10-702 Statistical Machine Learning: Assignment 1 Solutions

1. Review of Maximum Likelihood.

   Let $X_1, \ldots, X_n$ be a random sample where $X_i \in \{1, 2, \ldots, k\}$. Let $\theta \in [0, 1]$ and suppose that $\mathbb{P}(X_i = 1) = \theta$ and $\mathbb{P}(X_i = j) = \overline{\theta}$ for $j > 1$ where $\overline{\theta} = (1 - \theta)/(k - 1)$.

   (a) Find the mle $\widehat{\theta}$. Let $Y = 1$ when $X = 1$ and $Y = 0$ otherwise. $P(Y = 1) = \theta$ and $P(Y = 0) = 1 - \theta$. Hence, $P \sim$ Bernoulli(θ)
   $L(\theta) = \prod_{i=1}^{n} \theta^{Y_i}(1 - \theta)^{1-Y_i}$
   Solving $\frac{\partial}{\partial\theta} l(\theta) = 0$ we get, $\widehat{\theta} = \frac{1}{n}\sum_{i=1}^{n} Y_i = \frac{1}{n}\sum_{i=1}^{n} I(X_i = 1)$

   (b) Find the Fisher information.
   $I_n(\theta) = -\mathbb{E}[\frac{\partial^2 l(\theta)}{\partial\theta^2}]$
   Again assuming the tranformation to Y,

$$\begin{aligned} I_n(\theta) &= -\mathbb{E}[\frac{\partial}{\partial\theta^2}(log(\theta)\sum Y_i + log(1-\theta)\sum(1 - Y_i))] \\ &= -\mathbb{E}[-\frac{1}{\theta^2}\sum Y_i - \frac{1}{(1-\theta)^2}\sum(1 - Y_i)^2] \\ &= \frac{n}{\theta} + \frac{n}{1-\theta} \quad \because E(Y_i) = \theta \\ &= \frac{n}{\theta(1-\theta)} \end{aligned}$$

   (c) Find an approximate $1 - \alpha$ confidence interval for θ.
   $C_n = (\widehat{\theta} - z_{\alpha/2}se, \widehat{\theta} + z_{\alpha/2}se)$ where $se = \sqrt{\frac{1}{I_n(\widehat{\theta})}}$
   Here substitute $I_n(\theta)$ using (2) and $\widehat{\theta}$ from (1). $Z \sim N(0, 1)$.

   (d) Find the bias and variance of $\widehat{\theta}$.

$$\begin{aligned} \text{bias}(\widehat{\theta}) &= \mathbb{E}(\widehat{\theta}) - \theta \\ &= \mathbb{E}(\frac{1}{n}\sum Y_i) - \theta \\ &= \theta - \theta = 0 \end{aligned}$$

   Now, $\widehat{\theta} = \frac{1}{n}\sum Y_i$ where $Y_i \sim$ Bernoulli(θ). Hence, $\sum_{i=1}^{n} Y_i \sim$ Binominal(n, θ).

$$\begin{aligned} \text{Var}(\widehat{\theta}) &= \frac{1}{n^2}\text{Var}(\sum Y_i) \\ &= \frac{1}{n^2} n\theta(1-\theta) \\ &= \frac{\theta(1-\theta)}{n} \end{aligned}$$

(e) Show that $\widehat{\theta}$ is consistent.
MSE $= \text{bias}^2(\widehat{\theta}) + \text{Var}(\widehat{\theta}) = \frac{\theta(1-\theta)}{n}$
$\lim_{n\to\infty}$ MSE $= 0$. Hence, $\widehat{\theta}$ is consistent.

2. Probability.

Let $X_1, \ldots, X_n$ be iid and assume that $-1 \leq X_i \leq 1$. Also assume that X_i has mean 0.

