

# 2016 Election: Revisited

STAT 545 Project by Travis Benedict and Jordan Pflum  
November 30, 2018

Start



## 2016 Election Background

Brief overview of the 2016 Election and statistical political leanings commonly employed



## Data Overview

Describe data sets and predictors contained within.



## Exploratory Analysis

Initial Exploration of Data



## Project Goal

Central guiding question of project



## Variable Selection

Explanation of techniques and methods used



## Application and Comparison

Application to Ordinal Regression and comparison to other models



## Conclusion

Concluding thoughts



## Q&A

# 2016 Election Background

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## Historical Information

### Candidates



The Republican ticket was held by businessman **Donald Trump** while the Democratic ticket was held by former Secretary of State **Hillary Clinton**

### Result



While Donald Trump **lost the popular vote** to Hillary Clinton by more than 2.8 million votes, he **won 30 states** and a decisive **304 electoral votes** compared to 227, becoming the **47th president**

### Message



Donald Trump's populist, nationalist campaign, promising to "Make America Great Again", starkly contrasted Clinton's expansion and promotion of **racial, LGBTQ, and women's rights**

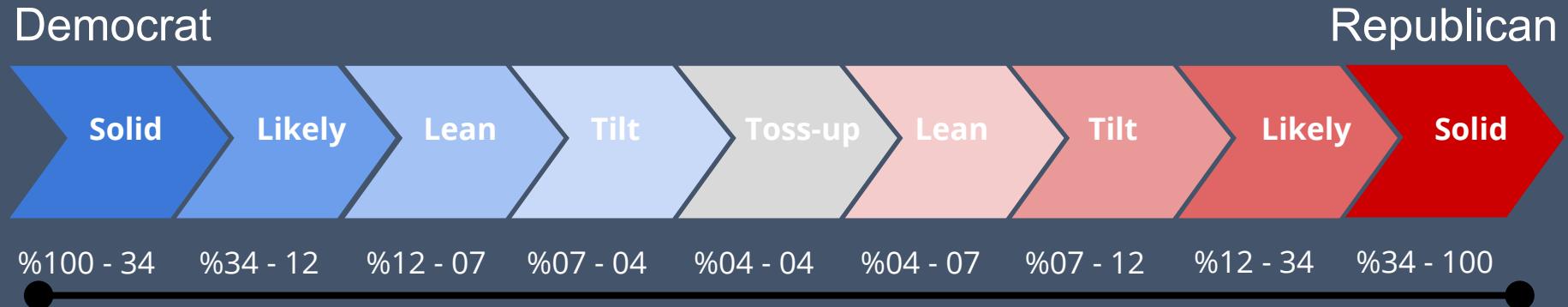
### Key Demographics



Trump's appeal to **white working-class** voters outside major cities in **pivotal manufacturing states** proved to be a key factor.

# 2016 Election Background

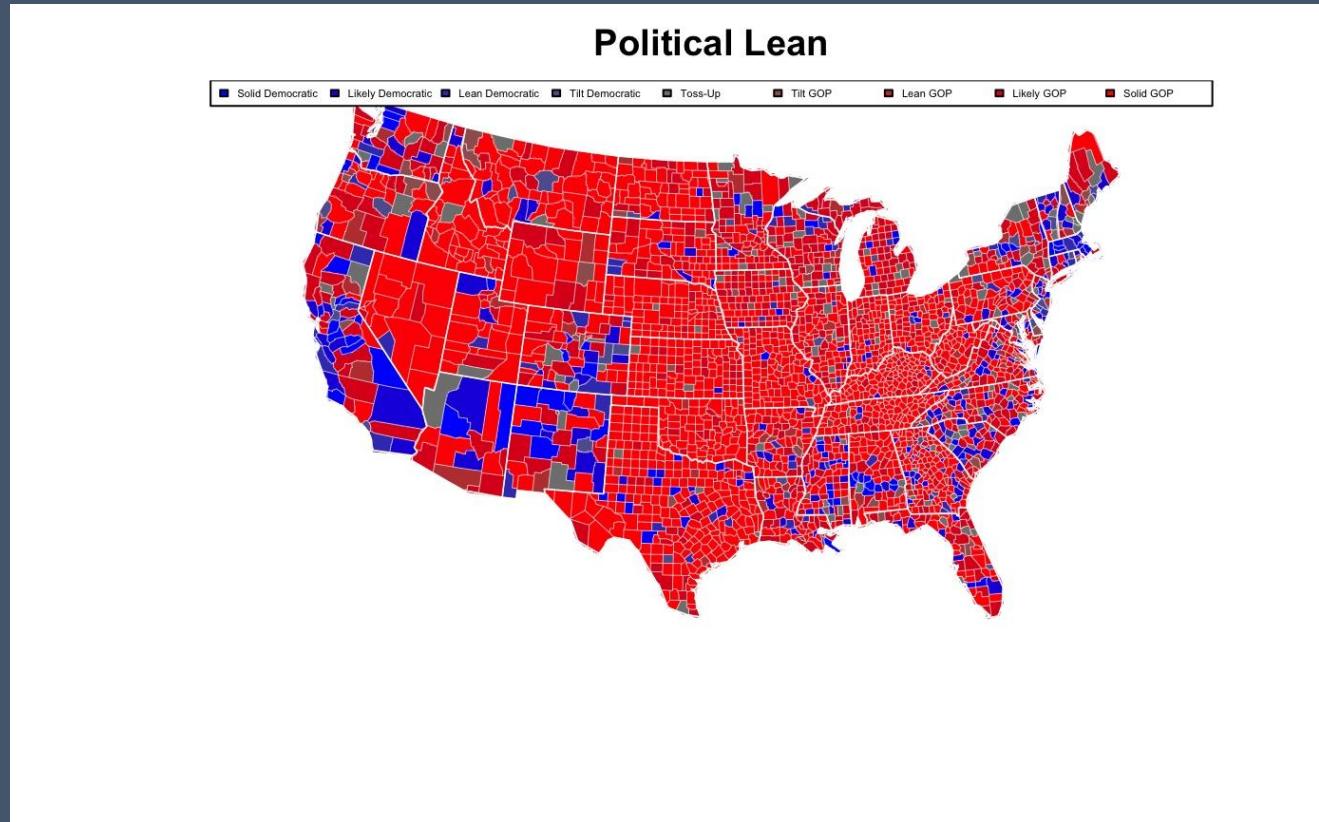
Statistical Political Lean



# 2016 Election Background

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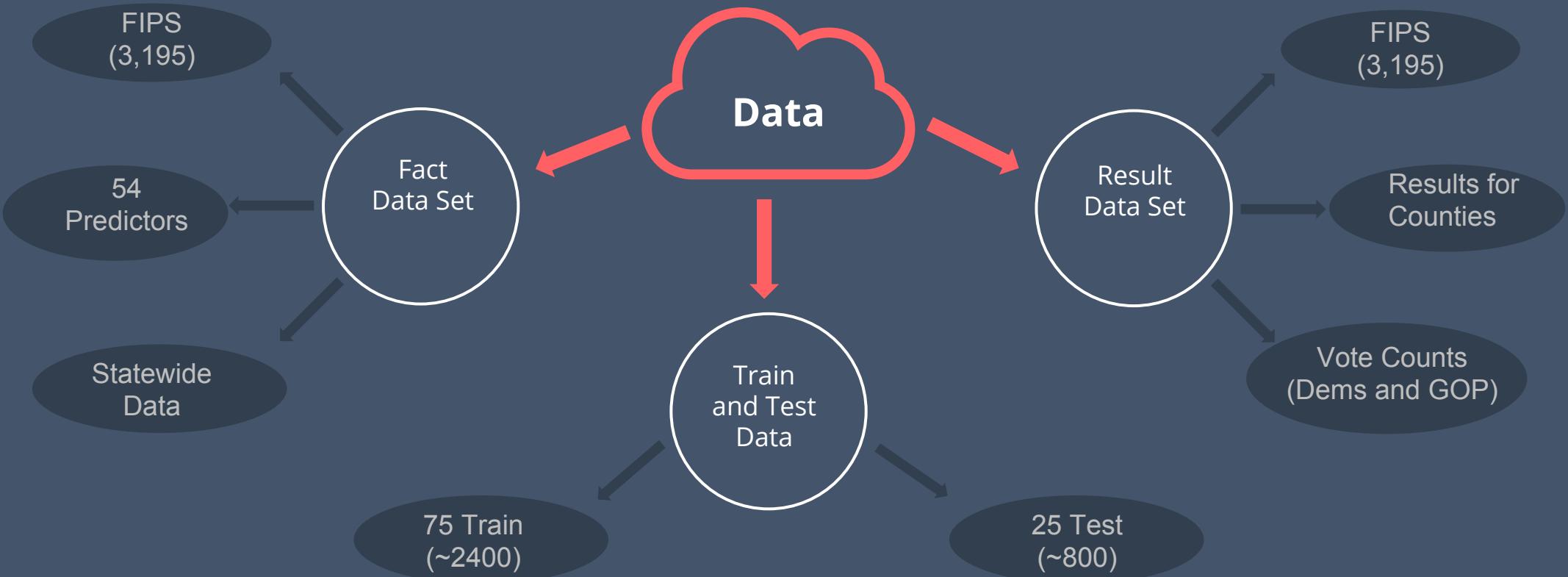
Statistical Political Lean Map



# Data Overview

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## Data Sets Description



# Data Overview

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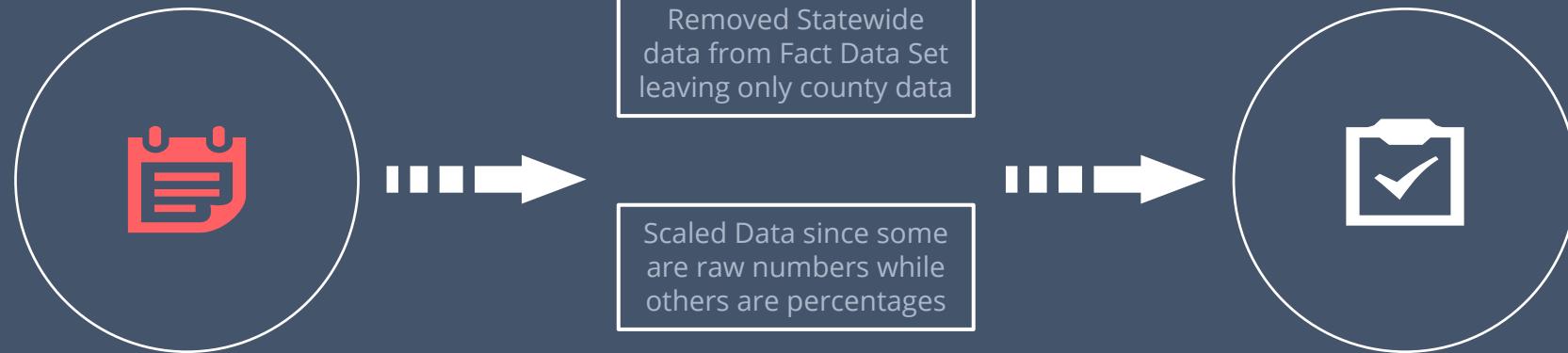
## Fact Data Set Predictors (Examples)

Predictor Code	Predictor Description
RHI725214	Hispanic or Latino, percent, 2014
POP815213	Language other than English spoken at home, pct age 5+, 2009-2013
EDU685213	Bachelor's degree or higher, percent of persons age 25+, 2009-2013
INC910213	Per capita money income in past 12 months (2013 dollars), 2009-2013
PVY020213	Persons below poverty level, percent, 2009-2013
PST045214	Population, 2014 estimate
AGE295214	Persons under 18 years, percent, 2014
AGE775214	Persons 65 years and over, percent, 2014
SEX255214	Female persons, percent, 2014
RHI225214	Black or African American alone, percent, 2014
VET605213	Veterans, 2009-2013

# Data Overview

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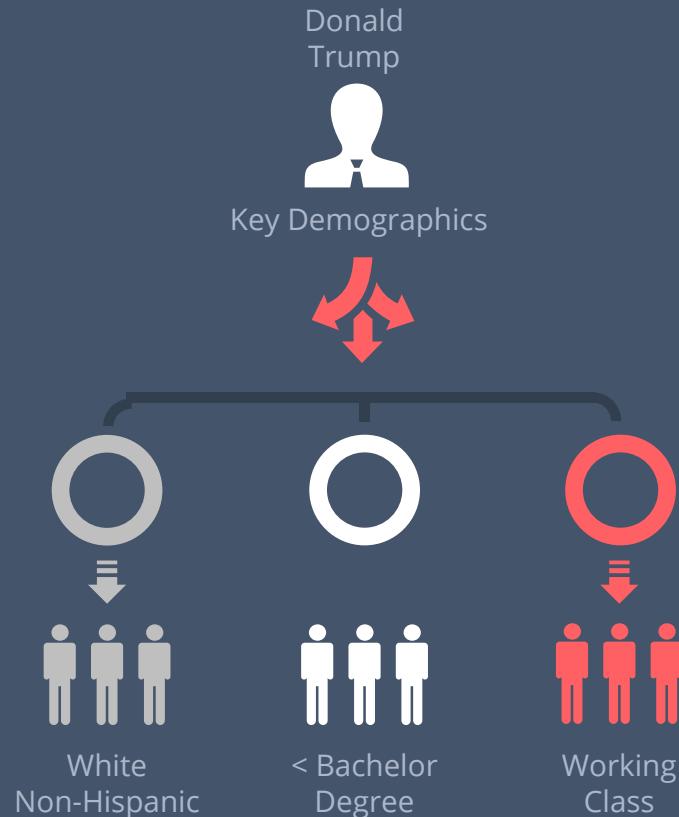
## Cleaning the Data



