

Another note on “Euclidean algorithms are Gaussian” by V. Baladi and B. Vallée

by

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1. Introduction. Every rational number $0 < r < 1$ has a unique, simple finite continued fraction expansion $r = [0; m_1, \dots, m_\ell]$ with integers $m_1, \dots, m_{\ell-1} \geq 1$ and $m_\ell \geq 2$. One can regard the length $\ell := \ell(r)$ of the continued fraction as a random variable on the set of rational numbers with a fixed denominator,

$$\Sigma_N = \{m/N \mid 1 \leq m < N, (m, N) = 1\},$$

equipped with the uniform probability. It has been expected that ℓ follows the asymptotic Gaussian distribution as N goes to infinity.

A prominent result goes back to Hensley [5] who showed an average version of this conjecture, i.e., the asymptotic Gaussian distribution of ℓ on the larger probability space

$$\Omega_N = \{u/v \mid 1 \leq u < v \leq N, (u, v) = 1\}$$

with the uniform probability \mathbb{P}_N . The result was further generalised by Baladi and Vallée [1] in a remarkable way that is based on the dynamical analysis of the Euclidean algorithm.

For $r \in \Omega_N$, Baladi and Vallée considered a non-negative real value $c(m)$ associated to each possible digit $m \geq 1$ of the continued fraction expansion of r , with one mild assumption $c(m) = O(\log m)$, and they defined the total cost C of r by $C(r) := \sum_{i=1}^{\ell(r)} c(m_i)$. Then C can be regarded as a random variable on Ω_N . They proved:

THEOREM A (Central Limit Theorem, [1]). *The distribution of the total cost C on Ω_N is asymptotically Gaussian, with speed of convergence*

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$O(1/\sqrt{\log N})$, i.e., for suitable positive constants μ and δ ,

$$\mathbb{P}_N \left[\frac{C - \mu \log N}{\delta \sqrt{\log N}} \leq x \right] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-t^2/2} dt + O\left(\frac{1}{\sqrt{\log N}}\right).$$

We remark that the work of Baladi–Vallée not only generalised Hensley’s result that corresponds to $c \equiv 1$, but also improved it with an optimal error.

1.1. Main results. We shall outline the main steps of the proof of Theorem A as follows. Let us first state a crucial criterion for the asymptotic Gaussian distribution.

THEOREM 1.1 (Hwang’s Quasi-Power Theorem, [1]). *Assume that the moment generating functions for a sequence of random variables X_N on probability spaces (Ξ_N, \mathbb{P}_N) are analytic in a neighborhood W of zero, and*

$$\mathbb{E}_N[\exp(wX_N)] = \exp(\beta_N U(w) + V(w))(1 + O(\kappa_N^{-1}))$$

with $\beta_N, \kappa_N \rightarrow \infty$ as $N \rightarrow \infty$, and $U(w), V(w)$ analytic on W , with $U''(0) \neq 0$. Then the mean and variance satisfy

$$\begin{aligned} \mathbb{E}(X_N) &= \beta_N U'(0) + V'(0) + O(\kappa_N^{-1}), \\ \mathbb{V}(X_N) &= \beta_N U''(0) + V''(0) + O(\kappa_N^{-1}). \end{aligned}$$

Further, the distribution of X_N on Ξ_N is asymptotically Gaussian, with speed of convergence $O(\kappa_N^{-1} + \beta_N^{-1/2})$.

To obtain the quasi-power expression for the moment generating function of the total cost C , Baladi and Vallée studied a certain Dirichlet series whose coefficients are related to the generating function. A crucial point is the observation that the Dirichlet series admits an alternative expression in terms of the so-called transfer operator, and a Tauberian argument to estimate the coefficients of the Dirichlet series is deduced from the spectral analysis of the transfer operator.