(a) Use Hoeffding's inequality to show that $\overline{X}_n = n^{-1}\sum_{i=1}^n X_i$ is close to 0 with high probability.
For X with mean 0, and bounded between [-1,1], Hoeffding's inequality says that

$$P(|\overline{X}_n| > \epsilon) \leq 2exp(\frac{-2n^2\epsilon^2}{\sum_{i=1}^n 4})$$

Thus,

$$P(|\overline{X}_n| > \epsilon) \leq 2exp(-n\epsilon^2/2)$$

If you assume that ϵ is fixed, then clearly, this probability is going down to 0 exponentially fast in n, and thus as $n \to \infty$, $\overline{X}_n$ is close to 0 with high probability.
However, usually, as n increases, we expect that our estimate $\overline{X}_n$ will get more accurate, and thus, we expect that as n increases, ϵ reduces, i.e. accuracy increases.
Let δ be the probability of error, i.e

$$P(|\overline{X}_n| > \epsilon) \leq 2exp(-n\epsilon^2/2) = \delta$$

Then, with high probability $1 - \delta$, $\overline{X}_n$ is close to zero, when ϵ is chosen as a function of n and δ as

$$2exp(-n\epsilon^2/2) = \delta$$

$$\epsilon = (\frac{2}{n}\log(\frac{2}{\delta}))^{\frac{1}{2}}$$

This allows us to claim that $\overline{X}_n$ is close to zero with high probability $1 - \delta$ even when ϵ reduces as a function of n.

(b) Show that there exists c such that

$$\frac{1}{n}\sum_{i=1}^n X_i^2 \xrightarrow{P} c$$

and find c.
Let $Y = X^2$. Then

$$\frac{1}{n}\sum_{i=1}^n X_i^2 = \frac{1}{n}\sum_{i=1}^n Y_i \xrightarrow{P} E(Y) = E(X^2) = Var(X) + [E(X)]^2 = Var(X)$$

(c) Say whether the following statements are true or false and explain why.

i. $\overline{X}_n = o(1)$.
FALSE. $\overline{X}_n$ converges in probability to 0, but this is not convergence everywhere. Specifically, we can construct a series of $X_1, ...X_n$ whose sample mean does not go to zero as $n \to \infty$.

ii. $\overline{X}_n = o_P(1)$.
TRUE. $\overline{X}_n$ converges in probability to 0, by Hoeffding's inequality.

iii. $\overline{X}_n = o_P(n)$.
TRUE. $\overline{X}_n = o_P(1)$ implies $\overline{X}_n = o_P(n)$

iv. $\overline{X}_n = o_P(1/n)$.
FALSE. $n\overline{X}_n = \sum_i X_i$ which is not bounded in probability.

v. $\overline{X}_n = O_P(n^{-1/2})$.
TRUE. Central Limit Theorem

vi. $\overline{X}_n = O_P(n^{-1})$.
FALSE. No known result that says this.

3. This question will help you explore the differences between Bayesian and frequentist inference. Let $X_1, \ldots, X_n$ be a sample from a multivariate Normal distribution with mean $\mu = (\mu_1, \ldots, \mu_p)^T$ and covariance matrix equal to the identity matrix I. Note that each X_i is a vector of length p.

The following facts will be helpful. If $Z_1, \ldots, Z_k$ are independent $N(0, 1)$ and $a_1, \ldots, a_k$ are constants, then we say that $Y = \sum_{j=1}^{p}(Z_j + a_j)^2$ has a non-central χ^2 distribution with k degrees of freedom and noncentrality parameter $||a||^2$. The mean and variance of Y are $k + ||a||^2$ and $2k + 4||a||^2$.

(a) Find the posterior under the improper prior $\pi(\mu) = 1$.

$$
\begin{aligned}
\pi(\mu|X) &\propto \prod_{i=1}^{n} P(X_i|\mu)\pi(\mu) \\
&\propto \prod_{i=1}^{n} exp\left(-\frac{1}{2}(X_i-\mu)^T(X_i-\mu)\right) \\
&= \prod_{i=1}^{n} exp\left(-\frac{1}{2}\left(X_i^T X_i - 2X_i^T\mu + \mu^T\mu\right)\right) \\
&= exp\left(-\frac{1}{2}\left(\sum_{i=1}^{n} X_i^T X_i - 2\sum_{i=1}^{n} X_i^T\mu + n\mu^T\mu\right)\right) \\
&= exp\left(-\frac{1}{2}n\left(\frac{1}{n}\sum_{i=1}^{n} X^T X - 2\bar{X}\mu + \mu^T\mu\right)\right) \\
&\text{completing the square around } \mu \\
&= exp\left(-\frac{1}{2}n\left((\mu-\bar{X})^T(\mu-\bar{X}) + \frac{1}{n}\sum_{i=1}^{n} X^T X - \bar{X}^T\bar{X}\right)\right) \\
&\propto exp\left(-\frac{1}{2}\left((\mu-\bar{X})^T n(\mu-\bar{X})\right)\right) \\
&\sim N(\bar{X}, \frac{1}{n}I)
\end{aligned}
$$

