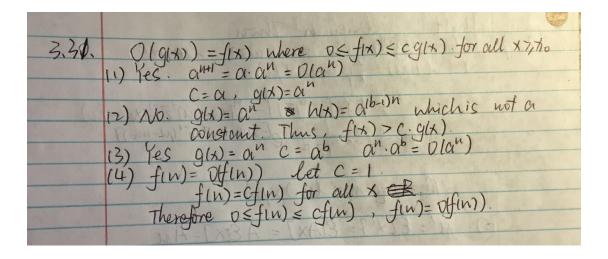
| Help Com thou | |
|---|---|
| $P(m) = \frac{1}{2\pi} 1$ | HWG Wigian Thou. |
| $P(m) = \frac{1}{2\pi} 1$ | 3.17 for MAP, we mousinize lepton |
| $P(m) = \frac{1}{2\pi} 1$ | (1) l(pi) = Zlup(xk/pi). |
| $ \mu' = \arg\max_{M} \lim_{N \to \infty} \lim$ | No trade 7 W. |
| $ \mu' = \arg\max_{M} \lim_{N \to \infty} \lim$ | =-= ln(00/21)- =1xx-10/2-1(xx-n) |
| $ \mu' = \arg\max_{M} \lim_{N \to \infty} \lim$ | P(M) = 17570/2 12 15 OL Zyu-mo) 20 (M-mo)] |
| 12) $M' = E[X'] = E[AX] = A E[X] = A\mu$. $Z' = E[(X'-\mu')(X'-\mu')^{T}]$ $= E[(X'-\mu')(X'-\mu')^{T}]$ $= E[(X'-\mu)(AX - A\mu)^{T}]$ $= A E[(X'-\mu)(AX - A\mu)^{T}]$ $= A E[(X'-\mu)(X'-\mu)^{T}]$ $= A E[(X'-\mu)(X'-\mu)^{T}]$ $= A E[(X'-\mu)(X'-\mu)^{T}]$ $= A E[(X'-\mu)(AX - A\mu)^{T}]$ $= A E[(X'-\mu)(AX $ | 1-0-6 |
| 12) $M' = E[X'] = E[AX] = A E[X] = A\mu$. $Z' = E[(X'-\mu')(X'-\mu')^{T}]$ $= E[(X'-\mu')(X'-\mu')^{T}]$ $= E[(X'-\mu)(AX - A\mu)^{T}]$ $= A E[(X'-\mu)(AX - A\mu)^{T}]$ $= A E[(X'-\mu)(X'-\mu)^{T}]$ $= A E[(X'-\mu)(X'-\mu)^{T}]$ $= A E[(X'-\mu)(X'-\mu)^{T}]$ $= A E[(X'-\mu)(AX - A\mu)^{T}]$ $= A E[(X'-\mu)(AX $ | 1û = ara max line) Dine) |
| $Z' = \mathcal{E} L(x' - \mu')(x' - \mu')^{\frac{1}{2}}$ $= \mathcal{E} L(x' - \mu)(x' - \mu')^{\frac{1}{2}}$ $= \mathcal{A} \mathcal{E} L(x' - \mu)(x' - \mu)^{\frac{1}{2}} L(x' - \mu)^{\frac{1}{2}}$ $= \mathcal{A} \mathcal{E} L(x' - \mu)(x' - \mu)^{\frac{1}{2}} L(x' - \mu)^{\frac{1}{2}} L($ | (CA) TO ME SOLL SPITES |
| $Z' = \mathcal{E} L(x' - \mu')(x' - \mu')^{\frac{1}{2}}$ $= \mathcal{E} L(x' - \mu)(x' - \mu')^{\frac{1}{2}}$ $= \mathcal{A} \mathcal{E} L(x' - \mu)(x' - \mu)^{\frac{1}{2}} L(x' - \mu)^{\frac{1}{2}}$ $= \mathcal{A} \mathcal{E} L(x' - \mu)(x' - \mu)^{\frac{1}{2}} L(x' - \mu)^{\frac{1}{2}} L($ | m' = Etx'J = EtAx7 = AEtx7 = AM |
| Therefore, for $l(\mu')p(\mu')$ ne home. $l(\mu') = \frac{1}{2\pi} ln p(Atk \mu')$ $= -\frac{n}{2} ln p(Atk Apu)$ $= -\frac{n}{2} ln $ | |
| Therefore, for $l(\mu')p(\mu')$ ne home: $l(\mu') = \frac{1}{2\pi} ln p(Atk A\mu)$ $= -\frac{n}{2} ln [12\pi)^{cl} [AZA^{\dagger}] - \frac{n}{2} [AXk - A\mu]^{\dagger} (AZA^{\dagger})^{-1}$ $= -\frac{n}{2} ln [12\pi)^{cl} [AZA^{\dagger}] - \frac{n}{2} [AXk - A\mu]^{\dagger} (AZA^{\dagger})^{-1} (Ak - A\mu)$ $= -\frac{n}{2} ln [12\pi)^{cl} [AZA^{\dagger}] - \frac{n}{2} [AXk - \mu]^{\dagger} Z^{\dagger} (Ak - \mu)$ $= \frac{1}{(2\pi)^{cl/2} [AZa^{\dagger}]^{\frac{1}{2}}} e^{[-\frac{1}{2}(\mu - \mu_0)^{\dagger}] Z^{-1} (\mu - \mu_0)}$ $= \frac{1}{(2\pi)^{cl/2} [AZa^{\dagger}]^{\frac{1}{2}}} e^{[-\frac{1}{2}(\mu - \mu_0)^{\dagger}] Z^{-1} (\mu - \mu_0)}$ | $z' = \varepsilon L(x'-\mu')(x'-\mu')$ |
