

*nonlinear :)*

# Novel Metrics for Time Series Analysis of Accreting Systems

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📱 @raphillipson

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UIUC The Transient and Variable Universe

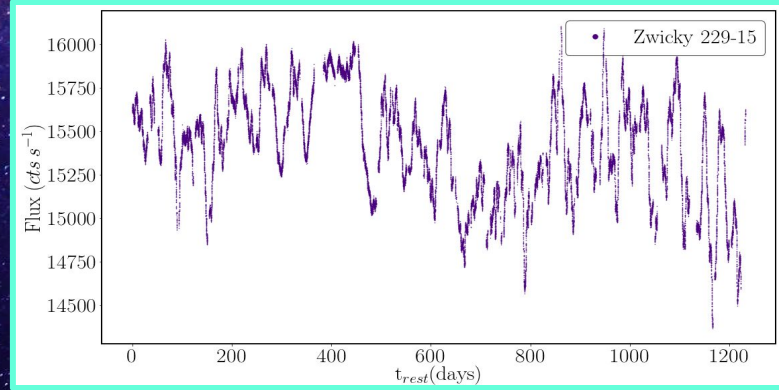
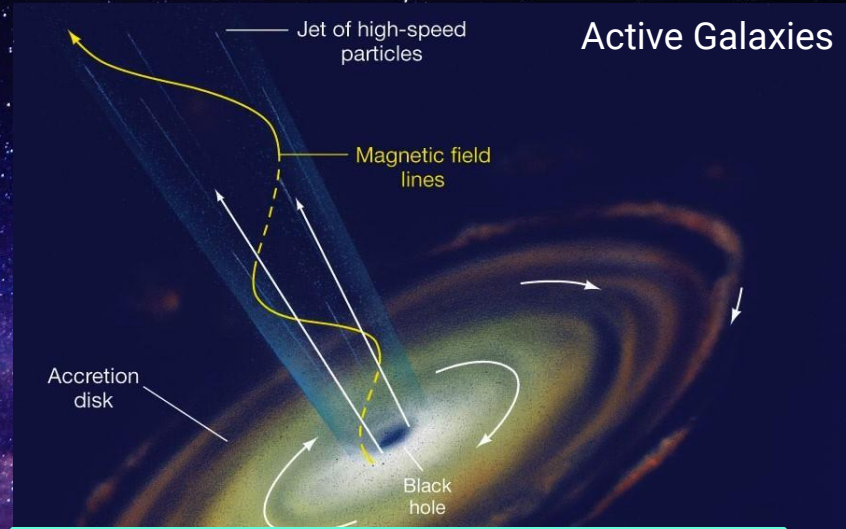
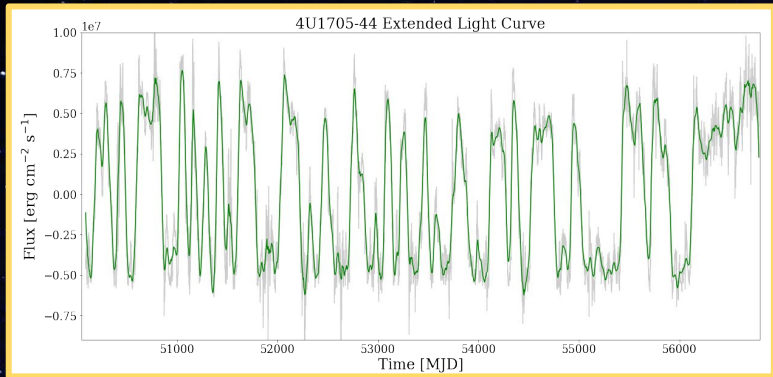
❖ June 21st, 2023



NSF Award Number:  
2138155

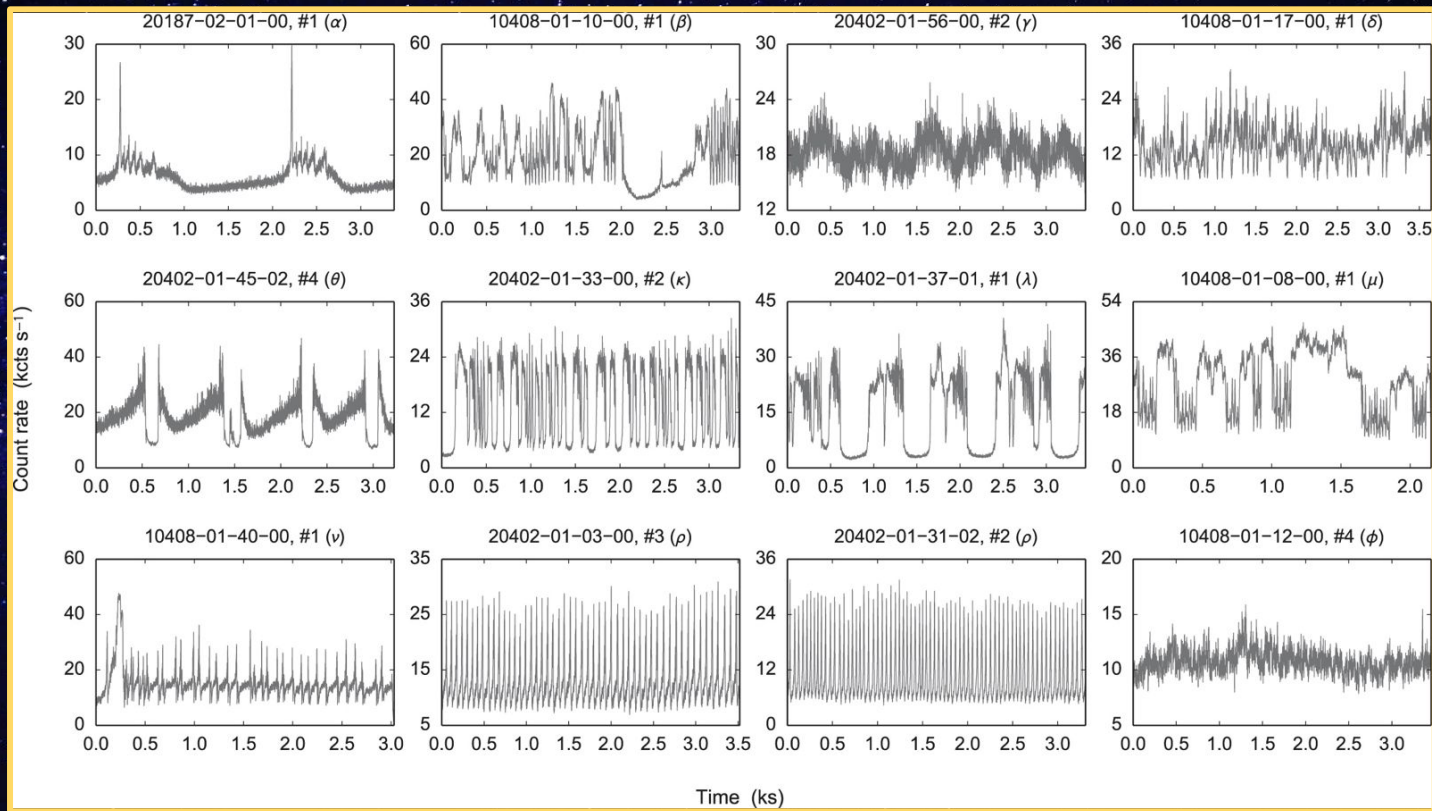


**VILLANOVA**  
UNIVERSITY



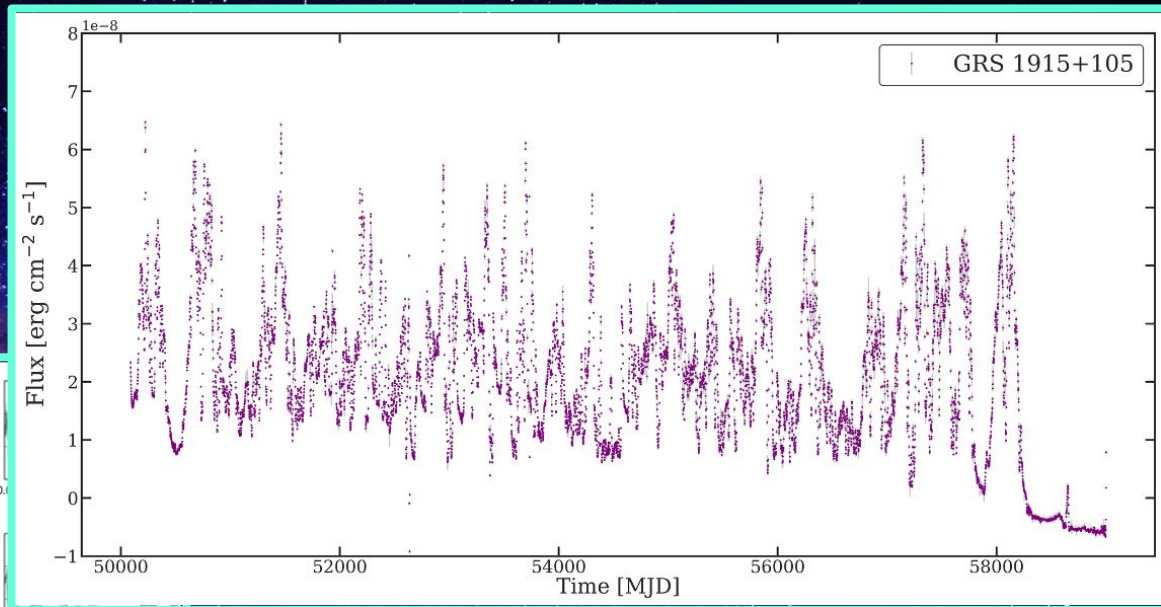
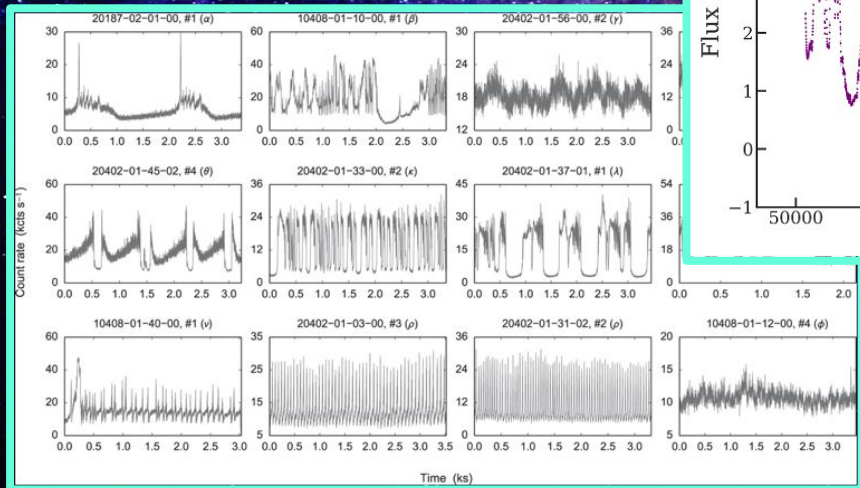
X-ray Binaries

# GRS 1915+105: Black Hole X-ray Binary



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*Mannattil, Gupta, and Chakraborty 2016*

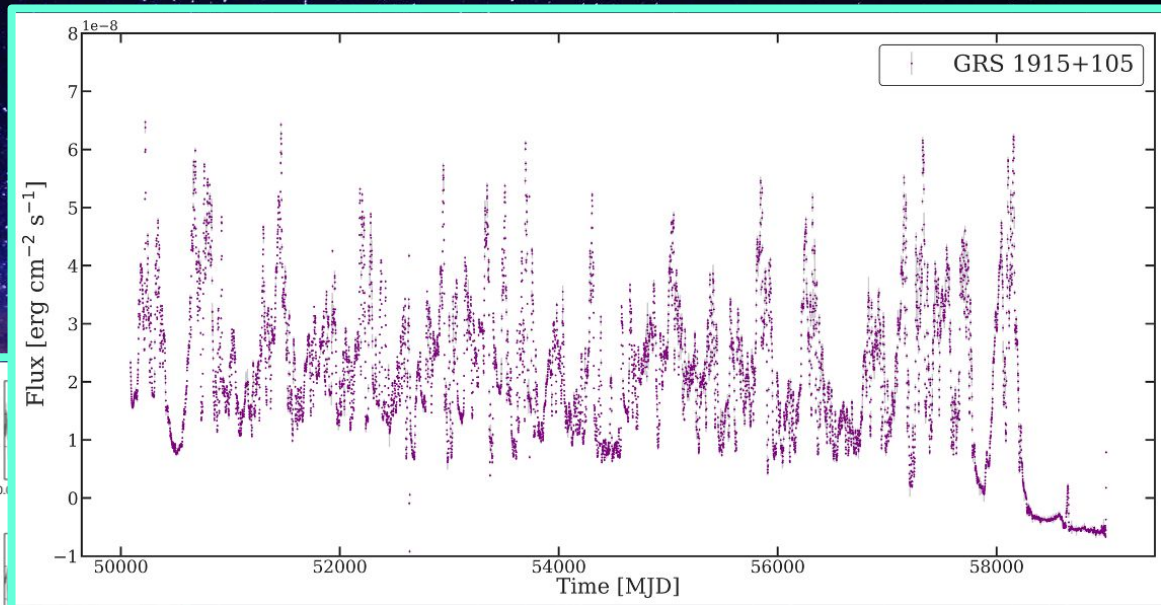
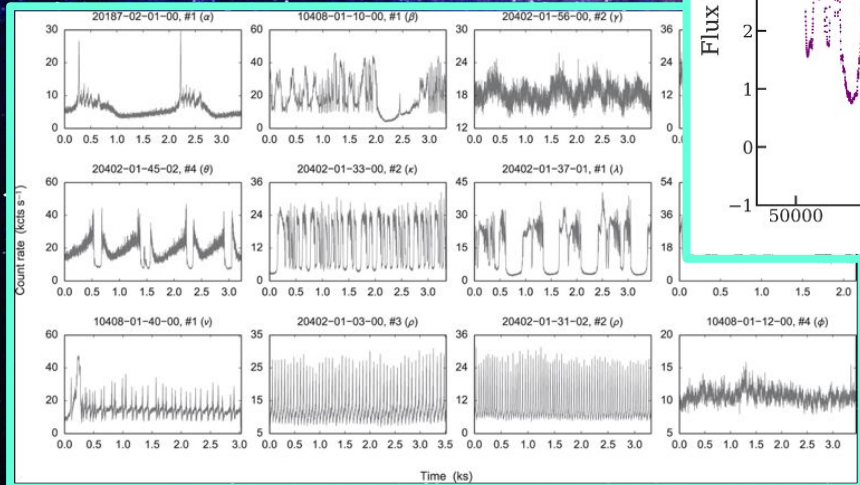


