

Set Connectivity Problems in Undirected Graphs and the Directed Steiner Network Problem

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Abstract

In the *generalized connectivity* problem, we are given an edge-weighted graph $G = (V, E)$ and a collection $\mathcal{D} = \{(S_1, T_1), \dots, (S_k, T_k)\}$ of distinct *demands*; each demand (S_i, T_i) is a pair of disjoint vertex subsets. We say that a subgraph $F \subseteq G$ *connects* a demand (S_i, T_i) when it contains a path with one endpoint in S_i and the other in T_i . The goal is to identify a minimum weight subgraph that connects all demands in \mathcal{D} . Alon et al. (SODA '04) introduced this problem to study online network formation settings and showed that it captures some well-studied problems such as Steiner forest, non-metric facility location, tree multicast, and group Steiner tree. Finding a non-trivial approximation ratio for generalized connectivity was left as an open problem. Our starting point is the first polylogarithmic approximation for generalized connectivity, attaining a performance guarantee of $O(\log^2 n \log^2 k)$. Here n is the number of vertices in G and k is the number of demands. We also prove that the cut-covering relaxation of this problem has an $O(\log^3 n \log^2 k)$ integrality gap.

Building upon the results for generalized connectivity, we obtain improved approximation algorithms for two problems that contain generalized connectivity as a special case. For the *directed Steiner network* problem, we obtain an $O(k^{1/2+\epsilon})$ approximation, which improves on the currently best performance guarantee of $\tilde{O}(k^{2/3})$ due to Charikar et al. (SODA '98). For the *set connector* problem, recently introduced by Fukunaga and Nagamochi (IPCO '07), we present a polylogarithmic approximation; this result improves on the previously known ratio which can be $\Omega(n)$ in the worst case.

1 Introduction

Network design problems have received a great deal of attention in the computer science and operations research communities, as they play an instrumental role in combinatorial optimization and algorithm engineering. In this paper we investigate the complexity of some network design problems that seek to find a minimum-cost subgraph that connects a collection of vertex sets. These problems generalize some previously studied network design problems and help in demarcating the boundary of tractability between the easier problems in undirected graphs and the more difficult ones in directed graphs. Interestingly, the algorithm we develop for an undirected set connectivity problem can be used to improve the approximation ratio for a more general directed connectivity problem. Our algorithms also illustrate the junction-scheme technique for designing approximation algorithms.

1.1 The underlying setting. In the *generalized connectivity* problem, we are given an edge-weighted graph $G = (V, E)$ and a collection $\mathcal{D} = \{(S_1, T_1), \dots, (S_k, T_k)\}$ of distinct *demands*, each of which comprises a pair of disjoint vertex sets. We say that a subgraph $F \subseteq G$ *connects* a demand (S_i, T_i) when it contains a path with one endpoint in S_i and the other in T_i . With this definition in mind, the goal is to identify a minimum weight subgraph that connects all demands in \mathcal{D} .

Alon et al. [2] introduced the generalized connectivity problem to study online network formation settings and showed that it captures several well-studied problems, such as Steiner forest, non-metric facility location, tree multicast, and group Steiner tree. Since the group Steiner tree problem is a special case, known lower bounds for it translate to lower bounds for generalized connectivity. In particular, Halperin and Krauthgamer [16] show that unless $\text{NP} \subseteq \text{ZTIME}(n^{\text{poly} \log(n)})$, there is no $O(\log^{2-\epsilon} n)$ approximation for group Steiner tree. Further, Halperin et al. [15] show an $\Omega(\log^2 k)$ lower bound on the integrality gap of a natural LP-relaxation for group Steiner tree. The above two lower bounds extend identically to general-

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ized connectivity.

On the positive side, Alon et al. [2] devised a multiplicative-update online algorithm for computing log-competitive *fractional* solutions to generalized connectivity. They show online rounding procedures for the previously-mentioned special cases by using problem-specific arguments. However, the following two problems are left open in their work. Is there a polylogarithmic approximation for generalized connectivity in the offline setting? Is there a randomized polylogarithmic competitive online algorithm for generalized connectivity? In this paper we address the offline problem.

New results: We present the first polylogarithmic approximation for generalized connectivity, attaining a performance guarantee of $O(\log^2 n \log^2 k)$. We also prove that the cut-covering relaxation of this problem has an $O(\log^3 n \log^2 k)$ integrality gap. Section 2 has the details of these results.

1.2 Application 1: directed Steiner network.

An instance of the *directed Steiner network* problem consists of an arc-weighted directed graph $G = (V, E)$ and a collection of distinct source-sink pairs, to which we refer as $(s_1, t_1), \dots, (s_k, t_k)$. The objective is to construct a minimum weight subgraph that connects all input pairs, where (s_i, t_i) is said to be connected by $F \subseteq G$ when the latter contains an s_i - t_i path.

The same problem in *undirected* graphs, also referred to as the Steiner forest problem, can be approximated to within a $2(1 - 1/k)$ factor [1, 12, 13]. The directed graph problem is, however, significantly harder; Dodis and Khanna [8] proved that directed Steiner network cannot be approximated to within a factor of $O(2^{\log^{1-\epsilon} n})$ for any fixed $\epsilon > 0$, unless $\text{NP} \subseteq \text{TIME}(n^{\text{poly} \log(n)})$. In terms of upper bounds, Charikar et al. [5] gave an $\tilde{O}(k^{2/3})$ -approximation algorithm. Their paper concludes by posing two open problems:

1. Can the $\tilde{O}(k^{2/3})$ guarantee be improved?
2. Is the analysis of the algorithm in [5] tight? The known lower bound on the performance was $\Omega(\sqrt{k})$.

New results: In Section 3, we present a polynomial-time algorithm that approximates directed Steiner network to within a factor of $O(k^{1/2+\epsilon})$, for any fixed $\epsilon > 0$. We also prove a lower bound of $\Omega(k^{2/3}/\log k)$ on the ratio achieved by the algorithm of Charikar et al. [5], thereby showing that their analysis is essentially tight.

1.3 Application 2: set connector. In order to describe the problem we introduce a few definitions. Given an undirected graph $G = (V, E)$, a *division* is a family $\mathcal{V} = \{X_1, \dots, X_h\}$ of pairwise-disjoint vertex subsets.

