

## Introduction to task 1

I On this list we look at linear regression from the optimisation point of view. We start by denoting equation that expresses relationship between predictors ( $x_i$ ) and outcomes ( $y_i$ )

$$y_i = x_i \beta_0 + \epsilon_i$$

- $y_i$  - denoted variable
- $x_i$  - vector of regressors  $[1 \times K]$
- $\beta_0$  - vector of regression coefficients
- $\epsilon_i$  - unobservable error term

Example:

We are estimating impact of different factors (year of production, KM, number of windows, brand) on price.  $\text{price} = \text{factors} \cdot \beta + \epsilon$

$\beta_0$  is vector of values that we are trying to estimate.

## II Matrix representation

For  $N$  observations, we can write this equation as

$$y = X \beta_0 + \epsilon \quad \text{where we add another } (N) \text{ dimension to each part of the equation}$$

## III Assumptions about error term

We make some assumptions about  $\epsilon$  (normality and independence)

- Mean is 0
- Variance is  $\sigma_0^2 I$ , where  $I$  is an identity matrix (so we have single variable representing variance that is constant for all errors in  $\epsilon$  term)
- Entries of  $\epsilon$  are independent:  $\text{Cov}(\epsilon_i, \epsilon_j) = 0, i \neq j$

## IV Cumulative Distribution Function

$$f_y(y_i | X) = (2\pi\sigma_0^2)^{-\frac{1}{2}} \exp\left(-\frac{1}{2} \frac{(y_i - x_i \beta_0)^2}{\sigma_0^2}\right)$$

This equation is expression of conditional distribution of  $y_i$  given  $X$  matrix.

## V Maximum Likelihood Estimate

We use MLE to estimate  $\beta_0$  and  $\sigma_0^2$ .  $\rightarrow$  We aim to find values that maximize the likelihood of observing the given data.

The likelihood function for entire dataset is product of the individual likelihoods for each observation:  $L(\beta_0, \sigma_0^2 | y, X) = \prod_{i=1}^N f_y(y_i | X)$

$\rightarrow$  ... the natural logarithm of the likelihood function (log-likelihood):

each observation.  $L(\beta_0, \sigma_0^2 | y, X) = \prod_{i=1}^N f_y(y_i | x_i)$

- Taking the natural logarithm of the likelihood function (log-likelihood):

$$\log L(\beta_0, \sigma_0^2 | y, X) = -\frac{N}{2} \ln(2\pi\sigma_0^2) - \frac{1}{2\sigma_0^2} \sum_{i=1}^N (y_i - x_i\beta_0)^2$$

- Which can be used to estimate  $\beta_0$  and  $\sigma_0^2$  parameters.