

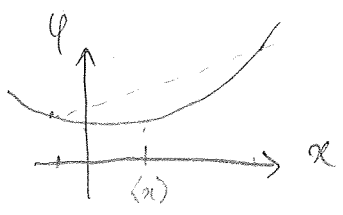
Gaussian calculus 1

$x \rightarrow g(m, \sigma); \langle e^{kx} \rangle = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{+\infty} e^{kx} e^{-\frac{(x-m)^2}{2\sigma^2}} dx, \quad y = x - m$

$\langle e^{kx} \rangle = e^{km} \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{+\infty} dy e^{\left[ky - \frac{y^2}{2\sigma^2} \right]}$

$= e^{km} \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{+\infty} dy e^{-\frac{y^2}{2\sigma^2} - ky} = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{+\infty} dy e^{-\frac{1}{2\sigma^2}(y - k\sigma^2)^2} e^{-\frac{1}{2\sigma^2}(k\sigma^2)^2} + \frac{1}{2} k\sigma^2$

For any convex-up function $\phi(x)$:



$\phi(\langle x \rangle) \leq \langle \phi(x) \rangle$
(Jensen inequality)

① Write $A_{ij} = \frac{1}{2} \underbrace{(A_{ij} + A_{ji})}_{\text{sym } A_0} + \frac{1}{2} \underbrace{(A_{ij} - A_{ji})}_{\text{antisym } A_a}$

${}^t A_0 = A_0$
 ${}^t A_a = -A_a$

We need ${}^t \vec{x} A \vec{x}$ which is scalar and thus equal to its transpose ${}^t \vec{x} {}^t A \vec{x}$

↳ this vanishes for any antisym matrix. Indeed, take Π antisym

$\Pi_{ij} = -\Pi_{ji}; \quad \sum_{i,j} \Pi_{ij} x_i x_j = -\sum_{i,j} \Pi_{ji} x_i x_j = -\sum_{i,j} \Pi_{ij} x_i x_j$

② $\vec{m} = \langle \vec{x} \rangle$

③ $\frac{1}{\mathcal{N}} = \int dx_1 dx_2 \dots dx_m \exp\left[-\frac{1}{2} {}^t \vec{x} A \vec{x}\right]$, A hermitian (real symmetric) \Rightarrow diagonalizable

$\Rightarrow \exists \Lambda$ diagonal and P
 $A = P^{-1} A P; \quad \Lambda = \begin{pmatrix} \lambda_1 & & 0 \\ & \dots & \\ 0 & & \lambda_n \end{pmatrix}$

where $P = {}^t P^{-1}$
 ${}^t P P = P {}^t P = 1 \rightarrow$ orthogonal matrix

change variables: $\vec{y} = P^{-1} \vec{x}$

${}^t \vec{x} A \vec{x} = {}^t (P \vec{y}) A P \vec{y} = {}^t \vec{y} \underbrace{({}^t P A P)}_{\Lambda} \vec{y} = \sum_{i=1}^m \lambda_i y_i^2$

↳ jacobian $|J| = \left| \frac{d\vec{y}}{d\vec{x}} \right| = |\det P| = 1$

$$\Rightarrow \frac{1}{\mathcal{N}} = \int dy_1 \dots dy_n \exp \left[-\frac{1}{2} \sum_{i=1}^n \lambda_i y_i^2 \right]; \quad \text{all } \lambda_i \text{ should be } > 0$$

$$= \prod_{i=1}^n \sqrt{\frac{2\pi}{\lambda_i}}$$

$$= \frac{(2\pi)^{n/2}}{(\det A)^{1/2}}$$

↳ A positive matrix

(4) $f(\vec{y}) = \frac{\sqrt{\det A}}{(2\pi)^{n/2}} \exp \left[-\frac{1}{2} \sum_{i,j} A_{ij} y_i y_j \right]$ Take $\vec{m} = \vec{0}$

