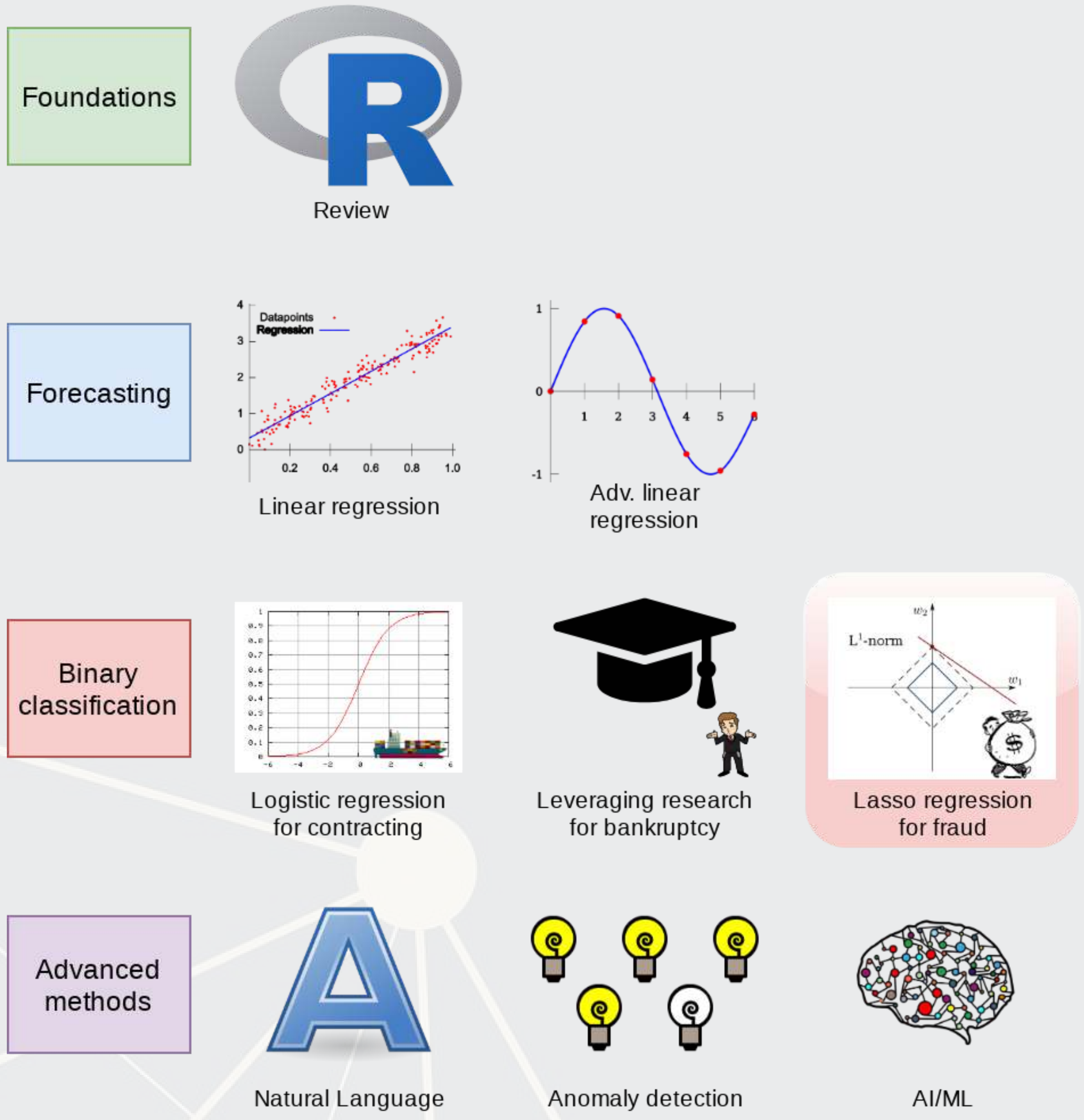
ACCT 420: Logistic Regression for Corporate Fraud

Session 6

Dr. Richard M. Crowley
rcrowley@smu.edu.sg
http://rmc.link/

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

- *Options backdating*: Apple (2001)
- Using an auditor that *isn't registered*: Commerce Group Corp (2003)
- Releasing financial statements that were *not reviewed by an auditor*: Cardiff International (2017)
- *Related party transactions* (transferring funds to family members): China North East Petroleum Holdings Limited
- *Insufficient internal controls*: Citigroup (2008-2014) via Banamex and Asia Pacific Breweries
- *Round-tripping*: Transactions to inflate revenue that have no substance: Suprema Specialties (1998-2001)
- *Bribery*: Keppel O&M (2001-2014), $55M USD in bribes to Brazilian officials for contracts
- *Fake the whole company*: ZZZZ Best (1982-1987)
  - Getting funding from insurance fraud, theft, credit card fraud, and fake contracts; faking a real project to get a clean audit to take the company public
- *Ponzi scheme*: Bernard Madoff
- *Material omissions and misstatements*: Imaging Diagnostic Systems (2013)
- *Failed to file annual and quarterly reports*: Applied Wellness Corporation (2008)
- *Aiding another company's fraud* (Take Two, by parking 2 video games): Capitol Distributing LLC
- *Misleading statements on Twitter*: Tesla (2018)

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

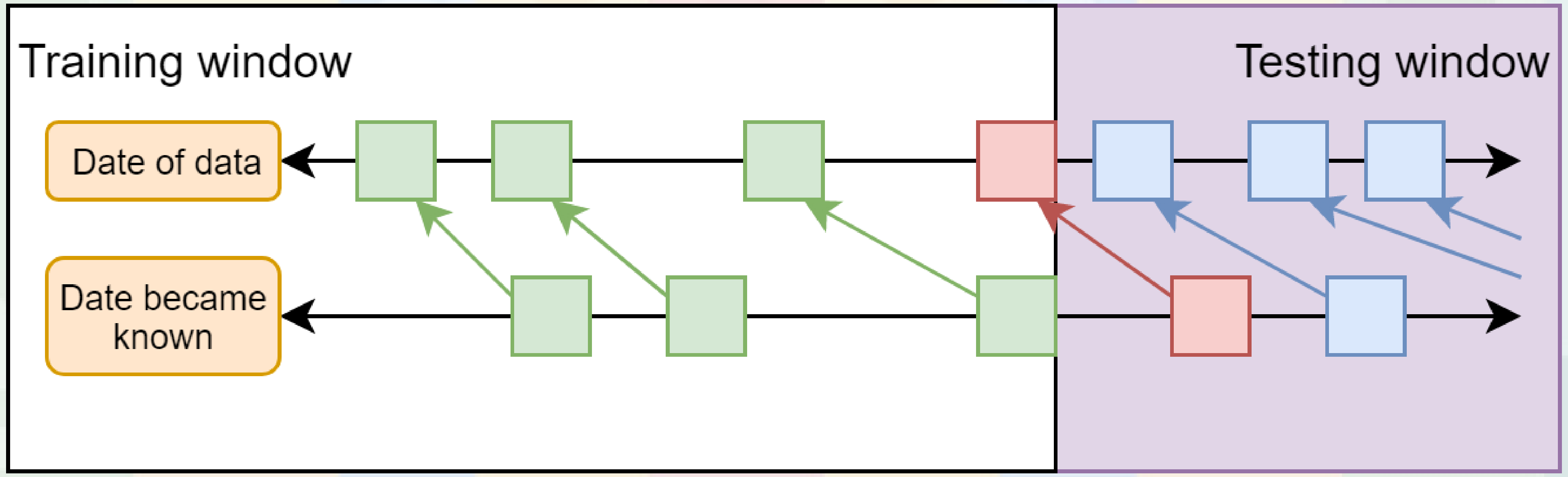
Training and Testing

- 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?

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

```r
df %>%
  group_by(year) %>%
  mutate(total_AAERS = sum(AAER==1), 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

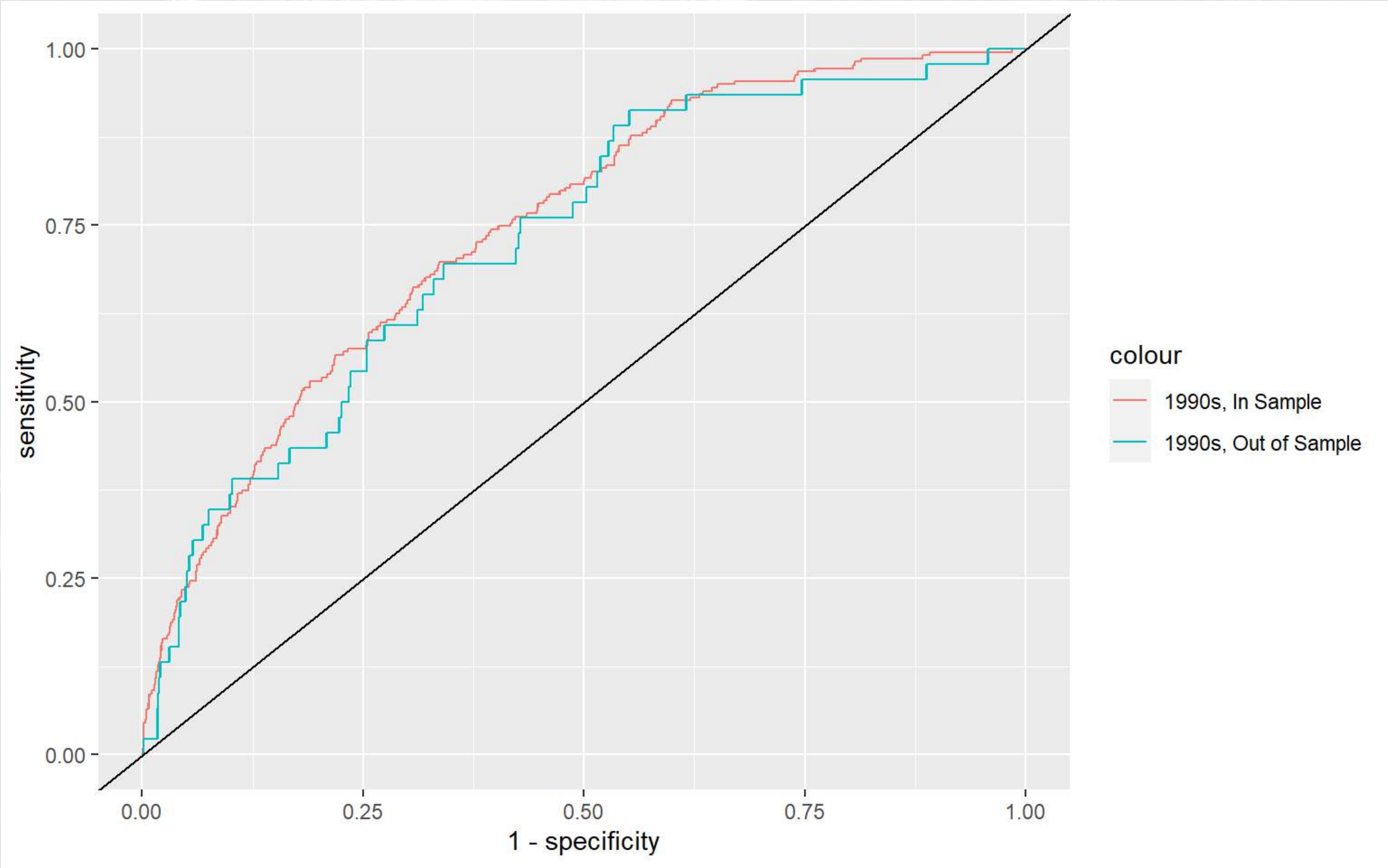
- Change in revenue
- Change in A/R + 1
- $> 10\%$ change in A/R
- Change in gross profit + 1
- $> 10\%$ change in gross profit
- Gross profit / assets
- Revenue minus gross profit
- Cash / assets
- Log of assets
- PP&E / assets
- Working capital

Approach

