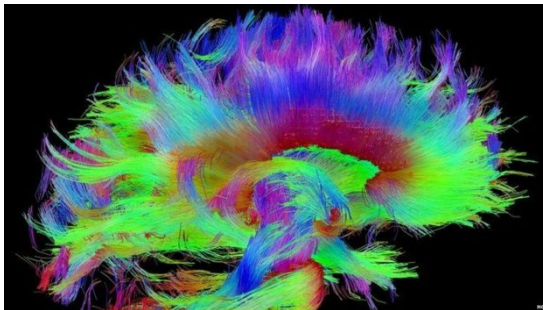


CS 4984: Connectivity Matrices and Node Degrees

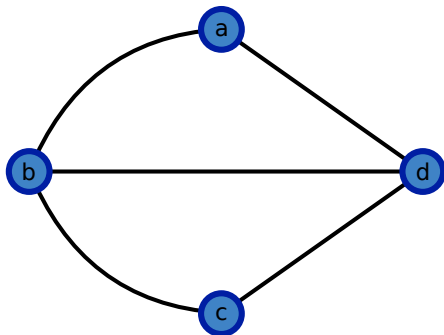
T. M. Murali

February 6, 2018



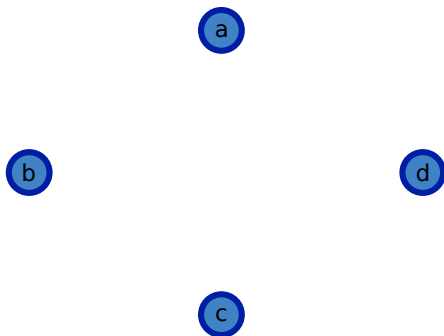
Definition of an Undirected Graph

- *Weighted, undirected graph* $G = (V, E, w)$:
 - ▶ set V of nodes.
 - ▶ set E of edges.
 - ★ Each element of E is an unordered pair of nodes.
 - ★ Exactly one edge between any pair of nodes (G is not a multigraph).
 - ★ G contains no self loops, i.e., edges of the form (u, u) .
 - ▶ Each edge (u, v) in E has a weight $w(u, v) \in \mathbb{R}$
 - ★ Weight of each edge is usually positive.
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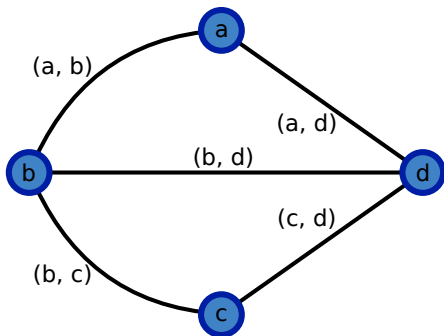
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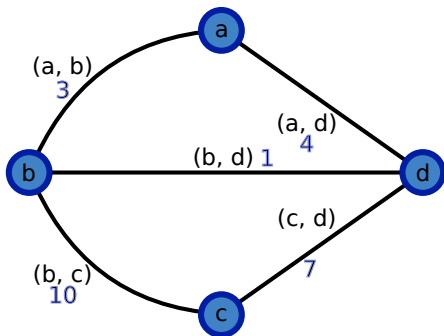
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Types of Brain Graphs

Structural connectivity

Functional connectivity

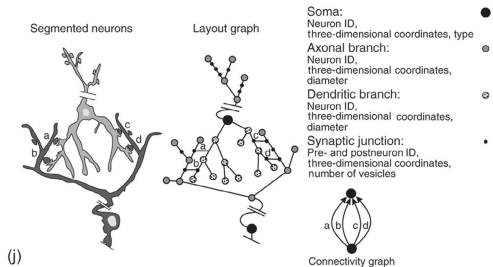
Microscale

Mesoscale

Macroscale

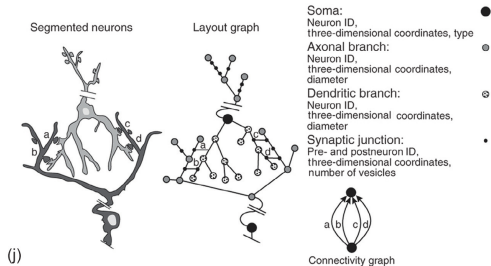
Types of Brain Graphs

	Structural connectivity	Functional connectivity
Microscale	SEM, Tracking neurons	
Mesoscale		
Macroscale		



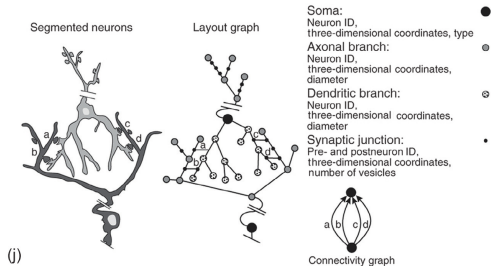
Types of Brain Graphs

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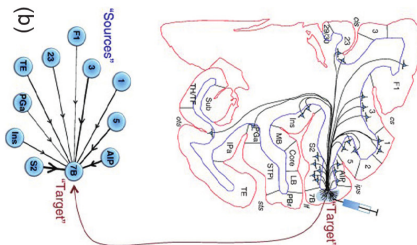
Types of Brain Graphs

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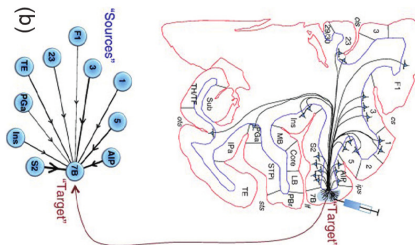
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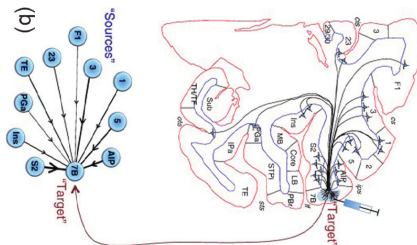
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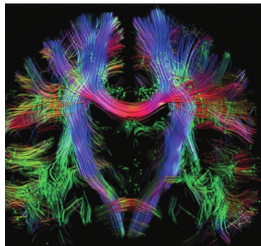
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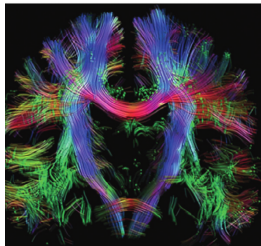
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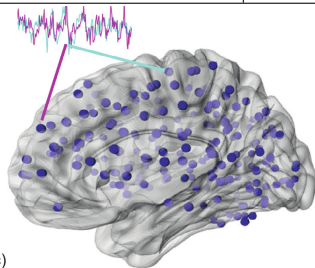
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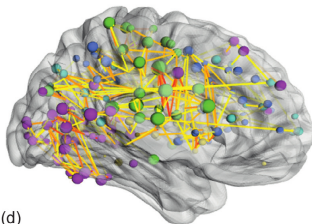
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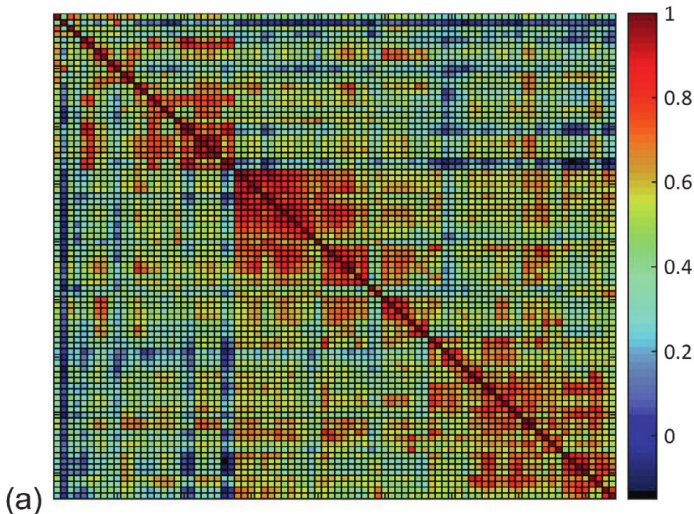
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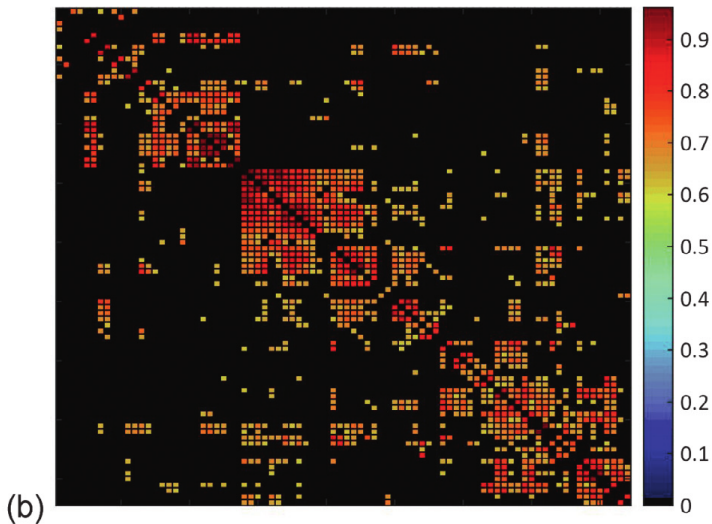


(d)

Thresholding and Binarisation

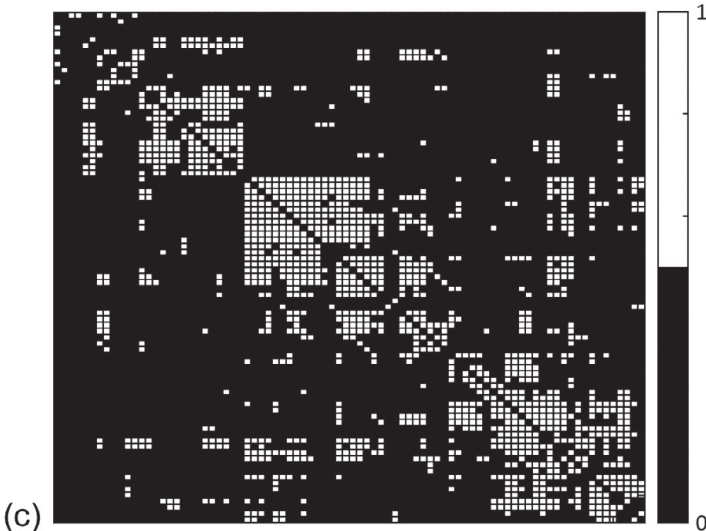


Thresholding and Binarisation



Matrix after thresholding to retain only the 20% strongest weights.

Thresholding and Binarisation



Matrix after thresholding and binarisation.

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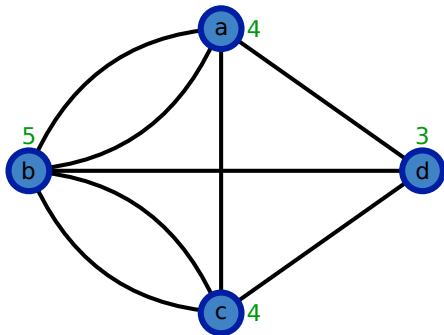
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- We can modify these ideas for directed graphs.

Implementing Hierholzer's Algorithm



$u \leftarrow s \neq u$ is the current node.

while $d(u) > 0$ **do**

 Output u .

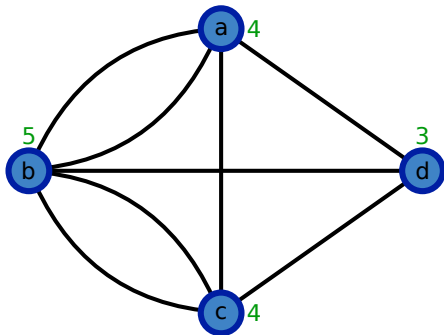
 Let v be a neighbour of u .

 Delete the edge (u, v) from G .

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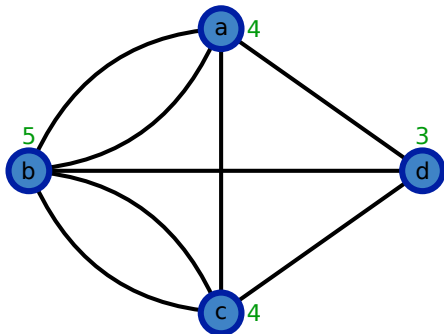
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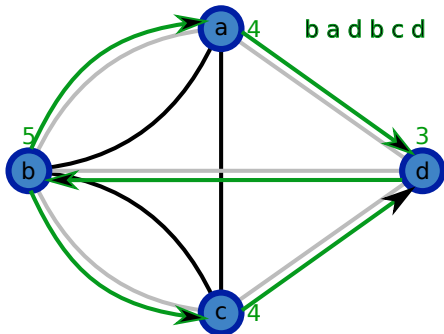
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	Adjacency matrix	Adjacency list
Determine $d(u)$		
Find a neighbour v of u		
Delete edge (u, v)		

Implementing Hierholzer's Algorithm



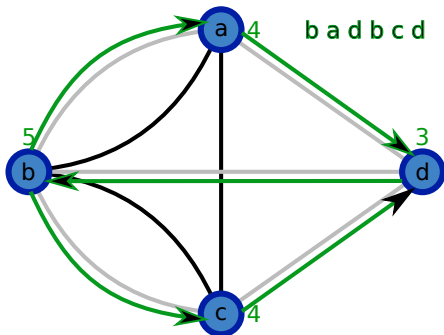
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	Adjacency matrix	Adjacency list
Determine $d(u)$	Maintain array of node degrees. $O(1)$ time	Same idea
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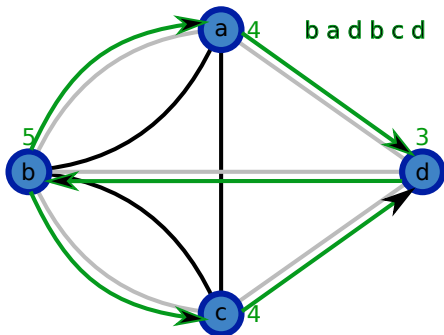
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Determine $d(u)$	Maintain array of node degrees. $O(1)$ time	Same idea
Find a neighbour v of u	Traverse row for u . $O(n)$ time.	v is first node in $\text{Adj}[u]$.
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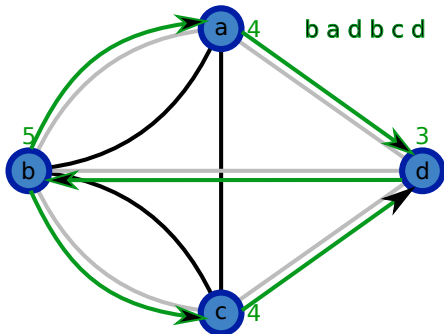
 Delete the edge (u, v) from G .

$u \leftarrow v$

end while

	Adjacency matrix	Adjacency list
Determine $d(u)$	Maintain array of node degrees. $O(1)$ time	Same idea
Find a neighbour v of u	Traverse row for u . $O(n)$ time.	v is first node in $\text{Adj}[u]$.
Delete edge (u, v)	Set <i>both</i> entries to 0; Update $d(v)$. $O(1)$ time.	Delete first element of $\text{Adj}[u]$. Update $d(v)$. $O(1)$ time.

Implementing Hierholzer's Algorithm



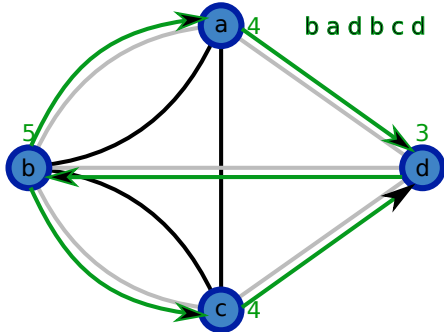
```

 $u \leftarrow s \neq u$  is the current node.
while  $d(u) > 0$  do
  Output  $u$ .
  Let  $v$  be a neighbour of  $u$ .
  Delete the edge  $(u, v)$  from  $G$ .
   $u \leftarrow v$ 
end while

