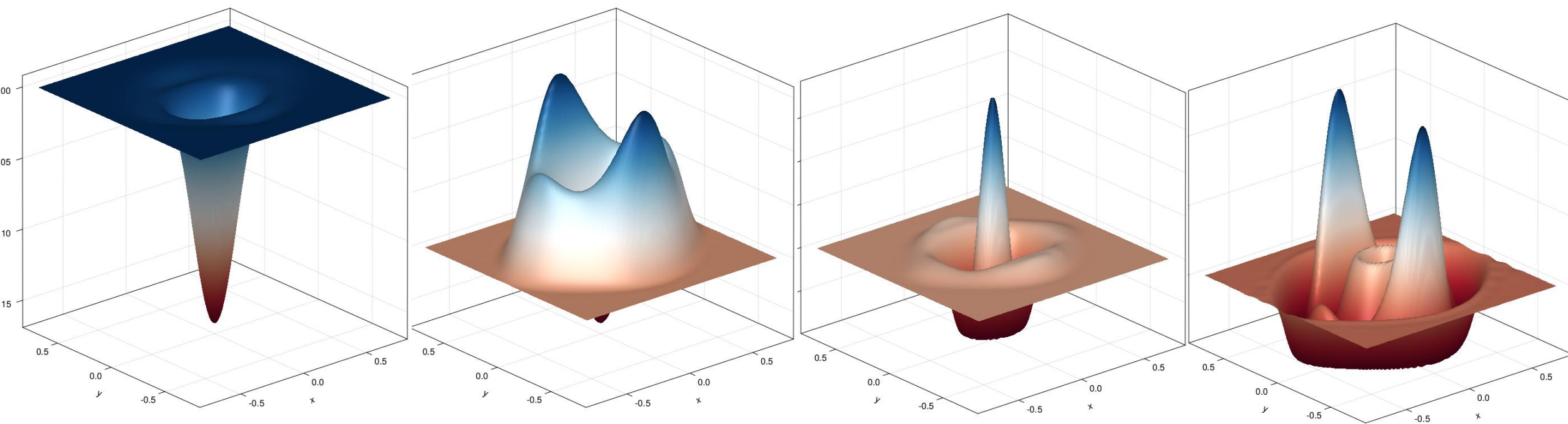


# Level Set Learning for Poincaré Plots of Symplectic Maps

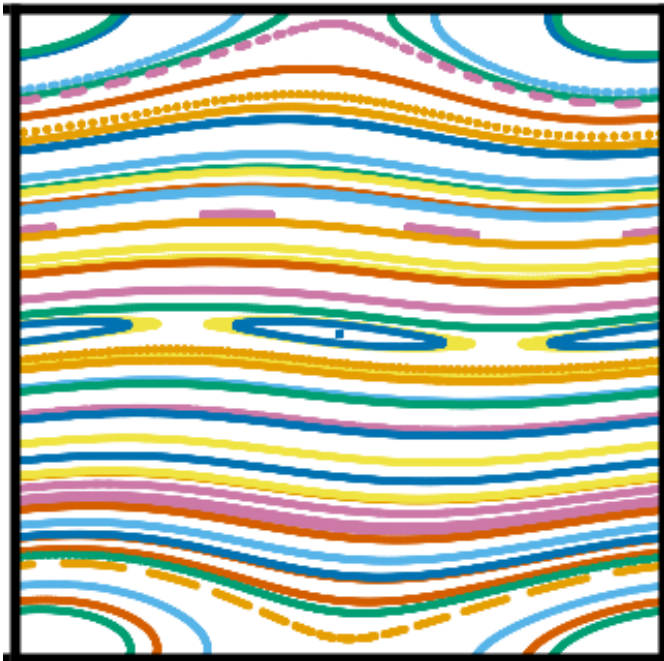
Max Ruth, David Bindel



## *How integrable is a magnetic field?*

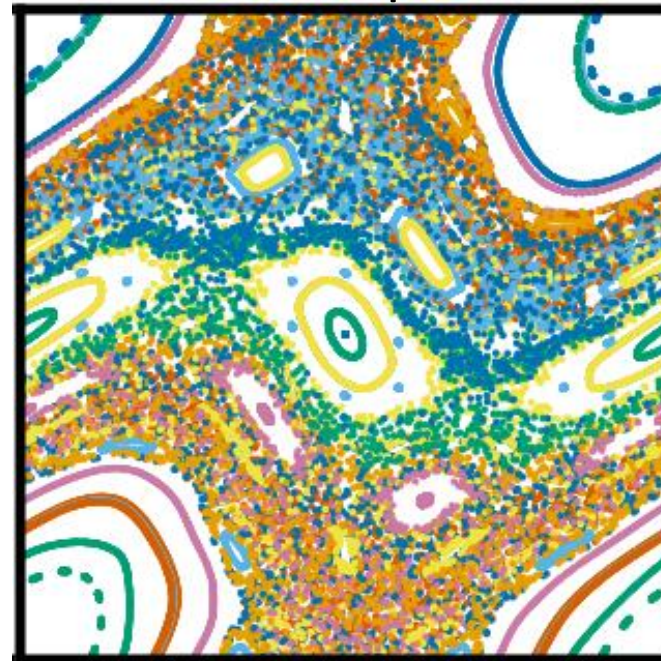
**“Integrable”**

Standard map  $k = 0.2$



**“Non-integrable”**

Standard map  $k = 1.2$



# Previous work

- **Periodic orbits:** Greene's Residue

- **Invariant Circles:**

- Quadratic Flux Minimization
- Boozer Least Squares
- Parameterization Method

- **Volume:** Anisotropic Diffusion

- **Trajectories:**

- Weighted Birkhoff Average
- Volume of chaos
- Birkhoff Reduced Rank Extrapolation

- Greene's residue: J. M. Greene, *Journal of Mathematical Physics*, 9 (1968), pp. 760–768.
- QFMin: R.L. Dewar and J.D. Meiss, *Physica D* 57 (1992) 476
- BoozerLS: A. Giuliani, F. Wechsung, A. Cerfon, M. Landreman, and G. Stadler, *PoP*, 30 (2023), p. 042511
- Parameterization: A. Haro and R. de la Llave, *Disc. Cont. Dyn. Sys.*, B6(6):1261–1300, 2006
- Heat Eq: E. J. Paul, S. R. Hudson, and P. Helander, *JPP*, 88 (2022), p. 905880107
- WBA: S. Das, Y. Saiki, E. Sander, and J.A. Yorke. Quantitative quasiperiodicity. *Nonlinearity*, 30(11):4111, 2017
- Volume of chaos: J.D. Meiss, *Reviews of Modern Physics* 64 (3) (1992), p. 795–848
- Birkhoff RRE: Me, see Simon's hour slides

