Urban Informatics

Fall 2015

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CUSP

Recap:

- Good practices with data: falsifiability, reproducibility
- Basic data retrieving and munging: APIs, Data formats
- Basic statistics: distributions and their moments
- Hypothesis testing: *p*-value, statistical significance
- Statistical and Systematic errors
- Goodness of fit tests
- OLS, residual minimization
- Likelihood, chisq

Recap:

- Good practices with data: falsifiability, reproducibility
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Today

- Topics in (time) series analysis

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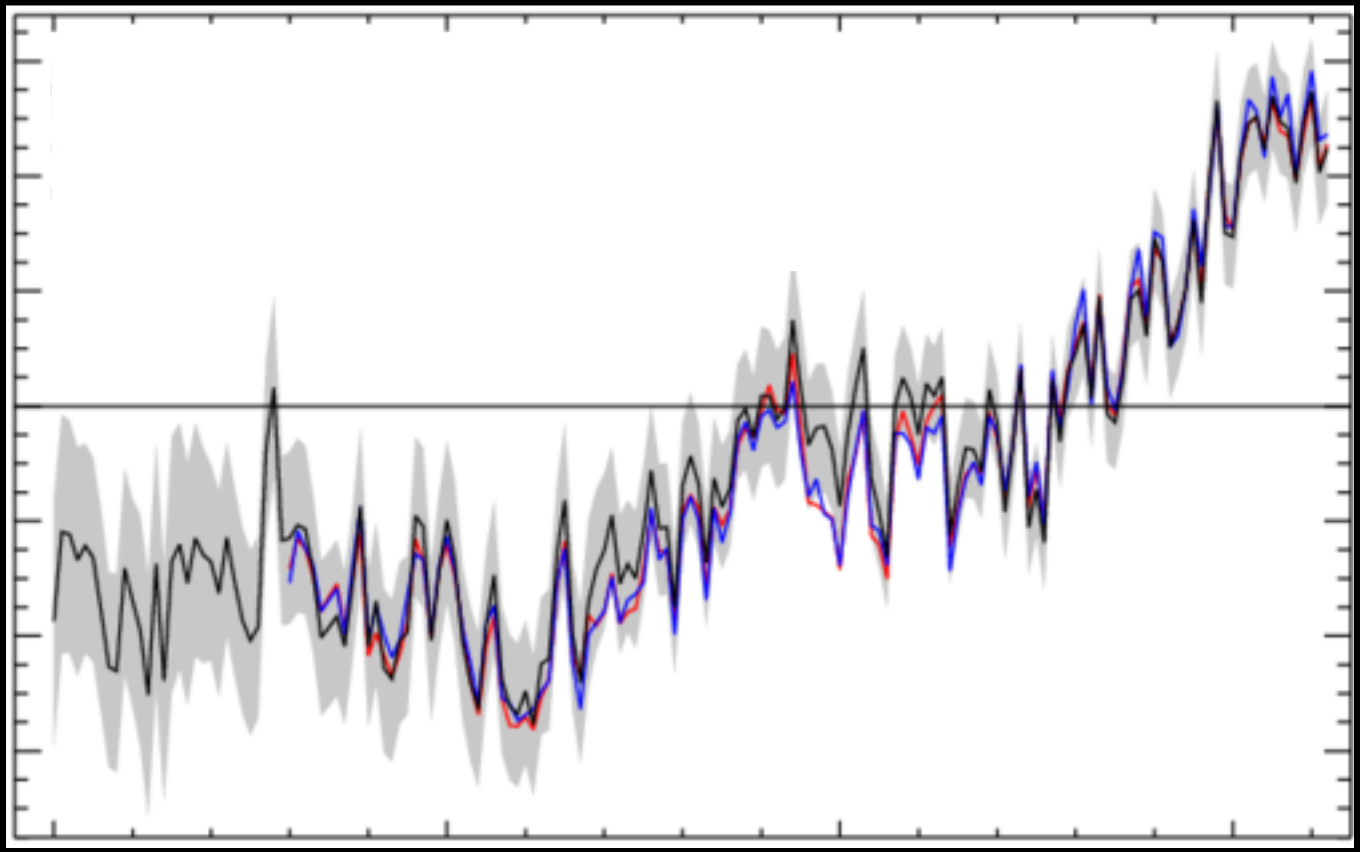
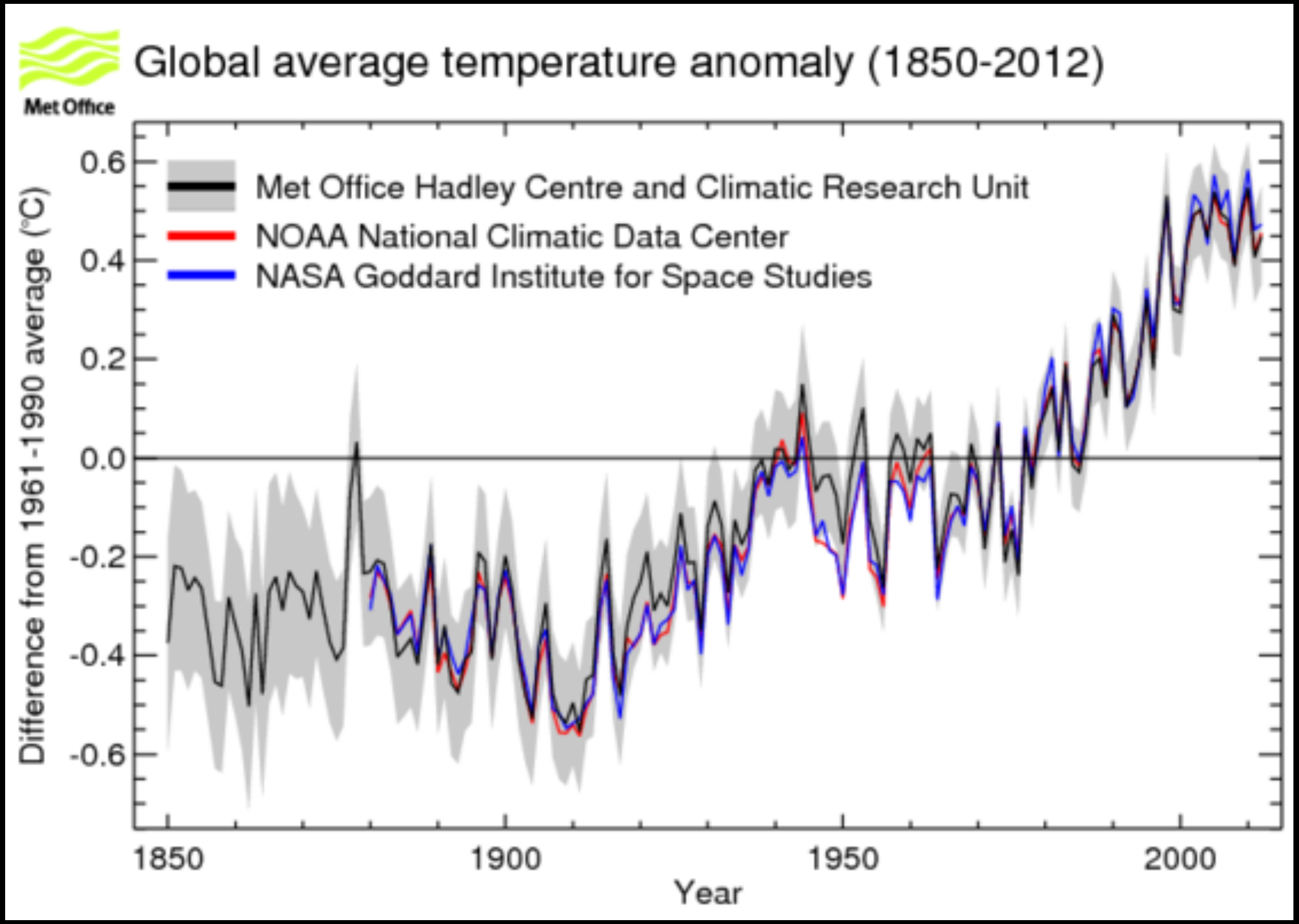
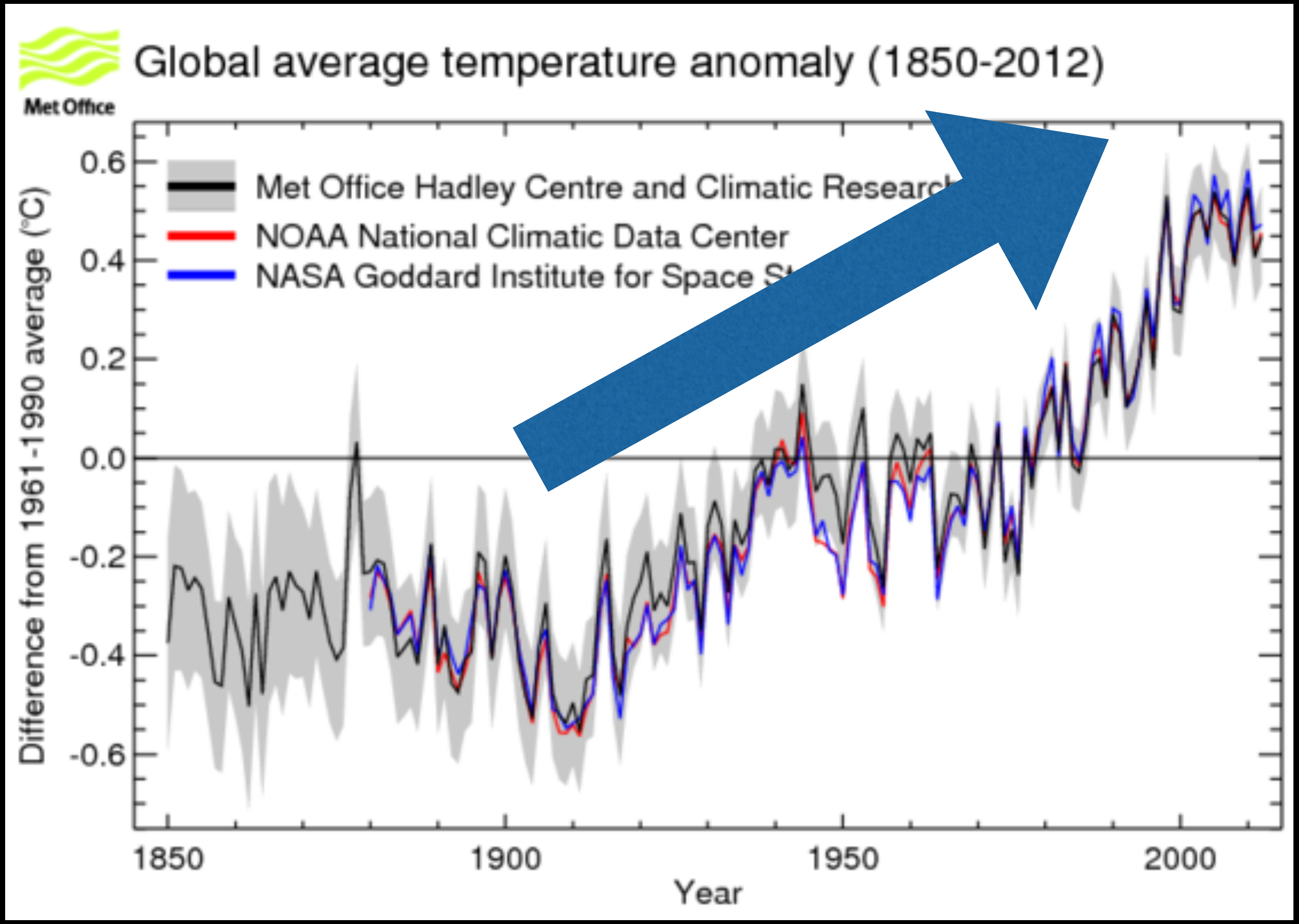
Topics in (time) series analysis

- smoothing
- de-trending
- event detection
- period finding (Fourier analysis)
- clustering




Met Office
Global average temperature anomaly (1850-2012)
Met Office Hadley Centre and Climatic Research Unit
NOAA National Climatic Data Center
NASA Goddard Institute for Space Studies
Difference from 1961-1990 average (°C)
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
1850
1900
1950
2000
Year

