

# A Mildly Exponential Time Algorithm for Approximating the Number of Solutions to a Multidimensional Knapsack Problem

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For Paul Erdős on his 80th birthday

We describe a  $2^{O(r\sqrt{n}(\log n)^{5/2})}e^{-2}$  time randomized algorithm that estimates the number of feasible solutions of a multidimensional knapsack problem within  $1 \pm \epsilon$  of the exact number. (Here  $r$  is the number of constraints and  $n$  is the number of integer variables.) The algorithm uses a Markov chain to generate an almost uniform random solution to the problem.

## 1. Introduction

An instance of the multidimensional knapsack problem in  $n$  variables is defined by a non-negative  $r \times n$  integer matrix  $A$ , a vector  $d \in \mathbb{Z}^n$ , and a vector  $b \in \mathbb{Z}^r$ . We assume, to avoid trivialities, that all components of  $b$  and  $d$  are positive. The set of feasible solutions  $K$  is then

$$K = \{x \in \mathbb{Z}^n \mid Ax \leq b, 0 \leq x \leq d\}. \quad (1)$$

We will assume, without loss of generality, that  $d_j \leq \min_i b_i/a_{ij}$ . Let  $d_{\max} = \max_j d_j$ . In particular, if  $d_{\max} = 1$ , we have the *zero-one* multidimensional knapsack problem, and if  $r = 1$  we have the knapsack problem. The *optimization* problem consists of finding the maximum value of a given linear function over  $K$ . This is known to be NP-complete, even for  $r = 1$  and zero-one variables. The *counting* problem seems to be even harder. This asks for  $|K|$ . This problem is #P-complete, again even for  $r = 1$  and zero-one variables.

Markov chains have been successfully used to approximately solve several #P-complete problems [1, 2, 3, 4, 6, 7, 10, 12, 14]. In all of these problems the running time of the algorithm is polynomial in problem size and relative error. On the other hand, the general zero-one permanent still resists polynomial time approximation, though Jerrum

Vazirani [9] have reduced the time complexity to  $2^{O(\sqrt{n}(\log n)^3)} \epsilon^{-2}$  for computing an approximation, i.e. an approximation with relative error in the range  $1 \pm \epsilon$ . In this paper we make similar progress in approximating  $|K|$ . We show that there is a  $\frac{1}{\pi(\log n)^{5/2}} \epsilon^{-2}$  time algorithm for computing an  $\epsilon$ -approximation to  $|K|$ . Furthermore,  $d_j \geq n^2$  for  $j \in [n] = \{1, 2, \dots, n\}$ , we can make the scheme polynomial.

We note that there is an easy randomized approximation algorithm, given by generating  $m$  points as follows. Suppose we simply choose  $x_j$  randomly in  $[0, d_j]$ . It is obvious

$$\Pr(x_j \leq \lfloor d_j/n \rfloor) \geq 1/(2n).$$

However, if  $x_j \leq \lfloor d_j/n \rfloor$  ( $j \in [n]$ ), we have

$$Ax \leq \frac{1}{n} Ad \leq b,$$

$a_j d_j \leq b_j$  for all  $i \in [r]$ ,  $j \in [n]$ . Therefore  $x \in K$ . Thus, by randomly generating  $x$  in this fashion, we have probability  $(2n)^{-n}$  of having  $x \in K$ . Hence, a uniformly distributed  $x$  in  $K$  can be generated in  $(2n)^{n+1}$  time with very high probability. This easily gives an approximation algorithm with the time complexity  $n^{O(n)} \epsilon^{-2}$ . As previously stated, our approximation algorithm runs in time  $2^{O(r\sqrt{n}(\log n)^{5/2})}$ , so we will assume here that  $r = O(n^k)$  for some fixed  $k < \frac{1}{2}$ . (In the zero-one case, an  $O(rn2^n)$  time exact deterministic algorithm course, trivial.) It may be worth pointing out that while there are fully polynomial approximation schemes for the optimisation version of the knapsack problem, there is none for the multidimensional problem unless P=NP. Furthermore, we have not been able to make any use of these optimisation results for knapsack in the associated counting problem.

We develop the argument in three steps. First we examine the zero-one knapsack problem in Section 3, then move to the general zero-one case in Section 4. Finally, we consider the general problem in Section 5.

As a tool in our proof, we prove a general fact about random sampling (Theorem 7.2) which may be of independent interest, so we shall mention it here: suppose we have a collection of  $n$  non-negative reals  $c_1, c_2, \dots, c_n$  with mean  $\mu$  and  $c_i \leq \alpha$ , for  $i = 1, 2, \dots, n$ . We pick without replacement a sample of  $t$   $c_i$ 's; let  $S_t$  be their sum. The Chernoff-bounding Theorems assert

$$\Pr(S_t - t\mu \geq x) \leq \exp \left\{ -\frac{2x^2}{t\alpha^2} \right\} \quad \text{for all } x \geq 0.$$

We prove a similar bound, but with  $\alpha$  replaced by a quantity that we have 'observed' from our samples. Let  $S_m$  be the sum of the  $m$  largest samples among the  $t$  we have picked. We prove

$$\Pr(S_t - t\mu > S_m) = O(\exp\{-m^2(t-m)^2/t^3\}) \quad \text{for } t = m + 1, \dots, n.$$

## 2. Rapidly mixing Markov chains

It is well known that the approximate counting of combinatorial objects is intimately related to their near uniform generation - see Jerrum, Valiant and Vazirani [8] for a formal statement of this relation.

In our problem this general reduction implies that if in time  $T(n)$  we can generate a solution  $x \in K$  with probability  $p(x)$  so that, say,  $p(x)/p(y) \leq 2$  for all  $x, y \in K$ , then it takes  $O(T(n)s(n)\epsilon^{-2} \log \delta^{-1})$  time to compute an  $\epsilon$ -approximation with probability at least  $1 - \delta$ , where  $s(n)$  is a polynomial in  $n$ . As our  $T(n)$  dominates the remaining terms, we concentrate on estimating its value from now on.

