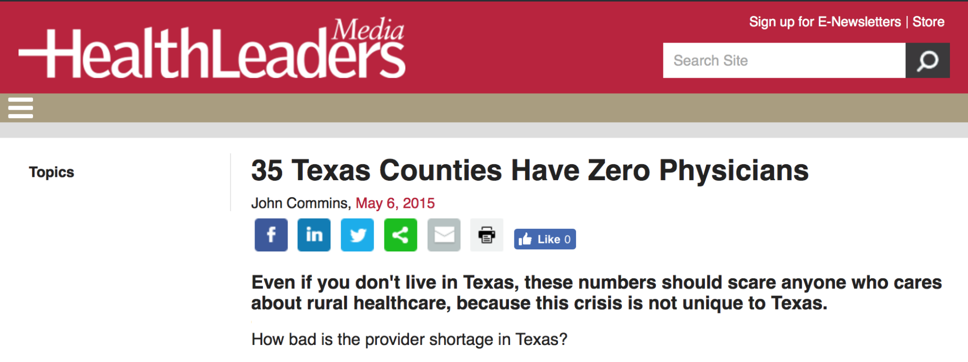
THE UNIVERSITY OF TEXAS AT AUSTIN
McCOMBS SCHOOL OF BUSINESS

Model Building 1

Lecture 14

STA 371G



35 Texas Counties Have Zero Physicians

John Commins, May 6, 2015

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?

- 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**.

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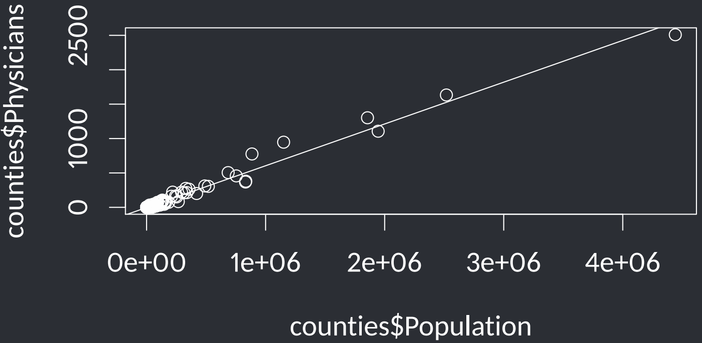
- Exploratory studies are observational studies, in that the variables are observed rather than controlled.
- Multicollinearity is much more likely in an exploratory study than in an experiment or a confirmatory study.
- Exploratory studies require the most in terms of model selection. Automated tools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

Population as a predictor of number of physicians

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



Transform and Subset the data

```
# Create a variable for physicians per 10,000 people
counties$PhysiciansPer10000 <-
  counties$Physicians / counties$Population * 10000

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

# Which medium counties have no physicians?
mcounties[mcounties$Physicians == 0, c(1,5,12)]

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

Potential predictor 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 $2^n - 1$ possible models, and we would need to look at every one 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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- But R^2 is not good for comparing models with different 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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- 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 (the reading calls it SBC) are other widely used criterion that have a similar intent as Adjusted-R^2 but may give different results.
- There are other selection criteria too (but we won't get into them in this course).

Stepping forwards

The `step` function uses the AIC criterion to compare models. First we'll build a "null model" with no variables, and a "full model" with all variables:

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

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

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

Stepping backwards and both ways

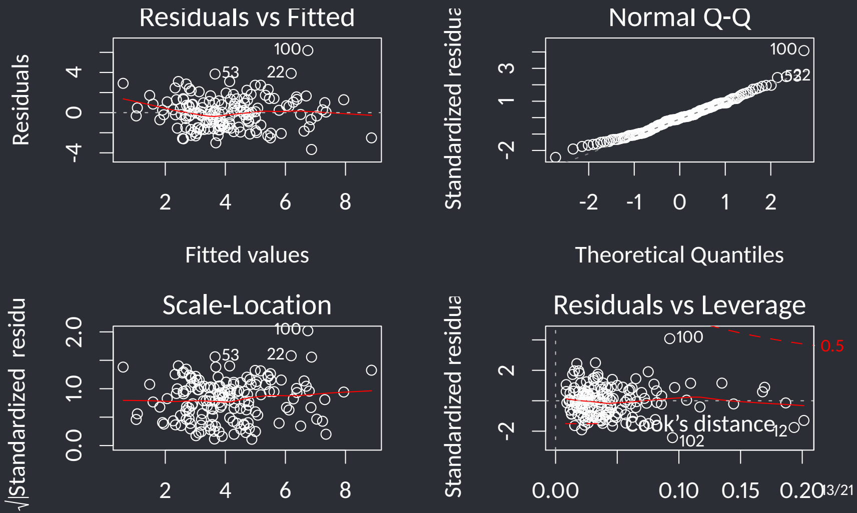
You can also step backwards (similar to what we have been doing manually), or in both directions:

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

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

Check assumptions

