

Tutorial 1

Monday, March 25, 2019 5:01 PM

1.3

$$u = \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} \quad x = a + Qu \quad a = \begin{pmatrix} 1 \\ 2 \end{pmatrix} \quad Q = \begin{pmatrix} 2 & 1 \\ 2 & 0 \end{pmatrix} \quad u_i \text{ i.i.d. } u_i \sim N(0, 1).$$

1.3.a) $\mu_x = E[X]$

$$C_x = E[(X - \mu_x)(X - \mu_x)^T]$$

$$E[X] = a + Q E[u] = \begin{pmatrix} 1 \\ 2 \end{pmatrix} + Q \begin{pmatrix} 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 1 \\ 2 \end{pmatrix} \quad \mu_x = a.$$

$$C_x = E[(Qu)u^TQ^T] = Q \underbrace{E[uu^T]}_{I_{2x2}} Q^T = QQ^T = \begin{pmatrix} 2 & 1 \\ 2 & 0 \end{pmatrix} \begin{pmatrix} 2 & 2 \\ 1 & 0 \end{pmatrix} = \begin{pmatrix} 5 & 4 \\ 4 & 4 \end{pmatrix}$$

1.3.b.) X

1.3.c) $x = \mu_x + P \begin{pmatrix} z_1 \\ z_2 \end{pmatrix}$ let $C_x = V \Lambda V^T$ $V V^T = I$. $\Lambda \triangleq \begin{pmatrix} \lambda_1 & \\ & \lambda_2 \end{pmatrix}$

then $P = V$ and $z_1 \sim N(0, \lambda_1)$

$$z_2 \sim N(0, \lambda_2)$$

x is gaussian because z_1, z_2 are Gaussian. Gaussian is fully specified by mean and covariance, hence if the mean and covariance match they follow the same distribution.

$$E[X] = \mu_x \checkmark$$

$$E[(X - \mu_x)(X - \mu_x)^T] = V E \left[\begin{pmatrix} z_1 \\ z_2 \end{pmatrix} (z_1, z_2) \right] V^T = V \Lambda V^T = C_x \checkmark$$

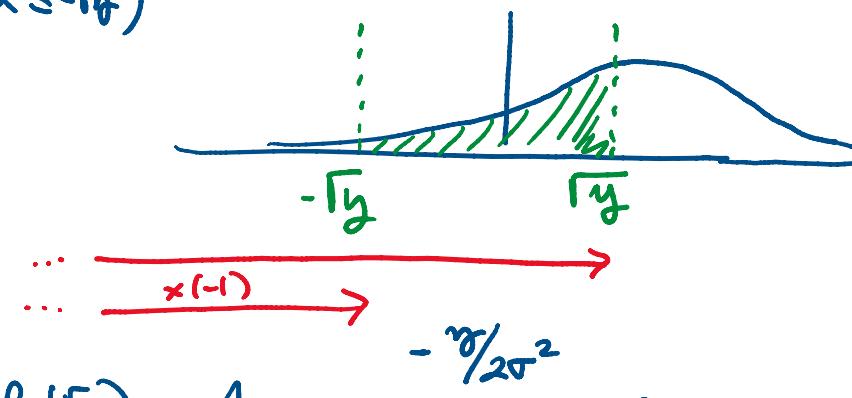
1.3.d.) X

1.8 $X \sim N(\mu, \sigma^2)$ density of Y : $F_Y(y) = P(Y \leq y) = P(X^2 \leq y) = P(-\sqrt{y} \leq X \leq \sqrt{y}) = P(X \leq \sqrt{y}) - P(X \leq -\sqrt{y})$; | |

$$Y = X^2$$

$$\begin{aligned} &= P(X \leq \sqrt{y}) - P(X \leq -\sqrt{y}) \\ &= F_X(\sqrt{y}) - F_X(-\sqrt{y}) \end{aligned}$$

$$f_Y(y) = \frac{d}{dy} F_Y(y) = \frac{1}{2\sqrt{y}} f_X(\sqrt{y}) + \frac{1}{2\sqrt{y}} f_X(-\sqrt{y}) \leftarrow \text{eval in solution}$$



when $\mu=0 \Rightarrow f_X(\sqrt{y}) = f_X(-\sqrt{y}) \Rightarrow f_Y(y) = \frac{1}{\sqrt{y}} f_X(\sqrt{y}) = \frac{1}{\sqrt{2\pi} \sqrt{y}} e^{-\frac{y}{2\sigma^2}}$

χ^2 1 degree of freedom $\underline{\sigma=1}$.

