

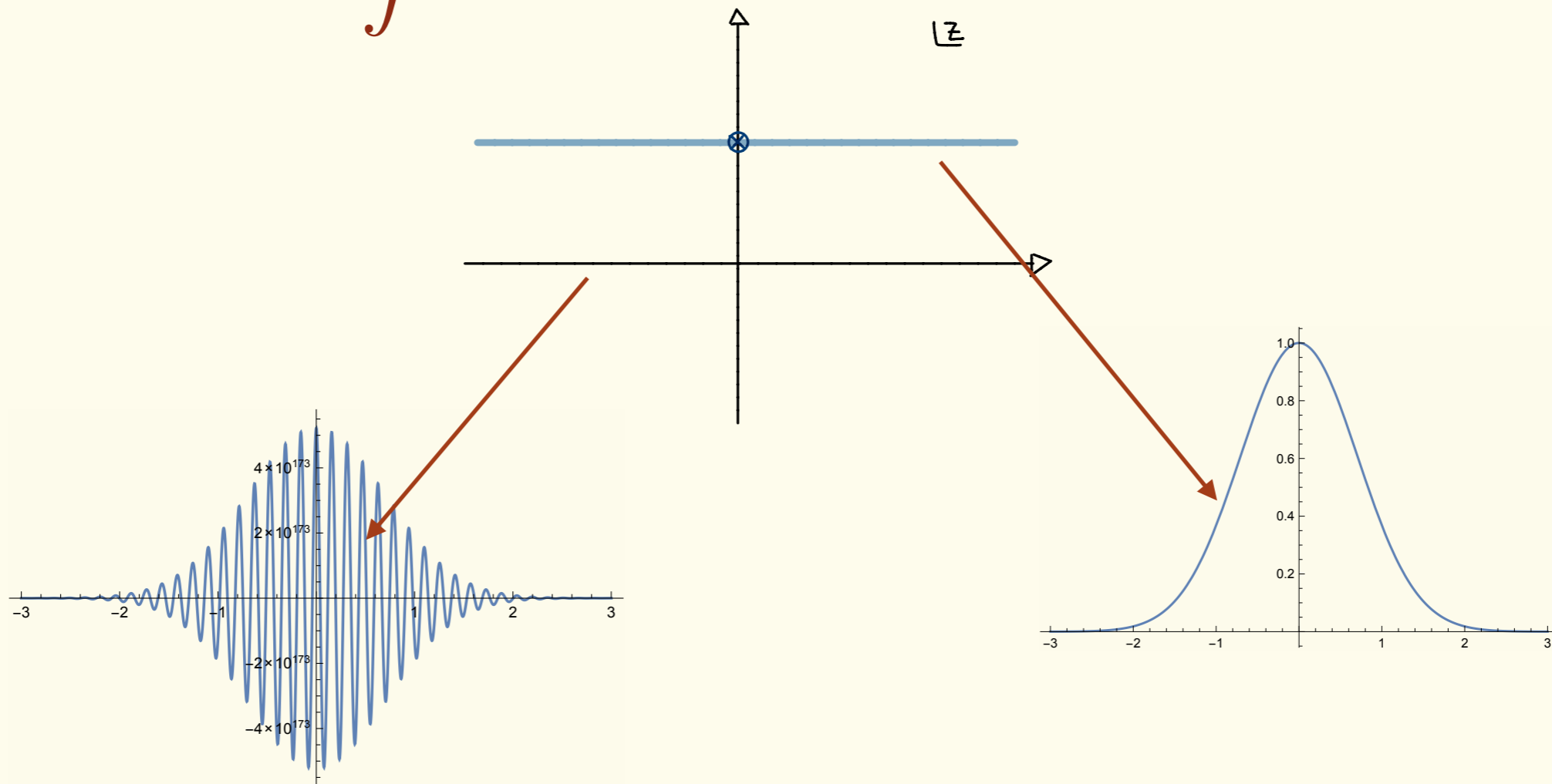
Generalized Thimble Method 2: The Return of the Thimbles

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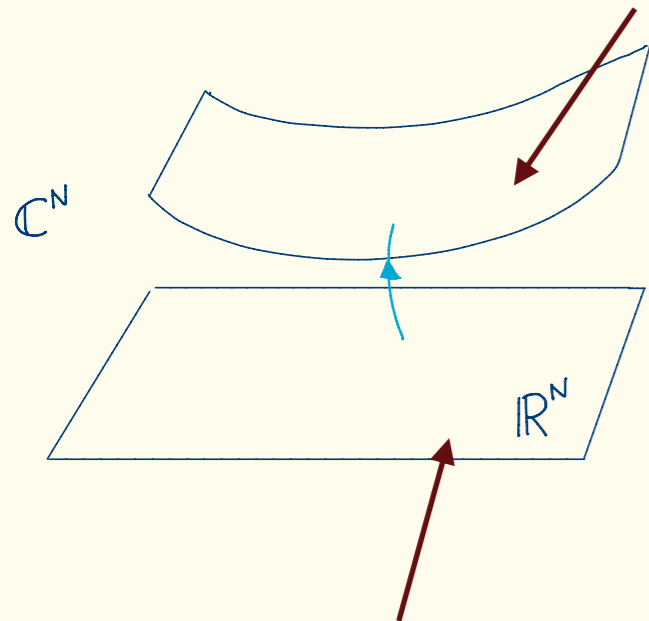
Central idea: deform the contour into the complex plane:

$$\int dx e^{-(z-i20)^2} = \sqrt{\pi}$$



How to find good deformations ?

new integration manifold



(real) field space

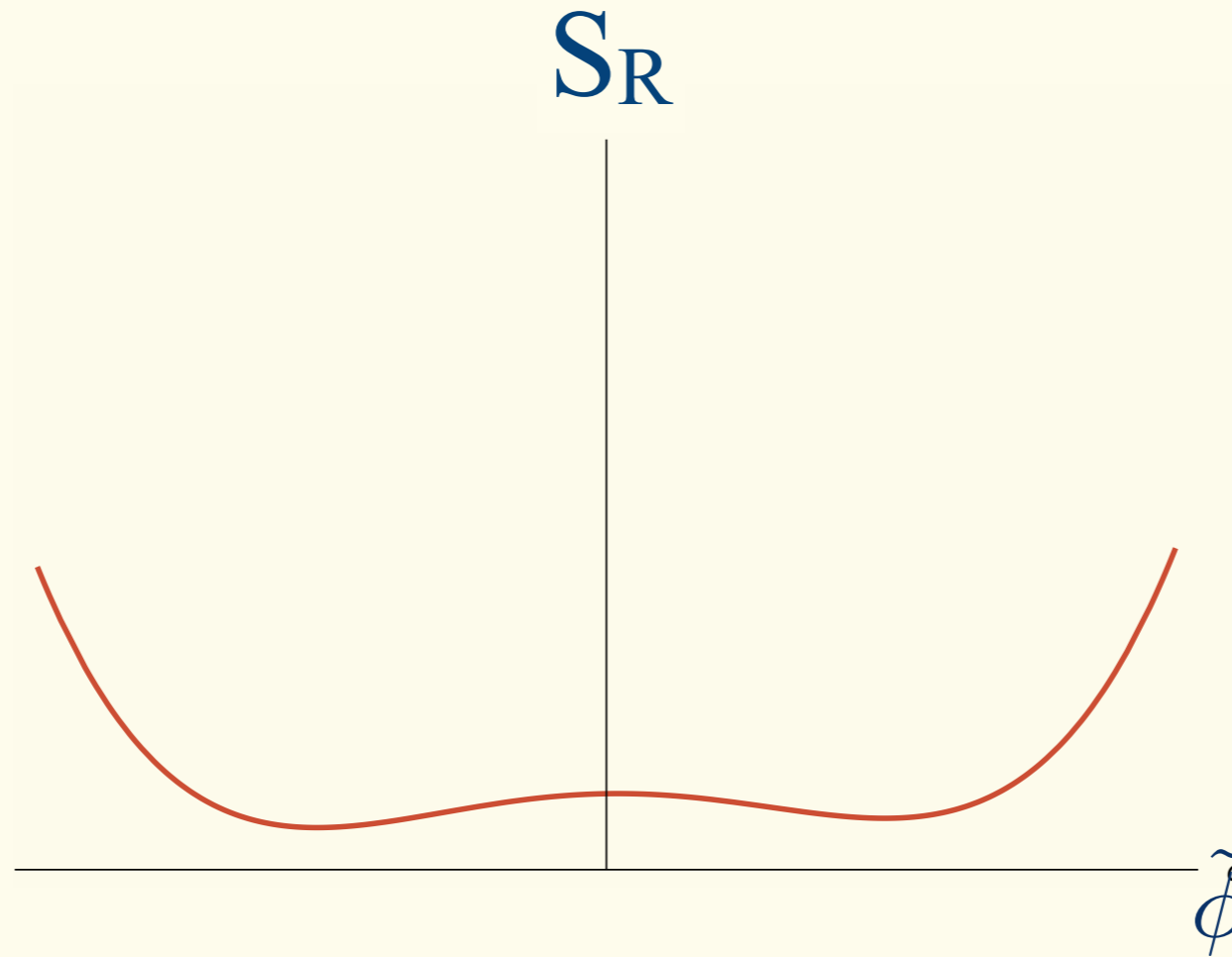
$$\frac{d\phi_i}{dt} = \overline{\frac{\partial S}{\partial \phi_i}} \Rightarrow$$

$$\begin{aligned} \frac{d\phi_i^R}{dt} &= \frac{\partial S^R}{\partial \phi_i^R} = \frac{\partial S^I}{\partial \phi_i^I} \\ \frac{d\phi_i^I}{dt} &= \frac{\partial S^R}{\partial \phi_i^I} = -\frac{\partial S^I}{\partial \phi_i^R} \end{aligned}$$

gradient flow of S^R , keeps integral well defined

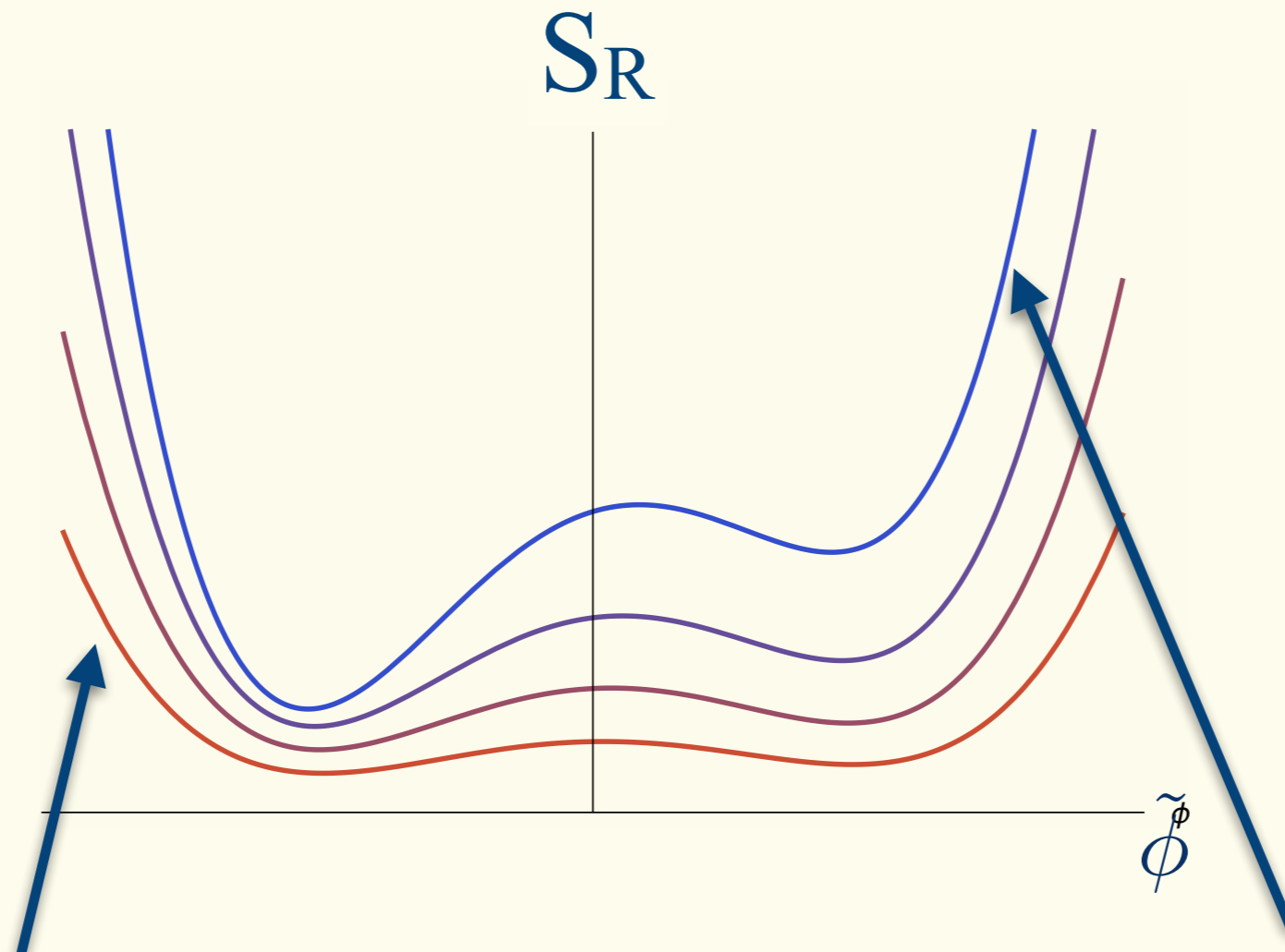
hamiltonian flow of S^I , keeps phase fixed

How to find good deformations ?



