

# Worst-case analysis of clique MIPs

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## Abstract

The usual integer programming formulation for the maximum clique problem has several undesirable properties, including a weak LP relaxation, a quadratic number of constraints and nonzeros when applied to sparse graphs, and poor guarantees on the number of branch-and-bound nodes needed to solve it. With this as motivation, we propose new mixed integer programs (MIPs) for the clique problem that have more desirable worst-case properties, especially for sparse graphs. The smallest MIP that we propose has just  $O(n + m)$  nonzeros for graphs with  $n$  vertices and  $m$  edges. Nevertheless, it ensures a root LP bound of at most  $d + 1$ , where  $d$  denotes the graph's degeneracy (a measure of density), and is solved in  $O(2^d n)$  branch-and-bound nodes. Meanwhile, the strongest MIP that we propose visits fewer nodes,  $O(1.62^d n)$ . Further, when a best-bound node selection strategy is used,  $O(2^g n)$  nodes are visited, where  $g = (d + 1) - \omega$  is the clique-core gap. Often,  $g$  is so small that it can be treated as a constant in which case  $O(n)$  nodes are visited. Experiments are conducted to understand their performance in practice.

## 1 Introduction

The maximum clique problem over graph  $G = (V, E)$  can be expressed as the following integer program. Letting  $n = |V|$  and  $m = |E|$ , it uses  $n$  binary variables and  $\binom{n}{2} - m$  conflict constraints—one for each edge of the complement graph  $\bar{G} = (V, \bar{E})$ .

$$\omega(G) = \max \sum_{i \in V} x_i \tag{1a}$$

$$\text{(conflict model)} \quad x_i + x_j \leq 1 \quad \forall \{i, j\} \in \bar{E} \tag{1b}$$

$$x_i \in \{0, 1\} \quad \forall i \in V. \tag{1c}$$

While this *conflict* model is simple to state, it can be impractical, especially when the graph is sparse. One reason is the large number of conflict constraints (1b). For example, for trees there are  $\binom{n}{2} - (n - 1)$  conflicts, which can make it difficult to build

or solve the root LP relaxation for graphs with thousands of vertices. A second reason is its poor linear programming (LP) relaxation; the all-half vector  $(\frac{1}{2}, \dots, \frac{1}{2})$  is always feasible, meaning that the root LP bound (at least  $n/2$ ) can be far from the optimal IP objective  $\omega$  (which equals 2 for trees). Third, this formulation generally provides little guarantee on how many branch-and-bound nodes will be needed to solve it.

Consequently, many have sought to improve this formulation—or, more generally, MIPs that have conflict constraints or set packing constraints. For example, one can generate valid inequalities to strengthen the LP relaxation (Padberg, 1973; Johnson and Padberg, 1982; Savelsbergh, 1994; Atamtürk et al., 2000). These inequalities can be added initially, or on-the-fly as cutting planes. Both approaches are employed by open-source MIP solvers like CBC (Brito and Santos, 2021) and proprietary MIP solvers like Gurobi (Achterberg et al., 2020). While these procedures significantly impact solve time in practice, they do not lead to nontrivial worst-case bounds on the number of branch-and-bound nodes, to our knowledge.

An alternative model proposed by Della Croce and Tadei (1994) is below, see a generalization by Balasundaram et al. (2011) for  $k$ -plex. It is obtained by aggregating the conflict constraints, giving the big- $M$  constraints (2b) where  $M_i = n - |N(i)| - 1$ .

$$\omega(G) = \max \sum_{i \in V} x_i \tag{2a}$$

$$\text{(dense model)} \quad \sum_{j \in V \setminus N[i]} x_j \leq M_i(1 - x_i) \quad \forall i \in V \tag{2b}$$

$$x_i \in \{0, 1\} \quad \forall i \in V. \tag{2c}$$

We call this the *dense* model because it uses approximately  $n^2 - 2m$  nonzeros, which is roughly the same as the conflict model. However, the number of nonzeros can be reduced to  $O(n + m)$  with a new variable  $z = \sum_{i \in V} x_i$ . This gives the *sparse* model.

$$\omega(G) = \max z \tag{3a}$$

$$z = \sum_{i \in V} x_i \tag{3b}$$

$$\text{(sparse model)} \quad z - \sum_{j \in N[i]} x_j \leq M_i(1 - x_i) \quad \forall i \in V \tag{3c}$$

$$x_i \in \{0, 1\} \quad \forall i \in V. \tag{3d}$$

Because this model is small, its LP relaxation is likely easier to solve than that of the conflict model. However, this comes at the cost of a weaker LP relaxation, which likely leads to more branch-and-bound nodes being visited.

**Contributions for Existing MIPs.** In Section 3, we observe that MIPs like these can perform quite poorly, even when applied to straightforward instances like co-lollipops, which are the complements of the lollipop graphs  $L_{3,p}$  shown in Figure 1. Namely, the co-lollipops are solved in  $\Theta(\varphi^n)$  branch-and-bound nodes when using the conflict model, where  $\varphi \approx 1.61803$  denotes the golden ratio.

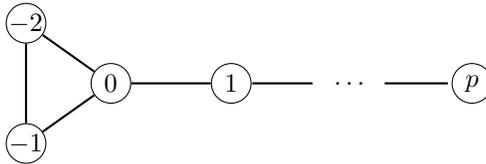


Figure 1: The lollipop graph  $L_{3,p}$ .

In response, we seek alternative MIPs with better worst-case properties. We are particularly interested in exploiting the characteristics of real-life graphs, such as small (graph) degeneracy  $d$  and small clique-core gap  $g := (d + 1) - \omega$ . Table 1 illustrates that the degeneracy and clique-core gap of real-life graphs are much smaller than the number of nodes. (The notions of degeneracy and clique-core gap are defined in Section 2.2.)

Table 1: Walteros and Buchanan (2020) observe that real-life graphs have small clique number  $\omega$ , degeneracy  $d$ , and clique-core gap  $g$  compared to the number of nodes  $n$ .

graph	$n$	$m$	$\omega$	$d$	$g$
as-22july06	22,963	48,436	17	25	9
citationCiteseer	268,495	1,156,647	13	15	3
ldoor	952,203	22,785,136	21	34	14
in-2004	1,382,908	13,591,473	489	488	0
cage15	5,154,859	47,022,346	6	25	20
uk-2002	18,520,486	261,787,258	944	943	0

**Contributions for New MIPs.** In Section 4, we conceive of four new MIPs for the maximum clique problem that take inspiration from the literature on cliques and disjunctive extended formulations. Each has a root LP objective of at most  $d + 1$ , which is typically much smaller than the root LP of the conflict model. In Section 5, we show that the weakest of these four MIPs is solved in  $O(2^d n)$  branch-and-bound nodes. Meanwhile, the strongest of the four MIPs is solved in  $O(\varphi^d n)$  nodes, improving on the  $O(\varphi^n)$  bound obtained by the conflict and sparse models; moreover, we show that the analysis is tight by providing a class of graphs (related to the co-lollipop graphs) for which  $\Omega(\varphi^d n)$  nodes are visited. Finally, we show that if branch-and-bound follows a best-bound node selection strategy, then a different (usually better) bound of  $O(2^g n)$  holds—a virtue not shared by the conflict model. In Section 6, we experiment with the MIPs to understand their performance in practice. We conclude and offer directions for future research in Section 7.

## 2 Background and Literature Review

Below, we review basic terminology from graph theory, the maximum clique problem, MIP techniques for clique finding, and disjunctive extended formulations generally.

## 2.1 Graph terminology

We consider a simple graph  $G = (V, E)$  with vertex set  $V$  and edge set  $E \subseteq \binom{V}{2}$ , where  $\binom{V}{2}$  denotes the collection of 2-vertex subsets of  $V$ . The subgraph of  $G$  induced by a vertex subset  $S \subseteq V$  is denoted by  $G[S] := (S, E \cap \binom{S}{2})$ . The (open) neighborhood of vertex  $v \in V$  is denoted  $N(v) := \{u \in V \mid \{u, v\} \in E\}$ . Meanwhile, the closed neighborhood  $N[v] := N(v) \cup \{v\}$  also includes  $v$ .

A graph  $G = (V, E)$  is *complete* if it has all possible edges, i.e., if  $E = \binom{V}{2}$ . A subset of vertices  $S$  is a *clique* if its induced subgraph  $G[S]$  is complete. The complete graph on  $n$  vertices is denoted by  $K_n$ . A clique is *maximal* if no proper superset of it is also a clique. A clique is *maximum* if it has largest size among all cliques. A maximum clique is necessarily maximal, but not vice versa. The clique number, denoted  $\omega(G)$ , is the size of a maximum clique. As an example,  $S = \{-2, -1, 0\}$  is a maximum (and thus maximal) clique of the lollipop graph  $L_{3,p}$  in Figure 1, implying that  $\omega(L_{3,p}) = 3$ . Also,  $S' = \{0, 1\}$  is a maximal (but not maximum) clique.

The complement of  $G = (V, E)$ , denoted by  $\bar{G} = (V, \bar{E})$ , has the same vertex set as  $G$  but has the complementary edge set  $\bar{E} = \binom{V}{2} \setminus E$ . An independent set (a.k.a. stable set) is a subset of vertices  $S$  such that  $G[S]$  has no edges. Easily,  $S$  is a clique in  $G$  if and only if  $S$  is an independent set in  $\bar{G}$ . Accordingly, the independence number  $\alpha(G)$ , which is the size of a largest independent set, satisfies  $\omega(G) = \alpha(\bar{G})$ . A vertex cover is a subset of vertices  $S$  that hits every edge, i.e.,  $S \cap e \neq \emptyset$  for all  $e \in E$ . Easily,  $S$  is an independent set if and only if  $V \setminus S$  is a vertex cover. Accordingly, the vertex cover number  $\tau(G)$ , which is the size of a smallest vertex cover, satisfies  $\tau(G) + \alpha(G) = n$ .

## 2.2 The clique problem

Cliques were originally introduced to model clusters in networks (Luce and Perry, 1949), and many clique-like structures have been proposed over the years (Pattillo et al., 2013). The maximum clique problem, which asks for a clique of largest size, is a well-known NP-hard problem (Cook, 1971; Karp, 1972; Bomze et al., 1999). It is notoriously hard to approximate; namely, getting a  $n^{1-\varepsilon}$ -approximation for any constant  $\varepsilon > 0$  is NP-hard (Håstad, 1999; Zuckerman, 2006), while an  $n$ -approximation is trivial to achieve by picking a single vertex.

With these observations, there is little hope for clique MIPs to have nice worst-case properties. In fact, even if  $P=NP$ , it would still be impossible to (always) construct small perfect (or well-approximating) MIPs for clique (Fiorini et al., 2015; Braun et al., 2015; Braverman and Moitra, 2013; Goos et al., 2018).

As a compromise, one could ask for a fixed-parameter tractable (fpt) algorithm, which is one that runs in time  $f(k)n^{O(1)}$ , where  $k$  is the parameter of choice and  $f$  is a computable function that depends only on  $k$ . For example, one could seek an algorithm that determines whether a graph has a clique of size  $k$  in time  $O(2^k n^2)$ . However, there are reasons to believe such algorithms do not exist (Cygan et al., 2015, Chapters 13-14).

Fortunately, there is some good news for a different parameter. Eppstein et al. (2013) show that all maximal cliques can be enumerated in time  $O(dn3^{d/3})$ , where  $d$  denotes the graph's degeneracy. Intuitively, graph degeneracy is a measure of density. For example, forests have  $d = 1$ ; cycle graphs have  $d = 2$ ; planar graphs have  $d \leq 5$ ; and complete graphs have  $d = n - 1$ . As Table 1 in the introduction shows, many real-life

graphs have small degeneracy, making the algorithm of Eppstein et al. (2013) practical in many cases. Degeneracy is defined as follows.

**Definition 1** (Lick and White (1970)). *A graph  $G$  is  $k$ -degenerate if each of its subgraphs  $G'$  has minimum degree  $\delta(G') \leq k$ . The degeneracy  $d$  of a graph is the smallest  $k$  for which it is  $k$ -degenerate.*

As observed by Lick and White (1970), if a graph has degeneracy  $d$ , then it admits a vertex ordering  $(v_1, v_2, \dots, v_n)$  in which each vertex  $v_i$  has at most  $d$  neighbors to its right. The converse also holds. Such an ordering can be found by applying the following algorithm to  $G' \leftarrow G$ :

1. for  $i = 1, 2, \dots, n$  do:
  - let  $v_i$  be a minimum degree vertex of  $G'$
  - remove  $v_i$  from  $G'$
2. return  $(v_1, v_2, \dots, v_n)$ .

This algorithm can be implemented to run in  $O(m + n)$  time, as shown by Matula and Beck (1983). Although their original implementation used linked lists, array-based implementations are faster in practice (Batagelj and Zaversnik, 2003; Walteros and Buchanan, 2020).

A key insight used in many clique algorithms is as follows. For each maximal clique  $S$  of the graph  $G$ , there is a (unique) vertex  $v_i$  for which  $S$  is contained in its *closed right-neighborhood*, i.e.,

$$S \subseteq N[v_i] \cap \{v_i, v_{i+1}, \dots, v_n\} =: V_i.$$

This allows for clique problems to be decomposed into  $n$  subproblems<sup>1</sup>,  $G[V_1], G[V_2], \dots, G[V_n]$ . Each has at most  $d + 1$  vertices by the degeneracy ordering. This leads to an  $O(dn3^{d/3})$  algorithm for listing maximal cliques (Eppstein et al., 2013) and an  $O((n - d)2^{d/4})$  algorithm for maximum clique (Buchanan et al., 2014; Manoussakis, 2014).

