

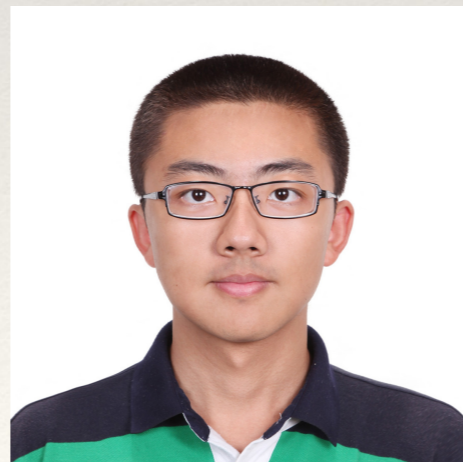


Computational methods for the study of stochastic dynamics with small noise

Maria Cameron

Department of Mathematics, University of Maryland, College Park, MD

Joint work with Daisy Dahiya, Shuo Yang, and Samuel Potter



What are rare events?

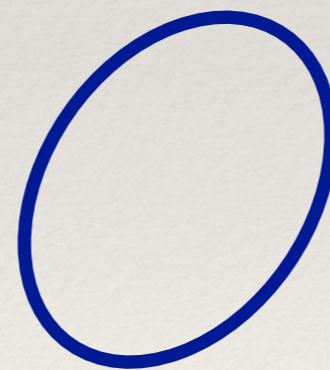
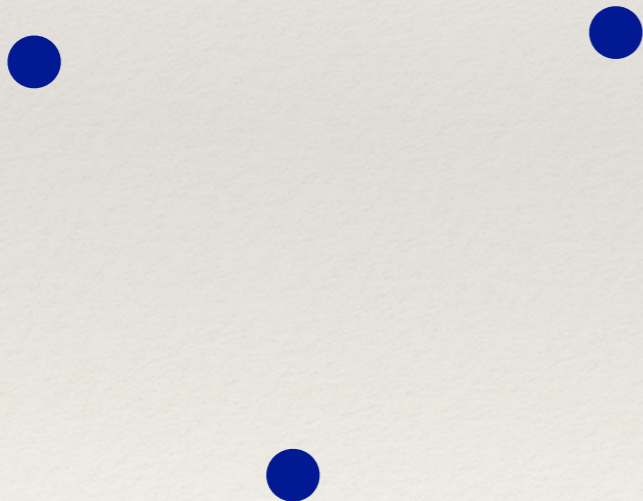
$$dx = \underbrace{b(x)}_{\substack{\text{C}^1 \text{ deterministic} \\ \text{vector field}}} dt + \underbrace{\sqrt{\epsilon}}_{\substack{\text{small} \\ \text{parameter}}} \underbrace{dw}_{\substack{\text{Brownian} \\ \text{motion}}}$$

C^1 deterministic
vector field

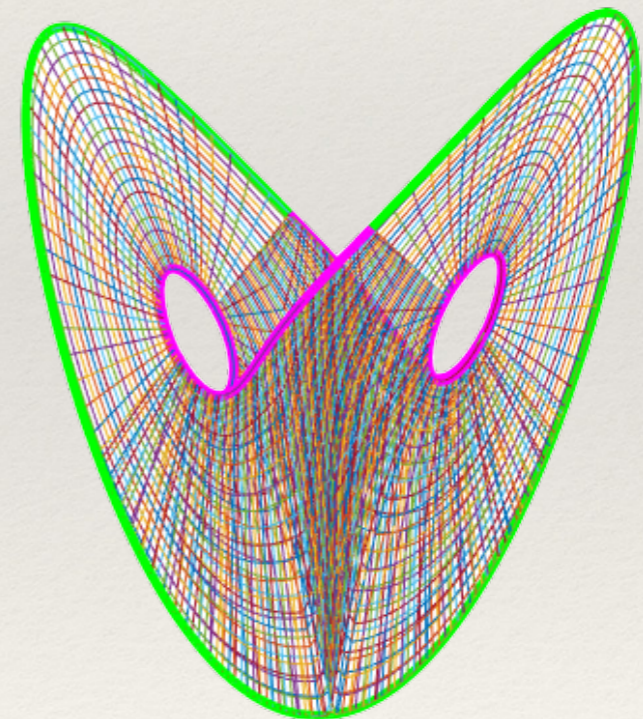
small
parameter

Brownian
motion

Stable equilibria



Stable limit cycle



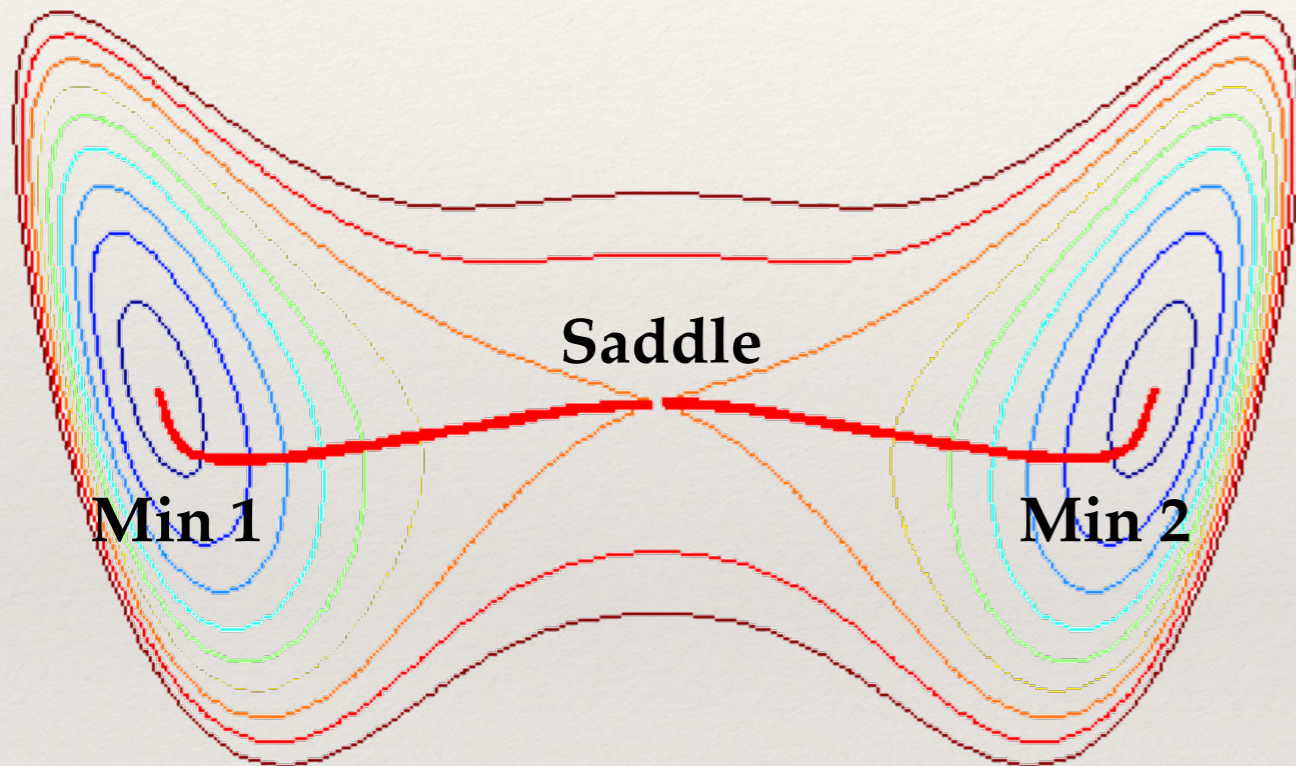
More complex attractors

We want to estimate:

- ❖ expected escape times from the basins of attraction
- ❖ maximum likelihood escape paths
- ❖ quasi-invariant probability measures in the neighborhoods of attractors

Gradient SDEs

$$dx = -\nabla V(x)dt + \sqrt{2\beta^{-1}}dw$$



Arrhenius formula (1884):

$$Rate \propto e^{-(V_{sad}-V_{min})/(RT)}$$

Gibbs (1839- 1903) measure:

$$f(x) = Z^{-1} e^{-V(x)/k_B T}$$

Kramers' / Langer's formula:

1940

1969

$$Rate \approx \frac{|\lambda|}{2\pi} \sqrt{\frac{\det H_{min}}{|\det H_{sad}|}} e^{-\beta(V_{sad}-V_{min})}$$

Where nongradient SDE models come from

Biological and ecological models.

❖ Genetic switches

- ❖ Lambda Phage (Shea et al. (1980s), Aurell and Sneppel (2002)), 2D
- ❖ Two-state gene expression model with positive feedback (Lv et al. 2014), 3D

❖ Population dynamics

- ❖ Dynamics of savanna landscapes (Touboul et al. 2017), 3D or 4D
- ❖ Consumer-resource model (Collie & Spencer (1994), Steele and Henderson (1981)), 2D

Large Deviation Theory

Freidlin and Wentzell, 1970s

$$dx = b(x)dt + \sqrt{\epsilon}dw$$

Freidlin-Wentzell action functional

$$S_T(\phi) = \frac{1}{2} \int_0^T \|\dot{\phi} - b(\phi)\|^2 dt$$

Quasipotential

$$U_A(x) = \inf_{\phi, T} \{S_T(\phi) \mid \phi(0) \in A, \phi(T) = x\}$$

Expected escape time

$$\tau_A(D) \asymp \inf_{x \in \partial D} e^{U_A(x)/\epsilon}$$

Transition state

Basin of attraction

A

Attractor

Large Deviation theory for Gradient Case

$$dx = -\nabla V(x)dt + \sqrt{\epsilon}dw$$

Freidlin-Wentzell Action

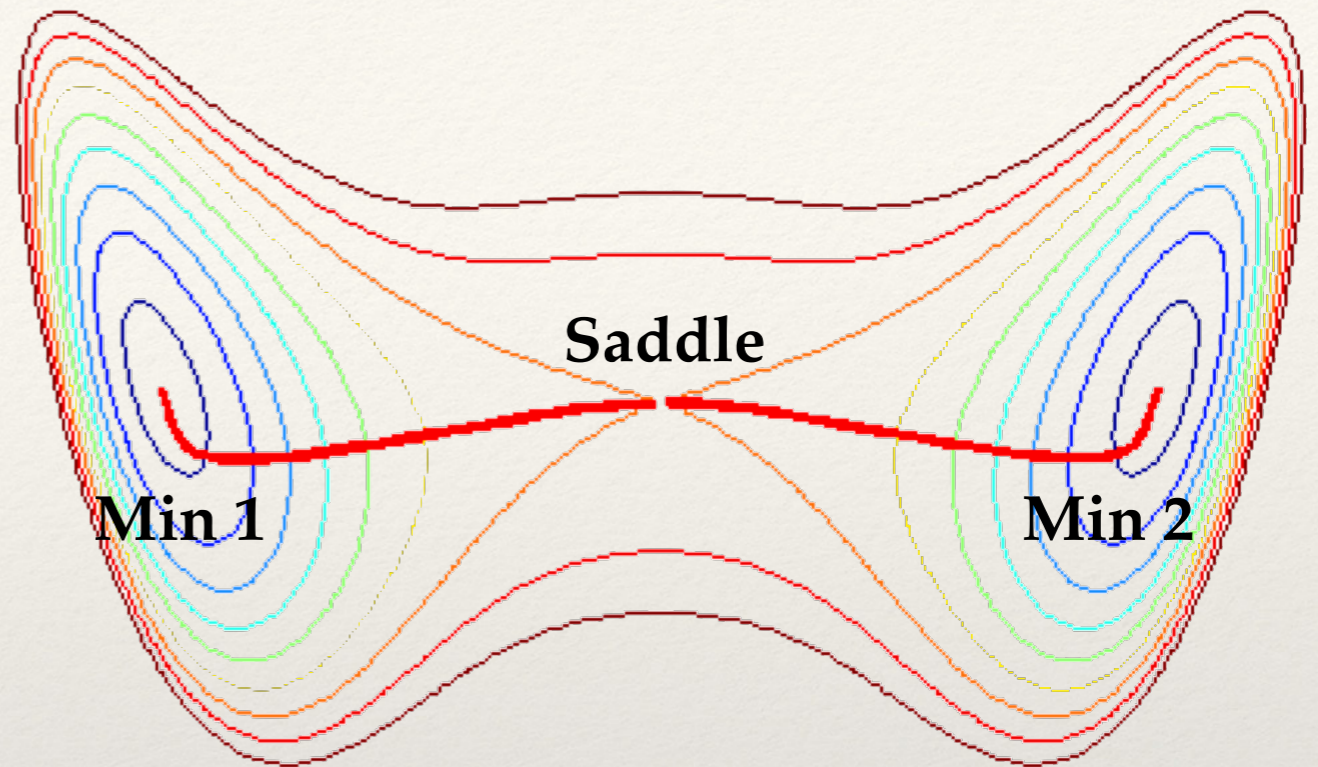
$$S_T(\phi) = \frac{1}{2} \int_0^T \|\dot{\phi} + \nabla V(\phi)\|^2 dt$$

Quasipotential

$$U_{\min 1}(x) = 2(V(x) - V_{\min 1})$$

Expected escape time

$$k_{12} \asymp e^{-2(V_{sad} - V_{\min 1})/\epsilon}$$



Minimum Action Path
(a.k.a. Maximum Likelihood Path
or instanton)

$$\|\dot{\phi}^*\| = \|b(\phi^*)\|$$
$$\dot{\phi}^* \parallel b(\phi^*)$$

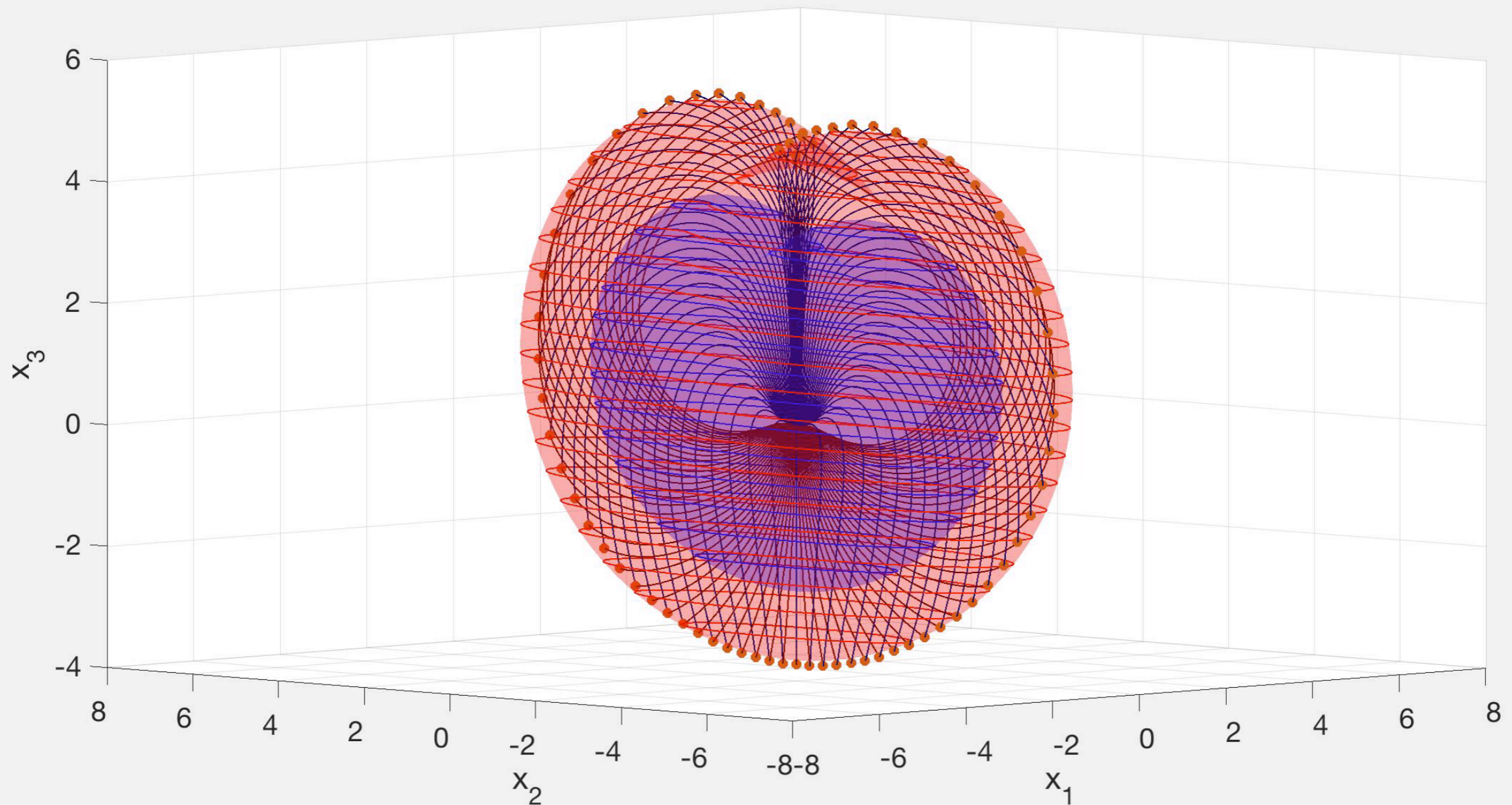
Nongradient case

Lorenz'63, $\sigma = 10$, $\beta = 8/3$, $\rho = 0.5$.

Surfaces: level sets of the quasipotential ($U = 20, 40$)

Indigo curves: trajectories

Dark red curves: MAPs



Nongradient Case

Hamilton-Jacobi-Bellman

PDE for the quasi-potential

$$\|\nabla U_A\|^2 + 2b(x) \cdot \nabla U_A = 0$$

$$U_A(x) = 0, \quad x \in A$$

The quasipotential is one of the solutions.