S_R under the flow

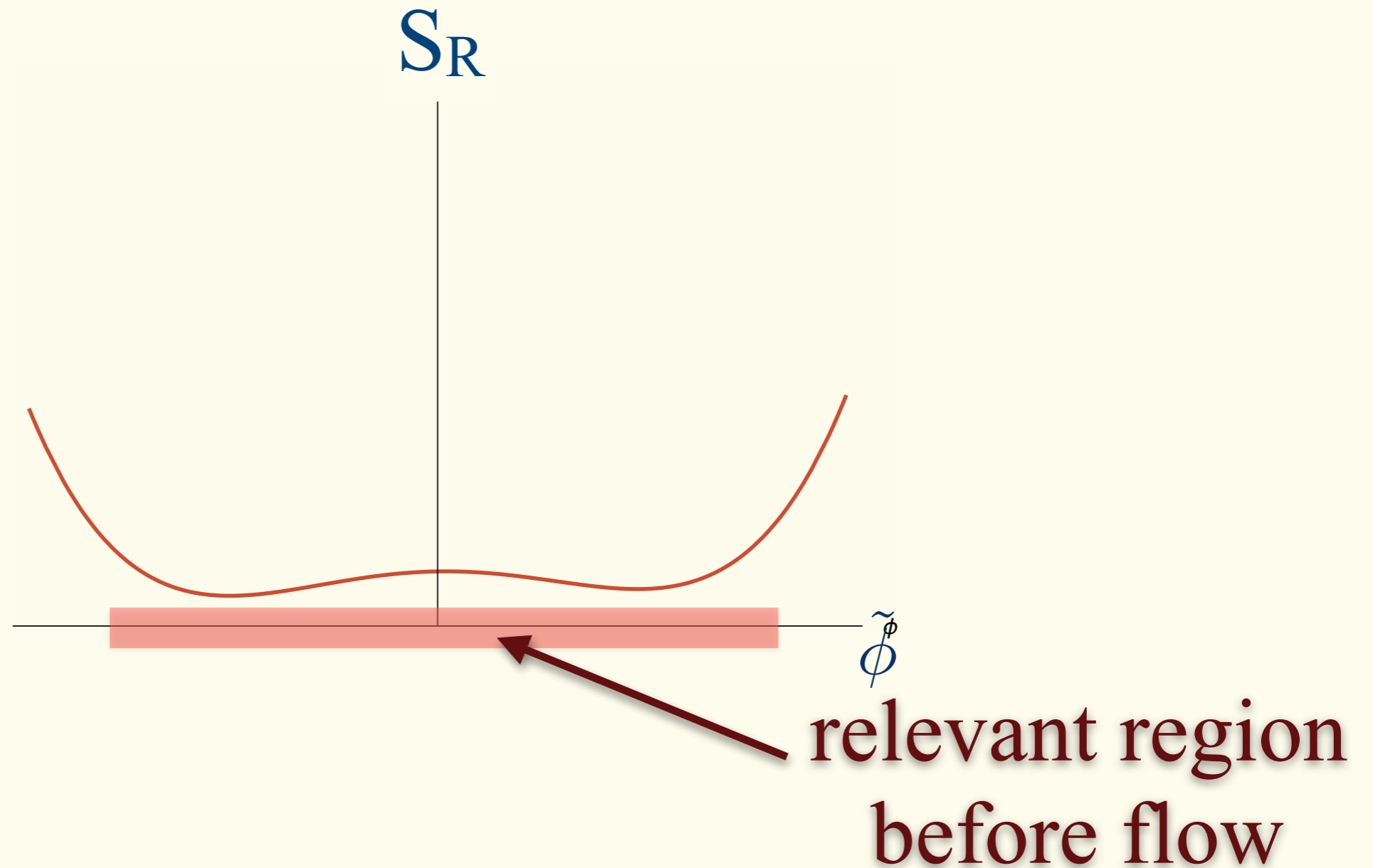
How to find good deformations ?



if this integral exists, so does that

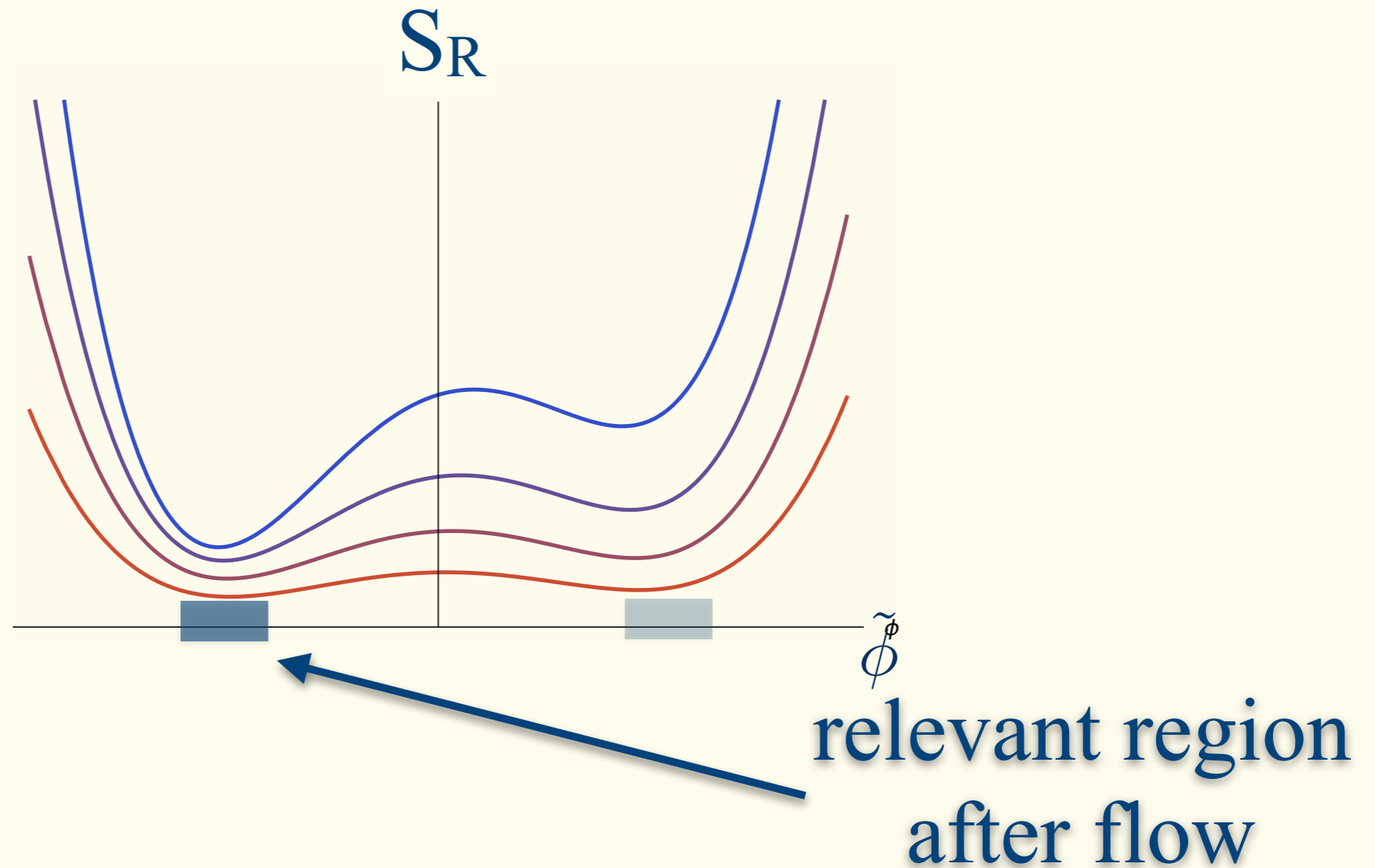
- 1) homology class preserved by the flow

How to find good deformations ?



S_R grows under the flow

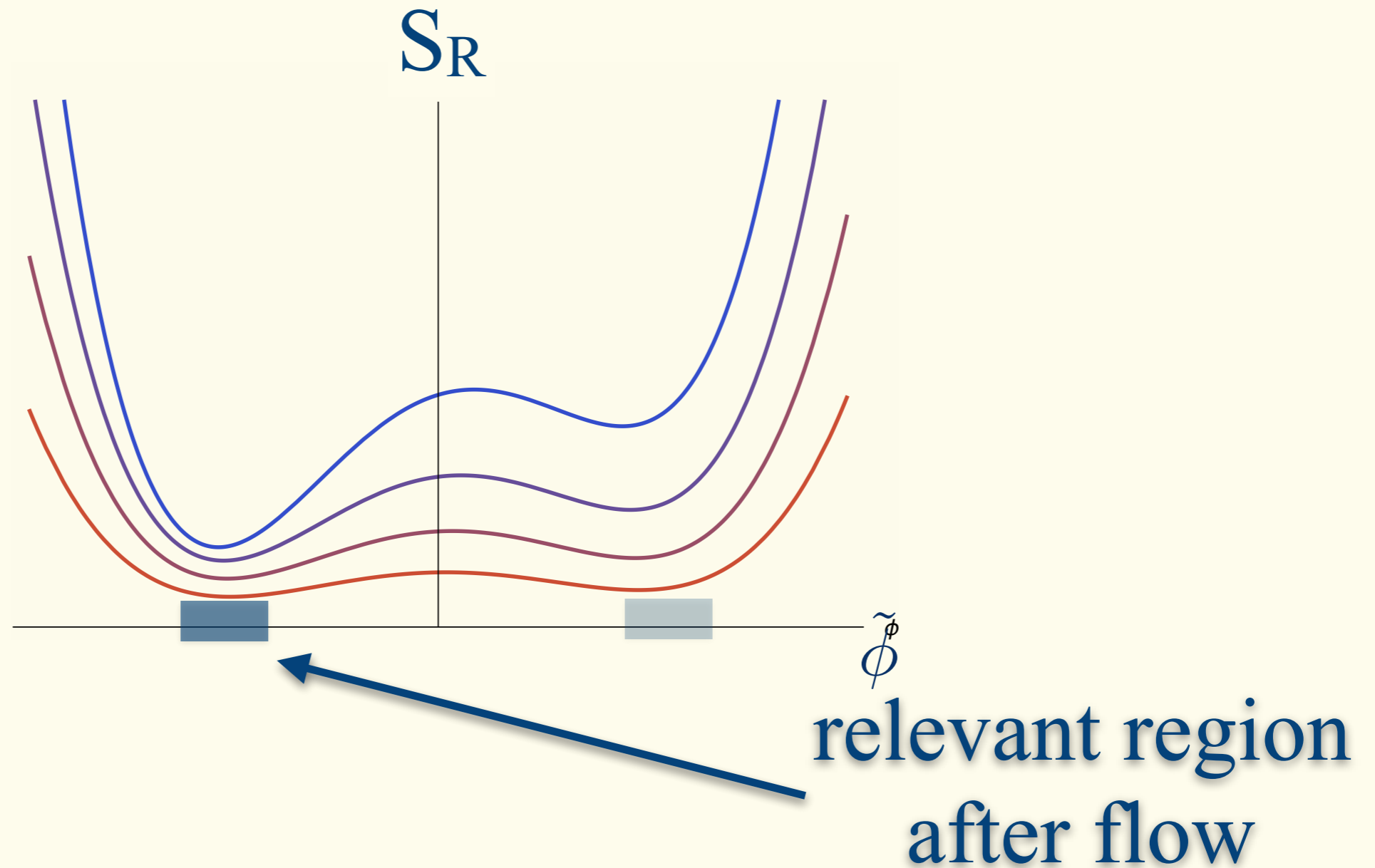
How to find good deformations ?



