



CIMAT

Centro de Investigación en Matemáticas, A.C.

# Quantitative Erdős-Kac theorem for additive functions

joint work with X. Yang y L. Chen

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Arturo Jaramillo Gil

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# Goal

Denote by  $\mathcal{P}$  the set of prime numbers.

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## Objectives

- Study the asymptotic law of  $\omega(J_n)$ , when  $n$  is large.

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## Objectives

- Study the asymptotic law of  $\omega(J_n)$ , when  $n$  is large.
- Generalize to the case where  $\omega$  is replaced by a general function  $\psi : \mathbb{N} \rightarrow \mathbb{R}$  only satisfying  $\psi(ab) = \psi(a) + \psi(b)$  for  $a, b \in \mathbb{N}$  coprime.

1. Historical context
2. Main results
3. Ideas of the proofs
  - Simplification of the model
  - Stein's method



## Historical context

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## Classical Erdős-Kac theorem (1940)

**Starting point:** Paul Erdős and Mark Kac proved that

$$Z_n := \frac{\omega(J_n) - \log \log(n)}{\sqrt{\log \log(n)}} \quad (1)$$

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**Intuition:** Define  $\mathcal{P}_n := \mathcal{P} \cap [1, n]$ . The convergence in (1) can be heuristically justified by the decomposition

$$\omega(J_n) = \sum_{p \in \mathcal{P}_n} \mathbb{1}_{\{p \text{ divide } J_n\}}. \quad (2)$$

## Question

Can we estimate the approximating error of the Gaussian approximation with respect to a suitable probability metric? Such as that defined by

$$d_K(X, Y) = \sup_{z \in \mathbb{R}} |\mathbb{P}[X \leq z] - \mathbb{P}[Y \leq z]|$$

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where  $\text{Lip}_1$  is the family of Lipschitz functions with Lipschitz constant less than or equal to one. We define additionally,

$$d_{TV}(X, Y) = \sup_{A \in \mathcal{B}(\mathbb{R})} |\mathbb{P}[X \in A] - \mathbb{P}[Y \in A]|.$$

## LeVeque's conjecture (1949)

LeVeque showed that

$$d_K(Z_n, \mathcal{N}) \leq C \frac{\log \log \log(n)}{\log \log(n)^{\frac{1}{4}}},$$

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*Main ingredients:* Perron's formula, Dirichlet series and some estimations of the Riemann  $\zeta$  function around the band  $\{z \in \mathbb{C} ; \Re(z) = 1\}$ .

# A probabilistic approach

For  $p \in \mathcal{P}$  given, we define  $\alpha_p : \mathbb{N} \rightarrow \mathbb{N}_0$  as

$$k = \prod_{p \in \mathcal{P}} p^{\alpha_p(k)}.$$

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What is the behavior of  $\alpha_p(J_n)$ ?

## Approximations for $\alpha_p(J_n)$

Let  $\{\xi_p\}_{p \in \mathcal{P}}$  be a family of independent geometric random variables with law

$$\mathbb{P}[\xi_p = k] = p^{-k}(1 - p^{-1}),$$

for  $k \in \mathbb{N}_0 := \mathbb{N} \cup \{0\}$ .

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for  $k \in \mathbb{N}_0 := \mathbb{N} \cup \{0\}$ . Our heuristic is based on the well-known approximation

$$(\alpha_{p_1}(J_n), \dots, \alpha_{p_m}(J_n)) \stackrel{\text{Ley}}{\approx} (\xi_{p_1}, \dots, \xi_{p_m}),$$

valid for  $m \in \mathbb{N}$  and  $p_1, \dots, p_m$  different.

## Main results

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# Central limit theorem for additive functions

Let  $\psi : \mathbb{N} \rightarrow \mathbb{R}$  be such that  $\psi(ab) = \psi(a) + \psi(b)$  for  $a, b$  co-prime. We will assume that

$$\sup_{p \in \mathcal{P}} |\psi(p)| < \infty \quad \text{y} \quad \sum_{p \in \mathcal{P}} \sum_{k \geq 2} \frac{\psi(p^k)^2}{p^k} < \infty.$$

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Define

$$\begin{aligned} \mu_n &= \sum_{p \in \mathcal{P}_n} \psi(p) p^{-1} (1 - p^{-1})^{-1} \\ \sigma_n^2 &= \sum_{p \in \mathcal{P}_n} \psi(p)^2 p^{-1} (1 - p^{-1})^{-2}. \end{aligned}$$



