Unexplained because it works

The unfound reasons for the practical effectiveness of force-directed network layouts and modularity clustering

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Case #1: Network layout algorithms

This case in short:
1. Those algos do work in practice
2. But we don’t know why
3. Yet algo designers say we do
4. Yet we actually do not
5. But we don’t care to not understand, because it works well enough.

Q: Should we care about understanding?
   Why or why not?
1. Network layout algorithms work in practice

1. Network layout algorithms work in practice

- They are inspiring
- They are popular
- You don't have a choice
  (i.e. there are few other options)

That network visualization became so famous it ended up ALSO the poster boy of the programmatic paper of computational social science!

**Social Science**

**Computational Social Science**

David Lazer,1* Alice Pentland,1 Lada Adamic,2 Sean Aral,2 Albert-László Barabási,3 Devon Brewer,4 Nicholas Christakis,1* Moshe Contractor,4 James Fowler,5 Myron Gutmann,6 Tony Jebara,3* Gary King,2 Michael Macy,1 Dan Ray,7 Marshall Van Alstyne,8

We live in the network. We check our e-mails regularly, make mobile phone calls from almost any location, swipe transit cards to use public transportation, and make purchases with credit cards. Our movements in public places may be captured by video cameras, and our medical records stored as digital files. We may post blog entries accessible to anyone, or maintain friendships through online social networks. Each of these transactions leaves digital traces that can be compiled into comprehensive pictures of both individual and group behavior, with the potential to transform our understanding of our lives, organizations, and societies.

The capacity to collect and analyze massive amounts of data has transformed such fields as biology and physics. But the emergence of a data-driven “computational social science” has been much slower. Leading journals in economics, sociology, and political science show little evidence of this field. But computational social science is occurring—in Internet companies such as Google and Yahoo, and in government agencies such as the U.S. National Security Agency. Computational social science could become the exclusive domain of private companies and government agencies. Alternatively, there might emerge a privileged set of academic researchers providing access to private data from which they produce papers that cannot be critiqued or replicated. Neither scenario will serve the long-term public interest of accumulating, verifying, and disseminating knowledge.

What value might a computational social science—based in an open academic environment—offer society, by enhancing understanding of individuals and collective action?

1. Network layout algorithms work in practice

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- They are popular
- You don’t have a choice (i.e. there are few)

That network visualization became so famous it ended up ALSO the poster boy of the programmatic paper of computational social science!

W
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The capacity to collect and analyze massive amounts of data has transformed such fields as biology and physics. But the emergence of a datadriven “computational social science” has been much slower. Leading journals in economics, sociology, and political science show little evidence of this field. But computational social science is occurring—in Internet companies such as Google and Yahoo, and in government agencies such as the Federal Trade Commission. What is going on? Many complex systems researchers are beginning to view social systems as “complex systems.” Complex systems research is a multi-disciplinary field that studies large-scale systems with emergent properties, such as ecosystems, economies, and societies. Complex systems researchers argue that the study of complex systems can provide insights into the behavior of social systems. For example, complex systems researchers have used computer simulations to study the emergence of social and network structures. These simulations have shown that social and network structures can emerge from simple rules that are applied to individual agents. In other words, complex systems researchers believe that the study of complex systems can provide insights into the behavior of social systems.

SO, IN OTHER WORDS:

My observation is that they work well enough for the people who use them, because they keep using them. You may think they still actually don’t work for them. I guess you know better.

The most common criteria for a good graph drawing are obsolete. For most people, they have been for 15 years. Arguably 30.

Introducing:
A history of graph drawing in 7 min.
I tried 5 but I can't.
EMOTIONS MAPPED BY NEW GEOGRAPHY

Charts Seek to Portray the Psychological Currents of Human Relationships.

It starts in the SSH. Drawn manually. Empirical data.

<table>
<thead>
<tr>
<th>AREA</th>
<th>minimize the area occupied by the drawing.</th>
</tr>
</thead>
<tbody>
<tr>
<td>BALAN</td>
<td>balance the diagram with respect to the vertical or horizontal axis.</td>
</tr>
<tr>
<td>BENDS</td>
<td>minimize the number of bends along the edges.</td>
</tr>
<tr>
<td>CONVEX</td>
<td>maximize the number of faces drawn as convex polygons.</td>
</tr>
<tr>
<td>CROSS</td>
<td>minimize the number of crossings between edges.</td>
</tr>
<tr>
<td>DEGREE</td>
<td>place nodes with high degree in the center of the drawing.</td>
</tr>
<tr>
<td>DIM</td>
<td>minimize differences among nodes’ dimensions.</td>
</tr>
<tr>
<td>LENGTH</td>
<td>minimize the global length of edges.</td>
</tr>
<tr>
<td>MAXCON</td>
<td>minimize length of the longest edge.</td>
</tr>
<tr>
<td>SYMM</td>
<td>symmetry of sons in hierarchies.</td>
</tr>
<tr>
<td>UNIDEN</td>
<td>uniform density of nodes in the drawing.</td>
</tr>
<tr>
<td>VERT</td>
<td>verticality of hierarchical structures.</td>
</tr>
</tbody>
</table>


A heuristic for graph drawing

Peter Eades
University of Queensland

Algorithm.

