

ML HW5

Date: 10/01/2025

Week: 5

Author: Alvin B. Lin

Student ID: 112652040

Problem 1: Integral of Multivariable Normal Distribution

Given

$$f(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^k |\boldsymbol{\Sigma}|}} e^{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})},$$

where $\mathbf{x}, \boldsymbol{\mu} \in \mathbb{R}^k$, $\boldsymbol{\Sigma}$ is a k -by- k positive definite matrix and $|\boldsymbol{\Sigma}|$ is its determinant. Show that

$$\int_{\mathbb{R}^k} f(\mathbf{x}) \, d\mathbf{x} = 1.$$

Solution:

We first do a substitution:

$$\mathbf{y} = \mathbf{x} - \boldsymbol{\mu}; \quad \Omega = \mathbb{R}^k \implies \mathbb{R}^k = \Omega'.$$

We need the following lemma:

Theorem 1: Symmetric \iff Orthogonally Diagonalisable

Given a matrix $\mathbf{A} \in \mathbb{M}_{k \times k}$, then it follows that

$$\mathbf{A} \text{ is symmetric } \iff \mathbf{A} = \mathbf{Q}\mathbf{D}\mathbf{Q}^\top$$

for some **orthogonal** $\mathbf{Q} \in \mathbb{M}_{k \times k}$, diagonal $\mathbf{D} \in \mathbb{M}_{k \times k}$.

Combine **Theorem 1** and the **positive definite** property on $\boldsymbol{\Sigma}$, we know that:

$$\boldsymbol{\Sigma} = \mathbf{Q}\mathbf{D}\mathbf{Q}^\top = (\mathbf{Q}\sqrt{\mathbf{D}}) (\mathbf{Q}\sqrt{\mathbf{D}})^\top := (\boldsymbol{\Sigma}^{1/2}) (\boldsymbol{\Sigma}^{1/2})^\top = (\boldsymbol{\Sigma}^{1/2}) (\boldsymbol{\Sigma}^{1/2}),$$

where \mathbf{Q} is orthogonal, \mathbf{D} is a diagonal matrix with all diagonal entries positive, $\sqrt{\mathbf{D}}^2 = \mathbf{D}$.

So now we have our exponent part becomes:

$$-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu}) = -\frac{1}{2}(\boldsymbol{\Sigma}^{-1/2} \mathbf{y})^\top (\boldsymbol{\Sigma}^{-1/2} \mathbf{y}) = -\frac{1}{2} \|\boldsymbol{\Sigma}^{-1/2} \mathbf{y}\|^2$$

By letting $\mathbf{z} = \boldsymbol{\Sigma}^{-1/2} \mathbf{y}$, we get $d\mathbf{z} = |\boldsymbol{\Sigma}^{-1/2}| d\mathbf{y} = \frac{1}{\sqrt{|\boldsymbol{\Sigma}|}} d\mathbf{y}$, where $|\boldsymbol{\Sigma}^{-1/2}|$ is the **Jacobian**.

Notice that $\|\mathbf{z}\|^2 = z_1^2 + z_2^2 + \dots + z_k^2$, and by **Fubini's Theorem**, we have:

$$\int_{\mathbb{R}^k} \varphi_1(x_1) \cdot \varphi_2(x_2) \cdots \varphi_k(x_k) \, d\mathbf{x} = \left(\int_{\mathbb{R}} \varphi_1(x_1) \, dx_1 \right) \left(\int_{\mathbb{R}} \varphi_2(x_2) \, dx_2 \right) \cdots \left(\int_{\mathbb{R}} \varphi_k(x_k) \, dx_k \right)$$

Also, there is a well-known result that $\int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \, dx = 1$. We are all set now.

