


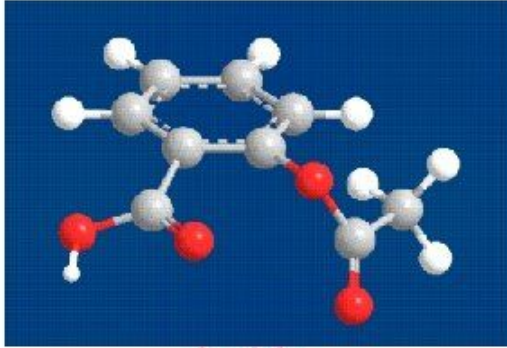
Spectral Graph Layout

by Peanut Butter

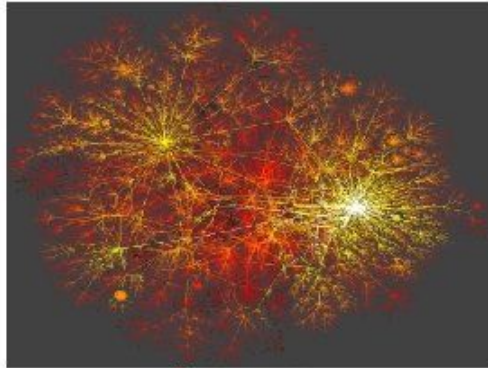
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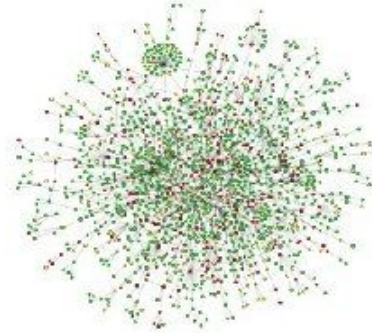
Graph, Graph, Everywhere



Aspirin



Internet



Yeast protein interaction network

from H. Jeong et al Nature 411, 41 (2001)



Co-author network

There are two potential advantages of the spectral approach that we ruminate on.

- First, it provides us with a mathematically-sound formulation leading into an exact solution to the layout problem, whereas, almost all other formulations result in an NP-hard problem, which can only be approximated.
- The second advantage is computation speed.

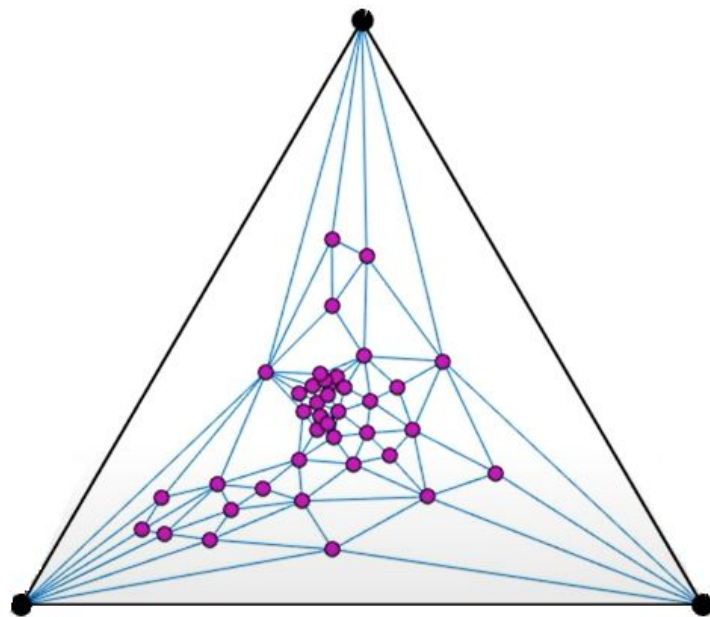
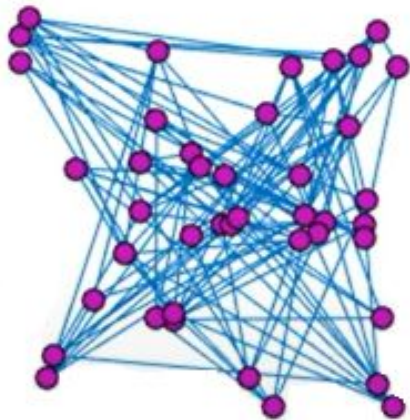
Laplacian

