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Tradeoffs in Targeted Fuzzing of Cyber Systems by Defenders and Attackers

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Fuzzing can locate faults and vulnerabilities in complex cyber systems

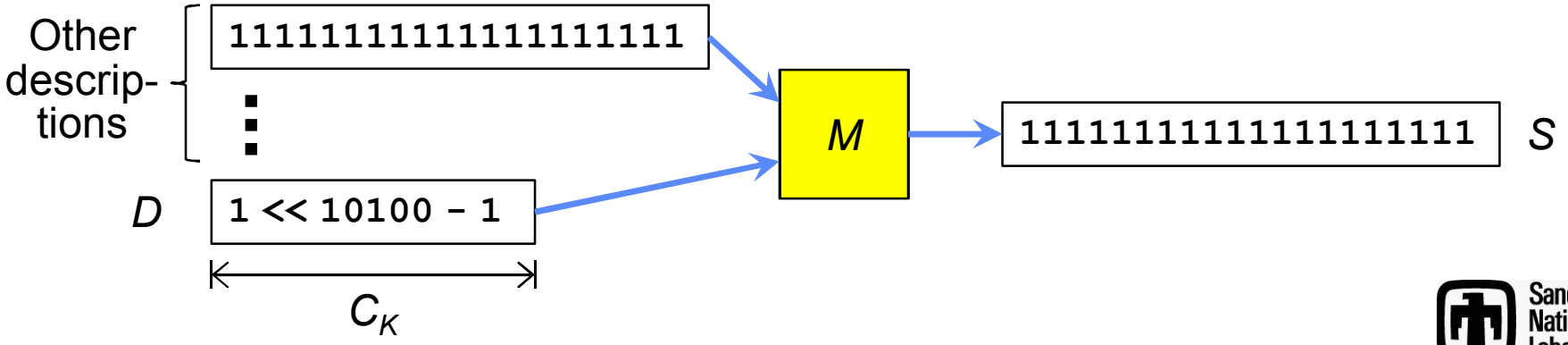
- **Fuzzing is automated randomized testing that samples vast input spaces to assess security**
  - Widely applicable, including for smart-grid devices
- **Fuzzing can operate on a black-box system but can also benefit from system understanding**
  - Complements analytical approaches that *reason* about the system (formal methods and complexity theory)
- **Effective fuzzing uses a targeted (non-uniform) distribution of test inputs**
- **Key questions:**
  - How should the sampling be targeted?
  - How can the resulting confidence be quantified?

Seek a relevant measure to organize the input space

- **A cyber system is taken as a general program**
- **Ultimately, the inputs of greatest interest – likely faults – are determined by the *semantics* of the program**
- **Some inputs are "simpler" than others in the natural representation that the program induces**
- **These simpler inputs are expected to be the most valuable fuzzing targets for defender and attacker**
  - Precedent 1: fuzzing by mutation of normal inputs
  - Precedent 2: cracking of low-entropy passwords
- **There is a rigorous notion of how "simple" a bit string is…**

Kolmogorov complexity distinguishes "natural" bit strings from noise

- **Given some universal Turing machine *M*: Kolmogorov complexity C_K of string *S* is length of shortest string *D* that, when fed to *M*, produces *S***
- ***D* is shortest "description" of *S* with respect to *M***
  - *D* is a "program" that runs on machine *M* to yield *S*
- **C_K is non-computable, but almost all *N*-bit strings have $C_K \approx N$ ("algorithmically random")**
- **Notional example showing low-complexity string:**



