Diagrammatic Monte-Carlo algorithms for large-N quantum field theories from **Schwinger-Dyson equations** Pavel Buividovich (Regensburg University) Lattice 2015, Kobe, Japan

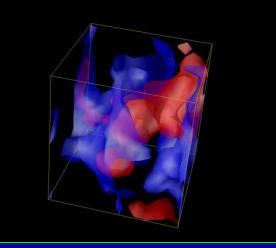
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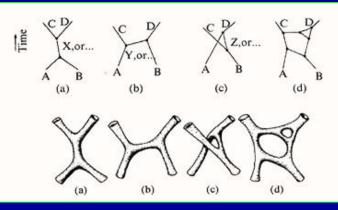
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Motivation: Diagrammatic Monte-Carlo Quantum field theory:

Sum over fields



Sum over interacting paths

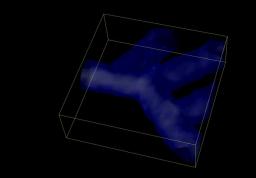


$$\mathcal{Z} = \operatorname{Tr} e^{-\hat{\mathcal{H}}/kT} =$$
$$= \int \mathcal{D}\phi \left(x^{\mu} \right) \, \exp \left(-S_E \left[\phi \left(x^{\mu} \right) \right] \right)$$

Euclidean action:

$$S_E = \int d^D x \, \left(\frac{1}{2} \,\partial_\mu \phi \partial_\mu \phi + \frac{m^2}{2} \,\phi^2 + V\left(\phi\right)\right)$$

Perturbative expansions



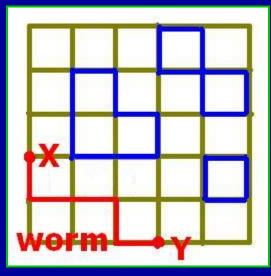
 $\mathcal{Z} = \sum_{k} \frac{\lambda^{k}}{k!} \exp\left(-L\left(\text{Paths connecting } k \text{ vertices}\right)\right)$

Motivation: QCD side

- Recent attempts to apply DiagMC to lattice QCD at finite density and reduce sign problem
- DiagMC relies on Abelian "Duality transformations"
- BUT: no convenient duality transformations for non-Abelian fields Weak-coupling expansions are also cumbersome and difficult to re-sum
- DiagMC in the non-Abelian case?
 Avoid manual duality transformations?
 How to avoid Borel resummations?

Worm Algorithm [Prokof'ev, Svistunov]

- Monte-Carlo sampling of closed vacuum diagrams: nonlocal updates, closure constraint
- Worm Algorithm: sample closed diagrams + open diagram
- Local updates: open graphs
- Direct sampling of field correlators (dedicated simulations)



x, y – head and tail of the worm

$$\langle \sigma_{\mathbf{x}}\sigma_{\mathbf{y}} \rangle \sim \mathbf{p}(\mathbf{x},\mathbf{y})$$

