# Math 170S <br> Lecture Notes Section $6.5{ }^{* \dagger}$ 

## Linear regression

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NOTE: The notes is a summary for materials discussed in the class and is not supposed to substitute the text-
book. Please send me an email if you find typos.
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${ }^{\dagger}$ This notes is based on Hanbaek Lyu's and Liza Rebrova's notes from the previous quarter, and I would like to thank them for their generosity. "Nanos gigantum humeris insidentes (I am but a dwarf standing on the shoulders of giants)".

## 1 Linear regression example

We list the average age of people infected, and killed by COVID-19 in fictional countries:

1. Atlantis, average age: 25 , fatality rate: 0.35 ;
2. Avalon, average age: 47 , fatality rate: 0.57 ;
3. Lemuria, average age: 54, fatality rate: 0.64;
4. Shangri-la, average age: 72 , fatality rate: 0.82 ;
5. Tartarus, average age: 90, fatality rate: 1.

Let $x_{1}, \ldots, x_{5}$ be the average age of the infectees in those 5 countries.

Let $y_{1}, \ldots, y_{5}$ be the corresponding fatality rate.


Figure 1: The plot of the average age of people infected by COVID-19 (the x-axes) and the corresponding fatality rate (y-axes).

From the figure, one predicts the relationship between $x_{i}$ and $y_{i}$ is

$$
y_{i}=0.1+0.01 x_{i}
$$

We would like to do the same thing for general data.

## 2 Linear regression

Suppose that $X$ and $Y$ are two unknown dependent random variables, and we want to model their relationship. We do it as follows:

- We perform $n$ experiments to get $n$ random samples, $\left(x_{1}, y_{1}\right),\left(x_{2}, y_{2}\right), \ldots,\left(x_{n}, y_{n}\right)$.
- The linear regression is the prediction that

$$
\begin{equation*}
Y=\alpha+\beta X+\epsilon, \tag{1}
\end{equation*}
$$

where $\alpha$ and $\beta$ are constants, and $\epsilon$ is a normal $N\left(0, \sigma^{2}\right)$ random variable independent from $X$.

- This prediction means that we expect $Y$ and $X$ to have a(n almost) linear relationship.
- The normal random variable $\epsilon \sim N\left(0, \sigma^{2}\right)$ is the Gaussian noise, which emulates the (unpredictable yet unavoidable) error made by measurement tools.
- Finally, use MLE to guess $\widehat{\alpha}, \widehat{\beta}, \widehat{\sigma}^{2}$.


## 3 Linear regression: problems

- Assumption Unknown random variables $X$ and $Y$ that obeys a linear relationship.
- Input: Samples $\left(x_{1}, y_{1}\right),\left(x_{2}, y_{2}\right), \ldots,\left(x_{n}, y_{n}\right)$
- Problem: Find $\widehat{\alpha}, \widehat{\beta}, \widehat{\sigma}^{2}$ that best estimates

$$
Y=\alpha+\beta X+\epsilon, \quad \epsilon \sim N\left(0, \sigma^{2}\right)
$$

- Method: Use MLE to estimate $\widehat{\alpha}, \widehat{\beta}, \widehat{\sigma}^{2}$.

Computing the MLE for $\widehat{\alpha}, \widehat{\beta}, \widehat{\sigma}^{2}$ is not hard, but can be time-consuming. Therefore, we provide you the following formulas for $\widehat{\alpha}, \widehat{\beta}, \widehat{\sigma}^{2}$.

