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## FROM GAP-EXPONENTIAL TIME HYPOTHESIS TO FIXED PARAMETER TRACTABLE INAPPROXIMABILITY: CLIQUE, DOMINATING SET, AND MORE\*

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LUCA TREVISAN<sup>||</sup>

**Abstract.** We consider questions that arise from the intersection between the areas of polynomial-time approximation algorithms, subexponential-time algorithms, and fixed-parameter tractable (FPT) algorithms. The questions, which have been asked several times, are whether there is a nontrivial *FPT-approximation* algorithm for the Maximum Clique (Clique) and Minimum Dominating Set (DomSet) problems parameterized by the size of the optimal solution. In particular, letting OPT be the optimum and  $N$  be the size of the input, is there an algorithm that runs in  $t(\text{OPT})\text{poly}(N)$  time and outputs a solution of size  $f(\text{OPT})$  for any computable functions  $t$  and  $f$  that are independent of  $N$  (for Clique, we want  $f(\text{OPT}) = \omega(1)$ )? In this paper, we show that both Clique and DomSet admit no nontrivial FPT-approximation algorithm, i.e., there is no  $o(\text{OPT})$ -FPT-approximation algorithm for Clique and no  $f(\text{OPT})$ -FPT-approximation algorithm for DomSet for any function  $f$ . In fact, our results imply something even stronger: The best way to solve Clique and DomSet, even approximately, is to essentially enumerate all possibilities. Our results hold under the *Gap Exponential Time Hypothesis* [I. Dinur. *ECCC*, TR16-128, 2016; P. Manurangsi and P. Raghavendra, preprint, arXiv:1607.02986, 2016], which states that no  $2^{o(n)}$ -time algorithm can distinguish between a satisfiable 3 SAT formula and one which is not even  $(1 - \varepsilon)$ -satisfiable for some constant  $\varepsilon > 0$ . Besides Clique and DomSet, we also rule out nontrivial FPT-approximation for the Maximum Biclique problem, the problem of finding maximum subgraphs with hereditary properties (e.g., Maximum Induced Planar Subgraph), and Maximum Induced Matching in bipartite graphs, and we rule out the  $k^{o(1)}$ -FPT-approximation algorithm for the Densest  $k$ -Subgraph problem.

**Key words.** hardness of approximation, parameterized complexity, subexponential-time algorithms, fine-grained complexity, clique, dominating set

**AMS subject classifications.** 68Q17, 68W25

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**1. Introduction.** *The fixed-parameter tractable approximation algorithm* (FPT-approximation algorithm) is a new concept emerging from a cross fertilization between two trends in coping with NP-hard problems: *approximation algorithms* and *FPT algorithms*. Roughly speaking, an FPT-approximation algorithm is similar to an FPT algorithm in that its running time can be of the form  $t(\text{OPT}) \text{poly}(N)$  (called the *FPT time*), where  $t$  is any computable function (possibly superexponentially growing),  $N$  is the input size, and  $\text{OPT}$  is the value of the optimal solution.<sup>1</sup> It is similar to an approximation algorithm in that its output is an *approximation* of the optimal solution; however, the approximation factor is analyzed in terms of the optimal solution ( $\text{OPT}$ ) and *not* the input size ( $N$ ). Thus, an algorithm for a maximization (respectively, minimization) problem is said to be an  $f(\text{OPT})$ -*FPT-approximation* for some function  $f$  if it outputs a solution of size at least  $\text{OPT}/f(\text{OPT})$  (respectively, at most  $\text{OPT} \cdot f(\text{OPT})$ ). For a maximization problem, such an algorithm is *nontrivial* if  $f(\text{OPT})$  is  $o(\text{OPT})$ , while for a minimization problem, it is nontrivial if  $f$  is a computable function depending only on  $\text{OPT}$ .

The notion of FPT-approximation is useful when we are interested in a small optimal solution, and in particular its existence connects to a fundamental question of *whether there is a nontrivial approximation algorithm when the optimal solution is small*. Consider, for example, the *Maximum Clique* (Clique) problem, where the goal is to find a clique (complete subgraph) with a maximum number of vertices in an  $n$ -vertex graph  $G$ . By outputting any single vertex, we get a trivial polynomial-time  $n$ -approximation algorithm. The bound can be improved to  $O(\frac{n}{\log n})$  and even to  $O(\frac{n(\log \log n)^2}{\log^3 n})$  with clever ideas [41]. Observe, however, that these bounds are quite meaningless when  $\text{OPT} = O(\frac{n(\log \log n)^2}{\log^3 n})$  since outputting a single vertex already guarantees such bounds. In this case, a bound such as  $O(\frac{\text{OPT}}{\log \log \text{OPT}})$  would be more meaningful. Unfortunately, no approximation ratio of the form  $o(\text{OPT})$  is known even when FPT-time is allowed.<sup>2</sup> (Note that outputting a single vertex gives an  $\text{OPT}$ -approximation guarantee.)

Similar questions can be asked for a minimization problem. Consider for instance, *Minimum Dominating Set* (DomSet): Find the smallest set of vertices  $S$  such that every vertex in an  $n$ -vertex input graph  $G$  has a neighbor in  $S$ . DomSet admits an  $O(\log n)$ -approximation algorithm via a basic greedy method. However, if we want the approximation ratio to depend on  $\text{OPT}$  and not  $n$ , no  $f(\text{OPT})$ -approximation ratio is known for any function  $f$  (not even  $2^{2^{\text{OPT}}}$ ).

In fact, the existence of nontrivial FPT-approximation algorithms for Clique and DomSet has been raised several times in the literature (e.g., [73, 46, 34]). So far, the progress towards these questions can only rule out  $O(1)$ -FPT-approximation algorithms for Clique. This was shown independently by Hajiaghayi, Khandekar and Kortsarz [49] and Bonnet et al. [15], assuming the *exponential time hypothesis* (ETH), which asserts that no subexponential time algorithm can decide whether a given 3SAT formula is satisfiable, and that a *linear-size probabilistically checkable proof* (PCP) exists. Alternatively, Khot and Shinkar [61] proved this under a rather nonstandard

<sup>1</sup>There are many ways to parameterize a problem. In this paper we focus on the *standard parameterization* which parameterizes the optimal solution.

<sup>2</sup>In fact, for maximization problems, it can be shown that a problem admits an  $f(\text{OPT})$ -FPT-approximation algorithm for some function  $f = o(\text{OPT})$  if and only if it admits a polynomial-time algorithm with approximation ratio  $f'(\text{OPT})$  for some function  $f' = o(\text{OPT})$  [48, 73] (also see [74]). So, it does not matter whether the running time is polynomial on the size of the input or depends on  $\text{OPT}$ .

assumption that solving quadratic equations over a finite field under a certain regime of parameters is not in FPT; unfortunately, this assumption was later shown to be false [56]. For DomSet, Chen and Lin [27] could rule out  $O(1)$ -FPT-approximation algorithms assuming  $\text{FPT} \neq \text{W}[1]$ . Moreover, they improved the inapproximability ratio to  $\log^{1/4+\epsilon}(\text{OPT})$  for any constant  $\epsilon > 0$  under ETH. Remark that ETH implies  $\text{FPT} \neq \text{W}[1]$ .

*Our results and techniques.* We show that there is no nontrivial FPT approximation algorithm for both Clique and DomSet. That is, there is no  $o(\text{OPT})$ -FPT-approximation algorithm for Clique and no  $f(\text{OPT})$ -FPT-approximation algorithm for DomSet, for any computable function  $f$ . Our results hold under the Gap-ETH, which states that distinguishing between a satisfiable 3-SAT formula and one which is not even  $(1 - \epsilon)$ -satisfiable requires exponential time for some constant  $\epsilon > 0$  (see section 2).

Gap-ETH, first formalized in [32, 72], is a stronger version of the aforementioned ETH. It has recently been shown to be useful in proving fine-grained hardness of an approximation for problems such as dense constraint satisfaction problem (CSP) with large alphabets [72] and Densest- $k$ -Subgraph with perfect completeness [70].

Note that Gap-ETH is implied by ETH if we additionally assume that a linear-size PCP exists. So, our result for Clique significantly improves the results in [49, 16] under the same (in fact, weaker) assumption. Our result for DomSet also significantly improves the results in [27], but our assumption is stronger.

In fact, we can show even stronger results: The best way to solve Clique and DomSet, even approximately, is to *enumerate all possibilities* in the following sense. Finding a clique of size  $r$  can be trivially done in  $n^r \text{poly}(n)$  time by checking whether any among all possible  $\binom{n}{r} = O(n^r)$  sets of vertices forms a clique. It was known under ETH that this is essentially the best one can do [23, 24]. We show further that this running time is still needed, even when we know that a clique of size much larger than  $r$  exists in the graph (e.g.,  $\text{OPT} \geq 2^{2^r}$ ), assuming Gap-ETH. Similarly, for DomSet, we can always find a dominating set of size  $r$  in  $n^r \text{poly}(n)$  time. Under Gap-ETH, we show that there is no better way even when we just want to find a dominating set of size  $q \gg r$ .

We now give an overview of our techniques. The main challenge in showing our results is that we want them to hold for the case where the optimal solution is *arbitrarily smaller* than the input size. (This is important to get the FPT-inapproximability results.) To this end, (i) reductions cannot blow up the size of the optimal solution by a function of the input size, and (ii) our reductions must start from problems with a large hardness gap while having small OPT. Fortunately, property (i) holds for the known reductions we employ.

The challenge of (ii) is that existing gap amplifying techniques (e.g., the parallel repetition theorem [79] or the randomized graph product [11]), while amplifying the gap to arbitrarily large, cause the input size to be too large so that existing OPT reduction techniques (e.g., [23, 77]) cannot be applied efficiently (in particular, in subexponential time). We circumvent this by a step that amplifies the gap and reduces OPT at the same time. In more detail, this step takes a 3-SAT formula  $\phi$  as an input and produces a “label cover”<sup>3</sup> instance  $J$  (roughly, a bipartite graph with constraints on edges) such that for any  $c > 0$ , (i) if  $\phi$  is satisfiable, then  $J$  is satisfiable, and (ii) if  $\phi$  is at most 0.99 satisfiable, then less than a  $c$ -fraction of constraints of  $J$  can be

<sup>3</sup>Our problem is an optimization problem on a Label Cover instance, with a slightly different objective from the standard Label Cover. Please refer to section 4 for more detail.

satisfied. Moreover, our reduction allows us to “compress” either the left-hand side or the right-hand side vertices to be arbitrarily small. This label cover instance is a starting point for all our problems. To derive our result for **Clique**, we would need the left-hand side to be arbitrarily small while for **DomSet**, we would need a small right-hand side.

The left-hand side vertex compression is similar to the randomized graph product [11] and, in fact, the reduction itself has been studied before [85, 84] but in a very different regime of parameters. For a more detailed discussion, please refer to subsection 4.2.

Once the inapproximability results for label cover problems with small left-hand side and right-hand side vertex sets are established, we can simply reduce it to **Clique** and **DomSet** using the standard reductions from [42] and [39], respectively.

Besides the above results for **Clique** and **DomSet**, we also show that no nontrivial FPT-approximation algorithm exists for a few other problems, including Maximum Biclique, the problem of finding maximum subgraphs with hereditary properties (e.g., maximum planar induced subgraph), and Maximum Induced Matching in bipartite graphs. Previously only the exact versions of these problems were known to be  $W[1]$ -hard [66, 60, 75]. Additionally, we rule out the  $k^{o(1)}$ -FPT-approximation algorithm for Densest  $k$ -Subgraph although this ratio does not yet match the trivial  $O(k)$ -approximation algorithm. Finally, we remark that, while our result for maximum subgraphs with hereditary properties follows from a reduction from **Clique**, the FPT inapproximability of other problems are shown not through the label cover problems but instead from a modification of the hardness of approximating Densest  $k$ -Subgraph in [70].

*Previous works.* Our results are based on the method of compressing (or reducing the size of) the optimal solution, which was first introduced by Chen et al. in [22] (the journal version appears in [23]). Assuming ETH, they showed that finding both **Clique** and **DomSet** cannot be solved in time  $n^{o(\text{OPT})}$ , where  $n$  is the number of vertices in an input graph. Later, Pătraşcu and Williams [77] applied similar techniques to sharpen the running time lower bound of **DomSet** to  $n^{\text{OPT}-\varepsilon}$  for any constant  $\varepsilon > 0$ , assuming the *Strong ETH* (SETH). The technique of compressing the optimal solution was also used in the hardness of approximation by Hajiaghayi, Khandekar, and Kortsarz in [49] and by Bonnet, Lampis, and Paschos in [16]. Our techniques can be seen as introducing gap amplification to the reductions in [23]. We emphasize that while [23, 77, 49, 15] (and also the reductions in this paper) are all based on the technique of compressing the optimal solution, Hajiaghayi, Khandekar, and Kortsarz [49] compress the optimal solution after reducing SAT to the designated problems, i.e., **Clique** and **DomSet**. The reductions in [23, 77, 15] and in our paper, on the other hand, compress the optimal solution of SAT prior to feeding it to standard reductions (with small adjustment). While this difference does not affect the reduction for **Clique**, it has a huge effect on **DomSet**. Specifically, compressing the optimal solution at the postreduction step results in a huge blowup because the blowup in the first step (i.e., from SAT to **DomSet**) becomes exponential after compressing the optimal solution. Our proof for **Clique** and the one in [49] bear a similarity in that both apply a graph product to amplify approximation hardness. The key difference is that we use a randomized graph product instead of the deterministic graph product used in [49].

Very recently, Chen and Lin [27] showed that **DomSet** admits no constant approximation algorithm unless  $\text{FPT} = W[1]$ . Their hardness result was derived from the seminal result of Lin [66], which shows that the *Maximum  $k$ -Intersection* problem

TABLE 1

The summaries of previous works on *Clique* and *DomSet*. Here  $t$  denotes any computable function  $t : \mathbb{N} \rightarrow \mathbb{N}$ ,  $\epsilon$  denotes any constant  $0 < \epsilon < 1$ ,  $\gamma$  denotes some constant  $0 < \epsilon < 1$ ,  $\rho$  denotes some nondecreasing function  $\rho : (0, 1) \rightarrow (0, 1)$ ,  $\delta$  denotes some constant  $\delta > 1$ . *PGC* and *LPCP* stands for the Projection Game Conjecture [76], and the Linear-Size PCP Conjecture [15], respectively.

Summary of works on <i>Clique</i>			
Inapprox factor	Running time lower bound	Assumption	References
any constant	$t(\text{OPT}) \cdot n^{o(\text{OPT})}$	ETH + LPCP	[15]
$\text{OPT}^{1-\epsilon}$	$\exp(\text{OPT}^{\rho(\epsilon)})$	ETH	[28]
$1/(1-\epsilon)$	$\exp(\exp(\text{OPT}^{\rho(\epsilon)}))^4$	ETH	[49]
No $\omega(\text{OPT})$	$t(\text{OPT}) \cdot n^{o(\text{OPT})}$	Gap-ETH	This paper

  

Summary of works on <i>DomSet</i>			
Inapprox Factor	Running Time Lower Bound	Assumption	References
$\text{OPT}^{1-\gamma}$	$\exp(\text{OPT}^{1-\rho(\gamma)})$	ETH	[28]
$(\log \text{OPT})^\delta$	$\exp(\exp((\log \text{OPT})^{\delta-1}))$	ETH + PGC	[49]
any constant	$t(\text{OPT}) \cdot n^{O(1)}$ (i.e., no FPT)	$W[1] \neq \text{FPT}$	[27]
$(\log \text{OPT})^{1/4+\epsilon}$	$t(\text{OPT}) \cdot n^{o(\sqrt{\text{OPT}})}$	ETH	[27, 23]
$f(\text{OPT})$	$t(\text{OPT}) \cdot n^{o(\text{OPT})}$	Gap-ETH	This paper

(also known as *One-side Gap-Biclique*) has no FPT approximation algorithm. Furthermore, they showed that, when assuming ETH, their result can be strengthened to rule out the  $\log^{1/4+\epsilon}(\text{OPT})$  FPT-approximation algorithm for any constant  $\epsilon > 0$ . The result of Chen and Lin follows from the  $W[1]$ -hardness of *Biclique* [66] and the proof of the ETH-hardness of *Clique* [22]. Note that while Chen and Lin did not discuss the size of the optimal solution in their paper, the method of compressing the optimal solution was implicitly used there. This is due to the running time lower bound of *Clique* that they quoted from [22].

Our method for proving the FPT inapproximability of *DomSet* is similar to that in [77]. However, the original construction in [77] does not require a “partition system.” This is because Pătraşcu and Williams’ reduction starts from SAT, which can be cast as *DomSet*. In our construction, the reduction starts from an instance of the CSP that is more general than SAT (because of the gap-amplification step) and hence requires the construction of a partition system. (Note that the partition system has been used in standard hardness reductions for *DomSet* [68, 39].)

We remark that our proof does not imply FPT-inapproximability for *DomSet* under ETH whereas Chen and Lin were able to prove the inapproximability result under ETH because their reduction can be applied directly to SAT via the result in [23]. If one introduced the Gap-ETH to the previous works, then the proofs in [23, 49, 15] yield the constant FPT-inapproximability of *Clique*, and the proof in [23] yields the constant FPT-inapproximability of *DomSet*.

The summaries of previous works on *Clique* and *DomSet* are presented in Table 1.

*Follow-up works.* Very recently, in the follow-up work [55] by Karthik, Laekhanukit, and Manurangsi, the totally-FPT-inapproximability of *DomSet* was shown under  $\text{FPT} \neq W[1]$ . Moreover, they are able to bypass Gap-ETH and show the same running time lower bounds as ours under ETH. They even show stronger running time lower bounds under *SETH* and the *k-Sum Hypothesis*. We stress here that their results apply only to *DomSet* but not to *Clique* nor other problems in this paper (e.g., *Biclique*, *Densest k-Subgraph*). Their proof builds on the insights from our work; in

<sup>4</sup>Constant FPT-inapproximability of *Clique* under ETH is claimed in [49] (arXiv version). However, as we investigated, the Gap-ETH is assumed there.

particular, our reduction from **MaxCov** (via **MinLab**) to **DomSet** (Theorem 5.4). The contrast between our proof for **DomSet** and the proof in [55] is that, while we obtain the gap of **MaxCov** from **Gap-ETH**, they take a different route and arrive at such a gap by designing specific communication protocols for certain communication problems, generalizing connections between communication complexity and fine-grained hardness of approximation pioneered in [2].

*Other related works.* All problems considered in this work are also well studied in terms of hardness of approximation beyond the aforementioned parameterized regimes; indeed many techniques used here are borrowed from or inspired by the nonparameterized settings.

**Maximum Clique.** Maximum Clique is arguably the first natural combinatorial optimization problem studied in the context of hardness of approximation; in a seminal work of Feige et al. (henceforth FGLSS) [42], a connection was made between interactive proofs and hardness of approximating **Clique**. This connection paves the way for later works on **Clique** and other developments in the field of hardness of approximations; indeed, the FGLSS reduction will serve as part of our proof as well. The FGLSS reduction, together with the PCP theorem [7, 6] and gap amplification via randomized graph products [11], immediately implies an  $n^\varepsilon$  ratio inapproximability of **Clique** for some constant  $\varepsilon > 0$  under the assumption that  $\text{NP} \subseteq \text{BPP}$ . Following FGLSS's work, there had been a long line of research on approximability of **Clique** [9, 43, 8, 10], which culminated in Håstad's work [51]. In [51], it was shown that **Clique** cannot be approximated to within a factor of  $n^{1-\varepsilon}$  in polynomial time unless  $\text{NP} \subseteq \text{ZPP}$ ; this was later derandomized by Zuckerman [86] via an efficient construction of *dispersers* with certain parameters, thus implying  $n^{1-\varepsilon}$  approximation hardness under  $\text{P} \neq \text{NP}$ . Since then, better inapproximability ratios are known [38, 57, 59], with the best ratio being  $n/2^{(\log n)^{3/4+\varepsilon}}$  for every  $\varepsilon > 0$  (assuming  $\text{NP} \not\subseteq \text{BPTIME}(2^{(\log n)^{O(1)}})$ ) due to Khot and Ponnuswami [59]. We note here that the best known polynomial-time algorithm for **Clique** achieves  $O(\frac{n(\log \log n)^2}{(\log n)^3})$ -approximation for the problem [41].