D - diagonal matrix with degrees of vertices on the diagonal

A - adjacency matrix

$L = D - A$, Laplacian, symmetric positive definite matrix

Example of spectral drawing



Algorithms

Hall's algorithm

To use the two smallest eigenvectors of the Laplacian for layout

Koren's algorithm

To use the p lowest degree-normalized eigenvectors

or the p leading nondegenerate eigenvectors of $D^{-1}A$

Tutte's algorithm

Find a cycle in the graph. Then, for each vertex outside the cycle, look for neighbours (adjacent vertices) and move this vertex to their centroid.

Dataset of graphs

- SuiteSparse Matrix Collection
- DIMACS10 group
- 34 graphs that have been very popular as benchmarks for graph algorithms

Shape-based quality metric

In order to estimate the quality of the layout of graph G_1 , we remove the edges from the graph and perform the Delaunay triangulation and get the graph G_2 . The more similar the original graph to G_2 , the better the layout. We have tried to build G_2 as Euclidean Minimal Spanning Tree, but this approach was too time-costly.

Shape-based quality metric

the similarity between two graphs that have the same sets of vertices is calculated as follows

Suppose that $G_1 = (V, E_1)$ and $G_2 = (V, E_2)$ are two graphs with the same vertex set. A simple measure for the similarity of G_1 and G_2 is the *mean Jaccard similarity*:

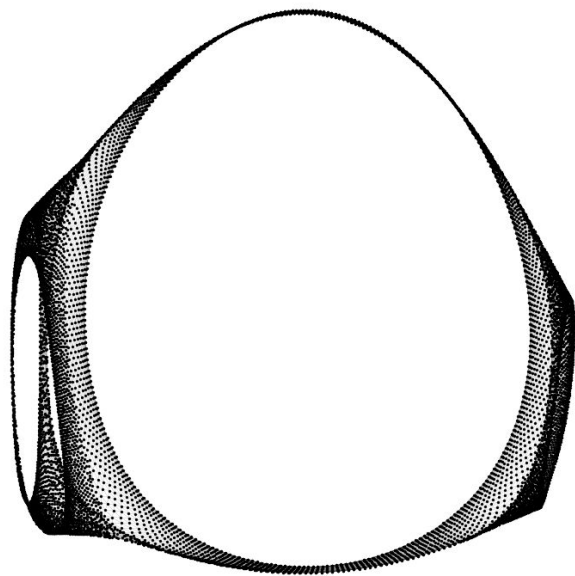
$$MJS(G_1, G_2) = \frac{1}{|V|} \sum_{u \in V} \frac{|N_1(u) \cap N_2(u)|}{|N_1(u) \cup N_2(u)|}, \quad (2)$$

where $N_i(u)$ is the set of neighbours of u in G_i for $i = 1, 2$. It is straight-forward to compute the mean Jaccard similarity in linear time.

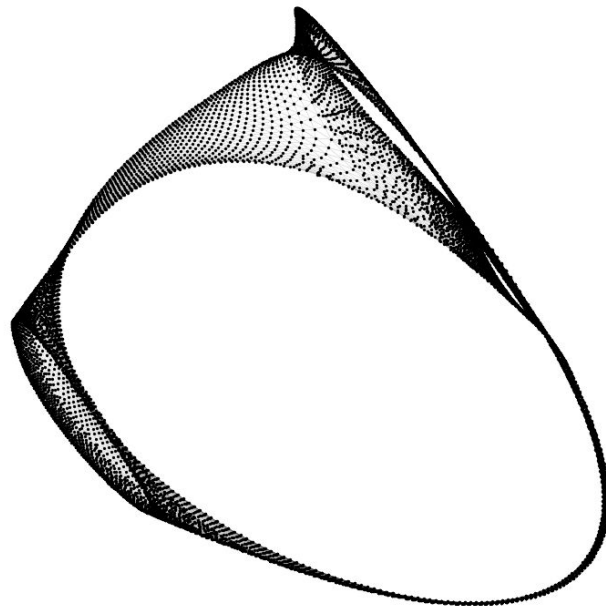
Note that $0 \leq MJS(G_1, G_2) \leq 1$. Also, if G_1 and G_2 share many edges, then $MJS(G_1, G_2)$ is close to 1; if they share very few edges then $MJS(G_1, G_2)$ is close to 0.

