Fourier Analysis and Change Detection

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Dynamic Network Analysis

- Key focus – Networks change over time
- Summary statistics – typically average all data
  - Useless for seeing changes over time
- Longitudinal Networks and Change
  - Getting longitudinal networks from communications logs
  - Stability, Evolution, Shock, Mutation
- Statistical Models of Networks to Detect Change
  - Link Probability Model (LPM) for Stability
  - Actor-Oriented Models for Evolution
  - Multi-Agent Simulation for Evolution, Shock, and Mutation
- Network Change Detection Algorithms
- Fourier Analysis to remove periodic variations

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Basic Issue

- Real Social Networks are not time independent
- Over time the set of nodes change
  - Agents die, agents are born
  - If data set has limited geographic focus,
    - Agents can enter region under study
    - Agents can leave region under study
- Network connections between agents can change
  - A network link between two agents can disappear
    - Two family members have a fight and refuse to talk to each other
  - A new network link can be created
    - People meet new people and form new relationships
    - Advertising campaigns can convince people to follow companies

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Types of Changes in Network Data

- Stability: Relationships remain statistically the same over time
  - If you are a signal processing person, the Network is "Ergodic"
- Evolution: Interaction among agents cause the relationships to change over time.
  - All link weights / costs are evolving over time during obervations
- Shock: Change is exogenous to the social group.
  - E.g., like an earthquake hits Southern California
- Mutation: A shock stimulates evolutionary behavior.
  - E.g., after earthquake, people form many new links trying to survive

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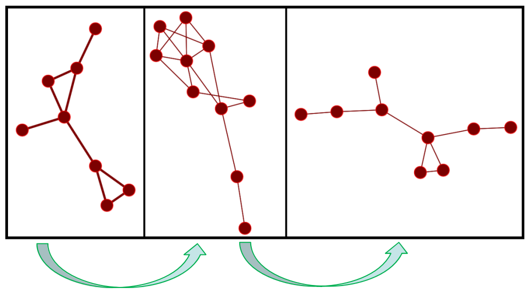
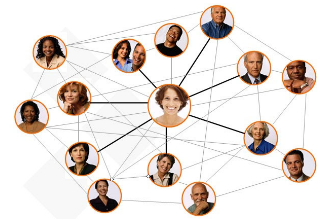
Dynamic Metrics on Over-Time Data

- *Identifying central nodes in a network*



T$_1$ T$_2$



Dynamically Changing Network Structure!!!

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Proxy for Network Data

- Ideal approach – directly sample network each time period
  - E.g., have every member of society fill out survey every time period
  - Limited to very small societies
- Or, tracking changes over time using communications data
  - Communication is "proxy" for a network tie
  - Taking large amounts of communication data gives an approximate picture of the underlying social network (with some concerns)
  - Can use it to find Key Agents and other Social Structure measures
- Communication log data available from many sources
  - Cell Phone Service Providers – call logs, txt logs
  - E-mail Data logs – available within organization
  - Twitter, Facebook, FourSquare, etc.
  - Building Sensors, Cell Phone Sensors, RFID Tags, etc.

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Example: Temporal Social Network

- ACM Hypertext 2009 Conference
  - Badges with RFIDs
- Close Range Face-to-Face Contact
  - 1 - 1.5 meters of one another
  - Human body acts as an RF shield
- Collect sensor data every 20 seconds for 2.5 days
  - 20,818 real time data updates
  - 113 participants, 2196 undirected, weighted links

New Interactions → **Stronger Relations** → **Different Interactions**

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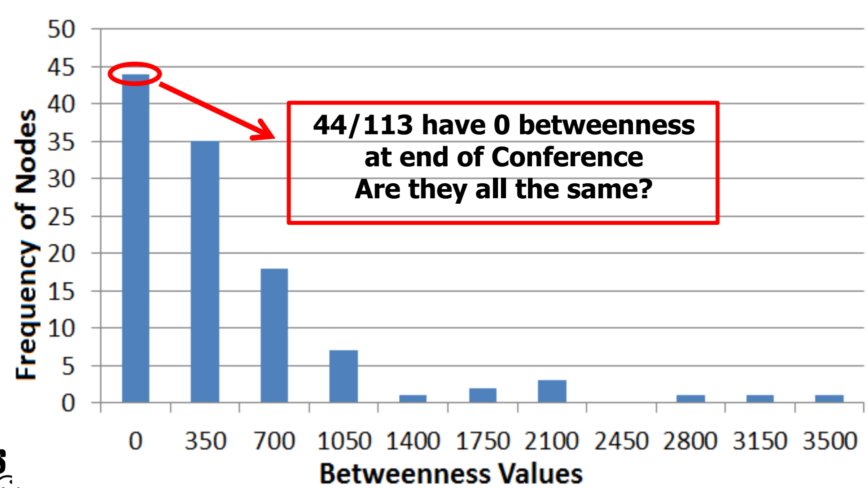
Socio-Patterns: Betweenness Centrality Distribution



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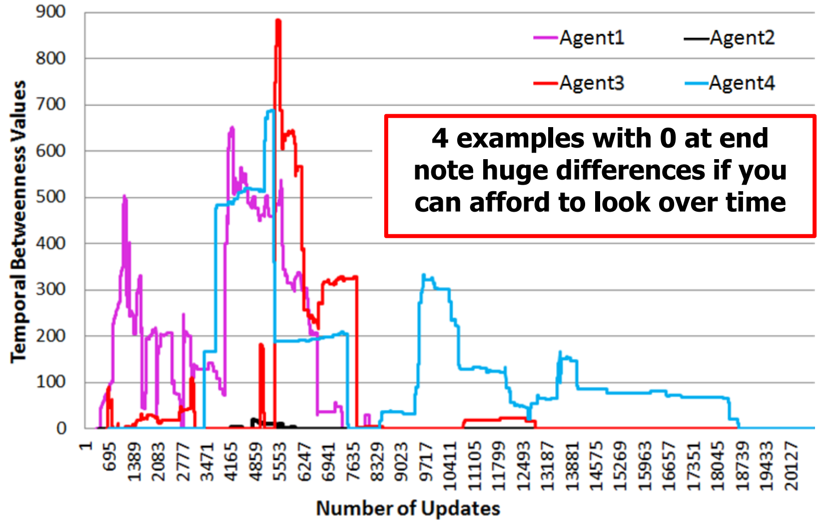
Socio-Patterns: Betweenness Over-Time Trends



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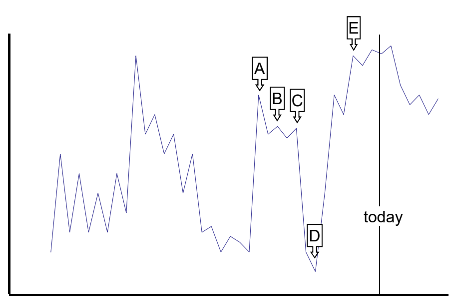
Changes in Network Data

- Various measures of a network are taken for a window at each time point.
- Change detection: quickly determine *that* a change occurs.
- Change point identification: *when* did the change occur.



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Change Detection

- Goal: Rapidly detect that a change has occurred
- Detect *shocks*, not evolutionary changes
  - Evolutionary change: change due to interaction among actors in a network
    - Example: change of interaction patterns over time among new students as they get to know each other
  - Shock: change reason is exogenous to the network
    - Example: change of interaction patterns among students after they graduate
  - Another way to say it: detect "fast" change not "slow" change
- Another goal is to identify *change point*
  - Likely time when change occurred
  - Limits the scope of explanation for network change

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Statistical Process Control (SPC)

- Change detection based on SPC
- Statistical Process Control
  - Used in manufacturing to maintain quality control
  - Monitors a process to detect potential changes
  - Calculates a statistic from observed measurements of a process and compares it to a decision interval
  - If the statistic exceeds the decision interval, it is said to "signal", that a potential change may have occurred
  - A quality engineer will then begin to search for the specific cause of change

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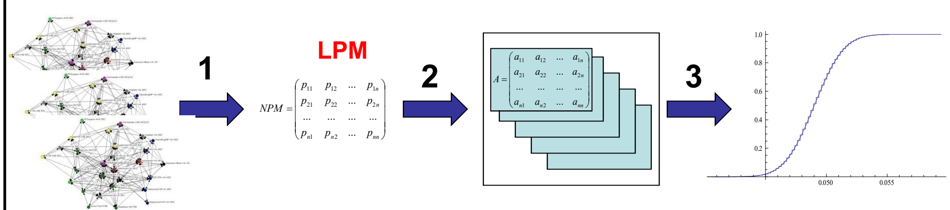
Statistical Models of Networks
Link Probability Model (LPM) for Stability

- LPM is a model for a network in *Stability*
- The probability that an email is sent from *i* to *j* within some period of time *t* is:

$$p = \int_0^t f_{ij}(x \mid \theta_{ij})\,dx$$

  – (p, as a function of t, is a CDF: f is the PDF that best fits cell ij in an NPM)
- LPM can be used to simulate stable longitudinal networks



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Statistical Models of Networks
Link Probability Model (LPM) for Stability

LPM simulated networks are compared to empirical networks and are shown to represent the network well.

