

Path Integral methods for solving stochastic problems

Carson C. Chow, NIH

Why?

- Often in neuroscience we run into stochastic ODEs of the form

$$\frac{dx}{dt} = f(x) + g(x)\eta(t)$$

$$\langle \eta(t) \rangle = 0 \quad \langle \eta(t)\eta(t') \rangle = \delta(t - t')$$

Examples

- Integrate-and-fire neuron with noise

$$\frac{dv}{dt} = I - g_L v - g_{NL}(v) + \sqrt{D}\eta(t)$$

Set $v \rightarrow v_R$ when $v = v_T$

- Want to know mean and variance, mean and variance of time to fire, etc.

- “Decision-theory” model

$$\frac{du}{dt} = f(u) + g(t) + \sigma\eta(t)$$

$$u(0) = b$$

- Decision is made when u reaches $\pm\theta$

- Population of neurons with noise

$$\partial_t a = -a + f \left(\int w(x, y) a(y) dy \right) + \eta(x, t)$$

$$\langle \eta(x, t) \rangle = 0 \quad \langle \eta(x, t) \eta(x', t') \rangle = \delta(x - x') \delta(t - t')$$

- Again interested in mean, variance, correlations, any statistic

Solving equations

- Traditional methods include Ito and Stratonovich calculus or Fokker-Planck equation
- For most nonlinear stochastic equations, closed form solutions do not exist
- Need to be solved with perturbation theory, which is nontrivial
- Path integral and field theory approaches were designed for perturbation theory

Generating Function

- Generating function lets you calculate moments of a probability density $P(x)$ by taking derivatives

moments

$$\langle x^n \rangle = \int x^n P(x) dx$$

generating function

$$Z[\lambda] = \langle e^{\lambda x} \rangle = \int e^{\lambda x} P(x) dx$$

$$\langle x^n \rangle = \frac{1}{Z[0]} \left. \frac{\partial^n}{\partial \lambda^n} Z[\lambda] \right|_{\lambda=0}$$

Goals

- Derive a generating function for moments of a stochastic process
- Solve for moments perturbatively using diagrammatic methods.

Computing Generating functions

- e.g. Normal or Gaussian distribution

$$P(x) \propto e^{-\frac{(x-a)^2}{2\sigma^2}}$$

$$Z[\lambda] = \int_{-\infty}^{\infty} e^{-\frac{(x-a)^2}{2\sigma^2} + \lambda x} dx$$

Most important trick: complete the square

$$-\frac{(x-a)^2}{2\sigma^2} + \lambda x = -A(x-x_c)^2 + B$$

x_c is given by $\frac{d}{dx} \left(-\frac{(x-a)^2}{2\sigma^2} + \lambda x \right) = 0$

$$x_c = \lambda\sigma^2 + a$$

$$A = \frac{1}{2\sigma^2} \quad B = \frac{x_c^2}{2\sigma^2} - \frac{a^2}{2\sigma^2} = \frac{\lambda^2\sigma^2}{2} + \lambda a$$

$$Z[\lambda] = \int_{-\infty}^{\infty} e^{-\frac{(x-\lambda\sigma^2-a)^2}{2\sigma^2} + \lambda a + \frac{\lambda^2\sigma^2}{2}} dx = Z[0] e^{\lambda a + \frac{\lambda^2\sigma^2}{2}}$$

$$Z[0] = \sqrt{2\pi}\sigma$$

$$\langle x \rangle = \left. \frac{d}{d\lambda} e^{\lambda a + \frac{\lambda^2 \sigma^2}{2}} \right|_{\lambda=0} = a$$

$$\langle x^2 \rangle = \left. \frac{d^2}{d\lambda^2} e^{\lambda a + \frac{\lambda^2 \sigma^2}{2}} \right|_{\lambda=0} = a^2 + \sigma^2$$

$$\langle x^3 \rangle = \left. \frac{d^3}{d\lambda^3} e^{\lambda a + \frac{\lambda^2 \sigma^2}{2}} \right|_{\lambda=0} = a^3 + 3a\sigma^2$$

$$\langle x^4 \rangle = \left. \frac{d^4}{d\lambda^4} e^{\lambda a + \frac{\lambda^2 \sigma^2}{2}} \right|_{\lambda=0} = a^4 + 6a^2\sigma^2 + 3\sigma^4$$