*Phillipson 2020*

# GRS 1915+105: Black Hole X-ray Binary

Unpredictable  
Self-similar  
Recurrent but not periodic

*Mannattil, Gupta, and Chakraborty 2016*



*Phillipson 2020*

# Uncovering Dynamics from Time Series

**Hyperion:** satellite of Saturn

- Wisdom, Peale, and Mignard (1984) predicted it exhibits chaotic rotation
- The time evolution of the angle between the long axis and a reference:

$$\frac{d^2\theta}{dt^2} + \left(\frac{\omega_0^2}{2r^3}\right) \sin 2(\theta - f) = 0$$

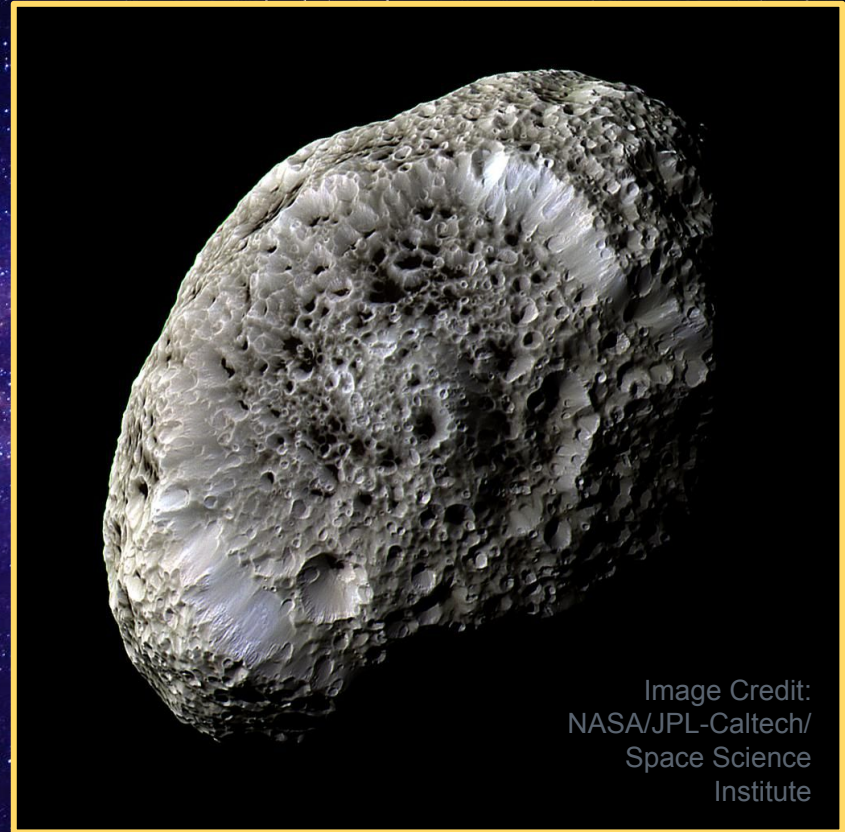


Image Credit:  
NASA/JPL-Caltech/  
Space Science  
Institute

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- The irregular rotation, shape, and reflectivity leads the brightness of Hyperion to also be chaotic
- **Klavetter (1989)** made time series measurements of Hyperion's brightness and confirmed chaos

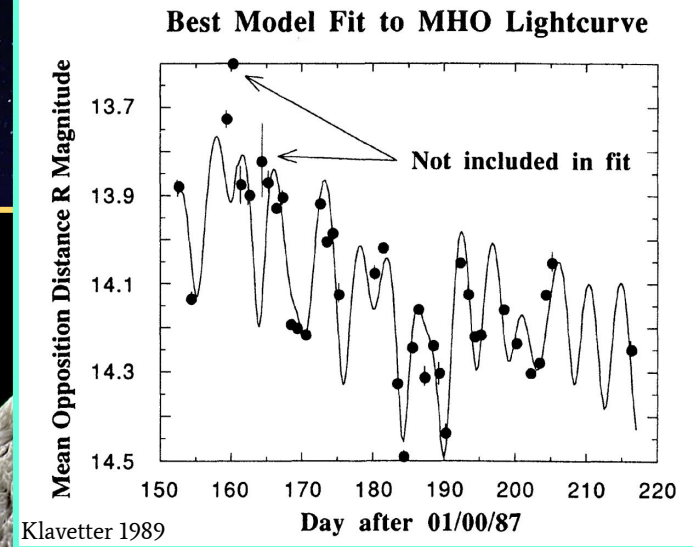
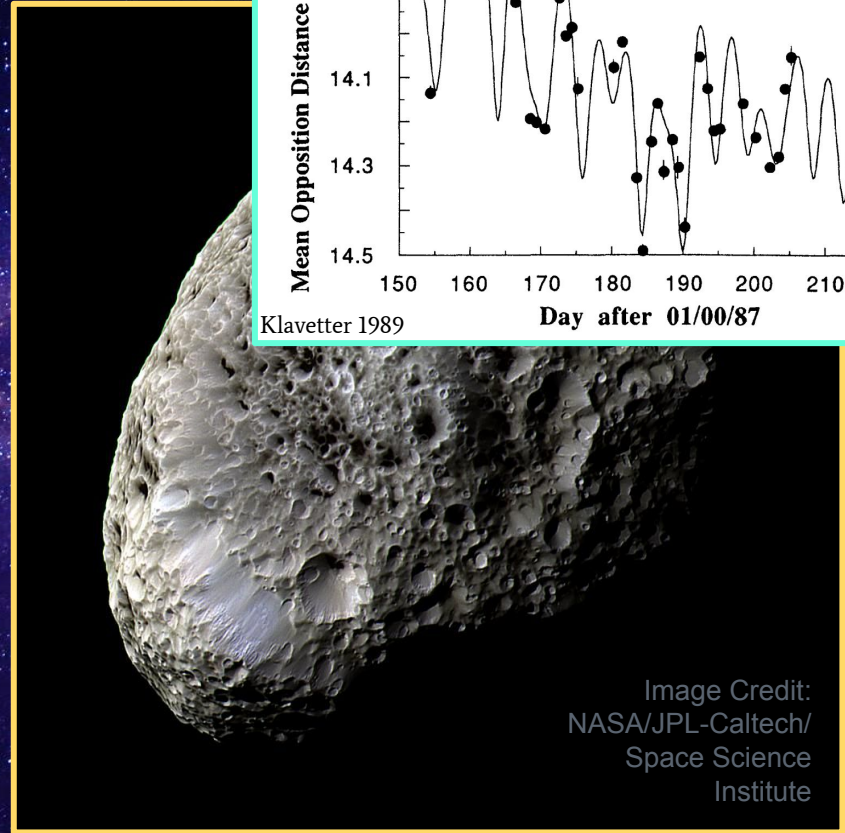
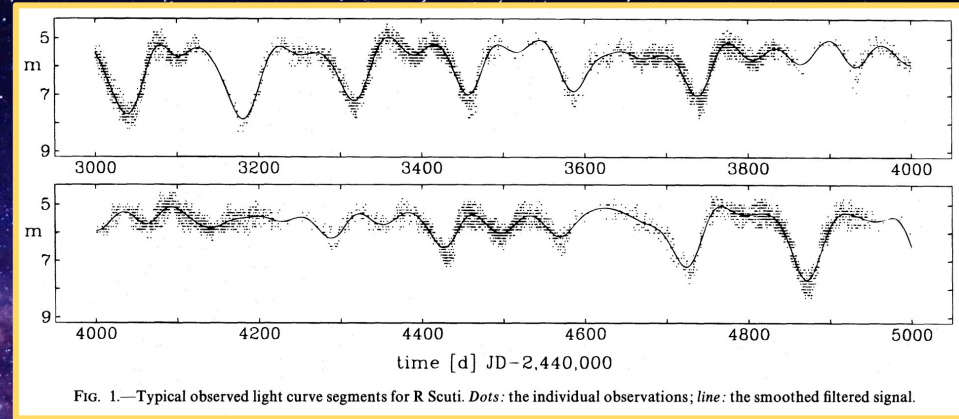


Image Credit:  
NASA/JPL-Caltech/  
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Institute

# Uncovering Dynamics from Time Series

## Variable Stars: R Scuti

- R Scuti is an aperiodic pulsating star
- [Buchler et al. \(1996\)](#) calculated a low fractal dimension ( $D=3.1$ ) and a positive Lyapunov exponent, strong indications of chaos

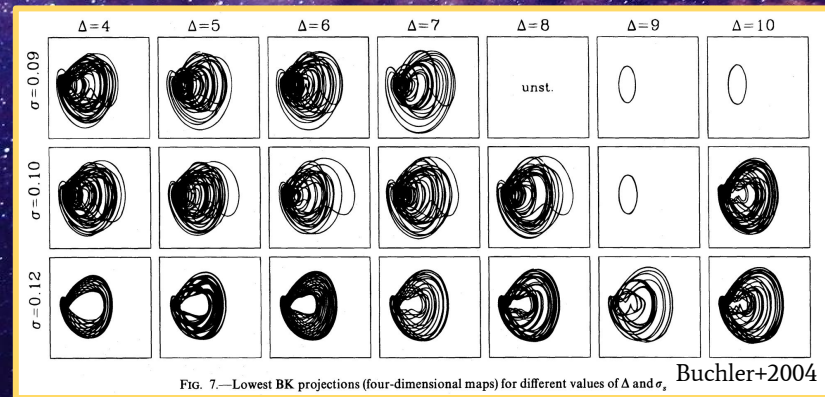
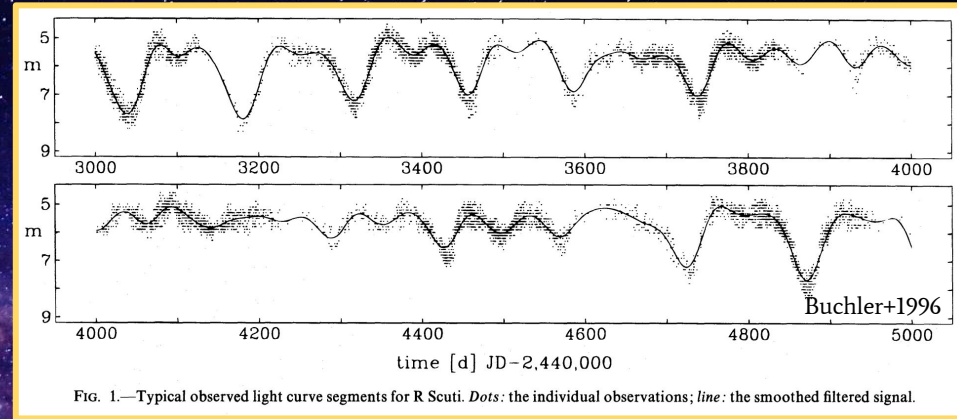




# Uncovering Dynamics from Time Series

## Variable Stars: R Scuti

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- Buchler et al. (1996) calculated a low fractal dimension ( $D=3.1$ ) and a positive Lyapunov exponent, strong indications of chaos
- Buchler et al. (2004) then applied the same technique to other semi-regular pulsating stars: R UMi, RS Cyg, V CVn, and UX Dra
- Dynamics of the stars take place in a 4D space: two vibrational modes involved in the pulsation



# Uncovering Dynamics from Time Series

## What about variable accreting sources?

### *Challenges:*

- Number of cycles of fundamental timescales (baseline)
- Quality of data (signal-to-noise)
- Sampling of time series (cadence)

