

Graph Partitioning

Edited by
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Introduction

Since the early 1970s, graph partitioning has been a widely researched topic. After 40 years of development, it is now time to evaluate the situation of the work done in this area.

Graph partitioning is a problem transverse to several fields in engineering, as well as research. The diversity of backgrounds of people working on this subject may explain why no real international community exists, despite the fact that some workshops have been organized on this subject over different periods of time. However, the number of people who work or have worked on this topic is quite significant, as shown by the abundant literature cited throughout the chapters of this book. Confronted with this profusion and diversity, it is interesting to gather the knowledge accumulated over so many years in order to synthesize it and draw the common theoretical fundamentals of the field.

This book intends to present to the neophyte reader, as well as the expert in applied mathematics or the computer science researcher, tools and methods to solve graph partitioning optimization problems. For this purpose, we have collected several methodological chapters detailing different graph partitioning optimization approaches such as the multilevel method, metaheuristics, partitioning parallelization, and hypergraph partitioning. In order to complete this theoretical part, several graph partitioning applications have been described on subjects as diverse as mobile networks, image segmentation, air traffic control, social networks, etc.

Despite the large number of studies in the domain of graph partitioning, it is clear that a lot of work remains to be done to solve this problem more efficiently. Recent years have seen the sizes of graphs to be partitioned soaring from a few thousand vertices to several million, or even billions of vertices. We hope that by reading this book the reader will feel inspired not only to take an interest in the problem, but also try to solve it more efficiently, both in terms of quality of partitions found and computation time required.

This book has three parts: [Part 1](#) is dedicated to the most common application of graph partitioning in numerical analysis; [Part 2](#) describes and implements several combinatorial optimization methods for graph partitioning; [Part 3](#) presents other uses of graph partitioning.

[Chapter 1](#) provides a general introduction to this book and is therefore independent of any part. It analyzes graph partitioning in order to identify the different problems associated with it.

A large number of studies on graph partitioning have been undertaken within the domain of numerical analysis. [Part 1](#) of this book is dedicated to their presentation. Thus, [Chapter 2](#) describes the methods and algorithms commonly used in numerical analysis to solve graph partitioning problems: the multilevel method, refinement algorithms like the Kernighan-Lin or Fiduccia-Mattheyses algorithms, and the spectral method. [Chapter 3](#) introduces the particular case of hypergraph partitioning, which often occurs in numerical analysis. [Chapter 4](#) presents several parallel algorithms to partition a graph. Finally, [Chapter 5](#) presents the problem of static mapping which occurs in parallel computing.

Graph partitioning is often studied through a combinatorial optimization point of view. This is the theme of [Part 2](#) of this book, which is dedicated to the study of combinatorial optimization methods and more particularly metaheuristics, for graph partitioning. This part consists of two theoretical chapters followed by two application chapters. [Chapter 6](#) focuses on the use of several local metaheuristics, like simulated annealing or iterated local search. [Chapter 7](#) provides details on the u

of population-based metaheuristics to optimize partitioning. This chapter explains the work done on Ant Colony algorithms and describes several adaptations of Genetic Algorithms to graph partitioning. It also introduces a recent method for graph partitioning optimization, fusion-fission, which works as a meta-method that overlooks a multilevel algorithm. The last 2 chapters of this part provide application examples for this part. [Chapter 8](#) applies a Genetic Algorithm to the problem of mobile network partitioning in tariff zones. [Chapter 9](#) describes an Air Traffic Control problem and solves it using the fusion-fission method.

[Part 3](#) of this book develops other approaches of graph partitioning. In this part, we have chosen to focus on graph partitioning optimization, and thus we limited the scope of this part, even if many other works on graph partitioning could have been added, like constraint programming for graph partitioning or graph decomposition. [Chapter 10](#) outlines the image segmentation problem and offers several methods to solve this problem, based on graph partitioning. [Chapter 11](#) compares several distances between vertices, in order to build communities, using classification methods. [Chapter 12](#) proposes to partition networks into unconnected or overlapping communities. Finally, [Chapter 13](#) concludes by describing how to partition very large networks into communities.

Further information that could not be included in this book is available at the book's Web address. In particular, as this book is being printed in black and white, some figures will have lost their clarity when compared to their original color version. This is especially true for images in [Chapters 9](#) and [10](#) respectively, about airspace partitioning and image segmentation. To overcome this problem, the original color versions of the figures concerned are also available at the book's Web address. You will also find at this Web address different graphs used in this book, as well as links to several software tools for graph partitioning.

Charles-Edmond BICHOT and Patrick SIARRAS
August 2011

[1](#) The book's Website, "Graph partitioning: optimization and applications", is available at perso.ec-lyon.fr/charles-edmond.bichot/.

General Introduction to Graph Partitioning ¹

1.1. Partitioning

The word “partitioning” represents the action of creating a partition by segmenting a set into several parts. In mathematics, a partition of a set X is a family of pairwise disjoint parts of X whose union is the set X . Therefore, each element of X belongs to one, and only one of the parts of the partition.

Partitioning is used to solve a large number of engineering problems. There are many examples of partitioning applications: data mining, VLSI design, load balancing, parallel computing, matrix computation, fluid dynamics, image analysis, air traffic control, etc.