For this purpose we define an ergodic reversible Markov chain with set of states  $K$  whose steady state distribution is uniform. We then run this chain for a sufficient number of steps that we can be sure we are close enough to the steady state. We then take the current state as our near uniform sample.

In detail, let  $K$  be the set of states of Markov chain  $\mathcal{M}$ . If  $x, y \in \mathbb{Z}^n$ , define the Hamming distance  $h(x, y) = |\{j : x_j \neq y_j\}|$ . (Normally this is defined only for zero-one vectors, and this will be the principal use here, but we also use the definition for general integer vectors.) The transition probabilities  $p(x, y)$  are then given by

$$p(x, y) = \begin{cases} 0 & \text{if } h(x, y) > 1 \\ \frac{1}{2nd_{\max}} & \text{if } h(x, y) = 1 \\ 1 - \sum_{z \neq x} p(x, z) & \text{if } y = x. \end{cases}$$

Note that  $\mathcal{M}$  can be simulated easily, as follows. Start at any point of  $K$  (e.g. the origin). At the 'current' point  $x \in K$ , repeat the following step. Do nothing with probability  $\frac{1}{2}$ , otherwise choose a coordinate direction  $k \in [n]$  uniformly at random. Choose an integer  $x'_k \neq x_k$  from  $[0, d_{\max}]$  uniformly at random. Let  $x'_j = x_j$  ( $j \in [n] \setminus \{k\}$ ). If  $x' \in K$ ,  $x'$  becomes the new current point, otherwise remain at  $x$ . Note also that since  $\mathcal{M}$  is symmetric, aperiodic and irreducible, its stationary distribution  $\pi$  is uniform over its states.

Now let  $p^{(t)}$  be the distribution of the current point after  $t$  steps starting at  $x = 0$ . The variational distance between  $p^{(t)}$  and  $\pi$  can be bounded in terms of the conductance  $\Phi$ :

$$\Phi = \min \{ \Phi_S : \pi(S) \leq \frac{1}{2} \},$$

where for  $S \neq \emptyset$ ,

$$\Phi_S = \frac{\sum_{x \in S, y \notin S} \pi(x)p(x, y)}{\pi(S)},$$

and

$$\pi(S) = \sum_{x \in S} \pi(x).$$

It will be useful to think in terms of a digraph  $\Gamma = (K, E)$ , where  $E = \{(x, y) \in K^2 : h(x, y) = 1\}$ . If we let  $E_{S, \bar{S}} = \{(x, y) \in E : x \in S, y \notin S\}$  and  $\rho(S) = |E_{S, \bar{S}}|/|S|$ , then

$$\Phi = \min_{|S| \leq N/2} \left\{ \frac{\rho(S)}{2nd_{\max}} \right\} \quad (2)$$

Now, letting  $N = |K|$ , it follows from results in Sinclair and Jerrum [15] that for all  $x \in K$

$$|p^{(t)}(x) - \pi(x)| \leq \sqrt{N}(1 - \Phi^2/2)^t.$$

Thus our claim about near uniform generation can be justified by showing that the

conductance  $\Phi$  of  $\mathcal{M}$  satisfies

$$\Phi = 2^{-O(r\sqrt{n}(\log n)^{3/2})}. \quad (3)$$

view of (2), assuming that  $d_{\max}$  is suitably bounded as a function of  $n$ , this will then follow from

$$\rho(S) = 2^{-O(r\sqrt{n}(\log n)^{3/2})} \quad \text{for all } S \subseteq K, |S| \leq N/2. \quad (4)$$

we will use a variation of the canonical path argument introduced by Jerrum and Sinclair [6]. Fix  $S \subseteq K, |S| \leq N/2$ . We will define a set  $T = T(S) \subseteq S \times \bar{S}$  with

$$|T| \geq \frac{|S| \cdot |\bar{S}|}{2}. \quad (5)$$

we will also define a canonical path  $P_{x,y}$  in  $\Gamma$  from  $x$  to  $y$  for every  $(x, y) \in T$ . For each  $(v, w) \in E_{S, \bar{S}}$ , we let  $W_{v,w}$  denote the set of canonical paths using the edge  $(v, w)$ . Let  $\lambda = |W_{v,w}|$  and let  $\lambda(S) = \max\{\lambda_{v,w} : (v, w) \in E_{S, \bar{S}}\}$ . Clearly

$$\begin{aligned} |E_{S, \bar{S}}| &\geq \frac{|T|}{\lambda} \\ &\geq \frac{|S| \cdot |\bar{S}|}{2\lambda}, \\ \rho(S) &\geq \frac{N}{4\lambda}. \end{aligned} \quad (6)$$

we will complete the proof of (4) by showing that for any  $S$

$$\lambda = 2^{O(r\sqrt{n}(\log n)^{3/2})} N.$$

### 3. The zero-one knapsack problem

we concentrate first on the zero-one case. The case  $r = 1$  has a special feature that allows a slightly simpler proof. We will give this, and then analyse the general zero-one case later. For simplicity of notation we now let  $K = \{x \in \{0, 1\}^n : a_1x_1 + a_2x_2 + \dots + a_nx_n \leq b\}$ , where  $a_1, a_2, \dots, a_n, b$  are positive integers.

#### Refining canonical paths

Consider a permutation  $\sigma$  on  $[n]$ , an offset  $u$  ( $0 \leq u < n$ ), and states  $x \in S$  and  $y \in \bar{S}$ . We define the sequence  $Q_{x,y}(\sigma, u) = v^0, v^1, \dots, v^n$  as follows:  $v^0 = x, v^n = y$ , and  $v^j = v^{j-1} \oplus \sigma(i \oplus u)$  and  $v^j_{\sigma(i \oplus u)} = y_{\sigma(i \oplus u)}$ ,  $i \oplus u = (i + u - 1 \bmod n) + 1$ . Thus, we go through components of  $x$  in the order  $\sigma(1 \oplus u), \sigma(2 \oplus u), \dots, \sigma(n \oplus u)$ , changing one component from  $x_j$  to  $y_j$  at each step. If all intermediate points are in  $K$ , we say  $Q_{x,y}$  is feasible. (We may remove the loops caused by  $v^i = v^{i+1}$ .)

