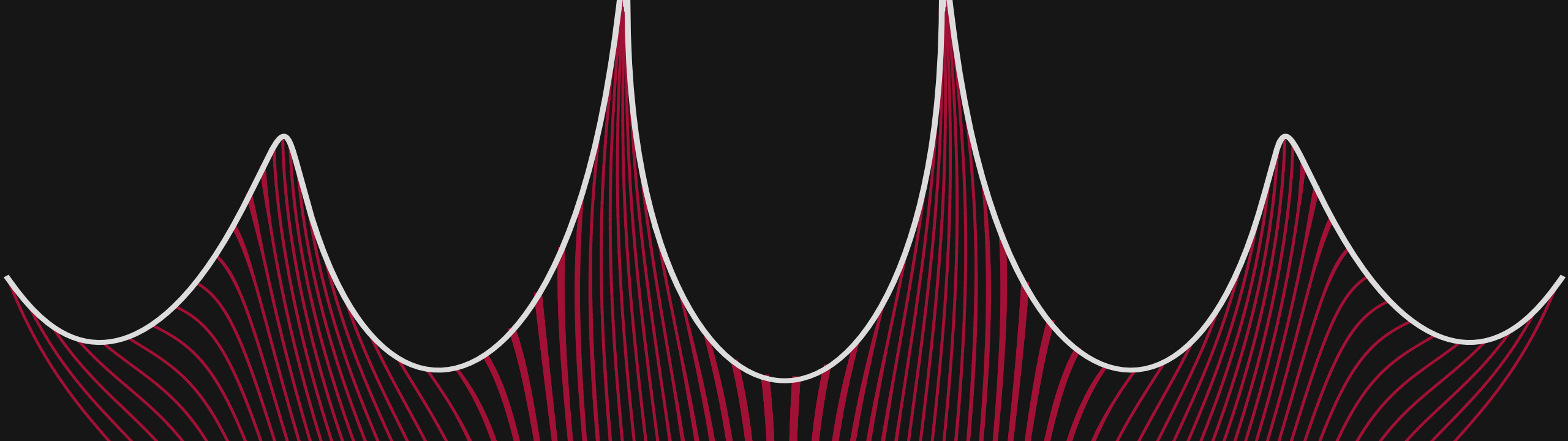




# USING MACHINE LEARNING TO ALLEVIATE THE SIGN PROBLEM IN THE HUBBARD MODEL

ECT\* WORKSHOP *MACHINE LEARNING FOR HIGH ENERGY PHYSICS, ON AND OFF THE LATTICE*, 09.30.2021

THOMAS LUU, IKP-3/IAS-4, FZJ/ HISKP, UNIVERSITÄT BONN

# MY PARTNERS IN CRIME . . .



Jan-Lukas Wynen



Marcel Rodekamp



Christoph Gántgen



Evan Berkowitz

Shout outs also go to:

Chelsea John, Stefan Krieg, Timo Lähde, Johann Ostmeyer, Estela Suarez, Carsten Urbach

# IF ONLY THERE WASN'T ANY SIGN PROBLEM...

- Path-integral formalism

$$\begin{aligned}\langle \hat{O} \rangle &= \frac{1}{Z} \int_{\phi \in \mathbb{R}^N} \mathcal{D}[\phi] e^{-S[\phi]} O[\phi] \\ &= \int_{\phi \in \mathbb{R}^N} \mathcal{D}[\phi] \mathbb{P}[\phi] O[\phi]\end{aligned}$$

“Probability density”

Note: If  $S[\phi] = S_R[\phi] + iS_I[\phi]$  then  $\mathbb{P}[\phi] \mathcal{D}[\phi] \notin [0, \infty)$

Question: How do we interpret such “Probabilities”?

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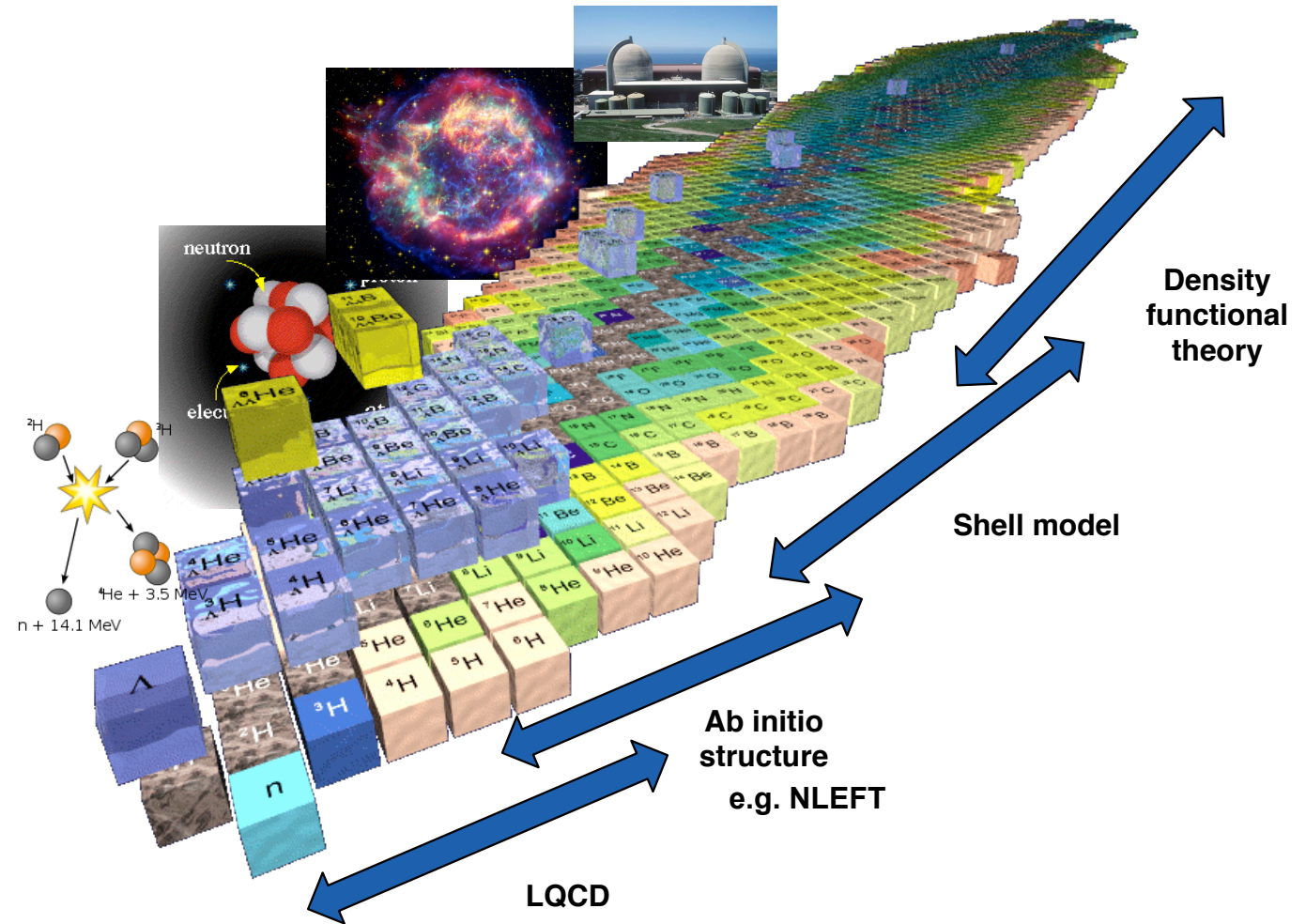
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“Complex Phase sign problem”

# WHEN DOES THE SIGN PROBLEM SHOW UP?

- Life in Minkowski space
- Finite density field theory
  - What are the phases of quark matter at high density?
  - Baryon chemical potential
- Complex term in Lagrangian (even after Wick rotation)
  - QCD theta term
- . . . and others . . .

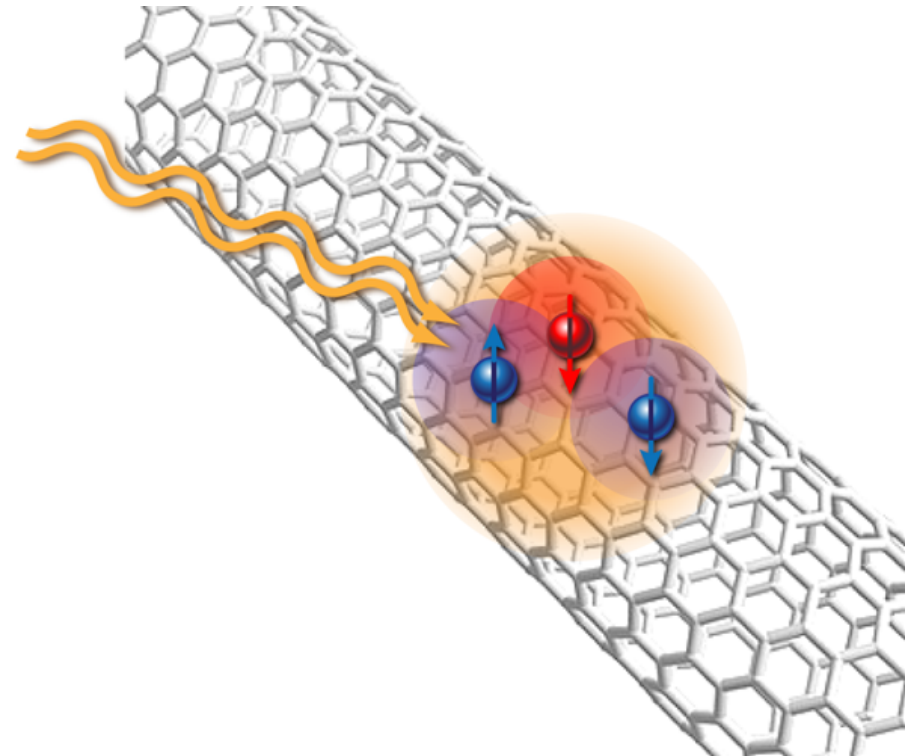


Sign problem shows up in the *most interesting problems in particle & nuclear physics!!*

# BUT THE SIGN PROBLEM IS NOT UNIQUE TO PARTICLE PHYSICS...

Condensed matter/solid state communities also share our pain. . .

- High density strongly correlated electrons
- Doped systems
  - Electron chemical potential
- Non-bipartite systems (geometry)



# PATH INTEGRAL FOR THE HUBBARD MODEL

## Introducing the Hamiltonian

$$H = - \sum_{x,y} \left( a_x^\dagger \kappa_{xy} a_y + b_x^\dagger \kappa_{xy} b_y \right) + \frac{U}{2} \sum_x (n_x - \tilde{n}_x)^2 - \mu \sum_x (n_x - \tilde{n}_x)$$

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$$Z = \text{Tr} e^{-\beta H}$$

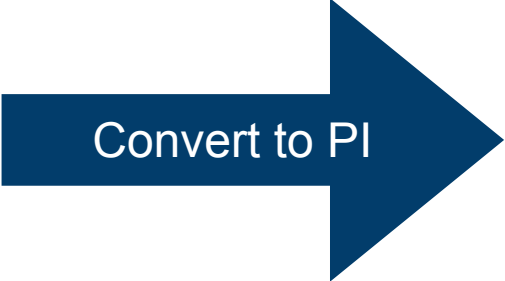
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$$\int \mathcal{D}[\phi] \det(M[\phi, \kappa, \mu] M[-\phi, -\kappa, -\mu]) e^{-\frac{1}{2U\delta} \sum_{x,t} \phi_{xt}^2}$$

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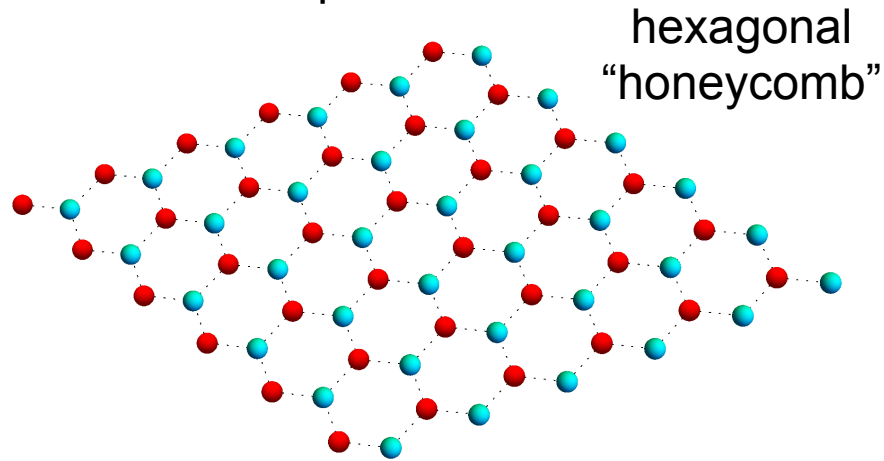
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$$\int \mathcal{D}[\phi] \underbrace{\det(M[\phi, \kappa, \mu] M[-\phi, -\kappa, -\mu]) e^{-\frac{1}{2U\delta} \sum_{x,t} \phi_{xt}^2}}_{\int \mathcal{D}[\phi] e^{-S[\phi]}}$$

# BOTH CHEMICAL POTENTIAL AND TYPE OF THE LATTICE CAN INFLUENCE THE SIGN PROBLEM

$$\mu \neq 0$$

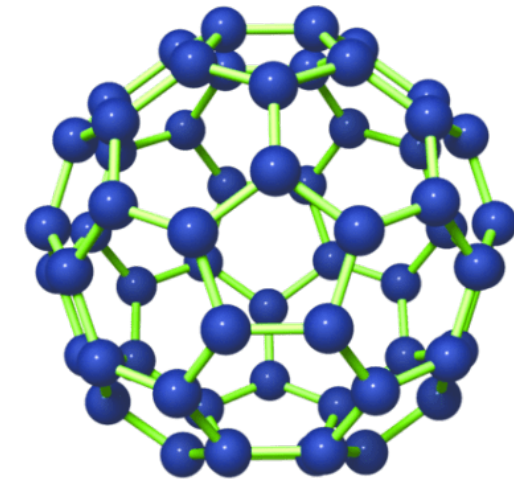
bipartite lattice



special feature of bipartite lattice:

$$M[-\phi, -\kappa, \mu = 0] = M^\dagger[\phi, \kappa, \mu = 0]$$

non-bipartite lattice



C60  
"soccer ball"

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Holomorphic flow (Lefschetz Thimbles)  
The subject of this talk. . .

