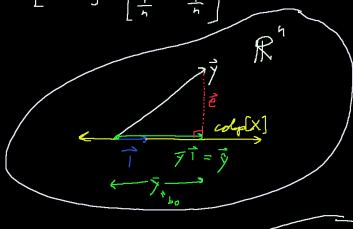


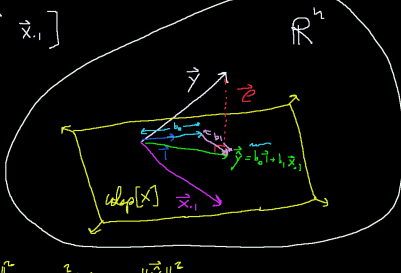
Let's examine the null model, $p = 0$ so that $X = [\mathbf{1}_n] \Rightarrow \hat{\mathbf{b}} = \mathbf{b}_0 = \bar{y}$

$$H = \underbrace{X X^T X^T X^T}_{\frac{1}{n} \mathbf{1}_n \mathbf{1}_n^T} = \frac{1}{n} \mathbf{1}_n \mathbf{1}_n^T = \frac{1}{n} \begin{bmatrix} 1 & \dots & 1 \\ \vdots & & \vdots \\ 1 & \dots & 1 \end{bmatrix} = \begin{bmatrix} \frac{1}{n} & \dots & \frac{1}{n} \\ \vdots & & \vdots \\ \frac{1}{n} & \dots & \frac{1}{n} \end{bmatrix}$$

$$\hat{\mathbf{y}} = H \mathbf{y} = \begin{bmatrix} \bar{y} \\ \bar{y} \\ \vdots \\ \bar{y} \end{bmatrix} = \bar{y} \mathbf{1}_n$$



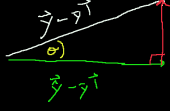
Consider $p = 1$ so that $X = [\mathbf{1}_n \quad \mathbf{x}_1]$



$$\hat{\mathbf{y}} \Rightarrow \|\hat{\mathbf{y}}\|^2 + \|\mathbf{e}\|^2 = \|\mathbf{y}\|^2, \quad \cos^2(\theta) = \frac{\|\hat{\mathbf{y}}\|^2}{\|\mathbf{y}\|^2}$$

Pythag. Thm

Is the following illustration accurate? *Yes*



$$\mathbf{e} := \mathbf{y} - \hat{\mathbf{y}} = \mathbf{y} - \mathbf{y} \mathbf{1}_n^T + \mathbf{y} \mathbf{1}_n^T - \hat{\mathbf{y}} = (\mathbf{y} - \mathbf{y} \mathbf{1}_n^T) - (\hat{\mathbf{y}} - \mathbf{y} \mathbf{1}_n^T)$$

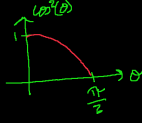
$$\text{proj}_{\text{colsp}[X]}(\mathbf{y} - \mathbf{y} \mathbf{1}_n^T) = H(\mathbf{y} - \mathbf{y} \mathbf{1}_n^T) = H\mathbf{y} - \mathbf{y} H \mathbf{1}_n^T = \hat{\mathbf{y}} - \mathbf{y} \mathbf{1}_n^T$$

Pythag. Thm.

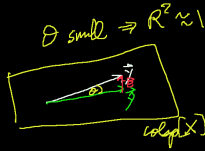
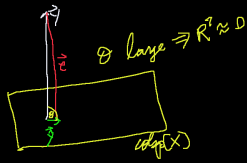
$$\|\mathbf{y} - \mathbf{y} \mathbf{1}_n^T\|^2 = \|\hat{\mathbf{y}} - \mathbf{y} \mathbf{1}_n^T\|^2 + \|\mathbf{e}\|^2, \quad R^2 = \frac{SSR - SSE}{SSR} = \frac{SSR}{SSR} = \cos^2(\theta) \in [0, 1]$$

$$\sum (y_i - \bar{y})^2 = \sum (\hat{y}_i - \bar{y})^2 + \sum e_i^2$$

$$SST = SSR + SSE$$



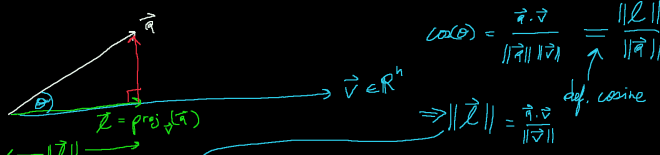
sum of squares total sum of squares regression sum of squares error



Back to linear algebra...