Creating a partition consists of distributing a set of objects into several subsets. In order to distribute the objects in these different subsets, it may be useful to compare them. Thus, each object will be associated with a few other objects. When each object is associated with all other objects, then the grouping is known as clustering, and not partitioning. The resulting associations would be quantified. If the set of all these objects is finite, then all the conditions would be met to create a graph from these objects, in other words to materialize the associations between objects. The next step will be to build a partition of this graph. Partitioning a set of objects generally aims to distribute the objects into parts having strong internal links and weak links between parts. That is known as the objective of partitioning or objective function. This objective function varies according to the specific problem which is to be solved. We emphasize the fact that in this book we mainly focus on the optimization problem of minimizing an objective function. Thus, we will generally seek to minimize the links between parts rather than maximize them.

The problem of graph partitioning optimization is common to several disciplines:

- it is part of graph theory problems and therefore discrete mathematics. Discrete mathematics relates to discrete structures, i.e. finite or countable sets;
- it is also part of the combinatorial optimization problems. A combinatorial optimization problem tries to find out the best solution within a set of discrete solutions;
- it is solved using computing.

Graph partitioning is, therefore, a discipline situated between computer science and applied mathematics.

Because of the diversity of its applications, the graph partitioning optimization problem evolves into a multitude of problems. However, we can group them into two large categories. The nature of a graph partitioning problem is very different according to whether we seek to obtain parts of very similar sizes or without any size constraint. This observation leads us to distinguish between two different graph partitioning problems:

- *constrained partitioning*, when the parts of the partition are of similar sizes;
- *unconstrained partitioning*, when the parts can be of (very) different sizes.

Before giving a precise definition of these two problems, this introductory chapter presents a few

reminders on mathematics in [section 1.2](#) and graph theory in [section 1.3](#). These will be followed by formal description of the graph partitioning optimization problem in [section 1.4](#) and its different objectives in [section 1.5](#). Then the two main categories of graph partitioning problems will be presented: first the constrained partitioning problem in [section 1.6](#), and then the unconstrained partitioning problem in [section 1.7](#). Finally, [section 1.10](#) will study the NP-hardness of several graph partitioning problems.

1.2. Mathematical notions

DEFINITION 1.1. (CARDINALITY OF A SET)– Let X be a finite set of n elements. The cardinality of the set is the number n of elements of X , and is denoted by $|X|$. Therefore, we have $|X| = n$.

In mathematics, the partition of a set V of objects is defined as follows:

DEFINITION 1.2. (PARTITION)– Let V be an ordinary set. A set P of subsets of V is called a partition of V if:

- no element of P is empty;
- the elements of P are pairwise disjoint;
- the union of the elements of P is equal to V .

The elements of P are called the parts of the partition P . The cardinality of the partition P is therefore the number of parts of P . In graph partitioning, the number of parts of P is often denoted k .

It is a bad habit to use the word partition instead of part, which creates ambiguity. Thus, instead of saying “the partition P_1 of P ”, it is better to say “the part P_1 of the partition P ”.

As previously mentioned, the graph partitioning problem is a combinatorial optimization problem which is a branch of discrete mathematics. Discrete mathematics represent the study of mathematical structures, where the notion of continuity doesn’t exist. Thus, sets studied in discrete mathematics are countable, and therefore countable sets are sometimes called discrete sets.

We can now give a formal definition of a combinatorial optimization problem:

DEFINITION 1.3. (COMBINATORIAL OPTIMIZATION PROBLEM)– A combinatorial optimization problem defined from a triplet (S, p, f) such that:

- S is a discrete set called research space (also called solution space);
- p is a predicate on S , i.e. a function of S in $\{\text{true}, \text{false}\}$;
- $f : S \rightarrow R$ associates with each element $x \in S$ a cost $f(x)$.

The function f is called the objective function or the cost function of the problem. The predicate p creates a set $S_a = \{x \in S \text{ such that } P(x) \text{ is true}\}$ which is called the set of admissible solutions of the problem. Each element of S is called a solution of the problem, and each element of S_a an admissible solution of the problem.

A combinatorial optimization problem aims to find the element $\bar{x} \in S_a$ (or the subset of elements S_a) that minimizes f :

$$[1.1] \quad f(\bar{x}) = \min_{x \in S_a} f(x)$$

Note: The combinatorial optimization problem which looks for a maximum element instead of minimum element, is of the same nature because:

$$[1.2] \quad \max_{x \in S_a} f(x) = - \min_{x \in S_a} (-f(x))$$

Combinatorial optimization problems are generally very expensive to solve optimally. This is particularly the case of graph partitioning problems, which are often NP-hard, as we will see in [section 1.10](#).

The research space S can be described as the set of solutions of the combinatorial optimization problem, which we seek to solve without taking into account the problem's constraints. For example, let's consider the combinatorial optimization problem aiming to find a partition of the vertices of a graph $G = (V, E)$ into k parts of equal sizes (we choose k divisor of $|V|$). This problem will have as research space S the set of all possible partitions of V , i.e. partitions of parts of any sizes whose number of parts ranges from one to $|V|$. However, the set of admissible solutions to problem S_a must take the constraints into account. Thus, in our example, the set S_a will be made of partitions of V into k parts of equal sizes.