# Main result for the Kolmogorov distance

## Theorem (Chen, Jaramillo, Yang)

*Under the above conditions,*

$$d_K \left( \frac{\psi(J_n) - \mu_n}{\sigma_n}, \mathcal{N} \right) \leq \frac{\kappa_1}{\sigma_n} + \frac{\kappa_2}{\sigma_n^2} + \frac{\kappa_3 \log \log(n)}{\log(n)}$$
$$d_1 \left( \frac{\psi(J_n) - \mu_n}{\sigma_n}, \mathcal{N} \right) \leq \frac{\kappa_4}{\sigma_n} + \frac{\kappa_5}{\sigma_n^2} + \kappa_6 \frac{\log \log(n)^{\frac{1}{2}}}{\log(n)^{\frac{1}{2}}},$$

where  $\kappa_1, \dots, \kappa_6$  are explicit functions of  $\psi$ .

## Ideas of the proofs

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## Simplified model: the harmonic distribution $H_n$

Let  $H_n$  be a random variable with  $\mathbb{P}[H_n = k] = \frac{1}{L_n k}$  for  $k \leq n$ , where  $L_n := \sum_{k=1}^n \frac{1}{k}$ .

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Notice that

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### Proposition

*Suppose that  $n \geq 21$ . We define the event*

$$A_n := \left\{ \prod_{p \in \mathcal{P}_n} p^{\xi_p} \leq n \right\}. \quad (3)$$

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We have

$$\mathcal{L}(\psi(H_n)) = \mathcal{L}\left(\sum_{p \in \mathcal{P}_n} \psi(p^{\alpha_p(H_n)})\right) = \mathcal{L}\left(\sum_{p \in \mathcal{P}_n} \psi(p^{\xi_p}) | A_n\right). \quad (4)$$

## Relation with the harmonic distribution

Let  $\{Q(k)\}_{k \geq 1}$  be a sequence of independent random variables and independent of  $(J_n, H_n)$ , where  $Q(k)$  is uniformly distributed over the set

$$\mathcal{P}_k^* := \{1\} \cup \mathcal{P}_k.$$

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### Lemma (Chen, Jaramillo y Yang)

For  $n \geq 21$ ,

$$d_{\text{TV}}(J_n, H_n Q(n/H_n)) \leq 61 \frac{\log \log n}{\log n}$$



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$$\mathbb{P}[Q(n/H_n) \text{ divides } H_n] \leq 6.4 \frac{\log \log n}{\log n}.$$

## Relation between $\psi(J_n)$ and $\psi(H_n)$

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Recall that conditionally over  $A_n := \left\{ \prod_{p \in \mathcal{P}_n} p^{\xi_p} \leq n \right\}$ ,

$$\psi(H_n) \stackrel{L_{aw}}{=} \sum_{p \in \mathcal{P}_n} \psi(p^{\xi_p}).$$

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**The problem reduces to estimate**

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**We will use Stein' s method.**



## **Lemma (Stein's lemma)**

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$$\mathbb{E}[f'(\mathcal{N})] = \mathbb{E}[\mathcal{N}f(\mathcal{N})]$$

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**Stein's heuristic:** If  $X$  is an  $\mathbb{R}$ -valued random variable such that

$$\mathbb{E}[f'(X)] \approx \mathbb{E}[Xf(X)],$$

for a sufficiently large class of functions  $f$ , then  $Z$  approximates  $\mathcal{N}$ .

## Lemma

Let  $h : \mathbb{R} \rightarrow \mathbb{R}$  be 1-Lipchitz. Then the equation

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$$\sup_{w \in \mathbb{R}} |f_h(w)| \leq 2 \quad \sup_{w \in \mathbb{R}} |f_h'(w)| \leq \sqrt{2/\pi} \quad \sup_{w \in \mathbb{R}} |f_h''(w)| \leq 2. \quad (5)$$

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Therefore, if  $X$  is a random variable,

$$d_K(X, \mathcal{N}) \leq \sup_f |\mathbb{E}[f'(X) - Xf(X)]|$$

where  $f$  belongs to the family of functions satisfying (5).