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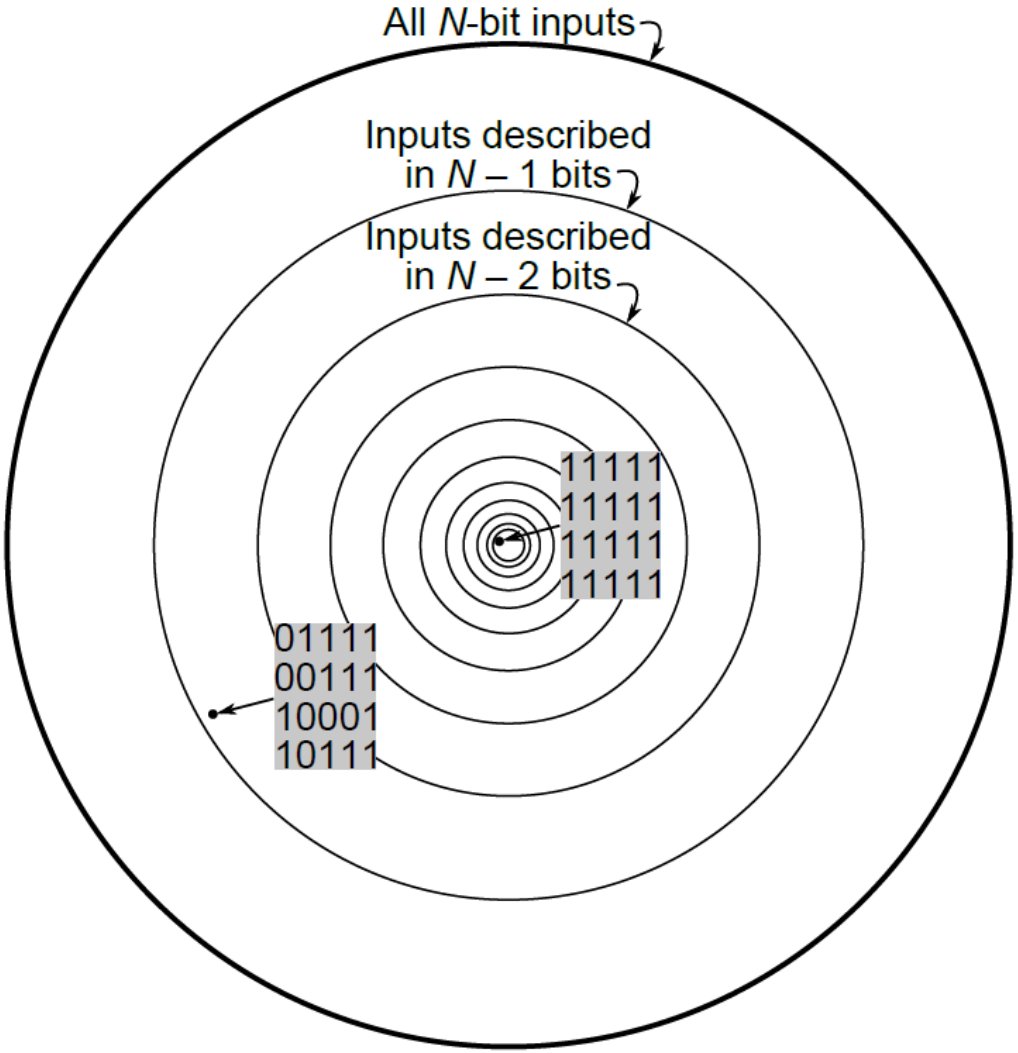
Kolmogorov complexity is relative but "asymptotically absolute"

- **View *S* as an input to the program being fuzzed**
  - Low C_K means *S* is "simple" and favored for sampling
- **Value of C_K depends on the Turing machine *M*, which is a "decompressor" that should reflect a natural input encoding for the program – e.g.:**
  - Databases: *M* most efficiently encodes SQL commands
  - Passphrases: *M* most efficiently encodes English words
- ***M* gives a semantically meaningful representation but, in the limit of long strings, C_K becomes independent of this representation**
  - A universal Turing machine can emulate any other via a *finite* interpreter (e.g., an English word table)

To quantify confidence in a generic program, must bound what attacker knows

- **If attacker grasps program semantics in a way defender does not, then attacker can embed this "key" in *M* and zero in on promising inputs that seem *high-complexity* (unguessable) to defender**
  - Shows the limits of fuzzing (effective undecidability)
- **Henceforth assume that defender and attacker share the same semantic understanding and thus employ essentially the same decompressor *M***
  - This seems plausible for very complex programs, and enables fuzzing to characterize security statistically
- **Define Kolmogorov complexity of inputs via this common representation**

Kolmogorov complexity organizes the input space



- **Inputs that have a simple description (relative to available information) should be targeted for defender coverage because they form a smaller "corner" space (also more attractive to attacker)**

