

## 9. Recap and Exercises

### Gram Schmidt Process:

Given a basis, GSP can turn it into an orthogonal basis:

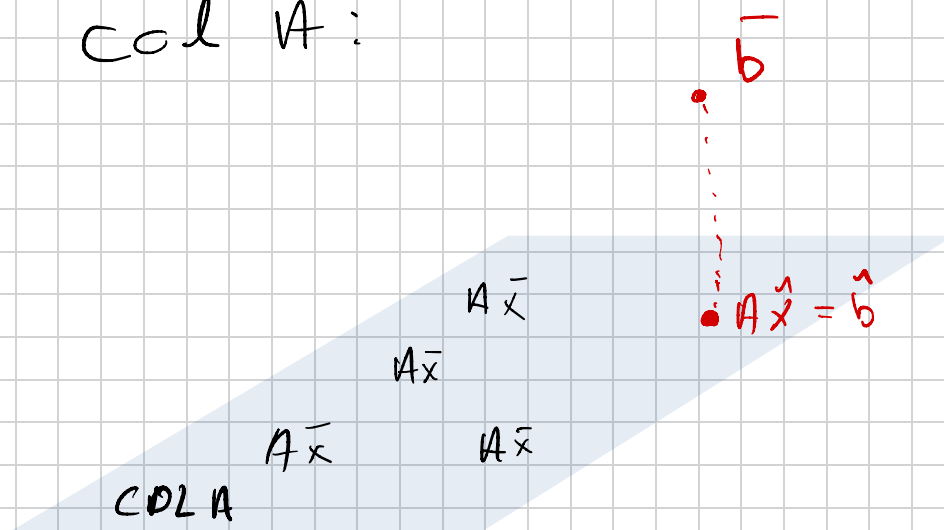
Let  $\{\bar{x}_1 \dots \bar{x}_p\}$  be a lin. ind. set:

$$\bar{v}_p = \bar{x}_p - \left( \sum_{i=1}^{p-1} \text{proj}_{\bar{v}_i} \bar{x}_p \right) = \bar{x}_p - \left( \sum_{i=1}^{p-1} \frac{\bar{x}_p \cdot \bar{v}_i}{\bar{v}_i \cdot \bar{v}_i} \bar{v}_i \right)$$

### Least Squares:

Given an inconsistent system  $A\bar{x} = \bar{b}$

least squares allows us to find the best approximate solution  $\hat{x}$  such that  $A\hat{x}$  has the smallest distance from  $\bar{b}$  to col  $A$ :



Method:

Solve  $[A^T A$

$A^T \bar{b}] \sim$  RREF

$\begin{bmatrix} I & \hat{x} \end{bmatrix}$

last column



$$\hat{x} = (A^T A)^{-1} \cdot (A^T \bar{b}) \quad \leftarrow \text{The normal Equation}$$

## Linear Models:

We use least squares to find the best fitted model for our data

Given  $n$  two tuples  $(x_i, y_i)$ , let

$$\bar{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \text{ and let } \bar{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix},$$

the design matrix  $X$  for  $\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i$

$$\text{is } \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix} \text{ and the observation matrix is } \bar{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$
$$\begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{bmatrix} X \hat{\beta} = \hat{\bar{y}}$$
$$\bar{e} = (\bar{y} - \hat{\bar{y}})$$

In order to estimate  $\begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{bmatrix}$  we solve

$$\begin{bmatrix} X^T X & X^T \bar{y} \end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix} I & \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{bmatrix} \end{bmatrix} \quad \text{last column}$$

We can modify the design matrix to accommodate our hypothesised models

We can find  $\hat{\bar{y}} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \vdots \\ \hat{y}_n \end{bmatrix}$  by either

calculating each  $\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i$  or all the  $\hat{y}_i$ 's by doing  $X \hat{\beta} = \hat{\bar{y}}$

We obtain the error by finding

$$e = \| \bar{y} - X \hat{\beta} \|^2$$