2.1 Monty Hall Problem:

1

2

3

WLOG assume that we select door 1 (selecting doors 2 or 3 yields the identical argument).

$$P(S=1) = P(S=2) = P(S=3) = \frac{1}{3}. \quad S \text{ state of nature.}$$

Then if we select 1; assume the host selects 2, the argument is identical if she opens 3:

$$P(H=2|S=1) = P(H=3|S=1) = \frac{1}{2}. \quad \hookrightarrow P(H=2) = P(H=3) = \frac{1}{2}.$$

$$P(H=2|S=2) = 0$$

$$P(H=2|S=3) = 1$$

$$\text{Then } P(S=1|H=2) = \frac{P(S=1) P(H=2|S=1)}{P(H=2)} = \frac{\frac{1}{3} \cdot \frac{1}{2}}{\frac{1}{2}} = \frac{1}{3}$$

$$P(S=2|H=2) = 0.$$

$$P(S=3|H=2) = \frac{P(S=3) P(H=2|S=3)}{P(H=2)} = \frac{\frac{1}{3} \cdot 1}{\frac{1}{2}} = \frac{2}{3}$$

$$P(S=3|H=2) = \frac{P(H=2, S=3)}{P(H=2)} = \frac{1}{2} = \frac{1}{2}$$

Strategy is to always change door.

2.5

$\{S_t\}_{t \geq 0}$ First order Markov chain $\Rightarrow P(S_t | S_{t-1}, S_{t-2}, \dots) = P(S_t | S_{t-1})$.

$$A = \begin{pmatrix} 0.7 & 0.1 & 0.2 \\ 0.1 & 0.8 & 0.1 \\ 0.1 & 0 & 0.9 \end{pmatrix}$$

$$a_{ij} = P(S_t = j | S_{t-1} = i)$$

2.5.a) $P_{S_{13}|S_{12}}(k|2)$

$$A = \begin{pmatrix} 0.7 & 0.1 & 0.2 \\ \boxed{0.1} & \boxed{0.8} & \boxed{0.1} \\ 0.1 & 0 & 0.9 \end{pmatrix}$$

2.5.b) $P_{S_{13}|S_{11}, S_{12}}(k|1,2) = P_{S_{13}|S_{12}}(k|2)$

$$A = \begin{pmatrix} 0.7 & 0.1 & 0.2 \\ \boxed{0.1} & \boxed{0.8} & \boxed{0.1} \\ 0.1 & 0 & 0.9 \end{pmatrix} \text{ from 2}$$

2.5.c) $P_{S_{11}}(i) = \frac{1}{3} \quad i=1,2,3.$

$$P_{S_{11}|S_{12}}(k|2) =$$

$$= \begin{cases} 0.1/0.9 & k=1 \\ 0.8/0.9 & k=2 \end{cases}$$

$$A = \begin{pmatrix} 0.7 & \boxed{0.1} & 0.2 \\ 0.1 & \boxed{0.8} & 0.1 \\ 0.1 & 0 & 0.9 \end{pmatrix} \text{ Read to 2}$$

2.5.d) $P_{S_{11}|S_{10}, S_{12}}(k|3,2)$

S_{12} ended up in 2
 $\Rightarrow S_{11}$ could not be 3

S_{10} was 3 $\Rightarrow S_{11}$ could not be 2

$$A = \begin{pmatrix} 0.7 & 0.1 & 0.2 \\ 0.1 & 0.8 & 0.1 \\ 0.1 & 0 & 0.9 \end{pmatrix}$$

$$P_{S_{11}|S_{10}, S_{12}}(k|3,2) = \begin{cases} 1 & k=1 \\ 0 & \text{elsewhere.} \end{cases}$$