However, Perron’s formula of order two used in [1, (2.19)] only provides an estimate for iterated average sums of coefficients, which does not directly yield the necessary quasi-power expression for the total cost C on Ω_N . So Baladi and Vallée introduced the smoothed probabilistic model $\Omega_N(\varepsilon)$ containing Ω_N for sufficiently small $\varepsilon = \varepsilon(N)$ and showed that the distribution of C on $\Omega_N(\varepsilon)$ is asymptotically Gaussian. By showing that the difference between the two probabilities, on Ω_N and $\Omega_N(\varepsilon)$, is $O(\varepsilon)$, they obtained the result.

The purpose of this short article is to make a few remarks on the work of Baladi–Vallée [1]. First, we obtain Theorem A without the smoothing process. More precisely, it is possible to get directly a quasi-power estimate for the moment generating function of C on Ω_N by applying a version of Perron’s formula with error terms. Furthermore, the smoothing process is

also doable for Σ_N , that is, there is an auxiliary space $\Sigma_N(\varepsilon)$ containing Σ_N (see Section 4 for a precise definition) on which the cost C is asymptotically Gaussian:

THEOREM B. *The distribution of the total cost C on $\Sigma_N(\varepsilon)$ is asymptotically Gaussian, with speed of convergence $O(1/\sqrt{\log N})$.*

Finally, we present Question C, which is a Σ_N -version of the last step of the smoothing process, i.e., the statement that the difference between two probabilistic models Σ_N and $\Sigma_N(\varepsilon)$ is $O(\varepsilon)$. The conjecture on the asymptotic Gaussian behavior of the length ℓ of continued fractions on Σ_N immediately follows from an affirmative answer to this question.

2. Work of Baladi–Vallée. The distribution of the cost C on Ω_N is determined by the Lévy moment generating function

$$\mathbb{E}_N[\exp(wC)] = \frac{1}{|\Omega_N|} \sum_{r \in \Omega_N} \exp[wC(r)]$$

for complex w close enough to 0. Baladi and Vallée studied the Dirichlet series

$$L(s, w) = \sum_{n \geq 1} \frac{c_n(w)}{n^s}, \quad c_n(w) = \sum_{r \in \Sigma_n} \exp[wC(r)],$$

for $\Re s > 1$ and $|w|$ sufficiently small. Note that

$$\sum_{n \leq N} c_n(w) = \sum_{r \in \Omega_N} \exp[wC(r)]$$

is essentially the moment generating function of C on Ω_N . Therefore, the statistics of C follows from Tauberian type arguments for $L(s, w)$.

A crucial point is that analytic properties of $L(s, w)$ can be investigated by the following thermodynamical formalism, the so-called transfer operator method. For $r = u/v \in \Omega_N$, executing the Euclidean algorithm on the inputs u and v yields a unique continued fraction expansion $r = [0; m_1, \dots, m_\ell]$ with $m_1, \dots, m_{\ell-1} \geq 1$ and $m_\ell \geq 2$. Observe that each digit can be written as $m_i = \lfloor T^{i+1}(r) \rfloor$, where T is the Gauss map

$$T : [0, 1] \rightarrow [0, 1], \quad T(x) = \frac{1}{x} - \left\lfloor \frac{1}{x} \right\rfloor \quad \text{for } x \neq 0, \quad T(0) = 0.$$

Here, $\lfloor x \rfloor$ denotes the integer part of x . The continued fraction expansions can be viewed as rational trajectories of a one-dimensional dynamical system $([0, 1], T)$ that reaches 0 in a finite number of steps.

Let \mathcal{H} be the set of inverse branches of T that are of the form $h_{[m]}(x) = 1/(m+x)$ for some $m \geq 1$. The digit cost c can be regarded as a function on \mathcal{H} via $c(h_{[m]}) := c(m)$. The weighted transfer operator $H_{s,w}$ on $C^1([0, 1])$,

which depends on two complex parameters s and w , is defined by

$$H_{s,w}[f](x) := \sum_{h \in \mathcal{H}} \exp[wc(h)] \cdot |h'(x)|^s \cdot f \circ h(x).$$

We write $F_{s,w}$ for the same operator with \mathcal{H} replaced by the final set $\mathcal{F} := \{\frac{1}{m+x} \mid m \geq 2\} \subseteq \mathcal{H}$.