M	8		N	60000			
e_mean	**e_stdev**		**s_mean**	**s_stdev**		**t-val**	**p**
409.2857	38.5604		358.0939	12.77466		3.754923	0.00
365.8571	18.2978		320.0974	12.7394		7.073195	0.00
365.8571	29.04266		320.1638	12.79331		4.449958	0.00
377.8571	38.24669		330.6744	12.77289		3.489244	0.00
375.2857	36.10039		328.3765	12.79551		3.675254	0.00
349.8571	38.15944		306.0783	12.7845		3.244918	0.00
373.8571	48.45076		327.0728	12.82622		2.731135	0.01
362.4286	55.63529		317.1509	12.77754		2.301849	0.02

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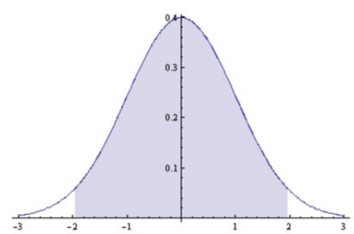
Probability Background

- Consider a normal distribution with μ=0 and σ=1.
- 95% of the time, observations are between ±1.9597
- When an observation occurs in the tail, we don't believe it and think that something unusual might be going on.



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Statistical Process Control

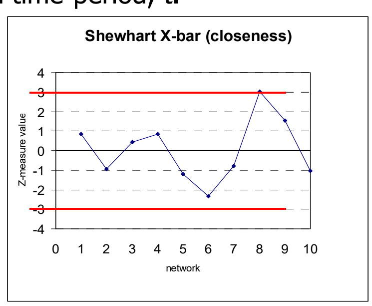
- Manufacturing processes are: stochastic, dependent, non-ergotic, complex, and involve human interaction.
- Shewhart (1927) X-bar Control Chart proposed to monitor change of any process
- Calculate Z_t transform value for each time-period, *t*.

$$Z_t = (x_t - \mu_0)/\sigma$$

- Calculate a control limit, *L*, based on risk for false alarm.

$$\int_L^{\infty} f(x)dx = \alpha$$

- Chart Signals when *Z* exceeds control limit, *L*.



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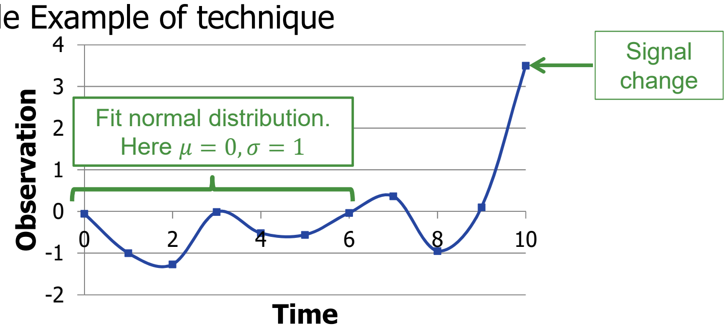
The Shewhart X-Bar Chart

- Overview
  - Fit normal distribution on "control period" (early observations)
    > assumed to represent the "normal state"
  - Signal change if a subsequent observation is outside confidence interval
- Simple Example of technique



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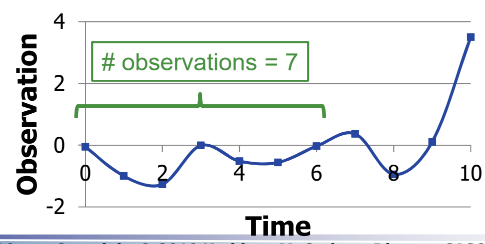
The Shewhart X-Bar Chart

- Parameters
  - # observations used to fit distribution (the "normal" period)
  - False positive risk or decision interval
    - Trade-off between False positive risk & detection speed
- Assumption
  - Observations are normally distributed as independent random vars
    - Shewhart X-Bar chart used even when assumption is violated. However, false positive risk probability may be inaccurate



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Statistical Process Control (cont.)

- Newer approaches detect change in fewer observations subject to the same rate of false positives.
- Scan Statistic (Fisher, 1934)
- Exponentially Weighted Moving Average (EWMA) (Roberts, 1959)
  - Good at detecting small changes in mean over time
  - Performs well on time series with closely spaced data samples

$$w_t = \lambda \bar{x}_t + (1-\lambda) w_{t-1} \qquad \mu_0 \pm L\sigma_{\bar{x}} \left(\frac{\lambda}{2-\lambda} \left[1 - (1-\lambda)^{2T} \right] \right)^{1/2},$$

- Cumulative-Sum (CUSUM) Control Chart (Page, 1961)
  - Good at detecting small changes in mean over time
  - Built-in change point detection
  - Two Charts (To Detect Increase and Decrease)

$$C_t^+ = \max\{0,\ Z_t - k + C_{t-1}^+\} \qquad C_t^- = \max\{0,\ -Z_t - k + C_{t-1}^-\}$$

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Cumulative Sum (CUMSUM)

- Cumulative-Sum Control Chart
  - Good at detecting small changes in mean over time
  - Built-in change point detection
- Calculate Z_t transform for each time-period, t

$$Z_t = (x_t - \mu_0)/\sigma$$

- Two Charts (To Detect Increase and Decrease)

$$C_t^+ = \max\{0,\ Z_t - \frac{\delta}{2} + C_{t-1}^+\}$$

- Chart Signals when C^+ or C^- statistic exceeds decision interval

$$C_t^- = \max\{0,\ -Z_t - \frac{\delta}{2} + C_{t-1}^-\}$$

- Sensitivity in CUSUM due to discrete integration of error

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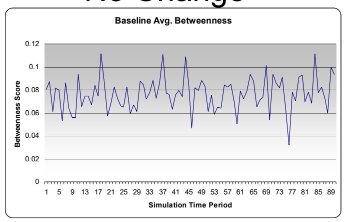
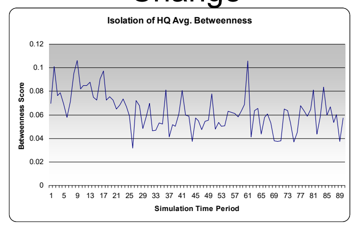
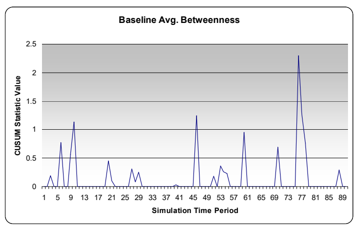
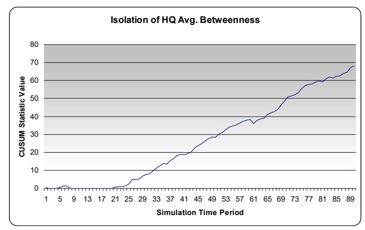
Comparison of Change Detection Approaches

	No Change	Change
Over-Time Meas		
CUSUM Statistic		

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Comparison of Change Detection Approaches

	CUSUM $k = 0.5$	EWMA $r = 0.1$	EWMA $r = 0.2$	EWMA $r = 0.3$	Scan Statistic
Average Betweenness	9.32	8.24	10.16	11.52	6.76
Maximum Betweenness	14.36	14.72	15.72	17.08	13.24
Std Dev. Betweenness	16.44	16.24	16.92	18.52	15.24
Average Closeness	10.68	9.08	13.60	17.52	10.48
Maximum Closeness	8.76	6.00	10.60	37.96	8.64
Std Deviation Closeness	34.48	34.72	34.52	35.68	27.08
Average Eigenvector	31.28	31.28	31.28	31.28	24.00
Minimum Eigenvector	14.36	14.36	14.28	15.56	14.88
Maximum Eigenvector	5.24	5.40	5.80	7.52	4.00
Std. Dev Eigenvector	5.92	4.88	6.40	6.96	3.64

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Network Change Detection: Analysis of Real World Data

	# Nodes	Time Periods	Method of Collection	Type of Relation	Design	Known Change
Fraternity	17	15	Survey	Ranking	Fixed	Yes
Leav 07	68	8	Survey	Rating	Free	Yes
Leav 05	158	9	Survey	Rating	Free	None
Al-Qaeda	62-260	17	Text	Rating	Free	Yes
Winter C	22	9	Observation & Survey	Rating	Fixed	Yes
Winter A	28	9	Observation & Survey	Rating	Fixed	Yes
IkeNet 2	22	46	Email	Count Msg	Free	Yes
IkeNet 3	68	121	Email	Count Msg	Free	Yes

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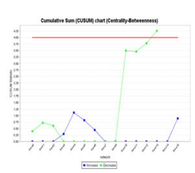
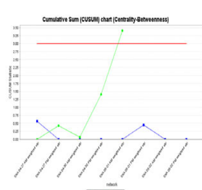
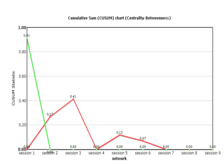
Network Change Detection: Analysis of Real World Data



