Homework 1

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1 Exercise 1

(a) Gaussian distribution is normalized

The Gaussian distribution is:

$$\mathcal{N}(x|\mu,\sigma^2) = \frac{1}{(2\pi\sigma^2)^{1/2}} exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right)$$

With $\sigma > 0$ and $x, \mu \in \mathbb{R}$, we have $\mathcal{N}(x|\mu,\sigma^2) > 0$.

To prove that Gaussian distribution is normalized, we prove $\displaystyle\int_{-\infty}^{\infty} \mathcal{N}(x|\mu,\sigma^2)dx = 1$, equivalent to:

$$\int_{-\infty}^{\infty} \frac{1}{(2\pi\sigma^2)^{1/2}} exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right)dx = 1$$

Or,

$$\int_{-\infty}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} exp\left(-\frac{1}{2}\Big(\frac{x-\mu}{\sigma}\Big)^2\right)dx = 1$$

Let $u = \dfrac{x-\mu}{\sigma}$, then $du = \frac{1}{\sigma}dx$.

$$\Rightarrow LHS = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} exp\Big(-\frac{1}{2}u^2\Big)du$$

Squaring both sides of above equation:

$$\begin{aligned} LHS^2 &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} exp\Big(-\frac{1}{2}u^2\Big)du \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} exp\Big(-\frac{1}{2}v^2\Big)dv \\ &= \frac{1}{2\pi}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} exp\Big(-\frac{u^2+v^2}{2}\Big)dudv \end{aligned}$$

We take the transformations of variables: $u = rcos(\theta)$ and $v = rsin(\theta)$.

Then, $u^2 + v^2 = r^2$ and $dudv = \left|\frac{\partial(u,v)}{\partial(r,\theta)}\right| drd\theta$. Applying Jacobian, we get:

$$\begin{aligned}
\frac{\partial(u,v)}{\partial(r,\theta)} &= \begin{vmatrix} \frac{\partial x}{\partial r} & \frac{\partial x}{\partial \theta} \\ \frac{\partial y}{\partial r} & \frac{\partial x}{\partial \theta} \end{vmatrix} \\
&= \begin{vmatrix} cos\theta & -rsin\theta \\ sin\theta & rcos\theta \end{vmatrix} \\
&= rcos^2\theta + rsin^2\theta \\
&= r
\end{aligned}$$

So, $dudv = rdrd\theta$ and:

$$\begin{aligned}
LHS^2 &= \frac{1}{2\pi} \int_0^{2\pi} \int_0^{\infty} exp\Big(-\frac{r^2}{2}\Big) rdrd\theta \\
&= -\frac{1}{2\pi} \int_0^{2\pi} \int_0^{\infty} exp\Big(-\frac{r^2}{2}\Big) d\Big(\frac{-r^2}{2}\Big) d\theta \\
&= -\frac{1}{2\pi} \int_0^{2\pi} \Big[exp\Big(-\frac{r^2}{2}\Big)\Big]_{r=0}^{r=\infty} d\theta \\
&= -\frac{1}{2\pi} \int_0^{2\pi} (0-1) d\theta \\
&= \frac{1}{2\pi} \int_0^{2\pi} d\theta \\
&= \frac{1}{2\pi}(2\pi - 0) \\
&= 1.
\end{aligned}$$

Because $\mathcal{N}(x|\mu,\sigma^2) > 0$, LHS = 1 = RHS. Therefore, Gaussian distribution is normalized.

(b) Expectation of Gaussian distribution is μ (mean)

From the definition of expected value for continuous random value:

$$E(X) = \int_{-\infty}^{\infty} xf(x)dx$$

We have:

$$\begin{aligned}
E(X) &= \int_{-\infty}^{\infty} x\frac{1}{\sigma\sqrt{2\pi}} exp\bigg(-\frac{1}{2\sigma^2}(x-\mu)^2\bigg) dx \\
&= \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} x \cdot exp\bigg(-\frac{(x-\mu)^2}{2\sigma^2}\bigg) dx
\end{aligned}$$

