Understanding the Brain as a Network

Satoru Hayasaka, Ph.D.
Understanding the Brain as a Network

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Slides for this lecture will be available at

http://lcbn.wakehealth.edu
Outline

• Part I: Graph Theory & Network Science  
  (Questions & Answers)
• Part II: Applications
Outline
(Part I)

- Graph Theory & Network Science
- Introduction
- Examining & Describing a Network
- Small-World Networks
- Brain Networks - Overview
Outline

(Part I)

• Graph Theory & Network Science
  • Introduction
• Examining & Describing a Network
• Small-World Networks
• Brain Networks - Overview
Seven Bridges of Königsberg

- There were 7 bridges in Königsberg, Prussia (modern day Kaliningrad, Russia)
- Connecting two islands and both sides of Pregel River
Seven Bridges of Königsberg

- Can one walk through the city?
- Crossing each bridge only once
- Coming back to where started
Seven Bridges of Königsberg

- Leonhard Euler proved that it is impossible (1736)
- Using graph theory
Seven Bridges of Königsberg

- Abstract representation of the lands and bridges

Graph
A collection of nodes and edges connecting them
Seven Bridges of Königsberg

- Each node can only have an even number of edges (unless it is the terminus)
- One walks into a node, then walks out of that node
- All Königsberg’s nodes have an odd number of edges
Graph Theory

• More formally, a graph $G(v,e)$ comprises
  
  • a collection of nodes $v$
  • a collection of edges $e$

Example: $G(v,e)$ where

$v=\{a, b, c, d, e\}$
$e=\{(a,b), (a,e), (b,c), (b,e), (c,d), (d,e)\}$
Graph Theory

- A graph can be described as a matrix known as an *adjacency matrix* $A$

\[
A = \begin{pmatrix}
0 & 1 & 0 & 0 & 0 & 1 \\
1 & 0 & 1 & 0 & 1 & 0 \\
0 & 1 & 0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 & 1 & 0 \\
1 & 1 & 0 & 0 & 1 & 0 \\
1 & 1 & 0 & 1 & 0 & 0 \\
\end{pmatrix}
\]

1 = connected, 0 = not connected
Graph Theory

- Degree $k = \# \text{ edges (or connections)}$
Graph Theory

• **Strength of connections**

[Diagram of an unweighted network with equal connection strengths and a weighted network with different connection strengths]
Network Science

- **Graph** synonymous for **Network**
  - **Nodes**: units
    - Persons, brain areas, genes, etc
  - **Edges**: relationship between units
    - Friendship, connections, associations, etc

- **Networks describe relationships**
  - Social / biological / technological
Networks are Everywhere

Interstate highway system

Marriage network
Renaissance era Florence

Wnt signaling pathway
Examples

Social network of Obesity from Framingham Heart Study

Christakis & Fowler, NEJM (2007)
Examples

Collaboration network at Santa Fe Institute

Examples

Functional Brain Connectivity
Outline
(Part I)

- Graph Theory & Network Science
- Introduction
- Examining & Describing a Network
- Small-World Networks
- Brain Networks - Overview
Size of a Network

- Number of nodes & edges

4 nodes → $N=4$
4 edges → $E=4$
# Size of a Network

- **Number of nodes & edges**

<table>
<thead>
<tr>
<th>Networks</th>
<th>N</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dolphin social network</td>
<td>62</td>
<td>159</td>
</tr>
<tr>
<td>C. Elegans neural network</td>
<td>277</td>
<td>1,918</td>
</tr>
<tr>
<td>Power grid (EU)</td>
<td>2,783</td>
<td>3,762</td>
</tr>
<tr>
<td>Physics co-authorship</td>
<td>52,909</td>
<td>245,300</td>
</tr>
<tr>
<td>Biology co-authorship</td>
<td>1,520,000</td>
<td>11,800,000</td>
</tr>
</tbody>
</table>

*Laurienti et al., Physica A (2011)*
Densely Connected?

- Average degree $K$

![Graph](image)
Densely Connected?

- Edge density \( d \)
- Also known as cost or wiring cost

\[
d = \frac{\text{Actual edges}}{\text{Possible edges}} = \frac{4}{6}
\]
Densely Connected?