**Set Cover.** Minimum Set Cover, which is equivalent to **DomSet**, is also among the first problems studied in hardness of approximation. Lund and Yannakakis proved that, unless  $\text{NP} \subseteq \text{DTIME}(2^{(\log n)^{O(1)}})$ , **SetCov** cannot be efficiently approximated to within  $c \log n$  factor of the optimum for some constant  $c > 0$  [68]. Not long after, Feige [39] both improved the approximation ratio and weakened the assumption by showing an  $(1 - \varepsilon) \ln n$ -ratio inapproximability for every  $\varepsilon > 0$  assuming only that  $\text{NP} \not\subseteq \text{DTIME}(n^{O(\log \log n)})$ . Recently, a similar inapproximability has been achieved under the weaker  $\text{NP} \not\subseteq \text{P}$  assumption [76, 33]. Since a simple greedy algorithm is known to yield  $(\ln n + 1)$ -approximation for **SetCov** [30], the aforementioned hardness result is essentially tight. A common feature in all previous works on hardness of **SetCov** [68, 39, 76] is that the constructions involve composing certain variants of CSPs with partition systems. As touched upon briefly earlier, our construction will also follow this approach; for the exact definition of CSPs and the partition system used in our work, please refer to subsection 5.2.

**Maximum subgraph with hereditary properties.** The complexity of finding and approximating maximum subgraph with hereditary properties have also been studied since the 1980s [65, 67, 44]; specifically, Feige and Kogan showed that, for every nontrivial property  $\Pi$  (i.e.,  $\Pi$  such that infinite many subgraphs satisfy  $\Pi$  and infinitely many subgraphs do not satisfy  $\Pi$ ), the problem is hard to approximate to within  $n^{1-\varepsilon}$  factor for every  $\varepsilon > 0$  unless  $\text{NP} \subseteq \text{ZPP}$  [44]. We also note that nontrivial approximation algorithms for the problem are known; for instance, when the prop-

erty fails for some clique or some independent set, a polynomial-time  $O\left(\frac{n(\log \log n)^2}{(\log n)^2}\right)$ -approximation algorithm is known [50].

**Maximum Balanced Biclique.** While the Maximum Balanced Biclique problem bears a strong resemblance to the Maximum Clique Problem, inapproximability of the latter cannot be directly translated to that of the former; in fact, despite numerous attempts, not even constant factor NP-hardness of approximation of the Maximum Balanced Biclique problem is known. Fortunately, under stronger assumptions, hardness of approximation for the problem is known:  $n^\varepsilon$ -factor hardness of approximation is known under Feige's random 3SAT hypothesis [40] or  $\text{NP} \not\subseteq \bigcap_{\varepsilon > 0} \text{BPTIME}(2^{n^\varepsilon})$  [58], and  $n^{1-\varepsilon}$ -factor hardness of approximation is known under strengthening of the Unique Games Conjecture [12, 71]. To the best of our knowledge, no nontrivial approximation algorithm for the problem is known.

**Densest  $k$ -Subgraph.** The Densest  $k$ -Subgraph problem has received considerable attention from the approximation algorithm community [63, 45, 13]; the best known polynomial time algorithm due to Bhaskara et al. [13] achieves  $O(n^{1/4+\varepsilon})$ -approximation for every  $\varepsilon > 0$ . On the other hand, similarly to Biclique, NP-hardness of approximating Densest  $k$ -Subgraph, even to some constant ratio, has so far eluded researchers. Nevertheless, in the same works that provide the hardness results for Biclique [40, 58], Densest  $k$ -Subgraph is shown to be hard to approximate to some constant factor under random 3-SAT hypothesis or  $\text{NP} \not\subseteq \bigcap_{\varepsilon > 0} \text{BPTIME}(2^{n^\varepsilon})$ . Furthermore,  $2^{\Omega(\log^{2/3} n)}$ -factor inapproximability is known under the planted clique hypothesis [4] and, under ETH (respectively, Gap-ETH),  $n^{1/\text{poly} \log \log n}$  (respectively,  $n^{o(1)}$ ) factor inapproximabilities are known [70]. (See also [17] in which a constant ratio ETH-hardness of approximating Densest  $k$ -Subgraph was shown.) In addition to these hardness results, polynomial ratio integrality gaps for strong LP and SDP relaxations of the problem are also known [14, 69, 29].

**Maximum Induced Matching on Bipartite Graphs.** The problem was shown to be NP-hard independently by Stockmeyer and Vazirani [81] and Cameron [18]. The approximability of the problem was first studied by Duckworth, Manlove, and Zito [36] who showed that the problem is APX-hard, even on bipartite graphs of degree three. Elbassioni et al. [37] then showed that the problem is hard to approximate to within  $n^{1/3-\varepsilon}$  factor for every  $\varepsilon > 0$ , unless  $\text{NP} \subseteq \text{ZPP}$ . Chalermsook, Laekhanukit, and Nanongkai [19] later improved the ratio to  $n^{1-\varepsilon}$  for every  $\varepsilon > 0$ .

*Organization.* We define basic notations in section 2. In section 3, we define the notion of inherently enumerative, which captures the fact that nothing better than enumerating all possibilities can be done. We show that a problem admits no nontrivial FPT-approximation algorithm by showing that it is inherently enumerative. In section 4, we define and prove results about our intermediate problems on label cover instances. Finally, in section 5 we derive results for Clique, DomSet, and other problems.

**2. Preliminaries.** We use standard terminology. For any graph  $G$ , we denote by  $V(G)$  and  $E(G)$  the vertex and edge sets of  $G$ , respectively. For each vertex  $u \in V(G)$ , we denote the set of its neighbors by  $N_G(v)$ ; when the graph  $G$  is clear from the context, we sometimes drop it from the notation. A *clique* of  $G$  is a complete subgraph of  $G$ . Sometime we refer to a clique as a subset  $S \subseteq V(G)$  such that there is an edge joining every pair of vertices in  $S$ . A *biclique* of  $G$  is a balanced complete bipartite subgraph of  $G$ . A biclique such that each partition has  $k$  vertices is called a  *$k$ -biclique* and is denoted by  $K_{k,k}$ . An *independent set* of  $G$  is a subset of vertices  $S \subseteq V(G)$  such there is no edge joining any pair of vertices in  $S$ . A *dominating set* of  $G$  is a subset of vertices  $S \subseteq V(G)$  such that every vertex in  $G$  is either in



$S$  or has a neighbor in  $S$ . The *clique number* (respectively, *independent number*) of  $G$  is the size of the largest clique (respectively, independent set) in  $G$ . The *biclique number* of  $G$  is the largest integer  $k$  such that  $G$  contains  $K_{k,k}$  as a subgraph. The *domination number* of  $G$  is defined similarly as the size of the smallest dominating set in  $G$ . The clique, independent, and domination numbers of  $G$  are usually denoted by  $\omega(G)$ ,  $\alpha(G)$ , and  $\gamma(G)$ , respectively. However, in this paper, we will refer to these numbers by  $\text{Clique}(G)$ ,  $\text{IndSet}(G)$ ,  $\text{DomSet}(G)$ . Additionally, we denote the biclique number of  $G$  by  $\text{Biclique}(G)$ .

**2.1. FPT-approximation.** Let us start by formalizing the the notation of optimization problems; here we follow the notation due to Chen, Grohe, and Grüber [25]. An *optimization problem*  $\Pi$  is defined by three components: (1) For each input instance  $I$  of  $\Pi$ , a set of valid solutions of  $I$  denoted by  $\text{SOL}_\Pi(I)$ ; (2) for each instance  $I$  of  $\Pi$  and each  $y \in \text{SOL}_\Pi(I)$ , the cost of  $y$  with respect to  $I$  is denoted by  $\text{COST}_\Pi(I, y)$ ; and (3) the goal of the problem by  $\text{GOAL}_\Pi \in \{\min, \max\}$  which specifies whether  $\Pi$  is a minimization or maximization problem. Throughout this work, we will assume that  $\text{COST}_\Pi(I, y)$  can be computed in time  $|I|^{O(1)}$ . Finally, we denote by  $\text{OPT}_\Pi(I)$  the optimal value of each instance  $I$ , i.e.,  $\text{OPT}_\Pi(I) = \text{GOAL}_\Pi \text{ COST}(I, y)$ , where  $y$  is taken over  $\text{SOL}_\Pi(I)$ .

We now continue on to define parameterized approximation algorithms. While our discussion so far has been on optimization problems, we will instead work with “gap versions” of these problems. Roughly speaking, for a maximization problem  $\Pi$ , the gap version of  $\Pi$  takes in an additional input  $k$  and the goal is to decide whether  $\text{OPT}_\Pi(I) \geq k$  or  $\text{OPT}_\Pi(I) < k/f(k)$ . As we will elaborate below, the gap versions are weaker (i.e., easier) than the optimization versions and, hence, our impossibility results for gap versions translate to those of optimization versions as well.

**DEFINITION 2.1** (FPT gap approximation). *For any optimization problem  $\Pi$  and any computable function  $f : \mathbb{N} \rightarrow [1, \infty)$ , an algorithm  $\mathbb{A}$ , which takes as input an instance  $I$  of  $\Pi$  and a positive integer  $k$ , is said to be an  $f$ -FPT gap approximation algorithm for  $\Pi$  if the following conditions hold on every input  $(I, k)$ :*

- $\mathbb{A}$  runs in time  $t(k) \cdot |I|^{O(1)}$  for some computable function  $t : \mathbb{N} \rightarrow \mathbb{N}$ .
- If  $\text{GOAL}_\Pi = \max$ , then the algorithm  $\mathbb{A}$  outputs 1 if  $\text{OPT}_\Pi(I) \geq k$  and outputs 0 if  $\text{OPT}_\Pi(I) < k/f(k)$ .  
If  $\text{GOAL}_\Pi = \min$ , then the algorithm  $\mathbb{A}$  outputs 1 if  $\text{OPT}_\Pi(I) \leq k$  and outputs 0 if  $\text{OPT}_\Pi(I) > k \cdot f(k)$ .

$\Pi$  is said to be  $f$ -FPT gap approximable if there is an  $f$ -FPT gap approximation algorithm for  $\Pi$ .

Next, we formalize the concept of *totally-FPT-inapproximable*, which encapsulates a nonexistence of nontrivial FPT approximations discussed earlier in the introduction.

**DEFINITION 2.2.** *A minimization problem  $\Pi$  is said to be totally-FPT-inapproximable if, for every computable function  $f : \mathbb{N} \rightarrow [1, \infty)$ ,  $\Pi$  is not  $f$ -FPT gap approximable.*

*A maximization problem  $\Pi$  is said to be totally-FPT-inapproximable if, for every computable function  $f : \mathbb{N} \rightarrow [1, \infty)$  such that  $f(k) = o(k)$  (i.e.,  $\lim_{k \rightarrow \infty} k/f(k) = \infty$ ),  $\Pi$  is not  $f$ -FPT gap approximable.*

With the exception of Densest  $k$ -Subgraph, every problem considered in this work will be shown to be totally-FPT-inapproximable. To this end, we remark that totally FPT inapproximable as defined above through gap problems imply the nonexistence

of a nontrivial FPT-approximation algorithm that was discussed in the introduction. These implications are stated more precisely in the two propositions below; their proofs are given in Appendix A. Note that Propositions 2.3 and 2.4 are implied by the results due to Chen, Grohe, and Grüber [25, 26].

**PROPOSITION 2.3** (see [25, Proposition 4], [26, Proposition 5]). *Let  $\Pi$  be any minimization problem. Then (1) implies (2), where (1) and (2) are as defined below.*

- (1)  $\Pi$  is totally FPT-approximable.
- (2) For all computable functions  $t : \mathbb{N} \rightarrow \mathbb{N}$  and  $f : \mathbb{N} \rightarrow [1, \infty)$ , there is no algorithm that, on every instance  $I$  of  $\Pi$ , runs in time  $t(\text{OPT}_{\Pi}(I)) \cdot |I|^{O(1)}$  and outputs a solution  $y \in \text{SOL}_{\Pi}(I)$  such that  $\text{COST}_{\Pi}(I, y) \leq \text{OPT}_{\Pi}(I) \cdot f(\text{OPT}_{\Pi}(I))$ .

**PROPOSITION 2.4** (see [26, Proposition 6]). *Let  $\Pi$  be any maximization problem. Then (1) implies (2) where (1) and (2) are as defined below.*

- (1)  $\Pi$  is totally FPT-approximable.
- (2) For all computable functions  $t : \mathbb{N} \rightarrow \mathbb{N}$  and  $f : \mathbb{N} \rightarrow [1, \infty)$  such that  $f(k) = o(k)$  and  $k/f(k)$  is nondecreasing, there is no algorithm that, on every instance  $I$  of  $\Pi$ , runs in time  $t(\text{OPT}_{\Pi}(I)) \cdot |I|^{O(1)}$  and outputs a solution  $y \in \text{SOL}_{\Pi}(I)$  such that  $\text{COST}_{\Pi}(I, y) \geq \text{OPT}_{\Pi}(I)/f(\text{OPT}_{\Pi}(I))$ .

**2.2. List of problems.** We will now list the problems studied in this work. While all the problems here can be defined in terms of optimization problems as discussed in the previous subsection, we will omit the terms **SOL**, **COST**, and **GOAL** whenever they are clear from the context.

**The Maximum Clique Problem (Clique).** In  $k$ -Clique, we are given a graph  $G$  together with an integer  $k$ , and the goal is to decide whether  $G$  has a clique of size  $k$ . The maximization version of  $k$ -Clique, called **Max-Clique** or simply **Clique**, asks to compute the maximum size of a clique in  $G$ .

The problem that is (computationally) equivalent to **Clique** is the *maximum independent set* problem (**IndSet**) which asks to compute the size of the maximum independent set in  $G$ . The two problems are equivalent since any clique in  $G$  is an independent set in the complement graph  $\bar{G}$ .

**The Minimum Dominating Set Problem (DomSet).** In  $k$ -DomSet, we are given a graph  $G$  together with an integer  $k$ , and the goal is to decide whether  $G$  has a dominating set of size  $k$ . The minimization version of  $k$ -DomSet, called **Min-DomSet** or simply **DomSet**, asks to compute the size of the minimum dominating set in  $G$ . The problem that is equivalent to **DomSet** is the *minimum set cover* problem (**SetCov**): Given a universe  $\mathcal{U}$  of  $n$  elements and a collection  $\mathcal{S}$  of  $m$  subsets  $S_1, \dots, S_m \subseteq \mathcal{U}$ , the goal is to find the minimum number of subsets of  $\mathcal{S}$  whose union equals  $\mathcal{U}$ . It is a standard fact that **DomSet** is equivalent to **SetCov**. See Appendix D for more detail.

**Maximum Induced Subgraph with Hereditary Properties.** A *property*  $\Pi$  is simply a subset of all graphs. We say that  $\Pi$  is a *hereditary property* if whenever  $G \in \Pi$ , all induced subgraphs of  $G$  are in  $\Pi$ . The Maximum Induced Subgraph problem with Property  $\Pi$  asks for a maximum cardinality set  $S \subseteq V(G)$  such that  $G[S] \in \Pi$ . Here  $G[S]$  denotes the subgraph of  $G$  induced on  $S$ . Notice that both **Clique** and **IndSet** belong to this class of problems. For more discussions on problems that belong to this class, see Appendix D.

**Maximum Induced Matching on Bipartite Graphs.** An induced matching  $\mathcal{M}$  of a graph  $G = (V, E)$  is a subset of edges  $\{(u_1, v_1), \dots, (u_{|\mathcal{M}|}, v_{|\mathcal{M}|})\}$  such that

there is no cross edge, i.e.,  $(u_i, u_j), (v_i, v_j), (u_i, v_j) \notin E$  for all  $i \neq j$ . The induced matching number  $\text{IM}(G)$  of graph  $G$  is simply the maximum value of  $|\mathcal{M}|$  among all induced matchings  $\mathcal{M}$ 's of  $G$ . In this work, we will be interested in the problem of approximating  $\text{IM}(G)$  in bipartite graphs; this is because, for general graphs, the problem is as hard to approximate as **Clique**. (See Appendix D for more details.)

**Maximum Balanced Biclique (Biclique).** In  $k$ -Biclique, we are given a bipartite graph  $G$  together with an integer  $k$ . The goal is to decide whether  $G$  contains a complete bipartite subgraph (biclique) with  $k$  vertices on each side. In other words, we are asked to decide whether  $G$  contains  $K_{k,k}$  as a subgraph. The maximization version of **Biclique**, called **Maximum Balanced Biclique**, asks to compute the maximum size of a balanced biclique in  $G$ .

**Densest  $k$ -Subgraph.** In the **Densest  $k$ -Subgraph** problem, we are given an integer  $k$  and a graph  $G = (V, E)$ . The goal is to find a subset  $S \subseteq V$  of  $k$  vertices that induces a maximum number of edges. For convenience, we define density of an induced subgraph  $G[S]$  to be  $\text{Den}(G[S]) \triangleq \frac{E(G[S])}{\binom{|S|}{2}} \in [0, 1]$  and we define the optimal density of **Densest  $k$ -Subgraph** to be  $\text{Den}_k(G) = \max_{S \subseteq V, |S|=k} \text{Den}(S)$ .

**2.3. Gap-ETH.** Our results are based on the **Gap-ETH**. Before we state the hypothesis, let us recall the definition of **3-SAT**. In  $q$ -SAT, we are given a CNF formula  $\phi$  in which each clause consists of at most  $q$  literals, and the goal is to decide whether  $\phi$  is satisfiable.

**Max  $q$ -SAT** is a maximization version of  $q$ -SAT which asks to compute the maximum number of clauses in  $\phi$  that can be simultaneously satisfied. We will abuse  $q$ -SAT to mean **Max  $q$ -SAT**, and for a formula  $\phi$ , we use  $\text{SAT}(\phi)$  to denote the maximum number of clauses satisfied by any assignment.

The **Gap-ETH** can now be stated in terms of **SAT** as follows.

*Conjecture 2.5* ((randomized) **Gap-ETH** [32, 72]). For some constant  $\delta, \epsilon > 0$ , no algorithm can, given a **3-SAT** formula  $\phi$  on  $n$  variables and  $m = O(n)$  clauses, distinguish between the following cases correctly with probability  $\geq 2/3$  in  $O(2^{\delta n})$  time:

- $\text{SAT}(\phi) = m$  and
- $\text{SAT}(\phi) < (1 - \epsilon)m$ .

The bound  $m = O(n)$  is obtained by a random sparsification of a gap instance of **3-SAT**, which allows us to bound  $m$  to be at most  $(2/(1 - \epsilon)) \cdot n$ .

Note that the case where  $\epsilon = 1/m$  (that is, the algorithm only needs to distinguish between the cases that  $\text{SAT}(\phi) = m$  and  $\text{SAT}(\phi) < m$ ) is known as **ETH** [54]. Another related conjecture is the strengthened version of **ETH** is called **SETH** [53]: for any  $\epsilon > 0$ , there is an integer  $k \geq 3$  such that there is no  $2^{(1-\epsilon)n}$ -time algorithm for  $k$ -SAT. **Gap-ETH** of course implies **ETH** but, to the best of our knowledge, no formal relationship is known between **Gap-ETH** and **SETH**. While **Gap-ETH** may seem strong due to the gap between the two cases, there are evidences suggesting that it may indeed be true or, at the very least, refuting it is beyond the reach of our current techniques. We discuss some of this evidence in Appendix F.

While **Gap-ETH** as stated above rules out not only deterministic but also randomized algorithms, the deterministic version of **Gap-ETH** suffices for some of our results, including inapproximability of **Clique** and **DomSet**. The reduction for **DomSet** as stated below will already be deterministic, but the reduction for **Clique** will be randomized. However, it can be easily derandomized and we sketch the idea behind this

in in subsection 4.2.1. Note that, on the other hand, we do not know how to derandomize some of our other results, including those of Biclique and Densest  $k$ -Subgraph.

### 3. FPT inapproximability via the Concept of Inherently Enumerative.

Throughout the paper, we will prove FPT inapproximability through the concept of *inherently enumerative* problems, which will be formalized shortly.

To motivate the concept, note that all problems  $\Pi$  considered in this paper admit an exact algorithm that runs in time<sup>5</sup>  $O^*(|I|^{\text{OPT}_\Pi(I)})$ . For instance, to find a clique of size  $k$  in  $G$ , one can enumerate all  $\binom{|V(G)|}{k} = |V(G)|^{O(k)}$  possibilities.<sup>6</sup> For many W[1]-hard problems (e.g., Clique), this running time is nearly the best possible assuming ETH: Any algorithm that finds a  $k$ -clique in time  $|V(G)|^{o(k)}$  would break ETH. In the light of such a result, it is natural to ask the following question. Assume that  $\text{Clique}(G) \geq 2^{2^k}$ , can we find a clique of size  $k$  in time  $|V(G)|^{o(k)}$ ?