Correlator = probability distribution of head and tail



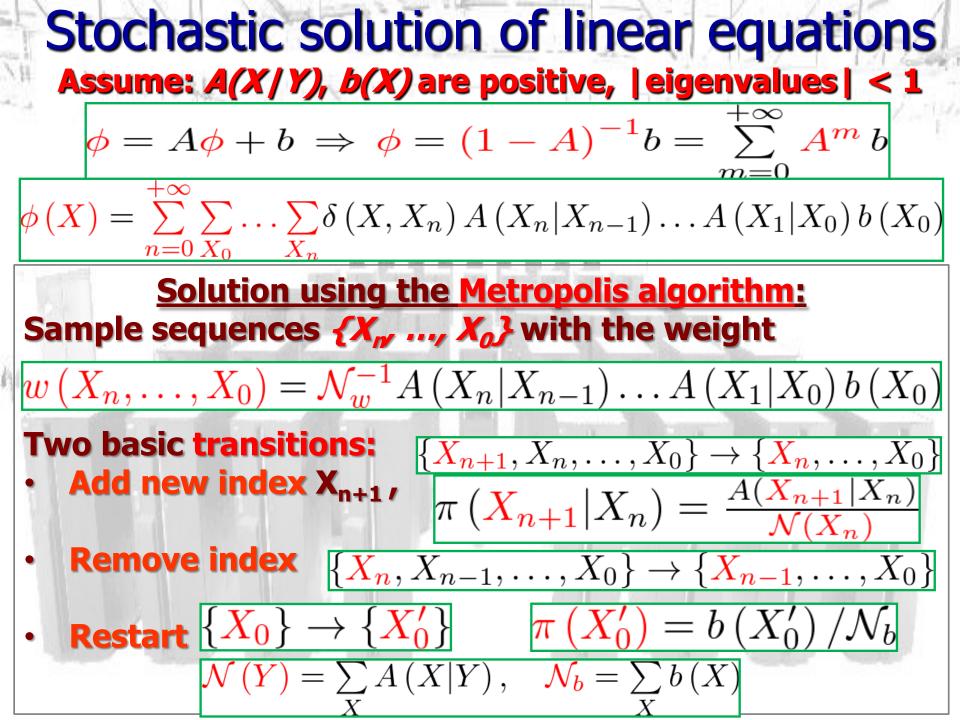
 Applications: systems with "simple" and convergent perturbative expansions (Ising, Hubbard, 2d fermions ...)
 Very fast and efficient algorithm!!!

General structure of SD equations
(everywhere we assume lattice discretization)

$$\int \mathcal{D}\phi \frac{\partial}{\partial \phi(X)} (O_1[\phi] \dots O_n[\phi] \exp(-S[\phi])) = 0$$

$$\int_{A=1}^n \langle O_1[\phi] \dots \frac{\partial O_A[\phi]}{\partial \phi(x)} \dots O_n[\phi] \rangle =$$

$$= \langle O_1[\phi] \dots O_n[\phi] \frac{\partial S[\phi]}{\partial \phi(x)} \rangle$$
Choose some closed set of observables $\phi(X)$
X is a collection of all labels, e.g. for scalar field theory
 $\phi(X) = \langle \phi(x_1) \dots \phi(x_n) \rangle, \quad X = \{x_1, \dots, x_n\}$
SD equations (with disconnected correlators) are linear:
 $\phi(X) = \sum_Y A(X|Y) \phi(Y) + b(X)$
A(X | Y): infinite-dimensional, but sparse linear operator
b(X): source term, typically only 1-2 elements nonzero



Stochastic solution of linear equations

With probability p₊: Add index step
 With probability (1-p₊): Remove index/Restart

Ergodicity: any sequence can be reached (unless A(X | Y) has some block-diagonal structure)

Acceptance probabilities (no detailed balance, Metropolis-Hastings)

$$\alpha\left(\mathcal{S}\to\mathcal{S}'\right) = \min\left(1,\frac{w(\mathcal{S}')\pi(\mathcal{S}'\to\mathcal{S})}{w(\mathcal{S})\pi(\mathcal{S}\to\mathcal{S}')}\right)$$

