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

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

Jeff Scargle
NASA Ames Research Center
Astrobiology and Space Science Division
jeffscargle@gmail.com

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

- 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

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

BATSE trigger 00551
N = 2894 photons

1
2
3
458
740
1084
1628
2050
2446
2770
3058
3388
4078
4284
4660
5028
5336
5648
5860
6230
6538
6728
7198
7542
...
941816
942270
942644

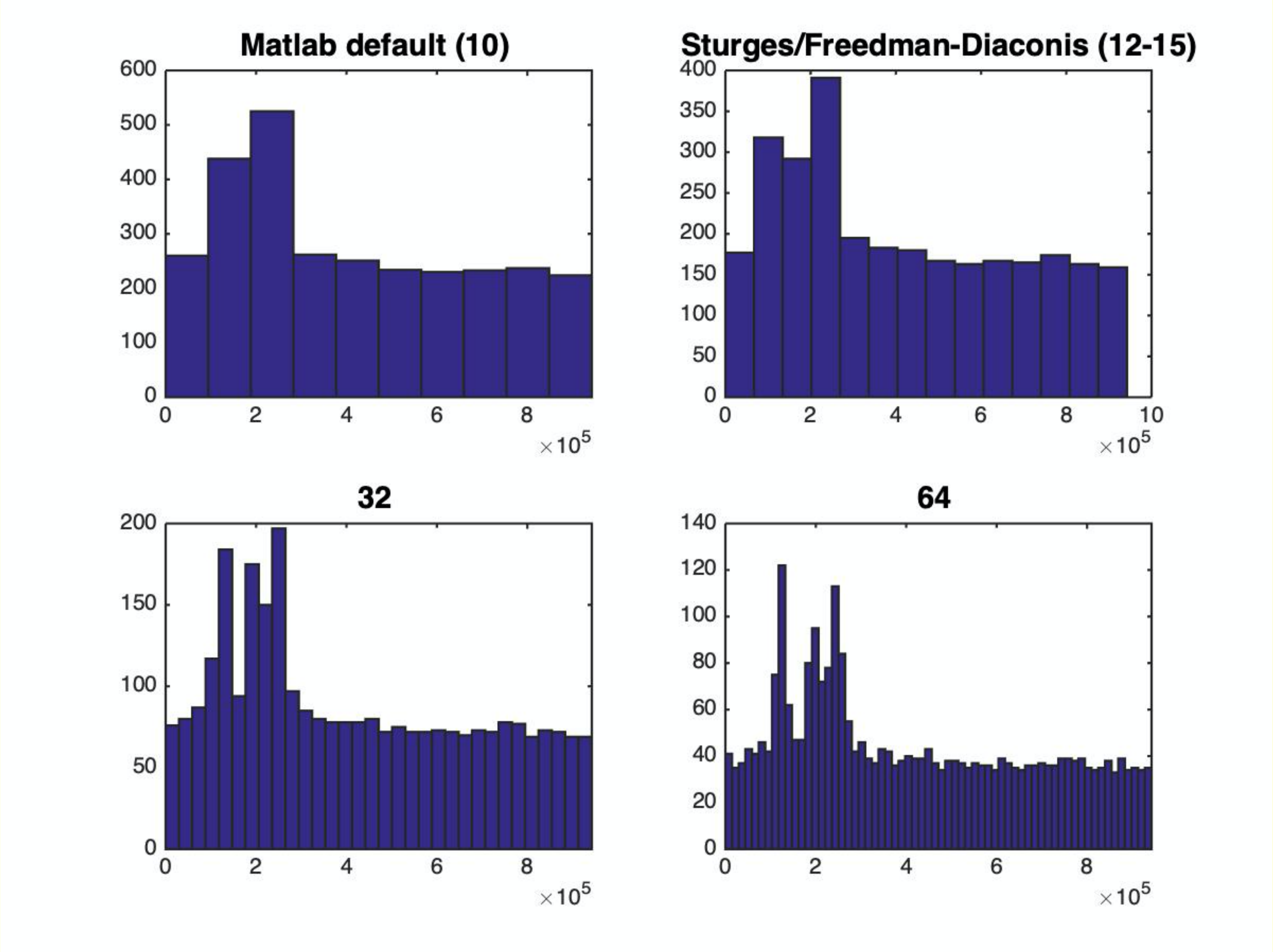
Time-Tagged Data

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

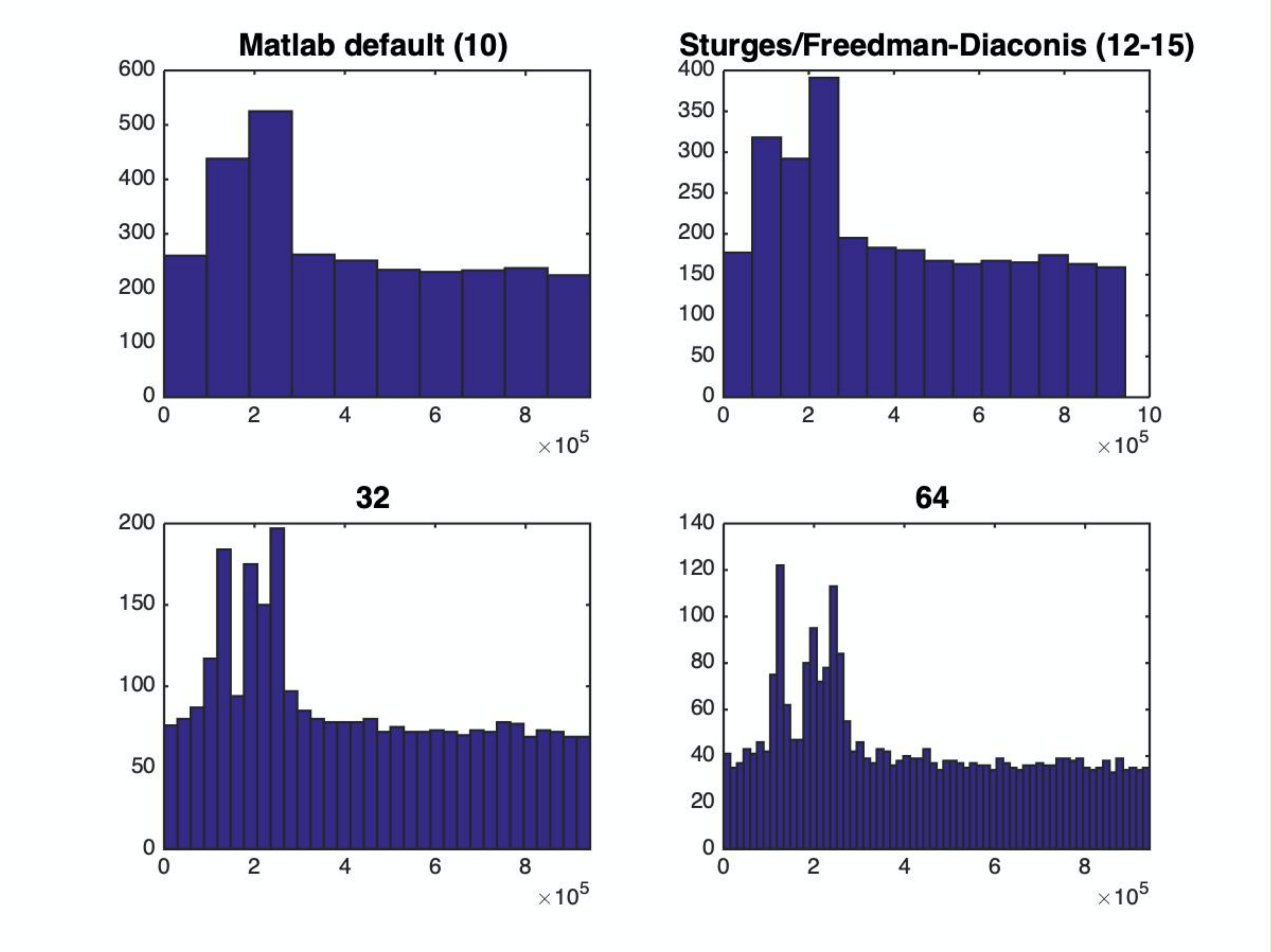
1
2
3
458
740
1084
1628
2050
2446
2770
3058
3388
4078
4284
4660
5028
5336
5648
5860
6230
6538
6728
7198
7542
…
941816
942270
942644



BATSE trigger 00551
N = 2894 photons

1
2
3
458
740
1084
1628
2050
2446
2770
3058
3388
4078
4284
4660
5028
5336
5648
5860
6230
6538
6728
7198
7542
…
941816
942270
942644

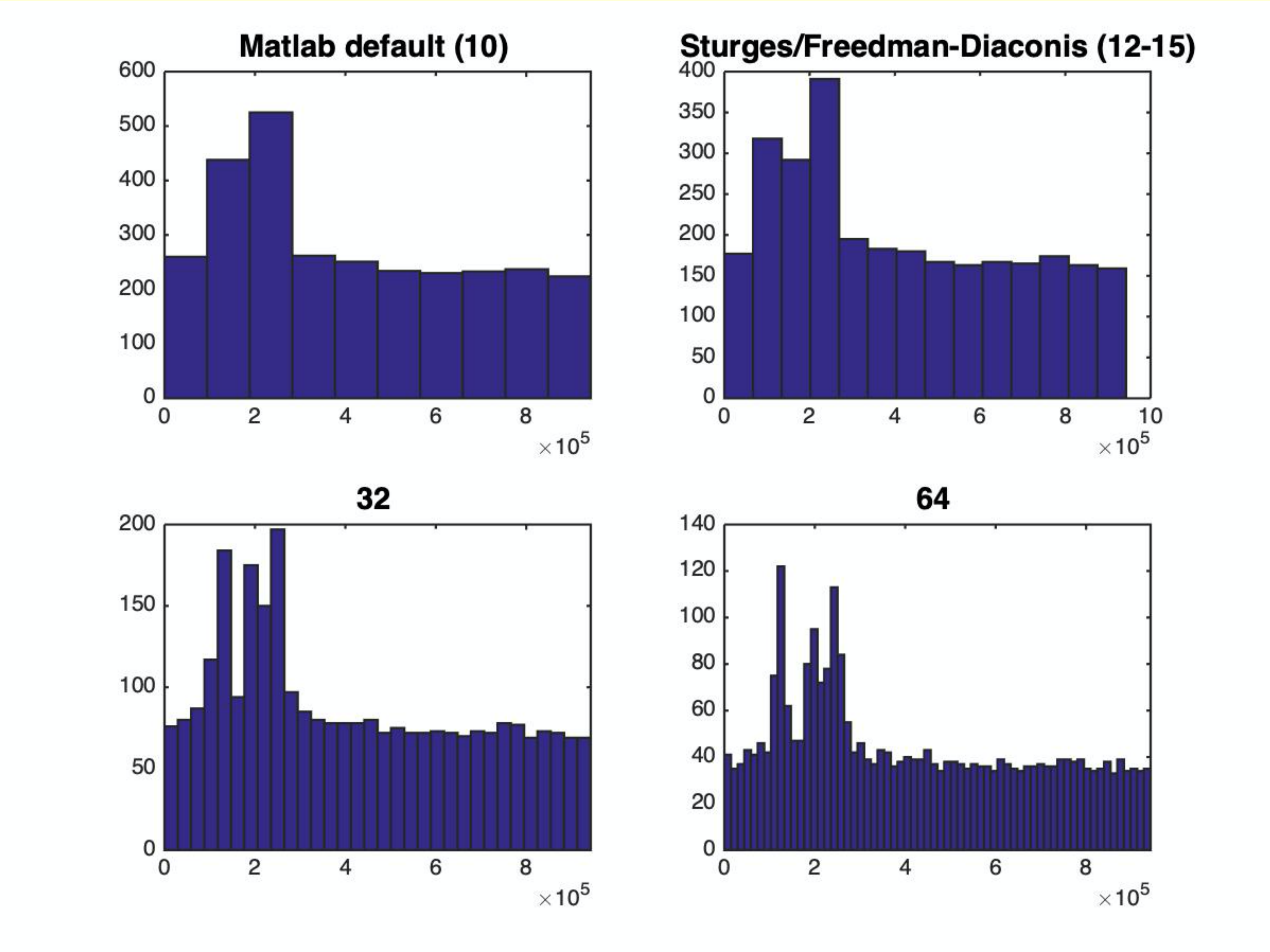
"The problem with Sturges' rule for constructing histograms"
Rob J Hyndman (1995)
It is known that Sturges' rule leads to oversmoothed histograms,
but Sturges' derivation of his rule has never been questioned.
… the argument leading to Sturges' rule is wrong



BATSE trigger 00551
N = 2894 photons

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

1
2
3
458
740
1084
1628
2050
2446
2770
3058
3388
4078
4284
4660
5028
5336
5648
5860
6230
6538
6728
7198
7542
…
941816
942270
942644

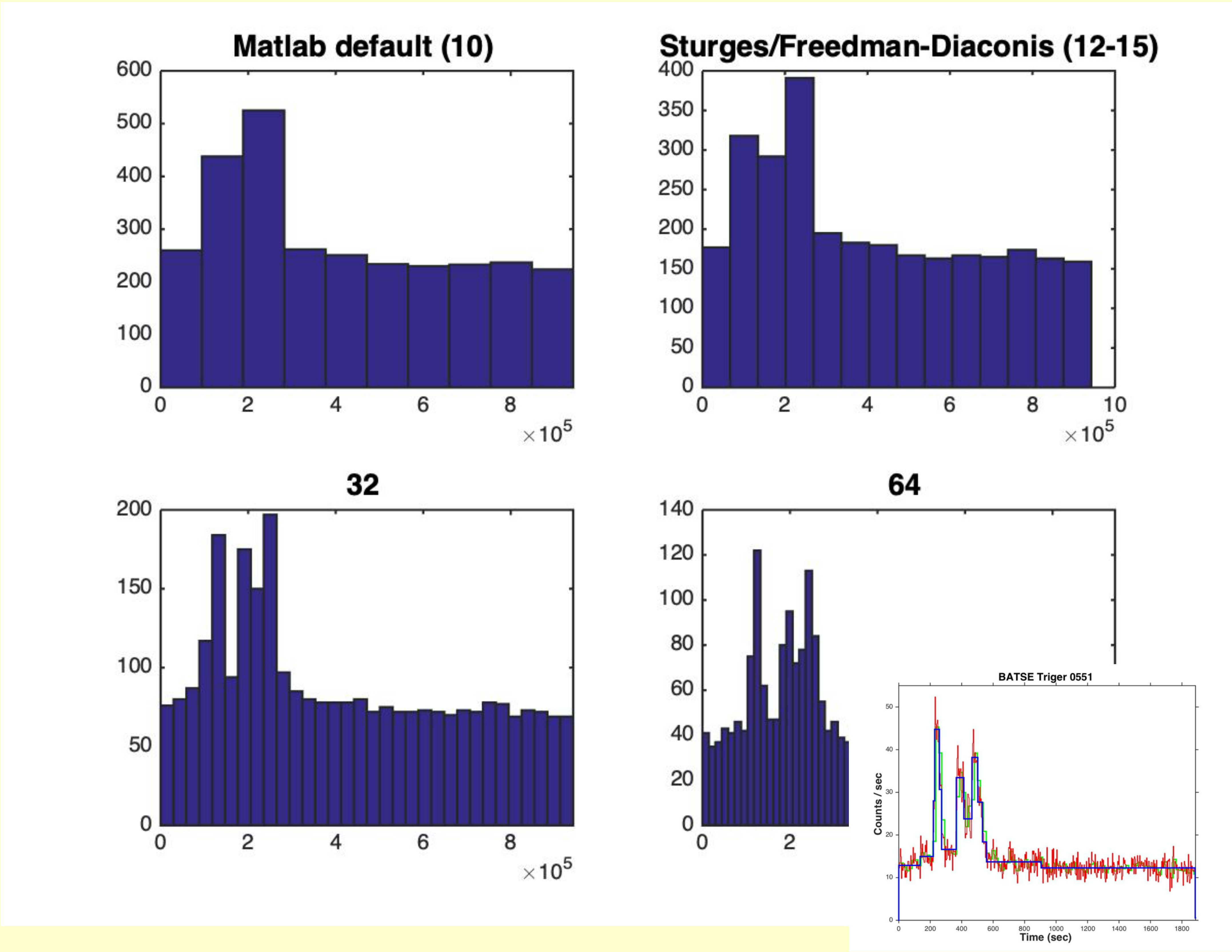


Better yet, discard constraint of equal bins: *Bayesian Blocks*

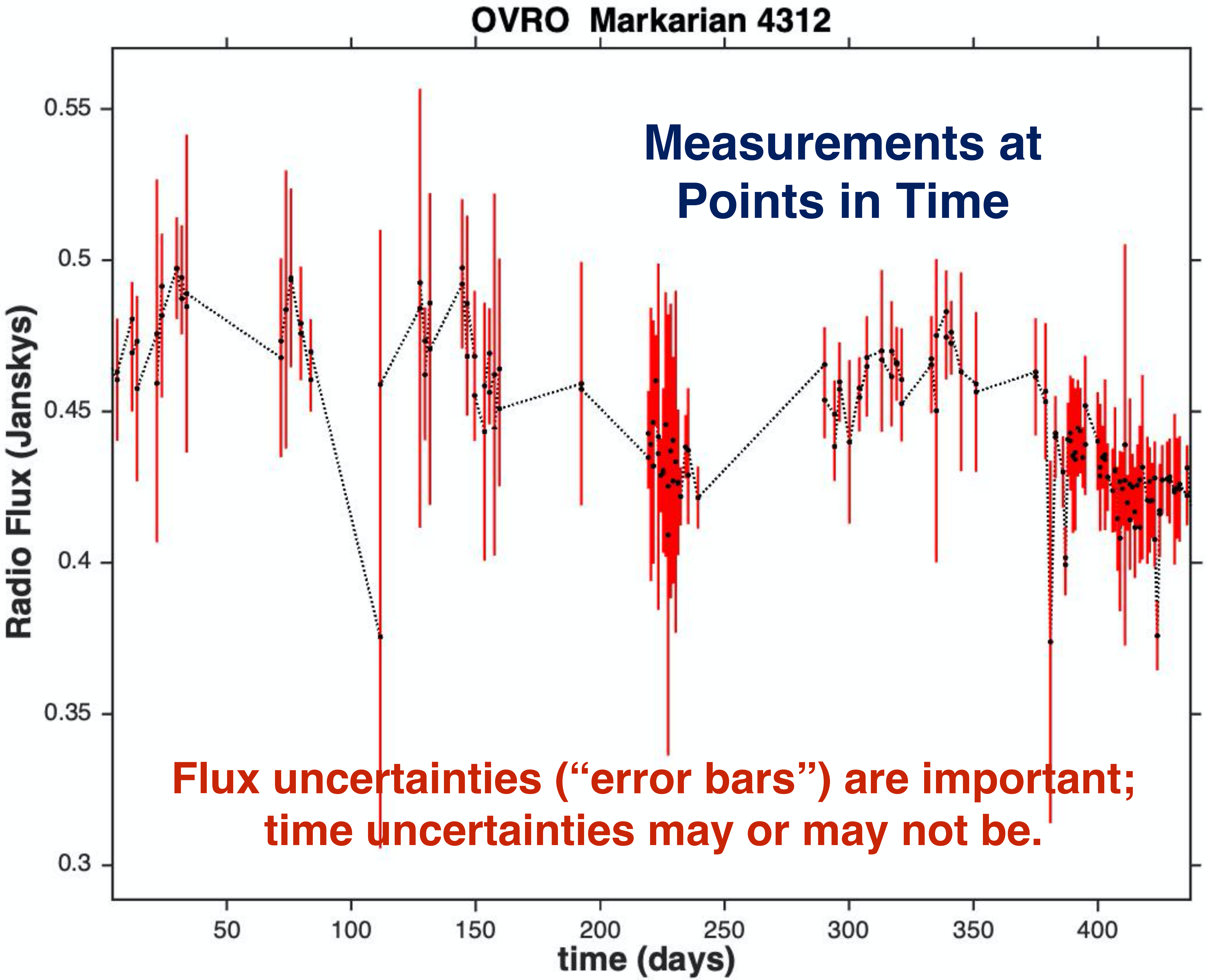
BATSE trigger 00551
N = 2894 photons

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

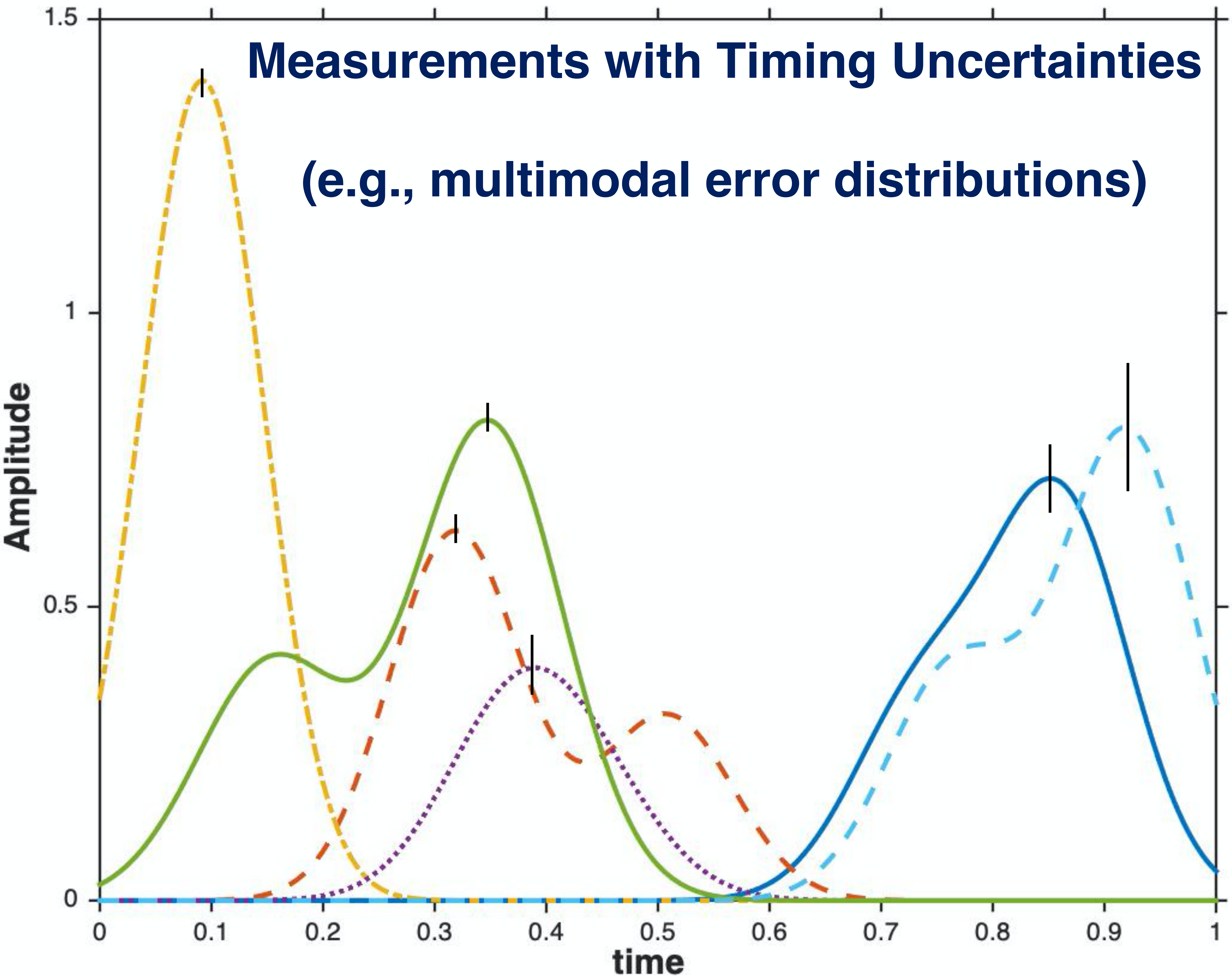
1
2
3
458
740
1084
1628
2050
2446
2770
3058
3388
4078
4284
4660
5028
5336
5648
5860
6230
6538
6728
7198
7542
…
941816
942270
942644