'General' way: $P_{S_{11}|S_{10}, S_{12}}(k|3,2) = \frac{P_{S_{11}, S_{12}|S_{10}}}{P_{S_{12}|S_{10}}} = \frac{P_{S_{11}, S_{12}|S_{10}}}{\sum_{S_{11}=k} P_{S_{11}, S_{12}|S_{10}}} =$

$$\begin{aligned} P_{S_{11}, S_{12}|S_{10}} &= P_{S_{12}|S_{11}, S_{10}} P_{S_{11}|S_{10}} = \\ &= P_{S_{12}|S_{11}} P_{S_{11}|S_{10}} = P(S_{12}=2|S_{11}=k) \cdot P_{S_{11}}(k|S_{10}=3) \end{aligned}$$

$$P_{S_{11}, S_{12}|S_{10}}(k, 2|3) = P(S_{12}=2|S_{11}=k) P_{S_{11}}(k|S_{10}=3) = \begin{cases} 0.1 \cdot 0.9 & k=1 \\ 0.8 \cdot 0 & k=2 \\ 0 \cdot 0.9 & k=3 \end{cases}$$

3.3 $s \in \{1, \dots, N\}$ known: $P_s(j)$ prior
 $f_{X|S}(x|j)$ likelihood function

Design classifier $d(x): X \rightarrow \{1, \dots, N, N+1\}$ class $N+1$ meaning 'cannot classify'.
 that minimizes expected loss given loss function:

$$L(d(x)=i|S=j) = \begin{cases} 0, & i=j=1, \dots, N \\ r, & i=N+1, j=1, \dots, N \\ c, & \text{otherwise} \end{cases}$$

3.3.a.

$$d(x) := \arg \min_N R(i|x)$$

$$d(x) := \arg \min_i R(i|x)$$

with $R(i|x) = \begin{cases} \sum_{j=1}^N L(d(x)=i | S=j) P_{S|X}(j|x), & i=1, \dots, N \\ r & , i=N+1 \end{cases}$

Hence whenever $\sum_{j=1}^N L(d(x)=i | S=j) P_{S|X}(j|x) \leq r$ for at least one $i=1, \dots, N$ we will minimize LHS otherwise we will choose r .

$$0 \cdot P_{S|X}(i|x) + \sum_{j \neq i} c P_{S|X}(j|x) = c(1 - P_{S|X}(i|x)) \leq r \quad 1 - P_{S|X}(i|x) \leq \frac{r}{c}$$

$$1 - \frac{r}{c} \leq P_{S|X}(i|x).$$

Hence if for at least one i $1 - r/c \leq P_{S|X}(i|x)$ we select i s.t. $i = \arg \min_i \sum_{j=1}^N L(d(x)=i | S=j) P_{S|X}(j|x)$

$$= \arg \min_x \sum_{j \neq i} c P_{S|X}(j|x) = \underset{i}{\arg \max} P_{S|X}(i|x).$$

Hence,

$$d(x) = \begin{cases} \underset{i}{\arg \max} P_{S|X}(i|x) & \text{if } P_{S|X}(i|x) \geq 1 - r/c \quad (\text{if holds forward, holds for at least 1}). \\ N+1 & \text{otherwise.} \end{cases}$$

3.3.b What happens if $r=0$ or $c \rightarrow \infty$?

\exists no reason to classify as it will result in an average higher cost. Then the classifier will

\exists no reason to clarify as it will result in an average higher wt. Then the clarifier will prefer to never pick anything.

3.3.c If $r > c$?

The do not clarify option is more expensive than making a mistake and therefore we will always clarify.

3.3.d. Show that $g_i(x) = \int_{\mathcal{X}} f_{S|X}(x|i) P_S(i) \quad i=1, \dots, N$

$$g_{N+1}(x) = \left(1 - \frac{r}{c}\right) \sum_{j=1}^N g_j(x)$$

get the minimum wt.

For this to be true it needs to happen that $P_{S|X}(s=i|x) \propto g_i(x)$
and that $(b) g_{N+1}(x) \geq g_i(x) \forall i=1, \dots, N$ when $P_{S|X}(i|x) \leq 1 - r/c \quad \forall i=1, \dots, N$.