# Uncovering Dynamics from Time Series

## What about variable accreting sources?

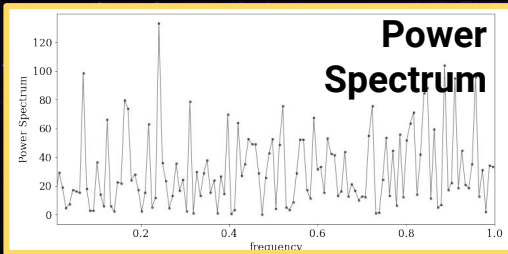
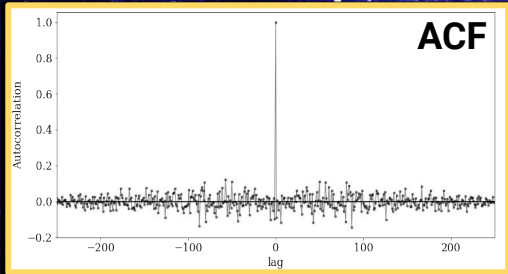
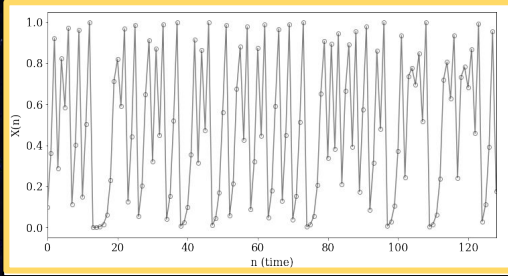
### *Challenges:*

- Number of cycles of fundamental timescales (baseline)
- Quality of data (signal-to-noise)
- Sampling of time series (cadence)

### *Ongoing and upcoming instruments (somewhat) relieve these challenges:*

- X-ray All-Sky Monitors (RXTE, MAXI) have provided \*long\* time series
- Improved sensitivity (NICER, STROBE-X)
- Use of optical exoplanet missions for other science: Kepler, TESS
- The abundance of data from ground-based observatories: ZTF, LSST

# A Brief Detour: The Logistic Map

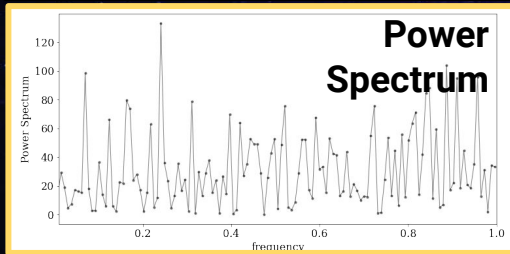
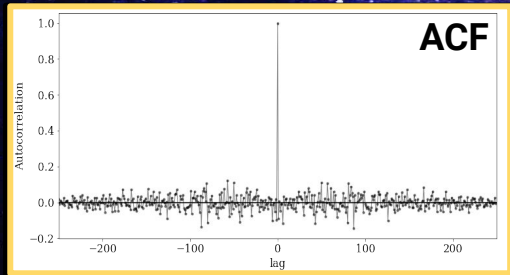
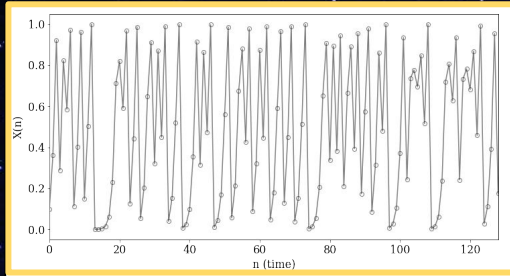


- The **Logistic Map**, from population studies:

$$X_{n+1} = f(X_n) = \lambda X_n(1 - X_n)$$

- It is **deterministic**, but for certain parameter values ( $\lambda=4$ ), it is maximally chaotic.

# A Brief Detour: The Logistic Map

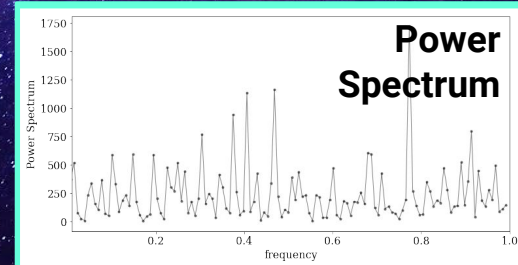
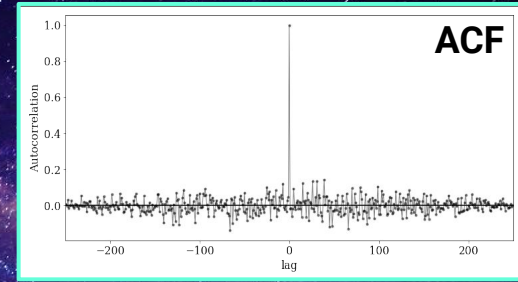
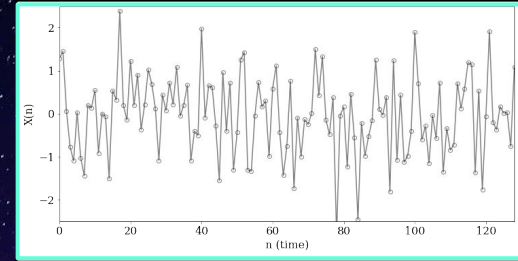


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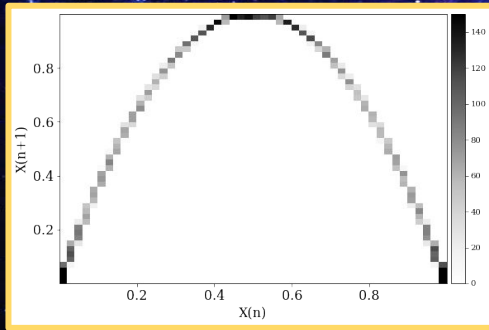
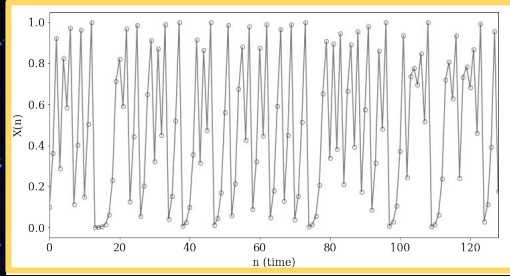
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- Autocorrelations and power spectrum are indistinguishable from white noise

## White Noise



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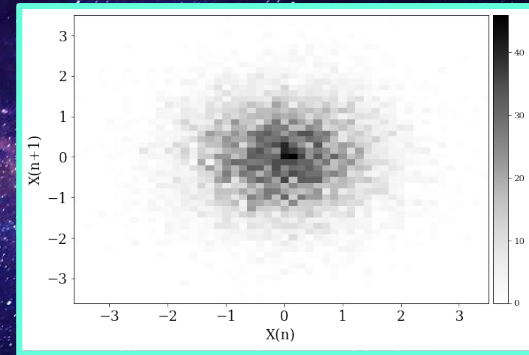
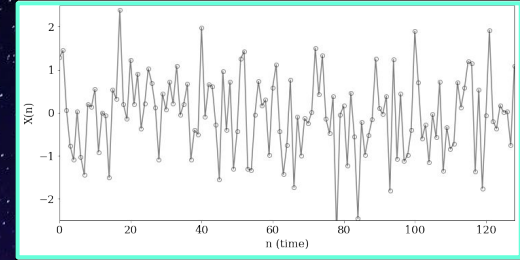


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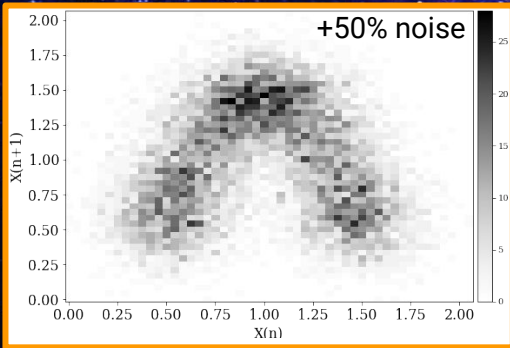
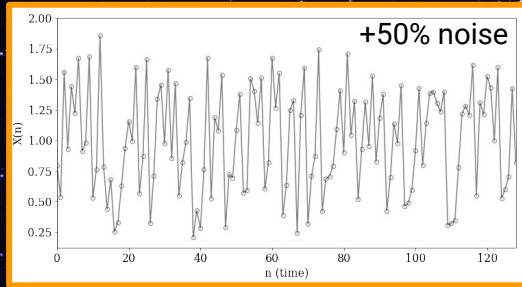
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- Autocorrelations and power spectrum are indistinguishable from white noise
- If  $X$  were random, then all points  $X_n$  would be independent of each other  
→ **Joint Probability Distribution**
- See *Scargle 2009 (Encyclopedia of Complexity and Systems Science)* for detailed review of this topic.

## White Noise



# A Brief Detour: The Logistic Map

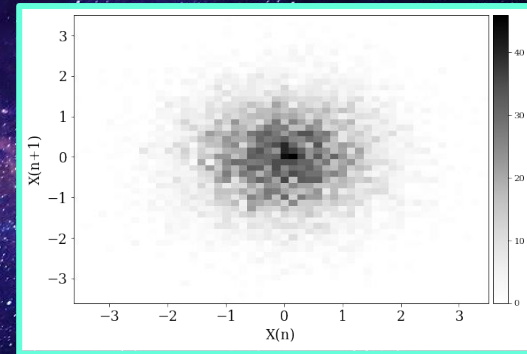
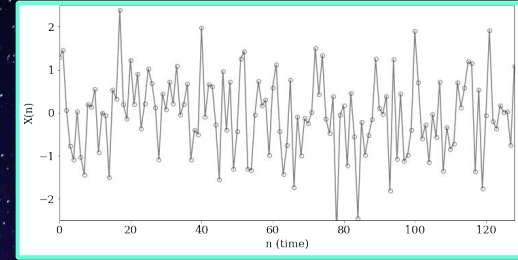


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## White Noise



# More on Joint Probability Distribution

- Nichols et al. 2009 demonstrates analytically how the **bispectrum** can be used to detect deviations from normality in the joint probability distribution of a system
- For a time series divided into K segments, the bispectrum is:

$$B(k, l) = \frac{1}{K} \sum_{i=0}^{K-1} X_i(k)X_i(l)X_i^*(k + l)$$

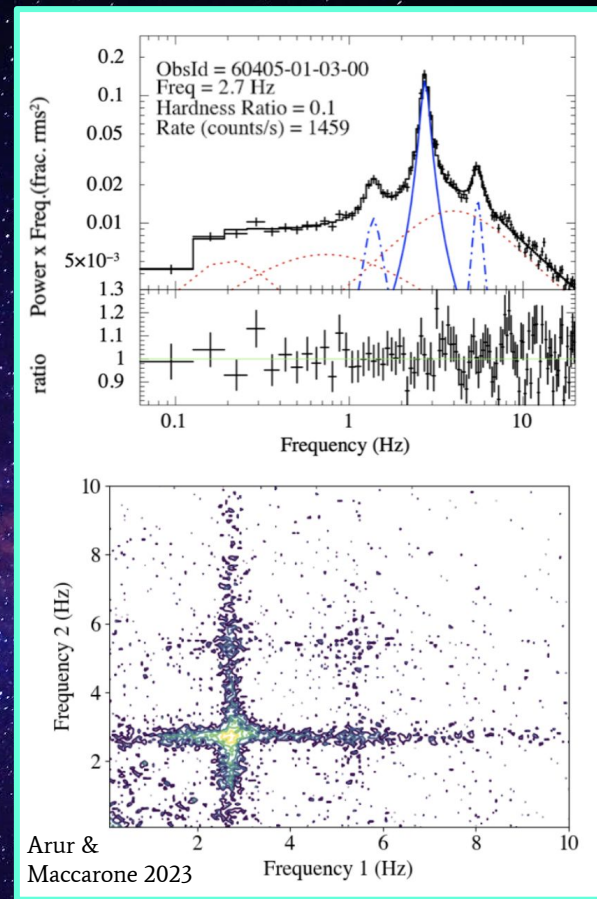
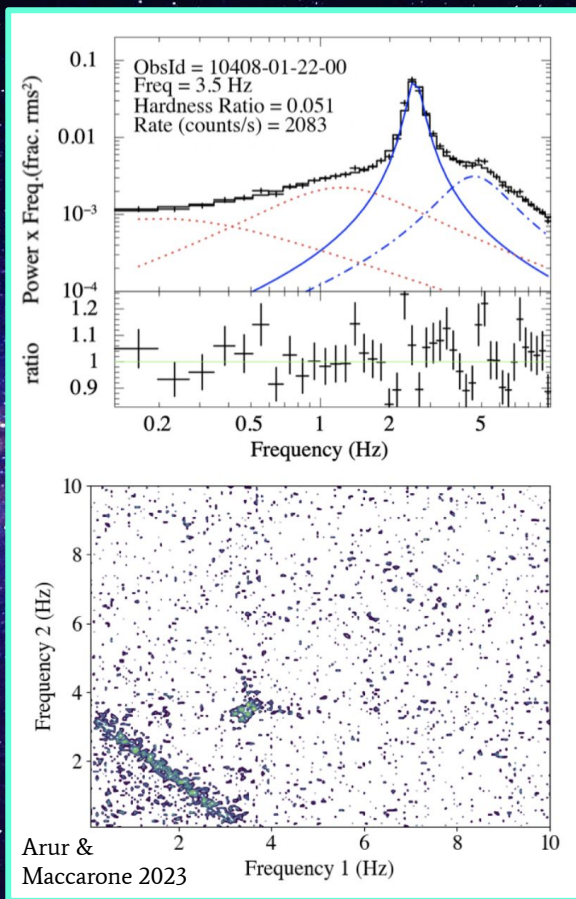
$X(f)$ : the Fourier transform at frequency  $f$

