

1., 4., 5.

# MACHINE LEARNING ASSIGNMENT

1.  $t_n =$  true label  
 $x_n =$  feature vector  
 $\tau_n > 0 \rightarrow$  importance of  $n^{\text{th}}$  example.

$$E(w) = \frac{1}{2} \sum_{n=1}^N \tau_n (t_n - w^T \phi(x_n))^2$$

Taking gradient,

$$\sum_{n=1}^N \tau_n \{t_n - w^T \phi(x_n)\} \phi(x_n)^T = 0$$

$$\sum_{n=1}^N \tau_n t_n \phi(x_n)^T = \sum_{n=1}^N \tau_n w^T \phi(x_n) \phi(x_n)^T$$

$$\text{If } \phi = \begin{pmatrix} \phi_0(x_1) & \phi_1(x_1) & \dots & \phi_{M-1}(x_1) \\ \phi_0(x_2) & \phi_1(x_2) & \dots & \phi_{M-1}(x_2) \\ \vdots & \vdots & \ddots & \vdots \\ \phi_0(x_N) & \phi_1(x_N) & \dots & \phi_{M-1}(x_N) \end{pmatrix}$$

$$\text{Taking } \phi_r = \begin{pmatrix} \sqrt{\tau_1} \phi_0(x_1) & \sqrt{\tau_1} \phi_1(x_1) & \dots & \sqrt{\tau_1} \phi_{M-1}(x_1) \\ \sqrt{\tau_2} \phi_0(x_2) & \sqrt{\tau_2} \phi_1(x_2) & \dots & \sqrt{\tau_2} \phi_{M-1}(x_2) \\ \vdots & \vdots & \ddots & \vdots \\ \sqrt{\tau_N} \phi_0(x_N) & \sqrt{\tau_N} \phi_1(x_N) & \dots & \sqrt{\tau_N} \phi_{M-1}(x_N) \end{pmatrix}$$

$$w_{ML} = (\phi_r^T \phi_r)^{-1} \phi_r^T (t \odot r)$$

$\odot \rightarrow$  element wise product.

4.  $P(w|t, x, d) \rightarrow$  predictive distribution of weight vector  $w$ , for MAP inference of linear regression.

For a given value of  $x$ , the corresponding value of  $t$  has a gaussian distribution with mean value  $y(x, w)$

$$p(t|x, w, \beta) = N(t|y(x, w), \beta^{-1})$$

$$\text{where } \beta^{-1} = \sigma^2 \quad y(x, w) = \mu,$$

$$p(\bar{t}|\bar{x}, w, \beta) = \prod_{n=1}^N N(t_n|y(x_n, w), \beta^{-1}).$$

$$\ln p(\bar{t}|\bar{x}, w, \beta) = -\frac{\beta}{2} \sum_{n=1}^N \{y(x_n, w) - t_n\}^2 + \frac{N}{2} \ln \beta - \frac{N}{2} \ln 2\pi.$$

minimizing over  $\beta$ . ①

$$\frac{1}{\beta_{ML}} = \frac{1}{N} \sum_{n=1}^N \{y(x_n, w_{ML}) - t_n\}^2$$

$w_{ML} \rightarrow$  minimization of ①. (least square errors).

using predictive distributions,

$$p(t|x, w_{ML}, \beta_{ML}) = N(t|y(x, w_{ML}), \beta_{ML}^{-1})$$

prior distribution of  $w$  w.r.t  $d$ .

$$p(\bar{w}|d) = N(\bar{w}, 0, d^{-1}I)$$

$$= \left(\frac{d}{2\pi}\right)^{\frac{M+1}{2}} e^{-\frac{d}{2} w^T w}$$

From probability,  $p(x, y) = p(x|y)p(y)$

$$p(x, y) = p(x)$$

for independent  $(x, y)$

$$\therefore p(w|\bar{x}, \bar{t}, d, \beta) \propto p(\bar{t}|\bar{x}, w, \beta) p(w|d)$$

$w \rightarrow$  independent of  $\beta$  and  $x$ .

