

# Prime number races with three or more competitors

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# Introduction and notations

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## Rubinstein and Sarnak (1994)

Assume GRH and LI. Let  $P_{q;a_1, \dots, a_r}$  be the set of real numbers  $x \geq 2$  such that

$$\pi(x; q, a_1) > \pi(x; q, a_2) > \dots > \pi(x; q, a_r).$$

The logarithmic density of  $P_{q;a_1, \dots, a_r}$  defined by

$$\delta_{q;a_1, \dots, a_r} := \lim_{x \rightarrow \infty} \frac{1}{\log x} \int_{t \in P_{q;a_1, \dots, a_r} \cap [2, x]} \frac{dt}{t},$$

exists and is positive.

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- It follows from the work of Rubinstein and Sarnak that

$$\delta_{q; a_1, \dots, a_r} = \mathbb{P}(\mathbb{X}(q, a_1) > \mathbb{X}(q, a_2) > \dots > \mathbb{X}(q, a_r)).$$



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where

$$\mathbb{X}(q, a) := -c(q, a) + \sum_{\substack{\chi \neq \chi_0 \\ \pmod q}} \operatorname{Re} \left( 2\chi(a) \sum_{\gamma_\chi > 0} \frac{U(\gamma_\chi)}{\sqrt{\frac{1}{4} + \gamma_\chi^2}} \right),$$

and  $c(q, a) := -1 + |\{n \pmod q : n^2 \equiv a \pmod q\}|$ , and  $\{U(\gamma_\chi)\}_{\gamma_\chi \in \Gamma}$  is a sequence of independent random variables uniformly distributed on the unit circle  $\mathbb{S}^1$ .

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- In the notation of G. Martin's notes, the random variable  $X_{q; a, b}$  has the same distribution as  $\mathbb{X}(q, a) - \mathbb{X}(q, b)$  defined above.

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$$\delta_{q; a, b} = \mathbb{P}(X_{q; a, b} > 0) = \mathbb{P}(\mathbb{X}(q, a) > \mathbb{X}(q, b)).$$

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## Ideas of the proof

- Show that the Fourier transform (properly normalized) of the joint distribution of the random vector  $(\mathbb{X}(q, a_1), \dots, \mathbb{X}(q, a_r))$  converges to the Fourier transform of a standard multivariate Gaussian vector  $(Z_1, \dots, Z_r)$  (i.e. the  $Z_j$  are I. I. D and  $\sim \mathcal{N}(0, 1)$ ).

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- By Levy's Continuity Theorem we deduce that

$$\delta_{q; a_1, \dots, a_r} = \mathbb{P}(\mathbb{X}(q, a_1) > \dots > \mathbb{X}(q, a_r)) \rightarrow \mathbb{P}(Z_1 > \dots > Z_r) = \frac{1}{r!}.$$

# Asymptotic formulas for the densities when $q \rightarrow \infty$

The case  $r = 2$  : Fiorilli and Martin (2013)

If  $a_1$  is a non-square and  $a_2$  is a square modulo  $q$ , then

$$\delta_{q;a_1,a_2} = \frac{1}{2} + \frac{c(q, a_2) - c(q, a_1)}{2\sqrt{\pi V(q)}}(1 + o(1)),$$

where

$$V(q) := 2 \sum_{\substack{\chi \neq \chi_0 \\ \chi \bmod q}} \sum_{\gamma_\chi > 0} \frac{1}{\frac{1}{4} + \gamma_\chi^2} \sim \varphi(q) \log q.$$



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## Corollary (Fiorilli and Martin, 2013)

$$\Delta_2(q) = \frac{1}{q^{1/2+o(1)}}.$$

# The case $r \geq 3$

- While the behaviour of the densities  $\delta_{q;a_1,a_2}$  is governed by the **means** of the random variables  $\mathbb{X}(q, a_1)$  and  $\mathbb{X}(q, a_2)$ , the behaviour of  $\delta_{q;a_1,a_2,\dots,a_r}$  for  $r \geq 3$  will be governed by the **correlations** of the  $\mathbb{X}(q, a_j)$ 's.