Substituting $t = \frac{x-\mu}{\sigma}$, we get:

$$x = t\sigma + \mu$$

$$dx = \sigma dt$$

Then,

$$\begin{aligned}
E(X) &= \frac{\sigma}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} (\sigma t + \mu) exp\left(-\frac{t^2}{2}\right) dt \\
&= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \sigma t \cdot exp\left(-\frac{t^2}{2}\right) dt + \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \mu \cdot exp\left(-\frac{t^2}{2}\right) dt \\
&= \frac{-\sigma}{\sqrt{2\pi}} \int_{-\infty}^{\infty} exp\left(-\frac{t^2}{2}\right) d\left(\frac{-t^2}{2}\right) + \frac{\mu}{\sqrt{2\pi}} \int_{-\infty}^{\infty} exp\left(-\frac{t^2}{2}\right) dt
\end{aligned}$$

We have:

$$\begin{aligned}
\int_{-\infty}^{\infty} exp\left(-\frac{t^2}{2}\right) d\left(\frac{-t^2}{2}\right) &= \left[exp\left(-\frac{t^2}{2}\right)\right]_{-\infty}^{\infty} \\
&= 0 - 0 = 0
\end{aligned}$$

From part (a),

$$LHS = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} exp\left(-\frac{1}{2}u^2\right) du = 1$$

$$\Rightarrow \int_{-\infty}^{\infty} exp\left(-\frac{u^2}{2}\right) du = \sqrt{2\pi}$$

Apply with variable t, we get

$$\int_{-\infty}^{\infty} exp\left(-\frac{t^2}{2}\right) dt = \sqrt{2\pi}$$

Replacing with $E(X)$:

$$E(X) = 0 + \frac{\mu}{\sqrt{2\pi}} \cdot \sqrt{2\pi} = \mu$$

(c) Variance of Gaussian distribution is σ^2 (variance)

We have $V(X) = E(X^2) - [E(X)]^2$. In part (b), we proved that $E(X) = \mu$.

Now we calculate $E(X^2)$. From definition of expected value stated in part (b), we get:

$$\begin{aligned} E(X^2) &= \int_{-\infty}^{\infty} x^2 \frac{1}{\sigma\sqrt{2\pi}} exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right)dx \\ &= \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} x^2 exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)dx \end{aligned}$$

We also substitute $t = \dfrac{x-\mu}{\sigma}$ and implement as part (b):

$$\begin{aligned} E(X^2) &= \frac{\sigma}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} (\sigma t+\mu)^2 exp\left(-\frac{t^2}{2}\right)dt \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} (\sigma t)^2 exp\left(-\frac{t^2}{2}\right)dt + \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} 2\sigma\mu t \cdot exp\left(-\frac{t^2}{2}\right)dt + \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} (\mu)^2 \cdot exp\left(-\frac{t^2}{2}\right)dt \\ &= \frac{\sigma^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} t^2 exp\left(-\frac{t^2}{2}\right)dt + \frac{2\sigma\mu}{\sqrt{2\pi}} \int_{-\infty}^{\infty} t \cdot exp\left(-\frac{t^2}{2}\right)dt + \frac{\mu^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} exp\left(-\frac{t^2}{2}\right)dt \\ &= \frac{\sigma^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} t^2 exp\left(-\frac{t^2}{2}\right)dt + \frac{2\sigma\mu}{\sqrt{2\pi}} \cdot 0 + \frac{\mu^2}{\sqrt{2\pi}} \cdot \sqrt{2\pi} \\ &= \frac{\sigma^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} t^2 exp\left(-\frac{t^2}{2}\right)dt + \mu^2 \end{aligned}$$

Using integration by parts with $u = t$, $du = dt$ and $v = -exp(\frac{-t^2}{2})$, $dv = t \cdot exp(-t^2/2)dt$:

$$\begin{aligned} I &= \int_{-\infty}^{\infty} t^2 exp\left(-\frac{t^2}{2}\right)dt \\ &= \int_{-\infty}^{\infty} t \cdot t \cdot exp\left(-\frac{t^2}{2}\right)dt \\ &= \Big[-t \cdot exp(\frac{-t^2}{2})\Big]_{-\infty}^{\infty} - \int_{-\infty}^{\infty} -exp(\frac{-t^2}{2})dt \\ &= 0 - (-\sqrt{2\pi}) = \sqrt{2\pi} \end{aligned}$$

