

# Geometric Partial Matchings and Unbalanced Transportation Problem

Pankaj K. Agarwal

Duke University, USA

pankaj@cs.duke.edu

Hsien-Chih Chang

Duke University, USA

hsienchih.chang@duke.edu

Allen Xiao

Duke University, USA

axiao@cs.duke.edu

## Abstract

Let  $A$  and  $B$  be two point sets in the plane of sizes  $r$  and  $n$  respectively (assume  $r \leq n$ ), and let  $k$  be a parameter. A matching between  $A$  and  $B$  is a family  $M \subseteq A \times B$  of pairs so that any point of  $A \cup B$  appears in at most one pair. Given two integers  $p, q \geq 1$ , we define the cost of  $M$  to be  $\text{cost}(M) = \sum_{(a,b) \in M} \|a - b\|_p^q$  where  $\|\cdot\|_p$  is the  $L_p$ -norm. The geometric partial matching problem asks to find the minimum-cost size- $k$  matching between  $A$  and  $B$ .

We present ~~the first set of~~ <sup>efficient</sup> algorithms for geometric partial matching that work for any powers of  $L_p$ -norm matching objective ~~whose running time is near-linear in  $n$~~ . An exact algorithm <sup>that</sup> runs in  $O((n + k^2) \text{polylog } n)$  time, and a  $(1 + \varepsilon)$ -approximation algorithm <sup>that</sup> runs in  $O((n + k\sqrt{k}) \text{polylog } n \cdot \log \varepsilon^{-1})$  time. Both algorithms are based on primal-dual flow augmentation scheme; the main improvements are obtained by using dynamic data structures to achieve efficient flow augmentations. Using similar techniques, we give an exact algorithm for the planar transportation problem <sup>that</sup> runs in  $O((r^2\sqrt{n} + rn^{3/2}) \text{polylog } n)$  time. For  $r = o(\sqrt{n})$ , this algorithm is faster than the state-of-art quadratic time algorithm by Agarwal *et al.* [SOCG 2016].

**2012 ACM Subject Classification** Theory of computation  $\rightarrow$  Design and analysis of algorithms

**Keywords and phrases** partial matching, transportation, minimum-cost flow, rms-distance, bi-chromatic closest pair, cost scaling, excess scaling, primal-dual

**Acknowledgements** We thank Haim Kaplan for useful discussion and suggesting to use Goldberg *et al.* [19] for our approximation algorithm.

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## 1 Introduction

Given two point sets  $A$  and  $B$  in  $\mathbb{R}^2$ , we consider the problem of finding the minimum-cost partial matching between  $A$  and  $B$ . Formally, suppose  $A$  has size  $r$  and  $B$  has size  $n$  where  $r \leq n$ . Let  $G(A, B)$  be the undirected complete bipartite graph between  $A$  and  $B$ , and let the cost of edge  $(a, b)$  be  $c(a, b) = \|a - b\|_p$ , for some  $1 \leq p < \infty$ . A *matching*  $M$  in  $G(A, B)$  is a set of edges sharing no endpoints. The *size* of  $M$  is the number of edges in  $M$ . Given  $q \geq 1$ , the cost of  $M$  is defined to be

$$\text{cost}(M) := \sum_{(a,b) \in M} \|a - b\|_p^q.$$



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The 35th International Symposium on Computational Geometry (SOCG 2019).



Leibniz International Proceedings in Informatics

LIPICs Schloss Dagstuhl – Leibniz-Zentrum für Informatik, Dagstuhl Publishing, Germany



For a parameter  $k \leq r$ , the problem of finding the minimum-cost size- $k$  matching in  $G(A, B)$  is called the *geometric partial matching problem*. We call the corresponding problem in general bipartite graphs (with arbitrary edge costs) the *partial matching problem*.<sup>1</sup>

We also consider the following generalization of the bipartite matching problem. Let  $\lambda : A \cup B \rightarrow \mathbb{Z}$  be a *supply-demand function* with positive value on points of  $A$  and negative value on points of  $B$ , satisfying  $\sum_{a \in A} \lambda(a) = -\sum_{b \in B} \lambda(b)$ . A *transportation map* is a function  $\tau : A \times B \rightarrow \mathbb{R}_{\geq 0}$  such that  $\sum_{b \in B} \tau(a, b) = \lambda(a)$  for all  $a \in A$  and  $\sum_{a \in A} \tau(a, b) = -\lambda(b)$  for all  $b \in B$ . We define the cost of  $\tau$  to be

$$\text{cost}(\tau) := \sum_{(a,b) \in A \times B} \|a - b\|_p^q \cdot \tau(a, b).$$

The *transportation problem* asks to compute a transportation map of minimum cost.

The transportation problem is essentially the discrete version of the *optimal transport problem*, which has been studied extensively in mathematics (see the books by Villani [41, 42]). Both discrete and continuous optimal transport have been used in a broad range of applications; for example, in computer vision and graphics [29, 33, 38], machine learning [7, 9], economics [18], engineering [27, 34], and medical imaging [21]. More recently, computational/numerical interest has expanded greatly due to the development of fast approximate solvers [5, 6, 11, 13]; see the book by Cuturi and Peyré [30] and the survey by Solomon [37].

## 1.1 Related work

Both minimum-cost bipartite matching and maximum-size bipartite matching are classical problems in the study of algorithms. Upper bounds for the latter include the  $O(m\sqrt{n})$  time algorithm by Hopcroft and Karp [22] and the  $O(m \min\{\sqrt{m}, n^{2/3}\})$  time algorithm by Even and Tarjan [16], where  $n$  is the number of vertices and  $m$  is the number of edges. The first improvement in over thirty years was made by Mądry [26], which uses an interior-point algorithm that runs in  $O(m^{10/7} \text{polylog } n)$  time.

The Hungarian algorithm [24] computes a minimum-weight maximum matching in a bipartite graph in roughly  $mn$  time. Faster algorithms have been developed since, such as the  $O(m\sqrt{n} \log(nC))$  time algorithms by Gabow and Tarjan [17] and the improved  $O(m\sqrt{n} \log C)$  time algorithm by Duan *et al.* [12]. Ramshaw and Tarjan [31] showed that the Hungarian algorithm can be extended to compute a minimum-cost partial matching of size  $k$  in time  $O(km + k^2 \log r)$  time. They also proposed a cost-scaling algorithm for partial matching that runs in time  $O(m\sqrt{n} \log(nC))$ , assuming that the costs are integral; here  $C$  is the maximum cost of an edge. By reduction to unit-capacity min-cost flow, Goldberg *et al.* [19] developed a cost-scaling algorithm for partial matching with running time  $O(m\sqrt{k} \log(kC))$ , again only for integral edge costs.

In geometric settings, the Hungarian algorithm can be implemented to compute an optimal perfect matching between  $A$  and  $B$  (assuming to have the same size) in time  $O(n^2 \text{polylog } n)$  [23] (see also [1, 39]). This algorithm computes an optimal size- $k$  matching in time  $O(kn \text{polylog } n)$ . Faster approximation algorithms have been developed for computing a perfect matching in geometric settings [4, 35, 39, 40]. The best algorithm to date by Sharathkumar and Agarwal [36] computes a  $(1 + \varepsilon)$ -approximation to the optimal perfect matching in  $O(n \text{polylog } n \cdot \varepsilon^{-\Omega(1)})$  expected time with high probability, assuming  $q$ —the power of the  $L_p$ -norm in the matching objective—is equal to one; in other words, the cost

<sup>1</sup> Partial matching is also called *imperfect matching* or *imperfect assignment* [19, 31].

Both matching and transportation problems arise

by Villani [41, 42] and by Cuturi and Peyré [30] and the survey by Solomon [37].

cost

assuming that the edge costs are integral; here  $C$  is the maximum cost of an edge.

what is weight?

again

66 of a matching is the sum of ~~edge costs  $c(a, b)$~~ . Their algorithm can also compute a  $(1 + \varepsilon)$ -  
 67 approximate optimal partial matching within the same time bound. For  $q > 1$ , the best known  
 68 approximation algorithm to compute a perfect matching runs in  $O(n^{3/2} \text{polylog } n \cdot \log \varepsilon^{-1})$   
 69 time [35]. It is not obvious how to extend it to the partial matching setting.

70 There is also some work on computing an optimal or near-optimal partial matching when  
 71  $B$  is fixed but  $A$  is allowed to translate and/or rotate [3, 8, 10, 32]. Here, the goal is to (i)  
 72 compute a (near-)optimal matching over all possible transformations of  ~~$A$~~ , or (ii) to compute  
 73 a set  $\mathcal{M}$  of matchings, such that for any translation/rotation  $\mathcal{T}$  of  $A$ , a (near-)optimal  
 74 matching of  $\mathcal{T}(A)$  and  $B$  in  $\mathcal{M}$ .

75 The transportation problem can also be formulated as a minimum-cost flow problem in a  
 76 graph. ~~Thus, the strongly polynomial uncapacitated min-cost flow algorithm by Orlin [28]~~  
 77 solves transportation in  $O((m + n \log n)n \log n)$  time. Lee and Sidford [25] give a weakly  
 78 polynomial algorithm that runs in  $O(m\sqrt{n} \text{polylog}(n, U))$  time, where  $U$  is the maximum  
 79 amount of vertex supply-demand. Agarwal *et al.* [2] showed that Orlin's algorithm can be  
 80 implemented in the ~~2D~~ geometric setting in time  $O(n^2 \text{polylog } n)$ . It is an open question whether  
 81 this algorithm can be implemented to run in  $O(rn \text{polylog } n)$  time (recall that  $r$  is the size  
 82 of  $A$ ). By adapting the Lee-Sidford algorithm, they developed a  $(1 + \varepsilon)$ -approximation  
 83 algorithm that runs in  $O(n^{3/2} \varepsilon^{-2} \text{polylog } n)$  time. They also gave a Monte-Carlo algorithm  
 84 which computes an  $O(\log^2(1/\varepsilon))$ -approximate solution in  $O(n^{1+\varepsilon})$  time with high probability.

## 85 1.2 Our results

86 There are three main results in this paper. First in Section 2 we present an efficient algorithm  
 87 for computing an optimal partial matching in  $\mathbb{R}^2$ .

88 ► **Theorem 1.1.** *Given two point sets  $A$  and  $B$  in  $\mathbb{R}^2$  each of size at most  $n$ , a minimum-cost*  
 89 *matching of size  $k$  between  $A$  and  $B$  can be computed in  $O((n + k^2) \text{polylog } n)$  time.*

90 We use *bichromatic closest pair (BCP)* data structures to implement the Hungarian  
 91 algorithm efficiently, similar to Agarwal *et al.* and Kaplan *et al.* [1, 23]. But unlike their  
 92 algorithms which take  $\Omega(n)$  time to find an augmenting path, we show that after  $O(n \text{polylog } n)$   
 93 preprocessing, an augmenting path can be found in  $O(k \text{polylog } n)$  time. We refer to this idea  
 94 as the *rewinding mechanism*. As a remark, by plugging in our results in a black-box fashion,  
 95 we improve the running time of computing an optimal or near-optimal partial matching  
 96 when  $B$  is fixed but  $A$  is allowed to translate and/or rotate [3, 8, 32]. **«what is the precise**  
 97 **statement?»**

98 Next in Sections 3 and 4, we obtain a  $(1 + \varepsilon)$ -approximation algorithm for the planar  
 99 geometric partial matching problem by providing an efficient implementation of the unit-  
 100 capacity min-cost flow algorithm by Goldberg *et al.* [19].

101 ► **Theorem 1.2.** *Given two point sets  $A$  and  $B$  in  $\mathbb{R}^2$  each of size at most  $n$ , a  $(1 + \varepsilon)$ -*  
 102 *approximate min-cost matching of size  $k$  between  $A$  and  $B$  can be computed in  $O((n +$   
 103  $k\sqrt{k}) \text{polylog } n \cdot \log \varepsilon^{-1})$  time.*

104 The main challenge here is the set of *null vertices* which do not play any role in the  
 105 augmentations, but still contribute to the size of the graph. Instead, we run the unit-capacity  
 106 min-cost flow algorithm on a *shortcut network*, circumventing all null vertices. The shortcut  
 107 graph itself may have  $\Omega(n^2)$  edges, but we can query the min-cost arcs efficiently using BCP  
 108 oracles without explicitly constructing the graph. Therefore we charge the execution time of  
 109 each iteration to the size of the *flow support*, which turns out to be of size  $O(k)$ .

Finally in Section 5 we present a faster algorithm for the planar transportation problem when the two point sets are unbalanced.

► **Theorem 1.3.** *Given two point sets  $A$  and  $B$  in  $\mathbb{R}^2$  of sizes  $r$  and  $n$  respectively along with supply-demand function  $\lambda: A \cup B \rightarrow \mathbb{Z}$ . An optimal transportation map between  $A$  and  $B$  can be computed in  $O((r^2\sqrt{n} + rn^{3/2}) \text{polylog } n)$  time.*

Our ~~third~~ algorithm uses the strongly polynomial uncapacitated minimum-cost flow algorithm by Orlin [28], adapted for geometric costs as in Agarwal *et al.* [2]. This improves over the  $O(n^2 \text{polylog } n)$  time algorithm when  $r = o(\sqrt{n})$ . Unlike in the case of matchings, the flow support for the transportation problem may have size  $\Omega(n)$  even when  $r$  is a constant; so naïvely we can no longer charge the execution time to flow support size anymore. However, we show that most of the support arcs are of degree one and thus can be partitioned into *stars* centered at vertices of  $A$ . We describe a data structure that process these stars in amortized  $O((r^2/\sqrt{n} + r\sqrt{n}) \text{polylog } n)$  time per augmentation.

## 2 Minimum-Cost Partial Matchings using Hungarian Algorithm

In this section, we solve the geometric partial matching problem and prove Theorem 1.1 by implementing the Hungarian algorithm for partial matching in  $O((n + k^2) \text{polylog } n)$  time.

The linear program dual to the standard linear program for partial matching has dual variables for each vertex, called *potentials*  $\pi$ . Given potentials  $\pi$ , we can define the *reduced cost* on the edges to be  $c_\pi(v, w) := c(v, w) - \pi(v) + \pi(w)$ . Potentials  $\pi$  are *feasible* if the reduced costs are nonnegative for all edges in  $G$ . We say that an edge  $(v, w)$  is *admissible* under potentials  $\pi$  if  $c_\pi(v, w) = 0$ .