Combine everything together, we get:

$$\begin{aligned}
\int_{\mathbb{R}^k} f(\mathbf{x}) \, d\mathbf{x} &= \int_{\mathbb{R}^k} \frac{1}{\sqrt{(2\pi)^k |\boldsymbol{\Sigma}|}} e^{-\frac{1}{2} \|\boldsymbol{\Sigma}^{-1/2} \mathbf{y}\|^2} \, d\mathbf{y} = \int_{\mathbb{R}^k} \frac{1}{\sqrt{(2\pi)^k}} e^{-\frac{1}{2} \sum_{i=1}^k z_i^2} \, d\mathbf{z} \\
&= \prod_{i=1}^k \left(\int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} z_i^2} \, dz_i \right) \\
&= 1^k \\
&= 1
\end{aligned}$$

Hence proved.

Problem 2: MLE of Multivariate Gaussian

- (a) Show that $\frac{\partial}{\partial \mathbf{A}} \text{Tr}(\mathbf{A}\mathbf{B}) = \mathbf{B}^\top$.
- (b) Show that $\mathbf{x}^\top \mathbf{A} \mathbf{x} = \text{Tr}(\mathbf{x} \mathbf{x}^\top \mathbf{A})$.
- (c) Derive the maximum likelihood estimator for the multivariate Gaussian.

Solution:

- (a) Given $\mathbf{M} \in \mathbb{M}_{n \times n}$, recall that the definition of the **trace** is stated as:

$$\text{Tr}(\mathbf{M}) = \sum_{i=1}^n m_{ii}.$$

Also, for matrices $\mathbf{A} \in \mathbb{M}_{n \times m}$ and $\mathbf{B} \in \mathbb{M}_{m \times n}$, the matrix multiplication gives:

$$(\mathbf{A}\mathbf{B})_{ij} = \sum_{k=1}^m a_{ik} b_{kj} \quad \text{Tr}(\mathbf{A}\mathbf{B}) = \sum_{i=1}^n \sum_{k=1}^m a_{ik} b_{ki}$$

Since all the entries of \mathbf{A} are pairwise independent, the derivative rule is given as:

$$\frac{\partial}{\partial a_{lm}} (a_{ik} b_{ki}) = \begin{cases} b_{ki} = b_{ml}, & \text{if } l = i \text{ and } m = k. \\ 0, & \text{otherwise} \end{cases}$$

Recall that the matrix derivative is given as:

$$\frac{\partial}{\partial \mathbf{A}} = \begin{pmatrix} \frac{\partial}{\partial a_{11}} & \cdots & \frac{\partial}{\partial a_{1m}} \\ \vdots & \ddots & \vdots \\ \frac{\partial}{\partial a_{n1}} & \cdots & \frac{\partial}{\partial a_{nm}} \end{pmatrix}$$

Combine everything, we get:

$$\frac{\partial \text{Tr}(\mathbf{A}\mathbf{B})}{\partial \mathbf{A}} = \sum_{i=1}^n \sum_{k=1}^m \begin{pmatrix} \frac{\partial}{\partial a_{11}} & \cdots & \frac{\partial}{\partial a_{1m}} \\ \vdots & \ddots & \vdots \\ \frac{\partial}{\partial a_{n1}} & \cdots & \frac{\partial}{\partial a_{nm}} \end{pmatrix} a_{ik} b_{ki} = \begin{pmatrix} b_{11} & b_{21} & \cdots & b_{m1} \\ b_{12} & b_{22} & \cdots & b_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ b_{1n} & b_{2n} & \cdots & b_{mn} \end{pmatrix} = \mathbf{B}^\top$$

Hence proved.

