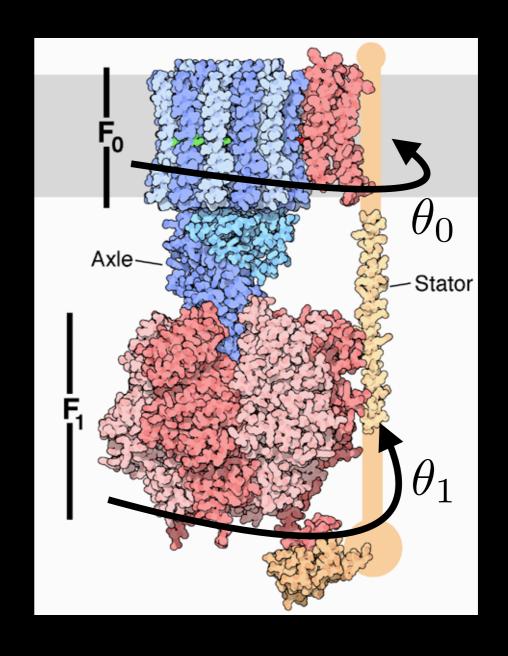
Pseudospectral Solutions to 2D-Advection Diffusion Equations

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ATP Synthase and Stochastic Dynamics

- ATP Synthase is responsible for creating the energy currency that is used to power cellular processes
 - Molecular motor that is able to converts between two forms of chemical energy
- It is about 10nm in diameter
 - The energy scale of its operation is the same as the scale of thermal energy fluctuations in the environment that surrounds it
- Its motion is inherently stochastic



How do you model stochastic behaviour?

Stochastic variables
$$\mathrm{d}\vec{\theta}(t) = \vec{\mu}(\vec{\theta}(t),t)\,\mathrm{d}t + \vec{\sigma}(\vec{\theta}(t),t) \circ \mathrm{d}\vec{W}(t) \quad \text{Langevin Equation}$$
 Diffusivity
$$\langle \mathrm{d}W(t) \rangle = 0$$

$$\langle \mathrm{d}W(t)\,\mathrm{d}W(s) \rangle = \delta(t-s)\,\mathrm{d}t$$

- Use stochastic differential equations
- These are effectively ordinary differential equations with a stochastic noise term
 - Stochastic noise term satisfies certain statistical relations

The Fokker-Planck Equation

Diffusion Tensor

$$\frac{\partial P(\vec{\theta}(t), t)}{\partial t} = -\sum_{i} \frac{\partial}{\partial \theta_{i}} \left[\mu_{i}(\vec{\theta}(t), t) P(\vec{\theta}(t), t) \right] + \sum_{i} \sum_{j} \frac{\partial^{2}}{\partial \theta_{i} \partial \theta_{j}} \left[D_{ij}(\vec{\theta}(t), t) P(\vec{\theta}(t), t) \right]$$

Probability Distribution

$$\mu_i(\vec{\theta}(t), t) = \mu_i(\vec{\theta})$$

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$$D_{ij}(\vec{\theta}, t) = \frac{1}{2}\vec{\sigma} \otimes \vec{\sigma} = D\delta_{ij}$$

$$\frac{\partial P(\vec{\theta}, t)}{\partial t} = -\sum_{i} \frac{\partial}{\partial \theta_{i}} \left[\mu_{i}(\vec{\theta}) P(\vec{\theta}, t) \right] + D \sum_{i} \frac{\partial^{2}}{\partial \theta_{i}^{2}} \left[P(\vec{\theta}, t) \right]
= -\nabla \cdot \left[\vec{\mu}(\vec{\theta}) P(\vec{\theta}, t) \right] + D \nabla^{2} \left[P(\vec{\theta}, t) \right]$$

