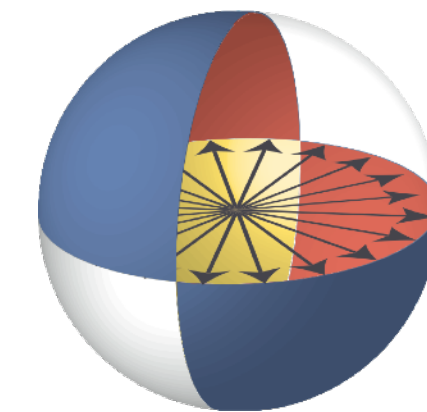


Efficient quantum algorithm for dissipative nonlinear differential equations

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arXiv:2011.03185

Quantum computation

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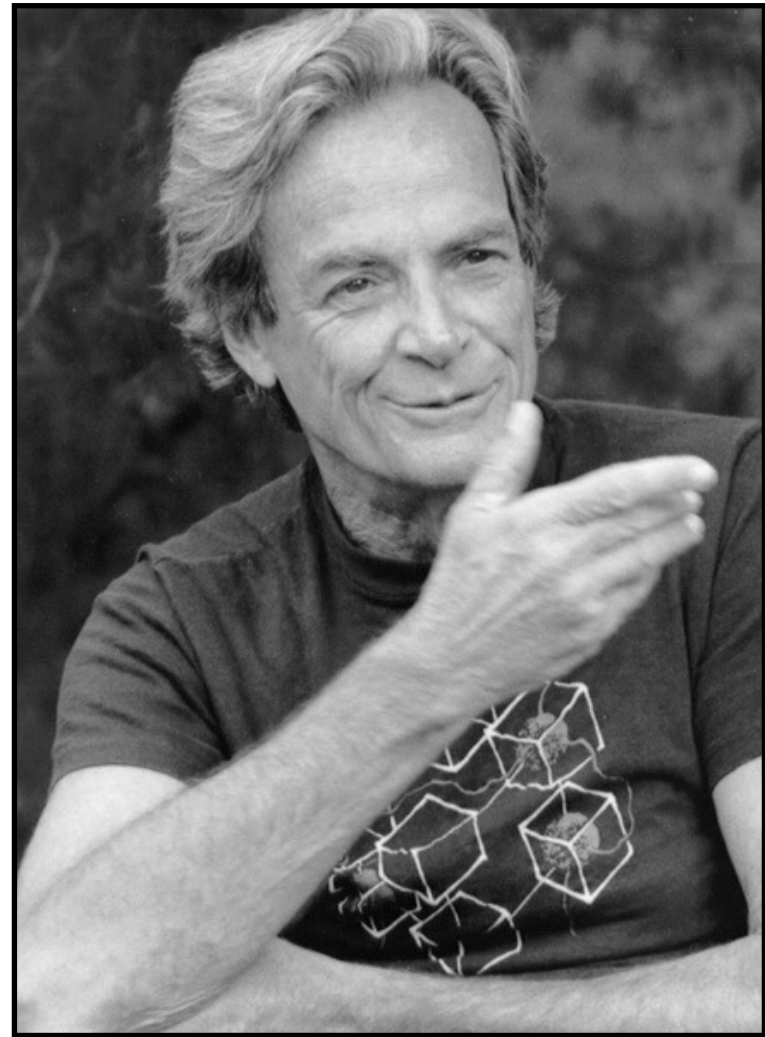
Quantum computers also provide a novel approach to problems in numerical analysis.

Main idea:

- Represent a vector $x \in \mathbb{C}^N$ by a quantum state $|x\rangle$ of $\log_2 N$ qubits.
- Show how to prepare such a state using $\text{poly}(\log N)$ operations.
- Produces a quantum encoding of the solution. Less informative than an explicit solution, but much faster and still potentially useful.

Quantum simulation

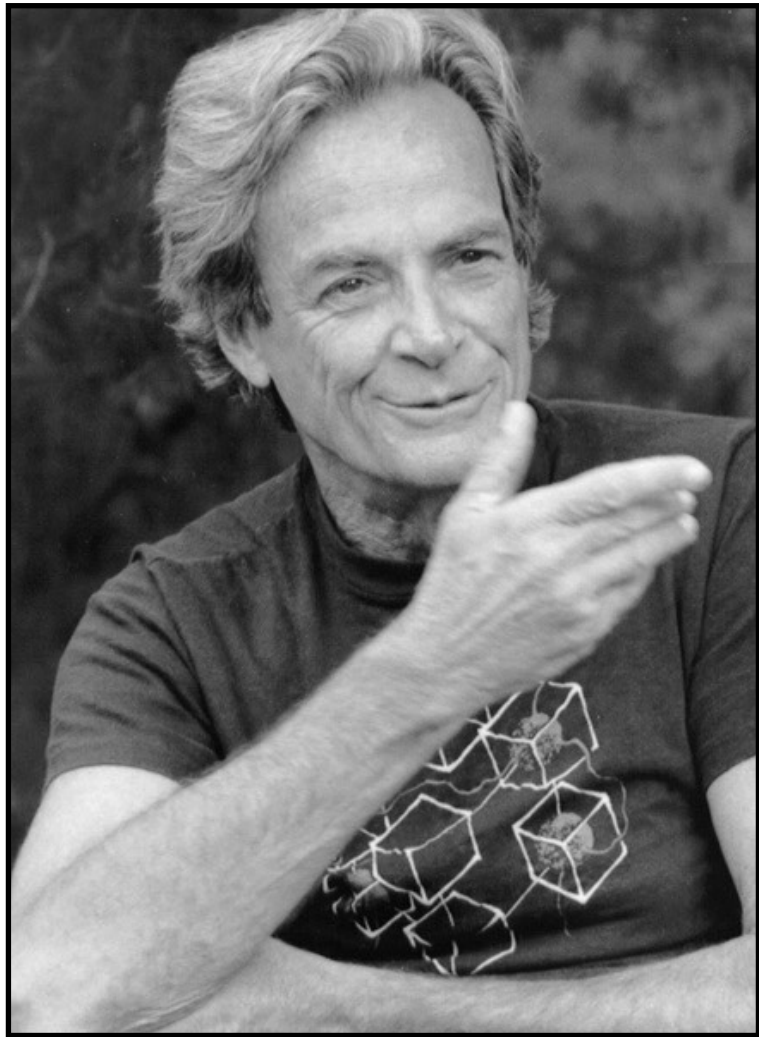
Quantum simulation



“... nature isn’t classical, dammit, and if you want to make a simulation of nature, you’d better make it quantum mechanical, and by golly it’s a wonderful problem, because it doesn’t look so easy.”

Richard Feynman (1981)
Simulating physics with computers

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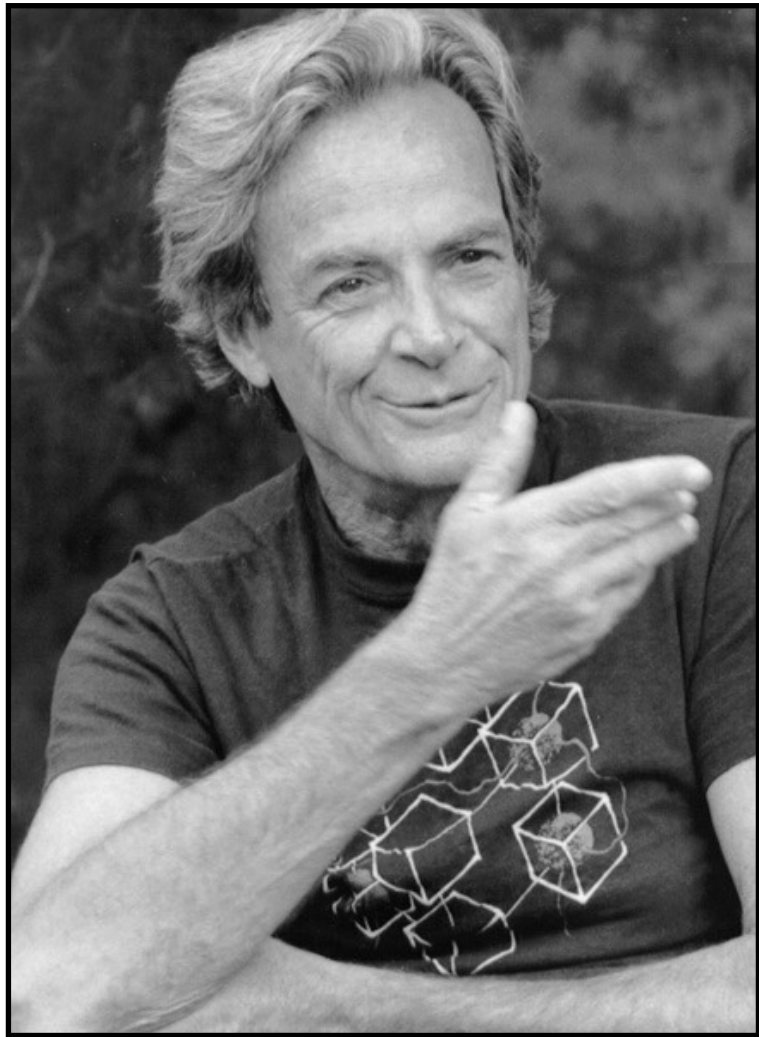