Given that these times are exponential in the degeneracy, these algorithms can be slow when  $d$  exceeds 100. However, Walteros and Buchanan (2020) observe that for many real-life graphs, the clique number  $\omega$  is quite close to the upper bound  $d + 1$ , differing by just 0, 1, or 2 units on half of their instances. For cases like this where the clique-core gap  $g := (d + 1) - \omega$  can be treated as a constant, the maximum clique problem can be solved in time  $O(dm) = O(m^{1.5})$ , as shown by Walteros and Buchanan (2020). This algorithm, which applies fpt vertex cover algorithms to the subproblems, is often fast in practice.

## 2.3 MIP techniques for clique

The clique problem has a long history in the MIP literature, as do related problems like independent set and vertex cover (Padberg, 1973; Nemhauser and Trotter, 1974, 1975);

<sup>1</sup>Actually,  $(n - d) + 1$  subproblems suffice:  $n - d$  subproblems  $G[V_1], G[V_2], \dots, G[V_{n-d}]$ , and a final subproblem  $G[\{v_q, v_{q+1}, \dots, v_n\}]$  where  $q = n - d + 1$ .

see Rebennack et al. (2012) for a more recent survey. This is partly because many practical problems have set packing constraints that can be conveniently modeled in terms of cliques or independent sets; techniques developed for the stylized problems can then be extended to the real problem. These abstractions have led to the discovery of valid inequalities like clique inequalities, odd-hole inequalities, and others that are used in modern-day MIP solvers to strengthen the LP relaxation (Achterberg et al., 2020). Notable concepts in this area include *conflict generation* (Savelsbergh, 1994), used to detect implicit conflicts between variable assignments, and *conflict graphs*, which are data structures used to store these conflicts (Atamtürk et al., 2000; Brito and Santos, 2021), cf. implication graphs (Aspvall et al., 1979).

Due to the complexity of the clique and independent set problems, these MIP techniques generally lack desirable worst-case guarantees. Exceptions do arise when restricted to particular classes of graphs. For example, there are polynomial-size perfect MIPs for independent set in comparability graphs and chordal graphs (Yannakakis, 1991) and in graphs with small treewidth (Bienstock and Ozbay, 2004; Laurent, 2009; Buchanan and Butenko, 2015; Kolman and Koutecký, 2015), which are essentially best-possible (Faenza et al., 2020). There exist perfect MIPs for  $k$ -vertex covers that use  $O(1.47^k + kn)$  inequalities (Buchanan, 2016), which can be seen as a polyhedral analogue to fpt algorithms for vertex cover (Chen et al., 2010, 2013). Other MIPs for clique, such as those given by Martins (2010) are not known to provide worst-case guarantees.

MIP solvers typically apply the branch-and-cut method, which is a combination of LP-based branch-and-bound and the cutting plane method. Consequently, the running time is largely dependent on the number of branch-and-bound nodes visited during its execution, as well as the time spent to solve the LP relaxations at each node. Generally speaking, one expects that stronger LP bounds will lead to fewer branch-and-bound nodes being explored. However, just because the gap is small, this does not *imply* a small or polynomial number of branch-and-bound nodes. For example, consider an instance of clique  $(G, k)$  in which we are to determine if graph  $G$  has a clique of size  $k$ . From this, one could quickly create an equivalent instance of clique  $(G', k)$  in which  $G' = (V', E')$  is the disjoint union of  $G$  and a complete graph on  $k - 1$  vertices (i.e.,  $K_{k-1}$ ). Now consider the following IP:

$$z_{IP} = \max \sum_{i \in V'} x_i \tag{4a}$$

$$x_i + x_j \leq 1 \quad \forall \{i, j\} \in \binom{V'}{2} \setminus E' \tag{4b}$$

$$\sum_{i \in V'} x_i \leq k \tag{4c}$$

$$x_i \in \{0, 1\} \quad \forall i \in V'. \tag{4d}$$

This IP has a feasible solution of size  $k - 1$ , since  $G'$  has  $K_{k-1}$  as a subgraph. Moreover, the root LP bound  $z_{LP}$  is at most  $k$  by constraint (4c). So,  $k - 1 \leq z_{IP} \leq z_{LP} \leq k$ , and so the (absolute) integrality gap  $z_{LP} - z_{IP}$  is at most one, yet solving this IP amounts to solving the clique problem over  $G$ . Thus, despite the small integrality gap, we expect this IP to be hard. Moreover, since the  $k$ -clique problem is not believed to be fpt, this IP should not be fpt either (with respect to  $k$ ). In contrast, the strongest

MIP that we propose has a small integrality gap  $z_{LP} - z_{IP} \leq (d + 1) - \omega = g$  and is solved in  $O(2^g n)$  branch-and-bound nodes under a best-bound node selection strategy.

## 2.4 Disjunctive extended formulations

When constructing MIPs, a helpful modeling primitive is the disjunctive constraint  $x \in \cup_{j=1}^k P^j$ , where each  $P_j = \{x \in \mathbb{R}^n \mid A^j x \leq b^j\}$  is a rational polytope. While the disjunctive constraint itself is not permitted in a MIP, it can be modeled as a MIP with new variables  $y_j$ , indicating whether  $x$  belongs to  $P^j$ , and copies of the  $x$  variables  $w^1, w^2, \dots, w^k$ , as Proposition 1 shows, see Vielma (2015). This is convenient for us, as it allows us to decompose the clique problem into multiple subproblems and then write a MIP for the disjunction.

**Proposition 1** (Balas (1985, 1998); Jeroslow and Lowe (1984); Lowe (1984)). *For each  $j \in [k]$ , let  $P^j = \{x \in \mathbb{R}^n \mid A^j x \leq b^j\}$  be a nonempty polytope<sup>2</sup>. Let  $P = \text{conv}(\cup_{j=1}^k P^j)$  be the convex hull of their union. Then,  $P = \text{proj}_x Q$  where  $Q$  is the set of all  $(w^1, w^2, \dots, w^k, x, y)$  satisfying*

$$A^j w^j \leq b^j y_j \quad \forall j \in [k] \quad (5a)$$

$$\sum_{j=1}^k w^j = x \quad (5b)$$

$$\text{(Balas model)} \quad \sum_{j=1}^k y_j = 1 \quad (5c)$$

$$w^j \in \mathbb{R}^n \quad \forall j \in [k] \quad (5d)$$

$$x \in \mathbb{R}^n \quad (5e)$$

$$y \in \mathbb{R}_+^k. \quad (5f)$$

Further, every extreme point of  $Q$  has binary  $y$ .

One drawback of model (5) is the large number of  $w$  variables (5d) and nonzeros in constraints (5b) and (5c). However, in some sense this is unavoidable if we require the convex hull and full generality (Conforti et al., 2020).

In the special case where the polytopes  $P^j$  are defined by box constraints, there is hope. Suppose each polytope  $P^j$  takes the form

$$P^j = \{x \in \mathbb{R}^n \mid l_i^j \leq x_i \leq u_i^j, \forall i \in [n]\}. \quad (6)$$

In this case, we can write the MIP:

$$\sum_{j=1}^k l_i^j y_j \leq x_i \leq \sum_{j=1}^k u_i^j y_j \quad \forall i \in [n] \quad (7a)$$

$$\text{(Jeroslow model)} \quad \sum_{j=1}^k y_j = 1 \quad (7b)$$

$$y \in \mathbb{R}_+^k. \quad (7c)$$

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<sup>2</sup>Something like Proposition 1 holds for unbounded polyhedra, but we will not need this.

This model (7) is nice because the  $w$  variables are not needed. It is also sharp; its projection onto the  $x$ -space is equal to  $\text{conv}(\cup_{j=1}^k P^j)$ , (Jeroslow, 1988, Section 3.1). More general forms of this model hold for polyhedra with the same left-hand-side,  $A = A^j$ , and have been studied by Balas (1988); Blair (1990); Jeroslow (1988) and more recently Vielma (2015).

This MIP (7) will be helpful for us, because each of the  $n$  different clique subproblems is defined by having some variables  $x_i$  being: fixed to one ( $l_i^j = u_i^j = 1$ ); fixed to zero ( $l_i^j = u_i^j = 0$ ); or unfixed ( $l_i^j = 0$  and  $u_i^j = 1$ ). Fortunately, model (7) will have just  $O(n+m)$  nonzeros when applied to the clique subproblems, even though it may appear to have  $\Theta(n^2)$  nonzeros at first glance.

### 3 Worst-Case Analysis for Existing Clique MIPs

To understand the worst-case behavior of the existing clique MIPs, we consider the simple branch-and-bound algorithm given in Algorithm 1, which directly applies to the conflict model (1) and the dense model (2). With a small change to account for the  $z$  variable, it applies to the sparse model (3). In its pseudocode,  $(F_0, F_1)$  denotes a node of the branch-and-bound tree, where  $F_0$  and  $F_1$  are the sets of variables fixed to zero and to one at that node, respectively.

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**Algorithm 1** Branch and bound

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1: initialize  $\mathcal{B} \leftarrow \{(\emptyset, \emptyset)\}$  and  $x^* \leftarrow \emptyset$ 
2: while  $\mathcal{B} \neq \emptyset$  do
3:   select and remove a node  $(F_0, F_1)$  from  $\mathcal{B}$ 
4:   solve the LP relaxation  $\text{LP}(F_0, F_1)$ 
5:   if  $\text{LP}(F_0, F_1)$  is infeasible then
6:     continue
7:   let  $\bar{x}$  be an optimal (extreme point) solution to  $\text{LP}(F_0, F_1)$ 
8:   if  $\bar{x}(V) \leq x^*(V)$  then
9:     continue
10:  if  $\bar{x} \in \{0, 1\}^n$  then
11:     $x^* \leftarrow \bar{x}$ 
12:    continue
13:  pick a variable  $x_i$  with  $0 < \bar{x}_i < 1$ 
14:  add  $(F_0 \cup \{x_i\}, F_1)$  and  $(F_0, F_1 \cup \{x_i\})$  to  $\mathcal{B}$ 
15: return  $x^*$ 

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In line 1, the root node  $(\emptyset, \emptyset)$  is added to the collection of branch-and-bound nodes  $\mathcal{B}$ . The incumbent solution  $x^*$  is initialized as null. In line 2, the algorithm continues as long as some node remains open. Line 3 is *node selection* in which an open node  $(F_0, F_1)$  is explored. The associated linear programming relaxation  $\text{LP}(F_0, F_1)$  is solved. If the LP is infeasible, the node is pruned by infeasibility in line 6. If the LP's objective value  $\bar{x}(V) = \sum_{i \in V} \bar{x}_i$  is no better than that of  $x^*$ , the node is pruned by bound in line 9. Next, if the LP solution  $\bar{x}$  is integer, then the incumbent  $x^*$  is updated, and the node is pruned by integrality in line 12. Finally, a variable  $x_i$  is selected for branching. Line 14

creates the left child  $(F_0 \cup \{x_i\}, F_1)$  and right child  $(F_0, F_1 \cup \{x_i\})$ .

For the worst-case analysis, recall the following definitions about rooted trees from Cormen et al. (2009). A *rooted tree* is a tree with a special node called the *root*. For each node  $v$  of the rooted tree, there is a unique (simple) path from the root  $r$  to  $v$ ; the nodes along this path (including  $v$ ) are the *ancestors* of  $v$ . If  $u$  is an ancestor of  $v$ , then  $v$  is a *descendant* of  $u$ . If  $u$  and  $v$  are neighbors and  $u$  is an ancestor of  $v$ , then  $u$  is the *parent* of  $v$  and  $v$  is a *child* of  $u$ . If two nodes have the same parent, they are *siblings*. If a node has zero descendants besides itself, then it is a *leaf*. The *depth* of a node is its distance from the root. The *lowest common ancestor* (LCA) of a subset of nodes is the node that is an ancestor to all of them that has the largest depth.

When branch-and-bound is applied to an integer program, there is a corresponding rooted tree which we denote by  $\mathcal{T}$ . The nodes of  $\mathcal{T}$  are the pairs  $(F_0, F_1)$  of fixed variables encountered during the algorithm, and the root of  $\mathcal{T}$  is the node  $(\emptyset, \emptyset)$ . The depth of node  $(F_0, F_1)$  is equal to  $|F_0| + |F_1|$ . If a variable  $x_i$  is branched on at node  $(F_0, F_1)$ , then  $(F_0, F_1)$  has two children  $(F_0 \cup \{x_i\}, F_1)$  and  $(F_0, F_1 \cup \{x_i\})$ .

