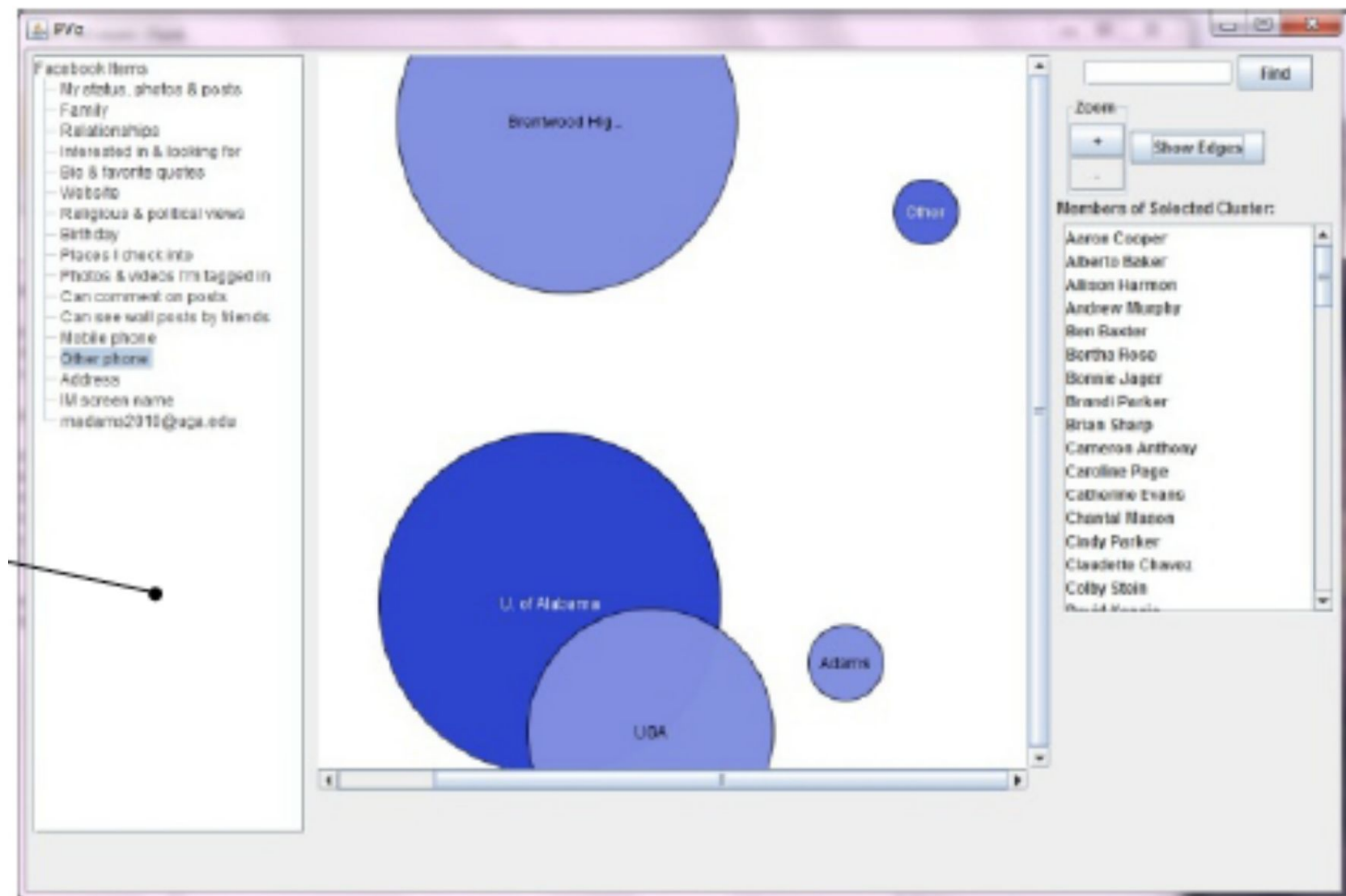
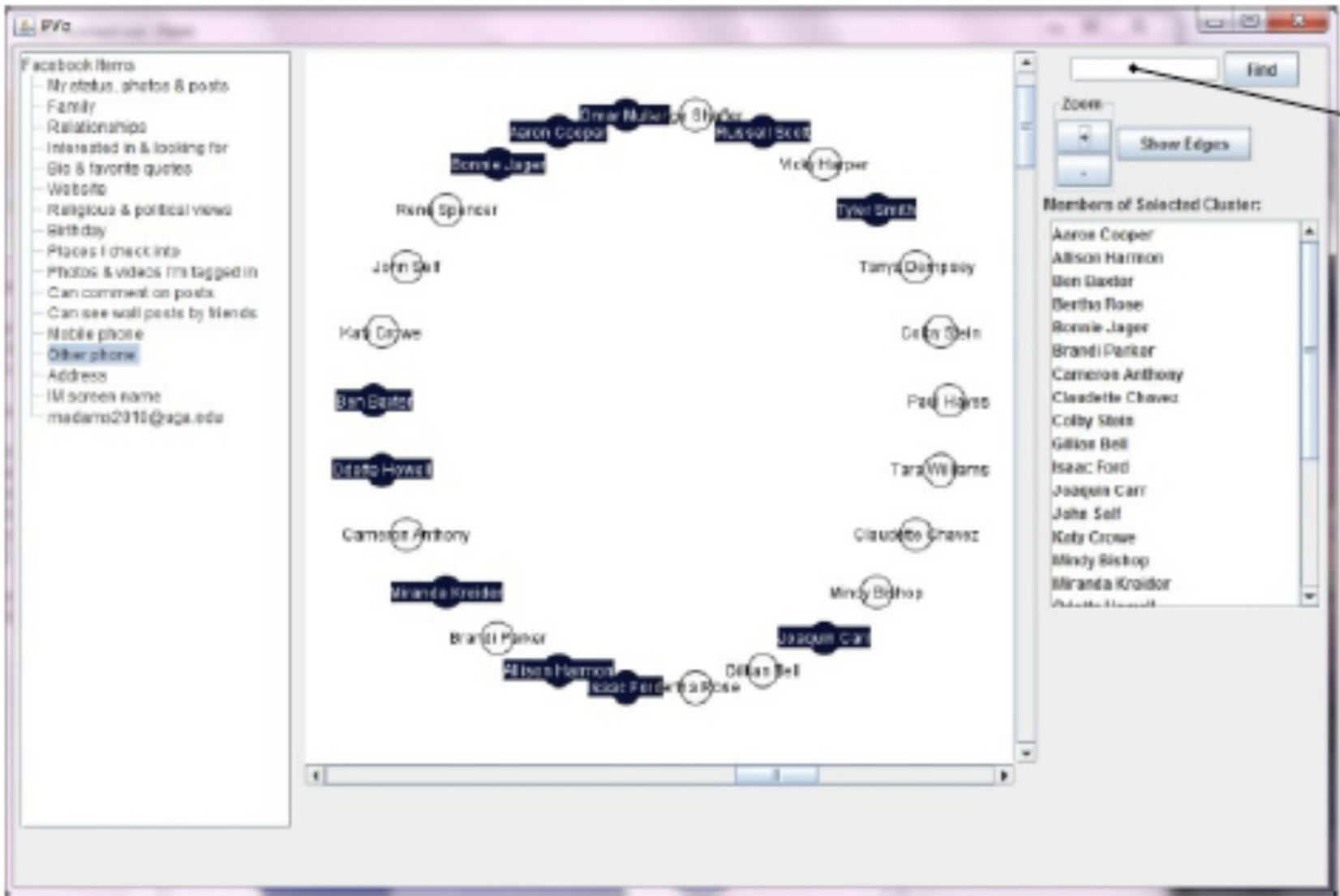


Computer Security: Access Control

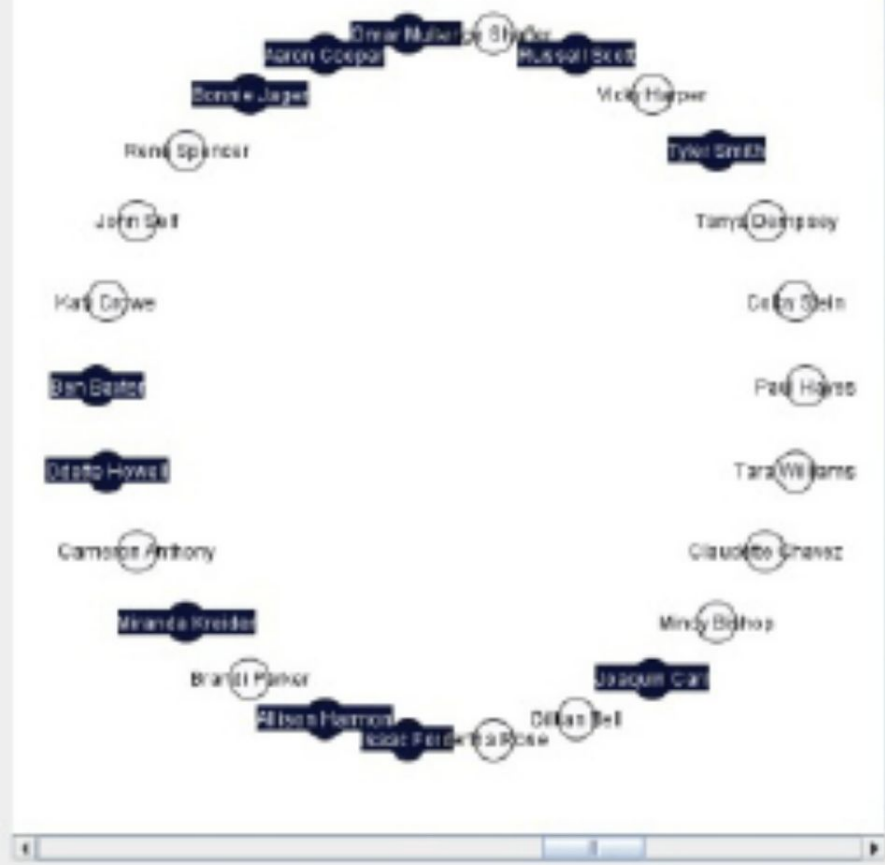
Privacy Settings in Social Networks

Jane Adams





- Facebook Items
- My photos, photos & posts
 - Family
 - Relationships
 - Interested in & looking for
 - Bio & favorite quotes
 - Website
 - Religious & political views
 - Birthday
 - Places I check into
 - Photos & videos I'm tagged in
 - Can comment on posts
 - Can see wall posts by friends
 - Mobile phone
 - Other phone**
 - Address
 - IM screen name
 - madams2010@aps.edu



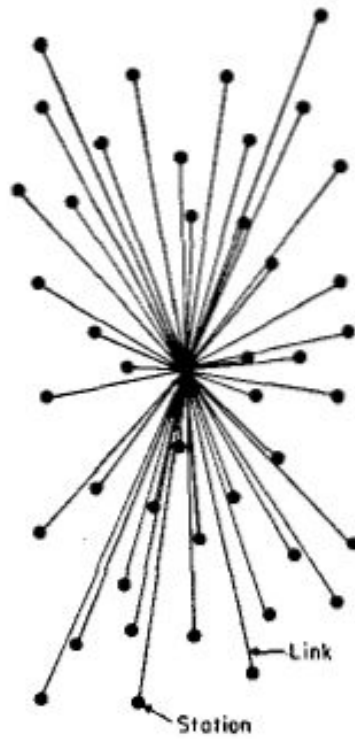
Find

Zoom: + -

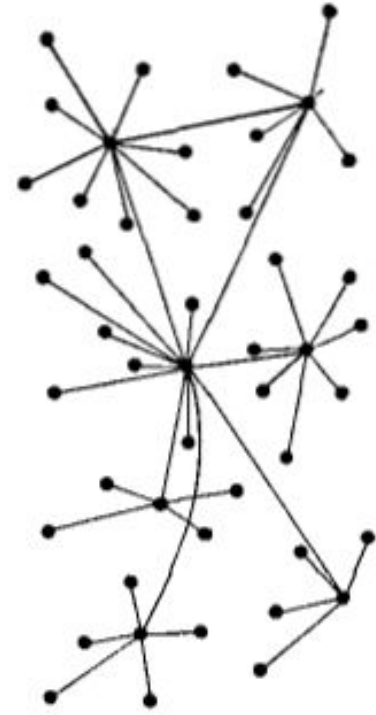
Show Edges

Members of Selected Cluster:

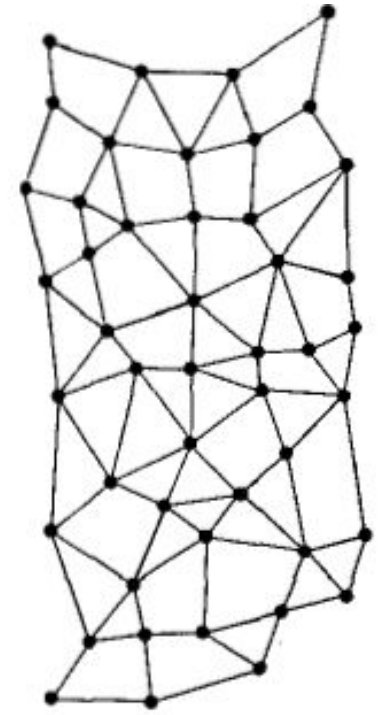
- Aaron Cooper
- Alison Harrison
- Ben Baxter
- Bertha Rose
- Ronnie Jager
- Brandi Parker
- Cameron Anthony
- Claudette Chavez
- Colby Stein
- Gilboa Bell
- Isaac Ford
- Jacques Carr
- John Sell
- Katy Crowe
- Mindy Bishop
- Miranda Kroidor



(a)



(b)



(c)

Fig. 1—(a) Centralized. (b) Decentralized. (c) Distributed networks.

a.k.a. centralized, federated, and peer-to-peer

Limits of individual consent and models of distributed consent in online social networks

Juniper Lovato¹, Antoine Allard^{1,2,3}, Randall Harp^{1,4}, and Laurent Hébert-Dufresne^{1,2,5,*}

1. the subject has sufficient accurate information and understands the nature of the agreement
2. the agreement is entered into without coercion
3. the agreement is entered into knowingly and intentionally
4. the agreement authorizes a specific course of action

A model of distributed consent and network observability

To account for the distributed nature of personal data (i.e. the distributed online self), we consider a simple model of distributed consent. Imagine a social network platform where individuals have the following privacy options:

0. Individuals share their data with all their connections and are vulnerable to third-party surveillance (similar to Facebook accounts with access for “Apps, Websites and Games” turned on).
1. Individuals share their data with all their connections but are not directly vulnerable to third-party surveillance.
2. Individuals only share their data with their connections whose privacy level are set at least to 1.
- N. Individuals only share their data with their connections whose privacy level are set at least to $N - 1$.

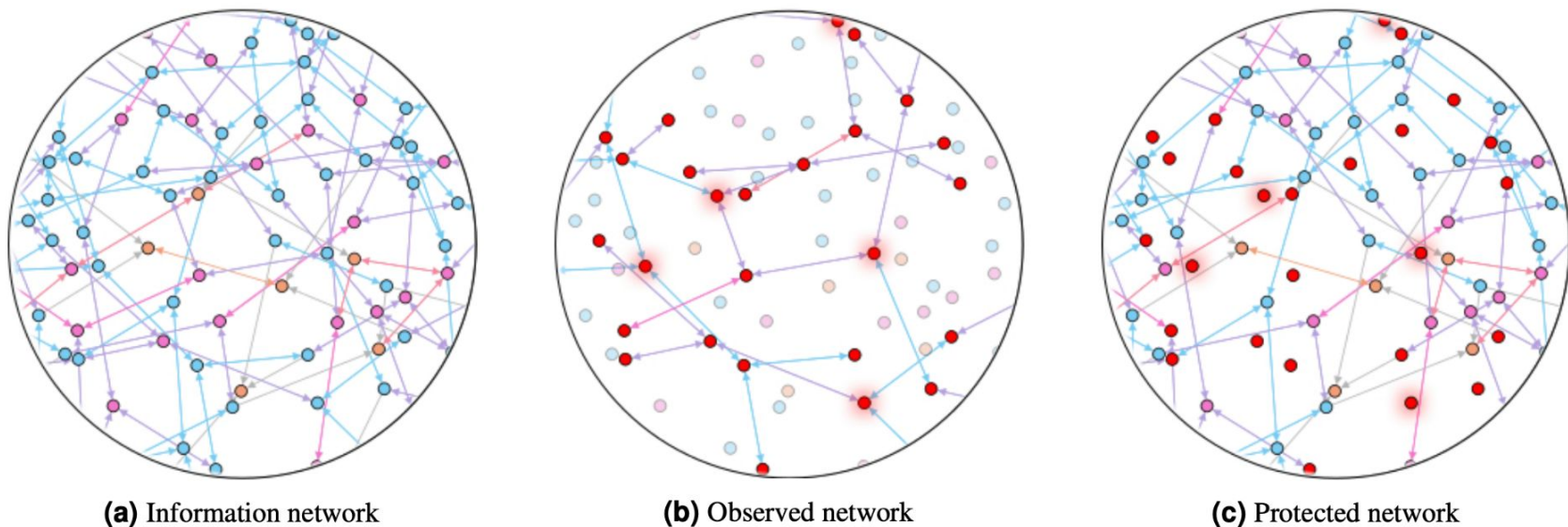


Figure 1. (a) Cartoon of information flow across a network with our basic implementation of distributed consent. Blue nodes have the lowest security settings, and are susceptible to surveillance from third-party applications or websites. Purple nodes have stricter security settings but share their posts and, therefore, data with all their neighbors. Orange nodes follow a distributed consent model and only share their data with purple nodes or other orange nodes. (b) The same network where a handful of low-security accounts are directly observed by a third party, highlighted in red with shading. All nodes sharing their data with directly observed accounts are de facto observed as well, and are also shown in red. Nodes at a distance $L > 1$ can also be observed if the third party leverages some statistical procedure, in this case inferring data up to a distance of two from directly observed nodes. (c) We show the remaining unobserved, or protected, component network. Note that, under this observability process, orange nodes who follow a distributed consent model are much less likely to be observed than nodes following traditional individual consent options. Importantly, they also help protect some of their neighbors with standard security settings.

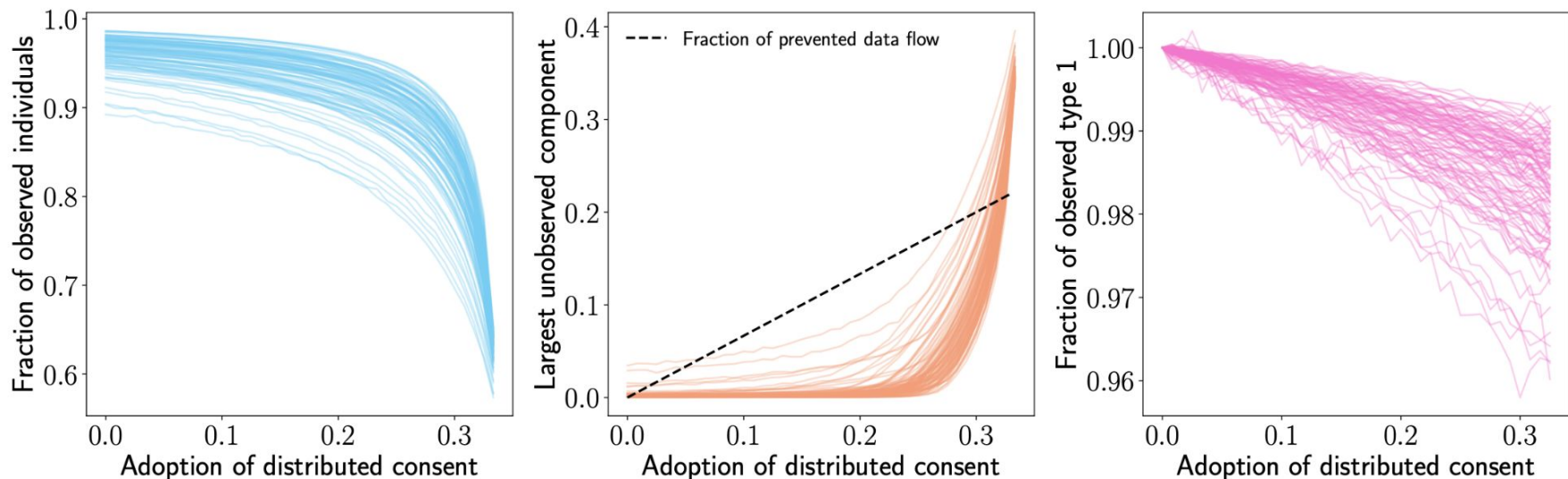
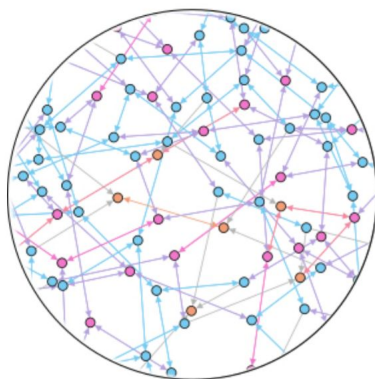
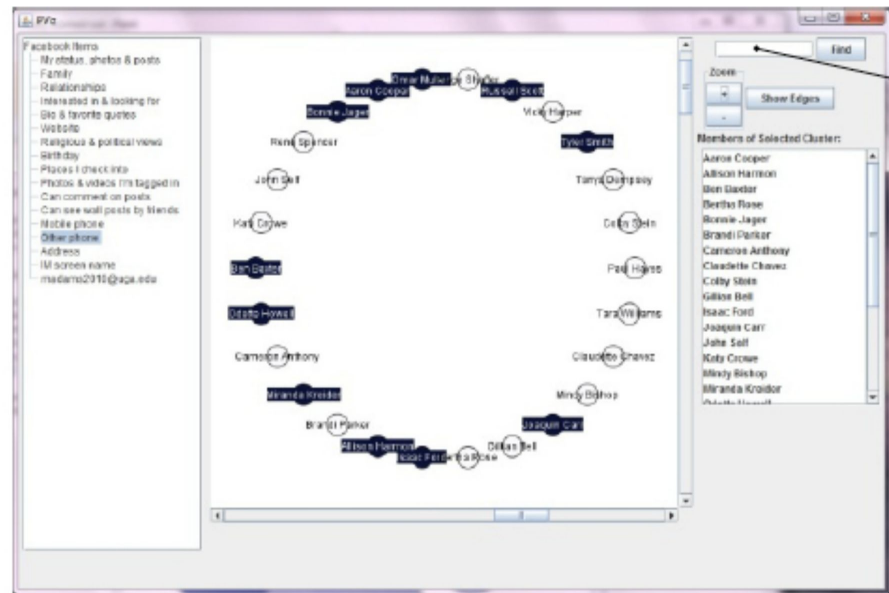
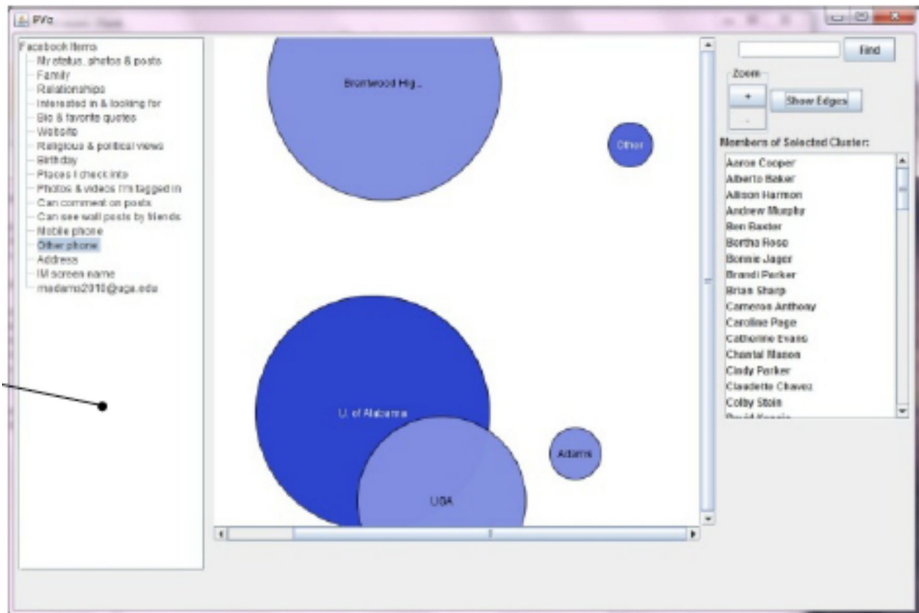
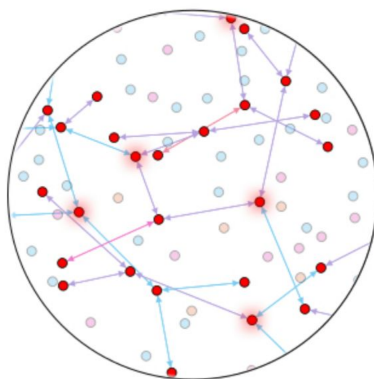


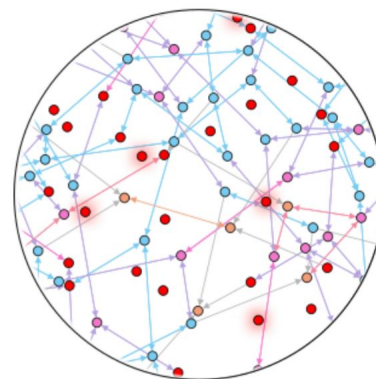
Figure 2. We use the anonymized Facebook100 dataset³⁶. We assume that one-third of the population has a taste for privacy³⁷, split between security options 1 and 2 (i.e., classic or distributed consent) according to the adoption rate of distributed consent shown on the horizontal axis, while the remaining two thirds will use the default setting with the lowest security, option 0. We set 1% of accounts with security option 0 to be directly observable by a third-party app, which can also observe neighbors up to two hops away in the network. We then vary the adoption rate and measure (a) the total fraction of observed accounts, (b) the relative size of the largest unobserved connected component, and (c) the fraction of observed individuals with security option 1.