Advection

Diffusion

In stochastic processes this is also known as the Forward-Kolmogorov Equation

The Fokker-Planck Equation

$$\frac{\partial P(\vec{\theta},t)}{\partial t} = -\nabla \cdot \left[\vec{\mu}(\vec{\theta}) P(\vec{\theta},t) \right] + D\nabla^2 \left[P(\vec{\theta},t) \right]$$

$$\frac{\text{Characteristic}}{\text{Function}}$$

$$P(\vec{\theta},t) = \left(\frac{1}{\sqrt{2\pi}} \right)^{\mathcal{N}} \int \mathrm{d}^{\mathcal{N}} \vec{\xi} \frac{P(\vec{\xi},t)}{P(\vec{\xi},t)} \exp \left[i \vec{\xi} \cdot \vec{\theta} \right]$$

$$\left\{ \frac{\partial \hat{P}(\vec{\xi}, t)}{\partial t} \right\} = -\left[\nabla \cdot \vec{\mu}(\vec{\theta}) \right] \left\{ \hat{P}(\vec{\xi}, t) \right\} - \left[\vec{\mu}(\vec{\theta}) \right] \cdot \left\{ i \vec{\xi} \hat{P}(\vec{\xi}, t) \right\} - \left\{ D |\vec{\xi}|^2 \hat{P}(\vec{\xi}, t) \right\}$$

Conditions on Solutions

	$P(ec{ heta},t)$	$\hat{P}(ec{\xi},t)$
Normalization	$\int d^{\mathcal{N}} \vec{\theta} P(\vec{\theta}, t) = 1$	$\hat{P}(\vec{0},t)=1$
Bounds	$P(\vec{\theta},t) \geq 0$	$ \hat{P}(\vec{\xi},t) \le 1$

Steady-State Distribution

$$\frac{\partial P(\vec{\theta},t)}{\partial t} = -\boldsymbol{\nabla} \cdot \left[\vec{\mu}(\vec{\theta}) P(\vec{\theta},t) \right] + D \nabla^2 \left[P(\vec{\theta},t) \right]$$

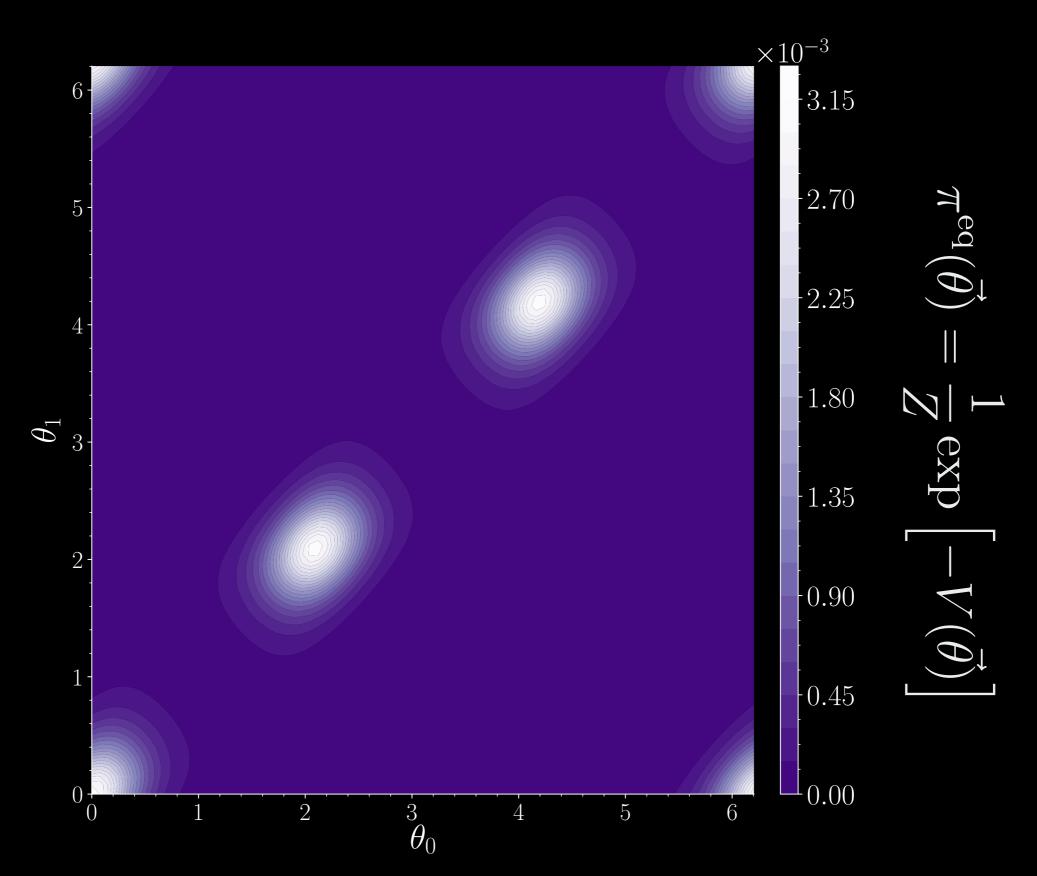
$$\mu_i(\vec{\theta}) = -D\left(\frac{\partial V(\vec{\theta})}{\partial \theta_i} - \psi_i\right) \quad V(\vec{\theta}) = \frac{1}{2} \left[E_0(1 - \cos(n_0\theta_0)) + E_c(1 - \cos(\theta_0 - \theta_1)) \right]$$

