Fair Constrained Spectral clustering

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Spectral Clustering

Data set X is converted into a graph or similarity matrix W. Let us denote D as degree matrix of W and L as the laplacian matrix

$$L = D - W \tag{1}$$

Spectral clustering find an embedding space in which the data points are easily separable by k means algorithm. This embedding space is given by the k smallest eigen vectors of L.



Spectral Clustering

Let us define an encoding H as follows

$$H_{il} = \begin{cases} \frac{1}{\sqrt{|C_l|}}, & i \in C_l \\ 0, & \text{otherwise} \end{cases}$$
 (2)

Spectral Clustering

From "A tutorial on spectral clustering" [1]

Spectral clustering problem

 $\downarrow \downarrow$

finding minimum cost cut

1

Objective Function of Spectral clustering

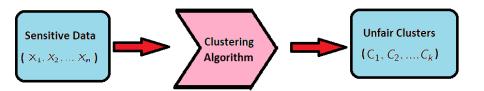
finding H that minimize $Tr(H^TLH)$



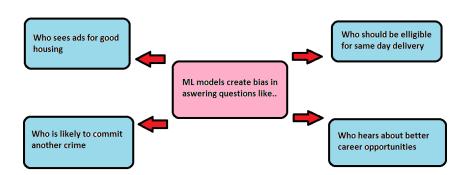
K eigen vectors of L



Why to incorporate fairness

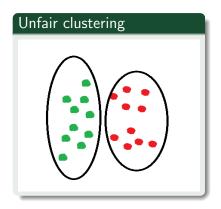


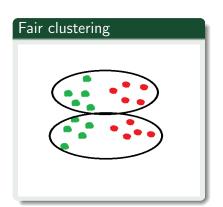
Why to incorporate fairness





Fairness in clustering





Fairness notion

Balance (A fairness notion): According to Chierichetti et al. (2017) [2], fairness notion is ensured if every cluster contains nearly the same number of data from each group V_s . Balance of any cluster C_l is defined as

$$Balance = \min_{i \in k} (\min_{s \in [h]} \frac{|C_i \cap V_s|}{|C_i|})$$
 (3)

Incorporating fairness in Spectral clustering

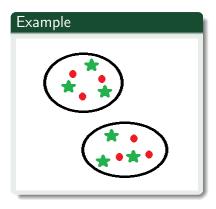
Let $f^{(s)}$ defines the group membership of V_s such that

$$f_s^{(i)} = \begin{cases} 1, & \text{if } v_i \in V_s \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

then the bellow equation guarantees fairness for each cluster, I

$$\forall s \in [h-1]: \sum_{i=1}^{n} (f_i^s - \frac{V_s}{n}) H_{il} = 0$$
 (5)

Fairness in clustering



Explanation

Defining for star data point and above cluster

$$0 = 3 * (1 - \frac{6}{12}) * (\frac{1}{\sqrt{6}}) +$$
$$3 * (0 - \frac{6}{12}) * (\frac{1}{\sqrt{6}}) +$$
$$3 * (1 - \frac{6}{12}) * 0 +$$
$$3 * (0 - \frac{6}{12}) * 0$$

Incorporating fairness in Spectral clustering

Objective function for Fair sepctral clustering

$$\underbrace{\min_{H} Tr(H^{T}LH)}_{SC} \quad \text{subject to} \quad \underbrace{F^{T}H = 0_{(h-1)xk}}_{FSC} \tag{6}$$

We can substitute H = ZY, where $Z \in \mathbb{R}^{n*(n-h+1)}$ and forms the orthonormal subspace of F^T and $Y \in \mathbb{R}^{(n-h+1)*k}$

$$\min_{Y} Tr(Y^{T}Z^{T}LZY) \text{ subject to } Y^{T}Y = I_{k}$$
 (7)

Embedding space is given by the k smallest eigenvectors of Z^TLZ



In constrained spectral clustering we impose some information as constraints to the data in the form of **Must-link** and **Cannot-link** to enhance accuracy.