(b) Let $\theta = \sum_{j=1}^{p} \mu_j^2$. Our goal is to learn θ. Find the posterior for θ. Express your answers in terms of noncentral χ^2 distributions. Find the posterior mean $\widetilde{\theta}$.
We have

$$
\theta = \sum_{i=1}^{p} \mu_i^2
$$

We also have $\mu_i|X \sim N(\bar{X}_i, \frac{1}{n})$ implies $(\sqrt{n}\mu_i)|X \sim N(\sqrt{n}\bar{X}_i, 1) = Z_i + \sqrt{n}\bar{X}_i$

$$
\begin{aligned}
\theta &= \frac{1}{n}\sum_{i=1}^{p}(\sqrt{n}\mu_i)^2 \\
&= \frac{1}{n}\sum_{i=1}^{p}(Z_i + \sqrt{n}\bar{X}_i)^2 \\
n\theta &= \sum_{i=1}^{p}(Z_i + \sqrt{n}\bar{X}_i)^2
\end{aligned}
$$

Then $n\theta$ is distributed as a noncentral χ^2 distribution with p degrees of freedom and non-central parameter $n\left\|\bar{X}\right\|^2$

the mean of $n\theta$ is $p + n\left\|\bar{X}\right\|^2$. Therefore $\widetilde{\theta} = \frac{p+n\left\|\bar{X}\right\|^2}{n} = \frac{p}{n} + \left\|\bar{X}\right\|^2$

(c) The usual frequentist estimator is $\widehat{\theta} = ||\overline{X}_n||^2 - p/n$. Show that, for any n,

$$\frac{\mathbb{E}_\mu|\theta - \widetilde{\theta}|^2}{\mathbb{E}_\mu|\theta - \widehat{\theta}|^2} \to \infty$$

as $p \to \infty$.

Lets consider the bias of $\widehat{\theta}$.

$$\begin{aligned}
E(\widehat{\theta}) - \theta &= E(|\bar{X}_n|^2) - \frac{p}{n} - \theta \\
&= \sum E(\bar{X}_i^2) - \frac{p}{n} - \theta \\
&= \sum \left(Var(\bar{X}_i) - E(\bar{X}_i)^2\right) - \frac{p}{n} - \theta \\
&= \sum \left(\frac{1}{n} - u_i^2\right) - \frac{p}{n} - \theta \\
&= \frac{p}{n} + \sum u_i^2 - \frac{p}{n} - \theta \\
&= 0
\end{aligned}$$

From this, we can also tell that the bias of $\widetilde{\theta} = 2\frac{p}{n}$

Lets consider the variance of $\widehat{\theta}$. First we note that the $Variance(\widehat{\theta}) = Variance(\widetilde{\theta})$

$$\begin{aligned}
Variance(\widetilde{\theta}) &= Variance(|\bar{X}_n|^2) \\
&= Variance(\textstyle\sum \bar{X}_i^2) \\
&\text{($\bar{X}_i's$ are independent)} \\
&= \sum_{i=1}^{p} Variance(\bar{X}_i^2) \\
&\text{(since X has a covariance matrix of I)} \\
&\text{(all terms have the same variance)} \\
&= p \times (Variance(\bar{X}_1^2))
\end{aligned}$$

We note that $Variance(\bar{X}_1^2)$ is independent of p (whatever it really is). and we let this value be k, therefore writing $Variance(\widetilde{\theta}) = Variance(\widehat{\theta}) = pk$.

Therefore $\widehat{\theta}$ is an unbiased estimator

$$
\begin{aligned}
\lim_{p\to\infty} \frac{E|\theta - \widetilde{\theta}|^2}{E|\theta - \widehat{\theta}|^2} &= \lim_{p\to\infty} \frac{Variance(\widetilde{\theta}) + Bias(\widetilde{\theta})^2}{Variance(\widehat{\theta}) + Bias(\widehat{\theta})^2} \\
&= \lim_{p\to\infty} \frac{pk + 4\frac{p^2}{n^2}}{pk} \\
&= \lim_{p\to\infty} \frac{k + 4\frac{p}{n^2}}{k} \\
&= \lim_{p\to\infty} 1 + 4\frac{p}{n^2 k} \\
&= \infty
\end{aligned}
$$

(d) Repeat the analysis with a $N(0, \tau^2 I)$ prior.