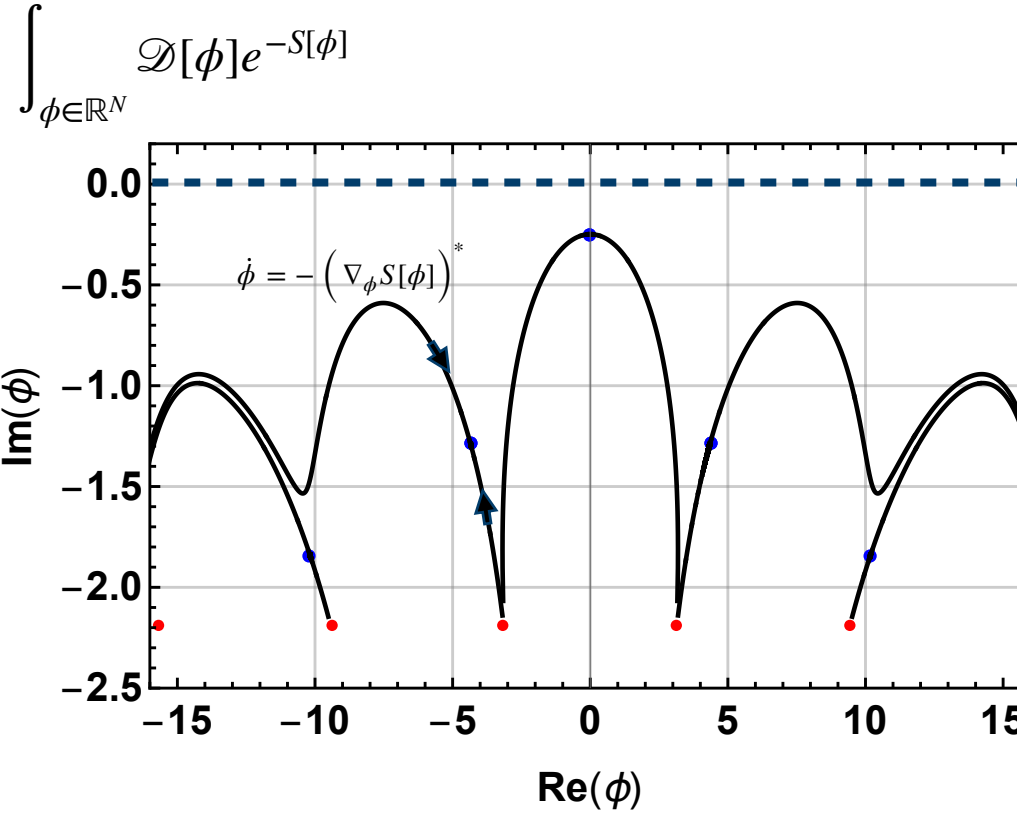
# LEFSCHETZ THIMBLE PRIMER 101

1d example:  $S(\phi) = \frac{1}{20} \left( \phi + \frac{3i}{2} \right)^2 - \log \left( 1 + \frac{1}{2} e^{i(\phi + \frac{3i}{2})} \right)$

flow equations

$$\dot{\phi} = -(\nabla_{\phi} S[\phi])^*$$

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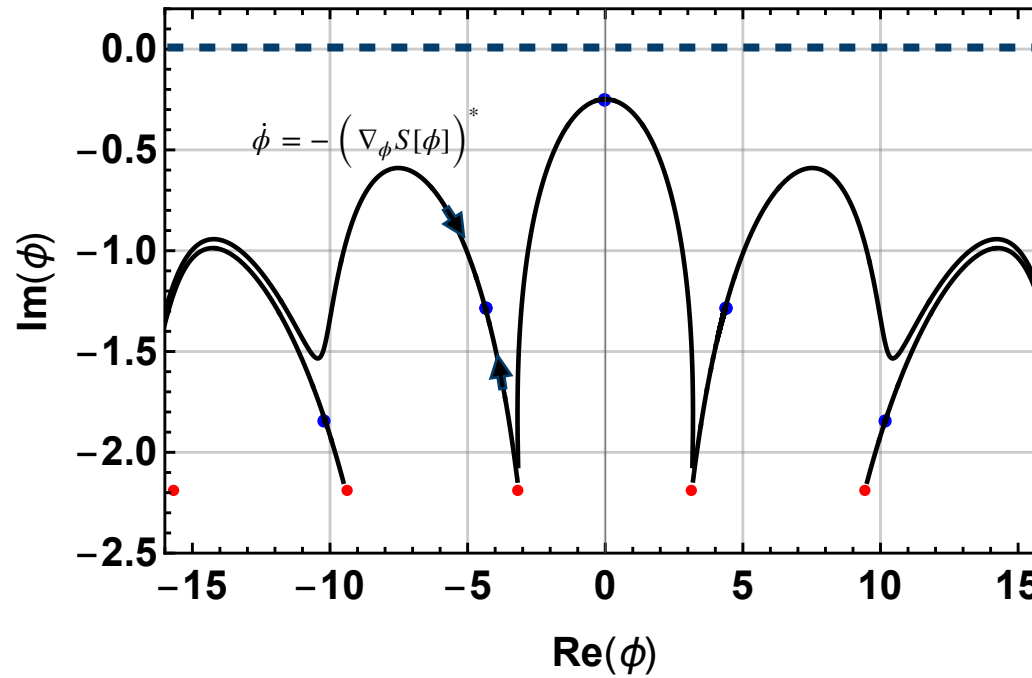
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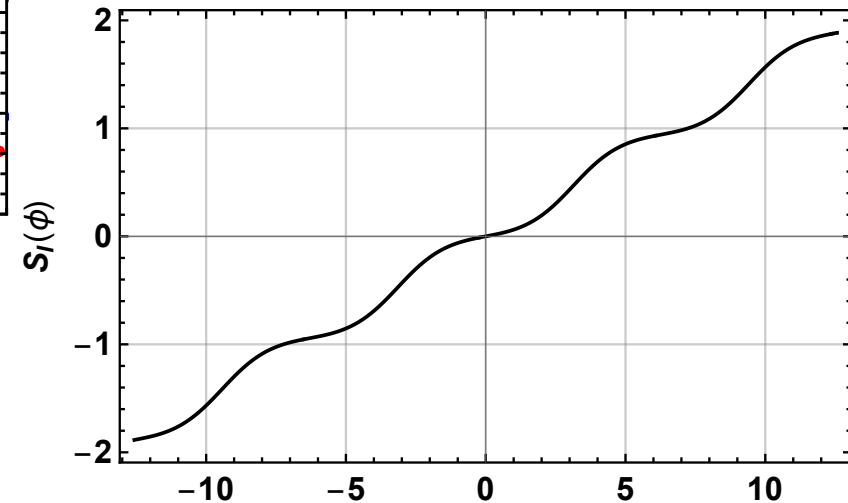
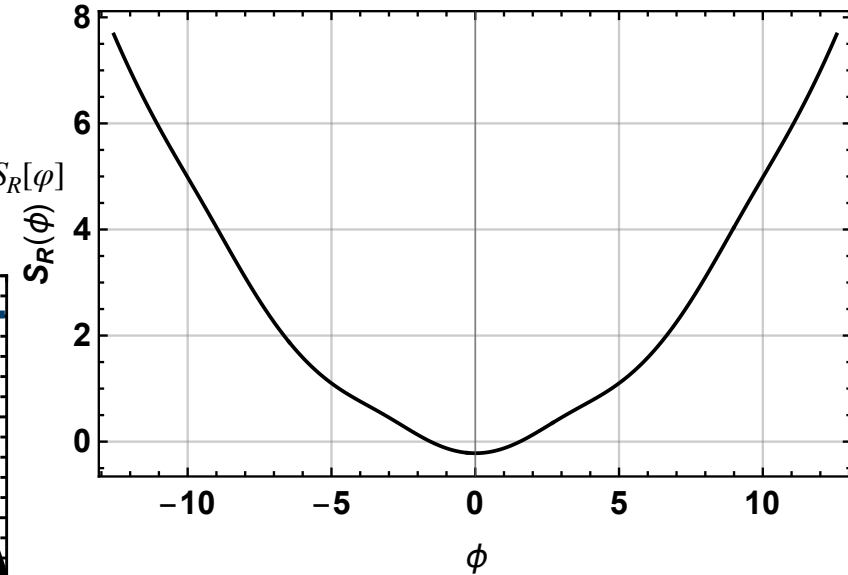
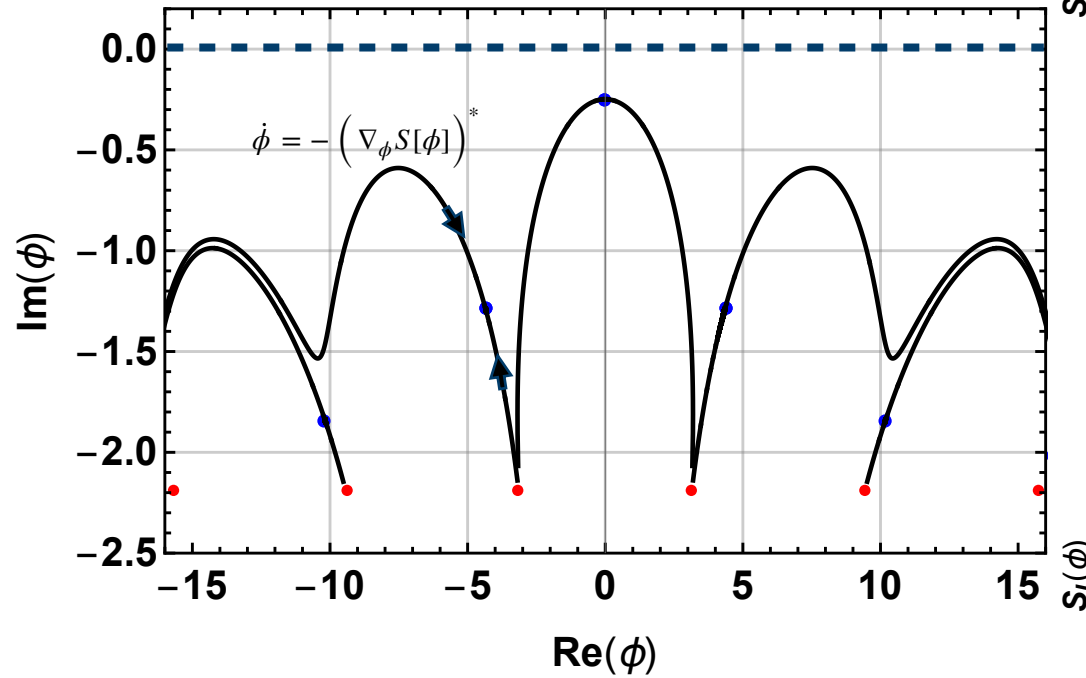
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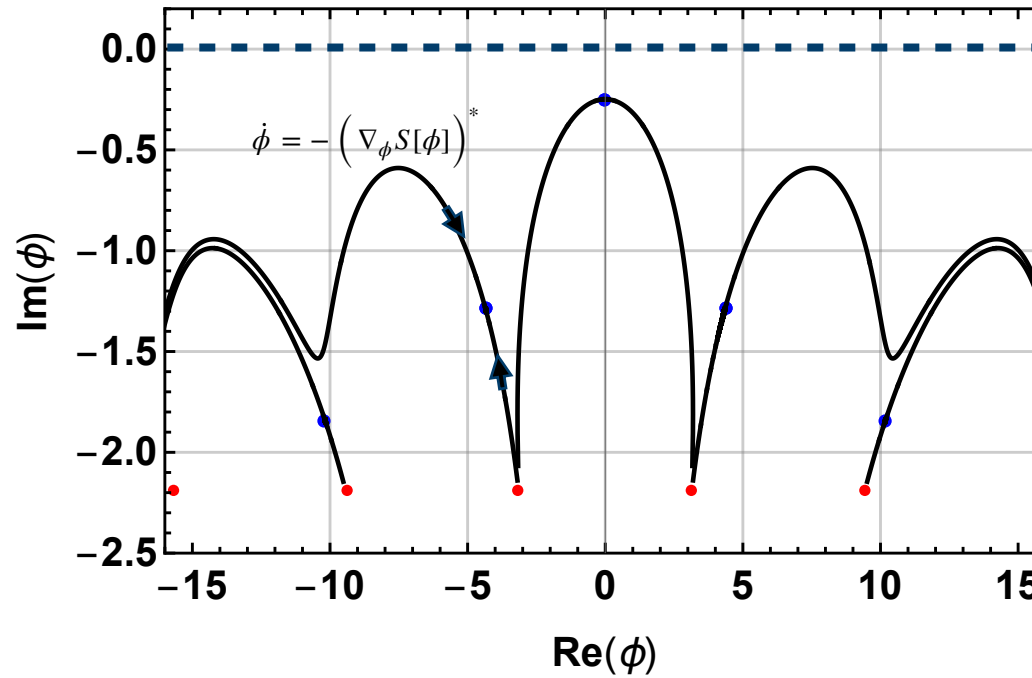
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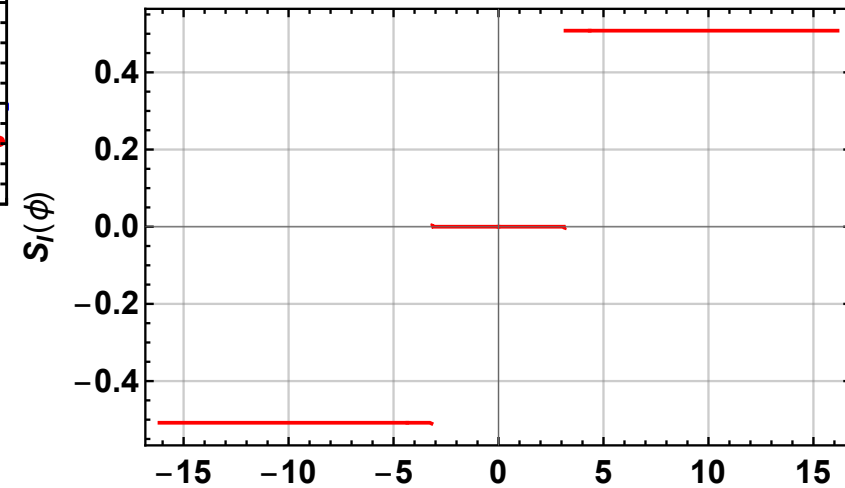
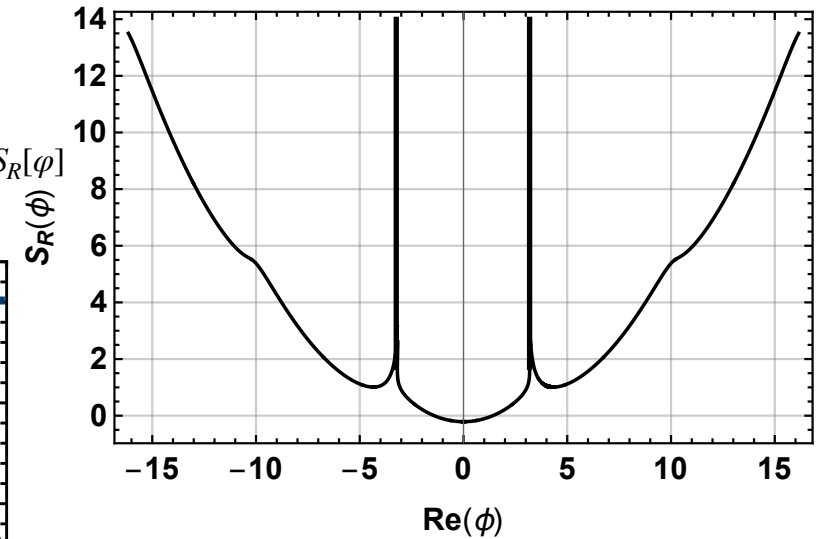
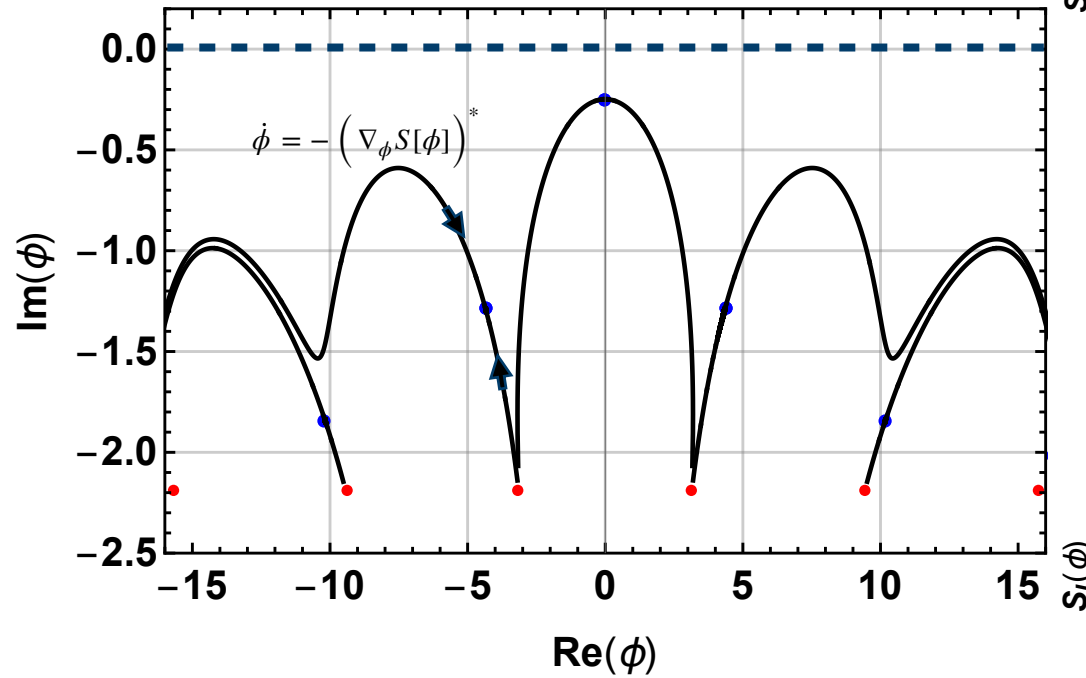
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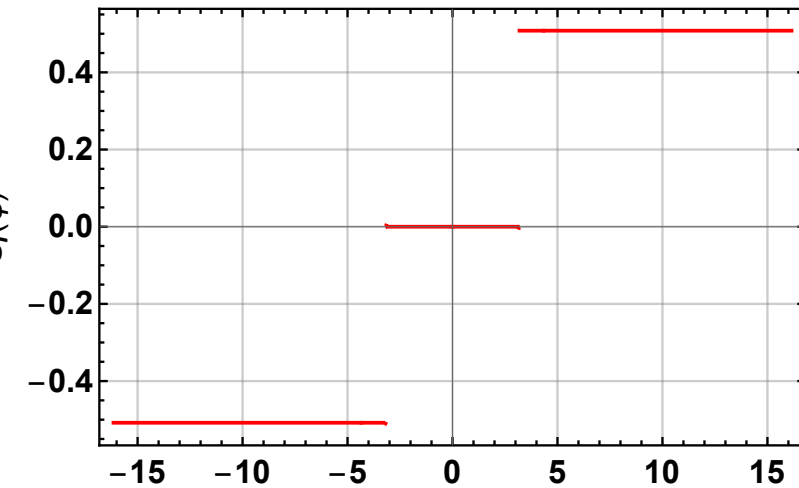
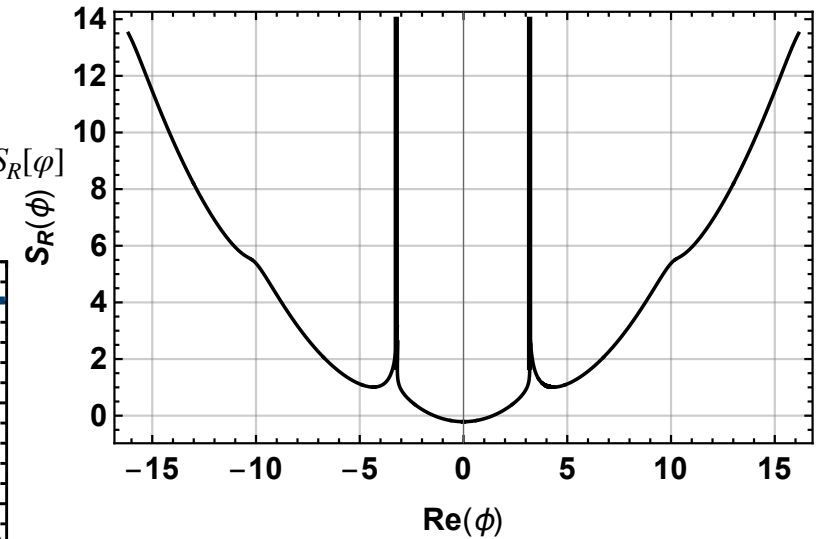
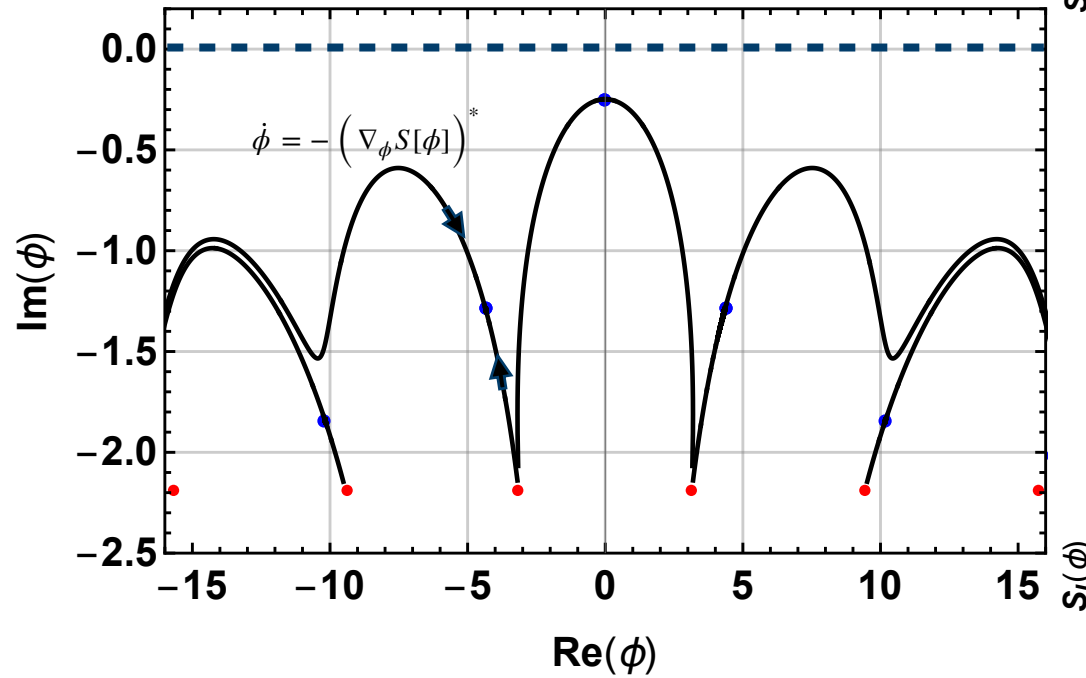
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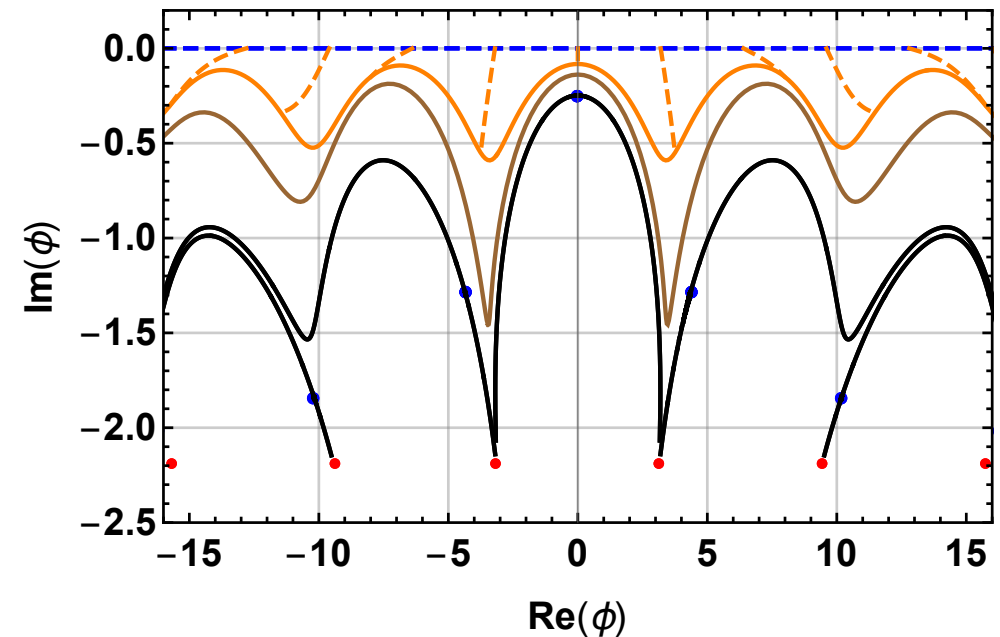
But we don't know *a priori* where these thimbles are!