Trend


Global average temperature anomaly (1850-2012)
Met Office
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0.6
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-0.4
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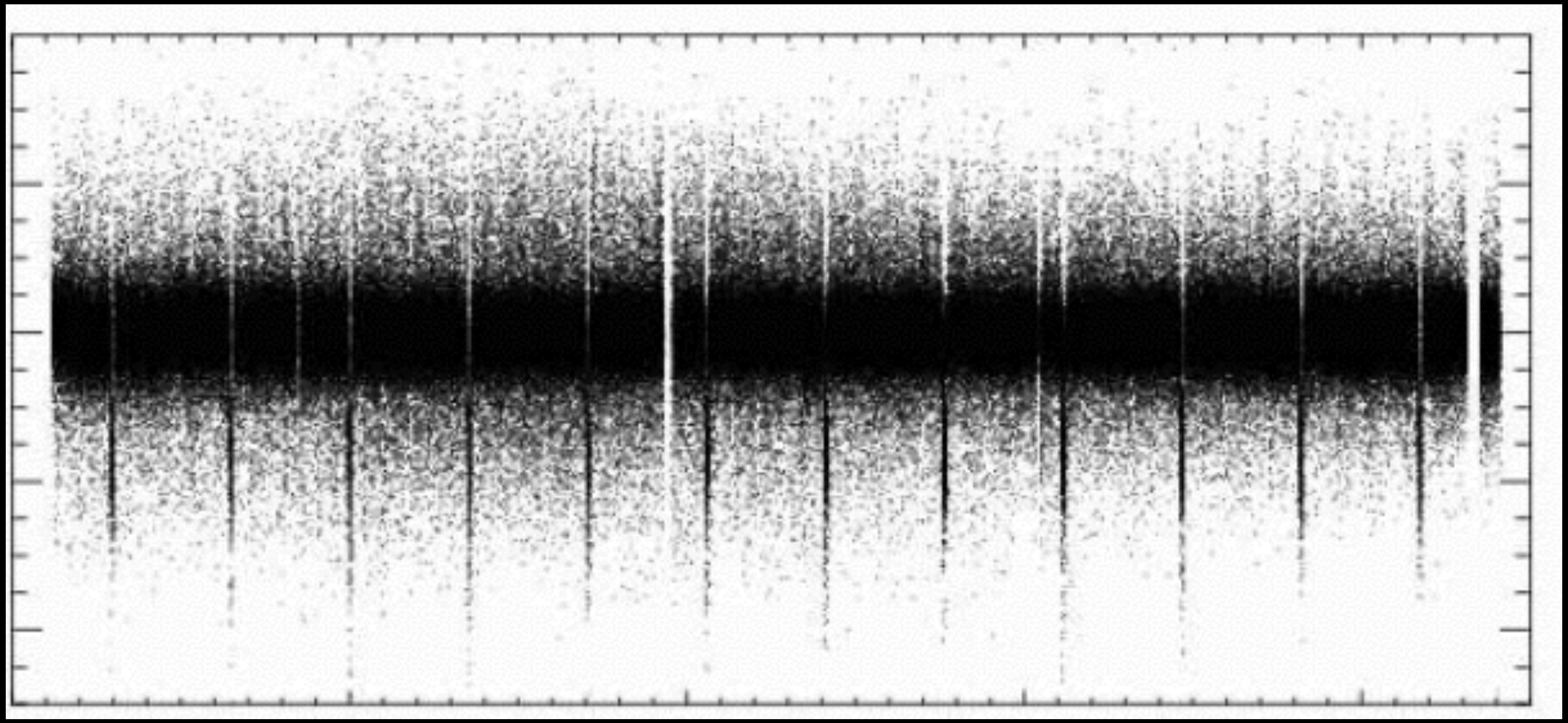
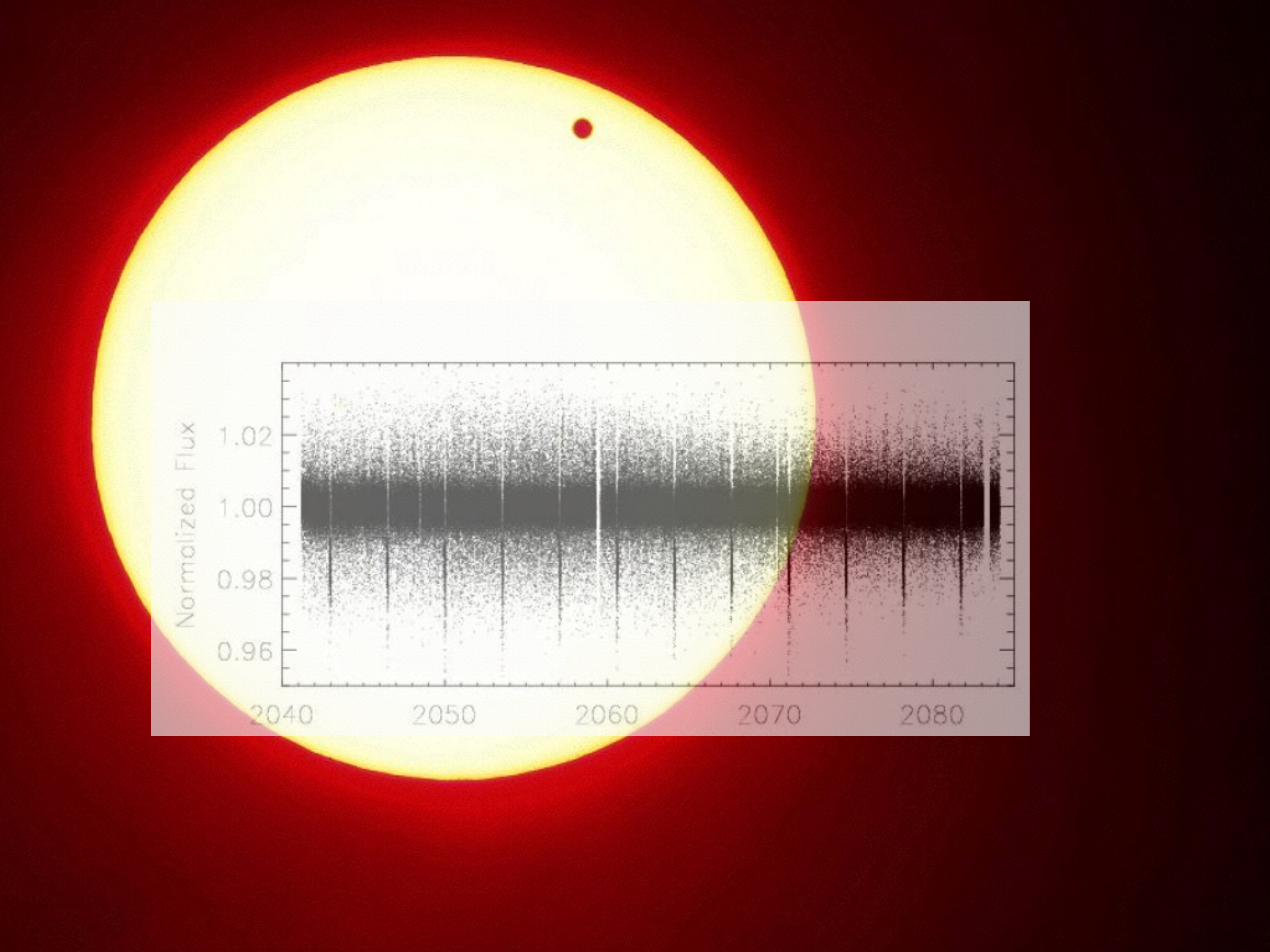
1850
1900
1950
2000
Year

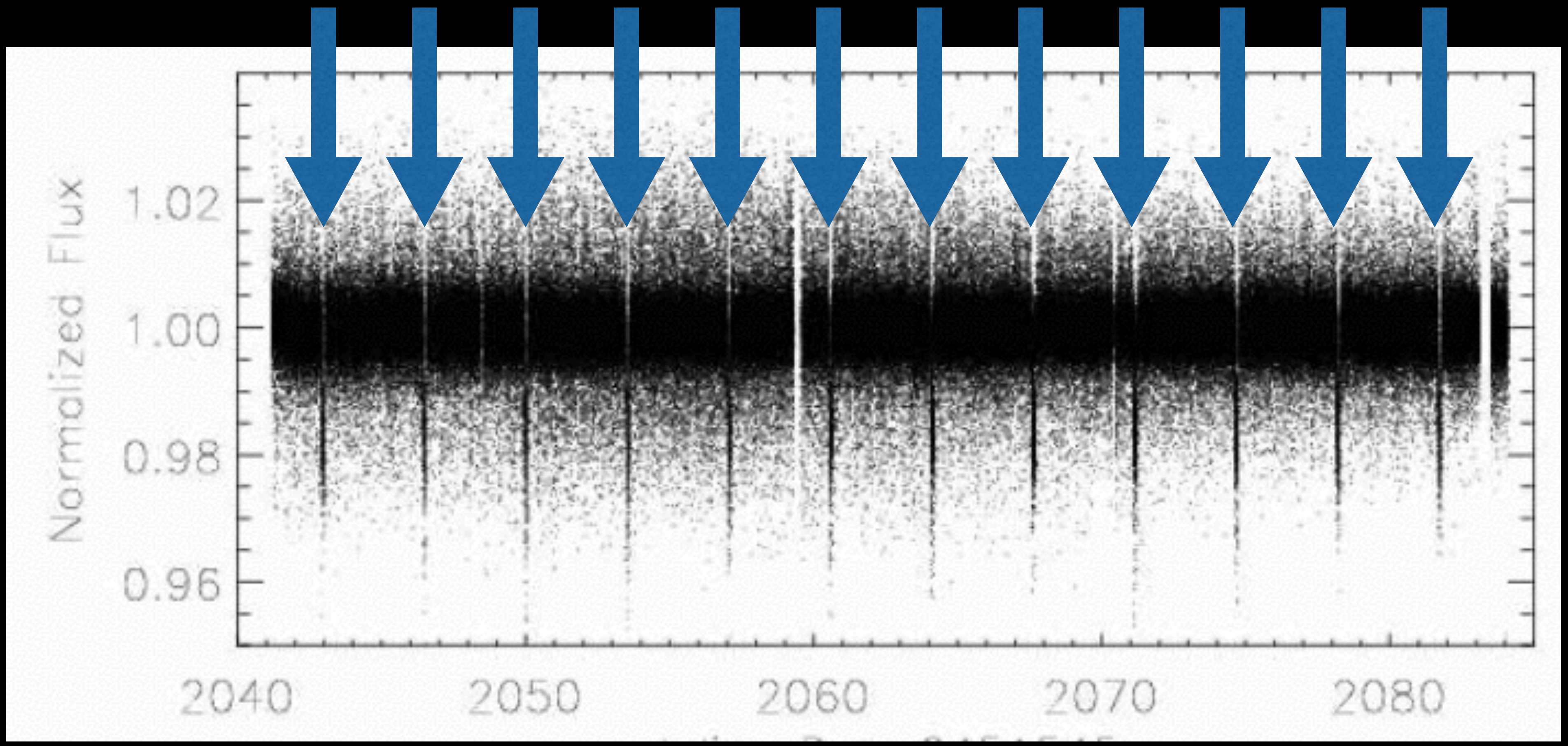
Trends





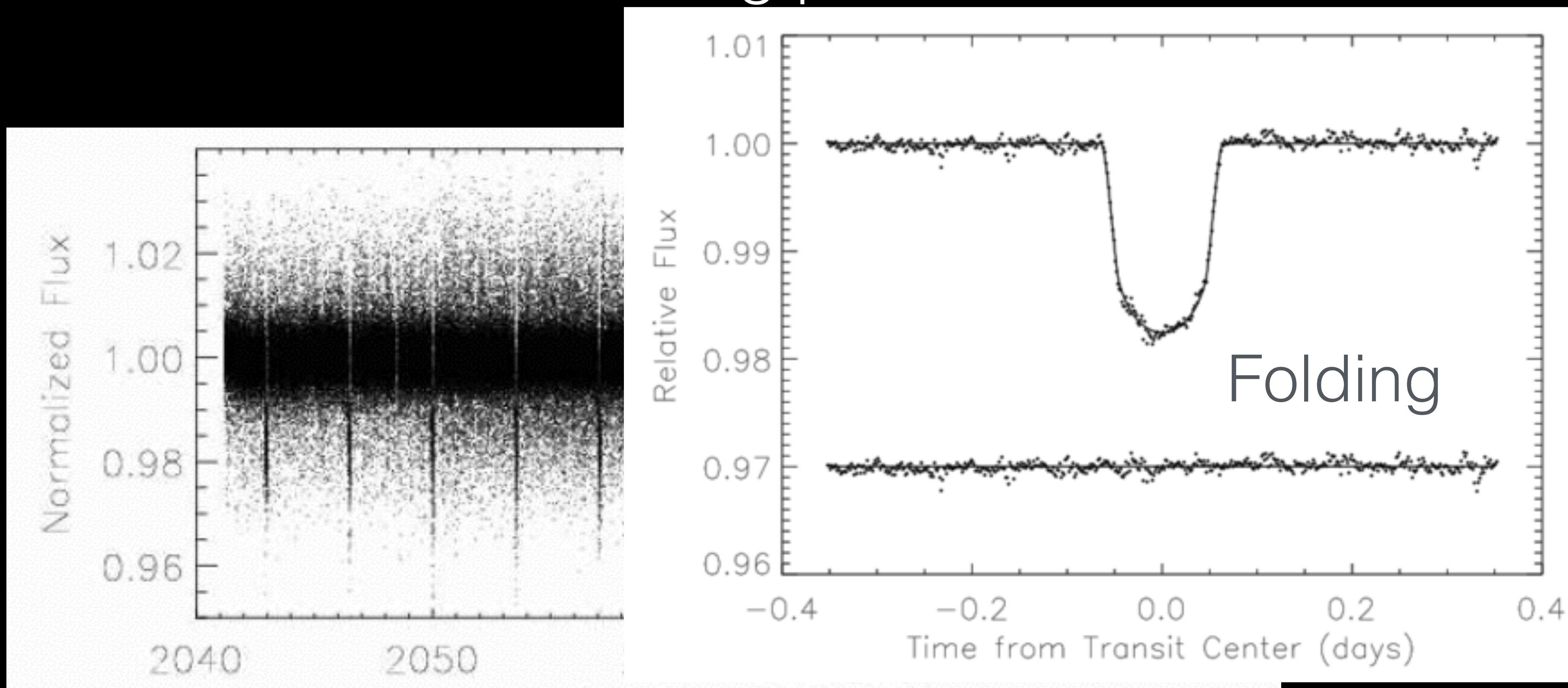
Normalized Flux
1.02
1.00
0.98
0.96
2040
2050
2060
2070
2080

HD 209458, the first transiting planet to be discovered.

