# Generating Random Factored Numbers, Easily 

Adam Kalai<br>Department of Mathematics, Massachusetts Institute of Technology, 77 Massachusetts Avenue,<br>Cambridge, MA 02139, U.S.A. akalai@mit.edu<br>Communicated by Moni Naor

Received August 2000 and revised May 2003
Online publication 5 September 2003

Consider the problem of generating a random "pre-factored" number, that is, a uniformly random number between 1 and $n$, along with its prime factorization. Of course, one could pick a random number in this range and try to factor it, but there are no known polynomialtime factoring algorithms. In his dissertation, Bach presents an efficient algorithm for this problem [1], [2]. Here, we present a significantly simpler algorithm and analysis for the same problem. Our algorithm is, however, $\operatorname{alog}(n)$ factor less efficient.

## Algorithm

Input: Integer $n>0$.
Output: A uniformly random number $1 \leq r \leq n$.

1. Generate a sequence $n \geq s_{1} \geq s_{2} \geq \cdots \geq s_{l}=1$ by choosing $s_{1} \in\{1,2, \ldots, n\}$ and $s_{i+1} \in\left\{1,2, \ldots, s_{i}\right\}$, until reaching 1 .
2. Let $r$ be the product of the prime $s_{i}$ 's.
3. If $r \leq n$, output $r$ with probability $r / n$.
4. Otherwise, RESTART.

A common class exercise is pick a random number between 1 and $n$ using a coin with $\operatorname{Pr}(H)=\operatorname{Pr}(T)=1 / 2$. Instead suppose we had $n$ coins $c_{1}, c_{2}, \ldots, c_{n}$ where,

$$
\text { coin } c_{i} \text { has } \quad \operatorname{Pr}(H)=\frac{1}{i} \quad \text { and } \quad \operatorname{Pr}(T)=1-\frac{1}{i}
$$

Hypothetically, one slow way to pick a number between 1 and $n$ is first to flip $c_{n}$ and choose $n$ if it is $H$, otherwise flip $c_{n-1}$ and choose $n-1$ if it is $H$, and so on.

Claim 1. One way to choose a uniformly random $1 \leq m \leq n$ is toflip coins $c_{n}, c_{n-1}, \ldots$ until we get $H$ on some coin $c_{m}$.

Proof. By induction. The base case $n=1$ is trivial. For a general $n$, we pick $n$ with probability $1 / n$ and otherwise, by induction hypothesis, all $1 \leq m \leq n-1$ are equally likely.

Claim 2. The output of our algorithm is uniform in $\{1,2, \ldots, n\}$.

Proof. Imagine that in step 1 we chose $s_{1}$ by flipping coins $c_{n}, c_{n-1}, \ldots$, until we got $T$ on some $c_{s_{1}}$, and chose $s_{2}$ by flipping $c_{s_{1}}, c_{s_{1}-1}, \ldots$, and so on. (Of course, in practice we would use some more efficient method.) Every coin will be flipped, and the number of occurrences of a number $m$ in the sequence is the number of $H$ 's we saw on coin $c_{m}$ before $T$.

Thus, in step 2, we get a particular $r=\prod_{p \leq n} p^{\alpha_{p}}$ with probability

$$
\begin{aligned}
\operatorname{Pr}\left[r=\prod_{p \leq n} p^{\alpha_{p}}\right] & =\operatorname{Pr}\left[\wedge_{p \leq n} \text { we had } \alpha_{p} H \text { 's followed by } T \text { on coin } c_{p}\right] \\
& =\prod_{p \leq n}\left(\frac{1}{p}\right)^{\alpha_{p}}\left(1-\frac{1}{p}\right) \\
& =\frac{1}{r} M_{n}
\end{aligned}
$$

where $M_{n}=\prod_{p \leq n}(1-1 / p)$. Next, the probability of generating such a $1 \leq r \leq n$ and outputting it in step 3 is

$$
\frac{M_{n}}{r} \frac{r}{n}=\frac{M_{n}}{n}
$$

Since this is the same for every $1 \leq r \leq n$, each time we reach step 3, we either output a uniformly random $1 \leq r \leq n$ or restart.

Intuition. The above analysis shows that in fact every number $m$ occurs at least once in the sequence with probability $1 / m$, and at least $k$ times with probability $1 / m^{k}$. This matches the intuition that a prime $p \ll n$ divides a random number in $1 \leq r \leq n$ at least once with probability $\approx p$ and at least $k$ times with probability $\approx 1 / p^{k}$.

Claim 3. The expected number of primality tests is $O\left(\log ^{2} n\right)$.

Proof. Since the probability of outputting any particular $1 \leq r \leq n$ is $M_{n} / n$, the probability of outputting any number in step 3 is $n\left(M_{n} / n\right)=M_{n}$. If we refer to a round as an execution of steps 1,2 , and 3 , then the probability of reaching round $t$ is $\left(1-M_{n}\right)^{t}$. During a round, we test $m$ with probability $1 / m$, the probability we get at least one $H$ on $c_{m}$. So

$$
\operatorname{Pr}[m \text { is tested during round } t]=\frac{\left(1-M_{n}\right)^{t}}{m}
$$

Thus the expected total number of primality tests is ${ }^{1}$

$$
\sum_{t=0}^{\infty} \sum_{m=1}^{n} \frac{\left(1-M_{n}\right)^{t}}{m}=H_{n} \sum_{t=0}^{\infty}\left(1-M_{n}\right)^{t}=\frac{H_{n}}{M_{n}}
$$

Since $H_{n} \leq 1+\ln n$ and $1 / M_{n} \approx 1.78 \ln n$ (Mertens' theorem [3]), $H_{n} / M_{n}$ is $O\left(\log ^{2} n\right)$.

## Acknowledgments

I thank Manuel Blum, Michael Rabin, Doug Rohde, Yael Tauman, and the referees for helpful comments.

## References

[1] E. Bach, Analytic Methods in the Analysis and Design of Number-Theoretic Algorithms, MIT Press, Cambridge, MA, 1985.
[2] E. Bach, How to generate factored random numbers, SIAM Journal on Computing, vol. 17 (1988), pp. 179193.
[3] E. Bach and J. Shallit, Algorithmic Number Theory, MIT Press, Cambridge, MA, 1996.

[^0]
[^0]:    ${ }^{1}$ It is tempting to take a shortcut and argue that the expected number of total primality tests is $H_{n} / M_{n}$ because the expected number of rounds is $1 / M_{n}$ and the expected number of tests per round is $H_{n}$, but this assumes independence.

