

WHAT DOES A RANDOM CONTINGENCY TABLE LOOK LIKE?

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ABSTRACT. Let $R = (r_1, \dots, r_m)$ and $C = (c_1, \dots, c_n)$ be positive integer vectors such that $r_1 + \dots + r_m = c_1 + \dots + c_n$. We consider the set $\Sigma(R, C)$ of non-negative $m \times n$ integer matrices (contingency tables) with row sums R and column sums C as a finite probability space with the uniform measure. We prove that a random table $D \in \Sigma(R, C)$ is close with high probability to a particular matrix (“typical table”) Z defined as follows. We let $g(x) = (x + 1) \ln(x + 1) - x \ln x$ for $x \geq 0$ and let $g(X) = \sum_{i,j} g(x_{ij})$ for a non-negative matrix $X = (x_{ij})$. Then $g(X)$ is strictly concave and attains its maximum on the polytope of non-negative $m \times n$ matrices X with row sums R and column sums C at a unique point, which we call the typical table Z .

1. INTRODUCTION AND THE MAIN RESULT

(1.1) Random contingency tables. Let $R = (r_1, \dots, r_m)$ be a positive integer m -vector and let $C = (c_1, \dots, c_n)$ be a positive integer n -vector such that

$$\sum_{i=1}^m r_i = \sum_{j=1}^n c_j = N.$$

A *contingency table with margins* (R, C) is a non-negative integer matrix $D = (d_{ij})$ with row sums R and column sums C :

$$\sum_{j=1}^n d_{ij} = r_i \quad \text{for } i = 1, \dots, m, \quad \sum_{i=1}^m d_{ij} = c_j \quad \text{for } j = 1, \dots, n,$$
$$d_{ij} \geq 0 \quad \text{and} \quad d_{ij} \in \mathbb{Z} \quad \text{for all } i, j.$$

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Let $\Sigma(R, C)$ be the set of all contingency tables with margins (R, C) . As is well known, $\Sigma(R, C)$ is non-empty and finite. Let us consider $\Sigma(R, C)$ as a finite probability space endowed with the uniform probability measure. In this paper we address the following question:

Suppose that $D \in \Sigma(R, C)$ is chosen at random. What is D likely to look like?

The problem is interesting in its own right, but the main motivation comes from statistics; see [Go63], [DE85], [DG95] and references therein. A contingency table $D = (d_{ij})$ may represent certain statistical data (for example, d_{ij} may be the number of people in a certain sample having the i -th hair color and the j -th eye color). One can condition on the row and column sums and ask what is special about a particular table $D \in \Sigma(R, C)$, considering all tables in $\Sigma(R, C)$ as equiprobable; see [DE85]. To answer this question we need to know what a random table $D \in \Sigma(R, C)$ looks like. Considerable effort was invested in finding an efficient (polynomial time) algorithm to *sample* a random table $D \in \Sigma(R, C)$; see [DG95], [D+97], [C+06]. Despite a number of successes, such an algorithm is still at large in many interesting situations. In this paper, we do not discuss how to sample a random table but describe instead what it is likely to look like.

We prove that a random contingency table D is close in a certain sense to some particular non-negative $m \times n$ matrix Z , which we call the *typical table*.

(1.2) The typical table. Let $\mathcal{P}(R, C)$ be the set of all $m \times n$ non-negative matrices $X = (x_{ij})$ with row sums R and column sums C :

$$\sum_{j=1}^n x_{ij} = r_i \quad \text{for } i = 1, \dots, m, \quad \sum_{i=1}^m x_{ij} = c_j \quad \text{for } j = 1, \dots, n \quad \text{and}$$

$$x_{ij} \geq 0 \quad \text{for all } i, j.$$

Geometrically, $\mathcal{P}(R, C)$ is a convex polytope of dimension $(m-1)(n-1)$, known as the *transportation polytope*. Let

$$g(x) = (x+1) \ln(x+1) - x \ln x \quad \text{for } x \geq 0$$

and let

$$g(X) = \sum_{i,j} g(x_{ij})$$

for a non-negative matrix $X = (x_{ij})$. One can easily check that g is strictly concave and hence achieves a unique maximum $Z = (z_{ij})$ on $\mathcal{P}(R, C)$. We call Z the *typical table* with margins (R, C) . Since the objective function g is concave, Z can be computed efficiently, both in theory and in practice, by existing methods of convex optimization, cf. [NN94].

The solution Z to the above optimization problem was first introduced in the author's paper [Ba09]. It was given the name of "typical table" (perhaps with not enough justification) in [B+08].

In this paper, we show that Z indeed captures some typical features of a random table $D \in \Sigma(R, C)$.

We prove our main result assuming certain regularity ("smoothness") of margins.

(1.3) Smooth margins. Let us fix a number $0 < \delta \leq 1$. First, we assume that the row sums and column sums are of the same order:

$$(1.3.1) \quad \begin{aligned} \frac{\delta N}{m} &\leq r_i \leq \frac{N}{\delta m} && \text{for } i = 1, \dots, m \quad \text{and} \\ \frac{\delta N}{n} &\leq c_j \leq \frac{N}{\delta n} && \text{for } j = 1, \dots, n. \end{aligned}$$

Second, we assume that the *density* of the table is separated from 0:

$$(1.3.2) \quad \frac{N}{mn} \geq \delta.$$

We say that the margins (R, C) are δ -*smooth* if conditions (1.3.1)–(1.3.2) are satisfied. This is a modification of the definition from [B+08]. We note that δ -smooth margins are also δ' -smooth for any $0 < \delta' < \delta$. As we remarked (see (1.3.2)), we are interested in tables with the density separated from 0. For the case of sparse tables, where $r_i \ll n$ and $c_j \ll m$, see [Ne69], [GM08] and references therein.

Without loss of generality, we assume that $n \geq m$.

(1.4) Definitions and notation. Let us choose a non-empty subset of entries of a matrix:

$$S \subset \{(i, j) : 1 \leq i \leq m, 1 \leq j \leq n\}.$$

For an $m \times n$ matrix $A = (a_{ij})$ let

$$\sigma_S(A) = \sum_{(i,j) \in S} a_{ij}$$

be the sum of the entries from S .

The cardinality of a finite set X is denoted by $|X|$.

Now we state our main result.

(1.5) Theorem. *Let us fix real numbers $0 < \delta \leq 1$ and $\kappa > 0$. Then there exists a positive integer $q = q(\delta, \kappa)$ such that the following holds:*

Suppose that (R, C) are δ -smooth margins such that $n \geq m \geq q$.

Let

$$S \subset \{(i, j) : 1 \leq i \leq m, 1 \leq j \leq n\}$$

be a set such that

$$|S| \geq \delta mn,$$

let Z be the typical table with margins (R, C) , and let

$$\epsilon = \delta \frac{\ln n}{m^{1/3}}.$$

If $\epsilon \leq 1$ then

$$\Pr \left\{ D \in \Sigma(R, C) : \right. \\ \left. (1 - \epsilon)\sigma_S(Z) \leq \sigma_S(D) \leq (1 + \epsilon)\sigma_S(Z) \right\} \geq 1 - 2n^{-\kappa n}.$$

In other words, asymptotically, as far as the sum over a positive fraction of entries is concerned, a contingency table D sampled uniformly at random from the set of contingency tables with given margins is very likely to be close to the typical table Z .

(1.6) The independence table. In [Go63], I.J. Good observes that the *independence table*

$$Y = (y_{ij}), \quad y_{ij} = r_i c_j / N \quad \text{for all } i, j,$$

maximizes the entropy

$$H(X) = \sum_{i,j} \frac{x_{ij}}{N} \ln \frac{N}{x_{ij}}$$

on the set of all matrices $X = (x_{ij})$ in the transportation polytope $\mathcal{P}(R, C)$. One may be tempted to think that the independence table Y , not the typical table Z , reflects the structure of a random table $D \in \Sigma(R, C)$.