Replacing I with $E(X^2)$:

$$E(X^2) = \frac{\sigma^2}{\sqrt{2\pi}} \cdot \sqrt{2\pi} + \mu^2 = \sigma^2 + \mu^2$$

Therefore, we get:

$$V(X) = E(X^2) - [E(X)]^2 = \sigma^2 + \mu^2 - (\mu)^2 = \sigma^2$$

(d) Multivariate Gaussian distribution is normalized

The multivariate Gaussian distribution takes the form:

$$\mathcal{N}(\mathbf{x}|\boldsymbol{\mu},\boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{D/2}}\frac{1}{|\boldsymbol{\Sigma}|^{1/2}} exp\left(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\right)$$

where $\boldsymbol{\mu}$ is a D-dimensional mean vector, $\boldsymbol{\Sigma}$ is a $D\times D$ covariance matrix, and $|\boldsymbol{\Sigma}|$ denotes the determinant of $\boldsymbol{\Sigma}$. We have a quadratic form of Gaussian distribution:

$$\begin{aligned}
\Delta^2 &= (\mathbf{x}-\boldsymbol{\mu})^T\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu}) \\
&= \mathbf{x}^T\boldsymbol{\Sigma}^{-1}\mathbf{x} - \boldsymbol{\mu}^T\boldsymbol{\Sigma}^{-1}\mathbf{x} - \mathbf{x}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} + \boldsymbol{\mu}\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} \\
&= \mathbf{x}^T\boldsymbol{\Sigma}^{-1}\mathbf{x} - 2\mathbf{x}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} + \boldsymbol{\mu}\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} \\
&= \mathbf{x}^T\boldsymbol{\Sigma}^{-1}\mathbf{x} - 2\mathbf{x}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} + const
\end{aligned}$$

Consider the eigenvector equation for the covariance matrix, $i = 1, ..., D$:

$$\boldsymbol{\Sigma}\mathbf{u}_i = \lambda_i\mathbf{u}_i$$

Because $\boldsymbol{\Sigma}$ is a real, symmetric matrix, its eigenvalues will be real and its eigenvectors form an orthonormal set.

$$\boldsymbol{\Sigma} = \sum_{i=1}^{D}\lambda_i\mathbf{u}_i\mathbf{u}_i^T$$

$$\Rightarrow \boldsymbol{\Sigma}^{-1} = \sum_{i=1}^{D}\frac{1}{\lambda_i}\mathbf{u}_i\mathbf{u}_i^T$$

Replacing $\boldsymbol{\Sigma}^{-1}$ with Δ^2, we get:

$$\begin{aligned}
\Delta^2 &= (\mathbf{x}-\boldsymbol{\mu})^T\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu}) \\
&= \sum_{i=1}^{D}\frac{1}{\lambda_i}(\mathbf{x}-\boldsymbol{\mu})^T\mathbf{u}_i\mathbf{u}_i^T(\mathbf{x}-\boldsymbol{\mu})
\end{aligned}$$

Setting $y_i = \mathbf{u}_i^T(\mathbf{x}-\boldsymbol{\mu})$, or vector $\mathbf{y} = \mathbf{U}^T(\mathbf{x}-\boldsymbol{\mu})$:

$$\Delta^2 = \sum_{i=1}^{D}\frac{y_i^2}{\lambda_i}$$

In going from the x to the y coordinate system, we have a Jacobian matrix J with elements given by

$$J_{ij} = \frac{\partial x_i}{\partial y_i} = U_{ij}$$

where U_{ij} are the elements of the matrix U^T. We have:

$$|\mathbf{J}|^2 = |\mathbf{U}^T|^2 = |\mathbf{U}^T||\mathbf{U}| = |\mathbf{U}^T\mathbf{U}| = |\mathbf{I}| = 1$$

$$\Rightarrow |\mathbf{J}| = 1$$

As the determinant of an $n \times n$ matrix is equal to the product of its eigenvalues $\Rightarrow |\mathbf{\Sigma}| = \prod_{j=1}^{D} \lambda_j$.
$\Rightarrow |\mathbf{\Sigma}|^{1/2} = \prod_{j=1}^{D} \lambda_j^{1/2}$
As a result, we get:

$$\begin{aligned} p(\mathbf{y}) = p(\mathbf{x})|\mathbf{J}| &= \frac{1}{(2\pi)^{D/2}} \frac{1}{\prod_{j=1}^{D} \lambda_j^{1/2}} exp\left(\sum_{i=1}^{D} \frac{-y_i^2}{2\lambda_i}\right) \\ &= \prod_{i=1}^{D} \frac{1}{(2\pi\lambda_i)^{1/2}} exp\Big(\frac{-y_i^2}{2\lambda_i}\Big) \end{aligned}$$

Integrating both sides of equation:

$$\int_{-\infty}^{\infty} p(\mathbf{y}) d\mathbf{y} = \prod_{i=1}^{D} \int_{-\infty}^{\infty} \frac{1}{(2\pi\lambda_i)^{1/2}} exp\Big(\frac{-y_i^2}{2\lambda_i}\Big) dy_i$$

Applying the result from part (a),

$$\int_{-\infty}^{\infty} p(\mathbf{y}) d\mathbf{y} = 1$$

Therefore, the multivariate Gaussian distribution is normalized.

2 Exercise 2

(a) The conditional of Gaussian distribution

Let $\mathbf{x}$ be a D-dimensional vector, $\mathbf{x} \sim \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \mathbf{\Sigma})$:

$$\mathbf{x} = \begin{pmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{pmatrix}$$

where x_1 and x_2 are 2 disjoint subsets of $\mathbf{x}$. We also define corresponding partitions of the mean vector $\boldsymbol{\mu}$ given by:

$$\boldsymbol{\mu} = \begin{pmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \end{pmatrix}$$

and of the covariance matrix $\mathbf{\Sigma}$ given by:

$$\mathbf{\Sigma} = \begin{pmatrix} \mathbf{\Sigma}_{11} & \mathbf{\Sigma}_{12} \\ \mathbf{\Sigma}_{21} & \mathbf{\Sigma}_{22} \end{pmatrix}$$

Let A be the inverse of the covariance matrix:

$$A = \mathbf{\Sigma}^{-1} = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix}$$

Σ is symmetric so Σ_{11} and Σ_{22} are symmetric while $\Sigma_{12} = \Sigma_{21}^T$.
We have:

$$\begin{aligned} (\mathbf{x} - \boldsymbol{\mu})^T \mathbf{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) &= (\mathbf{x} - \boldsymbol{\mu})^T A (\mathbf{x} - \boldsymbol{\mu}) \\ &= (\mathbf{x}_1 - \boldsymbol{\mu}_1)^T A_{11} (\mathbf{x}_1 - \boldsymbol{\mu}_1) + (\mathbf{x}_1 - \boldsymbol{\mu}_1)^T A_{12} (\mathbf{x}_2 - \boldsymbol{\mu}_2) \\ &\quad + (\mathbf{x}_2 - \boldsymbol{\mu}_2)^T A_{21} (\mathbf{x}_1 - \boldsymbol{\mu}_1) + (\mathbf{x}_2 - \boldsymbol{\mu}_2)^T A_{22} (\mathbf{x}_2 - \boldsymbol{\mu}_2) \\ &= \mathbf{x}_1^T A_{11} \mathbf{x}_1 - 2\mathbf{x}_1^T A_{11} \boldsymbol{\mu}_1 + \mathbf{x}_1^T A_{12} \mathbf{x}_2 - \mathbf{x}_1^T A_{12} \boldsymbol{\mu}_2 - \boldsymbol{\mu}_1^T A_{12} \mathbf{x}_2 \\ &\quad + \mathbf{x}_2^T A_{21} \mathbf{x}_1 - \mathbf{x}_2^T A_{21} \boldsymbol{\mu}_1 - \boldsymbol{\mu}_2^T A_{21} \mathbf{x}_1 + \mathbf{x}_2^T A_{22} \mathbf{x}_2 - 2\mathbf{x}_2^T A_{22} \boldsymbol{\mu}_2 + const \end{aligned}$$