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### Definition

The **covariance matrix** of the random vector  $(X_1, \dots, X_r)$  is the  $r \times r$  matrix  $K$  whose entries are

$$K_{i,j} = \mathbb{E}((X_i - \mathbb{E}(X_i))(X_j - \mathbb{E}(X_j))).$$

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In particular the diagonal entries of  $K$  are the variances of the  $X_j$ 's, namely

$$K_{j,j} = \text{Var}(X_j).$$

## Exercise 1

Let  $\mathcal{C} = \mathcal{C}_{q; a_1, \dots, a_r}$  be the covariance matrix of the random vector  $(\mathbb{X}(q, a_1), \dots, \mathbb{X}(q, a_r))$ . Show

$$C_{i,j} = \begin{cases} V(q) & \text{if } i = j \\ B_q(a_i, a_j) & \text{if } i \neq j, \end{cases}$$

where

$$V(q) = 2 \sum_{\substack{\chi \neq \chi_0 \\ \chi \bmod q}} \sum_{\gamma_\chi > 0} \frac{1}{\frac{1}{4} + \gamma_\chi^2} \sim \varphi(q) \log q,$$

and

$$B_q(a, b) = \sum_{\substack{\chi \neq \chi_0 \\ \chi \bmod q}} \sum_{\gamma_\chi > 0} \frac{\chi\left(\frac{a}{b}\right) + \chi\left(\frac{b}{a}\right)}{\frac{1}{4} + \gamma_\chi^2}.$$

## Proposition

For  $a, b$  such that  $1 \leq |a|, |b| \leq q/2$  we have

$$B_q(a, b) = -\varphi(q) \left( \ell(a, b) \log 2 + \frac{\Lambda(s_1)}{s_1} + \frac{\Lambda(s_2)}{s_2} \right) + O((|a| + |b|)(\log q)^2),$$

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- In particular, we have  $\max_{(a,b) \in \mathcal{A}_2(q)} |B_q(a, b)| \asymp \varphi(q)$ , and hence

$$\max_{(a,b) \in \mathcal{A}_2(q)} \frac{|B_q(a, b)|}{V(q)} \asymp \frac{1}{\log q}.$$

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$$\max_{(a,b) \in \mathcal{A}_2(q)} \frac{|B_q(a, b)|}{V(q)} \asymp \frac{1}{\log q}.$$

- However, we have  $|B_q(a, b)| \asymp \log q$  on average over all  $(a, b) \in \mathcal{A}_2(q)$ .

## Theorem 1 (L., 2013)

Let  $q$  be large. In the range  $2 \leq r = o((\log q / (\log \log q))^{1/2})$ , we have uniformly for all  $(a_1, \dots, a_r) \in \mathcal{A}_r(q)$

$$\delta_{q; a_1, \dots, a_r} = \left( 1 + O\left(\frac{r^4 (\log r)^2}{(\log q)^2}\right) \right) \left( \frac{1}{r!} + \sum_{1 \leq j < k \leq r} \beta_{j,k}(r) \frac{B_q(a_j, a_k)}{V(q)} \right),$$

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- Show that  $\sum_{1 \leq j < k \leq r} |\beta_{j,k}(r)| \ll (\log r) / (r-1)!$ , and deduce that the secondary term is smaller than the main term in the given range.

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- Show that  $\sum_{1 \leq j < k \leq r} |\beta_{j,k}(r)| \ll (\log r) / (r-1)!$ , and deduce that the secondary term is smaller than the main term in the given range.
- Show that  $\beta_{1,2}(2) = 0$  and for  $r \geq 3$  that  $\beta_{1,r}(r) < 0$  and  $\beta_{r-1,r}(r) > 0$ .

# Consequences of the asymptotic formula

Recall that

$$\Delta_r(q) := \max_{(a_1, a_2, \dots, a_r) \in \mathcal{A}_r(q)} \left| \delta_{q; a_1, \dots, a_r} - \frac{1}{r!} \right|.$$

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## Corollary 1 (L., 2013)

Let  $r \geq 3$  be a fixed integer. If  $q$  is large, then

$$\Delta_r(q) \asymp_r \frac{1}{\log q}.$$

# Biased races

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The races  $\{8; 3, 5, 7\}$  and  $\{12; 5, 7, 11\}$  are **biased**.

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## Corollary 2 (L., 2013)

Fix  $r \geq 3$ . There exists a constant  $q_0(r)$  such that if  $q \geq q_0(r)$  is a positive integer, then

- There exist distinct residue classes  $a_1, \dots, a_r \pmod q$ , with  $(a_i, q) = 1$ ,  $a_1, \dots, a_r$  are **squares** modulo  $q$  and the race  $\{q; a_1, \dots, a_r\}$  is **biased**.