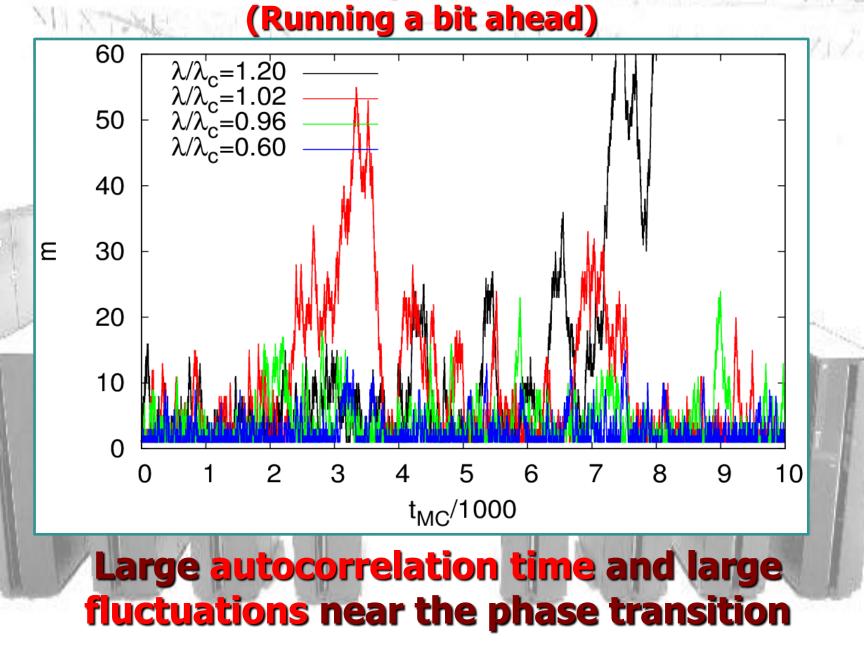
 $\alpha_{add} = \frac{\mathcal{N}(X_n)(1-p_+)}{p_+}, \quad \alpha_{remove} = \frac{p_+}{\mathcal{N}(X_{n-1})(1-p_+)}, \quad \alpha_{restart} = 1.$

- Parameter p_+ can be tuned to reach optimal acceptance
- Probability distribution of N(X) is crucial to asses convergence

Finally: make histogram of the last element X_n in the sequence

Solution $\varphi(X)$, normalization factor $\mathcal{N}_w = \frac{\mathcal{N}_b}{1 - \langle \mathcal{N}(X_n) \rangle} \Rightarrow \langle \mathcal{N}(X) \rangle < 1$

Illustration: ϕ^4 matrix model



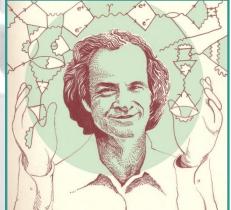
Practical implementation

- Keeping the whole sequence {X_n, ..., X₀} in memory is not practical (size of X can be quite large)
- Use the sparseness of A(X | Y), remember the sequence of transitions $X_n \rightarrow X_{n+1}$
- Every transition is a summand in a symbolic representation of SD equations
- Every transition is a "drawing" of some element of diagrammatic expansion (either weak- or strong-coupling one)

Save:

- current diagram
- history of drawing

Need DO and UNDO operations for every diagram element



Construction of algorithms is almost automatic and can be nicely combined with symbolic calculus software (e.g. Mathematica)

Sign problem and reweighting

- Now lift the assumptions A(X | Y) > 0, b(X) > 0
- Use the absolute value of weight for the Metropolis sampling

$$w(X_n, \dots, X_0) = \mathcal{N}_w^{-1} |A(X_n | X_{n-1})| \dots |A(X_1 | X_0)| |b(X_0)|$$

Sign of each configuration:

$$S(X_n, \dots, X_0) = \operatorname{sign} A(X_n | X_{n-1}) \dots \operatorname{sign} A(X_1 | X_0) \operatorname{sign} b(X_0)$$

Define
$$A(X|Y) = |A(X|Y)| \quad \tilde{b}(X) = |b(X)|$$

- Effectively, we solve the system $\,\phi=A\phi+b\,$
- The expansion convergence
- $ilde{\phi} = \sum\limits_{m=0}^{+\infty} ilde{A}^m ilde{b}$ has smaller radius of
- Reweighting fails if the system $\phi = A\phi + b$ approaches the critical point (one of eigenvalues approach 1)

One can only be saved by a suitable reformulation of equations which makes the sign problem milder

Resummation/Rescaling

Growth of field correlators $\langle \phi(x_n) \dots \phi(x_0) \rangle$ with n/ order:

- **Exponential in the large-N limit**
- Factorial at finite N, $\phi = A \phi + b$ has no perturbative solution

How to interprete $\langle \phi(x_n) \dots \phi(x_0) \rangle$ as a probability distribution?