In other words, can we exploit a prior knowledge that there is a clique of size much larger than  $k$  to help us find a  $k$ -clique faster? Roughly speaking, we will show later that, assuming Gap-ETH, the answer of this question is also negative, even when  $2^{2^k}$  is replaced by a much larger constant independent of  $k$ . This is encapsulated in the concept of inherently enumerative as defined below.

**DEFINITION 3.1** (inherently enumerative). *A problem  $\Pi$  is said to be inherently enumerative if there exist constants  $\delta, r_0 > 0$  such that, for any integers  $q \geq r \geq r_0$ , no algorithm can decide, on every input instance  $I$  of  $\Pi$ , whether (i)  $\text{OPT}_\Pi(I) < r$  or (ii)  $\text{OPT}_\Pi(I) \geq q$  in time<sup>7</sup>  $O_{q,r}(|I|^{\delta r})$ .*

While we will show that Clique and DomSet are inherently enumerative, we cannot do the same for some of the other problems, such as Biclique. Even for the exact version of Biclique, the best running time lower bound known is only  $|V(G)|^{\Omega(\sqrt{k})}$  [66] assuming ETH. In order to succinctly categorize such lower bounds, we define a similar but weaker notation of *weakly* inherently enumerative:

**DEFINITION 3.2** (weakly inherently enumerative). *For any function  $\beta = \omega(1)$  (i.e.,  $\lim_{r \rightarrow \infty} \beta(r) = \infty$ ), a problem  $\Pi$  is said to be  $\beta$ -weakly inherently enumerative if there exists a constant  $r_0 > 0$  such that, for any integers  $q \geq r \geq r_0$ , no algorithm can decide, on every input instance  $I$  of  $\Pi$ , whether (i)  $\text{OPT}_\Pi(I) < r$  or (ii)  $\text{OPT}_\Pi(I) \geq q$  in time  $O_{q,r}(|I|^{\beta(r)})$ .*

$\Pi$  is said to be weakly inherently enumerative if it is  $\beta$ -weakly inherently enumerative for some  $\beta = \omega(1)$ .

It follows from the definitions that any inherently enumerative problem is also weakly inherently enumerative. As stated earlier, we will prove total FPT inapproximability through it being inherently enumerative; the proposition below formally establishes a connection between the two.

**PROPOSITION 3.3.** *If  $\Pi$  is weakly inherently enumerative, then  $\Pi$  is totally FPT-inapproximable.*

*Proof.* We first consider maximization problems. We will prove the contrapositive of the statement. Assume that a maximization problem  $\Pi$  is not totally FPT-inapproximable, i.e.,  $\Pi$  admits an  $f$ -FPT gap approximation algorithm  $\mathbb{A}$  for some

<sup>5</sup>Recall that  $O^*(\cdot)$  hides terms that are polynomial in the input size.

<sup>6</sup>A faster algorithm that runs in time  $|V(G)|^{\omega k/3}$  can be done by a reduction to matrix multiplication.

<sup>7</sup> $O_{q,r}(\cdot)$  here and in Definition 3.2 hides any multiplicative term that is a function of  $q$  and  $r$ .

computable function  $f$  such that  $\lim_{k \rightarrow \infty} k/f(k) = \infty$ . Suppose that the running time of  $\mathbb{A}$  on every input  $(I, k)$  is  $t(k) \cdot |I|^D$  for some constant  $D$  and some function  $t$ . We will show that  $\Pi$  is not weakly inherently enumerative.

Let  $r_0 > 0$  be any constant and let  $\beta : \mathbb{N} \rightarrow \mathbb{R}^+$  be any function such that  $\beta = \omega(1)$ . Let  $r$  be the smallest integer such that  $r > r_0$  and  $\beta(r) \geq D$  and let  $q$  be the smallest integer such that  $q/f(q) > r$ . Note that  $r$  and  $q$  exist since  $\lim_{r \rightarrow \infty} \beta(r) = \infty$  and  $\lim_{q \rightarrow \infty} q/f(q) = \infty$ .

Given any instance  $I$  of  $\Pi$ , from the definition of  $f$ -FPT gap approximation algorithms (Definition 2.1) and from the fact that  $q/f(q) > r$ ,  $\mathbb{A}$  on the input  $(I, q)$  can distinguish between  $\text{OPT}_\Pi(I) \geq q$  and  $\text{OPT}_\Pi(I) < r$  in  $t(q) \cdot |I|^D \leq t(q) \cdot |I|^{\beta(r)} = O_{q,r}(|I|^{\beta(r)})$  time. Hence,  $\Pi$  is not weakly inherently enumerative, concluding our proof for maximization problems.

For any minimization problem  $\Pi$ , assume again that  $\Pi$  is not totally FPT-inapproximable, i.e.,  $\Pi$  admits an  $f$ -FPT gap approximation algorithm  $\mathbb{A}$  for some computable function  $f$ . Suppose that the running time of  $\mathbb{A}$  on every input  $(I, k)$  is  $t(k) \cdot |I|^D$  for some constant  $D$ .

Let  $r_0 > 0$  be any constant and let  $\beta : \mathbb{N} \rightarrow \mathbb{R}^+$  be any function such that  $\beta = \omega(1)$ . Let  $r$  be the smallest integer such that  $r > r_0$  and  $\beta(r) \geq D$  and let  $q = \lceil r \cdot f(r) \rceil$ .

Given any instance  $I$  of  $\Pi$ . From the definition of  $f$ -FPT gap approximation algorithms and from  $q \geq r \cdot f(r)$ ,  $\mathbb{A}$  on the input  $(I, r)$  can distinguish between  $\text{OPT}_\Pi(I) \geq q$  and  $\text{OPT}_\Pi(I) < r$  in  $t(r) \cdot |I|^D \leq t(r) \cdot |I|^{\beta(r)} = O_{q,r}(|I|^{\beta(r)})$  time. Hence,  $\Pi$  is not weakly inherently enumerative.  $\square$

An important tool in almost any branch of complexity theory, including parameterized complexity, is a notion of reductions. For the purpose of facilitating proofs of totally FPT inapproximability, we define the following reduction, which we call *FPT gap reductions*.

**DEFINITION 3.4** (FPT gap reduction). *For any functions  $f, g = \omega(1)$ , a problem  $\Pi_0$  is said to be  $(f, g)$ -FPT gap reducible to a problem  $\Pi_1$  if there exists an algorithm  $\mathbb{A}$  which takes an instance  $I_0$  of  $\Pi_0$  and integers  $q, r$  and then produces an instance  $I_1$  of  $\Pi_1$  such that the following conditions hold.*

- $\mathbb{A}$  runs in time  $t(q, r) \cdot |I_0|^{O(1)}$  for some computable function  $t : \mathbb{N} \times \mathbb{N} \rightarrow \mathbb{N}$ .
- For every positive integer  $q$ , if  $\text{OPT}_{\Pi_0}(I_0) \geq q$ , then  $\text{OPT}_{\Pi_1}(I_1) \geq f(q)$ .
- For every positive integer  $r$ , if  $\text{OPT}_{\Pi_0}(I_0) < g(r)$ , then  $\text{OPT}_{\Pi_1}(I_1) < r$ .

It is not hard to see that FPT gap reduction indeed preserves totally FPT inapproximability, as formalized in Proposition 3.5 below. The proof of the proposition can be found in Appendix B.

**PROPOSITION 3.5.** *If a problem  $\Pi_0$  is (i)  $(f, g)$ -FPT gap reducible to  $\Pi_1$  for some computable nondecreasing functions  $f, g = \omega(1)$ , and (ii) totally FPT-inapproximable, then  $\Pi_1$  is also totally FPT-inapproximable.*

As stated earlier, we mainly work with inherently enumerative concepts instead of working directly with totally FPT inapproximability; indeed, we will never use the above proposition and we alternatively use FPT gap reductions to prove that problems are weakly inherently enumerative. For this purpose, we will need the following proposition.

**PROPOSITION 3.6.** *If a problem  $\Pi_0$  is (i)  $(f, g)$ -FPT gap reducible to  $\Pi_1$  and (ii)  $\beta$ -weakly inherently enumerative for some  $f, g, \beta = \omega(1)$ , then  $\Pi_1$  is  $\Omega(\beta \circ g)$ -weakly inherently enumerative.*

*Proof.* We assume that (i) holds, and will show that if the “then” part does not hold, then (ii) also does not hold. Recall from Definition 3.4 that (i) implies that there exist  $C, D > 0$  such that the reduction from  $\Pi_0$  (with parameters  $q$  and  $r$ ) to  $\Pi_1$  takes  $O_{q,r}(|I_0|^C)$  time and always output an instance  $I_1$  of size at most  $O_{q,r}(|I_0|^D)$  on every input instance  $I_0$ . Now assume that the then part does *not* hold, in particular,  $\Pi_1$  is not  $(\beta \circ g)/D$ -weakly inherently enumerative. We will show the following claim which says that (ii) does not hold (by Definition 3.2).

CLAIM 3.7. *For every  $r_0 > 0$ , there exists  $q \geq r \geq r_0$  and an  $O_{q,r}(|I_0|^{\beta(r)})$ -time algorithm  $\mathbb{B}$  that can, on every input instance  $I_0$  of  $\Pi_0$ , distinguish between  $\text{OPT}_{\Pi_0}(I_0) \geq q$  and  $\text{OPT}_{\Pi_0}(I_0) < r$ .*

We now prove the claim. Consider any  $r_0$ . Since  $\beta, g = \omega(1)$ , there exists  $r'_0$  such that  $g(r') \geq r_0$  and  $\beta(r') \geq C$  for all  $r' \geq r'_0$ . From the assumption that  $\Pi_1$  is not  $(\beta \circ g)/D$ -weakly inherently enumerative, there exist  $q' \geq r' \geq r'_0$  such that there is an  $O_{q',r'}(|I_1|^{\beta(g(r'))/D})$ -time algorithm  $\mathbb{A}$  that can, on every input instance  $I_1$  of  $\Pi_1$ , distinguish between  $\text{OPT}_{\Pi_1}(I_1) \geq q'$  and  $\text{OPT}_{\Pi_1}(I_1) < r'$ .

Let  $r = g(r')$ , and let  $q$  be the smallest integer such that  $f(q) \geq q'$  and  $q \geq r$ . Note that  $q$  exists since  $\lim_{q \rightarrow \infty} f(q) = \infty$ , and that  $r \geq r_0$ . We use  $\mathbb{A}$  and the reduction to build an algorithm  $\mathbb{B}$  as follows. On input  $I_0$ , the algorithm  $\mathbb{B}$  runs the reduction on  $I_0$  and the previously defined  $q, r$ . Let us call the output of the reduction  $I_1$ . The algorithm  $\mathbb{B}$  then runs  $\mathbb{A}$  on the input  $(I_1, q', r')$  and outputs accordingly, i.e., if  $\mathbb{A}$  says that  $\text{OPT}_{\Pi_1}(I_1) \geq q'$ , then  $\mathbb{B}$  outputs  $\text{OPT}_{\Pi_0}(I_0) \geq q$  and, otherwise, if  $\mathbb{A}$  says that  $\text{OPT}_{\Pi_1}(I_1) < r'$ , then  $\mathbb{B}$  outputs  $\text{OPT}_{\Pi_0}(I_0) < r$ .

Now we show that the algorithm  $\mathbb{B}$  can distinguish whether  $\text{OPT}_{\Pi_0}(I_0) \geq q$  or  $\text{OPT}_{\Pi_0}(I_0) < r$  as desired by the claim: From our choice of  $q$ , if  $\text{OPT}_{\Pi_0}(I_0) \geq q$ , then  $\text{OPT}_{\Pi_1}(I_1) \geq f(q) \geq q'$ . Similarly, from our choice of  $r = g(r')$ , if  $\text{OPT}_{\Pi_0}(I_0) < r$ , then  $\text{OPT}_{\Pi_1}(I_1) < r'$ . Since  $\mathbb{A}$  can distinguish between the two cases,  $\mathbb{B}$  can distinguish between the two cases as well.

The total running time of  $\mathbb{B}$  is  $O_{q,r}(|I_0|^C) + O_{q',r'}(|I_1|^{\beta(g(r'))/D})$  (the first term is for running the reduction). Since  $I_1$  is of size at most  $O_{q,r}(|I_0|^D)$ ,  $\beta(r) \geq C$ , and  $q'$  and  $r'$  depend only on  $q$  and  $r$ , the running time can be bounded by  $O_{q,r}(|I_0|^{\beta(r)})$  as desired.  $\square$

**4. Covering problems on label cover instances.** In this section, we give intermediate results for the lower bounds on the running time of approximating variants of the *label cover* problem, which will be the source of our inapproximability results for Clique and DomSet.

**4.1. Problems and results.** First, we define a label cover instance.

*Label cover instance:* A label cover instance  $\Gamma$  consists of  $(G, \Sigma_U, \Sigma_V, \Pi)$ , where

- $G = (U, V, E)$  is a bipartite graph between vertex sets  $U$  and  $V$  and an edge set  $E$ ;
- $\Sigma_U$  and  $\Sigma_V$  are sets of *alphabets* to be assigned to vertices in  $U$  and  $V$ , respectively; and
- $\Pi = \{\Pi_e\}_{e \in E}$  is a set of *constraints*  $\Pi_e \subseteq \Sigma_U \times \Sigma_V$ .

We say that  $\Pi$  (or  $\Gamma$ ) has the *projection property* if for every edge  $uv \in E$  (where  $u \in U$  and  $V \in v$ ) and every  $\alpha \in \Sigma_U$ , there is exactly one  $\beta \in \Sigma_V$  such that  $(\alpha, \beta) \in \Pi_{uv}$ .

We will define two combinatorial optimization problems on an instance of the label cover problem. These two problems are defined on the same instance as the

standard label cover problem. We will briefly discuss how our problems differ from the standard one.

*Max-Cover problem:* A labeling of the graph is a pair of mappings  $\sigma_U : U \rightarrow \Sigma_U$  and  $\sigma_V : V \rightarrow \Sigma_V$ . We say that a labeling  $(\sigma_U, \sigma_V)$  covers edge  $uv$  if  $(\sigma_U(u), \sigma_V(v)) \in \Pi_{uv}$ . We say that a labeling covers a vertex  $u$  if it covers every edge incident to  $u$ . For any label cover instance  $\Gamma$ , let  $\text{MaxCov}(\Gamma)$  denote the maximum number of vertices in  $U$  that can be covered by a labeling; i.e.,

$$\text{MaxCov}(\Gamma) := \max_{\sigma_U:U \rightarrow \Sigma_U, \sigma_V:V \rightarrow \Sigma_V} |\{u \in U \mid (\sigma_U, \sigma_V) \text{ covers } u\}|.$$

The goal of the Max-Cover problem is to compute  $\text{MaxCov}(\Gamma)$ . We remark that the standard label cover problem (e.g., [83]) would try to maximize the number of covered edges, as opposed to our Max-Cover problem, which seeks to maximize the number of covered vertices.

*Min-Label Problem:* A multilabeling of the graph, is a pair of mappings  $\sigma_U : U \rightarrow \Sigma_U$  and  $\hat{\sigma}_V : V \rightarrow 2^{\Sigma_V}$ . We say that  $(\sigma_U, \hat{\sigma}_V)$  covers an edge  $uv$  if there exists  $\beta \in \hat{\sigma}_V(v)$  such that  $(\sigma(u), \beta) \in \Pi_{uv}$ . For any label cover instance  $\Gamma$ , let  $\text{MinLab}(\Gamma)$  denote the minimum number of labels needed to assign to vertices in  $V$  in order to cover all vertices in  $U$ , i.e.,

$$\text{MinLab}(\Gamma) := \min_{(\sigma_U, \hat{\sigma}_V)} \sum_{v \in V} |\hat{\sigma}_V(v)|,$$

where the minimization is over multilabelings  $(\sigma_U, \hat{\sigma}_V)$  that cover every edge in  $G$ .

It is worth noting that, in  $\text{MinLab}$ , we are allowed to assign multiple labels to vertices in  $V$  whereas each vertex in  $U$  must be assigned a unique label. This makes  $\text{MinLab}$  different from the problem known in the literature as  $\text{MinRep}$  (see, e.g., [21]) since, in  $\text{MinRep}$ , we are allowed to assign multiple labels to all nodes, including those in  $U$ .

*Results.* First, note that checking whether  $\text{MaxCov}(\Gamma) < r$  or not, for any  $r \geq 1$ , can be done by the following algorithms.

1. It can be done<sup>8</sup> in  $O^*((\binom{|U|}{r})^{|\Sigma_U|}) = O^*((|U| \cdot |\Sigma_U|)^r)$  time: First, enumerate all  $\binom{|U|}{r}$  possible subsets  $U'$  of  $U$  and all  $|\Sigma_U|^{|U'|}$  possible labelings on vertices in  $U'$ . Once we fix the labeling on  $U'$ , we only need polynomial time to check whether we can label other vertices so that all vertices in  $U'$  are covered.
2. It can be done in  $O^*(|\Sigma_V|^{|V|})$  time: Enumerate all  $O^*(|\Sigma_V|^{|V|})$  possible labelings  $\sigma_V$  on  $V$ . After  $\sigma_V$  is fixed, we can find labeling  $\sigma_U$  on  $U$  that maximizes the number of vertices covered in  $U$  in polynomial time.

ETH can be restated as that these algorithms are the best possible when  $|U| = \Theta(|V|)$ ,  $|\Sigma_U|, |\Sigma_V| = O(1)$ , and  $\Pi$  has the projection property. Gap-ETH asserts further that this is the case even to distinguish between  $\text{MaxCov}(\Gamma) = |U|$  and  $\text{MaxCov}(\Gamma) \leq (1 - \varepsilon)|U|$ .

**THEOREM 4.1.** *Gap-ETH (Conjecture 2.5) is equivalent to the following statement. There exist constants  $\varepsilon, \delta > 0$  such that no algorithm can take a label cover instance  $\Gamma$  and can distinguish between the following cases in  $O(2^{\delta|U|})$  time:*

- $\text{MaxCov}(\Gamma) = |U|$  and
- $\text{MaxCov}(\Gamma) < (1 - \varepsilon)|U|$ .

<sup>8</sup>Recall that we use  $O^*(\cdot)$  to hide factors of the polynomial in the input size.

This holds only when  $|\Sigma_U|, |\Sigma_V| = O(1)$ ,  $|U| = \Theta(|V|)$ , and  $\Pi$  has the projection property.

The proof of Theorem 4.1 is standard. To avoid distracting the readers, we provide the sketch of the proof in Appendix E.

We will show that Theorem 4.1 can be extended to several cases, which will be useful later. First, consider when the first ( $O^*((|U| \cdot |\Sigma_U|)^r)$ -time) algorithm is faster than the second one. We show that, in this case, the first algorithm is essentially the best even for  $r = O(1)$ , and this holds even when we know that  $\text{MaxCov}(\Gamma) = |U|$ .

For convenience, in the statements of Theorems 4.2 to 4.4 below, we will use the notation  $|\Gamma|$  to denote the size of the label cover instance; in particular,  $|\Gamma| = |\Sigma_U| + |\Sigma_V| + |U| + |V|$ . Furthermore, recall that the notation  $O_{k,r}(\cdot)$  denotes any multiplicative factor that depends only on  $k$  and  $r$ .

**THEOREM 4.2 (MaxCov with small  $|U|$ ).** *Assuming Gap-ETH, there exist constants  $\delta, \rho > 0$  such that, for any positive integers  $k \geq r \geq \rho$ , no algorithm can take a label cover instance  $\Gamma$  with  $|U| = k$  and distinguish between the following cases in  $O_{k,r}(|\Gamma|^{\delta r})$  time:*

- $\text{MaxCov}(\Gamma) = k$  and
- $\text{MaxCov}(\Gamma) < r$ .

*This holds even when  $|\Sigma_V| = O(1)$  and  $\Pi$  has the projection property.*

We emphasize that it is important for applications in later sections that  $r = O(1)$ . In fact, the main challenge in proving the theorem above is to prove it is true for  $r$  that is arbitrarily small compared to  $|U|$ .