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

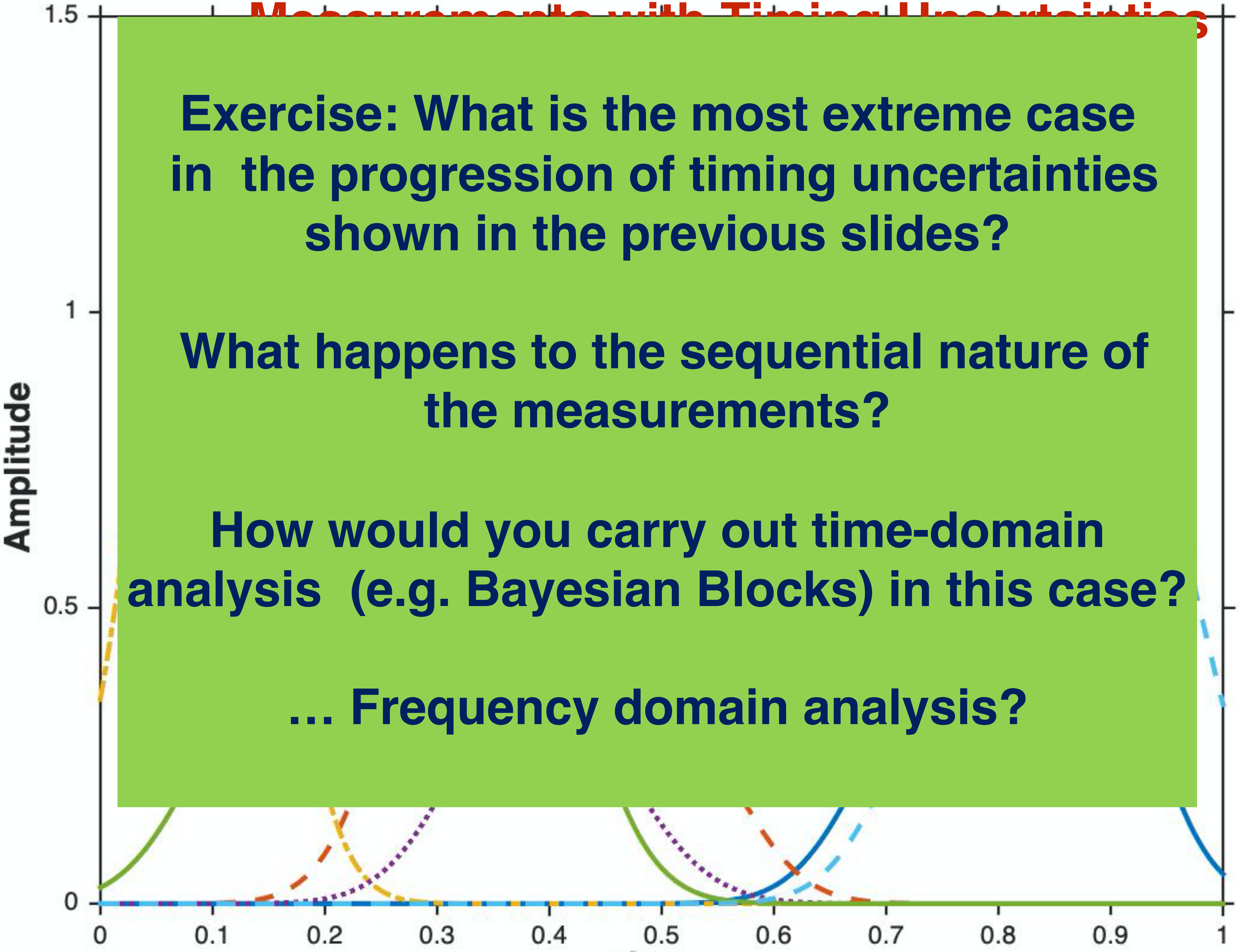


OVRO Markarian 4312
Measurements at
Points in Time
Flux uncertainties (“error bars”) are important;
time uncertainties may or may not be.
Radio Flux (Janskys)
time (days)
0.55
0.5
0.45
0.4
0.35
0.3
50
100
150
200
250
300
350
400



Measurements with Timing Uncertainties
(e.g., multimodal error distributions)
Amplitude
time
1.5
1
0.5
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

Measurements with Timing Uncertainties



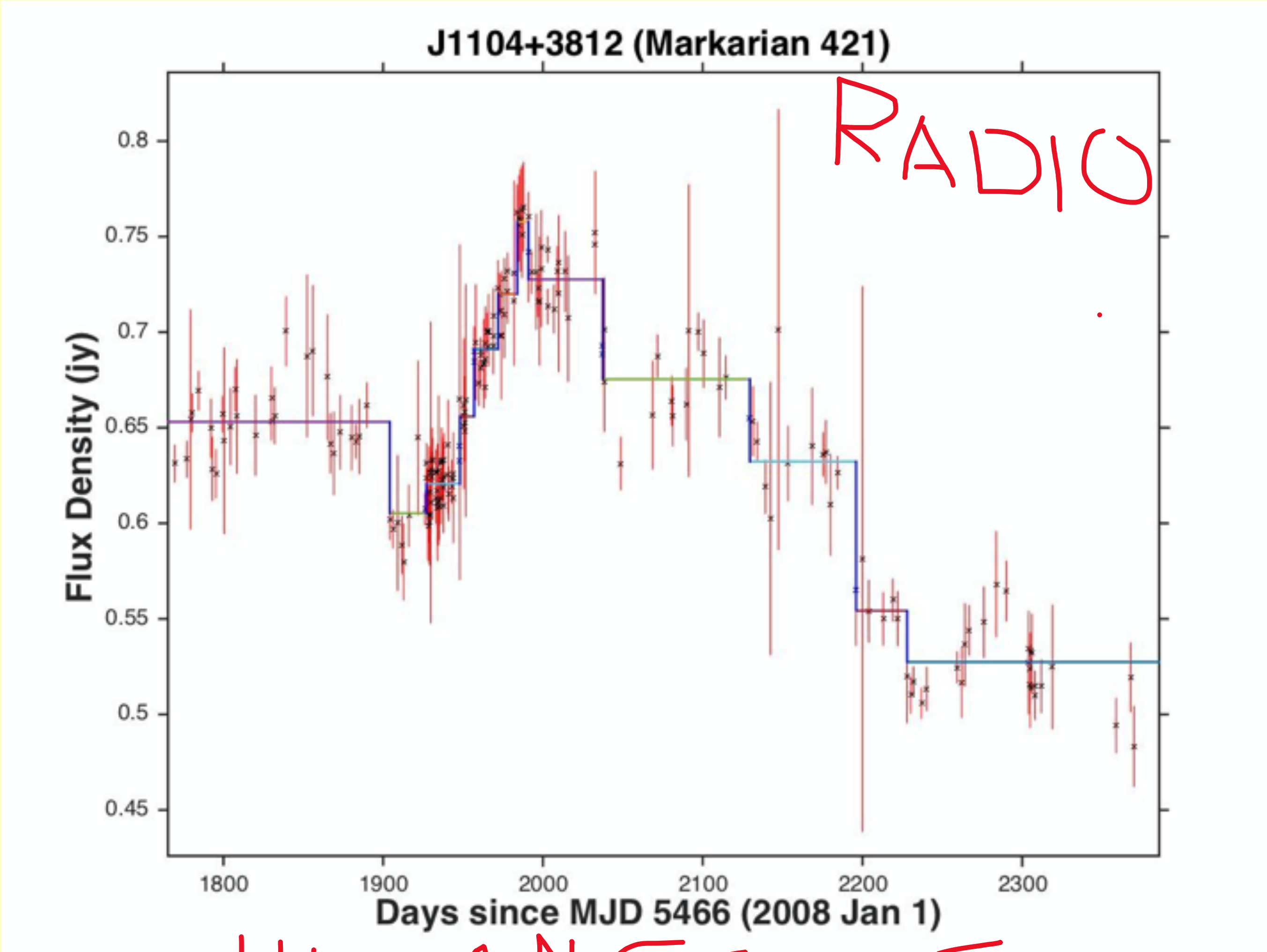
Exercise: What is the most extreme case in the progression of timing uncertainties shown in the previous slides?

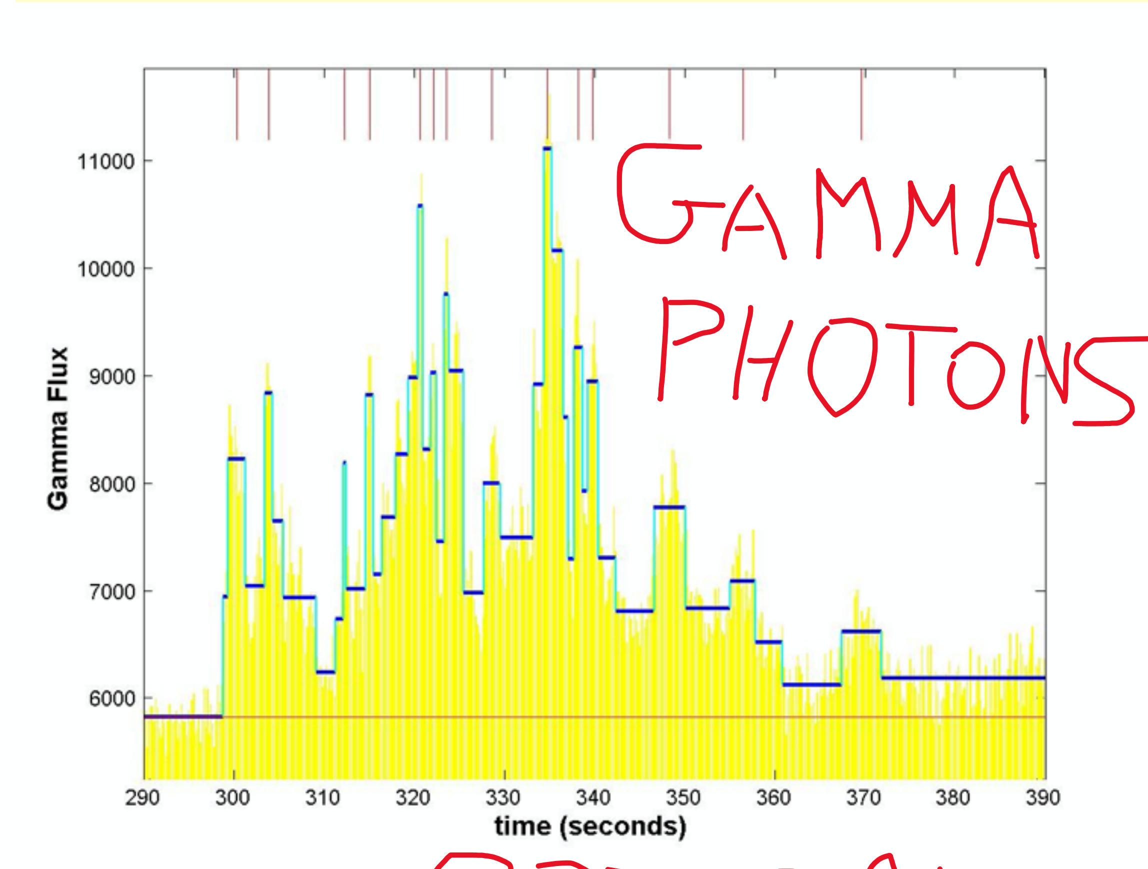
What happens to the sequential nature of the measurements?

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

… Frequency domain analysis?

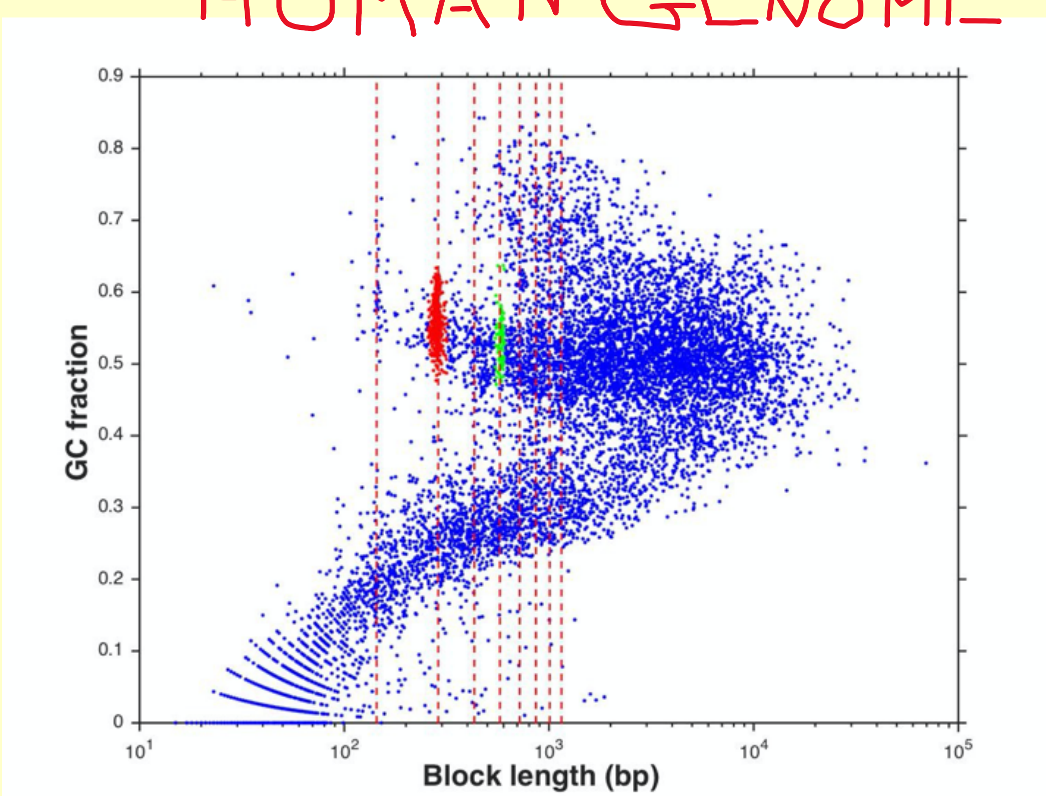
In short: lots of different kinds of sequential data!

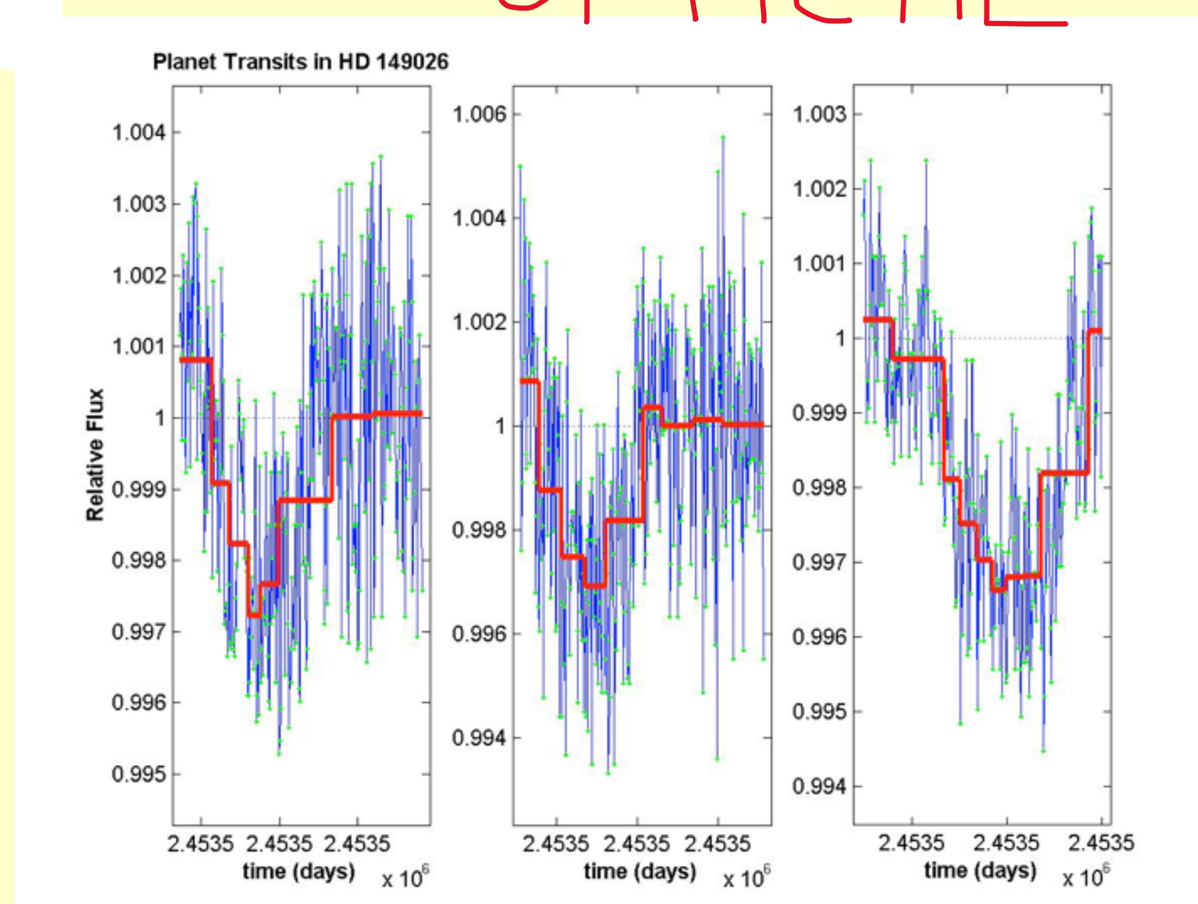




OPTICAL

HUMAN GENOME





Interlude:

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

1. Check the distribution of sample intervals: $\{t_i, X_i\}$—> 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.

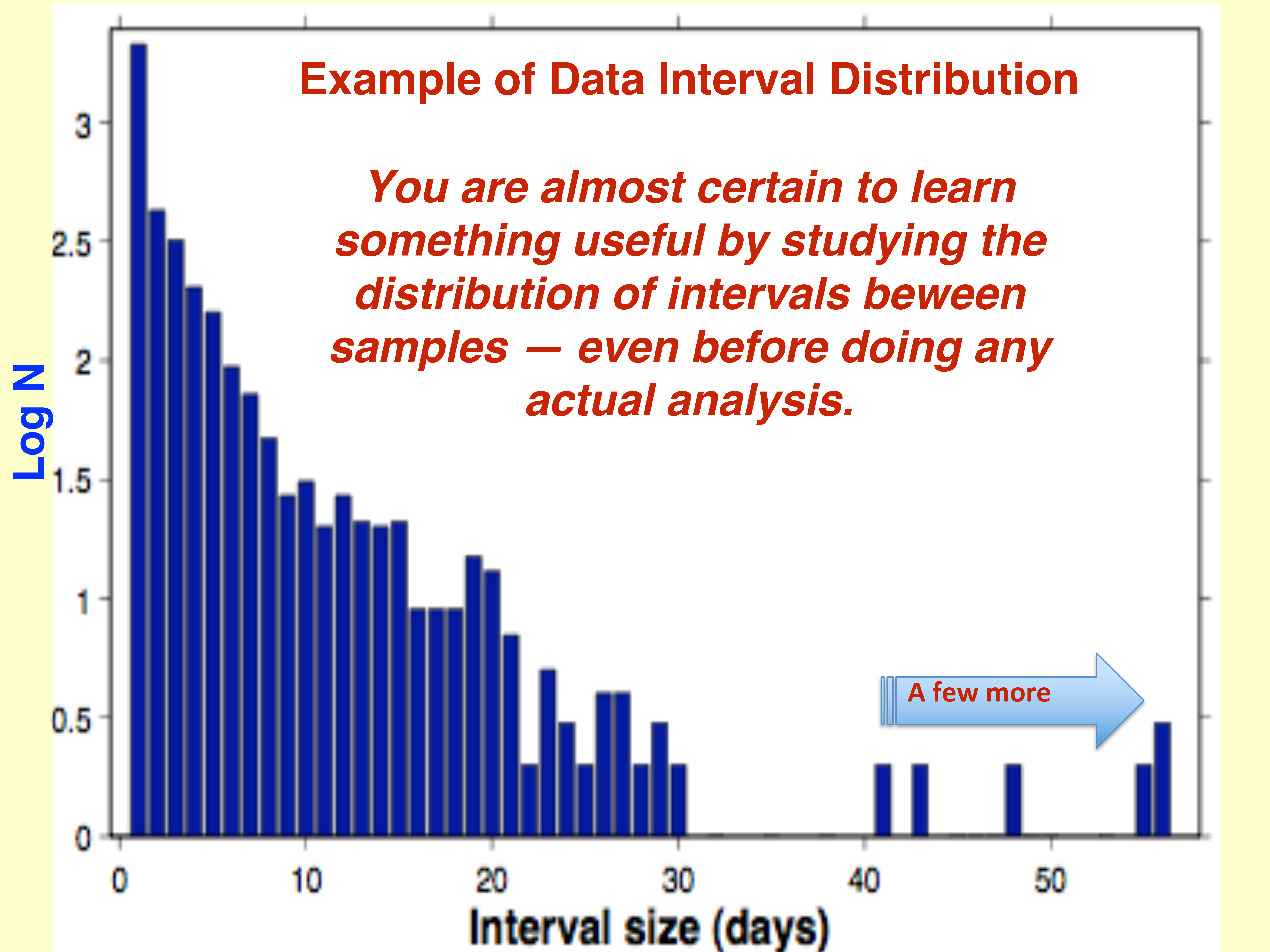
9. To measure relationships: correlation is weak; independence is strong

10. Remove the mean value at your own risk!

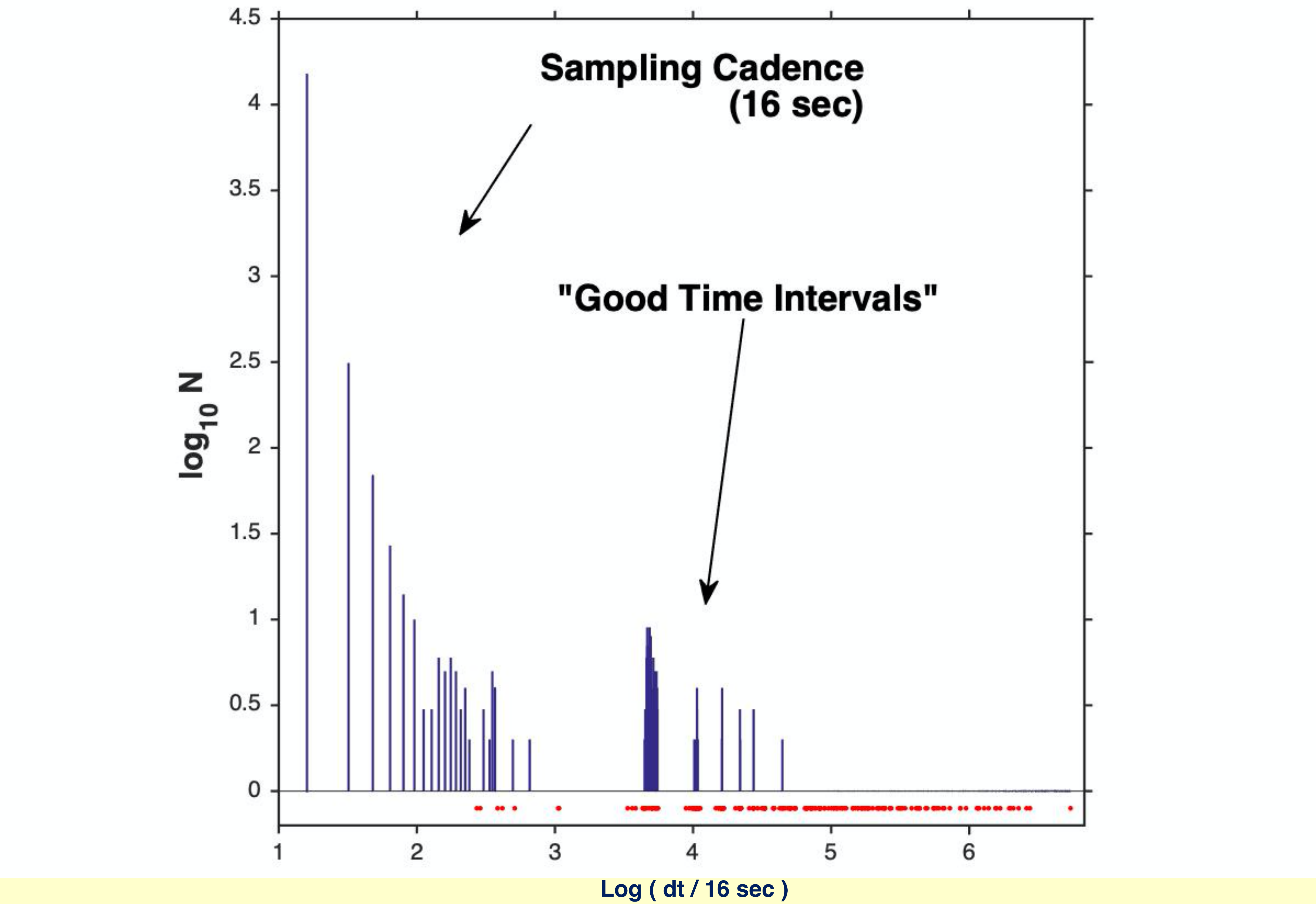
11. Errors are never the simple additive & Gaussian form often assumed.

