

Real time simulations of scalar fields with kernelled complex Langevin equation

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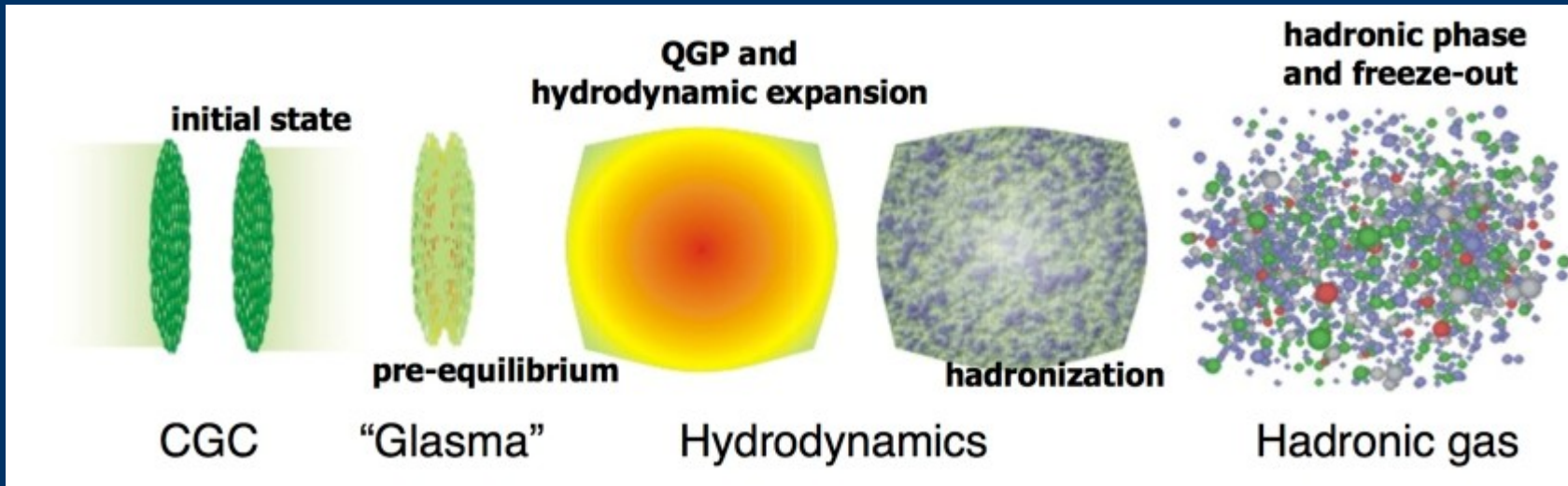
FWF Austrian
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Collaborators: Daniel Alvestad, Nina Maria Lampl, Alexander Rothkopf

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1. Introduction to Sign-problem of real-time physics and Complex Langevin
2. Kernels in the CLE – How to get rid of boundary terms
3. realtime scalars in $0+1$ and $1+1$ dimensions

Heavy-Ion collisions



How does the Glasma equilibrate?

Non-equilibrium Quantum Field theory

$$|\Psi(t=0)\rangle \rightarrow |\Psi(t)\rangle$$

For hydrodynamics one needs equilibrium values of:

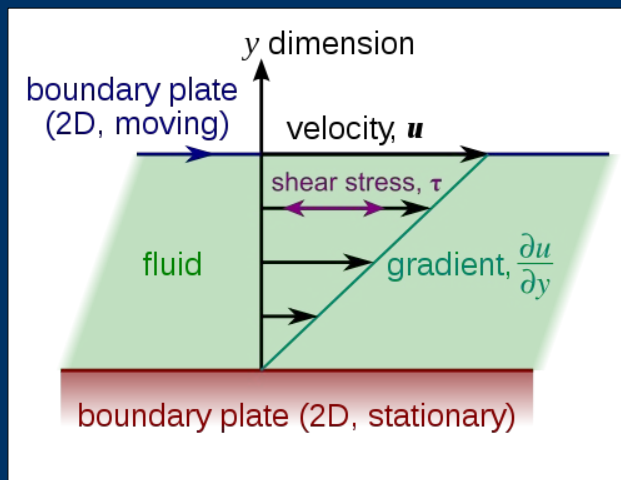
Equation of State

Transport coefficients: e.g. viscosity

← "easy" to calculate

Hard problem
Real-time correlator

$$\eta = \frac{1}{TV} \int_0^\infty dt \langle \sigma_{xy}(0) \sigma_{xy}(t) \rangle$$



Why is real-time QFT so hard?

→ Sign Problem

Path integral formulation of Quantum Mechanics

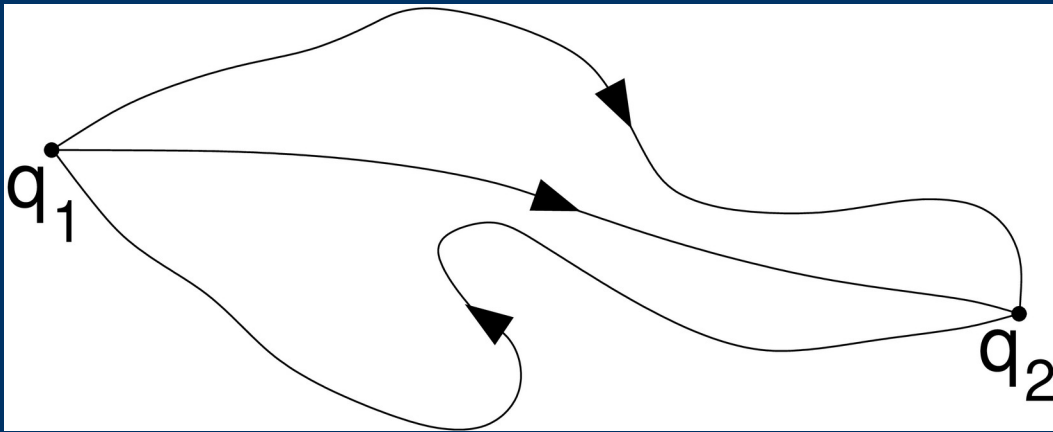
Quantum Mechanics with $\hat{H} = \frac{\hat{p}^2}{2m} + V(\hat{q})$

Time evolution given by Schrödinger eq. $i \partial_t \Psi(x, t) = \hat{H} \Psi(x, t)$ $|\Psi(x, t)\rangle = e^{-it\hat{H}} |\Psi(x, 0)\rangle$

Equivalent formulation

Transition amplitude: $\langle q_2 | e^{-it\hat{H}} | q_1 \rangle = \int_{q_1}^{q_2} Dq e^{iS[q(t)]}$

Path integral: $\int_{q_1}^{q_2} Dq =$ normalized sum for all functions $q(t_1 \leq t \leq t_2)$
with correct bound. cond. $q(t_1) = q_1$ $q(t_2) = q_2$



Numerically advantageous

$q(t)$ instead of $\Psi(x, t)$

Imaginary time: $t \rightarrow -i\tau$ $0 < \tau < -i\beta$

Thermodynamics

$$e^{-it\hat{H}} \rightarrow e^{-\beta\hat{H}}$$

$$\langle q_1 | e^{-\beta\hat{H}} | q_2 \rangle = \int_{q_1}^{q_2} Dq e^{-S_E[q(t)]}$$

$$S_E[q(t)] = \int_{t=0}^{t=\beta} dt \left(\frac{1}{2} m \dot{q}(t)^2 + V(q(t)) \right)$$

Langevin Equation (aka. stochastic quantisation)

Given an action $S(x)$

Stochastic process for x :
$$\frac{dx}{d\tau} = -\frac{\partial S}{\partial x} + \eta(\tau)$$