(5) $\sum_j A_{ij} \langle x_j x_k \rangle = \sum_j \mathcal{N} \int dx_1 \dots dx_n x_j x_k A_{ij} e^{-\frac{1}{2} \sum_{p,q} A_{pq} x_p x_q}$

$$= \mathcal{N} \int_{-b}^b dx_k x_k \left[-\frac{\partial}{\partial x_i} e^{-\frac{1}{2} \sum_{p,q} A_{pq} x_p x_q} \right]$$

$$= \underbrace{-\mathcal{N} [x_k e^{-\frac{1}{2} \sum_{p,q} A_{pq} x_p x_q}]}_0 + \mathcal{N} \int dx_k \frac{\partial x_k}{\partial x_i} e^{-\frac{1}{2} \sum_{p,q} A_{pq} x_p x_q}$$

by parts

$$= \delta_{ik}$$

$$\Rightarrow \langle x_j x_k \rangle = (A^{-1})_{jk}$$

(6) Same method $\sum_j \underbrace{\langle x_i x_j \rangle}_{A_{ij}^{-1}} \left\langle \frac{\partial f(\vec{x})}{\partial x_j} \right\rangle = \sum_j \int dx \underbrace{A^{-1}}_{ij} \frac{\partial f(\vec{x})}{\partial x_j} e^{-\frac{1}{2} \sum_{p,q} A_{pq} x_p x_q} \mathcal{N}$

$$= 0 - \sum_j A_{ij}^{-1} \int dx f(\vec{x}) \left(\sum_p A_{jp} x_p \right) e^{-\frac{1}{2} \sum_{p,q} A_{pq} x_p x_q}$$

by parts

$$= + \sum_p \delta_{ip} \mathcal{N} \langle f(\vec{x}) x_p \rangle$$

$$= \langle x_i f(\vec{x}) \rangle$$

⑦ $2l$ factors in the product: $(2l-1)(2l-3)\dots 1$

For $l=3$, 6 factors: $5 \times 3 = 15$ terms

Scalar case: $\langle x^4 \rangle = 3 \langle x^2 \rangle^2 = 3 \sigma^4$

$\langle x^6 \rangle = 15 \sigma^6$

$\langle x^8 \rangle = 7 \times 5 \times 3 = 105 \sigma^8$

Proof: $\langle x_i x_j x_k x_p \rangle = \langle x_i f(\vec{x}) \rangle$ for $f(\vec{x}) = x_j x_k x_p$

$= \sum_l \langle x_i x_l \rangle \left\langle \frac{\partial f}{\partial x_l} \right\rangle$; non zero for $l=j$ or k or p

$= \langle x_i x_j \rangle \langle x_k x_p \rangle + \langle x_i x_k \rangle \langle x_j x_p \rangle + \langle x_i x_p \rangle \langle x_j x_k \rangle$

⑧ $p(x,y) = c^p e^{-\dots}$ $A = \begin{pmatrix} 1 & 1 \\ 1 & 4 \end{pmatrix}$; $A^{-1} = \frac{1}{4-1} \begin{pmatrix} 4 & -1 \\ -1 & 1 \end{pmatrix}$

$= \frac{1}{3} \begin{pmatrix} 4 & -1 \\ -1 & 1 \end{pmatrix}$

thus $\langle x^2 \rangle = 4/3$

$\langle y^2 \rangle = 1/3$

$\langle xy \rangle = -1/3$

$\langle x^2 y^2 \rangle = \langle x^2 \rangle \langle y^2 \rangle + \langle xy \rangle \langle xy \rangle \times 2 = \frac{4}{9} + 2 \frac{1}{9} = \frac{6}{9} = \frac{2}{3}$

$\langle x^4 y^2 \rangle = \langle x x x x y y \rangle = 3 \langle x^2 \rangle^2 \langle y^2 \rangle + 12 \langle x^2 \rangle \langle xy \rangle^2$

15 pairing
3 have $\langle y^2 \rangle$ and $\langle x^4 \rangle$ $= 3 \left(\frac{4}{3}\right)^2 \frac{1}{3} + 12 \frac{4}{3} \frac{1}{9}$

12 have $\langle xy \rangle \langle xy \rangle \langle x^2 \rangle = \frac{16}{9} + \frac{16}{9} = \frac{32}{9}$

