



HAL
open science

Dense and Sparse Graph Partition

Julien Darlay, Nadia Brauner, Julien Moncel

► **To cite this version:**

Julien Darlay, Nadia Brauner, Julien Moncel. Dense and Sparse Graph Partition. *Discrete Applied Mathematics*, 2012, 160 (16 - 17), pp.2389-2396. hal-00454999

HAL Id: hal-00454999

<https://hal.science/hal-00454999>

Submitted on 9 Feb 2010

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Dense & Sparse Graph Partition

Julien Darlay

Nadia Brauner

Julien Moncel

January 26, 2010

Abstract

In a graph $G = (V, E)$, the density is the ratio between the number of edges $|E|$ and the number of vertices $|V|$. This criterion may be used to find communities in a graph: groups of highly connected vertices. We propose an optimization problem based on this criterion, the idea is to find the vertex partition that maximizes the sum of the densities of each class. We prove that this problem is NP-hard by giving a reduction from graph- k -colorability. Additionally, we give a polynomial time algorithm for the special case of trees.

1 Introduction

Let $G = (V, E)$ be a simple connected undirected graph; the density of G is given by $d(G) = \frac{|E|}{|V|}$. Let $X \subseteq V$ and $E(X) = \{\{u, v\} \in E, u \in X, v \in X\}$. The subgraph induced by X is $G[X] = (X, E(X))$ and the complement graph \bar{G} is the graph on V with the edge set $\bar{E} = V * V \setminus E$. Let Π be the set of all the partitions of V with no empty class. The *density* (in the definition of Goldberg [1]) of a partition $P \in \Pi$ is given by:

$$d(P) = \sum_{X \in P} d(G[X]) = \sum_{X \in P} \frac{|E(X)|}{|X|}$$

One can note that this definition is different from the definition of Szemerédi [2], where the density is the ratio $\frac{2|E(X)|}{|X|(|X|-1)}$. The *sparsity* of a partition $P \in \Pi$ is given by:

$$F(P) = \frac{|P|}{2} + d(P)$$

Notice that maximizing the density of a partition P in a graph G is equivalent to minimizing the sparsity in the complement graph \bar{G} . The proof is presented in the next section.

The usual optimization problem associated with the density, is to find a subset of vertices that maximizes it. This problem is solved in polynomial time using flow techniques [1] or linear programming [3]. When the number of vertices in the subgraph is part of the input, the problem becomes NP-hard [4].

The sparsity is a less classical objective function. When the number of classes is fixed $|P| = k$, the problem of minimizing F is equivalent to the minimization of the famous k -means criterion (see for instance [5, 6]). In this case the number of edges in a class is replaced by the sum of their weight in the definition of the density. This problem is shown to be NP-hard when the edges are weighted by the n dimensional Euclidean distance [7, 8].

In this paper we show that maximizing the density of a graph is equivalent to minimizing the sparsity of the complement graph. We also derive some results about the NP-hardness (Theorem 1) and the non-approximability (Theorem 2) of these problems. We finally give a polynomial time algorithm for the maximization of the density on a tree (Theorem 3).

The density can be used as a fitness function in the area of community detection. Many empirical problems can be modelled as networks that divide naturally into communities, for instance proteins interactions, social interactions... [9, 10, 11]. Intuitively, a community is a set of nodes

that are highly connected and only have a few links with nodes from the outside. Finding such groups provides help in understanding and visualizing the structure of the network. The general problem of community detection is widely studied and various models have been proposed [12, 13, 14].

We faced this problem of community detection while analysing data for clinical research in medicine. We used the Logical Analysis of Data [15] method where a large set of patterns is generated, a pattern being the characteristics of patients having similar properties for the studied pathology. Our objective was to group patterns representing almost the same sets of patients in order to decrease the size of the problem. This is modeled as community detection in a graph where each vertex is a pattern and an edge connects two vertices corresponding to similar patterns.

The paper is structured as follows: Section 2 describes notations and gives some properties on the density and the sparsity. Section 3 discusses the hardness and the non-approximability of minimizing the sparsity. Section 4 gives a polynomial time algorithm on trees.