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**

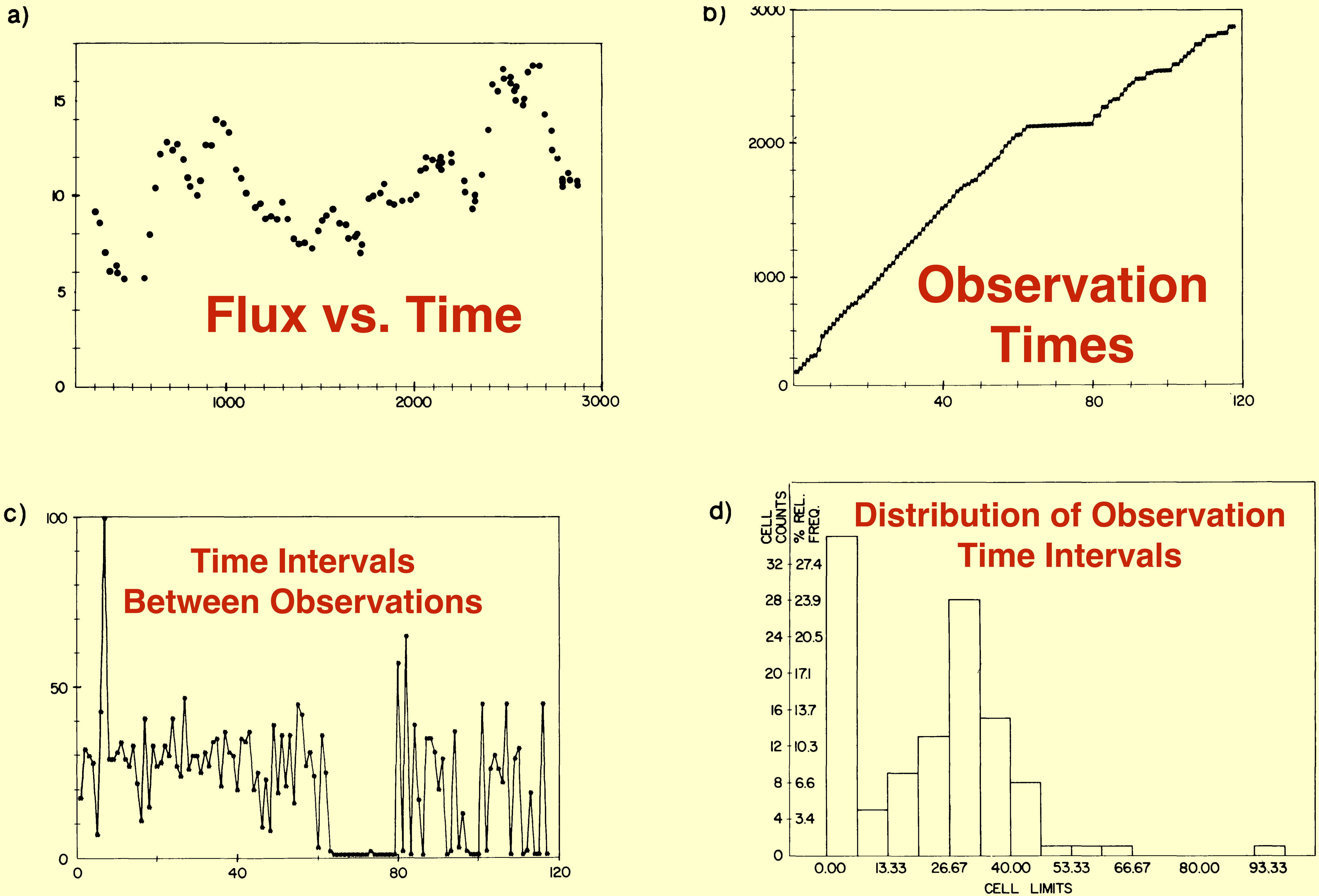

Example of Data Interval Distribution
You are almost certain to learn something useful by studying the distribution of intervals beween samples — even before doing any actual analysis.
Log N
3
2.5
2
1.5
1
0.5
0
0
10
20
30
40
50
Interval size (days)
A few more

Distribution of Intervals between Nicer Observations



KIC 9650712 Krista Lynne Smith

3C 120 Algonquin Radio Observatory



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

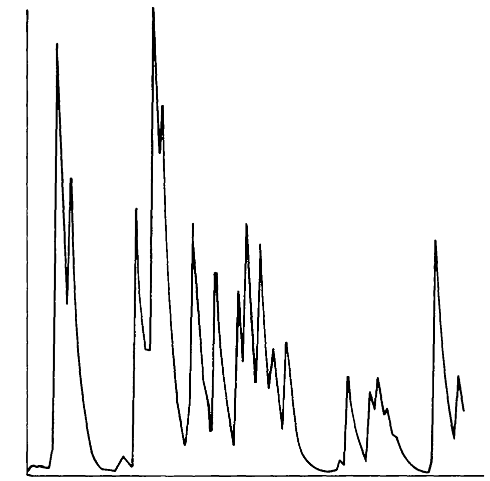
Given Arbitrarily Sampled Data, Algorithms for:

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

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

$$X = C * R + D$$

(random + deterministic)



Gaussian R —> 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: $\sum A(k)X(n-k) \leftrightarrows \sum C(k)R(n-k)$

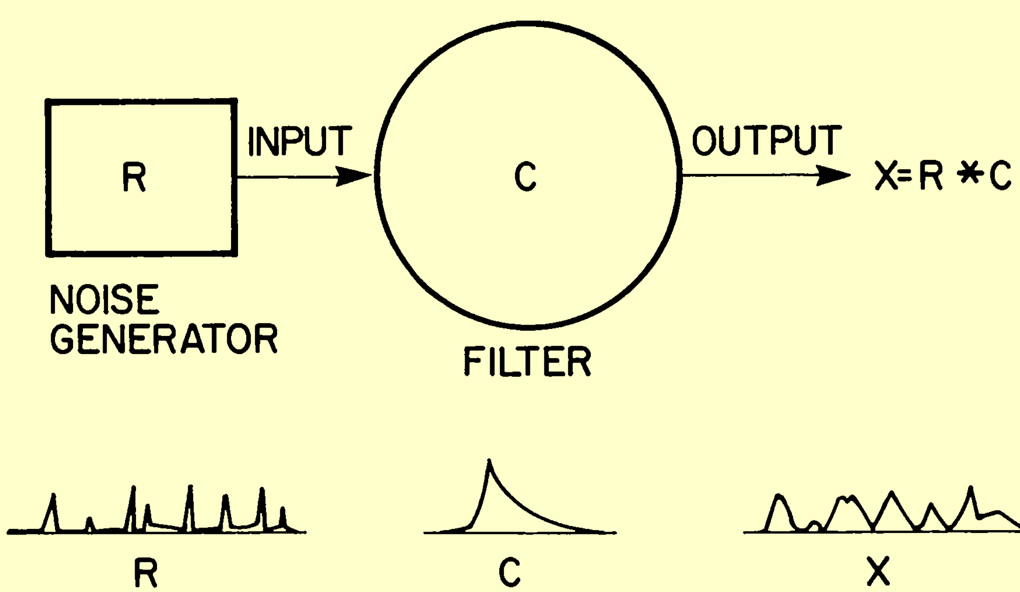
A *moving average* (MA) is a process X which can be written in the form:

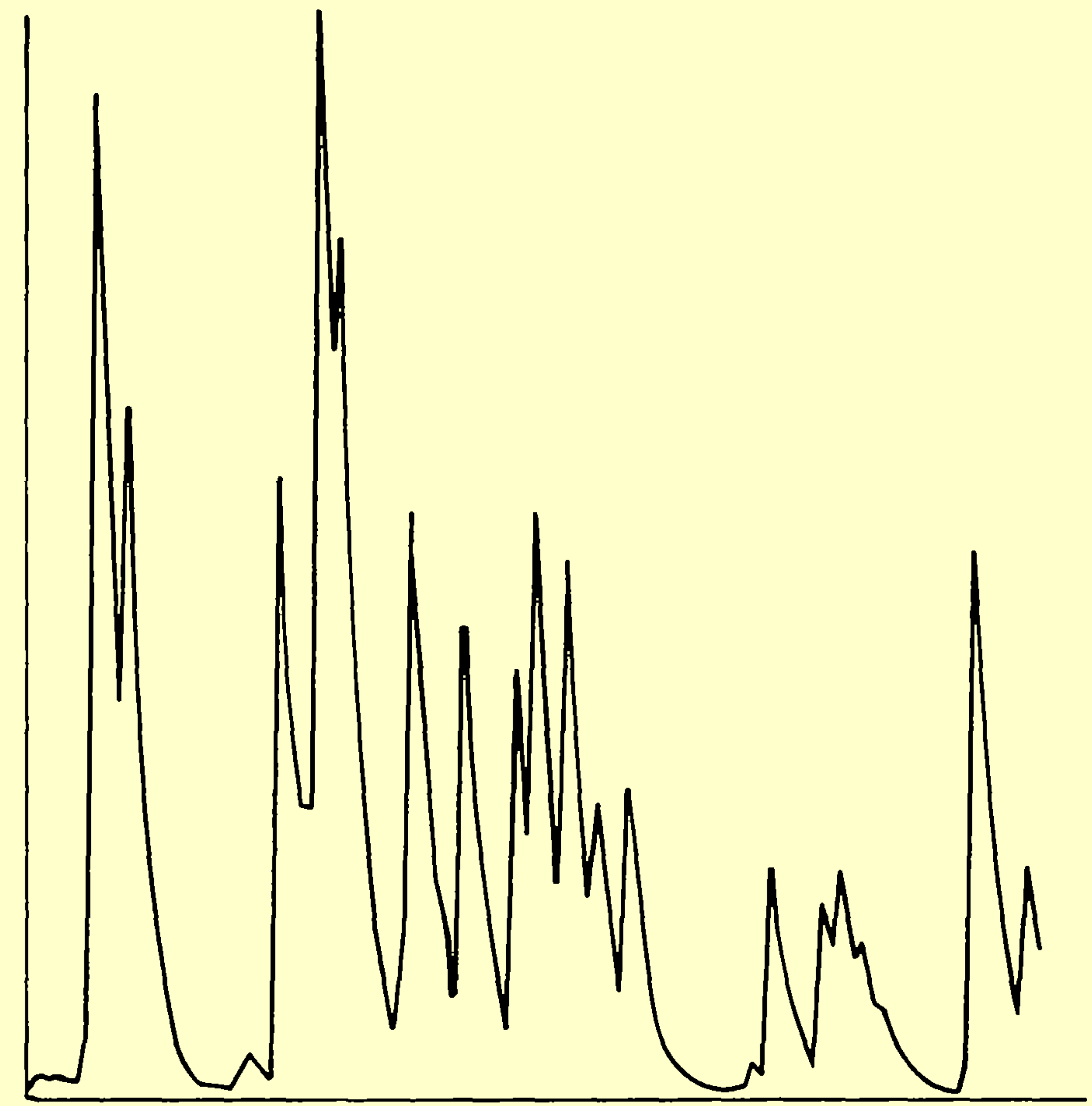
$$X_n = \sum_{i=-\infty}^{\infty} C_i R_{n-i} \quad (X = C * R), \qquad (15)$$

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

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

and the C_i are constants satisfying $\Sigma_{-\infty}^{\infty} C_i^2 < \infty$(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

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

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:

Moving Average | **Autoregressive**

“random pulses” | **“memory of random inputs”**

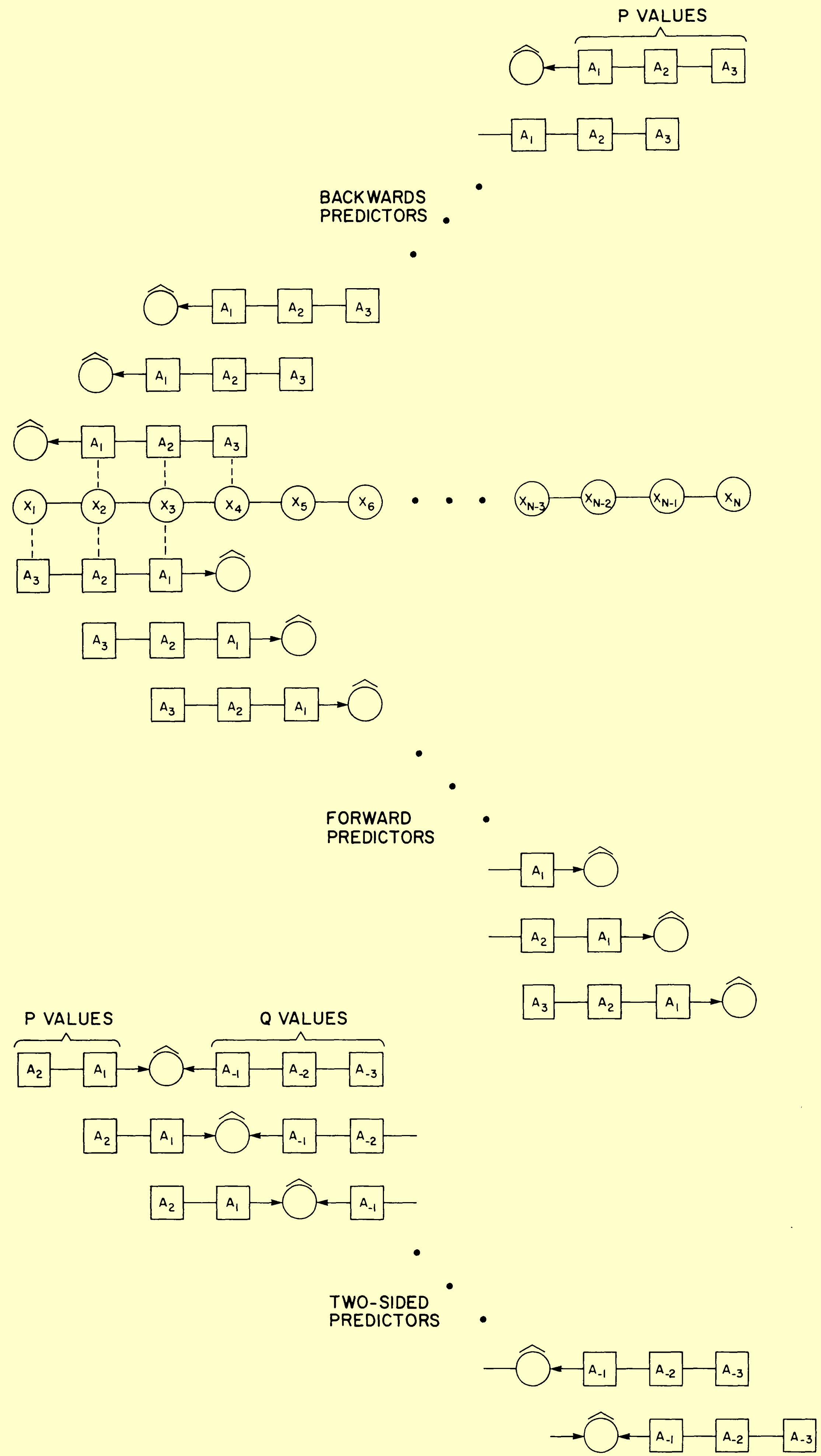
$X = C * R$ | $A * X = R$

MA ⇥⇤ **ARMA** ⇥⇤ **AR**

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

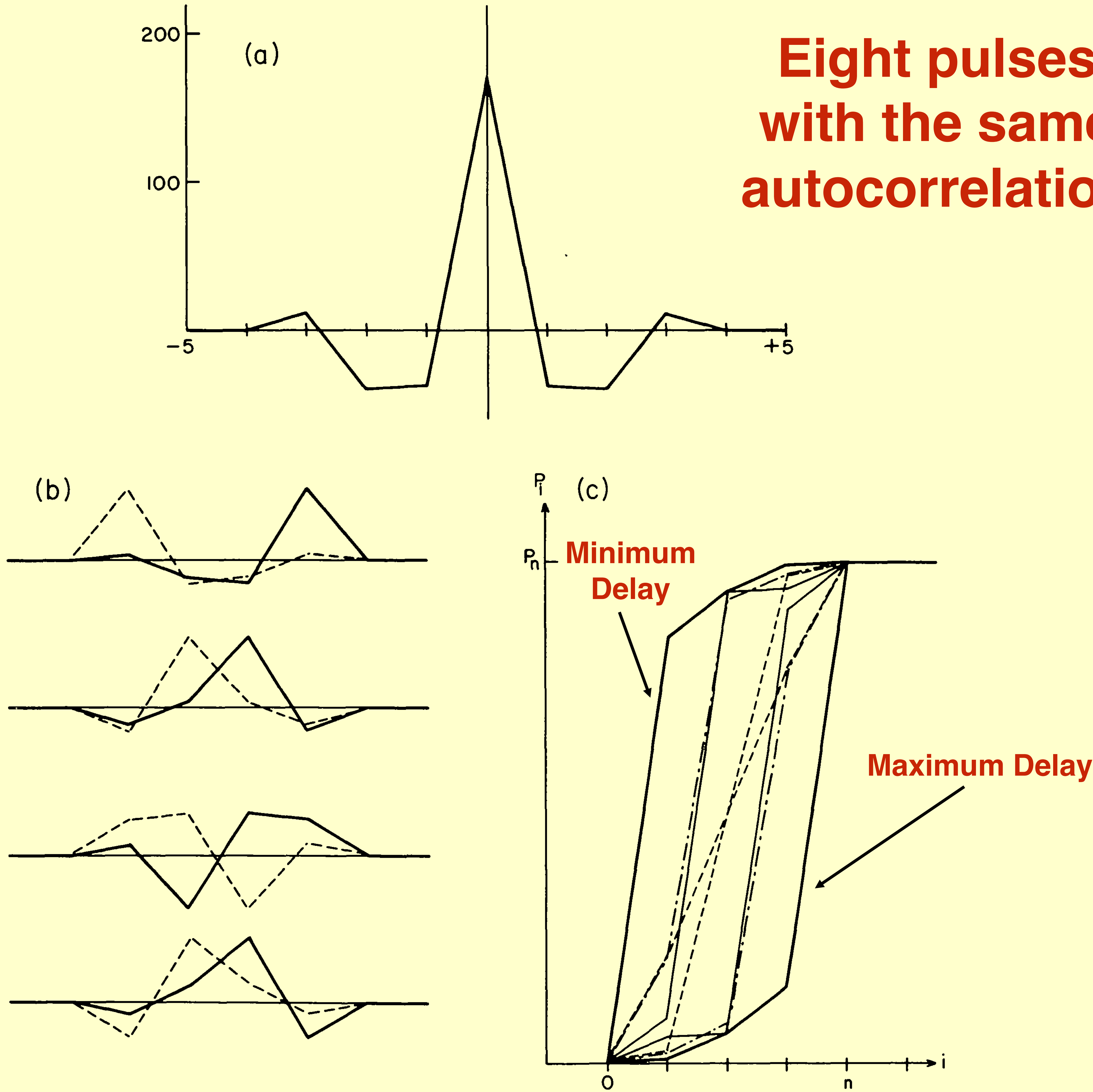
Autoregressive / Integrated / Moving Average
(for non stationary processes)

ARIMA



P VALUES
BACKWARDS PREDICTORS
FORWARD PREDICTORS
P VALUES
Q VALUES
TWO-SIDED PREDICTORS

Eight pulses with the same autocorrelation



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

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)

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

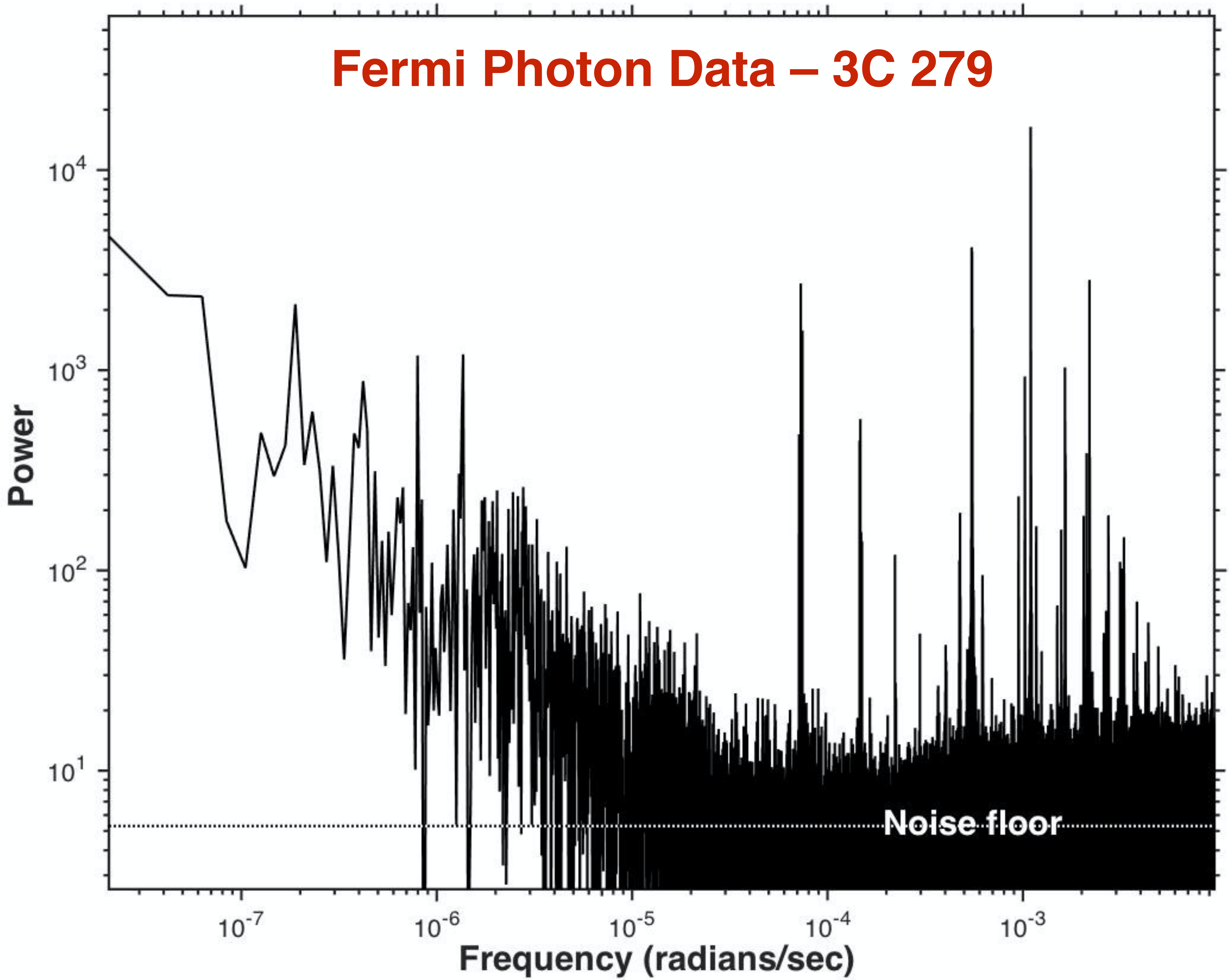
where

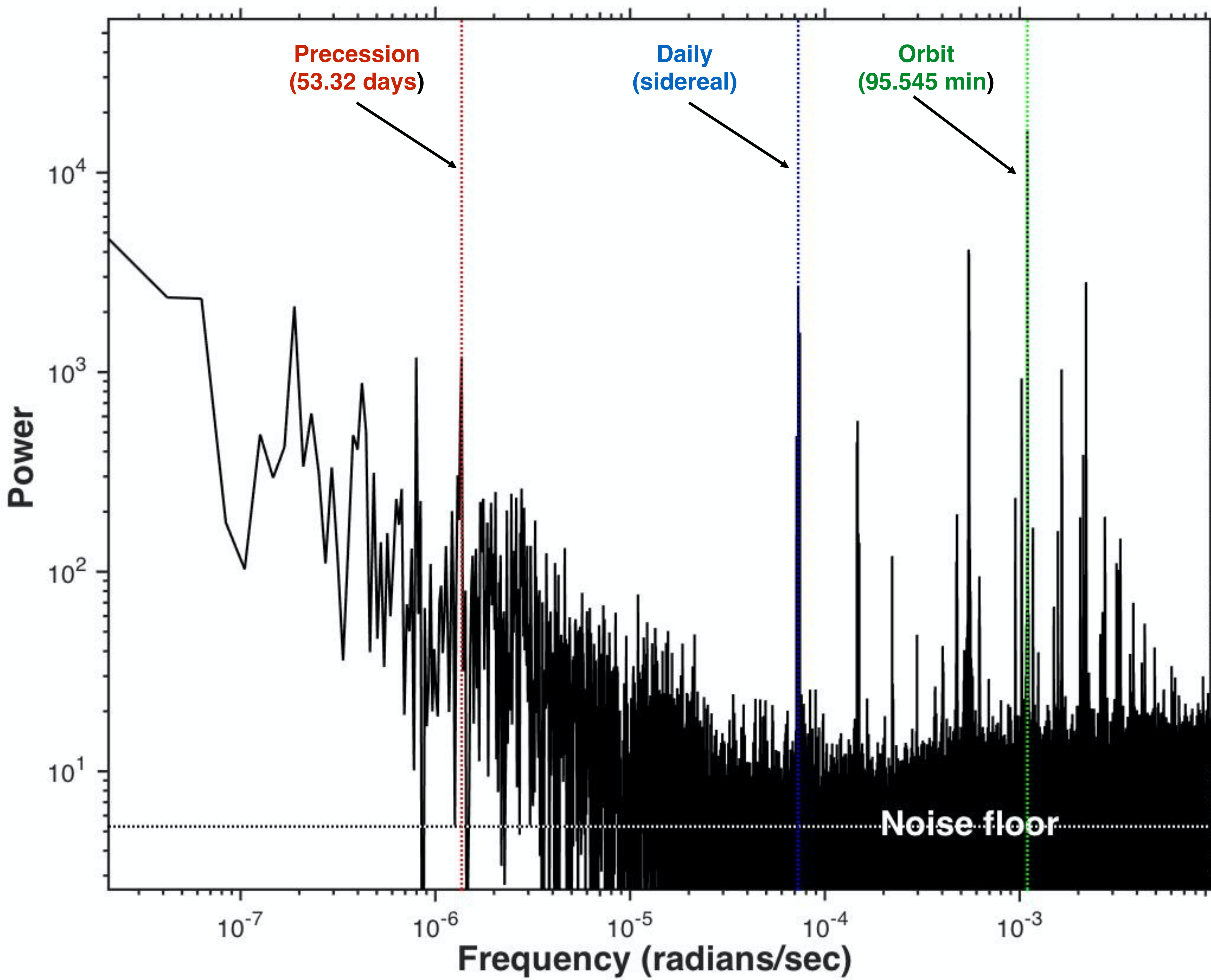
$$\tau(\omega) = \frac{1}{2\omega} \arctan[\ (\sum w_n \sin 2\omega t_n)\ /\ (\sum w_m \cos 2\omega t_m)\ ] \tag{2}$$

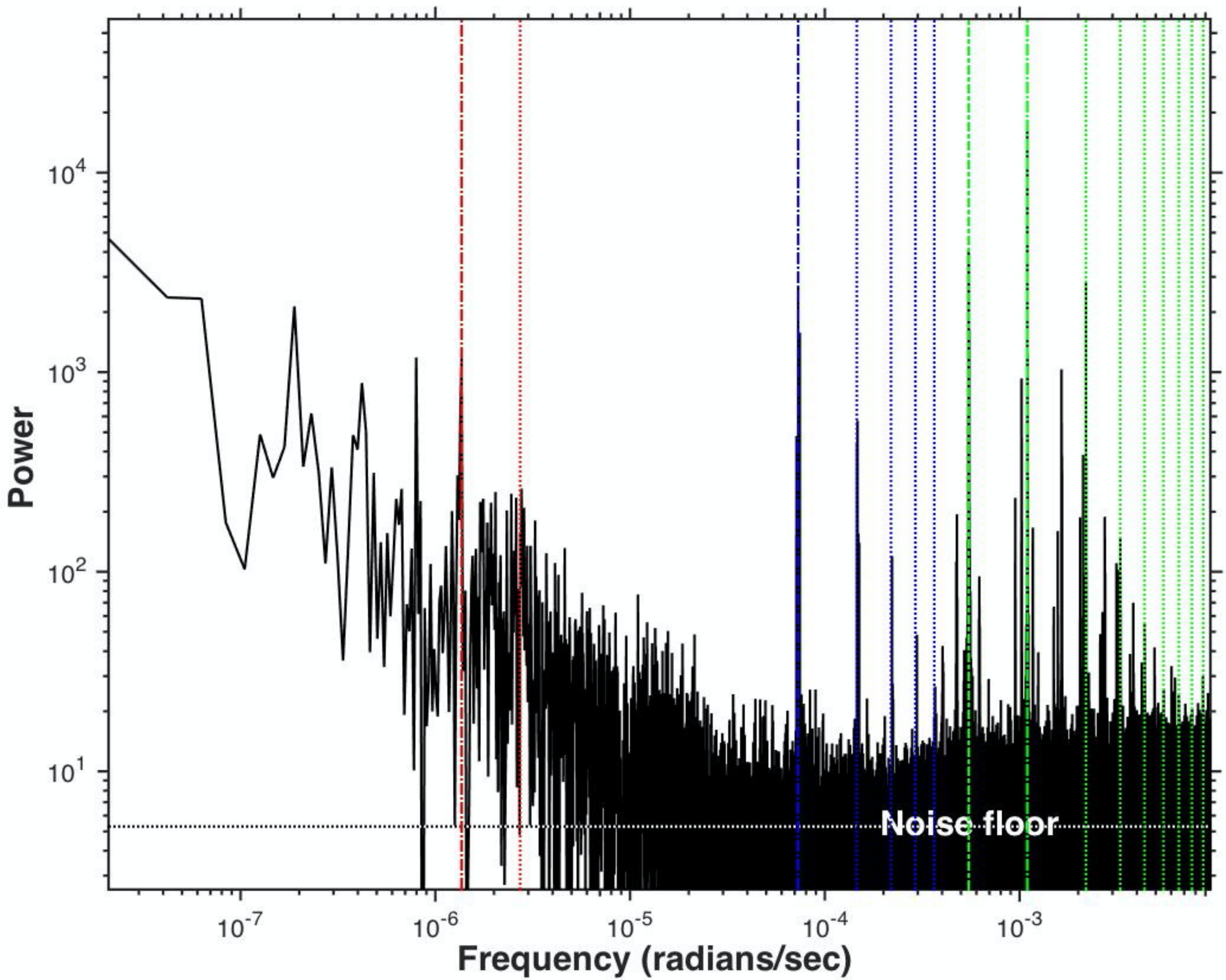
where all sums are over $n = 1, 2, ..., N$.

