# Clustering with Local Restrictions

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#### Abstract

We study a family of graph clustering problems where each cluster has to satisfy a certain local requirement. Formally, let  $\mu$  be a function on the subsets of vertices of a graph G. In the  $(\mu, p, q)$ -Partition problem, the task is to find a partition of the vertices into clusters where each cluster C satisfies the requirements that (1) at most q edges leave C and (2)  $\mu(C) \leq p$ . Our first result shows that if  $\mu$  is an arbitrary polynomial-time computable monotone function, then  $(\mu, p, q)$ -Partition can be solved in time  $n^{O(q)}$ , i.e., it is polynomial-time solvable for every fixed q. We study in detail three concrete functions  $\mu$  (the number of vertices in the cluster, number of nonedges in the cluster, maximum number of non-neighbors a vertex has in the cluster), which correspond to natural clustering problems. For these functions, we show that  $(\mu, p, q)$ -Partition can be solved in time  $2^{O(p)} \cdot n^{O(1)}$  and in time  $2^{O(q)} \cdot n^{O(1)}$  on n-vertex graphs, i.e., the problem is fixed-parameter tractable parameterized by p or by q.

## 1 Introduction

Partitioning objects into clusters or similarity classes is an important task in various applications such as data mining, facility location, interpreting experimental data, VLSI design, parallel computing, and many more. The partition has to satisfy certain constraints: typically, we want to ensure that objects in a cluster are "close" or "similar" to each other and/or objects in different clusters are "far" or "dissimilar." Additionally, we may want to partition the data into a certain prescribed number k of clusters, or we may have upper/lower bounds on the size of the clusters. Different objectives and different distance/similarity measures give rise to specific combinatorial problems.

Correlation clustering [1, 4, 21, 22] deals with a specific form of similarity measure: for each pair of objects, we know that either they are similar or dissimilar. This means that the similarity information can be expressed as an undirected graph, where the vertices represent the objects and similar objects are adjacent. In the ideal situation every connected component of the graph is a clique, in which case the components form a clustering that completely agrees with the similarity information. However, due to inconsistencies in the data or experimental errors, such a perfect partitioning might not always be possible. The goal in correlation clustering is to partition the vertices into an arbitrary number of clusters in a way that agrees with the similarity information as much as possible: we want to minimize the number of pairs for which the clustering disagrees with the input data (i.e., similar pairs that are put into different clusters, or dissimilar pairs that are clustered together).

In many cases, such as in variants of the correlation clustering problem defined in the previous paragraph, the objective is to minimize the total error of the solution. Thus the goal is to find a solution that is good in a global sense, but this does not rule out the possibility that the solution contains clusters that are very bad. In this paper, the opposite approach is taken:

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we want to find a partition where each cluster is "good" in a certain local sense. This means that the partition has to satisfy a set of local constraints on each cluster, but we do not try to optimize the total fitness of clusters.

The setting in this paper is the following. We want to partition the input n-vertex, m-edge graph into an arbitrary number of clusters such that (1) at most q edges leave each cluster, and (2) each cluster induces a graph that is "cluster-like." Defining what we mean by the abstract notion of cluster-like gives rise to a family of concrete problems. Formally, let  $\mu$  be a function that assigns a nonnegative integer to each subset of vertices in the graph and let us require  $\mu(X) \leq p$  for every cluster X of the partition. There are many reasonable choices for the measure  $\mu$  that correspond to natural problems. In particular, in this paper we will obtain concrete results for the following three measures:

- nonedge(X) is the number of nonedges induced by X,
- nondeg(X) is the maximum degree of the *complement* of the graph induced by X (i.e., each vertex of X is adjacent to all but at most nondeg(X) other vertices in X), and
- size(X) = |X| is the number of vertices of X.

The first two functions express that each cluster should induce a graph that is close to being a clique. Specifically, a vertex set S such that  $\mathsf{nonedge}(S) \leq p$  is called a p-defective clique, while a vertex set S such that  $\mathsf{nondeg}(S) \leq p$  is called a p-plex. These generalizations of cliques have been studied in the context of clustering [13, 14, 25], as well as in other contexts [3]. The third function only requires that each cluster is small. While this is not really a natural requirement for a clustering problem, partitioning graphs into small vertex sets such that each has few outgoing edges has applications in Field Programmable Data Array design [17] and hence is of independent interest. For a given function  $\mu$  and integers p and q, we denote by  $(\mu, p, q)$ -Partition the problem of partitioning the vertices into clusters such that at most q edges leave each cluster and  $\mu(X) \leq p$  for every cluster. Note that by solving this problem, we can also solve the optimization version where the goal is to minimize q subject to a fixed p (or the other way around).

Our first result is very simple yet powerful. Let  $\mu$  be a function satisfying the mild technical conditions that it is polynomial-time computable and monotone (i.e., if  $X \subseteq Y$ , then  $\mu(X) \le \mu(Y)$ ). Observe that for example all three functions defined above satisfy these conditions. Our first result shows that for every function  $\mu$  satisfying these conditions and every fixed integer q, the problem  $(\mu, p, q)$ -Partition can be solved in polynomial time (the value p is considered to be part of the input). For example, it can be decided in polynomial time if there is a clustering where at most 13 edges leave each cluster and each cluster induces at most 27 nonedges (or even the more general question, where the maximum number p of nonedges is given in the input). This might be surprising: we believe that most people would guess that this problem is NP-hard. The algorithm is based on a simple application of uncrossing of posimodular functions and on the fact that for fixed q we can enumerate every (connected) cluster with at most q outgoing edges. The crucial observation is that if every vertex can be covered by a good cluster, then the vertices can be partitioned into good clusters. Thus the problem boils down to checking for each vertex v if it is contained in a suitable cluster.

While the algorithm is simple in hind sight, considerable efforts have been spent on solving some very particular special cases. For example, Heggernes et al. [15] gave a polynomial-time algorithm for (nonedge, 1, 3)-Partition and Langston and Plaut [17] argued that the very deep results of Robertson and Seymour on graph minors and immersions imply that (size, p, q)-Partition is polynomial-time solvable for every fixed p and q. These results follow as straightforward corollaries from our first result.

Although this simple algorithm is polynomial for every fixed q, the running time on is about  $n^{\Theta(q)}$ , thus it is not efficient even for small values of q. We do not hope for polynomial

time algorithms for the general case, since both the (nonedge, p,q)-Partition and (size, p,q)-Partition problems are known to be NP-complete when both p and q are part of the input [15, 11]. Hence, to improve the running time, we consider the problem from the viewpoint of parameterized complexity. We show that for several natural measures  $\mu$ , including the three defined above, the clustering problem can be solved in time  $2^{O(q)} \cdot n^{O(1)}$ , that is, the problem is fixed-parameter tractable (FPT) parameterized by the bound q on the number of edges leaving a cluster. Moreover, the bound p can be assumed to be part of the input. Thus this algorithm can be efficient for small values of q (say,  $O(\log n)$ ) even if p is large. The problem (size, p,q)-Partition appears in the open problem list of the 1999 monograph of Downey and Fellows [9] under the name "Minimum Degree Partition," where it is suggested that the problem is probably W[1]-hard parameterized by q. Our result answers this question by showing that the problem is FPT, contrary to the expectation of Downey and Fellows.

A crucial ingredient of our parameterized algorithm is the notion of important separators, which has been used (implicitly or explicitly) to obtain fixed-parameter tractability results for various cut- or separator-related problems. In particular, we use the "randomized selection of important sets" argument that was introduced very recently in [19] to prove the fixed-parameter tractability of (edge and vertex) multicut. With these tools at hand, we can reduce  $(\mu, p, q)$ -Partition to a special case that we call the "Satellite Problem." We show that if the Satellite Problem is fixed-parameter tractable parameterized by q for a particular function  $\mu$ , then  $(\mu, p, q)$ -Partition is also fixed-parameter tractable parameterized by q. It seems that for many reasonable functions  $\mu$ , the Satellite Problem can be solved by dynamic programming techniques. In particular, this is true for the three functions defined above, and this results in algorithms with running time  $2^{O(q)} \cdot n^{O(1)}$ . Note that the reduction to the Satellite Problem works for every monotone  $\mu$ , and we need arguments specific to a particular  $\mu$  only in the algorithms for Satellite Problem.

We also investigate  $(\mu, p, q)$ -Partition parameterized by p and show that for  $\mu = \text{size}$ , nonedge, and nondeg, the problem is FPT parameterized by p: it can be solved in time  $2^{O(p)} \cdot n^{O(1)}$  (this time the value q is part of the input). For these results, we use a combination of color coding and dynamic programming. Interestingly, these algorithms rely on the assumption that there are no parallel edges in the graph (in contrast to parameterization by q, where our algorithms work the same even if parallel edges are allowed). In fact, if parallel edges are allowed, then in the case  $\mu = \text{nonedge}$  or nondeg, the problem is NP-hard even for p = 0, while for  $\mu = \text{size}$ , it is W[1]-hard parameterized by p (i.e., unlikely to be FPT).

Previous work on fixed-parameter tractability of clustering problems focused mostly on parameterization by the total error. In problems such as CLUSTER EDITING and CLUSTER VERTEX DELETION, the task is to modify the graph into a disjoint union of cliques by at most k edge deletions or additions [10, 12, 16]. Generalizations of the problem have been considered in [13, 14, 25], where the graph has to modified in such a way that every component is "clique-like" defined by measures similar to the ones in the current paper. It is not possible to directly compare these results with our results as we explore a different objective: instead of bounding the total number of operations required to turn the graph into clusters, we have a bound on the number of operations that can affect a each cluster. However, in general, we can say that FPT results are more interesting for parameters that are typically smaller. Intuitively, the number of editing operations affecting a single cluster is much smaller than the total number of operations, thus FPT algorithms for problems parameterized by local bounds on the clusters can be considered more interesting than FPT algorithms for problems parameterized by the total number of operations.

# 2 Clustering and uncrossing

Given an undirected graph G, we denote by  $\Delta(X)$  the set of edges between X and  $V(G) \setminus X$ , and define  $d(X) = |\Delta(X)|$ . We will use two well-known and easily checkable properties of the function d: for  $X, Y \subseteq V(G)$ , d satisfies the *submodular* inequality

$$d(X) + d(Y) \ge d(X \cap Y) + d(Y \cup X)$$

and the *posimodular* inequality

$$d(X) + d(Y) \ge d(X \setminus Y) + d(Y \setminus X).$$

Let  $\mu: 2^{V(G)} \to \mathbb{Z}^+$  be a function assigning nonnegative integers to sets of vertices of G. Let p and q be two integers. We say that a set  $C \subseteq V(G)$  is a  $(\mu, p, q)$ -cluster if  $\mu(C) \leq p$  and  $d(C) \leq q$ . A  $(\mu, p, q)$ -partition of G is a partition of V(G) into  $(\mu, p, q)$ -clusters. The main problem considered in this paper is finding such a partition. A necessary condition for the existence of  $(\mu, p, q)$ -partition is that for every vertex  $v \in V(G)$  there exists a  $(\mu, p, q)$ -cluster that contains v. Therefore, we are also interested in the problem of finding a cluster that contains a particular vertex.

