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# The $k$ -Sparsest Subgraph Problem<sup>\*</sup>

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**Abstract.** Given a simple undirected graph  $G = (V, E)$  and an integer  $k \leq |V|$ , the  $k$ -SPARSEST SUBGRAPH problem asks for a set of  $k$  vertices that induce the minimum number of edges. As a generalization of the classical INDEPENDENT SET PROBLEM,  $k$ -SPARSEST SUBGRAPH cannot admit (unless  $\mathcal{P} = \mathcal{NP}$ ) neither an approximation nor an FPT algorithm (parameterized by the number of edges in the solution) in all graph classes where INDEPENDENT SET is  $\mathcal{NP}$ -hard. Thus, it appears natural to investigate the approximability and fixed parameterized tractability of  $k$ -SPARSEST SUBGRAPH in graph classes where INDEPENDENT SET is polynomial, such as subclasses of perfect graphs. In this paper, we first present a simple greedy tight 2-approximation algorithm in proper interval graphs, and then we use dynamic programming to design a PTAS in proper interval graph and an FPT algorithm in interval graphs (parameterized by the number of edges in the solution).

## 1 Introduction and related Problems

### 1.1 Introduction

Given a graph  $G = (V, E)$  and  $k \leq |V|$  the  $k$ -SPARSEST SUBGRAPH problem (or the  $k$ -LIGHTEST SUBGRAPH for the weighted version) asks for a set  $S$  of exactly  $k$  vertices that minimizes the number of edges of  $G[S]$ , the subgraph induced by  $S$ . As a generalization of the classical INDEPENDENT SET problem (where the number of edges in the induced subgraph is required to be 0), this problem is  $\mathcal{NP}$ -hard in general graphs. Let us first recall the definition of some related problems, and then discuss their relation to  $k$ -SPARSEST SUBGRAPH.

In the MAXIMUM QUASI-INDEPENDENT SET (QIS) problem [5] (also called  $k$ -EDGE-IN in [10]), we are given a graph  $G$  and an integer  $C$ , and we ask for a set of vertices  $S$  of maximum size such that  $G[S]$  has less than  $C$  edges.

In the MINIMUM PARTIAL VERTEX COVER (PVC) problem [11], we are given a graph  $G$  and an integer  $C$ , and we ask for a set of vertices  $S$  of minimum size which covers at least  $C$  edges (an edge  $\{u, v\}$  is said to be covered by  $S$  if either  $u \in S$  or  $v \in S$ ).

Finally, we can mention the corresponding maximization problem of  $k$ -SPARSEST SUBGRAPH, namely  $k$ -DENSEST SUBGRAPH (or  $k$ -HEAVIEST SUBGRAPH for the weighted version), that consists in finding a subset  $S$  of exactly  $k$  vertices that maximizes the number of edges in  $G[S]$ .

The decision versions of QIS, PVC, and  $k$ -SPARSEST SUBGRAPH are polynomially equivalent. Indeed, QIS could be considered as a dual version of  $k$ -SPARSEST SUBGRAPH where the budget (the number of edges in the solution of  $k$ -SPARSEST SUBGRAPH) is fixed. PVC and  $k$ -SPARSEST SUBGRAPH are also polynomially equivalent as for any  $S$ , the number of edges in  $G[S]$  plus the number of edges covered by  $V \setminus S$  equals  $|E|$ . Finally, it is obvious that any exact result for  $k$ -DENSEST SUBGRAPH on a graph class immediately transfers to  $k$ -SPARSEST

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SUBGRAPH for the complementary class (and conversely).

As a consequence, the complexity status of  $k$ -SPARSEST SUBGRAPH is already known in several subclasses of perfect graphs, namely in co-comparability and co-chordal graphs for  $\mathcal{NP}$ -completeness, and in split graphs and in trees for polynomial algorithms. We believe that the  $\mathcal{NP}$ -hardness in interval graphs may be a tough question, as for example the complexity in bipartite graphs is still currently studied [2], and the complexity of  $k$ -DENSEST SUBGRAPH on interval graphs (and even proper interval graphs) is a classical three decades open question raised in [9]. Notice that despite this open question, a PTAS has been designed for  $k$ -DENSEST SUBGRAPH in interval graphs in [16].

Graphs classes	$k$ -DS	$k$ -SS	PVC
general	$\mathcal{NP}$ -h ( <i>c.f.</i> MAX CLIQUE) $n^{\frac{1}{4}+\epsilon}$ -approx. [4]	$\mathcal{NP}$ -h, not approx. ( <i>c.f.</i> INDEP. SET)	$\mathcal{NP}$ -h, $W[1]$ -h [11] 2-approx.[7] exact $O^*(1, 4^C)$ [12]
chordal	$\mathcal{NP}$ -h [9] 3-approx [15]	$\mathcal{NP}$ -h [?]	$\mathcal{NP}$ -h ( <i>c.f.</i> $k$ -SS)
interval	OPEN PTAS [16]	OPEN, $FPT(C)$ [?] 2-approx. (this paper)	OPEN $FPT(n - k)$ ( <i>c.f.</i> $k$ -SS)
proper interval	OPEN PTAS [16]	OPEN, PTAS (this paper)	OPEN
bipartite	$\mathcal{NP}$ -h [9]	$\mathcal{NP}$ -h ( <i>c.f.</i> PVC)	$\mathcal{NP}$ -h [?]
line	OPEN	$\mathcal{P}$ ( <i>c.f.</i> PVC)	$\mathcal{P}$ [1]
planar	OPEN	$\mathcal{NP}$ -h ( <i>c.f.</i> INDEP. SET)	$\mathcal{NP}$ -h ( <i>c.f.</i> $k$ -SS)
cographs, split, bounded treewidth	$\mathcal{P}$ [9]	$\mathcal{P}$ [6]	$\mathcal{P}$ ( <i>c.f.</i> $k$ -SS)
max. degree 2	$\mathcal{P}$ [9]	$\mathcal{P}$ [6]	$\mathcal{P}$ ( <i>c.f.</i> $k$ -SS)
max. degree 3	$\mathcal{NP}$ -h [9]	OPEN	OPEN

Fig. 1: Main results for  $k$ -DS,  $k$ -SS and PVC in some restricted graph classes.

## 1.2 Motivation and contributions

Unlike polynomial or  $\mathcal{NP}$ -hardness results, approximation results on  $k$ -DENSEST SUBGRAPH do not directly transfer to  $k$ -SPARSEST SUBGRAPH not PVC. Moreover, the approximability status of  $k$ -SPARSEST SUBGRAPH did not receive as much attention as the one of  $k$ -DENSEST SUBGRAPH. Indeed,  $k$ -SPARSEST SUBGRAPH is clearly inapproximable (unless  $\mathcal{P} = \mathcal{NP}$ ) on any class where INDEPENDENT SET is  $\mathcal{NP}$ -hard, as the optimal value of  $k$ -SPARSEST SUBGRAPH is 0 whenever  $k$  is lower than the maximum independent set of the input graph. Thus, it appears natural to investigate the approximability of  $k$ -SPARSEST SUBGRAPH in graph classes where INDEPENDENT SET is polynomial, such as subclasses of perfect graphs.

In this paper we first present a simple greedy tight 2-approximation algorithm, and we then use dynamic programming to provide a PTAS in proper interval graphs, and an  $FPT$  algorithm in (general) interval graphs parameterized by  $C$ , the number of edges in the solution

(notice that the last result implies an *FPT* algorithm for the *QIS* problem with standard parametrization by  $k$ , as well as an *FPT* algorithm for *PVC* parameterized by  $n - k$ ).

The intuition of parameterizing by  $C$  is that  $k$ -SPARSEST SUBGRAPH becomes easy when looking for a solution of cost 0 (as it corresponds to find an independent set). This motivates the design of an efficient algorithm for small  $C$  values. Moreover, parameterization by  $C$  is stronger than the natural parameterization by  $k$ , as we always have  $C \leq \binom{k}{2}$ .

