

## ON OPTIMAL MATCHINGS

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Given  $n$  random blue and  $n$  random red points on the unit square, the transportation cost between them is typically  $\sqrt{n \log n}$ .

Given two sets of points  $X_1, \dots, X_n$ , and  $Y_1, \dots, Y_n$ , the transportation cost is defined as

$$T_n = \min_{\pi} \sum_{i=1}^n d(X_{\pi(i)}, Y_i),$$

where  $d$  stands for distance, and the min is taken over all permutations  $\pi$  of the integers  $1, \dots, n$ . The purpose of the paper is to investigate the transportation cost for random input  $X, Y$ .

Assume that the points  $X_1, \dots, X_n, Y_1, \dots, Y_n$  are chosen at random, independently of each other, with a uniform distribution on the unit square  $Q$ .

**Theorem**

$$(1) \quad C_1(n \log n)^{1/2} < T_n < C_2(n \log n)^{1/2}$$

with probability  $1 - o(1)$ .

A slightly weaker upper bound

$$T_n = O(n^{1/2} \log n)$$

has been achieved by Karp.

In one sense the two dimensional case is the most interesting case, for in one dimension  $T_n$  can be determined explicitly and thus its magnitude is easily seen, while in dimension  $r \geq 3$   $T_n$  is as small as  $n^{1-1/r}$ , which is a trivial lower bound for typical  $T_n$ , since nearest neighbours are at a distance  $n^{-1/r}$ .

(Observe that in one dimension the optimal matching is the merging of the two ordered samples. In case  $r \geq 3$  the final transport cost is resulted by a convergent sum which fact explains the absence of an extra  $(\log n)^c$  term.)

The Theorem generalizes to

$$T_n(p) = \min_{\pi} \sum_{i=1}^n d^p(X_{\pi(i)}, Y_i)$$

leading to the estimate  $n(\log n/n)^{p/2}$ , reflecting that a typical blue point moves a distance  $(\log n/n)^{1/2}$  to the coupled red point.

**Proof.** First we will prove the lower part of (1). Following the method of Ford and Fulkerson, we construct a Lipschitzian function  $f$  on  $Q$  such that

$$(2) \quad A(f) = \sum_{i=1}^n f(X_i) - \sum_{i=1}^n f(Y_i) \cong LC_1(n \cdot \log n)^{1/2},$$

where  $L$  is the Lipschitzian parameter of  $f$  i.e.

$$(3) \quad |f(x) - f(y)| \leq L d(x, y), \quad x, y \in Q.$$

Then, for arbitrary permutation  $\pi$ ,

$$T_n = \sum_{i=1}^n d(X_{\pi(i)}, Y_i) \cong \frac{1}{L} \sum_{i=1}^n |f(X_{\pi(i)}) - f(Y_i)| \cong C_1(n \log n)^{1/2}.$$

Roughly saying the construction goes as follows. Let  $m = 0.1 \log n$ . For  $i = 1, 2, \dots, m$  let  $Q_{ij}$ ,  $j = 1, 2, \dots, 4^i$  denote the subsquares of  $Q$  obtained by dividing both coordinates into  $2^i$  equal parts. Set

$$(4) \quad X(Q_{ij}) = \sum_k I(X_k, Q_{ij}), \quad Y(Q_{ij}) = \sum_k I(Y_k, Q_{ij}), \quad V(Q_{ij}) = X(Q_{ij}) - Y(Q_{ij}),$$

where  $I(x, A) = 1$  for  $x \in A$  and  $I(x, A) = 0$  otherwise. Then for the function  $f(u) = \sum_{ij} V(Q_{ij}) I(u, Q_{ij})$

$$(5) \quad A(f) = \sum_{ij} V^2(Q_{ij}) \sim Cn \log n.$$

(Here and from now on  $C$  denotes absolute constants with values varying from formula to formula.) For each fixed index  $i$  in (5) the summation on  $j$  results terms of magnitude  $Cn$  while  $i$  runs up to  $m = 0.1 \log n$ .

