# How many smooth numbers and smooth polynomials are there? ViBrANT Seminar, May 2, 2023

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#### 1 Definition and motivation

A positive integer n is said to be y-smooth if its primes factors do not exceed y:  $p | n \implies p \leq y$ . The talk will be concerned with the counting function

$$
\Psi(x, y) := \#\{n \le x : n \text{ is } y\text{-smooth}\}.
$$

Note  $\Psi(x, x) = |x|, \Psi(x, 1) = 1$  and  $\Psi(x, 2) = 1 + |\log_2 x|$ , and that the indicator function of y-smooth numbers is completely multiplicative.

One can define an analogous quantity in the polynomial setting. A polynomial  $f \in \mathbb{F}_q[T]$  is said to be m-smooth if its irreducible factors have degrees bounded by m:  $P | f \implies \deg(P) \leq m$ . The talk will be focused today mostly on  $\Psi(x, y)$ .

Smooth numbers play an important role in cryptography. Pomerance, in the 80s, devised his Quadratic Sieve, an algorithm that (heuristically) factors integers in subexponential time, namely  $n$  is factored in  $\exp((\log n)^{1/2+o(1)})$  time. We describe it (in a loose way) below.

For  $i = 1, 2, ...$  we do the following. We take  $x_i := \lfloor \sqrt{n} \rfloor + i$ , square it and reduce it modulo n to obtain a number  $y_i$  in  $[0, n-1]$ :

$$
x_i^2 \equiv y_i \bmod n.
$$

We then check whether  $y_i$  is T-smooth – this can be done in  $O(T)$  operations obviously, but happens quite rarely: with probability  $(\Psi(N,T)/N)^{-1}$  the number  $y_i$  will be T-smooth (heuristically). When it is T-smooth, we obtain a relation of the form

$$
x_i^2 \equiv \prod_{p \le T} p^{e_{i,p}} \bmod n.
$$

We want to obtain T such relations, which takes  $T^2 \times (\Psi(N,T)/N)^{-1}$  operations. Then we can perform Gaussian elimination on the T **binary** vectors  $\{(e_{i,p2} \mod 2)_{p\leq T}\}_{i\in S}$  where S corresponds to  $y_i$  that are T-smooth. The complexity of Gaussian elimination is  $T^3$ . It finds subset(s)  $S' \subseteq S$  such that

$$
\sum_{i\in S'} (e_{i,p})_{p\leq T}\equiv 0\bmod 2
$$

as vectors in  $\prod_{p\leq T} \mathbb{F}_2$ . This means

$$
\prod_{i \in S'} x_i^2 \equiv \prod_{p \le T} p^{2b_p} \bmod n
$$

for  $b_p = \sum_{i \in S'} e_{i,p}/2$ . Given a relation  $A^2 \equiv B^2 \mod n$  we can compute  $gcd(A - B, n)$  and hope to find one the factors of n.

The complexity of this algorithm is  $T^2 \times (\Psi(N,T)/N)^{-1} + T^3$ , and is minimized when

$$
T \approx N/\Psi(N, T)
$$

which turn out to be solved for

$$
T = \exp((\log N)^{1/2 + o(1)})
$$

which is also the total complexity.

This uses the relation  $\Psi(N, T) \sim N \rho(\log N / \log T)$  which was established in a wide range by Hildebrand, where  $\rho$  is the Dickman function, which we discuss next.

## 2 The Dickman function

The function  $\rho: [0, \infty) \to (0, \infty)$  was introduced by Dickman. It has initial conditions  $\rho(u) = 1$  for  $u \in [0, 1]$ . For larger  $u$  it is defined via delay-differential equation:

$$
u\rho'(u) + \rho(u-1) = 0
$$
, or  

$$
\rho(u) = u^{-1} \int_0^1 \rho(u-t) dt.
$$

It is decreasing, and in fact we see it decreases rapidly:

$$
\rho(u) \leq u^{-1} \rho(u-1) \implies \rho(u) \leq \Gamma(u+1)^{-1} = u^{-u(1+o(1))}
$$
.

Dickman proved (30s) that  $\Psi(x, y) \sim x \rho(\log x / \log y)$  for  $x \geq y \geq x^{\varepsilon}$ .