$$+ E_1(1 - \cos(n_1\theta_1))$$

$$\lim_{t \to \infty} P(\vec{\theta}, t) = \pi^{\text{eq}}(\vec{\theta}) = \frac{1}{Z} \exp\left[-V(\vec{\theta})\right]$$

Gibbs-Boltzmann
Distribution

Steady-State Distribution



Numerical Schemes

$$\frac{\partial p(\vec{\theta},t)}{\partial t} = -\boldsymbol{\nabla} \cdot \left[\vec{\mu}(\vec{\theta}) p(\vec{\theta},t) \right] + D \nabla^2 \left[P(\vec{\theta},t) \right]$$

Forward Time, Central Space (FTCS)

Definition 16 (IDIOT) Anyone who publishes a calculation without checking it against an identical computation with smaller N OR without evaluating the residual of the pseudospectral approximation via finite differences is an IDIOT.

Real Space

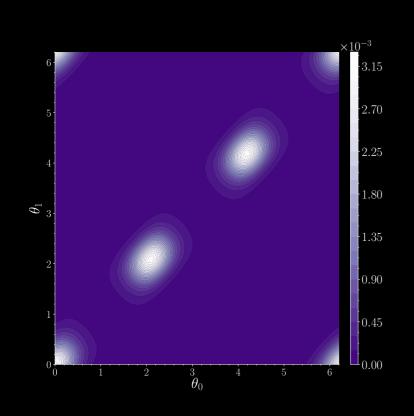
$$\left\{ \frac{\partial \hat{P}(\vec{\xi}, t)}{\partial t} \right\} = -\left[\nabla \cdot \vec{\mu}(\vec{\theta}) \right] \left\{ \hat{P}(\vec{\xi}, t) \right\} - \left[\vec{\mu}(\vec{\theta}) \right] \cdot \left\{ i \vec{\xi} \hat{P}(\vec{\xi}, t) \right\} - \left\{ D |\vec{\xi}|^2 \hat{P}(\vec{\xi}, t) \right\}$$

- Forward Time, Spectral Space (FTSS)
- Crank-Nicolson Forward Euler (IMEX)
- Integrating Factor RK4 (IFRK4)
- Exponential-Time Differencing RK4 (ETDRK4)

