Political Science 209 - Fall 2018

Prediction

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9th October 2018

In-class Exercise Measurement

Carvalho, Leandro S., Meier, Stephen, and Wang, Stephanie W. (2016). "Poverty and economic decision-making: Evidence from changes in financial resources at payday." American Economic Review, Vol. 106, No. 2, pp. 260-284.

In-class Exercise Measurement

Do changes in one's financial circumstances affect one's decision-making process and cognitive capacity? In an experimental study, researchers randomly selected a group of US respondents to be surveyed before their payday and another group to be surveyed after their payday. Under this design, the respondents of the Before Payday group are more likely to be financially strained than those of the After Payday group. The researchers were interested in investigating whether or not changes in people's financial circumstances affect their decision making and cognitive performance. Other researchers have found that scarcity induce an additional mental load that impedes cognitive capacity.

Poverty and economic decision-making

In this study, the researchers administered a number of decision-making and cognitive performance tasks to the Before Payday and After Payday groups. We focus on the numerical stroop task, which measures cognitive control. In general, taking more time to complete this task indicates less cognitive control and reduced cognitive ability. They also measured the amount of cash the respondents have, the amount in their checking and saving accounts, and the amount of money spent.

Poverty and economic decision-making

Load the poverty.csv data set.

Poverty and economic decision-making

Variables:

- *treatment*: Treatment conditions: Before Payday and After Payday
- *cash*: Amount of cash respondent has on hand
- *accts_amt* Amount in checking and saving accounts
- *stroop_time*: Log-transformed average response time for cognitive stroop test
- *income_less20k*: Binary variable: 1 if respondent earns less than 20k a year and 0 otherwise

Look at a summary of the poverty data set to get a sense of what its variables looks like.

Question 1

1. Use histograms to examine the univariate distributions of the two financial resources measures: cash and accts_amt. What can we tell about these variables' distributions from looking at the histograms? Evaluate what the shape of these distributions could imply for the authors' experimental design.
2. Now, take the natural logarithm of these two variables and plot the histograms of these tranformed variables. How does the distribution look now? What are the advantages and disadvantages of transforming the data in this way?

NOTE: Since the natural logarithm of 0 is undefined, researchers often add a small value (in this case, we will use $1 so that $\log 1 = 0$) to the 0 values for the variables being transformed.

Question 2a

Now, let's examine the primary outcome of interest for this study– the effect of a change in financial situation (in this case, getting paid on payday) on economic decision-making and cognitive performance. Begin by calculating the treatment effect for the stroop_time variable (a log-transformed variable of the average response time for the stroop cognitive test), using first the mean and then the median. What does this tell you about differences in the outcome across the two experimental conditions?

Question 2b

Secondly, let's look at the relationship between finanical circumstances and the cognitive test variable. Produce two scatter plots side by side (hint: use the par(mfrow)) before your plot commands to place graphs side-by-side), one for each of the two experimental conditions, showing the bivariate relationship between your log-transformed cash variable and the amount of time it took subjects to complete the stroop cognitive test administered in the survey (stroop_time). Place the stroop_time variable on the y-axis. Be sure to title your graphs to differentiate between the Before Payday and After Payday conditions. Now do the same, for the log-transformed accts_amt variable.

Question 3

Now, let's take a closer look at whether or not the Before Payday versus After Payday treatment created measurable differences in financial circumstances. What is the effect of payday on participants' financial resources? To help with interpretability, use the original variables cash and accts_amt to calculate this effect. Calculate both the mean and median effect. Does the measure of central tendency you use affect your perception of the effect?

Question 4

Compare the distributions of the Before Payday and After Payday groups for the log-transformed cash and accts_amt variables. Use quantile-quantile plots to do this comparison, and add a 45-degree line in a color of your choice (not black). Briefly interpret your results and their implications for the authors' argument that their study generated variation in financial resources before and after payday. When appropriate, state which ranges of the outcome variables you would focus on when comparing decision-making and cognitive capacity across these two treatment conditions.