- Reflects the coupling of three frequencies
- **Bicoherence**: the magnitude of the bispectrum
- See *MacCarone (2013) for an overview*



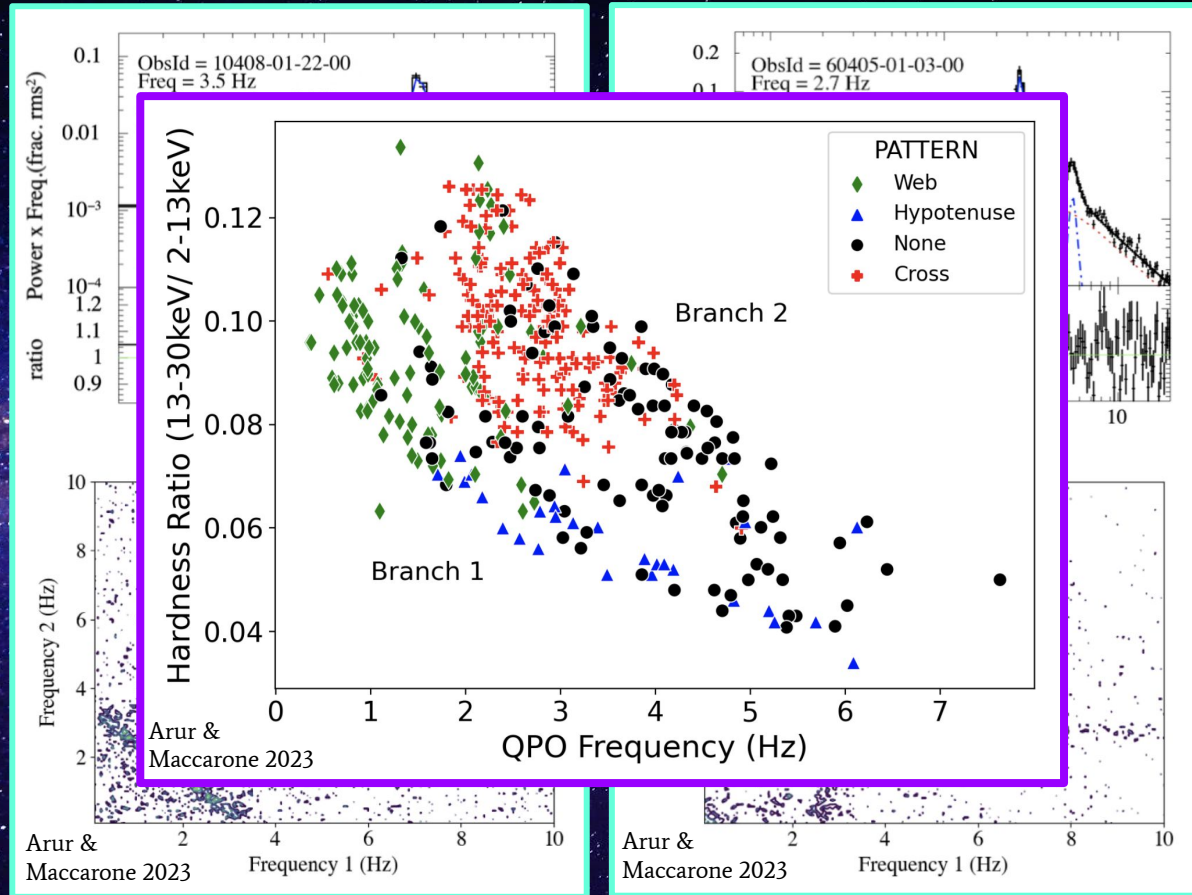
# Bispectrum of XRBs

Arur & Maccarone (2023) study GRS 1915+105 and find the bicoherence pattern correlates with the QPO frequency, hardness ratio, and radio properties



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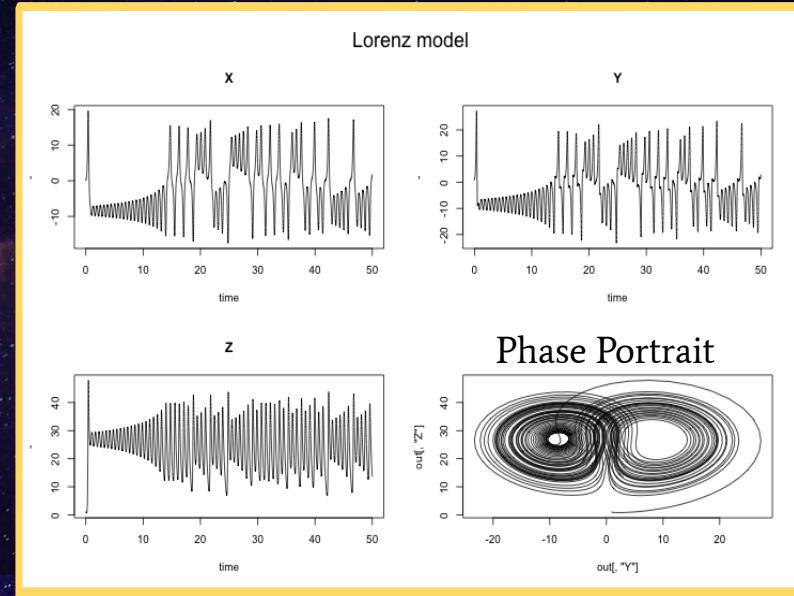
# Phase (State) Space

- The **bispectrum** and **bicoherence** describe nonlinearities in a signal and are sensitive to changes in the joint probability distribution of a system
  - **Unfortunately, requires lots of high-quality data**
- The **joint probability distribution** can be represented by  $X(n)$  vs.  $X(n+1)$  and is distinct from the power spectrum, ACF, etc.
  - **provides relationships between datapoints (not their absolute times)**
- **This feature is related to the importance of phase space (state space)**

# Phase Space encodes dynamical information

We can construct phase space from 1D time series:

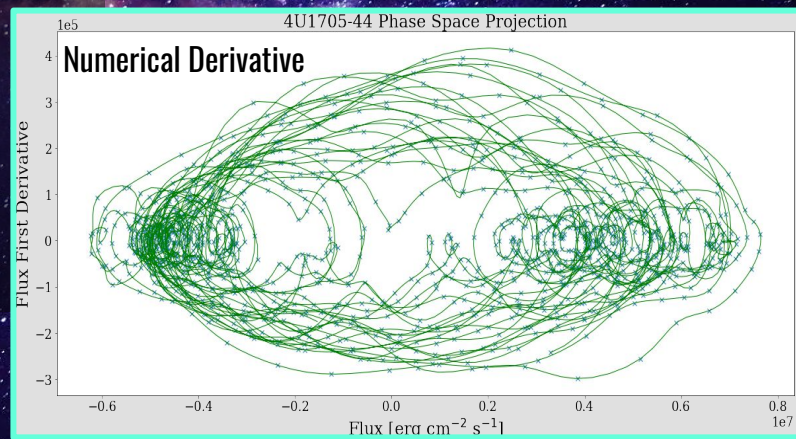
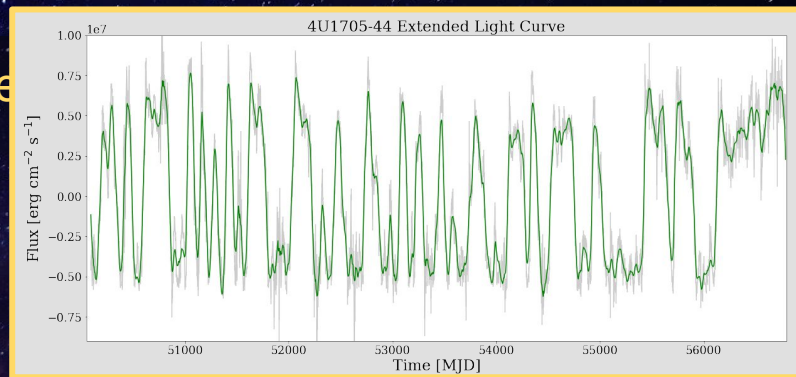
- Analytical systems: direct derivatives or multivariate



# Phase Space encodes dynamical information

We can construct phase space from 1D time series

- Analytical systems: direct derivatives
- Known observed systems: numerical derivatives



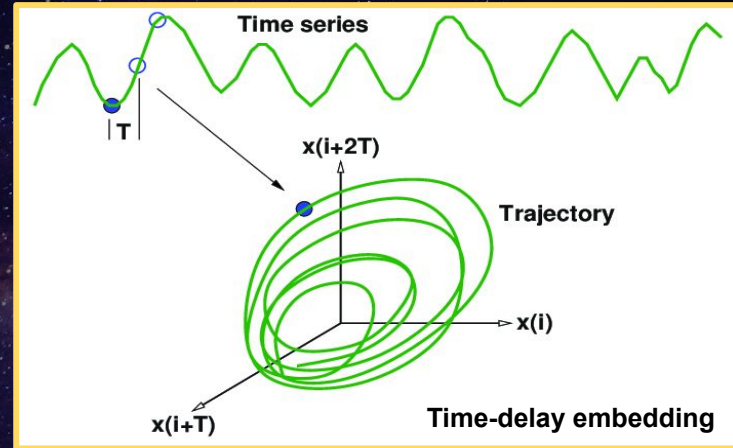
# Phase Space encodes dynamical information

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- Analytical systems: direct derivatives
- Known observed systems: numerical derivatives
- Unknown observed systems - most common: **Time Delay Embedding** (Takens 1981)

$$\vec{X} \rightarrow (X_n, X_{n+k}, X_{n+2k}, X_{n+3k} + \dots + X_{n+(M-1)k})$$

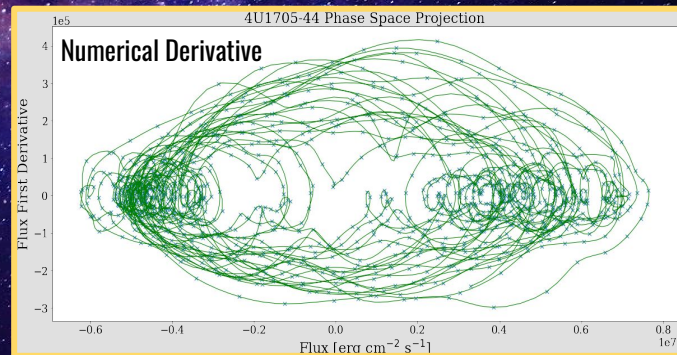
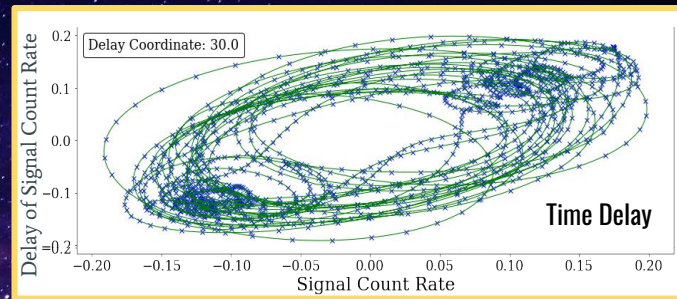
The trajectories in an embedding preserve the dynamics of the true state space (Packard et al. 1980)



# Phase Space encodes dynamical information

We can construct phase space from 1D time series:

- Analytical systems: direct derivatives
- Known observed systems: numerical derivatives
- Unknown observed systems - most common: Time Delay Embedding (*Takens 1981*)
  - Example: derivative of *sine* = phase-shifted *cosine*
  - Example: 4U1705-44 time delay embedding for a delay of 30 looks like its numerical derivative
- Phase space in its simplest form is merely  $X(n)$  vs.  $X(n+1)$



# Phase Space encodes dynamical information

## Advantages of the phase space framework:

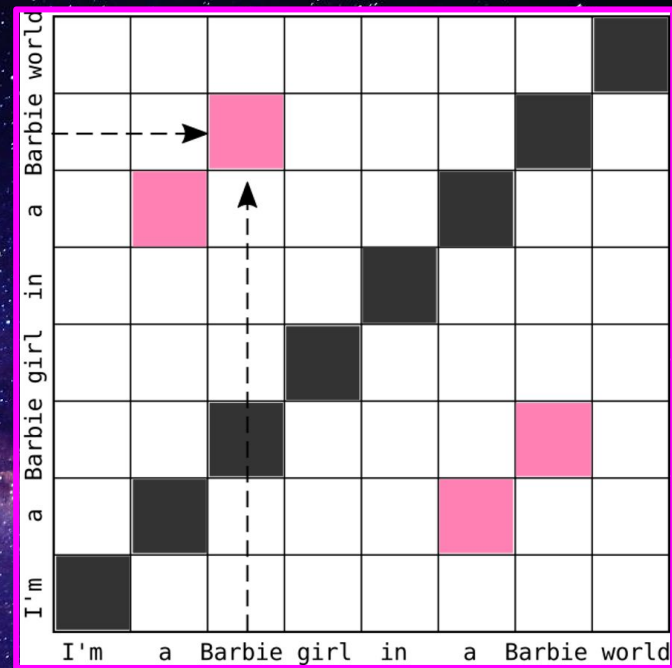
- Robust against noise
- No assumptions about linearity, stationarity, etc.
- Detect transitions to/from nonlinear or periodic regimes
- Methods require less data compared to other nonlinear techniques