If M is the set of must-link constraints then

$$M = (x_i, x_j) \mid x_i \text{ and } x_j \text{ are similar}$$
 (8)

If C is the set of cannot-link constraints then

$$C = (x_i, x_i) \mid x_i \text{ and } x_i \text{ are dissimilar}$$
 (9)

The constraint matrix Q is defined as

$$q_{ij} = \begin{cases} -1, & \text{if } (x_i, x_j) \in C \\ +1, & \text{if } (x_i, x_j) \in M \\ 0 & \text{otherwise} \end{cases}$$
 (10)

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Constrained spectral embedding for K-way data clustering[3]

$$J_{cSC} = \gamma J_{SC} + (1 - \gamma) J_{CM} \tag{11}$$

$$J_{cSC} = \gamma Tr(H^T L H) + (1 - \gamma) Tr(H^T L_Q H)$$
(12)

where $L_Q = D_Q - Q$

$$J_{cSC} = H^{T}(\gamma L + (1 - \gamma)L_{Q})H = H^{T}L_{cSC}H$$
(13)

where

$$L_{cSC} = D_{cSC} - W_{cSC} (14)$$

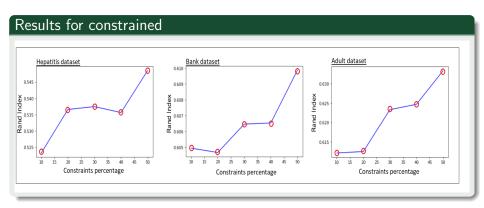
$$D_{cSC} = \gamma D + (1 - \gamma)D_q \tag{15}$$

$$W_{cSC} = \gamma W + (1 - \gamma)Q \tag{16}$$

Objective function of constrained spectral clustering

$$\min H^{\mathsf{T}} L_{cSC} H \tag{17}$$

The linearly separable embedding space is given by the eigenmap of L_{cSC}



Fairness in constrained spectral clustering

Fairness in constrained spectral clustering Hepatitis Adult data Bank Marketing 0.160 0.92 0.158 0.78 0.90 0.156 o 0.154 88.0 Balance 0.86 0.74 0.74 를 0.152 0.150 0.84 0.148 0.146 0.82 Percentage of constraints Percentage of constraints Percentage of constraints



Incorporating fairness in constraint set

Definition of fairness in constraints set

In order to improve fairness, the fraction of (v_i, v_j) where $i \neq j$ data pairs in must-link constraints set should be close to the fraction of (v_l, v_l) data pairs in cannot-link constraints set if V contains h groups V_s and $1 = \langle i, j, l \rangle = h$.

Let the data $V = v_1, v_2, ..., v_n$ has [h] groups. The constraint matrix Q is defined as

$$q_{ij} = \begin{cases} -1, & \text{if } (x_i, x_j) \in C \\ +1, & \text{if } (x_i, x_j) \in M \\ 0 & \text{otherwise} \end{cases}$$
 (18)

Let us defined two separate matrix Q_M and Q_C

$$Q_M = \begin{cases} +1, & \text{if } (x_i, x_j) \in M \\ 0 & \text{otherwise} \end{cases}$$
 (19)

and

$$Q_C = \begin{cases} -1, & \text{if } (x_i, x_j) \in C \\ 0 & \text{otherwise} \end{cases}$$
 (20)

 $group(v_i)$ indicates the group to which the data point v_i belongs to.

$$e = [1, 1, ..., 1]_{1*n} (21)$$

Let Q_M^S can be given as

$$Q_{M}^{S}(i,j) = \begin{cases} 1, & \text{if } group(v_{i}) \neq group(v_{j}), (v_{i}, v_{j}) \in M \\ 0 & \text{otherwise} \end{cases}$$
 (22)

Let Q_C^S can be given as

$$Q_C^S(i,j) = \begin{cases} -1, & \text{if } group(v_i) = group(v_j), (v_i, v_j) \in C \\ 0 & \text{otherwise} \end{cases}$$
 (23)

Total number of must-link constraints =
$$|e^T Q_M e|$$
 (24)

Total number of cannot-link constraints = $|e^T Q_C e|$ (25)

Proportion of (v_i, v_j) where $i \neq j$ data pairs in must-link constraints set

$$=\frac{e^T(Q_M\odot Q_M^S)e}{|e^TQ_Me|}\tag{26}$$

Proportion of (v_l, v_l) data pairs in cannot-link constraints set

$$=\frac{e^{T}(Q_{C}\odot Q_{C}^{S})e}{|e^{T}Q_{C}e|}$$
 (27)