Gaussian noise

$$\begin{aligned}\langle \eta(\tau) \rangle &= 0 \\ \langle \eta(\tau) \eta(\tau') \rangle &= \delta(\tau - \tau')\end{aligned}$$

Random walk in configuration space

Averages are calculated along the trajectories:

$$\langle O \rangle = \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T O(x(\tau)) d\tau = \frac{\int e^{-S(x)} O(x) dx}{\int e^{-S(x)} dx}$$

Numerically,
results are extrapolated to $\Delta\tau \rightarrow 0$

Complex Langevin Equation

Given an action $S(x)$

Stochastic process for x : $\frac{dx}{d\tau} = -\frac{\partial S}{\partial x} + \eta(\tau)$ Gaussian noise
 $\langle \eta(\tau) \rangle = 0$
 $\langle \eta(\tau) \eta(\tau') \rangle = \delta(\tau - \tau')$

The field is complexified

$$\frac{dx}{d\tau} = -\frac{\partial S}{\partial x} + \eta(\tau)$$

real scalar \longrightarrow complex scalar

link variables: $SU(N)$ \longrightarrow $SL(N, \mathbb{C})$
 compact non-compact
 $\det(U) = 1, \quad U^\dagger \neq U^{-1}$

Analytically continued observables are calculated along the trajectories:

$$\langle O \rangle = \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T O(x(\tau) + iy(\tau)) d\tau \quad \langle x^2 \rangle_{real} \rightarrow \langle x^2 - y^2 \rangle_{complexified}$$

$$\frac{1}{Z} \int P_{comp}(x) O(x) dx = \frac{1}{Z} \int P_{real}(x, y) O(x + iy) dx dy \quad ?$$

Gaussian Example

$$S[x] = \sigma x^2 + i\lambda x$$

CLE

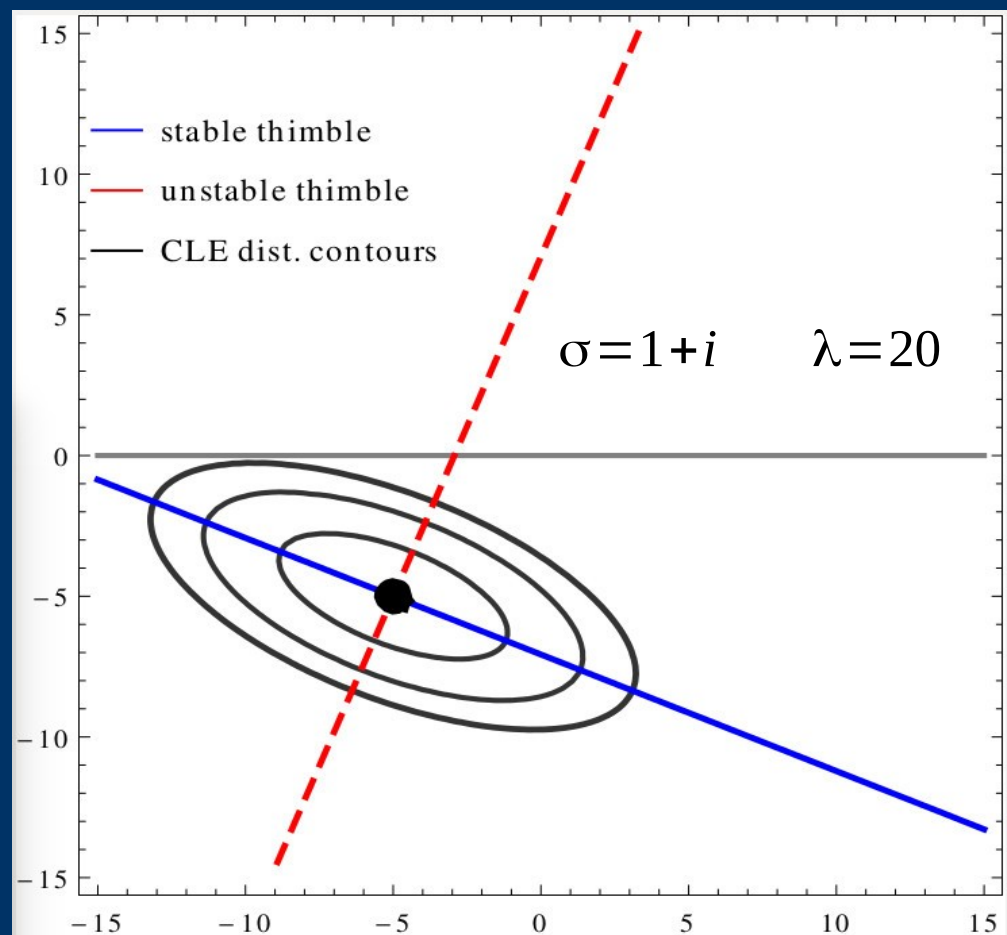
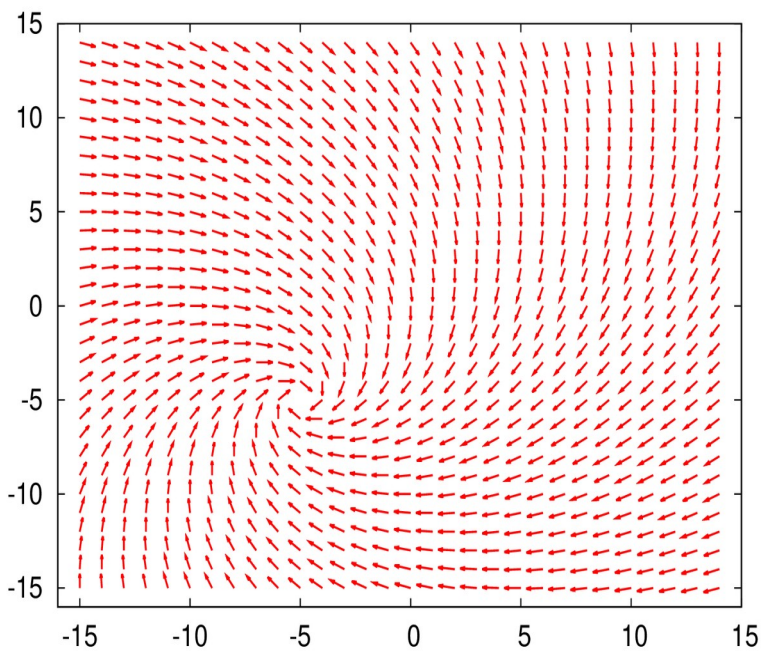
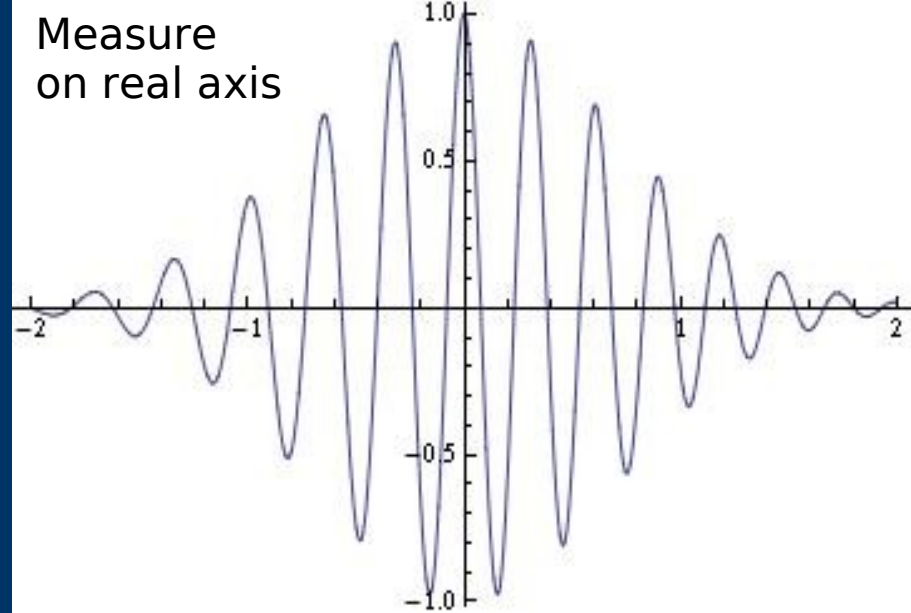
$$\frac{d}{d\tau}(x+iy) = -2\sigma(x+iy) - i\lambda + \eta$$