# The Recurrence Plot:

## A One-stop Shop for info contained in Phase Space

- The **Recurrence Plot** associates positions in time with closeness in phase space

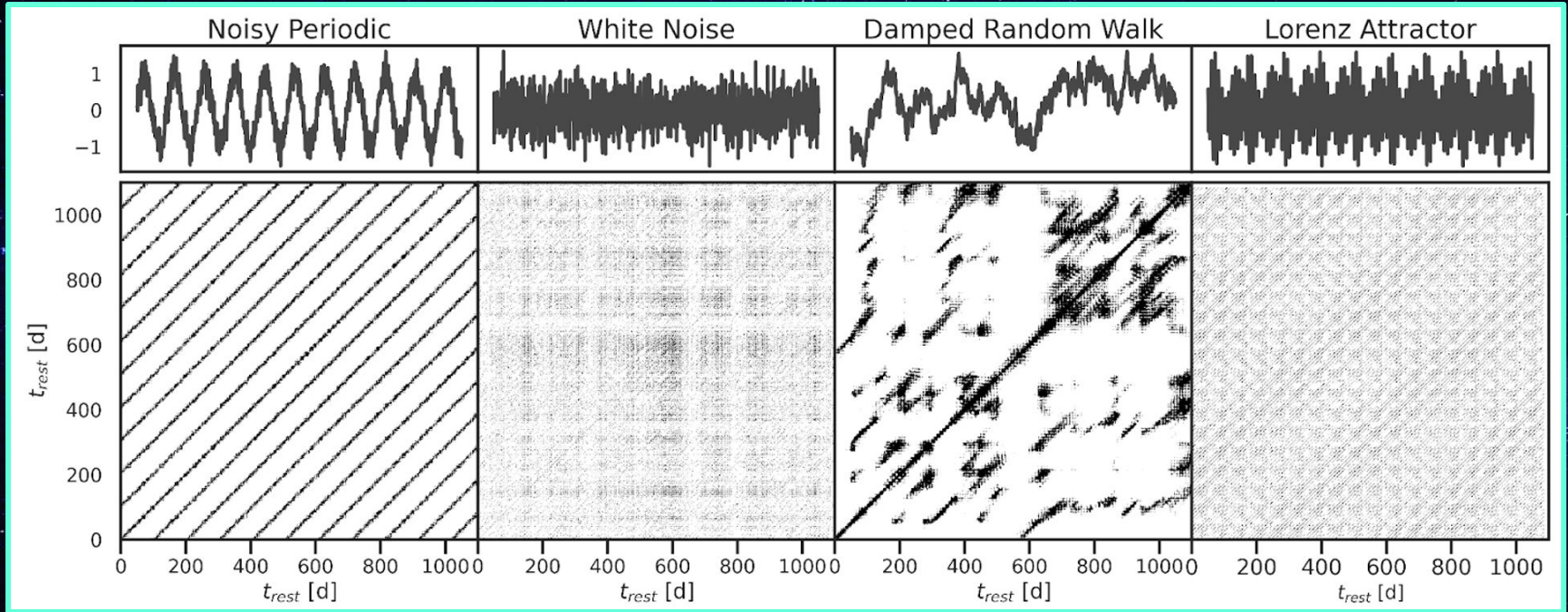


"SongSim":

<https://colinmorris.github.io/SongSim>

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A One-stop Shop for information contained in Phase Space

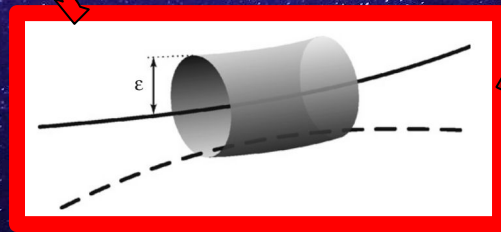
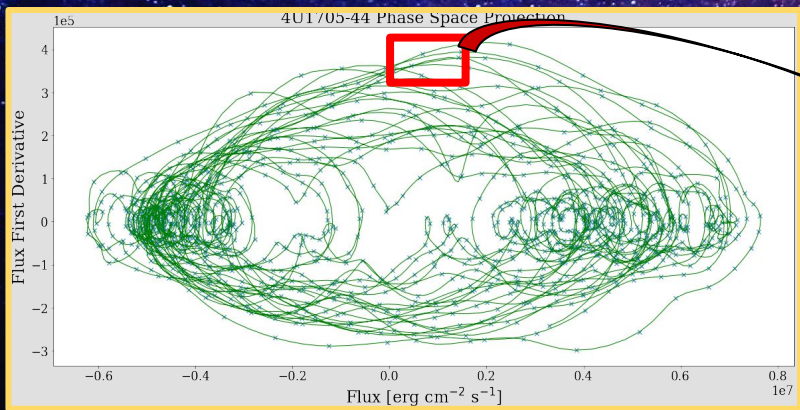
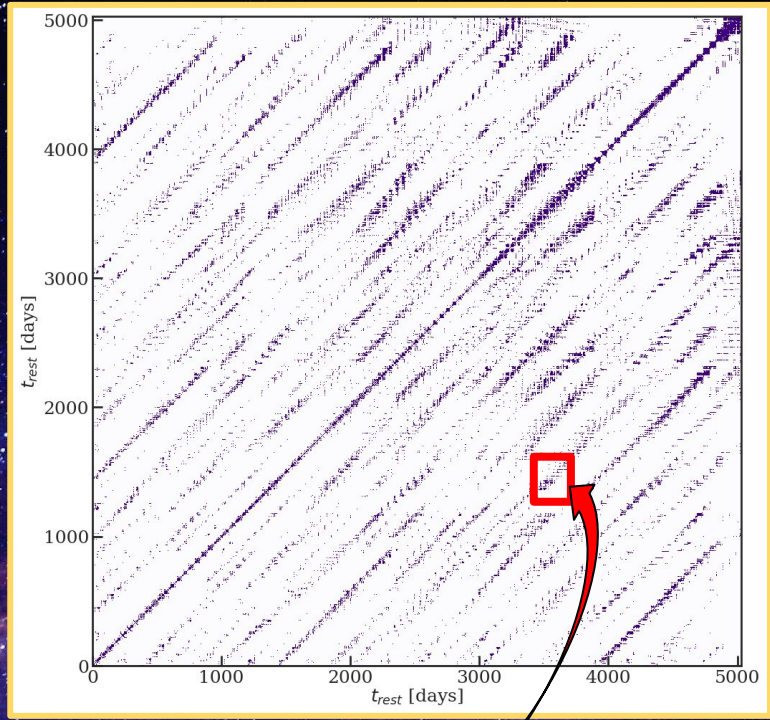


Broadbent & Phillipson 2023 (in review)

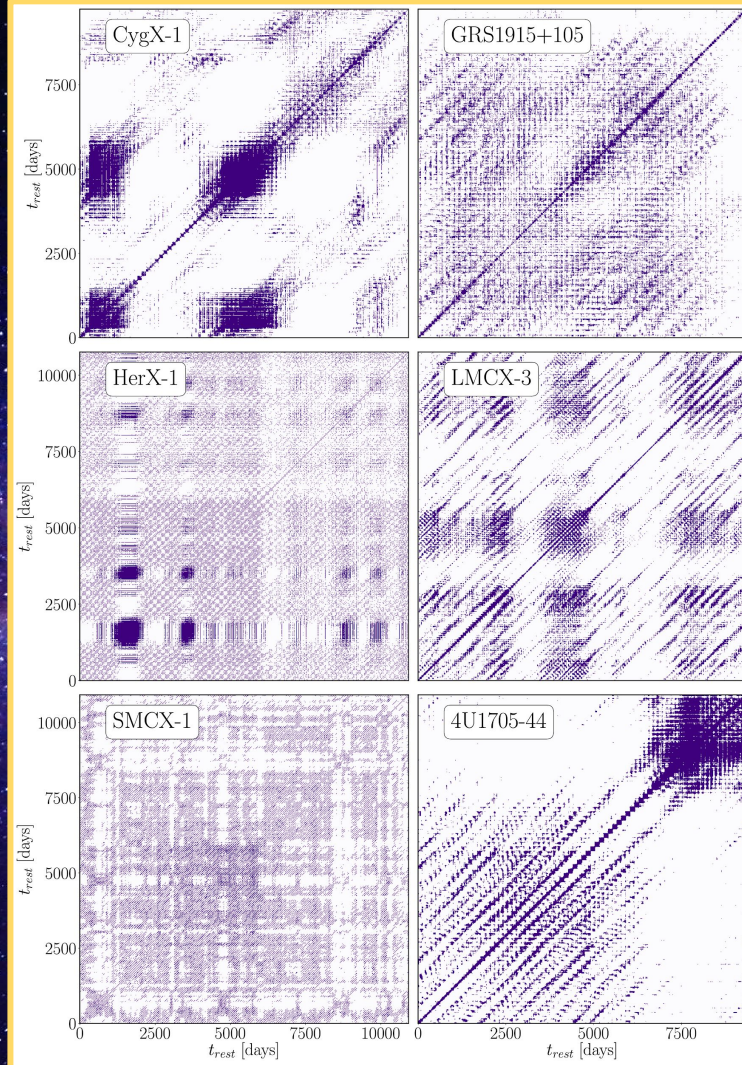
# The Recurrence Plot:

A One-stop Shop for info contained in Phase Space

- The **Recurrence Plot** associates positions in time with closeness in phase space
- Can be used with noise-like & deterministic systems



# The Recurrence Plot: X-ray Binaries!



Phillipson et al. 2020

# Back to Hyperion

Boyd et al. 1994 used a version of the recurrence plot (RP) to extract unstable periodic orbits responsible for the chaotic behavior.

The method is more robust against noise and supports the Buchler et al. results.

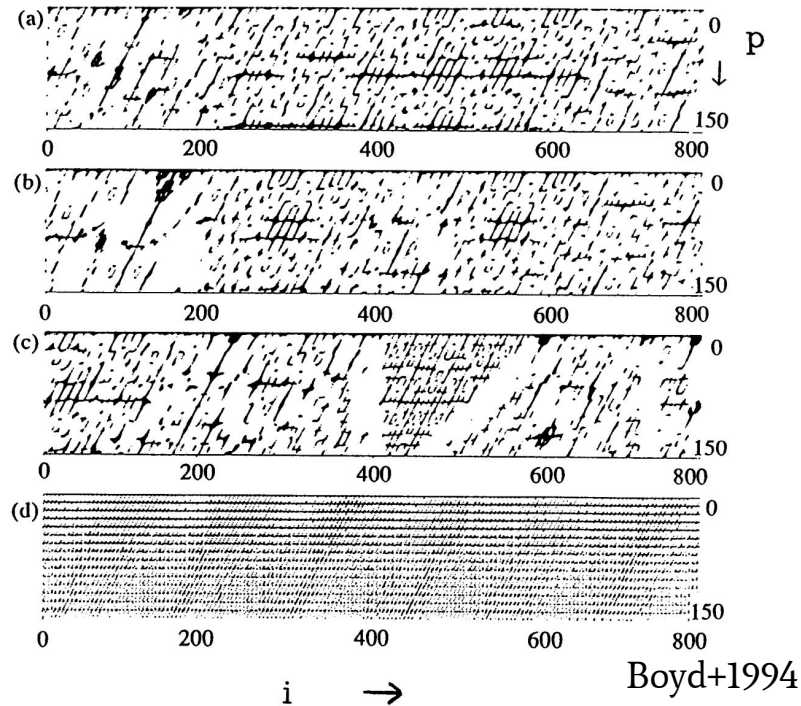


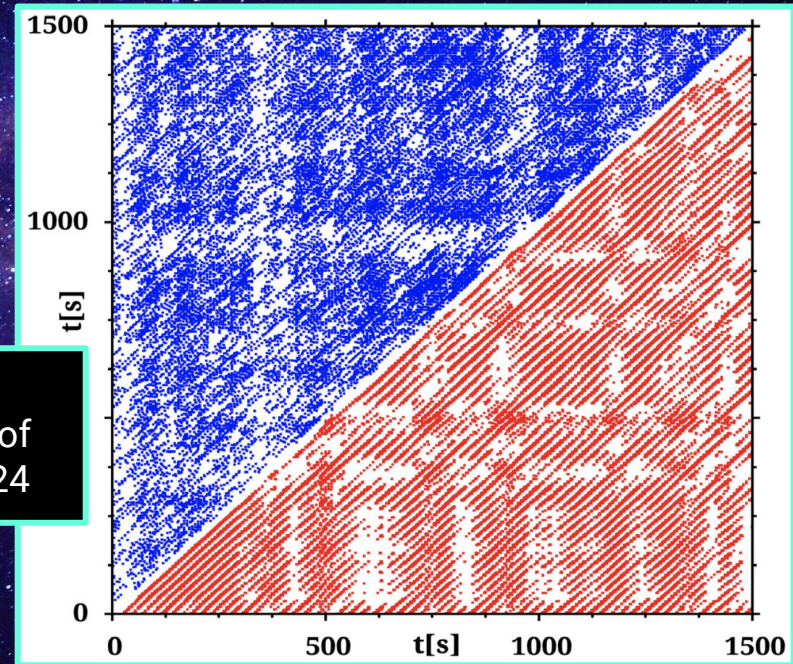
FIG. 3.—Close return images for four separate initial conditions of the Hyperion system. The body parameters are fixed, and the initial value of  $f$  is taken as zero in each experiment. The initial conditions are (a)  $\theta = 1.0$ ,  $\theta' = 0.5$ ; (b)  $\theta = 0.7$ ,  $\theta' = 1.0$ ; (c)  $\theta = 0.5$ ,  $\theta' = 0.5$ ; and (d)  $\theta = 2.0$ ,  $\theta' = 2.0$ . The horizontal axis is the position  $i$  of a point in the data file that is compared with another point in the data file separated by  $p$  nights, with  $p$  plotted vertically downward. If the phase-space distance between the two points is less than 10% of the maximum, we plot a black point at  $(i, p)$ .

