

# **Bayesian Statistics and Modeling**

## **Part III**

# Bayesian linear models

I love (for better or worse) rooting for the Seahawks. In many recent years, they have insisted on running a LOT more than most teams.

(Plot is frequency of Run-Run-Pass sequences by team)

TEAM	EPA	SUCCESS	FREQUENCY
Seattle	+0.17	41.2%	26%
Tennessee	-0.23	41.3	24
Buffalo	-0.26	43.9	21
L.A. Chargers	-0.13	41.2	20
San Francisco	-0.37	33.3	20
Houston	-0.32	38.9	18
Miami	-0.50	22.6	18
Denver	-0.47	32.4	17
<b>L.A. Rams</b>	<b>+0.28</b>	<b>60.0</b>	<b>16</b>
N.Y. Giants	+0.23	51.5	16
Indianapolis	-0.03	45.5	16
Minnesota	-0.28	41.9	16
Jacksonville	+0.05	40.0	16
Oakland	-0.72	33.3	16
Cleveland	+0.37	46.7	15
Chicago	-0.09	41.4	15
Pittsburgh	+0.70	61.5	14
Atlanta	+0.37	51.7	14
Detroit	+0.00	50.0	14
Tampa Bay	+0.44	47.8	14
New Orleans	+0.04	41.7	14
Arizona	-0.71	33.3	14
N.Y. Jets	+0.19	50.0	13
Dallas	+0.15	46.4	13
Baltimore	+0.32	44.4	12
Carolina	-0.14	40.9	12
New England	+0.03	39.1	12
Washington	-0.32	34.8	12
Cincinnati	-0.26	47.4	10
Green Bay	-0.10	40.0	10
<b>Kansas City</b>	<b>+1.19</b>	<b>53.3</b>	<b>9</b>
Philadelphia	+0.66	50.0	9

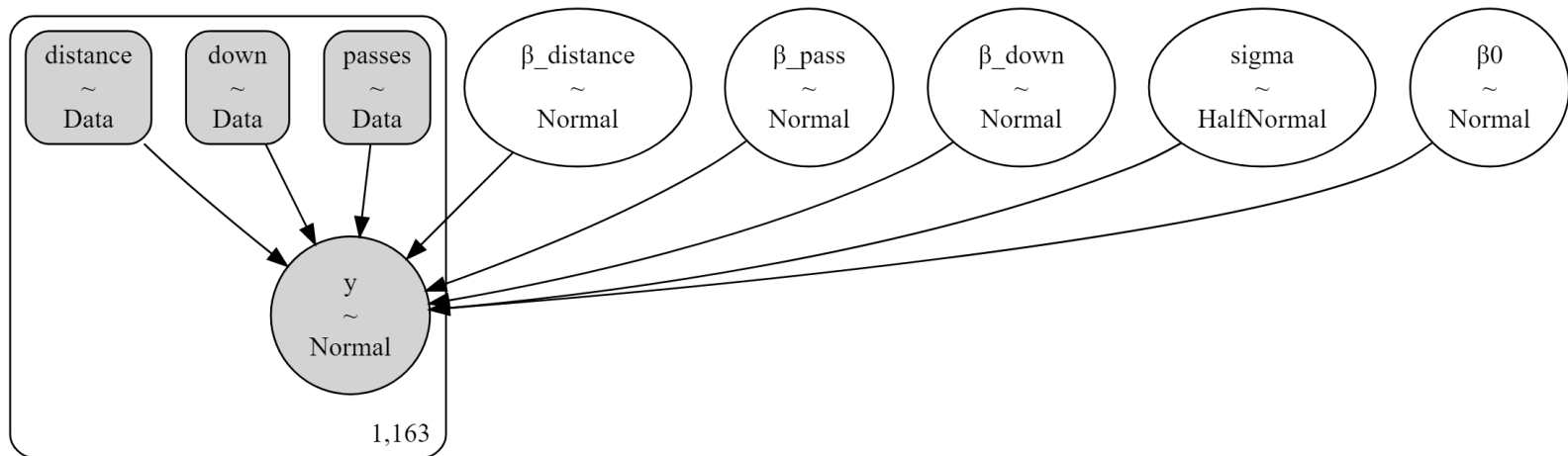
SOURCES: NFL, ELIAS SPORTS BUREAU

# Bayesian Linear Models

Can we determine the likelihood of a play being successful based on various characteristics of that play?