- Average degree $K$ and edge density $d$

<table>
<thead>
<tr>
<th>Networks</th>
<th>$N$</th>
<th>$K$</th>
<th>$d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dolphin social network</td>
<td>62</td>
<td>5.1</td>
<td>0.0841</td>
</tr>
<tr>
<td>C. Elegans neural network</td>
<td>277</td>
<td>13.8</td>
<td>0.0502</td>
</tr>
<tr>
<td>Power grid (EU)</td>
<td>2,783</td>
<td>2.7</td>
<td>0.000972</td>
</tr>
<tr>
<td>Physics co-authorship</td>
<td>52,909</td>
<td>9.3</td>
<td>0.000175</td>
</tr>
<tr>
<td>Biology co-authorship</td>
<td>1,520,000</td>
<td>15.5</td>
<td>0.0000102</td>
</tr>
</tbody>
</table>

Laurienti et al., Physica A (2011)
Densely Connected?

\[ R^2 = 0.928 \]

Connection density \((d)\)

Network size \((N)\)

\[ 7.890 N^{-0.986} \]

Laurienti et al., Physica A (2011)
Node Degree

- Number of connections at each node
- Often denoted by $k$
Degree Distribution

- Node degrees - tremendously heterogeneous
  - Vast majority of nodes:
  - Very few hubs:
Degree Distribution

Examples of degree distributions

Hollywood actors  World wide web  Power grid

Degree Distribution

- Heterogeneity in degree
  - Vast majority
    - $k = 10 \sim 80$
  - Very few hub nodes
    - $k = 300+$

Hayasaka & Laurienti, NeuroImage (2010)
Outline
(Part I)

• Graph Theory & Network Science
  • Introduction
  • Examining & Describing a Network
  • Small-World Networks
  • Brain Networks - Overview
Milgram Experiment (1967)

- Q: How connected are two complete strangers?
- A: About six steps

Milgram’s small-world experiment (1967)
Passing a letter from friends to friends

Stanley Milgram
Milgram Experiment (1967)

- Some letters did reach the target

Widowed clerk
Omaha, NE

Self-employed friend
Council Bluffs, IA

Publisher
Belmont, MA

Tanner
Sharon, MA

Printed worker
Sharon, MA

Stock broker
Sharon, MA

Clothing merchant
Sharon, MA

Dentist
Sharon, MA

Printer
Sharon, MA
Milgram Experiment (1967)

- On average, 6 intermediary acquaintances

  Small-world phenomenon

- Also known as “Six degrees of separation”
Milgram Experiment (1967)

• A simplistic picture
  • Say, each person knows 100 people
    • Separated by 1 step from 100 people
    • Separated by 2 steps from 10,000 people
    • Separated by 3 steps from 1,000,000 people
    • Separated by 4 steps from 100,000,000 people
    • Separated by 5 steps from 10,000,000,000 people ... and so on
Small-World Networks

- Small-world phenomenon meets graph theory

Regular network
Sitting at a stadium

Small-world network
Mobile phones at a stadium

Re-wiring a few edges randomly
Small-World Networks

- Small-world phenomenon meets graph theory (Watts & Strogatz, Nature (1998))

**Small-world characteristics**

- Efficient long-distance communication ➔ Any node is just a few steps away
- Clustering ➔ Highly interconnected neighborhoods

**Global distribution & Local specialization**

Mobile phones at a stadium
Small-World Characteristics

Efficient long-distance communication $\rightarrow$ Path length $L$

“$L$ steps of separation” summarizing shortest distances between nodes
Small-World Characteristics

Tight local interconnections $\Rightarrow$ Clustering coefficient $C$

Likelihood of nodes being interconnected $\Rightarrow$ Probability of your friends also being friends to each other

Low $C$ → High $C$
Small-World Characteristics

- Is a network is small-world?

→ By comparing to a random network

(Same size number of nodes & edges)

<table>
<thead>
<tr>
<th>Clustering coefficient</th>
<th>Small-world network</th>
<th>Random network</th>
</tr>
</thead>
<tbody>
<tr>
<td>C: very large</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C_{rand}: small</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Path length</th>
<th>L: very small</th>
<th>L_{rand}: very small</th>
</tr>
</thead>
</table>

Small-world metric

\[ \sigma = \frac{C/C_{\text{rand}}}{L/L_{\text{rand}}} \]

\( \sigma > 1 \rightarrow \) small-world network

Small-World Characteristics

- Most networks are small-world

According to $\sigma > 1$ criterion

<table>
<thead>
<tr>
<th>Network</th>
<th>$\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>C. Elegans</td>
<td>2.18</td>
</tr>
<tr>
<td>Email network</td>
<td>8.14</td>
</tr>
<tr>
<td>Protein interactions</td>
<td>1.47</td>
</tr>
<tr>
<td>Internet</td>
<td>2.28</td>
</tr>
</tbody>
</table>

