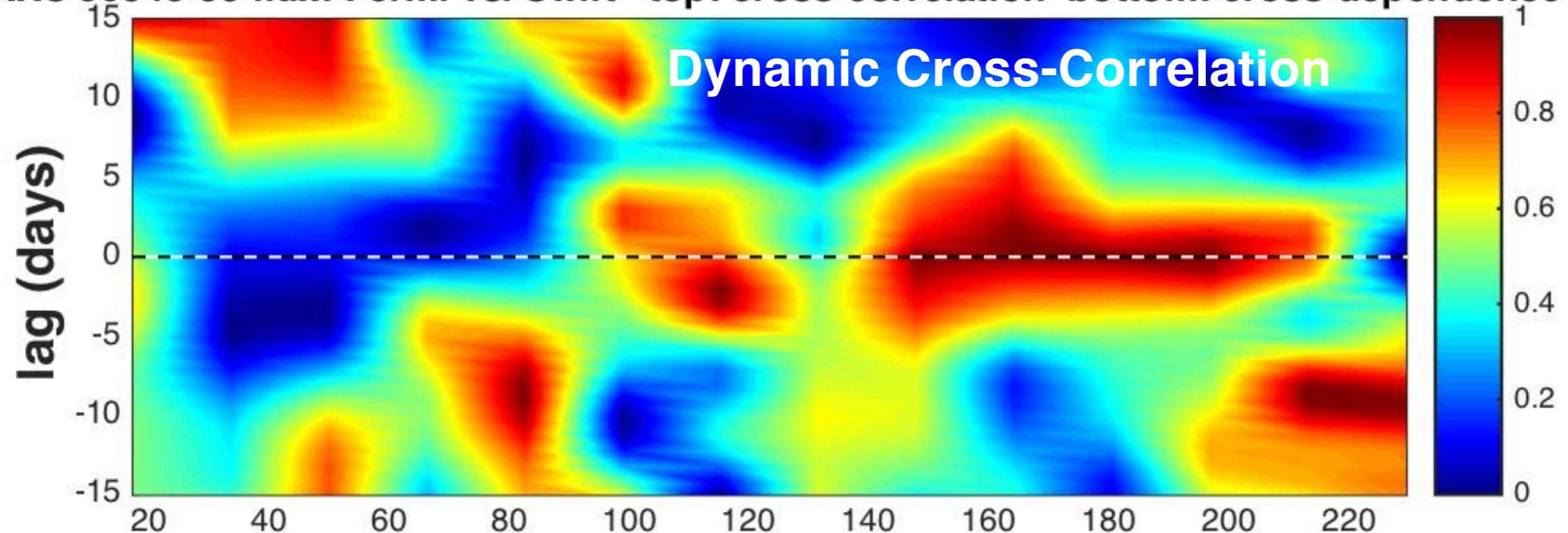
A combined radio and GeV γ -ray view of the 2012 and 2013 flares of Mrk 421
T. Hovatta et al., MNRAS 448, 3121–3131 (2015)

Mkn 421 Fermi x OVRO





1RXS J0543-55 flux: Fermi vs. Swift top: cross-correlation bottom: cross-dependence



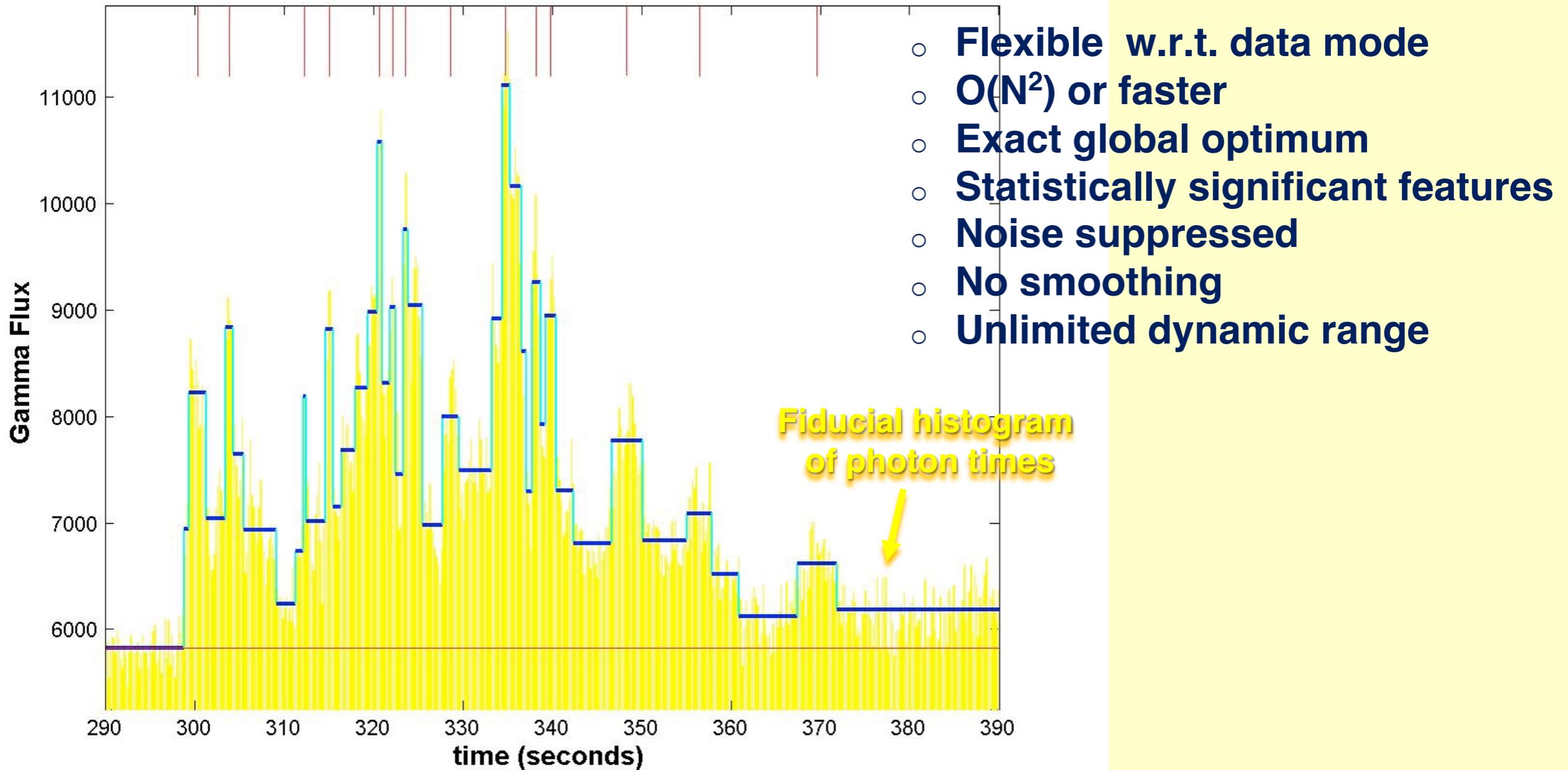
OUTLINE

- What are Time Series? Data Modes
- Models for Stationary Time Series

Given Arbitrarily Sampled Data, Algorithms for:

- Complex Fourier Transforms
 - Power Spectra
 - Phase Spectra
- Discrete Correlation Functions
- **Bayes Blocks**
- Applications: high-energy photon and LIGO data

Studies in Astronomical Time Series Analysis. VI. Bayesian Block Representations
Jeffrey D. Scargle, Jay P. Norris, Brad Jackson, James Chiang arxiv.org/abs/1207.5578
Listed in Astrophysics Source Code Library: <http://asci.net>



Bellman, R. 1961, On the approximation of curves by line segments using dynamic programming, Communications of the ACM, 4, 284.

15 Years of Reproducible Research in Computational Harmonic Analysis.

Donoho, D. et al. 2009, Computing in Science and Engineering, 11, 8

stats.stanford.edu/~donoho/Reports/2008/15YrsReproResch-20080426.pdf

Essential Elements of Bayesian Blocks

- *Data*

Points ordered in time

- *Blocks (sets of consecutive data points)*

Block Shape Model

Block Fitness (objective function)

- *Segmented Model: partition into blocks*

Total Fitness = Sum of Block Fitness

Optimize Total Fitness over all 2^N possible partitions

(Optimum number of blocks automatically determined)