Cumulant generating function

$$W[\lambda] = \ln Z[\lambda] \quad C_n = \left. \frac{d^n}{d\lambda^n} W[\lambda] \right|_{\lambda=0}$$

For Gaussian $W[\lambda] = \lambda a + \frac{1}{2}(\lambda^2 \sigma^2) + \ln Z[0]$

$$C_1 = \langle x \rangle = a$$

$$C_2 = \langle x^2 \rangle - \langle x \rangle^2 \equiv \text{var}(x) = \sigma^2$$

$$C_n = 0, \quad n > 2$$

Generalize to multi-dimensions

$$Z[\lambda_i] = \int \prod_i dx_i e^{-\frac{1}{2} \sum_{j,k} x_j K_{jk}^{-1} x_k + \sum_j \lambda_j x_j} \quad K_{jk}^{-1} \equiv (K^{-1})_{jk}$$

Assume K is symmetric and positive, thus it has full set of orthonormal eigenvectors

$$\sum_j K_{ij} v_j^\alpha = \omega_\alpha v_i^\alpha \quad \sum_j v_j^\alpha v_j^\beta = \delta_{\alpha\beta}$$

Expand $x_k = \sum_\alpha c_\alpha v_k^\alpha \quad \lambda_k = \sum_\alpha d_\alpha v_k^\alpha$

$$\sum_{j,k} x_j K_{jk} x_k = \sum_j \sum_{\alpha,\beta} c_\alpha \omega_\beta c_\beta v_j^\alpha v_k^\beta = \sum_{\alpha,\beta} c_\alpha \omega_\beta c_\beta \delta_{\alpha\beta} = \sum_\alpha \omega_\alpha c_\alpha^2$$

$$Z[\lambda_i] = \int \prod_i dx_i e^{-\frac{1}{2} \sum_{j,k} x_j K_{jk}^{-1} x_k + \sum_j \lambda_j x_j}$$

$$= \int \prod_\alpha dc_\alpha e^{\sum_\alpha (-\frac{1}{2} \omega_\alpha c_\alpha^2 + d_\alpha c_\alpha)}$$

$$= \prod_\alpha \int_{-\infty}^{\infty} dc_\alpha e^{-\frac{1}{2} \omega_\alpha c_\alpha^2 + d_\alpha c_\alpha}$$

$$= Z[0] \prod_\alpha e^{\frac{1}{2} \omega_\alpha^{-1} d_\alpha^2} \quad Z[0] = (2\pi \det K)^{n/2}$$

$$= Z[0] e^{\sum_{j,k} \frac{1}{2} \lambda_j K_{jk} \lambda_k} \quad \sum_j K_{ij}^{-1} K_{jk} = \delta_{ik}$$

Cumulant generating function

$$W[\lambda_i] = \ln Z[\lambda_i]$$

Moments

$$\langle \prod_i x_i \rangle = \frac{1}{Z[0]} \prod_i \frac{\partial}{\partial \lambda_i} Z[\lambda_i] \Big|_{\lambda_i=0}$$

Example

$$\begin{aligned} \langle x_3^2 x_7 x_{36} \rangle &= \frac{1}{Z[0]} \frac{\partial^2}{\partial \lambda_3^2} \frac{\partial}{\partial \lambda_7} \frac{\partial}{\partial \lambda_{36}} \exp \left(\sum_{ij} \frac{1}{2} \lambda_i K_{ij}^{-1} \lambda_j \right) \Big|_{\lambda_i=0} \\ &= K_{3,3} K_{7,36} + 2K_{3,7} K_{3,36} \end{aligned}$$