```
plot(backward.model)
```



Check for multicollinearity

```
vif(backward.model)
```

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

We can’t be sure this is the best possible model.

Sometimes, stepwise regression leads you down a suboptimal path and you end up discarding a valuable variable (or keeping a variable that is only marginally useful), because of the order in which the variables are considered.

Best-subsets regression

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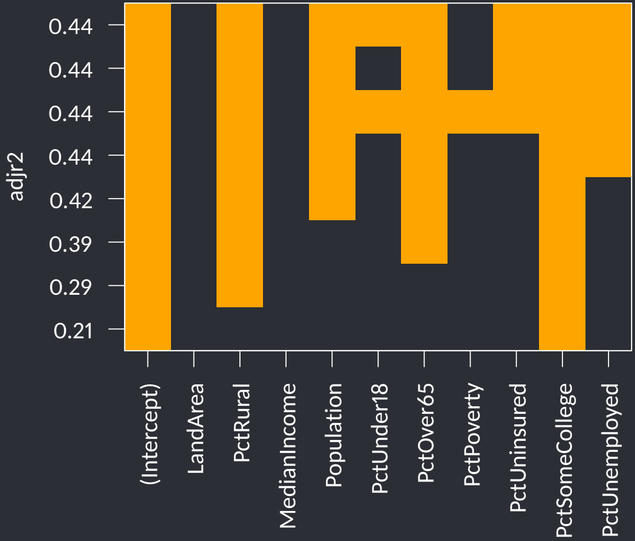
- Then we can compare the models using different model selection criteria and select the most parsimonious one

Best-subsets regression

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

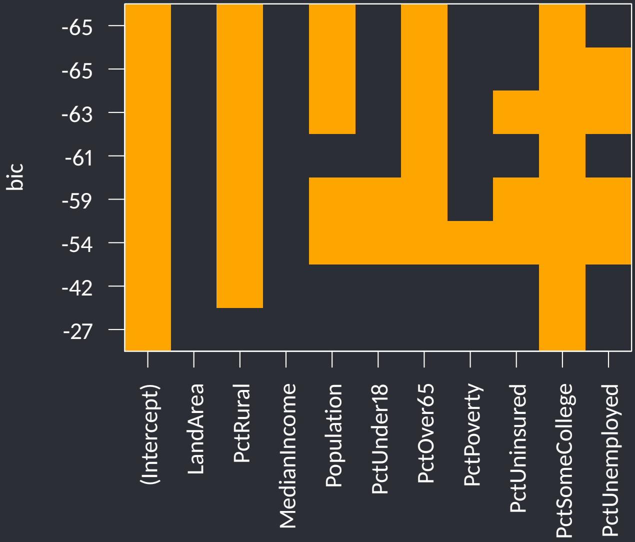
Let’s compare models using Adjusted R^2. Each row is a candidate model; filled-in squares indicate the variable is included in that model:

```r
plot(regsubsets.output, scale="adjr2")
```



Now let's compare models using BIC (SBC):

```
plot(regsubsets.output, scale="bic")
```



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- Look at multiple statistics. They generally say similar things.
- Find the **parsimonious** middle ground between an underspecified model and extraneous variables.
- Fine-tune the model to ensure the model meets assumptions and captures key relationships: 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.

Be careful of getting too crazy!

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- A general guideline is that you should not even consider more than one variable for every 10 to 15 cases in your dataset.
- Otherwise, you can select the ones that happen to fit the data the best and essentially create a spurious correlation!
- Remember to check for multicolliearity and the LINE assumptions!