For a set of edges $F \subseteq E$, let F/\mathcal{V} be the multigraph obtained from (V, F) by coalescing each subset $X_i \in \mathcal{V}$ into a single vertex (henceforth, *\mathcal{V} -terminal*). Finally, we say that $F \subseteq E$ *weakly connects* \mathcal{V} if all \mathcal{V} -terminals reside in the same connected component of F/\mathcal{V} .

In the *set connector* problem, we are given an edge-weighted graph $G = (V, E)$ and a collection $\mathcal{V}_1, \dots, \mathcal{V}_m$ of distinct divisions. The objective is to detect a minimum weight edge set $F \subseteq E$ that simultaneously weakly connects all input divisions. Generalized connectivity can be viewed as a special case of set connector in which each division consists of two disjoint vertex sets. It is important to mention that the seemingly obvious reduction in the opposite direction, where each division $\mathcal{V}_i = \{X_1, \dots, X_h\}$ is replaced by a collection of demands $\{(X_r, X_s) : 1 \leq r < s \leq h\}$, is *incorrect*.

The set connector problem has recently been investigated by Fukunaga and Nagamochi [10], whose main contribution in this context was a fractional packing theorem, leading to an approximation guarantee of $2(\alpha - 1)$ via LP-rounding methods, where $\alpha = \max_i(\sum_{X \in \mathcal{V}_i} |X|)$. However, this result does not ensure a reasonable upper bound for all possible instances, as α may very well be $\Omega(n)$.

New results: In Section 4, we present the first polylogarithmic approximation for set connector, showing that a performance guarantee of $O(\log^2 n \log^2(mn))$ can be achieved in polynomial time. We also prove that a natural LP-relaxation of this problem has an $O(\log^3 n \log^2(mn))$ integrality gap.

1.4 Techniques. Our results are based on a simple but effective technique that has recently been highlighted in the context of the work on the (non-uniform) buy-at-bulk network design problem [14, 6, 7]. Roughly speaking, we approximately reduce a multi-commodity connectivity problem to the density version of its single-source variant via the so-called *junction-scheme*. As single-source problems tend to be easier, this approach can lead to an algorithm for the multi-commodity problem. We informally describe the junction-scheme approach in approximation algorithms.

The junction-scheme. Given a connectivity problem that asks to link a collection of vertex pairs (or sets), a subgraph $F \subseteq G$ is called a *partial solution* if it is feasible for a non-empty subset of the input pairs; the *density* of F is defined as the ratio between its cost and the number of pairs it connects. Following greedy covering arguments [17, 18, 19], repeating a subroutine for assembling approximate minimum-density subgraphs ultimately leads to a complete solution, while incurring an additional logarithmic factor in the performance guar-

antee. The first step is to establish the existence of an “easy-to-compute” partial solution providing near-optimal density, or more specifically, the existence of a *junction* vertex through which pairs are connected. Having already fixed upon a particular vertex to serve as a junction (by means of exhaustive enumeration), the second step typically consists of guessing which pairs should be connected to this junction, which may very well be a challenging task. However, when the single-source variant admits a polynomial-time LP-rounding procedure, a bucketing-and-scaling mechanism allows one to bound the integrality gap of minimum-density junction structures, at the cost of losing polylogarithmic factors (see, for example, [6, 7]). In general, both of these conceptual steps, i.e., proving the existence of a junction-type solution and constructing a near-optimal subgraph of this class, are non-trivial.

We remark that it is typically easier to establish the existence of a junction-type solution by reasoning about an optimal integral solution. Therefore, an approximation algorithm obtained via the junction-scheme does not necessarily lead to a corresponding upper bound on the integrality gap of an LP relaxation for the problem.

Problem-specific adaptations. For the generalized connectivity problem, it turns out that we can indeed establish the existence of good-density junction-type solutions. In this case, the single-source variant happens to coincide with group Steiner tree, allowing us to employ known algorithms for rounding fractional solutions to its linear formulation [11, 15, 21]. With respect to directed Steiner network, proving the existence of good junction subgraphs is far from being enough, as its single-source variant corresponds to directed Steiner tree [5, 16, 20]; unfortunately, no polylogarithmic integrality gap is currently known for the natural LP-relaxation of directed Steiner tree. Nevertheless, we take advantage of several structural characteristics, and reduce the minimum-density junction problem on *directed* graphs to generalized connectivity on *undirected* trees. Finally, as previously noted, set connector does not admit a naive reduction to generalized connectivity, in spite of appearance. Therefore, to approximate the former problem, we present a refined reduction, along with an iterative greedy heuristic.

2 A Polylogarithmic Approximation for Generalized Connectivity

In what follows, we present a polylogarithmic approximation for the generalized connectivity problem. We use the junction-scheme that is described in Section 1, and hence the focus is on constructing partial solutions

of near-optimal “density”; an algorithm of this nature may be repeatedly applied in greedy fashion to approximate the original problem, incurring an additional logarithmic factor in the performance guarantee. The resulting approximation is with respect to an optimum integral solution. However, we also establish a polylogarithmic upper bound on the integrality gap of a cut-based LP-relaxation.

2.1 Preliminaries. We refer to each vertex in $\bigcup_{i=1}^k (S_i \cup T_i)$ as a *terminal*. When a subgraph $F \subseteq G$ connects only a subset of demands, we call it a *partial solution*. For $F \subseteq G$, let $\mathcal{D}(F)$ denote the set of demands in \mathcal{D} connected by F , and let $c(F) = \sum_{e \in F} c(e)$ denote its cost. Finally, the *density* of F is given by $\text{density}(F) = c(F)/|\mathcal{D}(F)|$, i.e., the ratio between its cost and the number of demands it connects.

Relating between density and accumulated cost.

Prior to formally defining the minimum density version of generalized connectivity, let us make some simplifications. By a simple averaging argument, if a forest $F \subseteq G$ consists of several connected components, there must be some tree $T \subseteq F$ whose density is at most $\text{density}(F)$. Moreover, given an algorithm for constructing a dense solution that contains a predetermined root vertex r , we can handle the unrooted density variant as well by testing all vertices as possible roots. In terms of the junction-scheme for generalized connectivity, this argument proves the existence of an r -rooted tree of optimal density. Consequently, we define the following problem.

