Urban Informatics

Fall 2017

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@fedhere

Recap:

- Good practices with data: falsifiability, reproducibility
- Basic data retrieving and munging: APIs, Data formats
- SQL
- Basic statistics: distributions and their moments
- Hypothesis testing: p-value, statistical significance
- Statistical and Systematic errors
- Goodness of fit tests
- Likelihood
- OLS
- topics in Geospatial analysis

Recap:

- Good practices with data: falsifiability, reproducibility
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- Statistical and Systematic errors
- Goodness of fit tests
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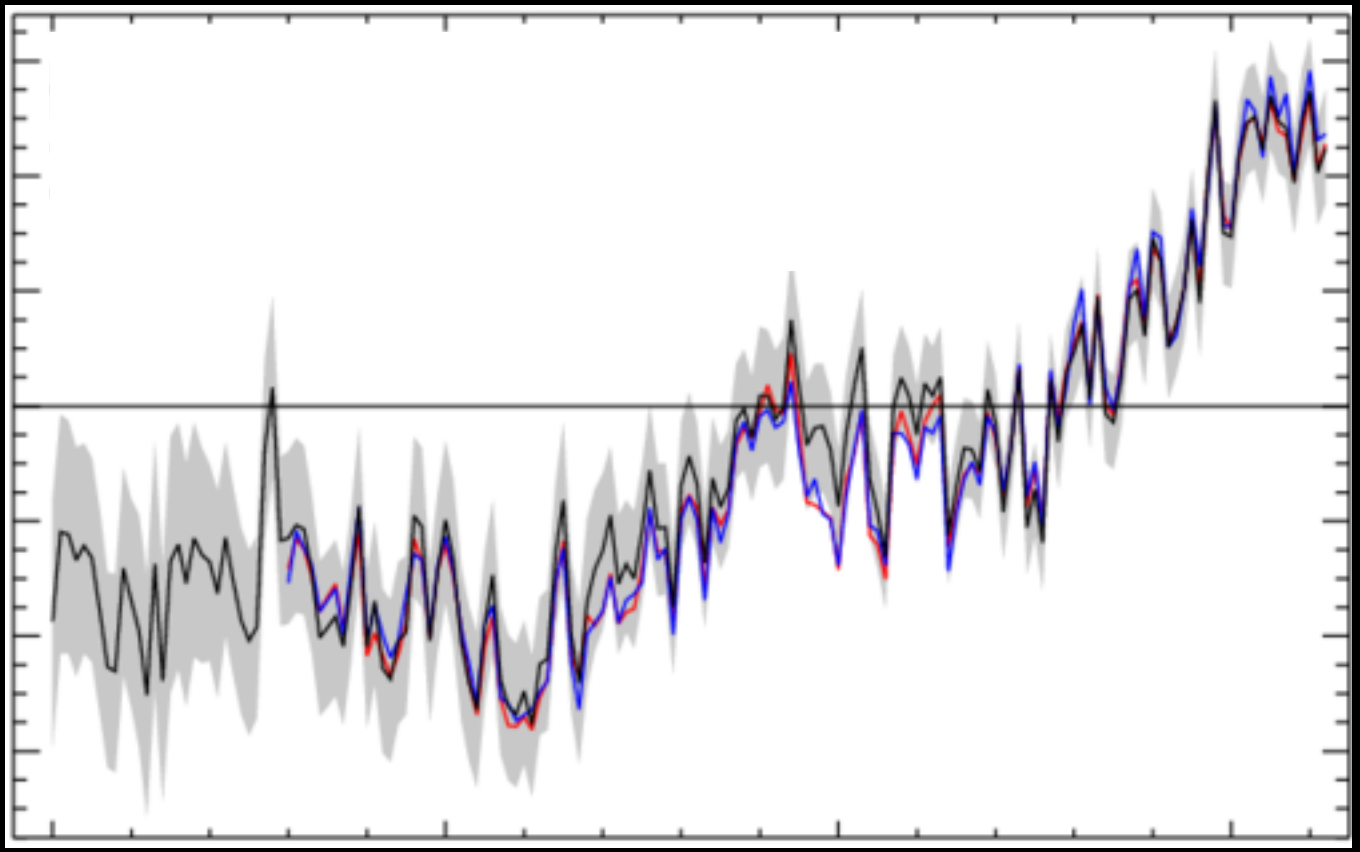
- topics in Geospatial analysis

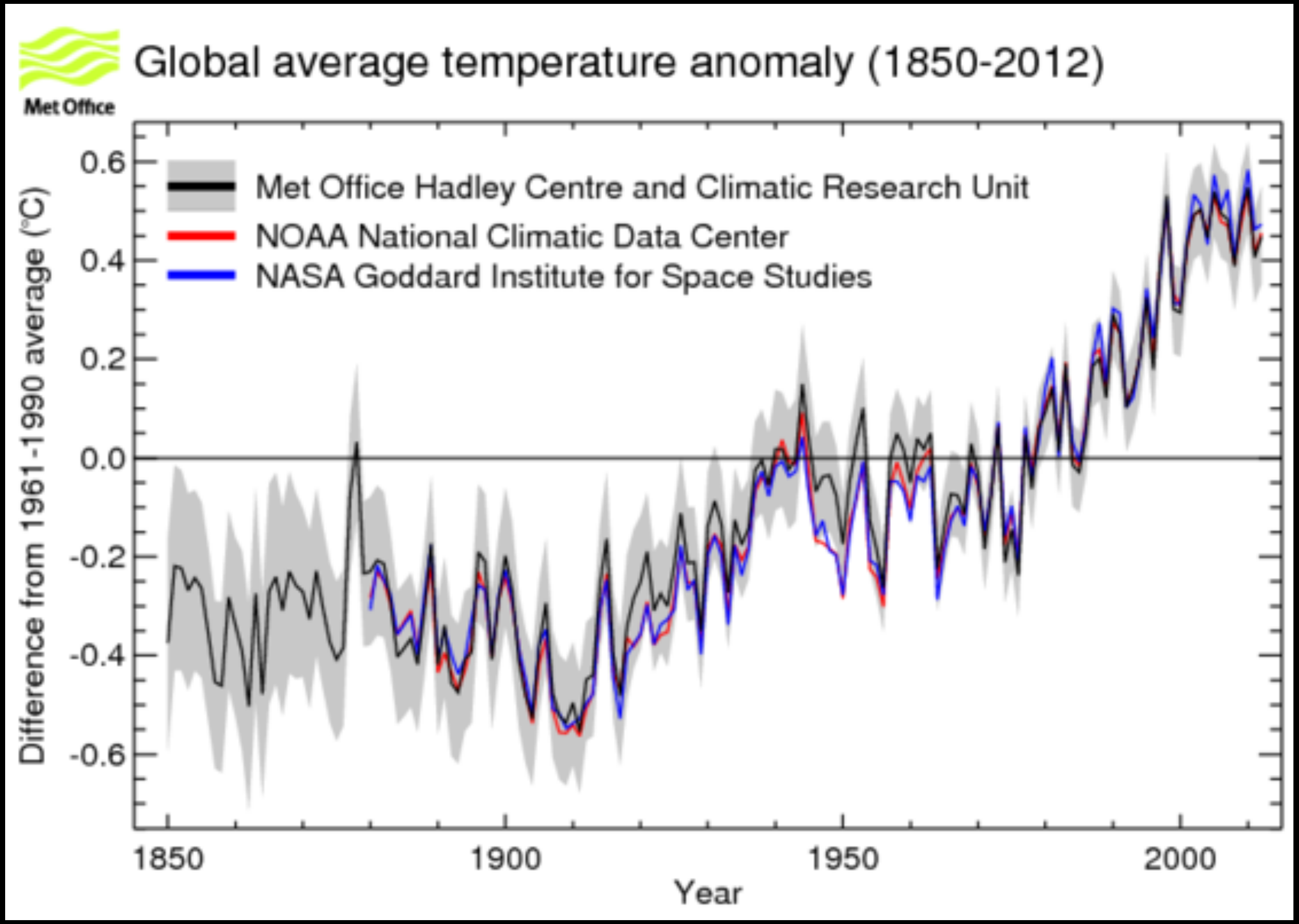
Today

- Topics in (time) series analysis

Topics in (time) series analysis

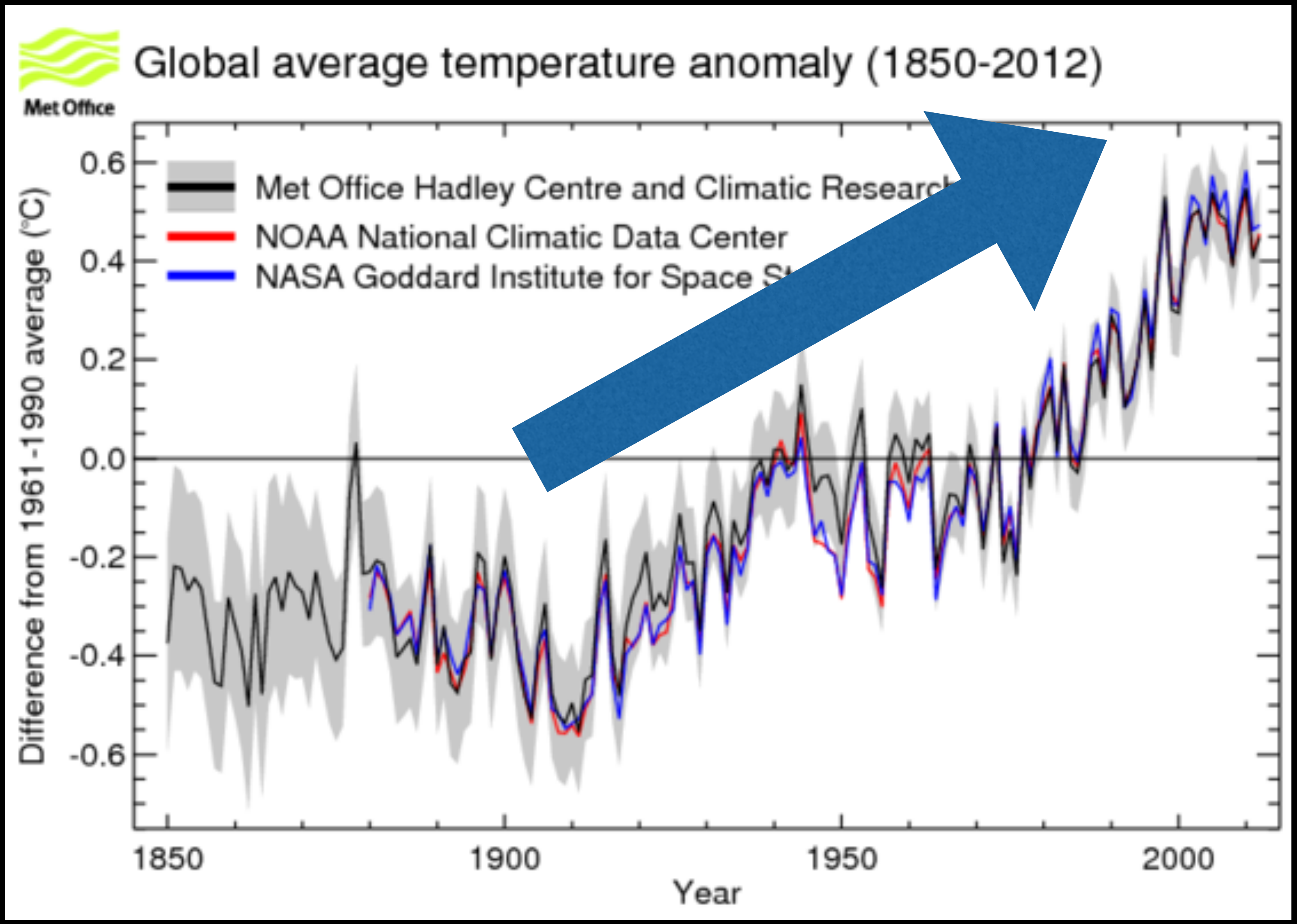
- smoothing
- de-trending
- event detection
- point of change detection
- period finding (Fourier analysis)
- clustering





