

Graph Ricci Flow and Applications in Network Analysis and Learning

Jie Gao

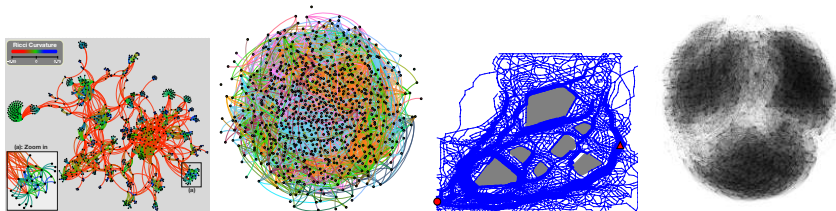
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Graph Data and Complex Networks

Complex networks in nature: social networks, biological networks, the Internet, WWW, mobility data.

- Small world phenomena
- Power law degree distribution
- Community structures (clustered, closely knit groups).



Analyzing Graph Data and Complex Networks

Understand a single network:

- Community detection.
- Graph learning (label propagation & prediction)

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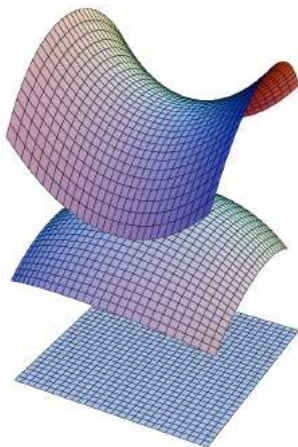
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Our project: use geometric tools, Ollivier Ricci curvature flow, to analyze complex networks.

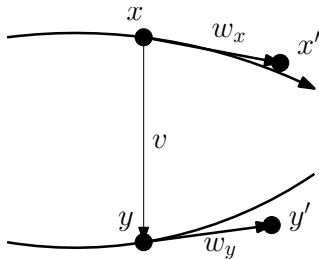
Curvature in Geometry

Sphere: positive curvature; Plane: zero curvature; Hyperbolic plane: negative curvature.



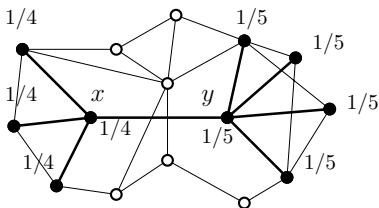
Sectional Curvature in Geometry

Consider a tangent vector $v = xy$ and another tangent vector w_x at x . Transport w_x along v to be a tangent vector w_y at y . If $|x'y'| < |xy|$, then sectional curvature is positive.



Ollivier Ricci Curvature

Take the analog: for an edge xy , consider the “distances” from x ’s **neighbors** to y ’s **neighbors** and compare it with the length of xy .



How to compute the “distances” between two neighborhoods? Use the optimal transport distance.

Ollivier Ricci Curvature

Definition (Ollivier)

Let (X, d) be a metric space and let m_1, m_2 be two probability measures on X . For any two distinct points $x, y \in X$, the (Ollivier-) Ricci curvature along xy is defined as

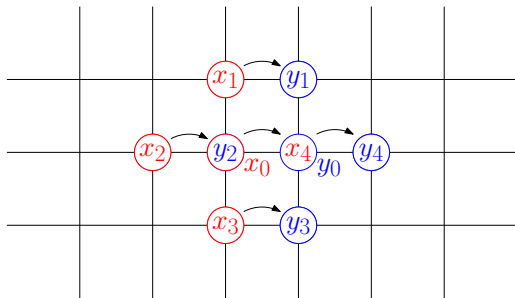
$$\kappa(x, y) := 1 - \frac{W_1(m_x, m_y)}{d(x, y)},$$

where m_x (m_y) is a probability distribution defined on x (y) and its neighbors, $W_1(\mu_1, \mu_2)$ is the L_1 **optimal transportation distance** between two probability measure μ_1 and μ_2 on X :

$$W_1(\mu_1, \mu_2) := \inf_{\psi \in \Pi(\mu_1, \mu_2)} \int_{(u, v)} d(u, v) d\psi(u, v)$$

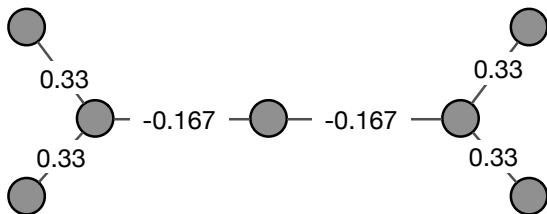
Examples

Zero curvature: 2D grid.