DEFINITION 1.4. (GLOBAL OPTIMUM, LOCAL OPTIMUM) – Let (S, p, f) be a combinatorial optimization problem and S_a the set of admissible solutions of the problem resulting from the predicate p . Let $\bar{x} \in S_a$.

– If we can prove that $\forall x \in S_a, f(\bar{x}) \leq f(x)$, then \bar{x} is called a global optimum (minimum) of the problem;

– If there is a set of admissible solutions $X \subset S_a, |X| \geq 2$, and $\bar{x} \in X$ such that $\forall x \in X, f(\bar{x}) \leq f(x)$, then \bar{x} is called a local optimum (minimum) of the problem.

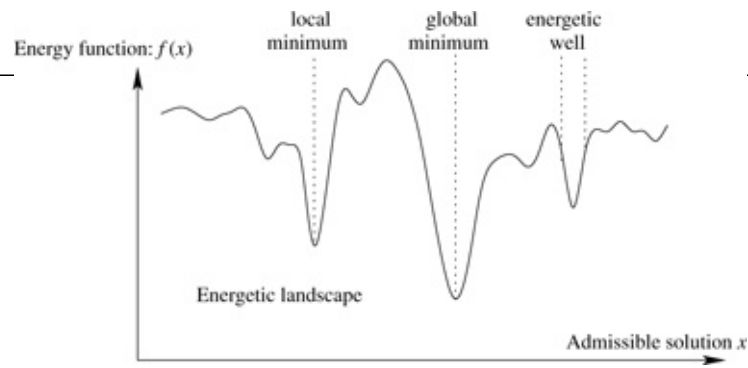
The research space S has a topology. It is very useful to know the characteristics of the topology of S in order to understand the purpose of the metaheuristics mechanisms and to improve them ([Chapters 6 and 7](#) present how to adapt metaheuristics to graph partitioning). This topology results from the notion of proximity between two solutions, also called configurations. The distance between two configurations represents the minimum number of elementary modifications necessary to go from one to another. Besides, because a value $f(x)$ is associated with each configuration x , the solution space is characterized by a multi-dimensional chart called *energetic landscape*¹. In this energetic landscape, the local or global optima form energetic wells around them; these *energetic wells* are also named basins of attraction. Before saying that an admissible solution $\bar{x} \in X$ (see [definition 1.4](#)) of the problem is a local minimum, we must generally check that the size of the set X is large enough in relation to the size of S_a . [Figure 1.1](#) represents the continuous equivalent of the energetic landscape of a cost function in a single-dimension solution space.

1.3. Graphs

This section is a reminder of some definitions of the graph theory.

DEFINITION 1.5. (GRAPH) – Let V be a non-empty set of n_V elements and E a set of n_E pairs of elements of V . A graph G is the pair (V, E) . The elements of V are called

Figure 1.1. Continuous equivalent of the energetic landscape of a cost function $f(x)$ in a single-dimension research space



vertices of the graph and those of E the arcs or edges of the graph, depending on whether they are directed or not.

An edge represents a connection between exactly two vertices. When there is a connection between at least three vertices, these vertices are connected by what is called a hyperedge. By extension, we can no longer use the term graph, but hypergraph.

DEFINITION 1.6. (HYPERGRAPH)— Let V be a non-empty set of elements and E a set of non-empty subsets of elements of V . A hypergraph G is the pair (V, E) . The elements of E are called hyperedges.

Note: The problem of hypergraph partitioning is presented in [Chapter 3](#).

When the associations between vertices are not reciprocal, for example, if the vertex v_1 is connected with the vertex v_2 , without the vertex v_2 being connected with v_1 , then the edges are said to be directed and are called arcs.

DEFINITION 1.7. (DIRECTED AND UNDIRECTED GRAPHS)— Let $G = (V, E)$ be a graph.

If for each edge $(v_1, v_2) \in E$, we have $(v_2, v_1) \in E$, then the graph is undirected and the elements of E are called edges of the graph. In that case, an edge is equally denoted by: $(v_1, v_2) = (v_2, v_1) = e \in E$ with v_1 and v_2 in V .

In the opposite case, the graph is said to be directed and the elements of E are called arcs of the graph.

DEFINITION 1.8. (ADJACENT VERTICES AND EDGES, INCIDENT EDGES)— Let $G = (V, E)$ be an undirected graph.

Let $e = (v_1, v_2) \in E$ be an edge. The vertices v_1 and v_2 are said to be the adjacent vertices of the edge e . Similarly, e is said to be incident to the vertices v_1 and v_2 .

Let e_1 and e_2 be two edges. e_1 and e_2 are said to be adjacent if they are incident to the same vertex, i.e. $e_1 = (v, v_1)$ and $e_2 = (v, v_2)$.

DEFINITION 1.9. (DEGREE OF A VERTEX)— In an undirected graph $G = (V, E)$, the degree of a vertex $v \in V$ is the number of edges incident to the vertex :

$$[1.3] \text{deg}(v) = |\{(v, v') \in E, v' \in V\}|$$

DEFINITION 1.10. (LOOP AND MULTIPLE EDGES)— An edge is called a loop if both of its extremities are identical.