Assume we have chosen  $\sigma, u$ , and for notational convenience assume that  $\sigma$  is the identity permutation and  $u = 0$ . Fix  $(v, w) \in E_{S, \bar{S}}$  and consider those  $(x, y) \in S \times \bar{S}$  for which the path  $Q_{x,y}$  uses  $(v, w)$ . Then, for some  $t \geq 1$ , we can write

$$v = (y_1 \dots y_{t-1} x_t x_{t+1} \dots x_n) \quad \text{and} \quad w = (y_1 \dots y_{t-1} y_t x_{t+1} \dots x_n).$$

When  $\sigma, u$ , and  $(v, w)$  together fix  $v_1, \dots, v_t$  and  $x_1, \dots, x_n$ , and  $\lambda_{v,w}$  is bounded by the number

of possibilities for  $x_1, \dots, x_{t-1}, y_{t+1}, \dots, y_n$ . This leads to the idea of the complementary point  $w' = (x_1, \dots, x_t, y_{t+1}, \dots, y_n)$  from Jerrum and Sinclair [15]. Let  $W' = W'(x, y)$  be the set of complementary points  $w'$  such that  $(v, w)$  is on  $Q_{x,y}$ . Clearly, if we use the same  $\sigma$  for each  $x, y$ , then the number of  $(x, y)$  pairs in  $S \times \bar{S}$  for which  $Q_{x,y}$  uses  $(v, w)$  is at most  $n$  times the total possible number of complementary points for  $(v, w)$ . (Since  $n$  is the number of choices for  $u$ .)

Now let  $D_\beta = \{\xi : h(\xi, \eta) \leq \beta \text{ for some } \eta \in K\}$ . Then, the following lemma holds:

**Lemma 3.1.** *There exist  $\sigma^*$  and  $T^* \subseteq S \times \bar{S}$  such that  $|T^*| \geq \frac{|S||\bar{S}|}{2}$  and*

- (i)  $W' \subseteq D_{4m}$ , where  $m = \lfloor 4\sqrt{n \log_2 n} \rfloor$ .
- (ii) For all  $(x, y) \in T^*$ , there exists  $u^* = u^*(x, y)$  such that  $P_{x,y} = Q_{x,y}(\sigma^*, u^*)$  is feasible.

**Proof.** Fix  $x \in S, y \in \bar{S}$ . Choose  $\sigma$  randomly,  $u$  arbitrarily and an intermediate point  $v$  of  $Q_{x,y}$ , say the  $\ell$ -th point in the sequence. For  $\eta \in \{0, 1\}^n$ , let its support  $I_\eta = \{j : \eta_j = 1\}$ . Let  $I = \{\sigma(1 \oplus u), \sigma(2 \oplus u), \dots, \sigma(\ell \oplus u)\}$ . Then

$$I_w = (I_x \cap I) \cup (I_y \setminus I),$$

where  $w'$  is the complementary point corresponding to the edge  $(v, w)$  of  $Q_{x,y}$  that starts with  $v$ .

Now, for  $X \subseteq [n]$ , let  $a(X) = \sum_{j \in X} a_j$ . Then  $a(I_x \cap I)$  is the sum of the elements of a random  $\ell$ -subset of the multiset  $A_x = \{a_j x_j : j \in [n]\}$ . Assume next that  $|I_x \cap I| \geq 2m$ , and let  $\Delta_x$  denote the sum of the  $m$  largest elements of the multiset  $\{a_j : j \in I_x \cap I\}$ . Now, if  $ax = \sum_{j \in [n]} a_j x_j$ ,

$$\begin{aligned} E(a(I_x \cap I)) &= \mu_x = \frac{\ell}{n} ax, \\ \Pr(a(I_x \cap I) \geq \mu_x + \Delta_x) &= O(e^{-m^2/4\ell}) \\ &= O(n^{-4}). \end{aligned}$$

so from Theorem 7.2 (see Section 7),

Thus, regardless of the size of  $I_x \cap I$ , we can assert that with probability  $1 - O(n^{-4})$  there exists a set  $J_x \subseteq I_x \cap I$  such that

$$\begin{aligned} |(J_x \cap I) \setminus J_x| &\leq 2m \\ a(J_x) &\leq \mu_x. \end{aligned} \quad (7)$$

Now consider  $I_y \setminus I$ .

$$E(a(I_y \setminus I)) = \mu_y = \frac{n - \ell}{n} ay.$$

Then, in an analogous fashion to  $I_x \cap I$ , we have that with probability  $1 - O(n^{-4})$  the exists a set  $J_y \subseteq I_y \setminus I$  such that

$$\begin{aligned} |(I_y \setminus I) \setminus J_y| &\leq 2m \\ a(J_y) &\leq \mu_y. \end{aligned} \quad (8)$$

define  $w''$  by  $I_{w''} = J_x \cup J_y$ . Then (7) and (9) imply

$$h(w', w'') \leq 4m.$$

that  $w'' \in K$ . Indeed, using (8) and (10)

$$\begin{aligned} aw'' &= a(J_x) + a(J_y) \\ &\leq \frac{\ell}{n}ax + \frac{n-\ell}{n}ay \\ &\leq \frac{\ell}{n}b + \frac{n-\ell}{n}b \\ &= b. \end{aligned} \tag{11}$$

each of the pairs  $(x, y)$  such that  $x \in S$  and  $y \in \bar{S}$ , we have that the probability a permutation satisfies

$$w' \in D_{4m} \text{ for all complementary points } w' \text{ arising from all offsets} \tag{12}$$

is at least  $1 - O(1/n^2)$ . Then by a simple counting argument we have that there must exist a permutation  $\sigma^*$  with at least a  $1 - O(1/n^2)$  fraction of  $x, y$  pairs satisfying (12).

