Welcome!

Nameplates please. And technology encouraged today!

All TF materials are available at github.com/nolankav/api-203.

If you want to follow along, download the dataset here:

In R: `df <- read.csv("http://tinyurl.com/api-203-tf-5")`

Prediction, Double Feature R

API 203: TF Session 5

Nolan M. Kavanagh
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Goals for today

1. **Briefly review strategies for predicting binary outcomes.**
2. **Learn how to generate classification models in R.**
3. **Practice evaluating the accuracy of classification models.**

We'll treat this session like a workshop with an interactive example.

Overview of our sample data

Dataset of ~17,000 U.S. adults surveyed in 2019

`casein`	**Respondent identifier**	*Cooperative Election Study*
`commonweight`	**Post-stratification survey weight**	*Cooperative Election Study*
`age`	**Respondent age (in years)**	*Cooperative Election Study*
`gender`	**Respondent gender**	*Cooperative Election Study*
`race_eth`	**Respondent race/ethnicity**	*Cooperative Election Study*
`education`	**Respondent educational attainment**	*Cooperative Election Study*
`marital`	**Respondent marital status**	*Cooperative Election Study*
`employment`	**Respondent employment status**	*Cooperative Election Study*
`device`	**Device respondent is using for survey**	*Cooperative Election Study*
`republican`	**Identifies as Republican (1) or not (0)**	*Cooperative Election Study*
`public_ins`	**Respondent has public health insurance (1) or not (0)**	*Cooperative Election Study*
`public_option`	**Supports a public option in Medicare (1) or not (0)**	*Cooperative Election Study*

What if we're predicting a binary outcome?

The classic story is that OLS is not appropriate for predicting a binary outcome because you might get predicted values above 1 or below 0.

This is impossible since we can't have a probability above 100% or below 0%.

For this reason, people turn to probit (common in economics) or logit (common everywhere else).

But here's the thing.

All three produce similar predicted probabilities!

And if you have only categorical predictors, they produce *identical* predicted probabilities.

So does it really matter? Not really.

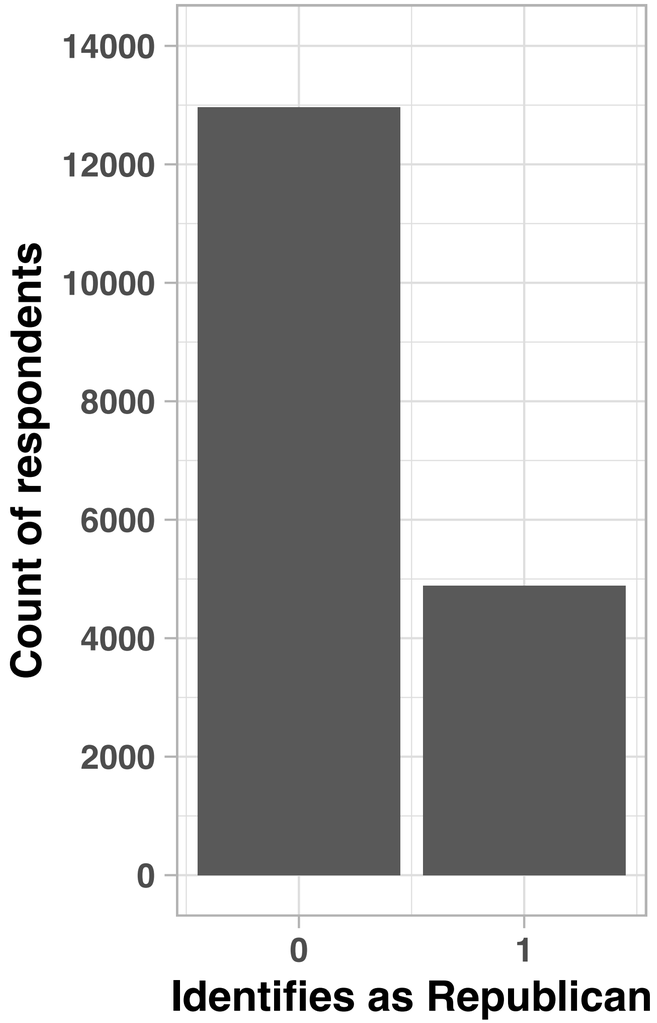
Use what's most useful to you.

We'll riff on the same idea as last week.

Parties want to know whom they can contact for fundraising, get out the vote, etc.