It is never unique!

$$S(\psi) = \int_0^L \|\psi'\| \|b(\psi)\| - \psi' \cdot b(\psi) ds$$

$$U(x) = \inf_{\psi} \{S(\psi) \mid \psi(0) \in A, \psi(L) = x\}$$

Minimization w.r.t. time can be done analytically leading to the geometric action
(FW, Heymann & Vanden-Eijnden)

Nongradient Case

Hamilton-Jacobi-Bellman

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$$U_A(x) = 0, \quad x \in A$$

Minimum Action Paths

$$(\psi^*)' \parallel \nabla U(\psi^*) + b(\psi^*)$$

Nongradient Case

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Minimum Action Paths

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Orthogonal decomposition

$$b(x) = -\frac{1}{2}\nabla U(x) + l(x)$$

$$l(x) := \frac{1}{2}\nabla U(x) + b(x)$$

$$l(x) \perp \nabla U(x)$$

Nongradient Case

Hamilton-Jacobi-Bellman

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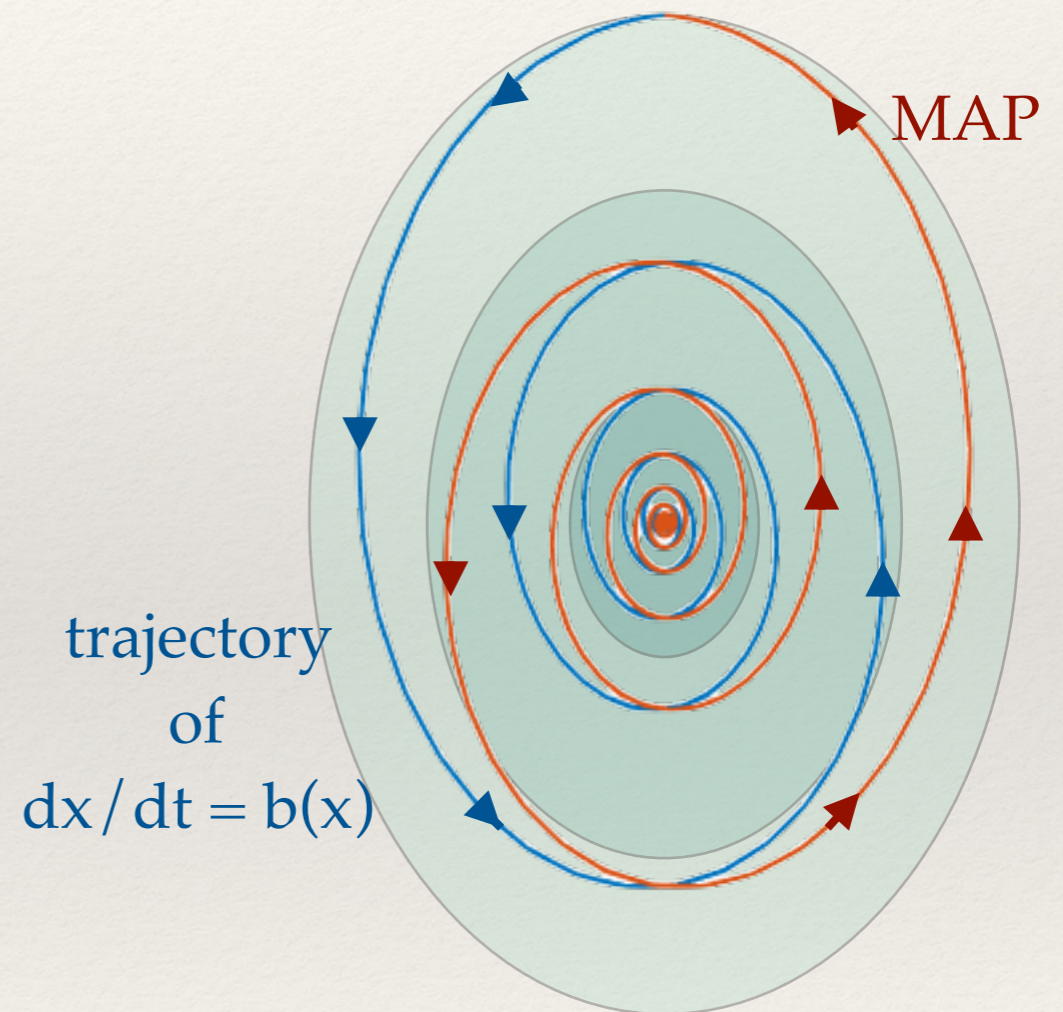
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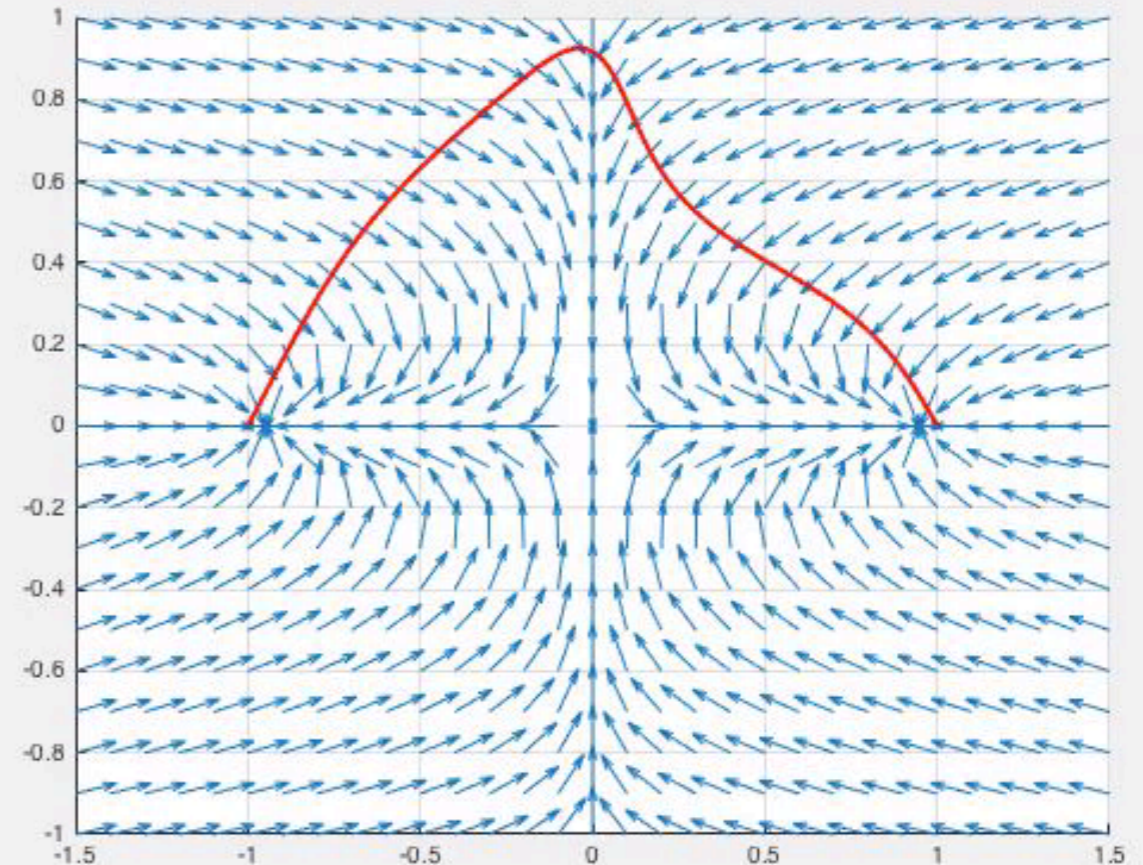
Goal

Develop numerical methods for computing

- ❖ Quasipotential
- ❖ Minimum Action Paths

Direction 1: Path-based methods

- ❖ E, Ren, Vanden-Eijnden: **MAM** (2004)
- ❖ Heymann and Vanden-Eijnden: **GMAM** (2008)
(numerical minimization of the geometric action)
- ❖ Zhou, Ren, and E: **AMAM** (2008)
(numerical minimization of the Freidlin-Wentzell action)



Maier-Stein model, 1990s

Direction 2: computing the quasipotential

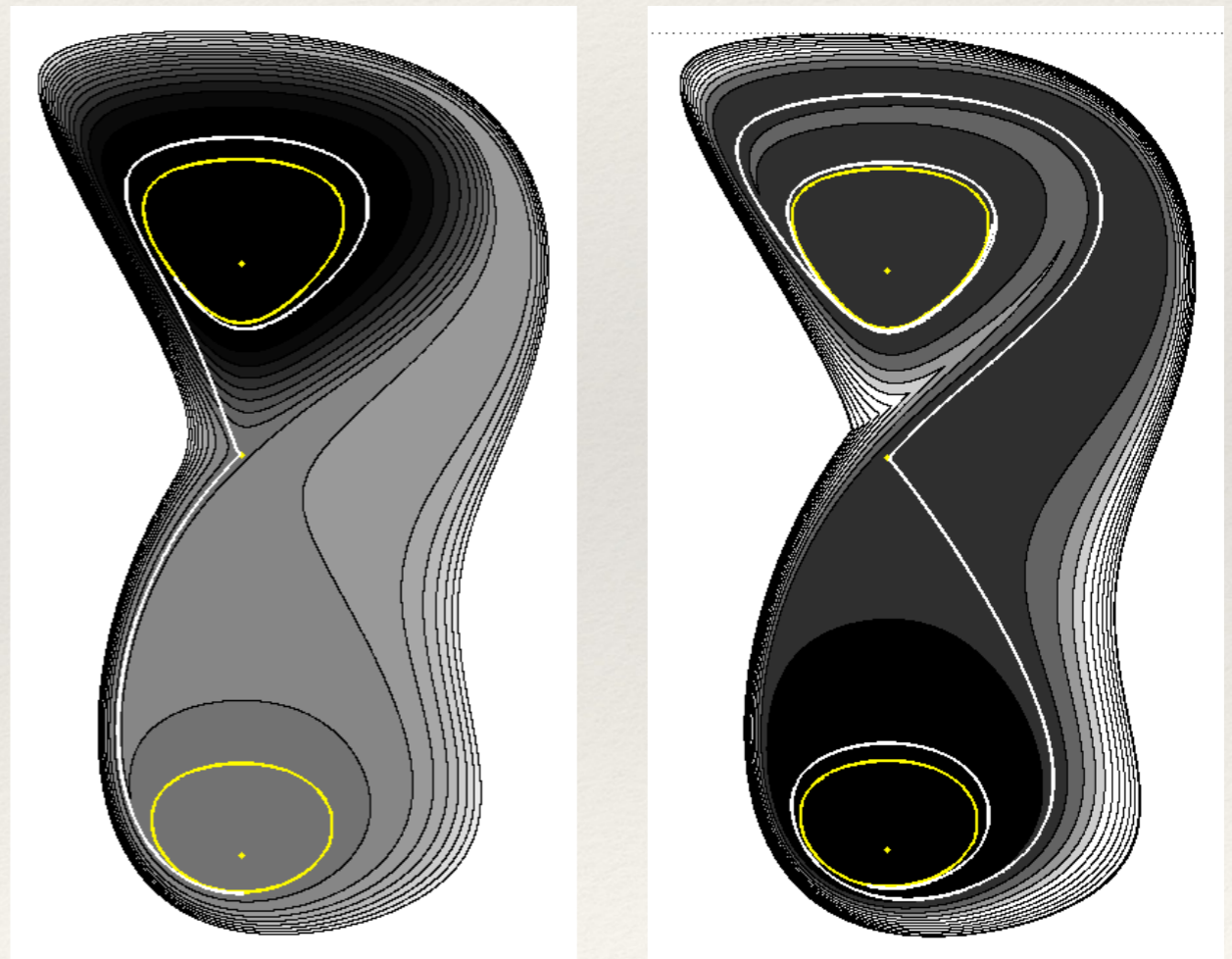
Cameron, 2012

- ❖ *Compute the quasipotential on a mesh*
- ❖ *Find MAPs by numerical integration*
 x = target point
 A = attractor

$$\psi' = - \frac{b(\psi) + \nabla U(\psi)}{\|b(\psi) + \nabla U(\psi)\|}$$

$$dx = \frac{1}{\varepsilon} \left(x - \frac{x^3}{3} + y - \frac{y^3}{9} \right) dt + \sqrt{2\beta^{-1}} dw_1$$

$$dy = (x + 0.9) dt + \sqrt{2\beta^{-1}} dw_2$$



Computing the quasipotential on mesh

Motivation: *Sethian and Vladimirsky* (2001, 2003):

Ordered Upwind Method for solving HJ PDEs:

$$F(x, a) \|\nabla U(x)\| = 1$$

where

$$a := \frac{\nabla U}{\|\nabla U\|}$$

$$0 < F_{\min} \leq F(x, a) \leq F_{\max} < \infty$$

Key Idea:

Dynamical Programming Principle

Motivated by:

Sethian's Fast Marching Method (1996)

for solving the eikonal equation

$$F(x) \|\nabla U\| = 1$$

Computing the quasipotential on mesh

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Dynamical Programming Principle

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for solving the eikonal equation

$$F(x) \|\nabla U\| = 1$$

The first quasipotential OUM-based solver

Cameron (2012): An adjustment of the **Ordered Upwind Method**

$$\|\nabla U\|^2 + 2b \cdot \nabla U = 0 \quad \Longrightarrow \quad \frac{1}{-2b \cdot a} \|\nabla U\| = 1$$

Unbounded!

The adjustment was
nontrivial

(will be explained later)

Applications and the Qpot R package

- ❖ B. C. Nolting and K. C. Abbot, Balls, cups, and quasi-potentials: quantifying stability in stochastic systems, *Ecology*, 97, 4, 850-864 (2016)
- ❖ B. Nolting, C. Moore, C. Stieha, M. Cameron, K. Abbott, QPot: An R package for stochastic differential equation quasi-potential analysis, *R Journal* 8, 2, 19-38 (2016)
- ❖ <https://cran.r-project.org/web/packages/QPot/index.html>
- ❖ Zhen Chen, Jinjie Zhu and Xianbin Liu, Crossing the quasi-threshold manifold of a noise-driven excitable system, *Proc. R. Soc. A* 473: 20170058.

Ordered line integral methods (OLIMs)

Dahiya and C. (2017, J Sci Comp): 2D

Dahiya and C. (2018, Physica D): 2D, anisotropic diffusion

Yang, Potter, and C. (2018, submitted): 3D

Key differences:

- ❖ **Solve the minimization problem directly:**

$$S(\psi) = \int_0^L \|\psi'\| \|b(\psi)\| - \psi' \cdot b(\psi) ds$$

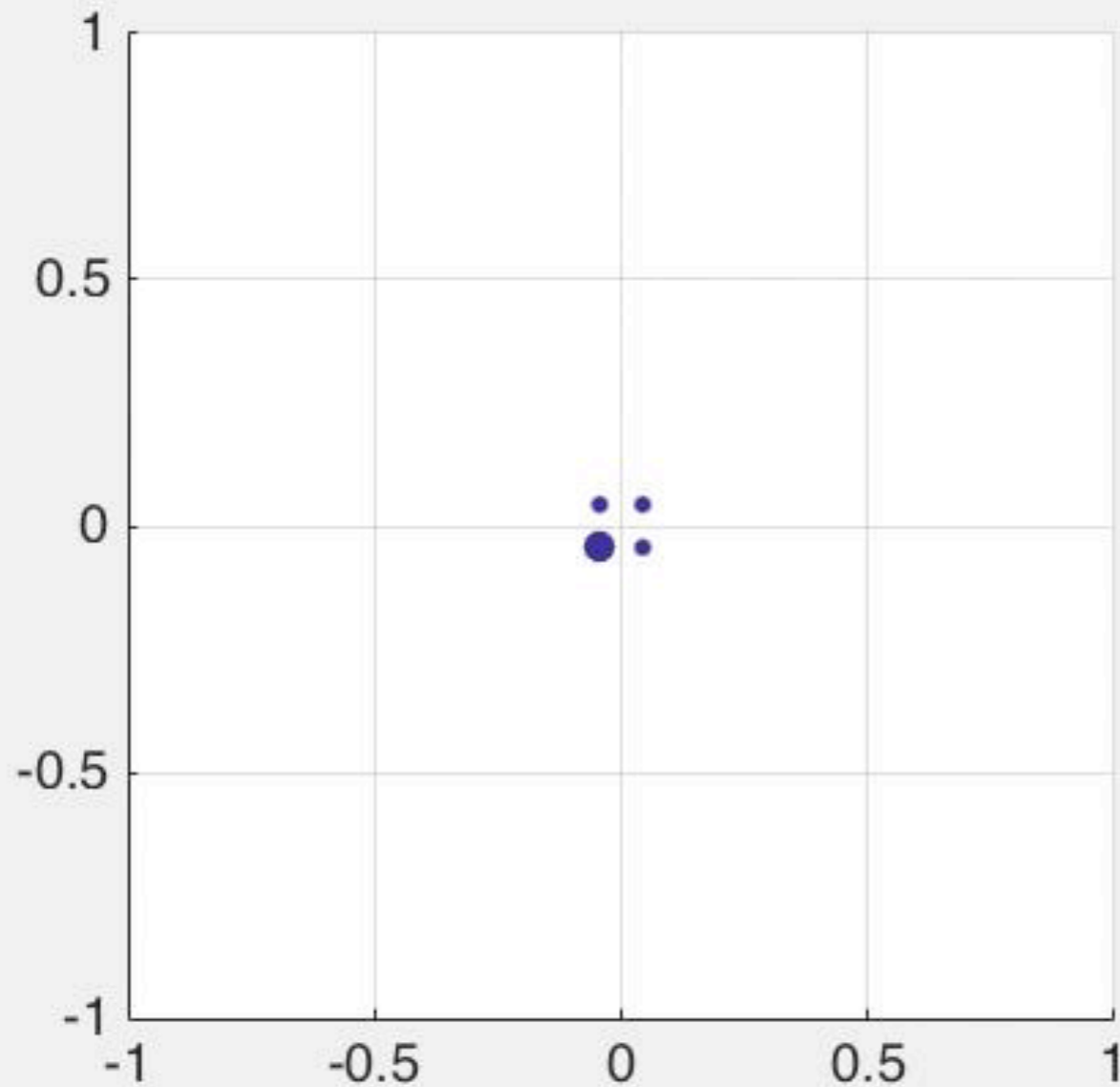
$$U(x) = \inf_{\psi} \{S(\psi) \mid \psi(0) \in A, \psi(L) = x\}$$

The geometric action.
Minimization w.r.t. time
is done analytically

- ❖ **Technical innovations making the solver efficient**

- ❖ A hierarchical update strategy
- ❖ Use of the KKT constrained optimization theory to reject unnecessary simplex updates
- ❖ Restricting the set of admissible simplexes and a fast search for them

Ordered Line Integral Methods



4 types of mesh points:

Unknown: U is not available

Considered: U is tentative

Accepted Front:
 U is finalized,
has Considered nearest neighbors

Accepted: U is finalized,
no Considered nearest neighbors

Ordered Line Integral Methods

WHILE < boundary is not reached >

1. make the **Considered** point x_0 with minimal U

Accepted Front

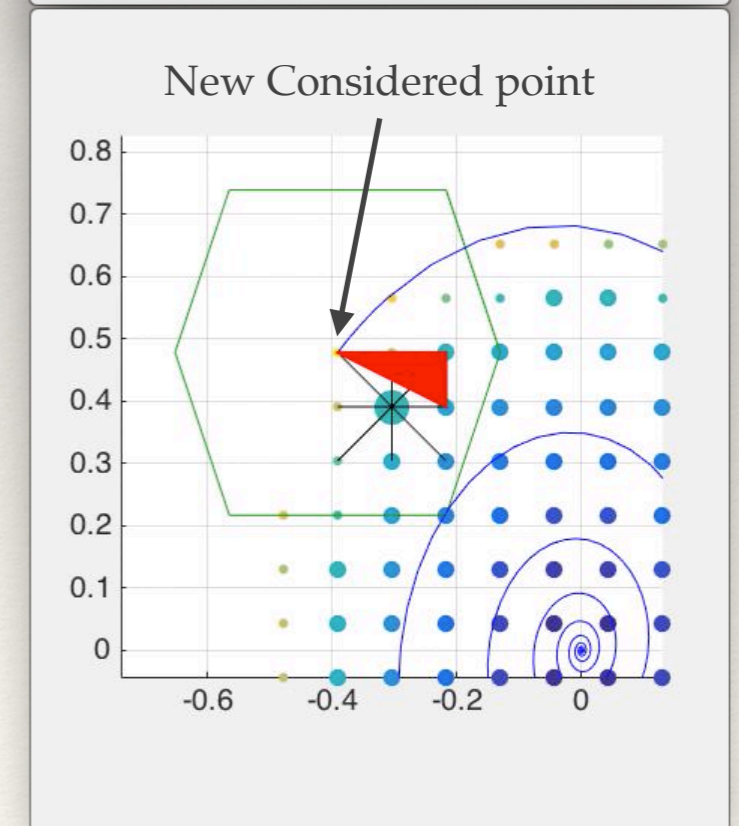
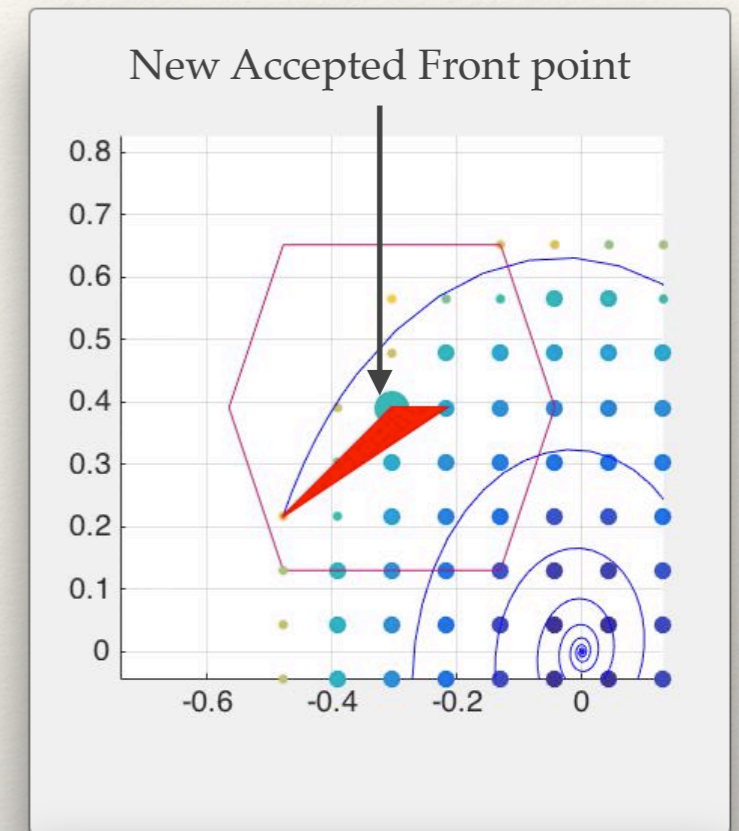
2. make **Accepted Front** points with no **Considered**

NNs **Accepted**

3. update all **Considered** points within update radius from x_0 with **using** x_0

4. make all **Unknown** NNs of x_0 **Considered** and update them using **Accepted Front** points within update radius from them

END WHILE



One-point and triangle updates

The minimization problem for the quasipotential

$$S(\psi) = \int_0^L \|\psi'\| \|b(\psi)\| - \psi' \cdot b(\psi) ds$$

$$U(x) = \inf_{\psi} \{S(\psi) \mid \psi(0) \in A, \psi(L) = x\}$$

Approximate $S(\psi)$ with a quadrature rule

One-point and triangle updates

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Approximate $S(\psi)$ with a quadrature rule

$Q(a, b)$ = quadrature rule:

Right-hand: OLIM-R

Midpoint: OLIM-MID

Trapezoid: OLIM-TR

Simpson: OLIM-SIM

One-point and triangle updates

The minimization problem for the quasipotential

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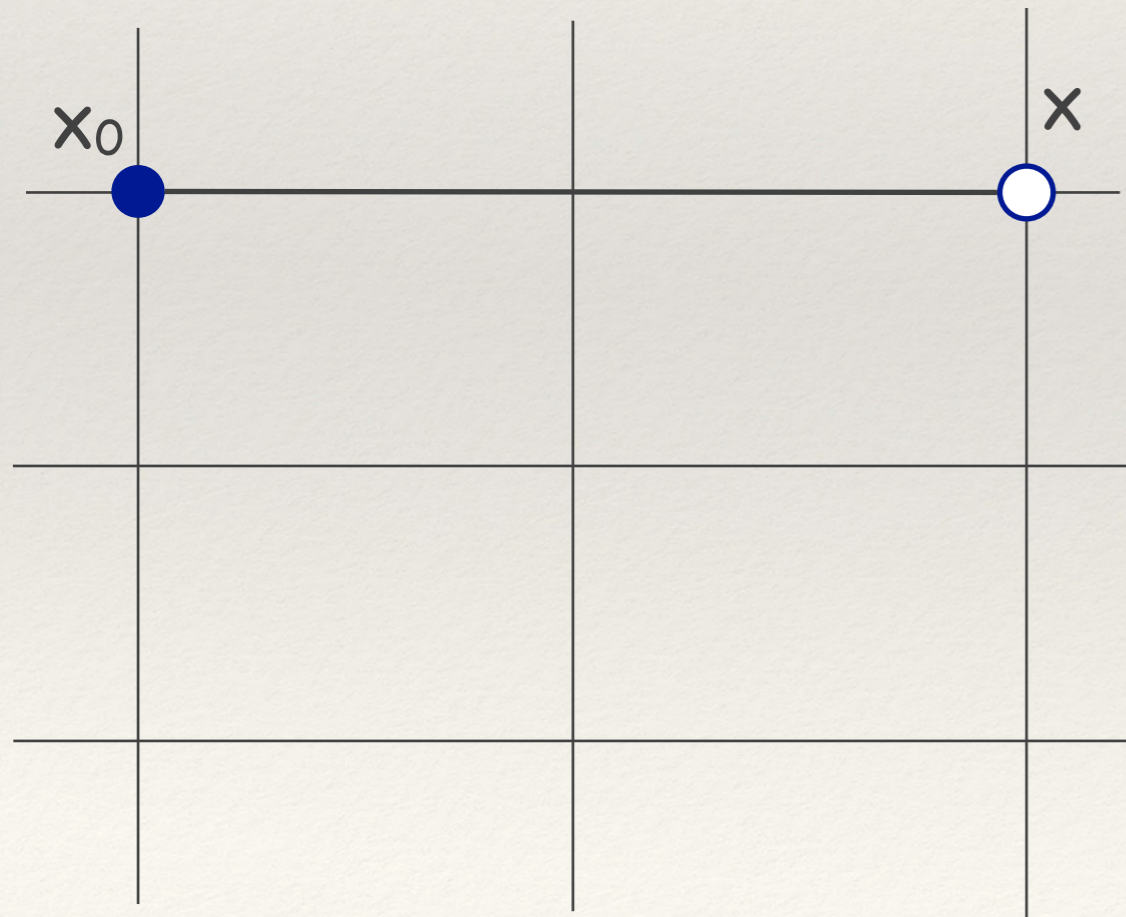
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One-point update

$$Q_{1pt}(x_0, x) = U(x_0) + Q(x_0, x),$$

$$U(x) = \min\{Q_{1pt}(x_0, x), U(x)\}.$$

One-point and triangle updates

The minimization problem for the quasipotential

$$S(\psi) = \int_0^L \|\psi'\| \|b(\psi)\| - \psi' \cdot b(\psi) ds$$

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Approximate $S(\psi)$ with a quadrature rule

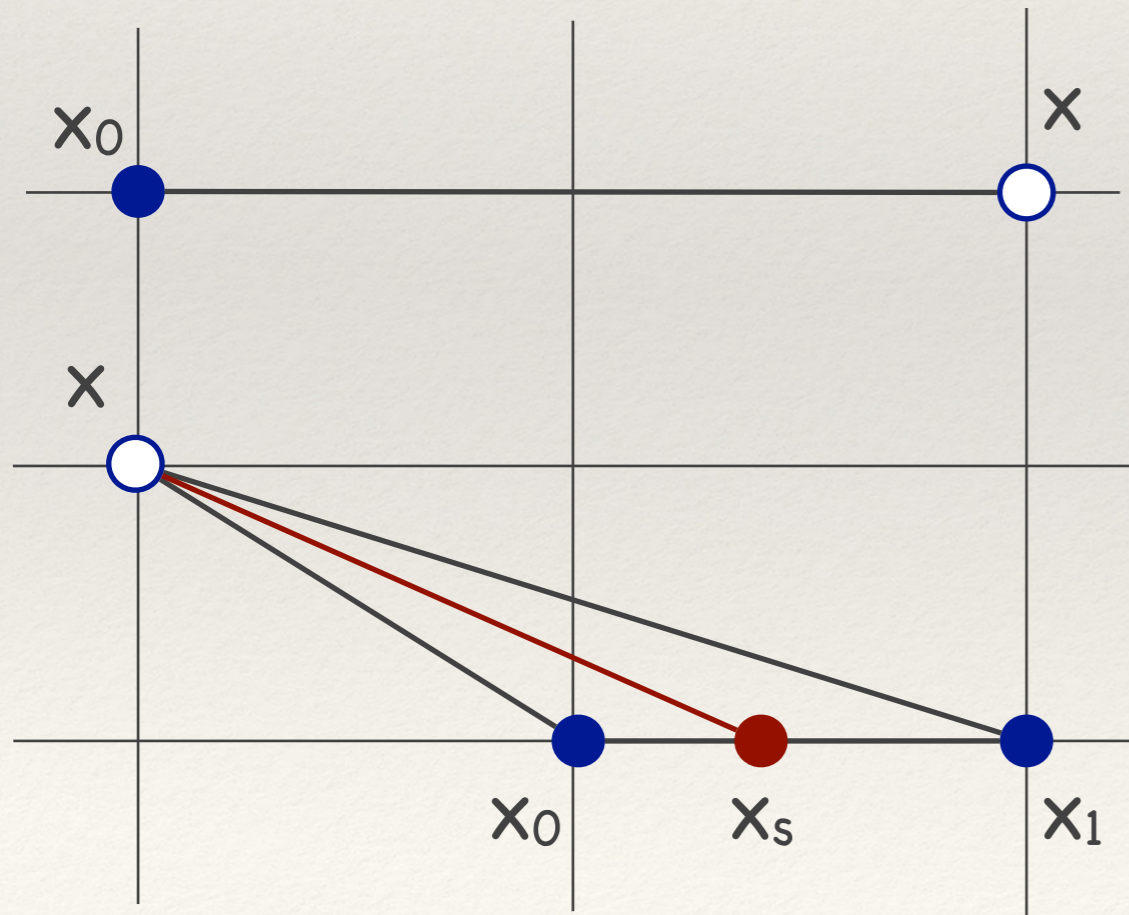
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One-point update

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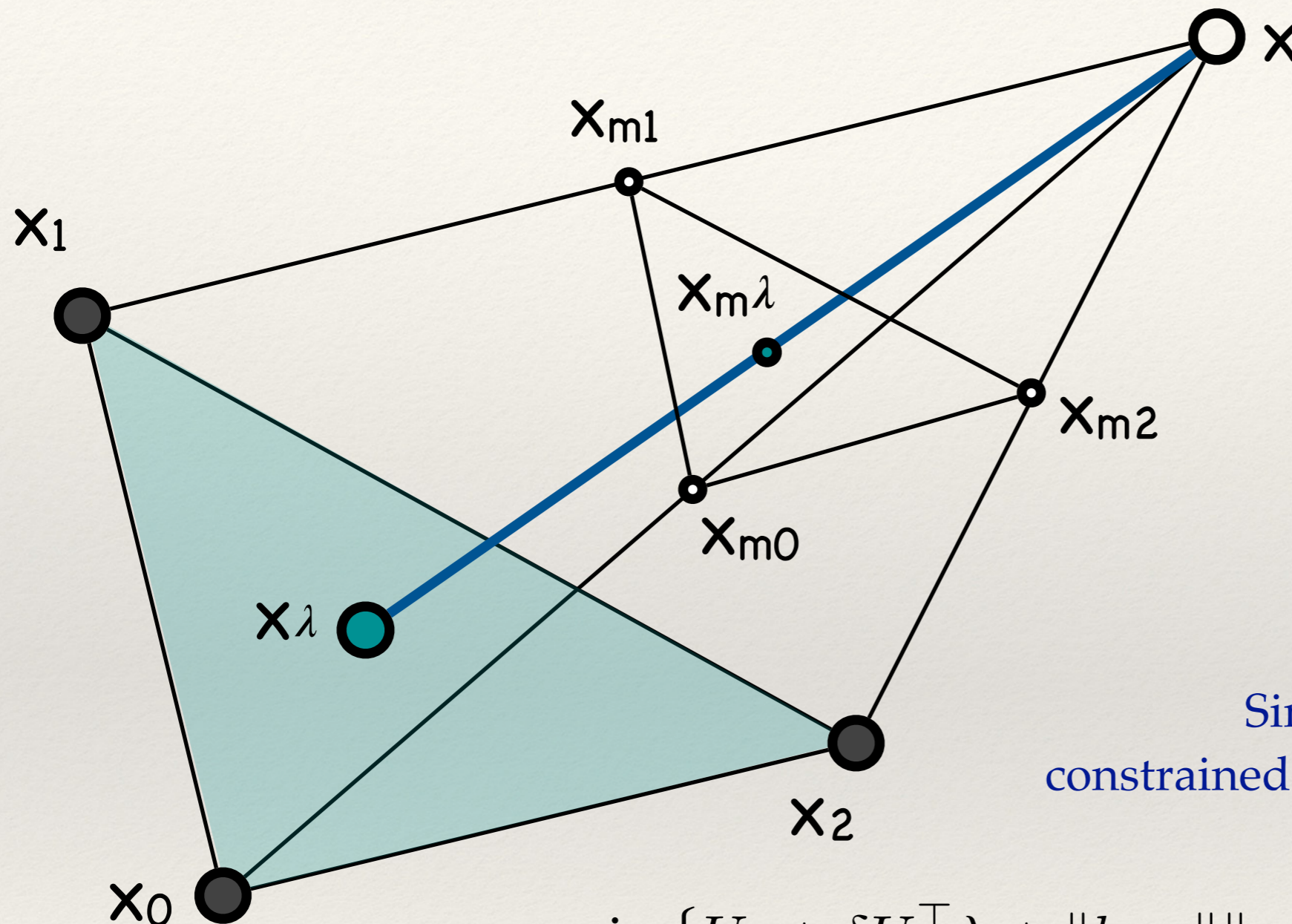
Triangle update

$$Q_{2pt}(x_0, x_1, x) =$$

$$\min_{s \in [0,1]} \{U_0 + s(U_1 - U_0) + Q(x_s, x)\}$$

$$U(x) = \min\{Q_{2pt}(x_0, x_1, x), U(x)\}$$

Simplex update



The midpoint rule is optimal in balancing CPU time and accuracy.