2 Preliminaries

For the sake of clarity we recall some notions of graph theory and matching theory. All the definitions and theorems can be found in [2]. A *path* is a non-empty graph $P = (V, E)$ of the form $V = \{x_0, x_1, \dots, x_n\}$ and $E = \{x_0x_1, x_1x_2, \dots, x_{n-1}x_n\}$. Let us denote by P_n a path containing n edges. A *star* is a tree where at most one vertex has degree greater than 1. A *matching* in an undirected simple graph is a set of pairwise distinct edges. A vertex is *covered* by a matching if it is incident to one edge of the matching. A matching M is called a *perfect matching* if all vertices are covered by M . A *vertex cover* in G is a set $S \subseteq V$ such that every edge of G is incident to at least one vertex in S . A path $P = (V, E)$ in a graph G is an *alternating path* with respect to a matching M if $E \setminus M$ is a matching. An alternating path is an *augmenting path* if its endpoints are not covered by M . We give two classical theorems in matching theory (proofs omitted):

Theorem (König). *Let G be a bipartite graph. Then the maximum cardinality of a matching in G is equal to the minimum cardinality of a vertex cover.*

Theorem (Berge). *Let G be a graph with a matching M . Then M is maximum if and only if there is no augmenting path.*

Let us define formally the decision problems we consider in the rest of the paper.

DENSE GRAPH PARTITION

Instance: An undirected graph $G = (V, E)$ and a positive rational D

Question: Is there a partition $P \in \Pi$ such that $d(P) \geq D$?

SPARSE GRAPH PARTITION

Instance: An undirected graph $G = (V, E)$ and a positive rational D

Question: Is there a partition $P \in \Pi$ such that $F(P) \leq D$?

GRAPH-K-COLORABILITY

Instance: An undirected graph $G = (V, E)$

Question: Is there a partition $P \in \Pi$ such that $|P| = k$ and for all $X \in P$, $G[X]$ is a stable set?

We also consider the optimization versions of these problems which will be prefixed by MIN or MAX. For instance:

MIN SPARSE GRAPH PARTITION

Instance: An undirected graph $G = (V, E)$

Solution: A partition $P^* \in \Pi$ such that $F(P^*) \leq F(P)$, $\forall P \in \Pi$.

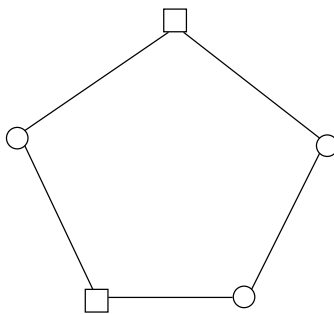


Figure 1: A partition of the cycle on 5 vertices with sparsity less than $\frac{3}{2}$. The vertex classes are represented by circles and squares

A first observation shows that maximizing the density is equivalent to minimizing the sparsity using a simple transformation on the instance.

Property 1. *The optimization problem MAX DENSE GRAPH PARTITION of a graph G is equivalent to MIN SPARSE GRAPH PARTITION on \overline{G} the complement graph of G .*

Proof. Let $\overline{E}(X)$ be the set of edges of the complement graph induced by the set of vertices X . One can rewrite the density of P in G using the set of edges of \overline{G} .

$$\begin{aligned} d(P) &= \sum_{X \in P} \frac{|E(X)|}{|X|} = \sum_{X \in P} \frac{\frac{|X|(|X|-1)}{2} - |\overline{E}(X)|}{|X|} = \sum_{X \in P} \frac{|X|-1}{2} - \frac{|\overline{E}(X)|}{|X|} \\ &= \frac{n}{2} - \frac{|P|}{2} - \sum_{X \in P} d(\overline{G}[X]) \end{aligned}$$

Thus $d_G(P) = \frac{n}{2} - F_{\overline{G}}(P)$ with $F_{\overline{G}}(P)$ being the sparsity of the complement graph G . \square

Since the two problems are equivalent we focus on minimizing the sparsity of a graph G . Every colouring of G is a feasible solution and thus we obtain the following upper bound:

Property 2. *Let $\chi(G)$ denote the chromatic number of a graph G and P^* a partition of V that minimizes F . Then we have the following inequality:*

$$F(P^*) \leq \frac{\chi(G)}{2}$$

Proof. Let P be the partition associated with a $\chi(G)$ -colouring of G where each color is a class of P . Since each class of P is a stable set, its density is equal to 0 and $F(P) = \frac{\chi(G)}{2}$. Since $F(P^*) \leq F(P)$ the inequality holds. \square

Notice that the bound is not always tight. For instance in the cycle on 5 vertices the optimal colouring uses 3 classes but there exists a partition of V of cardinality 2 with $F(P) = 1 + \frac{1}{3} < \frac{3}{2}$ (see Figure 1).