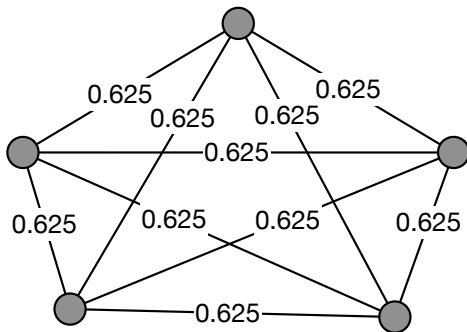
Examples

Negative curvature: tree: $\kappa(x, y) = 1/d_x + 1/d_y - 1$, d_x is degree of x .



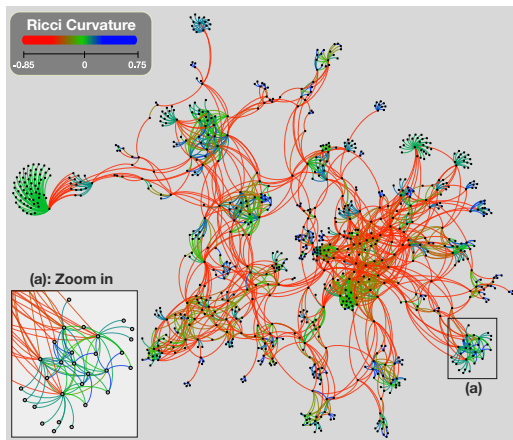
Examples

Positive curvature: complete graph.



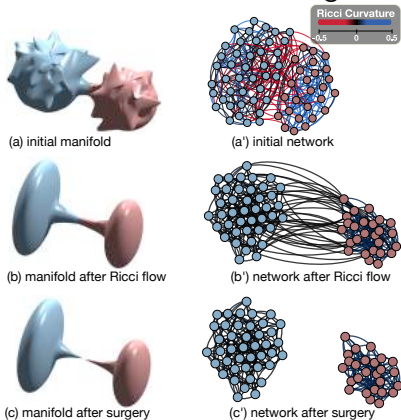
Curvature Distribution

Negatively curved edges are like “backbones”, maintaining the connectivity of clusters, in which edges are mostly positively curved.



Ricci Flow on Manifold vs. on Networks

Hamilton introduced Ricci flow, a curvature guided process.



Ricci Flow Metric

Intuition: flatten the network – shrink an edge if it is within a well connected community; stretch an edge if otherwise, s.t., the network curvature is uniform everywhere.

$$d_{i+1}(x, y) = (d_i(x, y) - \varepsilon \cdot \kappa_i(x, y) \cdot d_i(x, y)) \cdot N$$

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Distribution on a node x :

- Uniform distribution.
- $\exp(-d(x, x_i)^p)$, for a constant p .

Theory on Discrete Ricci Flow

Q: Does Ricci flow converge? Does it generate a unique solution?

- Classical manifold setting: contributes to the proof of the Poincare conjecture.
- Discrete Gaussian curvature on a triangulation: established [Gu, Luo, Wu 2019; Gu, Luo, Sun, Wu 2018 I, II].

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- Discrete curvature on graphs: largely unknown.

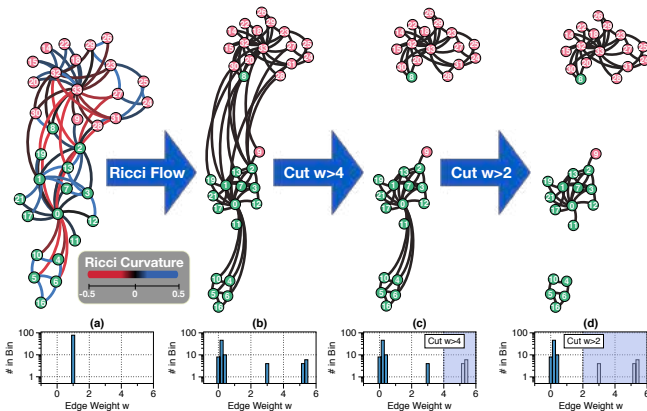
Ollivier Ricci flow:

- Analysis of a very special case. [Ni, Lin, Luo, Gao, 2019]
- Continuous flow, assumption that the edge uv is the shortest path from u to v . [Bai, Lin, Lu, Wang, Yau, 2021]