**Proposition 2.** *When branch-and-bound is applied to the conflict, dense, and sparse models, it visits  $O(\varphi^n)$  nodes, where  $\varphi < 1.6181$  denotes the golden ratio.*

*Proof.* At each branch-and-bound node  $(F_0, F_1)$ , the number of “free” variables is  $k = n - |F_0| - |F_1| - |I_0(F_0, F_1)|$ , where

$$I_0(F_0, F_1) = \{x_v \mid x_v \notin F_0 \text{ and } v \text{ has a nonneighbor } u \text{ with } x_u \in F_1\} \quad (8)$$

is the set of variables that are *implicitly* fixed to zero by  $F_1$  and conflict constraints (1b) or big- $M$  constraints (2b) or (3c). If  $T(k)$  denotes the number of its descendants, we have the recurrence

$$T(k) \leq \begin{cases} 1 + T(k-2) + T(k-1) & \text{if } k \geq 2 \\ 1 & \text{if } k \leq 1. \end{cases}$$

The reason is as follows. Suppose  $(F_0, F_1)$  were not pruned, then it had an LP solution  $\bar{x}$  and Algorithm 1 chose to branch on some free variable, say  $x_i$ , that was fractional, i.e.,  $0 < \bar{x}_i < 1$ . See that  $i$  has a nonneighbor  $j$  with  $x_j$  free, since otherwise  $\bar{x}_i$  can be increased to one and still be LP feasible. So, in the left child there is one fewer free variable ( $x_i$ ), while in the right child there are at least two fewer free variables ( $x_i$  and  $x_j$ ), so  $T(k) \leq 1 + T(k-1) + T(k-2)$ . Solving the recurrence gives  $T(n) = O(\varphi^n)$ , see (Fomin and Kratsch, 2010, Chapter 2.1).  $\square$

Below we show that the analysis in Proposition 2 is tight. That is, the conflict model (which is stronger than the dense and sparse models) sometimes visits  $\Theta(\varphi^n)$  branch-and-bound nodes. In fact, this occurs on the co-lollipops  $\bar{L}_{3,p}$ , which are the complements of the lollipops  $L_{3,p}$  depicted in Figure 1.

**Theorem 1.** *When branch-and-bound is applied to the conflict model, it can visit  $\Theta(\varphi^n)$  nodes for the co-lollipops  $\bar{L}_{3,p}$ .*

*Proof.* It suffices to show that Algorithm 1 visits  $\Theta(\varphi^n)$  branch-and-bound nodes when the lollipops  $L_{3,p}$  are solved with the *stable set* conflict model, whose LP relaxation is the fractional stable set polytope:

$$\text{FSTAB}(G) = \{x \in [0, 1]^n \mid x_i + x_j \leq 1, \forall \{i, j\} \in E\}.$$

We will suppose that Algorithm 1 makes the following choices:

1. at each node, pick an LP solution with the most fractional coordinates;
2. among the fractional variables, branch on the one  $x_t$  with largest index  $t$ ;
3. for the node-selection strategy, prioritize nodes with fractional solutions.

First, we claim that the all-half vector  $(\frac{1}{2}, \frac{1}{2}, \dots, \frac{1}{2})$  is an optimal extreme point of  $\text{FSTAB}(L_{3,p})$ . It is extreme because it is feasible and satisfies the  $n$  linearly independent constraints  $x_i + x_j \leq 1$  at equality. Now, when  $p$  is even, optimality follows because any LP-feasible solution  $\bar{x}$  satisfies

$$\begin{aligned} \bar{x}(V) &= (\bar{x}_{-1} + \bar{x}_0) + (\bar{x}_1 + \bar{x}_2) + \dots + (\bar{x}_{p-1} + \bar{x}_p) \\ &\leq 1 + 1 + \dots + 1 = 1 + \frac{p}{2} = \frac{n}{2}, \end{aligned}$$

and the all-half vector meets this bound. Meanwhile, when  $p$  is odd,

$$\begin{aligned} \bar{x}(V) &= \frac{1}{2}(\bar{x}_{-1} + \bar{x}_0) + \frac{1}{2}(\bar{x}_{-1} + \bar{x}_1) + \frac{1}{2}(\bar{x}_0 + \bar{x}_1) + (\bar{x}_2 + \bar{x}_3) + \dots + (\bar{x}_{p-1} + \bar{x}_p) \\ &\leq \frac{1}{2} + \frac{1}{2} + \frac{1}{2} + 1 + \dots + 1 = 1.5 + \frac{p-1}{2} = \frac{n}{2}. \end{aligned}$$

Now, consider the execution of Algorithm 1. First, the root LP is solved, giving the all-half vector (by choice 1). By choice 2, the algorithm branches on  $x_p$ . In the right child, the fixing  $x_p = 1$  forces  $x_{p-1} = 0$ ; the remaining LP is equivalent to that for  $L_{3,p-2}$ . In the left child, where  $x_p = 0$ , the remaining LP is equivalent to that for  $L_{3,p-1}$ . In this way, all (nontrivial) LPs that are encountered are over lollipop graphs with fractional LP solutions. Consider a node  $(F_0, F_1)$  in the branch-and-bound tree and let  $k$  denote the number of variables not (explicitly or implicitly) fixed to a binary value. If  $T(k)$  denotes the number of its descendants, we have the recurrence

$$T(k) = \begin{cases} 1 + T(k-2) + T(k-1) & \text{if } k \geq 3 \\ 1 & \text{if } k \leq 2. \end{cases}$$

By choice 3, there is no incumbent with which to prune until all fractional nodes have been processed. Solving the recurrence gives  $T(p) = \Theta(\varphi^p) = \Theta(\varphi^n)$ .  $\square$

The co-lollipops  $\bar{L}_{3,p}$  are quite unlike real-life graphs. For example, they have clique-core gaps  $g$  approximately equal to  $n/2$ , much larger than that of the real-life graphs in Table 1. One may wonder—is branch-and-bound quick when  $g$  is small? Theorem 2 shows this is false. The proof holds for any node selection strategy; even a best-bound strategy visits  $\Omega(1.2599^n)$  nodes.

**Theorem 2.** *When branch-and-bound is applied to the conflict model, it can visit exponentially many nodes even when the clique-core gap  $g$  is zero.*

*Proof.* To prove the claim, consider graphs of the form  $G_q = (V_q, E_q)$ , where

$$V_q = \{1, 1', 1''\} \cup \{2, 2', 2''\} \cup \dots \cup \{q, q', q''\} \quad (9)$$

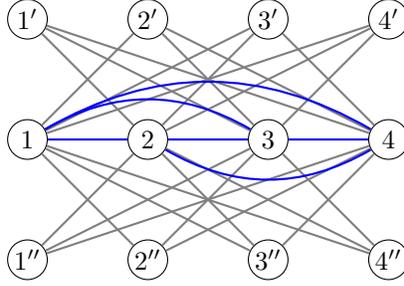


Figure 2: The graph  $G_q$  when  $q = 4$ .

and  $E_q$  is such that  $C = \{1, 2, \dots, q\}$  is a clique, and each of its vertices  $c \in C$  neighbors all vertices of  $V$  except for  $c'$  and  $c''$ . Figure 2 depicts the case  $q = 4$ .

The graph  $G_q$  has degeneracy  $d = q - 1$ ; letting  $a \frown b$  denote the concatenation of  $a$  and  $b$ , a degeneracy ordering is  $(1'', 2'', \dots, q'') \frown (1', 2', \dots, q') \frown (1, 2, \dots, q)$ . The clique number  $\omega$  equals  $q$ , because  $C$  is a clique of size  $q$  and because  $V$  can be partitioned into  $q$  independent sets of the form  $\{c, c', c''\}$ . So, the clique-core gap  $g$  equals zero, as  $g := (d + 1) - \omega = (q - 1 + 1) - q = 0$ .

The following claim says that, if only variables  $x_c$  with  $c \in C$  have been branched on, all “free” variables can be set to one-half. In fact, this is optimal and extreme. The claim uses the notation  $I_0(F_0, F_1)$ , as defined previously (8).

**Claim 1.** *Suppose branch-and-bound node  $(F_0, F_1)$  has  $F_0 \cup F_1 \subseteq \{x_c \mid c \in C\}$ . Then,  $x^*$ , defined below, is an optimal extreme point of  $\text{LP}(F_0, F_1)$ .*

$$x_i^* := \begin{cases} 1 & \text{if } x_i \in F_1 \\ 0 & \text{if } x_i \in F_0 \cup I_0(F_0, F_1) \\ \frac{1}{2} & \text{if otherwise} \end{cases}$$

*Proof.* The point  $x^*$  is optimal, since any  $\bar{x}$  that is feasible for  $\text{LP}(F_0, F_1)$  has:

$$\bar{x}(V) = \sum_{c \in C} (\bar{x}_c + \bar{x}_{c'} + \bar{x}_{c''}) \quad (10a)$$

$$= \sum_{c \in C: x_c \in F_0} (\bar{x}_{c'} + \bar{x}_{c''}) + \sum_{c \in C: x_c \in F_1} 1 + \sum_{c \in C: x_c \notin F_0 \cup F_1} (\bar{x}_c + \bar{x}_{c'} + \bar{x}_{c''}) \quad (10b)$$

$$\leq |F_0 \cup F_1| + \sum_{c \in C: x_c \notin F_0 \cup F_1} \left( \frac{1}{2}(\bar{x}_c + \bar{x}_{c'}) + \frac{1}{2}(\bar{x}_c + \bar{x}_{c''}) + \frac{1}{2}(\bar{x}_{c'} + \bar{x}_{c''}) \right) \quad (10c)$$

$$\leq |F_0 \cup F_1| + \frac{3}{2}(q - |F_0 \cup F_1|) = \frac{3}{2}q - \frac{1}{2}|F_0 \cup F_1| = x^*(V). \quad (10d)$$

Meanwhile,  $x^*$  is extreme, because it is the unique point satisfying the following  $n$

constraints from  $\text{LP}(F_0, F_1)$  at equality.

$$\begin{array}{ll}
x_c \geq 0 & \forall x_c \in F_0 \\
x_c \leq 1 & \forall x_c \in F_1 \\
x_c + x_{c'} \leq 1 & \forall c \in C : x_c \notin F_0 \cup F_1 \\
x_{c'} + x_{(c+1)'} \leq 1 & \forall c \in \{1, 2, \dots, q-1\} \\
x_{c''} + x_{(c+1)''} \leq 1 & \forall c \in \{1, 2, \dots, q-1\} \\
x_{1'} + x_{1''} \leq 1 & \\
x_{1'} + x_{2''} \leq 1. & 
\end{array}$$

■

By Claim 1, the root node's LP objective is  $\frac{3}{2}q$ . Meanwhile, the optimal IP objective is far away at  $q$ . Finally, we observe that branching on variables  $x_c$  with  $c \in C$  leads to slow, predictable progress in the LP bound. Specifically, by Claim 1, branching on a variable  $x_c$  with  $c \in C$  creates two child nodes, each having an LP objective that is one-half less than that of its parent: in the left child, the previously “free”  $x_c$  is added to  $F_0$ , while other variables remain unchanged; in the right child,  $x_c$  is added to  $F_1$ , forcing  $x_{c'}$  and  $x_{c''}$  into  $I_0$ . In both cases, the LP objective decreases by one-half.

In this way, if Algorithm 1 prioritizes variables  $x_c$  with  $c \in C$  for branching, then no node whose depth  $|F_0 \cup F_1|$  is *less* than  $q$  will be pruned. This follows since its LP objective will be greater than  $q$  by (10d). So, all  $2^{q+1} - 1$  nodes whose depth is *at most*  $q$  will be visited, and  $2^{q+1} - 1 > 2^q = 2^{n/3} > 1.2599^n$ . □

## 4 New Clique MIPs

Here, we conceive of four new MIPs for the clique problem. They all rely on a vertex ordering  $(v_1, v_2, \dots, v_n)$ , which we take to be a degeneracy ordering, see Section 2.2. The MIPs differ depending on the choice of base model (conflict vs. sparse) and the choice of extended formulation (Balas vs. Jeroslow). For brevity, we only explicitly define and analyze the two extremes: the smallest and weakest model (sparse-Jeroslow) and the largest and strongest model (conflict-Balas).

The new MIPs rely on the decomposition given in Lemma 1 which allows us to break the clique problem into  $n$  subproblems. Nicely, if a degeneracy ordering is used, then each of these subproblems will have at most  $d$  free variables.

**Lemma 1** (clique decomposition, folklore). *Suppose the vertices of a graph  $G = (V, E)$  are ordered  $(v_1, v_2, \dots, v_n)$ . Then, every nonempty clique  $Q \subseteq V$  of graph  $G$  satisfies the following inclusions for some (unique)  $i \in [n]$ .*

$$\{v_i\} \subseteq Q \subseteq N[v_i] \cap \{v_i, v_{i+1}, \dots, v_n\}. \quad (11)$$

*Proof.* Consider a clique  $Q = \{v_{i_1}, v_{i_2}, \dots, v_{i_q}\}$  indexed so that its vertices follow the ordering, i.e.,  $i_1 < i_2 < \dots < i_q$ . Then,

$$\{v_{i_1}\} \subseteq Q \subseteq N[v_{i_1}] \cap \{v_{i_1}, v_{i_1+1}, \dots, v_n\},$$

as desired. To prove uniqueness, observe that vertices  $v$  that do not belong to  $Q$  will not satisfy  $\{v\} \subseteq Q$ , thus violating the first inclusion of (11). Meanwhile, vertices  $v_{i_j} \in Q$  with  $j \geq 2$ , will not satisfy  $Q \subseteq N[v_{i_j}] \cap \{v_{i_j}, v_{i_j+1}, \dots, v_n\}$  as  $v_{i_1}$  will belong to the left side but not the right, thus violating the second inclusion of (11). So,  $i_1 \in [n]$  is the unique index satisfying (11).  $\square$

## 4.1 Sparse-Jeroslow model

By Lemma 1, we can break the clique problem into  $n$  subproblems. In each subproblem  $j \in [n]$ , one vertex is fixed in the clique, some vertices are “free”, and others are fixed out of the clique. The associated subsets of vertices are:

$$\begin{aligned} S_j^+ &:= \{v_j\} \\ S_j &:= N(v_j) \cap \{v_{j+1}, v_{j+2}, \dots, v_n\} \\ S_j^- &:= V \setminus (S_j^+ \cup S_j). \end{aligned}$$

In the sparse-Jeroslow model, we introduce a binary variable  $y_j$  for each subproblem  $j$ . These variables indicate which subproblem will be selected for our clique.

$$\max z \tag{12a}$$

$$z = \sum_{i \in V} x_i \tag{12b}$$

$$z - \sum_{j \in N[i]} x_j \leq M_i(1 - x_i) \quad \forall i \in V \tag{12c}$$

$$\text{(sparse-Jeroslow model)} \quad \sum_{j : i \in S_j^+} y_j \leq x_i \quad \forall i \in V \tag{12d}$$

$$x_i \leq \sum_{j : i \in S_j^+ \cup S_j} y_j \quad \forall i \in V \tag{12e}$$

$$\sum_{j=1}^n y_j \leq 1 \tag{12f}$$

$$(x, y) \in \{0, 1\}^{n+n}. \tag{12g}$$

This is the same as the sparse model, except for the addition of Jeroslow’s constraints (12d), (12e), (12f), which come from model (7). Notice that the bound constraints (12d) and (12e) are sparser than in Jeroslow’s model; the reason is that some of the bounds are zero and can be omitted. Also, notice that the constraint  $\sum_{j=1}^n y_j = 1$  has been relaxed to  $\sum_{j=1}^n y_j \leq 1$  to allow for the empty solution (where  $x = \mathbf{0}$  and  $y = \mathbf{0}$ ).