Extra $\langle x^2 y^4 \rangle = 3 \langle x^2 \rangle \langle y^2 \rangle^2 + 12 \langle xy \rangle^2 \langle y^2 \rangle = 3 \frac{4}{3} \frac{1}{9} + 12 \frac{1}{9} \frac{1}{3}$

15 pairings
3 have $\langle x^2 \rangle, \langle y^2 \rangle^2$ $= \frac{4}{9} + \frac{4}{9}$

12 have $\langle xy \rangle^2 \langle y^2 \rangle = \frac{8}{9}$

(9) $\langle e^{i\vec{k}\cdot\vec{x}} \rangle = \int dx_1 \dots dx_m e^{i(k_1 x_1 + k_2 x_2 + \dots + k_n x_n)} \int \mathcal{D}\vec{x} \exp\left(-\frac{1}{2} \vec{x}^T A \vec{x}\right)$

$$= \int \mathcal{D}\vec{x} e^{i\vec{x}^T \vec{k} - \frac{1}{2} \vec{x}^T A \vec{x}}$$

The idea is to shift \vec{x} by some vector $\vec{\delta}$ to be found:

$$\begin{aligned} \vec{x}^T (\vec{x} - \vec{\delta}) A (\vec{x} - \vec{\delta}) &= \vec{x}^T A \vec{x} - \underbrace{\vec{x}^T A \vec{\delta}}_{\text{equal}} - \underbrace{\vec{\delta}^T A \vec{x}}_{\text{since scalar}} + \vec{\delta}^T A \vec{\delta} \\ &= \vec{x}^T A \vec{x} - 2 \vec{x}^T A \vec{\delta} + \vec{\delta}^T A \vec{\delta} \end{aligned}$$

$$\Rightarrow -2 \vec{x}^T A \vec{\delta} = -2 i \vec{x}^T \vec{k} \quad ; \quad \text{take } i\vec{k} = A \vec{\delta} \quad ; \quad \vec{\delta} = i A^{-1} \vec{k}$$

$$\begin{aligned} \Rightarrow i \vec{k} \cdot \vec{x} - \frac{1}{2} \vec{x}^T A \vec{x} &= -\frac{1}{2} (\vec{x} - \vec{\delta})^T A (\vec{x} - \vec{\delta}) + \frac{1}{2} \vec{\delta}^T A \vec{\delta} \\ &\quad + \frac{1}{2} (-1) \vec{k}^T A^{-1} A A^{-1} \vec{k} \end{aligned}$$

Change variables: $\vec{y} = \vec{x} - i A^{-1} \vec{k}$

$$\langle e^{i\vec{k}\cdot\vec{x}} \rangle = e^{-\frac{1}{2} \vec{k}^T A^{-1} \vec{k}} \int \mathcal{D}\vec{y} e^{-\frac{1}{2} \vec{y}^T A \vec{y}}$$

without the $k_m x_m$ term

(10) Marginals The charact. fncd of $p_{m\alpha} \equiv \int dx_1 \dots dx_{m-1} dx_{m+1} \dots dx_n e^{i(k_1 x_1 + \dots + k_n x_n)}$

$$\hat{p}_{m\alpha} \left(\begin{matrix} \vec{k} \\ k_m \end{matrix} \middle| k_m \right) = \int e^{i(\vec{k}\cdot\vec{x} + k_m x_m)} p(x_1 \dots x_n)$$

$$= \hat{p}(\vec{k}) \quad \text{with } k_m = 0$$

The coupling matrix is read directly from $\hat{p}(\vec{k})$ and thus from A^{-1}

$$A^{-1} = \begin{pmatrix} \cdot & & & & \\ & \cdot & & & \\ & & \cdot & & \\ & & & \cdot & \\ & & & & \cdot \end{pmatrix}$$

↑ m ←

Erase line m and column m
↳ gives the coupling matrix of $p_{\setminus m}$

Trivial application to

$$A^{-1} = \frac{1}{3} \begin{pmatrix} 4 & -1 \\ -1 & 1 \end{pmatrix} ; \frac{1}{3} \begin{pmatrix} 4 & -1 \\ -1 & 1 \end{pmatrix} \rightarrow \frac{1}{3}$$