# Explanatory Analysis

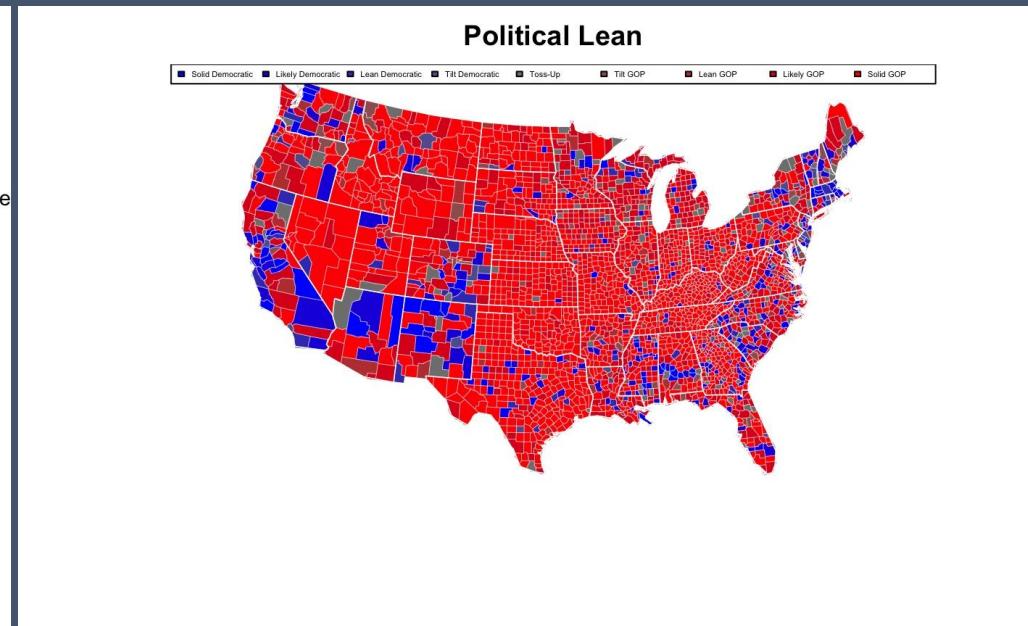
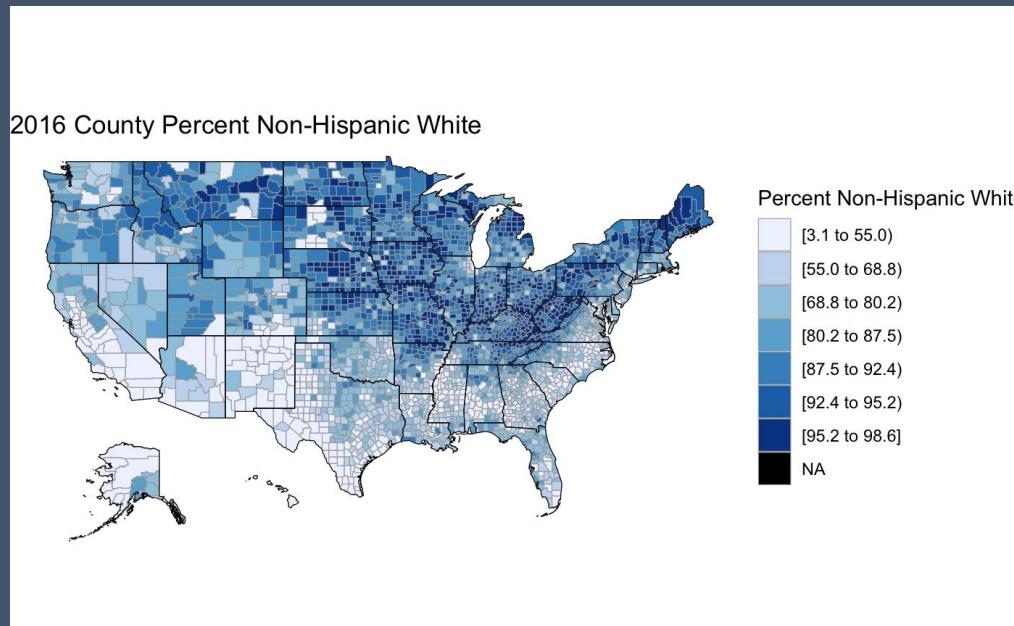
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Trump's Base



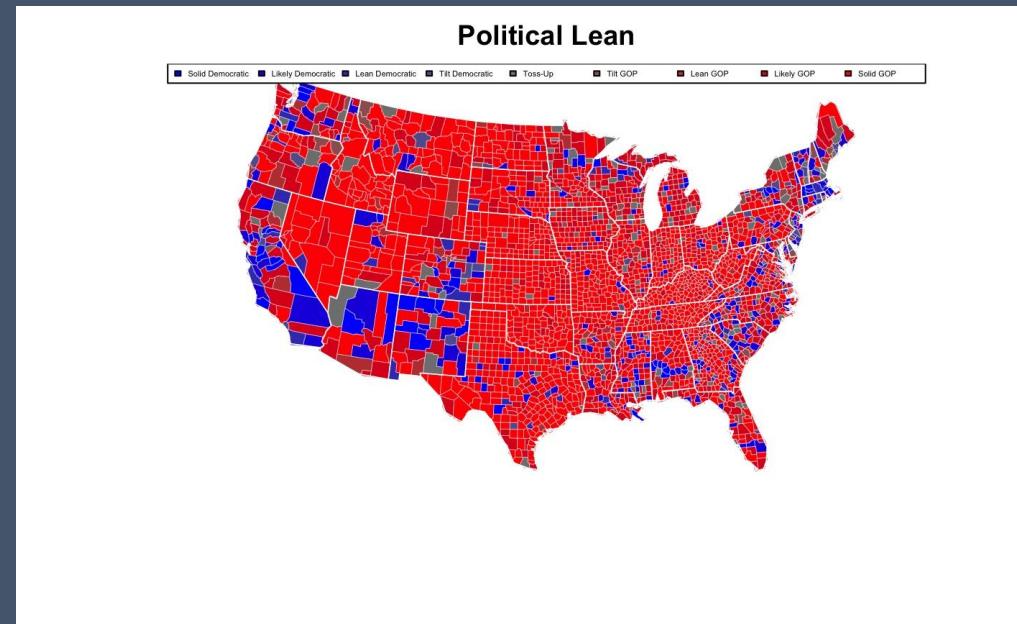
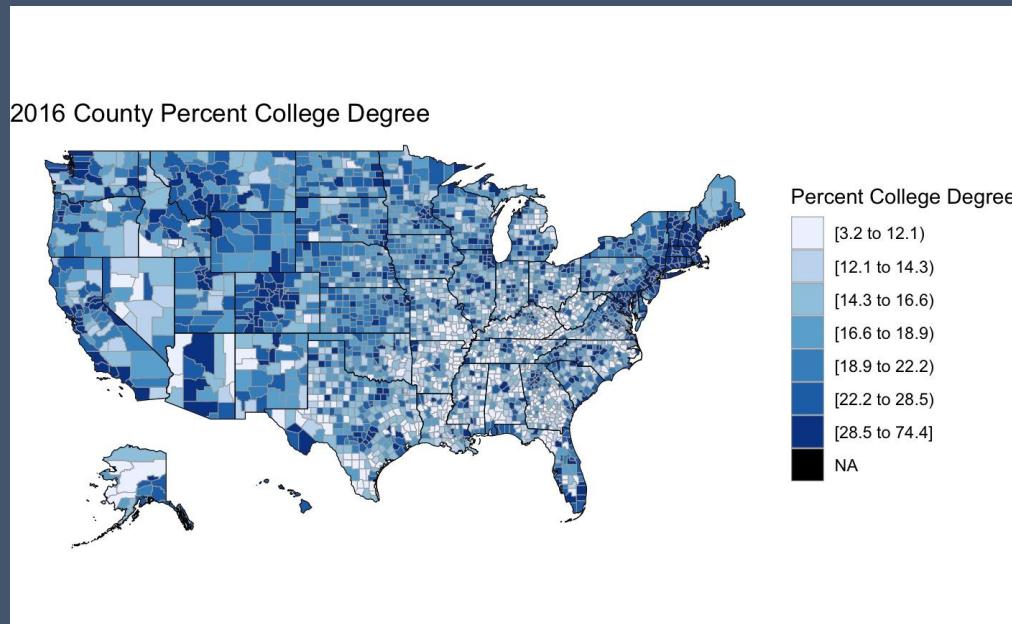
# Explanatory Analysis

