

The second moment method is an effective tool in number theory. Let  $\nu(n)$  denote the number of primes  $p$  dividing  $n$ . (We do not count multiplicity though it would make little difference.) The following result says, roughly, that “almost all”  $n$  have “very close to”  $\ln \ln n$  prime factors. This was first shown by Hardy and Ramanujan in 1920 by a quite complicated argument. We give a remarkably simple proof of Paul Turan [1934], a proof that played a key role in the development of probabilistic methods in number theory.

Theorem 2.1 Let  $\omega(n) \rightarrow \infty$  arbitrarily slowly. Then number of  $x$  in  $\{1, \dots, n\}$  such that

$$|\nu(x) - \ln \ln n| > \omega(n)\sqrt{\ln \ln n}$$

is  $o(n)$ .

Proof. Let  $x$  be randomly chosen from  $\{1, \dots, n\}$ . For  $p$  prime set

$$X_p = \begin{cases} 1 & \text{if } p|x \\ 0 & \text{otherwise} \end{cases}$$

Set  $M = n^{1/10}$  and set  $X = \sum X_p$ , the summation over all primes  $p \leq M$ . As no  $x \leq n$  can have more than ten prime factors larger than  $M$  we have  $\nu(x) - 10 \leq X(x) \leq \nu(x)$  so that large deviation bounds on  $X$  will translate into asymptotically similar bounds for  $\nu$ . (Here 10 could be any large constant.) Now

$$E[X_p] = \frac{\lfloor n/p \rfloor}{n}$$

As  $y - 1 < \lfloor y \rfloor \leq y$

$$E[X_p] = 1/p + O(1/n)$$

By linearity of expectation

$$E[X] = \sum_{p \leq M} \frac{1}{p} + O\left(\frac{1}{n}\right) = \ln \ln n + O(1)$$

Now we find an asymptotic expression for  $Var[X] = \sum_{p \leq M} Var[X_p] + \sum_{p \neq q} Cov[X_p, X_q]$ . As  $Var[X_p] = \frac{1}{p}(1 - \frac{1}{p}) + O(\frac{1}{n})$ ,

$$\sum_{p \leq M} Var[X_p] = \sum_{p \leq M} \frac{1}{p} + O(1) = \ln \ln n + O(1)$$

With  $p, q$  distinct primes,  $X_p X_q = 1$  if and only if  $p|x$  and  $q|x$  which occurs if and only if  $pq|x$ . Hence

$$\begin{aligned} \text{Cov}[X_p, X_q] &= E[X_p]E[X_q] - E[X_p X_q] \\ &= \frac{|n/pq|}{n} - \frac{|n/p| |n/q|}{n} \\ &\leq \frac{1}{pq} - \left(\frac{1}{p} - \frac{1}{n}\right)\left(\frac{1}{q} - \frac{1}{n}\right) \\ &\leq \frac{1}{n} \left(\frac{1}{p} + \frac{1}{q}\right) \end{aligned}$$

Thus

$$\sum_{p \neq q} \text{Cov}[X_p, X_q] \leq \frac{1}{n} \sum_{p \neq q} \frac{1}{p} + \frac{1}{q} \leq \frac{2M}{n} \sum \frac{1}{p}$$

Thus

$$\sum_{p \neq q} \text{Cov}[X_p, X_q] = O(n^{-9/10} \ln \ln n) = o(1)$$

That is, the covariances do not affect the variance,  $\text{Var}[X] = \ln \ln n + O(1)$  and Chebyshev's Inequality actually gives

$$\Pr[|X - \ln \ln n| > \lambda \sqrt{\ln \ln n}] < \lambda^{-2} + o(1)$$

for any constant  $\lambda$ . As  $|X - \nu| \leq 10$  the same holds for  $\nu$ .  $\square$

In a classic paper Paul Erdős and Marc Kac [1940] showed, essentially, that  $\nu$  does behave like a normal distribution with mean and variance  $\ln \ln n$ . Here is their precise result.

Theorem 2.2. Let  $\lambda$  be fixed, positive, negative or zero. Then

$$\lim_{n \rightarrow \infty} \frac{1}{n} |\{x : 1 \leq x \leq n, \nu(x) \geq \ln \ln n + \lambda \sqrt{\ln \ln n}\}| = \int_{\lambda}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt$$

We outline the argument, emphasizing the similarities to Turan's proof. Fix a function  $s(n)$  with  $s(n) \rightarrow \infty$  and  $s(n) = o((\ln \ln n)^{1/2})$  - e. g.  $s(n) = \ln \ln \ln n$ . Set  $M = n^{1/s(n)}$ . Set  $X = \sum X_p$ , the summation over all primes  $p \leq M$ . As no  $x \leq n$  can have more than  $s(n)$  prime factors greater than  $M$  we have  $\nu(x) - s(n) \leq X(x) \leq \nu(x)$  so that it suffices to show Theorem 2.2 with  $\nu$  replaced by  $X$ . Let  $Y_p$  be independent random variables with  $\Pr[Y_p = 1] = p^{-1}$ ,  $\Pr[Y_p = 0] = 1 - p^{-1}$  and set  $Y = \sum Y_p$ , the summation over all primes  $p \leq M$ . This  $Y$  represents an idealized version of  $X$ . Set

$$\mu = E[Y] = \sum_{p \leq M} p^{-1} = \ln \ln n + o((\ln \ln n)^{1/2})$$

and

$$\sigma^2 = \text{Var}[Y] = \sum_{p \leq M} p^{-1}(1 - p^{-1}) \sim \ln \ln n$$

and define the normalized  $\tilde{Y} = (Y - \mu)/\sigma$ . From the Central Limit Theorem (well, an appropriately powerful form of it!)  $\tilde{Y}$  approaches the standard normal  $N$  and  $E[\tilde{Y}^k] \rightarrow E[N^k]$  for every positive integer  $k$ . Set  $\tilde{X} = (X - \mu)/\sigma$ . We compare  $\tilde{X}, \tilde{Y}$ .

For any distinct primes  $p_1, \dots, p_s \leq M$

$$E[X_{p_1} \cdots X_{p_s}] - E[Y_{p_1} \cdots Y_{p_s}] = \frac{\lfloor \frac{n}{p_1 \cdots p_s} \rfloor}{n} - \frac{1}{p_1 \cdots p_s} = O(n^{-1})$$

We let  $k$  be an arbitrary fixed positive integer and compare  $E[\tilde{X}^k]$  and  $E[\tilde{Y}^k]$ . Expanding,  $\tilde{X}^k$  is a polynomial in  $X$  with coefficients  $n^{o(1)}$ . Further expanding each  $X^j = (\sum X_p)^j$  - always reducing  $X_p^a$  to  $X_p$  when  $a \geq 2$  - gives the sum of  $O(M^k) = n^{o(1)}$  terms of the form  $X_{p_1} \cdots X_{p_s}$ . The same expansion applies to  $\tilde{Y}$ . As the corresponding terms have expectations within  $O(n^{-1})$  the total difference

$$E[\tilde{X}^k] - E[\tilde{Y}^k] = n^{-1+o(1)} = o(1)$$

Hence each moment of  $\tilde{X}$  approach that of the standard normal  $N$ . A standard, though nontrivial, theorem in probability theorem gives that  $\tilde{X}$  must therefore approach  $N$  in distribution.  $\square$

We recall the famous quotation of G. H. Hardy:

317 is a prime, not because we think so, or because our minds are shaped in one way rather than another, but *because it is so*, because mathematical reality is built that way.

How ironic - though not contradictory - that the methods of probability theory can lead to a greater understanding of the prime factorization of integers.