3 NP-hardness and non-approximability

We show that the problem SPARSE GRAPH PARTITION is NP-complete by giving a reduction from GRAPH-K-COLORABILITY. The decision problem GRAPH-K-COLORABILITY is known to be NP-complete (see for instance [16]). Since SPARSE GRAPH PARTITION and DENSE GRAPH PARTITION are equivalent by Property 1, it implies that DENSE GRAPH PARTITION is also NP-complete. We first describe a graph transformation and a useful property for the reduction.

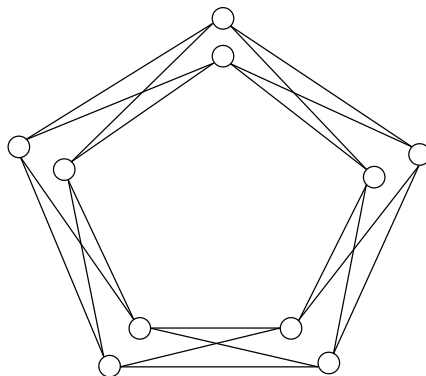


Figure 2: The graph C_5^2

Let G be a simple undirected graph, we define G^q the graph constructed from G where each vertex v is replaced by a stable set of cardinality q : $\{v^1 v^2 \dots v^q\}$. Each edge (i, j) of G is replaced by the complete bipartite subgraph: $(\{i^1 \dots i^q\}, \{j^1 \dots j^q\})$; for instance the graph C_5 of Figure 1 is transformed into the graph C_5^2 in Figure 2. This transformation intends to increase the density without changing the chromatic number.

Lemma 1. *Let $\chi(G)$ and $\chi(G^q)$ be the chromatic numbers of G and G^q . Then $\chi(G) = \chi(G^q)$.*

Proof. The inequality $\chi(G^q) \leq \chi(G)$ is trivial since any colouring of G gives a colouring for G^q . Suppose now that $\chi(G^q) < \chi(G)$ then by keeping one vertex in each $(v^1 \dots v^q)$ we obtain a colouring of G with less than $\chi(G)$ colors, which is a contradiction. Thus $\chi(G^q) \geq \chi(G)$ and hence $\chi(G) = \chi(G^q)$. \square

Now we show a reduction from GRAPH-K-COLORABILITY to SPARSE GRAPH PARTITION that uses the previous transformation.

Theorem 1. *The SPARSE GRAPH PARTITION problem is NP-complete.*

Proof. It is easy to see that SPARSE GRAPH PARTITION is in NP since there exists a non deterministic algorithm that can guess a partition $P \in \Pi$ and verify that $F(P) \leq D$ in polynomial time.

Let us consider an instance G of GRAPH-K-COLORABILITY. If G has less than k vertices then we are done. Else we transform G into an instance of SPARSE GRAPH PARTITION in polynomial time as follows.

Given a graph G on n vertices, we build the graph G^q with $q = n^4$. We claim that there exists a k -colouring of G if and only if there exists a partition P of G^q such that $F(P) \leq \frac{k}{2}$.

Clearly, from a k -colouring of G one can derive a k -colouring of G^q . Hence from Property 2 there exists a partition P of the vertices of G^q with $F(P) \leq \frac{k}{2}$.

Conversely, suppose that we have a partition P of G^q such that $F(P) \leq \frac{k}{2} \leq \frac{n}{2}$, this implies $|P| \leq k$. Consider an edge (i, j) of G and the sets of vertices $I = \{i^1, \dots, i^q\}$ and $J = \{j^1, \dots, j^q\}$ of G^q . By the pigeonhole principle there exists a class C_I of P containing more than $\frac{q}{k} \geq \frac{q}{n} = n^3$ vertices from I . Let S_I be the set of vertices of I in C_I . Using the same argument, there exists a class C_J containing more than n^3 vertices from J . If $C_I = C_J$ then $d(C_I) = \frac{|E(C_I)|}{|V(C_I)|} \geq \frac{|E(C_I)|}{|V(G^q)|} \geq \frac{n^3 \cdot n^3}{n^4} \geq n \geq k > \frac{k}{2}$ and $F(P) \geq d(C_I) > \frac{k}{2}$ which is a contradiction. Thus for each edge (i, j) of G , the sets S_I and S_J belong to different classes of P . One can construct a proper colouring with k colors of G using the partition P of G^q and the set S_U for each vertex u . \square

