

# Predicting the Winner of the 2026 Men's FIFA World Cup

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## Introduction

The Fifa World Cup is an international competition like no other. In 2022, 1.5 billion people tuned in to watch the games and 88,966 were there live in Qatar. With an event of this size, fans go all out in support of their favorite team(s), but how do we know who will end up as the champion? With this project, we will use machine learning and our knowledge of data science to answer this question. We plan to predict the outcome of the next men's soccer World Cup (2026) by using the previous year's team ranks from 1992 to 2023 and the outcomes of past games from 1930 to 2018.

## Exploratory Data Analysis

```
library(dplyr)
```

Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

`filter`, `lag`

The following objects are masked from 'package:base':

`intersect`, `setdiff`, `setequal`, `union`

```
library(tidyverse)
```

```
-- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
v forcats 1.0.0      v readr      2.1.4
v ggplot2  3.4.4      v stringr    1.5.1
v lubridate 1.9.3      v tibble     3.2.1
v purrr     1.0.2      v tidyr      1.3.0

-- Conflicts ----- tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()     masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become
```

```
library(readr)

data1 <- read.csv("fifa_ranking-2023-07-20.csv")

data2 <- read.csv("worldcups.csv")

data3 <- read.csv("wcmatches.csv")

# Use columns from data 3: Home score and away score
# Use columns from data 1: Rank
# Add these columns to data 2

# Make outcome a factor instead of a character
# One of columns was blank, remove na's

names(data1)[names(data1) == "country_full"] <- "Country"
names(data2)[names(data2) == "winner"] <- "Country"
names(data3)[names(data3) == "winning_team"] <- "Country"

first_join <- left_join(data2, data1, by = "Country")

second_join <- left_join(first_join, data3, by = "Country")

df <- second_join %>%
  select(-win_conditions) %>%
  na.omit()

colnames(df)
```

```
[1] "year.x"      "host"        "Country"     "second"
```

[5]	"third"	"fourth"	"goals_scored"	"teams"
[9]	"games"	"attendance"	"rank"	"country_abrv"
[13]	"total_points"	"previous_points"	"rank_change"	"confederation"
[17]	"rank_date"	"year.y"	"country"	"city"
[21]	"stage"	"home_team"	"away_team"	"home_score"
[25]	"away_score"	"outcome"	"losing_team"	"date"
[29]	"month"	"dayofweek"		

```
colnames(data1)
```

[1]	"rank"	"Country"	"country_abrv"	"total_points"
[5]	"previous_points"	"rank_change"	"confederation"	"rank_date"

```
colnames(data2)
```

[1]	"year"	"host"	"Country"	"second"	"third"
[6]	"fourth"	"goals_scored"	"teams"	"games"	"attendance"

```
colnames(data3)
```

[1]	"year"	"country"	"city"	"stage"
[5]	"home_team"	"away_team"	"home_score"	"away_score"
[9]	"outcome"	"win_conditions"	"Country"	"losing_team"
[13]	"date"	"month"	"dayofweek"	