Wick's Theorem

$$\begin{aligned} \left\langle \prod_1^{2s} x_i \right\rangle &= \frac{1}{Z[0]} \prod_1^{2s} \frac{\partial}{\partial \lambda_i} Z[\lambda_i] \Big|_{\lambda_i=0} \\ &= \sum_{\text{all possible pairings}} K_{i_1, i_2} \cdots K_{i_{2s-1}, i_{2s}} \end{aligned}$$

$$\begin{aligned} \langle x_a x_b x_c x_d \rangle &= \overbrace{x_a x_b} \overbrace{x_c x_d} + \overbrace{x_a x_b x_c} \overbrace{x_d} + \overbrace{x_a x_b} \overbrace{x_c} \overbrace{x_d} \\ &= K_{ab} K_{cd} + K_{ad} K_{bc} + K_{ac} K_{bd} \end{aligned}$$

make all pairings or "contractions"

Continuum limit

$$Z[\lambda_i] = \int \prod_i dx_i e^{-\frac{1}{2} \sum_{j,k} x_j K_{jk}^{-1} x_k + \sum_j \lambda_j x_j}$$

Let $i \rightarrow t$ $x_i \rightarrow x(t)$ $\lambda_i \rightarrow \lambda(t)$ $K_{ij} \rightarrow K(s, t)$

$$\sum_i \rightarrow \int dt \quad \prod_i dx_i \rightarrow \mathcal{D}x(t)$$

$$\begin{aligned} Z[\lambda(t)] &= \int \mathcal{D}x(t) e^{-\frac{1}{2} \int x(s) K^{-1}(s, t) x(t) ds dt + \int \lambda(t) x(t) dt} \\ &= Z[0] e^{\int \frac{1}{2} \lambda(s) K(s, t) \lambda(t) ds dt} \end{aligned}$$

functional
derivative

$$\frac{\partial}{\partial \lambda_i} \rightarrow \frac{\delta}{\delta \lambda(t)} \quad \frac{\delta \lambda(s)}{\delta \lambda(t)} = \delta(s - t)$$

Moments

$$\langle x(t_1)x(t_2) \rangle = \frac{1}{Z[0]} \frac{\delta}{\delta \lambda(t_1)} \frac{\delta}{\delta \lambda(t_2)} Z[\lambda(t)] = K(t_1, t_2)$$

$$\langle \prod_i x(t_i) \rangle = \frac{1}{Z[0]} \prod_i \frac{\delta}{\delta \lambda(t_i)} Z[\lambda(t)]$$

$$= \sum_{\text{all possible contractions}} K(t_{i_1}, t_{i_2}) \cdots K(t_{i_{2s-1}}, t_{i_{2s}})$$

Can generalize to higher dimensions

$$x(t) \rightarrow \varphi(\vec{t}) \quad \lambda(t) \rightarrow J(\vec{t}) \quad \vec{t} \in \mathbb{R}^d$$

$$\int dt \rightarrow \int d^d t$$

$$Z[\lambda(\vec{t})] = \int \mathcal{D}\varphi e^{-\frac{1}{2} \int \varphi(\vec{s}) K^{-1}(\vec{s}, \vec{t}) \varphi(\vec{t}) d^d s d^d t + \int \lambda(\vec{t}) \varphi(\vec{t}) d^d t}$$

$$= Z[0] e^{\int \frac{1}{2} \lambda(\vec{s}) K(\vec{s}, \vec{t}) \lambda(\vec{t}) d^d s d^d t}$$

Field Theory

Consider an arbitrary (infinite dimensional) probability distribution

$$P[\varphi(\vec{t})] = e^{-S[\varphi(\vec{t})]}$$

S is called the "action"

$$Z[J(\varphi(\vec{t}))] = \int \mathcal{D}\varphi e^{-S[\phi] + J \cdot \varphi}$$

$$J \cdot \varphi = \int J(\vec{t})\varphi(\vec{t})d^d t$$

e.g. φ^4 theory $S[\varphi(\vec{t})] = \int \varphi(\vec{t})K^{-1}(\vec{t}, \vec{t}')\varphi(\vec{t}')d^d t d^d t' + g \int \varphi^4(\vec{t})d^d t$

