

Trivializing Flow in 2D- $O(3)$ Model

Christopher Chamness

in collaboration with Daniel Kovner and Kostas Orginos

William & Mary

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Trivializing Map Overview

- ▶ A map can be used to connect two distinct probability distributions to each other.
- ▶ Trivializing Map is a bijective map between a trivial distribution and one that is difficult to sample.
- ▶ Typical methods for sampling these 'difficult' distributions is via Markov Chain Monte Carlo. MCMC has its own issues, long autocorrelation times
- ▶ With a trivializing map, it would then be possible to sample the trivial distribution to generate unique uncorrelated samples from the target distribution

Trivial Case

$$\psi \sim \mathcal{N}(0, 1) \leftrightarrow \phi \sim \mathcal{N}(100, 1)$$

Thus we define a map, $\mathcal{F} : \phi \rightarrow \psi$

$$\psi = \mathcal{F}(\phi) = \phi - 100$$

which is bijective

$$\phi = \mathcal{F}^{-1}(\psi) = \psi + 100$$

Trivializing Flow

A trivializing flow, is a trivializing map defined by a solution to a differential equation defined by a generating functional, \tilde{S} .

$$\dot{\phi}(x, y) = \partial_x \tilde{S}(\phi(t)) \quad \partial_x \equiv \frac{\partial}{\partial \phi(x)}$$

We may then consider 2 probability distributions, $p(\phi)$, $q(\psi)$, given by:

$$p(\phi) \equiv \frac{e^{-S(\phi)}}{Z} \quad q(\psi) \equiv \frac{e^{-S_0(\psi)}}{Z_0}$$

After applying the flow, which is a change of variables, where $J(\phi)$ is the determinate of the Jacobian matrix, \mathcal{J}_{xy} .

$$q(\psi)\mathcal{D}\psi = q(\mathcal{F}(\phi))\mathcal{J}(\phi)\mathcal{D}\phi$$

Thus our matching condition is that this is equal to our trivial distribution.

$$\begin{aligned} p(\phi) &= q(\mathcal{F}(\phi))\mathcal{J}(\phi) \\ \frac{e^{-S(\phi)}}{Z} &= \frac{e^{-S_0(\mathcal{F}(\phi))}}{Z_0} \\ S(\phi) &= S_0(\mathcal{F}(\phi)) - \ln[\mathcal{J}(\phi)] + \ln\left[\frac{Z_0}{Z}\right] \end{aligned}$$

Time Dependent Flow

Consider a time-dependent flow such that, $\phi(t) \equiv \mathcal{F}_t^{-1}(\psi, t)$ must satisfy a time-dependent probability distribution, $p_t(\phi(t), t)$. Where,

$$p_t(\phi(t), t) = \frac{e^{-S_t(\phi(t), t)}}{Z_t(t)}$$

Here the time-dependent map, $\mathcal{F}_t(\phi, t)$, is defined such that at $t = 1$, the distribution is trivial and at $t = 0$ is our target distribution.

$$p_t(\phi(1), 1) = q(\psi)$$

$$p_t(\phi(0), 0) = p(\phi)$$

$$\mathcal{F}_t(\phi(1), 1) = \mathcal{F}(\phi) = \psi$$

$$\mathcal{F}_t^{-1}(\phi(0), 0) = \phi$$

$$S_t(\phi(1), 1) = S_0(\psi)$$

$$S_t(\phi(0), 0) = \mathcal{S}(\phi)$$

$$Z_t(1) = Z_0$$

$$Z_t(0) = Z$$

This construction leads to the same condition as before, now with time-dependent pieces.

$$S_t(\phi(t), t) = S(\mathcal{F}(\phi(t), t)) - \ln[\mathcal{J}(\phi)] + C(t)$$

As Z and $Z_t(t)$ are independent of the fields, we may replace them with a time-dependent constant, $C(t)$. Note $C(0) = 0$

Time Dependent Flow

Consider the full time derivative of the previous equation.

$$\frac{d}{dt} \left[S_t(\phi(t), t) = \mathcal{S}(\mathcal{F}(\phi(t), t)) - \ln[\mathcal{J}(\phi)] + C(t) \right]$$

$$\sum_x \partial_x S_t(\phi(t), t) \dot{\phi}(x, t) + \partial_t S_t(\phi(t), t) = \sum_x \partial_x \mathcal{S}(\mathcal{F}(\phi(t), t)) \dot{\phi}(x, t) - \frac{d \ln[\mathcal{J}(t)]}{dt} + \dot{C}(t)$$