## 2 Preliminaries

Interval graphs are the intersection graph of a set of intervals on the real line. For a set of intervals, the associated intersection graph has one vertex for each interval, and an edge between two vertices corresponding to intervals  $I_1$  and  $I_2$  if and only if  $I_1$  overlaps  $I_2$ . A graph is a proper interval graph if it is the intersection graph of a set of intervals on the real line such that no interval properly contains any other interval. As the intersection model of an interval graph can be obtained in polynomial time, we will make no distinction between a vertex and its corresponding interval, as well as we will make no distinction between edges in the graph and overlaps in the corresponding interval model.

For the rest of the paper,  $G = (V, E)$  will denote the input graph of the problem, and we define as usually  $n = |V|$ ,  $m = |E|$ . The associated interval set will be denoted by  $\mathcal{I} = \{I_1, \dots, I_n\}$ . Without loss of polynomiality, we suppose that all endpoints are pairwise distinct. Given  $I \in \mathcal{I}$ , we denote by  $right(I) \in \mathbb{R}$  (resp.  $left(I) \in \mathbb{R}$ ) the right (resp. left) endpoint of  $I$ . By extension, for any set  $S \subseteq \mathcal{I}$ , we define  $left(S) = \arg \min_{I \in S} left(I)$  (resp.  $right(S) = \arg \max_{I \in S} right(I)$ ). Unless otherwise stated, we suppose that  $\mathcal{I}$  is sorted according to the right endpoints of the intervals (*i.e.* for all  $i \in \{2, \dots, n\}$  we have  $right(I_{i-1}) < right(I_i)$ ). For  $S \subseteq \mathcal{I}$  and  $r \leq |S|$ , we define the "*r*-leftmost intervals of  $S$ " as the  $r$  first intervals in an ordering of  $S$  (where intervals are sorted according to their right endpoints). Notice that the 1-leftmost interval will simply be called *the leftmost interval*. Given a set  $S \subseteq \mathcal{I}$ , we denote  $cost(S)$  the number of edges in the graph induced by intervals of  $S$ .

Finally, we refer the reader to the classical literature for definitions of approximation and *FPT* algorithms.

## 3 A Simple Greedy 2-Approximation Algorithm

### 3.1 Algorithm

Let us first define the notion of layer by layer decomposition of a given solution:

**Definition 1.** Given a solution  $S \subseteq \mathcal{I}$  of  $k$ -SPARSEST SUBGRAPH, a **layer by layer** decomposition of  $S$  is a partition  $(L_1, \dots, L_{Comp})$  of  $S$  such that :

- $L_1$  is a maximum independent set in the subgraph induced by  $S$  (notice that  $L_1$  is not necessarily a maximum independent set in  $G$ , the input graph)
- $L_{left}$  is recursively defined as a (non empty) maximum independent set in the subgraph induced by  $S \setminus \bigcup_{i=1}^{left-1} L_i$

Moreover, for all  $1 \leq l \leq Comp$ , we define  $x_{left} = |L_{left}|$ .

The idea of the Layer-by-Layer algorithm (see Algorithm 1) is to avoid big cliques by creating several layers. Each layer is created by parsing remaining intervals and selecting a maximum independent set in the remaining graph.

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**Algorithm 1** "Layer-by-Layer algorithm"