White Non-Hispanic



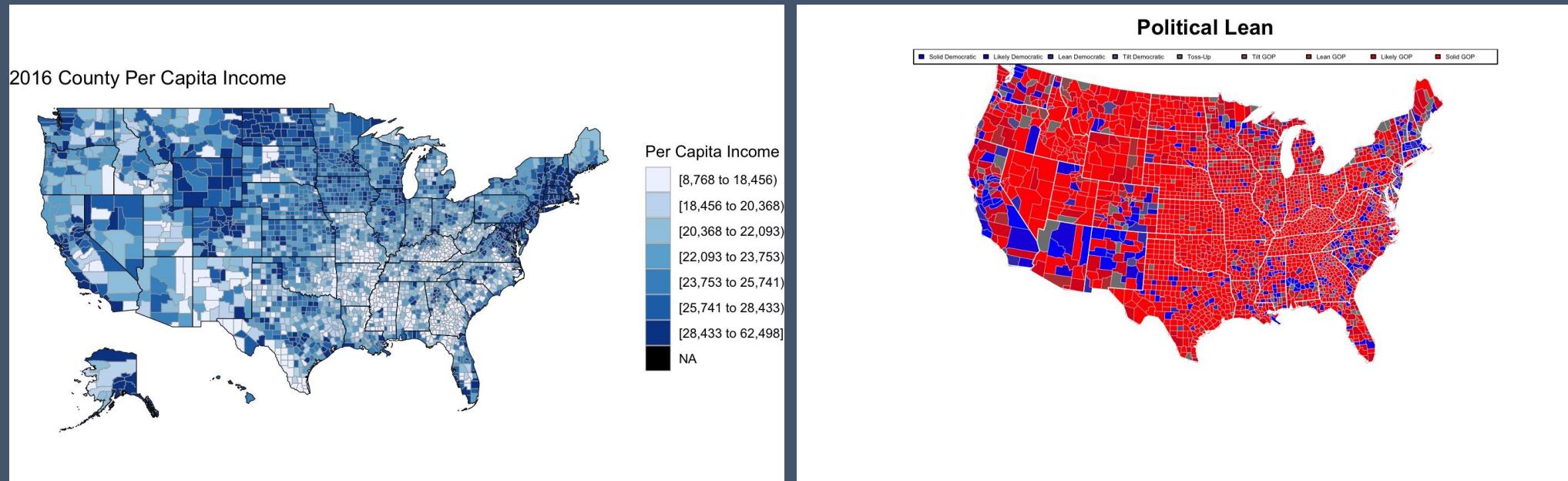
# Explanatory Analysis

< Bachelor Degree



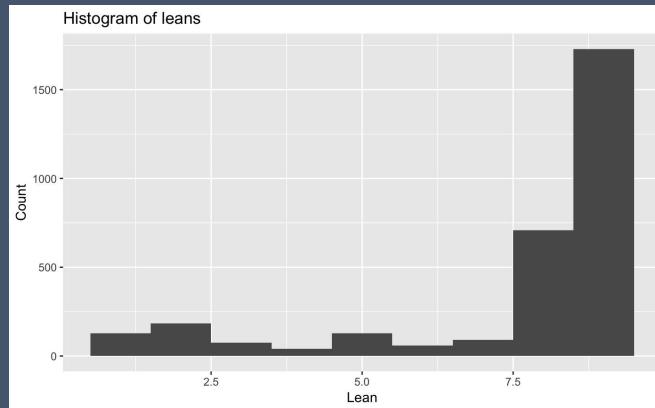
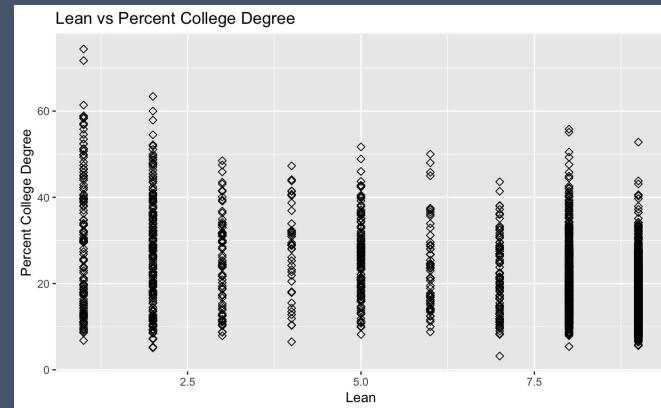
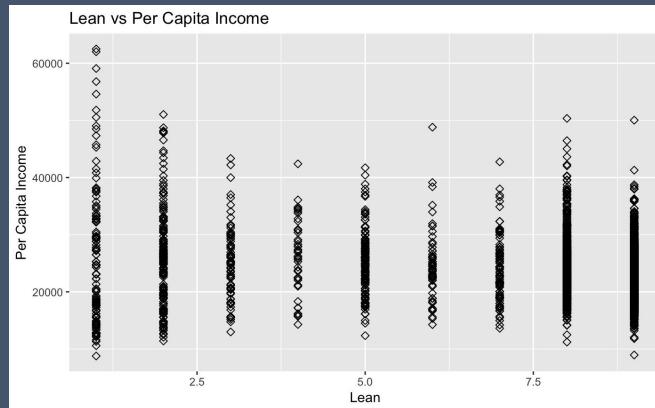
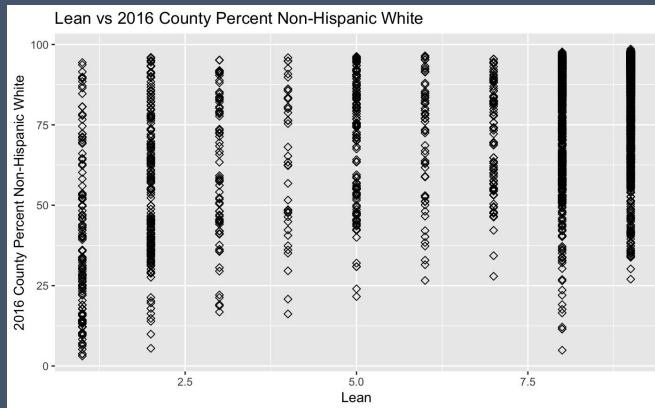
# Explanatory Analysis

## Working Class



# Explanatory Analysis

## Scatter Plots and Histogram



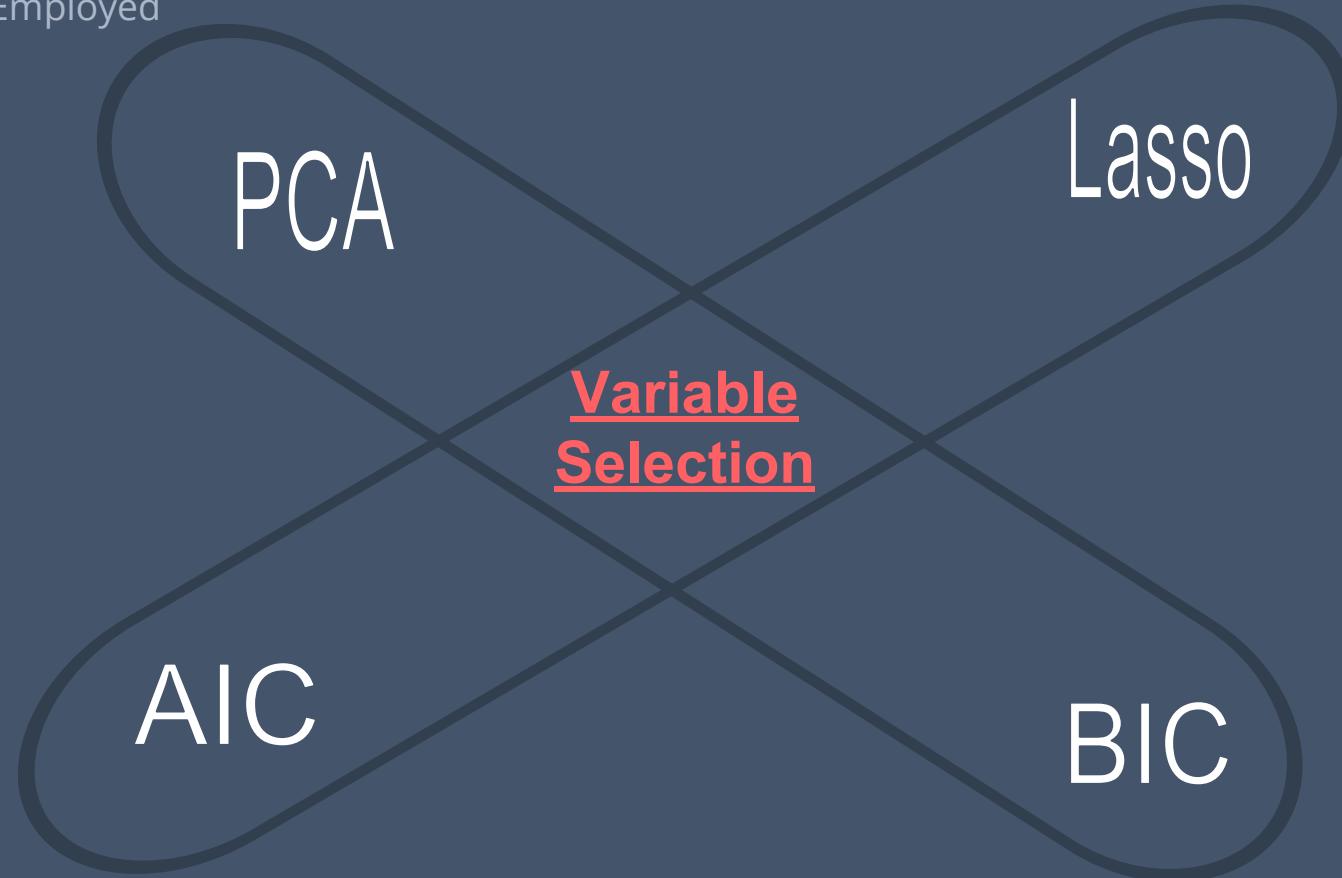
## Central Question

Does the probability associated with a logistic regression outcome provide insight for ordinal regression?

# Variable Selection

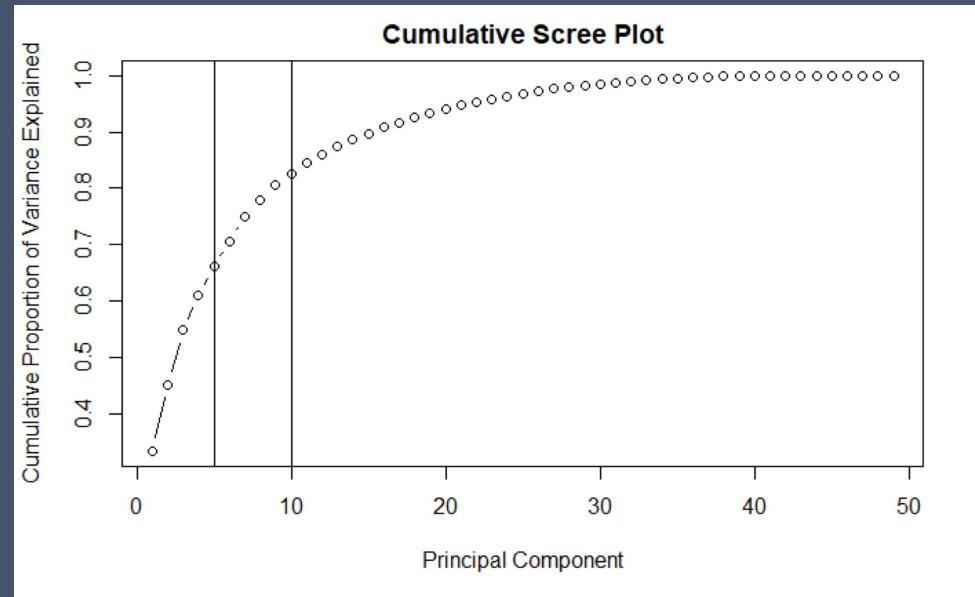
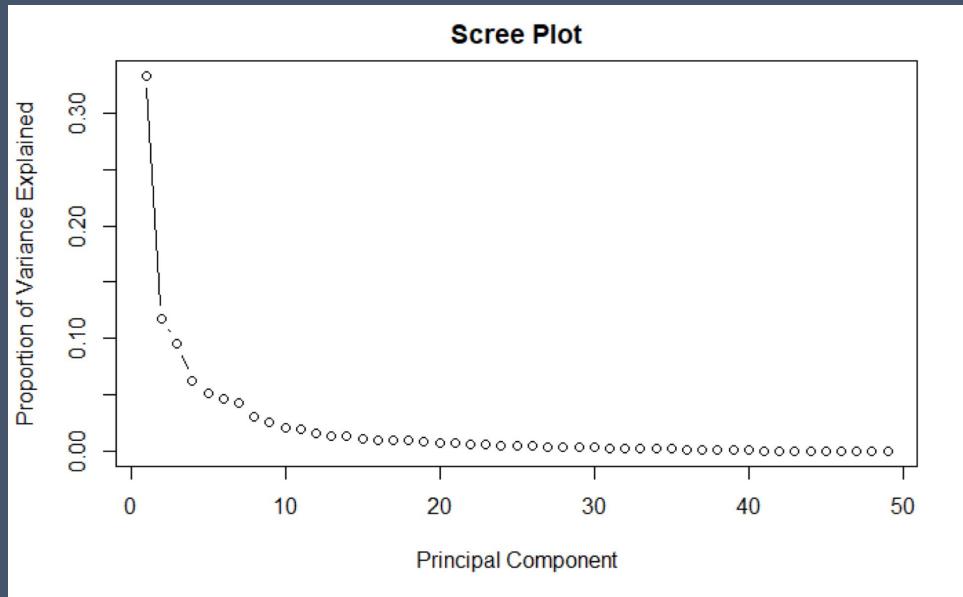
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Techniques Employed



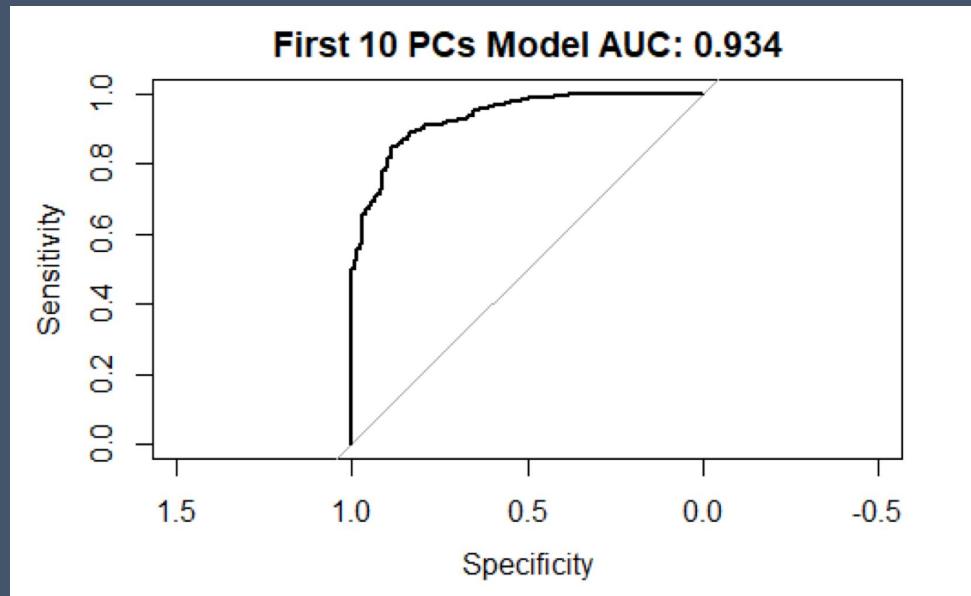
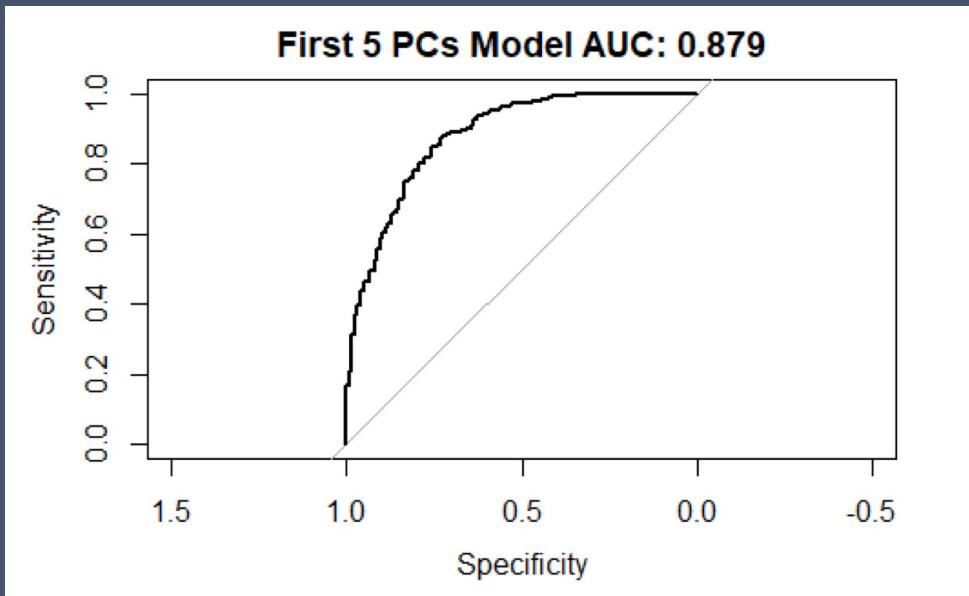
# Variable Selection