Treat event (photon) data as $\boldsymbol{\delta}(t - t_n)$
… that is, $x_n = 1$

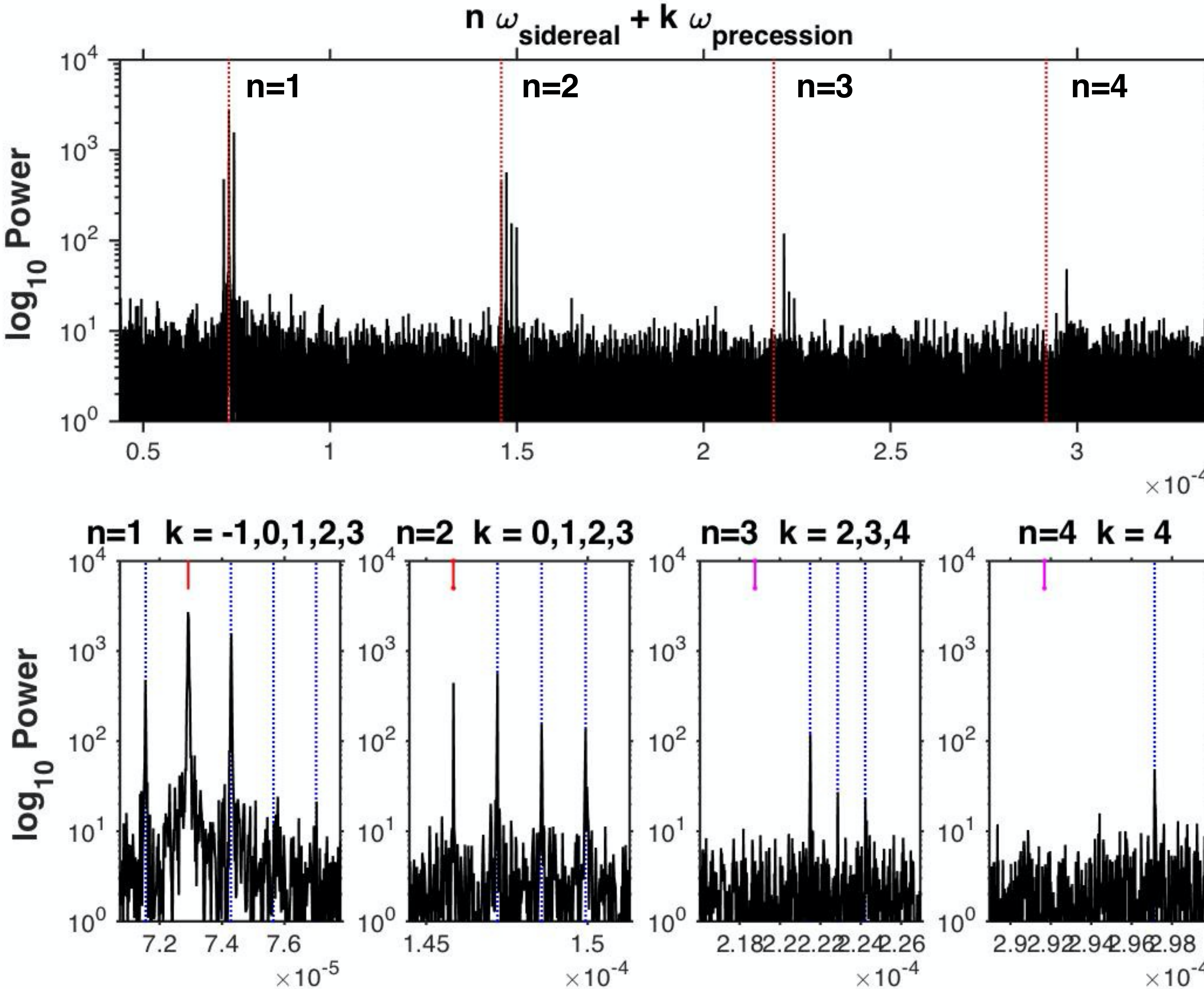
Studies in astronomical time series analysis. III.
Fourier Transforms, Autocorrelation Functions, and Cross-Correlation Functions of Unevenly Spaced Data.
JS, ApJ 343, 874-887


Fermi Photon Data – 3C 279
Power
Frequency (radians/sec)
Noise floor
10^4
10^3
10^2
10^1
10^-7
10^-6
10^-5
10^-4
10^-3

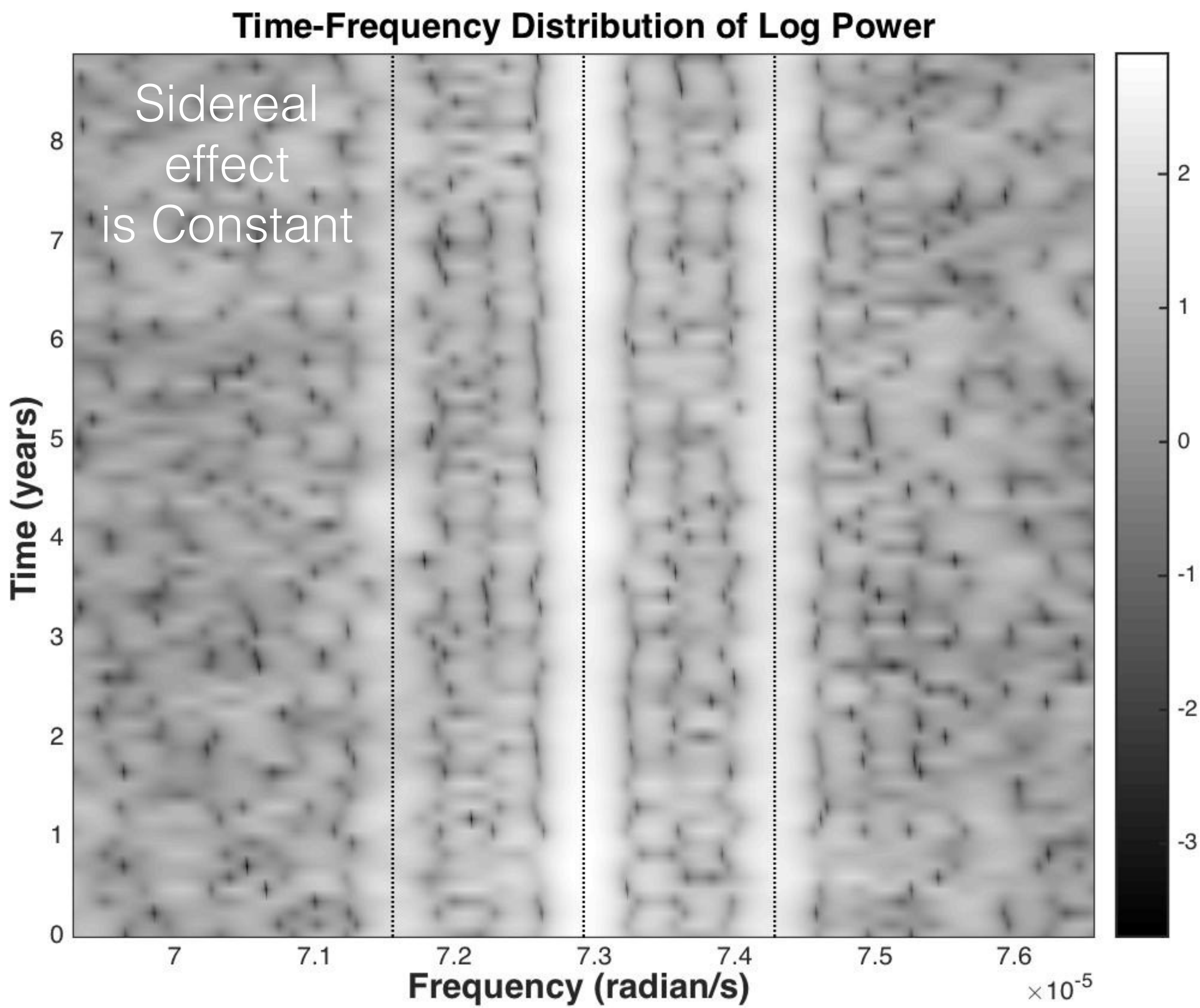

Precession
(53.32 days)
Daily
(sidereal)
Orbit
(95.545 min)
Noise floor
Power
Frequency (radians/sec)
10^{4}
10^{3}
10^{2}
10^{1}
10^{-7}
10^{-6}
10^{-5}
10^{-4}
10^{-3}



Power
10^4
10^3
10^2
10^1
Noise floor
10^{-7}
10^{-6}
10^{-5}
10^{-4}
10^{-3}
Frequency (radians/sec)

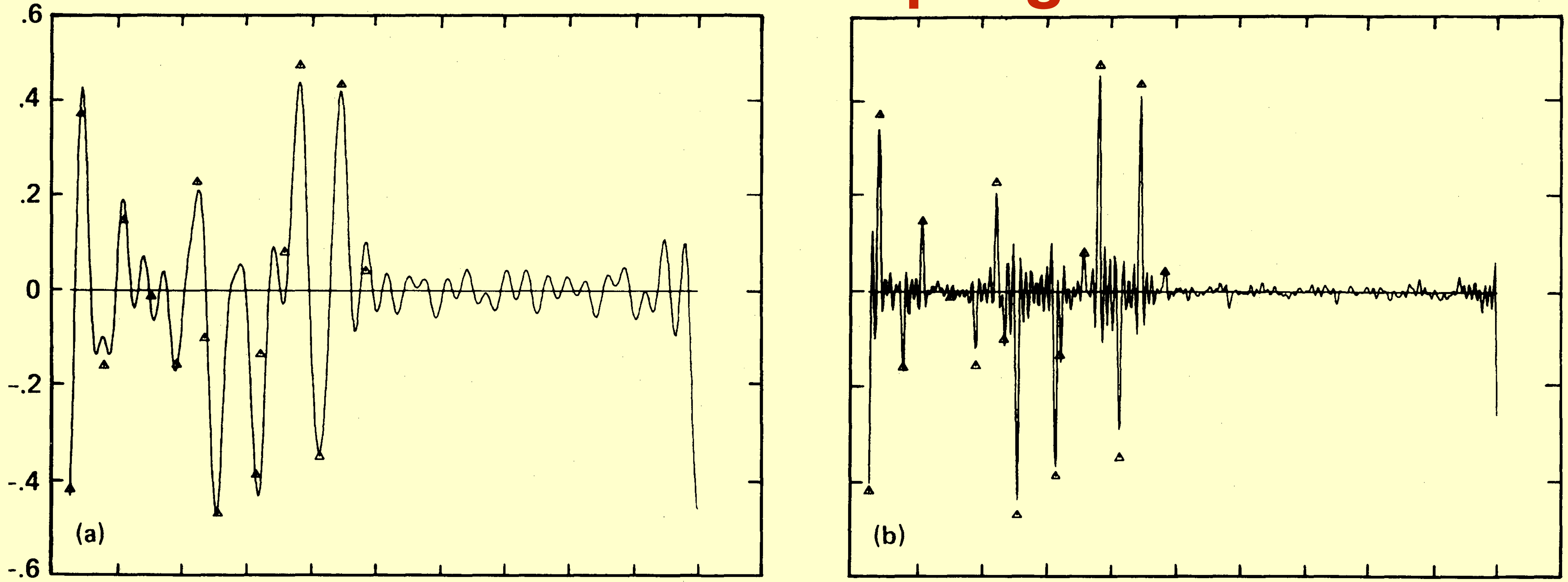


n ω_sidereal + k ω_precession
n=1
n=2
n=3
n=4
log10 Power
×10^-4
n=1 k = -1,0,1,2,3
n=2 k = 0,1,2,3
n=3 k = 2,3,4
n=4 k = 4
×10^-5



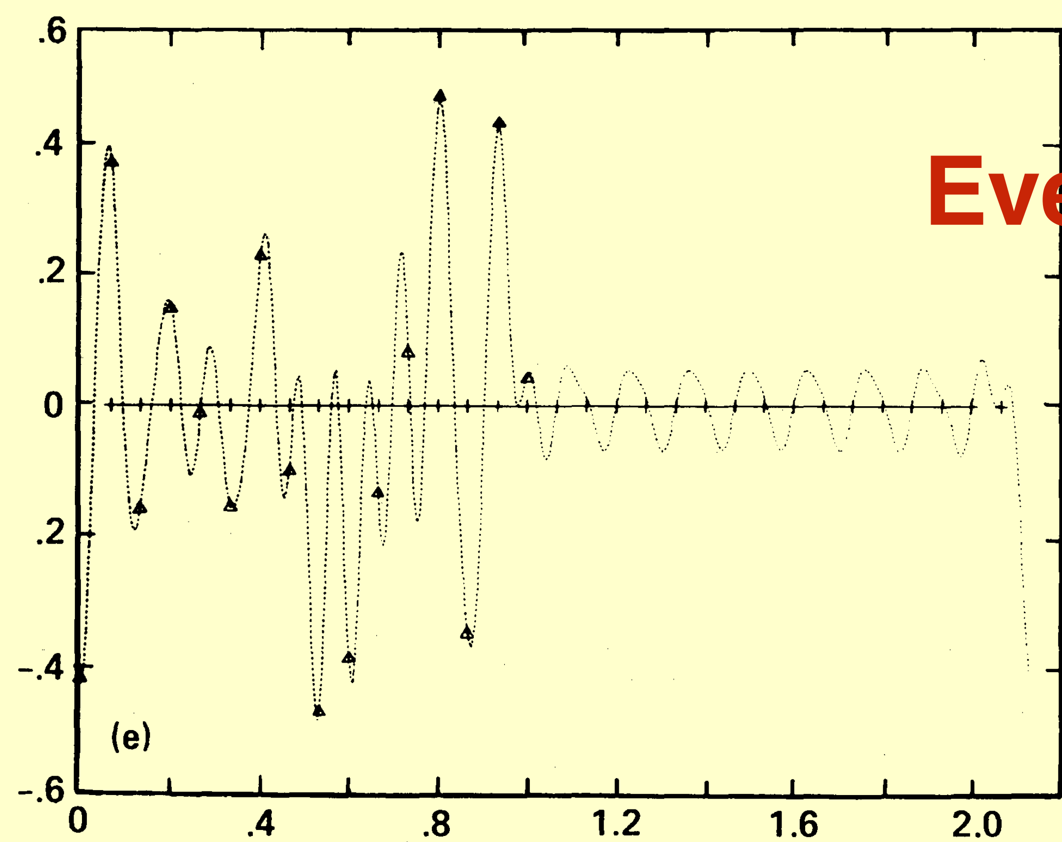
Time-Frequency Distribution of Log Power
Sidereal
effect
is Constant
Time (years)
0
1
2
3
4
5
6
7
8
Frequency (radian/s)
7
7.1
7.2
7.3
7.4
7.5
7.6
$\times 10^{-5}$
2
1
0
-1
-2
-3

Random Sampling

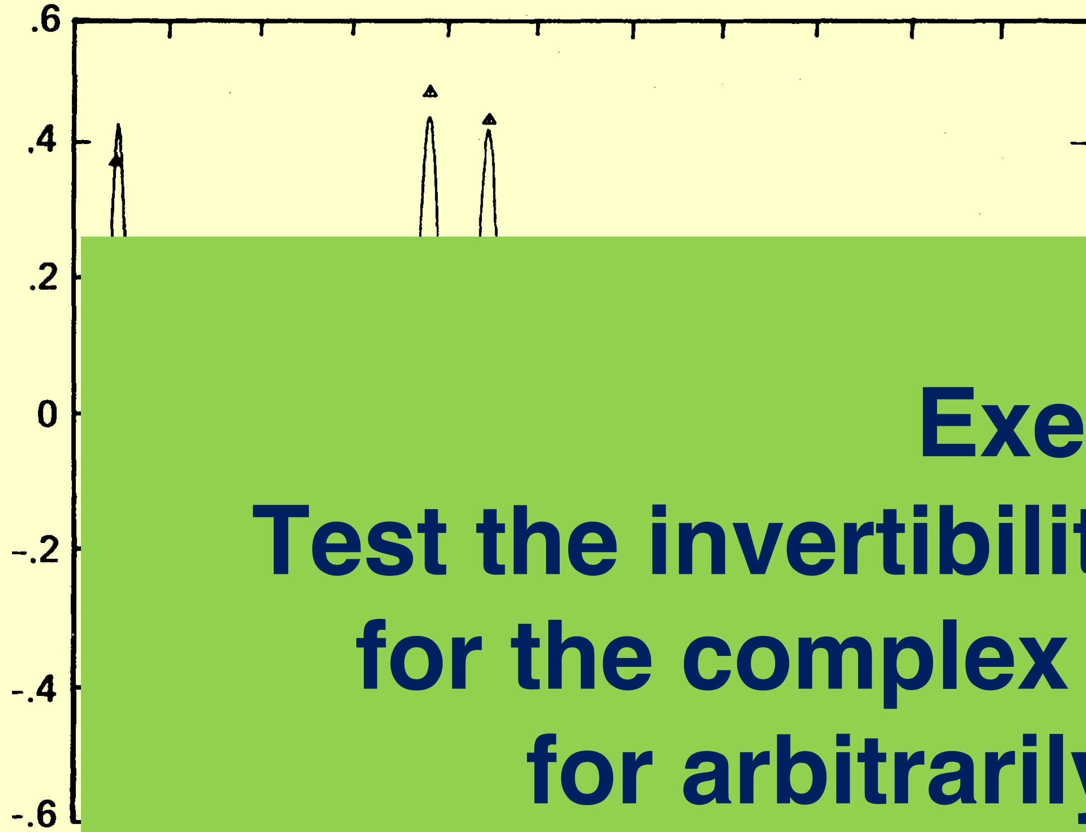


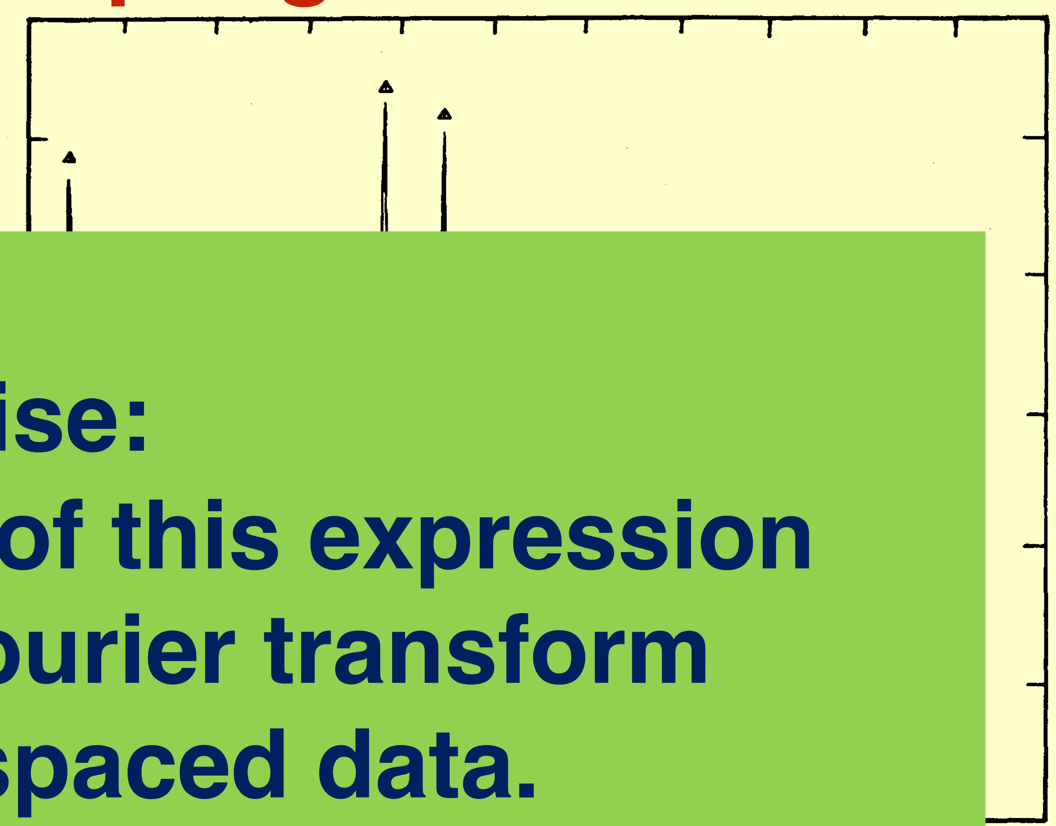
Test Invertibility of Fourier Transform

Even Sampling



Random Sampling

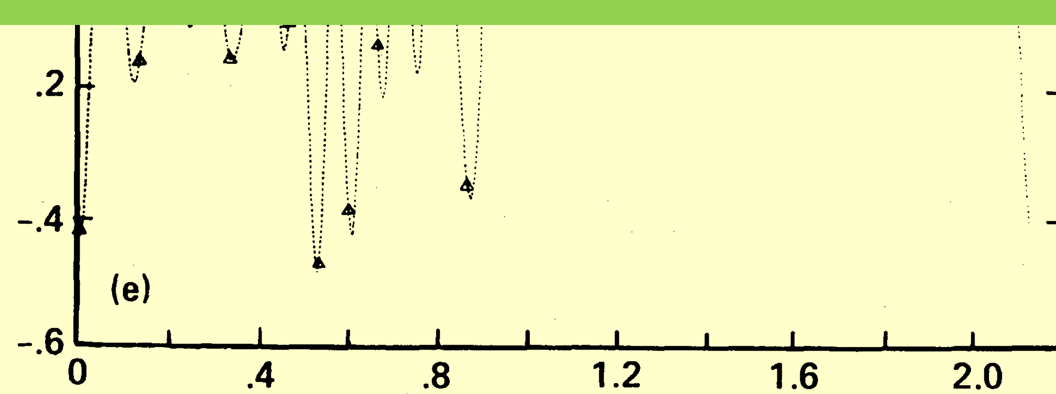




Exercise:
Test the invertibility of this expression for the complex Fourier transform for arbitrarily spaced data.

Explore the frequency grid needed.