(b) For $\mathbf{A} \in M_{n \times n}$ and $\mathbf{x} = (x_1, x_2, \dots, x_n)^\top \in \mathbb{R}^n$, we have:

$$\mathbf{x}^\top \mathbf{A} \mathbf{x} = \mathbf{x}^\top \begin{pmatrix} -\mathbf{A}_1 \mathbf{x} - \\ -\mathbf{A}_2 \mathbf{x} - \\ \vdots \\ -\mathbf{A}_n \mathbf{x} - \end{pmatrix} = \sum_{i=1}^n x_i \mathbf{A}_i \mathbf{x} = \sum_{i=1}^n \sum_{j=1}^n x_i a_{ij} x_j \quad (1)$$

For \mathbf{A}_i is the i th row of the matrix \mathbf{A} ; also:

$$\mathbf{x} \mathbf{x}^\top \mathbf{A} = \mathbf{x} \begin{pmatrix} \mathbf{x}^\top \mathbf{A}'_1 & \mathbf{x}^\top \mathbf{A}'_2 & \cdots & \mathbf{x}^\top \mathbf{A}'_n \\ | & | & & | \end{pmatrix},$$

where \mathbf{A}'_j is the j th column of matrix \mathbf{A} . Therefore,

$$\text{Tr}(\mathbf{x} \mathbf{x}^\top \mathbf{A}) = \sum_{j=1}^n (\mathbf{x} \mathbf{x}^\top \mathbf{A})_{jj} = \sum_{j=1}^n x_j \sum_{i=1}^n x_i a_{ij} = \sum_{i=1}^n \sum_{j=1}^n x_i a_{ij} x_j \quad (2)$$

We obtain the same result in (1) and (2), meaning that:

$$\mathbf{x}^\top \mathbf{A} \mathbf{x} = \sum_{i=1}^n \sum_{j=1}^n x_i a_{ij} x_j = \text{Tr}(\mathbf{x} \mathbf{x}^\top \mathbf{A})$$

Hence proved.

Or simply with “cyclic” property on $\text{Tr}(\cdot)$: $\text{Tr}(\mathbf{x} \mathbf{x}^\top \mathbf{A}) = \text{Tr}(\mathbf{x}^\top \mathbf{A} \mathbf{x}) = \mathbf{x}^\top \mathbf{A} \mathbf{x} \quad \square$

(c) The likelihood function of N k -dimensional multivariate Gaussian $\mathbf{X}_i \stackrel{i.i.d}{\sim} \mathcal{N}(\mu, \Sigma)$ is:

$$L(\mu, \Sigma) = \prod_{i=1}^N \frac{1}{\sqrt{(2\pi)^k |\Sigma|}} e^{-\frac{1}{2}(\mathbf{x}^{(i)} - \mu)^\top \Sigma^{-1}(\mathbf{x}^{(i)} - \mu)}$$

After taking log, the log-likelihood function is:

$$\ell(\mu, \Sigma) = \sum_{i=1}^N \left(-\frac{k}{2} \ln(2\pi) - \frac{1}{2} \ln |\Sigma| - \frac{1}{2} (\mathbf{x}^{(i)} - \mu)^\top \Sigma^{-1} (\mathbf{x}^{(i)} - \mu) \right).$$

If we take the derivative with respect to μ ,

$$\begin{aligned} \frac{\partial \ell}{\partial \mu} &= \sum_{i=1}^N \frac{1}{2} \left(\Sigma^{-1} (\mathbf{x}^{(i)} - \mu) \right)^\top + \frac{1}{2} (\mathbf{x}^{(i)} - \mu)^\top \Sigma^{-1} = \sum_{i=1}^N \frac{1}{2} (\mathbf{x}^{(i)} - \mu)^\top \left(\Sigma^{-1} + (\Sigma^{-1})^\top \right) \\ &= \sum_{i=1}^N (\mathbf{x}^{(i)} - \mu)^\top \Sigma^{-1} \end{aligned}$$

Letting $\frac{\partial \ell}{\partial \mu} = \mathbf{0}$, we must have $\hat{\mu} = \frac{1}{N} \sum_{i=1}^N \mathbf{x}^{(i)}$.

