PAC-Bayes Bound for Linear Regression

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Recall: Statistical Learning Theory

We define the dataset as $S = \{(x_i, y_i)\}_{i=1}^n$, where $x_i \in \mathbb{R}^d$ is the feature vector, and $y_i \in \mathbb{R}$ is the label. Each (x_i, y_i) is i.i.d. sampled from an unknown distribution $\mathcal{D}$.

The machine learning model is a predictor $f_\theta : \mathbb{R}^d \to \mathbb{R}$ where θ is the vector of parameters. The loss function of the predictor on the sample (x_i, y_i) is defined as $L(f_\theta(x_i), y_i)$. The empirical risk is defined as

$$R^{\mathsf{emp}}(\theta) = \frac{1}{n} \sum_{i=1}^{n} L(f_\theta(x_i), y_i)$$

The true risk is defined as

$$R^{\mathsf{true}}(\theta) = \mathbb{E}_{(x_i, y_i) \sim \mathcal{D}}[L(f_\theta(x_i), y_i)]$$

In this lecture, we will show the PAC-Bayes bound for the linear regression problem.

Recall: Moment Generating Function

Definition 0.1: Let X be a random variable and n be an integer, the nth moment of X is $\mathbb{E}[X^n]$.

Definition 0.2: Let X be a random variable, the Moment Generating Function (MGF), denoted by $M_X(t)$, is

$$M_X(t) = \mathbb{E}[e^{tX}]$$

Theorem 0.3: If X has MGF $M_X(t)$, let $M_X^{(n)}(t)$ be the nth derivative of $M_X(t)$, then

$$\mathbb{E}[X^n] = M_X^{(n)}(0)$$

Proof: By Taylor Theorem,

$$e^{tX} = \sum_{k=1}^{\infty} \frac{t^k}{k!} X^k \;\Rightarrow\; \mathbb{E}[e^{tX}] = \sum_{k=1}^{\infty} \frac{t^k}{k!} \mathbb{E}[X^k] \;\Rightarrow\; \frac{d^n}{dt^n} \mathbb{E}[e^{tX}] = \sum_{k=n}^{\infty} \frac{t^{(k-n)}}{k!/n!} \mathbb{E}[X^k]$$

$$\Rightarrow\; \frac{d^n}{dt^n} \mathbb{E}[e^{tX}]\Big|_{t=0} = \mathbb{E}[X^n]$$

□

Definition 0.4: Let $X_1, X_2, ..., X_n$ be random variables iid from $\mathcal{N}(0,1)$. Then $X = \sum_{i=1}^{n} X_i^2$ satisfies Chi-Squared distribution of n degree of freedom, denoted as $\chi^2(n)$.

Theorem 0.5: If $X \sim \chi^2(n)$, then $M_X(t) = (1-2t)^{-\frac{n}{2}}$.

Proof: For $\chi^2(1)$, i.e., when $n = 1$,

$$\begin{aligned} M_X(t) = \mathbb{E}[e^{tX^2}] &= \int e^{tx^2} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx \\ &= (1-2t)^{-\frac{1}{2}} \int \frac{1}{\sqrt{2\pi}(\frac{1}{1-2t})^{\frac{1}{2}}} \exp\left(-\frac{x^2}{\frac{2}{1-2t}}\right) dx \\ &= (1-2t)^{-\frac{1}{2}} \end{aligned}$$

For $\chi^2(n)$,

$$M_X(t) = \mathbb{E}[e^{tX}] = \mathbb{E}[e^{t\sum_{i=1}^{n} X_i}] = \prod_{i=1}^{n} \mathbb{E}[e^{tX_i}] = \mathbb{E}[e^{tX_i}]^n = (1-2t)^{-\frac{n}{2}}$$

$\square$

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Alquier's Bound

Theorem 1 (Alquier's Bound) [1]: Let π be a prior distribution of θ and $\lambda > 0$ be a real number. Then for any posterior distribution ρ and $\delta > 0$,

$$P\left(\mathbb{E}_{\theta\sim\rho}[R^{\text{true}}(\theta)] < \mathbb{E}_{\theta\sim\rho}[R^{\text{emp}}(\theta)] + \frac{1}{\lambda}\left[D(\,\rho\,||\,\pi\,) + \ln\frac{1}{\delta} + \Psi_{L,\pi,\mathcal{D}}(\lambda, n)\right]\right) \geq 1 - \delta$$

where

$$\Psi_{L,\pi,\mathcal{D}}(\lambda, n) = \ln \mathbb{E}_{\theta\sim\pi}\mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}[e^{\lambda(R^{\text{true}}(\theta) - R^{\text{emp}}(\theta))}]$$

Proof: By Donsker-Varadhan representation, for any distribution ρ, π and any function $g(\theta)$,

$$\mathbb{E}_{\theta\sim\rho}[g(\theta)] \leq D(\,\rho\,||\,\pi\,) + \ln \mathbb{E}_{\theta\sim\pi}[e^{g(\theta)}]$$

Let $g(\theta) = \lambda(R^{\text{true}}(\theta) - R^{\text{emp}}(\theta))$, we have

$$\lambda(\mathbb{E}_{\theta\sim\rho}[(R^{\text{true}}(\theta)] - \mathbb{E}_{\theta\sim\rho}[R^{\text{emp}}(\theta)]) \leq D(\,\rho\,||\,\pi\,) + \ln \mathbb{E}_{\theta\sim\pi}[e^{\lambda(R^{\text{true}}(\theta) - R^{\text{emp}}(\theta))}] \tag{1}$$

Consider Markov's Inequality. For any non-negative random variable X and constant $t > 0$,

$$P[X > t] \leq \frac{\mathbb{E}[X]}{t}$$

Let $\delta = \frac{\mathbb{E}[X]}{t}$, then

$$P[X > \frac{\mathbb{E}[X]}{\delta}] \leq \delta \quad \iff \quad P[X < \frac{\mathbb{E}[X]}{\delta}] \geq 1 - \delta$$

Let $X = \mathbb{E}_{\theta \sim \pi}[e^{\lambda(R^{\text{true}}(\theta) - R^{\text{emp}}(\theta))}]$, we have

$$P[\mathbb{E}_{\theta \sim \pi}[e^{\lambda(R^{\text{true}}(\theta) - R^{\text{emp}}(\theta))}] < \frac{\mathbb{E}_{(x_i, y_i) \sim \mathcal{D}} \mathbb{E}_{\theta \sim \pi}[e^{\lambda(R^{\text{true}}(\theta) - R^{\text{emp}}(\theta))}]}{\delta}] \geq 1 - \delta \quad \iff$$
$$P[\ln \mathbb{E}_{\theta \sim \pi}[e^{\lambda(R^{\text{true}}(\theta) - R^{\text{emp}}(\theta))}] < \ln \mathbb{E}_{(x_i, y_i) \sim \mathcal{D}} \mathbb{E}_{\theta \sim \pi}[e^{\lambda(R^{\text{true}}(\theta) - R^{\text{emp}}(\theta))}] + \ln \frac{1}{\delta}] \geq 1 - \delta$$

Plugging Eq (1) in, we have

$$P[\lambda(\mathbb{E}_{\theta \sim \rho}[(R^{\text{true}}(\theta)] - \mathbb{E}_{\theta \sim \rho}[R^{\text{emp}}(\theta)]) - D(\,\rho\,||\,\pi\,) <$$
$$\ln \mathbb{E}_{(x_i, y_i) \sim \mathcal{D}} \mathbb{E}_{\theta \sim \pi}[e^{\lambda(R^{\text{true}}(\theta) - R^{\text{emp}}(\theta))}] + \ln \frac{1}{\delta}] \geq 1 - \delta$$

Rearrange the above inequality and the Theorem is proved. $\square$

Remember that the Moment Generating Function (MGF) of a random variable X is $M_X(\lambda) = \mathbb{E}[e^{\lambda X}]$. In the proof above, λ is introduced by Markov inequality, and

$$\mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}\mathbb{E}_{\theta\sim\pi}[e^{\lambda(R^{\text{true}}(\theta)-R^{\text{emp}}(\theta))}]$$

is indeed the MGF of $R^{\text{true}}(\theta) - R^{\text{emp}}(\theta)$.

Like Catoni's Bound, Alquier's Bound holds for any $\lambda > 0$. Thus we can choose λ to minimize the right hand side of the inequality

$$\mathbb{E}_{\theta\sim\rho}[R^{\text{emp}}(\theta)] + \frac{1}{\lambda}\left[D(\,\rho\,||\,\pi\,) + \ln\frac{1}{\delta} + \Psi_{L,\pi,\mathcal{D}}(\lambda, n)\right]$$

to get the tightest bound. However, to calculate the minimizer λ^*, we need to know $D(\,\rho\,||\,\pi\,)$. If we fix π, then λ^* will be a function of ρ.

For convenience, we can let λ be a value independent of ρ, like n or $\sqrt{n}$. In this case, the bound will not be optimal but applicable to any ρ.

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Problem Settings

Consider the Linear Regression problem:

$$L(f_\theta(x_i) - y_i) = (y_i - \theta \cdot x_i)^2$$
$$R^{\mathsf{emp}}(\theta) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \theta \cdot x_i)^2$$

where $\theta \in \mathbb{R}^d$, $\theta \cdot x_i = \theta^T x_i \in \mathbb{R}$.

Assumption 2.1: Suppose $x_i \sim \mathcal{N}_d(0, \sigma_x^2 I)$ where $\sigma_x > 0$ is a constant. Suppose there exists θ^* such that for any i, $y_i = \theta^* \cdot x_i + e_i$ where $e_i \sim \mathcal{N}(0, \sigma_e^2)$ and $\sigma_e > 0$ is a constant. e_i and e_j are independent for any $i \neq j$.

Lemma 2.2: Suppose Assumption 2.1 holds, given $\theta^*, \sigma_x, \sigma_e$, then for any θ, $y_i - \theta \cdot x_i \sim \mathcal{N}(0, v_\theta)$, where $v_\theta = \sigma_x^2\|\theta - \theta^*\|^2 + \sigma_e^2$.

Proof: By Assumption 2.1, we have

$$y_i - \theta \cdot x_i = (\theta^* - \theta) \cdot x_i + e_i$$

Let $\theta' = (\theta^* - \theta)$, θ'_j be the jth element of θ', and x_{ij} be the jth element of x_i, then

$$y_i - \theta \cdot x_i = \sum_{i=1}^{d} \theta'_j x_{ij} + e_i$$

Since x_{ij}s are iid sampled from $\mathcal{N}(0, \sigma_x^2)$, e_i is sampled from $\mathcal{N}(0, \sigma_e^2)$, and θ'_js are scalars, then $y_i - \theta \cdot x_i$ is a random variable satisfying Gaussian distribution, with

$$\mathbb{E}[y_i - \theta \cdot x_i] = \sum_{i=1}^{d} \theta'_j \mathbb{E}[x_{ij}] + \mathbb{E}[e_i] = 0$$

$$\begin{aligned}\mathsf{Var}[y_i - \theta \cdot x_i] &= \sum_{i=1}^{d} {\theta'_j}^2 \mathsf{Var}[x_{ij}] + \mathsf{Var}[e_i] \\ &= \sigma_x^2 \|\theta^* - \theta\|^2 + \sigma_e^2\end{aligned}$$

□

Note that under Assumption 2.1, $\mathcal{D}$ will not be an arbitrary distribution but be one whose marginal of x_i is $\mathcal{N}_d(0, \sigma_x^2 I)$ and marginal of y_i is $\mathcal{N}(0, \sigma_x^2 \|\theta^*\|^2 + \sigma_e^2)$.

Bound for Linear Regression

Theorem 2.3 (Shalaeva's Bound) [2]: In Theorem 1, let the loss function be $L(f_\theta(x_i) - y_i) = (y_i - \theta \cdot x_i)^2$. Under Assumption 2.1, we have

$$P\left(\mathbb{E}_{\theta\sim\rho}[R^{\mathsf{true}}(\theta)] < \mathbb{E}_{\theta\sim\rho}[R^{\mathsf{emp}}(\theta)] + \frac{1}{\lambda}\left[D(\,\rho\,||\,\pi\,) + \ln\frac{1}{\delta} + \Psi_{L,\pi,\mathcal{D}}(\lambda, n)\right]\right) \geq 1-\delta$$

where

$$\Psi_{L,\pi,\mathcal{D}}(\lambda, n) = \ln \mathbb{E}_{\theta\sim\pi} \frac{e^{\lambda v_\theta}}{\left(1+\frac{\lambda v_\theta}{\frac{n}{2}}\right)^{\frac{n}{2}}} \leq \ln \mathbb{E}_{\theta\sim\pi} \exp\left(\frac{\lambda^2 v_\theta^2}{\frac{n}{2}}\right)$$

Proof: In Theorem 1,

$$\begin{aligned}\Psi_{L,\pi,\mathcal{D}}(\lambda, n) &= \ln \mathbb{E}_{\theta\sim\pi}\mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}[e^{\lambda(R^{\mathsf{true}}(\theta) - R^{\mathsf{emp}}(\theta))}] \\ &= \ln \mathbb{E}_{\theta\sim\pi}\left(e^{\lambda R^{\mathsf{true}}(\theta)}\mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}[e^{-\lambda R^{\mathsf{emp}}(\theta)}]\right)\end{aligned}$$

We have $R^{\text{true}}(\theta) = \mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}[(y_i - \theta\cdot x_i)^2] = v_\theta$ and

$$\mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}[e^{-\lambda R^{\text{emp}}(\theta)}] = \mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}[e^{-\frac{\lambda v_\theta}{n}\sum_{i=1}^{n}(\frac{y_i-\theta\cdot x_i}{\sqrt{v_\theta}})^2}] \tag{2}$$

Since $\frac{y_i-\theta\cdot x_i}{\sqrt{v_\theta}} \sim \mathcal{N}(0,1)$, $\sum_{i=1}^{n}(\frac{y_i-\theta\cdot x_i}{\sqrt{v_\theta}})^2 \sim \chi^2(n)$. Thus Eq (2) is the MGF of $\chi^2(n)$.

$$\mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}[e^{-\frac{\lambda v_\theta}{n}\sum_{i=1}^{n}(\frac{y_i-\theta\cdot x_i}{\sqrt{v_\theta}})^2}] = \left(1 + 2\frac{\lambda v_\theta}{n}\right)^{-\frac{n}{2}}$$

Therefore,

$$\Psi_{L,\pi,\mathcal{D}}(\lambda,n) = \ln \mathbb{E}_{\theta\sim\pi}\frac{e^{\lambda v_\theta}}{\left(1+\frac{\lambda v_\theta}{\frac{n}{2}}\right)^{\frac{n}{2}}}$$