One can show that $Y = Z$ if and only if all row sums r_i are equal or all column sums c_j are equal. In fact, particular entries of the matrices Z and Y may demonstrate very different behavior even for reasonably looking margins. Suppose, for example, that $m = n$, that $r_1 = c_1 = 3n$ and that $r_i = c_i = n$ for $i > 1$. Hence $N = 3n + n(n - 1) = n^2 + 2n$ and for the independence table we have

$$y_{11} = \frac{9n^2}{n^2 + 2n} \leq 9.$$

On the other hand, for the typical table Z the entry z_{11} grows linearly in n . Indeed, the optimality condition for Z (the gradient of g at Z is orthogonal to the affine span of the transportation polytope) implies that

$$\ln \left(\frac{z_{ij} + 1}{z_{ij}} \right) = \lambda_i + \mu_j \quad \text{for all } i, j$$

and some $\lambda_1, \dots, \lambda_m, \mu_1, \dots, \mu_n$; see Section 2.3. By symmetry, we can choose $\lambda_1 = \mu_1 = \alpha$ and $\lambda_i = \mu_i = \beta$ for $i > 1$. Moreover, we must have $0 < \alpha < \beta$. Since

$$z_{21} = \frac{1}{e^{\alpha+\beta} - 1} > \frac{1}{e^{2\beta} - 1} = z_{2j} \quad \text{for all } j > 1$$

and $r_2 = n$, we should have

$$\beta > \frac{\ln 2}{2}.$$

Therefore,

$$z_{1j} = \frac{1}{e^{\alpha+\beta} - 1} < \frac{1}{e^{\beta} - 1} < \frac{1}{\sqrt{2} - 1} \quad \text{for } j > 1.$$

Since $r_1 = 3n$ we must have

$$z_{11} > 3n - \frac{n}{\sqrt{2} - 1} > 0.58n.$$

Let us show that the independence table Y and the typical table Z may also produce different asymptotic behavior of the sums $\sigma_S(Y)$ and $\sigma_S(Z)$ as m and n grow and S is a subset of entries consisting of a positive fraction of all entries as in Theorem 1.5. For that, let us fix some margins $R = (r_1, \dots, r_m)$ and $C = (c_1, \dots, c_n)$ such that $z_{11} \neq y_{11}$. For a positive integer k let us consider the ‘‘cloned’’ margins

$$(1.6.1) \quad \begin{aligned} R_k &= \left(\underbrace{kr_1, \dots, kr_1}_{k \text{ times}}, \dots, \underbrace{kr_m, \dots, kr_m}_{k \text{ times}} \right) \quad \text{and} \\ C_k &= \left(\underbrace{kc_1, \dots, kc_1}_{k \text{ times}}, \dots, \underbrace{kc_n, \dots, kc_n}_{k \text{ times}} \right). \end{aligned}$$

In particular, tables $D \in \Sigma(R_k, C_k)$ are $km \times kn$ matrices whose total sum of entries is equal to k^2N , where $N = r_1 + \dots + r_m = c_1 + \dots + c_n$. Let $S = S_k$ be the set of entries in the upper left $k \times k$ corner of a matrix from $\Sigma(R_k, C_k)$, let Y_k be the independence table of margins (R_k, C_k) and let Z_k be the typical table of margins (R_k, C_k) . It is not hard to show that $\sigma_S(Z_k) = k^2z_{11}$ and $\sigma_S(Y_k) = k^2y_{11}$, so the ratio between the two sums remains fixed (and not equal to 1) as k grows.

It looks plausible that the independence table Y is indeed close with high probability to a random table $D \in \Sigma(R, C)$, if, instead of the uniform distribution in $\Sigma(R, C)$, a table $D = (d_{ij})$ is sampled from the Fisher-Yates probability measure, where

$$\mathbf{Pr}(D) = (N!)^{-1} \left(\prod_{i=1}^m r_i! \right) \left(\prod_{j=1}^n c_j! \right) \left(\prod_{ij} \frac{1}{d_{ij}!} \right);$$

see [DG95]. Compared with the uniform distribution, the Fisher-Yates measure gives less weight to tables with large entries.

Let $p, q > 0$ be real numbers such that $p + q = 1$. Recall that a discrete random variable x has *geometric distribution* if

$$\mathbf{Pr}\{x = k\} = pq^k \quad \text{for } k = 0, 1, \dots$$

We have

$$\mathbf{E}x = \frac{q}{p}.$$

Consequently,

$$\text{if } \mathbf{E}x = z \quad \text{then} \quad p = \frac{1}{1+z} \quad \text{and} \quad q = \frac{z}{1+z}.$$

The following interpretation of the typical matrix was suggested to the author by J.A. Hartigan; see [BH09].

(1.7) Theorem. Let $Z = (z_{ij})$ be the $m \times n$ typical table with margins (R, C) . Let $X = (x_{ij})$ be the random $m \times n$ matrix of independent geometric random variables x_{ij} such that

$$\mathbf{E} x_{ij} = z_{ij} \quad \text{for all } i, j.$$

Then the probability mass function of X is constant on the set $\Sigma(R, C)$ of contingency tables with margins (R, C) , and, moreover,

$$\Pr \{X = D\} = e^{-g(Z)} \quad \text{for all } D \in \Sigma(R, C),$$

where g is the function defined in Section 1.2.

In other words, the multivariate geometric distribution X whose expectation is the typical matrix Z , when conditioned on the set $\Sigma(R, C)$ of contingency tables, results in the uniform probability distribution on $\Sigma(R, C)$. It turns out that for a positive $m \times n$ matrix A the value of $g(A)$ is equal to the maximum possible entropy of a random matrix with expectation A and values in the set $\mathbb{Z}_+^{m \times n}$ of $m \times n$ non-negative integer matrices. Such a maximum entropy random matrix is necessarily a matrix with independent geometrically distributed entries. Therefore, the distribution of X in Theorem 1.7 can be characterized as the maximum entropy distribution in the class consisting of all probability distributions on $\mathbb{Z}_+^{m \times n}$ whose expectations lie in the affine subspace consisting of the matrices with row sums R and column sums C ; see [BH09].

(1.8) Possible ramifications and open questions. Theorem 1.7 allows one to interpret Theorem 1.5 as a law of large numbers for contingency tables: with respect to sums $\sigma_S(D)$ for sufficiently large sets S of entries, a random contingency table $D \in \Sigma(R, C)$ behaves approximately as the matrix of independent geometric variables whose expectation is the typical table. Similar concentration results can be obtained for other well-behaved functions on contingency tables. One can ask whether the distribution of a *particular entry* of a random table $D \in \Sigma(R, C)$ is asymptotically geometric, as the dimensions m and n of the table grow. For example, does the first entry d_{11} of the table converge in distribution to the geometric random variable with expectation z_{11} when the margins (R, C) are cloned, $(R, C) \mapsto (R_k, C_k)$, as in (1.6.1)?

Let us fix a subset

$$W \subset \{(i, j) : i = 1, \dots, m; j = 1, \dots, n\}.$$

Let us consider the set $\Sigma(R, C; W)$ of $m \times n$ non-negative integer matrices $D = (d_{ij})$ with row sums R , column sums C and such that $d_{ij} = 0$ for $(i, j) \notin W$. Assuming that $\Sigma(R, C; W)$ is non-empty, we can consider $\Sigma(R, C; W)$ as a finite probability space with the uniform measure and ask what a random table $D \in \Sigma(R, C; W)$ looks like.

As above, we define the typical table Z as the unique maximum of $g(X)$ on the polytope of non-negative matrices $X = (x_{ij})$ with row sums R , column sums C

and such that $x_{ij} = 0$ for $(i, j) \notin W$. One can prove versions of Theorem 1.5 and Theorem 1.7 in this more general context for subsets $S \subset W$. However, it appears that for Theorem 1.5 one has to assume, additionally, that there are no too large or too small values among the entries z_{ij} of the typical table $Z = (z_{ij})$, cf. the example in Section 1.6. In our case, when W is the set of all pairs (i, j) , Lemma 2.4 ensures that the entries z_{ij} are not too small while Lemma 3.3 ensures that they are not too large.

In [Ba08] another variation of the problem is considered: what if we require $d_{ij} \in \{0, 1\}$ for all i, j . It turns out that a random D is close to a particular matrix maximizing the sum of entropies of the entries among all matrices with row sums R , column sums C and entries between 0 and 1.

In the rest of the paper, we prove Theorem 1.5.

In Section 2, we recall the main results of [Ba09] connecting the typical table Z with an asymptotic estimate for the number $|\Sigma(R, C)|$ of tables and also prove Theorem 1.7.