(a) Information network



(b) Observed network



(c) Protected network

Interesting applications of network visualizations for analytics

A look into Graph Drawing for Data Analytics by Stephen G. Eick

Presented by Adam Foley

The Importance of Excitement in Data Analysis

- In order to have that **“wow factor”**, Eick says that Network visualizations can **create high value** for “Visual presentation and branding purposes.”¹
- He goes on to provide some useful techniques including **animation and colors to draw viewers in.**²

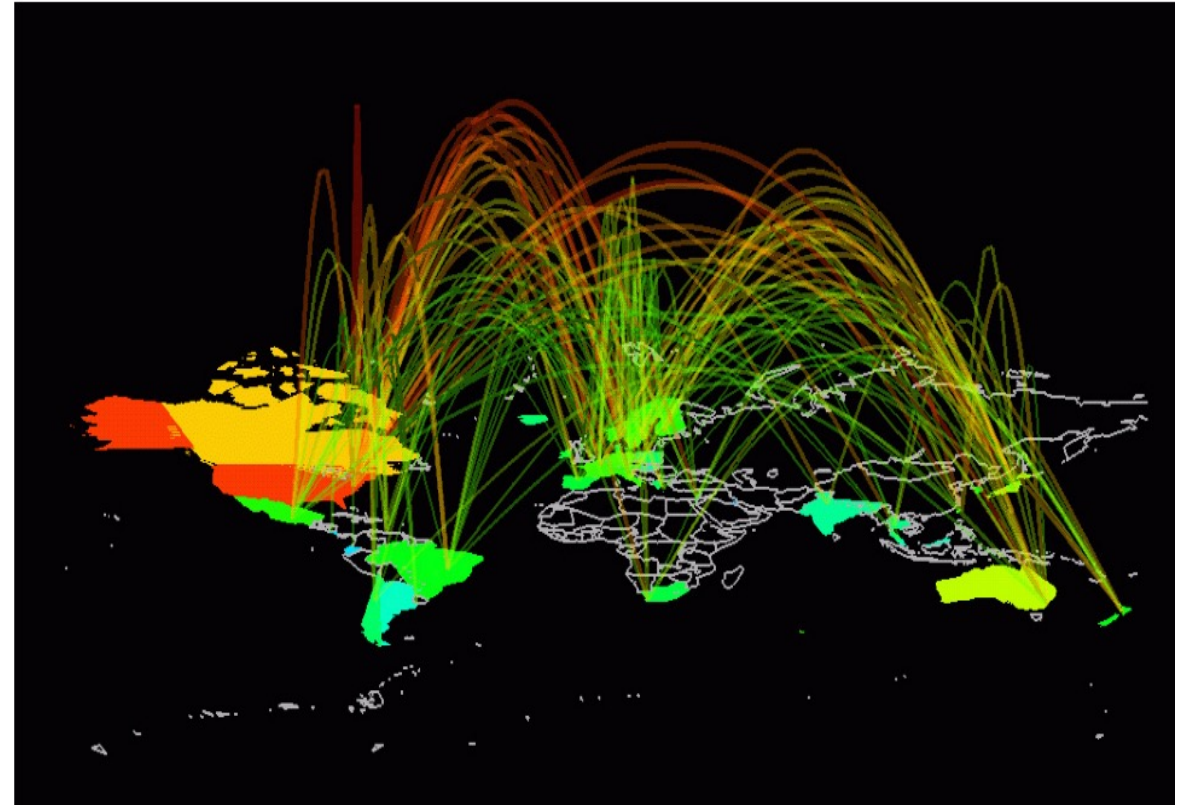


Figure 1: Internet traffic flows between countries³

1,2 . Tamassia, Roberto, and Stephen G Eick. “Graph Drawing for Data Analytics.” Essay. In *Handbook of Graph Drawing and Visualization*, 682. CRC Press, 2013.

3 . Tamassia, Roberto, and Stephen G Eick. “Graph Drawing for Data Analytics.” Essay. In *Handbook of Graph Drawing and Visualization*, 683. CRC Press, 2013.

Assumptive Based Analysis vs Visual Discovery

Pre-assumed Relationships through Assumptive Based Analysis ⁴

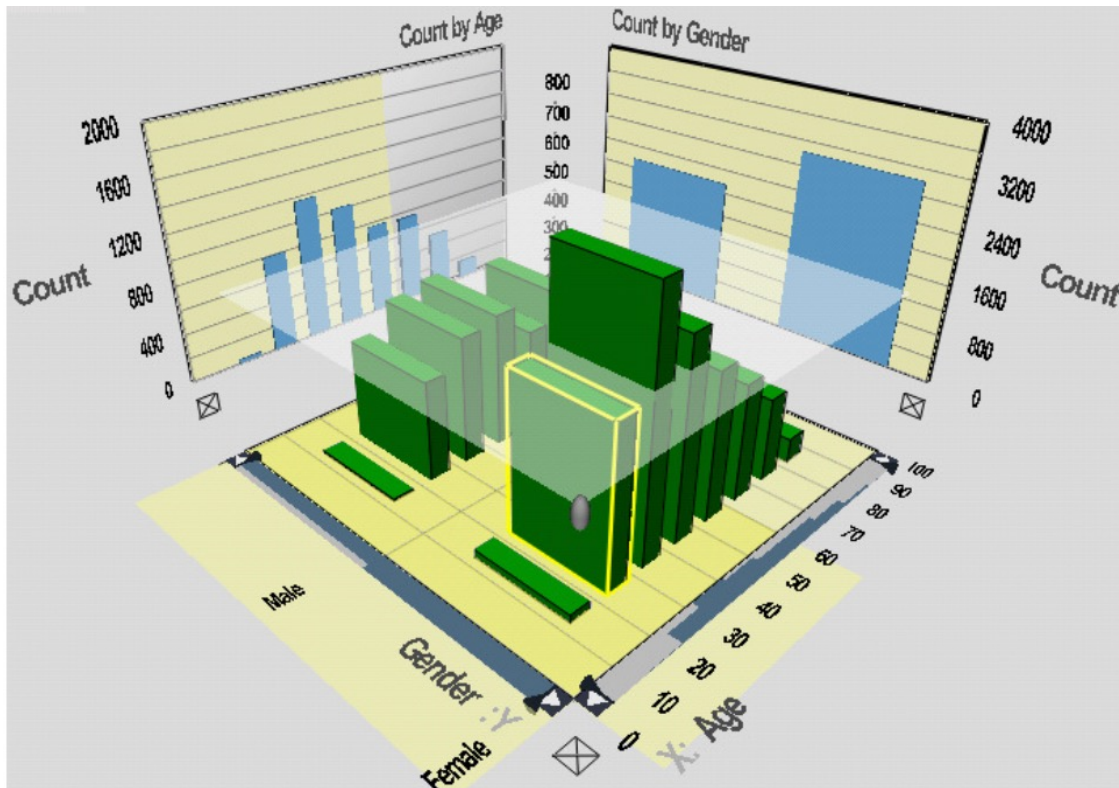


Figure 2: Real-time 3D visual ⁵

Novel Discovery through Visual Discovery ⁶

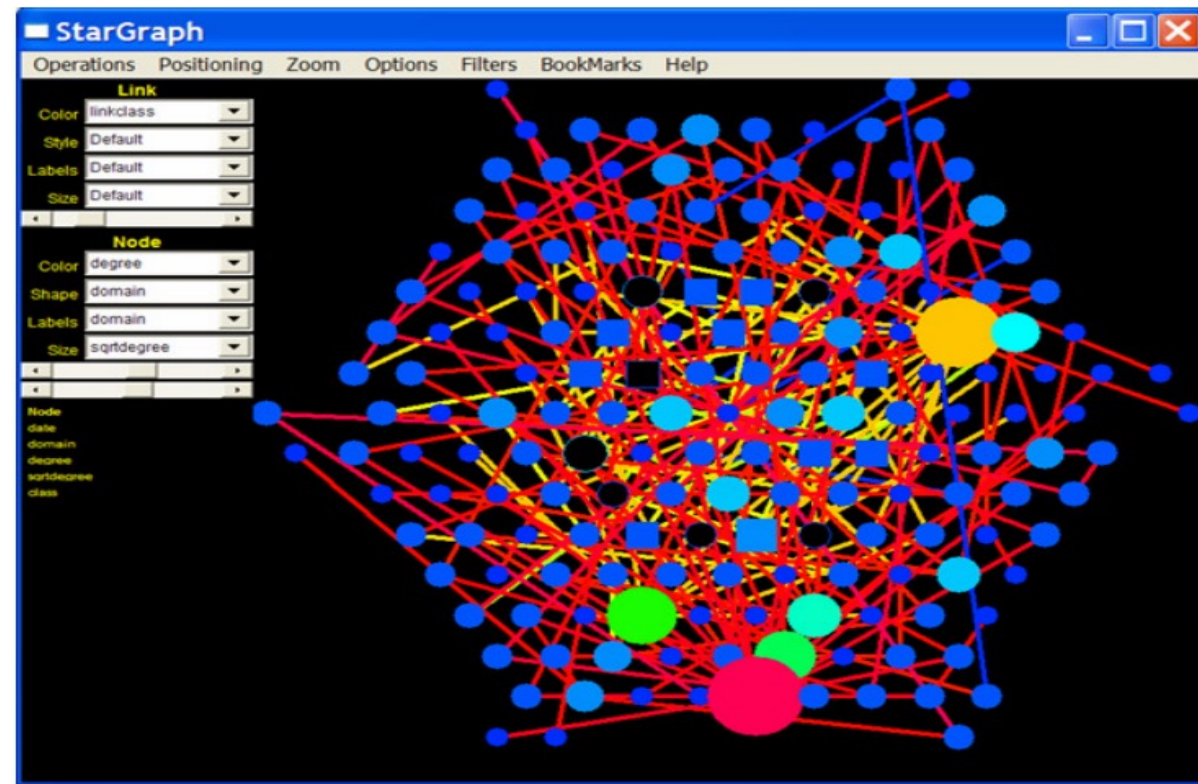


Figure 3: Real-time 3D visual ⁷

4,5. Tamassia, Roberto, and Stephen G Eick. "Graph Drawing for Data Analytics." Essay. In *Handbook of Graph Drawing and Visualization*, 685. CRC Press, 2013.

6.7 . Tamassia, Roberto, and Stephen G Eick. "Graph Drawing for Data Analytics." Essay. In *Handbook of Graph Drawing and Visualization*, 686. CRC Press, 2013.

