## HW1 - Principal Component Analysis

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## PCA algorithm - Maximum variance formulation

Our goal is to project the data onto a space having dimensionality M < D while maximizing the variance of the projected data. We consider an independent and identically distributed (i.i.d.) dataset  $X = x_1, x_2, ...x_n, x_n \in \mathbb{R}^D$ .

$$X = \begin{bmatrix} - & x_1^T & - \\ - & x_2^T & - \\ \vdots & \vdots & \vdots \\ - & x_n^T & - \end{bmatrix} \in R^{NxD}, \quad B = \begin{bmatrix} | & | & | \\ b_1 & b_2 & \dots & b_M \\ | & | & | & | \end{bmatrix} \in R^{DxM}$$

$$\Rightarrow Z = X.B = \begin{bmatrix} x_1^T b_1 & x_1^T b_2 & \dots & x_1^T b_n \\ x_2^T b_1 & x_2^T b_2 & \dots & x_2^T b_n \\ \vdots & \vdots & \dots & \vdots \\ x_n^T b_1 & x_n^T b_2 & \dots & x_n^T b_n \end{bmatrix} \in R^{NxM}$$
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We start by seeking a single vector  $b_1 \in \mathbb{R}^D$  that maximizes the variance of the projected data. So the variance of Z is given by:

$$\begin{split} V_Z &= \frac{1}{N} \sum_{n=1}^N (x_n^T b_1 - \mu_Z)^2 \\ &= \frac{1}{N} \sum_{n=1}^N (x_n^T b_1)^2 \quad \text{because } \mu_Z = 0 \\ &= \frac{1}{N} \sum_{n=1}^N b_1^T x_n x_n^T b_1 \\ &= b_1^T (\frac{1}{N} \sum_{n=1}^N x_n x_n^T) b_1 \\ &= b_1^T S b_1 \qquad \text{where S is covariance matrix.} \end{split}$$

Constrained optimization problem  $\max_{b_1} b_1^T Sb_1$  subject to  $||b_1||^2 = 1$ .

To enforce this constraint, we introduce a Lagrange multiplier that we shall denote by  $\lambda_1$ , and then make an unconstrained maximization of:

$$L(b_1, \lambda_1) = b_1^T S b_1 + \lambda_1 (1 - b_1^T b_1)$$
$$\frac{\partial L}{\partial b_1} = 0 \Leftrightarrow 2S b_1 - 2\lambda_1 b_1 = 0 \Leftrightarrow S b_1 = \lambda b_1$$
$$\frac{\partial L}{\partial \lambda_1} = 0 \Leftrightarrow b_1^T b_1 = 1$$

We can see that  $b_1, \lambda_1$  is an eigenvector and an eigenvalue of S respectively.

$$V = b_1^T S b_1 = b_1^T \lambda_1 b_1 = \lambda_1$$

The variance of the data projected onto a one-dimensional subspace equals the eigenvalue that is associated with the basis vector  $b_1$  that spans this subspace.