

Probabilistic Exponential Integrators

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Probabilistic ODE Solvers

Initial value problem:

$$y(t) = f(t, y(t)), \quad t \in [t_0, T], \quad y(t_0) = y_0$$

Classical numerical ODE solvers compute $\hat{y}(t) \approx y(t)$.

Probabilistic numerical ODE solution:

$$p(y(t) | y(t_0)) = y_0, \{y(t_n) - f(y(t_n)) = 0\}_{n=1}^N$$

for some time grid $\{t_n\}_{n=1}^N \subset [t_0, T]$.

ODEs as Bayesian State Estimation

Prior: Gauss–Markov process $Y(t) := [y(t), \dot{y}(t), \dots, y^{(q)}(t)]$,

$$dY(t) = AY(t) dt + B dW(t), \quad Y(t_0) \sim \mathcal{N}(\mu_0, \Sigma_0).$$

Equivalent in discrete time:

$$Y(t+h) | Y(t) \sim \mathcal{N}(\Phi(h)Y(t), Q(h))$$

Likelihood: $Z_n := E_0 Y(t_n) - f(E_1 Y(t_n), t) \triangleq 0$,

with E_0, E_1 selection matrices.

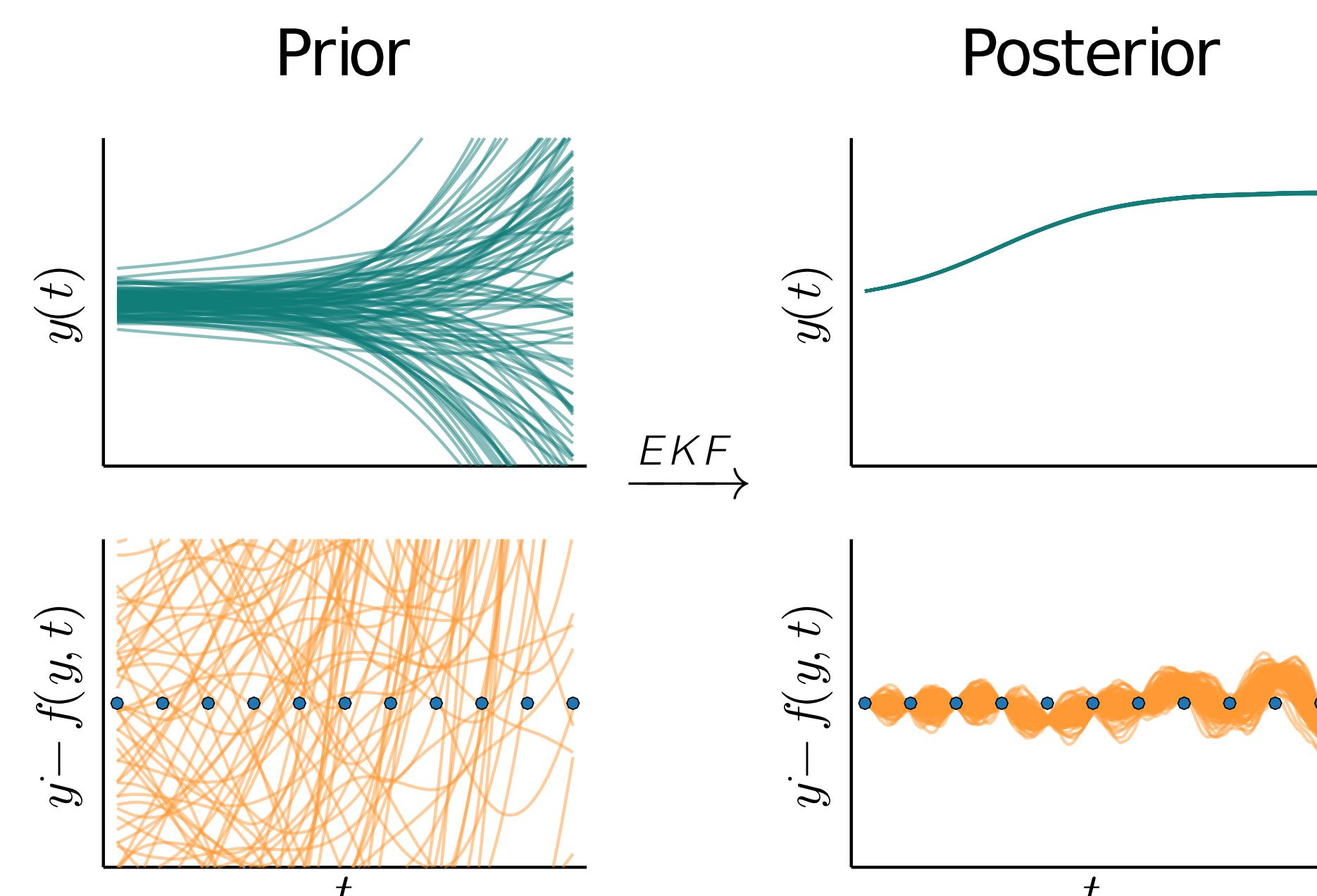
$\Rightarrow p(Y(t) | Z_{1:N})$ is a Bayesian state estimation problem!