The Sweet Spot for Network Visualization

Attribute	Low Value	High Value
Dataset size	10^1 to 10^2	10^4 to 10^6
Dataset complexity	2 or 3 dimensions	50 dimensions
Dataset change rate	minutes	months

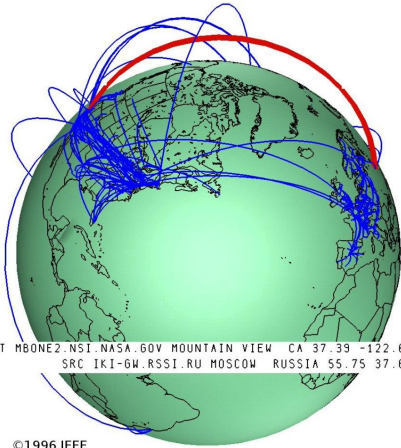
Figure 4: Network Visualization sweet spot ⁸

8. Tamassia, Roberto, and Stephen G Eick. "Graph Drawing for Data Analytics." Essay. In *Handbook of Graph Drawing and Visualization*, 691. CRC Press, 2013.

Computer Networks

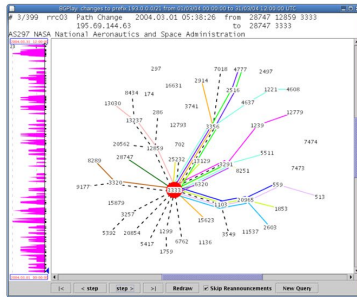
Different types of computer networks:

- Internet as a whole
- ISP (Internet Service Provider)
- Local/Singular Networks

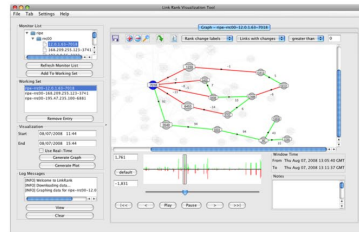


The good:

- Brought useful examples of data visualization
- Explored how the size of the data affects the ability to visualize it



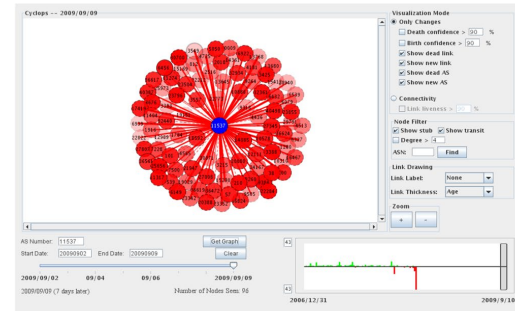
(a)



(b)

782

CHAPTER 25. COMPUTER NETWORKS



Uses absolute geographic coordinates	Yes	[AGN99], [BEW95], [Mei00], [HPF07], [PH99], [PN99], [Jac99], [kcH97], [HNkc97], [HJWkc98], [Dit09], [CE95], [CEH96], [KNK99], [KNTK99], [Kvi03], [MHkcF96], [SMW04], [oANTtE08], [Dar09], [CP], [Bou02], [Tel09], [UNI09], [Lim09], [Vis09], [Aug03], [YGM05], [YMMW09]
	No	[AHDBV05b], [AHDBV05a], [AGL ⁺ 08], [BBGW04], [BBP07], [BCD ⁺ 04], [BMB00], [CAI09], [GH02], [McR99], [Mun97], [Hyu05], [CBB00], [CDD ⁺ 00], [CDM ⁺ 06], [CDM ⁺ 05], [CRC ⁺ 08], [EHH ⁺ 00], [EW93], [FNMT94], [GGW07], [GKN04], [GMN03], [GT00], [kc97], [GMO ⁺ 03], [KGS07], [KMG88], [LMZ04], [LMZ06], [MB95], [MFKN07], [MKN ⁺ 07], [OCP ⁺ 07], [OCLZ08], [PIP05], [Piz07], [Sal00], [YSS05], [Sii01], [Mic09], [WCH ⁺ 03], [RIS09], [Bro01], [Oli09], [OC07], [AS06], [TvAG ⁺ 06], [Net09b], [Gro00], [Hir07], [RTU09], [IBM09], [Che07], [Pro02], [Net09c], [AHDBV], [Vol09], [LUM], [WAN08], [EHH ⁺ 05], [NoCSNCTUT09], [Com09b], [Wyv09], [net09a], [Hew09], [Tec09], [ea05], [Des09], [DLV97], [Cor09], [Sof09a], [Tec05], [Ips09], [WH09], [WS04], [ZW92]
	Unknown	[3Co09], [Ent09], [Cor], [Map08], [Sof09b], [Jon09]

Table 25.7 A classification of visualization methodologies according to the usage of absolute geographic coordinates for the placement of network nodes.

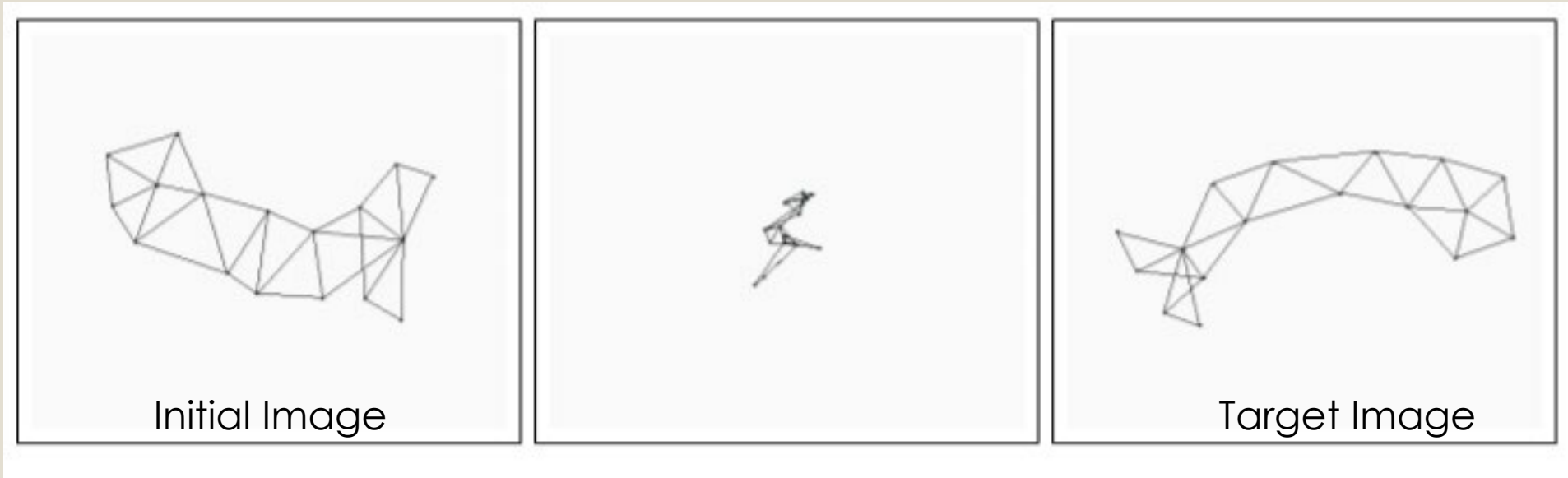
The bad:

- Relied too heavily on tables as seen on this slide. This is very confusing to look at, and does not lend itself to intuitive understanding of what the author is attempting to convey



GRAPH ANIMATIONS

V Lange



Friedrich, C., & Eades, P. (2000, September). The Marey graph animation tool demo. In *International Symposium on Graph Drawing* (pp. 396-406). Springer, Berlin, Heidelberg.

Friedrich and Eades - Properties of Good Animations

- Uniform motion—Groups of nodes should move together
- Separation— Nodes should move separate if they are moving in different directions
- No misleading layouts—Avoid overlaps as this can cause confusion/don't intentionally mislead

Friedrich and Eades - Properties of Good Animations

- Short motion paths— Keep motions short, unnecessary movements can be confusing
- Rigid motion—Keep motions consistent in the animation

Friedrich and Eades – Algorithm

Step 1: Fade out nodes and edges that cease to exist in the final stage

Step 2/ Step 3: Apply any transformations that are needed to the nodes and edges while moving them to their final destinations

Step 4: Fade in nodes and edges that did not exist in the initial animation

References

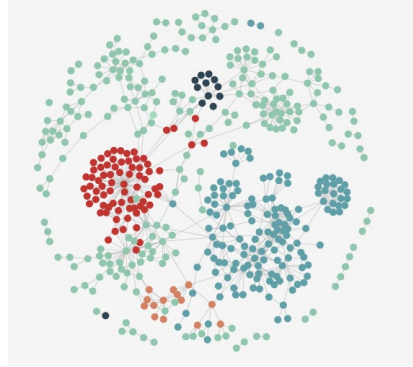
- Friedrich, C., & Eades, P. (2000, September). The Marey graph animation tool demo. In *International Symposium on Graph Drawing* (pp. 396-406). Springer, Berlin, Heidelberg.
- Tamassia, R. (Ed.). (2013). *Handbook of graph drawing and visualization*. CRC press.

Multi Layer Gene Networks

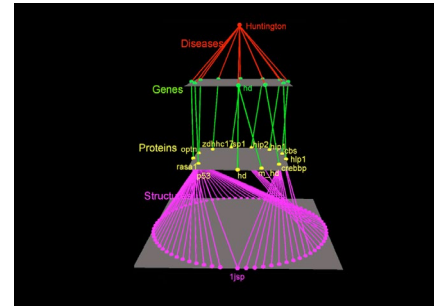
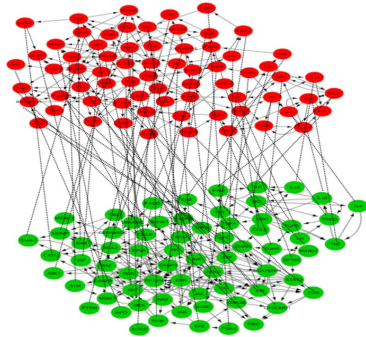
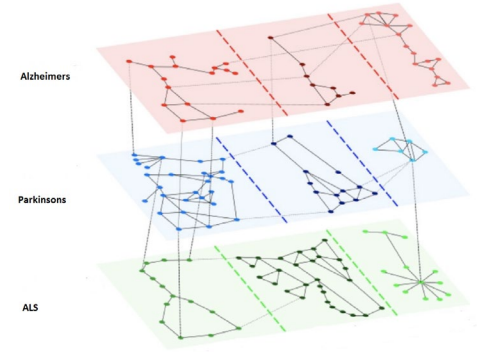
Likelihood of gene being associated with disease

SYMBOL	AlzheimersGWAS	PD_gene_Z	AD_gene
ASH1L	4	5.0537	0.31294
BCAM	26	-0.60902	7.565
BCL3	16	0.36776	12.302
CBLC	14	-0.83942	8.4516
CCSER1	4	4.9058	0.12166
CLPTM1	15	-0.48285	11.011
CRHR1	3	8.95	0.99928
DGKQ	3	14.51	1.7717
GAK	3	13.208	0.98227
GBA	3	6.9093	0.68945
HIP1R	4	4.1812	3.5529
KANSL1	3	8.4089	1.5754
LRRK2	3	11.985	0.67618