Second, consider when the second ( $O^*(|\Sigma_V|^{|V|})$ -time) algorithm is faster, i.e., when  $|V| \ll |U|$ . In this case, we cannot make the soundness (i.e., the parameter  $r$  in Theorem 4.2) be arbitrarily small. (Roughly speaking, the first algorithm can become faster otherwise.) Instead, we will show that the second algorithm is essentially the best possible for soundness as small as  $\gamma|U|$  for any constant  $\gamma > 0$ . More importantly, this holds for  $|V| = O(1)$  (thus independent from the input size). This is the key property of this theorem that we will need later.

**THEOREM 4.3 (MaxCov with small  $|V|$ ).** *Assuming Gap-ETH, there exist constants  $\delta, \rho > 0$  such that, for any positive integer  $q \geq \rho$  and any  $1 \geq \gamma > 0$ , no algorithm can take a label cover instance  $\Gamma$  with  $|V| = q$  and distinguish between the following cases in  $O_{q,\gamma}(|\Gamma|^{\delta q})$  time:*

- $\text{MaxCov}(\Gamma) = |U|$  and
- $\text{MaxCov}(\Gamma) < \gamma|U|$ .

*This holds even when  $|\Sigma_U| \leq (1/\gamma)^{O(1)}$ .*

We remark that the above label cover instance does not have the projection property.

In our final result, we turn to computing  $\text{MinLab}(\Gamma)$ . Since  $\text{MaxCov}(\Gamma) = |U|$  if and only if  $\text{MinLab}(\Gamma) = |V|$ , a statement similar to Theorem 4.1 intuitively holds for distinguishing between  $\text{MinLab}(\Gamma) \leq |V|$  and  $\text{MinLab}(\Gamma) > (1 + \varepsilon)|V|$ , i.e., we need  $O^*(|\Sigma_V|^{|V|})$  time. In the following theorem, we show that this gap can be substantially amplified while maintaining the property that  $|V| = O(1)$  (thus independent from the input size).

**THEOREM 4.4 (MinLab hardness).** *Assuming Gap-ETH, there exist constants  $\delta, \rho > 0$  such that, for any positive integers  $r \geq q \geq \rho$ , no algorithm can take a label cover instance  $\Gamma$  with  $|V| = q$  and distinguish between the following cases in  $O_{q,r}(|\Gamma|^{\delta q})$  time:*



- $\text{MinLab}(\Gamma) = q$  and
- $\text{MinLab}(\Gamma) > r$ .

This holds even when  $|\Sigma_U| = (r/q)^{O(q)}$ .

The rest of this section is devoted to proving Theorems 4.2 to 4.4.

**4.2. Proof of Theorem 4.2.** The proof proceeds by *compressing the left vertex set*  $U$  of a label cover instance from Theorem 4.1. More specifically, each new left vertex will be a subset of left vertices in the original instance. In the construction below, these subsets will just be random subsets of the original vertex set of a certain size; however, the only property of random subsets we will need is that they form a *disperser*. To clarify our proof, let us start by stating the definition of dispersers here. Note that, even though dispersers are often described in terms of graphs or distributions in literature (see, e.g., [82]), it is more convenient for us to describe it in terms of subsets.

**DEFINITION 4.5.** For any positive integers  $m, k, \ell, r \in \mathbb{N}$  and any constant  $\varepsilon \in (0, 1)$ , an  $(m, k, \ell, r, \varepsilon)$ -disperser is a collection  $\mathcal{I}$  of  $k$  subsets  $I_1, \dots, I_k \subseteq [m]$  each of size  $\ell$  such that the union of any  $r$  different subsets from the collection has size at least  $(1 - \varepsilon)m$ . In other words, for any  $1 \leq i_1 < \dots < i_r \leq k$ , we have  $|I_{i_1} \cup \dots \cup I_{i_r}| \geq (1 - \varepsilon)m$ .

The idea of using dispersers to amplify the gap in hardness of approximation bears a strong resemblance to the classical randomized graph product technique [11]. Indeed, similar approaches have been used before, both implicitly (e.g., [8]) and explicitly (e.g., [85, 84, 86]). In fact, even the reduction we use below has been studied before by Zuckerman [85, 84]!

What differentiates our proof from previous works is the setting of parameters. Since the reduction size (specifically, the left alphabet size  $|\Sigma_U|$ ) blows up exponentially in  $\ell$  and previous results aim to prove NP-hardness of approximating Clique, the  $\ell$  are chosen to be small (i.e.,  $O(\log m)$ ). On the other hand, we will choose our  $\ell$  to be  $\Theta_\varepsilon(m/r)$  since we would like to only prove a running time lower bound of the form  $|\Sigma_U|^{\Omega(r)}$ . Interestingly, dispersers for our regime of parameters are easier to construct deterministically and we will sketch the construction in subsection 4.2.1. Note that this construction immediately implies derandomization of our reduction.

The exact dependency of parameters can be found in the claim below, which also states that random subsets will be a disperser for such a choice of parameters with high probability. Here and throughout the proof,  $k$  and  $r$  should be thought of as constants where  $k \gg r$ ; these are the same  $k, r$  as the ones in the statement of Theorem 4.2.

**CLAIM 4.6.** For any positive integers  $m, k, r \in \mathbb{N}$  and any constant  $\varepsilon \in (0, 1)$ , let  $\ell = \max\{m, \lceil 3m/(\varepsilon r) \rceil\}$  and let  $I_1, \dots, I_k$  be  $\ell$ -element subsets of  $[m]$  drawn uniformly independently at random. If  $\ln k \leq m/r$ , then  $\mathcal{I} = \{I_1, \dots, I_k\}$  is an  $(m, k, \ell, r, \varepsilon)$ -disperser with probability at least  $1 - e^{-m}$ .

*Proof.* When  $\ell = m$ , the statement is obviously true; thus, we assume without loss of generality (w.l.o.g.) that  $\ell = \lceil 3m/(\varepsilon r) \rceil$ . Consider any indices  $i_1, \dots, i_r$  such that  $1 \leq i_1 < \dots < i_r \leq k$ . We will first compute the probability that  $|I_{i_1} \cup \dots \cup I_{i_r}| < (1 - \varepsilon)m$  and then take the union bound over all such  $(i_1, \dots, i_r)$ 's.

Observe that  $|I_{i_1} \cup \dots \cup I_{i_r}| < (1 - \varepsilon)m$  if and only if there exists a set  $S \subseteq [m]$  of size less than  $(1 - \varepsilon)m$  such that  $I_{i_1}, \dots, I_{i_r} \subseteq S$ . For a fixed set  $S \subseteq [m]$  of size less than  $(1 - \varepsilon)m$ , since  $I_{i_1}, \dots, I_{i_r}$  are independently drawn random  $\ell$ -element subsets

of  $[m]$ , we have

$$\begin{aligned} \Pr[I_{i_1}, \dots, I_{i_r} \subseteq S] &= \prod_{j \in [r]} \Pr[I_j \subseteq S] = \left( \frac{\binom{|S|}{\ell}}{\binom{m}{\ell}} \right)^r \leq \left( \frac{|S|}{m} \right)^{\ell r} \\ &< (1 - \varepsilon)^{\ell r} \leq e^{-\varepsilon \ell r} < e^{-3m}. \end{aligned}$$

Taking the union bound over all such  $S$ 's, we have

$$\Pr[|I_{i_1} \cup \dots \cup I_{i_r}| < (1 - \varepsilon)m] < \sum_{S \subseteq [m], |S| < (1 - \varepsilon)m} e^{-3m} < 2^m \cdot e^{-3m} < e^{-2m}.$$

Finally, taking the union bound over all  $(i_1, \dots, i_r)$ 's gives us the desired probabilistic bound:

$$\Pr[\mathcal{I} \text{ is not an } (m, k, \ell, r, \varepsilon)\text{-dispenser}] \leq \sum_{1 \leq i_1 < \dots < i_r \leq k} e^{-2m} \leq k^r \cdot e^{-2m} < e^{-m},$$

where the last inequality comes from our assumption that  $\ln k \leq m/r$ .  $\square$

With the definition of dispersers and the above claim ready, we move on to prove Theorem 4.2.

*Proof of Theorem 4.2.* First, we take a label cover instance, namely,

$$\tilde{\Gamma} = (\tilde{G} = (\tilde{U}, \tilde{V}, \tilde{E}), \Sigma_{\tilde{V}}, \Sigma_{\tilde{V}}, \tilde{\Pi}),$$

as in Theorem 4.1. We may assume that  $|\Sigma_{\tilde{V}}|, |\Sigma_{\tilde{V}}| = O(1)$ , and  $|\tilde{U}| = \Theta(|\tilde{V}|)$ . Moreover, let  $m = |\tilde{U}|$  and  $n = |\tilde{V}|$ ; for convenience, we rename the vertices in  $\tilde{U}$  and  $\tilde{V}$  so that  $\tilde{U} = [m]$  and  $\tilde{V} = [n]$ . Note that it might be useful for the readers to think of  $\tilde{\Gamma}$  as a 3-SAT instance, where  $\tilde{U}$  is the set of clauses and  $\tilde{V}$  is the set of variables.

We recall the parameter  $\varepsilon$  from Theorem 4.1 and the parameters  $k, r$  from the statement of Theorem 4.2. We introduce a new parameter  $\ell = \lceil 3m/(\varepsilon r) \rceil$ .

The new label cover (MaxCov) instance  $\Gamma = (G = (U, V, E), \Sigma_U, \Sigma_V, \Pi)$  is defined as follows.

- The right vertices and right alphabet set remain unchanged, i.e.,  $V = \tilde{V}$  and  $\Sigma_V = \Sigma_{\tilde{V}}$ .
- There will be  $k$  vertices in  $U$ , where each vertex is a random set of  $\ell$  vertices of  $\tilde{U}$ . More specifically, we define  $U = \{I_1, \dots, I_k\}$ , where each  $I_i$  is a random  $\ell$ -element subsets of  $[m]$  drawn independently of each other.
- The left alphabet set  $\Sigma_U$  is  $\Sigma_{\tilde{V}}^\ell$ . For each  $I \in U$ , we view each label  $\alpha \in \Sigma_U$  as a tuple  $(\alpha_u)_{u \in I} \in (\Sigma_{\tilde{V}})^\ell$ ; this is a partial assignment to all vertices  $u \in I$  in the original instance  $\tilde{\Gamma}$ .
- We create an edge between  $I \in U$  and  $v \in V$  in  $E$  if and only if there exists  $u \in I$  such that  $uv \in \tilde{E}$ . More formally,  $E = \{Iv : I \cap N_{\tilde{G}}(v) \neq \emptyset\}$ .
- Finally, we define the constraint  $\Pi_{Iv}$  for each  $Iv \in E$ . As stated above, we view each  $\alpha \in \Sigma_U$  as a partial assignment  $(\alpha_u)_{u \in I}$  for  $I \subseteq \tilde{U}$ . The constraint  $\Pi_{Iv}$  then contains all  $(\alpha, \beta)$  such that  $(\alpha_u, \beta)$  satisfies the constraint  $\tilde{\Pi}_{uv}$  for every  $u \in I$  that has an edge to  $v$  in  $\tilde{\Gamma}$ . More precisely,

$$\Pi_{Iv} = \{(\alpha, \beta) = ((\alpha_u)_{u \in I}, \beta) : \forall u \in I \cap N_{\tilde{G}}(v), (\alpha_u, \beta) \in \tilde{\Pi}_{uv}\}.$$

Readers who prefer the 3-SAT/CSP viewpoint of label cover may think of each  $I_i$  as a collection of clauses in the 3-SAT instance that are joined by an operator *AND*,

i.e., the assignment must satisfy all the clauses in  $I_i$  simultaneously in order to satisfy  $I_i$ .

We remark that, if  $\tilde{\Pi}$  has the projection property, then  $\Pi$  also has the projection property.

**Completeness.** Suppose there is a labeling  $(\sigma_{\tilde{U}}, \sigma_{\tilde{V}})$  of  $\tilde{\Gamma}$  that covers all  $|\tilde{U}|$  left vertices. We take  $\sigma_V = \sigma_{\tilde{V}}$  and construct  $\sigma_U$  by setting  $\sigma_U(I) = (\sigma_{\tilde{U}}(u))_{u \in I}$  for each  $I \in U$ . Since  $(\sigma_{\tilde{U}}, \sigma_{\tilde{V}})$  covers all the vertices of  $\tilde{U}$ ,  $(\sigma_U, \sigma_V)$  also covers all the vertices of  $U$ . Therefore,  $\text{MaxCov}(\Gamma) = |U|$ .

**Soundness.** To analyze the soundness of the reduction, first recall Claim 4.6 that  $\{I_1, \dots, I_k\}$  is an  $(m, k, \ell, r, \varepsilon)$ -disperser with high probability. Conditioned on this event happening, we will prove the soundness property, i.e., that if  $\text{MaxCov}(\tilde{\Gamma}) < (1 - \varepsilon)|\tilde{U}|$ , then  $\text{MaxCov}(\Gamma) < r$ .

We will prove this by the contrapositive. Assume that there is a labeling  $(\sigma_U, \sigma_V)$  that covers at least  $r$  left vertices  $I_{i_1}, \dots, I_{i_r} \in U$ . We construct a labeling  $(\sigma_{\tilde{U}}, \sigma_{\tilde{V}})$  as follows. First,  $\sigma_{\tilde{V}}$  is simply set to  $\sigma_V$ . Moreover, for each  $u \in I_{i_1} \cup \dots \cup I_{i_r}$ , let  $\sigma_{\tilde{U}}(u) = (\sigma_U(I_{i_j}))_u$ , where  $j \in [r]$  is an index such that  $u \in I_{i_j}$ ; if there are multiple such  $j$ 's, then we may pick an arbitrary one. Finally, for  $u \in U \setminus (I_{i_1} \cup \dots \cup I_{i_r})$ , we set  $\sigma_{\tilde{U}}(u)$  arbitrarily.

We claim that every  $u \in I_{i_1} \cup \dots \cup I_{i_r}$  is covered by  $(\sigma_{\tilde{U}}, \sigma_{\tilde{V}})$  in the original instance  $\tilde{\Gamma}$ . To see that this is the case, recall that  $\sigma_{\tilde{U}}(u) = (\sigma_U(I_{i_j}))_u$  for some  $j \in [r]$  such that  $u \in I_{i_j}$ . For every  $v \in V$ , if  $uv \in E$ , then, from how the constraint  $\Pi_{I_{i_j}v}$  is defined, we have  $(\sigma_{\tilde{U}}(u), \sigma_{\tilde{V}}(v)) = (\sigma_U(I_{i_j})_u, \sigma_V(v)) \in \tilde{\Pi}_{uv}$ . In other words,  $u$  is indeed covered by  $(\sigma_{\tilde{U}}, \sigma_{\tilde{V}})$ .

Hence,  $(\sigma_{\tilde{U}}, \sigma_{\tilde{V}})$  covers at least  $|I_{i_1} \cup \dots \cup I_{i_r}| \geq (1 - \varepsilon)m$ , where the inequality comes from the definition of dispersers. As a result,  $\text{MaxCov}(\tilde{\Gamma}) \geq (1 - \varepsilon)|\tilde{U}|$ , completing the soundness proof.

**Running Time Lower Bound.** Our construction gives a  $\text{MaxCov}$  instance  $\Gamma$  with  $|U| = k$  and  $|\Sigma_U| = |\Sigma_{\tilde{U}}|^\ell = 2^{\Theta(m/(\varepsilon r))}$ , whereas  $|V|$  and  $|\Sigma_V|$  remain  $n$  and  $O(1)$ , respectively. Assume that Gap-ETH holds and let  $\delta_0$  be the constant in the running time lower bound in Theorem 4.1. Let  $\delta$  be any constant such that  $0 < \delta < \delta_0 \varepsilon / c$ , where  $c$  is the constant such that  $|\Sigma_U| \leq 2^{cm/(\varepsilon r)}$ .

Suppose for the sake of contradiction that, for some  $k \geq r \geq \rho$ , there is an algorithm that distinguishes whether  $\text{MaxCov}(\Gamma) = k$  or  $\text{MaxCov}(\Gamma) < r$  in  $O_{k,r}(|\Gamma|^{\delta r})$  time. Observe that, in our reduction,  $|U|, |V|, |\Sigma_V| = |\Sigma_U|^{\sigma(1)}$ . Hence, the running time of the algorithm on input  $\Gamma$  is at most  $O_{k,r}(|\Sigma_U|^{\delta r(1+o(1))}) \leq O_{k,r}(|\Sigma_U|^{\delta_0 \varepsilon r / c}) \leq O(2^{\delta_0 m})$ , where the first inequality comes from our choice of  $\delta$  and the second comes from  $|\Sigma_U| \leq 2^{cm/(\varepsilon r)}$ . Thanks to the completeness and soundness of the reduction, this algorithm can also distinguish whether  $\text{MaxCov}(\tilde{\Gamma}) = |\tilde{U}|$  or  $\text{MaxCov}(\tilde{\Gamma}) < (1 - \varepsilon)|\tilde{U}|$  in time  $O(2^{\delta_0 m})$ . From Theorem 4.1, this is indeed a contradiction.  $\square$

**4.2.1. Derandomization.** While the reduction in the proof of Theorem 4.2 is a randomized reduction, it can be derandomized quite easily. We sketch the ideas behind the derandomization below.

One may notice that the only property we need from the random  $\ell$ -element subsets  $I_1, \dots, I_k$  is that it forms an  $(m, k, \ell, r, \varepsilon)$ -disperser. Hence, to derandomize the reduction, it suffices to deterministically construct such a disperser in  $2^{o(n)}$  time.

To do so, let us first note that Claim 4.6 implies that an  $(m', k, \ell', r, \varepsilon)$ -disperser exists, where  $m' = r \ln k$  and  $\ell' = 3m'/(\varepsilon r)$ . For convenience, we assume w.l.o.g.

that  $m', \ell'$  are integers and that  $m'$  divides  $m$ . Since  $m'$  is now small, we can find such a disperser by just enumerating over every possible collection of  $k$  subsets of  $[m']$  each of size  $\ell'$  and checking whether it has the desired property; this takes only  $(2^{m'})^k (k)^r \text{poly}(m') = 2^{O(rk \log k)}$  time, which is acceptable for us since  $r$  and  $k$  are both constants. Let the  $(m', k, \ell', r, \varepsilon)$ -disperser that we find be  $\{I'_1, \dots, I'_k\}$ . Finally, to get from here to the intended  $(m, k, \ell, r, \varepsilon)$ -disperser, we only need to view  $[m]$  as  $[m/m'] \times [m']$  and let  $I_1 = [m/m'] \times I'_1, \dots, I_k = [m/m'] \times I'_k$ . It is not hard to check that  $\{I_1, \dots, I_k\}$  is indeed an  $(m, k, \ell, r, \varepsilon)$ -disperser, which concludes our sketch.

**4.3. Proof of Theorem 4.3.** The proof proceeds by *compressing the right vertex set*  $V$  of a label cover instance from Theorem 4.1 plus amplifying the hardness gap. The gap amplification step is similar to that in the proof of Theorem 4.2 except that, since here  $\text{MaxCov}(\Gamma)$  is not required to be constant in the soundness case, we can simply take all subsets of appropriate sizes instead of random subsets as in the previous proof; this also means that our reduction is deterministic and thus requires no derandomization.

*Proof of Theorem 4.3.* First, we take a label cover instance, namely,  $\tilde{\Gamma} = (\tilde{G} = (\tilde{U}, \tilde{V}, \tilde{E}), \Sigma_{\tilde{U}}, \Sigma_{\tilde{V}}, \tilde{\Pi})$ , as in Theorem 4.1. We may assume that  $|\Sigma_{\tilde{U}}|, |\Sigma_{\tilde{V}}| = O(1)$  and  $|\tilde{U}| = \Theta(|\tilde{V}|)$ . For convenience, we assume w.l.o.g. that  $\tilde{U} = [m]$  and  $\tilde{V} = [n]$ . Again, it might be useful for the readers to think of  $\tilde{\Gamma}$  as a 3-SAT instance, where  $\tilde{U}$  are the set of clauses and  $\tilde{V}$  are the set of variables.

Recall the parameter  $\varepsilon$  from Theorem 4.1 and the parameters  $q, \gamma$  from Theorem 4.3. Let  $\ell = \ln(1/\gamma)/\varepsilon$ . We assume w.l.o.g. that  $\ell$  is an integer and that  $n$  is divisible by  $q$ . The new label cover ( $\text{MaxCov}$ ) instance  $\Gamma = (G = (U, V, E), \Sigma_U, \Sigma_V, \Pi)$  is defined as follows.

