Graph Clustering

Why graph clustering is useful?

- Distance matrices are graphs → as useful as any other clustering
- Identification of communities in social networks
- Webpage clustering for better data management of web data

Outline

- Min s-t cut problem
- Min cut problem
- Multiway cut
- Minimum k-cut
- Other normalized cuts and spectral graph partitionings

Min **s-t** cut

- Weighted graph **G(V,E)**

- An **s-t** cut **C = (S,T)** of a graph **G = (V, E)** is a cut partition of **V** into **S** and **T** such that **s∈S** and **t∈T**
- Cost of a cut: $\mathbf{Cost(C)} = \sum_{e(u,v)\ u \in S,\ v \in T} w(e)$

- **Problem:** Given **G**, **s** and **t** find the minimum cost **s-t** cut

Max flow problem

- Flow network
  - Abstraction for material **flowing** through the edges
  - **G = (V,E)** directed graph with no parallel edges
  - Two distinguished nodes: **s = source**, **t= sink**
  - **c(e) =** capacity of edge **e**

Cuts

- An s-t cut is a partition **(S,T)** of **V** with **s∈S** and **t∈T**

- capacity of a cut **(S,T)** is **cap(S,T) =** $\boldsymbol{\Sigma_{e \text{ out of } S} c(e)}$

- Find s-t cut with the minimum capacity: this problem can be solved optimally in polynomial time by using ***flow techniques***

Flows

- An s-t flow is a function that satisfies
  - For each **$e \in E$ $0 \leq f(e) \leq c(e)$** [capacity]
  - For each **$v \in V-\{s,t\}$: $\Sigma_{e \text{ in to } v} f(e) = \Sigma_{e \text{ out of } v} f(e)$** [conservation]

- The value of a flow f is: **$v(f) = \Sigma_{e \text{ out of } s}\, f(e)$**

Max flow problem

- Find **s-t** flow of maximum value

Flows and cuts

- Flow value lemma: Let f be any flow and let **(S,T)** be any **s-t** cut. Then, the net flow sent across the cut is equal to the amount leaving **s**

$$\Sigma_{e \text{ out of } S} f(e) - \Sigma_{e \text{ in to } S} f(e) = v(f)$$

Flows and cuts

- **Weak duality:** Let **f** be any flow and let **(S,T)** be any **s-t** cut. Then the value of the flow is at most the capacity of the cut defined by **(S,T)**:

$$v(f) \leq cap(S,T)$$

Certificate of optimality

- Let **f** be any flow and let **(S,T)** be any cut. If **v(f) = cap(S,T)** then **f** is a max flow and **(S,T)** is a min cut.

- The min-cut max-flow problems can be solved optimally in polynomial time!

Setting

- Connected, undirected graph **G=(V,E)**
- Assignment of weights to edges: **w: E→R⁺**
- **Cut:** Partition of V into two sets: **V', V-V'**. The set of edges with one end point in **V** and the other in **V'** define the cut
- The removal of the cut disconnects **G**
- **Cost of a cut:** sum of the weights of the edges that have one of their end point in **V'** and the other in **V-V'**