Applications of Discrete Ricci Flow

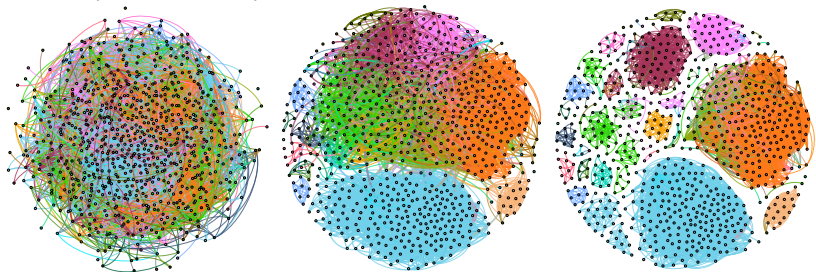
- Community detection
- Network alignment
- Graph neural network

Community Detection: Karate Club Network



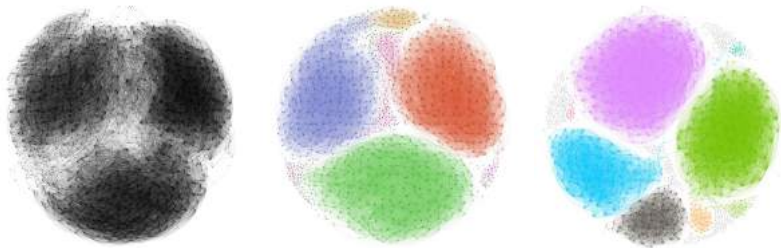
Community Detection: Facebook Ego Network

792 friends and 14025 edges. The colors represent 24 different friend circles (communities).



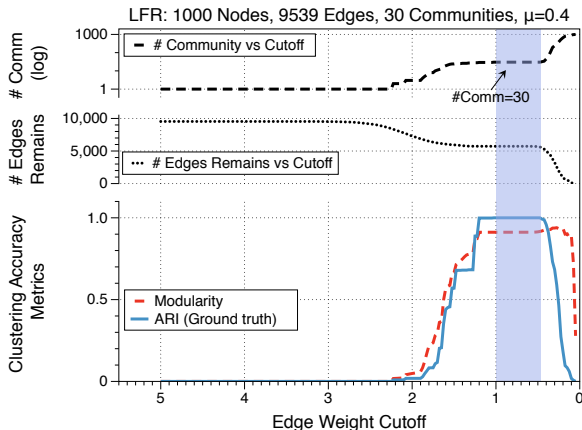
Community Detection: Brain Connectome Network

Brain network from resting-state (rs-fMRI) data, where edges with cross-correlation less than a threshold are removed.



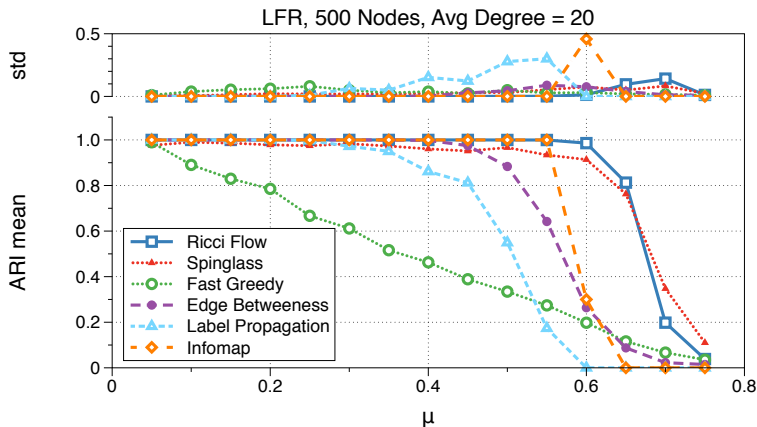
Cutoff Threshold vs Modularity

Adjusted Rand index (ARI) on Lancichinetti-Fortunato-Radicchi (LFR) benchmark network (community size \sim power law).



Performance Comparison

Adjusted Rand index (ARI) on Lancichinetti-Fortunato-Radicchi (LFR) benchmark network (community size \sim power law).