## Illustration / Figure

===== A figure or a diagram that illustrates the overall model or idea of your project. The idea is to make your report more accessible, especially to readers who are starting by skimming your work. For the project, taking a picture of a hand-drawn diagram is fine, as long as it's legible. PowerPoint is another option. You will not be penalized for hand-drawn illustrations – you are graded on the design and illustrative power

```
library(dplyr)
library(ggplot2)
```

```
# Filter matches where the home team won
```

```

home_wins <- filter(second_join, outcome == "H")

# Filter matches where the away team won
away_wins <- filter(second_join, outcome == "A")

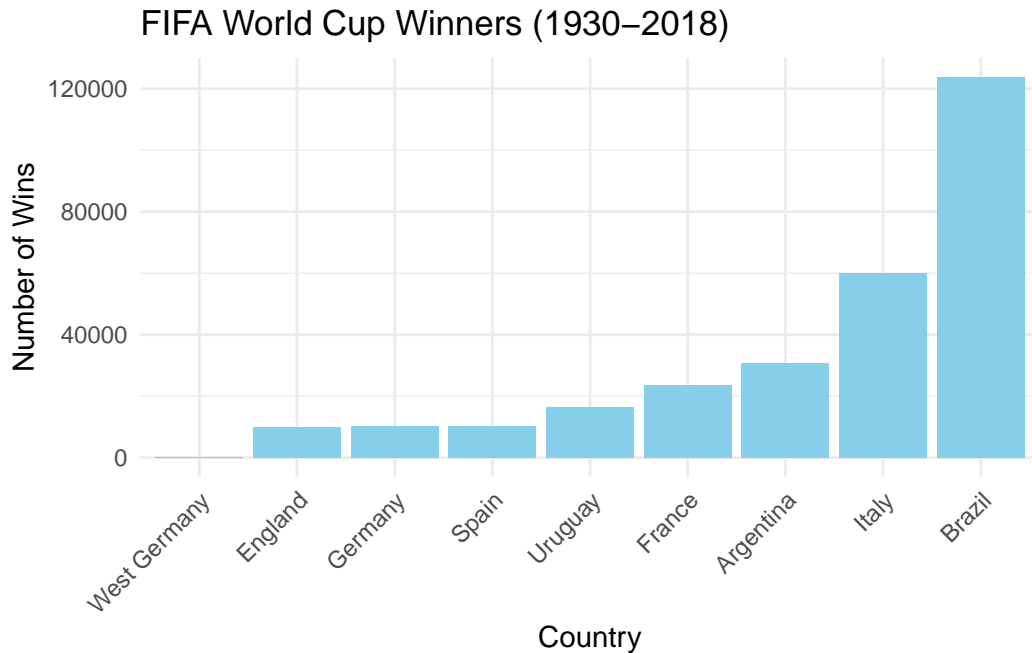
# Combine the home and away wins
all_wins <- bind_rows(home_wins, away_wins)

# Aggregate the data to count the number of wins for each country
world_cup_wins <- all_wins %>%
  group_by(Country) %>%
  summarise(Wins = n())

# Sort the data by the number of wins in descending order
world_cup_wins <- world_cup_wins[order(-world_cup_wins$Wins),]

# Create the bar plot
ggplot(world_cup_wins, aes(x = reorder(Country, Wins), y = Wins)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  labs(title = "FIFA World Cup Winners (1930-2018)",
       x = "Country",
       y = "Number of Wins") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

```



```
library(dplyr)
library(ggplot2)

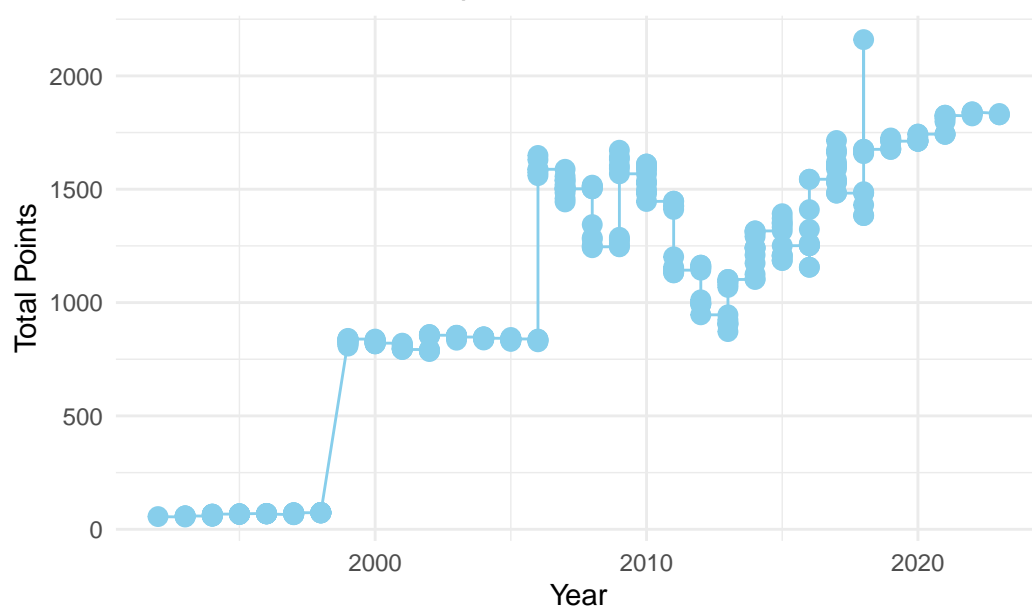
# Filter Brazil's rank data
brazil_rank <- filter(data1, Country == "Brazil")

# Extract the year from the rank_date column
brazil_rank$year <- substr(brazil_rank$rank_date, 1, 4)

# Convert year to numeric
brazil_rank$year <- as.integer(brazil_rank$year)

# Create the line plot
ggplot(brazil_rank, aes(x = year, y = total_points)) +
  geom_line(color = "skyblue") +
  geom_point(color = "skyblue", size = 3) +
  labs(title = "Brazil's FIFA World Cup Rank Over the Years",
       x = "Year",
       y = "Total Points") +
  theme_minimal()
```

# Brazil's FIFA World Cup Rank Over the Years



```
class(df$outcome)
```

```
[1] "character"
```

```
# Print first few rows of the data frame
head(df)
```

	year.x	host	Country	second	third	fourth	goals_scored	teams	games
1	1930	Uruguay	Uruguay	Argentina	USA	Yugoslavia	70	13	18
2	1930	Uruguay	Uruguay	Argentina	USA	Yugoslavia	70	13	18
3	1930	Uruguay	Uruguay	Argentina	USA	Yugoslavia	70	13	18
4	1930	Uruguay	Uruguay	Argentina	USA	Yugoslavia	70	13	18
5	1930	Uruguay	Uruguay	Argentina	USA	Yugoslavia	70	13	18
6	1930	Uruguay	Uruguay	Argentina	USA	Yugoslavia	70	13	18

	attendance	rank	country_abrv	total_points	previous_points	rank_change
1	434000	16	URU	48	0	0
2	434000	16	URU	48	0	0
3	434000	16	URU	48	0	0
4	434000	16	URU	48	0	0
5	434000	16	URU	48	0	0

```

6      434000    16          URU          48          0          0
  confederation rank_date year.y country      city      stage home_team
1      CONMEBOL 1992-12-31   1930 Uruguay    Montevideo    Group 3    Uruguay
2      CONMEBOL 1992-12-31   1930 Uruguay    Montevideo    Group 3    Uruguay
3      CONMEBOL 1992-12-31   1930 Uruguay    Montevideo  Semifinals    Uruguay
4      CONMEBOL 1992-12-31   1930 Uruguay    Montevideo    Final      Uruguay
5      CONMEBOL 1992-12-31   1950  Brazil Belo Horizonte    Group 4    Bolivia
6      CONMEBOL 1992-12-31   1950  Brazil    São Paulo Final Round    Sweden
  away_team home_score away_score outcome losing_team      date month
1      Peru          1          0      H      Peru 1930-07-18    Jul
2      Romania        4          0      H      Romania 1930-07-21    Jul
3      Yugoslavia      6          1      H      Yugoslavia 1930-07-27    Jul
4      Argentina       4          2      H      Argentina 1930-07-30    Jul
5      Uruguay         0          8      A      Bolivia 1950-07-02    Jul
6      Uruguay         2          3      A      Sweden 1950-07-13    Jul
  dayofweek
1      Friday
2      Monday
3      Sunday
4      Wednesday
5      Sunday
6      Thursday

```

## Background & Related Work (2 points)

With an event as big as the Fifa World Cup, many people have tried to determine who will win the next Cup for years. People will develop brackets and make bets with their friends, or for money, about who will win it all. Many times people simply go off their intuition but those with experience in data science and machine learning have gone on to develop models similar to ours to predict the next winning team. Each model utilizes different datasets and features to determine who will win the upcoming cup as well as different programming languages and visualizations to produce and showcase their work.

For example, from ProjectPro there is an article depicting ways machine learning was utilized in Fifa 2022 and includes a project which tries to predict the outcome of the 2022 games using the results from 1870 to 2018. The article sets up a competition through Kaggle where teams or individuals can compete to produce the best model for predicting the winning teams. This is similar to what we wish to do in this project although we will be using different data sets and doing our work using R instead of Python like the competition suggests. Another example of similar work is outlined in a Medium article about predicting the 2022 Fifa World Cup. The article goes into which features they found to be important in predicting the next winner and trying to simulate the results. Once the features from their datasets were found, they

were used to create different machine-learning models that take in team aspects to determine whether or not they could win the World Cup. Our project will be similar to this one as well but will use different data and work to predict the final winner of the competition based on existing teams.