This time, we will predict if someone is (or isn't) a Republican using the data we have.

```
# Generate bar plot of parties
plot_1 <- ggplot(data=df, aes(x=republican)) +
  geom_bar(stat="count") +
  xlab("Identification as Republican") +
  ylab("Count of respondents") +
  theme_light() +
  theme(text = element_text(size = 10, face = "bold")) +
  scale_x_continuous(breaks = seq(-3, 3, 1)) +
  scale_y_continuous(limits = c(0,14000),
                     breaks = seq(0,15000,2000))
```



Let's try a reasonable model.

This package is great for making ROC curves.
(We'll get to those soon enough.)

```
# Load libraries
library(pROC)     # ROC tools
library(rsample) # Analysis tools

# Designate training and test sets
set.seed(1234)
split    <- initial_split(df, 0.7)
df_train <- training(split)
df_test  <- testing(split)

# Logit regression
model_1 <- glm(republican ~ age + gender + race_eth + education + marital +
                  employment + device, data=df_train, family="binomial")

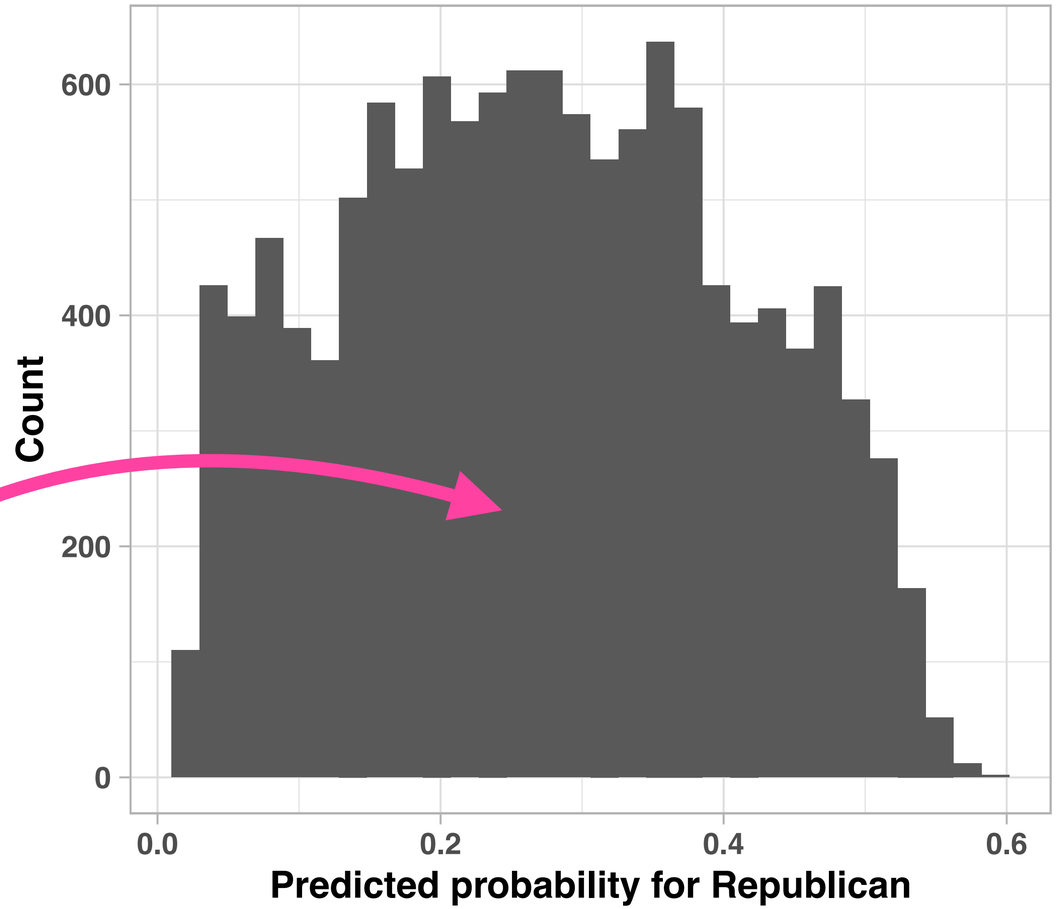
# In-sample prediction
df_train$predict <- predict(model_1, df_train, type="response")
```

Let's go with logit. Set family to binomial.