The sparse-Jeroslow model has  $2n + 1$  variables and  $3n + 2$  constraints. It has  $\Theta(n + m)$  nonzeros; the sparse model already had  $\Theta(n + m)$  nonzeros, and Jeroslow’s constraints add  $\Theta(n + m)$  nonzeros, in part because

$$\sum_{j=1}^n |S_j| = \sum_{j=1}^n |N(v_j) \cap \{v_j, v_{j+1}, \dots, v_n\}| = m. \tag{13}$$

Additionally, the model itself can be constructed in  $\Theta(n + m)$  time, including the degeneracy ordering. Finally, by Jeroslow (1988), we know that if constraints (12c) were omitted from the sparse-Jeroslow model (12), then its LP relaxation would have integer extreme points. Of course, the addition of constraints (12c) destroys this integrality. Nevertheless, the root LP bound is still strong. Proposition 3 shows it is at most  $d + 1$ . Consequently, its (absolute) integrality gap is at most  $g$ , by  $z_{LP} - z_{IP} \leq (d + 1) - \omega = g$ .

**Proposition 3.** *The LP objective of the sparse-Jeroslow model is at most  $d + 1$ .*

*Proof.* If  $(\bar{x}, \bar{y}, \bar{z})$  is LP feasible, then letting  $\text{rdeg}(v_j) := |N(v_j) \cap \{v_j, v_{j+1}, \dots, v_n\}|$ ,

$$\sum_{i \in V} \bar{x}_i \leq \sum_{i \in V} \sum_{j: i \in S_j^+ \cup S_j} \bar{y}_j = \sum_{j=1}^n (\text{rdeg}(v_j) + 1) \bar{y}_j \leq \sum_{j=1}^n (d + 1) \bar{y}_j \leq d + 1,$$

where the first inequality holds by (12e), the equality holds by rearrangement, the next inequality holds by the degeneracy ordering, and the last inequality holds by (12f).  $\square$

## 4.2 Conflict-Balas model

We now turn to the conflict-Balas model, which is obtained by writing the conflict model for each subproblem  $j$ :

$$\begin{aligned} P^j := \{x \in \mathbb{R}^n \mid & x_u + x_v \leq 1, & \forall \{u, v\} \in \bar{E}(S_j); \\ & x_i = 0, & \forall i \in S_j^-; \\ & x_i = 1, & \forall i \in S_j^+; \\ & 0 \leq x_i \leq 1, & \forall i \in S_j\}, \end{aligned}$$

and taking their union with Balas's model (5). It uses new variables  $w_i^j$  that equal one when vertex  $i \in V$  is picked from subproblem  $j \in [n]$ .

$$\max \sum_{i \in V} x_i \tag{15a}$$

$$w_u^j + w_v^j \leq y_j \quad \forall \{u, v\} \in \bar{E}(S_j), j \in [n] \tag{15b}$$

$$\sum_{j: i \in S_j^+ \cup S_j} w_i^j = x_i \quad \forall i \in V \tag{15c}$$

$$\text{(conflict-Balas model)} \quad w_i^j = y_j \quad \forall i \in S_j^+, j \in [n] \tag{15d}$$

$$0 \leq w_i^j \leq y_j \quad \forall i \in S_j, j \in [n] \tag{15e}$$

$$\sum_{j=1}^n y_j \leq 1 \tag{15f}$$

$$w, y \text{ binary.} \tag{15g}$$

Although there are  $n^2$  many  $w$  variables, most of them will equal zero by Balas's constraints, so model (15) omits these variables,  $w_i^j$  with  $i \in S_j^-$ . After this reduction,

the conflict-Balas model has  $\Theta(n + m)$  variables (recalling (13)),  $O(nd^2)$  constraints, and  $O(nd^2)$  nonzeros. While the  $x$  and  $y$  variables could be projected out via constraints (15c) and (15d), we leave them in for analysis.

The following remark states that the  $x$  variables, although “unrestricted” in the conflict-Balas model (15), will be binary in any MIP-feasible solution.

**Remark 1.** *If  $(\bar{w}, \bar{x}, \bar{y})$  is LP feasible for the conflict-Balas model (15), then  $\bar{x} \in [0, 1]^n$ . Further, if  $(\bar{w}, \bar{x}, \bar{y})$  is MIP feasible, then  $\bar{x}$  is binary.*

*Proof.* If  $(\bar{w}, \bar{x}, \bar{y})$  is LP feasible, then  $\bar{x}_i = \sum_{j: i \in S_j^+ \cup S_j} \bar{w}_i^j$  by (15c) and

$$0 \leq \sum_{j: i \in S_j^+ \cup S_j} \bar{w}_i^j \leq \sum_{j: i \in S_j^+ \cup S_j} \bar{y}_j \leq 1,$$

where the middle inequality holds by (15d) and (15e), and the last inequality holds by (15f) and  $\bar{y} \geq 0$ . Further,  $\bar{x}_i$  is integer (and thus binary) since it is written as the sum of binary values  $\bar{w}_i^j$ .  $\square$

We note that the conflict-Balas model is at least as strong as the sparse-Jeroslow model, and this inclusion can be strict. Thus, by Proposition 3, it gives an LP bound of at most  $d + 1$  and (absolute) integrality gap at most  $g$ . Additionally, Proposition 4 identifies when the conflict-Balas model is perfect.

**Proposition 4.** *The conflict-Balas model is perfect if and only if each subproblem’s  $S_j$  can be partitioned into two cliques (i.e., each  $G[S_j]$  is co-bipartite).*

*Proof.* For arbitrary graphs  $G'$ , the conflict model for  $\omega(G')$  is known to be perfect if and only if  $G'$  is co-bipartite. So, if each subproblem’s  $S_j$  induces a co-bipartite subgraph, then each  $P^j$  is integral, as is  $\text{conv}(\cup_j P^j)$ , so the conflict-Balas model (15) projects to the clique polytope. Meanwhile, if some subproblem’s  $S_j$  does not induce a co-bipartite subgraph, then it contains an odd antihole  $H \subseteq S_j$ . Then, there is a point  $(\bar{w}, \bar{x}, \bar{y})$  that belongs to the LP of conflict-Balas model, but  $\bar{x}$  lies outside of the clique polytope because it violates the valid inequality  $x(H) \leq \lfloor |H|/2 \rfloor$ . Specifically, set  $\bar{w}_i^j = 1$  for  $i \in S_j^+$ ,  $\bar{w}_i^j = 1/2$  for  $i \in H$ , and other  $w$ ’s to zero; set  $\bar{x}$  and  $\bar{y}$  by (15c) and (15d).  $\square$

As a consequence of Proposition 4, the conflict-Balas model (15) is perfect and has linear size  $O(n)$  when the degeneracy is at most two; this includes the class of series-parallel graphs (Bodlaender et al., 2006). For such graphs, each subproblem’s  $S_j$  can trivially be partitioned into two cliques, as  $|S_j| \leq d \leq 2$ , so Proposition 4 applies. Since  $d \leq 2$ , there are  $O(nd^2) = O(n)$  nonzeros, and thus  $O(n)$  variables and constraints.

## 5 Worst-Case Analysis for New Clique MIPs

Now, we analyze the worst-case performance of the sparse-Jeroslow and conflict-Balas models when solved with simple branch-and-bound algorithms. The algorithms are essentially the same as Algorithm 1, but with minor and straightforward changes because of the additional variables  $w$ ,  $y$ , and  $z$ . We will also consider the effects of other changes, like following a best-bound node selection strategy.

## 5.1 Shrunk trees

When conducting our analysis, we use the rooted tree terminology from Section 3. For example, associated with the algorithm's execution, there is rooted tree  $\mathcal{T}$  whose nodes are pairs  $(F_0, F_1)$  of fixed variables. Associated with each clique subproblem  $j \in \{1, 2, \dots, n\}$  there is also a *shrunk tree*, defined below.

**Definition 2.** *The shrunk tree for subproblem  $j$  is denoted by  $\mathcal{T}_j$ . Its node set  $V(\mathcal{T}_j)$  consists of two types of nodes:*

- (A) nodes from  $V(\mathcal{T})$  whose LP solution has  $\bar{y}_j = 1$ , and
- (B) (other) nodes from  $V(\mathcal{T})$  that are LCAs of type A node pairs.

*Consider two distinct nodes  $u$  and  $v$  from  $V(\mathcal{T}_j)$ . If the simple path between them in  $\mathcal{T}$  crosses no other nodes from  $V(\mathcal{T}_j)$ , then the edge  $\{u, v\}$  belongs to  $E(\mathcal{T}_j)$ . The root of  $\mathcal{T}_j$  is the LCA of  $V(\mathcal{T}_j)$  in  $\mathcal{T}$ .*

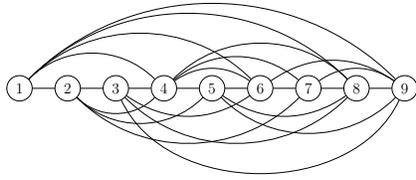
Figure 3 illustrates the branch-and-bound tree  $\mathcal{T}$  and shrunk trees  $\mathcal{T}_1$  and  $\mathcal{T}_2$  for the conflict-Balas model. Figure 3(a) depicts graph  $G$  with degeneracy ordering  $1, 2, 3, \dots, 9$ . Figure 3(d) shows the branch-and-bound tree  $\mathcal{T}$ . At its root, the LP solution  $(\bar{w}, \bar{x}, \bar{y})$  has objective 3.5, which is achieved, say, by setting  $\bar{y}_1 = 1$ ,  $\bar{w}_1^1 = 1$  (indicated by black fill), and  $\bar{w}_2^1 = \bar{w}_4^1 = \bar{w}_6^1 = \bar{w}_8^1 = \bar{w}_9^1 = 1/2$  (gray fill) from the first subproblem. Down the tree, we see solutions in which some  $w$  variables equal zero (indicated by white fill). Finally, Figure 3(e) and Figure 3(f) depict the shrunk trees  $\mathcal{T}_1$  and  $\mathcal{T}_2$ . They illustrate some ways in which shrunk trees are different than branch-and-bound trees. For example, while the nodes of  $\mathcal{T}$  all have zero or two children,  $\mathcal{T}_2$  has a node with one child. Also, the nodes of shrunk trees are not necessarily contiguous in  $\mathcal{T}$ , as  $\mathcal{T}_1$  shows. Nevertheless, shrunk trees do have some helpful traits, as we will see.