Method: PCA



# Variable Selection

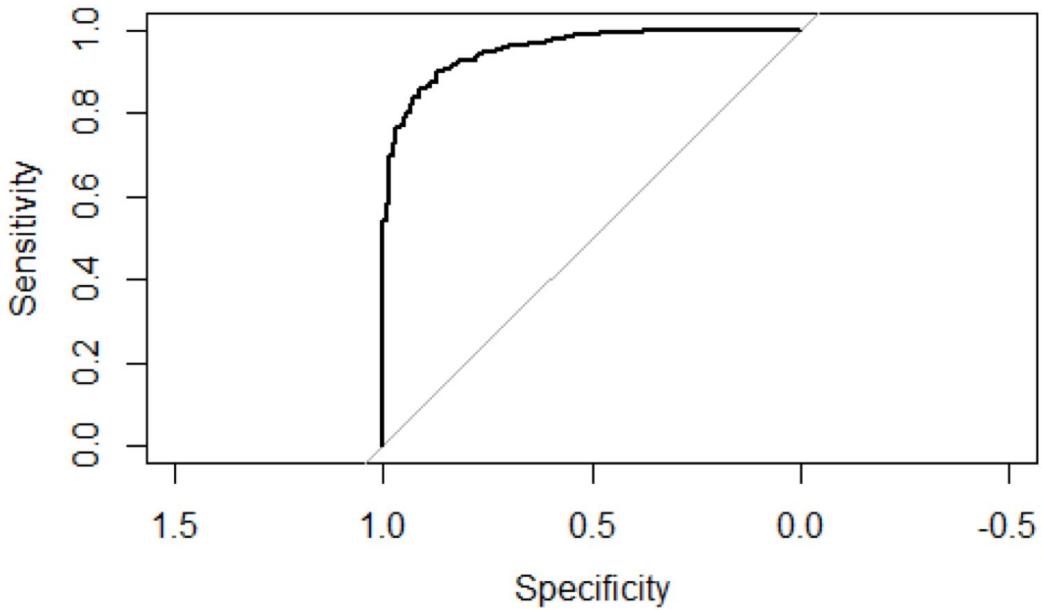
Method: PCA (cont.)



# Variable Selection

Method: Forward AIC

**Forward AIC Model AUC: 0.954**

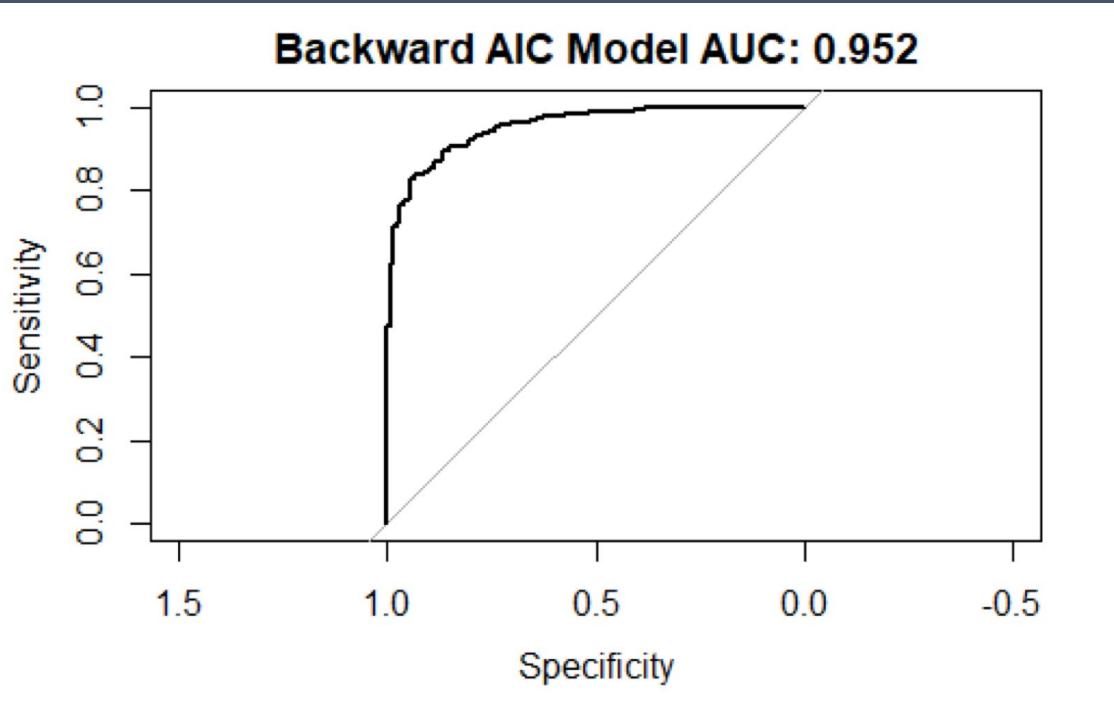


## Variables Selected

`"(Intercept)" "RHI825214" "EDU685213" "RHI225214"  
"HSG096213" "PST120214" "AGE295214" "SEX255214"  
"HSG495213" "INC910213" "POP715213" "SBO015207"  
"HSD310213" "AGE775214" "LFE305213" "INC110213"  
"POP645213" "RHI625214" "SBO215207" "SBO315207"  
"AGE135214" "SBO515207"`

# Variable Selection

Method: Backward AIC

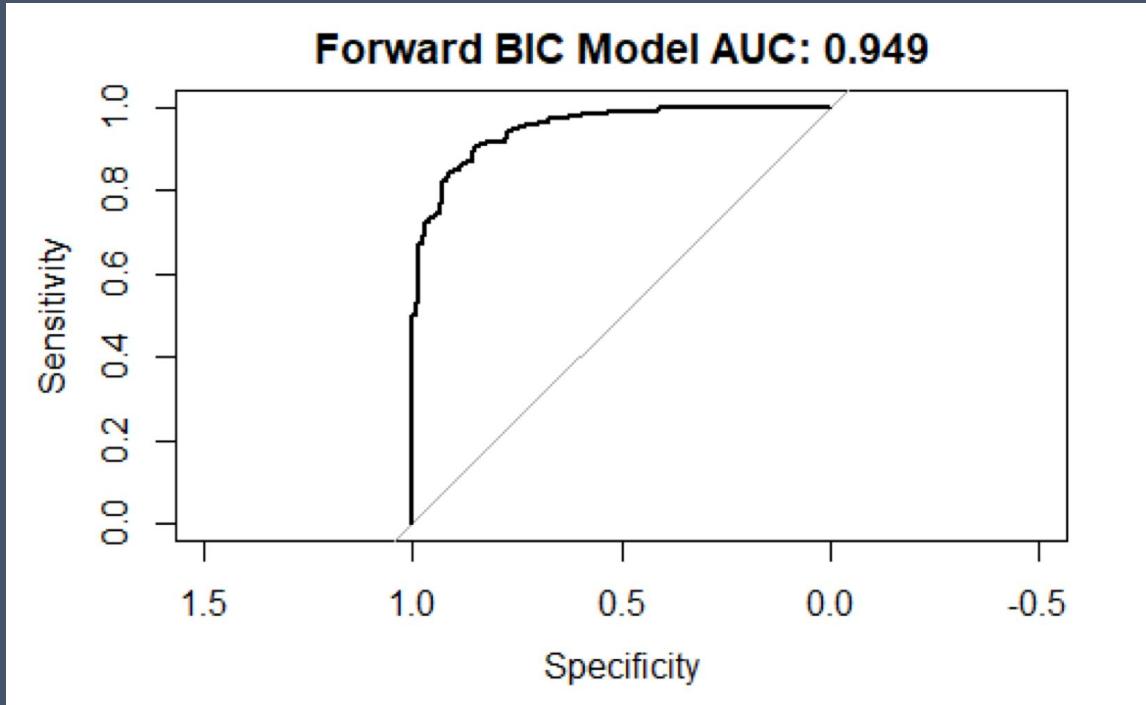


## Variables Selected

"(Intercept)" "PST120214" "POP010210" "AGE135214"  
"AGE295214" "AGE775214" "RHI225214" "RHI425214"  
"RHI625214" "RHI725214" "RHI825214" "POP715213"  
"EDU635213" "EDU685213" "VET605213" "LFE305213"  
"HSG010214" "HSG096213" "HSG495213" "HSD410213"  
"HSD310213" "INC910213" "INC110213" "BZA010213"  
"NES010213" "SBO001207" "SBO315207" "SBO215207"  
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# Variable Selection

Method: Forward BIC

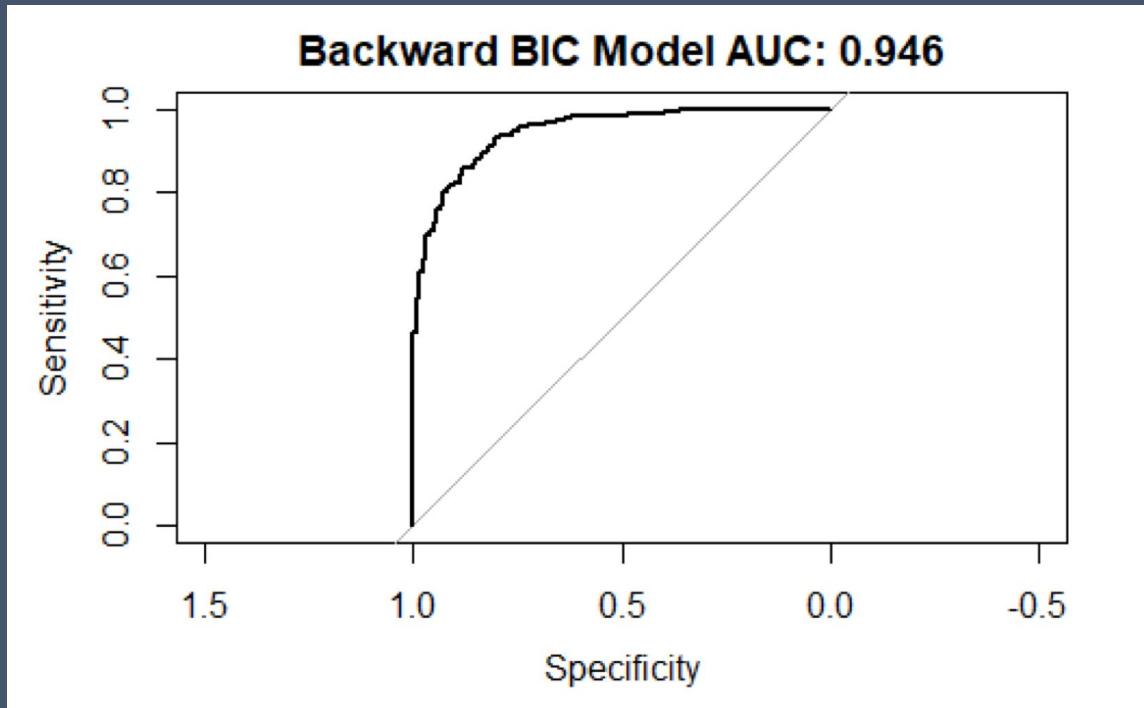


## Variables Selected

`"(Intercept)" "RHI825214" "EDU685213" "RHI225214"  
"HSG096213" "PST120214" "AGE295214" "SEX255214"  
"HSG495213" "INC910213" "POP715213" "SBO015207"  
"HSD310213" "AGE775214" "LFE305213"`