- First, we partition  $\tilde{V} = [n]$  into  $q$  parts  $J_1, \dots, J_q$ , each of size  $n/q$ . We then let  $V = \{J_1, \dots, J_q\}$ . In other words, we merge  $n/q$  vertices of  $\tilde{V}$  into a single vertex in  $V$ .
- Let  $U$  be  $\binom{[m]}{\ell}$ , the collection of all  $\ell$ -element subsets of  $[m] = \tilde{U}$ .
- The left alphabet set  $\Sigma_U$  is  $\Sigma_{\tilde{U}}^\ell$ . For each  $I \in U$ , we view each label  $\alpha \in \Sigma_U$  as a tuple  $(\alpha_u)_{u \in I} \in (\Sigma_{\tilde{U}})^\ell$ ; this is a partial assignment to all vertices  $u \in I$  in the original instance  $\tilde{\Gamma}$ .
- Our graph  $G$  is simply a complete bipartite graph, i.e., for every  $I \in U$  and  $J \in V$ ,  $IJ \in E(G)$ .
- The label set of  $V$  is  $\Sigma_V = \Sigma_{\tilde{V}}^{n/q}$ , and the label set of  $U$  is  $\Sigma_U = \Sigma_{\tilde{U}}^\ell$ . For each  $I \in U$ , we view each label  $\alpha \in \Sigma_U$  as a tuple  $(\alpha_u)_{u \in I} \in (\Sigma_{\tilde{U}})^\ell$ ; this is simply a partial assignment to all vertices  $u \in I$  in the original instance  $\tilde{\Gamma}$ . Similarly, for each  $J \in V$ , we view each label  $\beta \in \Sigma_V$  as  $(\beta_v)_{v \in J} \in (\Sigma_{\tilde{V}})^{n/q}$ .
- Finally, we define  $\Pi_{IJ}$  for each  $IJ \in E$ . The constraint  $\Pi_{IJ}$  contains all  $(\alpha, \beta)$  such that  $(\alpha_u, \beta_v)$  satisfies the constraint  $\tilde{\Pi}_{uv}$  for every  $u \in I, v \in J$  such that  $uv \in \tilde{E}$ . More precisely,  $\Pi_{IJ} = \{(\alpha, \beta) = ((\alpha_u)_{u \in I}, (\beta_v)_{v \in J}) : \forall u \in I, v \in J \text{ such that } uv \in \tilde{E}, (\alpha_u, \beta_v) \in \tilde{\Pi}_{uv}\}$ .

We remark that  $\Pi$  may not have the projection property even when  $\tilde{\Pi}$  has the property.

**Completeness.** Suppose that there is a labeling  $(\sigma_{\tilde{U}}, \sigma_{\tilde{V}})$  of  $\tilde{\Gamma}$  that covers all  $|\tilde{U}|$  left vertices. We construct  $(\sigma_U, \sigma_V)$  by setting  $\sigma_U(I) = (\sigma_{\tilde{U}}(u))_{u \in I}$  for each  $I \in U$  and  $\sigma_V(J) = (\sigma_{\tilde{V}}(v))_{v \in J}$  for each  $J \in V$ . It is easy to see that  $(\sigma_U, \sigma_V)$  covers all the vertices of  $U$ . Therefore,  $\text{MaxCov}(\Gamma) = |U|$ .

**Soundness.** Suppose that  $\text{MaxCov}(\tilde{\Gamma}) < (1 - \varepsilon)|\tilde{U}|$ . Consider any labeling  $(\sigma_U, \sigma_V)$  of  $\Gamma$ ; we will show that  $(\sigma_U, \sigma_V)$  covers less than  $\gamma|U|$  left vertices.

Let  $I_1, \dots, I_t \in U$  be the vertices covered by  $(\sigma_U, \sigma_V)$ . Analogously to the proof of Theorem 4.2, we define a labeling  $(\sigma_{\tilde{U}}, \sigma_{\tilde{V}})$  as follows. First,  $\sigma_{\tilde{V}}$  is naturally defined from  $\sigma_V$  by  $\sigma_{\tilde{V}} = \sigma_V(J)_v$ , where  $J$  is the partition that contains  $v$ . Moreover, for each  $u \in I_{i_1} \cup \dots \cup I_{i_r}$ , let  $\sigma_{\tilde{U}}(u) = (\sigma_U(I_{i_j}))_u$ , where  $j \in [r]$  is an index such that  $u \in I_{i_j}$ ; for  $u \in U \setminus (I_{i_1} \cup \dots \cup I_{i_r})$ , we set  $\sigma_{\tilde{U}}(u)$  arbitrarily.

Similarly to the proof of Theorem 4.2, it is not hard to see that every vertex in  $I_1 \cup \dots \cup I_t$  is covered by  $(\sigma_{\tilde{U}}, \sigma_{\tilde{V}})$  in  $\tilde{\Gamma}$ . Since  $\text{MaxCov}(\tilde{\Gamma}) < (1 - \varepsilon)|\tilde{U}|$ , we can conclude that  $|I_1 \cup \dots \cup I_t| < (1 - \varepsilon)|\tilde{U}|$ . Since each  $I_i$  is simply an  $\ell$ -size subset of  $I_1 \cup \dots \cup I_t$ , we can conclude that

$$t < \binom{(1 - \varepsilon)|\tilde{U}|}{\ell} \leq (1 - \varepsilon)^\ell \binom{|\tilde{U}|}{\ell} = (1 - \varepsilon)^\ell |U| \leq e^{-\varepsilon\ell} |U| = \gamma|U|.$$

Hence,  $(\sigma_U, \sigma_V)$  covers less than  $\gamma|U|$  left vertices as desired.

**Running Time Lower Bound.** Our construction gives a  $\text{MaxCov}$  instance  $\Gamma$  with  $|V| = q$  and  $|\Sigma_V| = |\Sigma_{\tilde{V}}|^{n/q} = 2^{\Theta(n/q)}$ ; note also that  $|U| = m^\ell$  and  $|\Sigma_U| = |\Sigma_{\tilde{U}}|^\ell = (1/\gamma)^{O(1)}$ . Assume that Gap-ETH holds and let  $\delta_0$  be the constant from Theorem 4.1. Moreover, let  $\delta$  be any positive constant such that  $\delta < \delta_0/c$ , where  $c$  is the constant such that  $|\Sigma_V| \leq 2^{cm/q}$ .

Suppose for the sake of contradiction that, for some  $q \geq \rho$  and  $1 \geq \gamma > 0$ , there is an algorithm that distinguishes whether  $\text{MaxCov}(\Gamma) = |U|$  or  $\text{MaxCov}(\Gamma) < \gamma|U|$  in  $O_{q,\gamma}(|\Gamma|^{\delta q})$  time. Observe that, in our reduction,  $|U|, |V|, |\Sigma_U| = |\Sigma_V|^{o(1)}$ . Hence, the running time of the algorithm on input  $\Gamma$  is  $O_{q,\gamma}(|\Sigma_V|^{\delta q(1+o(1))}) \leq O_{q,\gamma}(|\Sigma_V|^{\delta_0 q/c}) \leq O(2^{\delta_0 m})$ , where the first inequality comes from our choice of  $\delta$  and the second comes from  $|\Sigma_V| \leq 2^{cm/q}$ . Thanks to the completeness and soundness of the reduction, this algorithm can also distinguish whether  $\text{MaxCov}(\tilde{\Gamma}) = |\tilde{U}|$  or  $\text{MaxCov}(\tilde{\Gamma}) < (1 - \varepsilon)|\tilde{U}|$  in time  $O(2^{\delta_0 m})$ . From Theorem 4.1, this is a contradiction.  $\square$

**4.4. Proof of Theorem 4.4.** We conclude this section with the proof of Theorem 4.4. The proof proceeds simply by showing that if an algorithm can distinguish between the two cases in the statement of Theorem 4.4, it can also distinguish between the two cases in Theorem 4.3 (with an appropriate value of  $\gamma$ ).

*Proof of Theorem 4.4.* Consider the label cover instance given by Theorem 4.3, namely,  $\Gamma = (G = (U, V, E), \Sigma_U, \Sigma_V, \Pi)$ , when  $\gamma = (r/q)^{-q}$ . Let us assume w.l.o.g. that there is no isolated vertex in  $G$ .

**Completeness.** If  $\text{MaxCov}(\Gamma) = |U|$ , then there is a labeling  $\sigma_U : U \rightarrow \Sigma_U$  and  $\sigma_V : V \rightarrow \Sigma_V$  that covers every edge; this also induces a multilabeling that covers every edge. Hence,  $\text{MinLab}(\Gamma) = |V|$ .

**Soundness.** We will prove this by the contrapositive. Suppose that  $\text{MinLab}(\Gamma) \leq r$ . This implies that there exists a multilabeling  $\sigma_U : U \rightarrow \Sigma_U$  and  $\sigma_V : V \rightarrow 2^{\Sigma_V}$  such that  $\sum_{v \in V} |\sigma_V(v)| \leq r$  and every vertex is covered. Since there is no isolated vertex in  $G$ ,  $\sigma_V(v) \neq \emptyset$  for all  $v \in V$ .

Consider  $\sigma_V^{\text{rand}} : V \rightarrow \Sigma_V$  sampled randomly, for each  $v \in V$ , by independently picking a random element of  $\sigma_V(v)$  and letting  $\sigma_V^{\text{rand}}(v)$  be this element. Let us consider the expected number of  $u \in U$  that are covered by the labeling  $(\sigma_U, \sigma_V^{\text{rand}})$ .

From linearity of expectation, we can write this as

$$\begin{aligned}
\mathbb{E}_{\sigma_V^{\text{rand}}} |\{u \in U \mid (\sigma_U, \sigma_V^{\text{rand}}) \text{ covers } u\}| &= \sum_{u \in U} \Pr_{\sigma_V^{\text{rand}}} [(\sigma_U, \sigma_V^{\text{rand}}) \text{ covers } u] \\
&= \sum_{u \in U} \prod_{v \in N(u)} \Pr [(\sigma_U(u), \sigma_V^{\text{rand}}(v)) \in \Pi_{uv}] \\
&\geq \sum_{u \in U} \prod_{v \in N(u)} |\sigma_V(v)|^{-1} \\
&\geq \sum_{u \in U} \prod_{v \in V} |\sigma_V(v)|^{-1} \\
\text{(From AM-GM inequality)} &\geq \sum_{u \in U} \left( \frac{1}{q} \sum_{v \in V} |\sigma_V(v)| \right)^{-q} \\
&\geq \sum_{u \in U} (r/q)^{-q} \\
&= \gamma |U|,
\end{aligned}$$

where the first inequality comes from the fact that there exists  $\beta \in \sigma_V(v)$  such that  $(\sigma_U(u), \beta) \in \Pi_{uv}$ . This implies  $\text{MaxCov}(\Gamma) \geq \gamma |U|$ , which concludes our proof.  $\square$

## 5. Hardness for combinatorial problems.

**5.1. Maximum clique.** Recall that, for any graph  $G$ ,  $\text{Clique}(G)$  denotes the maximum size of any clique in  $G$ . Observe that we can check if there is a clique of size  $r$  by checking if any subset of  $r$  vertices forms a clique, and there are  $\binom{|V(G)|}{r} = O(|V(G)|^r)$  possible such subsets. We show that this is essentially the best we can do even when we are given a promise that a clique of size  $q \gg r$  exists.

**THEOREM 5.1.** *Assuming Gap-ETH, there exist constants  $\delta, r_0 > 0$  such that, for any positive integers  $q \geq r \geq r_0$ , no algorithm can take a graph  $G$  and distinguish between the following cases in  $O_{q,r}(|V(G)|^{\delta r})$  time:*

- $\text{Clique}(G) \geq q$  and
- $\text{Clique}(G) < r$ .

The above theorem simply follows from plugging the FGLSS reduction below into Theorem 4.2.

**THEOREM 5.2** (see [42]). *Given a label cover instance with projection property, namely,  $\Gamma = (G = (U, V, E), \Sigma_U, \Sigma_V, \Pi)$ , as in section 4, there is a reduction that produces a graph  $H_\Gamma$  such that  $|V(H_\Gamma)| = |U||\Sigma_U|$  and  $\text{Clique}(H_\Gamma) = \text{MaxCov}(\Gamma)$ . The reduction takes  $O(|V(H_\Gamma)|^2 |V|)$  time.*

For clarity, we would like to note that, while the original graph defined in [42] is for multiprover interactive proof, analogous graphs can be constructed for CSPs and label cover instances as well. In particular, in our case, the graph can be defined as follows:

- The vertex set  $V(H_\Gamma)$  is simply  $U \times \Sigma_U$ .
- There is an edge between two vertices  $(u, \alpha), (u', \alpha') \in V(H_\Gamma)$  if and only if  $\Pi_{uv}(\alpha) = \Pi_{u'v}(\alpha')$  (i.e., recall that we have a projection constraint, so we can represent the constraint  $\Pi_{uv}$  as a function  $\Pi_{uv} : \Sigma_U \rightarrow \Sigma_V$ ).

*Proof of Theorem 5.1.* Assume that Gap-ETH holds and let  $\delta, \rho$  be the constants from Theorem 4.2. Let  $r_0 = \max\{\rho, 2/\delta\}$ . Suppose for the sake of contradiction that

for some  $q \geq r \geq r_0$ , there is an algorithm  $\mathbb{A}$  that distinguishes between  $\text{Clique}(G) \geq q$  and  $\text{Clique}(G) < r$  in  $O_{q,r}(|V(G)|^{\delta r})$  time.

Given a label cover instance  $\Gamma$  with projection property, we can use  $\mathbb{A}$  to distinguish whether  $\text{MaxCov}(\Gamma) \geq q$  or  $\text{MaxCov}(\Gamma) < r$  as follows. First, we run the FGLSS reduction to produce a graph  $H_\Gamma$ , and we then use  $\mathbb{A}$  to decide whether  $\text{Clique}(H_\Gamma) \geq q$  or  $\text{Clique}(H_\Gamma) < r$ . From  $\text{Clique}(H_\Gamma) = \text{MaxCov}(\Gamma)$ , this indeed correctly distinguishes between  $\text{MaxCov}(\Gamma) \geq q$  and  $\text{MaxCov}(\Gamma) < r$ ; moreover, the running time of the algorithm is  $O_{q,r}(|V(H_\Gamma)|^{\delta r}) + O(|V(H_\Gamma)|^2|V|) \leq O_{q,r}(|\Gamma|^{\delta r})$ , where the term  $O(|V(H_\Gamma)|^2|V|)$  comes from the running time used to produce  $H_\Gamma$ . From Theorem 4.2, this is a contradiction, which concludes our proof.  $\square$

As a corollary of Theorem 5.1, we immediately arrive at FPT inapproximability of  $\text{Clique}$  and  $\text{IndSet}$ .

**COROLLARY 5.3** (clique is inherently enumerative). *Assuming Gap-ETH, the Maximum Clique and Maximum Independent Set problems are inherently enumerative and thus FPT-inapproximable.*

**5.2. Set cover, dominating set, and hitting set.** For convenience, we will be working with the *Set Cover* problem, which is computationally equivalent to  $\text{DomSet}$  (see Appendix D).

Let  $\mathcal{U}$  be a ground set (or a universe). A set system  $\mathcal{S}$  over  $\mathcal{U}$  is a collection of subsets  $\mathcal{S} = \{S_1, \dots, S_m\}$ , where  $S_i \subseteq \mathcal{U}$  for all  $i \in [m]$ . We say that  $\mathcal{S}' \subseteq \mathcal{S}$  is a feasible set cover of  $(\mathcal{U}, \mathcal{S})$  if  $\bigcup_{X \in \mathcal{S}'} X = \mathcal{U}$ . In the *Set Cover* problem ( $\text{SetCov}$ ), we are given a set system  $(\mathcal{U}, \mathcal{S})$  and we are interested in finding a set cover  $\mathcal{S}'$  with minimum cardinality  $|\mathcal{S}'|$ . Let  $\text{SetCov}(\mathcal{U}, \mathcal{S})$  denote the value of the optimal set cover for  $(\mathcal{U}, \mathcal{S})$ .  $\text{SetCov}$  has an alternative formulation called *Hitting Set* ( $\text{HitSet}$ ), where the goal is to find a collection of elements with minimum cardinality that *hits* every subset, i.e., each subset must contain at least one chosen element. It is not hard to see that one may interchange the role of elements and subsets to get an instance of  $\text{HitSet}$  from that of  $\text{SetCov}$  and vice versa.

Note that for any set cover instance  $(\mathcal{U}, \mathcal{S})$ , checking whether there is a set cover of size at most  $q$  can be done in  $O^*(|\mathcal{S}|^q)$  time by enumerating all  $\binom{|\mathcal{S}|}{q}$  subsets of  $\mathcal{S}$  of size  $q$ . We show that this is more or less the best we can do: Even when the algorithm is promised the existence of a set cover of size  $q$  (for some constant  $q$ ), it cannot find a set cover of size  $f(q)$  for any computable function  $f$  in time  $O_q(|\mathcal{S}||\mathcal{U}|)^{\delta q}$  for some constant  $\delta > 0$  independent of  $q$  and  $f$ .

**5.2.1. Results.** Our main technical contribution in this section is summarized in the following theorem.

**THEOREM 5.4.** *There is a reduction that on input  $\Gamma = (G = (U, V, E), \Sigma_U, \Sigma_V, \Pi)$  of  $\text{MinLab}$  instance, produces a set cover instance  $(\mathcal{U}, \mathcal{S})$  such that*

- $\text{MinLab}(\Gamma) = \text{SetCov}(\mathcal{U}, \mathcal{S})$ ;
- $|\mathcal{U}| = |U||V|^{|\Sigma_V|}$  and  $|\mathcal{S}| = |V||\Sigma_V|$ ;
- the reduction runs in time  $\text{poly}(|\mathcal{U}|, |\mathcal{S}|)$ .

We defer the proof of this theorem to subsection 5.2.2. For now, let us demonstrate that, by combining Theorems 4.3 and 5.4, we can derive hardness of approximating  $\text{SetCov}$ :

**THEOREM 5.5.** *Assuming Gap-ETH, there exist universal constants  $\delta, q_0 > 0$  such that, for any positive integers  $r \geq q \geq q_0$ , no algorithm can take a set cover instance  $(\mathcal{U}, \mathcal{S})$ , and distinguish between the following cases in  $O_{q,r}(|\mathcal{S}||\mathcal{U}|)^{\delta q}$  time:*

- $\text{SetCov}(\mathcal{U}, \mathcal{S}) \leq q$ .
- $\text{SetCov}(\mathcal{U}, \mathcal{S}) > r$ .

*Proof.* Assume that Gap-ETH holds and let  $\delta, \rho$  be the constants from Theorem 4.4. Let  $q_0 = \max\{\rho, c/\delta\}$ , where  $c$  is the constant such that the running time of the reduction in Theorem 5.4 is  $O((|\mathcal{U}||\mathcal{S}|)^c)$ . Suppose for the sake of contradiction that, for some  $r \geq q \geq q_0$ , there is an algorithm  $\mathbb{A}$  that distinguishes between  $\text{SetCov}(\mathcal{U}, \mathcal{S}) \leq q$  and  $\text{SetCov}(\mathcal{U}, \mathcal{S}) > r$  in  $O_{q,r}(|\mathcal{S}||\mathcal{U}|^{\delta q})$  time.

Given a label cover instance  $\Gamma$ , where  $|V|, |\Sigma_U| = O_{q,r}(1)$ , we can use  $\mathbb{A}$  to distinguish whether  $\text{MinLab}(\Gamma) \leq q$  or  $\text{MinLab}(\Gamma) > r$  as follows. First, we run the reduction from Theorem 5.4 to produce a  $\text{SetCov}$  instance  $(\mathcal{U}, \mathcal{S})$ , and we then use  $\mathbb{A}$  to decide whether  $\text{SetCov}(\mathcal{U}, \mathcal{S}) \leq q$  or  $\text{SetCov}(\mathcal{U}, \mathcal{S}) > r$ . From  $\text{SetCov}(\mathcal{U}, \mathcal{S}) = \text{MinLab}(\Gamma)$ , this indeed correctly distinguishes between  $\text{MinLab}(\Gamma) \leq q$  and  $\text{MinLab}(\Gamma) > r$ ; moreover, the running time of the algorithm is  $O_{q,r}((|\mathcal{U}||\mathcal{S}|)^{\delta q}) + O((|\mathcal{U}||\mathcal{S}|)^c) \leq O_{q,r}(|\Gamma|^{\delta q})$ , where the term  $O((|\mathcal{U}||\mathcal{S}|)^c)$  comes from the running time used to produce  $(\mathcal{U}, \mathcal{S})$ . From Theorem 4.4, this is a contradiction, which concludes our proof.  $\square$

As a corollary of Theorem 5.5, we immediately arrive at FPT inapproximability of  $\text{SetCov}$ ,  $\text{HitSet}$ , and  $\text{DomSet}$ .