**Lemma 2.** *If  $u$  and  $v$  are nodes of the shrunk tree  $\mathcal{T}_j$ , then their lowest common ancestor (LCA) in  $\mathcal{T}$  also belongs to the shrunk tree.*

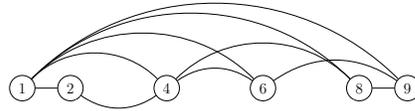
*Proof.* This is immediate when  $u$  and  $v$  are of type A. Generally, observe that every node of  $\mathcal{T}_j$  has a descendant of type A. So, if  $u$  and  $v$  are nodes of  $\mathcal{T}_j$  then the type A descendants of theirs,  $u'$  and  $v'$ , have a LCA  $t'$  that belongs to  $V(\mathcal{T}_j)$  by definition of shrunk tree, and  $t'$  is also the LCA of  $u$  and  $v$ .  $\square$

**Proposition 5.** *The shrunk tree  $\mathcal{T}_j$  is indeed a tree.*

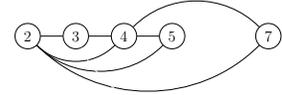
*Proof.* The shrunk tree  $\mathcal{T}_j$  is a forest because it is a minor of the tree  $\mathcal{T}$ . So, to show it is a tree, we just need it to be connected. Consider arbitrary nodes  $u$  and  $v$  from  $V(\mathcal{T}_j)$ . By Lemma 2, their LCA  $t$  also belongs to  $V(\mathcal{T}_j)$ , so it suffices to show that there is a  $u, t$ -path in  $\mathcal{T}_j$ . Consider the path from  $u$  to  $t$  in  $\mathcal{T}$ , and let  $u = i_0, i_1, i_2, \dots, i_q = t$  be the vertices along this path (in sequence) that belong to  $V(\mathcal{T}_j)$ . By definition of shrunk tree, each pair  $\{i_k, i_{k+1}\}$  of consecutive nodes in this sequence is an edge in  $E(\mathcal{T}_j)$ , thus giving a path from  $u$  to  $t$  in  $\mathcal{T}_j$ .  $\square$



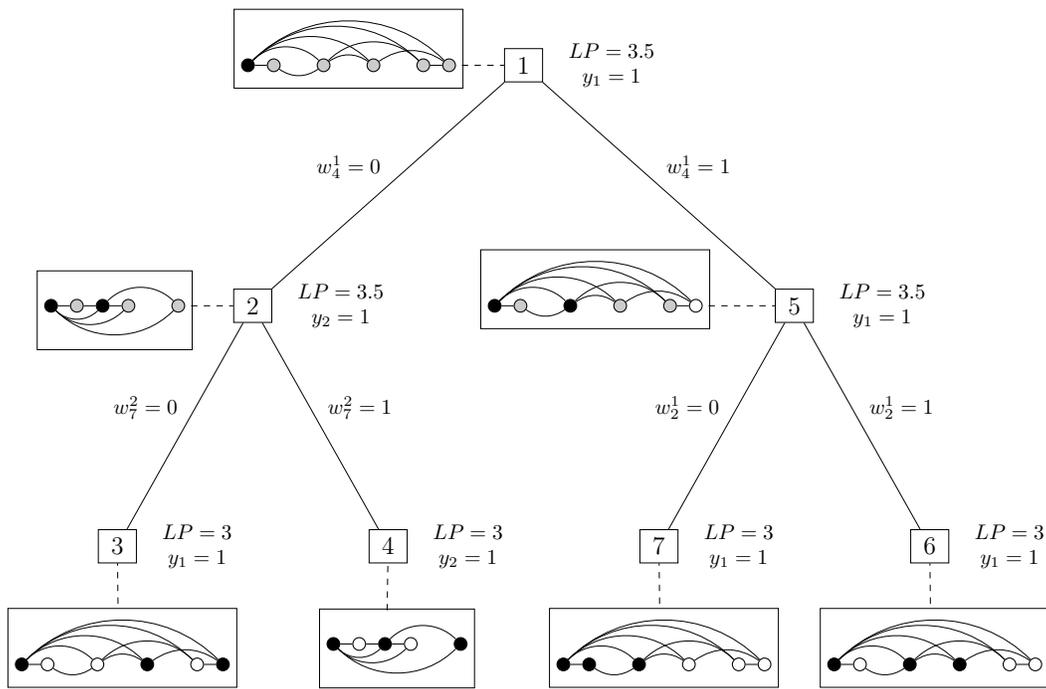
(a) Example graph  $G$ .



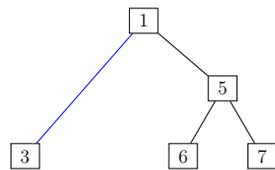
(b) The subgraph  $G[S_1 \cup S_1^+]$ .



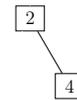
(c) The subgraph  $G[S_2 \cup S_2^+]$ .



(d) The branch-and-bound tree  $\mathcal{T}$ .



(e) The shrunk tree  $\mathcal{T}_1$ .



(f) The shrunk tree  $\mathcal{T}_2$ .

Figure 3: Illustration of shrunk trees. The vertices of  $G$  are round, while the nodes of  $\mathcal{T}$  and  $\mathcal{T}_j$  are square.

**Proposition 6.** *All shrunk tree nodes for the conflict-Balas model have type A.*

*Proof.* For contradiction purposes, suppose that  $t$  is a type B node from the shrunk tree  $\mathcal{T}_j$  and that it is the LCA of type A nodes  $u$  and  $v$ . At node  $t$ , the algorithm branched on a variable. It was not an  $x$  variable, as they are defined to be continuous. It was not a  $y$  variable (nor the  $w$  equivalent (15d)), because the extreme points of the conflict-Balas model have binary  $y$ , see Proposition 1. So, it must have been a variable of the form  $w_i^k$  with  $i \in S_k$ . In the first case, where  $k = j$ , the LP solution  $(\bar{w}, \bar{x}, \bar{y})$  at node  $t$  has  $0 < \bar{w}_i^j \leq \bar{y}_j$  by (15e) and  $\bar{y}_j$  is binary, so  $t$  is actually a type A node, a contradiction. In the other case, where  $k \neq j$ , the branch with  $w_i^k = 1$  forces  $y_k = 1$  by (15e), contradicting the assumption that LP solutions at  $u$  and  $v$  have  $y_j = 1$ .  $\square$

## 5.2 Analysis for sparse-Jeroslow

For our analysis with the sparse-Jeroslow model, we observe that the nodes visited by branch-and-bound can be partitioned into three sets:

- $N_1$  : nodes  $(F_0, F_1)$  for which  $\text{LP}(F_0, F_1)$  is infeasible;
- $N_2$  : nodes  $(F_0, F_1)$  whose LP solution  $(\bar{x}, \bar{y}, \bar{z})$  has fractional  $\bar{y} \notin \{0, 1\}^n$ ;
- $N_3$  : nodes  $(F_0, F_1)$  whose LP solution  $(\bar{x}, \bar{y}, \bar{z})$  has integral  $\bar{y} \in \{0, 1\}^n$ .

Denote their sizes by  $t_1 = |N_1|$ ,  $t_2 = |N_2|$ , and  $t_3 = |N_3|$ .

In the following lemma, we prioritize the  $y$  variables for branching. That is, if the LP solution  $(\bar{x}, \bar{y}, \bar{z})$  has fractional  $\bar{y}$ , then one of its variables  $y_j$  must be selected for branching. Most MIP solvers allow users to set the branching priority of variables.

**Lemma 3.** *If the  $y$  variables are prioritized for branching, then all nodes visited for the sparse-Jeroslow model are LP feasible (i.e.,  $t_1 = 0$ ), and the number of nodes with fractional  $\bar{y}$  is not too big ( $t_2 \leq 1 + 3t_3$ ), so  $t_1 + t_2 + t_3 \leq 1 + 4t_3$ .*

*Proof.* First we show  $t_1 = 0$ . The root node is clearly LP feasible, so consider a non-root node  $(F_0, F_1)$  encountered by the algorithm. Its parent  $(F'_0, F'_1)$  is LP feasible, say at  $(\bar{x}, \bar{y})$ . See that  $Q := \{v \in V \mid \bar{x}_v = 1\}$  is a clique. Additionally,  $Q \cup \{v\}$  is a clique for each  $v$  with  $\bar{x}_v > 0$ , because otherwise  $v$  has a nonneighbor  $q$  in  $Q$  with  $\bar{x}_q = 1$  giving the contradiction

$$0 < \bar{x}_v \leq \sum_{j \in N(q)} \bar{x}_j = \bar{z} - \sum_{j \in N[q]} \bar{x}_j \leq M_q(1 - \bar{x}_q) = 0,$$

where the last inequality holds by (12c). At parent node  $(F'_0, F'_1)$ , the algorithm branched on a variable, fixing it to zero or one, giving four cases for the child:

1. some variable  $x_v$  was fixed to zero,  $(F_0, F_1) = (F'_0 \cup \{x_v\}, F'_1)$ ;
2. some variable  $x_v$  was fixed to one,  $(F_0, F_1) = (F'_0, F'_1 \cup \{x_v\})$ ;
3. some variable  $y_k$  was fixed to zero,  $(F_0, F_1) = (F'_0 \cup \{y_k\}, F'_1)$ ;
4. some variable  $y_k$  was fixed to one,  $(F_0, F_1) = (F'_0, F'_1 \cup \{y_k\})$ .

For each case, we construct a feasible point  $(\hat{x}, \hat{y}, \hat{z})$  for  $\text{LP}(F_0, F_1)$ .

**Case 1:**  $x_v = 0$ . Since  $x_v$  was branched on,  $\bar{y} \in \{0,1\}^n$  holds by the branching priority. Let  $\hat{y} = \bar{y}$ ,  $\hat{x} = x^Q$  be the characteristic vector of clique  $Q$ , and  $\hat{z} = \sum_{i \in V} \hat{x}_i$  be its cardinality. Clearly,  $(\hat{x}, \hat{y}, \hat{z})$  satisfies constraints (12b), (12c), (12f), and the 0-1 fixings required by  $(F_0, F_1)$ . Now we show constraints (12d) and (12e) hold. Observe that each of the sums  $\sum_{j:i \in S_j^+} \hat{y}_j$  and  $\sum_{j:i \in S_j^+ \cup S_j} \hat{y}_j$  take binary values as  $\hat{y} \in \{0,1\}^n$  and  $\sum_{j=1}^n \hat{y}_j \leq 1$ . So, if  $i \in V \setminus Q$ , then

$$\sum_{j:i \in S_j^+} \hat{y}_j = \sum_{j:i \in S_j^+} \bar{y}_j = 0 \leq 0 = \hat{x}_i = 0 \leq \sum_{j:i \in S_j^+ \cup S_j} \hat{y}_j.$$

Note that  $\sum_{j:i \in S_j^+} \bar{y}_j = 0$ , as otherwise  $1 = \sum_{j:i \in S_j^+} \bar{y}_j \leq \bar{x}_i < 1$ . If  $i \in Q$ , then

$$\sum_{j:i \in S_j^+} \hat{y}_j \leq \sum_{j=1}^n \hat{y}_j \leq 1 = \hat{x}_i = 1 \leq 1 = \sum_{j:i \in S_j^+ \cup S_j} \bar{y}_j = \sum_{j:i \in S_j^+ \cup S_j} \hat{y}_j.$$

Note that  $1 = \sum_{j:i \in S_j^+ \cup S_j} \bar{y}_j$ , as otherwise  $0 < \bar{x}_i \leq \sum_{j:i \in S_j^+ \cup S_j} \bar{y}_j = 0$ .

**Case 2:**  $x_v = 1$ . The proof is the same as Case 1, using  $Q \cup \{v\}$  instead of  $Q$ .

**Case 3:**  $y_k = 0$ . If  $Q = \emptyset$  then  $(\hat{x}, \hat{y}, \hat{z}) = (\mathbf{0}, \mathbf{0}, 0)$  proves the claim, so suppose  $Q \neq \emptyset$ . There exists  $k' \neq k$  for which  $\bar{y}_{k'} > 0$ , as otherwise picking any vertex  $i \in Q$  gives the contradiction

$$1 = \bar{x}_i \leq \sum_{j:i \in S_j^+ \cup S_j} \bar{y}_j \leq \sum_{j=1}^n \bar{y}_j = \bar{y}_k < 1.$$

Let  $v$  be the (only) vertex of  $S_{k'}^+$ . Observe that  $\bar{y}_{k'} \leq \bar{x}_v$  by constraints (12d), so  $x_v \notin F'_0$  and also  $Q \cup \{v\}$  is a clique. Let  $\hat{y}$  be the binary vector that has  $\hat{y}_j = 1$  if and only if  $j = k'$ ,  $\hat{x} = x^{Q \cup \{v\}}$  be the characteristic vector of  $Q \cup \{v\}$ , and  $\hat{z} = \hat{x}(V)$  be its cardinality. Clearly,  $(\hat{x}, \hat{y}, \hat{z})$  satisfies constraints (12b), (12c), (12f), and the 0-1 fixings required by  $(F_0, F_1)$ . Now we show that constraints (12d) and (12e) hold for every vertex  $i \in V$ . If  $i \in V \setminus (Q \cup \{v\})$ , then  $i \notin S_{k'}^+$  and

$$\sum_{j:i \in S_j^+} \hat{y}_j = 0 \leq 0 = \hat{x}_i = 0 \leq \sum_{j:i \in S_j^+ \cup S_j} \hat{y}_j.$$

Observe that every vertex  $i \in Q$  also belongs to  $S_{k'}^+ \cup S_{k'}$  because otherwise

$$1 = \bar{x}_i \leq \sum_{j:i \in S_j^+ \cup S_j} \bar{y}_j \leq \sum_{j=1}^n \bar{y}_j - \bar{y}_{k'} < 1.$$

So, every vertex  $i \in Q \cup \{v\}$  belongs to  $S_{k'}^+ \cup S_{k'}$  and thus satisfies

$$\sum_{j:i \in S_j^+} \hat{y}_j \leq 1 = \hat{x}_i = 1 = \hat{y}_{k'} \leq \sum_{j:i \in S_j^+ \cup S_j} \hat{y}_j.$$

**Case 4:**  $y_k = 1$ . Let  $v$  be the (only) vertex that belongs to  $S_k^+$ . Let  $\hat{y}$  be the vector whose only nonzero entry is  $\hat{y}_k = 1$ ,  $\hat{x} = x^{Q \cup \{v\}}$  be the characteristic vector of clique  $Q \cup \{v\}$ , and  $\hat{z} = \hat{x}(V)$  be its cardinality. Note that  $Q \cup \{v\}$  is a clique as  $0 < \bar{y}_k \leq \bar{x}_v$ . Clearly,  $(\hat{x}, \hat{y}, \hat{z})$  satisfies constraints (12b), (12c), (12f), and the 0-1 fixings required by  $(F_0, F_1)$ . Now we show constraints (12d) and (12e) hold for every  $i \in V$ . If  $i \in V \setminus (Q \cup \{v\})$ , then  $i \notin S_k^+$  and

$$\sum_{j:i \in S_j^+} \hat{y}_j = 0 \leq 0 = \hat{x}_i = 0 \leq \sum_{j:i \in S_j^+ \cup S_j} \hat{y}_j.$$