Question 5

In class, we covered the difference-in-difference design for comparing average treatment effects across treatment and control groups. This design can also be used to compare average treatment effects across different ranges of a pre-treatment variable- a variable that asks about people's circumstances before the treatment and thus could not be affected by the treatment. This is known as heterogeneous treatment effects – the idea that the treatment may have differential effects for different subpopulations. Let's look at the pre-treatment variable income_less20k. Calculate the treatment effect of Payday on amount in checking and savings accounts separately for respondents earning more than 20,000 dollars a year and those earning less than 20,000 dollars. Use the original accts_amt variable for this calculation. Then take the difference between the effects you calculate. What does this comparison tell you about how payday affects the amount that people have in their accounts? Are you convinced by the authors' main finding from Question 2 in light of your investigation of their success in manipulating cash and account balances before and after payday?

Prediction

The Amazing Tale of Paul the Psychic Octopus: Germany's World Cup Soothsayer

Sure, Germany is back in the World Cup final. But it'll have to beat Argentina without Paul, the cephalopod that correctly predicted the results of all eight (!) German matches last go-around.

Emily Shire 07.12.14 12:00 AM ET

Prediction

- One important task of (social) scientists can be *prediction*
- Forecasting future events, e.g., conflict, unrest, elections
- Causal inference, also involves prediction, of what?

Prediction

- One important task of (social) scientists can be *prediction*
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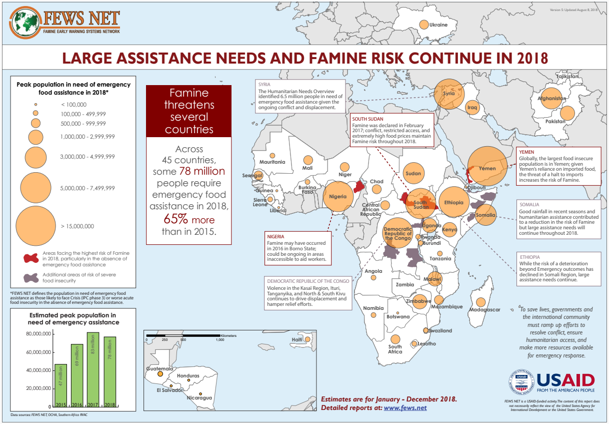
- Causal inference, also involves prediction, of what?

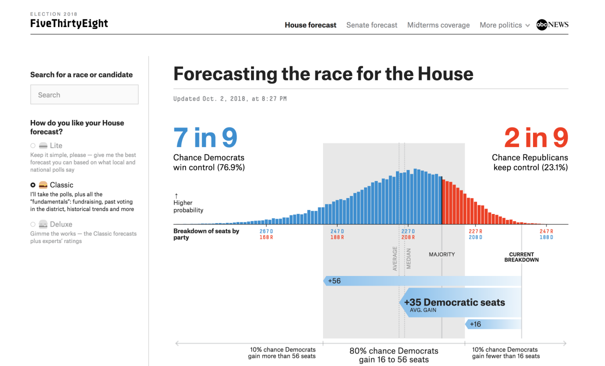
- To estimate the causal effect we are essentially predicting the *counterfactual*

