## Random Number Generator Designs

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## The Menu

- How to Design a Generator


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- How to Design a Generator
- Common Pitfalls


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- ANSI X9. 17


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- Intel Hardware


## Designing a PRNG

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An example of an attack that is theoretical but not practical is one where a bit could be predicted with probability $0.5+2^{-128}$.

Remember, a generator is said to be broken if we can predict what a bit in the generator will be with probability $0.5+\epsilon$ for some $\epsilon>0$.

## Is This a Good Generator?



## Requirements and Limitations (1)

The generator must not use only one source of randomness:

```
#include <unistd.h>
extern void* pgpRandomPool;
void
sample_dev_random() {
    int fd = open("/dev/random", O_RDONLY);
    char randBuf;
    /*\ldots*/
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sample_dev_random() {
    int fd = open("/dev/random", O_RDONLY);
    char randBuf;
    /* ... */
    randBuf = read(fd, &randBuf, 1);
    pgpRandomAddBytes(&pgpRandomPool, &randBuf, 1);
    /* ... */
}
```

This caused the "random" bytes to be added to consist exclusively of ' $0 \times 01$ ' bytes.

## Requirements and Limitations (2)

Here is the proposed fix:

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#include <unistd.h>
extern void* pgpRandomPool;
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sample_dev_random() {
    int fd = open('/dev/random', O_RDONLY);
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```

The return code from read(2) isn't checked; therefore, nonrandom data could be added if the read fails.

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- Some raw input methods may not exist on all operating systems, not even on all OS types: raw input on Unix system must be done using obscure ioct/(2) calls that aren't available everywhere;
- Even "direct" hardware access isn't: keystrokes are often processed through several processors before they arrive at the user process.


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- Networked applications transmit information about mouse events (usually in the clear), which makes the "random" (and secret) information publicly available.
- Networked applications maight collapse multiple mouse events into one to save bandwidth, making mouse-wiggling less random than it should (or could) be.


## Further Requirements

- Resistant to analysis of its input data.
- Resistant to manipulation of its input data.
- Resistant to analysis of its output data.
- Resistant to attempts at state recovery.
- Make explicit any actions so that conformance of code and design can be easily checked.
- Ensure that the internal state never leaks to the ouside world.
- Ensure that the initial randomness is good enough to generate good data.
- Ensure that the generator generates good numbers.


## Further Pitfalls: fork(2)

The fork(2) system call is the way in Unix to create new processes.
The fork() call makes a copy of the currently running process and then lets both run concurrently.


## Forking (2)

```
#include <sys/types.h>
#include <unistd.h>
void create_new_process() {
    pid_t pid;
    pid = fork();
    if (pid == - 1) {
        /* Some error has happened */
    } else if (pid == 0) {10
        /* Child code */
    } else {
        /* Parent code */
    }
}
```

The fork(2) system call returns twice: once in the parent and once in the child.

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And that is bad.
This problem is also difficult to avoid.

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3. Set newpid $\leftarrow$ getpid () . If oldpid $=$ newpid, we haven't forked in the meantime, or this is the parent. Return the generator's output and terminate the algorithm.

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4. (At this point, oldpid $\neq$ newpid, so we must have forked in the meantime, and this is the child process.) Return to step 1.

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This looks somewhat like two-phase-commit (because the technique was inspired by it).

## Message Digest Ciphers

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These ciphers are much faster than traditional block ciphers and are ideally suited to mix large amounts of data when the mixing process should not be reversible by an outsider.

## Recap: Hash Functions

$\qquad$
$\{0,1\}^{k}$ is the set of all bit strings of length $k ;\{0,1\}^{*}$ is the set of all bit strings, including the empty string. Any message can be viewed as a bit string by means of a suitable encoding. Hash functions have the form $h:\{0,1\}^{*} \rightarrow\{0,1\}^{k}$, for some fixed $k$, and we call $h(M)$ the hash of $M$.

A secure one-way hash function is a hash function with the following properties:

1. For each message $M$, it is easy to compute $h(M)$.
2. Given $M$, it is computationally infeasible to compute $M^{\prime}$ with $h(M)=h\left(M^{\prime}\right)$ (secure against forgery).
3. It is computationally infeasible to compute $M$ and $M^{\prime}$ with $h(M)=h\left(M^{\prime}\right)$ (secure against collisions).

