

City Clustering From Road Network Graph

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1. Background

1.1 Introduction The efficient plan and development of cities has become an important topic nowadays. Data of city are collected from different means including GPS, mobile phone and user-generated media. Urban geographers, economists and tech companies have been using these data, along with computing and analysis tools to study and make orderly city development plans.

Road graph network is one significant source of region data. It can improve traffic condition. In the taxi study, the travel time and speed can be predicted. Also, road pattern can be identified, which helps to find hotspot locations and detect the anomalies over time. Taxi drivers can utilize the information to categorize taxi pick-up and drop-off region in more accurate smaller units [1]. Also, road graph is the base of social road sharing problem. Companies like Uber and Lyft allows users to share their positions and arrange route sharing. Bistaffa et al. developed a coalition formation algorithm, which resulted in a 36.22% cost reduction from a 100-agent size system [2]. Furthermore, with the growth of electronic vehicles, the road graph research could guide the charging and storage infrastructure framework design, thus improves the energy efficiency systems [3].

Road graph is a good source to study the urban distribution. For this purpose, cluster identification becomes very useful. Homogeneous regions in spatial data can be identified from cluster study. Different size of cluster may correspond to different functional units. A summary of the cluster data may provide a new perspective for future planning of city development [4]. Also, the real world geographical information can be further used to develop the cities social economic indicator and track urban land use [5]. Shan Jiang et al. incorporate time dimension into the spatial data. Human activity patterns like phone usage are traced and studied. Individuals are clustered according to their daily activity pattern with spatial-temporal traces. As a result, the activities of different type of individuals are visualized in the time-cumulative spatial density, and will be crucial for city function region design [6].

1.2 Methods. Rather than using hierarchical clustering, we will use a quite different approach based from graph partitioning where a partition of the graph is determined by optimizing a merit function [7]. Defying intersections as nodes and the roads connecting these intersections as undirected edges (without edge weight information), we will deduce different clusters (cities) by calculating the conductance of different sets of nodes. The road network graph is from SNAP database [8].

However, finding cuts with exactly minimal conductance is NP-hard, thus, we will use several algorithms with good approximation performance guarantees. First, we will apply the spectral method, which uses an eigenvector of the graphs Laplacian matrix to find a cut whose conductance is no bigger than ϕ if the graph actually contains a cut with conductance $O(\phi^2)$ [9,10,11]. Also, we will use Metis+MQI, which consists of using the popular graph partitioning package Metis [12] followed by a flow-based MQI post-processing [13].

1.3 Previous Work. Very relevant to our work is that of Kannan, Vempala, and Vetta [14], who analyze spectral algorithms and describe a community concept in terms of a bicriterion depending on the conductance of the communities and the relative weight of inter-community edges. Flake, Tarjan, and Tsioutsoulis [15] introduce a similar bicriterion that is based on network flow ideas, and Flake et al. [16, 17] defined a community as a set of nodes that has more intra-edges than inter-edges. Similar edge-counting ideas were used by Radicchi et al. [18] to define and apply the notions of a strong community and a weak community.

1.4 This Project. In this project, we will be working on clustering cities from complicated road network graphs. We will approach the cut-improvement problem using the combination of spectral clustering method and max flow quotient cut improvement method, in contrast with the previous single method approach. In this project, the fundamental question we wish to answer is how to efficiently identify clusters

from an undirected graph with multiple connected components.

2. Methods and Techniques

Hierarchical clustering is a common method of cluster analysis which seeks to build a hierarchy of clusters, in which procedure, one first need to define distances between pairs of nodes and then produces a tree describing how nodes group into communities and how these group further into super-communities. A quite different approach that has received a great deal of attention is based on ideas from graph partitioning, in which case, the network is a module as simple undirected graph, where nodes and edges have no attributes, and a partition of the graph is determined by optimizing a merit function.