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



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

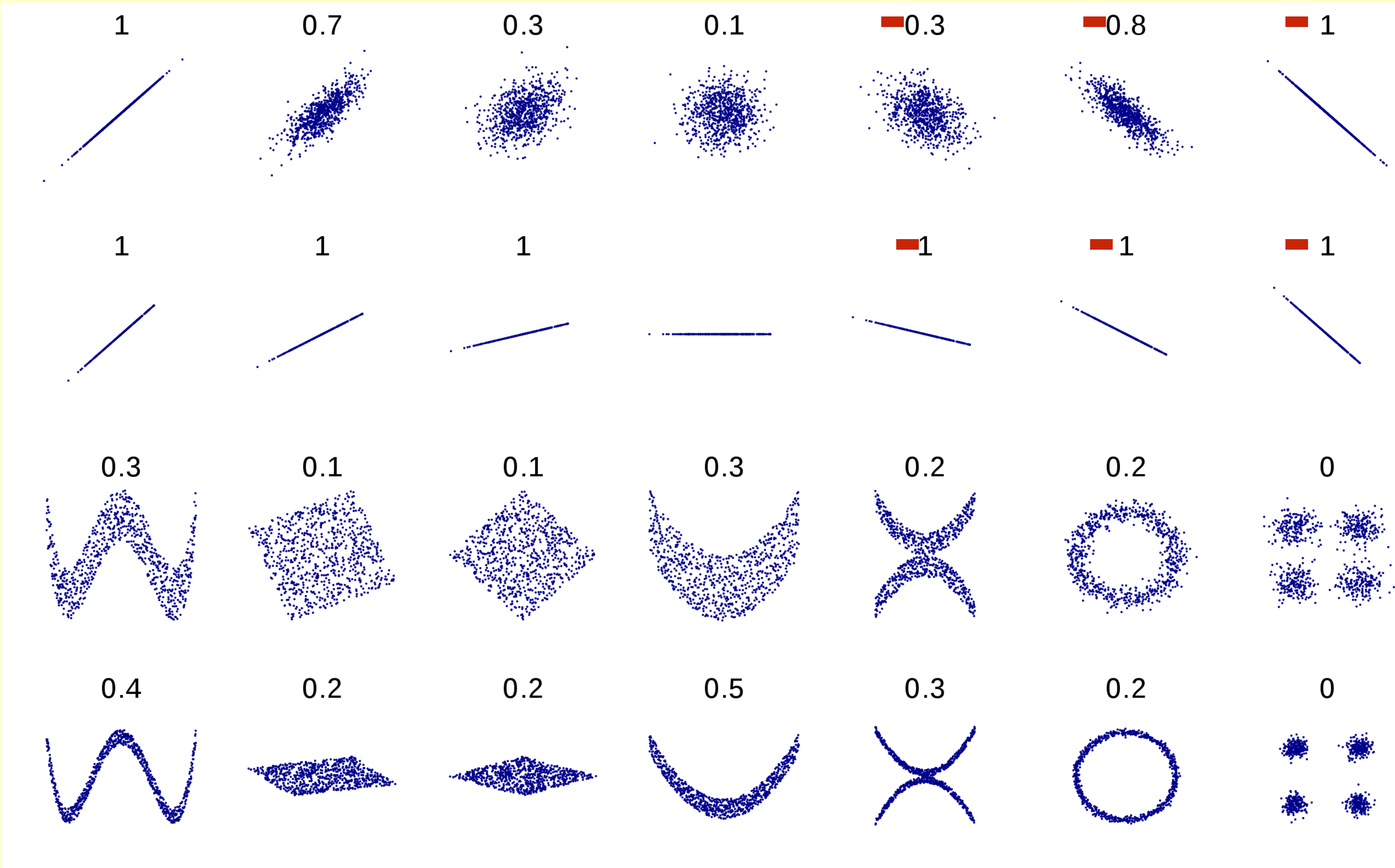
- Discrete Correlation (Dependence) Functions

- Bayes Blocks

- Applications: high-energy photon and LIGO data

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: $E[\,X(t)\,Y(t)\,] = 0$

$$\Uparrow \qquad \not\Downarrow$$

(Expectations)

Martingale Property: $E[\,X(t)\mid Y(t)] = E[\,X(t)\,]$

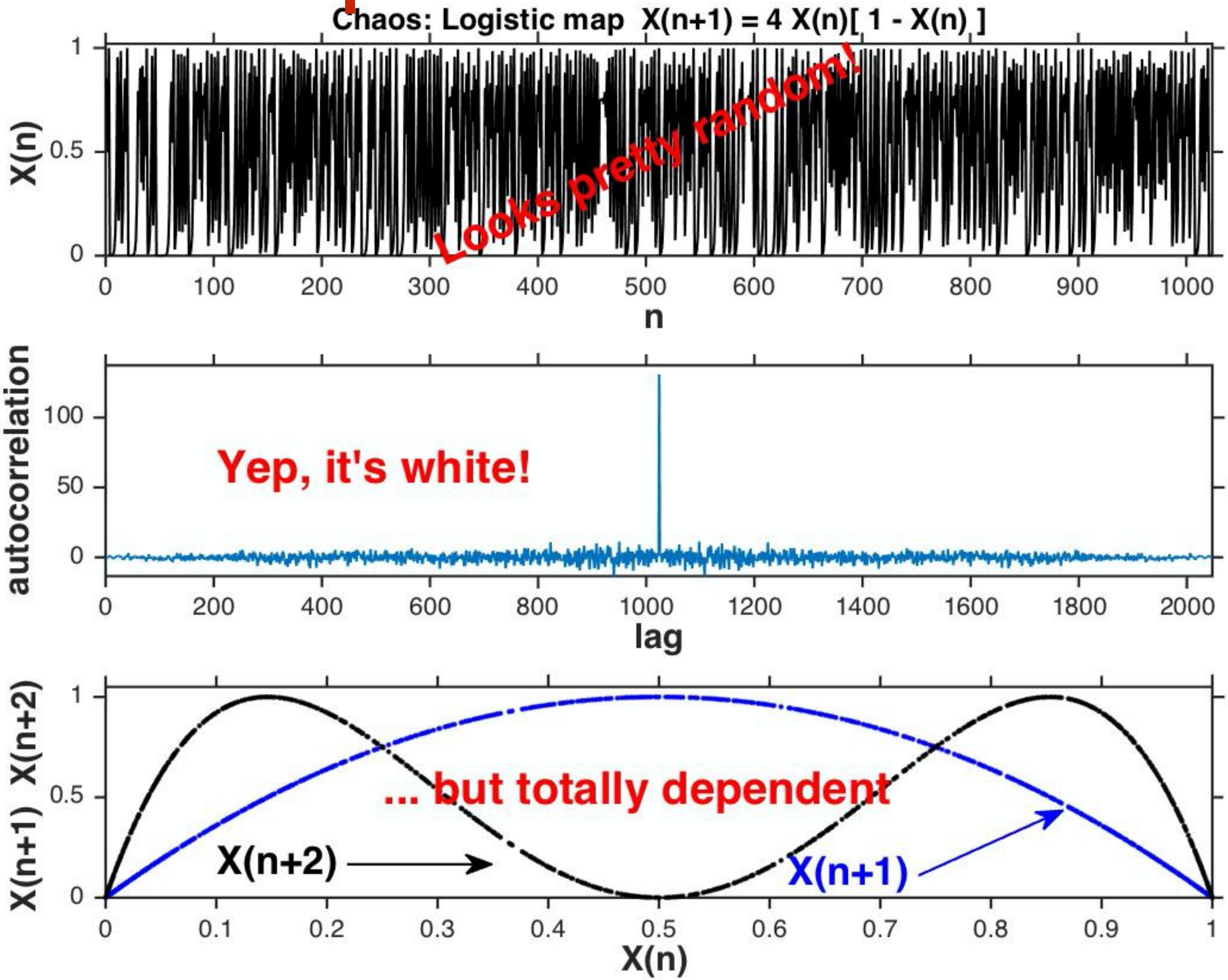
$E[\,Y(t)\mid X(t)] = E[\,Y(t)\,]$

$$\Uparrow \qquad \not\Downarrow$$

(Distributions)

Independent: $F(X,Y) = F(X)\,F(Y)$

white noise process for which correlation



Measure (in)dependence between two time series

$$D(X,Y) == < F(X,Y) \, , \, F(X)\, F(Y) >$$

F can be:

- Differential Probability Distribution
- Cumulative Probability Distribution
- Characteristic Function …

$<\ ,\ >$ 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 Homor of John W. Tukey, Princeton U. Press,

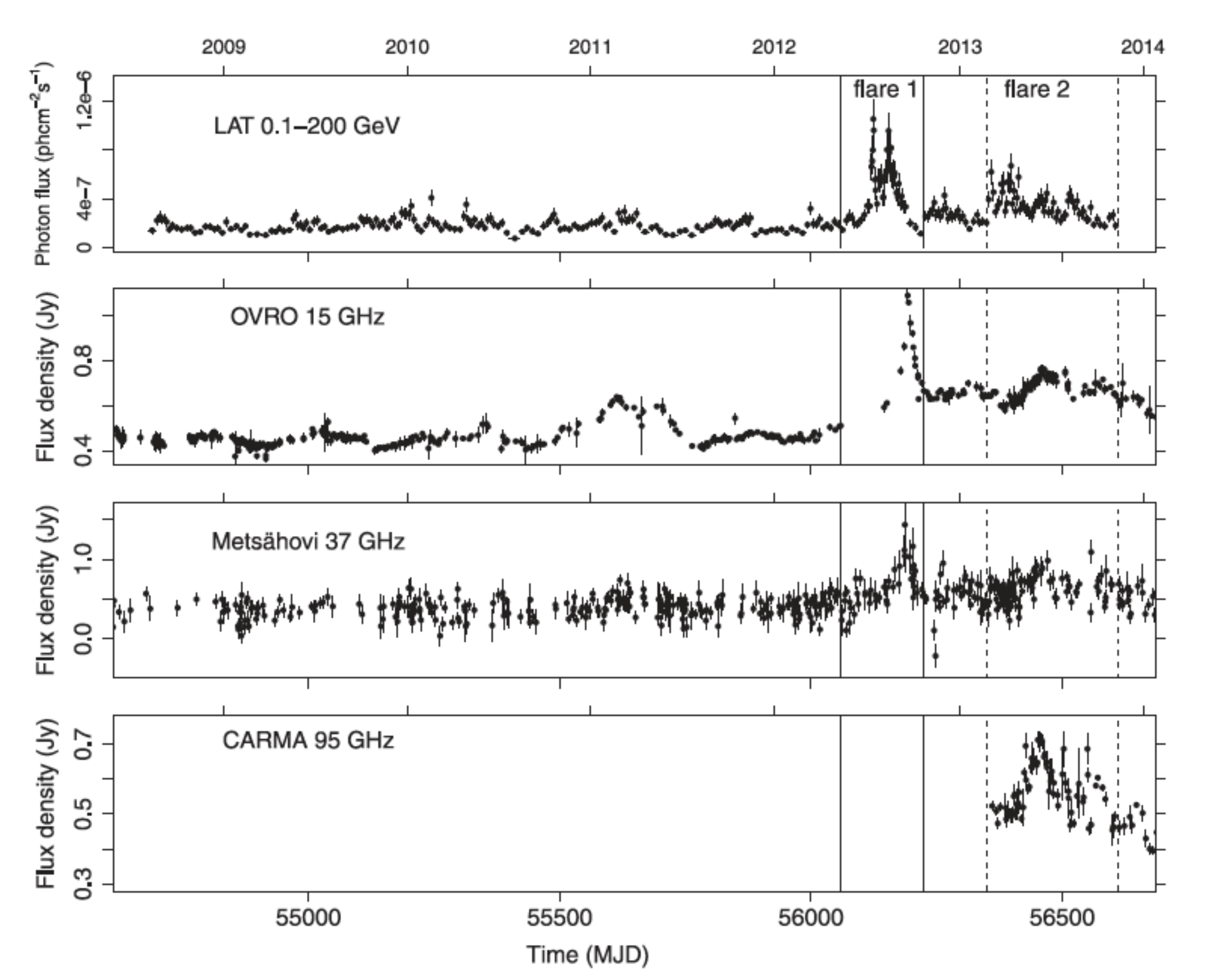
Szekely, Rizzo and Bakirov (2007)
Measuring and Testing Dependence by Correlation of Distances
Annals of Statistics, 35, 2769-2794.

Ding and Li (2015)
Copula Correlation: An Equitable Dependence Measure and Extension of Pearson's Correlation 1312.7214

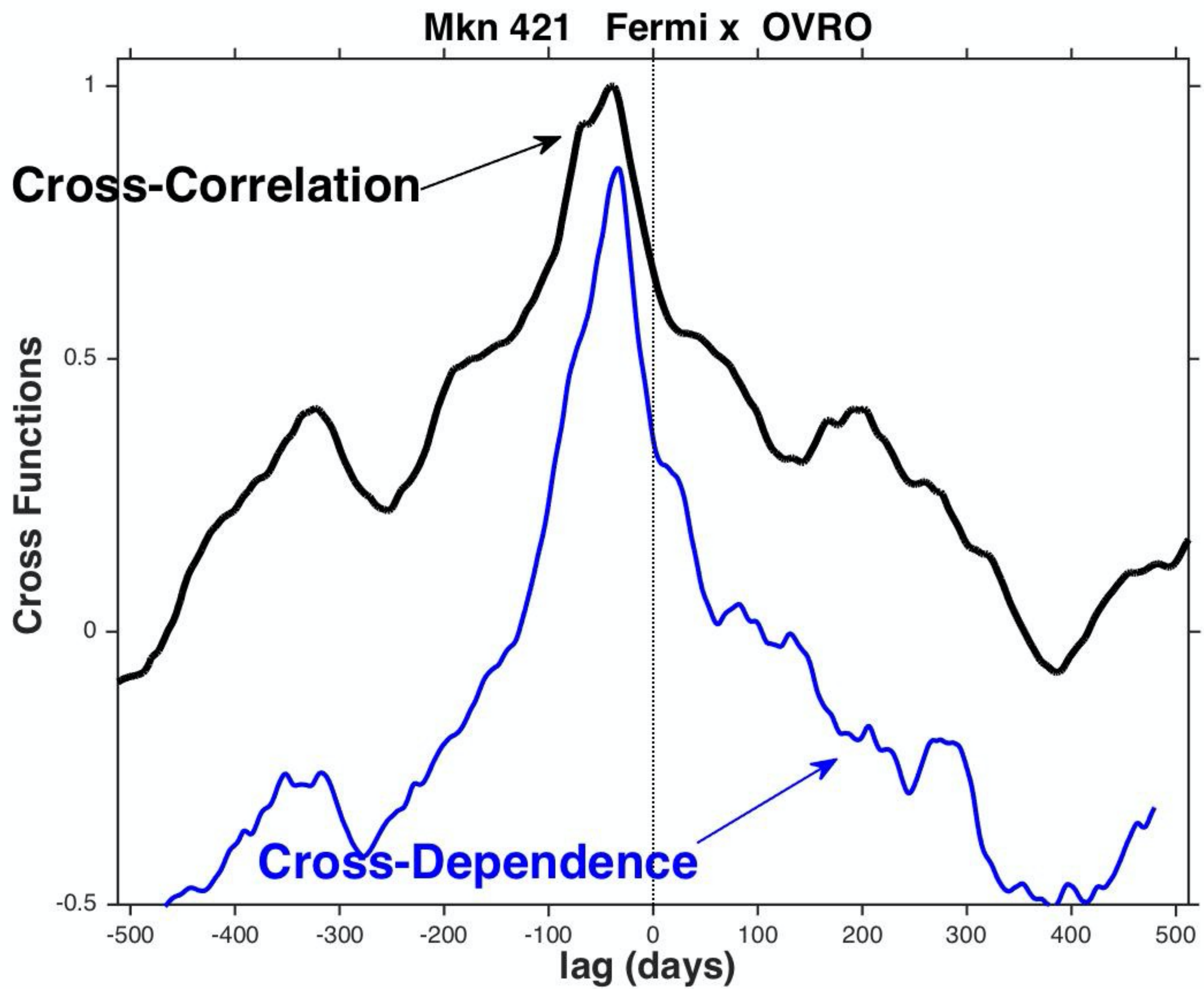
Yakir et al (2016)
Measuring Dependence Powerfully and Equitably 1505.02213

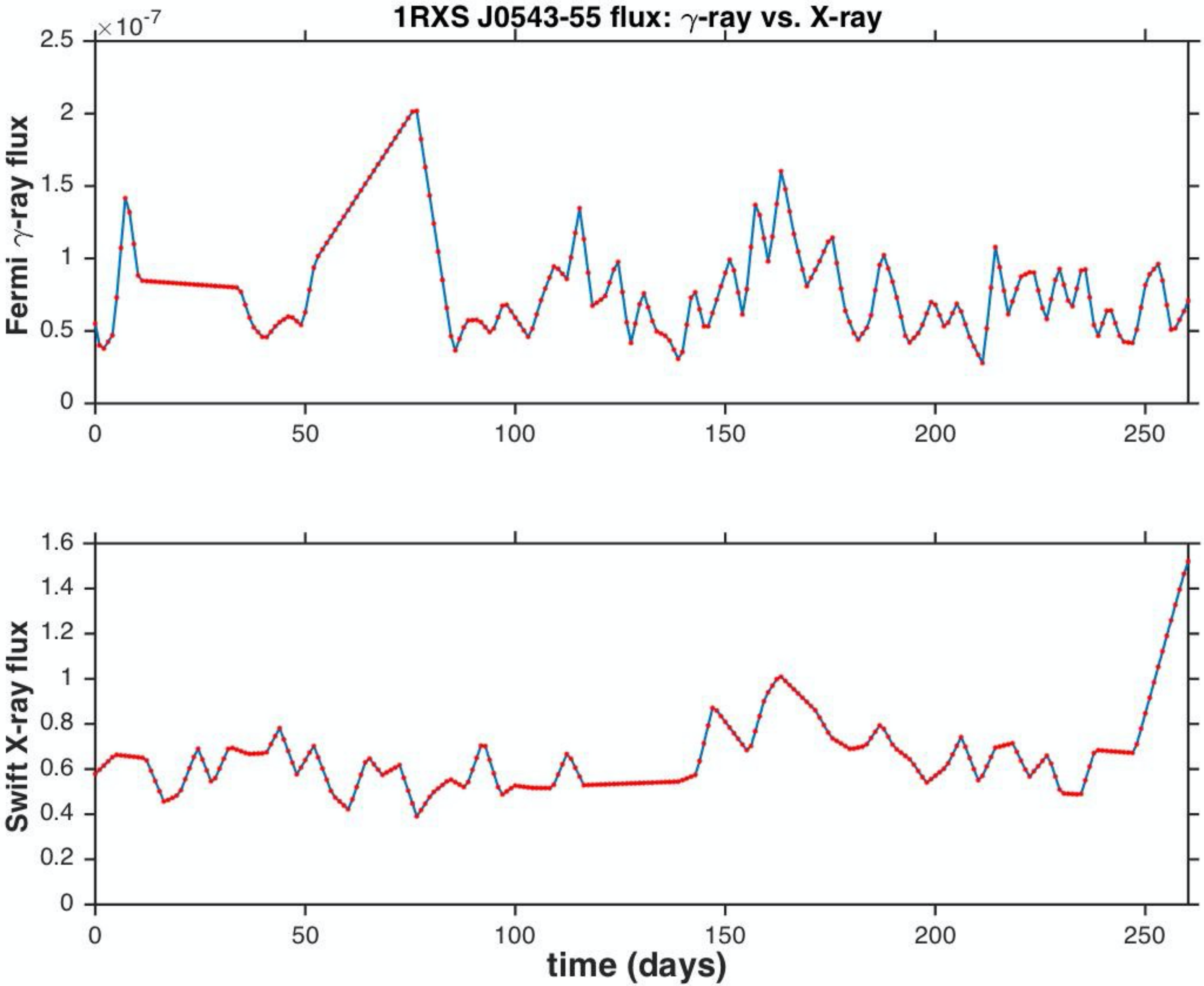
Richards (2017)
Distance Correlation: A New Tool for Detecting Association and Measuring Correlation Between Data Sets 1709.06400

Kagan and Szekely (2019)
Calibrating Dependence between Random Elements 1903.04663

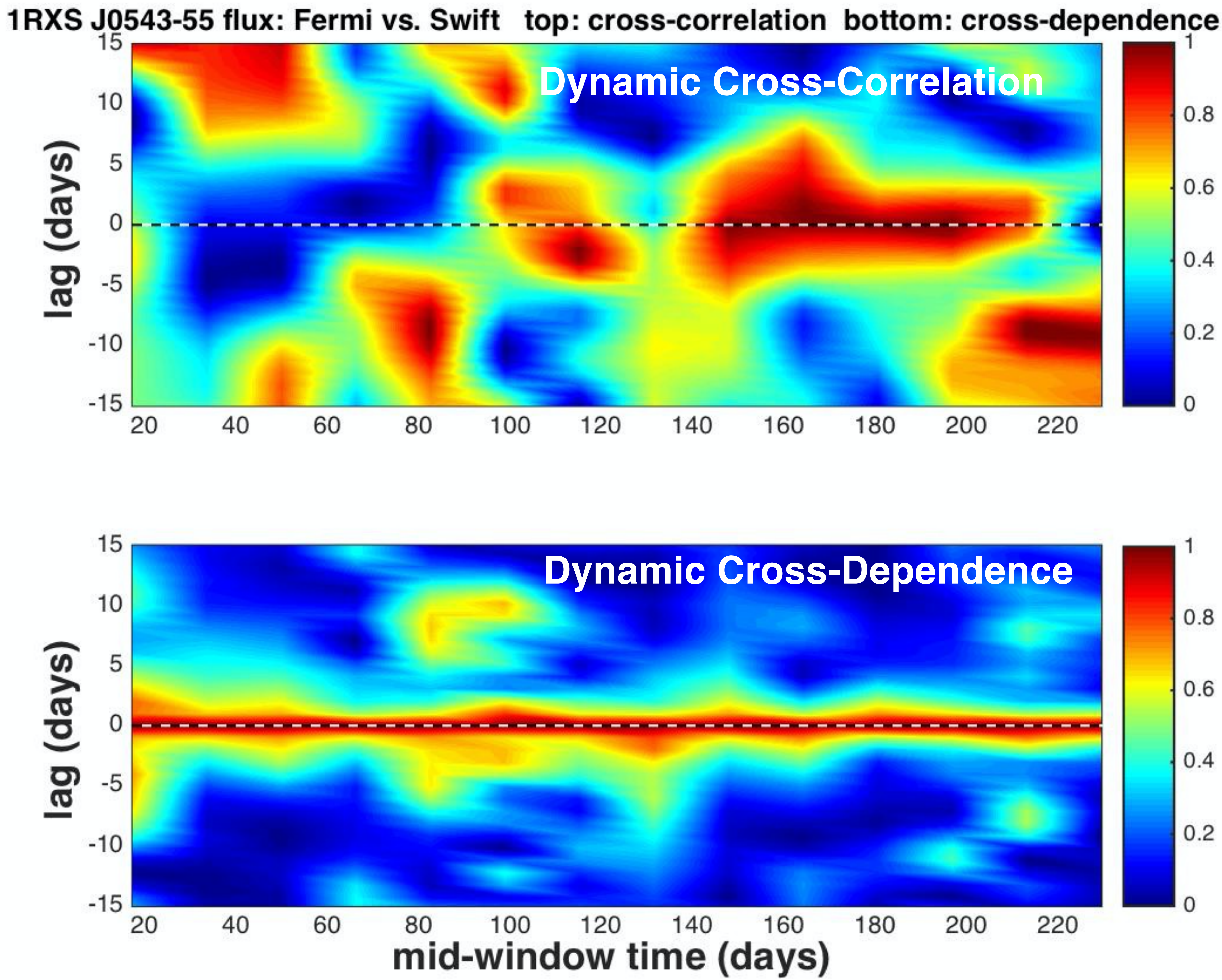


A combined radio and GeV γ -ray view of the 2012 and 2013 flares of Mrk 421
T. Hovatta et al., MNRAS 448, 3121–3131 (2015)


Mkn 421 Fermi x OVRO
Cross-Correlation
Cross-Dependence
Cross Functions
lag (days)
1
0.5
0
-0.5
-500
-400
-300
-200
-100
0
100
200
300
400
500



1RXS J0543-55 flux: γ-ray vs. X-ray
$\times 10^{-7}$
2.5
2
1.5
1
0.5
0
Fermi γ-ray flux
0
50
100
150
200
250
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
Swift X-ray flux
0
50
100
150
200
250
time (days)


1RXS J0543-55 flux: Fermi vs. Swift top: cross-correlation bottom: cross-dependence
Dynamic Cross-Correlation
Dynamic Cross-Dependence
lag (days)
mid-window time (days)
15
10
5
0
-5
-10
-15
20
40
60
80
100
120
140
160
180
200
220
1
0.8
0.6
0.4
0.2
0

OUTLINE

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

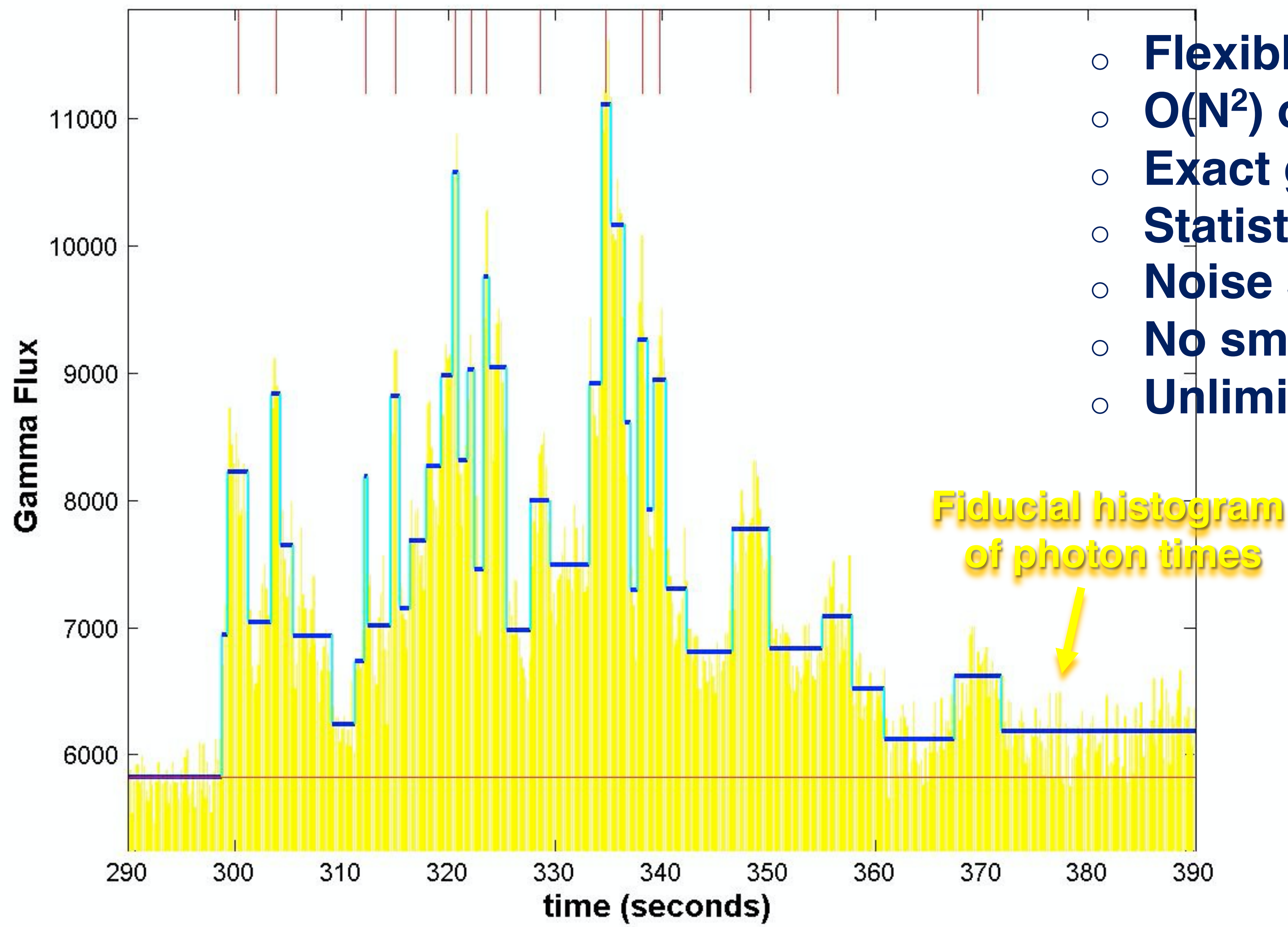
Given Arbitrarily Sampled Data, Algorithms for:

- 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



- **Flexible w.r.t. data mode**
- **O(N^2) or faster**
- **Exact global optimum**
- **Statistically significant features**
- **Noise suppressed**
- **No smoothing**
- **Unlimited dynamic range**

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.