```r
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

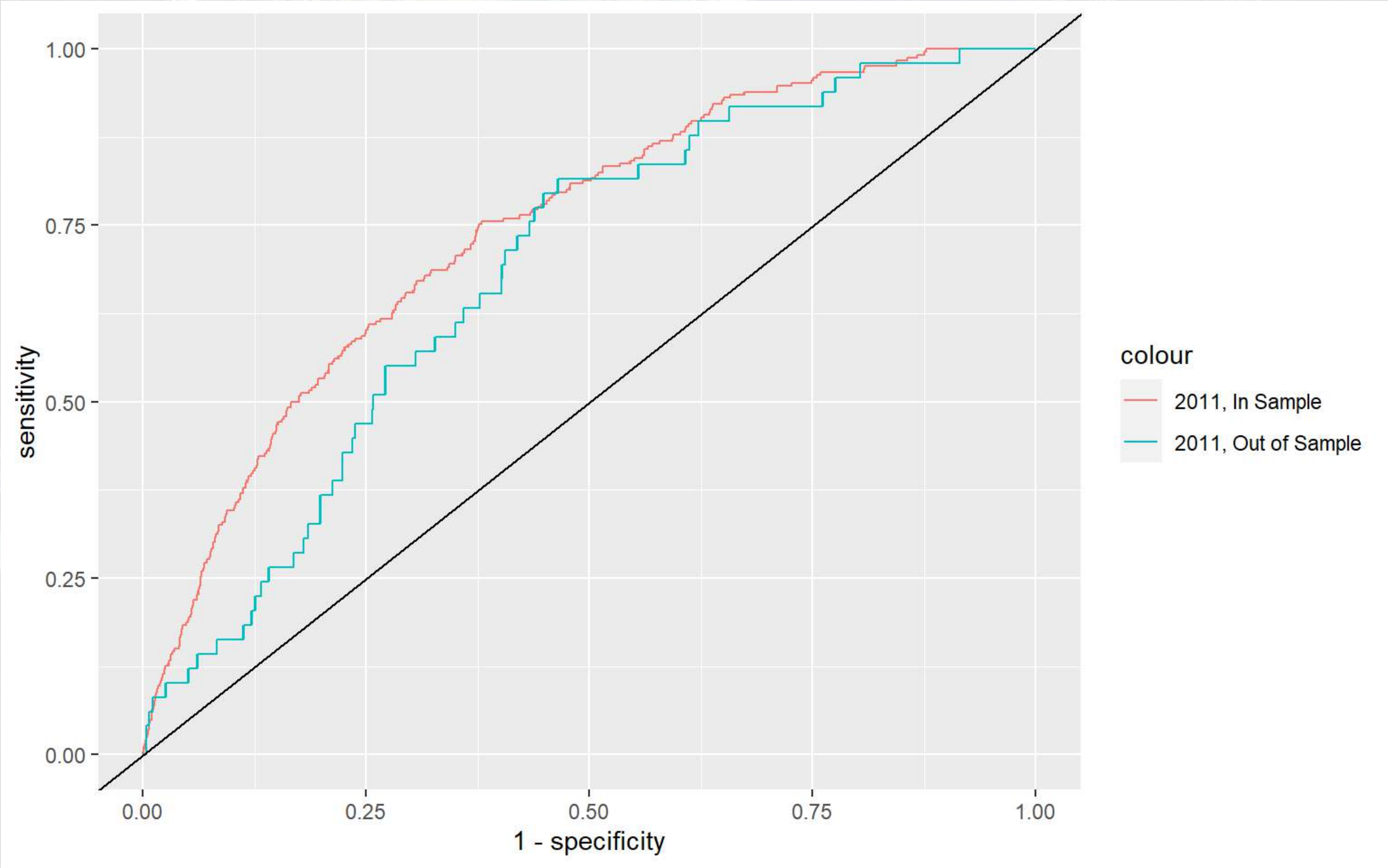
> Based on Dechow, Ge, Larson and Sloan (2011)

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

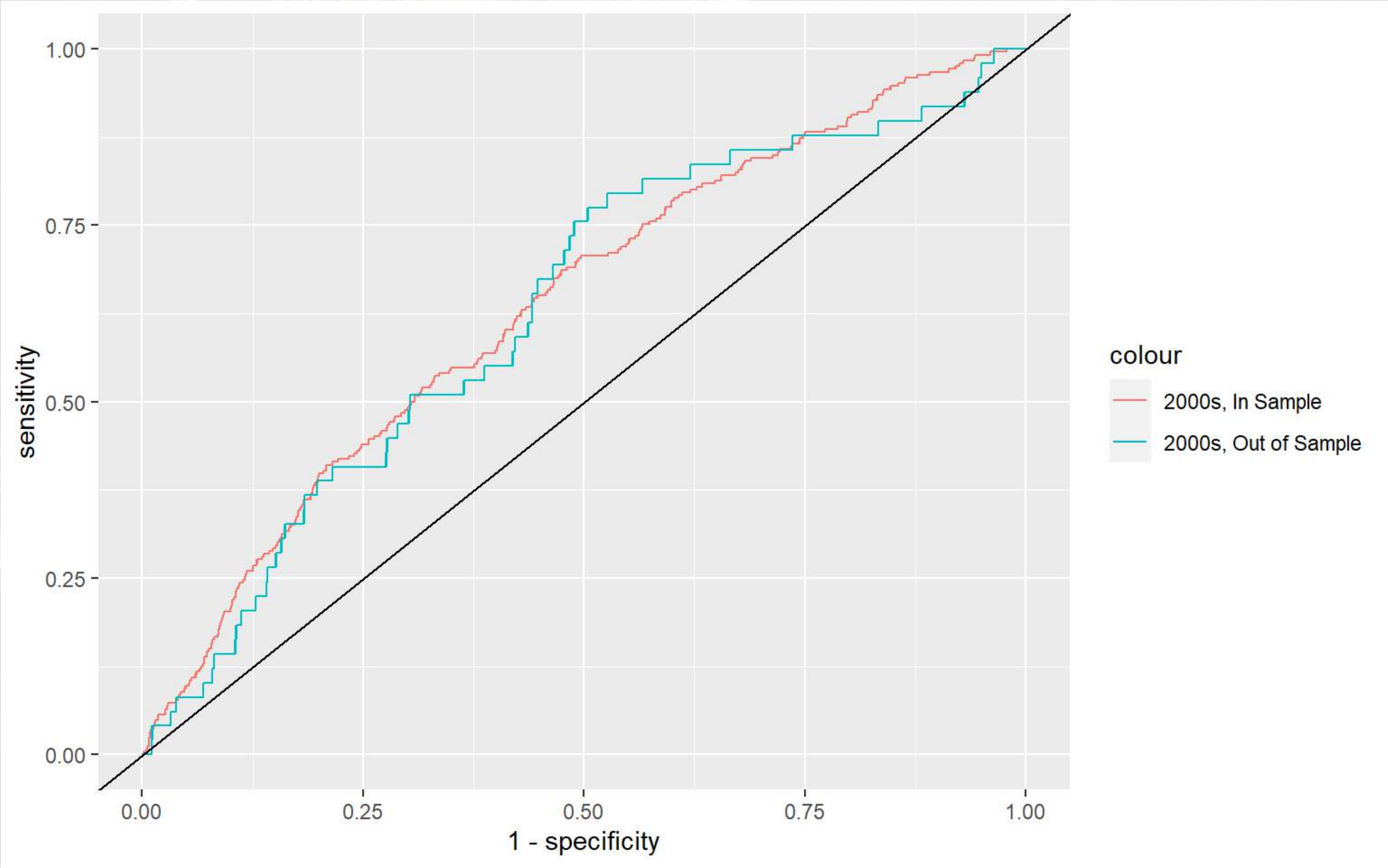
- Generally pulled from the communications literature
  - Sometimes ad hoc
- The main idea:
  - Companies that are misreporting probably write their annual report differently

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?

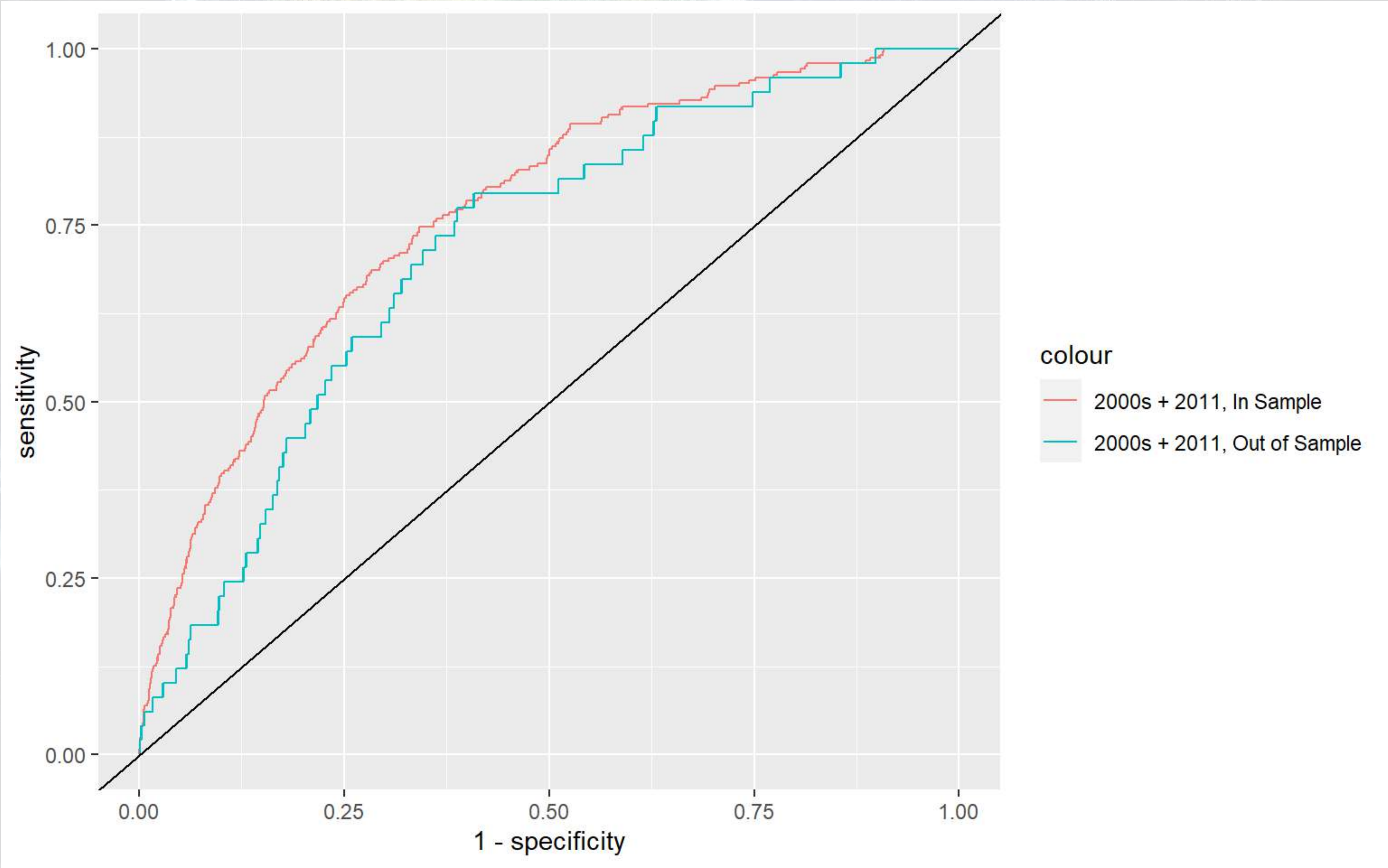
- 2011 model: Parsimonious financial model
- 2000s model: Textual characteristics