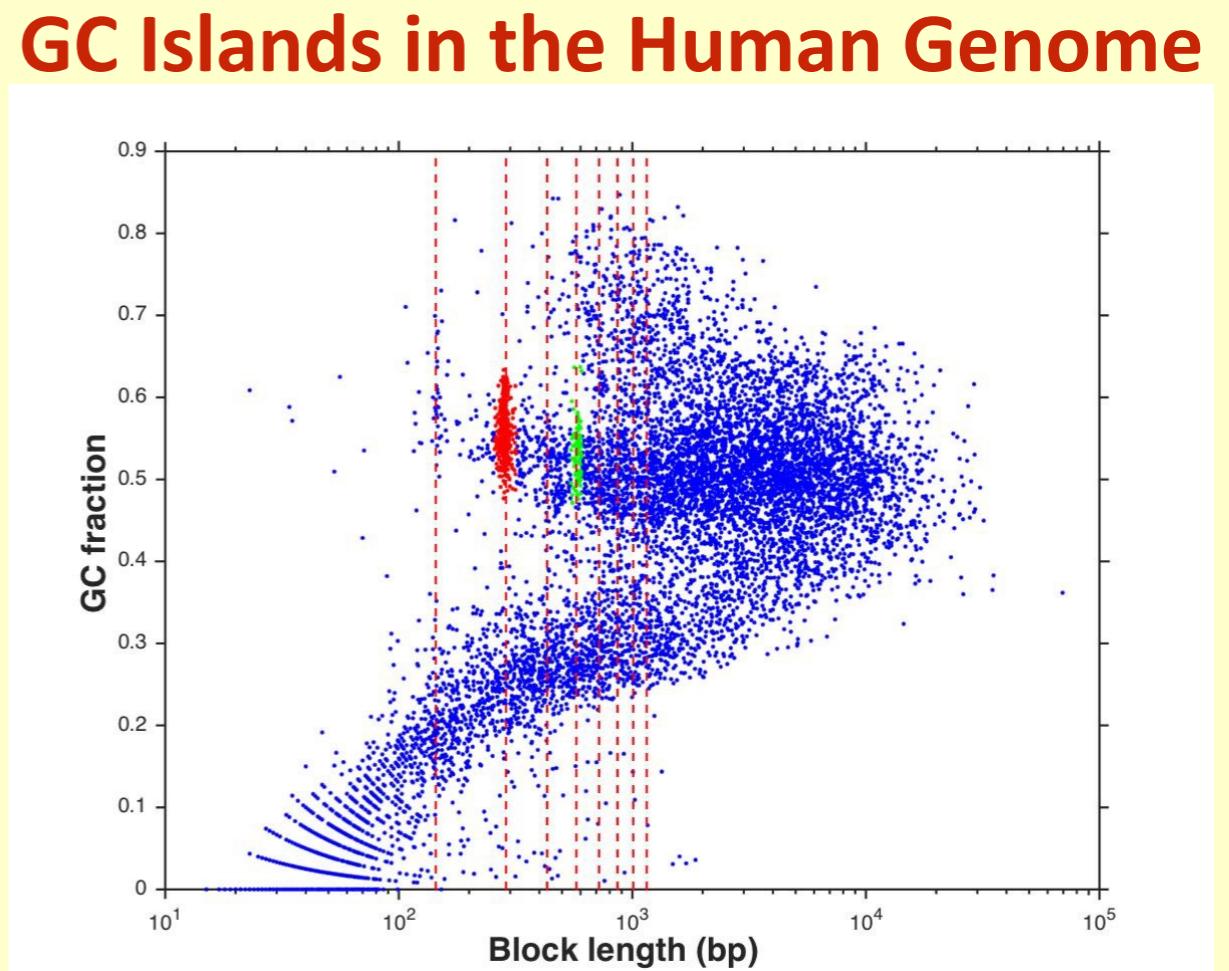
- *One parameter, a penalty constant, derived from the prior on the number of blocks; calibrate to an acceptable false positive rate.*

Bayesian Blocks can use ANY Data Mode

- *point measurements: $X(t_n)$*
- *time-tagged events: t_n*
- *time-to-spill*
- *categorical*
- *data with gaps*
- *circular data*
- *uneven sampling*
- *exposure variation*
- *real-time or retrospective*
- *arbitrary mixtures of data modes*
- *multivariate data (with or without the constraining the change-points to be the same)*
- *higher dimensions*
- *auxiliary information*

Bayesian Blocks can use ANY Data Mode

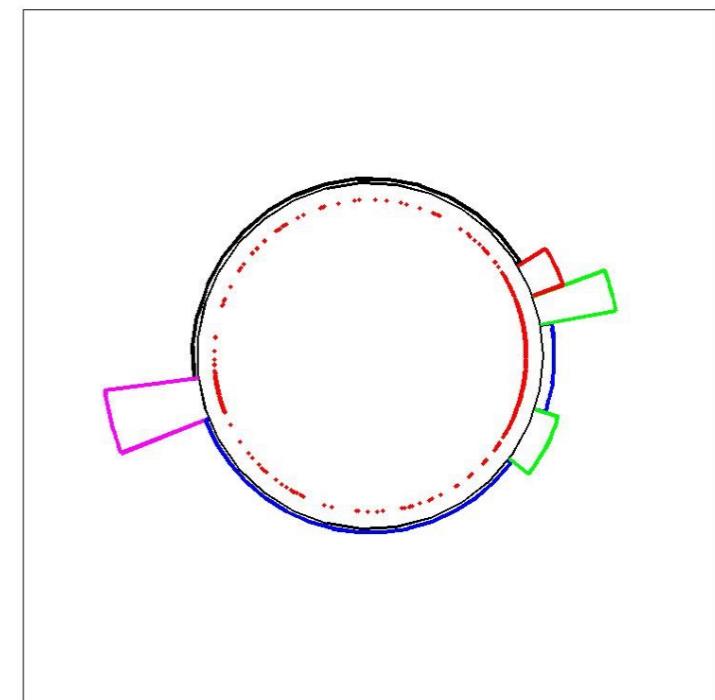
- *point measurements: $X(t_n)$*
- *time-tagged events: t_n*
- *time-to-spill*
- *categorical* —————→
- *data with gaps*
- *circular data*
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Bayesian Blocks can use ANY Data Mode

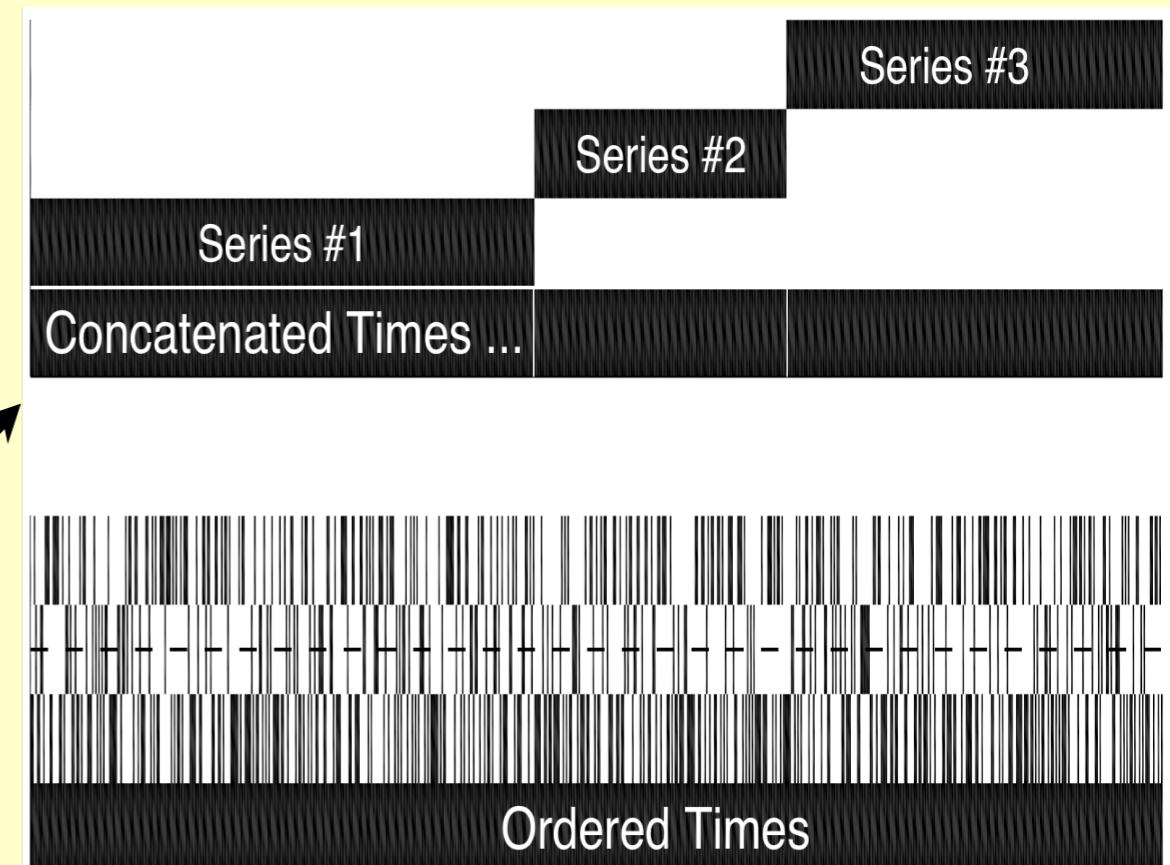
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Optimal Partitioning of
Data on the Circle



Bayesian Blocks can use ANY Data Mode

- *point measurements: $X(t_n)$*
- *time-tagged events: t_n*
- *time-to-spill*
- *categorical*
- *data with gaps*
- *circular data*
- *uneven sampling*
- *exposure variation*
- *real-time or retrospective*
- *arbitrary mixtures of data modes*
- *multivariate data* (*with or without the constraining the change-points to be the same*)
- *higher dimensions*
- *auxiliary information*



Bayesian Block Segmentation: Optimal, Exact, Global

- Data
- Time-tags, Binned Counts, Measures, Categorical, ...
 - Arbitrary Mixtures of Data Modes
 - Multivariate
 - Higher Dimensional
 - Real-time or Retrospective
 - Exposure Variation, Uneven Sampling/Gaps,
 - Circular

Fitness functions: Bayesian Posterior, Maximum Likelihood, ...