If two or more edges are incident to the same two vertices, then the edge is said to be multiple and these two edges are parallel. In that case, the multiplicity of an edge is the number of its parallel edges, including itself.

DEFINITION 1.11. (SIMPLE GRAPH)— An undirected graph is said to be simple if it has neither loop nor multiple edges.

DEFINITION 1.12. (REGULAR GRAPH)— An undirected graph is said to be regular when all its vertices

have the same number of neighbors.

When the associations between vertices are quantified, the edges of the graph have a weight, and the graph is said to be weighted.

DEFINITION 1.13. (WEIGHTED GRAPH)— Let $G = (V, E)$ be a graph. The graph is said to be weighted if a real value, $w(e)$, is associated with each edge $e \in E$. The value $w(e)$ is called the weight of e . In addition, a pair of vertices $(v_1, v_2) \in V^2$ such that $(v_1, v_2) \notin E$ is considered to have a zero weight $w(v_1, v_2) = 0$.

The weight of a subset X of edges of E is the sum of the weights of the elements of X : $w(X) = \sum_{e \in X} w(e)$.

Likewise, we often associate with the vertices $v \in V$ of the graph to a strictly positive integer called the weight of v and denoted by $w(v)$.

Note: In the case of graph partitioning, the weight of an edge or vertex is most often a strictly positive integer.

We must be careful not to confuse the cardinality of a set of vertices (respectively edges) and the weight of a set of vertices (respectively edges). They are equal if the vertices (respectively edges) are not weighted.

In the case of weighted graphs, we redefine the degree of a vertex $v \in V$ as the sum of the weights of the edges adjacent to this vertex. Thus:

$$[1.4] \quad \text{deg}(v) = \sum_{(v,v') \in E} w(v, v')$$

For an unweighted graph, we can associate with each edge, and each vertex a unit weight.

For any graph $G = (V, E)$, we can define a bijection $u: V \rightarrow \{1, \dots, n_V\}$ which associates an integer with every element of V . The function u can count the elements of V . For convenience, with each element of the set of vertices V of a graph G , we will associate a rank in V , and we will merge the vertex v_i of V with its rank i in V . For example, for each $(v_i, v_j) \in E$, $w(v_i, v_j)$ will be denoted by $w(i, j)$, and $w(v_i)$ by $w(i)$.

For any graph, we can define a unique function, $\text{weight}: E \rightarrow \mathbb{N}$, which associates each edge with its weight. This weight function can be represented as a matrix. The adjacency matrix of a graph G can be defined as the matrix that associates each edge of G with its weight.

DEFINITION 1.14. (ADJACENCY MATRIX)— Let $G = (V, E)$ be a simple graph. The matrix M_{Adj} has dimension $n_V \times n_V$, such that $\forall (i, j) \in \{1, \dots, n_V\}^2$:

$$[[1.5] \quad (M_{Adj})_{ij} = \begin{cases} 0 & \text{if } i = j \\ w(i, j) & \text{else} \end{cases}$$

is called the adjacency matrix of the graph G .

DEFINITION 1.15. (DEGREE MATRIX)— Let $G = (V, E)$ be a simple graph. The matrix M_{Deg} has dimension $n_V \times n_V$, such that $\forall (i, j) \in \{1, \dots, n_V\}^2$:

$$[[1.6] \quad (M_{Deg})_{ij} = \begin{cases} 0 & \text{if } i = j \\ w(i, j) & \text{else} \end{cases}$$

is called the degree matrix of the graph G .

DEFINITION 1.16. (LAPLACIAN MATRIX)— Let $G = (V, E)$ be a simple graph. The matrix

$$[[1.7] \quad (M_{Deg})_{ij} = \begin{cases} \text{deg}(i) = \sum_{k=1}^{n_V} w(i, k) & \text{if } i = j \\ 0 & \text{else} \end{cases}$$

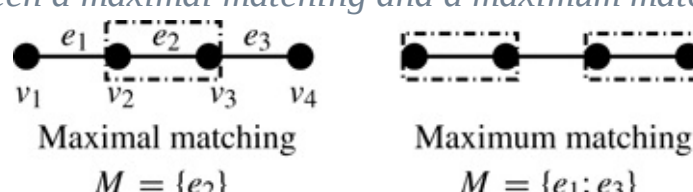
is called the Laplacian matrix of G .

DEFINITION 1.17. (PATH IN A GRAPH)– Let $G = (V, E)$ be a graph and (v_1, v_2) be two distinct vertices. If a succession of edges (or correctly directed arcs in the case of a directed graph) are allowed to reach v_2 from v_1 , then we can say that there is a path from v_1 to v_2 .

DEFINITION 1.18. (CONNECTED GRAPH)– Let $G = (V, E)$ be a graph. This graph is said to be connected if for any pair of vertices v_1 and v_2 a path from v_1 to v_2 exists.

The matching of a graph is a subset of edges of this graph which have no incident vertex in common.

Figure 1.2. Difference between a maximal matching and a maximum matching



DEFINITION 1.19. (MATCHING)– Let $G = (V, E)$ be a graph. The matching M of the graph G is a set of pairwise non-adjacent edges.

A matching M is maximal if every edge of the graph is incident with at least one edge of M .

A matching is maximum when it contains the highest possible number of edges.

