

# Assignment

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## Exercise 1

### 1. Exploring the Dataset

```
load("Data ST523 813 E2025 Exam.rdata")  
dim(Data)
```

```
[1] 300  9
```

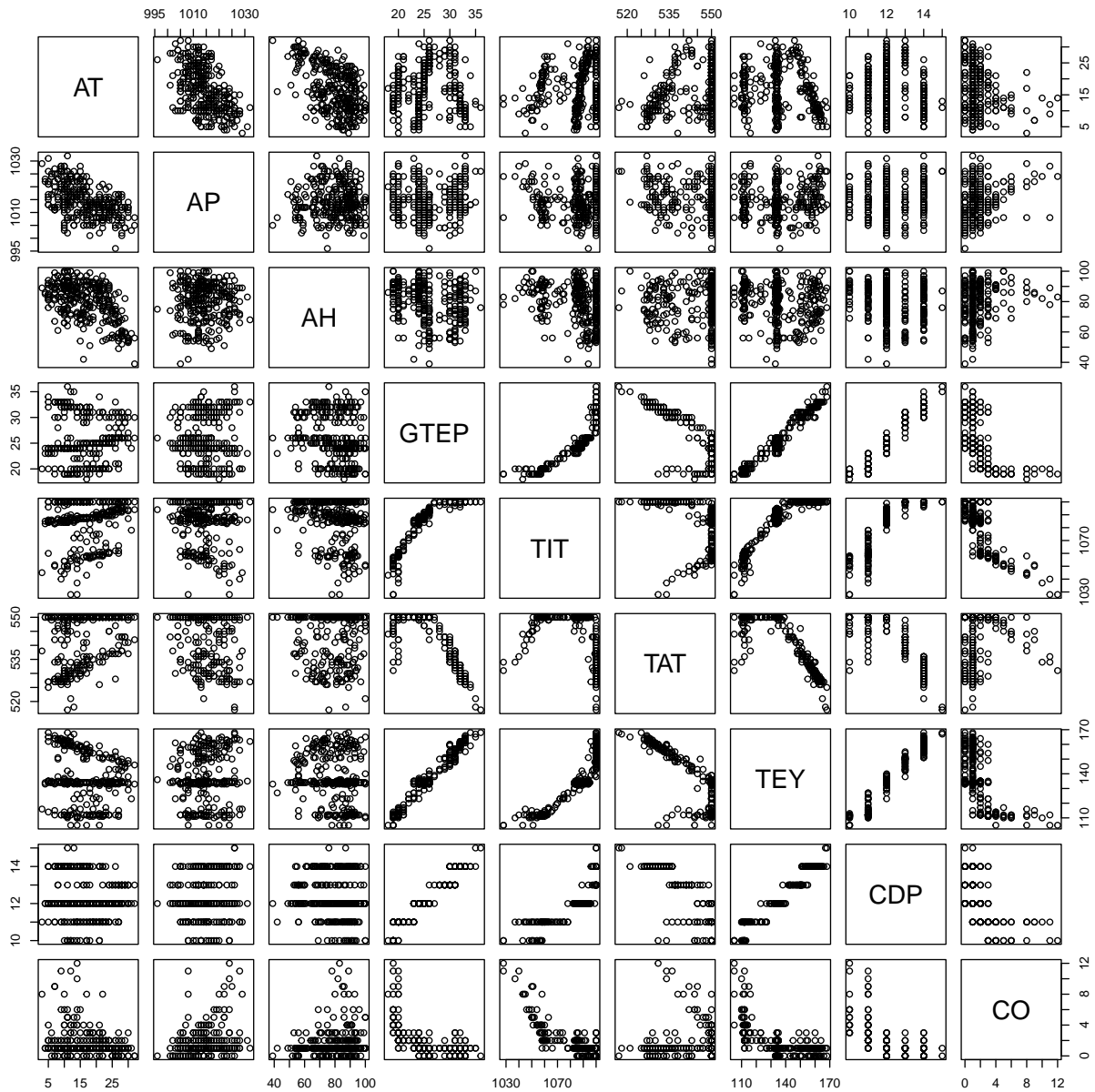
```
summary(Data)
```

AT	AP	AH	GTEP	TIT
Min. : 3.00	Min. : 996	Min. : 39.00	Min. :18.00	Min. :1028
1st Qu.:11.00	1st Qu.:1010	1st Qu.: 72.00	1st Qu.:23.00	1st Qu.:1083
Median :16.00	Median :1014	Median : 82.00	Median :25.00	Median :1089
Mean :16.74	Mean :1015	Mean : 79.82	Mean :25.85	Mean :1085
3rd Qu.:22.25	3rd Qu.:1019	3rd Qu.: 90.00	3rd Qu.:30.00	3rd Qu.:1100
Max. :32.00	Max. :1032	Max. :100.00	Max. :36.00	Max. :1100

TAT	TEY	CDP	CO
Min. :517.0	Min. :105.0	Min. :10.00	Min. : 0.0
1st Qu.:536.0	1st Qu.:130.0	1st Qu.:12.00	1st Qu.: 1.0
Median :550.0	Median :134.0	Median :12.00	Median : 1.0
Mean :543.8	Mean :136.5	Mean :12.29	Mean : 1.7
3rd Qu.:550.0	3rd Qu.:151.0	3rd Qu.:13.00	3rd Qu.: 2.0
Max. :550.0	Max. :168.0	Max. :15.00	Max. :12.0

```
pairs(Data)
```



So we have 9 non-categorical variables and a total of 300 observations.

## 2. Linear Model

```
fit = lm(CO ~ AT + AP + AH + GTEP + TIT + TAT + TEY + CDP, data = Data)
summary(fit)
```

```
Call:
lm(formula = CO ~ AT + AP + AH + GTEP + TIT + TAT + TEY + CDP,
    data = Data)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-2.8724	-0.5804	-0.0571	0.4270	4.3507

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	124.201441	17.933449	6.926	2.78e-11 ***
AT	-0.021611	0.028025	-0.771	0.441242
AP	0.009737	0.012831	0.759	0.448558
AH	-0.009622	0.005824	-1.652	0.099605 .
GTEP	-0.370650	0.158512	-2.338	0.020048 *
TIT	0.029652	0.058304	0.509	0.611437
TAT	-0.255241	0.072992	-3.497	0.000544 ***
TEY	-0.068439	0.071399	-0.959	0.338581
CDP	-0.463762	0.221422	-2.094	0.037083 *

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9744 on 291 degrees of freedom