In Section 3, we prove Theorem 1.5 under the additional assumption that the total sum N of the entries is bounded by a polynomial in m and n .

In Section 4, we complete the proof of Theorem 1.5.

2. PRELIMINARIES: AN ASYMPTOTIC FORMULA FOR THE NUMBER OF TABLES

In [Ba09], the following result was proved; see Theorem 1.1 there.

(2.1) Theorem. *Let $R = (r_1, \dots, r_m)$ and $C = (c_1, \dots, c_n)$ be positive integer vectors such that $r_1 + \dots + r_m = c_1 + \dots + c_n = N$. Let us define a function*

$$F(\mathbf{x}, \mathbf{y}) = \left(\prod_{i=1}^m x_i^{-r_i} \right) \left(\prod_{j=1}^n y_j^{-c_j} \right) \left(\prod_{i,j} \frac{1}{1 - x_i y_j} \right)$$

for $\mathbf{x} = (x_1, \dots, x_m)$ and $\mathbf{y} = (y_1, \dots, y_n)$.

Then $F(\mathbf{x}, \mathbf{y})$ attains its infimum

$$\rho(R, C) = \min_{\substack{0 < x_1, \dots, x_m < 1 \\ 0 < y_1, \dots, y_n < 1}} F(\mathbf{x}, \mathbf{y})$$

on the open cube $0 < x_i, y_j < 1$ and for the number $|\Sigma(R, C)|$ of non-negative integer $m \times n$ matrices with row sums R and column sums C we have

$$\rho(R, C) \geq |\Sigma(R, C)| \geq N^{-\gamma(m+n)} \rho(R, C),$$

where $\gamma > 0$ is an absolute constant.

□

As is remarked in [Ba09], the substitution $x_i = e^{-s_i}$, $y_j = e^{-t_j}$ transforms $\ln F(\mathbf{x}, \mathbf{y})$ into a convex function

$$G(\mathbf{s}, \mathbf{t}) = \sum_{i=1}^m r_i s_i + \sum_{j=1}^n c_j t_j - \sum_{i,j} \ln(1 - e^{-s_i - t_j})$$

for $\mathbf{s} = (s_1, \dots, s_m)$ and $\mathbf{t} = (t_1, \dots, t_n)$

on the positive orthant $\mathbb{R}_+^m \times \mathbb{R}_+^n$. It turns out that the typical table Z is the solution to the problem that is convex dual to the problem of minimizing G . The following result was proved in [Ba09]; see Lemma 1.4 there.

(2.2) Lemma. *Let $\mathcal{P} = \mathcal{P}(R, C)$ be the polytope of $m \times n$ non-negative matrices $X = (x_{ij})$ with row sums R and column sums C and let $Z \in \mathcal{P}(R, C)$ be the typical table; see Section 1.2.*

Then one can write $Z = (z_{ij})$,

$$z_{ij} = \frac{\xi_i \eta_j}{1 - \xi_i \eta_j} \quad \text{for all } i, j$$

and some $0 < \xi_1, \dots, \xi_m; \eta_1, \dots, \eta_n < 1$ such that the minimum $\rho(R, C)$ of the function $F(\mathbf{x}, \mathbf{y})$ in Theorem 2.1 is attained at $\mathbf{x}^ = (\xi_1, \dots, \xi_m)$ and $\mathbf{y}^* = (\eta_1, \dots, \eta_n)$:*

$$F(\mathbf{x}^*, \mathbf{y}^*) = \rho(R, C) = \min_{\substack{0 < x_1, \dots, x_m < 1 \\ 0 < y_1, \dots, y_n < 1}} F(\mathbf{x}, \mathbf{y}).$$

Moreover,

$$\rho(R, C) = \exp \{g(Z)\}.$$

□

Theorem 1.7 is a particular case of a more general result proved in [BH09]. Nevertheless, we present the proof of Theorem 1.7 here for completeness and since some elements of the proof will be recycled later.

(2.3) Proof of Theorem 1.7. From Lemma 2.2, we have $z_{ij} > 0$ for all i, j . Since Z lies in the relative interior of the transportation polytope $\mathcal{P}(R, C)$, the gradient of g at Z must be orthogonal to the subspace of $m \times n$ matrices with row and column sums equal to 0. Therefore,

$$(2.3.1) \quad \ln \left(\frac{z_{ij} + 1}{z_{ij}} \right) = \lambda_i + \mu_j \quad \text{for all } i, j$$

and some $\lambda_1, \dots, \lambda_m$ and μ_1, \dots, μ_n .

For the geometric random variables x_{ij} we have

$$\Pr \{x_{ij} = d_{ij}\} = p_{ij} q_{ij}^{d_{ij}} = \left(\frac{1}{1 + z_{ij}} \right) \left(\frac{z_{ij}}{1 + z_{ij}} \right)^{d_{ij}}$$

Using (2.3.1), for $D \in \Sigma(R, C)$, $D = (d_{ij})$, we obtain

$$\begin{aligned} \Pr \{X = D\} &= \left(\prod_{i,j} \frac{1}{1 + z_{ij}} \right) \prod_{i,j} \left(\frac{z_{ij}}{1 + z_{ij}} \right)^{d_{ij}} \\ &= \left(\prod_{i,j} \frac{1}{1 + z_{ij}} \right) \prod_{i,j} e^{-(\lambda_i + \mu_j) d_{ij}} \\ &= \left(\prod_{i,j} \frac{1}{1 + z_{ij}} \right) \left(\prod_{i=1}^m e^{-\lambda_i r_i} \right) \left(\prod_{j=1}^n e^{-\mu_j c_j} \right). \end{aligned}$$

Also,

$$\begin{aligned} e^{-g(Z)} &= \prod_{i,j} \frac{z_{ij}^{z_{ij}}}{(1 + z_{ij})^{z_{ij} + 1}} \\ &= \left(\prod_{i,j} \frac{1}{1 + z_{ij}} \right) \prod_{i,j} \left(\frac{z_{ij}}{1 + z_{ij}} \right)^{z_{ij}} \\ &= \left(\prod_{i,j} \frac{1}{1 + z_{ij}} \right) \prod_{i,j} e^{-(\lambda_i + \mu_j) z_{ij}} \\ &= \left(\prod_{i,j} \frac{1}{1 + z_{ij}} \right) \left(\prod_{i=1}^m e^{-\lambda_i r_i} \right) \left(\prod_{j=1}^n e^{-\mu_j c_j} \right), \end{aligned}$$

which completes the proof. \square

We will need a lower bound for the entries of the typical table $Z = (z_{ij})$ proved in [B+08]; see Theorem 3.3 there.

(2.4) Lemma. *Let*

$$\begin{aligned} r_+ &= \max_{i=1, \dots, m} r_i, & r_- &= \min_{i=1, \dots, m} r_i & \text{and} \\ c_+ &= \max_{j=1, \dots, n} c_j, & c_- &= \min_{j=1, \dots, n} c_j. \end{aligned}$$

Let $Z = (z_{ij})$ be the typical table with margins (R, C) . Then

$$z_{ij} \geq \frac{r_- c_-}{r_+ m} \quad \text{and} \quad z_{ij} \geq \frac{c_- r_-}{c_+ n} \quad \text{for all } i, j.$$

\square

(2.5) Corollary. *Let $Z = (z_{ij})$ be the typical table of δ -smooth margins (R, C) . Then*

$$z_{ij} \geq \frac{\delta^3 N}{mn} \quad \text{for all } i, j.$$

Proof. In Lemma 2.4, we have

$$r_- \geq \frac{\delta N}{m}, \quad c_- \geq \frac{\delta N}{n} \quad \text{and} \quad r_+ \leq \frac{N}{\delta m},$$

and the result follows. □

3. PROOF OF THEOREM 1.5 ASSUMING THAT N IS POLYNOMIALLY BOUNDED

In this section we prove Theorem 1.5 under the additional assumption that the total sum N of entries is bounded by a polynomial in m and n , specifically that $N \leq (mn)^{1/\delta}$. We use Theorem 1.7. We start with a standard large deviation inequality.