As in Case 3, every  $i \in Q \cup \{v\}$  belongs to  $S_k^+ \cup S_k$ . So, if  $i \in Q \cup \{v\}$ , then

$$\sum_{j:i \in S_j^+} \hat{y}_j \leq 1 = \hat{x}_i = 1 \leq 1 = \sum_{j:i \in S_j^+ \cup S_j} \hat{y}_j.$$

Now we show  $t_2 \leq 1 + 3t_3$ . Let  $r = (\emptyset, \emptyset)$  denote the root node. We create a function  $f : N_2 \setminus \{r\} \rightarrow N_3$  that maps non-root nodes from  $N_2$  to nodes from  $N_3$ . Let  $v$  be a node of  $N_2$  that is not the root and thus has a parent  $p$ . In the first case, where the algorithm branched on an  $x$  variable at  $p$ , node  $p$  belongs to  $N_3$ ; let  $f(v) = p$ . In the other case, where the algorithm branched on a variable  $y_j$  at  $p$ ,  $v$ 's sibling  $s$  belongs to  $N_3$ , since all nodes are LP feasible and its sibling has  $y_j = 1$ ; let  $f(v) = s$ . In this way, a node  $w$  from  $N_3$  has preimage  $f^{-1}(w)$  consisting of at most three nodes from  $N_2$  (its sibling and its two children), so  $|f^{-1}(w)| \leq 3$ . Thus, we have

$$t_2 = |N_2| \leq 1 + |N_2 \setminus \{r\}| \leq 1 + \sum_{w \in N_3} |f^{-1}(w)| \leq 1 + 3|N_3| = 1 + 3t_3.$$

□

**Theorem 3.** *When branch-and-bound is applied to the sparse-Jeroslow model, it visits  $O(2^d n)$  nodes if the  $y$  variables are prioritized for branching.*

*Proof.* We bound the total number of branch-and-bound nodes as follows:

$$t_1 + t_2 + t_3 \leq 1 + 4t_3 \leq 1 + 4 \left( 1 + \sum_{j=1}^n |V(\mathcal{T}_j)| \right) = O(2^d n). \quad (16)$$

The first inequality holds by Lemma 3. The second inequality holds because if the node's LP solution  $(\bar{x}, \bar{y}, \bar{z})$  has integer  $\bar{y}$ , then either  $\bar{y} = 0$  or  $\bar{y} = e_j$  for some  $j$ . At most one node can have  $\bar{y} = 0$  because  $\bar{y} = 0$  implies  $\bar{x} = 0$  and  $\bar{z} = 0$ , and no two nodes can have the same LP solution. In the latter case, where  $\bar{y} = e_j$  for some  $j$ , the node belongs to the shrunk tree  $\mathcal{T}_j$ . So, to prove (16), it remains to show that each shrunk tree has  $O(2^d)$  nodes.

At each branch-and-bound node  $(F_0, F_1)$  of the shrunk tree  $\mathcal{T}_j$ , the number of “free”  $x$  variables (from subproblem  $j$ ) is

$$k = |S_j| - |F_0 \cap X_j| - |F_1 \cap X_j| - |I_0(F_0, F_1) \cap X_j|,$$

where  $X_j = \{x_i \mid i \in S_j\}$  and  $I_0(F_0, F_1)$  is defined as (8). If  $T(k)$  denotes the number of its descendants in  $\mathcal{T}_j$ , we have the recurrence

$$T(k) \leq \begin{cases} 1 + 2T(k-1) & \text{if } k \geq 2 \\ 1 & \text{if } k \leq 1. \end{cases}$$

The reason is as follows. Suppose node  $(F_0, F_1)$  from  $\mathcal{T}_j$  was not pruned, then it had an LP solution  $(\bar{x}, \bar{y}, \bar{z})$  with integer  $\bar{y}$ , and the algorithm chose to branch on some free  $x$  variable, say  $x_s$ , that was fractional, i.e.,  $0 < \bar{x}_s < 1$ . So, any left child of  $(F_0, F_1)$  in  $\mathcal{T}_j$ , if one exists, has at least one fewer free variable ( $x_s$ ). Similarly, any right child of  $(F_0, F_1)$  in  $\mathcal{T}_j$ , if one exists, has at least one fewer free variable ( $x_s$ ). So, solving the recurrence gives  $T(k) = O(2^k)$ , and the root of the shrunk tree has  $k \leq |S_j| \leq d$ , giving  $|V(\mathcal{T}_j)| = O(2^d)$ , as desired.  $\square$

**Proposition 7.** *If the clique-core gap is zero, then when branch-and-bound is applied to the sparse-Jeroslow model it visits at most  $2n$  nodes if a best-bound node selection strategy is used and the  $y$  variables are prioritized for branching.*

*Proof.* When the clique-core gap  $g$  is zero, there is a MIP solution with objective  $d+1$ , and this is LP optimal by Proposition 3. Suppose the root LP solution  $(x^*, y^*, z^*)$  has binary  $y^*$ , say with  $y_k^* = 1$ . Then,  $x^*$  is binary as well; in fact, it must be the characteristic vector of  $S_k^+ \cup S_k$  as

$$d+1 = \sum_{i \in V} x_i^* \leq \sum_{i \in S_k^+ \cup S_k} x_i^* + 0 \leq d+1,$$

where the middle inequality holds by (12e). So, the node is pruned by feasibility. Otherwise,  $y^*$  is fractional, and the algorithm branches on some  $y_j$ . In the branch where  $y_j = 1$ , the LP solution either has objective  $d+1$  in which case it again has binary  $x$  and is pruned by feasibility, or it has objective strictly less than  $d+1$  in which case it produces no children by the best-bound strategy.  $\square$

### 5.3 Analysis for conflict-Balas

We have seen that the sparse-Jeroslow model (12) visits  $O(2^d n)$  nodes, provided that  $y$  variables are prioritized for branching. For the conflict-Balas model (15), we are able to prove a better bound,  $O(\varphi^d n)$ , which is achieved. That is, there are classes of graphs for which  $\Omega(\varphi^d n)$  nodes are visited. They are obtained by modifying the lollipop graphs.

Specifically, we define the *dessert* graph  $D_{p,q} = L_{3,p} \cup K_{q+3}$  as the disjoint union of the lollipop  $L_{3,p}$  and the complete ‘‘cotton candy’’ graph  $K_{q+3}$ . As shown in Figure 4, it has  $p+q+6$  vertices and is defined when  $p \geq 1$  and  $q \geq 1$ .

**Lemma 4.** *The dessert complement  $\overline{D}_{p,q}$  admits the degeneracy ordering*

$$(1', 2', \dots, q') \frown (0, 0') \frown (2, 4, \dots, p_e) \frown (-1', -1, -2', -2) \frown (1, 3, \dots, p_o),$$

where  $p_e$  and  $p_o$  are the largest even and odd integers, respectively, that do not exceed  $p$ . Its degeneracy  $d(\overline{D}_{p,q})$  is  $p+3$ .

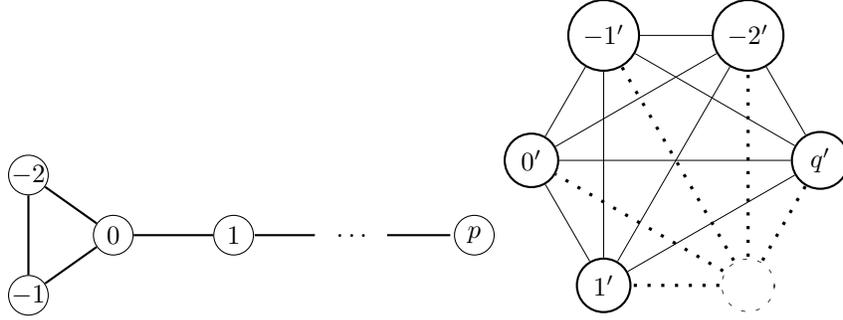


Figure 4: The dessert graph  $D_{p,q} := L_{3,p} \cup K_{q+3}$ .

*Proof.* This is a maximum degree ordering of  $D_{p,q}$ , thus a degeneracy ordering of  $\overline{D}_{p,q}$ . Also, vertex  $1'$  has the largest right-neighborhood, with  $p+3$  vertices.  $\square$

Without loss of generality, suppose that each subproblem  $j$  of  $\overline{D}_{p,q}$  has  $S_j^+ = \{j\}$  and is thus represented by the variable  $y_j$ . Now, for each subproblem defined by vertex  $u \in \{1', 2', \dots, q'\}$ , we can construct a point  $(\bar{w}, \bar{x}, \bar{y})$  given by

$$\bar{y}_v = \begin{cases} 1 & \text{if } v = u \\ 0 & \text{if } v \neq u; \end{cases} \quad \bar{w}_i^v = \begin{cases} \frac{1}{2} & \text{if } v = u, i \in \{-2, -1, 0, 1, 2, \dots, p\} \\ 1 & \text{if } v = u \text{ and } i = u \\ 0 & \text{if otherwise.} \end{cases}$$

and let each vertex  $i$  have  $\bar{x}_i = \sum_{j: i \in S_j^+ \cup S_j} \bar{w}_i^j$ . We argue that all such points  $(\bar{w}, \bar{x}, \bar{y})$  constructed in this way are LP optimal.

**Lemma 5.** *Assume the degeneracy ordering given in Lemma 4. For each vertex  $u \in \{1', 2', \dots, q'\}$ , the point  $(\bar{w}, \bar{x}, \bar{y})$  defined above is an optimal extreme point of the LP relaxation of the conflict-Balas model (15).*

*Proof.* Observe that  $(\bar{w}, \bar{x}, \bar{y})$  is LP feasible with objective value  $(p+5)/2$ . First, we show LP optimality. By Proposition 1, it suffices to show that the objective value over each conflict model subproblem  $P^j$  (defined in Section 4.2) is at most  $(p+5)/2$ . When  $j \in \{-2', -1', 0', 1', 2', \dots, q'\}$ , the conflict model subproblem is over a universal vertex  $j$  (contributing one to the objective) and a subgraph of the co-lollipop  $\overline{L}_{3,p}$  (contributing at most  $(p+3)/2$  as in the proof of Theorem 1), giving LP objective at most  $(p+5)/2$ . When  $j = 0$ , the conflict model subproblem is over the universal vertex 0, the co-path  $(2, 3, \dots, p)$ , and the co-triangle on  $\{-2', -1', 0'\}$ , giving LP objective  $1 + \lfloor p/2 \rfloor + (3/2) \leq (p+5)/2$ . Finally, for any other  $j \in \{-2, -1\} \cup \{1, 2, \dots, p\}$ , the conflict model subproblem is over a subset of the vertices  $\{-2, -1\} \cup \{1, 2, \dots, p\} \cup \{-2', -1'\}$ , giving an LP objective of at most  $1 + \lceil p/2 \rceil + 1 \leq (p+5)/2$ .

Now, to show  $(\bar{w}, \bar{x}, \bar{y})$  is extreme, see that it is the unique point satisfying the following  $3n+m$  constraints from (15) at equality, where  $n$  and  $m$  refer to the number

of vertices and edges of  $\overline{D}_{p,q}$ , respectively.

$$\begin{aligned}
y_j &\geq 0 && \forall j \neq u \\
\sum_j y_j &\leq 1 \\
w_i^j &\geq 0 && \forall i \in S_j, \forall j \neq u \\
w_i^j &= y_j && \forall i \in S_j^+, \forall j \neq u \\
w_i^j &= y_j && \forall i \in S_j^+, \forall j = u \\
w_r^u + w_s^u &\leq y_j && \forall \{r, s\} \in \overline{E}(S_u) \\
\sum_{j: i \in S_j^+ \cup S_j} w_i^j &= x_i && \forall i.
\end{aligned}$$

□

**Theorem 4.** *When branch-and-bound is applied to the conflict-Balas model, it can visit  $\Omega(\varphi^d n)$  nodes.*

*Proof.* We show that branch-and-bound visits  $\Theta(n\varphi^d)$  nodes when applied to the conflict-Balas model, for co-dessert graphs  $\overline{D}_{p,q}$  under the degeneracy ordering from Lemma 4. Namely, we exhibit a branch-and-bound tree with  $q'$  subtrees, each with  $\Omega(\varphi^{d-2})$  nodes.

The degeneracy of  $\overline{D}_{p,q}$  is  $d = p + 3$ , as shown in Lemma 4. The root LP solution can be taken as  $(\bar{w}, \bar{x}, \bar{y})$  for  $u = 1'$ , per Lemma 5. This solution has  $\bar{y}_{1'} = 1$  and  $\bar{w}_p^{1'} = 1/2$ . Suppose we branch on  $w_p^{1'}$ . In the right child, where  $w_p^{1'} = 1$ , constraints (15b) force  $y_{1'} = 1$ , so the model reduces to the conflict model for  $L_{3,p-2}$ ; so, by Theorem 1, this subtree consisting of the right child and its descendants has  $\Theta(\varphi^{p+1}) = \Theta(\varphi^{d-2})$  nodes. Meanwhile, in the left child of the root, where  $w_p^{1'} = 0$ , we can take the LP solution to be  $(\bar{w}, \bar{x}, \bar{y})$  for  $u = 2'$ , which is LP optimal and extreme by Lemma 5; similar to before, this solution has  $\bar{y}_{2'} = 1$  and  $\bar{w}_p^{2'} = 1/2$ , and branching on  $w_p^{2'}$  leads to a right subtree with  $\Theta(\varphi^{d-2})$  nodes. Repeating this scheme for  $u = \{3', 4', \dots, q'\}$  down the left side of the tree gives  $q$  subtrees, each with  $\Theta(\varphi^{d-2})$  nodes. This shows that the whole branch-and-bound tree has  $\Omega(q\varphi^{d-2})$  nodes, which is  $\Omega(n\varphi^d)$  over the class of co-desserts  $\{\overline{D}_{q,q} \mid q \in \mathbb{Z}_+\}$ . □

For further analysis with the conflict-Balas model, we again observe that the nodes visited by branch-and-bound can be partitioned into three sets:

- $N_1$  : nodes  $(F_0, F_1)$  for which  $\text{LP}(F_0, F_1)$  is infeasible;
- $N_2$  : nodes  $(F_0, F_1)$  whose LP solution  $(\bar{w}, \bar{x}, \bar{y})$  has fractional  $\bar{y} \notin \{0, 1\}^n$ ;
- $N_3$  : nodes  $(F_0, F_1)$  whose LP solution  $(\bar{w}, \bar{x}, \bar{y})$  has integral  $\bar{y} \in \{0, 1\}^n$ .