## 4 Formulas for $\widehat{\alpha}, \widehat{\beta}, \widehat{\sigma}^{2}$

Theorem 1. the LEs $\widehat{\alpha}, \widehat{\beta}, \widehat{\sigma}^{2}$ are given by

$$
\begin{aligned}
\widehat{\beta} & =\frac{E-\frac{A B}{n}}{C-\frac{A^{2}}{n}} ; \quad \widehat{\alpha}=\frac{B}{n}-\widehat{\beta} \frac{A}{n} ; \\
\widehat{\sigma}^{2} & =\frac{D}{n}-\left(\frac{B}{n}\right)^{2}-\widehat{\beta} \frac{E}{n}+\widehat{\beta} \frac{A B}{n^{2}},
\end{aligned}
$$

where

$$
\begin{aligned}
A & :=\sum_{i=1}^{n} x_{i}=x_{1}+\ldots+x_{n} \\
B & :=\sum_{i=1}^{n} y_{i}=y_{1}+\ldots+y_{n} \\
C & :=\sum_{i=1}^{n} x_{i}^{2}=x_{1}^{2}+\ldots+x_{n}^{2} \\
D & :=\sum_{i=1}^{n} y_{i}^{2}=y_{1}^{2}+\ldots+y_{n}^{2} \\
E & :=\sum_{i=1}^{n} x_{i} y_{i}=x_{1} y_{1}+\ldots+x_{n} y_{n}
\end{aligned}
$$

Remark 2. Note that the constant $\alpha$ in our notes is presented as $\alpha_{1}$ in the textbook, which explains why the formula for $\widehat{\alpha}$ in our theorem is off from the formula in textbook by a positive constant.

## 5 Example: linear regression

Let $x_{1}, \ldots, x_{n}$ be the midterm score of 10 students in a fictional statistics class:
$\begin{array}{llllllllll}70 & 74 & 72 & 68 & 58 & 54 & 82 & 64 & 80 & 61 .\end{array}$

Let $y_{1}, \ldots, y_{n}$ be the final score of the 10 students:
$\begin{array}{llllllllll}77 & 94 & 88 & 80 & 71 & 76 & 88 & 80 & 90 & 69 .\end{array}$

The key values $A, B, C, D, E$ are given by

$$
\begin{aligned}
A & =\sum_{i=1}^{n} x_{i}=70+74+72+68+58+54+82+64+80+61 \\
& =683 \\
B & =\sum_{i=1}^{n} y_{i}=77+94+88+80+71+76+88+80+90+69 \\
& =813 ; \\
C & =\sum_{i=1}^{n} x_{i}^{2} \\
& =70^{2}+74^{2}+72^{2}+68^{2}+58^{2}+54^{2}+82^{2}+64^{2}+80^{2}+61^{2} \\
& =47,405 ; \\
D & =\sum_{i=1}^{n} y_{i}^{2} \\
& =77^{2}+94^{2}+88^{2}+80^{2}+71^{2}+76^{2}+88^{2}+80^{2}+90^{2}+69^{2} \\
& =66,731 ;
\end{aligned}
$$

$$
\begin{aligned}
E= & \sum_{i=1}^{n} x_{i} y_{i} \\
= & (70)(77)+(74)(94)+(72)(88)+(68)(80)+(58)(71)+ \\
& (54)(76)+(82)(88)+(64)(80)+(80)(90)+(61)(69) \\
= & 56,089
\end{aligned}
$$

The MLEs are then given by

$$
\begin{aligned}
\widehat{\beta} & =\frac{E-\frac{A B}{n}}{C-\frac{A^{2}}{n}}=\frac{56,089-(683)(813) / 10}{47,405-(683)(683) / 10}=0.742 . \\
\widehat{\alpha} & =\frac{B}{n}-\widehat{\beta} \frac{A}{n}=813 / 10-(0.742)(683 / 10)=30.6214 \\
\widehat{\sigma}^{2} & =\frac{D}{n}-\left(\frac{B}{n}\right)^{2}-\widehat{\beta} \frac{E}{n}+\widehat{\beta} \frac{A B}{n^{2}} \\
& =66,731 / 10-(813 / 10)^{2}-(0.742)(56,089) / 10+(0.742)(683) \\
& =21.77638
\end{aligned}
$$