*Small-world metric*

$$\sigma = \frac{C/C_{\text{rand}}}{L/L_{\text{rand}}}$$

$\sigma > 1 \rightarrow$ small-world network


Telesford et al., Brain Connectivity (in press)
Small-World Metric $\omega$

Telesford et al., Brain Connectivity (in press)

$$\omega = \frac{L_{\text{rand}}}{L} - \frac{C}{C_{\text{latt}}}$$
Small-World Characteristics

- Some are small-world like ($\omega \approx 0$)
- Others are more random like ($\omega > 0$)

<table>
<thead>
<tr>
<th>Network</th>
<th>$\sigma$</th>
<th>$\omega$</th>
</tr>
</thead>
<tbody>
<tr>
<td>C. Elegans</td>
<td>2.18</td>
<td>0.12</td>
</tr>
<tr>
<td>Email network</td>
<td>8.14</td>
<td>0.56</td>
</tr>
<tr>
<td>Protein interactions</td>
<td>1.47</td>
<td>0.47</td>
</tr>
<tr>
<td>Internet</td>
<td>2.28</td>
<td>0.51</td>
</tr>
</tbody>
</table>

Telesford et al., Brain Connectivity (in press)
Centrality

• Which nodes are important?

• Various centrality metrics
  Borgatti & Everett, Social Networks (2006)

Degree centrality
Betweenness centrality
Eigenvector centrality
Leverage centrality

Joyce et al., PLoS ONE (2010)
Centrality

• Degree centrality
  • Most popular in brain networks

Top 20% degree centrality nodes

Hayasaka & Laurienti, NeuroImage (2010)
Community Structure

- Some nodes are interconnected
  - Forming neighborhoods or modules


Telesford et al., Brain Connectivity (2011)
Community Structure

- In functional brain networks

*Determining community structure is computationally intensive.*

Courtesy of Paul Laurienti
Examining Networks

• Comparing univariate metrics
  • Centrality, C, L, small-world metrics
  • Two-sample t-tests

• Qualitative description
  • Degree distributions, community structure
  • Describing the network structure
Examining Networks

- Summarizing by a single number
  - Over-simplifying

C=0.54
C=0.64
Examining Networks

- Summarizing by a single number
- Over-simplifying

$k > 18$

L=2.1
C=0.1
K=18

L=2.1
C=0.1
K=18

k=18 for all nodes
Examining Networks

- Focusing on particular nodes only
- Network analysis ≠ fMRI analysis

Top 20% degree centrality nodes

Hayasaka & Laurienti, NeuroImage (2010)
Examining Networks

• Focusing on particular nodes only
• Network analysis ≠ fMRI analysis

Edges originating from the highest degree node

Telesford et al., Brain Connectivity (2011)
Examining Networks

- Focusing on particular nodes only
- Network analysis ≠ fMRI analysis

Joyce et al., PLoS ONE (2010)
Outline
(Part I)

• Graph Theory & Network Science
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• Small-World Networks
• Brain Networks - Overview
Early Brain Networks

- C. Elegans - complete neural network

University of California Irvine
Network Data Repository
http://networkdata.ics.uci.edu/
Early Brain Networks

- Histological tracing of cat and macaque
Early Brain Networks

- Functional brain imaging

**fMRI**


**MEG**

Early Brain Networks

- Diffusion tensor and spectrum imaging


Brain Network Analysis

(a) Brain imaging data

Generating structural network

(b) Anatomical connections (DTI tractography)

(c) Adjacency matrix

(d) Structural network

(e) Network metric calculation

(f) Voxel time courses

(g) Correlation matrix

(h) Adjacency matrix

(i) Functional network
Brain Network Analysis

- Extracting a network from imaging data
  - Modality specific
    - Functional (fMRI, EEG, MEG, etc)
    - Structural (DTI / DSI tractography)
- Analysis is the same
  - Graph theory methods
Where to Start

- Olaf Sporns, Networks of the Brain (MIT Press, 2011)
  - Comprehensive review of brain networks from
    - Neuroscience perspective
    - Graph theory perspective
    - Complex systems perspective
Where to Start

• Review Articles
  • Stam & Reijneveld, Nonlinear Biomed Phys (2007)
  • Bullmore et al., NeuroImage (2009)
  • Bullmore & Sporns, Nature Rev Neurosci (2009)
  • Rubinov & Sporns, NeuroImage (2010)
  • Telesford et al., Brain Connectivity (2011)
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Understanding the Brain as a Network