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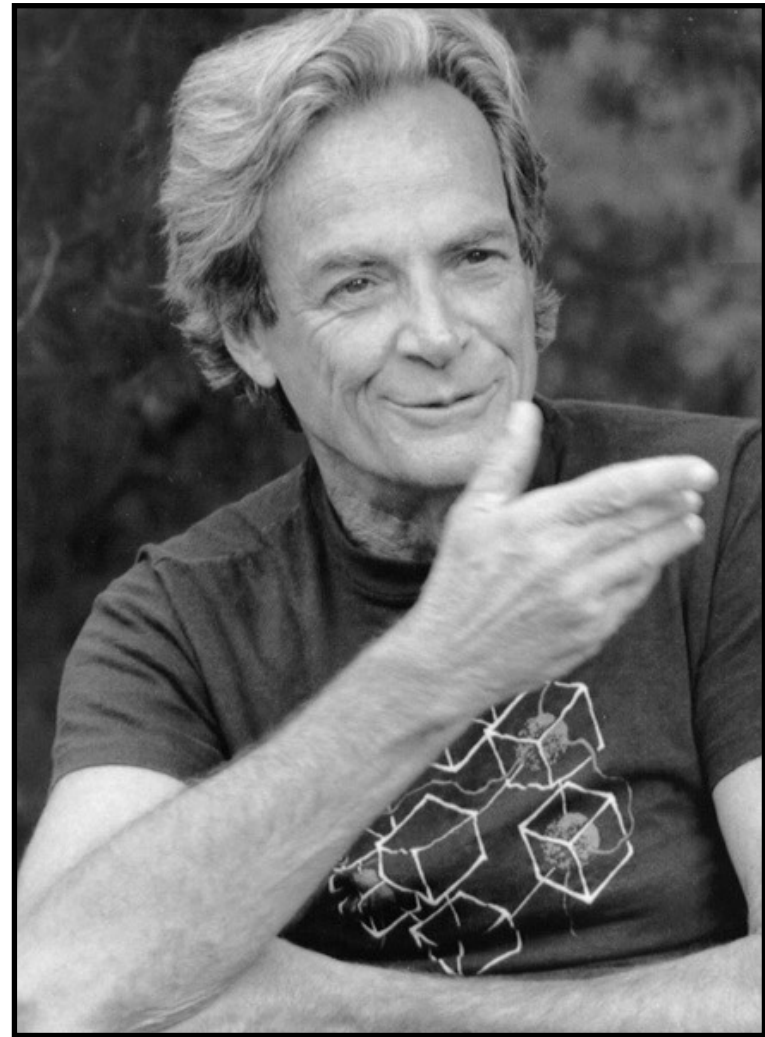
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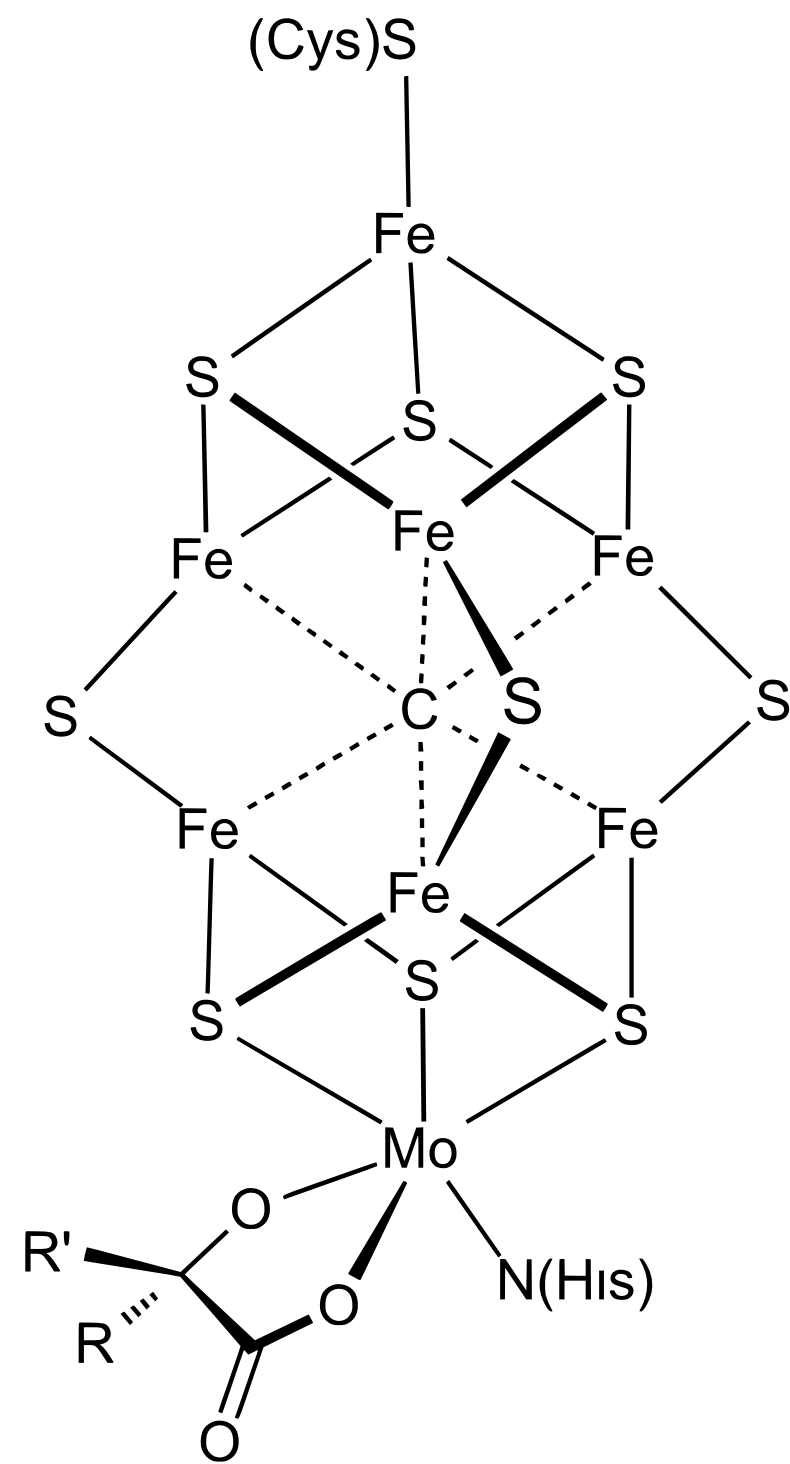
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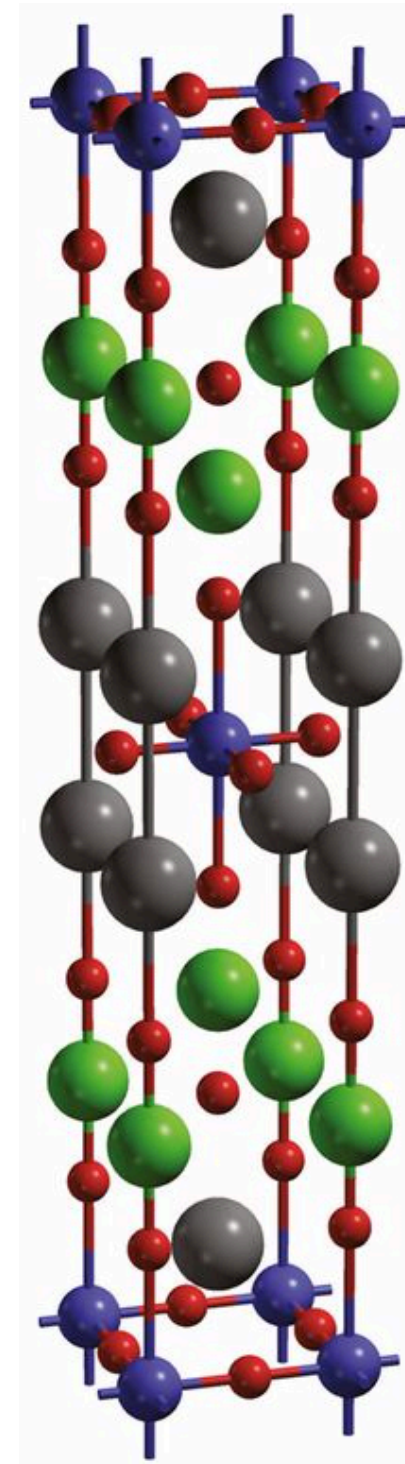
A classical computer cannot even represent the state efficiently