Simplex update
constrained minimization problem

$$\min \{ U_0 + \delta U^\top \lambda + \|b_{m\lambda}\| \|x - x_\lambda\| - b_{m\lambda}^\top (x - x_\lambda) \}$$

subject to $\lambda_1 \geq 0, \lambda_2 \geq 0, \lambda_1 + \lambda_2 \leq 1$

Making the solver efficient

- ❖ **Hierarchical update strategy**
- ❖ **Use the KKT theory** to reject simplex updates that are unlikely to succeed in finding an inner point solution
- ❖ **Restrict the set of admissible simplexes** and devise a **fast search** for them

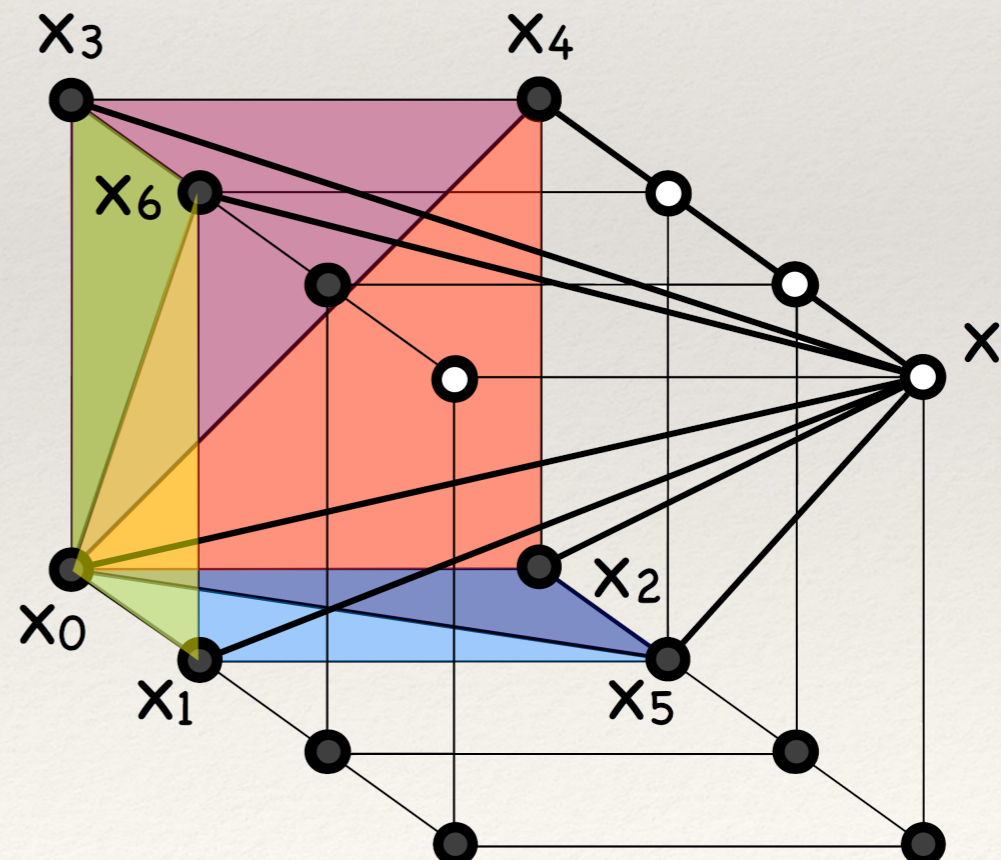
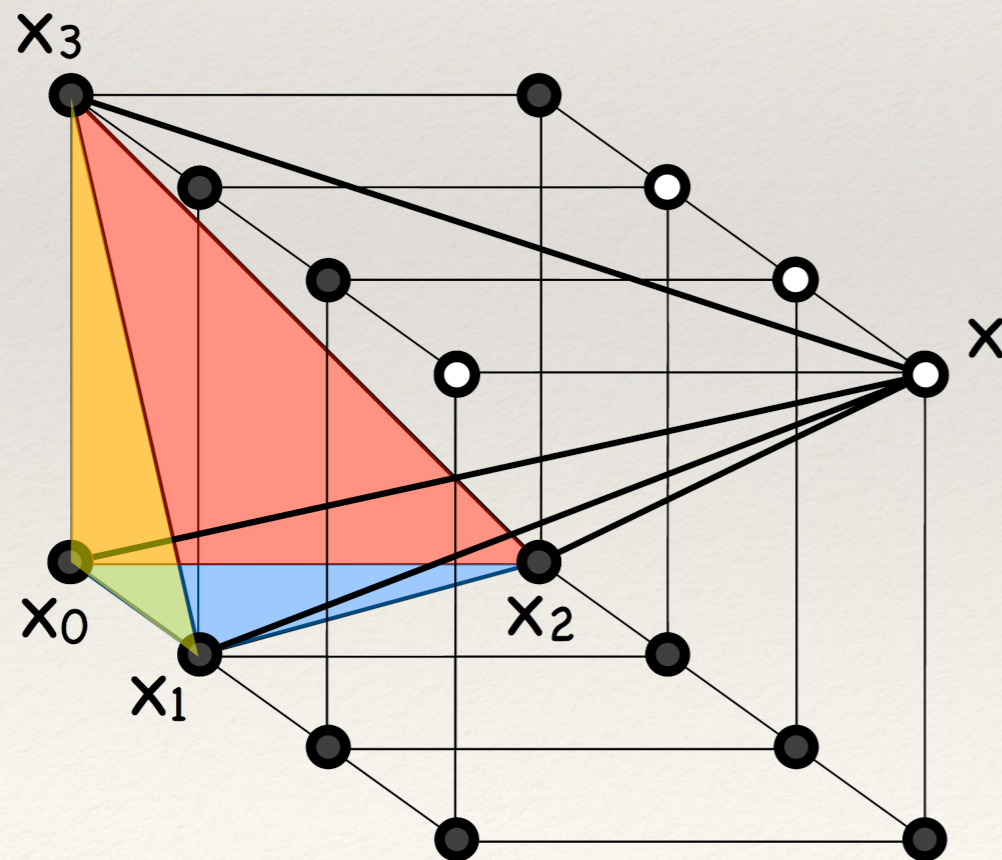
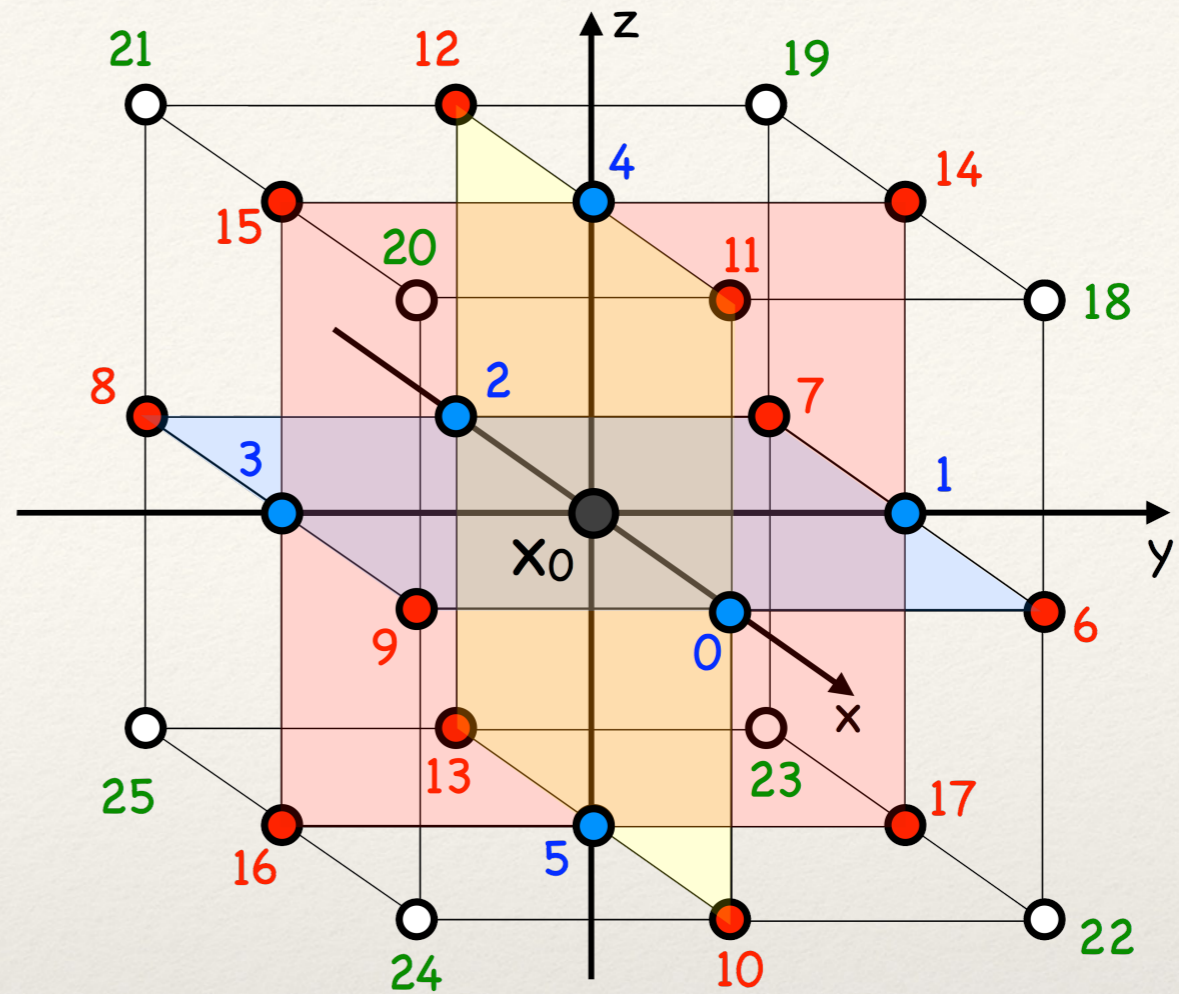
Making the solver efficient

- ❖ **Hierarchical update strategy**
 - ❖ Routine 1pt update
 - ❖ Minimizer of 1pt update \rightarrow triangle update
 - ❖ Successful 1pt update \rightarrow simplex update
- ❖ **Use the KKT theory** to reject simplex updates that are unlikely to succeed in finding an inner point solution
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Making the solver efficient

- ❖ **Hierarchical update strategy**
 - ❖ Routine 1pt update
 - ❖ Minimizer of 1pt update \rightarrow triangle update
 - ❖ Successful 1pt update \rightarrow simplex update
- ❖ **Use the KKT theory** to reject simplex updates that are unlikely to succeed in finding an inner point solution
 - ❖ Starting point = minimizer of a triangle update
 - ❖ Check sign of Lagrange multiplier,
 - ❖ Reject simplex update if the KKT criteria are met
- ❖ **Restrict the set of admissible simplexes** and devise a **fast search** for them

- ❖ Restrict the set of admissible simplexes and devise a fast search for them



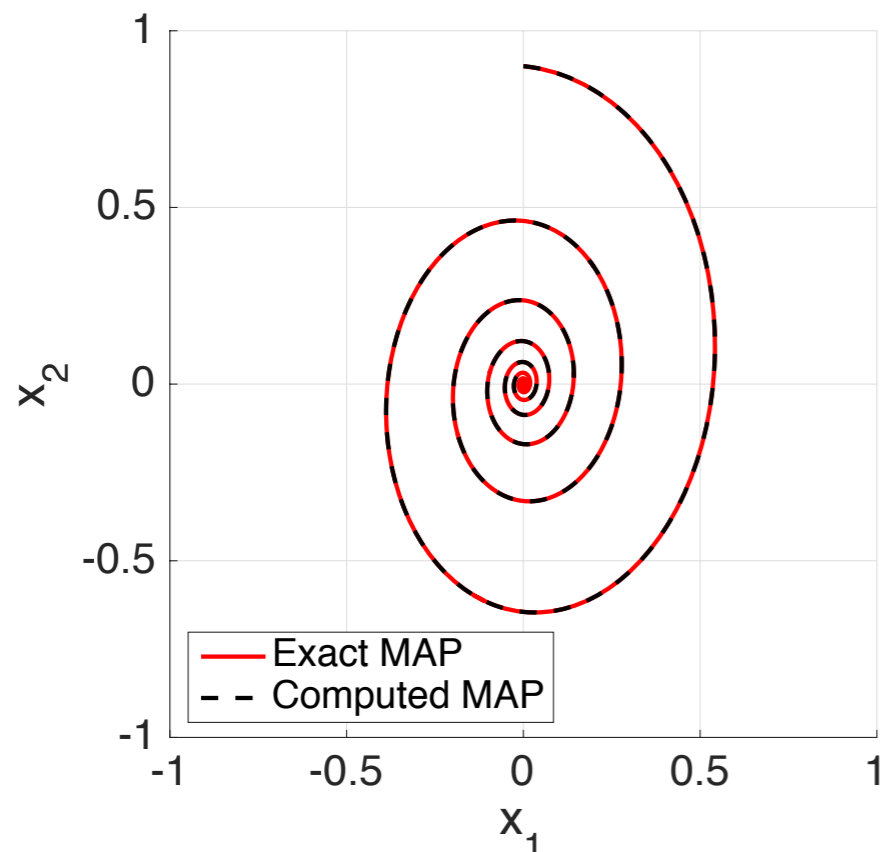
Performance tests

2D test problems

Linear

$$\begin{aligned} dx_1 &= (-2x_1 - 10x_2)dt + \sqrt{\epsilon}dw_1 \\ dx_2 &= (20x_1 - x_2)dt + \sqrt{\epsilon}dw_2 \end{aligned}$$

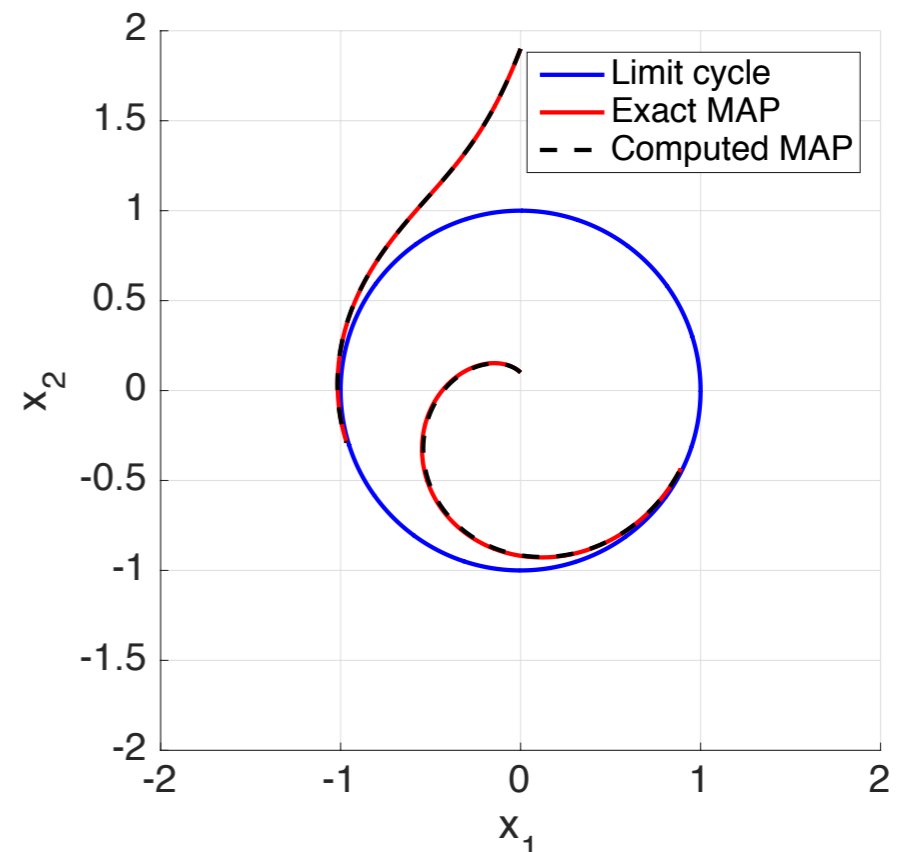
$$U(x_1, x_2) = 2x_1^2 + x_2^2$$



Circle

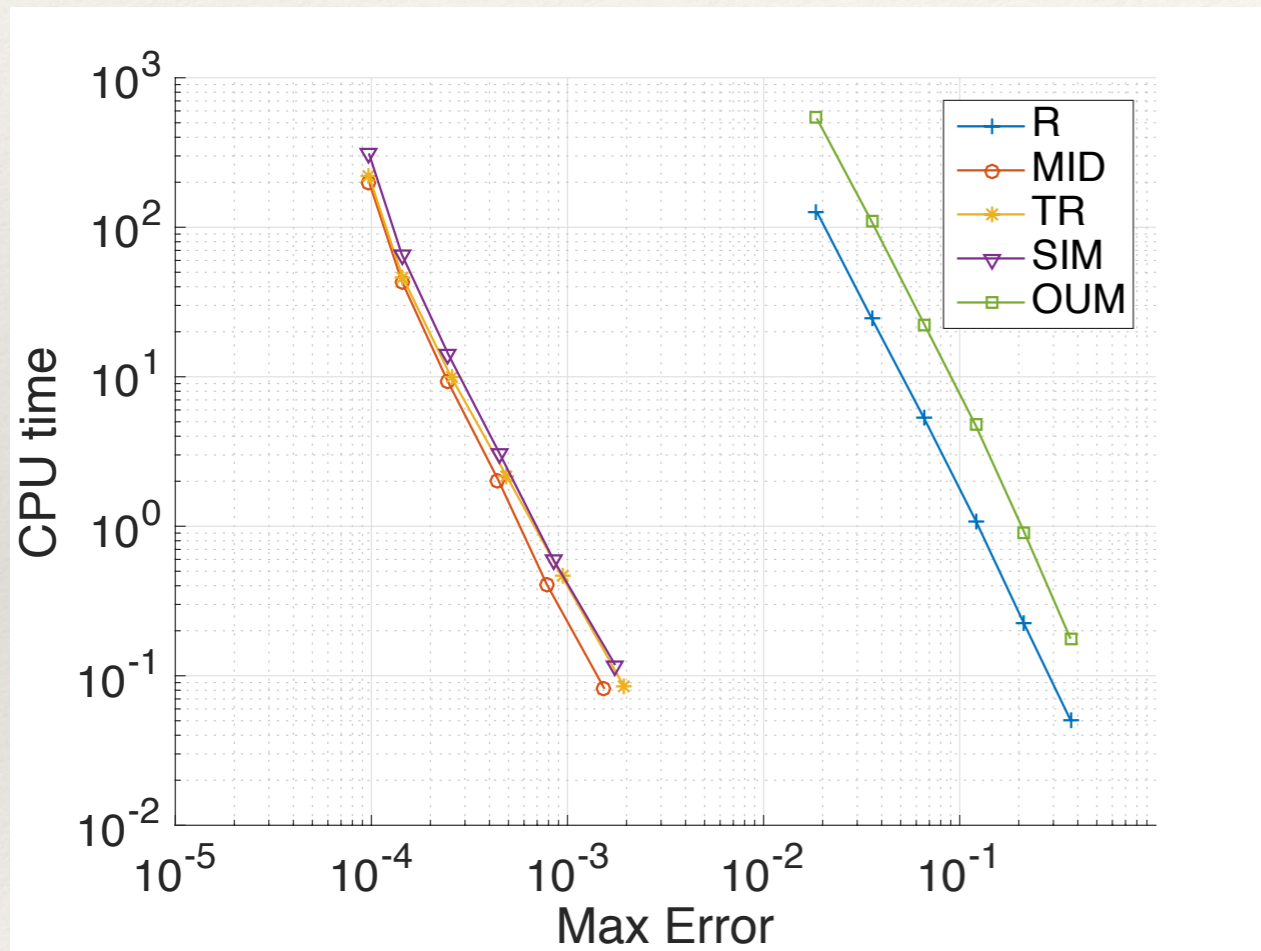
$$\begin{aligned} dx_1 &= (x_2 + x_1(1 - r^2))dt + \sqrt{\epsilon}dw_1 \\ dx_2 &= (-x_1 + x_2(1 - r^2))dt + \sqrt{\epsilon}dw_2 \\ r^2 &:= x_1^2 + x_2^2 \end{aligned}$$