 $(\mu, p, q)$ -Partition

Input: A graph G, integers p, q. Find: A  $(\mu, p, q)$ -partition of G.  $(\mu, p, q)$ -CLUSTER

Input: Graph G, integers p, q, vertex v. Find: A  $(\mu, p, q)$ -cluster C containing v.

The main observation of this section is that if  $\mu$  is monotone (i.e.,  $\mu(X) \leq \mu(Y)$  for every  $X \subseteq Y$ ), then every vertex v being in some cluster is actually a sufficient condition. Therefore, in these cases, it is sufficient to solve  $(\mu, p, q)$ -CLUSTER.

**Lemma 1.** Let G be a graph, let  $p,q \geq 0$  be two integers, and let  $\mu: 2^{V(G)} \to \mathbb{Z}^+$  be a monotone function. If every  $v \in V(G)$  is contained in some  $(\mu, p, q)$ -cluster, then G has a  $(\mu, p, q)$ -partition. Furthermore, given a set of  $(\mu, p, q)$ -clusters  $C_1, \ldots, C_n$  whose union is V(G), a  $(\mu, p, q)$ -partition can be found in polynomial time.

Proof. Let us consider a collection  $C_1, \ldots, C_n$  of  $(\mu, p, q)$ -clusters whose union is V(G). If the sets are pairwise disjoint, then they form a partition of V(G) and we are done. If  $C_i \subseteq C_j$ , then the union remains V(G) even after throwing away  $C_i$ . Thus we can assume that no set is contained in another. Suppose that  $C_i$  and  $C_j$  intersect. Now either  $d(C_i) \geq d(C_i \setminus C_j)$  or  $d(C_j) \geq d(C_j \setminus C_i)$  must be true: it is not possible that both  $d(C_i) < d(C_i \setminus C_j)$  and  $d(C_j) < d(C_j \setminus C_i)$  hold, as this would violate the posimodularity of d. Suppose that  $d(C_j) \geq d(C_j \setminus C_i)$ . Now the set  $C_j \setminus C_i$  is also a  $(\mu, p, q)$ -cluster: we have  $d(C_j \setminus C_i) \leq d(C_j) \leq q$  by assumption and  $\mu(C_j \setminus C_i) \leq \mu(C_j) \leq p$  from the monotonicity of  $\mu$ . Thus we can replace  $C_j$  by  $C_j \setminus C_i$  in the collection: it will remain true that the union of the clusters is V(G). Similarly, if  $d(C_i) \geq d(C_i \setminus C_j)$ , then we can replace  $C_i$  by  $C_i \setminus C_j$ .

Repeating these steps (throwing away subsets and resolving intersections), we eventually arrive at a pairwise disjoint collection of  $(\mu, p, q)$ -clusters. Each step decreases the number of cluster pairs  $C_i$ ,  $C_j$  that have non-empty intersection. Therefore, this process terminates after a polynomial number of steps.

The proof of Lemma 1 might suggest that we can obtain a partitition by simply taking, for every vertex v, a  $(\mu, p, q)$ -cluster  $C_v$  that is inclusionwise minimal with respect to containing v. However, such clusters can still cross. For example, consider a graph on vertices a, b, c, d where every pair of vertices expect a and d are adjacent. Suppose that  $\mu = \text{size}$ , p = 3, q = 2. Then  $\{a, b, c\}$  is a minimal cluster containing b (as more than two edges are going out of each

of  $\{b\}$ ,  $\{b,c\}$ , and  $\{a,b\}$ ) and  $\{b,c,d\}$  is a minimal cluster containing c. Thus unless we choose the minimal clusters more carefully in a coordinated way, they are not guaranteed to form a partition. In other words, there are two symmetric solutions  $(\{a,b,c\},\{d\})$  and  $(\{a\},\{b,c,d\})$  for the problem, and the clustering algorithm has to break this symmetry somehow.

In light of Lemma 1, it is sufficient to find a  $(\mu, p, q)$ -cluster  $C_v$  for each vertex  $v \in V(G)$ . If there is a vertex v for which there is no such cluster  $C_v$ , then obviously there is no  $(\mu, p, q)$ -partition; if we have such a  $C_v$  for every vertex v, then Lemma 1 gives us a  $(\mu, p, q)$ -partition in polynomial time. For fixed q,  $(\mu, p, q)$ -Cluster can be solved by brute force if  $\mu$  is polynomial-time computable: enumerate every set F of at most q edges and check if the component of  $G \setminus F$  containing v is a  $(\mu, p, q)$ -cluster. If  $C_v$  is a  $(\mu, p, q)$ -cluster containing v, then we find it when  $F = \Delta(C_v)$  is considered by the enumeration procedure.

**Theorem 2.** Let  $\mu$  be a polynomial-time computable monotone function. Then for every fixed q, there is an  $n^{O(q)}m$  time algorithm for  $(\mu, p, q)$ -Partition.

As we have seen, an algorithm for  $(\mu, p, q)$ -Cluster gives us an algorithm for  $(\mu, p, q)$ -Partition. In the rest of the paper, we devise more efficient algorithms for  $(\mu, p, q)$ -Cluster than the  $n^{O(q)}$  time brute force method described above.

## 3 Parameterization by q

The main result of this section is that  $(\mu, p, q)$ -Partition is fixed-parameter tractable parameterized by q for the three functions nonedge, nondeg, and size.

**Theorem 3.** (size, p, q)-Partition, (nonedge, p, q)-Partition, and (nondeg, p, q)-Partition can be solved in time  $2^{O(q)}n^{O(1)}$ .

By Lemma 1, all we need to show is that  $(\mu, p, q)$ -Cluster is fixed-parameter tractable parameterized by q. We introduce a somewhat technical variant of this question, the Satellite Problem, and show that for every monotone function  $\mu$ , if Satellite Problem is FPT, then  $(\mu, p, q)$ -Cluster is FPT as well. Thus we need arguments specific to a particular  $\mu$  only in solving the Satellite Problem.

SATELLITE PROBLEM

Input: A graph G, integers p, q, a vertex  $v \in V(G)$ , a partition  $V_0, V_1, \ldots, V_r$  of V(G) such that  $v \in V_0$  and there is no

edge between  $V_i$  and  $V_j$  for any  $1 \le i < j \le r$ .

Find: A  $(\mu, p, q)$ -cluster C with  $V_0 \subseteq C$  such that for every

 $1 \leq i \leq r$ , either  $C \cap V_i = \emptyset$  or  $V_i \subseteq C$ .

Since the sets  $\{V_i\}$  form a partition of V(G), we have  $r \leq n$ . For every  $V_i$   $(1 \leq i \leq r)$ , we have to decide whether to include or exclude it from the solution C (see Fig. 1). If we exclude  $V_i$  from C, then d(C) increases by the number of edges between  $V_0$  and  $V_i$ . If we include  $V_i$  into C, then  $\mu(C)$  increases accordingly. Thus we need to solve the knapsack-like problem of including sufficiently many  $V_i$  such that  $d(C) \leq q$ , but not including too many to ensure  $\mu(C) \leq p$ . As we shall see in Section 3.4, in many cases this problem can be solved by dynamic programming (and some additional arguments). The important fact that we use is that there are no edges between  $V_i$  and  $V_j$ , thus for many reasonable functions  $\mu$ , the way  $\mu(C)$  increases by including  $V_i$  is fairly independent from whether  $V_j$  is included in C or not.

The reduction to the SATELLITE PROBLEM uses the concept of important separators (Section 3.1) and in particular the technique of "randomly selecting important separators" introduced in [19]. As the reduction can be most conveniently described as a randomized algorithm,

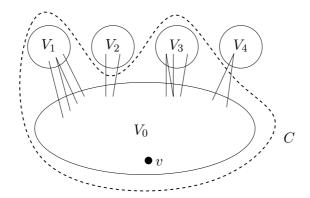


Figure 1: Instance of Satellite Problem with a solution C.

we present it this way in Section 3.2, and then show how it can be derandomized in Section 3.3. In Section 3.4, we show how the SATELLITE PROBLEM can be solved for the three functions nonedge, nondeg and size.

#### 3.1 Important separators

The notion of *important separators* was introduced in [18] to prove the fixed-parameter tractability of multiway cut problems. This notion turned out to be useful in other applications as well [6, 7, 24]. The basic idea is that in many problems where terminals need to be separated in some way, it is sufficient to consider separators that are "as far as possible" from one of the terminals.

Since there are some small differences between edge and vertex separators, and some of the results appear only implicitly in previous papers, we make the paper self-contained by restating all the definitions and by reproving all the required results in this section. Let s,t be two vertices of a graph G. An s-t separator is a set  $S\subseteq E(G)$  of edges separating s and t, i.e., there is no s-t path in  $G\setminus S$ . An s-t separator is inclusionwise minimal if there is an s-t path in  $G\setminus S'$  for every  $S'\subset S$ .

**Definition 4.** Let  $s,t \in V(G)$  be vertices,  $S \subseteq E(G)$  be an s-t separator, and let K be the component of  $G \setminus S$  containing s. We say that S is an important s-t separator if it is inclusionwise minimal and there is no s-t separator S' with  $|S'| \leq |S|$  such that  $K \subset K'$  for the component K' of  $G \setminus S'$  containing s.

Note that an important s-t separator is not necessarily an important t-s separator. Intuitively, we want to minimize the size of the s-t separator and at the same time we want to maximize the set of vertices that remain reachable from s after removing the separator. The important separators are the solutions that are Pareto-optimal with respect to these two objectives. Note that we do not want that the number of vertices reachable from s to be maximal, we just want that this set of vertices is  $inclusionwise\ maximal\ (i.e.,\ we\ have\ K\subset K'$  and  $not\ |K|<|K'|$  in the definition). The main observation of [18] is that the number of important s-t separators of size at most k can be bounded by a function of k.

**Theorem 5.** Let  $s, t \in V(G)$  be two vertices in graph G. For every  $k \geq 0$ , there are at most  $4^k$  important s-t separators of size at most k. Furthermore, these important s-t separators can be enumerated in time  $4^k \cdot n^{O(1)}$ .

The following lemma clearly proves the bound in Theorem 5: if the sum is at most 1, then there cannot be more than  $4^k$  important s-t separators of size at most k. Although this form of the statement is new, the proof follows the same ideas that appear implicitly in [7, 6].

**Lemma 6.** Let  $s, t \in V(G)$ . If S is the set of all important s-t separators, then  $\sum_{S \in S} 4^{-|S|} \le 1$ . Thus S contains at most  $4^k$  s-t separators of size at most k.

