THE UNIVERSITY OF TEXAS AT AUSTIN
McCOMBS SCHOOL OF BUSINESS

Model building: selecting a model

Lecture 9

STA 371G

Texas Suffers From A Doctor Shortage

By JONATHAN BAKER • NOV 1, 2017

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When it comes to having a high ratio of doctors to citizens, the State of Texas ranks near the bottom. In fact, as *The Dallas Morning News* reports, 43 states have a higher proportion of primary care physicians to residents than Texas.

And West Texas suffers from a lack of doctors more than other parts of the state. There are 80 counties in Texas with five or fewer practicing doctors - many in West Texas. Thirty-five Texas counties have no doctors at all.

What might explain why some counties have a doctor shortage?

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

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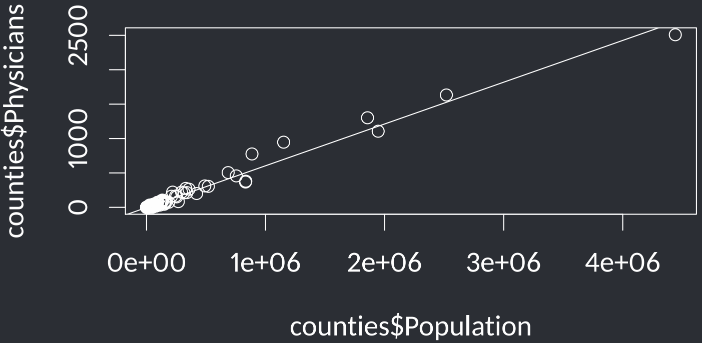
- Instead, we are using regression here to understand the underlying factors that explain doctor shortages.

Population as a predictor of number of physicians

```
> popmodel <- lm(Physicians ~ Population, data=counties)
> plot(counties$Population, counties$Physicians)
> abline(popmodel)
```



Transform and Subset the data

Let’s define a new variable for physicians per 10,000 people—this is important as absolute numbers aren’t really what we care about (large counties have lots of doctors, which isn’t a helpful fact!):

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> counties$PhysiciansPer10000 <-
+   counties$Physicians / counties$Population * 10000
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+   counties$Physicians / counties$Population * 10000
```

Then let’s remove the very small counties as we can’t reliably measure physician density in small counties:

```
> my.counties <- subset(counties, Population > 10000)
```

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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- We also want a model that is simple, so it's easy to explain to a non-expert.
- The ideal model is parsimonious: a good trade-off between simplicity (as few variables as possible) and a high R^2.

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But with k variables there are $2^k - 1$ possible models; for example, there are $k = 10$ possible predictor variables in the data set, so there are 1,023 possible combinations of predictors you could use!

General strategy

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2. Select the candidate model with a reasonable tradeoff simplicity and predictive power (high R^2).
3. Check assumptions and model diagnostics (more on this to come); apply transformations and other fixes if needed to the final model. If the problems are unfixable, select a different candidate model.

Backward stepwise regression

1. Start with a "full" model containing all of the predictors.
2. Remove the least significant (highest p-value / smallest t-statistic) predictor.
3. Re-run the model with that predictor removed.
4. Repeat steps 2-3 until all predictors are significant.

Forward stepwise regression

1. Start with a “null” model containing none of the predictors.
2. Try adding each predictor, one at a time, and pick the one that ends up being the most significant (lowest p-value / highest t-statistic) predictor.
3. Re-run the model with that predictor added.
4. Repeat steps 2-3 until no more significant predictors can be added.

Other stepwise regression possibilities

- Add (or remove) variables one at a time based on the change in R^2, Adjusted R^2, or AIC (another similar model fit criterion) when that variable is added (or removed).
- Run the stepwise regression in both directions, allowing addition or removal of a variable at each step.
- R's `step` function incorporates both of these methods.

The problem with stepwise regression

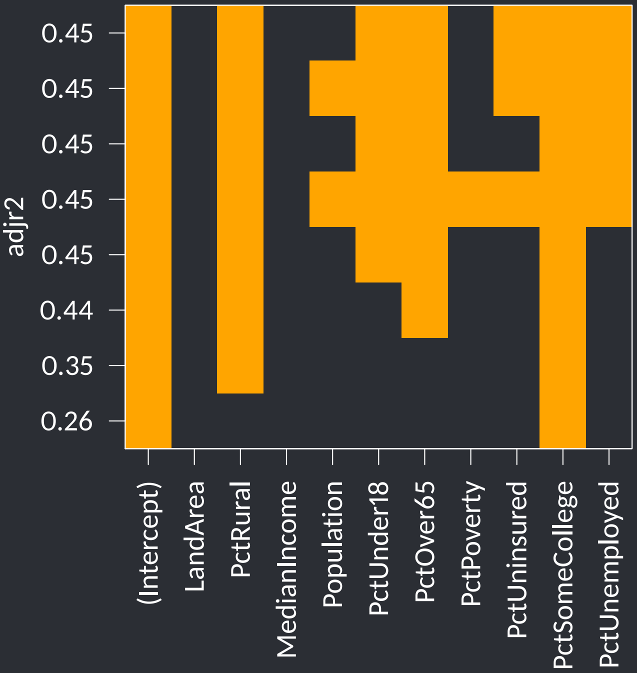
Stepwise regression will not necessarily give you the best model; by only adding or removing one variable at a time, you can get locked into a particular “path” that means you may never consider better models.

Best subsets regression

- Computers are fast! Just let R try out all of the $2^k - 1$ possible models for you.
- R will present you the model with the best Adjusted R^2 for each possible number of predictors.

Best-subsets regression

