

Bayesian Machine Learning Assignment 1.

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1. Suppose D_i = the prize is behind i th door, $i=1, 2, 3$.

S_i = she picks door i , $i=1, 2, 3$

H_i = Host opens door i , $i=1, 2, 3$

$$P(D_1|S_2, H_3) = \frac{P(H_3|D_1, S_2) P(D_1|S_2) P(S_2)}{P(S_2, H_3)} = \frac{P(H_3|D_1, S_2) P(D_1|S_2) P(S_2)}{\sum_{i=1}^3 P(H_3|D_i, S_2) P(D_i|S_2) P(S_2)}$$

$$= \frac{P(H_3|D_1, S_2)}{\sum_{i=1}^3 P(H_3|D_i, S_2)}$$

Since $P(H_3|D_1, S_2) = 1$, $P(H_3|D_2, S_2) = \frac{1}{2}$, $P(H_3|D_3, S_2) = 0$

$$\therefore P(D_1|S_2, H_3) = \frac{1}{1 + \frac{1}{2} + 0} = \frac{2}{3}$$

$$\text{Similarly, } P(D_1|S_3, H_2) = P(D_2|S_1, H_3) = P(D_2|S_3, H_1) = P(D_3|S_1, H_2) \\ = P(D_3|S_2, H_1) = \frac{2}{3}$$

Conclusion, if she switch the door, $\frac{2}{3}$ chance could win the prize, otherwise only $\frac{1}{3}$ chance to win. Thus, switch doors

2. $X_i \sim \text{multinomial}(\pi), i=1, \dots, N$

$$P(X|\pi) = \prod_{i=1}^N P(X_i|\pi) \propto \prod_{i=1}^N \prod_{j=1}^K \pi_j^{I(X_i=j)} = \prod_{j=1}^K \pi_j^{\sum_{i=1}^N I(X_i=j)}$$

Let $y_j = \sum_{i=1}^N I(X_i=j)$, the number of observations for category j , $j=1, \dots, K$

Thus $P(X|\pi) \propto \prod_{j=1}^K \pi_j^{y_j}$, the conjugate prior is Dirichlet Distribution

$$\text{Dir}(\pi|\alpha_1, \dots, \alpha_K) = \frac{T(\alpha_1 + \dots + \alpha_K)}{T(\alpha_1) \dots T(\alpha_K)} \prod_{j=1}^K \pi_j^{\alpha_j-1} \propto \prod_{j=1}^K \pi_j^{\alpha_j-1}$$

Thus the posterior $P(\underline{\pi} | \underline{x}, \underline{\alpha}) \propto P(\underline{x} | \underline{\pi}) P(\underline{\pi} | \underline{\alpha}) \propto \prod_{j=1}^K \pi_j^{y_j} \cdot \prod_{j=1}^K \pi_j^{\alpha_j-1} = \prod_{j=1}^K \pi_j^{y_j + \alpha_j - 1}$

Thus the posterior distribution is $\text{Dir}(\underline{\pi} | y_1 + \alpha_1 - 1, \dots, y_k + \alpha_k - 1)$ Where $y_j = \sum_{i=1}^N I(x_i = j)$, $j=1, \dots, k$

The posterior distribution is a Dirichlet Distribution

The most important feature about the parameters is the parameters are the sum of prior parameters and counts of the observations.

$$3. a) x_i \sim N(\mu, \lambda^{-1}), P(\underline{x} | \mu, \lambda) = \prod_{i=1}^N P(x_i | \mu, \lambda) \propto \prod_{i=1}^N \lambda^{\frac{1}{2}} \exp\left\{-\frac{(x_i - \mu)^2}{2} \lambda\right\} = \lambda^{\frac{N}{2}} \exp\left\{-\frac{\lambda}{2} \sum_{i=1}^N (x_i - \mu)^2\right\}$$

$$\mu | \lambda \sim N(0, a\lambda^{-1}), P(\mu | \lambda) \propto \lambda^{\frac{1}{2}} \exp\left\{-\frac{\mu^2}{2a}\right\}$$

$$\lambda \sim \text{Gamma}(b, c), P(\lambda) \propto \lambda^{b-1} \exp\{-c\lambda\}$$