*Proof.* Let  $\lambda$  be the size of the smallest s-t separator. We prove by induction on the number of edges of G that  $\sum_{S \in \mathcal{S}} 4^{-|S|} \leq 2^{-\lambda}$ . If  $\lambda = 0$ , then there is a unique important s-t separator of size at most k: the empty set. Thus we can assume that  $\lambda > 0$ .

For an s-t separator S, let  $K_S$  be the component of  $G\setminus S$  containing s (e.g., if S is an inclusionwise minimal s-t separator, then  $S=\Delta(K)$ ). First we show the well-known fact that there is a unique s-t separator  $S^*$  of size  $\lambda$  such that  $K_{S^*}$  is inclusionwise maximal, i.e., there is no other s-t separator S of size  $\lambda$  with  $K_{S^*}\subset K_S$ . Suppose that there are two separators S' and S'' with  $|S'|=|S''|=\lambda$  that are inclusionwise maximal in this sense. By the submodularity of d, we have

$$\underbrace{d(K_{S'})}_{=\lambda} + \underbrace{d(K_{S''})}_{=\lambda} \ge d(K_{S'} \cup K_{S''}) + \underbrace{d(K_{S'} \cap K_{S''})}_{\ge \lambda}.$$

The left hand side is exactly  $2\lambda$ , while the second term of the right hand side is at least  $\lambda$  (as  $\Delta(K_{S'}\cap K_{S''})$  is an s-t-separator). Therefore,  $d(K_{S'}\cup K_{S''})\leq \lambda$ . This means that  $\Delta(K_{S'}\cup K_{S''})$  is also a minimum s-t cut, contradicting the maximality of S' and S''.

Next we show that for every important s-t separator S, we have  $K_{S^*} \subseteq K_S$ . Suppose this is not true for some S. We use submodularity again:

$$\underbrace{d(K_{S^*})}_{=\lambda} + d(K_S) \ge d(K_{S^*} \cup K_S) + \underbrace{d(K_{S^*} \cap K_S)}_{\ge \lambda}.$$

By definition,  $d(K_{S^*}) = \lambda$ , and  $\Delta(K_{S^*} \cap K_S)$  is an s-t separator, hence  $d(K_{S^*} \cap K_S) \geq \lambda$ . This means that  $d(K_{S^*} \cup K_S) \leq d(K_S)$ . However this contradicts the assumption that S is an important s-t separator:  $\Delta(K_{S^*} \cup K_S)$  is an s-t separator not larger than S, but  $K_{S^*} \cup K_S$  is a proper superset of  $K_S$  (as  $K_{S^*}$  is not a subset of  $K_S$  by assumption).

We have shown that for every important separator S, the set  $K_S$  contains  $K_{S^*}$ . Let  $e \in S^*$  be an arbitrary edge of  $S^*$  (note that  $\lambda > 0$ , hence  $S^*$  is not empty) and let v be the endpoint of e not in  $K_{S^*}$ . An important s - t separator S either contains e or not. We will bound the contributions of these two types of separators to the sum.

Let S be an important s-t separator containing e. Then  $S \setminus e$  is an s-t separator in  $G \setminus e$ ; in fact, it is an important s-t separator of  $G \setminus e$ . Therefore, if  $\mathcal{S}'$  is the set of all important s-t separators in  $G \setminus e$ , then the set  $\mathcal{S}_1 = \{S' \cup e \mid S' \in \mathcal{S}'\}$  contains every important s-t separator of G containing e. Obviously, the size  $\lambda'$  of the minimum s-t separator in  $G \setminus e$  is at least  $\lambda-1$ . As  $G \setminus e$  has fewer edges than G, the induction statement shows that  $\sum_{S' \in \mathcal{S}'} 4^{-|S'|} \leq 2^{-\lambda'} \leq 2^{-(\lambda-1)}$  and therefore  $\sum_{S \in \mathcal{S}_1} 4^{-|S|} = \sum_{S' \in \mathcal{S}'} 4^{-|S'|-1} \leq 2^{-(\lambda-1)}/4 = 2^{-\lambda}/2$ .

Let us consider now the important s-t separators not containing e. We have seen that  $K_{S^*} \subseteq K_S$  for every such s-t separator S. As  $e \notin S$ , even  $K_{S^*} \cup \{v\} \subseteq K_S$  is true. Let us obtain the graph G' from G by removing  $(K_{S^*} \cup \{v\}) \setminus \{s\}$  and making s adjacent to the neighborhood of  $K_{S^*} \cup \{v\}$  in G (or equivalently, by contracting  $K_{S^*} \cup \{v\}$  into s). Note that G' has strictly fewer edges than G. There is no s-t separator S of size s in s in s in s would be an s-t separator of size s in s in s in s in s in s is strictly greater than s. Let s contain all the important s in s is an s in s

Note that the proof of Lemma 6 gives a branching procedure for enumerating all the important separators of a certain size. This proves the algorithmic claim in Theorem 5: as each branching step can be performed in polynomial time, the bound on the running time follows from the bound on the number of important separators.

#### 3.2 Reduction to the Satellite Problem

In this section we show how to reduce  $(\mu, p, q)$ -Cluster to the Satellite Problem by a randomized reduction (Lemma 7). Section 3.3 shows that the same result can be obtained by a deterministic algorithm as well (Lemmas 11 and 12). However, the randomized version is conceptually simpler, thus we present it first and then discuss the derandomization in the next section.

**Lemma 7.** If Satellite Problem can be solved in time  $f(q) \cdot n^{O(1)}$  for some monotone  $\mu$ , then there is a randomized  $2^{O(q)} \cdot f(q) \cdot n^{O(1)}$  algorithm with constant error probability that finds  $a(\mu, p, q)$ -cluster containing v (if one exists).

The crucial definition of this section is the following:

**Definition 8.** We say that a set  $X \subseteq V(G)$ ,  $v \notin X$  is important if

- 1.  $d(X) \leq q$ ,
- 2. G[X] is connected,
- 3. there is no  $Y \supset X$ ,  $v \notin Y$  such that  $d(Y) \leq d(X)$  and G[Y] is connected.

It is easy to see that X is an important set if and only if  $\Delta(X)$  is an important u-v separator of size at most q for every  $u \in X$ . Thus we can use Theorem 5 to enumerate every important set, and Lemma 6 to give an upper bound the number of important sets. Lemma 9 establishes the connection between important sets and finding  $(\mu, p, q)$ -clusters: we can assume that the components of  $G \setminus C$  for the solution C are important sets. In Lemma 10, we show that by randomly choosing important sets, with some probability we can obtain an instance of the Satellite Problem where  $V_1, \ldots, V_r$  includes all the components of  $G \setminus C$ . This gives us the reduction stated in Lemma 7 above.

**Lemma 9.** Let C be an inclusionwise minimal  $(\mu, p, q)$ -cluster containing v. Then every component of  $G \setminus C$  is an important set.

Proof. Let X be a component of  $G \setminus C$ . It is clear that X satisfies the first two properties of Definition 8 (note that  $\Delta(X) \subseteq \Delta(C)$ ). Thus let us suppose that there is a  $Y \supset X$ ,  $v \notin Y$  such that  $d(Y) \leq d(X)$  and G[Y] is connected. Let  $C' := C \setminus Y$ . Note that C' is a proper subset of C: every neighbor of X is in C, thus a connected superset of X has to contain at least one vertex of C. It is easy to see that C' is a  $(\mu, p, q)$ -cluster: we have  $\Delta(C') \subseteq (\Delta(C) \setminus \Delta(X)) \cup \Delta(Y)$  and therefore  $d(C') \leq d(C) - d(X) + d(Y) \leq d(C) \leq q$  and  $\mu(C') \leq \mu(C) \leq p$  (by the monotonicity of  $\mu$ ). This contradicts the minimality of C.

**Lemma 10.** Given a graph G, vertex  $v \in V(G)$ , integers p, q, and a monotone function  $\mu: 2^{V(G)} \to \mathbb{Z}^+$ , we can construct in time  $2^{O(q)} \cdot n^{O(1)}$  an instance I of the SATELLITE PROBLEM such that

- If some  $(\mu, p, q)$ -cluster contains v, then I is a yes-instance with probability  $2^{-O(q)}$ ,
- If there is no  $(\mu, p, q)$ -cluster containing v, then I is a no-instance.

*Proof.* For every  $u \in V(G)$ ,  $u \neq v$ , let us use the algorithm of Theorem 5 to enumerate every important u-v separator of size at most q. For every such separator S, let us put the component K of  $G \setminus S$  containing u into the collection  $\mathcal{X}$ . Note that the same component K can be obtained for more than one vertex u, but we put only one copy into  $\mathcal{X}$ .

Let  $\mathcal{X}'$  be a subset of  $\mathcal{X}$ , where each member K of  $\mathcal{X}$  is chosen with probability  $4^{-d(K)}$  independently at random. Let Z be the union of the sets in  $\mathcal{X}'$ , let  $V_1, \ldots, V_r$  be the connected components of G[Z], and let  $V_0 = V(G) \setminus Z$ . It is clear that  $V_0, V_1, \ldots, V_r$  give an instance I of the SATELLITE PROBLEM, and a solution for I gives a  $(\mu, p, q)$ -cluster containing v. Thus we only need to show that if there is a  $(\mu, p, q)$ -cluster C containing v, then I is a yes-instance with probability  $2^{-O(q)}$ .

Let C be an inclusionwise minimal  $(\mu, p, q)$ -cluster containing v. Let S be the set of vertices on the boundary of C, i.e., the vertices of C incident to  $\Delta(C)$ . Let  $K_1, \ldots, K_t$  be the components of  $G \setminus C$ . Note that every edge of  $\Delta(C)$  enters some  $K_i$ , thus  $\sum_{i=1}^t d(K_i) = d(C) \leq q$ . By Lemma 9, every  $K_i$  is an important set, and hence it is in  $\mathcal{X}$ . Consider the following two events:

(E1) Every component  $K_i$  of  $G \setminus C$  is in  $\mathcal{X}'$  (and hence  $K_i \subseteq Z$ ).

(E2) 
$$Z \cap S = \emptyset$$
.