Each  $x, y$  there is an offset  $u^* = u^*(x, y)$  such that  $Q_{x,y}(\sigma^*, u^*)$  is feasible (see [11], Problem 3.21 – the gas station problem). Thus there exists a set  $T^* \subseteq S \times \bar{S}$  at

$$|T^*| \geq |S| \cdot |\bar{S}| (1 - O(n^{-2})), \tag{13}$$

such that  $Q_{x,y}(\sigma^*, u^*)$  is feasible for all  $(x, y) \in T^*$ . This completes the proof of the lemma.  $\square$

Next we observe that for  $(v, w) \in E_{S, \bar{S}}$  we have

$$\begin{aligned} \lambda_{v,w} &\leq n |D_{4m}| \\ &\leq nN \binom{n}{4m} \\ &= 2^{O(\sqrt{n} \log n^{3/2})} N, \end{aligned}$$

which follows immediately.

#### 4. The general zero-one problem

Let  $\geq 2$  be the argument that the complementary points are almost always 'close' to  $K$ . We would like to find a permutation  $\sigma$  and  $R \subseteq J(x, y) = (I_x \setminus I_y) \cup (I_y \setminus I_x)$ , we define a permutation  $\tau = \tau(x, y, \sigma, R)$  and then take  $Q_{x,y}(\tau)$  as our path. Here  $\tau$  is defined as follows: let  $R_x = R \cap I_x$  and  $r_x = |R_x|$  for  $\alpha = x, y$ . Starting with the sequence

of points  $z \in R \subseteq [n]$  and  $x \in \{0, 1\}^n$ , we define  $z = z(x, R)$  by  $I_z = I_x \setminus R$ , i.e. to obtain  $z$ , simply permute  $J$  to zero for  $j \in R$ .

Let  $x, y \in K$ , permutation  $\sigma$  and  $R \subseteq J(x, y) = (I_x \setminus I_y) \cup (I_y \setminus I_x)$ , we define a permutation  $\tau = \tau(x, y, \sigma, R)$  and then take  $Q_{x,y}(\tau)$  as our path. Here  $\tau$  is defined as follows: let  $R_x = R \cap I_x$  and  $r_x = |R_x|$  for  $\alpha = x, y$ . Starting with the sequence

$\sigma(1), \sigma(2), \dots, \sigma(n)$ , we move the elements of  $R_x$  to the front (in natural order), and then move the elements of  $R_y$  to the back.  $\tau$  is defined by the sequence obtained. For example, if  $\sigma = (10, 9, 1, 3, 7, 4, 8, 5, 6, 2)$  and  $R_x = \{7, 9\}$ ,  $R_y = \{3, 5\}$ , then  $\tau = (7, 9, 10, 1, 4, 8, 6, 2, 3, 5)$ .

**Lemma 4.1.** *There exists  $\sigma^*$  and  $T^* \subseteq S \times \bar{S}$  such that  $|T^*| \geq \frac{|S||\bar{S}|}{2}$  and*

- (i)  $W' \subseteq D_{16mr \log_2 n + 4mr}$ ,  $(m = \lfloor 4\sqrt{n \log_2 n} \rfloor)$
- (ii) For all  $(x, y) \in T^*$ , there exists  $R = R(x, y)$ ,  $|R| \leq 16mr \log_2 n$  such that  $Q_{x,y}(\tau)$  is feasible.

**Proof.** Fix  $x \in S$ ,  $y \in \bar{S}$  and choose  $\sigma$  randomly. Observe first that no matter what choice we make for  $R$ , it is the case that each complementary point of  $Q_{x,y}(\tau)$  is within Hamming distance  $|R|$  of a complementary point of  $Q_{x,y}(\sigma)$ . Consider a complementary point  $w'$  of  $Q_{x,y}(\sigma)$ . The analysis of Lemma 3.1 shows that with probability  $1 - O(r/n^4)$  we can find sets  $X_1, X_2, \dots, X_r$ , all of size at most  $4m$  such that zeroising the  $X_i$ -components of  $w'$  produces a vector satisfying the  $i$ th constraint (here  $X_i$  is equal to  $J_x \cup J_y$  of the lemma). Hence zeroising all of the  $\bigcup_{i=1}^r X_i$ -components produces a member of  $K$ . Thus, in this case all complementary points of  $Q_{x,y}(\tau)$  are within Hamming distance  $|R| + 4mr$  of  $K$ , and the first part follows (modulo a definition of  $R$ ).

Our next observation is that if

$$R' \subseteq R \subseteq J(x, y),$$

and all intermediate points in  $Q_{x,y}(\tau(x, y, \sigma, R'))$  satisfy the  $i$ th constraint, the same is true for  $Q_{x,y}(\tau(x, y, \sigma, R))$ . This is simply because the intermediate points in the latter path have supports that are subsets of those in the former.

We will now define  $R = R_1 \cup R_2 \cup \dots \cup R_r$ , where all we claim is that the intermediate points of  $Q_{x,y}(\tau(x, y, \sigma, R_i))$  satisfy the  $i$ th constraint with probability  $1 - O(\log_2 n/n^4)$ .

We will now concentrate on  $R_1$ , which we decompose as  $\bigcup_{j=1}^p R_{1,j}$ , where  $p \leq \log_2 n$ . We will use the notation  $a^1(I) = \sum_{j \in I} a_{1,j}$  for  $I \subseteq [n]$ .