# Goal

***How integrable is a magnetic field?***

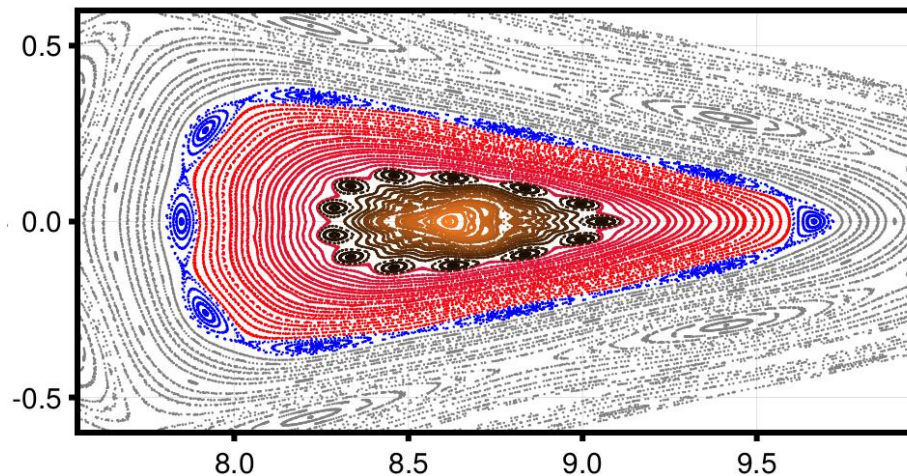
# Goal

## ~~How integrable is a magnetic field?~~

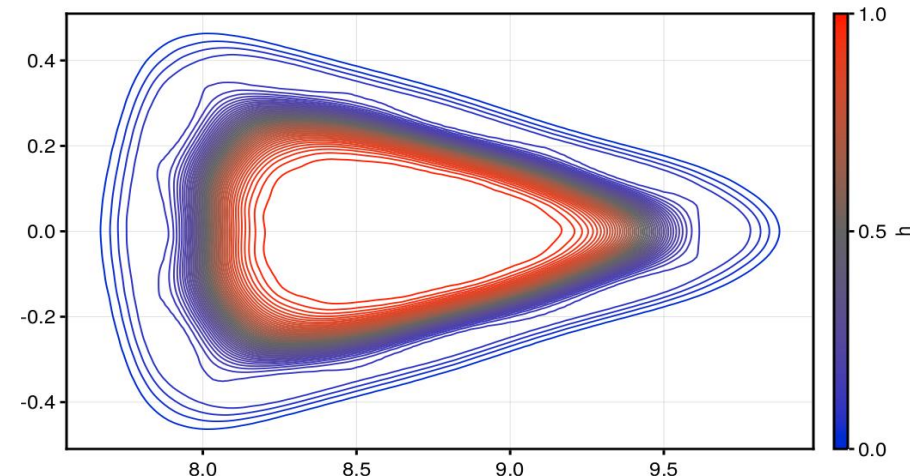
How can we *quickly* and *robustly* measure the integrability of a *volume* of magnetic field?

- Route: Attempt to find a flux label for the volume

Poincare Plot



Label Function



# Outline

1. Background / Motivation
2. **Approximately Invariant Functions (as defined by me)**
3. Method
4. Results
5. Conclusion

# Setup

- We consider a *symplectic map*  $F : X \rightarrow X$ 
  - E.g. from solving  $\dot{x} = B(x)$  and intersecting with a poloidal cross section  $X$
  - Or, the standard map with  $X = \mathbb{T} \times \mathbb{R}$
- On the state space, we define *observables* to be of the form  $h : X \rightarrow \mathbb{R}$
- A function  $h$  is *invariant* if it obeys the relationship
$$h(x) = h(F(x))$$
  - E.g. the Hamiltonian is always invariant

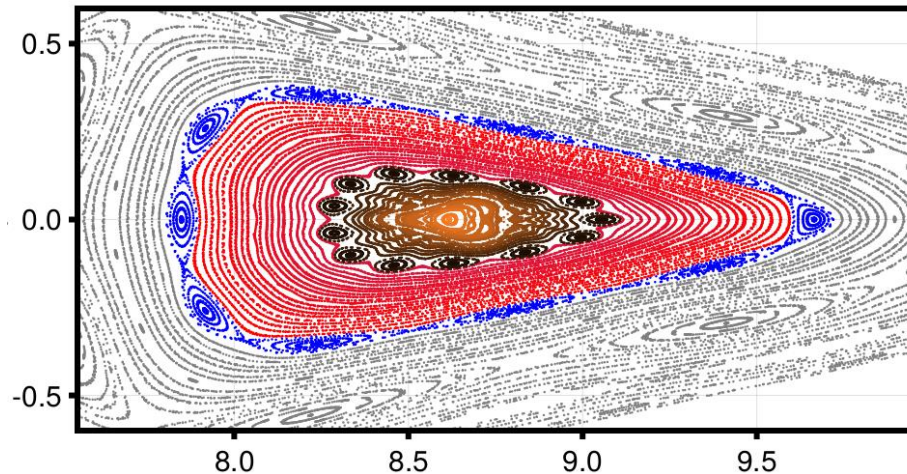
# Approximate Invariance

- Let  $\Omega \subset X$ . We consider  $h$  *approximately invariant* on  $\Omega$  if

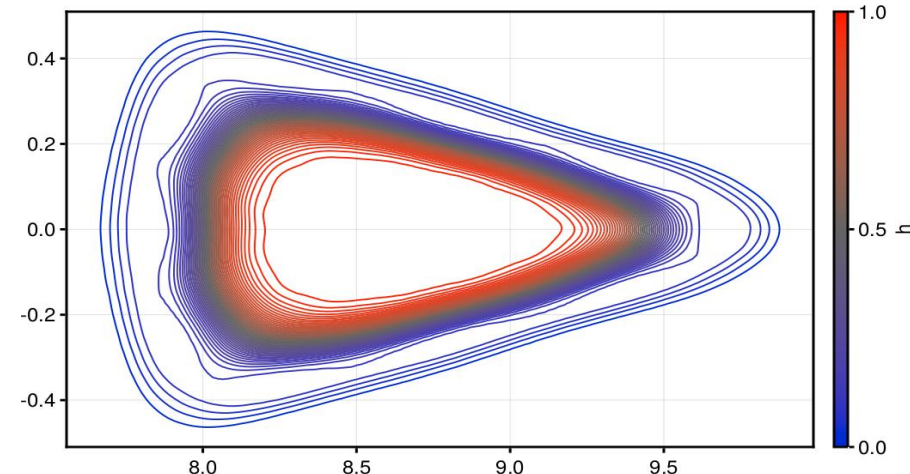
$$E_{Inv} = \|h - h \circ F\|_{L^2(\Omega)}^2 \ll \|\nabla h\|_{L^2(\Omega)}^2$$

- The norm on the right ignores the constant function
- **Our goal is to find an approximately invariant function**

Poincare Plot



Label Function





# Outline

1. Background / Motivation
2. Approximately Invariant Functions (as defined by me)
- 3. Method**
4. Results
5. Conclusion