# Variable Selection

Method: Backward BIC

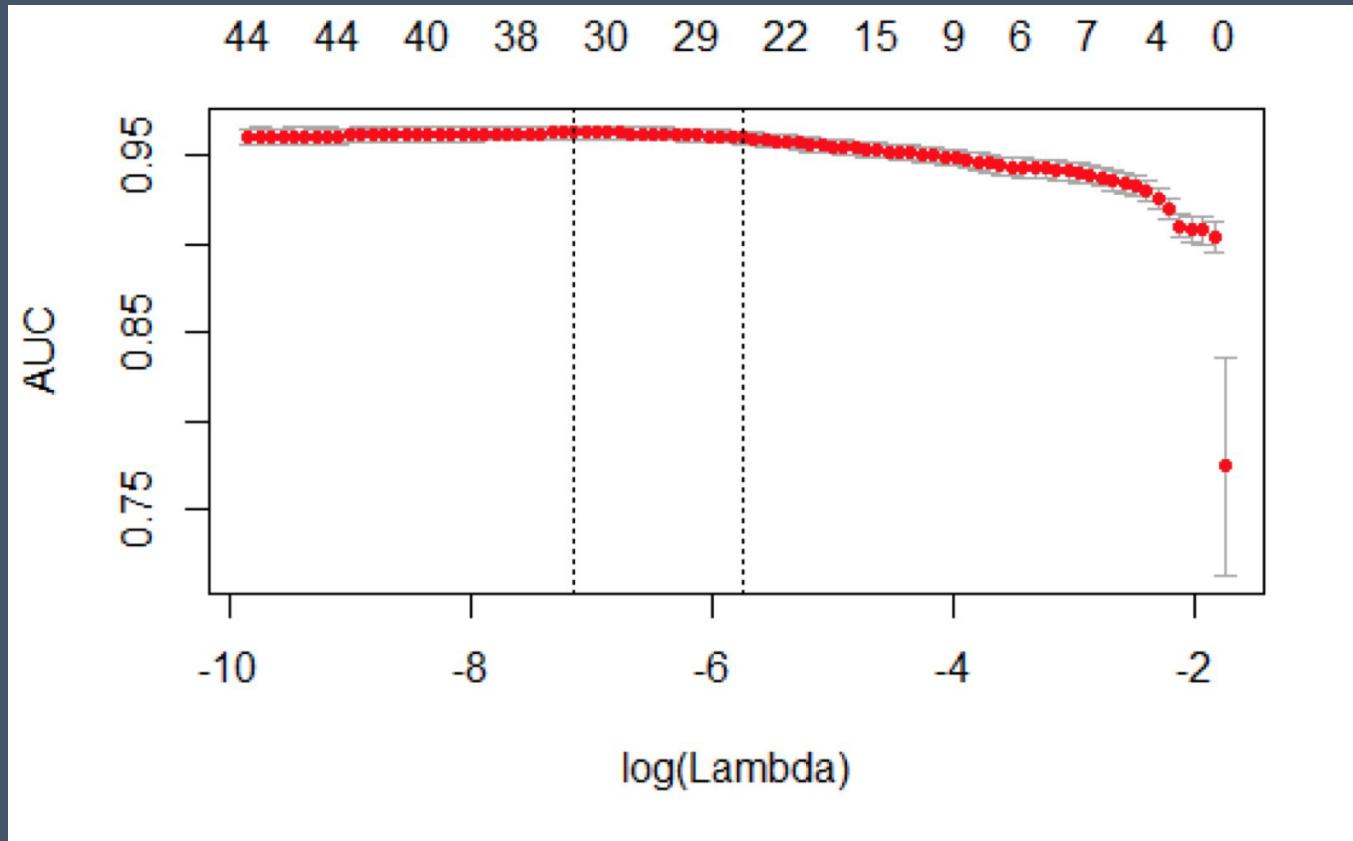


## Variables Selected

"(Intercept)" "AGE295214" "RHI825214" "POP715213"  
"EDU685213" "LFE305213" "HSG010214" "HSG096213"  
"HSG495213" "HSD410213" "HSD310213" "INC910213"  
"SBO015207"

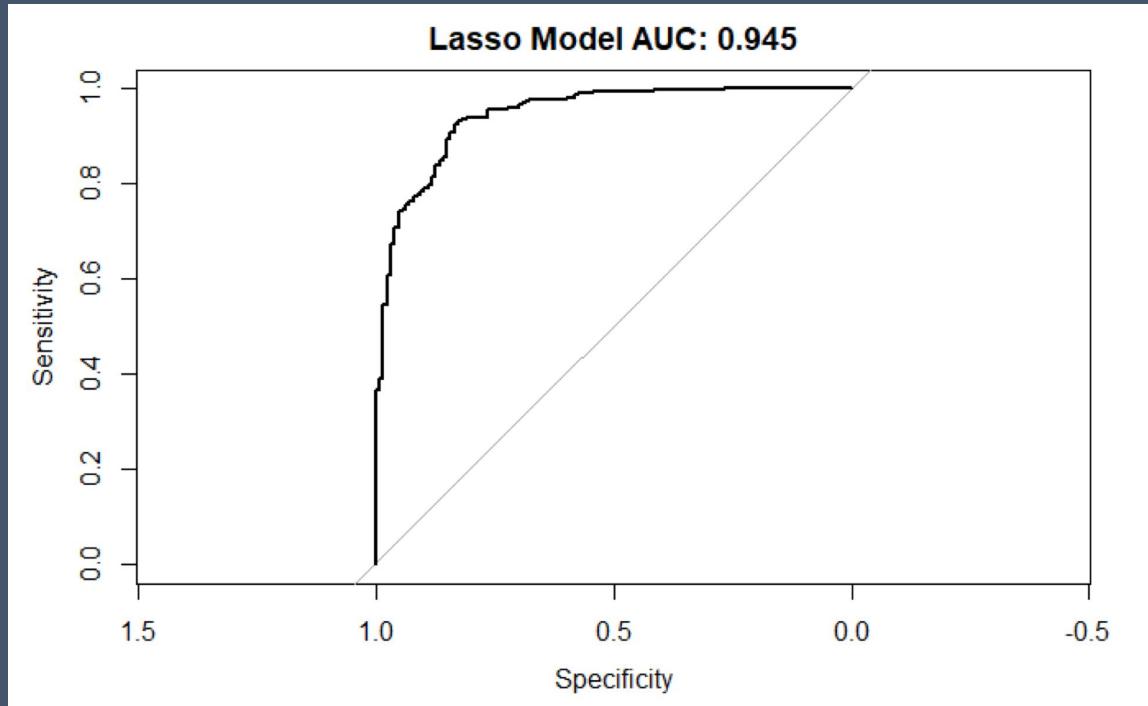
# Variable Selection

## Lasso Grid Search



# Variable Selection

Method: Lasso

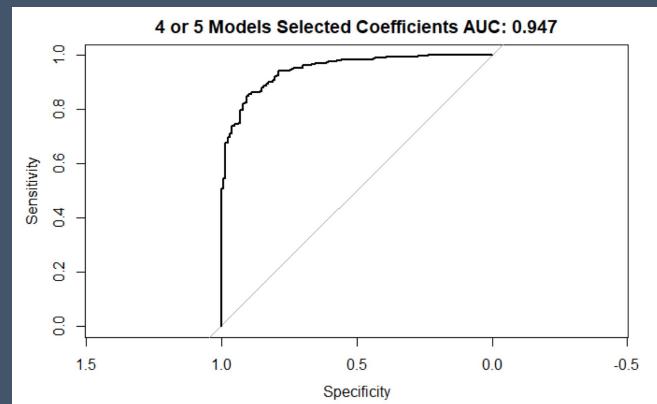
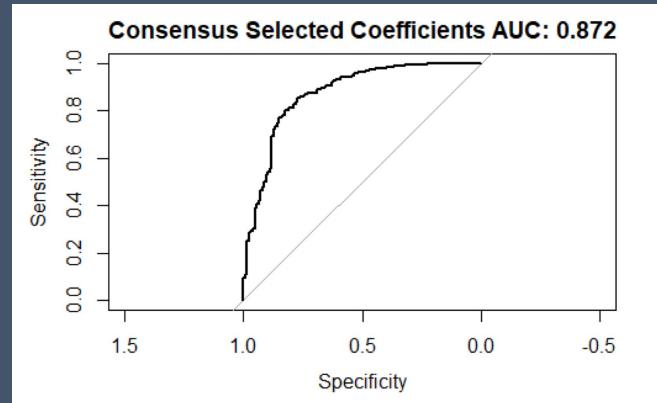
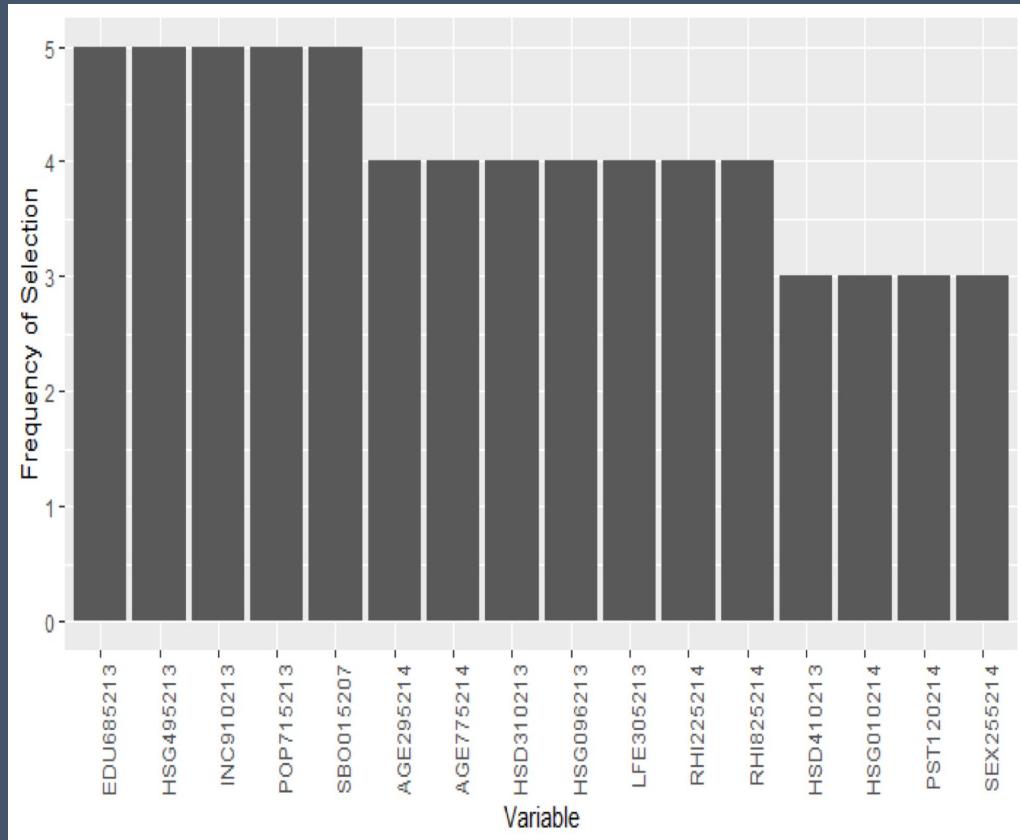


## Variables Selected

"PST045214" "POP010210" "AGE775214" "SEX255214"  
"RHI125214" "RHI225214" "RHI325214" "RHI725214"  
"POP715213" "POP645213" "POP815213"  
"EDU685213" "VET605213" "HSG010214" "HSG495213"  
"HSD410213" "INC910213" "PVY020213" "BZA010213"  
"SBO115207" "SBO515207" "SBO015207" "MAN450207"  
"WTN220207" "BPS030214"