Overall, there are other projects out there that attempt to accomplish the same goal as ours, meaning that it is possible. Although these projects exist, ours will differ in the data used and therefore also differ in which features are important for our particular models.

## Data Processing

Describe the data that you have collected and cleaned. Be clear and specific when describing what you've done, so that a classmate can reproduce your work. Show some statistics and examples of your data.

- 4/4 Clearly describes sources of data, and the steps you took to clean and format your data. Statistics and data example are well-chosen, and gives readers a “feel” for your data.
- 3/4 Mostly clear description, but some aspects of the data processing steps are vague. Statistics and data example are somewhat illustrative/helpful.
- 2/4 Vague description or missing key information about where your data comes from or what you did. No example data shown, or the ones shown are not illustrative.
- 1/4 Incomplete information.

## Architecture

```
library(glmnet)
```

```
Warning: package 'glmnet' was built under R version 4.3.3
```

```
Loading required package: Matrix
```

```
Attaching package: 'Matrix'
```

```
The following objects are masked from 'package:tidyr':
```

```
expand, pack, unpack
```

```
Loaded glmnet 4.1-8
```



```

df <- df[, !colnames(df) %in% c("outcome")]

# Extract rank variable
rank <- df$rank

# Remove rank variable from predictors
X <- df[, -which(names(df) == "rank")]

# Lasso regression
lasso <- cv.glmnet(x = as.matrix(X), y = rank, alpha = 1)

```

Warning in storage.mode(xd) <- "double": NAs introduced by coercion

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Warning in cbind2(1, newx) %\*% nbeta: NAs introduced by coercion

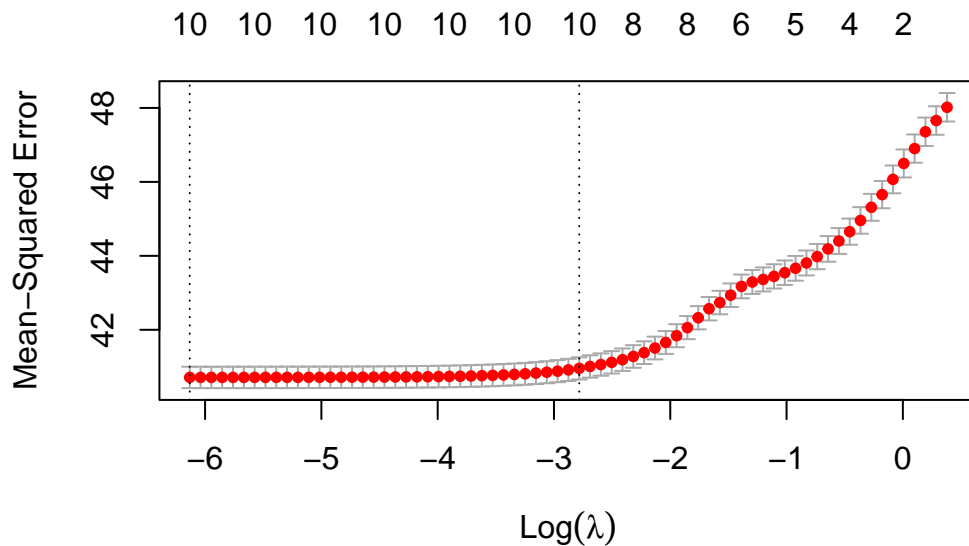
Warning in cbind2(1, newx) %\*% nbeta: NAs introduced by coercion

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Warning in cbind2(1, newx) %*% nbeta: NAs introduced by coercion
```

```
library(ggplot2)
```

```
# Extract lambda values and corresponding mean squared errors
plot(lasso)
```



