# Numerical sign problem and the tempered Lefschetz thimble method 

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Based on work with

## Nobuyuki Matsumoto, Yusuke Namekawa and Naoya Umeda (RIKEN/BNL) <br> (Dept Phys, Kyoto U)

-- MF and Umeda, "Parallel tempering algorithm for integration over Lefschetz thimbles" [PTEP2017(2017)073B01, arXiv:1703.00861]
-- MF, Matsumoto and Umeda, "Applying the tempered Lefschetz thimble method to the Hubbard model away from half filling" [PRD100(2019)114510, arXiv:1906.04243]
-- MF, Matsumoto and Umeda, "Implementation of the HMC algorithm on the tempered Lefschetz thimble method" [arXiv:1912.13303]
-- MF and Matsumoto, "Worldvolume approach to the tempered Lefschetz thimble method" [PTEP2021(2021)023B08, arXiv:2012.08468]
-- MF, Matsumoto and Namekawa, "Statistical analysis method for the Worldvolume Monte Carlo algorithm" [to appear in PTEP, arXiv:2107.06858]

1. Introduction

## Overview

The numerical sign problem is one of the major obstacles when performing first-principles calculations in various fields of physics
Typical examples:
(1) Finite density QCD
(2) Quantum Monte Carlo simulations of quantum statistical systems
(3) $\theta$ vacuum with finite $\theta$ (such as the Hubbard model)
(4) Real-time dynamics of quantum fields

Today, I would like to show that [MF-Umeda, 1703.00861]
a new algorithm "Tempered Lefschetz Thimble Method" (TLTM) and its extension "Worldvolume-TLTM" (WV-TLTM) [MF-Matsumoto, 2012.08468] may be a promising method towards solving the sign problem, by exemplifying its effectiveness for various models

- ( $0+1$ )-dim massive Thirring model [MF-Umeda, 1703.00861]
- 1-dim and 2-dim Hubbard model [MF-Matsumoto-Umeda, 1906.04243]
- chiral random matrix model (Stephanov model)
[MF-Matsumoto, 2012.08468]
I also would like to discuss the computational scaling of WV-TLTM
[MF-Matsumoto-Namekawa, work in progress]


## Sign problem

Our main concern is to estimate: $\langle\mathcal{O}(x)\rangle_{S} \equiv \frac{\int d x e^{-S(x)} \mathcal{O}(x)}{\int d x e^{-S(x)}}$

$$
\left\{\begin{array}{l}
x=\left(x^{i}\right) \in \mathbb{R}^{N}: \text { dynamical variable (real-valued) } \\
S(x): \text { action, } \mathcal{O}(x): \text { observable }
\end{array}\right.
$$

Markov chain Monte Carlo (MCMC) simulation:
probability distribution function
When $S(x) \in \mathbb{R}$, one can regard $p_{\text {eq }}(x) \equiv e^{-S(x)} / \int d x e^{-S(x)}$ as a PDF:

$$
0 \leq p_{\text {eq }}(x) \leq 1, \quad \int d x p_{\text {eq }}(x)=1
$$

$\square$ Generate a sample $\left\{x^{(k)}\right\}_{k=1, \ldots, N_{\text {conf }}}$ from $p_{\text {eq }}(x) \quad\left(N_{\text {conf }}\right.$ : sample size $)$
$\square\langle\mathcal{O}(x)\rangle_{S} \approx \frac{1}{N_{\text {conf }}} \sum_{k=1}^{N_{\text {conf }}} \mathcal{O}\left(x^{(k)}\right)$
Sign problem:
When $S(x)=S_{R}(x)+i S_{I}(x) \in \mathbb{C}$, one cannot regard $e^{-S(x)} / \int d x e^{-S(x)}$ as a PDF
Reweighting method:

## Sign problem

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$\square$ Reweighting method: treat $e^{-S_{R}(x)} / \int d x e^{-S_{R}(x)}$ as a PDF

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$\square\langle\mathcal{O}(x)\rangle_{S}=\frac{\left\langle e^{-i S_{I}(x)} \mathcal{O}(x)\right\rangle_{S_{R}}}{\left\langle e^{-i S_{I}(x)}\right\rangle_{S_{R}}}=\frac{e^{-O(N)}}{e^{-O(N)}}=O(1) \quad(N: D O F)$

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$\Rightarrow$
Require $O\left(1 / \sqrt{N_{\text {conf }}}\right) \lesssim e^{-O(N)}$
 sign problem!