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- There exist distinct residue classes  $a_1, \dots, a_r \pmod q$ , with  $(a_i, q) = 1$ ,  $a_1, \dots, a_r$  are **squares** modulo  $q$  and the race  $\{q; a_1, \dots, a_r\}$  is **biased**.
- There exist distinct residue classes  $b_1, \dots, b_r \pmod q$ , with  $(b_i, q) = 1$ ,  $b_1, \dots, b_r$  are **non-squares** modulo  $q$  and the race  $\{q; b_1, \dots, b_r\}$  is **biased**.

- Biased races with  $r$  squares:

Let  $q$  be positive integer with  $(q, 6) = 1$ . Consider the race  $\{q; 1, 6^4, 6^6, \dots, 6^{2(r-1)}, 4\}$ . If  $q$  is large, then

$$\delta(q; 1, 6^4, 6^6, \dots, 6^{2(r-1)}, 4) > \frac{1}{r!} > \delta(q; 6^4, 6^6, \dots, 6^{2(r-1)}, 1, 4).$$

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- **Biased races with  $r$  non-squares:**

Let  $q \equiv 3 \pmod{4}$  be a prime. Then  $-1$  is a non-square modulo  $q$ . Consider the race  $\{q; -1, -6^4, -6^6, \dots, -6^{2(r-1)}, -4\}$ . If  $q$  is large,

$$\delta(q; -1, \dots, -6^{2(r-1)}, -4) > \frac{1}{r!} > \delta(q; -6^4, \dots, -6^{2(r-1)}, -1, -4).$$

# Ingredients of the proof of Theorem 1: Multidimensional normal approximation, a result from probability

- Let  $S = \{b_1, \dots, b_r\}$  be a finite set.



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- We consider the following vector of random variables  $\mathbb{W} = (\mathbb{W}_1, \dots, \mathbb{W}_r)$  where

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- Our goal is to approximate the distribution of  $\mathbb{W}$  by a multivariate Gaussian with the **same covariance matrix**, uniformly in all parameters.

## Theorem (Reinert-Röllin (2009), Harper (2013))

Let  $\mathbb{Y} = (\mathbb{Y}_1, \dots, \mathbb{Y}_r)$  be a **multivariate normal random vector** with the **same covariance matrix** as  $\mathbb{W} = (\mathbb{W}_1, \dots, \mathbb{W}_r)$ . Let  $C := \max_{j,k} |c_k(b_j)|$  and assume that  $\mathbb{E}(|\mathbb{V}_k|^4) \leq \frac{K^4}{m^2}$  for all  $1 \leq k \leq m$  and some  $K \geq 1$ .

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$$|h|_2 := \sup_{1 \leq i, j \leq r} \left\| \frac{\partial^2}{\partial x_i \partial x_j} h \right\|_{\infty}, \text{ and } |h|_3 := \sup_{1 \leq i, j, k \leq r} \left\| \frac{\partial^3}{\partial x_i \partial x_j \partial x_k} h \right\|_{\infty}.$$

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Harper (2013) deduced this theorem from a general multivariate normal approximation result of Reinert and Röllin (2009), which they established using Stein's method of exchangeable pairs.



We will apply this result the random vector  $\mathbb{W} = (\mathbb{W}_1, \dots, \mathbb{W}_r)$  where

$$\mathbb{W}_j := \frac{\mathbb{X}(q, a_j) + c(q, a_j)}{\sqrt{V(q)}} = \sum_{\substack{\chi \neq \chi_0 \\ \chi \pmod{q}}} \operatorname{Re}(\chi(a_j) \mathbb{V}_\chi),$$

where

$$\mathbb{V}_\chi := \frac{2}{\sqrt{V(q)}} \sum_{\gamma_\chi > 0} \frac{U(\gamma_\chi)}{\sqrt{\frac{1}{4} + \gamma_\chi^2}},$$

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Here  $c_k(b_j) = \chi(a_j)$  and  $m = |\{\chi \neq \chi_0, \chi \pmod{q}\}| = \varphi(q) - 1$ .

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### Exercise 3

Show that for any  $\chi \neq \chi_0 \pmod{q}$  we have

$$\mathbb{E}(|\mathbb{V}_\chi|^4) \ll \frac{(\log q)^2}{V(q)^2} \ll \frac{1}{m^2}.$$

Hence we have  $C = \max_{j,\chi} |\chi(a_j)| = 1$  and we can take  $K$  to be a fixed constant.