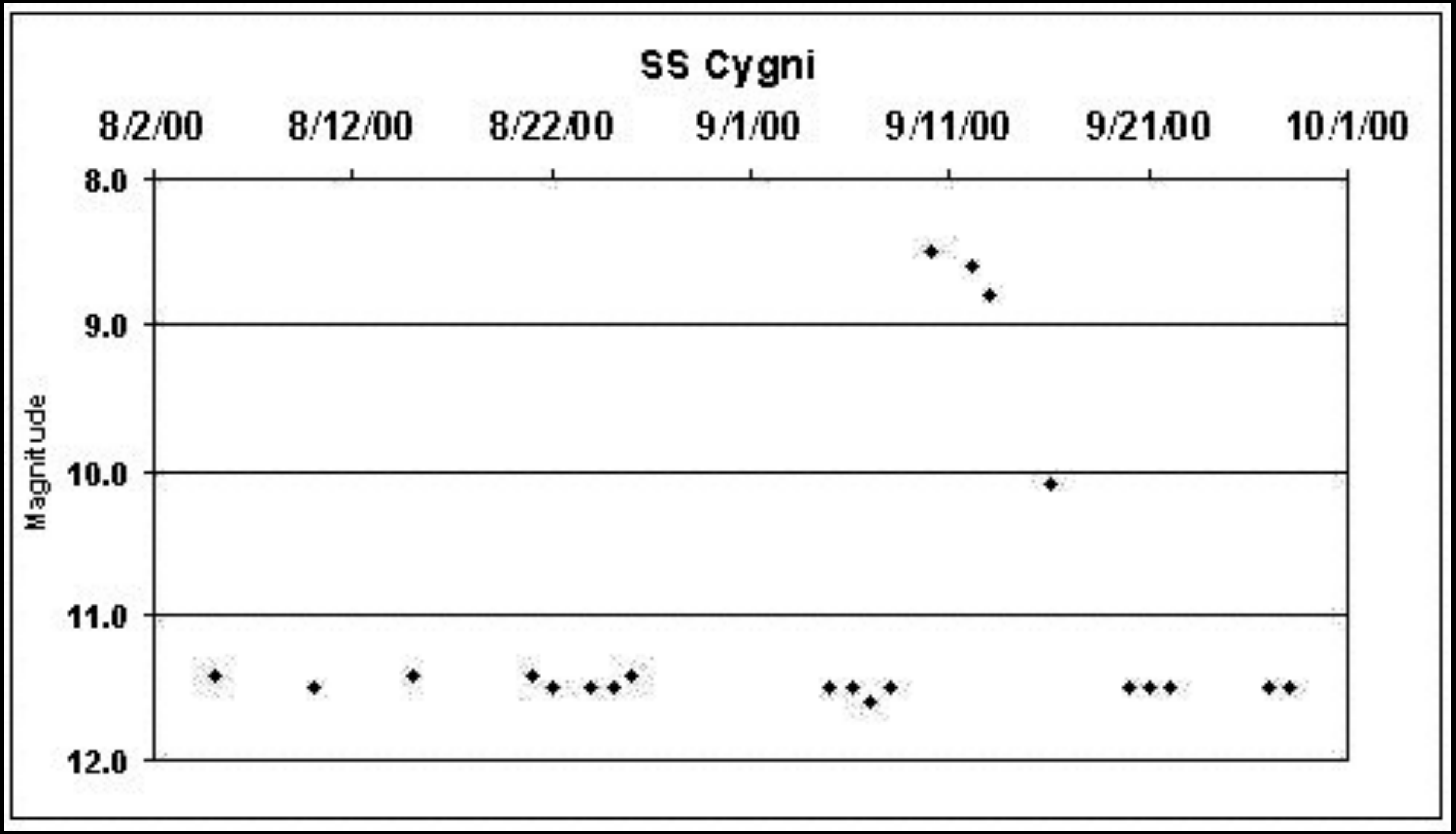


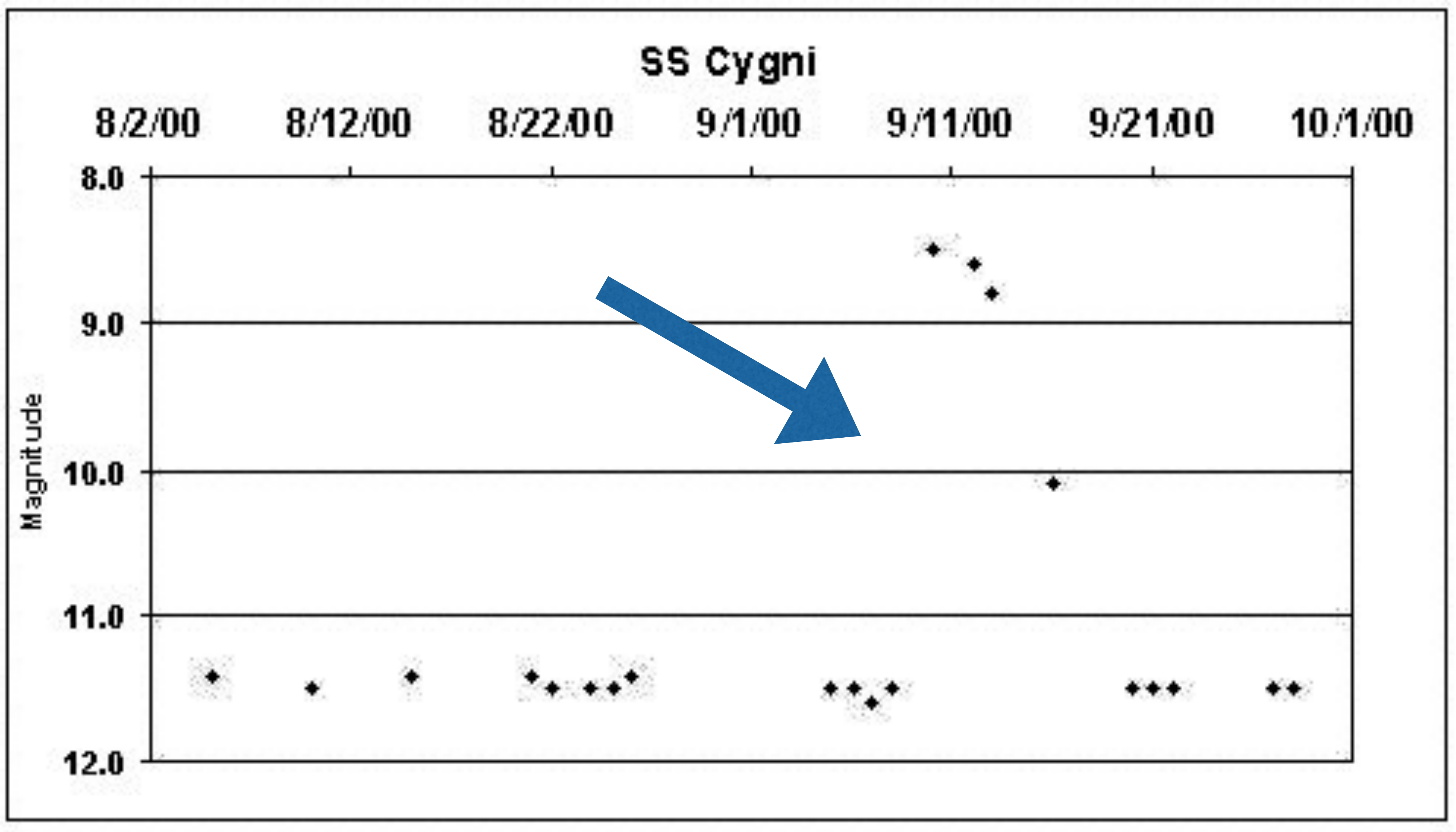
Periodicity

HD 209458, the first transiting planet to be discovered.