Difference between the fractions

$$= \left| \frac{e^{T}(Q_M \odot Q_M^S)e}{\left| e^{T}Q_M e \right|} - \frac{e^{T}(Q_C \odot Q_C^S)e}{\left| e^{T}Q_C e \right|} \right| \tag{28}$$

We can define a matrix Q_e such that

$$Q_{e} = \left| \frac{Q_{M} \odot Q_{M}^{S}}{\left| e^{T} Q_{M} e \right|} - \frac{Q_{C} \odot Q_{C}^{S}}{\left| e^{T} Q_{C} e \right|} \right| \tag{29}$$

Spectral clustering with fair constraints

$$\min_{H} \gamma_1 Tr(H^T L H) + \gamma_2 Tr(H^T L_Q H) + \gamma_3 Tr(H^T L_{Qe} H)$$

subject to $\gamma_1 + \gamma_2 + \gamma_3 = 1$, and $H^T H = I_k$ Taking $\gamma_1 = \gamma_2 = \gamma_3 = \frac{1}{3}$ Then the above objective function will become

$$\frac{1}{3} \min_{H} Tr(H^{T}(L + L_{Q} + L_{Qe})H) \text{ subject to } H^{T}H = I_{k}$$
 (30)

$$\frac{1}{3} \min_{Y} Tr(H^{T} L_{r} H) \text{ subject to } H^{T} H = I_{k}$$
 (31)

Where $L_r = L + L_Q + L_{Qe}$



SCFC

- **Input:** 1. Data set $V = x_1, x_2, ..., x_n$
 - 2. Group membership vectors f_s as given by 2.3
 - 3. Constraints in the form of ML and CL.
- Make similarity graph
- Find laplacian matrix, L_r
- Compute the k smallest eigenvectors of L_r .(columns of Y)
- Apply k-means clustering to the rows of Y
- Output:

Final Clusters

Fair spectral clustering with fair constraints

$$\begin{split} \min_{H} \gamma_1 \mathit{Tr}(H^T L H) + \gamma_2 \mathit{Tr}(H^T L_Q H) + \gamma_3 \mathit{Tr}(H^T L_{Qe} H) \\ \text{subject to} \quad \gamma_1 + \gamma_2 + \gamma_3 = 1, \ H^T H = \mathit{I}_k \quad \text{and} \quad \mathit{F}^T H = \mathit{0}_{(h-1) \times k} \end{split}$$

Substituting H = ZY

$$\frac{1}{3} \min_{Y} Tr(Y^{T}Z^{T}(L + L_{Q} + L_{Qe})ZY) \text{ subject to } Y^{T}Y = I_{k}$$

$$\frac{1}{3} \min_{Y} Tr(Y^{T}Z^{T}L_{p}ZY) \text{ subject to } Y^{T}Y = I_{k}$$

Where $L_P = L + L_Q + L_{Qe}$



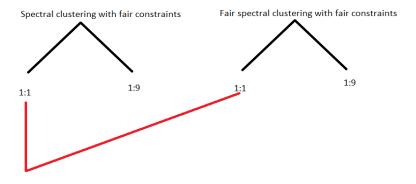
FSCFC

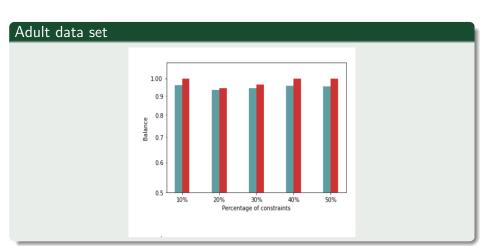
- **Input:** 1. Data set $V = x_1, x_2, ..., x_n$
 - 2. Group membership vectors f_s as given by 2.3
 - 3. Constraints in the form of ML and CL.
- Make similarity graph
- Find laplacian matrix, L_p
- Find $F \in R^{n \times (h-1)}$ having column vectors $f^{(s)} \frac{|V_s|}{n} \cdot 1_n$ $s \in [h-1]$
- Compute Z whose columns form the orthonormal basis of F^T .
- Compute the k smallest eigenvectors of $Z^T L_P Z$.(columns of Y)
- \bullet Apply k-means clustering to the rows of H = ZY
- Output:

Final Clusters

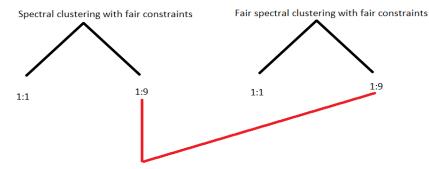


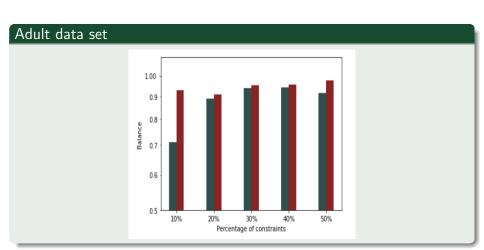
Experimental setup





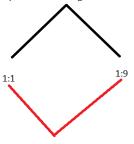
Experimental setup





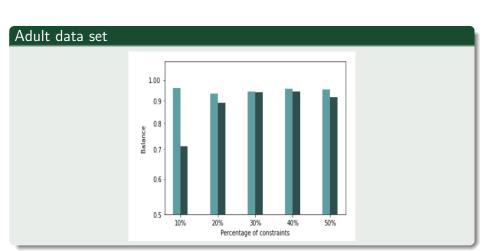
Experimental setup

Spectral clustering with fair constraints



Fair spectral clustering with fair constraints



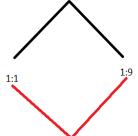


Experimental setup

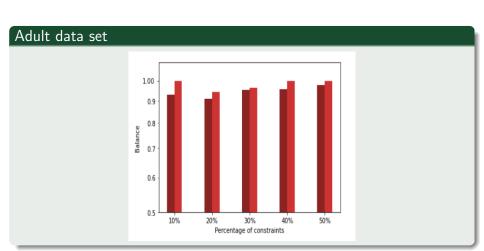
Spectral clustering with fair constraints



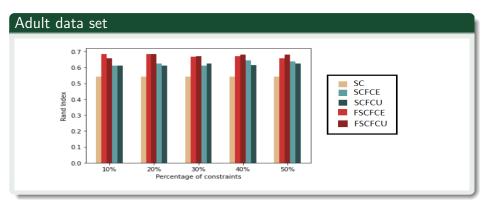
Fair spectral clustering with fair constraint

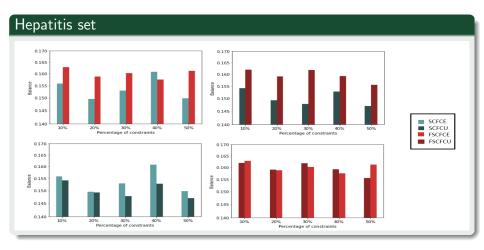


Spectral Clustering | Fair Spectral Clustering | Constrained Spectral Clustering | Fair constrained SC | Setup | Refrence | Occident | Occiden



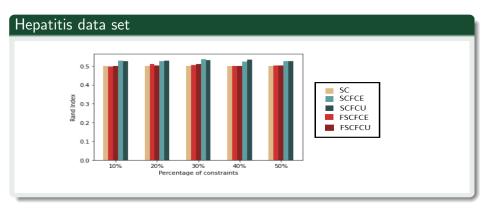
Spectral Clustering | Fair Spectral Clustering | Constrained Spectral Clustering | Fair Constrained SC | Setup | Refrence | Occident | Occiden







Spectral Clustering Fair Spectral Clustering constrained Spectral Clustering Fair constrained SC Setup Refrence constrained Science constrained S



Spectral Clustering Fair Spectral Clustering Constrained Spectral Clustering Fair constrained SC Setup Refrences

References



- "Chierichetti, F., Kumar, R., Lattanzi, S., and Vassilvitskii, S. Fair clustering through fairlets" 2017.
- G. Wacquet, É. Poisson Caillault 1, D. Hamad 1, P.-A. Hébert 1", "Constrained spectral embedding for K-way data clustering"
- "Guarantees for Spectral Clustering with Fairness Constraints"

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Thank You!!