Prediction



FEWS NET
FAMINE EARLY WARNING SYSTEMS NETWORK
LARGE ASSISTANCE NEEDS AND FAMINE RISK CONTINUE IN 2018
Peak population in need of emergency food assistance in 2018*
< 100,000
100,000 - 499,999
500,000 - 999,999
1,000,000 - 2,999,999
3,000,000 - 4,999,999
5,000,000 - 7,499,999
> 15,000,000
Areas facing the highest risk of Famine in 2018, particularly in the absence of emergency food assistance
Additional areas at risk of severe food insecurity
*FEWS NET defines the population in need of emergency food assistance as those likely to face Crisis (IPC phase 3) or worse acute food insecurity in the absence of emergency food assistance.
Famine threatens several countries
Across 45 countries, some 78 million people require emergency food assistance in 2018, 65% more than in 2015.
Estimated peak population in need of emergency assistance
80,000,000
60,000,000
40,000,000
20,000,000
0
47 million
69 million
83 million
78 million
2015
2016
2017
2018
Data sources: FEWS NET, OCHA, Southern Africa RVAC
SYRIA
The Humanitarian Needs Overview identified 6.5 million people in need of emergency food assistance given the ongoing conflict and displacement.
SOUTH SUDAN
Famine was declared in February 2017; conflict, restricted access, and extremely high food prices maintain Famine risk throughout 2018.
YEMEN
Globally, the largest food insecure population is in Yemen; given Yemen's reliance on imported food, the threat of a halt to imports increases the risk of Famine.
SOMALIA
Good rainfall in recent seasons and humanitarian assistance contributed to a reduction in the risk of Famine but large assistance needs will continue throughout 2018.
ETHIOPIA
While the risk of a deterioration beyond Emergency outcomes has declined in Somali Region, large assistance needs continue.
NIGERIA
Famine may have occurred in 2016 in Borno State; could be ongoing in areas inaccessible to aid workers.
DEMOCRATIC REPUBLIC OF THE CONGO
Violence in the Kasaï Region, Ituri, Tanganyika, and North & South Kivu continues to drive displacement and hamper relief efforts.
Ukraine
Syria
Iraq
Tajikistan
Afghanistan
Pakistan
Yemen
Djibouti
Mauritania
Mali
Niger
Senegal
Chad
Sudan
Guinea
Burkina Faso
Sierra Leone
Liberia
Nigeria
Central African Republic
South Sudan
Ethiopia
Somalia
Democratic Republic of the Congo
Uganda
Kenya
Rwanda
Burundi
Tanzania
Angola
Malawi
Zambia
Zimbabwe
Mozambique
Madagascar
Namibia
Botswana
Swaziland
South Africa
Lesotho
Kilometers
0
250
500
1,000
Haiti
Guatemala
Honduras
El Salvador
Nicaragua
Estimates are for January - December 2018.
Detailed reports at: www.fews.net
"To save lives, governments and the international community must ramp up efforts to resolve conflict, ensure humanitarian access, and make more resources available for emergency response.
USAID
FROM THE AMERICAN PEOPLE
FEWS NET is a USAID-funded activity. The content of this report does not necessarily reflect the view of the United States Agency for International Development or the United States Government.

Prediction



ELECTION 2018
FiveThirtyEight
House forecast
Senate forecast
Midterms coverage
More politics
abcNEWS
Search for a race or candidate
Search
How do you like your House forecast?
Lite
Keep it simple, please — give me the best forecast you can based on what local and national polls say
Classic
I'll take the polls, plus all the "fundamentals": fundraising, past voting in the district, historical trends and more
Deluxe
Gimme the works — the Classic forecasts plus experts' ratings
Forecasting the race for the House
Updated Oct. 2, 2018, at 8:27 PM
7 in 9
Chance Democrats win control (76.9%)
2 in 9
Chance Republicans keep control (23.1%)
Higher probability
Breakdown of seats by party
267 D 168 R
247 D 188 R
227 D 208 R
227 R 208 D
247 R 188 D
AVERAGE
MEDIAN
MAJORITY
CURRENT BREAKDOWN
+56
+35 Democratic seats
AVG. GAIN
+16
10% chance Democrats gain more than 56 seats
80% chance Democrats gain 16 to 56 seats
10% chance Democrats gain fewer than 16 seats

Prediction

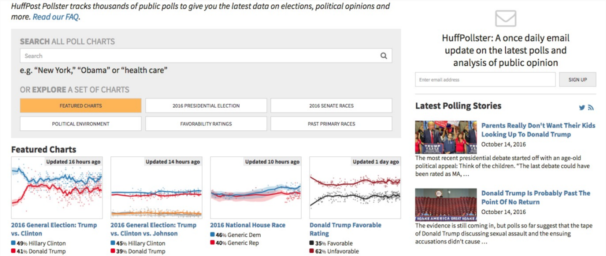
- Elections can be predicted using fundamentals

Prediction

- Elections can be predicted using fundamentals
- Or we can use polls to predict results

Prediction with polls

- We will use a nice *R* package called *pollstR*, which scrapes the data from Huffington Post:



Prediction with polls

```
library(pollstR)
chart_name <- "2016-general-election-trump-vs-clinton"
polls2016 <- pollster_charts_polls(chart_name)[["content"]]
```