# Kernel Approximation

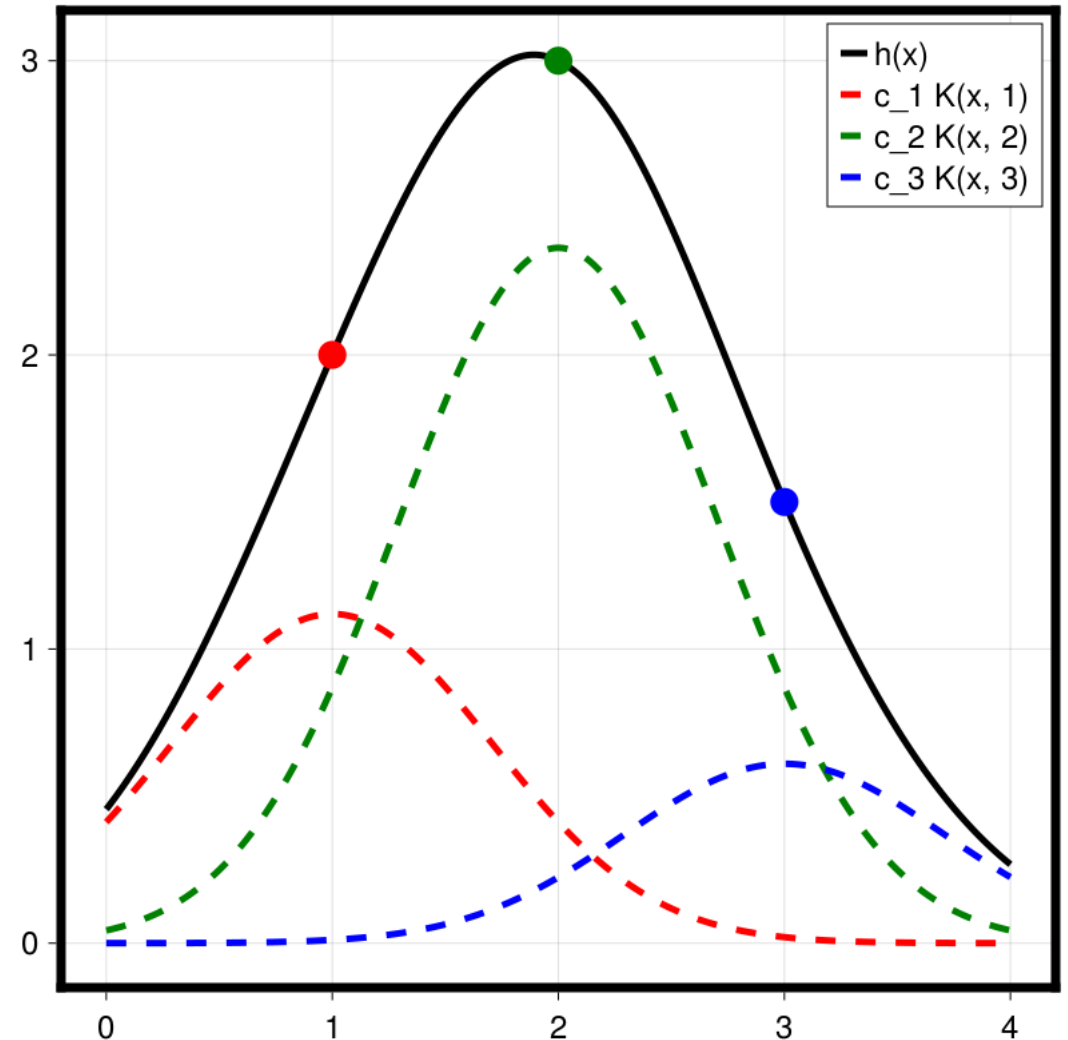
- A kernel is any function  $K : X \times X \rightarrow \mathbb{R}$
- E.g.

$$K(r, r') = e^{-\frac{\|r-r'\|^2}{2\sigma^2}} \text{ on } \mathbb{R}^2$$

- We represent  $h$  by kernels as

$$h(x) = \sum_j c_j K(x, x_j)$$

- where the  $x_j$  are our knots
- Kernels are good for arbitrary domains
- Positive definite kernels define Reproducing Kernel Hilbert Spaces
  - Useful for e.g. interpolation problems



# Method

1. Discretization
2. Regularization
3. Boundary conditions
4. The problem

$$h(z_m) = \sum_{n=1}^{2N} c_n K(z_m, z_n)$$

or

$$\mathbf{h} = \mathbf{K}\mathbf{c}$$

$$G_{Inv} = \begin{pmatrix} -1 & 1 & & & \\ & -1 & 1 & & \\ & & & \ddots & \ddots \\ & & & & \ddots & \ddots \end{pmatrix}$$

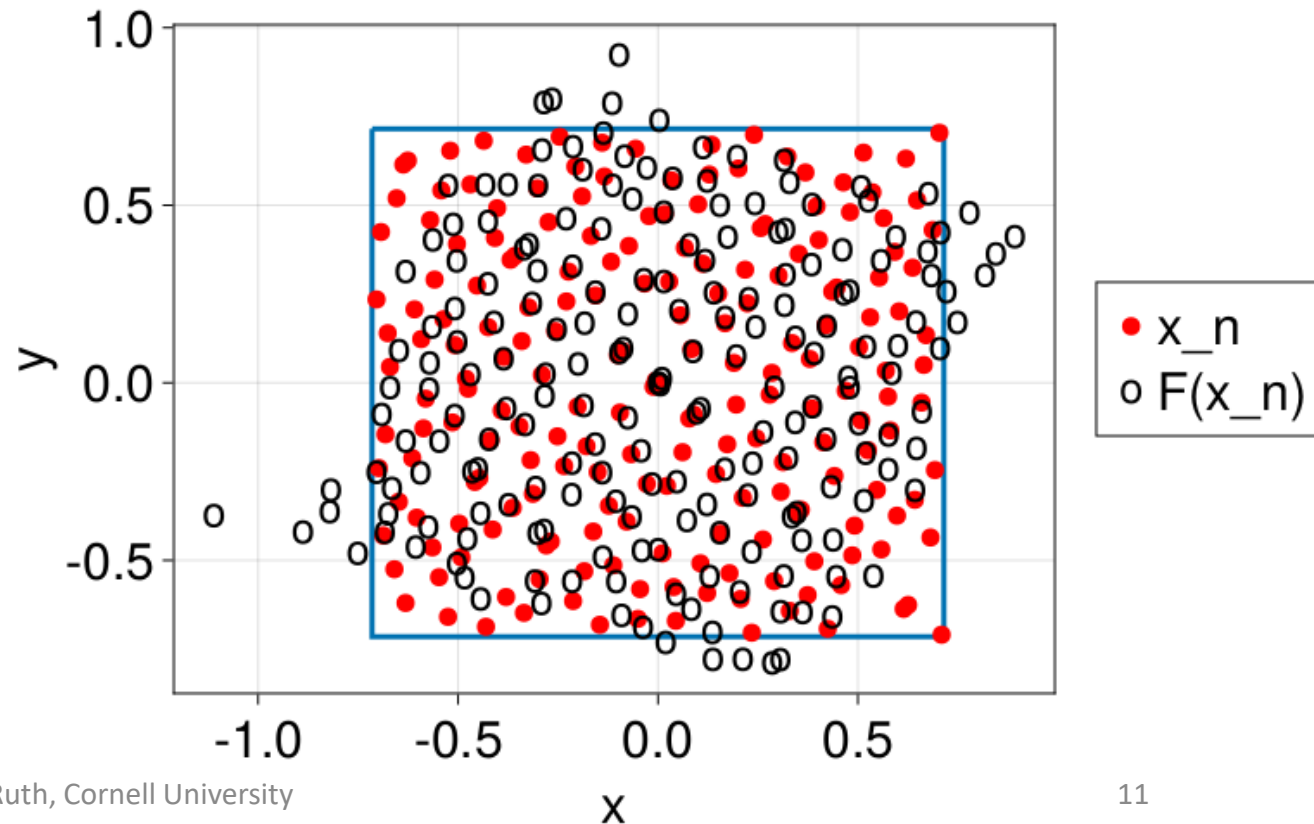
## Steps:

1. Sample  $N$  points  $x_n$  in domain  $\Omega$
2. Evaluate  $y_n = F(x_n)$  for each point
3. Concatenate  $\{z_n\} = \{x_1, y_1, x_2, y_2, \dots\}$

## Invariance

- Approximate invariance becomes

$$E_{Inv} = \sum_{n=1}^N |h(z_{2n}) - h(z_{2n-1})|^2$$
$$= \mathbf{h}^T G_{Inv}^T G_{Inv} \mathbf{h}$$