Complexity: $O(2N)$ → $O(N^2)$ (pruning) → $\sim O(N)$

Unlimited Dynamic Range:

- Signal Amplitude
- Timing (as supported by the data)

Block models: Constant: Linear, Exponential ...

Not a fully Bayesian analysis

No automatic uncertainty analysis

**What good are Segmented Time Series Representations?
Detect and characterize statistically significant
variability supported by the data.**

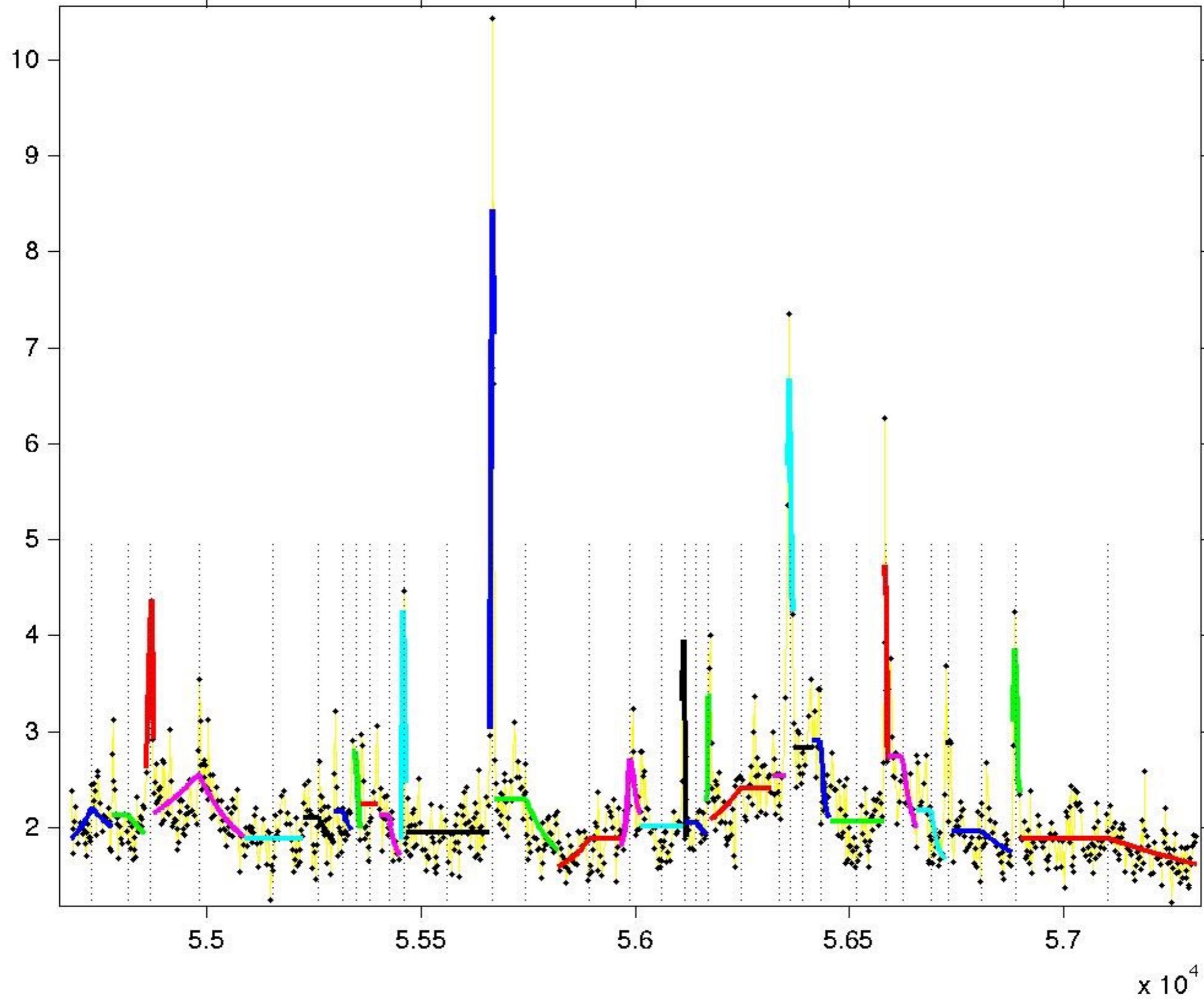
Detect and characterize, without bins or smoothing:

- ◆ **Pulses (aka “flares”)**
- ◆ **Pulse shapes (including the Arrow of Time)**
- ◆ **Variability index**
- ◆ **Variability time scales (min, max, distribution, ...)**
- ◆ **Transient event triggers (real-time mode)**

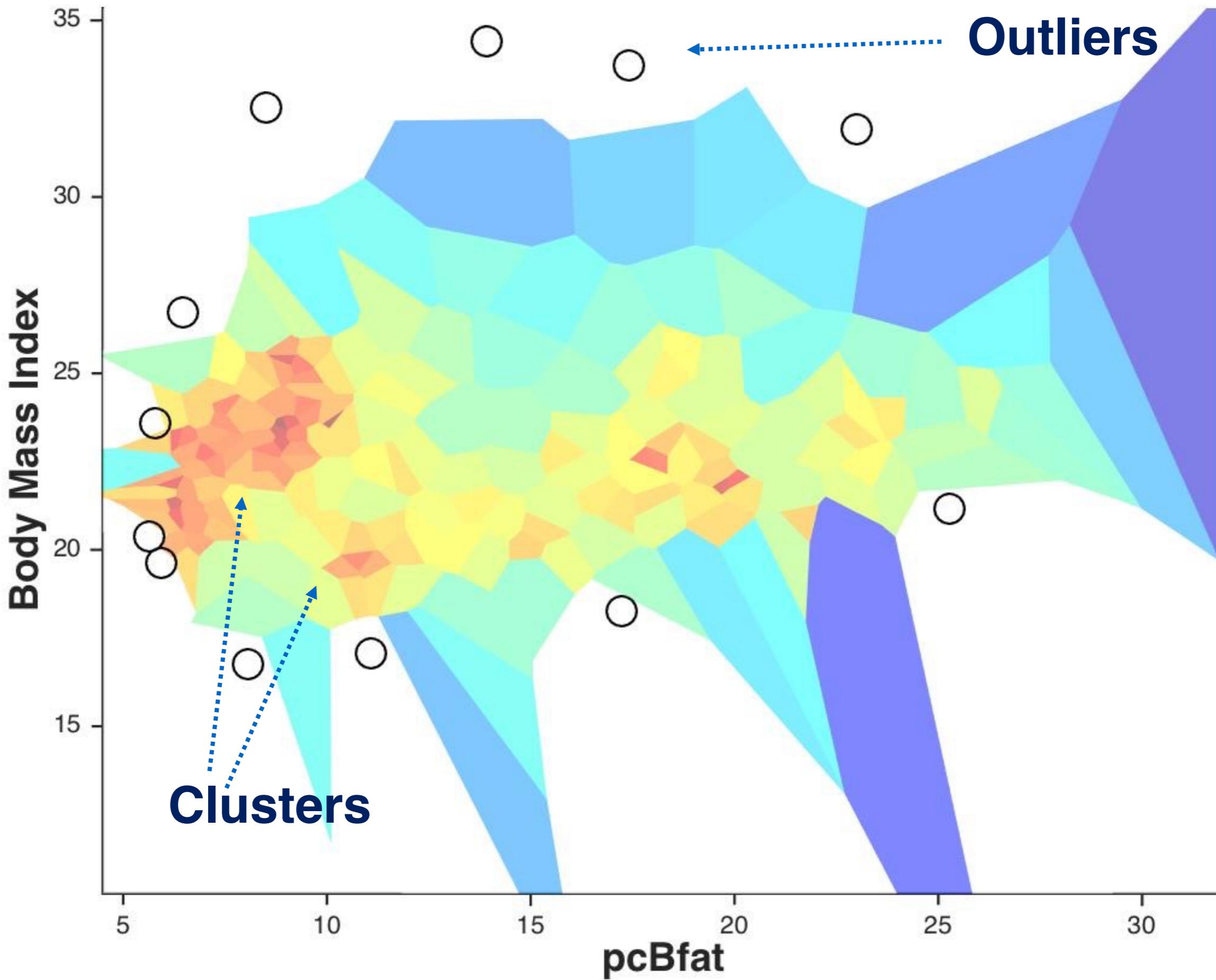
... and implement:

- ◆ **Exploratory Data Analysis**
- ◆ **Time series classification**
- ◆ **Noise suppression**
- ◆ **Visual displays**
- ◆ **Data compression**
- ◆ **Data adaptive histograms**