Semiotic features are back.

Some mid-sized graphs.
Graph Drawing by Force-directed Placement

THOMAS M. J. FRUCHTERMAN* AND EDWARD M. REINGOLD
Department of Computer Science, University of Illinois at Urbana-Champaign, 1304 W.
Springfield Avenue, Urbana, IL 61801-2987, U.S.A.

Algorithm.
Small networks.
No semiotic features.
Not empirical.

“We are concerned with drawing undirected graphs according to some generally accepted aesthetic criteria [Eades and Tamassia (1987)]. ... Our algorithm does not explicitly strive for these goals, but does well at distributing vertices evenly, making edge lengths uniform, and reflecting symmetry. Our goals for the implementation are speed and simplicity. ... We have only two principles for graph drawing: (1) Vertices connected by an edge should be drawn near each other. (2) Vertices should not be drawn too close to each other.”

User benchmark. The tested network has only 16 nodes.

<table>
<thead>
<tr>
<th>graph</th>
<th>bend-less</th>
<th>cross-less</th>
<th>minangle</th>
<th>orthog</th>
<th>sym</th>
</tr>
</thead>
<tbody>
<tr>
<td>b+</td>
<td>0.96</td>
<td>0.97</td>
<td>0.38</td>
<td>0.27</td>
<td>0.75</td>
</tr>
<tr>
<td>b-</td>
<td>0.47</td>
<td>0.99</td>
<td>0.44</td>
<td>0.28</td>
<td>0.71</td>
</tr>
<tr>
<td>c+</td>
<td>0.82</td>
<td>1</td>
<td>0.46</td>
<td>0.33</td>
<td>0.63</td>
</tr>
<tr>
<td>c-</td>
<td>0.87</td>
<td>0.88</td>
<td>0.35</td>
<td>0.29</td>
<td>0.84</td>
</tr>
<tr>
<td>m+</td>
<td>0.71</td>
<td>0.98</td>
<td>0.62</td>
<td>0.22</td>
<td>0.74</td>
</tr>
<tr>
<td>m-</td>
<td>0.82</td>
<td>0.98</td>
<td>0.16</td>
<td>0.26</td>
<td>0.79</td>
</tr>
</tbody>
</table>

Fig. 1. Six of the ten experimental graph drawings, and their aesthetic values.

GRIP: Graph dDrawing with Intelligent Placement*

Pawel Gajer¹ and Stephen G. Kobourov²

Fig. 5. Knotted rectangular (degree 4) meshes of 1600, 2500, and 10000 vertices.

Fig. 6. Cylinders of 1000, 4000, and 10000 vertices.

Fig. 7. Tori of various length and thickness: 1000, 2500, and 10000 drawn in four dimensions and projected down to three dimensions.

Fig. 8. Triangular (degree 6) meshes of 496, 1035, and 2016 vertices.

Fig. 9. Knotted triangular (degree 6) meshes of 496, 1035, and 2016 vertices.

Algorithm.
Large networks.
Not empirical.
Not scale-free.

Energy Models for Graph Clustering

Andreas Noack
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Algorithm.
Large networks.
Empirical again!
Scale-free!

(a) Kamada-Kawai
(b) Kamada-Kawai, adapted by Gansner et al.
(c) Fruchterman-Reingold
(d) Edge-repulsion Fruchterman-Reingold
(e) Node-repulsion LinLog
(f) Edge-repulsion LinLog

Figure 2: Pseudo-random graph

The goal of this work are layouts that group densely connected nodes and separate sparsely connected nodes; such layouts often violate aesthetic criteria like small edge lengths or uniformly distributed nodes.

