

Math 2270-3

Wednesday Oct 28

Lab on Friday LCB 115

(also is class lecture) on §5.5

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§5.4 Least squares approximate solns to $A\vec{x}=b$ & applications

• Finish Tuesday notes, which also include the end of §5.3

- transpose algebra
- matrix for projection linear transformation - if you have o.n. basis $\{\vec{u}_1, \vec{u}_2, \dots, \vec{u}_k\}$ for $W \subset \mathbb{R}^n$
- least squares solns, p. 3-4 Tuesday.

continue that chain of discussion & examples:

- Suppose $\{\vec{v}_1, \vec{v}_2, \dots, \vec{v}_k\}$ is a basis for W , not necessarily o.n. You can find the matrix for projection without 1st constructing o.n. basis!

from page 4 Tuesday: For $A = \begin{bmatrix} | & | & & | \\ \vec{v}_1 & \vec{v}_2 & \dots & \vec{v}_k \\ | & | & & | \end{bmatrix}$

$$\left. \begin{aligned} A\vec{x} &= \text{proj}_W b \\ \text{iff } A^T A \vec{x} &= A^T b \end{aligned} \right\}$$

notice, from, because cols of A are independent (basis for W)

exactly one \vec{x} solves this system, therefore the $[A^T A]_{k \times k}$ matrix has an inverse (by our "invertible" list)

$$\text{so, } \vec{x} = (A^T A)^{-1} A^T b$$

$$\& \text{proj}_W b = \underbrace{[A (A^T A)^{-1} A^T]}_{\downarrow} b$$

so this is the projection matrix !!

Example 4

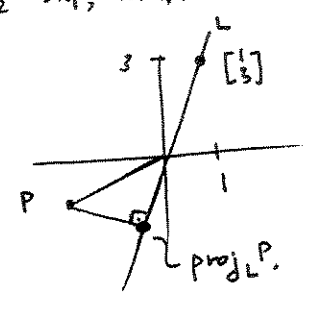
Check our amazing projection matrix formula!

4a) If the columns of A are orthonormal, is this the formula on p.2 Tuesday? Why? AA^T

4b) Example 1c): Use $A = \begin{bmatrix} 1 & 2 \\ 0 & 1 \\ 1 & 0 \end{bmatrix}$ to compute the matrix for projecting onto the plane $-x_1 + 2x_2 + x_3 = 0$, yet again. (Use back of this page.)

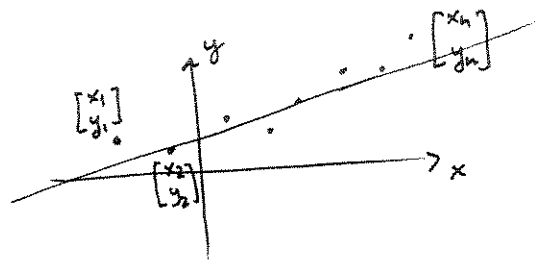
Example 5 : What's the matrix for projecting onto the line $x_2 = 3x_1$, in \mathbb{R}^2 ?

(this seemed so hard in chapter 2 - it should be easy now.)



Applications of least-squares to data fitting.

- find the best line formula $y = mx + b$ to fit n data points $(x_1, y_1) \dots (x_n, y_n)$



We seek $\begin{bmatrix} m \\ b \end{bmatrix}$ s.t.

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = m \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + b \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$$

i.e. $\begin{bmatrix} x_1 & 1 \\ x_2 & 1 \\ \vdots & \vdots \\ x_n & 1 \end{bmatrix} \begin{bmatrix} m \\ b \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$. Not solvable exactly, unless pts actually are on line!

\uparrow known \uparrow known

$$A \begin{bmatrix} m \\ b \end{bmatrix} = \vec{y}$$

Least square's soltn: $A^T A \begin{bmatrix} m \\ b \end{bmatrix} = A^T \vec{y}$. Unique soltn $\begin{bmatrix} m \\ b \end{bmatrix}$ exists (as long as at least 2 x_i -values are different) makes col's A ind.!

You are solving. $A \begin{bmatrix} m \\ b \end{bmatrix} = \text{proj}_W \vec{y}$, $W = \text{span} \left\{ \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \right\}$

so $\left\| m \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + b \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} - \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \right\|^2$ is as small as possible
 i.e. you're minimized $\sum_{i=1}^n (mx_i + b - y_i)^2$,

the sum of the squared vertical deviations between the line $y = mx + b$ & the n data points.