## Incremental Hash Functions

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The definition of a hash function then becomes
$h:\{0,1\}^{k} \times\{0,1\}^{*} \rightarrow\{0,1\}^{k}$, and the hashing process takes a message $M$, splits into chunks $\left(M_{1}, \ldots, M_{n}\right)$ and computes the hash of M as $h\left(h\left(h\left(\ldots h\left(I V, M_{1}\right), \ldots\right), M_{n-1}\right), M_{n}\right)$, or

$$
\begin{aligned}
h_{1} & =h\left(I V, M_{1}\right) \\
h_{j+1} & =h\left(h_{j}, M_{j}\right) \\
h(M) & :=h_{n} .
\end{aligned}
$$

Hash functions carry state between invocations.

## Message Digest Ciphers

Let $K$ be an arbitrarily long key, let $M=\left(M_{1}, \ldots, M_{n}\right)$ be a message, broken up into chunks of $k$ bits, and let $I V$ be an initialization vector. Then set

$$
\begin{aligned}
& C_{1}=M_{1} \oplus h(I V, K) \\
& C_{j}=M_{j} \oplus h\left(C_{j-1}, K\right) \quad \text { for } 1<j \leq n .
\end{aligned}
$$

The recipient easily recovers the plaintext by

$$
\begin{aligned}
& P_{1}=C_{1} \oplus h(I V, K) \\
& P_{j}=C_{j} \oplus h\left(C_{j-1}, K\right) \quad \text { for } 1<j \leq n .
\end{aligned}
$$

This should be familiar: it's Cipher Feedback Mode.

## A Model For RNGs



## Applied Cryptography




## PGP 2.x



## Curious PGP 2.x Implementation Bug

PGP 2.x contained the following function (paraphrased):
\#include <stdlib.h>

```
/* Exclusive-or the contents of the SRC buffer into the DST buffer. */
void xor_buffers(void* dst, const void* src, size_t length) {
    unsigned char* dst_buffer = dst;
    const unsigned char* src_buffer = src;
    while (length--)
        *dst++ = *src++;
}
```