Efficient approximate inference

Extended Kalman filtering and smoothing gives

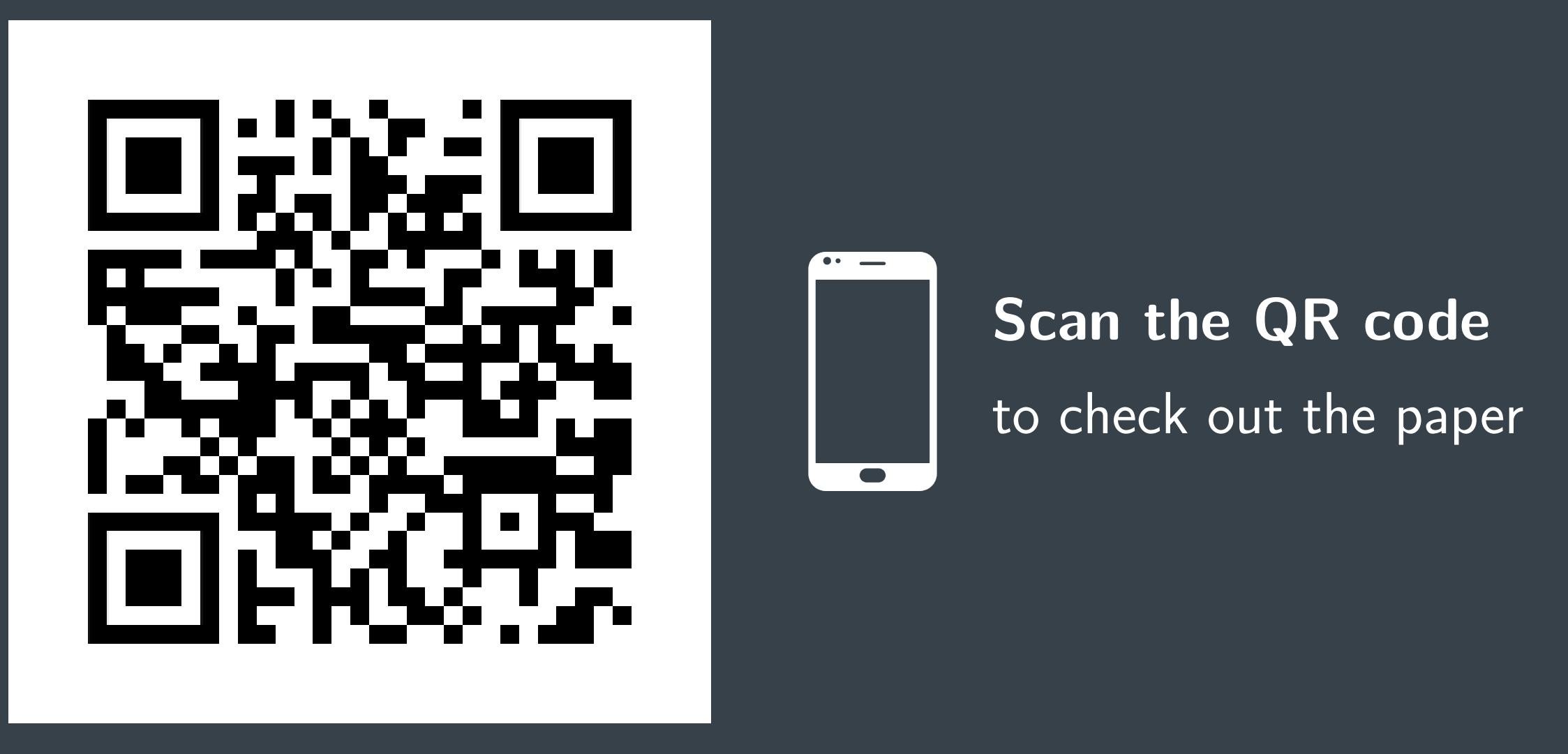
$$p(Y(t) | E_0 Y(t_0) = y_0, \{Z_n = 0\}_{n=1}^N) \approx \mathcal{N}(\mu(t), \Sigma(t))$$