Aesthetic criteria MUST be dropped.
OpenOrd: An Open-Source Toolbox for Large Graph Layout

Shawn Martin\textsuperscript{a}, W. Michael Brown\textsuperscript{a}, Richard Klavans\textsuperscript{b}, and Kevin W. Boyack\textsuperscript{b}

\textsuperscript{a}Sandia National Laboratories, PO Box 5800, Albuquerque, NM 87185
\textsuperscript{b}SciTech Strategies, Inc., 2405 White Horse Rd, Berwyn, PA, 19132


**Interpretation regime:**

<table>
<thead>
<tr>
<th>Diagrammatic</th>
<th>Topological</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Typical data visualized</strong></td>
<td>Complex network, 100-10M nodes, hyperconnected hubs and long tail</td>
</tr>
<tr>
<td><strong>Identify nodes, follow paths.</strong></td>
<td>Describe density distribution in different areas of the image.</td>
</tr>
</tbody>
</table>

- **Diagrammatic:** Diagram, 10-100 nodes, homogeneous degree distribution
- **Topological:**
TAKEAWAYS

Theory has ALWAYS followed practices.

With a considerable delay.

The field consists of recipes all the way down.
I mean: the field is full of heuristics.

In short: we don’t know why it works.
Noack says:

- The goal is cluster separability (I concur)
- It is decided by the attraction and repulsion forces (yes, BUT...)
- The optimal forces are linear and logarithmic. Hence “LinLog”. (I concur)

4. Yet algo designers don’t actually know

LinLog without edge repulsion sucks.

While with edge repulsion, it’s great.

It’s not (mainly) the forces, it’s the edge repulsion.

'=_=_'

5. Who cares?

Users care that:
• It works in practice
• They can justify the method

An algo designer does not care because:
• Their algo works,
• it has a rationale...
• ...that passed peer review.
Job done, right?

As long as we agree to not look under the hood, this is good science.

There is a risk to reopening a solved problem:
• Reopening a “cold case” may bring back existing conflicts/tensions
• It is inherently controversial (it goes against the consensus)
• There might be no benefits to the time and effort spent on it

Yet benefits may still come out:
• Innovation or breakthrough (who knows)
• Better methodological grounding
• Better explanation (teaching)
Interlude
What am I up against?

A tool maker’s perspective
What do the algorithm users want?

(and what do the tool makers want?)
Interlude: what am I up against?

The user of a tool or algorithm may have different goals than those expected by the author of that tool or algorithm.

Is this controversial?
Interlude: what am I up against?
Here is a point of view you find in the digital humanities

BLACK BOX

The tool is
EASY TO USE
HIDING COMPLEXITY

The user is
LAZY THINKING
UNREFLECTIVE
Interlude: what am I up against?
Here is a point of view you find in the digital humanities

CRITICAL THINKING

- The tool is difficult to use
- Exposing complexity

The user is

- Hard thinking
- Reflective
Interlude: what am I up against?
Here is a point of view you find in the digital humanities

Black Box

Ease-of-use axis
The tool is EASY TO USE
HIDING COMPLEXITY
The user is LAZY THINKING
UNREFLECTIVE

Critical Thinking
The tool is DIFFICULT TO USE
EXPOSING COMPLEXITY
The user is HARD THINKING
REFLECTIVE

I oppose this view!
Interlude: what am I up against?
The problem with ignoring the user’s own needs

The user needs to hammer the nail...

...but Mjölnir cannot be lifted!
Interlude: what am I up against?
The problem with ignoring the user’s own needs

The user needs to hammer the nail...

a. ...but Mjölnir cannot be lifted!

b. So the user finds another way: They hit Mjölnir with the nail.
Interlude: what am I up against?
The problem with ignoring the user’s own needs

The user needs to hammer the nail...

...but Mjölnir cannot be lifted!

So the user finds another way: They hit Mjölnir with the nail.
In my abstract for this conference I wrote:

“Observing network analysis practices shows that users have their own epistemic culture.”

(You’ll soon meet my Reviewer #2)

What are epistemic cultures:

“amalgams of arrangements ... which, in a given field, make up how we know what we know. ... cultures that create and warrant knowledge.”

Meet my reviewer #2

“If this contribution is accepted, it is to highlight how caricatural science has become in some areas where criticizing it is considered a problem, the user is always right even when wrong (because epistemic culture etc.), existing practices are perfect, and not understanding is great.”
Why would “users have their own goals” imply that “their practices are unproblematic”?

→ Because you think that practices should be bound by academic authority.