The Jacobian Term can be simplified,

$$\begin{aligned} \frac{d \ln(\mathcal{J}(t))}{dt} &= \text{Tr} \left[J_{xy}^{-1} \dot{J}_{yx} \right] = \sum_{x,y} \left[\left(\frac{\partial \phi(y, t)}{\partial \phi(x)} \right)^{-1} \frac{\partial \dot{\phi}(y, t)}{\partial \phi(x)} \right] \\ &= \sum_{x,y} \left[\frac{\partial \phi(x)}{\partial \phi(y, t)} \frac{\partial \dot{\phi}(y, t)}{\partial \phi(x)} \right] = \sum_y \frac{\partial \dot{\phi}(y, t)}{\partial \phi(y, t)} \\ &= \sum_y \frac{\partial}{\partial \phi(y, t)} \dot{\phi}(y, t) = \sum_y \frac{\partial}{\partial \phi(y, t)} \partial_y \tilde{S} = \sum_y \partial_y \partial_y \tilde{S} \\ \frac{d \ln(\mathcal{J}(t))}{dt} &= \partial^2 \tilde{S} \end{aligned}$$

In which case the full equation is,

$$-\partial^2 \tilde{S} + \sum_x \partial_x \mathcal{S} \partial_x \tilde{S} - \sum_x \partial_x S_t \partial_x \tilde{S} = \partial_t S_t - \dot{C}(t)$$

Model Freedom

At this point we have an equation related two unknown quantities, S_t and \tilde{S} . The choice of one determines the other. Consider a choice of S_t that linearly interpolates to the trivial action.

$$S_t(\phi(t), t) = \mathcal{S}(\phi(t)) + t \left(S_0(\phi(t)) - \mathcal{S}(\phi(t)) \right)$$

Then using this form,

$$- \partial^2 \tilde{S} + \sum_x \partial_x \mathcal{S} \partial_x \tilde{S} - \sum_x \partial_x (\mathcal{S} + t(S_0 - \mathcal{S})) \partial_x \tilde{S} = \partial_t (\mathcal{S} + t(S_0 - \mathcal{S})) - \dot{C}(t)$$

$$- \partial^2 \tilde{S} + \sum_x \partial_x \mathcal{S} \partial_x \tilde{S} - \sum_x \partial_x \mathcal{S} \partial_x \tilde{S} - t \sum_x \partial_x (S_0 - \mathcal{S}) \partial_x \tilde{S} = (S_0 - \mathcal{S}) - \dot{C}(t)$$

$$- \partial^2 \tilde{S} - t \sum_x \partial_x (S_0 - \mathcal{S}) \partial_x \tilde{S} = S_0 - \mathcal{S} - \dot{C}(t)$$

As S_0 is the trivial distribution, $S_0 = 0$, as long as the elements are part of a compact group.

$$- \partial^2 \tilde{S} + t \sum_x \partial_x \mathcal{S} \partial_x \tilde{S} = -\mathcal{S} - \dot{C}(t)$$

Small Flow Time Expansion

By expanding \tilde{S} , \dot{C} in flow time,

$$\tilde{S} \equiv \sum_n t^n S^{(n)} \qquad \dot{C} \equiv \sum_n t^n \dot{C}^{(n)}$$

we may find a perturbative solution for \tilde{S} .

$$\begin{aligned} -\partial^2 \left(\sum_{n=0}^{\infty} t^n S^{(n)} \right) + t \sum_x \left[\partial_x \mathcal{S} \left(\partial_x \left(\sum_{n=0}^{\infty} t^n S^{(n)} \right) \right) \right] &= -\mathcal{S} - \sum_{n=0}^{\infty} t^n \dot{C}^{(n)} \\ \sum_{n=0}^{\infty} \left[-t^n \partial^2 S^{(n)} + t^{n+1} \sum_x \left(\partial_x \mathcal{S} \partial_x S^{(n)} \right) \right] &= -\mathcal{S} - \sum_{n=0}^{\infty} t^n \dot{C}^{(n)} \end{aligned}$$

Then collecting powers of t . There are 2 classes of functions.¹

$$\begin{aligned} n = 0 : \quad & -\partial^2 S^{(0)} = -\mathcal{S} - \dot{C}^{(0)} \\ n \geq 1 : \quad & -\partial^2 S^{(n)} + \sum_x \partial_x \mathcal{S} \partial_x S^{(n-1)} = -\dot{C}^{(n)} \end{aligned}$$

¹Luscher, "Trivializing maps, the Wilson flow and the HMC algorithm".