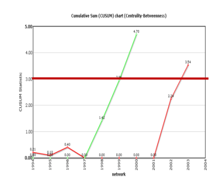
Fraternity



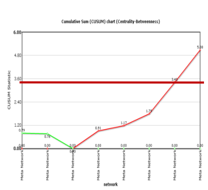
Leavenworth 2007



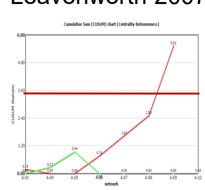
Leavenworth 2005



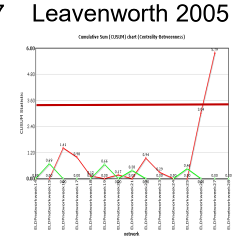
Al-Qaeda



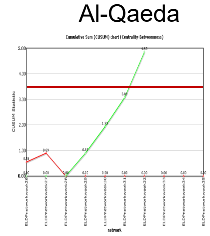
Winter A



Winter C



IkeNet 2



IkeNet 3

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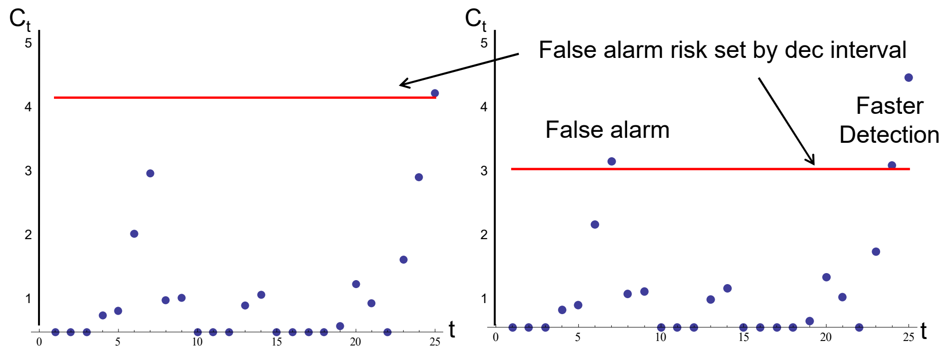
Summary of Change Detection Across Data Sets

There is a trade-off between false positive and rapid detection



Low risk of false alarm
Longer to detect change

High risk of false alarm
Faster to detect change

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Summary of Change Detection Across Data Sets

Too little risk may prevent change detection all together

Data	Change	$\alpha = 0.05$	$\alpha = 0.02$	$\alpha = 0.01$	$\alpha = 0.005$	$\alpha = 0.001$
Fraternity	8	10	10	10	13	Never
Leav 07	3	5	5	5	Never	Never
Leav 05	None	No F.A.	No F.A.	No F.A.	No F.A.	No F.A.
Al-Qaeda	1997	1999	1999	2000	2000	Never
Winter C	May	Sept	Sept	Oct	Oct	Never
Winter A	May	Aug	Sept	Sept	Sept	Oct
IkeNet 2	25	26	26	27	27	27
IkeNet 3	14	15	18	19	19	20

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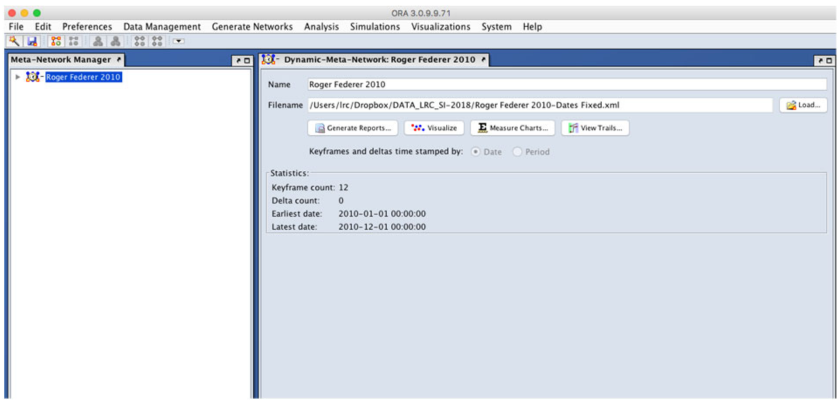
Change Detection Hands-On

- Based on Roger Federer 2010 data



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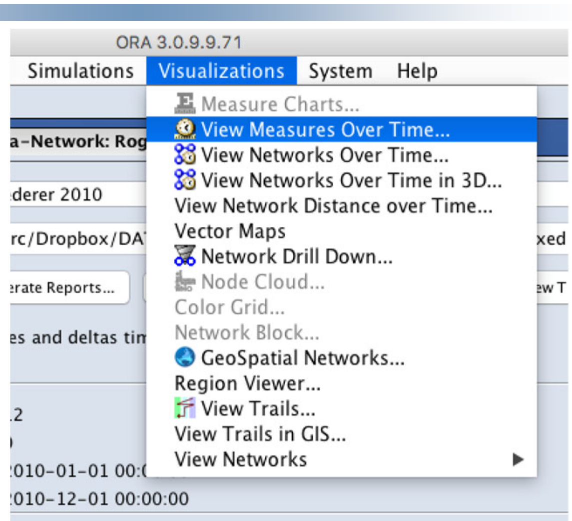
Change Detection Hands-On

- Analysis uses over-time changes in “measures” based on the network data



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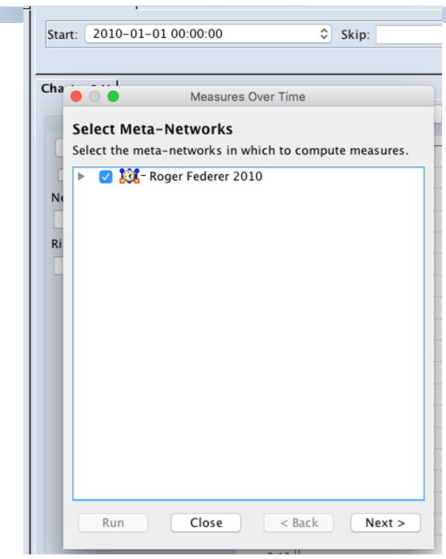
Select The Metanetwork



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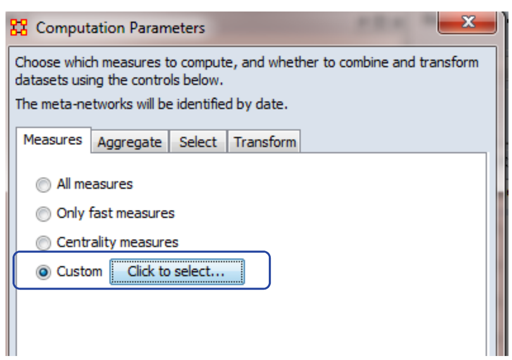
Custom Measure Selection



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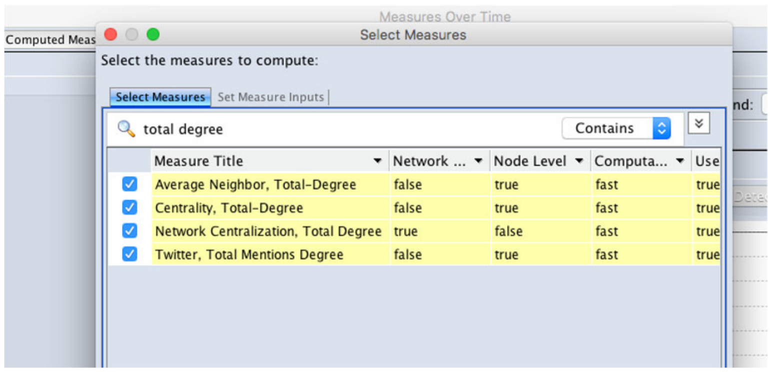
Use Search to Find Measure

Hint: Click Select Box at bottom to deselect all measure,
Then use search to find the ones you want



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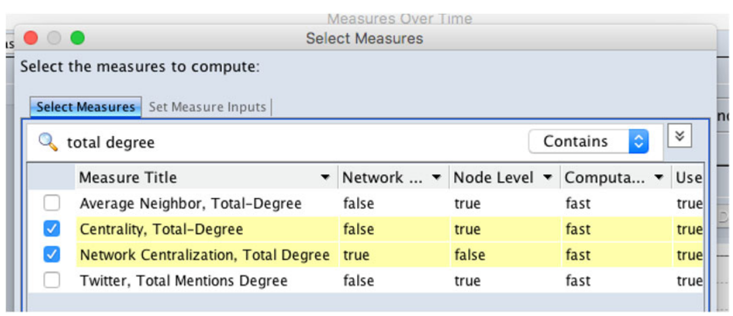
Two measures selected to run



Add Measure – Agent Based Measure – select “Centrality, Total Degree”

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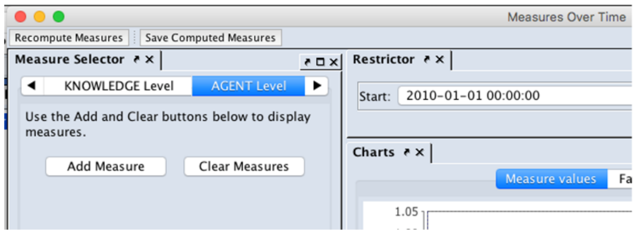
Now Select Display