A vertex  $v$  is *matched* by  $M$  if  $v$  is the endpoint of some matching edge in  $M$ ; otherwise  $v$  is *unmatched*. Given a matching  $M$ , an *augmenting path*  $\Pi = (a_1, b_1, \dots, a_\ell, b_\ell)$  is an odd-length path with unmatched endpoints  $(a_1$  and  $b_\ell)$ ;  $\Pi$  alternates between edges outside and inside of matching  $M$ . The symmetric difference  $M \oplus \Pi$  creates a new matching of size  $|M| + 1$ , called the *augmentation* of  $M$  by  $\Pi$ .

### 2.1 The Hungarian Algorithm

The Hungarian algorithm is initialized with  $M = \emptyset$  and  $\pi = 0$ . Each iteration of the Hungarian algorithm augments  $M$  with an admissible augmenting path  $\Pi$ , discovered using a procedure called the *Hungarian search*. The algorithm terminates once  $M$  has size  $k$ ; Ramshaw and Tarjan [31] showed that  $M$  is guaranteed to be an optimal partial matching.

The Hungarian search tries grow a set of *reachable vertices*  $S$  by augmenting paths consisting of admissible edges. Initially,  $S$  is the set of unmatched vertices in  $A$ . Let the *frontier* of  $S$  be the edges in  $(A \cap S) \times (B \setminus S)$ . In each iteration, the Hungarian search first *relaxes* the minimum-reduced-cost edge  $(a, b)$  in the frontier, raising  $\pi(a)$  by  $c_\pi(a, b)$  for all  $a \in S$  to make  $(a, b)$  admissible, and adding  $b$  into  $S$ . If  $b$  is already matched, then we also relax the matching edge  $(a', b)$  and add  $a'$  into  $S$ . The search finishes when  $b$  is unmatched, and an admissible augmenting path now can be recovered.

### 2.2 Fast implementation of Hungarian search [1, 39]

In the geometric setting, we find the min-reduced-cost frontier edge using a dynamic *bichromatic closest pair* (BCP) data structure, as observed in [1] ~~«cite»~~. Given two point sets  $P$  and  $Q$  in the plane, the bichromatic closest pair are two points  $a \in P$  and  $b \in Q$  minimizing

in [2]

our result

→ we finally remark that the algorithms in [3] use partial matching algorithms as a black box. By plugging our algorithm, we can improve the result in [3]. We omit the details from here.

the additively weighted distance  $c(a, b) - \omega(a) + \omega(b)$  for some real-valued vertex weights  $\omega$ . Thus, the minimum reduced-cost among the frontier edges is precisely the cost of the BCP of point sets  $P = A \cap S$  and  $Q = B \setminus S$ , with  $\omega(p) = \pi(p)$ .

The dynamic BCP data structure by Kaplan *et al.* [23] supports point insertions and deletions in  $O(\text{polylog } n)$  time and answers queries in  $O(\log^2 n)$  time for our setting. For each relaxation, we perform at most  $O(1)$  queries and updates.

**Rewinding mechanism.** We cannot afford to take  $O(n \text{ polylog } n)$  time to initialize the BCP data structure at the beginning of every Hungarian search beyond the first. To resolve the issue, observe that exactly one vertex is removed from the set of unmatched vertices in  $A$  after each Hungarian search. Thus we can recover the initial state of the data structure by keeping track of a list of the points added to  $S$  over the course of the Hungarian search. At the start of the next Hungarian search, *rewind* the data structure by tracing the list in reverse order, and perform a single deletion to remove the newly matched vertex in  $A$ .

The number of points in the list is at most  $O(k)$  as it is bounded by the number of relaxations per Hungarian search. Thus, in  $O(k \text{ polylog } n)$  time, we can recover the BCP data structure for each Hungarian search beyond the first. We refer to this procedure as the *rewinding mechanism*.

We adapt a trick from Vaidya [39] to batch potential updates under the rewinding mechanism, so that the time spent on potential updates per Hungarian search is  $O(k)$ . See Appendix A.1 for details. Putting everything together we obtain the following:

► **Lemma 2.1.** *Each Hungarian search can be implemented in  $O(k \text{ polylog } n)$  time after a one-time  $O(n \text{ polylog } n)$  preprocessing.*

Our implementation of the Hungarian algorithm therefore runs in  $O((n + k^2) \text{ polylog } n)$  time. This proves Theorem 1.1.

### 3 Approximating Min-Cost Partial Matching through Cost-Scaling

The goal of this section and the next is to prove Theorem 1.2; that is, to compute a size- $k$  geometric partial matching between two point sets  $A$  and  $B$  in the plane, with cost at most  $(1 + \varepsilon)$  times the optimal matching, in time  $O((n + k\sqrt{k}) \text{ polylog } n \log(1/\varepsilon))$ .

After introducing the necessary terminologies in Section 3.1, we reduce the partial matching problem to computing an approximate minimum-cost flow on a unit-capacity reduction network in Section 3.2. In Section 3.3 we prove a high-level overview of the cost-scaling algorithm, executed on the reduction network. We postpone the fast implementation using dynamic data structures to Section 4.

*maybe cite Goldberg et al. paper.*

#### 3.1 Preliminaries on Network Flows

Due to the space restriction, we omit the definitions of standard network flow theory terminologies from the main text. For a reference see Appendix B.1, or any texts on network flows [?] *«cite»*. We emphasize that a directed graph  $G = (V, E)$  is augmented by edge costs  $c$  and capacities  $u$ , and a supply-demand function  $\phi$  defined on the vertices. A *network*  $N = (V, \vec{E})$  turns each edge in  $E$  into a pair of *arcs*  $v \rightarrow w$  and  $w \rightarrow v$  in arc set  $\vec{E}$ . With the unit-capacity assumption on the network, all the pseudoflows in this section take integer values. The *support* of a pseudoflow  $f$  in  $N$ , is the set of arcs with positive

flows:  $\text{supp}(f) := \{v \rightarrow w \in \vec{E} \mid f(v \rightarrow w) > 0\}$ . If all vertices are *balanced*, the pseudoflow is a *circulation*. The *cost* of a pseudoflow is defined to be

$$\text{cost}(f) := \sum_{v \rightarrow w \in \text{supp}(f)} c(v \rightarrow w) \cdot f(v \rightarrow w).$$

The *minimum-cost flow problem (MCF)* asks to find a circulation of minimum cost inside a given directed graph.

**LP-duality and admissibility.** To solve the minimum-cost flow problem, we focus on the primal-dual algorithms using linear programming. Let  $G = (V, E)$  be a given directed graph with the corresponding network  $N = (V, \vec{E}, c, u, \phi)$ . Formally, the *potentials*  $\pi(v)$  are the variables of the linear program dual to the standard linear program for the minimum-cost flow problem with variables  $f(v, w)$  for each directed edge in  $E$ . Assignments to the primal variables satisfying the capacity constraints extend naturally into a pseudoflow on the network  $N$ . Let  $G_f = (V, \vec{E}_f)$  be the residual graph under pseudoflow  $f$ . The *reduced cost* of an arc  $v \rightarrow w$  in  $\vec{E}_f$  with respect to  $\pi$  is defined as

$$c_\pi(v \rightarrow w) := c(v \rightarrow w) - \pi(v) + \pi(w).$$

Notice that the cost function  $c_\pi$  is also antisymmetric.

The *dual feasibility constraint* says that  $c_\pi(v \rightarrow w) \geq 0$  holds for every directed edge  $(v, w)$  in  $E$ ; potentials  $\pi$  which satisfy this constraint are said to be *feasible*. Suppose we relax the dual feasibility constraint to allow some small violation in the value of  $c_\pi(v \rightarrow w)$ . We say that a pair of pseudoflow  $f$  and potential  $\pi$  is  *$\varepsilon$ -optimal* [?, ?] if  $c_\pi(v \rightarrow w) \geq -\varepsilon$  for every residual arc  $v \rightarrow w$  in  $\vec{E}_f$ . Pseudoflow  $f$  is  *$\varepsilon$ -optimal* if it is  *$\varepsilon$ -optimal* with respect to some potentials  $\pi$ ; potential  $\pi$  is  *$\varepsilon$ -optimal* if it is  *$\varepsilon$ -optimal* with respect to some pseudoflow  $f$ . Given a pseudoflow  $f$  and potentials  $\pi$ , a residual arc  $v \rightarrow w$  in  $\vec{E}_f$  is *admissible* if  $c_\pi(v \rightarrow w) \leq 0$ . We say that a pseudoflow  $g$  in  $G_f$  is *admissible* if all support arcs of  $g$  on  $G_f$  are admissible; in other words,  $g(v \rightarrow w) > 0$  holds only on admissible arcs  $v \rightarrow w$ . Throughout the rest of the paper we make use of the property that perform an admissible flow augmentation does not change the  $\varepsilon$ -optimality; see Lemma B.1 for a proof. *(Is this a new result? If yes, say so. This is a folklore result, but give a citation.)*

### 3.2 Reduction to Unit-Capacity Min-Cost Flow Problem

Here we reduce the min-cost partial matching problem to the unit-capacity min-cost flow problem with a polynomial bound on diameter of the underlying point set.

**Additive approximation.** Given a bipartite graph  $G = (A, B, E_0)$  for the geometric partial matching problem with cost function  $c$ , we construct the *reduction graph*  $H$  as follows: Direct the edges in  $E_0$  from  $A$  to  $B$ , and assign each directed edge with capacity 1. Now add a dummy vertex  $s$  with directed edges to all vertices in  $A$ , and add a dummy vertex  $t$  with directed edges from all vertices in  $B$ ; each edge added has cost 0 and capacity 1. Assign vertex  $s$  with supply  $k$  and vertex  $t$  with demand  $k$ ; the rest of the vertices in  $H$  have zero supply-demand. We call the network naturally corresponds to  $H$  as the *reduction network*  $N_H$ . It is straightforward to show that any integer circulation  $f$  on  $N_H$  uses exactly  $k$  of the  $A$ -to- $B$  arcs, which correspond to the edges of a size- $k$  matching  $M_f$ . Notice that the cost of the circulation  $f$  is equal to the cost of the corresponding matching  $M_f$ .

First we show that the number of arcs used by any integer pseudoflow in  $N_H$  is asymptotically bounded by the excess of the pseudoflow.



234 ► **Lemma 3.1.** *The size of  $\text{supp}(f)$  is at most  $3k$  for any integer circulation  $f$  in reduction*  
 235 *network  $N_H$ . As a corollary, the number of residual backward arcs is at most  $3k$ .*

236 Using the bound on the support size, we show that an  $\varepsilon$ -optimal integral circulation gives  
 237 an additive  $O(k\varepsilon)$ -approximation to the MCF problem.

238 ► **Lemma 3.2.** *Let  $f$  be an  $\varepsilon$ -optimal integer circulation in  $N_H$ , and  $f^*$  be an optimal integer*  
 239 *circulation for  $N_H$ . Then,  $\text{cost}(f) \leq \text{cost}(f^*) + 6k\varepsilon$ .*

240 **Multiplicative approximation.** Now we employ a technique from Sharathkumar and Agar-  
 241 wal [35] to convert the additive approximation into a multiplicative one. The reduction does  
 242 not work out of the box, as they were tackling a similar but different problem on geometric  
 243 transportations. See Appendix B.2 for details.

244 ► **Lemma 3.3.** *Computing  $(1 + \varepsilon)$ -approximate geometric partial matching reduces to the*  
 245 *following problem in  $O(n \text{ polylog } n)$  time: Given reduction network  $N$  over a point set*  
 246 *with diameter at most  $K \cdot kn^3$  «really?  $K \cdot kn^{q+2}$ ?» for some constant  $K$ , compute a*  
 247  *$(K \cdot \varepsilon/6k)$ -optimal circulation on  $N$ .*

### 248 3.3 High-Level Description of Cost-Scaling Algorithm

252 Our main algorithm for the unit-capacity minimum-cost flow problem is based on the *cost-*  
 253 *scaling* technique, originally due to Goldberg and Tarjan [20]; Goldberg *et al.* [19] applied  
 254 the technique on unit-capacity networks. The algorithm finds  $\varepsilon$ -optimal circulations for  
 255 geometrically shrinking values of  $\varepsilon$ . Each fixed value of  $\varepsilon$  is called a *cost scale*. Once  $\varepsilon$  is  
 256 sufficiently small, the  $\varepsilon$ -optimal flow is a suitable approximation according to Lemma 3.3.<sup>2</sup>

257 The cost-scaling algorithm initializes the flow  $f$  and the potential  $\pi$  to be zero. Note  
 258 that the zero flow is trivially a  $kC$ -optimal flow, where  $C$  is the maximum arc cost. At the  
 259 beginning of each scale starting at  $\varepsilon = kC$ ,

- 260 ■ SCALE-INIT takes the previous circulation (now  $2\varepsilon$ -optimal) and transforms it into an  
 261  $\varepsilon$ -optimal pseudoflow with  $O(k)$  excess.
- 262 ■ REFINE then reduces the excess in the newly constructed pseudoflow to zero, making it  
 263 an  $\varepsilon$ -optimal circulation.

264 Thus for any  $\varepsilon^* > 0$ , the algorithm produces an  $\varepsilon^*$ -optimal circulation after  $O(\log(kC/\varepsilon^*))$   
 265 scales. Using the reduction in Lemma 3.3, we have the diameter of the point set, thus  
 266 maximum cost  $C$ , bounded by  $O(K \cdot kn^3)$  for some value  $K$ . By setting  $\varepsilon^*$  to be  $K \cdot \varepsilon/6k$ ,  
 267 the number of cost scales is bounded above by  $O(\log(n/\varepsilon))$ .

268 **Scale initialization.** The vertex set of  $H$  consists of two point sets  $A$  and  $B$ , as well as  
 269 two dummy vertices  $s$  and  $t$ . The directed edges in  $H$  are pointed from  $s$  to  $A$ , from  $A$   
 270 to  $B$ , and from  $B$  to  $t$ . We call those arcs in  $N_H$  whose direction is consistent with their  
 271 corresponding directed edges as *forward arcs*, and those arcs that points in the opposite  
 272 direction as *backward arcs*.

