Homework 2

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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 $\int_{-\infty}^{\infty} \mathcal{N}(x|\mu,\sigma^2)dx = 1$, 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,

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

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

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

Squaring both sides of above equation:

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

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} exp\left(-\frac{u^2+v^2}{2}\right)dudv$$

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:

$$\frac{\partial(u,v)}{\partial(r,\theta)} = \begin{vmatrix} \frac{\partial u}{\partial r} & \frac{\partial u}{\partial \theta} \\ \frac{\partial v}{\partial r} & \frac{\partial v}{\partial \theta} \end{vmatrix}$$

$$= \begin{vmatrix} cos\theta & -rsin\theta \\ sin\theta & rcos\theta \end{vmatrix}$$

$$= rcos^2\theta + rsin^2\theta$$

$$= r$$

So, $dudv = rdrd\theta$ and:

$$LHS^2 = \frac{1}{2\pi} \int_0^{2\pi} \int_0^\infty exp\left(-\frac{r^2}{2}\right) rdrd\theta$$

$$= -\frac{1}{2\pi} \int_0^{2\pi} \int_0^\infty exp\left(-\frac{r^2}{2}\right) d\left(\frac{-r^2}{2}\right) d\theta$$

$$= -\frac{1}{2\pi} \int_0^{2\pi} \left[exp\left(-\frac{r^2}{2}\right) \right]_{r=0}^{r=\infty} d\theta$$

$$= -\frac{1}{2\pi} \int_0^{2\pi} (0 - 1)d\theta$$

$$= \frac{1}{2\pi} \int_0^{2\pi} d\theta$$

$$= \frac{1}{2\pi}(2\pi - 0)$$

$$= 1.$$

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:

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

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

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

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

$$dx = \sigma dt$$

Then,

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

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \sigma t \cdot exp\left(-\frac{t^2}{2}\right) dt + \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \mu \cdot exp\left(-\frac{t^2}{2}\right) dt$$

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

We have:

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

$$= 0 - 0 = 0$$

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:

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

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

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

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

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} (\sigma t)^2 exp\left(-\frac{t^2}{2}\right) dt + \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} 2\sigma\mu t \cdot exp\left(-\frac{t^2}{2}\right) dt + \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} (\mu)^2 \cdot exp\left(-\frac{t^2}{2}\right) dt$$

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

$$= \frac{\sigma^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} t^2 exp\left(-\frac{t^2}{2}\right) dt + \frac{2\sigma\mu}{\sqrt{2\pi}} \cdot 0 + \frac{\mu^2}{\sqrt{2\pi}} \cdot \sqrt{2\pi}$$

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

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

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

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

$$= \left[-t \cdot exp(\frac{-t^2}{2})\right]_{-\infty}^{\infty} - \int_{-\infty}^{\infty} -exp(\frac{-t^2}{2})dt$$

$$= 0 - (-\sqrt{2\pi}) = \sqrt{2\pi}$$

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:

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

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(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

$$J_{ij} = \frac{\partial x_i}{\partial y_j} = U_{ji}$$

where U_{ji} 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 $\Rightarrow |\boldsymbol{\Sigma}| = \prod_{j=1}^{D} \lambda_j$.

$\Rightarrow |\boldsymbol{\Sigma}|^{1/2} = \prod_{j=1}^{D} \lambda_j^{1/2}$

As a result, we get:

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

$$= \prod_{i=1}^{D} \frac{1}{(2\pi\lambda_i)^{1/2}} exp\left(\frac{-y_i^2}{2\lambda_i}\right)$$

Integrating both sides of equation:

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

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, $\mathbf{x} \sim \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}, \boldsymbol{\Sigma})$:

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

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 $\boldsymbol{\Sigma}$ given by:

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

Let A be the inverse of the covariance matrix:

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

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

We have:

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

We are looking for conditional distribution $p(\mathbf{x_1}|\mathbf{x_2})$, so we only consider the quadratic form of $\mathbf{x_1}$:

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

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:

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

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

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:

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

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:

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

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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:

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

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:

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