Global average temperature anomaly (1850-2012)
Met Office
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


Met Office
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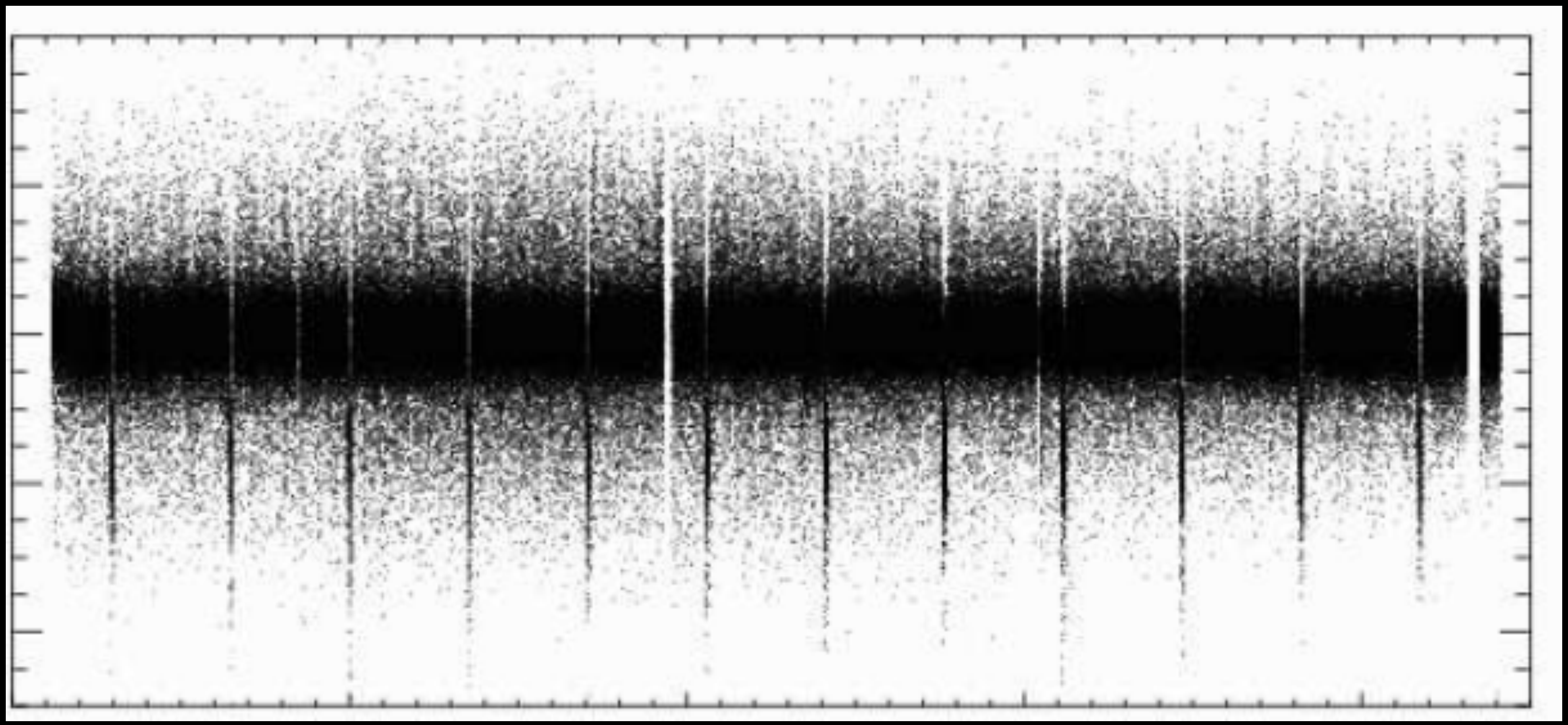
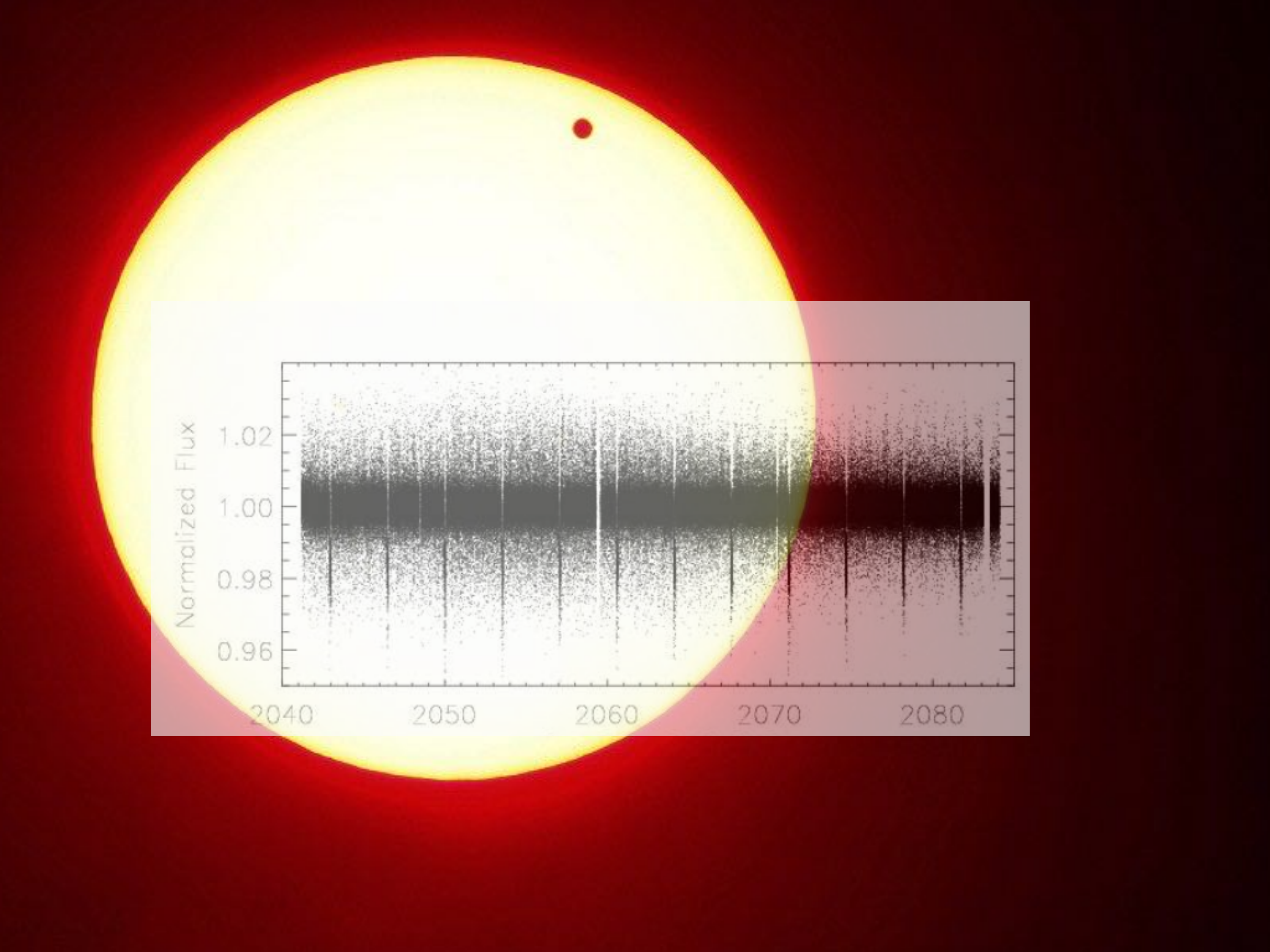
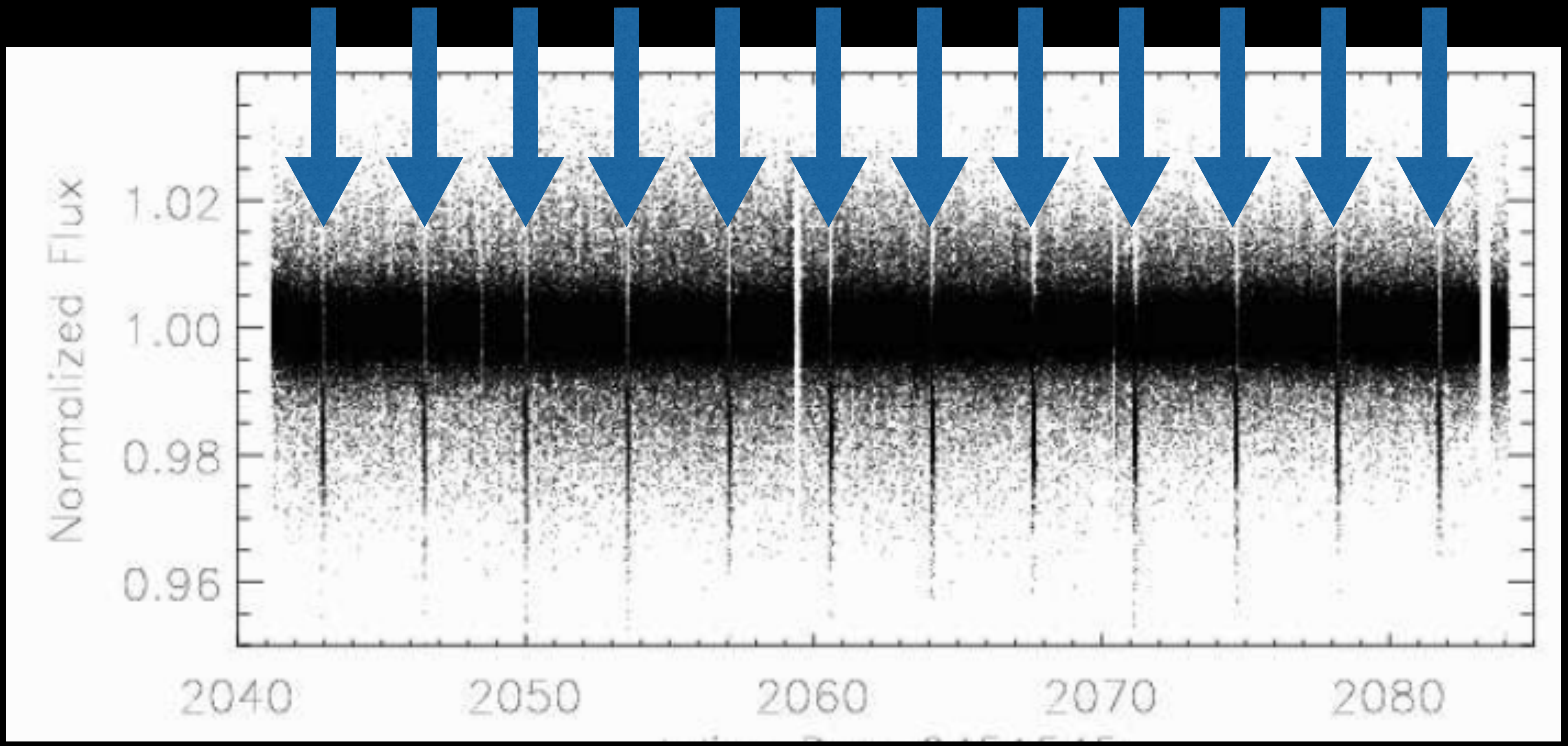
1850
1900
1950
2000
Year