Must compute perturbatively (asymptotic solutions of integrals in infinite dimensions)

Application to stochastic differential equations

$$\frac{dx}{dt} = f(x) + g(x)\eta(t)$$

Ito interpretation

$$dx = f(x)dt + g(x)dB_t$$

Discretization

$$x_{i+1} - x_i = f(x_i)dt + g(x_i)w_i\sqrt{dt} \quad dB_t = w_t\sqrt{t}$$

Probability density

$$\begin{aligned} P[x_i | w_i] &= \delta[x_{i+1} - x_i - f(x_i)dt - g(x_i)w_i\sqrt{dt}] \\ &= \cdots \delta(x_1 - x_0 - f(x_0)dt - g(x_0)w_0\sqrt{dt})\delta(x_2 - x_1 - \end{aligned}$$

Use Fourier transform representation

$$\delta(z) = \frac{1}{2\pi} \int e^{-ik_i z} dk_i$$

$$P[x_i | w_i] = \int \prod_i \frac{dk_i}{2\pi} e^{-i \sum_i k_i (x_{i+1} - x_i - f(x_i)dt - g(x_i)w_i\sqrt{t})}$$

$$P[x_i | w_i] = \int \prod_i \frac{dk_i}{2\pi} e^{-i \sum_i k_i (x_{i+1} - x_i - f(x_i) dt)} e^{ik_i g(x_i) w_i \sqrt{dt}}$$

w_i is Normal or Gaussian $N(0,1)$ with density

$$P[w_i] = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} w_i^2}$$

$$P[x_i] = \int \prod_i dw_i P[x_i | w_i] P[w_i]$$

$$= \int \prod_i \frac{dk_i}{2\pi} e^{-i \sum_i k_i (x_{i+1} - x_i - f(x_i) dt)} \int \prod_i \frac{dw_i}{\sqrt{2\pi}} e^{ik_i g(x_i) w_i \sqrt{dt}} e^{-\frac{1}{2} w_i^2}$$

Complete the square

$$P[x_i] = \int \prod_i \frac{dk_i}{2\pi} e^{-\sum_i (ik_i) \left(\frac{x_{i+1} - x_i}{dt} - f(x_i) \right) dt + \sum_i \frac{1}{2} g^2(x_i) (ik_i)^2 dt}$$

Make a change of variables $\tilde{k}_i = ik_i$

Take the continuum limit

$$P[x(t)] = \int \mathcal{D}\tilde{k} e^{-\int dt \tilde{k} (\dot{x} - f(x(t))) + \frac{1}{2} \tilde{k}^2 g^2(x(t))}$$

action $S[x(t), \tilde{k}(t)] = \int dt \tilde{k} (\dot{x} - f(x(t))) - \frac{1}{2} \tilde{k}^2 g^2(x(t))$

From SDE to action

$$\dot{x} = f(x) + g(x)\eta(t)$$

$$P[x] = \int \mathcal{D}\eta \delta[\dot{x} - f(x) - g(x)\eta(t)] e^{-\int \eta^2(t) dt}$$

$$P[x] = \int \mathcal{D}\eta \mathcal{D}\tilde{k} e^{-\int \tilde{k}(\dot{x} - f(x)) + \tilde{k}g(x)\eta(t) - \eta^2(t) dt}$$

$$P[x] = \int \mathcal{D}\tilde{k} e^{-\int \tilde{k}(\dot{x} - f(x)) + \frac{1}{2}\tilde{k}^2 g^2(x) dt}$$

$$S[x(t), \tilde{k}(t)] = \int dt \tilde{k}(\dot{x} - f(x(t))) - \frac{1}{2}\tilde{k}^2 g^2(x(t))$$