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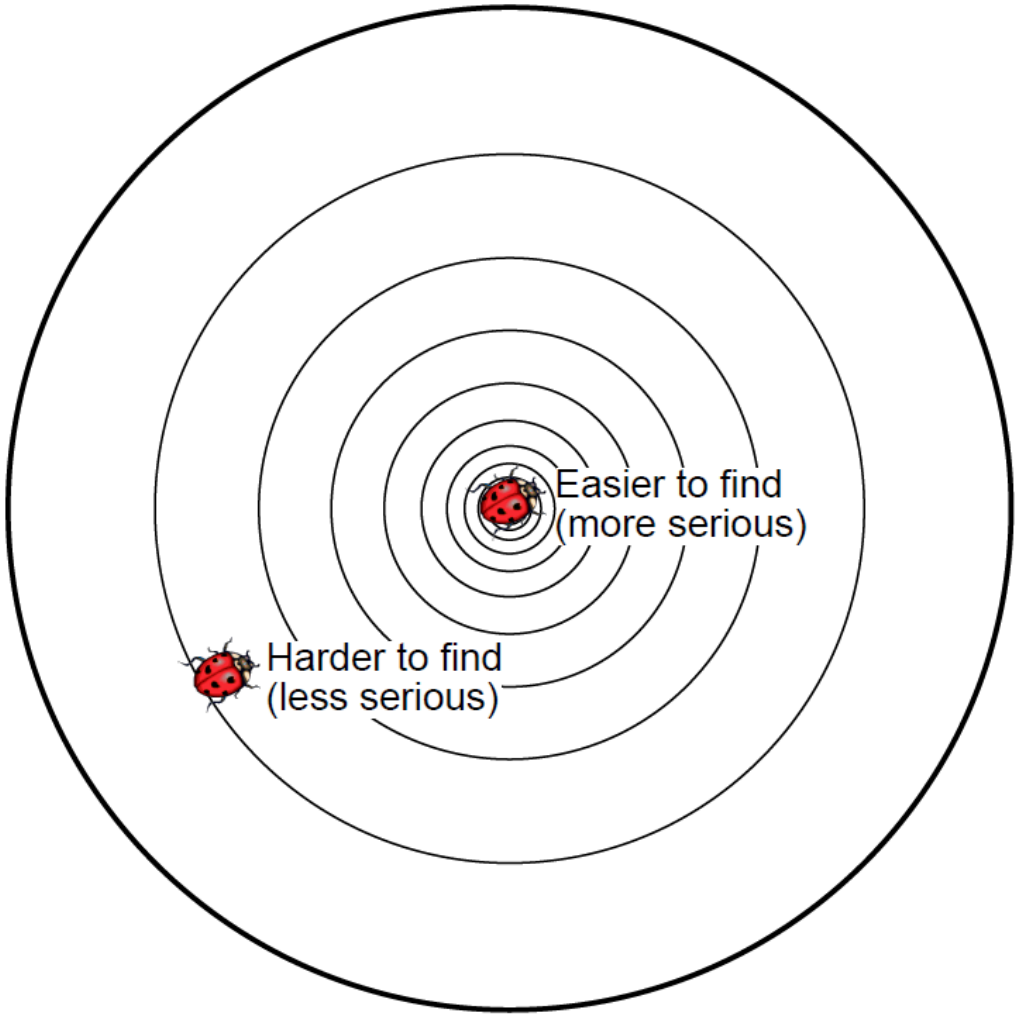

