(1) Linear Algebra: a brief overview (II)

1. Singular value decomposition

Let **A** be $n \times p$ with rank r. It can be decomposed as

$$\mathbf{A} = \mathbf{\Gamma}_{\mathbf{n} \times \mathbf{r}} \mathbf{\Lambda}_{\mathbf{r} \times \mathbf{r}} \mathbf{\Delta}_{\mathbf{r} \times \mathbf{p}}^{'}$$

where both Γ and Δ are column orthonormal. Further $\Lambda = diag(\sqrt{\lambda_1},...,\sqrt{\lambda_r})$ where $\lambda_i > 0, i = 1,...,r$ are the nonzero eigenvalues of the matrices $\mathbf{A}'\mathbf{A}$ and $\mathbf{A}\mathbf{A}'$. Γ and Δ consist of the corresponding r eigenvectors of these matrices.

2. Quadratic Forms $Q = \mathbf{x}' \mathbf{A} \mathbf{x} \ (\mathbf{A}_{\mathbf{p} \times \mathbf{p}} \text{ is symmetric})$

- If **A** is p.d.,
 - (a) A is invertible
 - (b) $|\mathbf{A}| > 0$
 - (c) All eigenvalues are positive (>0)

3. A maximization theorem

If $\mathbf{A}_{p \times p}$ and $\mathbf{B}_{p \times p}$ are symmetric and \mathbf{B} is p.d., then for an arbitrary non-zero vector \mathbf{x} , then

$$\max_{\mathbf{x}} \frac{\mathbf{x}' \mathbf{A} \mathbf{x}}{\mathbf{x}' \mathbf{B} \mathbf{x}} = \lambda_1 \ge \lambda_2 \ge \dots \ge \lambda_p = \min_{\mathbf{x}} \frac{\mathbf{x}' \mathbf{A} \mathbf{x}}{\mathbf{x}' \mathbf{B} \mathbf{x}}$$

where $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p$ are the ordered eigenvalues of $\mathbf{B^{-1}A}$. The vector which maximises (minimises) $\frac{\mathbf{x'Ax}}{\mathbf{x'Bx}}$ is the eigenvector of $\mathbf{B^{-1}A}$ which corresponds to the largest (smallest) eigenvalue of $\mathbf{B^{-1}A}$.

- 4. Idempotent Matrices $(\mathbf{A}^2 = \mathbf{A})$
 - All idempotent matrices (except I) are singular
 - $rank(\mathbf{A}) = tr\mathbf{A}$
 - Eigenvalues of idempotent matrices are either 0 or 1.

Proof:

Let λ , **x** be a pair of eigenvalue and eigenvector

$$\mathbf{A}\mathbf{x} = \lambda\mathbf{x}$$

$$\Rightarrow \mathbf{A}^2 \mathbf{x} = \mathbf{A}(\mathbf{A}\mathbf{x}) = \mathbf{A}(\lambda \mathbf{x}) = \lambda \mathbf{A}\mathbf{x} = \lambda^2 \mathbf{x}$$

But
$$\mathbf{A}^2\mathbf{x} = \mathbf{A}\mathbf{x} = \lambda\mathbf{x}$$

So,

$$\lambda^2 \mathbf{x} = \lambda \mathbf{x} \Rightarrow \lambda(\lambda - 1)\mathbf{x} = 0$$

Since $\mathbf{x} \neq 0$, hence $\lambda = 0$ or 1

 \bullet Let ${\bf A}$ be a symmetric matrix. If all eigenvalues are 1 or 0, ${\bf A}$ is idempotent

<u>Proof</u>:

If **A** is symmetric, there exists an orthogonal matrix **P** such that

$$P'AP = D$$

where \mathbf{D} is a diagonal matrix with eigenvalues of \mathbf{A} on the diagonal

So,
$$P'APP'AP = D^2$$

But,
$$P'APP'AP = P'AAP$$

However if all eigenvalues are 1 or 0, $\mathbf{D} = \mathbf{D}^2$

$$\Rightarrow$$
 P'AP = P'AAP

$$\Rightarrow$$
 $A = AA$

 \Rightarrow **A** is idempotent

5. Derivatives

Let $\mathbf{x} = (x_1, x_2, ..., x_p)'$ be a $p \times 1$ vector and assume that $f : \mathbb{R}^p \to \mathbb{R}$ is a scalar function of \mathbf{x} . Further, let \mathbf{a} be a $p \times 1$ vector and \mathbf{A} be a $p \times p$ symmetric matrix.