Unfortunately, this function  $f$  is not Lipschitzian. That is why we redefine  $V$  and  $f$  as follows. Let  $D(x, A)$  denote the distance of the point  $x$  and the set  $A$ , and  $D(A)$  the diameter of  $A$ . Now we set

$$(6) \quad V(Q_{ij}) = \sum_k \frac{D(X_k, \bar{Q}_{ij}) - D(Y_k, \bar{Q}_{ij})}{D(Q_{ij})},$$

and

$$f(u) = \sum_{i,j} \frac{V(Q_{ij})}{D(Q_{ij})} D(u, \bar{Q}_{ij}),$$

where bar indicates complementary set. This function is Lipschitzian already, but with a large constant. The Lipschitzian constant of the pyramidal function  $D(u, \bar{Q}_{ij})$  is 1, the value of the coefficient  $V(Q_{ij})/D(Q_{ij})$  is approximately normal with variance about  $n$ , and for any  $u \in Q$  the number of non-void terms in the sum is  $m =$

$0.1 \log n$ . The sum of these non-void terms is typically  $O((n \log n)^{1/2})$ , but at some points  $u$  the effects of the large deviations add up to  $n^{1/2} \log n$ .

For cutting down the Lipschitzian constant from  $n^{1/2} \log n$  to  $(n \log n)^{1/2}$  an appropriate stopping rule will be introduced.

Let  $Q_i^u$  denote the  $Q_{ij}$  that contains  $u$  and

$$f_i(u) = \frac{V(Q_i^u)}{D(Q_i^u)} D(u, \bar{Q}_i^u).$$

Then

$$f_i'(u) = \frac{V(Q_i^u)}{D(Q_i^u)} D'(u, \bar{Q}_i^u),$$

and the derivate  $D'(u, \bar{Q}_i^u)$  exists in the interiors of the four triangles into which the diagonals split the square  $Q_i^u$ . The values of this derivative are the four vectors  $(\pm 1, 0)$ ,  $(0, \pm 1)$ . Let the stopping time  $t(u)$  be defined as the largest  $t \leq m$  such that

$$(7) \quad \sup_{v \in Q_i^u} \max_{1 \leq k \leq t} \left| \sum_{i=1}^k f_i'(v) \right| \leq (Cn \log n)^{1/2}.$$

Now the final version of the function  $f$  is

$$(8) \quad f(u) = \sum_{i=1}^{t(u)} f_i(u).$$

This function  $f$  is continuous and piecewise differentiable, hence (7) implies that  $f$  is Lipschitzian with constant  $L = \sqrt{Cn \log n}$ .

Now we are going to show that for this  $f$  we still have  $A(f) \geq Cn \log n$  with probability  $1 - o(1)$ . Our stopping rule is such that the inequality  $t(u) \geq i$  implies  $t(v) \geq i$  for all  $v \in Q_i^u$ . Let  $U_{ij}$  be equal to 1 if  $t(u) \geq i$  on  $Q_{ij}$ , and zero otherwise.

Then

$$A(f) = \sum_{i,j} U_{ij} V^2(Q_{ij}).$$

The sequence of functions  $\tau_i$  defined by  $\tau_i(u) = 1$  if  $t(u) \geq i$ , and  $\tau_i(u) = 0$  otherwise, is monotone decreasing, hence so is the sequence of their integrals

$$U_i = \int_Q \tau_i(u) du = 4^{-i} \sum_j U_{ij}.$$

The main point is that

$$(9) \quad U_m \geq 1/2$$

with probability  $1 - o(1)$ . This implies that  $A(f) \geq Cn \log n$ , because with probability  $1 - o(1)$  we have

$$(10) \quad \sum_{j=1}^{4^i} \varepsilon_j V^2(Q_{ij}) \geq Cn$$

for any  $i$  and any choice of numbers  $\varepsilon_j = 0, 1$ , such that

$$\sum_{j=1}^{4^i} \varepsilon_j \geq \frac{1}{2} 4^i$$

if only  $C$  is small enough.