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
## logtotasset        3.437e-01  3.921e-02   8.766  < 2e-16 ***
## rsst_acc          -2.123e-01  2.995e-01  -0.709  0.47844
```

ROC



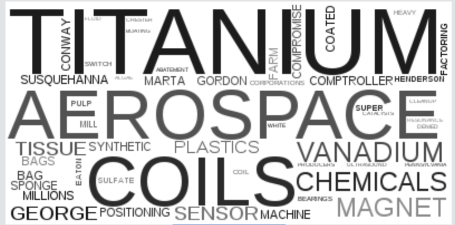

```
##     In sample AUC Out of sample AUC
##         0.7664115         0.7147021
```

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

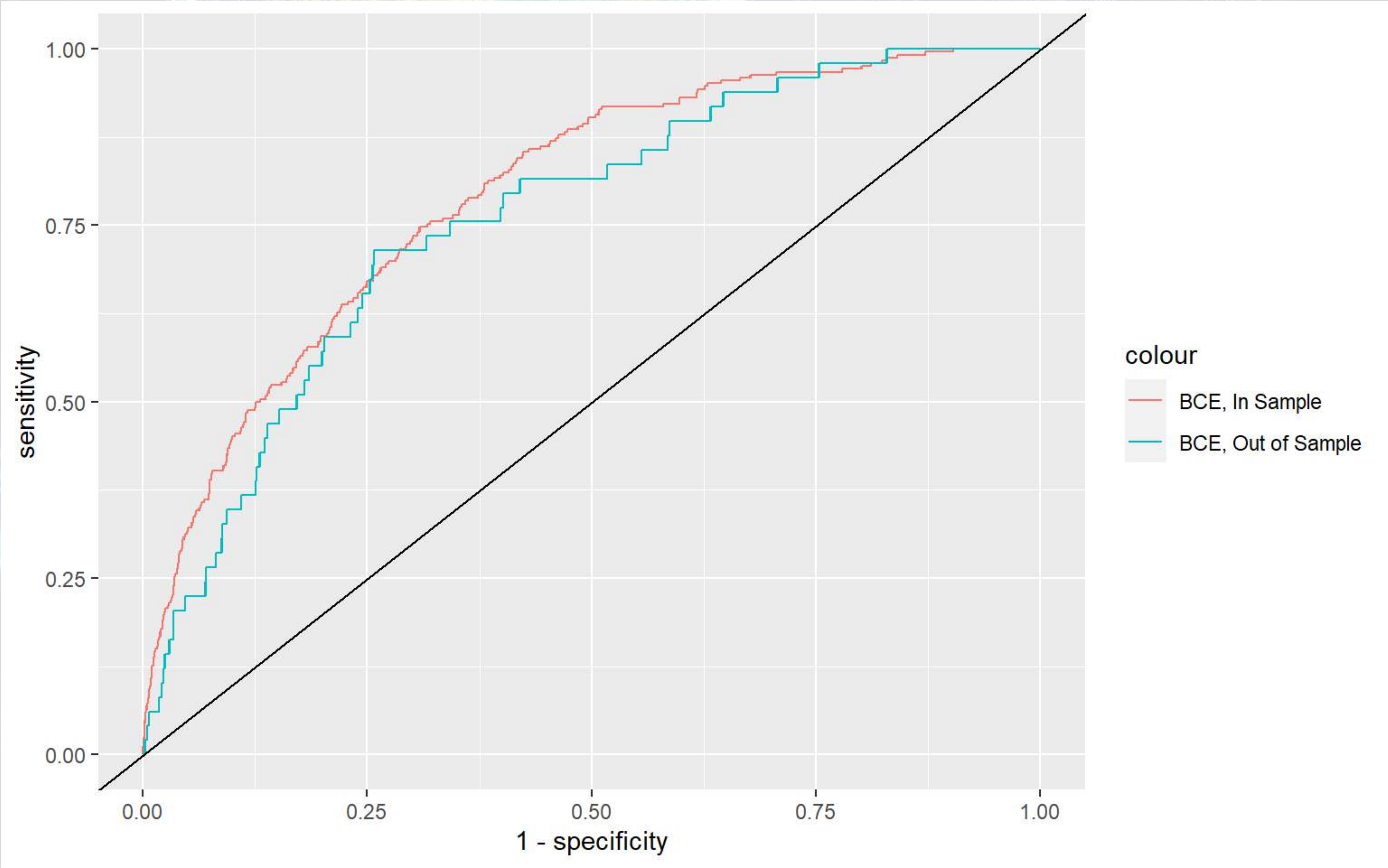
> Why use document content?

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)
```

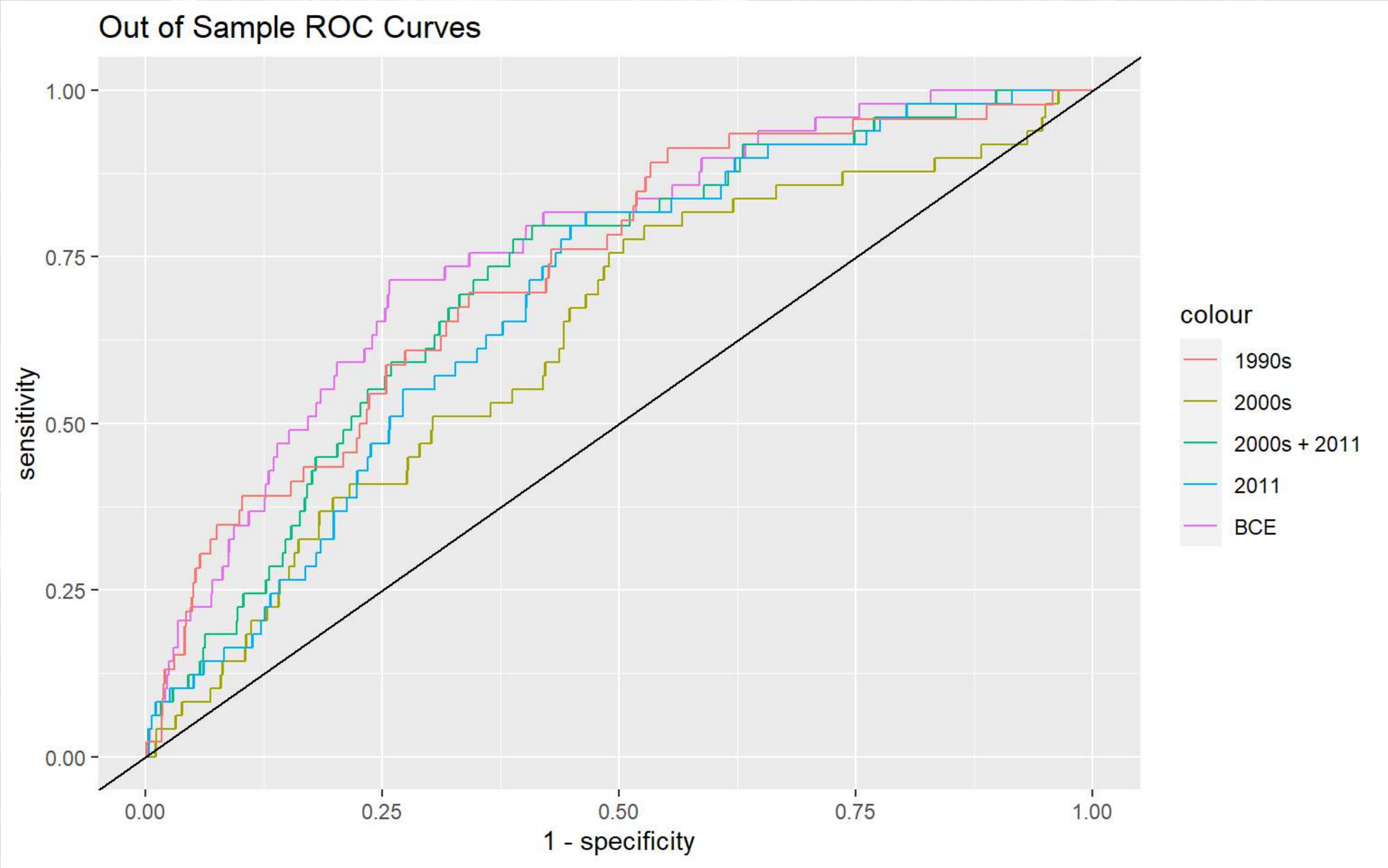
```
##
## Call:
## glm(formula = BCE_eq, family = binomial, data = df[df$Test ==
##     0, ])
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0887  -0.2212  -0.1478  -0.0940   3.5401
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -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 ***
## pct_chg_cashsales -1.976e-03  6.997e-03  -0.282  0.77767
## chg_roa           -2.532e-01  2.786e-01  -0.909  0.36354
## issuance           9.692e-02  3.269e-01   0.296  0.76687
## oplease_dum       -3.451e-01  2.097e-01  -1.645  0.09989 .
```

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., $|\varepsilon|$

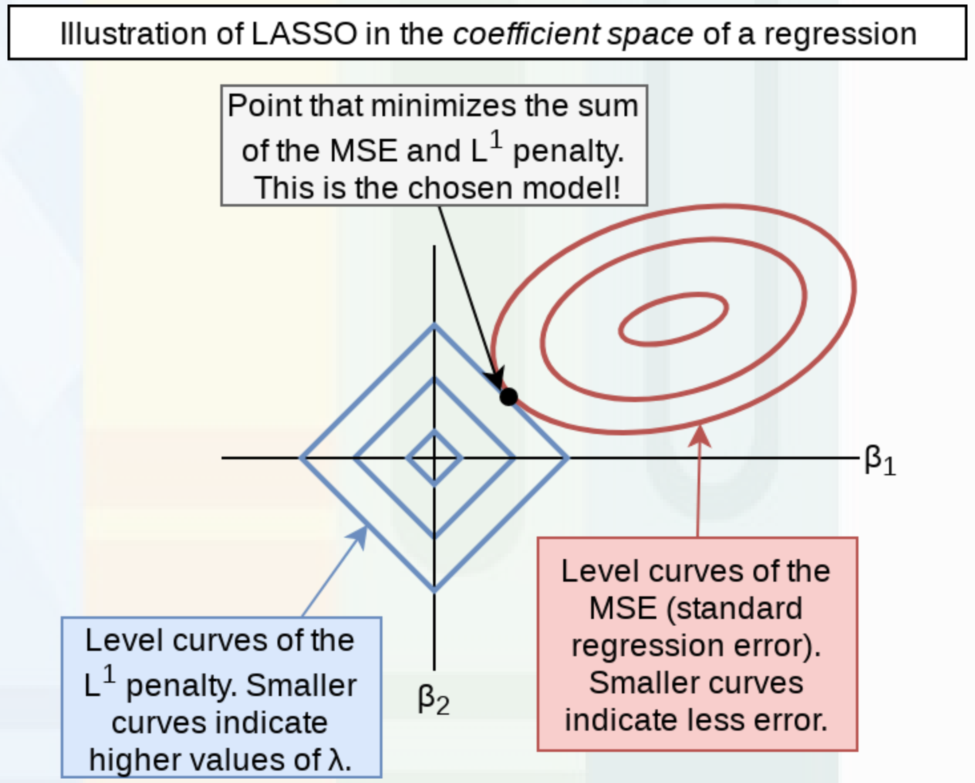
> Great if you have way too many inputs in your model

- 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)