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```
Output  $\leftarrow \emptyset$ 
left  $\leftarrow 0$ 
while  $|Output| \leq k$  do
   $l \leftarrow l + 1$ 
   $L_{left} \leftarrow \emptyset$ 
  while  $(|Output| + |L_{left}| \leq k)$  and  $(L_{left}$  is not a maximal independent set) do
    Add to  $L_{left}$  the leftmost interval that does not overlap any interval of  $L_{left}$ 
  end while
  Output  $\leftarrow Output \cup L_{left}$ 
end while
return Output
```

---

Notice that the tuple  $(L_1, \dots, L_{Comp})$  defined in the Layer-by-Layer algorithm is already a layer by layer decomposition of the algorithm output. By definition, any layer  $L_{left}$  is even a maximum independent set in  $G \setminus \bigcup_{i=1}^{left-1} L_i$ . This property is mandatory when  $k$  is lower than the maximum independent set of  $G$ . Indeed, in this case the optimal value is zero and thus any approximation algorithm must return an independent set.

### 3.2 Analysis

Before starting the proof, let us first introduce some notations and basic facts. Let us denote by  $(L_1^*, \dots, L_{Comp}^*)$  a layer by layer decomposition of  $Opt$ , an optimal solution of  $k$ -SPARSEST SUBGRAPH.

**Lemma 1.** *Let  $S$  be a feasible solution of the  $k$ -SPARSEST SUBGRAPH on proper interval graphs, and let  $(L_1, \dots, L_{Comp})$  be its layer by layer decomposition. The cost of  $S$  verifies  $\sum_{left=2}^C omp(left-1)x_{left} \leq cost(S) \leq 2 \sum_{left=2}^C omp(left-1)x_{left}$*

*Proof.* Let  $left \in \{1, \dots, Comp\}$  and  $I_j \in L_{left}$ . Let us count the number of edges between  $I_j$  and intervals in previous layers.

Let  $left' < left$ . The key argument is that the number of edges between  $I_j$  and intervals of  $L_{left'}$  is either one or two. Indeed, there is at least one interval  $I'_j \in L_{left'}$  such that  $I'_j$  and  $I_j$  are connected, otherwise  $L_{left'}$  would not be a maximum independent set. Moreover, if  $I_j$  overlap three (or more) intervals of  $L_{left'}$ , then one of these intervals would be included in  $I_j$ , which is impossible as  $G$  is a proper interval graph.

For any  $1 \leq l' < l \leq Comp$ , we define  $cost(l', l)$  the number of edges between intervals of  $L_{left'}$  and  $L_{left}$ . From the previous argument we get  $x_l \leq cost(l', l) \leq 2x_{l'}$ . Summing over all the layers, we get  $cost(S) = \sum_{left=2}^C omp \sum_{left'=1}^{left-1} cost(l', l) \leq 2 \sum_{left=2}^C omp(left-1)x_{left}$ . The lower bound is of course obtained using the same summation.

According to the previous proposition, we get  $cost(Opt) \geq \sum_{left=2}^{Comp^*} (left-1)x_{left}^*$ , and  $cost(Output) \leq 2 \sum_{left=2}^{Comp} (left-1)x_{left}$  (recall that  $x_{left}$  denotes the size of  $L_{left}$ , the layers defined in the Layer-by-Layer algorithm). Thus, to get an approximation ratio of two it remains now to prove that  $\sum_{left=2}^{Comp} (left-1)x_{left} \leq \sum_{left=2}^{Comp^*} (left-1)x_{left}^*$ . Roughly speaking, the last inequality is true as the Layer-by-Layer algorithm maximizes the first  $x_{left}$  (that have a small coefficient), as each layer is a maximum independent set in the remaining graph. More formally, let us prove the following lemma.

**Lemma 2.** Given respectively  $(L_1^*, \dots, L_{Comp^*}^*)$  and  $(L_1, \dots, L_{Comp})$ , the layer by layer decomposition of  $Opt$  and the output of the Layer-by-Layer algorithm, for all  $l \in \{1, \dots, \min(Comp, Comp^*)\}$  we have  $\sum_{i=1}^l efty_i \geq \sum_{i=1}^l efty_i^*$

*Proof.* Let  $\tilde{Comp} = \min(Comp, Comp^*)$ . Given any solution  $S$  and any  $left \in \{1, \dots, \tilde{Comp}\}$ , we define  $F_{left}(S) = \sum_{i=1}^l efty_i$  (where  $x_i$  is defined by the layer by layer decomposition of  $S$ ) and  $F(S) = (F_1(S), \dots, F_{\tilde{Comp}}(S))$ . Let  $Opt_1 = Opt$ . We will re-structure  $Opt_1$  in several steps by defining intermediate solutions  $Opt_i$  until  $Opt_i = Output$ , and such that  $F(Opt_{i+1}) \geq F(Opt_i)$  (where  $\geq$  is the product order over  $\mathbb{R}^{Comp}$ ).

Let us describe how to turn  $Opt_i$  into  $Opt_{i+1}$ . Let  $(L'_1, \dots, L'_{Comp'})$  be the layer by layer decomposition of  $Opt_i$ . Let us suppose that the  $(x-1)$  first layers of  $Opt_i$  are equal to the  $(x-1)$  first layers of  $Output$ , i.e. let  $x \geq 1$  be the minimum value such that  $L'_x \neq L_x$  and  $L_{left'} = L_{left}$ ,  $\forall 1 \leq left < x$ . Let  $L_x = \{i_1, \dots, i_a\}$  and  $L'_x = \{i'_1, \dots, i'_b\}$  (for the sake of clarity we simply denote by  $i_l$  the interval  $L_{i_l}$  when it is clear from the context). Notice that  $b \leq a$  as by construction  $L_x$  is a maximum independent set in the remaining graph  $G \setminus \bigcup_{i=1}^{x-1} L_i$ .

Let us now distinguish two different cases. We first consider the case where  $L'_x \subset L_x$ , implying that  $L'_x$  is not the last layer. In this case we define  $Opt_{i+1}$  by adding an interval  $I \in L_x \setminus L'_x$  to  $L'_x$  (notice that  $I$  is not contained in any  $L_{left'}$ ,  $left > x$  as  $L'_x$  is maximal), and we remove an interval from a layer  $L_{left'}$ ,  $l > x$ . This transformation ensures that  $F(Opt_{i+1}) \geq F(Opt_i)$ . In the other case, let  $j \leq b$  be the minimum value such that  $i'_j \neq i_j$  and  $i'_left = i_left$ ,  $\forall 1 \leq l < j$ . In other word, we consider the leftmost non common interval between  $L'_x$  and  $L_x$ . Notice that  $i_j < i'_j$  (meaning that interval  $i_j$  is on the left of  $i'_j$ ) as the algorithm created  $L_x$  by choosing  $i_j$  as the leftmost independent interval. Two sub-cases are now possible.

If  $i_j$  is not used in  $Opt_i$  ( $i_j \notin \bigcup_{left=x+1}^{Comp'} L_{left'}$ ), then we add  $i_j$  to  $L'_x$  and we remove  $i'_j$  from  $L'_x$ . Notice that  $L'_x$  is still an independent set as  $i_j < i'_j$ .

Finally, we consider the case where  $i_j$  is used in  $Opt_i$  in a layer  $L'_y$ ,  $y > x$  (as depicted in Figure 2). Let  $L'_y = \{i''_1, \dots, i''_{a''}\}$ , and let  $p$  such that  $i''_p = i_j$ . We will execute the following exchanges between  $L'_x$  and  $L'_y$ . First add  $i_j (= i''_p)$  to  $L'_x$ . As  $L'_x$  was maximal, we know that there is an edge between  $i_j$  and  $i'_j$ . Thus, we remove  $i'_j$  from  $L'_x$  and add it to  $L'_y$ . If there is no edge between  $i'_j$  and  $i''_{p+1}$ , the exchange is over (and  $Opt_{i+1}$  is defined). Otherwise, we have to continue the exchange until the last exchanged interval does not overlap any interval or one of the layer is empty.

More formally, let  $a \geq 0$  be the greatest integer such that  $(i''_p, i'_j), (i'_j, i''_{p+1}), (i''_{p+1}, i'_{j+1}), \dots, (i'_{j+a}, i''_{p+a+1})$  are in  $E$ . First, we remove  $\{i''_p, \dots, i''_{p+a+1}\}$  from  $L'_y$  and add it to  $L'_x$ . Then, we remove  $\{i'_j, \dots, i'_{j+a}\}$  from  $L'_x$  and we add it to  $L'_y$ . Finally, if  $(i''_{p+a+1}, i'_{j+a+1}) \in E$ , we also remove  $i'_{j+a+1}$  from  $L'_x$  and we add it to  $L'_y$ . Notice that after the exchange we either have  $|L'_x|_{new} = |L'_x|_{old}$  and  $|L'_y|_{new} = |L'_y|_{old}$ , or  $|L'_x|_{new} = |L'_x|_{old} + 1$  and  $|L'_y|_{new} = |L'_y|_{old} - 1$ . Thus, in both cases we get  $F(Opt_{i+1}) \geq F(Opt_i)$ .

**Lemma 3.** Given  $Comp \leq Comp^*$ ,  $(x_1, \dots, x_{Comp})$ ,  $(x_1^*, \dots, x_{Comp^*}^*)$  and  $(a_1, \dots, a_{Comp^*})$  such that:

- $\sum_{i=1}^{Comp} x_i = \sum_{i=1}^{Comp^*} x_i^*$
- $\forall l \in \{1, \dots, \min(Comp, Comp^*)\}, \sum_{i=1}^l efty_i left \geq \sum_{i=1}^l efty_i^* left$
- $a_i \leq a_{i+1}$

We have  $\sum_{left=1}^{Comp} a_i efty_i left \leq \sum_{left=1}^{Comp^*} a_i efty_i^* left$ .

*Proof.* The proof is simply by induction over  $\tilde{Comp} = \min(Comp, Comp^*)$ . Case  $\tilde{Comp} = 1$  is obvious. Let us assume that Lemma is true for any  $Comp \leq Comp^* \leq n-1$ , and consider the case  $Comp \leq Comp^* \leq n$ . According to the hypothesis, we know that in particular  $x_1 \geq x_1^*$ .