Graph	Method	Metric
Graph_4elt	Hall's algorithm	0,196
	Koren's algorithm	0.304
	Tutte method	0,024
Graph_144	Hall's algorithm	0,048
	Koren's algorithm	0.049
	Tutte method	0,003
Graph_data	Hall's algorithm	0.147
	Koren's algorithm	0.159
	Tutte method	0.108

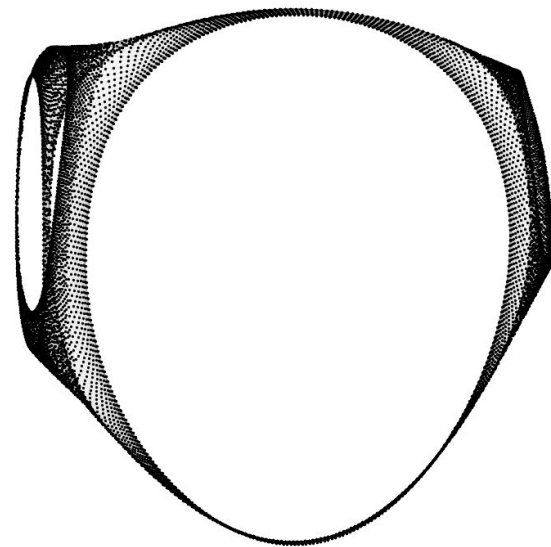
Graph_4elt



Hall's algorithm



Koren's algorithm

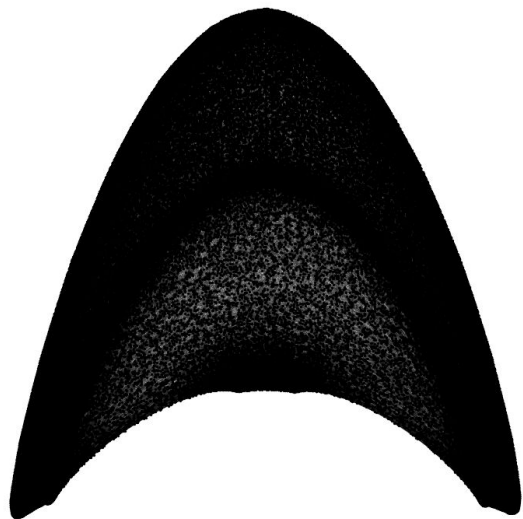


