

## Model selection

### Gaussian model selection in the simplified Georgopoulos setting.

In this setting, we measure  $n$  times the same cell but each time with a different angle of movement  $u_i = 2\pi(i/n)$  for  $i = 0 \dots (n-1)$ . We decompose the regression function on a Fourier basis until size  $p$  with  $2 * p + 1 \leq n$ .

1. Create a matrix  $X$  of size  $n$  times  $2 * p + 1$ . For  $u_i = 2\pi(i/n)$ , the coefficient  $X_{i,j}$  is given as follows
  - $X_{i+1,j} = 1$  if  $j = 1$ ,
  - $X_{i+1,j} = \cos(ku_i)$  if  $j = 2 * k$ ,
  - $X_{i+1,j} = \sin(ku_i)$  if  $j = 2 * k + 1$ .
2. By computing the different scalar products (with R), show that the columns of  $X$  are orthogonal but not of norm 1 and renormalize them: this gives you the matrix  $X'$ .
3. Give, for a given  $d < p$ , the projection estimator of the regression function composed of the first  $2 * d + 1$  Fourier coefficients. Transform this into a function in R.
4. Simulate two different experiments:

$$Y_i = 16 + 14 \cos(u_i) + 5\varepsilon_i \quad \text{and} \quad Y_i = 10 * \exp(-(u_i - \pi)^2 / 0.2) + 1 * \varepsilon_i$$

with  $\varepsilon_i$ 's i.i.d  $N(0, 1)$ . Plot the data, the true function to estimate and 4 or 5 different projection estimators in each cases. Explain the problem of overfitting and the problem of taking a model of too low dimension. *NB: you can try other regression function if you want*

5. Make a function in R which, for a given  $p$ , computes the Mallows's Cp criterion for all the models ( $d \leq p$ ) and gives the estimator which minimizes the criterion. *NB: the behavior would be similar for other models with - log-likelihood and AIC criterion*
6. Let us now fix  $p$  and look at all the subspaces  $V$  that can be written on the basis up to  $2 * p + 1$ . For instance, we could have a subspace generated by  $1, \cos(u), \sin(2u)$ . Let us look at the BIC criterion and assume  $\sigma^2$  is known. Simplify the formulas to show that this minimization problem is solved by taking as non-zeros coordinates the ones for which  $|\langle Y | e_i \rangle|$  is larger than  $\sqrt{\ln(n)\sigma^2}$ . Implement this method and show the resulting estimator on both previous cases.