```

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Implementing Hierholzer's Algorithm



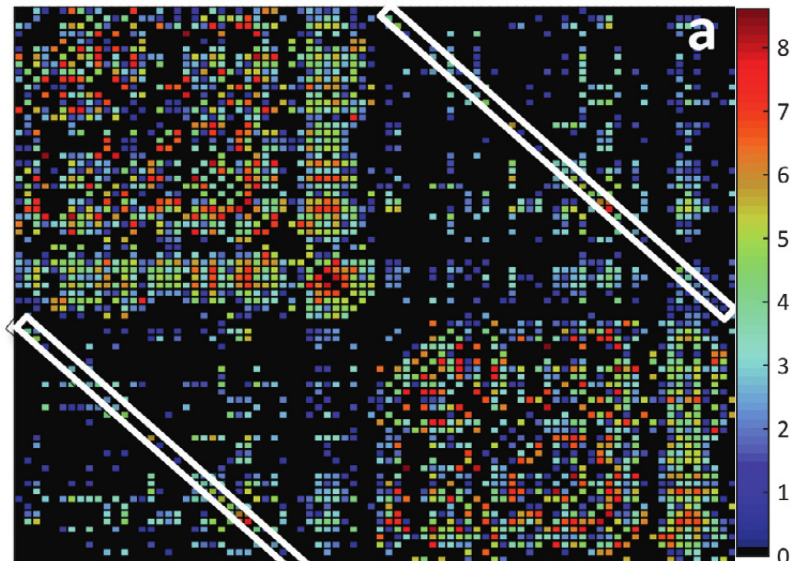
```

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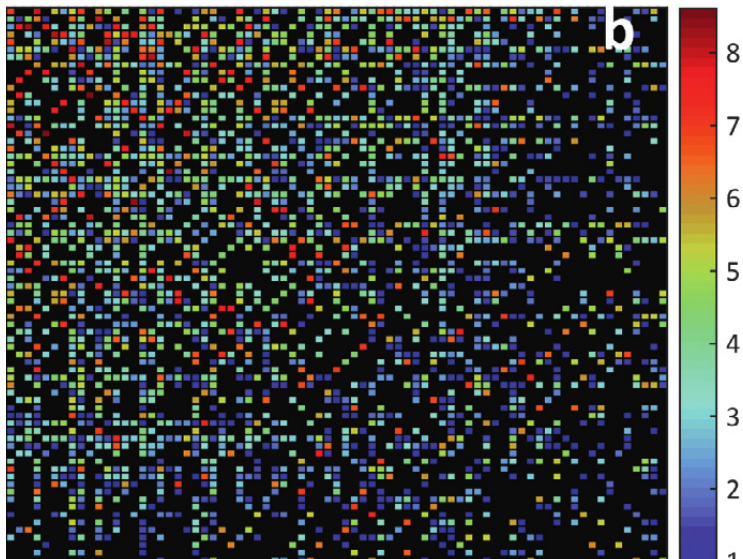
```

	Adjacency matrix $O(n^2)$ time.	Adjacency list $O(n)$ time.
Determine $d(u)$	Maintain array of node degrees. $O(1)$ time	Same idea
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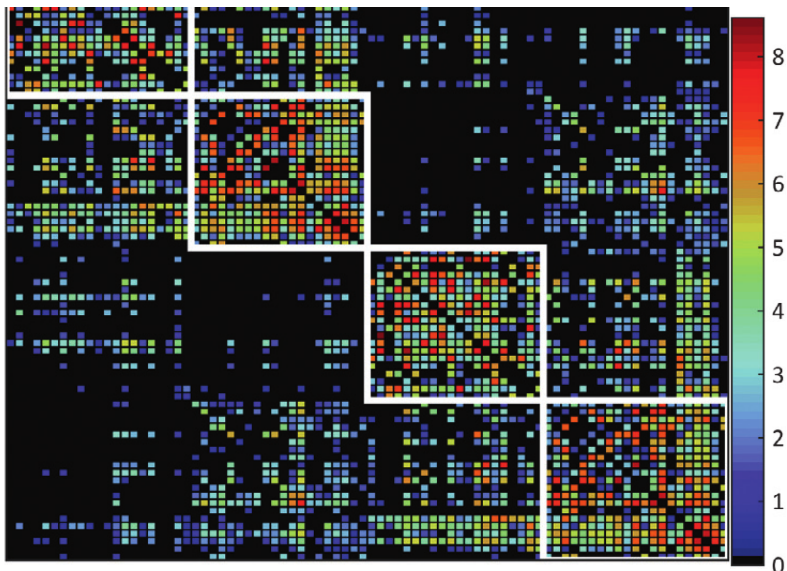
Visualising Matrices