Since for any $x > -1$, $\frac{x}{x+1} \leq \ln(x+1)$, let $k > 0$, we have $e^{\frac{xk}{x+1}} \leq (x+1)^k \Rightarrow e^{\frac{xk}{x+k}} \leq (\frac{x}{k}+1)^k$. Let $x = \lambda v_\theta, k = \frac{n}{2}$, we have

$$\left(1+\frac{\lambda v_\theta}{\frac{n}{2}}\right)^{\frac{n}{2}} \geq \exp\left(\frac{\lambda v_\theta \frac{n}{2}}{\lambda v_\theta + \frac{n}{2}}\right)$$

Therefore,

$$\Psi_{L,\pi,\mathcal{D}}(\lambda, n) = \ln \mathbb{E}_{\theta\sim\pi} \frac{e^{\lambda v_\theta}}{\left(1 + \frac{\lambda v_\theta}{\frac{n}{2}}\right)^{\frac{n}{2}}} \leq \ln \mathbb{E}_{\theta\sim\pi} \exp\left(\lambda v_\theta - \frac{\lambda v_\theta \frac{n}{2}}{\lambda v_\theta + \frac{n}{2}}\right)$$
$$= \ln \mathbb{E}_{\theta\sim\pi} \exp\left(\frac{\lambda^2 v_\theta^2}{\lambda v_\theta + \frac{n}{2}}\right) \leq \ln \mathbb{E}_{\theta\sim\pi} \exp\left(\frac{\lambda^2 v_\theta^2}{\frac{n}{2}}\right)$$

$\square$

We will show that with proper choice of λ, the bound will converge to 0 as $n \to \infty$.

(1) When λ does not depend on n, as $n \to \infty$, we have

$$P\left(\mathbb{E}_{\theta\sim\rho}[R^{\text{true}}(\theta)] < \mathbb{E}_{\theta\sim\rho}[R^{\text{emp}}(\theta)] + \frac{1}{\lambda}\left[D(\,\rho\,||\,\pi\,) + \ln\frac{1}{\delta}\right]\right) \geq 1 - \delta$$

This is because

$$\lim_{n\to\infty}\left(1 + \frac{\lambda v_\theta}{\frac{n}{2}}\right)^{\frac{n}{2}} = e^{\lambda v_\theta}$$

such that $\lim_{n\to\infty} \Psi_{L,\pi,\mathcal{D}}(\lambda, n) = 0$. In this case, even n goes to infinity, there is still a gap $\frac{1}{\lambda}\left[D(\,\rho\,||\,\pi\,) + \ln\frac{1}{\delta}\,\right]$ that cannot be minimized.

(2) When λ depends on n, we can let $\lambda = n^{\frac{1}{d}}$ such that

$$P\left(\mathbb{E}_{\theta\sim\rho}[R^{\mathsf{true}}(\theta)] < \mathbb{E}_{\theta\sim\rho}[R^{\mathsf{emp}}(\theta)] + \frac{D(\,\rho\,||\,\pi\,)}{n^{\frac{1}{d}}} + \frac{\ln\left(\frac{1}{\delta}\right)}{n^{\frac{1}{d}}} \right.$$
$$\left. + \frac{1}{n^{\frac{1}{d}}} \ln \mathbb{E}_{\theta\sim\pi} \exp\left(\frac{n^{\frac{2}{d}} v_\theta^2}{\frac{n}{2}}\right)\right) \geq 1 - \delta$$

Then the gap will converge to 0 as $n \to \infty$. We show the convergence of the third term:

$$\lim_{n\to\infty} \frac{1}{n^{\frac{1}{d}}} \ln \mathbb{E}_{\theta\sim\pi} \exp\left(\frac{n^{\frac{2}{d}} v_\theta^2}{\frac{n}{2}}\right) = \lim_{n\to\infty} \ln\left[\mathbb{E}_{\theta\sim\pi} \exp\left(2n^{\frac{2}{d}-1} v_\theta^2\right)\right]^{n^{-\frac{1}{d}}} = \ln\left[\mathbb{E}_{\theta\sim\pi} 1\right]^0 = 0$$

Extension to Non-i.i.d. Case

Let's consider a general case that x_i is sampled from a multivariate Gaussian distribution whose dimensions are not i.i.d..

Assumption 2.4: Suppose $x_i \sim \mathcal{N}_d(0, Q_x)$ where $Q_x \in \mathbb{R}^{d\times d}$ is a positive definite matrix. Suppose there exists θ^* such that for any i, $y_i = \theta^* \cdot x_i + e_i$ where $e_i \sim \mathcal{N}(0, \sigma_e^2)$ and $\sigma_e > 0$ is a constant. e_i and e_j are independent for any $i \neq j$.

The reason why we require Q_x to be positive definite is shown in Appendix 3.

Lemma 2.5: Suppose Assumption 2.4 holds, given $\theta^*, \sigma_x, \sigma_e$, then for any θ, $y_i - \theta \cdot x_i \sim \mathcal{N}(0, \breve{v}_\theta)$, where $\breve{v}_\theta = (\theta^* - \theta)^T Q_x (\theta^* - \theta) + \sigma_e^2$.

Proof: This Lemma is an extension of Lemma 2.2. Since $y_i - \theta \cdot x_i = (\theta^* - \theta)x_i + e_i$, and according to Theorem A.3.5, $(\theta^* - \theta)x_i \sim \mathcal{N}(0, (\theta^* - \theta)^T Q_x (\theta^* - \theta))$, we proved the theorem. $\square$

Theorem 2.6 discusses the case that x_is are i.i.d. from $\mathcal{N}_d(0, Q_x)$. Theorem 2.7 discusses the case that x_is are identically but not independently distributed from $\mathcal{N}_d(0, Q_x)$, for example, x_is may be sampled in a time series where the current sample depends on all the previous samples.

Theorem 2.6: In Theorem 1, let the loss function be $L(f_\theta(x_i), y_i) = (y_i - \theta \cdot x_i)^2$. Under Assumption 2.4, suppose x_is are i.i.d. sampled from $\mathcal{N}_d(0, Q_x)$, we have

$$P\left(\mathbb{E}_{\theta\sim\rho}[R^{\text{true}}(\theta)] < \mathbb{E}_{\theta\sim\rho}[R^{\text{emp}}(\theta)] + \frac{1}{\lambda}\left[D(\,\rho\,||\,\pi\,) + \ln\frac{1}{\delta} + \Psi_{L,\pi,\mathcal{D}}(\lambda, n)\right]\right) \geq 1 - \delta$$

where

$$\Psi_{L,\pi,\mathcal{D}}(\lambda, n) \leq \ln \mathbb{E}_{\theta\sim\pi} \frac{e^{\lambda \breve{v}_\theta}}{\left(1 + \frac{\lambda \breve{v}_\theta}{\frac{n}{2}}\right)^{\frac{n}{2}}}$$

The proof of Theorem 2.6 is exactly the same as Theorem 2.3, just replace v_θ by $\breve{v}_\theta$.

If x_is are identically but not independently distributed from $\mathcal{N}_d(0, Q_x)$, we still have $R^{\text{true}}(\theta) = \mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}[R^{\text{emp}}(\theta)]$, because

$$\begin{aligned}\mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}[R^{\text{emp}}(\theta)] &= \mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}[\frac{1}{n}\sum_{i=1}^{n} L(f_\theta(x_i), y_i)] \\ &= \frac{1}{n}\sum_{i=1}^{n} \mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}[L(f_\theta(x_i), y_i)] = R^{\text{true}}(\theta)\end{aligned}$$

This does not require $L(f_\theta(x_i), y_i)$ to be independent for different i. So the concentration inequality is still applicable. However, $R^{\text{emp}}(\theta)$ may not converge to $R^{\text{true}}(\theta)$ when $n \to \infty$, as the independency condition of Law of Large Numbers is not satisfied.