2.1 Definitions.

Definition 1 Given a graph $G = (V, E)$ with adjacency matrix $W = (w_{ij})_{i,j=1,\dots,n}$ the conductance ϕ of a set of nodes $A \subset V$ is defined as:

$$\phi(A) = \frac{\sum_{i \in A, j \notin A} w_{ij}}{\min\{Vol\{A\}, Vol\{\bar{A}\}\}}$$

where $Vol(A) = \sum_{i \in A} \sum_{j \in V} w_{ij}$, or equivalently $Vol(A) = \sum_{i \in A} d(i)$, where $d(i)$ is a degree of node i in G .

Thus, the conductance of a set provides a measure for the quality of the cut (A, \bar{A}) , or relatedly the goodness of a community A . Let $Vol(A)$ be the sum of degrees of nodes in A , and let c be the number of edges with one endpoint in A and one endpoint in \bar{A} , where \bar{A} denotes the complement of A . Then, the conductance of A is $\phi(A) = \frac{c}{Vol(A)}$.

In order to more finely resolve community structure in large networks, we introduce the network community profile plot (NCP plot). Intuitively, the NCP plot measures the quality of the best possible community in a large network, as a function of the community size. Formally, we may define it as the conductance value of the best conductance set of cardinality k in the entire network, as a function of k .

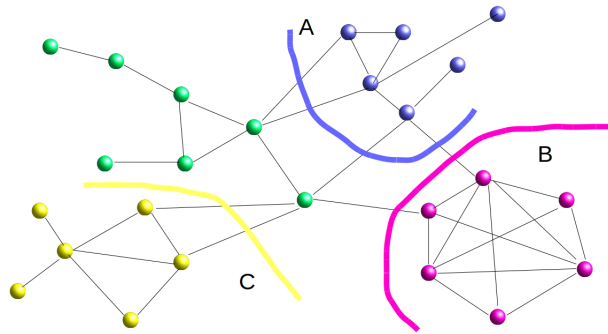


Figure 1: Network communities. Of the three 6-nodes sets that have been marked, B has the best (i.e., the lowest) conductance, as it has the lowest ratio between the number of edges cut and the number of edges inside.

Definition 2 Given a graph G with adjacency matrix $W = (w_{ij})_{i,j=1,\dots,n}$, the network community profile plot (NCP plot) plots $\phi(k)$ as a function of k , where

$$\Phi(k) = \min_{A \subset V, |A|=k} \phi(A)$$

where $|A|$ denotes the cardinality of the set A and the conductance $\phi(A)$ of A is given by definition 1.

There are two main advantages about NCP plots [7]. First, minima in the NCP plots, i.e., the best low-conductance cuts of a given size, correspond to communities-like sets of nodes. Second, the NCP plots are generally relatively gradually sloping downwards, meaning that smaller communities can be combined into larger sets of nodes that can also be meaningfully interpreted as communities.

However, finding cuts with exactly minimal conductance is NP-hard, thus, we are going to deal with this problem using several algorithms with provable approximation performance guarantees.

2.2 Approximation Methods.

2.2.1 Spectral Clustering[19]. Let $G = (V, E)$ be an undirected graph with vertex set $V = \{v_1, \dots, v_n\}$. In the following we assume that the graph G is weighted, that is each edge between two vertices v_i and v_j carries a non-negative weight $w_{ij} \geq 0$. The weighted adjacency matrix of the graph is the matrix $W = (w_{ij})_{i,j=1,\dots,n}$. If $w_{ij} = 0$ this means that the vertices v_i and v_j are not connected. As G is undirected we require $w_{ij} = w_{ji}$. The degree of a vertex $v_i \in V$ is defined as

$$d_i = \sum_{j=1}^n w_{ij}$$

Note that, in fact, this sum only runs over all vertices adjacent to v_i , as for all other vertices v_j the weight w_{ij} is 0. The degree matrix D is defined as the diagonal matrix with the degrees d_1, \dots, d_n on the diagonal. Given a subset of vertices $A \subset V$, we denote its complement $V - A$ by \bar{A} . For convenience, we introduce the shorthand notation $i \in A$ for the set of indices $\{i | v_i \in A\}$. We consider two different ways of measuring the size of a subset $A \subset V$:

$$\begin{aligned} |A| &:= \text{the number of vertices in } A \\ \text{vol}(A) &:= \sum_{i \in A} d_i \end{aligned}$$

A subset $A \subset V$ of a graph is connected if any two vertices in A can be joined by a path such that all intermediate points also lie in A . A subset A is called a connected component if it is connected and if there are no connections between vertices in A and \bar{A} . The sets A_1, \dots, A_k form a partition of the graph if $A_i \cap A_j = \emptyset$ and $A_1 \cup \dots \cup A_k = V$.

