L-16: Orthogonal Vectors and Subspaces

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October 29, 2022

1 Least Squares

1.1 Some more things about projection matrices.

- If b is in column space of A, P.b=b
- If $b \perp b$, P.b=0

1.1.1 P.b=b

$$N(A^T) \perp C(A)$$

$$P.b = A(A^T A)^{-1} A^T b$$

:.
$$P.b = 0$$

1.1.2 P.b=b

$$P.b = A(A^TA)^{-1}A^TAx$$
 {b=Ax}

$$P.b = A.x$$

$$\therefore P.b = b$$

1.2 I-P projection matrix

P is the projection matrix which projects a vector b onto the column space of matrix A. The other projection component lies on null space of A transpose, since $n(A^T)$ is orthogonal to the column space of A.

1.2.1 Proof that I-P is projecting onto the null space of A transpose

Suppose vector b lies on the column space of A.

$$\therefore P.b = b$$

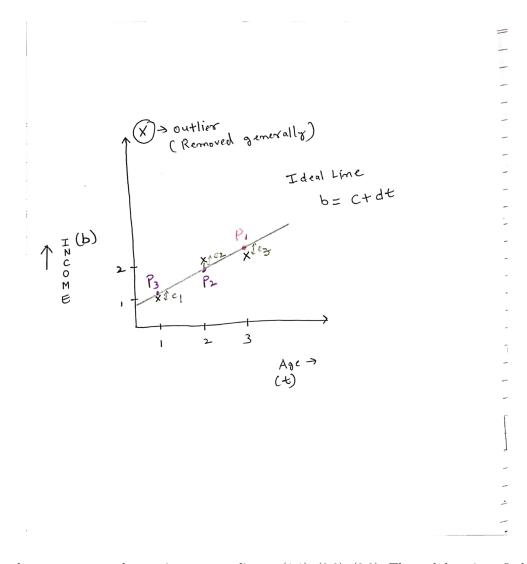
$$(I-P).b = I.b - P.b$$

=b - b
=0

(I-P).b = 0 means that there is no component of b vector along that subspace. Therefore, I-P must have projected onto $n(A^T)$, which is orthogonal to the column space of A.

Prove the same using the logic that P.y=0, where y lies on $n(A^T)$

2 Geometric Least Squares



In the figure above, we can see three points at co-ordinates (1,1), (2,2), (3,2). The task here is to find a line which best fits these points, so that the error is minimum.

b=c+dt is the required line in this case. The ideal line equation for the three given points would be:

C+D=1C+2D=2 C+3D=2

It is visibly obvious that there is no solution to these set of equations, even if we proceed by normal gaussian elimination.

We can rewrite the matrix in Ax=b form as:

$$\begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} C \\ D \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$

Now, b does not lie in column space of the A matrix. So we need to find \hat{x} , which is an estimated solution to the nearest projection of b onto the column space of A(best line).

 $\hat{x} = \begin{bmatrix} \hat{C} \\ \hat{D} \end{bmatrix}$, where the hat sign on C and D means that they are estimated values for the best line.

From lecture 15 we already know that:

$$A^T A \hat{x} = A^T b$$

Substituting values we get:

$$A^T A = \begin{bmatrix} 3 & 6 \\ 6 & 14 \end{bmatrix}$$

$$A^Tb = \begin{bmatrix} 5\\11 \end{bmatrix}$$

We get two equations from these:

$$3\hat{C} + 6\hat{D} = 5$$

 $6\hat{C} + 14\hat{D} = 11$

Solving these two equations, we get:

$$\hat{C} = \frac{2}{3}$$

$$\hat{D} = \frac{1}{2}$$

The resulting equation is : $p = \frac{2}{3} + \frac{1}{2}t$

The points on the line $p = \left[\frac{7}{6}, \frac{5}{3}, \frac{13}{6}\right]$

The error vector $e = \left[\frac{-1}{6}, \frac{2}{6}, \frac{-1}{6}\right]$

We can verify that b=p+e. This means that $e \perp C(A)$

Least Squares Calculus Approach 3

Under the calculus approach, we have to minimize the sum of squared error vector function. We square in order to not cancel out the -ve and +ve values (we can take absolute too).

The objective function is given as:

$$min(||Ax - b||)^2 = min(||e||^2)$$

$$= min(e_1^2 + e_2^2 + e_3^2)$$

= $min((C + D - 1)^2 + (C + 2D - 2)^2 + (C + 3D - 2)^2)$

Taking partial derivative w.r.t C, we get:

$$\frac{\partial F}{\partial C} = 6C + 12D - 10\tag{1}$$

Setting partial derivative to zero gives:

3C+6D=5

$$\frac{\partial F}{\partial D} = 12C + 28D - 22\tag{2}$$

12C + 28D = 22

We can solve these equations the same way as in the algebraic approach.

Bonus Proofs 4

If A has independent columns, then A^TA is invertible

Suppose $A^T A x = 0$ for some x.

Multiply both sides by x^T

$$x^T A^T A x = 0$$
$$(Ax)^T A x = 0$$
$$||Ax||^2 = 0$$

$$||Ax||^2 = 0$$

A.x = 0 [: length square is zero, length is zero, which means vector is zero, as length is component squared.]

A has independent columns(given) and A.x=0. This must mean x is zero.

$$A^T A x = 0 \implies x = 0$$

This means $A^T A$ is invertible if A has independent columns.

Q.E.D