Exercise 1: Efficient computation of least squares

- By taking `demo_LS01.m` as an example, implement least squares with these different techniques:
  1. By explicitly inverting \( X^\top X \) in the computation of \( \hat{A} = (X^\top X)^{-1}X^\top Y \)
  2. By using Cholesky decomposition (function `chol`)
  3. By using singular value decomposition (function `svd`)

- For each computation technique, evaluate the computation time (to do this, you can use the Matlab functions `tic` and `toc`). Use dimensions for \( D^I, D^O \) and \( N \) that are high enough to facilitate the comparison of the different techniques. Try also with \( N < D^I \) (by verifying the condition number before inverting matrices). What do you observe?

Exercise 2: Recursive least squares

- The example `demo_LS_recursive01.m` shows that the Sherman-Morrison-Woodbury formula can be exploited to update a least squares estimate when a new group of datapoints become available. Based on this example, write a program that iteratively updates the least squares estimate one datapoint at a time, by starting from the initial estimates \( A=0 \) and \( B^{-1}=10^{10} I \).

- Show that the final estimate of the iterative process is the same as the standard least squares batch estimate.

- Show that the recursive least squares does not require the use of a matrix inversion operator, by using only scalar divisions.

Exercise 3: Various forms of line fitting

- Fit a line to a small number of datapoints by considering the three minimization problems shown in the above figure, respectively displayed in red, green and blue colors (the segments connected to the points depict the errors to minimize). What do the different methods minimize?