The probability that (E1) holds is  $\prod_{i=1}^t 4^{-d(K_i)} = 4^{-\sum_{i=1}^t d(K_i)} \ge 4^{-q}$ . Event (E2) holds if for every  $w \in S$ , no set  $K \in \mathcal{X}$  with  $w \in K$  is selected into  $\mathcal{X}'$ . It follows directly from the definition of important separators that for every  $K \in \mathcal{X}$  with  $w \in K$ ,  $\Delta(K)$  is an important w - v separator. Thus by Lemma 6,  $\sum_{K \in \mathcal{X}, w \in K} 4^{-|d(K)|} \le 1$ . The probability that  $Z \cap S = \emptyset$  can be bounded by

$$\begin{split} \prod_{K \in \mathcal{X}, K \cap S \neq \emptyset} (1 - 4^{-d(K)}) &\geq \prod_{w \in S} \prod_{K \in \mathcal{X}, w \in K} (1 - 4^{-d(K)}) \geq \prod_{w \in S} \prod_{K \in \mathcal{X}, w \in K} \exp\left(\frac{-4^{-d(K)}}{(1 - 4^{-d(K)})}\right) \\ &\geq \prod_{w \in S} \prod_{K \in \mathcal{X}, w \in K} \exp\left(-\frac{4}{3} \cdot 4^{-d(K)}\right) = \prod_{w \in S} \exp\left(-\frac{4}{3} \cdot \sum_{K \in \mathcal{X}, w \in K} 4^{-d(K)}\right) \geq (e^{-\frac{4}{3}})^{|S|} \geq e^{-4q/3}. \end{split}$$

In the first inequality, we use that every term is less than 1 and every term on the right hand side appears at least once on the left hand side; in the second inequality, we use that  $1+x \ge \exp(x/(1+x))$  for every x > -1. Events (E1) and (E2) are independent: (E1) is a statement about the selection of a subcollection  $A \subseteq \mathcal{X}$  of at most q sets that are disjoint from S, while (E2) is a statement about not selecting any member of a subcollection  $B \subseteq \mathcal{X}$  of at most  $|S| \cdot 4^q$  sets intersecting S. Thus by probability  $2^{-O(q)}$ , both (E1) and (E2) hold.

Suppose that both (E1) and (E2) hold, we show that instance I of the SATELLITE PROBLEM is a yes-instance. In this case, every component  $K_i$  of  $G \setminus C$  is a component  $V_j$  of G[Z]:  $K_i \subseteq Z$  by (E1) and every neighbor of  $K_i$  is outside Z. Thus C is a solution of I, as it can be obtained as the union of  $V_0$  and some components of G[Z].

## 3.3 Derandomization of the Reduction to the Satellite Problem

To derandomize the proof of Lemma 10 and obtain a deterministic version of Lemma 7, we use the standard technique of splitters. A  $(n, k, k^2)$ -splitter is a family of functions from [n] to  $[k^2]$  such that for any subset  $X \subseteq [n]$  with |X| = k, one of the functions in the family is injective on X. Naor, Schulman, and Srinivasan [23] gave an explicit construction of an  $(n, k, k^2)$ -splitter of size  $O(k^6 \log k \log n)$ .

First we present a simpler version of the derandomization (Lemma 11), where the dependence on q is  $2^{O(q^2)}$  (instead of the  $2^{O(q)}$  dependence of the randomized algorithm). The derandomization is along the same lines as the analogous proof in [19]. Then we improve the dependence to  $2^{O(q)}$  by a somewhat more complicated scheme and analysis (Lemma 12).

**Lemma 11.** If Satellite Problem can be solved in time  $f(q) \cdot n^{O(1)}$  for some monotone  $\mu$ , then there is a  $2^{O(q^2)} \cdot f(q) \cdot n^{O(1)}$  algorithm for  $(\mu, p, q)$ -Cluster.

Proof. In the algorithm of Lemma 10, a random subset of a universe  $\mathcal{X}$  of size  $s = |\mathcal{X}| \leq 4^q \cdot n$  is selected. If the  $(\mu, p, q)$ -Cluster problem has a solution C, then there is a collection  $A \subseteq \mathcal{X}$  of at most a = q sets and a collection  $B \subseteq \mathcal{X}$  of at most  $b = q \cdot 4^q$  sets such that if every set in A is selected and no set in B is selected, then (E1) and (E2) hold. Instead of selecting a random subset, we try every function f in an  $(s, a + b, (a + b)^2)$ -splitter family and every subset  $F \subseteq [(a + b)^2]$  of size a (there are  $\binom{(a+b)^2}{a} = 2^{O(q^2)}$ ) such sets F). For a particular choice of f and F, we select those sets  $S \in \mathcal{X}$  into  $\mathcal{X}'$  for which  $f(S) \in F$ . The size of the splitter family is  $2^{O(q)} \log n$  and the number of possibilities for F is  $2^{O(q^2)}$ . Therefore, we construct  $2^{O(q^2)} \cdot \log n$  instances of the SATELLITE PROBLEM.

By the definition of the splitter, there will be a function f that is injective on  $A \cup B$ , and there is a subset F such that  $f(S) \in F$  for every set S in A and  $f(S) \notin F$  for every set S in B. For such an f and F, the selection will ensure that (E1) and (E2) hold. This means that the constructed instance of the SATELLITE PROBLEM corresponding to f and F has a solution as well. Thus solving every constructed instance of the SATELLITE PROBLEM with the assumed  $f(q) \cdot n^{O(1)}$  time algorithm gives a  $2^{O(q^2)} \cdot f(q) \cdot n^{O(1)}$  algorithm for  $(\mu, p, q)$ -CLUSTER.

The key modification that we need in order to improve the dependence on q is to do the selection of sets with different boundary sizes separately, and use a separate splitter for each boundary size. This modification makes the analysis of the running time much more complicated.

**Lemma 12.** If Satellite Problem can be solved in time  $f(q) \cdot n^{O(1)}$  for some monotone  $\mu$ , then there is a  $2^{O(q)} \cdot f(q) \cdot n^{O(1)}$  algorithm for  $(\mu, p, q)$ -Cluster.

Proof. Let the universe  $\mathcal{X}$ , the fixed solution C, and the collections A and B be as in the proof of Lemma 11. Let  $\mathcal{X}_i = \{K \in \mathcal{X} \mid d(K) = i\}$  and let  $a_i = |\mathcal{X}_i \cap A|$ , i.e., the number of sets  $K \in A$  that have i edges on its boundary. Observe that  $a_i = 0$  for i > q and  $\sum_{i=1}^q a_i \cdot i = d(C) \le q$ . In the first step of the algorithm, we guess the values  $a_1, \ldots, a_q$  that correspond to the fixed hypothetical solution C. The number of possibilities for these values can be bounded by  $2^{O(q)}$  (this is already true if we have only the weaker requirement  $\sum_{i=1}^q a_i \le q$ ). Therefore, the algorithm branches into  $2^{O(q)}$  directions and this guess introduces only a factor of  $2^{O(q)}$  into the running time. From now on, we assume that we have the correct values of  $a_i = |\mathcal{X}_i \cap A|$  corresponding to C. We do not know the size of  $\mathcal{X}_i \cap B$ , but  $b_i = q \cdot 4^i$  is an upper bound on  $|\mathcal{X}_i \cap B|$ : the set C has at most q boundary vertices, and each vertex is contained in at most  $4^i$  sets of  $\mathcal{X}$  (see the proof of Theorem 10).

We perform the selection separately for each  $\mathcal{X}_i$  for which  $a_i \neq 0$  (if  $a_i = 0$ , then it is safe not to select any member of  $\mathcal{X}_i$ ). For a particular  $\mathcal{X}_i$ , we proceed similarly to the simplified proof of Lemma 11. That is, for every  $1 \leq i \leq q$ , we construct an  $(|\mathcal{X}_i|, a_i + b_i, (a_i + b_i)^2)$ -splitter family  $\mathcal{F}_i$  and try every choice of a function  $f_i \in \mathcal{F}_i$  and a subset  $F_i \subseteq [(a_i + b_i)^2]$  of size  $a_i$ . For a given choice of  $f_1, \ldots, f_q$  and  $F_1, \ldots, F_q$ , we select a set  $K \in \mathcal{X}_i$  if and only if  $f_i(K) \in \mathcal{F}_i$ . As in the previous proof, it is clear that at least one choice of the  $f_i$ 's and  $F_i$ 's leads to the selection of every member of A without selecting any member of B.

To bound the running time of the algorithm, we need to bound the total number of possibilities for  $f_i$ 's and  $F_i$ 's. The family  $\mathcal{F}_i$  has size  $(a_i + b_i)^{O(1)} \log n$  and the number of possibilities for  $F_i$  is  $\binom{a_i + b_i}{a_i}$ . Therefore, we need to show that

$$\prod_{\substack{1 \le i \le q \\ a_i \ne 0}} (a_i + b_i)^{O(1)} \cdot \log n \cdot \binom{a_i + b_i}{a_i}$$
 (1)

can be bounded by  $2^{O(q)} \cdot n^{O(1)}$ .

We bound the product of the three factors in (1) separately. Note that it follows from  $\sum_{i=1}^{q} a_i \cdot i \leq q$  that  $a_i$  can be nonzero for at most  $O(\sqrt{q})$  values of i. Therefore, the product of the first factor in (1) can be bounded by

$$a_i = 1$$
  $a_i \cdot i \leq q$  that  $a_i$  can be nonzero for at most  $O(\sqrt{q})$  values of  $i$ . Therefore, the product  $a_i$  defirst factor in (1) can be bounded by 
$$\prod_{\substack{1 \leq i \leq q \\ a_i \neq 0}} (a_i + b_i)^{O(1)} \leq \prod_{\substack{1 \leq i \leq q \\ a_i \neq 0}} (2a_ib_i)^{O(1)} \leq \prod_{\substack{1 \leq i \leq q \\ a_i \neq 0}} (2 \cdot 2^{a_i} \cdot q \cdot 4^i)^{O(1)}$$

$$\leq 2^{O(\sqrt{q})} \cdot q^{O(\sqrt{q})} \cdot \prod_{1 \leq i \leq q} (2^{a_i \cdot i} \cdot 4^{a_i \cdot i}) \leq 2^{O(q)}$$
In the last inequality, we used  $\sum_{i=1}^q a_i \cdot i \leq q$ . To bound the product of the second factor in (1)

(in the last inequality, we used  $\sum_{i=1}^{q} a_i \cdot i \leq q$ ). To bound the product of the second factor in (1), we consider two cases. If  $\log n \leq 2^{\sqrt{q}}$ , then

$$\prod_{\substack{1 \leq i \leq q \\ a_i \neq 0}} \log n \leq \log^{O(\sqrt{q})} n \leq 2^{O(q)}.$$

Otherwise, if  $\log n > 2^{\sqrt{q}}$ , then  $\sqrt{q} < \log \log n$ , and hence  $\log^{O(\sqrt{q})} n = 2^{O(\sqrt{q} \cdot \log \log n)} < 1$  $2^{O((\log \log n)^2)} = O(n).$ 

Finally, let us bound the products of the last factor in (1). Note that  $a_i \leq q \leq b_i$ . Therefore, we have

$$\begin{split} \prod_{\substack{1 \leq i \leq q \\ a_i \neq 0}} \binom{a_i + b_i}{a_i} &\leq \prod_{\substack{1 \leq i \leq q \\ a_i \neq 0}} \binom{2b_i}{a_i} \leq \prod_{\substack{1 \leq i \leq q \\ a_i \neq 0}} \left(\frac{2eb_i}{a_i}\right)^{a_i} = \\ \prod_{\substack{1 \leq i \leq q \\ a_i \neq 0}} \left(2e \cdot 4^i \cdot \frac{q}{a_i}\right)^{a_i} &= 2^{O(q)} \cdot 4^{\sum_{i=1}^q a_i \cdot i} \cdot \prod_{\substack{1 \leq i \leq q \\ a_i \neq 0}} (q/a_i)^{a_i} = 2^{O(q)} \cdot \prod_{\substack{1 \leq i \leq q \\ a_i \neq 0}} (q/a_i)^{a_i}. \end{split}$$