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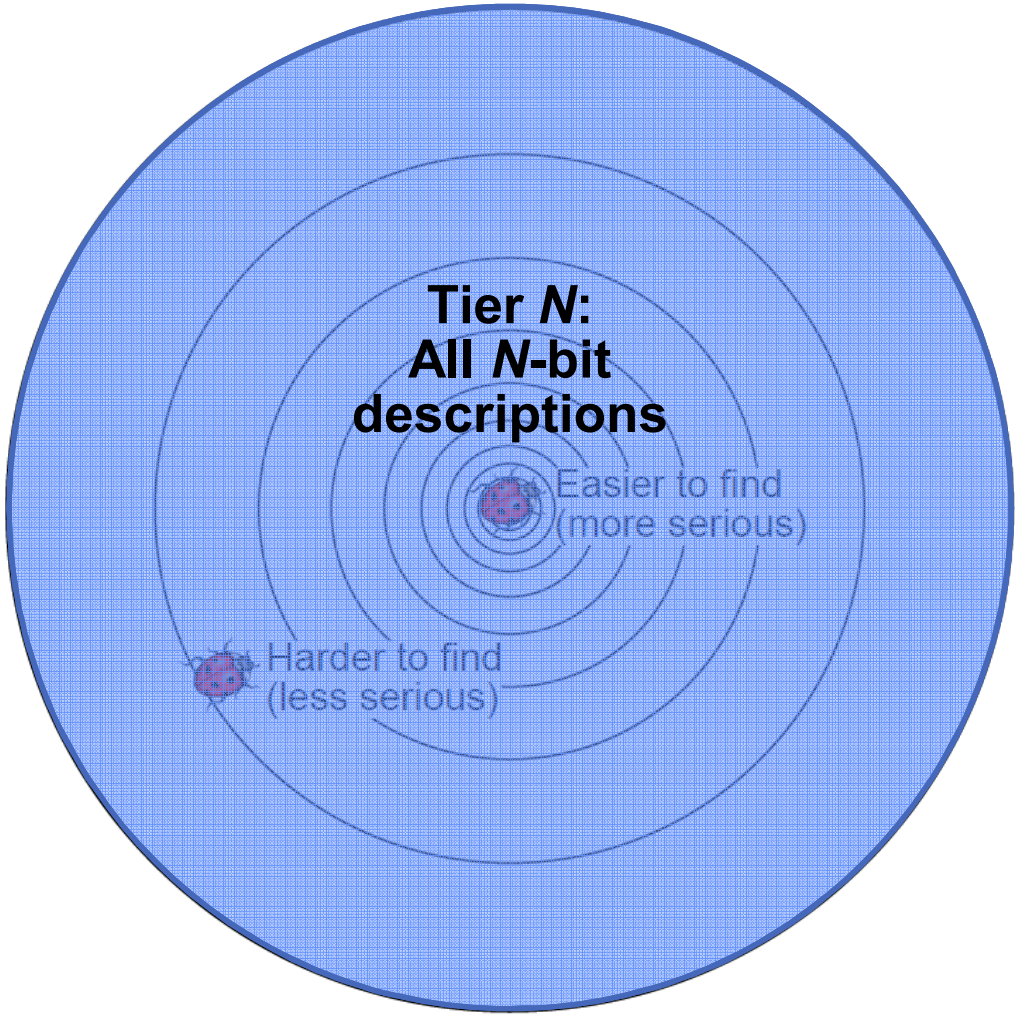
Complexity-based sampling generates a "wedding cake" distribution



- Although C_K is non-computable, descriptions of length *k* can be sampled, yielding inputs with $C_K \leq k$
- Because low C_K is a small part of the space, there is no advantage to *under*sampling there; instead, tiers pile up

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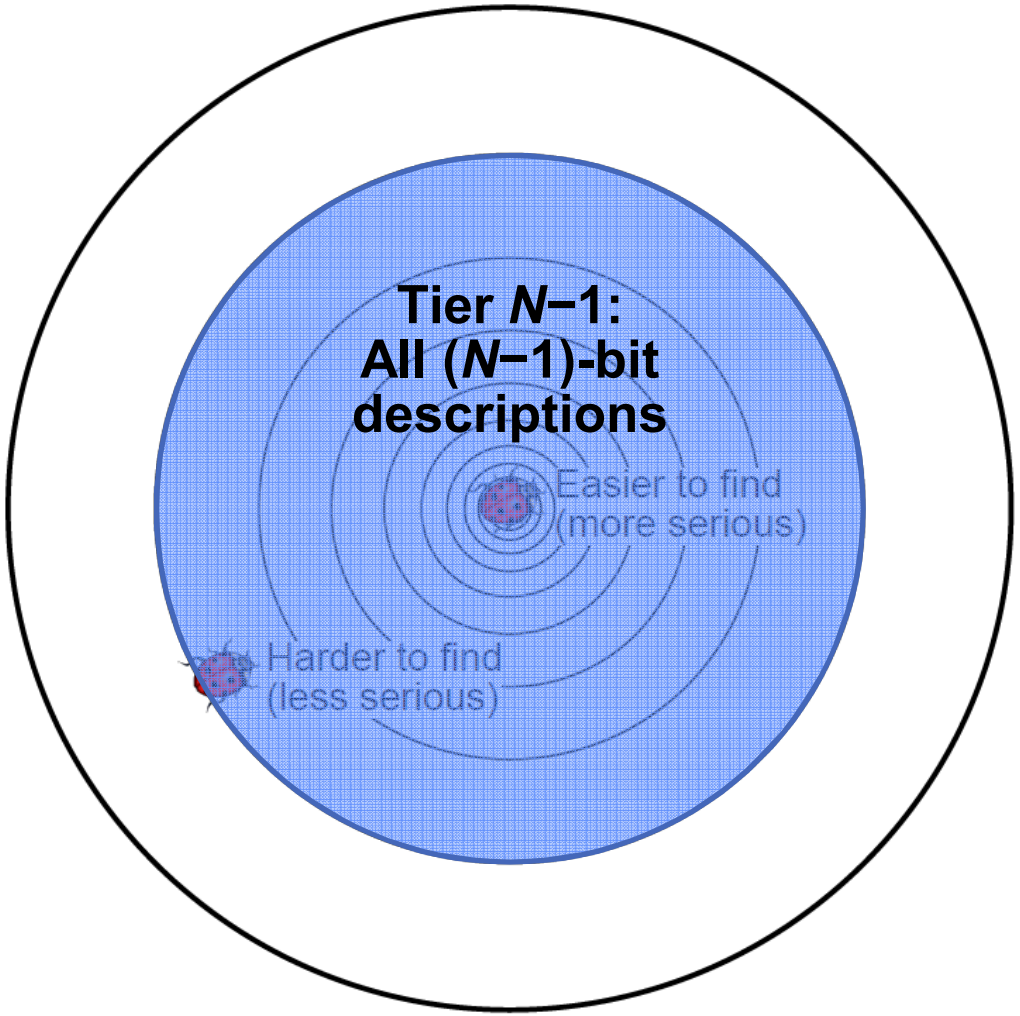

