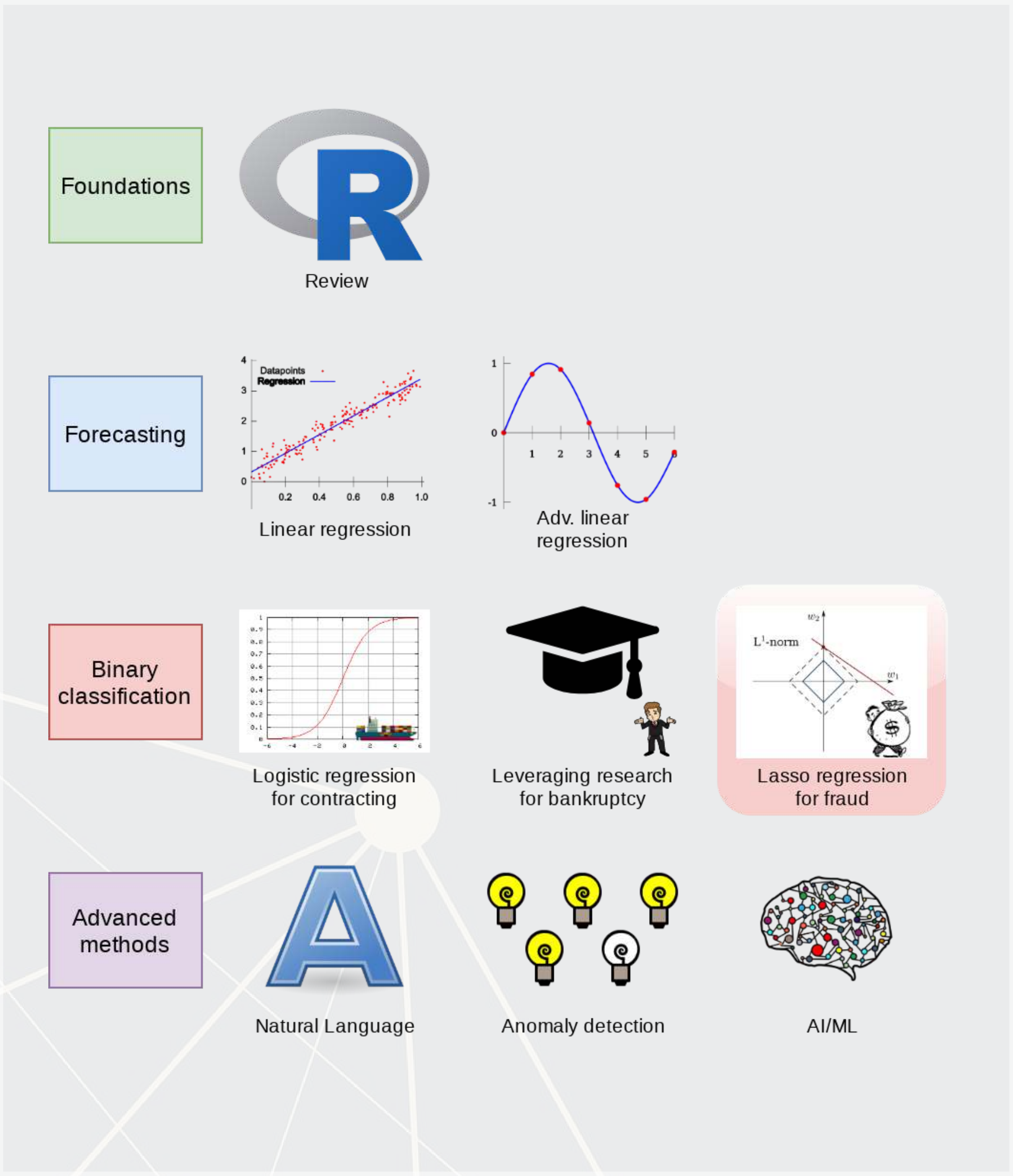
ACCT 420: Logistic Regression for Corporate Fraud

Session 6

Dr. Richard M. Crowley

Front matter

Learning objectives



- **Theory:**
  - Economics
  - Psychology
- **Application:**
  - Predicting fraud contained in annual reports
- **Methodology:**
  - Logistic regression
  - LASSO

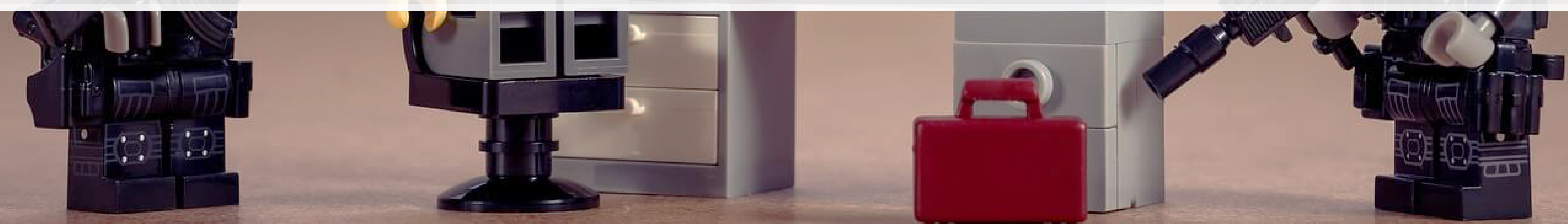
Datacamp

- Explore on your own
- No specific required class this week

Corporate/Securities Fraud

Traditional accounting fraud

1. A company is underperforming
2. Management cooks up some scheme to increase earnings
   - Worldcom (1999-2001)
     - Fake revenue entries
     - Capitalizing line costs (should be expensed)
   - Olympus (late 1980s-2011): Hide losses in a separate entity
     - “Tobashi scheme”
   - Wells Fargo (2011-2018?)
     - Fake/duplicate customers and transactions
3. Create accounting statements using the fake information

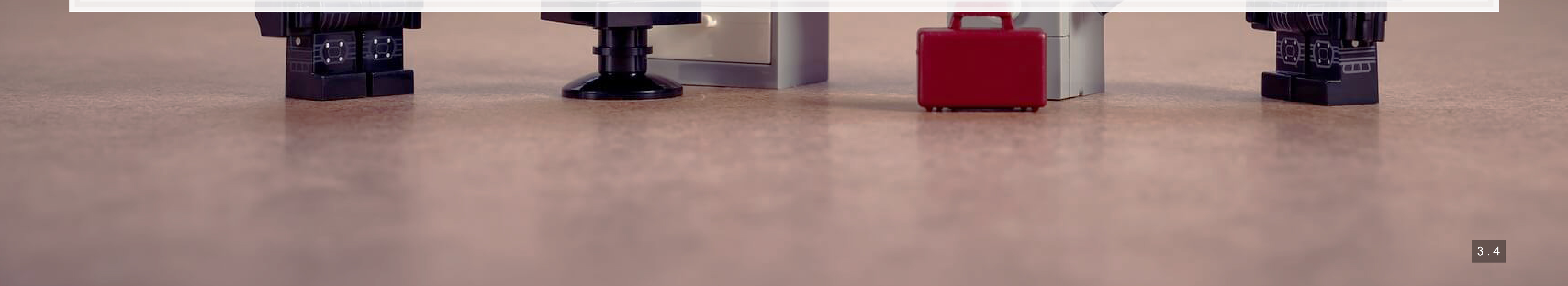


Reversing it

1. A company is overperforming
2. Management cooks up a scheme to “save up” excess performance for a rainy day
   - Dell (2002-2007)
     - Cookie jar reserve, from secret payments by Intel, made up to **76%** of quarterly income
   - Brystol-Myers Squibb (2000-2001)
3. Recognize revenue/earnings when needed in the future to hit earnings targets

Other accounting fraud types

- Apple (2001)
  - *Options backdating*
- Commerce Group Corp (2003)
  - Using an auditor that *isn't registered*
- Cardiff International (2017)
  - Releasing financial statements that were *not reviewed by an auditor*
- China North East Petroleum Holdings Limited
  - *Related party transactions* (transferring funds to family members)
- *Insufficient internal controls*
  - Citigroup (2008-2014) via Banamex
  - Asia Pacific Breweries



Other accounting fraud types

- Suprema Specialties (1998-2001)
  - *Round-tripping*: Transactions to inflate revenue that have no substance
- *Bribery*
  - Keppel O&M (2001-2014): $55M USD in bribes to Brazilian officials for contracts
  - Baker Hughes (2001, 2007): Payments to officials in Indonesia, and possibly to Brazil and India (2001) and to officials in Angola, Indonesia, Nigeria, Russia, and Uzbekistan (2007)
- ZZZZ Best (1982-1987): *Fake the whole company*, get funding from insurance fraud, theft, credit card fraud, and fake contracts
  - Also faked a real project to get a clean audit to take the company public

Other securities fraud types

- Bernard Madoff: Ponzi scheme
  1. Get money from individuals for “investments”
  2. Pretend as though the money was invested
  3. Use new investors’ money to pay back anyone withdrawing their money
- Imaging Diagnostic Systems (2013)
  - Material misstatements
  - Material omissions (FDA applications, didn’t pay payroll taxes)
- Applied Wellness Corporation (2008)
  - Failed to file annual and quarterly reports
- Capitol Distributing LLC
  - Aiding another company’s fraud (Take Two, by parking 2 video games)
- Tesla (2018)
  - Misleading statements on Twitter

Some of the more interesting cases

- AMD (1992-1993)
  - Claimed it was developing processor microcode independently, when it actually provided Intel’s microcode to it’s engineers
- Am-Pac International (1997)
  - Sham sale-leaseback of a bar to a corporate officer
- CVS (2000)
  - Not using mark-to-market accounting to fair value stuffed animal inventories
- Countryland Wellness Resorts, Inc. (1997-2000)
  - Gold reserves were actually… dirt.
- Keppel Club (2014)
  - Employees created 1,280 fake memberships, sold them, and retained all profits ($37.5M)

What will we look at today?

> Misstatements: Errors that affect firms' accounting statements or disclosures which were done seemingly *intentionally* by management or other employees at the firm.

How do misstatements come to light?

1. The company/management admits to it publicly
2. A government entity forces the company to disclose
   - In more egregious cases, government agencies may disclose the fraud publicly as well
3. Investors sue the firm, forcing disclosure

Where are these disclosed? (US)

1. US SEC AAERs: Accounting and Auditing Enforcement Releases
   - Highlight larger/more important cases, written by the SEC
   - Example: The *Summary* section of this AAER against Sanofi
2. 10-K/A filings ("10-K" $\Rightarrow$ annual report, "/A" $\Rightarrow$ amendment)
   - Note: not all 10-K/A filings are caused by fraud!
     - Benign corrections or adjustments can also be filed as a 10-K/A
     - Note: Audit Analytics' write-up on this for 2017
3. By the US government through a 13(b) action
4. In a note inside a 10-K filing
   - These are sometimes referred to as "little r" restatements
5. In a press release, which is later filed with the US SEC as an 8-K
   - 8-Ks are filed for many other reasons too though

Where are we at?

Fraud happens in many ways, for many reasons

- All of them are important to capture
- All of them affect accounting numbers differently
- None of the individual methods are frequent…

It is disclosed in many places. All have subtly different meanings and implications

- We need to be careful here (or check multiple sources)

This is a hard problem!

AAERs

- Today we will examine these AAERs
  - Using a proprietary data set of >1,000 such releases
- To get a sense of the data we're working with, read the *Summary* section (starting on page 2) of this AAER against Sanofi
  - rmc.link/420class6

> Why did the SEC release this AAER regarding Sanofi?

Predicting Fraud

Main question

> How can we *detect* if a firm *is* involved in a major instance of missreporting?

- This is a pure forensic analytics question
- “Major instance of misreporting” will be implemented using AAERs

Approaches

- In these slides, I'll walk through the primary detection methods since the 1990s, up to currently used methods
- 1990s: Financials and financial ratios
  - Follow up in 2011
- Late 2000s/early 2010s: Characteristics of firm's disclosures
- mid 2010s: More holistic text-based measures of disclosures
  - This will tie to next lesson where we will explore how to work with text

> All of these are discussed in a Brown, Crowley and Elliott (2020 JAR) – I will refer to the paper as **BCE** for short

The data

- I have provided some preprocessed data, sanitized of AAER data (which is partially public, partially proprietary)
- It contains 401 variables
  - From Compustat, CRSP, and the SEC (which I personally collected)
  - Many precalculated measures including:
    - Firm characteristics, such as auditor type (`bigNaudit`, `midNaudit`)
    - Financial measures, such as total accruals (`rsst_acc`)
    - Financial ratios, such as ROA (`ni_at`)
    - Annual report characteristics, such as the mean sentence length (`sentlen_u`)
    - Machine learning based content analysis (everything with `Topic_` prepended)

> Pulled from BCE's working files

Training and Testing

- Already has testing and training set up in variable `Test`
  - Training is annual reports released in 1999 through 2003
  - Testing is annual reports released in 2004

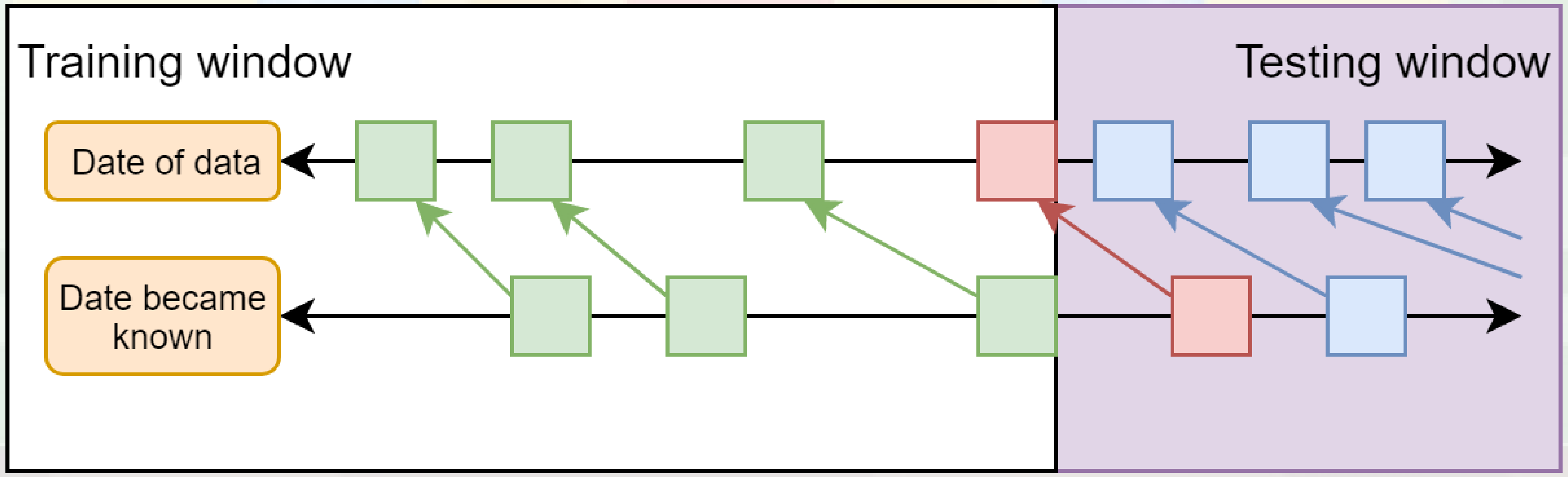
> What potential issues are there with our usual training and testing strategy?

- There is a significant lag between when a fraud is caught and when a fraud actually happened!
  - To mirror the available information in 2004, we should *censor* `AAER` for training such that it only captures AAERs known by 2003

year	year_found	aaer	aaer_as_of_2004
1999	2001	1	1
2001	2003	1	1
2003	2006	1	0

Censoring

- Censoring training data helps to emulate historical situations
  - Build an algorithm using only the data that was available at the time a decision would need to have been made
- **Do not censor the testing data**
  - Testing emulates where we want to make an optimal choice in real life
    - We want to find frauds regardless of how well hidden they are!