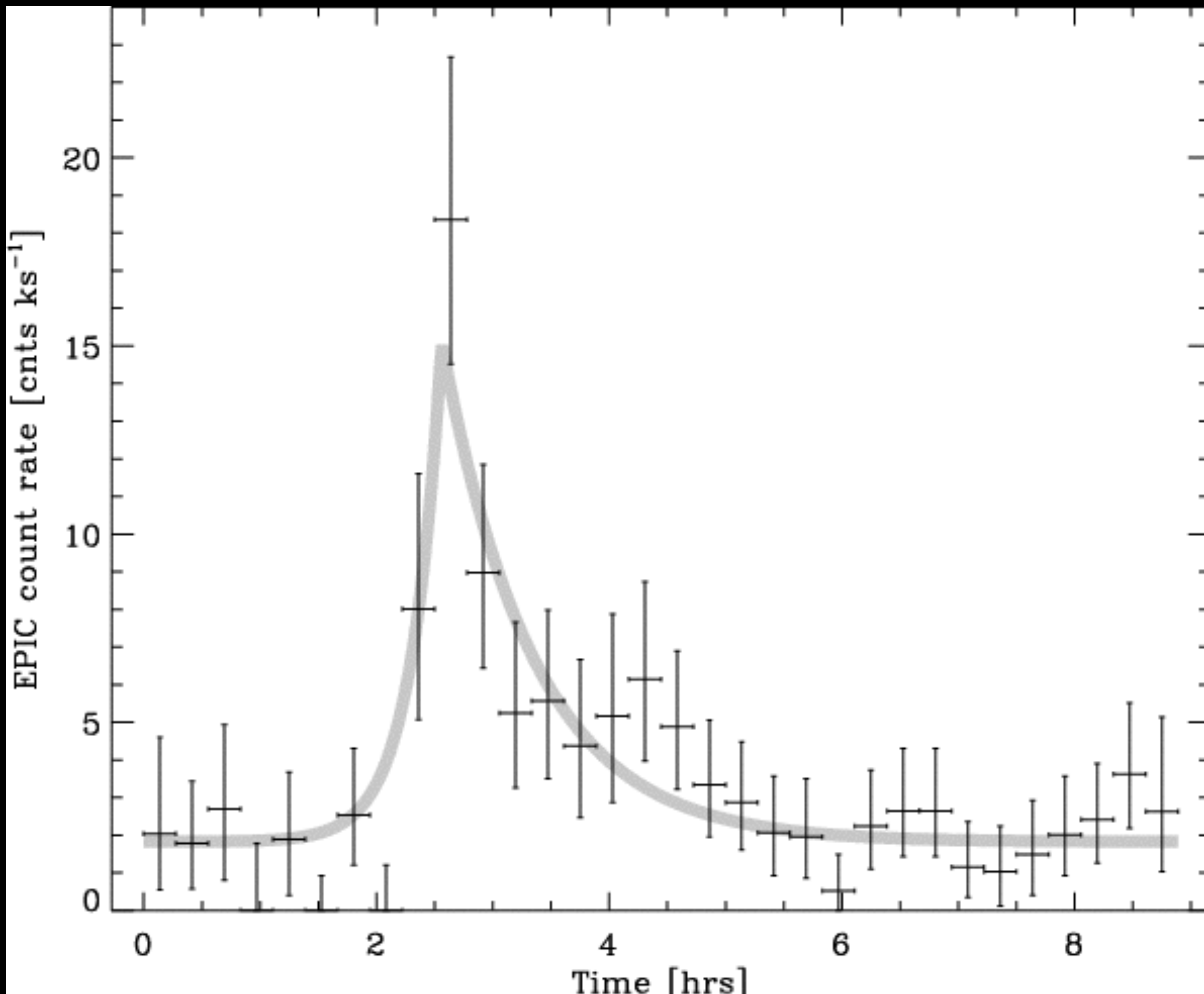


Periodicity

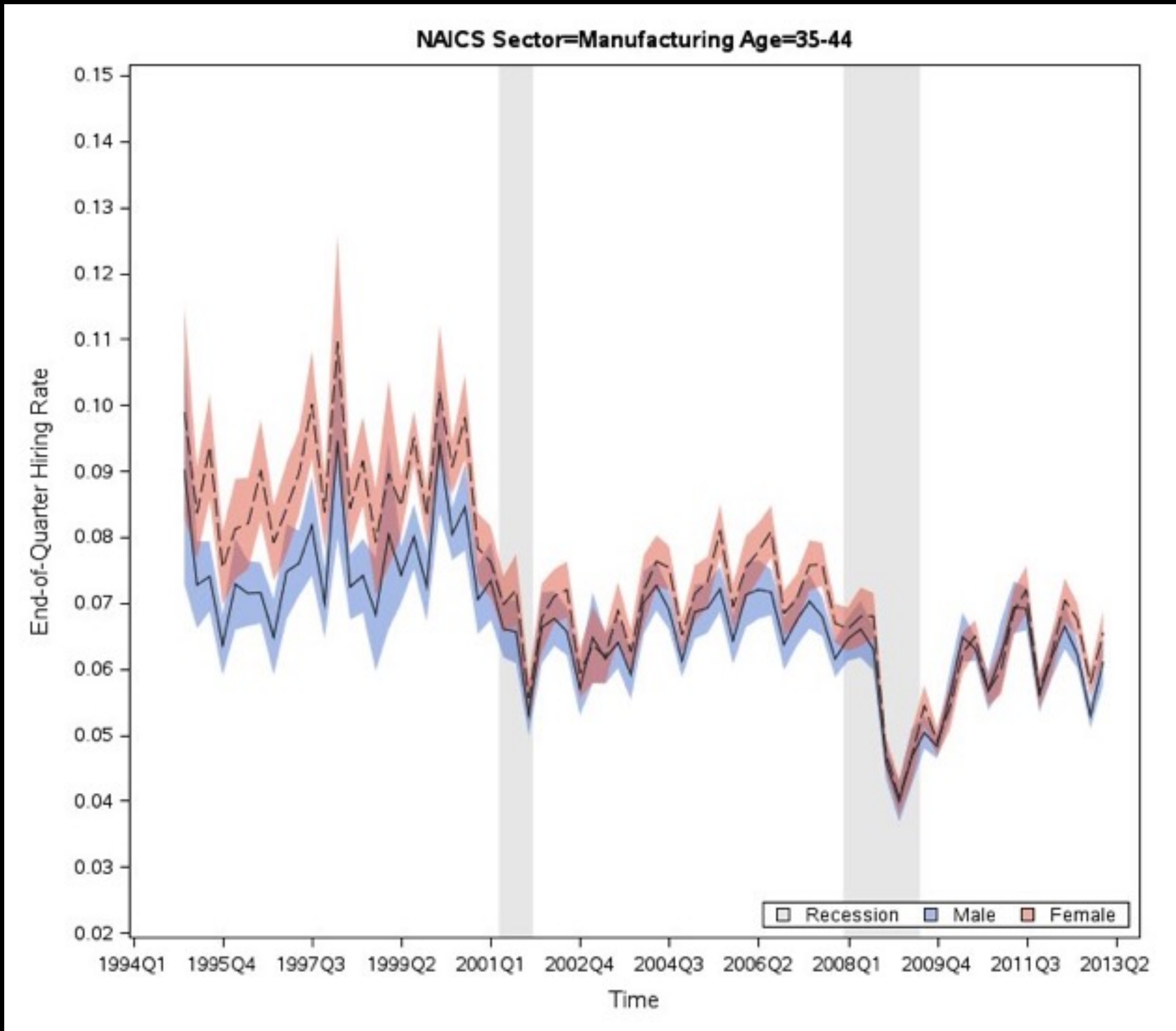

SS Cygni
8/2/00
8/12/00
8/22/00
9/1/00
9/11/00
9/21/00
10/1/00
8.0
9.0
10.0
11.0
12.0
Magnitude



event detection

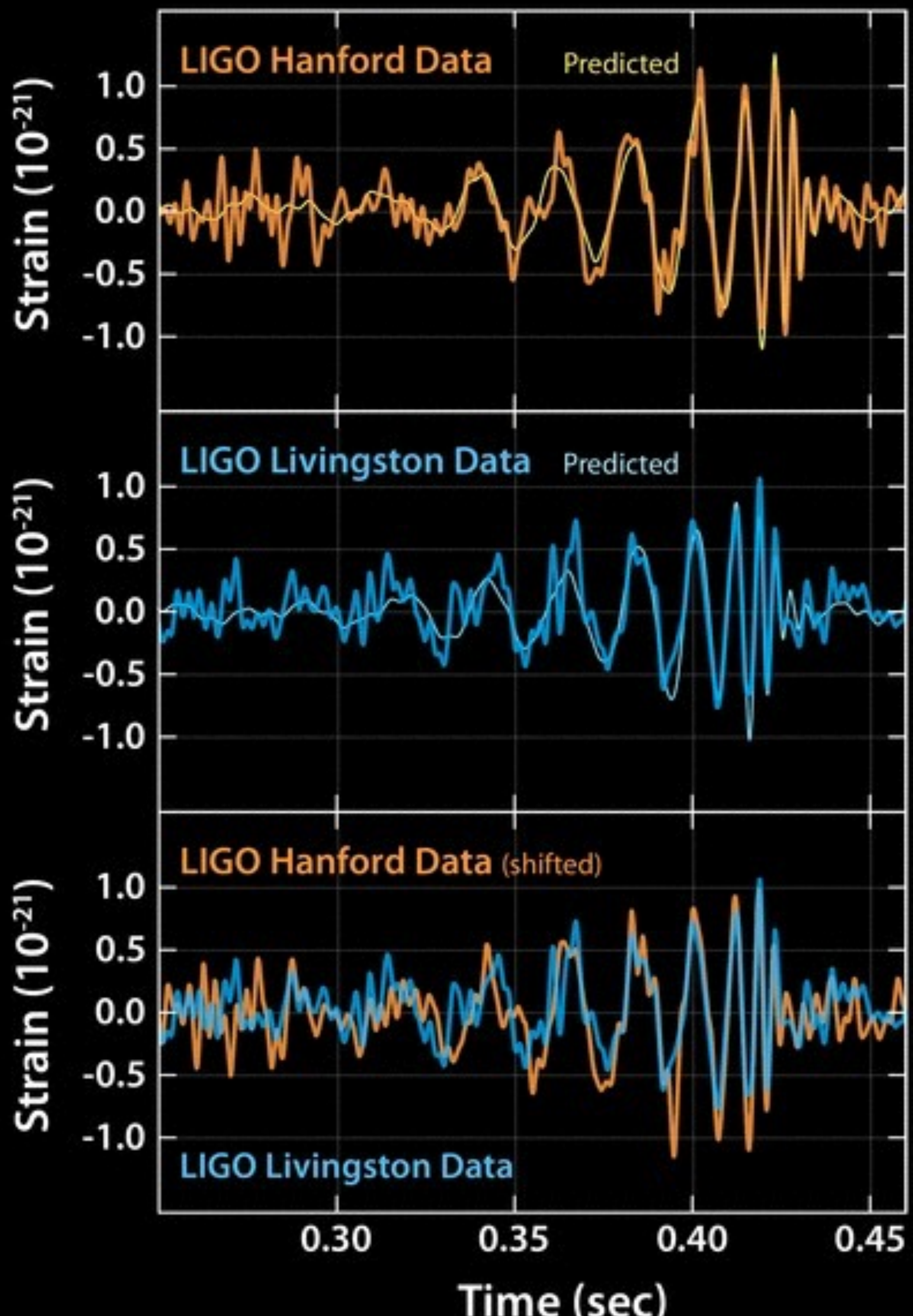


event detection



event detection

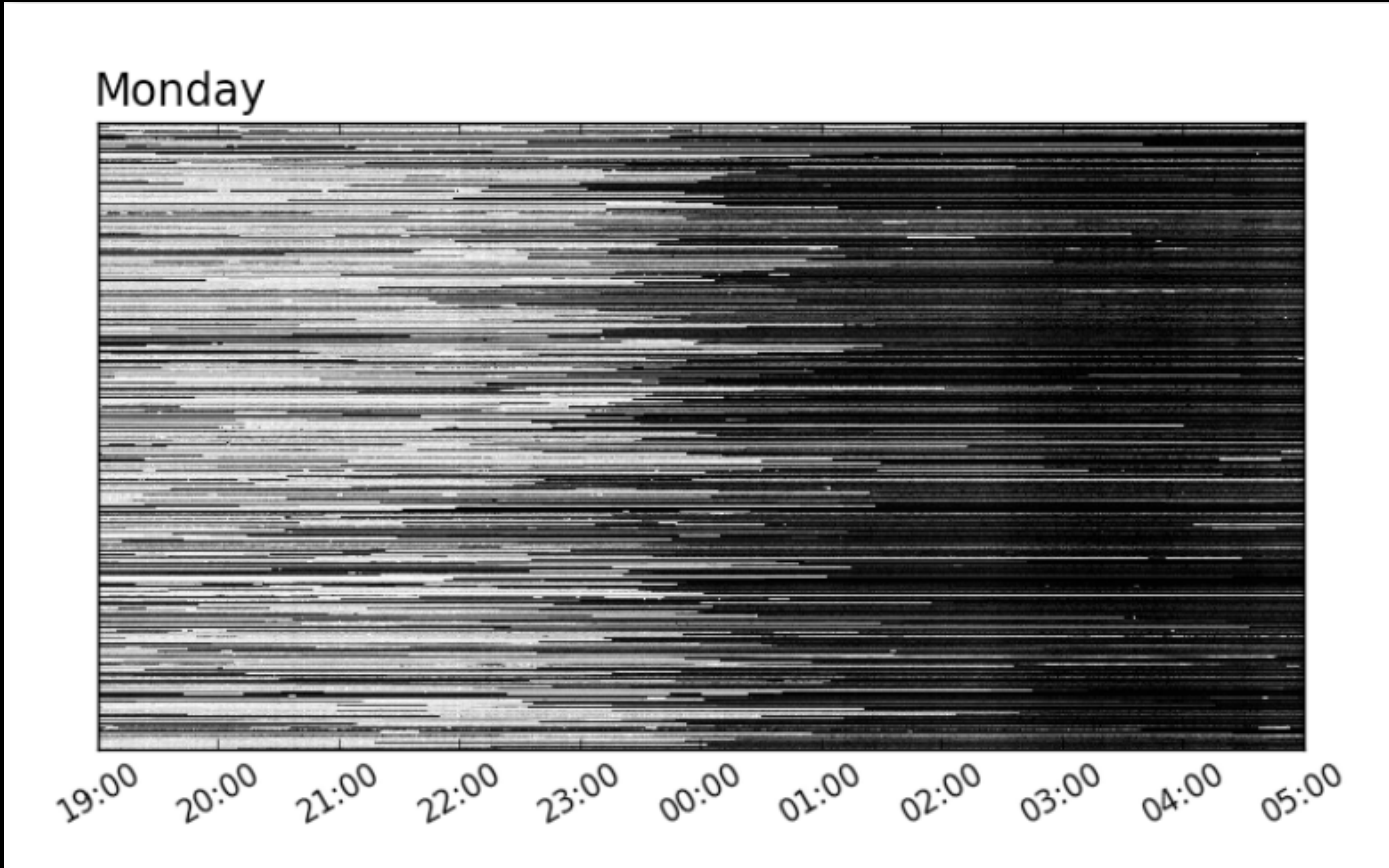
LEHD data (Prof. Julia Lane)