DEFINITION 2.1. *An instance of minimum density generalized connectivity (MDGC) consists of an edge-weighted graph $G = (V, E)$, a collection of demands $\mathcal{D} = \{(S_1, T_1), \dots, (S_k, T_k)\}$, and a root vertex r . The objective is to identify a minimum density r -rooted tree.*

In the remainder of this section, we focus our attention on approximating MDGC rather than directly dealing with the minimum cost version for two reasons. First, a ρ -approximation for the former problem immediately leads to a performance guarantee of $O(\rho \log k)$ for generalized connectivity, via a standard repeated covering procedure (see, for instance, [17, 18, 19]). Second, the minimum density version will considerably simplify the analysis of other applications studied in this paper.

2.2 Approximating the density version. Suppose we knew in advance the subset of demands $(S_{i_1}, T_{i_1}), \dots, (S_{i_h}, T_{i_h})$ connected by a minimum density r -rooted tree. Then, the computational task in question would be to find a low-cost tree connecting the

groups $S_{i_1}, T_{i_1}, \dots, S_{i_h}, T_{i_h}$ to r ; this is essentially an instance of the group Steiner tree problem. However, we obviously do not have such prior knowledge. To work around this difficulty, we formulate an LP-relaxation which is derived from that of group Steiner tree, and employ a bucketing-and-scaling mechanism to round its optimal solution.

LP-relaxation. For each demand (S_i, T_i) , we set up a variable y_i that indicates whether both S_i and T_i are connected to r . In addition, for each edge $e \in E$, there is a corresponding variable x_e , indicating whether e is picked. Given a y_i value for a demand (S_i, T_i) , the edges variables should model the constraint that both S_i and T_i are connected to the root r to the extent of y_i . Hence, for each cut $(U, V \setminus U)$ that separates r from some S_i or T_i , we require that $\sum_{e \in \delta(U)} x_e \geq y_i$, where $\delta(U)$ denotes the set of edges crossing $(U, V \setminus U)$. We can linearize the original objective function $\sum_e c(e)x_e / \sum_i y_i$ by normalizing $\sum_i y_i$ to 1. This discussion leads to the following linear program:

$$\begin{aligned}
(\text{LP}_{\mathcal{D}}) \quad & \min \sum_{e \in E} c(e)x_e \\
& \text{s.t.} \quad \sum_{i=1}^k y_i = 1 \\
& \quad \sum_{e \in \delta(U)} x_e \geq y_i \quad \forall U \subseteq V \forall 1 \leq i \leq k \text{ such that:} \\
& \quad \quad (1) \ r \in U; \text{ and} \\
& \quad \quad (2) \ U \cap S_i = \emptyset \text{ or } U \cap T_i = \emptyset \\
& \quad x_e, y_i \in [0, 1] \quad \forall e \in E, 1 \leq i \leq k
\end{aligned}$$

Note that although $\text{LP}_{\mathcal{D}}$ has exponentially many constraints, it admits a polynomial-time separation oracle; therefore, we can efficiently compute an optimal fractional solution (x^*, y^*) using the Ellipsoid method. Alternatively, one can formulate an equivalent, yet polynomial size, linear program by utilizing flow-like variables (see, e.g., [11, 21]). Letting $F^* \subseteq G$ be a minimum density solution to the given instance, it is not difficult to verify that $\text{OPT}(\text{LP}_{\mathcal{D}})$ provides a lower bound on the optimal density, that is, $\sum_{e \in E} c(e)x_e^* \leq \text{density}(F^*)$.

The bucketing-and-scaling reduction. Since (x^*, y^*) does not necessarily set $y_i^* \in \{0, 1\}$, even with proper scaling, this fractional solution does not explicitly allow us to identify which pairs should be connected. To this end, each demand $(S_i, T_i) \in \mathcal{D}$ is placed in one of $\ell = \lceil \log_2(2k) \rceil$ classes, depending on its y_i^* value. More specifically, for every $1 \leq j \leq \ell$, we define a class $I_j = \{i : y_i^* \in (2^{-j}, 2^{-j+1}]\}$. Since there are k demands and ℓ classes, a simple averaging argument implies that if I_{j^*} is the class over which the sum of y_i^* 's is maximized, then $\sum_{i \in I_{j^*}} y_i^* \geq 1/(2\ell)$ while $|I_{j^*}| \geq 2^{j^*}/(4\ell)$.

Using I_{j^*} we create a group Steiner tree instance (henceforth, Π) in G ; in this instance the groups are $\bigcup_{i \in I_{j^*}} \{S_i, T_i\}$, and the root r is to be connected to at least one representative of each terminal group. Now consider the natural LP-relaxation of this instance, formally defined as follows:

$$\begin{aligned}
(\text{LP}_{\Pi}) \quad & \min \sum_{e \in E} c(e)x_e \\
& \text{s.t.} \quad \sum_{e \in \delta(U)} x_e \geq 1 \quad \forall U \subseteq V \text{ such that } \exists i \in I_{j^*}: \\
& \quad \quad (1) \ r \in U; \text{ and} \\
& \quad \quad (2) \ U \cap S_i = \emptyset \text{ or } U \cap T_i = \emptyset \\
& \quad x_e \in [0, 1] \quad \forall e \in E
\end{aligned}$$

Note that the main constraint in LP_{Π} is nearly identical to the one in $\text{LP}_{\mathcal{D}}$, with an additional restriction stating that $y_i = 1$ if $i \in I_{j^*}$, and $y_i = 0$ otherwise. With this observation in mind, it is easy to verify that $\hat{x} = \min\{2^{j^*}x^*, 1\}$ constitutes a feasible solution to LP_{Π} , as $y_i^* \geq 2^{-j^*}$ for every $i \in I_{j^*}$. Furthermore, the objective function value of \hat{x} with respect to LP_{Π} is at most $2^{j^*} \sum_{e \in E} c(e)x_e^*$.

