

## **Linear Regression Models (II)**

## Lecture outline



- 1. Assumptions of Linear Regression
- 2. R Squared and Adjusted R Squared
- 3. F-test for model significance
- 4. t-test for parameter significance

#### **Assumptions of Linear Regression**



- •Normality: Multiple regression assumes that the error terms are normally distributed.
- •Linearity: There must be linear relationship between response variable and independent variables (Scatterplots).
- •No Multicollinearity: the independent variables are not highly correlated with each other (Correlation matrix).
- Homoscedasticity: the variance of error terms are similar across the values of the independent variables (Plot of residuals vs predictor variables).

# **Normality**

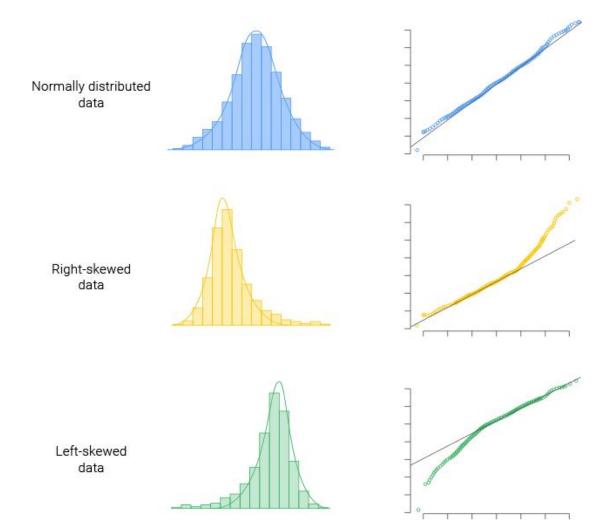


**Normality**: Multiple regression assumes that the error terms are normally distributed.

Plot QQ (Quantile-quantile) plots are used to visually check the normality of the data.

As all the points fall approximately along the straight line, we can assume normality.

R Syntax: plot(model\$residuals)

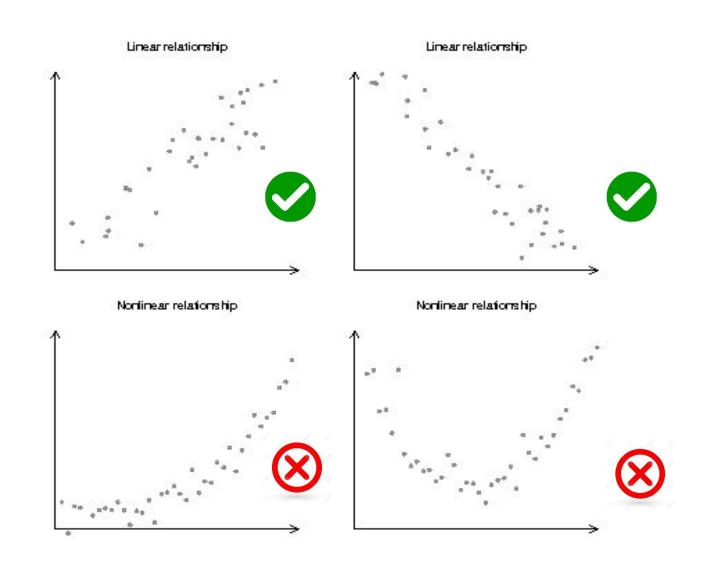


#### Linearity



#### **Linearity:**

There must be linear relationship between response variable and independent variables.



## **No Multicollinearity**



#### **No Multicollinearity:**

The independent variables are not highly correlated with each other.

	CompPrice	Income	Advertising
CompPrice	1.00	-0.08	-0.02
Income	-0.08	1.00	0.06
Advertising	-0.02	0.06	1.00

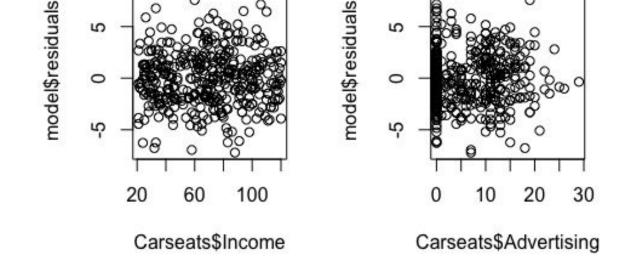


## Homoscedasticity



#### Homoscedasticity:

The variance of error terms are similar across the values of the independent variables (Plot of residuals vs predictor variables).



