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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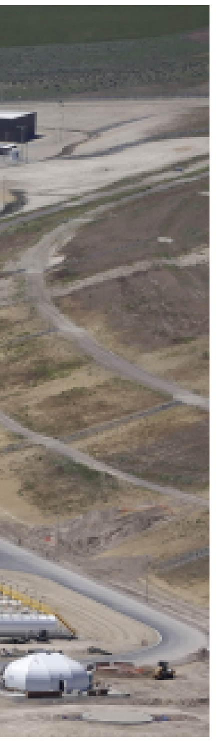

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This talk: $2 billion, 65MW.
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The interesting part: analyze
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Save even more time
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e.g. 1983 Rosenberg.

Huge engineering challenge.

2D allows easy scaling of
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3D is hard to scale.

Some limited progress
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Progress often exaggerated:
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Think ahead, add agility:
XYZZ? XZZY? XYQZZY?
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New CPU for each applicati
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Critical for algorithm designer and implementor:

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