Let $\Omega := \bigcup_{n \geq 1} \Omega_n$ and $\mathcal{H}^* := \bigcup_{n \geq 1} \mathcal{H}^n$. The above arguments show that each $r = u/v \in \Omega$ can be written as

$$u/v = h_{[m_1]} \circ \cdots \circ h_{[m_\ell(r)]}(0) =: h(0)$$

with $h_{[m_i]} \in \mathcal{H}$, $1 \leq i \leq \ell(r) - 1$ and $h_{[m_\ell(r)]} \in \mathcal{F}$. Finally, one can observe the following key relation between $L(2s, w)$ and the transfer operator $H_{s,w}$:

$$\begin{aligned} L(2s, w) &= \sum_{r \in \Omega} \frac{1}{v^{2s}} \exp[wC(r)] = \sum_{h \in \mathcal{H}^*} |h'(0)|^s \exp[wc(h)] \\ &= F_{s,w} \circ (I - H_{s,w})^{-1}[1](0). \end{aligned}$$

This relation and the estimate of the operator norm of $(I - H_{s,w})^{-1}$ due to Dolgopyat [3] enable Baladi and Vallée to show that $L(2s, w)$ can be meromorphically continued to \mathbb{C} and has a simple pole at $s = \sigma(w)$, which is analytic in w near 0 and $\sigma(0) = 1$. Furthermore, a crucial bound of $L(2s, w)$ is obtained on a vertical strip containing $s = 1$, as follows.

LEMMA 2.1. *For all ξ with $0 < \xi < 1/5$, we can find α_0 such that for any $\hat{\alpha}_0$ with $0 < \hat{\alpha}_0 < \alpha_0 \leq 1/2$, there exist a neighborhood W' of 0 and constants $M, M' > 0$ such that for all $w \in W'$ we have:*

- (1) $\Re \sigma(w) > 1 - (\alpha_0 - \hat{\alpha}_0)$.
- (2) $L(2s, w)$ has only a simple pole at $s = \sigma(w)$ in the strip $|\Re s - 1| \leq \alpha_0$.
- (3) $|L(2s, w)| \leq M \max(1, |t|^\xi)$ on the vertical line $\Re s = 1 \pm \alpha_0$, $t = \Im s$.
- (4) $|L(2s, w)| \leq M'|t|^\xi$ in the strip for sufficiently large $|t|$.

Proof. The first three statements are just [1, Lemma 8]. The statement (4) comes from [1, Theorem 2]. ■

Using the bound in Lemma 2.1 and the Perron formula of order two, Baladi and Vallée showed that for $0 < \hat{\gamma} < \alpha_0$,

$$(2.1) \quad \sum_{Q \leq N} \sum_{n \leq Q} c_n(w) = A(w) N^{2\sigma(w)+1} (1 + O(N^{-\hat{\gamma}}))$$

where $A(w)$ is non-vanishing.

In order to get a result on C for Ω_N , they first considered a smoothed version of (2.1). In other words, for $\varepsilon(N) = N^{-\hat{\gamma}/2}$, it can be deduced from

the formula (2.1) that

$$(2.2) \quad \sum_{Q=N-\lfloor N\varepsilon(N) \rfloor}^N \sum_{n \leq Q} c_n(w) = \lfloor N\varepsilon(N) \rfloor A(w) (2\sigma(w) + 1) N^{2\sigma(w)} (1 + O(N^{-\hat{\gamma}/2})).$$