Satoru Hayasaka, Ph.D.
Outline

(Part II)

• Applications
• Functional Connectivity Network
• Gene-Brain Network
• Resources
Outline

(Part II)

• Applications
  • Functional Connectivity Network
• Gene-Brain Network
• Resources
Functional Connectivity

- Brain is never “off”
  - Brain activity even during resting
- Resting activity $\rightarrow$ highly correlated
  - Despite lack of stimuli
Functional Connectivity

Correlated brain activity

Raichle & Snyder, NeuroImage (2007)
Functional Connectivity

High temporal correlation
➔ These areas are functionally connected

Raichle & Snyder, NeuroImage (2007)
An informal description of a complex network for systems biology. Adjacency matrix is specified for systems biology. For most brain networks, the adjacency matrix is symmetrical. The adjacency matrix is a binary matrix where each element is either 1 (if there is an edge between nodes) or 0 (if there is no edge). For an edge between nodes, the number of edges between each pair of nodes in a graph is estimated in random networks containing the same number of nodes and connections. Statistical testing of network parameters can be quantified in groups of subjects. High clustering, small-worldness, the presence of high-degree nodes or hubs, and assortativity, modularity or topological features, such as hierarchy, that are not typical of random graphs or regular lattices. Most real-life networks are complex by this definition, and analysis of complex networks with certain structural and functional brain networks can be explored using graph theory through the following four steps (see the figure):

1. **Histological or imaging data**
   - **Anatomical parcellation**
   - **Recording sites**
   - **Time series data**

2. **Structural brain network**
   - **Functional brain network**
     - **Sensorimotor**
     - **Parietal**
     - **Premotor**
     - **Prefrontal**
     - **Occipital**
     - **Inferior temporal**
     - **Orbitofrontal**
     - **Temporal pole**

3. **Graph theoretical analysis**

Each step entails choices that can influence the final results and must be carefully informed by the experimental question. Most graph theoretical network studies to date have used symmetrical measures of statistical association or functional connectivity — such as correlations, coherence and mutual information — to construct undirected graphs. This approach could be generalized to consider asymmetrical measures of causal association or effective connectivity — such as Granger causality model coefficients — to construct directed graphs. It is also possible to avoid the lack of statistical theory concerning the distribution of most network metrics. Parameters may best be conducted by permutation- or resampling-based methods of non-parametric inference given the equivalent parameters of a population of random networks.

The configuration of functional networks. At step 2, a range of different coupling metrics can be estimated, including measures estimated in groups of subjects. At step 1, parcellation schemes can use prior anatomical criteria or be informed by the functional connectivity profiles of individual diffusion tensor imaging data set, or the inter-regional correlations in cortical thickness or volume MRI or dynamic causal model coefficients — to construct directed graphs. It is also possible to avoid the lack of statistical theory concerning the distribution of most network metrics.

A brain network can be formed based on functional connectivity. **Bullmore & Sporns, Nat Rev Neurosci (2009)**
Functional Connectivity

- Functional brain networks
- Macro-scale (~100 nodes)
- Small-world networks

Achard et al., J Neurosci (2006)
Resting fMRI Network

- Data: resting-state fMRI data
  - fMRI images while resting (every 2s for 5min)
  - N =10 normal subjects

- Different network “resolutions”
  - Region (ROI)-based network
  - Voxel-based network
Resting fMRI Network

- Node $\equiv$ voxel ($\sim$20,000) or ROI ($\sim$90)
- Edge $\equiv$ functional connectivity
- Correlation coefficient $> R$
Preparing the Data

- Resting-state fMRI data
  - Can be steady-state fMRI data
    - Watching a movie, hearing a speech, etc.
  - Difficult for block or event-related design
- Sufficiently large number of scans (100+)
Preparing the Data

- Pre-processing: fMRI
  - Motion correction
  - Spatial normalization
  - NO SMOOTHING!
    - Induces artificial local correlation
    - Spurious local connectivity
Preparing the Data

• Pre-processing: functional connectivity  
  Fox et al., PNAS (2005)

• Temporal filtering
  • Band-pass 0.01-0.1 Hz

• Global correction via regressors
  • White matter, ventricle, whole-brain signals

• Motion parameters as regressors
  • Rigid-body motion parameters
Constructing Networks