Note: Every maximum matching is also a maximal matching. Let M be a maximum matching and assume that there is a set of edges M' of E , not in M , such that $M \cup M'$ is a maximal matching. Then M is not a maximum matching, as there is a matching, $M \cup M'$ that contains more edges. That is absurd, therefore M is a maximal matching. The reciprocal is not necessarily true: in a linear graph with four vertices, the matching made up of the edge formed by the two central vertices is maximal but not maximum (see Figure 1.2). A graph can have several maximum matchings (and a fortiori several maximal matchings).

1.4. Formal description of the graph partitioning problem

Before presenting the general problem of graph partitioning, we have to define the partition of a graph. As mentioned in the previous section, a graph is a pair formed by a set of vertices and a set of edges. It is therefore possible to partition, in a mathematical sense, the set of vertices as well as the set of edges. However, although some problems seek to partition the edges of a graph [HOL 81], graph partitioning is mostly understood as the partition of the vertices of the graph.

DEFINITION 1.20. (PARTITION OF THE VERTICES OF A GRAPH)– Let $G = (V, E)$ be a graph and $P_k = \{V_1, \dots, V_k\}$ a set of k subsets of V . P_k is said to be a partition of G if:

– no element of P_k is empty:

$$\forall i \in \{1, \dots, k\}, S_i \neq \emptyset;$$

$$\forall i \in \{1, \dots, k\}, S_i \neq \emptyset;$$

– the elements of P_k are pairwise disjoint:

$$\forall (i, j) \in \{1, \dots, k\}^2, i \neq j, V_i \cap V_j = \emptyset;$$

– the union of all the elements of P_k is equal to V :

$$\bigcup_{i=1}^k V_i = V$$

The elements V_i of P_k are called the parts of the partition. The number k is called the cardinality of the partition, or the number of parts of the partition.

The definition of a partition of the vertices of a graph does not restrict itself to the size of the parts. To remedy this and measure the size of the parts of a partition, the concept of a partition *balance* is introduced. The term balance refers to the *measure of the weight*.

DEFINITION 1.21. (BALANCE OF A PARTITION)– Let $G = (V, E)$ be a graph and $P_k = \{V_1, \dots, V_k\}$ a partition of this graph into k parts. The average weight of a part V_i of P_k is

$$weight_{avg} = \left\lceil \frac{w(V)}{k} \right\rceil$$

where $\lceil x \rceil \in \mathbb{N}$ is the first integer which is greater than or equal to x .

The balance $bal(P_k)$ of the partition P_k is the division of P_k 's maximal weighted element by the average weight of a part:

$$[[1.8] \quad bal(P_k) = \frac{\max_i w(V_i)}{weight_{avg}}$$

Thus, a partition whose partitioning balance is unitary has parts of identical weights (rounded to one). For example, the bisection of a graph of size $(2n + 1)$ will have a balance of 1.00, if and only if the largest part is of size $n + 1$ and the other part is of size n .

As we have previously seen, the graph partitioning problem is a combinatorial optimization problem. To present it simply, the general graph partitioning problem consists in finding a partition of a graph which satisfies a predicate p and minimizes an objective function f . Here a more formal definition is provided:

DEFINITION 1.22. (GENERAL GRAPH k -PARTITIONING OPTIMIZATION PROBLEM)– Let $G = (V, E)$ be a graph and let $k \geq 2$ be an integer. We can define the triplet (S, p, f) that characterizes the general graph k -partitioning optimization problem such that:

- the research space S is defined as the set of all possible partitions of V (these partitions have cardinality that ranges from 1 to $|V|$);
- let p' be a predicate defined by $P \in V$, $p'(P) = \text{true}$ if and only if $|P| = k$. The predicate p of the general problem is defined in S such that $p(P) = \text{true} \Rightarrow p'(P) = \text{true}$, thus it can be more restrictive than p' ;
- let $f : S \rightarrow \mathbb{R}$ be an objective function.

The set of admissible solutions of the problem is defined by:

$$S_a = \{P \in S \text{ such that } p(P) = \text{true}\}$$

The general graph partitioning problem consists in finding the partition $\tilde{P}_k \in S_a$ that minimizes f :

$$[1.9] \quad f(\tilde{P}_k) = \min_{P_k \in S_a} f(P_k)$$

It can be noticed that $S_a \subseteq \{P \in S \text{ such that } |P| = k\}$. This means that an admissible solution of the graph partitioning optimization problem can be more restrictive than merely satisfying the predicate p' (i.e. $|P| = k$). That is why we have introduced the predicate p and not just the predicate p' .

By definition, the set of vertices of the graph is finite. The number of partitions of a set of n elements is called the Bell number relative to n , and is denoted by B_n . It represents the number of distinct equivalence relations on a set of n elements. $B_0 = 1$. The Bell number satisfies the following recursive equation:

$$[1.10] \quad B_{n+1} = \sum_{k=0}^n C_n^k B_k$$

where $C_n^k = \frac{n!}{k!(n-k)!}$ is the binomial coefficient of n and k , i.e. the number of parts of k elements from a set of n elements.

