### Data Visualization (CSCI 627/490)

Networks

Dr. David Koop





## 3D to 2D: Projection

















### Projection Classification













# Choropleth (Two Hues)



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# Choropleth (Diverging Attribute)











# Don't Just Create Population Maps!





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PET PEEVE #208: GEOGRAPHIC PROFILE MAPS WHICH ARE BASICALLY JUST POPULATION MAPS









### Size Encoding



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### Cartograms













## House Races: Non-Contiguous "Cartogram"













### House Races: Cartogram?

Solid D	Likely D	Lean D	Toss-up	Lean R	Like
≥95% D	≥75% D	≥60% D	<60%	≥60% R	≥7



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# Maps Aren't Always Best: Close House Races

#### 12 Lean Democratic

- AZ-02 Open (McSally)
- CA-49 Open (Issa)
- CO-06 Coffman
- IA-01 Blum
- KS-03 Yoder
- MI-11 Open (Trott)
- MN-02 Lewis
- MN-03 Paulsen
- NV-03 Open (Rosen)
- NJ-11 Open (Frelinghuysen)
- PA-07 Vacant (formerly Dent)
- VA-10 Comstock

#### **31** Tossups

- CA-10 Denham
- CA-25 Knight
- CA-45 Walters
- FL-26
- FL-27
- IL-06
- IL-12
- IA-03
- KY-06 Barr

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- CA-39 Open (Royce)
- CA-48 Rohrabacher
  - Curbelo
  - Open (Ros-Lehtinen)
  - Roskam
  - Bost
  - Young
- KS-02 Open (Jenkins)

### 25 Lean Republicar

- AR-02 Hill
- CA-50 Hunter
- FL-15 Open (Ross)
- FL-16 Buchanan
- GA-06 Handel
- GA-07 Woodall
- IL-13 Davis
- IL-14 Hultgren
- MO-02 Wagner
- MT-AL Gianforte
- NE-02 Bacon
- NY-24
  - Katko [New York Times, 2018]





## Project Proposal

- Two Possibilities:
  - Create an interactive visualization
  - Work on a research project
- Dataset Choices
  - New Mexico School Discipline
  - NFL Data
  - Storm Events Database
  - Louisiana Home Rebuilding Grants
  - Others?
- Proposal Due Friday







### Assignment 4

• To be announced soon





### Next Week

• Barring any setbacks, return to in-person lectures and office hours on Monday





### D3 Map Examples





### Networks

- Why not graphs?
  - Bar graph
  - Graphing functions in mathematics
- Network: nodes and edges connecting the nodes
- Formally, G = (V, E) is a set of nodes V and a set of edges E where each edge connects two nodes.
- Nodes == items, edges connect items
- Both nodes and edges may have attributes







## Arrange Networks and Trees







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### Molecule Graph







### Molecule Graph







### Molecule Graph







### Web Sites as Graphs (amazon.com)



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### Social Networks











## Networks as Data

#### Nodes

ID	Atom	Electrons	Protons
0	Ν	7	7
1	С	6	6
2	S	16	16
3	С	6	6
4	Ν	7	7

Edges

ID1	ID2	Bonds
0	1	┱
1	2	1
T	3	2
З	4	1







# Node-Link Diagrams

- Data: nodes and edges
- Task: understand connectivity, paths, structure (topology)
- Encoding: nodes as point marks, connections as line marks
- Scalability: hundreds
- ...but high density of links can be problematic!
- Issue with the encoding?







### Arc Diagram











## Network Layout

- Need to use spatial position when designing network visualizations
- Otherwise, nodes can **occlude** each other, links hard to distinguish
- How?
  - With bar charts, we could order using an attribute...
  - the data usually)
- Possible metrics:
  - Edge crossings
  - Node overlaps
  - Total area

- With networks, we want to be able to see connectivity and topology (not in





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## Force-Directed Layout

- Nodes push away from each other but edges are springs that pull them together • Weakness: nondeterminism, algorithm may produce difference results each time it runs











# Constraint-Based Optimization (CoLa)

- Higher quality layout
- More **stable** in interactive applications (no "jitter")
- Allows user specified constraints such as alignments and grouping
- Can avoid overlapping nodes
- Provides flow layout for directed graphs
- May be less scalable to very large graphs
- Can route edges around nodes

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[T. Dwyer et al. (WebCoLa); M. Bostock (Example), 2018]



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## sfdp



JGD\_Homology@cis-n4c6-b14. 7220 nodes, 13800 edges.