$$U(x_1, x_2) = \frac{1}{2}(x_1^2 + x_2^2 - 1)^2.$$

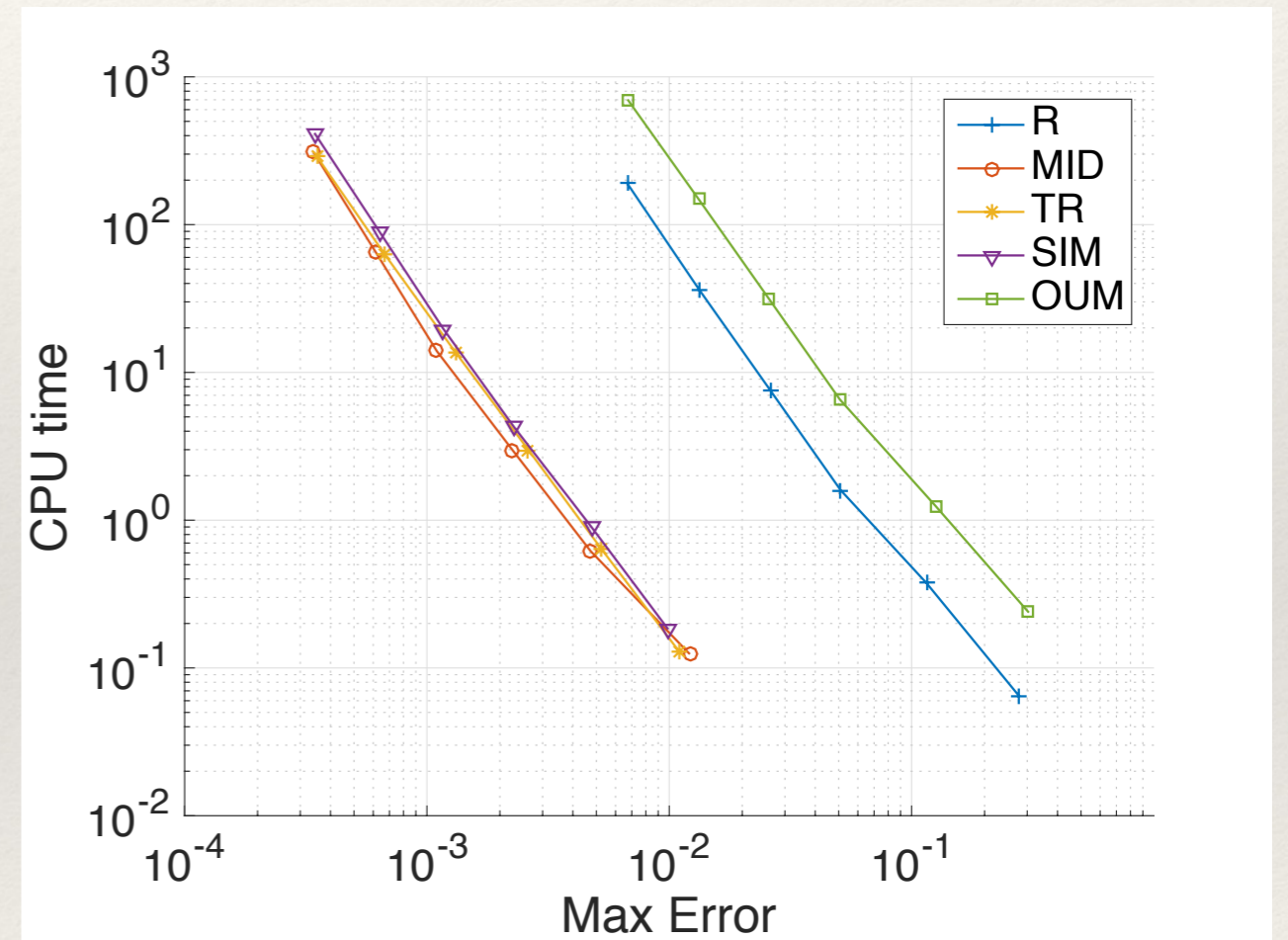


OLIMs vs OUM

Linear

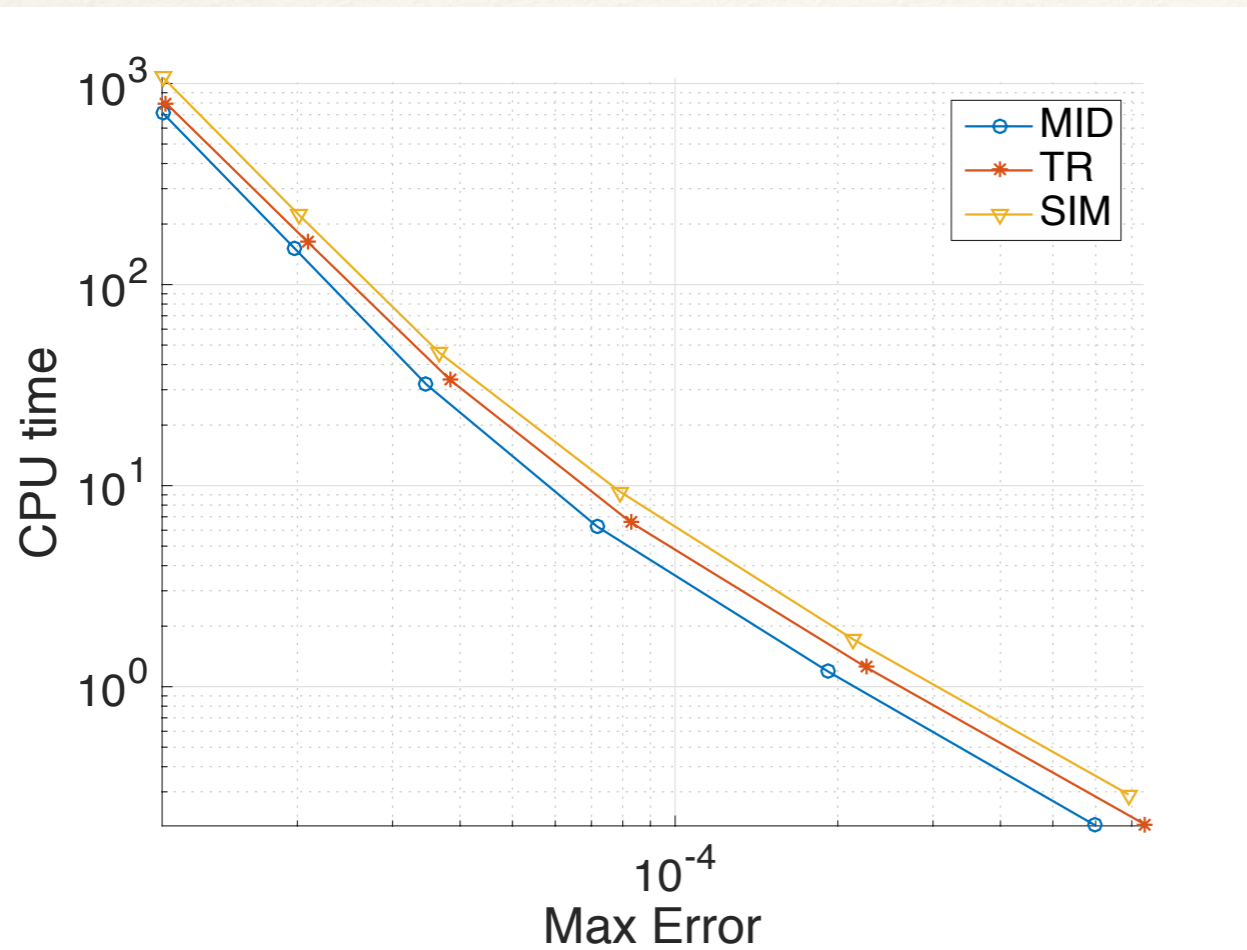


Circle

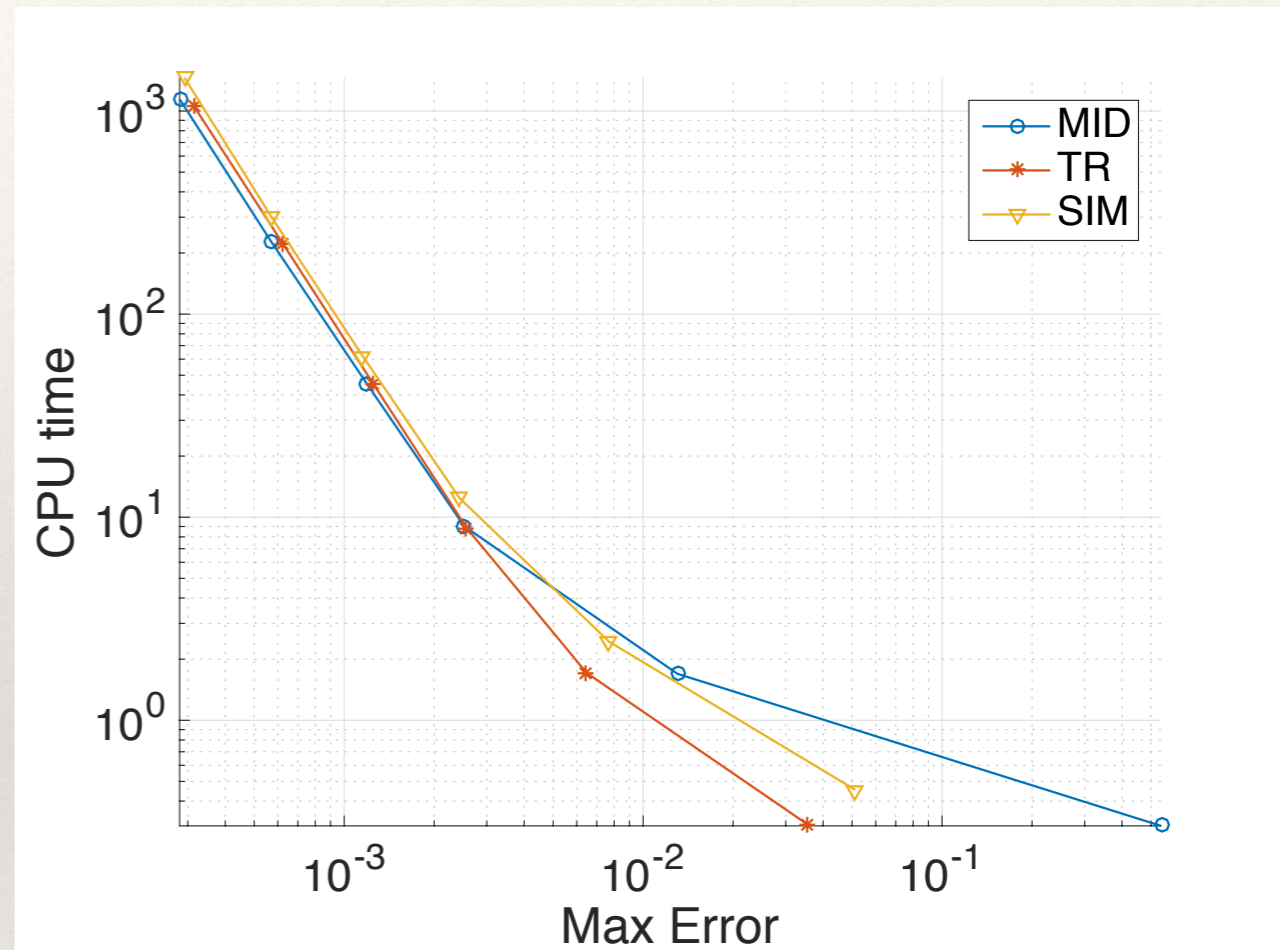


Comparison of OLIMs

Linear



Circle



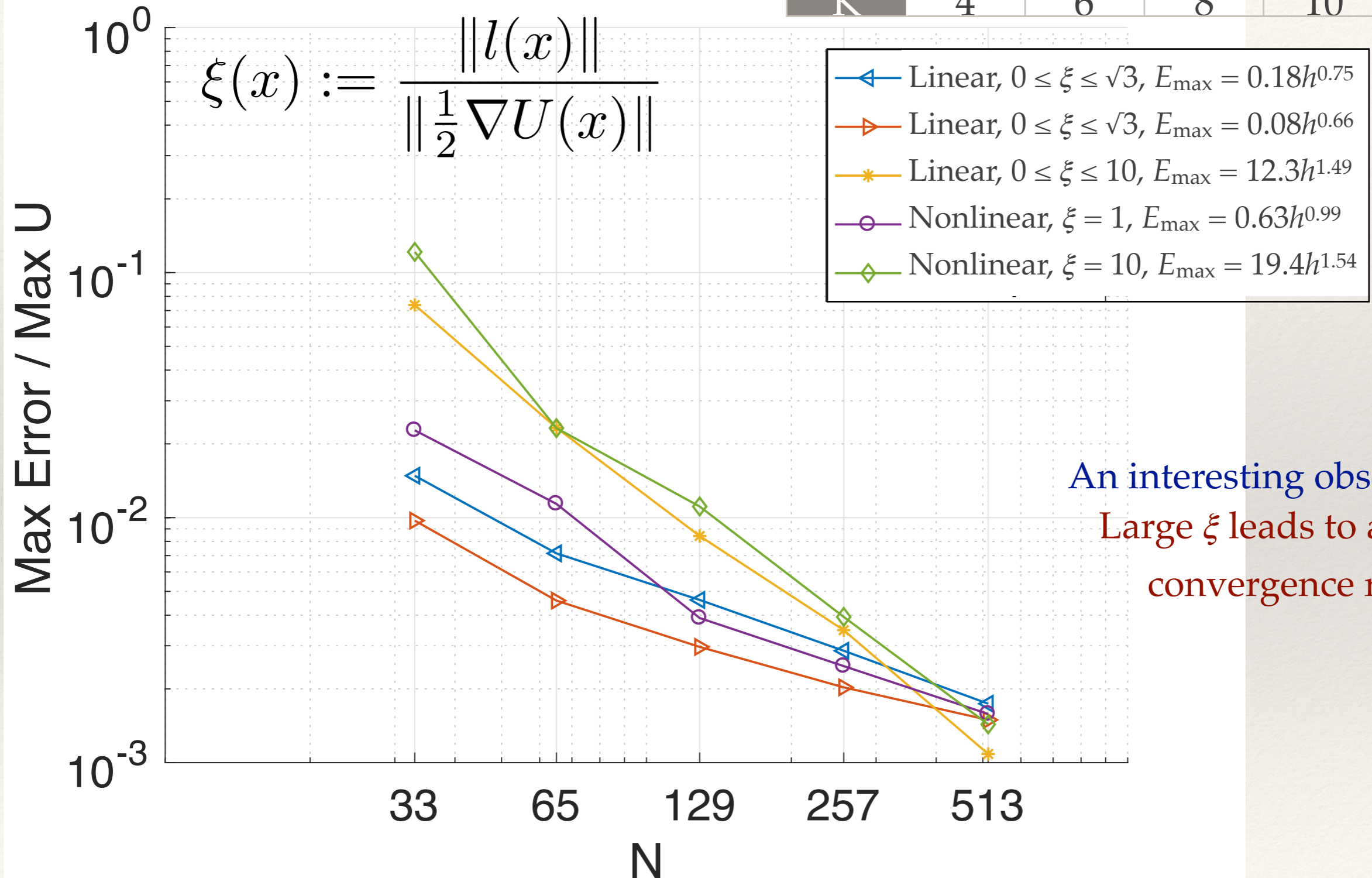
The winner is the midpoint rule!

