

Lecture 4 Linear Regression II

ECE 625: Data Analysis and Knowledge Discovery

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Outline

Multiple Linear Regression

Estimation and Inference

Indicator Variables

Summary and Remark

Multiple Linear Regression

- ▶ **Multiple Linear Regression** has more than one covariate,

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p + \varepsilon,$$

where usually $\varepsilon \sim N(0, \sigma^2)$.

- ▶ We interpret β_j as the **average** effect on Y due to one unit of increase in X_j , **while holding all the other covariates fixed**.
- ▶ In the advertising example, the model becomes

$$\text{Sales} = \beta_0 + \beta_1 \times \text{TV} + \beta_2 \times \text{Radio} + \beta_3 \times \text{Newspaper} + \varepsilon.$$

Coefficient Interpretation

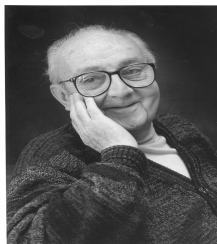
- ▶ The ideal scenario is when the predictors are uncorrelated — a **balanced design**.
 - ▶ Each coefficient can be estimated and tested **separately**.
 - ▶ Interpretations such as **a unit change in X_j is associated with a β_j change in Y , while all the other variables stay fixed**, are possible.
- ▶ Correlations amongst predictors cause problems.
 - ▶ The variance of all coefficient tends to increase, sometimes dramatically.
 - ▶ Interpretations become hazardous — when X_j changes, everything else changes.

The woes of regression coefficients

Data Analysis and Regression, Mosteller and Tukey 1977

- ▶ A regression coefficient β_j estimates the expected change in Y per unit change in X_j , with **all other predictors held fixed**. But predictors usually change **together!**
- ▶ Example: Y total amount of change in your pocket; $X_1 = \#$ of coins; $X_2 = \#$ of quarters and loonies. By itself, regression coefficient of Y on X_2 will be > 0 . But how about with X_1 in model?
- ▶ $Y =$ number of tackles by a football player in a season; W and H are his weight and height. Fitted regression model is $Y = \beta_0 + 0.50W - 0.10H$. How do we interpret $\hat{\beta}_2 < 0$?

Two famous quotes



1919 - 2013 (aged 93)

In real world, we are just
analyzing data passively

- ▶ Essentially, all models are wrong, but some are useful.
George Box
- ▶ The only way to find out what will happen when a complex system is disturbed is to disturb the system, not merely to observe it passively.

Fred Mosteller and John Tukey, paraphrasing George Box

Coefficient estimation

- ▶ Given the estimates $\hat{\beta}_0, \hat{\beta}_1, \dots$, and $\hat{\beta}_p$, the **estimated regression line** is

$$y = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \dots + \hat{\beta}_p x_p.$$

- ▶ We estimate all the coefficients $\beta_i, i = 0, 1, \dots, p$ as the values that minimize the sum of squared residuals

Residual Sum of Squares $\text{RSS} = \sum_{i=1, \dots, n} (y_i - \hat{y}_i)^2,$



convex optimization

where $\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \dots + \hat{\beta}_p x_p$ is the predicted values.

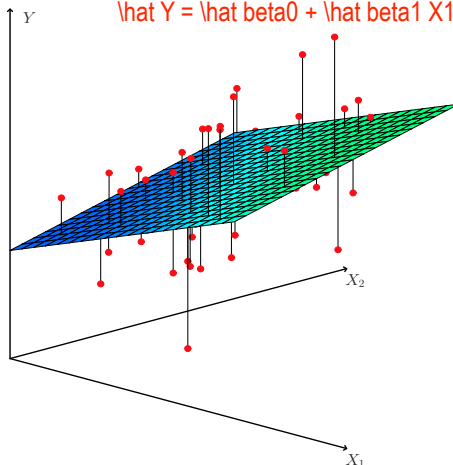
- ▶ This can be done using software. The values $\hat{\beta}_0, \hat{\beta}_1, \dots$, and $\hat{\beta}_p$ that minimize RSS are the multiple least squares regression coefficient estimates.

Estimation Example

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + e$$

Prediction is the hyperplane:

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2$$



Inference

feature
covariate

- ▶ Is at least one predictor useful? Use F statistic:

H_0 : all $\beta = 0$ (none of the predictors is useful)

$$F = \frac{(\text{TSS} - \text{RSS})/p}{\text{RSS}/(n - p - 1)} \sim F_{p, n-p-1}.$$

leads to a p-value
small: reject H_0 (at least one predictor is useful)

- ▶ What about an individual coefficient, say if β_i useful? Use t statistic

H_0 : $\beta_i = 0$ (predictor i is not useful)

$$t = \frac{\hat{\beta}_i - 0}{\text{SE}(\hat{\beta}_i)} \sim t_{n-p-1}.$$

leads to a p-value
small: reject H_0 (β_i useful)

- ▶ For given x_1, \dots, x_p , what is the prediction interval (PI) of the corresponding y ? PI is the CI of $(\hat{y} + e)$ that includes the effect of noise e
- ▶ What about the confidence interval (CI) of y ? CI is the CI of \hat{y}
- ▶ What is the difference — PI, individual and CI, average, PI is wider than CI.

Advertising example

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	2.938889	0.311908	9.422	<2e-16	***
TV	0.045765	0.001395	32.809	<2e-16	***
Radio	0.188530	0.008611	21.893	<2e-16	***
Newspaper	-0.001037	0.005871	-0.177	0.86	

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

Residual standard error: 1.686 on 196 degrees of freedom
Multiple R-squared: 0.8972, Adjusted R-squared: 0.8956
F-statistic: 570.3 on 3 and 196 DF, p-value: < 2.2e-16

```
> predict(TVadlm, newdata, interval="c", level=0.95)
      fit      lwr      upr
1 20.52397 19.99627 21.05168
with 95% probability, y is in [19.99627 21.05168]
confidence interval

> predict(TVadlm, newdata, interval="p", level=0.95)
      fit      lwr      upr
1 20.52397 17.15828 23.88967
prediction interval
```

Indicator Variables

- ▶ Some predictors are not **quantitative** but are **qualitative**, taking discrete values. These are also called **categorical** variables.
- ▶ Example: investigate difference in credit card balance between males and females, ignoring the other variables. We create a new variable,

$$x_i = \begin{cases} 1 & \text{if } i\text{-th person is female,} \\ 0 & \text{if } i\text{-th person is male} \end{cases}.$$

- ▶ Resulting model

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i = \begin{cases} \beta_0 + \beta_1 + \varepsilon_i & \text{if } i\text{-th person is female,} \\ \beta_0 + \varepsilon_i & \text{if } i\text{-th person is male} \end{cases}.$$

- ▶ Interpretation and more than two levels (categories)?

Indicator Variables

- ▶ In general, if we have k levels, we need $(k - 1)$ indicator variables.
- ▶ For example, we have 3 categories — A, B , and C for a covariate x ,

$$x_A = \begin{cases} 1 & \text{if } x \text{ is } A, \\ 0 & \text{if } x \text{ is not } A \end{cases} ; \quad x_B = \begin{cases} 1 & \text{if } x \text{ is } B, \\ 0 & \text{if } x \text{ is not } B \end{cases} .$$

- ▶ If x is C , then $x_A = x_B = 0$. We call C the **baseline** or **default** category.
- ▶ β_A is the **contrast** between A and C and β_B is the **contrast** between B and C .

Summary and Remark

- ▶ Multiple linear regression
- ▶ Estimation and inference
- ▶ Indicator variables
- ▶ Read textbook Chapter 3
- ▶ Do R lab