Large N limit

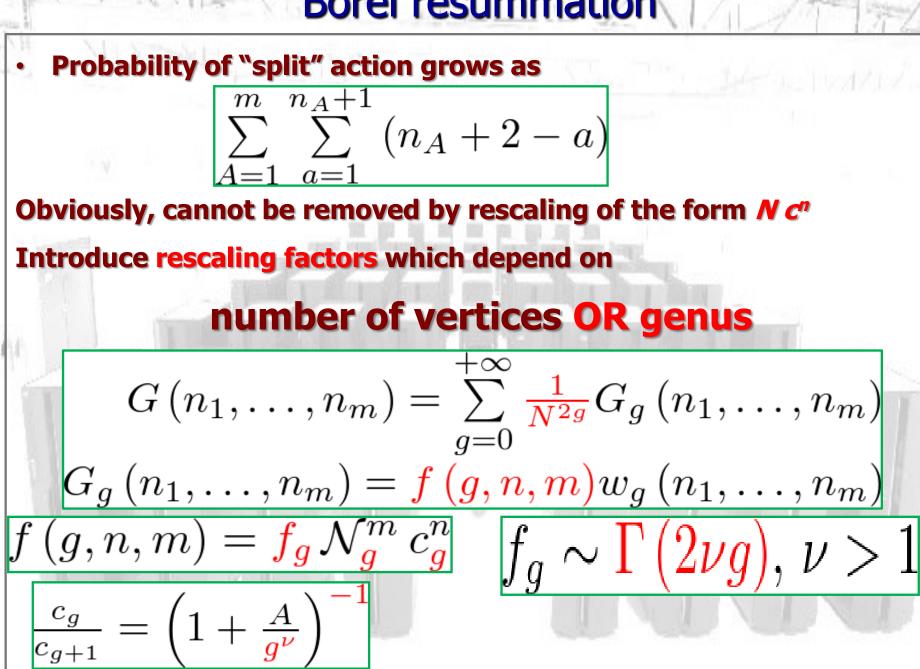
Exponential growth? Introduce "renormalization constants":

$$\left\langle \phi\left(x_{n}\right)\dots\phi\left(x_{0}\right)\right\rangle = \mathcal{N} c^{n} w\left(x_{n},\dots,x_{0}\right)$$

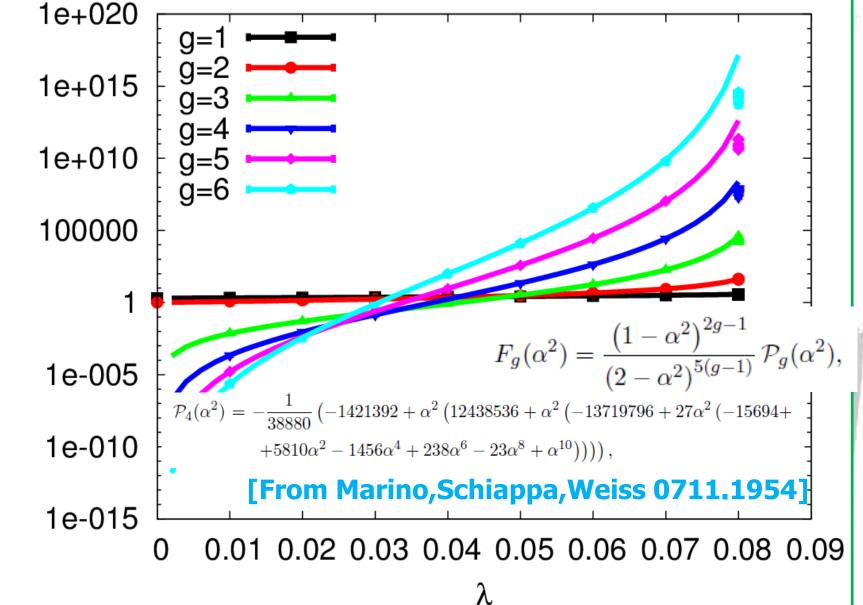
$$\sum_{n=1}^{+\infty} \sum_{x_{n}\dots x_{0}} w\left(x_{n},\dots,x_{0}\right)$$
is now finite,
can be interpreted as probability