3D performance test

Mesh size = N^3

N	33	65	129	256	513
K	4	6	8	10	14

$$\xi(x) := \frac{\|l(x)\|}{\|\frac{1}{2}\nabla U(x)\|}$$

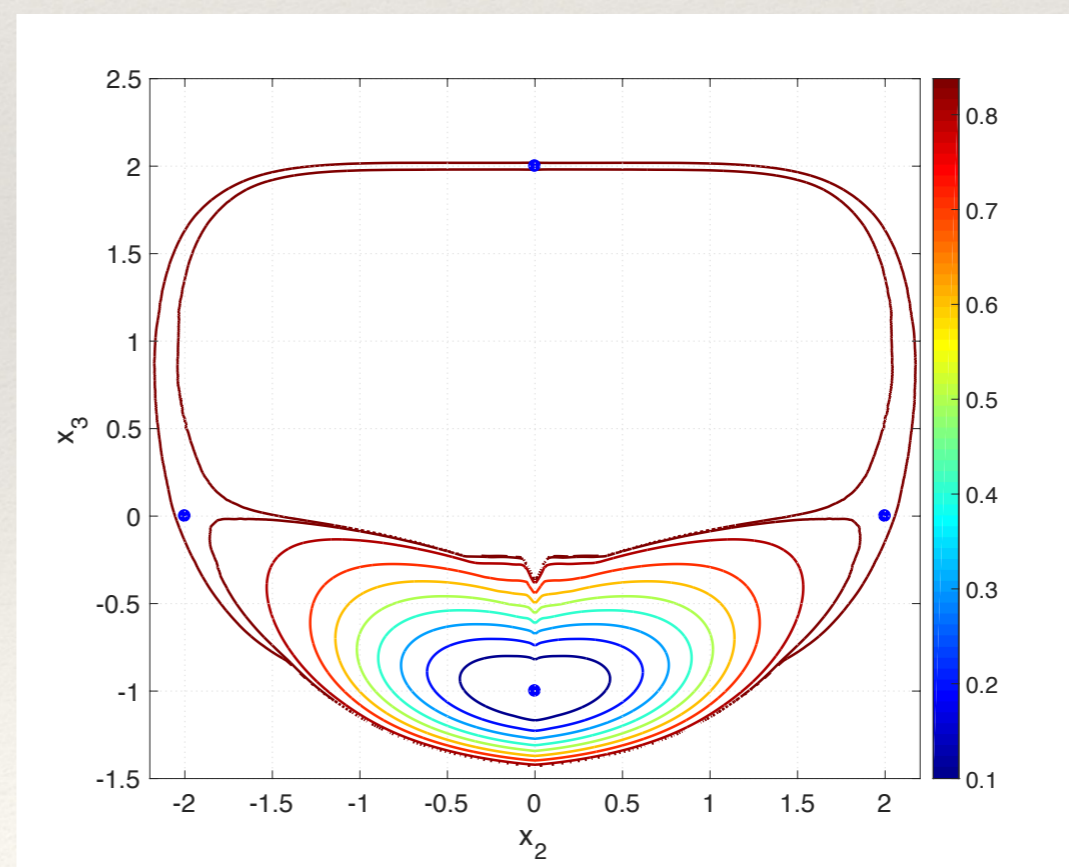
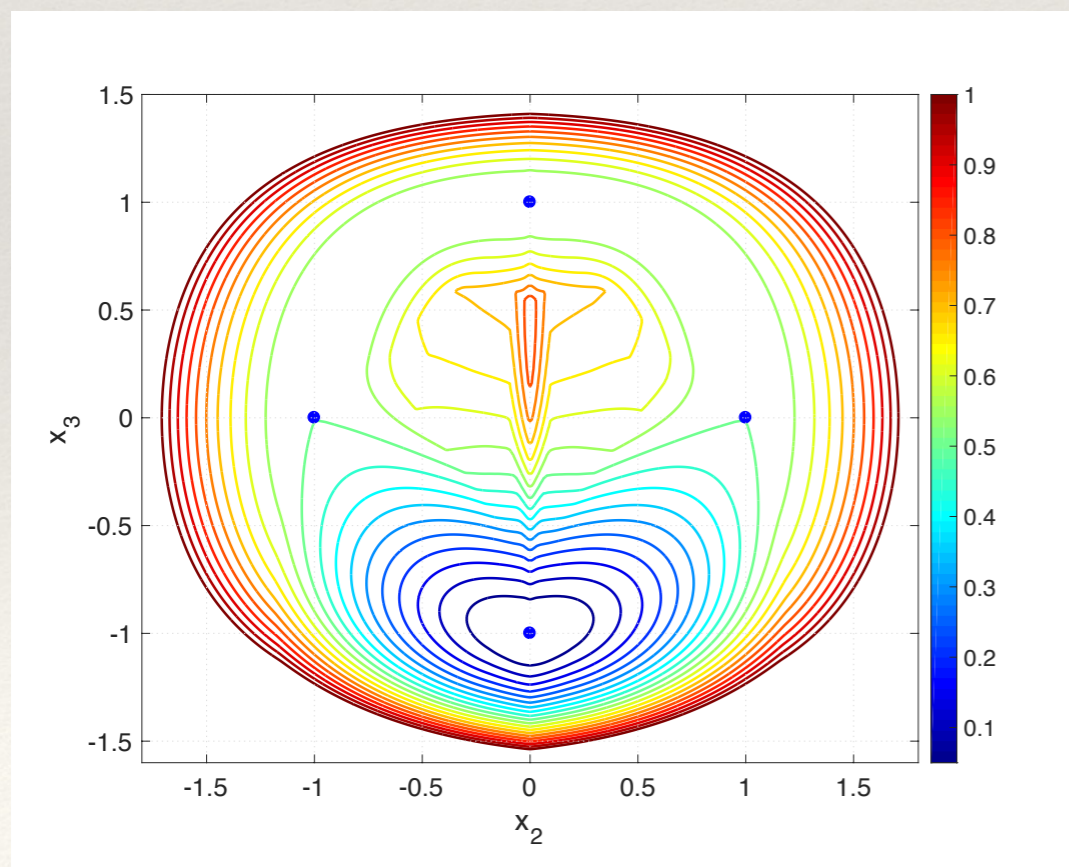
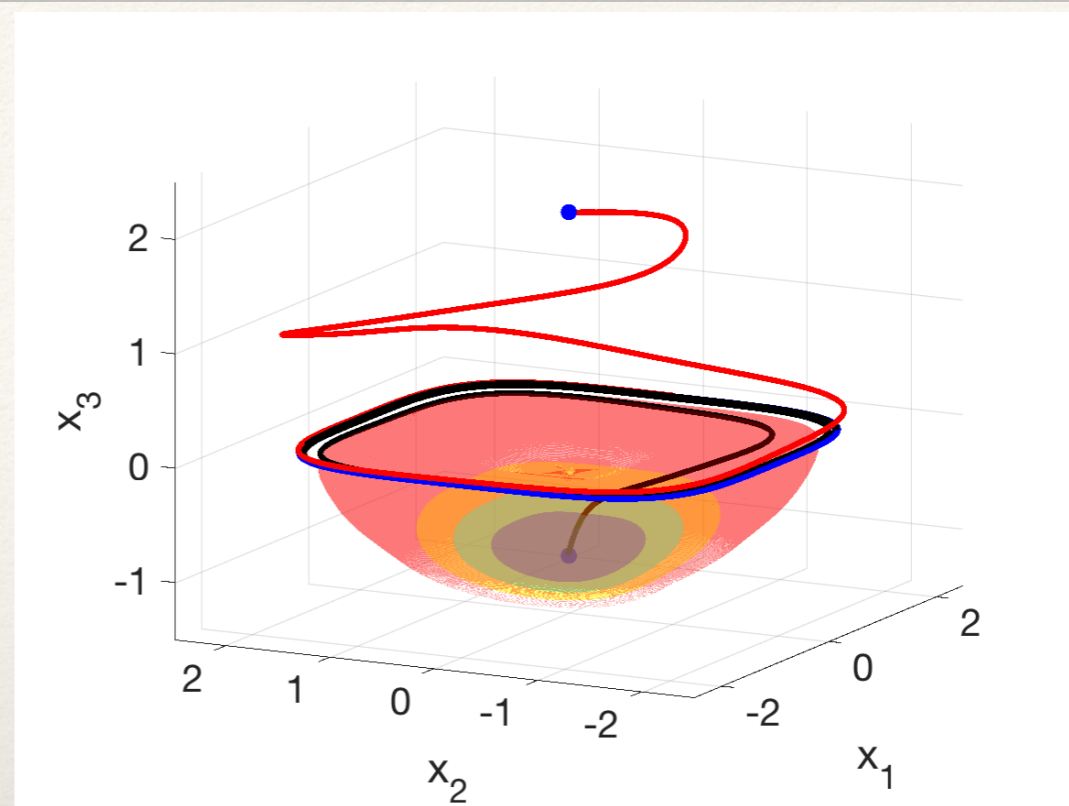
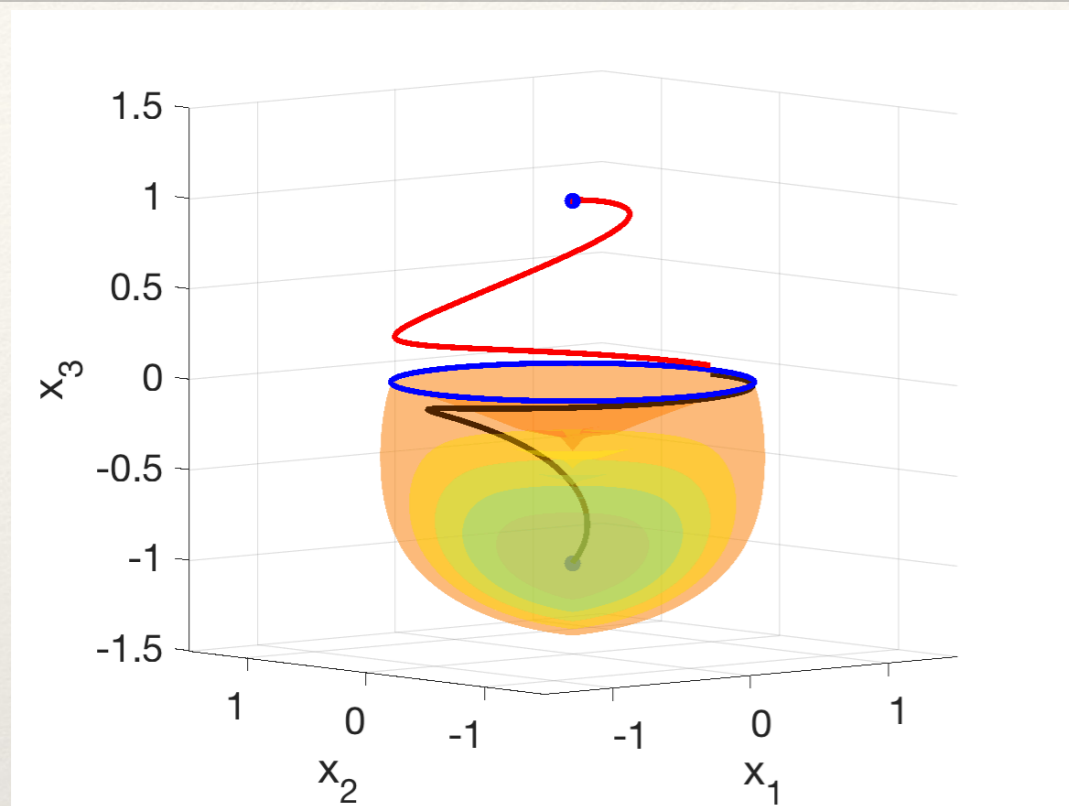


An interesting observation:
Large ξ leads to a faster convergence rate.

Applications

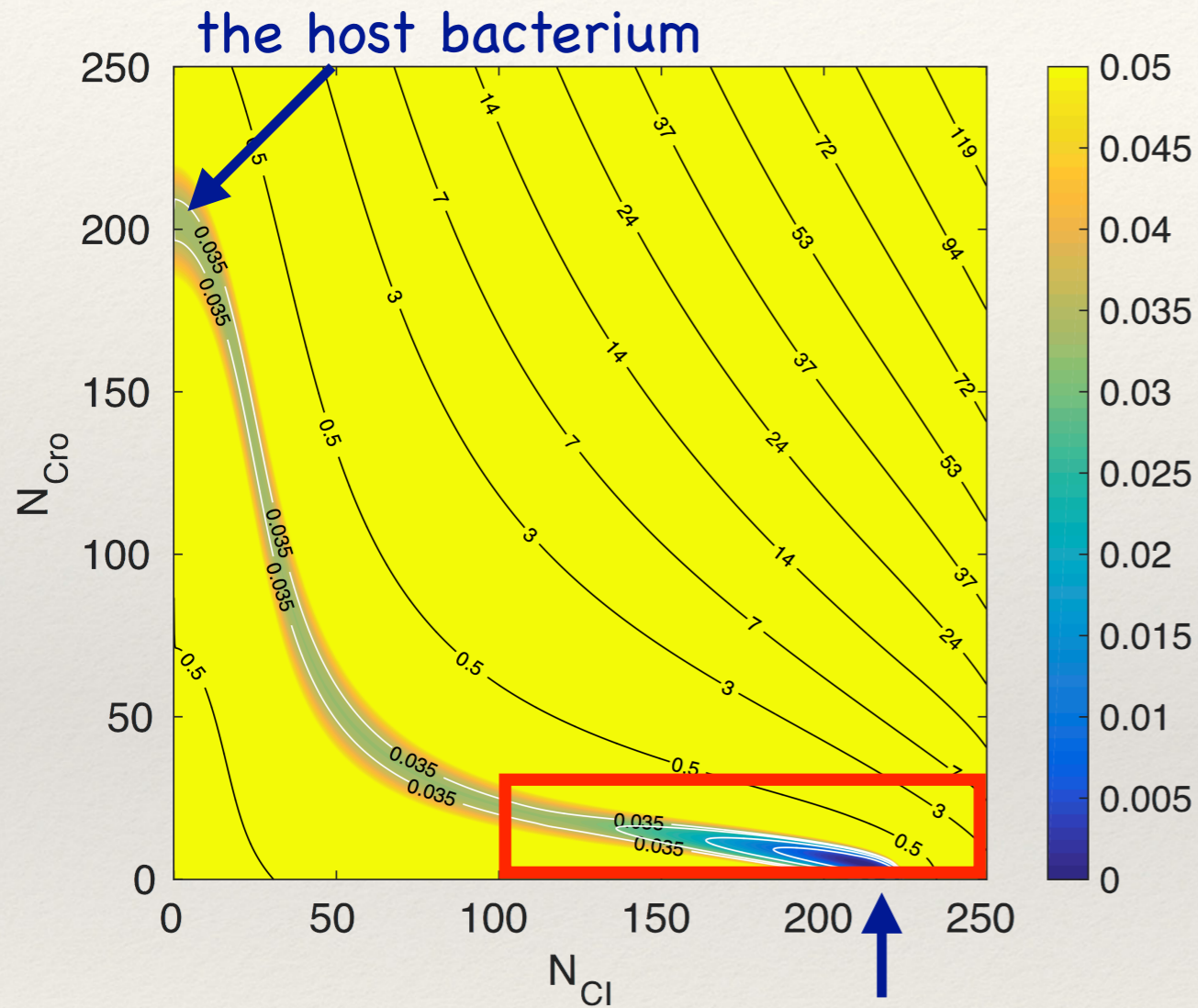
3D systems with hyperbolic periodic orbits