A quantum computer cannot produce a complete description of the state, but by performing measurements, it can answer questions that (apparently) a classical computer cannot

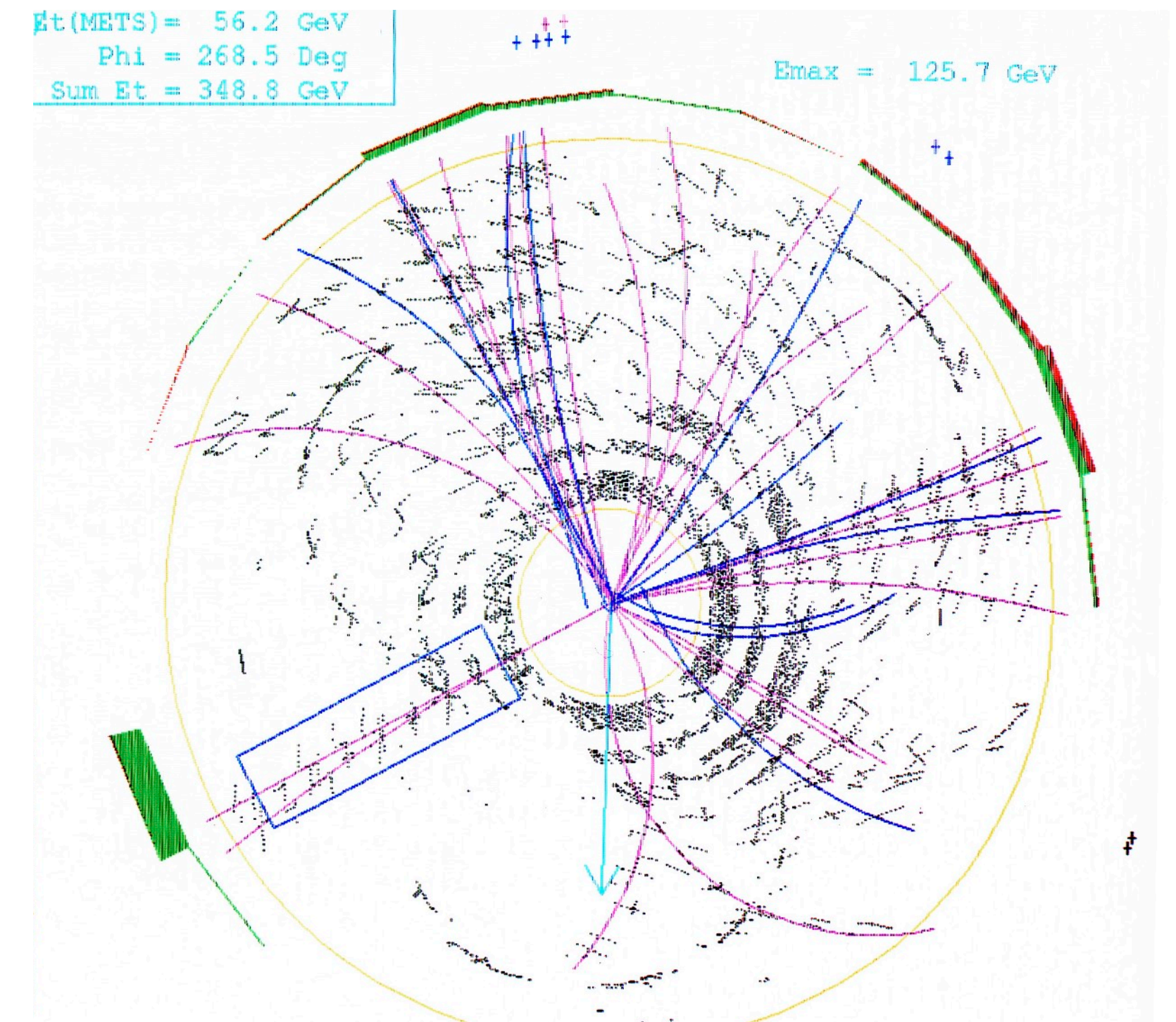
Computational quantum physics



quantum chemistry
(e.g., nitrogen fixation)