# BUT WE CAN APPROXIMATE THIMBLES BY FLOWING FROM REAL PLANE

$$\dot{\phi} = (\nabla_{\phi} S[\phi])^*$$

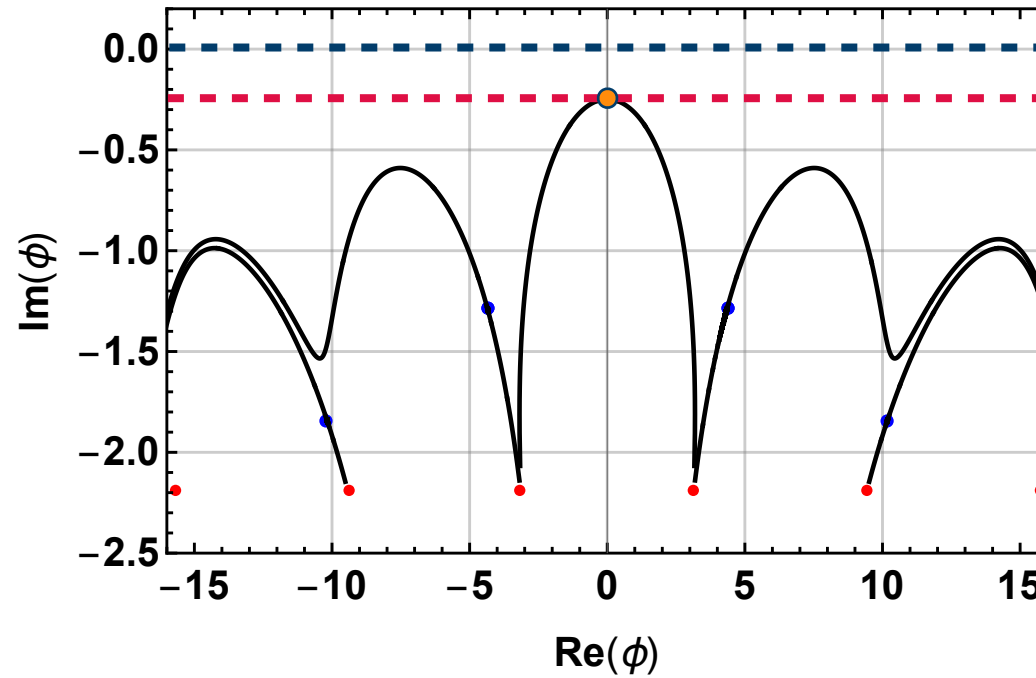
- For finite flow time, one has an approximation to the thimbles
  - Sign problem has been alleviated
  - Re-weighting should work!

“Generalized Thimble” approach



# THE SIMPLEST “FLOW”

## Constant contour deformation



“tangent plane”

# HOW DO WE SAMPLE FROM THE MANIFOLDS?

Integration on manifolds



Integration on real plane

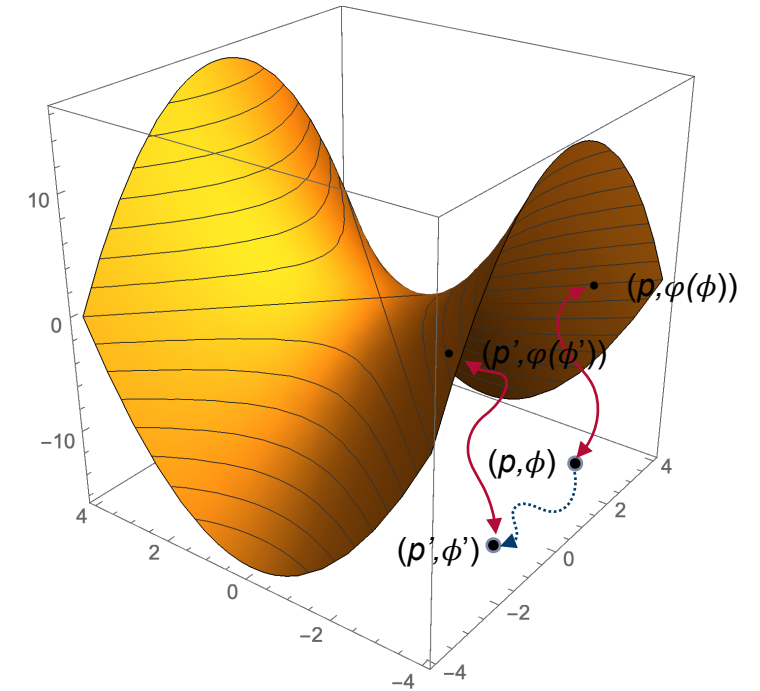
$$\begin{aligned} \frac{1}{\mathcal{Z}_{\mathcal{T}}} \int_{\mathcal{T}} D[\varphi] O[\varphi] \exp \{-S[\varphi]\} &= \frac{1}{\mathcal{Z}_{\mathcal{T}}} \int_{\mathbb{R}} D[\phi] O[\varphi(\phi)] \exp \{-S[\varphi(\phi)]\} \det J[\varphi(\phi)] \\ &= \frac{1}{\mathcal{Z}_{\mathcal{T}}} \int_{\mathbb{R}} D[\phi] O[\varphi(\phi)] \exp \{-S_{eff}[\varphi(\phi)]\} \end{aligned}$$

$$S_{eff}[\varphi(\phi)] \equiv S[\varphi(\phi)] - \log \det J[\varphi(\phi)]$$

Jacobian is induced due to the change of variables from the manifold to the real plane