(3.1) Lemma. *Let $X = (x_{ij})$ be the $m \times n$ matrix of independent geometric random variables x_{ij} such that $\mathbf{E} X = Z$, $Z = (z_{ij})$. Let*

$$S \subset \left\{ (i, j) : 1 \leq i \leq m, \quad 1 \leq j \leq n \right\}$$

be a non-empty set. Recall that

$$\sigma_S(X) = \sum_{(i,j) \in S} x_{ij}, \quad \sigma_S(Z) = \sum_{(i,j) \in S} z_{ij}$$

and let us denote

$$\nu_S(Z) = \sum_{(i,j) \in S} z_{ij}^2.$$

Then

(1) *For any real a and for any $0 < t \leq 2$, we have*

$$\Pr \left\{ \sigma_S(X) \leq -a + \sigma_S(Z) \right\} \leq \exp \left\{ -ta + \frac{t^2}{2} (\sigma_S(Z) + \nu_S(Z)) \right\}.$$

(2) *For any real a and for any $0 < t \leq \min\{1/3, 1/2z_{ij} : (i, j) \in S\}$, we have*

$$\Pr \left\{ \sigma_S(X) \geq a + \sigma_S(Z) \right\} \leq \exp \left\{ -ta + 2t^2 (\sigma_S(Z) + \nu_S(Z)) \right\}.$$

Proof. We use the Laplace transform method; see, for example, Section 1.6 of [Le01]. To prove Part (1), for any $t > 0$ we compute

$$\mathbf{E} e^{-t\sigma_S(X)} = \prod_{(i,j) \in S} \mathbf{E} e^{-tx_{ij}} = \prod_{(i,j) \in S} \frac{p_{ij}}{1 - e^{-t}q_{ij}},$$

where

$$\Pr \{x_{ij} = k\} = p_{ij}q_{ij}^k \quad \text{for } k = 0, 1, \dots$$

Using the fact that $e^{-t} \leq 1 - t + t^2/2$ for $t \geq 0$, we obtain

$$\mathbf{E} e^{-t\sigma_S(X)} \leq \prod_{(i,j) \in S} \frac{p_{ij}}{p_{ij} + (t - t^2/2)q_{ij}} = \prod_{(i,j) \in S} \frac{1}{1 + (t - t^2/2)z_{ij}}.$$

Using the fact that $t - t^2/2 \geq 0$ for $0 \leq t \leq 2$ and that $\ln(1+x) \geq x - x^2/2$ for $x \geq 0$, we obtain

$$\begin{aligned} \mathbf{E} e^{-t\sigma_S(X)} &\leq \exp \left\{ - \sum_{(i,j) \in S} \ln(1 + (t - t^2/2)z_{ij}) \right\} \\ &\leq \exp \left\{ - \sum_{(i,j) \in S} (t - t^2/2)z_{ij} + \frac{1}{2} \sum_{(i,j) \in S} (t - t^2/2)^2 z_{ij}^2 \right\} \\ &\leq \exp \left\{ -t\sigma_S(Z) + \frac{t^2}{2}(\sigma_S(Z) + \nu_S(Z)) \right\}. \end{aligned}$$

Then

$$\begin{aligned} \Pr \{ \sigma_S(X) \leq -a + \sigma_S(Z) \} &= \Pr \{ -t\sigma_S(X) \geq ta - t\sigma_S(Z) \} \\ &= \Pr \left\{ e^{-t\sigma_S(X)} \geq e^{ta - t\sigma_S(Z)} \right\} \\ &\leq e^{-ta + t\sigma_S(Z)} \mathbf{E} e^{-t\sigma_S(X)} \\ &\leq \exp \left\{ -ta + \frac{t^2}{2}(\sigma_S(Z) + \nu_S(Z)) \right\}. \end{aligned}$$

To prove Part (2), we observe that $e^t < 1 + t + t^2$ for all $0 < t \leq 1$. Therefore, for $0 < t \leq \min\{1/3, 1/2z_{ij} : (i,j)\}$, we have

$$e^t < 1 + 2t \leq \frac{1 + z_{ij}}{z_{ij}} = \frac{1}{q_{ij}}$$

and hence

$$\begin{aligned} \mathbf{E} e^{t\sigma_S(X)} &= \prod_{(i,j) \in S} \mathbf{E} e^{tx_{ij}} = \prod_{(i,j) \in S} \frac{p_{ij}}{1 - e^t q_{ij}} \\ &\leq \prod_{(i,j) \in S} \frac{p_{ij}}{p_{ij} - (t + t^2)q_{ij}} = \prod_{(i,j) \in S} \frac{1}{1 - (t + t^2)z_{ij}}. \end{aligned}$$

Since $t \leq 1/3$ we have $t + t^2 \leq (4/3)t$ and hence $(t + t^2)z_{ij} \leq 2/3$. Using the fact that $\ln(1 - x) \geq -x - x^2$ for $0 \leq x \leq 2/3$, we obtain

$$\begin{aligned} \mathbf{E} e^{t\sigma_S(X)} &\leq \exp \left\{ - \sum_{(i,j) \in S} \ln(1 - (t + t^2)z_{ij}) \right\} \\ &\leq \exp \left\{ \sum_{(i,j) \in S} (t + t^2) z_{ij} + \sum_{(i,j) \in S} (t + t^2)^2 z_{ij}^2 \right\} \\ &\leq \exp \left\{ t\sigma_S(Z) + 2t^2 (\sigma_S(Z) + \nu_S(Z)) \right\}. \end{aligned}$$

Therefore,

$$\begin{aligned} \Pr \{ \sigma_S(X) \geq a + \sigma_S(Z) \} &= \Pr \{ t\sigma_S(X) \geq ta + t\sigma_S(Z) \} \\ &= \Pr \left\{ e^{t\sigma_S(X)} \geq e^{ta + t\sigma_S(Z)} \right\} \\ &\leq e^{-ta - t\sigma_S(Z)} \mathbf{E} e^{t\sigma_S(X)} \\ &\leq \exp \left\{ -ta + 2t^2 (\sigma_S(Z) + \nu_S(Z)) \right\}. \end{aligned}$$

□

One can observe that $\sigma_S(Z) + \nu_S(Z)$ is the variance of $\sigma_S(X)$.

(3.2) Corollary. *Let (R, C) be δ -smooth margins with the typical table $Z = (z_{ij})$ and let $X = (x_{ij})$ be the matrix of independent geometric variables such that $\mathbf{E} X = Z$. Suppose that*

$$z_{ij} \leq \frac{\alpha N}{mn} \quad \text{for all } (i, j) \in S$$

and some $\alpha \geq 1$. Then

(1) For any $0 < \epsilon < 1$ we have

$$\Pr \{ \sigma_S(X) \leq (1 - \epsilon)\sigma_S(Z) \} \leq \exp \left\{ -\frac{\epsilon^2 \delta^4 |S|}{2 + 2\delta\alpha} \right\}.$$

(2) For any $0 < \epsilon < 1$ we have

$$\Pr \{ \sigma_S(X) \geq (1 + \epsilon)\sigma_S(Z) \} \leq \exp \left\{ -\frac{\epsilon^2 \delta^4 |S|}{8 + 8\delta\alpha} \right\}.$$

Proof. Choosing

$$a = \epsilon\sigma_S(Z) \quad \text{and} \quad t = \frac{\epsilon\sigma_S(Z)}{\sigma_S(Z) + \nu_S(Z)}$$

in Part (1) of Lemma 3.1, we obtain

$$(3.2.1) \quad \Pr \{ \sigma_S(X) \leq (1 - \epsilon) \sigma_S(Z) \} \leq \exp \left\{ - \frac{\epsilon^2 \sigma_S^2(Z)}{2(\sigma_S(Z) + \nu_S(Z))} \right\}.$$

Furthermore,

$$(3.2.2) \quad \nu_S(Z) = \sum_{(i,j) \in S} z_{ij}^2 \leq \frac{\alpha N}{mn} \sum_{(i,j) \in S} z_{ij} = \frac{\alpha N}{mn} \sigma_S(Z).$$

By Corollary 2.5,

$$(3.2.3) \quad \delta_S(Z) \geq |S| \frac{\delta^3 N}{mn}.$$

We recall that

$$(3.2.4) \quad \frac{N}{mn} \geq \delta.$$

Summarizing (3.2.1)–(3.2.4), we get

$$\begin{aligned} \Pr \{ \sigma_S(X) \leq (1 - \epsilon) \sigma_S(Z) \} &\leq \exp \left\{ - \frac{\epsilon^2 \sigma_S(Z) mn}{2(mn + \alpha N)} \right\} \\ &\leq \exp \left\{ - \frac{\epsilon^2 |S| \delta^3 N}{2(mn + \alpha N)} \right\} \\ &\leq \exp \left\{ - \frac{\epsilon^2 |S| \delta^3}{2(mn/N + \alpha)} \right\} \\ &\leq \exp \left\{ - \frac{\epsilon^2 \delta^4 |S|}{2 + 2\delta\alpha} \right\} \end{aligned}$$

and Part (1) follows.