Thus we need to bound only  $\prod_{i=1}^{q} (q/a_i)^{a_i}$ . For notational convenience, let  $x_i = q/a_i$  whenever  $a_i \neq 0$ . We bound separately the product of terms with  $x_i \leq e^i$  and  $x_i > e^i$ . In the first case,

$$\prod_{\substack{1 \le i \le q \\ x_i \le e^i}} (q/a_i)^{a_i} = \prod_{\substack{1 \le i \le q \\ x_i \le e^i}} x_i^{a_i} \le \prod_{\substack{1 \le i \le q \\ x_i \le e^i}} e^{a_i \cdot i} \le \exp\left(\sum_{i=1}^q a_i \cdot i\right) = 2^{O(q)}.$$

We use the fact that the function  $x^{1/x}$  is monotonically decreasing for  $x \geq e$ . Therefore, if  $x_i > e^i$ , then

$$\prod_{\substack{1 \le i \le q \\ x_i > e^i}} (q/a_i)^{a_i} = \prod_{\substack{1 \le i \le q \\ x_i > e^i}} \left( x_i^{1/x_i} \right)^q < \prod_{\substack{1 \le i \le q \\ x_i > e^i}} \left( (e^i)^{1/e^i} \right)^q \le \exp\left( q \cdot \sum_{i=1}^q i/e^i \right) = 2^{O(q)}.$$

#### 3.4 Solving the Satellite Problem

In this section, we give efficient algorithms for solving the SATELLITE PROBLEM when the function  $\mu$  is size, nonedge and nondeg. We describe the three algorithms by increasing difficulty. In the case when  $\mu$  is size, solving the Satellite Problem turns out to be equivalent to the classical KNAPSACK problem with polynomial bounds on the values and weights of the items.

Recall that the input to the SATELLITE PROBLEM is a graph G, integers p, q, a vertex  $v \in V(G)$ , a partition  $V_0, V_1, \ldots, V_r$  of V(G) such that  $v \in V_0$  and there is no edge between  $V_i$  and  $V_j$  for any  $1 \le i < j \le r$ . The task is to find a vertex set C, such that  $C = V_0 \cup \bigcup_{i \in S} V_i$  for a subset S of  $\{1, \ldots, r\}$  and C satisfies  $d(C) \le q$  and  $\mu(C) \le p$ . For a subset S of  $\{1, \ldots, r\}$  we define  $C(S) = V_0 \cup \bigcup_{i \in S} V_i$ .

**Lemma 13.** The Satellite Problem for size can be solved in  $O(qn \log n)$  time.

Proof. Notice that  $d(C(S)) = d(V_0) - \sum_{i \in S} d(V_i)$ . Hence, we can reformulate the SATELLITE PROBLEM with  $\mu = \text{size}$  as finding a subset S of  $\{1, \ldots, r\}$  such that  $\sum_{i \in S} d(V_i) \geq d(V_0) - q$  and  $\sum_{i \in S} |V_i| \leq p - |V_0|$ . Thus, we can associate with every i an item with value  $d(V_i)$  and weight  $|V_i|$ . The objective is to find a set of items with total value at least  $d(V_0) - q$  and total weight at most  $p - |V_0|$ . This problem is known as KNAPSACK and can be solved in  $O(rv \log w)$  time by a classical dynamic programming [5, 8] algorithm, where r is the number of items, v is the value we seek to attain and w is the weight limit. Since the number r of items is at most n, the value is bounded from above by q and the weight by n, the statement of the lemma follows.  $\square$ 

The case that  $\mu = \text{nonedge}$  is slightly more complicated, however we can still solve it using a polynomial-time dynamic programming algorithm.

**Lemma 14.** The Satellite Problem for nonedge can be solved in  $O(pn^2m)$  time.

*Proof.* Consider the set C(S) for a subset S of  $\{1, \ldots, i-1\}$ . We investigate what happens to  $\operatorname{nonedge}(C(S))$  and d(C(S)) when i is inserted into S. For  $\operatorname{nonedge}$  we have the following equation.

$$\operatorname{nonedge}(C(S \cup \{i\})) = \operatorname{nonedge}(C(S)) + \operatorname{nonedge}(V_i) + |C(S)| \cdot |V_i| - d(V_i)$$
 (2)

Furthermore,  $d(C(S \cup \{i\})) = d(C(S)) - d(V_i)$ . Define  $T[i, j, k, \ell]$  to be true if there is a subset S of  $\{1, \ldots i\}$  such that |C(S)| = j, d(C(S)) = k and  $\mathsf{nonedge}(C(S)) = \ell$ . If such a set S exists, then either  $i \in S$  or  $i \notin S$ . Together with Equation 2 this yields the following recurrence for  $T[i, j, k, \ell]$ .

$$T[i, j, k, \ell] = T[i-1, j, k, \ell] \vee T[i-1, j-|V_i|, k+d(V_i), \ell-\mathsf{nonedge}(V_i) - (j-|V_i|) \cdot |V_i| + d(V_i)] \tag{3}$$

The size of the table T is  $O(pn^2m)$  since  $1 \le i \le r \le n$ ,  $0 \le j \le n$ ,  $0 \le k \le m$ , and  $0 \le \ell \le p$ , as it makes no sense to add more sets to C after the threshold p of non-edges in C has been exceeded. We initialize the table to true in  $T[0, |V_0|, d(V_0), \mathsf{nonedge}(V_0)]$  and false everywhere else. Then we compute the values of the table using Equation 3, treating every time we go out of bounds as a false entry. The algorithm returns true if there is an entry of T which is true for i = r,  $k \le q$  and  $\ell \le p$ . The running time bound is immediate, while correctness follows from Equations 2 and 3.

For the version of SATELLITE PROBLEM when  $\mu = \text{nondeg}$  we do not have a polynomial time algorithm. Instead, we give an algorithm with running time  $(3e)^{q+o(q)}n^{O(1)}$  based on dynamic programming and the color coding technique of Alon et al. [2]. When using color coding, it is common to give a randomized algorithm first, and then derandomize it using appropriate hash functions. In our case, existing hash functions are sufficient to give a deterministic algorithm, and our deterministic algorithm is not conceptually more difficult than the randomized version. Therefore, we only present the deterministic version. For this we will need the following proposition.

**Proposition 15** ([23]). For every n, k there is a family of functions  $\mathcal{F}$  of size  $O(e^k \cdot k^{O(\log k)} \cdot \log n)$  such that every function  $f \in \mathcal{F}$  is a function from  $\{1, \ldots, n\}$  to  $\{1, \ldots, k\}$  and for every subset S of  $\{1, \ldots, n\}$  of size k there is a function  $f \in \mathcal{F}$  that is bijective when restricted to S. Furthermore, given n and k,  $\mathcal{F}$  can be computed in time  $O(e^k \cdot k^{O(\log k)} \cdot \log n)$ .

**Lemma 16.** There is a  $(3e)^{q+o(q)}n^{O(1)}$  time algorithm for nondeg-SATELLITE PROBLEM.

Proof. In Lemma 13, the set S described which sets  $V_i$  went into C. For this lemma, it is more convenient to let S describe the sets  $V_i$  which are not in C. Define  $U = \{1, \ldots, r\}$ , the task is to find a subset S of U such that  $d(C(U \setminus S)) \leq q$  and  $\mathsf{nondeg}(C(U \setminus S)) \leq p$ . We iterate over all possible values  $c \geq |V_0|$  of |C(S)|, and for each value of c we will only look for sets S such that  $|C(U \setminus S)| = c$ . This gives us the following advantage: for every vertex  $v \in V_i$  for  $i \geq 1$  if we choose to put  $V_i$  into C then v will have exactly c - d(v) - 1 non-neighbors in C. Hence for any i such that  $V_i$  contains a vertex v with degree less than c - p - 1 we know that  $i \in S$ . In other words, such a component  $V_i$  should not be in the solution C, hence we can remove  $V_i$  from the graph and decrease q by  $d(V_i)$  (as the edges  $\Delta(V_i) \subseteq \Delta(V_0)$  will leave C in any solution). Therefore, we can assume that every vertex  $v \notin V_0$  has degree at least c - p - 1.

From now on, we only need to worry about  $d(C(U \setminus S)) \leq q$  and about the non-degrees of vertices in  $V_0$ . A vertex  $v \in V_0$  will have exactly  $c - 1 - d(v) + |\Delta(v) \cap \Delta(C(U \setminus S))|$  non-neighbors. In particular, we need to make sure that no vertex  $v \in V_0$  will have more than p + d(v) - c + 1 neighbors outside of  $C(U \setminus S)$ . For every  $v \in V_0$  we define the capacity of v to be  $\operatorname{cap}(v) = p + d(v) - c + 1$ . If any vertex has negative capacity, we discard the choice of c, as it is infeasible.

Every vertex  $v \in V_0$  gets  $\operatorname{cap}(v)$  bins. At this point we construct using Proposition 15 a family  $\mathcal{F}$  of colorings of the bins with colors from  $\{1,\ldots,q\}$  such that for any set X of q bins there is a coloring  $f \in \mathcal{F}$  that colors the bins in X with different colors. The size of  $\mathcal{F}$  is bounded from above by  $O(e^q \cdot q^{O(\log q)} \cdot \log(n)) \leq O(e^{q+o(q)} \log(n))$ . The algorithm has an outer loop in which it goes over all the colorings in  $\mathcal{F}$ . Every vertex v in  $V_0$  is assigned a set of colors, namely all the colors of the bins that belong to v. In the remainder of the proof we will assume that each vertex  $v \in V_0$  has a set of colors attached to it. This set of colors is denoted by  $\operatorname{colors}(v)$ . Since v had  $\operatorname{cap}(v)$  bins assigned to it, we have that  $|\operatorname{colors}(v)| \leq \operatorname{cap}(v)$ .

In each iteration of the outer loop we will search for a special kind a solution: A map  $\gamma$  that colors a set of edges in  $\Delta(V_0)$  with colors from  $\{1,\ldots,q\}$  is called good if the following two conditions are satisfied: (i) all edges that are colored by  $\gamma$  receive different colors, and (ii) if an edge e is colored by  $\gamma$  and is incident to  $v \in V_0$ , then the color of e is one of the colors of v. In other words,  $\gamma(e) \in \operatorname{colors}(v)$ . A subset  $S \subseteq U$  is called  $\operatorname{colorful}$  if the edges in  $\Delta(C(U \setminus S))$  have a good coloring  $\gamma$ . What the algorithm will look for is a colorful set S such that  $|C(U \setminus S)| = c$  and a good coloring  $\gamma$  of  $\Delta(C(U \setminus S))$ . Observe that since there are only q different colors available and each edge of  $\Delta(C(U \setminus S))$  must have a different color, a colorful solution automatically satisfies  $d(C(U \setminus S)) \leq q$ . Furthermore since every vertex  $v \in V_0$  satisfies  $|\operatorname{colors}(v)| \leq \operatorname{cap}(v)$ , any colorful solution satisfies  $\operatorname{nondeg}(C(U \setminus S)) \leq p$ .