- Are runs more successful than passes? (unlikely, but Pete Carroll thinks so)
- We should probably also account for down and distance

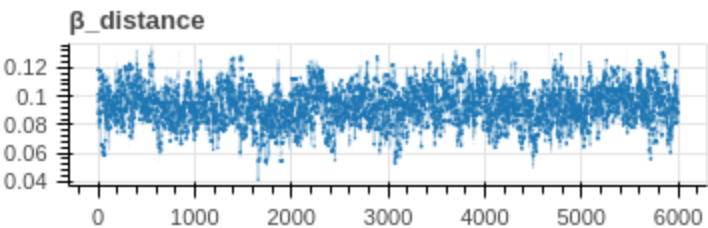
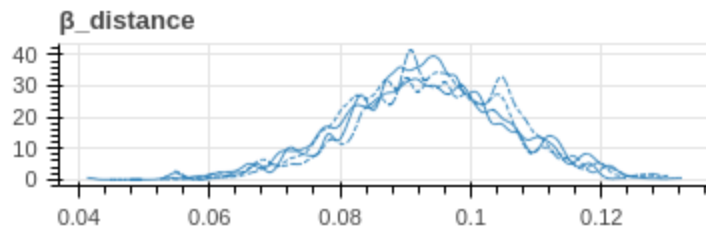
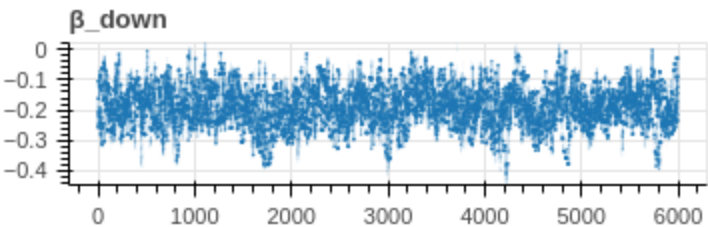
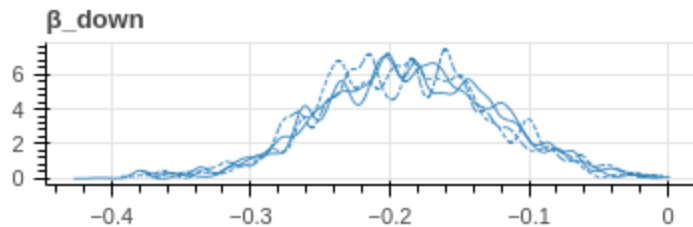
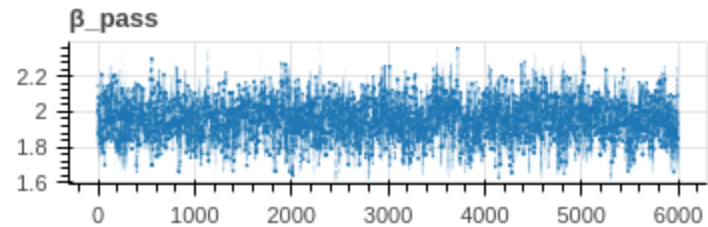
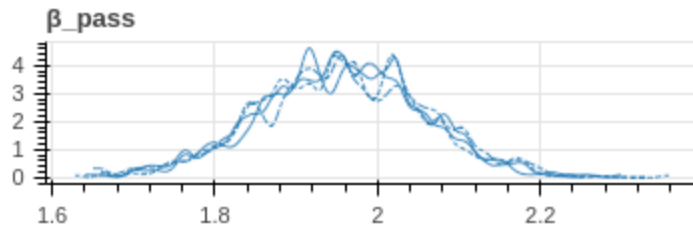
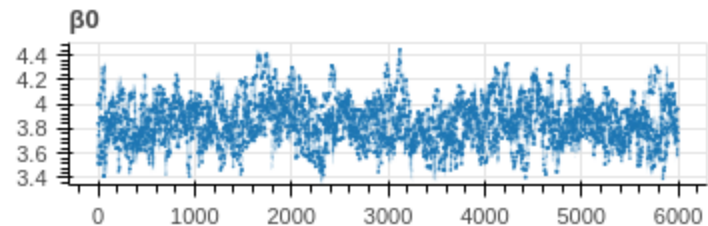
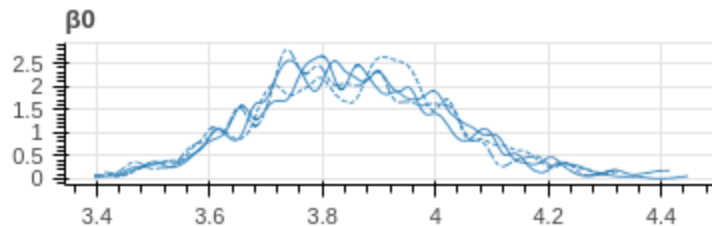
# What's the model?