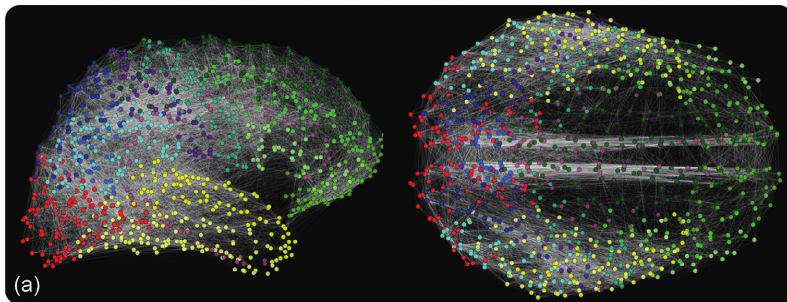
Visualising Matrices



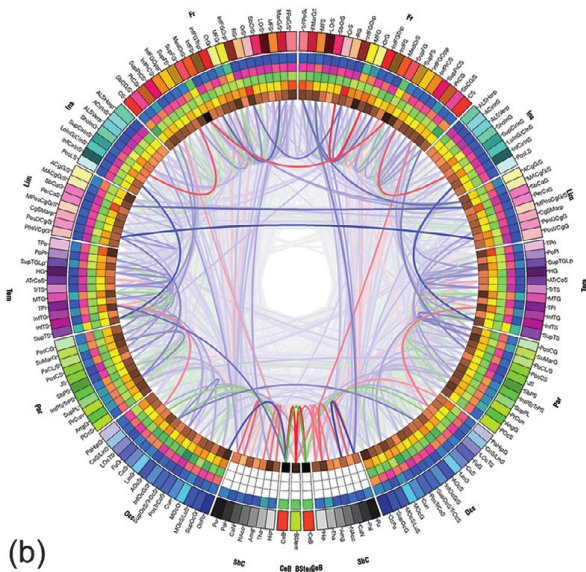
Visualising Matrices



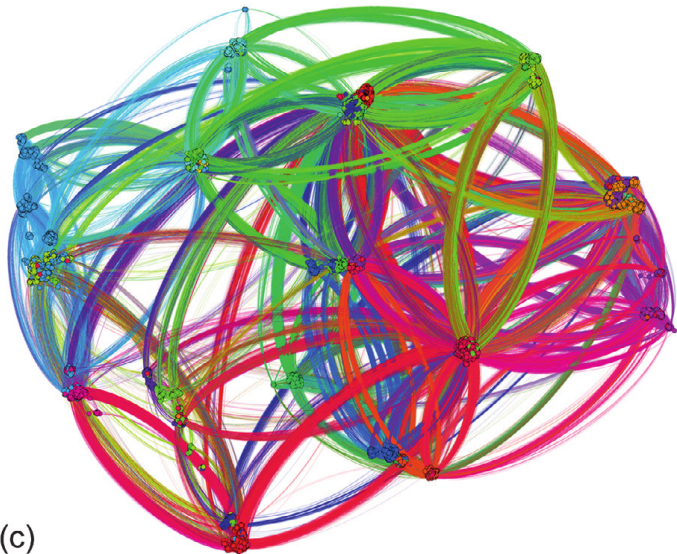
Anatomical Projection



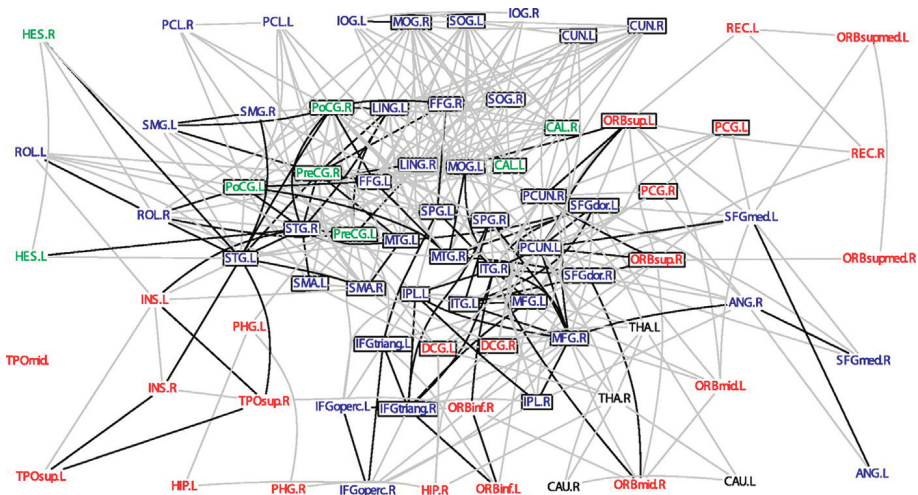
Circular Layout



Force-Directed Layout

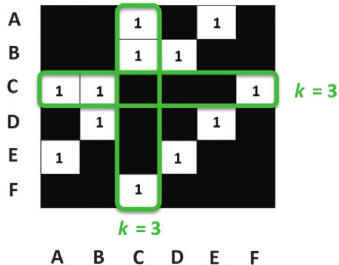
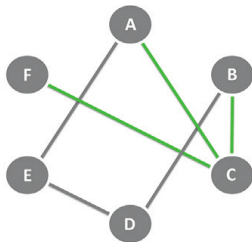


Spring-Embedded Layout

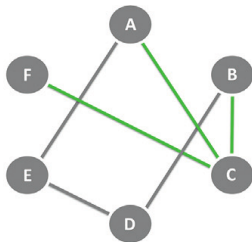


Node Degree

- Undirected graph $G = (V, E)$: *degree* $d(v)$ of a node v is the number of edges in E that are incident on v .

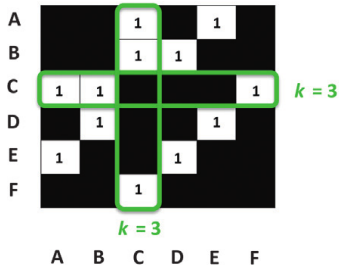


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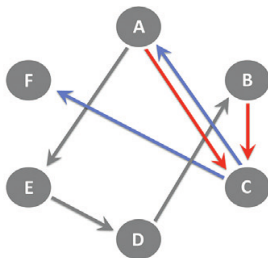
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(a)

Node Degree



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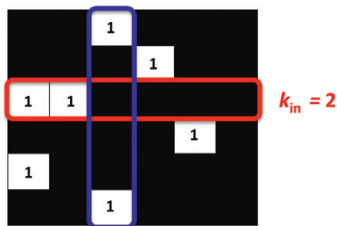
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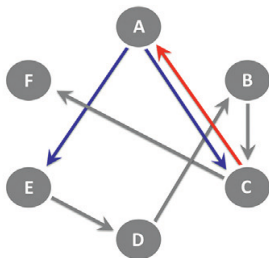
- Textbook also defines *strength* of a node: total weight of edges incident on that node.



$k_{out} = 2$

A B C D E F
(b)

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		1				
			1			
1	1					
					1	
1						
		1				

$k_{in} = 1$

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A B C D E F
(C)

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$$\sum_{k \geq 0} kp(k) = \frac{1}{n} \sum_{k \geq 0} kn(k) = \frac{1}{n} \sum_{v \in V} d(v) = \frac{2m}{n}$$