As before, let  $t_1 = |N_1|$ ,  $t_2 = |N_2|$ , and  $t_3 = |N_3|$  denote their sizes.

**Lemma 6.** *When the conflict-Balas model is solved with branch-and-bound, all visited nodes are LP feasible (i.e.,  $t_1 = 0$ ) and have binary  $\bar{y}$  (i.e.,  $t_2 = 0$ ).*

*Proof.* By Proposition 1, all extreme points  $(\bar{w}, \bar{x}, \bar{y})$  of the conflict-Balas LP have binary  $\bar{y}$ . Consequently, the same holds for *faces* of the conflict-Balas LP. This includes the LPs encountered at branch-and-bound nodes, as they are induced by valid inequalities of the form  $w_i^j \geq 0$  and  $w_i^j \leq 1$ . Thus,  $t_2 = 0$ .

The root node is clearly LP feasible, so consider a non-root node  $(F_0, F_1)$  encountered by the algorithm. Its parent  $(F'_0, F'_1)$  is LP feasible, say at  $(\bar{w}, \bar{x}, \bar{y})$ . As we know,  $\bar{y}$  is binary, say, with  $\bar{y}_j = 1$ . See that  $Q := \{v \in V \mid \bar{w}_v^j = 1\}$  is a clique. Additionally,  $Q \cup \{v\}$  is a clique for each  $v$  with  $\bar{w}_v^j > 0$ , because otherwise  $v$  has a nonneighbor  $q$  in  $Q$  with  $\bar{w}_q^j = 1$  giving the contradiction

$$0 < \bar{w}_v^j \leq \bar{y}_j - \bar{w}_q^j = 1 - 1 = 0,$$

where the second inequality holds by (15b). At parent node  $(F'_0, F'_1)$ , the algorithm branched on a variable, fixing it to zero or one. This branching variable must take the form  $w_v^j$  with  $v \in S_j$ , as  $x$  is defined continuous,  $\bar{y}$  is binary, and  $\bar{w}_i^j = \bar{y}_j$  for  $i \in S_j^+$  by (15d). This gives two cases for the child; in both we construct a feasible point  $(\hat{w}, \hat{x}, \hat{y})$  for  $\text{LP}(F_0, F_1)$ . In the first case,  $w_v^j$  was fixed to zero, i.e.,  $(F_0, F_1) = (F'_0 \cup \{w_v^j\}, F'_1)$ . Let  $\hat{y} = \bar{y} \in \{0, 1\}^n$  and let  $\hat{w}^j$  represent clique  $Q$ . Set other  $\hat{w}$ 's to zero and  $\hat{x}_i := \sum_{j: i \in S_j^+ \cup S_j} \hat{w}_i^j$  for all  $i \in [n]$ . Clearly,  $(\hat{w}, \hat{x}, \hat{y})$  satisfies all constraints in model (15) and the 0-1 fixings required by  $(F_0, F_1)$ . In the other case,  $w_v^j$  was fixed to one, i.e.,  $(F_0, F_1) = (F'_0, F'_1 \cup \{w_v^j\})$ . The construction follows the previous case, but using  $Q \cup \{v\}$  instead of  $Q$ .  $\square$

**Theorem 5.** *When branch-and-bound is applied to the conflict-Balas model, it visits  $O(\varphi^d n)$  nodes.*

*Proof.* We bound the total number of branch-and-bound nodes as follows:

$$t_1 + t_2 + t_3 = t_3 \leq 1 + \sum_{j=1}^n |V(\mathcal{T}_j)| = O(\varphi^d n). \quad (17)$$

The first equality holds by Lemma 6. The second inequality holds because if the node's LP solution  $(\bar{w}, \bar{x}, \bar{y})$  has integer  $\bar{y}$ , then either  $\bar{y} = 0$  or  $\bar{y} = e_j$  for some  $j$ . At most one node can have  $\bar{y} = 0$  because  $\bar{y} = 0$  implies  $\bar{w} = 0$  and  $\bar{x} = 0$ , and no two nodes can have the same LP solution. In the latter case, where  $\bar{y} = e_j$  for some  $j$ , the node belongs to the shrunk tree  $\mathcal{T}_j$ . So, to prove (17), it remains to show that each shrunk tree has  $O(\varphi^d)$  nodes.

At each node  $(F_0, F_1)$  of the shrunk tree  $\mathcal{T}_j$ , the number of “free”  $w$  variables from subproblem  $j$  is

$$k = |S_j| - |F_0 \cap W_j| - |F_1 \cap W_j| - |I_0^j(F_0, F_1) \cap W_j|, \quad (18)$$

where  $W_j := \{w_i^j \mid i \in S_j\}$  is the set of  $w$  variables from subproblem  $j$ , and  $I_0^j(F_0, F_1)$  is the set of  $w$  variables from subproblem  $j$  that are *implicitly* fixed to zero by the extended conflict constraints (15b):

$$I_0^j(F_0, F_1) := \{w_u^j \in W_j \setminus F_0 \mid v \text{ has a nonneighbor } u \text{ with } w_u^j \in F_1\}. \quad (19)$$

Now, if  $T(k)$  denotes the number of its descendants in  $\mathcal{T}_j$ , we have the recurrence

$$T(k) \leq \begin{cases} 1 + T(k-2) + T(k-1) & \text{if } k \geq 2 \\ 1 & \text{if } k \leq 1. \end{cases}$$

The reason is as follows. Suppose  $(F_0, F_1)$  from  $\mathcal{T}_j$  were not pruned, then it had an LP solution  $(\bar{w}, \bar{x}, \bar{y})$  with integer  $\bar{y}$ , and the algorithm chose to branch on some free  $w$  variable, say  $w_s^j$ , that was fractional, i.e.,  $0 < \bar{w}_s^j < 1$ . See that  $s$  has a nonneighbor  $t$  from  $S_j$  with  $w_t^j$  free since otherwise  $\bar{w}_s^j$  can be increased to one and still be LP feasible. So, any left child of  $(F_0, F_1)$  in  $\mathcal{T}_j$ , if one exists, has one fewer free variable ( $w_s^j$  added to  $F_0$ ). Meanwhile, any right child of  $(F_0, F_1)$  in  $\mathcal{T}_j$ , if one exists, has at least two fewer free variables ( $w_s^j$  added to  $F_1$ , and  $w_t^j$  added to  $I_0^j$ ), so  $T(k) \leq 1 + T(k-1) + T(k-2)$ . So, solving the recurrence gives  $T(k) = O(\varphi^k)$ , and the root of the shrunk tree has  $k \leq |S_j| \leq d$ , giving  $|V(\mathcal{T}_j)| = O(\varphi^d)$ , as desired.  $\square$

**Theorem 6.** *When branch-and-bound is applied to the conflict-Balas model, it visits  $O(2^g n)$  nodes if a best-bound node selection strategy is used.*

*Proof.* By the proof of Theorem 5 it suffices to show that  $|V(\mathcal{T}_j)| = O(2^g)$ . First, recall the notations  $W_j$  and  $I_0^j(F_0, F_1)$  from the proof of Theorem 5. At each node  $(F_0, F_1)$  of the shrunk tree, the number of  $w$  variables from subproblem  $j$  that are explicitly or implicitly fixed to zero is  $|F_0 \cap W_j| + |I_0^j(F_0, F_1) \cap W_j|$ . So, the LP bound at node  $(F_0, F_1)$  exceeds (“beats”) the IP objective  $\omega$  by at most

$$b = (|S_j| + 1) - |F_0 \cap W_j| - |I_0^j(F_0, F_1) \cap W_j| - \omega.$$

Crucially, if  $b < 0$ , then  $(F_0, F_1)$  produces no children by the best-bound node selection strategy. Now, if  $T(b)$  denotes the number of its descendants in  $\mathcal{T}_j$ , we have the recurrence

$$T(b) \leq \begin{cases} 1 + T(b-1) + T(b-1) & \text{if } b \geq 0 \\ 1 & \text{if } b < 0. \end{cases}$$

The reason is as follows. Suppose  $(F_0, F_1)$  from  $\mathcal{T}_j$  were not pruned, then it had an LP solution  $(\bar{w}, \bar{x}, \bar{y})$  with integer  $\bar{y}$ , and the algorithm chose to branch on some free  $w$  variable, say  $w_s^j$ , that was fractional. As in the proof of Theorem 5,  $s$  must have a nonneighbor  $t$  from  $S_j$  with  $w_t^j$  free. So, any left child of  $(F_0, F_1)$  in  $\mathcal{T}_j$ , if one exists, has an additional variable explicitly fixed to zero ( $w_s^j$  added to  $F_0$ ). Meanwhile, any right child of  $(F_0, F_1)$  in  $\mathcal{T}_j$ , if one exists, has an additional variable implicitly fixed to zero ( $w_t^j$  added to  $I_0^j$ ), so  $T(b) \leq 1 + T(b-1) + T(b-1)$ . Solving the recurrence gives  $T(b) = O(2^b)$ , and the root of the shrunk tree has  $b \leq (|S_j| + 1) - \omega \leq (d + 1) - \omega = g$ , giving  $|V(\mathcal{T}_j)| = O(2^g)$ , as desired.  $\square$

## 6 Experiments

To better understand the practical performance of the clique MIPs, we conduct some experiments. Our aim is shed light on two broad questions:

1. How does the practical performance compare to the worst-case analysis? How well do the parameterizations based on  $d$  and  $g$  match the actual number of branch-and-bound nodes visited?
2. In light of size/strength tradeoffs, which clique MIPs perform best in practice? Do the new clique MIPs outperform existing MIPs on the sparse, real-life instances that motivated them? What size instances are within reach?

For our experiments, we consider instances from the 10th DIMACS Implementation Challenge on Graph Partitioning and Graph Clustering (DIMACS, 2020), as well as from the Stanford Large Network Dataset Collection (Leskovec and Sosič, 2016, SNAP). These repositories include real-life graphs from a variety of applications (e.g., social networks, citation networks, web graphs, road networks, biological networks), and are used for benchmarking graph algorithms, including maximum clique algorithms (Eppstein et al., 2013; Verma et al., 2015; Walteros and Buchanan, 2020). Like Koch et al. (2011) and Gleixner et al. (2019), we select a subset of instances that are not too easy, not too hard, and come from diverse applications. We select instances with diverse values of degeneracy  $d$  and clique-core gap  $g$  to illustrate their relationship with MIP solve time. For comparison purposes, we also consider three hamming graphs from the 2nd DIMACS Implementation Challenge relating to coding theory. These graphs are much denser and structurally very different from the other test instances.

Our computer is a Dell Precision Tower 7000 Series (7810) machine running Windows 10 enterprise, x64, with Intel Xeon Processor E52630 v4 and 32 GB memory. The MIPs are implemented in Python 3.9.0 for Gurobi 9.1.1 (Gurobi Optimization, Inc, 2020). To mimic the simplicity of Algorithm 1 (branch and bound), we turn off presolve, heuristics, and cuts, yielding a *bare-bones* Gurobi MIP solver. For the sparse-Jeroslow model,  $y$  variables are prioritized for branching. We impose a time limit of 3600 seconds. The code, data, and results are available at <https://github.com/MohNaderi/Worst-case-analysis-of-clique-MIPs>.

In Table 2, we report results obtained from applying *bare-bones* Gurobi to the conflict (c), sparse (s), conflict-Balas (cB), and sparse-Jeroslow (sJ) models. The first several columns report the graph name, the number of vertices and edges ( $n$  and  $m$ ), the clique number ( $\omega$ ), the degeneracy ( $d$ ), and the clique-core gap ( $g := (d + 1) - \omega$ ). The graphs vary in size from small (e.g., `polbooks` with 105 vertices and 441 edges) to large (e.g., `belgium` with over a million vertices and edges). As Walteros and Buchanan (2020) observe, the clique-core gaps of the DIMACS10 and SNAP graphs are often very small—much smaller than that of the hamming graphs from DIMACS2.

The next two portions of the table report the number of branch-and-bound nodes and the time required to solve the MIPs. For the conflict, sparse, and sparse-Jeroslow models, we can easily calculate the number of nonzeros before building them. If the number of nonzeros exceeds 10,000,000, then the instance is skipped to avoid a memory crash, and we report DNA (did not attempt). If the MIP is not built within 3600 seconds, then we report DNFB (did not finish building). If the MIP was built but not solved within the 3600-second time-limit, we report the time as TLR (time limit reached). If the instance was attempted but not solved within 3600 seconds, then we report the number of branch-and-bound nodes visited at termination ( $\geq$  `bbnodes`).