273 «Describe how it's different from original.» The procedure SCALE-INIT transforms a  
 274  $2\varepsilon$ -optimal circulation from the previous cost scale into an  $\varepsilon$ -optimal flow with  $O(k)$  excess,  
 275 by raising the potentials  $\pi$  of all vertices in  $A$  by  $\varepsilon$ , those in  $B$  by  $2\varepsilon$ , and the potential of  $t$

249 <sup>2</sup> When the costs are integers, an  $\varepsilon$ -optimal circulation for a sufficiently small  $\varepsilon$  (say less than  $1/n$ ) is itself  
 250 an optimal solution [19, 20]. We present this algorithm without the integral-cost assumption because in  
 251 the geometric partial matching setting (with respect to  $L_p$  norms) the costs are generally not integers.

Indeed explain the difference with  
the original version and say we  
need new ideas to make it work.

276 by  $3\varepsilon$ . The potential of  $s$  remains unchanged. Now the reduced cost of every forward arc is  
 277 dropped by  $\varepsilon$ , and thus all the forward arcs have reduced cost at least  $-\varepsilon$ .

278 As for backward arcs, the procedure SCALE-INIT continues by setting the flow on  $v \rightarrow w$  to  
 279 zero for each backward arc  $w \rightarrow v$  violating the  $\varepsilon$ -optimality constraint. In other words, we  
 280 set  $f(v \rightarrow w) = 0$  whenever  $c_\pi(w \rightarrow v) < -\varepsilon$ . This ensures that all such backward arcs are no  
 281 longer residual, and therefore the flow (now with excess) is  $\varepsilon$ -optimal.

282 Because the arcs are of unit-capacity in  $N_H$ , each arc desaturation creates one unit of  
 283 excess. By Lemma 3.1 the number of backward arcs is at most  $3k$ . Thus the total amount of  
 284 excess created is also  $O(k)$ . In total, the whole procedure SCALE-INIT takes  $O(n)$  time.

285 **Refinement.** The procedure REFINES is implemented using a primal-dual augmentation  
 286 algorithm, which sends flows on admissible arcs to reduce the total excess. Unlike the  
 287 Hungarian algorithm, it uses *blocking flows* instead of augmenting paths. We call a pseudoflow  
 288  $f$  on residual network  $N_g$  a *blocking flow* if  $f$  saturates at least one residual arc in every  
 289 augmenting path in  $N_g$ . In other words, there is no admissible augmenting path in  $N_{f+g}$   
 290 from an excess vertex to a deficit vertex.

291 Each iteration of REFINES finds an admissible blocking flow that is then added to the  
 292 current pseudoflow in two stages:

- 293 1. A *Hungarian search*, which increases the dual variables  $\pi$  of vertices that are reachable  
 294 from an excess vertex by at least  $\varepsilon$ , in a Dijkstra-like manner, until there is an excess-deficit  
 295 path of admissible edges.
- 296 2. A *depth-first search* through the set of admissible arcs to construct a blocking flow. It  
 297 suffices to repeatedly extract admissible augmenting paths until no more admissible  
 298 excess-deficit paths remain.

299 The algorithm continues until the total excess becomes zero.

300 First we analyze the number of iterations executed by REFINES. The proof follows the  
 301 strategy in Goldberg *et al.* [19, Section 3.2]. Due to space constraint we omit all the proofs  
 302 here; see Appendix B.3 for complete proofs. *«Explain what is new here.»*

303 ► **Lemma 3.4.** Let  $f$  be a pseudoflow in  $N_H$  with  $O(k)$  excess. The procedure REFINES runs  
 304 for  $O(\sqrt{k})$  iterations before the excess of  $f$  becomes zero.

*Again does Lemma 3.4 follow from this Gold key paper, or we need to adapt?*

## 305 4 Fast Implementation of Refinement

306 The goal of the section is to show that after  $O(n \text{ polylog } n)$  time preprocessing, each Hungarian  
 307 search and depth-first search can be implemented in  $O(k \text{ polylog } n)$  time. Combined with  
 308 Lemma 3.4 the procedure REFINES can be implemented in  $O((n + k\sqrt{k}) \text{ polylog } n)$  time.  
 309 Together with our analysis on scale initialization and the bound on number of cost scales,  
 310 this concludes the proof to Theorem 1.2.

311 Both Hungarian search and depth-first search are implemented in a Dijkstra-like fashion,  
 312 traversing through the residual graph using admissible arcs starting from the excess vertices.  
 313 Each step of the search procedures *relaxes* a minimum-reduced-cost arc from the set of visited  
 314 vertices to an unvisited vertex, until a deficit vertex is reached. At a high level, our analysis  
 315 strategy is to charge the relaxation events to the support arcs of  $f$ , which has size at most  
 316  $O(k)$  by Corollary B.4.



## 4.1 Null vertices and shortcut graph

As it turns out, there are some vertices visited by a relaxation event which we cannot charge to  $\text{supp}(f)$ . Unfortunately the number of such vertices can be as large as  $\Omega(n)$ . To overcome this issue, we replace the residual graph with an equivalent graph that excludes all the null vertices, and run the Hungarian search and depth-first search on the resulting graph instead.

**Null vertices.** We say a vertex  $v$  in the residual graph  $N_f$  is a *null vertex* if  $\phi_f(v) = 0$  and no arcs of  $\text{supp}(f)$  is incident to  $v$ . We use  $A_\emptyset$  and  $B_\emptyset$  to denote the null vertices  $A$  and  $B$  respectively. Vertices that are not null are called *normal vertices*. A *null 2-path* is a length-2 subpath in  $N_f$  from a normal vertex to another normal vertex, passing through a null vertex. As every vertex in  $A$  has in-degree 1 and every vertex in  $B$  has out-degree 1 in the residual graph, the null 2-paths must be of the form either  $(s, v, b)$  for some vertex  $b$  in  $B \setminus B_\emptyset$  or  $(a, v, t)$  for some vertex  $a$  in  $A \setminus A_\emptyset$ . In either case, we say that the null 2-path *passes through* null vertex  $v$ . Similarly, we define the length-3 path from  $s$  to  $t$  that passes through two null vertices to be a *null 3-path*. Because reduced costs telescope for residual paths, the reduced cost of any null 2-path or null 3-path does not depend on the null vertices it passes through.

**Shortcut graph.** We construct the *shortcut graph*  $\tilde{H}_f$  from the reduction network  $H$  by removing all null vertices and their incident edges, followed by inserting an arc from the head of each null path  $\Pi$  to its tail, with cost equals to the sum of costs on the arcs. We call this arc the *shortcut* of null path  $\Pi$ , denoted as  $\text{short}(\Pi)$ . The resulting multigraph  $\tilde{H}_f$  contains only normal vertices of  $H_f$ , and the reduced cost of any path between normal vertices are preserved. We argue now that  $\tilde{H}_f$  is fine as a surrogate for  $H_f$ . Let  $\tilde{\pi}$  be an  $\varepsilon$ -optimal potential on  $\tilde{H}_f$ . Construct potentials  $\pi$  on  $H_f$  which extends  $\tilde{\pi}$  to null vertices, by setting  $\pi(a) := \tilde{\pi}(s)$  for  $a \in A_\emptyset$  and  $\pi(b) := \tilde{\pi}(t)$  for  $b \in B_\emptyset$ .

► **Lemma 4.1.** *Consider  $\tilde{\pi}$  an  $\varepsilon$ -optimal potential on  $\tilde{H}_f$  and  $\pi$  the corresponding potential constructed on  $H_f$ . Then, (1) potential  $\pi$  is  $\varepsilon$ -optimal on  $H_f$ , and (2) if arc  $\text{short}(\Pi)$  is admissible under  $\tilde{\pi}$ , then every arc in  $\Pi$  is admissible under  $\pi$ .*

## 4.2 Dynamic data structures for search procedures

**Hungarian search.** Conceptually, we are executing the Hungarian search on the shortcut graph  $\tilde{H}_f$ . We describe how we can query the minimum-reduced-cost arc leaving  $\tilde{S}$  in  $O(\text{polylog } n)$  time for the shortcut graph, without constructing  $\tilde{H}_f$  explicitly. For this purpose, let  $S$  be a set of “reached” vertices maintained, identical to  $\tilde{S}$  except whenever a shortcut is relaxed, we add the null vertices passed by the corresponding null path to  $S$  in addition to its (normal) endpoints. Observe that the arcs of  $\tilde{H}_f$  leaving  $\tilde{S}$  fall into  $O(1)$  categories:

- non-shortcut backward arcs  $(v, w)$  with  $(w, v) \in \text{supp}(f)$ ;
- non-shortcut  $A$ -to- $B$  forward arcs;
- non-shortcut forward arcs from  $s$ -to- $A$  and from  $B$ -to- $t$ ;
- shortcut arcs  $(s, b)$  corresponding to null 2-paths from  $s$  to  $b \in (B \setminus B_\emptyset) \setminus S$ ;
- shortcut arcs  $(a, t)$  corresponding to null 2-paths from  $a \in (A \setminus A_\emptyset) \cap S$  to  $t$ ; and
- shortcut arcs  $(s, t)$  corresponding to null 3-paths.

For each category of arcs we maintain a proper data structure (either heap or BCP) to answer to the min-cost arc query.

**Depth-first search.** Depth-first search is similar to Hungarian search in that it uses the relaxation of minimum-reduced-cost arcs/null paths, this time to identify admissible arcs/null paths in a depth-first manner. Similar to the Hungarian search, for each category of arcs in  $\tilde{H}_f$  leaving  $\tilde{S}$ , we maintain a proper data structure to answer the minimum-reduced-cost arc leaving a *fixed* vertex in  $\tilde{S}$  given by the query. Thus unlike Hungarian search which uses BCP data structures, we use dynamic nearest-neighbor data structures instead (cite).

Each of the above data structures requires  $O(1)$  queries and updates per relaxation. So in collaboration each relaxation can be implemented in  $O(\text{polylog } n)$  time [?, ?].

**Time analysis.** The complete time analysis can be found in Appendix C.2, C.3, and C.4; here we sketch the ideas. First we show (in Appendix C.2) that both Hungarian search and depth-first search performs  $O(k)$  relaxations before a deficit vertex is reached, by looking at shortcut and non-shortcut relaxations separately. Both types of relaxations are eventually charged to the support size of  $f$ . As for the time analysis (see Appendix C.3), using the same rewinding mechanism as in Section 2.2, the running time of the Hungarian search and depth-first search, other than the potential updates, can be charged to the number of relaxations. Again using the trick by Vaidya [39] we can charge the potential updates of normal vertices to the number of relaxations in the Hungarian search. We never explicitly maintain the potentials on the null vertices; instead they are reconstructed whenever needed, either at the end of each iteration of refinement or when an augmentation sends flow through a null vertex. We show that such updates does not happen often in Appendix C.4. This completes the time analysis, which we summarize as follows:

► **Lemma 4.2.** *After  $O(n \text{ polylog } n)$ -time preprocessing, each Hungarian search and depth-first search can be implemented in  $O(k \text{ polylog } n)$  time.*

## 5 Unbalanced Transportation

In this section, we give an exact algorithm which solves the planar transportation problem in  $O((n + k\sqrt{k}) \log(1/\varepsilon) \text{ polylog } n)$  time, proving Theorem 1.3. Our strategy is to use the standard reduction to the uncapacitated min-cost flow problem, and provide a fast implementation under the geometric setting for the uncapacitated min-cost flow algorithm by Orlin [28], combined with some of the tools developed in Sections 2 and 3.

We assume the readers are familiar with Orlin's strongly polynomial-time algorithm for uncapacitated min-cost flow problem [28]. For a brief introduction to Orlin's algorithm see Appendix D.1, as well as the original ~~well-written~~ paper. In short, Orlin's algorithm follows the *excess-scaling* paradigm under the primal-dual framework: Maintain a *scale parameter*  $\Delta$ , initially set to  $U$ . A vertex  $v$  is *active* if  $|\phi_f(v)| \geq \alpha\Delta$  for a fixed parameter  $\alpha \in (0.5, 1)$ . Repeatedly runs a *Hungarian search* that raises potentials (while maintaining dual feasibility) to create an admissible augmenting excess-deficit path between active vertices, on which we perform flow augmentations. Once there are no more active excess or deficit vertices,  $\Delta$  is halved. Each sequence of augmentations where  $\Delta$  holds a constant value is called an *excess scale*. On top of that, the algorithm performs contraction on arcs with flow value at least  $3n\Delta$  at the beginning of a scale, in which case the flow and potentials are no longer tracked, as well as aggressive  $\Delta$ -lowering under circumstances.

► **Theorem 5.1 (Orlin [28, Theorems 2 and 3]).** *Orlin's algorithm finds a set of optimal potentials after  $O(n \log n)$  scaling phases and  $O(n \log n)$  total augmentations.*

402 The remainder of the section focuses on showing that each augmentation can be im-  
 403 plemented in  $O((r^2/\sqrt{n} + r\sqrt{n}) \text{polylog } n)$  time (after preprocessing). A subtle issue is  
 404 that our geometric data structures must deal with real points in the plane instead of the  
 405 contracted components. A solution is provided by Agarwal *et al.* [2]; we supply the details  
 406 for maintaining contractions under dynamic data structures in Appendix D.2.

407 **Recovering optimal flow.** Use a strategy from Agarwal *et al.* [2], we can recover the optimal  
 408 flow in time  $O(n \text{polylog } n)$ . If furthermore the cost function is just the  $p$ -norm (without the  
 409  $q$ th-power), an even stronger result stands: In this case, the set of admissible arcs under an  
 410 optimal potential forms a planar graph, and thus we can apply the planar maximum-flow  
 411 algorithm [?, 14] which runs in  $O(n \log n)$  time. **«Careful. Multisource/sink? negative cost?»**  
 412 For details see Appendix D.3 and D.4.

## 413 5.1 Support stars

414 To find an augmenting path, we again use a Hungarian search with geometric data structures  
 415 to perform relaxations quickly. Our strategy is summarized as follows:

- 416 ■ Discard vertices <sup>that</sup> which lead to dead ends in the search (not on a path to a deficit vertex).
- 417 ■ Cluster parts of the flow support, such that the number of support arcs outside clusters  
 418 is  $O(r)$ . The number of relaxations we perform is proportional to the number of support  
 419 arcs outside of clusters.

420 Querying/updating clusters degrades our amortized time per relaxation from  $O(\text{polylog } n)$   
 421 to  $O(\sqrt{n} \text{polylog } n)$ . Thus overall each augmentation takes  $O(r\sqrt{n} \text{polylog } n)$  time.