Event frequency

- Very low event frequencies can make things tricky

```
df %>%
  group_by(year) %>%
  mutate(total_AAERS = sum(AAER), total_observations=n()) %>%
  slice(1) %>%
  ungroup() %>%
  select(year, total_AAERS, total_observations) %>%
  html_df
```

year	total_AAERS	total_observations
1999	46	2195
2000	50	2041
2001	43	2021
2002	50	2391
2003	57	2936
2004	49	2843

> 246 AAERs in the training data, 401 total variables…

Dealing with infrequent events

- A few ways to handle this
  1. Very careful model selection (keep it sufficiently simple)
  2. Sophisticated degenerate variable identification criterion + simulation to implement complex models that are just barely simple enough
     - The main method in BCE
  3. Automated methodologies for pairing down models
     - We'll discuss using LASSO for this at the end of class
       - Also implemented in BCE

1990s approach

The 1990s model

- Many financial measures and ratios can help to predict fraud

- EBIT
- Earnings / revenue
- ROA
- Log of liabilities
- liabilities / equity
- liabilities / assets
- quick ratio
- Working capital / assets
- Inventory / revenue
- inventory / assets
- earnings / PP&E
- A/R / revenue

- Change in revenue
- Change in A/R + 1
- $> 10\%$ change in A/R
- Change in gross profit + 1
- $> 10\%$ change in gross profit
- Gross profit / assets
- Revenue minus gross profit
- Cash / assets
- Log of assets
- PP&E / assets
- Working capital

Theory

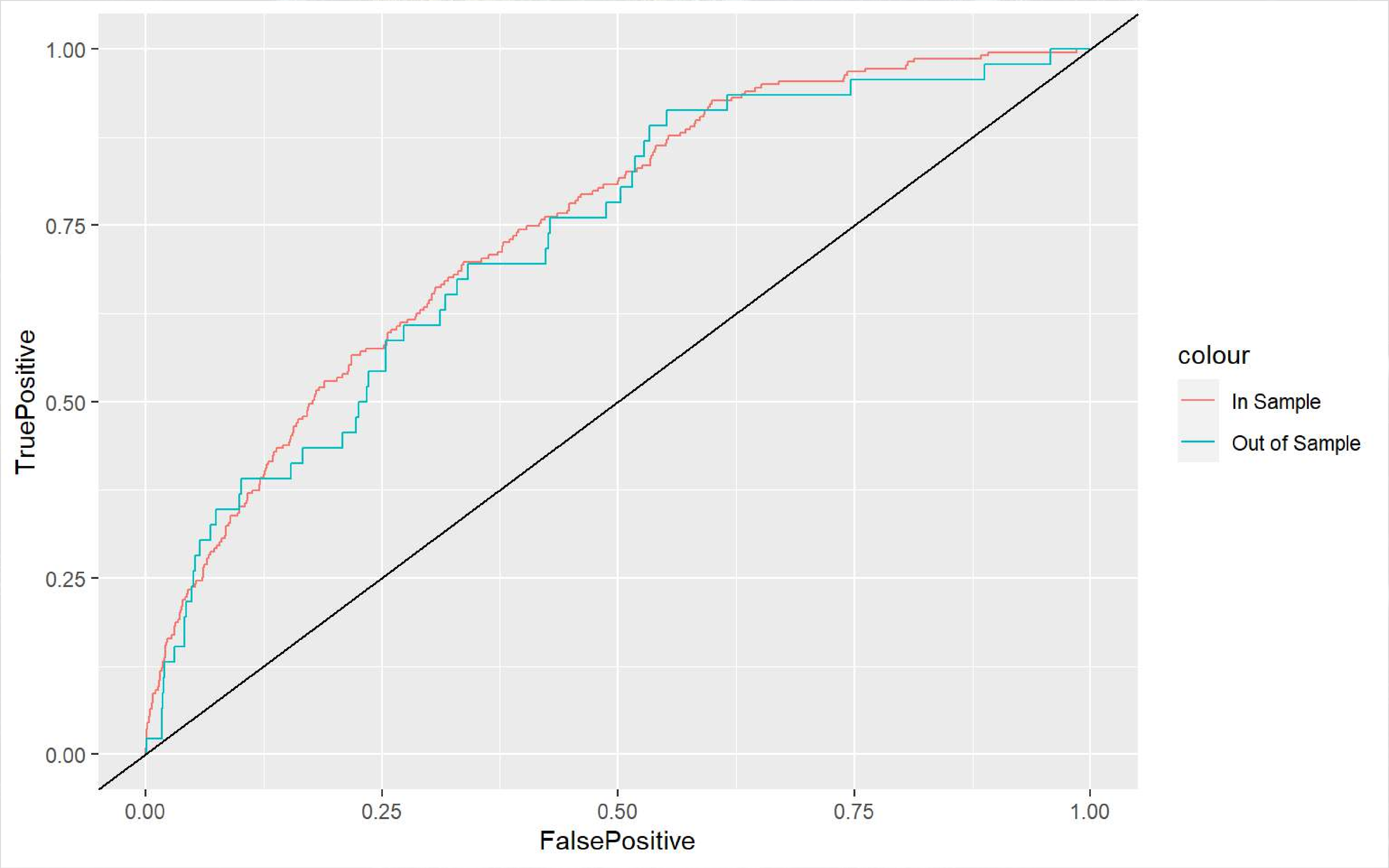
- Purely economic
- Misreporting firms' financials should be different than expected
  - Perhaps more income
  - Odd capital structure
  - Odd balance of receivables

Approach

```
fit_1990s <- glm(AAER ~ ebit + ni_revt + ni_at + log_lt + ltl_at + lt_seq +
                   lt_at + act_lct + aq_lct + wcap_at + invt_revt + invt_at +
                   ni_ppent + rect_revt + revt_at + d_revt + b_rect + b_rect +
                   r_gp + b_gp + gp_at + revt_m_gp + ch_at + log_at +
                   ppent_at + wcap,
                 data=df[df$Test==0,],
                 family=binomial)
summary(fit_1990s)
```

```
##
## Call:
## glm(formula = AAER ~ ebit + ni_revt + ni_at + log_lt + ltl_at +
##     lt_seq + lt_at + act_lct + aq_lct + wcap_at + invt_revt +
##     invt_at + ni_ppent + rect_revt + revt_at + d_revt + b_rect +
##     b_rect + r_gp + b_gp + gp_at + revt_m_gp + ch_at + log_at +
##     ppent_at + wcap, family = binomial, data = df[df$Test ==
##     0, ])
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.1391  -0.2275  -0.1661  -0.1190   3.6236
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -4.660e+00  8.336e-01  -5.591 2.26e-08 ***
## ebit        -3.564e-04  1.094e-04  -3.257  0.00112 **
## ni_revt      3.664e-02  3.058e-02   1.198  0.23084
## ni_at       -3.196e-01  2.325e-01  -1.374  0.16932
## log_lt       1.494e-01  3.409e-01   0.438  0.66118
## ltl_at      -2.306e-01  7.072e-01  -0.326  0.74438
```

ROC




```
##      In sample AUC Out of sample AUC
##          0.7483132         0.7292981
```

The 2011 follow up

The 2011 model

- Log of assets
- Total accruals
- % change in A/R
- % change in inventory
- % soft assets
- % change in sales from cash
- % change in ROA
- Indicator for stock/bond issuance
- Indicator for operating leases
- BV equity / MV equity
- Lag of stock return minus value weighted market return
- **Below are BCE's additions**
- Indicator for mergers
- Indicator for Big N auditor
- Indicator for medium size auditor
- Total financing raised
- Net amount of new capital raised
- Indicator for restructuring

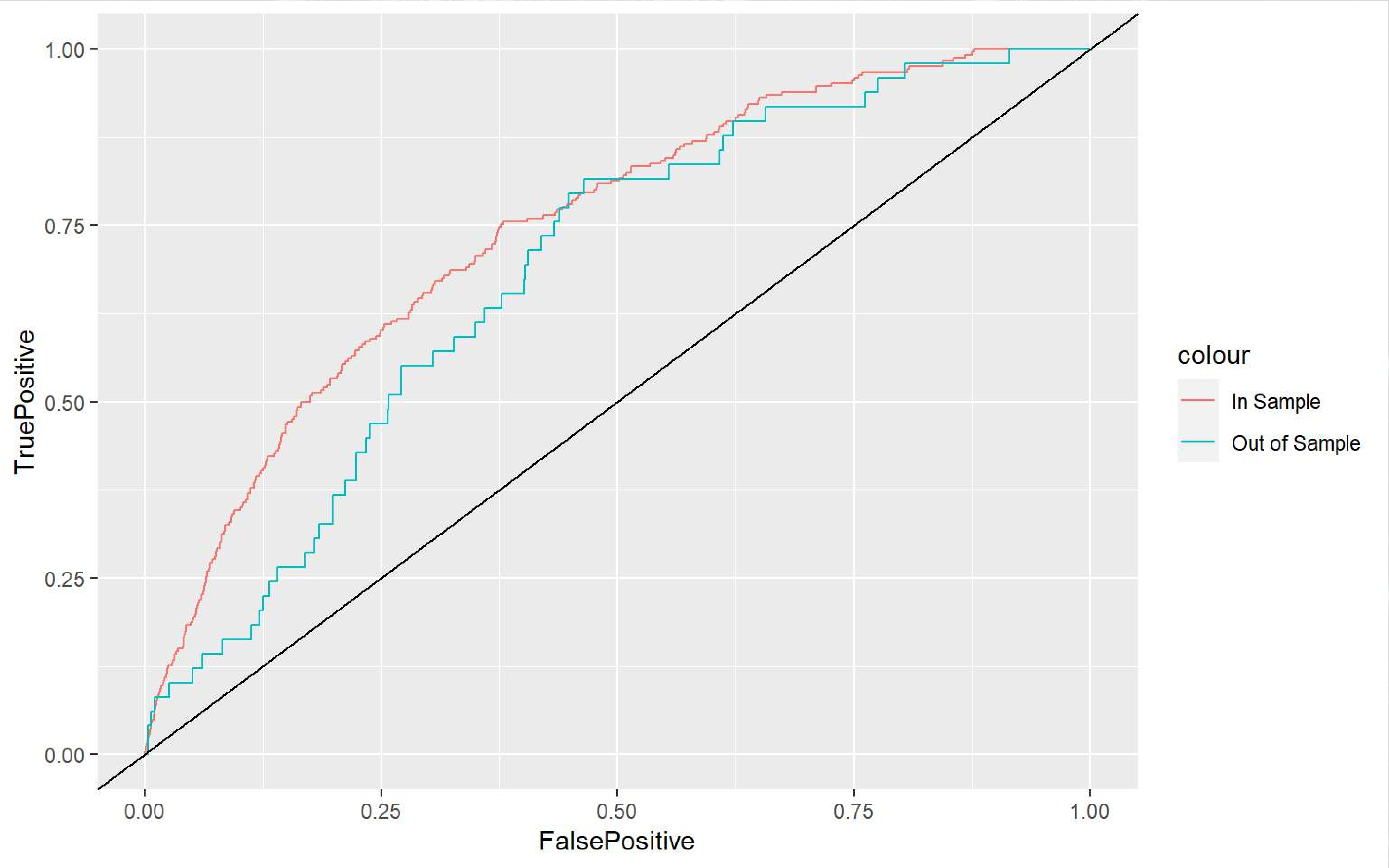
> Based on Dechow, Ge, Larson and Sloan (2011)

The model

```r
fit_2011 <- glm(AAER ~ logtotasset + rsst_acc + chg_recv + chg_inv +
                  soft_assets + pct_chg_cashsales + chg_roa + issuance +
                  oplease_dum + book_mkt + lag_sdvol + merger + bigNaudit +
                  midNaudit + cffin + exfin + restruct,
                data=df[df$Test==0,],
                family=binomial)
summary(fit_2011)
```

```
##
## Call:
## glm(formula = AAER ~ logtotasset + rsst_acc + chg_recv + chg_inv +
##     soft_assets + pct_chg_cashsales + chg_roa + issuance + oplease_dum +
##     book_mkt + lag_sdvol + merger + bigNaudit + midNaudit + cffin +
##     exfin + restruct, family = binomial, data = df[df$Test ==
##     0, ])
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8434  -0.2291  -0.1658  -0.1196   3.2614
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -7.1474558  0.5337491 -13.391  < 2e-16 ***
## logtotasset        0.3214322  0.0355467   9.043  < 2e-16 ***
## rsst_acc          -0.2190095  0.3009287  -0.728   0.4667
## chg_recv           1.1020740  1.0590837   1.041   0.2981
## chg_inv            0.0389504  1.2507142   0.031   0.9752
## soft_assets        2.3094551  0.3325731   6.944 3.81e-12 ***
## pct_chg_cashsales -0.0006912  0.0108771  -0.064   0.9493
```

ROC




```
##      In sample AUC Out of sample AUC
##          0.7445378         0.6849225
```

Late 2000s/early 2010s approach

The late 2000s/early 2010s model

- Log of # of bullet points + 1
- # of characters in file header
- # of excess newlines
- Amount of html tags
- Length of cleaned file, characters
- Mean sentence length, words
- S.D. of word length
- S.D. of paragraph length (sentences)

- Word choice variation
- Readability
  - Coleman Liau Index
  - Fog Index
- % active voice sentences
- % passive voice sentences
- # of all cap words
- # of !
- # of ?

From a variety of papers

Theory

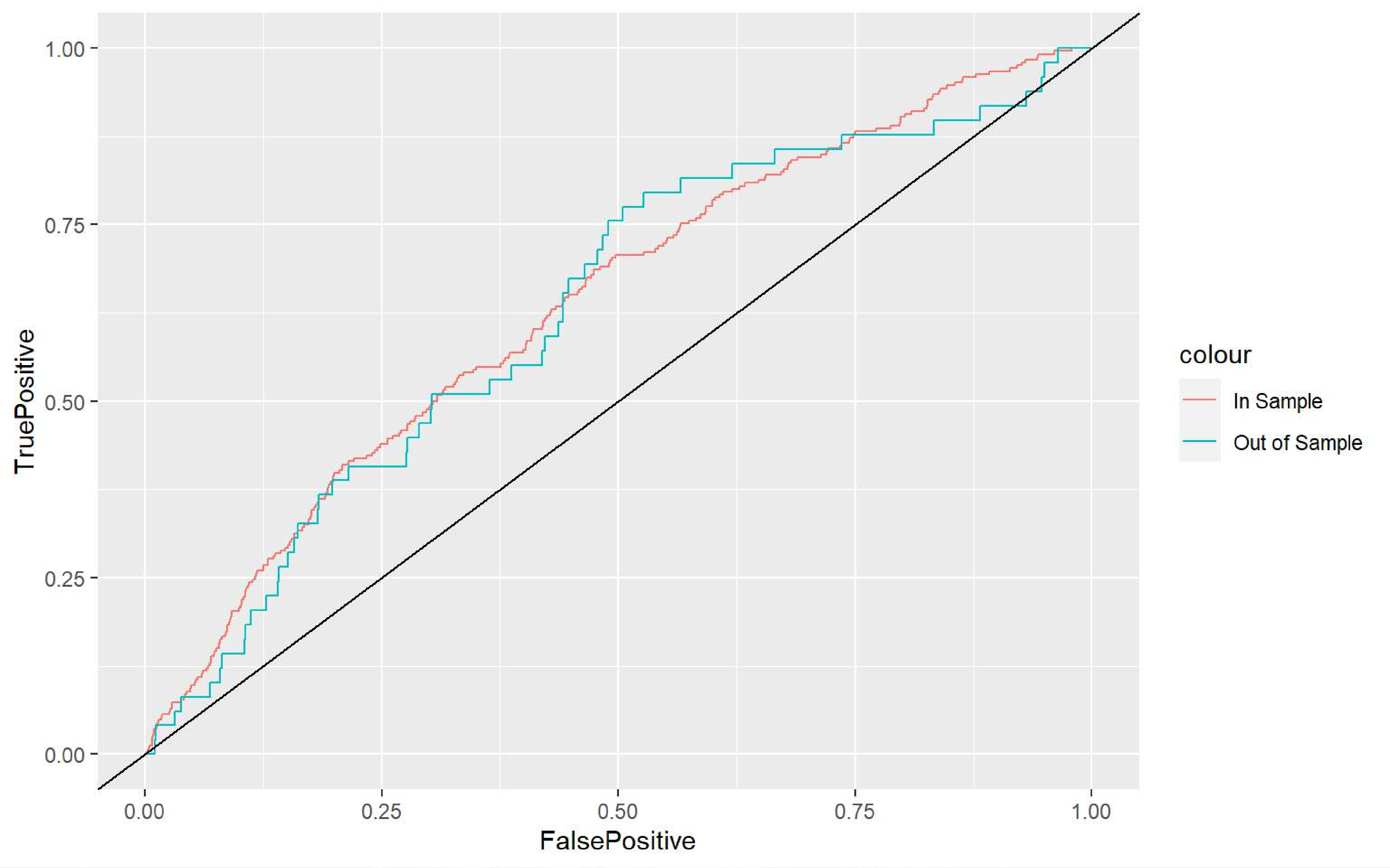
- Generally pulled from the communications literature
  - Sometimes ad hoc
- The main idea:
  - Companies that are misreporting probably write their annual report differently

The late 2000s/early 2010s model

```r
fit_2000s <- glm(AAER ~ bullets + headerlen + newlines + alltags +
                   processedsize + sentlen_u + wordlen_s + paralen_s +
                   repetitious_p + sentlen_s + typetoken + clindex + fog +
                   active_p + passive_p + lm_negative_p + lm_positive_p +
                   allcaps + exclamationpoints + questionmarks,
                 data=df[df$Test==0,],
                 family=binomial)
summary(fit_2000s)
```

```
##
## Call:
## glm(formula = AAER ~ bullets + headerlen + newlines + alltags +
##     processedsize + sentlen_u + wordlen_s + paralen_s + repetitious_p +
##     sentlen_s + typetoken + clindex + fog + active_p + passive_p +
##     lm_negative_p + lm_positive_p + allcaps + exclamationpoints +
##     questionmarks, family = binomial, data = df[df$Test == 0,
##     ])
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.9604  -0.2244  -0.1984  -0.1749   3.2318
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -5.662e+00  3.143e+00  -1.801  0.07165 .
## bullets           -2.635e-05  2.625e-05  -1.004  0.31558
## headerlen         -2.943e-04  3.477e-04  -0.846  0.39733
## newlines          -4.821e-05  1.220e-04  -0.395  0.69271
## alltags            5.060e-08  2.567e-07   0.197  0.84376
## processedsize      5.709e-06  1.287e-06   4.435 9.19e-06 ***
```

ROC




```
##      In sample AUC Out of sample AUC
##          0.6377783         0.6295414
```

Combining the 2000s and 2011 models

Why is it appropriate to combine the 2011 model with the 2000s model?