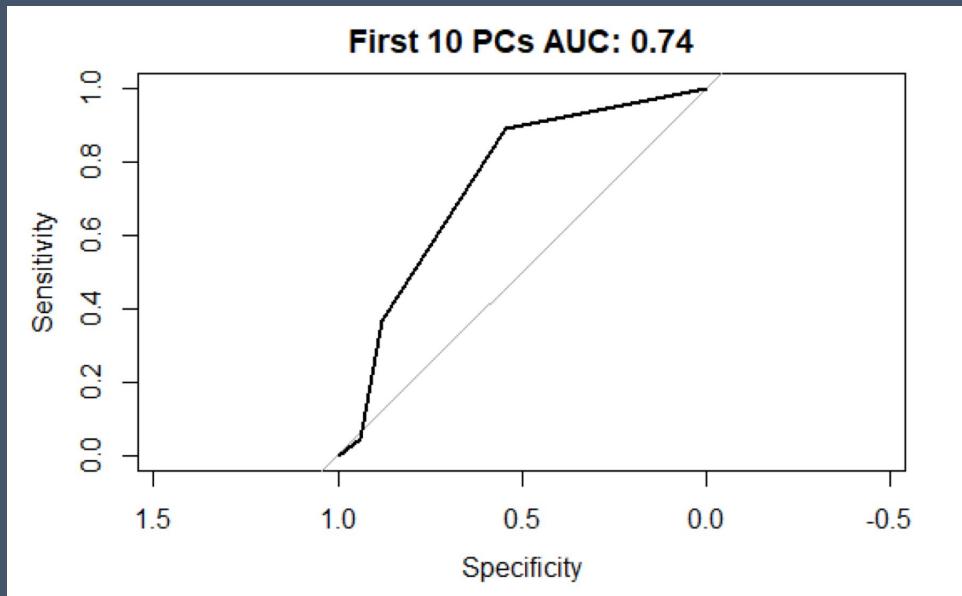
# Variable Selection

## Selected Coefficients



# Application to Ordinal Regression

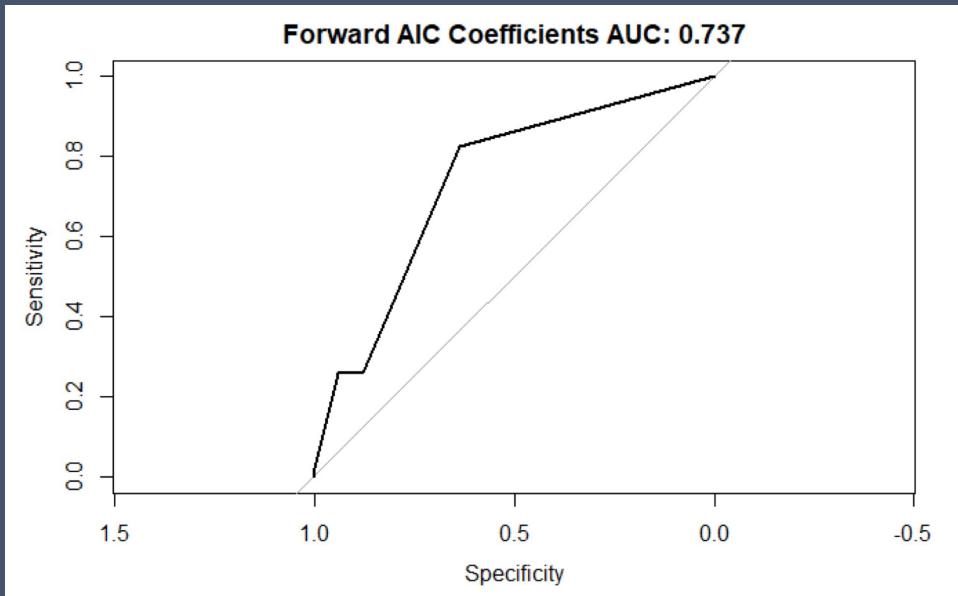
(Cumulative Logistic) PCA



	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss- Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	18	5	2	2	0	0	0	0	0
2	11	24	6	0	6	1	2	12	0
8	2	15	13	12	14	7	19	81	36
9	2	2	2	1	5	4	6	78	397

# Application to Ordinal Regression

(Cumulative Logistic) Forward AIC



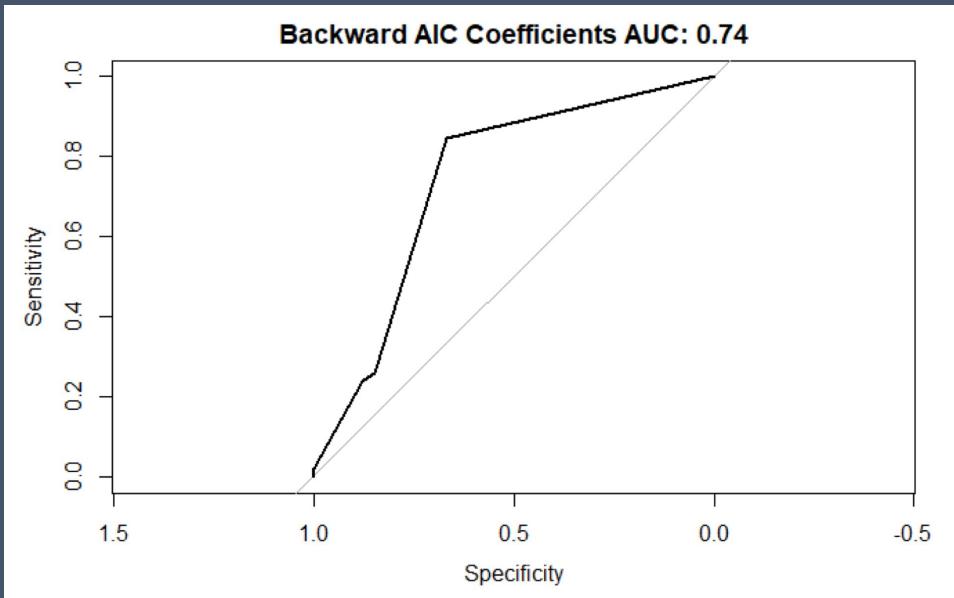
	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss- Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	21	8	2	0	1	0	0	0	0
2	8	26	9	4	3	2	3	14	1
5	2	0	0	0	0	0	0	1	0
8	2	11	12	10	19	7	19	93	42
9	0	1	0	1	2	3	5	63	390

## Variables Selected

"(Intercept)" "RHI825214" "EDU685213" "RHI225214" "HSG096213" "PST120214" "AGE295214" "SEX255214" "HSG495213"  
"INC910213" "POP715213" "SBO015207" "HSD310213" "AGE775214" "LFE305213" "INC110213" "POP645213"  
"RHI625214" "SBO215207" "SBO315207" "AGE135214" "SBO515207"

# Application to Ordinal Regression

(Cumulative Logistic) Backward AIC



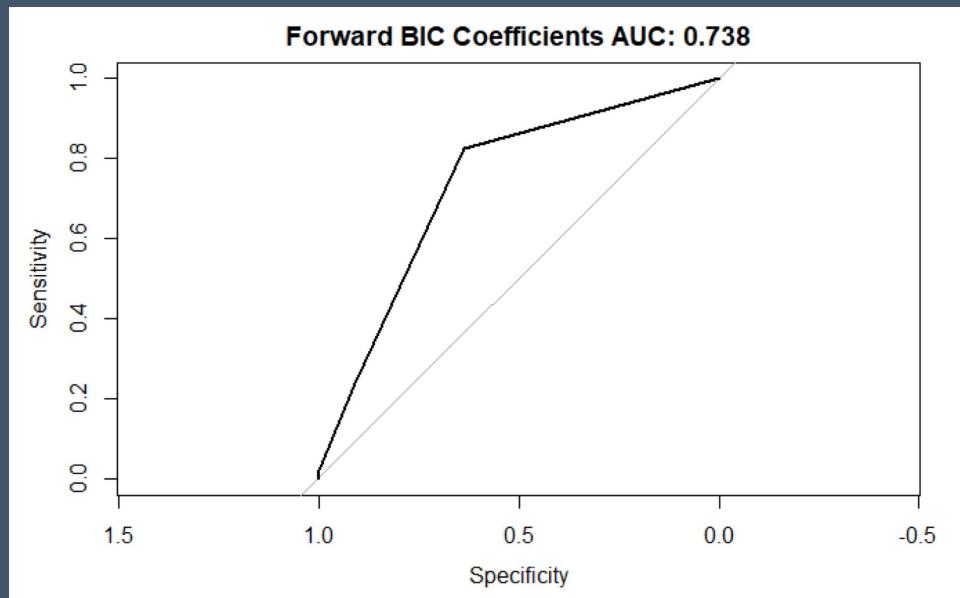
	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss-Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	22	7	2	0	1	0	0	0	0
2	6	27	10	2	3	2	4	13	2
5	1	1	1	2	1	0	0	2	0
8	4	10	10	10	19	8	19	99	50
9	0	1	0	1	1	2	4	57	381

## Variables Selected

```
"(Intercept)" "PST120214" "POP010210" "AGE135214" "AGE295214" "AGE775214" "RHI225214" "RHI425214" "RHI625214"  
"RHI725214" "RHI825214" "POP715213" "EDU635213" "EDU685213" "VET605213" "LFE305213" "HSG010214"  
"HSG096213" "HSG495213" "HSD410213" "HSD310213" "INC910213" "INC110213" "BZA010213" "NES010213"  
"SBO001207" "SBO315207" "SBO215207" "SBO015207" "RTN130207" "AFN120207"
```

# Application to Ordinal Regression

(Cumulative Logistic) Forward BIC



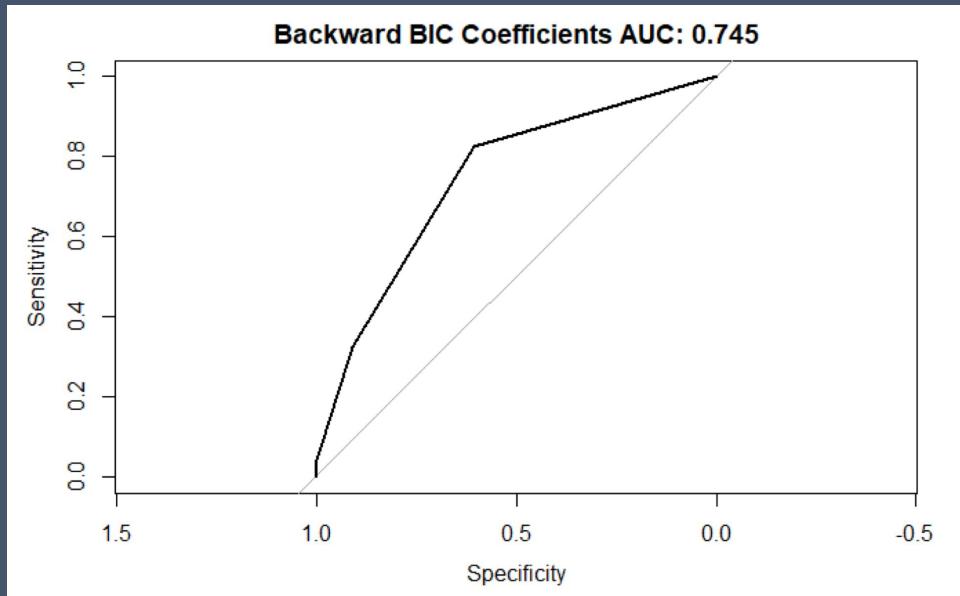
	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss-Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	21	8	2	0	1	0	0	0	0
2	9	27	8	5	3	1	2	14	1
8	3	10	12	9	18	7	21	92	41
9	0	1	1	1	3	4	4	65	391

## Variables Selected

"(Intercept)" "RHI825214" "EDU685213" "RHI225214" "HSG096213" "PST120214" "AGE295214" "SEX255214" "HSG495213"  
"INC910213" "POP715213" "SBO015207" "HSD310213" "AGE775214" "LFE305213"

# Application to Ordinal Regression

(Cumulative Logistic) Backward BIC



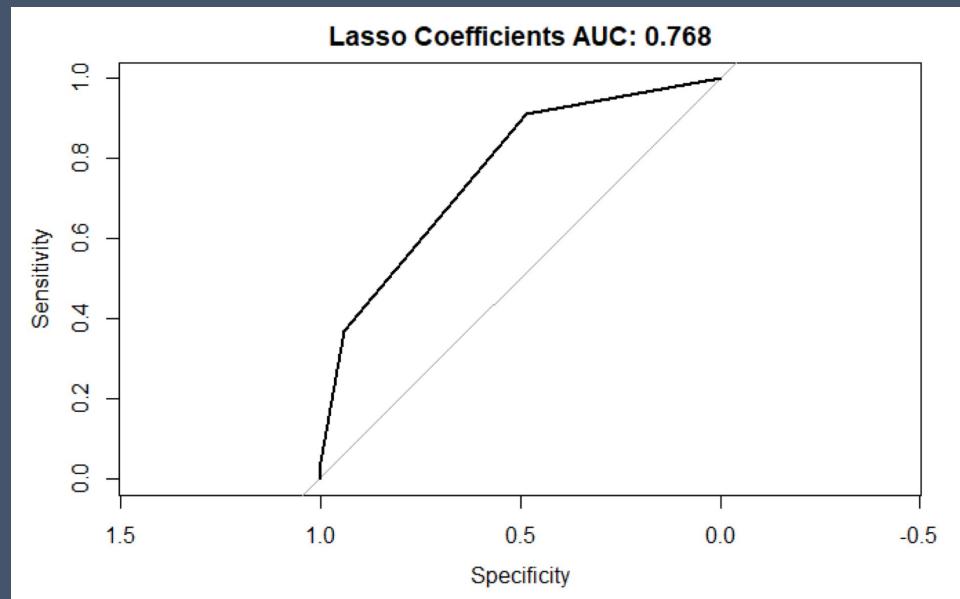
	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss- Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	20	8	2	0	1	0	0	0	0
2	10	23	9	4	2	1	3	11	2
8	3	13	11	10	20	7	19	96	42
9	0	2	1	1	2	4	5	64	389

## Variables Selected

"(Intercept)" "AGE295214" "RHI825214" "POP715213" "EDU685213" "LFE305213" "HSG010214" "HSG096213"  
"HSG495213" "HSD410213" "HSD310213" "INC910213" "SBO015207"