Trend



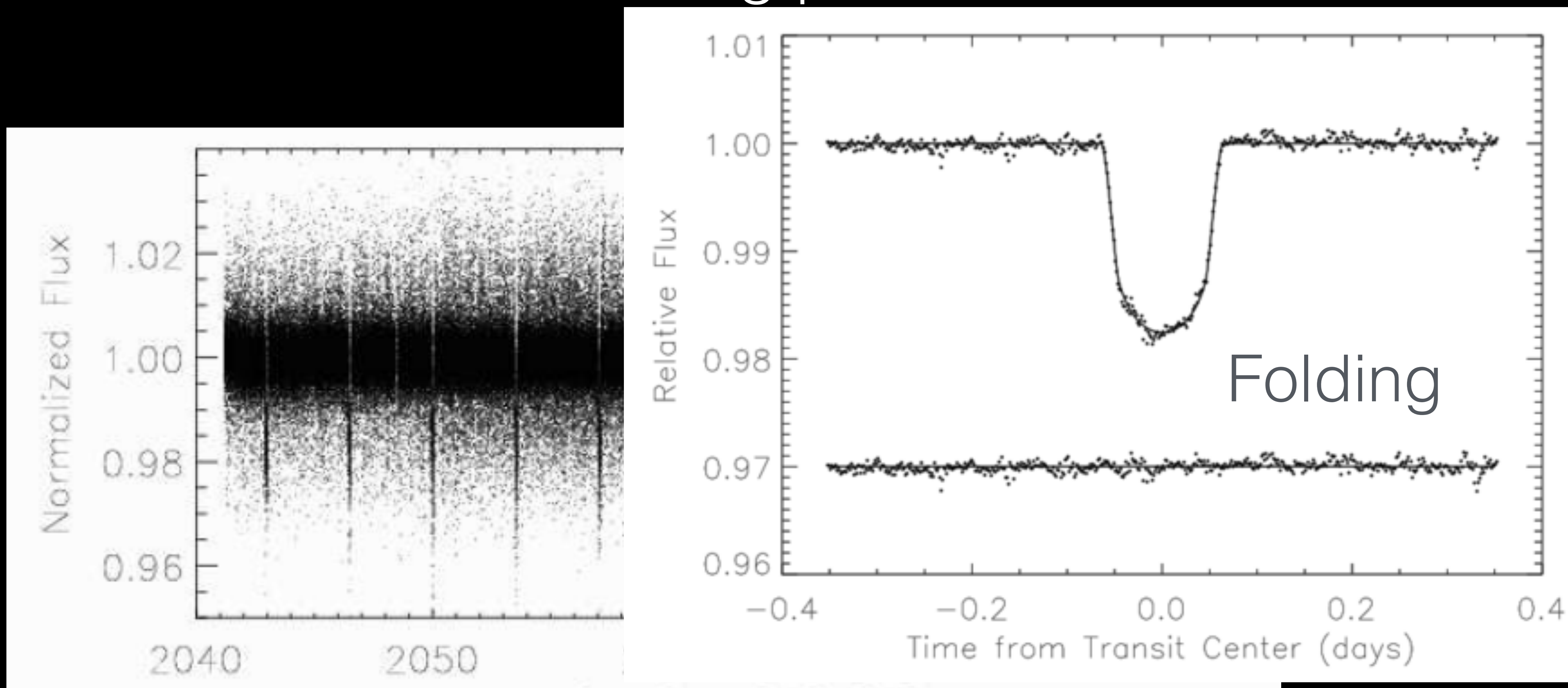

Normalized Flux
1.02
1.00
0.98
0.96
2040
2050
2060
2070
2080

HD 209458, the first transiting planet to be discovered.