In fact, independency of samples is a sufficient but not necessary assumption in statistical learning [7]. The feature samples can be dependent in some cases, for example, in language data, the words in a sentence are dependent. Suppose the feature x and label y comes from an unknown distribution $p(x, y)$, the goal of machine learning is to learn the posterior distribution $p(y|x)$, which is independent from the data distribution $p(x)$.

For language data, the model learns the distribution $p(y|x_k, x_{k-1}, ..., x_1)$, where k is the size of the window. $p(y|x_k, x_{k-1}, ..., x_1)$ is independent of the feature distribution $p(x_k, x_{k-1}, ..., x_1)$. The dependency of $x_1, ..., x_k$ will only affect $p(x_k, x_{k-1}, ..., x_1)$ and will not affect $p(y|x_k, x_{k-1}, ..., x_1)$.

Theorem 2.7: In Theorem 1, let the loss function be $L(f_\theta(x_i), y_i) = (y_i - \theta \cdot x_i)^2$. Under Assumption 2.4, suppose x_is are identically sampled from $\mathcal{N}_d(0, Q_x)$ but not independent. Let $X = [x_1^T, x_2^T, ..., x_n^T]^T \in \mathbb{R}^{dn\times 1}$ and let $Q_X = \mathbb{E}[XX^T] \in \mathbb{R}^{dn\times dn}$ be the joint covariance matrix. Let ω be the minimum eigenvalue of Q_X and assume $\omega > 0$. We have

$$P\left(\mathbb{E}_{\theta\sim\rho}[R^{\text{true}}(\theta)] < \mathbb{E}_{\theta\sim\rho}[R^{\text{emp}}(\theta)] + \frac{1}{\lambda}\left[D(\,\rho\,||\,\pi\,) + \ln\frac{1}{\delta} + \Psi_{L,\pi,\mathcal{D}}(\lambda, n)\right]\right) \geq 1-\delta$$

where

$$\Psi_{L,\pi,\mathcal{D}}(\lambda, n) \leq \ln \mathbb{E}_{\theta\sim\pi} \frac{e^{\lambda \breve{v}_\theta}}{\left(1 + \frac{\lambda\omega_\theta}{\frac{n}{2}}\right)^{\frac{n}{2}}}$$

and

$$\omega_\theta = \omega(\theta^* - \theta)^T(\theta^* - \theta) + \sigma_e^2$$

Proof: In Theorem 1,

$$\begin{aligned}\Psi_{L,\pi,\mathcal{D}}(\lambda, n) &= \ln \mathbb{E}_{\theta\sim\pi}\mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}\big[e^{\lambda(R^{\text{true}}(\theta)-R^{\text{emp}}(\theta))}\big] \\ &= \ln \mathbb{E}_{\theta\sim\pi}\left(e^{\lambda R^{\text{true}}(\theta)}\mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}\big[e^{-\lambda R^{\text{emp}}(\theta)}\big]\right)\end{aligned}$$

We have $R^{\text{true}}(\theta) = \mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}\big[(y_i - \theta\cdot x_i)^2\big] = \breve{v}_\theta$ and

$$\mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}\big[e^{-\lambda R^{\text{emp}}(\theta)}\big] = \mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}\big[e^{-\frac{\lambda}{n}\sum_{i=1}^{n}(y_i-\theta\cdot x_i)^2}\big]$$

Let $z_i = y_i - \theta\cdot x_i$ and $Z = [z_1, z_2, ..., z_n]^T \in \mathbb{R}^{n\times 1}$. Then

$$\sum_{i=1}^{n}(y_i - \theta\cdot x_i)^2 = \sum_{i=1}^{n} z_i^2 = Z^T Z$$

Since the z_is in Z are dependent, we need to convert them to independent random variables. The key idea is to use the covariance matrix. Denote $Q_Z = \mathbb{E}[ZZ^T] \in \mathbb{R}^{n\times n}$. Since for any z_i and z_j,

$$\begin{aligned}\mathbb{E}[z_i z_j] &= \mathbb{E}[(\theta^* - \theta)^T x_i(\theta^* - \theta)^T x_j] + \mathbb{E}[e_i e_j] \\ &= (\theta^* - \theta)^T\mathbb{E}[x_i x_j^T](\theta^* - \theta) + \sigma_e^2\mathbf{1}_{[i=j]}\end{aligned}$$

we have that $Q_Z = D_\theta^T Q_X D_\theta + \sigma_e^2 I$, where $I \in \mathbb{R}^{n\times n}$ is an identity matrix and

$$D_\theta = \text{diag}(\underbrace{(\theta^* - \theta), (\theta^* - \theta), .., (\theta^* - \theta)}_{n \text{ times}}) \in \mathbb{R}^{dn\times n}$$

Thus for any $p \in \mathbb{R}^d/\{0\}$,

$$\begin{aligned} p^T Q_Z p &= (D_\theta p)^T Q_X (D_\theta p) + \sigma_e^2 p^T p \\ &\geq \omega (D_\theta p)^T (D_\theta p) + \sigma_e^2 p^T p \qquad (3) \\ &= \left[\omega(\theta^* - \theta)^T(\theta^* - \theta) + \sigma_e^2\right] p^T p \qquad (4) \end{aligned}$$

where Eq (3) is because: Suppose $Q_X = Q^T \Lambda Q$ is the eigenvalue decomposition of Q_X where $\Lambda = \text{diag}(\omega_1, \omega_2, ..., \omega_{dn})$, let $\omega = \min\{\omega_1, \omega_2, ..., \omega_{dn}\}$, $v = D_\theta p, u = Qv$, we have,

$$v^T Q_X v = u^T \Lambda u = \sum_{i=1}^{dn} \omega_i u_i^2 \geq \omega \sum_{i=1}^{dn} u_i^2 = \omega v^T Q^T Q v = \omega v^T v$$

Since $\omega(\theta^* - \theta)^T(\theta^* - \theta) + \sigma_e^2 > 0$, we have $p^T Q_Z p > 0$. Thus Q_Z is positive definite. Hence (1) Z is from $\mathcal{N}_n(0, Q_Z)$; (2) Q_Z must have an inverse Q_Z^{-1}. Let $Q_Z = Q^T \Lambda Q$, then $Q_Z^{-1} = Q^T \Lambda^{-1} Q$.

Let $Q_Z^{-1} = Q_Z^{-1/2} Q_Z^{-1/2}$ where $Q_Z^{-1/2} = Q^T \Lambda^{-1/2} Q$, we can write

$$Z^T Z = Z^T Q_Z^{-1/2} Q_Z Q_Z^{-1/2} Z = (Q_Z^{-1/2} Z)^T Q_Z (Q_Z^{-1/2} Z)$$

Let $S = Q_Z^{-1/2} Z = [s_1, s_2, ..., s_n] \in \mathbb{R}^{n \times 1}$. By Theorem A.3.5, each s_i is a Gaussian random variable. We have $\mathbb{E}[S] = Q_Z^{-1/2} \mathbb{E}[Z] = 0$ and

$$\mathbb{E}[SS^T] = Q_Z^{-1/2} \mathbb{E}[ZZ^T] Q_Z^{-1/2} = Q_Z^{-1/2} Q_Z Q_Z^{-1/2} = I$$

which means all elements in S are i.i.d. from $\mathcal{N}(0,1)$. By Eq (4), let $p = S$, then

$$Z^T Z = S^T Q_Z S \geq \left[\omega(\theta^* - \theta)^T (\theta^* - \theta) + \sigma_e^2\right] S^T S = \omega_\theta S^T S = \omega_\theta (\sum_{i=1}^n s_i^2)$$

where $\sum_{i=1}^n s_i^2 \sim \chi^2(n)$. Therefore,

$$\Psi_{L,\pi,\mathcal{D}}(\lambda, n) = \ln \mathbb{E}_{\theta\sim\pi} \left(e^{\lambda \breve{v}_\theta} \mathbb{E}_{(x_i,y_i)\sim\mathcal{D}} [e^{-\frac{\lambda}{n} \sum_{i=1}^n z_i^2}] \right)$$

$$\leq \ln \mathbb{E}_{\theta\sim\pi} \left(e^{\lambda \breve{v}_\theta} \mathbb{E}_{(x_i,y_i)\sim\mathcal{D}} [e^{-\frac{\lambda \omega_\theta}{n} \sum_{i=1}^n s_i^2}] \right) = \ln \mathbb{E}_{\theta\sim\pi} \frac{e^{\lambda \breve{v}_\theta}}{\left(1 + \frac{\lambda \omega_\theta}{\frac{n}{2}}\right)^{\frac{n}{2}}}$$