Tutte's method

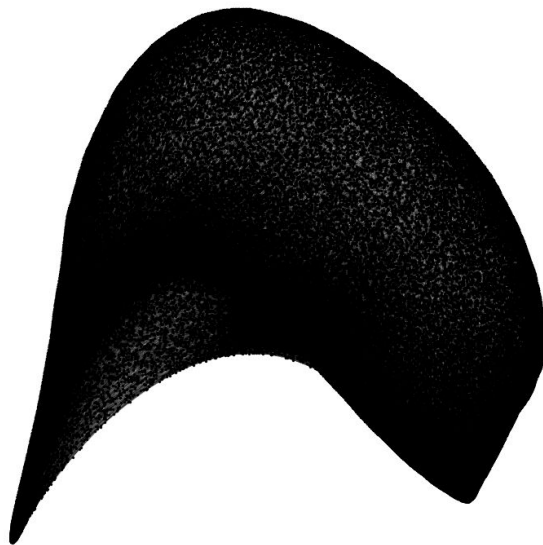
Skoltech

Skolkovo Institute of Science and Technology

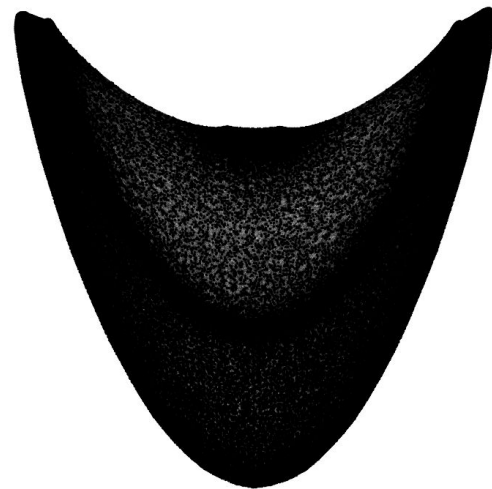
Graph_144



Hall's algorithm

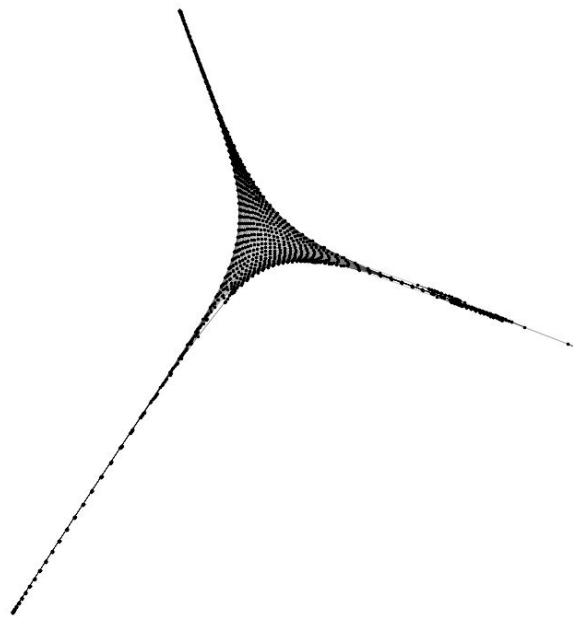


Koren's algorithm

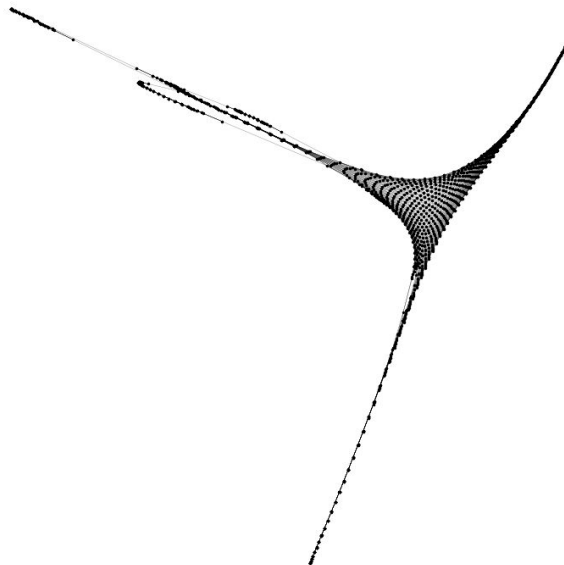


Tutte's method

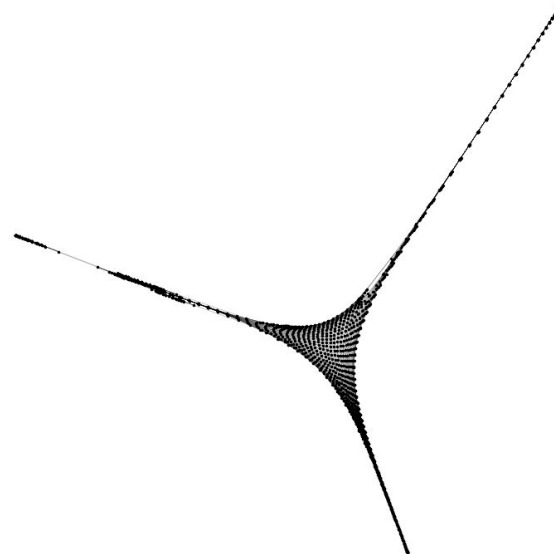
Graph_data



Hall's algorithm

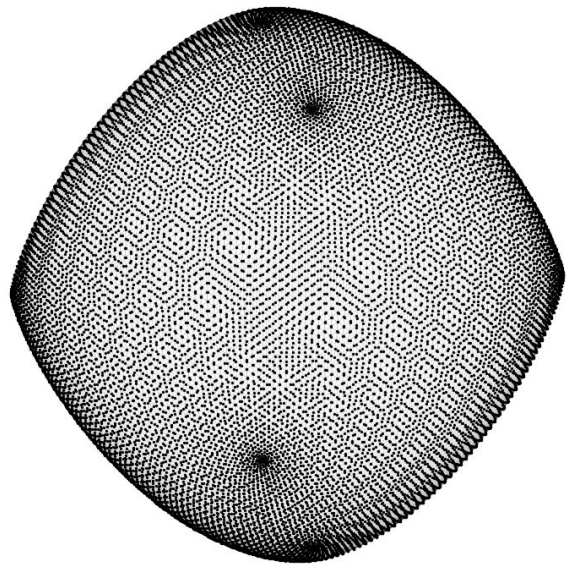


