From COM4509 Lecture 9

PCA: Eigenvalue = Variance

- Focus on first PC: maximise the variance in projected space (i.e. maximise variance of $y = u^{T}x$)
 - o x = original data
 - o y = the compressed projection
 - μ = average
 - o u = projection vector (the vector of transformations of all of the pcs)

$$\mathbf{S} = \frac{1}{n} \sum_{i=1}^{n} \left(\mathbf{x}^{(i)} - \boldsymbol{\mu} \right) \left(\mathbf{x}^{(i)} - \boldsymbol{\mu} \right)^{\top}$$

$$\circ \quad \mathbf{S} = (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^{\mathsf{T}} = \text{variance of } \mathbf{x}$$

$$\operatorname{var}(y) = \frac{1}{n} \sum_{i=1}^{n} \left(y^{(i)} - \mu_y \right)^2 = \frac{1}{n} \sum_{i=1}^{n} \mathbf{u}^{\top} \left(\mathbf{x}^{(i)} - \boldsymbol{\mu}_{\mathbf{x}} \right) \left(\mathbf{x}^{(i)} - \boldsymbol{\mu}_{\mathbf{x}} \right)^{\top} \mathbf{u} = \mathbf{u}^{\top} \mathbf{S} \mathbf{u}$$

- The projection **u** is what we want to find
- Projection vector u, we use the unit norm constraint then take the derivative of the variance w.r.t u
 - λ the variance(s) captured by u

$$L(\mathbf{u}, \lambda) = \mathbf{u}^{\top} \mathbf{S} \mathbf{u} + \lambda \left(1 - \mathbf{u}^{\top} \mathbf{u} \right)$$
$$dL(\mathbf{u}, \lambda) / d\mathbf{u} \implies \mathbf{S} \mathbf{u} = \lambda \mathbf{u}$$

- Question: which solution (eigen-pair) to choose?
 - There are many solutions for eigenvalues so we take the maximum eigenvalue
 - Maximum eigenvalue = maximum variance = most useful

$$\operatorname{var}(y) = \mathbf{u}^{\top} \mathbf{S} \mathbf{u} = \lambda \mathbf{u}^{\top} \mathbf{u} = \lambda$$

PCA: Max Variance <-> Min MSE

- Maximum Variance Direction what you maximise
 - For the below, mean = 0 so S simplifies to XX^T

$$\frac{1}{n} \sum_{i=1}^{n} (\mathbf{v}^T \mathbf{x}_i)^2 = \mathbf{v}^T \mathbf{X} \mathbf{X}^T \mathbf{v}$$

- Minimum Reconstruction Error what you minimise
 - v = u = projection matrix
 - Mse of original data reconstruction $Y = U^{T}X$, $YU = U^{T}XU = X^{A}$

$$\frac{1}{n} \sum_{i=1}^{n} \|\mathbf{x}_i - (\mathbf{v}^T \mathbf{x}_i) \mathbf{v}\|^2$$