# Application to Ordinal Regression

(Cumulative Logistic) Lasso



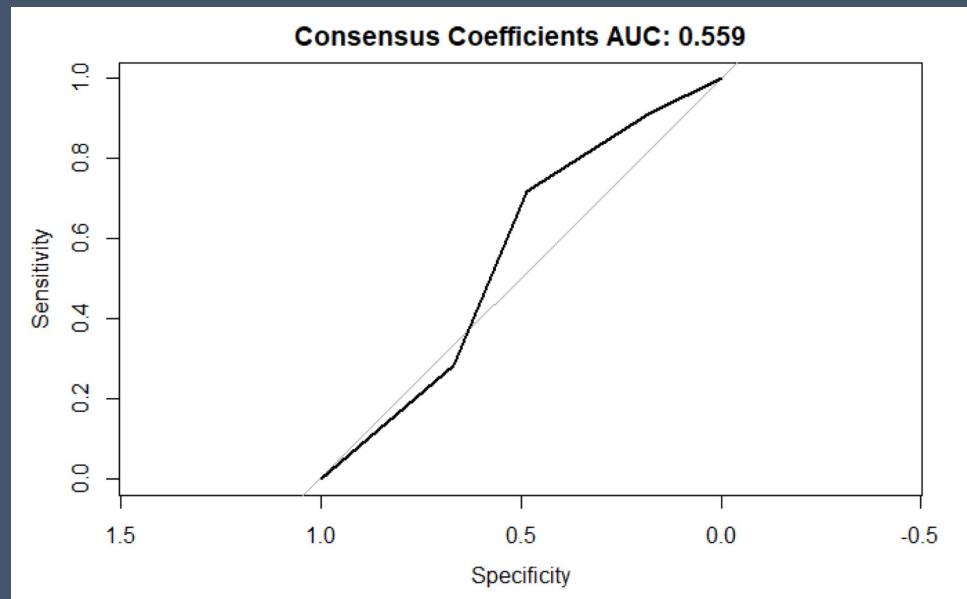
	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss- Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	16	4	2	0	1	0	0	1	0
2	15	25	10	4	3	2	3	7	0
8	2	15	10	10	17	7	17	87	43
9	0	2	1	1	4	3	7	76	390

## Variables Selected

"PST045214" "POP010210" "AGE775214" "SEX255214" "RHI125214" "RHI225214" "RHI325214" "RHI725214" "POP715213"  
"POP645213" "POP815213" "EDU685213" "VET605213" "HSG010214" "HSG495213" "HSD410213" "INC910213" "PVY020213"  
"BZA010213" "SBO115207" "SBO515207" "SBO015207" "MAN450207" "WTN220207" "BPS030214"

# Application to Ordinal Regression

(Cumulative Logistic) Consensus



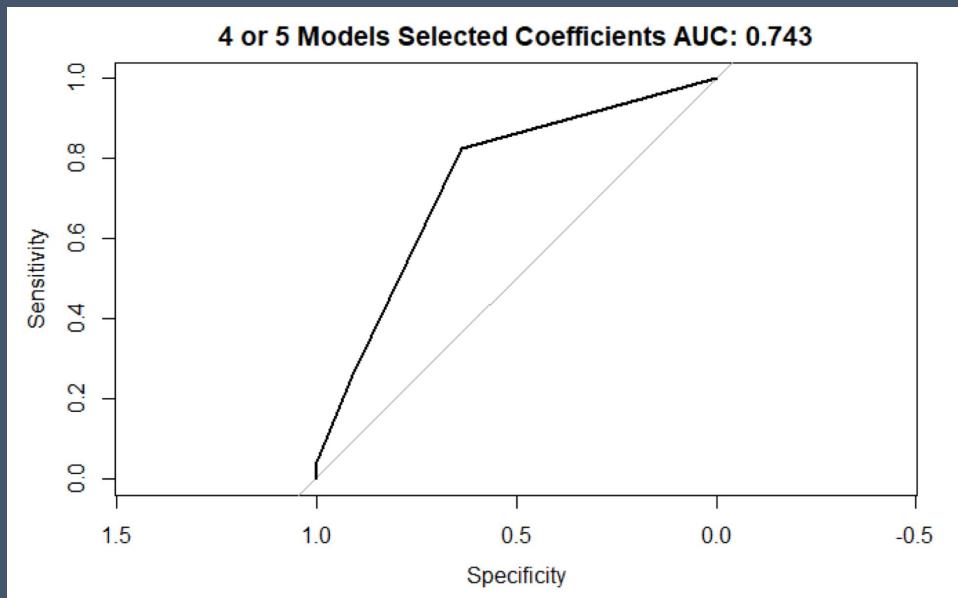
	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss-Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	6	4	3	0	1	0	0	0	0
2	10	9	0	3	1	0	0	6	1
8	6	20	11	6	9	3	7	41	22
9	11	13	9	6	14	9	20	124	410

## Variables Selected

"EDU685213" "HSG495213" "INC910213" "POP715213" "SBO015207"

# Application to Ordinal Regression

(Cumulative Logistic) 4 out of 5 models



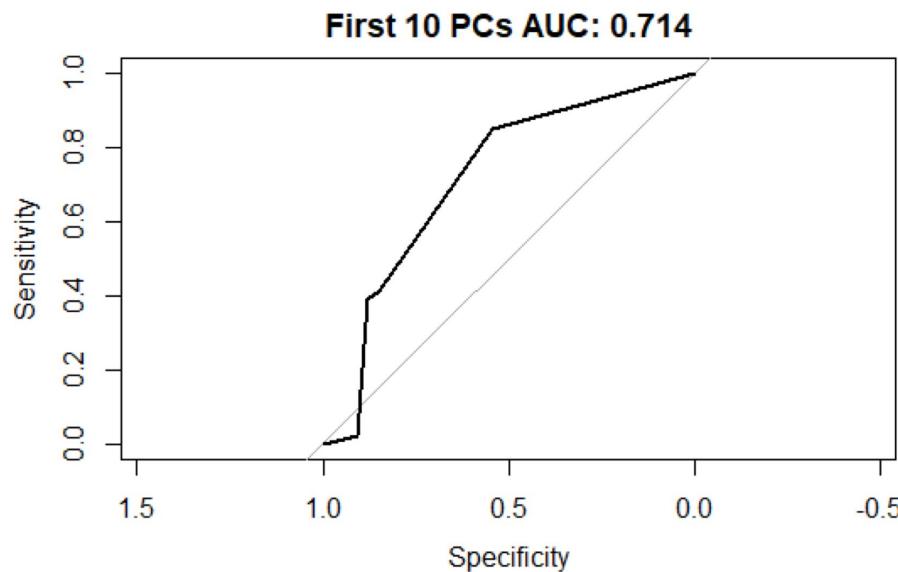
	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss- Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	21	8	2	0	1	0	0	0	0
2	9	26	9	5	3	1	2	13	2
8	3	10	11	9	19	7	20	95	37
9	0	2	1	1	2	4	5	63	394

## Variables Selected

"EDU685213" "HSG495213" "INC910213" "POP715213" "SBO015207" "AGE295214" "AGE775214" "HSD310213" "HSG096213"  
"LFE305213" "RHI225214" "RHI825214"

# Application to Multinomial Regression

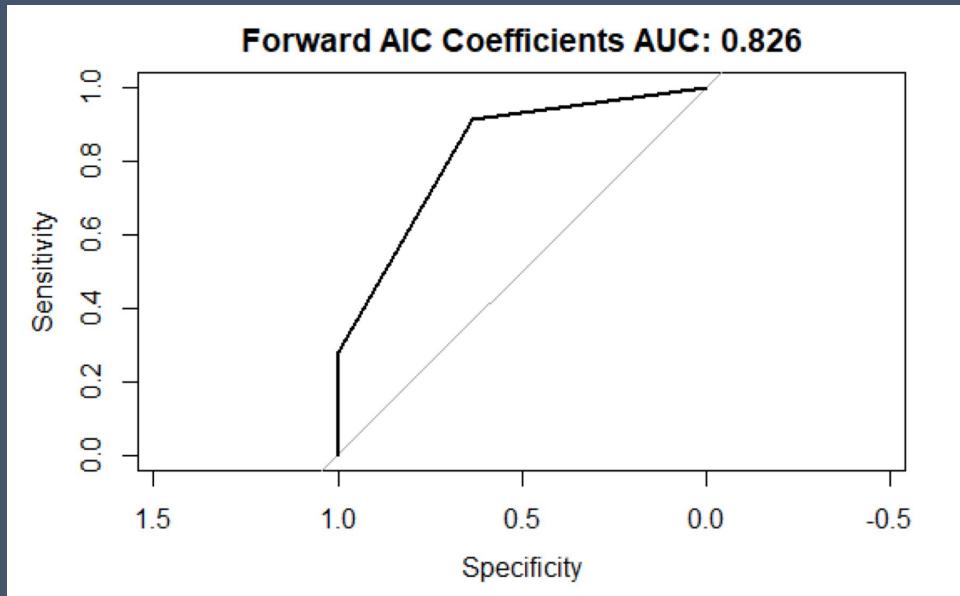
(Baseline Categorical Logit Model) PCA



	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss- Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	18	7	1	0	0	1	0	1	0
2	10	20	8	2	7	0	2	10	0
5	1	1	0	0	1	0	1	2	1
8	1	17	13	12	14	7	17	83	30
9	3	1	1	1	3	4	7	75	402

# Application to Multinomial Regression

(Baseline Categorical Logit Model) Forward AIC



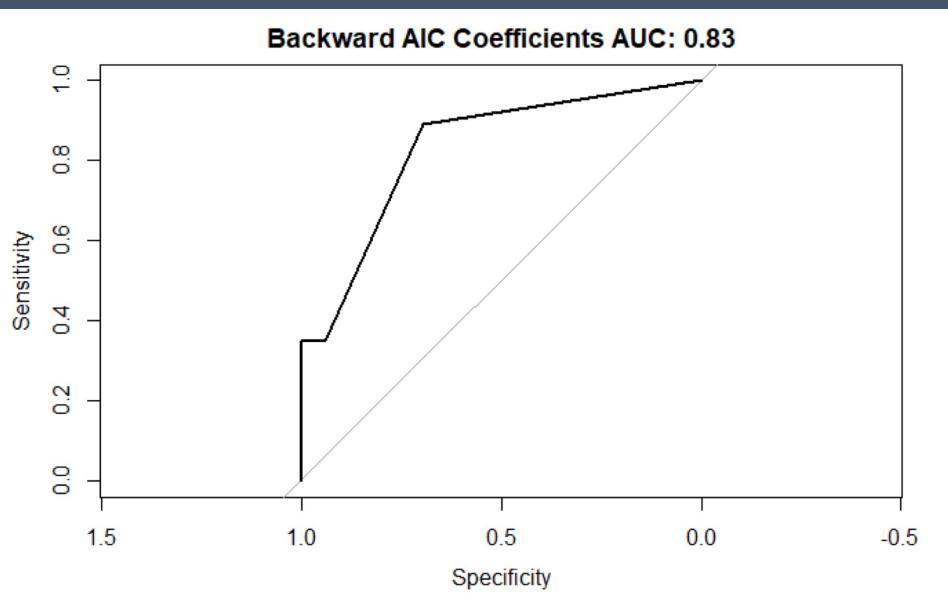
	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss- Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	21	4	3	0	1	2	0	0	0
2	12	29	7	3	3	0	3	13	2
3	0	0	1	0	0	0	0	1	0
4	0	0	0	1	0	0	0	0	0
5	0	4	1	3	3	1	1	5	2
6	0	0	1	0	0	0	0	0	0
8	0	8	9	6	16	4	19	88	30
9	0	1	1	2	2	5	4	64	399

## Variables Selected

"(Intercept)" "RHI825214" "EDU685213" "RHI225214" "HSG096213" "PST120214" "AGE295214" "SEX255214" "HSG495213"  
"INC910213" "POP715213" "SBO015207" "HSD310213" "AGE775214" "LFE305213" "INC110213" "POP645213"  
"RHI625214" "SBO215207" "SBO315207" "AGE135214" "SBO515207"

# Application to Multinomial Regression

(Baseline Categorical Logit Model) Backward AIC



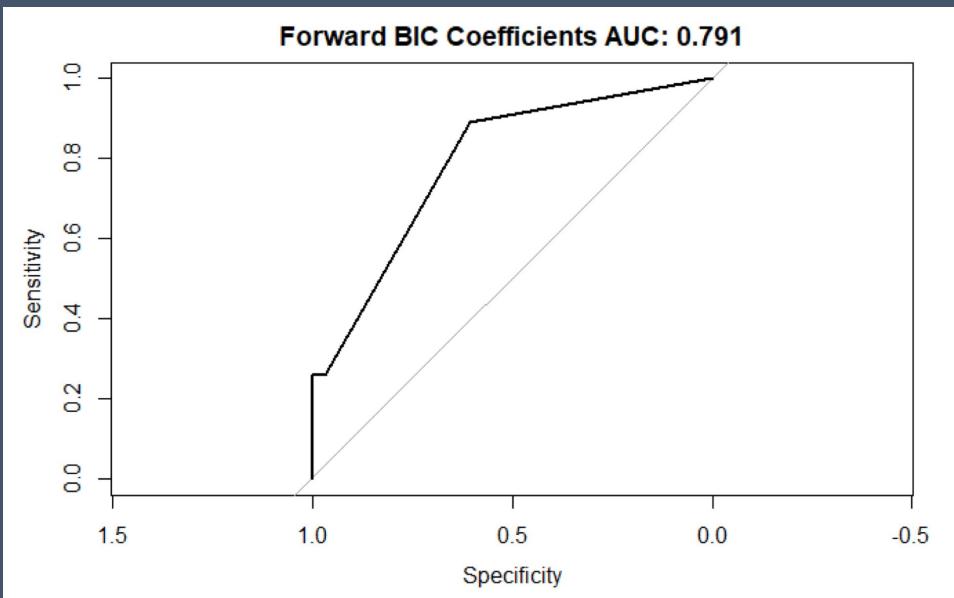
Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss- Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
23	5	0	0	1	1	0	0	0
8	25	7	3	3	1	5	11	2
2	0	1	1	0	0	0	0	0
0	0	2	1	0	0	0	0	0
0	5	4	1	5	1	1	8	0
0	0	1	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0
0	9	8	8	14	7	18	86	42
0	1	0	1	2	2	3	66	389