Conversely, consider a subset S of U such that  $|C(U \setminus S)| = c$ ,  $d(C(U \setminus S)) \leq q$  and  $\operatorname{nondeg}(C(U \setminus S)) \leq p$ . For each edge  $e \in \Delta(C(U \setminus S))$ , select a bin that belongs to the vertex  $v \in V_0$  which is incident to e. Since each vertex  $v \in V_0$  is incident to at most  $\operatorname{cap}(v)$  edges in  $\Delta(C(U \setminus S))$ , we can select a different bin for each edge  $e \in \Delta(C(U \setminus S))$ . In total at most q bins are selected, and hence there is an iteration of the outer loop where all of these bins are colored with different colors. Let  $\gamma$  be a coloring of the edges in  $\Delta(C(U \setminus S))$  that colors each edge with the color of the bin that the edge is assigned to. By construction,  $\gamma$  is a good coloring of  $\Delta(C(U \setminus S))$  in this iteration of the outer loop, and hence S is colorful.

To complete the proof, we need an algorithm that decides whether there exists a colorful set  $S \subseteq U$  such that  $|C(U \setminus S)| = c$ . For every  $0 \le i \le r$ ,  $0 \le j \le n$  and  $R \subseteq \{1, \ldots, q\}$ , we define T[i, j, R] to be true if there is a subset S of  $\{1, \ldots, i\}$  such that  $|C(U \setminus S)| = j$ , and a good coloring  $\gamma$  of  $\Delta(C(U \setminus S))$  with colors from R. Suppose that such a set S and map  $\gamma$  exists. We have that either  $i \in S$  or  $i \notin S$ . If  $i \notin S$ , then S is a subset of  $\{1, \ldots, i-1\}$  and hence T[i-1,j,R] is true. If on the other hand  $i \in S$ , then let  $S' = S \setminus \{i\}$  and  $R_i$  be the set of colors of edges in  $\Delta(V_i)$ . In this case, we have that  $|C(U \setminus S')| = j + |V_i|$ , and  $\gamma$  colors the

edges of  $\Delta(C(U \setminus S'))$  with colors from  $R \setminus R_i$ , so  $T[i-1, j+|V_i|, R \setminus R_i]$  is true. Define  $\mathcal{R}_i$  to be a family of sets of colors such that  $R^* \in \mathcal{R}_i$  if there exists a good coloring of  $\Delta(V_i)$  with colors from  $R^*$ . Clearly  $R_i \in \mathcal{R}_i$ . This yields the following recurrence for T[i, j, R].

$$T[i, j, R] = T[i - 1, j, R] \vee \bigvee_{\substack{R_i \in \mathcal{R}_i \\ R_i \subseteq R}} T[i - 1, j + |V_i|, R \setminus R_i]$$

$$\tag{4}$$

Using Equation 4 we can find a colorful C in  $3^q n^{O(1)}$  time as follows. We initialize the table to true in T[0, |C(U)|, R] for all  $R \subseteq \{1, \ldots, q\}$ . Then we use Recurrence 4 to fill the table for T[i, j, R]. The algorithm returns true if T[r, c, R] is true for some subset R of  $\{1, \ldots, q\}$ . The running time of the algorithm for finding a colorful set S is upper bounded by the size of the table, which is  $2^q n^2$ , times the time it takes to use Equation 4 to fill a single table entry. To fill a table entry we go through all subsets  $R_i \subset R$  and check whether  $R_i \in \mathcal{R}_i$  in polynomial time by using a maximum matching algorithm. Specifically, we can build a bipartite graph with edges in  $\Delta(V_i)$  on one side and elements of  $R_i$  on the other. In this graph there is an edge between  $e \in \Delta(V_i)$  and a color  $r \in R_i$  if e is incident to a vertex  $v \in V_0$  such that  $r \in \operatorname{colors}(v)$ . Matchings in this graph that match all edges in  $\Delta(V_i)$  to a color correspond exactly to good colorings of  $\Delta(V_i)$  with colors from  $R_i$ . Thus the total running time is bounded by  $O(\sum_{R \subseteq \{1,\ldots,q\}} \sum_{R' \subset R} n^{O(1)}) = O(3^q n^{O(1)})$ . Correctness of the algorithm follows from Equation 4. The total runtime of the algorithm is bounded by  $O(3^q n^{O(1)})$  times the number of iterations of the outer loop, which is  $O(e^{q+o(q)} \log(n))$ . This completes the proof of the lemma.

Lemmata 12, 13, 14 and 16 give Theorem 3.

# 4 Parameterization by p

We prove in Section 4.1 that the  $(\mu, p, q)$ -Partition is fixed-parameter tractable parameterized by p for  $\mu = \text{size}$ , nonedge, or nondeg. Our algorithms work only on simple graphs, i.e, graphs without parallel edges. In fact, as we show in Section 4.2, the problem becomes hard if parallel edges are allowed.

## 4.1 Algorithms

In this section, we give algorithms with running time  $2^{O(p)}n^{O(1)}$ :

**Theorem 17.** There is a  $2^{O(p)}n^{O(1)}$  time algorithm for (size, p,q)-Partition, for (nonedge, p,q)-Partition and for (noneg, p,q)-Partition.

Because of Lemma 1, it is sufficient to solve the corresponding  $(\mu, p, q)$ -Cluster problem within the same time bound. The setting is as follows. We are given a graph G, integers p and q and a vertex v in G. The objective is to find a set C not containing v such that  $d(C \cup \{v\}) \le q$  and, depending on which problem we are solving, either  $|C \cup \{v\}| = \text{size}(C \cup \{v\}) \le p$ , nonedge $(C \cup \{v\}) \le p$  or nondeg $(C \cup \{v\}) \le p$ .

For a set S and vertex v, define  $\Delta(S,v)$  to be the set of edges with one endpoint in S and one in  $\{v\}$ . Define  $\overline{\Delta}(S,v)$  to be  $\Delta(S)\setminus\Delta(S,v)$ , and let  $d(S,v)=|\Delta(S,v)|$  and  $\overline{d}(S,v)=|\overline{\Delta}(S,v)|$ . We will say that a set C is v-minimal if  $v\notin C$  and  $d(C'\cup\{v\})>d(C\cup\{v\})$  for every  $C'\subset C$ . As size,nonedge and nondeg are monotone we can focus on v-minimal sets: if there is a solution for the cluster problem, then there is a solution of the form  $C\cup\{v\}$  for some v-minimal set C. The following fact uses that there are no parallel edges:

**Observation 18.** Let C be a v-minimal set. Then  $\overline{d}(C,v) < d(C,v) \le |C|$ .

In particular, if  $\overline{d}(C,v) \geq d(C,v)$ , then  $d(v) \leq d(C \cup \{v\})$ , contradicting that C is v-minimal. Since  $\overline{d}(C,v) < |C|$ , it follows that C must contain a vertex u such that  $N[u] \subseteq C \cup \{v\}$ . Now we show that there are not too many v-minimal sets C of size at most p such that G[C] is connected.

**Lemma 19.** For any graph G, vertex v and integer p, there are at most  $4^p n$  v-minimal sets C such that  $|C| \leq p$  and G[C] is connected. Furthermore, all such sets can be listed in time  $O(4^p n)$ .

Proof. By Observation 18, any v-minimal set C of size at most p satisfies  $\overline{d}(C,v) < p$ . Let S be a set such that  $|S| \leq p$  and G[S] is connected. Let F be a subset of  $N(S) \setminus \{v\}$  of size at most p-1. We prove by downward induction on |S| and |F| that there are at most  $2^{2p-|S|-|F|-1}v$ -minimal sets such that  $|C| \leq p$ , G[C] is connected,  $S \subseteq C$ , and  $F \cap C = \emptyset$ . If |S| = p then the only possibility for C is S, while  $2^{2p-|S|-|F|-1} \geq 1$ . Similarly, consider the case that |F| = p-1. Now, every vertex of F has at least one edge into C and hence  $F \cup \{v\} \subseteq N(C)$  and  $\overline{d}(C,v) = p-1$ . By Observation 18, we have that  $N(C) = F \cup \{v\}$  and the only possibility for C is the connected component of  $G \setminus (F \cup \{v\})$  that contains S. Hence there is at most one possibility for C and  $2^{2p-|S|-|F|-1} \geq 1$ .

For the inductive step, consider a set S such that  $|S| \leq p$ , and G[S] is connected and a subset F of  $N(S) \setminus \{v\}$  of size at most p-1. We want to bound the number of v-minimal sets such that  $|C| \leq p$  and G[C] is connected,  $S \subseteq C$  and  $F \cap C = \emptyset$ . If  $N(S) \setminus (F \cup \{v\})$  is empty, then there is only one choice for C, namely S, and  $2^{2p-|S|-|F|-1} \geq 1$ . Otherwise, consider a vertex  $u \in N(S) \setminus (F \cup \{v\})$ . By the induction hypothesis, the number of v-minimal sets such that  $|C| \leq p$  and G[C] is connected,  $S \cup \{u\} \subseteq C$  and  $F \cap C = \emptyset$  is at most  $2^{2p-|S|-|F|-2}$ . Similarly, the number of v-minimal sets such that  $|C| \leq p$  and G[C] is connected,  $S \subseteq C$  and  $(F \cup \{u\}) \cap C = \emptyset$  is at most  $2^{2p-|S|-|F|-2}$ . Since either  $u \in C$  or  $u \notin C$ , the two cases cover all possibilities for C and hence there are at most  $2 \cdot 2^{2p-|S|-|F|-2} = 2^{2p-|S|-|F|-1}$  possibilities for C.

For a fixed S and F, the above proof can be translated into a procedure which lists all v-minimal sets such that  $|C| \leq p$  and G[C] is connected,  $S \subseteq C$  and  $F \cap C = \emptyset$ . We run the procedure for  $S = \{u\}$  and  $F = \emptyset$  for every possible choice of u. Hence, there are at most  $4^p n$  v-minimal sets C such that  $|C| \leq p$  and G[C] is connected, and the sets can be efficiently listed.

The following observation is handy for using Lemma 19.

**Observation 20.** Let C be a v-minimal set of G and G[S] be a connected component of G[C]. Then S is a v-minimal set.

In particular, if S is not a v-minimal set, then it contains a v-minimal set  $S' \subset S$  and it is easy to see that  $d(\{v\} \cup (C \setminus S) \cup S') \leq d(\{v\} \cup C)$ , contradicting the minimality of C. Observation 20 tells us that any v-minimal set is the union of connected v-minimal sets. This makes it possible to use Lemma 19. We are now ready to give an algorithm for (size, p,q)-Cluster, the easiest of the three clustering problems. Our algorithm is based on a combination of color coding [2] with dynamic programming.