- 2011 model: Parsimonious financial model
- 2000s model: Textual characteristics

Little theoretical overlap

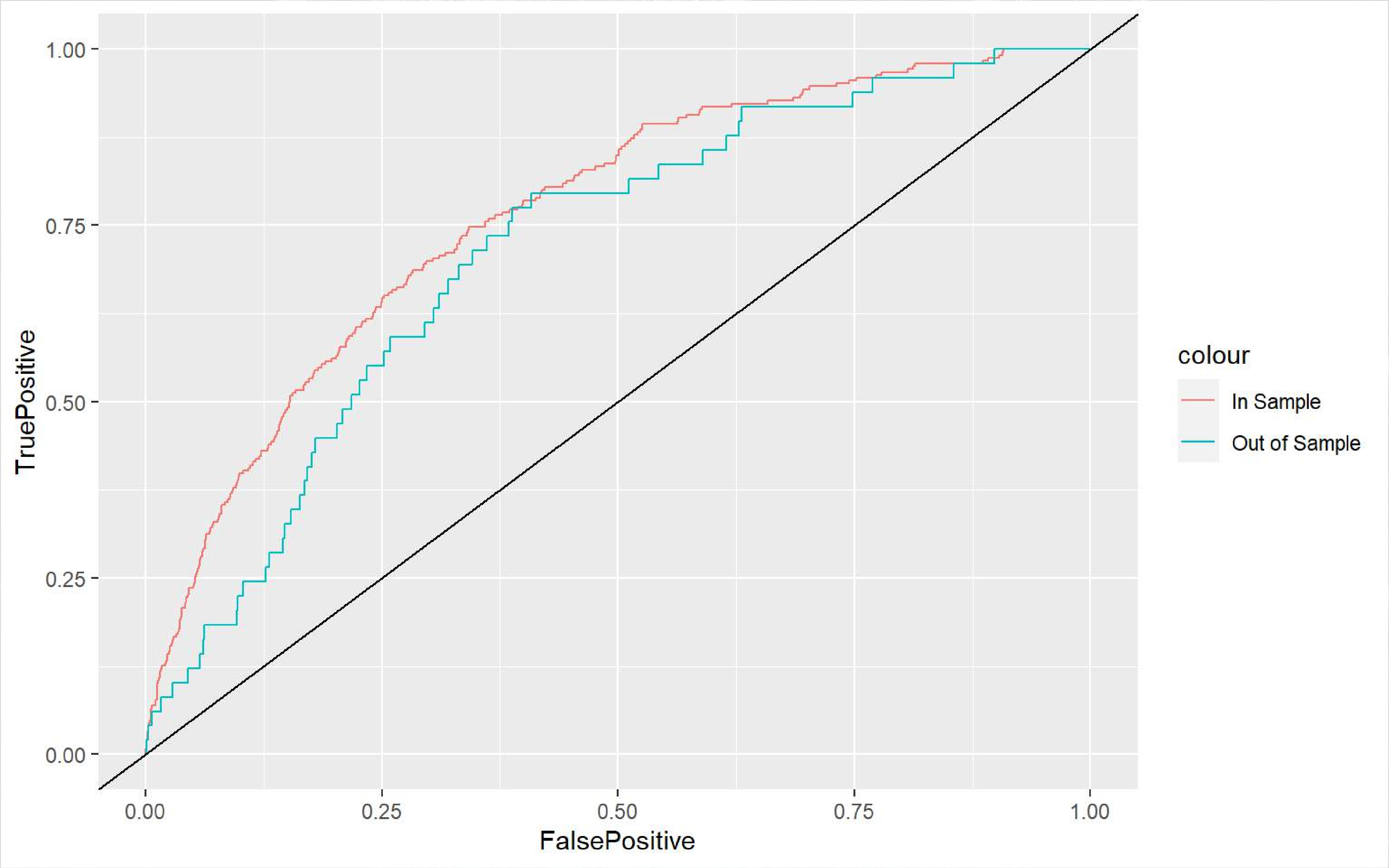
Limited multicollinearity across measures

The model

```r
fit_2000f <- glm(AAER ~ logtotasset + rsst_acc + chg_recv + chg_inv +
                   soft_assets + pct_chg_cashsales + chg_roa + issuance +
                   oplease_dum + book_mkt + lag_sdvol + merger + bigNaudit +
                   midNaudit + cffin + exfin + restruct + bullets + headerlen +
                   newlines + alltags + processedsize + sentlen_u + wordlen_s +
                   paralen_s + repetitious_p + sentlen_s + typetoken +
                   clindex + fog + active_p + passive_p + lm_negative_p +
                   lm_positive_p + allcaps + exclamationpoints + questionmarks,
                 data=df[df$Test==0,],
                 family=binomial)
summary(fit_2000f)
```

```
##
## Call:
## glm(formula = AAER ~ logtotasset + rsst_acc + chg_recv + chg_inv +
##     soft_assets + pct_chg_cashsales + chg_roa + issuance + oplease_dum +
##     book_mkt + lag_sdvol + merger + bigNaudit + midNaudit + cffin +
##     exfin + restruct + bullets + headerlen + newlines + alltags +
##     processedsize + sentlen_u + wordlen_s + paralen_s + repetitious_p +
##     sentlen_s + typetoken + clindex + fog + active_p + passive_p +
##     lm_negative_p + lm_positive_p + allcaps + exclamationpoints +
##     questionmarks, family = binomial, data = df[df$Test == 0,
##     ])
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.9514  -0.2237  -0.1596  -0.1110   3.3882
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -1.634e+00  3.415e+00  -0.479  0.63223
```

ROC




```
##     In sample AUC Out of sample AUC
##         0.7664115         0.7147021
```

The BCE model

The BCE approach

- Retain the variables from the other regressions
- Add in a machine-learning based measure quantifying how much documents talked about different topics common across all filings
    - Learned on just the 1999-2003 filings

What the topics look like

Topic 6

Topic 11

Topic 21

Topic 30

Topic 2

Topic 9

Topic 12

Topic 26

Topic 8

Topic 19

Theory behind the BCE model

> Why use document content?

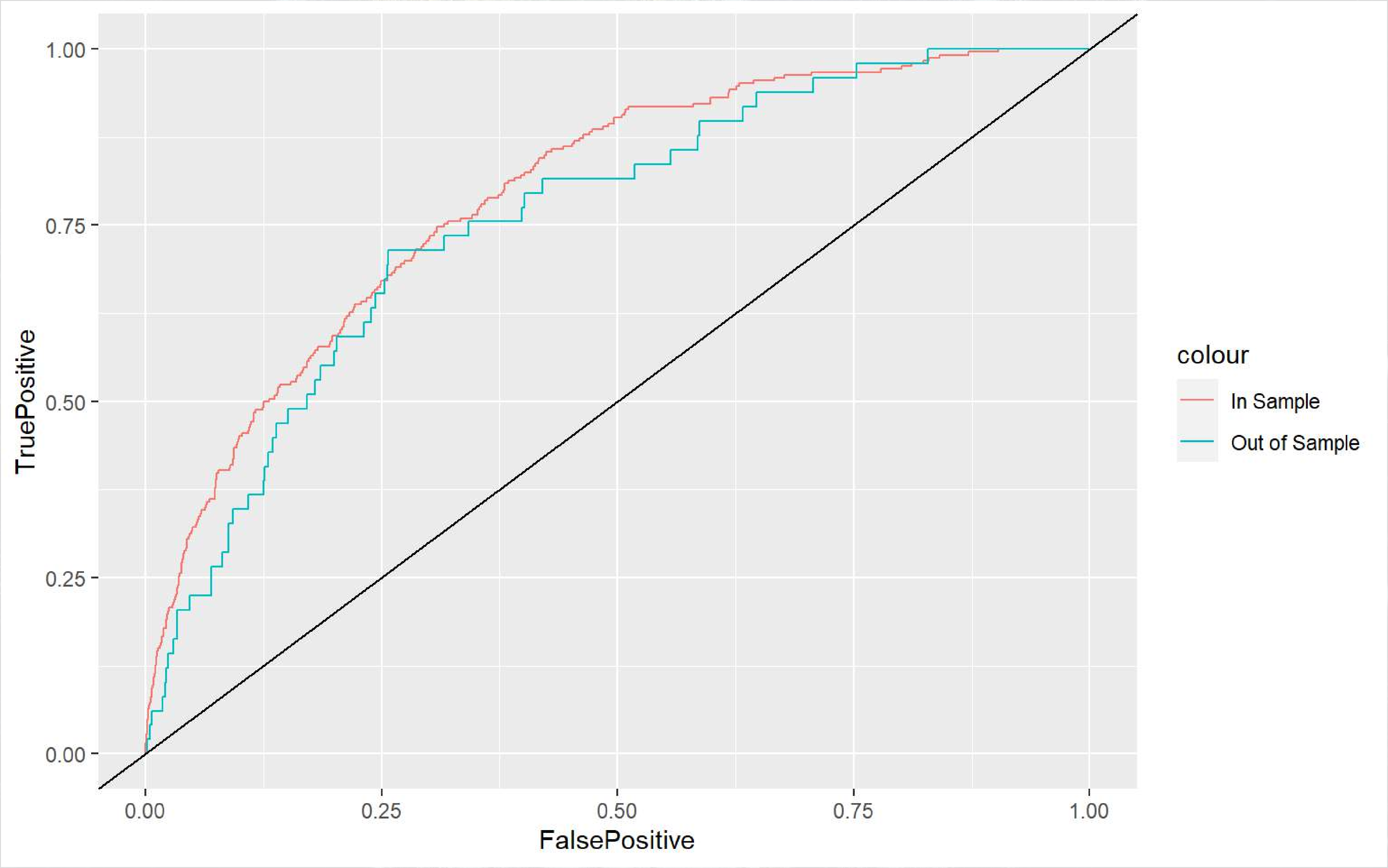
- From communications and psychology:
  - When people are trying to deceive others, what they say is carefully picked
    - Topics chosen are intentional
- Putting this in a business context:
  - If you are manipulating inventory, you don’t talk about it

The model

```r
BCE_eq = as.formula(paste("AAER ~ logtotasset + rsst_acc + chg_recv + chg_inv +
  soft_assets + pct_chg_cashsales + chg_roa + issuance +
  oplease_dum + book_mkt + lag_sdvol + merger + bigNaudit +
  midNaudit + cffin + exfin + restruct + bullets + headerlen +
  newlines + alltags + processedsize + sentlen_u + wordlen_s +
  paralen_s + repetitious_p + sentlen_s + typetoken +
  clindex + fog + active_p + passive_p + lm_negative_p +
  lm_positive_p + allcaps + exclamationpoints + questionmarks + ",
  paste(paste0("Topic_",1:30,"_n_oI"), collapse=" + "), collapse=""))
fit_BCE <- glm(BCE_eq,
               data=df[df$Test==0,],
               family=binomial)
summary(fit_BCE)
```

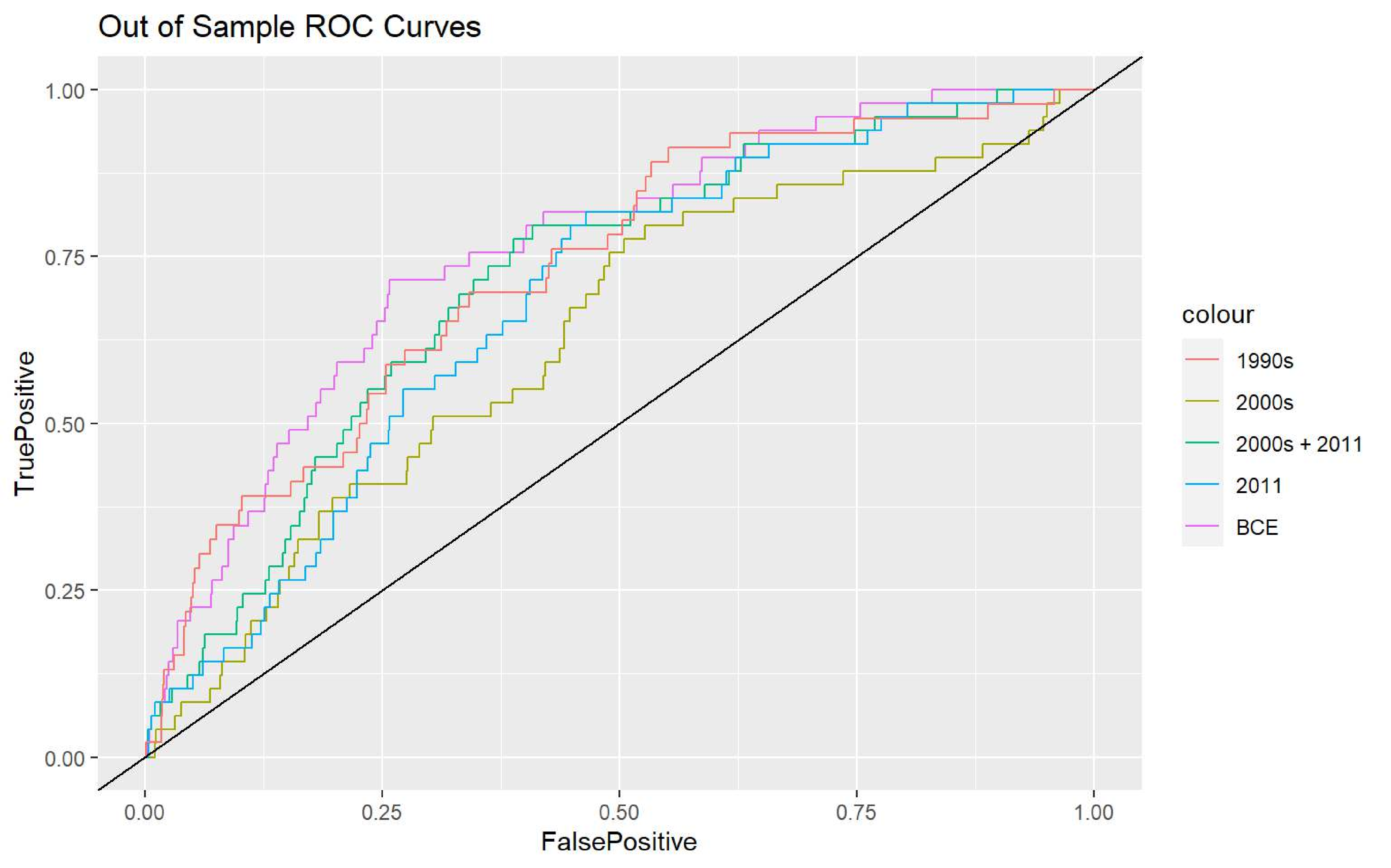
```
##
## Call:
## glm(formula = BCE_eq, family = binomial, data = df[df$Test ==
##     0, ])
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0887  -0.2212  -0.1478  -0.0940   3.5401
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)        -8.032e+00  3.872e+00  -2.074  0.03806 *
## logtotasset         3.879e-01  4.554e-02   8.519  < 2e-16 ***
## rsst_acc           -1.938e-01  3.055e-01  -0.634  0.52593
## chg_recv            8.581e-01  1.071e+00   0.801  0.42296
## chg_inv            -2.607e-01  1.223e+00  -0.213  0.83119
## soft_assets         2.555e+00  3.796e-01   6.730  1.7e-11 ***
```

ROC




```
##      In sample AUC Out of sample AUC
##          0.7941841         0.7599594
```

Comparison across all models




```
##       1990s         2011        2000s 2000s + 2011          BCE
##   0.7292981    0.6849225    0.6295414    0.7147021    0.7599594
```

Simplifying models with LASSO

What is LASSO?

