

# COMPUTATIONAL STATISTICS

## LAB II - LINEAR REGRESSION

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# OUTLINE

1 MAXIMUM LIKELIHOOD REGRESSION

2 BAYESIAN REGRESSION

TASK 1

$$E(w) = E_D(w) + \lambda \frac{w^T w}{\|w\|^2}$$

- 1) RIDGE R ( $X, t, M, \lambda$ )  
return  $w_{RR}$
- 2) RMSE ( $w, X_E, t, \epsilon$ )
- 3) CV ( $n, X, t, \lambda$ )  
return RMSE( $\lambda$ )

FOR  $\lambda \in [0, \infty)$   
 $e(\lambda) = CV(y, \hat{y})$   
 PLOT ( $\lambda, e$ )

$$w_{MLR} = (\lambda I + \Phi^T \Phi)^{-1} \Phi^T t$$

- Consider the non-linear data of lab 1. Implement a regularised linear regression (ridge regression) with a polynomial model of degree  $M = 12$ .

log  $\lambda \in$

$[-20; 0; 2; 5]$

- Set  $\lambda$  by  $n$ -fold cross-validation (choose a reasonable  $n$ ), and by using a validation dataset. Compare the two approaches.



$$RMSE(\lambda) = \frac{1}{n} RMSE(\lambda, D, D_n)$$

do it for many  $\lambda$ , minimise RMSE.

IN MATLAB.

$$J = 30:60;$$

$$X_1 = X; \quad X_1(J) = \bar{J}; \quad (X_1 \text{ is } X \text{ at } X(J))$$

$$t_1 = t; \quad t_1(J) = \bar{J};$$

$$(OR \quad X_1(J,:) = \bar{J}; \quad \text{FOR A MATRIX})$$

$$\rightarrow X_e = X(J);$$

$$\rightarrow t_e = t(J);$$

## TASK 2



- Get the 2-dimensional data from moodle (lab2), and fit a model using gaussian basis functions:

$$\phi_i(\mathbf{x}) = \exp(-\|\mathbf{x} - \mathbf{x}_i\|^2 / \gamma^2)$$

$$\gamma \in [10^{-3}, 1]$$

Consider basis functions centered in a  $k \times k$  regular grid in  $[0, 1]^2$  (choose e.g.  $k = 5$ ).

- Fit the model using ML, and use a validation set to identify the best  $\gamma$ .
- Fit the model using ridge regression, identifying both  $\gamma$  and  $\lambda$  by cross validation.