Prediction with polls

- Let's calculate a variable that is *days until the election*

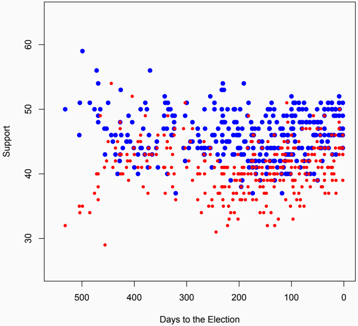
```
class(polls2016$end_date)
polls2016$DaysToElection <-
    as.Date("2016-11-8") - polls2016$end_date
```

Prediction with polls

We could make a very simple plot of all the polls over time

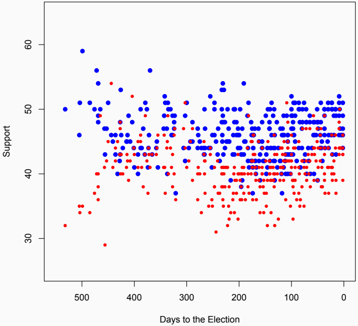
```
plot(polls2016$DaysToElection, polls2016$Clinton,
     xlab = "Days to the Election", ylab = "Support",
     xlim = c(550, 0), ylim = c(25, 65), pch = 19,
     col = "blue")
points(polls2016$DaysToElection, polls2016$Trump,
       pch = 20, col = "red")
```

Prediction with polls



But that looks kind of dumb

Prediction with polls



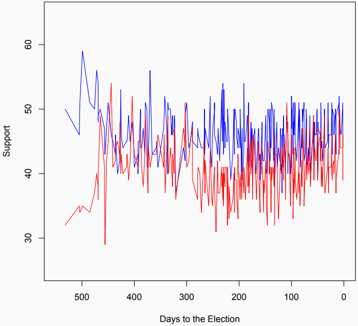
But that looks kind of dumb

Lines?

Plotting polls

```
plot(polls2016$DaysToElection, polls2016$Clinton, type = "l",
     xlab = "Days to the Election", ylab = "Support",
     xlim = c(550, 0), ylim = c(25, 65), pch = 19,
     col = "blue")
lines(polls2016$DaysToElection, polls2016$Trump,
      col = "red")
```

Prediction with polls



Prediction with polls

- Never trust a single poll
- Maybe we could smoothe the polls over time?
- Average the polls that are close to each other

Prediction with polls

- This is called a *moving average*
- Average all the polls within a certain time window
- Window size determines amount of smoothing

Creating a Moving Average

- In *R*, for each day, we subset the relevant polls and compute the average
- That's a lot of subsetting and averaging (532 days)
- Any ideas of how to do this fast?

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Loops

Loops in R

```
for (i in X) {
    expression1
    expression2
    ...
    expressionN
}
```

Loops in R

Elements of a loop:

- *i*: counter (can use any object name other than *i*)
- *X*: vector containing a set of ordered values the counter takes
- *expression*: a set of expressions that will be repeatedly evaluated

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{ }: curly braces to define the beginning and the end

Loops in R

Simple Example:

```
for (i in c(1,2,3,4,5) {
    print(i)
}
```

What does this loop do?

Loops in R

- Indentation is important for the readability of code (Rstudio does this automagically)
- Test Code without loop first by setting the counter to a specific value

Loops in R

Printing out an iteration number can be helpful for debugging:

```r
values <- c(1, -1, 2)
results <- rep(NA, 3)
for (i in 1:3) {
    cat("iteration", i, "\n")
    results[i] <- log(values[i])
}
```

Let's write a practice loop

- Load state ideology data
- Subset to state of choice
- Write loop that prints the following for each year:
    1. Mean Democrat Ideology
    2. Mean Republican Ideology
    3. Polarization

Let's write a practice loop

```
data <- subset(data, state == "TX")
for(i in unique(data$year)){
    sub.set <- subset(data, year == i)
    dems <- mean(sub.set$ideology_score[sub.set$party == "Democrat"])
    cat("Dem ideology", i, dems, "\n")
    repub <- mean(sub.set$ideology_score[sub.set$party == "Republican"])
    cat("Repub ideology", i, repub, "\n")
    cat("Polarization", i, (repub - dems), "\n")
}
```

Loops in R

Let's create a moving average:

- Begin by creating vector for counter & setting window size

```
days <- 500:26
window <- 7
```

Loops in R

Create empty vectors

```
Clinton.pred <- Trump.pred <- rep(NA, length(days))
```