Gamma Ray Flaring in the Crab Nebula



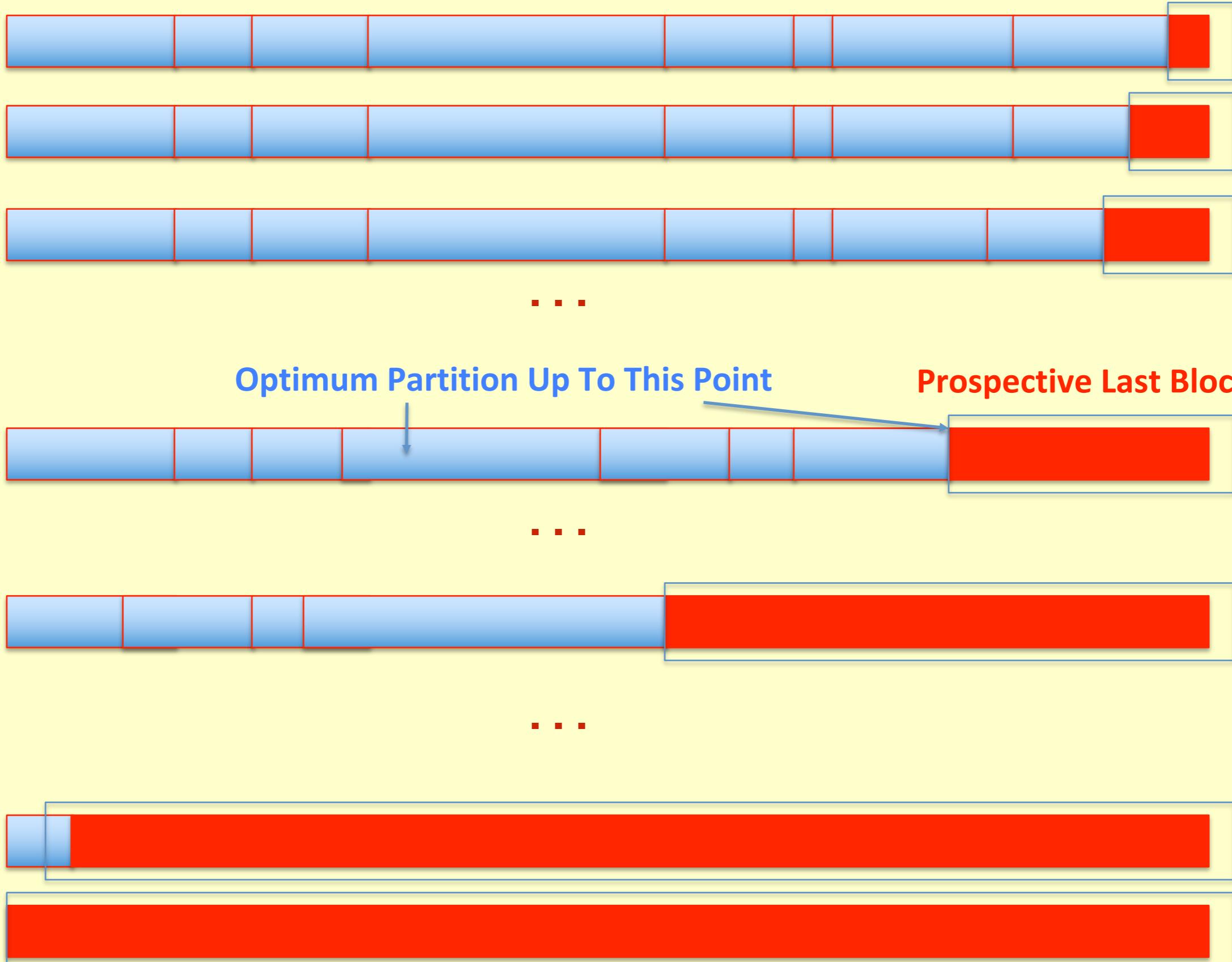
Aside: Bayesian Blocks in higher dimensions





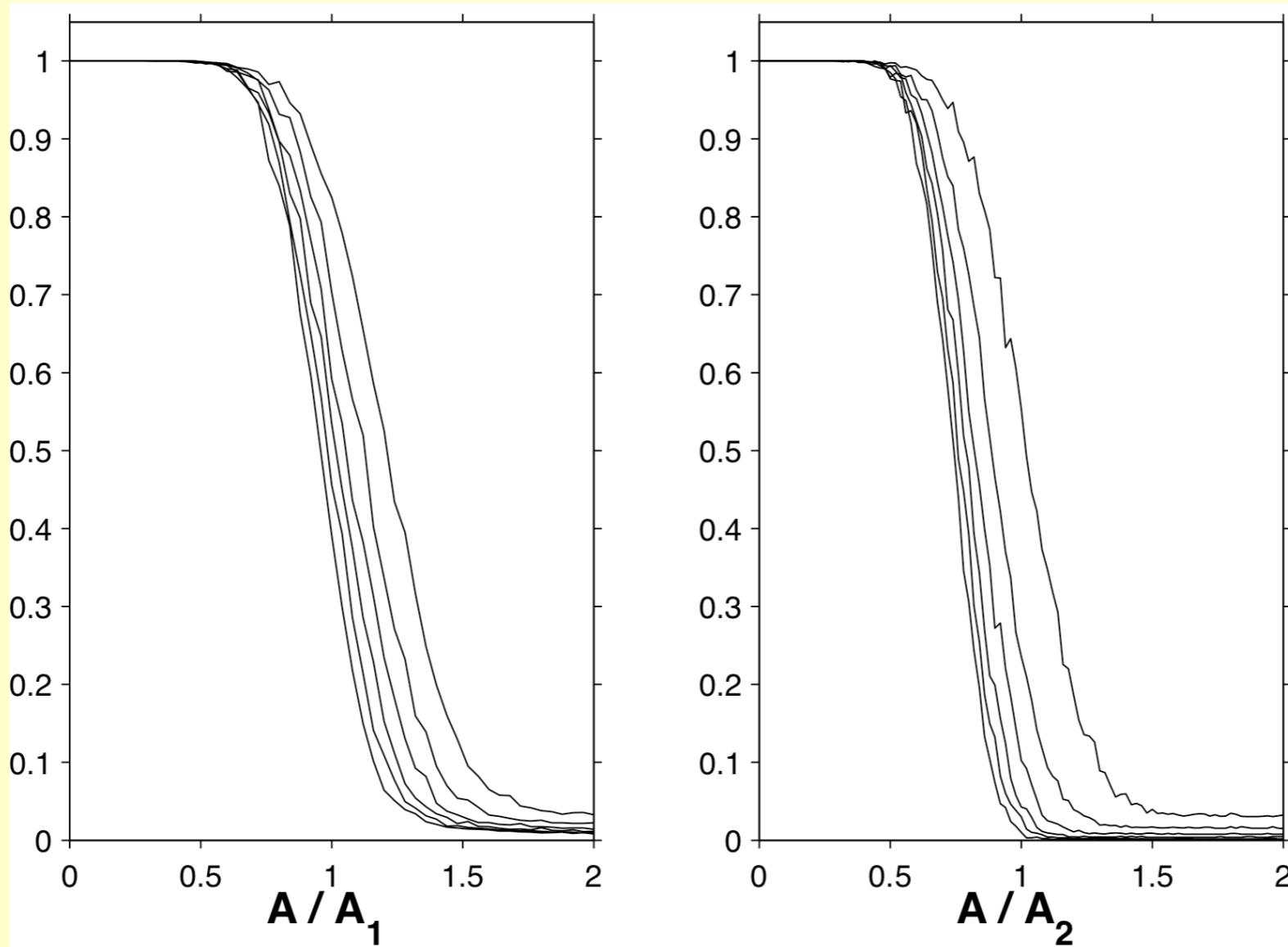
Exact Global Optimum via the BB Algorithm

Objective Function's Block additivity: $2^N \rightarrow N^2$



BB Nearly Achieves Theoretical Detection Limit

Detection error rate vs. signal amplitude in units of asymptotic result.



Arias-Castro, E., , Donoho, D., & Huo, X. 2003, Near-Optimal Detection of Geometric Objects by Fast Multiscale Methods IEEE Transactions on Information Theory, 51, 2402-2425

Real-Time Data Analysis

Bayesian Blocks can be implemented in a real-time or trigger mode:

*Return the Next Significant Change-Point
in Any Streaming Time Series*

Generalized Block Shape

Original Algorithm:

Piecewise constant (step function) model

Block shape: flat

Cost function cumulative sum of sufficient statistics

Generalize to arbitrary block shape:

Parametric (e.g. two sided exponential)

Numerical template - scales with block size

Numerical template - fixed scale

Mixture of shape (“pick the best one”)

Can mix data modes (points, counts, measurements)

Later: examples and higher dimensions (spatial)
62

Bayesian Blocks Bibliography

Studies in Astronomical Time Series Analysis.

VI. Bayesian Block Representations

Scargle, J., Norris, J., Jackson, B. and Chiang, J.

The Astrophysical Journal, 764, 167 (2013)

Our Blog: <http://bayesianblocks.blogspot.com/>

Jake Vanderplas' Blog ***Dynamic Programming in Python: Bayesian Blocks***

<http://jakevdp.github.com/blog/2012/09/12/dynamic-programming-in-python/>

Starship Asterisk* APOD and General Astronomy Discussion Forum

Bayesian Blocks: Detecting local variability in time series

<http://asterisk.apod.com/viewtopic.php?f=35&t=29458>

An algorithm for optimal partitioning of data on an interval

Jackson, Scargle, Barnes, Arabhi, Gioumousis, Gwin, Sangtrakulcharoen, Tan, Tun Tao Tsai

IEEE Signal Processing Letters, 2005, 12, 105

Studies in Astronomical Time Series Analysis.