# What's the model?

Let's go look at our code now, and generate a regression model using the Bayesian method

# Complete Regression Results

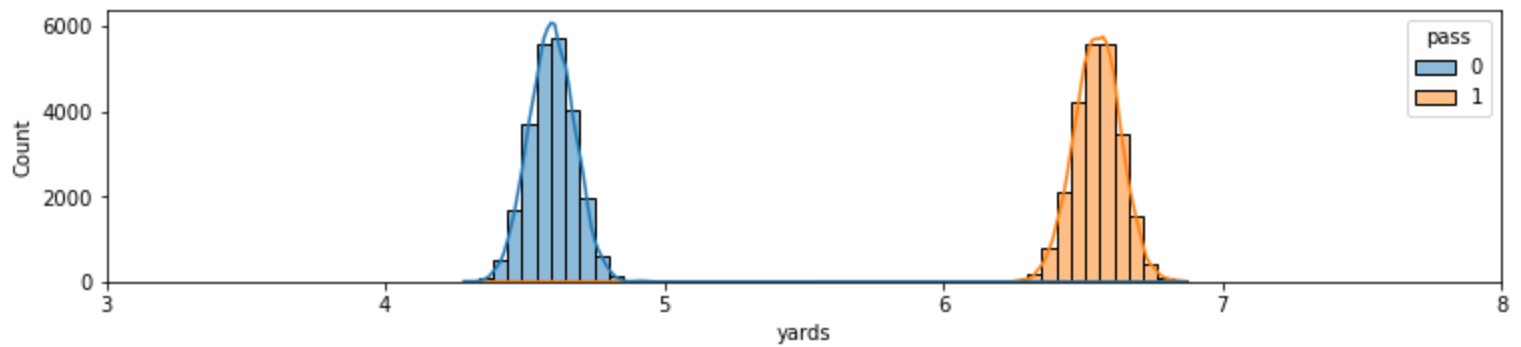


# Making sense of choices

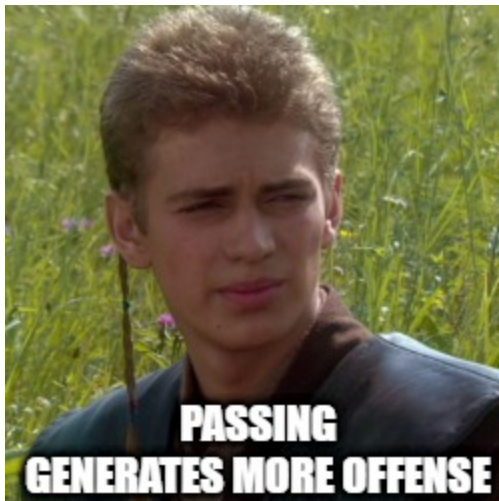
What if we want to be able to look at specific contexts?

We write quick function and are off to the races!

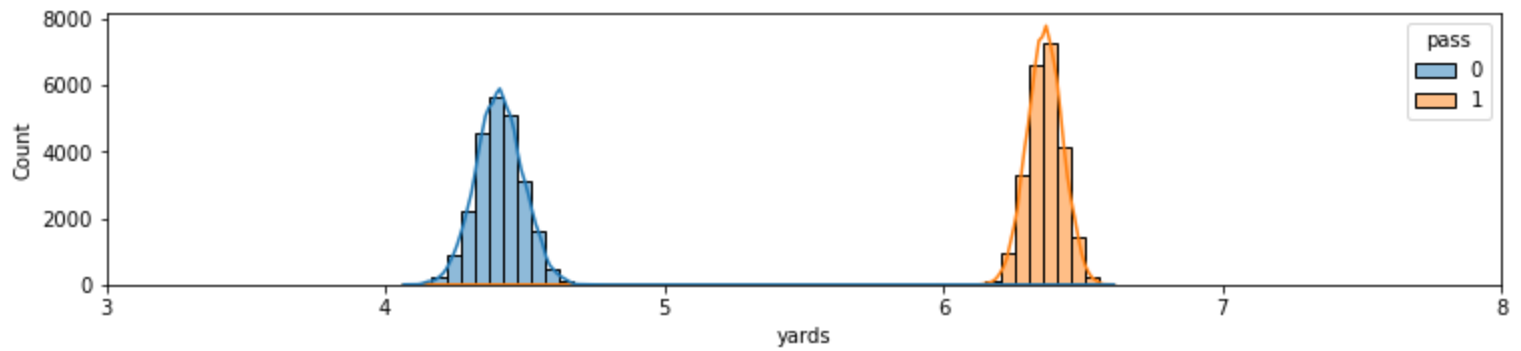
# 1st and 10...