A first observation is that the conflict model is typically too large that it cannot be built. This was expected from the beginning. There are also a handful of instances

where the sparse and sparse-Jeroslow models cannot be built. Perhaps surprisingly, the conflict-Balas model can be built for all the DIMACS10 and SNAP instances, despite providing a worst-case size bound  $O(nd^2)$  that is seemingly no better than that of the sparse and sparse-Jeroslow models,  $O(n+m)$ . An explanation is that the subgraphs  $G[S_j]$  are dense in practice and require few extended conflict constraints (15b) compared to the worst-case bound  $\binom{d}{2}$ ; all other constraints contribute  $O(n+m)$  nonzeros.

To our astonishment, the conflict-Balas model solves all but a few of the DIMACS10 and SNAP instances *at the root node!* While we expected that some of the instances with  $g = 0$  would solve at the root given that they guarantee an integrality gap of zero, by  $z_{LP} - z_{IP} \leq (d+1) - \omega = g = 0$ , we did not expect this phenomenon to be so widespread. In fact, even the instance **Cit-HepTh** is solved at the root, despite having a clique-core gap of 15. At first, we suspected this to be an error, but a deeper analysis confirms the result; the root LP solution is indeed integral. Figure 5 shows the (complement) subgraph  $\overline{G}[S_j]$  associated with the subproblem  $j$  that the LP selects. The top row of vertices, which form a clique in  $G[S_j]$ , are selected by the LP, and the bottom vertices are not. Depicted in the figure are vertical edges that form a matching between the *head* (bottom row) and the *crown* (top row). The conflict constraints associated with this matching show that the crown is optimal for the subproblem’s LP. For more, we refer the reader to the influential paper of Nemhauser and Trotter (1975) and the textbook of Cygan et al. (2015) for more on crown decomposition.

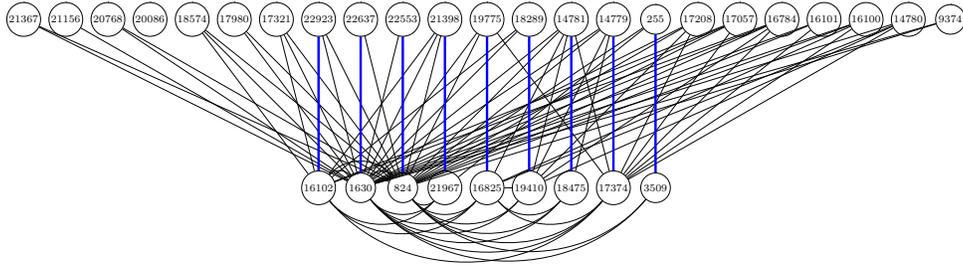


Figure 5: The LP relaxation of the conflict-Balas model on **Cit-HepTh** gives an integral solution even though  $g = 15$ . Depicted is the complement subgraph  $\overline{G}[S_j]$  for the chosen subproblem  $j$ . The top row of vertices were selected, and the bottom vertices were not.

Inspecting the MIP solve times, we see that the conflict-Balas model is the clear winner on the DIMACS10 and SNAP instances. It is followed by the sparse-Jeroslow model in (a distant) second place, the sparse model in third, and the conflict model in (a distant) fourth place. Meanwhile, on the DIMACS2 instances, the situation is much different, almost the reverse, with the conflict model in first place, and the conflict-Balas model in last place. To explain this behavior, recall that the clique MIPs developed in this paper are designed to exploit sparsity, but the hamming graphs are quite dense. They have lost their size advantage and with little gain in terms of strength. Figure 6 illustrates the models’ constraint matrices when applied to **email** and **hamming8-4**.

Table 2: MIP results when applying *bare-bones* Gurobi to the conflict (c), sparse (s), conflict-Balas (cB), and sparse-Jeroslow (sJ) models. If the number of nonzeros is known to exceed 10,000,000, then the instance is skipped, and we report DNA (did not attempt). If the MIP is not built within 3600 seconds, then we report DNFB (did not finish building). If the MIP was built but not solved, we report the time as TLR (time limit reached). If the instance was attempted but not solved within 3600 seconds, then we report the number of branch-and-bound nodes visited so far ( $\geq$  `bbnodes`).

graph	$n$	$m$	$\omega$	$d$	$g$	Number of B&B nodes				MIP solve time			
						c	s	cB	sJ	c	s	cB	sJ
polbooks	105	441	6	6	1	184	257	0	16	1.15	0.12	0.07	13.99
adjnoun	112	425	5	6	2	203	531	0	87	1.26	0.18	0.06	0.55
celegans_metabolic	453	2,025	9	10	2	868	1,306	0	39	60.16	0.69	0.11	0.64
delaunay_n10	1,024	3,056	4	4	1	DNFB	2,490	0	936	DNFB	6.34	0.14	12.35
email	1,133	5,451	12	11	0	DNFB	1,965	0	0	DNFB	4.16	0.33	0.91
polblogs	1,490	16,715	20	36	17	DNFB	288,255	3	7,867	DNFB	209.73	24.80	42.70
delaunay_n11	2,048	6,127	4	4	1	DNFB	5,201	0	2,135	DNFB	71.18	0.24	120.75
power	4,941	6,594	6	5	0	DNA	695	0	0	DNA	21.18	0.25	7.32
PGPgiantcompo	10,680	24,316	25	31	7	DNA	4,913	0	692	DNA	177.93	1.36	84.60
astro-ph	16,706	121,251	57	56	0	DNA	1,592	0	0	DNA	339.94	21.39	272.29
cond-mat	16,726	47,594	18	17	0	DNA	1,969	0	0	DNA	339.31	1.82	88.43
as-22july06	22,963	48,436	17	25	9	DNA	7,266	0	1,747	DNA	856.66	2.71	308.61
Cit-HepTh	27,770	352,285	23	37	15	DNA	$\geq 3,557$	0	$\geq 0$	DNA	TLR	317.14	TLR
cond-mat-2003	31,163	120,029	25	24	0	DNA	5,762	0	0	DNA	1,021.08	10.93	288.41
Cit-HepPh	34,546	420,877	19	30	12	DNA	$\geq 3,507$	3	$\geq 0$	DNA	TLR	653.71	TLR
cond-mat-2005	40,421	175,691	30	29	0	DNA	9,553	0	0	DNA	2,974.00	29.33	683.29
preferentialAttachment	100,000	499,985	6	5	0	DNA	$\geq 0$	0	DNFB	DNA	TLR	844.32	DNFB
smallworld	100,000	499,998	6	7	2	DNA	$\geq 0$	0	DNFB	DNA	TLR	2,254.89	DNFB
G_n_pin_pout	100,000	501,198	4	7	4	DNA	$\geq 0$	$\geq 0$	DNFB	DNA	TLR	TLR	DNFB
luxembourg	114,599	119,666	3	2	0	DNA	$\geq 2$	0	0	DNA	TLR	3.64	1,501.11
cnr-2000	325,557	2,738,969	84	83	0	DNA	DNFB	0	DNFB	DNA	DNFB	2,505.75	DNFB
web-NotreDame	325,729	1,090,108	155	155	1	DNA	DNFB	0	DNFB	DNA	DNFB	201.28	DNFB
belgium	1,441,295	1,549,970	3	3	1	DNA	DNFB	0	DNFB	DNA	DNFB	56.63	DNFB
hamming8-2	256	31,616	128	247	120	0	0	0	0	0.98	0.24	3.65	0.49
hamming8-4	256	20,864	16	163	148	3,468,318	6,410,637	$\geq 3,704$	5,993,645	1,184.02	2,496.82	TLR	2,233.63
hamming10-2	1,024	518,656	512	1,013	502	0	0	DNFB	0	0.44	5.00	DNFB	6.92

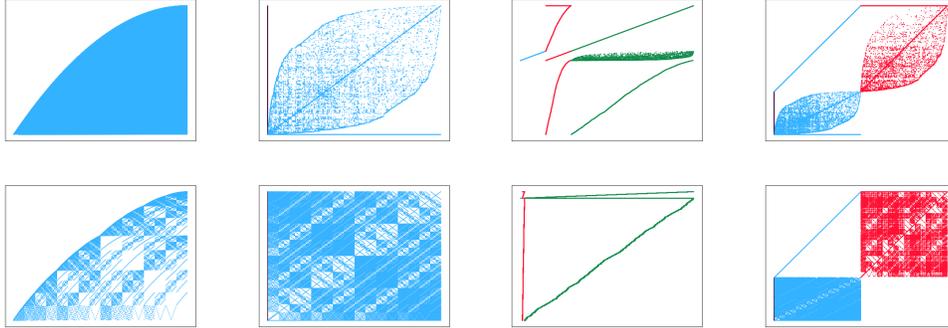


Figure 6: Constraint matrices for the conflict, sparse, conflict-Balas, and sparse-Jeroslow models on the graphs `email` (top row) and `hamming8-4` (bottom row).

Finally, we observe that even though the new clique MIPs outperform previously existing MIPs, they cannot compete with combinatorial algorithms for the maximum clique problem like those of Rossi et al. (2015), Verma et al. (2015), and Walteros and Buchanan (2020). For example, Walteros and Buchanan (2020) report solving the instance `web-NotreDame` in 0.07 seconds. Meanwhile, the conflict-Balas model takes 201.28 seconds to solve, and the conflict, sparse, and sparse-Jeroslow models cannot even be built in the one-hour time limit. The MIP overhead is too costly.

## 7 Conclusion and Future Research

In this paper, we observe that the usual *conflict*-based IP formulation for the maximum clique problem has several undesirable properties. Specifically, when it is applied to sparse, real-life graphs, it has a weak LP relaxation, it involves a large number of constraints, and it can take  $\Omega(\varphi^n)$  branch-and-bound nodes to solve, where  $\varphi \approx 1.618$  denotes the golden ratio. Even on easy instances with zero clique-core gap  $g := (d+1) - \omega$ , it can visit  $\Omega(1.2599^n)$  nodes, regardless of the node-selection strategy. An alternative *sparse* formulation, which aggregates the conflict constraints into big-M constraints, is shown to be smaller,  $\Theta(n+m)$ , but still lacks other desirable worst-case properties.

In response, we conceive of four new MIPs for the clique problem that take inspiration from the literature on disjunctive extended formulations and clique finding. Of these four MIPs, two are detailed and analyzed. The *sparse-Jeroslow* model, which is the smallest and weakest of the four, requires  $\Theta(n+m)$  nonzeros. It achieves an LP bound of at most  $d+1$ , implying that its (absolute) integrality gap is at most the clique-core gap. With a simple branch-and-bound algorithm, it is solved in  $O(2^d n)$  nodes. Further, when the clique-core gap is zero, it is solved in at most  $2n$  nodes. The *conflict-Balas* model is the strongest and (possibly) largest of the four new MIPs. We prove that the simplest of branch-and-bound algorithms solves it in  $O(\varphi^d n)$  nodes, and also exhibit a class of instances for which  $\Omega(\varphi^d n)$  nodes are visited. Moreover, when it is solved with a best-bound node selection strategy, we show that it visits  $O(2^g n)$  nodes. Walteros and Buchanan (2020) observed that on sparse, real-life graphs, the clique-core gap  $g$  can

often be treated as a (small) constant—over half of their instances have  $g \in \{0, 1, 2\}$ . In this case, the conflict-Balas model visits just  $O(n)$  nodes. Experiments on real-life instances show that the conflict-Balas model indeed visits very few nodes in practice; in fact, the LP solution is integral in a majority of cases.

Nevertheless, the clique MIPs proposed here cannot compete with purely combinatorial methods, largely due to the overhead required for the LP relaxations. An alternative approach to ours would be to construct and solve  $n$  different MIPs, one for each of the (small) subproblems identified in Lemma 1, and report the best solution found. By Proposition 2, this would visit a combined  $O(\varphi^d n)$  branch-and-bound nodes if using the conflict, dense, or sparse models. One practical disadvantage to such an approach is that it is not known up front which subproblem will contain the best solution. In an unlucky scenario, one may spend considerable effort on the first subproblem, only to find out the princess is in another castle; meanwhile, the princess is waiting unguarded in the  $n$ -th castle to be visited. To avoid such a scenario, one may want to go back-and-forth between the subproblems, working a little on whichever one is currently most promising. This is the idea behind the best-bound node selection strategy that leads to a  $O(2^g n)$  bound for the conflict-Balas model. Such a back-and-forth strategy would be nontrivial to implement if using the MIP solver as a black box. However, we are able to mimic this with the conflict-Balas model in one black-box call to the MIP solver.

The new clique MIPs may also be practically relevant for variants and extensions that are not pure maximum clique problems, but still have clique-like sub-structures. In analogous examples, the shortest path problem and minimum spanning tree problem can be solved very quickly with specialized combinatorial algorithms, but the ability to express them via an integer program is nevertheless useful. When other constraints are added to them, a general-purpose MIP solver can still be used without much trouble.

In future work, it would be interesting to see whether known classes of valid inequalities that are useful in practice for the clique problem lead to nontrivial bounds on the number of branch-and-bound nodes. Additionally, what guarantees, if any, come from a branch-and-bound algorithm where the Lovász theta semidefinite program is used as the bounding mechanism instead of an LP relaxation? This would be particularly interesting, as this relaxation “includes” all maximal independent set inequalities (Lovász, 1979; Knuth, 1994). Similar questions would be interesting for other problems besides clique. For a given problem, what is the best-performing formulation in practice? Does it come with worst-case branch-and-bound guarantees? If the associated worst-case guarantees are inadequate, can an alternative formulation be developed that performs better in theory? Is it more practical than existing MIPs?

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