THE UNIVERSITY OF TEXAS AT AUSTIN
McCOMBS SCHOOL OF BUSINESS

Model Building

Lecture 14

STA 371G

There is a Primary Care Physician Shortage in Texas!

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35 Texas Counties Have Zero Physicians

John Commins, May 6, 2015

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How bad is the provider shortage in Texas?

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Even if you don't live in Texas, these numbers should scare anyone who cares about rural healthcare, because this crisis is not unique to Texas.

How bad is the provider shortage in Texas?

What might explain this? There are many potential predictors!

- Small counties
- Poverty
- Health insurance
- Unemployment
- Large rural areas
- Something else?

smallest population

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- However, selecting the explanatory variables, or figuring out what predicts the number of physicians that a county has, is a large part of the analysis in this case.
- This type of analysis is an exploratory study.

An exploratory study of the Texas physician shortage

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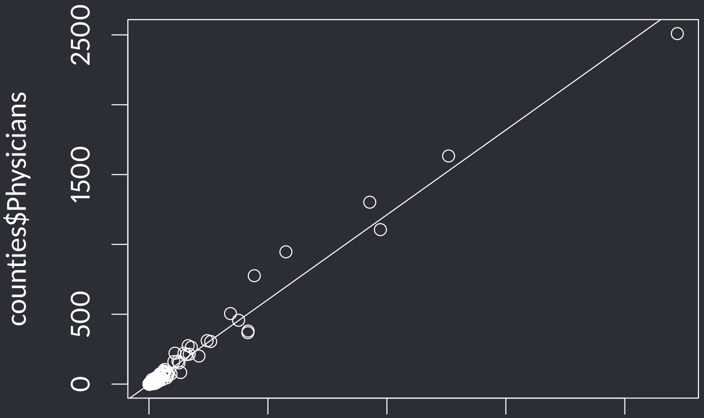
- Exploratory studies are observational studies, in that the variables are observed rather than controlled, which is different from an experiment.
- Multicollinearity is much more likely in an exploratory study than in an experiment or a confirmatory study.
- Exploratory studies require the most in terms of model selection. Automated tools are helpful, but judgement is still needed!

Population as a predictor of number of physicians

```r
plot(counties$Population, counties$Physicians)
popmodel <- lm(counties$Physicians ~ counties$Population)
abline(popmodel)
```



Transform and Subset the data

```
# Transform Physians
counties$PhysiciansPer10000 <-
     (counties$Physicians/counties$Population)*10000

# Remove the very small and very large counties
mcounties <- counties[counties$Population < 500000 &
                      counties$Population > 10000,]

# Show medium counties with no physicians
mcounties[mcounties$Physicians == 0, c(1,5,12)]
```

```
      X MedianIncome PctUnemployed
157 157        51481           3.5
159 159        35069           5.5
```

The 10 potential x variables

- LandArea: Area in quare miles
- PctRural: Percentage rural land
- MedianIncome: Median household income
- Population: Population
- PctUnder18: Percent children
- PctOver65: Percent seniors
- PctPoverty: Percent below the poverty line
- PctUninsured: Percent without health insurance
- PctSomeCollege: Percent with some higher education
- PctUnemployed: Percent unemployed

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- If there are n candidate predictor variables, there are 2^n possible models, and we need to look at ALL of them to be sure that we have found the best model.
- This is where R's automated model building tools help.

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- We have used R^2 and Adjusted-R^2 to select the best models
- But R^2 is not good for comparing models with differnet numbers of variables because it tends to increase a little bit with each additional variable just due to randomness.
- Adjusted-R^2 is better because it multiplies R^2 by a penalty that depends on the number of variables, but the penalty is somewhat arbitrary and increases as the number of variables increases.

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- All model measuring criteria try to find a balance between the predictive power of the model and the number of variables.
- No method is ideal in all situations, so it is generally best to use multiple methods and look at the results.
- AIC (Akaike's Information Criterion) and the very similar BIC (your reading calls it SBC) are other widely used criterion that often gives different results than Adjusted-R^2.

