

SDSC3006 Lab 2-Linear Regression

Langming LIU langmiliu2-c@my.cityu.edu.hk

School of Data Science City University of Hong Kong

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Simple Linear Regression

Preliminary

- Boston data set in the MASS library
- Predict medv of a neighborhood based on various predictors such as rm, age, and Istat (Meaning of variable: ?Boston)
- n = 506 neighborhoods around Boston
- Fit a simple linear regression:

$$Y = medv, X = Istat$$

Construct Linear Model

 Use function lm(Y~X,data=datasets_name) to construct model and function summary() to show information of model:

```
library(MASS)
attach(Boston)
lm.fit=lm(medv~lstat)
summary(lm.fit)
```

Result Analysis

- Analyze result:
 - Is the parameter estimate accurate?
 - what's the type of their relationship?
- Plot the Fitting Line plot(lstat,medv,pch=20,col="black") abline(lm.fit,lwd=3,col="red")

Prediction and Interval

Prediction of f(X) of given X:
 predict(lm.fit,data.frame(lstat=c(5,10,15)))

- Interval
 - Confidence interval: intervals of prediction of f(x) predict(lm.fit,data.frame(lstat=c(5,10,15)),interval="confidence")
 - **Prediction interval**: intervals of prediction of y given x predict(lm.fit,data.frame(lstat=c(5,10,15)), interval="prediction")
 - Prediction intervals are wider than confidence intervals because of the random error.

Multiple Linear Regression

Multivariate-model

- Data set: Boston in MASS
- Bivariate model: Y = medv, X1 = lstat, X2=age
- Use function lm(Y~X1+X2,data=datasets_name): lm.fit=lm(medv~lstat+age,data=Boston) summary(lm.fit)
- Using all predictors: lm.fit=lm(medv~.,data=Boston) summary(lm.fit)

Interaction Terms

Interaction

- Data set: Boston in MASS
- Interaction model: Y = medv, X1 = lstat, X2=age,
 X3=lstat:age (interaction term in R)

Non-linear Regression

Quadratic Model

- Data set: Boston in MASS
- Quadratic model: Y = medv, X1 = lstat, X2=lstat^2
- Use function Im(Y~X1+I(X1^2),data=datasets_name): #Linear model Im.fit=Im(medv~lstat,data=Boston) summary(Im.fit) #Add a quadratic term Im.fit=Im(medv~lstat+I(lstat^2),data=Boston) summary(Im.fit)

Polynomial Model

- Data set: Boston in MASS
- Polynomial model: Y = medv, X1 = lstat,
 X2=lstat^2,...,X5=lstat^5
- Use function for polynomial model lm(Y~poly(lstat,5),data=datasets_name): lm.fit=lm(medv~poly(lstat,5),data=Boston) summary(lm.fit)

Polynomial Model

- Is it good if order is very high?
 No, higher order means high computational cost and
 - No, higher order means high computational cost and may cause over-fitting (What is it?)
- Test polynomial models of different orders and plot them:

```
plot(lstat,medv,pch=20,col="black")
test_data=seq(0,40,0.2)
lm.fit=lm(medv~poly(lstat,order),data=Boston)
data_predict=predict(lm.fit,data.frame(lstat=test_data))
points(test_data,data_predict,pch=20,col='color')
```

Notice you should set the order and color! Try 3,5,10,15

Qualitative Predictors

Qualitative Predictors

- Data set: Carseats in ISLR2
- Predict Sales based on predictors such as Price, Urban(No/Yes), US(No/Yes), ShelveLoc(Bad/Medium/Good) library(ISLR2) attach(Carseats) head(Carseats)
- R generates dummy variables for qualitative predictors automatically.
 - n classes lead to n-1 dummy variables
- Modeling directly using function lm(): lm.fit=lm(Sales~.,data=Carseats) summary(lm.fit)