The unnormalized graph Laplacian matrix is defined as

$$L = D - W$$

Then we can compute the first k eigenvectors v_1, \dots, v_k of L . Let V be the matrix containing the vectors v_1, \dots, v_k as columns. For $i = 1, \dots, n$, let y_i be the vector corresponding to the i th row of V . Cluster the points $(y_i)_{i=1,\dots,n}$ with the k -means algorithm into clusters C_1, \dots, C_k and output clusters A_1, \dots, A_k with $A_i = \{j | y_j \in C_i\}$. Through this method, we will be able to identify connected components in a complicated graph. Formally, we have the following proposition:

Proposition 1 (Number of connected components) *Let G be an undirected graph with non-negative weights. Then the multiplicity k of the eigenvalue 0 of L equals the number of connected components A_1, \dots, A_k in the graph. The eigenspace of eigenvalue 0 is spanned by the indicator vectors $\vec{1}_{A_1}, \dots, \vec{1}_{A_k}$ of those components, where the indicator vector $\vec{1}_A = (f_1, \dots, f_n) \in \mathbb{R}^n$ as the vector with entries $f_i = 1$ if $v_i \in A$ and $f_i = 0$ otherwise.*

2.2.2 Max Flow Quotient Cut Improvement (MQI)[20]. For this technique, our input is an undirected graph and an initial cut, that is, an initial partitioning of the graphs nodes into two sets A and

$B = \bar{A}$. WLOG $Vol(A) \leq Vol(B)$. There are c edges crossing the cut, so the initial quotient cut score (conductance) is $c/Vol(A)$. Figure 2-left is a schematic diagram of the flow problem that we will build.

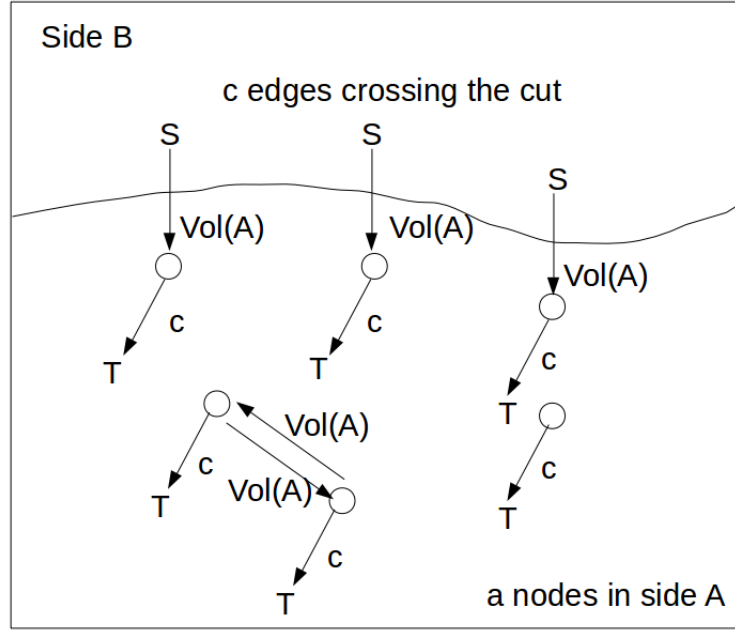


Figure 2: Setting up the max flow problem.