## Example: Gaussian

Let us consider $\left\{\begin{array}{ll}S(x)=\frac{\beta}{2}(x-i)^{2} \equiv S_{R}(x)+i S_{I}(x) \\ \mathcal{O}(x)=x^{2} & \beta \gg 1\end{array}\binom{S_{R}(x)=\frac{\beta}{2}\left(x^{2}-1\right)}{S_{I}(x)=-\beta x}\right.$

$$
\square\left\langle x^{2}\right\rangle_{S}=\frac{\left\langle e^{-i S_{I}(x)} x^{2}\right\rangle_{S_{R}}}{\left\langle e^{-i S_{I}(x)}\right\rangle_{S_{R}}}=\frac{\left(\beta^{-1}-1\right) e^{-\beta / 2}}{e^{-\beta / 2}} \quad \text { large } \beta \text { mimics large } \operatorname{DOF}(\beta \sim N)
$$

$\longmapsto$
Necessary sample size:

$$
1 / \sqrt{N_{\text {conf }}} \lesssim O\left(e^{-\beta / 2}\right) \Leftrightarrow N_{\text {conf }} \gtrsim O\left(e^{\beta}\right)
$$

[Essence]


## Various approaches

## $\square$ method 1: no use of reweighting

V complex Langevin method [Parisi 1983, Klauder 1983, Aarts et al. 2009] (may show a wrong convergence problem) $\binom{$ wrong results }{$\mathrm{w} / \mathrm{small}$ stat errors }
$\square$ method 2: deformation of the integration surface
V Lefschetz thimble method [Witten 2010, Cristoforetti et al. 2012,
 Fujii et al. 2013, Alexandru et al. 2015]

Tempered Lefschetz thimble method (TLTM) [MF-Umeda 2017]
[MF-Umeda-Matsumoto 2019]
worldvolume TLTM (WV-TLTM) [MF-Matsumoto 2020]
$\boldsymbol{\nabla}$ path optimization method (POM) [Mori-Kashiwa-Ohnishi 2017, Alexandru et al. 2018]
$\square$ method 3: no use of MC in the first place
$\boldsymbol{\nabla}$ tensor network [Levin-Nave 2007, ...]
(- good at calculating the free energy)

- but not so much for correl fcns
- complementary to MC approach?


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## Plan

1. Introduction (done)
2. Lefschetz thimble method
3. Tempered Lefschetz thimble method (TLTM) and its worldvolume extension (WV-TLTM)
4. Application to various models

- Hubbard model
- Chiral random matrix model (Stephanov model)
- Computational scaling of WV-TLTM

5. Summary and outlook

## 2. Lefschetz thimble method

## Basic idea of the thimble method $(1 / 2)$

■ complexification of dyn variable: $x=\left(x^{i}\right) \in \mathbb{R}^{N} \Rightarrow z=\left(z^{i}=x^{i}+i y^{i}\right) \in \mathbb{C}^{N}$ assumption (satisfied for most cases) $\quad(S(x)$ : action, $\mathcal{O}(x)$ : observable) $e^{-S(z)}, e^{-S(z)} \mathcal{O}(z)$ : entire fcns over $\mathbb{C}^{N}$ (can have zeros)

Cauchy's theorem


Integrals do not change under continuous deformation of integration surface : $\Sigma_{0}=\mathbb{R}^{N} \rightarrow \Sigma\left(\subset \mathbb{C}^{N}\right)$
(boundary at $|x| \rightarrow \infty$ kept fixed)

$$
\langle\mathcal{O}(x)\rangle \equiv \frac{\int_{\Sigma_{0}} d x e^{-S(x)} \mathcal{O}(x)}{\int_{\Sigma_{0}} d x e^{-S(x)}}=\frac{\int_{\Sigma} d z e^{-S(z)} \mathcal{O}(z)}{\int_{\Sigma} d z e^{-S(z)}}
$$

severe sign problem
sign problem will be significantly reduced if $\operatorname{Im} S(z)$ is almost constant on $\Sigma$

## Basic idea of the thimble method $(2 / 2)$

■ prescription for deformation anti-holomorphic gradient flow

$$
\dot{z}_{t}=\overline{\partial S\left(z_{t}\right)} \text { with } z_{t=0}=x
$$

property


$$
\left[S\left(z_{t}\right)\right]^{\cdot}=\partial S\left(z_{t}\right) \cdot \dot{z}_{t}=\left|\partial S\left(z_{t}\right)\right|^{2} \geq 0
$$