FYI the `predict` function returns a "latent" value by default. It's not readily interpretable.
We got actual predicted probabilities by adding `type = "response"`. But it works fine either way.

But here's the problem.

```
# Histogram of predictions
plot_2 <- ggplot(df_train, aes(x=predict)) +
  geom_histogram() +
  theme_light() +
  theme(text = element_text(size = 10, face = "bold")) +
  xlab("Predicted Republican") +
  ylab("Count")
print(plot_2)
```



With classification models, we get continuous predicted values. We have to set a threshold for what we think qualifies as Republican or not.

But which threshold do we pick?

FYI the `predict` function returns a "latent" value by default. It's not readily interpretable.
We got actual predicted probabilities by adding `type = "response"`. But it works fine either way.

Let’s try two different thresholds.

```
# Set potential thresholds
df_train <- df_train %>% mutate(
  threshold_1 = case_when(
    predict > 0.4 ~ 1, TRUE ~ 0),
  threshold_2 = case_when(
    predict > 0.2 ~ 1, TRUE ~ 0
  ))

# Evaluate thresholds
table(df_train$republican, df_train$threshold_1)

      0    1
  0 7782 1315
  1 2199 1203

table(df_train$republican, df_train$threshold_2)

      0    1
  0 3640 5457
  1  504 2898
```

Let’s try 0.4 and 0.2 as thresholds.

Let's try two different thresholds.

```
# Set potential thresholds
df_train <- df_train %>% mutate(
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      0    1
  0 3640 5457
  1  504 2898
```

		Predicted party	
		Not Rep.	**Republican**
True party	**Not Rep.**	True negatives	False positives
	Republican	False negatives	True positives

A brief aside on terminology.

Calculation	Terminology
FP / (TN + FP)	**False positive rate**, 1–Specificity, Type I error
TP / (TP + FN)	**True positive rate, Recall, Sensitivity**, 1–Type II error, Power
TP / All predicted positives	**Precision**, Positive predicted value
TN / All predicted negatives	Negative predicted value


The poor souls in API 203
“My job is just… dealing with ever so slightly different versions of the exact same statistical concepts”

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  1 2199 1203

table(df_train$republican, df_train$threshold_2)

      0    1
  0 3640 5457
  1  504 2898
```

So for 40%:

		Predicted party	
		Not Rep.	**Republican**
True party	**Not Rep.**	7782	1315
	Republican	2199	1203

Precision = True positives / All positives =

Recall = True positives / (TP + FN) =

Let's try two different thresholds.

```
# Set potential thresholds
df_train <- df_train %>% mutate(
  threshold_1 = case_when(
    predict > 0.4 ~ 1, TRUE ~ 0),
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      0    1
  0 3640 5457
  1  504 2898
```

So for 40%:

		Predicted party	
		Not Rep.	**Republican**
True party	**Not Rep.**	7782	1315
	Republican	2199	1203

Precision = True positives / All positives = 1203 / (1203 + 1315) = **0.48**

Recall = True positives / (TP + FN) = 1203 / (1203 + 2199) = **0.35**

Let's try two different thresholds.

```
# Set potential thresholds
df_train <- df_train %>% mutate(
  threshold_1 = case_when(
    predict > 0.4 ~ 1, TRUE ~ 0),
  threshold_2 = case_when(
    predict > 0.2 ~ 1, TRUE ~ 0
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# Evaluate thresholds
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  0 7782 1315
  1 2199 1203

table(df_train$republican, df_train$threshold_2)

      0    1
  0 3640 5457
  1  504 2898
```

So for 20%:

		Predicted party	
		Not Rep.	**Republican**
True party	**Not Rep.**	3640	5457
	Republican	504	2898

Precision = True positives / All positives =

Recall = True positives / (TP + FN) =

Let's try two different thresholds.

```
# Set potential thresholds
df_train <- df_train %>% mutate(
  threshold_1 = case_when(
    predict > 0.4 ~ 1, TRUE ~ 0),
  threshold_2 = case_when(
    predict > 0.2 ~ 1, TRUE ~ 0
  ))

# Evaluate thresholds
table(df_train$republican, df_train$threshold_1)

      0    1
  0 7782 1315
  1 2199 1203

table(df_train$republican, df_train$threshold_2)