S_R grows under the flow

S_I stays constant

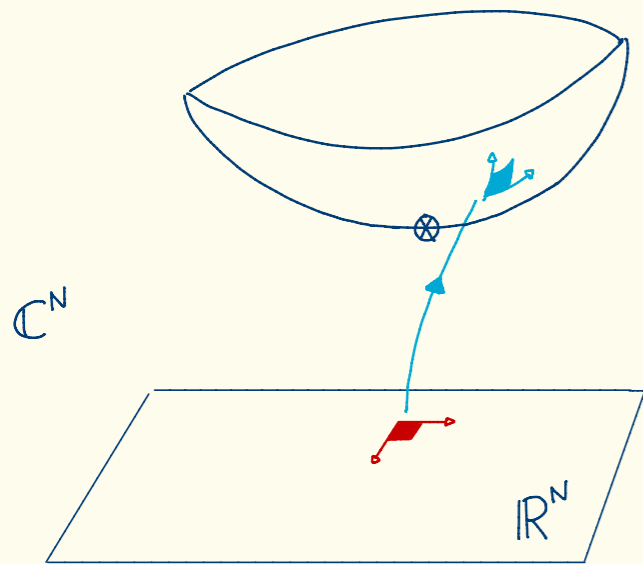
How to find good deformations ?



2) sign fluctuations are reduced

The algorithm

$$\begin{aligned}
 \langle \mathcal{O} \rangle &= \frac{\int d\phi_i \mathcal{O} e^{-S_R - iS_I}}{\int d\phi_i e^{-S_R - iS_I}} = \frac{\int d\tilde{\phi}_i \det \left(\frac{\partial \phi_i}{\partial \tilde{\phi}_i} \right) \mathcal{O} e^{-S_R - iS_I}}{\int d\tilde{\phi}_i \det \left(\frac{\partial \phi_i}{\partial \tilde{\phi}_i} \right) e^{-S_R - iS_I}} \\
 &= \frac{\int d\tilde{\phi}_i \mathcal{O} e^{-iS_I + i\text{Im}J} e^{-\overbrace{(S_R - \text{Re}J)}^{S_{eff}}}}{\int d\tilde{\phi}_i e^{-iS_I + i\text{Im}J} e^{-\overbrace{(S_R - \text{Re}J)}^{S_{eff}}}} = \frac{\langle \mathcal{O} e^{-iS_I + i\text{Im}J} \rangle_{S_{eff}}}{\langle e^{-iS_I + i\text{Im}J} \rangle_{S_{eff}}}
 \end{aligned}$$

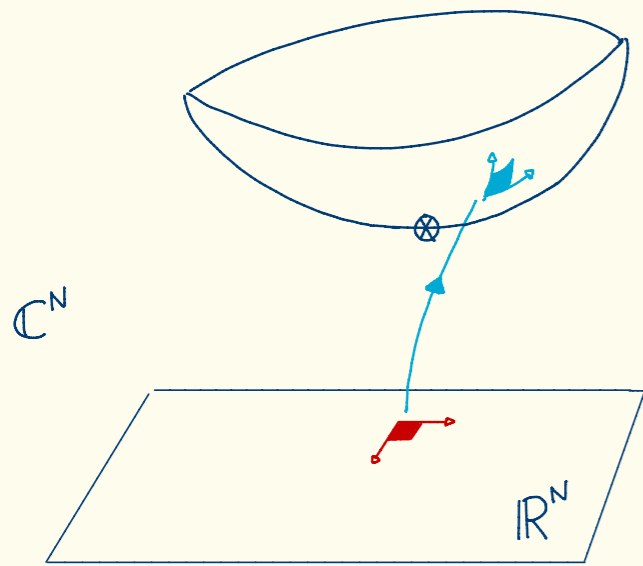


$$\begin{aligned}
 \frac{dJ_{ij}}{dt} &= \frac{\partial^2 S}{\partial z_i \partial z_k} J_{jk} \\
 J_{ij}(0) &= \mathbb{I}
 \end{aligned}
 \quad \longrightarrow \quad
 J = \det J(T)$$

this is the expensive part

The algorithm

$$\begin{aligned}
 \langle \mathcal{O} \rangle &= \frac{\int d\phi_i \mathcal{O} e^{-S_R - iS_I}}{\int d\phi_i e^{-S_R - iS_I}} = \frac{\int d\tilde{\phi}_i \det \left(\frac{\partial \phi_i}{\partial \tilde{\phi}_i} \right) \mathcal{O} e^{-S_R - iS_I}}{\int d\tilde{\phi}_i \det \left(\frac{\partial \phi_i}{\partial \tilde{\phi}_i} \right) e^{-S_R - iS_I}} \\
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 \end{aligned}$$



our algorithm

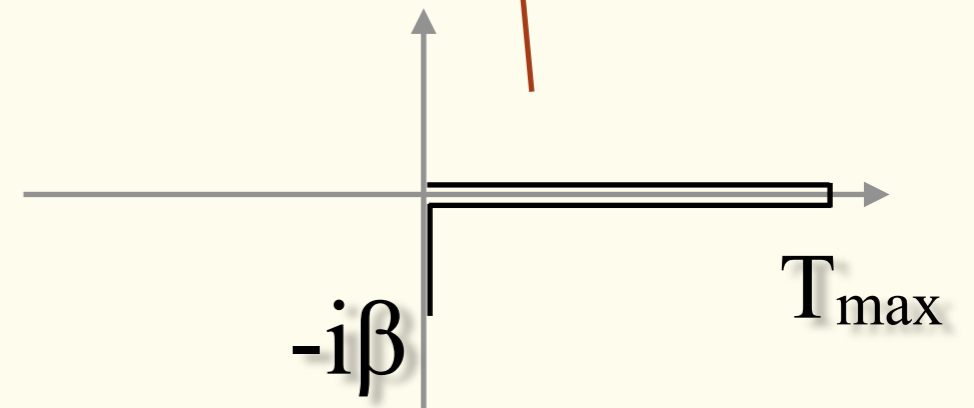
=

Metropolis in the real space,
action S_{eff} and
reweighted phase $e^{i \text{Im}(\ln J) - i \text{Im}(S)}$

Application: Real Time Dynamics

Viscosities, conductivities, ... require:

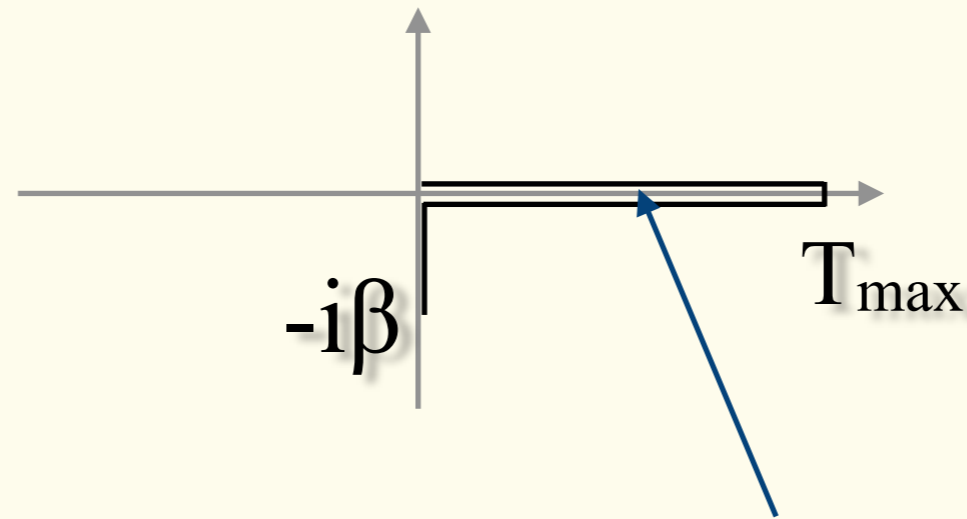
$$\langle \phi(t)\phi(t') \rangle_\beta = \frac{1}{Z} \text{Tr}(e^{-\beta H} \phi(t)\phi(t')) = \frac{1}{Z} \int D\phi e^{iS_c[\phi]} \phi(t)\phi(t')$$



Schwinger-Keldysh
contour

(works also out of equilibrium)

Real Time: The Mother of All Sign Problems



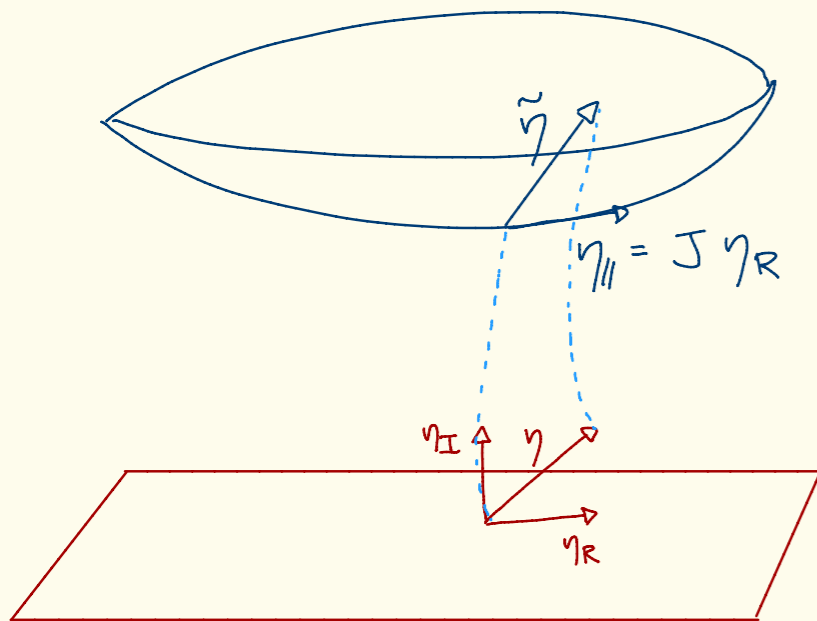
field at a point in the real axis does not contribute to the damping factor in e^{iS_c}

$$\langle e^{i\text{Im}(iS_c)} \rangle = 0$$

Problems

- tangent space in wrong homology class
- large flow needed (from \mathbb{R}^N)
- jacobian expensive (no known estimator)
- anisotropic proposals

“Grady algorithm” for the jacobian (Grady '85, Creutz '92)