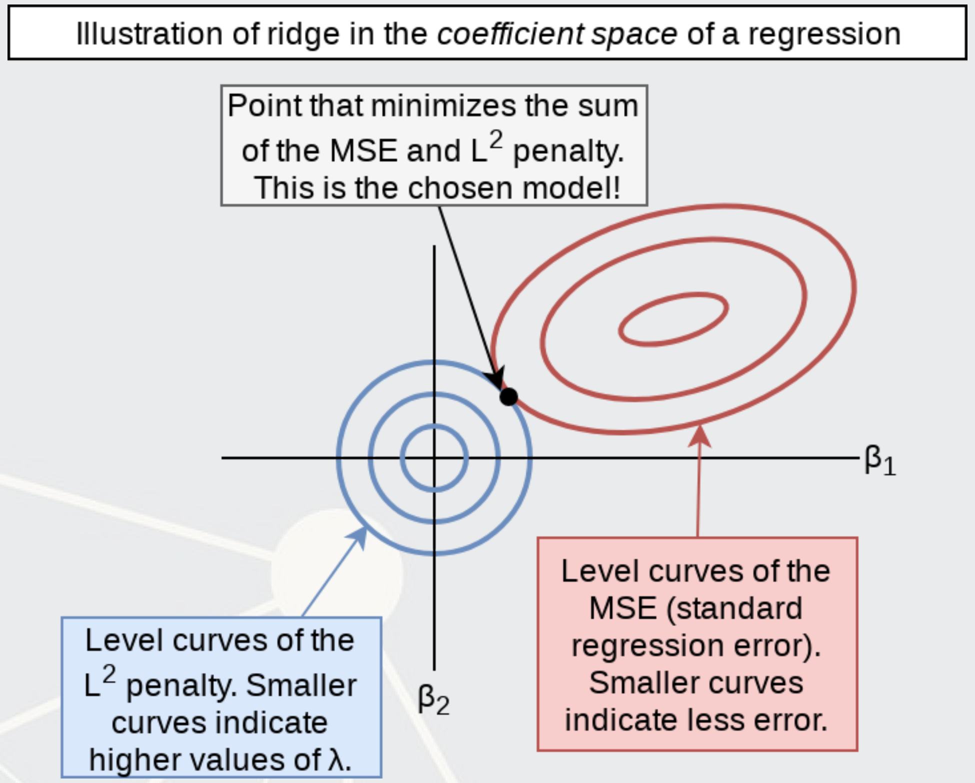
Package for LASSO

- `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?

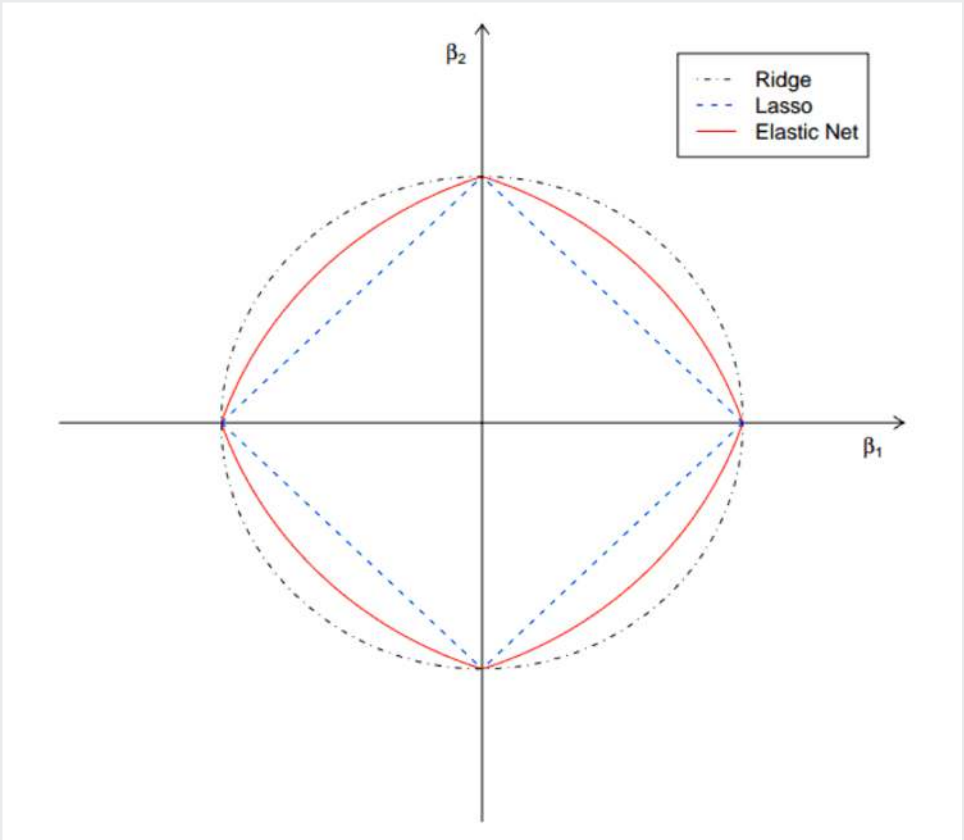
Ridge regression

- 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

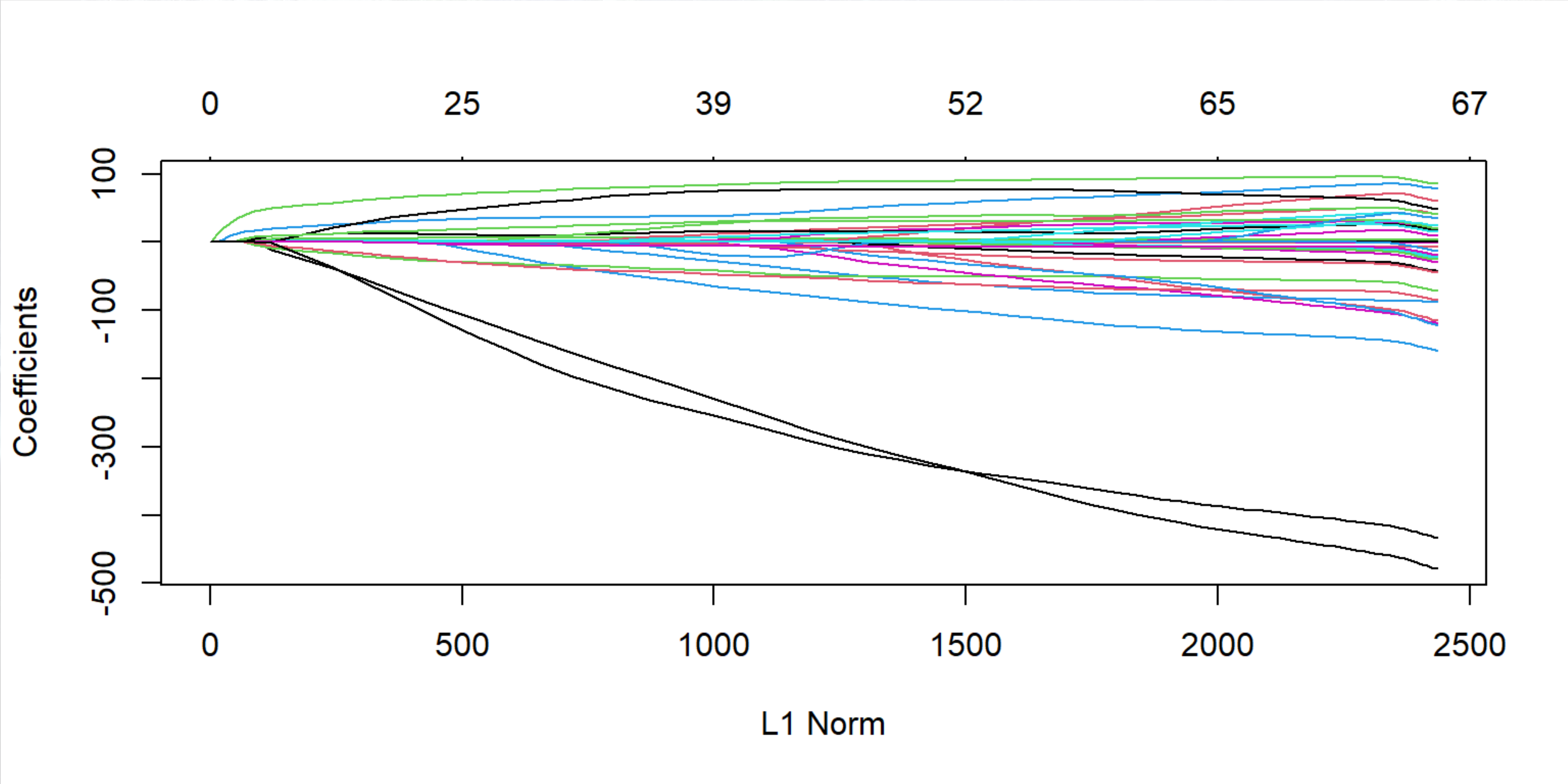
- To run a simple LASSO model, use `glmnet()`
- Let's LASSO the BCE model

```r
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

```r
plot(fit_LASSO)
```



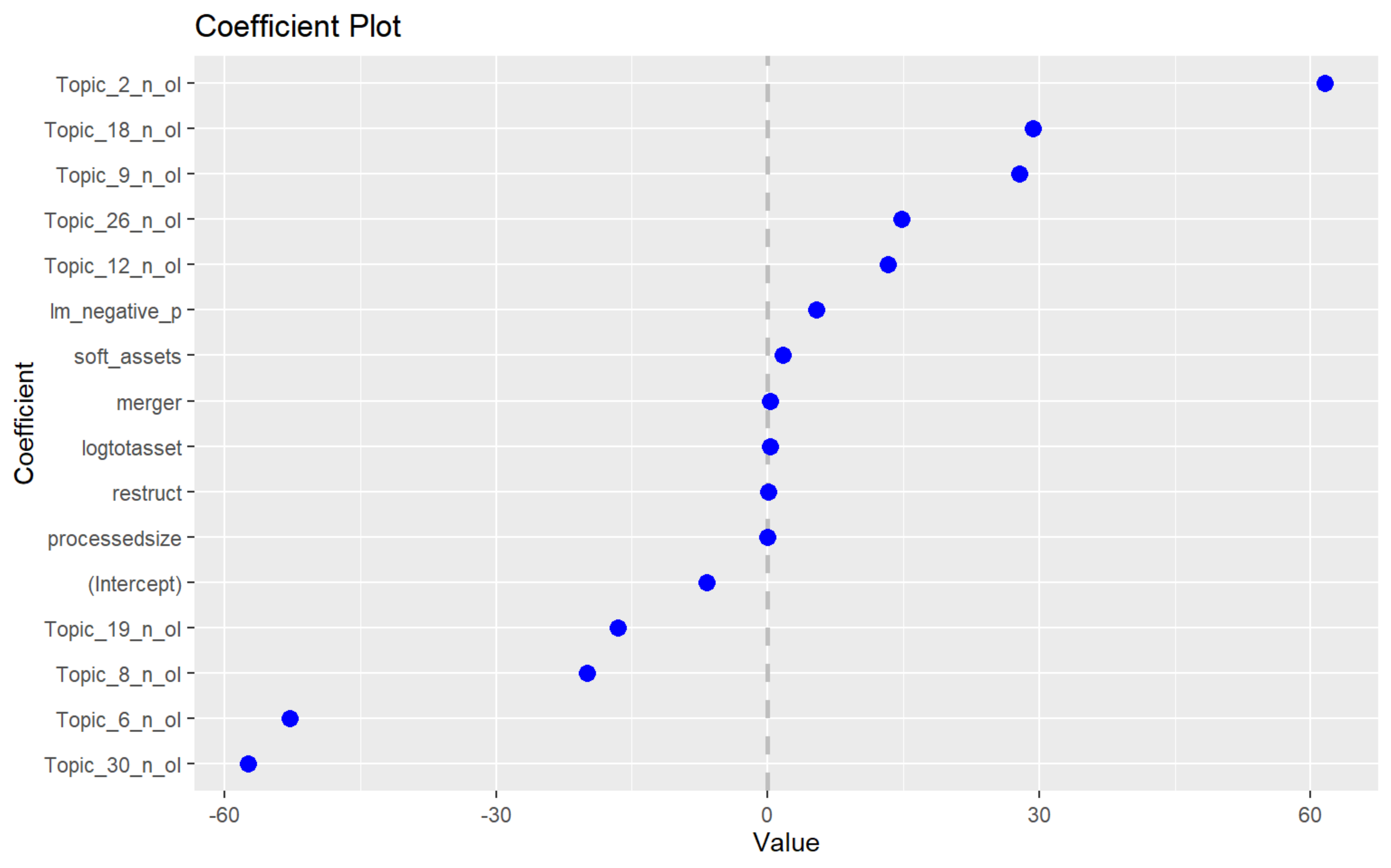
What’s under the hood?