Let us choose $a = \epsilon \sigma_S(Z)$ in Part (2) of Lemma 3.1. Let

$$t_0 = \frac{\epsilon \sigma_S(Z)}{4(\sigma_S(Z) + \nu_S(Z))}.$$

Clearly, $t_0 \leq 1/4 < 1/3$. If $t_0 < mn/2\alpha N$, we choose $t = t_0$ and if $t_0 \geq mn/2\alpha N$, we choose $t = mn/2\alpha N$ in Part (2) of Lemma 3.1. Hence if $t_0 < mn/2\alpha N$, we obtain as above in Part (1)

$$(3.2.5) \quad \begin{aligned} \Pr \{ \sigma_S(X) \geq (1 + \epsilon) \sigma_S(Z) \} &\leq \exp \left\{ - \frac{\epsilon^2 \sigma_S^2(Z)}{8(\sigma_S(Z) + \nu_S(Z))} \right\} \\ &\leq \exp \left\{ - \frac{\epsilon^2 \delta^4 |S|}{8 + 8\delta\alpha} \right\}. \end{aligned}$$

If $t_0 \geq mn/2\alpha N$ then

$$\sigma_S(Z) + \nu_S(Z) \leq \frac{\epsilon \sigma_S(Z) \alpha N}{2mn}.$$

Therefore, choosing $t = mn/2\alpha N$ in Part (2) of Lemma 3.1, we obtain

$$\begin{aligned} \Pr \{ \sigma_S(X) \geq (1 + \epsilon) \sigma_S(Z) \} &\leq \exp \left\{ -\frac{\epsilon mn \sigma_S(Z)}{2\alpha N} + \frac{m^2 n^2 (\sigma_S(Z) + \nu_S(Z))}{2\alpha^2 N^2} \right\} \\ &\leq \exp \left\{ -\frac{\epsilon \sigma_S(Z) mn}{4\alpha N} \right\}. \end{aligned}$$

Using (3.2.3), we obtain

$$(3.2.6) \quad \Pr \{ \sigma_S(X) \geq (1 + \epsilon) \sigma_S(Z) \} \leq \exp \left\{ -\frac{\epsilon \delta^3 |S|}{4\alpha} \right\}.$$

Comparing (3.2.5) and (3.2.6), we complete the proof. \square

Now we can prove the following weaker version of Theorem 1.5.

(3.3) Proposition. *Let us fix real numbers $0 < \delta \leq 1$ and $\kappa > 0$. Then there exists a positive integer $q = q(\delta, \kappa)$ such that the following holds:*

Suppose that (R, C) are δ -smooth margins such that $n \geq m \geq q$ and let $Z = (z_{ij})$ be the typical table with margins (R, C) . Let

$$S \subset \{(i, j) : 1 \leq i \leq m, 1 \leq j \leq n\}$$

be a set such that

$$|S| \geq \delta mn$$

and suppose that the entries z_{ij} of the typical table satisfy the inequalities

$$z_{ij} \leq \frac{\alpha N}{mn} \quad \text{for } \alpha = 2\delta^{-1}m^{1/3}$$

and all $(i, j) \in S$.

Suppose further that for the total sum N of entries we have

$$N \leq (mn)^{1/\delta}.$$

Let

$$\epsilon = \frac{\delta \ln n}{m^{1/3}}.$$

If $\epsilon \leq 1$, we have

$$\begin{aligned} \Pr \{ D \in \Sigma(R, C) : \sigma_S(D) \leq (1 - \epsilon) \sigma_S(Z) \} &\leq n^{-\kappa n} \quad \text{and} \\ \Pr \{ D \in \Sigma(R, C) : \sigma_S(D) \geq (1 + \epsilon) \sigma_S(Z) \} &\leq n^{-\kappa n}. \end{aligned}$$

Proof. Let $X = (x_{ij})$ be the $m \times n$ matrix of independent geometric random variables x_{ij} such that $\mathbf{E}X = Z$. By Theorem 1.7, the distribution of X conditioned on $X \in \Sigma(R, C)$ is uniform and hence

$$\begin{aligned} & \Pr \{D \in \Sigma(R, C) : \sigma_S(D) \leq (1 - \epsilon)\sigma_S(Z)\} \\ &= \frac{\Pr \{X : \sigma_S(X) \leq (1 - \epsilon)\sigma_S(Z) \text{ and } X \in \Sigma(R, C)\}}{\Pr \{X : X \in \Sigma(R, C)\}}. \end{aligned}$$

Similarly,

$$\begin{aligned} & \Pr \{D \in \Sigma(R, C) : \sigma_S(D) \geq (1 + \epsilon)\sigma_S(Z)\} \\ &= \frac{\Pr \{X : \sigma_S(X) \geq (1 + \epsilon)\sigma_S(Z) \text{ and } X \in \Sigma(R, C)\}}{\Pr \{X : X \in \Sigma(R, C)\}}. \end{aligned}$$

By Theorem 1.7, Lemma 2.2 and Theorem 2.1 we get

$$\Pr \{X \in \Sigma(R, C)\} = e^{-g(Z)} |\Sigma(R, C)| \geq N^{-\gamma(m+n)}$$

for some absolute constant $\gamma > 0$. Since $N \leq (mn)^{1/\delta}$, we obtain

$$\begin{aligned} & \Pr \{D \in \Sigma(R, C) : \sigma_S(D) \leq (1 - \epsilon)\sigma_S(Z)\} \\ & \leq (mn)^{\gamma_1(m+n)} \Pr \{X : \sigma_S(X) \leq (1 - \epsilon)\sigma_S(Z)\} \end{aligned}$$

and similarly

$$\begin{aligned} & \Pr \{D \in \Sigma(R, C) : \sigma_S(D) \geq (1 + \epsilon)\sigma_S(Z)\} \\ & \leq (mn)^{\gamma_1(m+n)} \Pr \{X : \sigma_S(X) \geq (1 + \epsilon)\sigma_S(Z)\} \end{aligned}$$

for some constant $\gamma_1 = \gamma(\delta) > 0$. By Part (1) of Corollary 3.2,

$$\Pr \{X : \sigma_S(X) \leq (1 - \epsilon)\sigma_S(Z)\} \leq \exp \left\{ -\frac{\delta^7 mn \ln^2 n}{m^{2/3}(2 + 4m^{1/3})} \right\},$$

while by Part (2) of Corollary 3.2

$$\Pr \{X : \sigma_S(X) \geq (1 + \epsilon)\sigma_S(Z)\} \leq \exp \left\{ -\frac{\delta^7 mn \ln^2 n}{m^{2/3}(8 + 16m^{1/3})} \right\},$$

and the result follows. \square

Next, we prove that large entries of the typical table Z belong to a small number of rows.

(3.4) Lemma. Let (R, C) be δ -smooth margins and let $Z = (z_{ij})$ be the $m \times n$ typical table with margins (R, C) . Let $\alpha \geq 2mn/N$ be a real number. Let

$$I = \left\{ i : z_{ij} \geq \frac{\alpha N}{mn} \text{ for some } j \right\}.$$

Then

$$|I| \leq \frac{4m}{\delta\alpha}.$$

Proof. By (2.3.1), we can write

$$\ln \left(\frac{z_{ij} + 1}{z_{ij}} \right) = \lambda_i + \mu_j \quad \text{for all } i, j$$

and some $\lambda_1, \dots, \lambda_m$ and μ_1, \dots, μ_n . Since $\lambda_i + \mu_j > 0$ for all i and j , without loss of generality we may assume that $\lambda_1, \dots, \lambda_m$ and μ_1, \dots, μ_n are positive.