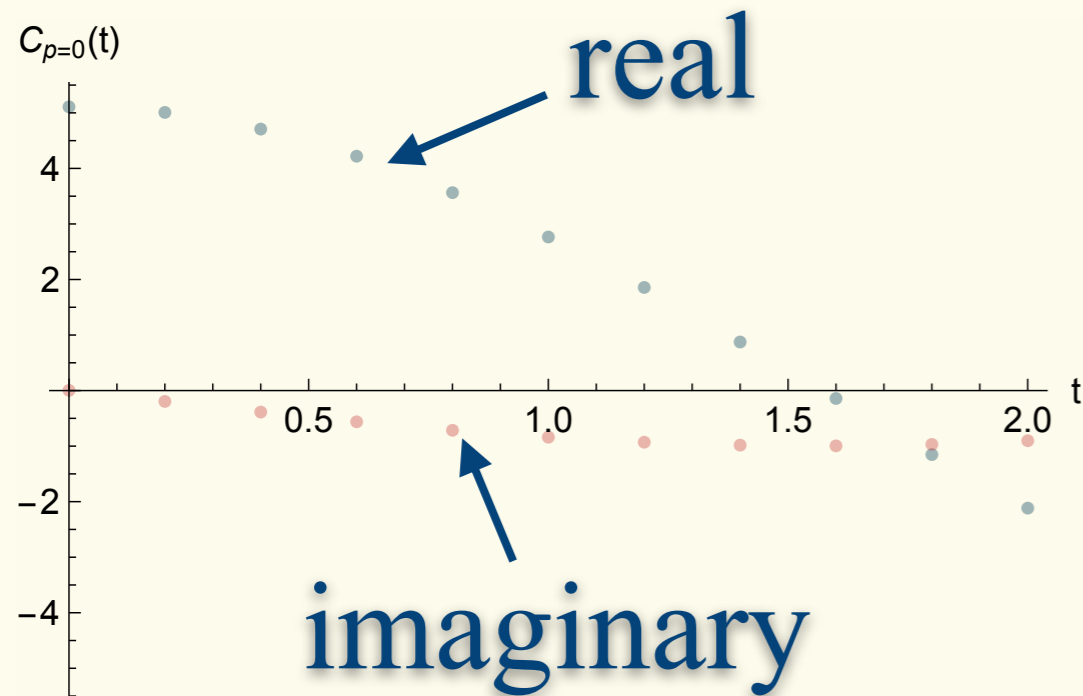


$$J\eta = \tilde{\eta} \quad \tilde{\eta}_{||} = JRe(\eta)$$

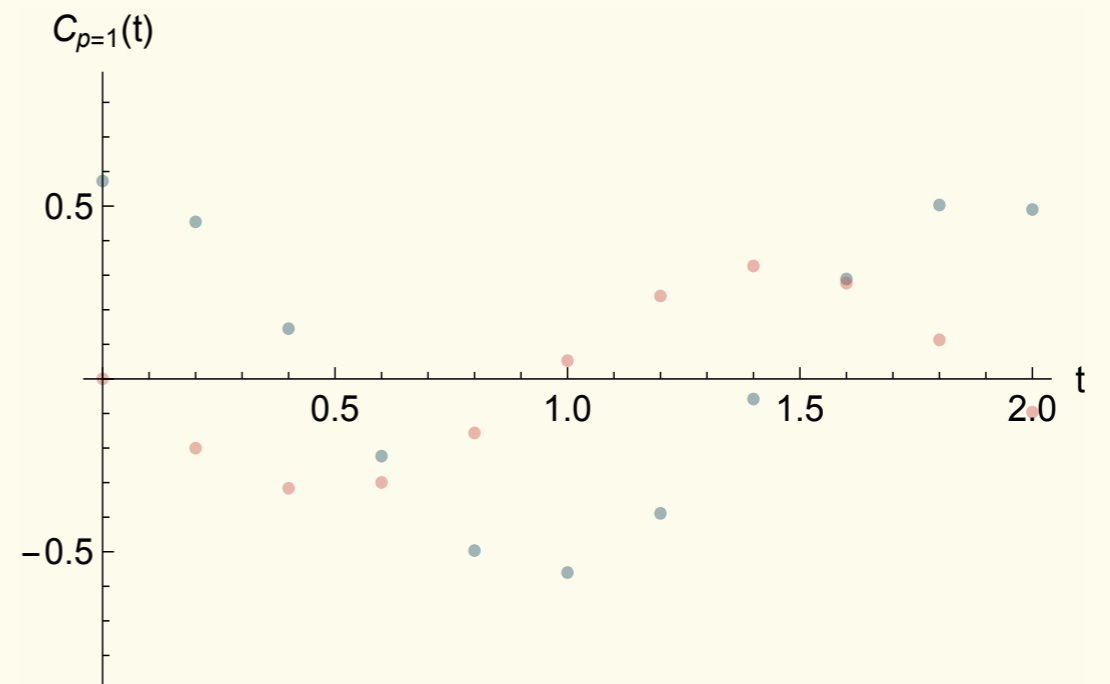
- isotropic proposal
- no need to compute $\det(J)$

1+1D φ^4 : $n_t=10, n_x=10, n_\beta=2, \lambda=0.1$

weak coupling



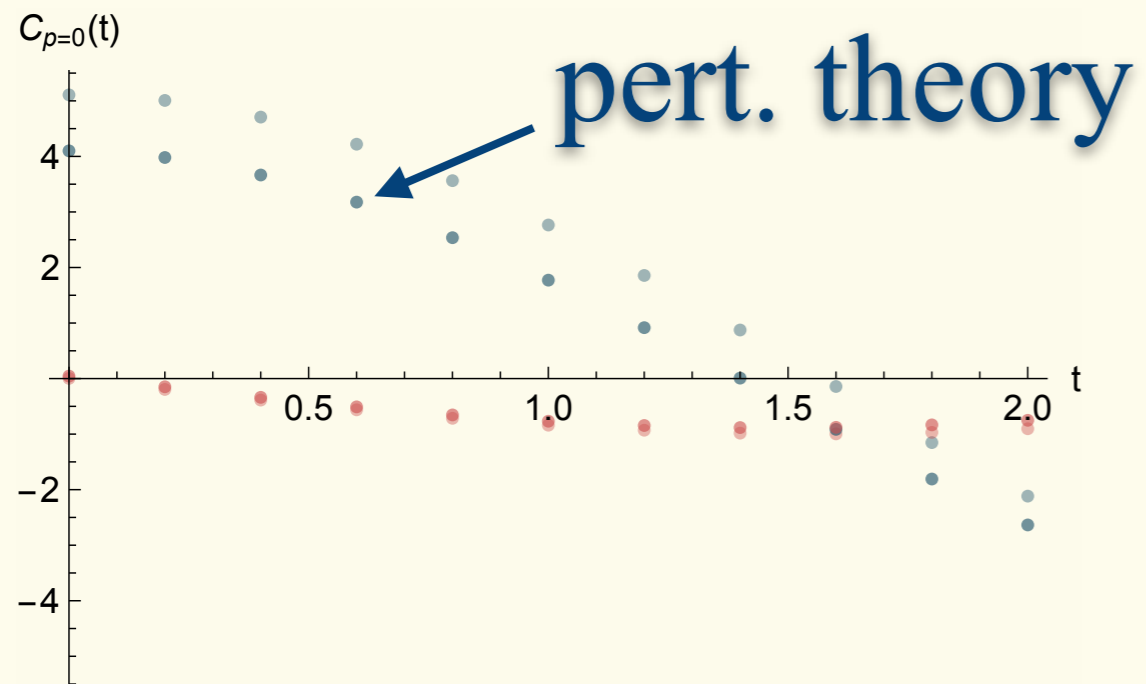
$p=0$



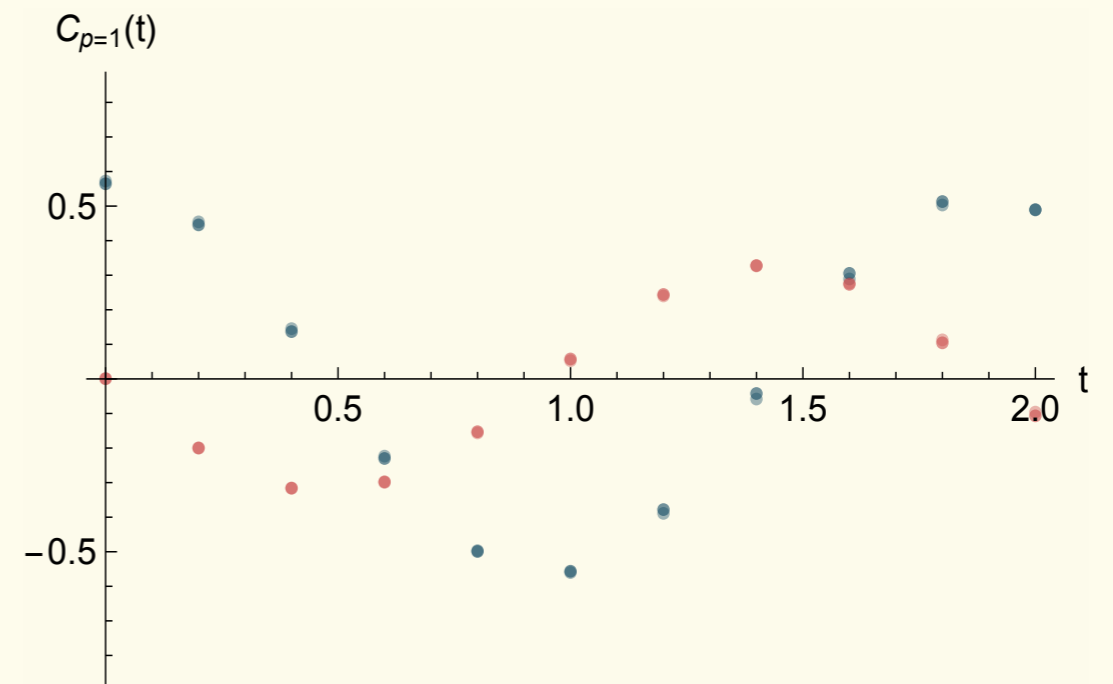
$p=2\pi/L$

1+1D φ^4 : $n_t=10, n_x=10, n_\beta=2, \lambda=0.1$

weak coupling



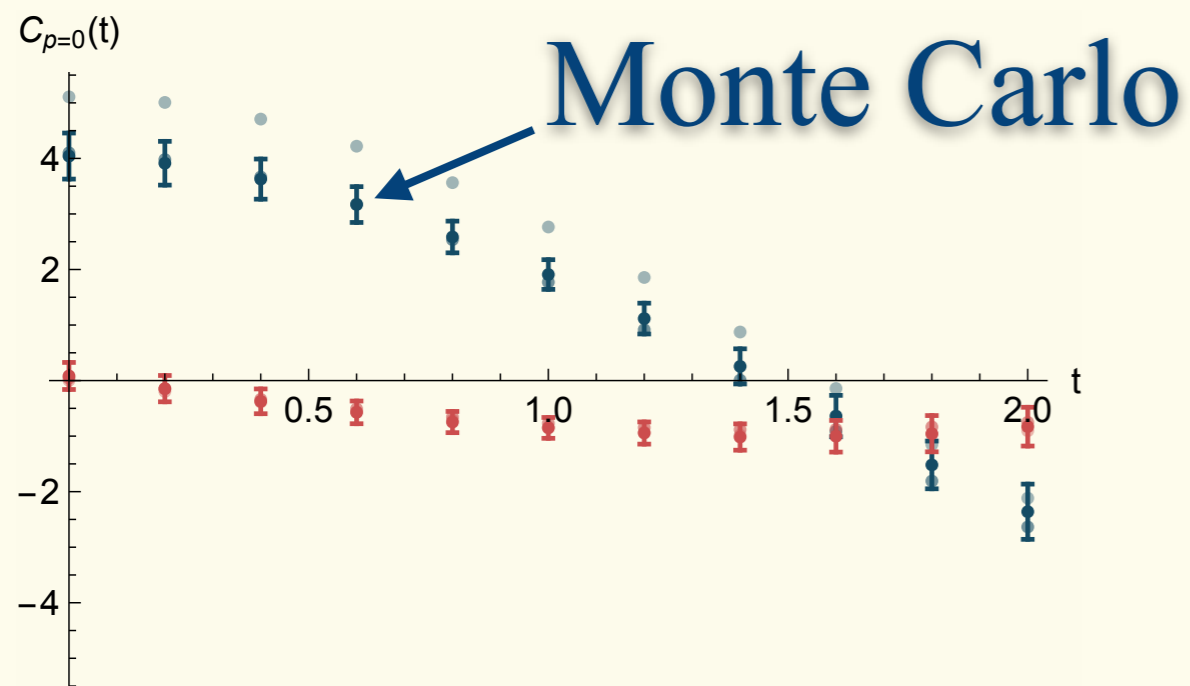
$p=0$



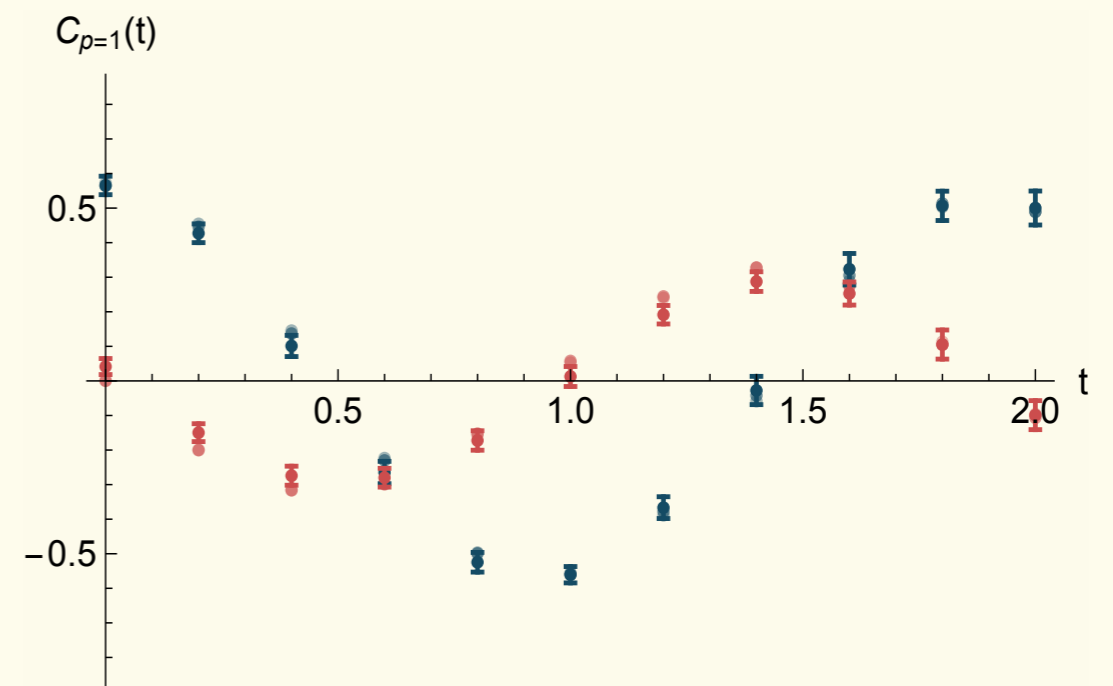
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weak coupling