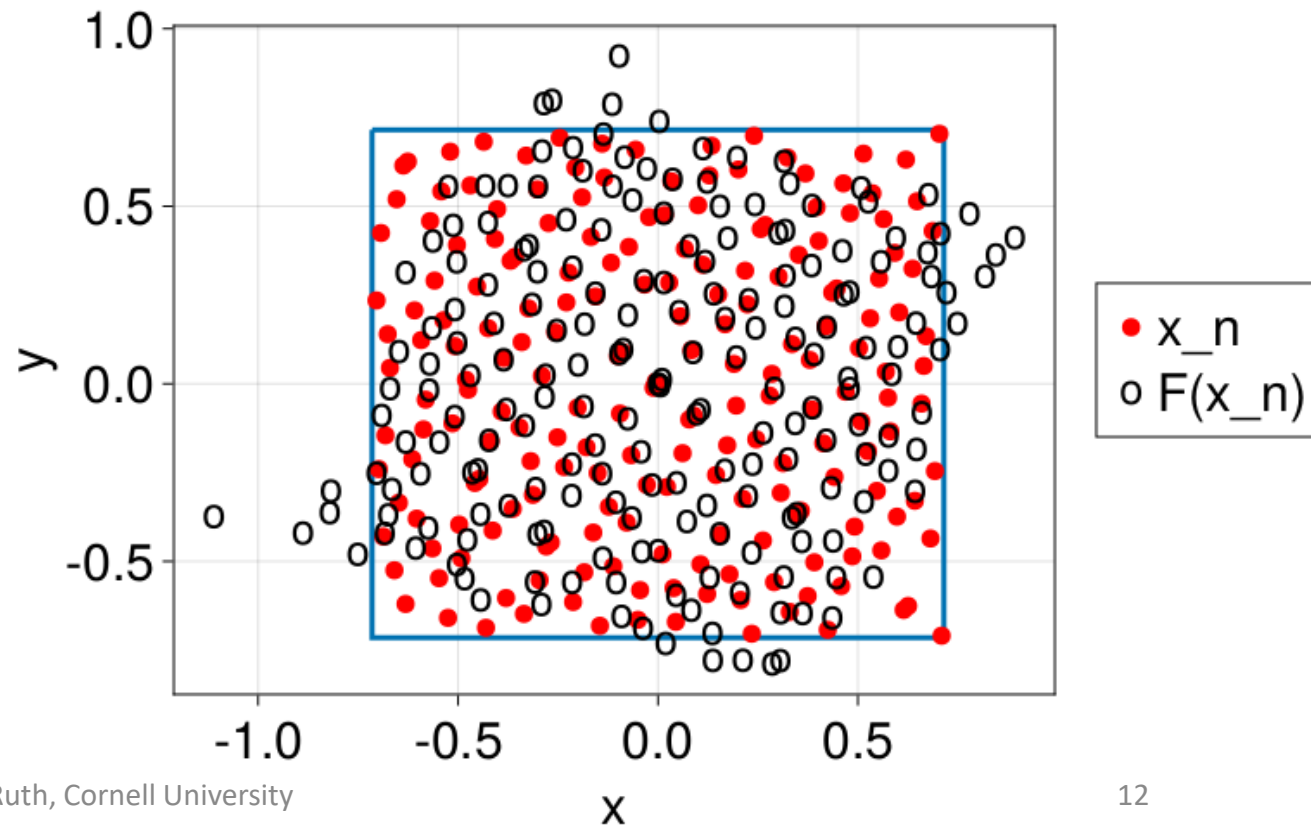
# Method

1. Discretization
2. **Regularization**
3. Boundary conditions
4. The problem

**Invariant:**  $E_{Inv} = \frac{1}{N} \sum_{n=1}^N |h(z_{2n}) - h(z_{2n-1})|^2 = \frac{1}{N} \mathbf{h}^T G_{Inv}^T G_{Inv} \mathbf{h}$

$$h(z_m) = \sum_{n=1}^{2N} c_n K(z_m, z_n)$$
$$\mathbf{h} = K \mathbf{c}$$

- Counting equations:
  - $h$  parameterized by  $2N$  elements  $\mathbf{c}$
  - Invariance condition energy rank  $N$
- $N$  invariant functions; regularize for smoothness
- For this, use reproducing kernel Hilbert space norm
$$E_K = \mathbf{h}^T K^{-1} \mathbf{h} = \mathbf{c}^T K \mathbf{c}$$
- RKHS norms are *smoothing*



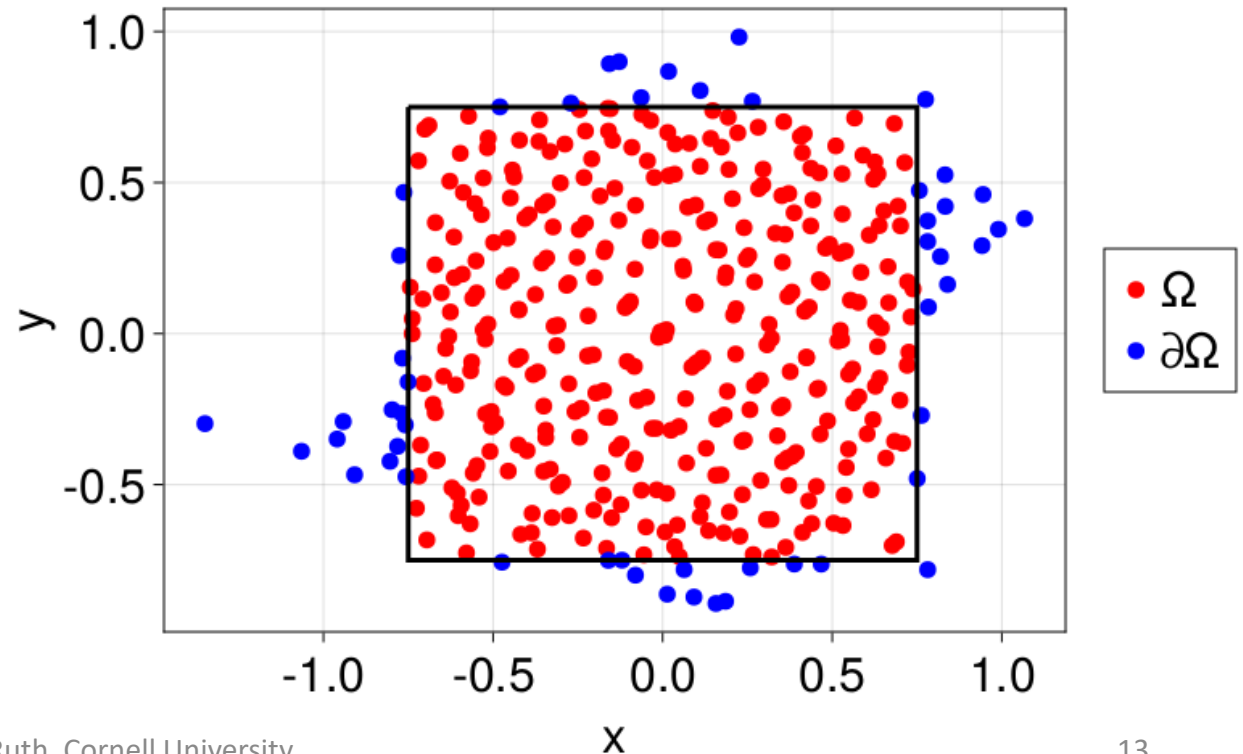
# Method

1. Discretization
2. Regularization
3. **Boundary conditions**
4. The problem

**Invariant:**  $E_{Inv} = \frac{1}{N} \sum_{n=1}^N |h(z_{2n}) - h(z_{2n-1})|^2 = \frac{1}{N} \mathbf{h}^T G_{Inv}^T G_{Inv} \mathbf{h}$   
**Smooth:**  $E_K = \mathbf{h}^T K^{-1} \mathbf{h}$