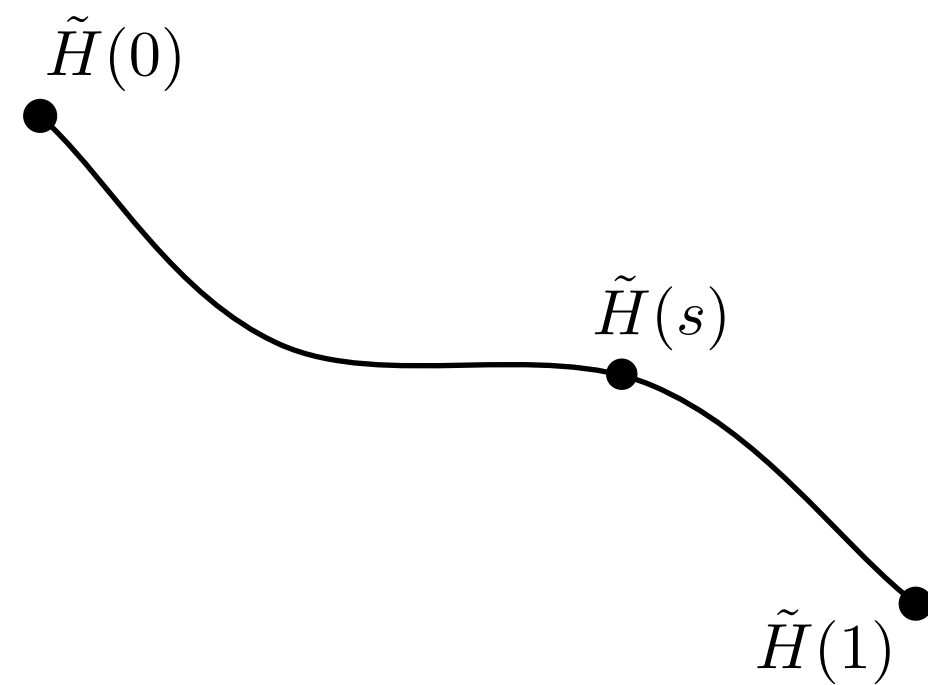


condensed matter physics/
properties of materials

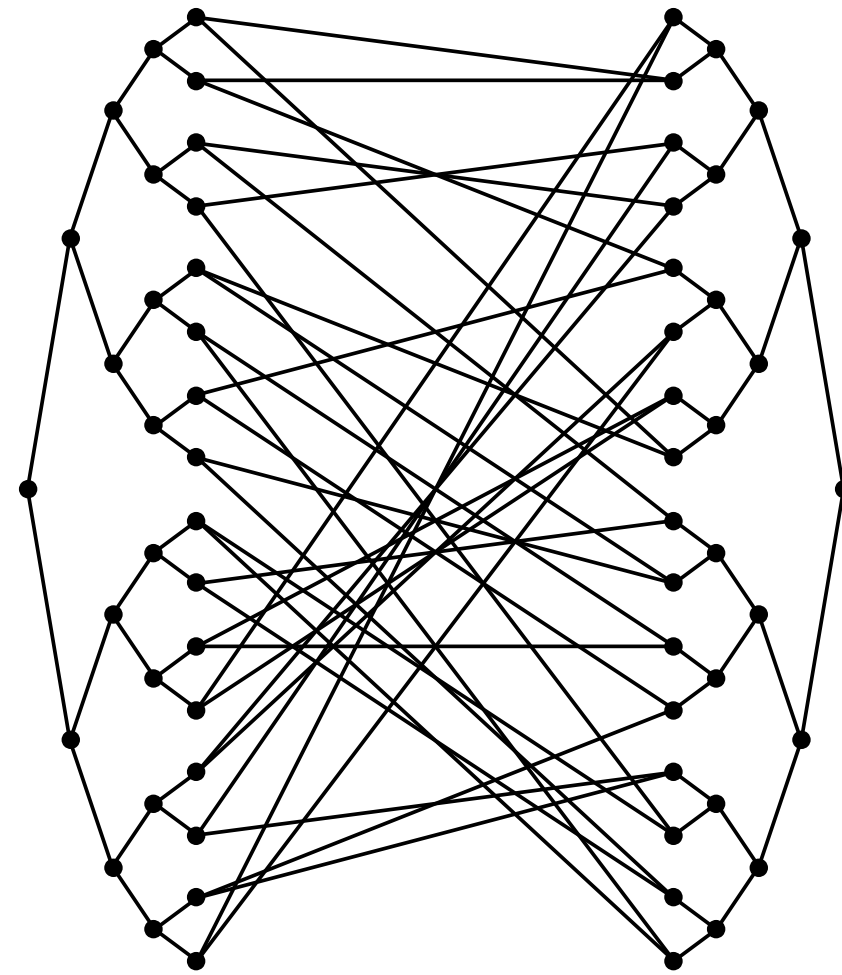


nuclear/particle
physics

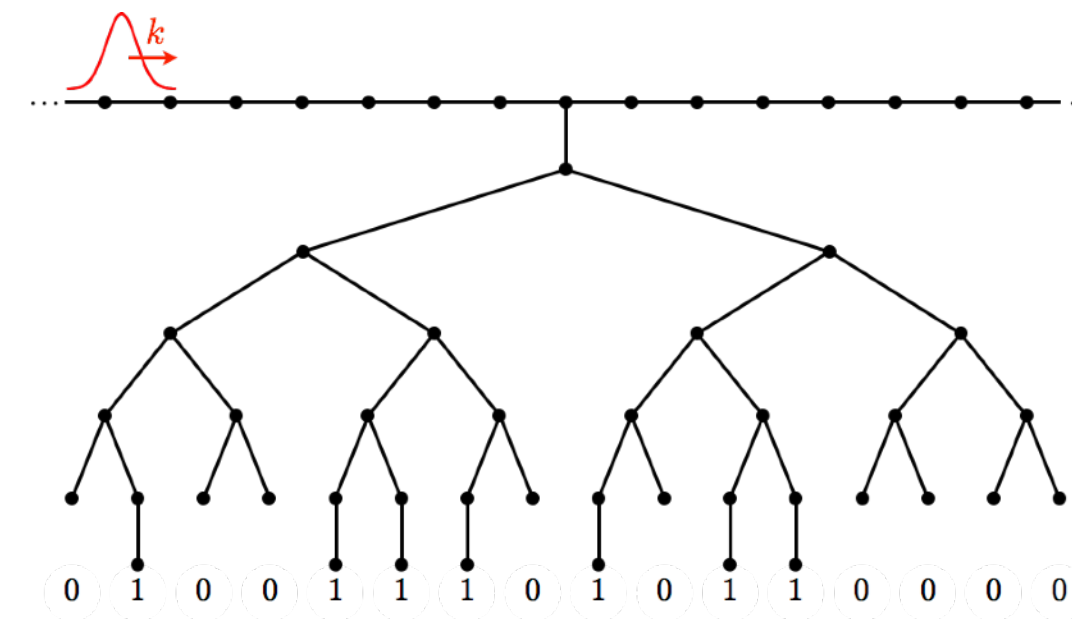
Implementing quantum algorithms



adiabatic
optimization



exponential
speedup by
quantum walk



evaluating
Boolean
formulas

$$A|x\rangle = |b\rangle$$

linear/
differential
equations,
convex
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Subsequent improvements do the same with complexity $\kappa \text{poly}(\log(1/\epsilon))$ using variable-time amplitude amplification and LCU [Ambainis 12; Childs, Kothari, Somma 17]

Quantum algorithms for differential equations

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Later work gives improved/generalized algorithms (time-dependent coefficients, BVPs, PDEs)

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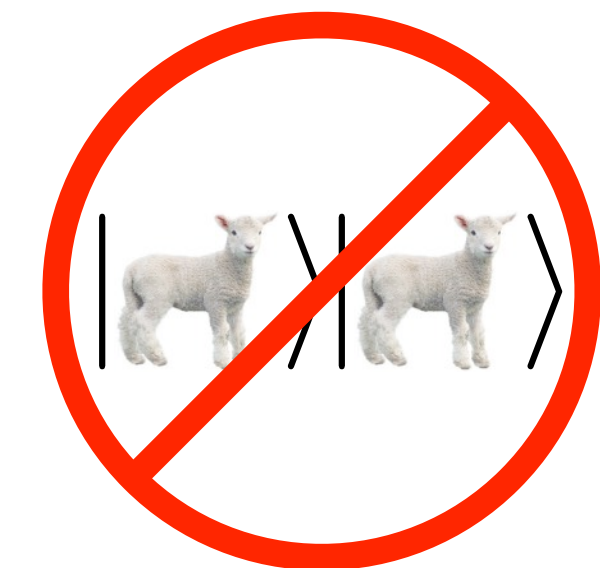
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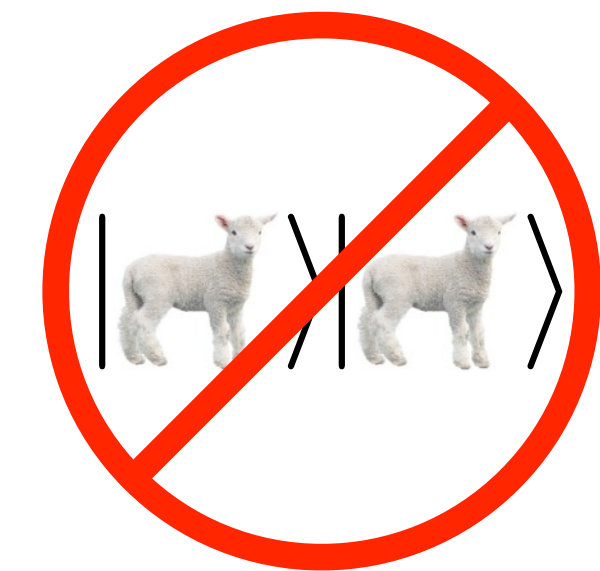
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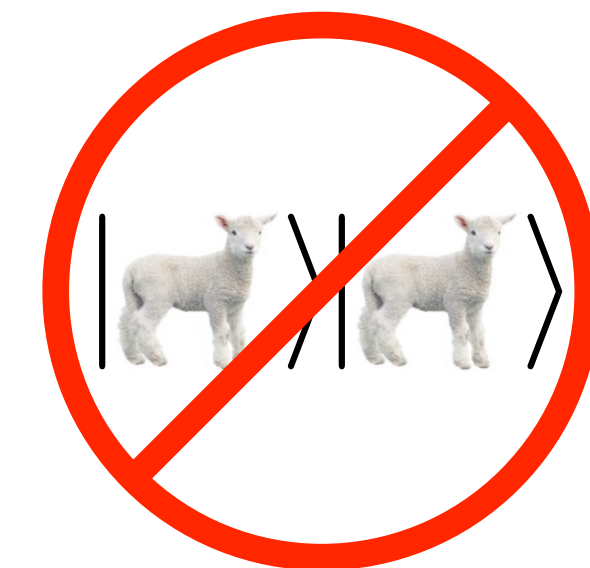
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So maybe there is a fundamental obstacle?

