Statistical Learning: STA 7934 and CIS 6930

Exercises: Sections 4.1 - 4.3

Rebecca Steorts

1.  $\sum_{k} \hat{Y}_{k}(\boldsymbol{x}) = 1$  for any  $\boldsymbol{x}$  as long as there is an intercept in the model. We assume that  $\boldsymbol{x}$  is a column vector.

Proof:

$$\sum_{k} \hat{Y}_{k}(\boldsymbol{x}) = \mathbf{1}'_{K \times 1}[(1, \boldsymbol{x})' \ \hat{B}]'.$$

$$= \mathbf{1}'_{K \times 1} \hat{B}'(1, \boldsymbol{x}).$$

$$= [\hat{B} \ \mathbf{1}_{K \times 1}]'(1, \boldsymbol{x}).$$

Note that

$$\hat{B}\mathbf{1}_{K\times 1} = (X'X)^{-1}X'Y\mathbf{1}_{K\times 1}.$$

Then

$$Y\mathbf{1}_{K\times 1} = \mathbf{1}_{N\times 1} \implies \hat{B}\mathbf{1}_{K\times 1} = (X'X)^{-1}X\mathbf{1}_{N\times 1}.$$

Recall  $(X'X)^{-1}(X'X) = I$ . This implies that

$$(X'X)^{-1}X\mathbf{1}_{N\times 1}=e_1.$$

Then

$$[\hat{B} \ \mathbf{1}_{K \times 1}]'(1, x) = e'_{1}(1, x) = 1.$$

2. Fisher's problem amounts to maximizing

$$\max_{\boldsymbol{a}} \frac{\boldsymbol{a}' B \boldsymbol{a}}{\boldsymbol{a}' W \boldsymbol{a}}.$$

Proof: Let  $\boldsymbol{y} = W^{1/2}\boldsymbol{a}$ . Then

$$\frac{\boldsymbol{a}'B\boldsymbol{a}}{\boldsymbol{a}'W\boldsymbol{a}} = \frac{\boldsymbol{y}'W^{-1/2}BW^{-1/2}\boldsymbol{y}}{\boldsymbol{y}'\boldsymbol{y}}.$$

Consider

$$\frac{\boldsymbol{y}'W^{-1/2}BW^{-1/2}\boldsymbol{y}}{\boldsymbol{y}'\boldsymbol{y}} = \frac{\left(\frac{\boldsymbol{y}}{||\boldsymbol{y}||}\right)'W^{-1/2}BW^{-1/2}\left(\frac{\boldsymbol{y}}{||\boldsymbol{y}||}\right)}{\left(\frac{\boldsymbol{y}}{||\boldsymbol{y}||}\right)'\left(\frac{\boldsymbol{y}}{||\boldsymbol{y}||}\right)}.$$

But  $\left(\frac{y}{||y||}\right)'\left(\frac{y}{||y||}\right)=1$  so without loss of generality, we can assume y'y=1 and simply maximize

$$y'W^{-1/2}BW^{-1/2}y$$

subject to this constraint.

Let  $A=W^{-1/2}BW^{-1/2}$  and note that it is symmetric. By the Spectral Decomposition Theorem, there exists an orthogonal matrix P and diagonal matrix D such that

$$y'Ay = y'PDP'y,$$

where  $D = Diag(\lambda_1 \dots \lambda_p)$  and P is composed of the eigenvectors of A.

Then let x = P'y which implies that

$$oldsymbol{y}'PDP'oldsymbol{y} = oldsymbol{x}'Doldsymbol{x} = \sum_i \lambda_i x_i^2.$$

Thus,

$$\max_{x} \mathbf{y}' A \mathbf{y} = \max_{\mathbf{x}} \sum_{i} \lambda_{i} x_{i}^{2}.$$

Now consider

$$\sum_{i} \lambda_{i} x_{i}^{2} \le \sum_{i} \lambda_{max} x_{i}^{2} = \lambda_{max}.$$

Note the last equality holds because y'y = 1 implies x'x = 1.

Suppose  $\lambda_{max} = \lambda_k$  and take  $y = e_k$ . Then

$$\sum_{i} \lambda_{max} x_i^2 = \lambda_{max},$$

which implies given what we just showed that

$$\max_{y} \sum_{i} \lambda_{i} x_{i}^{2} = \lambda_{max}.$$

By what we just showed above this implies that

$$\max_{y} \mathbf{y}' W^{-1/2} B W^{-1/2} \mathbf{y} = \max \text{ eigenvalue} \{ W^{-1/2} B W^{-1/2} \}$$
$$= \max \text{ eigenvalue} \{ W^{-1} B \}.$$