- Finally, we use boundary conditions to
  1. Remove constant functions
  2. Handle non-invariant  $\Omega$
  3. Introduce “knowledge”
- Define boundary value  $h_{bd} : X \rightarrow \mathbb{R}$  and weight  $w_{bd} : X \rightarrow [0,1]$

$$E_{bd} = \sum_{n=1}^{2N} w_{bd}(z_n) |h(z_n) - h_{bd}(z_n)|^2$$



# Method

1. Discretization
2. Regularization
3. Boundary conditions
4. **The problem**

**Invariant:**  $E_{Inv} = \frac{1}{N} \sum_{n=1}^N |h(z_{2n}) - h(z_{2n-1})|^2 = \frac{1}{N} \mathbf{h}^T G_{Inv}^T G_{Inv} \mathbf{h}$

**Smooth:**  $E_K = \mathbf{h}^T K^{-1} \mathbf{h}$

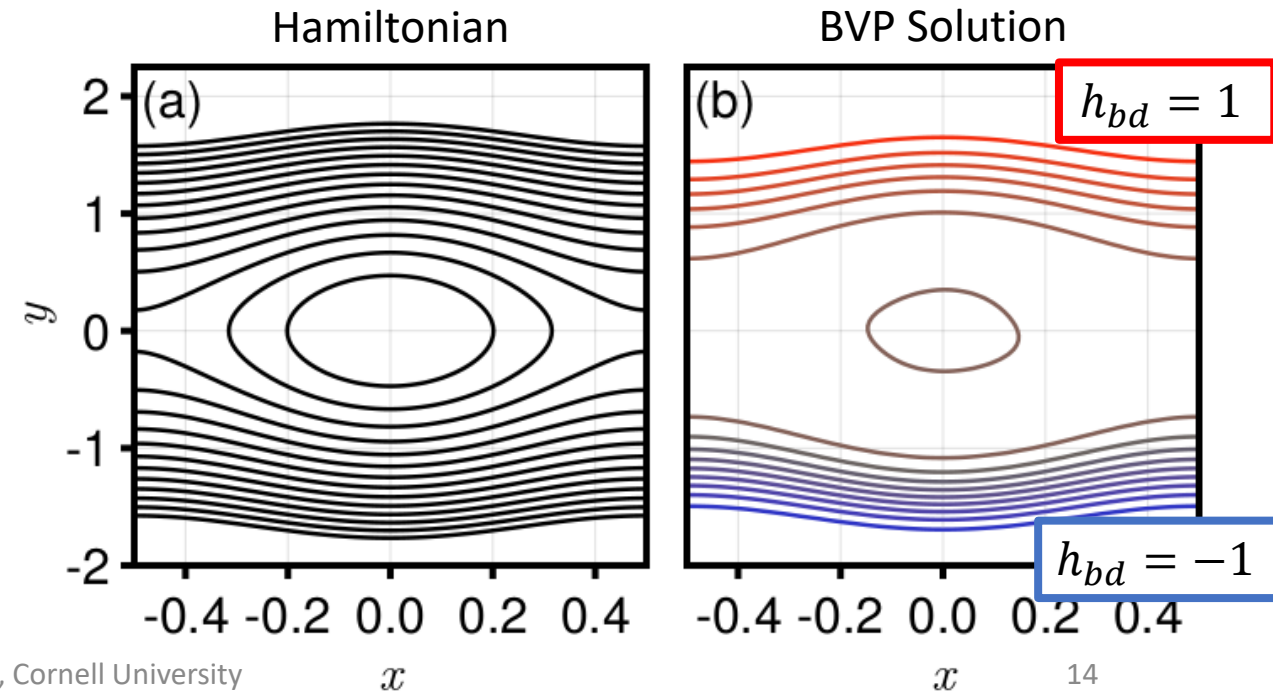
**Boundary:**  $E_{bd} = \sum_{n=1}^{2N} w_{bd}(z_n) |h(z_n) - h_{bd}(z_n)|^2 = (\mathbf{h} - \mathbf{h}_{bd})^T W_{bd} (\mathbf{h} - \mathbf{h}_{bd})$

**Example:** Nonlinear pendulum  $\dot{x} = y, \dot{y} = -\sin(2\pi x)$   
Trajectories evolved for time  $T = \sqrt{2}$   
 $N = 100, \epsilon = 10^{-6}$ , Gaussian kernel w/ width  $\sigma = 0.5$

## Problem 1: Least Squares BVP

- Good for transport from one barrier to another

$$R = \min_{\mathbf{c} \in \mathbb{R}^{2N}} E_{Inv} + E_{bd} + \epsilon E_K$$



# Method

1. Discretization
2. Regularization
3. Boundary conditions
4. **The problem**

**Invariant:**  $E_{Inv} = \frac{1}{N} \sum_{n=1}^N |h(z_{2n}) - h(z_{2n-1})|^2 = \frac{1}{N} \mathbf{h}^T G_{Inv}^T G_{Inv} \mathbf{h}$

**Smooth:**  $E_K = \mathbf{h}^T K^{-1} \mathbf{h}$

**Boundary:**  $E_{bd} = \sum_{n=1}^{2N} w_{bd}(z_n) |h(z_n) - h_{bd}(z_n)|^2 = (\mathbf{h} - \mathbf{h}_{bd})^T W_{bd} (\mathbf{h} - \mathbf{h}_{bd})$

**Example:** Nonlinear pendulum  $\dot{x} = y, \dot{y} = -\sin(2\pi x)$   
Trajectories evolved for time  $T = \sqrt{2}$   
 $N = 100, \epsilon = 10^{-6}$ , Gaussian kernel w/ width  $\sigma = 0.5$

## Problem 1: Least Squares BVP

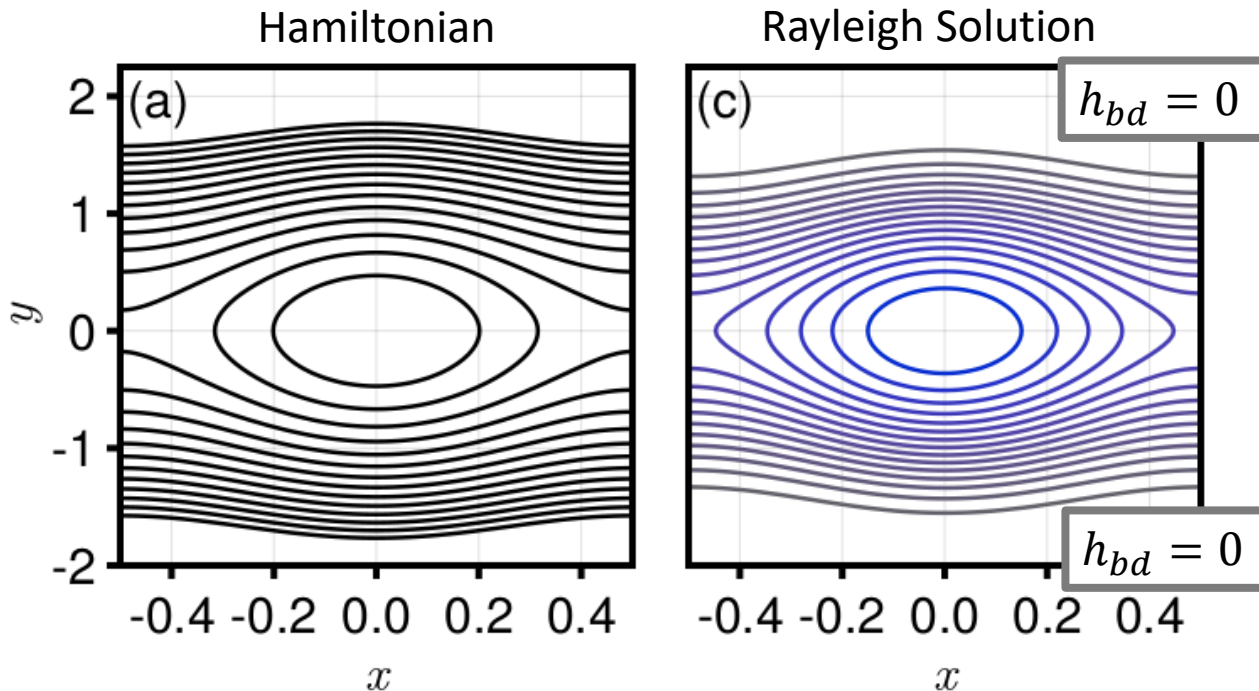
- Good for transport from one barrier to another