Ornstein-Uhlenbeck

$$\dot{x} = -ax + \sqrt{D}\eta(t)$$

$$P[x] = \int \mathcal{D}\tilde{k} e^{-\int \tilde{k}(\dot{x} + ax) + \frac{D}{2} \tilde{k}^2 dt} \quad G^{-1}(t-t') = \left(\frac{d}{dt} + a\right)\delta(t-t')$$

$$P[x] = \int \mathcal{D}\tilde{k} e^{-\int dt dt' \tilde{k}(t) G^{-1}(t-t') x(t') + \int dt \frac{D}{2} \tilde{k}^2}$$

$$S[x, \tilde{k}] = \int dt dt' \tilde{k}(t) G^{-1}(t-t') x(t') - \int dt \frac{D}{2} \tilde{k}^2$$

Generating functional

$$Z[J(t), \tilde{J}(t)] = \int \mathcal{D}x \mathcal{D}\tilde{k} e^{-\int dt dt' \tilde{k} G^{-1} x + \int \frac{D}{2} \tilde{k}^2 dt + \int \tilde{J} x dt + \int J \tilde{k} dt}$$

$$= \int \mathcal{D}x \mathcal{D}\tilde{k} e^{-\int dt dt' \tilde{k} G^{-1} x} \left(1 + \mu + \frac{1}{2!} \mu^2 + \frac{1}{3!} \mu^3 + \dots \right)$$

where $\mu = \int \frac{D}{2} \tilde{k}^2 dt + \int \tilde{J} x dt + \int J \tilde{k} dt$

Expansion in moments of "complex" Gaussian

$$Z_{CG}[J(t), \tilde{J}(t)] = \int \mathcal{D}x \mathcal{D}k e^{-\int dt dt' ik G^{-1} x + \int ik(t) J(t) dt + \int x(t) \tilde{J}(t) dt}$$

Restore $\tilde{k} = ik$ for convenience

Discretize and diagonalize $\int dt' G^{-1} x \rightarrow \lambda(\omega) \hat{x}(\omega)$

Expand in $\hat{x}(\omega)$ $k, J, \tilde{J} \rightarrow \hat{k}(\omega), \hat{J}(\omega), \hat{\tilde{J}}(\omega)$

$$\begin{aligned} Z_{CG}[\hat{J}, \hat{\tilde{J}}] &= \int \mathcal{D}\hat{x} \mathcal{D}\hat{k} e^{-\sum_{\omega} i\hat{k}\hat{x}\lambda + i\hat{k}\hat{J} + \hat{x}\hat{\tilde{J}}} \\ &= \prod_{\omega} \int \frac{d\hat{x} d\hat{k}}{2\pi} e^{-i\hat{k}\hat{x}\lambda + i\hat{k}\hat{J} + \hat{x}\hat{\tilde{J}}} \end{aligned}$$

$$= \prod_{\omega} \int \frac{d\hat{x} d\hat{k}}{2\pi} e^{-i\hat{k}(\hat{x}\lambda - \hat{J}) + \hat{x}\hat{\tilde{J}}}$$

$$= \prod_{\omega} \int d\hat{x} \delta(\hat{x}\lambda - \hat{J}) e^{\hat{x}\hat{\tilde{J}}}$$

$$= \prod_{\omega} e^{\lambda^{-1} \hat{J} \hat{\tilde{J}}}$$

Transform back to get

$$Z_{CG}[J, \tilde{J}] = e^{\int J(t)G(t,t')\tilde{J}(t')}$$

Propagator

$$\left(\frac{d}{dt} + a\right)x = \int G^{-1}(t, t')x(t')dt'$$

$$G^{-1}(t, t') = \left(\frac{d}{dt} + a\right)\delta(t - t')$$

$$\int G^{-1}(t, t')G(t', t'')dt' = \delta(t - t'')$$

$$\left(\frac{d}{dt} + a\right)G(t_1, t_2) = \delta(t_1 - t_2) \quad \text{Green's function}$$

Moments

$$\langle \prod_{ij} x(t_i) \tilde{k}(t_j) \rangle = \prod_{ij} \frac{\delta}{\delta \tilde{J}(t_i)} \frac{\delta}{\delta J(t_j)} e^{\int \tilde{J}(t) G(t, t') J(t') dt dt'} \Big|_{J=\tilde{J}=0}$$