This implies that the moment generating function $\mathbb{E}_N[\exp(wC) | \Omega_N(\varepsilon)]$ of C on the auxiliary probability space

$$\Omega_N(\varepsilon) := \bigcup_{Q=N-\lfloor N\varepsilon(N) \rfloor}^N \Omega_Q \times \{Q\}$$

satisfies a quasi-power estimate

$$(2.3) \quad \mathbb{E}_N[\exp(wC) | \Omega_N(\varepsilon)] = \frac{A(w)(2\sigma(w) + 1)}{3A(0)} N^{2(\sigma(w) - \sigma(0))} (1 + O(N^{-\hat{\gamma}/2})).$$

The definition of $\Omega_N(\varepsilon)$ in [1] is invalid and the correct one can be found in Cesaratto [2]. The formula (2.3) corresponds to the fact that C asymptotically follows the Gaussian distribution on the smoothed probability space $\Omega_N(\varepsilon)$ due to Theorem 1.1.

For the last step, with the choice of $\varepsilon(N)$, Baladi and Vallée proved that the difference between the probabilities \mathbb{P}_N on Ω_N and $\mathbb{P}_{N,\varepsilon}$ on $\Omega_N(\varepsilon)$ is $O(\varepsilon(N))$. Note that \mathbb{P}_N and $\mathbb{P}_{N,\varepsilon}$ are not defined on the same probability space. However, they can be compared by dealing with sets $A_{N,\varepsilon} \subseteq \Omega_N(\varepsilon)$ coming from subsets $A \subseteq \Omega_N$, which are essentially of the form

$$A_{N,\varepsilon} := \bigcup_{Q=N-\lfloor N\varepsilon \rfloor}^N (A \cap \Omega_Q) \times \{Q\}.$$

In other words, for any $A \subseteq \Omega_N$,

$$|\mathbb{P}_N(A) - \mathbb{P}_{N,\varepsilon}(A_{N,\varepsilon})| = O(\varepsilon(N)),$$

from which Baladi and Vallée deduced Theorem A.

REMARK 2.2. They also established the Local Limit Theorem [1, Theorem 4] for ℓ on Ω_N . The result basically follows from the quasi-power estimate for the moment generating function with the saddle-point method. With the same μ and δ ,

$$\begin{aligned} \mathbb{P}_N \left[x - \frac{1}{2\delta\sqrt{\log N}} < \frac{\ell(r) - \mu \log N}{\delta\sqrt{\log N}} \leq x + \frac{1}{2\delta\sqrt{\log N}} \right] \\ = \frac{e^{-x^2/2}}{\delta\sqrt{2\pi \log N}} + O\left(\frac{1}{\log N}\right). \end{aligned}$$

3. Distributional analysis of C on Ω_N . In this section, we give a direct proof of Theorem A without using the smoothing process. Instead of Perron's formula of order two used in [1], we use a version of Perron's formula with error terms that is Lemma 3.19 in Titchmarsh [6]. Recall that Baladi-Vallée used one without error estimates and that the smoothing process is required to obtain the desired estimate for the moment generating function of C on Ω_N . However, the following version of the formula enables us to obtain a direct quasi-power estimate for the original cost by taking the optimal error term. Thus, we deduce the asymptotic Gaussian distribution of C on Ω_N from Theorem 1.1.

THEOREM 3.1 (Truncated Perron's Formula). *Let $F(s) = \sum_{n \geq 1} a_n/n^s$ for $\Re(s) := \sigma > \sigma_a$, the abscissa of absolute convergence of $F(s)$. Then for $D > \sigma_a$, one has*

$$\sum_{n \leq x} a_n = \frac{1}{2\pi i} \int_{D-iT}^{D+iT} F(s) \frac{x^s}{s} ds + O\left(\frac{x^D |F|(D)}{T}\right) + O\left(\frac{A(2x)x \log x}{T}\right) \\ + O\left(A(N) \min\left\{\frac{x}{T|x-N|}, 1\right\}\right),$$

where

$$|F|(\sigma) = \sum_{n \geq 1} \frac{|a_n|}{n^\sigma}$$

for $\sigma > \sigma_a$, N is the nearest integer to x , and $a_n = O(A(n))$, with $A(n)$ non-decreasing.