- Least Absolute Shrinkage and Selection Operator
  - Least absolute: uses an error term like $|\varepsilon|$
  - Shrinkage: it will make coefficients smaller
    - Less sensitive → less overfitting issues
  - Selection: it will completely remove some variables
    - Less variables → less overfitting issues
- Sometimes called L^1 regularization
  - L^1 means 1 dimensional distance, i.e., $|\varepsilon|$

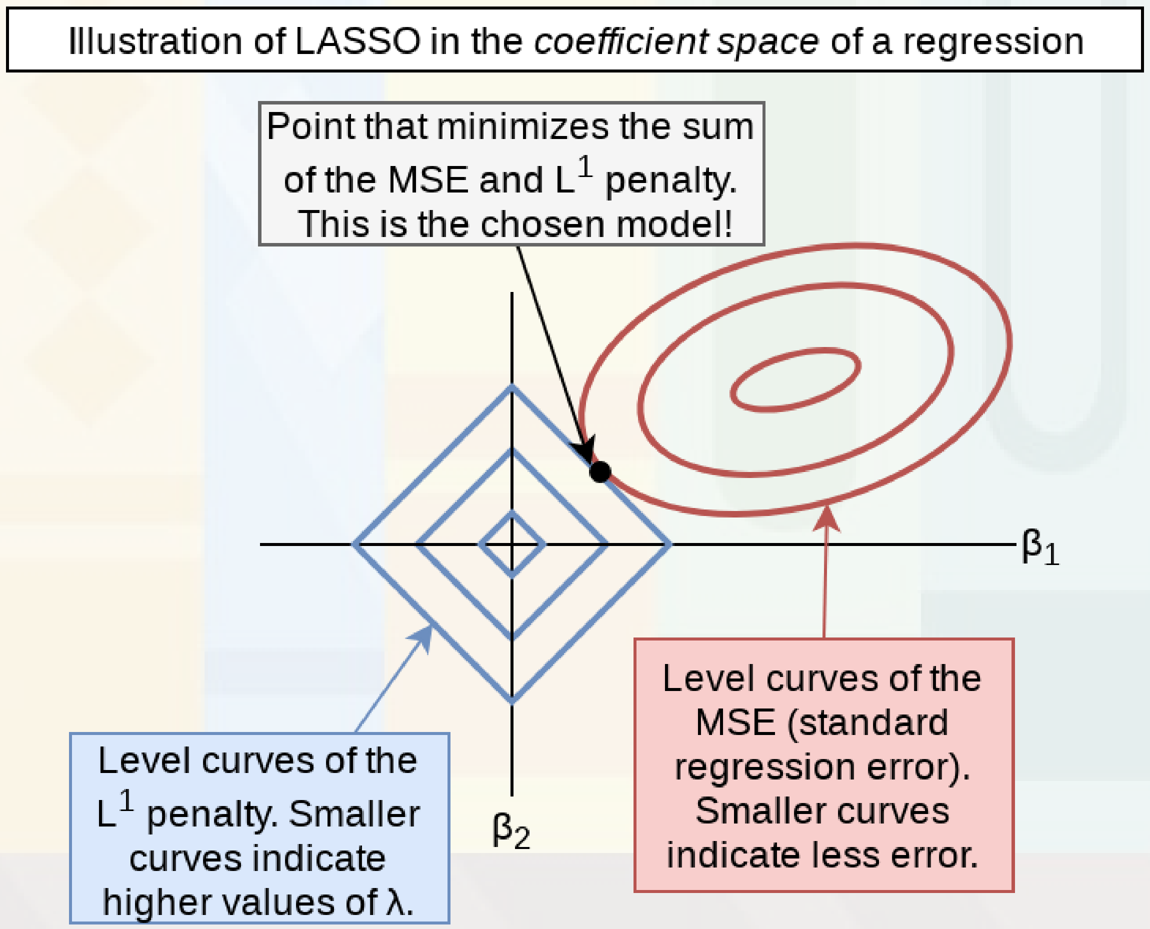
> Great if you have way too many inputs in your model

- This is how we can, in theory, put more variables in our model than data points

How does it work?

$$\min_{\beta \in \mathbb{R}} \left\{ \frac{1}{N} |\varepsilon|_2^2 + \lambda |\beta|_1 \right\}$$

- Add an additional penalty term that is increasing in the absolute value of each β
  - Incentivizes lower βs, *shrinking* them
- The selection is part is explainable geometrically



Why use it?

1. We have a preference for simpler models
2. Some problems are naturally very complex
   - Many linkages between different theoretical constructs
3. We don't have a good judgment on what theories are better than others for the problem

> LASSO lets us implement all of our ideas, and then it econometrically kicks out the ineffective ideas (model selection)

Package for LASSO

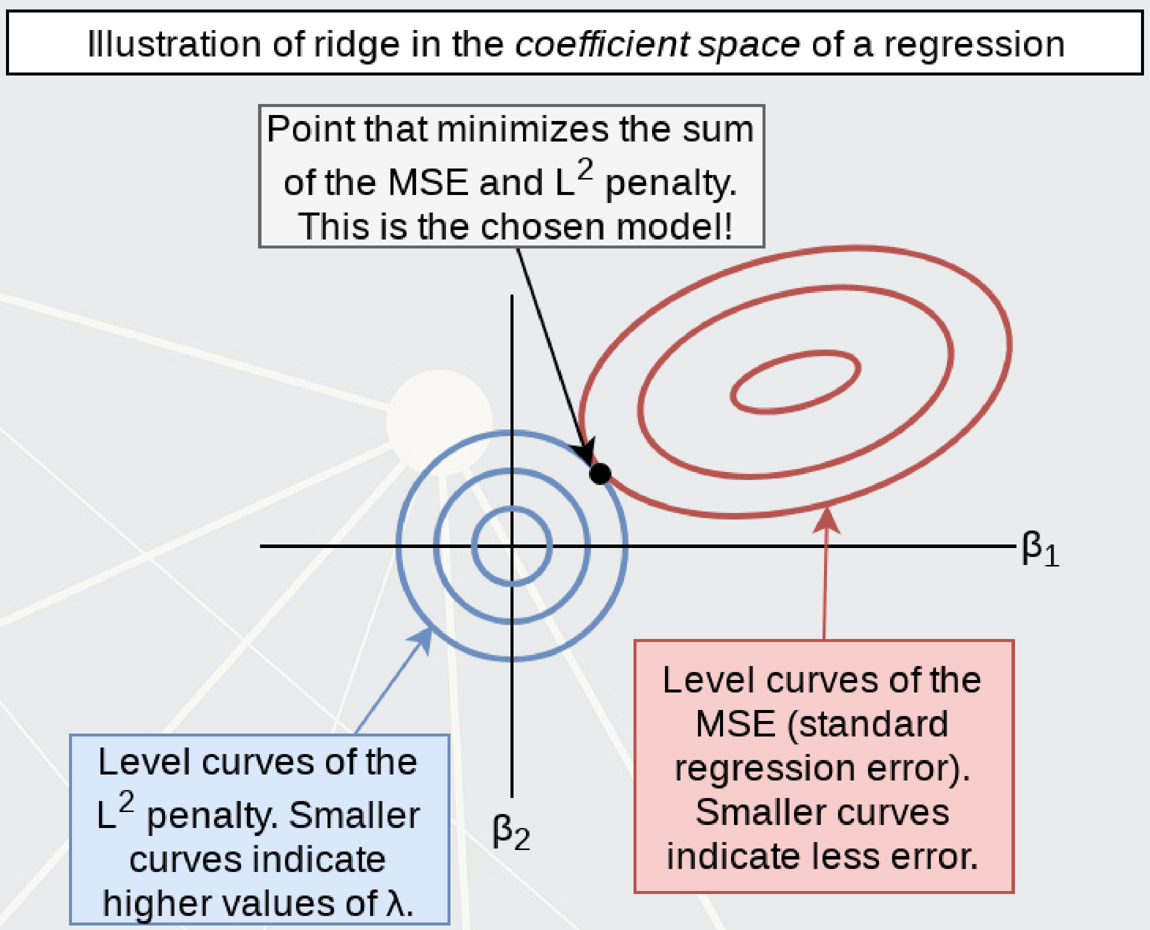
- `glmnet`

1. For all regression commands, they expect a `y` vector and an `x` matrix instead of our usual `y ~ x` formula
   - R has a helper function to convert a formula to a matrix: `model.matrix()`
     - Supply it the right hand side of the equation, starting with `~`, and your data
     - It outputs the matrix `x`
   - Alternatively, use `as.matrix()` on a data frame of your input variables
2. It’s family argument should be specified in quotes, i.e., `"binomial"` instead of `binomial`

What else can the package do?

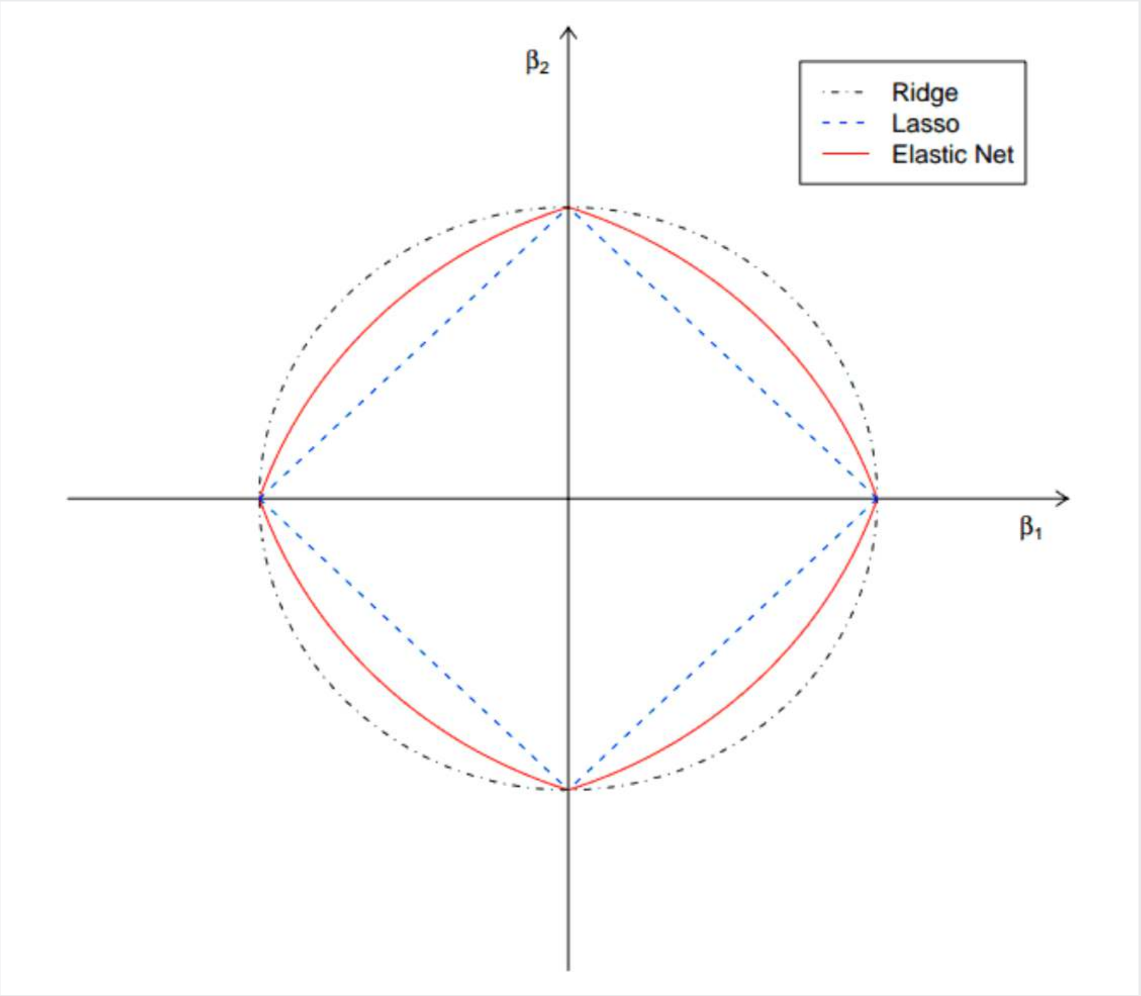
Ridge regression

- Similar to LASSO, but with an L^2 penalty (Euclidean norm)



Elastic net regression

- Hybrid of LASSO and Ridge
- Below image by Jared Lander



How to run a LASSO

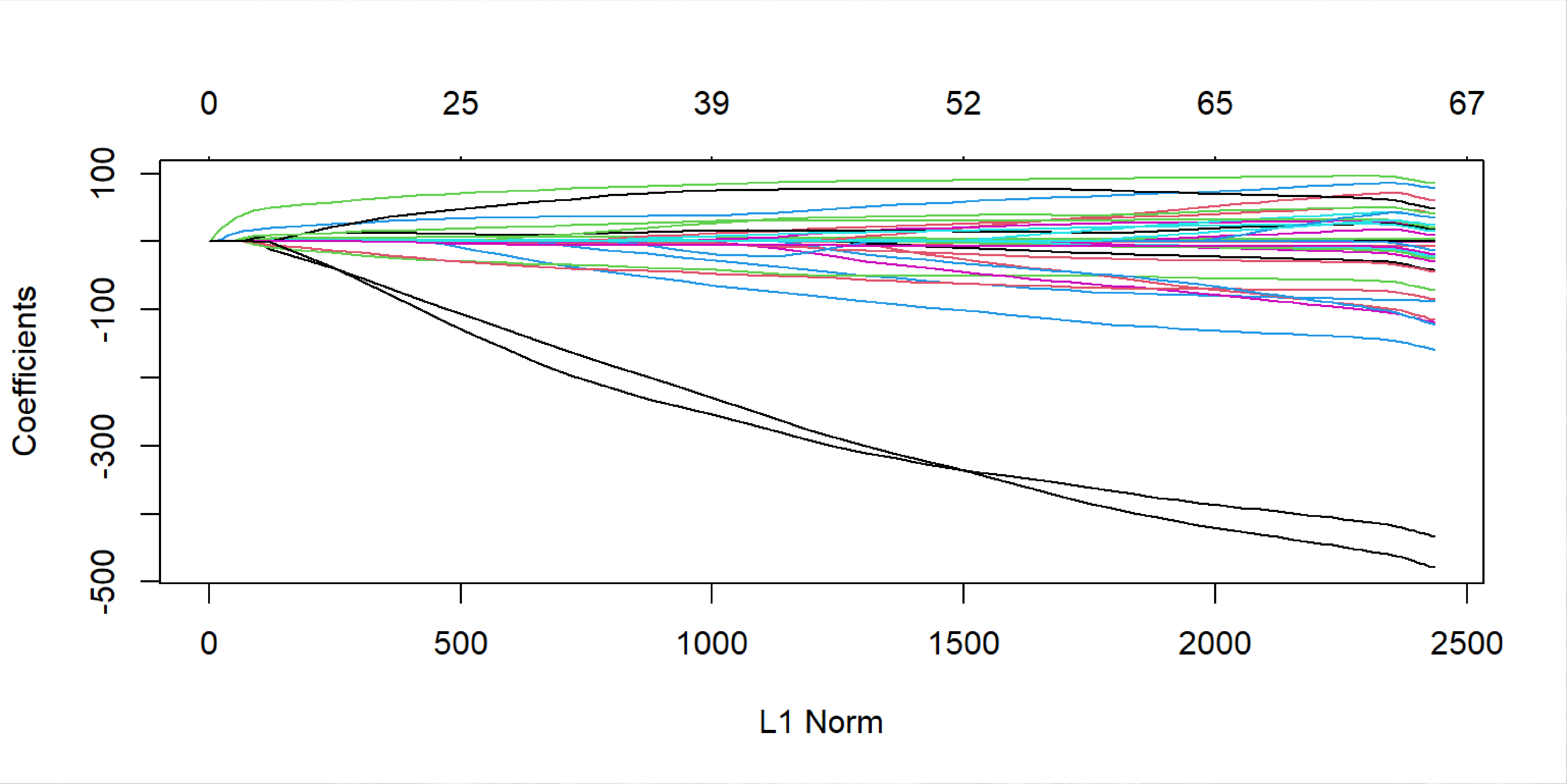
- To run a simple LASSO model, use `glmnet()`
- Let's LASSO the BCE model

```
library(glmnet)
x <- model.matrix(BCE_eq, data=df[df$Test==0,])[,-1]  # [,-1] to remove intercept
y <- model.frame(BCE_eq, data=df[df$Test==0,])[,"AAER"]
fit_LASSO <- glmnet(x=x, y=y,
                    family = "binomial",
                    alpha = 1  # Specifies LASSO.  alpha = 0 is ridge
                    )
```

- Note: the model selection can be more elegantly done using the `useful` package, see here for an example