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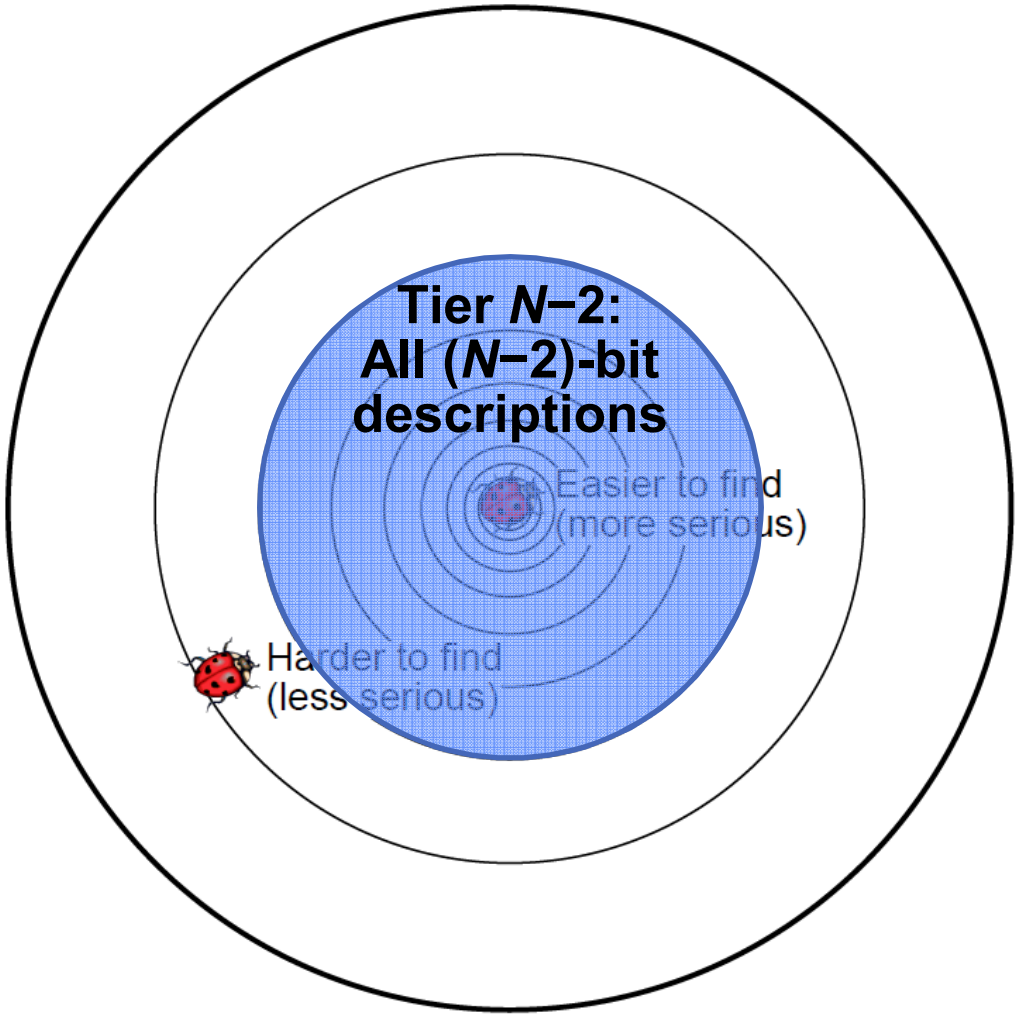