$\pi(\mu) \sim N(0, \tau^2 I)$

$$
\begin{aligned}
\pi(\mu|X) &\propto \prod_{i=1}^{n} P(X_i|\mu)\pi(\mu) \\
&\propto exp\left(-\frac{1}{2}\frac{1}{\tau^2}\mu^T\mu\right) \prod_{i=1}^{n} exp\left(-\frac{1}{2}(X_i - \mu)^T(X_i - \mu)\right) \\
&= exp\left(-\frac{1}{2}\frac{1}{\tau^2}\mu^T\mu\right) \prod_{i=1}^{n} exp\left(-\frac{1}{2}\left(X_i^T X_i - 2X_i^T\mu + \mu^T\mu\right)\right) \\
&= exp\left(-\frac{1}{2}\left(\sum_{i=1}^{n} X_i^T X_i - 2\sum_{i=1}^{n} X_i^T\mu + (n + \frac{1}{\tau^2})\mu^T\mu\right)\right) \\
&\propto exp\left(-\frac{1}{2}\left(n + \frac{1}{\tau^2}\right)\left(\mu^T\mu - 2\left(\frac{n}{n+\tau^{-2}}\right)\bar{X}\mu\right)\right) \\
&\text{completing the square around } \mu \\
&= exp\left(-\frac{1}{2}\left(n + \frac{1}{\tau^2}\right)\left(\mu - \frac{n\bar{X}}{n+\tau^{-2}}\right)^T\left(\mu - \frac{n\bar{X}}{n+\tau^{-2}}\right)\right) \\
&\sim N\left(\frac{n\bar{X}}{n+\tau^{-2}}, \frac{\tau^2}{n\tau^2+1}I\right)
\end{aligned}
$$

Using the same argument, $\widetilde{\theta}' = \frac{\tau^2}{n\tau^2+1}\left(p + \frac{n^2\tau^2}{n\tau^2+1}\left\|\bar{X}\right\|\right)$

Continuing from **3c**,

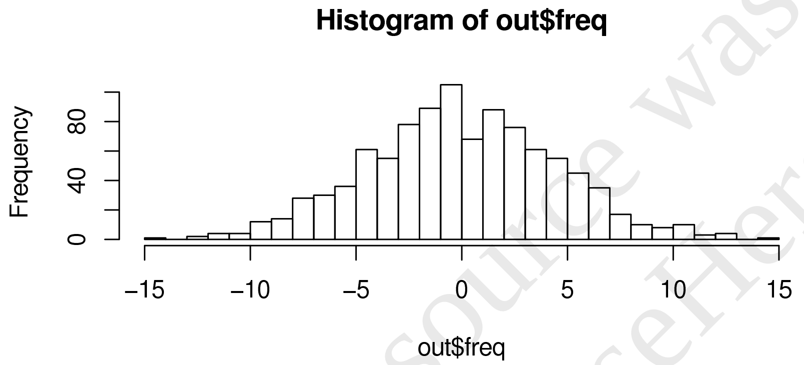
Now, we have $Variance(\widetilde{\theta}') = (\frac{n\tau^2}{n\tau^2+1})^4 pk$.

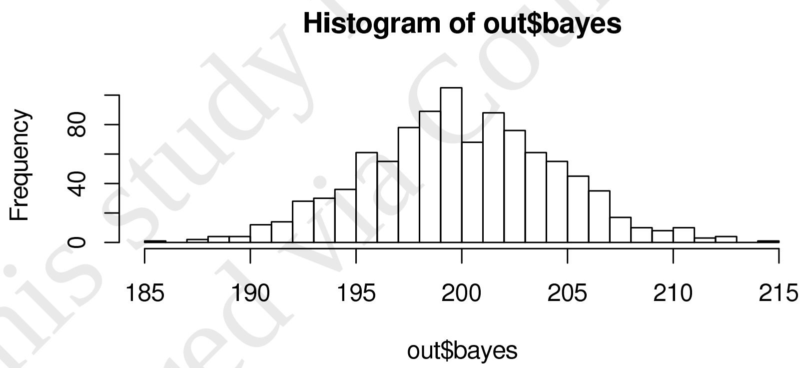
And

$$
\begin{aligned}
Bias(\widetilde{\theta}') &= E(\widetilde{\theta}') - \theta \\
&= \frac{\tau^2}{n\tau^2+1}p + \frac{n\tau^4}{(n\tau^2+1)^2}p + \left[\left(\frac{n\tau^2}{n\tau^2+1}\right)^2 - 1\right]\theta
\end{aligned}
$$