```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
```

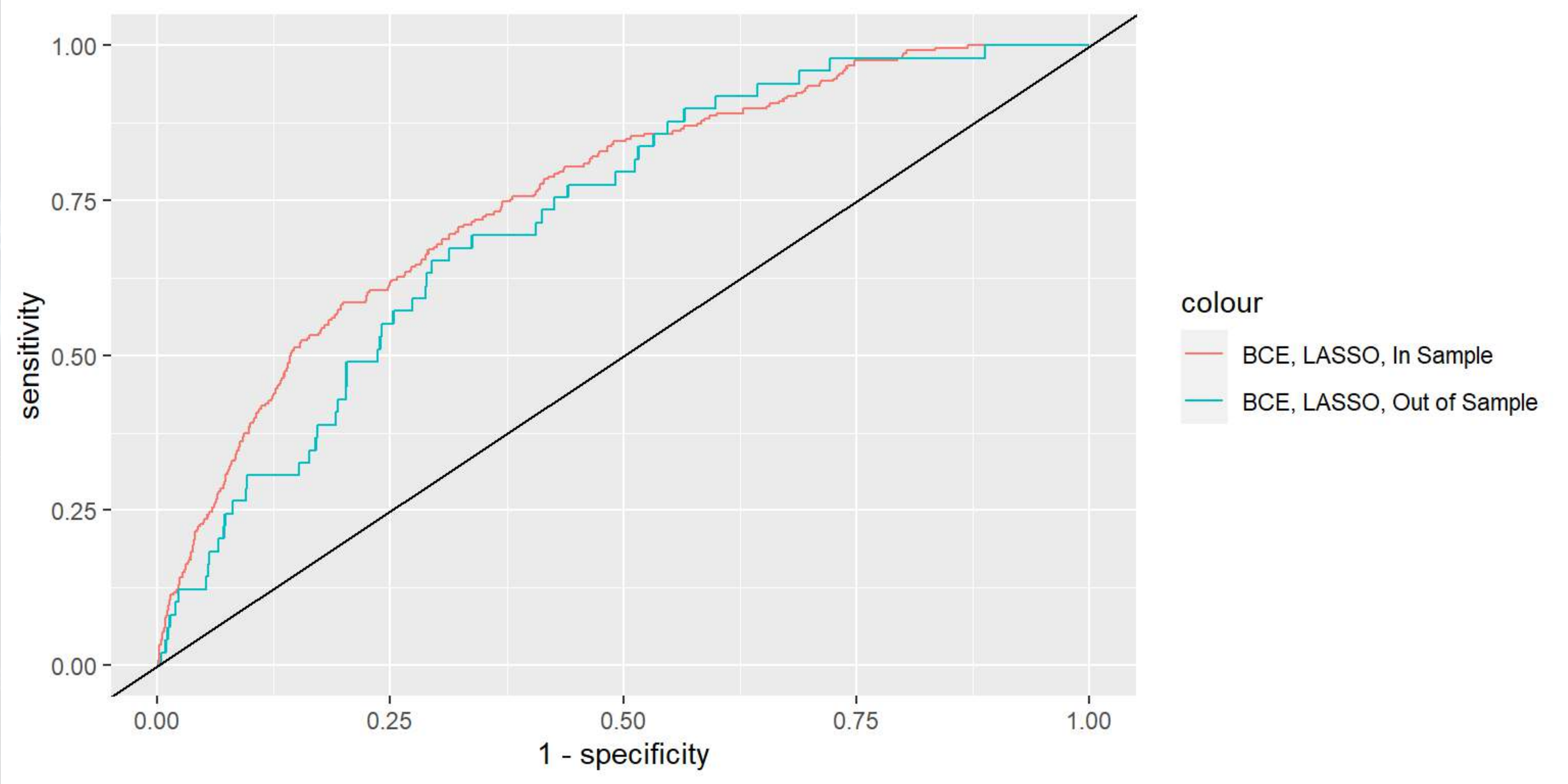
One of the 100 models

```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
df$pred_L1 <- c(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
```

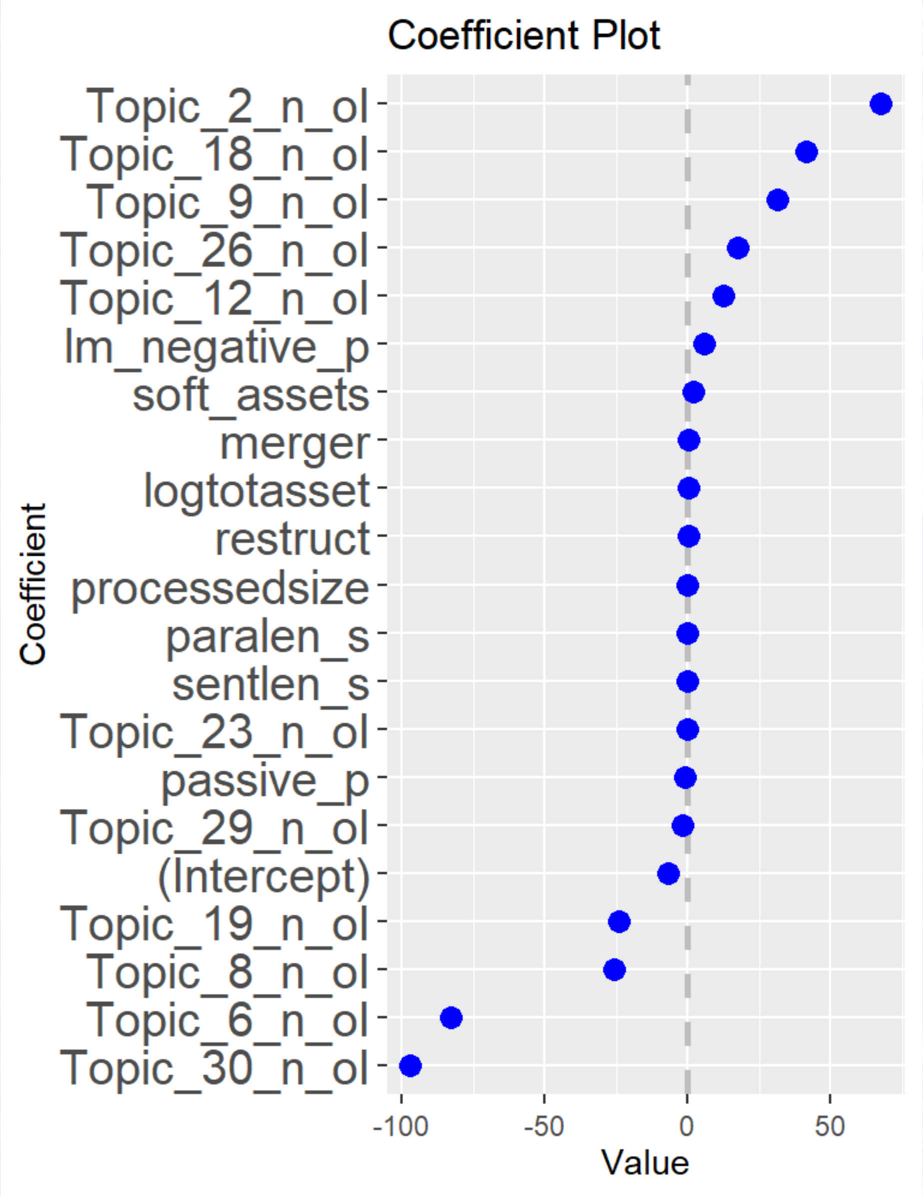
```
## [1] 0.001685798
```

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

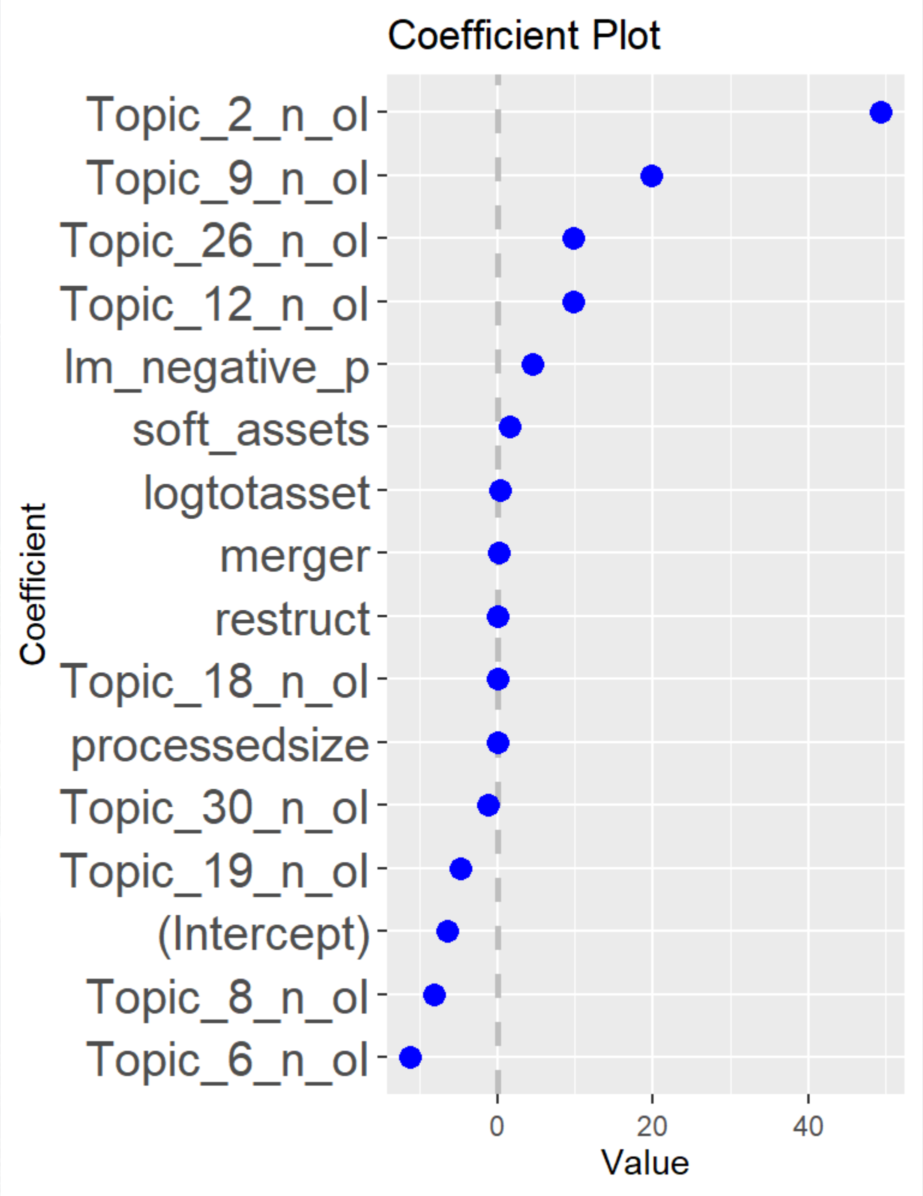
```
## [1] 0.002684268
```

These are the dashed lines on the plot

Models



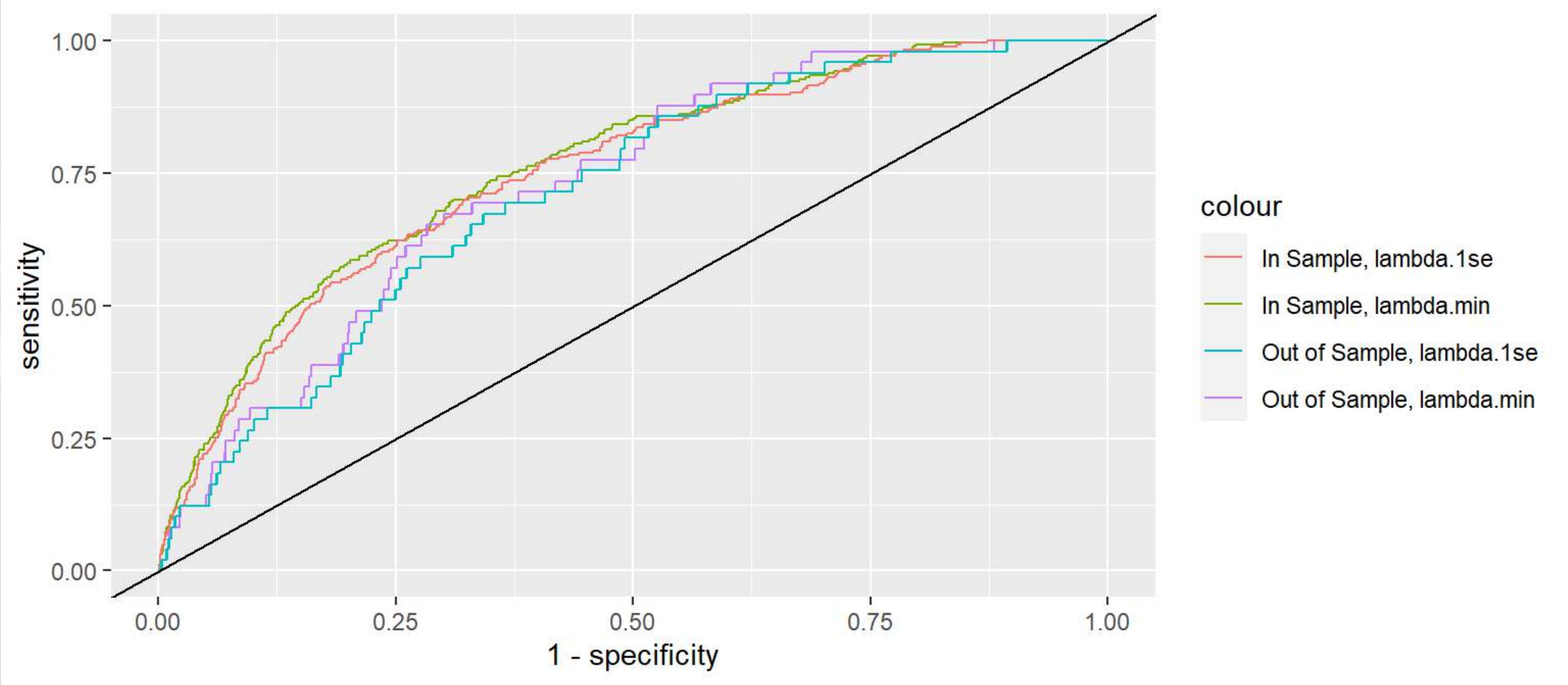
lambda.min



lambda.1se

CV LASSO performance