Putting it all together. At this point in time, we can round the fractional solution \hat{x} using the procedure of Garg, Konjevod and Ravi [11]. Their rounding procedure proves that the integrality gap of the cut-based LP for the group Steiner problem is $O(\log^2 n \log k)$. In fact they show a stronger property; for any fixed constant $c < 1$, there is an integral solution that connects at least ck groups to the root and the cost of this solution is $O(\log^2 n)$ times the LP cost — here k is the number of groups in the initial instance. Moreover, such a solution can be obtained in polynomial time from the given LP solution. We use this stronger property to obtain a tree $F \subseteq G$ that connects r to representatives of at least $3|I_{j^*}|/2$ groups in $\bigcup_{i \in I_{j^*}} \{S_i, T_i\}$ such that the cost of F is $O(\log^2 n) \sum_{e \in E} c(e)\hat{x}_e = O(2^{j^*} \log^2 n) \sum_{e \in E} c(e)x_e^*$. Recall that the number of groups in Π is $2|I_{j^*}|$. Since r is connected to at least $3|I_{j^*}|/2$ groups in $\bigcup_{i \in I_{j^*}} \{S_i, T_i\}$, the number of demands $(S_i, T_i) \in I_{j^*}$ for which r is connected to both S_i and T_i is at least $|I_{j^*}|/2$; implying that $|\mathcal{D}(F)| \geq |I_{j^*}|/2 \geq 2^{j^*}/(8\ell)$. Since $\ell = \lceil \log_2(2k) \rceil$, we have

$$\begin{aligned}
\text{density}(F) &= \frac{O(2^{j^*} \log^2 n) \sum_{e \in E} c(e)x_e^*}{2^{j^*}/(8\ell)} \\
&= O(\log^2 n \log k) \cdot \text{density}(F^*) .
\end{aligned}$$

This leads to the following results.

LEMMA 2.1. *MDGC can be approximated to within a factor of $O(\log^2 n \log k)$.*

THEOREM 2.1. *There is a polynomial-time algorithm that approximates generalized connectivity to within a factor of $O(\log^2 n \log^2 k)$.*

2.3 Integrality gap. As previously mentioned, the junction-scheme does not automatically yield an integrality gap result in multi-commodity settings, even when it depends upon an LP-relaxation of the corresponding single-source problem (see, for example, [6, 7]). The primary bottleneck is our existence proof of low-density rooted trees, which compares the densities of *integral* solutions. In what follows, we take advantage of a reduction to instances in which the input graph is a tree, and prove that a natural LP-relaxation of generalized connectivity has a polylogarithmic integrality gap. The resulting upper bound is worse than the one stated in Theorem 2.1 by a logarithmic factor.

LP-relaxation. We consider the natural cut relaxation, in the spirit of Section 2.2, with a variable x_e for each edge $e \in E$, and a crossing constraint for each cut $(U, V \setminus U)$ that separates a demand (S_i, T_i) .

$$\begin{aligned}
 & \text{(LP}_{\text{GC}}) \\
 & \min \sum_{e \in E} c(e)x_e \\
 & \text{s.t.} \quad \sum_{e \in \delta(U)} x_e \geq 1 \quad \forall U \subseteq V \text{ such that } \exists i \\
 & \quad \quad \quad \quad \quad \quad \quad S_i \subseteq U \text{ and } T_i \subseteq V \setminus U \\
 & \quad \quad \quad x_e \in [0, 1] \quad \forall e \in E
 \end{aligned}$$

The remainder of this section is devoted to proving the next theorem.

THEOREM 2.2. *The integrality gap of LP_{GC} is $O(\log^3 n \log^2 k)$.*

Integrality gap on rooted trees. We begin by arguing that, when the underlying graph is a rooted tree of height h , the integrality gap of LP_{GC} is $O(\min\{h, \log n\} \cdot h \log^2 k)$. For this purpose, consider a generalized connectivity instance on a tree $H = (V, E)$ of height h . We can assume without loss of generality that all terminals are at the leaves of H .

Let x^* be an optimal solution to LP_{GC} , of value $\text{OPT}(\text{LP}_{\text{GC}})$. We assign a *level* $\ell(i)$ to each demand (S_i, T_i) as follows. Noting that x^* supports a unit flow from S_i to T_i , let us arbitrarily fix such a flow. Since the underlying graph is a tree and all terminals are at the leaves, this flow must travel upwards towards the root, turn at some vertex, and then travel downwards towards the leaves. Let f_i^j be the total S_i - T_i flow that *turns* at level j of H . We remark that since $\sum_j f_i^j = 1$ and there are only h levels, there must be a level j for

which $f_i^j \geq 1/h$; we set $\ell(i)$ to be such a level. We assign the demand (S_i, T_i) to level $\ell(i)$.

Now let $H^j = \{H_1^j, \dots, H_p^j\}$ be the collection of vertex-disjoint subtrees rooted at level j of H , with respective roots r_1, \dots, r_p . Let D_t^j be the restriction of level- j assigned demands to the tree H_t^j ; in other words, if $\ell(i) = j$ then $(S'_i, T'_i) \in D_t^j$, where S'_i and T'_i denote the vertex subsets of S_i and T_i that appear in H_t^j , respectively. We claim that there is an index $1 \leq s \leq p$ such that $\text{OPT}(\text{LP}_{\mathcal{D}}) \leq h \cdot \text{OPT}(\text{LP}_{\text{GC}})/k$ for some r_s -rooted MDGC instance on H_s^j with a demand set D_s^j . For a demand (S_i, T_i) , let $z(i, t)$ be the total S_i - T_i flow routed in H_t^j , and let $\text{OPT}_t^j = \sum_{e \in H_t^j} c(e)x_e^*$. Since the subtrees at level j are disjoint, $\sum_t \sum_i z(i, t) \geq k/h$ whereas $\sum_t \text{OPT}_t^j \leq \text{OPT}(\text{LP}_{\text{GC}})$. Therefore, there is an index s such that $\text{OPT}_s^j / \sum_i z(i, s) \leq h \cdot \text{OPT}(\text{LP}_{\text{GC}})/k$. We define a candidate solution (x', y') to $\text{LP}_{\mathcal{D}}$ on H_s^j by setting $x'_e = x_e^* / \sum_i z(i, s)$ for each $e \in H_s^j$ and $y'_i = z(i, s) / \sum_i z(i, s)$ for each demand (S_i, T_i) . By construction, the entire S_i - T_i flow in H_s^j goes through the root r_s , implying that (x', y') is indeed a feasible solution to $\text{LP}_{\mathcal{D}}$; in addition, our scaling method ensures that $\sum_e c(e)x'_e \leq h \cdot \text{OPT}(\text{LP}_{\text{GC}})/k$, as desired.