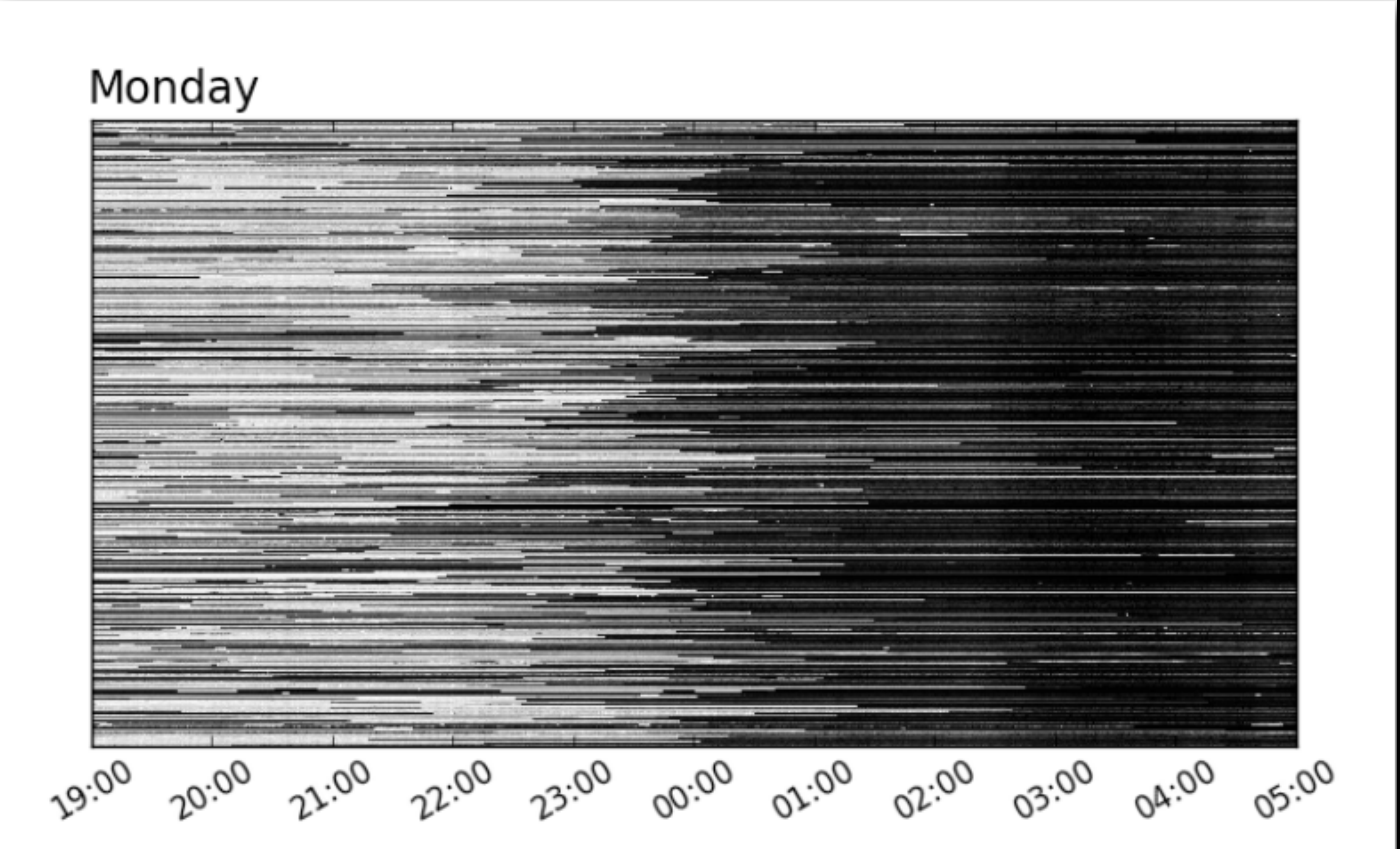
event detection

LIGO gravitational wave detection

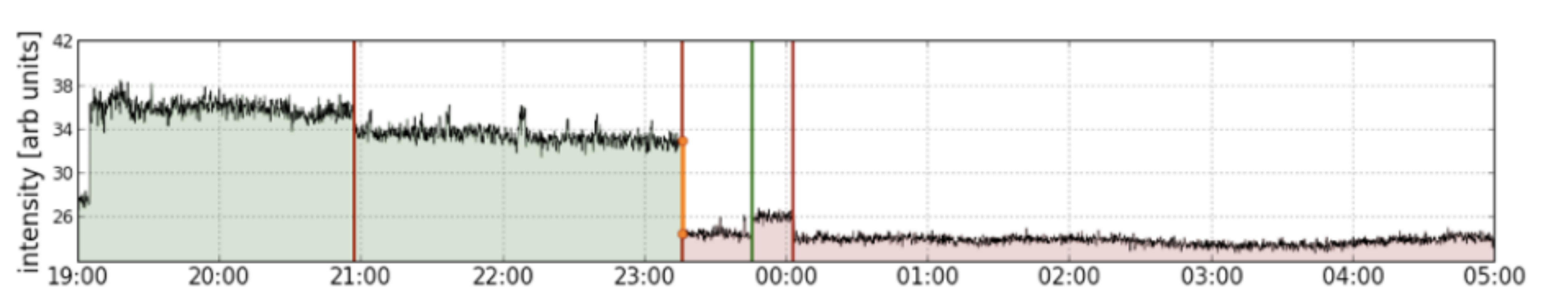
Abbott et al. Physical Review Letters 116, 061102 (2016)



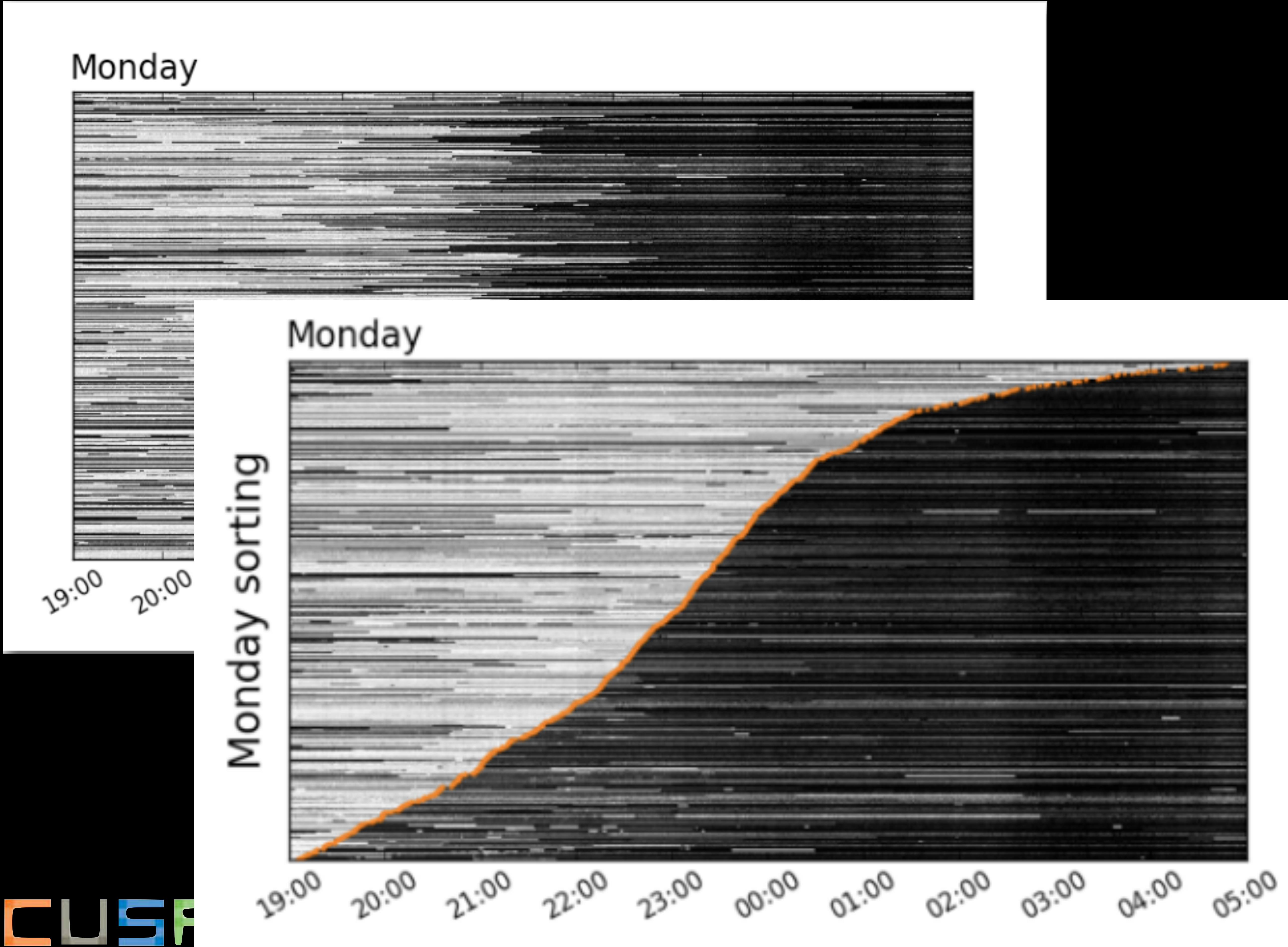
http://www.sciencedirect.com/science/article/pii/S0306437915001167

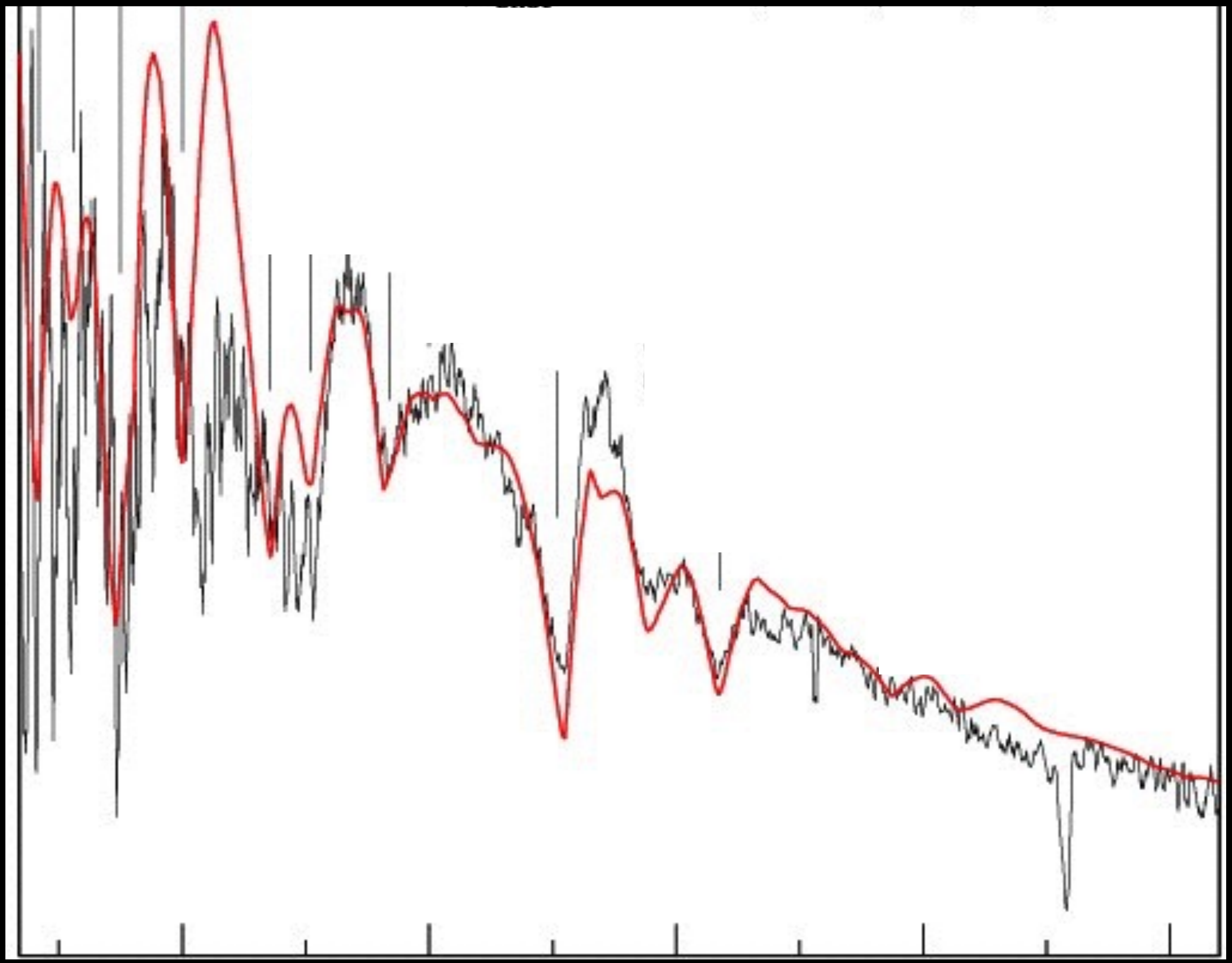


Monday
19:00
20:00
21:00
22:00
23:00
00:00
01:00
02:00
03:00
04:00
05:00

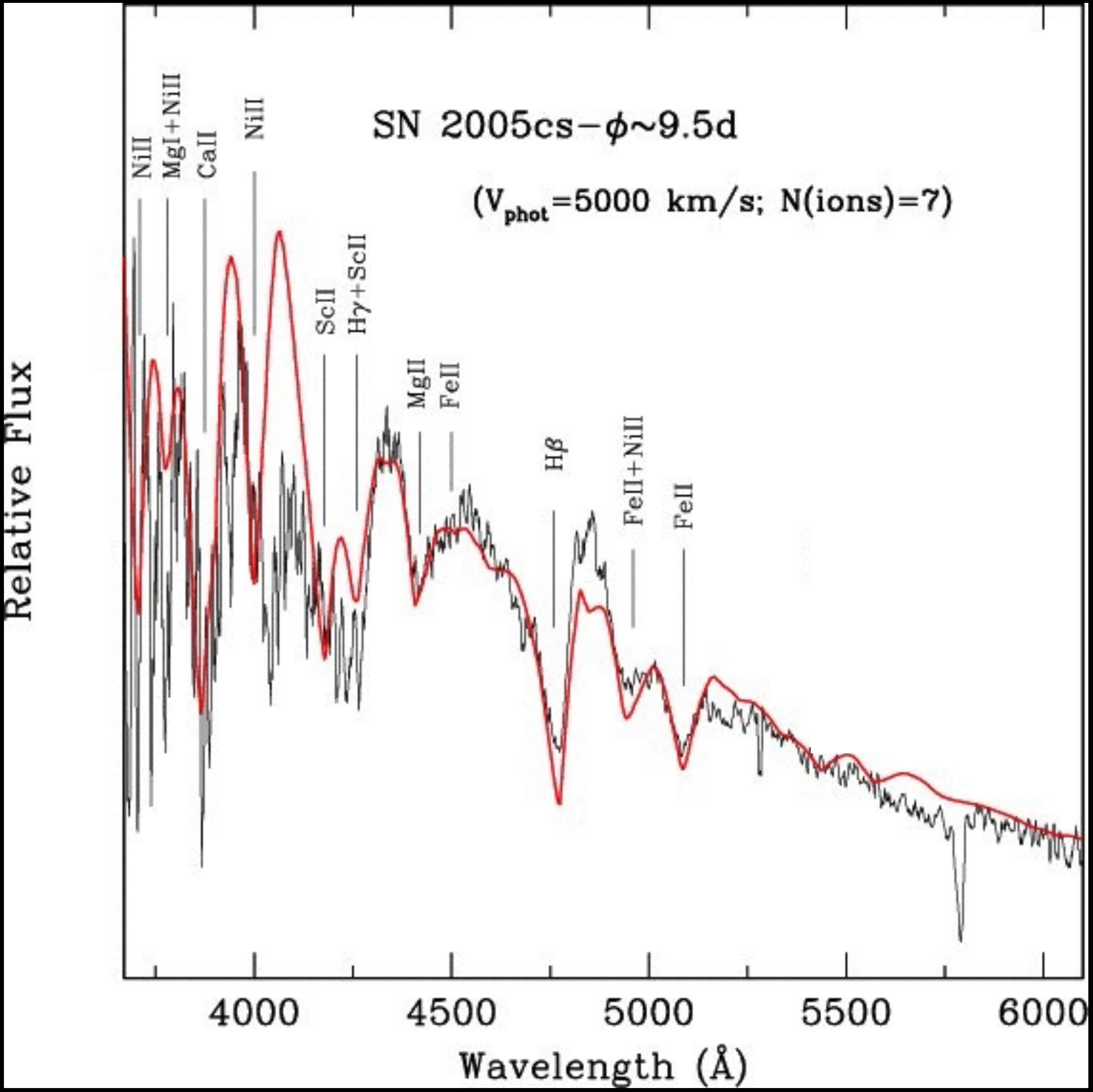


intensity [arb units]
42
38
34
30
26
19:00
20:00
21:00
22:00
23:00
00:00
01:00
02:00
03:00
04:00
05:00