$$P(x, y) = e^{-a(x-x_0)^2 - b(y-y_0)^2 - c(x-x_0)(y-y_0)}$$

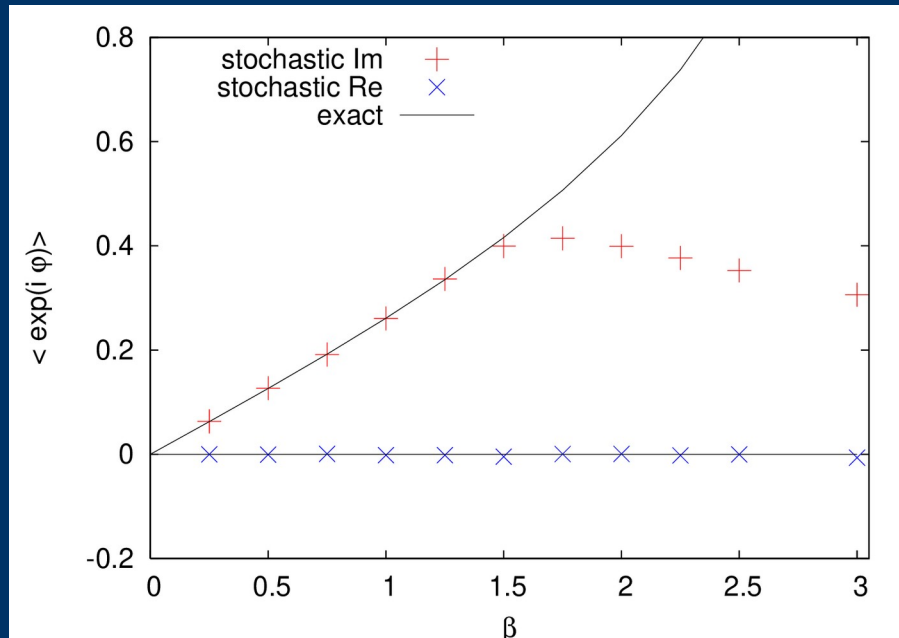
Gaussian distribution
around critical point

$$\left. \frac{\partial S(z)}{\partial z} \right|_{z_0} = 0$$

Measure
on real axis



For nontrivial models CLE may or may not give a correct answer



$$S(\varphi) = i\beta \cos \varphi + i\varphi$$

Do we know if it's correct?

Reasons for incorrect results: slowly decaying distributions (Boundary terms)
different cycles contributing [See talk of Michael Mandl]
non-holomorphic actions

Diagnostic observables: boundary terms
certain non-holomorphic observables, histograms

What can we do if it's incorrect?

Change variables
Use a kernel (see below)
Use a "regularization" [See talk of Michael Hansen]

Quantum oscillator

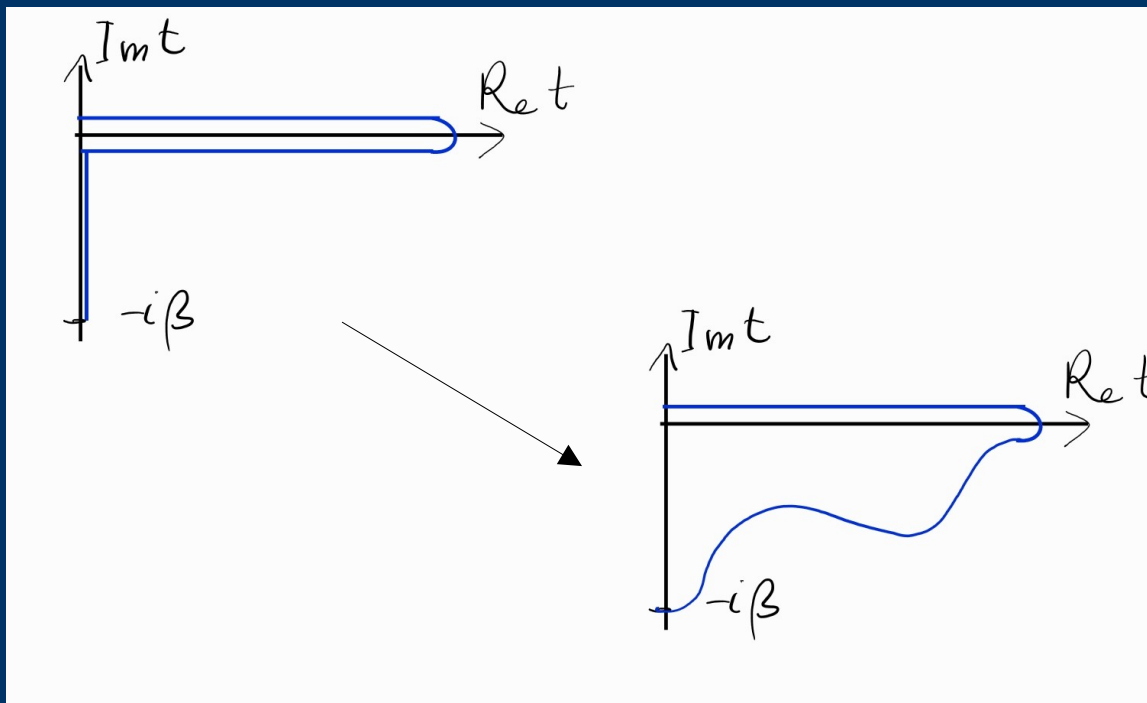
$$S = \int dt \frac{1}{2} \left(\frac{d\phi}{dt} \right)^2 - \frac{1}{2} m^2 \phi^2 - \frac{\lambda}{4} \phi^4$$

Path integral $\int D\phi e^{iS}$

Suppose we are interested in $\langle e^{-\beta \hat{H}} \hat{\phi}(t) \hat{\phi}(0) \rangle = \text{Tr} (e^{-\beta \hat{H}} e^{it \hat{H}} \hat{\phi} e^{-it \hat{H}} \hat{\phi})$

This is time ordered if we take a complex time contour

Schwinger-Keldysh contour



$$e^{-\beta \hat{H}} e^{it \hat{H}} = e^{\int_t^{-i\beta} dt \hat{H}}$$

We can shift the contour into the complex plane

Discretisation

given t_n on a complex time-plane

$$\Delta t_n = t_{n+1} - t_n$$

$$S = \sum \Delta t_n \left(\frac{1}{2} \left(\frac{\phi_{n+1} - \phi_n}{\Delta t_n} \right)^2 - \frac{1}{2} m^2 \phi_n^2 - \frac{\lambda}{4} \phi_n^4 \right)$$

Thermal average

$$\text{Tr}(e^{-\beta \hat{H}} e^{it \hat{H}} \hat{\phi} e^{-it \hat{H}} \hat{\phi})$$

Path starts at $t=0$

Path ends at $t=-i\beta$

Periodical boundary conditions

Non-equilibrium time evolution

[Berges, Borsányi, Sexty, Stamatescu (2006)]