Let  $v$  be one of the first  $n/2$  points of  $Q_{x,y}(\sigma)$ . Let  $B_x = I_v \cap (I_x \setminus I_y)$  and  $B_y = I_v \cap (I_y \setminus I_x)$  so that  $I_v = B_x \cup B_y \cup (I_x \cap I_y)$ . We can argue, as in the proof of Lemma 3.1, that with probability  $1 - O(n^{-4})$  there exist  $B'_x \subseteq B_x, B'_y \subseteq B_y$  with  $|B_x - B'_x|, |B_y - B'_y| \leq 2m$  and  $a^1(I_{v'}) \leq b_1$ , where  $I_{v'} = B'_x \cup B'_y \cup (I_x \cap I_y)$ . If  $|I_x \setminus I_y| > 8m$ , then  $L_x$  is the index set of the  $8m$  largest elements in  $I_x \setminus I_y$ . Otherwise  $L_x = I_x \setminus I_y$ . Define  $L_y$  similarly with respect to  $I_y \setminus I_x$ . It follows from Theorem 7.1 (below) that if  $|L_x| \geq 8m$ , then  $|L_x \cap I_v| \geq 2m$  with probability  $1 - O(n^{-4})$ . (An element of  $L_x$  is in  $I_v$  with probability at least one half.) Similarly,  $|L_y| \geq 8m$  implies  $|L_y \cap I_v| \geq 2m$  with probability  $1 - O(n^{-4})$ . Hence with high probability, if  $\bar{v}$  is defined by  $I_{\bar{v}} = I_v \setminus (L_x \cup L_y)$ , then  $a^1(I_{\bar{v}}) \leq a^1(I_{v'}) \leq b_1$ .

Thus with probability  $1 - O(n^{-4})$ , the first  $n/2$  points of  $Q_{x,y}(\tau(x, y, \sigma, L_x \cup L_y))$  satisfy the first inequality. We therefore take  $R_{1,1} = L_x \cup L_y$ . Let  $x'$  denote the  $\frac{1}{2}n$ th point of  $Q_{x,y}(\tau(x, y, \sigma, L_x \cup L_y))$ , and condition on its value. The remaining  $n/2$  components are changed by  $\sigma$  in random order in going from  $x'$  to  $y$ . To define  $R_{1,2}$ , repeat the above argument with  $x'$  in place of  $x$ , and  $n/4$  in place of  $n/2$ . In this way we obtain a set  $R_{1,2}$  such that with probability  $1 - O(n^{-4})$ , the first  $3n/4$  points of  $Q_{x,y}(\tau(x, y, \sigma, R_{1,1} \cup R_{1,2}))$

satisfy the inequality. The remaining sets in the partition of  $R_1$  are obtained similarly. We stop when we have at most  $16m$  components to change in order to get to  $y$ . The existence of  $T^*$  is now inferred as at the end of the proof of Lemma 3.1.  $\square$

We can now prove (6) fairly easily. Fix  $(t, w) \in E_{S,S}$ . If  $Q_{x,y}$  uses  $(t, w)$ , we can fix  $x, y$  by using the permutation  $\tau$  and the complementary point. But there are at most  $\binom{n}{16mr \log_2 n}$  choices for  $\tau$ , given  $\sigma^*$ . Hence,

$$\lambda_{t,w} \leq n |D_{16mr \log_2 n + 4mr}| \binom{n}{16mr \log_2 n} \quad (14)$$

$$\leq n \binom{n}{16mr \log_2 n + 4mr} N \binom{n}{16mr \log_2 n} \quad (15)$$

$$= 2^{O(r\sqrt{n}(\log n)^{3/2})} N, \quad (16)$$

(6) follows immediately.

### 5. The general problem

now consider the general case (1). Observe from (2) that  $\Phi$  will be very small if  $d_{\max}$  is very large. Note also that the commonly used device of replacing a general integer variable  $x_j$  by a sum of zero-one variables  $\sum_{s=0}^{\ell_j} 2^s z_{sj}$ , where  $\ell_j$  is suitably chosen, does seem to work here for two reasons:

If  $d_j \neq 2^{\ell_j+1} - 1$ , the number of solutions is not preserved (unless we add a further constraint).

The number of variables  $n$  is increased by a factor  $\sum_j \log_2(d_j + 1)$ . If any  $d_j$  is nonpolynomially large in  $n$ , this leads to a significant increase in the algorithm's time complexity.

As we will adopt a different strategy. We need to be able to deal with the possibility of very large  $d_j$ , but first consider the case where  $d_{\max} < n^3$ . If canonical paths and complementary points are defined exactly as before, the arguments of Section 4 require a minor modification.

Thus, given  $x, y \in K$ , consider two zero-one vectors  $\xi^{(1)}, \xi^{(2)}$ , where  $\xi_j^{(1)} = 1, \xi_j^{(2)} = 0$  if  $x_j > y_j$ , and  $\xi_j^{(1)} = 0, \xi_j^{(2)} = 1$  if  $y_j > x_j$ . (If  $x_j = y_j$ , the values of  $\xi_j^{(1)}, \xi_j^{(2)}$  can be chosen arbitrarily.) Now, the canonical path from  $x$  to  $y$  can be chosen using that from  $\xi^{(1)}$  to  $\xi^{(2)}$  in the zero-one polytope defined by the system

$$\sum_{j=1}^n (a_{ij}|x_j - y_j|)\xi_j \leq (b_i - \sum_{j=1}^n a_{ij} \min\{x_j, y_j\}) \quad (i \in [r]),$$

where  $x, y$  are to be treated as constant vectors. We simply interpret changing a component from  $\xi_j^{(1)}$  to  $\xi_j^{(2)}$  as requiring the change of a component from  $x_j$  to  $y_j$ . We can apply Lemma 4.1 to this system and the bound on Hamming distance still applies. Now the number of points within Hamming distance  $\beta$  of  $K$  is clearly at most  $n^{3\beta}$  times the estimate (15). This additional factor does not, however, inflate the estimate (16).