Machine learning to cluster genes together

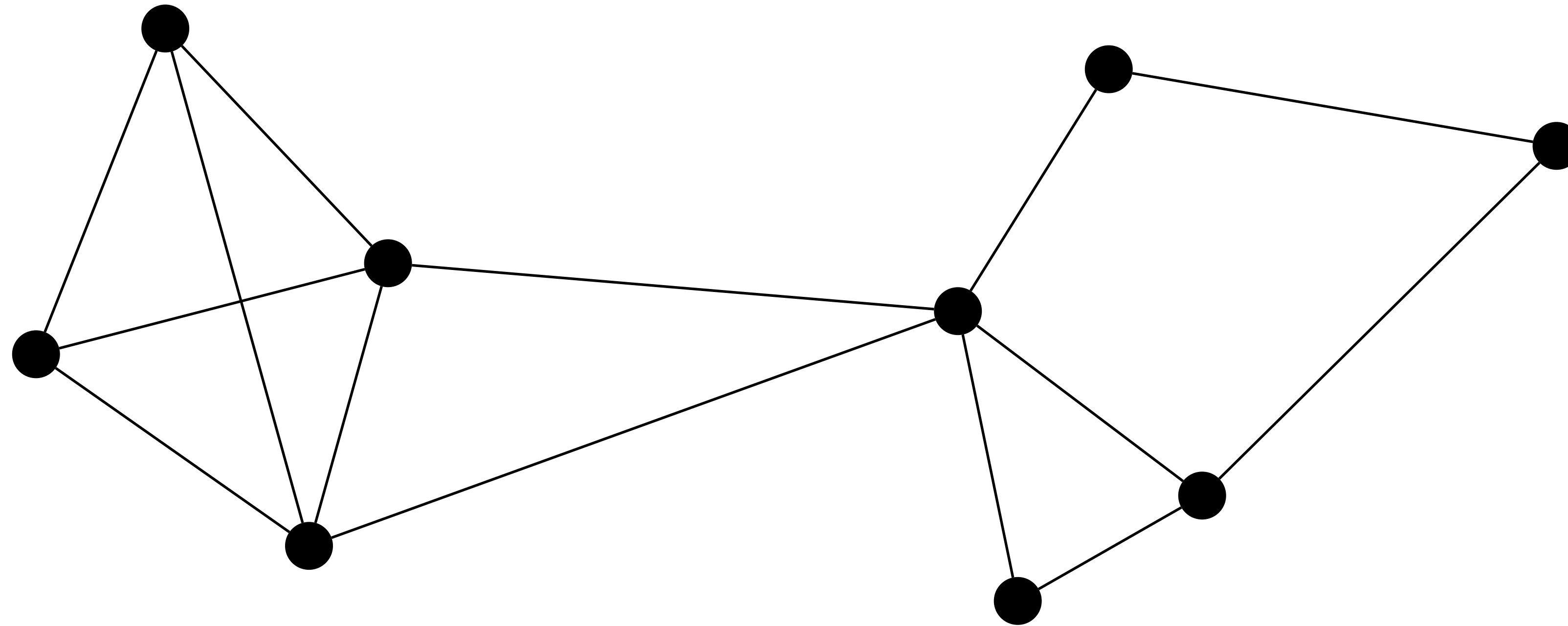


Multi layers to show gene interactions across diseases



How to represent incidence structures?

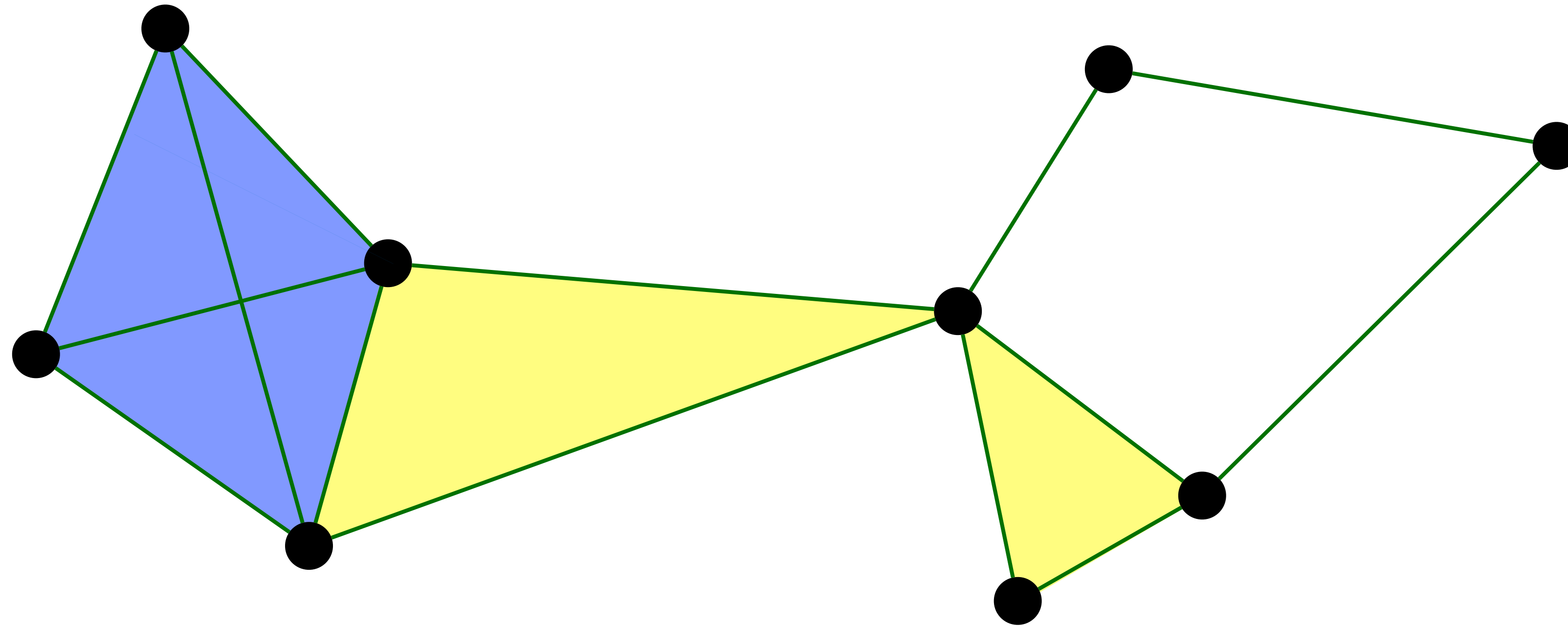
Example structures taken from 6.2.4 of Sugiyama[1]



A graph G is a pair $G = (V, E)$ where V is a finite set [called *vertices*] and $E \subseteq V \times V$ is a (possibly ordered) set of relations [called *edges*]

How to represent incidence structures?

Example structures taken from 6.2.4 of Sugiyama[1]

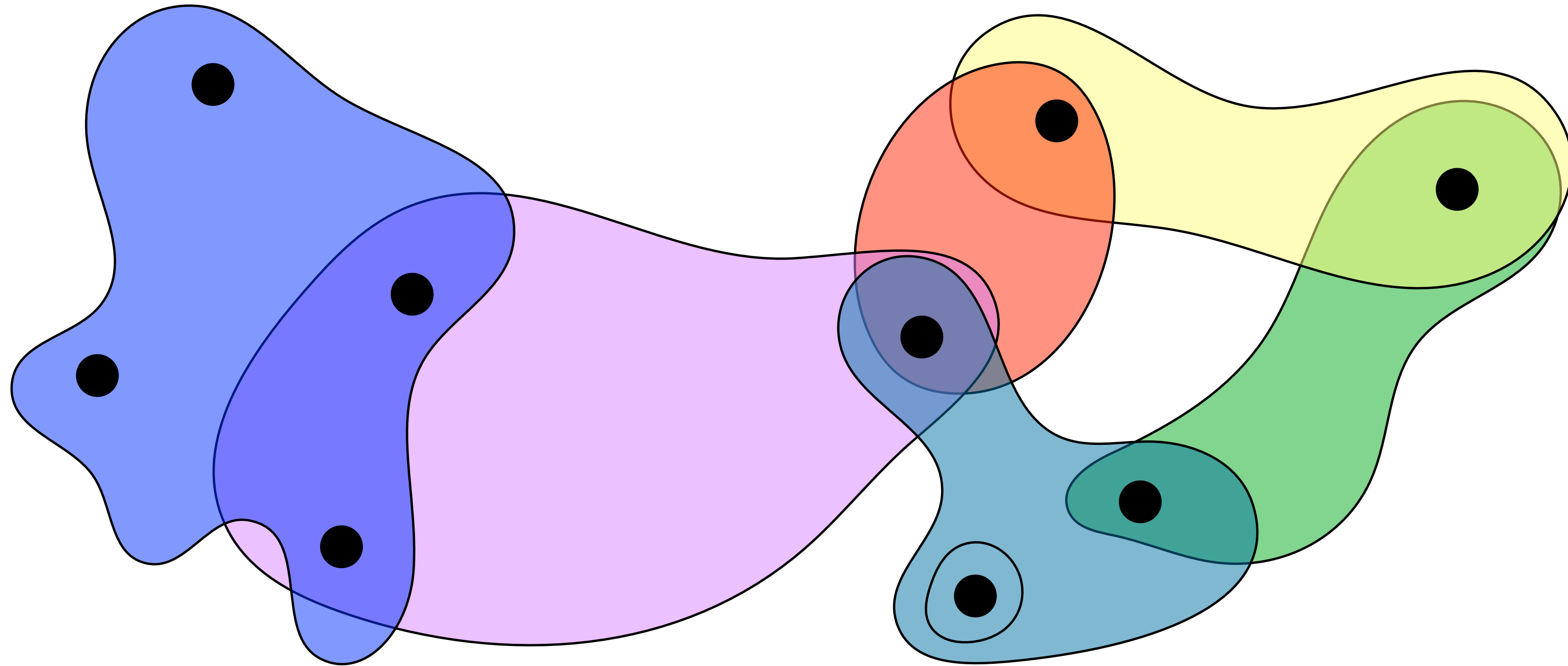


A simplicial complex K is a pair $K = (V, S)$ where V is a finite set [called *vertices*] and S is a set of non-empty subsets [called *simplices*] of V satisfying:

1. $p \in V \implies \{p\} \in S$
2. $\sigma \in S, \tau \subseteq \sigma \implies \tau \in S$

How to represent incidence structures?

Example structures taken from 6.2.4 of Sugiyama[1]



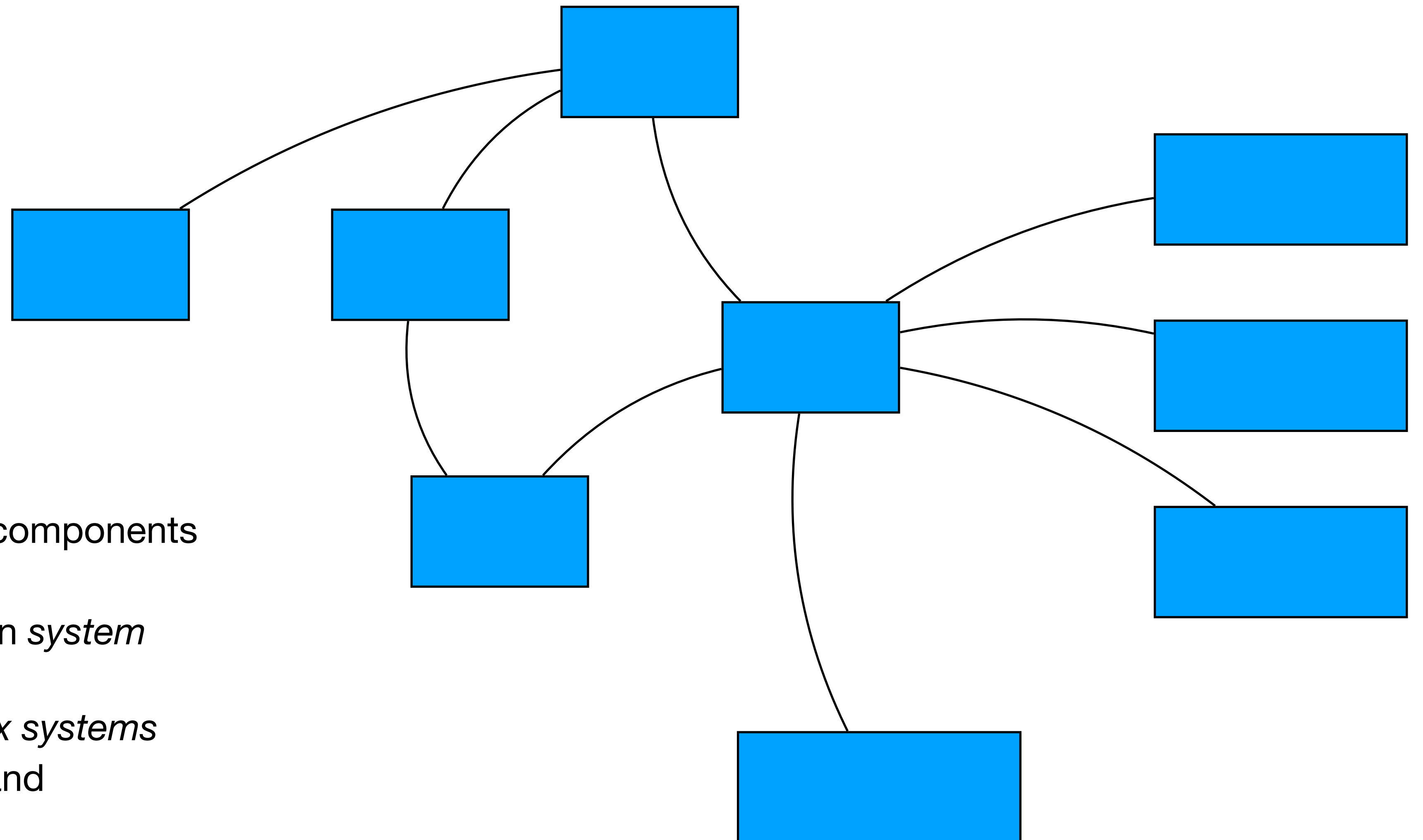
An hypergraph H is a pair $H = (V, \mathcal{E})$ where V is a finite set [called *vertices*] and $\mathcal{E} \subseteq \mathcal{P}(V)$ is a set of non-empty subsets [called *hyper-edges*] of V

$$G \subseteq K \subseteq H$$

(unordered)

