

# Simultaneous Graph Signal Clustering and Graph Learning

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Selin Aviyente

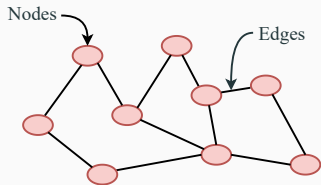
July, 2021

Michigan State University



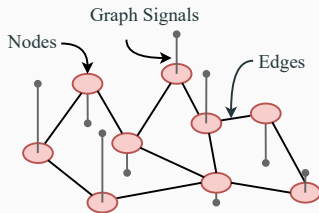
# Graph Learning

- **Graphs** are used to study relational data.



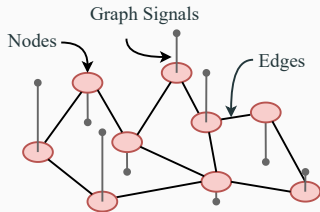
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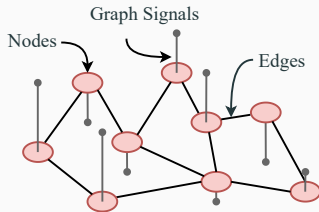
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- **Graph Signal Processing** aims to extend ML/SP concepts to graph signals.
  - Signal recovery, sampling, filtering...



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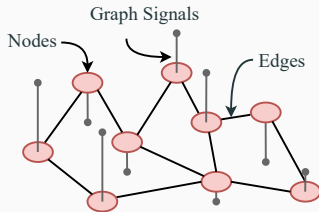
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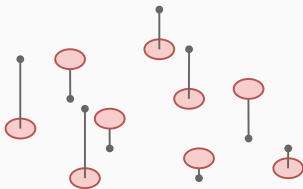
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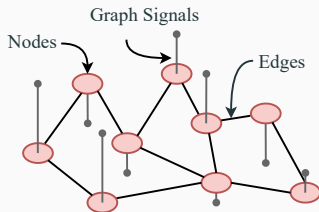
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Given graph signals:

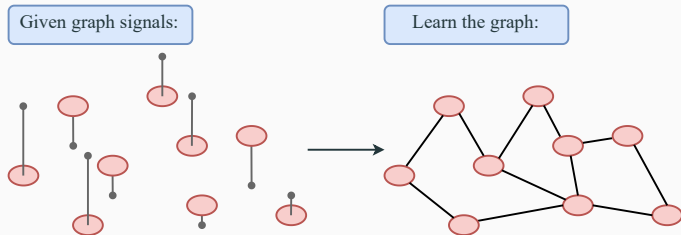


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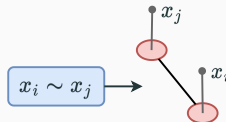
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- Methods proposed for learning graphs based on:
  - Statistical modeling, stationarity, smoothness...



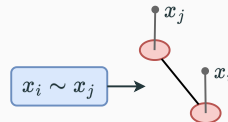
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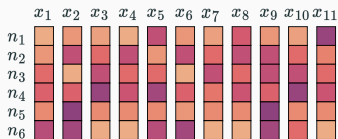


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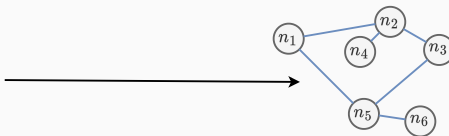
- Methods proposed for learning graphs based on:
  - Statistical modeling, stationarity, **smoothness**...



- These works mostly assume that data is **homogeneous**.

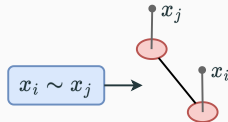


Graph Signals

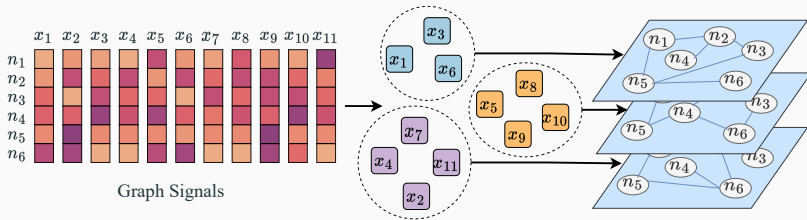


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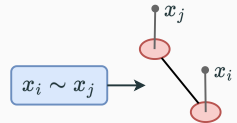


- However, many problems include **heterogeneous** data.