First step is to select type of variables to display
– AGENT Level in this case



Then click on "Add Measure" to add a new plot line

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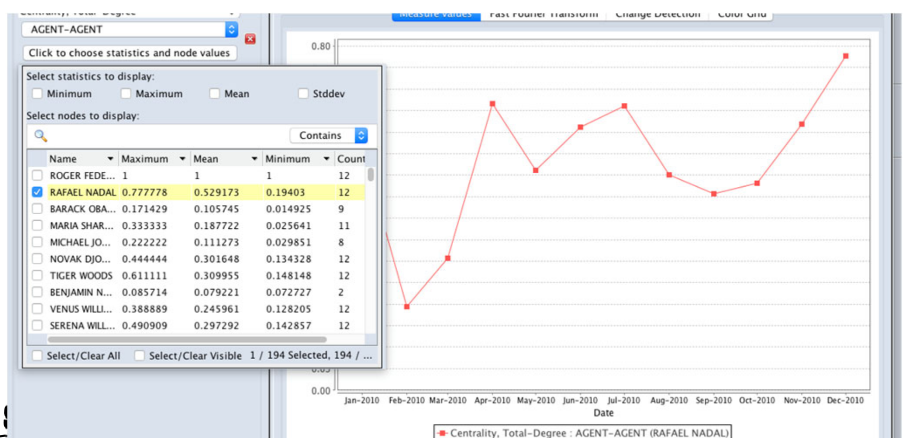
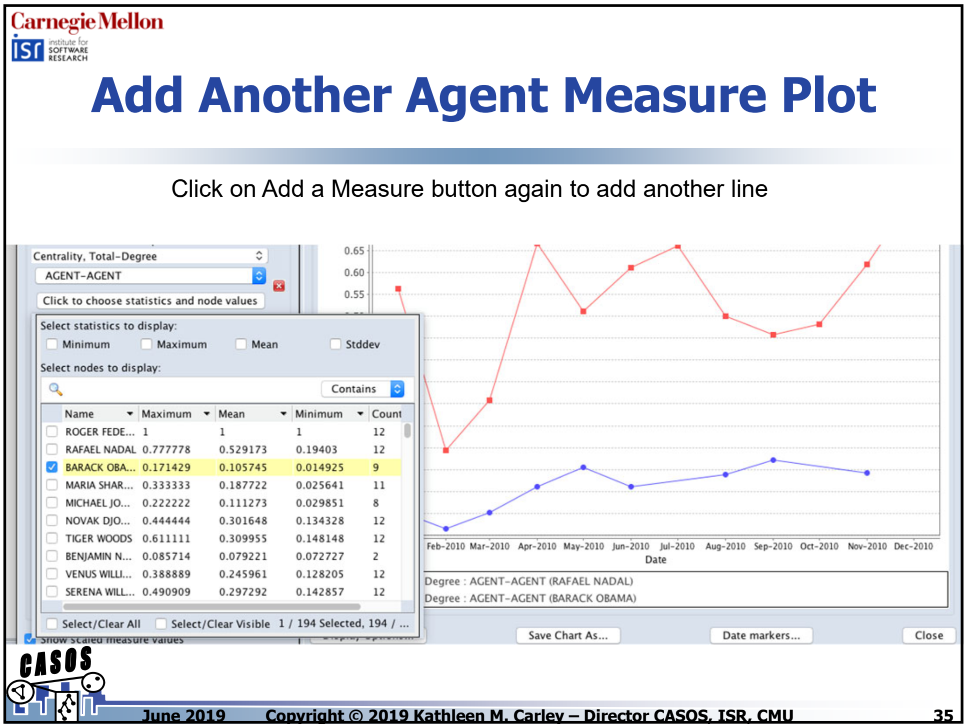
Select Agent for Measure

Click on the "Click to choose ...." button
and select second agent for analysis (Federer is always primary)

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Add Another Agent Measure Plot
Click on Add a Measure button again to add another line
Centrality, Total-Degree
AGENT-AGENT
Click to choose statistics and node values
Select statistics to display:
Minimum
Maximum
Mean
Stddev
Select nodes to display:
Contains
Name
Maximum
Mean
Minimum
Count
ROGER FEDE... 1 1 1 12
RAFAEL NADAL 0.777778 0.529173 0.19403 12
BARACK OBA... 0.171429 0.105745 0.014925 9
MARIA SHAR... 0.333333 0.187722 0.025641 11
MICHAEL JO... 0.222222 0.111273 0.029851 8
NOVAK DJO... 0.444444 0.301648 0.134328 12
TIGER WOODS 0.611111 0.309955 0.148148 12
BENJAMIN N... 0.085714 0.079221 0.072727 2
VENUS WILLI... 0.388889 0.245961 0.128205 12
SERENA WILL... 0.490909 0.297292 0.142857 12
Select/Clear All
Select/Clear Visible
1 / 194 Selected, 194 / ...
Feb-2010 Mar-2010 Apr-2010 May-2010 Jun-2010 Jul-2010 Aug-2010 Sep-2010 Oct-2010 Nov-2010 Dec-2010
Date
Degree : AGENT-AGENT (RAFAEL NADAL)
Degree : AGENT-AGENT (BARACK OBAMA)
Save Chart As...
Date markers...
Close
June 2019
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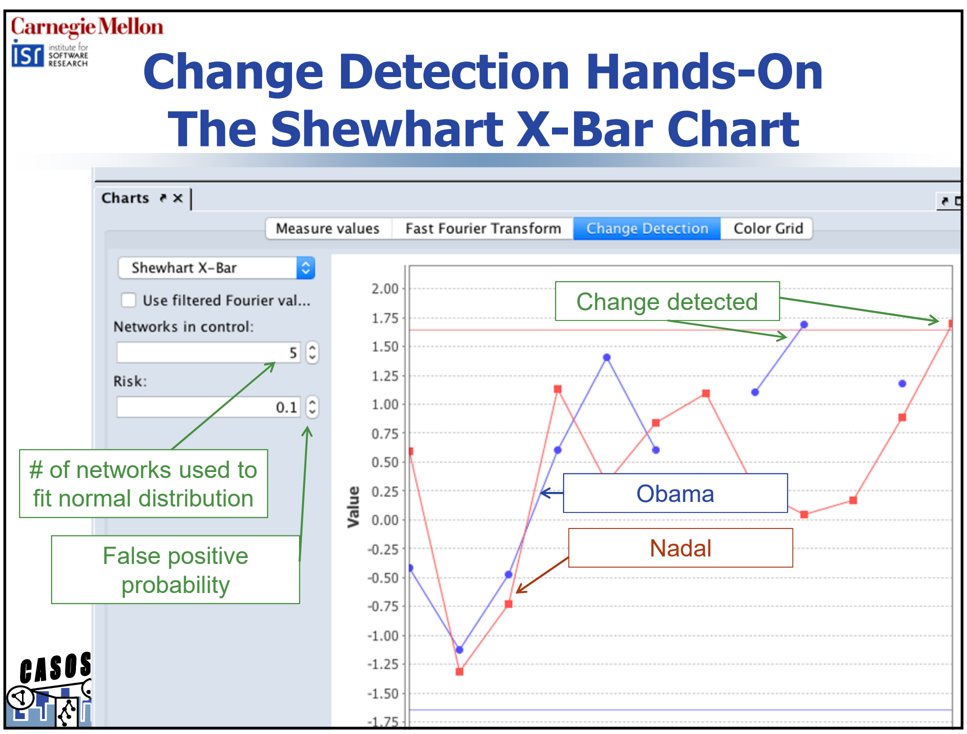
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Change Detection Hands-On
The Shewhart X-Bar Chart
Charts
Measure values
Fast Fourier Transform
Change Detection
Color Grid
Shewhart X-Bar
Use filtered Fourier val...
Networks in control:
5
Risk:
0.1
# of networks used to fit normal distribution
False positive probability
Change detected
Obama
Nadal
Value

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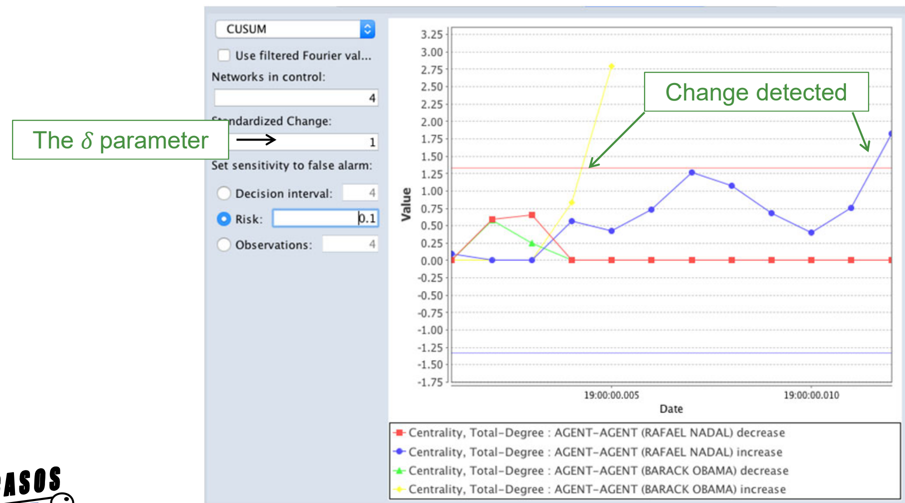
Change Detection Hands-On CUMSUM Method



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Fast Fourier Transform (FFT)

- Goal: detect periodicity in over-time data
- Examples
  - Weekly periodicity in email data
  - Time of the day effects
- Fourier's theorem
  - Any time signal can be represented by a sum of sinusoidal functions with different frequencies, amplitudes and phase shifts
- Fourier transform finds sinusoids that decompose a signal
  - Analogy: given a dish, find the ingredients
  - Sinusoids have the advantage that they are orthogonal