For proving (9) and (10) the following embedding theorem can be used ([3], [5]): Set

$$G(u) = \sum_{k=1}^n I(X_k, R^u), \quad u \in Q,$$

where  $R^u$  denotes the rectangle connecting the origin with the point  $u$ . Then there is a two-dimensional Wiener process  $W(u)$  such that the Brownian bridge

$$B(u) = W(u) - \lambda(R^u)W(1)$$

(where  $\lambda(A)$  stands for the area of the set  $A$ ) approximates  $G(u)$  in the following sense

$$(11) \quad P\left(\sup_{u \in Q} |G(u) - (n\lambda(R^n) + n^{1/2}B(n))| \geq \log n(C \log n + x)\right) \leq Ke^{-\alpha x},$$

$C, K, \alpha$  are positive absolute constants. Hence the process  $V(Q_{ij})$  is approximated by the corresponding Gaussian process  $W(Q_{ij})$  as near as  $C \log^2 n$  with probability  $1 - o(1)$ . For the Gaussian process  $W(Q_{ij})$  (9) and (10) are easily seen.

For defining the Wiener process  $W(Q_{ij})$  it is enough to postulate that for fixed index  $i$  the random variables  $W(Q_{ij})$  are independent Gaussian variables, and the set-function  $W(\cdot)$  is additive.

This implies the validity of (10) for the process  $V(Q_{ij})$  since the number of terms in (10) is  $4^i \leq 4^m \ll n/\log^2 n$ . Similarly, (9) is implied for  $V(Q_{ij})$  with a possibly smaller  $C$  in definition (7). Now we turn to proving the upper part of (1). We are going to assign to every point  $X_i$  a rectangle  $R_i^x$  of area  $1/n$  such that these rectangles form a partition of  $Q$ , and the transportation cost

$$S_n^X = \sum_{i=1}^n \int_{R_i^x} d(x_i, u) du$$

satisfies

$$S_n^X < C(n \log n)^{1/2}$$

with probability  $1 - o(1)$ . A similar construction for the points  $Y_i$  and the triangle inequality

$$T_n \leq S_n^X + S_n^Y$$

yield the upper part of (1). (Indeed, spreading the points  $X_i$  uniformly on the corresponding  $R_i^x$  and spreading the points  $Y_i$  uniformly on the corresponding  $R_i^y$  lead to the same uniform measure on  $Q$ , and thus they together determine a transportation from the points  $X_i$  to the points  $Y_i$ . The best transportation however is always a matching.)

Now given a set of points  $X_1, \dots, X_n$  in  $Q$ , we construct a monotone sequence of partitions  $\{R_{i1}, R_{i2}, \dots\}$   $i=1, 2, \dots$  such that the  $R_{ij}$  are (possibly degenerated) rectangles and

$$(12) \quad \lambda(R_{ij}) = \frac{1}{n} \lambda(Q_{ij}), \quad i = 1, 2, \dots, \quad j = 1, 2, \dots, 4^i,$$

(see (4)). Let us number the four quadrants  $Q_{11}, Q_{12}, Q_{13}, Q_{14}$  of  $Q$  as follows:

$\begin{pmatrix} 1 & 2 \\ 3 & 4 \end{pmatrix}$ . We push the horizontal bisector of  $Q$  for getting two halves of areas

$$\frac{1}{n}(X(Q_{11})+X(Q_{12})) \quad \text{and} \quad \frac{1}{n}(X(Q_{13})+X(Q_{14})).$$

In the upper half we push the vertical bisector to obtain the rectangles  $R_{11}$  and  $R_{12}$  with areas given in (12), and then do the same in the lower half. Note that the new vertical walls are not necessarily collinear. We can imagine the unit square  $Q$  as being made of a flexible membrane, and when pushing the walls the interiors of the quadrants transform in an affine way. In the next step we draw the bisectors within each quadrant  $R_{11}, R_{12}, R_{13}, R_{14}$  and then pushing the walls just as above we get the subrectangles  $R_{2,1}, \dots, R_{2,16}$  satisfying (12). We follow the same refining for all  $i \leq M = \log n$ . For a typical random sample  $X_i$ , every cell  $Q_{Mj}$  contains at most one sample point and thus every non-degenerate  $R_{Mj}$  is of area  $1/n$ .