Using slight modifications on the previous proof, we have the following theorem on the approximability of MIN SPARSE GRAPH PARTITION:

Theorem 2. *There is no polynomial-time r -approximation algorithm to MIN SPARSE GRAPH PARTITION problem for some constant r unless $P = NP$.*

Proof. Assume that a polynomial time algorithm can find a partition P such that $F(P) \leq rF(P^*)$. Using the same proof as Theorem 1 with $q = rn^4$ one can obtain a r -approximation of $\chi(G)$ for every graph G using the r -approximation algorithm on G^q . Consider an edge (i, j) of G and assume that the classes C_I and C_J are the same in P . Then $F(P) \geq d(C_I) \geq rn > r\frac{\chi(G^q)}{2} \geq rF(P^*)$ which is a contradiction. Then S_I and S_J belong to different classes of P and one can construct a proper colouring of G using $|P| \leq r\chi(G)$ colors. This reduction preserves approximation and since MIN GRAPH COLOURING does not belong to APX [17], MIN SPARSE GRAPH PARTITION is not in APX either. \square

4 The polynomial case of trees

We give a polynomial time algorithm for the maximization of the density but first we derive some properties:

Property 3. *Let T be a tree such that $|V| > 1$ then we have:*

$$d(T) = \frac{m}{n} = \frac{n-1}{n} = 1 - \frac{1}{n}$$

From this equality we can derive an upper bound on the density of any tree T : $d(T) < 1$ and a lower bound $d(T) \geq \frac{1}{2}$.

The following lemmas describe the structure of an optimal dense partition. They show that each class of P^* is a star.

Lemma 2. *Let G be a connected graph and P^* an optimal dense partition. Then for any class X of P^* , the graph $G[X]$ is connected.*

Proof. If $G[X]$ is not connected in a partition P , one can construct a new partition P' by replacing X by a new class for each connected component X_1, \dots, X_k of $G[X]$. The new partition is better than P :

$$d(P') - d(P) = \left(\sum_{i=1}^k \frac{|E(X_i)|}{|X_i|} \right) - \left(\frac{\sum_{i=1}^k |E(X_i)|}{\sum_{i=1}^k |X_i|} \right) \geq 0$$

since $\forall a_i \geq 0, b_i > 0$ we have $\sum_i \left(\frac{a_i}{b_i} \right) \geq \frac{\sum_i a_i}{\sum_i b_i}$. \square

Lemma 3. *Let T be a tree and P^* an optimal partition. Then no class of P^* contains only an isolated vertex.*

Proof. Suppose there exists $C \in P^*$ such that $C = \{u\}$ with $u \in V$. Since T is connected, there exist v such that $\{u, v\}$ is an edge. Suppose that $v \in C'$ and let $C'' = C' \cup C$. Since C' is connected C'' is also connected. Then one has $d(C'') - d(C') - d(C) = \frac{|C'|}{|C'+1|} - \frac{|C'|-1}{|C'|} > 0$ and P^* is not optimal. \square

Lemma 4. *Let T be a tree and P^* an optimal partition. Then for any class X of P^* , the graph $G[X]$ does not contain a path of length 3.*

Proof. Suppose there exists $X \in P^*$ such that $\{u, r, s, t\} \subseteq X$ and (u, r, s, t) is a P_3 . By removing the edge (r, s) we create two connected components X' and X'' . Since $G[X]$, $G[X']$ and $G[X'']$ are trees we have the following inequalities $d(X) < 1$ and $d(X') + d(X'') \geq \frac{1}{2} + \frac{1}{2}$ and P^* is not optimal. \square

As a corollary, we get:

Corollary 1. *Let T be a tree and P^* an optimal partition. Then for each X a class of P , $G[X]$ is a star.*

The following properties give upper bounds on the density of a bipartite graph and on a densest partition.