Using some initial density matrix ρ

$$\text{Tr}(\rho e^{it \hat{H}} \hat{\phi} e^{-it \hat{H}} \hat{\phi})$$

Fields no longer periodic

at $t=0$: two separate integrals for ϕ_i and ϕ_f

Especially easy in CLE with gaussian initial density matrix

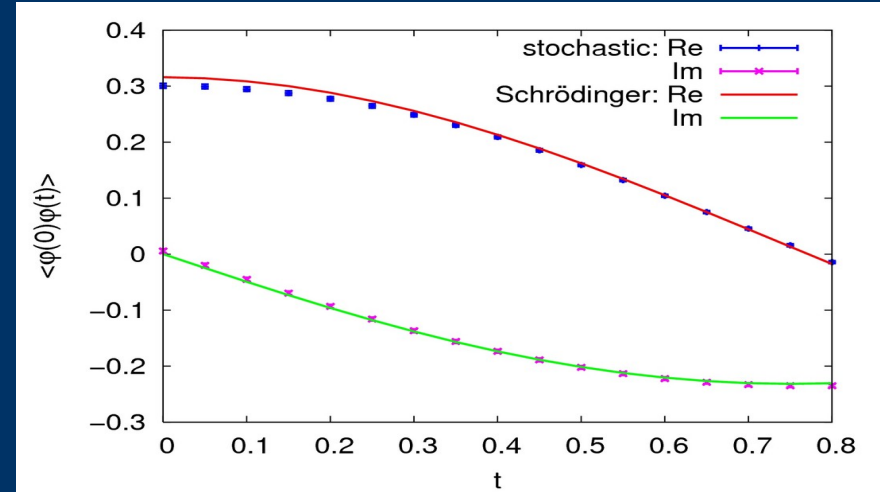
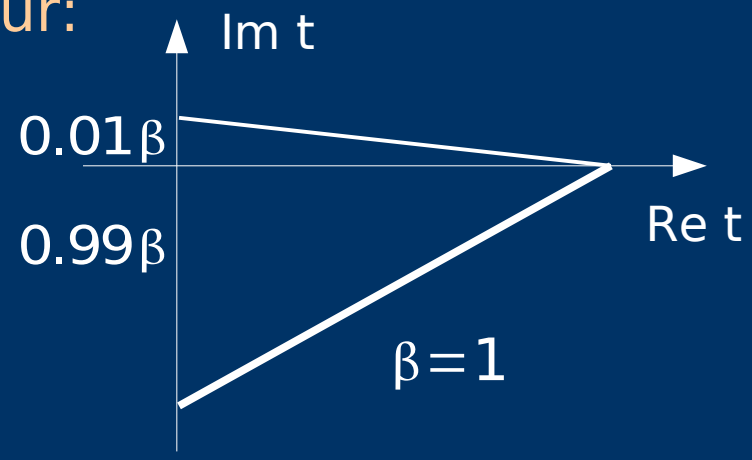
Real-time two point function of quantum oscillator

Thermal equilibrium:
periodic boundary cond.

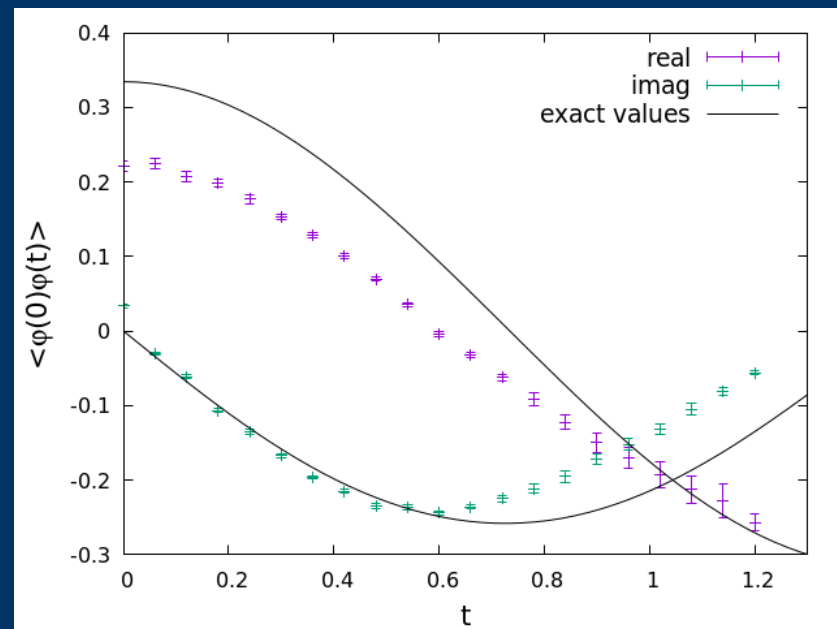
[Berges, Borsanyi, Sexty, Stamatescu (2006)]

Imaginary extent gives $\beta = \frac{1}{T}$
short real-time extent

Asymmetric
contour:



large real-time extent
Boundary terms appear



Kernels in the Langevin equation

Introducing a Kernel [Soderberg (1987), Okamoto et. al. (1988)]

$$\dot{z} = -\frac{\partial S}{\partial z} + \eta \quad \rightarrow \quad \dot{z} = -K(z) \frac{\partial S}{\partial z} + \frac{\partial K(z)}{\partial z} + \sqrt{K(z)} \eta$$

For real action,
equilibrium distribution unchanged.

Fokker-Planck equation:

$$\partial_\tau P = \partial_x K(x) (\partial_x + S') P$$

Kernel = field dependent diffusion const.

For complex action

Complexified distribution might change,

boundary terms may or may not appear/disappear

results are still a linear combination of integration cycles for zero boundary

Many variables - matrix Kernel

$$\frac{d\phi_i}{d\tau} = -H_{ij}(\phi) H_{jk}^T(\phi) \frac{\partial S}{\partial \phi_k} + \partial_k (H_{ij}(\phi) H_{jk}^T(\phi)) + H_{ij}(\phi) \eta_j$$

Can one use a Kernel to decrease boundary terms in the CLE?

[see also: Michael Mandl's talk]

Yes! search for a kernel using stochastic gradient descent

Loss function: Size of the distribution in imaginary directions

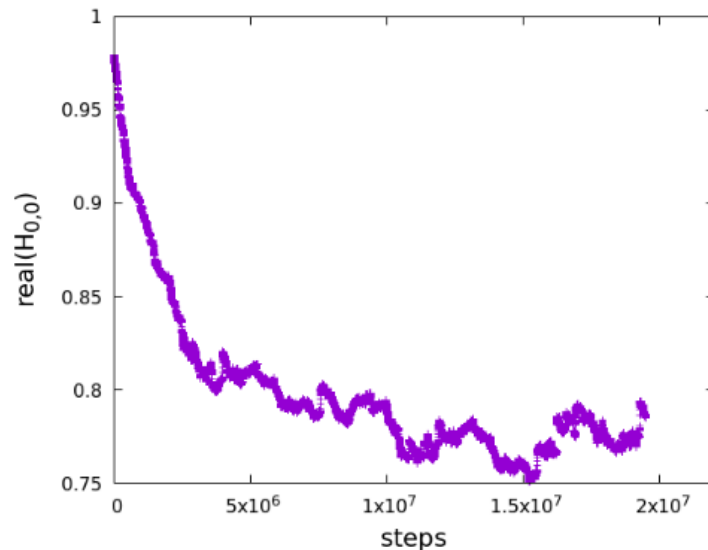
[Rothkopf, Larsen, Alvestad(2023); Lampl, Sexty (2024)]