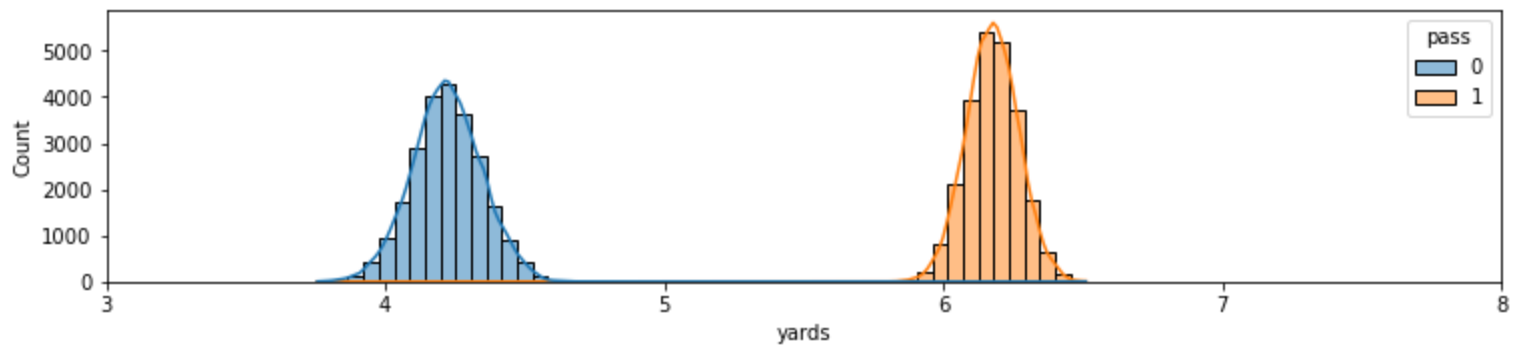




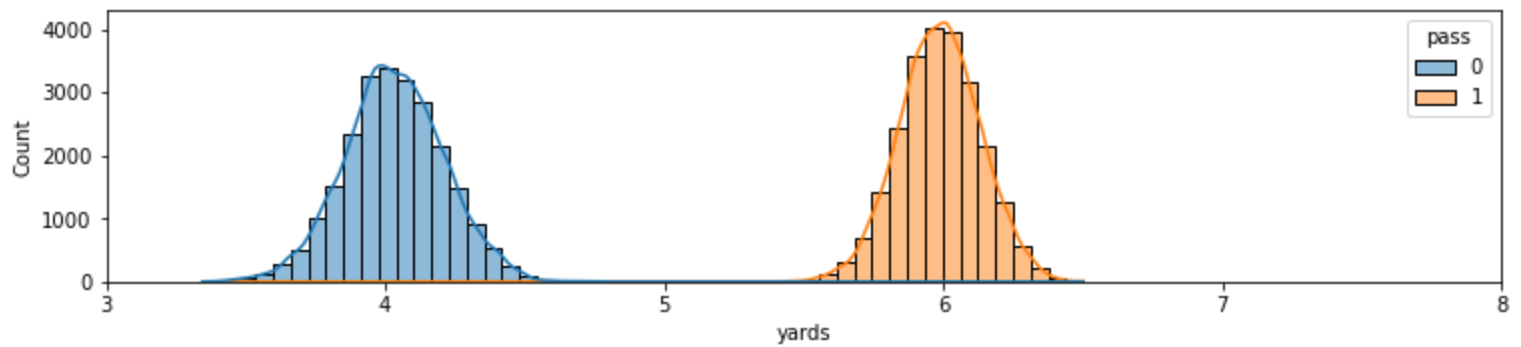
## 2nd and 10...