The $O(3)$ Model

The $O(3)$ model is defined by the 2D Euclidean lattice action

$$\mathcal{S}[s] = -\frac{1}{2}\beta \sum_{x, \hat{\mu}} \langle s_x | s_{x+\hat{\mu}} \rangle$$

where $s \in \mathcal{S}^2$. Thus they have a probability distribution defined by this action

$$p[s] = \frac{e^{-\mathcal{S}[s]}}{\mathcal{Z}}, \quad \mathcal{Z} = \int \mathcal{D}s e^{-\mathcal{S}[s]}$$

and the integration measure, $\mathcal{D}s$, is over \mathcal{S}^2 .

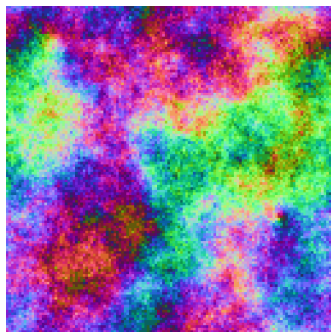
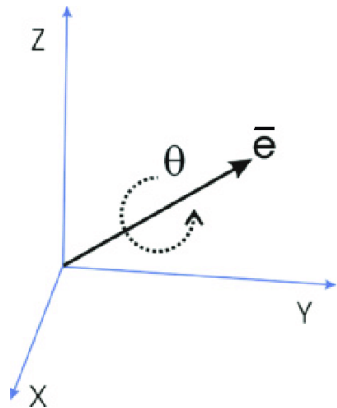


Figure: Example distribution $(x, y, z) \rightarrow (r, g, b)$

¹Bietenholz et al., "Topological susceptibility of the 2D $O(3)$ model under gradient flow".

Defining a Flow Equation



When determining a gradient flow it is important to choose dynamics that preserve properties of the elements.

$$\forall R \in SO(3) \quad \& \quad \forall s \in S^2 \\ R * s \in S^2$$

Therefore, a general map that takes an S^2 valued vector field s and maps to an S^2 valued vector field σ , can be written as

$$\sigma(x) = R(x) s(x),$$

where $R(x)$ is an element of $SO(3)$ which is determined up to an $SO(2)$ rotation.

The quotient $SO(3)/SO(2)$ subgroup of $SO(3)$ is diffeomorphic to the sphere S^2 manifold.

Unit Vectors to Rotations

By parameterizing the field with respect to rotation of a reference vector, s_0 ,

$$s_x = R(x)s_{0,x}$$

the fields may be represented in the Lie algebra, $\mathfrak{so}(3)$ of $SO(3)$, which is isomorphic to \mathbb{R}^3 with cross product. The Lie derivative, ∂_x^α , is well defined on these elements.

$$R(x) = \sum_{\alpha} \omega_x^{\alpha} T_{\alpha}$$
$$\partial_y^{\beta} R(x) = \sum_{\alpha} \omega_x^{\alpha} T_{\alpha} \delta_{\alpha,\beta} \delta_{x,y}$$

Using a scalar functional of the fields, \tilde{S} , whose gradient defines the generator of the flow,

$$\dot{s}(x, t) = - \sum_a T_a \partial_x^{\alpha} \tilde{S}[s(x, t)] s_x,$$

we may preserve the symmetries of the system.

0th Order

We want to solve:

$$-\partial^2 S^{(0)} = -\mathcal{S}$$

with,

$$\mathcal{S} = \frac{-\beta}{2} \sum_x \sum_{\mu} \langle s_x | s_{x+\mu} \rangle \quad S^{(0)} = \gamma_0 \sum_x \sum_{\mu} \langle s_x | s_{x+\mu} \rangle$$