| Therefore, for $l(\mu')p(\mu')$ ne home: $l(\mu') = \frac{1}{2\pi} ln p(Atk A\mu)$ $= -\frac{n}{2} ln [12\pi)^{cl} [AZA^{\dagger}] - \frac{n}{2} [AXk - A\mu]^{\dagger} (AZA^{\dagger})^{-1}$ $= -\frac{n}{2} ln [12\pi)^{cl} [AZA^{\dagger}] - \frac{n}{2} [AXk - A\mu]^{\dagger} (AZA^{\dagger})^{-1} (Ak - A\mu)$ $= -\frac{n}{2} ln [12\pi)^{cl} [AZA^{\dagger}] - \frac{n}{2} [AXk - \mu]^{\dagger} Z^{\dagger} (Ak - \mu)$ $= \frac{1}{(2\pi)^{cl/2} [AZa^{\dagger}]^{\frac{1}{2}}} e^{[-\frac{1}{2}(\mu - \mu_0)^{\dagger}] Z^{-1} (\mu - \mu_0)}$ $= \frac{1}{(2\pi)^{cl/2} [AZa^{\dagger}]^{\frac{1}{2}}} e^{[-\frac{1}{2}(\mu - \mu_0)^{\dagger}] Z^{-1} (\mu - \mu_0)}$ | = ETIAX - Apr) (Ax - Apr)+3 |
| Therefore, for $l(\mu')p(\mu')$ ne home: $l(\mu') = \frac{1}{2\pi} ln p(Atk A\mu)$ $= -\frac{n}{2} ln [12\pi)^{cl} [AZA^{\dagger}] - \frac{n}{2} [AXk - A\mu]^{\dagger} (AZA^{\dagger})^{-1}$ $= -\frac{n}{2} ln [12\pi)^{cl} [AZA^{\dagger}] - \frac{n}{2} [AXk - A\mu]^{\dagger} (AZA^{\dagger})^{-1} (Ak - A\mu)$ $= -\frac{n}{2} ln [12\pi)^{cl} [AZA^{\dagger}] - \frac{n}{2} [AXk - \mu]^{\dagger} Z^{\dagger} (Ak - \mu)$ $= \frac{1}{(2\pi)^{cl/2} [AZa^{\dagger}]^{\frac{1}{2}}} e^{[-\frac{1}{2}(\mu - \mu_0)^{\dagger}] Z^{-1} (\mu - \mu_0)}$ $= \frac{1}{(2\pi)^{cl/2} [AZa^{\dagger}]^{\frac{1}{2}}} e^{[-\frac{1}{2}(\mu - \mu_0)^{\dagger}] Z^{-1} (\mu - \mu_0)}$ | $= A \in (1 \times -\mu) (1 \times -\mu) + 7 A^{\dagger}$ |
| $= \frac{n}{2} ln p[Ahk Apu)$ $= -\frac{n}{2} ln [12\pi]^{0} [AZA^{\dagger}] - \frac{n}{2} [Ahk - Apu]^{\dagger} (AZA^{\dagger})^{-1}$ $= -\frac{n}{2} ln [12\pi]^{0} [AZA^{\dagger}] - \frac{n}{2} [Ahk - pu]^{\dagger} Z^{\dagger} [hk - pu]$ $= -\frac{1}{2} ln [12\pi]^{0} [AZA^{\dagger}] - \frac{n}{2} [Ahk - Amo]^{\dagger} (AZA^{\dagger})^{-1} (Am - Amo)$ $= \frac{1}{2\pi} [2ln - Amo]^{\dagger} [AZA^{\dagger}]^{\frac{1}{2}} e^{-\frac{1}{2}} [m - mo]^{\frac{1}{2}} [m - mo]^{\frac{1}{2}}$ $= \frac{1}{2\pi} [n]^{0} [aZa^{\dagger}]^{\frac{1}{2}} e^{-\frac{1}{2}} [m - mo]^{\frac{1}{2}} [n]^{-\frac{1}{2}} [m - mo]^{\frac{1}{2}}$ | Therefore for (101) (11) |
| $= \frac{n}{2} ln p[Ahk Apu)$ $= -\frac{n}{2} ln [12\pi]^{0} [AZA^{\dagger}] - \frac{n}{2} [Ahk - Apu]^{\dagger} (AZA^{\dagger})^{-1}$ $= -\frac{n}{2} ln [12\pi]^{0} [AZA^{\dagger}] - \frac{n}{2} [Ahk - pu]^{\dagger} Z^{\dagger} [hk - pu]$ $= -\frac{1}{2} ln [12\pi]^{0} [AZA^{\dagger}] - \frac{n}{2} [Ahk - Amo]^{\dagger} (AZA^{\dagger})^{-1} (Am - Amo)$ $= \frac{1}{2\pi} [2ln - Amo]^{\dagger} [AZA^{\dagger}]^{\frac{1}{2}} e^{-\frac{1}{2}} [m - mo]^{\frac{1}{2}} [m - mo]^{\frac{1}{2}}$ $= \frac{1}{2\pi} [n]^{0} [aZa^{\dagger}]^{\frac{1}{2}} e^{-\frac{1}{2}} [m - mo]^{\frac{1}{2}} [n]^{-\frac{1}{2}} [m - mo]^{\frac{1}{2}}$ | SIM'S TILL THE Name. |