V. Bayesian Blocks, a New Method to Analyze Structure in Photon Counting Data

~~Scargle, 1998, Astrophysical Journal, 504, 405~~

Obsolete algorithm

OUTLINE

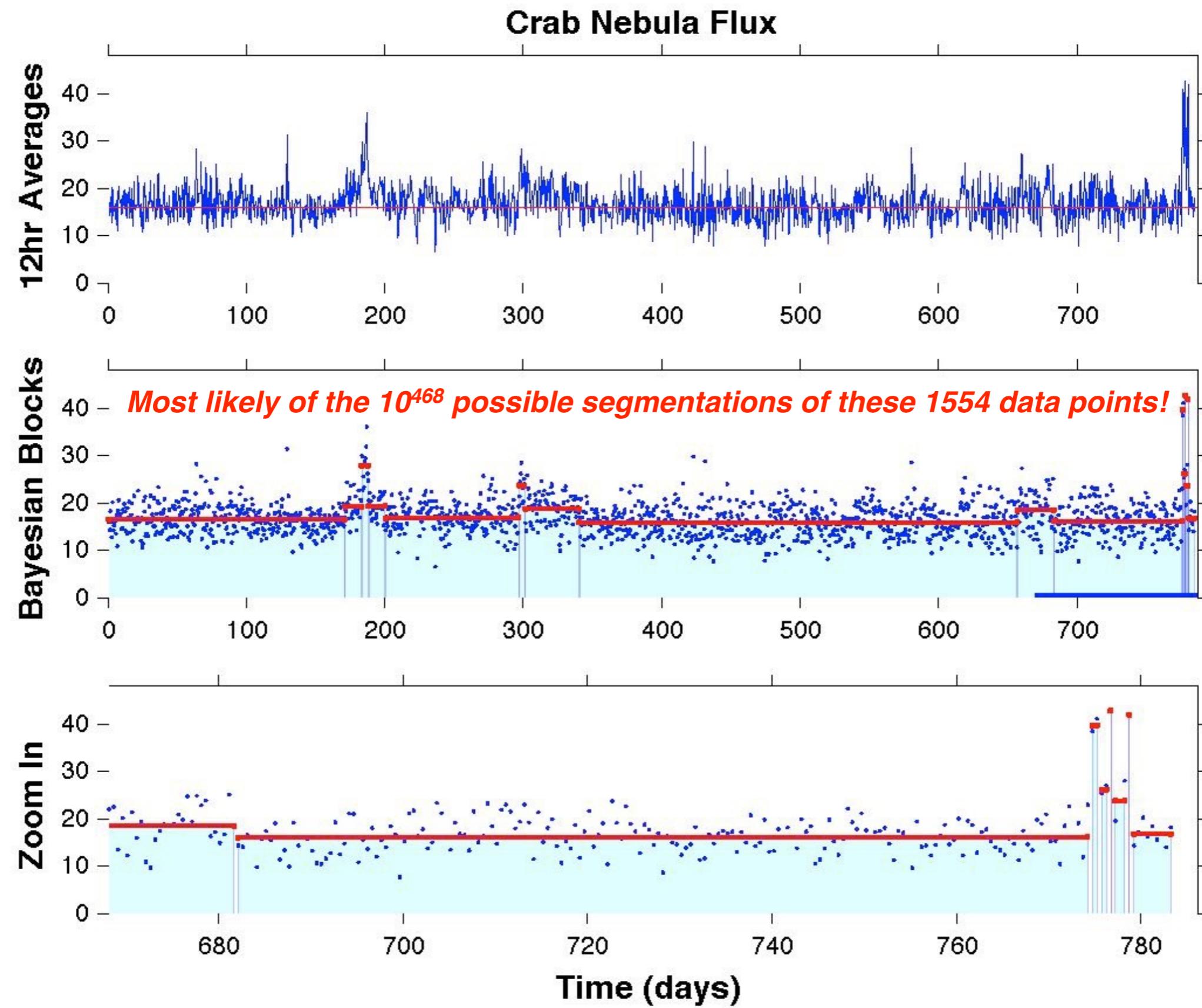
- What are Time Series? Data Modes
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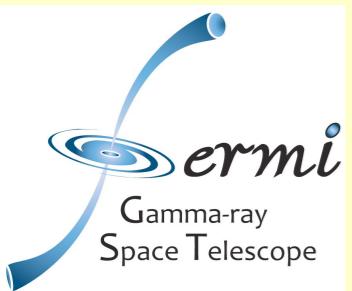
Given Arbitrarily Sampled Data, Algorithms for:

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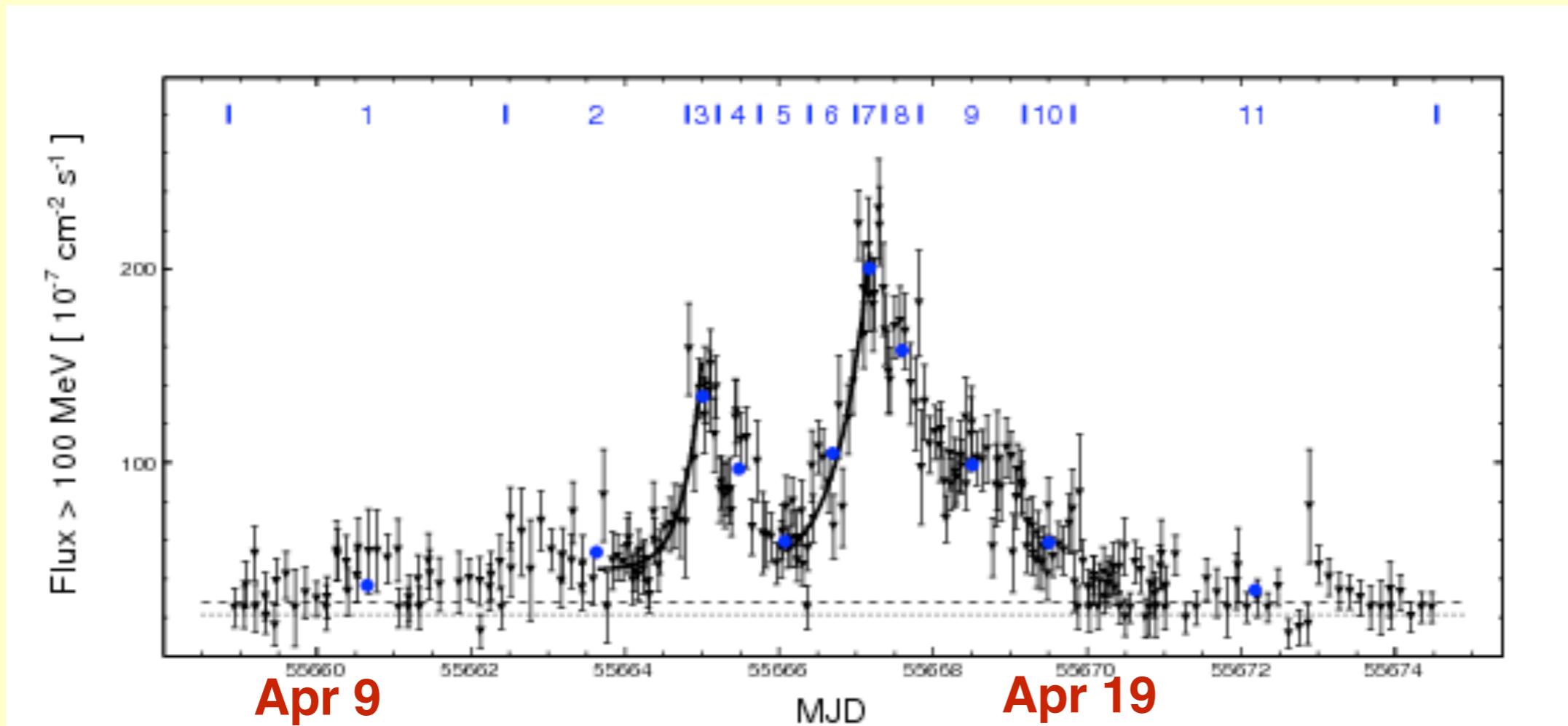


Crab Nebula rises above the status of a constant calibration source!





Gamma Ray Flare in the Crab Nebula, April, 2011 Luminosity vs. time, in bins of ~9 minutes