Visualizing Lasso

```
plot(fit_LASSO)
```



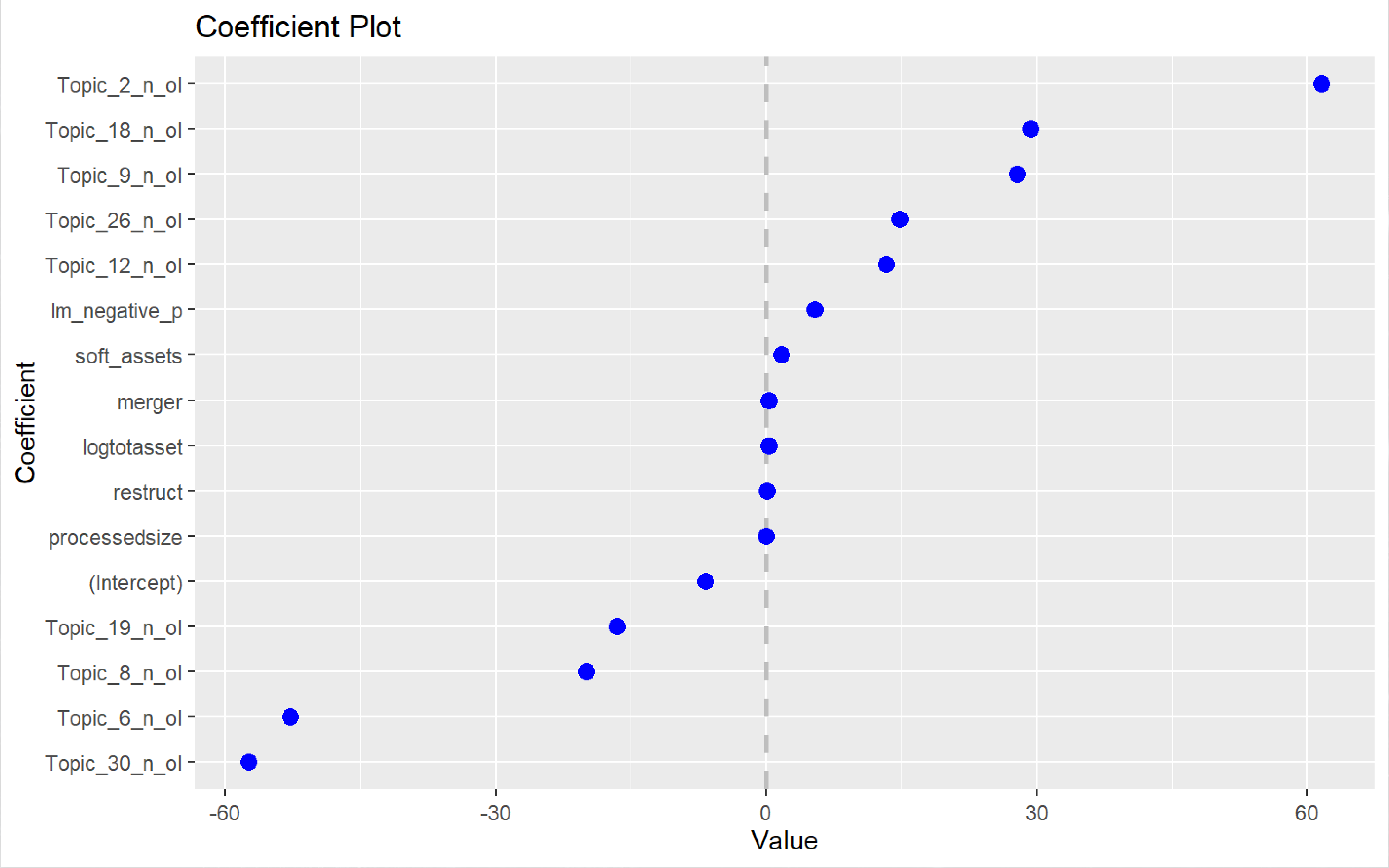
What’s under the hood?

```r
print(fit_LASSO)
```

```
##
## Call:  glmnet(x = x, y = y, family = "binomial", alpha = 1)
##
##    Df  %Dev    Lambda
## 1   0  0.00 0.0143300
## 2   1  0.81 0.0130500
## 3   1  1.46 0.0118900
## 4   1  2.00 0.0108400
## 5   2  2.47 0.0098740
## 6   2  3.22 0.0089970
## 7   2  3.85 0.0081970
## 8   2  4.37 0.0074690
## 9   2  4.81 0.0068060
## 10  3  5.22 0.0062010
## 11  3  5.59 0.0056500
## 12  4  5.91 0.0051480
## 13  4  6.25 0.0046910
## 14  5  6.57 0.0042740
## 15  7  6.89 0.0038940
## 16  8  7.22 0.0035480
## 17 10  7.52 0.0032330
```

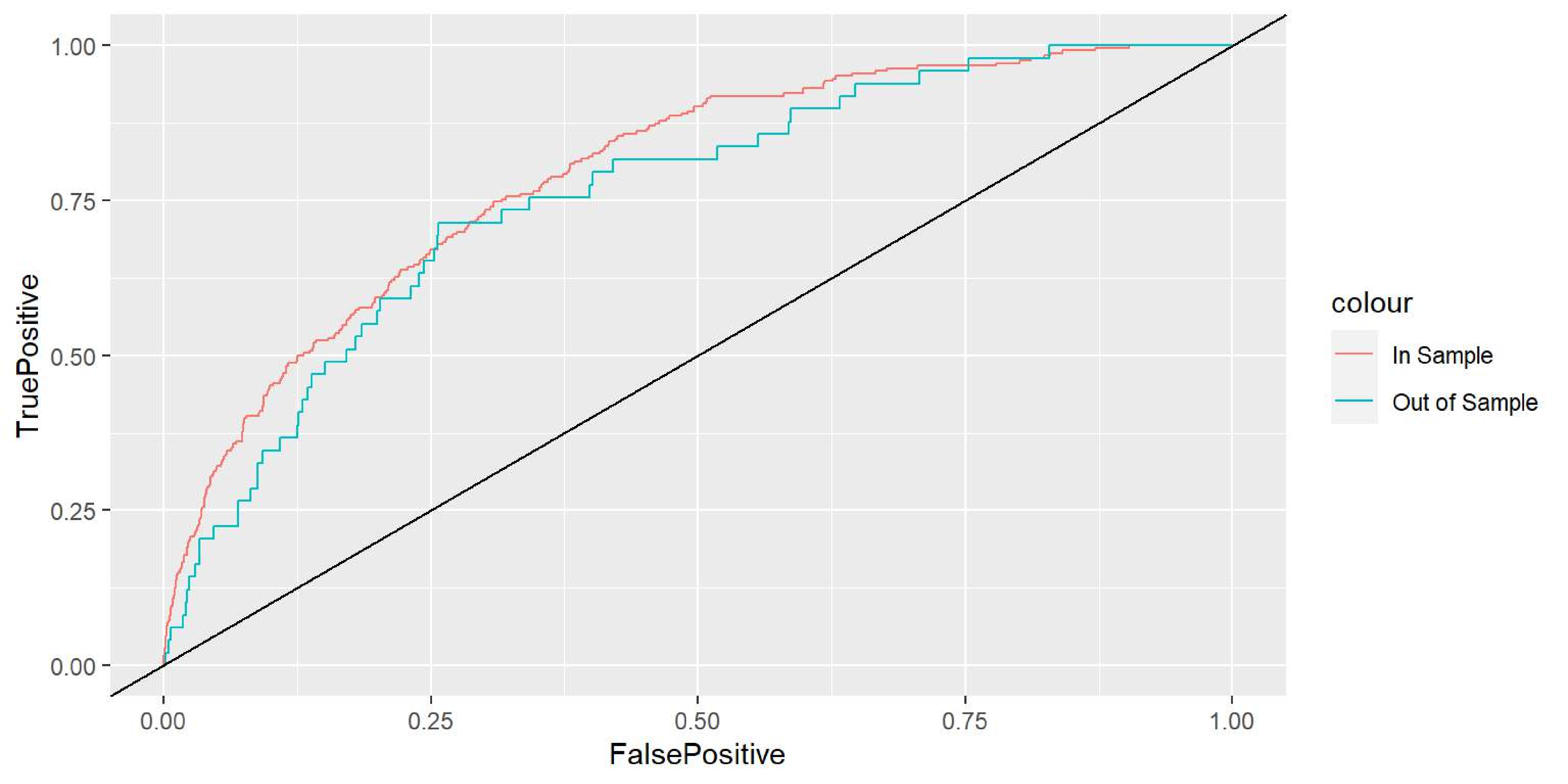
One of the 100 models

```r
#coef(fit_LASSO, s=0.002031)
coefplot(fit_LASSO, lambda=0.002031, sort='magnitude')
```



How does this perform?

```r
# na.pass has model.matrix retain NA values (so the # of rows is constant)
xp <- model.matrix(BCE_eq, data=df, na.action='na.pass')[,-1]
# s= specifies the version of the model to use
pred <- predict(fit_LASSO, xp, type="response", s = 0.002031)
```




```
##     In sample AUC Out of sample AUC
##         0.7593828         0.7239785
```

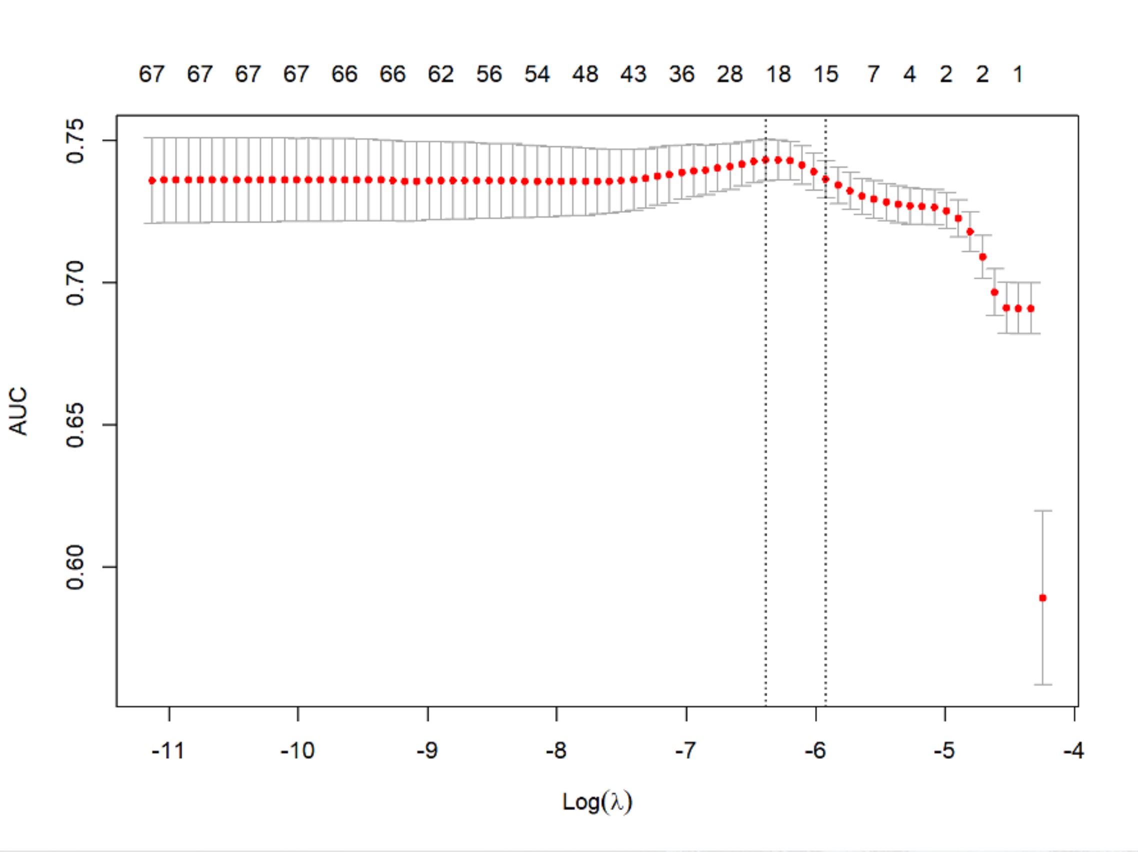
Automating model selection

- LASSO seems nice, but picking between the 100 models is tough!
- It also contains a method of *k-fold cross validation* (default, $k = 10$)
  1. Randomly splits the data into k groups
  2. Runs the algorithm on 90% of the data ($k - 1$ groups)
  3. Determines the best model
  4. Repeat steps 2 and 3 $k - 1$ more times
  5. Uses the best overall model across all k hold out samples
- It gives 2 model options:
  - `"lambda.min"`: The best performing model
  - `"lambda.1se"`: The simplest model within 1 standard error of `"lambda.min"`
    - This is the better choice if you are concerned about overfitting

Running a cross validated model

```r
# Cross validation
set.seed(697435)  #for reproducibility
cvfit = cv.glmnet(x=x, y=y,family = "binomial", alpha = 1, type.measure="auc")
```

```r
plot(cvfit)
```




```r
cvfit$lambda.min
```

```
## [1] 0.001685798
```

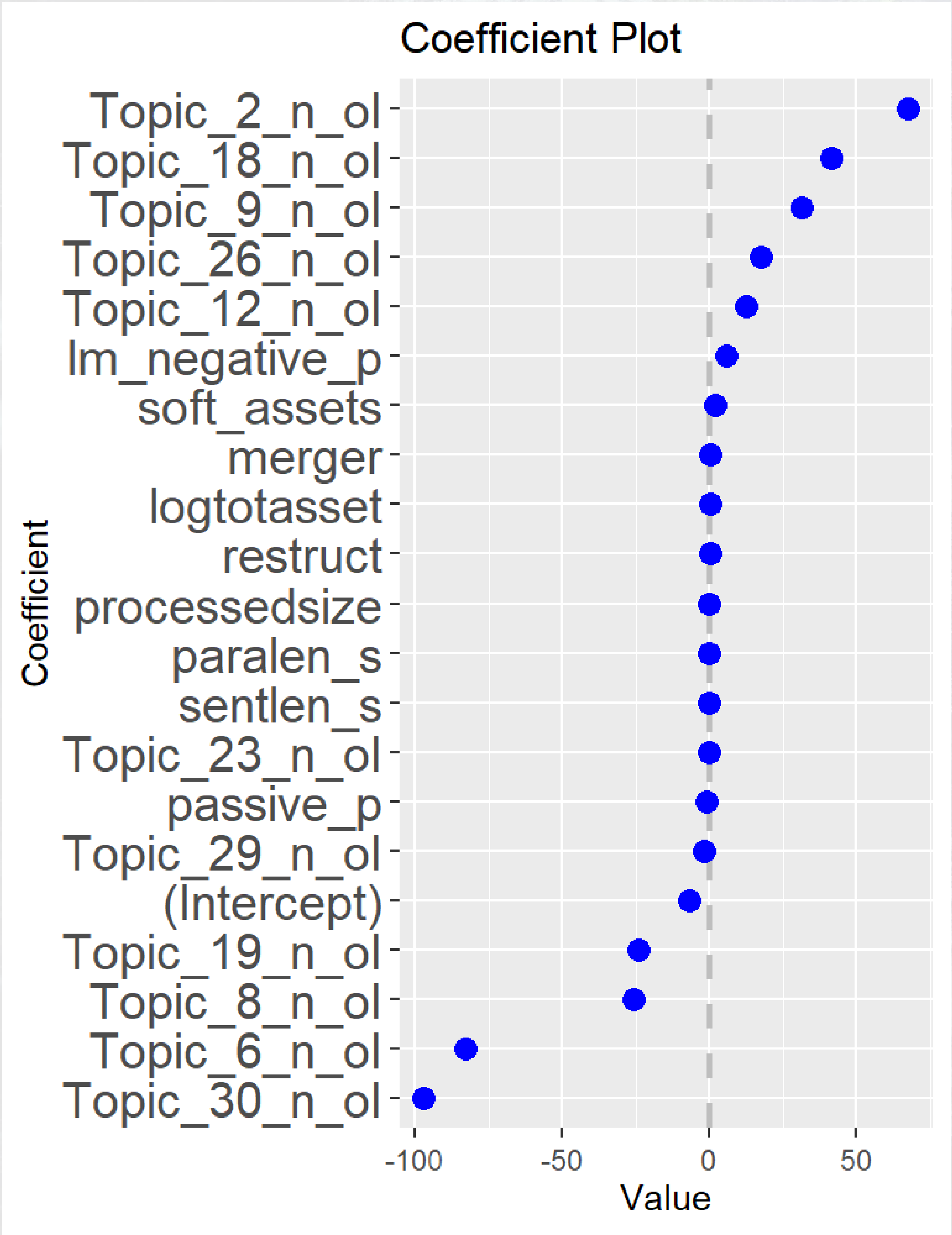
```r
cvfit$lambda.1se
```

```
## [1] 0.002684268
```