We are looking for conditional distribution $p(\mathbf{x}_1|\mathbf{x}_2)$, so we only consider the quadratic form of $\mathbf{x_1}$:

$$\begin{aligned}(\mathbf{x}-\boldsymbol{\mu})^T\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu}) &= \mathbf{x}_1^T A_{11}\mathbf{x}_1 - 2\mathbf{x}_1^T A_{11}\boldsymbol{\mu}_1 + 2\mathbf{x}_1^T A_{12}\mathbf{x}_2 - 2\mathbf{x}_1^T A_{12}\boldsymbol{\mu}_2 + const \\ &= \mathbf{x}_1^T A_{11}\mathbf{x}_1 - 2\mathbf{x}_1^T[A_{11}\boldsymbol{\mu}_1 - A_{12}(\mathbf{x}_2-\boldsymbol{\mu}_2)] + const\end{aligned}$$

Hence conditional distribution $p(\mathbf{x_1}|\mathbf{x_2})$ will be Gaussian, because this distribution is characterized by its mean and its variance. Compare with Gaussian distribution from Exercise 1:

$$\Delta^2 = \mathbf{x}^T\boldsymbol{\Sigma}^{-1}\mathbf{x} - 2\mathbf{x}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} + const$$

We can infer that $\boldsymbol{\Sigma}_{1|2}^{-1} = A_{11}$ or $\boldsymbol{\Sigma}_{1|2} = A_{11}^{-1}$, and:

$$\boldsymbol{\Sigma}_{1|2}^{-1}\boldsymbol{\mu}_{1|2} = A_{11}\boldsymbol{\mu}_1 - A_{12}(\mathbf{x}_2-\boldsymbol{\mu}_2)$$

$$\begin{aligned}\Rightarrow \boldsymbol{\mu}_{1|2} &= \boldsymbol{\Sigma}_{1|2}[A_{11}\boldsymbol{\mu}_1 - A_{12}(\mathbf{x}_2-\boldsymbol{\mu}_2)] \\ &= A_{11}^{-1}[A_{11}\boldsymbol{\mu}_1 - A_{12}(\mathbf{x}_2-\boldsymbol{\mu}_2)] \\ &= \boldsymbol{\mu}_1 - A_{11}^{-1}A_{12}(\mathbf{x}_2-\boldsymbol{\mu}_2)\end{aligned}$$

Using Schur complement with $M = (A - BD^{-1}C)^{-1}$:

$$\begin{pmatrix} A & B \\ C & D\end{pmatrix}^{-1} = \begin{pmatrix} M & -MBD^{-1} \\ -D^{-1}CM & D^{-1} + D^{-1}CMBD^{-1}\end{pmatrix}$$

we have:

$$A_{11} = (\boldsymbol{\Sigma}_{11} - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\Sigma}_{21})^{-1}$$

and

$$A_{12} = -(\boldsymbol{\Sigma}_{11} - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\Sigma}_{21})^{-1}\boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}$$

Then we get:

$$\begin{aligned}\boldsymbol{\mu}_{1|2} &= \boldsymbol{\mu}_1 - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}(\mathbf{x}_2-\boldsymbol{\mu}_2) \\ \boldsymbol{\Sigma}_{1|2} &= \boldsymbol{\Sigma}_{11} - \boldsymbol{\Sigma}_{12}\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\Sigma}_{21}\end{aligned}$$

As a result,

$$p(\mathbf{x}_1|\mathbf{x}_2) = \mathcal{N}(\mathbf{x}_{1|2}|\boldsymbol{\mu}_{1|2}, \boldsymbol{\Sigma}_{1|2})$$

(b) The marginal of Gaussian distribution

The marginal distribution is given by:

$$p(\mathbf{x}_1) = \int p(\mathbf{x}_1,\mathbf{x}_2)d\mathbf{x}_2$$

We have the quadratic form for the joint distribution from part (a). Because our goal is to integrate out $\mathbf{x}_2$, this is most easily achieved by first considering the terms involving $\mathbf{x}_2$ and then completing the square in order to facilitate integration. Picking out just those terms that involve $\mathbf{x}_2$, we have:

$$(\mathbf{x}-\boldsymbol{\mu})^T\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu}) = \mathbf{x}_2^T A_{22}\mathbf{x}_2 - 2\mathbf{x}_2^T[A_{22}\boldsymbol{\mu}_2 - A_{21}(\mathbf{x}_1-\boldsymbol{\mu}_1)] + const$$