Based on the above claim, in conjunction with a specialization of Lemma 2.1 to rooted trees¹, we can construct an r_s -rooted tree $F \subseteq H_s^j$ of density $O(\min\{h, \log n\} \cdot h \log k) \cdot \text{OPT}(\text{LP}_{\text{GC}})/k$. Note that F is also a partial solution to the original generalized connectivity instance. Therefore, when we discard all demands connected by F , the fractional solution x^* remains feasible for the residual problem. Using standard covering arguments, these findings establish the existence of an integral solution of cost $O(\min\{h, \log n\} \cdot h \log^2 k) \cdot \text{OPT}(\text{LP}_{\text{GC}})$, which proves the desired integrality gap.

Integrality gap on arbitrary graphs. We attain an upper bound for general graphs as follows. A feasible LP solution on the input graph is transformed into a feasible solution on a rooted tree obtained by probabilistically embedding the given metric into a distribution over dominating tree metrics [3, 4, 9]. Consequently, an integrality gap of α on rooted trees translates to a gap of $O(\alpha \log n)$ on general graphs. The height of the resulting tree is guaranteed to be $O(\log \Delta)$, where Δ is the original aspect ratio. Standard scaling tricks can be used to ensure that the ratio of the largest edge cost to the smallest edge cost in the original graph is bounded

¹In trees of height h , we save an additional logarithmic factor, by observing that the rounding method of Garg et al. [11] connects a constant fraction of the input groups while incurring only an $O(\min\{h, \log n\})$ loss in the performance guarantee.

by a polynomial in n , with a negligible increase in the objective function value. This modification ensures that the probabilistic embedding will produce $O(\log n)$ -height trees. We then apply the previously obtained bound for rooted trees.

3 An $O(k^{1/2+\epsilon})$ Approximation for Directed Steiner Network

The main result of this section is a polynomial-time algorithm that approximates directed Steiner network to within a factor of $O(k^{1/2+\epsilon})$, for any fixed $\epsilon > 0$. Along the way, we demonstrate that our analysis is essentially tight. We also prove a lower bound of $\Omega(k^{2/3}/\log k)$ on the approximation ratio achieved by the algorithm of Charikar et al. [5]. We remind the reader that an instance of directed Steiner network consists of a directed graph $G = (V, E)$, with non-negative arc costs specified by $c : E \rightarrow \mathbb{R}_+$, and a collection $\mathcal{D} = \{(s_1, t_1), \dots, (s_k, t_k)\}$ of distinct source-sink pairs. The objective is to construct a minimum cost subgraph that connects all input pairs, where $(s_i, t_i) \in \mathcal{D}$ is said to be connected by a given subgraph when the latter contains an s_i - t_i path.

3.1 A lower bound for bunches. The $\tilde{O}(k^{2/3})$ -approximation proposed by Charikar et al. [5] repeatedly connects new pairs by minimum density “bunches” until all source-sink pairs are connected. A *bunch* is simply the union of an in-star and an out-star that share a common arc or center; hence, a minimum density bunch can be computed efficiently. Most of the effort in establishing the $\tilde{O}(k^{2/3})$ upper bound is devoted to proving the existence of a bunch whose density does not exceed that of an optimal solution by a factor of more than $O(k^{2/3} \log^{1/3} k)$. However, the best possible lower bound provided by Charikar et al. [5] for the density of bunches was $\Omega(\sqrt{k})$; improving on this bound had been posed as an open question. In the full version of this paper, we demonstrate that their analysis is indeed tight up to polylogarithmic factors, by proving the next theorem.

THEOREM 3.1. *There are instances of the directed Steiner network problem in which the density of every bunch is $\Omega(k^{2/3}/\log k) \cdot \text{OPT}/k$.*

3.2 Junction trees and their density. In retrospect, one can view the algorithm proposed by Charikar et al. [5] as an application of the junction-scheme, restricted to a very simple structure that can be easily computed. Our approach follows the same paradigm. However, instead of being interested in bunches, whose height is extremely limited, we focus our attention on

junction subgraphs of arbitrary height, shooting for a provable density of $O(\sqrt{k})$.

Definitions and notation. For this purpose, an r -rooted *junction tree* $\mathcal{J} \subseteq G$ is defined as the union of an in-tree T_{in} and an out-tree T_{out} , both rooted at $r \in V$ (see Figure 1). It is worth pointing out that the trees T_{in} and T_{out} are allowed to overlap in both nodes and arcs. Note that a sufficient condition for \mathcal{J} to connect a node pair $(s_i, t_i) \in \mathcal{D}$ is that $s_i \in T_{\text{in}}$ while $t_i \in T_{\text{out}}$. Following previously used notation, let $\mathcal{D}(\mathcal{J})$ denote the set of source-sink pairs connected by \mathcal{J} , and let $c(\mathcal{J}) = \sum_{e \in \mathcal{J}} c(e)$ denote its cost. In addition, the *density* of \mathcal{J} is given by $c(\mathcal{J})/|\mathcal{D}(\mathcal{J})|$.

Bounding the density of junction trees. With the above definitions in mind, we say that a junction tree $\mathcal{J} \subseteq G$ is ρ -optimal if $\text{density}(\mathcal{J}) \leq \rho \cdot \text{OPT}/k$, where OPT denotes the cost of an optimal solution. In the following lemma, we establish the existence of \sqrt{k} -optimal junction trees; this result is complemented by proving a coinciding lower bound, which is tight up to constant multiplicative factors.