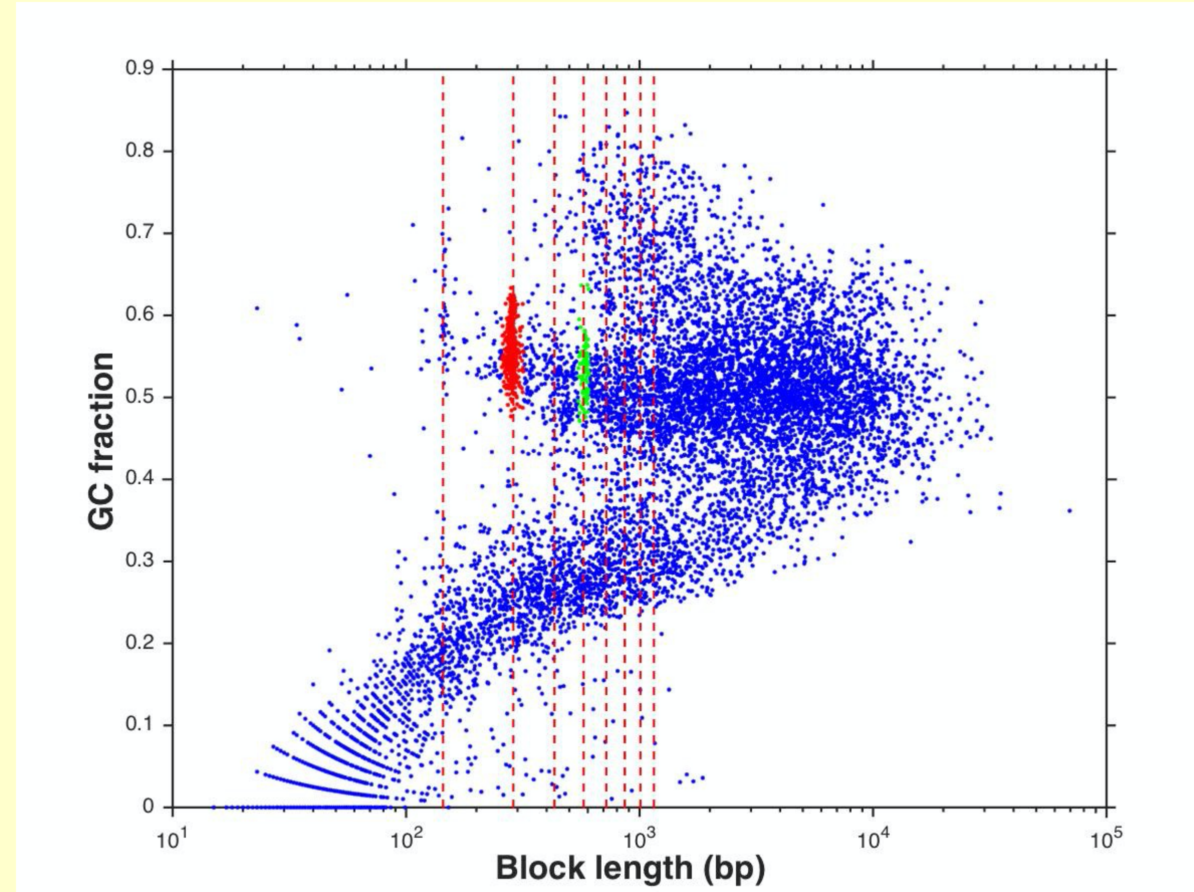
Bayesian Blocks can use ANY Data Mode

- 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
- 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

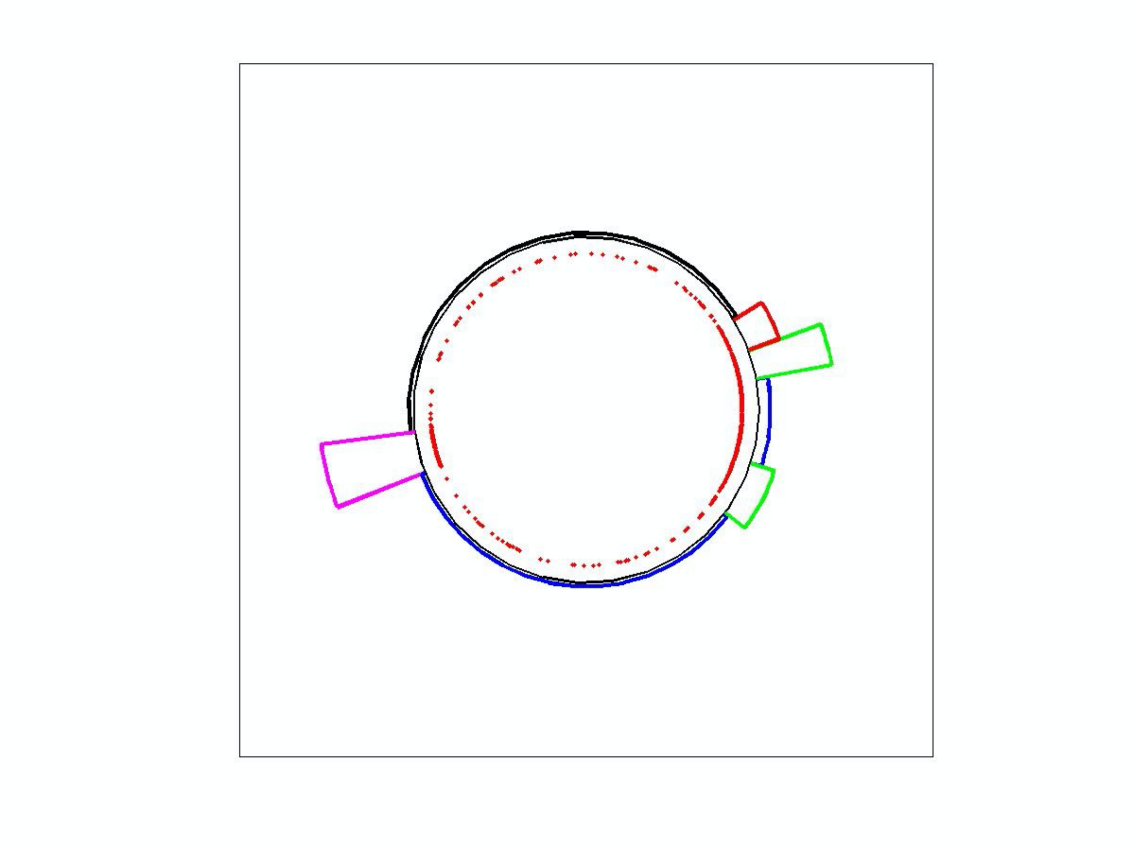
GC Islands in the Human Genome



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***

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(N2) (pruning)→ ~ 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:

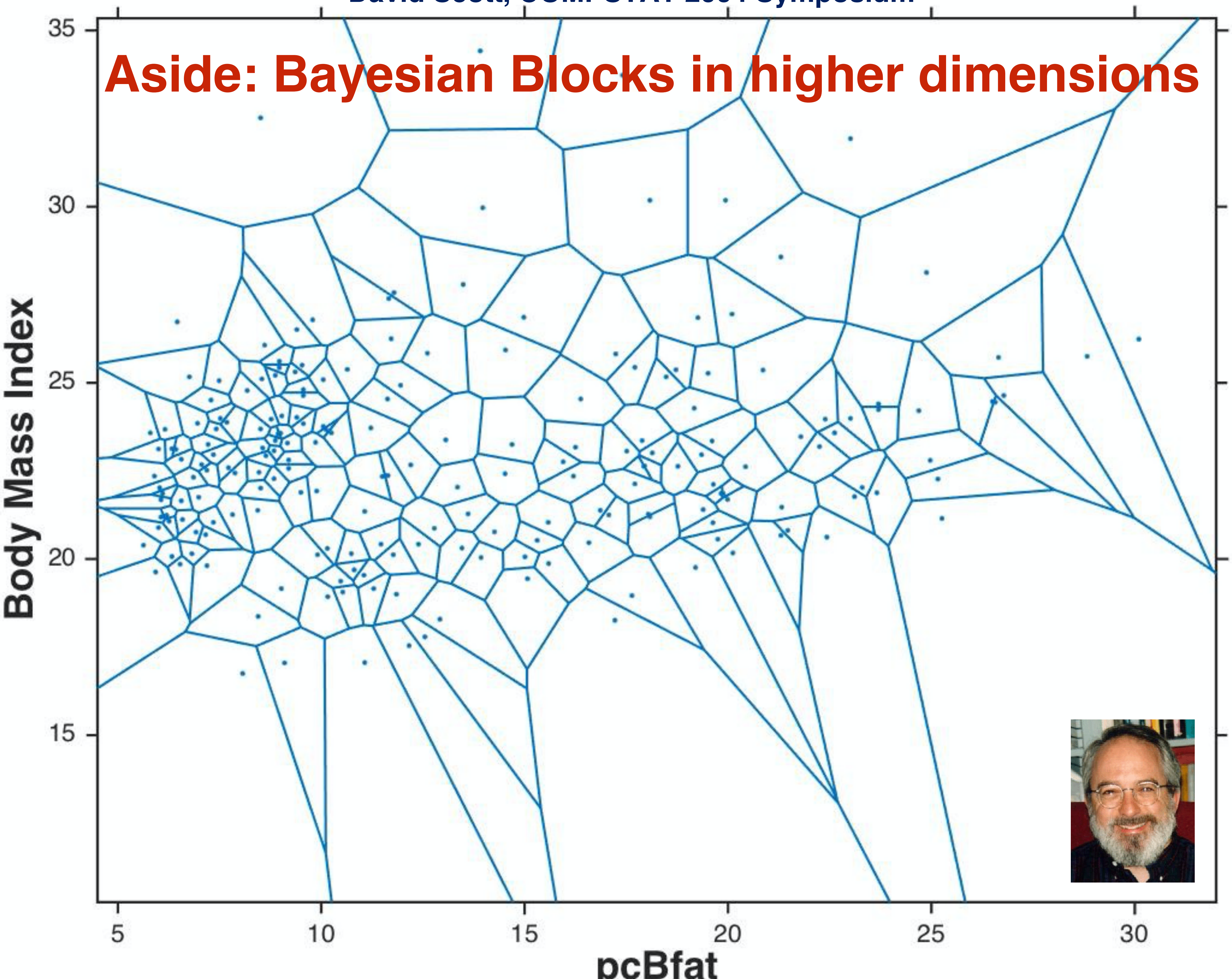
- ***Pulses (aka "flares")***
- ***Pulse shapes (including the Arrow of Time)***
- ***Variability index***
- ***Variability time scales (min, max, distribution, …)***
- ***Transient event triggers (real-time mode)***

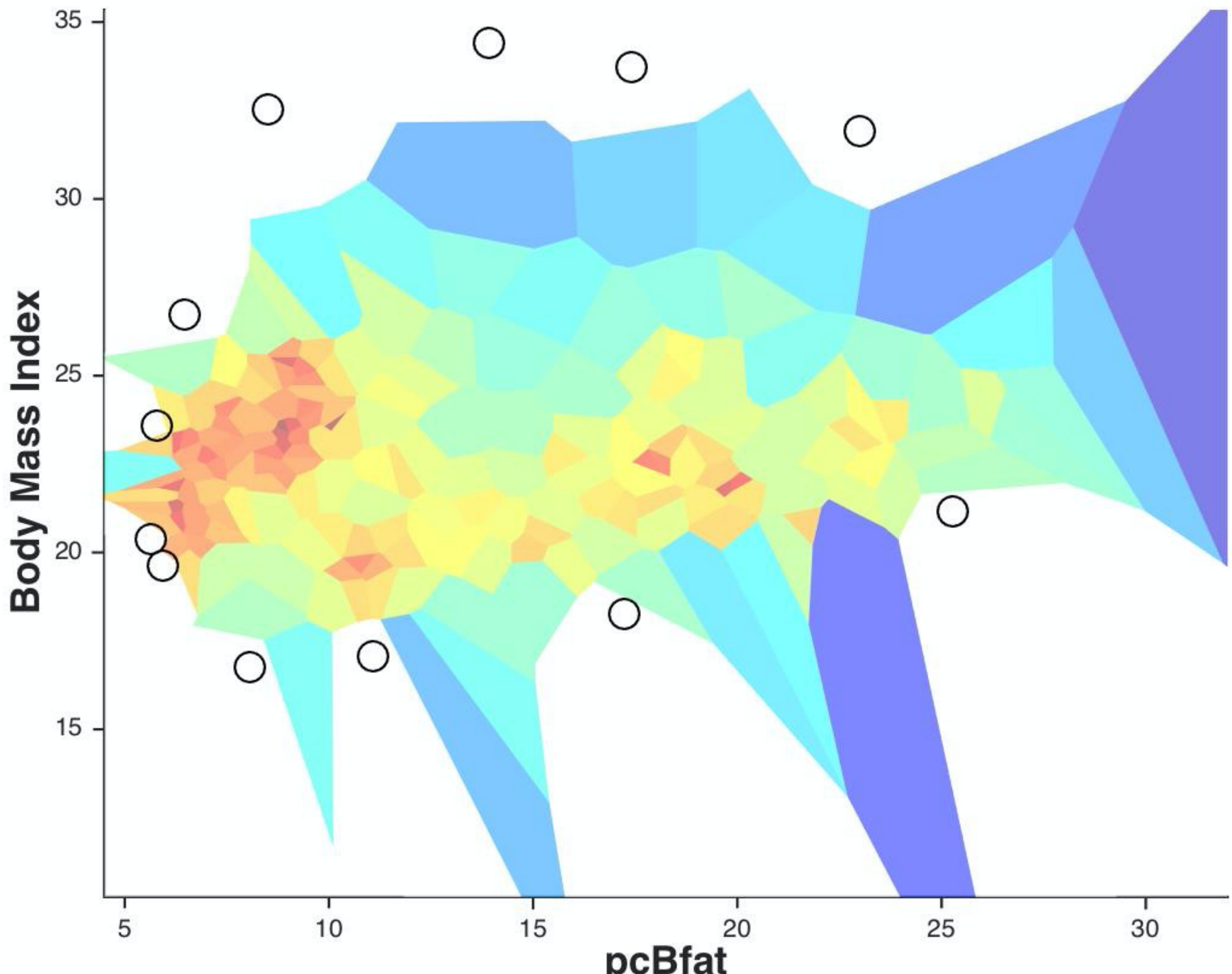
… and implement:

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

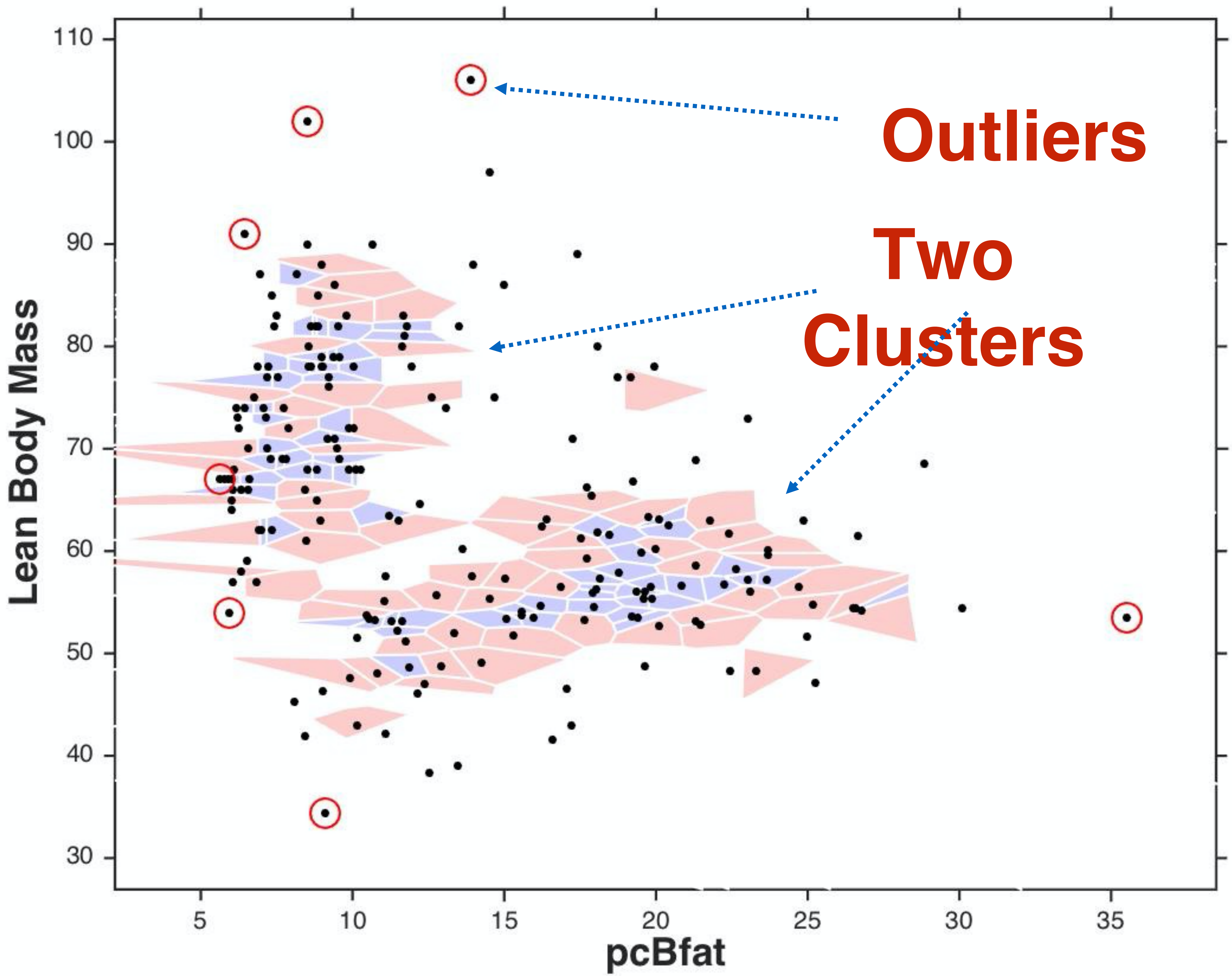
Australian Athlete Data:
David Scott, COMPSTAT 2004 Symposium

Aside: Bayesian Blocks in higher dimensions





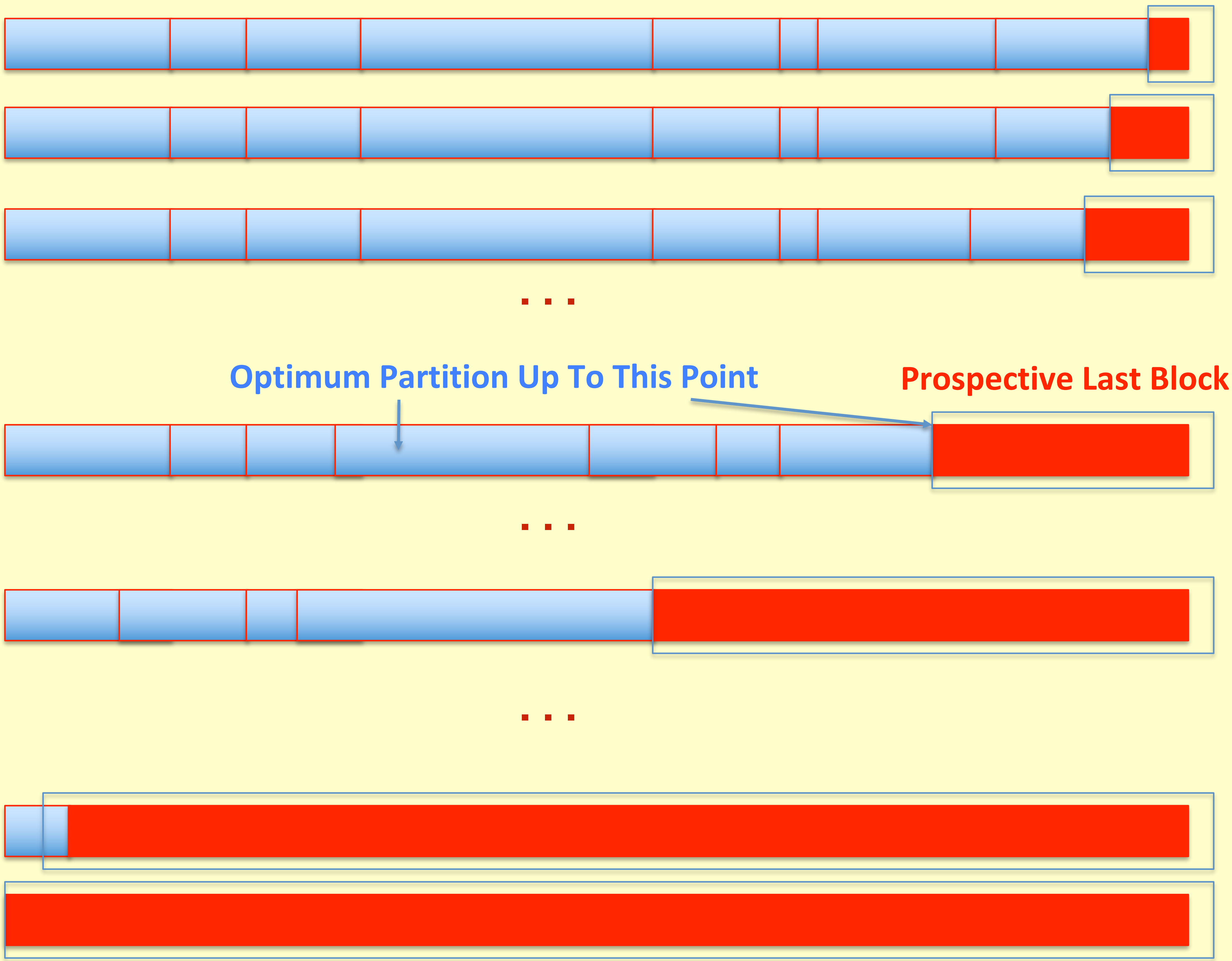
Body Mass Index
35
30
25
20
15
5
10
15
20
25
30
pcBfat



Outliers
Two
Clusters
Lean Body Mass
pcBfat
110
100
90
80
70
60
50
40
30
5
10
15
20
25
30
35