Tao's
examples,
2018



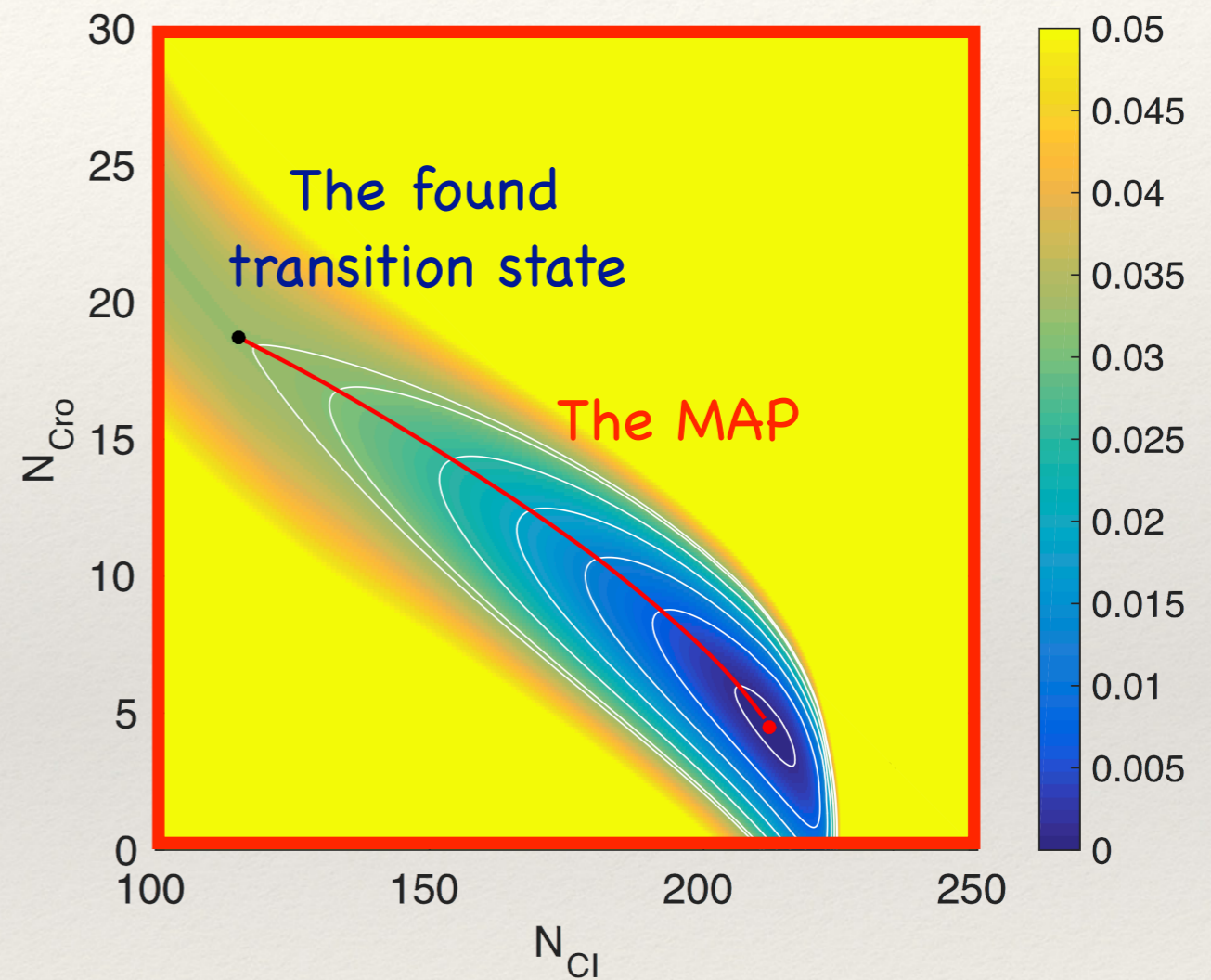
2D: Genetic switch in phage λ

Lytic state:
phage λ kills
the host bacterium



Lysogenic state:
phage λ reproduces without
killing the host bacterium

SDE model: Aurell/Sneppel, 2002

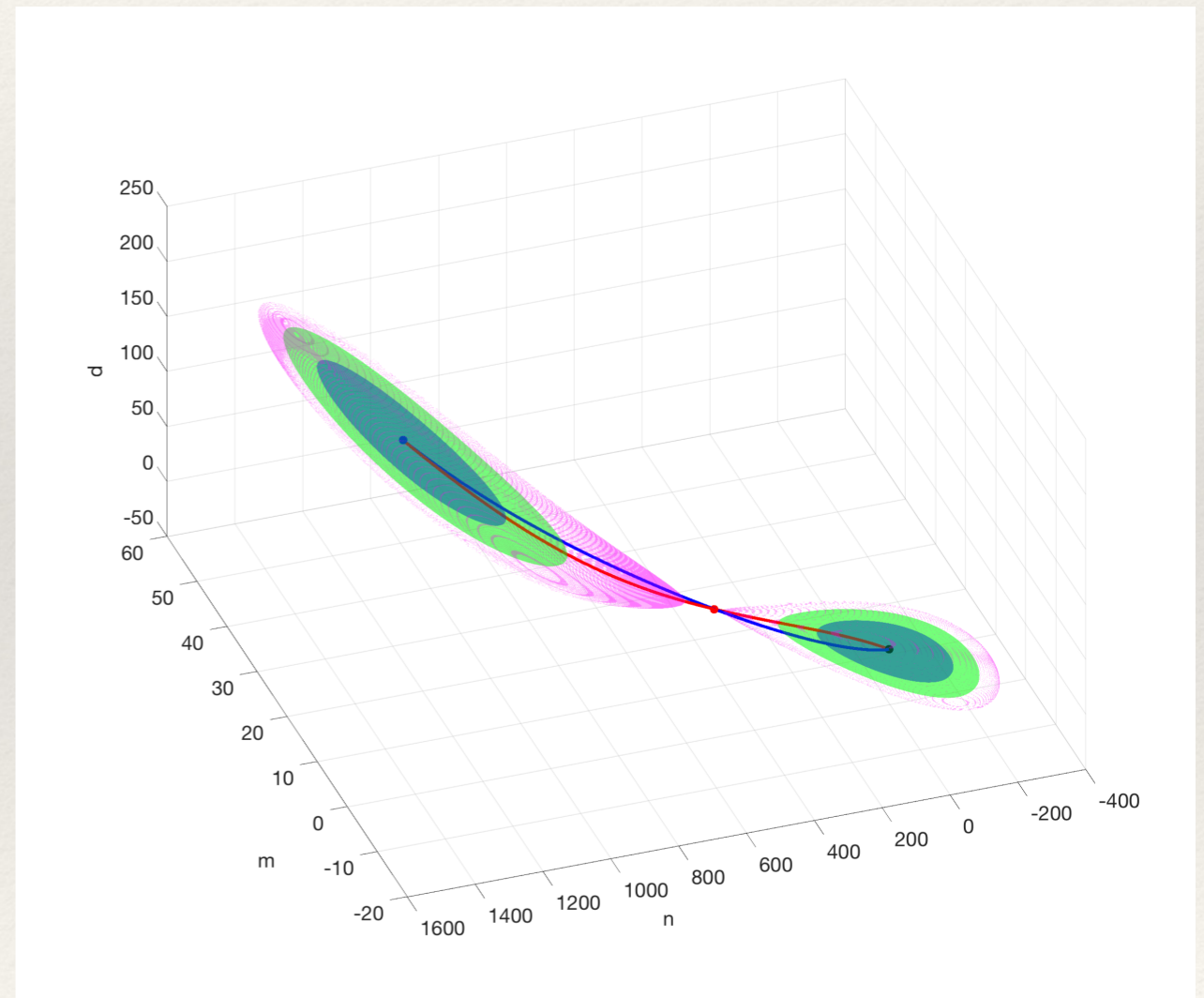
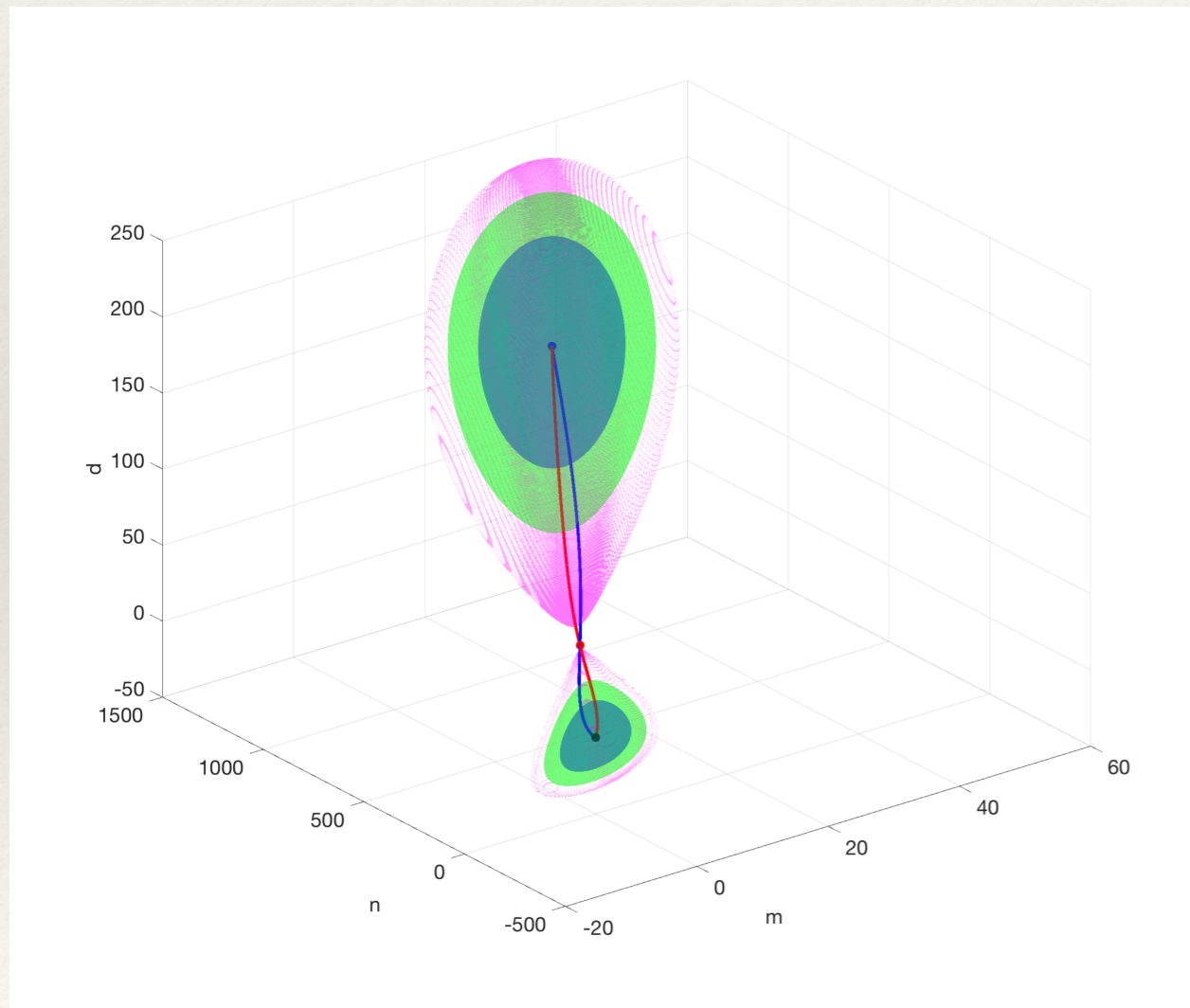


3D: Genetic switch model with a positive feedback

Lv, Li, Li, Li, 2014

$$\begin{aligned}dm &= \left(\frac{a_0\gamma_0 + ak_0d}{\gamma_0 + k_0d} - \gamma_m m \right) + \sqrt{\epsilon}dw_1, \\dn &= (bm - \gamma_n n - 2k_1n^2 + 2\gamma_1d) + \sqrt{\epsilon}dw_2, \\dd &= (k_1n^2 - \gamma_1d) + \sqrt{\epsilon}dw_3.\end{aligned}$$

$m = \# \text{mRNA}$, $n = \# \text{protein}$, $d = \# \text{dimer}$



Lorenz'63

$$\begin{bmatrix} dx \\ dy \\ dz \end{bmatrix} = \begin{bmatrix} \sigma(y - x) \\ x(\rho - z) - y \\ xy - \beta z \end{bmatrix} dt + \sqrt{\epsilon} dw \quad \sigma = 10, \quad \beta = 8/3, \quad 0 < \rho < \infty$$

Some critical values of ρ :

$\rho = 1$: the origin turned from a sink to a saddle, equilibria C_+ and C_-
at $(\pm\sqrt{\beta(\rho - 1)}, \pm\sqrt{\beta(\rho - 1)}, \rho - 1)$ are born

$\rho \approx 13.926$: "preturbulence" starts (Kaplan & Yorke, 1979)

$\rho \approx 24.06$: the strange attractor is born (Yorke & Yorke, 1979)

$\rho \approx 24.74$: equilibria lose stability

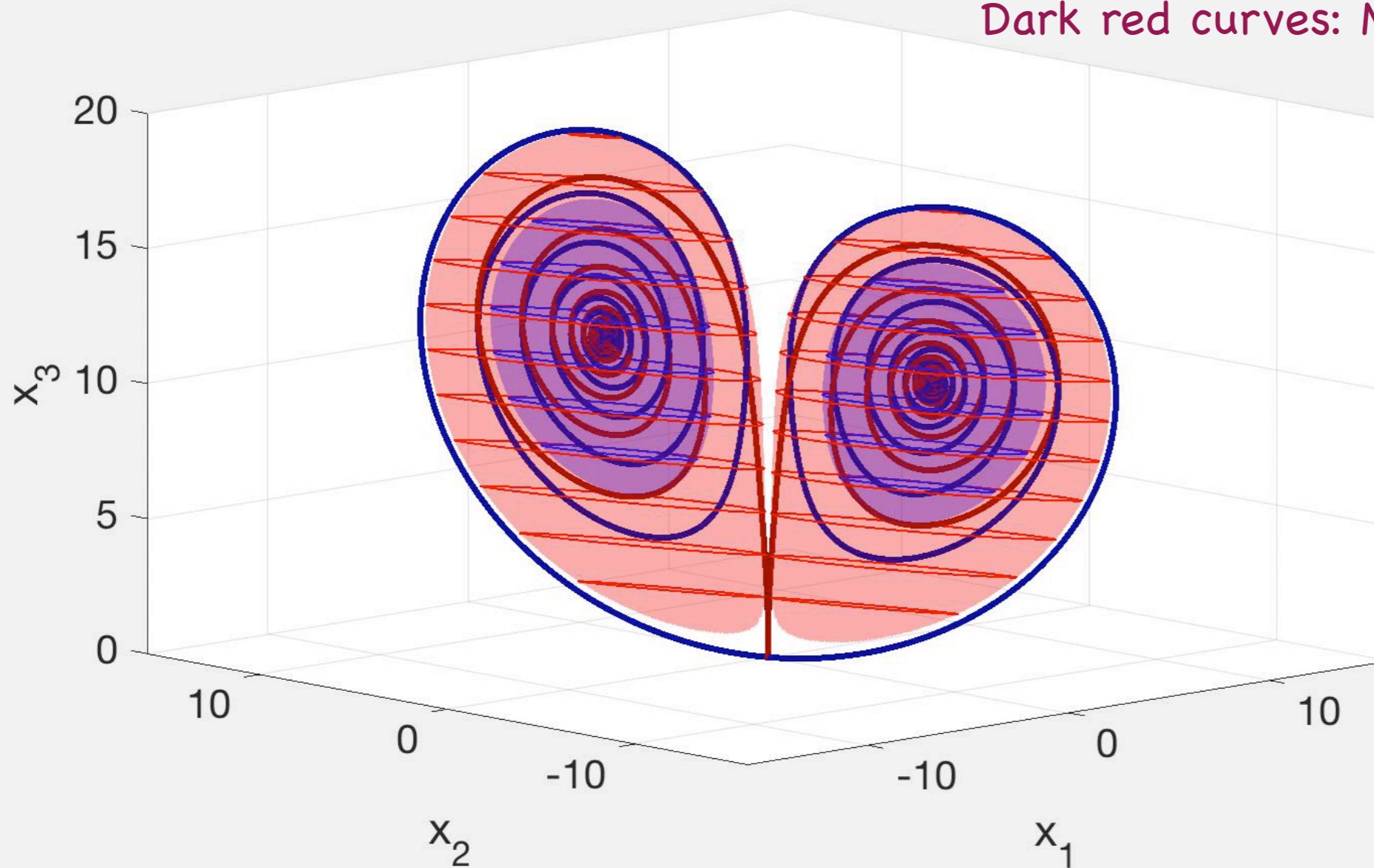
$$\rho = 12$$

Surfaces: level sets of the quasipotential

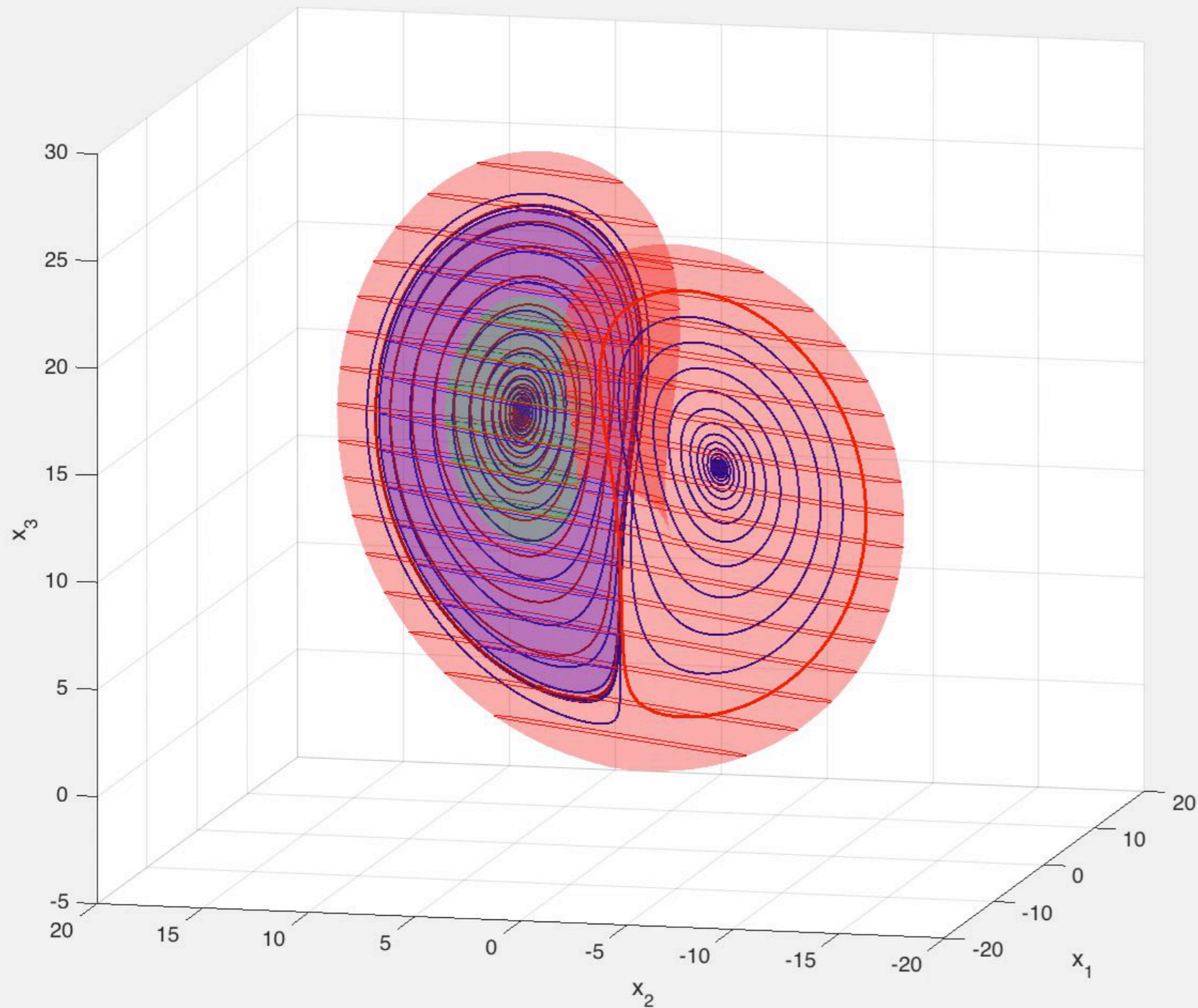
($U = 10$, $U_{\text{origin}} = 0.05$)

Indigo curves: trajectories

Dark red curves: MAPs



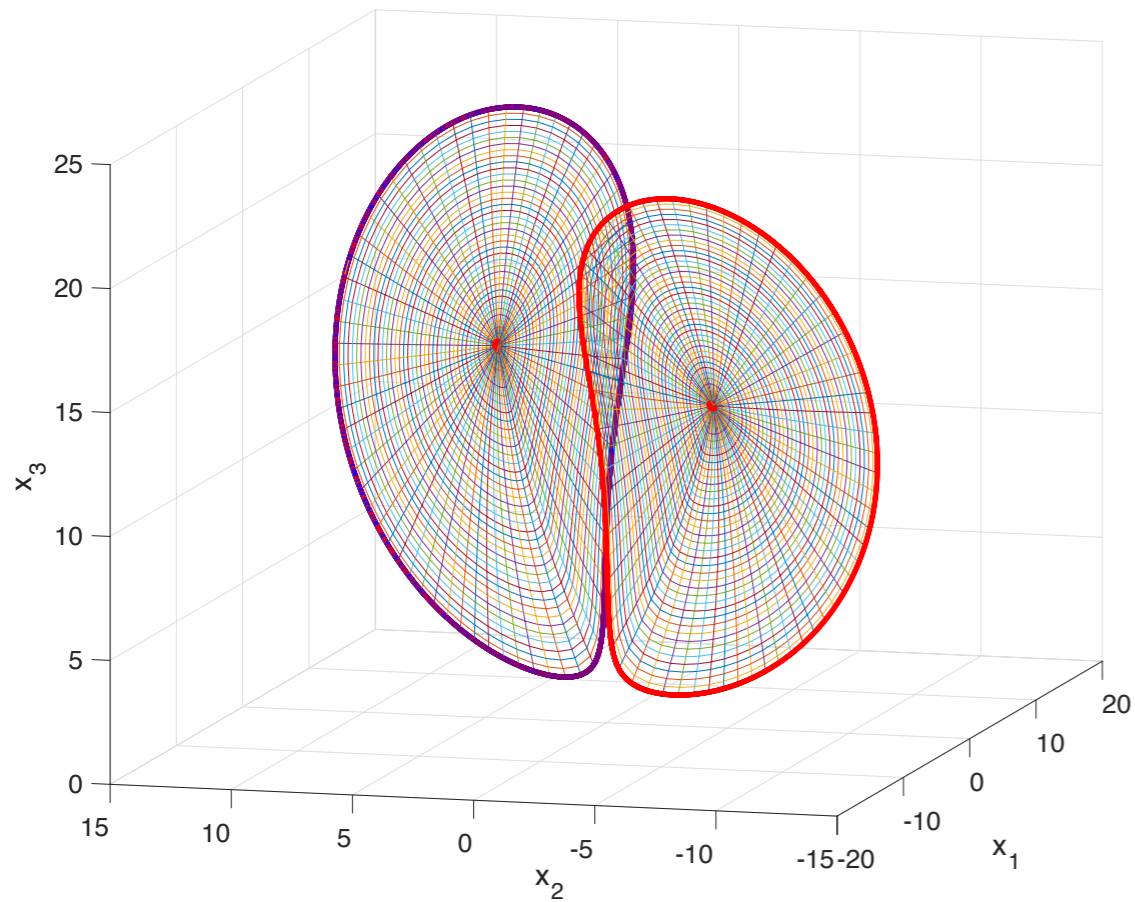
$$\rho = 15$$



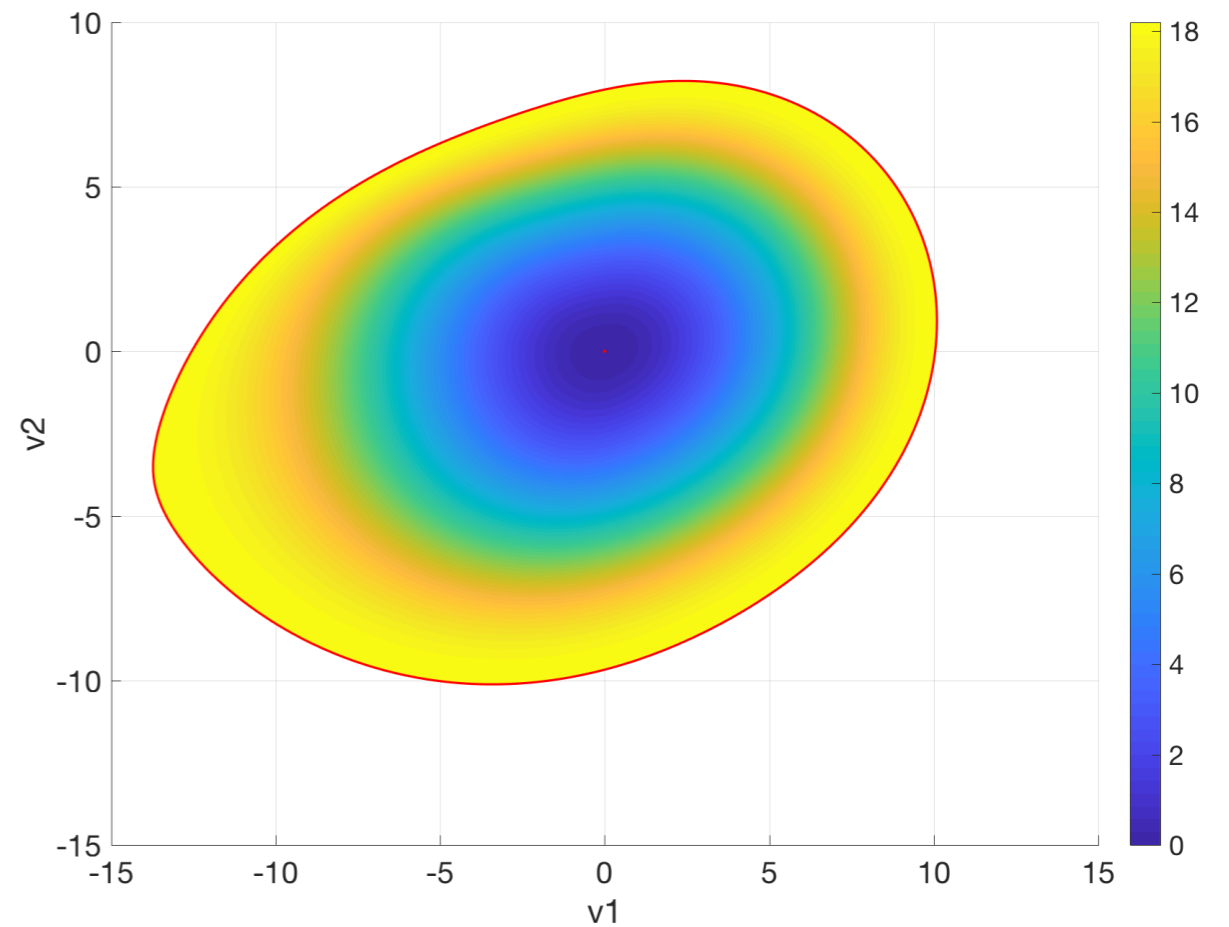
Surfaces: level sets of
the quasipotential
($U = 8$, $U_{\text{limit cycle}} = 0.01$, 20)
Indigo curves: trajectories
Dark red curves: MAPs