Problem statement

Quantum quadratic ODE problem. Consider an ODE $\frac{du}{dt} = F_2 u^{\otimes 2} + F_1 u + F_0(t)$ with $u(t), F_0(t) \in \mathbb{R}^n$, $F_1 \in \mathbb{R}^{n \times n}$, $F_2 \in \mathbb{R}^{n \times n^2}$. Assume we are given an oracle to prepare a quantum state proportional to $u(0) = u_{\text{in}}$, and sparse matrix oracles for $F_0(t), F_1, F_2$. Let the eigenvalues λ_j of F_1 satisfy $\text{Re}(\lambda_n) \leq \dots \leq \text{Re}(\lambda_1) < 0$. Parametrize the problem in terms of

$$R := \frac{1}{|\text{Re}(\lambda_1)|} \left(\|u_{\text{in}}\| \|F_2\| + \frac{\|F_0\|}{\|u_{\text{in}}\|} \right)$$

and assume the values $\|u_{\text{in}}\|, \|F_0(t)\|, \|F_1\|, \|F_2\|, \text{Re}(\lambda_1), \max_t \|F_0(t)\|, \max_t \|F'_0(t)\|$ are known.

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$\mathcal{R}$ quantifies the strength of the nonlinearity and driving relative to dissipation.
Qualitatively similar to Reynolds number.

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Theorem I. For $R < 1$, there is a quantum algorithm for the quantum quadratic ODE problem with query and gate complexity

$$\frac{sqT^2}{\epsilon} \text{poly}(\log T, \log n, \log(1/\epsilon))$$

where s is the sparsity of the input, $q := \|u_{\text{in}}\|/\|u(T)\|$, and ϵ is the error in the approximation of $u(T)/\|u(T)\|$.

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Ingredients:

- Carleman linearization (novel convergence analysis)
- Forward Euler discretization
- State preparation procedure
- Condition number and success probability analysis

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Approximate the nonlinear ODE by an infinite sequence of linear ODEs in $u, u^{\otimes 2}, u^{\otimes 3}, \dots$

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Lemma. $N = O(\log(T\|F_2\|/\delta)/\log(1/\|u_{\text{in}}\|))$ suffices to approximate the solution within δ .

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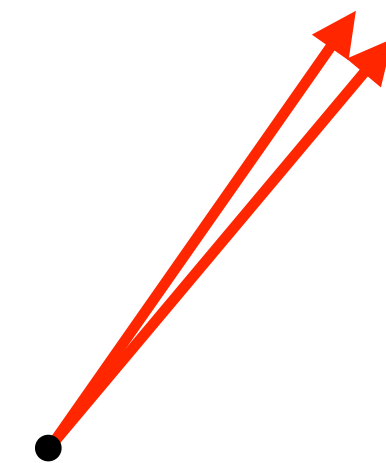
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- Hardness of distinguishing nonorthogonal quantum states



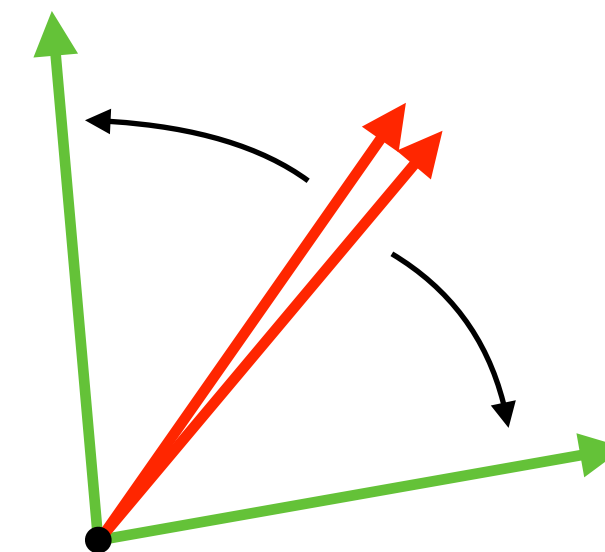
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Ingredients:

- Hardness of distinguishing nonorthogonal quantum states
- Quadratic ODE that rapidly distinguishes nonorthogonal states



Hardness of state distinguishability

Lemma. Let $|\psi\rangle, |\phi\rangle$ be quantum states with $|\langle\psi|\phi\rangle| = 1 - \epsilon$. Suppose we are either given a black box that prepares $|\psi\rangle$ or a black box that prepares $|\phi\rangle$. Then any bounded-error protocol for determining whether the state is $|\psi\rangle$ or $|\phi\rangle$ must take time $\Omega(1/\epsilon)$.

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Proof:

- If we use the box k times, we produce states with overlap $(1 - \epsilon)^k$.
- These states have trace distance $\Theta(\sqrt{k\epsilon})$.
- By the Helstrom bound, need $k = \Omega(1/\epsilon)$ to distinguish with bounded error.

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But for small θ , the state $\cos(\frac{\pi}{4} + \theta)|0\rangle + \sin(\frac{\pi}{4} + \theta)|1\rangle$ changes exponentially in t