Property 4. *Let $G = (V_1 \cup V_2, E)$ be a bipartite graph. Then $d(G) \leq \frac{n}{4}$.*

Proof. We derive an upper bound on the density in the case of bipartite graphs:

$$d(G) = \frac{m}{n_1 + n_2} \leq \frac{n_1 n_2}{n_1 + n_2} \leq \frac{n_1 + n_2}{4}$$

The first inequality is trivial and the second one comes from:

$$(n_1 + n_2)^2 - 4n_1 n_2 = (n_1 - n_2)^2 \geq 0$$

□

Since every subgraph of a bipartite graph is bipartite, one can derive an upper bound for the density of the partition. For each class X of P^* , we have $d(X) \leq \frac{|X|}{4}$ and since P^* is a partition of the vertex set we have the following:

Property 5. *If $G = (V_1 \cup V_2, E)$ is a bipartite graph, then the following inequality holds:*

$$d(P^*) = \sum_{X \in P^*} d(X) \leq \sum_{X \in P^*} \frac{|X|}{4} = \frac{n}{4}$$

Notice that the bound is tight if G admits a perfect matching. It shows a link between the classes of P^* and a perfect matching of a bipartite graph. In the case of trees the link is stronger as stated in the next lemma.

Lemma 5. *Let M^* be a maximum cardinality matching of T and P^* an optimal dense partition. Then $|M^*| = |P^*|$.*

Proof. The inequality $|M^*| \geq |P^*|$ comes from Corollary 1. Indeed one can construct a matching M by choosing an edge in each class of P^* . Now we show that M is a maximum matching. By way of contradiction, if not, then by Berge Theorem there exists an augmenting path. Let C be a minimum (in the number of edges) augmenting path and u, v its extremities.

We show that u and v cannot be in the same class. If $C \neq (u, v)$, then C has a length greater than 3 and u and v belong to different classes according to Lemma 4. If $C = (u, v)$ since u and v are not covered by the matching then they belong to different classes otherwise it contradicts Corollary 1. Furthermore, their classes contain at least 3 vertices, otherwise u and v would be covered by the matching. Let X_u (resp. X_v) be the class of u (resp. v) and let $x \in X_u$ (resp. $y \in X_v$) be the closest vertex to v (resp. u) on C (note that x could be u and y could be v). Since x and y belong to different classes then $x \neq y$. Let C_{xy} be the subpath of C from x to y . We denote by a (resp. b) the neighbour of u (resp. v) on C .

Since C is minimum every vertex of $C \setminus \{a, b\}$ has a degree at most two in the subgraph induced by its class. Indeed u (resp. v) is not saturated by the matching and since X_u (resp. X_v) is a star, the degree of u (resp. v) in X_u (resp. X_v) is one. If the degree of at least one of the remaining vertices is greater than two then there exists a smaller augmenting path which is in contradiction with the minimality of C .

Let M' be the matching obtained from M by exchanging the edges on the augmenting path. Now we create a new partition P' from P^* by removing x from X_u and y from X_v . Each edge of C that is not in M forms a new class of P' . Notice that the neighbours of a (resp. b) which were in X_a (resp. X_b) and that do not belong to C are in the new class of a (resp. b).

Since (u, a) and (v, b) are in M' and since $u \neq v$, we have $a \neq b$ and X'_a the class of a in P' is different from X'_b the class of b in P' . Thus all classes of the partition P' are stars.

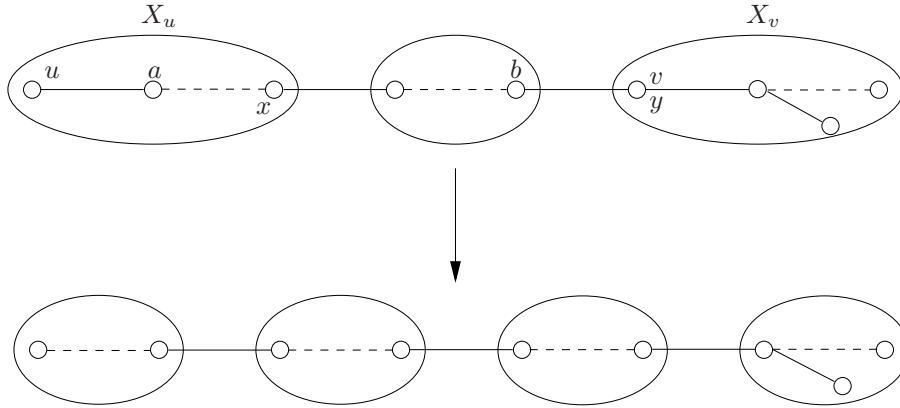


Figure 3: Example of an augmenting chain and a partition transformation on a tree with 5 edges in C and $|X_u| = 3$, $|X_v| = 4$, $v = y$ and $u \neq x$. Each class of P is represented by circled vertices, the edges of M are represented by dashed lines.