**Lemma 21.** (size, p, q)-Cluster can be solved in time  $2^{O(p)}n^{O(1)}$ .

*Proof.* We are given as input a graph G together with a vertex v and integers p and q. The task is to find a vertex set C of size at most p-1 such that  $d(\{v\} \cup C) \leq q$ . It is sufficient to search for a v-minimal set C satisfying these properties. The algorithm of Lemma 19 can be used to list all *connected* v-minimal sets  $S_1, \ldots, S_\ell$  of size at most p-1; we have  $\ell \leq 4^p n$ . For a subset Z of  $\{1, \ldots, \ell\}$ , define  $C(Z) = \{v\} \cup \bigcup_{i \in Z} S_i$ . By Observation 20, for any v-minimal set C of

size at most p-1 there exists a  $Z \subseteq \{1, \ldots, \ell\}$  such that  $C(Z) = C \cup \{v\}$ . This set Z satisfies the following properties.

- 1. For every  $i, j \in Z$  with  $i \neq j$ , we have  $S_i \cap S_j = \emptyset$ .
- 2.  $|C(Z)| = 1 + \sum_{i \in Z} |S_i| \le p$ .
- 3.  $d(C(Z)) = d(v) + \sum_{i \in Z} (\overline{d}(S_i, v) d(S_i, v)) \le q$ .

However, for any subset Z of  $\{1,\ldots,\ell\}$  we have  $|C(Z)| \leq 1 + \sum_{i \in Z} |S_i|$ , and for any Z that satisfies property (1), we have

$$d(C(Z)) \le d(v) + \sum_{i \in Z} (\overline{d}(S_i, v) - d(S_i, v)).$$

Hence it is sufficient to search for a set Z such that for every  $i, j \in Z$  with  $i \neq j$ , we have  $S_i \cap S_j = \emptyset$ ,  $1 + \sum_{i \in Z} |S_i| \leq p$  and  $d(v) + \sum_{i \in Z} (\overline{d}(S_i, v) - d(S_i, v)) \leq q$ .

To ensure that the algorithm picks Z such that the sets  $S_i$  and  $S_j$  will be disjoint for every pair of distinct integers  $i, j \in Z$  we will use color coding. In particular, we construct a family  $\mathcal{F}$  of functions from  $V(G) \setminus \{v\}$  to  $\{1, \ldots, p-1\}$  as described in Proposition 15. The family  $\mathcal{F}$  has size  $O(e^p \cdot p^{O(\log p)} \cdot \log n)$ . For each function  $f \in \mathcal{F}$  we will think of the function as a coloring of  $V(G) \setminus \{v\}$  with colors from  $\{1, \ldots, p-1\}$ . We will only look for a v-minimal set C whose vertices have different colors. This will not only ensure that any two sets  $S_i$  and  $S_j$  that we pick will be disjoint, it also automatically ensures that  $1 + \sum_{i \in Z} |S_i| \leq p$ . If the input instance was a yes-instance then a solution set C exists, and the construction of  $\mathcal{F}$  ensures that there will be a function  $f \in \mathcal{F}$  which colors all vertices in C with different colors.

When considering a particular coloring f, we discard all sets from  $S_1, \ldots, S_\ell$  which have two vertices of the same color, so from this point, without loss of generality, all sets in  $S_1, \ldots, S_\ell$  have at most one vertex of each color. For a vertex set S, define  $\operatorname{colors}(S)$  to be the set of colors occuring on vertices on G. For every  $0 \le i \le \ell$ ,  $0 \le j \le m$  and  $R \subseteq \{1, \ldots, p-1\}$ , we define T[i,j,S] to be true if there is a set  $Z \subseteq \{1,\ldots,i\}$  such that all vertices of C(Z) have distinct colors,  $d(v) + \sum_{i \in Z} (\overline{d}(S_i,v) - d(S_i,v)) = j$  and  $\operatorname{colors}(C(Z)) \subseteq R$ . Clearly, there is a v-minimal set C such that  $d(\{v\} \cup C) \le q$  and all vertices of C have different color if and only if  $T[\ell,j,\{1,\ldots,p-1\}]$  is true for some  $j \le q$ . We can fill the table T using the following recurrence.

$$T[i,j,R] = \begin{cases} T[i-1,j,R] & \text{if } \mathsf{colors}(S_i) \setminus R \neq \emptyset \\ T[i-1,j,R] \vee T[i-1,\\ j+d(S_i,v) - \overline{d}(S_i,v), R \setminus \mathsf{colors}(S_i)] & \text{otherwise} \end{cases}$$

Here we initialize  $T[0,d(v),\emptyset]$  to true. The table has size  $4^p n^{O(1)} \cdot 2^p n^{O(1)} = 8^p n^{O(1)}$  and can be filled in time proportional to its size. Hence the total running time for the algorithm is  $(8e)^{p+o(p)} n^{O(1)}$ .

For (size, p, q)-Cluster the size of the set C we look for is already bounded by p. For (nonedge, p, q)-Cluster and (nondeg, p, q)-Cluster, we cannot make this assumption, however the next lemma gives us a way to handle all large v-minimal sets C for (nonedge, p, q)-Cluster and (nondeg, p, q)-Cluster.

**Lemma 22.** For any graph G, vertex v and integer p, there are at most  $O(2^p n)$  v-minimal sets C such that  $\mathsf{nondeg}(C \cup \{v\}) \leq p$  and  $|C| \geq 3p$ . These sets can be listed in time  $2^p n^{O(1)}$ .

*Proof.* By Observation 18, any v-minimal set C contains a vertex u such that  $N[u] \setminus \{v\} \subseteq C$ . Thus, we go over every possibility for u, and we will enumerate all v-minimal sets C of size at

least 3p such that that  $\operatorname{nondeg}(C \cup \{v\}) \leq p$  and  $N[u] \setminus \{v\} \subseteq C$ . Notice that  $|C \setminus N[u]| \leq p$  since every vertex  $w \in C \setminus N[u]$  is a non-neighbor of u. Thus, if  $|C| \geq 3p$  then  $|N[u] \setminus \{v\}| \geq 2p$ . Hence, every vertex in  $C \setminus N[u]$  has at least  $|N[u] \setminus \{v\}| - p \geq p$  edges to  $N[u] \setminus \{v\}$ . Let S be the set of vertices in  $V(G) \setminus (N[u] \cup \{v\})$  which have at most p non-neighbors in  $N[u] \setminus \{v\}$ . If  $|S| \geq p + 3$ , then no v-minimal set C satisfying the constraints and the requirement  $N[u] \setminus \{v\} \subseteq C$  can exist. To see this, suppose for contradiction that such a set C exists, then  $|S \setminus C| \geq 3$ . Since each vertex in  $S \setminus C$  has at most p non-neighbors in  $N[u] \setminus \{v\}$  it follows that

$$\overline{d}(C, v) \ge 3(|N[u] \setminus \{v\}| - p) \ge 3(|C| - 2p) \ge |C|$$

contradicting Observation 18. The second inequality holds since  $|N[u] \setminus \{v\}| \ge |C| - p$  and the third since  $|C| \ge 3p$ . Finally, since  $|S| \le p+3$  and  $C \setminus (N[u] \setminus \{v\}) \subseteq S$  there are at most  $2^{p+3}$  possible sets C for every choice of u. Thus there are at most  $O(2^p n)$  such sets, and they can be enumerated in time  $2^p n^{O(1)}$ .

Since every set C such that  $\operatorname{nonedge}(C) \leq p$  satisfies  $\operatorname{nondeg}(C) \leq p$ , we can use Lemma 22 to find out whether there is a set C such that  $v \notin C$ ,  $d(C \cup \{v\}) \leq q$ ,  $\operatorname{nonedge}(C \cup \{v\}) \leq p$  and  $|C| \geq 3p$  in time  $2^p n^{O(1)}$ . Thus we can concentrate on sets C of size at most 3p for (nonedge, p, q)-Cluster and for (nondeg, p, q)-Cluster. For finding appropriate sets C of size at most 3p for the two problems, we can give algorithms that are almost identical to the algorithm described in Lemma 21. Since the two algorithms are so similar, we describe both in one go.

**Lemma 23.** There is a  $2^{O(p)}n^{O(1)}$  time algorithm for the (nonedge, p,q)-Cluster and the (nondeg, p,q)-Cluster problems.

*Proof.* We are given as input a graph G together with a vertex v and integers p and q. The task is to find a vertex set C such that  $d(\{v\} \cup C) \le q$  and  $\mathsf{nonedge}(\{v\} \cup C) \le p$ , or  $\mathsf{nondeg}(\{v\} \cup C) \le p$ . It is sufficient to search for a v-minimal set C satisfying these properties. Using Lemma 22 we can check whether such a set of size at least 3p exists in time  $2^p n^{O(1)}$ . From now on, we only need to consider sets C of size at most 3p.

By Observation 20, C can be decomposed into  $C = S_1 \cup S_2 \ldots \cup S_t$  such that  $S_i$  is a connected v-minimal set for every  $i, S_i \cap S_j = \emptyset$  for every  $i \neq j$ , and no edge of G has one endpoint in  $S_i$  and the other in  $S_j$  for every  $i \neq j$ . Using Lemma 19 we list all connected v-minimal sets  $S_1, \ldots, S_\ell$  of size at most 3p where  $\ell \leq 4^{3p}n$ . For a set S and vertex v, define nondeg<sub>v</sub>(S) to be the maximum number of non-edges to vertices in S over all vertices in  $S \setminus v$ . For a subset S of  $\{1, \ldots, \ell\}$  define  $S_i \cap S_j = \emptyset$ . We have that  $S_i \cap S_j = \emptyset$  we have that  $S_i \cap S_j = \emptyset$  where  $S_i \cap S_j = \emptyset$  we have that  $S_i \cap S_j = \emptyset$  and that

$$d(C(Z)) \leq d(v) + \sum_{i \in Z} \left(\overline{d}(S_i, v) - d(S_i, v)\right)$$
 
$$\operatorname{nonedge} \left(C(Z)\right) \leq |C(Z)| + \sum_{i \in Z} \left(\operatorname{nonedge}(S_i) - d(S_i, v)\right) + \sum_{i \in Z} \sum_{i < j \in Z} |S_i||S_j| \qquad (5)$$
 
$$\operatorname{nondeg} \left(C(Z)\right) \leq \max \left\{ \sum_{i \in Z} \left(|S_i| - d(S_i, v)\right), \max_{i \in Z} \left(\operatorname{nondeg}_v(S_i \cup \{v\}) + \sum_{j \in Z \setminus \{i\}} |S_j|\right) \right\}$$

If there is no edge with one endpoint in  $S_i$  and the other in  $S_j$  for any  $i \neq j, i \in Z, j \in Z$ , then the inequalities hold with equality. Our algorithm will select a Z such that  $C = \bigcup_{i \in Z} S_i$ . To ensure that the algorithm picks Z such that the sets  $S_i$  and  $S_j$  will be disjoint for every pair of distinct integers  $i, j \in Z$  we will use color coding. In particular, we construct a family  $\mathcal{F}$  of functions from  $V(G) \setminus \{v\}$  to  $\{1, \ldots, 3p\}$  as described in Proposition 15. The family  $\mathcal{F}$  has size  $O(e^{3p} \cdot p^{O(\log p)} \cdot \log n)$ .