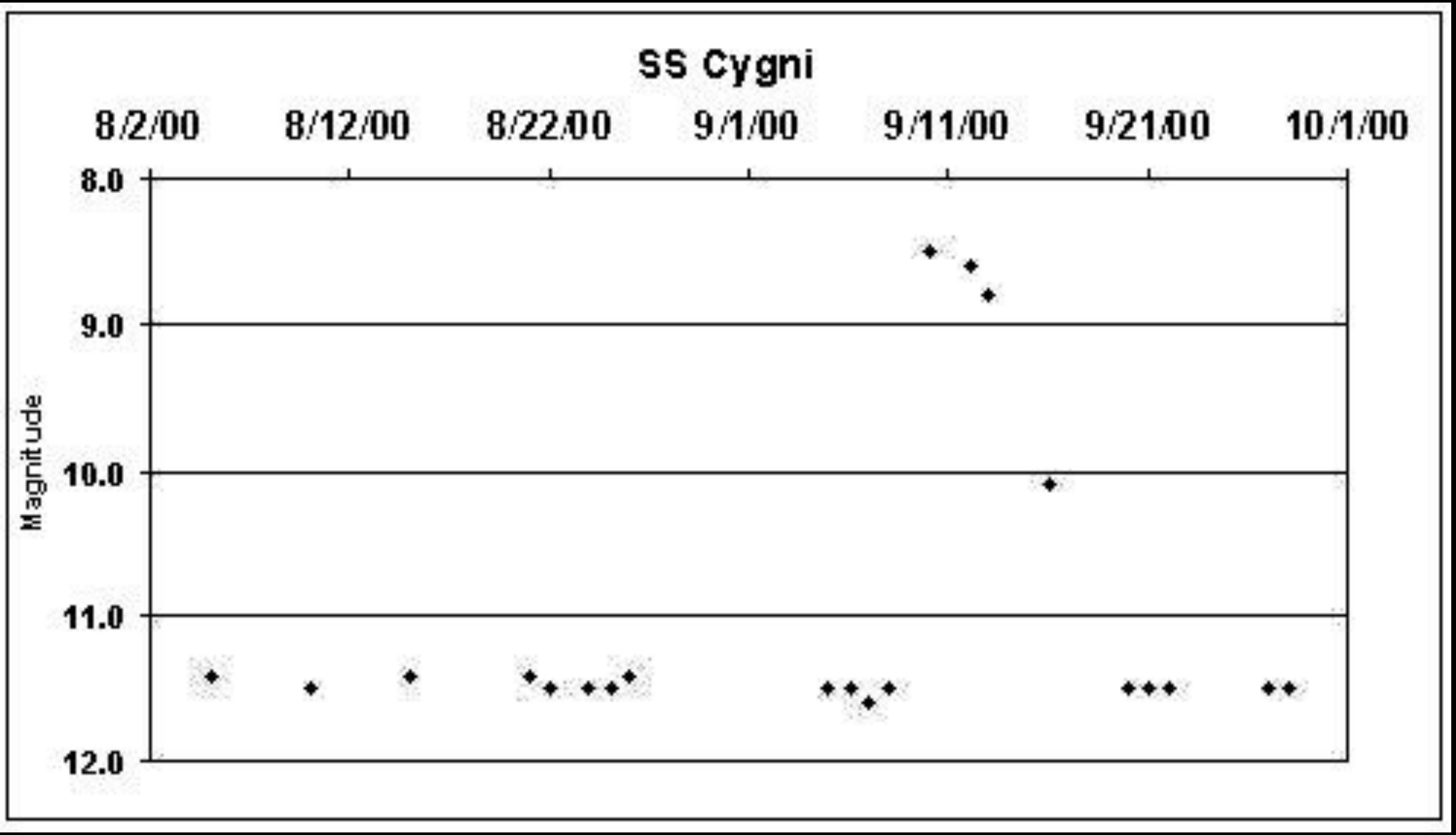


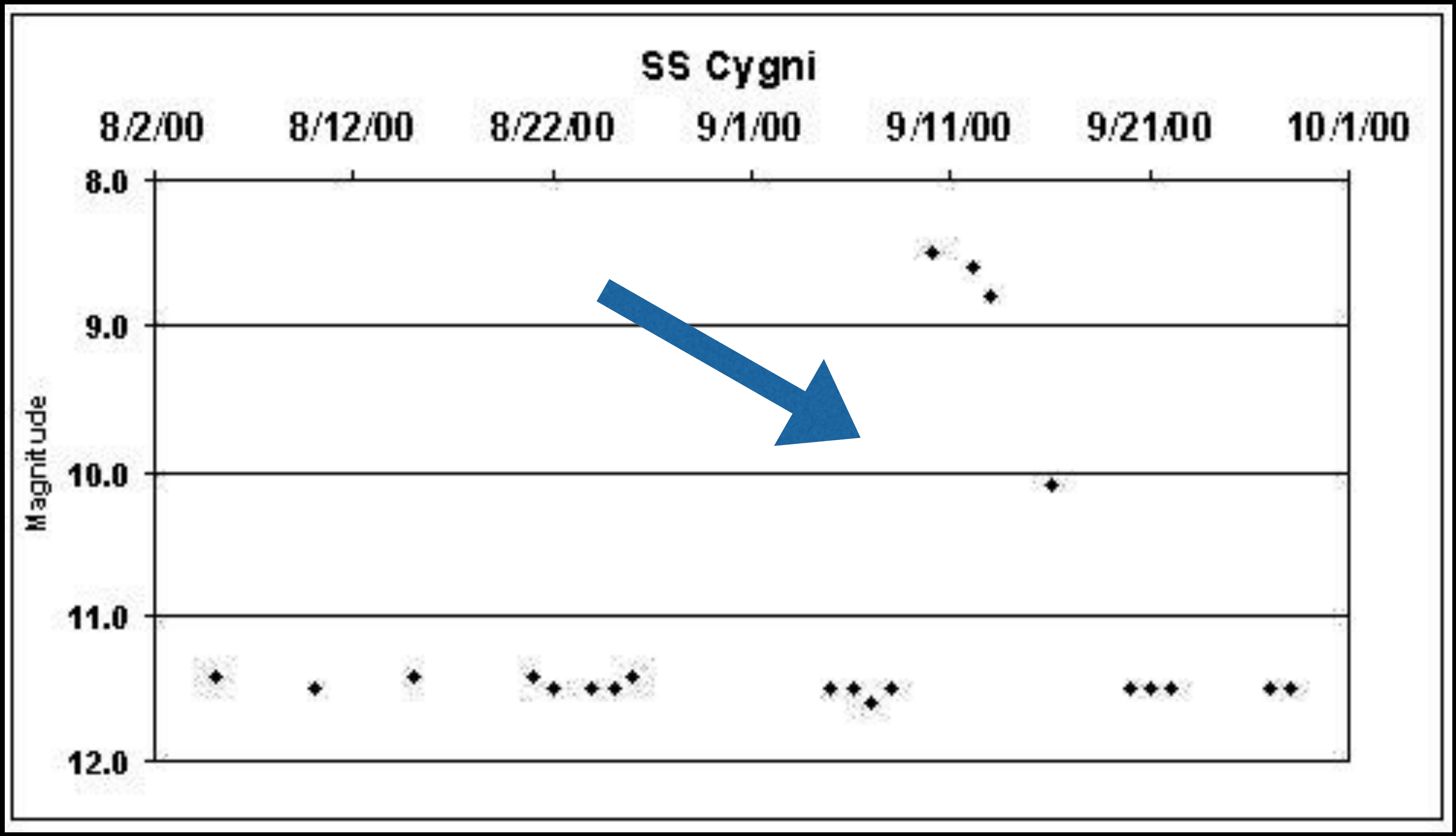
Period

HD 209458, the first transiting planet to be discovered.