In the Metropolis algorithm: all the transition weights should be finite, otherwise unstable behavior How to deal with factorial growth? Borel resummation

Borel resummation

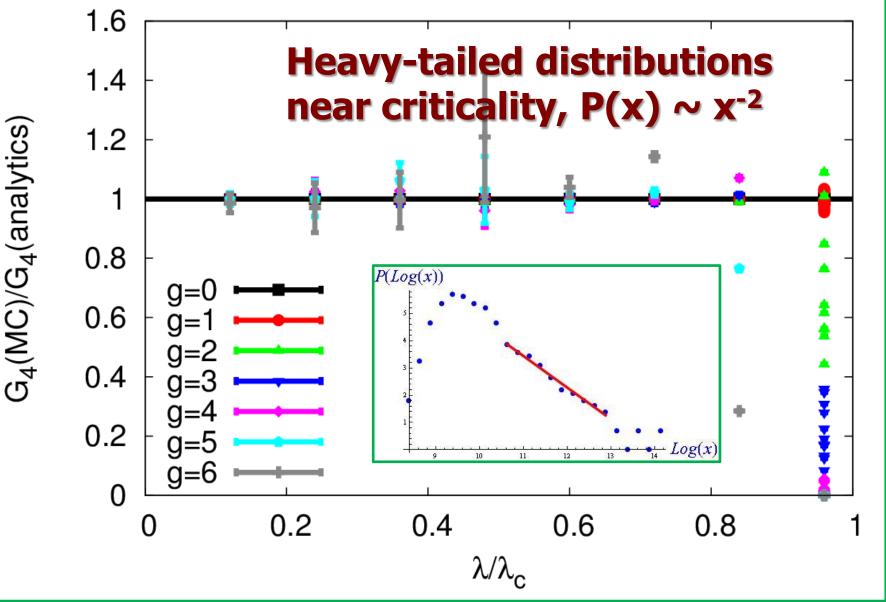


Genus expansion: ϕ^4 matrix model



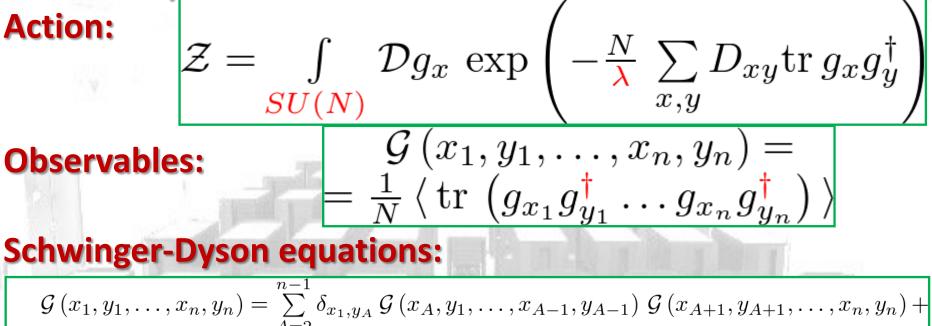
 ${\sf G_4}^{(g)}(\lambda)$

Genus expansion: ϕ^4 matrix model



Lessons from SU(N) sigma-model

Nontrivial playground similar to QCD!!!



$$+ \delta_{x_{1},y_{1}} \mathcal{G}(x_{2},y_{2},\ldots,x_{n},y_{n}) + \delta_{x_{1},y_{n}} \mathcal{G}(x_{n},y_{1},\ldots,x_{n-1},y_{n-1}) - \sum_{A=2}^{n} \delta_{x_{1},x_{A}} \mathcal{G}(x_{1},y_{1},\ldots,x_{A-1},y_{A-1}) \mathcal{G}(x_{A},y_{A},\ldots,x_{n},y_{n}) - \frac{1}{2} D - \mathcal{G}(x_{1},x_{1},x_{1},y_{1},\ldots,x_{n-1},y_{A-1}) \mathcal{G}(x_{1},x_{1},x_{1},y_{1},\ldots,x_{n},y_{n}) - \frac{1}{2} D - \mathcal{G}(x_{1},x_{1},y_{1},\ldots,x_{n},y_{n}) - \frac{1}{2} D - \mathcal{G}(x_{1},x_{1},y_{1},\ldots,x_{n},y_{n}) - \frac{1}{2} D - \mathcal{G}(x_{1},y_{1},\ldots,x_{n},y_{n}) - \frac{1}{2} D$$