We first introduce the set up. For $r \in \Omega_N$, we write $r = [0; m_1, \dots, m_\ell]$. Note that ℓ corresponds to the case $c \equiv 1$ and satisfies $\ell(r) = O(\log N)$. Now, for a general c satisfying $c(m) = O(\log m)$, the Dirichlet series

$$\sum_{m \geq 1} \exp[wc(m)] \cdot \frac{1}{(m+x)^{2s}}$$

converges when $(\Re s, \Re w)$ belongs to a real neighborhood of $(1, 0)$. That is, for $\Re s$ near 1, $\exp[\Re w \cdot c(m)] < m^{\Re s}$ ($\sim m^1$). Thus for each r , the total cost satisfies

$$C(r) = c(m_1) + \dots + c(m_\ell) < \eta \cdot \log(m_1 \cdots m_\ell)$$

with η being sufficiently small. This implies that $C(r) = O(\log N)$ once we show $m_1 \cdots m_\ell \leq N$.

LEMMA 3.2. *For $r \in \Omega_N$, let $r = [0; m_1, \dots, m_\ell]$. Then*

$$m_1 \cdots m_\ell \leq N.$$

Proof. Recall that we have the expression $r = h_{[m_1]} \circ \dots \circ h_{[m_\ell]}(0)$ with inverse branches $h_{[m_i]}(x) = \frac{1}{m_i+x}$ which correspond to $\begin{bmatrix} 0 & 1 \\ 1 & m_i \end{bmatrix} \in \mathrm{GL}_2(\mathbb{Z})$.

With the canonical $\mathrm{GL}_2(\mathbb{Z})$ -action on the rational numbers, r can be written as

$$r = h_{[m_1]} \circ \cdots \circ h_{[m_\ell]}(0) = \begin{bmatrix} 0 & 1 \\ 1 & m_1 \end{bmatrix} \cdots \begin{bmatrix} 0 & 1 \\ 1 & m_\ell \end{bmatrix} \cdot \frac{0}{1} = \frac{b}{d}$$

where $\begin{bmatrix} a & b \\ c & d \end{bmatrix}$ with $ad - bc = \pm 1$ is the product of the matrices on the L.H.S. Therefore, we get $m_1 \cdots m_\ell < d \leq N$ by looking at the $(2, 2)$ -component. ■

In this case,

$$c_n(w) = \sum_{r \in \Sigma_n} \exp[wC(r)] = O(n^{1+k\Re w})$$

for some $k > 0$. Therefore, we may take $A(n) = n^{1+k\Re w}$ in Perron's formula. Together with a choice of optimal T , we have the following.

THEOREM 3.3. *For a non-vanishing $B(w)$ and $\gamma > 0$, we have*

$$\sum_{n \leq N} c_n(w) = B(w)N^{2\sigma(w)}(1 + O(N^{-\gamma})).$$

Proof. The analytic properties of $L(2s, w)$, summarized in Lemma 2.1, allow us to do contour integration using Cauchy's residue theorem:

$$\frac{1}{2\pi i} \int_{\mathcal{U}_T(w)} L(2s, w) \frac{N^{2s}}{2s} d(2s) = \frac{E(w)}{\sigma(w)} N^{2\sigma(w)}.$$

