

Statistics 452: Statistical Learning and Prediction

Chapter 3, Part 2: Multiple Linear Regression

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Multiple Linear Regression Model

- ▶ Recall our general model from Chapter 2:

$$Y = f(X) + \epsilon$$

- ▶ Multiple linear regression assumes the function f is linear in $p \geq 1$ predictors $X = (X_1, \dots, X_p)$; i.e.,
 $f(X) = \beta_0 + \beta_1 X_1 + \dots + \beta_p X_p$.
 - ▶ β_0 is the intercept and
 - ▶ β_i is the slope for the i th predictor: A one unit increase in X_i *holding all other predictors fixed* is associated with a β_i increase in f .

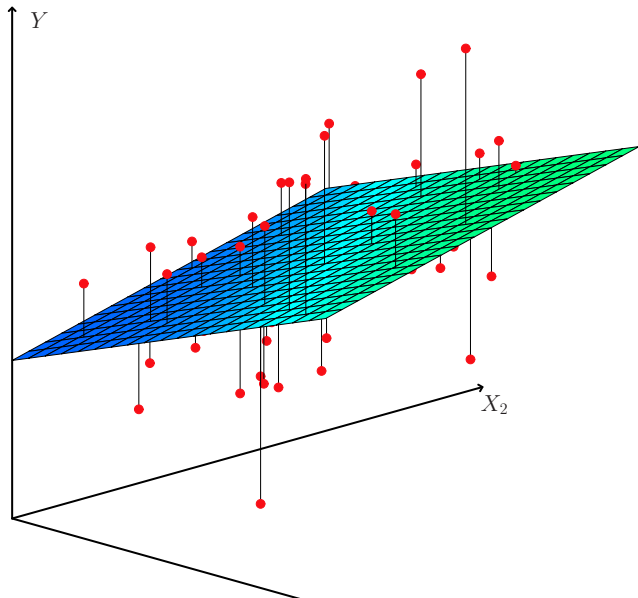
Fitting the line

- ▶ We use the method of least squares to fit the line.
- ▶ Goal: Using observed data $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ (where now x_i is a vector of length p) fit the model

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \dots + \hat{\beta}_p x_{ip}$$

where \hat{y}_i is the fitted value of Y for $X = x_i$.

- ▶ The residuals are still defined as vertical distances $e_i = y_i - \hat{y}_i$ (see Figure 3.4, page 73 of text).
- ▶ Least squares finds the $\hat{\beta}_0, \dots, \hat{\beta}_p$ that minimize $RSS = \sum_{i=1}^n e_i^2$.



Advertising Example

```
afit <- lm(sales ~ TV + newspaper + radio, data=advert)
summary(afit)$coefficients
```

##	Estimate	Std. Error	t value	Pr(> t)
## (Intercept)	2.938889369	0.311908236	9.4222884	1.267295e-17
## TV	0.045764645	0.001394897	32.8086244	1.509960e-81
## newspaper	-0.001037493	0.005871010	-0.1767146	8.599151e-01
## radio	0.188530017	0.008611234	21.8934961	1.505339e-54

```
confint(afit)
```

##	2.5 %	97.5 %
## (Intercept)	2.32376228	3.55401646
## TV	0.04301371	0.04851558
## newspaper	-0.01261595	0.01054097
## radio	0.17154745	0.20551259

- ▶ We are 95% confident that an increase of \$1000 in TV advertising, holding newspaper and radio ads fixed, is associated with an increase in sales of between 43 and 49 units.
 - ▶ Compare to interval estimate (42,53) from simple linear regression.

Advertising Example: Affect of Newspaper Ads

```
afitN <- lm(sales ~ newspaper, data=advert)
summary(afitN)$coefficients
```

```
##              Estimate Std. Error   t value    Pr(>|t|)
## (Intercept) 12.3514071 0.62142019 19.876096 4.713507e-49
## newspaper   0.0546931 0.01657572  3.299591 1.148196e-03
```

```
summary(afit)$coefficients
```

```
##              Estimate Std. Error   t value    Pr(>|t|)
## (Intercept) 2.938889369 0.311908236  9.4222884 1.267295e-17
## TV          0.045764645 0.001394897 32.8086244 1.509960e-81
## newspaper  -0.001037493 0.005871010 -0.1767146 8.599151e-01
## radio       0.188530017 0.008611234 21.8934961 1.505339e-54
```

- ▶ Newspaper ads are significantly associated with sales in the simple but not the multiple regression.