(a)
$$\frac{\partial \mathbf{a}' \mathbf{x}}{\partial \mathbf{x}} = \frac{\partial \mathbf{x}' \mathbf{a}}{\partial \mathbf{x}} = \mathbf{a}$$

(b)
$$\frac{\partial \mathbf{x}' \mathbf{A} \mathbf{x}}{\partial \mathbf{x}} = 2 \mathbf{A} \mathbf{x}$$

(c)
$$\frac{\partial^2 \mathbf{x}' \mathbf{A} \mathbf{x}}{\partial \mathbf{x} \partial \mathbf{x}'} = 2\mathbf{A}$$

6. Descriptive statistics

• Data (X)

Example 3.2 (textbook) A textile shop manager is studying the sales of pullovers over ten different periods. He observes the number of pullovers sold (X_1) , variation in price $(X_2$, in EUR), the advertisement costs in local newspaper $(X_3$, in EUR) and the presence of a sales assistant $(X_4$, in hours per period).

$$\mathbf{X} = \begin{pmatrix} 230 & 125 & 200 & 109 \\ 181 & 99 & 55 & 107 \\ 165 & 97 & 105 & 98 \\ 150 & 115 & 85 & 71 \\ 97 & 120 & 0 & 82 \\ 192 & 100 & 150 & 103 \\ 181 & 80 & 85 & 111 \\ 189 & 90 & 120 & 93 \\ 172 & 95 & 110 & 86 \\ 170 & 125 & 130 & 78 \end{pmatrix} = \begin{pmatrix} \mathbf{x}_1' \\ \mathbf{x}_2' \\ \vdots \\ \mathbf{x}_n' \end{pmatrix}$$

• Mean $(\overline{\mathbf{x}})$

$$\overline{\mathbf{x}} = \begin{pmatrix} \overline{x}_1 \\ \cdot \\ \cdot \\ \cdot \\ \overline{x}_p \end{pmatrix} = n^{-1} \mathbf{X}' \mathbf{1_n}$$

With reference to the pullover data set,

$$\overline{\mathbf{x}} = \begin{pmatrix} 172.7 \\ 104.6 \\ 104 \\ 93.8 \end{pmatrix}$$

• Sample covariance matrix (unbiased: S)

$$\mathbf{S} = \frac{1}{n-1} \sum_{i=1}^{n} (\mathbf{x}_i - \overline{\mathbf{x}}) (\mathbf{x}_i - \overline{\mathbf{x}})' = \frac{1}{n-1} \mathbf{X}' \mathbf{H} \mathbf{X}$$

where $\mathbf{H} = \mathbf{I}_n - n^{-1} \mathbf{1}_n \mathbf{1}'_n$.

With reference to the pullover data set,

$$\mathbf{S} = \begin{pmatrix} 1152.5 & -88.9 & 1589.7 & 301.6 \\ -88.9 & 244.3 & 102.3 & -101.8 \\ 1589.7 & 102.3 & 2915.6 & 233.7 \\ 301.6 & -101.8 & 233.7 & 197.1 \end{pmatrix}$$

• Correlation (R)

$${\bf R}={\bf D}^{-1/2}{\bf S}{\bf D}^{-1/2}$$

where \mathbf{D} is a diagonal matrix with form by using the diagonal elements of \mathbf{S} .

With reference to the pullover data set,

$$\mathbf{R} = \begin{pmatrix} 1 & -0.17 & 0.87 & 0.63 \\ -0.17 & 1 & 0.12 & -0.46 \\ 0.87 & 0.12 & 1 & 0.31 \\ 0.63 & -0.46 & 0.31 & 1 \end{pmatrix}$$