# HMC WITH HOLOMORPHIC FLOW

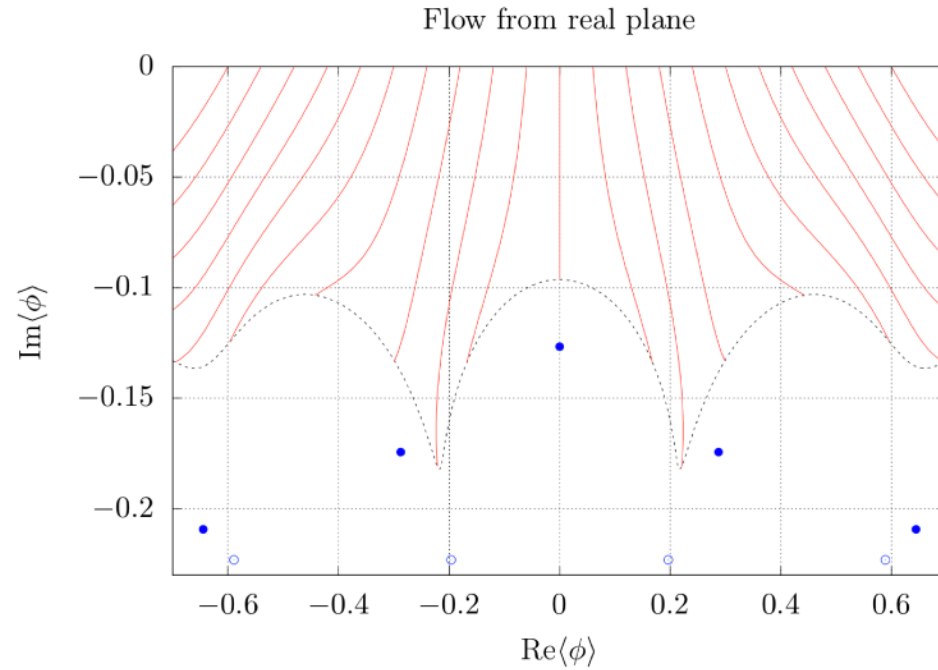
- Perform HMC on the real plane to make proposal  $(p, \phi) \rightarrow (p', \phi')$
- Then flow up (close) to manifold  $\varphi(\phi')$
- Accept/reject with  $\mathbb{P}_{a/r} = \min \left( 1, \frac{e^{-p'^2/2 - \text{Re}S_{eff}[\varphi(\phi')]} }{e^{-p^2/2 - \text{Re}S_{eff}[\varphi(\phi)]}} \right)$
- Reversible, satisfies detailed balance



HMC directly on the thimble:  
Ulybyshev et al. [[arXiv:1906.02726](https://arxiv.org/abs/1906.02726)]

# FLOWING THE ACTION

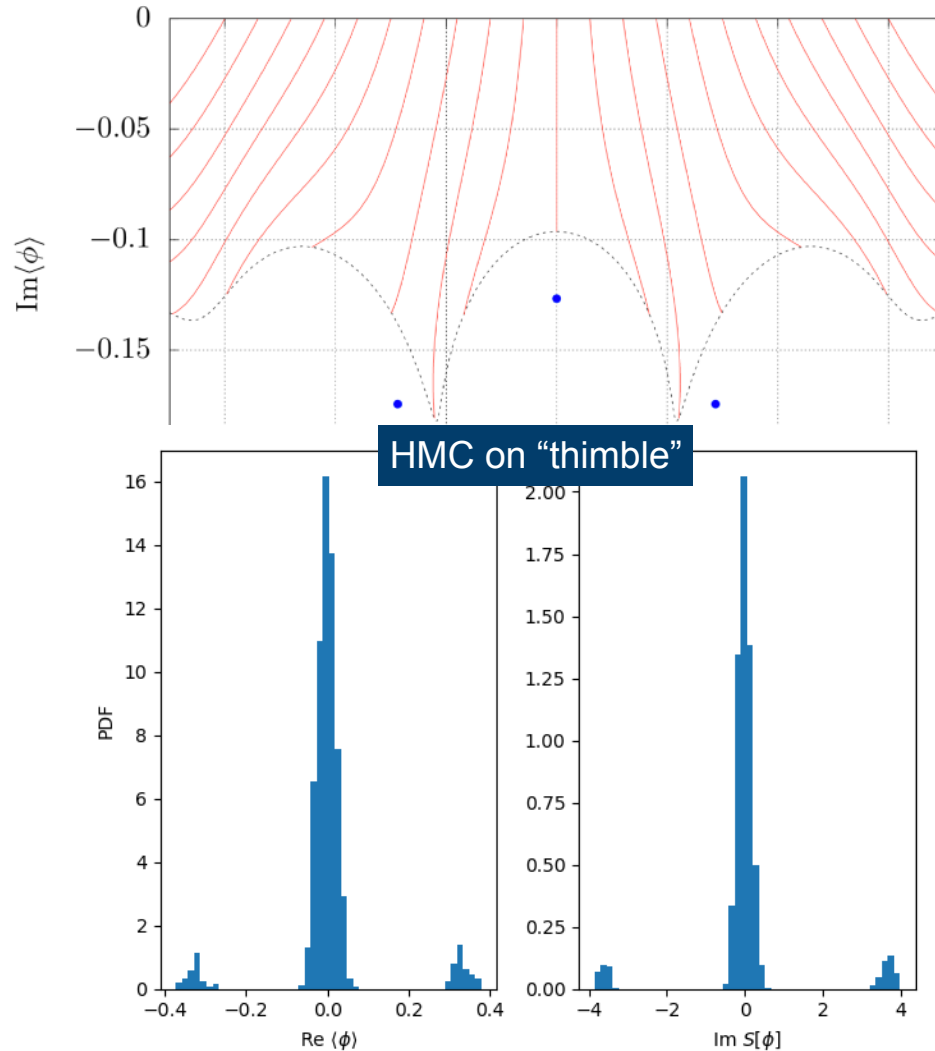
Flow from real plane  $\dot{\phi} = (\nabla_{\phi} S[\phi])^*$



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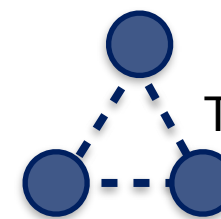
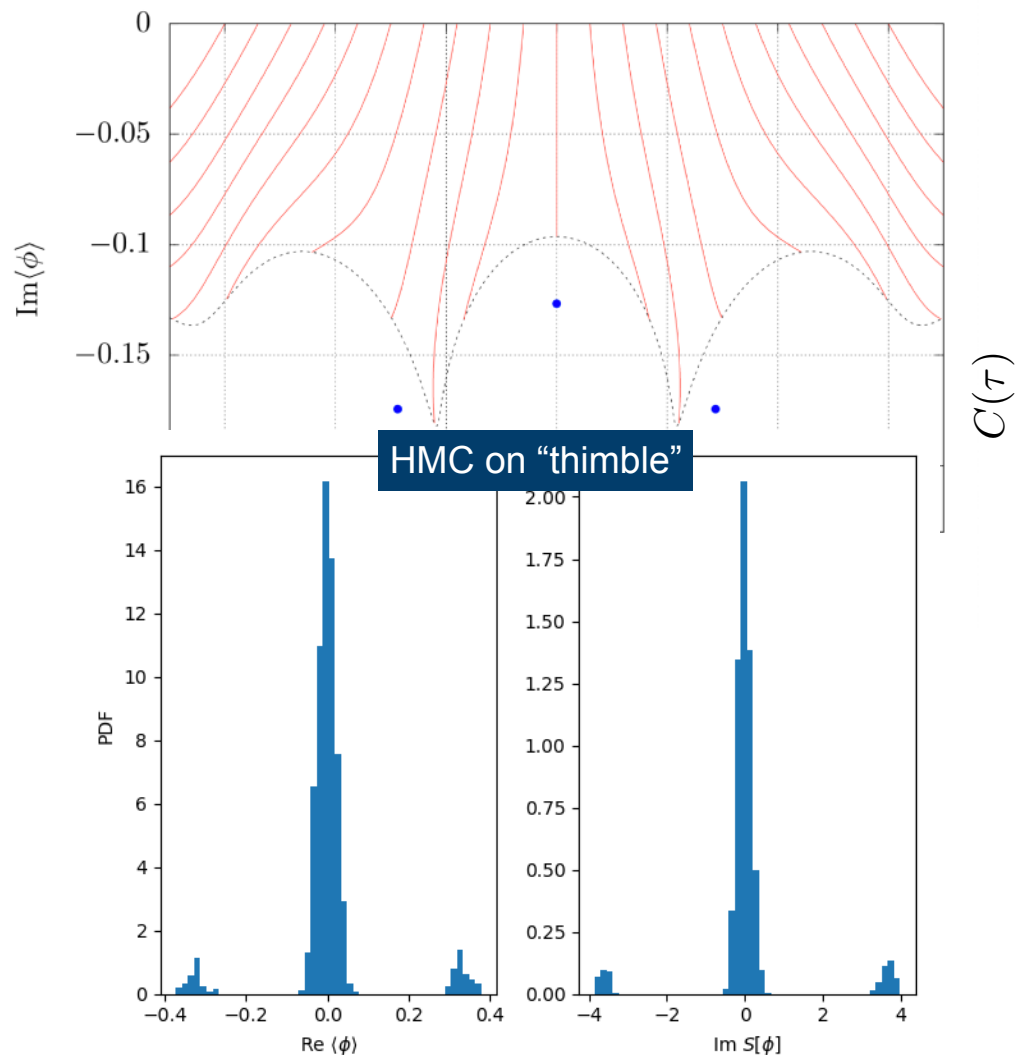
Flow from real plane



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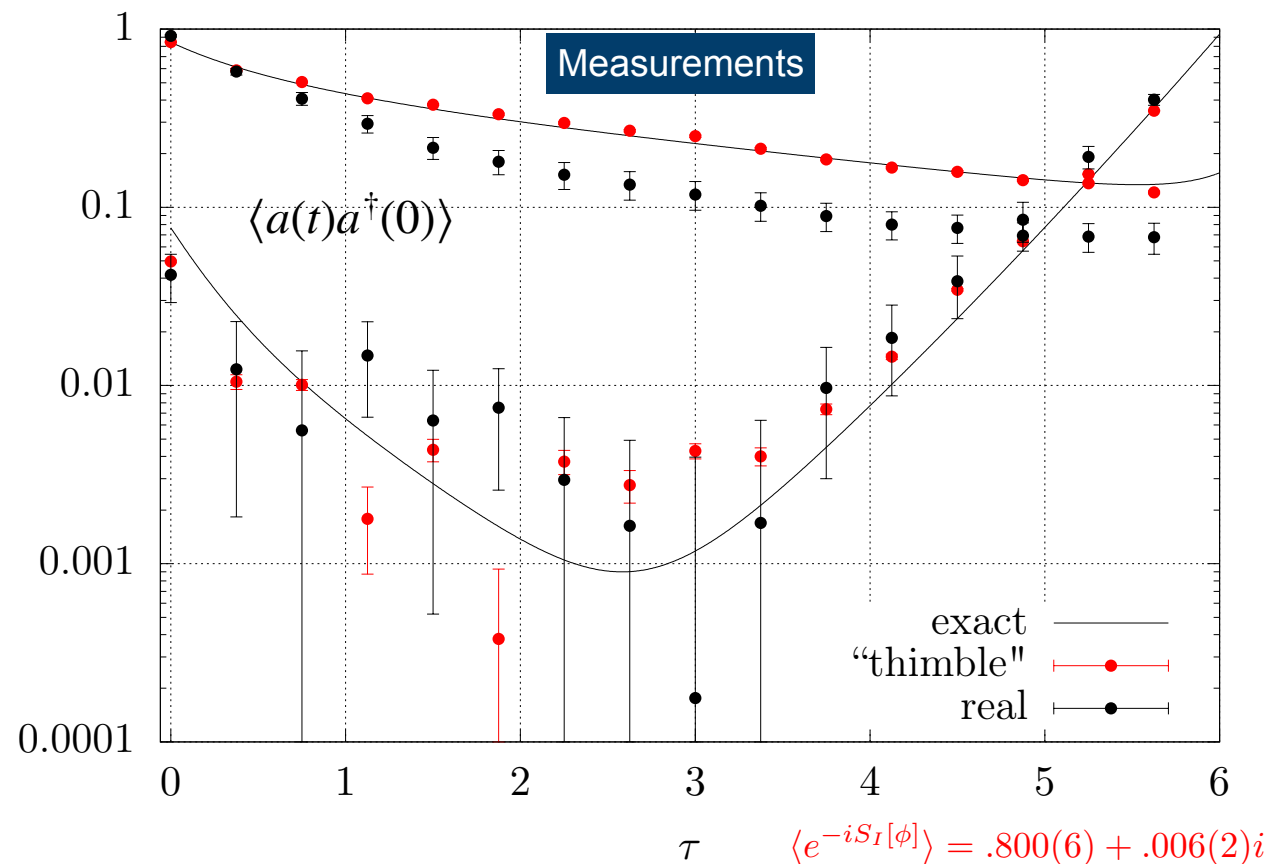
Flow from real plane  $\dot{\phi} = (\nabla_{\phi} S[\phi])^*$

Flow from real plane



Three-site problem

$$U = 3, \beta = 6, N_t = 16$$

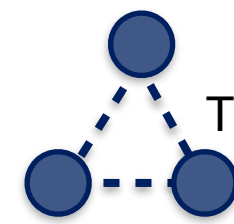
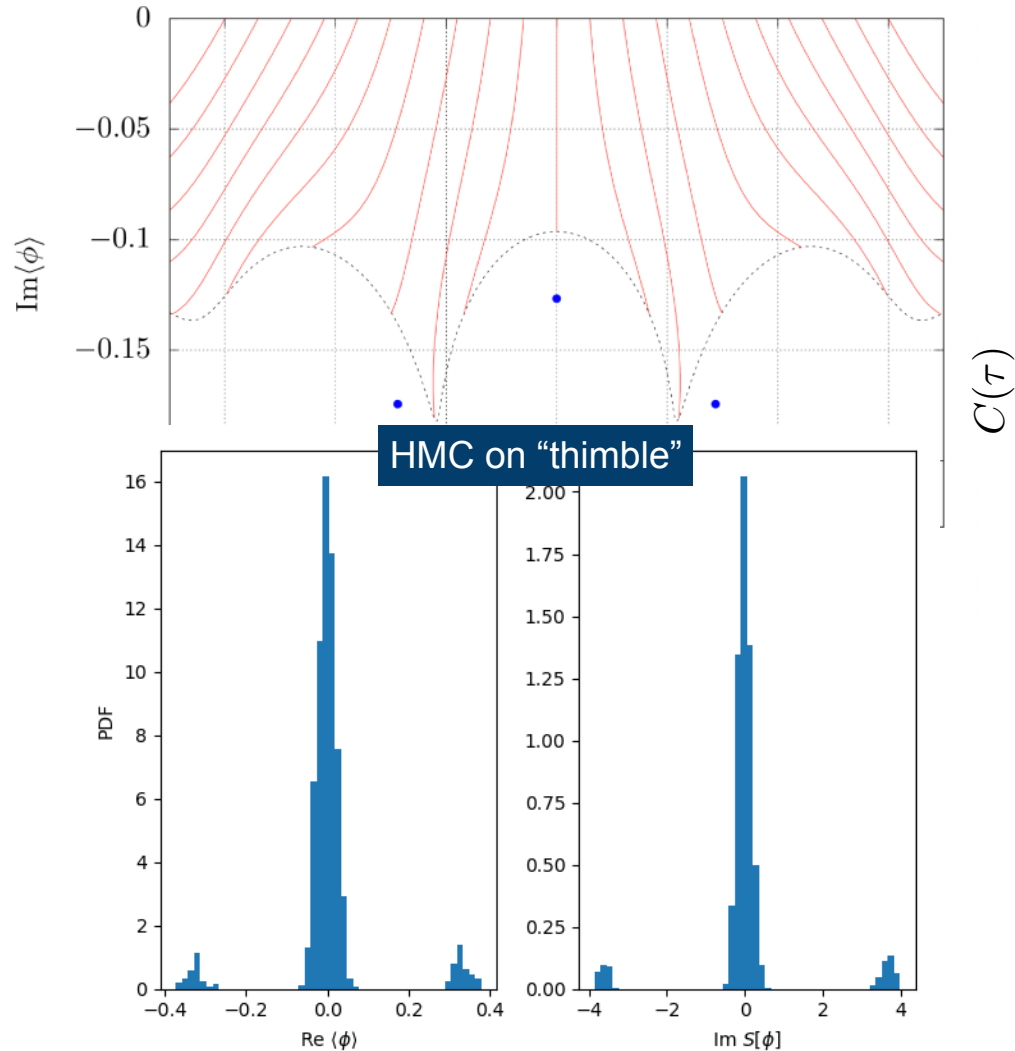