Let

$$I_0 = \left\{ i : \lambda_i \leq \frac{mn}{\alpha N} \right\} \quad \text{and} \quad J_0 = \left\{ j : \mu_j \leq \frac{mn}{\alpha N} \right\}.$$

If $i \in I$ then for some j we have

$$\frac{mn}{\alpha N} \geq \frac{1}{z_{ij}} \geq \ln \left(\frac{z_{ij} + 1}{z_{ij}} \right) \geq \lambda_i$$

and therefore $I \subset I_0$. Similarly, if $z_{ij} \geq \alpha N/mn$ for some i then $j \in J_0$. Hence without loss of generality, we may assume that $J_0 \neq \emptyset$.

Let us fix a $j_0 \in J_0$. Then for any $i \in I_0$ we have

$$\ln \left(\frac{z_{ij_0} + 1}{z_{ij_0}} \right) \leq \frac{2mn}{\alpha N}.$$

Hence for all $i \in I_0$ we have

$$\frac{1}{z_{ij_0}} \leq \exp \left\{ \frac{2mn}{\alpha N} \right\} - 1 \leq \frac{4mn}{\alpha N}$$

(using the fact that $e^x \leq 1 + 2x$ for $0 \leq x \leq 1$). Hence

$$z_{ij_0} \geq \frac{\alpha N}{4mn} \quad \text{for } i \in I_0.$$

Since

$$\sum_{i=1}^m z_{ij_0} = c_{j_0} \leq \frac{N}{\delta n},$$

we conclude that

$$|I| \leq |I_0| \leq \frac{4c_{j_0}mn}{\alpha N} \leq \frac{4m}{\delta\alpha}.$$

□

Finally, we prove the main result of this section.

(3.5) Proposition. *In Theorem 1.5 assume, additionally, that $N \leq (mn)^{1/\delta}$ (equivalently, drop the upper bound assumption for z_{ij} in Proposition 3.3). Then the conclusion of Theorem 1.5 holds (equivalently, the conclusion of Proposition 3.3 holds).*

Proof. Let us choose

$$\alpha = 2\delta^{-1}m^{1/3}$$

and let

$$I = \left\{ i : z_{ij} \geq \frac{\alpha N}{mn} \text{ for some } j \right\}.$$

Since $N/mn \geq \delta$, we have $\alpha \geq 2mn/N$ and by Lemma 3.4 we have

$$|I| \leq 2m^{2/3}.$$

Let

$$S_0 = \{(i, j) \in S : i \notin I\}.$$

Then

$$|S \setminus S_0| \leq n|I| \leq 2nm^{2/3},$$

and hence for $\delta_0 = \delta/2$ and m sufficiently large, $n \geq m \geq q(\delta)$, we have

$$|S_0| \geq \delta_0 mn.$$

Furthermore, we have

$$\sigma_{S \setminus S_0}(D), \sigma_{S \setminus S_0}(Z) \leq \sum_{i \in I} r_i \leq |I| \frac{N}{\delta m} \leq \frac{2N}{\delta m^{1/3}}.$$

On the other hand, by Corollary 2.5, we have

$$\sigma_S(Z) \geq |S| \frac{\delta^3 N}{mn} \geq \delta^4 N.$$

Therefore,

$$(3.5.1) \quad \sigma_{S_0}(Z) = \sigma_S(Z) - \sigma_{S \setminus S_0}(Z) \geq \left(1 - \frac{2}{\delta^5 m^{1/3}}\right) \sigma_S(Z)$$

and, similarly,

$$(3.5.2) \quad \sigma_S(Z) - \sigma_{S \setminus S_0}(D) \geq \left(1 - \frac{2}{\delta^5 m^{1/3}}\right) \sigma_S(Z).$$

We have

$$\begin{aligned} & \Pr \{D \in \Sigma(R, C) : \sigma_S(D) \leq (1 - \epsilon)\sigma_S(Z)\} \\ & \leq \Pr \{D \in \Sigma(R, C) : \sigma_{S_0}(D) \leq (1 - \epsilon)\sigma_S(Z)\}. \end{aligned}$$

By (3.5.1) we obtain

$$\begin{aligned} (1 - \epsilon)\sigma_S(Z) &= \left(1 - \frac{\delta \ln n}{m^{1/3}}\right) \sigma_S(Z) \leq (1 - \epsilon_0) \left(1 - \frac{2}{\delta^5 m^{1/3}}\right) \sigma_S(Z) \\ &\leq (1 - \epsilon_0) \sigma_{S_0}(Z), \quad \text{where} \\ &\quad \epsilon_0 = \frac{\delta \ln n}{2m^{1/3}}, \end{aligned}$$

and m is sufficiently large, $n \geq m \geq q(\delta)$.

Applying Proposition 3.3 with $S_0 \subset S$ and $\delta_0 = \delta/2$, we conclude that if m is sufficiently large, $n \geq m \geq q(\delta, \kappa)$, we have

$$\begin{aligned} & \Pr \{D \in \Sigma(R, C) : \sigma_{S_0}(D) \leq (1 - \epsilon)\sigma_S(Z)\} \\ & \leq \Pr \{D \in \Sigma(R, C) : \sigma_{S_0}(D) \leq (1 - \epsilon_0)\sigma_{S_0}(Z)\} \leq n^{-\kappa n}. \end{aligned}$$

Similarly, we have

$$\begin{aligned} & \Pr \{D \in \Sigma(R, C) : \sigma_S(D) \geq (1 + \epsilon)\sigma_S(Z)\} \\ & = \Pr \{D \in \Sigma(R, C) : \sigma_{S_0}(D) \geq (1 + \epsilon)\sigma_S(Z) - \sigma_{S \setminus S_0}(D)\} \\ & \leq \Pr \{D \in \Sigma(R, C) : \sigma_{S_0}(D) \geq (1 + \epsilon)(\sigma_S(Z) - \sigma_{S \setminus S_0}(D))\}. \end{aligned}$$

By (3.5.2) we obtain

$$\begin{aligned} (1 + \epsilon)(\sigma_S(Z) - \sigma_{S \setminus S_0}(D)) &\geq (1 + \epsilon) \left(1 - \frac{2}{\delta^5 m^{1/3}}\right) \sigma_S(Z) \\ &\geq (1 + \epsilon_0) \sigma_{S_0}(Z), \quad \text{where} \\ &\quad \epsilon_0 = \frac{\delta \ln n}{2m^{1/3}}, \end{aligned}$$

and m is sufficiently large, $n \geq m \geq q(\delta)$.

Applying Proposition 3.3 with $S_0 \subset S$ and $\delta_0 = \delta/2$, we conclude that if m is sufficiently large, $n \geq m \geq q(\delta, \kappa)$, we have

$$\begin{aligned} & \Pr \{D \in \Sigma(R, C) : \sigma_{S_0}(D) \geq (1 + \epsilon)(\sigma_S(Z) - \sigma_{S \setminus S_0}(D))\} \\ & \leq \Pr \{D \in \Sigma(R, C) : \sigma_{S_0}(D) \geq (1 + \epsilon_0)\sigma_{S_0}(Z)\} \leq n^{-\kappa} \end{aligned}$$

and the result follows. □

4. PROOF OF THEOREM 1.5

It remains to prove Theorem 1.5 in the case of a large (superpolynomial in mn) total sum N of entries. More precisely, we assume that $N > (mn)^7$ since the case of $N \leq (mn)^7$ is covered by Proposition 3.5 with a sufficiently small $\delta \leq 1/7$ (we recall that δ -smooth margins are also δ' -smooth with any $0 < \delta' < \delta$).

The idea of the proof is as follows: given margins (R, C) whose total sum of entries is N , we construct new margins (R', C') whose total sum of entries N' is bounded by a polynomial in mn and a scaling map

$$\mathcal{T} : \Sigma(R, C) \longrightarrow \Sigma(R', C'),$$

which, roughly, scales every table $D \in \Sigma(R, C)$ by the same factor t . We then deduce Theorem 1.5 for margins (R, C) from that for margins (R', C') .

We have

$$R' \approx t^{-1}R, \quad C' \approx t^{-1}C \quad \text{and} \quad \mathcal{T}(D) \approx t^{-1}D,$$

where “ \approx ” stands for rounding in some consistent way.

In constructing the map \mathcal{T} we essentially follow the ideas of [D+97].

