

- 1) As the probability density function of multivariate normal distribution is $p(x) = \frac{1}{2\pi^{d/2}|\Sigma|^{1/2}} \exp \left[-\frac{1}{2}(x - \mu)^T \Sigma^{-1}(x - \mu) \right]$ for $\mu^T = [\mu_1, \mu_2]$ and $\Sigma = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}$.

$$\begin{aligned}
p(x) &= \frac{1}{2\pi^2|\Sigma|^{1/2}} \exp \left[-\frac{1}{2}(x - \mu)^T \Sigma^{-1}(x - \mu) \right] \\
&= \frac{1}{2\pi \cdot \det \left(\begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix} \right)^{1/2}} \exp \left[-\frac{1}{2} \begin{bmatrix} x_1 - \mu_1 & x_2 - \mu_2 \end{bmatrix} \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}^{-1} \begin{bmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{bmatrix} \right] \\
&= \frac{1}{2\pi(\sigma_1^2\sigma_2^2 - \rho^2\sigma_1^2\sigma_2^2)^{1/2}} \exp \left[-\frac{1}{2} \begin{bmatrix} z_1\sigma_1 & z_2\sigma_2 \end{bmatrix} \frac{1}{\det \Sigma} \begin{bmatrix} \sigma_2^2 & -\rho\sigma_1\sigma_2 \\ -\rho\sigma_1\sigma_2 & \sigma_1^2 \end{bmatrix} \begin{bmatrix} z_1\sigma_1 \\ z_2\sigma_2 \end{bmatrix} \right] \\
&= \frac{1}{2\pi((1-\rho^2)\sigma_1^2\sigma_2^2)^{1/2}} \exp \left[-\frac{1}{2\det \Sigma} \begin{bmatrix} z_1\sigma_1\sigma_2^2 - \rho z_2\sigma_1\sigma_2^2 & z_2\sigma_2\sigma_1^2 - \rho z_1\sigma_2\sigma_1^2 \end{bmatrix} \begin{bmatrix} z_1\sigma_1 \\ z_2\sigma_2 \end{bmatrix} \right] \\
&= \frac{1}{2\pi\sigma_1\sigma_2(1-\rho^2)^{1/2}} \exp \left[-\frac{1}{2(1-\rho^2)\sigma_1^2\sigma_2^2} (z_1^2\sigma_1^2\sigma_2^2 - \rho z_1 z_2 \sigma_1^2\sigma_2^2 + z_2^2\sigma_2^2\sigma_1^2 - \rho z_1 z_2 \sigma_1^2\sigma_2^2) \right] \\
&= \frac{1}{2\pi\sigma_1\sigma_2(1-\rho^2)^{1/2}} \exp \left[-\frac{1}{2(1-\rho^2)^{1/2}} (z_1^2 - \rho z_1 z_2 + z_2^2 - \rho z_1 z_2) \right] \\
&= \frac{1}{2\pi\sigma_1\sigma_2(1-\rho^2)^{1/2}} \exp \left[-\frac{1}{2(1-\rho^2)^{1/2}} (z_1^2 - 2\rho z_1 z_2 + z_2^2) \right]
\end{aligned}$$

- 2) To make a quadratic fit using the two variable x_1 and x_2 , we first have the model of linear regression $g(x|\theta) = w_0 + w_1y_1 + w_2y_2 + w_3y_3 + w_4y_4 + w_5y_5$ where $y_3 = x_1$, $y_2 = x_2$, $y_3 = x_1x_2$, $y_4 = (x_1)^2$ and $y_5 = (x_2)^2$ with parameters w_i from $i=0$ to 5 be randomly initialized. Then with the given sample of $\chi = \{x_1^t, x_2^t, r^t\}$, the parameters can be optimized by calculating the expected outcome by $g(x|\theta)$ and performing gradient descent to find the minimum of the loss function i.e. $\mathcal{L}(\theta) = \frac{1}{2t} \sum (g(x^t|\theta) - r^t)^2$. [where the optimization equation is $w_i = w_i - \alpha \frac{d\mathcal{L}(\theta)}{dw_i}$]