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Let  $\mathbb{Y} = (\mathbb{Y}_1, \dots, \mathbb{Y}_r)$  denote a multivariate normal random vector whose components have mean zero, variance 1, and correlations

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Then for any three times differentiable function  $h : \mathbb{R}^n \rightarrow \mathbb{R}$  we have

$$|\mathbb{E}(h(\mathbb{W})) - \mathbb{E}(h(\mathbb{Y}))| \ll \frac{r^2 |h|_2 + r^3 |h|_3}{\sqrt{\varphi(q)}}.$$

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Now we need to find a nice choice of the function  $h$  that approximates the characteristic function of the set  $\{(x_1, \dots, x_r) \in \mathbb{R}^n : x_1 > x_2 > \dots > x_r\}$ .

# The choice of the function $h$

- Let  $\delta > 0$  be a parameter to be chosen. Let  $g : \mathbb{R} \rightarrow \mathbb{R}$  be a three times differentiable function such that

$$g(x) = \begin{cases} 1 & \text{if } x \geq \delta, \\ \in [0, 1] & \text{if } 0 < x \leq \delta, \\ 0 & \text{if } x \leq 0, \end{cases}$$

and such that  $g^{(\ell)}(x) \ll (1/\delta)^\ell$  for  $1 \leq \ell \leq 3$ .



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- Note that such  $g$  exists since the interval on which  $g$  changes from 0 to 1 has length  $\delta$ .
- Let  $h_\delta^-, h_\delta^+ : \mathbb{R}^r \rightarrow \mathbb{R}$  be three times differentiable functions defined by

$$h_\delta^-(x_1, \dots, x_r) := \prod_{1 \leq i < j \leq r} g(x_i - x_j),$$

and

$$h_\delta^+(x_1, \dots, x_r) := \prod_{1 \leq i < j \leq r} g(x_i - x_j + \delta).$$

## Exercise 4

- a. Show that  $\mathbb{E}(h_{\delta}^{-}(W)) \leq \mathbb{P}(W_1 > W_2 > \dots > W_r) \leq \mathbb{E}(h_{\delta}^{+}(W))$ , and that the same holds for  $Y$ .

## Exercise 4

- a. Show that  $\mathbb{E}(h_{\delta}^{-}(\mathbb{W})) \leq \mathbb{P}(\mathbb{W}_1 > \mathbb{W}_2 > \dots > \mathbb{W}_r) \leq \mathbb{E}(h_{\delta}^{+}(\mathbb{W}))$ , and that the same holds for  $\mathbb{Y}$ .
- b. Let  $\delta_1, \dots, \delta_r$  be such that  $|\delta_j| \leq \delta$ . Show that

$$|\mathbb{P}(\mathbb{W}_1 + \delta_1 > \dots > \mathbb{W}_r + \delta_r) - \mathbb{P}(\mathbb{W}_1 > \dots > \mathbb{W}_r)| \ll r^2 \delta,$$

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- c. Use 1) and 2) to show that  $|\mathbb{E}(h_{\delta}^{\pm}(\mathbb{W})) - \mathbb{P}(\mathbb{W}_1 > \mathbb{W}_2 > \dots > \mathbb{W}_r)| \ll r^2 \delta$ , and that the same holds for  $\mathbb{Y}$ .

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- d. Show that

$$|h_{\delta}^{-}|_2 \ll \frac{r^2}{\delta^2}, \text{ and } |h_{\delta}^{-}|_3 \ll \frac{r^3}{\delta^3},$$

and that the same bounds hold for  $h_{\delta}^{+}$ .

## Corollary 4

Let  $\mathbb{Y} = (\mathbb{Y}_1, \dots, \mathbb{Y}_r)$  denote a multivariate normal random vector whose components have mean zero, variance 1, and correlations

$$\mathbb{E}(\mathbb{Y}_j \mathbb{Y}_k) := \mathbb{E}(\mathbb{W}_j \mathbb{W}_k) = \frac{B_q(a_j, a_k)}{V(q)}.$$

Then we have

$$|\delta_{q; a_1, \dots, a_r} - \mathbb{P}(\mathbb{Y}_1 > \dots > \mathbb{Y}_r)| \ll \frac{r^3}{\varphi(q)^{1/8}}.$$