Visualization of probabilistic ODE solvers:



Simulation is inference!

For better *stability*, encode
some problem structure in
the *prior*!



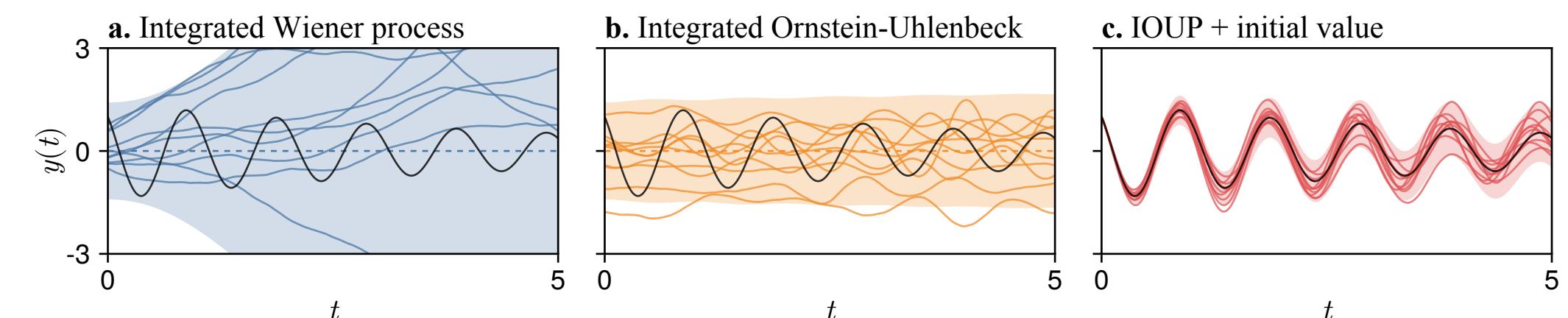
Exponential Integrators

Semi-linear ODE: $\dot{y} = Ly + f(y, t)$,

Goal: Leverage the linearity to improve the method.

Approach: Include it in the prior and solve the linear part exactly.