Multiple R-squared: 0.7386, Adjusted R-squared: 0.7314

F-statistic: 102.8 on 8 and 291 DF, p-value: < 2.2e-16

$$n = 300 \quad p = 9$$

We can see the estimated intercept and other 8 parameters in the “Estimate” column above. We have  $300 - 9 = 291$  degrees of freedom.

Judging by the coefficient of Ambient Temperature predictor we can expect a 0.021611 decrease in CO-level for every  $1^\circ\text{C}$  increase in Ambient Temperature.

### 3. F - test

- Hypothesis:

$$H_0 : \beta_2 = \beta_3 = \dots = \beta_p = 0 \quad H_1 : \exists_{j \in 2 \dots p} \beta_j \neq 0$$

```
fit.0 = lm(CO ~ 1, data = Data)
anova(fit.0, fit)
```

#### Analysis of Variance Table

Model 1: CO ~ 1

Model 2: CO ~ AT + AP + AH + GTEP + TIT + TAT + TEY + CDP

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	299	1057.00				
2	291	276.31	8	780.69	102.77	< 2.2e-16 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

As we can see the RSS drastically dropped in the wider model, compared to the null, which already gives us an indication that it might explain the data much better.

- The observed test statistic can be read from the table:  $F = 102.77$
- The probability of getting such a high value is very small:  $p_{val} < 2.2 \cdot 10^{-16}$
- Under the Null Hypothesis  $F$  should follow the  $F_{8,291}$  distribution.

(Because the difference in parameters / degrees of freedom is 8, and the wider model has 291 degrees of freedom, which we've shown before)

The p-value is much smaller than the significance level therefore we can definitely reject the null hypothesis - we know that our test statistic must be much higher than the 0.95th quantile of the null distribution.

## 4. Reduced Models

### Model A

Similarly as before, we state the hypothesis:

$$H_0 : \beta_5 = \beta_6 = \dots = \beta_p = 0 \quad H_1 : \exists_{j \in 5 \dots p} \beta_j \neq 0$$