```
> library(leaps)
> plot(regsubsets(PhysiciansPer10000 ~ LandArea + PctRural
+                  + MedianIncome + Population + PctUnder18
+                  + PctOver65 + PctPoverty + PctUninsured
+                  + PctSomeCollege + PctUnemployed,
+                  data=my.counties), scale="adjr2")
```



adjr2
0.45
0.45
0.45
0.45
0.45
0.44
0.35
0.26
(Intercept)
LandArea
PctRural
MedianIncome
Population
PctUnder18
PctOver65
PctPoverty
PctUninsured
PctSomeCollege
PctUnemployed

- Best-subsets regression presents us with a candidate model for each possible number of predictors.
- The label on the y-axis show the Adjusted R^2 value for the model corresponding to the filled-in squares for that row.

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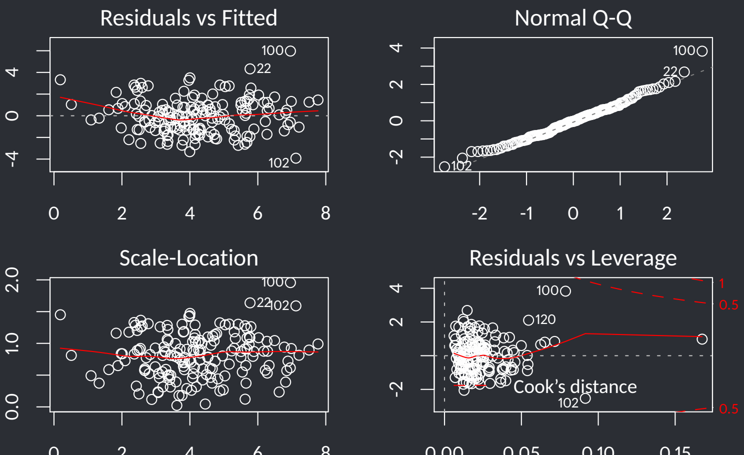
- Find the **parsimonious** middle ground between an underspecified model and extraneous variables.
- Fine-tune the model to ensure the model meets assumptions and captures key relationships: you may need to transform predictors and/or add interactions.
- Think about logical reasons why certain predictors might be useful; don’t just focus on *p*-values.

Check assumptions of the best model

```
> candidate <- lm(PhysiciansPer10000 ~ PctRural + PctOver65
+                          + PctSomeCollege, data=my.counties)
> plot(candidate)
```




MYSTERY SPOT
PLEASE SMOKE
OPEN
50¢
SANTA CRUZ

How reliable is R^2?

- The mystery data set contains 20 predictor variables X1-X20.

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- The mystery data set contains 20 predictor variables X1-X20.
- Backwards stepwise regression or best subsets regression yields a data set with multiple significant predictors.

```
> parsimonious.model <- lm(Y ~ X10 + X13 + X16, data=mystery)
> summary(parsimonious.model)


Call:
lm(formula = Y ~ X10 + X13 + X16, data = mystery)

Residuals:
    Min      1Q  Median      3Q     Max
-2.5839 -0.6636 -0.0255  0.6312  3.5081

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.006384   0.031188   0.205   0.8379
X10          0.074640   0.030694   2.432   0.0152 *
X13         -0.065601   0.030809  -2.129   0.0335 *
X16          0.071064   0.032880   2.161   0.0309 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9857 on 996 degrees of freedom
Multiple R-squared:  0.01434,Adjusted R-squared:  0.01137
F-statistic: 4.829 on 3 and 996 DF,  p-value: 0.00242
```

Mystery revealed!

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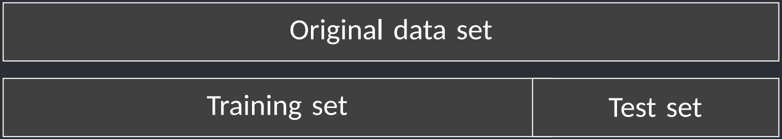
- As a result, it's dangerous to build a model by just selecting the most significant from among a large list of variables.
- Doing so can result in overfitting: creating a model that fits the noise in the data well but won't generalize well to new data.
- In general, the R^2 of a model gives an overoptimistic view of how well it will generalize to new data.

Combatting overfitting with training and test sets



- Split the data into a training set and a test set (a typical split is 70% training set / 30% test set).
- We use the training set to build the model, and then evaluate the quality of the model on how well it predicts Y in the test set.

First, we'll take 50 random cases for the test set (about 30% of the $n = 168$ cases in the whole data set), and the rest for the training set:

```
> test.cases <- sample(1:168, 50)
> training.cases <- setdiff(1:168, test.cases)
> training.set <- my.counties[training.cases,]
> test.set <- my.counties[test.cases,]
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Then, we "train" the model using the cases in the training set, instead of the whole data set:

```
> candidate <- lm(PhysiciansPer10000 ~ PctRural + PctOver65
+                   + PctSomeCollege, data=training.set)
```

Finally, we predict Y for each value in the test set using this model:

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> y <- test.set$PhysiciansPer10000
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This is somewhat lower than the R^2 from the original model (0.45), but it's a fairer estimate of how good our model will perform on unseen data.

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- Do not just use a mechanical process for model selection and call it a day; you need to use your judgement and select a parsimonious model.
- Consider using a training/test set split to ensure you are not "capitalizing on chance."
- Don't forget to check the model assumptions for your final model!