```
lambda <- log(lasso$lambda)
mse <- lasso$cvm
```

```
# Ridge regression
```

```
ridge <- cv.glmnet(x = as.matrix(X), y = rank, alpha = 0)
```

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Warning in cbind2(1, newx) %\*% nbeta: NAs introduced by coercion

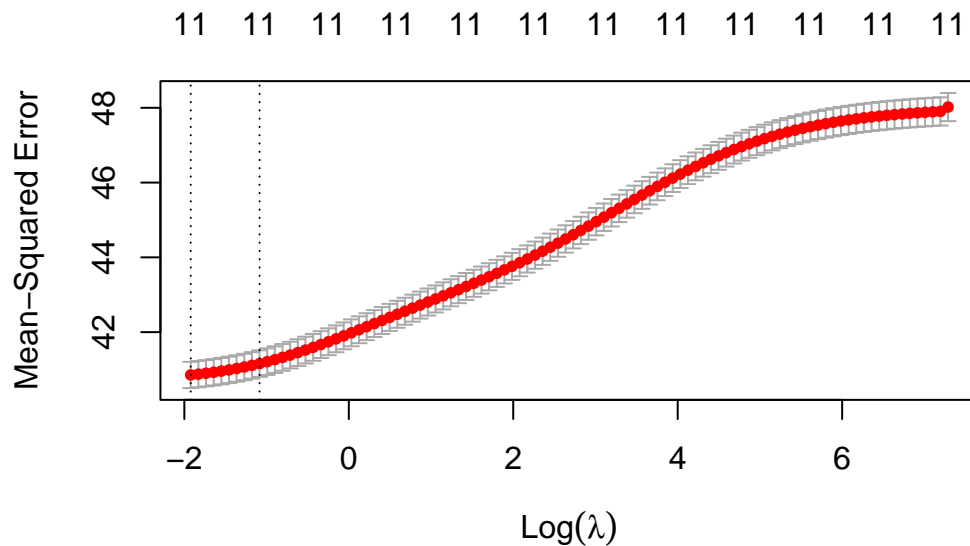
Warning in cbind2(1, newx) %\*% nbeta: NAs introduced by coercion

Warning in cbind2(1, newx) %\*% nbeta: NAs introduced by coercion

Warning in cbind2(1, newx) %\*% nbeta: NAs introduced by coercion

Warning in cbind2(1, newx) %\*% nbeta: NAs introduced by coercion

```
plot(ridge)
```



```
lambda <- log(ridge$lambda)
mse <- ridge$cvm

# Extract MSE for Lasso model
lasso_mse <- min(lasso$cvm)

# Extract MSE for Ridge model
ridge_mse <- min(ridge$cvm)

# Output MSE for both models
print(paste("Mean Squared Error (Lasso):", lasso_mse))
```

```
[1] "Mean Squared Error (Lasso): 40.7116236317294"
```

```
print(paste("Mean Squared Error (Ridge):", ridge_mse))
```

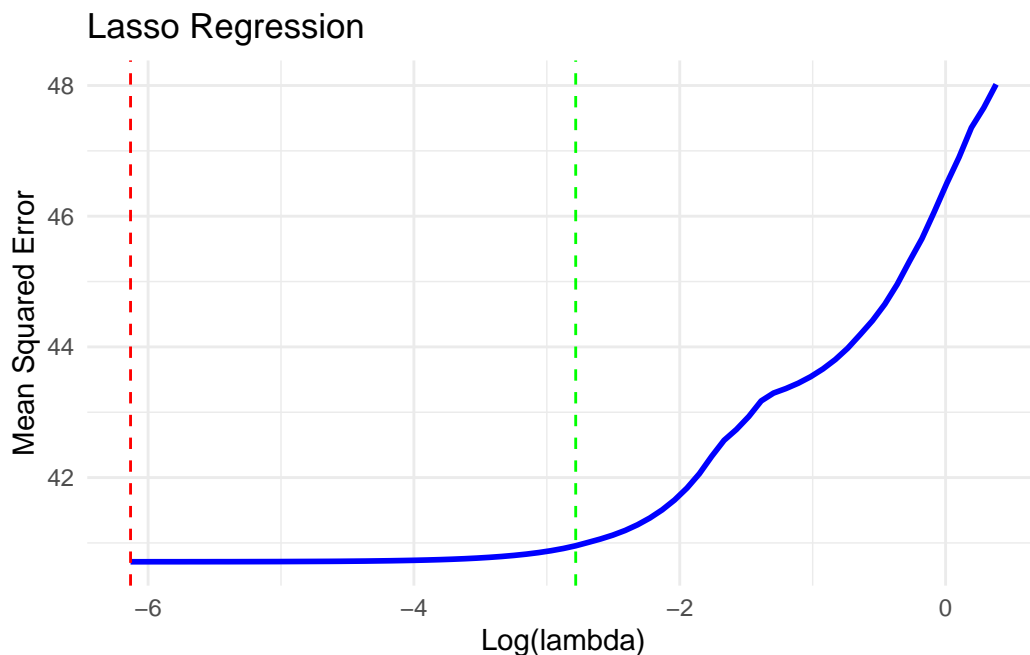
```
[1] "Mean Squared Error (Ridge): 40.8543266734552"
```