Distinguishing states with dissipative nonlinear dynamics

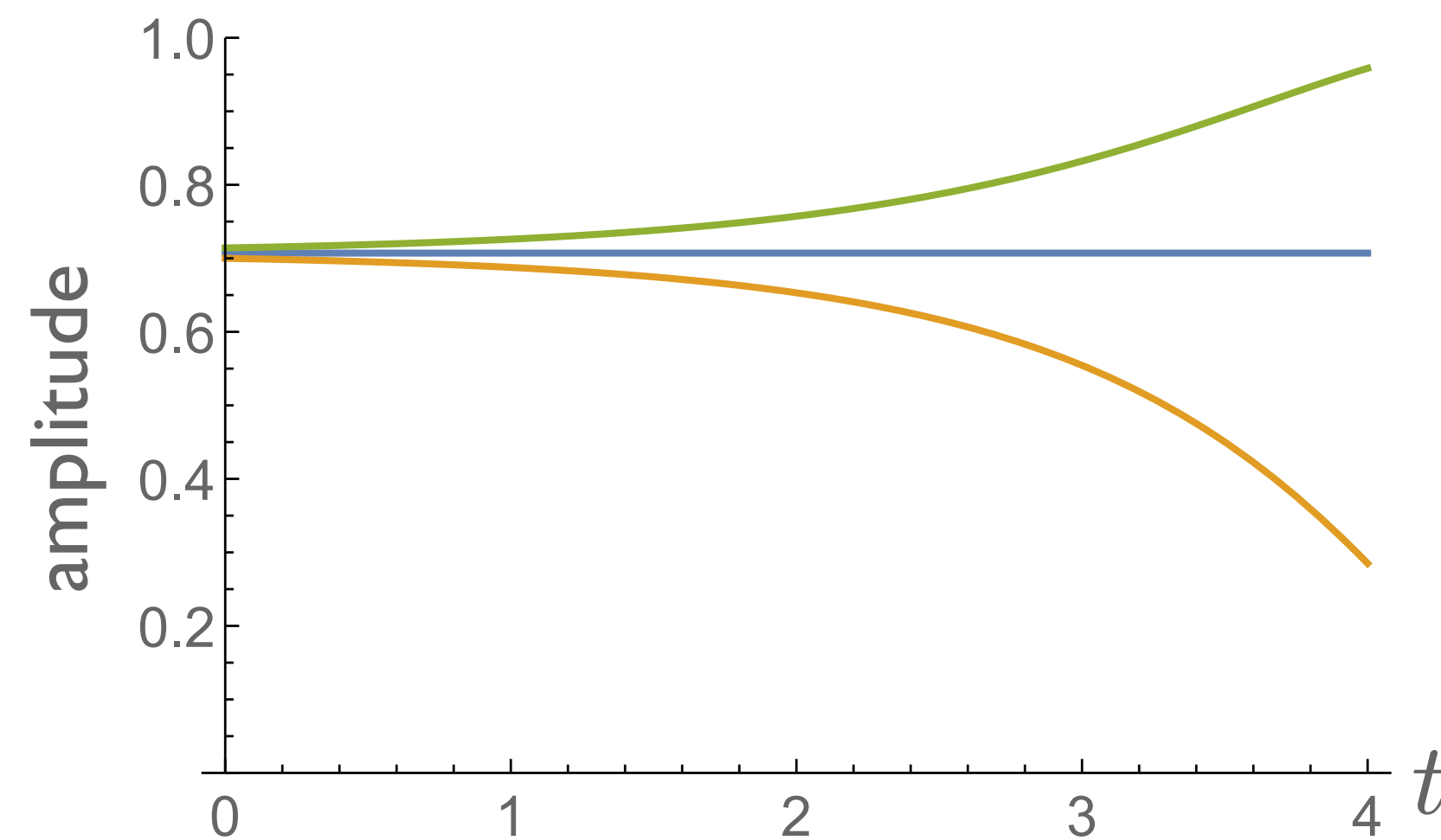
Consider the ODE $\frac{du}{dt} = -u + Ru^2$ Solution: $u(t) = \frac{1}{R - e^t(R - 1/u(0))}$

Let this act on both basis states of a qubit

The uniform superposition $\frac{1}{\sqrt{2}}(|0\rangle + |1\rangle)$ does not evolve (up to normalization)

But for small θ , the state $\cos(\frac{\pi}{4} + \theta)|0\rangle + \sin(\frac{\pi}{4} + \theta)|1\rangle$ changes exponentially in t

Example. $R = \sqrt{2}$, $\theta = 0.01$



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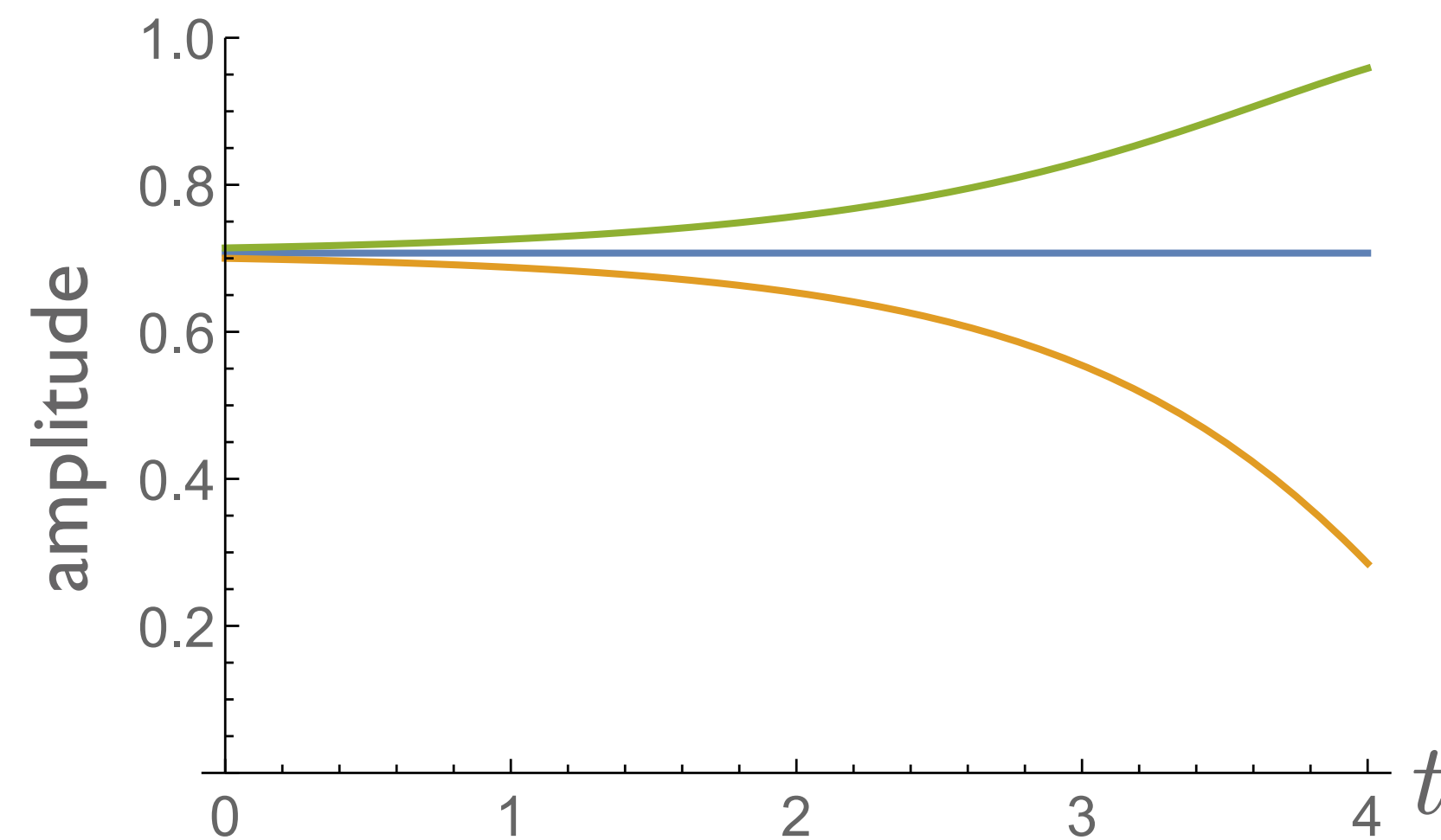
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In general, the time to separate states with overlap $1 - \epsilon$ by a constant amount is $O(\log(1/\epsilon))$.

Applications: Epidemiology

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SEIR model of a pandemic:

$$\frac{dP_S}{dt} = -\Lambda \frac{P_S}{P} - r_{\text{vac}} P_S + \Lambda - r_{\text{tra}} P_S \frac{P_I}{P}$$

$$\frac{dP_E}{dt} = -\Lambda \frac{P_E}{P} - \frac{P_E}{T_{\text{lat}}} + r_{\text{tra}} P_S \frac{P_I}{P}$$

$$\frac{dP_I}{dt} = -\Lambda \frac{P_I}{P} + \frac{P_E}{T_{\text{lat}}} - \frac{P_I}{T_{\text{inf}}}$$

$$\frac{dP_R}{dt} = -\Lambda \frac{P_R}{P} + r_{\text{vac}} P_S + \frac{P_I}{T_{\text{inf}}}$$

Applications: Epidemiology

SEIR model of a pandemic:

$$\begin{array}{ll} \text{susceptible} & \frac{dP_S}{dt} = -\Lambda \frac{P_S}{P} - r_{\text{vac}} P_S + \Lambda - r_{\text{tra}} P_S \frac{P_I}{P} \\ \text{exposed} & \frac{dP_E}{dt} = -\Lambda \frac{P_E}{P} - \frac{P_E}{T_{\text{lat}}} + r_{\text{tra}} P_S \frac{P_I}{P} \\ \text{infected} & \frac{dP_I}{dt} = -\Lambda \frac{P_I}{P} + \frac{P_E}{T_{\text{lat}}} - \frac{P_I}{T_{\text{inf}}} \\ \text{recovered} & \frac{dP_R}{dt} = -\Lambda \frac{P_R}{P} + r_{\text{vac}} P_S + \frac{P_I}{T_{\text{inf}}} \end{array}$$