# 3rd and 10...



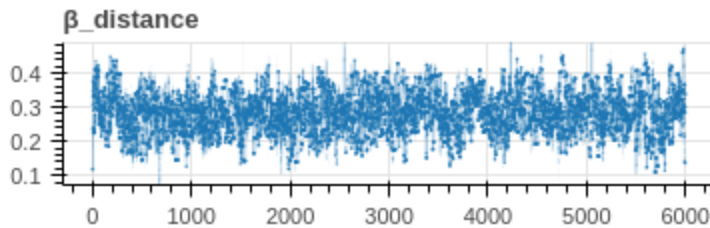
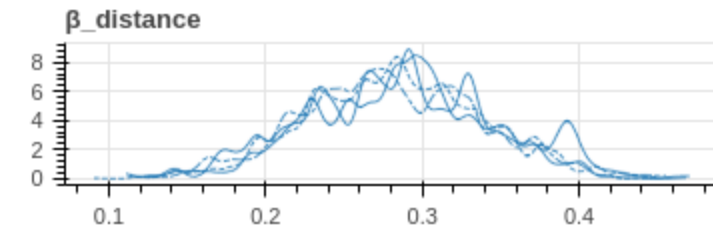
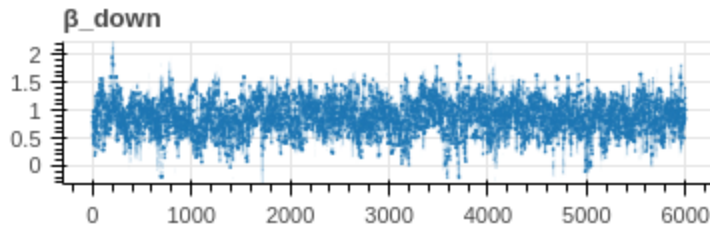
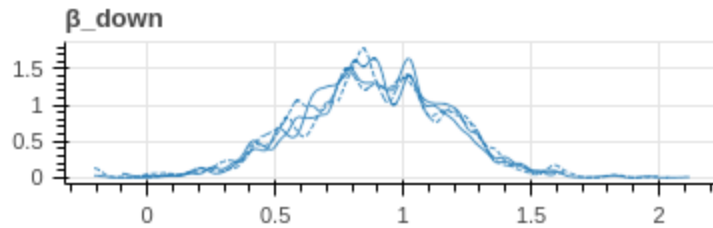
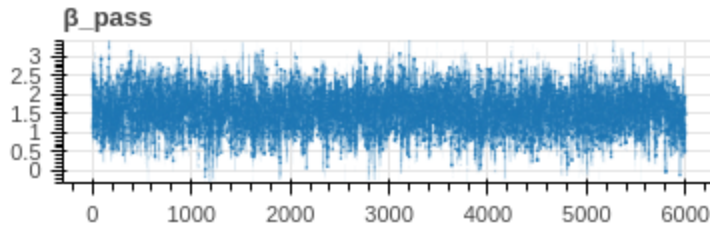
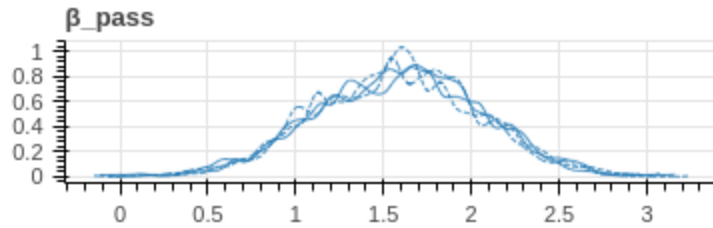
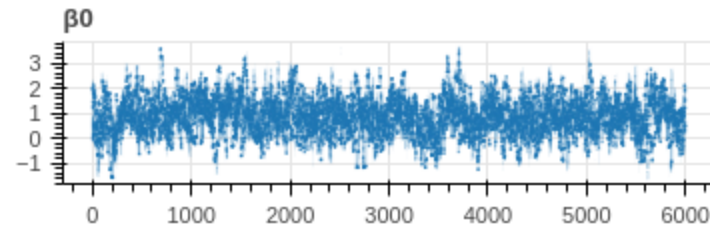
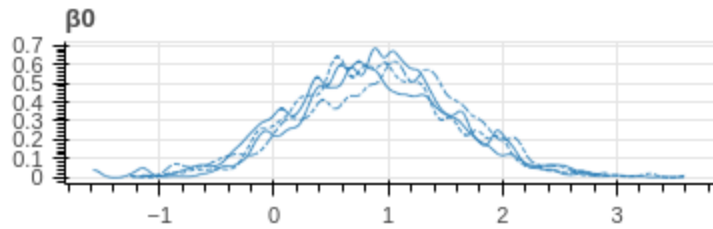
# 4th and 10!!