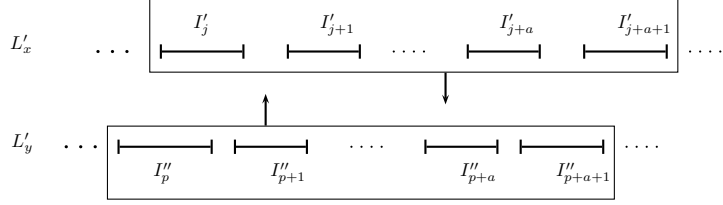


Fig. 2: Example of swap when turning  $Opt_i$  into  $Opt_{i+1}$

Let  $\Delta \geq 0$  such that  $x_1 = x_1^* + \Delta$ . We re-balance the coefficient by defining  $x_1'^* = x_1^* + \Delta$ ,  $x_2'^* = x_2^* - \Delta$  (we may have  $x_2'^* \leq 0$ ), and  $x_l'^*eft = x_l^*$  for  $left \geq 3$ . Then, we get  $\sum_{left=1}^{Comp} a_l eft x_l eft = a_1 x_1 + \sum_{left=2}^{Comp} a_l eft x_l eft = a_1 x_1'^* + \sum_{left=2}^{Comp} a_l eft x_l eft$  (as  $x_1'^* = x_1$ ). By induction, the last expression is lower than  $\sum_{left=1}^{Comp^*} a_l eft x_l'^* eft$ , which itself is lower than  $\sum_{left=1}^{Comp^*} a_l eft x_l^* eft$  (as  $(a_i)_i$  is non increasing).

Putting all the pieces together, we can now prove the following result:

**Theorem 1.** *The Layer-by-Layer algorithm is a tight 2-approximation algorithm.*

*Proof.* Let *Output* denote the solution given the Layer-by-Layer algorithm, and  $x_l$  the coefficient defined in a layer by layer decomposition of *Output*. According to Lemma 1 and Lemma 3 we get  $cost(Output) \leq 2 \sum_{left=2}^{Comp} (left - 1) x_l eft \leq 2 \sum_{left=2}^{Comp^*} (left - 1) x_l^* eft \leq 2Opt$ . Finally, Figure 3 represents a set of 7 proper intervals, for which with  $k = 5$ , the Layer-by-Layer algorithm produces a solution of cost 4, whereas a solution of cost 2 exists, implying a ratio of 2.

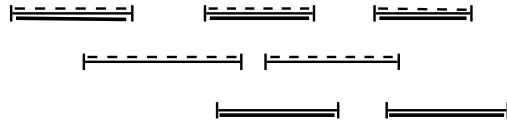


Fig. 3: Tight instance for the Layer-by-layer algorithm for  $k = 5$  on an instance with 7 intervals. Instance is drawn with continuous lines, algorithm output in dashed, and the optimal solution in bold.

## 4 FPT Algorithm by Dynamic Programming

The objective of this section is to provide an FPT algorithm for the  $k$ -SPARSEST SUBGRAPH on general (*i.e.* non proper) interval graphs, parameterized by the cost of the solution.

#### 4.1 Preliminaries

Given  $x \in \mathbb{R}$  we define  $\mathcal{I}_{\geq x} = \{I \in \mathcal{I} : x \leq \text{left}(I)\}$  the set of intervals that are after  $x$ ,  $\mathcal{I}_{=x} = \{I \in \mathcal{I} : \text{left}(I) < x < \text{right}(I)\}$  the set of intervals that cross  $x$ , and  $\mathcal{I}_{\leq x} = \{I \in \mathcal{I} : \text{right}(I) \leq x\}$  the set of intervals that are before  $x$ .

Let us start with two lemmas that allow us to restructure optimal solutions by "flushing" intervals to the left.

**Lemma 4.** *Let  $S \subseteq \mathcal{I}$  be a solution, and  $s \in \mathbb{R}$  such that  $\text{left}(S) < s < \text{right}(S)$  and  $S \cap \mathcal{I}_{=s} = \emptyset$ . Let  $\tilde{I}$  be the leftmost interval of  $S \cap \mathcal{I}_{\geq s}$  and  $I^*$  be the leftmost interval of  $\mathcal{I}_{\geq s}$ . Then we can swap  $\tilde{I}$  and  $I^*$  to get a solution  $S' = (S \setminus \{\tilde{I}\}) \cup \{I^*\}$  such that  $\text{cost}(S') \leq \text{cost}(S)$ .*

*Proof.* Let us suppose that  $\tilde{I} \neq I^*$ , and let  $I \in S$  such that  $I \neq \tilde{I}, I^*$ . We will show that if  $I$  overlaps  $I^*$ , then it also overlaps  $\tilde{I}$ . Thus, suppose that  $I$  overlaps  $I^*$ . By definition of  $\tilde{I}$  and  $S$ , we have  $\text{right}(I^*) < \text{right}(\tilde{I}) < \text{right}(I)$ , and since  $I$  overlaps  $I^*$ , we have  $I \in \mathcal{I}_{=\text{right}(I^*)}$  and thus  $I$  also overlaps  $\tilde{I}$  (see Figure 4a).

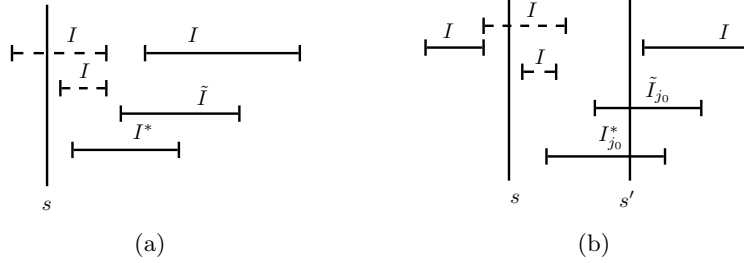


Fig. 4: Different positions of interval  $I$  in Lemma 4 (Figure (a)) and Lemma 6 (Figure (b)). Dashed intervals represent forbidden positions.

**Lemma 5.** *Let  $S \subseteq \mathcal{I}$  be a solution,  $I_{i_1} \in S$  and  $s \in \mathbb{R}$  such that:*

- (i)  $I_{i_1}$  is the leftmost interval of  $S \cap \mathcal{I}_{=s}$
- (ii)  $\exists \tilde{I} \in S \cap \mathcal{I}_{\geq s}$  such that  $\tilde{I}$  overlaps  $I_{i_1}$

*Let  $I^*$  be the leftmost interval of  $\mathcal{I}_{\geq s}$ . Then, we can swap  $I^*$  and  $\tilde{I}$  to get a solution  $S' = (S \setminus \{\tilde{I}\}) \cup \{I^*\}$  such that  $\text{cost}(S') \leq \text{cost}(S)$ .*

*Proof.* Let us suppose that  $\tilde{I} \neq I^*$ , otherwise the proof is obvious, and let  $I \in S$  such that  $I \neq \tilde{I}, I^*$ . We will show that if  $I$  overlaps  $I^*$ , then it also overlaps  $\tilde{I}$ . Thus, suppose that  $I$  overlaps  $I^*$ . If  $I \in \mathcal{I}_{=s}$ , then by definition of  $I_{i_1}$ , we must have  $\text{right}(I_{i_1}) < \text{right}(I)$ , and since  $s < \text{left}(\tilde{I}) < \text{right}(I_{i_1})$ ,  $I$  must overlap  $\tilde{I}$ . Otherwise if  $I \in \mathcal{I}_{\geq s}$ , as in the proof of Lemma 4, by definition of  $\tilde{I}$  we have  $\text{right}(I^*) < \text{right}(\tilde{I}) < \text{right}(I)$ , and since  $I$  overlaps  $I^*$ , we have  $I \in \mathcal{I}_{=\text{right}(I^*)}$  and thus  $I$  also overlaps  $\tilde{I}$ .

**Lemma 6.** *Let  $S \subseteq \mathcal{I}$  be a solution and  $s, s' \in \mathbb{R}$  with  $s < s'$  and such that  $\forall I \in S$  we have  $\text{right}(I) \notin [s, s']$ . Let  $\tilde{X} = S \cap \mathcal{I}_{\geq s} \cap \mathcal{I}_{=s'}$  and  $X^*$  be the  $|\tilde{X}|$ -leftmost intervals of  $\mathcal{I}_{\geq s} \cap \mathcal{I}_{=s'}$ . Then we can swap  $\tilde{X}$  and  $X^*$  to get a solution  $S' = (S \setminus \tilde{X}) \cup X^*$  such that  $\text{cost}(S') \leq \text{cost}(S)$ .*



*Proof.* We suppose that  $\tilde{X} \neq X^*$  and that both sets are non empty. Let  $\tilde{X} = \{\tilde{I}_1, \dots, \tilde{I}_{|\tilde{X}|}\}$ , and  $X^* = \{I_1^*, \dots, I_{|\tilde{X}|}^*\}$ . We suppose moreover that for all  $j \in \{2, \dots, |\tilde{X}|\}$  we have  $\text{right}(\tilde{I}_{j-1}) < \text{right}(\tilde{I}_j)$  and  $\text{right}(I_{j-1}^*) < \text{right}(I_j^*)$  (i.e.  $\tilde{X}$  and  $X^*$  are sorted by their right endpoints). Let  $j_0$  be the minimum index such that  $\tilde{I}_{j_0} \neq I_{j_0}^*$ , and let  $I \in S \setminus (\tilde{X} \cup X^*)$  (we thus have  $\text{right}(I_{j_0}^*) < \text{right}(\tilde{I}_{j_0})$ ). We will show that if  $I$  overlaps  $I_{j_0}^*$ , then  $I$  also overlaps  $\tilde{I}_{j_0}$ . To do so, suppose that  $I$  overlaps  $I_{j_0}^*$ , and let us distinguish between two cases (see Figure 4b). If  $s' < \text{right}(I)$ , then since  $\text{right}(I_{j_0}^*) < \text{right}(\tilde{I}_{j_0})$ , it is clear that  $I$  also overlaps  $\tilde{I}_{j_0}$ . Otherwise, if  $\text{right}(I) < s'$ , then by definition  $\text{right}(I) < s$ , and thus  $I$  cannot overlap  $I_{j_0}^*$ .

## 4.2 Algorithm

Recall that our objective is to prove that the decision problem "given an instance  $(\mathcal{I}, k)$  of  $k$ -SPARSEST SUBGRAPH, does  $\text{Opt}(\mathcal{I}, k) \leq C^*$  ?", is FPT parametrized by  $C^*$ .

We construct in Algorithm 2 a dynamic programming algorithm that given any  $\text{next} \in \mathbb{R}$ ,  $t \leq k$  and  $C \leq C^*$  returns a set  $S$  of  $t$  vertices in  $\mathcal{I}_{\geq \text{next}}$  of cost at most  $C$  if it was possible, and returns *NO* otherwise.

We define  $\Omega_{\text{next}}(C) \subseteq \mathcal{P}(\mathcal{I})$  (where  $\mathcal{P}(\mathcal{I})$  is the set of all subsets of  $\mathcal{I}$ ) such that for all  $T \in \Omega_{\text{next}}(C)$  we have:

- $G[T]$  is connected
- $\text{cost}(T) \leq C$
- $\text{left}(T) = \text{left}(\mathcal{I}_{\geq \text{next}})$

Roughly speaking,  $\Omega_{\text{next}}(C)$  is the set of all connected components of cost at most  $C$  that start immediately after  $\text{next}$ . Given  $\text{next}$  and  $t$ , the algorithm branches on a subset of  $\Omega_{\text{next}}(C)$  (namely  $\Gamma_{\text{next}}(C)$ ) to find what could be the next optimal connected component, and then invokes a recursive call.

We prove in Lemma 7 that each  $T \in \Omega_{\text{next}}(C)$  can be restructured into a "well-structured" component of smaller cost, and in Lemma 8 that the size of the set of all "well-structured" components ( $\Gamma_{\text{next}}(C)$ ) can be enumerated in *FPT* time.

---

### Algorithm 2 $DP(\text{next}, t, C)$

---