LEMMA 3.1. *A minimum density junction tree is \sqrt{k} -optimal.*

Proof. Let $\mathcal{H}^* \subseteq G$ be a minimum cost subgraph that connects all node pairs in \mathcal{D} . In addition, for $1 \leq i \leq k$, let $p_i \subseteq \mathcal{H}^*$ be a directed s_i - t_i path in \mathcal{H}^* ; when s_i and t_i are connected by more than one path, p_i is arbitrarily picked. The proof proceeds by distinguishing between two cases:

1. *There is a node $r \in V$ that appears in at least \sqrt{k} of the paths p_1, \dots, p_k .* In this case, consider the junction tree \mathcal{J} formed by the union of all paths in p_1, \dots, p_k passing through r . Since \mathcal{J} is a subgraph of \mathcal{H}^* , its cost is at most OPT. Therefore, by observing that \mathcal{J} connects at least \sqrt{k} pairs, we have $\text{density}(\mathcal{J}) \leq \text{OPT}/\sqrt{k} = \sqrt{k} \cdot \text{OPT}/k$.
2. *There is no such node.* In particular, every arc of \mathcal{H}^* appears in at most \sqrt{k} of the paths p_1, \dots, p_k . Hence, by creating \sqrt{k} copies of each arc, all node pairs can be connected via arc-disjoint paths. Since the overall duplication cost is $\sqrt{k} \cdot \text{OPT}$, at least one of these paths is associated with a cost of at most $\sqrt{k} \cdot \text{OPT}/k$. This path constitutes a (trivial) junction tree whose density is at most $\sqrt{k} \cdot \text{OPT}/k$. ■

LEMMA 3.2. *There are directed Steiner network instances in which every junction tree is $\Omega(\sqrt{k})$ -optimal.*

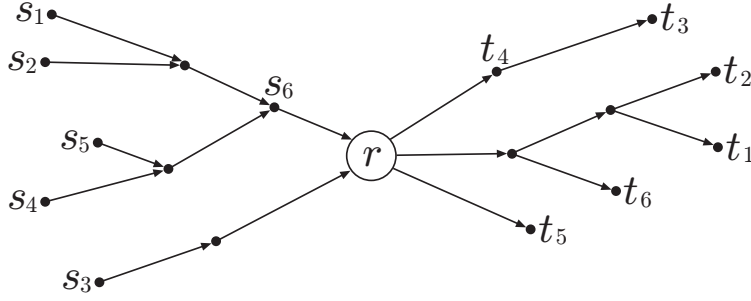


Figure 1: A junction tree.

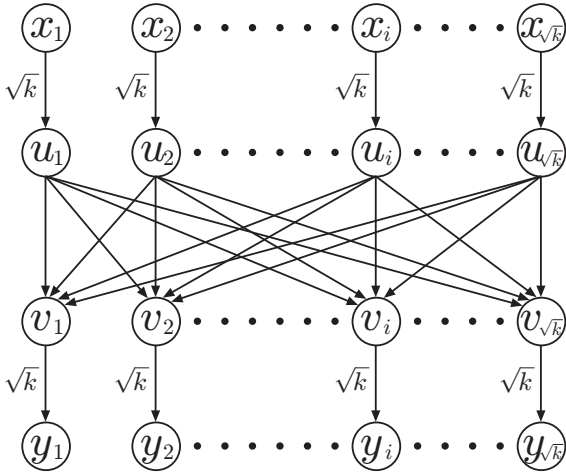


Figure 2: An example demonstrating that the density of any junction tree is $\Omega(\sqrt{k}) \cdot \text{OPT}/k$.

Proof. Consider the following instance of directed Steiner network, schematically described in Figure 2:

1. The input graph consists of four layers, with nodes $x_1, \dots, x_{\sqrt{k}}$ in the first layer, $u_1, \dots, u_{\sqrt{k}}$ in the second, $v_1, \dots, v_{\sqrt{k}}$ in the third, and $y_1, \dots, y_{\sqrt{k}}$ in the fourth.
2. For every $1 \leq i \leq \sqrt{k}$, there are two \sqrt{k} -cost arcs, (x_i, u_i) and (v_i, y_i) . In addition, every u_i is linked to all v_j 's by zero-cost arcs.
3. The collection of k distinct pairs to be connected is $\mathcal{D} = \{(x_i, y_j) : 1 \leq i, j \leq \sqrt{k}\}$.

Note that the instance under consideration has a unique optimal solution, in which all arcs must be picked. Since the overall cost is $2k$, we have $\text{OPT}/k = 2$. Now let \mathcal{H} be a minimum density junction tree. Without loss of generality, we may assume that the root of \mathcal{H} belongs to $\{u_1, \dots, u_{\sqrt{k}}, v_1, \dots, v_{\sqrt{k}}\}$.

Consequently, $c(\mathcal{H}) = (1 + |\mathcal{D}(\mathcal{H})|)\sqrt{k}$, implying that the density of \mathcal{H} is at least \sqrt{k} . ■

3.3 Finding low-density junction trees.

Overview. We had already observed that junction trees are strongly related to *directed Steiner trees* [5, 16, 20]. In particular, identifying a low-density junction tree would have been rather straightforward, should the natural LP-relaxation of directed Steiner tree had a reasonably small integrality gap; unfortunately, Zosin and Khuller [21] demonstrated that the latter gap is $\Omega(\sqrt{k})$. To overcome this difficulty, given a fixed accuracy parameter $\epsilon > 0$, we limit our attention to junction trees of height $1/\epsilon$, while incurring an $O(k^\epsilon)$ penalty in the performance guarantee via a height restriction lemma due to Zelikovsky [20]. We then reduce the problem of finding a low density $(1/\epsilon)$ -height junction tree to MDGC (see Section 2.1), blowing up the final approximation ratio by only logarithmic factors. In essence, the remainder of this section will be devoted to proving the next lemma.

LEMMA 3.3. *For any fixed $\epsilon > 0$, there is a polynomial-time algorithm that constructs a junction tree $\mathcal{J} \subseteq G$ satisfying $\text{density}(\mathcal{J}) = O(k^\epsilon) \cdot \text{density}(\mathcal{J}^*)$, where \mathcal{J}^* is a minimum density junction tree.*

Preliminaries. For ease of presentation, it would be convenient to assume that $1/\epsilon$ is an integer. In addition, we can assume without loss of generality that G is transitively closed. Finally, we may assume that the root r of \mathcal{J}^* is known in advance; otherwise, all nodes can be tested as potential roots by means of exhaustive search.