Stepping forwards

The step() function uses the AIC criterion to compare models. You must build the null and the full models first.

```
null <- lm(PhysiciansPer10000~1, data=mcounties)

full <- lm(PhysiciansPer10000 ~ LandArea+PctRural+
           MedianIncome+Population+PctUnder18+
           PctOver65+PctPoverty+PctUninsured+
           PctSomeCollege+PctUnemployed, data=mcounties)

stepforward.out <- step(null, scope=list(lower=null, upper=
                                direction ="forward")

Start:  AIC=238.65
PhysiciansPer10000 ~ 1
```

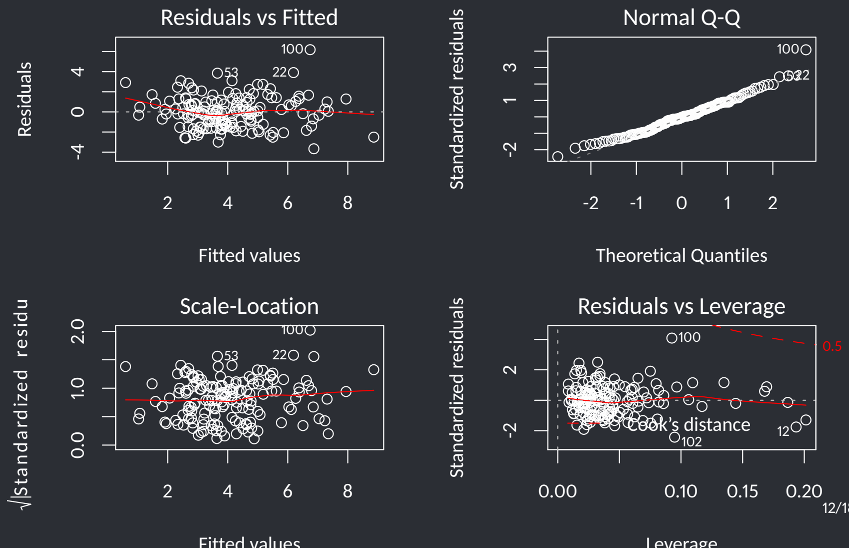
Stepping backwards and both ways

You can also step backward or on both directions

```
stepbackward.out <-
    step(null, scope=list(lower=null, upper=full),
         direction ="backward")

Start:  AIC=238.65
PhysiciansPer10000 ~ 1

stepboth.out <-
    step(null, scope=list(lower=null, upper=full),
         direction ="both")

Start:  AIC=238.65
PhysiciansPer10000 ~ 1
```

Check the LINE assumptions

```
plot(stepforward.out)
```



Check for multicollinearity

This model looks pretty good, but is it the best that can be done?

```
# Check the model for multicollinearity

vif(stepforward.out)

PctSomeCollege       PctRural      PctOver65     Population
      1.541539       1.911623       1.776352       1.843085
  PctUninsured
      1.029993
```

Best Subsets Regression

Step only uses AIC criterion for comparing models. regsubsets is more flexible about criteria and calculates all possible subsets.

```
library(leaps)
regsubsets.out <- regsubsets(PhysiciansPer10000 ~ LandArea+
            MedianIncome+Population+PctUnder18+
            PctOver65+PctPoverty+PctUninsured+
            PctSomeCollege+PctUnemployed, data=mcounties)
```

Best Subsets Regression

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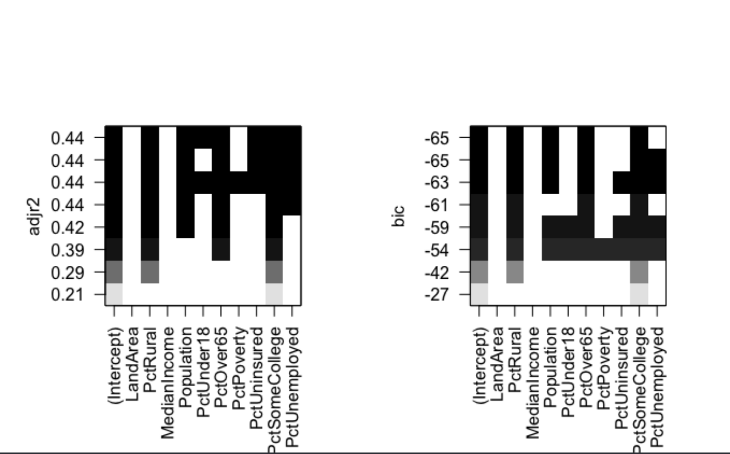
```
# Set the plot window up so you can examine the output side
layout(matrix(1:2, ncol=2))
#plot(regsubsets.out, scale="adjr2")  # use adjusted R^2
#plot(regsubsets.out, scale="bic")    # use SBC

# Don't forget to reset the plot window!
layout(matrix(1:1, ncol=1))
```

Look at this interesting plot



Black indicates that a variable is included in the model, while white indicates that it is not.

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- Find the middle ground between an underspecified model and extraneous variables.
- Fine tune the model to get a correctly specified model - you may need to transform predictors and/or add interactions.
- Think about logical reasons why certain predictors might be useful, don't just focus on p-values.

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- Otherwise, you can select the ones that happen to fit the data the best and essentially create a spurious correlation!
- Rember to check for multicollieearity and the LINE assumptions!