To finish this case we must check that the intermediate points of the path  $Q_{x,y}$  so

defined are feasible. Consider the  $k$ th point and for notational convenience assume that  $\tau = (1, 2, \dots, n)$ . Then we know that

$$\sum_{i=1}^k ((a_{ij}|x_j - y_j|)\xi_j^{(2)} + \sum_{j=k+1}^n (a_{ij}|x_j - y_j|)\xi_j^{(1)}) \leq (b_i - \sum_{j=1}^n a_{ij} \min\{x_j, y_j\}) \quad (i \in [r]).$$

But

$$\min\{x_j, y_j\} + |x_j - y_j|\xi_j^{(2)} \geq y_j$$

and

$$\min\{x_j, y_j\} + |x_j - y_j|\xi_j^{(1)} \geq x_j.$$

Thus,

$$\sum_{i=1}^k a_{ij}y_j + \sum_{j=k+1}^n a_{ij}x_j \leq b_i \quad (i \in [r]),$$

and the path  $Q_{x,y}$  is feasible. Thus we may conclude that (6) remains valid when  $d_{\max} < n^3$  (and, in fact, for any polynomial bound on  $d_{\max}$ ).

Thus suppose, for some  $k$  ( $0 \leq k < n$ ), that  $d_j < n^3$  for  $j = 1, 2, \dots, k$ , and  $d_j \geq n^3$  for  $j = k+1, k+2, \dots, n$ . Define  $\sigma_j = [(d_j + 1)/n^3]$ , and let  $x'_j = \lfloor x_j/\sigma_j \rfloor, d'_j = \lfloor d_j/\sigma_j \rfloor$  for  $j \in [n]$ . Also let  $d'_{ij} = \sigma_j a_{ij}$  for  $i \in [r], j \in [n]$ . We can generate a point (near) uniformly in  $K' = \{x' \in \mathbb{Z}^n : A'x' \leq b, 0 \leq x' \leq d'\}$  by the above method, since

$$d'_j \leq d_j/\sigma_j \leq n^3 d_j/(d_j + 1) < n^3.$$

After generating such an  $x'$ , we then choose  $x$  by

$$x_j = \sigma_j x'_j + Z_j, \quad (j \in [n]), \quad (17)$$

where  $Z_j$  is an integer chosen uniformly from  $[0, \sigma_j - 1]$ . We accept the point  $x$  if it lies in  $K$ , otherwise we try again. Now (17) determines a bijection between the integer  $x$ 's in some set  $H$  and the pairs  $(x', Z)$ . The generated  $x$ 's are evidently uniform on  $H$ , a union of hyper-rectangles, one corresponding to each  $x'$ . Note that  $K \subseteq H$ , since for each  $x \in K$  there is a unique pair  $(x', Z)$  with  $x' \in K'$  given by  $x'_j = \lfloor x_j/\sigma_j \rfloor, Z_j = x_j \bmod \sigma_j, j \in [n]$ . The accepted points will, therefore, be (near) uniform in  $K$ , as required. However, the generated  $x$  may be rejected, so we must check that acceptance occurs with sufficiently high probability. It is clearly enough that the acceptance probability be large in comparison with the estimate of conductance (3). In that case the number of repetitions required for acceptance will not significantly affect the total time to generate a (near) uniform point in  $K$ .

Suppose we have some 'good' set  $G \subseteq K'$  such that

- (i)  $\Pr(x \in K \mid x' \in G) \geq \frac{1}{2}$ ,
- (ii)  $\Pr(x' \in G) \geq n^{-4r}$ .

Then it is easy to see that

$$\Pr(x \in K) \geq \Pr(x \in K \mid x' \in G) \Pr(x' \in G) \geq \frac{1}{2} n^{-4r},$$

which is large compared to (3), and we are done.

it remains only to define the set  $G$  and prove that it has properties (i) and (ii). To do this, let  $y \in \mathbb{R}^n$ , let  $\hat{y} = (\hat{y}, \bar{y})$ , where  $\hat{y} \in \mathbb{R}^k$ ,  $\bar{y} \in \mathbb{R}^{n-k}$ , and  $k$  is as defined above. We use the same notation for the corresponding partition of a matrix by its first  $k$  and last  $n-k$  columns. Note that  $\hat{x} = \hat{x}'$ ,  $\hat{A} = \hat{A}'$ , since  $\sigma_j = 1$  for  $j \leq k$ . Now define

$$G = \{x' \in K' : \hat{A}\hat{x} \leq \frac{k}{k+1}b\} \text{ and } \hat{G} = \{\hat{x}' : x' \in G\}.$$

5.1.  $\Pr(x \in K \mid x' \in G) \geq \frac{1}{2}$ .

For  $x \in H$  let

$$D(x) = \{y \in \mathbb{R}^{n-k} : x_{k+j}/\sigma_{k+j} \leq y_j < (x_{k+j} + 1)/\sigma_{k+j}, j \in [n-k]\}.$$

$\hat{x} \in \hat{G}$ . Clearly  $(\hat{g}, \xi) \in K'$  if and only if  $\xi$  lies in the polytope

$$\bar{P} = \{\xi \in \mathbb{R}^{n-k} : \bar{A}'\xi \leq b - \hat{A}\hat{g} = b^*, 0 \leq \xi \leq \bar{a}'\},$$

where  $\bar{a}' \geq \frac{1}{k+1}b$ . Now

$$\Pr(x \in K \mid \hat{x}' = \hat{g}) = \frac{\text{vol}(H')}{\text{vol}(H^n)}, \tag{18}$$

$$H' = \bigcup_{\substack{x \in K \\ \hat{x}' = \hat{g}}} D(x) \text{ and } H'' = \bigcup_{\substack{x \in H \\ \hat{x}' = \hat{g}}} D(x).$$

$\bar{P} \supseteq \bar{P}'$ , since if  $\xi \in \bar{P}'$ , then  $\xi \in D(x)$ , where  $\hat{x} = \hat{g}$ ,  $x_{j+k} = \lfloor \sigma_{j+k}\xi_{j+k} \rfloor$  for  $j \in [n-k]$  and  $x$  is a member of  $K$ .