Loops in R

Create empty vectors

```
Clinton.pred <- Trump.pred <- rep(NA, length(days))
```

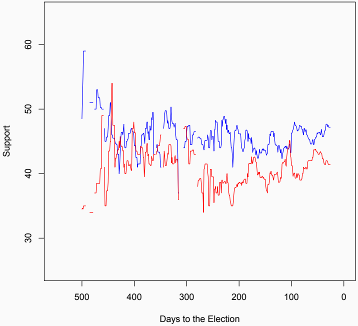
Now the loops:

```
for (i in 1:length(days)) {
    week.data <-
        subset(polls2016,
               subset = ((DaysToElection < (days[i] + window))
                   & (DaysToElection >= days[i])))
    Clinton.pred[i] <- mean(week.data$Clinton)
    Trump.pred[i] <- mean(week.data$Trump)
}
```

Smoothed Plot:

```
plot(days, Clinton.pred, type = "l", col = "blue",
     xlab = "Days to the Election", ylab = "Support",
     xlim = c(550, 0), ylim = c(25, 65))
lines(days, Trump.pred, col = "red")
```

Smoothed Plot:



2 week Smoothing

```
Clinton.pred <- Trump.pred <- rep(NA, length(days))
window <- 14
```

2 week Smoothing

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}
```

2 week Smoothing

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plot(days, Clinton.pred, type = "l", col = "blue",
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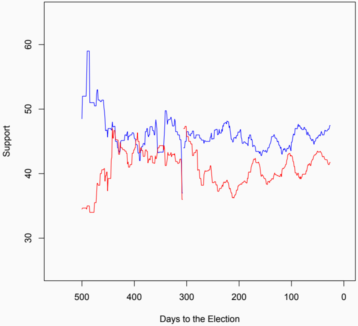
Smoothed Plot:



Smoothed Plot:

Let's add some explanations/legend to the plot

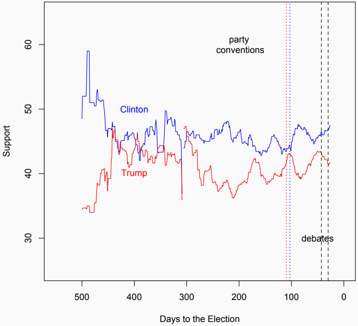
```
text(400, 50, "Clinton", col = "blue")
text(400, 40, "Trump", col = "red")
```

Smoothed Plot:

Let's add some explanations/legend to the plot

```
text(200, 60, "party\n conventions")
abline(v = as.Date("2016-11-8") - as.Date("2016-7-28"),
       lty = "dotted", col = "blue")
abline(v = as.Date("2016-11-8") - as.Date("2016-7-21"),
       lty = "dotted", col = "red")
text(50, 30, "debates")
abline(v = as.Date("2016-11-8") - as.Date("2016-9-26"),
       lty = "dashed")
abline(v = as.Date("2016-11-8") - as.Date("2016-10-9"),
       lty = "dashed")
```

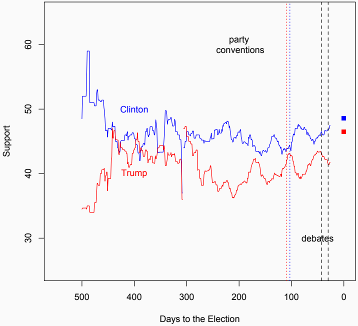
Smoothed Plot:



Add points for actual result

```
plot(days, Clinton.pred, type = "l", col = "blue",
     xlab = "Days to the Election", ylab = "Support",
     xlim = c(550, 0), ylim = c(25, 65))
lines(days, Trump.pred, col = "red")
text(400, 50, "Clinton", col = "blue")
text(400, 40, "Trump", col = "red")
text(200, 60, "party\n conventions")
abline(v = as.Date("2016-11-8") - as.Date("2016-7-28"),
       lty = "dotted", col = "blue")
abline(v = as.Date("2016-11-8") - as.Date("2016-7-21"),
       lty = "dotted", col = "red")
text(50, 30, "debates")
abline(v = as.Date("2016-11-8") - as.Date("2016-9-26"),
       lty = "dashed")
abline(v = as.Date("2016-11-8") - as.Date("2016-10-9"),
       lty = "dashed")
points(0,46.47, col = "red", pch = 15)
points(0,48.59, col = "blue", pch = 15)
```

Add points for actual result



Prediction and Prediction Error

- Prediction Error = Result (actual outcome) - Prediction
- Mean prediction error = mean(error)
- Root mean squared error (RMS) $=\sqrt{mean(error^2)}$

Prediction and Prediction Error