```
# Lasso regression
lambda_lasso <- log(lasso$lambda)
mse_lasso <- lasso$cvm
lambda_min_lasso <- log(lasso$lambda.min)
lambda_1se_lasso <- log(lasso$lambda.1se)

plot_data_lasso <- data.frame(lambda = lambda_lasso, mse = mse_lasso)

ggplot(plot_data_lasso, aes(x = lambda, y = mse)) +
  geom_line(color = "blue", size = 1) +
  geom_vline(xintercept = lambda_min_lasso, linetype = "dashed", color = "red") +
  geom_vline(xintercept = lambda_1se_lasso, linetype = "dashed", color = "green") +
  labs(x = "Log(lambda)", y = "Mean Squared Error", title = "Lasso Regression") +
  theme_minimal()
```

Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.  
i Please use `linewidth` instead.



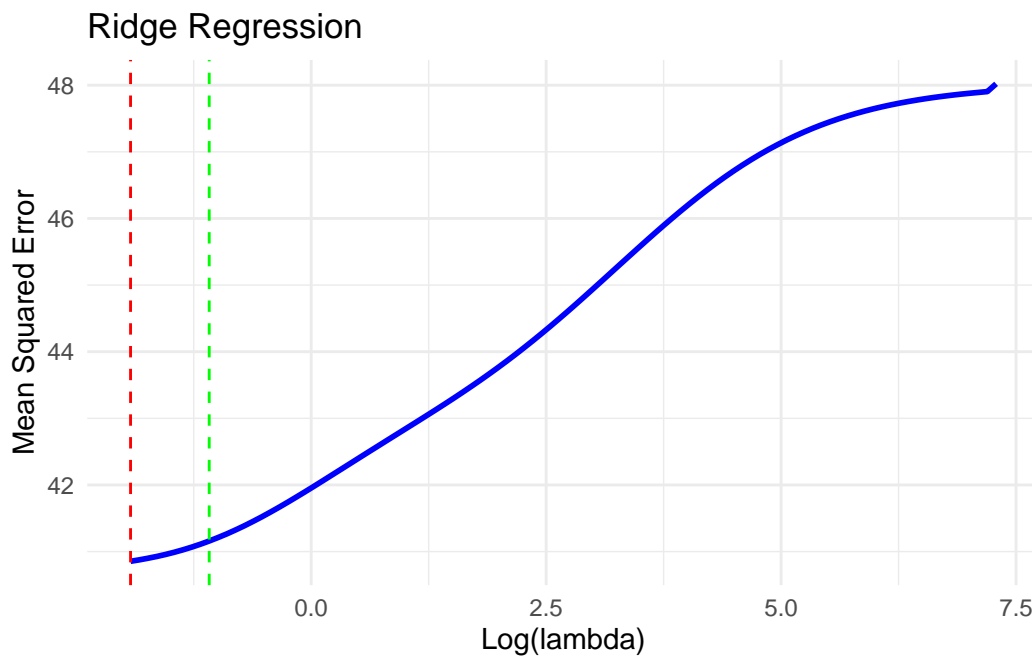
```

# Ridge regression
lambda_ridge <- log(ridge$lambda)
mse_ridge <- ridge$cvm
lambda_min_ridge <- log(ridge$lambda.min)
lambda_1se_ridge <- log(ridge$lambda.1se)

plot_data_ridge <- data.frame(lambda = lambda_ridge, mse = mse_ridge)

ggplot(plot_data_ridge, aes(x = lambda, y = mse)) +
  geom_line(color = "blue", size = 1) +
  geom_vline(xintercept = lambda_min_ridge, linetype = "dashed", color = "red") +
  geom_vline(xintercept = lambda_1se_ridge, linetype = "dashed", color = "green") +
  labs(x = "Log(lambda)", y = "Mean Squared Error", title = "Ridge Regression") +
  theme_minimal()

```



```
head(data3)
```

	year	country	city	stage	home_team	away_team	home_score	away_score
1	1930	Uruguay	Montevideo	Group 1	France	Mexico	4	1
2	1930	Uruguay	Montevideo	Group 4	Belgium	United States	0	3
3	1930	Uruguay	Montevideo	Group 2	Brazil	Yugoslavia	1	2

4	1930	Uruguay	Montevideo	Group 3	Peru	Romania	1	3
5	1930	Uruguay	Montevideo	Group 1	Argentina	France	1	0
6	1930	Uruguay	Montevideo	Group 1	Chile	Mexico	3	0

	outcome	win_conditions	Country	losing_team	date	month	dayofweek
1	H		France	Mexico	1930-07-13	Jul	Sunday
2	A		United States	Belgium	1930-07-13	Jul	Sunday
3	A		Yugoslavia	Brazil	1930-07-14	Jul	Monday
4	A		Romania	Peru	1930-07-14	Jul	Monday
5	H		Argentina	France	1930-07-15	Jul	Tuesday
6	H		Chile	Mexico	1930-07-16	Jul	Wednesday

```
head(df)
```

	year.x	host	Country	second	third	fourth	goals_scored	teams	games
1	1930	Uruguay	Uruguay	Argentina	USA	Yugoslavia	70	13	18
2	1930	Uruguay	Uruguay	Argentina	USA	Yugoslavia	70	13	18
3	1930	Uruguay	Uruguay	Argentina	USA	Yugoslavia	70	13	18
4	1930	Uruguay	Uruguay	Argentina	USA	Yugoslavia	70	13	18
5	1930	Uruguay	Uruguay	Argentina	USA	Yugoslavia	70	13	18
6	1930	Uruguay	Uruguay	Argentina	USA	Yugoslavia	70	13	18

	attendance	rank	country_abrv	total_points	previous_points	rank_change
1	434000	16	URU	48	0	0
2	434000	16	URU	48	0	0
3	434000	16	URU	48	0	0
4	434000	16	URU	48	0	0
5	434000	16	URU	48	0	0
6	434000	16	URU	48	0	0

	confederation	rank_date	year.y	country	city	stage	home_team
1	CONMEBOL	1992-12-31	1930	Uruguay	Montevideo	Group 3	Uruguay
2	CONMEBOL	1992-12-31	1930	Uruguay	Montevideo	Group 3	Uruguay
3	CONMEBOL	1992-12-31	1930	Uruguay	Montevideo	Semifinals	Uruguay
4	CONMEBOL	1992-12-31	1930	Uruguay	Montevideo	Final	Uruguay
5	CONMEBOL	1992-12-31	1950	Brazil	Belo Horizonte	Group 4	Bolivia
6	CONMEBOL	1992-12-31	1950	Brazil	São Paulo	Final Round	Sweden

	away_team	home_score	away_score	losing_team	date	month	dayofweek
1	Peru	1	0	Peru	1930-07-18	Jul	Friday
2	Romania	4	0	Romania	1930-07-21	Jul	Monday
3	Yugoslavia	6	1	Yugoslavia	1930-07-27	Jul	Sunday
4	Argentina	4	2	Argentina	1930-07-30	Jul	Wednesday
5	Uruguay	0	8	Bolivia	1950-07-02	Jul	Sunday
6	Uruguay	2	3	Sweden	1950-07-13	Jul	Thursday

A description of the final model. Do not describe all the intermediate models that you have tried. Instead, present the model (or models) whose quantitative results you will show. These should be your most interesting models. Be as specific as you can while being concise. Readers should be able to reproduce a model similar enough to yours and obtain a similar performance.

## **Baseline Model**

Describe a simple, baseline model that you will compare your neural network against. This can be a simple model that you build.

## **Quantitative Results**

A description of the quantitative measures of your result. What measurements can you use to illustrate how your model performs?

## **Qualitative Results**

Include some sample outputs of your model, to help your readers better understand what your model can do. The qualitative results should also put your quantitative results into context (e.g. Why did your model perform well? Is there a type of input that the model does not do well on?)

## **Discussion**

Discuss your results. Do you think your model is performing well? Why or why not? What is unusual, surprising, or interesting about your results? What did you learn?

## **Ethical Considerations**

Description of a use of the system that could give rise to ethical issues. Are there limitations of your model? Your training data?

(Note that the expectations are higher here than in the project proposal.)

## **Conclusion(Optional)**

Summarize the whole report.