Gradient descent

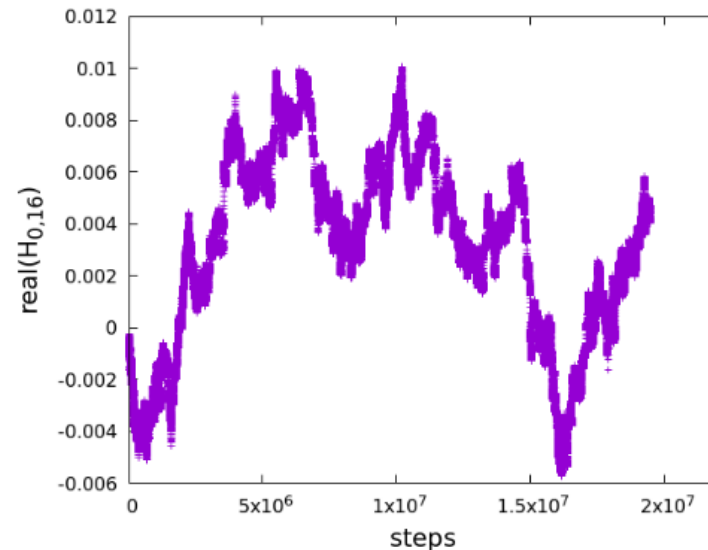
$$\phi_i' = -H_{ij} H_{jk}^T \frac{\partial S}{\partial \phi_k} \Delta \tau + H_{ij} \eta_j \sqrt{2 \Delta \tau} \epsilon_i$$

1. collect average for $\frac{\partial \sum (\text{Im } \phi_i')^2}{\partial H_{ij}} = \partial_{H_{ij}} \text{Loss}$ during CL simulation with current H

2. update H $H_{ij} \rightarrow H_{ij} - \partial_{H_{ij}} \text{Loss}$



(a) Convergence of the real part of the matrix element $H_{0,0}$

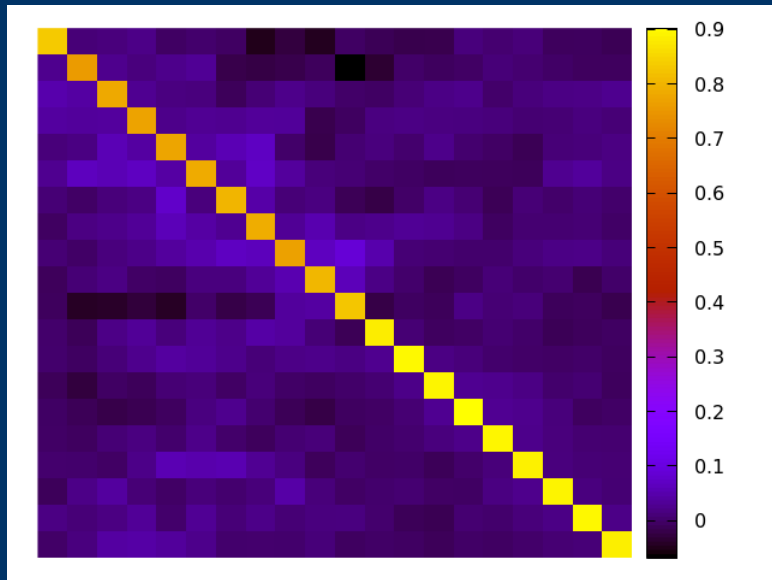


(b) Convergence of the real part of the matrix element $H_{0,16}$

First step: Field independent matrix kernel

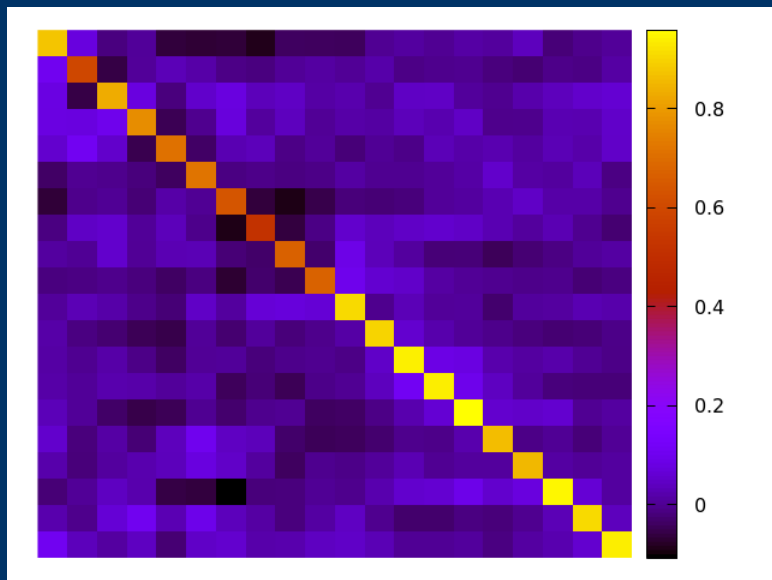
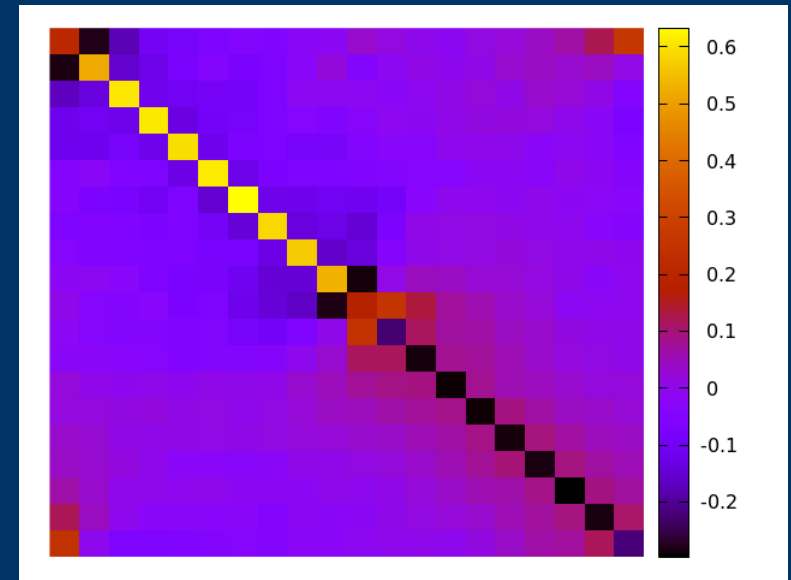
[Lampl, Sexty (2024)]