For each function  $f \in \mathcal{F}$  we will think of the function as a coloring of  $V(G) \setminus \{v\}$  with colors from  $\{1, \ldots, 3p\}$ . We will only look for a v-minimal set C whose vertices have different colors. This will ensure that any two sets  $S_i$  and  $S_j$  that we pick will be disjoint, and controls the total size of the set picked. If the input instance was a yes-instance, then a solution set C exists, and the construction of  $\mathcal{F}$  ensures that there will be a function  $f \in \mathcal{F}$  which colors all vertices in C with different colors. When considering a particular coloring f, we discard all sets from  $S_1, \ldots S_\ell$  which have two vertices of the same color, so from this point, without loss of generality, all sets in  $S_1, \ldots S_\ell$  have at most one vertex of each color. For a vertex set S, define colors S to be the set of colors occurring on vertices on S.

To solve (nonedge, p,q)-Cluster we define a table  $T_1$ . For every  $0 \le i \le \ell$ ,  $0 \le j \le m$ ,  $0 \le k \le p$  and  $R \subseteq \{1,\ldots,3p\}$  we define  $T_1[i,j,k,S]$  to be true if there is a set  $Z \subseteq \{1,\ldots,i\}$  such that all vertices of C(Z) have distinct colors annot

$$\begin{split} d(v) + \sum_{i \in Z} (d(S_i, v) - \overline{d}(S_i, v)) &\leq j, \\ |R| + \sum_{i \in Z} \left( \mathsf{nonedge}(S_i) - d(S_i, v) \right) + \sum_{i \in Z} \sum_{i < j \in Z} |S_i| |S_j| &\leq k, \\ \mathsf{colors}(C(Z)) &= R. \end{split}$$

For (nondeg, p,q)-Cluster we define a table  $T_2$  in a similar manner. That is, for every  $0 \le i \le \ell$ ,  $0 \le j \le m$ ,  $0 \le k \le p$ ,  $0 \le x \le p$ , and  $R \subseteq \{1, \ldots, 3p\}$  we define  $T_2[i, j, k, x, S]$  to be true if there is a set  $Z \subseteq \{1, \ldots, i\}$  such that all vertices of C(Z) have distinct colors and

$$\begin{split} d(v) + \sum_{i \in Z} (d(S_i, v) - \overline{d}(S_i, v)) &\leq j, \\ \max_{i \in Z} \left( \mathsf{nondeg}_v(S_i \cup \{v\}) + \sum_{j \in Z \setminus \{i\}} |S_j| \right) &\leq k, \\ \sum_{i \in Z} \left( |S_i| - d(S_i, v) \right) &\leq x, \\ \mathsf{colors}(C(Z)) &= R. \end{split}$$

There is a v-minimal set C such that  $d(\{v\} \cup C) \leq q$ , nonedge( $\{v\} \cup C$ )  $\leq p$  and all vertices of C have different color if and only if  $T_1[\ell,j,k,R]$  is true for some  $j \leq q, k \leq p$  and  $R \subseteq \{1,\ldots,3p\}$ . This follows directly from the definition of  $T_1$  and the fact that Equation 5 holds with equality when there is no edge with one endpoint in  $S_i$  and the other in  $S_j$  for some  $i \neq j, i \in Z$ ,  $j \in Z$ . By an identical argument, there is a v-minimal set C such that  $d(\{v\} \cup C) \leq q$ , nondeg( $\{v\} \cup C$ )  $\leq p$ , and all vertices of C have different color if and only if  $T_2[\ell,j,k,x,R]$  is true for some  $j \leq q, k \leq p, x \leq p$  and  $R \subseteq \{1,\ldots,3p\}$ . We can fill the tables  $T_1$  and  $T_2$  using the following recurrences.

$$T_1[i, j, k, R] = \begin{cases} T_1[i-1, j, k, R] & \text{if colors}(S_i) \nsubseteq R \\ T_1[i-1, j, k, R] \lor T_1[i-1, j', k'_1, R'] & \text{otherwise} \end{cases}$$

$$T_2[i,j,k,\ell,R] = \begin{cases} T_2[i-1,j,k,x,R] & \text{if } \mathsf{colors}(S_i) \not\subseteq R \\ T_2[i-1,j,k,x,R] & \text{if } |R| - |S_i| + \mathsf{nondeg}_v(S_i \cup \{v\}) > k \\ T_2[i-1,j,k,x,R] \vee T_2[i-1,j',k'_2,x',R'] & \text{otherwise} \end{cases}$$

where 
$$j' = j - d(S_i, v) + \overline{d}(S_i, v)$$
,  $k'_1 = k - \mathsf{nonedge}(S_i) - |S_i| + d(S_i, v) - |C_i|(|R| - |C_i|)$ ,  $k'_2 = k - |S_i|$ , and  $x' = x - |S_i| + d(S_i, v)$  and  $R' = R \setminus \mathsf{colors}(S_i)$ .

The recurrences above are correct for the following reason. Let Z be a subset of  $Z\subseteq \{1,\ldots,i-1\}$  such that all vertices of C(Z) have distinct colors,  $d(v)+\sum_{i\in Z}d(S_i,v)-\overline{d}(S_i,v)=j$ ,  $|R|+\sum_{i\in Z}\operatorname{nonedge}(S_i,v)-d(S_i,v)+\sum_{i\in Z}\sum_{i< j\in Z}|S_i||S_j|=k$ , and  $\operatorname{colors}(C(Z))=R$ . Since every vertex in C(Z) has a different color, it follows that |C(Z)|=|R|. Inserting i into Z is only possible if  $\operatorname{colors}(C(Z))=R$ . In that case, when we insert i into Z,  $d(v)+\sum_{p\in Z}(d(S_p,v)-\overline{d}(S_p,v))$  increases by  $d(S_i,v)-\overline{d}(S_i,v)$ . The sum  $|R|+\sum_{i\in Z}\operatorname{nonedge}(S_i,v)-d(S_i,v)+\sum_{i\in Z}\sum_{i< j\in Z}|S_i||S_j|$  increases by  $\operatorname{nonedge}(S_i)+|S_i|-d(S_i,v)+|C_i|(|R|-|C_i|)$ . The expression  $\max_{p\in Z}(\operatorname{nondeg}_v(S_p\cup\{v\})+\sum_{j\in Z\setminus\{p\}}|S_j|)$  increases by  $|S_i|$  or to  $\operatorname{nondeg}_v(S_i\cup\{v\})+\sum_{j\in Z}|S_j|$ , whichever yields the largest result. The expression  $\sum_{p\in Z}(|S_p|-d(S_p,v))$  increases by  $|S_i|-d(S_i,v)$ . Finally, the set of colors used, will now be  $R\cup\operatorname{colors}(S_i)$ .

We initialize the tables  $T_1$  and  $T_2$  as follows.  $T_1[0,j,k,\emptyset]$  is set to true for every  $j \geq d(v)$ ,  $k \geq 0$ .  $T_2[0,j,k,x,\emptyset]$  is set to true for every  $j \geq d(v)$ ,  $k \geq 0$ ,  $x \geq 0$ . Then we fill the tables using the recurrences above. The tables have size  $4^{3p}n^{O(1)} \cdot 2^{3p}n^{O(1)} = 8^{3p}n^{O(1)}$  and can be filled in time proportional to their size. Hence the total running time for the algorithms is  $(8e)^{3p+o(p)}n^{O(1)}$ .

Lemma 1 together with Lemma 21 and Lemma 23 yield Theorem 17.

#### 4.2 Hardness results

The algorithmic results in Section 3 still hold when parallel edges are allowed. Interestingly, the results in Section 4.1 do not: in particular, Observation 18 breaks down if there are parallel edges. The following hardness result shows that allowing parallel edges indeed make the problems more difficult:

**Theorem 24.** (nonedge, p, q)-Partition and (nondeg, p, q)-Partition are NP-complete for p = 0 on graphs with parallel edges. The problem (size, p, q)-Partition is W[1]-hard parameterized by p on graphs with parallel edges (but in P for every fixed p).

To prove the Theorem 24, we reduce from the k-CLIQUE problem in d-regular graphs. Here we are given a graph G in which all vertices have degree d, and an integer k. The task is to find a clique C in G of size at least k. This problem is NP-complete and W[1]-complete when parameterized by k (cf. [20]). Given a d-regular graph G with n vertices and m = dn/2 edges and an integer k, we construct a multigraph G' by adding a vertex v incident to all vertices of G with m+1 parallel edges to each vertex of G.

**Lemma 25.** There is a clique C in G if size k if and only if there is a clique C' in G' such that  $v \in C$  and  $d(C) \leq (n-k)(m+1) + k(d-k)$ .

*Proof.* In the forward direction, suppose G contains a clique C of size k. Then  $C' = C \cup \{v\}$  is a clique in G' and the number of edges leaving C' is exactly (n-k)(m+1) + k(d-k) (the first term is the number of edges leaving from v, the second term is the number of edges leaving from the k vertices of C).

In the backward direction, suppose there is a C' in G' such that  $v \in C'$  and  $d(C') \leq (n-k)(m+1)+k(d-k)$ . Then  $C=C'\setminus\{v\}$  is a clique in G. It suffices to argue that  $|C|\geq k$ . Suppose not. Then the number of edges leaving C' is at least (n-k+1)(m+1)>(n-k)(m+1)+k(d-k), a contradiction.

Notice that G' can be partitioned into cliques with at most q=(n-k)(m+1)+k(d-k) edges leaving each clique if and only if there is a clique C' in G' such that  $v\in C'$  and  $d(C')\leq q$ . If such a clique C' exists then there exists such a clique of size k+1. Hence, by Lemma 25, if (nonedge, 0, q)-Partition or (nondeg, 0, q)-Partition can be solved in polynomial time on graphs with parallel edges, then Clique in d-regular graphs can. Similarly, if (size, p, q)-Partition can

be solved in  $f(p)n^c$  time on graphs with parallel edges then CLIQUE in d-regular graphs can be solved in  $f(k+1)n^c$  time. This proves Theorem 24.

Observe that Lemma 1 automatically yields an  $O(n^{p+O(1)}m)$  time algorithm for (size, p, q)-Partition on graphs with parallel edges, and hence the lower bounds of Theorem 24 are tight.

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