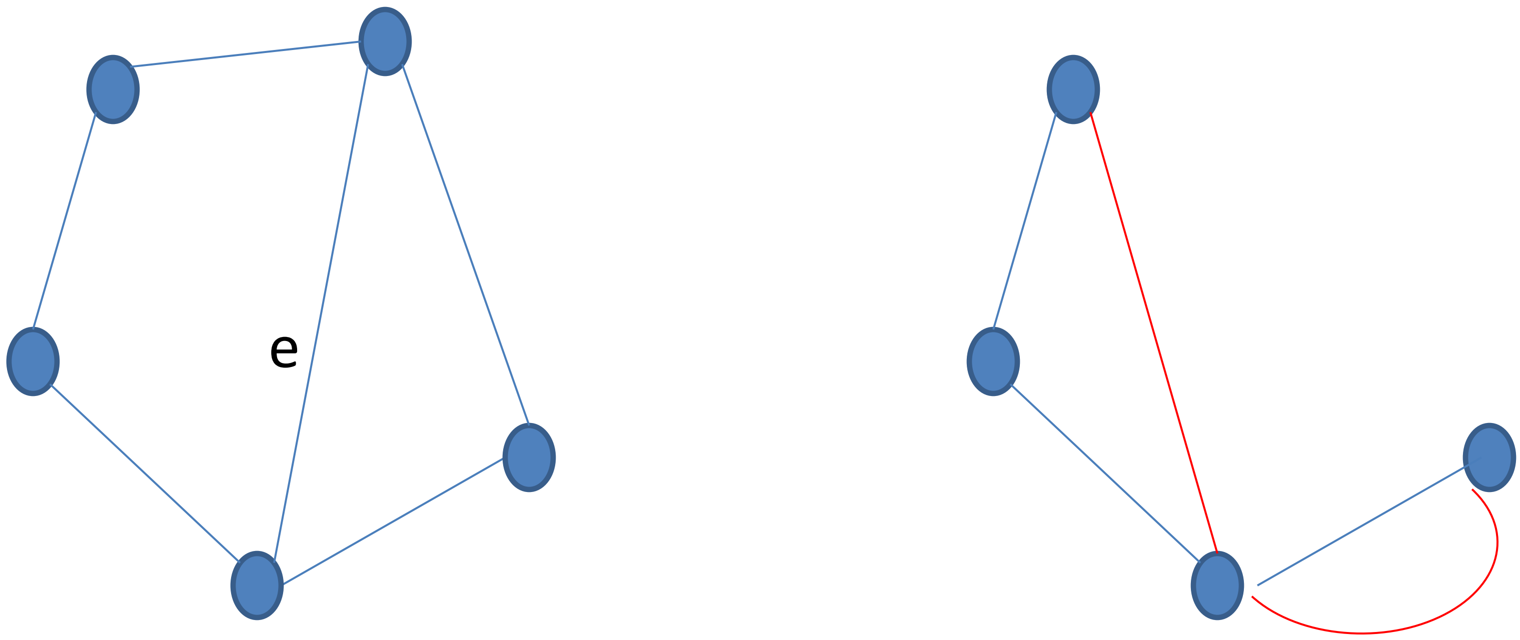
Min cut problem

- Can we solve the min-cut problem using an algorithm for s-t cut?

Randomized min-cut algorithm

- **Repeat :** pick an edge uniformly at random and merge the two vertices at its end-points
  - If as a result there are several edges between some pairs of (newly-formed) vertices retain them all
  - Edges between vertices that are merged are removed (***no self-loops***)
- **Until** only ***two*** vertices remain
- The set of edges between these two vertices is a cut in **G** and is output as a candidate min-cut

Example of **contraction**



Observations on the algorithm

- Every cut in the graph at any intermediate stage is a cut in the original graph

Analysis of the algorithm

- **C** the min-cut of size **k** → **G** has at least **kn/2** edges
  - Why?
- E_i: the event of not picking an edge of **C** at the **i**-th step for $1 \leq i \leq n-2$
- ***Step 1:***
  - Probability that the edge randomly chosen is in **C** is at most $2k/(kn)=2/n$ → $Pr(E_1) \geq 1-2/n$
- ***Step 2:***
  - If E_1 occurs, then there are at least $k(n-1)/2$ edges remaining
  - The probability of picking one from C is at most $2/(n-1)$ → $Pr(E_2|E_1) = 1 - 2/(n-1)$
- ***Step i:***
  - Number of remaining vertices: $n-i+1$
  - Number of remaining edges: $k(n-i+1)/2$ (since we never picked an edge from the cut)
  - $Pr(Ei|\Pi_{j=1\ldots i-1} E_j) \geq 1 - 2/(n-i+1)$
  - Probability that no edge in **C** is ever picked: $Pr(\Pi_{i=1\ldots n-2} E_i) \geq \Pi_{i=1\ldots n-2}(1-2/(n-i+1))=2/(n^2-n)$
- The probability of discovering a particular min-cut is larger than $2/n^2$
- Repeat the above algorithm $n^2/2$ times. The probability that a min-cut is not **found** is $(1-2/n^2)^{n\wedge 2/2} < 1/e$

Multiway cut (analogue of s-t cut)

- **Problem:** Given a set of terminals $\mathbf{S = \{s_1,\ldots,s_k\}}$ subset of **V,** a multiway cut is a set of edges whose removal disconnects the terminals from each other. The multiway cut problem asks for the minimum weight such set.