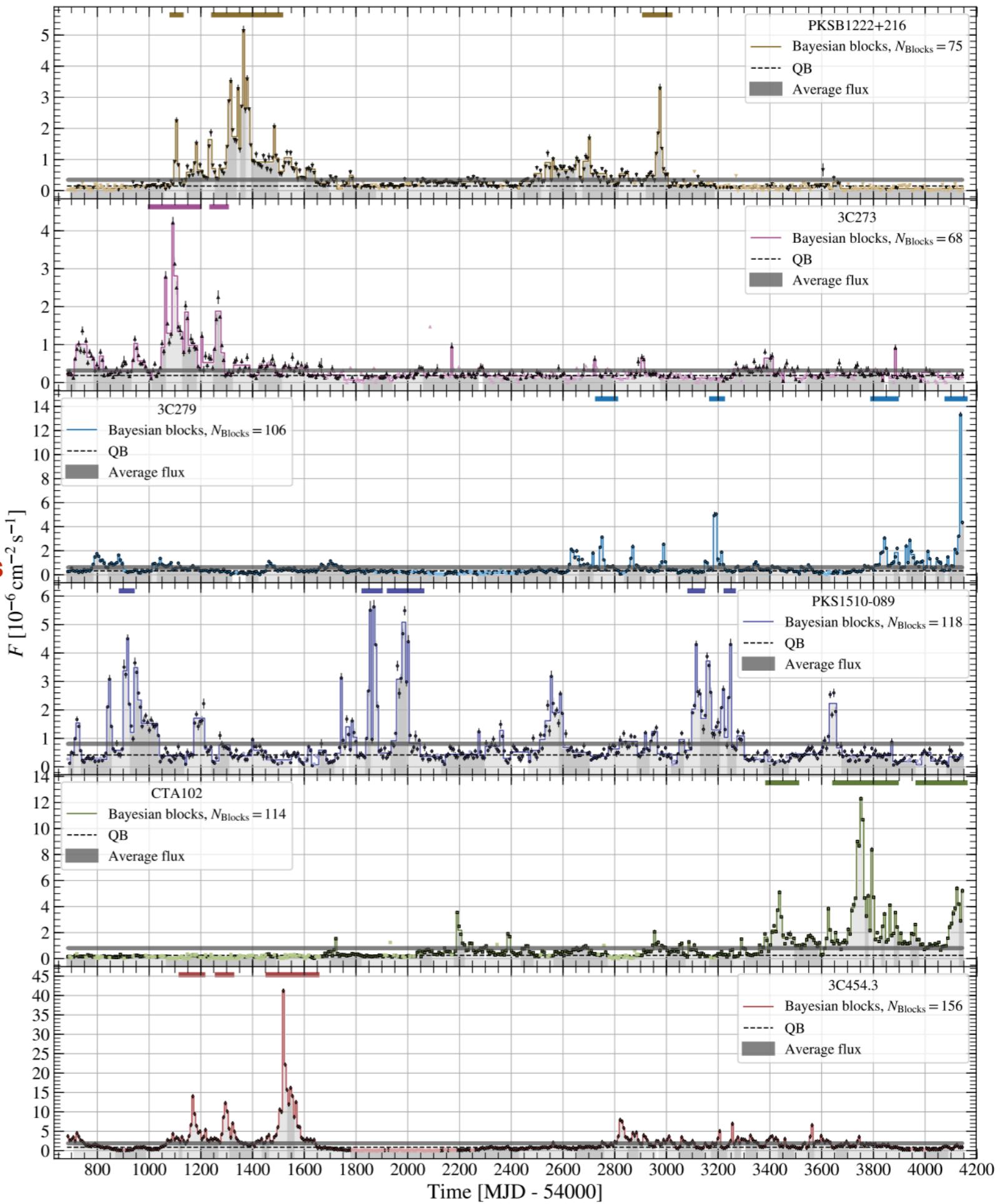


**Flux doubling in 8 hours constrains size of
the emission region < ~1 astronomical unit
(Buehler, R. et al. 2011, Astrophysical Journal)**

Bayesian Block Representations Of AGN Gamma-Ray Variability

**Characterizing the Gamma-Ray Variability
of the Brightest Flat Spectrum Radio Quasars
Observed with the Fermi LAT**

M. Meyer, JDS, R. Blandford
ApJ, 877, 39



The Six Impossible Things that made LIGO work:

Existence of Gravitational Waves (Einstein, GR)

Astrophysical GW Sources Strong Enough

Technology to Measure Strains $\sim 10^{-21}$

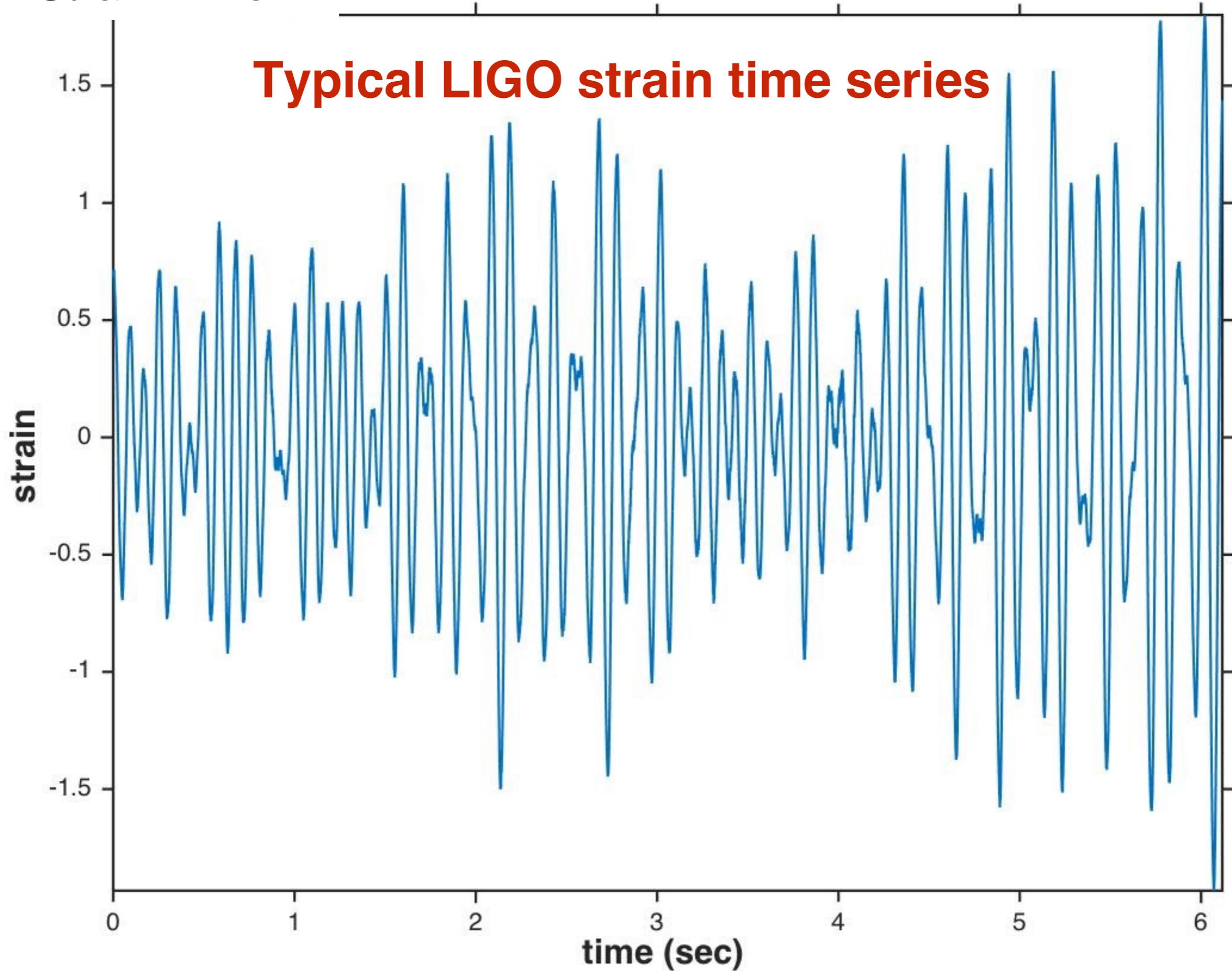
Scientists Devoting Many Decades to this High Risk Project

4 Decades of NSF Funding for this High Risk Project - \$1.1B

Detection of VERY Weak Signals in HUGE Non-Gaussian Noise

“ ... sometimes I've believed as many as six impossible things before breakfast.” ... Alice, Through the Looking-Glass