Stochastic solution naturally leads to strong-coupling series! Alternating sign already @ leading order

Lessons from SU(N) sigma-model

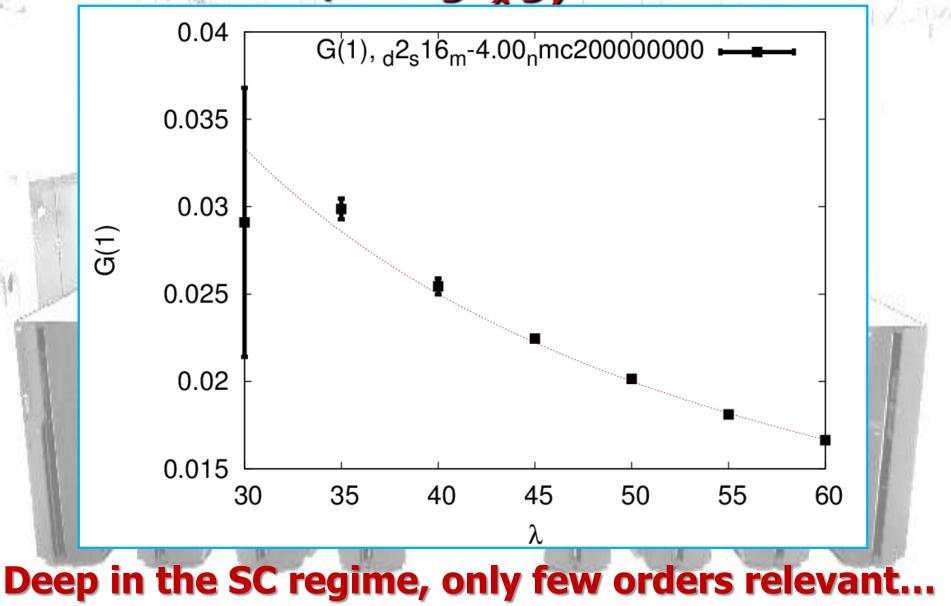
SD equations in momentum space:

$$\begin{aligned} \mathcal{G}(p_{1},q_{1},\ldots,p_{n},q_{n}) &= \frac{1}{V^{2n}} \sum_{x_{1},y_{1}} \cdots \sum_{x_{n},y_{n}} \\ \exp\left(i\sum_{A} p_{A}x_{A} + i\sum_{A} q_{A}y_{A}\right) \mathcal{G}(x_{1},y_{1},\ldots,x_{n},y_{n}) \\ \mathcal{G}(p) &= \left(\lambda + D\left(p\right)\right)^{-1} \end{aligned}$$

$$\begin{aligned} \mathcal{G}(p_{1},q_{1}) &= \lambda \frac{\mathcal{G}_{0}(p_{1})\delta(p_{1}+q_{1})}{V} + \mathcal{G}_{0}\left(p_{1}\right) \sum_{\tilde{p}_{1},\tilde{q}_{1},\tilde{p}_{2}} \delta\left(p_{1},\tilde{p}_{1} + \tilde{q}_{1} + \tilde{p}_{2}\right) D\left(\tilde{q}_{1}\right) \mathcal{G}\left(\tilde{p}_{1},\tilde{q}_{1},\tilde{p}_{2},q_{1}\right) \end{aligned}$$