**Ok, but maybe the Seahawks are different!**

Are they? Let's estimate our model with only Seahawks data

# Complete Regression Results

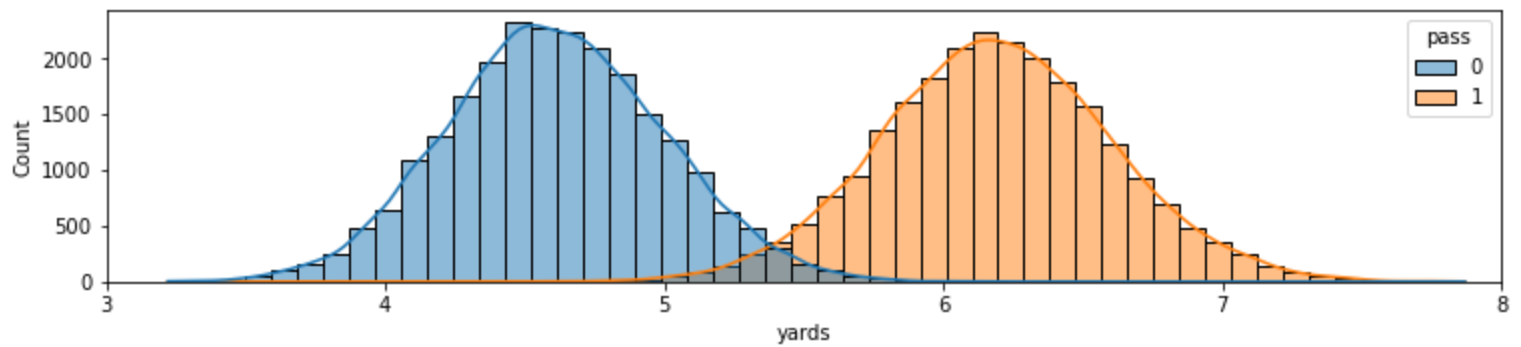


# Making sense of choices

What if we want to be able to look at specific contexts?

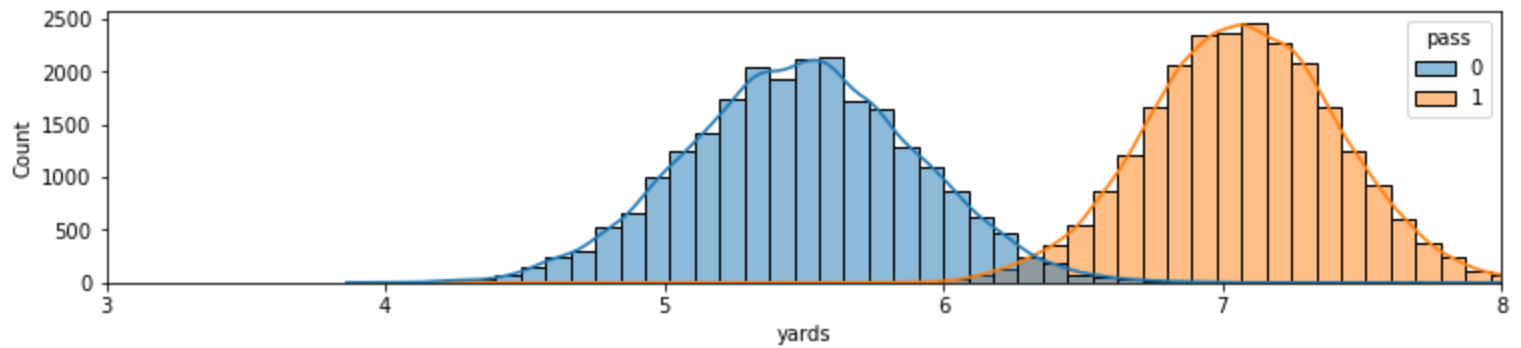
We write quick function and are off to the races!

