

# Predictions I

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# Introduction

- The objective of inferential statistics is to draw conclusions about the population from the sample.
- So far we have used linear regression to draw conclusions about the nature of linear relationships in a population based on data.
- Next we are going to use linear regression to predict outcomes of combinations of explanatory variables.

# Predictions

- A **prediction** (forecast) is a statement about a future event or unknown data.
- Can may use previous knowledge (statistical models) to make informed predictions.
- Sometimes referred to as *statistical learning*.

## Review: Reading Models

- Understanding your results is extremely important.
- Visualizations can be useful to examine the relationships.
- Quantitative ways to read a model:
  - 1 Read out the ***model value***.
  - 2 Characterize the relationship *described* by the model.

## Review: Read out the Model Value

- Plug in specific values for the explanatory variables and read out the resulting model value.
- Essentially examining the fitted values for specific combinations of explanatory variables.
- Specific *point*, not a general description of the relationship.
- **Looking at these values for new values of  $X$ , sometimes denoted at  $X_*$**

## Making Predictions

- Once the linear regression model is estimated predictions can be made.
- Predictions can be made on new combinations of values of explanatory variables.
- *Generally this should be done within the range of your sampled data.*
- Simple linear regression:

$$\widehat{E[Y]} = b_0 + b_i X_* \quad (1)$$

## Making Predictions in R

- Create a data frame of different combinations of explanatory variables you are interested in predicting using your model (`model`).
- In R (predict  $m$  observations):
  - `new.data <- data.frame(XA = c(valueA1, valueA2, ..., valueAm), XB = c(valueB1, valueB2, ..., valueBm), ...)`
  - `predict(model,new.data)`



## Example 1

- Run the given code to simulate some data.
- Estimate the linear regression model for  $Y \sim 1 + X_1$
- What do the coefficients and the Adjusted- $R^2$  say about the linear relationship?
- Use the `predict()` function to predict the  $Y$  values for the 20 simulated observations.
- Add these predicted observations to the scatterplot.
  - What do you notice?

## Confidence Intervals for $b_j$

- Confidence intervals for our coefficient estimates can be obtained using R:
  - `confint(model, 'variable.name', level=0.95)`

$$b_j = \pm t_{\frac{\alpha}{2}, n-k} \cdot SE(b_j)$$

- The same information is used to calculate the  $p$ -value used to test the significance of the coefficient.

## Example 2

- Use R to obtain a confidence interval for  $b_1$  from Example 1.

## Prediction Intervals

- Sometimes it may be important to assign confidence to your linear predictions.
- In general the prediction interval is larger than the confidence intervals.
- Now there are multiple sources of errors:
  - 1 Estimation Error
  - 2 Prediction Error
- Prediction intervals in R:
  - `predict(model,new.data, interval = 'predict')`

## Example 3

- Use R to obtain a **prediction** interval for the predictions we made in Example 1.

## Model Assumption Violations (If Violated:)

- ① Linearity
  - **May lead to serious inaccuracies when making predictions.**
- ② Normality (multivariate normal for multiple independent variables)
  - Causes problems in determining if model coefficients are significantly different from zero.
  - **Also causes problems in any confidence/prediction interval estimation.**
- ③ Homoscedasticity
  - As we are minimizing the residual sum of squares, extra *weight* may be given to observations with a higher variability during estimation.
  - **Also causes problems with prediction intervals.**
- ④ Independence
  - **May lead to bias (over/under estimate) the nature of the linear relationship.**

## Example 4

- Load the *Football22.csv* data into R.
- Set your seed to 2020 and take a stratified sample of 75% with League as the stratifying variable.
- Using your stratified sample estimate the following linear regression model:  
$$\text{Points} \sim 1 + \text{Goals\_For} + \text{Goals\_Against}$$
- Use the code provided to make predictions on the number of league points the clubs not in the stratified sample should earn.
  - Combine your results in a data frame.
  - How accurate are these predictions?
  - Examine the prediction intervals.

## Exercise 1

- Take some time to make some predictions from other linear regression models we have estimated this term.
- Be sure to examine the prediction intervals.
  - Are they wide or narrow?



## References & Resources

- ❶ Kaplan, Daniel T. (2017). *Statistical Modelling: A Fresh Approach. (Second Edition)*. Retrieved from <https://dtkaplan.github.io/SM2-bookdown/>
  - ❷ Fox, J. (2015). *Applied regression analysis and generalized linear models (Third Edition)*. Sage Publications.
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- `predict()`
  - `confint()`
  - `anti_join()`