$$\langle e^{-iS_I[\phi]} \rangle = .800(6) + .006(2)i$$

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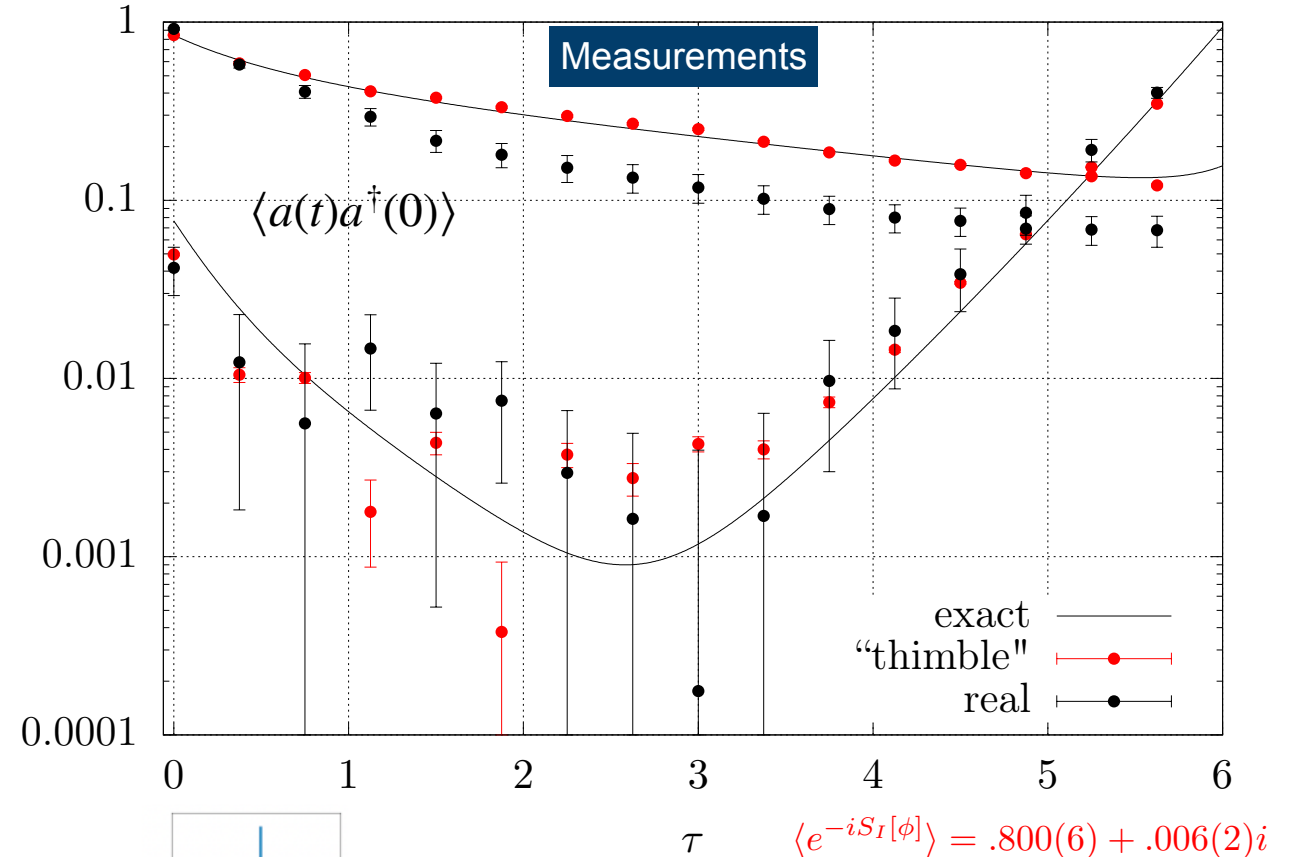
Flow from real plane  $\dot{\phi} = (\nabla_{\phi} S[\phi])^*$

Flow from real plane



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$$\langle e^{-iS_I[\phi]} \rangle = .049(6) + .008(6)i$$

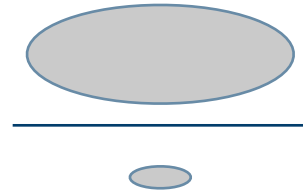
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# UNFORTUNATELY, THIS “SOLUTION” IS NOT VIABLE NUMERICALLY

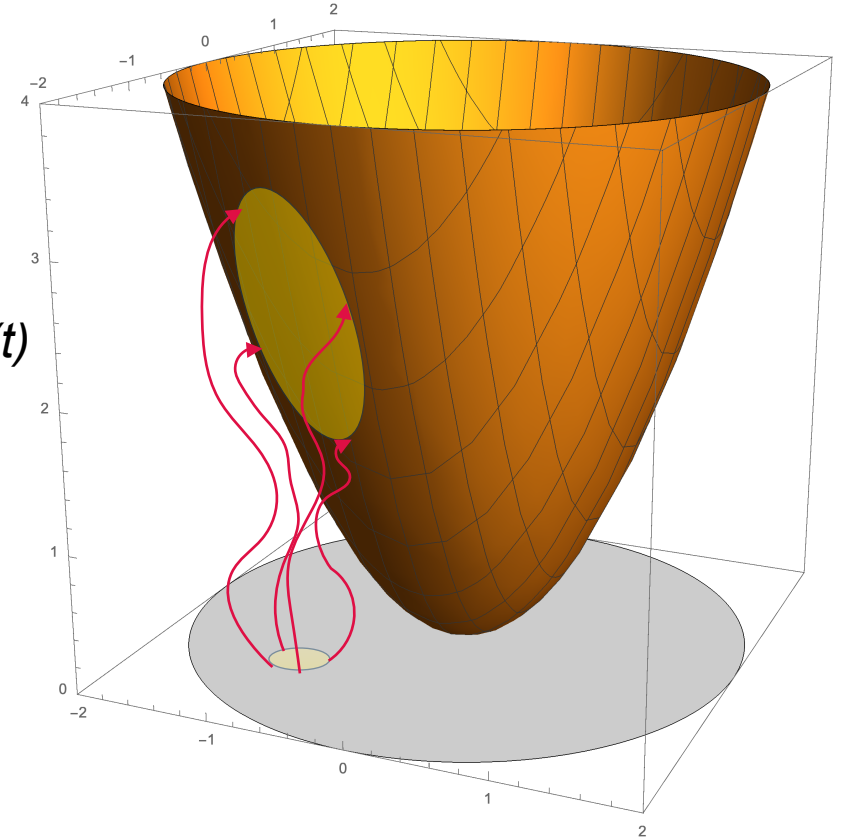
“No free lunch theorem”

$$\dot{\phi}(t) = [\nabla_{\phi} S[\phi(t)]]$$

$$\dot{J}(t) = [H[\phi(t)]J(t)]^*$$



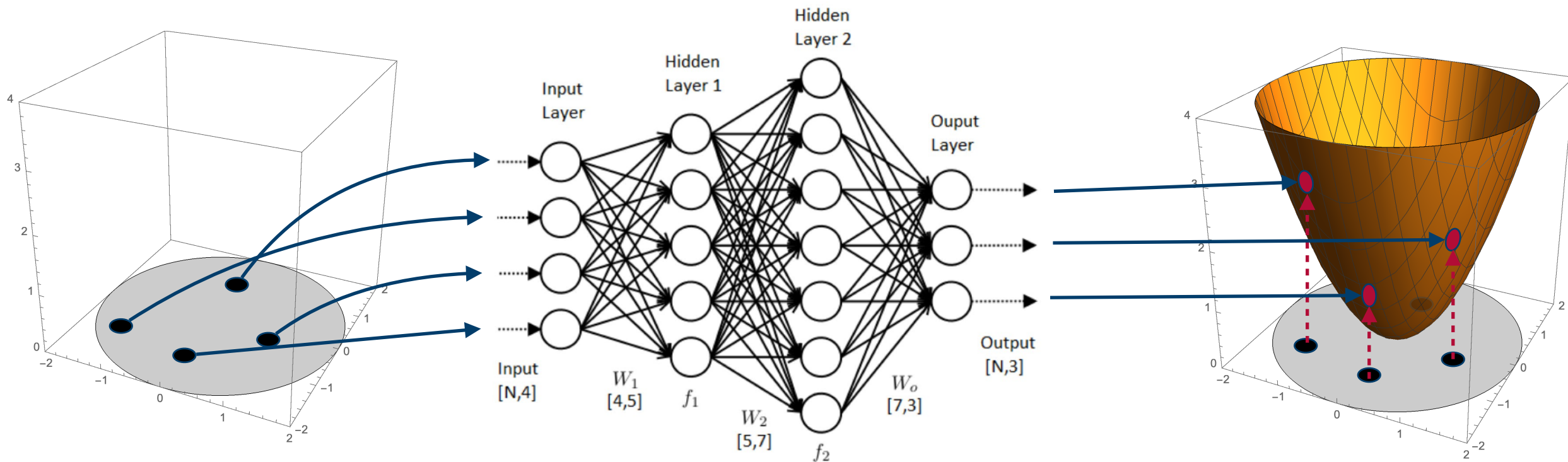
= det  $J(t)$



- Flowing of fields is not cheap
- Calculation of Jacobian due to flow is extremely time consuming!
- At every step of the flow integration, must compute a dense matrix!

# MACHINE LEARNING TO THE RESCUE!

Pushing all our ignorance into one black box called a neural network (NN)

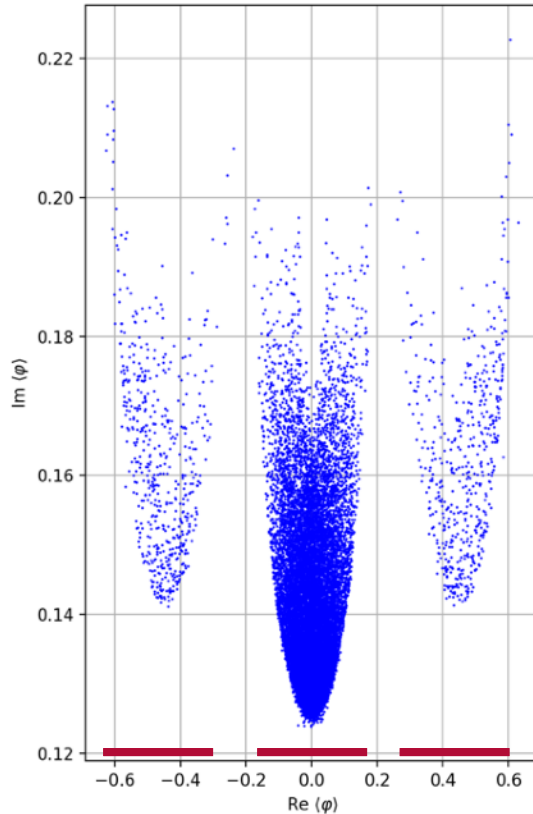


“learnifolds”

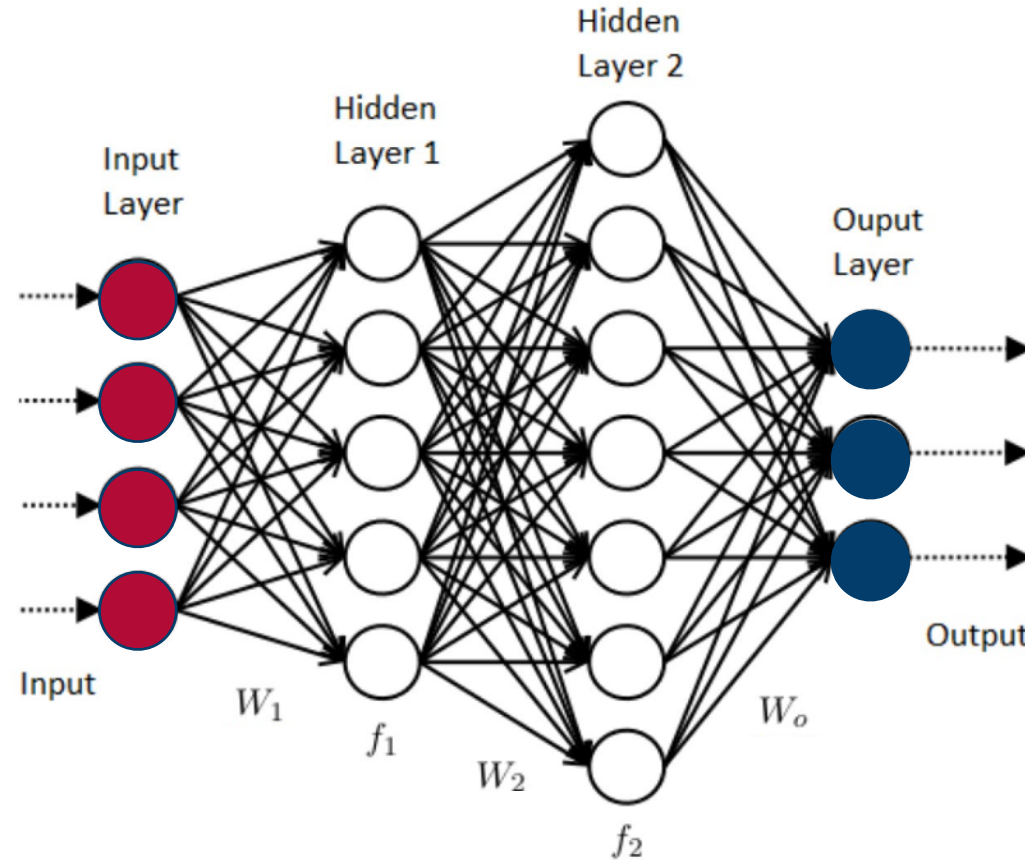
# TRAINING THE NETWORK

Trying to get a computer to do what you want. . .