```r
# s= specifies the version of the model to use
df$pred_L1.min <- c(predict(cvfit, xp, type="response", s = "lambda.min"))
df$pred_L1.1se <- c(predict(cvfit, xp, type="response", s = "lambda.1se"))
```




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

Drawbacks of LASSO

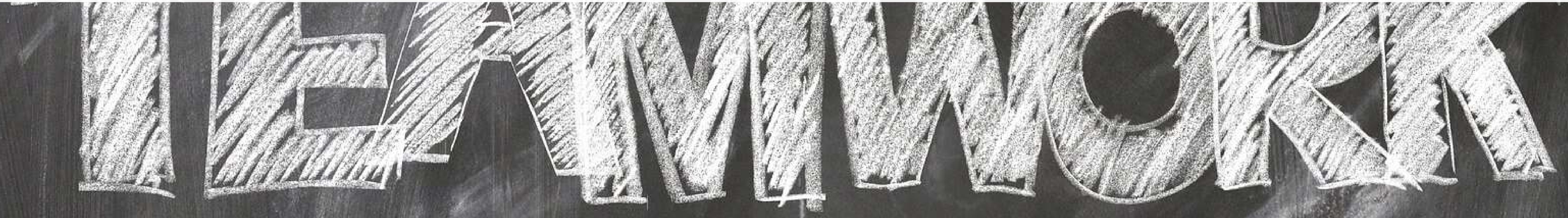
1. No p-values on coefficients
   - Simple solution – run the resulting model with `glm()`
   - Solution only if using `family="gaussian"`:
     - Run the lasso use the `lars` package
       - `m <- lars(x=x, y=y, type="lasso")`
     - Then test coefficients using the `covTest` package
       - `covTest(m, 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 in three weeks
    - 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`
- `tidyverse`
- `yardstick`

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)
```

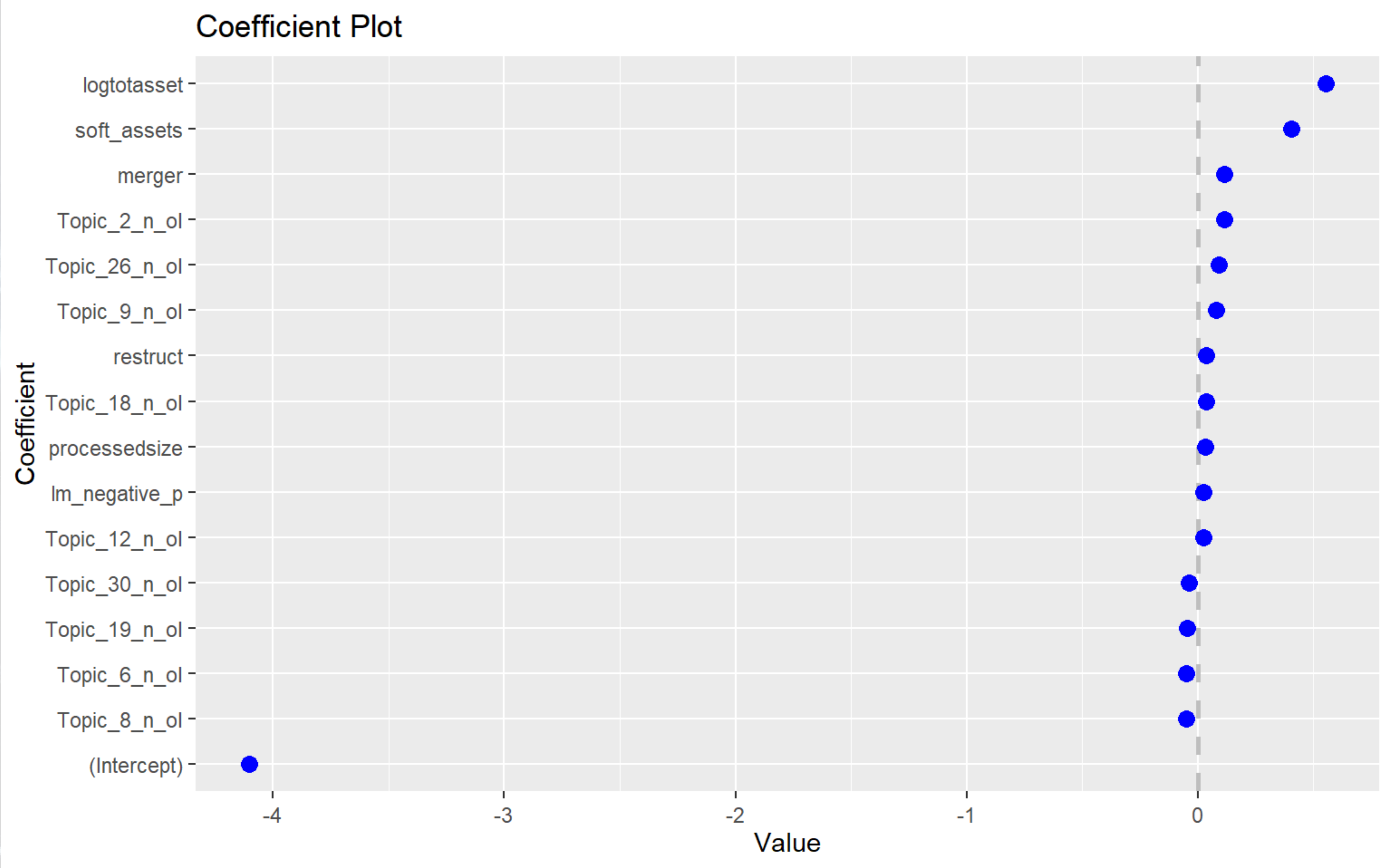
Running a model with `parsnip`

```r
# "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, penalty=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()`