Yet academic authority follows from the practices.
Case #2: Community detection (in networks)

This case in short:
1. People like the Louvain method
2. The Leiden and Bayesian Inference methods are claimed to be superior by their designers
3. Some users still prefer Louvain
4. That’s because they do something else than what algorithm designer consider should be done with these algos
5. Those designers still contend that these users are wrong
6. This boils down to my reviewer #2: Users cannot have their own goals
Network of airports: countries (ground truth)
Network of airports: countries (ground truth)

Europe:
• Many countries
• But a self-consistent airspace

North America:
• Three countries
• Also a self-consistent airspace
Network of airports: **Louvain method**

Europe is a single community

North America is a single community
Network of airports: \textit{Leiden} method

Europe is one big and a few small communities

North America is one big and a few small communities
Network of airports: Peixoto’s Bayesian inference method

Europe is many smaller communities

North America is many smaller communities
What makes Leiden and Bayesian Inference better

**LOUVAIN**
With Louvain you can set “resolution”:
How big you want the communities.

The Louvain method has a known bias:
It finds same-size communities.

**LEIDEN**
The Leiden method fixes that bias.
Still has the resolution setting.
Better mathematical justification.

**PEIXOTO’s Bayesian Inference**
Also fixes the bias.
Even better mathematical justification.
(explicitates model assumptions)
Has no resolution. (non-parametric)
Countries
(ground truth?)
(or maybe not?)

LOUVAIN
Few big chunks.
Useful to summarize
the structure of the
network.

LEIDEN
Mixed chunks.
Useful to retrieve
macro & micro
structures.

BAYESIAN INFERENCE
Can predict
communities that
follow the model’s
assumptions.
For some users, Louvain’s “bias” is a feature.

Countries
(ground truth?)
(or maybe not?)

LOUVAIN
Few big chunks.
Useful to **summarize**
the structure of the
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Can predict
communities that
follow the model’s
assumptions.
Descriptive methods like Louvain “do not articulate precisely what constitutes community structure” contrary to inferential methods. Therefore they “carry no explanatory power.” The communities obtained from descriptive methods “can be seen and described, but they cannot explain.”

“Every descriptive method can be mapped to an inferential one, according to some implicit model.”

Descriptive methods are inferential methods that do not state their model, which makes them inherently worse.

“There is no such thing as a ‘model-free’ community detection method.”

→ For Tiago Peixoto, you would be wrong to prefer Louvain over Bayesian inference.

→ But he assumes that you always aim to predict, since there always is a model.
Dear algorithm designer,

Users will repurpose your creation, and if you want to criticize it, you must put the effort to understand why.

I am sorry for your loss,
Mathieu

PS: I’ve been there. Feel free to give me a call.
Scientific and technical work is made invisible by its own success.”
— Bruno Latour

When technology works, the science of understanding why is often undone.

Yet it could help us:
• Find new purposes to existing algorithms (invented by users)
• Find out when users are actually wrong, and help them improve
• Do science that supports existing practices

My wishful thinking for doing that undone:

1. Peer review should allow an algorithm author to not know why it works. (they may still show it does!)

2. Algo designers should face user practices. Understanding before gatekeeping.

3. Explaining should have academic currency. Not just novelty or efficiency.

Conclusion:
How to keep the gate of the algorithm
Thank you for your attention.

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Attraction force

n1

Repulsion force

n2

Attraction force
Too close: Repulsion is the strongest

At equilibrium: Attraction = Repulsion

Too far: Attraction is the strongest
Different algorithms produce different results.
Color = ATTRIBUTE X

Is there an attribute-topology CORRELATION?

No color

No layout

Layout = TOPOLOGY (edges)

Nodes of same attribute $X$ are more often connected

Attribute $X$ and edges are unrelated
The blue dots gather on the left, the red dots gather on the right (image layer).

...which means that...

The layout placed the nodes of the same kind together (layout layer).

...which means that...

The blogs tend to connect more with blogs of the same political affiliation (network layer).

...which means that...

When bloggers add a blog to their blogroll, it generally has a similar political content (phenomenon layer).

...interpretation:

The behavior of political bloggers features homophily (tendency to link to the same) which results in the polarization of the political web.
Layers of mediation

**STEP**
- **BEINGS REPRESENTED BY THE DATA** (empirical phenomena)
- **DATA SOURCE** (any kind of data)
- **NETWORK DATA** (nodes & edges)
- **LAYOUT/EMBEDDING** (node coordinates)
- **NETWORK MAP** (picture)

**Examples**
- Person, website, book, friendship, influence...
- Database of documents, list of tagged items, XML file(s)...
- List of nodes + list of edges (with attributes)
- (X, Y) coordinates for all nodes
- An image on a physical substrate (screen, paper...)

**MEDIATION**
- Reduction to formal inscriptions
- Processing
- Network extraction (reduction)
- Processing
- Compute layout (embedding)
- Image rendering (semiotic building)
- Image reading

*Situating visual network analysis, Jacomy, 2021.*