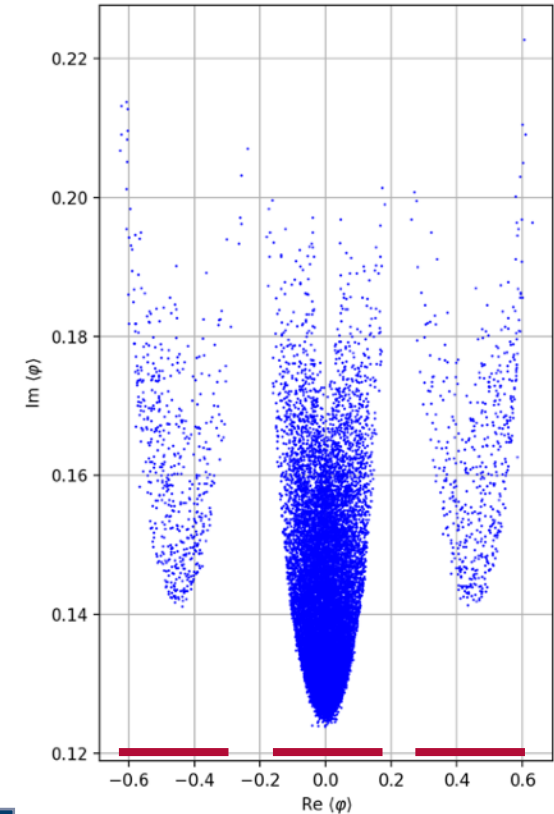
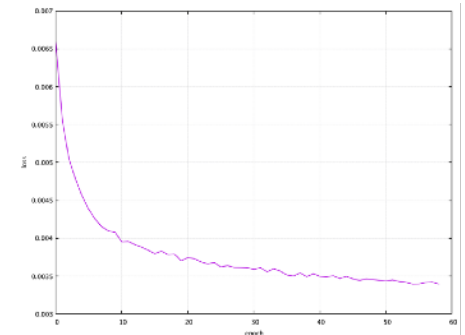
Single dense layer  
“softmax” activation



training data

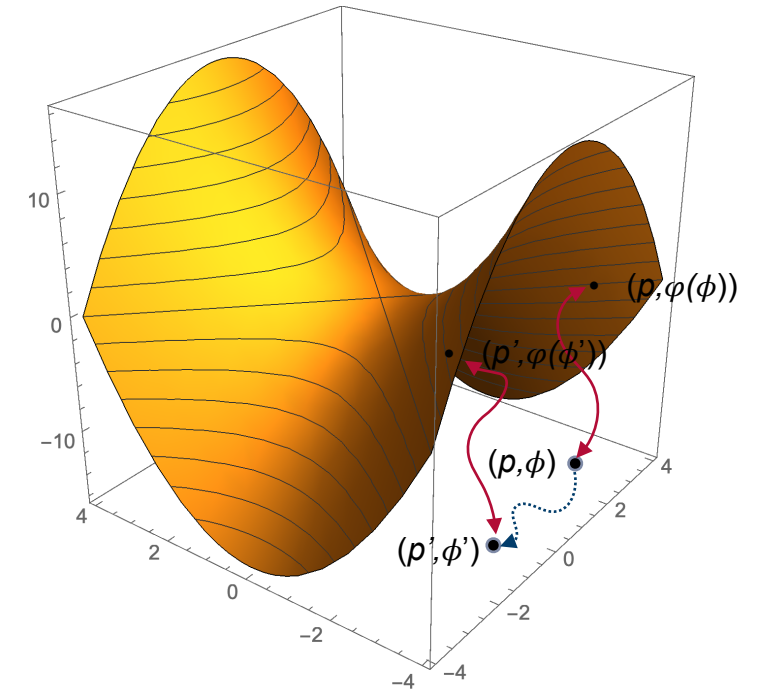


- Minimization of loss function
- Parameters tuned via stochastic gradient descent
- “Supervised training”

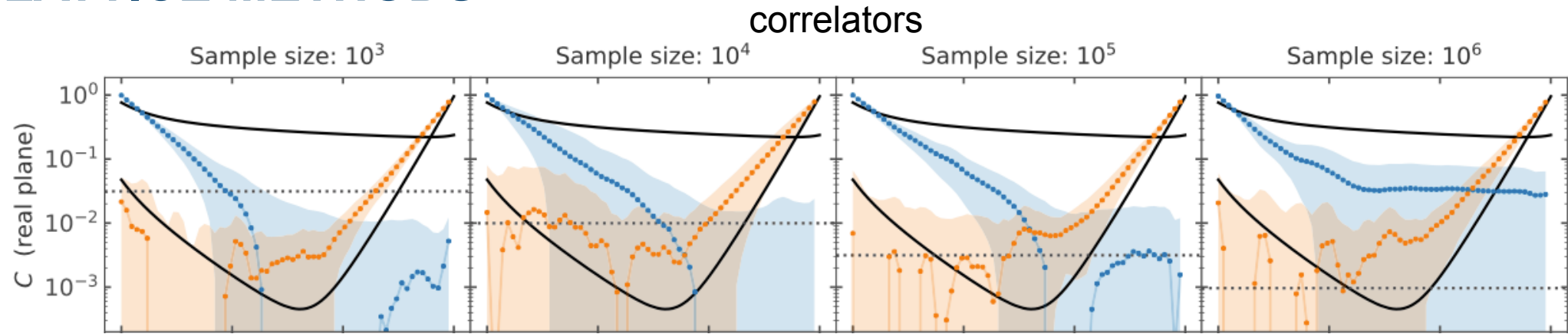


# HMC WITH NEURAL NETWORKS

- Perform HMC on the real plane to make proposal  $(p, \phi) \rightarrow (p', \phi')$
- $\phi' \rightarrow \text{NN} \rightarrow \varphi(\phi')$
- Accept/reject with  $\mathbb{P}_{a/r} = \min \left( 1, \frac{e^{-p'^2/2 - \text{Re}S_{eff}[\varphi(\phi')]} }{e^{-p^2/2 - \text{Re}S_{eff}[\varphi(\phi)]}} \right)$
- Reversible, satisfies detailed balance

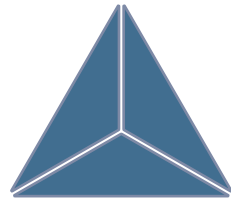
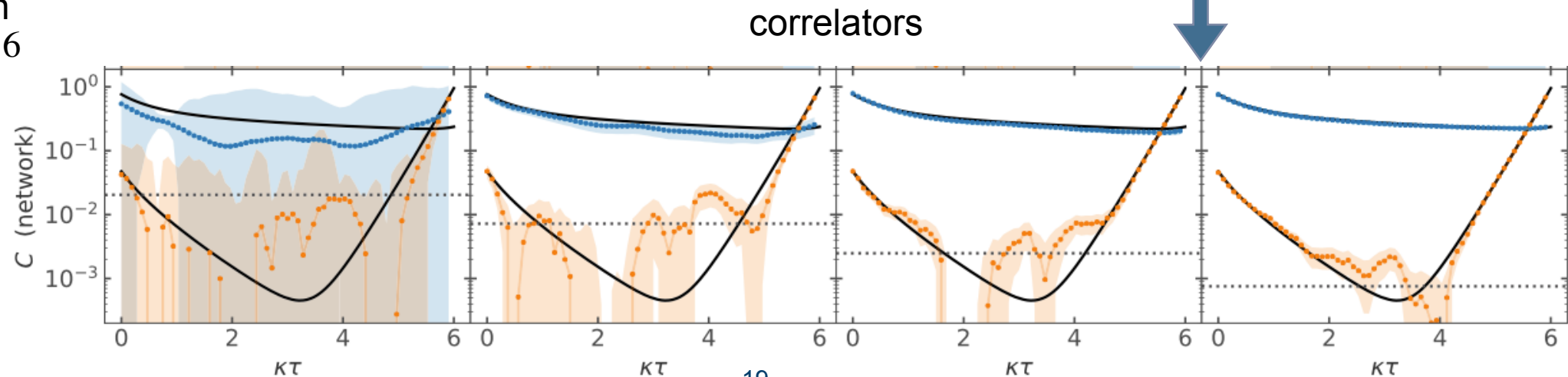


# WE CAN NOW SIMULATE SYSTEMS THAT WERE NOT POSSIBLE BEFORE WITH LATTICE METHODS



Standard HMC

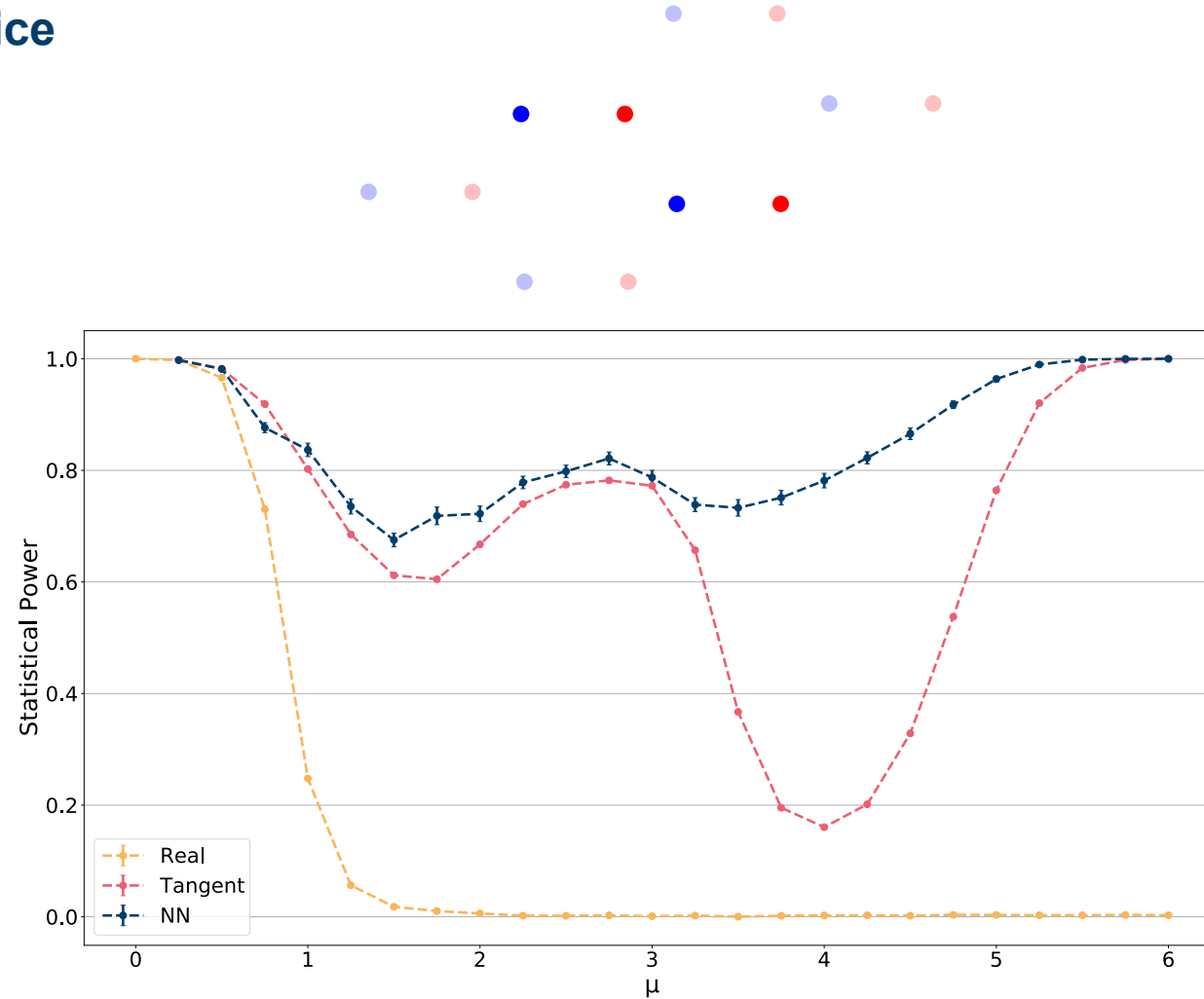
HMC with complex manifolds & NN



tetrahedron  
 $U = 3$     $\beta = 6$

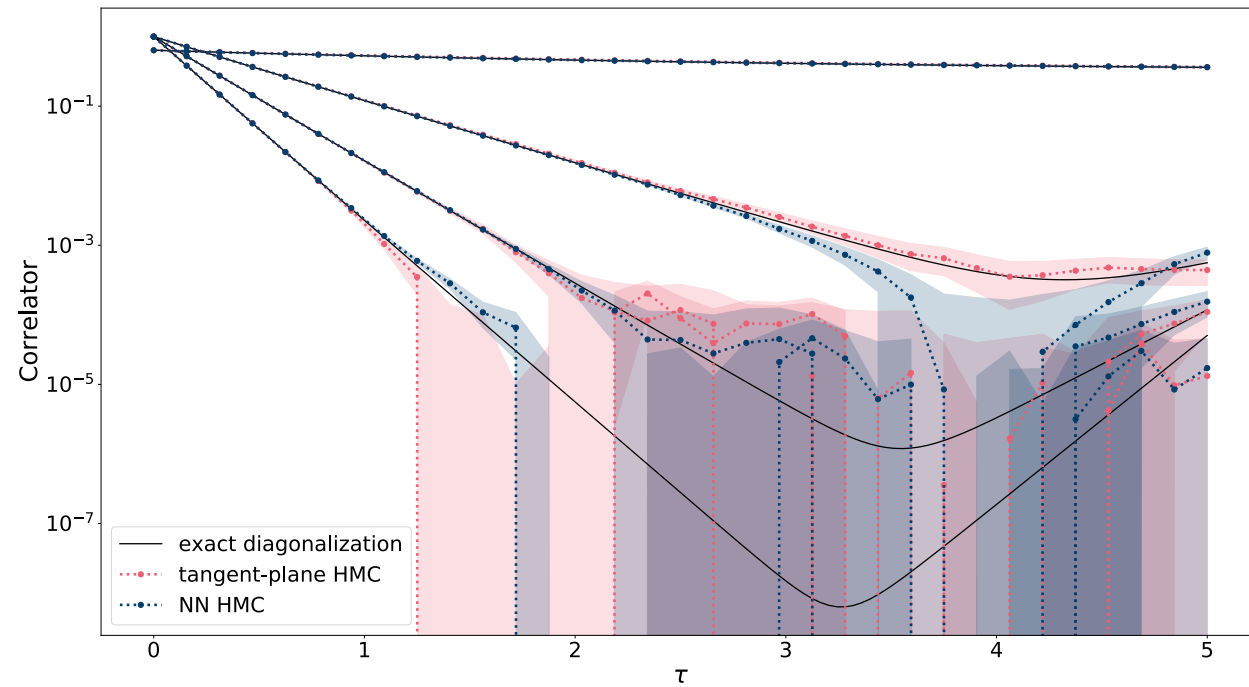
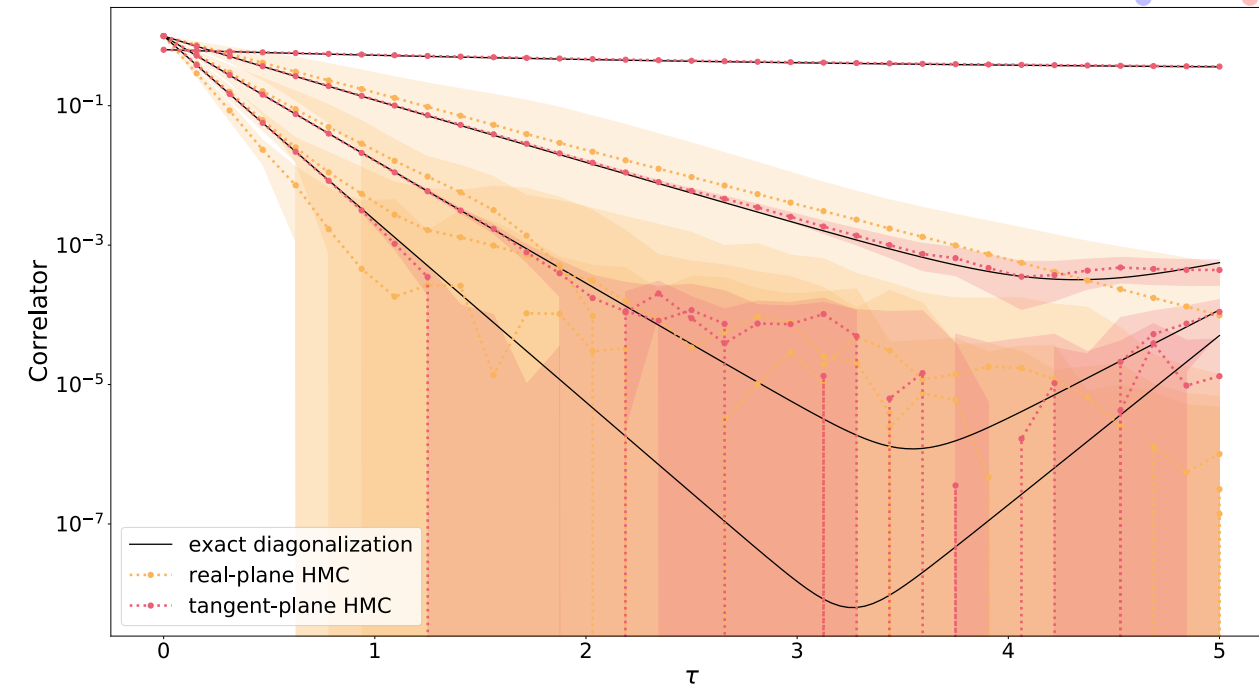
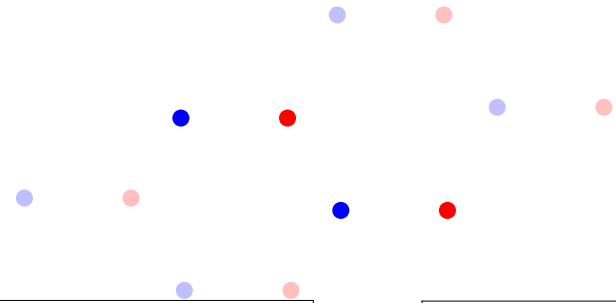
# CALCULATIONS WITH NON-ZERO CHEMICAL POTENTIAL