□

Theorem 2.7 implies that when the dimensions of x_i are not i.i.d Gaussian, as $n \to \infty$, $\Psi_{L,\pi,\mathcal{D}}(\lambda, n)$ will converge but not converge to 0. This is because

$$\lim_{n\to\infty} \ln \mathbb{E}_{\theta\sim\pi} \frac{e^{\lambda \breve{v}_\theta}}{\left(1 + \frac{\lambda\omega_\theta}{\frac{n}{2}}\right)^{\frac{n}{2}}} = \ln \mathbb{E}_{\theta\sim\pi} e^{\lambda(\breve{v}_\theta - \omega_\theta)}$$

And as we have shown in the proof, $\breve{v}_\theta \geq \omega_\theta$. The equality is obtained only when all of the eigenvalues of Q_Z are equal, which is not likely to happen.

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This section introduces some fundamental ideas of concentration inequalities from the book [4]. Concentration inequalities explains under what conditions the random variables will concentrate around their expectations.

Given a random variable X satisfying $\mathbb{E}X = 0$. For any $t > 0$, we say $P(X > t)$ is the right tail probability of X and $P(X < -t)$ is the left tail probability of X.

Now we show the connection between MGF and tail probabilities. Denote

$$\psi_X(\lambda) = \ln \mathbb{E}[e^{\lambda X}]$$

as the logarithm of the MGF of X.

Definition A.1.1: If $\psi_X(\lambda) \leq \frac{\lambda^2 v}{2}$, then X satisfies sub-Gaussian distribution with variance factor v.

Theorem A.1.2: If X satisfies sub-Gaussian distribution with variance v, then for any $t > 0$,

$$P(X > t) \leq e^{-\frac{t^2}{2v}} \quad \text{and} \quad P(X < -t) \leq e^{-\frac{t^2}{2v}}$$

Proof:
Let $\lambda > 0$, applying Chernoff inequality

$$P(X > t) = P(e^{\lambda X} > e^{\lambda t}) \leq e^{-\lambda t}\mathbb{E}[e^{\lambda X}] \leq e^{-\lambda t}e^{\frac{\lambda^2 v}{2}} = e^{\frac{\lambda^2 v}{2} - \lambda t}$$

Now we find λ to minimize the upper bound. When $\lambda = \frac{t}{v}$, we get $\min_\lambda\{\frac{\lambda^2 v}{2} - \lambda t\} = -\frac{t^2}{2v}$. The $P(X < -t)$ case can be proved similarly. Just applying Chernoff bound with $\lambda < 0$. $\square$

Theorem A.1.2 says the tail probability of a sub-Gaussian random variable is upper-bounded by a Gaussian distribution with 0 mean and v variance.

Theorem A.1.3: If $X \sim \mathcal{N}(\mathbb{E}[X], v)$, then $Y = X - \mathbb{E}X$ is sub-Gaussian with variance v.

Proof: Since $Y \sim \mathcal{N}(0, v)$, for any $\lambda > 0$,

$$
\begin{aligned}
P(Y > t) \leq -e^{\lambda t}\mathbb{E}[e^{\lambda Y}] &= e^{-\lambda t} \int e^{\lambda y} \frac{1}{\sqrt{2\pi v}} e^{-\frac{y^2}{2v^2}} dy \\
&= e^{-\lambda t + \frac{\lambda^2 v}{2}} \int \frac{1}{\sqrt{2\pi v}} e^{-\frac{(y - v\lambda)^2}{2v}} dy \\
&= e^{-\lambda t + \frac{\lambda^2 v}{2}} \leq e^{-\frac{t^2}{2v}}
\end{aligned}
$$

$P(Y < -t)$ case can be proved in a similar way. $\square$

Definition A.1.4: If $\psi_X(\lambda) \leq \frac{\lambda^2 v}{2(1-c\lambda)}$ and $0 < \lambda < \frac{1}{c}$, then X satisfies sub-Gamma distribution with variance factor v and scale parameter c.

The upper bound of MGF of sub-Gamma distribution is looser than sub-Gaussian distribution. For those random variables that are not quite sub-Gaussian but nearly, we can assume them to be sub-Gamma.

The PDF of the distribution Gamma(a, b) is

$$f(x) = \frac{x^{a-1} e^{-\frac{x}{b}}}{\Gamma(a) b^a}\ , \quad x \geq 0$$

If $X \sim$ Gamma(a, b), then $\mathbb{E}[X] = ab$ and Var$[X] = ab^2$.

Theorem A.1.5: Let $X \sim$ Gamma(a, b), $Y = X - \mathbb{E}[X]$, then for any $t > 0$,

$$\psi_Y(\lambda) \leq \frac{\lambda^2 v}{2(1 - c\lambda)}$$

where $v = ab^2, c = b$, and $0 < \lambda < \frac{1}{b}$.

Proof:

$$\begin{aligned}
\mathbb{E}[e^{\lambda Y}] &= \int_0^\infty e^{\lambda(x-ab)} \frac{x^{a-1} e^{-x/b}}{\Gamma(a) b^a} dx = \frac{e^{-\lambda ab}}{\Gamma(a) b^a} \int_0^\infty x^{a-1} e^{(\lambda - \frac{1}{b})x} dx \\
&= \frac{e^{-\lambda ab}}{\Gamma(a) b^a} \Gamma(a) (\frac{1}{\frac{1}{b} - \lambda})^a = \frac{e^{-\lambda ab}}{(1 - b\lambda)^a} = e^{-\lambda ab - a \ln(1 - b\lambda)} \qquad (5)
\end{aligned}$$

Use the following Lemma:

Lemma A.1.6: For all $u \in (0, 1)$,

$$-\ln(1-u) - u \leq \frac{u^2}{2(1-u)}$$

Proof: By Taylor Theorem,

$$\ln(1-u) = \sum_{k=1}^{\infty} -\frac{u^k}{k} \geq -u - \sum_{k=2}^{\infty} \frac{u^k}{2} = -u - \frac{u^2}{2(1-u)}$$

$\square$

Therefore, let $u = \lambda b$ where $0 < \lambda < \frac{1}{b}$, we have

$$e^{-\lambda ab - a\ln(1-b\lambda)} = \exp\left(\frac{\lambda^2 ab^2}{2(1-\lambda b)}\right)$$

And

$$\psi_Y(\lambda) = \ln \mathbb{E}[e^{\lambda Y}] \leq \frac{\lambda^2 ab^2}{2(1-\lambda b)}$$

$\square$

Theorem shows that if X satisfies the Gamma distribution, then $Y = X - \mathbb{E}X$ satisfies sub-Gamma distribution. This bound holds for both right tail and left tail probability. Note that Y is a shifted Gamma distribution. Its left tail and right tail are not symmetric. In fact, for the left tail, we have a tighter bound.