$\left[\operatorname{Re} S\left(z_{t}\right)\right]^{\cdot} \geq 0$ : always increases except at crit pt $\zeta(\zeta: \underline{\text { crit pt }}$
$\left[\operatorname{lm} S\left(z_{t}\right)\right]^{\circ}=0$ : always constant $\left.\quad \Leftrightarrow \partial S(\zeta)=0\right)$
$\Sigma_{t} \xrightarrow{t \rightarrow \infty} \mathcal{J}$ (Lefschetz thimble) $\equiv$ set of orbits starting from $\zeta$

$$
\operatorname{Im} S(z): \text { constant on } \mathcal{J}(=\operatorname{Im} S(\zeta))
$$

Sign problem is expected to disappear on $\Sigma_{t}$ at a sufficiently large $t$

## How does the sign problem disappear?

- Integration on the original surface $\Sigma_{0}=\mathbb{R}^{N}$ (flow time $t=0$ )

$$
\langle\mathcal{O}(x)\rangle \equiv \frac{\left\langle e^{-i \operatorname{lm} S(x)} \mathcal{O}(x)\right\rangle_{\Sigma_{0}(\text { rewt })}}{\left\langle e^{-i \operatorname{lm} S(x)}\right\rangle_{\Sigma_{0}(\text { rewt })}} \approx \frac{e^{-O(N)} \pm O\left(1 / \sqrt{N_{\text {conf }}}\right)}{e^{-O(N)} \pm O\left(1 / \sqrt{N_{\text {conf }}}\right)} \quad\binom{N: \text { DOF }}{N_{\text {conf }}: \text { sample size }}
$$

$\square$ need a huge size of sample : $N_{\text {conf }} \simeq e^{O(N)}$
sign problem
flow

- Integration on a deformed surface $\Sigma_{t}$ (flow time $t$ )

$$
\begin{aligned}
& \text { ation on a deformed surface } \Sigma_{t}(\text { flow time } t) \\
& \begin{aligned}
&\langle\mathcal{O}(x)\rangle=\frac{\left\langle e^{i \theta(z)} \mathcal{O}(z)\right\rangle_{\Sigma_{t}}}{\left\langle e^{i \theta(z)}\right\rangle_{\Sigma_{t}}} \approx \frac{e^{-e^{-\lambda t} O(N)} \pm O\left(1 / \sqrt{N_{\text {conf }}}\right)}{e^{-e^{-\lambda t} O(N)} \pm O\left(1 / \sqrt{N_{\text {conf }}}\right)} \\
& \begin{aligned}
\left(e^{i \theta(z)} \equiv e^{-i l m s(z)} \frac{d z}{|d z|}\right)^{2} \\
{\left[e^{\lambda t}=O(N) \Leftrightarrow t=O(\log N)\right] }
\end{aligned} \\
&=\frac{O(1) \pm O\left(1 / \sqrt{N_{\text {conf }}}\right)}{O(1) \pm O\left(1 / \sqrt{N_{\text {conf }}}\right)}
\end{aligned}
\end{aligned}
$$

## Example: Gaussian revisited

Gradient flow: $\quad\left[S(z)=(\beta / 2)(z-i)^{2} \Rightarrow S^{\prime}(z)=\beta(z-i)\right]$
$\dot{z}_{t}=\overline{S^{\prime}\left(z_{t}\right)}=\beta(\bar{z}+i)$ with $z_{t=0}=x$
$\square z_{t}(x)=x e^{\beta t}+i\left(1-e^{-\beta t}\right) \quad \therefore|d z|=e^{\beta t} d x$

$\square\langle f(z)\rangle_{\Sigma_{t}}=\frac{\int_{\Sigma_{t}}|d z| e^{-\operatorname{Re} S(z)} f(z)}{\int_{\Sigma_{t}}|d z| e^{-\operatorname{Re} S(z)}}=\frac{\int d x e^{-\beta e^{2 \beta t} x^{2} / 2} f\left(z_{t}(x)\right)}{\int d x e^{-\beta e^{2 \beta t} x^{2} / 2}}$
No small numbers appear
if we take a large $t(\equiv T)$ s.t. $\mathrm{e}^{-\beta T} \ll \frac{1}{\sqrt{\beta}}$

$$
\begin{aligned}
\left\langle x^{2}\right\rangle & =\frac{\left\langle e^{i \theta(z)} z^{2}\right\rangle_{\Sigma_{T}}}{\left\langle e^{i \theta(z)}\right\rangle_{\Sigma_{T}}} \\
& =\frac{e^{-(\beta / 2) e^{-2 \beta T}}\left(\beta^{-1}-1\right)}{e^{-(\beta / 2) e^{-2 \beta T}}}=\frac{O(1)}{O(1)}
\end{aligned}
$$