⑪ Linear combination of components

$\vec{y} = B\vec{x}$; $\langle e^{i\vec{k}\cdot\vec{y}} \rangle = ?$

$\langle e^{i\vec{k}\cdot\vec{y}} \rangle = \langle e^{i \sum_{\alpha} k_{\alpha} \sum_{\beta} B_{\alpha\beta} x_{\beta}} \rangle = \langle e^{i \sum_{\beta} q_{\beta} x_{\beta}} \rangle$

$= e^{-\frac{1}{2} \sum_{ij} q_i A^{-1}_{ij} q_j}$
 $= e^{-\frac{1}{2} \sum_{ij} \sum_{\alpha, \beta} A^{-1}_{ij} k_{\alpha} B_{\alpha i} k_{\beta} B_{\beta j}}$
 $= e^{-\frac{1}{2} \sum_{\alpha, \beta} k_{\alpha} k_{\beta} \sum_{ij} A^{-1}_{ij} B_{\alpha i} B_{\beta j}}$

$q_{\beta} = \sum_{\alpha} k_{\alpha} B_{\alpha\beta}$

$\tilde{A}_{\alpha\beta} ; \tilde{A} = B A^{-1} B$
 $= e^{-\frac{1}{2} \sum_{\alpha\beta} k_{\alpha} \tilde{A}_{\alpha\beta} k_{\beta}}$

quadratic \Rightarrow the \vec{y} is a Gaussian vector
 All its components are Gaussian themselves

⑫ Take $X \rightarrow g(0,1)$; X and X^2 are not independent

but $\langle X X^2 \rangle - \langle X \rangle \langle X^2 \rangle = 0$; 0 2-point correlation.

this provides a counterexample of 2 variables that are 2pt uncorrelated, but dependent

⑬ Random walk:

a) $\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} \eta_1 \\ \eta_1 + \eta_2 \\ \vdots \\ \eta_1 + \dots + \eta_n \end{pmatrix} = B \begin{pmatrix} \eta_1 \\ \vdots \\ \eta_n \end{pmatrix}$

where B is the appropriate matrix $\Rightarrow \vec{x}$ is Gaussian

b) $p(x_1) \propto \exp(-\frac{x_1^2}{2})$
 $p(x_2|x_1) = p(\eta = x_2 - \eta_1) \propto \exp(-\frac{(x_2 - x_1)^2}{2})$

$\Rightarrow p(x_1, x_2) = p(x_2|x_1) p(x_1)$
 $\propto \exp[-\frac{1}{2}(x_1^2 + x_2^2 - 2x_1x_2 + x_1^2)]$
 $\propto \exp[-\frac{1}{2}(2x_1^2 + x_2^2 - 2x_1x_2)]$

$A = \begin{pmatrix} 2 & -1 \\ -1 & 1 \end{pmatrix}$; then for 3-var: $A = \begin{pmatrix} 2 & -1 & 0 \\ -1 & 2 & -1 \\ 0 & -1 & 1 \end{pmatrix}$

then $A = \begin{pmatrix} 2 & -1 & 0 & 0 \\ -1 & 2 & -1 & 0 \\ 0 & -1 & 2 & -1 \\ 0 & 0 & -1 & 1 \end{pmatrix}$ special

c) $\langle x_i x_j \rangle = \sum_{\alpha=1}^i \sum_{\beta=1}^j \langle \eta_{\alpha} \eta_{\beta} \rangle = \sum_{\alpha=1}^{\min(i,j)} \langle \eta_{\alpha}^2 \rangle = \min(i,j)$

Hence $C = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 2 & 2 & 2 \\ 1 & 2 & 3 & 3 \\ 1 & 2 & 3 & 4 \end{pmatrix}$ yielding $\langle x_i^2 \rangle = i$ as it should

$AC = CA = 11$ (check)

d) Marginals from erasing lines & columns from $C = A^{-1}$.