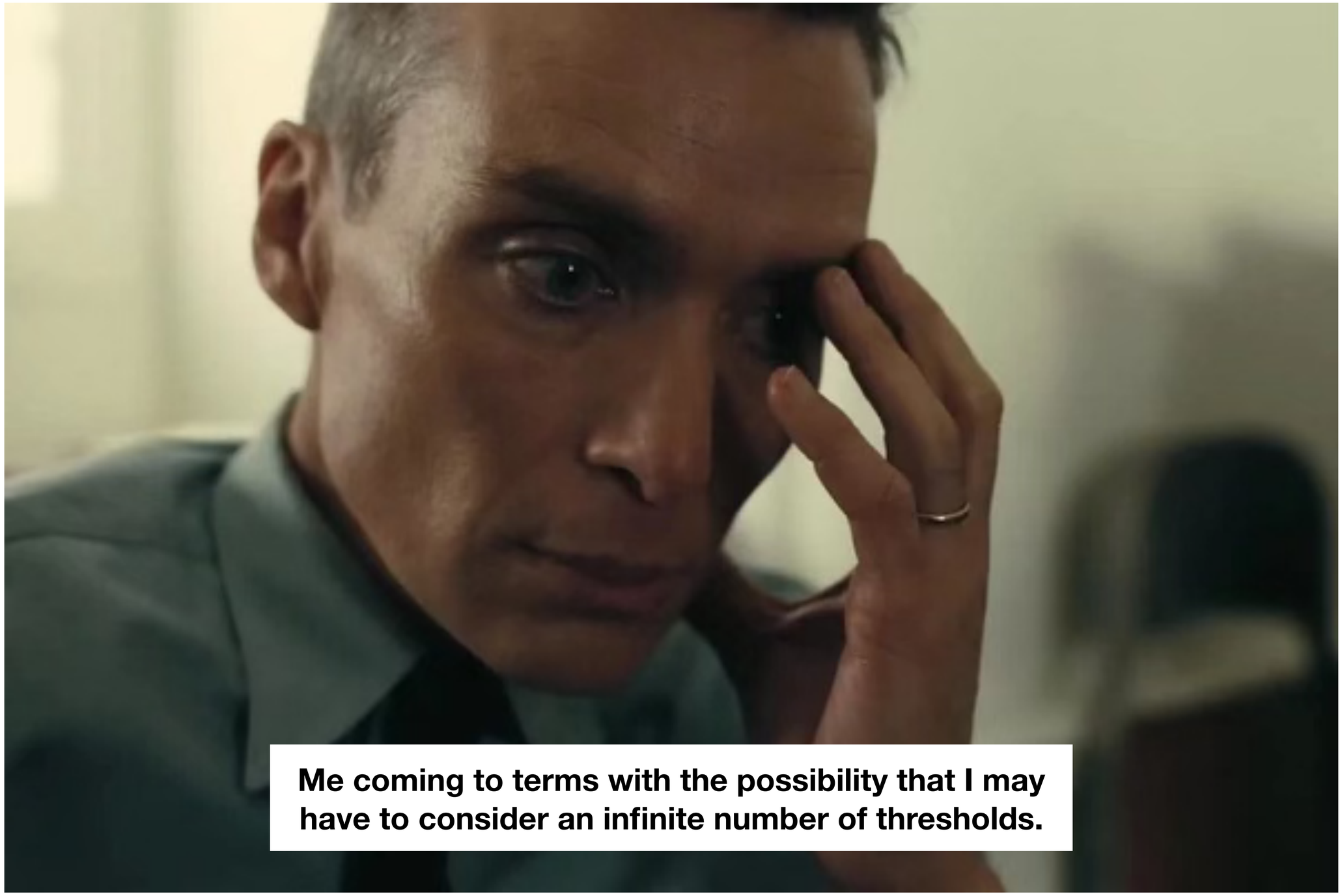
      0    1
  0 3640 5457
  1  504 2898
```

So for 20%:

		Predicted party	
		Not Rep.	**Republican**
True party	**Not Rep.**	3640	5457
	Republican	504	2898

Precision = True positives / All positives = 2898 / (2898 + 5457) = **0.35**