real part

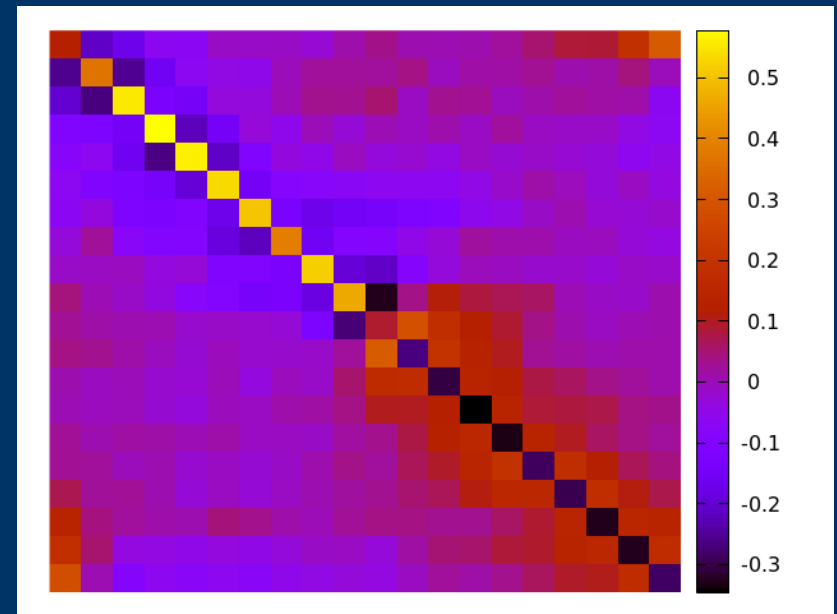


Real-time extent
 $t=1.2$

imaginary part



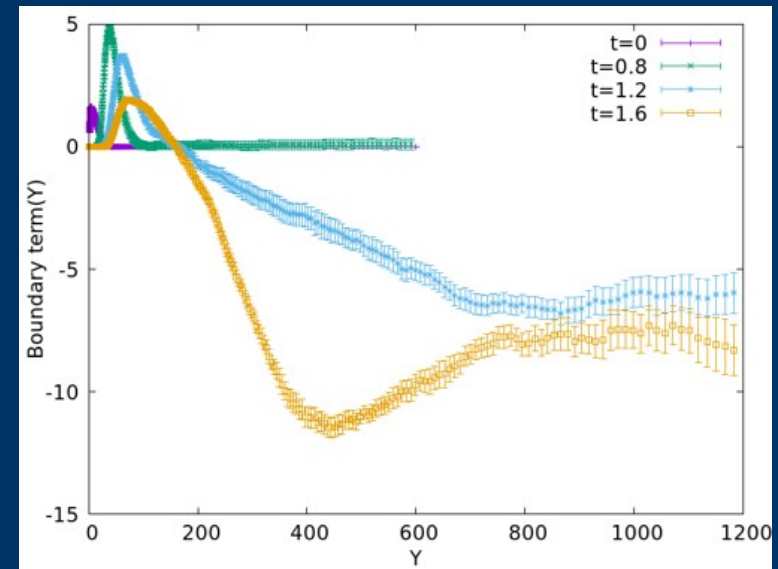
$t=2.0$



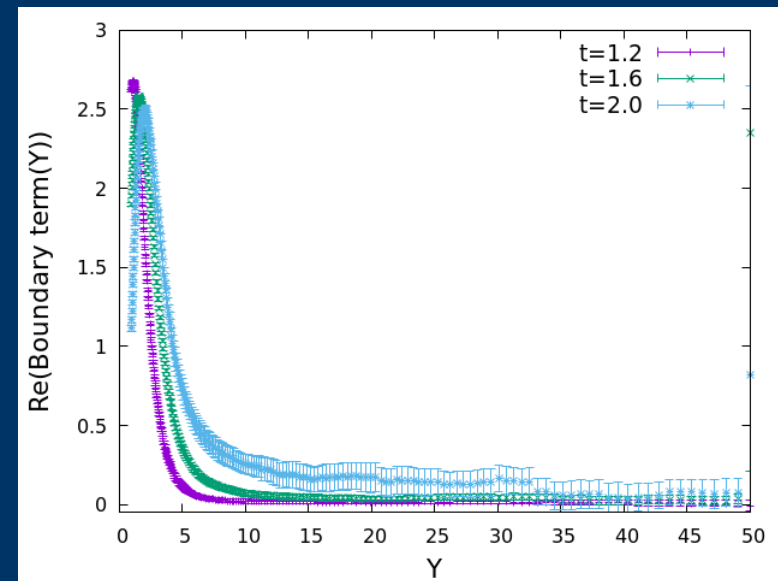
Boundary terms

Boundary terms of $\phi(t)^2$

Without Kernel:



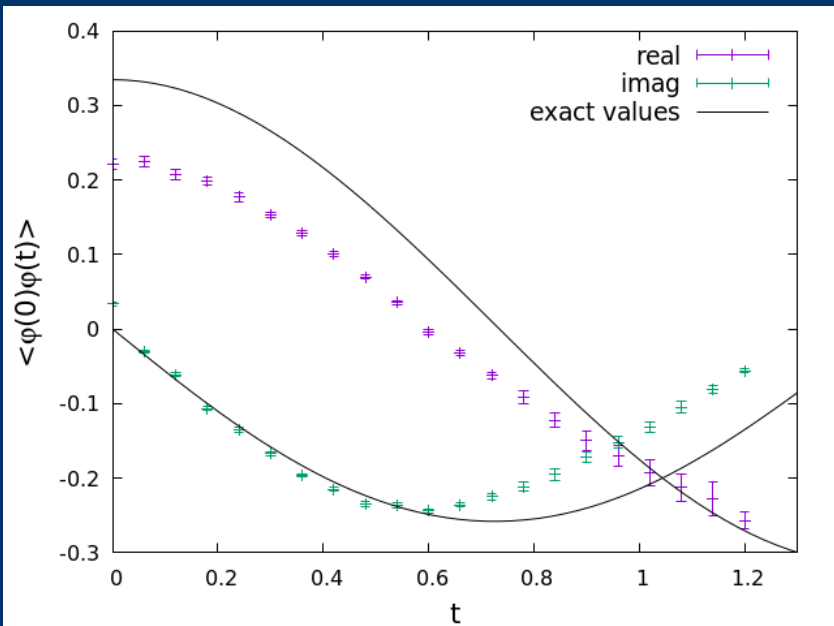
With optimized kernel:



Actually, for an anharmonic quantum oscillator it's also easy to calculate exact results (e.g. diagonalize Hamiltonian)

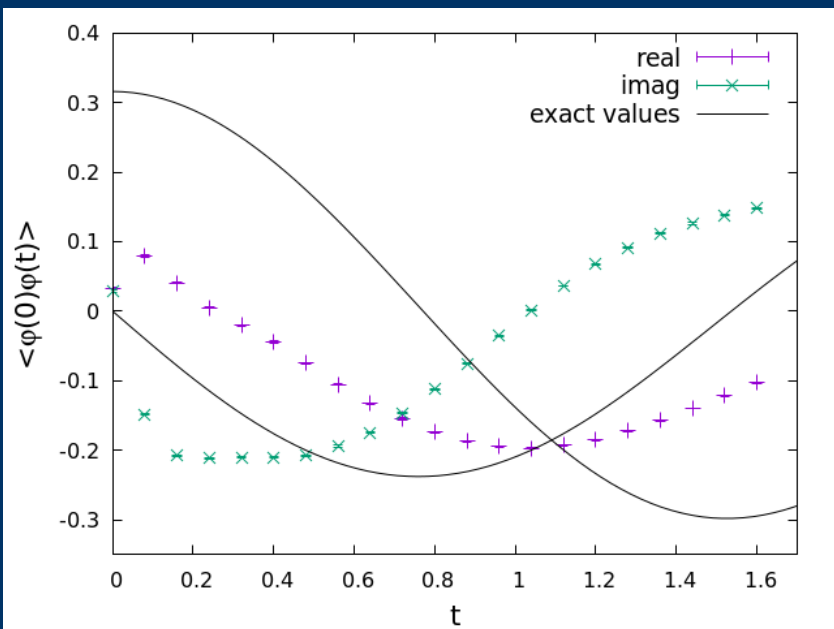
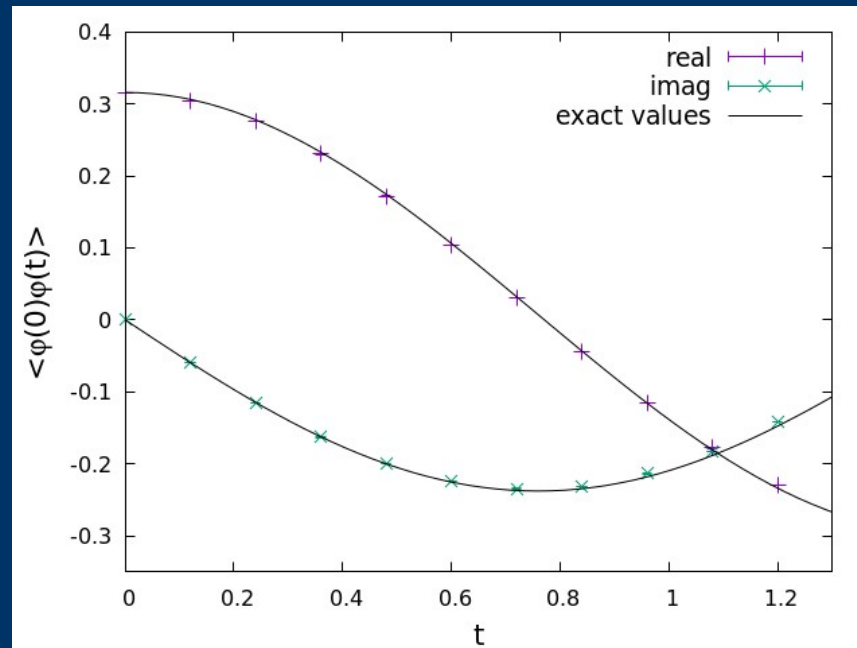
————▶ Compare to exact