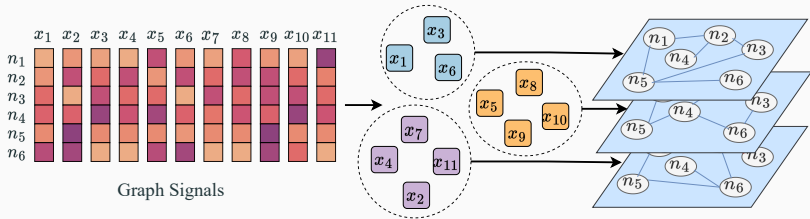


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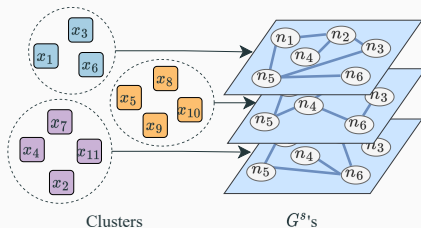
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- Applications:
  - **scRNAseq**: Cluster cells while learning GRNs,
  - **Recommendation**: Cluster users while learning item graphs.

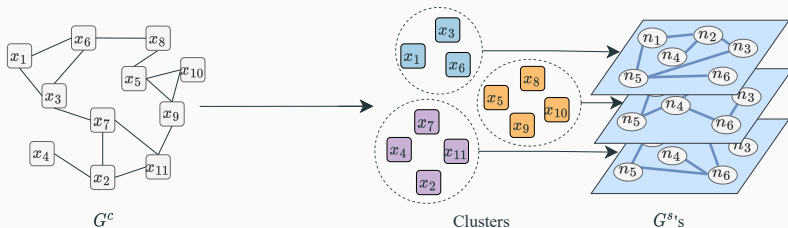
# GRAScale

- Existing works use smoothness of the signals to perform clustering.



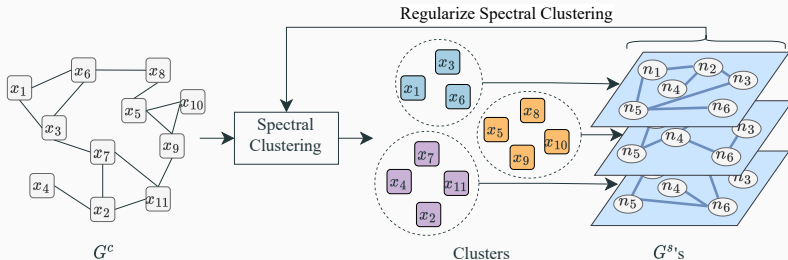
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- Clustering can benefit from pairwise relations between signals.

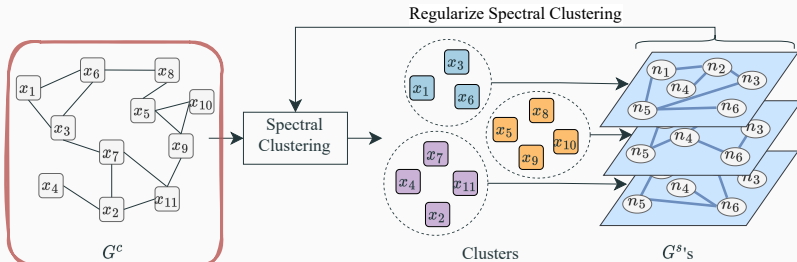


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$$\underset{Z \in \mathbb{R}^{n \times k}}{\text{minimize}} \quad \underbrace{\text{tr}(Z^T L^c Z)}_{\text{Graph Cut}}$$

$$\text{s. t.} \quad Z \in \mathbb{D}$$

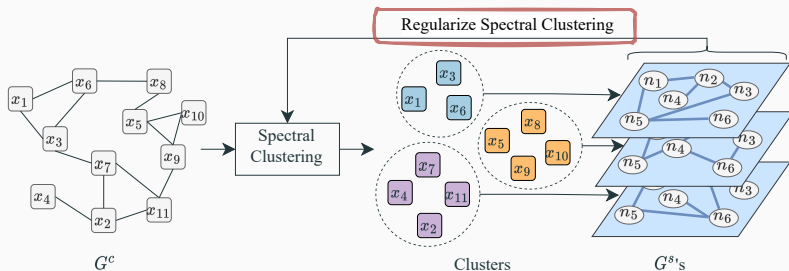
(1)