# 1st and 10...

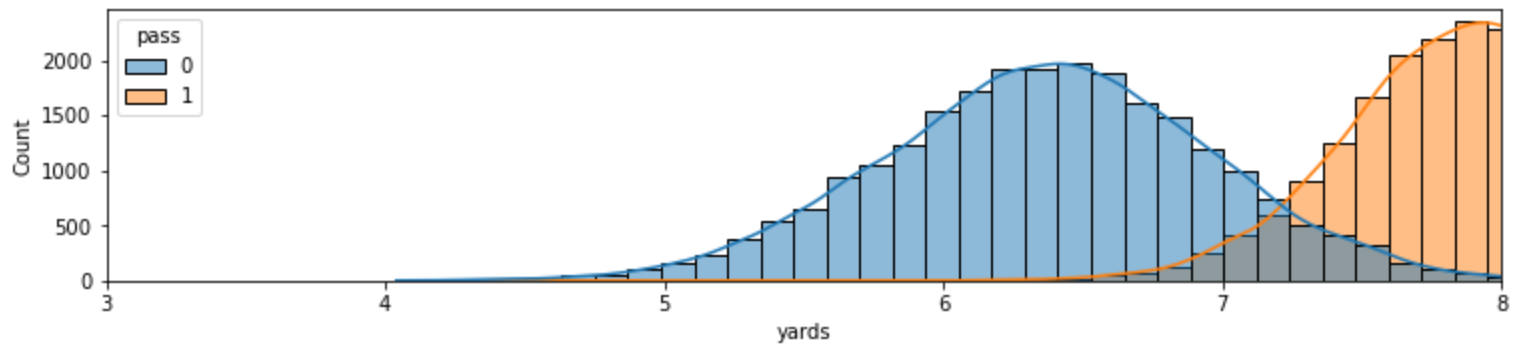




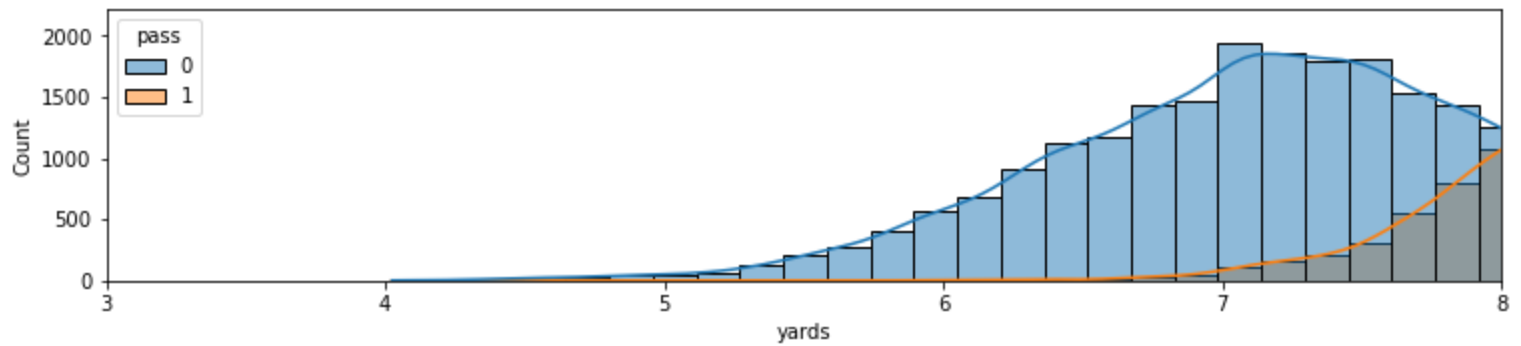
## 2nd and 10...



## 3rd and 10...



# 4th and 10!!



# How does it work?

1. Our model creates a `trace` object
2. Each trace contains however many samples (in this case ~40k) of the estimated parameter
3. We use these to look at the **distribution of parameter values**

# Credible intervals

Rather than having Confidence Intervals, we have Credible Intervals in Bayesian statistics.

- 95% of sampled parameter values fall inside a 95% CI
- We can shape them arbitrarily
- We can also just use them to measure the likelihood that one measure exceeds another!
  - For example, our distributions for the seahawks overlap, but that doesn't mean running is EVER better!

# More flexibility

We have only scratched the surface, but we are starting to see how we can create flexible models that allow us to ask much more **real** questions than we might with a null-hypothesis framework

**Lab Time!**