# Poisson space representation

Define

$$W_n := \frac{\sum_{p \in \mathcal{P}_n} \psi(p) \xi_p - \mu_n}{\sigma_n}$$

$$y \mid I_n := \mathbb{1}_{A_n}.$$

# Poisson space representation

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$$W_n := \frac{\sum_{p \in \mathcal{P}_n} \psi(p) \xi_p - \mu_n}{\sigma_n}$$

and  $I_n := \mathbb{1}_{A_n}$ . One can verify that

$$|\mathbb{E}[Z_n f(W_n) - f'(W_n) | A_n]| = \mathbb{P}[A_n]^{-1} |\mathbb{E}[f(W_n) W_n I_n] - \mathbb{E}[f'(W_n) I_n]|$$

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Let  $\eta$  be a Poisson point process over  $\mathbb{X}$ , with intensity  $\lambda : \mathbb{X} \rightarrow \mathbb{R}_+$  given by

$$\lambda(p, k) = \frac{1}{k p^k}, \quad \text{para } p \in \mathcal{P}, k \in \mathbb{N}.$$

Using characteristic functions, one can show that

$$W_n \stackrel{Law}{=} \tilde{\eta}(\rho_n), \quad (6)$$

where  $\tilde{\eta} = \eta(\rho, k) - \mathbb{E}[\eta(\rho, k)]$  is the compensation of  $\eta(\rho, k)$  and

$$\rho_n(k, \rho) := \sigma_n^{-1} k \psi(\rho) \mathbb{1}_{\{\rho \in \mathcal{P}_n\}}. \quad (7)$$

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# Stein's method

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We will suppose that the identity holds pointwise. As a consequence, if  $G_n(\eta)$  for some function  $G_n$ ,

$$\mathbb{E}[\tilde{\eta}(\rho_n) G_n(\eta)] = \int_{\mathbb{X}} \rho_n(x) \mathbb{E}[D_x G_n(\eta)] \lambda(dx), \quad (8)$$

where  $D_x G_n(\eta) := G_n(\eta + \delta_x) - G_n(\eta)$ .



For the case where  $G_n = f(W_n)I_n$ , by the previous formula,

$$\mathbb{E}[W_n f(W_n)] = \int_{\mathbb{X}} \rho_n(x) \mathbb{E}[D_x G_n(\eta)] \lambda(dx).$$

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One can verify the approximation  $D_x(f(W_n)I_n) \approx f'(W_n)\rho_n(x)I_n$ , so that

$$\mathbb{E}[W_n f(W_n)I_n] \approx \int_{\mathbb{X}} \rho_n(x)^2 \mathbb{E}[f'(W_n)I_n] \lambda(dx) = \mathbb{E}[f'(W_n)I_n].$$

From the above analysis we get

$$d_1(Z_n, \mathcal{N})$$

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## Theorem (Chen, Jaramillo y Yang)

*Suppose that*

$$\lambda_n := \sum_{p \in \mathcal{P}_n} \frac{\psi(p)}{p-1} > 0, \quad n \in \mathbb{N}. \quad (9)$$



## Theorem (Chen, Jaramillo y Yang)

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Let  $M_n$  be a Poisson random variable with intensity  $\lambda_n$ . Then,

$$d_{TV}(\psi(J_n), M_n) \leq \frac{\gamma_1}{\sqrt{\lambda_n}} + \frac{\gamma_2}{\lambda_n} + \frac{2\gamma_3}{\lambda_n} \sum_{p \in \mathcal{P}_n} \frac{|\psi(p) - 1|}{p}. \quad (10)$$

for  $\gamma_1, \dots, \gamma_3$  explicit in terms of  $\psi$ .

## References

-  Chen L., Jaramillo A., Yang X. A probabilistic approach to the Erdős-Kac theorem for additive functions. Soon in Arxiv.
-  R. Arratia. On the amount of dependence in the prime factorization of a uniform random integer. In Contemporary combinatorics, volume 10 of Bolyai Soc. Math. Stud., pages 29–91. János Bolyai Math. Soc., Budapest, 2002.
-  A. D. Barbour, E. Kowalski, and A. Nikeghbali. Mod-discrete expansions. Probab. Theory Related Fields, 158(3-4):859–893, 2014.
-  Adam J. Harper. Two new proofs of the Erdős-Kac theorem, with bound on the rate of convergence, by Stein's method for distributional approximations. Math. Proc. Cambridge Philos. Soc., 147(1):95–114, 2009.