- The multiway cut problem is NP-hard (for k>2)

Algorithm for multiway cut

- For each **i=1,…,k,** compute the minimum weight **isolating cut** for s_i, say C_i
- Discard the heaviest of these cuts and output the union of the rest, say **C**

- **Isolating cut** for s_i: The set of edges whose removal disconnects s_i from the rest of the terminals

- How can we find a minimum-weight isolating cut?
  - Can we do it with a single s-t cut computation?

Approximation result

- The previous algorithm achieves an approximation guarantee of **2-2/k**
- **Proof**

Minimum k-cut

- A set of edges whose removal leaves **k** connected components is called a **k**-cut. The minimum k-cut problem asks for a **minimum-weight** **k**-cut
- Recursively compute cuts in G (and the resulting connected components) until there are **k** components left
- This is a **(2-2/k)**-approximation algorithm

Minimum k-cut algorithm

- Compute the *Gomory-Hu* tree **T** for **G**
- Output the union of the *lightest* **k-1** cuts of the **n-1** cuts associated with edges of **T** in **G;** let **C** be this union
- The above algorithm is a **(2-2/k)**-approximation algorithm

Gomory-Hu Tree

- **T** is a tree with vertex set **V**
- The edges of **T** need not be in **E**
- Let **e** be an edge in **T**; its removal from **T** creates two connected components with vertex sets **(S,S')**
- The cut in **G** defined by partition **(S,S')** is the *cut associated with* **e** in **G**

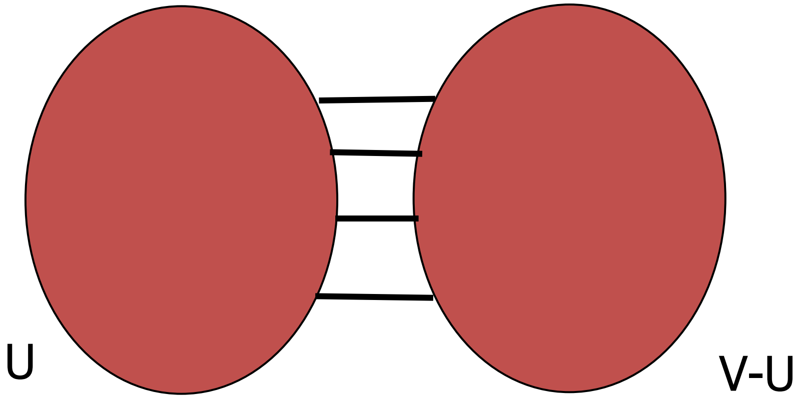
Gomory-Hu tree

- Tree **T** is said to be the Gomory-Hu tree for **G** if
  - For each pair of vertices **u,v** in **V**, the weight of a minimum **u-v** cut in **G** is the same as that in **T**
  - For each edge **e** in **T**, **w'(e)** is the weight of the cut associated with **e** in **G**

Min-cuts again

- What does it mean that a set of nodes are well or sparsely interconnected?

