

# Unexplained because it works

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

When facing relational data, some analysts in different fields rely on the practice of visual network analysis (Jacomy, 2021). In this practice, one observes the widespread use of two techniques: using a force-driven algorithm to compute the node placement, also called layout or embedding (Cheong and Si, 2020; Gibson et al., 2012); and using a modularity maximization algorithm such as Louvain (Blondel et al., 2008) or Leiden (Traag et al., 2019) to detect communities. As Noack stated in the title of an influential article, “Modularity clustering is force-directed layout” (Noack, 2009; see also Gouvêa et al., 2021). These two types of algorithms are in some sense equivalent, and play a similar role in the situation I aim to unpack.

This piece unpacks and reflects on the following situation: layout and modularity algorithms work, but we do not know why, and there are no incentives to look for a scientific explanation. At the heart of this situation, we find that the effectiveness of these techniques does not require an explanation. Yet this core fact is covered by layers of complication that I aim to peel one after the other.

First, the authors of those algorithms *do* provide justifications, and the users rely on them; however, I contend that those justifications do not explain the effectiveness. Yet their existence prevents better, more appropriate justifications from being sought out. At the heart of this question lie disagreements on the nature of effectiveness. What tasks is an algorithm supporting, for whom, and in which situations? Different users may disagree, and disagree with the algorithm designers.

Second, the academic criticism of those justifications produced counter-justifications, i.e. arguments against the use of force-directed networks (Krzyszynski et al., 2012) or modularity clustering (Peixoto, 2021), but not better explanations for the actual behavior of existing techniques. Critiques aimed at changing practices rather than supporting the interpretability of existing ones. Algorithm designers see their creations as solutions to their own problems, not to different problems; yet users do repurpose them to meet their own needs. Users are not necessarily right, but also not necessarily wrong. Many algorithm designers dismiss this repurposing as misuse without actually assessing whether it is legitimate.

By producing algorithms as vessels for their own agenda (why not), they forget to also see them as empirical objects that have unintended effects.

Third, the goals stated by the algorithm designers may differ from that of users. Observing network analysis practices shows that different users have different epistemic cultures with distincts characterization of effectiveness (Jacomy and Jokubauskaitė, 2022). As users repurpose algorithms for their own needs, their practices can disconnect from the justifications stated in the academic articles. For instance, recent alternatives to the Louvain method for community detection (Blondel et al., 2008) provide a better statistical grounding that eliminates a known bias towards cluster size homogeneity (Peixoto, 2021; Traag et al., 2019) while many users actively seek cluster homogeneity because it better alleviates the burden of manual classification in a time-constrained situation (Jacomy and Jokubauskaitė, 2022). The point I make here is independent of whether users are right or wrong, and in the eyes of whom. I merely highlight that users want something that is unaddressed in the literature. Some papers do argue that the users should *not* have such goals (ex: Peixoto, 2011), but they do not argue that the algorithms are ineffective at addressing those goals.

Fourth, the justification issue is left undetected by the division of labor between those who write the specifications of algorithms in academic publications, and those who implement them in tools. In the case of a force-directed layout like the *LinLog* (Noack, 2007), implementation shows that the expected effectiveness (“separation of clusters”, idem) depends more on an implementation detail (“edge-repulsion”, idem) than on the object of the justification (the “energy model”, idem). The crucial implementation detail is left unexplained. The theoretical justification lives in the world of academic publications, while the practical justification lies in the code and in people’s practices. As those two worlds rarely overlap, there are few occasions to detect and address such discrepancies.

Fifth, because network algorithms are akin to complex systems, describing how they function does not suffice to explicate why, when, and how the desired effects emerge. Consequently, the assessment of effectiveness was allowed by academics and users alike to disconnect from the discussion about algorithm design, where explanations are usually produced. In other words, how an algorithm works does not explain what effects it produces. In that sense, the experience built by users when using an algorithm (which effects arise and when) remains disconnected from the justifications provided by the algorithm designer (why its functioning solves a given problem).

Those network algorithms have become blackboxed (Latour, 1999): the academic community has tacitly agreed to stop discussing why they work, i.e. why they produce the effects that their users deem productive to them. To quote Latour, this is the usual situation where “scientific and technical work is made invisible by its own success” (idem). Explanations were not deemed necessary, yet the lack of proper justification impairs the interpretability of network visualization (Jacomy, 2021; Venturini et al., 2021). Such research could lead to improvements of the network analysis apparatus. By reversing the five complications stated above, we can sketch five ways to help this undone science getting done (Hess, 2016):

1. Do not punish algorithm designers for ignoring why their algorithm performs better (whatever that means), as long as they can show it does.
2. Foster the circulation of feedback on user practices to algorithm designers.
3. Accept the right of users to have their own distinct goals and repurpose existing tools to their own needs.
4. Support the academic currency of practical implementation: good science is not just about novelty, but also interpretability.
5. Value post-hoc interpretability over principled justifications, especially for opaque technologies.

# References

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of statistical mechanics: theory and experiment*, 2008(10), P10008.

Cheong, S. H., & Si, Y. W. (2020). Force-directed algorithms for schematic drawings and placement: A survey. *Information Visualization*, 19(1), 65–91.

Gibson, H., Faith, J., & Vickers, P. (2012). A survey of two-dimensional graph layout techniques for information visualisation. *Information Visualization*, 12(3–4), 324–357.

<https://doi.org/10.1177/1473871612455749>

Gouvêa, A. M., da Silva, T. S., Macau, E. E., & Quiles, M. G. (2021). Force-directed algorithms as a tool to support community detection. *The European Physical Journal Special Topics*, 230(14–15), 2745–2763.

Hess, D. J. (2016). *Undone science: Social movements, mobilized publics, and industrial transitions*. MIT Press.

Jacomy, M. (2021). *Situating Visual Network Analysis*. PhD thesis, Aalborg University.

Jacomy, M., & Jokubauskaitė, E. (2022). Unblackboxing Gephi: How a user culture shapes its scientific instrument.

Krzywinski, M., Birol, I., Jones, S. J., & Marra, M. A. (2012). Hive plots—rational approach to visualizing networks. *Briefings in bioinformatics*, 13(5), 627–644.

Latour, B. (1999). *Pandora's hope: Essays on the reality of science studies*. Harvard university press.

Noack, A. (2007). Energy models for graph clustering. *J. Graph Algorithms Appl.*, 11(2), 453–480.

Peixoto, T. P. (2021). Descriptive vs. inferential community detection: pitfalls, myths and half-truths. *arXiv preprint arXiv:2112.00183*, 10.

Traag, V. A., Waltman, L., & Van Eck, N. J. (2019). From Louvain to Leiden: guaranteeing well-connected communities. *Scientific reports*, 9(1), 5233.

Noack, A. (2009). Modularity clustering is force-directed layout. *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, 79(2). <https://doi.org/10.1103/PhysRevE.79.026102>

Venturini, T., Jacomy, M., & Jensen, P. (2021). What do we see when we look at networks: Visual network analysis, relational ambiguity, and force-directed layouts. *Big Data & Society*, 8(1), 20539517211018488.

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