$$R = \min_{\mathbf{c} \in \mathbb{R}^{2N}} E_{Inv} + E_{bd} + \epsilon E_K$$

## Problem 2: Rayleigh Quotient

- Good when only the stellarator region is known

$$\lambda = \min_{\mathbf{c} \in \mathbb{R}^{2N}} \frac{E_{Inv} + E_{bd} + \epsilon E_K}{\|\mathbf{h}\|^2}, \quad h_{bd} = 0$$



# Outline

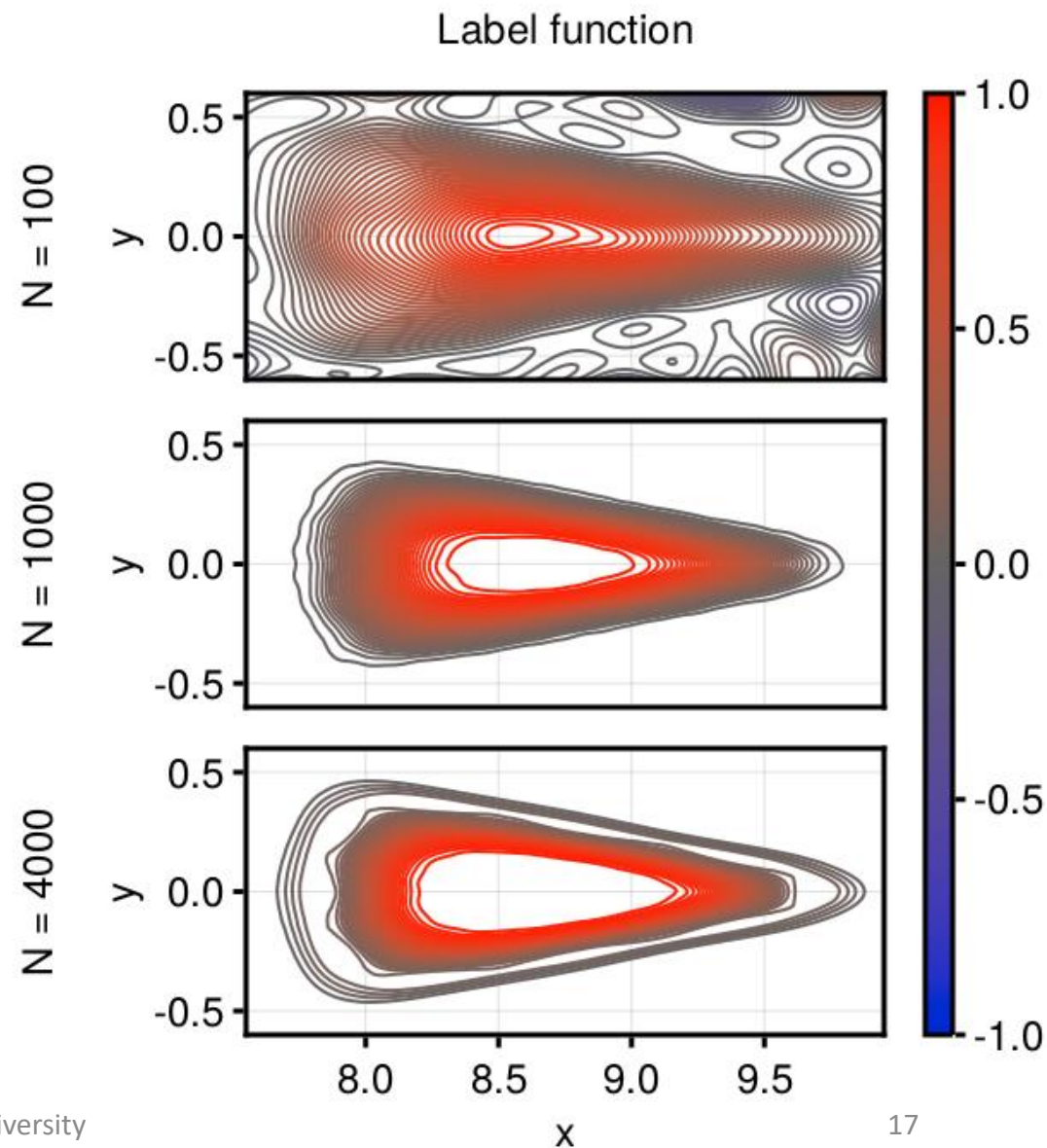
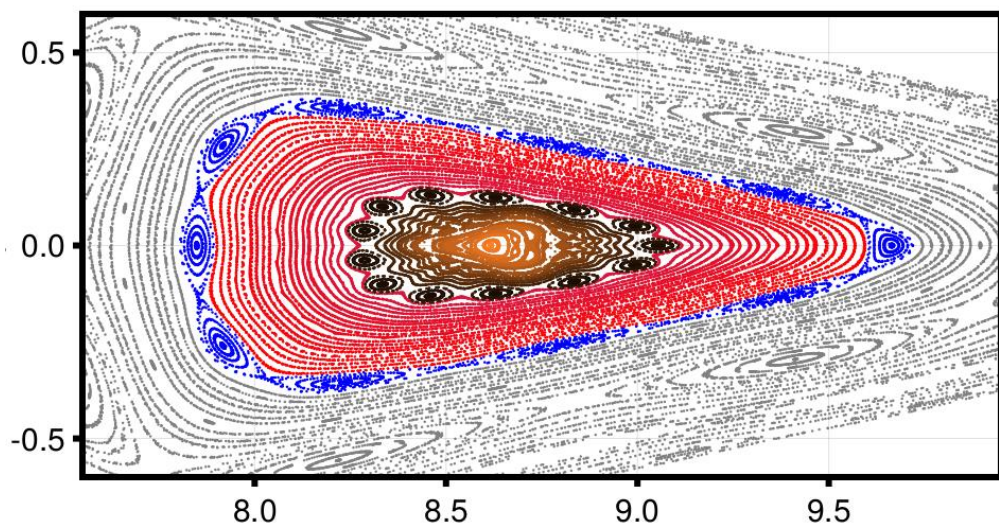
1. Background / Motivation
2. Approximately Invariant Functions (as defined by me)
3. Method
- 4. Results**
5. Conclusion