Recall = True positives / (TP + FN) = 2809 / (2898 + 504) = **0.83**

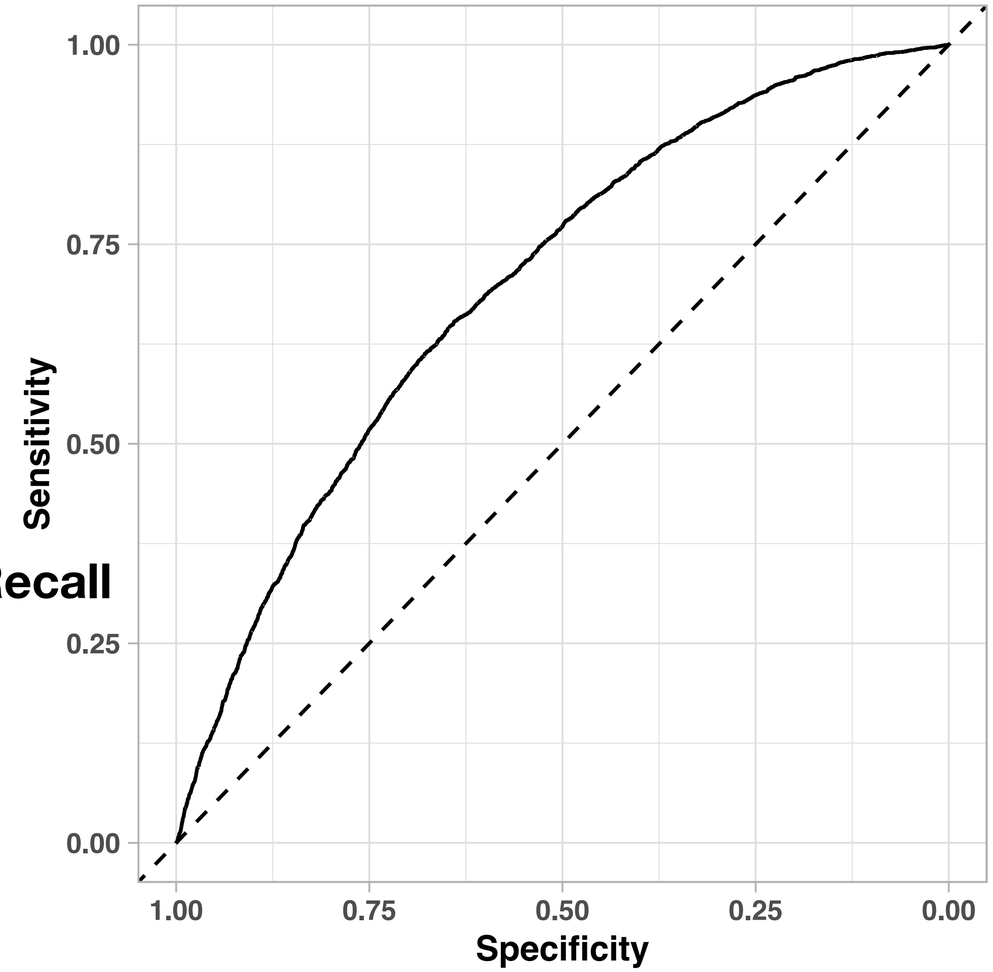

Me coming to terms with the possibility that I may have to consider an infinite number of thresholds.

There must be a better way.