Step 1: layering. An ℓ -layering of $G = (V, E)$ is an operation that produces a directed acyclic graph as follows. The newly formed node set consists of $\ell + 1$ copies of V , to which we refer as V_0, \dots, V_ℓ . For every $0 \leq i \leq \ell - 1$, two types of arcs are added from V_i to V_{i+1} : *regular* and *parallel*. Every arc $(u, v) \in E$ induces

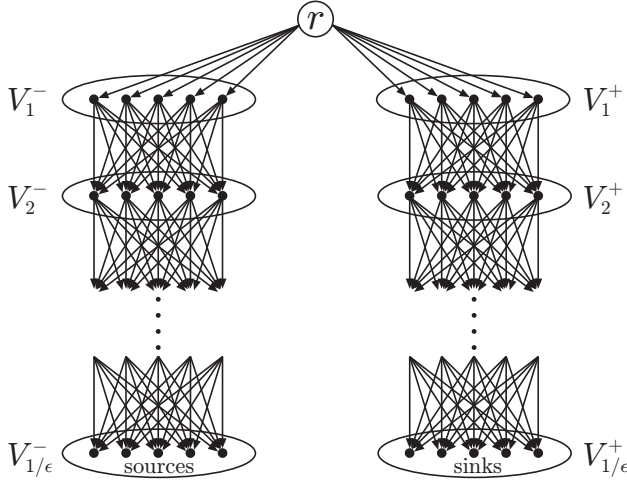


Figure 3: The directed acyclic graph D .

a regular arc from the image of u in V_i to the image of v in V_{i+1} , whose cost is identical to that of (u, v) . On the other hand, for every $v \in V$, a zero-cost parallel arc is added between the image of v in V_i and in V_{i+1} .

Having formally defined layering, we move on to assemble a directed acyclic graph D by unifying a $(1/\epsilon)$ -layering D^+ of G and a $(1/\epsilon)$ -layering D^- of the graph obtained from G by reversing its arcs. More precisely, assuming that D^+ and D^- consist of the node sets $V_0^+, \dots, V_{1/\epsilon}^+$ and $V_0^-, \dots, V_{1/\epsilon}^-$, respectively, the first layers of these graphs (i.e., V_0^+ and V_0^-) are identified as one layer, V_0 , while other layers are kept separated, as shown in Figure 3. It is instructive to omit nodes from V_0 , $V_{1/\epsilon}^+$ and $V_{1/\epsilon}^-$ as follows: only r is left in V_0 ; only sinks are left in $V_{1/\epsilon}^+$; and only sources are left in $V_{1/\epsilon}^-$.

The next claim is due to Zelikovsky [20, Thm. 2]; a rooted tree in a transitively closed graph can be transformed into an ℓ -level tree defined on the same set of nodes, while blowing up the overall cost by no more than $O(\ell k^{1/\ell})$. In this context, k denotes the number of leaves in the original tree.

CLAIM 3.1. *There exists an r -rooted tree $\mathcal{T}_r \subseteq D$ that satisfies the following properties:*

1. For every $(s_i, t_i) \in \mathcal{D}(\mathcal{J}^*)$, \mathcal{T}_r connects r to both $s_i \in V_{1/\epsilon}^-$ and $t_i \in V_{1/\epsilon}^+$.
2. $c(\mathcal{T}_r) = O(k^\epsilon) \cdot c(\mathcal{J}^*)$.

We remark that any r -rooted tree $\mathcal{T}_r \subseteq D$ can be efficiently translated to a junction tree $\mathcal{J} \subseteq G$ such that

$c(\mathcal{J}) \leq c(\mathcal{T}_r)$, and such that $\mathcal{D}(\mathcal{J})$ consists of all source-sink pairs (s_i, t_i) for which both $s_i \in V_{1/\epsilon}^-$ and $t_i \in V_{1/\epsilon}^+$ are reachable from r in \mathcal{T}_r .

Step 2: path splitting. We proceed by creating an *undirected tree* T as follows. Consider the star formed by constructing a collection of $O(n^{1/\epsilon})$ disjoint paths, one for each path in D connecting r to a node in $V_{1/\epsilon}^+ \cup V_{1/\epsilon}^-$, and unifying their roots. We repeatedly merge common prefixes of these paths, until every branching corresponds to an actual branching in D . Alternatively, one can also provide a recursive definition:

1. When $u \in V_{1/\epsilon}^+ \cup V_{1/\epsilon}^-$, the resulting tree consists of the singleton vertex u .
2. When $u \in V_i^+$, for some $0 \leq i \leq 1/\epsilon - 1$, we begin by recursively computing a fresh collection of rooted trees, $\{T_v : v \in V_{i+1}^+\}$. The root of each T_v is then joined to u by an edge whose cost is equal to that of the arc (u, v) in D . The case $u \in V_i^-$ is handled analogously.

With the underlying tree T in place, we create an instance of MDGC by setting up a unique demand (S_i, T_i) for each node pair $(s_i, t_i) \in \mathcal{D}$. Specifically, since each source node $s_i \in V_{1/\epsilon}^-$ has just been duplicated $O(n^{1/\epsilon})$ times, its corresponding vertex set S_i is defined to be the collection of leaves in T that are duplicates of s_i . Similarly, the set T_i contains all duplicates of $t_i \in V_{1/\epsilon}^+$. It is not difficult to verify that there is a one-to-one correspondence between r -rooted trees in D and T , namely, for each tree $\mathcal{T}_r \subseteq D$ there is a matching tree $\mathcal{T}_r' \subseteq T$ of identical cost, such that \mathcal{T}_r' connects r to both S_i and T_i if and only if \mathcal{T}_r connects r to both $s_i \in V_{1/\epsilon}^-$ and $t_i \in V_{1/\epsilon}^+$. Moreover, this bijection can be efficiently computed.

Consequently, it remains to approximate an MDGC instance defined on a $(1/\epsilon)$ -height tree spanning $O(n^{1/\epsilon})$ vertices. As a result of specializing Lemma 2.1 to rooted trees (see footnote on page 5), such instances can be approximated to within a factor of $O(\log k)$. By combining the latter observation with an additional $O(k^\epsilon)$ factor lost during our layering step, Lemma 3.3 follows.

Summary. Lemma 3.3, in conjunction with Lemma 3.1 and a standard repeated covering procedure, immediately implies the main result of this section, formally stated in the following theorem.

THEOREM 3.2. *The directed Steiner network problem can be approximated to within a factor of $O(k^{1/2+\epsilon})$, for any fixed $\epsilon > 0$.*

Remark: The layering and path splitting ideas, combined with Zelikovsky’s height-reduction lemma, give a reduction from the directed Steiner tree problem to the group Steiner problem. This reduction leads to an $O(i^2 k^{1/i} \log k)$ approximation in $n^{O(i)}$ time for the directed Steiner tree problem and is an alternative to the greedy scheme in [5]. Although unpublished, this reduction was known to several people.

