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

Joint work with:

Tung Chou

Technische Universiteit Eindhoven

Algorithms in CS courses

"WHAT is your algorithm?"

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"If you can efficiently simulate a quantum algorithm using a pre-quantum computer then you have an efficient pre-quantum algorithm for the same problem."

Compute $s_0, s_1, s_2, ...$ and t_0, t_1, t_2, \ldots such that *s*; represents algorithm state at time t_i .

Prove that the computation matches the original algorithm.

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Childs: Yes. Typo, already fixed in 2005 journal version.