Now we take the derivative with respect to Σ :

$$\frac{\partial \ell}{\partial \Sigma} = -\frac{N}{2} \underbrace{\frac{\partial \ln |\Sigma|}{\partial \Sigma}}_{(i)} - \frac{1}{2} \sum_{i=1}^N \underbrace{\frac{\partial}{\partial \Sigma} \left((\mathbf{x}^{(i)} - \mu)^\top \Sigma^{-1} (\mathbf{x}^{(i)} - \mu) \right)}_{(ii)}$$

In the equation, we have two derivatives to deal with:

(i) For this part, we need several lemmas to cover:

Lemma 1: Jacobi's Formula

For $\mathbf{A} \in \mathbb{M}_{n \times n}$ invertible matrix, we have the following identity:

$$\frac{d}{dt} |\mathbf{A}(t)| = \text{tr} \left((\mathbf{A}^*(t)) \frac{d\mathbf{A}(t)}{dt} \right) = |\mathbf{A}(t)| \cdot \text{tr} \left(\mathbf{A}(t)^{-1} \cdot \frac{d\mathbf{A}(t)}{dt} \right)$$

In special case:

$$\frac{\partial |\mathbf{A}|}{\partial \mathbf{A}} = \frac{\partial |\mathbf{A}|}{\partial \mathbf{A}_{ij}} = \mathbf{A}_{ji}^* = (\mathbf{A}^*)^\top$$

Where \mathbf{A}^* be the **adjoint matrix** of \mathbf{A} .

Lemma 2: Adjoint Matrix Identity

For a **invertible** matrix $\mathbf{A} \in \mathbb{M}_{n \times n}$, and \mathbf{A}^* be \mathbf{A} 's adjoint, we have:

$$\mathbf{A}\mathbf{A}^* = |\mathbf{A}| \cdot \mathbf{I} \quad \text{and} \quad \mathbf{A}^* = |\mathbf{A}| \cdot \mathbf{A}^{-1}$$

With the assist of **lemma 1, 2**, we have:

$$\frac{\partial \ln |\Sigma|}{\partial \Sigma} = \frac{\partial \ln |\Sigma|}{\partial |\Sigma|} \cdot \frac{\partial |\Sigma|}{\partial \Sigma} = \frac{1}{|\Sigma|} \cdot (|\Sigma| \cdot \Sigma^{-1})^\top = \frac{1}{|\Sigma|} \cdot |\Sigma| \cdot \Sigma^{-1} = \Sigma^{-1}$$

(ii) We use the result in (b), we get:

$$\frac{\partial}{\partial \Sigma} \left((\mathbf{x}^{(i)} - \mu)^\top \Sigma^{-1} (\mathbf{x}^{(i)} - \mu) \right) = \frac{\partial}{\partial \Sigma} \text{Tr} \left((\mathbf{x}^{(i)} - \mu) (\mathbf{x}^{(i)} - \mu)^\top \Sigma^{-1} \right)$$

Recall that $\text{Tr}(\cdot, \cdot)$ is **reflexive**, *i.e.* $\text{Tr}(\mathbf{A}\mathbf{B}) = \text{Tr}(\mathbf{B}\mathbf{A})$:

$$\frac{\partial}{\partial \Sigma} \text{Tr} \left((\mathbf{x}^{(i)} - \mu) (\mathbf{x}^{(i)} - \mu)^\top \Sigma^{-1} \right) = \frac{\partial}{\partial \Sigma} \text{Tr} \left(\Sigma^{-1} (\mathbf{x}^{(i)} - \mu) (\mathbf{x}^{(i)} - \mu)^\top \right)$$

Lemma 3: Inverse Matrix Differential

For $\mathbf{A} \in \mathbb{M}_{n \times n}$, and \mathbf{A}^{-1} be its inverse:

$$d(\mathbf{A}^{-1}) = -\mathbf{A}^{-1}(d\mathbf{A})\mathbf{A}^{-1} \iff d\mathbf{A} = -\mathbf{A}d(\mathbf{A}^{-1})\mathbf{A}$$