(a)

We first establish that $P_{S|X}(s=i|x) \propto g_i(x)$

$$g_i(x) = \int_{\mathcal{X}} f_{S|X}(x|i) P_S(i) = P_{S|X}(s=i|x) f_X(x) \Rightarrow g_i(x) \propto P_{S|X}(s=i|x).$$

$$(b) \quad \sum_{i=1}^N g_i(x) = \sum_{i=1}^N f_{S|X}(x|i) P_S(i) = f_X(x) \quad \forall i$$

$$\text{Then if } g_{N+1}(x) = \left(1 - \frac{r}{c}\right) \sum_{j=1}^N g_j(x) = \left(1 - \frac{r}{c}\right) f_X(x) \geq P_{S|X}(s=i|x) f_X(x)$$

condition (b) is also fulfilled.

3.3.e. Sketch discriminants when $N=2$:

$S=1$	$N(1, 1)$
$S=2$	$N(-1, 1)$

$$P(S=1) = P(S=2) = \frac{1}{2}$$

$$S=2 \mid N'(-1,1)$$

choose 'not classify' when $P_{S|x}(i|x) \leq 3/4$.

$$P_{S|x}(1|x) = \frac{f_{x|S}(x|1) P(S=1)}{f_x(x)}$$

Abuse of notation $\pi(r, c)(x)$

$$P_{S|x}(2|x) = \frac{f_{x|S}(x|2) P(S=2)}{f_x(x)}$$

$$P_{S|x}(1|x) = \frac{\frac{1}{2} \pi(1,1)(x)}{\frac{1}{2} \pi(1,1)(x) + \frac{1}{2} \pi(1,-1)(x)}$$

$$P_{S|x}(2|x) = \frac{\frac{1}{2} \pi(-1,1)(x)}{\frac{1}{2} \pi(1,1)(x) + \frac{1}{2} \pi(-1,1)(x)}$$

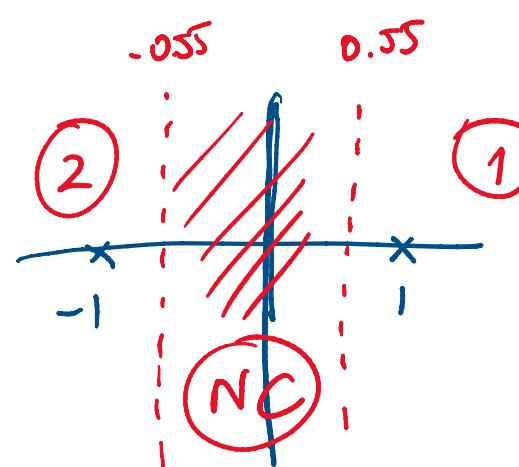
$$P_{S|x}(1|x) = \frac{\pi(1,1)(x)}{\pi(1,1)(x) + \pi(1,-1)(x)} = \frac{3}{4} \Rightarrow \pi(1,1)(x) = 3\pi(1,-1)(x).$$

$$\cancel{\frac{1}{\sqrt{2\pi}} e^{-(x-1)^2/2}} = \cancel{\frac{1}{\sqrt{2\pi}} e^{-(x+1)^2/2}} \cdot e^{\log(3)}$$

$$\Rightarrow (x-1)^2/2 = (x+1)^2/2 - \log(3)$$

$$x^2 - 2x - 1 = x^2 + 2x + 1 - 2\log(3)$$

$$4x = 2\log(3) \quad x = \frac{1}{2}\log(3) \approx 0.55$$



... | D-1-class. or "most" decision in the situation 3.3 e?