### "Hairball"



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JGD\_Homology@cis-n4c6-b4. 26028 nodes, 100290 edges.



![](_page_29_Picture_6.jpeg)

![](_page_29_Picture_7.jpeg)

![](_page_29_Picture_8.jpeg)

## Hierarchical Edge Bundling

![](_page_30_Picture_1.jpeg)

![](_page_30_Picture_3.jpeg)

![](_page_30_Picture_4.jpeg)

![](_page_30_Picture_5.jpeg)

![](_page_30_Picture_6.jpeg)

![](_page_30_Picture_7.jpeg)

## Hierarchical Edge Bundling

![](_page_31_Picture_1.jpeg)

![](_page_31_Picture_3.jpeg)

![](_page_31_Picture_4.jpeg)

![](_page_31_Picture_6.jpeg)

![](_page_31_Picture_7.jpeg)

![](_page_31_Picture_8.jpeg)

# Hierarchical Edge Bundling

- Flexible and generic method
- - information
  - explicit adjacency edges between their respective child nodes

 Reduces visual clutter when dealing with large numbers of adjacency edges Provides an intuitive and continuous way to control the strength of bundling. - Low bundling strength mainly provides low-level, node-to-node connectivity

- High bundling strength provides high-level information as well by implicit visualization of adjacency edges between parent nodes that are the result of

![](_page_32_Picture_9.jpeg)

![](_page_32_Picture_10.jpeg)

![](_page_32_Picture_12.jpeg)

![](_page_32_Picture_14.jpeg)

![](_page_32_Picture_15.jpeg)

## Bundling Strength

![](_page_33_Figure_1.jpeg)

![](_page_33_Figure_2.jpeg)

![](_page_33_Picture_4.jpeg)

![](_page_33_Picture_5.jpeg)

![](_page_33_Picture_6.jpeg)

![](_page_33_Picture_7.jpeg)

![](_page_33_Picture_8.jpeg)

![](_page_33_Picture_9.jpeg)

## Adjacency Matrix

- Change network to tabular data and use a matrix representation
- Derived data: nodes are keys, edges are boolean values
- Task: lookup connections, find wellconnected clusters
- Scalability: millions of edges
- Can encode edge weight, too

![](_page_34_Picture_9.jpeg)

![](_page_34_Figure_10.jpeg)

![](_page_34_Picture_11.jpeg)

![](_page_34_Picture_12.jpeg)

![](_page_34_Picture_14.jpeg)

![](_page_34_Picture_15.jpeg)

### Cliques in Adjacency Matrices

a

![](_page_35_Figure_2.jpeg)

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![](_page_35_Figure_4.jpeg)

![](_page_35_Picture_5.jpeg)

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![](_page_35_Picture_7.jpeg)

![](_page_35_Picture_8.jpeg)

![](_page_35_Picture_9.jpeg)

### Structures from Adjacency Matrices

![](_page_36_Figure_1.jpeg)

![](_page_36_Picture_4.jpeg)

![](_page_36_Picture_6.jpeg)

![](_page_36_Picture_7.jpeg)

![](_page_36_Picture_8.jpeg)

# Node-Link or Adjacency Matrix?

- adjacency better for large graphs
- Multi-link paths are hard with adjacency matrices
- Immediate connectivity or neighbors are ok, estimating size (nodes & edges also ok)
- People tend to be more familiar with node-link diagrams
- Link density is a problem with node-link but not with adjacency matrices

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• Empirical study: For most tasks, node-link is better for small graphs and

![](_page_37_Picture_8.jpeg)

![](_page_37_Picture_10.jpeg)

![](_page_37_Picture_11.jpeg)

### Irees

- Trees are directed acyclic networks
  - each edge has a direction: the origin is the parent, the destination is the child
  - cannot get back to a node after leaving it
- ...plus each node has at most one parent node
- A tree has a **root** (every other node hangs off it)
- Can consider enclosure in trees using parent-child relationships

![](_page_38_Picture_9.jpeg)

![](_page_38_Picture_11.jpeg)

### Tree Visualizations

![](_page_39_Figure_1.jpeg)

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![](_page_39_Figure_3.jpeg)

![](_page_39_Figure_4.jpeg)

![](_page_39_Picture_5.jpeg)

![](_page_39_Picture_6.jpeg)

Η

G

![](_page_39_Picture_8.jpeg)

![](_page_39_Picture_9.jpeg)

![](_page_39_Picture_10.jpeg)