NB. Logarithmic increase is enough:

$$
\begin{equation*}
T \sim O(\log \beta)(=O(\log N)) \tag{8/25}
\end{equation*}
$$


3. Tempered Lefschetz thimble method and its worldvolume extension (TLTM \& WV-TLTM)

## Ergodicity problem

Sign problem resolved? NO!
Actually, there comes out another problem at large $t$ : Ergodicity problem

difficult to communicate with each other
[Marinari-Parisi 1992]
[Swendsen-Wang 1986, Geyer 1991
Hukushima-Nemoto 1996]

## Tempered Lefschetz thimble method (TLTM) $(1 / 2)$

## TLTM

(1) Introduce replicas in between the initial integ surface $\Sigma_{0}=\mathbb{R}^{N}$
and the target deformed surface $\Sigma_{T}$ as $\left\{\Sigma_{t_{0}=0}, \Sigma_{t_{1}}, \Sigma_{t_{2}}, \ldots, \Sigma_{t_{A}=T}\right\}$
(2) Setup a Markov chain for the extended config space $\left\{\left(x, t_{a}\right)\right\}$
(3) After equilibration, estimate observables with a subsample on $\Sigma_{T}$

easy transition through a detour
Sign and ergodicity problems solved simultaneously !

## Tempered Lefschetz thimble method (TLTM) (2/2)

## Important point in TLTM:

NO "tiny overlap problem" in TLTM


Distribution functions have peaks at the same positions $x_{\sigma}$ for varying tempering parameter (which is $t$ in our case)

We can expect significant overlap between adjacent replicas!

## Pros and cons of original TLTM

## [TLTM [MF-Umeda 2017]

Replicas introduced in between $\Sigma_{0}$ and $\Sigma_{T}:\left\{\Sigma_{t_{0}=0}, \Sigma_{t_{1}}, \Sigma_{t_{2}}, \ldots, \Sigma_{t_{A}=T}\right\}$

finite discrete set of replicas

Pros: can be applied to any systems in principle once formulated by path integrals with continuous variables
Cons: large comput cost at large DOF

- necessary \# of replicas $\propto O\left(N^{0-1}\right)$
- need to calculate Jacobian $J_{t}(x)=\partial z_{t}(x) / \partial x \propto O\left(N^{3}\right)$ everytime we exchange configs between adjacent replicas


## Worldvolume TLTM (WV-TLTM) (1/2)

HMC on a continuous accumulation of integ surfaces, $\mathcal{R} \equiv \bigcup_{0 \leq t \leq T} \Sigma_{t}$


Pros: can be applied to any systems
once formulated by path integrals with continuous variables
$\oplus$ major reduction of comput cost at large DOF

- No need to introduce replicas explicitly
- No need to calculate Jacobian $J_{t}(x)=\partial z_{t}(x) / \partial x$ in MD process
- Configs can move largely due to the use of HMC


## Worldvolume TLTM (WV-TLTM) (2/2)

Basic Idea

$$
\begin{aligned}
& \langle\mathcal{O}(x)\rangle \equiv \frac{\int_{\Sigma_{0}} d x e^{-S(x)} \mathcal{O}(x)}{\int_{\Sigma_{0}} d x e^{-S(x)}}=\frac{\int_{\Sigma_{t}} d z_{t} e^{-S(z)} \mathcal{O}(z)}{\int_{\Sigma_{t}} d z_{t} e^{-S(z)}} \\
& \square t \text {-independent } \\
& \text { (Cauchy's theorem) } \\
& t \text {-independent } \\
& =\frac{\int_{0}^{T} d t e^{-W(t)} \int_{\Sigma_{t}} d z_{t} e^{-S(z)} \mathcal{O}(z)}{\int_{0}^{T} d t e^{-W(t)} \int_{\Sigma_{t}} d z_{t} e^{-S(z)}} \quad \begin{array}{l}
(W(t) \text { : arbitrary function }) \\
\binom{\text { chosen s.t. the appearance prob }}{\text { at different } t \text { are almost the same }}
\end{array} \\
& =\frac{\int_{\mathcal{R}} d t d z_{t} e^{-W(t)} e^{-S(z)} \mathcal{O}(z)}{\int_{\mathcal{R}} d t d z_{t} e^{-W(t)} e^{-S(z)}} \Leftarrow \text { Path integrals over the worldvolume } \mathcal{R}
\end{aligned}
$$