De Bruijn (50s) worked out precise asymptotics for  $\rho(u)$ . To explain them we need to introduce the Laplace transform of  $\rho$ :

$$
\hat{\rho}(s) := \int_0^\infty e^{-st} \rho(t) dt.
$$

De Bruijn showed

$$
\hat{\rho}(s) = \exp\left(\gamma + \int_0^{-s} \frac{e^t - 1}{t} dt\right).
$$

A short proof of this follows from differentiating  $\hat{\rho}(s)$  under the integral sign:

$$
\hat{\rho}'(s) = -\int_0^\infty t e^{-st} \rho(t) dt = -\int_0^1 t e^{-st} dt - \int_1^\infty (\int_{t-1}^t \rho(v) dv) e^{-st} dt
$$

$$
= -\int_0^\infty \rho(v) (\int_v^{v+1} e^{-st} dt) dv = \frac{e^{-s} - 1}{s} \hat{\rho}(s).
$$

(This determines  $\hat{\rho}$  up to a multiplicative constant; see de Bruijn's work for working out the constant.) For any  $c \in \mathbb{R}$  we have

$$
\rho(u) = \frac{1}{2\pi i} \int_{(-c)} e^{su} \hat{\rho}(s) ds.
$$

We choose c so that  $e^{-cu}\hat{\rho}(-c)$  is minimized, i.e. c is the minimizer of

$$
c \mapsto -cu + \gamma + \int_0^c \frac{e^t - 1}{t} dt.
$$

Differentiating (with respect to  $c$ ) we find

$$
-u+\frac{e^c-1}{c}=0
$$

So the optimal c is  $\xi(u)$  (a function of u) where  $\xi(u) \sim \log u$  is defined implicitly via

$$
\frac{e^{\xi}-1}{\xi}=u.
$$

Let us write

$$
\rho(u) = \frac{1}{2\pi i} \int_{(-\xi(u))} e^{su} \hat{\rho}(s) ds = e^{-\xi(u)u} \hat{\rho}(-\xi(u)) \frac{1}{2\pi} \int_{\mathbb{R}} G(t) dt
$$

for

$$
G(t) = e^{itu}\hat{\rho}(-\xi(u) + it)/\hat{\rho}(-\xi(u)).
$$

By construction  $G(0) = 1$ . By definition of  $\xi$ ,  $G'(0) = 0$ . It is not hard to approximate  $G(t)$  as  $e^{-ut^2(1+o(1))/2}$ for small t (details omitted;  $u(1+o(1))$  arises from  $(\log G)''(0)$ ). We expect

$$
\rho(u) = \frac{1}{2\pi i} \int_{(-\xi(u))} e^{su} \hat{\rho}(s) ds \sim e^{-\xi(u)u} \hat{\rho}(-\xi(u)) \frac{1}{2\pi} \int_{\mathbb{R}} e^{-ut^2/2} dt \sim \frac{e^{-\xi(u)u} \hat{\rho}(-\xi(u))}{\sqrt{2\pi u}}
$$

and this asymptotic relation was established rigorously by de Bruijn. The quantity  $-\xi(u)$  is called the *saddle point* for  $\rho(u)$ .

## 3 Hildebrand's work

Let

<span id="page-2-0"></span>
$$
u = \frac{\log x}{\log y}.
$$

Hildebrand (80s) proved the following:

$$
\Psi(x,y) = x\rho(u)\left(1 + O\left(\frac{\log(u+1)}{\log y}\right)\right)
$$

holds for  $x \ge y \ge \exp((\log \log x)^{5/3+\epsilon})$ . Under RH he showed that

$$
\Psi(x,y) = x\rho(u) \exp\left(O\left(\frac{\log(u+1)}{\log y}\right)\right) \tag{3.1}
$$

holds for  $y \geq (\log x)^{2+\epsilon}$ . Note this does not give an asymptotic formula for  $y = (\log x)^C$ .

These two results admit alternative proofs due to Saias (80s). Hildebrand used a physical space argument while Saias used Dirichlet series and complex analysis.

Two questions that were asked:

- 1. (Hildebrand) Can one show the asymptotic relation [\(3.1\)](#page-2-0) fails for  $y \leq (\log x)^{2-\epsilon}$ ?
- 2. (Pomerance) Is it true that  $\Psi(x, y) \ge x\rho(u)$  for all  $x/2 \ge y \ge 2$ ? (Intuition: for very large y, there is a lower order term in  $\Psi(x, y) - x\rho(u)$ , found by de Bruijn, which is positive. Moreover,  $x\rho(u) \leq \Psi(x, y)$ for  $y \leq \log x$  trivially since  $\Psi(x, y) \geq 1$ ,  $x \rho(u) < 1$ .