$$\therefore \phi(\mu, \lambda | \underline{x}) \propto P(\underline{x} | \mu, \lambda) P(\mu | \lambda) P(\lambda) \propto \lambda^{\frac{N}{2}} \exp\left\{-\frac{\lambda}{2} \sum_{i=1}^N (x_i - \mu)^2\right\} \lambda^{\frac{1}{2}} \exp\left\{-\frac{\mu^2}{2a}\right\} \lambda^{b-1} \exp\{-c\lambda\}$$

$$\propto \lambda^{\frac{N+1}{2}} \exp\left\{-\frac{\lambda}{2} \left(\sum_{i=1}^N x_i^2 - 2\mu \sum_{i=1}^N x_i + N\mu^2 \right) - \frac{\mu^2}{2a} - c\lambda\right\}$$

$$\propto \lambda^{\frac{N+1}{2}} \exp\left\{-\frac{\lambda}{2} \left(\sum_{i=1}^N x_i^2 - 2\mu \sum_{i=1}^N x_i + N\mu^2 \right) - \frac{\mu^2}{2a} - c\lambda\right\}$$

$$\propto \lambda^{\frac{1}{2}} \exp\left\{-\frac{\lambda}{2} \left(\sum_{i=1}^N x_i^2 - 2\mu \sum_{i=1}^N x_i + N\mu^2 \right) - \frac{\mu^2}{2a} - c\lambda\right\}$$

$$\therefore P(\mu, \lambda | \underline{x}) = \text{Normal}\left(\mu \mid \frac{\sum_{i=1}^N x_i}{N+a}, \lambda(N+a)\right) * \text{Gamma}\left(\lambda \mid b + \frac{N}{2}, c + \frac{\sum_{i=1}^N x_i^2}{2(N+a)} - \frac{(\sum_{i=1}^N x_i)^2}{2(N+a)}\right)$$

$$\text{Let } \mu^* = \frac{\sum_{i=1}^N x_i}{N+a}, \lambda^* = \lambda(N+a), \boxed{\mu | \lambda, \underline{x} \sim \text{Normal}(\mu^*, \lambda^{*-1})}$$

$$\text{Let } \alpha = b + \frac{N}{2}, \beta = c + \frac{\sum_{i=1}^N x_i^2}{2(N+a)} - \frac{(\sum_{i=1}^N x_i)^2}{2(N+a)} = c + \frac{1}{2} \left[(N-1)s^2 + \frac{N\bar{x}^2}{1+N} \right] \text{ where } s^2 = \frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N-1}$$

$$\boxed{\lambda | \underline{x} \sim \text{Gamma}(\alpha, \beta)}$$

$$\begin{aligned}
 b) \quad p(x^* | x_1, \dots, x_n) &= \int_0^\infty \int_{-\infty}^\infty p(x^* | u, \lambda) p(u, \lambda | x_1, \dots, x_n) du d\lambda \\
 &= \int_0^\infty p(\lambda | x) \int_{-\infty}^\infty p(x^* | u, \lambda) p(u | \lambda, x) du d\lambda \\
 &= \int_0^\infty p(\lambda | x) \int_{-\infty}^\infty \left(\frac{\lambda}{2\pi}\right)^{\frac{1}{2}} \exp\left(-\frac{\lambda(x^* - u)^2}{2}\right) \left(\frac{\lambda}{2\pi}\right)^{\frac{1}{2}} \exp\left(-\frac{\lambda(u - \mu^*)^2}{2}\right) du d\lambda \\
 &= \int_0^\infty p(\lambda | x) \int_{-\infty}^\infty \left(\frac{\lambda}{2\pi}\right)^{\frac{1}{2}} \exp\left(-\frac{\lambda(x^* - u)^2}{2}\right) \left(\frac{\lambda(N + \frac{1}{a})}{2\pi}\right)^{\frac{1}{2}} \exp\left\{-\frac{\lambda(N + \frac{1}{a})}{2}(u - \mu^*)^2\right\} du d\lambda \\
 &= \int_0^\infty p(\lambda | x) \int_{-\infty}^\infty \left(\frac{\lambda}{2\pi}\right)^{\frac{1}{2}} \left(\frac{\lambda(N + \frac{1}{a})}{2\pi}\right)^{\frac{1}{2}} \exp\left\{-\frac{\lambda(x^* - u)^2}{2} - \frac{\lambda(N + \frac{1}{a})(u - \mu^*)^2}{2}\right\} du d\lambda
 \end{aligned}$$