| $= -\frac{n}{2} \ln \left[(2\pi)^{cl} [AZA^{\dagger}] \right] - \frac{n}{2} (AX_{k} - A_{ju})^{\dagger} (AZA^{\dagger})^{-\dagger}$ $= -\frac{n}{2} \ln \left[(2\pi)^{cl} [AZA^{\dagger}] \right] - \frac{n}{2} (AX_{k} - A_{ju})^{\dagger} (AX_{k} - A_{ju})^{\dagger}$ $= -\frac{1}{2} \ln \left[(2\pi)^{cl} [AZA^{\dagger}] \right] - \frac{1}{2} (AX_{k} - A_{ju})^{\dagger} (AX_{k} - A_{ju})^{\dagger} (AX_{k} - A_{ju})^{\dagger}$ $= \frac{1}{(2\pi)^{cl} (AZ_{k} + 1)^{\dagger}} e^{\frac{1}{2}} e^{\frac{1}{2}} [AX_{k} - A_{ju})^{\dagger} (AX_{k} - A_{ju})^{\dagger} (AX_{k} - A_{ju})^{\dagger}$ $= \frac{1}{(2\pi)^{cl} (AZ_{k} + 1)^{\dagger}} e^{\frac{1}{2}} e^{\frac{1}{2}} [AX_{k} - A_{ju})^{\dagger} (AX_{k} - A_{ju})^{\dagger} (AX_{k} - A_{ju})^{\dagger}$ $= \frac{1}{(2\pi)^{cl} (AZ_{k} + 1)^{\dagger}} e^{\frac{1}{2}} e^{\frac{1}{2}} [AX_{k} - A_{ju}]^{\dagger} (AX_{k} - A_{ju})^{\dagger} (AX_{k} - A_{ju})^{\dagger}$ $= \frac{1}{(2\pi)^{cl} (AZ_{k} + 1)^{\dagger}} e^{\frac{1}{2}} e^{\frac{1}{2}} [AX_{k} - A_{ju}]^{\dagger} (AX_{k} - A_{ju})^{\dagger} (AX_{k} - A_{ju})^{\dagger}$ $= \frac{1}{(2\pi)^{cl} (AZ_{k} + 1)^{\dagger}} e^{\frac{1}{2}} e^{\frac{1}{2}} [AX_{k} - A_{ju}]^{\dagger} (AX_{k} - A_{ju})^{\dagger} (AX_{k} - A$ | to fire the |
| $= -\frac{1}{2} \ln \left[\frac{1}{2\pi} \right]^{d} \left[\frac{A \times A + 1}{A \times A + 1} \right] - \frac{1}{2} \left[A \times A + A \times $ | = Elup(AAK) |
| $= -\frac{1}{2} \ln \left[\frac{1}{2\pi} \right]^{d} \left[\frac{A \times A + 1}{A \times A + 1} \right] - \frac{1}{2} \left[A \times A + A \times $ | = - " lut 12 t 10/10 2 At 17 10 10 1 10 Transit |
| $P(\mu') = \frac{1}{(2\pi)^{\alpha/2} AZ_0A^{\dagger} ^{\frac{1}{2}}} e^{\frac{1}{2} (A\mu - Am_0)^{\frac{1}{2}} (AZ_0A^{\dagger})^{-\frac{1}{2}} (A\mu - Am_0)}$ $= \frac{1}{(2\pi)^{\alpha/2} AZ_0A^{\dagger} ^{\frac{1}{2}}} e^{\frac{1}{2} (\mu - m_0)^{\frac{1}{2}} e^{\frac{1}{2}} (\mu - m_0)^{\frac{1}{2}}} e^{\frac{1}{2} (\mu - m_0)^{\frac{1}{2}} e^{\frac{1}{2}} (\mu - m_0)^{\frac{1}{2}}}$ | Z LING (AZA) |
| $P(\mu') = \frac{1}{(2\pi)^{\alpha/2} AZ_0A^{\dagger} ^{\frac{1}{2}}} e^{\frac{1}{2} (A\mu - Am_0)^{\frac{1}{2}} (AZ_0A^{\dagger})^{-\frac{1}{2}} (A\mu - Am_0)}$ $= \frac{1}{(2\pi)^{\alpha/2} AZ_0A^{\dagger} ^{\frac{1}{2}}} e^{\frac{1}{2} (\mu - m_0)^{\frac{1}{2}} (\mu - m_0)}$ | =- = hottonyd (AZA+1] - ELASAL-MISTIAN-14) |
| | |
| | P(M) = Ot- = LAM-Amo) (AZOA+) (AM-AMO) |
| | (Th) of 1 A Zo At 12 |
| | = - e-= (M-mo) 7 = (M-mo)] |
| A' = arg max elpi)p(pi). | Th) ME (AZOAT) & |
| M' = arg max elpi)p(pi). | |
| | M = arg max cipi)p(pi). |
| | |
| | |
| | |