With **lemma 3**, we get the following:

$$\begin{aligned} \frac{\partial}{\partial \Sigma} \text{Tr}(\Sigma^{-1} (\mathbf{x}^{(i)} - \mu) (\mathbf{x}^{(i)} - \mu)^\top) &= \text{Tr}(\frac{\partial}{\partial \Sigma} (\Sigma^{-1} (\mathbf{x}^{(i)} - \mu) (\mathbf{x}^{(i)} - \mu)^\top)) \\ &= \text{Tr}(-\Sigma^{-1} (\frac{\partial \Sigma}{\partial \Sigma}) \Sigma^{-1} (\mathbf{x}^{(i)} - \mu) (\mathbf{x}^{(i)} - \mu)^\top) \\ &= \text{Tr}(-(\frac{\partial \Sigma}{\partial \Sigma}) \Sigma^{-1} (\mathbf{x}^{(i)} - \mu) (\mathbf{x}^{(i)} - \mu)^\top \Sigma^{-1}) \end{aligned}$$

Therefore, with the result in (a),

$$\begin{aligned}\frac{\partial}{\partial \Sigma} \text{Tr} \left(\Sigma^{-1} (\mathbf{x}^{(i)} - \mu) (\mathbf{x}^{(i)} - \mu)^\top \right) &= - \left(\Sigma^{-1} (\mathbf{x}^{(i)} - \mu) (\mathbf{x}^{(i)} - \mu)^\top \Sigma^{-1} \right)^\top \\ &= - \Sigma^{-1} (\mathbf{x}^{(i)} - \mu) (\mathbf{x}^{(i)} - \mu)^\top \Sigma^{-1}\end{aligned}$$

Bring everything back to the original identity:

$$\frac{\partial \ell}{\partial \Sigma} = - \frac{N}{2} \underbrace{\Sigma^{-1}}_{(i)} + \frac{1}{2} \sum_{i=1}^N \underbrace{\Sigma^{-1} (\mathbf{x}^{(i)} - \mu) (\mathbf{x}^{(i)} - \mu)^\top \Sigma^{-1}}_{(ii)}$$

By letting $\frac{\partial \ell}{\partial \Sigma} = \mathbf{0}$, we multiply the equations on the left and right by Σ :

$$\mathbf{0} = -N\Sigma + \sum_{i=1}^N (\mathbf{x}^{(i)} - \mu) (\mathbf{x}^{(i)} - \mu)^\top \implies \hat{\Sigma} = \frac{1}{N} \sum_{i=1}^N (\mathbf{x}^{(i)} - \hat{\mu}) (\mathbf{x}^{(i)} - \hat{\mu})^\top$$

Since $\log \cdot$ is an increasing function, likelihood function and log-likelihood function will share the same **MLE**.

Hence, finally, we get our maximum likelihood estimators are:

$$\begin{cases} \hat{\mu} = \frac{1}{N} \sum_{i=1}^N \mathbf{x}^{(i)} \\ \hat{\Sigma} = \frac{1}{N} \sum_{i=1}^N (\mathbf{x}^{(i)} - \hat{\mu}) (\mathbf{x}^{(i)} - \hat{\mu})^\top \end{cases}$$

My Question 1: Theoretical Limitations of Logistic Regression on Imbalanced Data

In classification problems with **severe class imbalance**, standard Logistic Regression models often exhibit a bias toward the majority class. Could you elaborate on how the **Maximum Likelihood Estimation (MLE)** objective function, which underlies Logistic Regression, fundamentally contributes to this bias, and what the theoretical justification is for its reduced effectiveness in maximizing a performance metric like **F1-score** or **Recall** for the minority class? (This question is refined by **Gemini**.)

Example:

Suppose I have a data set with data **99%** in the class 0 and merely **1%** is in the class 1 and we aim to predict the class for each data. Logistic regression is used for classifying.

What I Expect To Get: The hypothesis function is very close to my data structure, *i.e.* the F1 score is high and accurate for each class.

What I End Up Getting: A high F1 score, but **nearly all (>99.9%)** the data have been classified into class 0, even if the data themselves are in class 1 originally, **FN** is high, but does not affect the overall score.