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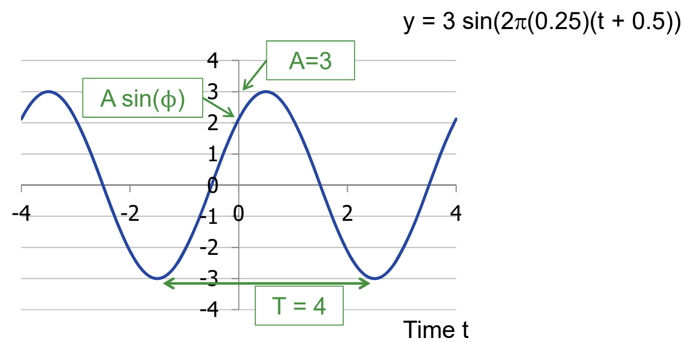
Sinusoidal Function

- A sinusoidal function $y = A\sin(2\pi f t + \phi)$ has
  - A amplitude
  - f frequency $(T = \frac{1}{f}$ is the period)
  - ϕ phase



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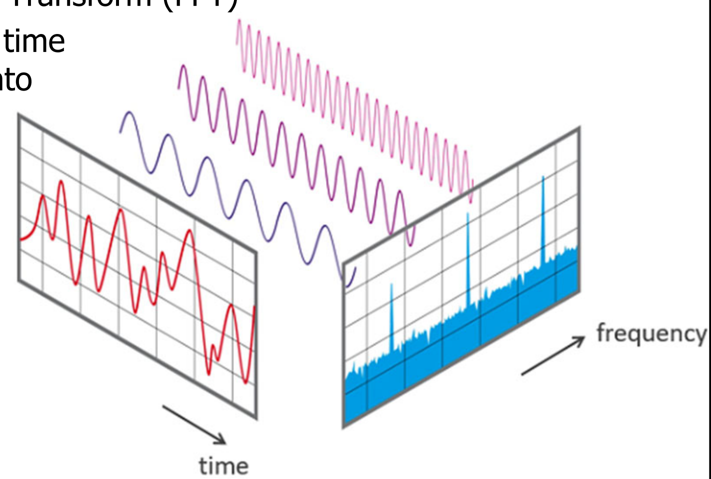
Frequency Domain: The FFT

- Fast Fourier Transform (FFT)
- Decompose time waveform into sum of sinewaves



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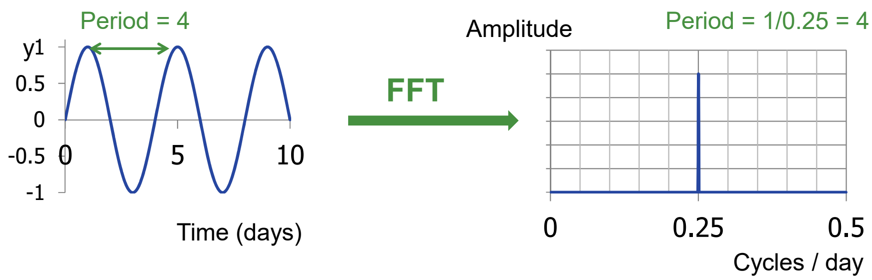
FFT Example: Sum of Sinusoids

- Fast Fourier transform of sinusoidal function is a spike at the sinusoidal frequency
- Example $y = sin(2\,\pi\, 0.25\, t)$



Over-time signal

FFT

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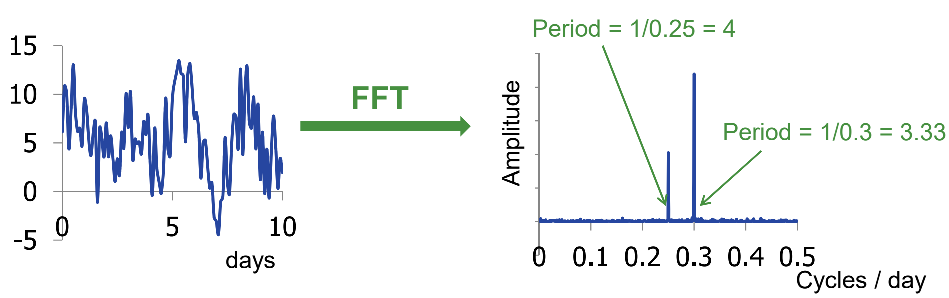
FFT Example 2

- FFT finds periodicities that may be unclear in over-time signal



Over-time signal

FFT

Hidden “recipe”: over – time signal computed as
y(t) = 2 sin(2 pi 0.25 t) + 3 sin(2 pi 0.3 t + 0.2) + noise

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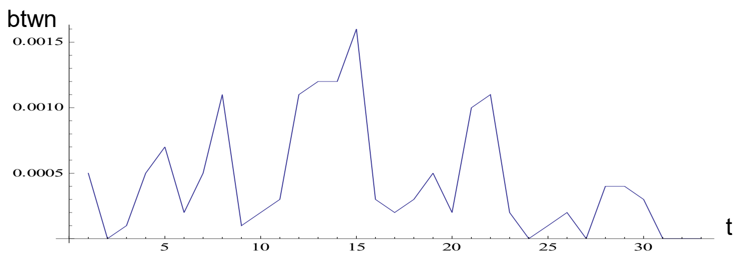
Fourier Analysis Example 3

- 24 cadets in a regimental chain of command agreed to have their email monitored to form a social network data set known as IkeNet3.
- The betweenness was calculated based on the e-mail communications observations over the first month in their duty positions.



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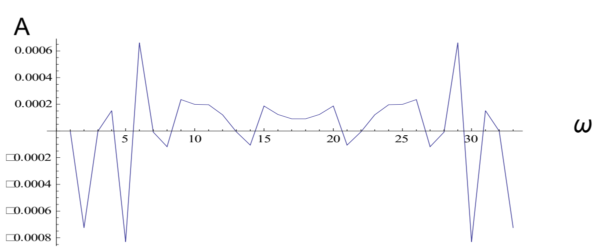
Fourier Analysis – Example 3



Fourier transform
Symmetric around the midpoint
3 main components (in terms of magnitude)

That is why we typically only display from origin up to midpoint

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Digital Signal Processing

Time Sampled Input sampling period T_S → FFT → Sum of Sinusoids (Amplitude, frequency, phase)

→ Digital Signal Processing (DSP)

(e.g., emphasize some frequencies and attenuate other frequencies)

→ Sum of Sinusoids (Amplitude, frequency, phase) → Inverse FFT → Time Sampled Input sampling period T_S

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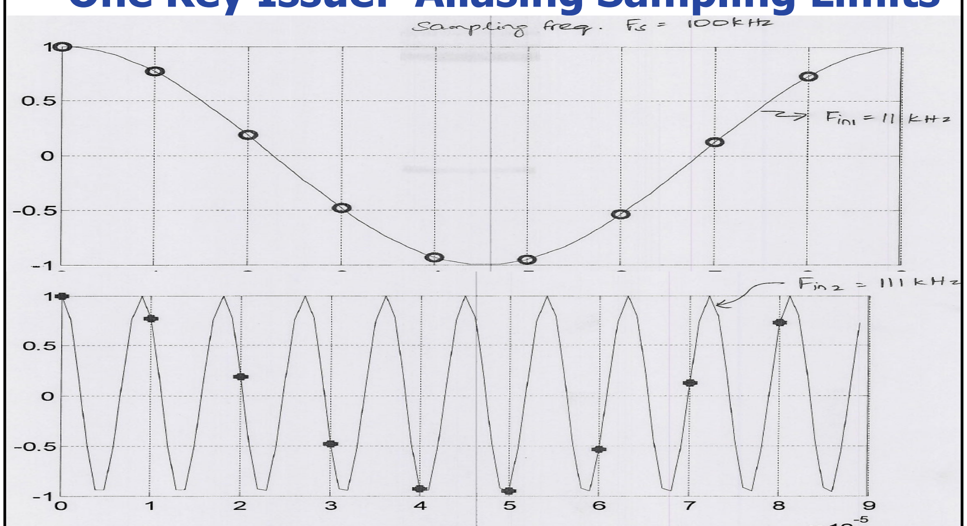
One Key Issue: Aliasing Sampling Limits



If we want DSP to work unambiguously, we choose to limit maximum input frequency to $\leq 1 / (2\, T_S) = F_S / 2$ = "Nyquist Frequency"

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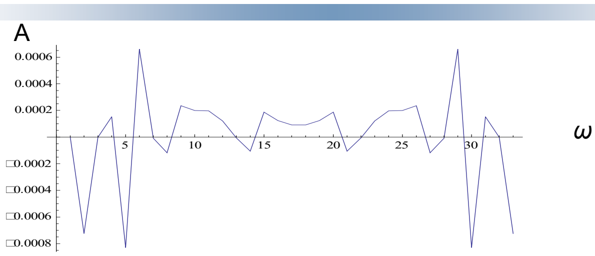
Digital Signal Processing



Fourier transform
Symmetric around the midpoint
3 main components (in terms of magnitude)

That is why we typically only display from origin up to midpoint

How do we use this?