**Region-based network**
- Popular approach
- Simple to generate
- Computationally easy
- Limited localization

**Voxel-based network**
- Difficult to generate
- Computationally taxing
- Excellent localization

Hayasaka & Laurienti, arXiv (2009)
Constructing Networks

• How to threshold a correlation matrix?
  • Fixed R (same R value, FDR-corrected, etc.)
  • A range of R (e.g., $R=0.3 - 0.7$)
  • Matching cost (connection density $d$)
    • $d$ is dependent on size of networks
  • Matching path lengths  *Hayasaka & Laurienti, NeuroImage (2010)*
    • Theoretically, matching $S=\log(N)/\log(K)$
Network Analysis

- Degree distributions

Hayasaka & Laurienti, NeuroImage (2010)
Network Analysis

Top 20% nodes  

Hayasaka & Laurienti, Neurolmage (2010)

Region-based  

Voxel-based

Node degree $k$

Standardized $L$  
(Global efficiency)

Range:
- 0 (least optimal)
- 1 (most optimal)

Standardized $C$  
(Local efficiency)
Network Analysis

- Key nodes tend to spatially coincide

Height: node degree \((k)\)
Color: efficiency (Global: \(E_{\text{glob}}\), Local: \(E_{\text{loc}}\))

*Hayasaka & Laurienti, NeuroImage (2010)*
Network Analysis

• Key nodes consistent across subjects

Hayasaka & Laurienti, NeuroImage (2010)
Network Analysis

- Consistent location of hub nodes
- Similar to brain anatomical network

Hayasaka & Laurienti, NeuroImage (2010)  
Summary

Highlight of findings

• Heterogeneous degree distribution
• Consistent location of key nodes
  • Posterior cingulate, precuneus
  • Across subjects
  • Similar to anatomical network
What Else Can We Do?

- Community structure

(Note: This is a different data set)

Precuneus community

Courtesy of Paul Laurienti
What Else Can We Do?

- Community structure

(Note: This is a different data set)

Consistency of hippocampus module across subjects

Burdette et al., Frontiers Aging Neurosci (2010)
What Else Can We Do?

- Cognitive states & network re-organization

Consistency of high-degree nodes across subjects (n=20)

Moussa et al., Frontiers Hum Neurosci (2011)
Outline

(Part II)

• Applications
• Functional Connectivity Network
• Gene-Brain Network
• Resources
Gene-Brain Network

- Genetic influence on the brain is localized rather than global

Anatomical circuitry used as endophenotypes in a GWAS
Potkin et al., Molecular Psychiatry (2008)
Gene-Brain Network

- Genetic influence on the brain is localized rather than global

Whole-brain GWAS on AD cohort
Shen et al., NeuroImage (2010)
Gene-Brain Network

• Combining the gene network and the brain network

Genetically-mediated brain network
Schmitt et al., Cerebral Cortex (2008)
Gene-Disease Network

Diseasome Network

Goh et al., PNAS (2007)
Gene-Disease-Brain Network

- How about connecting brain areas to gene-disease network?
- Regional differences in genetic influence
- Where do genetic diseases affect the brain?
Gene-Disease-Brain Network

Gene-disease connection
OMIM database
(Goh et al, PNAS 2007)

Disease-brain connection
Co-occurrence in PubMed
(www.pubbrain.org)
Disparity in Connections

- Some nodes are disproportionately more connected than others

Brain areas affected by many diseases:

<table>
<thead>
<tr>
<th>Brain area</th>
<th>#Diseases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypothalamus</td>
<td>379</td>
</tr>
<tr>
<td>Hippocampus</td>
<td>258</td>
</tr>
<tr>
<td>Thalamus</td>
<td>220</td>
</tr>
<tr>
<td>Cerebellar cortex</td>
<td>219</td>
</tr>
<tr>
<td>Corpus callosum</td>
<td>213</td>
</tr>
<tr>
<td>Pons</td>
<td>204</td>
</tr>
</tbody>
</table>

Degree distribution of brain areas

- Exponentially truncated power law
- Median = 32

Graph showing the distribution of diseases connected to brain areas.
Disparity in Connections

- Some nodes are disproportionately more connected than others

Degree distribution of diseases

Genetic diseases affecting many brain areas

<table>
<thead>
<tr>
<th>Disease</th>
<th>#Areas</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dementia</td>
<td>53</td>
</tr>
<tr>
<td>Epilepsy</td>
<td>53</td>
</tr>
<tr>
<td>Forebrain defects</td>
<td>52</td>
</tr>
<tr>
<td>Stroke</td>
<td>52</td>
</tr>
<tr>
<td>Schizophrenia</td>
<td>51</td>
</tr>
</tbody>
</table>
Disparity in Connections