The number of partitions into k parts of a set of n elements is called the Stirling number of the second kind. This number is denoted by $S_{n,k}$ and its value is:

$$[1.11] \quad S_{n,k} = \sum_{i=0}^k (-1)^i \frac{(k-i)^n}{i!(k-i)!}$$

There is a relation between the Bell number and the Stirling number of the second kind:

$$[1.12] \quad B_n = \sum_{i=1}^n S_{n,i}$$

Thus, because the set of vertices is finite, the set of solutions S is a finite set. It is therefore a discrete set, according to the definition of a combinatorial optimization problem (see [section 1.2](#)).

The general graph partitioning optimization problem is defined by using a pair formed by a predicate and an objective function: (p, f) . Thus, graph partitioning can be divided into numerous problems, depending on the nature of p and f . However, these problems can be classified into two main different categories, depending on the nature of the predicate p : the constrained graph partitioning problem introduced in [section 1.6](#) and the unconstrained graph partitioning problem described in [section 1.7](#).

[1.5. Objective functions for graph partitioning](#)

The different objective functions for graph partitioning are based on two concepts: inter-class disparities and intra-class similarities. The cut between parts often represents inter-class disparities and the weight of parts is used to characterize intra-class similarities.

DEFINITION 1.23. (CUT FUNCTION)—Let $G = (V, E)$ be a graph. Let V_a and V_b be two subsets of V , and we can define the cut between these two subsets as:

$$[1.13] \quad \text{cut}(V_a, V_b) = \sum_{u \in V_a} \sum_{v \in V_b} w(u, v)$$

For the rest of this section, let $P_k = \{V_1, \dots, V_k\}$ be a partition of V into k parts. The objective functions presented will be defined with regard to this partition.

The simplest of the objective functions used in graph partitioning is called the cut of a partition. It aims to minimize the sum of the weight of the edges between parts of the partition P_k . It is already used by B. Kernighan and S. Lin [KER 70]:

DEFINITION 1.24. (CUT OBJECTIVE FUNCTION)

$$[1.14] \quad \begin{aligned} \text{cut}(P_k) &= \sum_{i < j} \text{cut}(V_i, V_j) \\ &= \frac{1}{2} \sum_{i=1}^k \text{cut}(V_i, V - V_i) \end{aligned}$$

The objective function that aims to minimize, for each part, the ratio between its cut and its weight is called ratio cut. It was introduced by Y.-C. Wei and C.-K. Cheng [WEI 89]:

DEFINITION 1.25. (RATIO CUT OBJECTIVE FUNCTION)

$$[1.15] \quad \text{ratio}(P_k) = \sum_{i=1}^k \frac{\text{cut}(V_i, V - V_i)}{w(V_i)}$$

However, when the term ratio cut is used, we have to be careful that other objective functions are also called by the same name in the literature [WAN 03].

The third and last function widely used in graph partitioning is called normalized cut. This function, which is the most recent, was presented by J. Chi and J. Malik [SHI 00]. It aims to minimize, for each part, the ratio between its cut and the sum of the weight of the edges adjacent to at least one of its vertices. In other words, it aims to minimize, for each part, the ratio between the sum of the weight of the edges adjacent to exactly one of its vertices and the sum of the weight of the edges adjacent to at least one of its vertices:

DEFINITION 1.26. (NORMALIZED CUT OBJECTIVE FUNCTION)

$$[1.16] \quad \begin{aligned} \text{norm}(P_k) &= \sum_{i=1}^k \frac{\text{cut}(V_i, V - V_i)}{\text{cut}(V_i, V)} \\ &= \sum_{i=1}^k 1 - \frac{\text{cut}(V_i, V_i)}{\text{cut}(V_i, V)} \end{aligned}$$

The normalized cut function can isolate regions of the graph where the vertices are strongly interconnected. Its authors created it to replace the ratio cut in their image segmentation problem.

Note: In the case of graphs weighted by strictly positive weights, which is almost always the case in graph partitioning problems, all the objective functions presented before are positive.

All these objective functions can define the *energy* of a part of a partition. The term energy is used in reference to the concept of energetic landscape presented in [section 1.2](#). This energy is the value brought by the part of the partition to the objective function. In the case of the cut objective function, the energy of a part V_i will be:

$$[1.17] \quad \text{energy}_{cc}(V_i) = \text{cut}(V_i, V - V_i)$$

In the case of the ratio cut, the energy of a part V_i will be:

$$[1.18] \quad \text{energy}_{rc}(V_i) = \frac{\text{cut}(V_i, V - V_i)}{w(V_i)}$$

In the case of the normalized cut, the energy of a part V_i will be:

$$[1.19] \quad \text{energy}_{cn}(V_i) = \frac{\text{cut}(V_i, V - V_i)}{\text{cut}(V_i, V)}$$

[1.6. Constrained graph partitioning](#)

Classic literature on graph partitioning focuses on the constrained graph partitioning optimization problem. Most graph partitioning tools solve this problem, such as METIS, JOSTLE, CHACO, SCOTCH PARTY, as we will see in [Chapter 2](#) and in the [Appendix](#).

One of the first chapters to present this problem was from B. Kernighan and S. Lin [KER 70]. The constrained graph partitioning problem is often used to illustrate new graph partitioning methods. Indeed, in the chapter introducing the spectral method [POT 90], A. Pothen, H. Simon and K.-P. Liou applied this new method to this problem. Moreover, the chapters of S. Barnard and H. Simon introducing the multilevel method [BAR 93, BAR 94] again applied this new method to a constrained graph partitioning problem.