One possible approach – big peaks are periodic “background”

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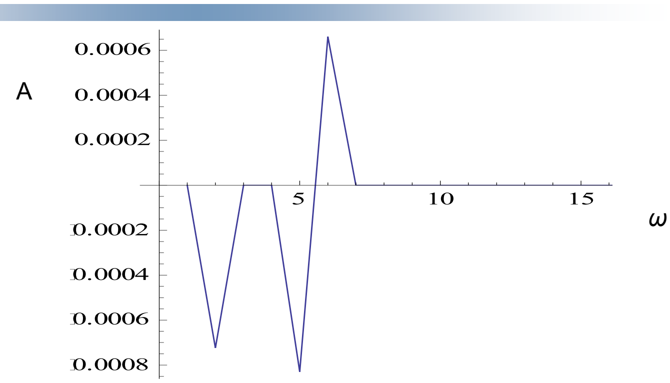
Filtering



e.g., identify 3 main (high magnitude) components
keep them and remove FFT components
at all other frequencies

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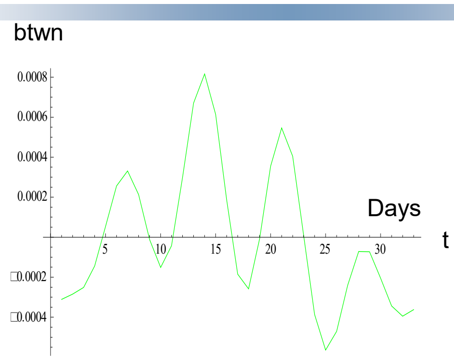
Inverse Fast Fourier Transform



This is the inverse Fourier transform of just the 3
selected components, which are then reconverted to time waveform

There is a weekly, two week and three week cycle

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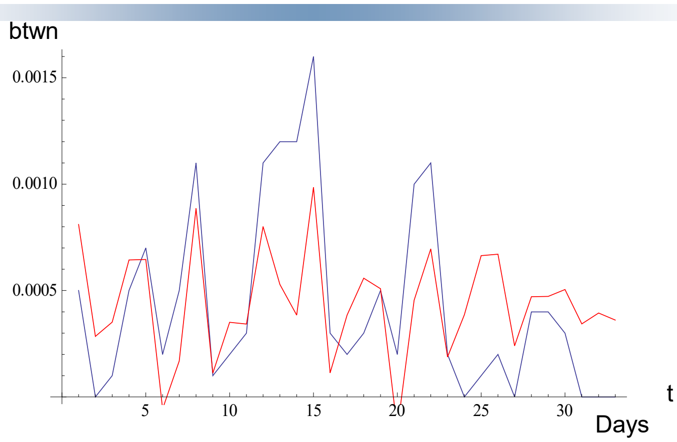
Anomaly Detection



The filtered pattern has been subtracted from the original
The red is what is left – the anomalies

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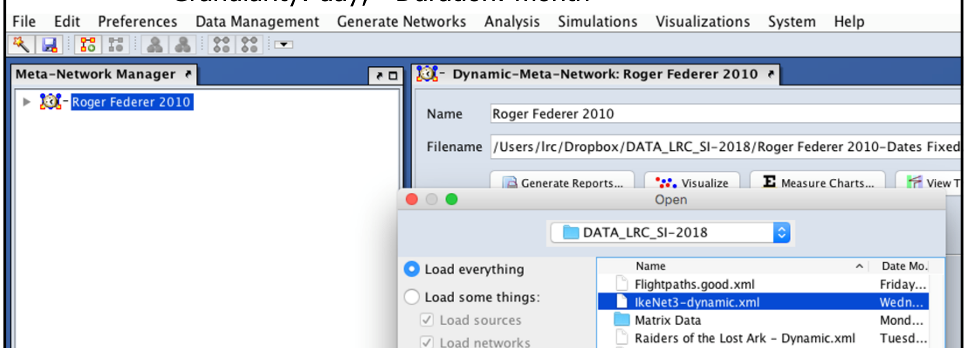
FFT Example Hands-On

- IkeNet data (IkeNet3-dynamic.xml)
  - Email exchange data among mid-career officers in a one-year graduate program at Columbia University
  - Granularity: day; Duration: month



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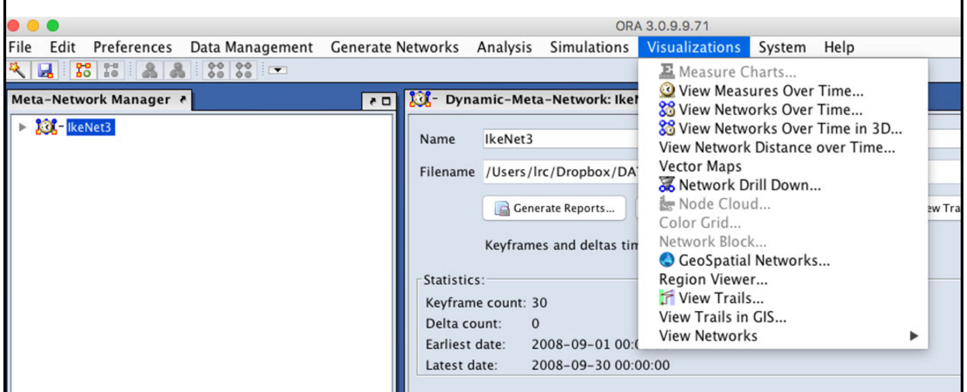
Over Time Measures

Again View Measures Over Time



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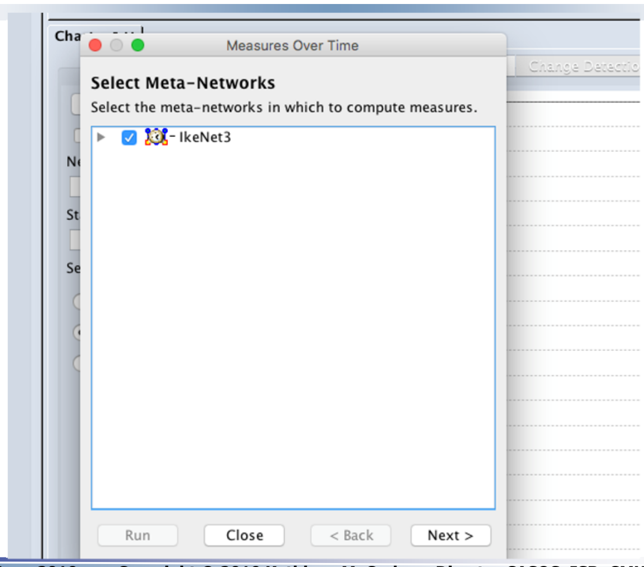
Selecting MetaNetwork



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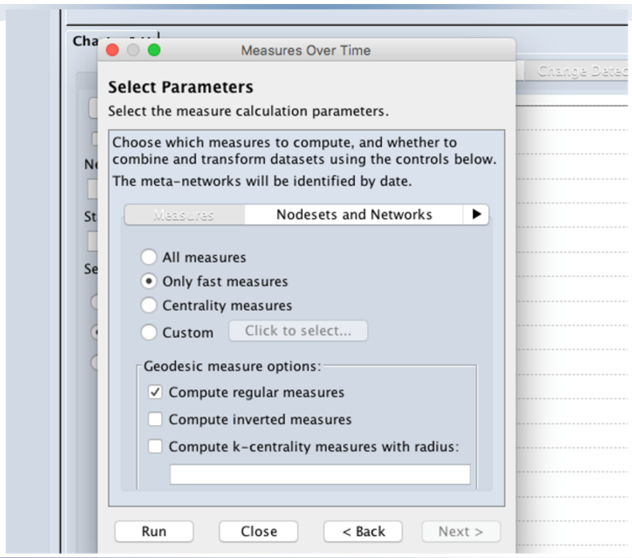
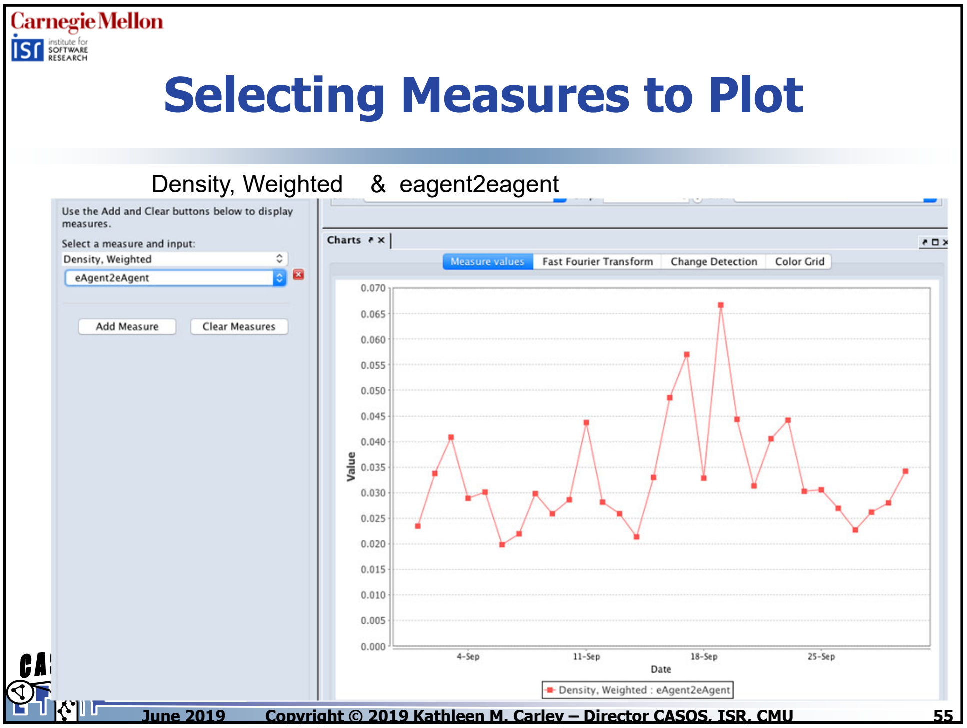
Selecting Measures