$$\rho = 15$$

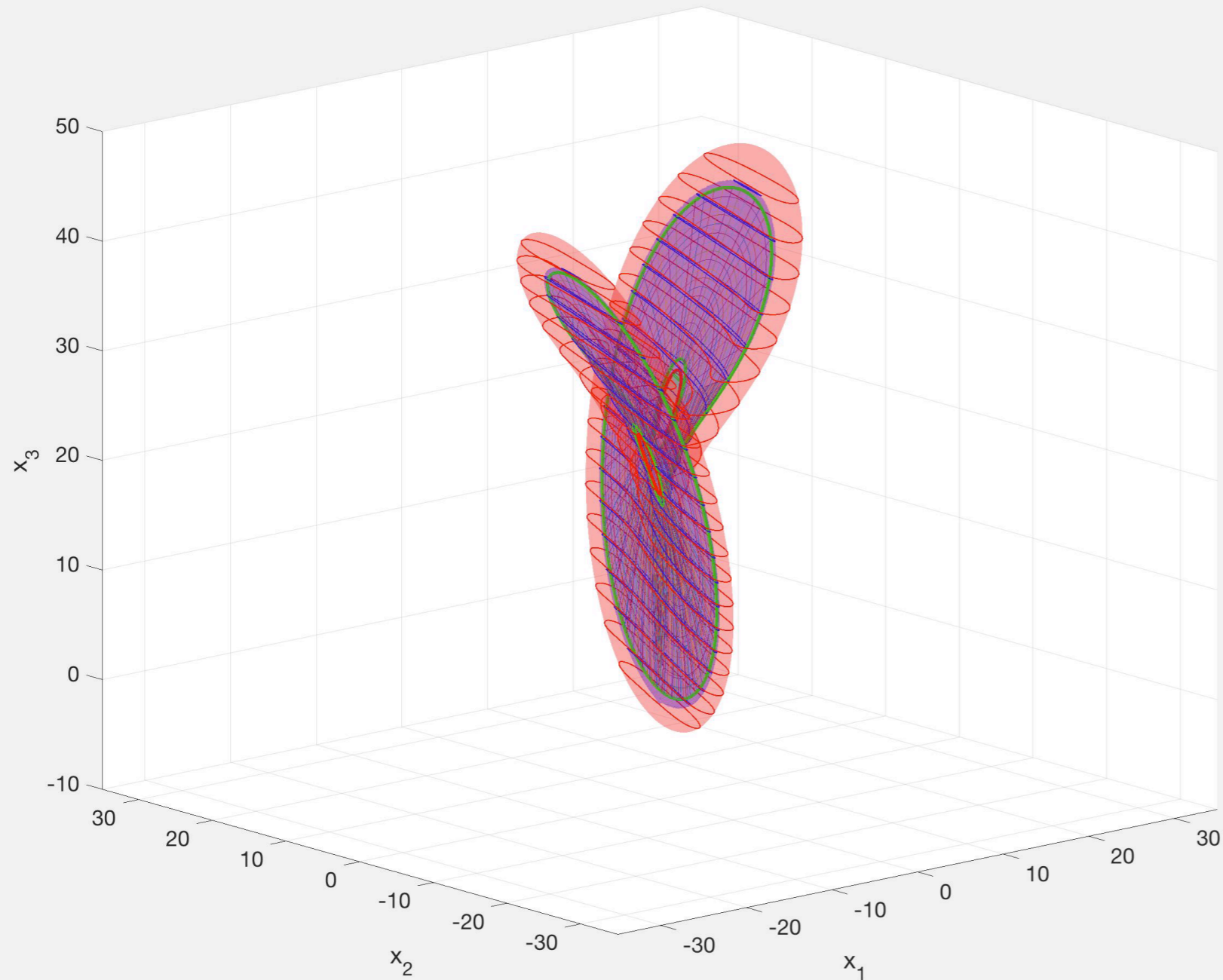
A 2D mesh on manifolds near which
the dynamics are focused



The quasi potential computed
on this 2D mesh

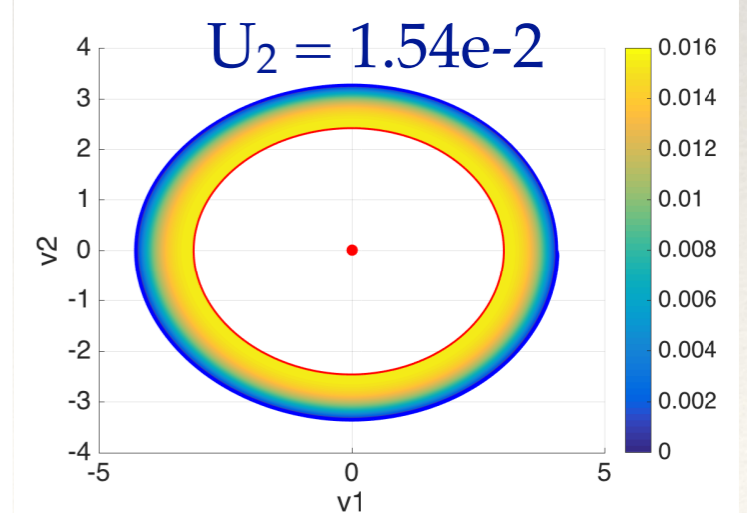
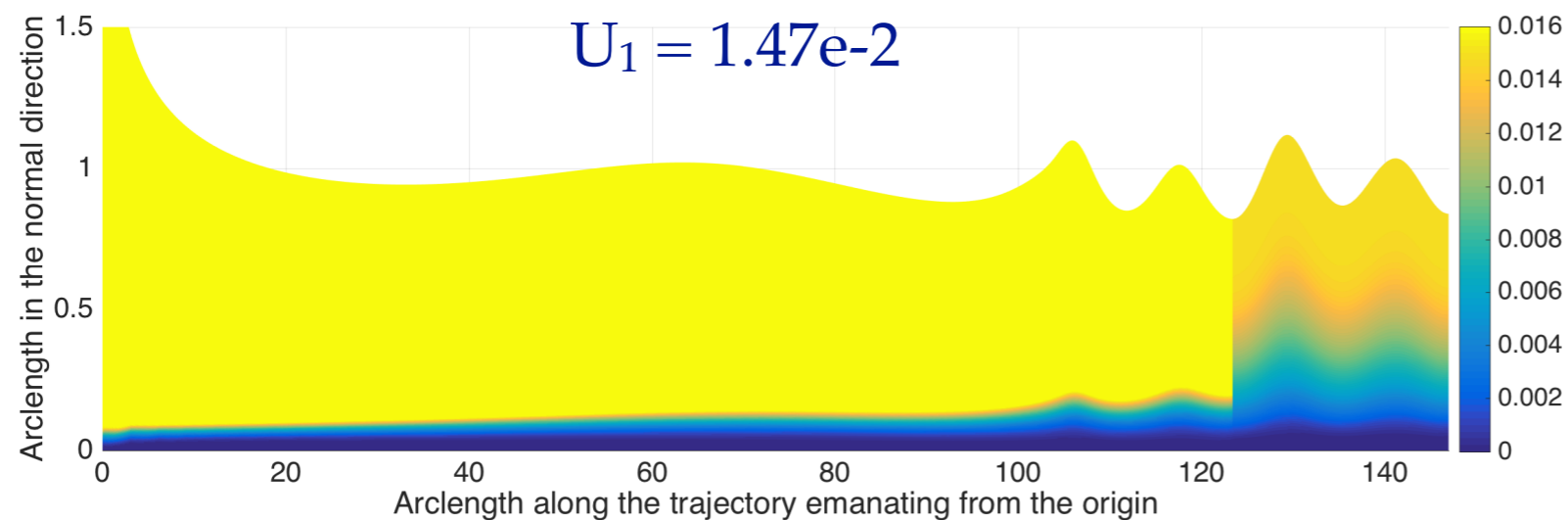
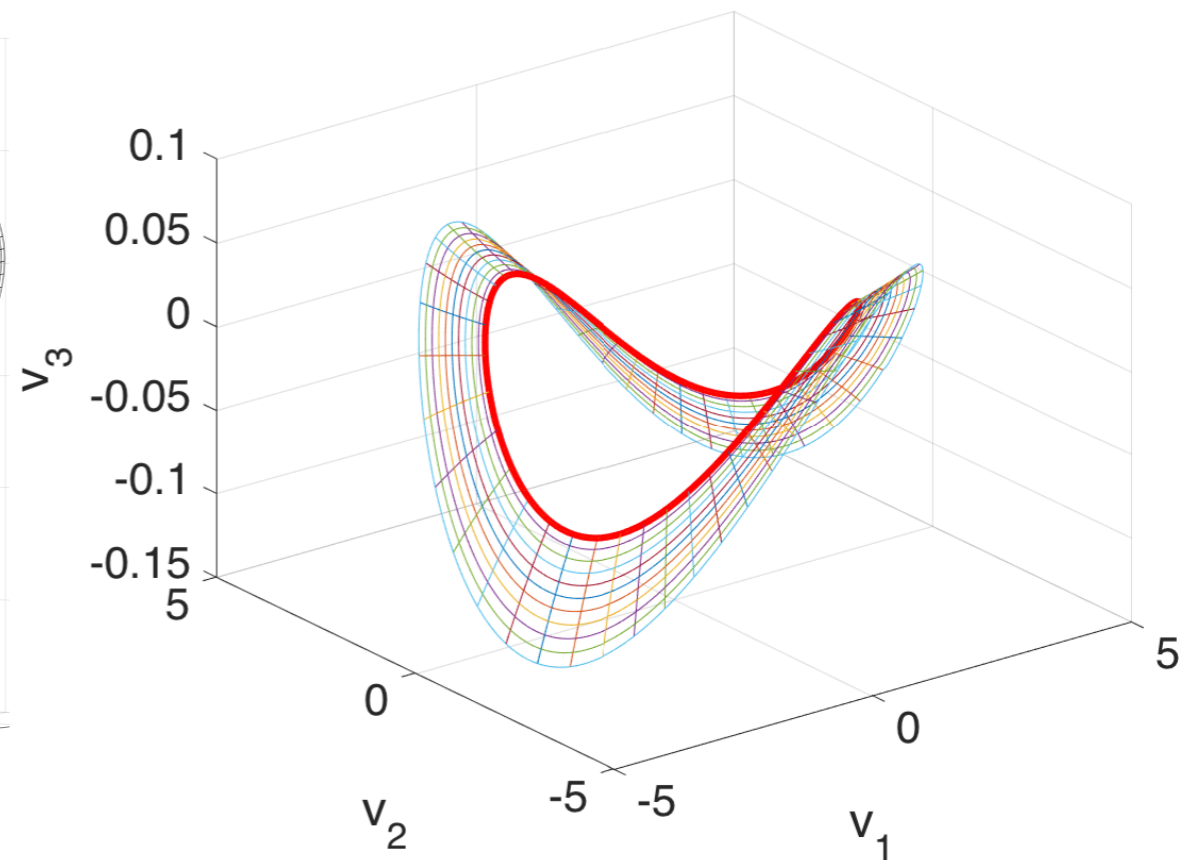
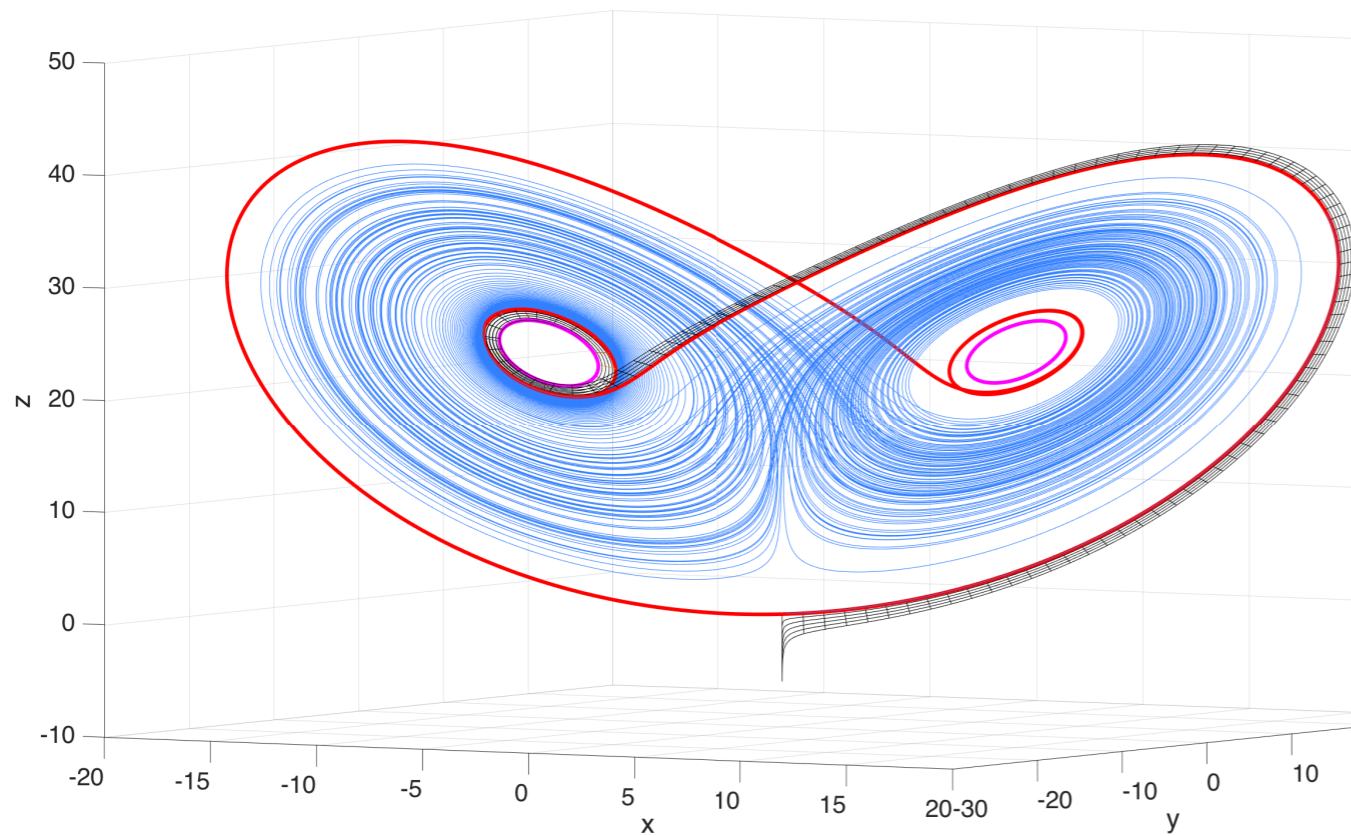


$$\rho = 24.4$$



Surfaces: level sets of
the quasipotential
($U = U_{\text{limit cycle}} - 0.01, 2, 20$)
Red loops: limit cycles
Green curves:
borders of manifolds
whose union approximates
the strange attractor

$\rho = 24.4$: from the strange attractor to stable equilibria: which way we go?



Conclusion

- ❖ The OLIM quasipotential solver is a numerical tool for analysis of dynamical systems perturbed by small noise
 - ❖ It **visualizes** the dynamics and allows us to find **maximum likelihood transition paths**, estimate **expected escape times**, and **invariant probability measure**
- ❖ Way to high dimensions: look for a low-dimensional manifold near which the dynamics are focused

References:

- Dahiya & C., [Ordered line integral methods for computing the quasipotential](#), J. Sci. Comp., 75/3, 1351—1384 (2018), [arXiv: 1706.07509](#)
- Dahiya & C., [An ordered line integral method for computing the quasipotential in the case of variable and anisotropic diffusion](#), Physica D (2018) *to appear*, [arXiv: 1806.05321](#)
- Yang, Potter, & C., [Computing the quasipotential for nongradient SDEs in 3D](#), *submitted* (2018), [arXiv: 1808.00562](#)
- **C codes and user's guides:** <http://www.math.umd.edu/~mariakc/index.html>