```
// For the sake of clarity we drop the classical operations related to the "marking
// table" that avoid multiple computations with same arguments
build  $\Gamma_{\text{next}}(C)$  (see Definition 2)
if  $\Gamma_{\text{next}}(C) = \emptyset$  then
    return NO
else if  $\exists T \in \Gamma_{\text{next}}(C)$  with  $|T| \geq t$  then
    return  $t$  vertices of  $T$ 
else
    return  $\arg \min_{C \in \Gamma_{\text{next}}(C)} [\text{cost}(T) + \text{cost}(DP(\text{right}(T), t - |T|, C - \text{cost}(T)))]$ 
end if
```

---

Let us now show how to restructure a connected component of a given solution. As one could expect, the idea is to apply the domination rules of Lemmas 4, 5 and 6 that consist in "flushing" the intervals to the left. Thus, for any connected component  $T$ , we define (recursively on  $s$ )  $\text{restruct}(s, T, i)$  that turns  $T \cap \mathcal{I}_{\geq s}$  (the part of  $T$  which is after  $s$ ) into a well structured solution (see Algorithm 3 and Definition 2). Notice that the parameter  $i$  and the  $y_i$  values will be used in Lemma 8 to show that the output of the algorithm can be encoded in an efficient way.

**Definition 2.** Given  $s$  and  $T \in \Omega_s(C)$ , we define:

- $WSS(T) = \text{restruct}(\text{start}(T), T, 0)$  the Well Structured Solution corresponding to  $T$ , where  $\text{start}(T)$  is defined as the point after the left endpoint of the leftmost interval of  $T$  (see Figure 5).
- $\Gamma_s(C) = \{WSS(T), T \in \Omega_s(C)\}$  the set of well structured connected component of cost at most  $C$  that starts just after  $s$ .

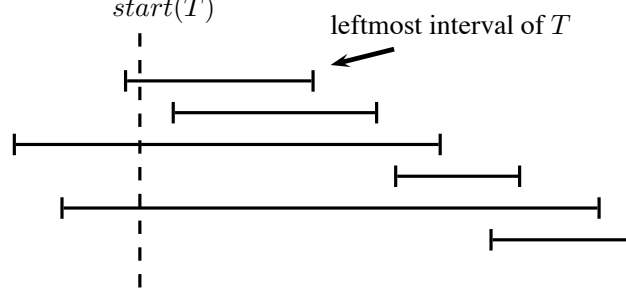


Fig. 5: Example of a connected component  $T$  and its corresponding  $\text{start}(T)$

*Remark 1.* Notice that at each step of the dynamic programming we branch on  $\Gamma_{\text{next}}(\text{cost})$ , which is the set of all restructured connected component  $T$  such that  $\text{left}(C) = \text{left}(\mathcal{I}_{\geq \text{next}})$ . By Lemma 4, we can suppose that for all optimal solution  $S^*$ , we have  $\text{left}(S^* \cap \mathcal{I}_{\geq \text{next}}) = \text{left}(\mathcal{I}_{\geq \text{next}})$ . Roughly speaking, we can suppose that for all optimal solution, the connected component that starts after  $\mathcal{I}_{\geq \text{next}}$  contains the leftmost interval of  $\mathcal{I}_{\geq \text{next}}$ . As a consequence, the  $\text{start}(T)$  in Definition 2 forces  $I_{i_1}$  to be this leftmost interval.

**Lemma 7.** For any  $s$  and any  $T \in \Omega_s(C)$  we have

- $|WSS(T)| = |T|$ , i.e. the restructured set has same size
- $\text{right}(WSS(T)) \leq \text{right}(T)$
- $\text{cost}(WSS(T)) \leq \text{cost}(T)$ .

*Proof.* The first item is clearly true as we only swap sets of intervals of same size. The second item is true as all swapping arguments shift intervals to the left. Let us now turn to the last item. Notice that in the two cases where *restruct* modifies  $T$ , the hypothesis of Lemmas 5 and 6 are verified. Thus, according to these Lemmas the cost of the solution cannot increase.

Lemma 7 confirms that the dynamic programming algorithm can only branch on  $\Gamma_s(C)$ , avoiding thus branching on  $\Omega_s(C)$ . It remains now to prove that the dynamic programming algorithm is FPT.

**Lemma 8.** For any  $s$ ,  $|\Gamma_s(C)| \leq (\sqrt{2C} + 2)^{C+1}$ .

*Proof.* Let  $T \in \Omega_s(C)$ , and  $WSS(T)$  the associated restructured solution. The key argument is to remark that  $WSS(T)$  is entirely determined by the  $y_i$  values defined in the *restruct* algorithm. Thus, to each restructured solution  $WSS(T)$  we associate the vector

---

**Algorithm 3** *restruct*( $s, T, i$ )

---