## Appendix: Details on WV-TLTM (1/2)

- Preparation
[MF-Matsumoto 2012.08468]

$$
\langle\mathcal{O}(x)\rangle=\frac{\int_{\mathcal{R}} d t d z_{t} e^{-W(t)} e^{-S(z)} \mathcal{O}(z)}{\int_{\mathcal{R}} d t d z_{t} e^{-W(t)} e^{-S(z)}}
$$

natural measure to appear in HMC on $\mathcal{R}$
$=$ vol element $D z$ of the induced metric

$$
d s^{2}=\alpha^{2} d t^{2}+\gamma_{a b}\left(d x^{a}+\beta^{a} d t\right)\left(d x^{b}+\beta^{b} d t\right)(\alpha: \text { lapse })
$$



$$
D z=\alpha d t\left|d z_{t}(x)\right|=\alpha|\operatorname{det} J| d t d x \quad\left(J=\frac{\partial z_{t}(x)}{\partial x}\right)
$$

$$
d t d z_{t}(x)=D z \frac{d t d z_{t}(x)}{D z}=D z \frac{d t d x \operatorname{det} J}{d t d x \alpha|\operatorname{det} J|}=D z \alpha^{-1}(z) e^{i \varphi(z)}\left(e^{i \varphi(z)} \equiv \frac{\operatorname{det} J}{|\operatorname{det} J|}\right)
$$

$$
\langle\mathcal{O}(x)\rangle=\frac{\int_{\mathcal{R}} d t d z_{t} e^{-W(t)} e^{-S(z)} \mathcal{O}(z)}{\int_{\mathcal{R}} d t d z_{t} e^{-W(t)} e^{-S(z)}}=\frac{\int_{\mathcal{R}} D z \alpha^{-1}(z) e^{i \varphi(z)} e^{-W(t)} e^{-\operatorname{ReS(z)-i\operatorname {Im}S(z)} \mathcal{O}(z)}}{\int_{\mathcal{R}} D z \alpha^{-1}(z) e^{i \varphi(z)} e^{-W(t)} e^{-\operatorname{ReS(z)-i\operatorname {Im}S(z)}}}
$$

$$
=\frac{\int_{\mathcal{R}} D z e^{-\operatorname{Re} S(z)} e^{-W(t)} \alpha^{-1}(z) e^{i \varphi(z)} e^{-i \operatorname{Im} S(z)} \mathcal{O}(z)}{\int_{\mathcal{R}} D z e^{-\operatorname{Re} S(z)} e^{-W(t)} \alpha^{-1}(z) e^{i \varphi(z)} e^{-i \operatorname{Im} S(z)}}
$$

$$
=\frac{\int_{\mathcal{R}} D z e^{-V(z)} A(z) \mathcal{O}(z)}{\int_{\mathcal{R}} D z e^{-V(z)} A(z)} \equiv \frac{\langle A(z) \mathcal{O}(z)\rangle_{\mathcal{R}}}{\langle A(z)\rangle_{\mathcal{R}}} \quad\left(\langle f(z)\rangle_{\mathcal{R}} \equiv \frac{\int_{\mathcal{R}} D z e^{-V(z)} f(z)}{\int_{\mathcal{R}} D z e^{-V(z)}}\right)
$$

## Appendix: Details on WV-TLTM (2/2)

## - Algorithm

$$
\langle\mathcal{O}(x)\rangle=\frac{\langle A(z) \mathcal{O}(z)\rangle_{\mathcal{R}}}{\langle A(z)\rangle_{\mathcal{R}}} \quad\left(\langle f(z)\rangle_{\mathcal{R}} \equiv \frac{\int_{\mathcal{R}} D z e^{-V(z)} f(z)}{\int_{\mathcal{R}} D z e^{-V(z)}}\right)
$$

$$
\left\{\begin{array}{l}
V(z)=\operatorname{Re} S(z)+W(t(z)) \quad: \text { potential } \\
A(z)=\alpha^{-1}(z) e^{i \varphi(z)} e^{-i \operatorname{Im} S(z)}: \text { reweighting factor }
\end{array}\right.
$$