Possible applications of Graph drawing

(as predicated by Sugiyama in 2002)

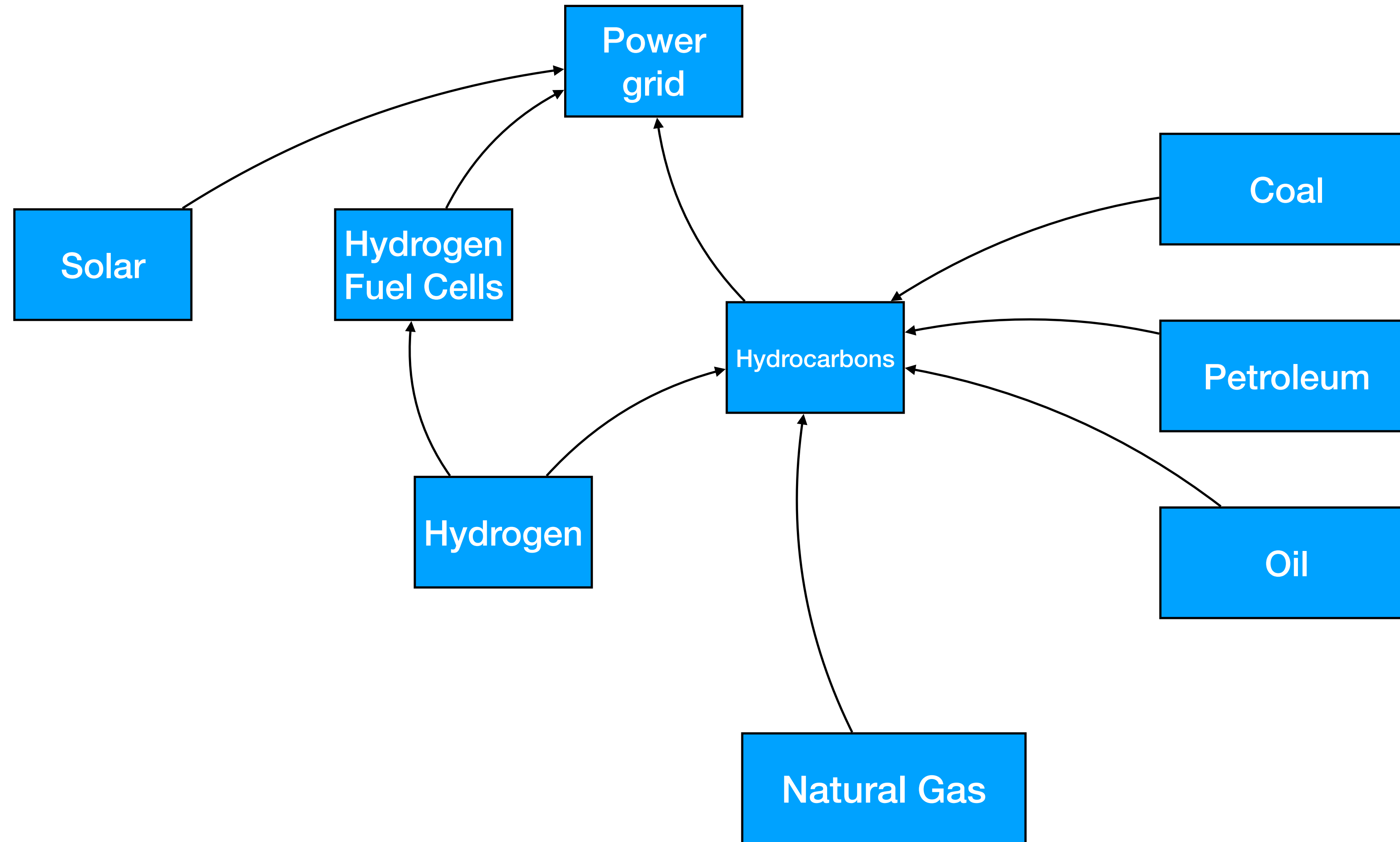


Predicated applications

- *Documentation* of a system components
- Monitoring system *state*
- Allowing *interactions* between system components
- Enabling *planning* of complex systems
- Showing idea *collaboration* and *consensus*