Koren's algorithm

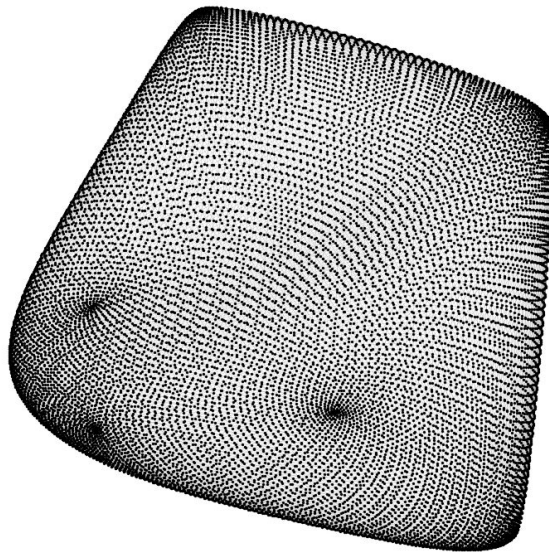


Tutte's method

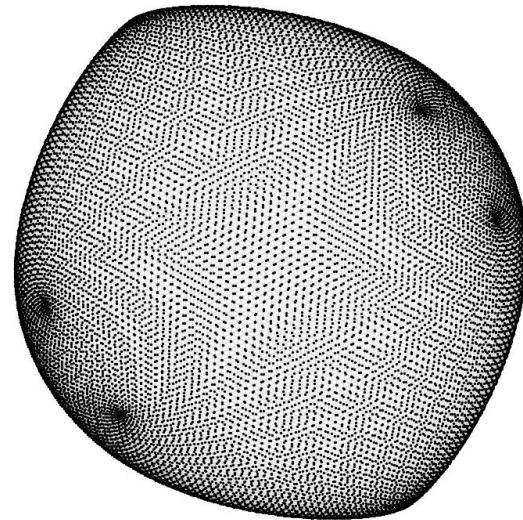
Graph_fe_sphere



Hall's algorithm



Koren's algorithm



Tutte's method

Our contributions:

- New implementations of the Koren's, Hall's and Tutte algorithms
- Implementation of Jaccard similarity metric
- Evaluating these algorithms on a collection of graphs