3.3.f.] Probability of "reject" decision in the situation 3.3 e?

$$\begin{aligned}
 P(\text{reject}) &= \int_{-\frac{1}{2} \log(3)}^{\frac{1}{2} \log(3)} f_X(x) dx = \frac{1}{2} \int_{-\frac{1}{2} \log(3)}^{\frac{1}{2} \log(3)} (N(1,1)(x) + N(-1,1)(x)) dx \\
 &= \frac{1}{2} \int_{-\frac{1}{2} \log(3)-1}^{\frac{1}{2} \log(3)-1} N(0,1)(x) dx + \frac{1}{2} \int_{-\frac{1}{2} \log(3)+1}^{\frac{1}{2} \log(3)+1} N(0,1)(x) dx \\
 &= \frac{1}{2} \int_{-\frac{1}{2} \log(3)-1}^{\infty} N(0,1)(x) dx - \int_{\frac{1}{2} \log(3)-1}^{\infty} N(0,1)(x) dx + \text{analogous} \\
 &= \frac{1}{2} Q\left(-\left(\frac{1}{2} \log(3)+1\right)\right) - \frac{1}{2} Q\left(\frac{1}{2} \log(3)-1\right) + \frac{1}{2} Q\left(-\frac{1}{2} \log(3)+1\right) - \frac{1}{2} Q\left(\frac{1}{2} \log(3)+1\right) \\
 &= \frac{1}{2} \left(1 - Q\left(\frac{1}{2} \log(3)+1\right)\right) - \frac{1}{2} Q\left(\frac{1}{2} \log(3)+1\right) + \frac{1}{2} Q\left(-\frac{1}{2} \log(3)+1\right) \\
 &\quad - \frac{1}{2} \left(1 - Q\left(1 - \frac{1}{2} \log(3)\right)\right) = Q\left(1 - \frac{1}{2} \log(3)\right) - Q\left(1 + \frac{1}{2} \log(3)\right)
 \end{aligned}$$

range of relation σ/c will the reject decision never be chosen? $\frac{\sigma}{c} > 0.5$.

Because one of the two P_{SIX} will always be equal or larger than 0.5.

3.13 $X = (X_1, \dots, X_T)$ input data

$$\sigma_{T \times 7} = \begin{cases} -1 & s=0 \\ 1 & s \neq 0 \end{cases} \rightarrow \text{equal probabilities}$$

$\text{Var}(X_t) = 4$ for both.

3.13

 $X = (X_1, \dots, X_T)$ input dataGenerated with either state $S=0$ or $S=1$

$$E[X_t] = \begin{cases} -1 & S=0 \\ +1 & S=1 \end{cases}$$

Gaussian

 $\text{var}(X_t) = 4$ for both. $T=9$.

3.13.a Smallest probability of error for ideal classifier?

log-likelihood functions : $\log \left(\prod_{t=1}^T \frac{1}{\sqrt{2\pi} \cdot 2} e^{-\frac{(x_t - \mu_i)^2}{2 \cdot 4}} \right)$

only difference between the
two classes : exponent

$$-\sum_{t=1}^T (x_t - \mu_i)^2$$

Hence if

$$\sum_{t=1}^T (x_t - \mu_1)^2 \geq \sum_{t=1}^T (x_t - \mu_0)^2$$

\uparrow

choose 0

$$\Rightarrow \sum_{t=1}^T (x_t^2 - 2x_t \mu_1 + \mu_1^2) \stackrel{0}{\geq} \sum_{t=1}^T (x_t^2 - 2x_t \mu_0 + \mu_0^2)$$

$$\sum_{t=1}^T -x_t \stackrel{0}{\geq} \sum_{t=1}^T x_t$$

hence if

$$\sum_{t=1}^T x_t \leq 0 \text{ we choose } S=0$$

 x_i are iid and Gaussian $\Rightarrow \sum_{t=1}^T x_t$ i.i.d. and Gaussian.

$$Y \stackrel{D}{=} \sum_{t=1}^T x_t - \{ E[Y|S=0] = -T \quad \text{var}[Y] = T4 \}$$

$$Y \stackrel{D}{=} \sum_{t=1}^T X_t = \begin{cases} \mathbb{E}[Y|S=0] = -T \\ \mathbb{E}[Y|S=1] = T \end{cases} \quad \text{var}[Y] = T^4$$

$Y \leq 0$ where $S=0$.

$$\begin{aligned} P(\text{error}) &= P(Y \geq 0 | S=0) P(S=0) + P(Y < 0 | S=1) P(S=1) \\ &= P(Y \geq 0 | S=0) \\ &= \int_0^\infty \frac{1}{\sqrt{(2\pi)2T}} e^{-\frac{(y+T)^2}{2\cdot 2T}} dy = \left\{ z = \frac{y+T}{\sqrt{2T}} \right\} = \int_{\frac{T}{\sqrt{2}}}^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz = Q\left(\frac{T}{\sqrt{2}}\right). \end{aligned}$$