Without kernel

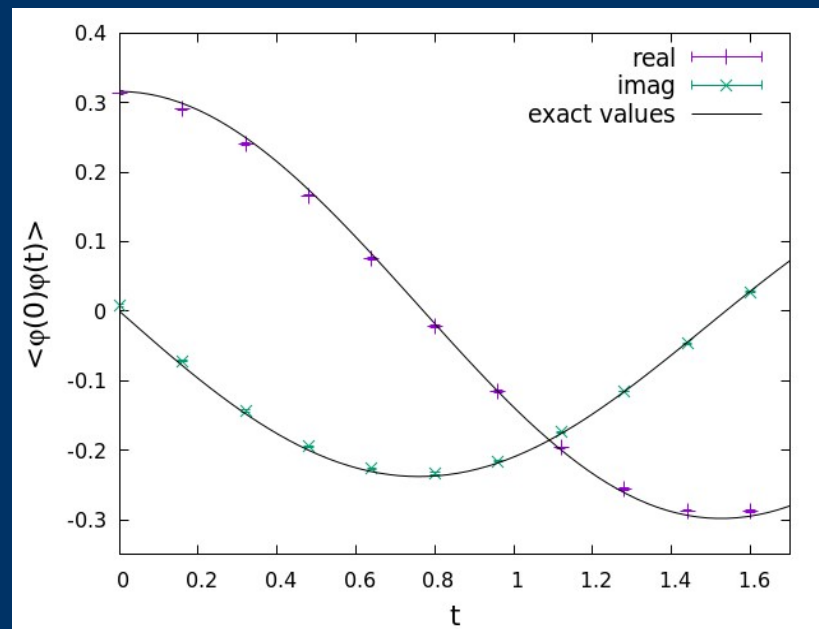


$t = 1.2$

With learned kernel

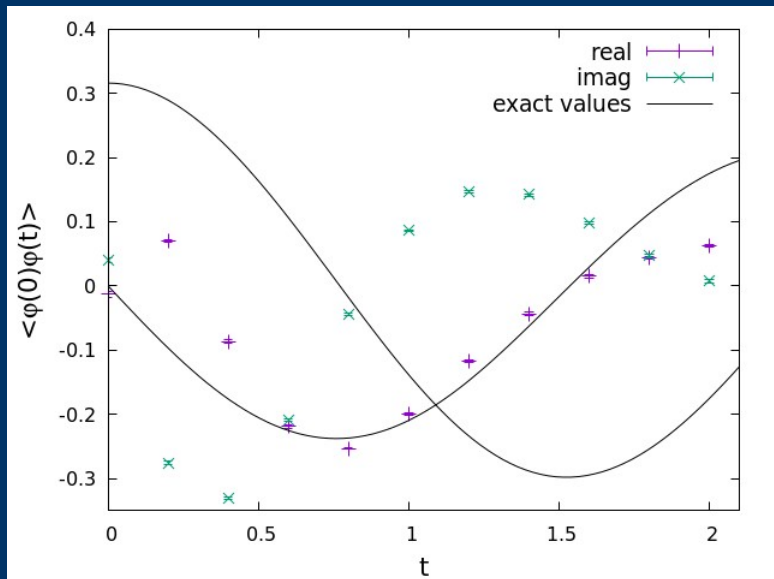


$t = 1.6$



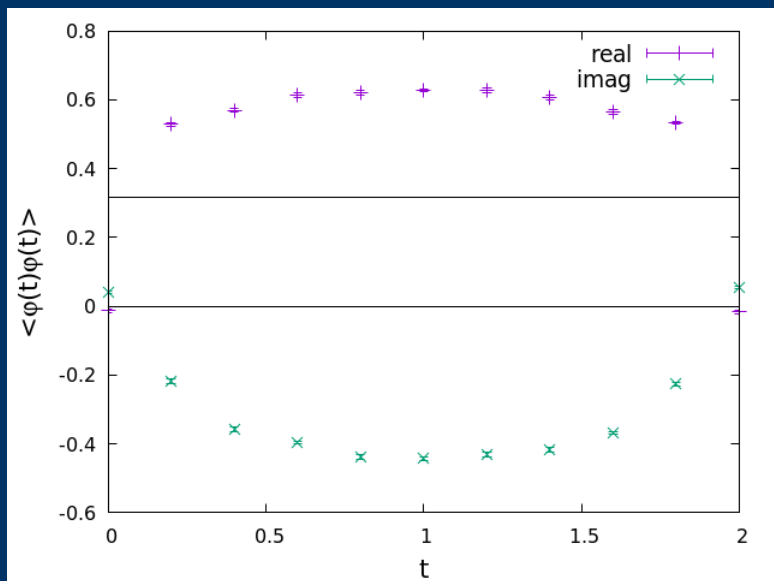
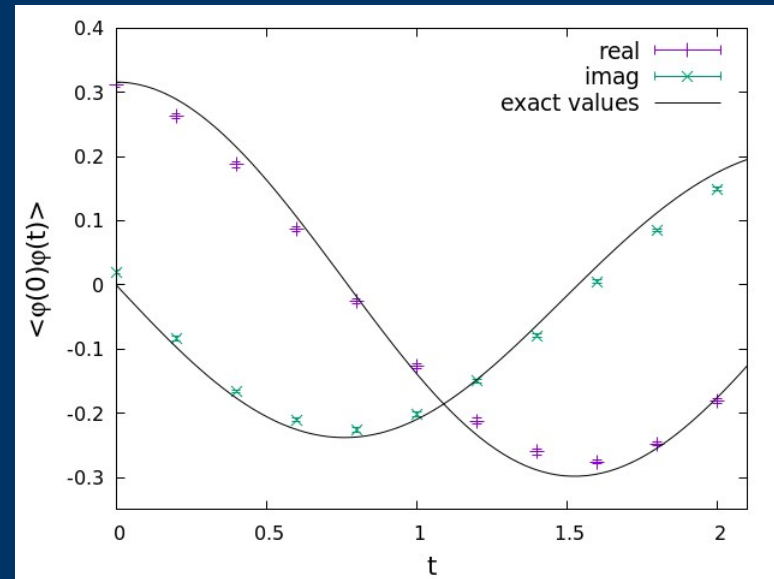
Increasing real time extent, boundary terms appear again