```
last.week.data <- subset(polls2016, subset = DaysToElection < 15)

margin <- last.week.data$Clinton - last.week.data$Trump
true_margin <- 48.59 - 46.47

pred.error <- true_margin - margin

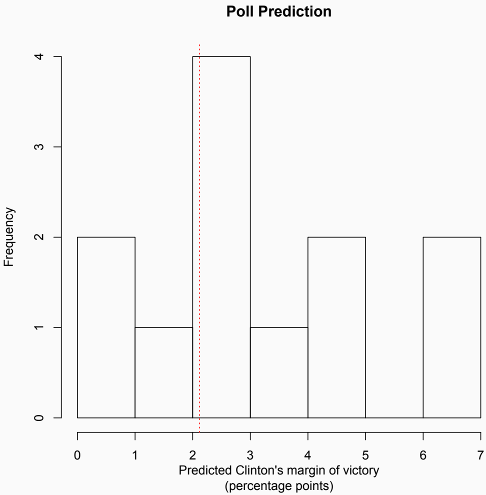
mean.error <- mean(pred.error)

rmse <- sqrt(mean(pred.error^2))
```

National Polls actually weren't that far off

```
hist(margin, main = "Poll Prediction",
     xlab = "Predicted Clinton's margin of victory
(percentage points)")
abline(v = true_margin,
       lty = "dotted", col = "red")
```

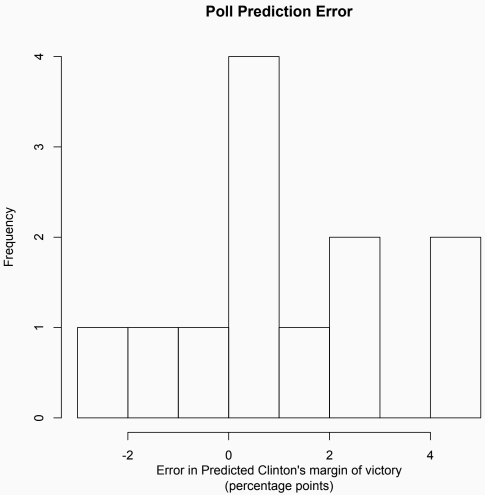
National Polls actually weren't that far off



National Polls actually weren't that far off

```
average_error <- margin - true_margin
hist(average_error, main = "Poll Prediction Error",
     xlab = "Error in Predicted Clinton's margin of victory
(percentage points)")
```

National Polls actually weren't that far off



National Polls actually weren't that far off

"Trump outperformed his national polls by only 1 to 2 percentage points in losing the popular vote to Clinton, making them slightly closer to the mark than they were in 2012. Meanwhile, he beat his polls by only 2 to 3 percentage points in the average swing state"

Nate Silver (The Real Story of 2016)[https://fivethirtyeight.com/features/the-real-story-of-2016/]

Classification

- Often we care about binary outcomes
- Did Trump win electoral college?
- Did civil war occur?
- Did it rain?
- Prediction of binary outcome variable = classification problem

(Mis)Classification

- Wrong prediction $\rightarrow$ misclassification
  1. true positive: correctly predicting civil war in country X at time T
  2. false positive: incorrectly predicting civil war in country X at time T
  3. true negative: correctly predicting no civil war in country X at time T
  4. false negative: incorrectly predicting no civil war in country X at time T
- Sometimes false negatives are more (less) important: e.g., civil war

(Mis)Classification

		Actual outcome	
		Positive	Negative
Predicted outcome	Positive	True Positive	False Positive
	Negative	False Negative	True Negative

(Mis)Classification

- Be aware: the threshold at which we count a prediction as positive matters!
- What happens to misclassifications if we lower the threshold?

(Mis)Classification

- Lower threshold $\rightarrow$ more *false positives*
- Higher threshold $\rightarrow$ more *false negatives*
- Need to balance both!