**COROLLARY 5.6.** *Assuming Gap-ETH, Set cover, Dominating set, and Hitting set are inherently enumerative and thus FPT-inapproximable.*

**5.2.2. Proof of Theorem 5.4.** Our construction is based on a standard hypercube set system, as used by Feige [39] in proving the hardness of the  $k$ -Maximum Coverage problem. We explain it here for completeness.

*Hypercube set system:* Let  $z, k \in \mathbb{N}$  be parameters. The hypercube set system  $H(z, k)$  is a set system  $(\mathcal{U}, \mathcal{S})$  with the ground set  $\mathcal{U} = [z]^k$ . We view each element of  $\mathcal{U}$  as a length- $k$  vector  $\vec{x}$ , where each coordinate assumes a value in  $[z]$ . There is a collection of *canonical sets*  $\mathcal{S} = \{X_{i,a}\}_{i \in [z], a \in [k]}$  defined as

$$X_{i,a} = \{\vec{x} : \vec{x}_a = i\}.$$

In other words, each set  $X_{i,a}$  contains the vectors whose  $a$ th coordinate is  $i$ . A nice property of this set system is that it can only be covered completely if all canonical sets corresponding to some  $a$ th coordinate are chosen.

**PROPOSITION 5.7.** *Consider any subcollection  $\mathcal{S}' \subseteq \mathcal{S}$ . We have  $\bigcup \mathcal{S}' = \mathcal{U}$  if and only if there is a value  $a \in [k]$  for which  $X_{1,a}, X_{2,a}, \dots, X_{z,a} \in \mathcal{S}'$ .*

*Proof.* The if part is obvious. For the “only if” part, assume that for each  $a \in [k]$ , there is a value  $i_a \in [z]$  for which  $X_{i_a,a}$  is not in  $\mathcal{S}'$ . Define the vector  $\vec{x}$  by  $\vec{x}_a = i_a$ . Notice that  $\vec{x}$  does not belong to any set in  $\mathcal{S}'$ . (By definition, if  $X_{i',a'}$  contains  $\vec{x}$ , then it must be the case that  $\vec{x}_{a'} = i' = i_{a'}$ .)  $\square$

*The construction:* Our reduction starts from the  $\text{MinLab}$  instance, namely,  $\Gamma = (G, \Sigma_U, \Sigma_V, \Pi)$ . We will create the set system  $\mathcal{I} = (\mathcal{U}, \mathcal{S})$ . We make  $|U|$  different copies of the hypercube set system: For each vertex  $u \in U$ , we have the hypercube set system  $(\mathcal{U}^u, \mathcal{S}^u) = H(N_G(u), \Sigma_U)$ , i.e., the ground set  $\mathcal{U}^u$  is a copy of  $N_G(u)^{\Sigma_U}$  and  $\mathcal{S}^u$  contains  $|N_G(u)||\Sigma_U|$  “virtual” sets that we call  $\{S_{v,a}^u\}_{v \in N_G(u), a \in \Sigma_U}$ , where each such set corresponds to a canonical set of the hypercube. We remark that these virtual sets are not the eligible sets in our instance  $\mathcal{I}$ . For each vertex  $v \in V$ , for each label  $b \in \Sigma_V$ , we define a set

$$S_{v,b} = \bigcup_{u \in N_G(v), (a,b) \in \Pi_{uv}} S_{v,a}^u.$$



The set system  $(\mathcal{U}, \mathcal{S})$  in our instance is simply

$$\mathcal{U} = \bigcup_{u \in U} \mathcal{U}^u \quad \text{and} \quad \mathcal{S} = \{S_{v,b} : v \in V, b \in \Sigma_V\}.$$

Notice that the number of sets is  $|V||\Sigma_V|$ , and the number of elements in the ground set is  $|\mathcal{U}| = |U||V|^{|\Sigma_U|}$ . This completes the description of our instance.

*Analysis:* We argue that the optimal value of  $\Gamma$  is equal to the optimal of  $(\mathcal{U}, \mathcal{S})$ .

First, we will show that  $\text{MinLab}(\Gamma) \leq \text{SetCov}(\mathcal{U}, \mathcal{S})$ . Let  $(\sigma_U, \hat{\sigma}_V)$  be a feasible  $\text{MinLab}$  cover for  $\Gamma$  (recall that  $\hat{\sigma}_V$  is a multilabeling, while  $\sigma_U$  is a labeling.) For each  $v \in V$ , the  $\text{SetCov}$  solution chooses the set  $S_{v,b}$  for all  $b \in \hat{\sigma}_V(v)$ . Denote this solution by  $\mathcal{S}' \subseteq \mathcal{S}$ . The total number of sets chosen is exactly  $\sum_v |\hat{\sigma}(v)|$ , exactly matching the cost of  $\text{MinLab}(\Gamma)$ . We argue that this is a feasible set cover: For each  $u$ , the fact that  $u$  is covered by  $(\sigma_U, \hat{\sigma}_V)$  implies that, for all  $v \in N_G(u)$ , there is a label  $b_v \in \hat{\sigma}_V(v)$  such that  $(\sigma_U(u), b_v) \in \Pi_{uv}$ . Notice that  $S_{v, \sigma_U(u)}^u \subseteq S_{v, b_v} \in \mathcal{S}'$  for every  $v \in N_G(u)$ , so we have

$$\bigcup_{S \in \mathcal{S}'} S \supseteq \bigcup_{v \in N_G(u)} S_{v, b_v} \supseteq \bigcup_{v \in N_G(u)} S_{v, \sigma_U(u)}^u = \mathcal{U}^u,$$

where the last equality comes from Proposition 5.7. In other words,  $\mathcal{S}'$  covers all elements in  $\mathcal{U}^u$ . Hence,  $\mathcal{S}'$  is indeed a valid  $\text{SetCov}$  solution for  $(\mathcal{U}, \mathcal{S})$ .

To prove the converse, consider a collection of sets  $\{S_{v,b}\}_{(v,b) \in \Lambda}$  that covers the whole universe  $\mathcal{U}$ . We define the (multi)labeling  $\hat{\sigma}_V : V \rightarrow 2^{\Sigma_V}$ , where  $\hat{\sigma}_V(v) = \{b : (v,b) \in \Lambda\}$  for each  $v \in V$ . Clearly,  $\sum_{v \in V} |\hat{\sigma}_V(v)| = |\Lambda|$ , so the cost of  $\hat{\sigma}_V$  as a solution for  $\text{MinLab}$  is exactly the cost of  $\text{SetCov}$ . We verify that all left vertices  $u \in U$  of  $\Gamma$  are covered (and along the way will define  $\Sigma_U(u)$  for all  $u \in U$ ). Consider each vertex  $u \in U$ . The fact that the ground elements in  $\mathcal{U}^u$  are covered implies that (from Proposition 5.7) there is a label  $a_u \in \Sigma_U$  where all virtual sets  $\{S_{v, a_u}^u\}_{v \in N_G(u)}$  are included in the solution. Therefore, for each  $v \in N_G(u)$ , there must be a label  $b_v \in \hat{\sigma}_V(v)$  such that  $a_u b_v \in \Pi_{uv}$ . We simply define  $\sigma_U(u) = a_u$ . Therefore, the vertex  $u$  is covered by the assignment  $(\sigma_U, \hat{\sigma}_V)$ .

**5.3. Maximum induced subgraph with hereditary properties.** In this section, we prove the hardness of maximum induced subgraphs with hereditary property. Let  $\Pi$  be a graph property. We say that a subset  $S \subseteq V(G)$  has property  $\Pi$  if  $G[S] \in \Pi$ . Denote by  $A_\Pi(G)$  the maximum cardinality of a set  $S$  that has property  $\Pi$ .

Khot and Raman [60] proved a dichotomy theorem for the problem: If  $\Pi$  contains all independent sets but not all cliques or if  $\Pi$  contains all cliques but not all independent sets, then the problem is  $W[1]$ -hard. For all other  $\Pi$ 's, the problem is in FPT. We will show that Khot and Raman's dichotomy theorem holds even for FPT approximation as stated more precisely below.

**THEOREM 5.8.** *Let  $\Pi$  be any hereditary property.*

- *If  $\Pi$  contains all independent sets but not all cliques or vice versa, then computing  $A_\Pi(G)$  is weakly inherently enumerative (and therefore totally FPT-inapproximable).*
- *Otherwise,  $A_\Pi(G)$  can be computed exactly in FPT.*

Surprisingly, the fact that there is a gap in the optimum of our starting point helps make our reduction simpler than that of Khot and Raman. For convenience,

let us focus only on the properties  $\Pi$ 's which contain all independent sets but not all cliques. The other case can be proved analogously. The main technical result is summarized in the following lemma.

**THEOREM 5.9.** *Let  $\Pi$  be any graph property that contains all independent sets but not all cliques. Then there is a function  $g_\Pi = \omega(1)$  such that the following hold:*

- *If  $\text{IndSet}(G) \geq q$ , then  $A_\Pi(G) \geq q$ .*
- *If  $A_\Pi(G) \geq r$ , then  $\text{IndSet}(G) \geq g_\Pi(r)$ .*

*Proof.* Since  $\Pi$  contains all independent sets, when  $\text{IndSet}(G) \geq q$ , we always have  $A_\Pi(G) \geq q$ .

Now, to prove the converse, let  $g_\Pi(r)$  denote  $\max_{H \in \Pi, |V(H)|=r} \text{IndSet}(H)$ . If  $A_\Pi(G) = r$ , then there exists a subset  $S \subseteq V(G)$  of size  $r$  that has property  $\Pi$ ; from the definition of  $g_\Pi$ ,  $\text{IndSet}(H) \geq g_\Pi(r)$ , which implies that  $\text{IndSet}(G) \geq g_\Pi(r)$  as well. Hence, we are only left to show that  $g_\Pi = \omega(1)$ .

To show that this is the case, recall the Ramsey theorem.

**THEOREM 5.10 (Ramsey's theorem).** *For any  $s, t \geq 1$ , there is an integer  $R(s, t)$  such that every graph on  $R(s, t)$  vertices contains either an  $s$ -clique or a  $t$ -independent set. Moreover,  $R(s, t) \leq \binom{s+t-2}{s-1}$ .*

Recall that, from our assumption of  $\Pi$ , there exists a fixed integer  $s_\Pi$  such that  $\Pi$  does not contain an  $s_\Pi$ -clique. Hence, from Ramsey's theorem,  $g_\Pi(r) \geq \max\{t \mid R(s_\Pi, t) \leq r\}$ . In particular, this implies that  $g_\Pi(r) \geq \Omega_{s_\Pi}(r^{1/(s_\Pi-1)})$ . Hence,  $\lim_{r \rightarrow \infty} g_\Pi(r) = \infty$  (i.e.,  $g_\Pi = \omega(1)$ ) as desired.  $\square$

In other words, the identical transformation  $G \mapsto G$  is a  $(q, g_\Pi(r))$ -FPT gap reduction from Clique to Maximum Induced Subgraph with property  $\Pi$ . Hence, by applying Proposition 3.6, we immediately arrive at the following corollary.

**COROLLARY 5.11.** *Assuming Gap-ETH, for any property  $\Pi$  that contains all independent sets but not all cliques (or vice versa), Maximum Induced Subgraph with property  $\Pi$  is  $\Omega(g_\Pi)$ -weakly inherently enumerative, where  $g_\Pi$  is the function from Theorem 5.9.*

We remark here that, for some properties,  $g_\Pi$  can be much larger than the bound given by Ramsey's theorem; for instance, if  $\Pi$  is planarity, then Ramsey's theorem only gives  $g_\Pi(r) = \Omega(r^{1/5})$  but it is easy to see that, for planar graphs, there always exist an independent set of linear size and  $g_\Pi(r)$  is hence as large as  $\Omega(r)$ .

**5.4. Maximum Balanced Biclique, Maximum Induced Matching on Bipartite Graphs, and Densest  $k$ -Subgraph.** We next prove FPT inapproximability for the Maximum Balanced Biclique, Maximum Induced Matching on Bipartite Graphs, and Densest  $k$ -Subgraph. Unlike the previous proofs, we will not reduce from any label cover problem. The starting point for the results in this section will instead be a recent construction of Manurangsi for the ETH-hardness of Densest  $k$ -Subgraph [70]. By interpreting this construction in a different perspective, we can modify it in such a way that we arrive at a stronger form of inherently enumerative hardness for Clique. More specifically, the main theorem of this section is the following theorem, which is a stronger form of Theorem 5.1 in that the soundness not only rules out cliques, but also rules out bicliques as well.

**THEOREM 5.12.** *Assuming Gap-ETH, there exist constants  $\delta, \rho > 0$  such that, for any positive integers  $q \geq r \geq \rho$ , no algorithm can take a graph  $G$  and distinguish between the following cases in  $O_{q,r}(|V(G)|^{\delta\sqrt{r}})$  time:*

- $\text{Clique}(G) \geq q$ .
- $\text{Biclique}(G) < r$ .

The weakly inherently enumerativeness (and therefore totally FPT inapproximability) of Maximum Balanced Biclique and Maximum Induced Matching on Bipartite Graphs follows easily from Theorem 5.12. We will show these results in the subsequent subsections; for now, let us turn our attention to the proof of the theorem.

The main theorem of this section can be stated as follows.

**THEOREM 5.13.** *For any  $d, \varepsilon > 0$ , there is a constant  $\gamma = \gamma(d, \varepsilon) > 0$  such that there exists a (randomized) reduction that takes in a parameter  $r$  and a 3-SAT instance  $\phi$  with  $n$  variables and  $m$  clauses where each variable appears in at most  $d$  constraints and produces a graph  $G_{\phi,r} = (V_{\phi,r}, E_{\phi,r})$  such that, for any sufficiently large  $r$  (depending only on  $d, \varepsilon$  but not  $n$ ), the following properties hold with high probability:*

- (Size)  $N := |V_{\phi,r}| \leq 2^{O_{d,\varepsilon}(n/\sqrt{r})}$ .
- (Completeness) if  $\text{SAT}(\phi) = m$ , then  $\text{Clique}(G_{\phi,r}) \geq N^{\gamma/\sqrt{r}}$ .
- (Soundness) if  $\text{SAT}(\phi) \leq (1 - \varepsilon)m$ , then  $\text{Biclique}(G_{\phi,r}) < r$ .

It is not hard to see that, in the Gap-ETH assumption, we can, w.l.o.g., assume that each variable appears in only a bounded number of clauses (see [72, p. 21]). Hence, Theorem 5.13 together with Gap-ETH implies Theorem 5.12.

As mentioned earlier, our result builds upon an intermediate lemma used in proving the hardness of approximating Densest  $k$ -Subgraph in [70]. Due to this, it will be easier to describe our reduction in terms of the reduction from [70]; In this regard, our reduction can be viewed as vertex subsampling (with appropriate Probability) of the graph produced by the reduction from [70]. The reduction is described formally in Figure 1. Note that the two parameters  $\ell$  and  $p$  will be chosen as  $\Theta_{d,\varepsilon}(n/\sqrt{r})$  and  $2^{\Theta_{d,\varepsilon}(\ell^2/n)} / \binom{n}{\ell}$ , respectively, where the constants in  $\Theta_{d,\varepsilon}(\cdot)$  will be selected based on the parameters from the intermediate lemma in [70].

The main lemma of [70] is stated below. Roughly speaking, when  $\text{SAT}(\phi) \leq (1 - \varepsilon)m$ , the lemma gives an upper bound on the number of occurrences of  $K_{t,t}$  for every  $t > 0$ . When  $p$  and  $t$  are chosen appropriately, this implies that with high probability (w.h.p.) there is no  $t$ -biclique in our subsampled graph. Note that the size and completeness properties are obvious from the construction while the exact statement of the soundness can be found in the proof of Theorem 8 in [70].

**LEMMA 5.14** (see [70]). *Let  $d, \varepsilon, \phi, n, m, \ell$  be as in Theorem 5.13 and Figure 1. There is a constant  $\delta, \lambda > 0$  depending only on  $d, \varepsilon$  such that, for any sufficiently large  $n$ , the graph  $G_{\phi,\ell} = (V_{\phi,\ell}, E_{\phi,\ell})$  described in Figure 1 has the following properties:*

- (Size)  $|V_{\phi,\ell}| = \binom{n}{\ell} 2^\ell$ .
- (Completeness) If  $\text{SAT}(\phi) = m$ , then the graph  $\tilde{G}_{\phi,\ell}$  contains an  $\binom{n}{\ell}$ -clique.
- (Soundness) If  $\text{SAT}(\phi) \leq (1 - \varepsilon)m$ , then the graph  $\tilde{G}_{\phi,\ell}$  contains at most  $2^{4n} (2^{-\lambda \ell^2/n} \binom{n}{\ell})^{2t}$  occurrences<sup>9</sup> of  $K_{t,t}$  for any  $t > 0$ .

Theorem 5.13 follows rather easily from the above lemma by choosing appropriate  $\ell$  and  $p$ .

<sup>9</sup>We say that  $S, T \subseteq V_{\phi,\ell}$  is an occurrence of  $K_{t,t}$  if  $|S| = |T| = t$ ,  $S \cap T = \emptyset$ , and, for every  $s \in S, t \in T$ , there is an edge between  $s$  and  $t$  in  $G_{\phi,\ell}$ . The number of occurrences of  $K_{t,t}$  of  $G_{\phi,\ell}$  is simply the number of such pairs  $(S, T)$ 's.

Input: a 3-SAT instance  $\phi$  and parameters  $p \in (0, 1)$  and  $\ell \in \mathbb{N}$  such that  $\ell \leq n$ .

Output: a graph  $G_{\phi, \ell, p} = (V_{\phi, \ell, p}, E_{\phi, \ell, p})$ .

The graph  $G_{\phi, \ell, p}$  is generated as follows.

- First, we create a graph  $\tilde{G}_{\phi, \ell} = (\tilde{V}_{\phi, \ell}, \tilde{E}_{\phi, \ell})$  as constructed in [70]. More specifically, the vertex set  $\tilde{V}_{\phi, \ell}$  and the edge set  $\tilde{E}_{\phi, \ell}$  are defined as follows.
  - The vertex set  $\tilde{V}_{\phi, \ell}$  consists of all partial assignments of  $\ell$  variables, i.e.,  $\tilde{V}_{\phi, \ell} := \{\sigma : S \rightarrow \{0, 1\} \mid S \in \binom{\mathcal{X}}{\ell}\}$ , where  $\mathcal{X}$  is the set of all variables in  $\phi$ .
  - There exists an edge between two vertices  $\sigma_1 : S_1 \rightarrow \{0, 1\}$  and  $\sigma_2 : S_2 \rightarrow \{0, 1\} \in \tilde{V}_{\phi, \ell}$  if and only if (1) they are consistent (i.e.,  $\sigma_1(S_1 \cap S_2) = \sigma_2(S_1 \cap S_2)$ ) and (2) the partial assignment induced by  $\sigma_1, \sigma_2$  does not violate any constraint (i.e., every constraint that lies entirely inside  $S_1 \cup S_2$  is satisfied by the partial assignment induced by  $\sigma_1, \sigma_2$ ).
- Our graph  $G_{\phi, \ell, p} = (V_{\phi, \ell, p}, E_{\phi, \ell, p})$  can then be easily generated as follows.
  - Let  $V_{\phi, \ell, p}$  be a random subset of  $\tilde{V}_{\phi, \ell}$  such that each vertex  $v \in \tilde{V}_{\phi, \ell}$  is included independently and randomly in  $V_{\phi, \ell, p}$  with probability  $p$ .
  - We connect  $u, v \in V_{\phi, \ell, p}$  if and only if  $(u, v) \in \tilde{E}_{\phi, \ell}$ .

FIG. 1. The reduction from Gap-3-SAT to Maximum Balanced Biclique.