$$p(\bar{t}|\bar{x}, w, \beta) \rightarrow N(\mu_1, \sigma_1^2)$$

$$p(w|d) \rightarrow N(\mu_2, \sigma_2^2)$$

$$\Rightarrow p(w|\bar{x}, \bar{t}, d, \beta) \propto N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2).$$

$$\frac{\mu_1 \sigma_2^2 + \mu_2 \sigma_1^2}{\sigma_2^2 + \sigma_1^2} \sqrt{\frac{\sigma_2^2 \sigma_1^2}{\sigma_2^2 + \sigma_1^2}}$$

5.  $M$  variables,  $D^{\text{th}}$  degree polynomial.

A Homogenous polynomial is one of the form such that  $(x_1, \dots, x_n) \rightarrow$  variables of degree ' $d$ '

$$P(\lambda x_1, \dots, \lambda x_n) = \lambda^d P(x_1, \dots, x_n)$$

$$P(x_1, \dots, x_n) = 0 \Rightarrow P(\lambda x_1, \dots, \lambda x_n) = 0$$

given a polynomial ring  $R = K[x_1, \dots, x_n]$   
over a field  $K$

the homogenous polynomials of degree  $d$  form a vector space  $R_d$

$R$  is the direct sum of  $R_d$  (non negative integers  $d$ )  
(all polynomials can be represented as a sum of homogenous polynomials).

$\dim(\text{vector space } R_d) \rightarrow$  no of different monomials of degree  $d$  in  $M$  variables.

$\rightarrow$  which is the maximal number of non zero terms in a homogenous polynomials of degree  $d$  in  $M$  variables

from binomial theorem for degree  $d$  no of terms of homogenous poly  $\rightarrow \binom{d+n-1}{n-1} = \frac{(d+M-1)!}{d!(M-1)!}$

for the polynomial of degree  $D$ . no of terms

$$= \sum_{d=0}^D \frac{(M+d-1)!}{(M-1)! d!}$$

## 2. Training set error with a random division of 60:40

S.NO	Lambda value	M.S. Error(E)
1.	0.00001	6.3969
2.	0.0001	6.3969
3.	0.001	6.3969
4.	0.01	6.3969
5.	0.1	6.3969
6.	1	6.3981
7.	10	6.4047
8	100	6.4391
9	1000	6.5201

Test set error:

S.NO	Lambda value	M.S. Error(E)
1.	0.00001	5.2902
2.	0.0001	5.2902
3.	0.001	5.2902
4.	0.01	5.2902
5.	0.1	5.2896
6.	1	5.2622
7.	10	
8	100	5.1991
9	1000	5.2024

## 3. **Weka results** with a random division of 60:40

Mean absolute error	4.4703
Root mean squared error	6.0108
Relative absolute error	68.5806 %
Root relative squared error	66.9563 %

## 7. Mean squared errors:

	Lambda1	Lambda2	Lambda3	Lambda4	Lambda5	Lambda6	Lambda7
a 1	0.10676623726 7103	0.094480122747 7411	0.10971386783 2934	0.10069714216 6924	0.19887969531 3357	0.32090067540 5592	0.32365504435 4624
a 2	0.50912698210 8216	0.486898005162 651	0.42604668388 4917	0.44644468161 9496	0.51800105118 6376	0.52732030971 0945	0.64268334835 0416
a 3	0.95290530050 8052	1.014995112630 51	0.88807361618 6469	1.01513912269 988	0.82779081987 5525	1.04173110348 522	0.98047901865 9859
a 4	1.63278214089 663	1.621224994388 06	2.00100738565 873	1.95366832890 328	1.63424671219 276	2.06143587584 463	1.99208300491 247
a 5	8.40552901392 863	9.186524250835 71	10.7510405697 484	7.81720856478 126	9.44903406962 857	10.0252928121 391	9.13949004483 804

8.

Bias of the Mean =

0.0155

Bias of the Variance =

-0.2621

Variance of the Mean =

0.2152

Variance of the Variance =

0.7529