```
fit.A = lm(CO ~ AT + AP + AH, data = Data)
anova(fit.A, fit)
```

### Analysis of Variance Table

Model 1: CO ~ AT + AP + AH

Model 2: CO ~ AT + AP + AH + GTEP + TIT + TAT + TEY + CDP

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	296	971.35				
2	291	276.31	5	695.04	146.4	< 2.2e-16 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

And similarly as before we can see that the test statistic is very high (146.4), while the p-value is very low (close to 0) - which strongly speaks against the null hypothesis.

The conclusion is - we cannot reduce the full model to Model A.

### Model B

$$H_0 : \beta_2 = \beta_3 = \beta_4 = \beta_9 = 0 \quad H_1 : \exists_{j \in \{2,3,4,9\}} \beta_j \neq 0$$

```
fit.B = lm(CO ~ GTEP + TIT + TAT + TEY, data = Data)
anova(fit.B, fit)
```

### Analysis of Variance Table

Model 1: CO ~ GTEP + TIT + TAT + TEY

Model 2: CO ~ AT + AP + AH + GTEP + TIT + TAT + TEY + CDP

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	295	286.13				
2	291	276.31	4	9.8158	2.5844	0.0373 *

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Here the situation is slightly different. The test statistic is much lower (2.5844), and the p-value is much higher than with the previous 2 models (0.0373) - but it's still quite low. Depending on our significance level we might reject the null hypothesis or not. For signif. level  $\alpha = 0.05$  we would reject the null and say that the model can't be reduced. For signif. level  $\alpha = 0.01$  however we would be able to say that the full model can be reduced to Model B.

## Exercise 2

Model:

$$\begin{aligned} Y_i &= \mu + \alpha_{j(i)} + \beta' \cdot X_i + \epsilon_i \\ i &\in [1 \dots n] \\ n &= 45 \end{aligned}$$

Model Matrix and Coefficients

$$\mathbf{X} = \begin{bmatrix} 1 & 0 & 0 & 0 & X_1 \\ \vdots & 1 & 0 & 0 & \vdots \\ \vdots & 0 & 1 & 0 & \vdots \\ 1 & 0 & 0 & 1 & X_n \end{bmatrix} \quad \beta = \begin{bmatrix} \mu \\ \alpha_{TempResearch} \\ \alpha_{TempPrivate} \\ \alpha_{Freelance} \\ \beta' \end{bmatrix}$$

$p = 5$

### 1. Confidence Interval

$$\begin{aligned} c^T &= [0 \quad 1 \quad -1 \quad 0 \quad 0] \\ c^T \beta &= \alpha_{TempResearch} - \alpha_{TempPrivate} \\ CI &= c^T \hat{\beta} \pm \widehat{SE}_{c^T \hat{\beta}} \cdot t_{n-p; 1-\frac{\alpha}{2}} \end{aligned}$$

The only thing in the above formula that we don't have is the  $\widehat{SE}_{c^T \hat{\beta}}$ . We usually used RSS to get it, but since we don't have access neither to the predictors nor responses we can use the output of the program to calculate it differently:

$$\begin{aligned} \widehat{SE}_{c^T \hat{\beta}} &= \sqrt{Var(c^T \hat{\beta})} \\ Var(c^T \hat{\beta}) &= Var(\hat{\alpha}_{TempResearch} - \hat{\alpha}_{TempPrivate}) = \\ &= Var(\hat{\alpha}_{TempResearch}) + Var(\hat{\alpha}_{TempPrivate}) - 2Cov(\hat{\alpha}_{TempResearch}, \hat{\alpha}_{TempPrivate}) = \\ &= \widehat{SE}_{\hat{\alpha}_{TempResearch}}^2 + \widehat{SE}_{\hat{\alpha}_{TempPrivate}}^2 - 2Cov(\hat{\alpha}_{TempResearch}, \hat{\alpha}_{TempPrivate}) \end{aligned}$$

Now we have everything we need to calculate the confidence interval.