On the other hand, the assumptions on  $d_j$  imply

$$a_{ij} \leq a_{ij}(2d_j/n^3) \leq 2b_i/n^3 \leq 2(k+1)b_i^*/n^3. \tag{19}$$

For  $z \in H''$  implies

$$\bar{A}'z \leq b^* + \bar{A}'1 \leq (1 + \frac{2(k+1)(n-k)}{n^3})b^*,$$

so  $z$  is the vector of all 1's, using (19). So

$$H'' \subseteq \left(1 + \frac{2(k+1)(n-k)}{n^3}\right)\bar{P}. \tag{20}$$

$$\Pr(x \in K \mid \hat{x}' = \hat{g}) \geq (1 + \frac{2(k+1)(n-k)}{n^3})^{-n-k} \geq \exp\{-2(k+1)(n-k)^2/n^3\} \geq \frac{1}{2},$$

completing the proof. □

5.2.  $\Pr(x' \in G) \geq n^{-4r}$ .

For each  $x' \in K' \setminus G$ , consider the rows  $i \in [r]$  such that  $(\hat{A}\hat{x})_i > \frac{k}{k+1}b_i$ . For each such  $i$  there exists a smallest  $t = t(i)$  ( $1 \leq t \leq k$ ) such that  $a_{it}x_t > b_i/(k+1)$ . Thus define a

function  $g : K' \rightarrow G$  by

$$g_j(x') = \begin{cases} x'_j & \text{if } j \neq t(i) \text{ for any } i, \\ 0 & \text{otherwise.} \end{cases}$$

Clearly  $g(x') \in G$ , as required. Since  $g(x')$  differs from  $x'$  in at most  $\min\{r, k\}$  coordinates, the point-to-set map  $g^{-1}$  clearly partitions  $K'$  into classes of size at most

$$\binom{n}{r} n^{3 \min\{r, k\}} \leq n^{4r},$$

since  $x' < n^3 \mathbf{1}$ . Hence  $|K'| \leq n^{4r}|G|$  and

$$\Pr(x' \in G) = |G|/|K'| \geq n^{-4r},$$

as claimed. □

### 6. A polynomially solvable case

In this section we prove a stronger result in a special case. If  $d_j \geq n^2$ ,  $j = 1, 2, \dots, n$ , we can construct a fully polynomial randomized approximation scheme for  $|K|$ , i.e. our algorithm is polynomial in  $n, \epsilon^{-1}$ . Thus such cases are 'easy', since the counting closely resembles volume computation [4].

We can use the scaling of the previous section to 'round' the feasible polytope  $K$  to  $K'$ . Then we have  $B(n/2) \subseteq K' \subseteq B(n^2)$ , where  $B(v) = \{0 \leq x' \leq v\mathbf{1}\}$ . The first inclusion follows from  $a_{ij}\sigma_j \leq 2a_{ij}d_j/n^2 \leq 2b_i/n^2$  for  $j \in [n]$ , while the second is a restatement of  $d_j < n^3$ . We perform a biased random walk on the integer lattice points  $x' \in B(n^2)$  with the weighting function  $T(x') = e^{-2n(x')}$ , where

$$t(x') = \min\{t \geq 0 : A'x' \leq (1+t)b\}.$$

At a point  $x'$  we do nothing with probability  $1/2$ . Otherwise we randomly choose  $\pm j$  from  $\{\pm 1, \pm 2, \dots, \pm n\}$ . We then let  $y' = x' \pm e_j$ , where  $e_j$  denotes the  $j$ th unit vector. If  $y' \in B(n^2)$ , we move there with probability  $\min\{1, T(y')/T(x')\}$ . This completes a step of the walk.

It is easily shown that  $t$  varies by only a constant factor over any unit cube in  $B(n^2)$ , using the rounding property. Indeed, if  $A'x' \leq (1+t)b$ ,

$$A'(x' + \mathbf{1}) \leq \left(1 + t + \frac{2}{n}\right)b. \tag{21}$$

Walks of this type were studied in Applegate and Kannan [1] (see also Dyer and Frieze [3] or Lovász and Simonovits [13] for some improvements). The function  $T$  is log-concave and  $\log T$  has a Lipschitz constant of  $O(n)$ . It follows that the walk mixes rapidly, i.e. the conductance is  $1/p(n)$  for some polynomial  $p$ , and we can obtain a near uniform random point in  $K'$  in polynomial time.

A point  $x$  is generated from a random  $x' \in K'$  as in the previous section - see (17).

ending property ensures a probability of at least  $e^{-2}$  that  $x \in K$ .

$$\begin{aligned} \Pr(x \in K) &\geq \text{vol}(K')/\text{vol}(K' + B(1)) \\ &\geq \left(1 + \frac{2}{n}\right)^{-n}. \end{aligned}$$

We can therefore sample nearly uniformly from  $K$  in polynomial time, and we fully polynomial time approximation scheme as stated.

### 7. Modification of a theorem of Hoeffding

population  $C$  consist of  $n$  real values  $c_1 \geq c_2 \geq \dots \geq c_n \geq 0$ . Let  $c_{i_1}, c_{i_2}, \dots, c_{i_t}$ ,  $i_1 > \dots > i_t$  denote a random sample drawn without replacement from  $C$ . Let  $c_{i_2} + \dots + c_{i_k} + c_{i_k}$  for  $k = 1, 2, \dots, t$ . Let  $\mu = \frac{1}{n} \sum_{i=1}^n c_i$ . Hoeffding proved

7.1. If  $0 \leq c_i \leq \alpha$  for  $i = 1, 2, \dots, n$ ,

$$\Pr(S_t - t\mu > x) \leq \exp\left\{-\frac{2x^2}{t\alpha^2}\right\} \quad \text{for all } x \geq 0.$$

not suitable for us, because we do not have enough control over the size of  $\alpha$  in the following theorem, which we believe is of interest in its own right.