```
if  $T \cap \mathcal{I}_{\geq s} \neq \emptyset$  then
   $I_{i_1} \leftarrow$  leftmost interval of  $\mathcal{I}_{=s} \cap T$ 
  //  $I_{i_1}$  is always defined, as in the first call  $s$  is set to  $start(T)$ 
  if  $\nexists I \in T \cap \mathcal{I}_{\geq s}$  which overlaps  $I_{i_1}$  then
     $y_i \leftarrow 0$ 
     $restruct(right(I_{i_1}), T, i + 1)$ 
  else
    // we restructure a first interval using Lemma 5
     $\tilde{I} \leftarrow$  leftmost interval of  $T \cap \mathcal{I}_{\geq s}$  which overlaps  $I_{i_1}$ 
     $I^* \leftarrow$  leftmost interval of  $\mathcal{I}_{\geq s}$  which overlaps  $I_{i_1}$ 
     $T \leftarrow (T \setminus \{\tilde{I}\}) \cup \{I^*\}$ 
    // we restructure a set of intervals using Lemma 6
     $s' \leftarrow \min(right(I^*), right(I_{i_1}))$ 
     $\tilde{X} \leftarrow T \cap \mathcal{I}_{\geq s} \cap \mathcal{I}_{=s'}$ 
     $X^* \leftarrow |\tilde{X}|$ -leftmost intervals of  $\mathcal{I}_{\geq s} \cap \mathcal{I}_{=s'}$ 
     $T \leftarrow (T \setminus \tilde{X}) \cup X^*$ 
     $y_i \leftarrow |X^*| + 1$ 
     $restruct(s', T, i + 1)$ 
end if
end if
```

---

$Y(WSS(T)) = (y_0, \dots, y_{l_{max}})$ . Then, the dynamic program will enumerate  $\Gamma_s(C)$  by enumerating the set  $Y = \{Y(WSS(T)), T \in \Omega_s(C)\}$  of all possible  $Y$  vectors.

Notice first that for any  $i$  we have  $y_i \leq \sqrt{2C} + 2$ . Indeed, in the two possible cases of the restructuration ( $s' = right(I^*)$  or  $s' = right(I_{i_1})$ ) the  $|X^*|$  intervals all overlap  $s'$ , corresponding to the right endpoint of another interval ( $I^*$  or  $I_{i_1}$ ). Thus, there is at least a clique of size  $y_i = |X^*| + 1$  in the solution, whose cost is lower than  $C$ .

It remains now to bound  $l_{max}$ , the length of the  $Y$  vector.

To do that, we show that for any step  $i \in \{0, \dots, l_{max} - 1\}$  and corresponding  $s$ , we can find  $I \in \mathcal{I}_{=s}$  and  $I' \in \mathcal{I}_{\geq s}$  such that  $I$  and  $I'$  overlaps, and such that in the next recursive call (with parameter  $s'$ ), either  $I$  or  $I'$  belongs to  $\mathcal{I}_{\leq s'}$ , avoiding multiple counts of same pairs, and implying that  $C \geq l_{max} - 1$ . Let  $i \in \{0, \dots, l_{max} - 1\}$ . If  $y_i \neq 0$ , then by definition of  $I^*$ ,  $I_{i_1}$  and  $I^*$  are overlapping. Then, since the next recursive call has parameter  $s' = \min\{right(I^*), right(I_{i_1})\}$ , either  $I^*$  or  $I_{i_1}$  belongs to  $\mathcal{I}_{\leq s'}$ . If  $y_i = 0$ , then  $s' = right(I_{i_1})$ , and as  $i \neq l_{max}$ , we know that there exists  $I_{i_2} \in \mathcal{I}_{=s'}$  implying that  $I_{i_2}$  overlaps  $I_{i_1}$ . Finally, it is clear that  $I_{i_1} \in \mathcal{I}_{\leq s'}$ .

**Theorem 2.**  $k$ -SPARSEST SUBGRAPH can be solved in  $\mathcal{O}(n^2 \cdot k^3 \cdot C^* \cdot (\sqrt{2C^*} + 2)^{C^*+1})$ .

*Proof.* The dynamic programming algorithm has at most  $n \cdot k \cdot C^*$  different inputs. Given fixed parameters, it runs in  $\mathcal{O}(|\Gamma_s(C^*)| \cdot k^2 n)$ . Indeed, given a  $Y$  vector, the corresponding connected component can be built in  $\mathcal{O}(l_{max} n) \subseteq \mathcal{O}(C^* n) \subseteq \mathcal{O}(k^2 n)$  as for any  $i \leq l_{max}$  it takes  $\mathcal{O}(n)$  to find the corresponding  $y_i$  intervals.

## 5 PTAS for Proper Intervals Graphs

In this section we design a PTAS for  $k$ -SPARSEST SUBGRAPH in proper interval. We first assume that the instance has one connected component. We prove that we can re-structure

an optimal solution  $Opt$  into a near optimal solution  $Opt'$  such that the pattern used in  $Opt'$  in each "block" (a block corresponds to a subset of consecutive intervals in the input) is simple enough to be enumerated in polynomial time. Then, a dynamic programming algorithm will process the graph blocks by blocks from left to right and enumerate for each one all the possible patterns.

## 5.1 Definitions

Let us define some notation that will be used in the algorithm. Recall that we are now given a set of proper intervals  $\mathcal{I} = \{I_1, \dots, I_n\}$  sorted by their right endpoints (and by their left endpoints equivalently).

First, we define by induction the following decomposition of the input graph: Let  $I_{m_1} = I_1$ ,  $L_1 = I_{m_1}$ ,  $R_1 = \{I_j, j > m_1, I_j \text{ overlaps } I_{m_1}\}$ . Then, given any  $i \geq 1$  we define (while there remains some intervals after  $R_i$ ):

- $I_{m_{i+1}}$  is the rightmost interval of the set  $X = \{I \notin R_i, \exists I' \in R_i \text{ s.t. } I \text{ overlaps } I'\}$  ( $X$  is well defined as the instance has a unique connected component)
- $L_{i+1} = \{I_j, j \leq m_{i+1}, I_j \text{ overlaps } I_{m_{i+1}} \text{ and } I_j \notin R_i\}$
- $R_{i+1} = \{I_j, j > m_{i+1}, I_j \text{ overlaps } I_{m_{i+1}}\}$ .

Let  $a$  denote the maximum  $i$  such that  $I_{m_i}$  is defined. Notice that  $R_a$  may be empty, and that  $I_{m_i} \in L_i$  for all  $i \in \{1, \dots, a\}$ .

For any  $i \in \{1, \dots, a\}$  we define the block  $i$  as  $B_i = L_i \cup R_i$ . Thus, the set of intervals is partitioned into blocs  $B_i$  for  $1 \leq i \leq a$ . Such a decomposition is depicted in Figure 6.

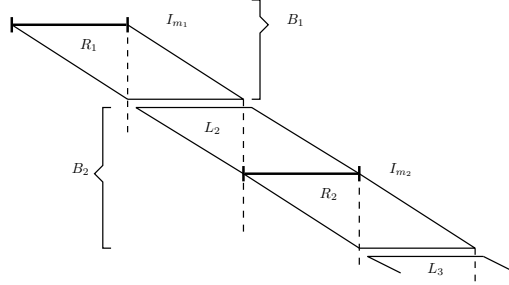


Fig. 6: Schema of the decomposition used in the algorithm.

For any  $1 \leq i \leq a$  and any solution  $S$  (a subset of  $k$  intervals), let  $L_i^S = L_i \cap S$ ,  $R_i^S = R_i \cap S$ , and  $B_i^S = B_i \cap S$ .

Notice that for any  $S$  and  $i$ , intervals of  $R_i^S$  do not intersect intervals of  $R_{i-1}^S$ , and intervals of  $L_i^S$  do not intersect  $I_{m_{i-1}}$  nor intervals of  $L_{i-1}^S$ .

We can now write the cost of a solution as the sum of the costs inside the blocks and the costs between the blocks. Thus, we have  $cost(S) = \sum_{i=1}^a cost(B_i^S) + \sum_{i=1}^{a-1} cost(R_i^S, L_{i+1}^S)$ , where  $cost(B_i^S)$  is the number of edges in the subgraph induced by  $B_i^S$ , and  $cost(X_1, X_2) = |\{(I_l, I_{l'}) \in E, I_l \in X_1, I_{l'} \in X_2\}|$ . Indeed, by definition, the only edges between blocks  $B_i$  and  $B_{i+1}$  are edges between  $R_i$  and  $L_{i+1}$ .

## 5.2 Compacting blocks

Let  $Comp$  be an injective function from  $\mathcal{I}$  to  $\mathcal{I}$ . For any  $S \subseteq \mathcal{I}$ , we define  $Comp(S) = \bigcup_{I \in S} Comp(I)$ . The function  $Comp$  is called a *compaction* if for any  $S \subseteq \mathcal{I}$  and any  $1 \leq i \leq a$  the following holds:

- for all  $I \in R_i^S$  we have  $Comp(I) \in R_i$  and  $right(Comp(I)) \leq right(I)$ .
- for all  $I \in L_i^S$  we have  $Comp(I) \in L_i$  and  $right(I) \leq right(Comp(I))$ .

Roughly speaking, a compaction "pushes" intervals of  $B_i^S$  toward the center  $I_{m_i}$ . The idea is that a compaction may increase the cost of a solution inside the blocks, but cannot increase the costs between the blocks. Thus, let us define a  $\rho$ -compaction as a compaction  $Comp$  such that for any  $S \subseteq \mathcal{I}$  and for all  $i \in \{1, \dots, a\}$  we have  $cost(Comp(B_i^S)) \leq \rho \cdot cost(B_i^S)$ .

**Lemma 9.** *If  $Comp$  is a  $\rho$ -compaction, then for any solution  $S$ ,  $cost(Comp(S)) \leq \rho \cdot cost(S)$ .*

*Proof.* By definition of the decomposition, we have

$$\begin{aligned} cost(Comp(S)) &= \sum_{i=1}^a cost(Comp(B_i^S)) + \sum_{i=1}^{a-1} cost(Comp(R_i^S), Comp(L_{i+1}^S)) \\ &\leq \sum_{i=1}^a \rho \cdot cost(B_i^S) + \sum_{i=1}^{a-1} cost(Comp(R_i^S), Comp(L_{i+1}^S)) \end{aligned}$$

We now prove that  $\sum_{i=1}^{a-1} cost(Comp(R_i^S), Comp(L_{i+1}^S)) \leq \sum_{i=1}^{a-1} cost(R_i^S, L_{i+1}^S)$ . Indeed, let  $I_R \in R_i^S$  and  $I_L \in L_{i+1}^S$  such that  $I_R$  and  $I_L$  do not overlap. Then by definition of a compaction, we have  $right(Comp(I_R)) \leq right(I_R)$  and  $left(I_L) \leq left(Comp(I_L))$ . Thus, intervals  $Comp(I_R)$  and  $Comp(I_L)$  do not overlap as well, which proves the result.