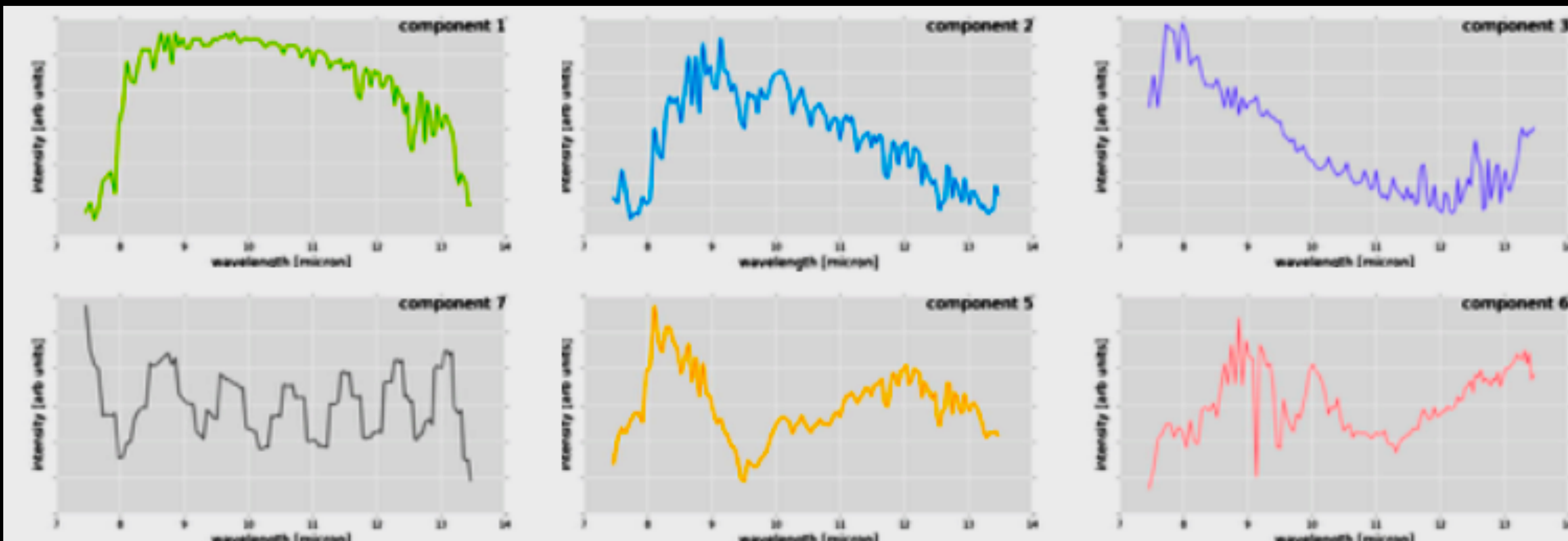

Monday
19:00
20:00
Monday
Monday sorting
19:00
20:00
21:00
22:00
23:00
00:00
01:00
02:00
03:00
04:00
05:00



they do not have to be *TIME* series!



CUSP-UO spectra of urban lights for light technology assessment



- event detection

- event detection
- identification of trends

- event detection
- identification of trends
- periodicity detection

- event detection
- identification of trends
- periodicity detection
- prediction

- event detection
- identification of trends
- periodicity detection
- prediction
- classification (clustering)

- event detection

Thresholding

jupyter

- event detection:

Thresholding

jupyter

- take the mean (possibly a local mean)
- take the standard deviation (possibly a local stdev)
- find points that deviate from the mean by more than N standard deviation

https://github.com/fedhere/UInotebooks/blob/master/FDNYdeaths.ipynb

- event detection
- identification of trends

Stationary data
Smoothing (Rolling mean)
ADFuller test for unit root (for non-stationarity)

jupyter

https://github.com/fedhere/UInotebooks/blob/master/timeseries/stationarity.ipynb

- event detection
- identification of trends
- periodicity detection

ARMA/ARIMA

jupyter

http://www.statsref.com/HTML/index.html?arima.html

http://www.econ.ohio-state.edu/dejong/note2.pdf

ARIMA

Moving Average Model

$$x(t) = \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t + \mu$$

ARIMA

Autoregression

$$x(t)=a_1 x(t-1)+\epsilon_t$$

Moving Average Model

$$x(t)=\sum_{i=1}^{q}\theta_i \varepsilon_{t-i}+\varepsilon_t$$

ARIMA

Autoregression

$$x(t) = a_1 x(t-1) + \epsilon_t$$

$$x(t) = a_1 x(t-1) + a_2 x(t-2) + \ldots + a_n x(t-n) + \epsilon_t$$

Moving Average Model

$$x(t) = \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t$$

Integration

$$x'(t)=x(t)-x(t-i)$$

ARIMA

Autoregression

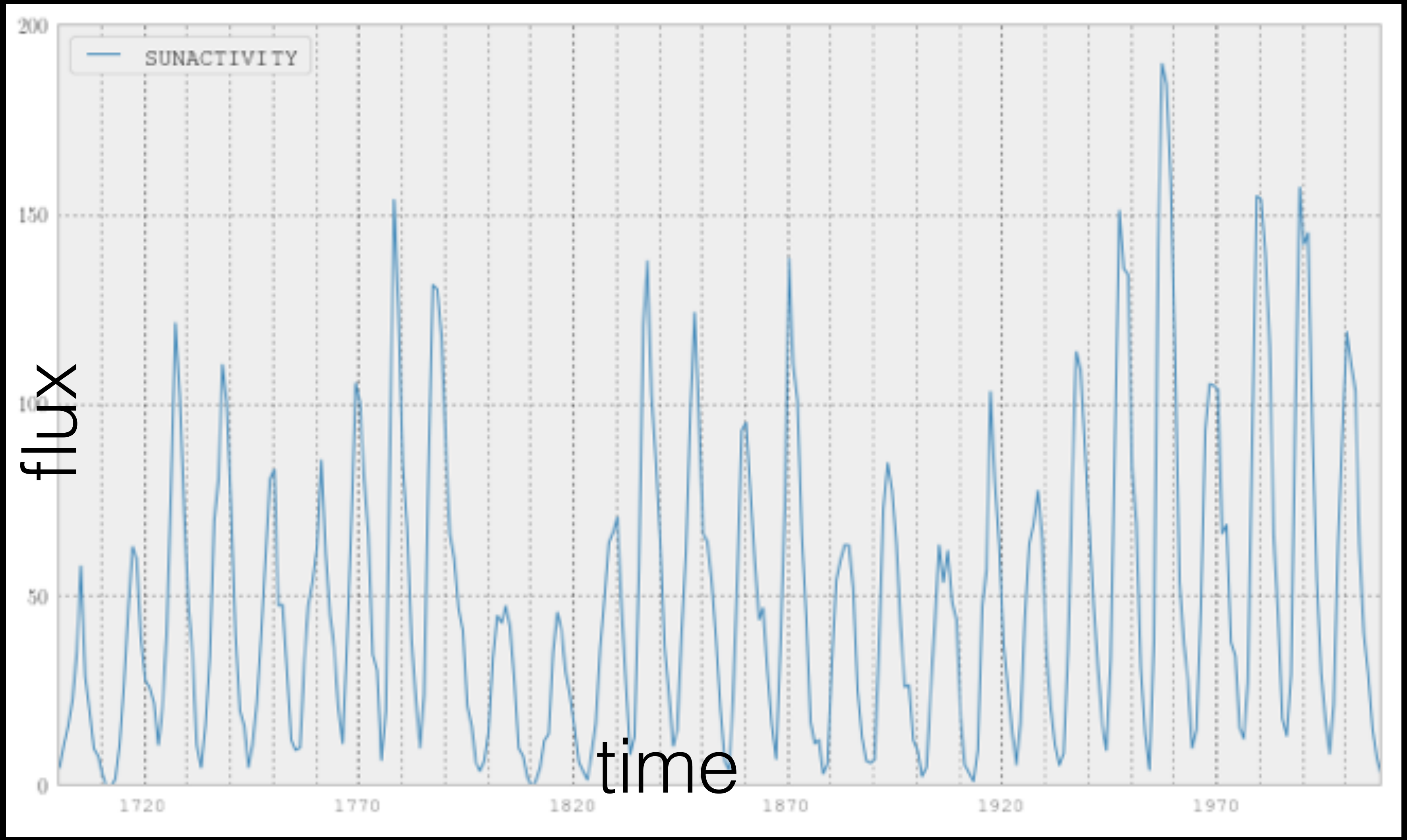
$$x(t)=\sum_{i=1}^{p} a_i x_{t-i} + \varepsilon_t$$