Confounding

- ▶ The effect of newspaper is different depending on whether or not we include TV and radio ads in the model.
 - ▶ TV and radio are said to **confound** the newspaper effect.
- ▶ Correlation between radio and newspaper is behind the confounding.
 - ▶ More radio ads, more sales. More radio adds more newspaper ads. \Rightarrow More newspaper ads, more sales.

```
cor(advert)
```

##		TV	radio	newspaper	sales
##	TV	1.00000000	0.05480866	0.05664787	0.7822244
##	radio	0.05480866	1.00000000	0.35410375	0.5762226
##	newspaper	0.05664787	0.35410375	1.00000000	0.2282990
##	sales	0.78222442	0.57622257	0.22829903	1.0000000

Testing the Overall Effect of Predictors

- ▶ Hypothesis of no association between the outcome and the predictors is

$$H_0 : \beta_1 = \cdots = \beta_p = 0$$

and the alternative hypothesis is

$$H_a : \text{at least one } \beta_j \text{ is non-zero}$$

- ▶ We test H_0 vs H_a with an F test. The F statistic is MSM/MSE , where
 - ▶ $MSM = SSM/p$, with $SSM = TSS - RSS$, and
 - ▶ $MSE = RSS/(n - p - 1)$.
- ▶ F is compared to an F -distribution with p numerator and $n - p - 1$ denominator df.

Advertising Example

```
summary(afit)
```

```
##
## Call:
## lm(formula = sales ~ TV + newspaper + radio, data = advert)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -8.8277 -0.8908  0.2418  1.1893  2.8292
##
## 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 ***
## newspaper    -0.001037   0.005871  -0.177    0.86
## radio        0.188530   0.008611  21.893  <2e-16 ***
## ---
## 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
```

- ▶ There is strong evidence that TV, radio and newspaper advertising is associated with sales.

Testing the Effect of a Subset of Predictors

- ▶ E.G., suppose we are interested in testing $H_0 : \beta_2 = \beta_3 = 0$ vs $H_a : \beta_2$ and β_3 are not both zero.
- ▶ We do a multiple-partial F test.
- ▶ The test statistic is

$$\frac{(RSS(red) - RSS(full))/q}{RSS(full)/(n - p - 1)}$$

where

- ▶ $RSS(red)$ is the RSS from the reduced model,
 - ▶ $RSS(full)$ is the RSS from the full model, and
 - ▶ q is the difference in the number of model parameters in the two models.
-
- ▶ The test statistic is compared to an F -distribution with q numerator and $n - p - 1$ denominator df.

Advertising Example

```
afitTV <- lm(sales ~ TV, data=advert) # reduced model
anova(afitTV,afit)
```

```
## Analysis of Variance Table
##
## Model 1: sales ~ TV
## Model 2: sales ~ TV + newspaper + radio
##   Res.Df    RSS Df Sum of Sq    F    Pr(>F)
## 1     198 2102.53
## 2     196  556.83  2    1545.7 272.04 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

- There is strong evidence that newspaper and radio ads are associated with sales, adjusting for TV ads.

Variable Selection

- ▶ Multiple-partial F-tests can be used for selecting subsets of variables that explain the association between Y and X .
- ▶ Alternately, we can think of variable selection as selecting $f(X)$ to avoid over-fitting.
- ▶ We will study modern methods for variable selection in Chapter 6.
- ▶ Here we mention three classical approaches, forward selection, backward selection and mixed (stepwise) selection.

Selection Strategies

1. Forward selection. Start with a smallest model (e.g., null model) and try to add terms up to some largest model.
 2. Backward selection. Start with a largest model and try to drop terms, down to some smallest model.
 3. Stepwise selection. Try adding *and* dropping terms, staying between a smallest and largest model.
- (1-3) can be described in terms of adding (ADD1) and dropping (DROP1) steps.

ADD1 and DROP1

- ▶ ADD1:
 - ▶ Given a current model (subset of X) M_c , try to find a model term *not* in M_c that will improve the model.
 - ▶ Whether or not a particular term improves the model is a model comparison.
 - ▶ If can't find a term to add that will improve the model, do nothing.
- ▶ DROP1:
 - ▶ Given a current model M_c , find a term *in* M_c that can be dropped to improve the model.
 - ▶ Whether or not a particular term improves the model is a model comparison.
 - ▶ If can't find a term to drop that will improve the model, do nothing.
- ▶ Both ADD1 and DROP1 make model comparisons and need to know when adding/dropping terms is an improvement.

Model Comparisons

- ▶ In Chapter 6 we will consider several types of comparisons of M_{full} to M_{red} .
- ▶ Given what we know now, we could use partial F tests or t tests of the null hypothesis that the coefficient being added/dropped is zero vs the two-sided alternative.

Forward Selection

- ▶ Starting from the smallest model, apply ADD1 to try adding a term.
- ▶ If we can add a term, do so. Otherwise stop.
- ▶ Repeat until we stop or reach the largest model.

Backward Selection

- ▶ Starting from the largest model, apply DROP1 to try dropping a term.
- ▶ If we can drop a term, do so. Otherwise stop.
- ▶ Repeat until we stop or reach the smallest model.

Stepwise Selection

- ▶ Starting from either the largest or smallest model, apply ADD1 and DROP1 to try to find a better model
 - ▶ But never add to largest or drop from smallest models.
- ▶ If we can either add or drop a term, do so. Otherwise stop.
- ▶ Repeat until we stop or reach the model at the opposite extreme.
 - ▶ That is, if we reach the smallest having started from the largest, or if we reach the largest having started from the smallest.

Advertising Example

- ▶ Output from `lm` summary makes it easiest to use t tests and backward selection.
- ▶ Though not possible if $p > n$. More on this in Chapter 6.