Without kernel

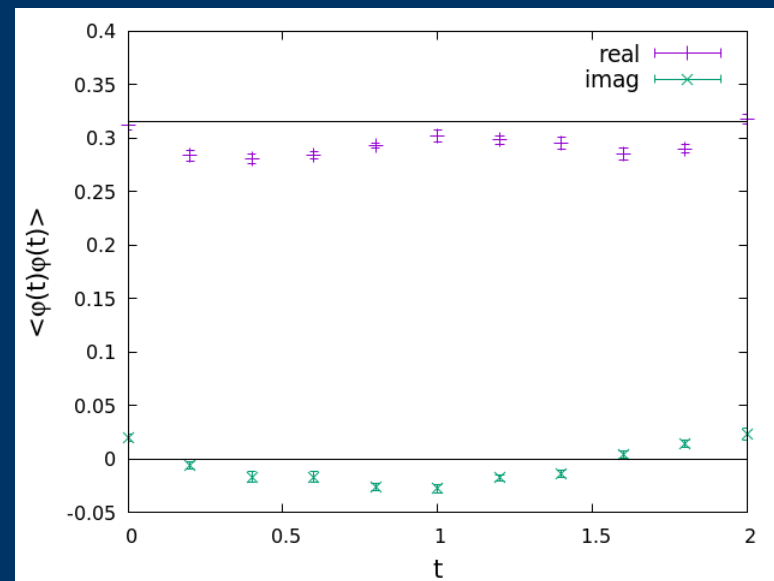


$t=2.0$

With learned kernel

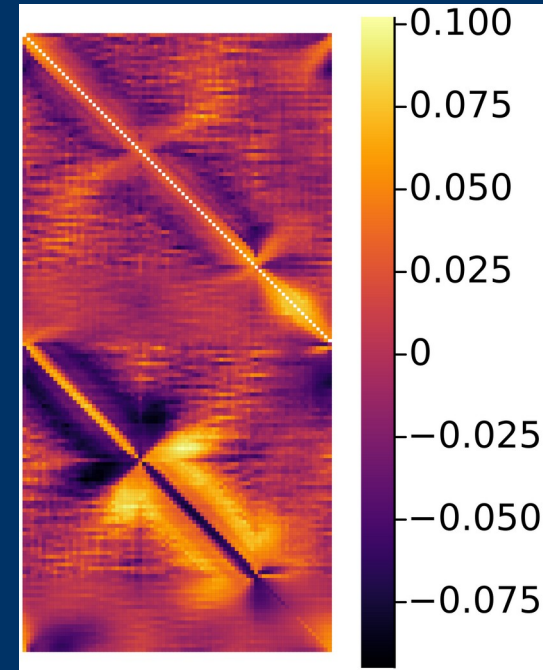
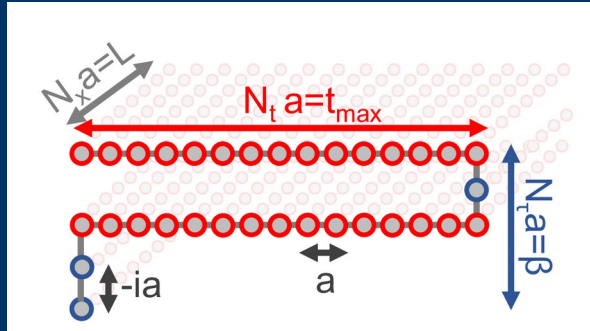


$t=2.0$

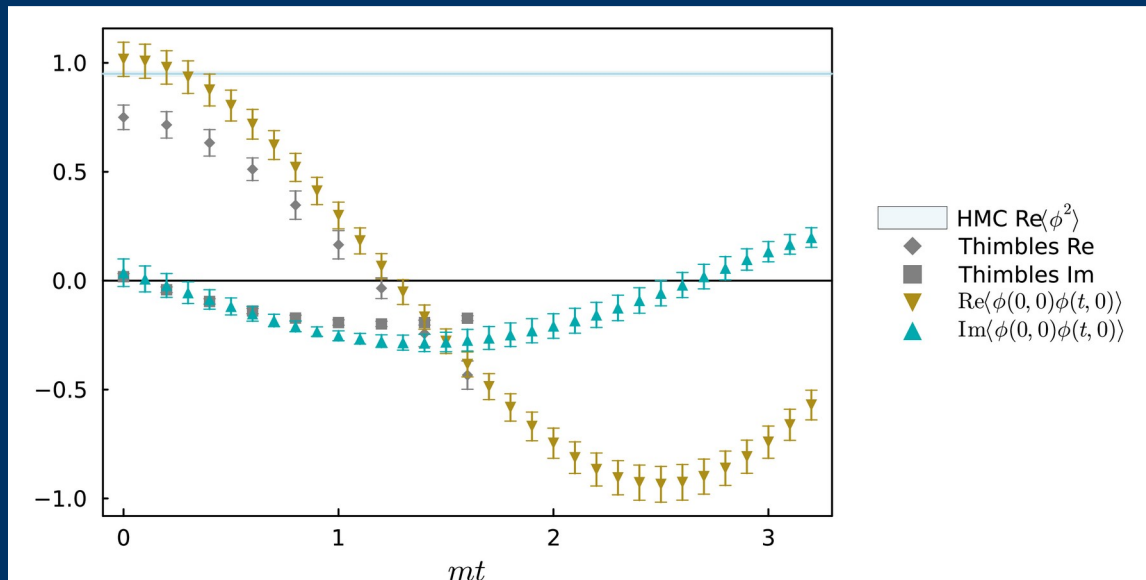


Scalar fields in 1+1 dimension [Alvestad, Rothkopf, Sexty (2024)]

Dense constant Kernel
on the Schwinger-Keldysh contour



two point function: $\langle \phi(0)\phi(t) \rangle$



Thimble result till $t=1.6$
[Alexandru et. al. (2022)]

CLE till $t=3.2$ (at least)

$$N_x=16 \quad N_t=32 \quad N_\tau=4$$

Summary

Real-time QFT Severe Sign problem

Studying quantum oscillator and scalar field theory
Discretised on a Schwinger-Keldysh-like temporal contour

Breakdown of CLE at large time-extents due to boundary terms
kernels change breakdown time
optimal kernel through machine learning

For 1+1d scalars CLE with optimal kernel
Reaches furthest from ab initio methods at hand

Boundary terms as a volume integral

[Scherzer, Seiler, Sexty, Stamatescu (2018+2019)]

Calculating an observable defined on a compact boundary in many dimensions can be inconvenient

$$\partial_\tau F_O(Y, t, \tau=0) = B_O(Y, t, \tau=0) = \int_{-Y}^Y P(x, y, t) L_c O(x+iy) - \int_{-Y}^Y (L^T P) O(x+iy, 0)$$

Observable with a cutoff
easy to do in many dimensions

Vanishes as process equilibrates

$$L_c O(x+iy) \quad \text{consistency conditions} \quad \approx \text{Schwinger-Dyson eqs.}$$

Order of limits crucial

$$\lim_{t \rightarrow \infty} \lim_{Y \rightarrow \infty} \int_{-Y}^Y P(x, y, t) L_c O(x+iy) \quad \text{can be undefined}$$

Measuring boundary terms

$$\int_{-Y}^Y P(x, y, t) L_c O(x+iy) = \int P(x, y, t) L_c O(x+iy) \theta(Y-y)$$

$$L_c = \sum \partial_i^2 + K_i \partial_i$$

Many variables: define cutoff to extend SU(N) manifold
to compact submanifold of SL(N,C)

e.g. $\text{Im } z$; $\max_i \text{Tr}(U_i^\dagger U_i - 1)^2$

Measure “unitarity norm” and observable



Analyze for any cutoff

Trick for second term:

$$\sum K_i \partial_i O = \frac{1}{\epsilon} [O(z(\tau + \epsilon, \eta=0)) - O(z(\tau))]$$

Measure observable after doing a noiseless update step with stepsize ϵ