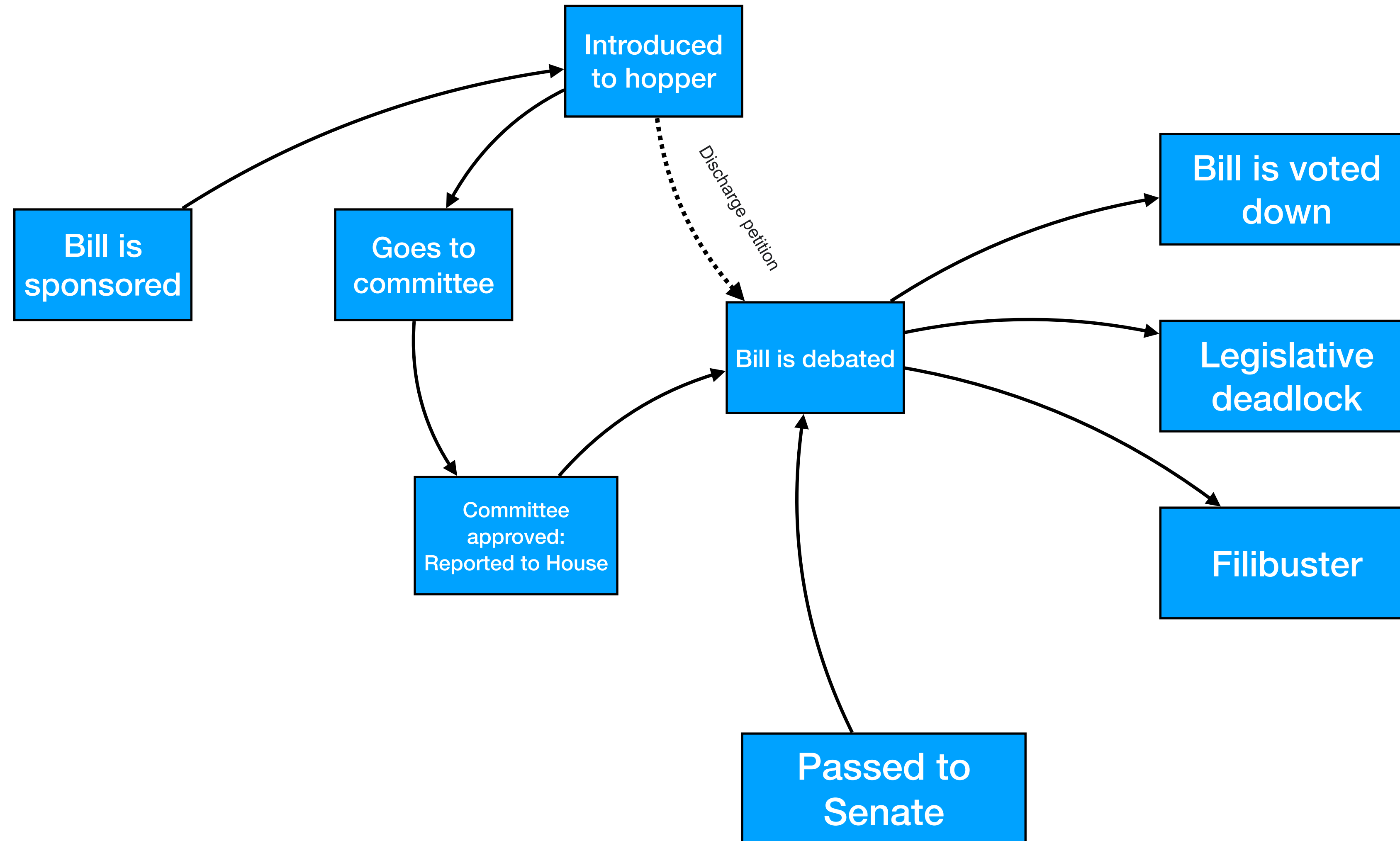
Possible applications of Graph drawing

Showing resource dependencies



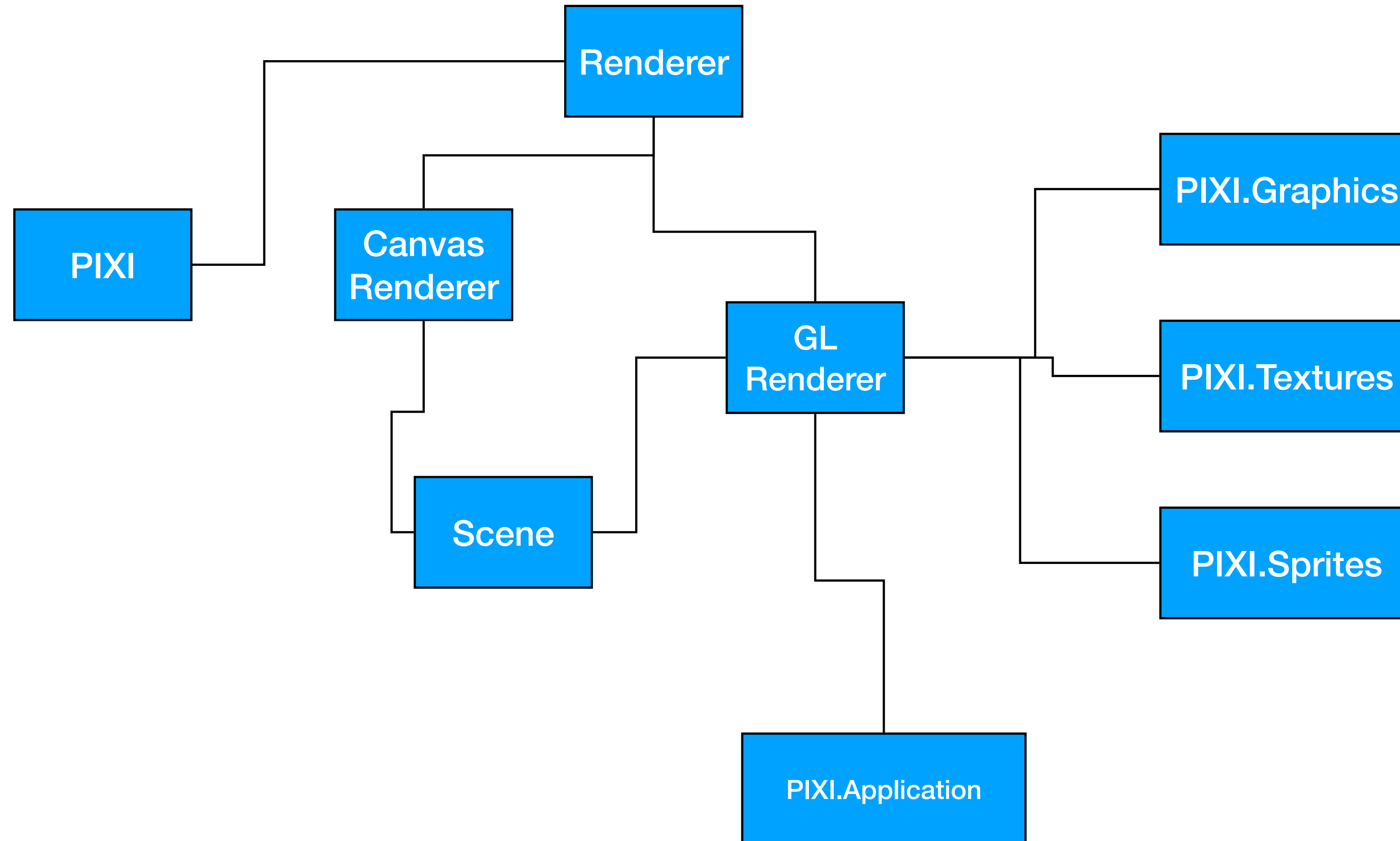
Possible applications of Graph drawing

Representing states and transitions



Possible applications of Graph drawing

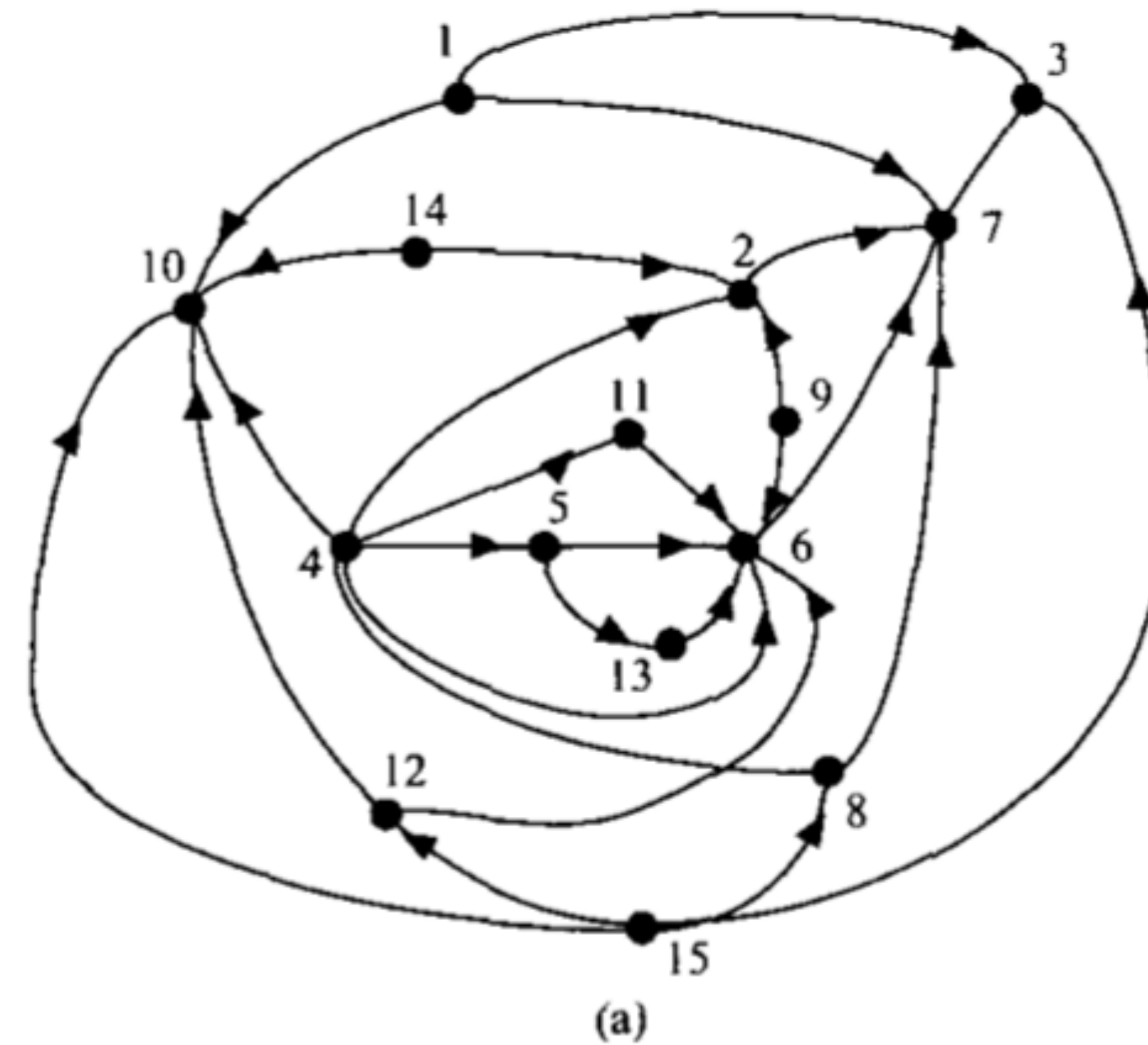
Documenting module components



The need for *correct* layout optimization

On the right:

1. Food chain graph
2. Minimizes edge crossings
3. Interpretable?



Key :

1. Bear	6. Insect	11. Salamander
2. Bird	7. Plant	12. Skunk
3. Deer	8. Rabbit	13. Toad
4. Fox	9. Raccoon	14. Wildcat
5. Gartersnake	10. Rodent	15. Wolf

Figure originally from: Casti, John L. *Connectivity, complexity and catastrophe in large-scale systems*. Vol. 7. John Wiley & Sons, 1979.

Figure taken from: Sugiyama, Kozo. *Graph drawing and applications for software and knowledge engineers*. Vol. 11. World Scientific, 2002.

The same food chain graph

On the right:

1. Same food chain graph
2. Automated hierarchical layout
3. More interpretable?

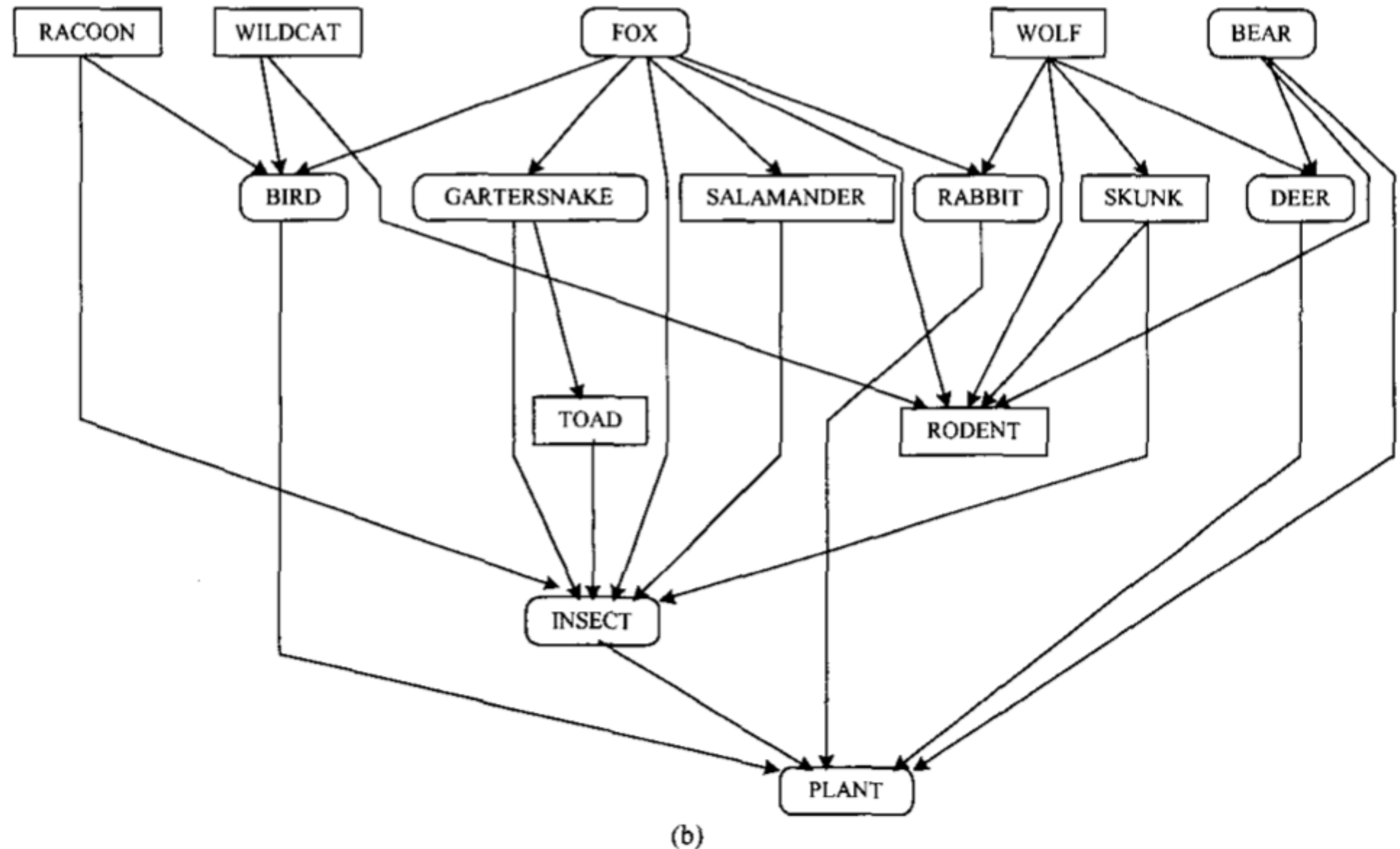


Figure 6.2.1. Diagram of the structure of a food chain [Sugiyama (82)].

Cartography

Wolf (2013) Graph drawing and cartography. Chapter 23 in: *Handbook on graph drawing and visualization*.

Hong Qu

CS 7295 Visualizing Layered Networks

9/20/2021

Geo-Spatial Visualizations

Use Cases	Goals and Challenges
1. Flow	<p>Explain movement across locations</p> <ul style="list-style-type: none">• Conform to users' mental map• Maintain geographic orientation and direction• Strike a balance between big picture overview and specific details
2. Navigation	<p>Provide reliable directions by generalizing roads and locations</p> <ul style="list-style-type: none">• Match users' mental map expectations for direction and relative distance and position• Dense areas must have legible labels for crucial element• Strategic use of distortion to squeeze info into tight spots
3. Schematic Map	<p>Minimize visual complexity and clutter to be functional</p> <ul style="list-style-type: none">• Edges shouldn't cross if there is no connection – planar graph• Angles should be 90 or 45 degrees – 8 directions octilinear• Should provide full view as of the entire (subway) system

1. Flow

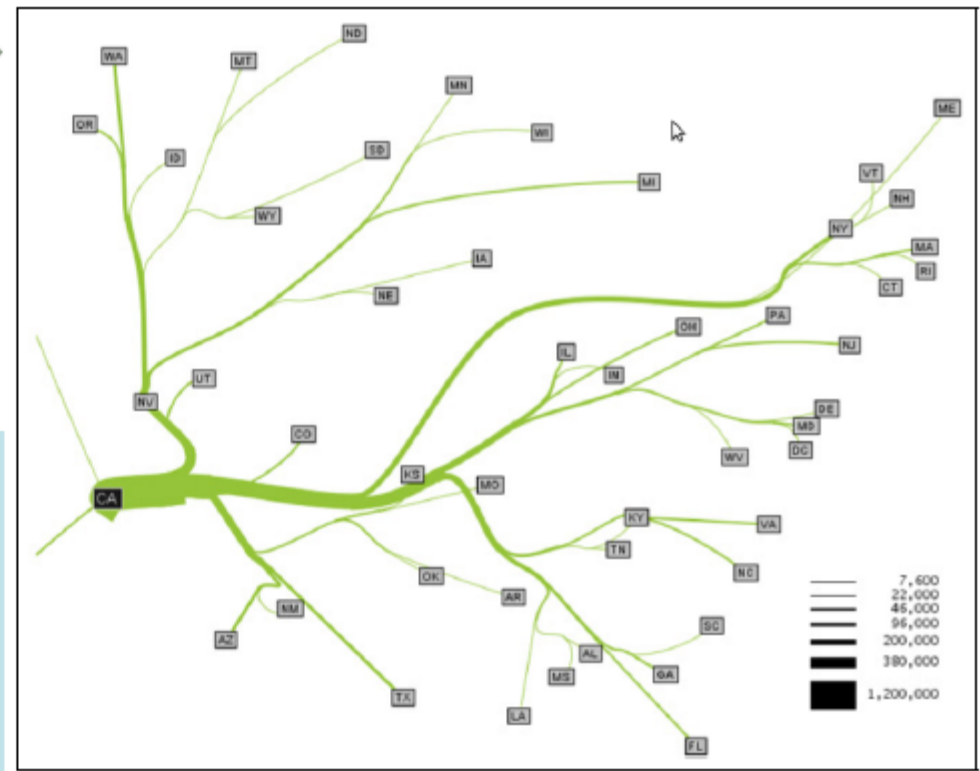
“the flow between two nodes of the underlying network is depicted by curves whose width is proportional to the amount of flow.”