Applications: Epidemiology

SEIR model of a pandemic:

influx

↓

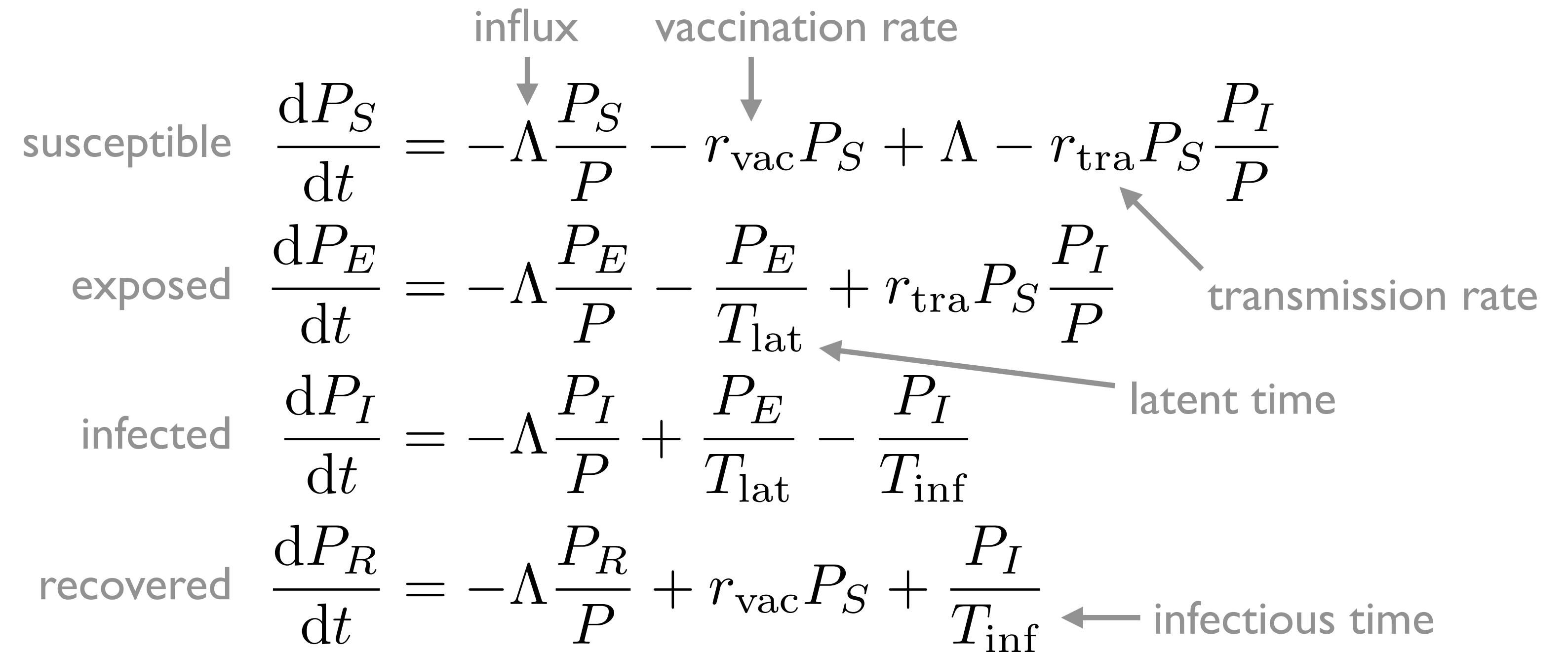
vaccination rate

↓

susceptible	$\frac{dP_S}{dt} = -\Lambda \frac{P_S}{P} - r_{\text{vac}} P_S + \Lambda - r_{\text{tra}} P_S \frac{P_I}{P}$	
exposed	$\frac{dP_E}{dt} = -\Lambda \frac{P_E}{P} - \frac{P_E}{T_{\text{lat}}} + r_{\text{tra}} P_S \frac{P_I}{P}$	transmission rate
infected	$\frac{dP_I}{dt} = -\Lambda \frac{P_I}{P} + \frac{P_E}{T_{\text{lat}}} - \frac{P_I}{T_{\text{inf}}}$	latent time
recovered	$\frac{dP_R}{dt} = -\Lambda \frac{P_R}{P} + r_{\text{vac}} P_S + \frac{P_I}{T_{\text{inf}}}$	infectious time

Applications: Epidemiology

SEIR model of a pandemic:



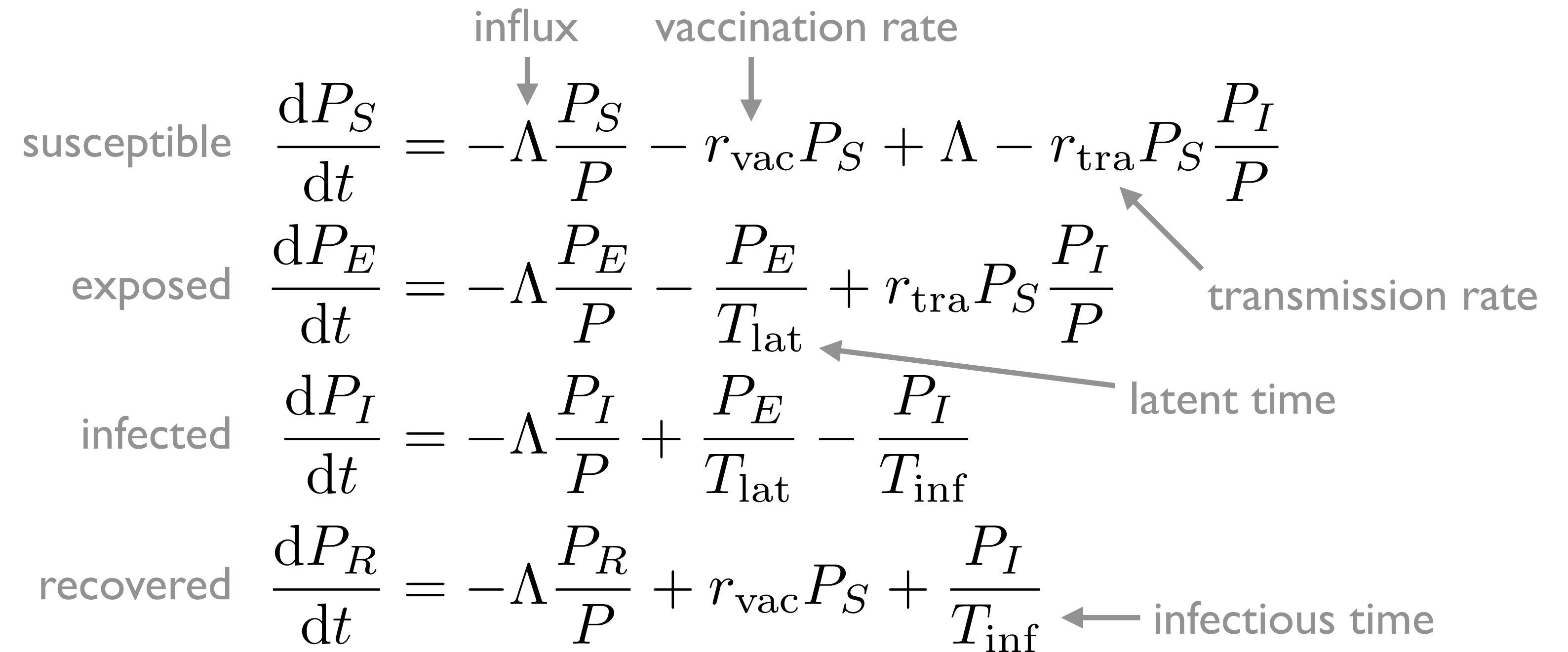
The diagram shows the SEIR model equations with four compartments: susceptible, exposed, infected, and recovered. Each compartment has a differential equation. Annotations with arrows point to specific terms in the equations: 'influx' points to the Λ term in the susceptible equation; 'vaccination rate' points to the $r_{\text{vac}} P_S$ term in the susceptible and recovered equations; 'transmission rate' points to the $r_{\text{tra}} P_S \frac{P_I}{P}$ term in the susceptible and exposed equations; 'latent time' points to the $\frac{P_E}{T_{\text{lat}}}$ term in the infected equation; and 'infectious time' points to the $\frac{P_I}{T_{\text{inf}}}$ term in the recovered equation.