Thus expanding on the Left Hand Side:

$$\begin{aligned} -\partial^2 S^{(0)} &= -\sum_x \sum_a \partial_x^a \partial_x^a \left[\gamma_0 \sum_y \sum_{\mu} \langle s_y | s_{y+\mu} \rangle \right] \\ &= -\gamma_0 \sum_x \sum_a \partial_x^a \left[\sum_y \sum_{\mu} -\langle s_y | T^a | s_{y+\mu} \rangle \delta_{x,y} + \langle s_y | T^a | s_{y+\mu} \rangle \delta_{x,y+\mu} \right] \\ &= -\gamma_0 \sum_x \sum_a \left[\sum_{\mu} \langle s_x | T^a T^a | s_{x+\mu} \rangle + \langle s_{x-\mu} | T^a T^a | s_x \rangle \right] \\ &= \gamma_0 \sum_x \left[\sum_{\mu} \langle s_x | C_F | s_{x+\mu} \rangle + \langle s_{x-\mu} | C_F | s_x \rangle \right] \\ -\partial^2 S^{(0)} &= 2C_F \gamma_0 \sum_x \sum_{\mu} \langle s_x | s_{x+\mu} \rangle = 2C_F S^{(0)} \end{aligned}$$

Therefore

$$S^{(0)} = \frac{\beta}{8} \sum_x \sum_{\mu} \langle s_x | s_{x+\mu} \rangle$$

1st Order - Gradient Product

We want to solve

$$-\partial^2 S^{(1)} + \sum_x \sum_a (\partial_x^a S) (\partial_x^a S^{(0)}) = 0$$

First lets consider the term

$$\begin{aligned} \sum_x \sum_a (\partial_x^a S) (\partial_x^a S^{(0)}) &= \frac{-\beta^2}{16} \sum_{x,a} \left[\left(\partial_x^a \sum_{y,\mu} \langle s_y | s_{y+\mu} \rangle \right) \left(\partial_x^a \sum_{z,\nu} \langle s_z | s_{z+\nu} \rangle \right) \right] \\ &= \frac{-\beta^2}{16} \sum_{x,a} \left[\left(\sum_{\mu} - \langle s_x | T^a | s_{x+\mu} \rangle + \langle s_{x-\mu} | T^a | s_x \rangle \right) \right. \\ &\quad \left. \left(\sum_{\nu} - \langle s_x | T^a | s_{x+\nu} \rangle + \langle s_{x-\nu} | T^a | s_x \rangle \right) \right] \\ &= \frac{-\beta^2}{16} \sum_{x,a} \left[\left(\sum_{\mu} -2 \langle s_x | T^a | s_{x+\mu} \rangle \right) \left(\sum_{\nu} -2 \langle s_x | T^a | s_{x+\nu} \rangle \right) \right] \\ &= \frac{-\beta^2}{4} \sum_{x,a} \left[\sum_{\mu,\nu} \langle s_x | T^a | s_{x+\mu} \rangle \langle s_x | T^a | s_{x+\nu} \rangle \right] \\ &= \frac{-\beta^2}{4} \sum_x \left[\sum_{\mu,\nu} \langle s_x | s_x \rangle \langle s_{x+\mu} | s_{x+\nu} \rangle - \langle s_x | s_{x+\mu} \rangle \langle s_x | s_{x+\nu} \rangle \right] \\ \sum_x \sum_a (\partial_x^a S) (\partial_x^a S^{(0)}) &= \frac{-\beta^2}{4} \sum_x \left[\sum_{\mu,\nu} \langle s_x | s_{x+\mu+\nu} \rangle - \langle s_x | s_{x+\mu} \rangle \langle s_x | s_{x+\nu} \rangle \right] \end{aligned}$$

1st Order - Solution

Again we choose $S^{(1)}$ to be parameterized by terms we are trying to cancel.

$$S^{(1)} = \gamma_1 \Psi^{(2)} + \gamma_2 \tilde{\Psi}^{(1,1)}$$

where,

$$\Psi^{(2)} = \sum_x \sum_{\mu, \nu} \langle s_x | s_{x+\mu+\nu} \rangle \quad \tilde{\Psi}^{(1,1)} = \sum_x \sum_{\mu, \nu} \langle s_x | s_{x+\mu} \rangle \langle s_x | s_{x+\nu} \rangle$$