(4.1) Lattices, bases, and fundamental parallelepipeds. Let \mathcal{V} be a finite-dimensional real vector space and let $\Lambda \subset \mathcal{V}$ be a *lattice*, that is, a discrete additive subgroup of \mathcal{V} which spans \mathcal{V} . Suppose that $\dim \mathcal{V} = k$ and let u_1, \dots, u_k be a basis of Λ . The set

$$\Pi = \left\{ \sum_{i=1}^k \lambda_i u_i : 0 \leq \lambda_i < 1 \quad \text{for} \quad i = 1, \dots, k \right\}$$

is called the *fundamental parallelepiped* associated with the basis u_1, \dots, u_k .

Suppose that \mathcal{A} is an affine space, with $\dim \mathcal{A} = \dim \mathcal{V}$, on which \mathcal{V} acts by translations: $a + v \in \mathcal{A}$ for all $a \in \mathcal{A}$ and $v \in \mathcal{V}$ and $a + (v_1 + v_2) = (a + v_1) + v_2$ for all $a \in \mathcal{A}$ and $v_1, v_2 \in \mathcal{V}$. Let us choose $a \in \mathcal{A}$. The set $\Lambda_a = a + \Lambda$ is called a *point lattice* in \mathcal{A} . As is known, the translations $v + \Pi : v \in \Lambda_a$ cover \mathcal{A} without overlapping.

We will also use the following standard fact. Suppose that $\Lambda_1 \supset \Lambda$ is a finer lattice and let $|\Lambda_1/\Lambda| < \infty$ be its index. Then, for any $a, b \in \mathcal{A}$ we have

$$|(a + \Pi) \cap (b + \Lambda_1)| = |\Lambda_1/\Lambda|,$$

see for example Chapter VII of [Ba02].

Let us fix a point lattice $\Lambda_a \subset \mathcal{A}$ and a fundamental parallelepiped $\Pi \subset \mathcal{V}$ of Λ . Given a point $x \in \mathcal{A}$, we define its *rounding* $y = [x]_{\Lambda_a, \Pi}$ as the unique point $y \in \Lambda_a$ such that $x \in y + \Pi$.

In our case, \mathcal{V} is the space of real $m \times n$ matrices with the row and column sums equal to 0, so $\dim \mathcal{V} = (m-1)(n-1)$, while \mathcal{A} is the affine space of $m \times n$ matrices

with prescribed integer row and column sums, so that for all $D \in \mathcal{A}$ and $U \in \mathcal{V}$ we have $D + U \in \mathcal{A}$. Furthermore, let $\Lambda \subset \mathcal{V}$ be the lattice of integer matrices and let $\Lambda' \subset \mathcal{A}$ be the point lattice consisting of integer matrices.

As is shown, for example, in [D+97], lattice Λ has a basis consisting of the matrices U_{ij} for $1 \leq i \leq n-1$, $1 \leq j \leq m-1$ that have 1 in the (i, j) and $(i+1, j+1)$ positions, -1 in the $(i+1, j)$ and $(i, j+1)$ positions and zeros elsewhere. Let Π be the fundamental parallelepiped of this basis $\{U_{ij}\}$. We call this parallelepiped Π *standard*. We note that

$$(4.1.1) \quad -2 \leq x_{ij} \leq 2 \quad \text{for all } i, j \quad \text{and all } X \in \Pi, \quad X = (x_{ij}).$$

Finally, for positive integer t let $\Lambda_1 = t^{-1}\Lambda$. Hence $|\Lambda_1/\Lambda| = t^{(m-1)(n-1)}$.

(4.2) The t -scaling map \mathcal{T} . Let us choose a positive integer t and an arbitrary $D_0 \in \Sigma(R, C)$, where $R = (r_1, \dots, r_m)$ and $C = (c_1, \dots, c_n)$. Let us define a positive $m \times n$ matrix B as follows. First, we obtain D_1 by rounding up to the nearest integer every entry of $t^{-1}D_0$ and adding 2 to the result. In particular, D_1 is a positive integer matrix. Let

$$B = D_1 - t^{-1}D_0, \quad \text{so} \quad D_1 = B + t^{-1}D_0.$$

Clearly, $B = (b_{ij})$ is an $m \times n$ matrix with

$$(4.2.1) \quad 2 \leq b_{ij} < 3 \quad \text{for all } i, j.$$

Let $R' = (r'_1, \dots, r'_m)$ and $C' = (c'_1, \dots, c'_n)$ be the row and column sums of D_1 respectively. Thus R' and C' are positive integer vectors and

$$(4.2.2) \quad \begin{aligned} t^{-1}r_i + 2n &\leq r'_i \leq t^{-1}r_i + 3n \quad \text{for } i = 1, \dots, m \\ &\text{and} \end{aligned}$$

$$t^{-1}c_j + 2m \leq c'_j \leq t^{-1}c_j + 3m \quad \text{for } j = 1, \dots, n.$$

Let \mathcal{A} be the affine subspace of matrices with row sums R' and column sums C' and let $\Lambda' \subset \mathcal{A}$ be the point lattice of integer matrices. Thus $\Lambda' = D_1 + \Lambda$, where Λ is the lattice of $m \times n$ integer matrices with zero row and column sums, see Section 4.1. For a matrix $D \in \Sigma(R, C)$ we define a matrix $\mathcal{T}(D)$ by

$$\mathcal{T}(D) = \lfloor t^{-1}D + B \rfloor_{\Lambda', \Pi},$$

where Π is the standard parallelepiped of Λ ; see Section 4.1. In words: given a table $D \in \Sigma(R, C)$, matrix $\mathcal{T}(D)$ is the unique integer matrix such that the translation $\mathcal{T}(D) + \Pi$ of the standard parallelepiped Π contains $t^{-1}D + B$. Clearly, $\mathcal{T}(D)$ is an $m \times n$ integer matrix with row sums R' and column sums C' . Moreover, since every entry of $t^{-1}D + B$ is at least 2 and because of (4.1.1), matrix $\mathcal{T}(D)$ is non-negative.

Hence we have defined a map

$$\mathcal{T} : \Sigma(R, C) \longrightarrow \Sigma(R', C').$$

We summarize some of its properties below.

(4.3) Lemma.

(1) For all $Y \in \Sigma(R', C')$ we have

$$|\mathcal{T}^{-1}(Y)| \leq t^{(m-1)(n-1)};$$

(2) Let $S \subset \{(i, j) : i = 1, \dots, m, j = 1, \dots, n\}$ be a set of indices. Then

$$t^{-1}\sigma_S(D) \leq \sigma_S(\mathcal{T}(D)) \leq t^{-1}\sigma_S(D) + 5|S|$$

for all $D \in \Sigma(R, C)$.

Proof. Given $Y \in \Sigma(R', C')$, we compute $\mathcal{T}^{-1}(Y)$ as follows: we consider the translation $(Y - B) + \Pi$ of the standard parallelepiped Π and observe that

$$\mathcal{T}^{-1}(Y) = \left\{ D : \begin{array}{l} t^{-1}D \in (Y - B) + \Pi \quad \text{and} \\ D \text{ is a non-negative integer matrix} \end{array} \right\}.$$

Recall that $\Lambda \subset \mathcal{V}$ is the lattice of $m \times n$ integer matrices with the row and column sums equal to 0 and that $\Lambda_1 = t^{-1}\Lambda$. In the affine space of $m \times n$ matrices with row sums $t^{-1}R$ and column sums $t^{-1}C$ let us consider the point lattice $\Lambda'_1 = t^{-1}D_0 + \Lambda_1$ consisting of matrices $t^{-1}D$ where D is an integer matrix. Then

$$|((Y - B) + \Pi) \cap \Lambda'_1| = |\Lambda_1/\Lambda| = t^{(m-1)(n-1)}$$

and Part (1) follows. Part (2) follows because of (4.1.1) and (4.2.1). \square

(4.4) Lemma. Suppose that

$$r'_i, c'_j \geq (mn)^2 \quad \text{for all } i, j.$$

Then, for any $\zeta \geq 0$ we have

$$\Pr \left\{ D \in \Sigma(R, C) : \sigma_S(D) \geq t\zeta \right\} \leq \beta \Pr \left\{ Y \in \Sigma(R', C') : \sigma_S(Y) \geq \zeta \right\}$$

and

$$\Pr \left\{ D \in \Sigma(R, C) : \sigma_S(D) \leq t\zeta \right\} \leq \beta \Pr \left\{ Y \in \Sigma(R', C') : \sigma_S(Y) \leq \zeta + 5|S| \right\},$$

where $\beta > 0$ is an absolute constant.