Here $E(w)$ is the residue of $L(2s, w)$ at the simple pole $s = \sigma(w)$, and $\mathcal{U}_T(w)$ is the positively oriented rectangle with vertices $1 + \alpha_0 + iT$, $1 - \alpha_0 + iT$, $1 - \alpha_0 - iT$, and $1 + \alpha_0 - iT$. Together with Perron's formula in Theorem 3.1, we have

$$\begin{aligned} \sum_{n \leq N} c_n(w) &= \frac{E(w)}{\sigma(w)} N^{2\sigma(w)} + O\left(\frac{N^{2(1+\alpha_0)}}{T}\right) \\ &\quad + O\left(\frac{A(2N)N \log N}{T}\right) + O(A(N)) \\ &\quad + O\left(\int_{1-\alpha_0-iT}^{1-\alpha_0+iT} |L(2s, w)| \frac{N^{2(1-\alpha_0)}}{|s|} ds\right) \\ &\quad + O\left(\int_{1-\alpha_0 \pm iT}^{1+\alpha_0 \pm iT} |L(2s, w)| \frac{N^{2\Re s}}{T} ds\right). \end{aligned}$$

Note that the last two error terms are from the contour integral, corresponding to the left vertical side and the horizontal sides of the rectangle $\mathcal{U}_T(w)$.

Let us write the last formula as

$$\sum_{n \leq N} c_n(w) = \frac{E(w)}{\sigma(w)} N^{2\sigma(w)} (I + II + III + IV + V).$$

We choose $\widehat{\alpha}_0$ with

$$\frac{32}{79}\alpha_0 < \widehat{\alpha}_0 < \alpha_0$$

and set

$$T = N^{2\alpha_0 + 4\widehat{\alpha}_0}.$$

Notice that $\frac{E(w)}{\sigma(w)}$ is bounded in the neighborhood W' since $\sigma(0) = 1$. Then, the error terms are bounded as follows:

- The error term I is $O(N^{2(1-2\widehat{\alpha}_0-\Re\sigma(w))})$. By Lemma 2.1, the exponent satisfies

$$2(1 - 2\widehat{\alpha}_0 - \Re\sigma(w)) < 2(\alpha_0 - 3\widehat{\alpha}_0) < 0.$$

- For any ε_1 with $0 < \varepsilon_1 < \widehat{\alpha}_0/2$, we can choose W' again from Lemma 2.1 small enough to have $k\Re w < \varepsilon_1/2$ so that $A(N) = O(N^{1+\varepsilon/2})$. Then the exponent of N in II is equal to

$$1 - 2(\Re\sigma(w) + k\Re w) - (2\alpha_0 + 4\widehat{\alpha}_0) \leq -2\alpha_0 + \frac{5}{2}\widehat{\alpha}_0 < 0.$$

Here, recall that $0 < \alpha_0 \leq 1/2$.

- Similarly, the error term III is $O(N^{1+k\Re w-2\Re\sigma(w)})$. The exponent satisfies

$$\begin{aligned} 1 + k\Re w - 2\Re\sigma(w) &< -1 + 2(\alpha_0 + \widehat{\alpha}_0) + \varepsilon_1/2 \\ &< -1 + 2\alpha_0 - \frac{7}{4}\widehat{\alpha}_0 \leq -\frac{7}{4}\widehat{\alpha}_0 < 0. \end{aligned}$$

- For any $0 < \xi < 1/5$, we also have $|L(2s, w)| \leq M|t|^\xi$ by Lemma 2.1 where $\Im s = t$. The error term IV is $O(N^{2(1-\alpha_0-\Re\sigma(w))}T^\xi)$ and the exponent of N is

$$\begin{aligned} 2(1 - \alpha_0 - \Re\sigma(w)) + (2\alpha_0 + 4\widehat{\alpha}_0)\xi \\ < 2(1 - \alpha_0 - (1 - \alpha_0 + \widehat{\alpha}_0)) + \frac{1}{5}(2\alpha_0 + 4\widehat{\alpha}_0) = \frac{2}{5}(\alpha_0 - 3\widehat{\alpha}_0) < 0. \end{aligned}$$