<span id="page-2-2"></span>**Theorem 3.1** (G., 2022). Fix  $\varepsilon > 0$ . Unconditionally, there are sequences  $x_n, y_n \to \infty$  such that

$$
y_n = (\log x_n)^{2 - \varepsilon + o(1)}
$$

and

$$
\frac{\Psi(x_n, y_n)}{x_n \rho(\log x_n / \log y_n)} = \exp((\log x_n)^{\varepsilon + o(1)}).
$$

<span id="page-2-1"></span>**Theorem 3.2** (G., 2022). Under RH, for  $(\log x)^{1+\epsilon} \leq y \leq (\log x)^{2-\epsilon}$  we have

$$
\frac{\Psi(x,y)}{x\rho(\log x/\log y)} = \exp\left(\Theta\left(\frac{(\log x)^2}{y\log y}\right)\right).
$$

An analogue of Theorem [3.2](#page-2-1) holds unconditionally for polynomials. Here  $\Theta(f)$  stands for a function g such that  $C \geq g/f \geq c > 0$  for some positive constants  $C, c$ .

<span id="page-2-3"></span>**Theorem 3.3** (G., 2022). 1. Unconditionally,  $\Psi(x, y) \geq x\rho(u)$  holds outside of

$$
y \in [\log x \exp((\log \log x)^{3/5-\varepsilon}), \exp((\log \log x)^{5/3+\varepsilon})].
$$

2. Under RH,  $\Psi(x, y) \geq x \rho(u)$  holds outside of

$$
y \in [(\log x)^{2-\varepsilon}, (\log x)^{2+\varepsilon}].
$$

3. Assume RH. If  $\psi(y) := \sum_{n \le y} \Lambda(n) \sim y$  satisfies  $\psi(y) - y = o(\sqrt{y} \log y)$  then  $\Psi(x, y) \ge x \rho(u)$  holds for  $y \in [(\log x)^{2-\varepsilon}, (\log x)^{2+\varepsilon}]$ . Some intuition comes from the relation

$$
\Psi(x,y) \sim x \rho(u) (-\zeta(1/2) \sqrt{2}) \exp\left(\frac{\psi(y)-y}{\sqrt{y} \log y}\right)
$$

for  $y = (1 + (\log x)/2)^2$  (RH is used in the derivation of this relation as well).

4. If RH fails, and  $\Theta > 1/2$  is the supremum of the real parts of zeros of  $\zeta$ , then for any  $\beta \in (1 - \Theta, \Theta)$ there are sequences  $x_n, y_n$  with  $y_n = (\log x_n)^{1/(1-\beta)+o(1)}$  such that

$$
\Psi(x_n, y_n) < x_n \rho(\log x_n / \log y_n) \exp(-y_n^{\Theta - \beta - \varepsilon}).
$$

## 4 First oscillation result

The rest of the talk will concentrate on Theorem [3.1](#page-2-2) and the last part of Theorem [3.3.](#page-2-3)

Let us start with the last part of Theorem  $3.3<sup>1</sup>$  $3.3<sup>1</sup>$  $3.3<sup>1</sup>$  Rankin (30s) observed that

$$
\Psi(x, y) \le x^c \zeta(c, y)
$$

for any  $c > 0$ , where  $\zeta(c, y) = \prod_{p \le y} (1 - p^{-c})^{-1}$  is the partial zeta function. The optimal c, that minimizes the RHS, is denoted  $\alpha = \alpha(x, y)$ :

$$
\Psi(x,y) \le x^{\alpha} \zeta(\alpha, y) = \min_{c>0} x^c \zeta(c, y).
$$

Recall also that

$$
\rho(u) \sim \frac{e^{-\xi(u)u}\hat{\rho}(-\xi(u))}{\sqrt{2\pi u}}.
$$

Our aim is to 'marry' two classical ideas: saddle point analysis and Landau's Oscillation result (the same result that allows one to deduce  $\psi(y) - y = \Omega_{\pm}(y^{\Theta - \varepsilon})$ .

We introduce

$$
\beta = \beta(x, y) := 1 - \xi(u) / \log y
$$

where  $u = \log x / \log y$ , which allows us to rewrite

$$
x\rho(u) \sim \frac{x^{\beta}\hat{\rho}(\log y(\beta-1))}{\sqrt{2\pi u}}.
$$

Now let's divide  $\Psi(x, y)$  by  $x \rho(u)$ :

$$
\frac{\Psi(x,y)}{x\rho(u)} \ll \sqrt{u} \frac{x^{\alpha} \zeta(\alpha, y)}{x^{\beta} \hat{\rho}(\log y(\beta - 1))}.
$$