# The Recurrence Plot for Accretion Studies

- [Sukova et al. 2016](#): identifies determinism and chaos among several variability states of 6 microquasars using RPs relating to thermal-viscous instability

Two different  
spectral states of  
IGR J17091-3624

Sukova et al. 2016

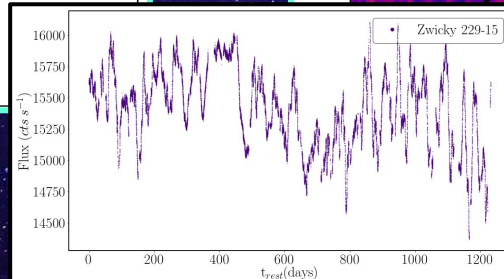
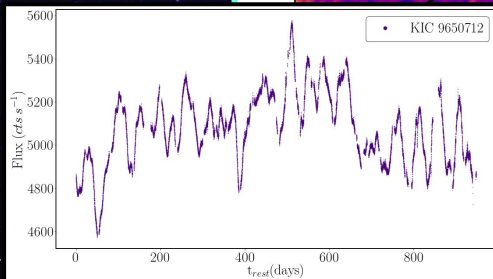
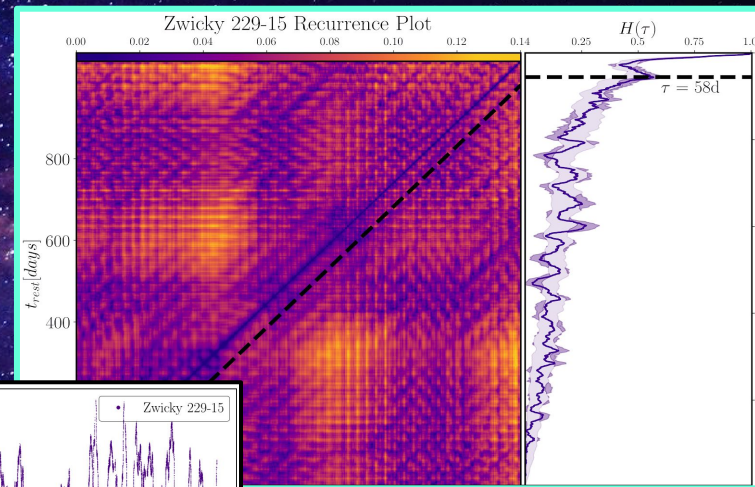
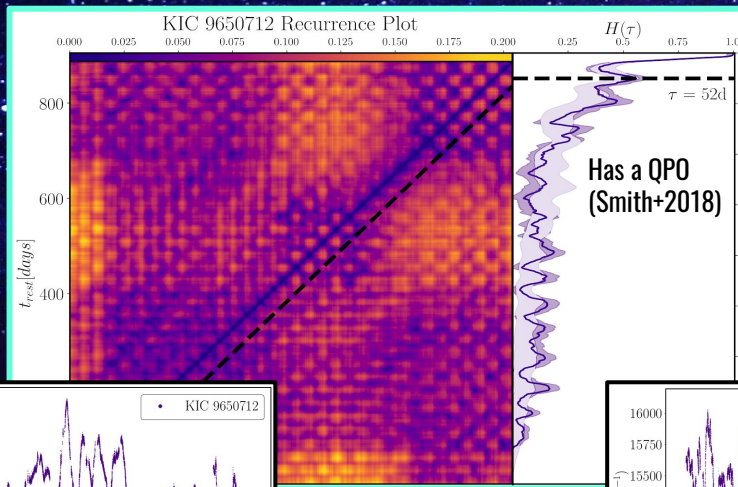


# The Recurrence Plot for Accretion Studies

- [Bhatta et al. 2020](#): computes RP statistics of blazars and found several with traces of determinism, with most containing a combination of determinism & stochastic processes

# The Recurrence Plot for Accretion Studies

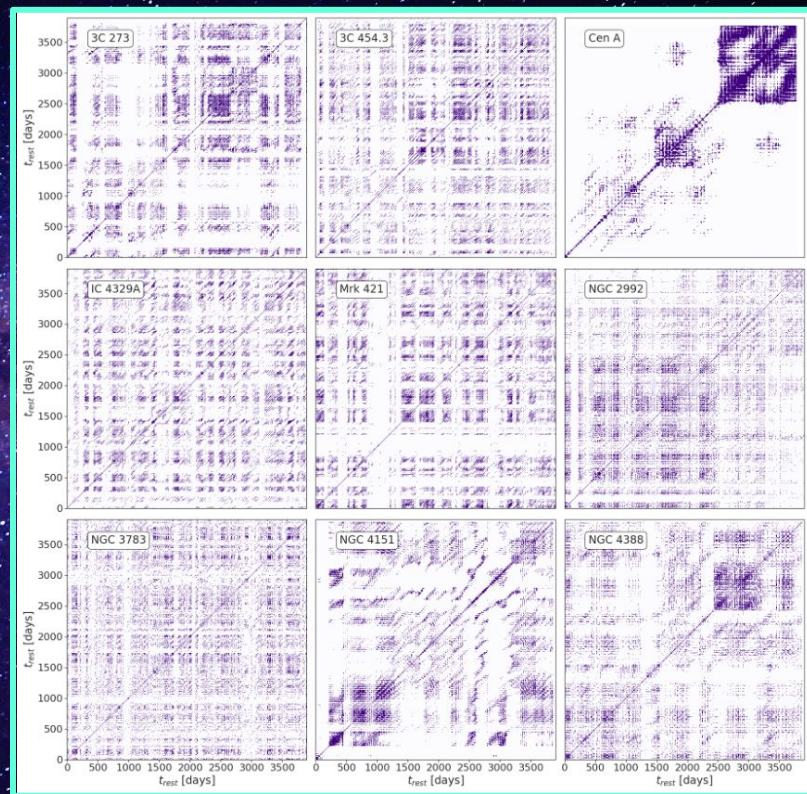
- [Phillipson et al. 2020](#): computes the Renyi entropy from the RPs of two Kepler-monitored AGN. One is deterministic (with an optical QPO) and the other is not: two classes of AGN?





# The Recurrence Plot for Accretion Studies

- Phillipson et al. 2023: compute RP statistics of 46 Swift/BAT AGN.
- Type II contain higher measures of determinism relative to Type I, but no distinction is found in obscuration.
- Some dependencies on Eddington ratio.

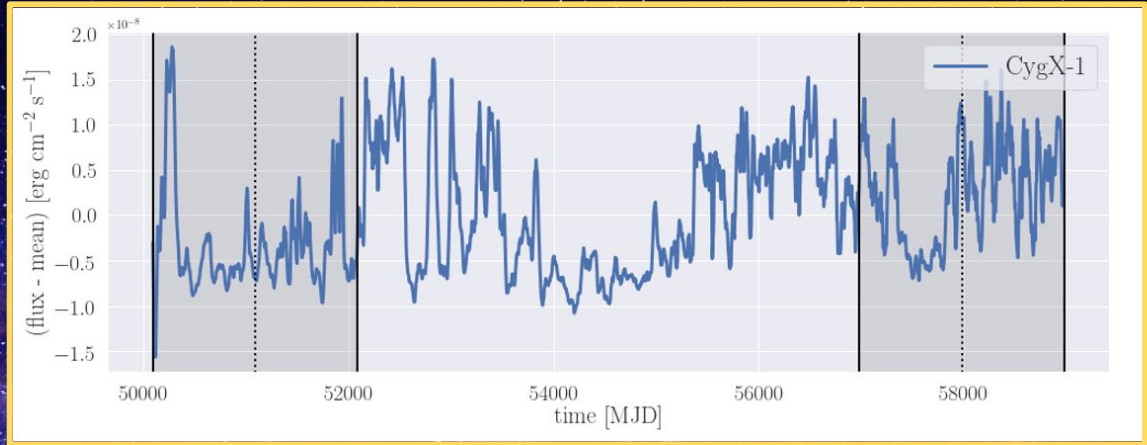


# Accretion State Changes of Cyg X-1

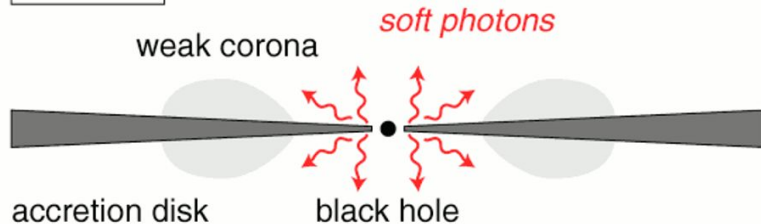
Broadbent & Phillipson 2023 (in review)

**Data:** 2-20 keV Flux, Rossi X-ray Timing Explorer (RXTE) All-sky Monitor (ASM) and MAXI

**Cyg X-1:** Known to undergo state changes regularly



soft state



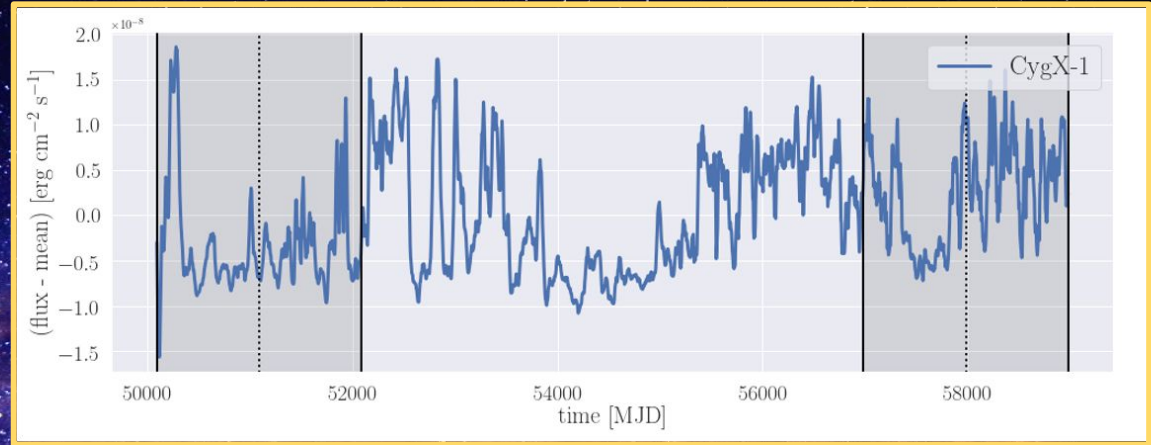
**Disk-dominated “soft” state:** mostly thermal photons, lower energies

# Accretion State Changes of Cyg X-1

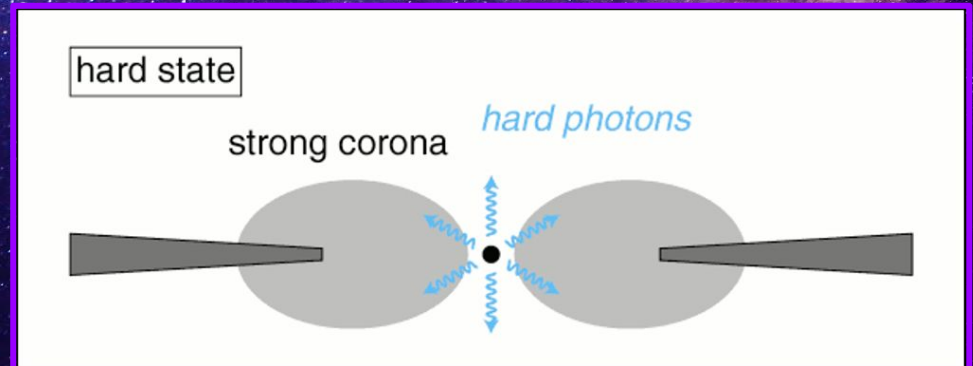
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**Corona-dominated "hard" state:**  
power-law energy spectrum  
(Comptonized), higher energy photons