Corollary A.1.7: Consider the settings of Theorem A.1.5. When $Y < 0$, we have

$$\psi_Y(\lambda) \leq \frac{\lambda^2 v}{2}$$

where $v = ab^2$ and $0 < \lambda < \frac{1}{b}$.

Proof: For any $u < 0$, we have

$$-\ln(1-u) - u < \frac{u^2}{2} \tag{6}$$

Apply Eq (6) to Eq (5) by letting $u = \lambda b$, and theorem is proved. □

Corollary A.1.7 shows that the left tail probability of Y is sub-Gaussian, which is tighter than sub-Gamma. This means Y is more concentrated on left tail than right tail.

Theorem A.1.8: If a random variable X is of sub-Gamma with variance factor v and scale parameter c, then for any $t > 0$, we have

$$P(X > t) \leq \exp\left(-\frac{v}{c^2} h\left(\frac{ct}{v}\right)\right)$$

where $h(u) = 1 + u - \sqrt{1 + 2u}$ for $u > 0$. Or equivalently, for any $s > 0$,

$$P(X > \sqrt{2vs} + cs) \leq e^{-s}$$

Proof: Given that

$$\psi_X(\lambda) \leq \frac{\lambda^2 v}{2(1 - c\lambda)}$$

By Chernoff inequality, we have

$$P(X > t) \leq e^{-\lambda t}\mathbb{E}[e^{\lambda X}] \leq \exp\left(\frac{\lambda^2 v}{2(1 - c\lambda)} - \lambda t\right)$$

Let $f(\lambda) = \frac{\lambda^2 v}{2(1-c\lambda)} - \lambda t$, we want to find $\lambda \in (0, \frac{1}{c})$ to minimize $f(\lambda)$.

$$f'(\lambda) = -t + \frac{2\lambda v - c\lambda^2 v}{2(1-c\lambda)^2}\ , \quad f''(\lambda) = \frac{4v(1-c\lambda)^3 + 4\lambda cv(1-c\lambda)(2-c\lambda)}{4(1-c\lambda)^4}$$

Since $f''(\lambda) \geq 0$ on $(0, \frac{1}{c})$, solving $f'(\lambda) = 0$, we get

$$\lambda^* = \frac{1}{c} - \frac{\sqrt{v}}{c} \cdot \frac{1}{\sqrt{2tc+v}}$$

Thus

$$\min f(\lambda) = f(\lambda^*) = -\frac{v}{c^2} - \frac{t}{c} + \frac{\sqrt{v}}{c^2}\sqrt{2tc+v} = -\frac{v}{c^2} h\left(\frac{ct}{v}\right)$$

Since $h(u) = 1 + u - \sqrt{1+2u}$, we know that $h^{-1}(u) = u + \sqrt{2u}$. Thus

$$s = \frac{v}{c^2} h\left(\frac{ct}{v}\right) \iff t = \frac{v}{c} h^{-1}\left(\frac{sc^2}{v}\right) = sc + \sqrt{2sv}$$

$\square$

Appendix 2: Germain's Bound

The Germain's bound is an earlier work of Theorem 2.3 (Shalaeva's Bound) given by Germail et al [3]. This bound is looser than Shalaeva's Bound. Moreover, it does not converge to 0 as $n \to \infty$ for any $\lambda > 0$.

In Theorem 1 we denote

$$\Psi_{L,\pi,\mathcal{D}}(\lambda, n) = \ln \mathbb{E}_{\theta\sim\pi}\mathbb{E}_{(x_i,y_i)\sim\mathcal{D}}[e^{\lambda(R^{\text{true}}(\theta)-R^{\text{emp}}(\theta))}]$$

Here we can consider $\Psi_{L,\pi,\mathcal{D}}(\lambda, n)$ as the logarithm MGF of the random variable $R^{\text{true}}(\theta) - R^{\text{emp}}(\theta)$, which is a function of both dataset $S = \{(x_i, y_i)\}_{i=1}^{n}$ and parameter θ. The following theorem shows that when the loss function L is squared loss, $R^{\text{true}}(\theta) - R^{\text{emp}}(\theta)$ is a sub-Gamma random variable.

Theorem A.2.1 (Germain's Bound): Under the same settings of Theorem 2.3, assume $\theta \sim \mathcal{N}_d(0, \sigma_\pi^2 I)$ where $\sigma_\pi > 0$ is a constant. Then

$$\Psi_{L,\pi,\mathcal{D}}(\lambda, n) \leq \frac{\lambda^2 v}{2(1 - c\lambda)}$$

where $v = \frac{2}{\lambda}[\sigma_x^2(\sigma_\pi^2 d + \|w^*\|^2) + \sigma_e^2(1 - \lambda c)]$ and $c = 2\sigma_x^2\sigma_\pi^2$.

Proof:

$$
\begin{aligned}
\Psi_{L,\pi,\mathcal{D}}(\lambda,n) &= \ln \mathbb{E}_\theta \mathbb{E}_{(x_i,y_i)}[e^{\lambda(R^{\text{true}}(\theta)-R^{\text{emp}}(\theta))}] \\
&\le \ln \mathbb{E}_\theta \mathbb{E}_{(x_i,y_i)}[e^{\lambda R^{\text{true}}(\theta)}] && (7)\\
&= \ln \mathbb{E}_\theta \mathbb{E}_{(x_i,y_i)}[e^{\lambda \mathbb{E}_{(x_i,y_i)}[(y_i-\theta\cdot x_i)^2]}] \\
&= \ln \mathbb{E}_\theta [e^{\lambda \mathbb{E}_{(x_i,y_i)}[(y_i-\theta\cdot x_i)^2]}] && (8)\\
&= \ln \mathbb{E}_\theta [e^{\lambda(\sigma_x^2\|\theta^*-\theta\|^2+\sigma_e^2)}] && (9)\\
&= \ln \left[\frac{1}{(1-2\lambda\sigma_x^2\sigma_\pi^2)^{\frac{d}{2}}} \exp\left(\frac{\lambda\sigma_x^2\|\theta^*\|^2}{1-2\lambda\sigma_x^2\sigma_\pi^2}+\lambda\sigma_e^2\right)\right] && (10)\\
&= -\frac{d}{2}\ln(1-2\lambda\sigma_x^2\sigma_\pi^2) + \frac{\lambda\sigma_x^2\|w^*\|^2}{1-2\lambda\sigma_x^2\sigma_\pi^2}+\lambda\sigma_e^2 \\
&\le \frac{\lambda\sigma_x^2\sigma_\pi^2 d}{1-2\lambda\sigma_x^2\sigma_\pi^2} + \frac{\lambda\sigma_x^2\|w^*\|^2}{1-2\lambda\sigma_x^2\sigma_\pi^2}+\lambda\sigma_e^2 && (11)\\
&= \frac{\lambda(\sigma_x^2\sigma_\pi^2 d+\sigma_x^2\|w^*\|^2+(1-2\lambda\sigma_x^2\sigma_\pi^2)\sigma_e^2)}{1-2\lambda\sigma_x^2\sigma_\pi^2} = \frac{\lambda^2 v}{2(1-c\lambda)}
\end{aligned}
$$

where we let $v = \frac{2}{\lambda}[\sigma_x^2(\sigma_\pi^2 d + \|w^*\|^2) + \sigma_e^2(1-\lambda c)]$ and $c = 2\sigma_x^2\sigma_\pi^2$.