Setting $\mathbf{m} = A_{22}\boldsymbol{\mu}_2 - A_{21}(\mathbf{x}_1-\boldsymbol{\mu}_1)$, we have:

$$\begin{aligned}\mathbf{x}_2^T A_{22}\mathbf{x}_2 - 2\mathbf{x}_2^T[A_{22}\boldsymbol{\mu}_2 - A_{21}(\mathbf{x}_1-\boldsymbol{\mu}_1)] &= \mathbf{x}_2^T A_{22}\mathbf{x}_2 - 2\mathbf{x}_2^T\mathbf{m} \\ &= (\mathbf{x}_2 - A_{22}^{-1}\mathbf{m})^T A_{22}(\mathbf{x}_2 - A_{22}^{-1}\mathbf{m}) - \mathbf{m}^T A_{22}^{-1}\mathbf{m}\end{aligned}$$

The second term in above equation does not depend on $\mathbf{x}_2$. Thus, when we take the exponential of this quadratic form, we see that the integration over $\mathbf{x}_2$ will take the form:

$$\int exp\Big(-\frac{1}{2}(\mathbf{x}_2 - A_{22}^{-1}\mathbf{m})^T A_{22}(\mathbf{x}_2 - A_{22}^{-1}\mathbf{m})\Big)d\mathbf{x}_2 = (2\pi)^{n/2}|A_{22}^{-1}|^{1/2}$$

$\big($Applying $\int exp\Big(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T U^{-1}(\mathbf{x}-\boldsymbol{\mu})\Big)d\mathbf{x} = (2\pi)^{n/2}|U|^{1/2}\big)$.

Combining the second term with the remaining terms from the expansion of the quadratic form Δ^2 that depend on $\mathbf{x}_1$, we obtain:

$$\begin{aligned}
& -\mathbf{m}^T A_{22}^{-1}\mathbf{m} + \mathbf{x}_1^T A_{11}\mathbf{x}_1 - 2\mathbf{x}_1^T[A_{11}\boldsymbol{\mu}_1 + A_{12}\boldsymbol{\mu}_2] + const \\
&= -(A_{22}\boldsymbol{\mu}_2 - A_{21}(\mathbf{x}_1 - \boldsymbol{\mu}_1))^T A_{22}^{-1}(A_{22}\boldsymbol{\mu}_2 - A_{21}(\mathbf{x}_1 - \boldsymbol{\mu}_1)) \\
&\qquad + \mathbf{x}_1^T A_{11}\mathbf{x}_1 - 2\mathbf{x}_1^T[A_{11}\boldsymbol{\mu}_1 + A_{12}\boldsymbol{\mu}_2] + const \\
&= \mathbf{x}_1^T(A_{11} - A_{12}A_{22}^{-1}A_{21})\mathbf{x}_1 - 2\mathbf{x}_1^T(A_{11} - A_{12}A_{22}^{-1}A_{21})\boldsymbol{\mu}_1 + const
\end{aligned}$$

Comparing to Gaussian distribution, we get:

$$\boldsymbol{\Sigma}_1 = (A_{11} - A_{12}A_{22}^{-1}A_{21})^{-1}$$

Using Schur complement again, we obtain: $\boldsymbol{\Sigma}_1 = \boldsymbol{\Sigma}_{11}$.
So, the mean and covariance of the marginal distribution of $p(\mathbf{x}_1)$ are:

$$\mathbb{E}[\mathbf{x}_1] = \boldsymbol{\mu}_1$$

$$cov[\mathbf{x}_1] = \boldsymbol{\Sigma}_{11}$$

Thus, we have:

$$p(\mathbf{x}_1) = \mathcal{N}(\mathbf{x}_1|\boldsymbol{\mu}_1, \boldsymbol{\Sigma}_{11})$$