*Proof of Theorem 5.13.* We let  $G_{\phi, r} = G_{\phi, \ell, p}$  from the reduction in Figure 1 with parameters  $\ell = \frac{4n}{\sqrt{\lambda r}}$  and  $p = 2^{\frac{\lambda \ell^2}{2n}} / \binom{n}{\ell}$ . For convenience, we assume w.l.o.g. that  $\lambda < 1$ .

*Size.* Since each vertex in  $V_{\phi, \ell}$  is included that  $V_{\phi, \ell, p}$  independently with probability  $p$ , we have  $\mathbb{E}[|V_{\phi, \ell, p}|] = p|V_{\phi, \ell}| = 2^{\ell + \frac{\lambda \ell^2}{2n}} \leq 2^{2\ell}$ . Hence, from the Chernoff bound,  $|V_{\phi, \ell, p}| \leq 2^{10\ell} = 2^{\Omega_{d, \varepsilon}(n/\sqrt{r})}$  w.h.p.

*Completeness.* Suppose that  $\phi$  is satisfiable. Let  $C$  be the clique of size  $\binom{n}{\ell}$  in  $\tilde{G}_{\phi, \ell}$ , which is guaranteed to exist by Lemma 5.14. From how  $G_{\phi, \ell, p}$  is defined,  $C \cap V_{\phi, \ell, p}$  induces a clique in  $G_{\phi, \ell, p}$ . Moreover,  $\mathbb{E}[|C \cap V_{\phi, \ell, p}|] = p|C| = 2^{\frac{\lambda \ell^2}{2n}}$ . Again, from Chernoff bound,  $\text{Clique}(G_{\phi, \ell, p}) \geq 2^{\frac{\lambda \ell^2}{2n}}$  w.h.p. Combined with the above bound on  $N$ ,  $\text{Clique}(G_{\phi, \ell, p}) \geq N^{\gamma/\sqrt{r}}$  w.h.p. when  $\gamma := \sqrt{\lambda}/20 = O_{d, \varepsilon}(1)$ .

*Soundness.* Suppose that  $\text{SAT}(\phi) \leq (1 - \varepsilon)m$ . Consider any subsets  $S, T \subseteq \tilde{V}_{\phi, \ell}$  that are an occurrence of  $K_{r, r}$  in  $\tilde{G}_{\phi, \ell}$ . From how  $G_{\phi, \ell, p}$  is defined,  $\text{Biclique}(G_{\phi, \ell, p}) \geq r$  if and only if, for at least one such pair  $(S, T)$ ,  $S \cup T \subseteq V_{\phi, \ell, p}$ . The probability of this event is bounded above by

$$\begin{aligned} \sum_{\substack{S, T \subseteq \tilde{V}_{\phi, \ell} \\ S, T \text{ is an occurrence of } K_{r, r} \text{ in } \tilde{G}_{\phi, \ell}}} \Pr[S, T \subseteq V_{\phi, \ell, p}] &\leq 2^{4n} \left( 2^{-\lambda \ell^2/n} \binom{n}{\ell} \right)^{2r} \cdot p^{2r} \\ &= 2^{4n} \left( 2^{-\frac{\lambda \ell^2}{2n}} \right)^{2r} \\ &= o(1), \end{aligned}$$

where the first inequality comes from the bound in the soundness of Lemma 5.14 and the fact that the sampling of each vertex is done independently.

As a result, the subsampled graph  $G_{\phi,\ell,p}$  is  $K_{r,r}$ -free w.h.p. as desired.  $\square$

**5.4.1. Maximum Balanced Biclique.** We now give a simple reduction from the ‘‘Clique versus Biclique’’ problem (from Theorem 5.12) to the Maximum Balanced Biclique problem, which yields FPT inapproximability of the latter.

LEMMA 5.15. *For any graph  $G = (V, E)$ , let  $B_e[G] = (V_{B_e[G]}, E_{B_e[G]})$  be the bipartite graph whose vertex set is  $V_{B_e[G]} := V \times [2]$  and two vertices  $(u, i), (v, j)$  are connected by an edge if and only if  $(u, v) \in E$  or  $u = v$ , and  $i \neq j$ . Then the following properties hold for any graph  $G$ .*

- $\text{Biclique}(B_e[G]) \geq \text{Clique}(G)$ .
- $\text{Biclique}(B_e[G]) \leq 2\text{Biclique}(G) + 1$ .

*Proof.* It is easy to see that  $\text{Biclique}(B_e[G]) \geq \text{Clique}(G)$  since, for any  $C \subseteq V$  that induces a clique in  $G$ ,  $C \times [2] \subseteq V_{B_e[G]}$  induces a  $|C|$ -biclique in  $B_e[G]$ .

To see that  $\text{Biclique}(B_e[G]) \leq 2\text{Biclique}(G) + 1$ , consider any  $S \subseteq V_{B_e[G]}$  that induces a  $k$ -biclique in  $B_e[G]$ . Note that  $S$  can be partitioned into  $S_1 = S \cap (V \times \{1\})$  and  $S_2 = S \cap (V \times \{2\})$ .

Now consider the projections of  $S_1$  and  $S_2$  into  $V(G)$ , i.e.,  $T_1 = \{v : (v, 1) \in S\}$  and  $T_2 = \{v : (v, 2) \in S\}$ . Note that  $|T_1| = |T_2| = k$ . Since  $S_1 \cup S_2$  induces a biclique in  $B_e[G]$ , we have, for every  $u \in T_1$  and  $v \in T_2$ , either  $u = v$  or  $(u, v) \in E$ . Observe that if there were no former case (i.e.,  $T_1 \cap T_2 = \emptyset$ ), then we would have a  $k$ -biclique in  $G$ . Even if  $T_1 \cap T_2 \neq \emptyset$ , we can still get back a  $\lfloor k/2 \rfloor$ -biclique in  $G$  by uncrossing the sets  $T_1$  and  $T_2$  in a natural way by assigning half of the intersection to  $T_1$  and the other half to  $T_2$ . To be formal, we partition  $T_1 \cap T_2$  into roughly equal sets  $U_1$  and  $U_2$  (i.e.,  $\|U_1| - |U_2| \leq 1$ ), and we then define new sets  $T'_1$  and  $T'_2$  by

$$T'_1 = (T_1 \setminus T_2) \cup U_1 \text{ and } T'_2 = (T_2 \setminus T_1) \cup U_2.$$

It is not hard to see that  $G$  has an edge between every pair of vertices between  $T'_1, T'_2$  and that  $|T'_1|, |T'_2| \geq \lfloor k/2 \rfloor$ . Thus,  $\text{Biclique}(G) \geq \lfloor k/2 \rfloor \geq (k-1)/2$ . Therefore,  $\text{Biclique}(B_e[G]) \leq 2\text{Biclique}(G) + 1$  as desired.  $\square$

Thanks to the above lemma, we can conclude that the reduction  $G \mapsto B_e[G]$  is a  $(2q, (r+1)/2)$ -FPT gap reduction from the Clique versus Biclique problem to Maximum Balanced Biclique, although the former is not a well-defined optimization problem. Nevertheless, it is easy to check that a proof along the line of Proposition 3.6 still works and it gives the following result.

COROLLARY 5.16. *Assuming Gap-ETH, Maximum Balanced Biclique are  $\Omega(\sqrt{r})$ -weakly inherently enumerative and thus FPT-inapproximable.*

It is worth noting that the Maximum Edge Biclique problem, a well-studied variant of the Maximum Balanced Biclique problem where the goal is to find a (not necessarily balanced) complete bipartite subgraph of a given bipartite graph that contains as many edges as possible, is in FPT. This is because the optimum is at least the maximum degree, but when the degree is bounded above by  $r$ , all bicliques can be enumerated in  $2^{O(r)}$  poly( $n$ ) time.

**5.4.2. Maximum induced matching on bipartite graphs.** Next, we prove the FPT hardness of approximation for the Maximum Induced Matching problem on bipartite graphs. Again, the proof will be a simple reduction from Theorem 5.12. The

argument below is similar to that used in Lemma IV.4 of [20]. We include it here for completeness.

LEMMA 5.17. *For any graph  $G = (V, E)$ , let  $B_e[\bar{G}] = (V_{B_e[\bar{G}]}, E_{B_e[\bar{G}]})$  be the bipartite graph whose vertex is  $V_{B_e[\bar{G}]} := V \times [2]$  and two vertices  $(u, i), (v, j)$  are connected by an edge if and only if  $(u, v) \notin E$  or  $u = v$ , and  $i \neq j$ . Then, the following properties hold for any graph  $G$ .*

- $\text{IM}(B_e[\bar{G}]) \geq \text{Clique}(G)$ .
- $\text{IM}(B_e[\bar{G}]) \leq 2\text{Biclique}(G) + 1$ .

*Proof.* Consider any  $S \subseteq V$  that induces a clique in  $G$ . It is obvious that  $S \times [2] \subseteq V_{B_e[\bar{G}]}$  induces a matching in  $B_e[\bar{G}]$ .

Next, consider any induced matching  $\{(u_1, v_1), \dots, (u_m, v_m)\}$  of size  $m$ . Assume w.l.o.g. that  $u_1, \dots, u_m \in V \times \{1\}$  and  $v_1, \dots, v_m \in V \times \{2\}$ . Define  $\pi_1 : V \times [2] \rightarrow V$  to be a projection operator that projects on to the first coordinate.

Let  $S_1 = \pi_1(\{u_1, \dots, u_{\lfloor m/2 \rfloor}\})$  and  $S_2 = \pi_1(\{v_{\lfloor m/2 \rfloor + 1}, \dots, v_m\})$ . From the definition of  $B_e[\bar{G}]$  and from the fact that there is no edge between  $(S_1 \times \{1\})$  and  $(S_2 \times \{2\})$ , it is easy to check that  $S_1 \cap S_2 = \emptyset$  and, for every  $u \in S_1$  and  $v \in S_2$ ,  $(u, v) \in E$ . In other words,  $(S_1, S_2)$  is an occurrence of  $\lfloor m/2 \rfloor$  in  $G$ . Hence, we conclude that  $\text{IM}(B_e[\bar{G}]) \leq 2\text{Biclique}(G) + 1$ .  $\square$

Similarly to **Biclique**, it is easy to see that the above reduction implies the following running time lower bound and FPT inapproximability for Maximum Induced Matching on Bipartite Graphs.

COROLLARY 5.18. *Assuming Gap-ETH, Maximum Induced Matching on Bipartite Graphs are  $\Omega(\sqrt{r})$ -weakly inherently enumerative and thus FPT-inapproximable.*

**5.4.3. Densest  $k$ -subgraph.** Finally, we will show the FPT inapproximability result for Densest  $k$ -Subgraph. Alas, we are not able to show an  $o(k)$ -ratio FPT inapproximability, which would have been optimal since the trivial algorithm gives an  $O(k)$ -approximation for the problem. Nonetheless, we will show a  $k^{o(1)}$ -factor FPT inapproximability for the problem. We note that below we will state the result as if  $k$  is the parameter. This is the same as using the optimum as the parameter since (in the nontrivial case) the optimum is always between  $\lfloor k/2 \rfloor$  and  $\binom{k}{2}$  (inclusive).

To derive our result, we resort to a well-known result in extremal combinatorics called the Kővári–Sós–Turán (KST) theorem, which basically states that if a graph contains no small bicliques, then it is sparse. The KST theorem is stated formally below.

THEOREM 5.19 (KST theorem [62]). *For every positive integer  $n$  and  $t \leq n$ , every  $K_{t,t}$ -free graph on  $n$  vertices has at most  $O(n^{2-1/t})$  edges (i.e., density  $O(n^{-1/t})$ ).*

We remark that a generalization of the KST theorem was also a crucial ingredient in the proof of ETH-hardness of approximating Densest  $k$ -Subgraph in [70]. The situation is simpler for us here since we can simply apply the KST theorem to Theorem 5.12, which yields the following theorem.

THEOREM 5.20. *Assuming Gap-ETH, there exist a constant  $\delta > 0$  and an integer  $\rho > 0$  such that, for any integer  $q \geq r \geq \rho$ , no algorithm can take a graph  $G = (V, E)$  and distinguish between the following cases in  $O_{q,r}(|V|^{\delta\sqrt{r}})$  time:*

- $\text{Den}_q(G) = 1$ .
- $\text{Den}_q(G) < O(q^{-1/r})$ .

From the above theorem, it is easy to show the  $k^{o(1)}$ -factor FPT inapproximability of Densest  $k$ -Subgraph as formalized below. We note here that our result applies to a special case of Densest  $k$ -Subgraph in which the input graph is promised to contain a  $k$ -clique; this problem is sometimes referred to as *Densest  $k$ -Subgraph with perfect completeness* [17, 70].

LEMMA 5.21. *Assuming Gap-ETH, for every function  $f = o(1)$  and every function  $t$ , there is no  $t(k) \cdot n^{O(1)}$ -time algorithm such that, given an integer  $k$  and any graph  $G = (V, E)$  on  $n$  vertices that contains at least one  $k$ -clique, always outputs  $S \subseteq V$  of size  $k$  such that  $\text{Den}(S) \geq k^{-f(k)}$ .*

*Proof.* Suppose for the sake of contradiction that there is a  $t(k) \cdot |V|^D$ -time algorithm  $\mathbb{A}$  that, given an integer  $k$  and any graph  $G = (V, E)$  that contains a  $k$ -clique, always outputs  $S \subseteq V$  of size  $k$  such that  $\text{Den}(S) \geq k^{-f(k)}$  for some function  $f = o(1)$ , some function  $t$ , and some constant  $D > 0$ .

Let  $r = \max\{\lceil \rho \rceil, \lceil (D/\delta)^2 \rceil\}$ , where  $\rho$  is the constant from Theorem 5.20. Note that  $O(q^{-1/r}) = q^{O(1)/\log q - 1/r}$ . Now, since  $\lim_{q \rightarrow \infty} f(q) + O(1)/\log q = 0$ , there exists a sufficiently large  $q$  such that the term  $O(q^{-1/r})$  is less than  $q^{-f(q)}$ . In other words,  $\mathbb{A}$  can distinguish between the two cases in Theorem 5.20 in time  $t(q) \cdot n^D = O_{q,r}(|V|^{\delta\sqrt{r}})$ , which would break Gap-ETH.  $\square$

**6. Conclusion and discussions.** In this paper, we prove that Clique and DomSet are totally FPT-inapproximable under Gap-ETH. In fact, we show a stronger property that they are inherently enumerative, i.e., the best way to approximate both problems is to essentially enumerate all possibilities. Since Clique and DomSet are complete problems for the class  $W[1]$  and  $W[2]$ , respectively, it might be possible that these two problems can be sources of FPT-inapproximabilities for many other problems that admit no FPT algorithms.

We would like to also mention that there are some problems that are known to be totally FPT-inapproximable under weaker assumptions. Examples of such problems are *independent dominating set* and *induced path*. The former has been shown to be FPT-inapproximable under the assumption  $\text{FPT} \neq W[2]$  in [35]. For the induced path problem, we show in Appendix C that it is FPT-inapproximable under the assumption  $\text{FPT} \neq W[1]$ . It would be interesting to understand whether it is possible to also base the total FPT-inapproximabilities of Clique and DomSet under assumptions that are weaker than Gap-ETH, such as  $\text{FPT} \neq W[1]$ ,  $\text{FPT} \neq W[2]$  or ETH. As discussed in the introduction, it was recently shown in [55] that DomSet is totally FPT-inapproximable under  $\text{FPT} \neq W[1]$ , and the more refined running time lower bounds were also shown under ETH and SETH. Nevertheless, we are not aware of any FPT inapproximability result for Clique under an assumption weaker than Gap-ETH.

Another interesting further research direction is to study the trade-off between the running time and the approximation ratio of problems that are known to be FPT-approximable or admit FPT (exact) algorithms. The exploration of such a trade-off may be useful in both theory and practice.

**Appendix A. Gap problems versus approximation algorithms.** In this section, we establish the connections between gap problems and the FPT approximation algorithm by proving Propositions 2.3 and 2.4. Proposition 2.3 is, in fact, implied by a result due to Chen, Grohe, and Grüber [25, Proposition 4], and Proposition 2.4 appears in the ECCC version [26, Proposition 6]. We provide the proof here for completeness.

*Proof of Proposition 2.3.* We prove this by the contrapositive. Suppose that (2) is false, i.e., there exist computable functions  $t : \mathbb{N} \rightarrow \mathbb{N}$ ,  $f : \mathbb{N} \rightarrow [1, \infty)$  and an algorithm  $\mathbb{B}$  such that, for every instance  $I$  of  $\Pi$ , the algorithm  $\mathbb{B}$  runs in time  $t(\text{OPT}_\Pi(I)) \cdot |I|^D$  on the input  $I$  for some constant  $D > 0$  and outputs  $y \in \text{SOL}_\Pi(I)$  of cost at most  $\text{OPT}_\Pi(I) \cdot f(\text{OPT}_\Pi(I))$ .

Let  $t' : \mathbb{N} \rightarrow \mathbb{N}$  and  $f' : \mathbb{N} \rightarrow [1, \infty)$  be functions that are defined by  $t'(k) = \max_{i=1, \dots, k} t(i)$  and  $f'(k) = \max_{i=1, \dots, k} f(i)$ . Since  $t$  and  $f$  are computable,  $t'$  and  $f'$  are also computable.

Let  $\mathbb{A}$  be an algorithm that takes an instance  $I$  of  $\Pi$  and a positive integer  $k$  and then works as follows. The algorithm  $\mathbb{A}$  simulates an execution of  $\mathbb{B}$  on  $I$  step-by-step. If  $\mathbb{B}(I)$  does not finish within  $t'(k) \cdot |I|^D$  time steps, then  $\mathbb{A}$  terminates the execution and returns 0. Otherwise, let  $y$  be the output of  $\mathbb{B}(I)$ . Then algorithm  $\mathbb{A}$  computes  $\text{COST}_\Pi(I, y)$  and then returns 1 if this value is at most  $k \cdot f'(k)$ ; otherwise,  $\mathbb{A}$  returns 0.

We claim that  $\mathbb{A}$  is an  $f'$ -FPT gap approximation algorithm of  $\Pi$ . To see that this is the case, first notice that the running time of  $\mathbb{A}$  is  $O(t'(k) \cdot |I|^D + |I|^{O(1)})$ , where  $|I|^{O(1)}$  denotes the time used to compute the solution cost. Moreover, if  $\text{OPT}_\Pi(I) > k \cdot f'(k)$ , then it is obvious to see that  $\mathbb{A}$  always outputs 0. Finally, if  $\text{OPT}_\Pi(I) \leq k$ , then, by our assumption on  $\mathbb{B}$  and the definitions of  $t'$  and  $f'$ ,  $\mathbb{B}(I)$  finishes in time  $t(\text{OPT}_\Pi(I)) \cdot |I|^D \leq t'(k) \cdot |I|^D$  and the output solution  $y$  has cost at most  $\text{OPT}_\Pi(I) \cdot f(\text{OPT}_\Pi(I)) \leq k \cdot f'(k)$ . Hence,  $\mathbb{A}$  always outputs 1 in this case.

As a result,  $\mathbb{A}$  is an  $f'$ -FPT gap approximation algorithm for  $\Pi$ , which concludes our proof.  $\square$

*Proof of the Proposition 2.4.* We again prove this by the contrapositive. Suppose that (2) is false, i.e., there exist computable functions  $t : \mathbb{N} \rightarrow \mathbb{N}$ ,  $f : \mathbb{N} \rightarrow [1, \infty)$  such that  $k/f(k)$  is nondecreasing and  $\lim_{k \rightarrow \infty} k/f(k) = \infty$ , and an algorithm  $\mathbb{B}$  such that, for every instance  $I$  of  $\Pi$ ,  $\mathbb{B}$  runs in time  $t(\text{OPT}_\Pi(I)) \cdot |I|^D$  on the input  $I$  for some constant  $D > 0$  and outputs  $y \in \text{SOL}_\Pi(I)$  of cost at least  $\text{OPT}_\Pi(I)/f(\text{OPT}_\Pi(I))$ .

Let  $t' : \mathbb{N} \rightarrow \mathbb{N}$  be a function defined by  $t'(k) = \max_{i=1, \dots, k} t(i)$ . Then clearly,  $t'$  is computable.