# Example: Stellarator

## Example:

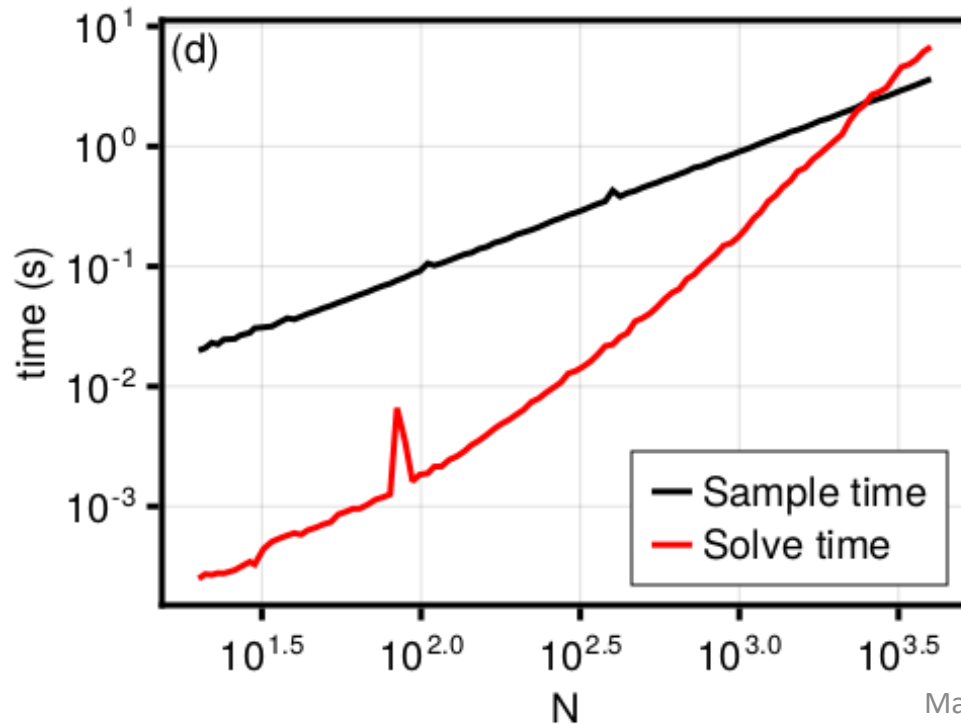
- Stellarator with islands return map
- Eigenvalue problem
- Vary  $N$  from 100 to 4000
- $\epsilon = 10^{-8}$
- Gaussian kernel w/ width  $\sigma = 2.43/\sqrt{N}$



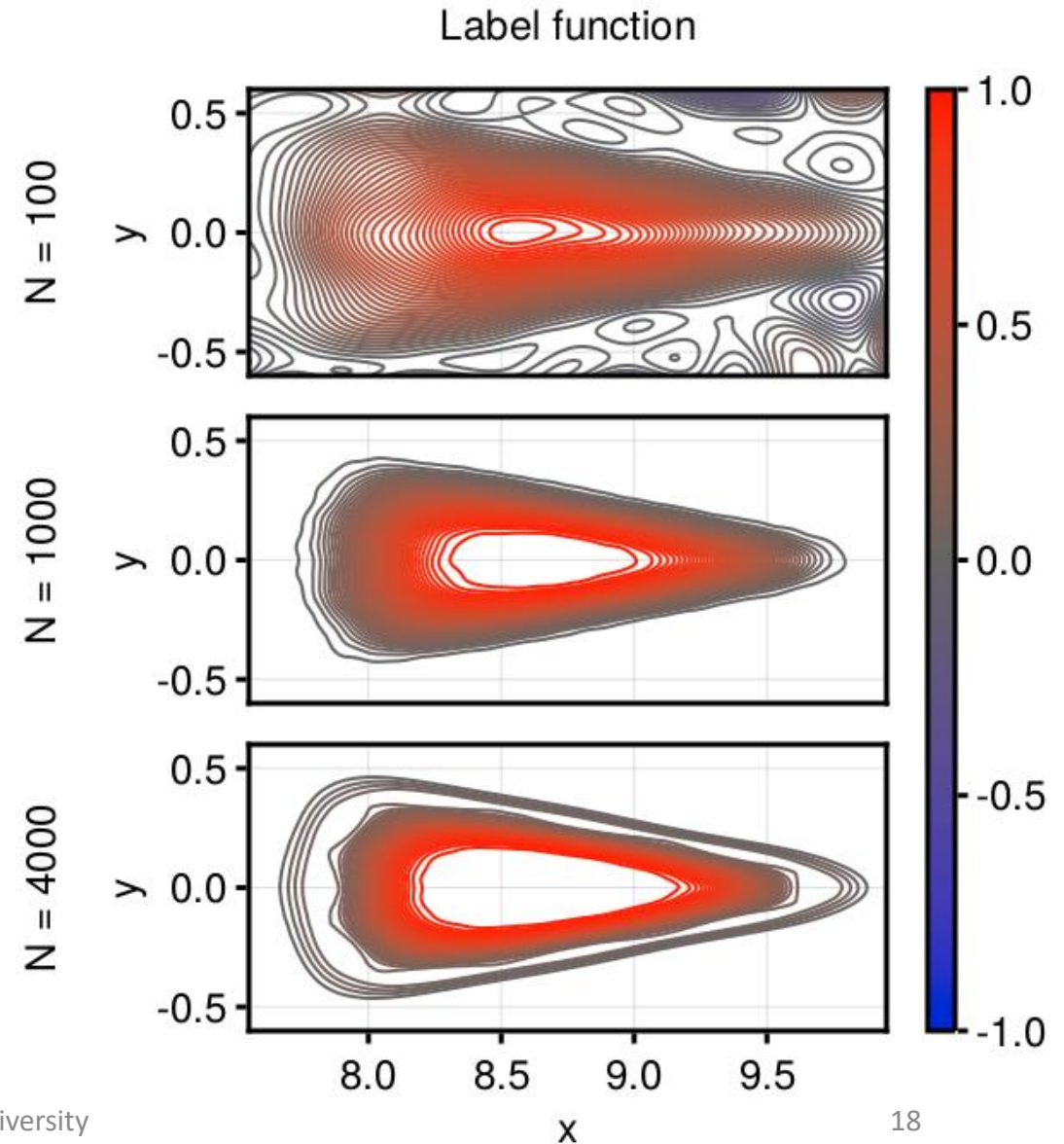
# Single-Core Timing

## Example:

- Stellarator with islands return map
- Trajectory solve time scales linearly
- Eigenvalue problem scales cubically
- $N = 1000 \sim 1$  sec
- $N = 4000 \sim 15$  sec