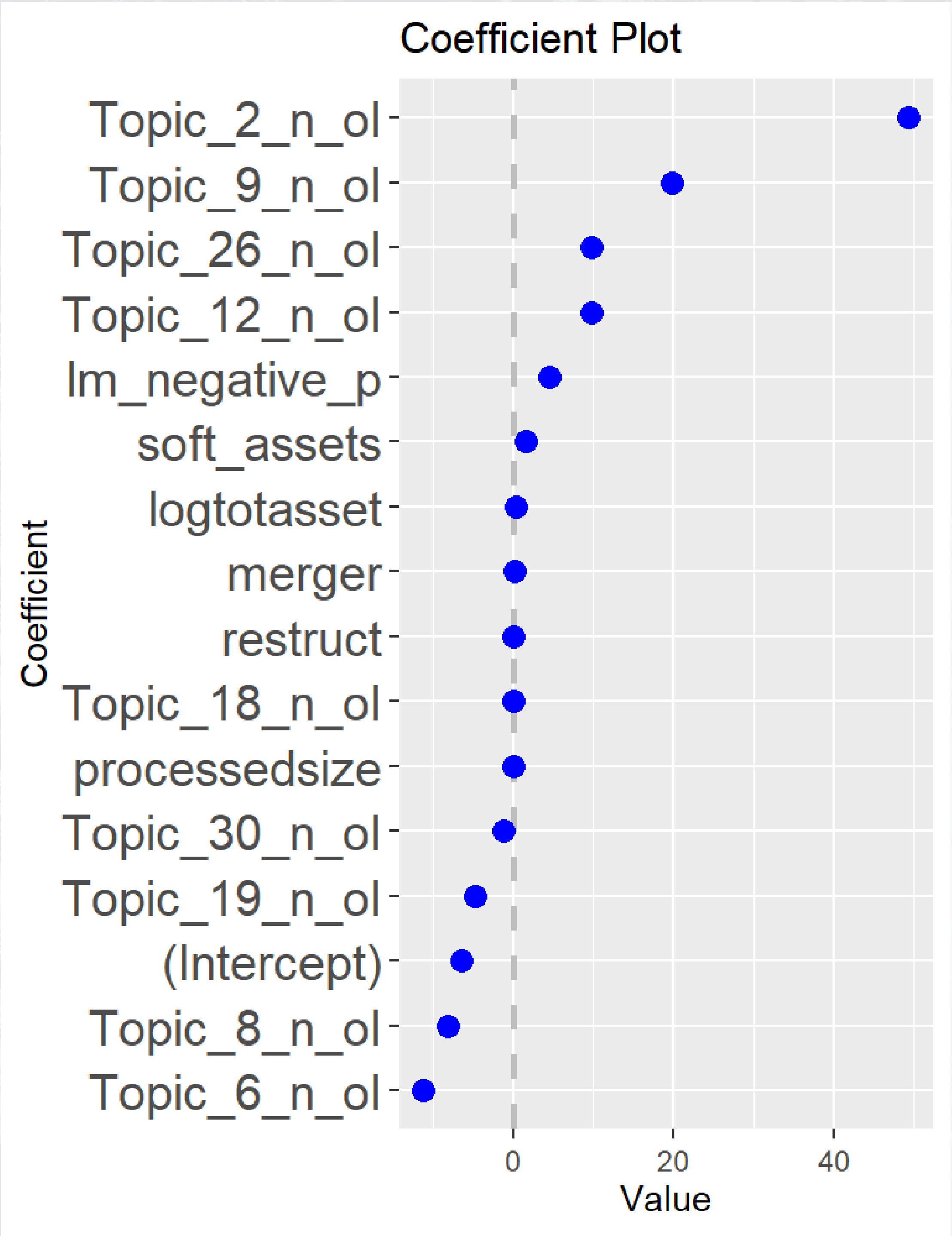
> These are the dashed lines on the plot

Models

`lambda.min`

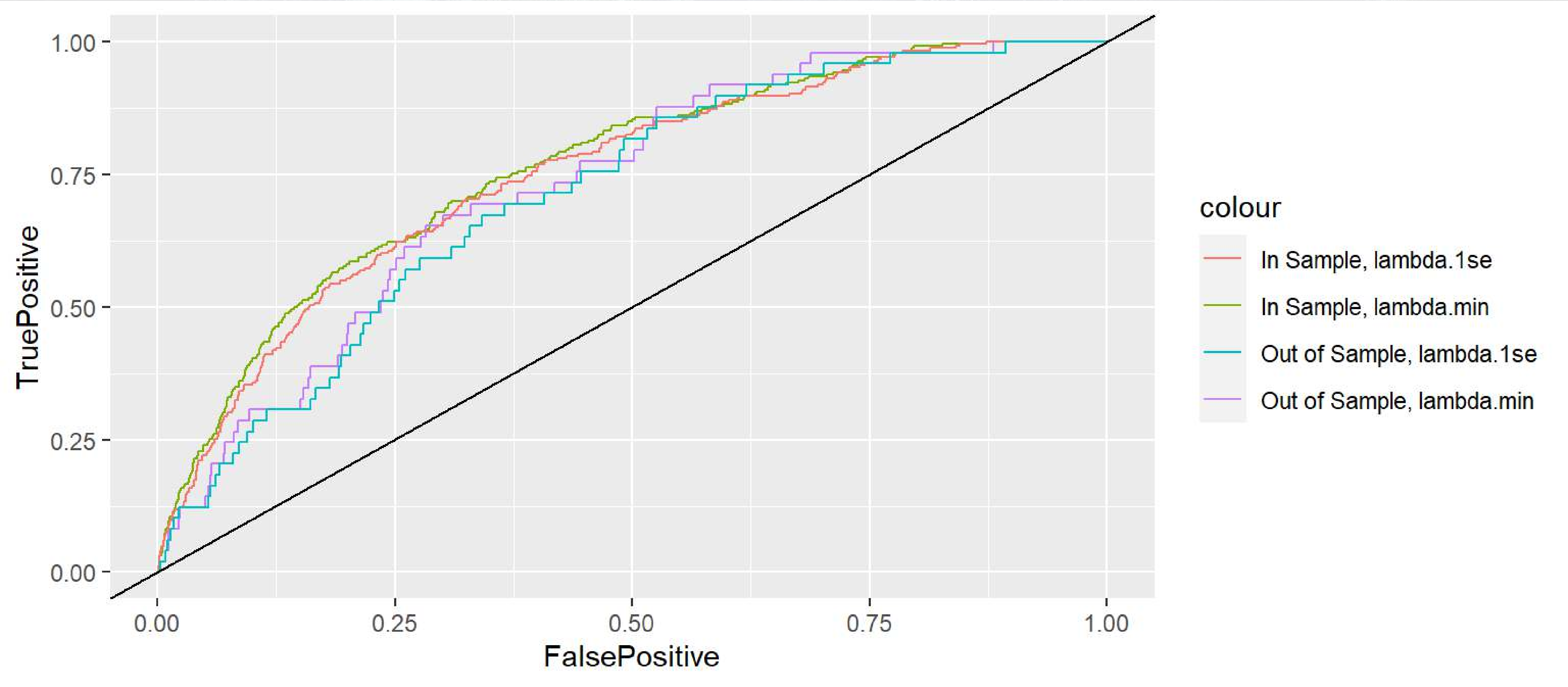


`lambda.1se`



CV LASSO performance

```r
# s= specifies the version of the model to use
pred <- predict(cvfit, xp, type="response", s = "lambda.min")
pred2 <- predict(cvfit, xp, type="response", s = "lambda.1se")
```




```
##      In sample AUC, lambda.min Out of sample AUC, lambda.min
##                      0.7631710                     0.7290185
##      In sample AUC, lambda.1se Out of sample AUC, lambda.1se
##                      0.7509946                     0.7124231
```

Drawbacks of LASSO

1. No p-values on coefficients
   - Simple solution – run the resulting model with `glm()`
   - Solution only if using `family="gaussian"`:
     - Run the lasso use the `lars` package
       - `m <- lars(x=x, y=y, type="lasso")`
     - Then test coefficients using the `covTest` package
       - `covTest(m, x, y)`
2. Generally worse in sample performance
3. Sometimes worse out of sample performance (short run)
   - BUT: predictions will be more stable

Wrap up

Predicting fraud

> What other data could we use to predict corporate fraud?

- What is the reason that this event or data would be useful for prediction?
  - I.e., how does it fit into your mental model?
- What if we were…
  - Auditors?
  - Internal auditors?
  - Regulators?
  - Investors?

End matter

For next week

- Next week:
  - Third assignment
    - On binary prediction
    - Finish by the end of next week
    - Can be done in pairs
    - Submit on eLearn
  - Datacamp
    - Practice a bit more to keep up to date
      - Using R more will make it more natural

Homework 3

> Predicting class action lawsuits

- Another question that has both forecasting and forensic flair to it
  - Forensic: Often these companies were doing something wrong for a while in the past
  - Forecasting: Predicting the actions of the firms' investors
- Methods
  - A simple logistic model from 1994
  - A better logistic model from 2012
  - A LASSO model including firms' disclosure text
  - [Optional] e**X**treme **G**radient **Boost**ing (XGBoost)

Packages used for these slides

- `coefplot`
- `glmnet`
- `kableExtra`
- `knitr`
- `magrittr`
- `revealjs`
- `ROCR`
- `tidyverse`

Appendix on `parsnip` with LASSO

LASSO using `tidymodels`

- There are many convenience packages in R to simplify workflows
  - `tidymodels` is a collection of such packages
    - `parsnip` helps run models on many different backends
    - `recipes` helps process and prep data
    - `rsample` for cross validation
    - `workflows` to tie it all together

> We will use `tidymodels` to run a LASSO and an XGBoost model for misreporting detection

- Jared Lander gave a good talk on using tidy models, [Many ways To Lasso](), at DSSG

Data prep with `recipes`

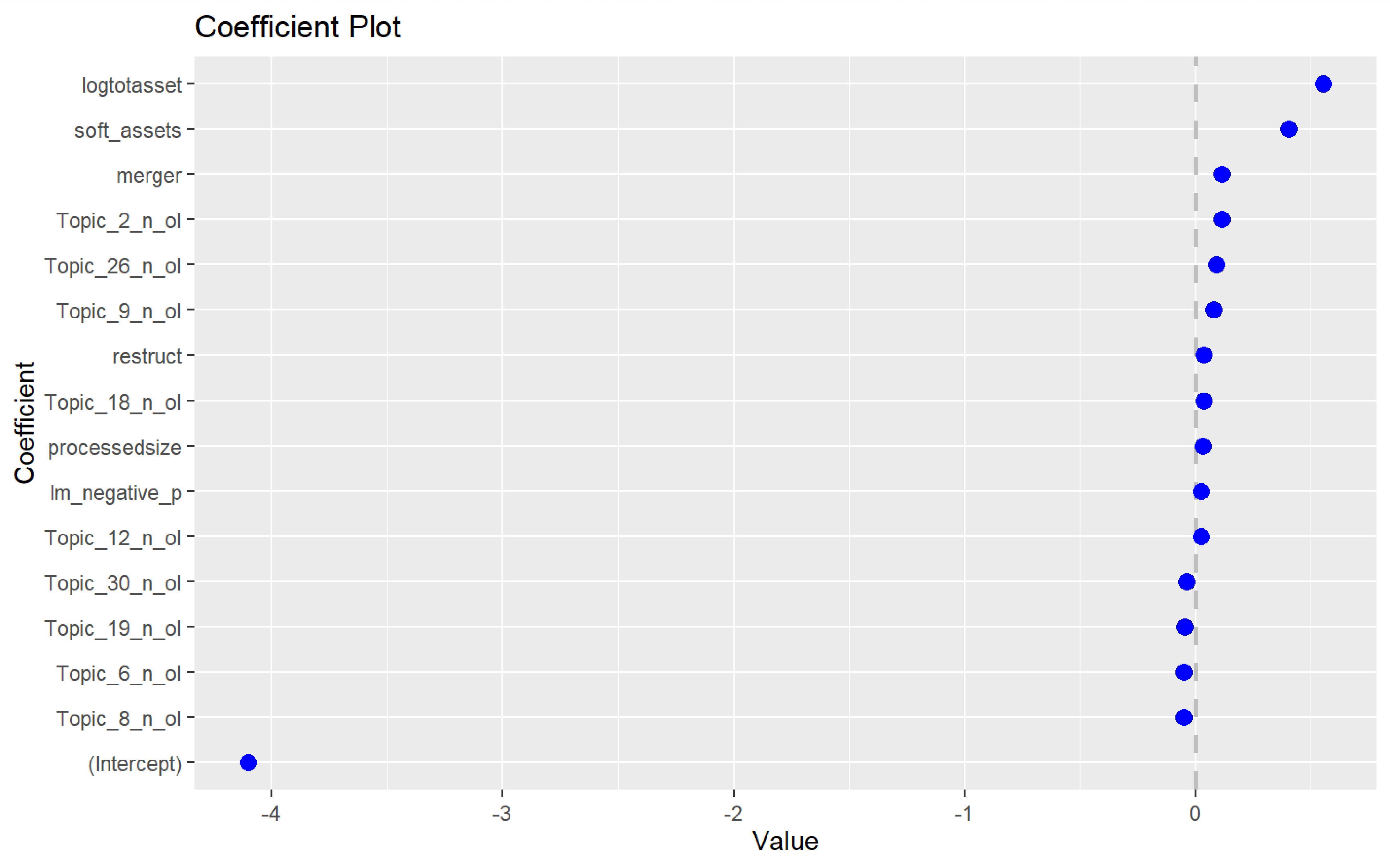
```r
library(recipes)
library(parsnip)

df <- read_csv("../../Data/Session_6.csv")
BCEformula <- BCE_eq

train <- df %>% filter(Test == 0)
test <- df %>% filter(Test == 1)

rec <- recipe(BCEformula, data = train) %>%
  step_zv(all_predictors()) %>%  # Drop any variables with zero variance
  step_center(all_predictors()) %>%  # Center all prediction variables
  step_scale(all_predictors()) %>%  # Scale all prediction variables
  step_intercept() %>%  # Add an intercept to the model
  step_num2factor(all_outcomes(), ordered = T, levels=c("0","1"),
                  transform = function(x) x + 1)  # Convert DV to factor

prepped <- rec %>% prep(training=train)
```

Running a model with `parsnip`

```
# "bake" your recipe to get data ready
train_baked  <- bake(prepped, new_data = train)
test_baked  <- bake(prepped, new_data = test)

# Run the model with parsnip
train_model <- logistic_reg(mixture=1) %>%  # mixture = 1 sets LASSO
  set_engine('glmnet') %>%
  fit(BCEformula, data = train_baked)
```

Visualizing `parsnip`'s output

```r
# train_model$fit is the same as fit_LASSO earlier in the slides
coefplot(train_model$fit, lambda=0.002031, sort='magnitude')
```



Plugging in to cross validation

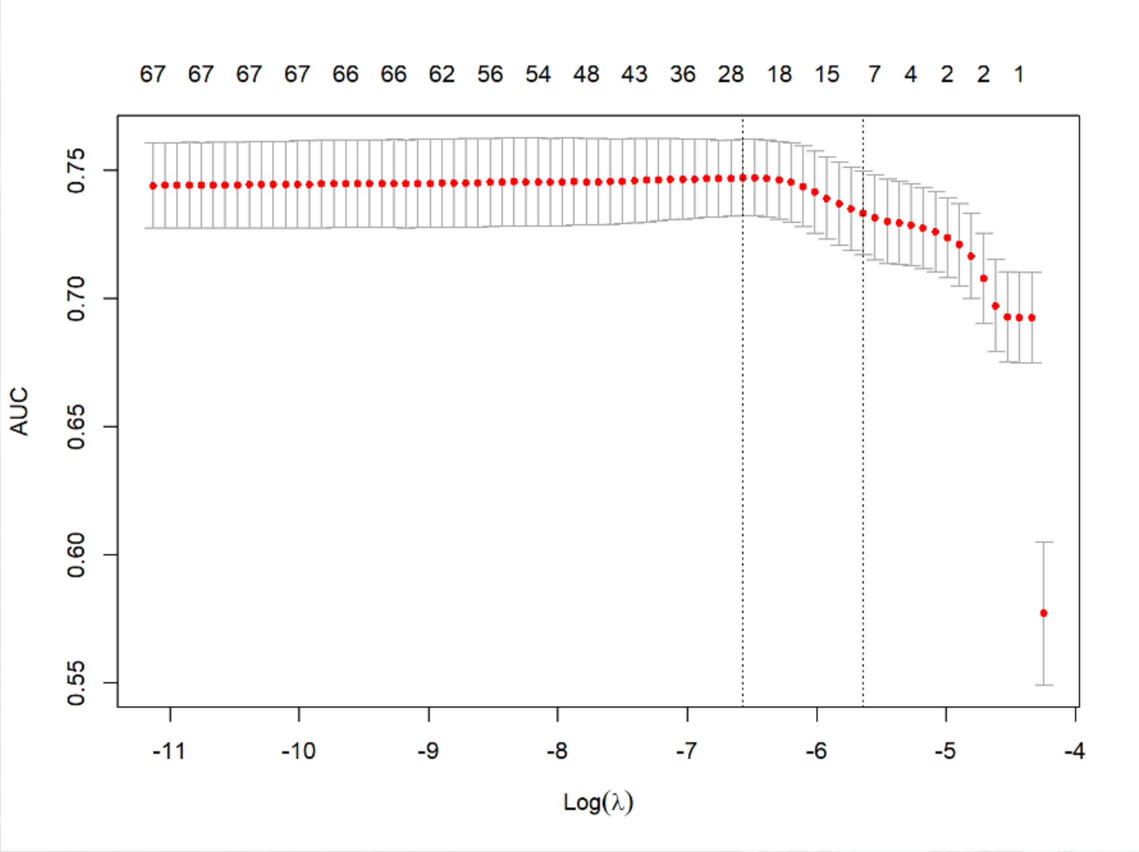
- `parsnip` can plug into cross validation through `rsample`, usingthrough `vfold_cv()`
  - Easy to do surface level analysis with it
  - Difficult to do anything more in depth still
- We can `juice()` out our data and just use `cv.glmnet()`

```
rec <- recipe(BCEformula, data = train) %>%
  step_zv(all_predictors()) %>%  # Drop any variables with zero variance
  step_center(all_predictors()) %>%  # Center all prediction variables
  step_scale(all_predictors()) %>%  # Scale all prediction variables
  step_intercept()  # Add an intercept to the model

prepped <- rec %>% prep(training=train)
test_prepped <- rec %>% prep(training=test)

# "Juice" your recipe to get data for other packages
train_x <- juice(prepped, all_predictors(), composition = "dgCMatrix")
train_y <- juice(prepped, all_outcomes(), composition = "matrix")
test_x <- juice(test_prepped, all_predictors(), composition = "dgCMatrix")
test_y <- juice(test_prepped, all_outcomes(), composition = "matrix")
```