By law of cosines,

$$\cos(\theta) = \frac{\vec{a} \cdot \vec{v}}{\|\vec{a}\| \|\vec{v}\|} = \frac{\|\vec{e}\|}{\|\vec{a}\|}$$

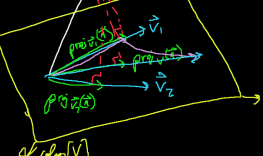


$$\Rightarrow \vec{e} = \|\vec{e}\| \cdot \frac{\vec{v}}{\|\vec{v}\|} = \frac{\vec{a} \cdot \vec{v}}{\|\vec{v}\|^2} \vec{v} = \frac{\vec{a}^T \vec{v} \vec{v}}{\|\vec{v}\|^2} = \frac{\vec{v} \vec{v}^T \vec{a}}{\|\vec{v}\|^2} = \underbrace{\frac{\vec{v} \vec{v}^T}{\|\vec{v}\|^2}}_H \vec{a} = H \vec{a}$$

$$H = \frac{1}{\|\vec{v}\|^2} \vec{v} \vec{v}^T = \left[\frac{1}{\|\vec{v}_1\|^2} \vec{v}_1 \vec{v}_1^T \mid \frac{1}{\|\vec{v}_2\|^2} \vec{v}_2 \vec{v}_2^T \mid \dots \mid \frac{1}{\|\vec{v}_n\|^2} \vec{v}_n \vec{v}_n^T \right], \quad \text{rank}[H] = 1$$

$$H H = \left(\frac{1}{\|\vec{v}_1\|^2} \vec{v}_1 \vec{v}_1^T \right) \left(\frac{1}{\|\vec{v}_2\|^2} \vec{v}_2 \vec{v}_2^T \right) = \frac{1}{\|\vec{v}_1\|^2 \|\vec{v}_2\|^2} \vec{v}_1 \vec{v}_1^T \vec{v}_2 \vec{v}_2^T = \frac{1}{\|\vec{v}_1\|^2 \|\vec{v}_2\|^2} \vec{v}_1 \vec{v}_2^T \vec{v}_2 \vec{v}_1^T = H$$

$$V = [\vec{v}_1 \mid \vec{v}_2] \quad \text{proj}_V(\vec{a}) \stackrel{?}{=} \underbrace{\text{proj}_{\vec{v}_1}(\vec{a})}_{H_1 \vec{a}} + \underbrace{\text{proj}_{\vec{v}_2}(\vec{a})}_{H_2 \vec{a}} = (H_1 + H_2) \vec{a}$$



will always project onto $\text{colsp}[V]$ but it may not be the correct length (it can over/under count). The correct length gives you the right angle:

$$\text{proj}_V(\vec{a})^T (\vec{a} - \text{proj}_V(\vec{a})) = 0$$

angle between \vec{a}, \vec{v}

$$\Rightarrow \text{proj}_V(\vec{a})^T \vec{a} - \text{proj}_V(\vec{a})^T \text{proj}_V(\vec{a})$$

$$= (H_1 \vec{a} + H_2 \vec{a})^T \vec{a} - (H_1 \vec{a} + H_2 \vec{a})^T (H_1 \vec{a} + H_2 \vec{a}) = (\vec{a}^T H_1 + \vec{a}^T H_2) \vec{a} - \left(\underbrace{\vec{a}^T H_1 \vec{a}}_{\geq 0} + \underbrace{\vec{a}^T H_2 \vec{a}}_{\geq 0} + 2 \underbrace{\|\vec{H}_1 \vec{a}\| \|\vec{H}_2 \vec{a}\| \cos(\theta)}_{\in [0, 1]} \right)$$