4 sites honeycomb lattice



# SINGLE PARTICLE CORRELATORS

4 sites honeycomb lattice

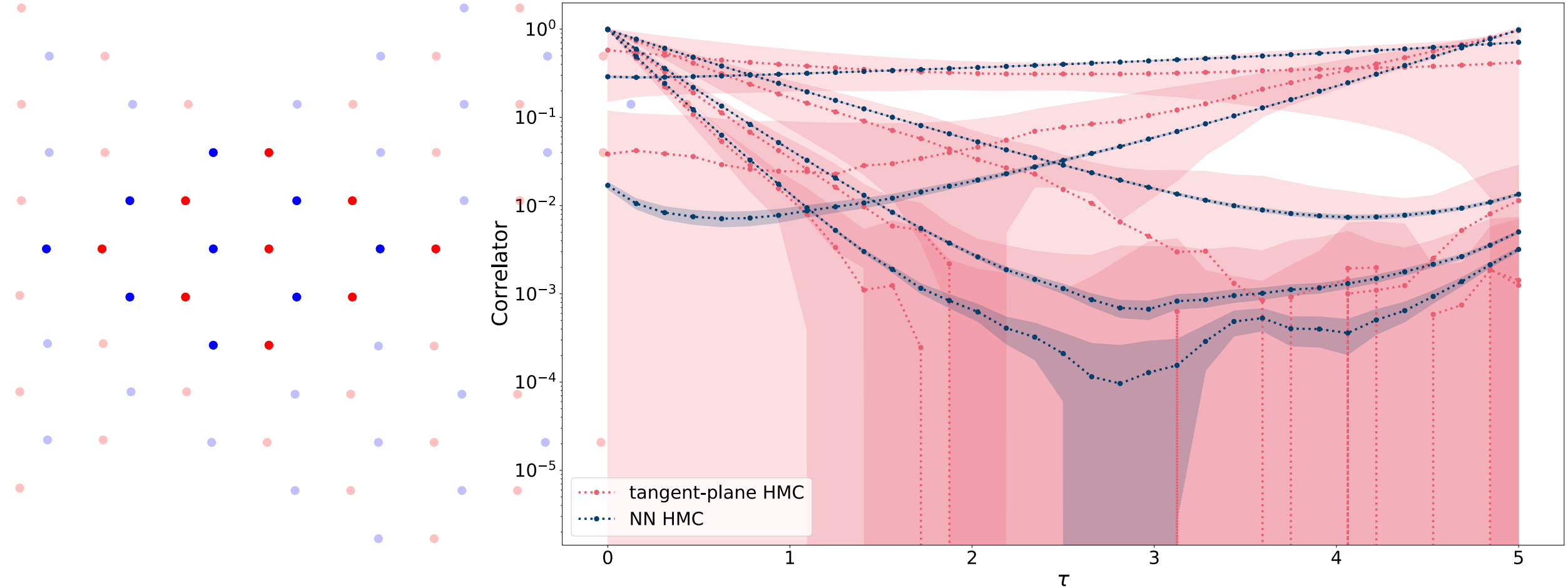


$$U = 2, \mu = 4, \beta = 5, N_t = 32$$

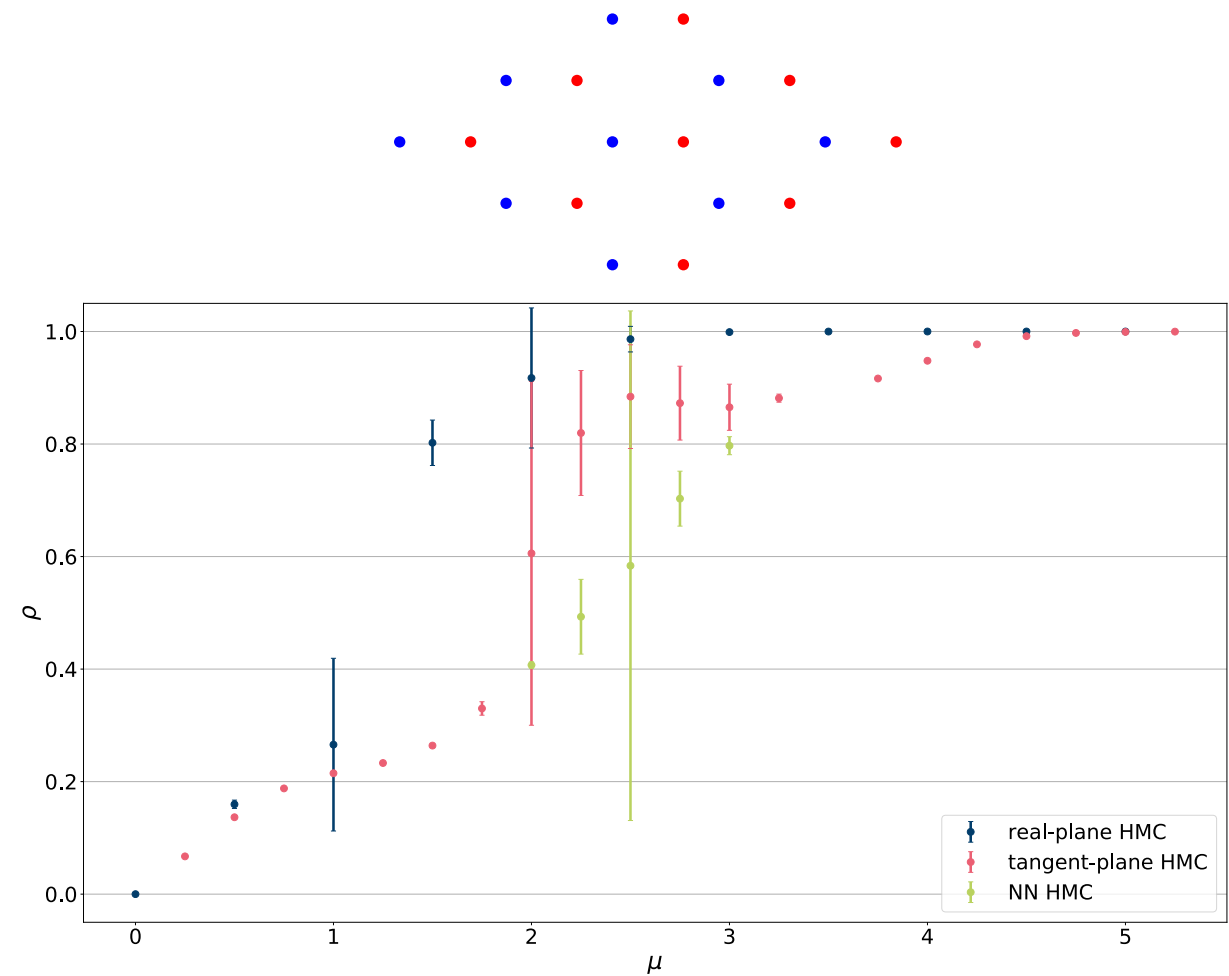
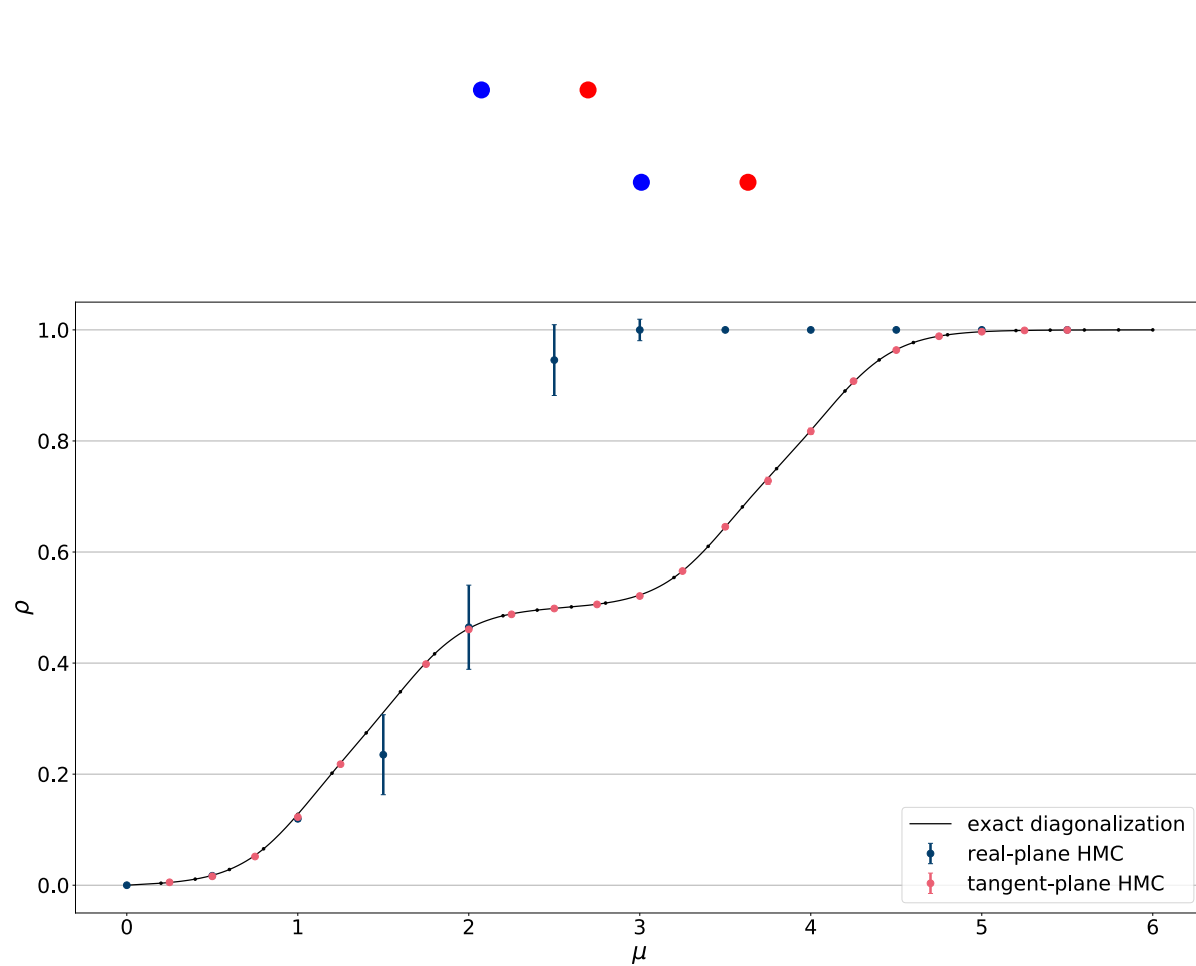
# OUR BENCHMARK RESULTS GIVE US CONFIDENCE TO GO TO BIGGER SYSTEMS

18 sites Honeycomb lattice

$$U = 2, \mu = 2, \beta = 5, N_t = 32$$



# CHARGE DENSITY AS A FUNCTION OF CHEMICAL POTENTIAL



$$U = 2, \beta = 5$$

# COMING BACK TO THE ISSUE OF $\det(J)$

## Complex-valued neural network (CVNN)

- Current transformation has  $\Phi_r \rightarrow \Phi_r + i\mathbb{N}\mathbb{N}(\Phi_r)$ 
  - mitigates ergodicity issues, but. . .
- $\det(J) = \det(1 + J_{\mathbb{N}\mathbb{N}}) = \det\left(1 + \prod_{i \in \text{layers}} j_{\mathbb{N}\mathbb{N}}^i\right)$
- scales  $\propto \mathcal{O}(V^3)$

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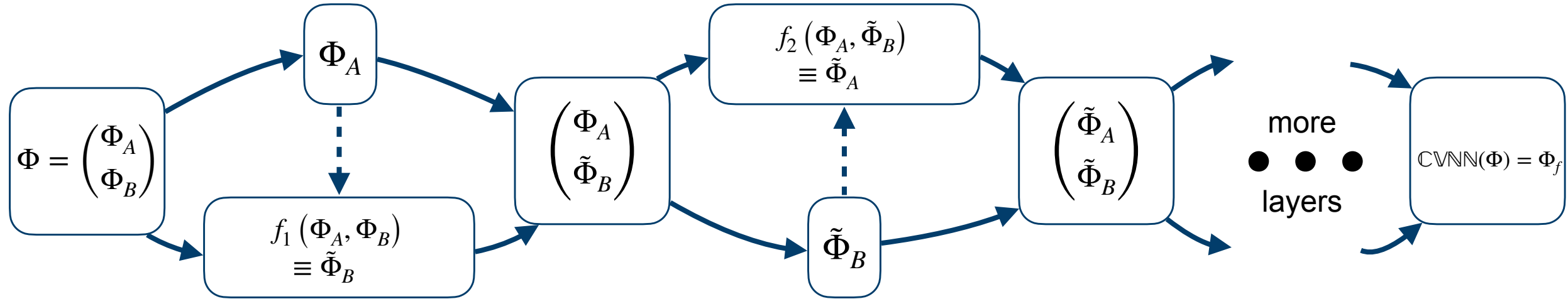
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- Instead consider  $\Phi \rightarrow \mathbb{C}\mathbb{V}\mathbb{N}\mathbb{N}(\Phi)$  where  $\Phi \in \mathbb{C}$  and  $\mathbb{C}\mathbb{V}\mathbb{N}\mathbb{N}(\Phi) \in \mathbb{C}$ 
  - flow modestly from tangent plane to mitigate ergodicity issues (sufficient??)
- $\det(J) = \det(J_{\mathbb{C}\mathbb{V}\mathbb{N}\mathbb{N}}) = \det\left(\prod_{i \in \text{layers}} j_{\mathbb{C}\mathbb{V}\mathbb{N}\mathbb{N}}^i\right)$
- Affine coupling layer provides scaling  $\propto \mathcal{O}(V)$