422 **Support stars.** The vertices of  $B$  with support degree 1 are partitioned into subsets  $\Sigma_a \subset B$   
 423 by the  $a \in A$  lying on the other end of their single support arc. We call  $\Sigma_a$  the *support star*  
 424 centered at  $a \in A$ .

425 Roughly speaking, we would like to handle each support star as a single unit. When the  
 426 Hungarian search reaches  $a$  or any  $b \in \Sigma_a$ , the entirety of  $\Sigma_a$  (as well as  $a$ ) is also admissibly-  
 427 reachable and can be included into  $S$  without further potential updates. Additionally, the  
 428 only outgoing residual arcs of every  $b \in \Sigma_a$  lead to  $a$ , thus the only way to leave  $\Sigma_a \cup \{a\}$   
 429 is through an arc leaving  $a$ . Once a relaxation step reaches some  $b \in \Sigma_a$  or  $a$  itself, we  
 430 would like to quickly update the state such that the rest of  $b \in \Sigma_a$  is also reached without  
 431 performing relaxation steps to each individual  $b \in \Sigma_a$ .

## 432 5.2 Implementation details

433 Before describing our workaround for support stars, we analyze the number of relaxation steps  
 434 for arcs outside of support stars. To this end we need to strip of some *dead* vertices—having  
 435 no incident flow support edges and not an active excess or deficit vertex—that does not  
 436 affect the search. We use  $A_\ell$  and  $B_\ell$  to denote vertices of points in  $A$  and  $B$  that are not  
 437 dead. The details for handling such vertices can be found in Appendix D.5. For a proof of  
 438 the following lemma, see Appendix D.6.

439 ► **Lemma 5.2.** Suppose we have stripped the graph of dead vertices. The number of relaxation  
 440 steps in a Hungarian search outside of support stars is  $O(r)$ .

**Relaxations outside support stars.** For relaxations that don't involve support star vertices, we can once again maintain a BCP data structure to query the minimum  $A_\ell$ -to- $B_\ell$  arc. To elaborate, this is the BCP between  $P = A_\ell \cap S$  and  $Q = (B_\ell \setminus (\bigcup_{a \in A_\ell} \Sigma_a)) \setminus S$ , weighted by potentials. Since the query is outside the support stars, there is at most one update per relaxation. Backward (support) arcs are kept admissible by the invariant, so we relax them immediately when they arrive at the frontier.

**Relaxing support stars.** We classify support stars into two categories: *big stars* with  $|\Sigma_a| > \sqrt{n}$ , and *small stars* with  $|\Sigma_a| \leq \sqrt{n}$ . Let  $A_{big} \subseteq A$  denote the centers of big stars and  $A_{small} \subseteq A$  denote the centers of small stars.

■ For each big star  $\Sigma_a$ , we use a data structure  $\mathcal{D}_{big}(a)$  to maintain BCP between  $P = A_\ell \cap S$  and  $Q = \Sigma_a$ . We query this until  $a \in S$  or any vertex of  $\Sigma_a$  is added to  $S$ .

■ All small stars are added to a single BCP data structure  $\mathcal{D}_{small}$  between  $P = A_\ell \cap S$  and  $Q = (\bigcup_{a \in A_{small}} \Sigma_a) \setminus S$ . When an  $a \in A_{small}$  or any vertex of its support star is added to  $S$ , we remove the points of  $\Sigma_a$  from  $\mathcal{D}_{small}$  using  $|\Sigma_a|$  deletion operations.

We will update these data structures as each support star center is added into  $S$ . If a relaxation step adds some  $b \in B_\ell$  and  $b$  is in a support star  $\Sigma_a$ , then we immediately relax  $b \rightarrow a$ , as all support arcs are admissible.

Suppose a relaxation step adds  $a \in A_\ell$  to  $S$ . We must (i) remove  $a$  from every  $\mathcal{D}_{big}$ , (ii) remove  $a$  from  $\mathcal{D}_{small}$ . If  $a \in A_{big}$ , we also (iii) deactivate  $\mathcal{D}_{big}(a)$ . If  $a \in A_{small}$ , we also (iv) remove the points of  $\Sigma_a$  from  $\mathcal{D}_{small}$ . The operations (i–iii) can be performed in  $O(\text{polylog } n)$  time each, but (iv) may take up to  $O(\sqrt{n} \text{polylog } n)$  time. On the other hand, there are now  $O(\sqrt{n})$  data structures to query during each relaxation step, which takes  $O(\sqrt{n} \log^2 n)$  time in total. Together with Lemma 5.2 we bound the time for each Hungarian search.

► **Lemma 5.3.** *Hungarian search takes  $O(r\sqrt{n} \text{polylog } n)$  time.*

**Updating support stars.** As the flow support changes, the membership of support stars may shift causing a big star to become small or vice versa. To efficiently support this, we introduce a soft boundary in determining whether a support star is big or small. Standard charging argument shows that the amortized update time per membership change is  $O((r^2\sqrt{n} + rn) \text{polylog } n)$ ; see Appendix D.7. The number of star membership changes by adding a single augmenting path is bounded above by twice of its length, so  $O(r)$ . By Theorem 5.1, the total number of membership changes is  $O(rn \log n)$ . The total time spent on big-to-small updates is  $O(rn \text{polylog } n)$ , and the total time spent on small-to-big updates is  $O(r^2\sqrt{n} \text{polylog } n)$ . Membership changes themselves can be performed in  $O(\text{polylog } n)$  time each.

**Preprocessing time.** It takes  $O(rn \text{polylog } n)$  time to build the very first set of data structures. There are  $r \cdot |\Sigma_a|$  points to insert for each  $\mathcal{D}_{big}(a)$ , so the number of points to insert is  $O(rn)$ . At most  $O(rn)$  points have to be inserted for  $\mathcal{D}_{small}$ . So the total preprocessing time is  $O(rn \text{polylog } n)$ .

**Between searches.** After each augmentation, we reset the data structures to their initial state plus the change from augmentation using rewinding mechanism (see Section 2.2). This takes time proportional to the time for Hungarian search, which is  $O(r\sqrt{n} \text{polylog } n)$  by Lemma 5.3. The most recent augmentation may have deactivated  $O(1)$  active excess and deficit vertices, which takes  $O(\sqrt{n} \text{polylog } n)$  time to update. Finally, we note that an augmenting path cannot reduce the support degree of a vertex to zero, and therefore no new dead vertices are created by augmentation.

**Between excess scales.** When the excess scale changes, vertices that were previously inactive may become active, and vertices that were dead may be revived. If we have the data structures built at the end of the previous scale, then we can add in each new active vertex  $a \in A$  and charge the insertion to the (future) augmenting path or contraction which eventually causes the vertex being inactive or absorbed. By Theorem 5.1, there are  $O(n \log n)$  such newly active vertices; each of them takes  $O(\sqrt{n} \text{ polylog } n)$  to update. So the total time spent is  $O(n^{3/2} \text{ polylog } n)$ .

**Putting it together.** After  $O(rn \text{ polylog } n)$  preprocessing, we spend  $O(r\sqrt{n} \text{ polylog } n)$  time on relaxations each Hungarian search by Lemma 5.3, for a total of  $O(rn^{3/2} \text{ polylog } n)$  time over the course of the algorithm. Rewinding takes the same amount of time. We spend up to  $O((r^2\sqrt{n} + rn) \text{ polylog } n)$  time switching stars between big/small. We spend  $O(n^{3/2} \text{ polylog } n)$  time activating and reviving vertices. Adding, the algorithm takes  $O(r^2\sqrt{n} + rn^{3/2}) \text{ polylog } n$  time to produce optimal potentials  $\pi^*$ , from which we can recover  $f^*$  in  $O(r\sqrt{n} \text{ polylog } n)$  additional time. This completes the proof of Theorem 1.3.

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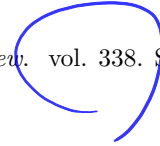


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## A Missing Details and Proofs from Section 2

### A.1 Potential updates

We modify a trick from Vaidya [39] to batch potential updates. Potentials have a *stored value*, i.e. the currently recorded value of  $\pi(v)$ , and a *true value*, which may have changed from  $\pi(v)$ . The resulting algorithm queries the minimum-reduced-cost under the true values of  $\pi$  and updates the stored value occasionally.

Throughout the entire Hungarian algorithm, we maintain a nonnegative scalar  $\delta$  (initially set to 0) which aggregates potential changes. Vertices  $a \in A$  that are added to  $S$  are inserted into BCP with weight  $\omega(a) \leftarrow \pi(a) - \delta$ , for whatever value  $\delta$  is at the time of insertion. Similarly, vertices  $b \in B$  that are added to  $S$  have  $\omega(b) \leftarrow \pi(b) - \delta$  recorded ( $B \cap S$  points aren't added into a BCP set). When the Hungarian search wants to raise the potentials of points in  $S$ ,  $\delta$  is increased by that amount instead. Thus, true value for any potential of a point in  $S$  is always  $\omega(p) + \delta$ . For points of  $(A \cup B) \setminus S$ , the true potential is equal to the stored potential. Since all the points of  $A \cap S$  have weights uniformly offset from their true potentials, the minimum edge returned by the BCP does not change. *«why?»*

Once a point is removed from  $S$  (i.e. by an augmentation or the rewinding mechanism), we update its stored potential  $\pi(p) \leftarrow \omega(p) + \delta$ , again for the current value of  $\delta$ . Most importantly,  $\delta$  is not reset at the end of a Hungarian search and persists through the entire algorithm. Thus, the initial BCP sets constructed by the rewinding mechanism have true potentials accurately represented by  $\delta$  and  $\omega(p)$ .

We update  $\delta$  once per edge relaxations; thus  $O(k)$  times in total per Hungarian search. There are  $O(k)$  stored values updated per Hungarian search during the rewinding process. The time spent on potential updates per Hungarian search is therefore  $O(k)$ .

## B Missing Details and Proofs from Section 3

### B.1 Preliminaries on Network Flows

**Network.** Let  $G = (V, E)$  be a directed graph, augmented by edge costs  $c$  and capacities  $u$ , and a supply-demand function  $\phi$  defined on the vertices. One can turn the graph  $G$  into a *network*  $N = (V, \vec{E})$ : For each directed edge  $(v, w)$  in  $E$ , insert two *arcs*  $v \rightarrow w$  and  $w \rightarrow v$  into the arc set  $\vec{E}$ ; the *forward arc*  $v \rightarrow w$  inherits the capacity and cost from the directed graph  $G$ , while the *backward arc*  $w \rightarrow v$  satisfies  $u(w \rightarrow v) = 0$  and  $c(w \rightarrow v) = -c(v \rightarrow w)$ . This we ensure that the graph  $(V, \vec{E})$  is *symmetric* and the cost function  $c$  is *antisymmetric* on  $N$ . The positive values of  $\phi(v)$  are referred to as *supply*, and the negative values of  $\phi(v)$  as *demand*. We assume that all capacities are nonnegative, all supplies and demands are integers, and the sum of supplies and demands is equal to zero. A *unit-capacity* network has all its edge capacities equal to 1. In this section we assume all networks are of unit-capacity.

**Pseudoflows.** Given a network  $N := (V, \vec{E}, c, u, \phi)$ , a *pseudoflow* (or *flow* to be short)  $f: \vec{E} \rightarrow \mathbb{Z}^3$  on  $N$  is an antisymmetric function on the arcs of  $N$  satisfying  $f(v \rightarrow w) \leq u(v \rightarrow w)$  for every arc  $v \rightarrow w$ . We sometimes abuse the terminology by allowing pseudoflow to be defined on a directed graph, in which case we are actually referring to the pseudoflow on the corresponding network by extending the flow values anti-symmetrically to the arcs.

<sup>3</sup> In general the pseudoflows are allowed to take real-values. Here under the unit-capacity assumption any optimal flows are integer-valued.

We say that  $f$  *saturates* an arc  $v \rightarrow w$  if  $f(v \rightarrow w) = u(v \rightarrow w)$ ; an arc  $v \rightarrow w$  is *residual* if  $f(v \rightarrow w) < u(v \rightarrow w)$ . The *support* of  $f$  in  $N$ , denoted as  $\text{supp}(f)$ , is the set of arcs with positive flows:

$$\text{supp}(f) := \left\{ v \rightarrow w \in \vec{E} \mid f(v \rightarrow w) > 0 \right\}.$$

Given a pseudoflow  $f$ , we define the *imbalance* of a vertex (with respect to  $f$ ) to be

$$\phi_f(v) := \phi(v) + \sum_{w \rightarrow v \in \vec{E}} f(w \rightarrow v) - \sum_{v \rightarrow w \in \vec{E}} f(v \rightarrow w).$$

We call positive imbalance *excess* and negative imbalance *deficit*; and vertices with positive and negative imbalance *excess vertices* and *deficit vertices*, respectively. A vertex is *balanced* if it has zero imbalance. If all vertices are balanced, the pseudoflow is a *circulation*. The *cost* of a pseudoflow is defined to be

$$\text{cost}(f) := \sum_{v \rightarrow w \in \text{supp}(f)} c(v \rightarrow w) \cdot f(v \rightarrow w).$$

The *minimum-cost flow problem (MCF)* asks to find a circulation of minimum cost inside a given directed graph.

**Residual graph.** Given a pseudoflow  $f$ , one can define the *residual network* as follows. Recall that the set of *residual arcs*  $\vec{E}_f$  under  $f$  are those arcs  $v \rightarrow w$  satisfying  $f(v \rightarrow w) < u(v \rightarrow w)$ . In other words, an arc that is not saturated by  $f$  is a residual arc; similarly, given an arc  $v \rightarrow w$  with positive flow value, the backward arc  $w \rightarrow v$  is a residual arc.

Let  $N = (V, \vec{E}, c, u, \phi)$  be a network constructed from graph  $G$ , with a pseudoflow  $f$  on  $N$ . The *residual graph*  $G_f$  of  $f$  has  $V$  as its vertex set and  $\vec{E}_f$  as its arc set. The *residual capacity*  $u_f$  with respect to pseudoflow  $f$  is defined to be  $u_f(v \rightarrow w) := u(v \rightarrow w) - f(v \rightarrow w)$ . Observe that the residual capacity is always nonnegative. We can define residual arcs differently using residual capacities:

$$\vec{E}_f = \{ v \rightarrow w \mid u_f(v \rightarrow w) > 0 \}.$$

In other words, the set of residual arcs are precisely those arcs in the residual graph, each of which has nonzero residual capacity.

### Admissible flow augmentation.

► **Lemma B.1.** *Let  $f$  be an  $\varepsilon$ -optimal pseudoflow in  $G$  and let  $f'$  be an admissible flow in  $G_f$ . Then  $f + f'$  is also  $\varepsilon$ -optimal.*

**Proof.** Augmentation by  $f'$  will not change the potentials, so any previously  $\varepsilon$ -optimal arcs remain  $\varepsilon$ -optimal. However, it may introduce new arcs  $v \rightarrow w$  with  $u_{f+f'}(v \rightarrow w) > 0$ , that previously had  $u_f(v \rightarrow w) = 0$ . We will verify that these arcs satisfy the  $\varepsilon$ -optimality condition.

If an arc  $v \rightarrow w$  is newly introduced this way, then by definition of residual capacities  $f(v \rightarrow w) = u(v \rightarrow w)$ . At the same time,  $u_{f+f'}(v \rightarrow w) > 0$  implies that  $(f + f')(v \rightarrow w) < u(v \rightarrow w)$ . This means that  $f'$  augmented flow in the reverse direction of  $v \rightarrow w$  ( $f'(w \rightarrow v) > 0$ ). By assumption, the arcs of  $\text{supp}(f')$  are admissible, so  $w \rightarrow v$  was an admissible arc ( $c_\pi(w \rightarrow v) \leq 0$ ). By antisymmetry of reduced costs, this implies  $c_\pi(v \rightarrow w) \geq 0 \geq -\varepsilon$ . Therefore, all arcs with  $u_{f+f'}(v, w) > 0$  respect the  $\varepsilon$ -optimality condition, and thus  $f + f'$  is  $\varepsilon$ -optimal. ◀

► **Lemma 3.1.** *The size of  $\text{supp}(f)$  is at most  $3k$  for any integer circulation  $f$  in reduction network  $N_H$ . As a corollary, the number of residual backward arcs is at most  $3k$ .*

**Proof.** Because  $f$  is a circulation,  $\text{supp}(f)$  can be decomposed into  $k$  paths from  $s$  to  $t$ . Each  $s$ -to- $t$  path in  $N_H$  is of length three, so the size of  $\text{supp}(f)$  is at most  $3k$ . As every backward arc in the residual network must be induced by positive flow in the opposite direction, the total number of residual backward arcs is at most  $3k$ . ◀

► **Lemma 3.2.** *Let  $f$  be an  $\varepsilon$ -optimal integer circulation in  $N_H$ , and  $f^*$  be an optimal integer circulation for  $N_H$ . Then,  $\text{cost}(f) \leq \text{cost}(f^*) + 6k\varepsilon$ .*

**Proof.** By Lemma 3.1, the total number of backward arcs in the residual network  $N_f$  is at most  $3k$ . Consider the residual flow in  $N_f$  defined by the difference between  $f^*$  and  $f$ . Since both  $f$  and  $f^*$  are both circulations and  $N_H$  has unit-capacity, the flow  $f - f^*$  is comprised of unit flows on a collection of edge-disjoint residual cycles  $\Gamma_1, \dots, \Gamma_\ell$ . Observe that each residual cycle  $\Gamma_i$  must have exactly half of its arcs being backward arcs, and thus we have  $\sum_i |\Gamma_i| \leq 6k$ .

Let  $\pi$  be some potential certifying that  $f$  is  $\varepsilon$ -optimal. Because  $\Gamma_i$  is a residual cycle, we have  $c_\pi(\Gamma_i) = c(\Gamma_i)$  since the potential terms telescope. We then see that

$$\text{cost}(f) - \text{cost}(f^*) = \sum_i c(\Gamma_i) = \sum_i c_\pi(\Gamma_i) \geq \sum_i (-\varepsilon) \cdot |\Gamma_i| \geq -6k\varepsilon,$$

where the second-to-last inequality follows from the  $\varepsilon$ -optimality of  $f$  with respect to  $\pi$ . Rearranging the terms we have that  $\text{cost}(f) \leq \text{cost}(f^*) + 6k\varepsilon$ . ◀

## B.2 Multiplicative approximation

Let  $T$  be the minimum spanning tree on input graph  $G$  and order its edges by increasing length as  $e_1, \dots, e_{r+n-1}$ . Let  $T_\ell$  denote the subgraph of  $T$  obtained by removing the heaviest  $\ell$  edges in  $T$ . Let  $i$  be the largest index so that the optimal solution to the geometric partial matching problem has edges between components of  $T_i$ . Choose  $j$  to be the smallest index larger than  $i$  satisfying  $c(e_j) \geq kn \cdot c(e_i)$ . For each component  $K$  of  $T_j$ , let  $G_K$  be the subgraph of  $G$  induced on vertices of  $K$ ; let  $A_K := K \cap A$  and  $B_K := K \cap B$ , respectively. We partition  $A$  and  $B$  into the collection of sets  $A_K$  and  $B_K$  according to the components  $K$  of  $T_j$ . Since  $j < i$ , the optimal partial matching in  $G$  can be partitioned into edges between  $A_K$  and  $B_K$  within  $G_K$ ; no optimal matching edges lie between components.

► **Lemma B.2 (Sharathkumar and Agarwal [35, §3.5]).** *Let  $G = (A, B, E_0)$  be the input to geometric partial matching problem, and consider the partitions  $A_K$  and  $B_K$  defined as above. Let  $M^*$  be the optimal partial matching in  $G$ . Then,*

- (i)  $c(e_i) \leq \text{cost}(M^*) \leq kn \cdot c(e_i)$ , and
- (ii) the diameter of  $G_K$  is at most  $kn^2 \cdot c(e_i)$  for every  $K \in T_j$ ,

To prove Lemma 3.3, we need to further modify the point set so that the cost of the optimal solution does not change, while the diameter of the *whole* point set is bounded. Move the points within each component in *translation* so that the minimum distances between points across components are at least  $kn \cdot c(e_i)$  but at most  $O(n \cdot kn^2 \cdot c(e_i))$ . This will guarantee that the optimal solution still uses edges within the components by Lemma B.2. The simplest way of achieving this is by aligning the components one by one into a “straight line”, so that the distance between the two farthest components is at most  $O(n)$  times the maximum diameter of the cluster.

Now one can prove Lemma 3.3 by computing an  $(\varepsilon c(e_i)/6k)$ -optimal circulation  $f$  on the point set after translations using additive approximation from Lemma 3.2, together with the bound  $c(e_i) \leq \text{cost}(M^*)$  from Lemma B.2.

One small problem remains: We need to show that such reduction can be performed in  $O(n \text{ polylog } n)$  time. Sharathkumar and Agarwal [35] have shown that the partition of  $A$  and  $B$  into  $A_K$ s and  $B_K$ s can be computed in  $O(n \text{ polylog } n)$  time, assuming that the indices  $i$  and  $j$  can be determined in such time as well. However in our application the choice of index  $i$  depends on the optimal solution of geometric partial matching problem which we do not know.

To solve this issue we perform a binary search on the edges  $e_1, \dots, e_{r+n-1}$ . **«Hmm, we have no way to check Lemma 4.5(i); but in fact a polynomial bound is good enough.»**  
**«UNRESOLVED ISSUE»**

### B.3 Number of iterations during refinement.

To this end we need a bound on the size of the support of  $f$  right before and throughout the execution of REFINE. This bound will also be used in the analysis for the running time of REFINE.

► **Lemma B.3.** *Let  $f$  be an integer pseudoflow in  $N_H$  with  $O(k)$  excess. Then, the size of the support of  $f$  is at most  $O(k)$ .*

**Proof.** Observe that the reduction graph  $H$  is a directed acyclic graph, and thus the support of  $f$  does not contain a cycle. Now  $\text{supp}(f)$  can be decomposed into a set of inclusion-maximal paths, each of which contributes a single unit of excess to the flow if the path does not terminate at  $t$  or if more than  $k$  paths terminate at  $t$ . By assumption, there are  $O(k)$  units of excess to which we can associate to the paths, and at most  $k$  paths (those that terminate at  $t$ ) that we cannot associate with a unit of excess. The length of any such paths is at most three by construction of the reduction graph  $H$ . Therefore we can conclude that the number of arcs in the support of  $f$  is  $O(k)$ . ◀

► **Corollary B.4.** *The size of  $\text{supp}(f)$  is at most  $O(k)$  for pseudoflow  $f$  right before or during the execution of REFINE.*

► **Lemma 3.4.** *Let  $f$  be a pseudoflow in  $N_H$  with  $O(k)$  excess. The procedure REFINE runs for  $O(\sqrt{k})$  iterations before the excess of  $f$  becomes zero.*

**Proof.** Let  $f_0$  and  $\pi_0$  be the flow and potential at the start of the procedure REFINE. Let  $f$  and  $\pi$  be the current flow and the potential. Let  $d(v)$  defined to be the amount of potential increase at  $v$ , measured in units of  $\varepsilon$ ; in other words,  $d(v) := (\pi(v) - \pi_0(v))/\varepsilon$ .

Now divide the iterations executed by the procedure REFINE into two phases: The transition from the first phase to the second happens when every excess vertex  $v$  has  $d(v) \geq \sqrt{k}$ . At most  $\sqrt{k}$  iterations belong to the first phase as each Hungarian search increases the potential  $\pi$  by at least  $\varepsilon$  for each excess vertex (and thus increases  $d(v)$  by at least one).

The number of iterations belonging to the second phase is upper bounded by the amount of total excess at the end of the first phase, because each subsequent push of a blocking flow reduces the total excess by at least one. We now show that the amount of such excess is at most  $O(\sqrt{k})$ . Consider the set of arcs  $E^+ := \{v \rightarrow w \mid f(v \rightarrow w) < f_0(v \rightarrow w)\}$ . The total amount of excess is upper bounded by the number of arcs in  $E^+$  that crosses an arbitrarily given cut  $X$  that separates the excess vertices from the deficit vertices, when the network has unit-capacity [19, Lemma 3.6]. Consider the set of cuts  $X_i := \{v \mid d(v) > i\}$  for  $0 \leq i < \sqrt{k}$ ; every such cut separates the excess vertices from the deficit vertices at the end of first phase. Each arc in  $E^+$  crosses at most 3 cuts of type  $X_i$  [19, Lemma 3.1]. So there is one  $X_i$  crossed



by at most  $3|E^+|/\sqrt{k}$  arcs in  $E^+$ . The size of  $E^+$  is bounded by the sum of support sizes of  $f$  and  $f_0$ ; by Corollary B.4 the size of  $E^+$  is  $O(k)$ . This implies an  $O(\sqrt{k})$  bound on the total excess after the first phase, which in turn bounds the number of iterations in the second phase. ◀

## C Missing Details and Proofs from Section 4

► **Lemma 4.1.** *Consider  $\tilde{\pi}$  an  $\varepsilon$ -optimal potential on  $\tilde{H}_f$  and  $\pi$  the corresponding potential constructed on  $H_f$ . Then, (1) potential  $\pi$  is  $\varepsilon$ -optimal on  $H_f$ , and (2) if arc  $\text{short}(\Pi)$  is admissible under  $\tilde{\pi}$ , then every arc in  $\Pi$  is admissible under  $\pi$ .*

**Proof.** Reduced costs for any arc from a normal vertex another is unchanged under either  $\tilde{\pi}$  or  $\pi$ . Recall that a null path is comprised of one  $A$ -to- $B$  arc, and one or two zero-cost arcs (connecting the null vertex/vertices to  $s$  and/or  $t$ ). With our choice of null vertex potentials, we observe that the zero-cost arcs still have zero reduced cost. It remains to prove that an arbitrary **«residual?»** arc  $(a, b)$  **«arc or directed edge?»** satisfies the  $\varepsilon$ -optimality condition and admissibility when either  $a$  or  $b$  is a null vertex.

By construction of the shortcut graph, there is always a null path  $\Pi$  that contains  $(a, b)$ . Observe that  $c_\pi(a, b) = c_\pi(\Pi)$ , independent to the type of null path. Again by construction,  $c_\pi(\Pi) = c_{\tilde{\pi}}(\text{short}(\Pi))$ , so we have  $c_\pi(a, b) = c_{\tilde{\pi}}(\text{short}(\Pi)) \geq -\varepsilon$ . Additionally, if  $\text{short}(\Pi)$  is admissible under  $\tilde{\pi}$ , then so is  $(a, b)$  under  $\pi$ . This proves the lemma. ◀

### C.1 Dynamic data structures for search procedures

Here we formally describe in details the set of dynamic data structure we use for the Hungarian search and depth-first search procedures.

For Hungarian search, we maintain the following for each type of outgoing arcs of  $\tilde{H}_f$  leaving  $\tilde{S}$ :

1. Non-shortcut backward arcs  $(v, w)$  with  $(w, v) \in \text{supp}(f)$ . For these, we can maintain a min-heap on  $\text{supp}(f)$  arcs as each  $v$  arrives in  $\tilde{S}$ .
2. Non-shortcut  $A$ -to- $B$  forward arcs. For these, we can use a BCP data structure between  $(A \setminus A_\emptyset) \cap \tilde{S}$  and  $(B \setminus B_\emptyset) \setminus \tilde{S}$ , weighted by potential.
3. Non-shortcut forward arcs from  $s$ -to- $A$  and from  $B$ -to- $t$ . For  $s$ , we can maintain a min-heap on the potentials of  $B \setminus \tilde{S}$ , queried while  $s \in \tilde{S}$ . For  $t$ , we can maintain a max-heap on the potentials of  $A \cap \tilde{S}$ , queried while  $t \notin \tilde{S}$ .
4. Shortcut arcs  $(s, b)$  corresponding to null 2-paths from  $s$  to  $b \in (B \setminus B_\emptyset) \setminus S$ . For these, we maintain a BCP data structure with  $P = A_\emptyset$ ,  $Q = (B \setminus B_\emptyset) \setminus S$  with weights  $\omega(p) = \pi(s)$  for all  $p \in P$ , and  $\omega(q) = \pi(q)$  for all  $q \in Q$ . A response  $(a, b)$  corresponds to th null 2-path  $(s, a, b)$ . This is only queried while  $s \in S$ .
5. Shortcut arcs  $(a, t)$  corresponding to null 2-paths from  $a \in (A \setminus A_\emptyset) \cap S$  to  $t$ . For these, we maintain a BCP data structure with  $P = (A \setminus A_\emptyset) \cap S$ ,  $Q = B_\emptyset \setminus S$  with weights  $\omega(p) = \pi(p)$  for all  $p \in P$ , and  $\omega(q) = \pi(t)$  for all  $q \in Q$ . A response  $(a, b)$  corresponds to th null 2-path  $(a, b, t)$ . This is only queried while  $t \notin S$ .
6. Shortcut arcs  $(s, t)$  corresponding to null 3-paths. For these, we maintain in a BCP data structure with  $P = A_\emptyset \setminus S$ ,  $Q = B_\emptyset \setminus S$  with weights  $\omega(p) = \pi(s)$  for all  $p \in P$ , and  $\omega(q) = \pi(t)$  for all  $q \in Q$ . A response  $(a, b)$  corresponds to th null 3-path  $(s, a, b, t)$ . This is only queried while  $s \in S$  and  $t \notin S$ .