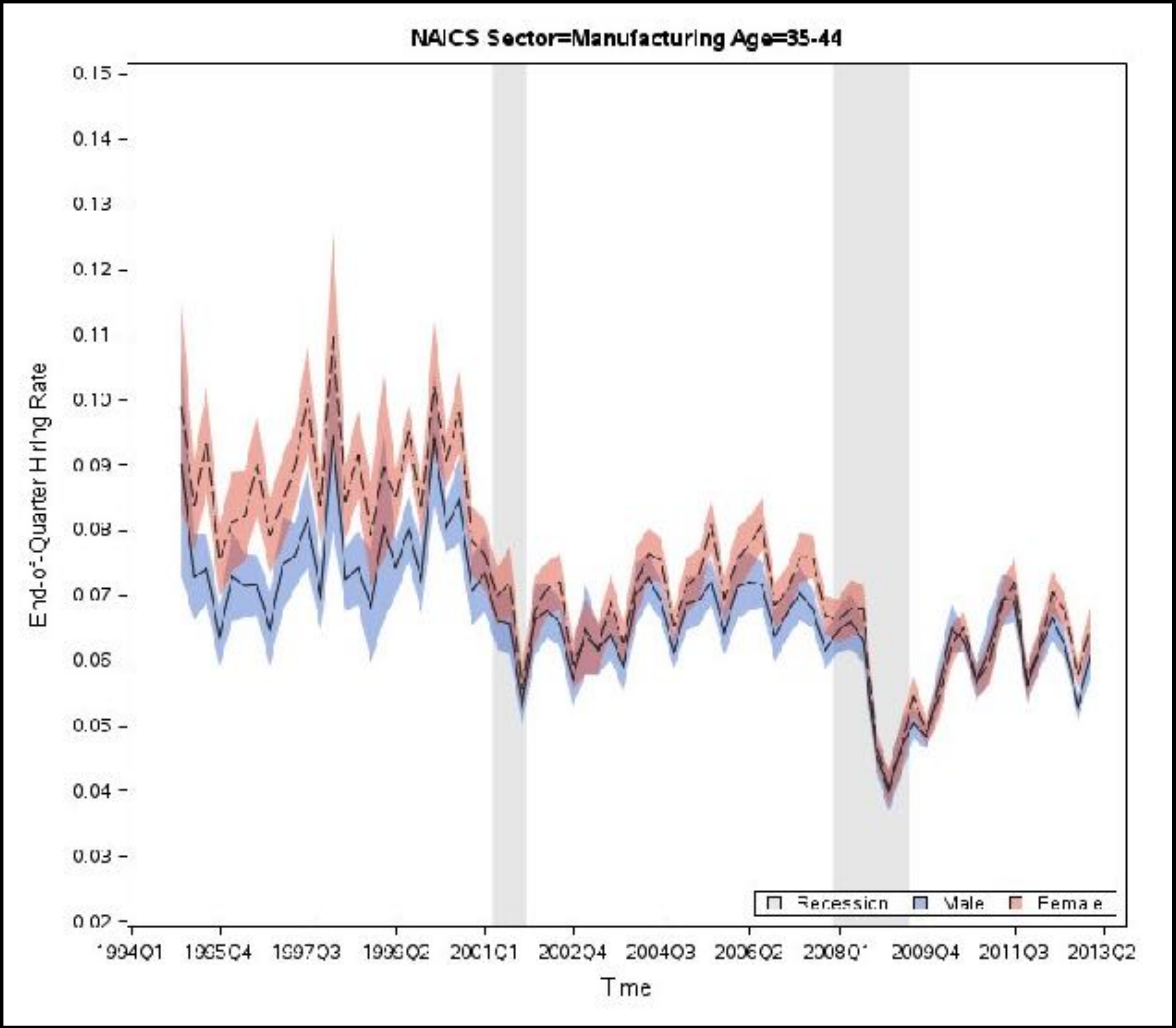


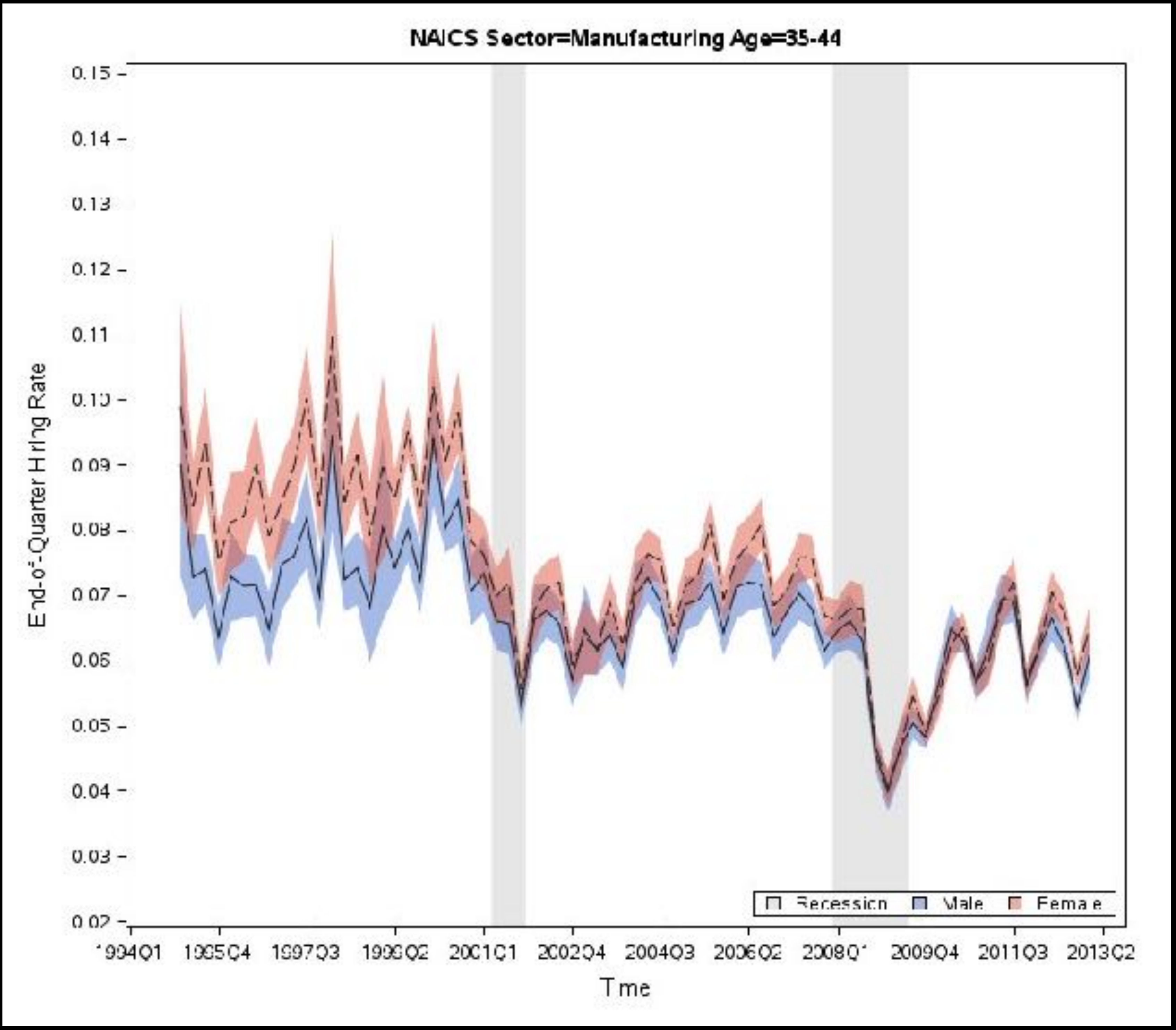
Period


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

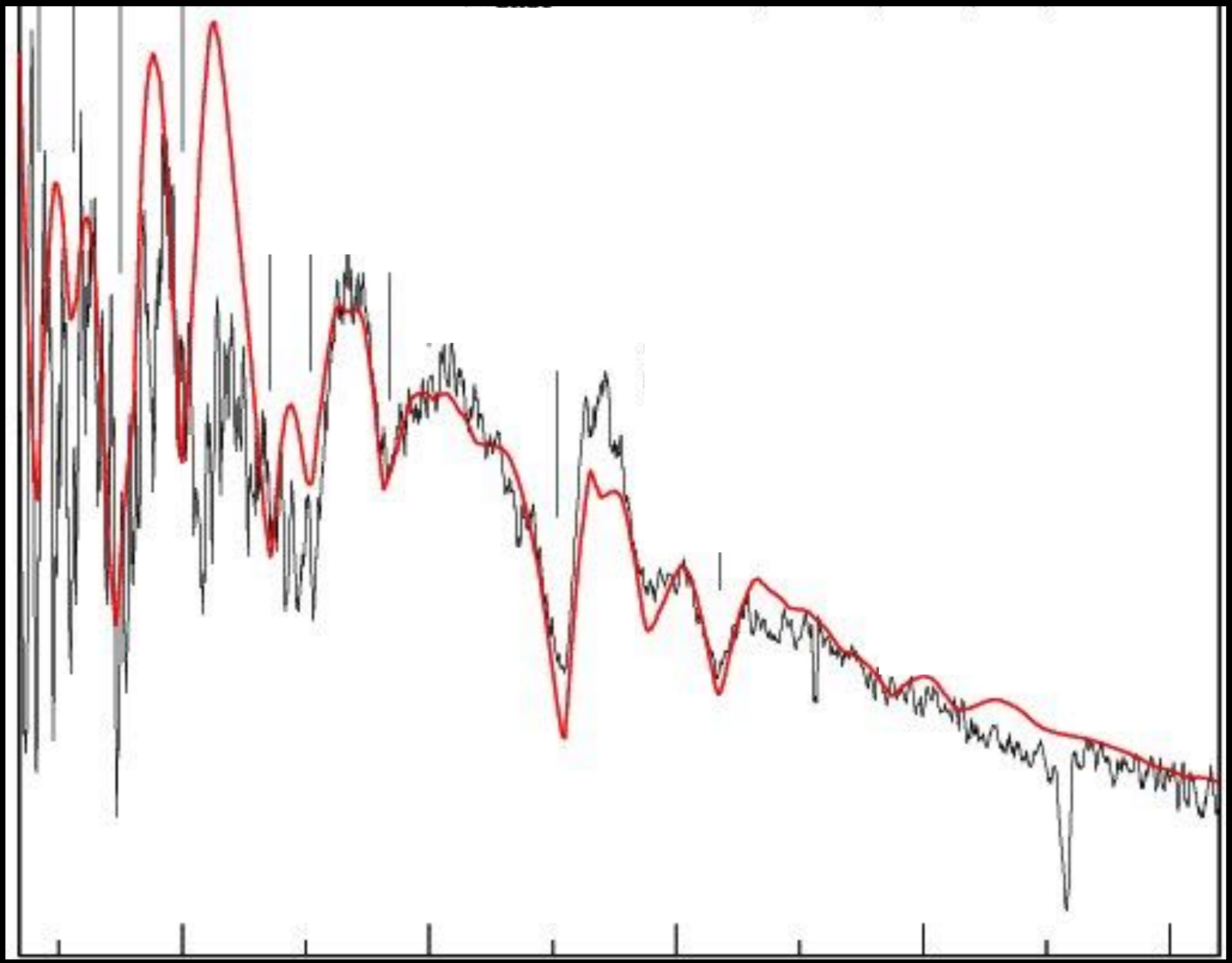


event detection

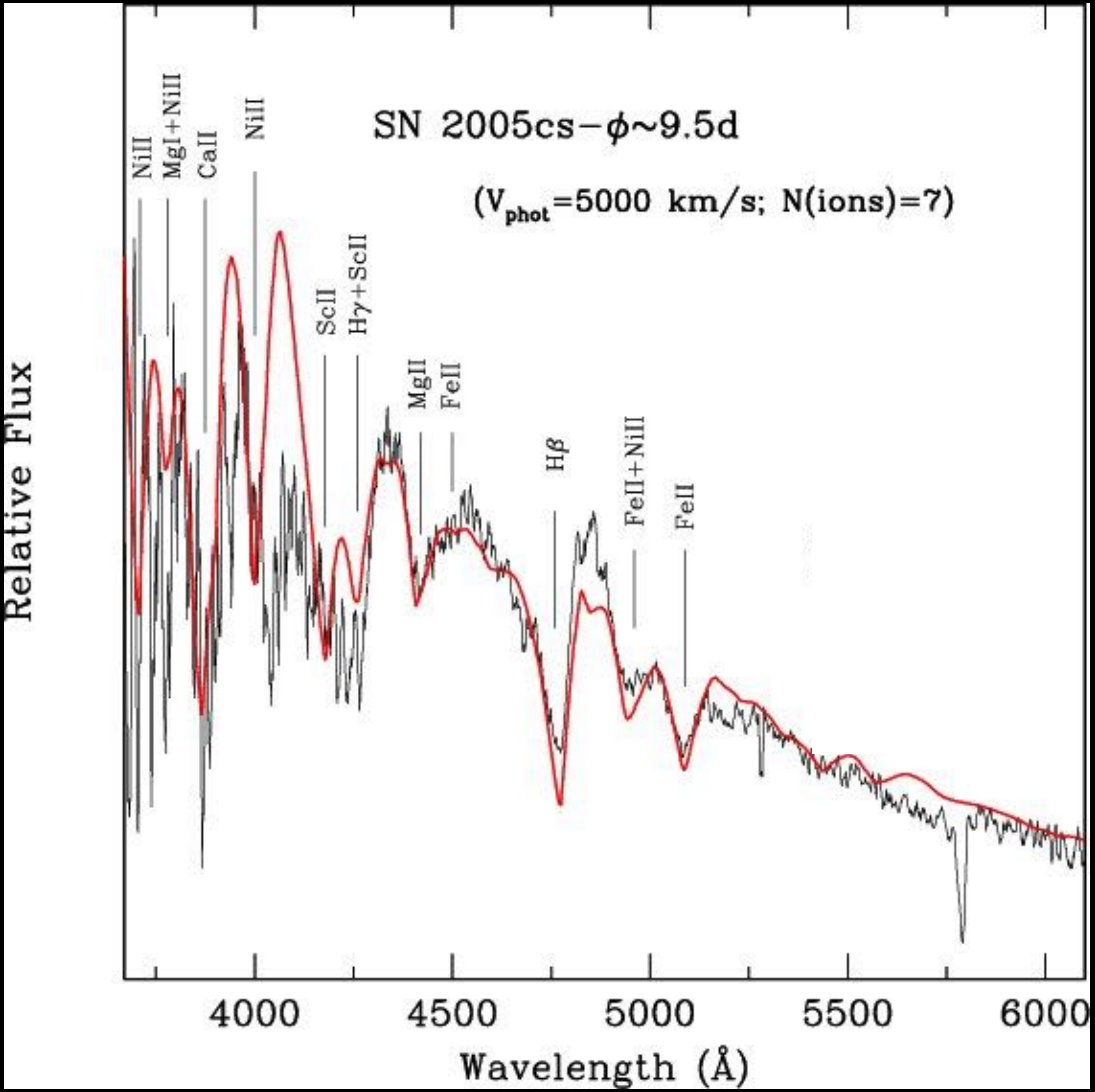

NAICS Sector=Manufacturing Age=35-44
End-of-Quarter Hiring Rate
Time
Recession Male Female
1994Q1 1995Q4 1997Q3 1999Q2 2001Q1 2002Q4 2004Q3 2006Q2 2008Q1 2009Q4 2011Q3 2013Q2
0.15 0.14 0.13 0.12 0.11 0.10 0.09 0.08 0.07 0.06 0.05 0.04 0.03 0.02