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A statistical strategy for fuzzing illustrates ability to quantify confidence

- Defender and attacker both can sample *N*-bit inputs from tiers $k = 0, 1, \ldots, N$ to locate faults
- Once program is deployed, attacker will find tier with highest fault rate and focus fuzzing there
- So defender wants to focus fault-patching effort on *minimizing* the *maximum* tier fault rate
- In tier k, after R_k random tests have yielded F_k faults of which P_k have been patched, defender's Bayesian estimate of tier fault rate is

$$\langle f_k \rangle = \frac{2^k - R_k}{2^k} \frac{F_k + 1}{R_k + 2} + \frac{F_k - P_k}{2^k}$$

A statistical strategy for fuzzing illustrates ability to quantify confidence

- **Defender samples each successive test from tier with current highest estimated fault rate**
  - Estimated fault rates decline due to increasing statistics and elimination of faults
  - High confidence (even for large *k*) can be obtained well short of exhaustive (2^k) fuzzing effort
- **Patching has negligible effect for large *k* but can dramatically reduce fault rates at small *k***
  - Purging "weak passwords" from the system

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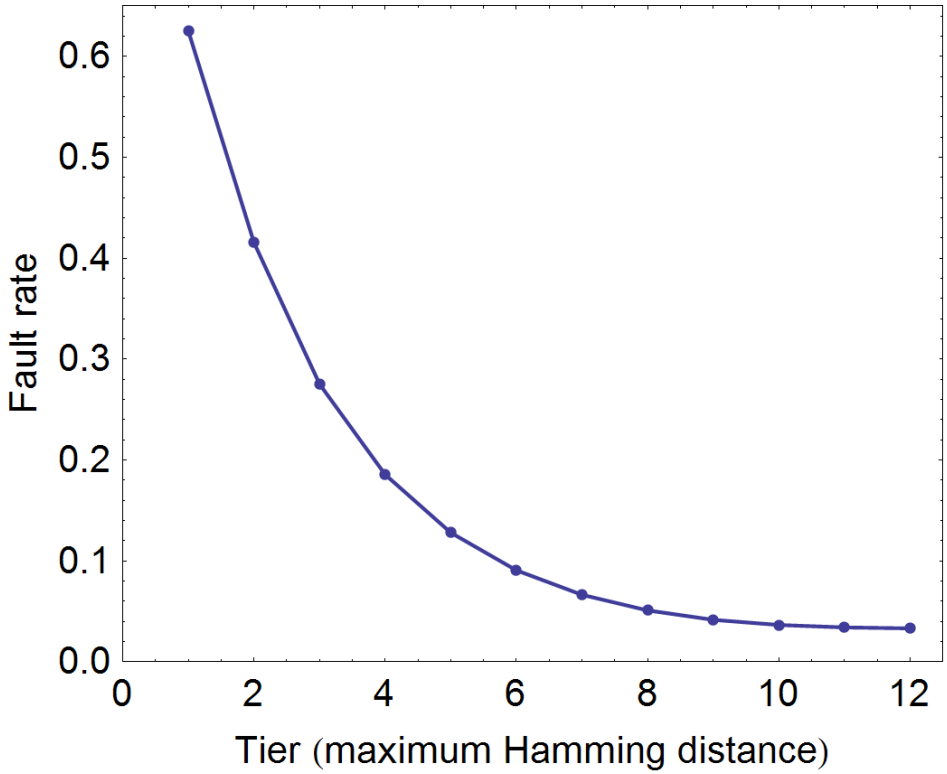
Experiments with programs developed by machine learning seem to corroborate

- **Boolean networks (BNs) are a flexible representation of digital logic**
- **Create BN circuits to perform string recognition: output 1 for a particular "gold" input string and 0 for all other inputs**
  - A fault is a non-gold input that produces a 1
- **Ensure objectivity and number of programs sufficient to gather meaningful statistics**
  - Create the programs automatically by machine learning
  - Using a genetic algorithm (mutation and recombination) to arrive at implementations with small but non-zero fault rates representative of more complex programs

These simple "grown" programs give a preliminary example of fault statistics

- 16-bit string recognizer has small enough input space for *exhaustive* fuzzing
- Model for machine *M*: an edit function based on the gold string, initially using bitwise edits (approximate C_K by Hamming distance)
- As expected, faults are most common close to the gold string



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