Running a cross validated model

```
# Cross validation
set.seed(75347)  #for reproducibility
cvfit = cv.glmnet(x=train_x, y=train_y, family = "binomial", alpha = 1,
                  type.measure="auc")
```

```
plot(cvfit)
```




```
cvfit$lambda.min
```

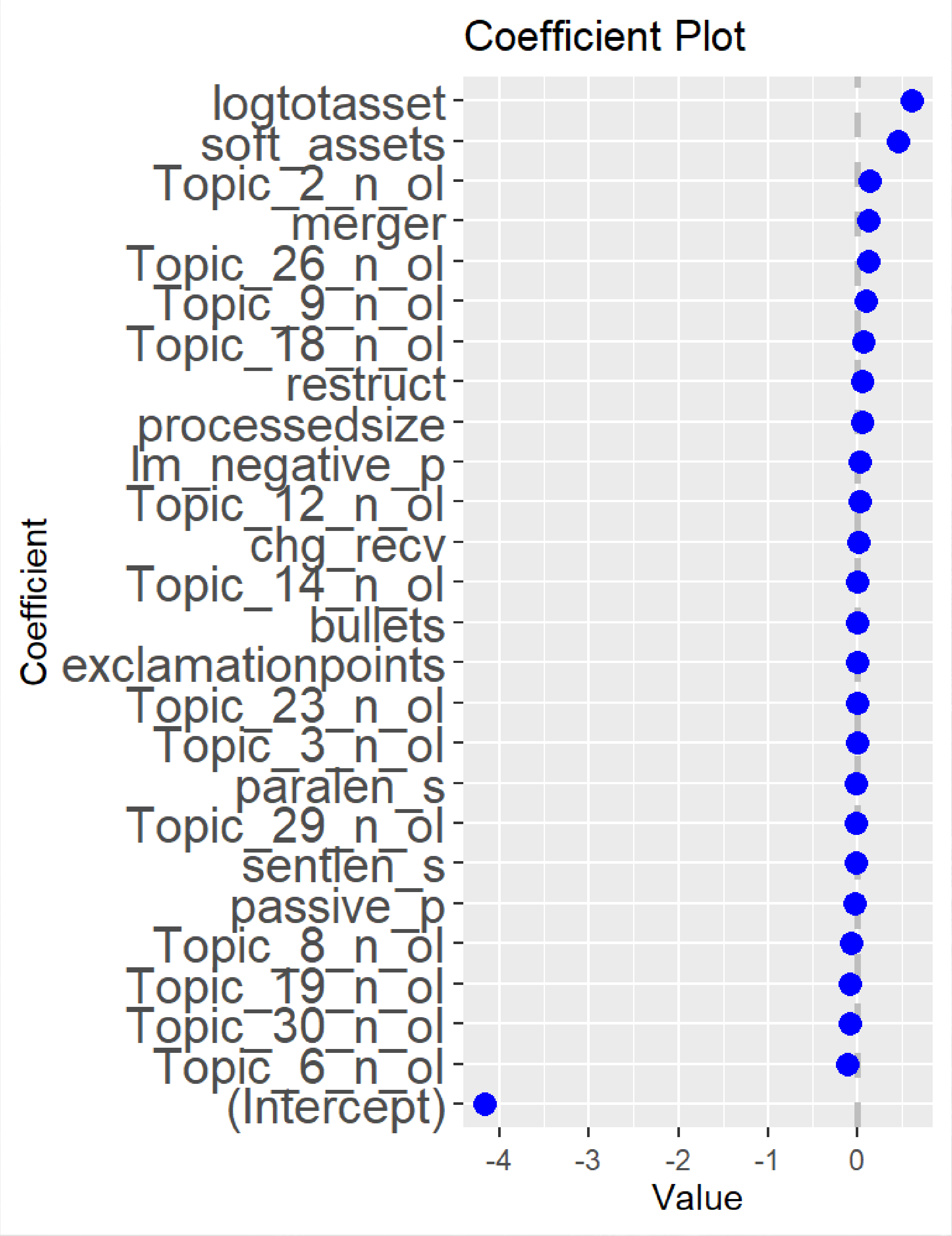
```
## [1] 0.00139958
```

```
cvfit$lambda.1se
```

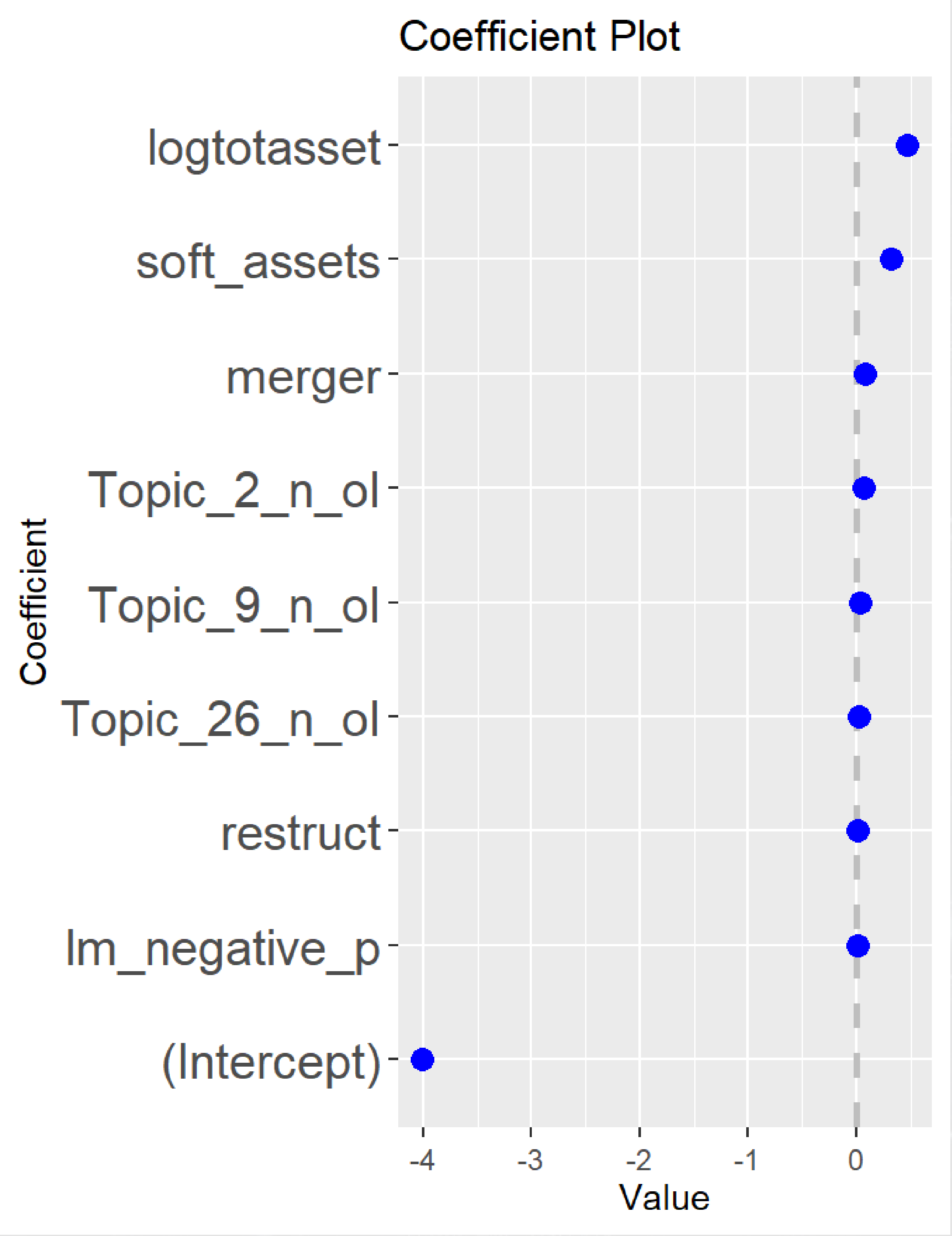
```
## [1] 0.003548444
```

Models

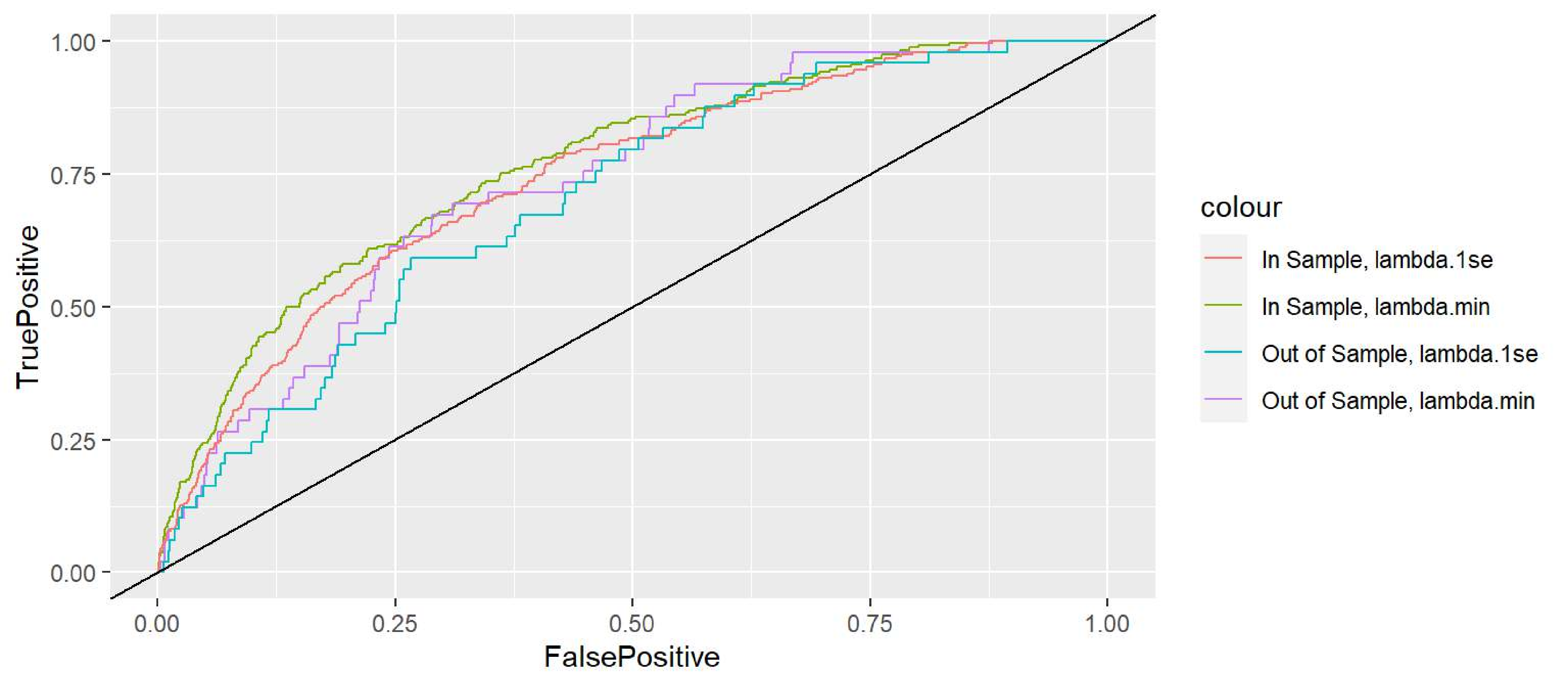
`lambda.min`



`lambda.1se`



CV LASSO performance




```
##     In sample AUC, lambda.min Out of sample AUC, lambda.min
##                     0.7665463                     0.7364834
##     In sample AUC, lambda.1se Out of sample AUC, lambda.1se
##                     0.7417082                     0.7028034
```

Packages used for these slides

- `glmnet`
- `parsnip`
- `recipes`

If you really want to use `parsnip` for CV LASSO

Data prep with `recipes` (Same as before)

```
library(tidyr)
library(tidymodels)
library(tidyverse)

df <- read_csv("../../Data/Session_6.csv")
BCEformula <- BCE_eq

train <- df %>% filter(Test == 0)
test <- df %>% filter(Test == 1)

LASSO_rec <- recipe(BCEformula, data = train) %>%
  step_zv(all_predictors()) %>%  # Drop any variables with zero variance
  step_center(all_predictors()) %>%  # Center all prediction variables
  step_scale(all_predictors()) %>%  # Scale all prediction variables
  step_intercept() %>%  # Add an intercept to the model
  step_num2factor(all_outcomes(), ordered = T, levels=c("0","1"),
                  transform = function(x) x + 1)  # Convert DV to factor
```

Define a tuning with `tune` and `tidyr`

```
LASSO_mod <- logistic_reg(penalty=tune(), mixture=1) %>%  # mixture = 1 sets LASSO
  set_engine('glmnet')

# Define a grid to tune over
grid <- expand_grid(penalty = exp(seq(-11,-4, length.out=100)))
```

- `tune()` replaces any parameters you would like to tune over
- Unlike with `cv.glmnet()`, we'll need to specify the range to tune over
  - The `expand_grid()` function from `tidyr` makes this easy
  - The `exp(seq())` part is to emulate `cv.glmnet()`'s tuning behavior

Define a workflow with `workflows`

```
LASSO_wfl <- workflow() %>%
  add_model(LASSO_mod) %>%
  add_recipe(LASSO_rec)
```

> A workflow tells the various fitting and tuning functions in `tune` how to handle the data. In other words, this will combine our model and recipe into 1 object.