According to the previous lemma, we only have now to find compactations that preserve costs inside the blocks. Given a fixed  $\epsilon$ , the objective is now to define a  $(1 + \epsilon)$ -compaction that has a simple structure.

**Lemma 10.** *For any fixed  $P \in \mathbb{N}$ , there is a  $(1 + \frac{4}{P})$ -compaction such that for any  $X$ ,  $Comp(X)$  can be described by  $(2P + 4)$  variables ranging in  $\{0, \dots, n\}$ .*

*Proof.* According to Lemma 9, we only describe  $Comp(X)$  for  $X \subseteq B_i$ , given any  $1 \leq i \leq a$ . Let  $X = X_L \cup X_R$  with  $X_L \subseteq L_i$  and  $X_R \subseteq R_i$ . We define  $x_L = |X_L|$ ,  $x_R = |X_R|$ . Moreover, we set  $x_L = q_L P + r_L$  (with  $r_L < P$ ) and  $x_R = q_R P + r_R$  (with  $r_R < P$ ).

Let us split  $X_L$  into  $P$  subsets  $(G_t^L)_{1 \leq t \leq P}$  of consecutive intervals (in the ordering of their right endpoints), with  $|G_t^L| = q_L + 1$  for  $t \in \{1, \dots, r_L\}$  and  $|G_t^L| = q_L$  for  $t \in \{(r_L + 1), \dots, P\}$  (see Figure 7). Similarly, we split  $X_R$  into  $P$  subsets  $(G_t^R)_{1 \leq t \leq P}$  of consecutive intervals, with  $|G_t^R| = q_R + 1$  for  $t \in \{1, \dots, r_R\}$  and  $|G_t^R| = q_R$  for  $t \in \{(r_R + 1), \dots, P\}$ .

For all  $t \in \{1, \dots, P\}$ , let  $I_t^L$  (resp.  $I_t^R$ ) be the rightmost (resp. leftmost) interval of  $G_t^L$  (resp.  $G_t^R$ ). The principle of the compaction is to flush every intervals of  $G_t^L$  (resp.  $G_t^R$ ) to the right (resp. left). Thus, for  $t \in \{1, \dots, r_L\}$ ,  $Comp(G_t^L)$  is defined as the  $(q_L + 1)$ -rightmost intervals  $I$  such that  $right(I) \leq right(I_t^L)$ , and for  $t \in \{(r_L + 1), \dots, P\}$ ,  $Comp(G_t^L)$  is defined as the  $q_L$ -rightmost intervals  $I$  such that  $right(I) \leq right(I_t^L)$ .

Similarly, for  $t \in \{1, \dots, r_R\}$ ,  $Comp(G_t^R)$  is defined as the  $(q_R + 1)$ -leftmost intervals  $I$  such that  $right(I_t^R) \leq right(I)$ , and for  $t \in \{(r_R + 1), \dots, P\}$ ,  $Comp(G_t^R)$  is defined as the  $q_R$ -rightmost intervals  $I$  such that  $right(I_t^R) \leq right(I)$ . The construction for a block  $L_i$  is depicted in Figure 7. It is clear that the mapping  $Comp$  described above is a compaction. Moreover, given  $x_L, r_L, x_R, r_R$  and  $I_t^L$  (resp.  $I_t^R$ ) for all  $1 \leq t \leq P$ , we are clearly able to construct  $Comp(X)$  in polynomial time. Thus, it remains to prove that  $Comp$  is a  $(1 + \frac{4}{P})$ -compaction.

The two key arguments are the following:

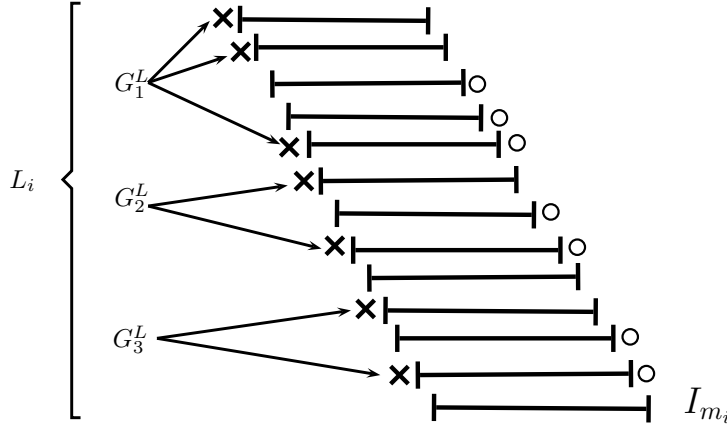


Fig. 7: Example of a compaction of a set  $X$  for a block  $L_i$ , with  $P = 3$ , and  $x_L = 7$ . Intervals marked with a cross represent  $X$ . Intervals marked with a circle represent  $Comp(X)$

- (i) all intervals of  $L_i$  form a clique, as well as all intervals of  $R_i$ .
  - (ii) for any  $t_1, t_2 \in \{1, \dots, P\}$  with  $t_1 \neq P$  and  $t_2 \neq 1$ , if an interval of  $Comp(G_{t_1}^L)$  overlaps an interval of  $Comp(G_{t_2}^R)$ , then for any  $s_1 \in \{(t_1 + 1), \dots, P\}$  and any  $s_2 \in \{1, \dots, (t_2 - 1)\}$ , all intervals of  $G_{s_1}^L$  overlap all intervals of  $G_{s_2}^R$ .
- For all  $t \in \{1, \dots, P\}$ , we define  $x_t^L = |G_t^L| = |Comp(G_t^L)|$ ,  $x_t^R = |G_t^R| = |Comp(G_t^R)|$ . By our construction and (i), we have

$$cost(Comp(X)) \leq \binom{x_L}{2} + \binom{x_R}{2} + \sum_{t=1}^P cost(Comp(G_t^L), Comp(X) \cap R_i)$$

$$cost(X) \geq \binom{x_L}{2} + \binom{x_R}{2} + \sum_{t=1}^P cost(G_t^L, X \cap R_i)$$

Then, for all  $t \in \{1, \dots, P\}$ , let  $\lambda_t \in \{0, 1, \dots, P\}$  be the maximum  $s$  such that an interval of  $Comp(G_t^L)$  overlaps an interval of  $Comp(G_s^R)$  (we set  $\lambda_t = 0$  if no interval of  $Comp(G_t^L)$  overlaps an interval of  $Comp(G_1^R)$ ). By (ii), for all  $t \in \{1, \dots, P\}$ , we have  $cost(Comp(G_t^L), Comp(X) \cap R_i) \leq x_t^L \sum_{u=1}^{\lambda_t} x_u^R$  and for all  $t \in \{2, \dots, P\}$ , we have  $cost(G_t^L, X \cap R_i) \geq x_t^L \sum_{u=1}^{\lambda_{t-1}-1} x_u^R$  (since some intervals of  $G_{t-1}^L$  overlap some intervals of  $G_{\lambda_{t-1}}^R$ , it implies that all intervals of  $G_t^L$  overlap all intervals of  $G_{\lambda_{t-1}-1}^R$ ).

Combining the previous inequalities, we now have

$$cost(Comp(X)) \leq \binom{x_L}{2} + \binom{x_R}{2} + \sum_{t=1}^P x_t^L \sum_{u=1}^{\lambda_t} x_u^R$$

$$cost(X) \geq \binom{x_L}{2} + \binom{x_R}{2} + \sum_{t=2}^P x_t^L \sum_{u=1}^{\lambda_{t-1}-1} x_u^R$$

Thus, we have  $\Delta = cost(Comp(X)) - cost(X) \leq x_1^L \sum_{u=1}^{\lambda_1} x_u^R + \sum_{t=2}^P x_t^L \sum_{u=\lambda_{t-1}}^{\lambda_t} x_u^R$ . As in our case we have  $x_t^L \leq (q_L + 1)$ , we get  $\Delta \leq (q_L + 1)(\sum_{u=1}^{\lambda_P} x_u^R + \sum_{u=1}^P x_{\lambda_u}^R) \leq 2(q_L + 1)x_R \leq 2(\frac{x_L}{P} + 1)x_R$ .

It remains now to handle particular cases, according to the values of  $x_L$  and  $x_R$ .

- If  $x_L \geq P$ , then  $2(\frac{x_L}{P} + 1)x_R \leq \frac{4}{P}x_Lx_R$ , and  $\frac{\Delta}{\text{cost}(X)} \leq \frac{\frac{4}{P}x_Lx_R}{(x_L-1)x_L + (x_R-1)x_R} \leq \frac{\frac{4}{P}x_Lx_R}{\frac{1}{2}(x_L^2 + x_R^2)} \leq \frac{4}{P}$  (we lower bounded  $(x_R - 1)$  by  $\frac{x_R}{2}$  as cases with  $x_R \leq 1$  lead to even better ratio).
- If  $x_L < P$ , then we set  $\text{Comp}(X \cap L_i) = X_L$  (i.e. we keep the left part unchanged). If  $x_R < P + 1$ , then we set  $\text{Comp}(X) = X$  and we get a 1-compaction. Notice that in these cases we are still able to construct  $\text{Comp}(X)$  in polynomial time. Suppose now that  $x_R \geq P + 1$ . One can improve the previous lower bound and write  $\text{cost}(X) \geq \frac{(x_L-1)x_L}{2} + \frac{(x_R-1)x_R}{2} + \sum_{t=1}^P x_t^L (\sum_{u=1}^{\lambda_t-1} x_u^R)$ . Indeed, for all  $t \in \{1, \dots, x_L\}$  the set  $G_t^L$  is a singleton (and  $G_t^L = \emptyset$  for  $t \in \{x_L + 1, \dots, P\}$ ), and thus the interval of  $G_t^L$  overlaps some intervals of  $G_{\lambda_t}^R$ , which implies that it overlaps all intervals of  $G_{\lambda_t-1}^R$ . Thus, we get  $\Delta \leq \sum_{t=1}^P x_t^L x_{\lambda_t}^R \leq \sum_{t=1}^{x_L} x_{\lambda_t}^R \leq x_R$ , and  $\frac{\Delta}{\text{cost}(X)} \leq \frac{2x_R}{(x_L-1)x_L + (x_R-1)x_R} \leq \frac{2}{P}$ , which terminates the proof of the lemma.

### 5.3 Algorithm

Let us now write a dynamic programming algorithm for the instances that have a unique connected component (we will drop this hypothesis after). Let  $\text{Opt}$  be an optimal solution,  $P$  a fixed integer and  $\text{Comp}$  the previous  $(1 + \frac{4}{P})$ -compaction. The algorithm constructs a solution which is at least as good as  $\text{Comp}(\text{Opt})$  by enumerating for all blocks all the possible compacted patterns (i.e. all the possible  $\text{Comp}(X)$ ).

Let us now define more formally the algorithm, starting with the parameters. The first parameter  $k' \leq k$  is the number of interval to choose.  $i$  is the starting block, meaning that the  $k'$  interval must be chosen in  $\bigcup_{l=i}^a B_l$ . Finally,  $B_{i-1}^S$  represents the set of  $2P + 4$  variables that encode the set of intervals  $X_{i-1}$  chosen in block  $(i - 1)$ . Since we can construct  $X_{i-1}$  from  $B_{i-1}^S$  in polynomial time, we will directly use  $B_{i-1}^S$  to denote  $X_{i-1}$ , for the sake of readability.

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#### Algorithm 4 $DP(k', i, B_{i-1}^S)$

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```
// For the sake of clarity we drop the classical operations related to the "marking
// table" that avoid multiple computations with same arguments
// We also drop the base case  $i = a + 1$  (i.e. there are no more remaining intervals in the instance)
 $\Omega \leftarrow$  all possible patterns for block  $i$  using less or equal than  $k'$  intervals
return  $\arg \min_{B \in \Omega} \text{cost}(B_{i-1}^S \cup B \cup DP(k' - |B|, i + 1, B))$ 
```