Only surviving moments have equal numbers of x and \tilde{k}

Wick's theorem still applies but only for contractions between x and \tilde{k}

e.g. $\langle x(t_1)x(t_2)\tilde{k}(t_3)\tilde{k}(t_4) \rangle = G(t_1, t_3)G(t_2, t_4) + G(t_1, t_4)G(t_2, t_3)$

Back to the OU problem

$$Z[J(t), \tilde{J}(t)] = \int \mathcal{D}x \mathcal{D}\tilde{k} e^{-\int dt dt' \tilde{k} G^{-1} x + \int \frac{D}{2} \tilde{k}^2 dt + \int \tilde{J} x dt + \int J \tilde{k} dt}$$

$$= \int \mathcal{D}x \mathcal{D}\tilde{k} e^{-\int dt dt' \tilde{k} G^{-1} x} \left(1 + \mu + \frac{1}{2!} \mu^2 + \frac{1}{3!} \mu^3 + \dots \right)$$

where $\mu = \int \frac{D}{2} \tilde{k}^2 dt + \int \tilde{J} x dt + \int J \tilde{k} dt$

$$\equiv \mu_1 + \mu_2 + \mu_3$$

Can see that only some combinations of the μ terms will survive i.e. $\mu_2\mu_3$ and $\mu_1\mu_2^2$

$$Z[J(t), \tilde{J}(t)] = \int \langle \tilde{J}(t) J(t') x(t) \tilde{k}(t') \rangle dt dt' + \frac{D}{4} \int \langle \tilde{J}(t) \tilde{J}(t') x(t) x(t') \tilde{k}^2(t'') \rangle dt dt' dt'' + \dots$$

$$\langle x(t_1) x(t_2) \rangle = \frac{D}{2} \int \langle x(t_1) x(t_2) \tilde{k}^2(t'') \rangle dt''$$

$$= D \int G(t_1, t'') G(t_2, t'') dt''$$

Feynman diagrams

Each term in action can be represented by a "diagram"

Turn perturbation theory into rules for assembling diagrams

Diagrams consist of edges and nodes, representing terms in the action

Every factor of \tilde{k} is given an outgoing edge

Every factor of x is given an incoming edge

Convention is time goes from right to left

Propagators are lines, other terms are vertices

$$S[x, \tilde{k}] = \int dt dt' \tilde{k}(t) G^{-1}(t, t') x(t') - \int dt \frac{D}{2} \tilde{k}^2$$

Assign a diagram to each term in the action

Propagator $G(t, t')$



Other diagrams are called vertices

Vertex $\frac{D}{2}$



sign negative
from action

Feynman rules

Surviving terms in perturbation series of generating functional consist of equal numbers of \tilde{k} and x factors

For vertices, this means that outgoing edges are joined to incoming edges*

Propagators are then attached to all edges in all possible ways (accounts for Wick's theorem)*

Vertices are integrated over

Moment rules

Moments of x are given by derivatives over \tilde{J} ,
moments of \tilde{k} are given by derivatives over J

Thus moments can also be expressed as
diagrams

Each factor of x is given an outgoing edge and
each factor of \tilde{k} is given an incoming edge

Cumulants are connected diagrams

Examples

Propagator:

$$\langle x(t_1) \tilde{k}(t_2) \rangle = \text{---} \leftarrow \text{---} = G(t_1, t_2)$$

2nd moment:

$$\langle x(t_1) x(t_2) \rangle = \text{---} \rangle \text{---} = 2 \times \int G(t_1, t') G(t_2, t') \frac{D}{2} dt'$$