```r
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

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

```r
plot(cvfit)
```

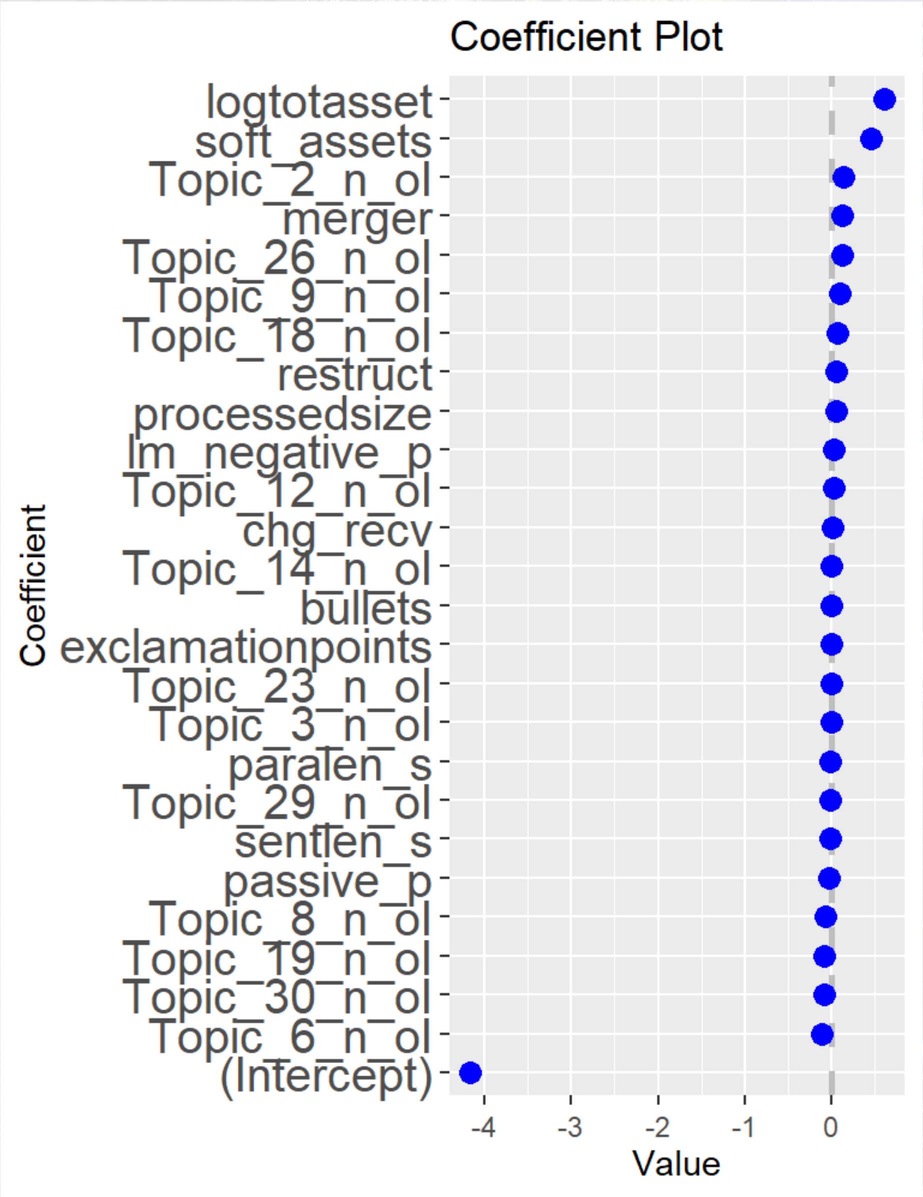
```r
cvfit$lambda.min
```

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

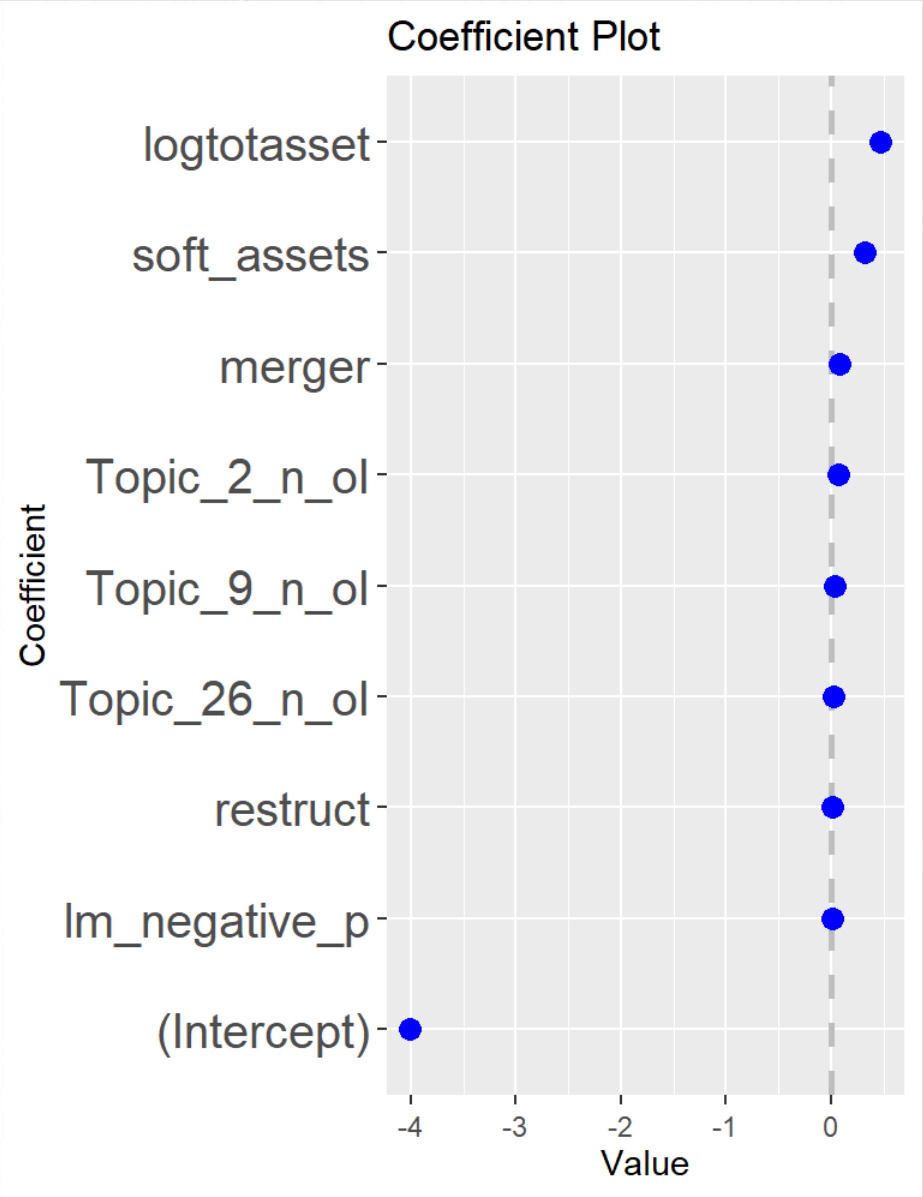
```r
cvfit$lambda.1se
```

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

Models

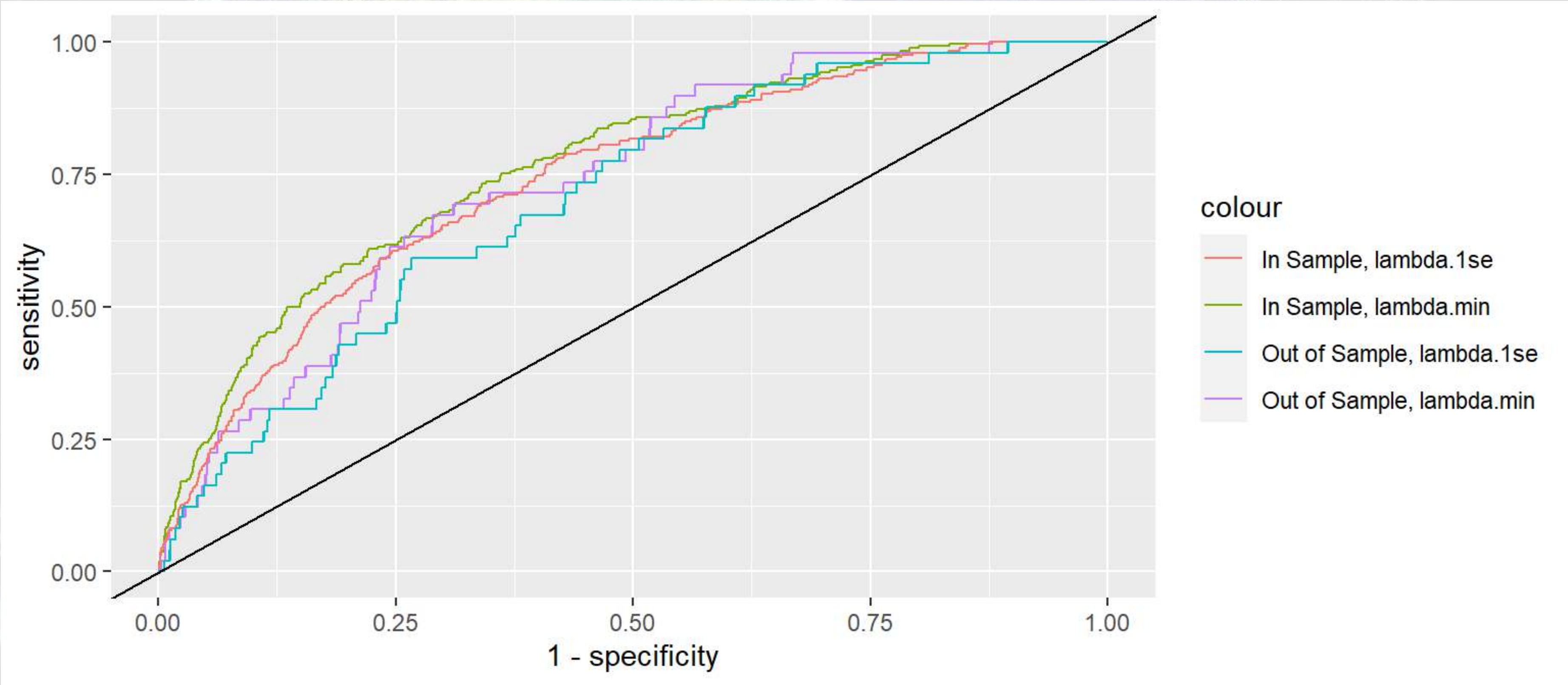


`lambda.min`



`lambda.1se`

CV LASSO performance




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

Packages used for these slides

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

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

Data prep with `recipes` (Same as before)

```r
library(tidyr)
library(tidymodels)
```

```
## Warning: package 'infer' was built under R version 4.1.1
```

```r
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`

```r
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`

```r
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`

```r
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

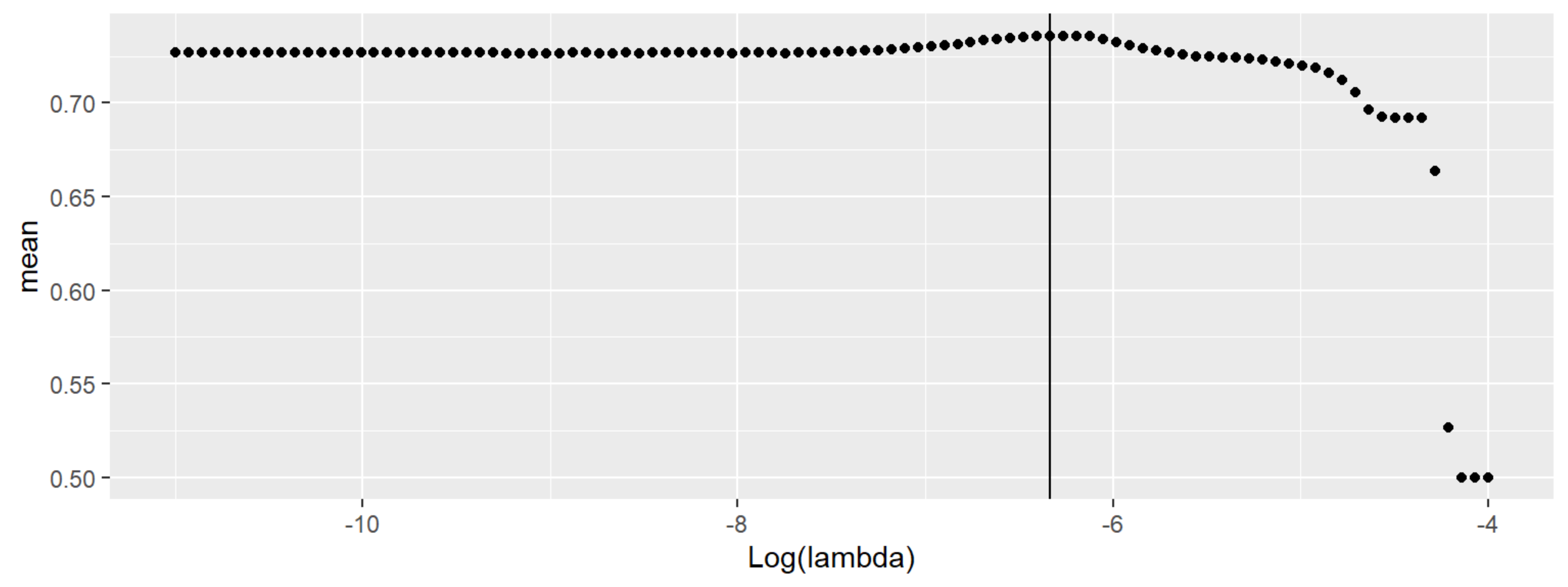
```r
LASSO_fit_tuned %>%
  collect_metrics()
```

```
## # 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 Preprocessor1_Model001
##  2 0.0000179 roc_auc binary     0.727    10  0.0257 Preprocessor1_Model002
##  3 0.0000192 roc_auc binary     0.727    10  0.0257 Preprocessor1_Model003
##  4 0.0000206 roc_auc binary     0.727    10  0.0257 Preprocessor1_Model004
##  5 0.0000222 roc_auc binary     0.727    10  0.0257 Preprocessor1_Model005
##  6 0.0000238 roc_auc binary     0.727    10  0.0257 Preprocessor1_Model006
##  7 0.0000255 roc_auc binary     0.727    10  0.0257 Preprocessor1_Model007
##  8 0.0000274 roc_auc binary     0.727    10  0.0256 Preprocessor1_Model008
##  9 0.0000294 roc_auc binary     0.727    10  0.0256 Preprocessor1_Model009
## 10 0.0000316 roc_auc binary     0.727    10  0.0256 Preprocessor1_Model010
## # ... with 90 more rows
```