For depth-first search, we maintain the following for each type of outgoing arcs of  $\tilde{H}_f$  leaving  $\tilde{S}$ :

1. Non-shortcut backward arcs  $(v', w')$  with  $(w', v') \in \text{supp}(f)$ . For these, we can maintain a min-heap on  $(w', v') \in \text{supp}(f)$  arcs for each normal  $v' \in V$ .
2. Non-shortcut  $A$ -to- $B$  forward arcs. For these, we maintain a NN data structure over  $P = (B \setminus B_\emptyset) \setminus \tilde{S}$ , with weights  $\omega(p) = \pi(p)$  for each  $p \in P$ . We subtract  $\pi(v')$  from the NN distance to recover the reduced cost of the arc from  $v'$ .
3. Non-shortcut forward arcs from  $s$ -to- $A$  and from  $B$ -to- $t$ . For  $s$ , we can maintain a min-heap on the potentials of  $B \setminus \tilde{S}$ , queried only if  $v' = s$ . For  $B$ -to- $t$  arcs, there is only one arc to check if  $v' \in B$ , which we can examine manually.
4. Shortcut arcs  $(s, b)$  corresponding to null 2-paths from  $s$  to  $b \in (B \setminus B_\emptyset) \setminus S$ . For these, we maintain a NN data structure with  $P = A_\emptyset$ ,  $Q = (B \setminus B_\emptyset) \setminus S$  with weights  $\omega(p) = \pi(s)$  for all  $p \in P$ , and  $\omega(q) = \pi(q)$  for all  $q \in Q$ . A response  $(a, b)$  corresponds to th null 2-path  $(s, a, b)$ . This is only queried if  $v' = s$ .
5. Shortcut arcs  $(a, t)$  corresponding to null 2-paths from  $a \in (A \setminus A_\emptyset) \cap S$  to  $t$ . For these, we maintain a NN data structure over  $P = B_\emptyset \setminus S$  with weights  $\omega(p) = \pi(t)$  for each  $p \in P$ . A response  $(v', b)$  corresponds to th null 2-path  $(v', b, t)$ . We subtract  $\pi(v')$  from the NN distance to recover the reduced cost of the arc from  $v'$ . This is not queried if  $t \in \tilde{S}$ .
6. Shortcut arcs  $(s, t)$  corresponding to null 3-paths. For these, we maintain in a NN data structure with  $P = A_\emptyset \setminus S$ ,  $Q = B_\emptyset \setminus S$  with weights  $\omega(p) = \pi(s)$  for all  $p \in P$ , and  $\omega(q) = \pi(t)$  for all  $q \in Q$ . A response  $(a, b)$  corresponds to th null 3-path  $(s, a, b, t)$ . This is only queried while  $v' = s$  and  $t \notin S$ .

## C.2 Number of relaxations

First we bound the number of relaxations performed by both the Hungarian search and the depth-first search.

► **Lemma C.1.** *Hungarian search performs  $O(k)$  relaxations before a deficit vertex is reached.*

**Proof.** **«TO BE REWRITTEN.»** First we prove that there are  $O(k)$  non-shortcut relaxations. Each edge relaxation adds a new vertex to  $S$ , and non-shortcut relaxations only add normal vertices. The vertices of  $V \setminus S$  fall into several categories: (i)  $s$  or  $t$ , (ii) vertices of  $A$  or  $B$  with 0 imbalance, and (iii) deficit vertices of  $A$  or  $B$  ( $S$  contains all excess vertices). The number of vertices in (i) and (iii) is  $O(k)$ , leaving us to bound the number of (ii) vertices.

An  $A$  or  $B$  vertex with 0 imbalance must have an even number of  $\text{supp}(f)$  edges. There is either only one positive-capacity incoming arc (for  $A$ ) or outgoing arc (for  $B$ ), so this quantity is either 0 or 2. Since the vertex is normal, this must be 2. We charge 0.5 to each of the two  $\text{supp}(f)$  arcs; the arcs of  $\text{supp}(f)$  have no more than 1 charge each. Thus, the number of type (ii) vertex relaxations is  $O(|\text{supp}(f)|)$ . By Corollary B.4,  $O(|\text{supp}(f)|) = O(k)$ .

Next we prove that there are  $O(k)$  shortcut relaxations. Recall the categories of shortcuts from the list of data structures above. We have shortcuts corresponding to (i) null 2-paths surrounding  $a \in A_\emptyset$ , (ii) null 2-paths surrounding  $b \in B_\emptyset$ , and (iii) null 3-paths, which go from  $s$  to  $t$ . There is only one relaxation of type (iii), since  $t$  can only be added to  $S$  once. The same argument holds for type (ii).

Each type (i) relaxation adds some normal  $b \in B \setminus B_\emptyset$  into  $S$ . Since  $b$  is normal, it must either have deficit or an adjacent arc of  $\text{supp}(f)$ . We charge this relaxation to  $b$  if it is deficit, or the adjacent arc of  $\text{supp}(f)$  otherwise. No vertex is charged more than once, and no  $\text{supp}(f)$  edge is charged more than twice, therefore the total number of type (i) relaxations is  $O(|\text{supp}(f)|)$ . By Corollary B.4,  $O(|\text{supp}(f)|) = O(k)$ . ◀

Similarly we can prove that there are  $O(k)$  relaxations during the DFS.

► **Corollary C.2.** *Depth-first search performs  $O(k)$  relaxations before a deficit vertex is reached.*

### C.3 Time analysis

Now we complete the time analysis by showing that each Hungarian search and depth-first search can be implemented in  $O(k \text{ polylog } n)$  time after a one-time  $O(n \text{ polylog } n)$ -time preprocessing.

► **Lemma C.3.** *After  $O(n \text{ polylog } n)$ -time preprocessing, each Hungarian search can be implemented in  $O(k \text{ polylog } n)$  time.*

**Proof.** Each of the constant number of data structures used by the Hungarian search can be constructed in  $O(n \text{ polylog } n)$  time. For each data structure queried during a relaxation, the new vertex moved into  $S$  causes a constant number of updates, each of which can be implemented in  $O(\text{polylog } n)$  time. We first prove that the number of BCP operations during the Hungarian search over is bounded by  $O(k)$ .

1. Let  $S^t$  denote the initial set  $S$  at the beginning of the  $t$ -th Hungarian search. Assume for now that, at the beginning of the  $(t + 1)$ -th Hungarian search, we have the set  $S^t$  from the previous iteration. To construct  $S^{t+1}$ , we remove the vertices that had excess decreased to zero by the  $t$ -th blocking flow. Thus, we are able to initialize  $S$  at the cost of one BCP deletion per excess vertex, which sums to  $O(k)$  over the entire course of REFINE. **«Too strong as a bound? Is it enough to look at one Hungarian search?»**
2. During each Hungarian search, a vertex entering  $S$  may incur one BCP insertion/deletion. We can charge the updates to the number of relaxations over the course of Hungarian search. The number of relaxations in a Hungarian search is  $O(k)$  by Lemma C.1.
3. To obtain  $S^t$ , we keep track of the points added to  $S^t$  since the last Hungarian search. After the augmentation, we remove those points added to  $S^t$ . By (2) there are  $O(k)$  such points to be deleted, so reconstructing  $S^t$  takes  $O(k)$  BCP operations.

For potential updates, we use the same trick by Vaidya [39] to lazily update potentials after vertices leave  $S$  (similar to Lemma ??), but this time only for normal vertices. Normal vertices are stored in each data structure with weight  $\omega(v) = \pi(v) - \delta$ , and  $\delta$  is increased in lieu of increasing the potential of vertices in  $S$ . When a vertex leave  $S$  (through the rewind mechanism above), we restore its potential as  $\pi(v) \leftarrow \omega(v) + \delta$ . With lazy updates, the number of potential updates on normal vertices is bounded by the number of relaxations in the Hungarian search, which is  $O(k)$  by Lemma C.1. Note that null vertex potentials are not handled in the Hungarian search. **«then where? Lemma C.6»** ◀

There are no potentials to update within DFS, so the running time of DFS boils down to the time spent to querying and updating the data structures.

► **Lemma C.4.** *After  $O(n \text{ polylog } n)$ -time preprocessing, each depth-first search can be implemented in  $O(k \text{ polylog } n)$  time.*

**Proof.** At the beginning of REFINE, we can initialize the  $O(1)$  data structures used in DFS in  $O(n \text{ polylog } n)$  time. We use the same rewinding mechanism as in Hungarian search (Lemma C.3) to avoid reconstructing the data structures across iterations of REFINE, so the total time spent is bounded by the  $O(\text{polylog } n)$  times the number of relaxations. By Corollary C.2, the running time for depth-first search is  $O(k \text{ polylog } n)$ . ◀

## C.4 Number of potential updates on null vertices

In our implementation of REFINE, we do not explicitly construct  $\tilde{H}_f$ ; instead we query its edges using BCP/NN oracles and min/max heaps on elements of  $H_f$ . Potentials on the null vertices are only required right before an augmentation sends a flow through a null path, making the null vertices it passes normal. We use the construction from Lemma 4.1 to obtain potential  $\pi$  on  $H_f$  such that the flow  $f$  is both  $\varepsilon$ -optimal and admissible with respect to  $\pi$ .

**Size of blocking flows.** Now we bound the total number arcs whose flow is updated by a blocking flow during the course of REFINE. This bounds both the time spent updating the flow on these arcs and also the time spent on null vertex potential updates (Lemma C.6).

► **Lemma C.5.** *The support of each blocking flow found in REFINE is of size  $O(k)$ .*

**Proof.** Let  $i$  be fixed and consider the invocation of DFS which produces the  $i$ -th blocking flow  $f_i$ . DFS constructs  $f_i$  as a sequence of admissible excess-deficit paths, which appear as path  $P$  in Algorithm ?? . Every arc in  $P$  is an arc relaxed by DFS, so  $N_i$  is bounded by the number of relaxations performed in DFS. Using Corollary C.2, we have  $N_i = O(k)$ . ◀

► **Lemma C.6.** *The number of end-of-REFINE null vertex potential updates is  $O(n)$ . The number of augmentation-induced null vertex potential updates in each invocation of REFINE is  $O(k \log k)$ .*

**Proof.** The number of end-of-REFINE potential updates is  $O(n)$ . Each update due to flow augmentation involves a blocking flow sending positive flow through a null path, causing a potential update on the passed null vertex. We charge this potential update to the edges of that null path, which are in turn arcs with positive flow in the blocking flow. For each blocking flow, no positive arc is charged more than twice. It follows that the number of augmentation-induced updates is at most the size of support of the blocking flow, which is  $O(k)$  by Lemma C.5. According to Lemma 3.4 there are  $O(\sqrt{k})$  iterations of REFINE before it terminates. Summing up we have an  $O(k\sqrt{k})$  bound over the course of REFINE. ◀

Now combining Lemma C.3, Lemma C.4, and Lemma C.6 completes the proof of Theorem 1.2.

## D Missing Details and Proofs from Section 5

### D.1 Uncapacitated MCF by excess scaling

We give an outline of the strongly polynomial-time algorithm for uncapacitated min-cost flow problem from Orlin [28]. Orlin's algorithm follows an *excess-scaling* paradigm originally due to Edmonds and Karp [14]. Consider the basic primal-dual framework used in the previous sections: The algorithm begins with both flow  $f$  and potentials  $\pi$  set to zero. Repeatedly runs a *Hungarian search* that raises potentials (while maintaining dual feasibility) to create an admissible augmenting excess-deficit path, on which we perform flow augmentations. In terms of cost,  $f$  is maintained to be 0-optimal with respect to  $\pi$  and each augmentation over admissible edges preserves 0-optimality (by Lemma B.1). Thus, the final circulation must be optimal. The excess-scaling paradigm builds on top of this skeleton by specifying (i) between which excess and deficit vertices we send flows, and (ii) how much flow is sent by the augmentation.

The excess-scaling algorithm maintains a *scale parameter*  $\Delta$ , initially set to  $U$ . A vertex  $v$  with  $|\phi_f(v)| \geq \Delta$  is called *active*. Each augmenting path is chosen between an active

excess vertex and an active deficit vertex. Once there are no more active excess or deficit vertices,  $\Delta$  is halved. Each sequence of augmentations where  $\Delta$  holds a constant value is called an *excess scale*. There are  $O(\log U)$  excess scales before  $\Delta < 1$  and, by integrality of supplies/demands,  $f$  is a circulation.

With some modifications to the excess-scaling algorithm, Orlin [28] obtains a strongly polynomial bound on the number of augmentations and excess scales. First, an *active* vertex is redefined to be one satisfying  $|\phi_f(v)| \geq \alpha\Delta$ , for a fixed parameter  $\alpha \in (0.5, 1)$ . Second, arcs with flow value at least  $3n\Delta$  at the beginning of a scale are *contracted* to create a new vertex, whose supply-demand is the sum of those on the two endpoints of the contracted arc. We use  $\hat{G} = (\hat{V}, \hat{E})$  to denote the resulting *contracted graph*, where each  $\hat{v} \in \hat{V}$  is a contracted component of vertices from  $V$ . Intuitively, the flow is so high on contracted arcs that no set of future augmentations can remove the arc from  $\text{supp}(f)$ . Third, in addition to halving,  $\Delta$  is aggressively lowered to  $\max_{v \in V} \phi_f(v)$  if there are no active excess vertices and  $f(v \rightarrow w) = 0$  holds for every arc  $v \rightarrow w \in \hat{E}$ . Finally, flow values are not tracked within contracted components, but once an optimal circulation is found on  $\hat{G}$ , optimal potentials  $\pi^*$  can be *recovered* for  $G$  by sequentially undoing the contractions. The algorithm then performs a post-processing step which finds the optimal circulation  $f^*$  on  $G$  by solving a max-flow problem on the set of admissible arcs under  $\pi^*$ .