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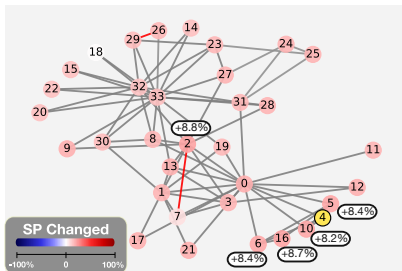
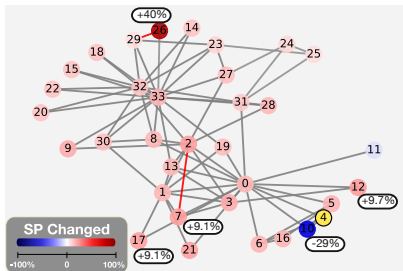
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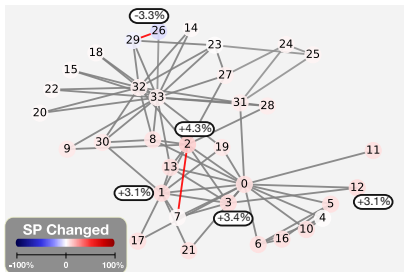
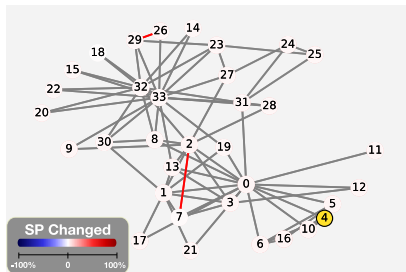
Robustness of Ricci Flow Metric: Remove Two Edges

Left: Spectral embedding; Right: Tutte/Spring embedding.



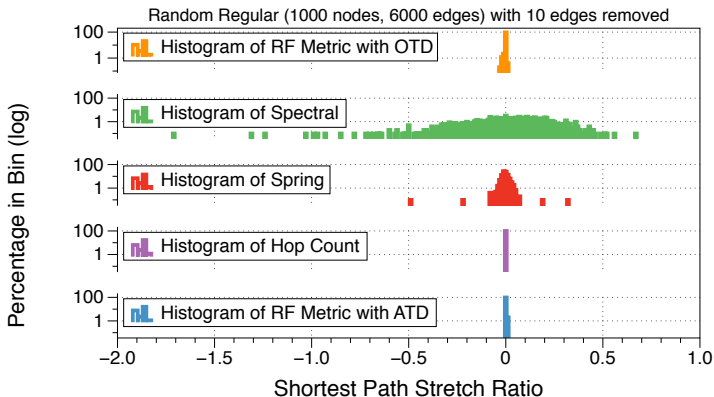
Robustness: Remove Two Edges

Left: Hop count; Right: our metric.



Evaluation on Resilience

Randomly remove 10 edges in a random regular graph.

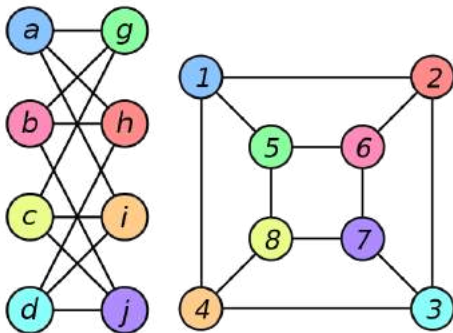


Graph Isomorphism

Given a pair of graphs G_1, G_2 , find a one-to-one correspondence of the vertices in G_1 to vertices in G_2 such that (u, v) is an edge in G_1 if and only if their corresponding nodes $f(u), f(v)$ are connected in G_2 .

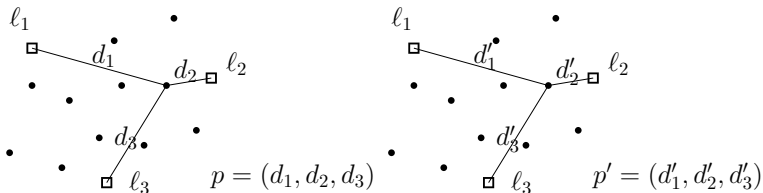
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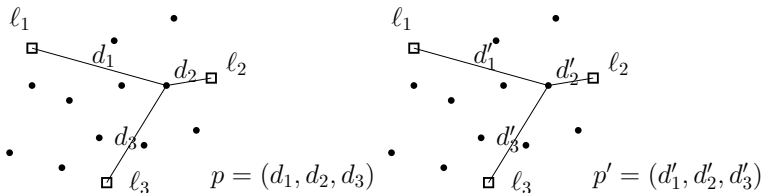
Our Solution: A Geometric Approach

How to align two sets of points in the plane, assuming that some landmarks ℓ_i are already aligned?