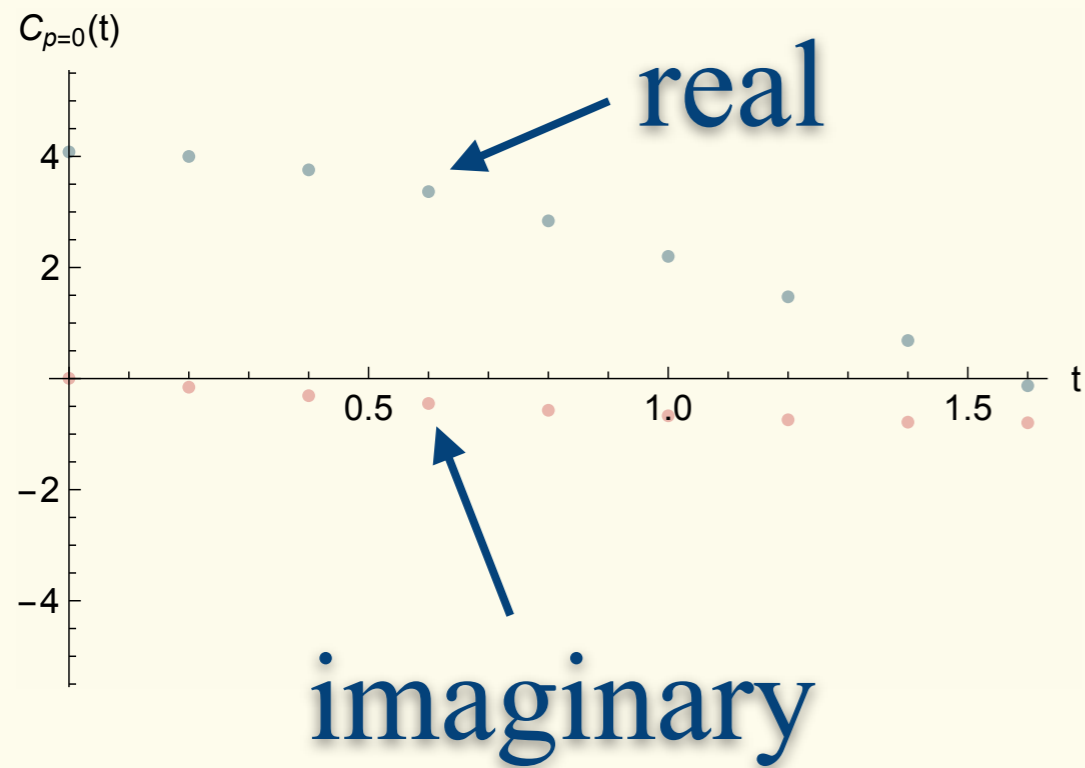
$p=0$



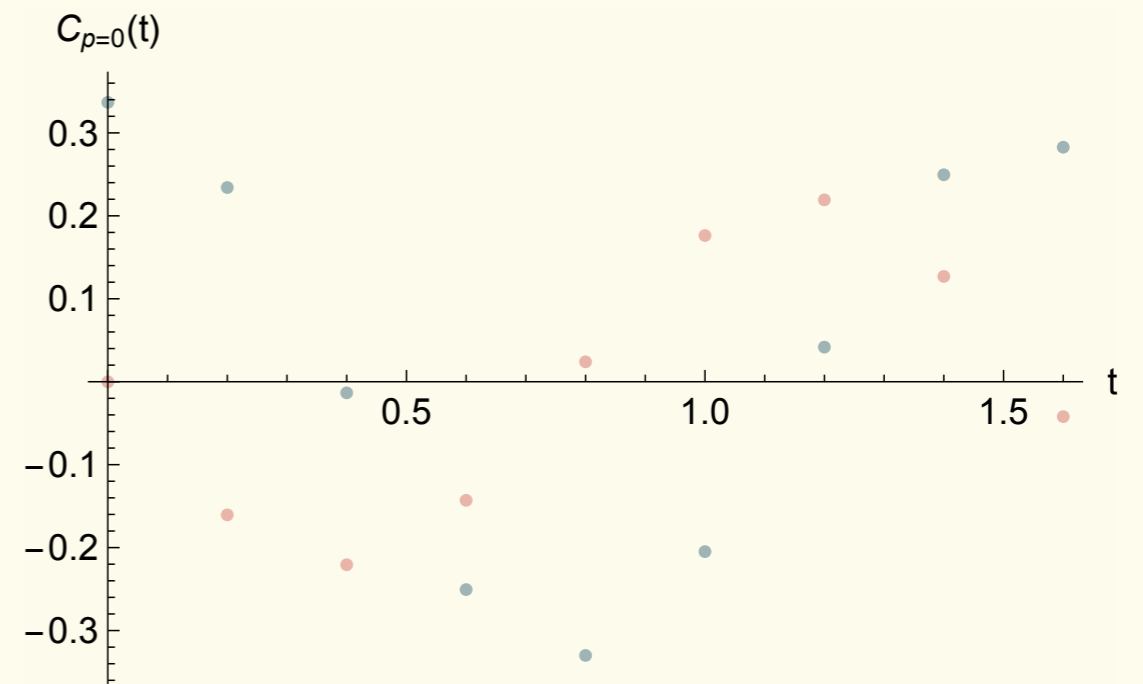
$p=2\pi/L$

1+1D ϕ^4 : $n_t=10, n_x=10, n_\beta=2, \lambda=1.0$

strong coupling



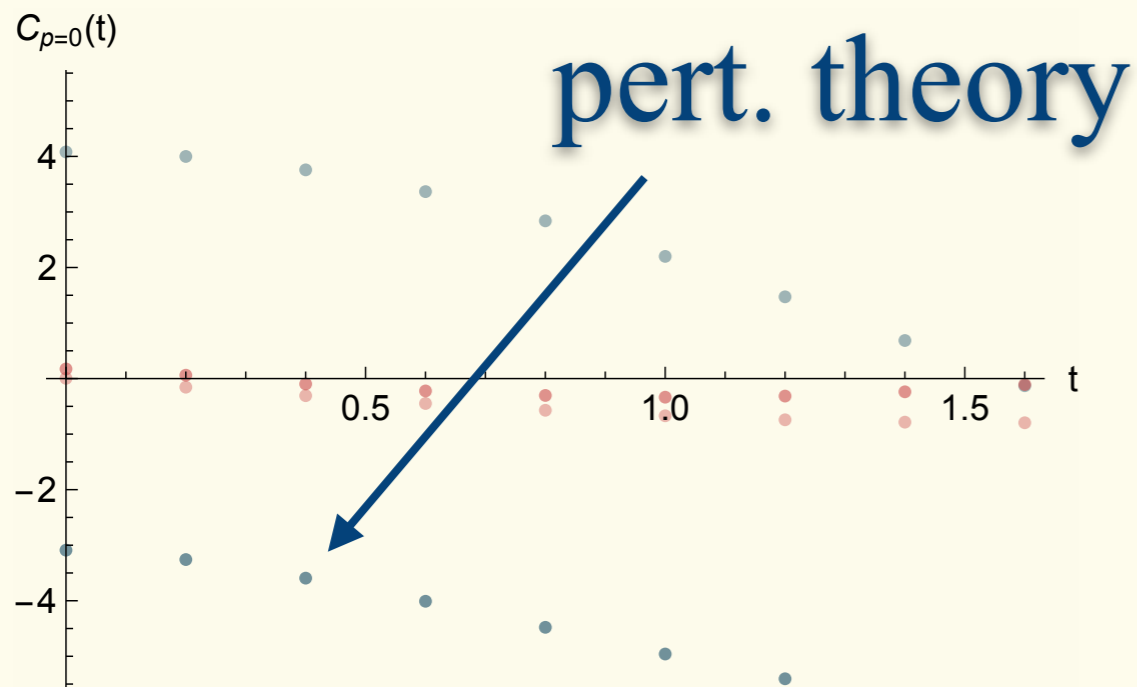
$p=0$



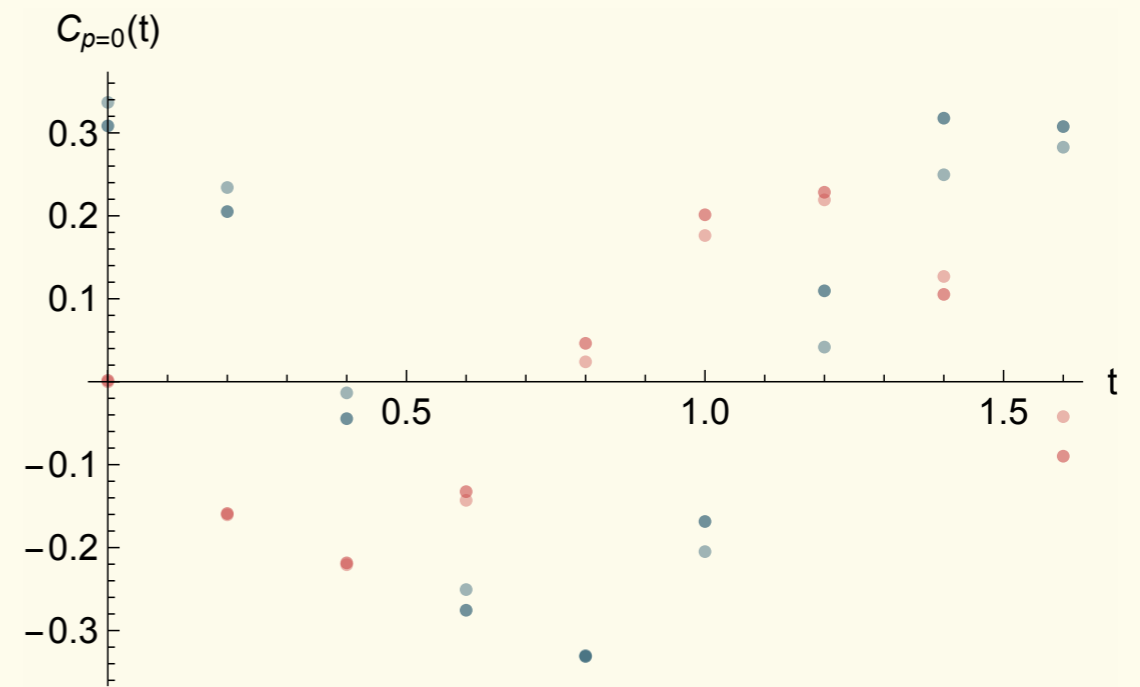
$p=2\pi/L$

1+1D ϕ^4 : $n_t=10, n_x=10, n_\beta=2, \lambda=1.0$

strong coupling



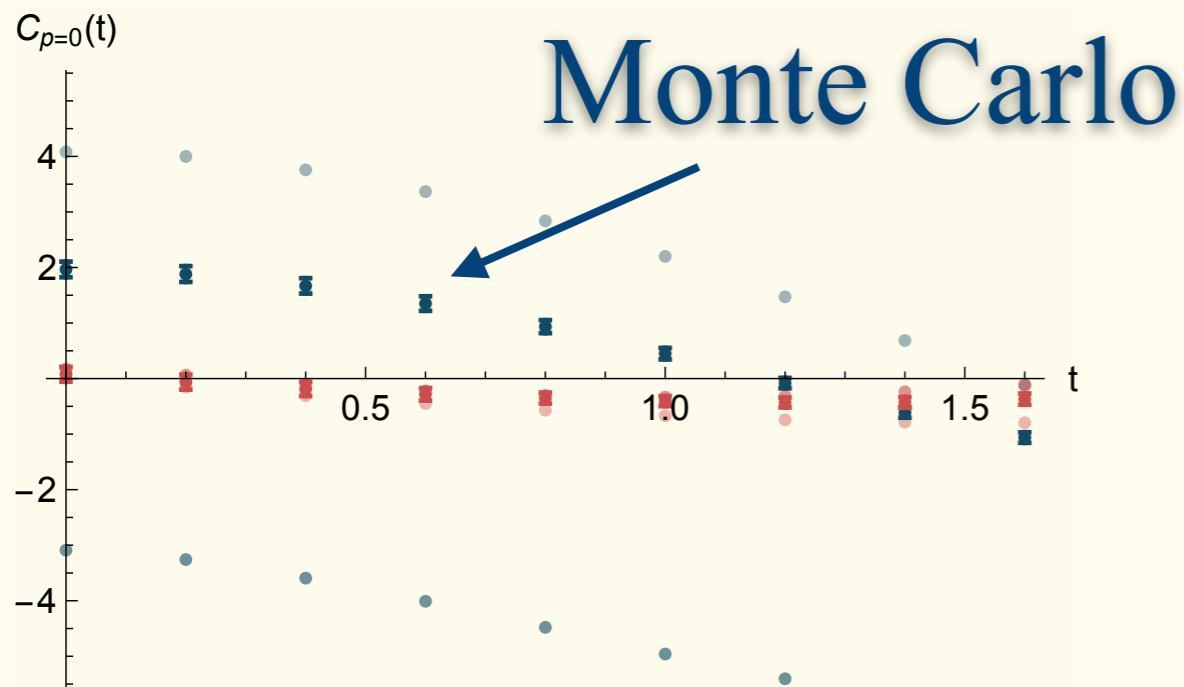
$p=0$



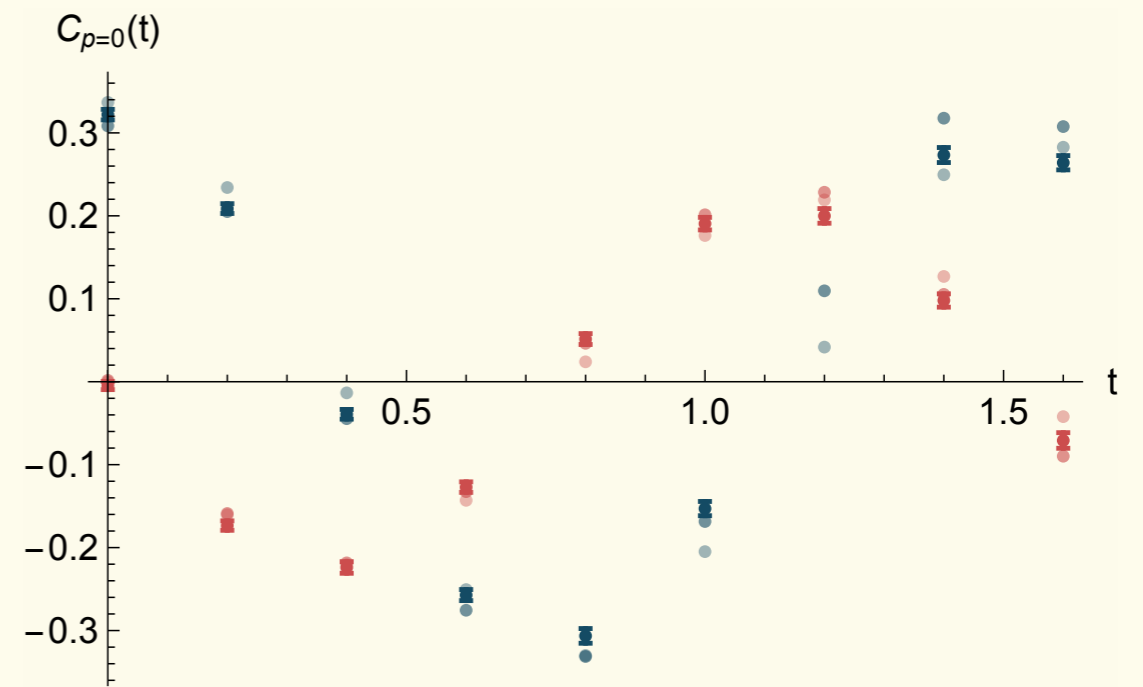