\Rightarrow Integrated Ornstein–Uhlenbeck process priors

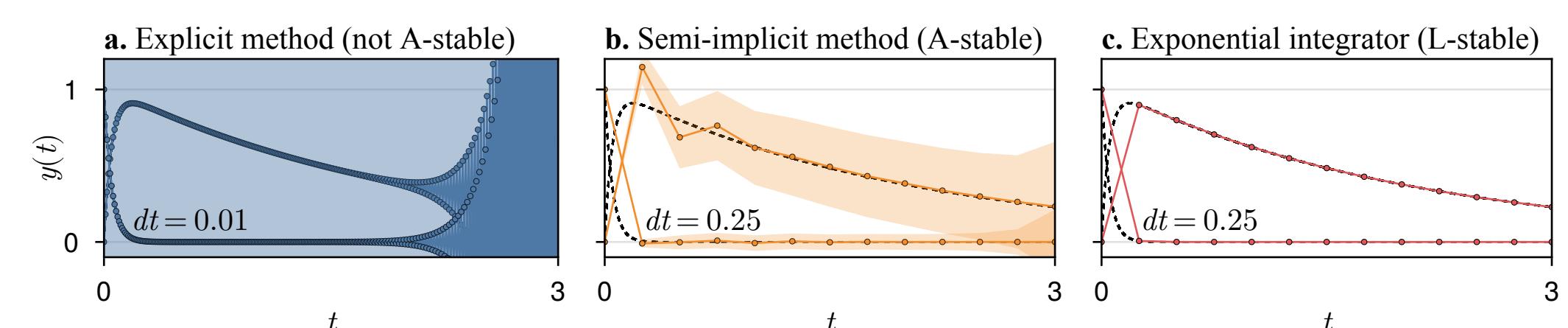


Stability

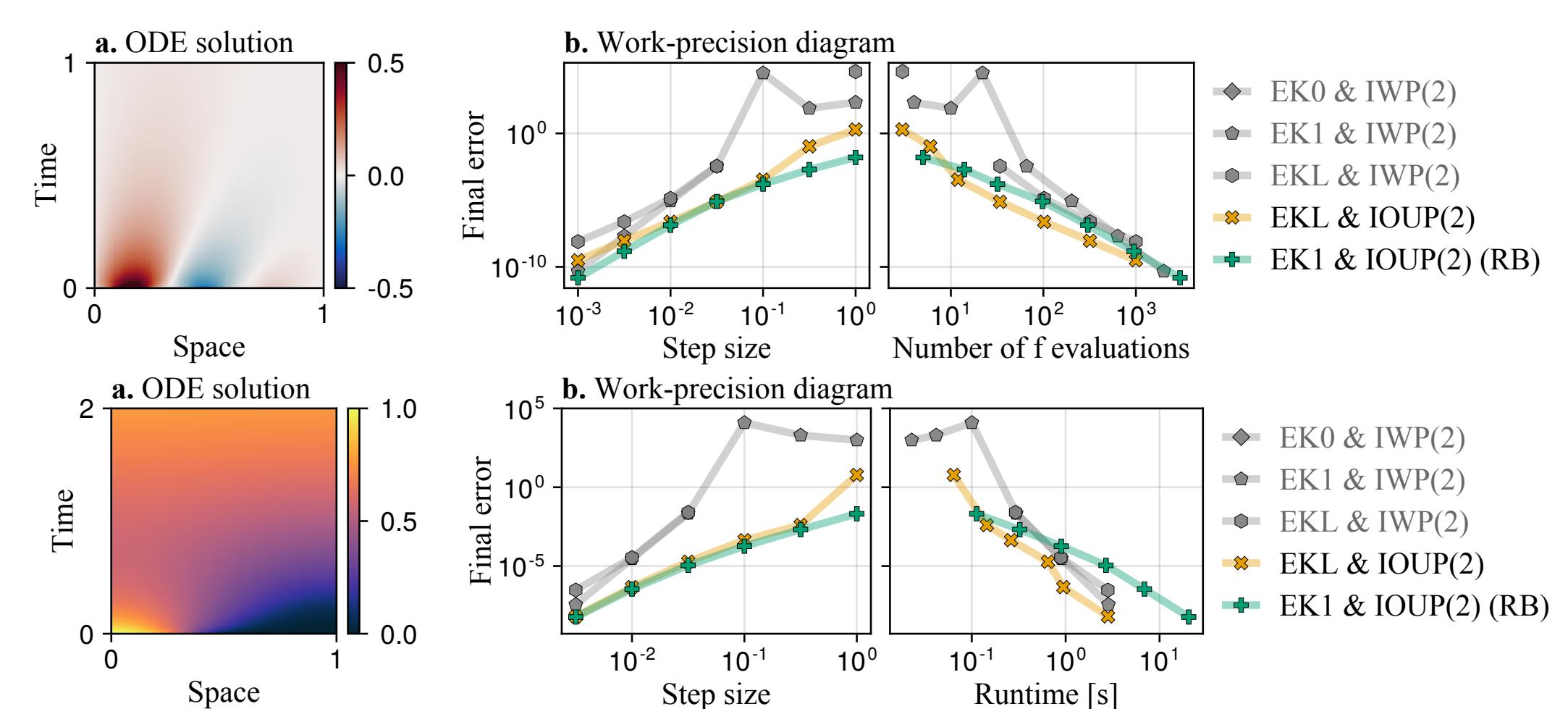
Given the test equation $\dot{y} = \lambda y$ with $\lambda < 0$,

- A-stable: numerical solution decays eventually.
- L-stable: numerical solution decays *at the right rate*.

Probabilistic exponential integrators are “L-stable”!



Experiments



\Rightarrow Probabilistic exponential integrators can take larger steps than non-exponential methods!

Software Library

] add ProbNumDiffEq

