Machine Learning Worksheet 4

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Problem 1

The Inverse of a diagonal atrix is just a diagonal matrix with each of the elements inverted.

$$\Lambda^{-1} = \begin{pmatrix} \frac{1}{\lambda_1} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \frac{1}{\lambda_d} \end{pmatrix}, U = \begin{pmatrix} u_{1,1} & \dots & u_{1,d} \\ \vdots & \ddots & \vdots \\ u_{d,1} & \dots & u_{d,d} \end{pmatrix}$$
(1)

Just multiplying $U\Lambda U^T$ results in what should be proven.

$$U\Lambda U^{T} = \begin{pmatrix} u_{1,1} & \dots & u_{1,d} \\ \vdots & \ddots & \vdots \\ u_{d,1} & \dots & u_{d,d} \end{pmatrix} \begin{pmatrix} \frac{1}{\lambda_{1}} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \frac{1}{\lambda_{d}} \end{pmatrix} \begin{pmatrix} u_{1,1} & \dots & u_{d,1} \\ \vdots & \ddots & \vdots \\ u_{1,d} & \dots & u_{d,d} \end{pmatrix}$$
(2)

$$\begin{pmatrix}
u_{d,1} & \cdots & u_{d,d} \\
\frac{u_{1,1}}{\lambda_{1}} & \cdots & \frac{u_{1,d}}{\lambda_{d}} \\
\vdots & \ddots & \vdots \\
\frac{u_{d,1}}{\lambda_{1}} & \cdots & \frac{u_{d,d}}{\lambda_{d}}
\end{pmatrix}
\begin{pmatrix}
u_{1,1} & \cdots & u_{d,1} \\
\vdots & \ddots & \vdots \\
u_{1,d} & \cdots & u_{d,d}
\end{pmatrix}$$

$$= \begin{pmatrix}
\frac{u_{1,1}u_{1,1}}{\lambda_{1}} + \cdots + \frac{u_{1,d}u_{1,d}}{\lambda_{d}} & \cdots & \frac{u_{1,1}u_{d,1}}{\lambda_{1}} + \cdots + \frac{u_{1,d}u_{d,d}}{\lambda_{d}} \\
\vdots & \ddots & \vdots \\
\frac{u_{d,1}u_{1,1}}{\lambda_{1}} + \cdots + \frac{u_{1,d}u_{d,d}}{\lambda_{d}} & \cdots & \frac{u_{d,1}u_{d,1}}{\lambda_{1}} + \cdots + \frac{u_{d,d}u_{d,d}}{\lambda_{d}}
\end{pmatrix}$$

$$(3)$$

$$= \begin{pmatrix} \frac{u_{1,1}u_{1,1}}{\lambda_1} + \dots + \frac{u_{1,d}u_{1,d}}{\lambda_d} & \dots & \frac{u_{1,1}u_{d,1}}{\lambda_1} + \dots + \frac{u_{1,d}u_{d,d}}{\lambda_d} \\ \vdots & \ddots & \vdots \\ \frac{u_{d,1}u_{1,1}}{\lambda_1} + \dots + \frac{u_{1,d}u_{d,d}}{\lambda_d} & \dots & \frac{u_{d,1}u_{d,1}}{\lambda_1} + \dots + \frac{u_{d,d}u_{d,d}}{\lambda_d} \end{pmatrix}$$
(4)

$$= \frac{1}{\lambda_1} \begin{pmatrix} u_{1,1}u_{1,1} & \dots & u_{1,1}u_{d,1} \\ \vdots & \ddots & \vdots \\ u_{d,1}u_{1,1} & \dots & u_{d,1}u_{d,1} \end{pmatrix} + \dots + \frac{1}{\lambda_d} \begin{pmatrix} u_{1,d}u_{1,d} & \dots & u_{1,d}u_{d,d} \\ \vdots & \ddots & \vdots \\ u_{1,d}u_{d,d} & \dots & u_{d,d}u_{d,d} \end{pmatrix}$$
 (5)

$$= \frac{1}{\lambda_1} u_1 u_1^T + \dots + \frac{1}{\lambda_d} u_d u_d^T \tag{6}$$

$$= \sum_{i=1}^{d} \frac{1}{\lambda_i} u_i u_i^T \tag{7}$$

Problem 2

 $L = \mathbb{R}^{nxn}$ and is invertible and Y = LX with $X \sim \mathcal{N}(\mu_X, \Sigma_X)$ then $X = L^{-1}Y$. So

$$p_Y(Y) = p_X(X)|\det(\frac{\partial x}{\partial y})| = p_X(X)|\det(J_{Y\to X})| = p_X(L^{-1}Y)|\det(J_{Y\to X})|$$
(8)

with

$$J_{Y \to X} = \frac{\partial x}{\partial y} = \frac{\partial L^{-1}Y}{\partial Y} = L^{-1} \tag{9}$$