```
# Generate ROC curve for training set
roc_train <- roc(df_train$republican, df_train$predict)
roc_train$auc

Area under the curve: 0.6988

# Plot ROC curve
plot_3 <- ggroc(roc_train) +
  theme_light() +
  theme(text = element_text(size = 10, face = "bold")) +
  geom_abline(slope=1, intercept=1, linetype="dashed") +
  xlab("Specificity") +
  ylab("Sensitivity")
print(plot_3)
```



= Recall

The ROC tests the performance of our model for all thresholds and summarizes that information in one graph.

Sadly, not the same as precision.

There must be a better way.

```
# Generate ROC curve for training set
roc_train <- roc(df_train$republican, df_train$predict)
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Area under the curve: 0.6988

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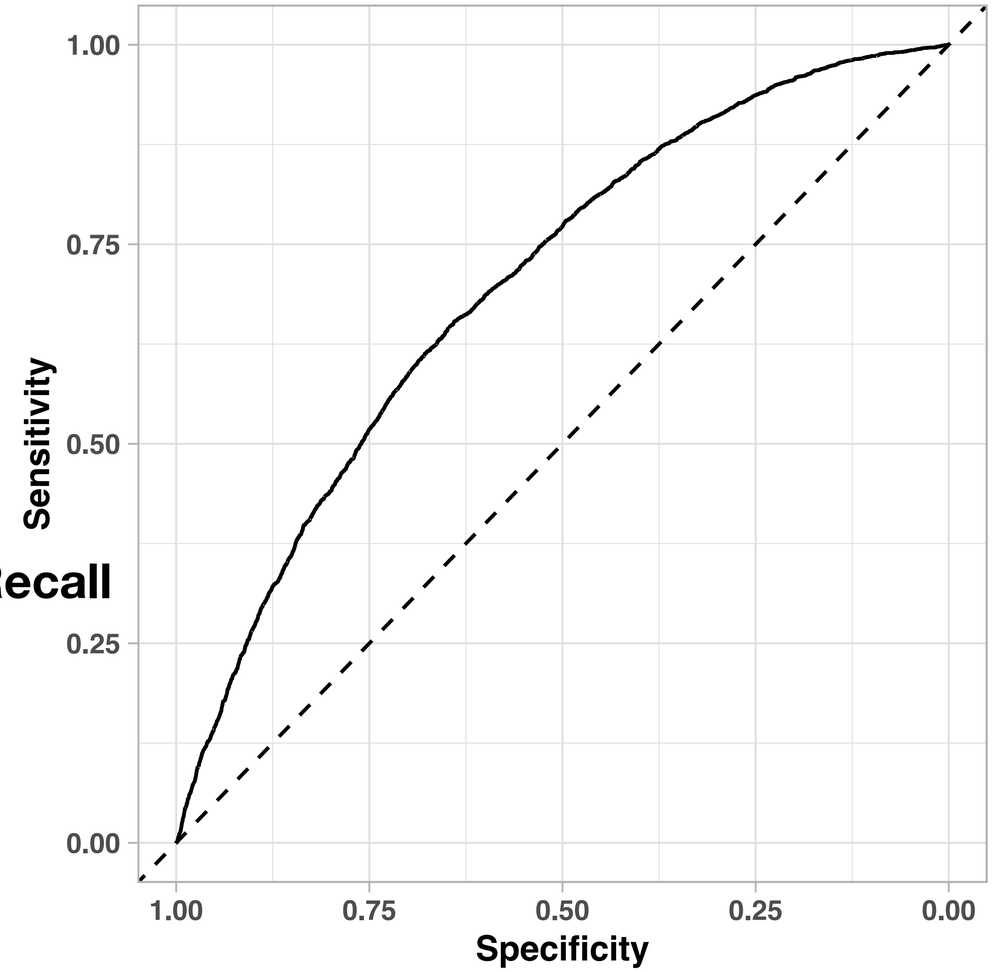
  theme(text = element_text(size = 10, face = "bold")) +
  geom_abline(slope=1, intercept=1, linetype="dashed") +
  xlab("Specificity") +
  ylab("Sensitivity")
print(plot_3)
```



= Recall

Area under the curve let's use numerically summarize the overall performance. It's the area under the ROC curve.

1 is perfect prediction. 0.5 is no better than chance. Ours is about halfway between perfect and chance.

Sadly, not the same as precision.

Let's evaluate the test set.

```
# Out-of-sample prediction
df_test$predict <- predict(model_1, df_test)

# Set potential thresholds
df_test <- df_test %>% mutate(
  threshold_1 = case_when(
    predict > 0.4 ~ 1, TRUE ~ 0),
  threshold_2 = case_when(
    predict > 0.2 ~ 1, TRUE ~ 0
  ))

# Evaluate thresholds
table(df_test$republican, df_test$threshold_1)

      0    1
  0 3225  646
  1  947  540

table(df_test$republican, df_test$threshold_2)

      0    1
  0 1497 2374
  1  202 1285
```

Let's evaluate the test set.

```
# Out-of-sample prediction
df_test$predict <- predict(model_1, df_test)

# Set potential thresholds
df_test <- df_test %>% mutate(
  threshold_1 = case_when(
    predict > 0.4 ~ 1, TRUE ~ 0),
  threshold_2 = case_when(
    predict > 0.2 ~ 1, TRUE ~ 0
  ))