$p=2\pi/L$

1+1D ϕ^4 : $n_t=10, n_x=10, n_\beta=2, \lambda=1.0$

strong coupling



$p=0$

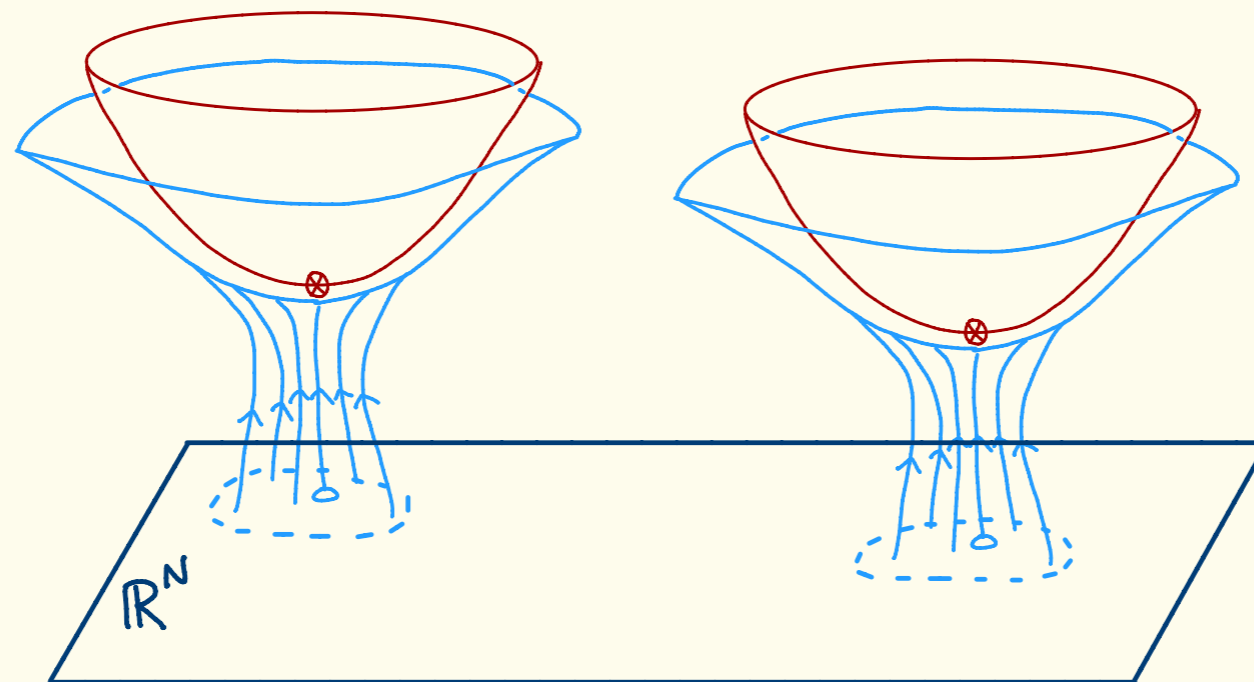


$p=2\pi/L$

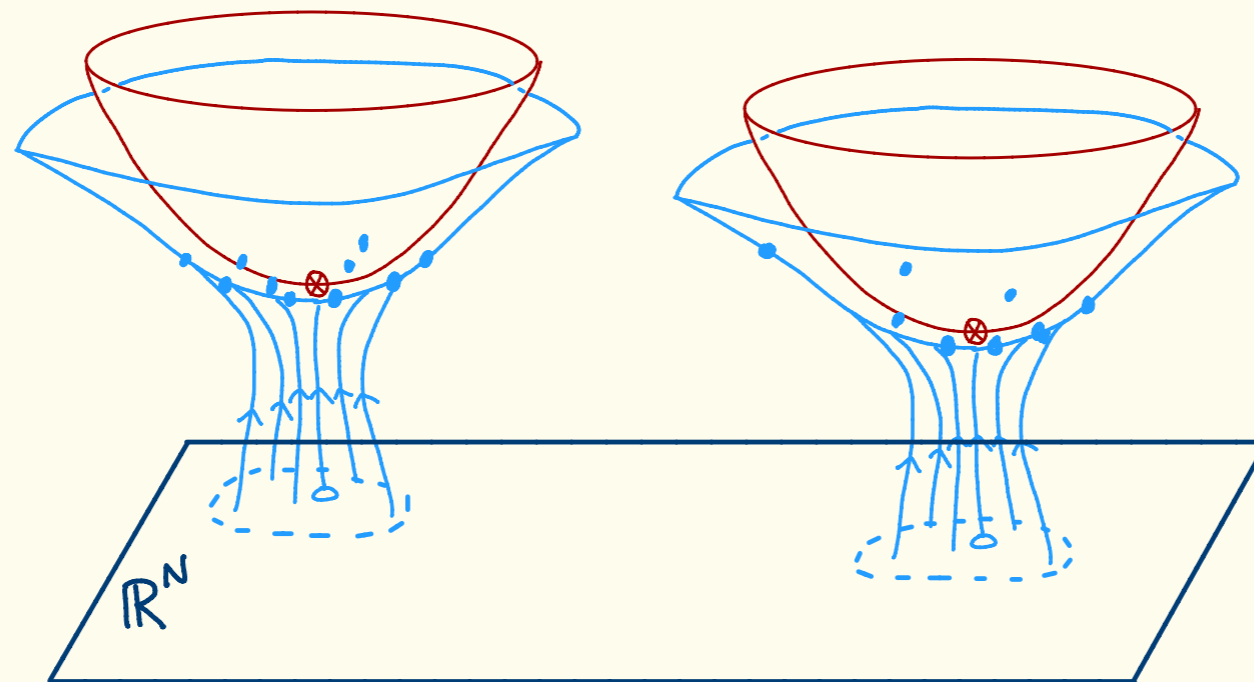
Application: Real Time Dynamics

- Currently limited to small times : $t < 5/T$
- Cost increases sharply with t
- There has to be a catch:
simulation of a quantum computer performing
the Schor algorithm
= nonsense
classical $O(\log^2 N)$ time factorization