Eq (7) is because $R^{\mathsf{emp}}(\theta) \geq 0$. Eq (8) is because $e^{\lambda \mathbb{E}_{(x_i, y_i)}[(y_i - \theta \cdot x_i)^2]}$ is independent of x_i and y_i. Eq (9) is obtained by Lemma 2.2.

For Eq (10), since the elements of θ are iid,

$$\begin{aligned} \ln \mathbb{E}_\theta [e^{\lambda(\sigma_x^2 \|\theta^* - \theta\|^2 + \sigma_e^2)}] &= \ln \left[\mathbb{E}_\theta [e^{\lambda \sigma_x^2 \sum_{i=1}^d (\theta_i^* - \theta_i)^2}] e^{\lambda \sigma_e^2} \right] \\ &= \ln \left[\prod_{i=1}^d \mathbb{E}_\theta [e^{\lambda \sigma_x^2 (\theta_i^* - \theta_i)^2}] e^{\lambda \sigma_e^2} \right] \end{aligned} \tag{12}$$

where each $\theta_i^* - \theta_i \sim \mathcal{N}(\theta_i^*, \sigma_\pi^2)$. Then we will utilize the following Lemma.

Lemma A.2.2: If $Y \sim \mathcal{N}(\mu, \sigma^2)$, then

$$\mathbb{E}_Y[e^{tY^2}] = (1 - 2t\sigma^2)^{-\frac{1}{2}} \exp\left(\frac{t\mu^2}{1 - 2t\sigma^2} \right)$$

Proof: Let $X \sim \mathcal{N}(0, 1)$, by transformation,

$$\mathbb{E}_Y[e^{tY^2}] = \int e^{ty^2} f_Y(y) dy = \int e^{t(\sigma x+\mu)^2} f_X(x) \frac{d}{dy}\left(\frac{y-\mu}{\sigma}\right) d(\sigma x + \mu)$$
$$= \int e^{t(\sigma x+\mu)^2} f_X(x) dx = \mathbb{E}_X[e^{t(\sigma X+\mu)^2}]$$

And

$$\mathbb{E}_X[e^{t(\sigma X+\mu)^2}] = \int e^{t(\sigma x+\mu)^2} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx$$
$$= \sqrt{\frac{1}{1-2t\sigma^2}} \int \frac{1}{\sqrt{2\pi}\sqrt{\frac{1}{1-2t\sigma^2}}} \exp\left(-\frac{\left(x - \frac{t\sigma}{\frac{1}{2}-t\sigma^2}\right)^2}{2\frac{1}{1-2t\sigma^2}}\right) dx \exp\left(\frac{t\mu^2}{1-2t\sigma^2}\right)$$

The blue part of the above equation equals to 1. $\square$

Applying Lemma A.2.2 to Eq (12) by letting $t = \lambda\sigma_x^2, \mu = \theta_i^*, \sigma = \sigma_\pi$, we get

$$\ln \mathbb{E}_\theta[e^{\lambda(\sigma_x^2\|\theta^*-\theta\|^2+\sigma_e^2)}] = \ln\left[\prod_{i=1}^{d}\left[(1-2\lambda\sigma_x^2\sigma_\pi^2)^{-\frac{1}{2}} \exp\left(\frac{\lambda\sigma_x^2\theta_i^{*2}}{1-2\lambda\sigma_x^2\sigma_\pi^2}\right)\right] e^{\lambda\sigma_e^2}\right]$$
$$= \ln\left[\frac{1}{(1-2\lambda\sigma_x^2\sigma_\pi^2)^{\frac{d}{2}}} \exp\left(\frac{\lambda\sigma_x^2\|\theta^*\|^2}{1-2\lambda\sigma_x^2\sigma_\pi^2} + \lambda\sigma_e^2\right)\right]$$

Eq (11) is because $-\ln(1-x) \leq \frac{x}{1-x}$ for $x < 1$ and apply $x = 2\lambda\sigma_x^2\sigma_\pi^2$.

$\square$

Note that the bound of Theorem A.2.1 does not depend on n. This is because we removed $R^{\mathsf{emp}}(\theta)$ in Eq (7), which is the only term containing n. So the bound will not converge as $n \to \infty$.

Appendix 3: Multivariate Gaussian Distribution

Definition A.3.1 (Covariance Matrix): Let $x \in \mathbb{R}^d$ be a random vector and $\mu = \mathbb{E}[x]$ be the expectation of x. The covariance matrix is defined as $\Sigma = \mathbb{E}[(x-\mu)(x-\mu)^T] \in \mathbb{R}^{d\times d}$, where $\Sigma_{ij} = \mathrm{Cov}(x_i, x_j)$ for $1 \leq i, j \leq d$.

Definition A.3.2: Let $A \in \mathbb{R}^{d\times d}$ be a symmetric matrix,

- A is said to be positive definite if $x^T Ax > 0$ for all $x \in \mathbb{R}^d/\{0\}$.
- A is said to be positive semi-definite if $x^T Ax \geq 0$ for all $x \in \mathbb{R}^d$.

Theorem A.3.3: Let $A \in \mathbb{R}^{d\times d}$ be a symmetric matrix. A is positive definite if and only if all of its eigenvalues are positive.

Proof: First we show that A must have a eigenvalue decomposition $A = Q\Lambda Q^T$ where $Q \in \mathbb{R}^{d\times d}$ is an orthogonal matrix and $\Lambda \in \mathbb{R}^{d\times d}$ is a diagonal matrix. Since every square matrix A has a Schur factorization $A = QTQ^T$ where T is an upper-triangular matrix (see Theorem 24.9 of [5]), if A is symmetric, then T is diagonal.

The diagonal matrix Λ must contain all the eignevalues of A. This is because Q being orthogonal means there are d linearly independent eigenvectors, which implies the sum of geometric multiplicity of the eigenvalues is d. Since the geometric multiplicity of each eigenvalue must be not greater than its algebraic multiplicity and the sum of algebraic multiplicity of all eigenvalues is d, if one eigenvalue is missing in Λ, the sum of geometric multiplicity must be smaller than d, which is contradict.

Now we prove the theorem:

$\Longrightarrow$: For any $x \in \mathbb{R}^d/\{0\}$, let $y = Q^T x$, then $y \neq 0$. Hence $x^T A x = y^T \Lambda y$ $= \sum_{i=1}^d \lambda_i y_i^2$. If there exists $\lambda_i \leq 0$ for $i \in \{1, 2, ..., d\}$, then we can find a non-zero x by letting $x = Qy$, $y_i \neq 0$ and $y_j = 0$ for all $j \neq i$ to make $x^T A x = \lambda_i y_i^2 \leq 0$, which is contradict.

$\Longleftarrow$: If $\lambda_i > 0$ for any $i = 1, ..., d$, then for any nonzero x, $x^T A x = \sum_{i=1}^d \lambda_i y_i^2$ > 0, which means A is positive definite.

$\square$

Similar as how we prove Theorem A.3.3, one can prove that A is positive semi-definite if and only if all of its eigenvalues are non-negative.

Definition A.3.4 (Multivariate Gaussian): The PDF of the Multivariate Gaussian Distribution $\mathcal{N}_d(\mu, \Sigma)$ is

$$f(x; \mu, \Sigma) = \frac{1}{\sqrt{(2\pi)^d \det \Sigma}} e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1} (x-\mu)}$$

where $x \in \mathbb{R}^d$ is the vector of d variables. $\mu = \mathbb{E}[x] \in \mathbb{R}^d$ is the mean. $\Sigma = \mathbb{E}[(x-\mu)(x-\mu)^T] \in \mathbb{R}^{d \times d}$ is the covariance matrix.