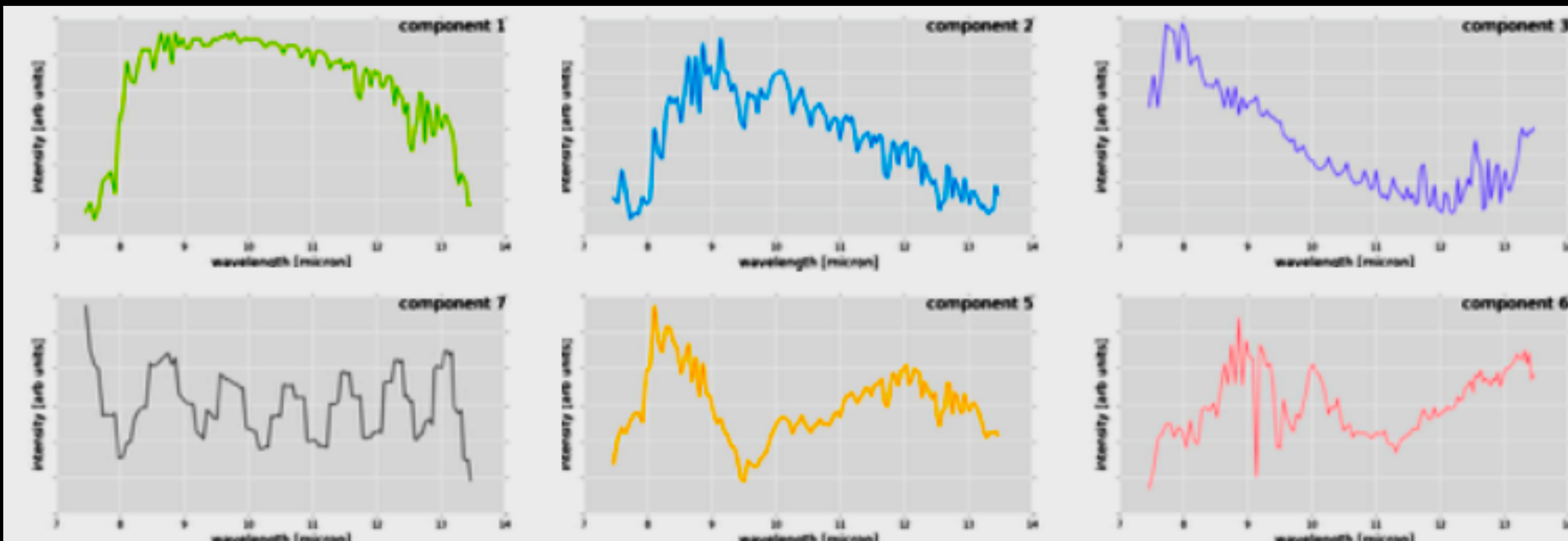
point of change detection



they do not have to be *TIME* series!



CUSP-UO spectra of urban lights for light technology assessment



- anomaly detection

- anomaly detection
- identification of trends

- anomaly detection
- identification of trends
- point of change detection

- anomaly detection
- identification of trends
- point of change detection
- prediction

- anomaly detection
- identification of trends
- point of change detection
- prediction
- periodicity detection

- anomaly detection
- identification of trends
- point of change detection
- prediction
- periodicity detection
- classification (clustering)

Problem

- anomaly (event) detection

Method

Thresholding

jupyter

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

Problem | *Method*

- anomaly (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

CUSP

Problem

Method

- anomaly (event) detection
- identification of trends

jupyter

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

Problem

- anomaly (event) detection
- identification of trends

Method

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

jupyter

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

CUSP

Problem

- anomaly (event) detection
- identification of trends
- point of change search

Method

Bayesian
Point of Change Search

jupyter

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

CUSP

Problem

- anomaly (event) detection
- identification of trends
- point of change search

Method

Bayesian
Point of Change Search

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

https://www.slideshare.net/FrankKelly3/changepoint-detection-with-bayesian-inference

Adam, MacKay 2007

Rasmussen 2001

Problem

- anomaly (event) detection
- identification of trends
- point of change search
- periodicity

Method

Fourier Transforms

jupyter

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

https://www.slideshare.net/FrankKelly3/changepoint-detection-with-bayesian-inference

Adam, MacKay 2007

Rasmussen 2001

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

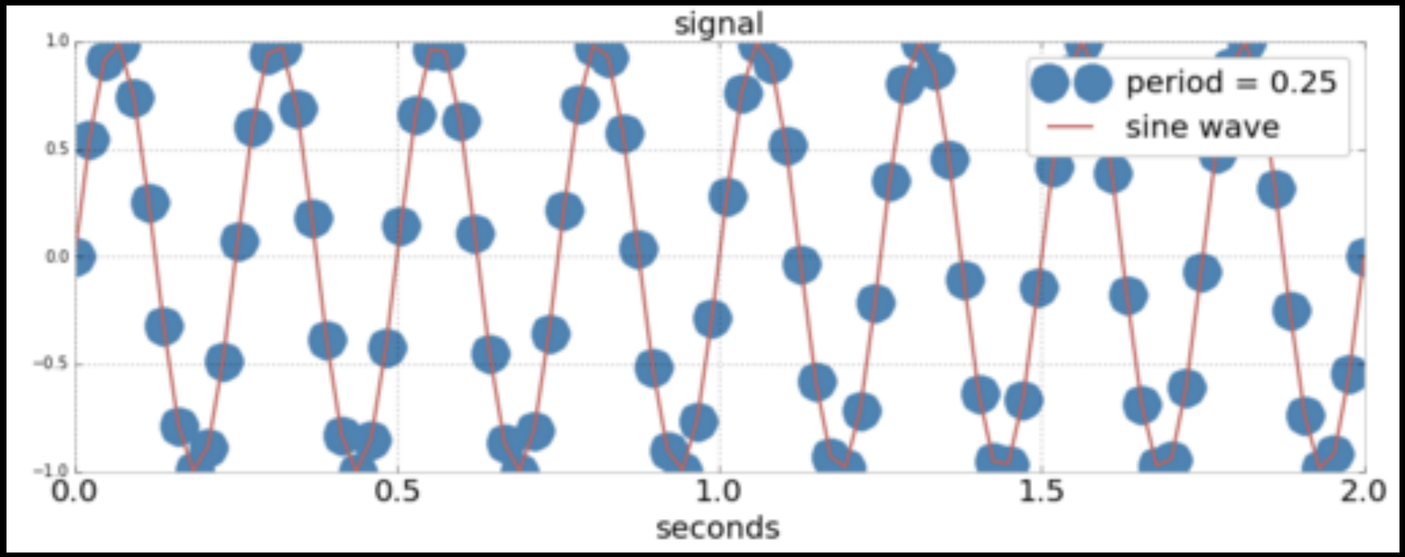
Fourier

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

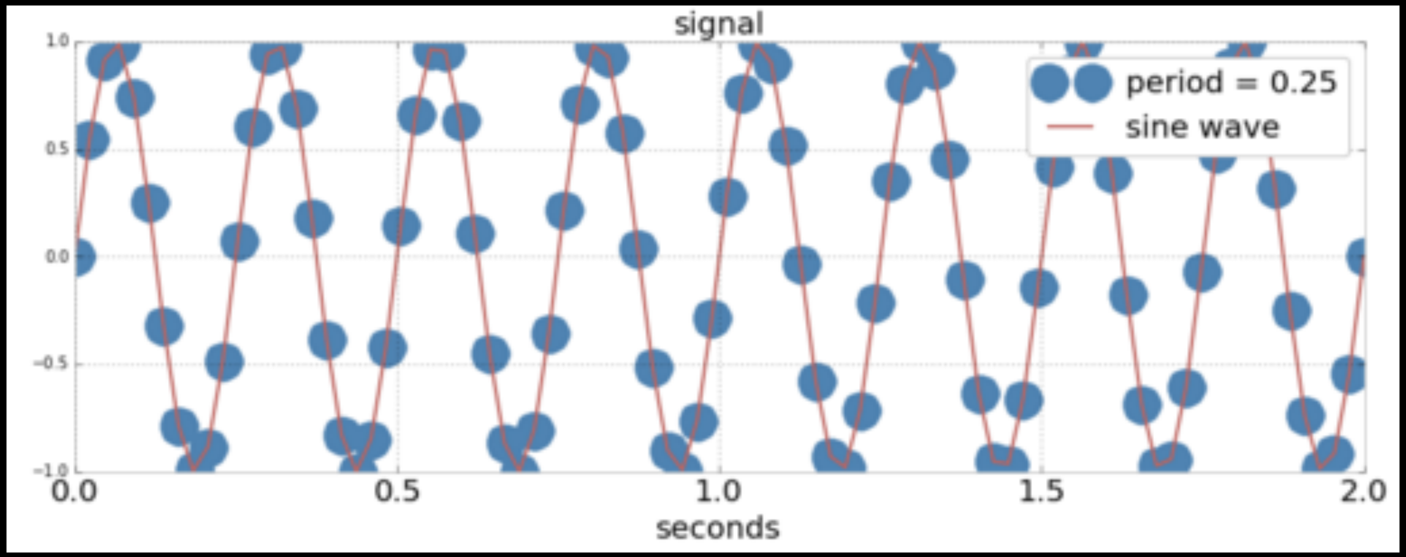
takes a function in space domain
f(t) is measured in seconds

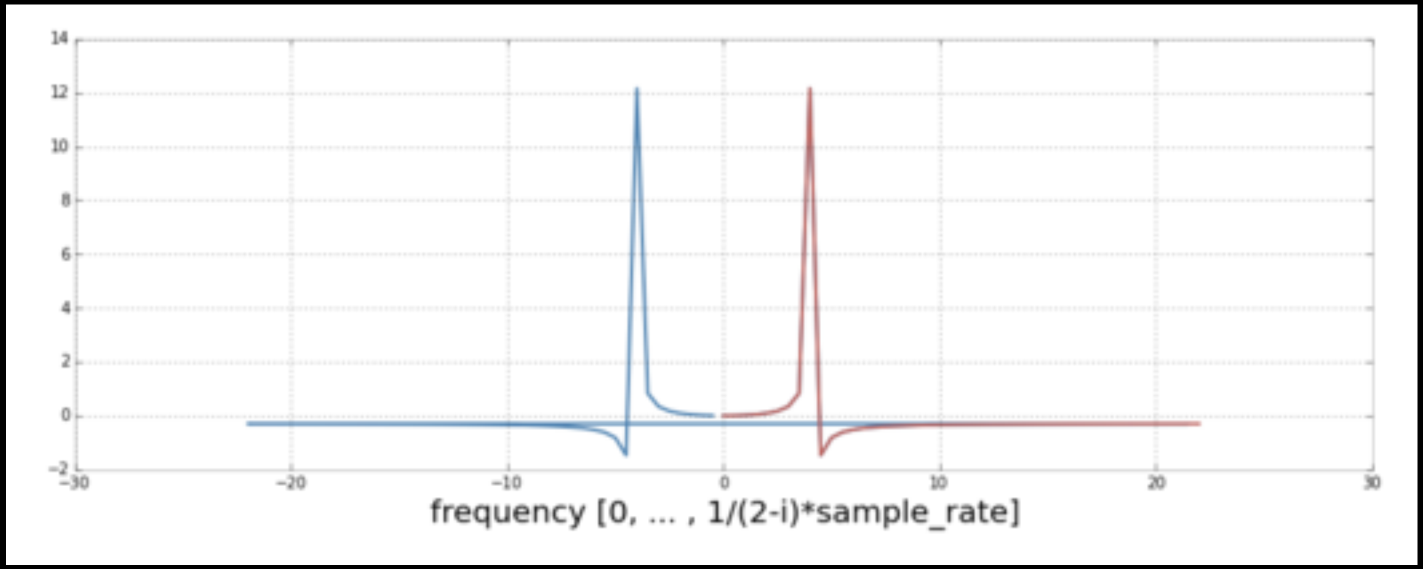
to a function in spatial frequency domain
f(t) is measured in 1/seconds
or Hz