HMC on a constrained space [Andersen 1983, Leimkuhler-Skeel 1994]
$\langle f(z)\rangle_{\mathcal{R}}$ is estimated with RATTLE

$$
\left\{\begin{aligned}
\pi_{1 / 2} & =\pi-\Delta s \bar{\partial} V(z)-\lambda^{a} F_{a}(z) \\
z^{\prime} & =z+\Delta s \pi_{1 / 2} \\
\pi^{\prime} & =\pi-\Delta s \bar{\partial} V\left(z^{\prime}\right)-\lambda^{\prime a} F_{a}\left(z^{\prime}\right)
\end{aligned}\right.
$$

$\lambda^{a}$ and $\lambda^{\prime a}$ are determined s.t.

$$
\left\{\begin{array}{l}
z^{\prime} \in \mathcal{R} \text { and } \lambda^{a} \operatorname{Im}\left[J_{a}^{\dagger}(z) E_{0}(z)\right]=0 \\
\pi^{\prime} \in T_{z^{\prime}} \mathcal{R} \text { and } \lambda^{a} \operatorname{Im}\left[J_{a}^{\dagger}\left(z^{\prime}\right) E_{0}\left(z^{\prime}\right)\right]=0
\end{array}\right.
$$


cf) RATTLE on $\mathcal{J}=\Sigma_{\infty}$ [Fujii et al. 2013]
RATTLE on $\Sigma_{t}$ [Alexandru@Lattice2019, MF-Matsumoto-Umeda 2019]

## 4. Application to various models

## (WV-)TLTM has been successfully applied to

- ( $0+1$ )dim massive Thirring model [MF-Umeda 1703.00861]
— 2dim Hubbard model [MF-Matsumoto-Umeda 1906.04243, 1912.13303]
- chiral random matrix model (a toy model of finite density QCD) [MF-Matsumoto 2012.08468]
- anti-ferro Ising on triangular lattice [MF-Matsumoto 2020, JPS meeting] | So far successful for all the models when applied, |
| :--- |
| though the system sizes are yet small (DOF $N \leq 200$ ) |


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4-1. Hubbard model
(using original TLTM)

## Hubbard model (1/3)

$$
\begin{aligned}
& H=\underbrace{-\kappa \sum_{\mathbf{x}, \mathbf{y}} \sum_{\sigma} K_{\mathbf{x y}} c_{\mathbf{x}, \sigma}^{\dagger} c_{\mathbf{y}, \sigma}-\mu \sum_{\mathbf{x}}\left(n_{\mathbf{x}, \uparrow}+n_{\mathbf{x}, \downarrow}-1\right)}_{H_{1}}+\underbrace{U \sum_{\mathbf{x}}\left(n_{\mathbf{x}, \uparrow}-\frac{1}{2}\right)\left(n_{\mathrm{x}, \downarrow}-\frac{1}{2}\right)}_{\text {(fermion bilinear) }} \\
& \left\{\begin{array}{l}
n_{\mathbf{x}, \sigma} \equiv c_{\mathbf{x}, \sigma}^{\dagger} c_{\mathbf{x}, \sigma}(\mathbf{x}: \text { site, } \sigma=\uparrow, \downarrow: \text { spin) } \\
\kappa(>0): \text { hopping parameter, } K=\left(K_{\mathbf{x y}}\right): \text { adjacent matrix } \\
\mu: \text { chemical potential } \\
U(>0) \text { : strength of on-site replusive potential }
\end{array}\right\}
\end{aligned}
$$


( $N_{s}$ : \# of sites)

$$
n_{\mathrm{x}, \sigma} \rightarrow n_{\mathrm{x}, \sigma}-1 / 2 \text { s.t. } \mu=0 \Leftrightarrow \text { half-filling } \sum_{\sigma=\uparrow, \downarrow}\left\langle n_{\mathrm{x}, \sigma}-1 / 2\right\rangle=0
$$

$$
\begin{array}{r}
Z_{\beta, \mu}=\int[d \phi] e^{-S\left[\phi_{\ell, \mathbf{x}}\right]} \equiv \int \prod_{\ell=1}^{N_{\tau}} \prod_{\mathbf{x}} d \phi_{\ell, \mathbf{x}} e^{-(1 / 2) \sum_{\ell, \mathbf{x}} \phi_{\ell, \mathbf{x}}{ }^{2}} \operatorname{det} M_{a}[\phi] \operatorname{det} M_{b}[\phi] \\
M_{a / b}[\phi] \equiv 1_{N_{s}}+e^{ \pm \beta \mu} \prod_{\ell}\left(e^{\epsilon \kappa K} \operatorname{diag}\left[e^{ \pm i \sqrt{\epsilon U} \phi_{\ell, \mathbf{x}}}\right]\right): N_{s} \times N_{s} \text { matrix }
\end{array}
$$

