

# midterm1WIP

## Exercise 3.

Consider the linear regression model from exercise 1. Suppose, that the target of estimation is  $h^\top \theta$  for some determinate non-zero vector  $h \in R^p$ . Find expression for the LSE of  $h^\top \theta$ . Is this estimate optimal in sense of Gauss-Markov theorem, i.e. does it have the smallest variance among all linear unbiased estimators?

Using our findings from exercise 2, we have an unbiased LSE estimator in  $\gamma^\top \hat{\theta}$  since  $E[\gamma^\top \hat{\theta} - \gamma^\top \theta] = \gamma^\top E[(XW X^\top)^{-1} XW Y] - \gamma^\top \theta = \gamma^\top \theta - \gamma^\top \theta = 0$ . Using another finding from exercise 2 we have,  $Var(\gamma^\top \hat{\theta}) = \gamma^\top Var(\hat{\theta}) \gamma = \gamma^\top (XW X^\top)^{-1} \gamma$ .

To show that  $\gamma^\top \hat{\theta}$  is BLUE, we compare its variance, to another estimator  $\tilde{\theta} = ((XW X^\top)^{-1} XW + D)Y$ , where  $D$  is another  $p \times n$  matrix. The variance of  $\gamma^\top \tilde{\theta}$  is then:

## Section 2.1

Exercise 7. (a) Using the notation from section 2.1, consider  $X \sim N(\mu, I_n)$  for some  $\mu \in R^n$ . Find  $E(Q(X))$  and  $Var(Q(X))$

For  $Q(X) = \sum_i \sum_j a_{ij} X_i X_j = X^\top A X$ ,  $X \sim N(\mu, I_n)$ , we have, using the property of trace operator:

$$E(Q(X)) = tr(E(Q(X))) = E(tr(Q(X))) = E(tr(X^\top A X)) = E(tr(A X X^\top)) = tr(AE(X X^\top))$$

Since  $E(X X^\top) = I_n + \mu \mu^\top$ , we have,

$$tr(AE(X X^\top)) = tr(A(I_n + \mu \mu^\top)) = tr A + tr(A \mu \mu^\top) = tr A + \mu^\top A \mu$$

$$Var(Q(X)) =$$

(b) Generalize the results from part (a) to the case  $X \sim N(\mu, \Sigma)$  for some positive-definite covariance matrix  $\Sigma \in R^{n \times n}$ . For  $X \sim N(\mu, \Sigma)$  we have,

$$E(Q(X)) = tr(AE(X X^\top)) = tr(A(\Sigma + \mu \mu^\top)) = tr(A \Sigma) + tr(A \mu \mu^\top) = tr(A \Sigma) + \mu^\top A \mu$$

$$Var(Q(X)) =$$

## Section 2.2

## Exercise 11.

Find an elliptical confidence set for the expected response  $E[Y]$  in model (3).

For the model  $Y = X^\top \theta^* + \varepsilon$ ,  $\varepsilon \sim N(0, \sigma^2 I_n)$ ,  $\hat{Y} = X^\top \hat{\theta} = X^\top (X X^\top)^{-1} X Y = \Pi Y$ , we have

$$E(\hat{Y} - Y) = E(\hat{Y}) - Y = E[X^\top (X X^\top)^{-1} X (X^\top \theta^* + \varepsilon)] - Y = E[X^\top \theta^*] - Y = Y - Y = 0$$

and

$$Var(\hat{Y} - Y) = Var((\Pi - I_n)Y) = (\Pi - I_n)Var(X^\top \theta^* + \varepsilon)(\Pi - I_n)^\top = (\Pi - I_n)\sigma^2 I_n(\Pi - I_n)^\top = \sigma^2(\Pi - I_n)$$

and assume that  $\hat{Y} - Y \sim N(0, \sigma^2(\Pi - I_n))$ , and  $\frac{(I_n - \Pi)^{-1/2}(\hat{Y} - Y)}{\sigma} \sim N(0, I_n)$  Using this information we can set up a confidence region for  $\hat{Y}$ ,

Exercise 12. Construct simultaneous confidence intervals (e.g., as in Corollary 2.2.1) for the expected responses  $E[Y_1], \dots, E[Y_n]$  in model (3).