Constrained graph partitioning is mainly used to solve different engineering problems like high performance computing, linear systems resolution, meshing, and VLSI circuits conception. However, criticism has been raised regarding the use of this approach to model these problems, more particularly the case for [HEN 98].

In literature, constrained graph partitioning is often called *multi-way graph partitioning* [YAR 00] or *k-way graph partitioning* [KAR 98].

The problem of constrained graph partitioning consists of finding a partition into k parts, which should imperatively respect a strict balance while minimizing an objective function f .

The objective function, minimized by constrained partitioning, is most often the *cut* objective function (see [definition 1.24](#)).

Let's consider the other objective functions. If a partition P_k has parts of identical weights, then its ratio cut ([section 1.5](#)) is equal to its cut, up to a multiplicative constant. In fact, in that case:

$$\begin{aligned}
 \text{ratio}(P_k) &= \sum_{i=1}^k \frac{\text{cut}(V_i, V - V_i)}{w(V_i)} \\
 &= \frac{k}{w(V)} \sum_{i=1}^k \text{cut}(V_i, V - V_i) \\
 &= \frac{k}{w(V)} \text{cut}(P_k)
 \end{aligned}$$

[1.20]

Thus, for the problem of constrained graph partitioning, minimizing the ratio cut is equivalent to minimizing the cut.

Besides, when considering a partition P_k whose parts have identical weight, the use of the normalized cut loses its meaning. Indeed, this cost function has been created to isolate from other regions those whose vertices are connected, which is often contradictory to the search for equal parts. Therefore, to the best of our knowledge, this cost function is never used in problems of constrained graph partitioning.

DEFINITION 1.27. (CONSTRAINED GRAPH PARTITIONING)— Let $G = (V, E)$ be a graph, k a number of parts, and bal_max a maximal partitioning balance. Let S be the solution space, defined by the general graph partitioning problem. The set S_a of admissible solutions of the problem is defined by:

$$S_a = \{P_i \in S \text{ such that } |P_i| = k \text{ and } bal(P_i) \leq bal_max\}$$

The constrained graph partitioning problem consists of finding $\bar{x} \in S_a$ that minimizes the cost function f :

$$[1.21] \quad f(\bar{x}) = \min_{x \in S_a} f(x)$$

Notes:

- the maximal partitioning balance of constrained graph partitioning problems is often very small, $bal_max \in [1, 0; 1, 05]$;

- within constrained graph partitioning problems, a small relaxation of the partitioning balance is often accepted. Indeed, with a value of the balance slightly greater than the unit, partitions of low cut can be found, and such solutions are often technically not detrimental to the resolution of the problem [SIM 97].

[1.7. Unconstrained graph partitioning](#)

The unconstrained graph partitioning optimization problem is slightly more exotic than the constrained graph partitioning optimization problem. We used the term exotic because this problem is not divided into very similar problems and its objective functions have been regularly improved, or at least modified. Finally the main aim of constrained graph partitioning consists of finding a partition respecting a restrictive balance, the main aim of unconstrained graph partitioning is to minimize an objective function. Moreover, if there is no other aim for unconstrained graph partitioning, there is a second one for constrained graph partitioning, which is to minimize the cost function.

Unconstrained graph partitioning is quite similar, in its formulation, to data partitioning or *clustering*. The data partitioning problem consists of merging similar elements into sets that are as distinct as possible. To compare two elements, the notion of distance is used. That brings the data partitioning problem down to the creation of subsets of elements as distinct from each other as possible. And yet, we can easily create a graph whose vertices are these elements and whose edges have for weight the inverse of the distance between two elements. In the case where the number of parts is fixed, a data partitioning problem is similar to an unconstrained graph partitioning problem. As a result, many studies have sought to solve data partitioning problems using graph partitioning tools. However, graphs modeled in this way are often complete, because there is a distance for each pair of elements, and so, all the vertices of the graph will be connected.

Unconstrained graph partitioning is widely used not only in image segmentation [SHI 98b, SHI 98a, PER 98, MEI 00, SHI 00, GDA 01, WAN 01, MAR 04, BEN 05], but also in texts classification [DIE 01, ZHA 01, DIN 01, ZHA 04, BIC 09]. In the case of image segmentation, numerous chapters compare different objective functions and suggest new functions including new criteria [SHI 98b, SHI 00, PER 98, GDA 01, WAN 01, FEL 04]. Several chapters solve VLSI circuit partitioning problems by using an unconstrained graph partitioning approach [HAG 92, RIE 94, ALP 95]. However, in that case VLSI circuits are more often considered as hypergraphs than graphs [KER 70]. Other more unusual problems, such as airspace partitioning (see [Chapter 9](#)), are also unconstrained graph partitioning problems.