This gives complex actions for non half-filling states ( $\mu \neq 0$ )
(For half filling $(\mu=0): \operatorname{det} M_{a}[\phi] \operatorname{det} M_{b}[\phi]=\left|\operatorname{det} M_{a}[\phi]\right|^{2} \geq 0 \Rightarrow$ No sign problem)
$\Rightarrow$ We apply the Tempered LTM to this system
[MF-Matsumoto-Umeda 1906.04243]

$$
\binom{x=\left(x^{i}\right)=\left(\phi_{\ell, \mathbf{x}}\right) \in \mathbb{R}^{N}}{i=1, \ldots, N\left(N=N_{\tau} N_{s}\right)}[18 / 24]
$$

## Hubbard model (2/3)



## Hubbard model (2/3)



## Hubbard model (3/3)

[MF-Matsumoto-Umeda 1906.04243]
Distribution of flowed configs at flow time $T=0.5(\beta \mu=5)$
$\left(\right.$ projected on a plane : $\left.\hat{z}=\left(N_{\tau} N_{s}\right)^{-1} \sum_{\ell, \mathbf{x}} z_{\ell, \mathbf{x}}\right)$

stuck to a small \# of thimbles

distributed widely over many thimbles

## Comment on the Generalized LTM

[MF-Matsumoto-Umeda 1906.04243]
Alexandru et al. (2015) made a very interesting proposal for reconciling the sign and ergodicity problems:
Choose a flow time that is sufficiently large so as to resolve the sign problem but at the same time is not too large so as to avoid the ergodicity problem.

Our experience says it is NOT possible in many cases.

In fact, in most cases, the sign problem gets relaxed only after $\Sigma_{t}$ reaches a zero

We confirm this for various values of $\beta \mu$ $\left[\begin{array}{l}N_{\tau}=5, N_{s}=2 \times 2 \\ \beta \kappa=3, \beta U=13,0 \leq T \leq 0.4(\Leftrightarrow 0 \leq a \leq 10) \\ N_{\text {conf }}=5,000 \sim 25,000 \text { depending on } \beta \mu \\ \langle n\rangle=\frac{\left\langle e^{i \theta(z)} n(z)\right\rangle_{\Sigma_{t a}}}{\left\langle e^{i \theta(z)}\right\rangle_{\Sigma_{t a}}} \approx \bar{n}_{a}\end{array}\right]$

It is a hard task to find an intermediate flow time that solves both the sign and ergodicity problems simultaneously

Example: $\beta \mu=5$
large stat errors (due to sign problem) (due to multimodality)


# 4-2. Chiral random matrix model and the computational scaling <br> (using WV-TLTM) 

## Chiral random matrix model (1/2)

$\square$ finite density QCD
[MF-Matsumoto 2012.08468]

$$
\begin{aligned}
& Z_{\mathrm{QCD}}=\operatorname{tr} e^{-\beta(H-\mu N)} \\
&=\int\left[d A_{\mu}\right][d \psi d \bar{\psi}] e^{\left(1 / 2 g^{2}\right) \int \operatorname{tr} F_{\mu \nu}^{2}+\int\left[\bar{\psi}\left(\gamma_{\mu} D_{\mu}+m\right) \psi+\mu \gamma^{\dagger} \psi\right]} \\
&\left.=\int\left[d A_{\mu}\right] e^{\left(1 / 2 g^{2}\right)}\right] \operatorname{tr} F_{\mu \nu}^{2} \\
& \operatorname{Det}\left(\begin{array}{cc}
m & \sigma_{\mu}\left(\partial_{\mu}+A_{\mu}\right)+\mu \\
\sigma_{\mu}^{\dagger}\left(\partial_{\mu}+A_{\mu}\right)+\mu & m
\end{array}\right)
\end{aligned}
$$

toy model
■ chiral random matrix model [Stephanov 1996, Halasz et al. 1998]

$$
Z_{\text {Steph }}=\int d^{2} W e^{-n \operatorname{tr} W^{\dagger} W} \operatorname{det}\left(\begin{array}{cc}
m & i W+\mu \\
i W^{\dagger}+\mu & m
\end{array}\right) \quad\binom{\text { quantum field replaced by }}{\text { a matrix incl spacetime DOF }}
$$