Maximilian Ruth, Cornell University



# Example: Standard Map

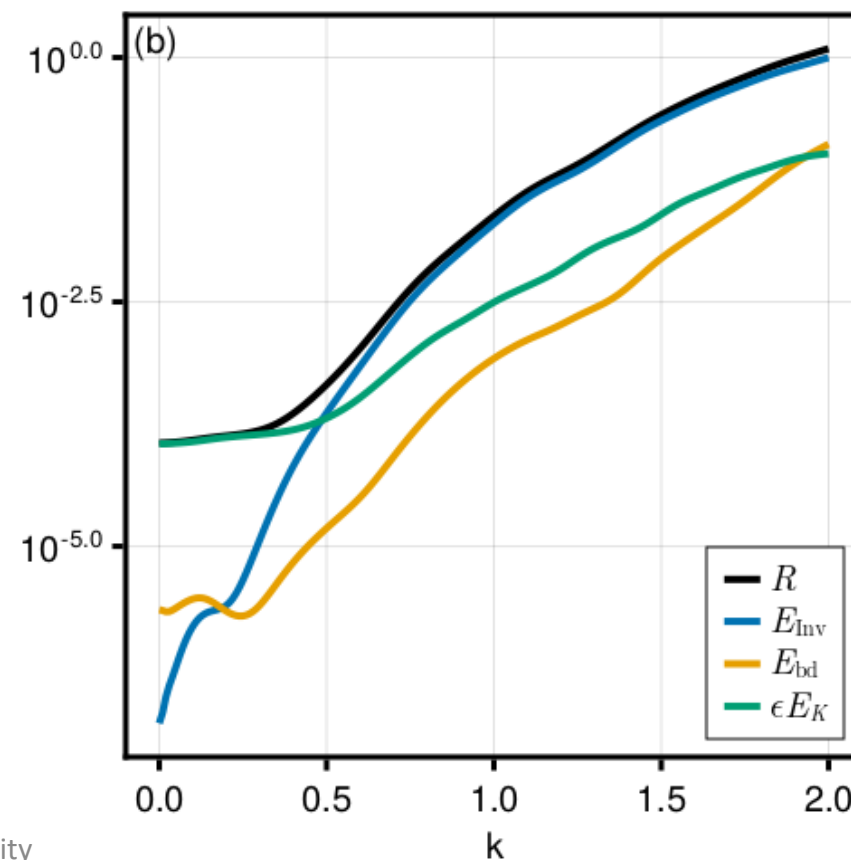
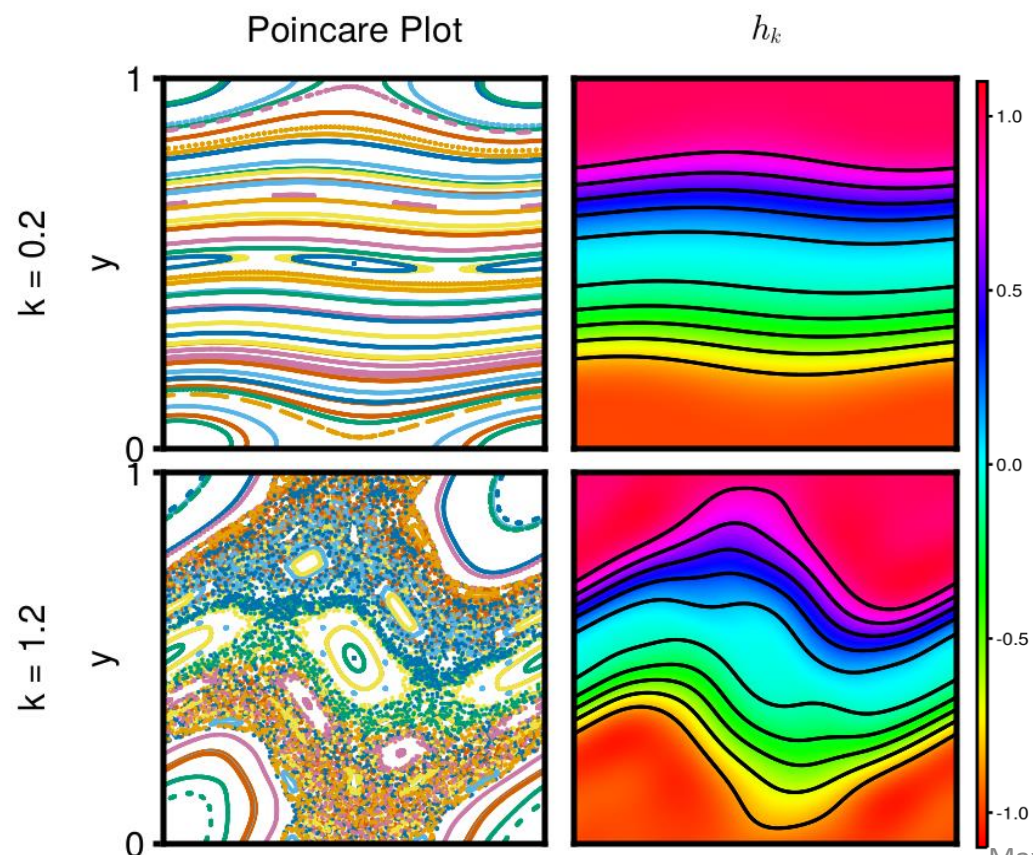
## Example:

- Chirikov standard map

$$x' = x + y', \quad y' = y - \frac{k}{2\pi} \cos(2\pi x)$$

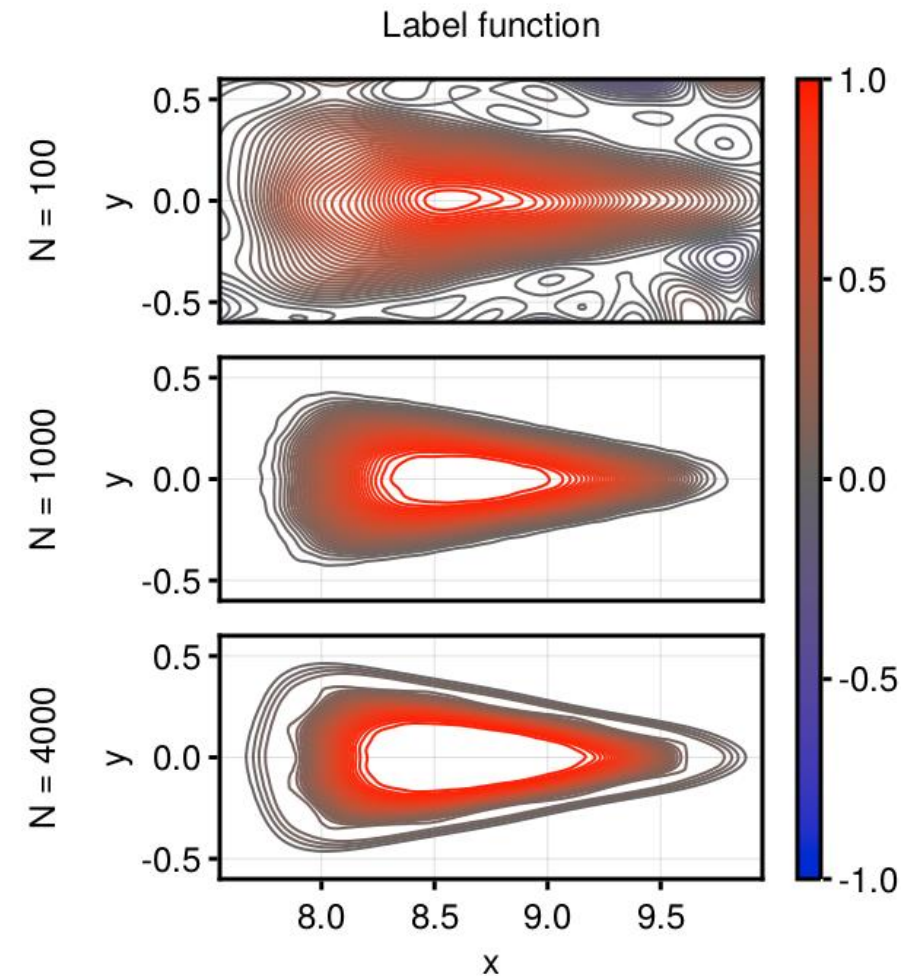
- $k$  controls the size of perturbation

- Boundary value problem,  $\epsilon = 10^{-5}$ ,  $N = 1000$
- Squared sine exponential kernel,  $\sigma = 0.2$
- Vary  $k$  from 0 to 2.0



# Conclusion

- We provide two mesh-free methods for finding approximately invariant functions
- Level sets of functions approximately give invariant tori
- Residual gives level of belief in the function (a measure of integrability)
- The measure is cheap to evaluate and smooth in the level of chaos
- Kernel width and regularization allow for tuning



M. Ruth and D. Bindel, arXiv:2312.00967 (2023)

Code at <https://github.com/maxeruth/SymplecticMapTools.jl>, or **jadd SymplecticMapTools** in Julia