By Definition A.3.1, the covariance matrix Σ is positive semi-definite. This is because for any $a \in \mathbb{R}^d$,

$$a^T \Sigma a = a^T \mathbb{E}[(x-\mu)(x-\mu)^T] a = \mathbb{E}[\big(a^T (x-\mu)\big)^2] \geq 0$$

However, in Definition A.3.4, the Σ for multivariate Gaussian requires to be positive definite. This is because $\det \Sigma = \prod_{i=1}^d \lambda_i$. If there exists $\lambda_i = 0$, then $\det \Sigma = 0$, and the PDF cannot be formulated.

Theorem A.3.5: Let $x = [x_1, x_2, ..., x_d]^T$ be a random vector of d dimensional multivariate Gaussian distribution $\mathcal{N}_d(\mu, \Sigma)$, and $a = [a_1, a_2, ..., a_d] \in \mathbb{R}^d$ be a vector. Then $z = a^T x \in \mathbb{R}$ satisfies the Gaussian distribution $\mathcal{N}(a^T\mu, a^T\Sigma a)$.

Proof: The main idea of the proof comes from [6]. Let $X \in \mathbb{R}, t \in \mathbb{R}$, the MGF of $X \sim \mathcal{N}(\nu, \sigma^2)$ is

$$
\begin{aligned}
M_X(t) = \mathbb{E}[e^{tX}] &= \int e^{tx} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\nu)^2}{2\sigma^2}} dx \\
&= e^{\nu t + \frac{t^2\sigma^2}{2}} \int \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\nu-t\sigma^2)^2}{2\sigma^2}} dx = e^{\nu t + \frac{t^2\sigma^2}{2}}
\end{aligned}
$$

Let $Y \in \mathbb{R}^d$, $\lambda \sim \mathbb{R}^d$, the MGF of $Y \sim \mathcal{N}_d(\mu, \Sigma)$ is

$$
\begin{aligned}
M_Y(\lambda) = \mathbb{E}[e^{\lambda^T Y}] &= \int e^{\lambda^T y} \frac{1}{\sqrt{(2\pi)^d \det \Sigma}} e^{-\frac{1}{2}(y-\mu)^T \Sigma^{-1}(y-\mu)} dy \\
&= \int \frac{1}{\sqrt{(2\pi)^d \det \Sigma}} e^{-\frac{1}{2}(y-\mu)^T \Sigma^{-1}(y-\mu) + \lambda^T(y-\mu) + \lambda^T\mu} dy
\end{aligned}
$$

Let $m \in \mathbb{R}^d$. Since

$$\begin{aligned}
&-\frac{1}{2}(y-\mu-m)^T\Sigma^{-1}(y-\mu-m) \\
=&-\frac{1}{2}(y-\mu)^T\Sigma^{-1}(y-\mu)+m^T\Sigma^{-1}(y-\mu)-\frac{1}{2}m^T\Sigma^{-1}m
\end{aligned}$$

Let $m^T\Sigma^{-1}=\lambda^T$, then $\frac{1}{2}m^T\Sigma^{-1}m=\frac{1}{2}\lambda^T\Sigma\lambda$. Therefore,

$$\begin{aligned}
M_Y(\lambda)=\mathbb{E}[e^{\lambda^T Y}]&=\int\frac{1}{\sqrt{(2\pi)^d\det\Sigma}}e^{-\frac{1}{2}(y-\mu-m)^T\Sigma^{-1}(y-\mu-m)+\lambda^T\mu+\frac{1}{2}\lambda^T\Sigma\lambda}dy \\
&=e^{\lambda^T\mu+\frac{1}{2}\lambda^T\Sigma\lambda}
\end{aligned}$$

Define a new random variable $Z=a^TY$. The MGF of Z is

$$M_Z(t)=\mathbb{E}[e^{tZ}]=\mathbb{E}[e^{ta^TY}]$$

Let $\lambda^T=ta^T$, then

$$\mathbb{E}[e^{ta^TY}]=e^{ta^T\mu+\frac{1}{2}a^T\Sigma at^2}$$

which means Z is of Gaussian distribution with mean $a^T\mu$ and variance $a^T\Sigma a$. $\square$

Appendix 4: Relationship with Least Squares

This section explains the relationship between the posterior distribution ρ and the least squares solution.

It is well known that for a given dataset $S = \{(x_i, y_i)\}_{i=1}^n, x_i \in \mathbb{R}^d, y_i \in \mathbb{R}$, the linear regression problem

$$\operatorname*{argmin}_\theta R^{\text{emp}}(\theta) = \min_\theta \frac{1}{n} \sum_{i=1}^{n} (y_i - \theta \cdot x_i)^2 \tag{13}$$

has a unique solution

$$\hat{\theta} = (X^T X)^{-1} X^T Y \tag{14}$$

where $X = [x_1, x_2, ..., x_n]^T \in \mathbb{R}^{n \times d}$ and $Y = [y_1, y_2, ..., y_n]^T \in \mathbb{R}^{n \times 1}$.

We obtain the lease squares solution without assuming any distribution for the data (x_i, y_i). In this case, $\hat{\theta}$ is a constant, and the regressor $\hat{\theta} \cdot x_i$ fits best for the given data S. However, to evaluate the prediction of the regressor on unseen data, we usually assume x_i or y_i or both satisfy a distribution $\mathcal{D}$. Once x_i or y_i becomes random variable, $\hat{\theta}$ will become a random variable.

The least squares solution that minimizes empirical risk in Eq (13) will only be a point estimator but not a Bayes estimator, where the former estimates a fixed value and the latter estimates a distribution. Since when x_i is given, y_i is fixed, we can consider $\hat{\theta}$ in Eq (14) as a function of x_is, i.e., $\hat{\theta} = W(x_1, x_2, ..., x_n)$. When each x_i is considered as a random sample from $p(x_i)$, $\hat{\theta}$ is a point estimator.

The difference between point estimator and Bayes estimator is, point estimator considers θ as an unknown but fixed quantity, while Bayes estimator considers θ as a variable whose variation can be described by a probability distribution. Given dataset S, the Bayes estimation obtains ρ by

$$\rho(\theta|S) = \frac{p(S|\theta)\pi(\theta)}{p(S)}$$

where $p(S) = \int p(S|\theta)\pi(\theta)dS$. The point estimator like MLE treats $\frac{\pi(\theta)}{p(S)}$ as a constant and does not allow us to inject our prior beliefs $\pi(\theta)$ [1]. This means we let $\rho(\theta|S) = \alpha\, p(S|\theta)$, and the θ^* that maximizes the likelihood $p(S|\theta)$ gains the greatest probability in $\rho(\theta|S)$.

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[1] https://stats.stackexchange.com/questions/74082/what-is-the-difference-in-bayesian-estimate-and-maximum-likelihood-estimate

The posterior ρ exists but unknown, since $p(S|\theta)$ is unknown. Remember that the Alquier's Bound holds for any ρ. In practice, to calculate Alquier's Bound, we usually assume ρ to be the one that gives the tightest bound, i.e.,

$$\operatorname*{argmin}_{\rho} \mathbb{E}_{\theta\sim\rho}[R^{\text{emp}}(\theta)] + \frac{1}{\lambda} D(\,\rho\,||\,\pi\,)$$

The solution of the above problem is

$$\rho(\theta|S) = \frac{e^{-\lambda R^{\text{emp}(\theta)}}\pi(\theta)}{\mathbb{E}_{\theta\sim\pi}[e^{-\lambda R^{\text{emp}(\theta)}}]}$$

which is named as the Gibbs posterior.