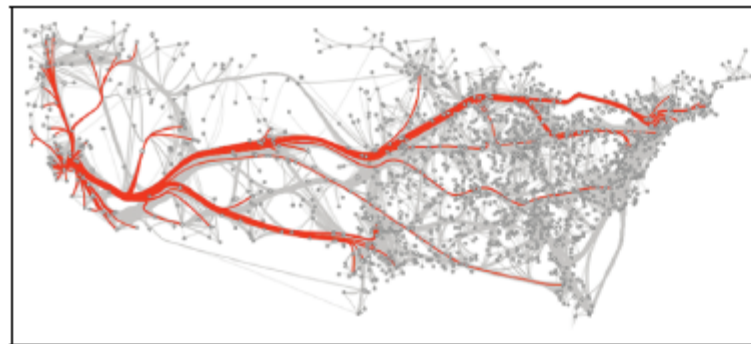
(a) Tobler [Tob87]



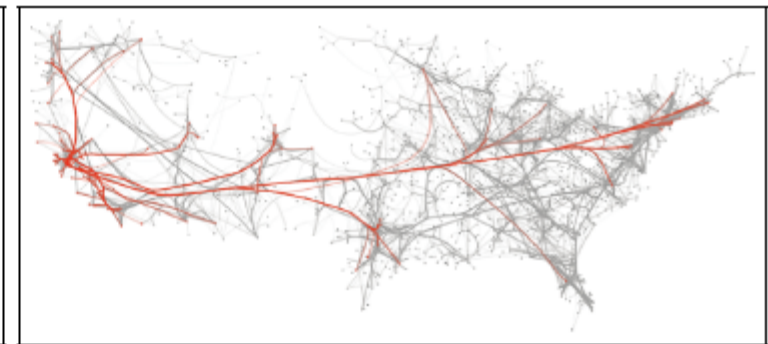
(c) Verbeek et al. [VBS11]



(b) Phan et al. [PXY+05]



(d) Cui et al. [CZQ+08]



(e) Holten and van Wijk [HVW09]

Figure 23.9 Flow maps showing migration leaving California in the years 1995–2000.

2. Street navigation using enlarge focus regions

“a street map within the same view frame as the original map, but such that a region specified by the user is enlarged by a given factor.”

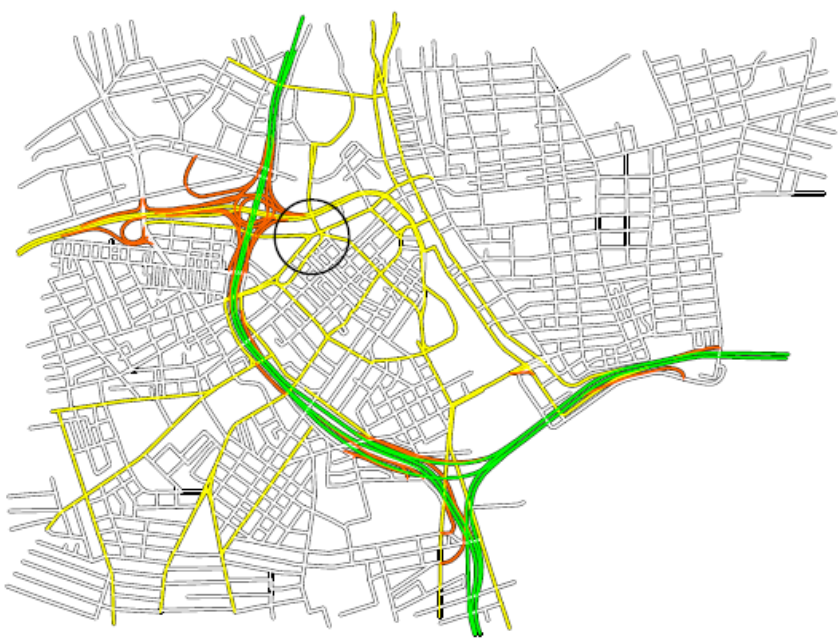
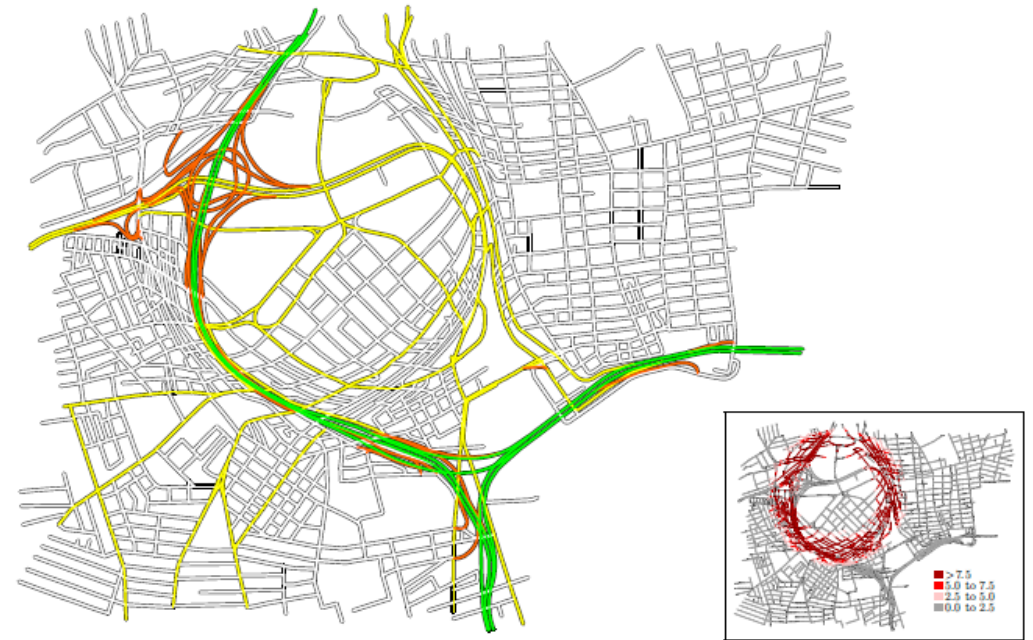


Figure 23.14 A street map (showing a detail of Providence, Rhode Island, U.S.A.) with a circular focus region that contains the conference site of InfoVis 2011.



(a) the method of Haunert and Sering [HS11]



(b) the fish-eye transformation of Yamamoto et al. [YOT09]

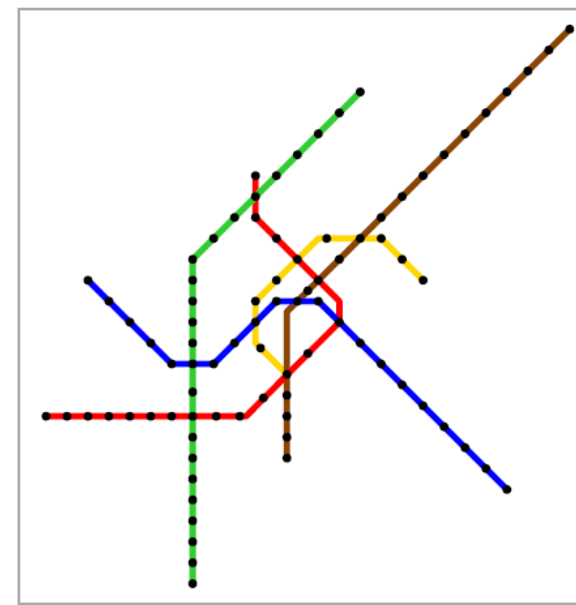
Figure 23.15 The results of applying two deformation methods to the map in Figure 23.14. The insets show edges with residuals in red.

3. Schematic Maps

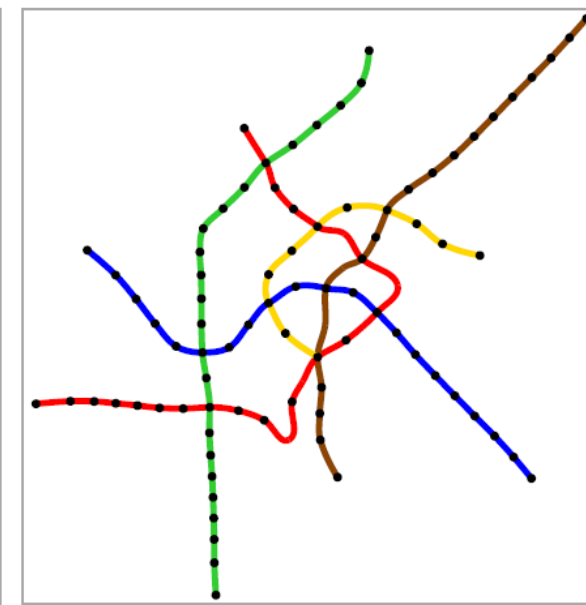
“schematic metro map not just scale, but also the change in scale is (highly) non-uniform.”

- (R1) Restrict the drawing of edges to the octilinear directions.
- (R2) Do not change the geographical network topology. This is crucial to support the mental map of the passengers.
- (R3) Avoid bends along individual metro lines, especially in interchange stations, to keep them easy to follow for map readers. If bends cannot be avoided, obtuse angles are preferred over acute angles.
- (R4) Preserve the relative position between stations to avoid confusion with the mental map. For example, a station being north of some other station in reality should not be placed south of it in the metro map.
- (R5) Keep edge lengths between adjacent stations as uniform as possible with a strict minimum length. This usually implies enlarging the city center at the expense of the periphery.
- (R6) Stations must be labeled and station names should not obscure other labels or parts of the network. Horizontal labels are preferred and labels along the track between two interchanges should use the same side of the corresponding path if possible.
- (R7) Use distinctive colors to denote the different metro lines. This means that edges used by multiple lines are drawn thicker and use colored copies for each line.

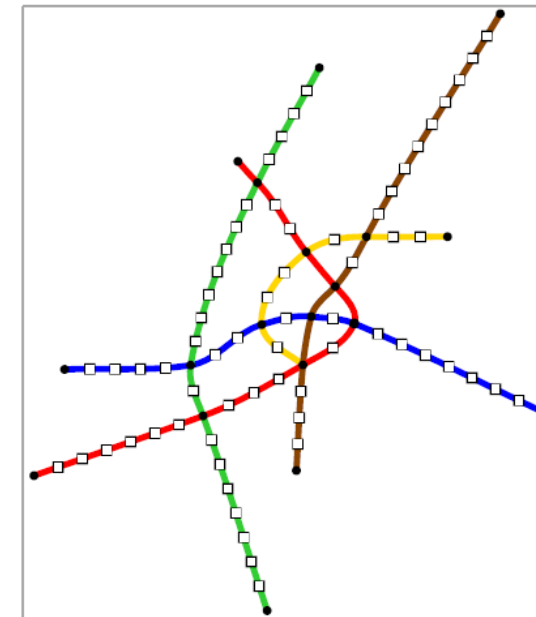
Nollenburg and Wolff [NW11]



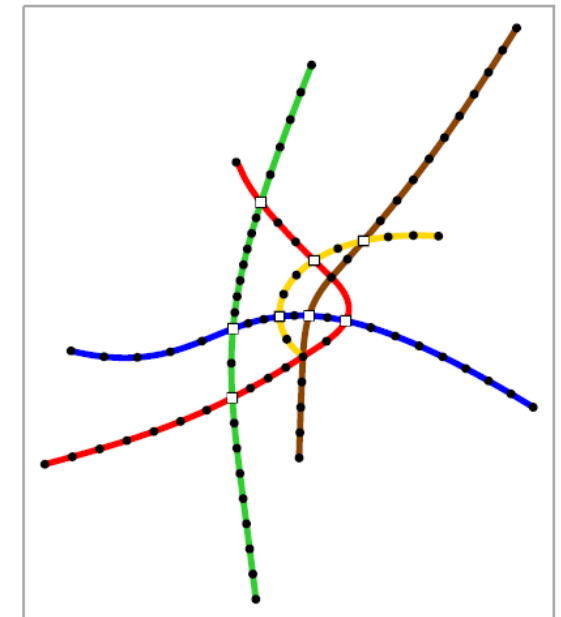
(a) octilinear input drawing,



(b) drawing without virtual vertices



(c) drawing with virtual degree-2 vertices



(d) additionally, with virtual degree-4 vertices

Figure 23.13 Metro network of Vienna drawn using Bézier curves [FHN⁺13].

Social Network