And applying the ∂^2 , we find a new term to arise,

$$\begin{aligned} &= - \sum_{x,a} \partial_x^a \partial_x^a \sum_y \sum_{\mu, \nu} [\langle s_y | s_{y+\mu} \rangle \langle s_y | s_{y+\nu} \rangle] \\ &\quad - \langle s_y | s_{y+\mu} \rangle \langle s_y | T^a | s_{y+\nu} \rangle \delta_{x,y} + \langle s_y | s_{y+\mu} \rangle \langle s_y | T^a | s_{y+\nu} \rangle \delta_{x,y+\nu}] \\ &= - \sum_{x,a} \sum_{\mu, \nu} \partial_x^a \left[\langle s_{x-\mu} | T^a | s_x \rangle \langle s_{x-\mu} | s_{x-\mu+\nu} \rangle + \dots \right] \\ &= - \sum_{x,a} \sum_{\mu, \nu} \left[\langle s_{x-\mu} | T^a | s_x \rangle \langle s_{x-\mu} | T^a | s_{x-\mu+\nu} \rangle \delta_{x,x-\mu+\nu} + \dots \right] \\ &= - \sum_x \sum_{\mu} \left[\langle s_{x-\mu} | s_{x-\mu} \rangle \langle s_x | s_x \rangle - \langle s_{x-\mu} | s_x \rangle \langle s_{x-\mu} | s_x \rangle + \dots \right] \\ &= - \sum_x \sum_{\mu} \left[1 - \langle s_x | s_{x+\mu} \rangle^2 + \dots \right] = \sum_x \sum_{\mu} \langle s_x | s_{x+\mu} \rangle^2 + \dots \end{aligned}$$

Therefore, we can define this new term, and add it to our parameterization of $S^{(1)}$.

$$\Psi^{(1,1f)} = \sum_x \sum_{\mu} \langle s_x | s_{x+\mu} \rangle^2$$

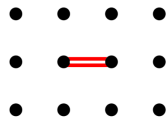
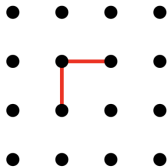
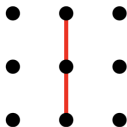
$$S^{(1)} = \gamma_1 \Psi^{(2)} + \gamma_2 \tilde{\Psi}^{(1,1)} + \gamma_3 \Psi^{(1,1f)}$$

then including this term, we may find a solution,

$$S^{(1)} = \frac{\beta^2}{40} \left[2\Psi^{(2)} - \tilde{\Psi}^{(1,1)} + \frac{1}{6} \Psi^{(1,1f)} \right]$$

Combining with the previous order,

$$\tilde{S} = \frac{\beta}{8} \Psi^{(1)} + \frac{\beta^2}{40} \left[2\Psi^{(2)} - \tilde{\Psi}^{(1,1)} + \frac{1}{6} \Psi^{(1,1f)} \right] t + \mathcal{O}(t^2)$$



2nd Order - Terms

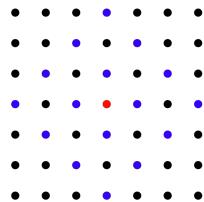


Figure: $\Psi^{(3)}$

$$\Psi^{(1)} \equiv \sum_x \sum_{\mu} \langle s_x | s_{x+\mu} \rangle$$

$$\Psi^{(3)} \equiv \sum_x \sum_{\mu, \nu, \lambda} \langle s_x | s_{x+\mu+\nu+\lambda} \rangle$$

$$\tilde{\Psi}^{(2,1)} \equiv \sum_x \sum_{\mu, \nu, \lambda} \langle s_x | s_{x+\mu+\nu} \rangle \langle s_x | s_{x+\lambda} \rangle$$

$$\tilde{\Psi}_{disc}^{(1,2)} \equiv \sum_x \sum_{\mu, \nu, \lambda} \langle s_x | s_{x+\mu} \rangle \langle s_{x+\nu} | s_{x+\lambda} \rangle$$

$$\tilde{\Psi}_{branch}^{(1,1,1)} \equiv \sum_x \sum_{\mu, \nu, \lambda} \langle s_x | s_{x+\mu} \rangle \langle s_x | s_{x+\nu} \rangle \langle s_x | s_{x+\lambda} \rangle$$

$$\tilde{\Psi}_{chain}^{(1,1,1)} \equiv \sum_x \sum_{\mu, \nu, \lambda} \langle s_x | s_{x+\mu} \rangle \langle s_{x+\mu} | s_{x+\mu+\nu} \rangle \langle s_{x+\mu+\nu} | s_{x+\mu+\nu+\lambda} \rangle$$

$$\tilde{\Psi}^{(1,2f)} \equiv \sum_x \sum_{\mu, \nu} \langle s_x | s_{x+\mu} \rangle \langle s_x | s_{x+\mu+\nu} \rangle$$

$$\tilde{\Psi}^{(1,1f,1)} \equiv \sum_x \sum_{\mu, \nu} \langle s_x | s_{x+\mu} \rangle^2 \langle s_x | s_{x+\nu} \rangle$$

$$\tilde{\Psi}^{(1,1f,1f)} \equiv \sum_x \sum_{\mu} \langle s_x | s_{x+\mu} \rangle^3$$