- The last term V is $O(T^{\xi-1} \cdot N^{2(1+\alpha_0-\Re\sigma(w))} \log N)$. Hence, the exponent satisfies

$$\begin{aligned} (2\alpha_0 + 4\widehat{\alpha}_0)(\xi - 1) + 2(1 + \alpha_0 - \Re\sigma(w)) + \varepsilon_1/2 \\ < -\frac{4}{5}(2\alpha_0 + 4\widehat{\alpha}_0) + \frac{1}{4}\widehat{\alpha}_0 + 2(2\alpha_0 - \widehat{\alpha}_0) < \frac{12}{5}(\alpha_0 - \frac{99}{48}\widehat{\alpha}_0) < 0. \end{aligned}$$

By taking

$$\gamma = \min\left(\frac{7}{4}\widehat{\alpha}_0, \frac{2}{5}(3\widehat{\alpha}_0 - \alpha_0), \frac{12}{5}\left(\frac{99}{48}\widehat{\alpha}_0 - \alpha_0\right)\right),$$

we obtain the theorem. ■

Finally, with $0 < \gamma < \alpha_0$ from Theorem 3.3, the moment generating function of the total cost C on Ω_N admits a quasi-power expression

$$\mathbb{E}_N[\exp(wC)] = \frac{B(w)}{B(0)} N^{2(\sigma(w) - \sigma(0))} (1 + O(N^{-\gamma})).$$

REMARK 3.4. Of course, this theorem enables us to prove Theorem A directly from Theorem 1.1 without the smoothing process. In the following section, we observe that the smoothing process is also doable for Σ_N . This yields the asymptotic Gaussian distribution of C on $\Sigma_N(\varepsilon)$.

4. Distributional analysis of C on Σ_N . As before, we also define a smoothed probability space $\Sigma_N(\varepsilon)$ as follows. For $\varepsilon(N) = N^{-\gamma/2}$ and $\gamma > 0$ from Theorem 3.3, we consider the probability space

$$\Sigma_N(\varepsilon) := \bigcup_{Q=N-\lfloor N\varepsilon(N) \rfloor}^N \Sigma_Q$$

with the uniform probability $\mathbb{P}_{N,\varepsilon}$. Then the moment generating function of C on $\Sigma(\varepsilon)$ is

$$\mathbb{E}_N[\exp(wC) | \Sigma_N(\varepsilon)] = \frac{1}{|\Sigma_N(\varepsilon)|} \sum_{Q=N-\lfloor N\varepsilon(N) \rfloor}^N c_Q(w).$$

Let us write $\Psi_w(N) = \sum_{n \leq N} c_n(w)$. Clearly,

$$\sum_{Q=N-\lfloor N\varepsilon(N) \rfloor}^N c_Q(w) = \Psi_w(N) - \Psi_w(N - \lfloor N\varepsilon(N) \rfloor),$$

and $|\Sigma_N(\varepsilon)| = \sum_{Q=N-\lfloor N\varepsilon(N) \rfloor}^N c_Q(0)$. The following smoothing process is similar to the one in Baladi–Vallée [1] and gives information on C for $\Sigma_N(\varepsilon)$.

PROPOSITION 4.1. *With the same setting as in Theorem 3.3, we have*

$$\sum_{Q=N-\lfloor N\varepsilon(N) \rfloor}^N c_Q(w) = 2\lfloor N\varepsilon(N) \rfloor B(w) \sigma(w) N^{2\sigma(w)-1} (1 + O(N^{-\gamma/2})).$$

Proof. For simplicity, we may write $F_w(N) = B(w) N^{2\sigma(w)}$. By Theorem 3.3, we have

$$\begin{aligned} & \Psi_w(N) - \Psi_w(N - \lfloor N\varepsilon(N) \rfloor) \\ &= [F_w(N) - F_w(N - \lfloor N\varepsilon(N) \rfloor)] + O(F_w(N) N^{-\gamma}) \\ &= \lfloor N\varepsilon(N) \rfloor F'_w(N) + O(F_w(N) N^{-\gamma}) \\ &= \lfloor N\varepsilon(N) \rfloor F'_w(N) \left[1 + O\left(\frac{1}{\lfloor N\varepsilon(N) \rfloor} \cdot \frac{F_w(N) N^{-\gamma}}{F'_w(N)} \right) \right]. \end{aligned}$$

