PageRank Embedding == Spectral Embedding

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Low Dimensional Embeddings

Low dimensional representations are useful for learning and visualization

[CLS]

of

to









Two dimensional "user" embedding





Spectral Embedding

Input: G Output: Vertex coordinates R^d





Eigenvectors of the symmetric Laplacian

$$\begin{split} \tilde{\mathbf{L}} &= \mathbf{I} - \mathbf{D}^{-1/2} \mathbf{G} \mathbf{D}^{-1/2} = \mathbf{Q} \mathbf{\Lambda} \mathbf{Q}^T \\ & \mathbf{Z} = \mathbf{D}^{-1/2} \mathbf{Q} \\ & i : (\mathbf{Z}[i,2],\mathbf{Z}[i,3]) \end{split}$$





Spectral Embedding



Similar Embeddings, Distinct Procedure



PageRank Embeddings



My Thesis!



Generalizable?



Generalizable?





 $s = \frac{Z[:,2]^T \tilde{L} Z[:,2]}{Z[:,2]^T Z[:,2]}$ $p = \frac{U[:,2]^T \tilde{L} U[:,2]}{U[:,2]^T U[:,2]}$



Generalizable? - Small Nearest Neighbour graph



Generalizable? - Large Nearest Neighbour Graph



Generalizable? - Large Nearest Neighbour Graph

 $\lambda = \begin{bmatrix} 0.0000\\ 0.0005617\\ 0.0005958\\ 0.001243\\ 0.002170 \end{bmatrix}$





Generalizable? - Minnesota Network



Generalizable? - Tapir



Generalizable? - Planted Partition Model

Sbm3000 (50,60,0.001,0.005)



Generalizable? - Planted Partition Model

Sbm3000 (50,60,0.25,0.001)



Generalizable? - Planted Partition Model

Sbm3000 (1000,3,0.25,0.001)



Embedding with larger alpha

Graph	X(0.99)	X(0.99999)
Tapir	10.17%	15.41%
Minnesota	16.07%	11.15%
3000 - 6	47.6%	5.06%
Original	75.92%	81.14%
Sbm3000 (50,60,0.001,0.005)	51.77%	51.32%
Sbm3000(50,60,0.25,0.001)	17.88%	90.13%
Sbm3000 (1000,3,0.25,0.001)	53.7%	16.21%

Embedding with log

Graph	X(0.99)	log.X(0.99)
Tapir	10.17%	1.13%
Minnesota	16.07%	1.97%
3000 - 6	47.6%	0.37%
Original	75.92%	4.11%
Sbm3000(50,60,0.001,0.005)	51.77%	15.22%
Sbm3000(50,60,0.25,0.001)	17.88%	15.2%
Sbm3000 (1000,3,0.25,0.001)	53.7%	1.04%

Spectral & PageRank Embedding use the same information

$$\begin{split} \tilde{\mathbf{L}} &= \mathbf{I} - \mathbf{D}^{-1/2} \mathbf{A} \mathbf{D}^{-1/2} = \mathbf{Q} \mathbf{\Lambda} \mathbf{Q}^{\mathrm{T}} \\ &\rightarrow \left(\mathbf{I} - \alpha \mathbf{A} \mathbf{D}^{-1}\right)^{-1} = \mathbf{D}^{1/2} \mathbf{Q} (\mathbf{I} - \alpha \mathbf{E})^{-1} \mathbf{Q}^{\mathrm{T}} \mathbf{D}^{-1/2} \text{ , where } \mathbf{E} = \mathbf{I} - \mathbf{\Lambda} \\ &\mathbf{X} = (1 - \alpha) (\mathbf{I} - \alpha \mathbf{A} \mathbf{D}^{-1})^{-1} = (1 - \alpha) \mathbf{D} \mathbf{Z} (\mathbf{I} - \alpha \mathbf{E})^{-1} \mathbf{Z}^{\mathrm{T}} \\ &= \left[\frac{1 - \alpha}{1 - \alpha \epsilon_{1}} \mathbf{d} \mathbf{z}_{1} \cdots \frac{1 - \alpha}{1 - \alpha \epsilon_{n}} \mathbf{d} \mathbf{z}_{n}\right] \begin{bmatrix} \mathbf{z}_{1}^{T} \\ \vdots \\ \mathbf{z}_{n}^{T} \end{bmatrix} \text{ , where } \mathbf{d} = \mathbf{D} \mathbf{e} \end{split}$$