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**Proof** : First, recall that

$$\begin{aligned} \delta_{q; a_1, \dots, a_r} &= \mathbb{P}(\mathbb{X}(q, a_1) > \dots > \mathbb{X}(q, a_r)) \\ &= \mathbb{P}\left(\frac{\mathbb{X}(q, a_1)}{\sqrt{V(q)}} > \dots > \frac{\mathbb{X}(q, a_r)}{\sqrt{V(q)}}\right). \end{aligned}$$



- Moreover, we have

$$\mathbb{W}_j = \frac{\mathbb{X}(q, a_j) + c(q, a_j)}{\sqrt{V(q)}} = \frac{\mathbb{X}(q, a_j)}{\sqrt{V(q)}} + O(q^{-1/2+o(1)}).$$

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- Hence by Exercise 4b we deduce that

$$|\delta_{q; a_1, \dots, a_r} - \mathbb{P}(\mathbb{W}_1 > \dots > \mathbb{W}_r)| \ll \frac{r^2}{q^{1/2-o(1)}}. \quad (1)$$

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- Furthermore, by Corollary 3 and Exercise 4d we have

$$|\mathbb{E}(h_\delta^\pm(\mathbb{W})) - \mathbb{E}(h_\delta^\pm(\mathbb{Y}))| \ll \frac{r^2|h|_2 + r^3|h|_3}{\sqrt{\varphi(q)}} \ll \frac{r^4/\delta^2 + r^6/\delta^3}{\sqrt{\varphi(q)}}.$$

- Moreover, we have

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- We now use Exercise 4c to get

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- The result follows upon making the optimal choice  $\delta = r/\varphi(q)^{1/8}$  and combining this estimate with (1).

# The joint distribution of weakly correlated Gaussians

- Let  $\mathbb{Y} = (\mathbb{Y}_1, \dots, \mathbb{Y}_r)$  denote a multivariate normal random vector whose components have mean zero, variance 1, and correlations

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- Let  $\mathcal{C}^{-1} = (\tilde{c}_{j,k})_{1 \leq j, k \leq r}$ . The joint density function of the random vector  $\mathbb{Y}$  is given by

$$\begin{aligned} f(x_1, \dots, x_r) &= \frac{1}{(2\pi)^{r/2} \sqrt{\det(\mathcal{C})}} \exp\left(-\frac{1}{2} \mathbf{x}^T \mathcal{C}^{-1} \mathbf{x}\right) \\ &= \frac{1}{(2\pi)^{r/2} \sqrt{\det(\mathcal{C})}} \exp\left(-\frac{1}{2} \sum_{1 \leq j, k \leq r} \tilde{c}_{j,k} x_j x_k\right). \end{aligned}$$



## Lemma (L., 2012)

Let  $r \geq 2$  be an integer and  $0 < \varepsilon \leq 1/(2r)$ . Let  $\mathcal{M}_r(\varepsilon)$  be the set of  $r \times r$  symmetric matrices whose diagonal entries are 1, and whose off-diagonal entries have absolute value at most  $\varepsilon$ .

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- $\det(A) = 1 + O(\varepsilon^2 r^2)$ .
- $A$  is invertible and if we denote by  $\tilde{a}_{j,k}$  the entries of the inverse matrix  $A^{-1}$  then we have

$$\tilde{a}_{j,k} = \begin{cases} 1 + O(\varepsilon^2 r^2) & \text{if } j = k \\ -a_{j,k} + O(\varepsilon^2 r^2) & \text{if } j \neq k. \end{cases}$$

**Proof :** Exercise.

We have  $\mathcal{C} \in \mathcal{M}_r(\varepsilon)$  where  $\varepsilon = c/\log q$  for some constant  $c > 0$ .

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- If  $\mathcal{C}^{-1} = (\tilde{c}_{j,k})_{1 \leq j, k \leq r}$ , then

$$\tilde{c}_{j,k} = \begin{cases} 1 + O\left(\frac{r^2}{(\log q)^2}\right) & \text{if } j = k, \\ -c_{j,k} + O\left(\frac{r^2}{(\log q)^2}\right) & \text{if } j \neq k. \end{cases}$$