$$
\begin{aligned}
\lim_{p\to\infty} \frac{E|\theta - \widetilde{\theta}'|^2}{E|\theta - \widehat{\theta}|^2} &= \lim_{p\to\infty} \frac{Variance(\widetilde{\theta}') + Bias(\widetilde{\theta}')^2}{Variance(\widehat{\theta}) + Bias(\widehat{\theta})^2} \\
&= \infty
\end{aligned}
$$

(e) Set $n = 10$, $p = 1000$, $\mu = (0, \ldots, 0)^T$. Simulate (in R) data N times, with $N = 1000$. Draw a histogram of the Bayes estimator (with flat prior) and the frequentist estimator. (R code for this question can be found on the web site.)





(f) Interpret your findings.

The Bayes estimator and the frequentist estimator are extremely far apart. The true value of θ should be $\theta = 0$, but the Bayes estimator was unable to obtain that. As we calculated, the Bayes estimator has a bias of $\frac{2p}{n}$ which matches the plot.

4. Minimaxity and Bayes.

Let $X_1, \ldots, X_n \sim \text{Bernoulli}(p)$. In what follows we use squared error loss.

(a) Find the mle $\widehat{p}$. Find the bias, variance and risk (mean squared error) $R(p, \widehat{p})$ of $\widehat{p}$.
From question 1, we know that $\widehat{p} = \overline{X}_n$.

$$\text{Bias } = p - E(\overline{X}_n) = 0$$

$$\text{Variance } = \frac{1}{n^2} \sum_i Var(X_i) = \frac{p(1-p)}{n}$$

$$\text{Risk } = \text{Variance } + \text{Bias}^2 = \frac{p(1-p)}{n}$$

(b) Recall that a Beta(α, β) density has the form

$$\pi(p) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} p^{\alpha-1}(1-p)^{\beta-1} \propto p^{\alpha-1}(1-p)^{\beta-1}.$$

Let p have a Beta(v,v) prior. Find the Bayes estimator $\overline{p}$. Find the bias, variance and risk $R(p, \overline{p})$ of $\overline{p}$.
Since the Beta distribution is conjugate prior for Bernoulli, the posterior

$$p|X \sim Beta(n\overline{X}_n + v, n - n\overline{X}_n + v)$$

The Bayes Estimator $\overline{p}$ is the mean of the posterior distribution. Thus,

$$\overline{p} = \frac{n\overline{X}_n + v}{n + 2v}$$

$$\text{Bias } = E(\frac{n\overline{X}_n + v}{n + 2v}) - p = \frac{np + v}{n + 2v} - p = \frac{v(1-2p)}{n + 2v}$$

$$\text{Variance } = Var(\frac{n\overline{X}_n + v}{n + 2v}) = \frac{n^2}{(n+2v)^2} Var(\overline{X}_n) + 0 = \frac{np(1-p)}{(n+2v)^2}$$

$$\text{Risk } = \text{Variance } + \text{Bias}^2 = \frac{v^2(1-2p)^2 + np(1-p)}{(n+2v)^2}$$

(c) Show that $R(p, \overline{p})$ is contant (as a function of p) if v is chosen appropriately. Since $\overline{p}$ is a Bayes estimator and has constant risk, it is the minimax estimator.

$$R(p, \overline{p}) = \frac{v^2(1-2p)^2 + np(1-p)}{(n+2v)^2}$$

Substitue $v = \sqrt(n/4)$ to get

$$R(p, \overline{p}) = \frac{n/4(1 - 4p + 4p^2) + np(1-p)}{(n + 2\sqrt{n}/2)^2}$$

$$R(p, \overline{p}) = \frac{n/4 - np + np^2 + np - np^2)}{(n + \sqrt{n})^2}$$

$$R(p, \overline{p}) = \frac{n}{4(n + \sqrt{n})^2}$$

which is a constant (as a function of p), thus, $\overline{p}$ is the minimax estimator.