Picture credit: Rick Bowmer/AP

How to use the new 65-megawatt Bluffdale supercomputer: a gentle introduction to cryptanalysis

D. J. Bernstein
University of Illinois at Chicago &
Technische Universiteit Eindhoven

Disclaimers

Picture credit: Rick Bowmer/AP

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Hypothesize attacker resources.
This talk: $2 billion, 65MW.
Alternative: millions of
compromised Internet computers.

The interesting part: analyze
optimal use of those resources.

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The attacker's supercomputer

Enough theory+experiment
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But can the attacker perform
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Hypothesize attacker resources.
This talk: $2 billion, 65MW.
Alternative: millions of
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The interesting part: analyze
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NSA's computations have a mix
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with 3D arrangement of ALUs?
e.g. 1983 Rosenberg.

Huge engineering challenge.

2D allows easy scaling of
energy input, heat output
up to very large chip area.
3D is hard to scale.

Some limited progress
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Progress often exaggerated:
e.g., $4 \times 16384 \times 16384$
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Unpredictable application mix.
NSA will want some agility
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Quantify using historical data:
how long is an ASIC useful?

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Take a general-purpose CPU
Add exactly the big insn
XYZZY needed by applicatio
plus some vectorization.
Think ahead, add agility:
XYZZ? XZZY? XYQZZY?
Still similar cost to ASIC.

New CPU for each applicati
Merge similar applications
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o old computations.

y using historical data:
g is an ASIC useful?

Obvious solution for NSA:
some ASICs, plus heterogeneous
mix of **application-tuned**
integrated circuits (ATICs).

Take a general-purpose CPU.
Add exactly the big insn
XYZZY needed by application,
plus some vectorization.
Think ahead, add agility:
XYZZ? XZZY? XYQZZY?
Still similar cost to ASIC.

New CPU for each application.
Merge similar applications
if not much cost in area.

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Need to understand cryptanalysis:
ECM, sparse linear algebra,
differentials, FFTs, much more.