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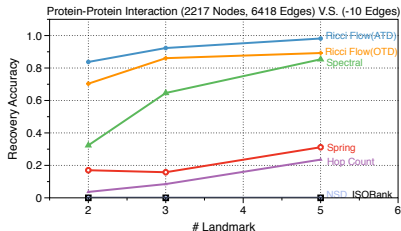
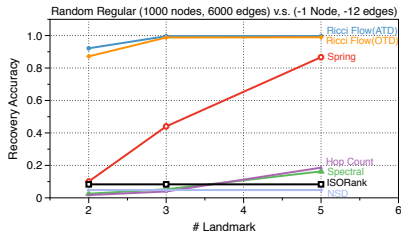
How to align two sets of points in the plane, assuming that some landmarks ℓ_i are already aligned?



- Any point p can be represented by the barycentric coordinates (d_1, d_2, d_3) , d_i is distance to ℓ_i .
- If the barycentric coordinates of p and p' are similar, we match p and p' .

Evaluation on Matching Performance

- Randomly remove one node in a random regular graph w/ degree 12.
- Right: remove randomly 10 edges in a protein protein network.

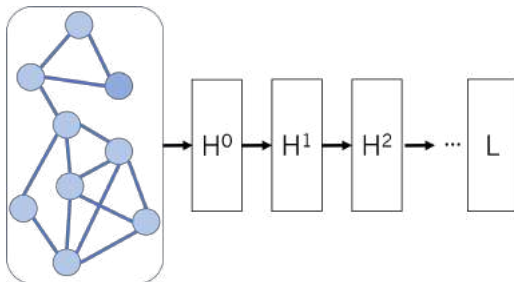


Graph Neural Network

Graph Neural Network for node classification: given labels of a subset of nodes, predict the labels of the rest.

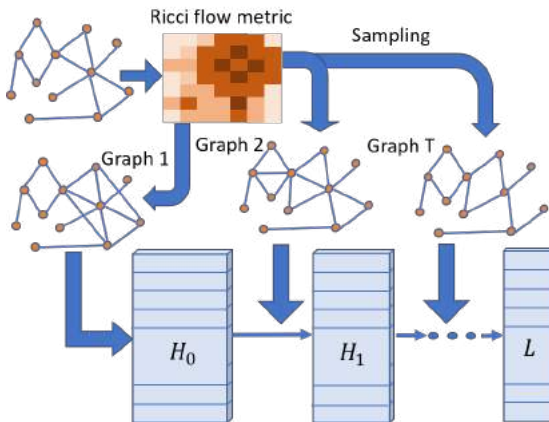
- Graph topology $G = (V, E)$
- Vertex features H

Vulnerability: Removal/insertion of fake edges can dramatically hurt model performance.

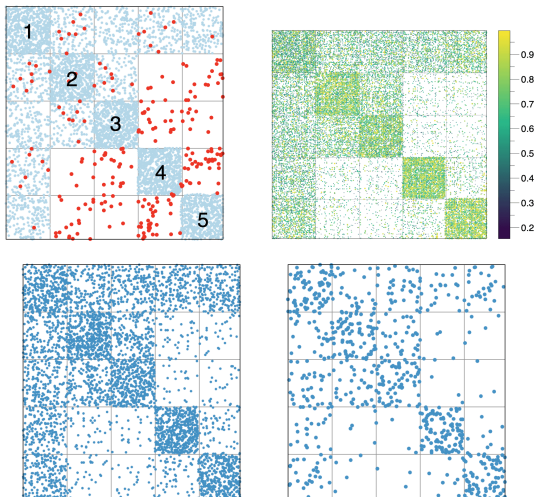


Robust Graph Neural Network through Resampling

- Recover the underlying metric of G using Ricci flow.
- Re-sample an ensemble of graphs for training.