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Selecting Measures to Plot
Density, Weighted & eagent2eagent
Use the Add and Clear buttons below to display measures.
Select a measure and input:
Density, Weighted
eAgent2eAgent
Add Measure
Clear Measures
Charts
Measure values
Fast Fourier Transform
Change Detection
Color Grid
Value
Date
Density, Weighted : eAgent2eAgent
June 2019
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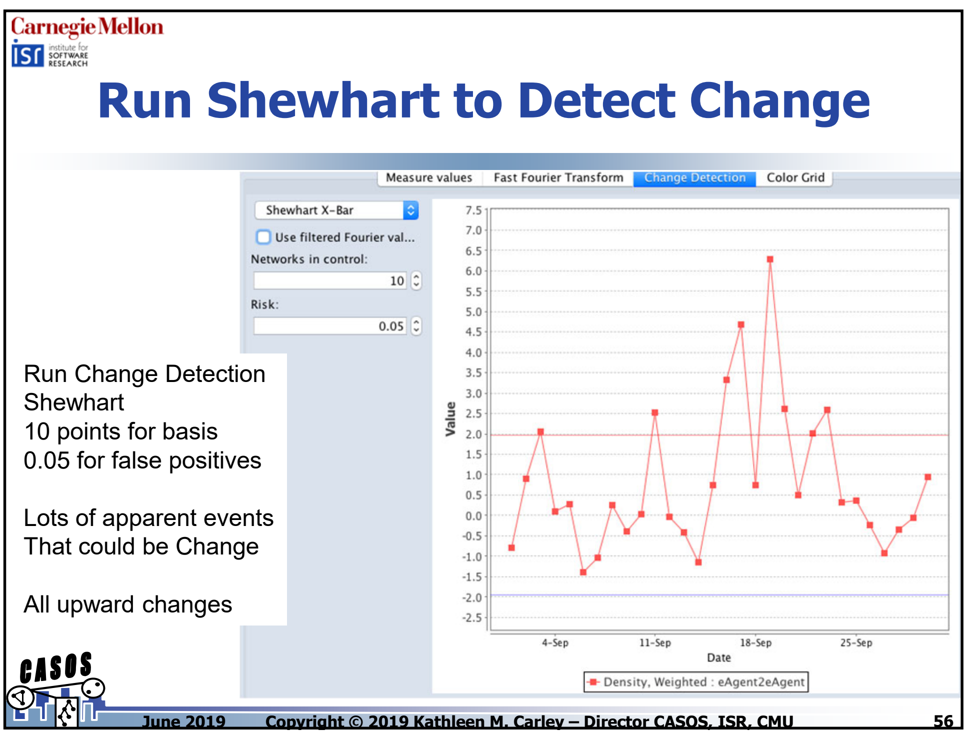
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Run Shewhart to Detect Change
Measure values
Fast Fourier Transform
Change Detection
Color Grid
Shewhart X-Bar
Use filtered Fourier val...
Networks in control:
10
Risk:
0.05
Run Change Detection
Shewhart
10 points for basis
0.05 for false positives
Lots of apparent events
That could be Change
All upward changes
Value
Date
Density, Weighted : eAgent2eAgent
CASOS
June 2019
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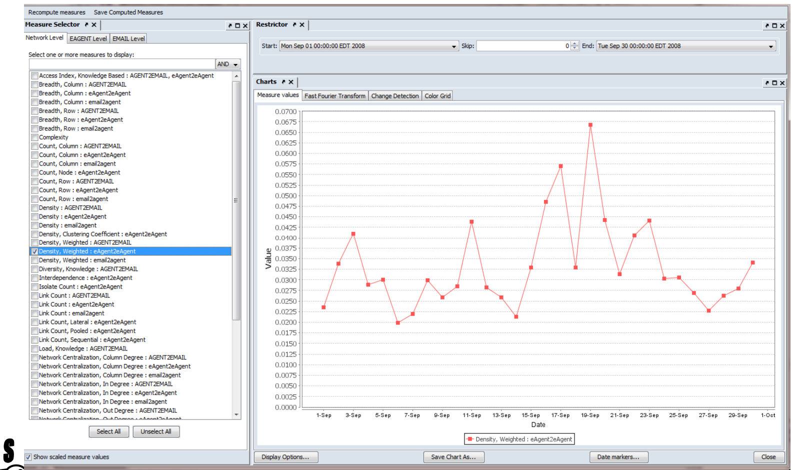
FFT Can Help with Periodic Patterns

Network Level / Density, Weighted / eAgent2eAgent



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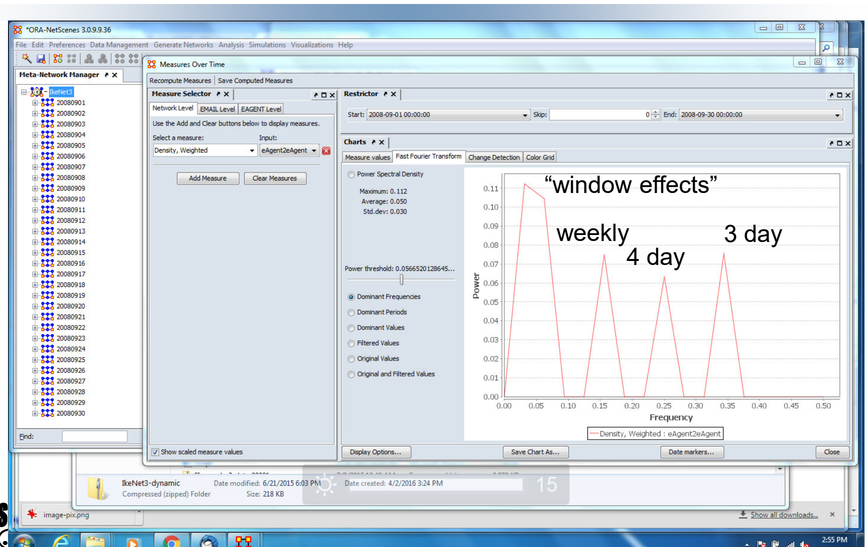
FFT Power Spectral Density



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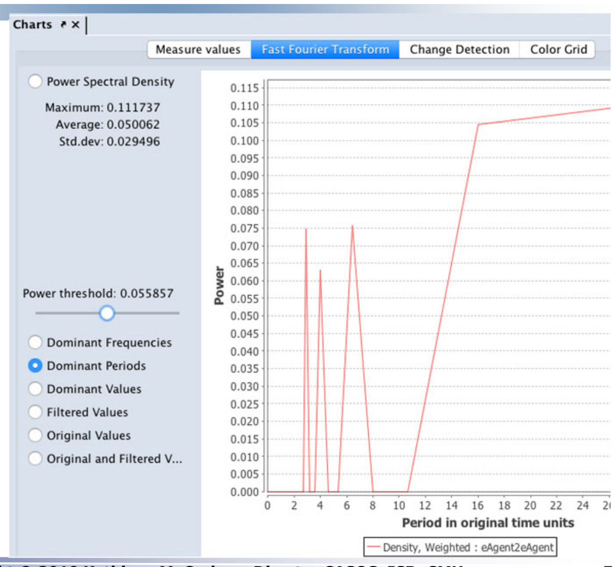
FFT Power vs. Period

Adjust Power Threshold to just select “background” periodic variations to be removed

NOTE – viewing the Dominant Periods is often more intuitive than PSD

The long period values are artifact of finite length of data



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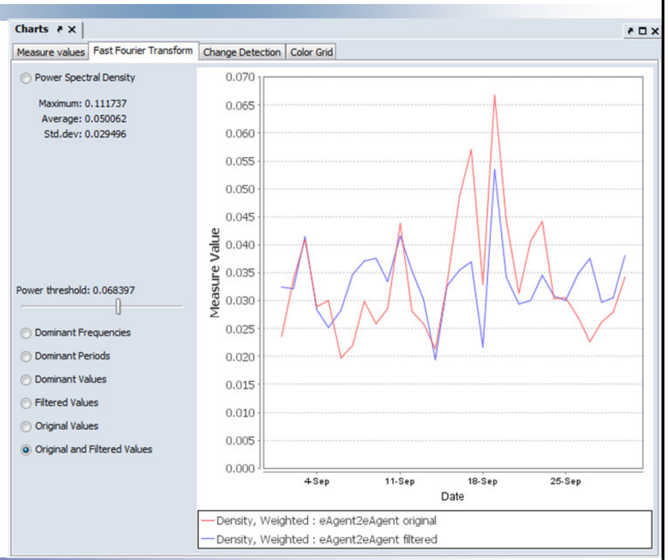
Original vs. FFT subtracted data

Remaining FFT components are converted back to time values (inverse FFT) and subtracted