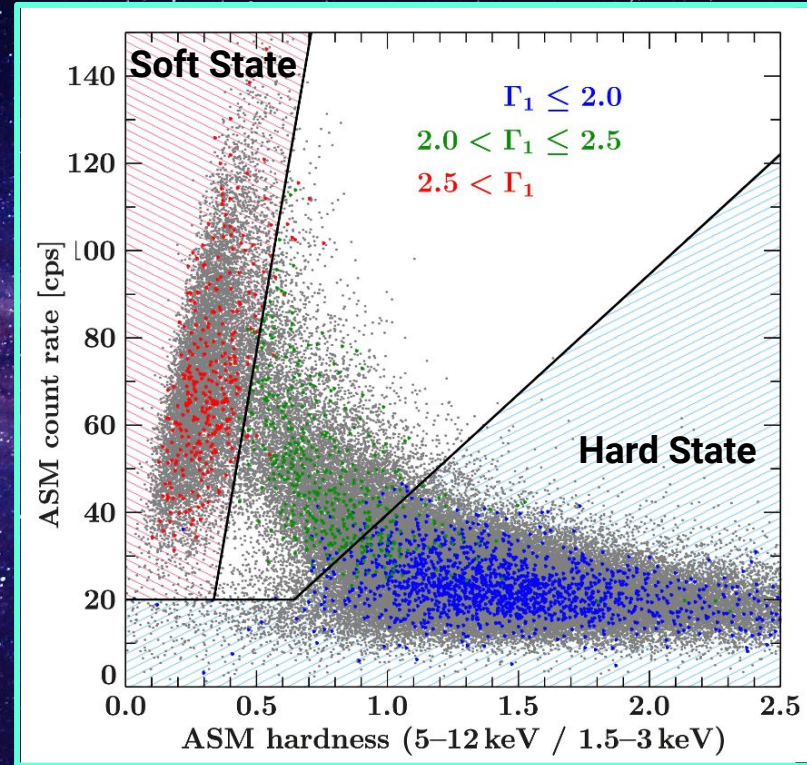


# Accretion State Changes of Cyg X-1

Grinberg+2013

Pointed observations  
(colored points) provide  
spectral classification ( $\Gamma_1$ )

Hardness-Intensity as a  
proxy for accretion state



# Accretion State Changes of Cyg X-1

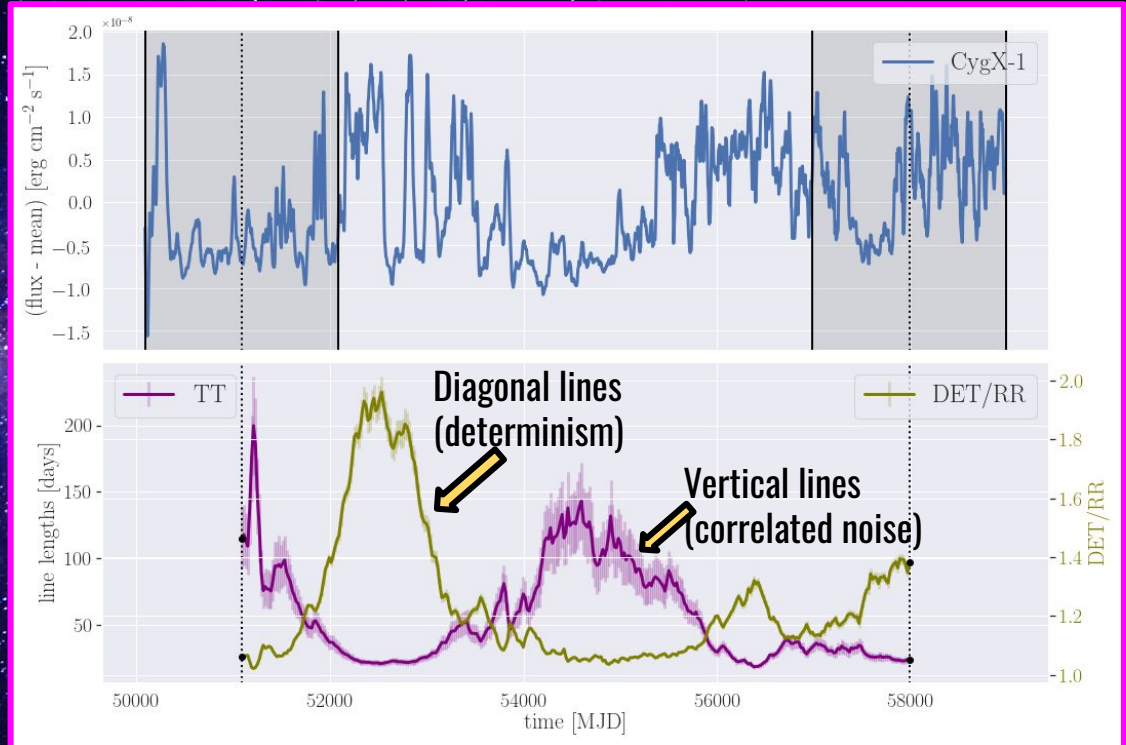
Broadbent & Phillipson 2023 (in review)

Features from the RP:

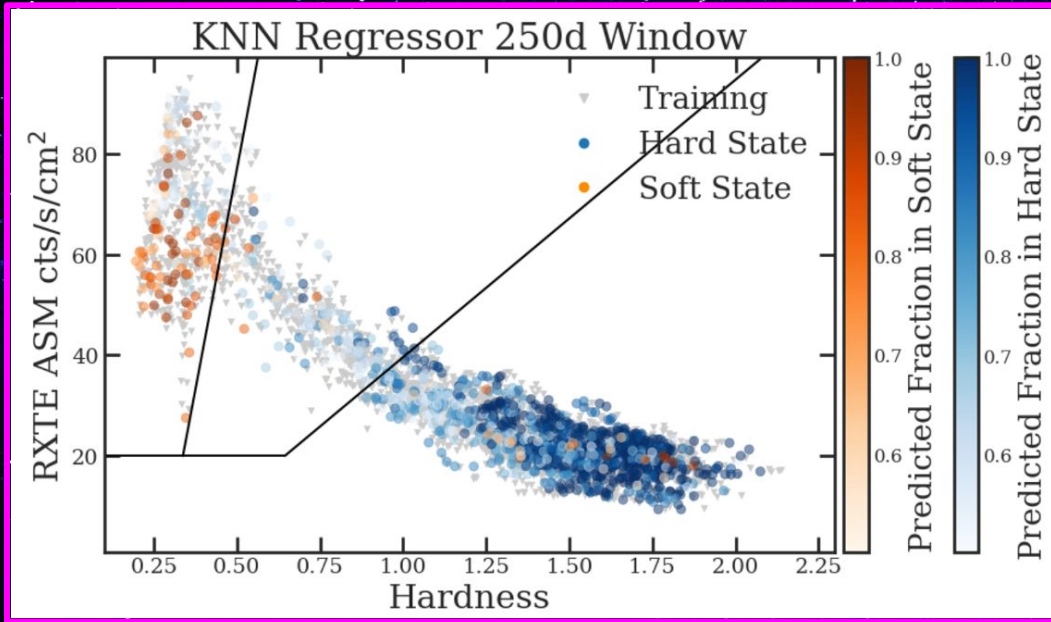
**DET**: “Determinism” – proportion of points in RP that are part of diagonal lines

**TT**: “Trapping Time” – average length of vertical line

A total of 10 features



# Changes in Variability States



## K-Nearest Neighbors Regression model:

- Use RP features as predictors and %RP in each spectral state as targets in training set
- Test on unlabeled data
- Predicts with up to **95% accuracy** the state given **only** RP features

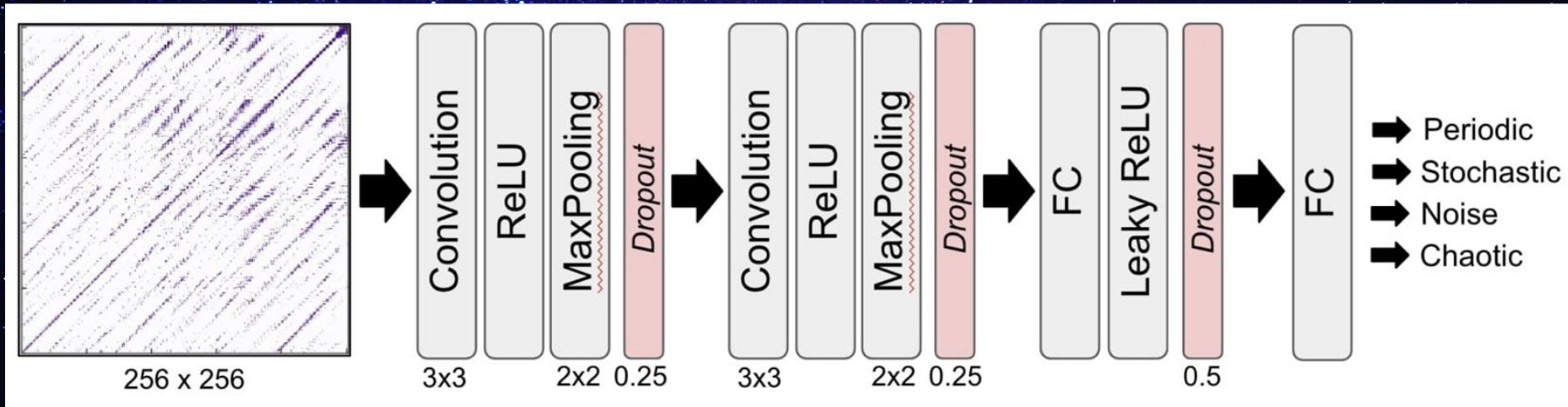
Broadbent & Phillipson 2023 (in review)

# The Future

**Pair Nonlinear Time Series Analysis with AI/ML Techniques**

# The Future

## Pair Nonlinear Time Series Analysis with AI/ML Techniques

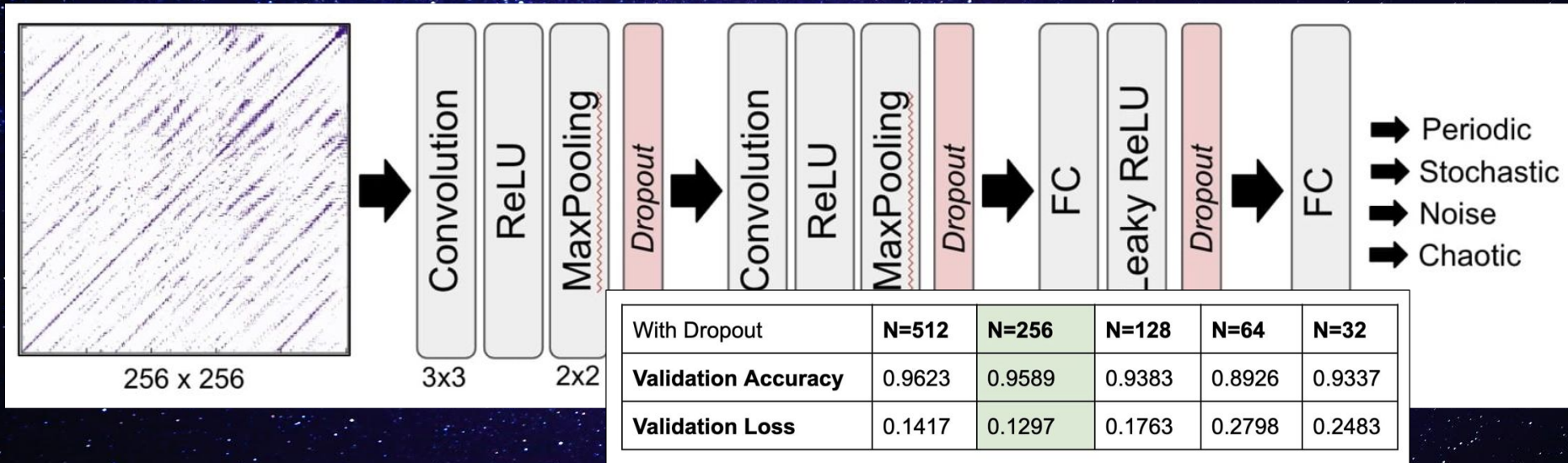


Use a Convolutional Neural Network to classify RPs of ZTF light curves into 4 dynamical classes