$W=\left(W_{i j}\right)=\left(X_{i j}+i Y_{i j}\right): n \times n$ complex matrix

$$
\left(\text { DOF : } N=2 n^{2} \Leftrightarrow 4 L^{4}\left(N_{c}^{2}-1\right)\right)
$$

- role as an important benchmark model
- well approximates the qualitative behaviour of QCD at large $n$
- complex Langevin suffers from wrong convergence [Bloch et al. 2018]


## Chiral random matrix model (2/2)

## matrix size : $n=10$ (DOF : $N=200$ )

[MF-Matsumoto 2012.08468]
(now easy at large DOF compared to the original TLTM)
chiral condensate $\langle\bar{\psi} \psi\rangle \equiv \frac{1}{2 n} \frac{\partial}{\partial m} \ln Z_{\text {Steph }}[m=0.004, T=0]$

## sample size

reweighting : 10k complex Langevin :10k WV-TLTM : 4k-17k

$\mu$
baryon \# density $\left\langle\psi^{\dagger} \psi\right\rangle \equiv \frac{1}{2 n} \frac{\partial}{\partial \mu} \ln Z_{\text {Steph }}$



## Scaling of computational cost

[MF-Matsumoto-Namekawa, work in progress]
We need to make a linear inversion of $J_{t} x=b$ several times in generating a config. The code on this part is currently being updated: Phase $1 \Rightarrow$ Phase 2

Phase 1 - Use a direct method (LU decomp) in linear inversion $\Leftarrow O\left(N^{3}\right)$

- $J_{t}$ is calculated explicitly by solving a diff eq $\dot{J}_{t}=\overline{\partial^{2} S\left(z_{t}\right) \cdot J_{t}} \Leftarrow O\left(N^{3}\right)$ computational cost (1 transition)

$O\left(N^{3}\right)$ (not exponential)
$\left[O\left(N^{\gtrsim 3.5}\right)\right.$ with original TLTM $]$
(Ongoing: comput scaling with fixed statistical errors
computed on Yukawa-21@YITP
$\binom{$ CPU: Xeon Platinum 8280 }{ GPU: NVIDIA Tesla V100 }

Phase 2 - Use an iterative method (BiCGStab) in linear inversion $\Leftarrow O\left(N^{2 \sim 3}\right)$

- Only need to solve a flow eq for a vector $v_{t}$ tangent to $\Sigma_{t}, \dot{v}_{t}=\overline{\partial^{2} S\left(z_{t}\right) \cdot v_{t}}$

We expect $O\left(N^{2 \sim 3}\right)$ for generating a config (work in progress)

## 5. Summary and outlook

## Summary and outlook

## ■ Summary

V TLTM has a potential to be a solution to the sign problem

- Sign and ergodicity problems are solved simultaneously
- TLTM has been successfully applied to various models
(yet only to toy models w/ small DOF at this stage)
- finite density QCD $\Longleftarrow$ chiral random matrix model [MF-Matsumoto]
- QMC : $\left\{\begin{array}{l}\text { strongly correl electron systems } \Longleftarrow 1 \mathrm{C} \\ \text { frustrated classical / quatum spin systems }\end{array}\right.$

1D/2D Hubbard model
[MF-Matsumoto-Umeda]
antiferro Ising on trianglular lattice
[MF-Matsumoto]
■ Outlook [MF-Matsumoto-Namekawa, work in progress]
$\boldsymbol{\nabla}$ Large-scale computation for large-size systems w/ WV-TLTM

- Further improvements of algorithm
- Combining various algorithms
(e.g.) TRG (non-MC): good at calculating free energy $\begin{aligned} & \text { cf) TRG for 2D YM: } \\ & \text { [MF-Kadoh-Matsumoto 2107.14149] }\end{aligned}$
$\boldsymbol{\nabla}$ Particularly important: MC calc for time-dependent systems
$\Rightarrow$
first-principles calc of nonequilibrium processes such as early universe, heavy ion collision experiments, ...

Thank you.