During this process, X_u and X_v lose one vertex and a new class is created. Thus $\Delta = d(P') - d(P^*) = \frac{1}{2} - \frac{1}{|X_u|(|X_u|-1)} - \frac{1}{|X_v|(|X_v|-1)}$ with $|X_u|$ and $|X_v|$ greater or equal to 3. Thus $\Delta > 0$ and P^* is not optimal. \square

Using some classical results in graph theory we have the following corollary:

Corollary 2. *Let T^* be a minimum vertex cover and P^* an optimal dense partition. Then each class of P^* contains exactly one vertex of T^* .*

Proof. From Corollary 1 we know that each class of P^* is a non trivial star. Thus each class of P^* contains at least a vertex of T^* . Since from Lemma 5 and König's theorem we have

$$|P^*| = |M^*| = |T^*|$$

then each class of P^* contains exactly one vertex of T^* . \square

Let T be a rooted tree in u and let T_i be the subtree induced by i a child of u and its descendants. Let F'_i be the forest induced by the vertices of $T_i \setminus \{i\}$, see Figure 4. The basic idea is to construct the densest partition of T by a recursive construction using the densest partition of T_i and F'_i . This algorithm gives the following theorem.

Theorem 3. *The problem MAX DENSE GRAPH PARTITION is polynomial on trees.*

Proof. Let T^* be a minimum vertex cover on T and $W \subseteq V$ be the set of the children of u . Remark that the computation of T^* is polynomial on trees.

Suppose that $u \in T^*$, then u has two types of children: $W' = W \setminus T^*$ and $W \cap T^*$. By Corollary 2, u and another vertex of T^* cannot be in the same class in an optimal partition of T . For the children of u that are in T^* we use the optimal partition of their subtrees.

Thus we only consider the children of u that are in W' and that are not isolated (isolated vertices have to be in the class of u). Let Δ_i be the difference between the value of the optimal partition of T_i and the value of the optimal partition of F'_i . It is clear that $\Delta_i > 0$. We create an order on W' defined by $i \prec j$ if $\Delta_i < \Delta_j$. Let X_u be the class containing u in P^* an optimal dense partition of T . If $j \in X_u$ then $\forall i \in W'$ such that $i \prec j$ we have $i \in X_u$, otherwise by exchanging i and j in X_u one can create a new partition P' of T and $d(P') - d(P^*) = \Delta_j - \Delta_i > 0$ and P^* is not optimal. The class X_u can be constructed by adding each $i \in W'$ using the order \prec until $d(X_u \cup \{j\}) - d(X_u) < \Delta_j$. The optimal partition of T is obtained by the class X_u , the optimal

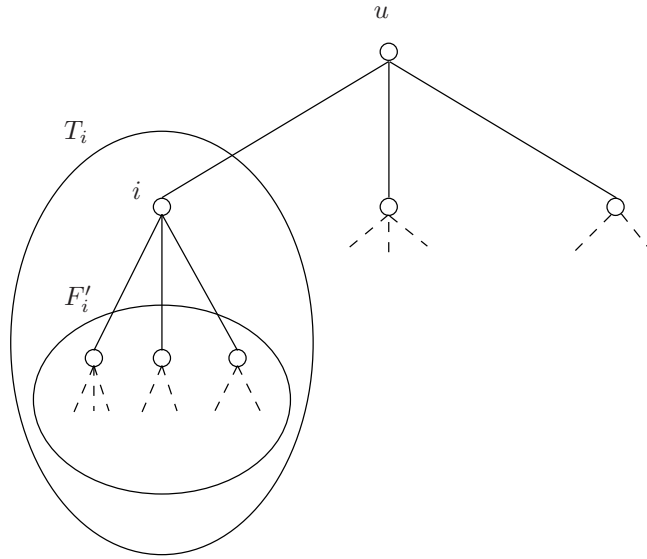


Figure 4: A rooted tree in u with a child i , a subtree T_i and the forest F'_i .

partition of F'_i for each $i \in X_u \setminus \{u\}$ and the optimal partition of T_j for each j a child of u that is not in X_u .