par(mfrow=c(1,2))
plot(Carseats\$Income,model\$residuals)
plot(Carseats\$Advertising, model\$residuals)

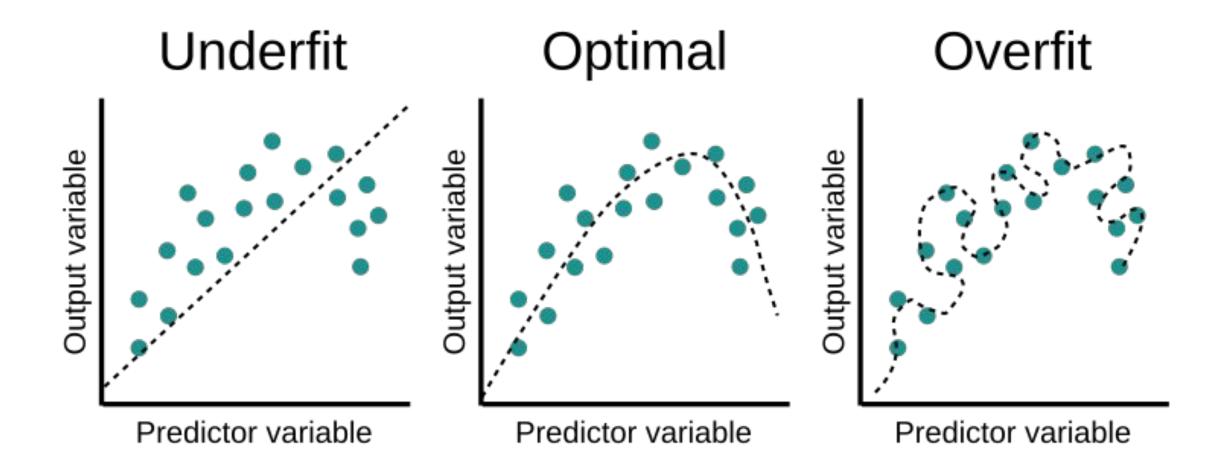
# R-Squared

**R-squared** (R<sup>2</sup>), also known as a Coefficient of Determination, is a statistical measure that represents the proportion of the variance for a dependent variable that's explained by an independent variable or variables in a regression model.

$$R^{2} = 1 - \frac{SS_{RES}}{SS_{TOT}} = 1 - \frac{\sum_{i} (y_{i} - \hat{y}_{i})^{2}}{\sum_{i} (y_{i} - \overline{y}_{i})^{2}}$$

#### Coefficients:

Residual standard error: 2.701 on 396 degrees of freedom Multiple R-squared: 0.09221, Adjusted R-squared: 0.08533 F-statistic: 13.41 on 3 and 396 DF, p-value: 2.374e-08





## **Adjusted R-Squared**

- The **adjusted R-squared** is a modified version of R-squared that has been adjusted for the number of predictors in the model.
- The adjusted R-squared increases only if the new term improves the model more than would be expected by chance.

Adj R<sup>2</sup> = 1 - 
$$\frac{\frac{SSE}{n-k}}{\frac{SST}{n-1}}$$
 = 1 -  $\frac{(1-R^2)(n-1)}{n-k-1}$ 

Here n- # of observations k - # of independent variables

#### Coefficients:

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

Residual standard error: 2.701 on 396 degrees of freedom Multiple R-squared: 0.09221, Adjusted R-squared: 0.08533

F-statistic: 13.41 on 3 and 396 DF, p-value: 2.374e-08

#### **Testing for Significance: F-test**



The *F* test is used to determine whether a significant relationship exists between the dependent variable and the set of <u>all the independent variables</u>.

The *F* test is referred to as the <u>test for overall</u> <u>significance</u>.

### **Testing for Significance: F-test**



Hypotheses

$$H_0: \ \beta_1 = \beta_2 = \ldots = \beta_k = 0$$

 $H_a$ : At least one of the parameters (betas) is not equal to zero.

**Test Statistics** 

$$F = MSR/MSE$$

Rejection Rule

Reject  $H_0$  if p-value  $\leq \alpha$  or if  $F > F_\alpha$  where  $F_\alpha$  is based on an F distribution with k d.f. in the numerator and n - k - 1 d.f. in the denominator.

### **Example**



Let's use the insurance dataset to predict health care charges based on age, gender, bmi (body mass index) and smoker status.