4 A Polylogarithmic Approximation for Set Connector

The main result of this section is a polylogarithmic performance guarantee for set connector. We remind the reader that an instance of the latter problem consists of an undirected graph $G = (V, E)$, whose edges are associated with non-negative costs specified by $c : E \rightarrow \mathbb{R}_+$. Given a collection of divisions $\mathcal{V}_1, \dots, \mathcal{V}_m$, the objective is to construct a minimum cost subset of edges $F \subseteq E$ that simultaneously weakly connects all input divisions. Our principal finding in this context can be briefly summarized as follows.

THEOREM 4.1. *The set connector problem admits an $O(\log^2 n \log^2(mn))$ approximation. Moreover the integrality gap of a natural LP-relaxation is $O(\log^3 n \log^2(mn))$.*

Prior to proving the above theorem, we demonstrate that a naive reduction to generalized connectivity, in which each division $\mathcal{V}_i = \{X_1, \dots, X_h\}$ is replaced by a collection of demands $\{(X_r, X_s) : 1 \leq r < s \leq h\}$ is incorrect. To this end, consider a set connector instance defined on a complete graph with vertex set $\{v_1, v_2, v_3, v_4\}$, and suppose that we are given a single division $\mathcal{V}_1 = \{X_1, X_2, X_3\}$, where $X_1 = \{v_1\}$, $X_2 = \{v_2\}$ and $X_3 = \{v_3, v_4\}$. It is not difficult to verify that $F = \{(v_1, v_3), (v_2, v_4)\}$ forms a feasible solution to this instance. However, F is infeasible for the resulting generalized connectivity instance, since it does not contain a path with one endpoint in X_1 and the other in X_2 .

Proof of Theorem 4.1. The proof proceeds by relating the approximability of set connector to that of generalized connectivity. We say that $X \in \mathcal{V}_i$ is *covered* by an edge set $F \subseteq E$ when the subgraph (V, F) contains a path connecting a vertex in X to a vertex in $Y \neq X$, for some $Y \in \mathcal{V}_i$. Note that the optimal solution F^* covers every set in $\bigcup_{i=1}^m \mathcal{V}_i$. In addition, given a set of edges $F \subseteq E$ that covers all sets in $\bigcup_{i=1}^m \mathcal{V}_i$, we can create a new set connector instance as follows. For each division $\mathcal{V}_i = \{X_1, \dots, X_h\}$, let $G_i(F)$ be a graph on the vertex set $\{1, \dots, h\}$, in which r and s are joined by an edge when X_r and X_s are connected

by F . Since all vertex sets are covered, $G_i(F)$ consists of at most $h/2$ connected components, $\mathcal{C}_1, \dots, \mathcal{C}_\ell$. We define $\mathcal{V}'_i = \{Y_1, \dots, Y_\ell\}$, where $Y_t = \bigcup_{j \in \mathcal{C}_t} X_j$, noting that $|\mathcal{V}'_i| \leq |\mathcal{V}_i|/2$. It is easy to ascertain that F^* remains a feasible solution to the new instance induced by $\mathcal{V}'_1, \dots, \mathcal{V}'_m$, and furthermore, any feasible solution to this instance can be combined with F to form a feasible solution with respect to $\mathcal{V}_1, \dots, \mathcal{V}_m$. We conclude that an α -approximation for covering $\bigcup_{i=1}^m \mathcal{V}_i$ implies an $O(\alpha \log \beta)$ -approximation for the set connector problem where, $\beta = \max_i |\mathcal{V}_i| \leq n$.

We now show that a generalized connectivity heuristic can be straightforwardly employed as a subroutine, to detect an approximate edge set covering all sets in $\bigcup_{i=1}^m \mathcal{V}_i$. For this purpose, an instance of the former problem is assembled as follows. For each division $\mathcal{V}_i = \{X_1, \dots, X_h\}$, we introduce a collection of h demands $(X_1, (\bigcup_{j=1}^h X_j) \setminus X_1), \dots, (X_h, (\bigcup_{j=1}^h X_j) \setminus X_h)$. We observe that $F \subseteq E$ covers $\bigcup_{i=1}^m \mathcal{V}_i$ if and only if this edge set constitutes a feasible solution to the generalized connectivity instance obtained via the above reduction. Therefore, by plugging in the $O(\log^2 n \log^2 k)$ -approximation for generalized connectivity stated in Theorem 2.1, we attain a performance guarantee of $O(\log^3 n \log^2(mn))$ for set connector.

The reader will notice that the procedure described above loses an extra logarithmic term in comparison to the approximation ratio claimed in Theorem 4.1. Technically speaking, the additional factor is incurred since we make use of our generalized connectivity algorithm in black-box fashion; this redundancy can be avoided by noting that the latter is an iterative greedy algorithm by itself. The specifics of achieving such an improvement and establishing an $O(\log^3 n \log^2(mn))$ integrality gap are deferred to the final version of this paper.

5 Conclusions

It is interesting to note that the following slight variant of the generalized connectivity problem makes it very hard to approximate: for each pair (S_i, T_i) we are also given a relation $R_i \subseteq S_i \times T_i$, and a solution F is now considered feasible if it connects some pair (u, v) from R_i for each set-pair i . Using a reduction from the Label Cover problem as in [8], one can establish that this variant is hard to approximate to within an $O(2^{\log^{1-\epsilon} n})$ factor.

Obvious open problems are to improve the approximation ratios for the problems considered in this paper. For generalized connectivity it may be possible to get a ratio that matches the one known for the group Steiner problem - the ratio we give is worse by a logarithmic factor. It is also of interest to prove an integrality gap

bound that matches the approximation ratio.

Finally, can we obtain a poly-logarithmic competitive ratio for generalized connectivity in the online setting? Alon et al. [2] show an $O(\log m)$ competitive ratio to compute a fractional solution to the relaxation LP_{GC} for generalized connectivity. The framework of [2] requires a specific kind of rounding procedure to convert the fractional solution to an integral solution in an online fashion. Although we showed a poly-logarithmic integrality gap for LP_{GC} , our rounding procedure is not applicable to the online setting. Generalized connectivity and set connector are closely related to the group Steiner problem for which [2] gives an online rounding algorithm by adapting the randomized rounding algorithm of [11]. Is there an online rounding algorithm for generalized connectivity and set connector that gives a poly-logarithmic competitive ratio?

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