## Variables Selected

```
"(Intercept)" "PST120214" "POP010210" "AGE135214" "AGE295214" "AGE775214" "RHI225214" "RHI425214" "RHI625214"  
"RHI725214" "RHI825214" "POP715213" "EDU635213" "EDU685213" "VET605213" "LFE305213" "HSG010214"  
"HSG096213" "HSG495213" "HSD410213" "HSD310213" "INC910213" "INC110213" "BZA010213" "NES010213"  
"SBO001207" "SBO315207" "SBO215207" "SBO015207" "RTN130207" "AFN120207"
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# Application to Multinomial Regression

(Baseline Categorical Logit Model) Forward BIC



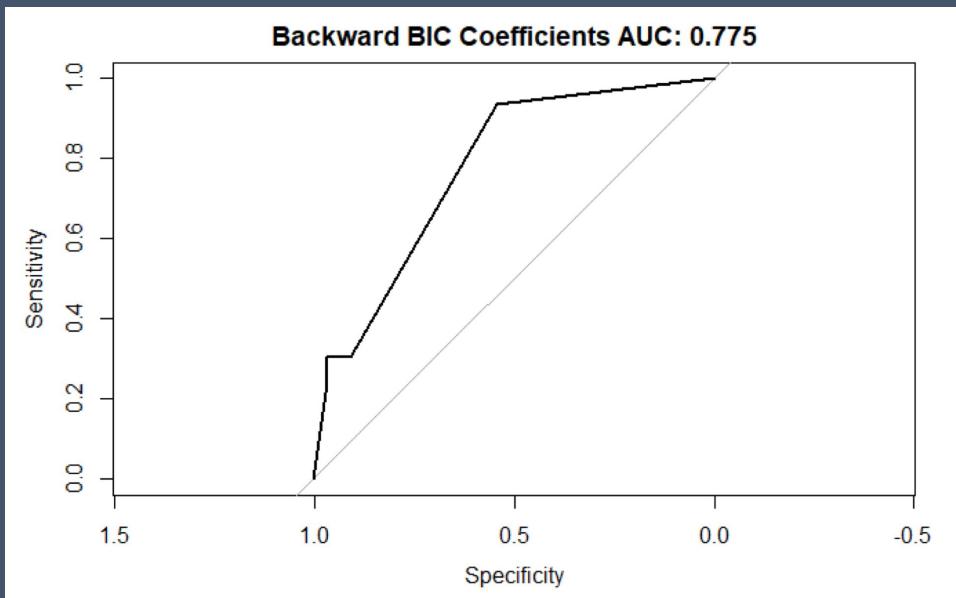
	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss- Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	20	5	2	0	1	0	0	0	0
2	12	29	8	5	3	2	3	13	2
3	0	0	1	0	0	0	0	0	0
4	1	0	0	0	0	0	0	0	0
5	0	4	1	3	1	0	1	2	0
8	0	7	11	5	18	5	19	89	36
9	0	1	0	2	2	5	4	67	395

## Variables Selected

"(Intercept)" "RHI825214" "EDU685213" "RHI225214" "HSG096213" "PST120214" "AGE295214" "SEX255214" "HSG495213"  
"INC910213" "POP715213" "SBO015207" "HSD310213" "AGE775214" "LFE305213"

# Application to Multinomial Regression

(Baseline Categorical Logit Model) Backward BIC



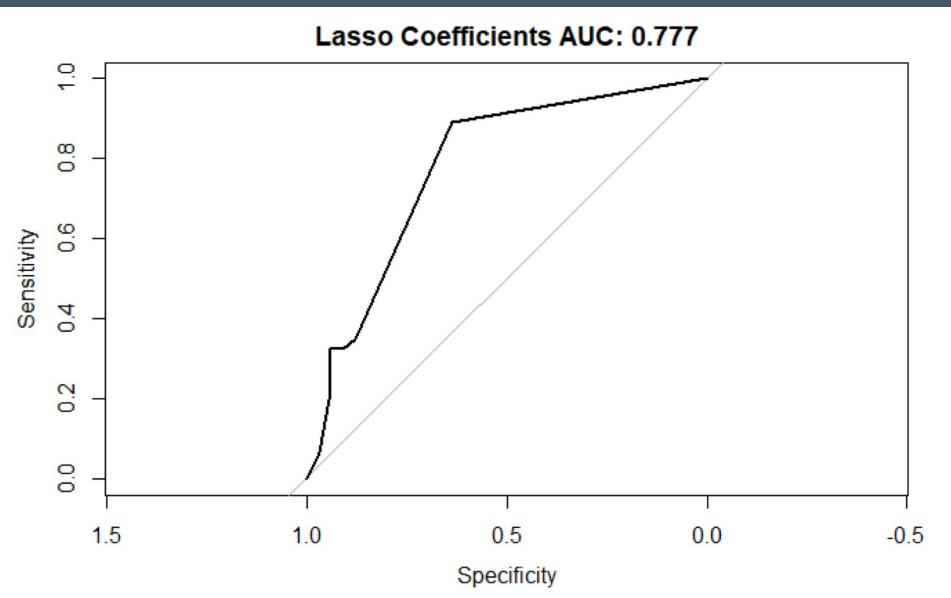
	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss- Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	18	3	2	1	1	0	0	1	0
2	12	29	10	3	4	1	4	11	2
3	1	0	0	0	0	0	0	0	0
4	1	0	0	0	0	0	0	0	0
5	0	3	2	3	1	1	3	3	0
8	1	10	9	6	16	5	15	87	35
9	0	1	0	2	3	5	5	69	396

## Variables Selected

"(Intercept)" "AGE295214" "RHI825214" "POP715213" "EDU685213" "LFE305213" "HSG010214" "HSG096213"  
"HSG495213" "HSD410213" "HSD310213" "INC910213" "SBO015207"

# Application to Multinomial Regression

(Baseline Categorical Logit Model) Lasso



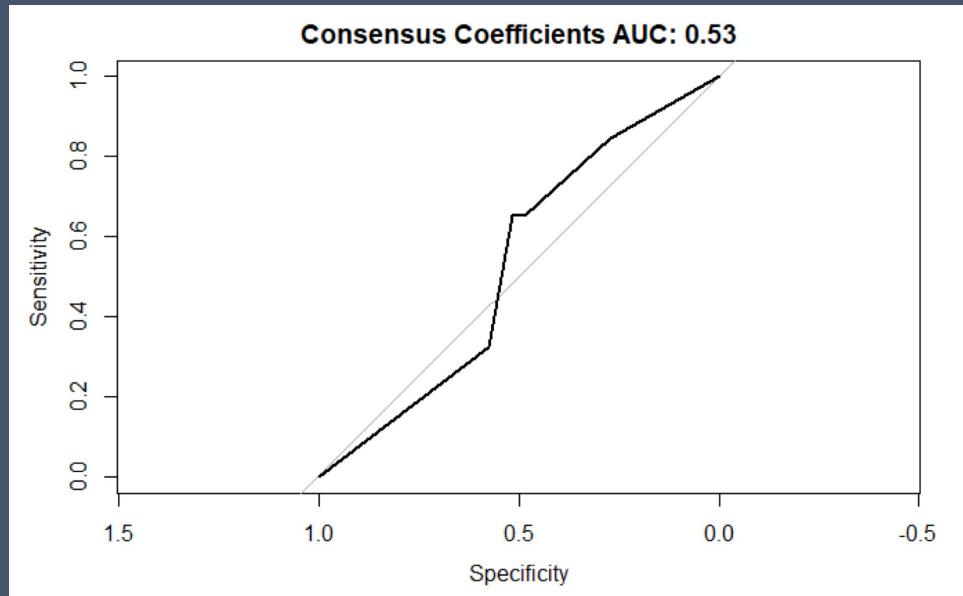
	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss- Up	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	21	5	1	0	1	1	0	0	0
2	8	25	8	3	4	1	2	7	0
3	1	1	0	0	0	0	1	0	0
4	1	0	2	1	0	0	0	0	0
5	0	4	2	2	2	1	2	6	2
7	0	1	0	1	0	0	0	0	0
8	1	7	9	7	14	6	15	74	30
9	1	3	1	1	4	3	7	84	401

## Variables Selected

"PST045214" "POP010210" "AGE775214" "SEX255214" "RHI125214" "RHI225214" "RHI325214" "RHI725214" "POP715213"  
"POP645213" "POP815213" "EDU685213" "VET605213" "HSG010214" "HSG495213" "HSD410213" "INC910213" "PVY020213"  
"BZA010213" "SBO115207" "SBO515207" "SBO015207" "MAN450207" "WTN220207" "BPS030214"

# Application to Multinomial Regression

(Baseline Categorical Logit Model) Consensus



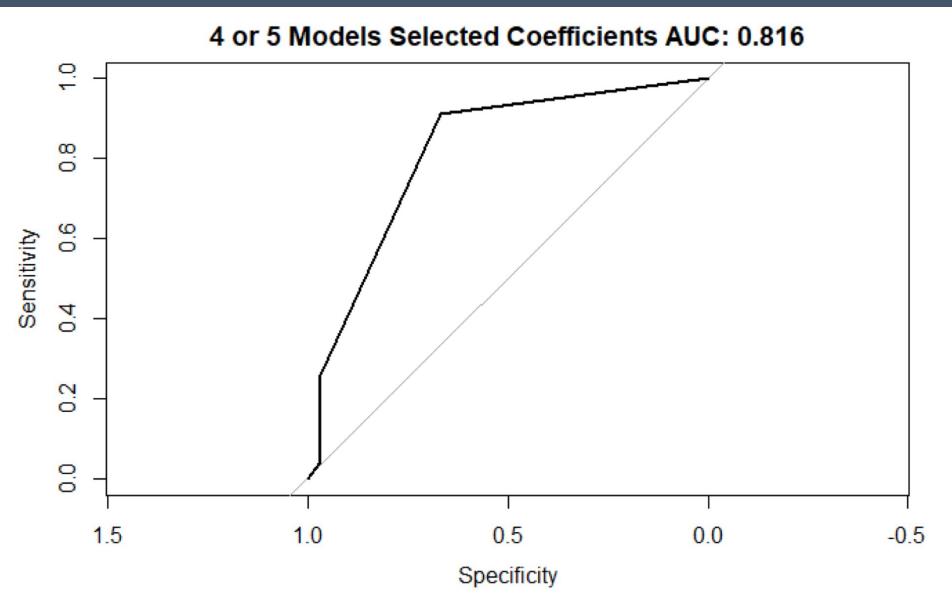
	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss-Up GOP	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	9	7	2	0	1	0	0	1	0
2	7	9	2	3	2	0	0	4	2
5	1	0	0	0	1	0	0	1	0
8	2	15	9	6	7	3	6	30	12
9	14	15	10	6	14	9	21	135	419

## Variables Selected

"EDU685213" "HSG495213" "INC910213" "POP715213" "SBO015207"

# Application to Multinomial Regression

(Baseline Categorical Logit Model) 4 out of 5 models



	Solid Democratic	Likely Democratic	Lean Democratic	Tilt Democratic	Toss- Up GOP	Tilt GOP	Lean GOP	Likely GOP	Solid GOP
1	22	4	2	1	1	0	0	1	0
2	10	30	9	3	3	1	3	11	2
3	0	0	1	0	0	0	0	0	0
5	0	3	1	2	1	0	0	3	1
8	0	7	10	7	17	6	19	91	32
9	1	2	0	2	3	5	5	65	398

## Variables Selected

"EDU685213" "HSG495213" "INC910213" "POP715213" "SBO015207" "AGE295214" "AGE775214" "HSD310213" "HSG096213"  
"LFE305213" "RHI225214" "RHI825214"

# Conclusion

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## Conventional Wisdom

Conventional Wisdom about the 2016 election says that Trump won because of white non-college educated voters. Our top models seem to confirm this.

## Principal Components

Using the first 10 principal components performs arguably just as well as other top variable selection methods for logistic regression but performs worse for the multiple category methods. Likely due to the variance lost.



## Variable Selection

For this data there is no “best” variable selection method. Seemingly the best way to select variables is to use multiple methods and get the most selected variables from each of those.

## Ordinal vs Multinomial

Though the election results can be thought of as ordered, the multinomial regression models were able to more accurately predict the political lean of a county.



**QUESTIONS TIME!**  
Have a question? Ask NOW!