Doing the integrals

$$\left(\frac{d}{dt} + a\right)G(t_1, t_2) = \delta(t_1 - t_2)$$

$$G(t_1, t_2) = e^{-a(t_1 - t_2)} H(t_1 - t_2) \quad H(t) = \begin{cases} 1 & t > 0 \\ 0 & t \leq 0 \end{cases}$$

$$D \int G(t_1, t') G(t_2, t') dt' = D \int_0^{t_2} e^{-a(t_1 - t')} e^{-a(t_2 - t')} dt' \quad t_2 > t_1$$

$$= D \frac{e^{2a(t_1 - t_2)} - e^{-2a(t_1 + t_2)}}{2a}$$

$$= \frac{D}{2a} (1 - e^{-2at}) \quad t_1 = t_2 = t$$

Nonlinear terms

$$\dot{x} = -ax + bx^2 - cx^3 + \sqrt{A + Bx + Cx^2}\eta(t) + x_0\delta(t - t_0)$$

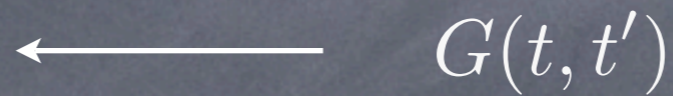
Using the action formula

$$S[x(t), \tilde{k}(t)] = \int dt \tilde{k}(\dot{x} - f(x(t))) - \frac{1}{2} \tilde{k}^2 g^2(x(t))$$

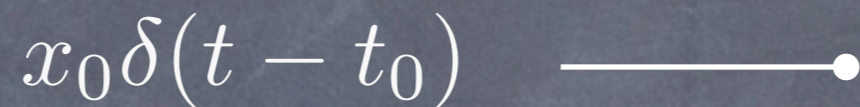
$$S[x(t), \tilde{k}(t)] = \int dt \tilde{k}(\dot{x} + ax - bx^2 + cx^3 - x_0\delta(t - t_0)) - \tilde{k}^2 \frac{A + Bx + Cx^2}{2}$$

$$S[x(t), \tilde{k}(t)] = \int dt \tilde{k} (\dot{x} + ax - bx^2 + cx^3 - x_0 \delta(t - t_0)) - \tilde{k}^2 \frac{A + Bx + Cx^2}{2}$$

Propagator



Vertices



b



c



$\frac{A}{2}$



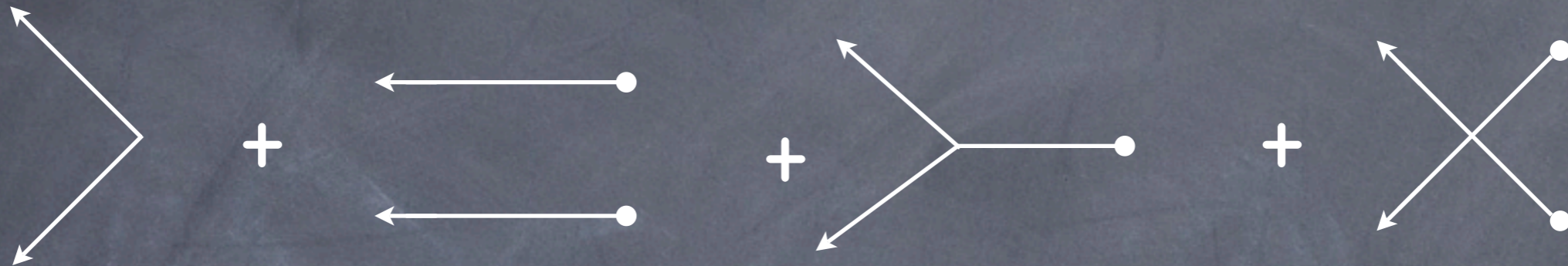
$\frac{B}{2}$



$\frac{C}{2}$



$$\langle x(t_1)x(t_2) \rangle =$$



$$2\frac{B}{2}x_0 \int G(t_1, t')G(t_2, t')G(t', t_0)dt'$$

Tree level



One loop

Acknowledgments and References

I will be writing a review that will be posted on my blog at sciencehouse.wordpress.com

- Michael Buice
- Zinn-Justin, Quantum Field Theory and Critical Phenomena
- Kardar, Statistical Physics of Fields