# Evaluate thresholds
table(df_test$republican, df_test$threshold_1)
```

```
      0    1
  0 3225  646
  1  947  540
```

```
table(df_test$republican, df_test$threshold_2)
```

```
      0    1
  0 1497 2374
  1  202 1285
```

For a threshold of 40%:

Precision
= True positives / All predicted positives
= 540 / (540 + 646) = **0.46**

Recall (Sensitivity)
= True positives / (TP + FN)
= 540 / (540 + 947) = **0.36**

For a threshold of 20%:

Precision
= True positives / All predicted positives
= 1285 / (1285 + 2374) = **0.35**

Recall (Sensitivity)
= True positives / (TP + FN)
= 1285 / (1285 + 202) = **0.86**

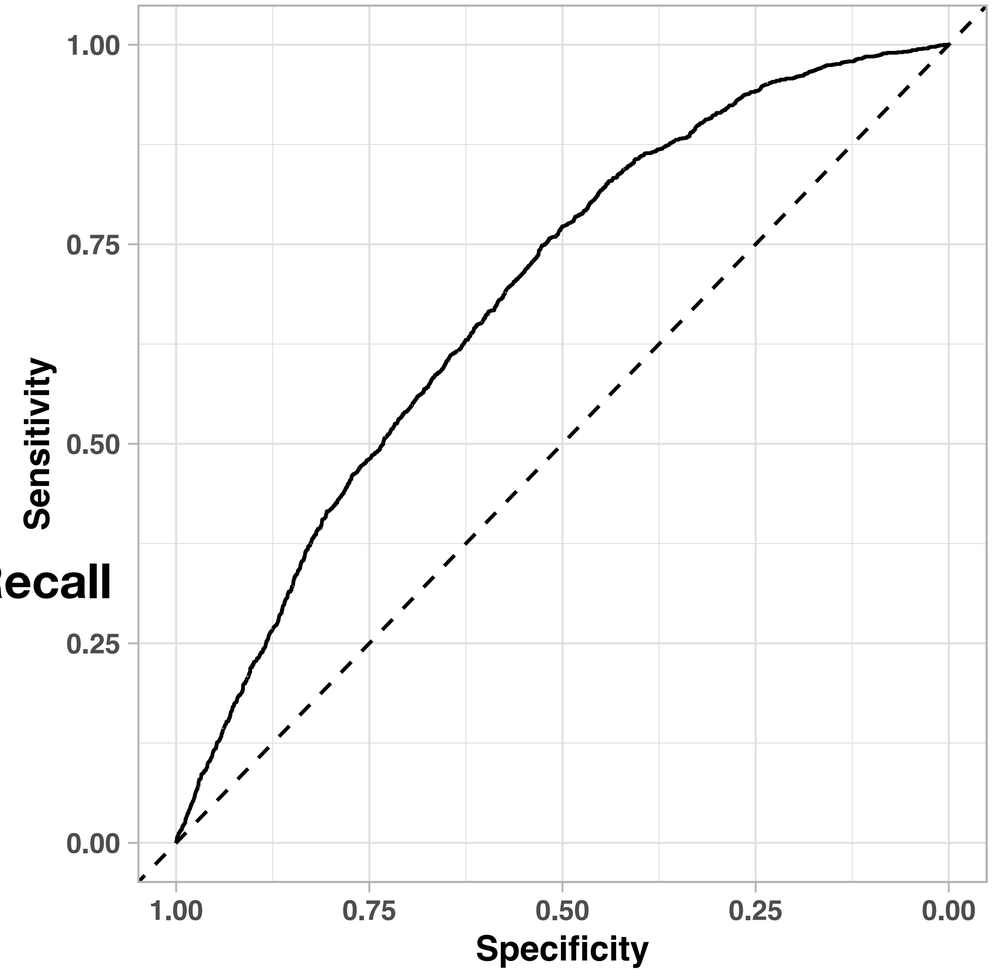
Let's evaluate the test set.

```
# Generate ROC curve for test set
roc_test <- roc(df_test$republican, df_test$predict)
roc_test$auc

Area under the curve: 0.6842

# Plot ROC curve
plot_4 <- ggroc(roc_test) +
  theme_light() +
  theme(text = element_text(size = 10, face = "bold")) +
  geom_abline(slope=1, intercept=1, linetype="dashed") +
  xlab("Specificity") +
  ylab("Sensitivity")
print(plot_4)
```

= Recall



The training set's AUC was 0.70.

So on the whole, we perform a little worse in the test set, which is to be expected, but not too much worse!

Predictions, Part 2.

We could enhance the model with LASSO.

It looks like we did last week; we just have to add `family = "binomial"` to the model.

But note that even for binary outcomes, the model itself generates a continuous “latent” prediction, so the principles are the all same.

We just evaluate binary vs. continuous models using different quantities (MSE vs. recall, etc.).