Question 2

a) Maximum-likelihood values mu and sigma

```
% a) maximum-likelihood

function [mu,sigma] = ML_estimate(x)
len = length(x);
mu = sum(x) / len;
sigma = sum((x - mu).^2) / len;
end
```

Three features xi of category w1

```
% a) three features xi of category wl
[mul,sigmal] = ML_estimate(pxwl(:,1));
[mu2,sigma2] = ML_estimate(pxwl(:,2));
[mu3,sigma3] = ML_estimate(pxwl(:,3));
disp('a) estimation for mean and variance for wl')
disp(['mean for xl = ', num2str(mul)]);
disp(['variance for xl = ',num2str(sigmal)]);
disp(['mean for x2 = ', num2str(mu2)]);
disp(['variance for x2 = ',num2str(sigma2)]);
disp(['mean for x3 = ', num2str(mu3)]);
disp(['variance for x3 = ',num2str(sigma3)]);
```

Result:

```
a) estimation for mean and variance for wl mean for x1 = -0.0709 variance for x1 = 0.90618 mean for x2 = -0.6047 variance for x2 = 4.2007 mean for x3 = -0.911 variance for x3 = 4.5419
```

b/c) Multi-dimension estimation

```
% b/c) multi-dimensional Gaussian
function [mu,sigma] = ML estimate2(x)
      len = size(x,1);
      mu = sum(x) / len;
      tmp = x - repmat(mu, len, 1);
      sigma = (tmp'*tmp) / len;
 -end
b) Two-dimension
 % b) two-dimension
 [mul, sigmal] = ML estimate2(pxwl(:,1:2));
 [mu2,sigma2] = ML_estimate2(pxwl(:,2:3));
 [mu3, sigma3] = ML estimate2(pxwl(:,[1,3]));
 disp('b) 2-dimension estimation for mean and variance for wl')
 disp('mean for x1, x2 = '); disp(mul);
 disp('variance for x1,x2 = '); disp(sigmal);
 disp('mean for x2, x3 = '); disp(mu2);
 disp('variance for x2,x3 = '); disp(sigma2);
 disp('mean for x1, x3 = '); disp(mu3);
 disp('variance for x1,x3 = '); disp(sigma3);
Result:
b) 2-dimension estimation for mean and variance for wl
mean for x1, x2 =
   -0.0709 -0.6047
variance for x1, x2 =
    0.9062 0.5678
    0.5678 4.2007
mean for x2, x3 =
   -0.6047 -0.9110
variance for x2, x3 =
    4.2007 0.7337
    0.7337
             4.5419
mean for x1, x3 =
   -0.0709 -0.9110
variance for x1, x3 =
    0.9062 0.3941
    0.3941
             4.5419
```

