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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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?

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- However, figuring out what variables to use to predict the number of physicians that a county has, is a critical portion 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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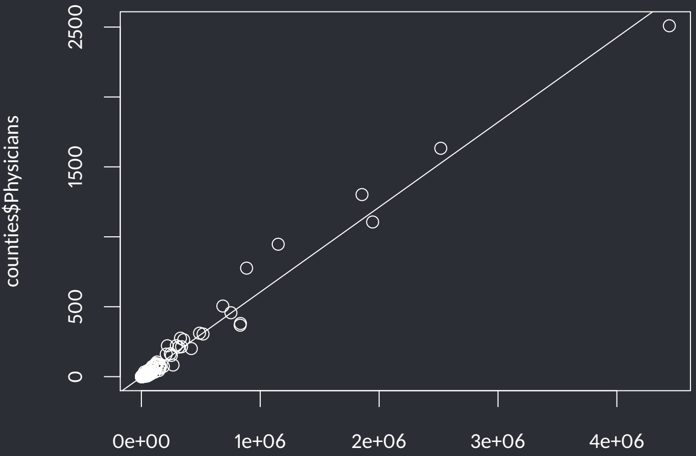
- Exploratory studies are observational studies, in that the variables are observed rather than controlled.
- Multicollinearity is much more likely in an exploratory study than in an experiment or a confirmatory study.
- Exploratory studies require the most in terms of model selection. Automated tools are helpful, but judgement is still needed!

Population as a predictor of number of physicians

```
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)]
```

```
      County Population Physicians
157 Live Oak      12091          0
159    Duval      11533          0
```

The 10 potential x variables

- LandArea: Area in square 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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- 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 compare the results.

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- There more, but we won't go into them.

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)

stepforwardOut <- step(null, scope=list(lower=null, upper=full),
                            direction ="forward")
```

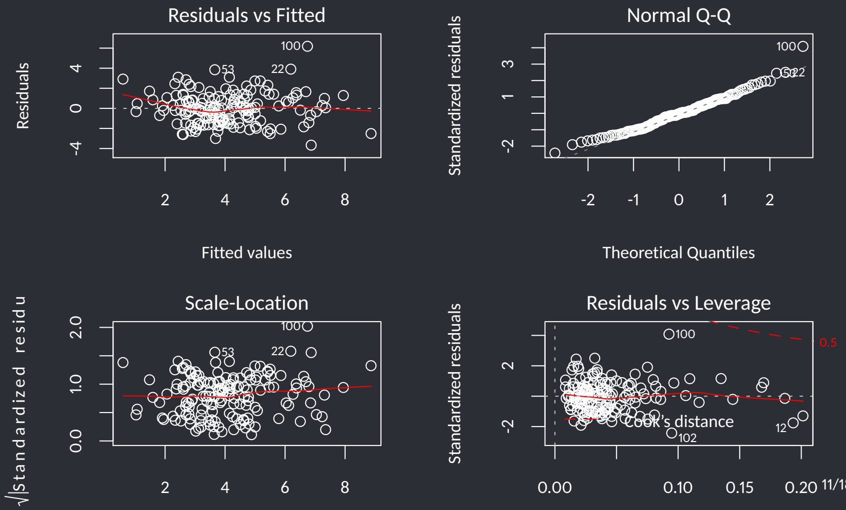
```
Start:  AIC=238.65
PhysiciansPer10000 ~ 1

                 Df Sum of Sq    RSS    AIC
+ PctSomeCollege  1   150.125 558.67 203.28
+ Population      1   132.562 576.23 208.14
+ PctRural        1   119.850 588.94 211.57
+ PctUnemployed   1    32.121 676.67 233.37
+ MedianIncome    1    30.413 678.38 233.76
```

Check the LINE assumptions

model stepforwardOut's residuals look ok

```
plot(stepforwardOut)
```



Examine stepforwardOut

```
# check the summary
#summary(stepforwardOut)

# Check stepForwardOut for multicollinearity
vif(stepforwardOut)
```

```
PctSomeCollege       PctRural      PctOver65     Population  PctUnemployed 
      1.541539       1.911623       1.776352       1.843085       1.125032 
  PctUninsured 
      1.029993 
```

Stepping backwards and both ways

This model looks pretty good, but is it the best? You can also step backward or on both directions.

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


Start:  AIC=238.65
PhysiciansPer10000 ~ 1

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


Start:  AIC=238.65
PhysiciansPer10000 ~ 1

                 Df Sum of Sq    RSS    AIC
+ PctSomeCollege  1   150.125 558.67 203.28
+ Population      1   132.562 576.23 208.14
+ PctRural        1   119.850 588.94 211.57
+ PctUnemployed   1    32.121 676.67 233.37
+ MedianIncome    1    30.413 678.38 233.76
+ PctPoverty      1    14.337 694.45 237.44
<none>                        708.79 238.65
```

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 + PctRural
                             + MedianIncome + Population + PctUnder18
                             + PctOver65 + PctPoverty + PctUninsured
                             + PctSomeCollege + PctUnemployed, data=mcounties)
```

Best Subsets Regression

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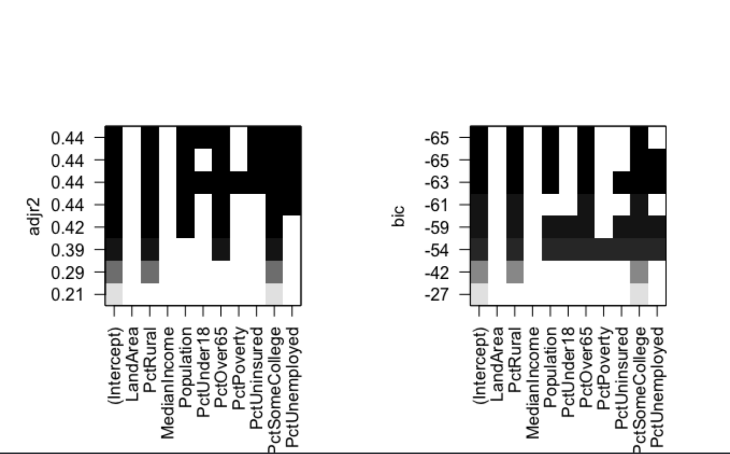
```
# Set the plot window up so you can examine the output side by side
layout(matrix(1:2, ncol=2))
#plot(regsubsets.out, scale="adjr2")  # use adjusted R^2
#plot(regsubsets.out, scale="bic")    # use SBC

# 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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- Look at multiple statistics. They generally say similar things.
- 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 multicollieаrity and the LINE assumptions!