Fourier Space

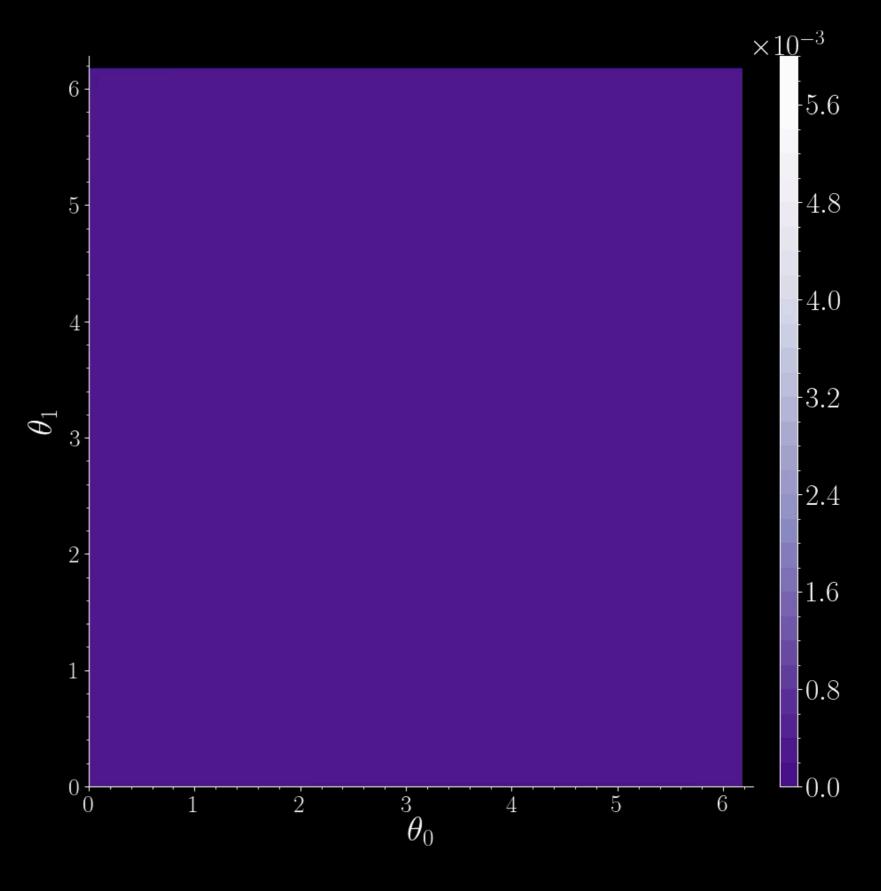
Results

Time Evolution

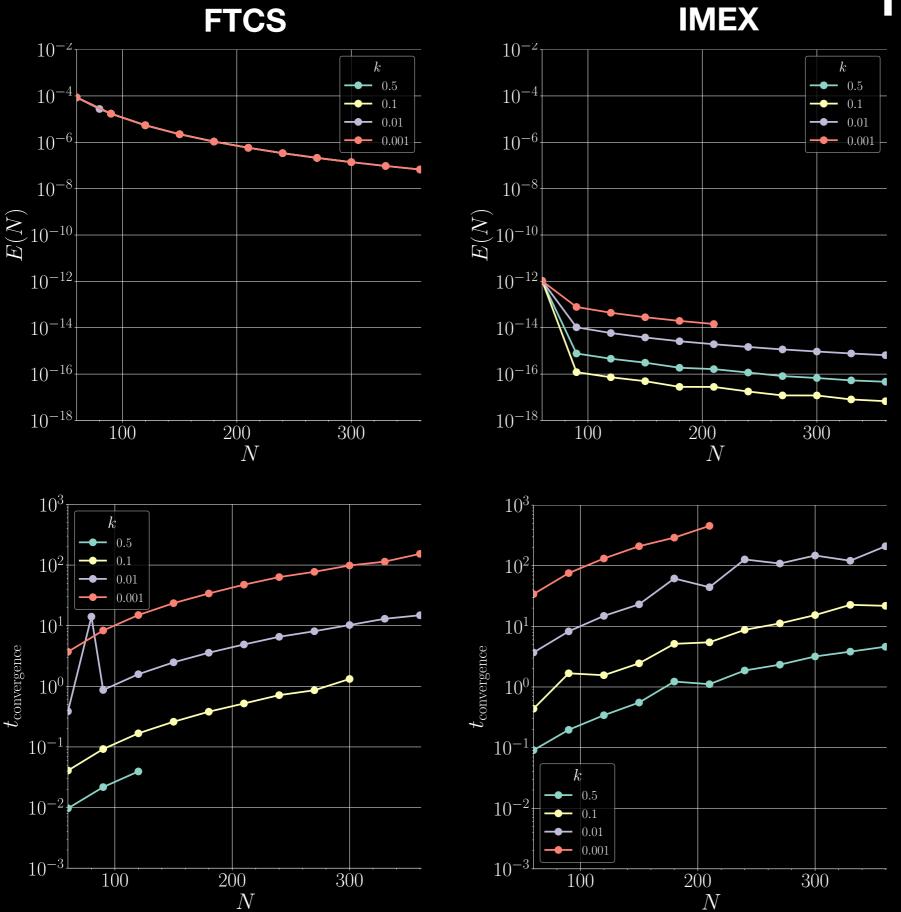


Stopping Criteria

$$\frac{1}{2} \sum_{ij} |\hat{P}_{ij}^{n-1} - \hat{P}_{ij}^{n}| < \varepsilon$$



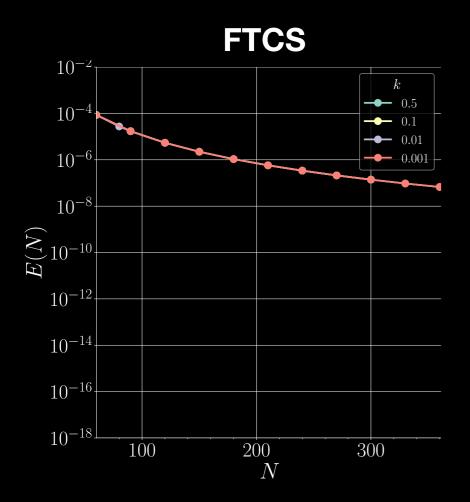
FTCS vs. IMEX

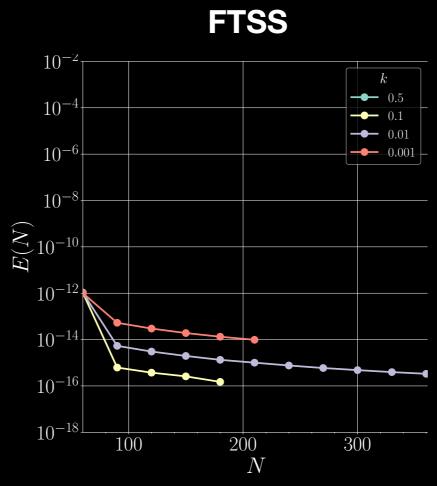


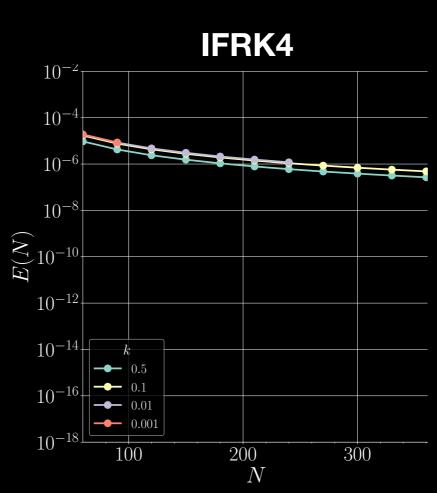
Spatial Accuracy

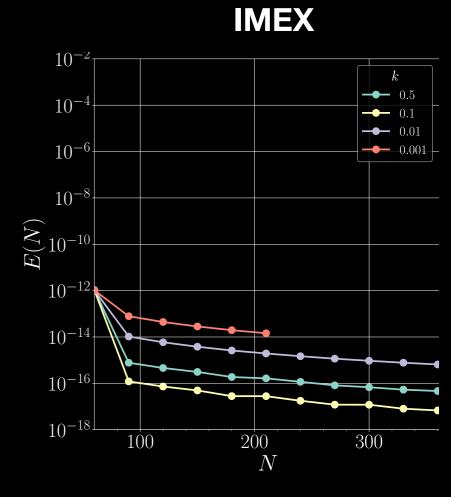