• Some nodes are disproportionately more connected than others

Genetic diseases associated with many genes

<table>
<thead>
<tr>
<th>Disease</th>
<th>#Genes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deafness</td>
<td>41</td>
</tr>
<tr>
<td>Leukemia</td>
<td>37</td>
</tr>
<tr>
<td>Colon cancer</td>
<td>34</td>
</tr>
<tr>
<td>Retinitis pigmentosa</td>
<td>30</td>
</tr>
<tr>
<td>Diabetes mellitus</td>
<td>27</td>
</tr>
<tr>
<td>Cardiomyopathy</td>
<td>25</td>
</tr>
</tbody>
</table>
Disparity in Connections

- Some nodes are disproportionately more connected than others.

**Degree distribution of genes**

- Median = 1

**Graph**

- X-axis: Number of diseases connected (k)
- Y-axis: Counts

- TP53, PTEN, PAX6, TP53

**Bar graph**

- Counts: 0 to 10
Same Diseases?

Hippocampus
258 diseases

Thalamus
220 diseases
Collapsing Network

- Are there similarity among brain areas?
- Affected by same diseases
- Associated with same genes
- A network of brain areas
- Edges: shared diseases / genes
Collapsing Network

- Common disease network
- Edge weight = # common diseases

Diseases

1
2
3
4

Brain area A

Brain area B

4 common diseases

Brain area A

Brain area B

Edge weight = 4
Collapsing Network

- Common gene network
- Edge weight = # common genes

Brain area A

Diseases

1 2 3

Genes

X Y Z

3 common genes

Brain area A

Diseases

2 4

Brain area B

Edge weight = 3
Collapsing Network

- Almost all brain areas are interconnected

Hayasaka et al., PLoS ONE (2011)
Connection Weights

- Connections are not equally weighted
Core Network

- Networks formed by edges with top 10% weights

Hayasaka et al., PLoS ONE (2011)
Core Network

- Similar nodes - areas of strong genetic influence
- Affected by a large number of same genetic diseases
- Associated with a large number of same genes

Hayasaka et al., PLoS ONE (2011)
Summary

• Data mining approach
  • From existing databases
• Disparity in associations / influences
  • Small number of genes / diseases / brain areas
    • Disproportionately large connections
Summary

• Disparity in common diseases / genes
  • Small number of brain areas
    • Affected by a large number of same diseases / genes

• Focus in future imaging genetics studies
Outline
(Part II)

- Applications
- Functional Connectivity Network
- Gene-Brain Network
- Resources
To Get Started

- Brain network analysis - relatively new field
  - Methodological development
  - Novel applications
- Many new discoveries and developments
  - Driven by small labs
Data

• 1000 Connectome Project
  • Collection of fMRI data from various labs
  • http://fcon_1000.projects.nitrc.org/

• Human Connectome Project
  • Consortia to collect functional & structural data
  • http://www.humanconnectomeproject.org/
  • http://humanconnectome.org/
Tools

- Image data processing
  - Modality specific (MEG, fMRI, DTI, etc)

- Basic network analysis tools (MATLAB)
  - BCT (brain connectivity toolbox)
    - https://sites.google.com/a/brain-connectivity-toolbox.net/bct/Home
  - MatlabBGL (Boost Graph Library, for MATLAB)
    - http://dgleich.github.com/matlab-bgl/
Tools

- Basic network analysis tools (Other)
- Collection of functions
  - R
  - Python
Tools

• Community structure
  • QCut (J Ruan, U of Texas San Antonio)
    • http://cs.utsa.edu/~jruan/Software.html

• Visualization
  • Pajek
    • http://vlado.fmf.uni-lj.si/pub/networks/pajek/
  • Other commercially available software tools
Acknowledgements

• Funding
  • Translational Science Institute, Wake Forest University
  • National Institute of Neurological Disorders and Stroke
    • NS070917
    • NS039426-09S1
Acknowledgements

• People (Figures, Slides, Analyses)

  Paul Laurienti
  Karen Joyce
  Qawi Telesford
  Ashley Morgan
  Debra Hege
  Malaak Moussa
  Crystal Vechlekar
  Christina Hugenschmidt
  Matt Steen
  Jonathan Burdette
Slides for this lecture will be available at

http://lcbn.wakehealth.edu