Plotting it out

```r
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)
```



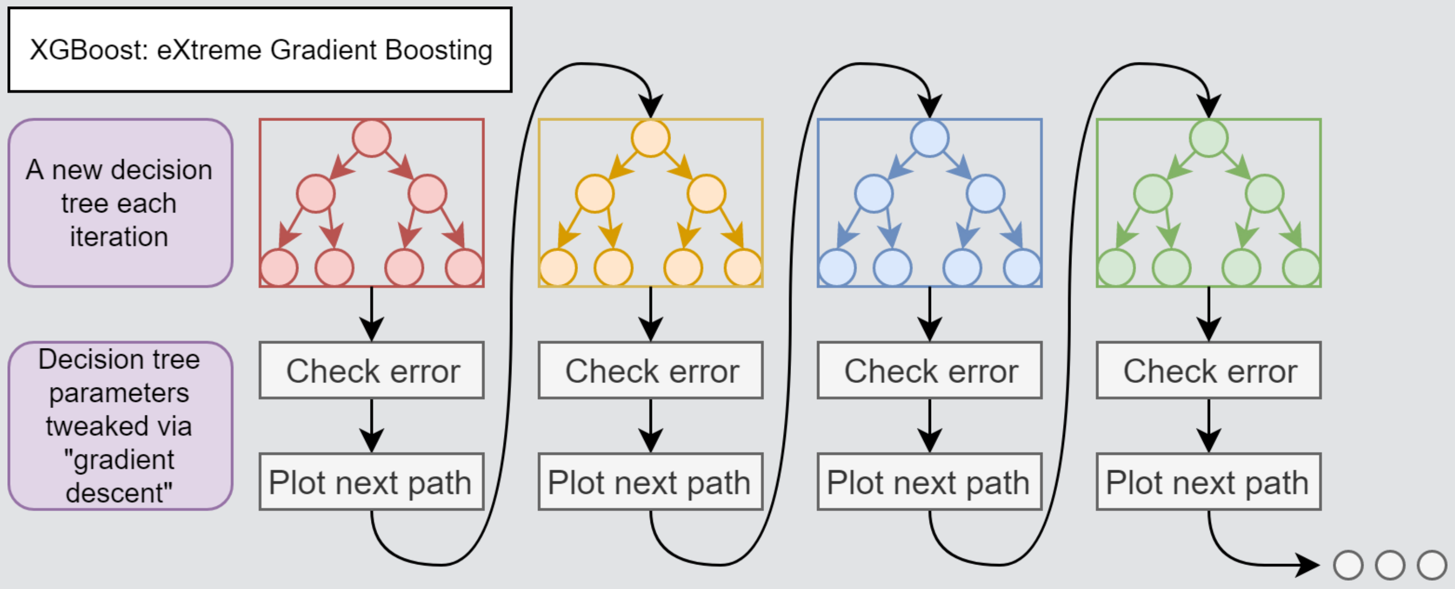
Packages used for these slides

- `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 reproducibility
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 test-auc:0.538707+0.0
## [2]  train-auc:0.586947+0.087237 test-auc:0.563604+0.0
## [3]  train-auc:0.603035+0.084511 test-auc:0.583011+0.0
## [4]  train-auc:0.663903+0.057212 test-auc:0.631184+0.0
## [5]  train-auc:0.677173+0.064281 test-auc:0.639249+0.0
## [6]  train-auc:0.707156+0.026578 test-auc:0.663628+0.0
## [7]  train-auc:0.716727+0.025892 test-auc:0.666075+0.0
## [8]  train-auc:0.728506+0.026368 test-auc:0.671749+0.0
## [9]  train-auc:0.768085+0.025756 test-auc:0.682083+0.0
## [10] train-auc:0.783654+0.030705 test-auc:0.687617+0.0
## [11] train-auc:0.796643+0.027157 test-auc:0.701862+0.0
```

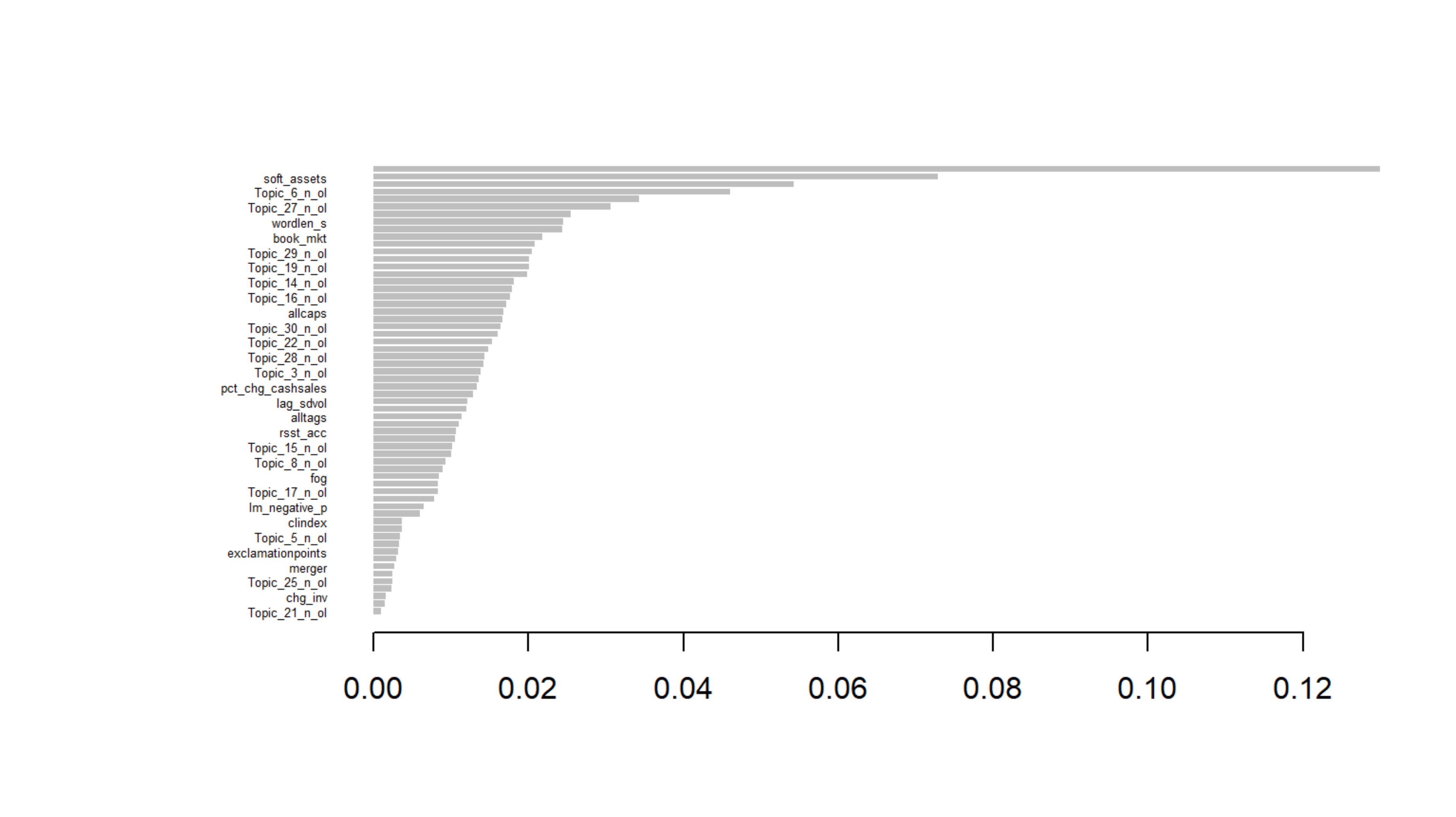
```r
numTrees <- min(
 which(
  xgbCV$evaluation_log$test_auc_mean ==
  max(xgbCV$evaluation_log$test_auc_mean)
 )
)

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

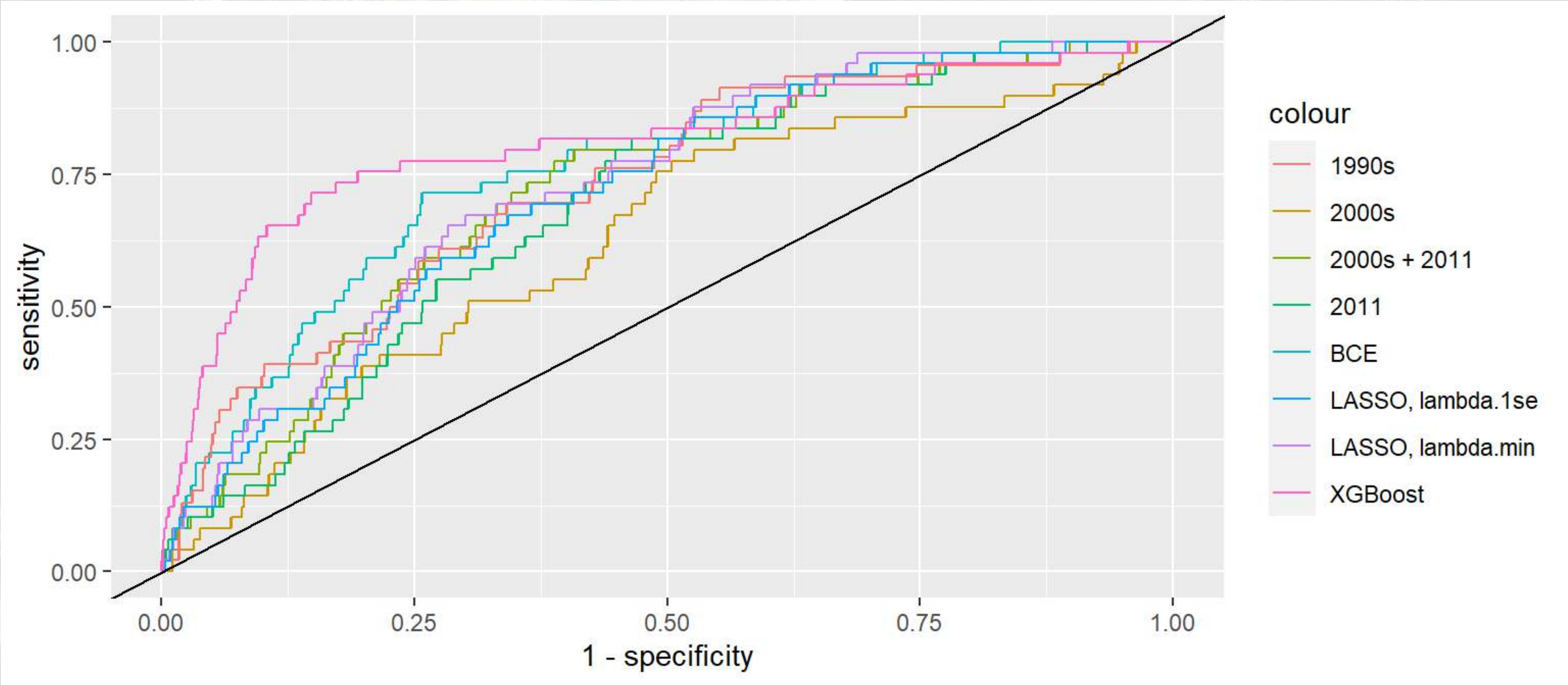
```
## [1]  train-auc:0.500000
## [2]  train-auc:0.663489
## [3]  train-auc:0.663489
## [4]  train-auc:0.703386
## [5]  train-auc:0.703386
## [6]  train-auc:0.704123
## [7]  train-auc:0.727506
## [8]  train-auc:0.727506
## [9]  train-auc:0.727506
## [10] train-auc:0.784639
## [11] train-auc:0.818359
## [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
## [18] train-auc:0.899875
## [19] train-auc:0.902216
```

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: Out of sample




```
##         1990s         2000s     2000s + 2011         2011
##     0.7292981     0.6295414        0.7147021    0.6849225
##            BC LASSO, lambda.1se LASSO, lambda.min      XGBoost
##     0.7599594     0.7124231        0.7290185    0.8083503
```

Packages used for these slides

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