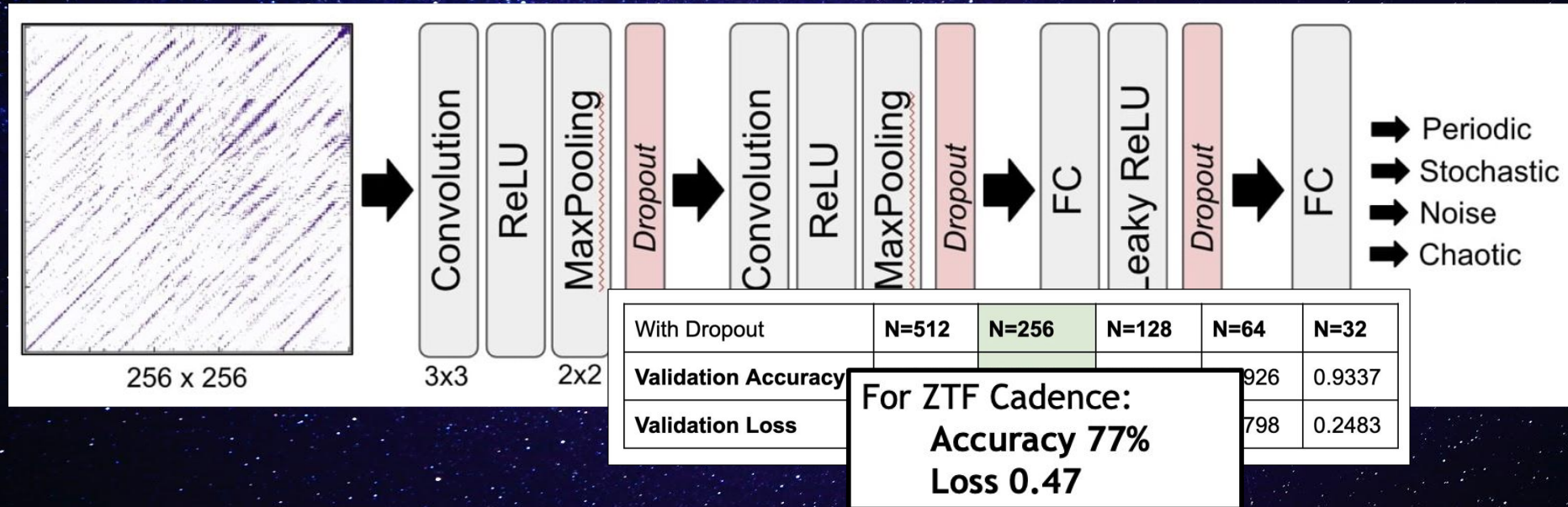
# The Future

## Pair Nonlinear Time Series Analysis with AI/ML Techniques



# The Future

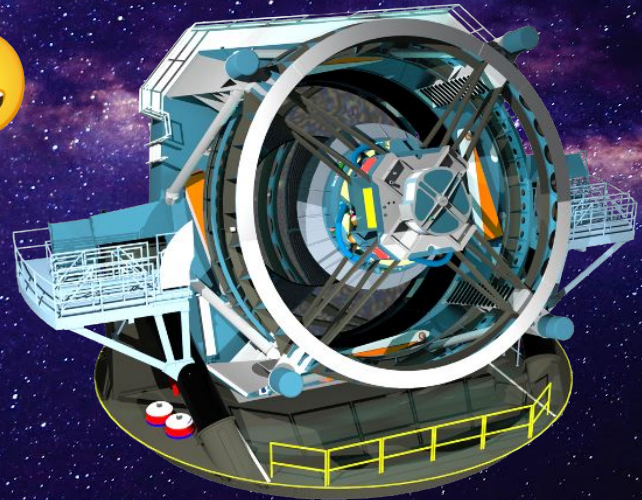
## Pair Nonlinear Time Series Analysis with AI/ML Techniques



# The Future

## Pair Nonlinear Time Series Analysis with AI/ML Techniques

- Preliminary success with ZTF promises bright future with LSST



# The Future

**Revisit the data problems of traditional NLTS**

# The Future

## Revisit the data problems of traditional NLTS

Dimension & Lyapunov exponent calculations:

- Require very long and detailed time series
- Very sensitive to noise

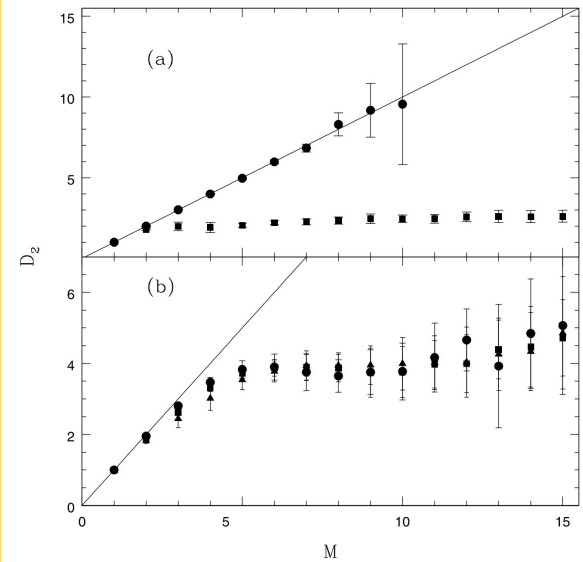
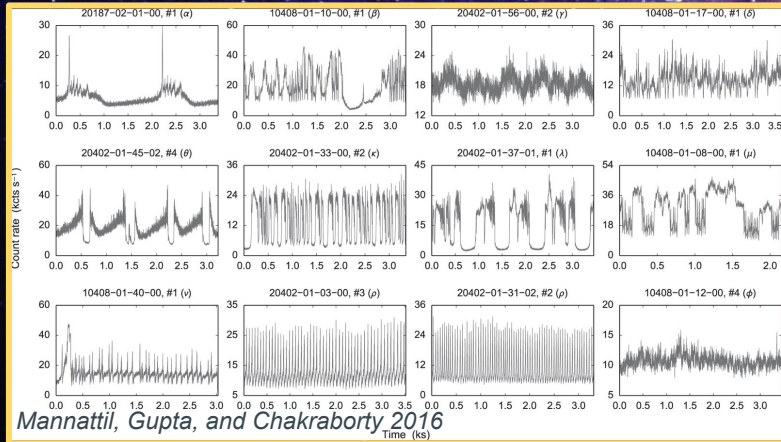


FIG. 1.—(a)  $D_2$  vs.  $M$  for random points (circles) and for a Lorenz system (squares). For both curves the number of points used is 30,000, and the number of centers used in the computation is 2000. The straight line represents the  $D_2 = M$  case, which is the expected result for random variation. (b)  $D_2$  vs.  $M$  for GRS 1915+105 data obtained during class  $\kappa$  for three different values of the delay time:  $\tau = 15$  s (triangles), 25 s (squares), and 100 s (circles).

**Correlation dimension,  $D$ :** the rate at which the volume in  $M$ -dim space grows with radius  $R^M$

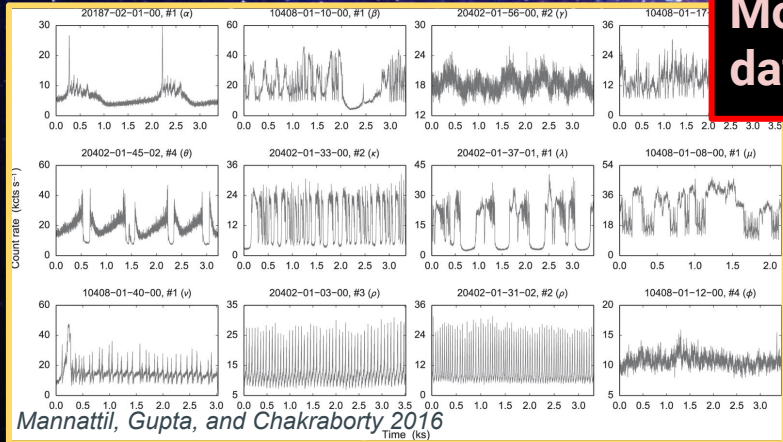
**Data limit:  $D \sim \log(N)$**

# The Future

## Revisit the data problems of traditional NLTS

Dimension & Lyapunov exponent calculations:

- Require very long and detailed time series
- Very sensitive to noise



**More high-quality data, please, thanks**

**Correlation dimension,  $D$ :** the rate at which the volume in  $M$ -dim space grows with radius  $R^M$

**Data limit:  $D \sim \log(N)$**

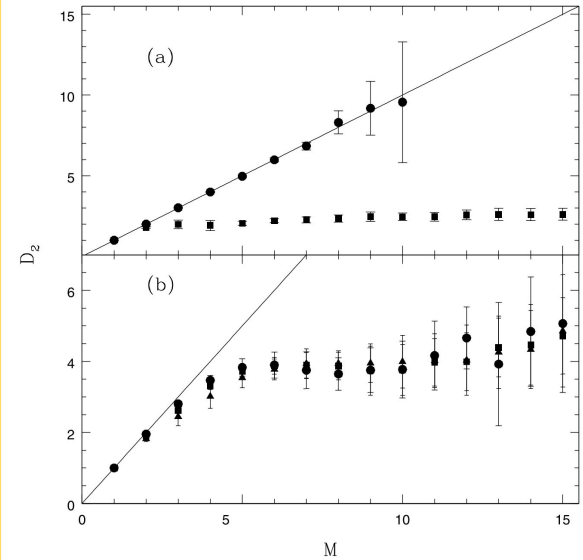


FIG. 1.—(a)  $D_2$  vs.  $M$  for random points (circles) and for a Lorenz system (squares). For both curves the number of points used is 30,000, and the number of centers used in the computation is 2000. The straight line represents the  $D_2 = M$  case, which is the expected result for random variation. (b)  $D_2$  vs.  $M$  for GRS 1915+105 data obtained during class  $\kappa$  for three different values of the delay time:  $\tau = 15$  s (triangles), 25 s (squares), and 100 s (circles).

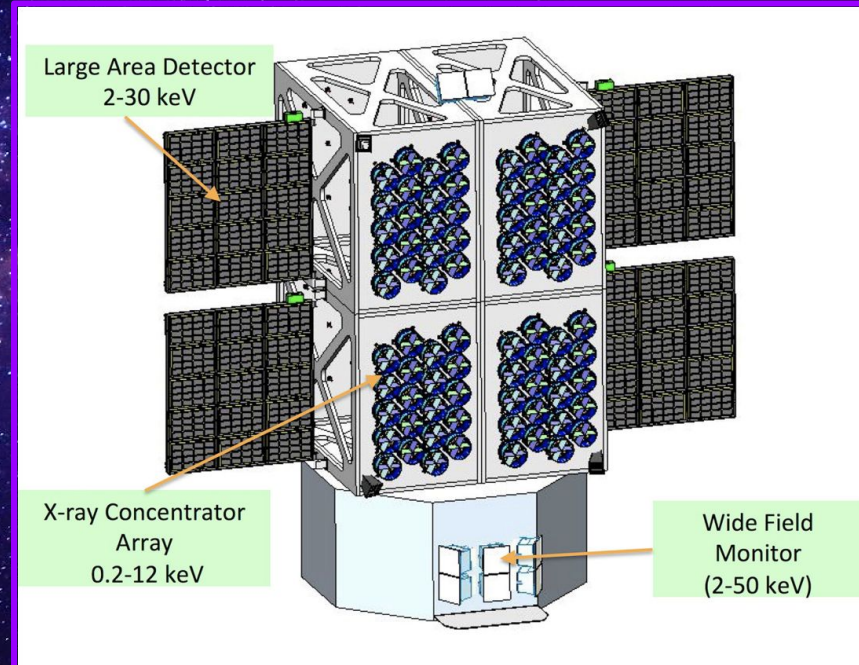
# The Future

<https://strobe-x.org>

Revisit the data problems of traditional NLTS

## X-ray Probe Concept: STROBE-X

STROBE-X	RXTE/NICER
<b>Wide Field Monitor (WFM)</b> <ul style="list-style-type: none"><li>•Energy Range 2–50 keV</li><li>•# of Camera Pairs: 4</li><li>•FOV/Camera Pair 70° × 70° FWHM</li><li>•Energy Resolution 300 eV FWHM</li><li>•Sky Coverage (Instantaneous) 4.1 sr</li><li>•Angular Resolution 4.3 arcmin</li><li>•Position Accuracy 1 arcmin</li><li>•Sensitivity (1 s) 600 mcrab</li><li>•Sensitivity (1 day) 2 mcrab</li></ul>	<b>All-Sky Monitor (ASM)</b> <ul style="list-style-type: none"><li>•Energy range: 2 - 10 keV</li><li>•Time resolution: 80% of the sky every 90 minutes</li><li>•Spatial resolution: 3' x 15'</li><li>•Number of shadow cameras: 3, each with 6 x 90 degrees FOV</li><li>•Collecting area: 90 square cm</li><li>•Detector: Xenon proportional counter, position-sensitive</li><li>•Sensitivity: 30 mCrab</li></ul>



# The Future

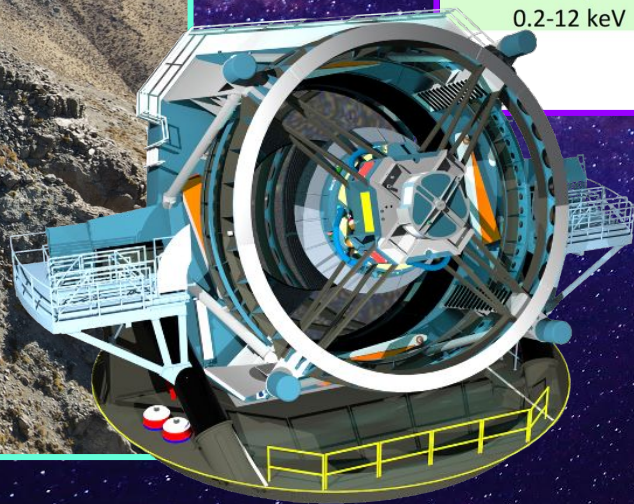
## Revisit the data problems of traditional NLTS

STROBE-X and other X-ray satellites enable:

- Ensemble studies with X-ray light curves
- Correlations with accretion state and energy spectra
- Use bispectrum, RPs, and correlation dimension calculations alike



# The Future



Large Area Detector  
2-30 keV

X-ray Concentrator  
Array  
0.2-12 keV

Wide Field  
Monitor  
(2-50 keV)