Note that $\frac{F_w(N)}{F'_w(N)} = \frac{N}{2\sigma(w)}$ and $\sigma(w)$ is bounded, holomorphic on a neighborhood W' . Since $\varepsilon(N) = N^{-\gamma/2}$, the last error term is equal to $O(N^{-\gamma/2})$, and this finishes the proof. ■

Therefore the moment generating function of C on $\Sigma_N(\varepsilon)$ satisfies

$$\mathbb{E}_N[\exp(wC)|\Sigma_N(\varepsilon)] = \frac{B(w)\sigma(w)}{B(0)} N^{2(\sigma(w)-\sigma(0))} (1 + O(N^{-\gamma/2})),$$

and from Theorem 1.1 we are able to conclude the following.

THEOREM B. *The distribution of the total cost C on $\Sigma_N(\varepsilon)$ is asymptotically Gaussian, with speed of convergence $O(1/\sqrt{\log N})$.*

REMARK 4.2. The smoothing process for Ω_N and $\Omega_N(\varepsilon)$ in [1] is possible, since $\Omega_{N'}$ is a subset of Ω_N for $N' < N$. Thus, one can compare the different probabilities $\mathbb{P}_{N,\varepsilon}$ and \mathbb{P}_N by only dealing with subsets $A_{N,\varepsilon}$ in $\Omega_N(\varepsilon)$ which naturally come from Ω_N . However, there is no such inclusion among Σ_N 's. Hence, in order to have the statistical indistinguishability of the probabilistic models Σ_N and $\Sigma_{N,\varepsilon}$, we should specify which sets should be compared. It is sufficient to consider $C^{-1}(S)$ in Σ_N and $\Sigma_N(\varepsilon)$ for any $S \subset \mathbb{R}_{\geq 0}$.

Let us denote by $\mathbb{P}_{N,\varepsilon}$ the probability on $\Sigma_N(\varepsilon)$ with uniform density. It is now natural to ask:

QUESTION C. *For any $S \subset \mathbb{R}_{\geq 0}$, do we have*

$$|\mathbb{P}_{N,\varepsilon}(C \in S) - \mathbb{P}_N(C \in S)| = O(\varepsilon(N))?$$

The conjecture on the asymptotic Gaussian distribution of the length ℓ of continued fractions on Σ_N from the introduction immediately follows from an affirmative answer to this question since we can deduce (2.4) for $\Sigma_N(\varepsilon)$ from Theorem B, which enables us to estimate $\mathbb{P}_{N,\varepsilon}(\ell = k)$ for any integer k . However, at this time there is no explicit idea how to study \mathbb{P}_N on Σ_N . Some computations in [4] suggest that to answer this question it may be necessary to obtain a fundamental result on properties of ℓ on Σ_N .

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References

- [1] V. Baladi and B. Vallée, *Euclidean algorithms are Gaussian*, J. Number Theory 110 (2005), 331–386.
- [2] E. Cesaratto, *A note on “Euclidean algorithms are Gaussian” by V. Baladi and B. Vallée*, J. Number Theory 129 (2009), 2267–2273.

- [3] D. Dolgopyat, *On decay of correlations in Anosov flows*, Ann. of Math. (2) 147 (1998), 357–390.
- [4] S. R. Finch, *Mathematical Constants*, Cambridge Univ. Press, 2003.
- [5] D. Hensley, *The number of steps in the Euclidean algorithm*, J. Number Theory 49 (1994), 142–182.
- [6] E. C. Titchmarsh, *The Theory of the Riemann Zeta-Function*, 2nd ed., Clarendon Press, Oxford, 1986.

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