- $Z$ : Relaxation of 0-1 clustering indicator matrix,
- $L^c$ : Laplacian matrix of  $G^c$ ,



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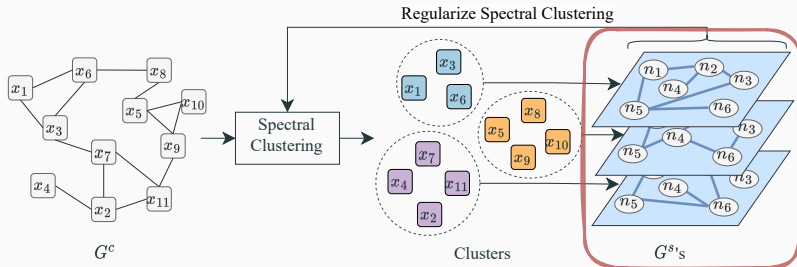
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 & \underset{Z \in \mathbb{R}^{n \times k}}{\text{minimize}} \underbrace{\text{tr}(Z^T L^c Z)}_{\text{Graph Cut}} + \alpha_1 \sum_{s=1}^k \underbrace{\text{tr}(\text{dg}(Z_{\cdot s}) X^T L^s X)}_{\text{Smoothness}} \\
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 \end{aligned} \tag{1}$$

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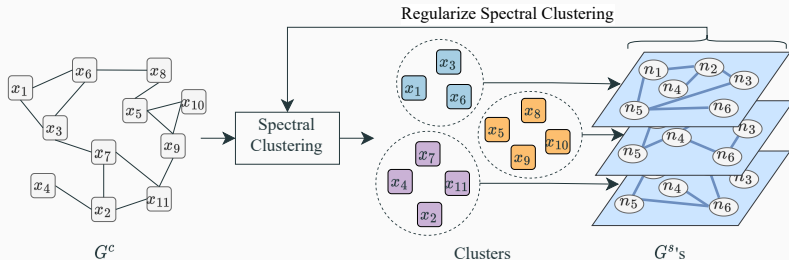
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$$\begin{aligned}
 & \underset{\mathbf{Z}, \mathbf{L}^1, \dots, \mathbf{L}^k}{\text{minimize}} \underbrace{\text{tr}(\mathbf{Z}^\top \mathbf{L}^C \mathbf{Z})}_{\text{Graph Cut}} + \alpha_1 \sum_{s=1}^k \underbrace{\text{tr}(\text{dg}(\mathbf{Z}_{\cdot s}) \mathbf{X}^\top \mathbf{L}^S \mathbf{X})}_{\text{Smoothness}} + (\mathbf{Z}_{\cdot s}^\top \mathbf{1}) \alpha_2 \|\mathbf{L}^S\|_F^2 \\
 & \text{s.t.} \quad \mathbf{Z} \in \mathbb{D}, \mathbf{L}^S \in \mathbb{L}, \text{tr}(\mathbf{L}^S) = 2n \quad \forall s \in \{1, \dots, k\}
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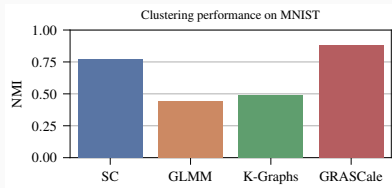
- Solve with **Block Coordinate Descent** with **prox-linear updates**.

# Results

- Clustering MNIST while learning a graph for each digit.

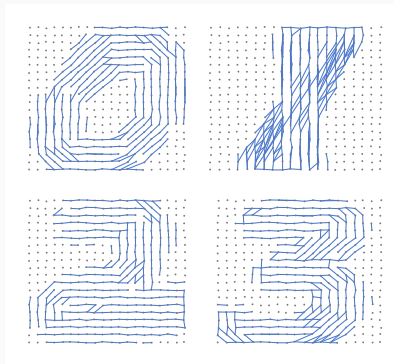
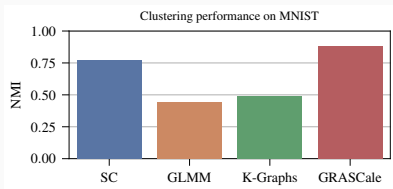
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- Compared to previous works, it extends spectral clustering algorithm to use
  - Pairwise relations between graph signals, and
  - Smoothness of the signals with respect to graphs associated with clusters.