Convergence Time

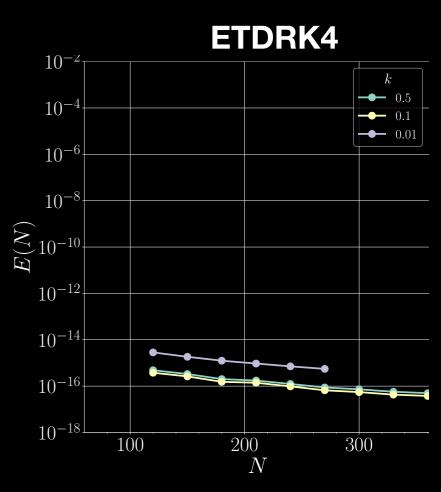
Spatial Accuracy









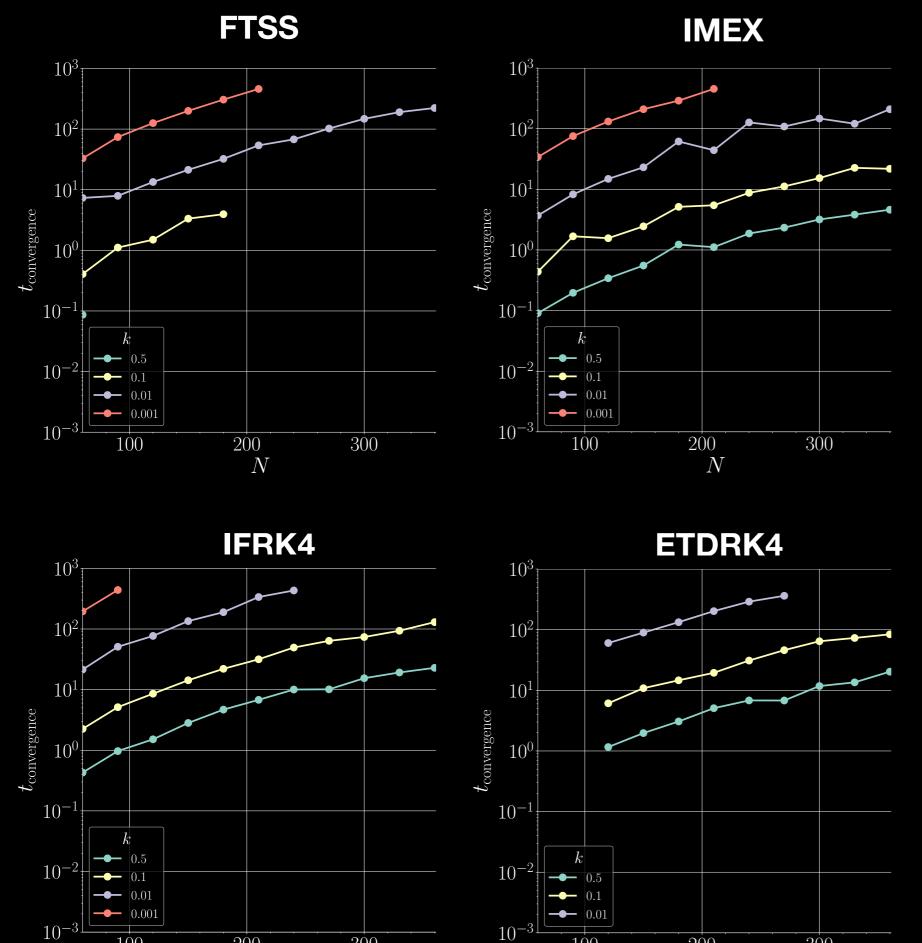


*Accuracy is measured using the inf-norm

Conclusions

- The generalized Langevin Equation (SDE) governing a set of random variables can be recast in terms of an equation of motion for the joint probability distribution of the random variables known as the Fokker-Planck Equation (FPE)
- We solved the FPE numerically using pseudo-spectral methods and showed that this improved the accuracy of solutions by more than 4 orders of magnitude relative to finite differences (!!!!)
- Was it worth all the pain and hours debugging?
 - Maybe...

Extra Slides



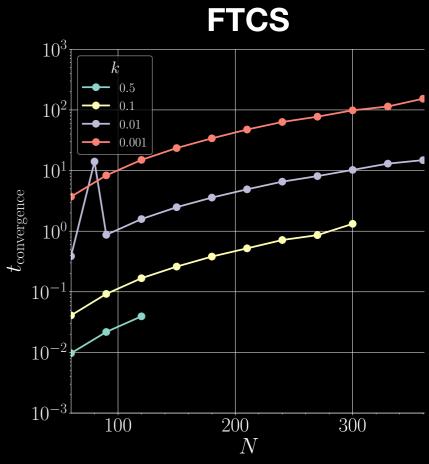
200

N

100

300

Convergence Time



*All times reported are in minutes

100

200

N

300