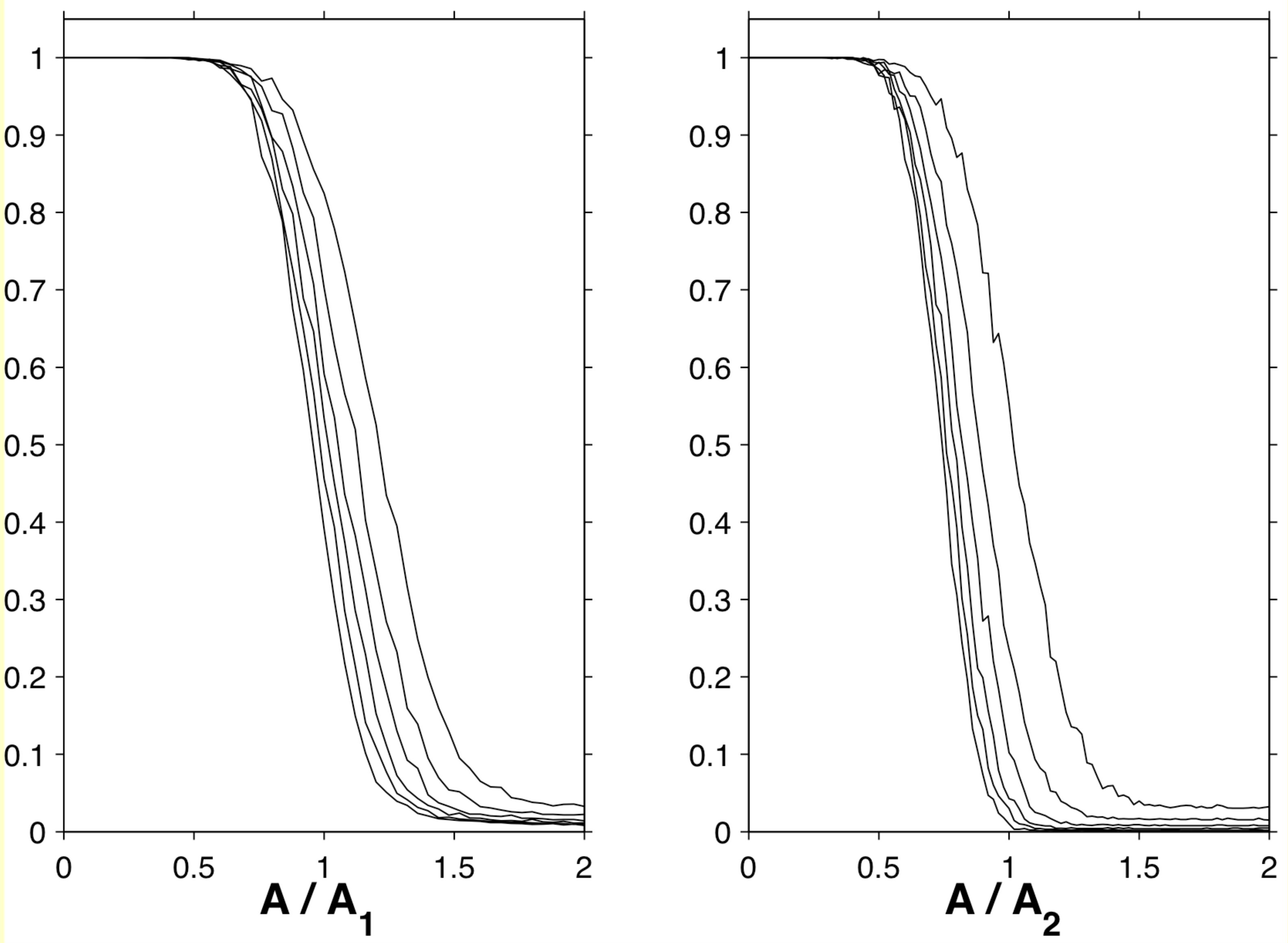
Exact Global Optimum via the BB Algorithm

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



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)

Bayesian Blocks Bibliogrpahy

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

- Models for Stationary Time Series

Given Arbitrarily Sampled Data, Algorithms for:

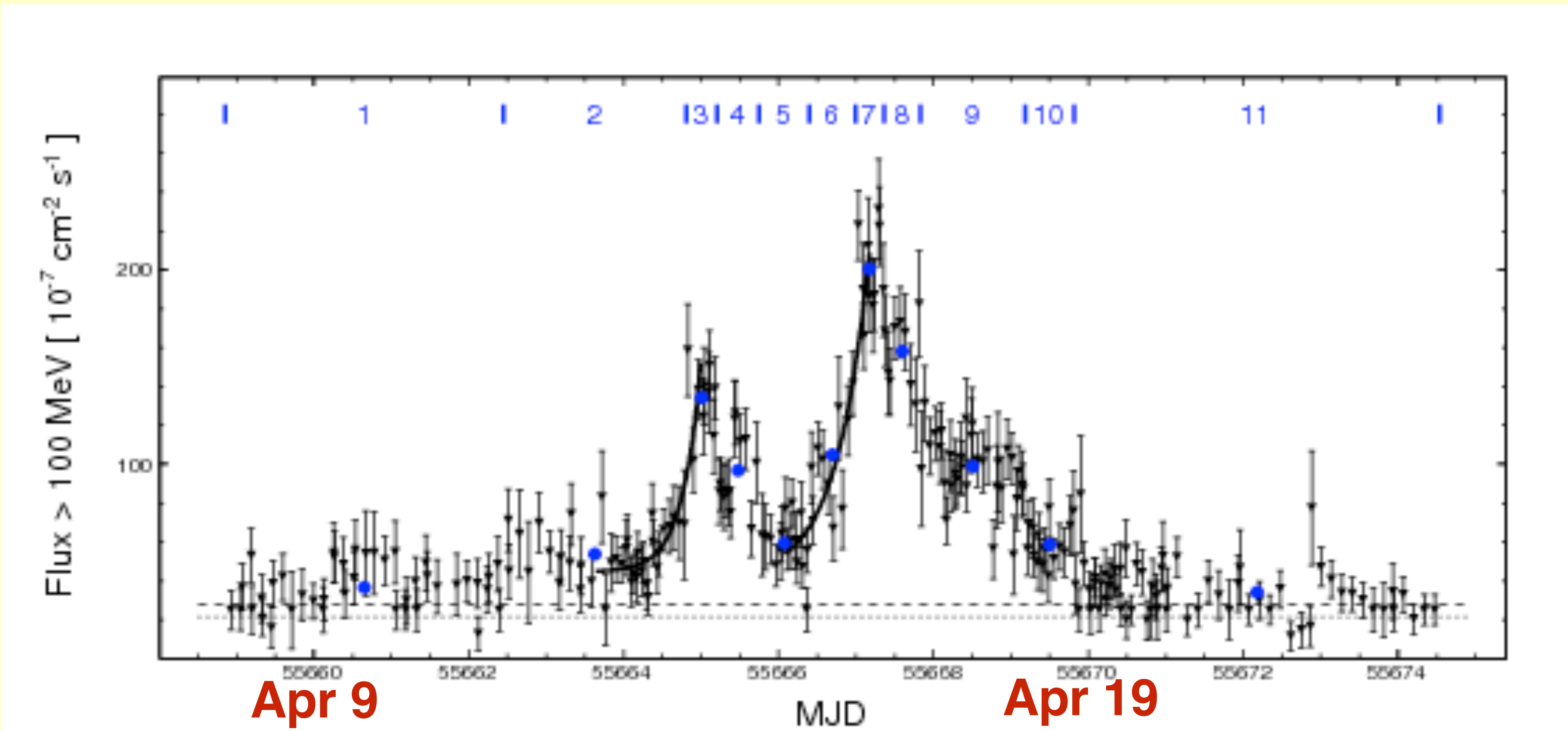
- Complex Fourier Transforms
  - Power Spectra
  - Phase Spectra

- Discrete Correlation Functions

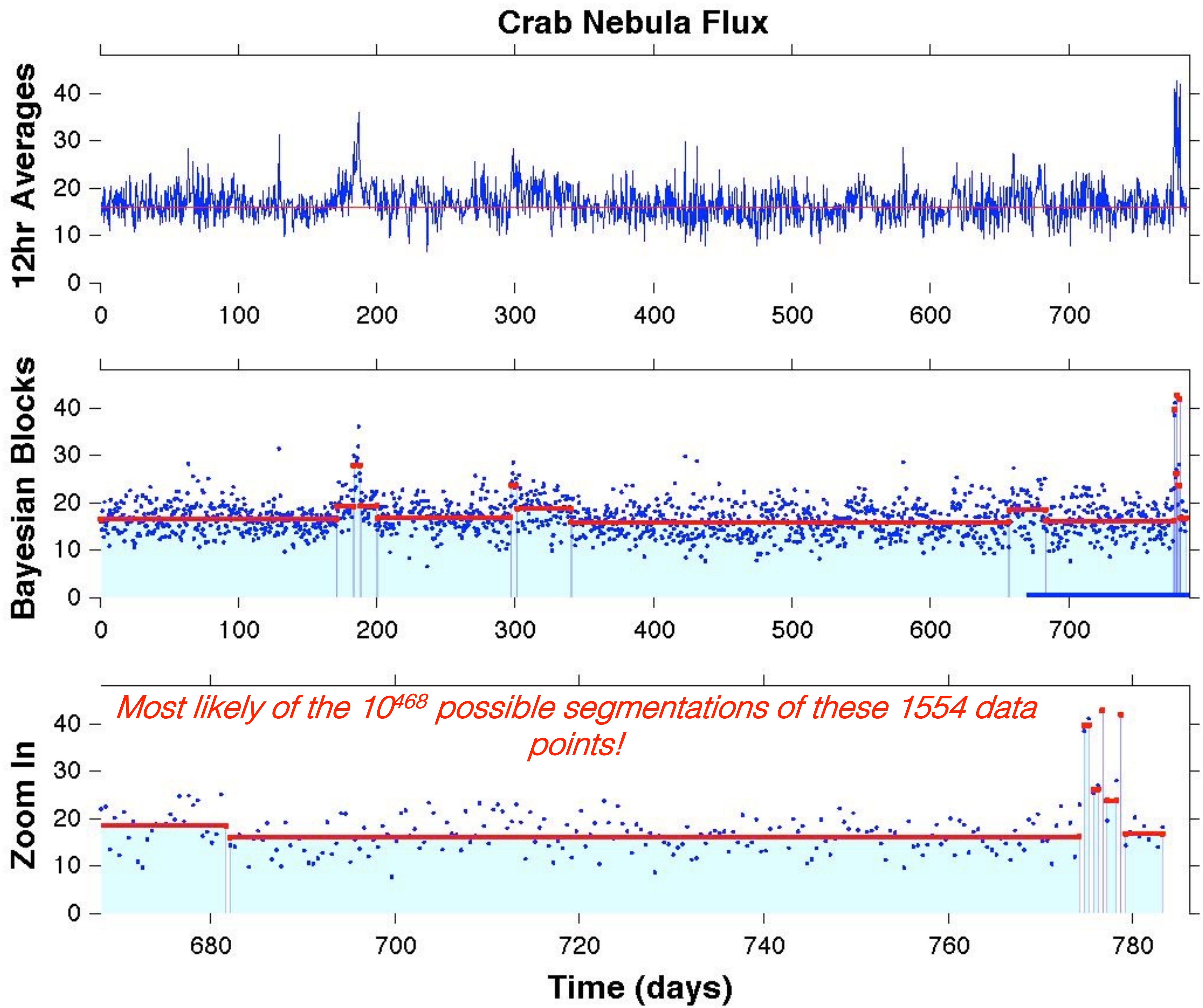
- Bayes Blocks

- Applications: high-energy photon and LIGO data

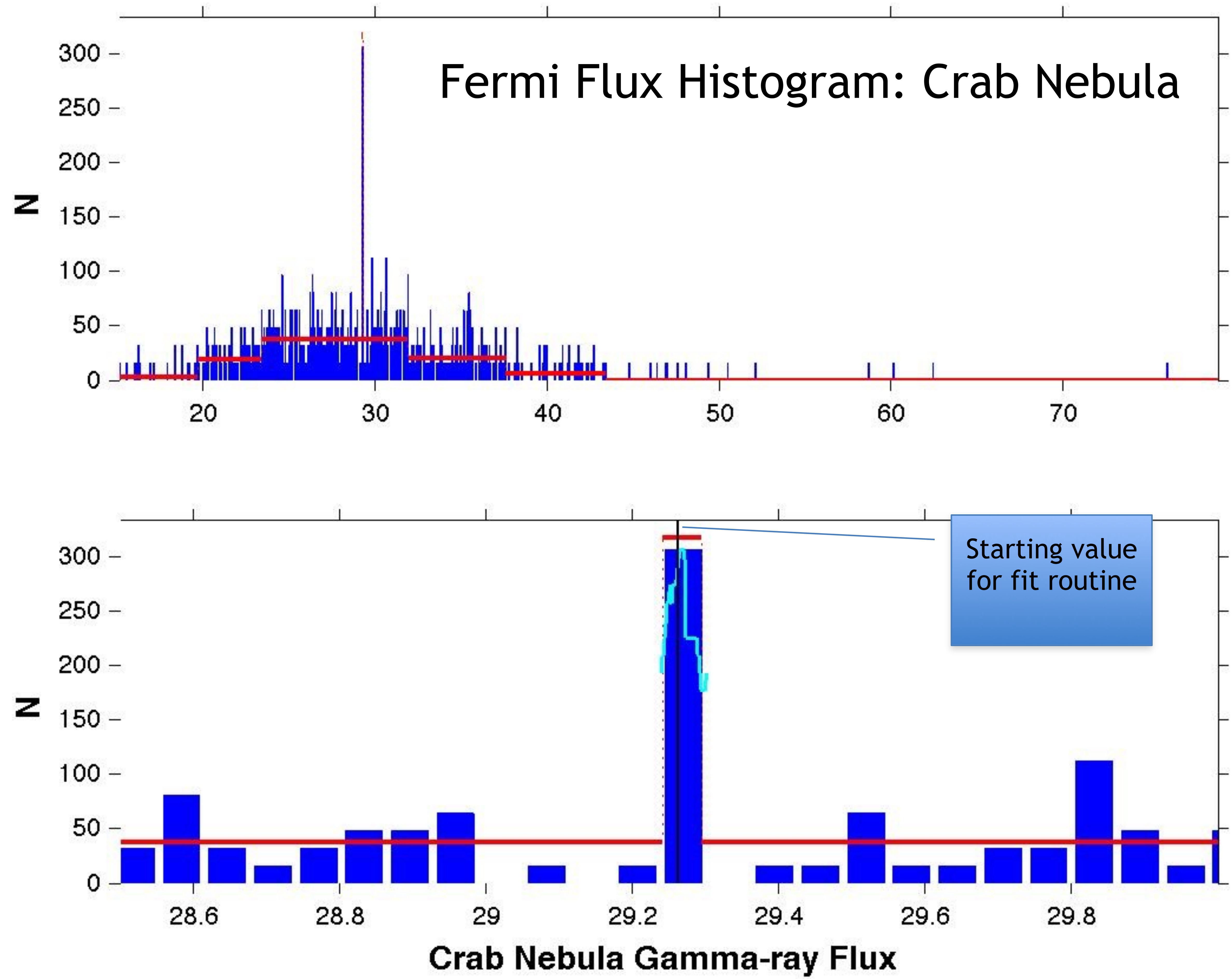
Gamma Ray Flare in the Crab Nebula, April, 2011
Luminosity vs. time, in bins of ~9 minutes



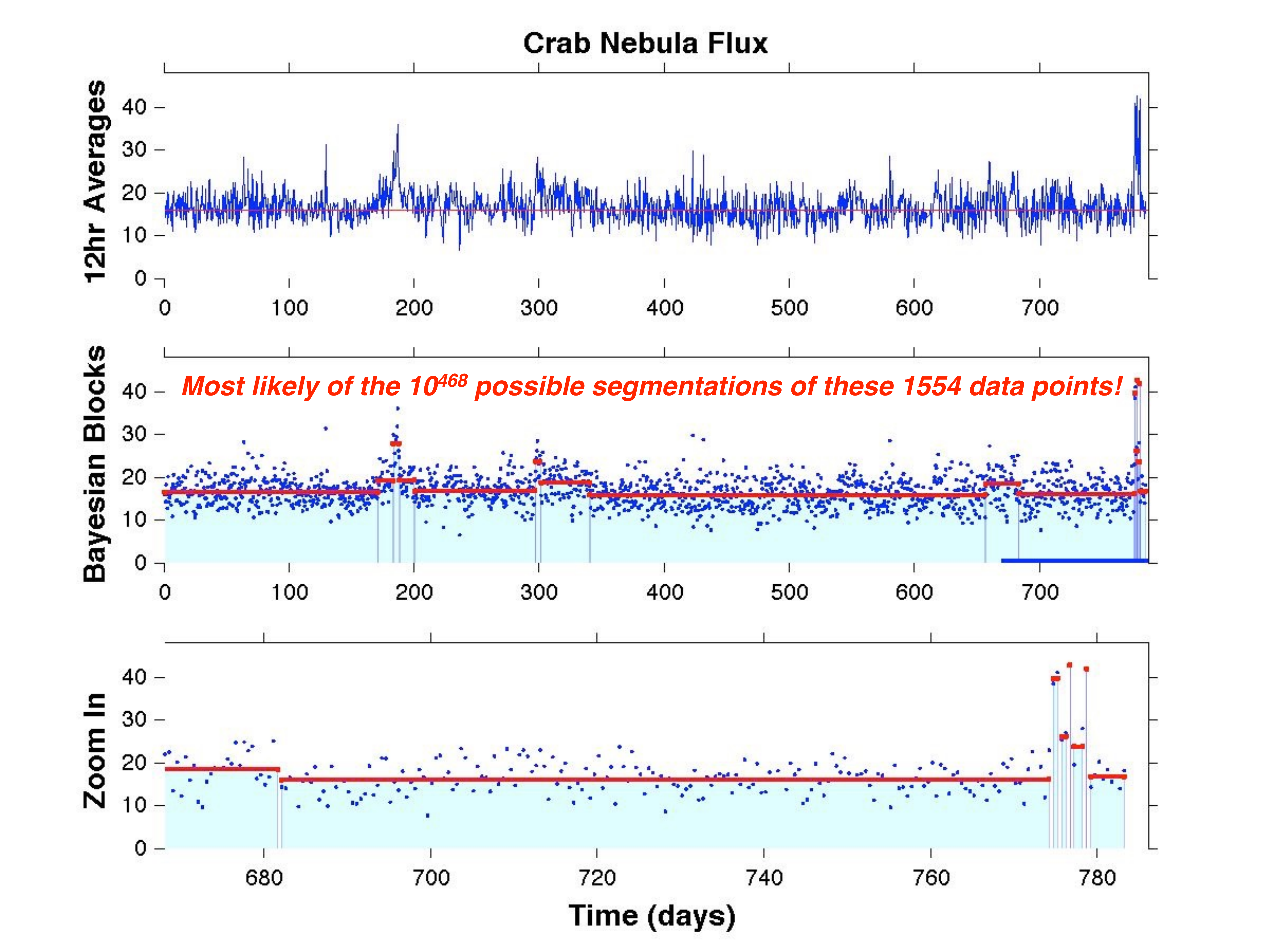
Flux doubling in 8 hours constrains size of the emission region < ~1 astronomical unit
(Buehler, R. et al. 2011, Astrophysical Journal)



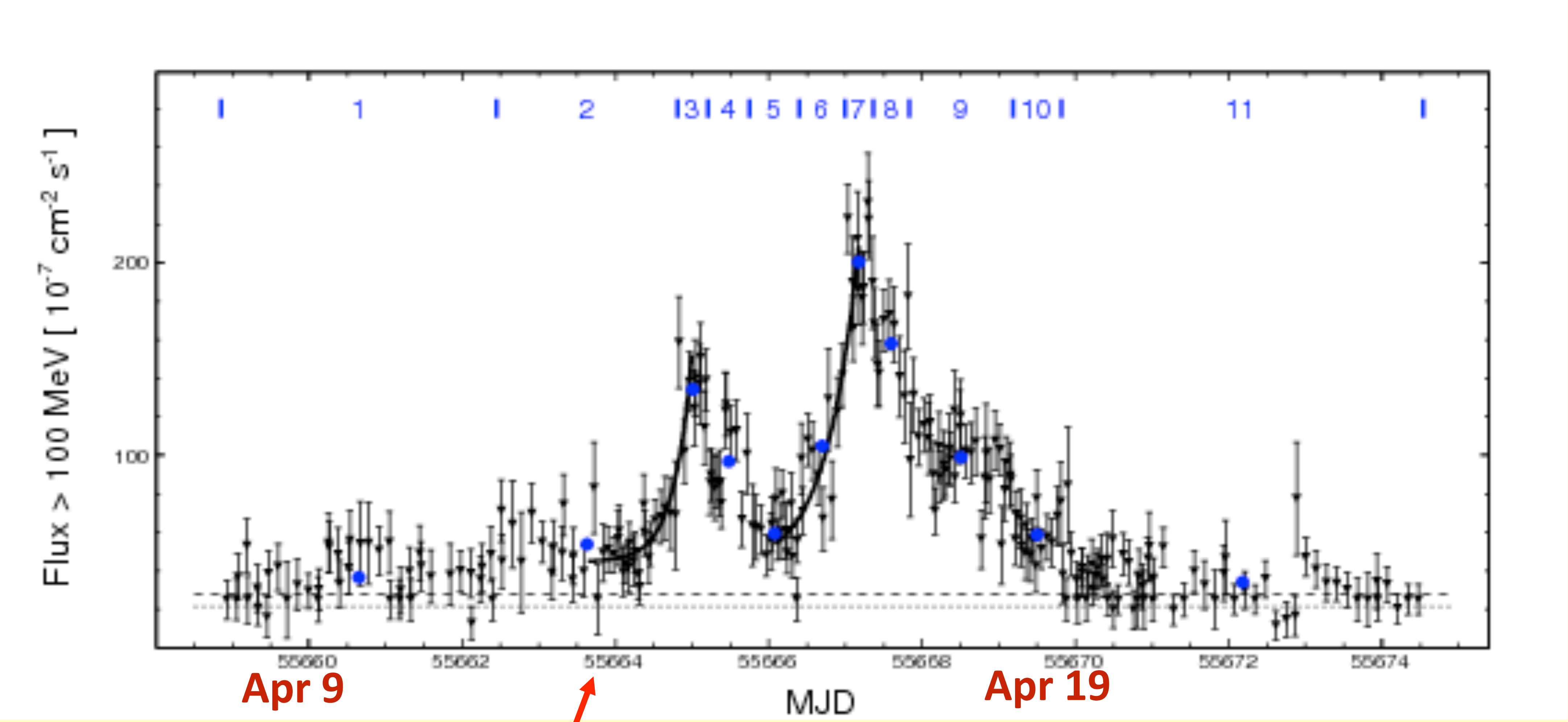
Crab Nebula Flux
12hr Averages
Bayesian Blocks
Zoom In
Most likely of the 10^468 possible segmentations of these 1554 data points!
Time (days)


Fermi Flux Histogram: Crab Nebula
300
250
200
150
100
50
0
N
20
30
40
50
60
70
Starting value for fit routine
28.6
28.8
29
29.2
29.4
29.6
29.8
Crab Nebula Gamma-ray Flux

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



Lightcurve in bins of equal exposure (mean 9 minutes!)