Now we estimate the transportation cost. The height of  $R_{k1}$  is

$$h_{k1} = \prod_{i=1}^k \frac{X(Q_{i1}) + X(Q_{i2})}{X(Q_{i1}) + X(Q_{i2}) + X(Q_{i3}) + X(Q_{i4})} = \prod_{i=1}^k \frac{X(Q_{i1}) + X(Q_{i2})}{X(Q_{i-1,1})},$$

(where  $Q_{01} = Q$ ), and the width of  $R_{k1}$  is

$$w_{k1} = \prod_{i=1}^k \frac{X(Q_{i1})}{X(Q_{i1}) + X(Q_{i2})}.$$

The numbers  $h_{kj}$  and  $w_{kj}$  are of similar form. It is more complicated to follow the movement of the points of  $Q$ . Let  $u$  be an arbitrary point in  $Q$ . If  $Q_{ij}$  contains  $u$ , and  $w$  and  $h$  denote the distances of  $u$  from the nearest vertical and horizontal walls of  $Q_{ij}$ , then after the  $i$ -th step the image  $u_i$  of  $u$  in  $R_{ij}$  will have corresponding distances  $w2^i w_{ij}, h2^i h_{ij}$ . Hence in the  $(i+1)$ -st step the vertical shift of  $u_i$  will be

$$h2^{i+1} h_{i+1,j_1} - h2^i h_{ij} = h2^i h_{ij} \frac{X(Q_{i+1,j_1}) + X(Q_{i+1,j_2}) - X(Q_{i+1,j_3}) - X(Q_{i+1,j_4})}{X(Q_{i+1,j_1}) + X(Q_{i+1,j_2}) + X(Q_{i+1,j_3}) + X(Q_{i+1,j_4})}$$

and the horizontal shift will be

$$w2^{i+1} w_{i+1,j_1} - w2^i w_{ij} = w2^i w_{ij} \frac{X(Q_{i+1,j_1}) - X(Q_{i+1,j_2})}{X(Q_{i+1,j_1}) + X(Q_{i+1,j_2})},$$

where  $Q_{i+1,j_1}, Q_{i+1,j_2}, Q_{i+1,j_3}, Q_{i+1,j_4}$  are the four quadrants of  $Q_{ij}$  numbered as before and for simplicity of notation we assumed that  $u$  lies in  $Q_{i+1,j_1}$ . The magnitude of both  $w$  and  $w_{ij}$  is  $2^{-i}$ , that of  $X(Q_{i+1,j_1}) + X(Q_{i+1,j_2})$  is  $n4^{-i}$ , and that of  $X(Q_{i+1,j_1}) - X(Q_{i+1,j_2})$  is  $n^{1/2}2^{-i}$ . Hence the magnitude of the horizontal shift is  $n^{-1/2}$ . The same holds for the vertical shift. These shifts are symmetrically distributed random variables and the shifts of a given point in different steps are nearly independent, thus it can be expected that their sum is of order  $M^{1/2}n^{-1/2}$ . For proving this latter statement one can again use the embedding (11) as long as  $n2^{-i} \gg \log n$  and estimating the effect of the remaining  $\log \log n$  steps simply by the sum of absolute values of the shifts, i.e. by  $o(n^{-1/2} \log \log n)$ .

### References

- [1] L. R. FORD, JR. and D. R. FULKERSON, A simple algorithm for finding maximal network flows and an application to the Hitchcock problem. *Canad. J. Math.* **9** (1957), 210—218.
- [2] R. KARP, Private communication (1982).
- [3] J. KOMLÓS, P. MAJOR and G. TUSNÁDY, An approximation of partial sums of independent RV's, and the sample DF. *I. Z. Wahrscheinlichkeitstheorie verw. Gebiete* **32** (1975), 111—131.
- [4] G. SCHAY, Nearest random variables with given distributions. *Ann. of Probab.* **2** (1974), 163—166.
- [5] G. TUSNÁDY, A remark on the approximation of the sample DF in the multidimensional case. *Periodica Mathematica Hungarica* **8** (1977), 53—55.

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