```
afit<-lm(sales ~ TV + newspaper + radio,data=advert)
summary(afit)$coefficients
```

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## radio	0.188530017	0.008611234	21.8934961	1.505339e-54

```
afit2<-lm(sales ~ TV + radio,data=advert)
summary(afit2)$coefficients
```

##	Estimate	Std. Error	t value	Pr(> t)
## (Intercept)	2.92109991	0.294489678	9.919193	4.565557e-19
## TV	0.04575482	0.001390356	32.908708	5.436980e-82
## radio	0.18799423	0.008039973	23.382446	9.776972e-59

Model Fit

- ▶ Can use R^2 to describe the fit of the model

```
summary(afit2)$r.squared
```

```
## [1] 0.8971943
```

```
# Compare with summary(afit)$r.squared
```

- ▶ TV and radio advertising expenditures explain about 90% of the variation in sales.

Predictions

- ▶ The fitted model can be used to make predictions.
- ▶ For value x_0 of X , the prediction is

$$\hat{\beta}_0 + \hat{\beta}_1 x_{01} + \dots + \hat{\beta}_p x_{0p}$$

```
newdat <- data.frame(TV=150,radio=20)
predict(afit2,newdata=newdat)
```

```
##           1
## 13.54421
```

Sources of Uncertainty

- ▶ Three sources:
 1. Model bias: The model $f(X)$ may be wrong. We will ignore this for now.
 2. Estimation: Our \hat{f} is based on $\hat{\beta}_1, \dots, \hat{\beta}_p$, which will not be equal to β_1, \dots, β_p . This is part of the reducible error.
 3. Irreducible error: $Y = f(X) + \epsilon$, and so even if $\hat{f} = f$, predictions will not be perfect.
- ▶ We construct confidence intervals for $f(X)$ to quantify estimation uncertainty, and prediction intervals to quantify estimation uncertainty plus irreducible error.

Confidence Intervals for $f(X)$.

- ▶ For fixed X , $f(X)$ is a function of parameters, and so is a parameter.
- ▶ We can construct a confidence interval for $f(X)$ based on the sampling distribution of $\hat{f}(X)$.
 - ▶ Details are not important. We will use R.

```
predict(afit2,newdata=newdat,interval="confidence",level=0.95)
```

```
##           fit      lwr      upr
## 1 13.54421 13.30387 13.78454
```

- ▶ We are 95% confident that the average sales for cities in which there are \$150,000 in TV ads and \$20,000 in radio ads is between 13,304 and 13,785.

Prediction Intervals

- ▶ Prediction intervals are constructed to contain a given proportion of future observations.
- ▶ The intervals must account for both the reducible error from estimating f and the irreducible error ϵ .
 - ▶ Details are not important. We will use R.

```
predict(afit2,newdata=newdat,interval="prediction",level=0.95)
```

```
##           fit      lwr      upr
## 1 13.54421 10.21973 16.86868
```

- ▶ We believe that 95% of future observations of cities with \$150,000 in TV ads and \$20,000 in radio ads will have sales between 10,220 and 16,869.