Here is a trivial (but new) observation. Since  $\alpha$  minimizes the numerator we trivially have

$$
\frac{\Psi(x,y)}{x\rho(u)} \ll \sqrt{u} \frac{x^{\beta} \zeta(\beta,y)}{x^{\beta} \hat{\rho}(-\xi(u))} = \sqrt{u} \frac{\zeta(\beta,y)}{\hat{\rho}(-\xi(u))}.
$$

Letting

$$
F(s, y) := \log \zeta(s, y) - \log \hat{\rho}(\log y(s - 1)),
$$

we see

$$
\frac{\Psi(x,y)}{x\rho(u)} \ll \sqrt{u}e^{F(\beta,y)}.
$$

By an earlier computation,

$$
\log \hat{\rho}(\log y(s-1)) = \gamma + I((1-s)\log y).
$$

As for  $\log \zeta(s, y)$ , we find

$$
\log \zeta(s, y) = \sum_{p \le y} -\log(1 - p^{-s}) = \sum_{n \le y} \frac{\Lambda(n)}{n^s \log n} + o(1)
$$

if  $s \geq 1/2 + \varepsilon$ . The  $o(1)$  terms come from proper prime powers. Since  $\beta = 1 - \xi(u)/\log y \approx 1 - \log u/\log y$ , we certainly have  $s \geq 1/2 + \varepsilon$  if  $y \geq (\log x)^{2+\varepsilon}$ .

In summary: we want to show

$$
\sum_{n\leq y} \frac{\Lambda(n)}{n^{\beta} \log n} - I((1-\beta) \log y)
$$

<span id="page-3-0"></span><sup>&</sup>lt;sup>1</sup>For simplicity we shall assume  $\sigma \in (1/2, \Theta)$  (instead of  $\sigma \in (1-\Theta, \Theta)$ ), and concentrate on  $y \geq (\log x)^{2+\epsilon}$ .

can be 'very' negative if RH fails. Strategy: we fix  $\beta \in (1/2, 1)$ , namely require  $1 - \xi(u)/\log y = \beta$ , which is easy to solve:

$$
\xi(u) = \log y(1 - \beta) \implies
$$
  

$$
e^{\xi(u)} = 1 + u\xi(u) = y^{1-\beta}
$$

and

$$
1 + u\xi(u) = 1 + u\log y(1 - \beta)
$$

so

$$
1 + \log x (1 - \beta) = y^{1 - \beta}
$$

i.e.

$$
y = (1 + \log(1 - \beta))^{1/(1 - \beta)}.
$$

Given a function  $A(x)$  on  $x \geq 1$ , its Mellin transform is

$$
\mathcal{M}A(s) := \int_1^\infty A(x)x^{-s}ds.
$$

Landau proved the following.

**Theorem 4.1.** Suppose  $A(x)$  is a bounded integrable function on every interval  $[1, X]$ , which is eventually non-negative. Let  $\sigma_c$  be the infimum of  $\sigma$  such that  $MA(\sigma)$  converges. Then  $MA(s)$  is analytic in  $\Re(s) > \sigma_c$ but not at  $s = \sigma_c$ .

To illustrate, let us revisit the proof that  $\psi(x) - x < -x^{\Theta-\varepsilon}$  holds infinitely often, where  $\Theta$  is as before. Consider  $A(x) = \sum_{n \leq x} \Lambda(n) - x + x^{\Theta-\varepsilon}$ . Let us suppose  $A(x)$  is eventually positive. Not hard to show

$$
\mathcal{M}A(s) = -\frac{\zeta'(s-1)}{(s-1)\zeta(s-1)} - \frac{1}{s-2} + \frac{1}{s-1-\Theta+\varepsilon}.
$$

This function is analytic for real  $s > 1 + \Theta - \varepsilon$ , but is not analytic at  $s = 1 + \Theta - \varepsilon$ . Hence, by Landau,  $\mathcal{M}A(s)$  is analytic in the half-plane  $\Re(s) > 1 + \Theta - \varepsilon$ . But this is false – it is only analytic in  $\Re(s) > 1 + \Theta$ due to zeros with real part  $> \Theta - \varepsilon$  for any  $\varepsilon > 0$ ; contradiction.

Another example: Diamond and Pintz (2009) showed

$$
\sum_{n \le x} \frac{\Lambda(n)}{n \log n} - \log \log x - \gamma < -\frac{C}{\sqrt{x} \log x}
$$

holds infinitely often for any given  $C > 0$ , and same with  $\frac{\partial C}{\partial x \log x}$ . This shows that  $\sqrt{x}$  ( $\prod_{p \leq x}$  (1 –  $1/p$ <sup>-1</sup> –  $e^{\gamma} \log x$ ) exhibits arbitrarily large positive and negative values as  $x \to \infty$ . They studied the Mellin transform of the LHS.