Spectral & PageRank Embedding use the same information

$$\mathbf{X} = \begin{bmatrix} \frac{1-\alpha}{1-\alpha\epsilon_1} \mathbf{d}\mathbf{z_1} \cdots \frac{1-\alpha}{1-\alpha\epsilon_n} \mathbf{d}\mathbf{z_n} \end{bmatrix} \begin{bmatrix} \mathbf{z_1}^T \\ \vdots \\ \mathbf{z_n}^T \end{bmatrix}$$

$$\epsilon_{i} = 1 - \lambda_{i}$$
$$\mathbf{X} = \begin{bmatrix} \mathbf{d}\mathbf{z}_{1} \cdots \frac{1-\alpha}{1-\alpha\epsilon_{n}} \mathbf{d}\mathbf{z}_{n} \end{bmatrix} \begin{bmatrix} \mathbf{z}_{1}^{T} \\ \vdots \\ \mathbf{z}_{n}^{T} \end{bmatrix} \xrightarrow{\alpha \to 1} \mathbf{X} = \mathbf{d}\mathbf{z}_{1}\mathbf{z}_{1}^{T}$$

Spectral & PageRank Embedding use the same information







$$\to X_{i,j} = \sum_{t=1}^{n} \frac{1-\alpha}{1-\alpha\epsilon_t} z_{ti} z_{tj} d_i$$

$$\log(X_{i,j}) = \log(1 - \alpha) + \log(d_i) + \log\left(\frac{1}{2}\right) + \log$$

$$\left(\sum_{t=1}^{n} \frac{z_{ti} z_{tj}}{1 - \alpha \epsilon_t}\right)$$

PageRank on Chain

 $(\alpha/2)x_2 = x_1$ $\alpha x_1 + (\alpha/2)x_3 = x_2$ $(\alpha/2)x_2 + (\alpha/2)x_4 = x_3$ $(\alpha/2)x_{k-2} + (\alpha/2)x_k = x_{k-1}$ $(\alpha/2)x_{k-1} + (\alpha/2)x_{k+1} = x_k - (1 - \alpha)$ $(\alpha/2)x_k + (\alpha/2)x_{k+1} = x_{k+1}$ $(\alpha/2)x_{n-3} + (\alpha/2)x_{n-1} = x_{n-2}$ $(\alpha/2)x_{n-2} + \alpha x_n = x_{n-1}$ $(\alpha/2)x_{n-1} = x_n$ $\sum x_i = 1$ i=1



PageRank on Chain



PageRank on Chain



Generalizable? - Chain graph



Why does this work?



 $\left({
m D^{-1/2}GD^{-1/2}}
ight)^r \left({
m D^{-1/2}GD^{-1/2}v_k}
ight)$



Why does this work?

$$(\alpha = 0.9)^{1000} = 1.7e^{-46} \quad (\alpha = 0.99999)^{1000} = 0.99$$
$$1000 \log(\alpha = 0.9) = -105.36$$

Graph	Matrix Power	Distance	Power attained
30 Chain	100	13	e^{-2}
3000 Chain	100	106	e^{-30}
3000 Chain	1000	106	e^{-3}
30 nearest neighbor	100	13	e^{-1}
3000 nearest neighbor	100	1792	e^{-20}
3000 nearest neighbor	1000	1792	e^{-4}

Summarizing

- Embedding procedure for the local environment of a seed node
- Embeddings created by using the left singular vectors of PageRank personalized on individual nodes resemble the spectral embeddings for graph where the log of PageRank is a function of the graph distance from the seed nodes.
- Reliable representation

Extension to higher order



Questions