Robust Graph Neural Network through Resampling



Robustness to Graph Topology Attacks

Dataset	Pth rate%	GCN	GAT	RGCN	GCN-Jaccard	GCN-SVD	Pro-GNN	Ricci-GNN
Cora	0	83.50±0.44	83.97±0.65	83.09±0.44	82.05±0.51	80.63±0.45	82.98±0.23	83.03 ±0.59
	5	76.55±0.79	80.44±0.74	77.42±0.39	79.13±0.59	78.39±0.54	82.78 ±0.45	82.80 ±0.43
	10	70.39±1.28	75.61±0.59	72.22±0.38	76.16±0.76	71.47±0.83	77.91±0.86	79.70 ±0.43
	15	65.10±0.71	69.78±1.28	66.82±0.39	71.03±0.64	66.69±1.18	76.01 ±1.12	77.28 ±0.50
	20	59.56±2.72	59.94±0.92	59.27±0.37	65.71±0.89	58.94±1.13	68.78 ±5.84	74.10 ±0.63
	25	47.53±1.96	54.78±0.74	50.51±0.78	60.82±1.08	52.06±1.19	56.54 ±2.58	71.73 ±0.60
Citeseer	0	71.96±0.55	73.26±0.83	71.20±0.83	72.10±0.63	70.65±0.32	73.26 ±0.69	73.95 ±0.53
	5	70.88±0.62	72.89±0.83	70.50±0.43	70.51±0.97	68.84±0.72	73.09 ±0.34	73.39 ±0.52
	10	67.55±0.89	70.63±0.48	67.71±0.30	69.64±0.56	68.87±0.62	72.43 ±0.75	72.51 ±0.62
	15	64.52±0.62	69.02±0.62	65.69±0.62	65.95±0.62	63.26±0.62	70.82 ±2.38	71.99 ±0.71
	20	62.03±3.49	61.04±1.52	62.49±1.22	59.30±1.40	58.55±1.09	66.19 ±2.57	68.40 ±0.51
	25	56.94±2.09	61.85±1.12	55.35±0.66	59.89±1.47	57.18±1.87	66.40 ±2.57	68.84 ±0.51
Polblogs	0	95.69±0.38	95.35±0.20	95.22±0.14	-	95.31±0.18	93.20 ±0.64	95.72 ±0.24
	5	73.07±0.80	83.69±1.45	74.34±0.19	-	89.09±0.22	93.29 ±0.18	90.54 ±0.47
	10	70.72±0.62	76.32±0.62	71.04±0.62	-	81.24±0.62	89.42 ±1.09	86.88±0.85
	15	64.96±1.91	68.80±1.14	67.28±0.38	-	68.10±3.73	86.04 ±2.21	86.10 ±0.96
	20	51.27±1.23	51.50±1.63	59.89±0.34	-	57.33±3.15	79.56 ±5.68	81.37 ±1.24
	25	49.23±1.36	51.19±1.49	56.02±0.56	-	48.66±9.93	63.18 ±4.40	79.95 ±1.89

Robustness to Graph Topology Attacks

Is the gain coming from graph ensembling or from the choice of metrics?

Ptb rate %	Cora			Citeseer			Polblogs		
	HC	Spectral	Ricci	HC	Spectral	Ricci	HC	Spectral	Ricci
5	81.4	76.1	82.8	73.0	71.3	73.4	85.6	88.2	90.5
10	77.5	73.1	79.7	71.0	69.3	72.5	85.6	88.0	86.9
15	75.5	65.1	77.3	70.7	67.6	72.0	70.6	80.3	86.1
20	72.8	60.2	74.1	67.9	67.8	68.4	65.8	79.4	81.4
25	65.4	54.7	71.7	65.4	65.6	68.8	62.0	74.6	80.0

Cora: sparse

Polblogs: dense, diameter =4.

Conclusion and Discussion

- Classical geometric notions for discrete graph analysis.
- Network embedding: Euclidean, hyperbolic, hybrid?
- Network evolution: why?
- More applications due to robustness of the metric?

Acknowledgement

- Chien-Chun Ni, Yu-Yao Lin, Jie Gao, Xianfeng Gu, Emil Saucan, INFOCOM'15.
- Chien-Chun Ni, Yu-Yao Lin, Jie Gao, Xianfeng Gu, Network Alignment by Discrete Ollivier-Ricci Flow, Symposium on Graph Drawing and Network Visualization (GD'18).
- Chien-Chun Ni, Yu-Yao Lin, Jie Gao, Feng Luo, Community Detection on Networks with Ricci Flow, Scientific Reports 9, 9984, July 2019.
- Ye Ze, Kin Sum Liu, Tengfei Ma, Jie Gao and Chao Chen, Curvature Graph Network, ICLR, 2020.
- Ze Ye, Chien-Chun Ni, Tengfei Ma, Chao Chen, Jie Gao, Ricci-GNN: Defending Against Structural Attacks Through a Geometric Approach, under submission.

Github Code

- `https://github.com/saibalmars/GraphRicciCurvature`

Questions and comments?