Experiments

In the following experiments, the number n of data points or graph vertices is no less than 1,000 in at least two datasets/graphs.

1. Objective: feature-to-graph conversion.

Provided a feature data (vectors/points) X in a d-dimensional metric space, construct a near-neighbor graph G(V, E) such that the X-to-V mapping is one to one and that E preserves spatial proximity to some extent.

- (a) Gather at least 2 feature datasets (such as color images or other types of feature points);
- (b) Construct a **rnn** graph (with the radius parameter r) or a **knn** graph (k is the number of nearest neighbors;
- (c) Convert the pairwise distances to pairwise similarity scores with a chosen weight kernel function;
 - Weight kernel examples: the Hinton-Roweis kernel function in SNE or t-SNE (2008) (the P-function, not the Q-function); the Shi-Malik kernel (1997)
- (d) Identify the types of the degree distribution and describe the variation in degree distribution as r or k changes;
- (e) Optional. Obtain and observe distributions of additional measures and their variation.
- (f) Optional. If the feature data are categorical, find or propose an approach to converting the categorical data into numerical.
- 2. Objective: vertex-to-vector encoding and embedding.

Provided with a graph G(V, E), weighted or unweighted, map the vertices in V to a vector set X in a metric space so that the pairwise adjacency is preserved in the pairwise distances, to some extent.

- (a) Use at least two graphs (directly available or converted from feature data), at least one is weighted
- (b) Spectral embedding space via a normalized Laplacian, with the dimension d > 2;
- (c) For a weighted graph, show the difference in pairwise distances (in matrix or in distribution);
- (d) Use the Fiedler vector of each graph to identify two dominant communities (two labels/colors) and the (high-centrality) cut edges between the two communities, which is a bipartite subgraph of G; Show the communities (in blue and red colors) in a 2D/3D scatter plot, and show the cut edges;
- (e) [Optional.] Apply the Fiedler cut to the subgraphs induced by the sub-communities; add the new labels/colors to the previous 2D/3D space;
- (f) [Optional.] Stochastic vertex embedding in a 2D/3D space.

1.euclidean
2.
3.

4.p=2, euclidean p=1, norm 1

- 3. Objective: empirical analysis of a digraph G representing a real-world network, which may be a knn graph.
 - (a) Preprocessing: describe the entities and relationship represented by G; find the number of (weakly) connected components; determine whether or not the largest connected component (LCC) is strongly connected;
 - (b) Computationally get the Perron distribution x_p of the LCC in two cases: case b-1: the LCC is strongly connected; case b-2: the LCC is not strongly connected (for instance, it has sink or source nodes). Use the BP-approach to get a variational, and conditional Perron distribution $x_p(\alpha_i, b_j)$, $\alpha_i \in (0.85, 1)$, i = 1: 4, b_j is a probing vector $b_j > 0$, $e^T b_= 1$, j = 1: 5. Use a figure or plot to describe the structure and structural variation with α and b.
 - (c) [Optional to undergrads:] Apply the Laplacian embedding to a digraph.
- 4. [Optional to undergrads:] Differential description of a graph sequence $G_i(V_i, E_i)$, i = 1 : q, q > 1. There are overlaps in the vertex sets: $V_i \cap V_j \neq \emptyset$. For example, a characteristic property of a BA graph is the growth; a WS graph can be obtained by a rewiring process, the vertex set does not change.
 - Let G(V, E) be the graph to serve as a global reference, $V = \cup V_i$, $E = \cup E_i$. Let X be the vertex encoding (embedding, mapping) of V in a 2D/3D spatial space. Show the difference and connection between G_i and G_{i+1} on the global spatial reference map.