2nd Order - Laplacians

$$\begin{aligned}-\partial^2 \Psi^{(1)} &= 4\Psi^{(1)} \\ -\partial^2 \Psi^{(3)} &= 4\Psi^{(3)} \\ -\partial^2 \tilde{\Psi}^{(2,1)} &= 10\tilde{\Psi}^{(2,1)} - 2\Psi^{(3)} - 16\Psi^{(1)} \\ -\partial^2 \tilde{\Psi}_d^{(1,2)} &= 8\tilde{\Psi}_d^{(1,2)} - 32\Psi^{(1)} + 4\tilde{\Psi}^{(1,2f)} \\ -\partial^2 \tilde{\Psi}_{branch}^{(1,1,1)} &= 18\tilde{\Psi}_{branch}^{(1,1,1)} - 6\tilde{\Psi}_d^{(1,2)} - 24\Psi^{(1)} + 6\tilde{\Psi}^{(1,1f,1)} \\ -\partial^2 \tilde{\Psi}_{chain}^{(1,1,1)} &= 16\tilde{\Psi}_{chain}^{(1,1,1)} - 16\Psi^{(1)} + 8\tilde{\Psi}^{(1,1f,1)} - 4\tilde{\Psi}^{(2,1)} - 4\tilde{\Psi}^{(1,2f)} \\ -\partial^2 \tilde{\Psi}^{(1,2f)} &= 10\tilde{\Psi}^{(1,2f)} - 12\Psi^{(1)} \\ -\partial^2 \tilde{\Psi}^{(1,1f,1)} &= 20\tilde{\Psi}^{(1,1f,1)} - 20\Psi^{(1)} - 4\tilde{\Psi}^{(1,2f)} + 4\tilde{\Psi}^{(1,1f,1f)} \\ -\partial^2 \tilde{\Psi}^{(1,1f,1f)} &= 24\tilde{\Psi}^{(1,1f,1f)} - 12\Psi^{(1)}\end{aligned}$$

Our goal is to solve,

$$\begin{aligned}-\partial^2 S^{(1)} + \sum_x \sum_a (\partial_x^a S) (\partial_x^a S^{(0)}) &= 0 \\ \partial^2 S^{(1)} &= \sum_x \sum_a (\partial_x^a S) (\partial_x^a S^{(0)})\end{aligned}$$

which can be translated to,

$$\hat{A}\vec{x} = \vec{b} \implies \vec{x} = \hat{A}^{-1}\vec{b}$$

2nd Order - Solution

Solving the next order gives:

$$S^{(2)} = \frac{\beta^3}{72000} \left[-4467\Psi^{(1)} + 1305\Psi^{(3)} - 990\tilde{\Psi}^{(2,1)} - 300\tilde{\Psi}_d^{(1,2)} + 200\tilde{\Psi}_{branch}^{(1,1,1)} \right. \\ \left. + 225\tilde{\Psi}_{chain}^{(1,1,1)} + 246\tilde{\Psi}^{(1,2f)} - 210\tilde{\Psi}^{(1,1f,1)} + 35\tilde{\Psi}^{(1,1f,1f)} \right]$$

Procedure can be repeated to any order but this is where our analytic approach ends.
2nd Order has > 30 unique terms, 3rd Order has > 100 unique terms