Fourier


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

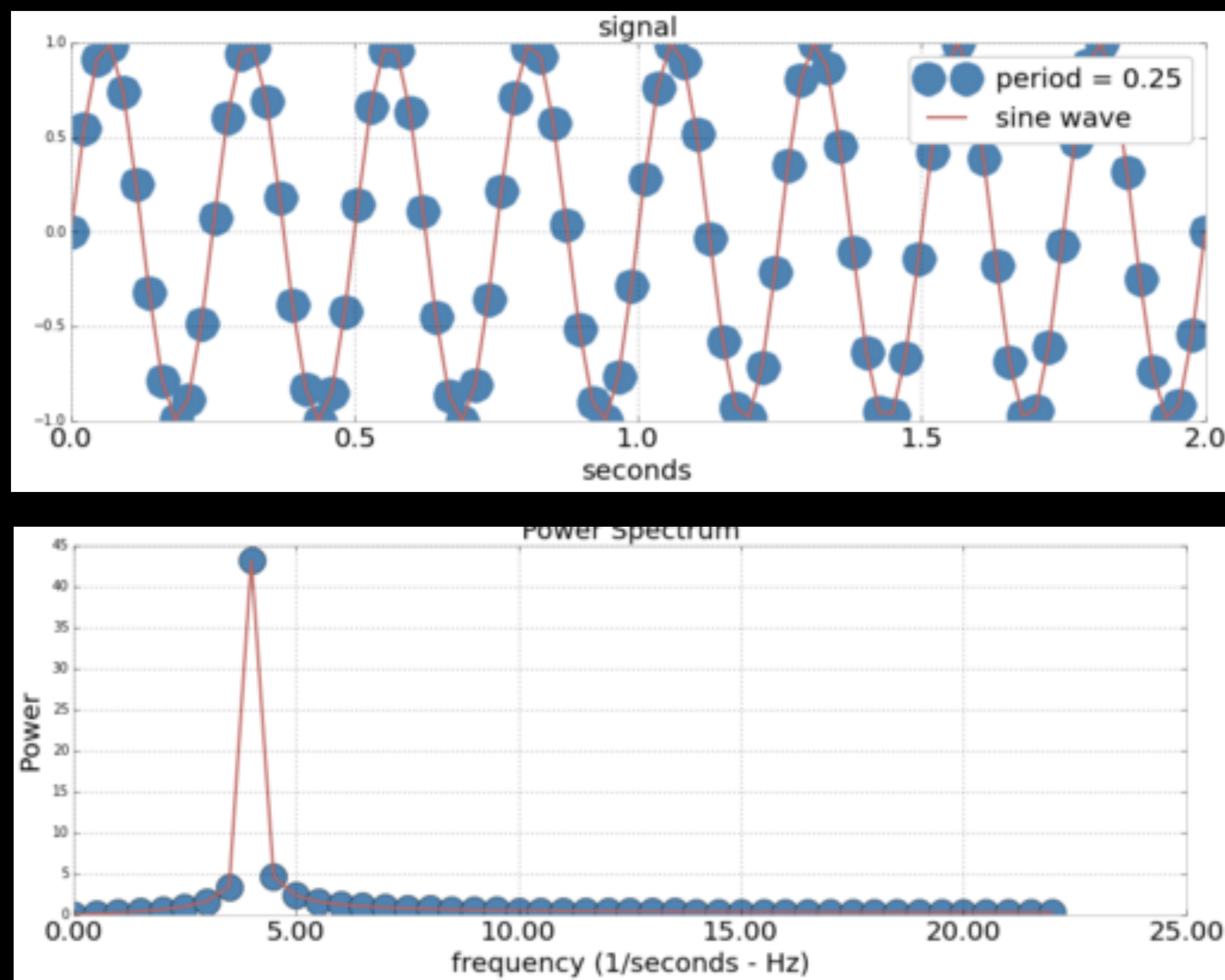
Fourier


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

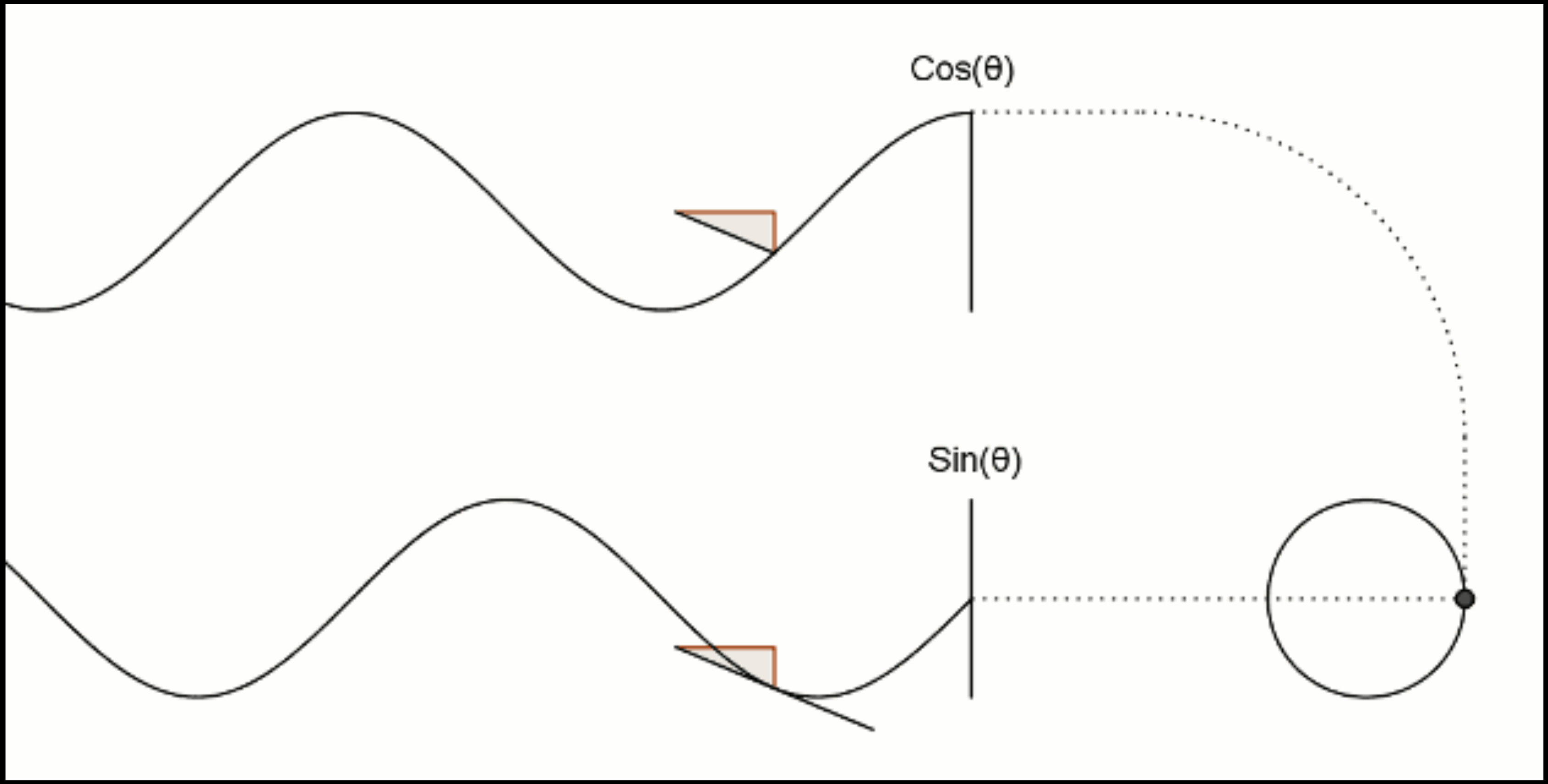

14
12
10
8
6
4
2
0
−2
−30
−20
−10
0
10
20
30
frequency [0, ... , 1/(2-i)*sample_rate]