The objective functions that an unconstrained graph partitioning problem seeks to minimize are various. [Section 1.5](#) presents the ratio cut and the normalized cut. These two objective functions, with several similar variants, are those that occur the most within unconstrained graph partitioning problems. In some cases, and to some extent, we can consider, for unconstrained graph partitioning, that the constraint on the partitioning balance is integrated with the objective function. Thus, unlike the constrained case, most problems omit the constraint on the partitioning balance and only enunciate the objective function to minimize. The constraint on the partition balance will therefore not be included in the definition of unconstrained graph partitioning, but may be added afterward:

DEFINITION 1.28. (UNCONSTRAINED GRAPH PARTITIONING)— *Let $G = (V, E)$ be a graph and k a number of parts. Let S be the solution space, defined by the general graph partitioning problem. The set S_a of admissible solutions of the problem is defined by:*

$$S_a = \{P_i \in S \text{ such that } |P_i| = k\}$$

The problem of constrained graph partitioning consists of finding a partition $\bar{x} \in S_a$ that minimizes the cost function f (as the normalized cut or the ratio cut):

$$[1.22] \quad f(\bar{x}) = \min_{x \in S_a} f(x)$$

As the set of admissible solutions in the constrained case is much smaller than in the unconstrained case, finding a partition that satisfies the latter is easier. In constraint case, an algorithm that deviates from the required balance will struggle to find a partition that verifies it afterward. It is therefore

difficult to start a search outside the admissible solution space in order to get back to it. Thus, it may seem easier to find a good solution with a smooth balance than a strong one. However, this is not the case. Indeed, if it is easier to find an admissible solution in the unconstrained case, this is because the admissible solution space is bigger. This does not mean that the admissible solution space is easier to explore, and that it is easier to seek a good solution. Besides, a local minimum in the constrained case is not necessarily close to a local minimum in the unconstrained case.

To a certain extent and when a maximal balance is imposed, unconstrained graph partitioning can be considered as a multiobjective optimization problem that consists of minimizing one of the objective functions of [section 1.5](#) and minimizing the balance of the partition [RUM 02, GIL 06, SEL 03, SEL 06]. To overcome the shortcomings of the classic objective functions and to integrate other partial conflicting objectives, other chapters have considered the graph partitioning problem as a multiobjective problem [SCH 99].

[1.8. Differences between constrained and unconstrained partitioning](#)

In the previous sections, we have presented the two main graph partitioning optimization problem categories: the constrained graph partitioning problem and the unconstrained graph partitioning problem. However, although these two problems have a similar formulation, algorithms used to solve them are generally quite different, if not in their principles then in their implementations and purposes. In fact, at the risk of oversimplifying, these two problems primarily differ in their priorities:

- the first purpose of the **constrained graph partitioning** problem is to find a partition with parts of identical weights. Its second purpose is to reduce the cut of the partition;
- the **unconstrained graph partitioning** problem aims to maximize the cut inside parts while minimizing the cut between parts. The principle adopted is to avoid extremely different parts sizes except in the case of an extremely low cut between parts. Thus, the first purpose of unconstrained graph partitioning is to minimize the cut, and a second, but not obligatory purpose, is to balance the parts.

If we take an efficient algorithm designed for one of these two problems and then we use it to solve the other problem, then we are very likely to get poor results. Indeed, reversing the order of priorities between these two problems leads to poor results [BIC 06, BIC 07].

To the best of our knowledge, we deplore the absence of chapters in the literature, which address and exhaustively compares these two problems. However, unconstrained graph partitioning problems are numerous and efforts have been made by Inderjit S. Dhillon to synthesize them [DHI 04, DHI 07].

1.9. From bisection to k -partitioning: the recursive bisection method

Many graph partitioning algorithms only focus on the case of graph bisection [RON 05, MAR 06, MAR 06, CHA 07]. In this section we will present two ways of creating k -partitions from a graph bisection algorithm. The method used will depend on the characteristics of the bisection algorithm.

When it is possible to precisely adjust the partitioning balance, the recursive bisection technique can adapt a bisection algorithm to k -partitioning. However, when it is not possible to adjust the partitioning balance, the recursive bisection technique can only create 2^l -partitions (with l an integer) where the partitions with the number of parts are a power of 2.

We draw the reader's attention to the fact that, despite all the interest in being able to adapt bisection methods to k -partitioning, it was shown that the recursive bisection method could not explore, and therefore find, some solutions to the k -partitioning problem [SIM 97]. These solutions can only be found using direct k -partitioning methods, hence their interest. However, in practice recursive bisection methods are generally at least as efficient as the direct k -partitioning methods.

Initially we will study the case of a recursive bisection algorithm that can create 2^l -partitions from an ordinary bisection algorithm. Secondly, we will study the case of a bisection algorithm that can create a bisection that is strongly unbalanced, which means that both parts have significantly different weights. We will see that this bisection algorithm can be used recursively to create a k -partition.

1.9.1. *Creating a partition with a number of parts a power of 2, from a graph bisection algorithm*

In this section, we present a simple and efficient algorithm that allows us to create a 2^l -partition (with l an integer), from an ordinary bisection algorithm. In practice, only strongly balanced bisection algorithms are used within this algorithm, those allowing a configurable partition balance rather than the algorithm presented in the next section.

[Algorithm 1.1](#) describes the method of adapting a *bisection* algorithm named *bisection* to 2^l -partitioning. It uses the recursive function *Iterate* that takes as parameters the part V' of the graph to be partitioned, the number of parts k' into which we will partition V' , and the rank num of the first part of the partition of V' in the final partition P_k .

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