Note that although this problem will be based on our undirected input graph and cut, we are building a completely new directed graph here. It is convenient to specify this new graph as the output of the following procedure that begins with a copy of the input graph. The algorithm is as follow:

1. Discard all B -side nodes.
2. Discard every edge that used to connect a pair of B -side nodes.
3. Replace every edge that used to connect a pair of A -side nodes with a pair of directed edges, one pointing in each direction, and each with capacity $Vol(A)$.
4. Add a source node S and a sink node T .
5. Discard each edge that used to connect a B -side node with an A -side node x , replacing it with a single directed edge from S to x , with capacity $Vol(A)$.
6. Add a single directed edge from every A -side node to T , with capacity c .

After we build up the above max flow problem, we need to find a solution to this max flow problem and then use this solution to build up the new partition A' and $B' = \bar{A}'$. First, here is a theorem we will use:

Theorem 1. *There is an improved quotient cut (A', B') (with A' a strict subset of A) if and only if the maximum flow is less than ca , where $a = |A|$.*

In the new partition, the small side A' is the set of nodes reachable from the sink by a depth-first search along reversed unsaturated edges. This backwards DFS procedure advances from a node y to a node x if and only if there is an unsaturated edge leading from node x to node y . The conductance of the new cut A' , $\frac{c'}{Vol(A')}$, is smaller than the conductance of the old cut A , $\frac{c}{Vol(A)}$. A single call to MQI determines

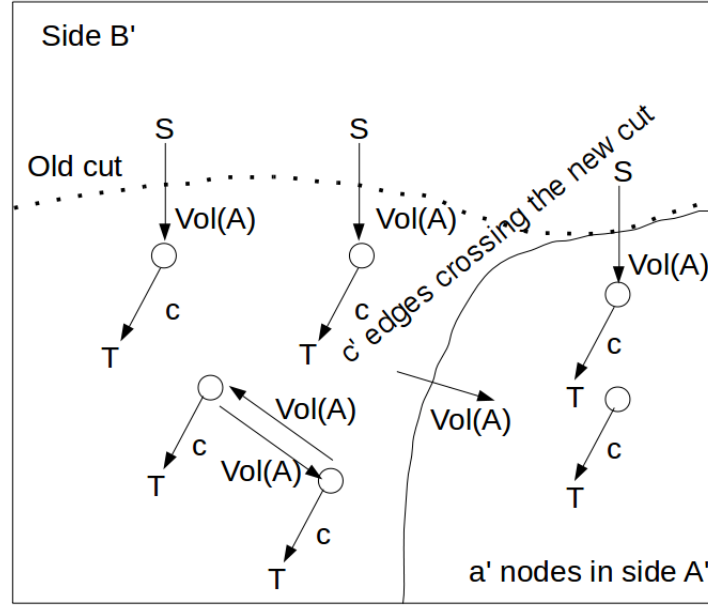


Figure 3: Interpreting the solution of the maximum flow problem and building up the new quotient cut A', B' .

whether any reachable improved quotient cut exists, and if so, it returns one of them. To find the minimum conductance cut, we simply perform multiple tries of MQI with different RNG seeds for the initial partition.

2.3 Main Algorithm.

So far, we have introduced our two main methods, spectral clustering method and max flow quotient cut improvement method. In order to efficiently and accurately tackle undirected road graphs with multiple connected components, we combine these two methods and form our main algorithm as follow:

1. Load the data and form undirected graph G
2. Build up the adjacency matrix W and degree matrix D . Since our input graph has no weight, we simply set each edge has the same weight 1.
3. Build up the Laplacian matrix $L = D - W$.
4. Solve the Laplacian matrix L and get corresponding eigenvalues and eigenvectors. Partition the original graph G into k , which is the multiplicity of the eigenvalue 0 of L , connected components A_1, A_2, \dots, A_k , so that each subset $A_i \subset G$ has no connections with \bar{A}_i .
5. For each subset $A_i \subset G$, repeatedly use random initial partition + max flow quotient cut improvement method to collect data for NCP plot.
6. For each subset $A_i \subset G$, draw its NCP plot and conclude its best possible community in that subset from the minimum point in its NCP plot.

3. Results and Analysis

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