c) Three-dimension

```
% c) three-dimension
 [mu,sigma] = ML estimate2(pxwl);
disp('c) 3-dimension estimation for mean and variance for wl')
disp('mean for x1,x2,x3 of w1 = '); disp(mu);
disp('variance for x1,x2,x3 of w1 = '); disp(sigma);
Result:
c) 3-dimension estimation for mean and variance for wl
mean for x1, x2, x3 of w1 =
   -0.0709 -0.6047 -0.9110
variance for x1, x2, x3 of w1 =
    0.9062 0.5678 0.3941
    0.5678 4.2007 0.7337
    0.3941 0.7337
                       4.5419
d) Diagonal of the covariance
  % d) diagonal component of coveriance
function [mu,sigma] = ML diagonal(x)
     len = size(x,1);
     mu = sum(x) / len;
     tmp = x - repmat(mu, len, 1);
     sigma = (tmp'*tmp) / len;
     sigma = diag(sigma);
 end
Result:
d) mean and diagnoal variance for w2
mean for x1, x2, x3 of w2 =
   -0.1126 0.4299 0.0037
```

e/f) compare the mean and variance calculated in above ways.

variance for x1, x2, x3 of w2 =

0.0539 0.0460 0.0073

```
[mul, sigmal] = ML estimate2([pxwl(:,1),pxw2(:,1),pxw3(:,1)]);
[mu2,sigma2] = ML_estimate2([pxw1(:,2),pxw2(:,2),pxw3(:,2)]);
[mu3,sigma3] = ML_estimate2([pxw1(:,3),pxw2(:,3),pxw3(:,3)]);
disp('e/f) mean and variance of each feature x1,x2,x3 using function ML estimate2')
disp('mean for xl = '); disp(mul);
disp('variance for xl = '); disp(sigmal);
disp('mean for x2 = '); disp(mu2);
disp('variance for x2 = '); disp(sigma2);
disp('mean for x3 = '); disp(mu3);
disp('variance for x3 = '); disp(sigma3);
[mul, sigmal] = ML diagonal([pxwl(:,1),pxw2(:,1),pxw3(:,1)]);
[mu2, sigma2] = ML diagonal([pxwl(:,2),pxw2(:,2),pxw3(:,2)]);
[mu3, sigma3] = ML diagonal([pxwl(:,3),pxw2(:,3),pxw3(:,3)]);
disp('e/f) mean and variance of each feature x1,x2,x3 using function ML diagonal')
disp('mean for xl = '); disp(mul);
disp('variance for xl = '); disp(sigmal);
disp('mean for x2 = '); disp(mu2);
disp('variance for x2 = '); disp(sigma2);
disp('mean for x3 = '); disp(mu3);
disp('variance for x3 = '); disp(sigma3);
Result:
e/f) mean and variance of each feature x1, x2, x3 using function ML estimate2
mean for x1 =
                      0.2747
   -0.0709 -0.1126
variance for x1 =
    0.9062 0.0753 -0.2760
    0.0753 0.0539 -0.0718
   -0.2760 -0.0718 0.3019
mean for x2 =
   -0.6047 0.4299 0.3001
variance for x2 =
    4.2007 0.1320 -0.5137
    0.1320 0.0460 0.0047
   -0.5137 0.0047 0.6450
mean for x3 =
   -0.9110 0.0037
                       0.6786
variance for x3 =
    4.5419 -0.0650 0.5060
   -0.0650 0.0073 0.0344
    0.5060 0.0344 1.2621
```

% e/f) mean and variance of each feature

```
e/f) mean and variance of each feature x1,x2,x3 using function ML_diagonal
mean for x1 =
  -0.0709 -0.1126 0.2747
variance for x1 =
   0.9062
   0.0539
   0.3019
mean for x2 =
 -0.6047 0.4299 0.3001
variance for x2 =
   4.2007
   0.0460
   0.6450
mean for x3 =
  -0.9110 0.0037 0.6786
variance for x3 =
   4.5419
   0.0073
   1.2621
```

Conclusion:

The value of estimation of mean and covariance are the same.

For the mean, using the maximum-likelihood estimation, the estimated mean is the sample mean. Therefore, it doesn't matter the variance is diagonal matrix or not.

As for the variance, the diagonal one is actually the diagonal value of the covariance matrix in the former function. They are calculated by the same way and thus they are the same.