Then

$$p_y(Y) = p_x(L^{-1}Y)|\det(L^{-1})$$
(10)

$$= p_x(L^{-1}Y) \frac{1}{|det(L)|} \tag{11}$$

$$= \frac{1}{\sqrt{(2\pi)^d |det(\Sigma_X|)}} exp(-\frac{1}{2}(L^{-1}Y - \mu_X)^T \Sigma_X^{-1}(L^{-1}Y - \mu_X)) \frac{1}{|det(L)|}$$
(12)

$$= \frac{1}{\sqrt{(2\pi)^d |det(\Sigma_X|)}|det(L)|} exp(-\frac{1}{2}(L^{-1}Y - \mu_X)^T \Sigma_X^{-1}(L^{-1}Y - \mu_X))$$
(13)

$$= \frac{1}{\sqrt{(2\pi)^d |det(\Sigma_X)| |det(L)|^2}} exp(-\frac{1}{2}(L^{-1}Y - \mu_X)^T \Sigma_X^{-1}(L^{-1}Y - \mu_X))$$
(14)

$$= \frac{1}{\sqrt{(2\pi)^d |det(\Sigma_X)||det(LL^T)|}} exp(-\frac{1}{2}(L^{-1}Y - \mu_X)^T \Sigma_X^{-1}(L^{-1}Y - \mu_X))$$
 (15)

$$= \frac{1}{\sqrt{(2\pi)^d |det(L\Sigma_X L^T)|}} exp(-\frac{1}{2}(L^{-1}Y - \mu_X)^T \Sigma_X^{-1}(L^{-1}Y - \mu_X))$$
(16)

$$= \frac{1}{\sqrt{(2\pi)^d |det(L\Sigma_X L^T)|}} exp(-\frac{1}{2}(Y - L\mu_X)^T \Sigma_X^{-1}(Y - L\mu_X)$$
(17)

$$= \frac{1}{\sqrt{(2\pi)^d |\det(L\Sigma_X L^T)|}} exp(-\frac{1}{2}L^{-1}(Y - L\mu_X)^T \Sigma_X^{-1} L^{-1}(Y - L\mu_X)$$
(18)

$$= \frac{1}{\sqrt{(2\pi)^d |det(L\Sigma_X L^T)|}} exp(-\frac{1}{2}(Y - L\mu_X)^T L^{-T} \Sigma_X^{-1} L^{-1}(Y - L\mu_X)$$
(19)

$$= \frac{1}{\sqrt{(2\pi)^d |\det(L\Sigma_X L^T)|}} exp(-\frac{1}{2}(Y - L\mu_X)^T (L\Sigma_X L^T)^{-1} (Y - L\mu_X)$$
 (20)

$$Y \sim \mathcal{N}(L\mu_X, L\Sigma_X L^T) \tag{21}$$

$$Y \sim \mathcal{N}(\mu_Y, \Sigma_Y) \tag{22}$$

Problem 3

With $p(x) = \mathcal{N}(0, \Sigma_X)$ and Y = TX + Z with $Z \sim \mathcal{N}(0, \Sigma_{Y|X})$ then

$$\mu_Y = E[TX + Z] = TE[X] + E[Z] = TE[X]$$
 (23)

$$\Sigma_Y = T\Sigma_X T^T + \Sigma_Z = T\Sigma_X T^T + \Sigma_{Y|X}$$
(24)

$$= T\Sigma_X T^T + \Sigma_Y - \Sigma_{Y,X} \Sigma_X^{-1} \Sigma_{X,Y}$$
 (25)

This means for T it must hold that

$$T\Sigma_X T^T = \Sigma_{Y,X} \Sigma_X^{-1} \Sigma_{X,Y} \tag{26}$$

Problem 4

HW4