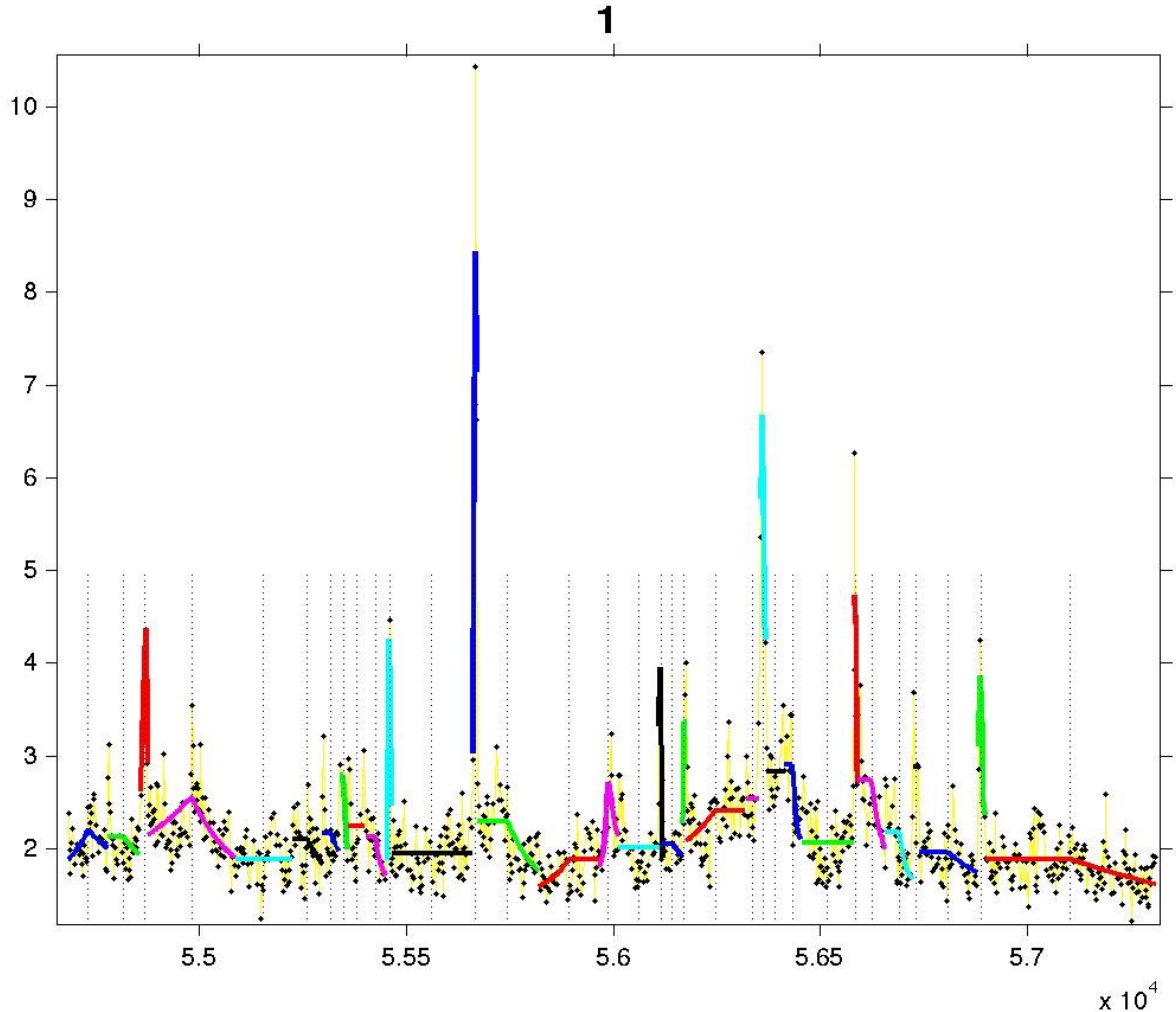


Beginning of LAT TOO

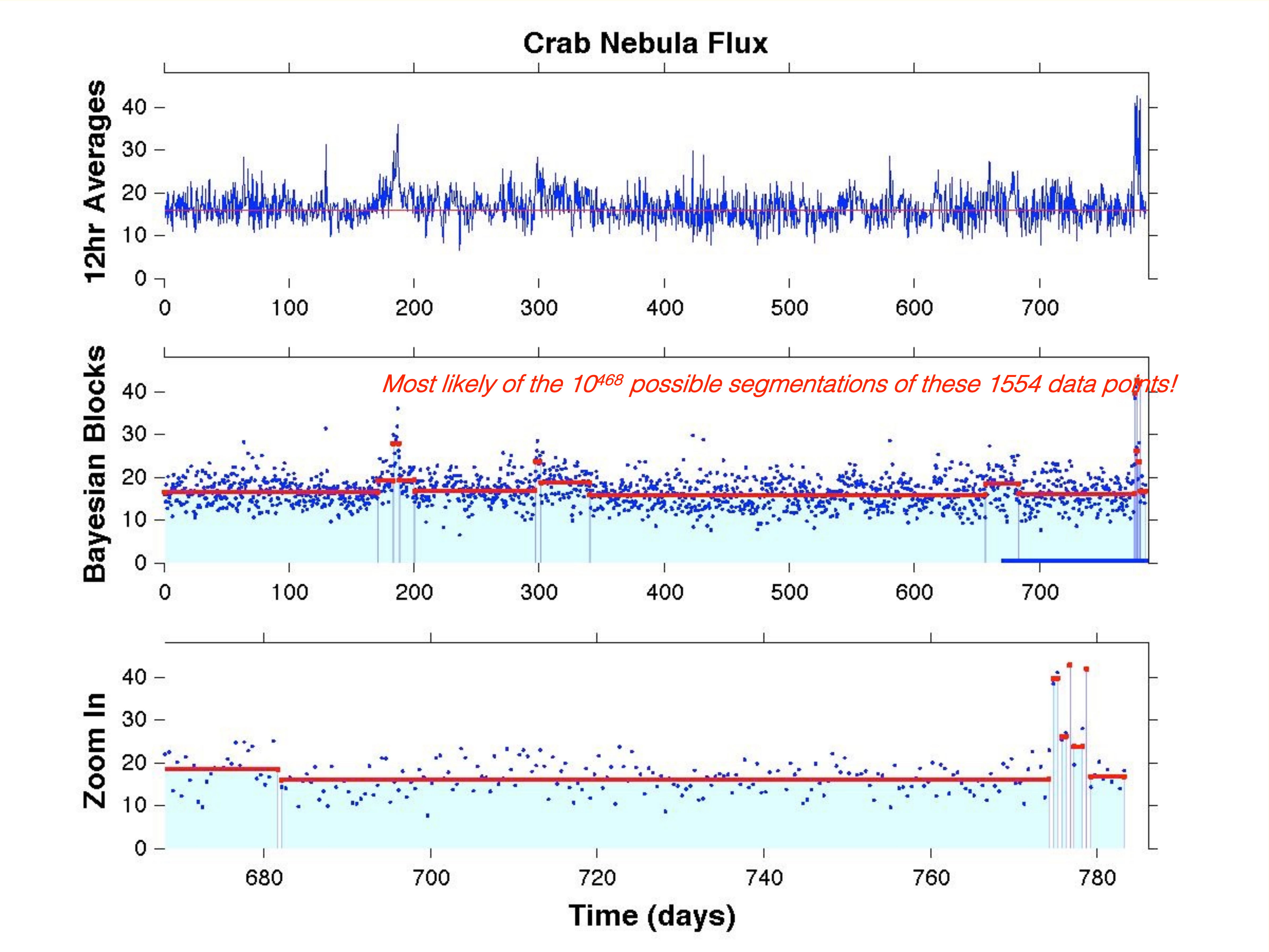
Flux doubling in 8 hours constrains emission region size <0.0003 pc

Buehler, R. et al. 2011, ApJ

No corresponding variability found in radio, optical, infrared, soft and hard X-rays around time of Sept. 2010 flare.


1
10
9
8
7
6
5
4
3
2
5.5
5.55
5.6
5.65
5.7
x 10^4

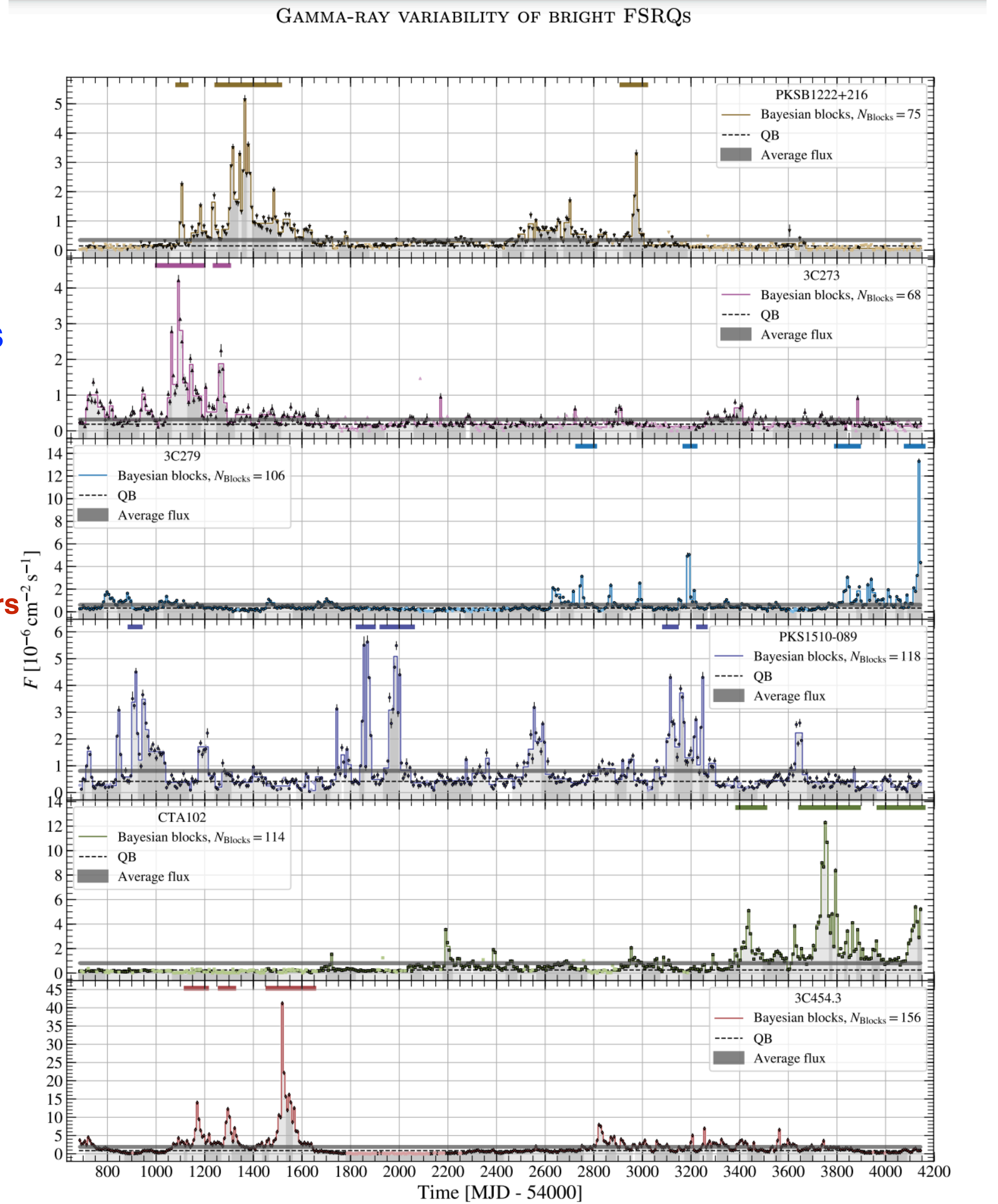
Crab Nebula rises above the status of a constant calibration source!



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 ~ 10^{-21}

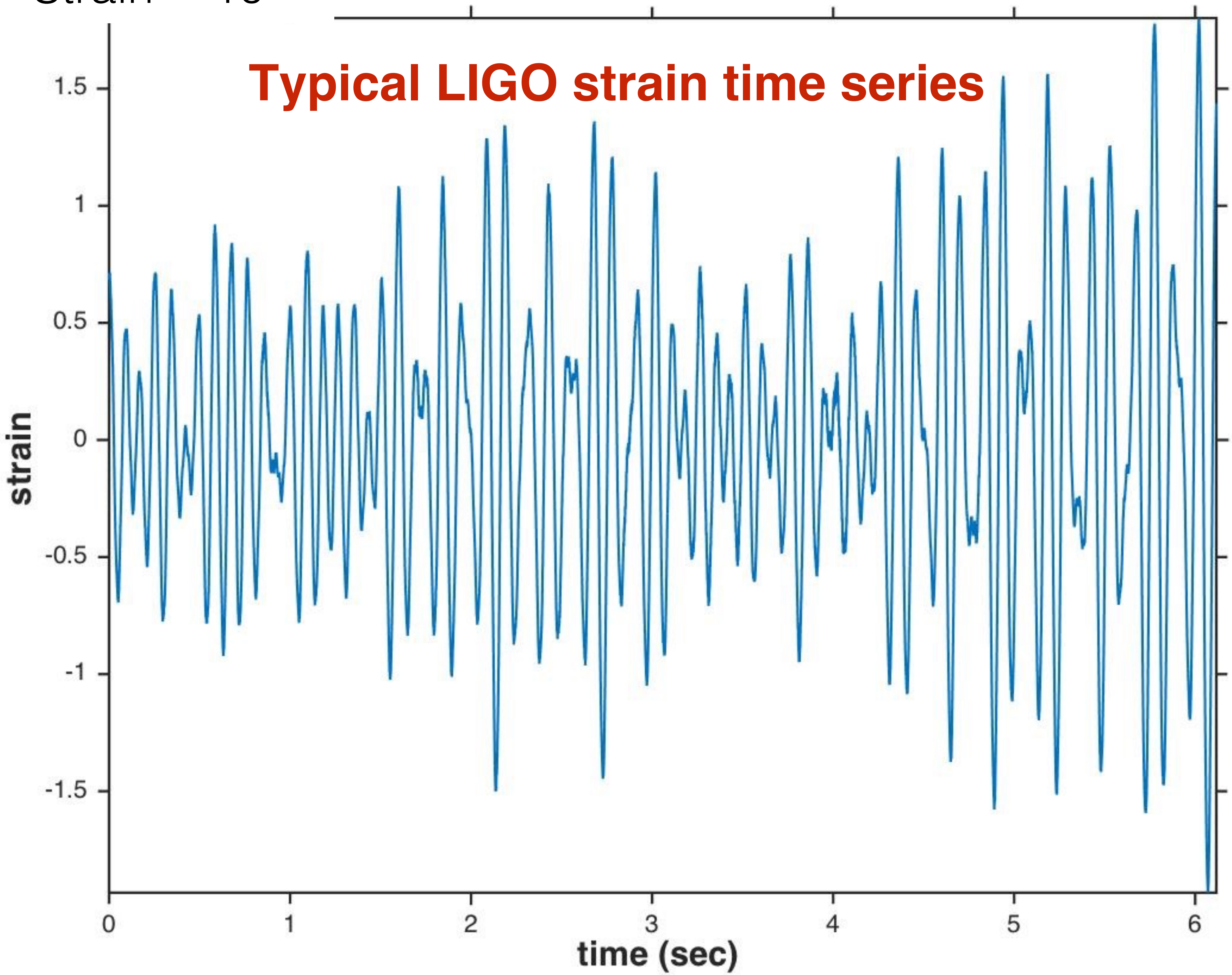
Scientists Devoting Many Decades to this High Risk Project

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 ~ 10 $^{-19}$

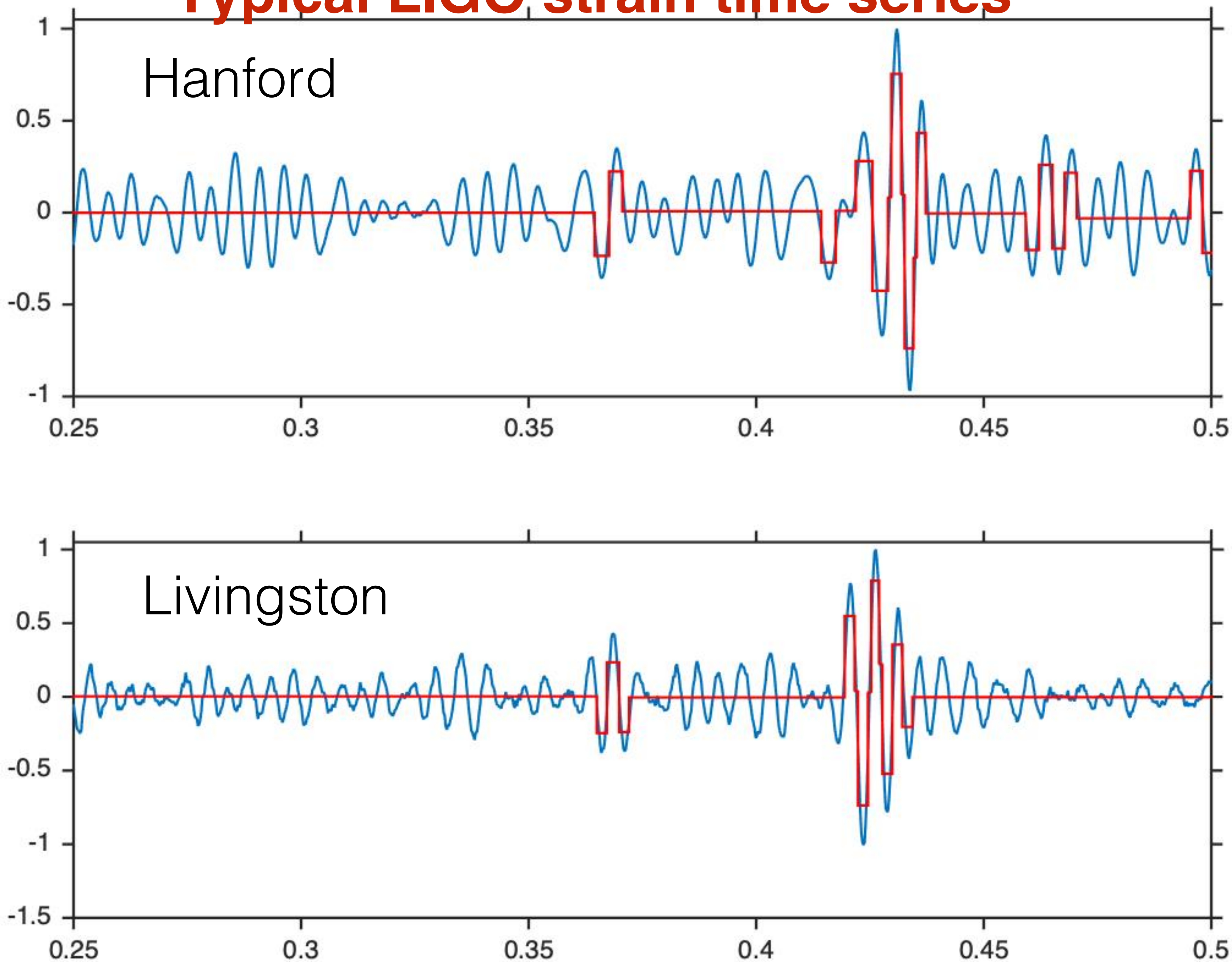


Typical LIGO strain time series
1.5
1
0.5
0
-0.5
-1
-1.5
strain
0
1
2
3
4
5
6
time (sec)

Strain ~ 10 $^{-21}$

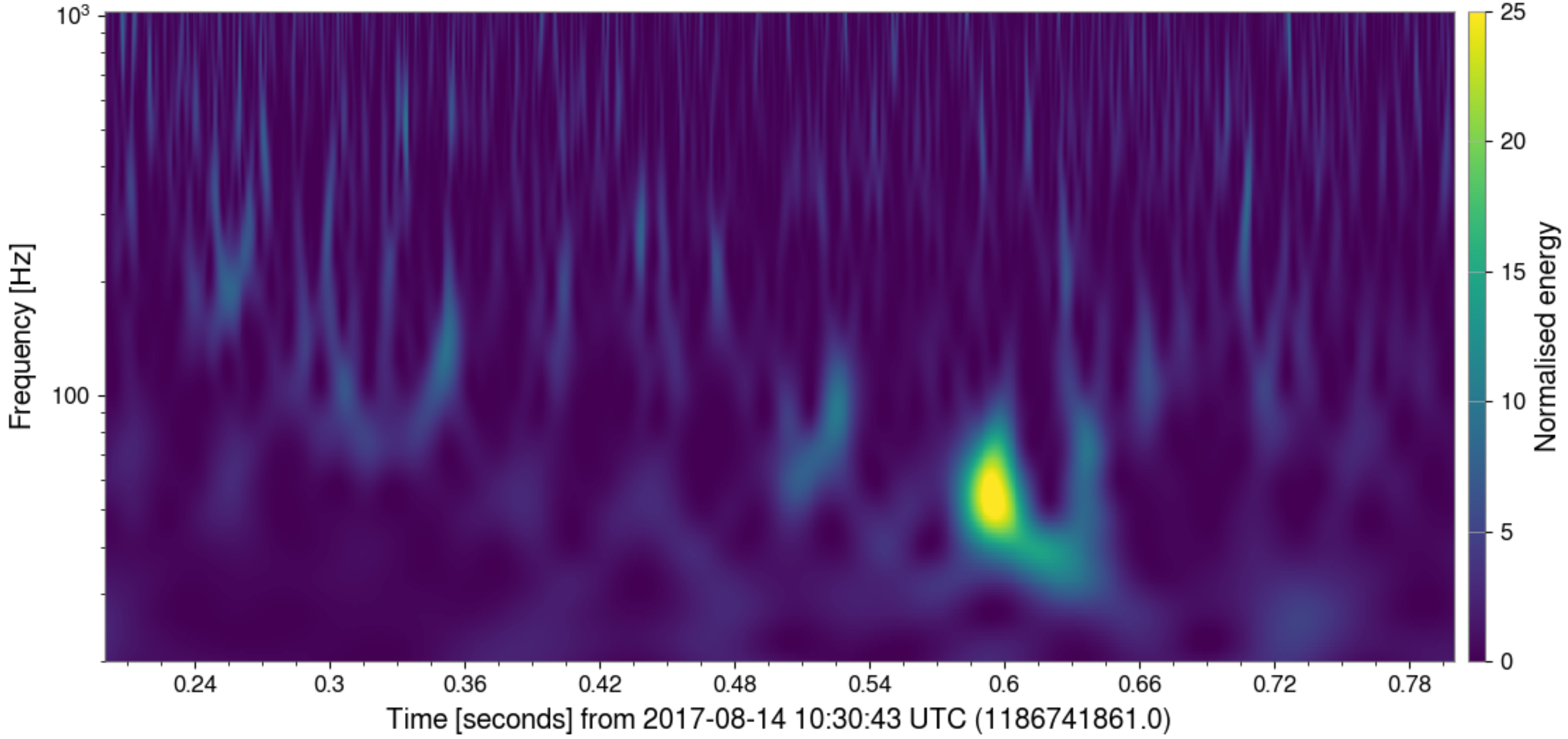
GW150914

Typical LIGO strain time series

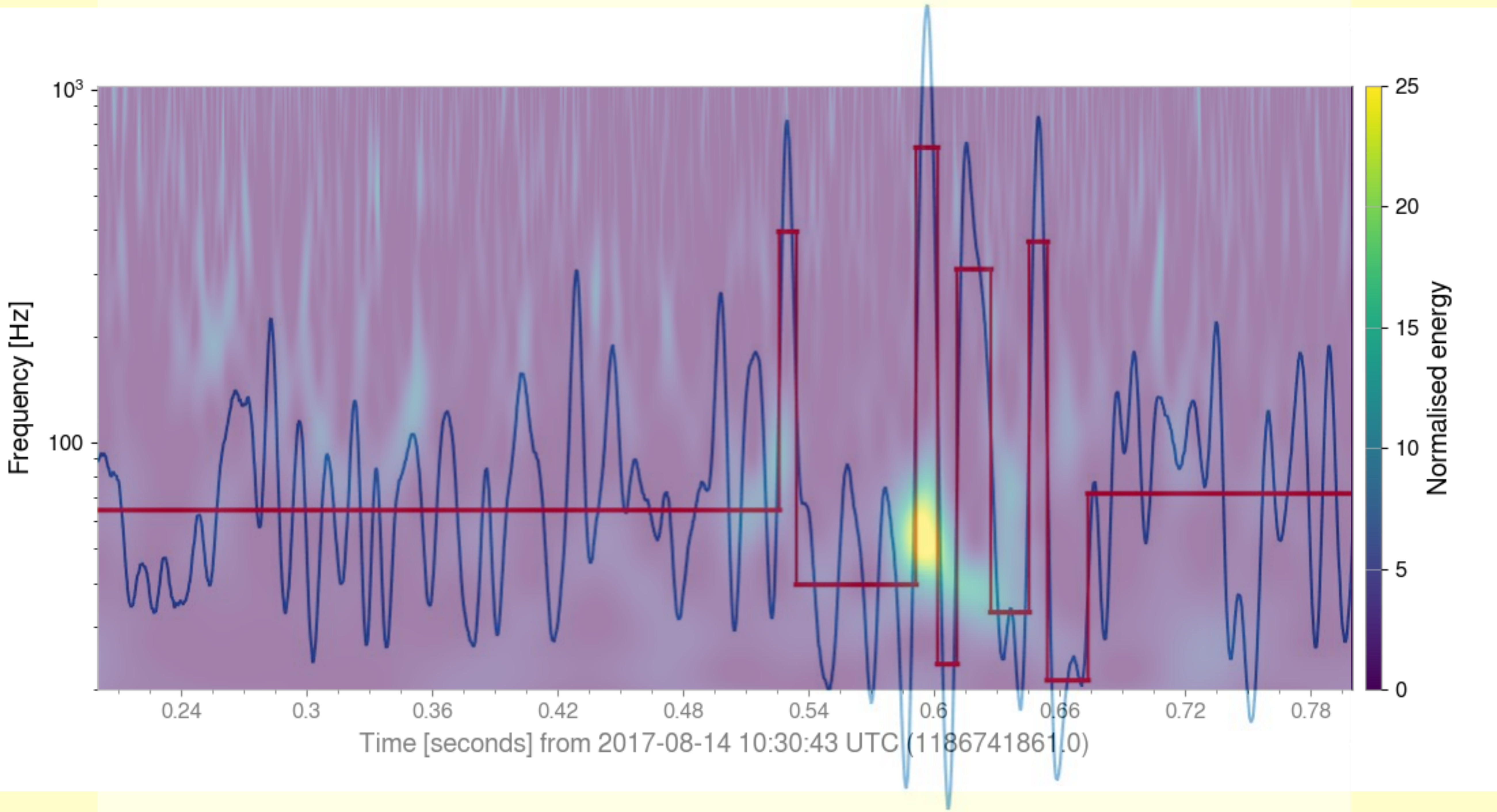


JS, Chris Henze and Javier Pascual-Grenado

GW170814 Virgo Data



GW170814 Virgo Data



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

Haiku for a Martingale

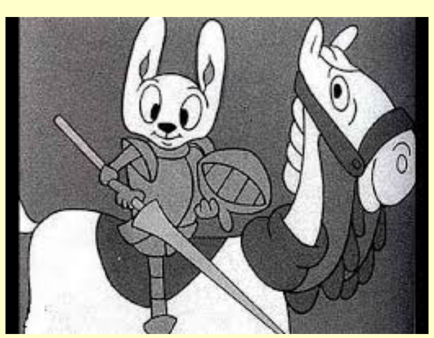
Binning is sinning.
Correlations are feeble.
Are there better tools?

Histograms	Bayesian Block histograms
Correlation Coefficients	Dependence Measures
Correlation Functions	Dependence Functions
Cross-Correlations	Cross-Dependences
Correlation Matrices	Dependence Matrices
FFT of correlation functions	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

jeffscargle@gmail.com