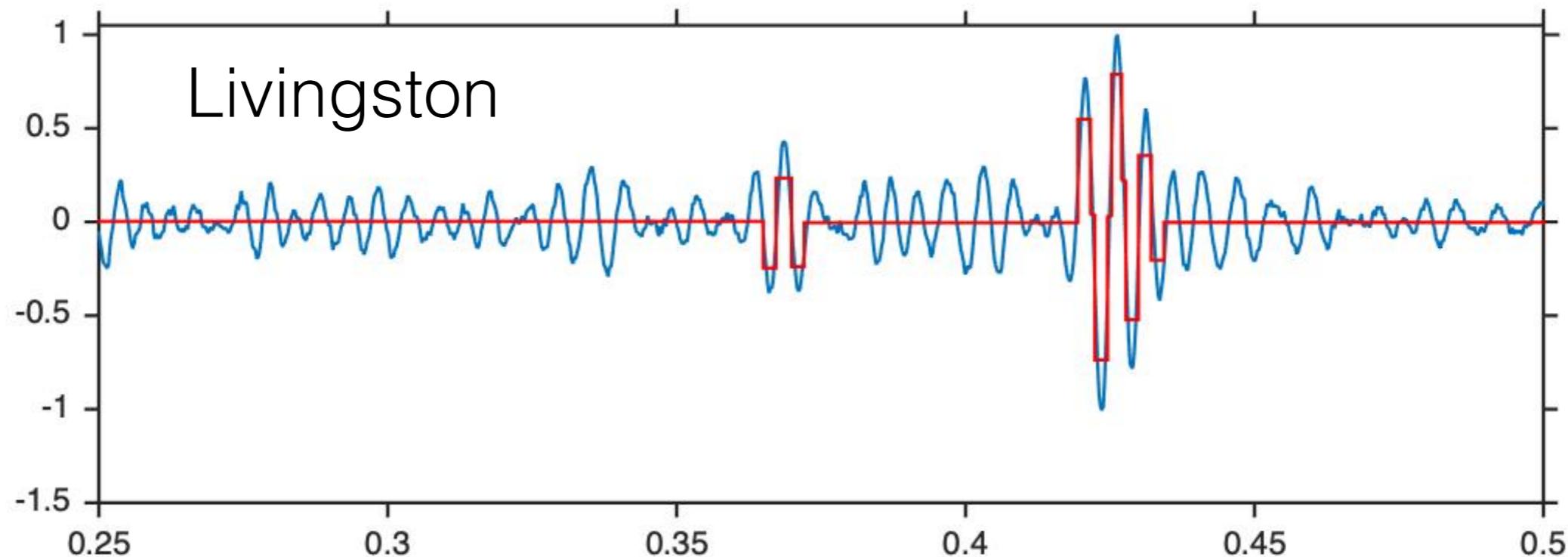
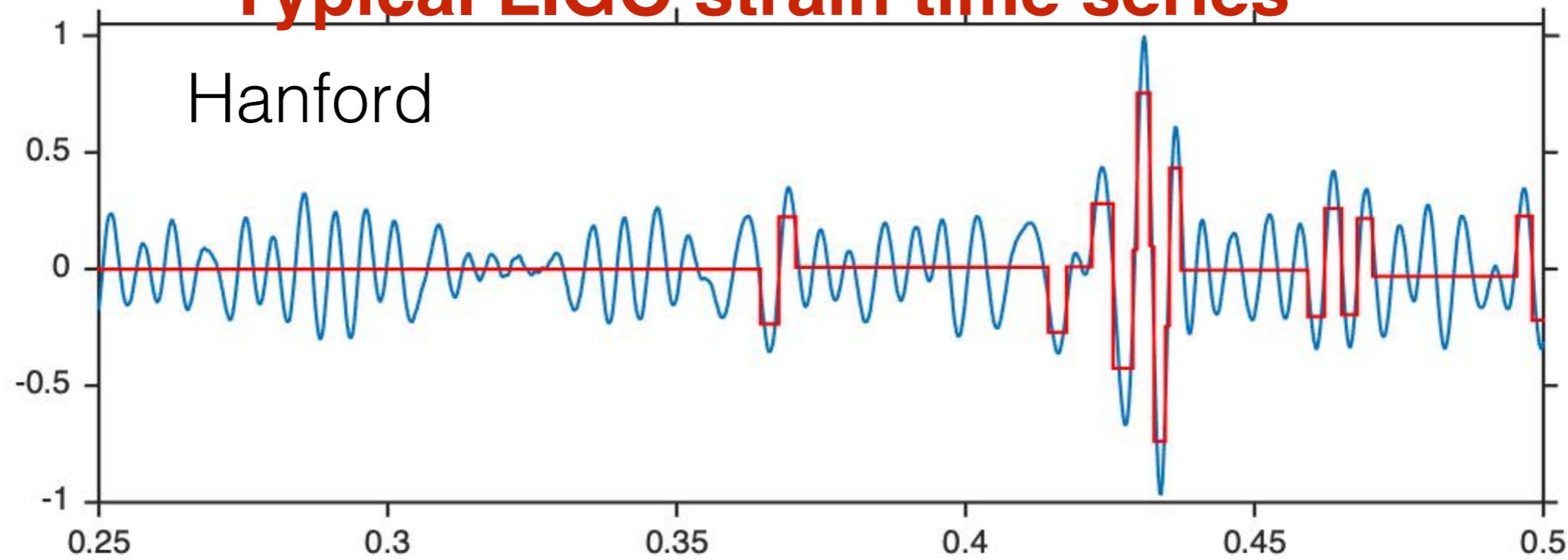
Strain $\sim 10^{-19}$