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**Lemma 11.** For any  $P$ ,  $DP(k, 1, \emptyset)$  outputs a  $(1 + \frac{4}{P})$ -approximation for the  $k$ -SPARSEST SUBGRAPH in  $\mathcal{O}(n^{\mathcal{O}(P)})$ .

*Proof.* The objective is to prove that  $\text{cost}(DP(k, 1, \emptyset)) \leq \text{cost}(\text{Comp}(\text{Opt}))$ , where  $\text{Comp}$  is the previous  $(1 + \frac{4}{P})$ -compaction. According to Lemma 10, it is sufficient to get a  $(1 + \frac{4}{P})$ -approximation.

For sake of readability, for all  $i \in \{1, \dots, a\}$ , we define  $B_i^* = \text{Comp}(\text{Opt}) \cap B_i$  and  $k_i^* = |\bigcup_{l=i}^a B_l^*|$ .

We prove by induction on  $i$  (starting from  $i = a + 1$ ) that  $\text{cost}(B_{i-1}^* \cup DP(k_i^*, i, B_{i-1}^*)) \leq \text{cost}(\text{Comp}(\text{Opt}) \cap \bigcup_{l=i-1}^a B_l)$ .

Let us suppose that the hypothesis is true for  $i + 1$  and prove it for  $i$ . Considering the iteration where  $DP$  chooses  $B = B_i^*$ .

$$\text{cost}(B_{i-1}^* \cup DP(k_i^*, i, B_{i-1}^*)) \leq \text{cost}(B_{i-1}^*) + \text{cost}(B_{i-1}^*, B_i^*) + DP(k_i^* - |B_i^*|, i + 1, B_i^*)$$

(recall that  $\text{cost}(X_1, X_2) = |\{(I_l, I_{l'}) \in E, I_l \in X_1, I_{l'} \in X_2\}|$ ). Using the induction hypothesis we get the desired result.

The dependency in  $P$  in the running time is due to the  $n^{2P+\mathcal{O}(1)}$  possible values for the set of parameters and the branching time in  $n^{2P+\mathcal{O}(1)}$  when enumerating sets  $B_i^S$ .

Finally, let us extend the previous result to instances having several connected component. We only sketch briefly the algorithm as it follows the same idea as, for example, [8] for the  $k$  densest.

Let us suppose that for any  $k' \leq k$  we have an algorithm  $A(k', X)$  which is a  $\rho$ -approximation for  $k'$ -SPARSEST SUBGRAPH on a instance  $X$  having one connected component.

Let  $(C_i)_{1 \leq i \leq x}$  denote the connected component of a (general) instance of  $k$ -SPARSEST SUBGRAPH. It is sufficient to define a dynamic programming algorithm  $DP(k', i)$  that computes a  $\rho$  approximation of the  $k'$ -SPARSEST SUBGRAPH on  $\bigcup_{t=i}^x (C_t)$  by keeping the best of all the  $A(l, C_i) + DP(k' - l, i + 1)$ , for  $1 \leq l \leq k'$ .

Thus, we get the following result:

**Theorem 3.** *There is a PTAS for  $k$ -SPARSEST SUBGRAPH on proper interval graphs running in  $n^{\mathcal{O}(\frac{1}{\epsilon})}$*

## 6 Conclusion and Future Work

In this paper, we studied the fixed-parameter tractability and approximation of the  $k$ -SPARSEST SUBGRAPH problem in subclasses of chordal graphs. More precisely, we designed a *PTAS* in proper interval graphs and an *FPT* in interval graphs when parameterized by the cost of the solution. Given that obtaining a negative result for our problem in interval graphs seems to be a tough question, it would be interesting to determine the complexity of the problem in chordal graphs, and then to extend our approximation and fixed parameterized algorithms in case of  $\mathcal{NP}$ -hardness.

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