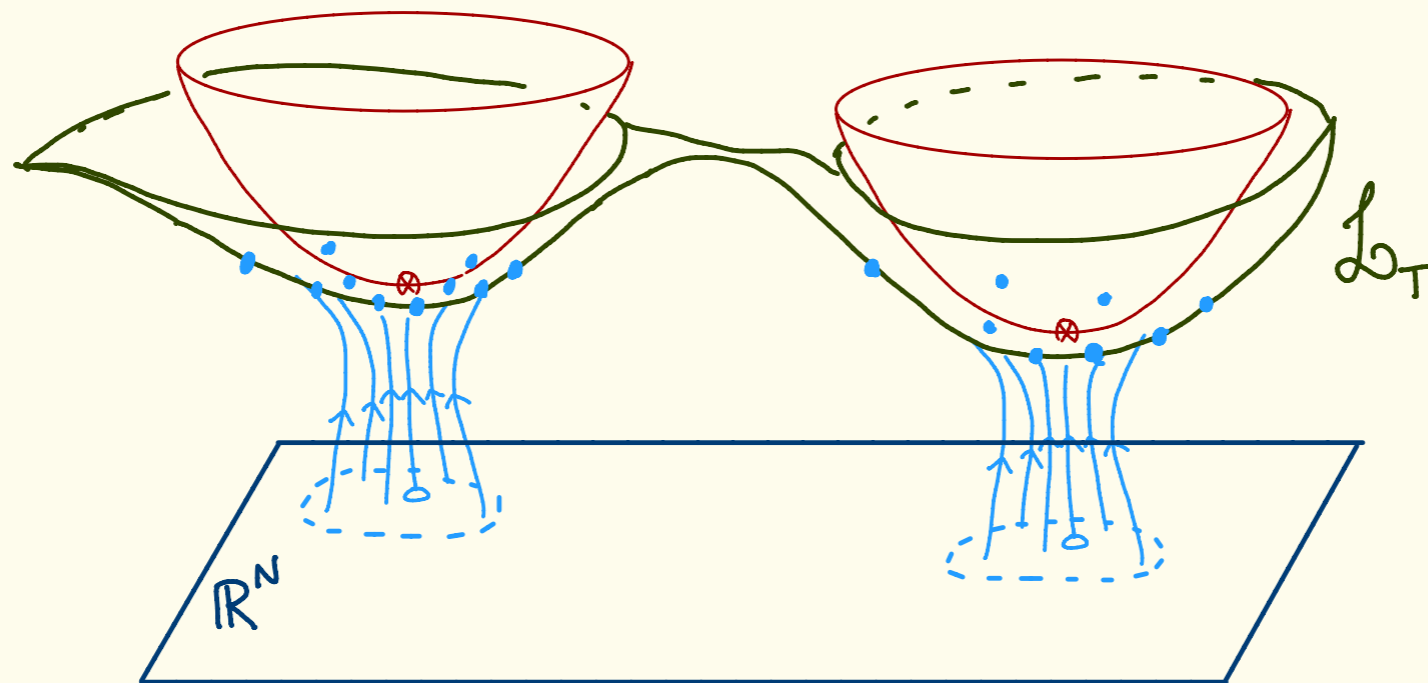
Bypassing the flow: machine learning



Bypassing the flow: machine learning



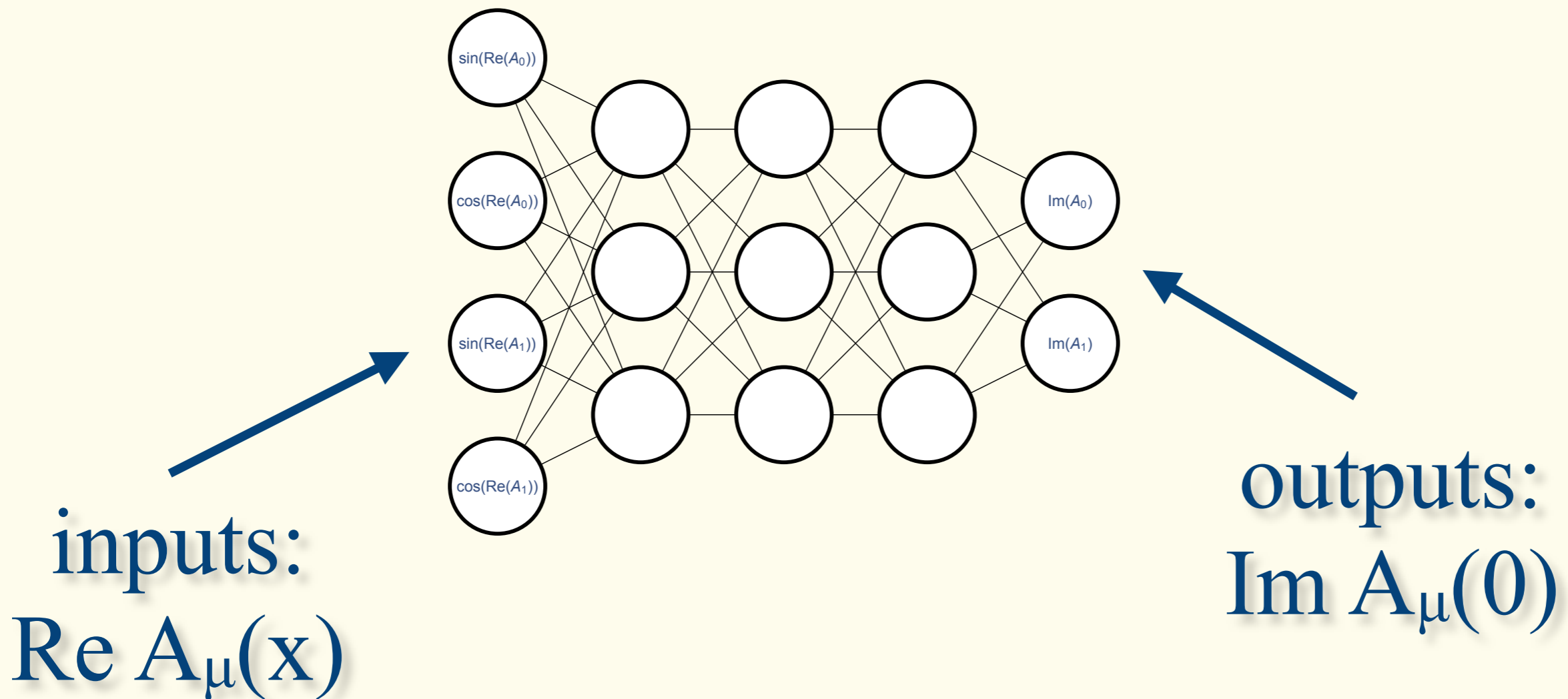
Bypassing the flow: machine learning



$\mathcal{L}_T =$ (rough?) interpolation of points of \mathcal{M}_T

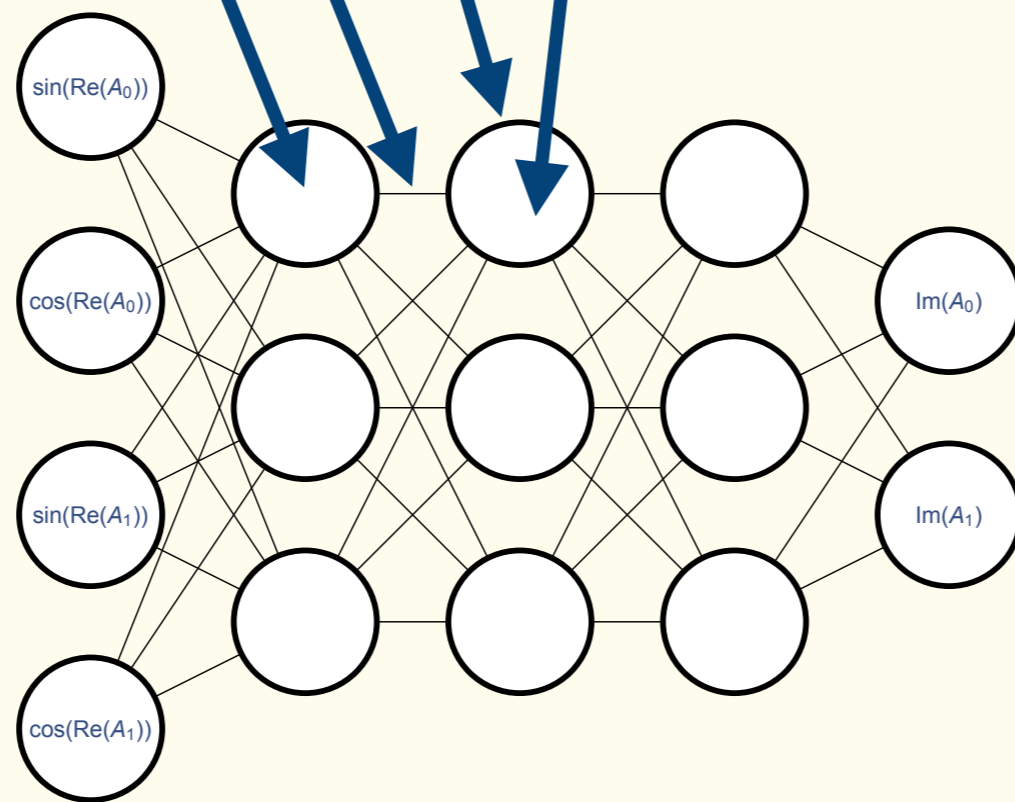
Bypassing the flow: machine learning

feed-forward neural net
(supervised training)



Bypassing the flow: machine learning

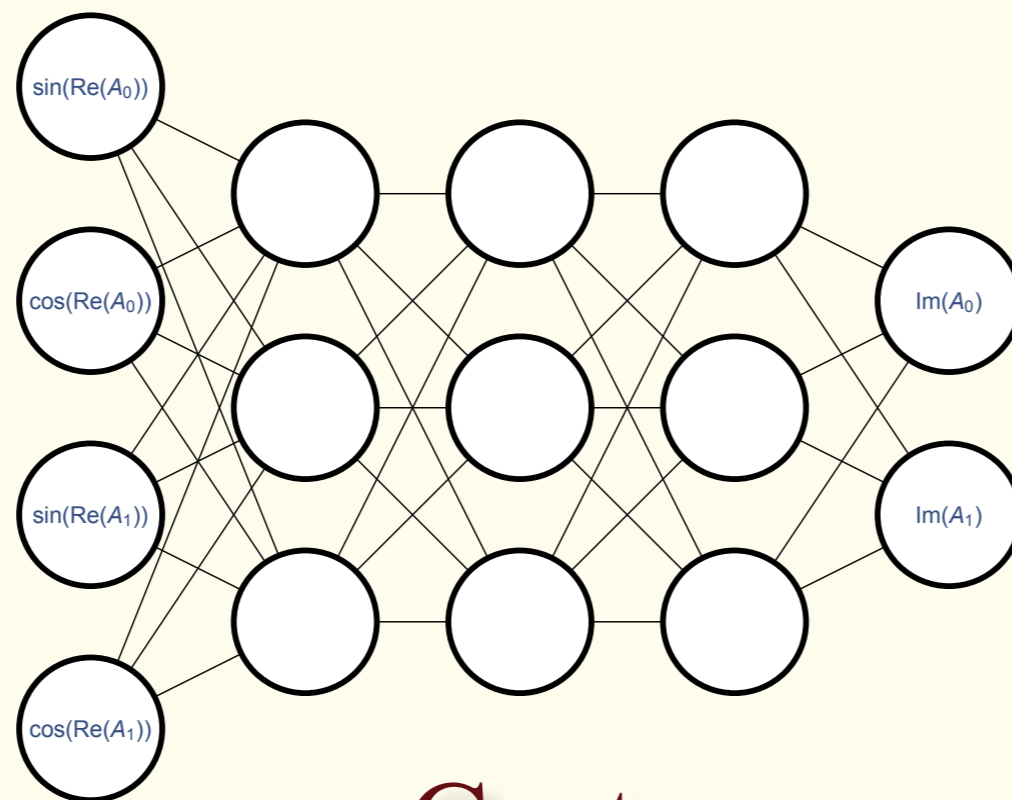
$$\sigma(x_i w_i + b) = y$$



inputs:
 $\text{Re } A_\mu(x)$

outputs:
 $\text{Im } A_\mu(0)$

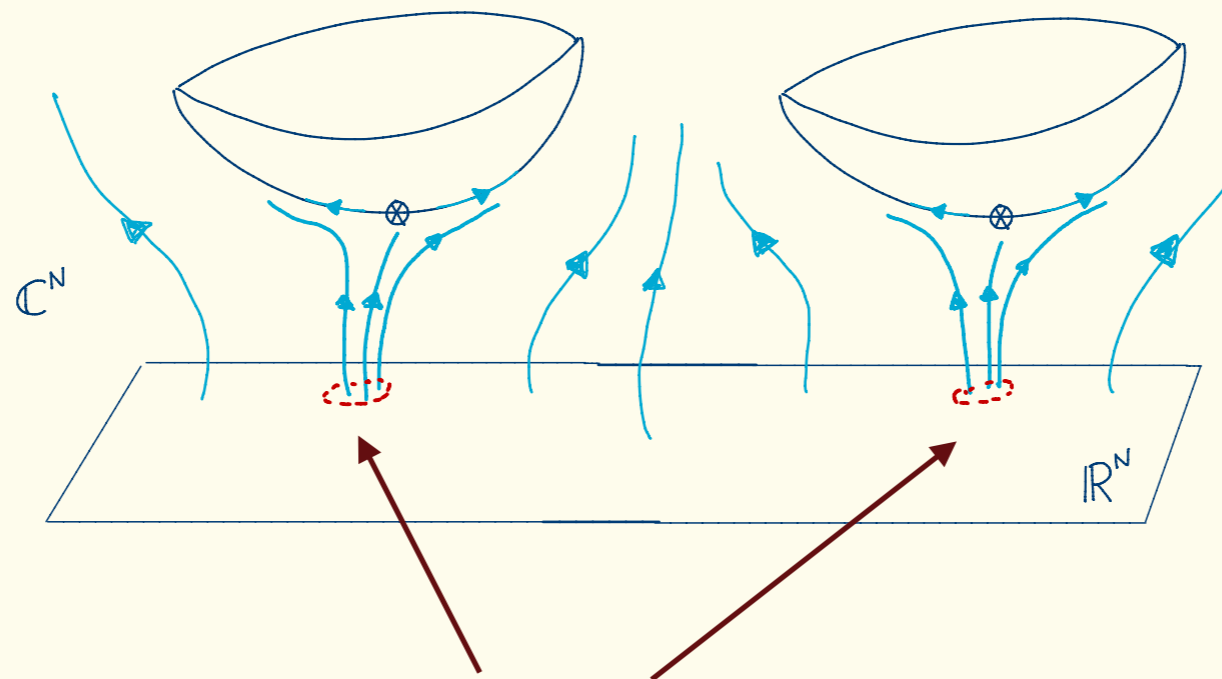
Bypassing the flow: machine learning feed-forward neural net (supervised training)



Cost:

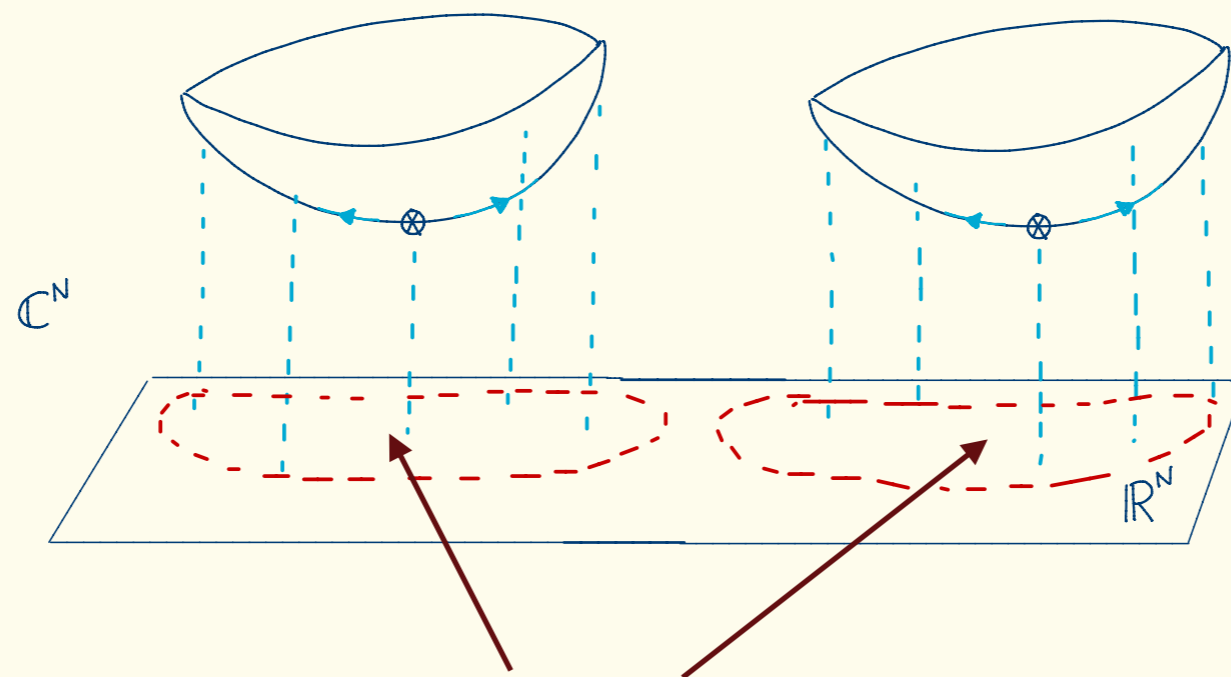
flowed configurations >> training >> sampling