Hence we get

$$\begin{aligned} f(x_1, \dots, x_r) &= \frac{1}{(2\pi)^{r/2} \sqrt{\det(C)}} \exp\left(-\frac{1}{2} \mathbf{x}^T C^{-1} \mathbf{x}\right) \\ &= \left(1 + O\left(\frac{r^2}{(\log q)^2}\right)\right) \frac{1}{(2\pi)^{r/2}} \exp\left(-\frac{1}{2} \sum_{1 \leq j, k \leq r} \tilde{c}_{j,k} x_j x_k\right) \\ &= \left(1 + O\left(\frac{r^2}{(\log q)^2}\right)\right) \\ &\quad \times \frac{1}{(2\pi)^{r/2}} \exp\left(-\frac{\|\mathbf{x}\|_2^2}{2} + \sum_{1 \leq j < k \leq r} c_{j,k} x_j x_k + O\left(\frac{r^3 \|\mathbf{x}\|_2^2}{(\log q)^2}\right)\right), \end{aligned}$$

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since  $c_{j,k} = c_{k,j}$  and

$$\sum_{1 \leq j, k \leq r} |x_j x_k| \leq r \sum_{j=1}^r |x_j|^2 = r \|\mathbf{x}\|_2^2,$$

by the Cauchy-Schwarz inequality.



Recall that  $c_{j,j} = \mathbb{E}(|Y_j|^2) = 1$  and  $c_{j,k} = \mathbb{E}(Y_j Y_k) \ll \frac{1}{\log q}$ , if  $j \neq k$ .

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## Exercise 5

If  $r = o((\log q)^{2/3})$  show that

$$f(x_1, \dots, x_r) \ll \frac{1}{(2\pi)^{r/2}} \exp\left(-\frac{\|\mathbf{x}\|_2^2}{4}\right).$$

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- $$f(x_1, \dots, x_r) \ll \frac{1}{(2\pi)^{r/2}} \exp\left(-\frac{\|x\|_2^2}{4}\right).$$

- Deduce that

$$\mathbb{P}(\|Y\|_2 > R) \ll \exp\left(-\frac{R^2}{4} + O(r)\right).$$

We now have all the ingredients to prove our theorem.

### Theorem 1 (L., 2013)

Let  $q$  be large. In the range  $2 \leq r = o((\log q / (\log \log q))^{1/2})$ , we have uniformly for all  $(a_1, \dots, a_r) \in \mathcal{A}_r(q)$

$$\delta_{q; a_1, \dots, a_r} = \left(1 + O\left(\frac{r^4 (\log r)^2}{(\log q)^2}\right)\right) \left(\frac{1}{r!} + \sum_{1 \leq j < k \leq r} \beta_{j,k}(r) \frac{B_q(a_j, a_k)}{V(q)}\right),$$

where

$$\beta_{j,k}(r) := \frac{1}{(2\pi)^{r/2}} \int_{x_1 > \dots > x_r} x_j x_k \exp\left(-\frac{x_1^2 + \dots + x_r^2}{2}\right) dx_1 \dots dx_r.$$

# Proof of Theorem 1

By Corollary 4 we have

$$|\delta_{q;a_1,\dots,a_r} - \mathbb{P}(Y_1 > \dots > Y_r)| \ll \frac{r^3}{\varphi(q)^{1/8}}.$$

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Let  $R > c_0 \sqrt{r}$  be a parameter to be chosen, where  $c_0$  is a sufficiently large constant. By Exercise 5 we have

$$\begin{aligned} & \mathbb{P}(Y_1 > \dots > Y_r) \\ &= \mathbb{P}(Y_1 > \dots > Y_r \text{ and } \|\mathbf{Y}\|_2 \leq R) + O\left(\exp\left(-\frac{R^2}{4} + O(r)\right)\right) \\ &= \int_{\substack{x_1 > \dots > x_r \\ \|\mathbf{x}\|_2 \leq R}} f(x_1, \dots, x_r) dx_1 \cdots dx_r + O\left(\exp\left(-\frac{R^2}{5}\right)\right). \end{aligned}$$



Now if  $\|\mathbf{x}\|_2 \leq R$  then we have

$$\begin{aligned} & f(x_1, \dots, x_r) \\ &= \left( 1 + O\left(\frac{r^2}{(\log q)^2}\right) \right) \\ & \quad \times \frac{1}{(2\pi)^{r/2}} \exp\left(-\frac{\|\mathbf{x}\|_2^2}{2} + \sum_{1 \leq j < k \leq r} c_{j,k} x_j x_k + O\left(\frac{r^3 \|\mathbf{x}\|_2^2}{(\log q)^2}\right)\right) \\ &= \left( 1 + O\left(\frac{r^3 R^2}{(\log q)^2}\right) \right) \frac{1}{(2\pi)^{r/2}} \exp\left(-\frac{\|\mathbf{x}\|_2^2}{2} + \sum_{1 \leq j < k \leq r} c_{j,k} x_j x_k\right) \end{aligned}$$