$$\begin{aligned}
 \text{Denote } N + \frac{1}{a} &= \frac{1}{N^*}, \quad \int_{-\infty}^\infty \left(\frac{\lambda}{2\pi}\right)^{\frac{1}{2}} \left(\frac{\lambda(N + \frac{1}{a})}{2\pi}\right)^{\frac{1}{2}} \exp\left\{-\frac{\lambda(x^* - u)^2}{2} - \frac{\lambda(N + \frac{1}{a})(u - \mu^*)^2}{2}\right\} du \\
 &= \int_{-\infty}^\infty \left(\frac{\lambda}{2\pi}\right)^{\frac{1}{2}} \left(\frac{\lambda}{2\pi N^*}\right)^{\frac{1}{2}} \left(\frac{\lambda(N + \frac{1}{a})}{2\pi}\right)^{\frac{1}{2}} \left(\frac{\lambda(N + \frac{1}{a})}{2\pi}\right)^{\frac{1}{2}} \exp\left\{-\frac{\lambda}{2(N + \frac{1}{a})}(u - \frac{\lambda x^* + \frac{\lambda \mu^*}{N^*}}{\lambda(N + \frac{1}{a})})^2\right\} \\
 &\quad \times \exp\left\{-\frac{\lambda(x^*)^2}{2} - \frac{\lambda \mu^{*2}}{2N^*} + \frac{\lambda(x^* + \frac{\lambda \mu^*}{N^*})^2}{2\lambda(N + \frac{1}{a})}\right\} du \\
 &= \left(\frac{\lambda}{2\pi(N^* + 1)}\right)^{\frac{1}{2}} \exp\left(-\frac{\lambda(x^* - \mu^*)^2}{2(N^* + 1)}\right) \int_{-\infty}^\infty \left(\frac{\lambda(N + \frac{1}{a})}{2\pi}\right)^{\frac{1}{2}} \exp\left\{-\frac{\lambda(N + \frac{1}{a})}{2}(u - \frac{\lambda x^* + \frac{\lambda \mu^*}{N^*}}{\lambda(N + \frac{1}{a})})^2\right\} du
 \end{aligned}$$

$$\text{Since } \int_{-\infty}^\infty \left(\frac{\lambda(N + \frac{1}{a})}{2\pi}\right)^{\frac{1}{2}} \exp\left\{-\frac{\lambda(N + \frac{1}{a})}{2}(u - \frac{\lambda x^* + \frac{\lambda \mu^*}{N^*}}{\lambda(N + \frac{1}{a})})^2\right\} du = \int_{-\infty}^\infty \text{Normal}\left(u \mid \frac{\lambda x^* + \frac{\lambda \mu^*}{N^*}}{\lambda(N + \frac{1}{a})}, \left(\lambda(N + \frac{1}{a})\right)^{-1}\right) du = 1$$

$$\begin{aligned}
 \therefore p(x^* | x) &= \int_0^\infty p(\lambda | x) \cdot \left(\frac{\lambda}{2\pi(N^* + 1)}\right)^{\frac{1}{2}} \exp\left(-\frac{\lambda(x^* - \mu^*)^2}{2(N^* + 1)}\right) d\lambda \\
 &= \int_0^\infty \frac{\beta^\alpha \lambda^{\alpha-1} \exp(-\beta\lambda)}{\Gamma(\alpha)} \left(\frac{\lambda}{2\pi(N^* + 1)}\right)^{\frac{1}{2}} \exp\left(-\frac{\lambda(x^* - \mu^*)^2}{2(N^* + 1)}\right) d\lambda \\
 &= \int_0^\infty \frac{\beta^\alpha \lambda^{\alpha+\frac{1}{2}-1} \exp(-\lambda(\beta + \frac{(x^* - \mu^*)^2}{2(N^* + 1)}))}{\Gamma(\alpha) \Gamma(\frac{1}{2})} \cdot \left(\frac{1}{2\pi(N^* + 1)}\right)^{\frac{1}{2}} d\lambda \\
 &= \frac{\Gamma(\alpha + \frac{1}{2})}{\Gamma(\alpha)} \cdot \left(\frac{1}{2\pi(N^* + 1)}\right)^{\frac{1}{2}} \cdot \frac{\beta^\alpha}{(\beta + \frac{(x^* - \mu^*)^2}{2(N^* + 1)})^{\alpha+\frac{1}{2}}} \int_0^\infty \frac{(\beta + \frac{(x^* - \mu^*)^2}{2(N^* + 1)})^{\alpha+\frac{1}{2}} \cdot \lambda^{\alpha+\frac{1}{2}-1} \exp(-\lambda(\beta + \frac{(x^* - \mu^*)^2}{2(N^* + 1)}))}{\Gamma(\alpha + \frac{1}{2})} d\lambda
 \end{aligned}$$