The only way to make this expression zero is if $\cos(\theta) = 0$ i.e. $\theta = \text{a right angle}$. Thus, the full projection is a sum of the component projections if the components are orthogonal.

$$\text{Let } V = [\vec{v}_1 \mid \vec{v}_2 \mid \dots \mid \vec{v}_d] \in \mathbb{R}^{n \times d}, \quad \forall i, j \quad \vec{v}_i \cdot \vec{v}_j = 0$$

$$\Rightarrow \text{proj}_{\text{colsp}[V]}(\vec{a}) = \text{proj}_{\vec{v}_1}(\vec{a}) + \dots + \text{proj}_{\vec{v}_d}(\vec{a})$$

$$= \frac{\vec{v}_1 \vec{v}_1^T}{\|\vec{v}_1\|^2} \vec{a} + \dots + \frac{\vec{v}_d \vec{v}_d^T}{\|\vec{v}_d\|^2} \vec{a}$$

$$= \left(\frac{\vec{v}_1 \vec{v}_1^T}{\|\vec{v}_1\|^2} + \dots + \frac{\vec{v}_d \vec{v}_d^T}{\|\vec{v}_d\|^2} \right) \vec{a} = (\vec{v}_1 \vec{v}_1^T + \dots + \vec{v}_d \vec{v}_d^T) \vec{a}$$

If $\|\vec{v}_1\| = \|\vec{v}_2\| = \dots = \|\vec{v}_d\| = 1$, i.e. all unit length

$$Q = [\vec{v}_1 \mid \dots \mid \vec{v}_d], \quad \text{which is an "orthonormal matrix"}$$

$$Q^T Q = \begin{bmatrix} \leftarrow \vec{v}_1^T \rightarrow \\ \vdots \\ \leftarrow \vec{v}_d^T \rightarrow \end{bmatrix} \begin{bmatrix} \downarrow \vec{v}_1 \\ \vdots \\ \downarrow \vec{v}_d \end{bmatrix} = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & 1 \end{bmatrix} = I_d$$

$$Q Q^T = \begin{bmatrix} \downarrow \vec{v}_1 \\ \vdots \\ \downarrow \vec{v}_d \end{bmatrix} \begin{bmatrix} \leftarrow \vec{v}_1^T \rightarrow \\ \leftarrow \vec{v}_2^T \rightarrow \\ \leftarrow \vec{v}_d^T \rightarrow \end{bmatrix} = \vec{v}_1 \vec{v}_1^T + \vec{v}_2 \vec{v}_2^T + \dots + \vec{v}_d \vec{v}_d^T = H$$

$$= [A_1 \mid A_2 \mid \dots \mid A_d] \begin{bmatrix} B_1 \\ B_2 \\ \vdots \\ B_d \end{bmatrix} = A_1 B_1 + A_2 B_2 + \dots + A_d B_d$$

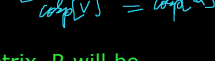
$$\Rightarrow Q Q^T = V (V^T V)^{-1} V^T = H$$

where the columns of Q are the orthonormalized columns of $V = [\vec{v}_1 \mid \dots \mid \vec{v}_d]$. Further $\text{colsp}[Q] = \text{colsp}[V]$ since the column vectors in Q represents a change of basis of the column vectors of V .

$$\text{proj}_{\text{colsp}[Q]}(\vec{a}) = Q \underbrace{(Q^T Q)^{-1}}_I Q^T \vec{a} = Q Q^T \vec{a}$$

How can we convert matrix V to matrix Q ? There is a computational algorithm called "Gram-Schmidt" and during the computation, you can collect a matrix that is the change of basis:

$$V = Q R \Rightarrow V R^{-1} = Q$$



This is also called Q-R decomposition of a matrix. R will be upper triangular and full rank (and invertible).