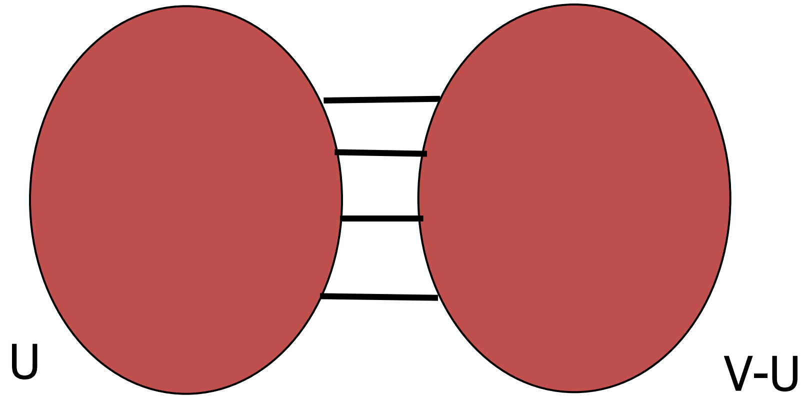
- min-cut: the min number of edges such that when removed cause the graph to become disconnected
  - small min-cut implies sparse connectivity
  - $\min_{U} E(U, V-U) = \sum_{i \in U} \sum_{j \in V-U} A[i,j]$

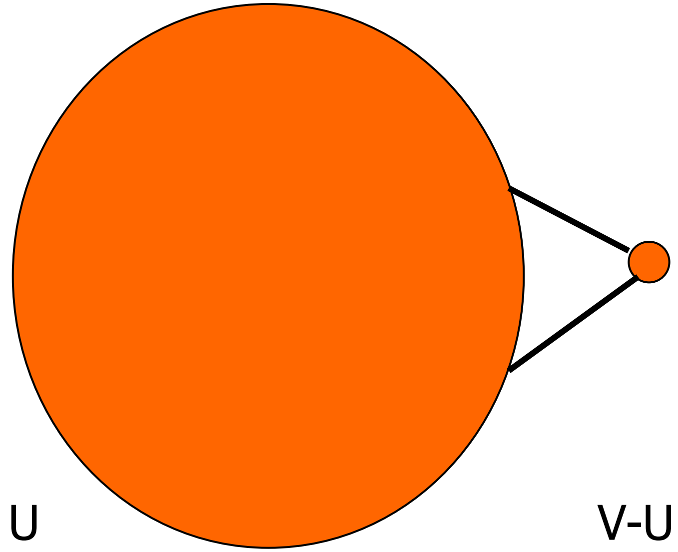


Measuring connectivity

- What does it mean that a set of nodes are well interconnected?

- min-cut: the min number of edges such that when removed cause the graph to become disconnected
  - not always a good idea!





Graph expansion

- Normalize the cut by the size of the smallest component
- Cut ratio:

$$\alpha = \frac{E(U, V - U)}{\min\{|U|, |V - U|\}}$$

- Graph expansion:

$$\alpha(G) = \min_{U} \frac{E(U, V - U)}{\min\{|U|, |V - U|\}}$$

- We will now see how the graph expansion relates to the eigenvalue of the adjacency matrix A

Spectral analysis

- The Laplacian matrix $L = D - A$ where
  - A = the adjacency matrix
  - $D = \text{diag}(d_1,d_2,\ldots,d_n)$
    - d_i = degree of node i
- Therefore
  - $L(i,i) = d_i$
  - $L(i,j) = -1$, if there is an edge (i,j)

Laplacian Matrix properties

- The matrix L is symmetric and positive semi-definite
  - all eigenvalues of L are positive

- The matrix L has 0 as an eigenvalue, and corresponding eigenvector $w_1 = (1,1,\ldots,1)$
  - $\lambda_1 = 0$ is the smallest eigenvalue

The second smallest eigenvalue

- The second smallest eigenvalue (also known as Fielder value) λ_2 satisfies

$$\lambda_2 = \min_{x \perp w_1, \|x\|=1} x^T L x$$

- The vector that minimizes λ_2 is called the Fielder vector. It minimizes

$$\lambda_2 = \min_{x \neq 0} \frac{\sum_{(i,j)\in E} (x_i - x_j)^2}{\sum_i x_i^2} \quad \text{where} \quad \sum_i x_i = 0$$

Spectral ordering

- The values of x minimize

$$\min_{x \neq 0} \frac{\sum_{(i,j) \in E} \left(x_i - x_j\right)^2}{\sum_i x_i^2} \qquad \sum_i x_i = 0$$