An almost identical argument works for showing

$$
y \mapsto \sum_{n \le y} \frac{\Lambda(n)}{n^{\beta} \log n} - I((1 - \beta) \log y) \le -y^{\Theta - \beta - \varepsilon}
$$

holds infinitely often.

We conclude that if RH fails, and  $\Theta > 1/2$  is the supremum of the real parts of zeros of  $\zeta$ , then for any  $\beta \in (1/2, \Theta)$  there are sequences  $x_n, y_n$  with  $y_n = (\log x_n)^{1/(1-\beta)+o(1)}$  such that

$$
\Psi(x_n, y_n) < x_n \rho(\log x_n / \log y_n) \exp(-y_n^{\Theta - \beta - \varepsilon}).
$$

If RH holds,  $\Theta - \beta = 1/2 - \beta < 0$  so this is useless.

**Remark 4.1.** Under RH we can show that  $\Psi(x, y) \sim x\rho(u)F(\beta, y)$  holds for  $y \geq (\log x)^{3/2+\epsilon}$  and this range is optimal. A similar result holds for polynomials over finite fields, unconditionally.

## 5 Second oscillation result

Finally, let us turn to Theorem [3.1.](#page-2-2) We assume  $y \leq (\log x)^{2-\epsilon}$ , so that  $\beta \leq 1/2 - \epsilon$  (and also  $\alpha \leq 1/2 - \epsilon$ : it is known that  $\alpha = \beta + O(1/\log y)$ .

We have seen

$$
\frac{\Psi(x,y)}{x\rho(u)} \ll \sqrt{u} \frac{x^{\alpha} \zeta(\alpha,y)}{x^{\beta} \hat{\rho}(-\xi(u))} \ll \sqrt{u} \frac{x^{\beta} \zeta(\beta,y)}{x^{\beta} \hat{\rho}(-\xi(u))} = \sqrt{u} \frac{\zeta(\beta,y)}{\hat{\rho}(-\xi(u))}.
$$

This used  $\Psi(x, y) \leq x^{\alpha} \zeta(\alpha, y)$ . We also have  $\Psi(x, y) \gg x^{\alpha} \zeta(\alpha, y) / (\sqrt{u} \log y)$  (Hildebrand and Tenenbaum, 80s) if  $y \geq (\log x)^{1+\varepsilon}$ , so

$$
\frac{\Psi(x,y)}{x\rho(u)} \gg \frac{x^{\alpha}\zeta(\alpha,y)}{x^{\beta}\hat{\rho}(-\xi(u))\log y} \ge \frac{x^{\alpha}\zeta(\alpha,y)}{x^{\alpha}\hat{\rho}((1-\alpha)\log y)\log y} = \frac{\zeta(\alpha,y)}{\hat{\rho}((1-\alpha)\log y)\log y}.
$$

The second inequality is trivial (but new): it uses the fact that  $\beta$  minimizes  $s \mapsto x^s \hat{\rho}((1-s) \log y)$ . Recall

$$
F(s, y) = \log \zeta(s, y) - \log \hat{\rho}(\log y(s - 1)).
$$

We have just shown

$$
\frac{\Psi(x,y)}{x\rho(u)} \gg e^{F(\alpha,y)}/\log y.
$$

Unconditionally, Landau's Theorem shows that, if we fix  $\alpha > 0$ ,

$$
y \mapsto \sum_{n \le y} \frac{\Lambda(n)}{n^{\alpha} \log n} - I((1 - \alpha) \log y)
$$

is non-negative. When  $y \leq (\log x)^{2-\varepsilon}$  we have that  $\log F(\alpha, y)$  is larger than  $\sum_{n \leq y} \frac{\Lambda(n)}{n^{\alpha} \log n}$  by a very large quantity, leading to large values of  $\Psi(x, y)/(x \rho(u))$ . Indeed,

$$
\log \zeta(s,y) = \sum_{p \le y} -\log(1-p^{-s}) = \sum_{n \le y} \frac{\Lambda(n)}{n^s \log n} + \sum_{k \ge 2} \sum_{y^{1/k} < p \le y} p^{-ks}/k.
$$

The k-sum can easily be shown to tend to infinity when  $s \leq 1/2 - \varepsilon$  (this uses nothing more than the Prime Number Theorem), which is the case when  $s = \alpha$  and  $y \leq (\log x)^{2-\epsilon}$ .