Now suppose that $u \notin T^*$ then all the children of u are in T^* . By Corollary 2, u must be in the class of one of its children. For each i a child of u , consider the tree T_i^u consisting of T_i , the vertex u and an edge between u and i . Using the same argument as in the previous paragraph one can obtain its densest partition. The densest partition of T is obtained by adding u to the class of its child that leads to the densest partition and by taking the densest partition of the tree T_i for all the other children i of u .

Finally, one can obtain the optimal partition of F'_u with the optimal partition of each T_i . By applying this procedure from the leaves to the root, one can obtain the densest partition of a rooted tree T . \square

5 Conclusion

In this paper we presented some hardness results on maximizing the density of a vertex partition. We showed that this problem is equivalent to minimize the sparsity of a vertex partition. Theorem 1 states that these two problems are NP-hard and Theorem 2 gives a non-approximability result. Due to the strong link with the MIN GRAPH COLOURING problem in the reduction, it should be interesting to study MIN SPARSE GRAPH PARTITION on special classes of graph for which the graph colouring problem is easy. In Section 4, we give a polynomial time algorithm for MAX DENSE GRAPH PARTITION on trees. The next step would be the extension of these results to bipartite graphs. From a more practical point of view some empirical tests could be done to study the behavior of the density in the context of community detection.

References

- [1] A. V. Goldberg. Finding a maximum density subgraph. Technical Report UCB/CSD-84-171, EECS Department, University of California, Berkeley, 1984.
- [2] R Diestel. *Graph Theory*, volume 173 of *Graduate Texts in Mathematics*. Springer-Verlag, Heidelberg, third edition, 2005.

- [3] M. Charikar. Greedy approximation algorithms for finding dense components in a graph. In *APPROX*, pages 84–95, 2000.
- [4] U. Feige, G. Kortsarz, and D. Peleg. The dense k-subgraph problem. *Algorithmica*, 29:2001, 1999.
- [5] I. H. Witten and E. Frank. *Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations (The Morgan Kaufmann Series in Data Management Systems)*. Morgan Kaufmann, 1st edition, October 1999.
- [6] M. Brusco and S. Stahl. *Branch-and-Bound Applications in Combinatorial Data Analysis*. Springer, 2005.
- [7] S. Dasgupta. The hardness of k-means clustering. Technical report, University of California, 2008.
- [8] D. Aloise, A. Deshpande, P. Hansen, and P. Popat. NP-hardness of euclidean sum-of-squares clustering. *Machine Learning*, 75(2):245–248, 2009.
- [9] N. Gulbahce and S. Lehmann. The art of community detection. *BioEssays*, 30:934–938, 2008.
- [10] A. Clauset, C. Moore, and M. Newman. Hierarchical structure and the prediction of missing links in networks. *Nature*, 453:98–101, 2008.
- [11] J. P. Scott. *Social Network Analysis: A Handbook*. SAGE Publications, January 2000.
- [12] M. E. J. Newman and M. Girvan. Finding and evaluating community structure in networks. *Phys. Rev. E*, 69, 2004.
- [13] J. Síma and S. E. Schaeffer. On the NP-completeness of some graph cluster measures. In Springer Berlin / Heidelberg, editor, *SOFSEM 2006: Theory and Practice of Computer Science*, volume 3831 of *Lecture notes in computer science*, pages 530–537, 2006.
- [14] U. Brandes. A faster algorithm for betweenness centrality. *Journal of Mathematical Sociology*, 25:163–177, 2001.
- [15] E. Boros, P. L. Hammer, T. Ibaraki, A. Kogan, E. Mayoraz, and I. Muchnik. An implementation of logical analysis of data. *IEEE Transactions on Knowledge and Data Engineering*, 12(2):292–306, 2000.
- [16] M. Garey and D. Johnson. *Computers and Intractability: A Guide to the Theory of NP-Completeness*. W. H. Freeman and Co., New York, 1979.
- [17] G. Ausiello, M. Protasi, A. Marchetti-Spaccamela, G. Gambosi, P. Crescenzi, and V. Kann. *Complexity and Approximation: Combinatorial Optimization Problems and Their Approximability Properties*. Springer-Verlag New York, Inc., Secaucus, NJ, USA, 1999.