Charges = 
$$\beta_0 + \beta_1$$
\*Age +  $\beta_2$ \*Male +  $\beta_3$ \*Bmi +  $\beta_4$ \*Smoker +  $\varepsilon$ 

Hypotheses for Overall Significance (F-test):

Ho: 
$$\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$$

Ha: At least one of the betas is not zero.

Since p-value =  $0.000...22 < \alpha = 0.01$ ,

We reject Ho and conclude that overall model is

Significant in predicting insurance charges.

#### Coefficients:

	Estimate	Std. Error	t value	Pr(>ltl)	
(Intercept)	-11633.49	947.27	-12.281	<2e-16	***
age	259.45	11.94	21.727	<2e-16	***
sexmale	-109.04	334.66	-0.326	0.745	
bmi	323.05	27.53	11.735	<2e-16	***
smokeryes	23833.87	414.19	57.544	<2e-16	***

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

Residual standard error: 6094 on 1333 degrees of freedom Multiple R-squared: 0.7475, Adjusted R-squared: 0.7467 F-statistic: 986.5 on 4 and 1333 DF, p-value: < 2.2e-16

### **Testing for Significance: t-test**



Hypotheses

$$H_0: \beta_i = 0$$

$$H_a: \beta_i \neq 0$$

**Test Statistics** 

$$t_{stat} = \frac{b_i}{s_{b_i}}$$

Rejection Rule

Reject  $H_0$  if p-value  $\leq \alpha$  or if  $|t| \geq t_{\alpha/2}$  where  $t_{\alpha/2}$  is based on a t distribution with n - k - 1 degrees of freedom.

# Example



Let's use the insurance dataset to predict health care charges based on age, gender, bmi (body mass index) and smoker status.

Charges = 
$$\beta_0 + \beta_1 *Age + \beta_2 *Male + \beta_3 *Bmi + \beta_4 *Smoker + \varepsilon$$

Hypotheses for numerical variables for their significance (t-test): Age, Bmi

#### For Age:

Ho: 
$$\beta_1 = 0$$

Ha: 
$$\beta_1 \neq 0$$

#### For Bmi:

Ho: 
$$\beta_3 = 0$$

Ha: 
$$\beta_3 \neq 0$$

Since both p-values are smaller than alpha of 0.01, We reject Ho and conclude that age and bmi variables are significant.

#### Coefficients:

	LS CLINACC .	Jea. Liloi	CVULUC	11(/101)	
(Intercept)	-11633.49	947.27	-12.281	<2e-16	***
age	259.45	11.94	21.727	<2e-16	***
sexmale	-109.04	334.66	-0.326	0.745	
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Signif. code	es: 0 '***	' 0.001'**	° 0.01	'*' 0.05 '	.'0.1 '1

Estimate Std. Frror t value Pr(>|t|)

Residual standard error: 6094 on 1333 degrees of freedom Multiple R-squared: 0.7475, Adjusted R-squared: 0.7467 F-statistic: 986.5 on 4 and 1333 DF, p-value: < 2.2e-16

#### **Exercise 1**



38 random movies were selected to develop a model for predicting their revenues.

We have the following variables in the dataset:

- *USRevenue* movie's revenue in the US (mln\$)
- *Rating* restrictions based on age (PG, PG-13, R)
- *Budget* budget (expenditure) of the movie (mln\$)
- *Opening* revenue on the opening weekend (mln\$)
- *Theaters* number of theaters the movie was in for the opening weekend
- *Opinion* IMDb rating (1 to 10, 10 being the best)



## **Exercise 1**



- a) Fit a model to predict USRevenue using Rating, Budget, Opening as independent variables.
- b) Check the assumptions of the linear regression
- c) Interpret the value of  $R^2$  in part a.
- d) Add Opinion as another explanatory variable into your model and see how your R<sup>2</sup> and adjusted R<sup>2</sup> changed. How would you explain this?
- e) Test for overall significance of the model. Use  $\alpha = 0.05$ .
- f) Test whether Budget, Opening and Opinion are significant variables separately. Use  $\alpha = 0.05$ .



# Thank you for your attention!

## Homework:



- a) Refer to Housing Data. Fit a model to predict Price using all independent variables.
- a) Check the assumptions of the linear regression
- a) Interpret the value of  $R^2$  in part a.
- a) Test for overall significance of the model. Use  $\alpha = 0.01$ .
- a) Test whether numerical variables are significant separately. Use  $\alpha = 0.01$ .
- a) Now remove rooms and bathrooms from the model and compare with the original