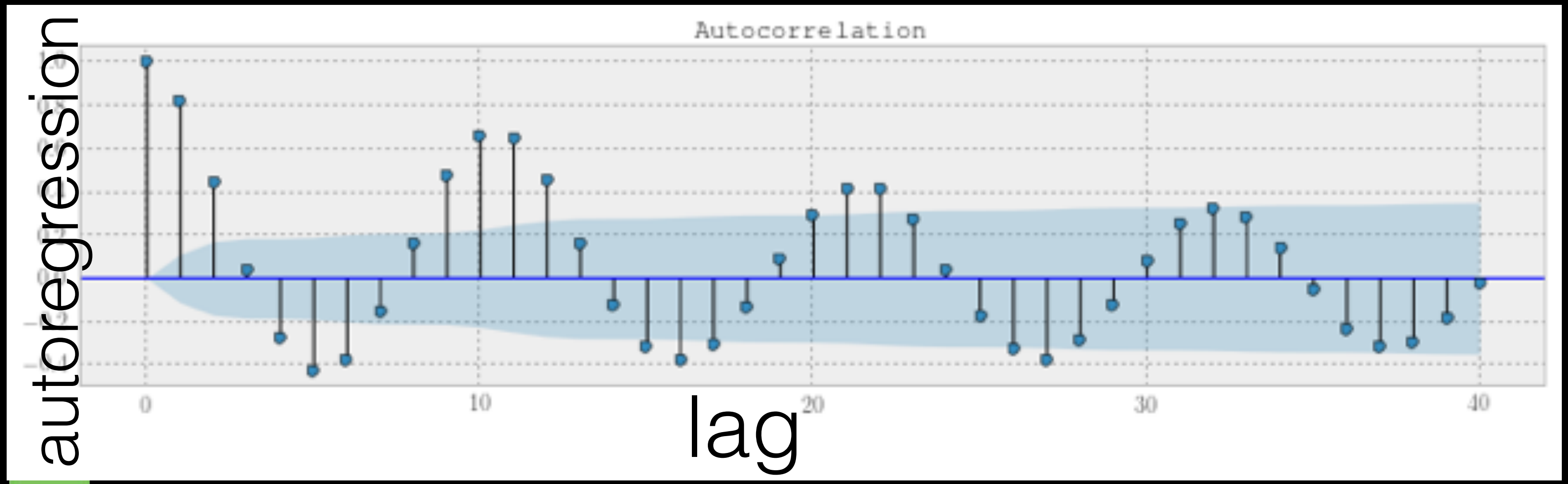
Moving Average Model

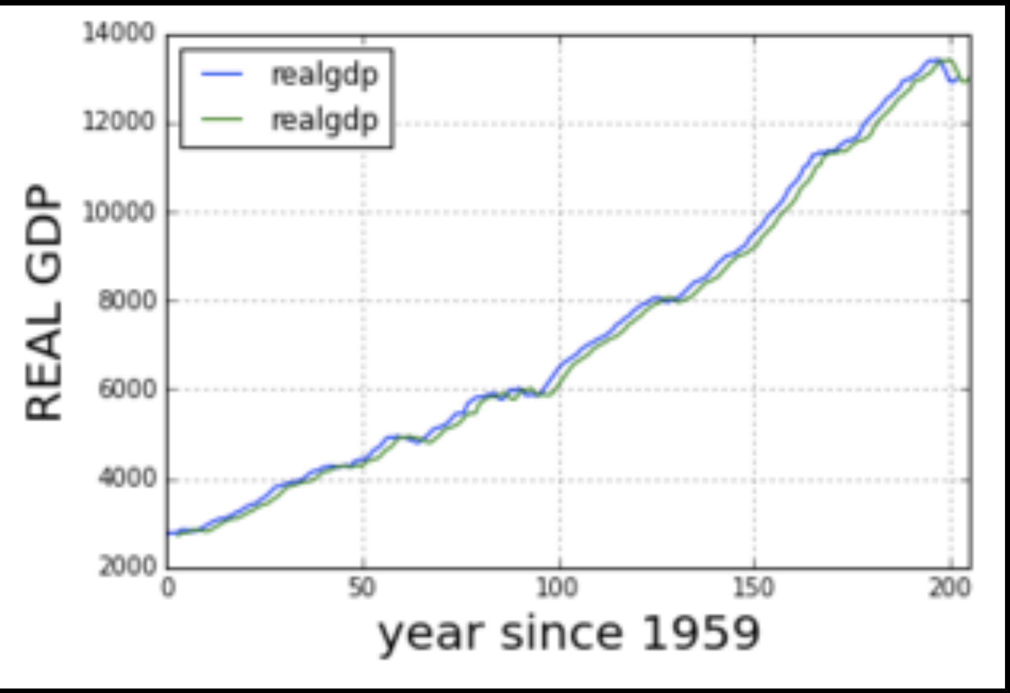
$$x(t)=\sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t + \mu$$

jupyter

http://statsmodels.sourceforge.net/devel/examples/notebooks/generated/tsa_arma_0.html

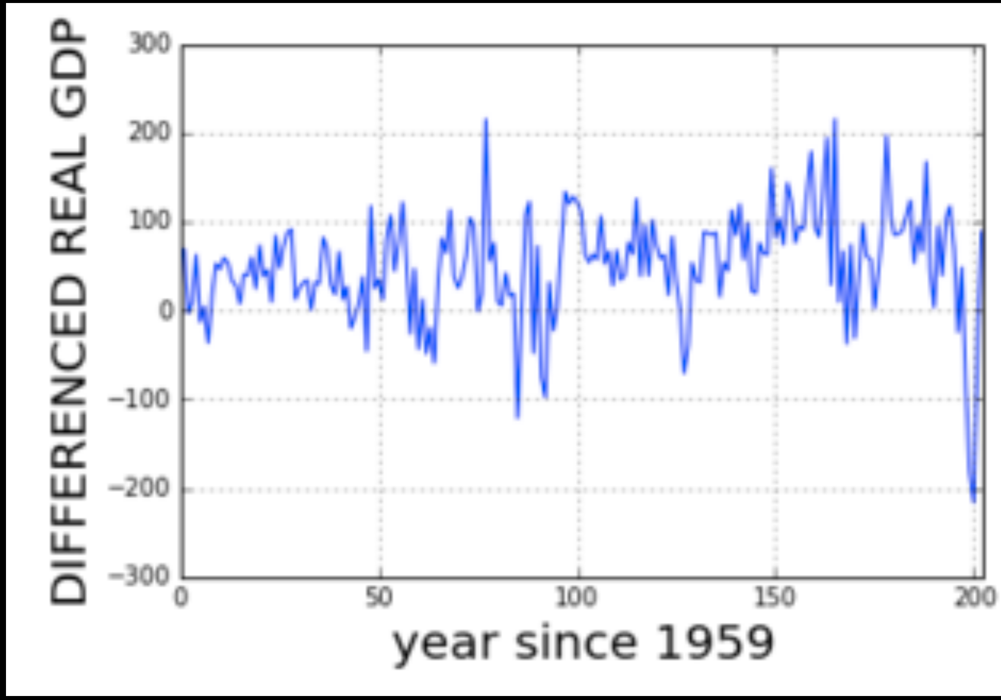






Integration

$$x'(t)=x(t)-x(t-i)$$



ARIMA

Autoregression

$$x(t)=\sum_{i=1}^{p} a_i x_{t-i}+\varepsilon_t$$

Moving Average Model

$$x(t)=\sum_{i=1}^{q} \theta_i \varepsilon_{t-i}+\varepsilon_t + \mu$$

jupyter

https://github.com/fedhere/UInotebooks/blob/master/ARMA_microdata.ipynb

CUSP

Fourier

$$F(\omega) = \frac{1}{2\pi} \int f(t) e^{-i\omega t} \, dt$$

Fourier

$$F(\omega)=\frac{1}{2\pi}\int f(t)e^{-i\omega t}\ dt$$

takes a function in time domain

Fourier

$$F(\omega)=\frac{1}{2\pi}\int f(t)e^{-i\omega t}\ dt$$

takes a function in time domain

to a function in frequency domain

Fourier

$$F(\omega) = \frac{1}{2\pi} \int f(t) e^{-i\omega t} \; dt$$

takes a function in space domain

to a function in spatial frequency domain

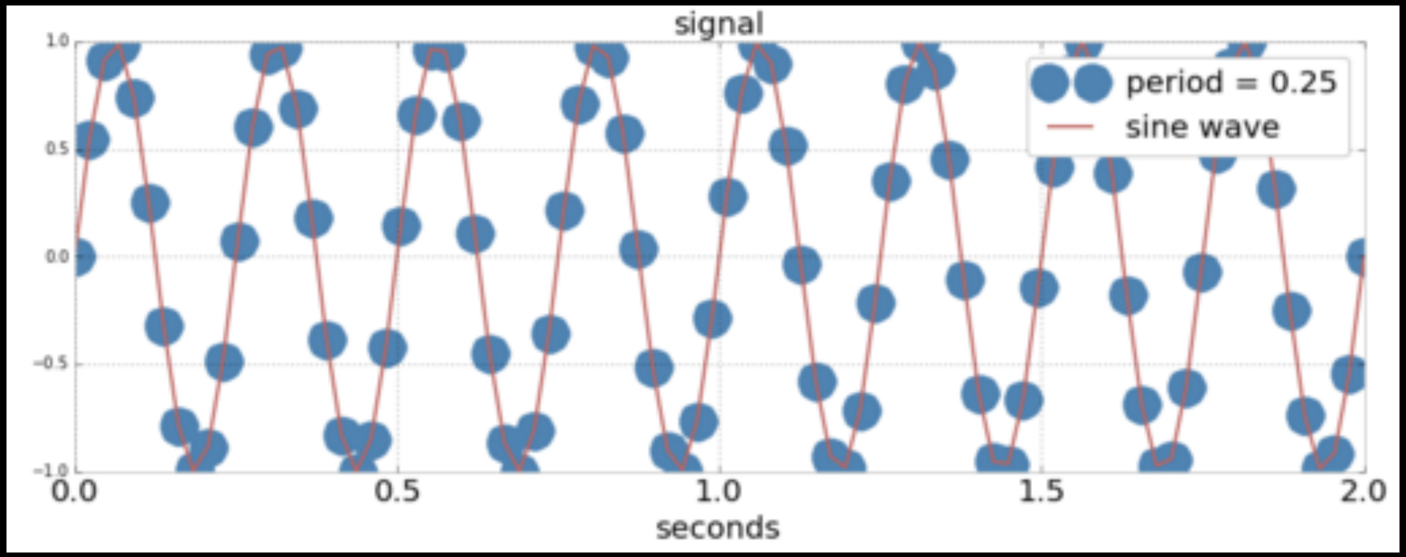
Fourier

$$F(\omega)=\frac{1}{2\pi}\int f(t)e^{-i\omega t}\ dt$$

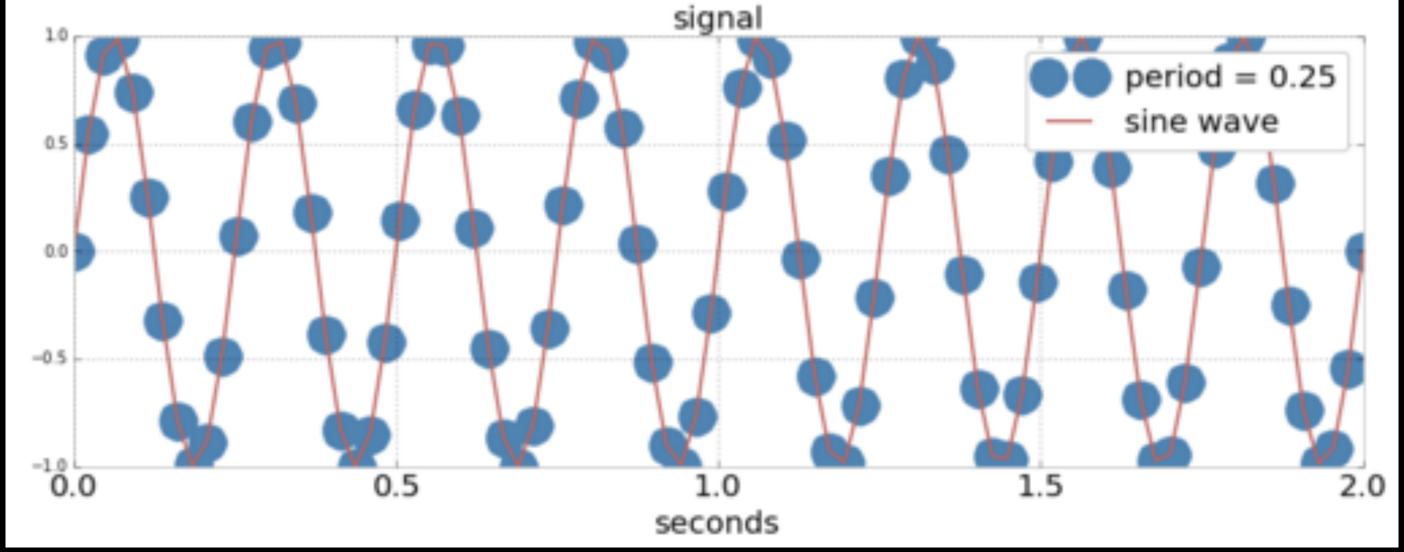
takes a function in space domain
f(t) is measured in seconds

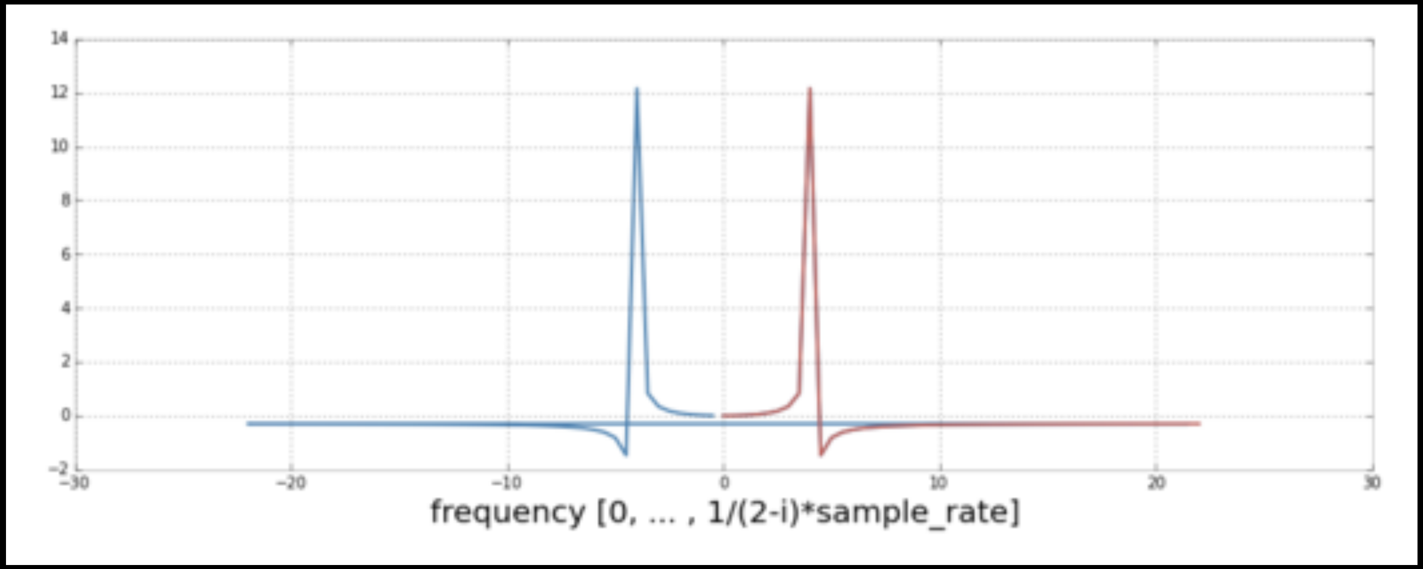
to a function in spatial frequency domain
f(t) is measured in 1/seconds
or Hz