$$\begin{aligned}
 \text{susceptible} \quad \frac{dP_S}{dt} &= -\overset{\text{influx}}{\Lambda} \frac{P_S}{P} - \overset{\text{vaccination rate}}{r_{\text{vac}}} P_S + \Lambda - r_{\text{tra}} P_S \frac{P_I}{P} \\
 \text{exposed} \quad \frac{dP_E}{dt} &= -\Lambda \frac{P_E}{P} - \frac{P_E}{T_{\text{lat}}} + r_{\text{tra}} P_S \frac{P_I}{P} \\
 \text{infected} \quad \frac{dP_I}{dt} &= -\Lambda \frac{P_I}{P} + \frac{P_E}{T_{\text{lat}}} - \frac{P_I}{T_{\text{inf}}} \\
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 \end{aligned}$$

Realistic parameters [Wang et al., JAMA 20] (with fairly rapid vaccination) can satisfy $R < 1$

Applications: Epidemiology

SEIR model of a pandemic:



The diagram shows the SEIR model equations with various parameters annotated with arrows:

- influx**: points to Λ in the susceptible equation.
- vaccination rate**: points to r_{vac} in the susceptible equation.
- transmission rate**: points to r_{tra} in the exposed equation.
- latent time**: points to T_{lat} in the infected equation.
- infectious time**: points to T_{inf} in the recovered equation.

The equations are:

$$\begin{aligned} \text{susceptible} \quad \frac{dP_S}{dt} &= -\Lambda \frac{P_S}{P} - r_{\text{vac}} P_S + \Lambda - r_{\text{tra}} P_S \frac{P_I}{P} \\ \text{exposed} \quad \frac{dP_E}{dt} &= -\Lambda \frac{P_E}{P} - \frac{P_E}{T_{\text{lat}}} + r_{\text{tra}} P_S \frac{P_I}{P} \\ \text{infected} \quad \frac{dP_I}{dt} &= -\Lambda \frac{P_I}{P} + \frac{P_E}{T_{\text{lat}}} - \frac{P_I}{T_{\text{inf}}} \\ \text{recovered} \quad \frac{dP_R}{dt} &= -\Lambda \frac{P_R}{P} + r_{\text{vac}} P_S + \frac{P_I}{T_{\text{inf}}} \end{aligned}$$

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A high-dimensional version can model many interacting cities

Applications: Fluid dynamics

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$$\partial_t u + u \partial_x u = \nu \partial_x^2 u + f$$

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Discretize space with central differences to
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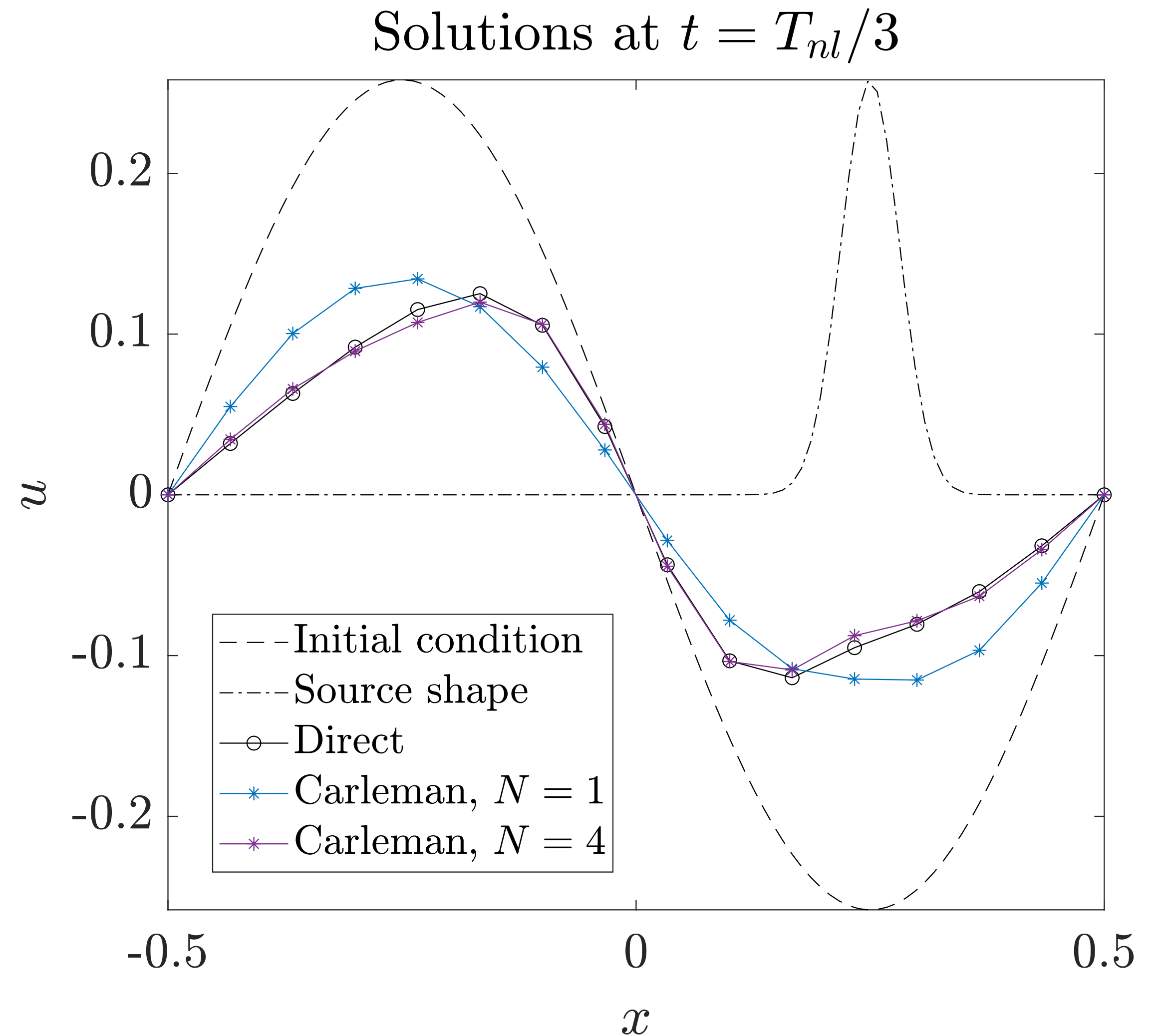
Applications: Fluid dynamics

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Discretize space with central differences to give an ODE

Carleman method shows good convergence even for $R \approx 40$



Summary

We have shown how to efficiently produce a quantum encoding of the solution of a system of dissipative nonlinear ODEs provided the nonlinearity and forcing are sufficiently weak relative to dissipation ($R < 1$) and the solution does not decay exponentially.

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We have also shown that there can be no efficient quantum algorithm for general nonlinear ODEs with $R \geq \sqrt{2}$.

However, numerical evidence suggests that the algorithm may be efficient for certain cases even with R much larger.

Open questions

- What can we say about efficiency/hardness for $1 \leq R < \sqrt{2}$?
- Our algorithm has complexity quadratic in T . Can this be improved?
- Our algorithm has complexity $\tilde{O}(1/\epsilon)$, whereas other quantum algorithms for simulation/linear equations/ODEs have complexity $\text{poly}(\log(1/\epsilon))$. Can this be improved?
- Can we identify conditions under which the algorithm is efficient for larger R ?
- End-to-end applications