```
n = 45
p = 5

a.re = -40000
a.pr = -10000
```

```

psi = a.re - a.pr

SE.re = 24000
SE.pr = 23000
COV.re.pr = 22000000

SE = sqrt(SE.re ^ 2 + SE.pr ^ 2 - 2 * COV.re.pr)

CI.lower = psi - SE * qt(0.95, n - p)
CI.upper = psi + SE * qt(0.95, n - p)

c(CI.lower, CI.upper)

```

```
[1] -84848.07 24848.07
```

## 2. Hypothesis Testing

$$H_0 : \alpha_{TempResearch} \geq \alpha_{TempPrivate} \quad H_1 : -c^T \beta > 0 \\ \implies -c^T \beta \leq 0$$

We've shown on the lecture that if  $H_0$  holds then:

$$T = \frac{-c^T \hat{\beta} - 0}{SE_{c^T \hat{\beta}}} \\ P(T > t_{n-p; 1-\alpha}) \leq \alpha$$

Which means we will have statistical evidence to reject  $H_0$  if the test statistic is bigger than the 0.95 quantile of the given above  $t_{n-p}$  - distribution.

```

T = -psi / SE
t.95 = qt(0.95, n - p)

c(T, t.95)

```

```
[1] 0.9210083 1.6838510
```

As we can see, the test statistic - even though it's positive - is not bigger than the quantile, therefore we don't have sufficient statistical evidence to reject the null hypothesis and say that temporary researches are earning less than temporary private consultants.

## Exercise 3

### Model Matrix and Coefficients

For a simple linear relationship we have the model matrix and the parameter vector as so:

$$X = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix} \quad \beta = \begin{bmatrix} \beta_{intercept} \\ \beta_{slope} \end{bmatrix}$$

Since we want to estimate  $\beta_{slope}$  as precisely as possible, we would like to minimize  $Var(\hat{\beta}_{slope}) = Var(\hat{\beta})_{22}$ .

We know that for the Least Square Estimator  $\hat{\beta} Var(\hat{\beta}) = \sigma^2(X^T X)^{-1}$

$$(X^T X)^{-1} = \left( \begin{bmatrix} 1 & 1 & \dots & 1 \\ x_1 & x_2 & \dots & x_n \end{bmatrix} \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix} \right)^{-1} = \begin{bmatrix} n & \sum x_i \\ \sum x_i & \sum x_i^2 \end{bmatrix}^{-1}$$

We can find it's reverse using any method.

$$\begin{aligned} & \left[ \begin{array}{cc|cc} n & \sum x_i & 1 & 0 \\ \sum x_i & \sum x_i^2 & 0 & 1 \end{array} \right] \\ & \left[ \begin{array}{cc|cc} 1 & \bar{x} & \frac{1}{n} & 0 \\ \sum x_i & \sum x_i^2 & 0 & 1 \end{array} \right] \\ & \left[ \begin{array}{cc|cc} 1 & \bar{x} & \frac{1}{n} & 0 \\ 0 & \sum x_i^2 - \bar{x} \sum x_i & -\bar{x} & 1 \end{array} \right] \\ & \left[ \begin{array}{cc|cc} 1 & \bar{x} & \frac{1}{n} & 0 \\ 0 & \sum x_i(x_i - \bar{x}) & -\bar{x} & 1 \end{array} \right] \\ & \left[ \begin{array}{cc|cc} 1 & \bar{x} & \frac{1}{n} & 0 \\ 0 & 1 & \frac{-\bar{x}}{\sum x_i(x_i - \bar{x})} & \frac{1}{\sum x_i(x_i - \bar{x})} \end{array} \right] \end{aligned}$$

At this point we don't even need to calculate further, because we only want  $Var(\hat{\beta})_{22}$  which we can see is equal to  $\frac{\sigma^2}{\sum x_i(x_i - \bar{x})}$