Fourier


signal
period = 0.25
sine wave
1.0
0.5
0.0
−0.5
−1.0
0.0
0.5
1.0
1.5
2.0
seconds

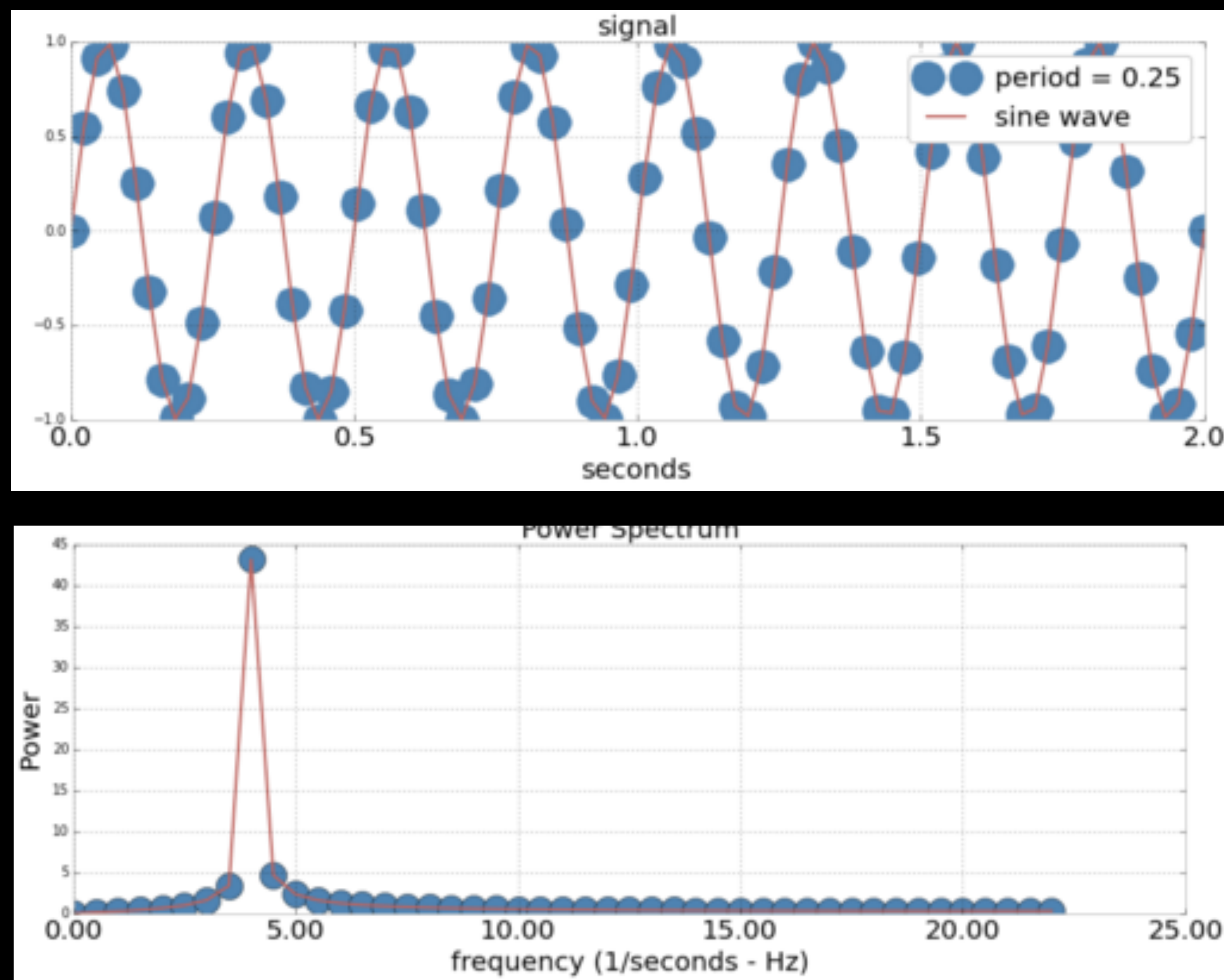
Fourier


signal
period = 0.25
sine wave
1.0
0.5
0.0
−0.5
−1.0
0.0
0.5
1.0
1.5
2.0
seconds

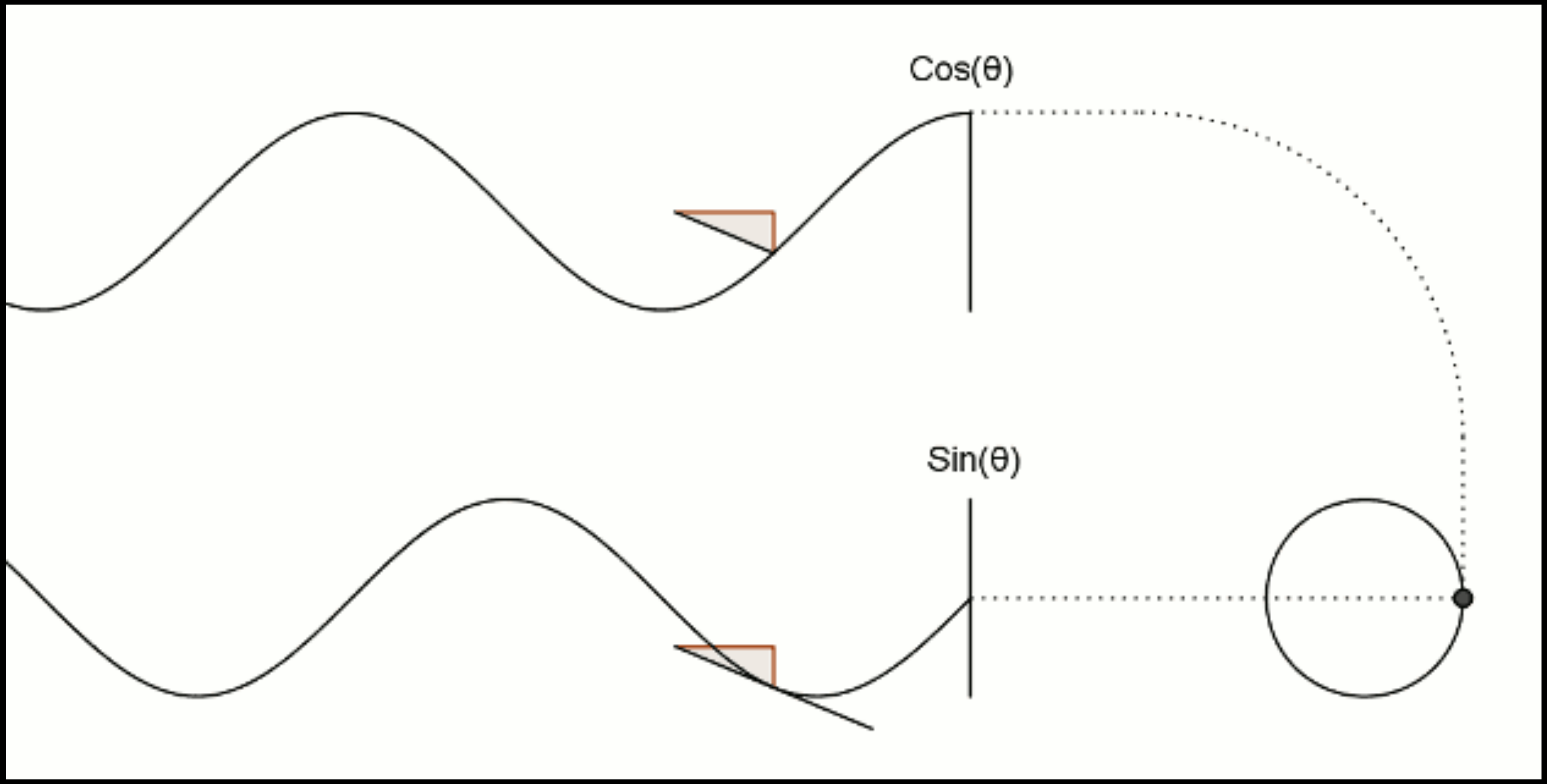

14
12
10
8
6
4
2
0
−2
−30
−20
−10
0
10
20
30
frequency [0, ... , 1/(2-i)*sample_rate]

The absolute value of the square of the Fourier transform this is called a Power spectrum.
High value of the power spectrum indicate periodicity at the corresponding frequency

Fourier



Cosine and Sine… just in case



http://www.businessinsider.com/7-gifs-trigonometry-sine-cosine-2013-5

Fourier

https://github.com/fedhere/UInotebooks/blob/master/fourier.ipynb

Homework:

Technical reading on SM time analysis tools. Get through ARMA

http://conference.scipy.org/proceedings/scipy2011/pdfs/statsmodels.pdf

https://jakevdp.github.io/blog/2014/06/10/is-seattle-really-seeing-an-uptick-in-cycling/

Reading: an excellent analysis of time series
by Jake Vander Plas
(UW e-science center)

Homework:

Data:

MTA subway fares. It is a complete dataset of rides logged by card swipes for 600 Manhattan stations.

It contains 23 different subway card types (e.g. monthly pass, daily pass, Act for Disability pass… i will give you this as a list)

Each time series (per station, per ticket type) contains the number of swipes per week for 194 weeks from 05/21/2010 to 02/21/2014.

it is given to you as a python data cube.
you can load it as np.load("MTA_Fare.npy") and you will end up with a python numpy array of shape (600,23,194)

Homework:

Goal 1:

Some of the time series are stationary, some show a downward trend: Identify the time series with the most prominent downward trend.

Goal 2:

Event detection: Identify the most prominent event. There is a very significant drop (>3-sigma) in *all* time series.
Identify it and figure out what it is due to.

Goal 3:

Several stations show a prominent annual periodicity. Identify the 5 stations that show the most prominent periodic trend on an annual period. Figure out what the increase in rides is due to.

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Homework Hints:

Goal 1:

Some of the time series are stationary, some show a downward trend: Identify the time series with the most prominent downward trend.

work with all time series individually. you can use the rolling mean to find trends: compare rolling mean near beginning and end of time series.

Goal 2:

Event detection: Identify the most prominent event. There is a very significant drop (>3-sigma) in *all* time series.
Identify it and figure out what it is due to.

Since I am telling you the event is in all time series you can work with averages: for example average over all rise types per station. Since i am telling you it is a highly significant event you can find it by thresholding

Goal 3:

Several stations show a prominent annual periodicity. Identify the 5 stations that show the most prominent periodic trend on an annual period. Figure out what the increase in rides is due to.

Work in Fourier space: find the series that have the most prominent peak at ~1 year frequency

Homework ExtraCredit:

Cluster:

Cluster the time series: you can use KMeans for example to identify common trends. or PCA. Since this is extra credit I will leave it entirely to you to figure out the details.

for KMeans for e.g.:

```
#i am flattening the first 2 dimensions of the cube to cluster all light curves for all stations and all types
tots = data.transpose(2,0,1).reshape(data.shape[2], data.shape[1]*data.shape[0]).T
#removing empty light curves
tots = tots[tots.std(1)>0]
#ith Kmeans you have to choose the number of clusters ahead km = KMeans(n_clusters=10)
#and standardize the lightcurves before clustering
vals = ((tots.T - tots.mean(1))/tots.std(1)).T
km.fit(vals)
```

Key points:

- Time series analysis may be done for a number of purposes: classification, prediction, event detection, period finding
- smoothing, binning, detrending (difference, regression)
- prediction tools: autoregression, ARMA, ARIMA
- period finding (Fourier analysis)

References:

Statistical Analysis Handbook
http://www.statsref.com/HTML/index.html

Stationary and non stationary time series
http://www.cas.usf.edu/~cconnor/geolsoc/html/chapter11.pdf

ARMA & ARIMA
http://www.econ.ohio-state.edu/dejong/note2.pdf

A basic but quite intuitive Fourier Transform tutorial
http://www.thefouriertransform.com/

Fourier Transform for Imaging: it is actually a very common image analysis technique and urban science relies a lot on imaging and computer-vision techniques http://homepages.inf.ed.ac.uk/rbf/HIPR2/fourier.htm

Time series classification in python, not covered but you should read about it!
http://alexminnaar.com/time-series-classification-and-clustering-with-python.html

References on clustering

Clustering: Science or Art??
Ulrike von Luxburg, Robert C. Williamson, Isabelle Guyon, 2009
http://users.cecs.anu.edu.au/~williams/papers/P184.pdf

Determining the number of groups from
measures of cluster stability
G. Bel Mufti, P. Bertrand and L. El Moubarki, 2005
http://citeseerx.ist.psu.edu/viewdoc/download?
doi=10.1.1.98.4941&rep=rep1&type=pdf

Clustering technique-based least square support vector machine for EEG signal classification
Siulya, Yan Lia, Peng (Paul) Wenb, 2010
(This is in the field of neuroscience, but it discusses clustering of time series. You should have access to it from an NYU internet connection)
http://www.sciencedirect.com/science/article/pii/S0169260710002907