Run the model using `rsample`, `tune`, and `yardstick`

```
set.seed(354351)
folds <- vfold_cv(train, v=10)  # from rsample
metrics = metric_set(roc_auc)  # from yardstick

LASSO_fit_tuned <- tune_grid(LASSO_wfl,
                             grid = grid,
                             resamples = folds,
                             metrics=metrics)
```

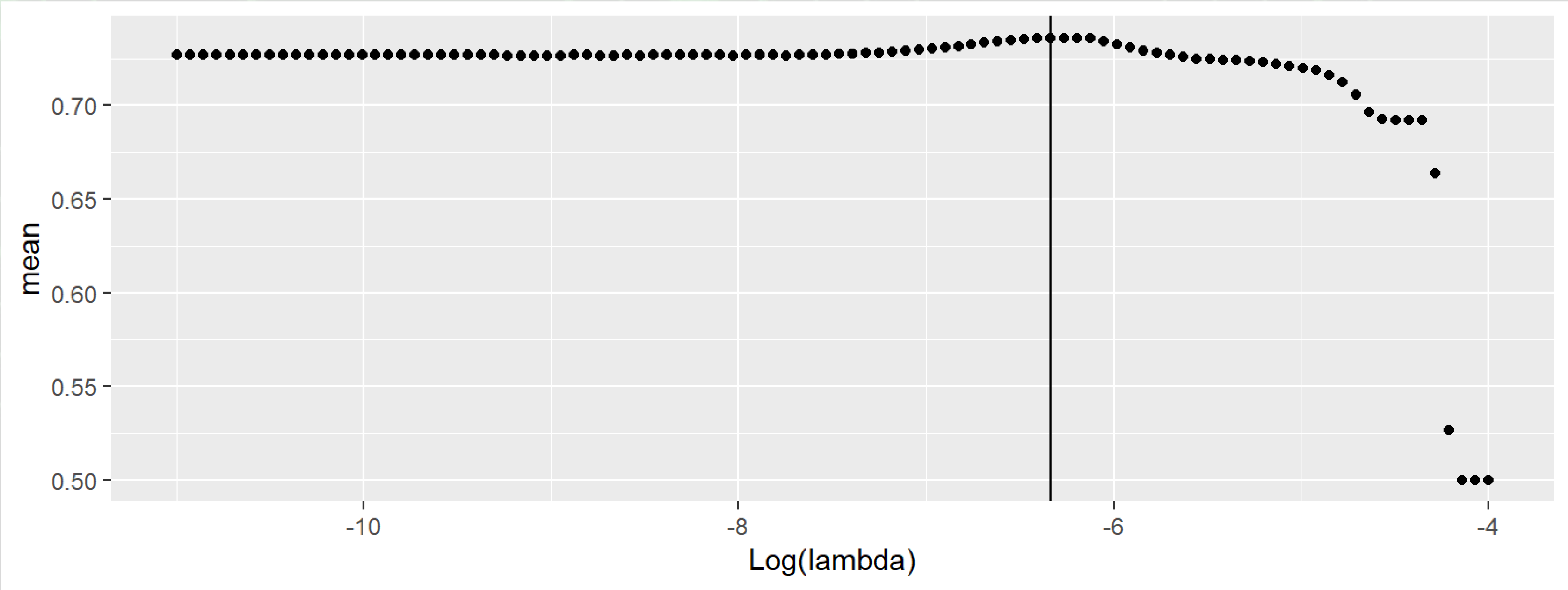
Take a look at the output

```
LASSO_fit_tuned %>%
  collect_metrics()
```

```
## # A tibble: 100 x 7
##      penalty .metric .estimator  mean     n std_err .config
##        <dbl> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
##  1 0.0000167 roc_auc binary     0.727    10  0.0257 Model001
##  2 0.0000179 roc_auc binary     0.727    10  0.0257 Model002
##  3 0.0000192 roc_auc binary     0.727    10  0.0257 Model003
##  4 0.0000206 roc_auc binary     0.727    10  0.0257 Model004
##  5 0.0000222 roc_auc binary     0.727    10  0.0257 Model005
##  6 0.0000238 roc_auc binary     0.727    10  0.0257 Model006
##  7 0.0000255 roc_auc binary     0.727    10  0.0257 Model007
##  8 0.0000274 roc_auc binary     0.727    10  0.0256 Model008
##  9 0.0000294 roc_auc binary     0.727    10  0.0256 Model009
## 10 0.0000316 roc_auc binary     0.727    10  0.0256 Model010
## # ... with 90 more rows
```

Plotting it out

```
lambda.min <- LASSO_fit_tuned %>%
  collect_metrics() %>%
  arrange(-mean) %>%
  slice(1) %>%
  pull(penalty) %>%
  log()

LASSO_fit_tuned %>%
  collect_metrics() %>%
  ggplot(aes(x=log(penalty), y=mean)) +
  geom_point() +
  xlab("Log(lambda)") +
  geom_vline(xintercept = lambda.min)
```



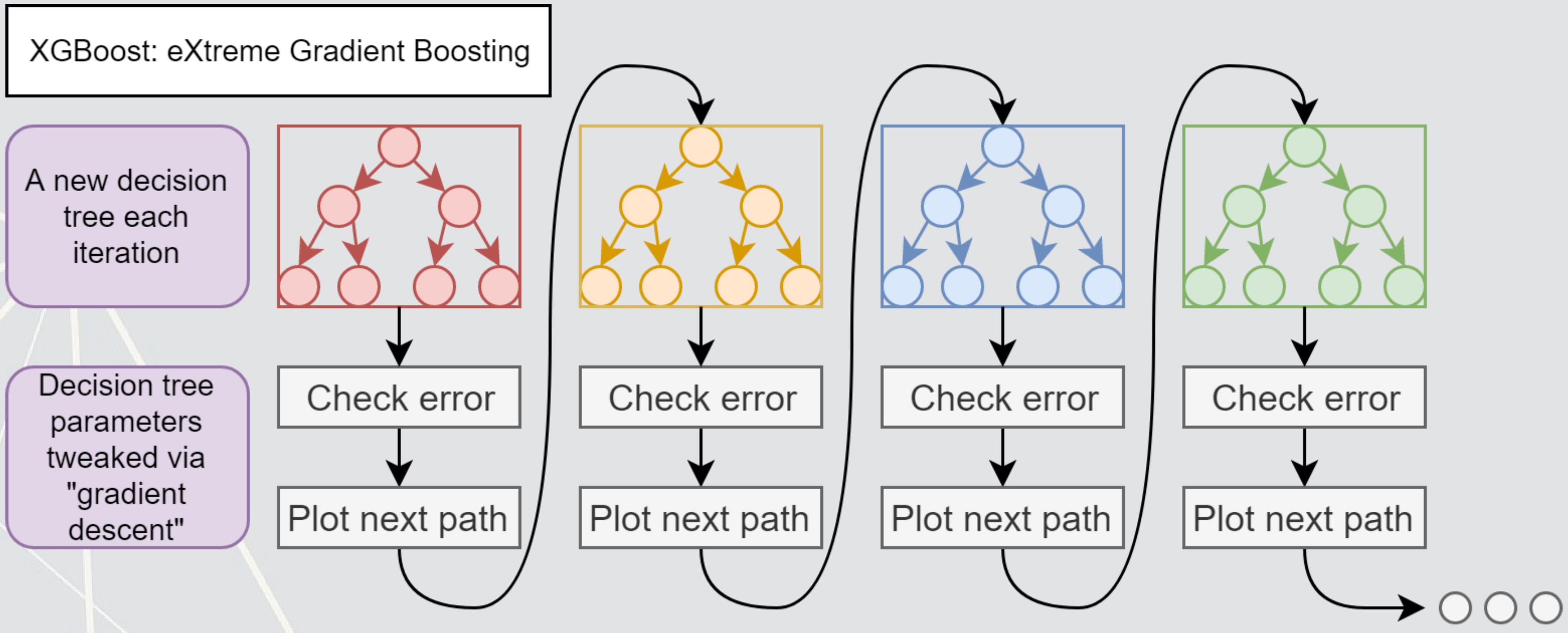
Packages used for these slides

- `glmnet`
- `parsnip`
- `recipes`
- `rsample`
- `tidyr`
- `tune`
- `workflows`
- `yardstick`

Appendix on XGBoost

What is XGBoost

- e**X**treme **G**radient **B**oosting
- A simple explanation:
  1. Start with 1 or more decision trees & check error
  2. Make more decision trees & check error
  3. Use the difference in error to guess a another model
  4. Repeat #2 and #3 until the model's error is stable



Data prep with `recipes`

```r
library(recipes)
library(parsnip)

df <- read_csv("../../Data/Session_6.csv")
BCEformula <- BCE_eq

train <- df %>% filter(Test == 0)
test <- df %>% filter(Test == 1)

rec <- recipe(BCEformula, data = train) %>%
  step_zv(all_predictors()) %>%  # Drop any variables with zero variance
  step_center(all_predictors()) %>%  # Center all prediction variables
  step_scale(all_predictors()) %>%  # Scale all prediction variables
  step_intercept()  # Add an intercept to the model
```

```r
# Juice our data
prepped <- rec %>% prep(training=train)
train_x <- juice(prepped, all_predictors(), composition = "dgCMatrix")
train_y <- juice(prepped, all_outcomes(), composition = "matrix")
test_prepped <- rec %>% prep(training=test)
test_x <- juice(test_prepped, all_predictors(), composition = "dgCMatrix")
test_y <- juice(test_prepped, all_outcomes(), composition = "matrix")
```

Running a cross validated model

```r
# Cross validation
set.seed(482342)  #for reproducibilit
library(xgboost)

# model setup
params <- list(max_depth=10,
               eta=0.2,
               gamma=10,
               min_child_weight = 5,
               objective =
                 "binary:logistic")

# run the model
xgbCV <- xgb.cv(params=params,
                data=train_x,
                label=train_y,
                nrounds=100,
                eval_metric="auc",
                nfold=10,
                stratified=TRUE)
```

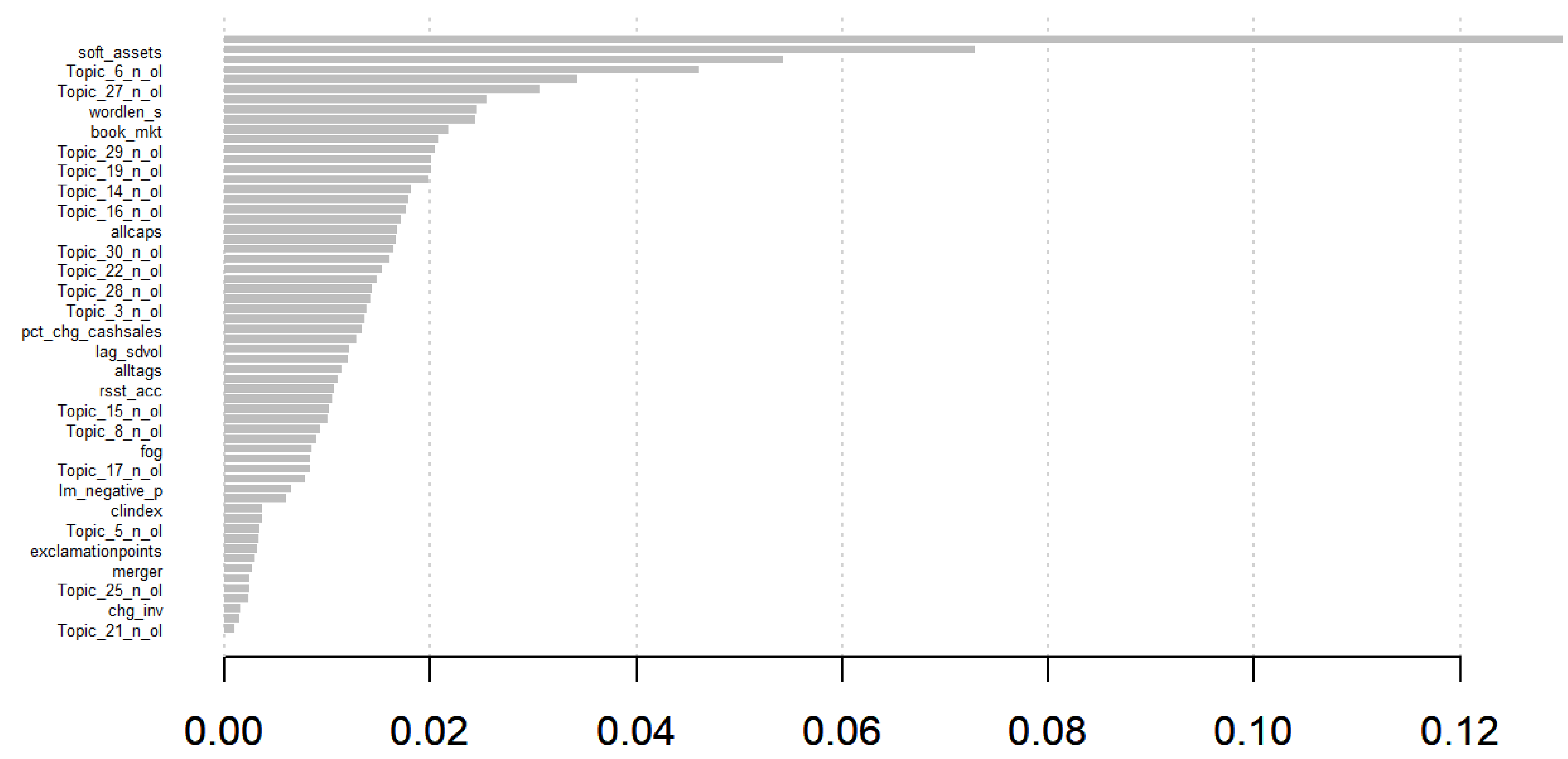
```
## [1]  train-auc:0.552507+0.080499 t
## [2]  train-auc:0.586947+0.087237 t
## [3]  train-auc:0.603035+0.084511 t
## [4]  train-auc:0.663903+0.057212 t
## [5]  train-auc:0.677173+0.064281 t
## [6]  train-auc:0.707156+0.026578 t
## [7]  train-auc:0.716727+0.025892 t
## [8]  train-auc:0.728506+0.026368 t
## [9]  train-auc:0.768085+0.025756 t
```

```r
numTrees <- min(
 which(
  xgbCV$evaluation_log$test_auc_mean
  max(xgbCV$evaluation_log$test_auc_m
 )
)

fit4 <- xgboost(params=params,
                data = train_x,
                label = train_y,
                nrounds = numTrees,
                eval_metric="auc")
```

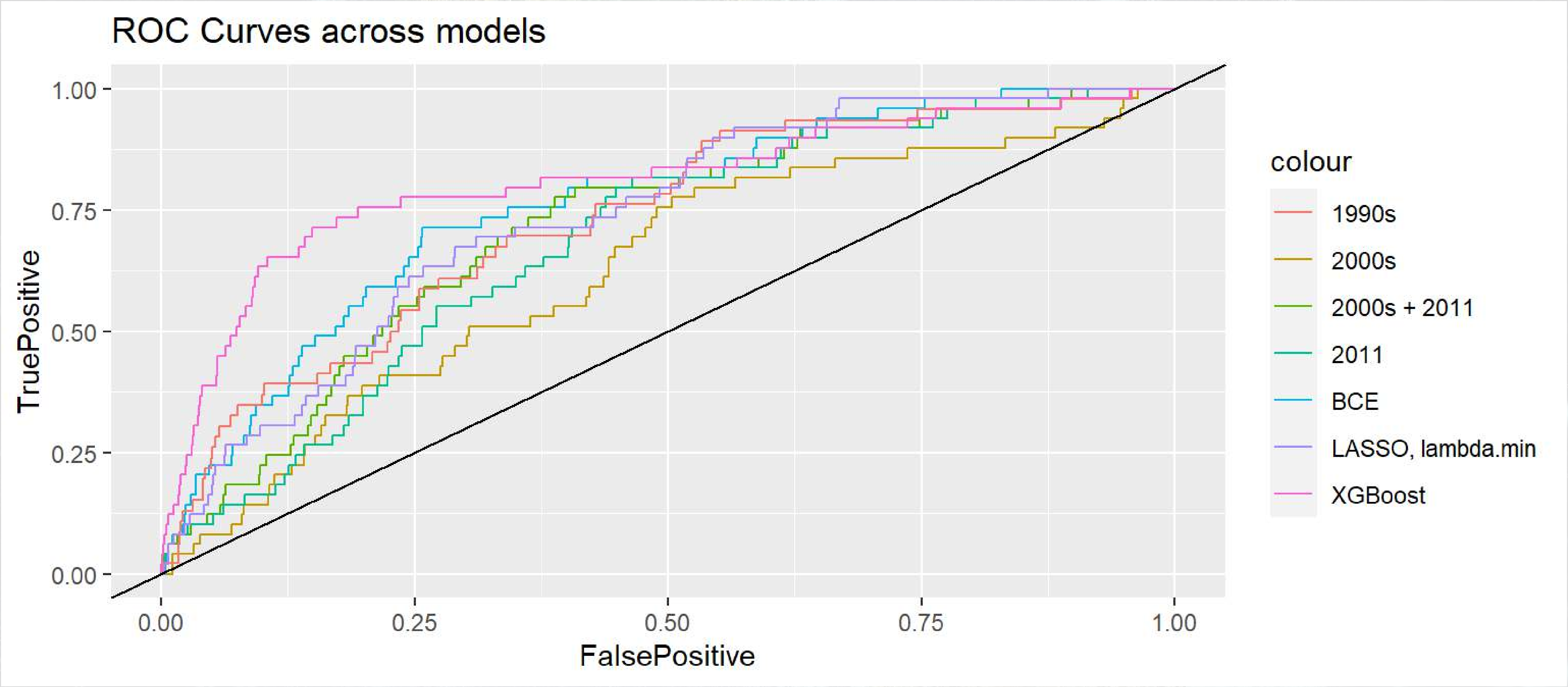
```
## [1]  train-auc:0.500000
## [2]  train-auc:0.663489
## [3]  train-auc:0.663489
## [4]  train-auc:0.703386
## [5]  train-auc:0.703386
## [6]  train-auc:0.704123
## [7]  train-auc:0.727506
## [8]  train-auc:0.727506
## [9]  train-auc:0.727506
## [10] train-auc:0.784639
## [11] train-auc:0.818359
## [12] train-auc:0.816647
## [13] train-auc:0.851022
## [14] train-auc:0.864434
## [15] train-auc:0.877787
## [16] train-auc:0.883615
## [17] train-auc:0.885182
```

Model explanation

```r
xgb.train.data = xgb.DMatrix(train_x, label = train_y, missing = NA)
col_names = attr(xgb.train.data, ".Dimnames")[[2]]
imp = xgb.importance(col_names, fit4)
# Variable importance
xgb.plot.importance(imp)
```



Model comparison




```
##              1990s               2011              2000s       2000s + 2011
##          0.7292981          0.6849225          0.6295414          0.7147021
##                BCE LASSO, lambda.min        XGBoost AUC
##          0.7599594          0.7364834          0.8083503
```

Packages used for these slides

- `parsnip`
- `recipes`
- `xgboost`