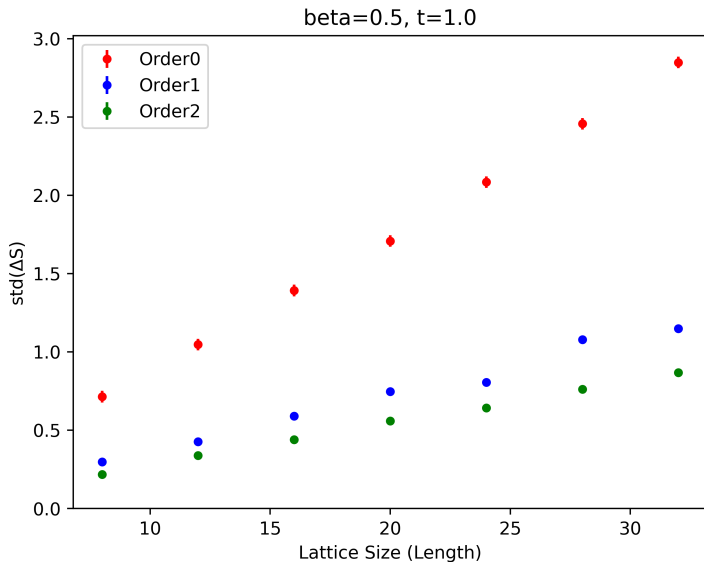
$$\tilde{S} = \frac{\beta}{8}\Psi^{(1)} + \frac{\beta^2}{40} \left[2\Psi^{(2)} - \tilde{\Psi}^{(1,1)} + \frac{1}{6}\Psi^{(1,1f)} \right] t + \frac{\beta^3}{72000} \left[-4467\Psi^{(1)} + 1305\Psi^{(3)} \right. \\ \left. - 990\tilde{\Psi}^{(2,1)} - 300\tilde{\Psi}_d^{(1,2)} + 200\tilde{\Psi}_{branch}^{(1,1,1)} + 225\tilde{\Psi}_{chain}^{(1,1,1)} + 246\tilde{\Psi}^{(1,2f)} \right. \\ \left. - 210\tilde{\Psi}^{(1,1f,1)} + 35\tilde{\Psi}^{(1,1f,1f)} \right] t^2 + \mathcal{O}(t^3)$$

By applying the flow, and observing the variance of the error between, the action and our flowed ensemble, we may determine how well the flow preforms

$$\Delta S \equiv \mathcal{S}(\phi) - \left[S_0(\mathcal{F}(\phi)) - \ln \mathcal{J}(\phi) \right] + C(\mathcal{Z}, \mathcal{Z}_0)$$

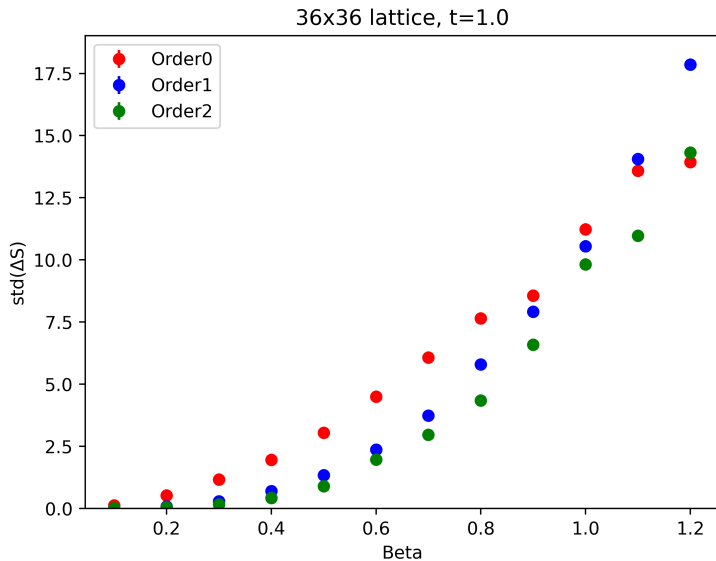
Scaling with Lattice Size

We observe linear scaling with the lattice side length



Scaling with Beta

We observe quadratic scaling with beta with the method breaking as $\beta > 1$



Future Steps

It is worth noting $S^{(0)}$, appears in $S^{(2)}$, therefore all terms of $S^{(1)}$ will appear in $S^{(3)}$. So a subset of the higher order terms is already known.

$$S^{(2n)} = \beta^{2n+1} \sum_a \gamma_a^{(2n)} \Psi_{even}^a$$
$$S^{(2n+1)} = \beta^{2(n+1)} \sum_a \gamma_a^{(2n+1)} \Psi_{odd}^a$$

By non-perturbative tuning of the γ_a , it might be possible to increase performance further with little cost to preforming the flow.

Conclusion

- ▶ It is possible to solve the Luscher equation analytically
- ▶ Scaling with lattice volume is inevitable
- ▶ Non-perturbative tuning may still improve solution
- ▶ Performing the flow may be just as computationally expensive as HMC