- For weighted matrices

$$\min_{x \neq 0} \frac{\sum_{(i,j)} A[i,j] \left(x_i - x_j\right)^2}{\sum_i x_i^2} \qquad \sum_i x_i = 0$$

- The ordering according to the x_i values will group similar (connected) nodes together

- Physical interpretation: The stable state of springs placed on the edges of the graph

Spectral partition

- Partition the nodes according to the ordering induced by the Fielder vector
- If $u = (u_1,u_2,\ldots,u_n)$ is the Fielder vector, then split nodes according to a value s
  - bisection: s is the median value in u
  - ratio cut: s is the value that minimizes α
  - sign: separate positive and negative values ($s=0$)
  - gap: separate according to the largest gap in the values of u
- This works well (provably for special cases)

Fielder Value

- The value λ_2 is a good approximation of the graph expansion

$$\frac{\alpha(G)^2}{2d} \leq \lambda_2 \leq 2\alpha(G)$$

d = maximum degree

$$\frac{\lambda_2}{2} \leq \alpha(G) \leq \sqrt{\lambda_2 (2d - \lambda_2)}$$

- For the minimum ratio cut of the Fielder vector we have that

$$\frac{\alpha^2}{2d} \leq \lambda_2 \leq 2\alpha(G)$$

- If the max degree d is bounded we obtain a good approximation of the minimum expansion cut

Conductance

- The expansion does not capture the inter-cluster similarity well
  - The nodes with high degree are more important
- Graph Conductance

$$\varphi(G) = \min_{U} \frac{E(U, V - U)}{\min\{d(U), d(V - U)\}}$$

  - weighted degrees of nodes in U

$$d(U) = \sum_{i \in U} \sum_{j \in U} A[i, j]$$

Conductance and random walks

- Consider the normalized stochastic matrix $M = D^{-1}A$
- The conductance of the Markov Chain M is

$$\varphi(M) = \min_{U} \frac{\sum_{i \in U} \sum_{j \notin U} \pi(i) M[i, \; j]}{\min\{\pi(U), \pi(V-U)\}}$$

  - the probability that the random walk escapes set U

- The conductance of the graph is the same as that of the Markov Chain, $\phi(A) = \phi(M)$

- Conductance ϕ is related to the second eigenvalue of the matrix M

$$\frac{\varphi^2}{8} \leq 1 - \mu_2 \leq \varphi$$

Interpretation of conductance

- Low conductance means that there is some bottleneck in the graph
  - a subset of nodes not well connected with the rest of the graph.

- High conductance means that the graph is well connected

Clustering Conductance

- The conductance of a clustering is defined as the maximum conductance over all clusters in the clustering.
- Minimizing the conductance of clustering seems like a natural choice

A spectral algorithm

- Create matrix $M = D^{-1}A$
- Find the second largest eigenvector v
- Find the best ratio-cut (minimum conductance cut) with respect to v
- Recurse on the pieces induced by the cut.

- The algorithm has provable guarantees

A divide and merge methodology

- Divide phase:
  - Recursively partition the input into two pieces until singletons are produced
  - output: a tree hierarchy
- Merge phase:
  - use dynamic programming to merge the leafs in order to produce a tree-respecting flat clustering

Merge phase or dynamic-progamming on trees

- The **merge** phase finds the optimal clustering in the tree **T** produced by the **divide** phase

- **k**-means objective with cluster centers $c_1,\ldots,c_k$:

$$F(\{C_1,\ldots,C_k\}) = \sum_i \sum_{u \in C_i} d(u, c_i)^2$$

Dynamic programming on trees

- **OPT(C,i):** optimal clustering for **C** using **i** clusters
- **C_l, C_r** the left and the right children of node **C**

- Dynamic-programming recurrence

$$OPT(C,i) = \begin{cases} C, \text{ when } \mathrm{i} = 1 \\ \arg\min_{1 \le j \le i} F(OPT(C_l, j) \cup OPT(C_r, i-j)), \text{ otherwise} \end{cases}$$