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

Problem

- event detection
- identification of trends
- periodicity
- prediction

Method

ARMA/ARIMA

jupyter

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

ARIMA

Autoregression

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

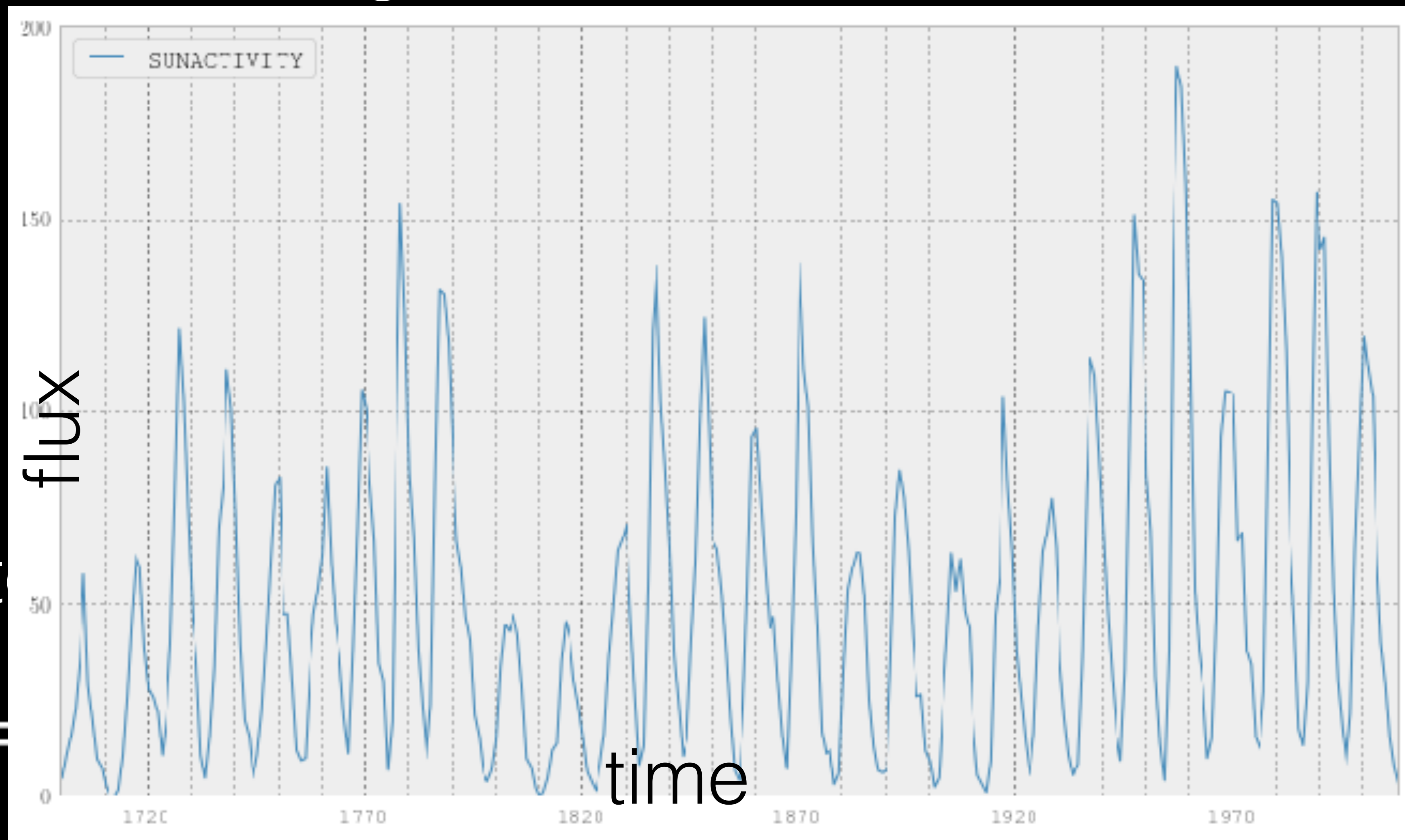
ARIMA

Autoregression

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

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

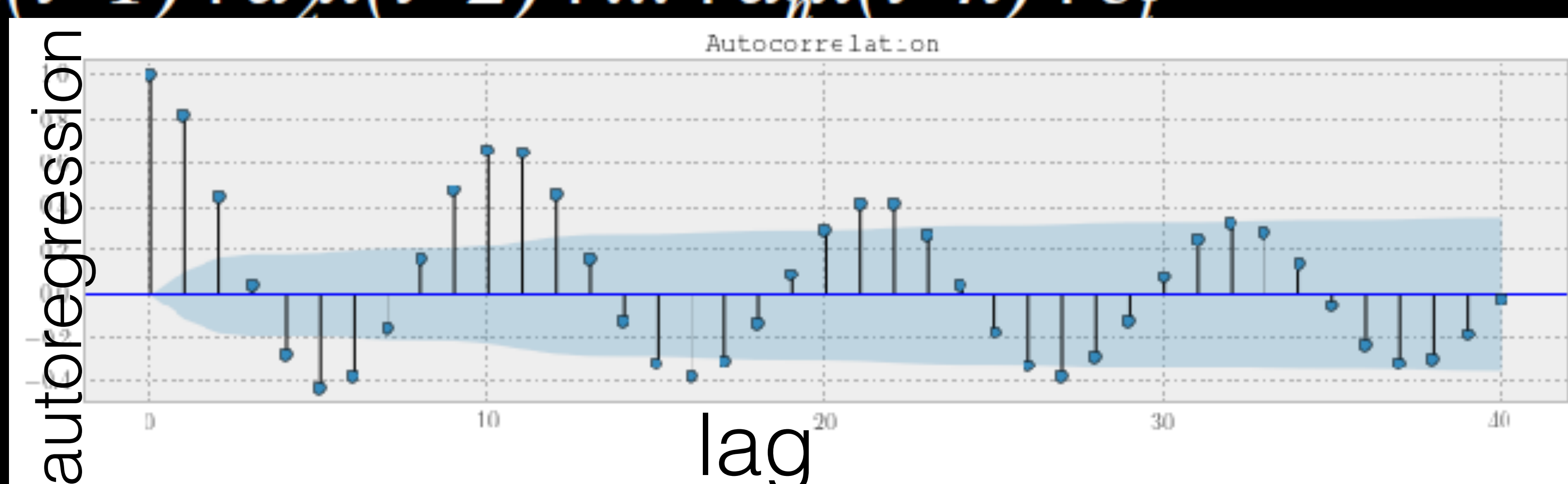
http://statsmodels.sourceforge.net/devel/examples/notebooks
generated/tsa_arma_0.html



Aut

$x(t)=$

$$x(t)=a_1x(t-1)+a_2x(t-2)+\ldots+a_nx(t-n)+\epsilon_t$$



ARIMA

Autoregression

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

Moving Average Model

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

Integration

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

ARIMA

Autoregression

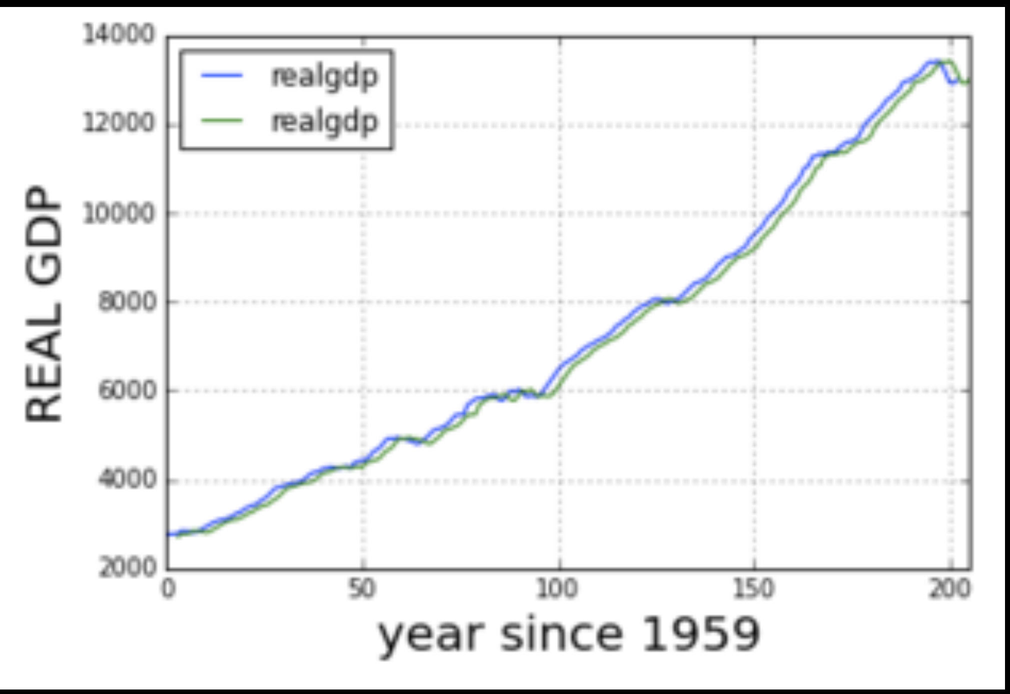
$$x(t)=\sum_{i=1}^{p} a_i x_{t-i}+\varepsilon_t$$

Moving Average Model

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

jupyter

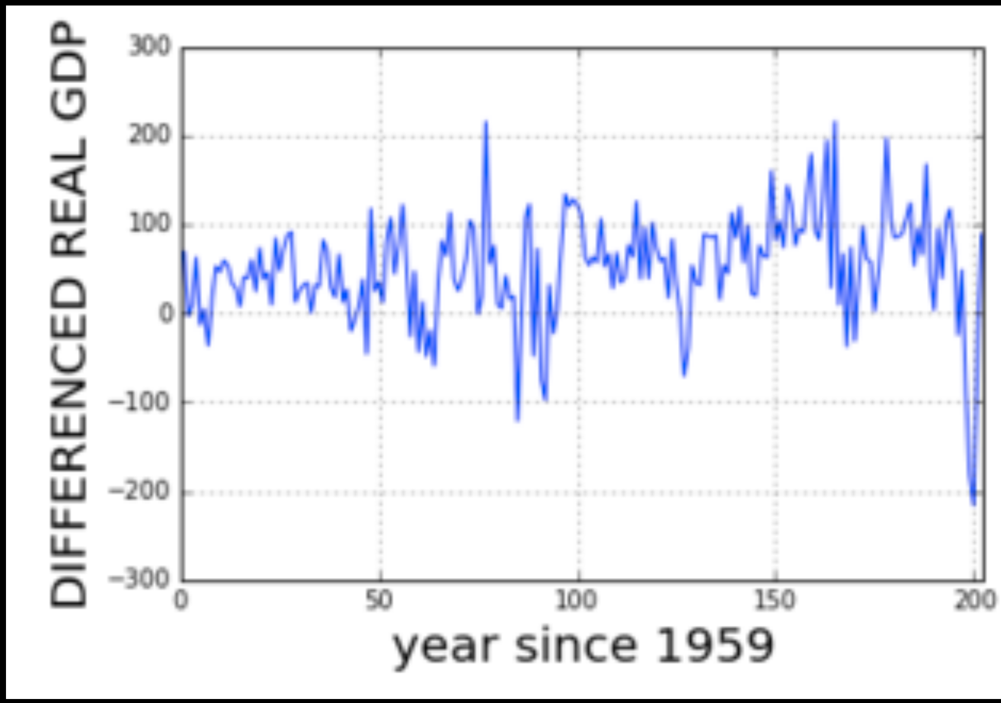
CUSP



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

Homework:

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

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

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.

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:

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

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

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

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