$$\text{Since } \int_0^\infty \frac{(\beta + \frac{(x^* - \mu^*)^2}{2(N^* + 1)})^{\alpha+\frac{1}{2}} \cdot \lambda^{\alpha+\frac{1}{2}-1} \exp(-\lambda(\beta + \frac{(x^* - \mu^*)^2}{2(N^* + 1)}))}{\Gamma(\alpha + \frac{1}{2})} d\lambda = \int_0^\infty \text{Gamma}\left(\lambda \mid \alpha + \frac{1}{2}, \beta + \frac{(x^* - \mu^*)^2}{2(N^* + 1)}\right) d\lambda = 1$$

$$\begin{aligned}
 \therefore p(x^* | x) &= \frac{\Gamma(\alpha + \frac{1}{2})}{\Gamma(\alpha)} \cdot \left(\frac{1}{2\pi(N^* + 1)}\right)^{\frac{1}{2}} \cdot \frac{\beta^\alpha}{(\beta + \frac{(x^* - \mu^*)^2}{2(N^* + 1)})^{\alpha+\frac{1}{2}}} \\
 &= \frac{\Gamma(\frac{2\alpha+1}{2})}{\Gamma(\frac{2\alpha}{2})} \cdot \left(\frac{1}{\pi \cdot 2\alpha}\right)^{\frac{1}{2}} \cdot \left(\frac{1}{\beta(N^* + 1)\alpha}\right)^{\frac{1}{2}} \cdot \left[1 + \frac{1}{2\alpha} \cdot \frac{2}{\beta(N^* + 1)} \cdot (x^* - \mu^*)^2\right]^{-\frac{2\alpha+1}{2}}
 \end{aligned}$$

$\sim t_{2\alpha}(x^* | \mu^*, \frac{\beta(N^* + 1)}{2\alpha})$ a student's t -distribution with $df = 2\alpha$, $\text{loc} = \mu^*$, $\text{scale} = \frac{\beta(N^* + 1)}{2\alpha}$

$$\text{where } \mu^* = \frac{\sum_{i=1}^N x_i}{N + \frac{1}{a}}, \quad \alpha = b + \frac{N}{2}, \quad \beta = c + \frac{1}{2}[(N-1)s^2 + \frac{N\bar{x}^2}{N+1}], \quad s^2 = \frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N-1}, \quad N^* = \frac{1}{N + \frac{1}{a}}$$

4.

a). Shown in the code

b). The cross table is shown below:

	0	1
0	930	52
1	82	927

Accuracy = 0.9327

c). 3 misclassified images

Image Index: 223

True label: 0

Predicted label: 1

Logit: 0.639793214237

$P(y^* = 0 \mid x^*, X, y) = 0.3902$

$P(y^* = 1 \mid x^*, X, y) = 0.6098$

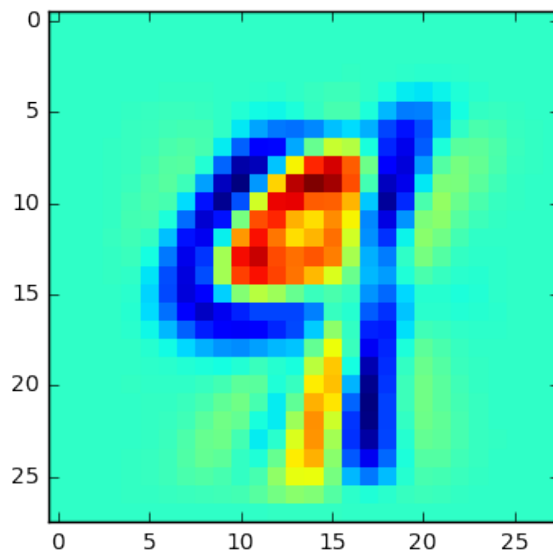


Image Index: 676

True label: 0

Predicted label: 1

Logit: 0.926222661075

$P(y^* = 0 \mid x^*, X, y) = 0.4808$

$P(y^* = 1 \mid x^*, X, y) = 0.5192$

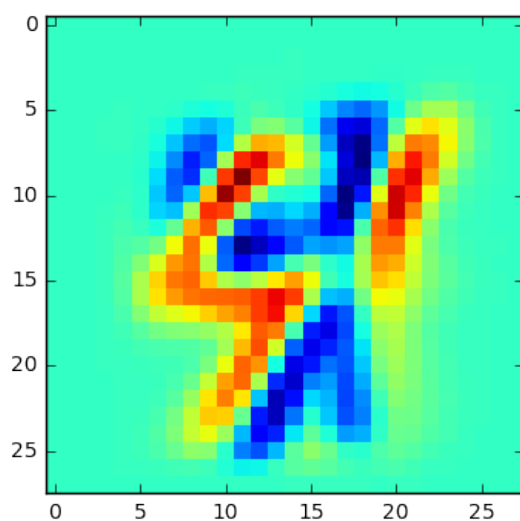


Image Index: 1842

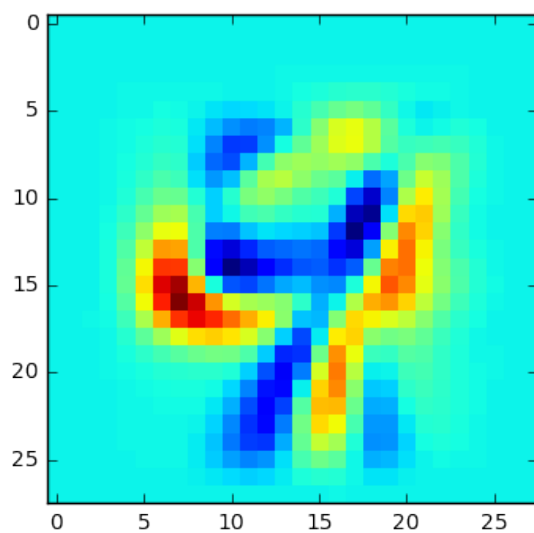
True label: 1

Predicted label: 0

Logit: 1.79610067819

$P(y^* = 0 \mid x^*, X, y) = 0.6424$

$P(y^* = 1 \mid x^*, X, y) = 0.3576$



d). 3 most ambiguous predictions

Image Index: 822

True label: 0

Predicted label: 0

Logit: 1.00118731725

$P(y^* = 0 \mid x^*, X, y) = 0.5003$

$P(y^* = 1 \mid x^*, X, y) = 0.4997$

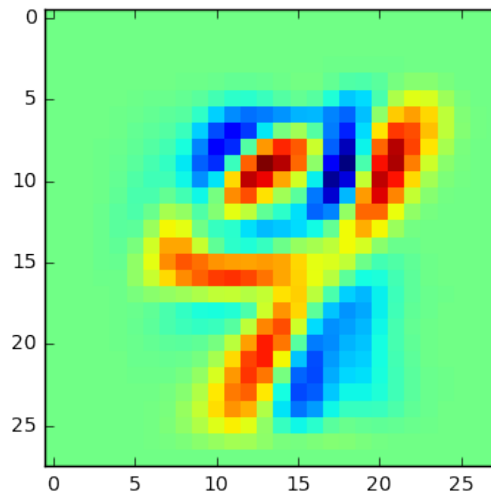


Image Index: 1130

True label: 1

Predicted label: 1

Logit: 0.990875806066

$P(y^* = 0 \mid x^*, X, y) = 0.4977$

$P(y^* = 1 \mid x^*, X, y) = 0.5023$

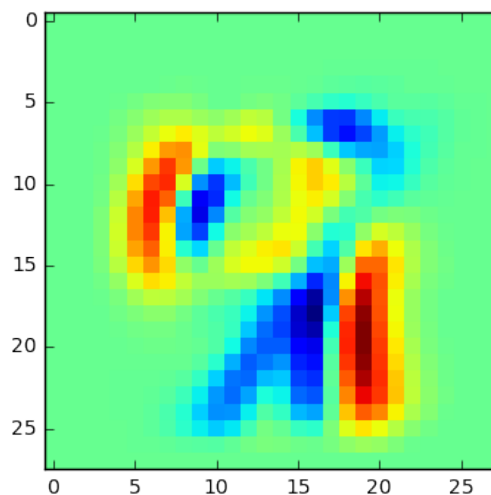


Image Index: 357

True label: 0

Predicted label: 0

Logit: 1.01456469643

$P(y^* = 0 \mid x^*, X, y) = 0.5036$

$P(y^* = 1 \mid x^*, X, y) = 0.4964$