Let  $\mathbb{A}$  be an algorithm that takes an instance  $I$  of  $\Pi$  and a positive integer  $k$  and then works as follows. The algorithm  $\mathbb{A}$  simulates an execution of  $\mathbb{B}$  on  $I$  step-by-step. If  $\mathbb{B}(I)$  does not finish within  $t'(k) \cdot |I|^D$  time steps, then  $\mathbb{A}$  terminates the execution and returns 1. Otherwise, let  $y$  be the output of  $\mathbb{B}(I)$ .  $\mathbb{A}$  computes  $\text{COST}_\Pi(I, y)$ . The algorithm  $\mathbb{A}$  then returns 1 if this value is at least  $k/f(k)$ ; otherwise,  $\mathbb{A}$  returns 0.

We claim that  $\mathbb{A}$  is an  $f$ -FPT gap approximation algorithm of  $\Pi$ . To see that this is the case, first notice that the running time of  $\mathbb{A}$  is  $O(t'(k) \cdot |I|^D + |I|^{O(1)})$ , where  $|I|^{O(1)}$  denotes the time used to compute the solution cost. Moreover, if  $\text{OPT}_\Pi(I) < k/f(k)$ , then the running time of  $\mathbb{B}(I)$  is at most  $t(\text{OPT}_\Pi(I)) \cdot |I|^D \leq t'(k) \cdot |I|^D$ , which implies that  $\mathbb{A}$  returns 0.

Suppose, on the other hand, that  $\text{OPT}_\Pi(I) \geq k$ . If  $\mathbb{B}(I)$  finishes in time  $t'(k) \cdot |I|^D$ , then, from the guarantee of  $\mathbb{B}$ , it must output  $y \in \text{SOL}_\Pi(I)$  with  $\text{COST}_\Pi(I, y) \geq \text{OPT}_\Pi(I)/f(\text{OPT}_\Pi(I))$ , which is at least  $k/f(k)$  since  $k/f(k)$  is nondecreasing. Furthermore, if  $\mathbb{B}(I)$  does not finish in the specified time, then  $\mathbb{A}$  also returns 1 as desired.

As a result,  $\mathbb{A}$  is an  $f$ -FPT gap approximation algorithm for  $\Pi$ , which concludes our proof.  $\square$

**Appendix B. Totally FPT inapproximable through FPT gap reductions (proof of Proposition 3.5).** We will only show the proof when both  $\Pi_0$  and  $\Pi_1$  are maximization problems. Other cases can be proved analogously and therefore omitted.



We assume that (i) holds and will show that if the then part does not hold, then (ii) also does not hold. Recall from Definition 3.4 that (i) implies that there exist  $C, D > 0$  such that the reduction from  $\Pi_0$  (with parameters  $q$  and  $r$ ) to  $\Pi_1$  takes  $O_{q,r}(|I_0|^C)$  time and always outputs an instance  $I_1$  of size at most  $O_{q,r}(|I_0|^D)$  on every input instance  $I_0$ . Now assume that the then part does not hold, i.e.,  $\Pi_1$  admits a  $(t(k)|I_1|^F)$ -time  $h$ -FPT gap approximation algorithm  $\mathbb{A}$  for some function  $h(k) = o(k)$  and constant  $F$ . We will show the following claim which says that (ii) does not hold (by Definition 2.1).

**CLAIM B.1.** *There exists a function  $k \geq g'(k) = \omega(1)$  and an algorithm  $\mathbb{B}$  that takes any input instance  $I_0$  of the problem  $\Pi_0$  and an integer  $k$ , and in  $O_k(|I_0|^{O(1)})$  time can distinguish between  $\text{OPT}_{\Pi_0}(I_0) \geq k$  and  $\text{OPT}_{\Pi_0}(I_0) < g'(k)$ .*

We now prove the claim by constructing an algorithm  $\mathbb{B}$  that performs the following steps. Given  $I_0$  and  $k$ ,  $\mathbb{B}$  applies the reduction on the instance  $I_0$  with the parameters  $k$  and  $r = \frac{f(k)}{h(f(k))}$ . Denote by  $I_1$  the instance of  $\Pi_1$  produced by the reduction, so we have that  $|I_1| = O_k(|I_0|^{O(1)})$ . The following properties are immediate from the definitions of the FPT gap reductions (Definition 3.4).

- If  $\text{OPT}_{\Pi_0}(I_0) \geq k$ , then we have  $\text{OPT}_{\Pi_1}(I_1) \geq f(k)$ .
- If  $\text{OPT}_{\Pi_0}(I_0) < g'(k) := g(\frac{f(k)}{h(f(k))})$ , then we have  $\text{OPT}_{\Pi_1}(I_1) < r = \frac{f(k)}{h(f(k))}$ .

Since  $\mathbb{A}$  is an  $h$ -FPT gap approximation algorithm, running  $\mathbb{A}$  on  $(I_1, f(k))$  can distinguish between the above two cases. Consequently, one can also invoke  $\mathbb{A}$  to distinguish between the cases that  $\text{OPT}_{\Pi_0}(I_0) \geq k$  and that  $\text{OPT}_{\Pi_0}(I_0) < g'(k) = g(\frac{f(k)}{h(f(k))})$  in time  $O_k(|I_1|^F) = O_k(|I_0|^{DF}) = O_k(|I_0|^{O(1)})$ . Notice also that

$$g'(k) = g\left(\frac{f(k)}{h(f(k))}\right) \leq g(f(k)) \leq k,$$

where the first inequality is because  $f(k)/h(f(k)) \leq f(k)$  (recall that  $h(f(k)) \geq 1$  by Definition 2.1) and because  $g$  is nondecreasing, and the second inequality is by the claim below.

**CLAIM B.2.** *For any totally-FPT-inapproximable problem  $\Pi_0$  and any functions  $g$  and  $f$  that satisfy conditions in Definition 3.4, it holds for any integer  $x$  that  $g(f(x)) \leq x$ .*

*Proof.* For any integer  $x$ , consider an instance  $I_0$  such that  $\text{OPT}_{\Pi_0}(I_0) \geq x$  (such  $I_0$  exists because  $\text{OPT}_{\Pi_0} = \omega(1)$ ; otherwise,  $\Pi_0$  is not totally-FPT-inapproximable (e.g., we can always output 1 if  $\Pi_0$  is a maximization problem)). By the second condition in Definition 3.4,  $\text{OPT}_{\Pi_1}(I_1) \geq f(x)$ . Applying the contrapositive of the third condition with  $r = f(x)$  (thus,  $\text{OPT}_{\Pi_1}(I_1) \geq r$ ), we have  $\text{OPT}_{\Pi_0}(I_0) \geq g(r) = g(f(x))$ . Thus,  $x \geq \text{OPT}_{\Pi_0}(I_0) \geq g(f(x))$  as claimed.  $\square$

To complete the proof, one only needs to argue that  $g(\frac{f(k)}{h(f(k))}) = \omega(1)$ , and this simply follows from the fact that  $f(k) = \omega(1)$ ,  $g(k) = \omega(1)$ , and that  $k/h(k) = \omega(1)$ .

**Appendix C. FTP-inapproximability under  $\mathbf{W}[1]$ -hardness.** Here we show an example of problems whose totally FPT-inapproximable holds under  $\mathbf{W}[1] \neq \text{FPT}$ , namely the *maximum induced path* problem (**InducedPath**).

In **InducedPath**, we are given a graph  $G$ , and the goal is to find a maximum size subset of vertices  $S \subseteq V(G)$  such that  $S$  induces a path in  $G$ . We will show that **InducedPath** has no FPT-approximation algorithm. Implicit in our reduction is a reduction from  $k$ -Clique to the *multicolored clique* problem.

**THEOREM C.1.** *Unless  $W[1]=FPT$ , for any positive integers  $q : 1 \leq q \leq n^{1-\delta}$  for any  $\delta < 0$ , given a graph  $G$  on  $n$  vertices and for any function  $t : \mathbb{R} \rightarrow \mathbb{R}$ , there is no  $t(k)$  poly( $n$ )-time algorithm that distinguishes between the following two cases:*

- $\text{InducedPath}(G) \geq 2q \cdot k$ .
- $\text{InducedPath}(G) \leq 4(k-1)$ .

*Proof.* The reduction is as follows. Take a graph  $H$  of a  $k$ -Clique instance. Then we construct a graph  $G$  as follows. First, we create intermediate graphs  $Z_1, \dots, Z_q$ . Each graph  $Z_i$  for  $i \in [q]$  is created by making  $k$  copies of  $V(H)$ , namely,  $V_{i,1}, \dots, V_{i,k}$  and forming a clique on  $V_{i,j}$  for each  $j \in [k]$ . So, now, we have  $k$  disjoint cliques. For each vertex  $v \in V(H)$ , we pick a copy of  $v$ , one from each  $V_{i,j}$ , say  $v_{i,j}$ , and we form a clique on  $\{v_{i,1}, \dots, v_{i,k}\}$ . Next, for each edge  $uv \notin E(H)$ , we add edges  $u_{i,j}v_{i,j'}$  for all  $j, j' \in [k]$ , where  $u_{i,j}$  and  $v_{i,j'}$  are the copy of  $u$  in  $V_{i,j}$  and the copy of  $v$  in  $V_{i,j'}$ , respectively. Next, we add a dummy vertex  $x_{i,j}$  for each  $V_{i,j}$  and add edges joining  $x_{i,j}$  to every vertex of  $V_{i,j}$  and to every vertex of  $V_{i,j-1}$  if  $j \geq 2$ . Finally, we join the graph  $Z_i$  for all  $i \in [q]$  to be of the form  $(Z_1, Z_2, \dots, Z_k)$ . To be precise, for each graph  $Z_i$  with  $i \geq 2$ , we join the vertex  $x_{i,1}$  (which belongs to  $Z_i$ ) to every vertex of  $V_{i-1,q}$  (which belongs to  $Z_{i+1}$ ).

**Completeness.** Suppose that  $\text{Clique}(H) \geq k$ . We will show that  $\text{InducedPath}(G) \geq 2q \cdot k$ . We take a subset of vertices  $S \subseteq V(H)$  that induces a clique on  $H$ . Let us name vertices in  $S$  by  $v^1, \dots, v^k$ . For each  $j \in [k]$ , we pick the copies  $v_{i,j}^j$  of  $v^j$  from  $V_{i,j}$  for all  $i \in [q]$ . We then pick all the vertices  $x_{i,j}$  for  $i \in [k]$  and  $j \in [q]$ . We denote this set of vertices by  $S'$ . It is not hard to see that for any distinct vertices  $v^j, v^{j'} \in S$ , their copies  $v_{i,j}^j$  and  $v_{i',j'}^{j'}$  are not adjacent, and each vertex  $x_{i,j}$  has exactly two neighbors:  $v_{i,j}^j$  and  $v_{i,j-1}^{j-1}$  (or  $v_{i-1,k}^k$ ). Therefore,  $S'$  induces a path in  $G$  of size  $2qk$ .

**Soundness.** Suppose that  $\text{Clique}(H) < k$ , i.e.,  $H$  has no clique of size  $k$ . We will show that  $\text{InducedPath}(G) \leq 4(k-1)$ . To see this, let  $S' \subseteq V(G)$  be a subset of vertices that induces a path  $G[S']$  in  $G$ . Observe that, for  $i \in [q]$ ,  $G[S'] \cap Z_i$  must be a path of the form  $(x_{i,a}, v_{i,a}^a, \dots, x_{i,k}, v_{i,b}^b)$ . Moreover,  $v_{i,\ell}^\ell$  and  $v_{i,\ell'}^{\ell'}$  are not adjacent in  $G$  for any  $\ell \neq \ell'$ , meaning that  $v_{i,\ell}^\ell$  and  $v_{i,\ell'}^{\ell'}$  are not copies of the same vertex in  $H$ , while the set  $\{v^\ell\}_{a \leq \ell \leq b}$  induces a clique in  $H$ . Thus,  $a-b+1 < k$  and  $G[S'] \cap Z_i$  can have at most  $2(k-1)$  vertices. It follows that any induced path  $G[S']$  of  $G$  can contain vertices from at most two subgraphs, say  $Z_i$  and  $Z_{i+1}$ . Therefore, we conclude that  $|S'| \leq 4(k-1)$ .  $\square$

The FPT-inapproximable of  $\text{InducedPath}$  follows directly from Theorem C.1.

**COROLLARY C.2.** *Unless  $W[1] = FPT$ , there is no  $f(k)$ -approximation algorithm for  $\text{InducedPath}$  that runs in  $t(k)$  poly( $n$ )-time for any functions  $f$  and  $t$  depending only on  $k$ .*

**Appendix D. Known connections between problems.** In this section, we discuss known equivalences between problems in more detail.

*Dominating Set and Set Cover:* It is easy to see that  $\text{DomSet}$  is a special case of  $\text{SetCov}$ , and the reduction from  $\text{SetCov}$  to  $\text{DomSet}$  is by phrasing  $\mathcal{U}$  and  $\mathcal{S}$  as vertices, thereby forming a clique on  $\mathcal{S}$ , and there is an edge joining a subset  $S_i \in \mathcal{S}$  and element  $u_j \in \mathcal{U}$  if and only if  $u_j$  is an element in  $S_i$ .

*Induced Matching and Independent Set:* We show that  $\text{Induced Matching}$  is at least as hard to approximate as  $\text{Independent Set}$ . Let  $G$  be an input graph of  $\text{Independent Set}$ . We create a graph  $G'$ , for each vertex  $v \in V(G)$ , by creating a vertex  $v'$  and an edge  $vv'$ . Notice that any independent set  $S$  of  $G$  corresponds to an induced

matching in  $G'$ : For each  $v \in S$ , we have an edge  $vv'$  in the set  $\mathcal{M}$ . Conversely, for any induced matching  $\mathcal{M}$  of  $G'$ , we may assume that the matching only chooses edges of the form  $vv'$ .

*More hereditary properties:* We discuss some more natural problems in this class. If we define  $\Pi$  to be a set of all planar graphs, this is hereditary. The corresponding optimization problem is that of computing a maximum induced planar graph. If we define  $\Pi$  to be a set of all forests, this is also hereditary, and it gives the problem of computing a maximum induced forest.

**Appendix E. Proof sketch of Theorem 4.1.** We will sketch the proof of Theorem 4.1.

In the forward direction, we use a standard reduction, which is sometimes referred to as the *clause-variable game* [1]. Specifically, we transform a 3-SAT instance  $\psi$  on  $n$  variables  $x_1, \dots, x_n$  and  $m$  clauses  $C_1, \dots, C_m$  into a label cover instance  $\Gamma = (G = (U, V, E), \Sigma_U, \Sigma_V, \Pi)$  by transforming clauses into left vertices in  $U$  and variables into right vertices in  $V$ , and there is an edge joining a pair of vertices  $C_i$  and  $x_j$  if  $x_j$  appears in  $C_i$ . We take partial assignments as the label sets  $\Sigma_U$  and  $\Sigma_V$ , and a constraint on each edge asks for a pair  $(\alpha, \beta)$  of labels that are *consistent*, i.e., they assign the same value to the same variable (e.g.,  $\alpha = (x_1 : 1, x_2 : 0, x_3 : 1)$  and  $\beta = (x_1 : 1)$  are consistent whereas  $\alpha$  is not consistent with  $\beta' = (x_2 : 1)$ ), and  $\alpha$  causes  $C_i$  to evaluate to true (i.e., some of the literal in  $C_i$  is assigned to true by  $\alpha$ ). We denote the evaluation of a clause  $C_i$  on a partial assignment  $\alpha$  by  $C_i(\alpha)$ .

To be precise, we have

$$\begin{aligned} U &= \{C_1, \dots, C_m\}, & V &= \{x_1, \dots, x_n\}, \\ E &= \{C_i x_j : x_j \text{ appears in the clause } C_i\}, \\ \Sigma_U &= \{0, 1\}^3, & \Sigma_V &= \{0, 1\}, \\ \Pi_{C_i x_j} &= \{(\alpha, \beta) : \alpha \text{ and } \beta \text{ are consistent} \wedge C_i(\alpha) = \text{true}\}. \end{aligned}$$

It can be seen that  $\text{MaxCov}(\Gamma) = \text{SAT}(\psi)$  since the only way to cover each node  $C_i \in U$  is to pick assignments to all vertices adjacent to  $C_i$  so that they are all consistent with the assignment  $\alpha = \sigma_V(C_i)$  (and that  $C_i(\alpha) = \text{true}$ ).

The converse direction is not straightforward. We apply Håstad [52] reduction<sup>10</sup> to reduce an instance  $\Gamma$  of MaxCov to a 3-SAT instance of size  $f(|\Sigma_U| + |\Sigma_V|) \cdot O(|U| + |V|)$  with a hardness gap  $1 - \varepsilon$  for some constant  $\varepsilon > 0$  (the hardness gap is different from the original MaxCov instance). Note that  $f$  in Håstad's construction is a doubly exponential function. The equivalence between MaxCov and 3-SAT holds only when  $|\Sigma_U| + |\Sigma_V|$  is constant (or at most  $\log \log(|V| + |U|)$ ).

**Appendix F. On Gap-ETH.** While Gap-ETH may sound like a very strong assumption, as pointed out in [32, 72], there are few pieces of evidence suggesting that the conjecture may indeed be true:

- In a simplified and slightly inaccurate manner, the PCP theorem [7, 6] can be viewed as a polynomial-time reduction that takes a 3-CNF formula  $\Phi$  and then produces another 3-CNF formula  $\Phi'$  such that, if  $\Phi$  is satisfiable, then  $\Phi'$  is satisfiable, and, if  $\Phi$  is unsatisfiable,  $\Phi'$  is not only unsatisfiable but also not even 0.99-satisfiable. To date, it is known that the size of  $\Phi'$  can be made as small as  $n \text{ polylog}(n)$  where  $n$  is the size of  $\Phi$  [31]. This means that,

<sup>10</sup>Here we apply only Håstad's reduction from label cover to 3-SAT, without parallel repetition.

assuming ETH, Gap-3SAT cannot be solved in  $2^{o(n/\text{polylog } n)}$  time, which is only a factor of  $\text{polylog } n$  away from what we need in Gap-ETH. Indeed, as stated earlier, if a linear-size PCP exists (which implies that the size of  $\Phi'$  can be made linear in  $n$ ), then Gap-ETH would follow from ETH.

- No subexponential-time algorithm is known even for the following (easier) problem, which is sometimes referred to as *refutation of random 3-SAT*: for a constant density parameter  $\Delta$ , given a 3-CNF formula  $\Phi$  with  $n$  variables and  $m = \Delta n$  clauses, devise an algorithm that outputs either SAT or UNSAT such that the following two conditions are satisfied:
  - If  $\Phi$  is satisfiable, then the algorithm always outputs SAT.
  - Over all possible 3-CNF formulas  $\Phi$  with  $n$  clauses and  $m$  variables, the algorithm outputs UNSAT on at least 0.5 fraction of them.

Note that, when  $\Delta$  is a sufficiently large constant (say 1000), a random 3-CNF formula is, w.h.p., not only unsatisfiable but also not even 0.9-satisfiable. Hence, if Gap-ETH fails, then the algorithm that refutes Gap-ETH will also be a subexponential time algorithm for refutation of random 3-SAT with density  $\Delta$ .

Refutation of random 3-SAT and, more generally, random CSPs, is an important question that has connections to many other fields, including hardness of approximation, proof complexity, cryptography and learning theory. We refer the readers to [3] for a more comprehensive survey on the problem and its applications in various areas. Despite being intensively studied for almost three decades, no subexponential-time algorithm is known for the above regime of parameters. In fact, it is known that the sum-of-squares hierarchies cannot refute random 3-SAT with constant density in subexponential time [47, 80]. Given how powerful SDP [78] and, more specifically, sum-of-squares [64], are for solving (and approximating) CSPs, this suggests that refutation of random 3-SAT with constant density and, hence, Gap-3SAT, may indeed be exponentially hard or, at the very least, beyond our current techniques.

- Dinur speculated that Gap-ETH might follow as a consequence of some cryptographic assumption [32]. This was recently confirmed by Applebaum [5] who showed that Gap-ETH follows from an existence of any exponentially hard locally computable one-way function. In fact, he proved an even stronger result that Gap-ETH follows from ETH for some CSPs that satisfy certain “smoothness” properties.

Last, we note that the assumption  $m = O(n)$  made in the conjecture can be made without loss of generality. As pointed out in both [32] and [72], this follows from the fact that, given a 3-SAT formula  $\phi$  with  $m$  clauses and  $n$  variables, if we create another 3-SAT formula  $\phi'$  by randomly selected  $m' = \Delta n$  clauses, then, with high probability,  $|\text{SAT}(\phi)/m - \text{SAT}(\phi')/m'| \leq O(1/\Delta)$ .

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