## PGP 2.x Implementation Fix

## PGP 2.x should have contained the following function:

\#include <stdlib.h>

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/* Exclusive-or the contents of the SRC buffer into the DST buffer. */
void xor_buffers(void* dst, const void* src, size_t length) {
    unsigned char* dst_buffer = dst;
    const unsigned char* src_buffer = src;
    while (length--)
        *dst++ ^= *src++;
}
\}
```

Can you spot the difference?

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In light of this, is it really true that "Many eyes make all bugs shallow" (Eric S. Raymond)?

## PGP 2.x Mixing Function


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$\oplus$


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(key for next time)

## Problems With The 2.x Generator

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## /dev/random Generator



## /dev/random Mixing Function



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## /dev/random Mixing Function



## /dev/random Postprocessing



## Intel Generator



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It only has a partial state update function.
It only has a single source of entropy with no preprocessing
It runs tests at power-up (when the chip is cold), but no continuous tests (when the chip is hot). How would you know whether the quality of the numbers degenerates after some time?

## cryptlib Generator



## cryptlib Mixing Function



## cryptlib Mixing Function



The mixing function takes bytes $n-20$ through $n+63$, hashes them and replaces bits $n$ through $n+19$ with the result. (There is considerable overlap.)

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This output is then folded in half (by XORing both halves): "an attacker doesn't even get the triple-DES encrypted one-way hash of a no longer existing version of the pool contents".

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Perhaps the author got a bit carried away; this level of paranoia seems excessive, even for a cryptographer. Then again, it's a good place to start...

## Tests: What Are They?

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4. You compute the probability that the statistic has this value (or is higher, or lower) if the null hypothesis is true. If this probability is less than $p$, we reject the null hypothesis.

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- A statistical dependency is not a cause-effect chain!


## Yet More About Tests

- In general, the statistic that you compute will be some measure of the sample's deviation from the ideal. For example, if you count the number $k$ of 0 bits in a sample of $n$ bits, the statistic could be $0.5 n-k$


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- That means that generally, large values of the statistic signify large deviations from the distribution that would occur if the null hypothesis were true.
- Therefore, most tables of statistics are computed to answer the question, "what is the probability of the statistic being this high, or higher, if the null hypothesis is in fact true?"


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- the long runs test.


## The Monobit Test

"A single bit stream of 20,000 consecutive bits of output from each RNG shall be subjected to the following four tests: [...]. Count the number of ones in the 20,000 bit stream. Denote this quantity by $X$. The test is passed if $9,725 \leq X \leq 10,275$."

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Where do these magic numbers ( $20,000,9,725$, and 10,275 ) come from?

What is the confidence level for this test?
One thing is immediately obvious: the 20,000 comes from the desire to have a meaningful test (so that the number of bits sampled must not be too low), that is yet practical to carry out (so that the number of bits sampled must not be too high).

## The Chi-Square Test

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If each experiment has probability $p_{k}$ to end up in category $k$ if the null hypothesis is true, then the $\chi^{2}$ test computes

$$
\chi^{2}=\sum_{k=0}^{K} \frac{\left(Y_{k}-n p_{k}\right)^{2}}{n p_{k}}
$$

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where $d$ is the number of degrees of freedom, which is in our case equal to $K-1$, and $\gamma(a, x)$ and $\Gamma(x)$ are the incomplete gamma function and the gamma function defined by

$$
\begin{aligned}
\gamma(a, x) & =\int_{0}^{x} e^{-t} t^{a-1} d t & \text { for } a>0 ; \text { and } \\
\Gamma(x) & =\int_{0}^{\infty} e^{-t} t^{x-1} d t & \text { for } x \neq 0,-1,-2, \ldots
\end{aligned}
$$

## Chi-Square For One Degree of Freedom


(Note that gnuplot defines igamma $(a, x)=\gamma(a, x) / \Gamma(a)$ and calls that the incomplete gamma function.)

## What About the Monobit Test?

The monobit test is a $\chi^{2}$ test in disguise. We set $n=20,000$ and $K=2$ and call the number of 1 bits $N$. We have $p_{1}=p_{2}=0.5$. Then the $\chi^{2}$ statistic for $N=10275$ (or $N=9725)$ is

$$
\begin{aligned}
x^{2} & =\left((n-N)-n p_{1}\right)^{2} / n p_{1}+\left(N-n p_{2}\right)^{2} / n p_{2} \\
& =\frac{((20,000-10,275)-10,000)^{2}}{10,000}+\frac{(10,275-10,000)^{2}}{10,000} \\
& =\left((10,000-10,275)^{2}+(10,275-10,000)^{2}\right) / 10,000 \\
& =275^{2} / 5,000 \\
& =15.125,
\end{aligned}
$$

and $Q(15.125,1) \approx 10^{-4}$ (to nearly three significant digits).

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No, because "equidistributed" does not mean "random". For example, the generator that alternately outputs 0 and 1 bits will pass this test every time, even though its output isn't particularly random.

Good LCPRNGs will also pass this test every time, even though they are trivially broken.

## What Does That Mean?

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We must also try to break the design of the generator, something that no statistical test can do for us.

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## References

- Peter Gutmann, Cryptographic Security Architecture, Springer


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- Peter Gutmann, Cryptographic Security Architecture, Springer
- Bruce Schneier, Applied Cryptography, Wiley \& Sons


## References

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- Peter Gutmann, Cryptographic Security Architecture, Springer
- Bruce Schneier, Applied Cryptography, Wiley \& Sons
- National Institute of Standards (NIST), Federal Information Processing Standard 140: Security Requirements for Cryptographic Modules, http://csrc.nist.gov/cryptva1/140-2.htm.
- George Marsaglia, DIEHARD, a Battery of Statistical Tests for Random Number Generators, http://stat.fsu.edu/~geo/diehard.htm1.
- Stan Kladko, Re: Does FIPS 140-2 mandate statistical tests for PRNGs or not?, Message-Id [7b557a3b.0404201314.ff07fc3@posting.goog1e.com](mailto:7b557a3b.0404201314.ff07fc3@posting.goog1e.com)