Proof. By Part (2) of Lemma 4.3, if $\sigma_S(D) \geq t\zeta$ then $\sigma_S(Y) \geq \zeta$ for $Y = \mathcal{T}(D)$. Using Part (1) of Lemma 4.3, we can write

$$\begin{aligned} \Pr \left\{ D \in \Sigma(R, C) : \sigma_S(D) \geq t\zeta \right\} &= \frac{|D \in \Sigma(R, C) : \sigma_S(D) \geq t\zeta|}{|\Sigma(R, C)|} \\ &\leq t^{(m-1)(n-1)} \frac{|Y \in \Sigma(R', C') : \sigma_S(Y) \geq \zeta|}{|\Sigma(R, C)|} \\ &= \frac{|\Sigma(R', C')|}{|\Sigma(R, C)|} t^{(m-1)(n-1)} \Pr \left\{ Y \in \Sigma(R', C') : \sigma_S(Y) \geq \zeta \right\}. \end{aligned}$$

Similarly, by Part (2) of Lemma 4.3, if $\sigma_S(D) \leq t\zeta$ then $\sigma_S(Y) \leq \zeta + 5|S|$ for $Y = \mathcal{T}(D)$ and

$$\begin{aligned} \Pr \left\{ D \in \Sigma(R, C) : \sigma_S(D) \leq t\zeta \right\} \\ \leq \frac{|\Sigma(R', C')|}{|\Sigma(R, C)|} t^{(m-1)(n-1)} \Pr \left\{ Y \in \Sigma(R', C') : \sigma_S(Y) \leq \zeta + 5|S| \right\}. \end{aligned}$$

It is shown in [D+97] that for sufficiently large margins, the number of contingency tables is approximated within a constant factor by the volume of the corresponding transportation polytope; see Section 1.2. In particular, estimates of [D+97] imply that

$$|\Sigma(R', C')| \leq \beta_1 \text{vol } \mathcal{P}(R', C') \quad \text{and} \quad |\Sigma(R, C)| \geq \beta_2 \text{vol } \mathcal{P}(R, C)$$

for some absolute constants $\beta_1, \beta_2 > 0$.

From (4.2.2), we have

$$\begin{aligned} r_i &\geq t(r'_i - 3n) \geq tr'_i \left(1 - \frac{3}{m^2n} \right) \quad \text{for } i = 1, \dots, m \quad \text{and} \\ c_j &\geq t(r'_j - 3m) \geq tc'_j \left(1 - \frac{3}{mn^2} \right) \quad \text{for } j = 1, \dots, n. \end{aligned}$$

It follows then that

$$\text{vol } \mathcal{P}(R, C) \geq \beta_3 t^{(m-1)(n-1)} \text{vol } \mathcal{P}(R', C')$$

for some absolute constant $\beta_3 > 0$. The result now follows. \square

Next, we show that the t -scaling map \mathcal{T} almost scales the typical table provided the margins R', C' are large enough, that is, $Z' \approx t^{-1}Z$. The idea of the proof is roughly the following: if margins (R', C') and (R, C) are large enough, then the corresponding typical tables Z' and Z roughly optimize the functional $\sum_{i,j} \ln x_{ij}$ on the corresponding transportation polytopes and hence the map $X \mapsto tX$ roughly maps Z' to Z .

(4.5) Lemma. *Let $Z = (z_{ij})$ be the typical table with margins (R, C) , let $Z' = (z'_{ij})$ be the typical table with margins (R', C') obtained by t -scaling and suppose that*

$$z'_{ij} \geq (mn)^4 + 3 \quad \text{for all } i, j.$$

Then

$$\left| \frac{z_{ij}}{tz'_{ij}} - 1 \right| \leq \frac{\beta}{mn} \quad \text{for all } i, j$$

and some absolute constant $\beta > 0$.

Proof. First, we prove some useful inequalities for the function

$$g(x) = (x + 1) \ln(x + 1) - x \ln x.$$

We have

$$g(tx) - g(x) = \int_x^{tx} g'(y) dy = \int_x^{tx} \ln\left(\frac{y+1}{y}\right) dy \leq \int_x^{tx} \frac{dy}{y} = \ln(tx) - \ln x = \ln t.$$

Also,

$$\begin{aligned} g(x) &= (x + 1) \ln(x + 1) - (x + 1) \ln x + (x + 1) \ln x - x \ln x \\ &= (x + 1) \ln\left(\frac{x + 1}{x}\right) + \ln x = \ln x + 1 + O\left(\frac{1}{x}\right) \quad \text{for } x \geq 1. \end{aligned}$$

Finally, we note that

$$g''(x) = -\frac{1}{x(x+1)}.$$

Since from (4.2.2) we have

$$r_i \leq tr'_i \quad \text{and} \quad c_j \leq tc'_j \quad \text{for all } i, j$$

we have

$$(4.5.1) \quad \max_{X \in \mathcal{P}(R, C)} g(X) \leq \ln t + \max_{X \in \mathcal{P}(R', C')} g(X).$$

Let B be the matrix constructed in Section 4.2 and let $W = t(Z' - B) \in \mathcal{P}(R, C)$. Hence

$$w_{ij} \geq t(mn)^4 \quad \text{for all } i, j.$$

Since

$$g(w_{ij}) = 1 + \ln w_{ij} + O\left(\frac{1}{m^4 n^4}\right) \quad \text{and} \quad g(z'_{ij}) = 1 + \ln z'_{ij} + O\left(\frac{1}{m^4 n^4}\right),$$

we have

$$g(W) = g(Z') + \ln t + O\left(\frac{1}{m^3 n^3}\right).$$

From (4.5.1) it follows that

$$(4.5.2) \quad g(Z) - g(W) = O\left(\frac{1}{m^3 n^3}\right).$$

Next, we are going to exploit the strong concavity of g and use the following standard inequality:

if $g''(x) \leq -\alpha$ for some $\alpha > 0$ and all $a \leq x \leq b$ then

$$g\left(\frac{a+b}{2}\right) - \frac{1}{2}g(a) - \frac{1}{2}g(b) \geq \frac{\alpha(b-a)^2}{8}.$$

If for some i, j we have $|w_{ij} - z_{ij}| \geq (mn)^{-1}w_{ij}$, then in view of (4.5.2), for some point U on the interval connecting W and Z and all sufficiently large mn , we will have

$$g(U) > g(Z),$$

which is a contradiction. Thus

$$\left| \frac{z_i}{w_{ij}} - 1 \right| \leq \frac{1}{mn} \quad \text{for all } i, j$$

and all sufficiently large mn . Since

$$\left| \frac{w_{ij}}{tz'_{ij}} - 1 \right| \leq \frac{3}{z'_{ij}} \leq \frac{3}{(mn)^4},$$

the proof follows. \square

(4.6) Proof of Theorem 1.5. Without loss of generality we assume that $N \geq (mn)^7$ since the case of a polynomially bounded N is handled in Proposition 3.5.

Let us choose

$$t = \left\lfloor \frac{N}{(mn)^6} \right\rfloor$$

and consider the t -scaling map $\mathcal{T} : \Sigma(R, C) \longrightarrow \Sigma(R', C')$. Since margins (R, C) are δ -smooth, we have

$$(mn)^6 \leq N' \leq (mn)^7 \quad \text{and} \quad r'_i, c'_j \geq (mn)^4 \quad \text{for all } i, j$$

and all sufficiently large $n \geq m$.

Let us choose $0 < \delta_1 < \delta$. It follows by (4.2.2) that the margins (R', C') are δ_1 -smooth for all sufficiently large $n \geq m$. Let Z' be the typical table of (R', C') , $Z' = (z'_{ij})$. By Corollary 2.5,

$$z'_{ij} \geq (\delta_1)^3 \frac{N'}{mn}.$$

Therefore, for all sufficiently large $m + n$ we have

$$z'_{ij} \geq (mn)^4 + 3.$$

The result now follows by Lemmas 4.4, 4.5, and Proposition 3.5 applied to (R', C') . \square

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