This removes some of the periodic patterns covering up the fundamental changes to be detected



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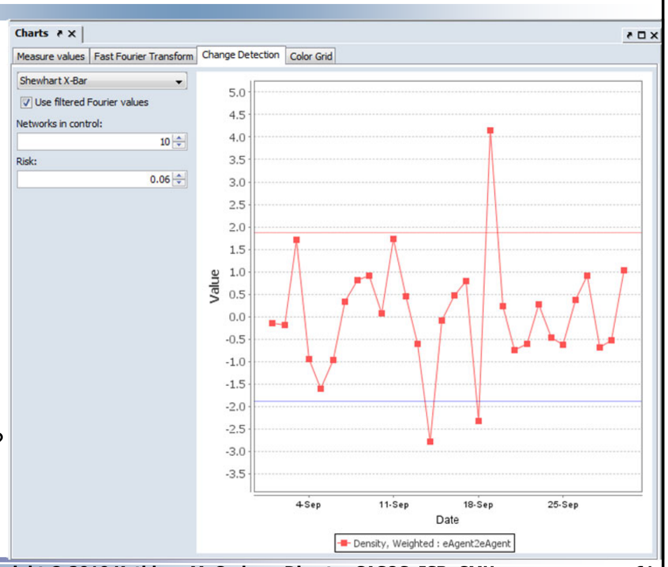
Shewhart on FFT subtracted data

Now use the Filtered Data

Run Change Detection Shewhart
10 points for basis
0.05 for false positives

Only 1 + event and
2 – events

Open Question – is this better than original or not?



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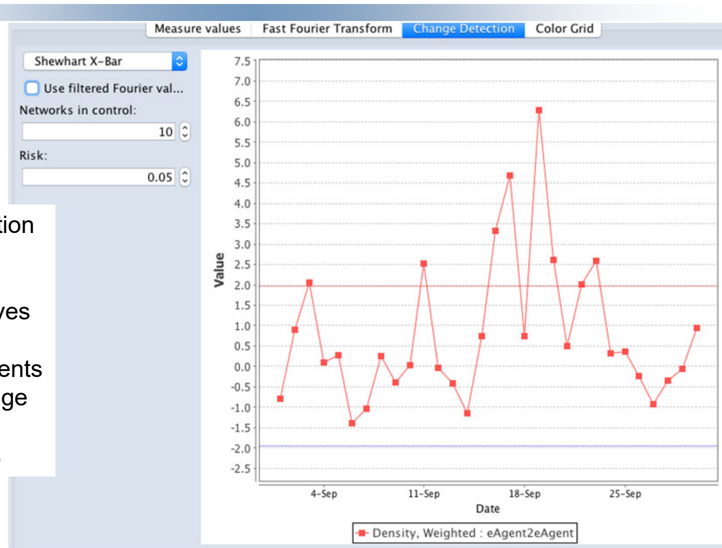
Shewhart on original data



Run Change Detection Shewhart
10 points for basis
0.05 for false positives

Lots of apparent events
That could be Change

All upward changes

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Fourier Analysis to Handle Periodicity

- Fourier analysis can effectively identify periodic trends in longitudinal network data.
- Identification of periodic trends can allow the analyst to aggregate relational data over the period to remove over-time dependence.
- The inverse Fourier transform of the significant period can be used to subtract off periodicity from longitudinal network data measures over time.
- Further exploration of wavelets may produce greater insights in to network dynamics.

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Scalability

- The change detection algorithm is linear, thus the time consuming part is calculating network measures.
- Networks with less than 20 nodes tend to have a higher variance in over time measures. When a link is added or removed, it affects (n-1)(n-2) triads.
- Requires at least 3 time periods: >2 to determine typical behavior and 1 to compare at each time point. In practice, 10+ network time points are preferred.
- No difference in number of required networks for each technique: CUSUM, EWMA, Scan Statistic, x-bar, etc.
- Wavelet/Fourier based approach needs many more time periods and complexity grows roughly as #T(log(#T))

Limitations

- View findings on data with caution
- Slicing and dicing can distort conclusions
- Examine errors associated with technique through extensive simulations.
- Investigate more real world data sets.
- Investigate the degree to which network measures are correlated to understand the effects of compounding error.
- Investigate multi-dimensional network properties such as the cosine similarity between the triad census at different time periods.

Summary of Change Detection

- Rapid change detection may allow an analyst to get inside a decision cycle and shape network evolution.
- Simulation is important for modeling longitudinal network behavior.
- Isolating when networks change enables more focused study on the causes of evolution, shock, and mutation, which may lead to future predictive analysis.
- Statistical process control is a useful tool for understanding social behavior.

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FFT Hands On Session

File – Fourier-Example-3.xml

Walk through analysis on screen and on your laptops

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FFT Example Hands-On (1/4)

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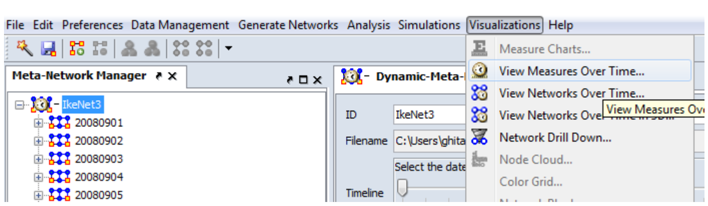

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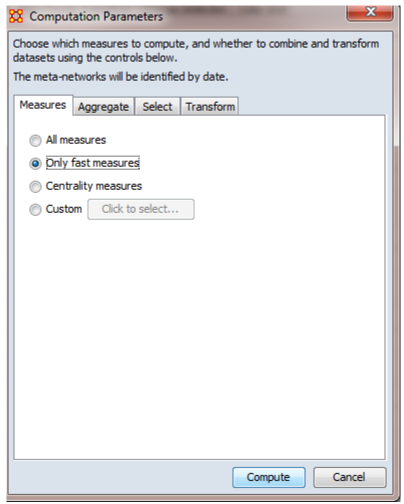
FFT Example Hands On (2/4)



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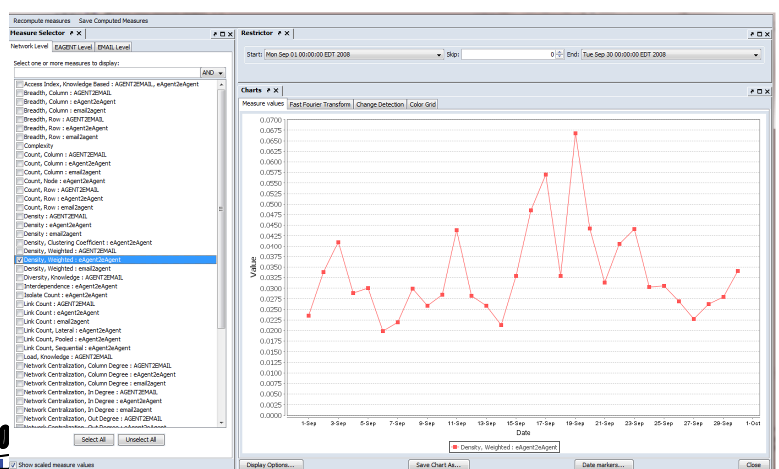
FFT Example Hands On (3/4)



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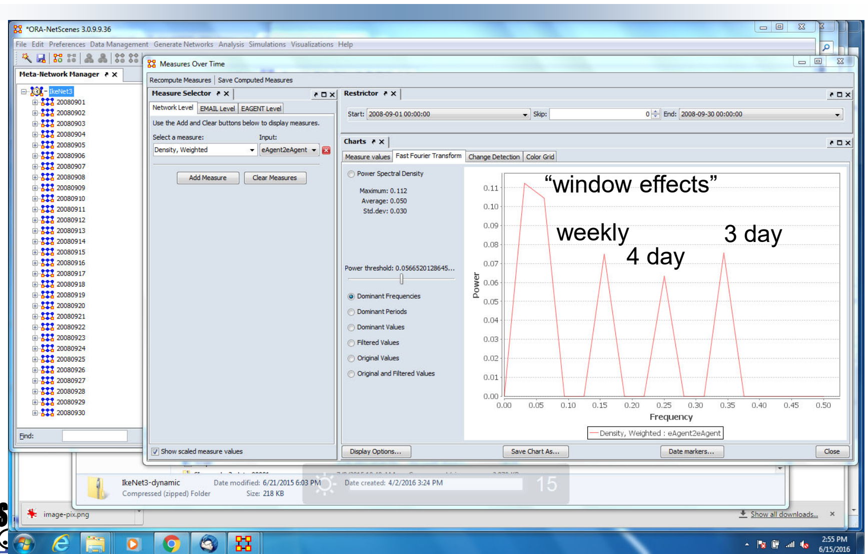
FFT Example Hands On (4/4)



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Summary Results

- Rapid change detection may allow an analyst to get inside a decision cycle and shape network evolution.
- Simulation is important for modeling longitudinal network behavior.
- Isolating when networks change enables more focused study on the causes of evolution, shock, and mutation, which may lead to future predictive analysis.
- Statistical process control is a useful tool for understanding social behavior.

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Conclusions

- Change detection
  - Detect occurrence of shocks i.e. change due to reasons exogenous to the network
- Fourier analysis
  - Detect periodicity in over-time data