## D.2 Implementing contractions

«**REWRITE**» Following Agarwal *et al.* [2], our geometric data structures must deal with real points in the plane instead of the contracted components. We will track the contracted components described in  $\hat{G}$  (e.g. with a disjoint-set data structure) and mark the arcs of  $\text{supp}(f)$  that are contracted. We maintain potentials on the points  $A$  and  $B$  directly, instead of the contracted components.

When conducting the Hungarian search, we initialize  $S$  to be the set of vertices from *active excess contracted components* who (in sum) meet the imbalance criteria. «**unclear**» Upon relaxing any  $v \in \hat{v}$ , we immediately relax all the contracted support arcs which span  $\hat{v}$ . Since the input network is uncapacitated, each contracted component is strongly connected in the residual network by the admissible forward/backward arcs of each contracted arc. «**unparsable**» To relax arcs in  $\hat{E}$ , we relax the support arcs before attempting to relax any non-support arcs. «**mention the reason to make support acyclic**» Relaxations of support arcs can be performed without further potential changes, since they are admissible by invariant.

During the augmentations, contracted residual arcs are considered to have infinite capacity, and we do not update the value of flows on these arcs. We allow augmenting paths to begin from any point  $a \in \hat{v} \cap A$  in an active excess component  $\hat{v}$ , and end at any point  $b \in \hat{w} \cap B$  in an active deficit component  $\hat{w}$ .

## D.3 Recovering the optimal flow

We use the recovery strategy from Agarwal *et al.* [2], which runs in  $O(n \text{ polylog } n)$  time. The main idea is that, if  $\mathcal{T}$  is an undirected *spanning tree of admissible edges* under optimal potentials  $\pi^*$ , then there exists an optimal flow  $f^*$  with support only on arcs corresponding to edges of  $\mathcal{T}$ . Intuitively,  $\mathcal{T}$  is a maximal set of linearly independent dual LP constraints for the optimal dual ( $\pi^*$ ), so there exists an optimal primal solution ( $f^*$ ) with support only on these arcs. To see this, we can use a perturbation argument: raising the cost of each non-tree edge by  $\varepsilon > 0$  does not change  $\text{cost}(\pi^*)$  or the feasibility of  $\pi^*$ , but does raise the cost of

any circulation  $f$  using non-tree edges. Strong duality suggests that  $\text{cost}(f^*) = \text{cost}(\pi^*)$  is unchanged, therefore  $f^*$  must have support only on the tree edges.

Since the arcs corresponding to edges of  $\mathcal{T}$  have no cycles, we can solve the maximum flow in linear time using the following greedy algorithm. Let  $\text{par}(v)$  be the parent of vertex  $v$  in  $\mathcal{T}$ . We begin with  $f^* = 0$  and process  $\mathcal{T}$  from its leaves upwards. For a supply leaf  $v$ , we satisfy its supply by choosing  $f^*(v \rightarrow \text{par}(v)) \leftarrow \phi(v)$ . Otherwise if leaf  $v$  is a demand vertex, we choose  $f^*(\text{par}(v) \rightarrow v) \leftarrow -\phi(v)$ . Once we've solved the supplies/demands for each leaf, then we can *trim* the leaves, removing them from  $\mathcal{T}$  and setting the supply/demand of each parent-of-a-leaf to its current imbalance. Then, we can recurse on this smaller tree and its new set of leaves.

► **Lemma D.1.** *Let  $G(\mathcal{T})$  be the subnetwork of  $G$  corresponding to edges of the undirected spanning tree  $\mathcal{T}$ . If there exists a flow in  $G(\mathcal{T})$  which satisfies every supply and demand, then the greedy algorithm finds the maximum flow in  $G(\mathcal{T})$  in  $O(n)$  time.*

**Proof.** Observe that, for any flow  $f$  in  $G$ ,  $\text{supp}(f)$  has no paths of length longer than one. Thus, if a flow  $f^*$  satisfying supplies/demands exists within  $G(\mathcal{T})$ , then each supply vertex has flow paths that terminate at its parent/children. Similarly, each demand vertex receive all its flow from its parent/children. Since there is only one option for a supply leaf (resp. demand leaf) to send its flow (resp. receive its flow), the greedy algorithm correctly identifies the values of  $f^*$  for arcs adjoining  $\mathcal{T}$  leaves. Trimming these leaves, we can apply this argument recursively for their parents. The running time of the greedy algorithm is  $O(n)$ , as leaves can be identified in  $O(n)$  time and no vertex becomes a leaf more than once. ◀

It remains to show how we construct  $\mathcal{T}$ . We begin with a (spanning) *shortest path tree* (SPT)  $T$  in the residual network of  $f$ , under reduced costs and rooted at an arbitrary vertex  $r$ . For the SPT to span, we need the additional assumption that  $G$  is strongly connected. We can make  $G$  strongly connected by adding a 0-supply vertex  $s$  with arcs  $s \rightarrow a$  for all  $a \in A$  and  $b \rightarrow a$  for all  $b \in B$ , with some high cost  $M$ . Following Orlin [28], these arcs cannot appear in an optimal flow if  $M$  is sufficiently high, and we can extend  $\pi^*$  to include  $s$  using  $\pi^*(s) = 0$  if  $M > \max_{b \in B} \pi^*(b)$ . This extension to  $\pi^*$  preserves feasibility.

The edges corresponding to arcs of  $T$  do not suffice for  $\mathcal{T}$ , since some SPT arcs may be inadmissible. Let  $d_r(v)$  be the shortest path distance of  $v \in A \cup B \cup \{s\}$  from  $r$ , and consider potentials  $\pi^\# = \pi^* - d_r$ .

► **Lemma D.2 Orlin [28] Lemma 3.** *Let  $f$  be a flow satisfying the optimality conditions with respect to  $\pi^*$ . Then, (i)  $f$  satisfies the optimality conditions with respect to  $\pi^\#$ , and (ii) all SPT arcs are admissible under  $\pi^\#$ .*

We can use this lemma to argue that  $\pi^\#$  is still optimal. Recall that  $f$  has values defined only on the non-contracted residual arcs; we can apply the first part of Lemma D.2 on these arcs. For arcs within contracted components, we use a different argument. Observe that each  $\hat{v} \in \hat{V}$  is spanned by a set of  $\text{supp}(f)$  arcs, which are admissible by invariant. Thus, all  $v \in \hat{v}$  are equidistant from  $r$ , and they will have the same value  $d_r(v)$ . It follows that the reduced costs of arcs with both endpoints in  $\hat{v}$  do not change when replacing  $\pi^*$  with  $\pi^\#$ , so arcs contained in  $\hat{v}$  that met the optimality conditions for  $\pi^*$  still meet them for  $\pi^\#$ .

From the second part of Lemma D.2, the SPT  $T$  is a spanning tree of admissible arcs under  $\pi^\#$ . We set  $\mathcal{T}$  to be the set of undirected edges corresponding to  $T$ .

**Computing the SPT.** We conclude by describing the procedure for building the SPT, i.e. by running Dijkstra's algorithm in the residual network. We use a geometric implementation



that is very similar to Hungarian search. We begin with  $S = \{r\}$  and  $d_r(r) = 0$ , where  $r$  is our arbitrary root. For all other vertices,  $d_r(v)$  is initially unknown. In each iteration, we relax the minimum-reduced cost arc  $v \rightarrow w$  in the frontier  $S \times (A \cup B) \setminus S$ , adding  $w$  to  $S$ , and setting  $d_r(w) = d_r(v) + c_{\pi^*}(v, w)$ . Once  $S = A \cup B$ , the SPT  $T$  is the set of relaxed arcs.

If an either direction of an arc of  $\text{supp}(f)$  enters the frontier, we relax it immediately. To detect support arcs, we build a list for each  $v \in A \cup B$  of the support arcs which use  $v$  as an endpoint, and once  $v \in S$  we check its list. There are  $O(n)$  support arcs in total (by acyclicity of  $E(\text{supp}(f))$ ), so the total time spent searching these lists is  $O(n)$ . Such relaxations are correct for the shortest path tree, since the support edges are admissible and reduced costs are nonnegative.

Other edges appearing in the frontier can be split into three categories:

1. Forward  $A$ -to- $B$  arcs. We query these using a BCP with  $P = A \cap S$  and  $Q = B \setminus S$ .
2.  $B$ -to- $s$  arcs. These will never have flow support. We can query the minimum with a max-heap on potentials of  $B \cap S$ . We query these while  $s \in S$ .
3.  $s$ -to- $A$  arcs. These will also never have flow support. We can query the minimum with a min-heap on potentials of  $A \setminus S$ . We query these while  $s \in S$ .

We perform  $O(n)$  relaxations and takes  $O(\text{polylog } n)$  time per relaxation, for non-support relaxations. An additional  $O(n)$  time is spent relaxing support edges. The total running time of Dijkstra's algorithm is  $O(n \text{ polylog } n)$ . Combining with Lemma D.1, we obtain the following.

► **Lemma D.3.** *Given optimal potentials  $\pi^*$  and an optimal contracted flow  $f$ , the optimal flow  $f^*$  can be computed in  $O(n \text{ polylog } n)$  time.*

#### D.4 Recovering the optimal flow for sum-of-distances.

When the matching objective uses the just the  $p$ -norms (that is, when  $q = 1$ ), we can prove that the subgraph formed by admissible arcs is in fact *planar*. Planarity gives us two things towards a simple  $f^*$  recovery: there are only a linear number of admissible arcs, and the max-flow on them can be solved in near-linear time with planar graph max-flow algorithms.

Up until now, we have not placed restrictions on coincidence between  $A$  and  $B$ , but for the next proof it is useful to do so. We can assume that all points within  $A \cup B$  are distinct, otherwise we can replace all points coincident at  $x \in \mathbb{R}^2$  with a single point whose supply/demand is  $\sum_{v \in A \cup B: v=x} \lambda(v)$ . This is roughly equivalent to transporting as much as we can between coincident supply and demand, and is optimal by triangle inequality.

Without loss of generality, assume  $\pi^*$  is nonnegative (raising  $\pi^*$  uniformly on all points does not change the objective or feasibility). Recall that  $\pi^*$  is feasibility if for all  $a \in A$  and  $b \in B$

$$c_{\pi^*}(a, b) = \|a - b\|_p - \pi^*(a) + \pi^*(b) \geq 0.$$

An arc  $a \rightarrow b$  is admissible when

$$c_{\pi^*}(a, b) = \|a - b\|_p - \pi^*(a) + \pi^*(b) = 0.$$

We note that these definitions have a nice visual: Place disks  $D_q$  of radius  $\pi(q)$  at each  $q \in A \cup B$ . Feasibility states that for all  $a \in A$  and  $b \in B$ ,  $D_a$  cannot contain  $D_b$  with a gap between their boundaries. The arc  $a \rightarrow b$  is admissible when  $D_a$  contains  $D_b$  and their boundaries are tangent.

► **Lemma D.4.** *Let  $\pi^*$  be a set of optimal potentials for the point sets  $A$  and  $B$ , under costs  $c(a, b) = \|a - b\|_p$ . Then, the set of admissible arcs under  $\pi^*$  form a planar graph.*

**Proof.** We assume the points of  $A \cup B$  are in general position (e.g. by symbolic perturbation) such that no three points are collinear. Let  $a_1 \rightarrow b_1$  and  $a_2 \rightarrow b_2$  be any pair of admissible arcs under  $\pi^*$ . We will isolate them from the rest of the points, considering  $\pi^*$  restricted to the four points  $\{a_1, a_2, b_1, b_2\}$ . Clearly, this does not change whether the two arcs cross. Observe that we can raise  $\pi^*(a_2)$  and  $\pi^*(b_2)$  uniformly, until  $c_\pi(a_2, b_1) = 0$ , without breaking feasibility or changing admissibility of  $a_1 \rightarrow b_1$  and  $a_2 \rightarrow b_2$ . Henceforth, we assume that we have modified  $\pi^*$  in this way to make  $a_2 \rightarrow b_1$  admissible. Given positions of  $a_1$ ,  $a_2$ , and  $b_1$ , we now try to place  $b_2$  such that  $a_1 \rightarrow b_1$  and  $a_2 \rightarrow b_2$  cross. Specifically,  $b_2$  must be placed within a region  $\mathcal{F}$  that lies between the rays  $\overrightarrow{a_2 a_1}$  and  $\overrightarrow{a_2 b_1}$ , and within the halfplane bounded by  $\overleftrightarrow{a_1 b_1}$  that does not contain  $a_2$ .

Let  $g_a(q) := \|a - q\| - \pi^*(a)$  for  $a \in A$  and  $q \in \mathbb{R}^2$ . Let the *bisector* between  $a_1$  and  $a_2$  be  $\beta := \{q \in \mathbb{R}^2 \mid g_{a_1}(q) = g_{a_2}(q)\}$ .  $\beta$  is a curve subdividing the plane into two open faces, one where  $g_{a_1}$  is minimized and the other where  $g_{a_2}$  is. From these definitions, admissibility of  $a_1 \rightarrow b_1$  and  $a_2 \rightarrow b_1$  imply that  $b_1$  is a point of the bisector.

We show that  $\mathcal{F}$  lies entirely on the  $g_{a_1}$  side of the bisector. First, we prove that the closed segment  $\overline{a_1 b_1}$  lies entirely on the  $g_{a_1}$  side, except  $b_1$  which lies on  $\beta$ . Any  $q \in \overline{a_1 b_1}$  can be written parametrically as  $q(t) = (1 - t)b_1 + ta_1$  for  $t \in [0, 1]$ . Consider the single-variable functions  $g_{a_1}(q(t))$  and  $g_{a_2}(q(t))$ .

$$\begin{aligned} g_{a_1}(q(t)) &= (1 - t)\|a_1 - b_1\| - \pi(a_1) \\ g_{a_2}(q(t)) &= \|(a_2 - b_1) - t(a_1 - b_1)\| - \pi(a_2) \end{aligned}$$

At  $t = 0$ , these expressions are equal. Observe that the derivative with respect to  $t$  of  $g_{a_1}(q(t))$  is less than  $g_{a_2}(q(t))$ . Indeed, the value of  $\frac{d}{dt}\|(a_2 - b_1) - t(a_1 - b_1)\|$  is at least  $-\|a_1 - b_1\| = \frac{d}{dt}g_{a_1}(q(t))$ , which is realized if and only if  $\frac{(a_2 - b_1)}{\|a_2 - b_1\|} = \frac{(a_1 - b_1)}{\|a_1 - b_1\|}$ . This corresponds to  $\overrightarrow{a_2 b_1}$  and  $\overrightarrow{a_1 b_1}$  being parallel, but this is disallowed since  $a_1, a_2, b_1$  are in general position. Thus,  $g_{a_1}(q(t)) \leq g_{a_2}(q(t))$  with equality only at  $b_1$ .