Bypassing the flow: machine learning



isolated modes: trapping

Bypassing the flow: machine learning



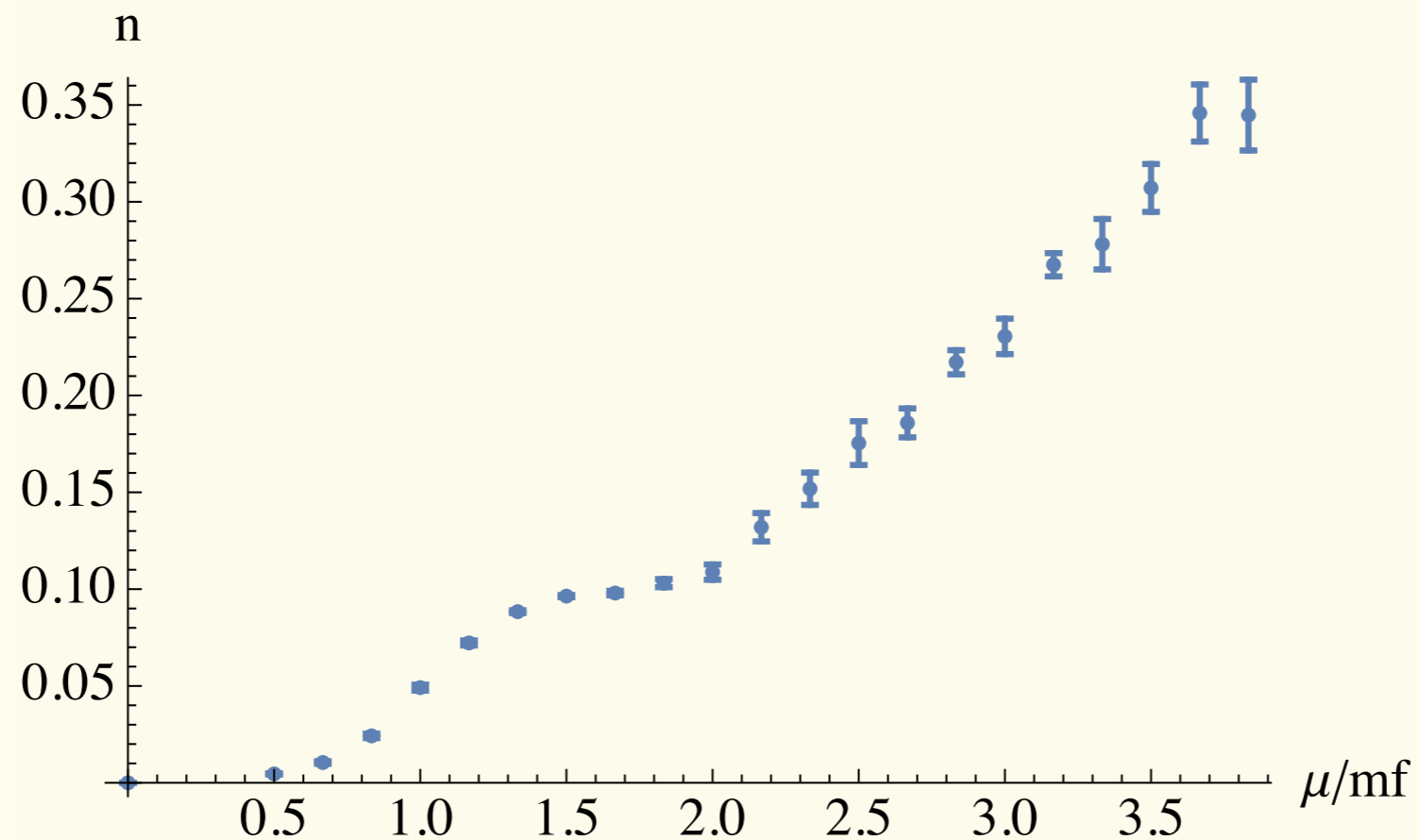
no trapping

continuous map
between manifolds:

$$\phi = \tilde{\phi}_R + t \phi_I$$

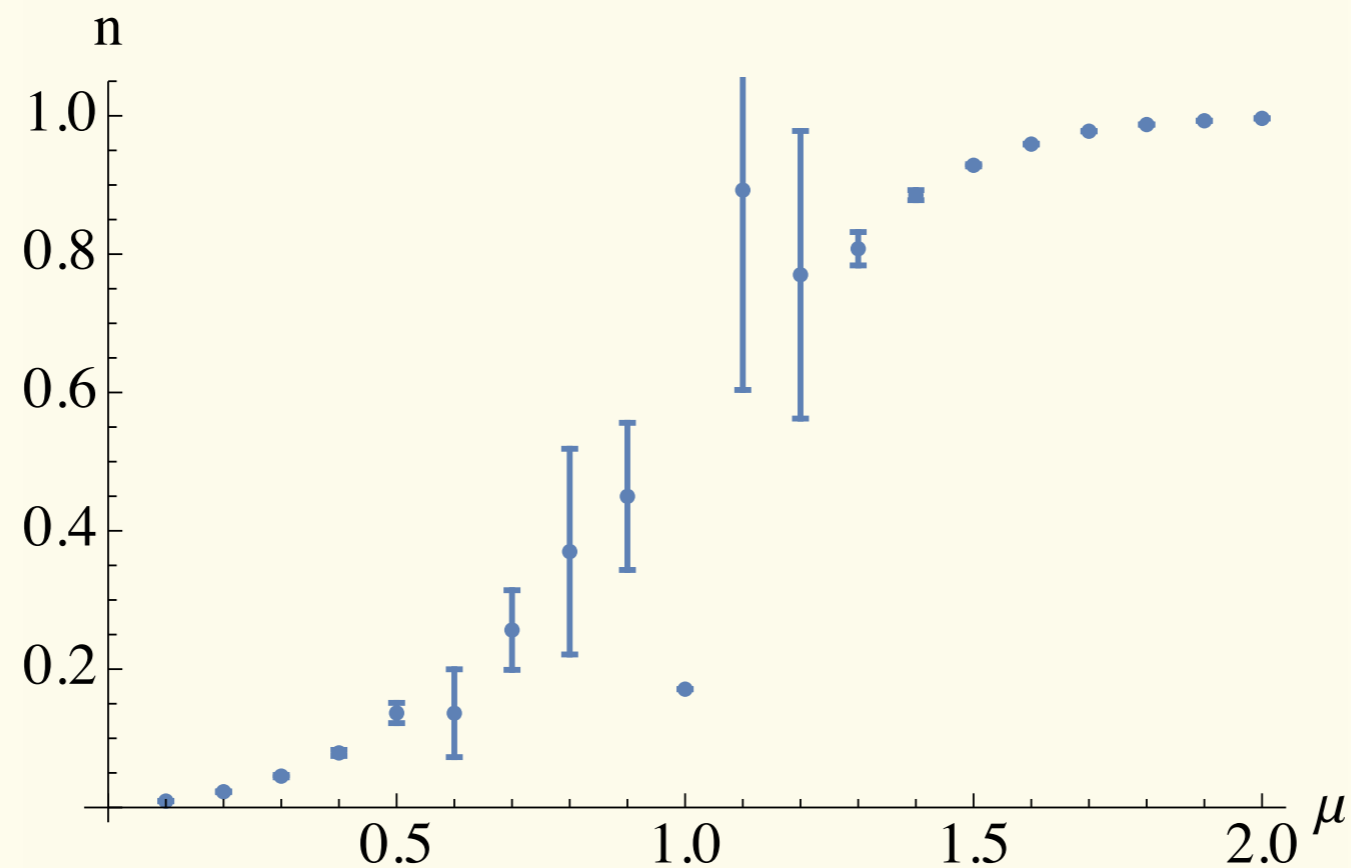
Bypassing the flow: machine learning

Wilson, 20 x10 lattice, $N_F=2$, $am_f=0.3$



Why stop there: let the network find a manifold with a “good” sign

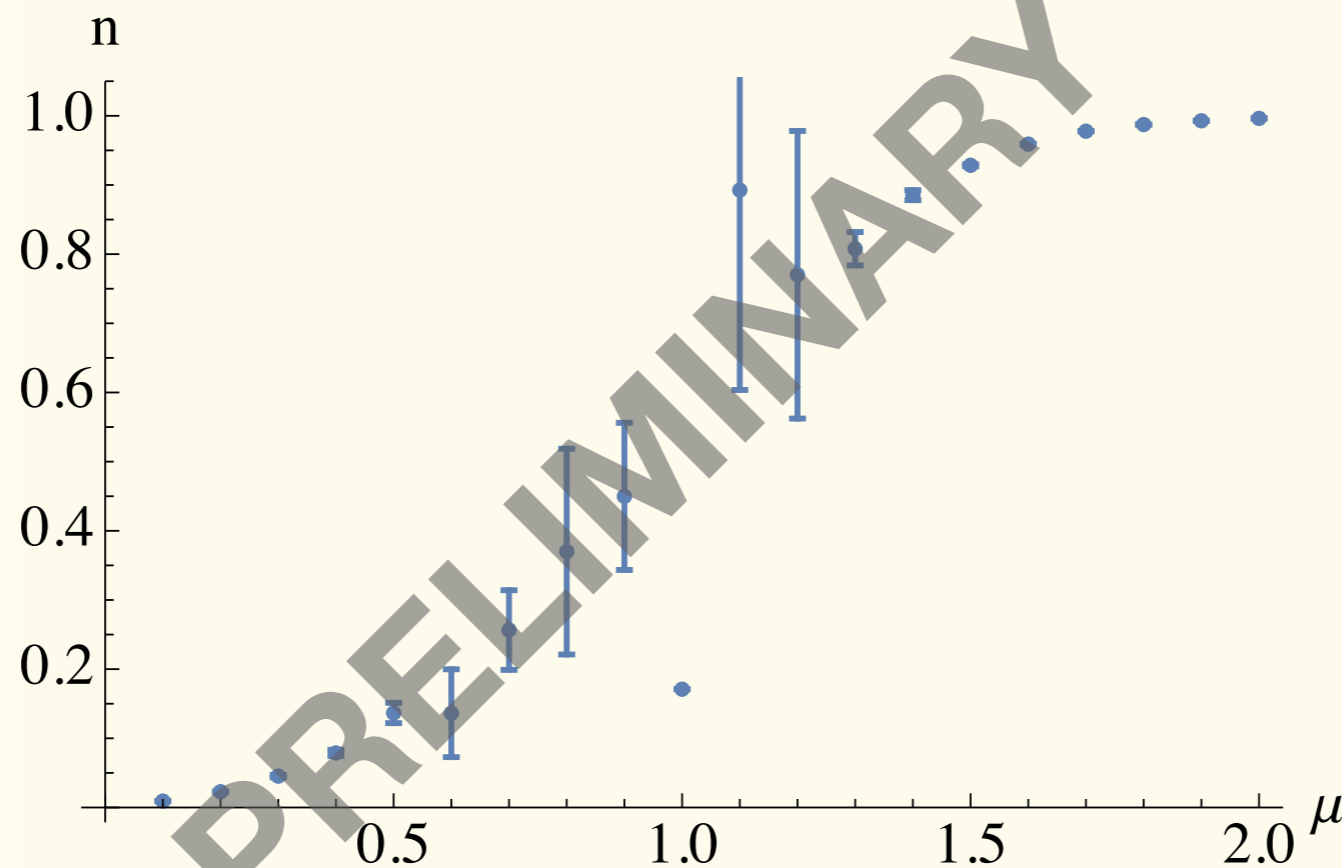
6^3 lattice



- It finds the shift to tangent plane in the 1st minute; then it finds a better “renormalized tangent plane”
- It doesn’t get terribly better fast

Why stop there: let the network find a manifold with a “good” sign

6^3 lattice



- It finds the shift to tangent plane in the 1st minute; then it finds a better “renormalized” thimble
- It doesn’t get terribly better fast

To take home:

- Deforming the integration on complex space is a good thing
- Thimbles are just one possibility
- Jacobians are expensive: estimators, “Grady-style” algorithm, ansatze, alternative flows, machine learned manifolds, ...