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Moreover, we have

$$\exp\left(\sum_{1 \leq j < k \leq r} c_{j,k} x_j x_k\right) = 1 + \sum_{1 \leq j < k \leq r} c_{j,k} x_j x_k + O\left(\frac{r^2 \|\mathbf{x}\|_2^4}{(\log q)^2}\right).$$

Therefore, we deduce that

$$f(x_1, \dots, x_r) = \left(1 + O\left(\frac{r^2 R^4}{(\log q)^2}\right)\right) \frac{1}{(2\pi)^{r/2}} \exp\left(-\frac{\|\mathbf{x}\|_2^2}{2}\right) \left(1 + \sum_{1 \leq j < k \leq r} c_{j,k} x_j x_k\right).$$

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To complete the proof we choose  $R = c_1 \sqrt{r \log r}$  for some large constant  $c_1 > 0$  and insert this last estimate in the asymptotic formula

$$\mathbb{P}(Y_1 > \dots > Y_r) = \int_{\substack{x_1 > \dots > x_r \\ \|\mathbf{x}\|_2 \leq R}} f(x_1, \dots, x_r) dx_1 \cdots dx_r + O\left(\exp\left(-\frac{R^2}{5}\right)\right).$$

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Indeed the result follows upon completing the integrals and noting that

$$\frac{1}{(2\pi)^{r/2}} \int_{x_1 > \dots > x_r} \exp\left(-\frac{\|\mathbf{x}\|_2^2}{2}\right) dx_1 \dots dx_r = \frac{1}{r!},$$

and

$$\frac{1}{(2\pi)^{r/2}} \int_{x_1 > \dots > x_r} x_j x_k \exp\left(-\frac{\|\mathbf{x}\|_2^2}{2}\right) dx_1 \dots dx_r = \beta_{j,k}(r).$$

# What happens if $r$ is larger ?

## Question (Feurverger and Martin, 2000)

- Is there a function  $r_0(q) \rightarrow \infty$  as  $q \rightarrow \infty$  such that for  $r \geq r_0$  we have

$$\limsup_{q \rightarrow \infty} \max_{(a_1, \dots, a_r) \in \mathcal{A}_r(q)} r! \delta_{q; a_1, \dots, a_r} = \infty$$

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- If so how quickly must  $r_0(q)$  grow with  $q$  for these phenomena to emerge?

## Conjecture (Ford and L., 2011)

1. If  $2 \leq r \leq (\log q)^{1-\varepsilon}$ , then

$$\lim_{q \rightarrow \infty} \max_{a_1, \dots, a_r \pmod{q}} |r! \delta(q; a_1, \dots, a_r) - 1| = 0.$$



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2. If  $(\log q)^{1+\varepsilon} \leq r \leq \varphi(q)$ , then

$$\lim_{q \rightarrow \infty} \max_{a_1, \dots, a_r \pmod{q}} r! \delta(q; a_1, \dots, a_r) = \infty,$$

$$\lim_{q \rightarrow \infty} \min_{a_1, \dots, a_r \pmod{q}} r! \delta(q; a_1, \dots, a_r) = 0.$$

## Theorem (Harper and L., 2018)

The first part of the Ford-Lamzouri Conjecture is true in the extended range  $r = o((\log q)/(\log \log q)^4)$ . More precisely, we have uniformly for  $(a_1, \dots, a_r) \in \mathcal{A}_r(q)$

$$\delta_{q; a_1, \dots, a_r} = \frac{1}{r!} \left( 1 + O \left( \frac{r(\log r)^4}{\log q} \right) \right).$$

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## Theorem (Ford, Harper and L., 2019)

The second part of the Ford-Lamzouri Conjecture is true as soon as  $r/\log q \rightarrow \infty$ . More precisely, in this range we have

$$\lim_{q \rightarrow \infty} \max_{a_1, \dots, a_r \pmod{q}} r! \delta(q; a_1, \dots, a_r) = \infty,$$

$$\lim_{q \rightarrow \infty} \min_{a_1, \dots, a_r \pmod{q}} r! \delta(q; a_1, \dots, a_r) = 0.$$

Thank you very much for your attention!