Now, we parameterize each point of  $\mathcal{F}$  in terms of points on  $\overline{a_1 b_1}$ . Every  $q \in \mathcal{F}$  can be written as  $q(t') = q' + t'(q' - a_2)$  for some  $q' \in \overline{a_1 b_1}$  and  $t \geq 0$ , i.e.  $q' = \overline{a_1 b_1} \cap \overrightarrow{a_2 q}$ . We call  $q'$  the *projection* of  $q$  onto  $\overline{a_1 b_1}$ . We can write  $g_{a_1}$  and  $g_{a_2}$  in terms of  $t'$  and observe that  $\frac{d}{dt'}g_{a_1}(q(t')) \leq \frac{d}{dt'}g_{a_2}(q(t'))$ , as the derivative of  $g_a(q(t'))$  is maximized if  $(q(t') - a)$  is parallel to  $(q(t') - a_2)$  and lower otherwise. Notably,  $q(t')$  with projection  $b_1$  have  $\frac{d}{dt'}g_{a_1}(q(t')) < \frac{d}{dt'}g_{a_2}(q(t'))$ , since  $a_1, a_2, b_1$  are in general position. Any  $q(t')$  with a different projection do not have strict inequality, but the projection itself has  $g_{a_1}(q') < g_{a_2}(q')$  for  $q' \neq b_1$  since it lies on  $\overline{a_1 b_1}$ . Therefore, for all  $q \in \mathcal{F} \setminus \{b_1\}$ ,  $g_{a_1}(q') < g_{a_2}(q')$ , and  $\mathcal{F}$  lies on the  $g_{a_1}$  side of the bisector except for  $b_1$  which lies on  $\beta$ . We can eliminate  $b_1$  as a candidate position for  $b_2$ , since points of  $B$  cannot coincide.

Observe that  $g_{a_1}(b) < g_{a_2}(b)$  for  $b \in B$  implies that  $c_\pi(a_1, b) < c_\pi(a_2, b)$ , and  $c_\pi(a_1, b) = c_\pi(a_2, b)$  if and only if  $b$  lies on  $\beta$ . This holds for all  $b \in \mathcal{F}$  including our prospective  $b_2$ , but then  $c_\pi(a_1, b_2) < c_\pi(a_2, b_2) = 0$  since  $a_2 \rightarrow b_2$  is admissible. This violates feasibility of  $a_1 \rightarrow b_2$ , so there is no feasible placement of  $b_2$  which also crosses  $a_1 \rightarrow b_1$  with  $a_2 \rightarrow b_2$ . ◀

We can construct the entire set of admissible arcs by repeatedly querying the minimum-reduced-cost outgoing arc for each  $a \in A$  until the result is not admissible. By Lemma D.4 the resulting arc set forms a planar graph, so by Euler's formula the number of arcs to query is  $O(n)$ . We can then find the maximum flow in time  $O(n \log n)$  time, using for example the planar maximum-flow algorithm by Erickson [15]. **◀cite others like Klein▶**

► **Lemma D.5.** *If the transportation objective is sum-of-costs, then given the optimal potentials  $\pi^*$ , we can compute an optimal flow  $f^*$  in  $O(n \text{ polylog } n)$  time.*

## D.5 Dead vertices

Let the *support degree* of a vertex be its degree in the graph induced by the underlying edges of  $\text{supp}(f)$ . We call a vertex  $b \in B$  *dead* if  $b$  has support degree 0 and is not an active excess or deficit vertex; call it *living* otherwise. Dead vertices are essentially equivalent to the *null vertices* of Section 3. However, since the reduction in this section does not use a super-source/super-sink, we can simply remove these from consideration during a Hungarian search — they will not terminate the search, and have no outgoing residual arcs. Like the null vertices, we ignore dead vertex potentials and infer feasible potentials when they become live again. We use  $A_\ell$  and  $B_\ell$  to denote the living vertices of points in  $A$  and  $B$ , respectively. Note that being dead/alive is a notion strictly defined only for vertices, and not for contracted components.

We say a dead vertex is *revived* when it stops meeting either condition of the definition. Dead vertices are only revived after  $\Delta$  decreases (at the start of a subsequent excess scale) as no augmenting path will cross a dead vertex and they cannot meet the criteria for contractions. When a dead vertex is revived, we must add it back into each of our data structures and give it a feasible potential. For revived  $b \in B$ , a feasible choice of potential is  $\pi(b) \leftarrow \max_{a \in A} (\pi(a) - c(a, b))$  which we can query by maintaining a weighted nearest neighbor data structure on the points of  $A$ . The total number of revivals is bounded above by the number of augmentations: since the final flow is a circulation on  $\hat{G}$  and a newly revived vertex  $v$  has no incident arcs in  $\text{supp}(f)$  and cannot be contracted, there is at least one subsequent augmentation which uses  $v$  as its beginning or end. Thus, the total number of revivals is  $O(n \log n)$ .

## D.6 Number of relaxations

By prioritizing the relaxation of support arcs, we also have the following lemma.

► **Lemma D.6 (Agarwal et al. [2]).** *If arcs of  $\text{supp}(f)$  are relaxed first as they arrive on the frontier, then  $E(\text{supp}(f))$  is acyclic.*

**Proof.** Let  $f_i$  be the pseudoflow after the  $i$ -th augmentation, and let  $T_i$  be the forest of relaxed arcs generated by the Hungarian search for the  $i$ -th augmentation. Namely, the  $i$ -th augmenting path is an excess-deficit path in  $T_i$ , and all arcs of  $T_i$  are admissible by the time the augmentation is performed. Let  $E(T_i)$  be the undirected edges corresponding to arcs of  $T_i$ . Notice that,  $E(\text{supp}(f_{i+1})) \subseteq E(\text{supp}(f_i)) \cup E(T_i)$ . We prove that  $E(\text{supp}(f_i)) \cup E(T_i)$  is acyclic by induction on  $i$ ; as  $E(\text{supp}(f_{i+1}))$  is a subset of these edges, it must also be acyclic. At the beginning with  $f_0 = 0$ ,  $E(\text{supp}(f_0))$  is vacuously acyclic.

Let  $E(\text{supp}(f_i))$  be acyclic by induction hypothesis. Since  $T_i$  is a forest (thus, acyclic), any hypothetical cycle  $\Gamma$  that forms in  $E(\text{supp}(f_i)) \cup E(T_i)$  must contain edges from both  $E(\text{supp}(f_i))$  and  $E(T_i)$ . To give a visual analogy, we will color  $e \in \Gamma$  *purple* if  $e \in E(\text{supp}(f_i)) \cap E(T_i)$ , *red* if  $e \in E(\text{supp}(f_i))$  but  $e \notin E(T_i)$ , and *blue* if  $e \in E(T_i)$  but  $e \notin E(\text{supp}(f_i))$ . Then,  $\Gamma$  is neither entirely red nor entirely blue. We say that red and purple edges are *red-tinted*, and similarly blue and purple edges are *blue-tinted*. Roughly speaking, our implementation of the Hungarian search prioritizes relaxing red-tinted admissible arcs over pure blue arcs.

We can sort the blue-tinted edges of  $\Gamma$  by the order they were relaxed into  $S$  during the Hungarian search forming  $T_i$ . Let  $(v, w) \in \Gamma$  be the last pure blue edge relaxed, of all the blue-tinted edges in  $\Gamma$  — after  $(v, w)$  is relaxed, the remaining unrelaxed, blue-tinted edges of  $\Gamma$  are purple.

Let us pause the Hungarian search the moment before  $(v, w)$  is relaxed. At this point,  $v \in S$  and  $w \notin S$ , and the Hungarian search must have finished relaxing all frontier support arcs. By our choice of  $(v, w)$ ,  $\Gamma \setminus (v, w)$  is a path of relaxed blue edges and red-tinted edges which connect  $v$  and  $w$ . Walking around  $\Gamma \setminus (v, w)$  from  $v$  to  $w$ , we see that every vertex of the cycle must be in  $S$  already:  $v \in S$ , relaxed blue edges have both endpoints in  $S$ , and any unrelaxed red-tinted edge must have both endpoints in  $S$ , since the Hungarian search would have prioritized relaxing the red-tinted edges to grow  $S$  before relaxing  $(v, w)$  (a blue edge). It follows that  $w \in S$  already, a contradiction.

No such cycle  $\Gamma$  can exist, thus  $E(\text{supp}(f_i)) \cup E(T_i)$  is acyclic and  $E(\text{supp}(f_{i+1})) \subseteq E(\text{supp}(f_i)) \cup E(T_i)$  is acyclic. By induction,  $E(\text{supp}(f_i))$  is acyclic for all  $i$ . ◀

Let  $E(\Sigma_a)$  **◀only used once▶** be the underlying edges of the support star centered at  $a$  and  $F := E(\text{supp}(f)) \setminus \bigcup_{a \in A} E(\Sigma_a)$ . Using Lemma D.6, we can show that the number of support arcs outside support stars  $(|F|)$  is small.

▶ **Lemma D.7.**  $|B_\ell \setminus \bigcup_{a \in A} \Sigma_a| \leq r$ .

**Proof.**  $F$  is constructed from  $E(\text{supp}(f))$  by eliminating edges in support stars, therefore all edges in  $F$  must adjoin vertices in  $B$  of support degree at least 2. By Lemma D.6,  $E(\text{supp}(f))$  is acyclic and therefore forms a spanning forest over  $A \cup B_\ell$ , so  $F$  is also a bipartite forest. All leaves of  $F$  are therefore vertices of  $A$ .

Pick an arbitrary root for each connected component of  $F$  to establish parent-child relationships for each edge. As no vertex in  $B$  is a leaf, each vertex in  $B$  has at least one child. Charge each vertex in  $B$  to one of its children in  $F$ , which must belong to  $A$ . Each vertex in  $A$  is charged at most once. Thus, the number of  $B_\ell$  vertices outside of support stars is no more than  $r$ . ◀

▶ **Lemma 5.2.** *Suppose we have stripped the graph of dead vertices. The number of relaxation steps in a Hungarian search outside of support stars is  $O(r)$ .*

**Proof.** If there are no dead vertices, then each non-support star relaxation step adds either (i) an active deficit vertex, (ii) a non-deficit vertex  $a \in A_\ell$ , or (iii) a non-deficit vertex  $b \in B_\ell$  of support degree at least 2. There is a single relaxation of type (i), as it terminates the search. The number of vertices of type (ii) is  $r$ , and the number of vertices of type (iii) is at most  $r$  by Lemma D.7. The lemma follows. ◀

▶ **Lemma 5.3.** *Hungarian search takes  $O(r\sqrt{n} \text{polylog } n)$  time.*

**Proof.** The number of relaxation steps outside of support stars is  $O(r)$  by Lemma 5.2. The time per relaxation outside of support stars is  $O(\sqrt{n} \text{polylog } n)$ . The time spent processing relaxations within a support star is  $O(\sqrt{n} \text{polylog } n)$ , and at most  $r$  are relaxed during the search. The total time is therefore  $O(r\sqrt{n} \text{polylog } n)$ . ◀

## D.7 Updating support stars

Initially, we label stars big or small according to the  $\sqrt{n}$  threshold. Afterwards, a star that is currently big is turned into a small star once  $|\Sigma_a| \leq \sqrt{n}/2$ , and star that is currently small is turned into a big star once  $|\Sigma_a| \geq 2\sqrt{n}$ . We say a star which crosses one of these size thresholds is **changing state** (from small-to-big or big-to-small), and must be represented in the opposite type of data structure. Our strategy is to charge the data structure update time associated with a state change to the **membership changes** in  $\Sigma_a$  that preceeded the state change.

1241 A star  $\Sigma_a$  undergoing a big-to-small state change has size  $|\Sigma_a| \leq \sqrt{n}/2$ . The state change  
 1242 deletes  $\mathcal{D}_{\text{big}}(a)$  and inserts  $\Sigma_a$  into  $\mathcal{D}_{\text{small}}$ . Thus, the time spent for a big-to-small state  
 1243 change is  $O(\sqrt{n} \text{polylog } n)$ , and there were at least  $\sqrt{n}/2$  points removed from  $\Sigma_a$  since it  
 1244 last changed state. The amortized time for a big-to-small state change per star membership  
 1245 change is  $O(\text{polylog } n)$ .

1246 A star  $\Sigma_a$  undergoing a small-to-big state change has size  $|\Sigma_a| \geq 2\sqrt{n}$ . We can write its  
 1247 size as  $|\Sigma_a| = \sqrt{n} + x$  for some integer  $x \geq \sqrt{n}$ , so we also have  $|\Sigma_a| \leq 2x$ . When switching,  
 1248 we delete all  $|\Sigma_a|$  points from  $\mathcal{D}_{\text{small}}$  and construct a new  $\mathcal{D}_{\text{big}}(a)$ . Constructing  $\mathcal{D}_{\text{big}}(a)$   
 1249 requires inserting up to  $r$  points of  $A$  (into  $P$ ) and the  $|\Sigma_a|$  points of the star (into  $Q$ ). Thus,  
 1250 the time spent for a small-to-big state change is  $(r + 2x) \cdot O(\text{polylog } n)$ , and there were at  
 1251 least  $x$  points added to  $\Sigma_a$  since it last changed state. The amortized time for a small-to-big  
 1252 state change per star membership change is  $O((r/x) \text{polylog } n)$ . Since  $x \geq \sqrt{n}$ , this is at  
 1253 most  $O((r/\sqrt{n}) \text{polylog } n)$ .

1254 Star membership can only be changed by augmenting paths passing through the vertex,  
 1255 therefore the total number of membership changes is  $O(rn \log n)$  by Lemmas 5.1 and 5.2.  
 1256 Thus, the total time spent on state changes is  $O((r^2\sqrt{n} + rn) \text{polylog } n)$ .