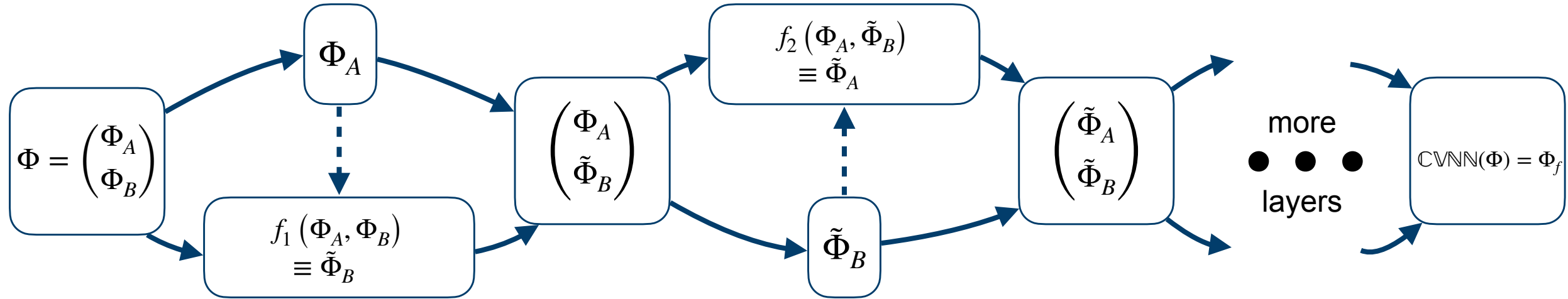
# AFFINE COUPLING LAYERS

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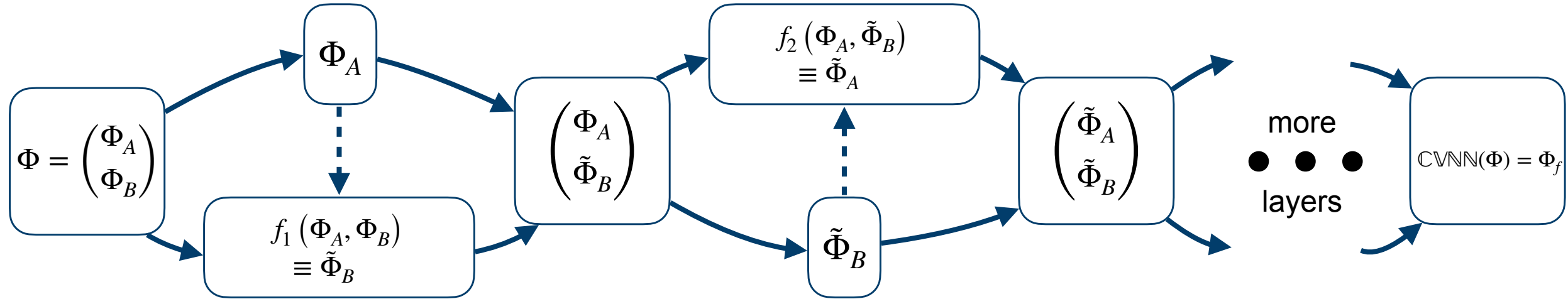


Calculation of Jacobian:

$$\begin{pmatrix} \mathbb{I} & 0 \\ \frac{df_1(\Phi_A, \Phi_B)}{d\Phi_A} & \frac{df_1(\Phi_A, \Phi_B)}{d\Phi_B} \end{pmatrix} \times \begin{pmatrix} \frac{df_2(\Phi_A, \tilde{\Phi}_B)}{d\Phi_A} & \frac{df_2(\Phi_A, \tilde{\Phi}_B)}{d\tilde{\Phi}_B} \\ 0 & \mathbb{I} \end{pmatrix} \times \dots = J_{\text{CVNN}}$$

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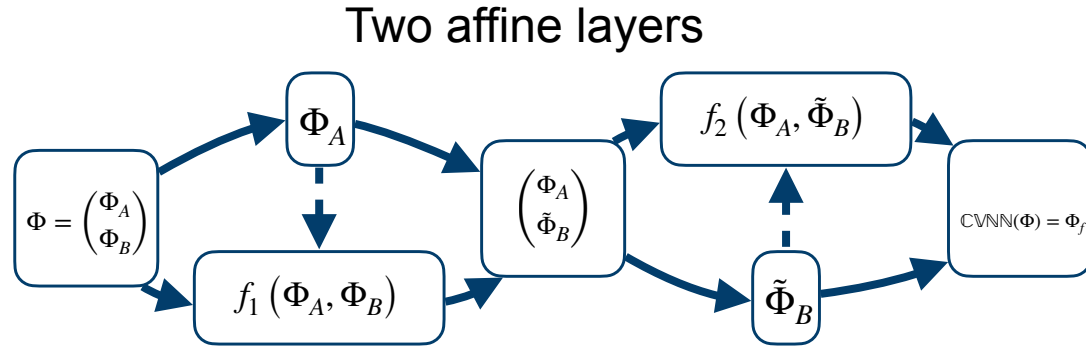
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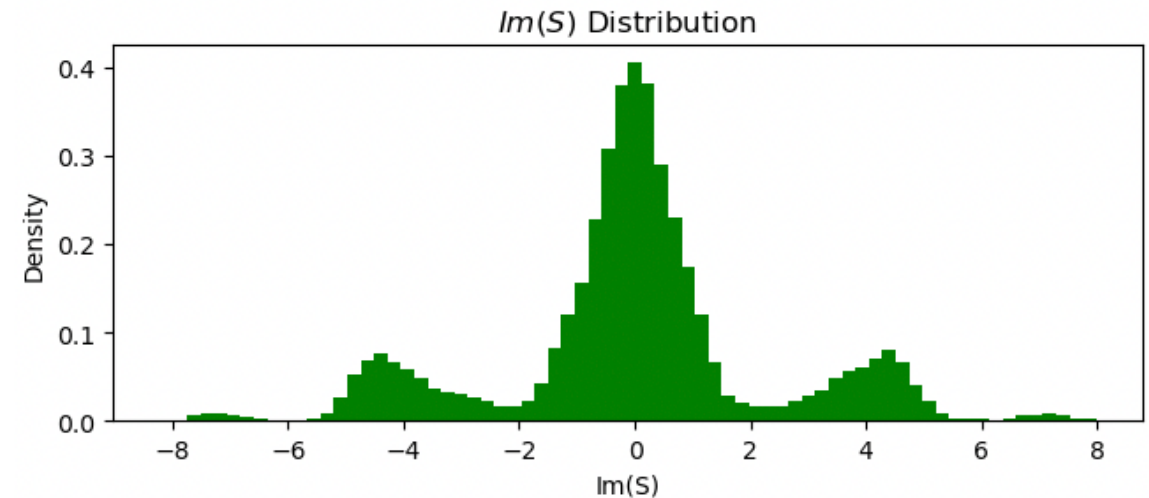
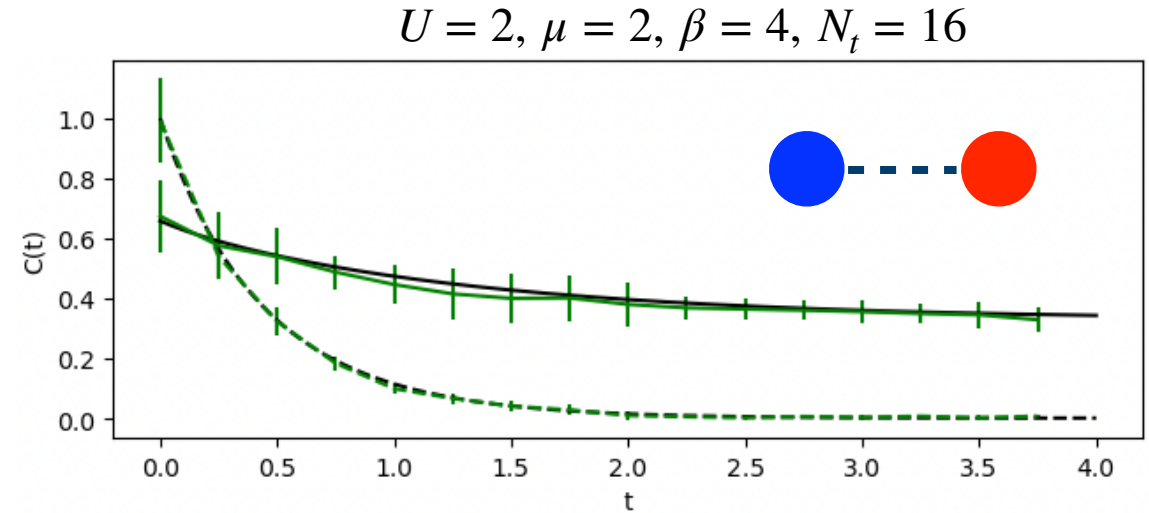
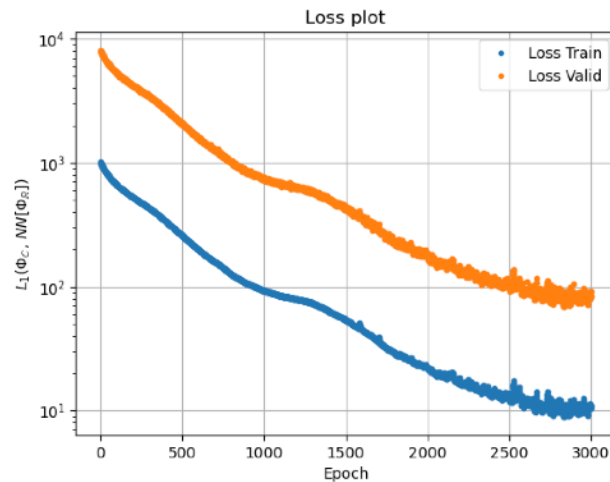
Calculation of  $\det J$ :  $\det(J_{\text{CVNN}}) = \prod_{i \in \text{layers}} \det j_{\text{CVNN}}^i = \prod j_{dd}^i \propto \mathcal{O}(V) \times (\# \text{ of layers})$

# OUR INITIAL RESULTS WITH CVNN ARE VERY PROMISING!

## Two sites problem

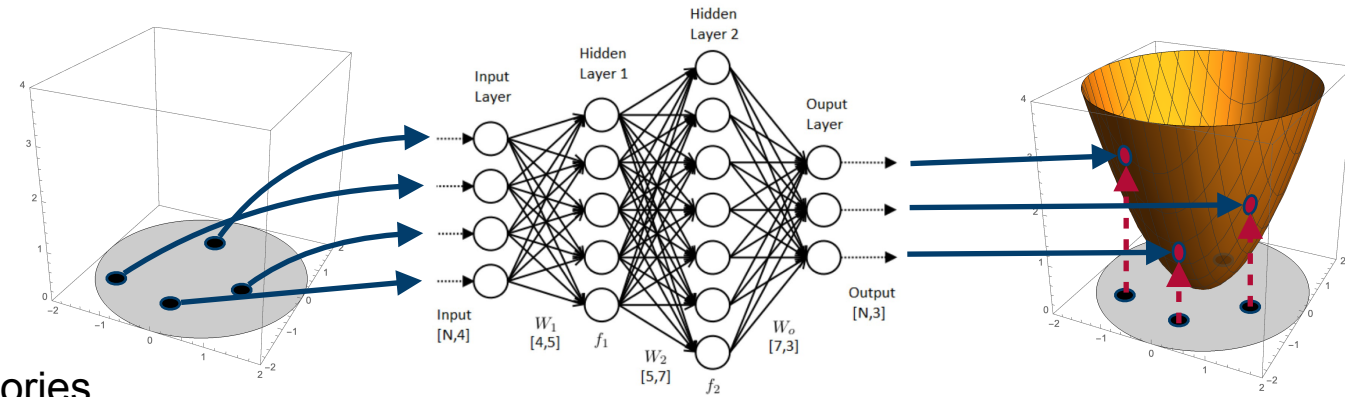
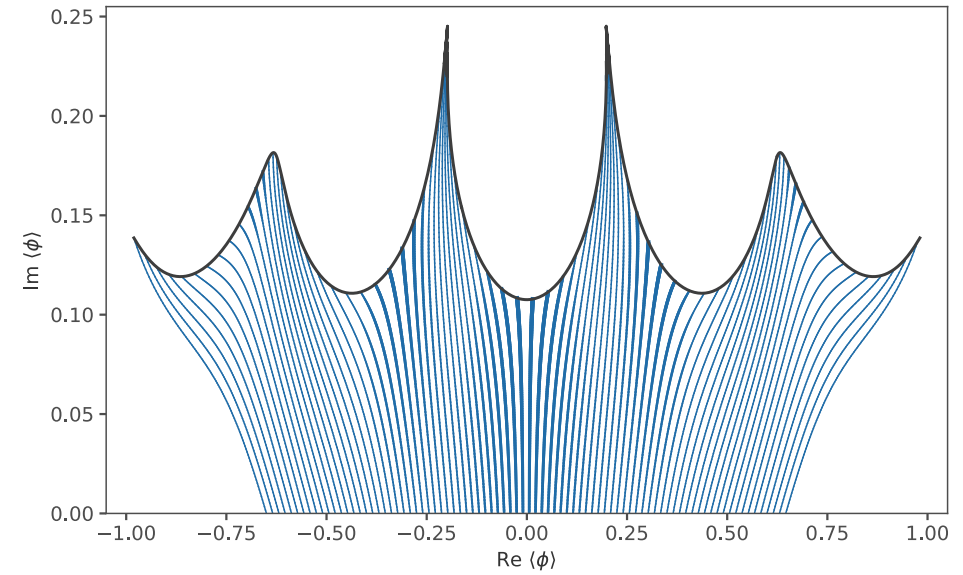


Training data was flowed from tangent plane



# CONCLUSIONS

- Hubbard model sign problem can be alleviated
  - by holomorphic flow
  - calculation of Jacobian prohibitive (numerically)
- Used NN to train location of manifolds
  - Fast/efficient interpolation routine
  - With CVNN,  $\det J$  scales as  $\mathcal{O}(V)$ !
- Found success in simple systems, moving now to larger systems
  - C20, C60
  - doped graphene/tubes
- Ultimate goal: apply holomorphic flow to lattice gauge theories
  - Fermions, fermions, fermions!



Thank you!