3.13.6. X_t a discrete 'vote' for $S=1$ if $X_t > 0$
 $S=0$ otherwise

$$Z = \#\ X_t > 0 \quad \begin{array}{ll} S=0 & \text{if } z < T/2 \\ S=1 & \text{otherwise} \end{array}$$

Probability of error.

$$T=9$$

$$P(\text{error}) = P(Z \geq T/2 | S=0) P(S=0) + P(Z < T/2 | S=1) P(S=1) = P(Z \leq 4 | S=1).$$

There are total of $\binom{T}{n}$ # of ways n objects can be chosen among T objects
 (disregarding order).

$$\frac{1}{n!} = \frac{1}{1 \cdot 2 \cdot \dots \cdot n} = 1 - s$$

$$P(X_T > 0 | S=0) = \int_0^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-1)^2}{2 \cdot 4}} = Q(-\frac{1}{2}) = 1 - Q(\frac{1}{2}) = 1 - \varepsilon$$

$$P(X_T > 0 | S=1) = Q(\frac{1}{2}) = \varepsilon$$

$$P(Z=n | S=0) = \binom{T}{n} (1-\varepsilon)^n \varepsilon^{T-n} \quad P(Z=n | S=1) = \binom{T}{n} (\varepsilon)^n (1-\varepsilon)^{T-n}$$

$$P(Z \geq \frac{T}{2} | S=0) = \sum_{n=\lceil \frac{T}{2} \rceil}^T \binom{T}{n} (1-\varepsilon)^n (\varepsilon)^{T-n}$$

$$P(Z < \frac{T}{2} | S=1) = \sum_{n=1}^{\lceil \frac{T}{2} \rceil - 1} \binom{T}{n} (\varepsilon)^n (1-\varepsilon)^{T-n}$$

$$P(Z \leq 4 | S=1) = \sum_{n=1}^4 \binom{9}{n} (\varepsilon)^n (1-\varepsilon)^{9-n} \approx 0.11$$

3.4

$$\begin{array}{ll} 0 & \text{fair} \\ 1 & P(\text{head} | S=1) = p > \frac{1}{2} \quad P(\text{tail} | S=1) = 1-p. \end{array}$$

Koisser \leq k heads

$$\begin{aligned} \underline{3.6.a.} \quad g(x) &> 0 \text{ when } 1 \\ g(x) &\leq 0 \text{ when } 0. \end{aligned}$$

of heads in a sequence of length K

$$P(H=k | S=0) = (0.5)^k (0.5)^{K-k} = (0.5)^K$$

$$P(H=k | S=1) = p^k (1-p)^{K-k}$$

$$g(x) > 0 \text{ when } 1 \rightarrow P(H=k | S=1) > P(H=k | S=0) \quad \text{log monotonically increasing}$$

$$\begin{aligned} g(x) &= k \ln(p) + (K-k) \ln(1-p) - K \ln(0.5) \\ &= k(\ln(p) - \ln(1-p)) + K(\ln(1-p) + \ln(2)) \end{aligned}$$

$$k \ln(p) - \ln(1-p) + K(\ln(1-p) + \ln(2)) = 0$$

$$k_{th} = \frac{-K(\ln(1-p) + \ln(2))}{-\ln(1-p) + \ln(p)} = K \cdot \frac{\ln\left(\frac{1}{2(1-p)}\right)}{\ln\left(\frac{p}{1-p}\right)}$$

3.6.b. average probability of error for $k=5$ and $p=0.6$.

$$k_{th} = 2.75.$$

$$P(\text{error}) = P(H \geq 3 | p=0.5) \underbrace{\frac{1}{2}}_{p=0.5} + P(H \leq 2 | p=0.6) \underbrace{\frac{1}{2}}_{p=0.6} \approx 0.409.$$

$$P(\text{error}) = P(H \geq 0) \underbrace{P_{S=0}}_{S=0} + P(H < 0) \underbrace{P_{S=1}}_{S=1}.$$