$$\begin{aligned} \mathcal{G}(p_{1},q_{1},\ldots,p_{n},q_{n}) &= \\ &= \sum_{A=2}^{n-1} \lambda \frac{\mathcal{G}_{0}(p_{1})\delta(p_{1}+q_{A})}{V} \mathcal{G}\left(p_{A},q_{1},\ldots,p_{A-1},q_{A-1}\right) \mathcal{G}\left(p_{A+1},q_{A+1},\ldots,p_{n},q_{n}\right) + \\ &+ \lambda \frac{\mathcal{G}_{0}(p_{1})\delta(p_{1}+q_{n})}{V} \mathcal{G}\left(p_{2},q_{2},\ldots,p_{n},q_{n}\right) + \\ &+ \lambda \frac{\mathcal{G}_{0}(p_{1})\delta(p_{1}+q_{n})}{V} \mathcal{G}\left(p_{n},q_{1},p_{2},q_{2},\ldots,p_{n-1},q_{n-1}\right) - \\ &- \lambda \frac{\mathcal{G}_{0}(p_{1})}{V} \sum_{A=2}^{n} \sum_{\tilde{p}_{1}\tilde{p}_{A}} \delta\left(p_{1} + p_{A},\tilde{p}_{1} + \tilde{p}_{A}\right) \mathcal{G}\left(\tilde{p}_{1},\tilde{q}_{1},\tilde{p}_{2},q_{1},p_{2},q_{2},\ldots,p_{n},q_{n}\right) + \\ &+ \mathcal{G}_{0}(p_{1}) \sum_{\tilde{p}_{1},\tilde{q}_{1},\tilde{p}_{2}} \delta\left(p_{1},\tilde{p}_{1} + \tilde{q}_{1} + \tilde{p}_{2}\right) D\left(\tilde{q}_{1}\right) \mathcal{G}\left(\tilde{p}_{1},\tilde{q}_{1},\tilde{p}_{2},q_{1},p_{2},q_{2},\ldots,p_{n},q_{n}\right) \end{aligned}$$

Lessons from SU(N) sigma-model <1/N tr g^+ , $g_v > vs \lambda$



Lessons from SU(N) sigma-model Matrix Lagrange Multiplier

$$\mathcal{Z} = \int dg_x \int d\xi_x \exp\left(-\frac{N}{\lambda} \sum_{x \neq y} D_{xy} \operatorname{tr} \left(g_x^{\dagger} g_y\right) - \frac{iN}{\lambda} \sum_x \operatorname{tr} \left(\xi_x g_x^{\dagger} g_x - \xi_x\right)\right) =$$

$$= \int d\xi_x \exp\left(\operatorname{Ntr} \ln\left(D_{xy} + i\xi_x \delta_{xy}\right) + \frac{iN}{\lambda} \sum_x \operatorname{tr} \xi_x\right)$$

$$G_{xy} = \left(D_{xy} + i\xi_x \delta_{xy}\right)^{-1} \qquad m^2 \equiv \lambda + 2D\left(1 - \left\langle\operatorname{tr} g_x^{\dagger} g_{x+\hat{0}}\right\rangle\right)$$

$$\operatorname{Nonperturbative improvement!!!} \left[\operatorname{Vicari, Rossi, ...}\right]$$

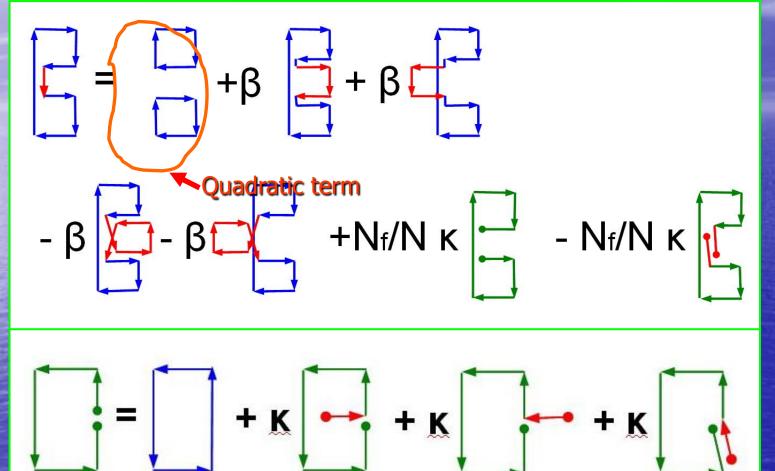
$$\langle G_{p_1q_1} \dots G_{p_nq_n} \rangle = \frac{1}{V} \mathcal{G}(p_1) \delta(p_1 + q_1) \langle G_{p_2q_2} \dots G_{p_nq_n} \rangle +$$