Strain $\sim 10^{-21}$

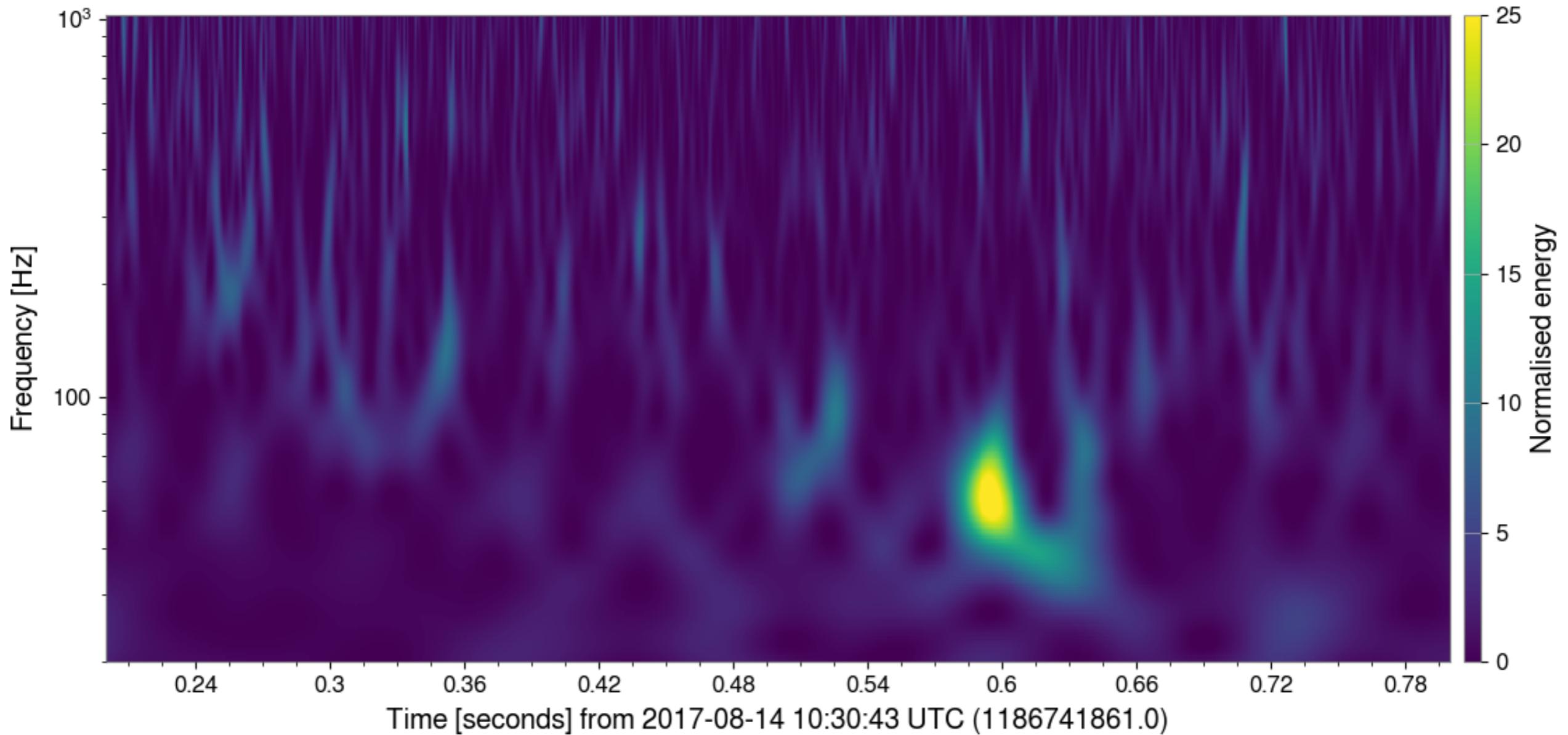
GW150914

Typical LIGO strain time series

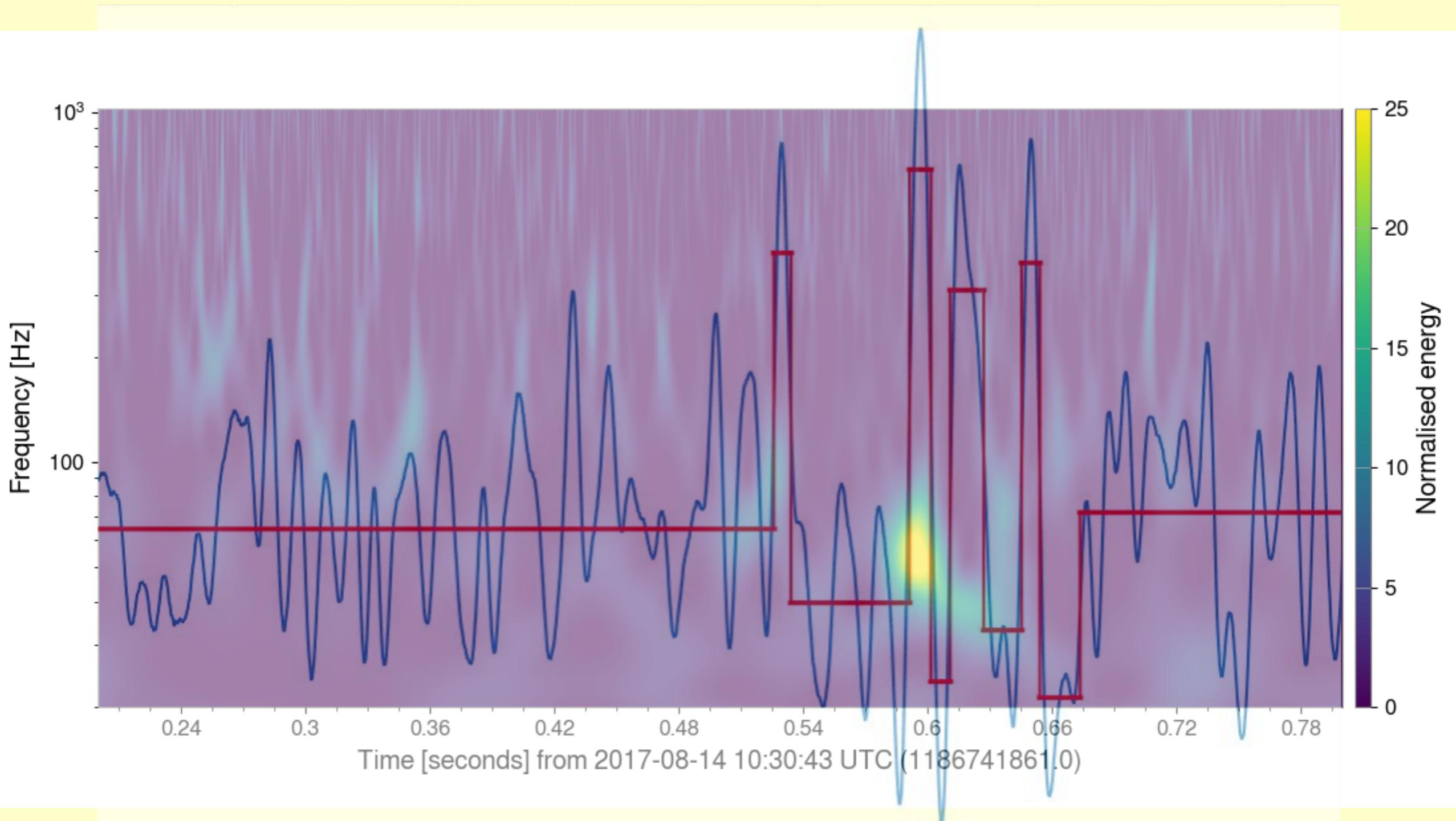


JS, Chris Henze and Javier Pascual-Grenado

GW170814 Virgo Data

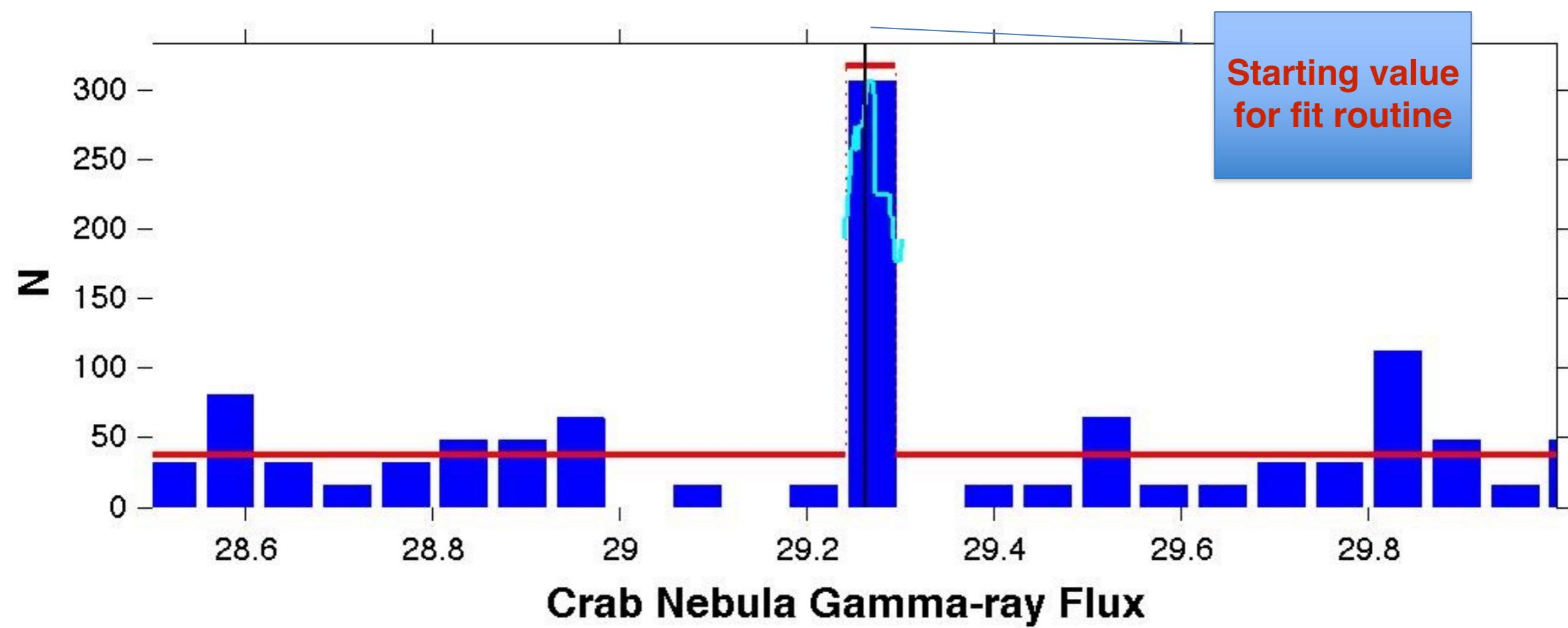
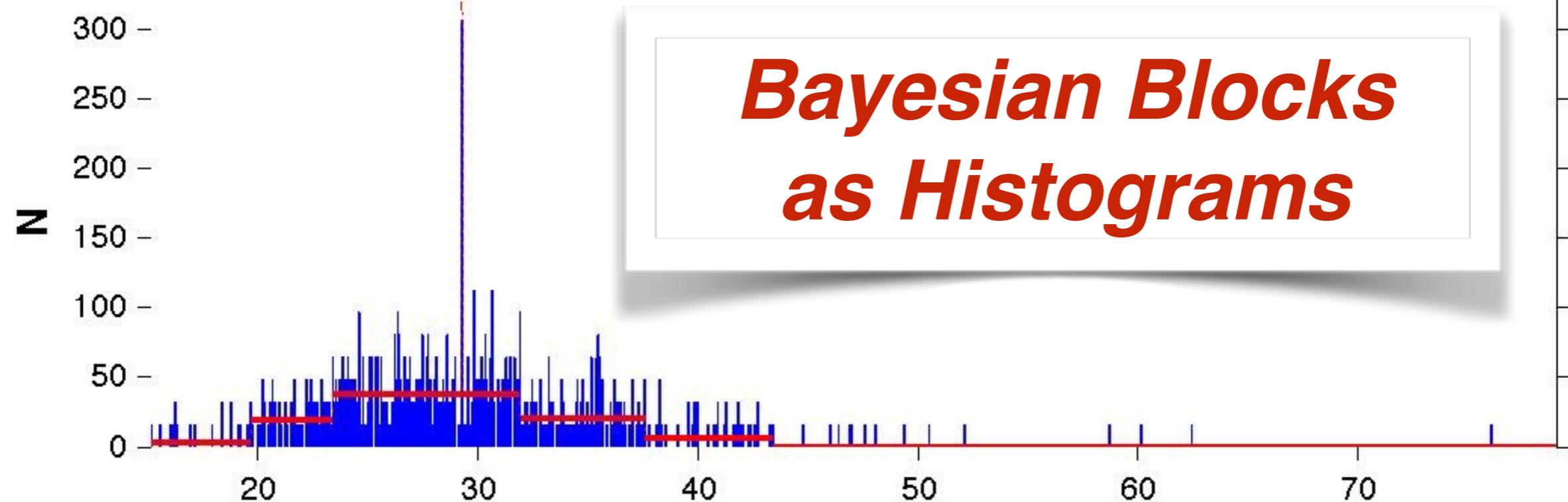


GW170814 Virgo Data



Special denoising method + BB to search for non-chirps.

Bayesian Blocks as Histograms



Haiku for a Martingale

Binning is sinning. Correlations are feeble. Are there better tools?

Histograms

Correlation Coefficients

Correlation Functions

Cross-Correlations

Correlation Matrices

FFT of correlation functions



Bayesian Block histograms

Dependence Measures

Dependence Functions

Cross-Dependences

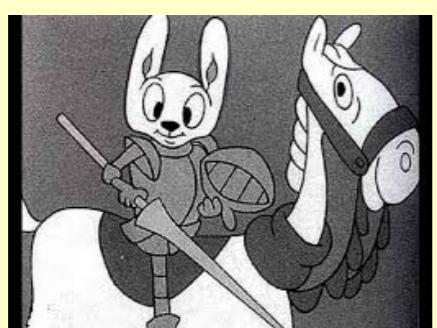
Dependence Matrices

FFT of dependence functions

...

pre-binned
histograms

correlation
functions



**A glorious future where all histograms
use Bayesian Blocks
and all association measures are based
on dependence.**



Studies in Astronomical Time Series Analysis:

I. Modeling Random Processes in the Time Domain
JS, ApJS, 45, 1, 1981

II. Statistical Aspects of Spectral Analysis of Unevenly Spaced Data,
JS, ApJ, 263, 835-853.

**III. Fourier Transforms, Autocorrelation Functions,
and Cross-Correlation Functions of Unevenly Spaced Data.**
JS, ApJ, 343, 874-887

IV. Modeling chaotic and random processes with linear filters
JS, ApJ, 359, 469-482

IV. Bayesian Blocks, a New Method to Analyze Structure in Photon Counting Data
JS, ApJ, 504, 405-418

Scargle, J., Norris, J., Jackson, B. and Chiang, J. 2013
VI. Bayesian Block Representations
ApJ, 764, 167

**VII. An Enquiry Concerning Non-Linearity, the RMS-Mean Flux Relation, and log-Normal
Flux Distributions**

jeffscargle@gmail.com