7.2. With the above notation

$$S_t - t\mu > S_m) = O(\exp\{-m^2(t-m)^2/t^3\}) \quad \text{for } t = m+1, \dots, n.$$

Let  $T_j = c_1 + c_2 + \dots + c_j$  for  $j = 1, \dots, n$  and  $c = c_{i_m}$ . If  $S_t > t\mu + S_m$ , then for  $S_m > (t-m)\frac{T_n - T_{i_m}}{n - i_m} + cx$ , be chosen later) either

$$\frac{T_n - T_{i_m}}{n - i_m} + cx > t\mu. \quad (22)$$

or (ii), we define  $\delta$  by  $n - i_m = \frac{n}{t}(t-m)(1-\delta)^{-1}$  and replace (ii) by the inequality  $\frac{T_n - T_{i_m}}{n - i_m}(1-\delta) > t\mu\delta$ .

that

$$T_{i_m}/i_m \geq \max\{\mu, c\}. \quad (23)$$

point we bound  $|\delta|$  probabilistically. Now  $i_m$  is distributed as the  $m$ th largest element in a random  $t$ -set  $X$  chosen from  $[n]$ . Thus  $\bar{i}_m = E(i_m) = nm/t$ . Let  $\theta = \bar{i}_m - i_m$  so  $\theta/(n - \bar{i}_m + \theta)$  and  $\theta = \delta n(1 - \frac{m}{t})(1-\delta)^{-1}$ . Now let  $Z_k = |X \cap [k]|$ . We observe  $n\theta > 0$ ,

$$\theta > y \Rightarrow Z_{[\bar{i}_m - y]} \geq m$$

and

$$\theta < -y \Rightarrow Z_{[\bar{i}_m + y]} \leq m.$$

But for any  $k$ ,  $Z_k$  is distributed as the random variable  $S_t$  of Theorem 7.1, where  $C$  consists of  $k$  1's and  $n-k$  0's. Thus  $E(Z_k) = kt/n$ , and applying the theorem gives

$$\Pr(|\theta| \geq y) \leq 2e^{-2y^2/n^2}. \quad (24)$$

Case 1:  $\delta < 0$ . It follows from (23) that

$$\begin{aligned} \text{(ii')} \Rightarrow \frac{T_{i_m}}{i_m}x - \frac{T_{i_m}t}{n}(1-\delta) &\geq \frac{T_{i_m}}{i_m}\delta, \\ \Rightarrow x - \frac{i_m t}{n}(1-\delta) &\geq t\delta. \end{aligned}$$

Substituting  $i_m = \frac{nm(1-\delta)}{n(1-\delta)}$ , we obtain

$$\text{(ii')} \Rightarrow x \geq m.$$

We take  $x = m/2$  from now on, so

$$\Pr(\text{iii}) \text{ and } \delta < 0 = 0. \quad (25)$$

Case 2:  $\delta \geq 0$ . Applying (23), we see now that (with  $x = m/2$ )

$$\begin{aligned} \text{(ii')} \Rightarrow \frac{m}{2} - \frac{i_m}{n}t(1-\delta) &\geq 0 \\ \Rightarrow \frac{m}{2} - \frac{t-m}{i_m} \frac{t-m}{n-i_m} &\geq 0 \\ \Rightarrow i_m &\leq \frac{nm}{2t-m} \\ \Rightarrow \theta &> \frac{mn}{2t} \left(1 - \frac{m}{t}\right). \end{aligned}$$

Hence, from (24) we have

$$\Pr(\text{ii}) \text{ and } \delta \geq 0 = O(\exp\{-m^2(t-m)^2/t^3\}). \quad (26)$$

The theorem follows from (22), (25) and (26).  $\square$

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## Factorization in $F_q[x]$ and Brownian Motion

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For Paul Erdős on his 80th birthday

We consider the set of polynomials of degree  $n$  over a finite field and put the uniform probability measure on this set. Any such polynomial factors uniquely into a product of its irreducible factors. To each polynomial we associate a step function on the interval  $[0,1]$  such that the size of each jump corresponds to the number of factors of a certain degree in the factorization of the random polynomial. We normalize these random functions and show that the resulting random process converges weakly to Brownian motion as  $n \rightarrow \infty$ . This result complements earlier work by the author on the order statistics of the degree sequence of the factors of a random polynomial.

### 1. Introduction

In this paper we study the factorization of random polynomials over the finite field  $F_q$ ,  $q$  a prime power. Specifically, let  $\Pi_n$  denote the monic polynomials of degree  $n$  over  $F_q$  and let  $\mu_n$  denote the uniform measure on  $\Pi_n$ . Any  $f(x) \in \Pi_n$  factors uniquely, and the degrees of its factors determine a partition of the integer  $n$ . To investigate the limiting distribution of such partitions with respect to the measure  $\mu_n$  as  $n \rightarrow \infty$ , we introduce the counting functions  $\alpha_k : \cup_{n=1}^{\infty} \Pi_n \rightarrow \mathbb{Z}$  defined by setting  $\alpha_k(f)$  equal to the number of factors in  $f$  of degree  $k$ . Now let  $p(n) = |\Pi_n| = q^n$  and let  $c(n)$  denote the number of irreducible monic polynomials of degree  $n$ . Then the joint distribution of  $\alpha_1, \alpha_2, \dots, \alpha_n$  with respect to  $\mu_n$  can be expressed in terms of  $p(n)$  and  $c(1), c(2), \dots, c(n)$  as follows:

$$\mu_n(\alpha_1 = m_1, \dots, \alpha_n = m_n) = \frac{1}{p(n)} \prod_{k=1}^n \binom{m_k + c(k) - 1}{m_k}, \quad (1)$$

provided  $\sum_{k=1}^n km_k = n$ , ( $\mu_n(\alpha_1 = m_1, \dots, \alpha_n = m_n) = 0$  otherwise). We call the vector  $(\alpha_1(f), \dots, \alpha_n(f))$  the type vector of  $f \in \Pi_n$ .