$$+ \frac{\lambda}{V} \mathcal{G}(p_1) \sum_{A=2}^n \sum_{\tilde{p}_1, \tilde{p}_A} \delta(p_1 - p_1 - \tilde{p}_A - \tilde{p}_A) K^2\left(\tilde{q}_A\right) \langle G_{\tilde{p}_1q_1} \dots G_{p_A\tilde{q}_A} \rangle \langle G_{\tilde{p}_Aq_A} \dots G_{p_nq_n} \rangle +$$

$$+ \lambda \mathcal{G}(p_1) \sum_{\tilde{q}_x, \tilde{q}_x, \tilde{q}_x, \tilde{q}_x, \delta(p_1 - \tilde{p}_1 - \tilde{p}_2 - \tilde{q}_1) K^2\left(\tilde{q}_1\right) \langle G_{\tilde{p}_1\tilde{q}_1} G_{\tilde{p}_2q_1} G_{p_2q_2} \dots G_{p_nq_n} \rangle$$

But: A in $\phi = A \phi + b$ has unit eigenvalue...

Large-N gauge theory, Veneziano limit



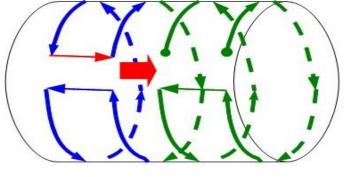
Migdal-Makeenko loop equations illustrated

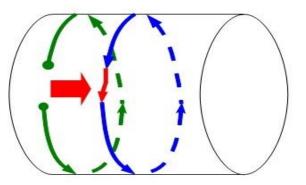
Temperature and chemical potential

No signs

or phases!

Veneziano limit: open strings wrap and close
Chemical potential:





 Strings oriented in the time direction are favoured

к -> к exp(+/- µ)

Phase diagram of the theory: a sketch

High temperature (small cylinder radius) OR Large chemical potential Numerous winding strings Nonzero Polyakov loop Deconfinement phase

0.12

0.1

ĸ

0.0001 $LT = 2, \beta = 0.0, \mu = 0.00$ $LT = 2, \beta = 0.8, \mu = 0.00$ 9e-005 $\begin{array}{l} \mathsf{LT}=2,\ \beta=0.0,\ \mu=0.10\\ \mathsf{LT}=2,\ \beta=0.0,\ \mu=0.50\end{array}$ 8e-005 deconfinement $LT = 2, \beta = 0.0, \mu = 1.00$ 7e-005 <P> ≠ 0 Polyakov loop < P > = 06e-005 confinement 5e-005 4e-005 0.14 $\begin{array}{c} \mathsf{LT} = 2, \ \beta = 0.0, \ \mu = 0.00 \\ \mathsf{LT} = 2, \ \beta = 0.8, \ \mu = 0.00 \\ \mathsf{LT} = 2, \ \beta = 0.0, \ \mu = 5.00 \\ \mathsf{LT} = 3, \ \beta = 0.0, \ \mu = 1.00 \end{array}$ -¥ 3e-005 0.12 0.1 Chiral condensate 2e-005 0.08 1e-005 0.06 0.04 0 0.08 0.1 0.12 0.02 0.02 0.04 0.06 к 0.02 0.04 0.06 0.08

Conclusions

 Schwinger-Dyson equations provide a convenient framework for constructing DiagMC algorithms 1/N expansion is quite natural (other algorithms) cannot do it AUTOMATICALLY) Good news: it is easy to construct DiagMC algorithms for non-Abelian field theories • Then, chemical potential does not introduce additional sign problem Bad news: sign problem already for higher-order terms of SC expansions Can be cured to some extent by choosing proper observables (e.g. momentum space)