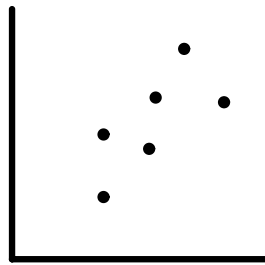


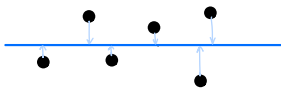
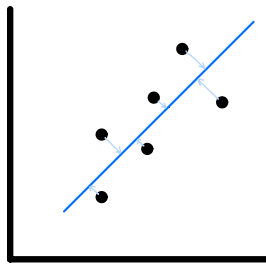
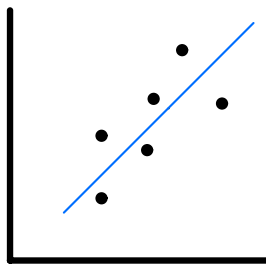
PRINCIPAL COMPONENTS ANALYSIS ILLUSTRATION

ORIGINAL DATA

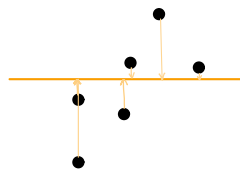
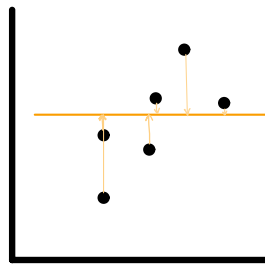
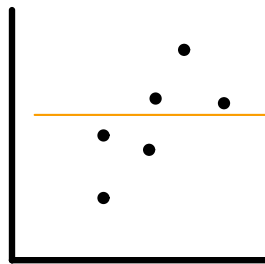


PCA searches over all possible hyperplanes to find the one that maximizes the variance of the projected data
"directions"

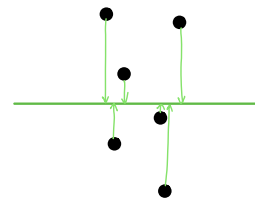
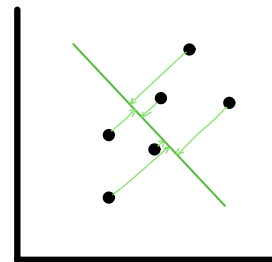
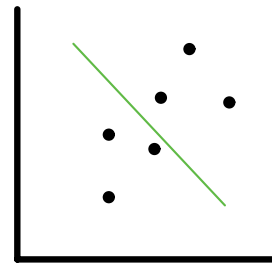
Ex. CANDIDATE HYPERPLANE 1



CANDIDATE HYPERPLANE 2

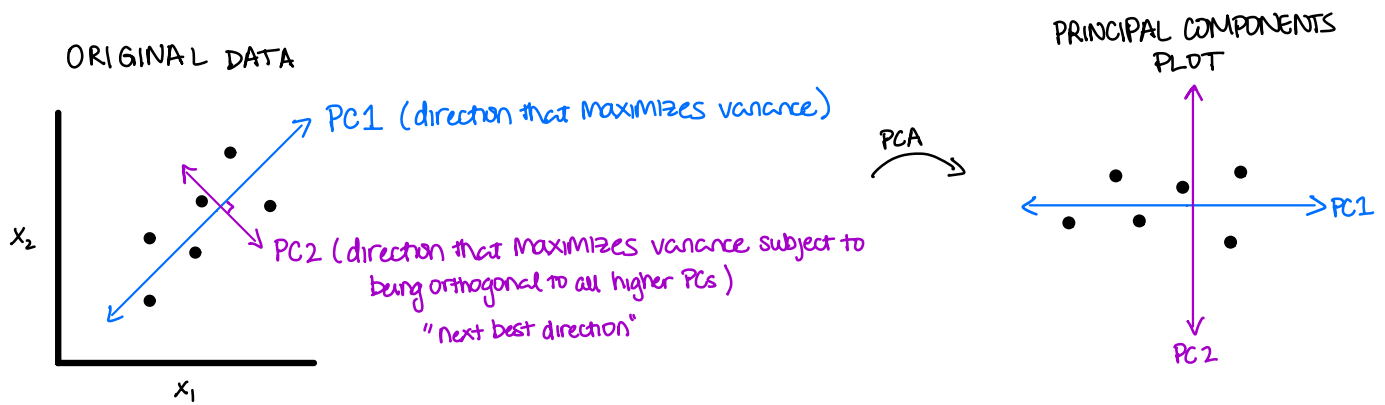


CANDIDATE HYPERPLANE 3



DATA
PROJECTED
ONTO
HYPERPLANE

$$\text{var}(\begin{array}{c} \bullet \quad \bullet \bullet \quad \bullet \quad \bullet \bullet \end{array}) > \text{var}(\begin{array}{c} \bullet \quad \bullet \bullet \quad \bullet \quad \bullet \end{array}) > \text{var}(\begin{array}{c} \bullet \bullet \quad \bullet \bullet \end{array})$$

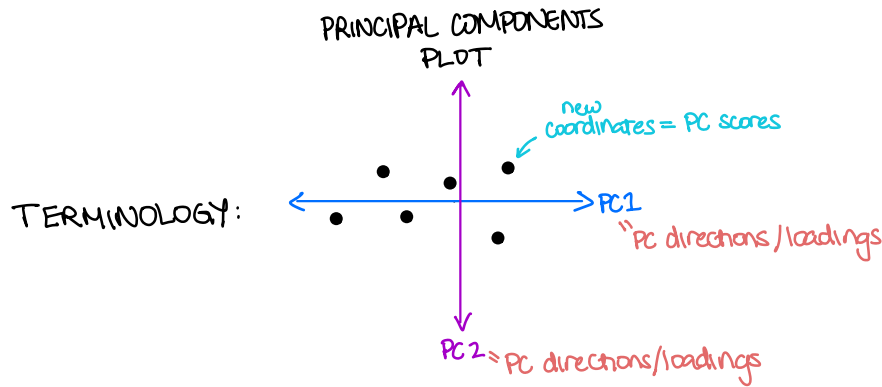


INTERPRETING PCA:

Since PCA is essentially a linear projection method, it is by far the most interpretable dimension reduction method

★ PCs are a weighted linear combination of x_1, x_2, \dots, x_p

Ex. If $PC1 = 0.4x_1 + 0.6x_2$, then x_2 is "more important" or "contributes more" to $PC1$ than x_1



Moreover, in PCA, we can also measure the proportion of variance explained by each PC_k ← the k^{th} PC

$$PVE_k = \frac{\text{variance of data projected on } PC_k}{\text{total amount of variance in } X}$$

⇒ SCREEN PLOT:

