UNITED STATES MILITARY ACADEMY

SCORE MODULE FINAL PRODUCT

MA388: SABERMETRICS

SECTION D1

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KB JC I CERTIFY THAT I HAVE COMPLETELY DOCUMENTED ALL SOURCES THAT I USED TO COMPLETE THIS ASSIGNMENT AND THAT I ACKNOWLEDGED ALL ASSISTANCE I RECEIVED IN THE COMPLETION OF THIS ASSIGNMENT.

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MA388 Sabermetrics: SCORE

NFL Touchdown vs. Field Goal Expectancy Matrices

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1. Learning Goals:

The list of the learning outcomes for those who complete the module:

- (1) Understand how to build expectancy matrices for touchdowns and field goals in terms of distance and yards-to-go with NFL (American Football) data
- (2) Use a Generalized Additive Model (GAM) to fit the non-linear scoring data for the matrices
- (3) Be able to read the matrices and explain the functions used to build them
- (4) Understand how to compare the matrices to determine the higher-scoring play-call in each situation

2. Introduction:

This module seeks to answer this question: What are the expected points for a touchdown and field goal in each 4th down situation?

Touchdown and field goal expectancy are the expected number of points that will be scored by the respective plays. The plays are subdivided into different 4th down situations by (1) yards until 1st down (anywhere from 1-10), also known as yards-to-go, and (2) the distance in yards from the goal line, which marks the beginning and front of the end zone (where touchdowns are scored). The expected points in these different 4th down situations are the generalized mean of the points scored in each situation.

Here is the background for why yds-to-go is anywhere from 1-10: In American football, teams have four attempts, called downs, to advance the ball at least 10 yards down the field. If they succeed in advancing the ball 10 yards or more, they earn a new set of downs. The phrase "yards to go" specifies how many yards the team must advance the ball to reach the next first down.

The data used is restricted to plays within 40 yards of the goal line (double the Red Zone distance). The Red Zone is defined as the last 20 yards heading into an opponent's end zone. The Red Zone distance was doubled in this module to provide more data points but mainly to make the decision between the two play options harder, since calling a traditional play is advantageous in the red zone.

Being able to answer the module's question is important because it allows coaches and players to determine whether or not a field goal should be called instead of going for a 1st down. Furthermore, this module's results give an insight on the situations that are easiest to score a touchdown in and when it is advantageous to pursue a field goal instead. This matters significantly because in close games, going for and scoring a field goal can prevent a loss or overtime, but also if a team is playing the strategic long game, going for an early field goal can set them up to win in the end.

(see the section *4. Methods* for an in-depth explanation of GAMs and Matrices and how they will be used in this module.)

3. Data: https://www.kaggle.com/datasets/maxhorowitz/nflplaybyplay2009to2016

This data set was found on Kaggle through Google searching. It is detailed NFL play-by-play data from 2009-2018. It was compiled by Ron Yurko, Sam Ventura, and Mark Horowitz in order to makeup for the lack of publicly available NFL data sources. This is basically the equivalent of PitchF/x for baseball. It can be downloaded from the link above as an Excel (.csv) file. It can be imported to RStudio by placing it in your working directory and read-in using the notation found below in the example.

The sample size of the file is 449,371. Variables (255 total) included are gameID, playID, side of field, teams, game seconds, drive number, downs, yardage line, yards to go, play type, yards gained, pass length, air yards, run yards, and more. The variables ranges' are dependent on their categories: air yards or total yards on a play can be negative all the way up to 100, but yards to go varies from 0 to around 20 at most. Other variables are binary and represented by a 0 or 1, like if the QB dropped back or not on the play. Below is a sample of the data and some of the variables included:

```r
library(tidyverse)
library(mgcv)
library(broom)
library(knitr)

#Read in the data from the csv file

footballData = read.csv("NFLPlayByPlay.csv")

#Columns are selected to provide a sample of the dataset

sample_example <- footballData %>%
  select(GameID, HomeTeam, AwayTeam, Drive, down,
         yrdln, ydstogo, PlayType) %>%
  filter(down == 4) %>%
  head(10)

sample_example %>%
  kable()
```

GameID	HomeTeam	AwayTeam	Drive	down	yrdln	ydstogo	PlayType
2009091000	PIT	TEN	1	4	44	8	Punt
2009091000	PIT	TEN	2	4	4	8	Punt
2009091000	PIT	TEN	3	4	41	21	Punt
2009091000	PIT	TEN	4	4	19	7	Field Goal
2009091000	PIT	TEN	5	4	21	16	Punt
2009091000	PIT	TEN	8	4	44	22	Punt
2009091000	PIT	TEN	9	4	38	5	Punt
2009091000	PIT	TEN	10	4	13	6	Field Goal
2009091000	PIT	TEN	15	4	45	1	Punt
2009091000	PIT	TEN	16	4	4	11	Punt

In the table above, the columns are variables selected for each data point (each play). They are filtered so only those plays that occurred on 4th down are available (notice there are either punts or field goals). Then, only the first 10 plays were taken, as this is just a sample to show what the data looks like.

4. Methods / Instructional Content:

https://www.espn.com/nfl/story/_/id/33059528/nfl-game-management-cheat-sheet-punt-go-kick-field-goal-fourth-downs-plus-2-point-conversion-recommendations

The article above from ESPN provides a graph based on a model that determines whether a coach should go for a 1st down, kick a field goal, or punt. The graph's variables include yards to go and yards to end zone. The model is considered more aggressive than the average coach (as stated by the author), as it goes for 4th downs most of the time, especially when within 3 yards of a 1st down. "ESPN's model considers the win probability expected given a fourth-down success and fourth-down failure, and weighs those by the expected conversion rate of that fourth down." Our model is simpler than this, but we still focus on the idea of when a FG is more beneficial than to go for a conversion. From this article we streamlined our module idea to create two expectancy matrices, one for touchdowns and a second for field goals, which can then be contrasted against one another every play to see which will score more points.

www.sportingnews.com/us/nfl/news/nfl-fourth-down-conversion-chart-rate-by-distance/vofkeub6xwms6imajxqkfipp

The article above provided the evidence that showed how significant our analysis could be. "Based on data going back to 2013, teams have had a success rate of 39.4 percent going for it on fourth-and-8. If teams wanted to try for it on fourth-and-9, that success rate dips a whopping 9.8 percent down to 29.6 percent." This stark contrast in conversion rate, especially when factoring in field position, can greatly affect what play is called. This effected the content and structure of our model because it made us specifically have each yard to go be its own state in the matrix, due to how strong of an effect it has historically had on the league in regards to conversion rate.

A matrix is a two-dimensional data structure consisting of rows and columns, where each element is of the same data type. Matrices are commonly used for storing and manipulating structured data, such as numeric values, in a tabular format.

For this module, we will use a Generalized Additive Model (GAM) to fit the data to produce our touchdown points expectancy matrix. In a similar manner to a linear regression, a GAM produces an output based off a set of input parameters. However, a GAM can be used to fit nonlinear data.

In practice, the GAM equation can be seen below where β_0 is an intercept, and each variable is the input to a function eg. $f_n(x_n)$.

$$g(E[y]) = \beta_0 + f_1(x_1) + f_2(x_2) + \ \dots\ f_n(x_n)$$

An example of a GAM in practice is the expected points matrix for field goals. In this case, the expected amount of points is $g(E[y])$ which is some function of the distance from the end zone $f_{YardLine}(x_{YardLine})$. See how to apply a GAM to the data in R below.

```
#Field Goal GAM

#Step 1 Isolate field goal data from the play by play data. The variables of interest
#are the FieldGoalResult which is binary (Successful or Unsuccessful) and the FieldGoalDistance.

footballFG <-footballData %>%
  filter(PlayType == "Field Goal") %>%
  select(FieldGoalResult, FieldGoalDistance)

#Step 2 Create a GAM for Field Goal probability as a function of yardline.

gamFGMatrix <- footballFG %>%
   gam((FieldGoalResult == "Good") ~ s(FieldGoalDistance), family = binomial, data = .)

#Step 3 Create a dataframe for field goal probabilities.

FGMatrix <- data.frame(FieldGoalDistance = 1:40)

#Step 4 Apply the model to the field goal dataframe and add a column for
#the point value of a field goal. (Multiply the probability by the value of a field goal)
```

```r
PredictedFG <- gamFGMatrix %>%
  augment(type.predict = "response",
          newdata = FGMatrix) %>%
  rename(FGProbability = .fitted) %>%
  mutate(ExpectedPoints = 3 * FGProbability) %>%
  select(FieldGoalDistance, ExpectedPoints, FGProbability)

#Step 5 Output the data to a table.

PredictedFG %>%
  kable(caption = "Table 1: Point Expectancy and Probability Matrix for a Field Goal
        given Yard Line", digits = 3)
```

Table 2: Table 1: Point Expectancy and Probability Matrix for a Field Goal given Yard Line

FieldGoalDistance	ExpectedPoints	FGProbability
1	2.997	0.999
2	2.997	0.999
3	2.996	0.999
4	2.996	0.999
5	2.995	0.998
6	2.994	0.998
7	2.993	0.998
8	2.992	0.997
9	2.991	0.997
10	2.989	0.996
11	2.988	0.996
12	2.986	0.995
13	2.983	0.994
14	2.981	0.994
15	2.978	0.993
16	2.974	0.991
17	2.970	0.990
18	2.965	0.988
19	2.960	0.987
20	2.953	0.984
21	2.946	0.982
22	2.938	0.979
23	2.928	0.976
24	2.918	0.973
25	2.906	0.969
26	2.893	0.964
27	2.878	0.959
28	2.862	0.954
29	2.843	0.948
30	2.822	0.941
31	2.798	0.933
32	2.772	0.924
33	2.744	0.915
34	2.713	0.904
35	2.679	0.893

FieldGoalDistance	ExpectedPoints	FGProbability
36	2.645	0.882
37	2.609	0.870
38	2.572	0.857
39	2.534	0.845
40	2.497	0.832

5. Exercises / Activities:

Now that you have seen the fundamentals of how a GAM works and how it can be applied to map a nonlinear relationship with one parameter, we will do the same but now with two parameters to model touch down point expectancy based off of yardline and how many yards until the next first down.

```
# Gather data to find the success of touchdowns in the fourth down.
# (Isolate the desired dataset)

footballDataTD <- footballData %>%
  group_by(GameID, Drive) %>%
  mutate(pts_scored = ifelse(PlayType == "Field Goal", (FieldGoalResult == "Good")*3,
                             max(Touchdown)*6)) %>%
  mutate(pts_scored = max(pts_scored)) %>%
  select(down, yrdln, ydstogo, PlayType, pts_scored) %>%
  ungroup() %>%
  filter(down == 4, ydstogo <= 10) %>%
  mutate(ydstogo = ifelse(ydstogo > yrdln, yrdln, ydstogo)) %>%
  group_by(yrdln, ydstogo) %>%
  summarize(mean_points = mean(pts_scored),n = n()) %>%
  filter(!is.na(mean_points))
```

With the desired data isolated, create a dataframe for yardline and yards to go until the next first down. This will serve as the skeleton to which you will apply the GAM you create.

```
TDMatrix <- data.frame(yrdln = rep(1:100, 10)) %>%
  group_by(yrdln) %>%
  mutate(ydstogo = 1:10)
```

Now use the data isolated to produce a GAM for the expected touchdown values using the desired parameters. The code for the model should follow a similar format to the GAM created for the field goal matrix.

```
gamTDMatrix <- footballDataTD %>%
   gam((mean_points / 6) ~ s(yrdln, ydstogo), family = binomial, data = .)
```

Use the GAM to fill in the blank dataframe and multiply each value by the points of a touchdown to create the expectancy matrix.

```
PredictedPoints <- gamTDMatrix %>%
  augment(type.predict = "response",
          newdata = TDMatrix) %>%
  rename(mean_points = .fitted)

PredictedPoints <- PredictedPoints %>%
```

```r
  mutate(Values = 6 * mean_points)

# Turn the dataframe into a matrix

TouchDownMatrix <- PredictedPoints %>%
  group_by(yrdln, ydstogo) %>%
  select(-c(mean_points, .se.fit)) %>%
  pivot_wider(
    names_from = ydstogo,
    values_from = Values,
    names_prefix = "YdsToGo"
  ) %>%
  ungroup()
```

With this newly created expectancy matrix, you can now display the data using a table or heatmap.

```r
# Output the matrix as a table

TouchDownMatrix %>%
  head(40) %>%
  kable(caption = "Table 2: Point Expectancy Matrix on Fourth Down given
    Yard Line and Yards until First Down", digits = 3)
```

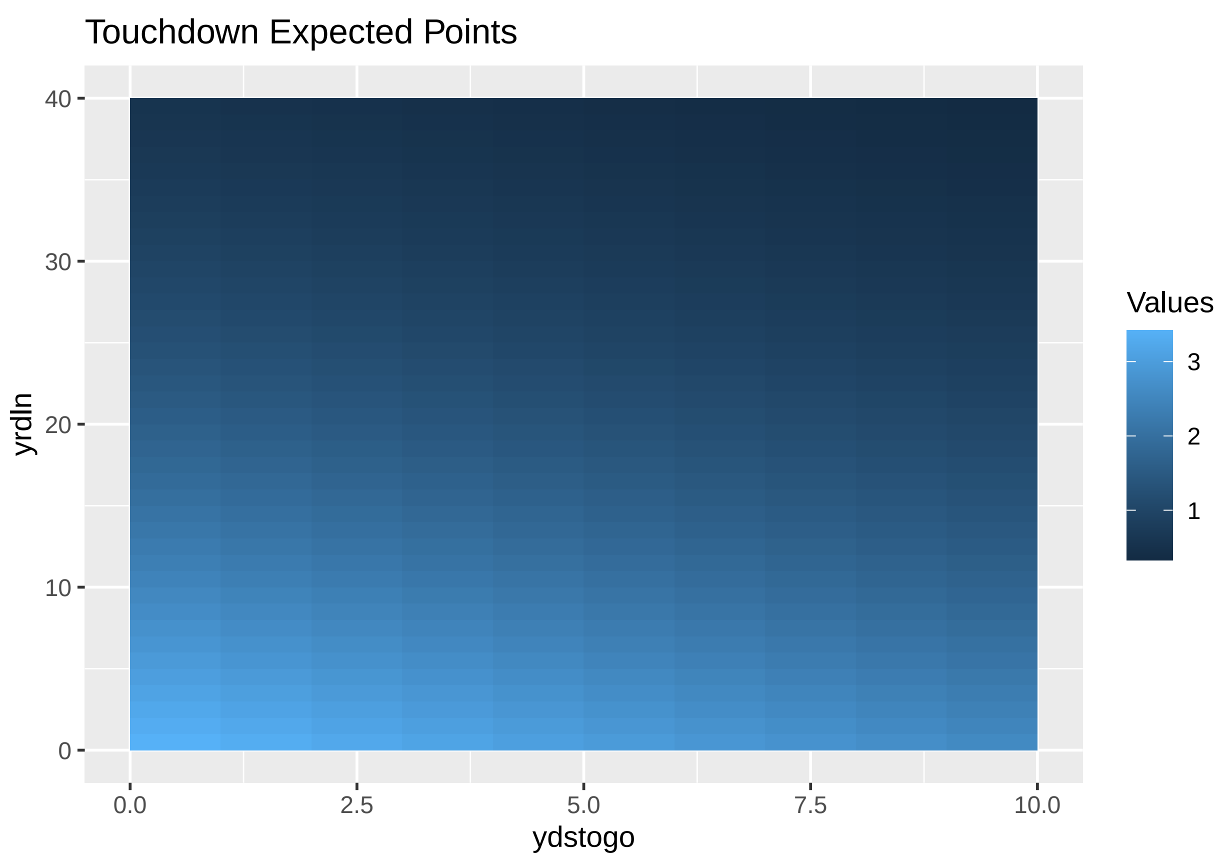
Table 3: Table 2: Point Expectancy Matrix on Fourth Down given Yard Line and Yards until First Down

yrdln	YdsToGo1	YdsToGo2	YdsToGo3	YdsToGo4	YdsToGo5	YdsToGo6	YdsToGo7	YdsToGo8	YdsToGo9	YdsToGo10
1	3.419	3.327	3.233	3.139	3.045	2.951	2.857	2.763	2.670	2.577
2	3.322	3.229	3.135	3.041	2.947	2.853	2.759	2.666	2.573	2.481
3	3.224	3.131	3.037	2.942	2.848	2.755	2.661	2.569	2.477	2.386
4	3.126	3.032	2.938	2.844	2.750	2.657	2.564	2.473	2.382	2.292
5	3.028	2.934	2.840	2.746	2.653	2.560	2.468	2.378	2.288	2.200
6	2.929	2.835	2.742	2.648	2.556	2.464	2.374	2.284	2.196	2.109
7	2.831	2.737	2.644	2.552	2.460	2.369	2.280	2.192	2.105	2.020
8	2.733	2.640	2.547	2.456	2.365	2.276	2.188	2.101	2.016	1.933
9	2.635	2.543	2.451	2.361	2.272	2.184	2.097	2.013	1.929	1.848
10	2.539	2.447	2.357	2.268	2.180	2.093	2.009	1.926	1.845	1.765
11	2.443	2.353	2.263	2.176	2.089	2.005	1.922	1.841	1.762	1.685
12	2.348	2.259	2.172	2.085	2.001	1.918	1.837	1.758	1.681	1.606
13	2.255	2.168	2.081	1.997	1.914	1.833	1.754	1.677	1.603	1.530
14	2.164	2.078	1.993	1.910	1.830	1.751	1.674	1.599	1.527	1.456
15	2.074	1.989	1.907	1.826	1.747	1.670	1.596	1.523	1.453	1.385
16	1.985	1.903	1.822	1.744	1.667	1.592	1.520	1.450	1.382	1.316
17	1.899	1.819	1.740	1.663	1.589	1.517	1.447	1.379	1.313	1.250
18	1.815	1.736	1.660	1.586	1.513	1.444	1.376	1.310	1.247	1.186
19	1.733	1.656	1.582	1.510	1.440	1.373	1.307	1.244	1.184	1.125
20	1.653	1.579	1.507	1.437	1.370	1.304	1.241	1.181	1.122	1.066
21	1.575	1.504	1.434	1.367	1.301	1.239	1.178	1.120	1.064	1.010
22	1.500	1.431	1.363	1.298	1.236	1.175	1.117	1.061	1.007	0.956
23	1.428	1.360	1.295	1.233	1.172	1.114	1.059	1.005	0.953	0.904
24	1.357	1.293	1.230	1.170	1.112	1.056	1.002	0.951	0.902	0.855
25	1.290	1.227	1.167	1.109	1.053	1.000	0.949	0.900	0.853	0.808

yrdln	YdsToGo1	YdsToGo2	YdsToGo3	YdsToGo4	YdsToGo5	YdsToGo6	YdsToGo7	YdsToGo8	YdsToGo9	YdsToGo10
26	1.224	1.164	1.106	1.051	0.998	0.946	0.898	0.851	0.806	0.763
27	1.162	1.104	1.048	0.995	0.944	0.895	0.849	0.804	0.761	0.720
28	1.101	1.046	0.993	0.942	0.893	0.846	0.802	0.759	0.718	0.680
29	1.043	0.990	0.940	0.891	0.844	0.800	0.757	0.717	0.678	0.641
30	0.988	0.937	0.889	0.842	0.798	0.755	0.715	0.676	0.639	0.604
31	0.935	0.886	0.840	0.796	0.753	0.713	0.674	0.638	0.603	0.570
32	0.884	0.838	0.794	0.751	0.711	0.673	0.636	0.601	0.568	0.537
33	0.836	0.792	0.750	0.709	0.671	0.634	0.600	0.567	0.535	0.505
34	0.790	0.748	0.707	0.669	0.633	0.598	0.565	0.534	0.504	0.476
35	0.746	0.706	0.667	0.631	0.597	0.564	0.532	0.503	0.475	0.448
36	0.704	0.666	0.630	0.595	0.562	0.531	0.501	0.473	0.447	0.421
37	0.664	0.628	0.593	0.561	0.530	0.500	0.472	0.445	0.420	0.396
38	0.626	0.592	0.559	0.528	0.499	0.471	0.444	0.419	0.395	0.373
39	0.590	0.558	0.527	0.497	0.469	0.443	0.418	0.394	0.372	0.350
40	0.556	0.525	0.496	0.468	0.442	0.417	0.393	0.371	0.349	0.329

```r
# Create a visual of the matrix

PredictedPoints %>%
  filter(yrdln <= 40) %>%
  ggplot(aes(x = ydstogo, y = yrdln, fill = Values)) +
  geom_raster(hjust = 0, vjust = 0) +
  labs(title = "Touchdown Expected Points")
```



In the produced heatmap are the expected points of a touchdown attempt for a certain yds-to-go and distance position on the field.

After completing the exercise above and the walkthrough in Section 4, one should be able to see two tables, produced by the expectancy matrices, and a heat map, based on the touchdown expectancy matrix. In the Touchdown expectancy matrix table, each value within the table is the expected points of 4th down plays in different field positions. As one moves from left to right on the table, the values almost always go down. As one moves from the top to the bottom of the table, the values almost always go down. Each value is the expected number of points that will be scored, which are the generalized mean of the points scored in each situation in actuality. The heat map (the gradient chart with a blue scale) depicts these results in color with the brighter blue being more points than the darker blue. The Field Goal expectancy matrix is simpler than the touchdown one as it only has one value for expected points per row (each row being the distance from the goal line). As one moves down the table, the expected points slowly goes down, with the difference between 1 and 40 yards away being much closer compared to the the touchdown matrix's difference between 1 and 40.

An example of using these charts would be determining which play to call when 5 yards away. For a field goal, that has a set expected points value of 2.995 with a 0.998 probability of the field goal being made. On the other hand, the touchdown matrix presents the expected points for 5 yards in 10 different states, based on yard-to-go until a first down. With 1 yard-to-go, the expected points value is higher at 3.028, however, from 2 to 10 yards-to-go, it is lower, ranging from 2.934 down to 2.200 expected points. In conclusion, if you want to score more points on that specific play, or score in general, if you don't have 1 yard-to-go, you should kick a field goal because the expected points for a field goal are higher. But it isn't that simple. Although in that moment the field goal is better in terms of scoring in that position, that doesn't meant that a touchdown won't be scored after getting a littler closer and getting a few more first downs, but, you run the risk of turning over the ball if you don't convert the first down. Essentially, play calling comes down to long-term game planning, the current situation, and a team's preference based on their offensive options, which isn't accounted for in this module, but this module provides the data to inform decision-making.

Still though, this analysis takes time. Is there a simplified visual that would be better? (Combine both field goal and touchdown expectancy matrices)

```
# Create a new matrix for the point difference between field goals and touchdown expected values

PointDifferential <- TouchDownMatrix %>% head(40)

# Iterate through the columns and take away the expected field goal values

for(i in 2:length(PointDifferential)) {
  PointDifferential[i] <- (TouchDownMatrix[i] %>% head(40) - PredictedFG[2])
}

# Output the new matrix in a table

PointDifferential %>%
  kable(caption = "Table 3: Point Expectancy Differential Matrix on Fourth Down given
    Yard Line and Yards until First Down", digits = 3)
```

Table 4: Table 3: Point Expectancy Differential Matrix on Fourth Down given Yard Line and Yards until First Down

yrdln	YdsToGo1	YdsToGo2	YdsToGo3	YdsToGo4	YdsToGo5	YdsToGo6	YdsToGo7	YdsToGo8	YdsToGo9	YdsToGo10
1	0.422	0.329	0.236	0.142	0.048	-0.046	-0.140	-0.234	-0.327	-0.420
2	0.325	0.232	0.138	0.044	-0.050	-0.144	-0.238	-0.331	-0.424	-0.516

yrdln	YdsToGo1	YdsToGo2	YdsToGo3	YdsToGo4	YdsToGo5	YdsToGo6	YdsToGo7	YdsToGo8	YdsToGo9	YdsToGo10
3	0.228	0.134	0.040	-0.054	-0.148	-0.242	-0.335	-0.428	-0.519	-0.610
4	0.131	0.037	-0.058	-0.152	-0.245	-0.339	-0.431	-0.523	-0.614	-0.703
5	0.033	-0.061	-0.155	-0.249	-0.342	-0.435	-0.527	-0.617	-0.707	-0.795
6	-0.065	-0.159	-0.253	-0.346	-0.438	-0.530	-0.621	-0.710	-0.798	-0.885
7	-0.162	-0.256	-0.349	-0.442	-0.533	-0.624	-0.713	-0.801	-0.888	-0.973
8	-0.259	-0.352	-0.445	-0.536	-0.627	-0.716	-0.804	-0.891	-0.976	-1.059
9	-0.355	-0.448	-0.539	-0.630	-0.719	-0.807	-0.893	-0.978	-1.061	-1.143
10	-0.451	-0.542	-0.633	-0.722	-0.810	-0.896	-0.981	-1.064	-1.145	-1.224
11	-0.545	-0.635	-0.724	-0.812	-0.898	-0.983	-1.066	-1.147	-1.226	-1.303
12	-0.637	-0.726	-0.814	-0.900	-0.985	-1.068	-1.149	-1.228	-1.305	-1.380
13	-0.728	-0.816	-0.902	-0.986	-1.069	-1.150	-1.229	-1.306	-1.381	-1.453
14	-0.817	-0.903	-0.988	-1.070	-1.151	-1.230	-1.307	-1.381	-1.454	-1.524
15	-0.904	-0.988	-1.071	-1.152	-1.230	-1.307	-1.382	-1.454	-1.525	-1.593
16	-0.989	-1.071	-1.152	-1.231	-1.307	-1.382	-1.454	-1.524	-1.592	-1.658
17	-1.071	-1.151	-1.230	-1.307	-1.381	-1.453	-1.523	-1.591	-1.657	-1.720
18	-1.150	-1.229	-1.305	-1.380	-1.452	-1.522	-1.589	-1.655	-1.718	-1.779
19	-1.227	-1.303	-1.377	-1.450	-1.519	-1.587	-1.652	-1.715	-1.776	-1.835
20	-1.300	-1.375	-1.446	-1.516	-1.584	-1.649	-1.712	-1.773	-1.831	-1.887
21	-1.371	-1.442	-1.512	-1.580	-1.645	-1.707	-1.768	-1.826	-1.882	-1.936
22	-1.438	-1.507	-1.574	-1.639	-1.702	-1.763	-1.821	-1.877	-1.930	-1.982
23	-1.501	-1.568	-1.633	-1.696	-1.756	-1.814	-1.870	-1.924	-1.975	-2.024
24	-1.561	-1.625	-1.688	-1.748	-1.806	-1.862	-1.915	-1.967	-2.016	-2.063
25	-1.617	-1.679	-1.739	-1.797	-1.853	-1.906	-1.957	-2.006	-2.053	-2.098
26	-1.669	-1.729	-1.787	-1.842	-1.895	-1.947	-1.996	-2.042	-2.087	-2.130
27	-1.717	-1.774	-1.830	-1.883	-1.934	-1.983	-2.030	-2.074	-2.117	-2.158
28	-1.760	-1.816	-1.869	-1.920	-1.969	-2.015	-2.060	-2.102	-2.143	-2.182
29	-1.800	-1.853	-1.903	-1.952	-1.999	-2.043	-2.086	-2.126	-2.165	-2.202
30	-1.834	-1.885	-1.933	-1.980	-2.024	-2.067	-2.107	-2.146	-2.182	-2.217
31	-1.863	-1.912	-1.958	-2.003	-2.045	-2.085	-2.124	-2.161	-2.195	-2.229
32	-1.888	-1.934	-1.979	-2.021	-2.061	-2.100	-2.136	-2.171	-2.204	-2.236
33	-1.908	-1.952	-1.994	-2.034	-2.073	-2.109	-2.144	-2.177	-2.208	-2.238
34	-1.923	-1.965	-2.005	-2.043	-2.080	-2.114	-2.147	-2.179	-2.208	-2.237
35	-1.934	-1.974	-2.012	-2.048	-2.083	-2.116	-2.147	-2.177	-2.205	-2.232
36	-1.941	-1.979	-2.015	-2.050	-2.083	-2.114	-2.143	-2.171	-2.198	-2.223
37	-1.945	-1.981	-2.015	-2.048	-2.079	-2.109	-2.137	-2.163	-2.188	-2.212
38	-1.946	-1.980	-2.013	-2.044	-2.073	-2.101	-2.128	-2.153	-2.177	-2.199
39	-1.944	-1.977	-2.008	-2.037	-2.065	-2.091	-2.116	-2.140	-2.163	-2.184
40	-1.940	-1.971	-2.001	-2.028	-2.055	-2.080	-2.103	-2.126	-2.147	-2.167

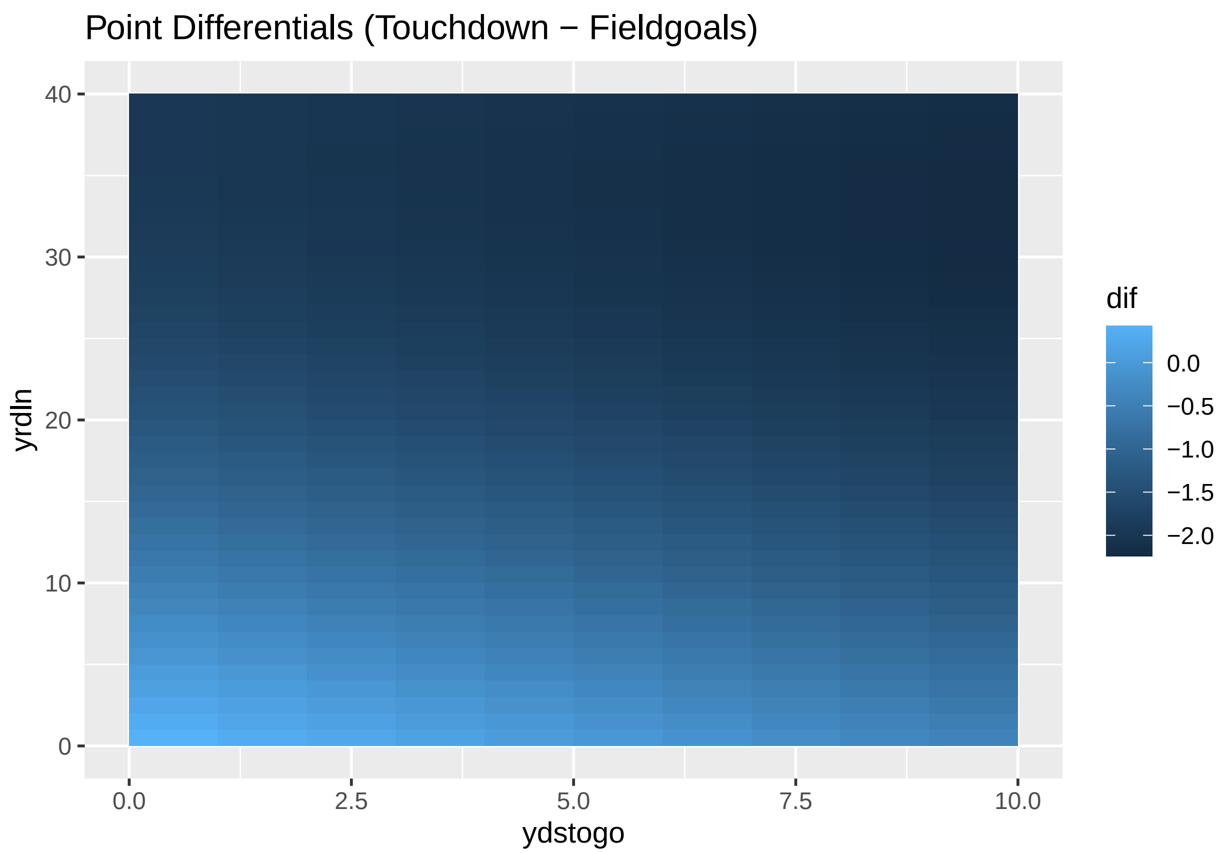
```r
# Create a dataframe for the heat map

PredictedFG <- PredictedFG %>%
  rename(yrdln = FieldGoalDistance)

HeatMapDifferential <- PredictedPoints %>%
  filter(yrdln <= 40) %>%
  left_join(PredictedFG, by = "yrdln") %>%
  mutate(dif = Values - ExpectedPoints) %>%
  select(yrdln, ydstogo, dif)

# Produce a visual
```

```r
HeatMapDifferential %>%
  ggplot(aes(x = ydstogo, y = yrdln, fill = dif)) +
  geom_raster(hjust = 0, vjust = 0) +
  labs(title = "Point Differentials (Touchdown - Fieldgoals)")
```



With this new matrix, the decisions are made even clearer. Positive values suggest more expected points for a touchdown while negative ones suggest that a field goal would be more effective. This same matrix is visualized on the heatmap.

6. Wrap-Up/Conclusions:

By completing this module, the learning outcomes below were hopefully accomplished:

- (1) Understand how to build expectancy matrices for touchdowns and field goals in terms of distance and yards-to-go with NFL (American Football) data
- (2) Use a Generalized Additive Model (GAM) to fit the non-linear scoring data for the matrices
- (3) Be able to read the matrices and explain the functions used to build them
- (4) Understand how to compare the matrices to determine the higher-scoring play-call in each situation

The first goal was accomplished in Sections 4 and 5. In Section 4, matrices were explained and the field goal matrix was built, and in Section 5 the touchdown matrix was built. In Section 5, you grouped 4th down plays initially by drives and assigned scoring outcomes so that one could filter the plays by yards-to-go and distance. Then you built a less complex matrix for field goal probability to compare with in Section

4. The second goal was accomplished in Sections 4 and 5 as Section 4 explained GAMs and in Sections 4 and 5 you used them. In Section 5, you used a GAM to fit the touchdown data because the data itself isn't linear i.e. being closer and closer to the end zone will not increase the expected points by a constant amount every yard you get closer. Goal 3 was accomplished throughout Section 5. Finally, goal 4 was accomplished towards the end of Section 5.

Through accomplishing these lesson objectives, one can answer what the touchdown and field goal expectancy is in each 4th down situation and thus, which play is the best call.

In comparison with findings online, our results are somewhat similar. When looking at the results of the ESPN article referenced in Section 4 of this module, one can observe that the touchdown option, also known as "go," is more prominent. In this module's final heatmap field goal expected points, even initially, are very close to the touchdown expected points, yet they decrease much slower. However, the ESPN model factors in punting and how that affects expected points due to the importance of field position. Thus, our models are quite different, but that was expected because they used more variables and their model was more complex.

Another way the exercise and information above can be applied in a different sport is observing the value difference between a 3-pointer and a 2-pointer in the NBA, specifically looking at an in-the-paint shot vs. a 3-pointer to see which is more effective. Today, the 3-pointer is a more efficient shot, but it wasn't always seen that way.

A future skill that could be used to build on what's presented here is adding pace or number of possessions as variables and then looking at them through a "+" statistic to see how eras in football have affected them. This would show how different eras affected play calling and use of time, which in turn effected plays on 4th downs, displaying thoughts on the importance of general field position (specifically in regards to turnovers) vs. the importance of scoring position.

Think About it:

Below are some questions to think about after achieving the learning outcomes of the module:

- (1) What are other variables not accounted for in the module that could affect either scoring or take into account field positions?
- (2) What is another approach to this module that could have focused more on predicted play-calling, which would benefit defenses?
- (3) What are statistical methods could be added to benefit this module and its goal? Or how could the current ones be improved?

Acknowledgement of Assistance

Powell, Mike LTC. Assistance given to the authors, oral and written discussion. We met with LTC Powell to help us with our touchdown matrix because our result didn't make sense. Some scoring situations like 38 yards away and 10 to go had a higher probability to score then 15 yards away with 2 to go (a fabricated but logically correct example). LTC Powell helped us by correcting our code and instead of looking at individual plays, we grouped by drives and found the expectancy using that approach. Due to this, we assigned points to play types, allowing us to accurately track which plays (ones where scoring occurred) were being observed. He then recommended that we make a heat map of the data as well which we implemented in the Exercises section of our SCORE module. West Point, NY. 23APR2024.

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