

# Predicting Football Match Results of Spanish League using Bayesian Hierarchical Model



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# Introduction

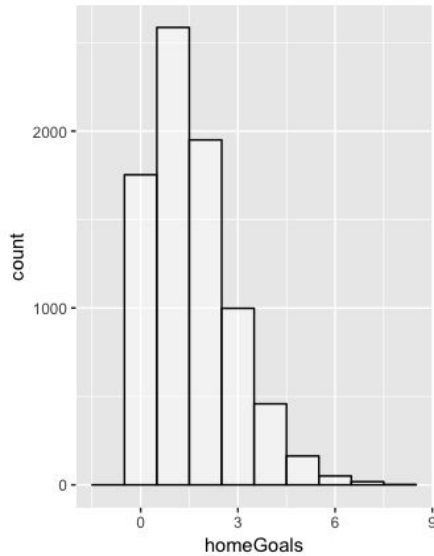
- Soccer is one of the most popular sports on our planet, with a well-developed industry worth more than \$400 billion and billions of fans(estimated) around the world
- Predicting the matches results have always attracted many attentions
- Bayesian approach could be very helpful in this scenario (**given reliable historical data**).
- We will work on the data from the **Spanish League** with 2 approaches
  - From Kaggle: <https://www.kaggle.com/ricardomoya/football-matches-of-spanish-league>



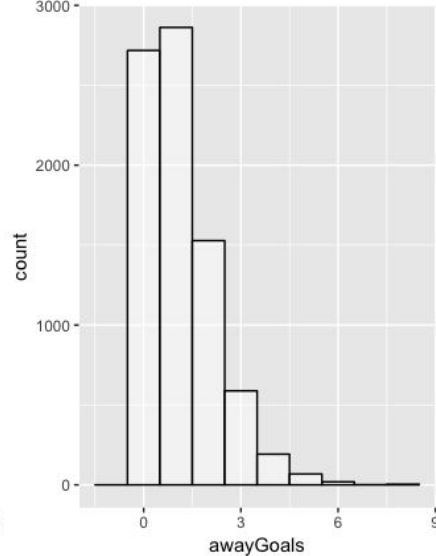
# EDA - Home Advantage

Game Results since 1997, Comparison of home goals and away goals

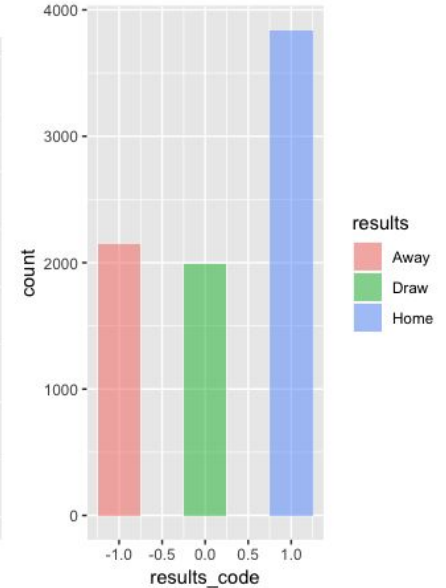
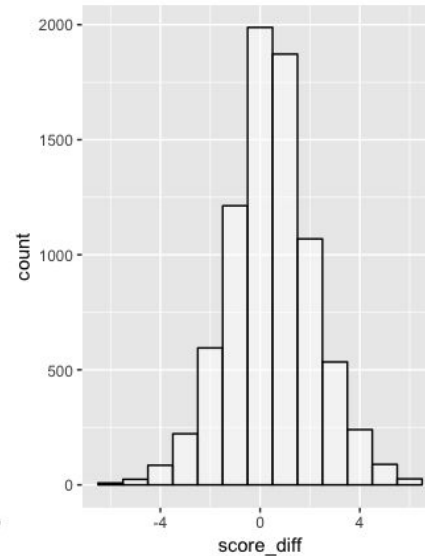
Histogram of Home Goals



Histogram of Away Goals

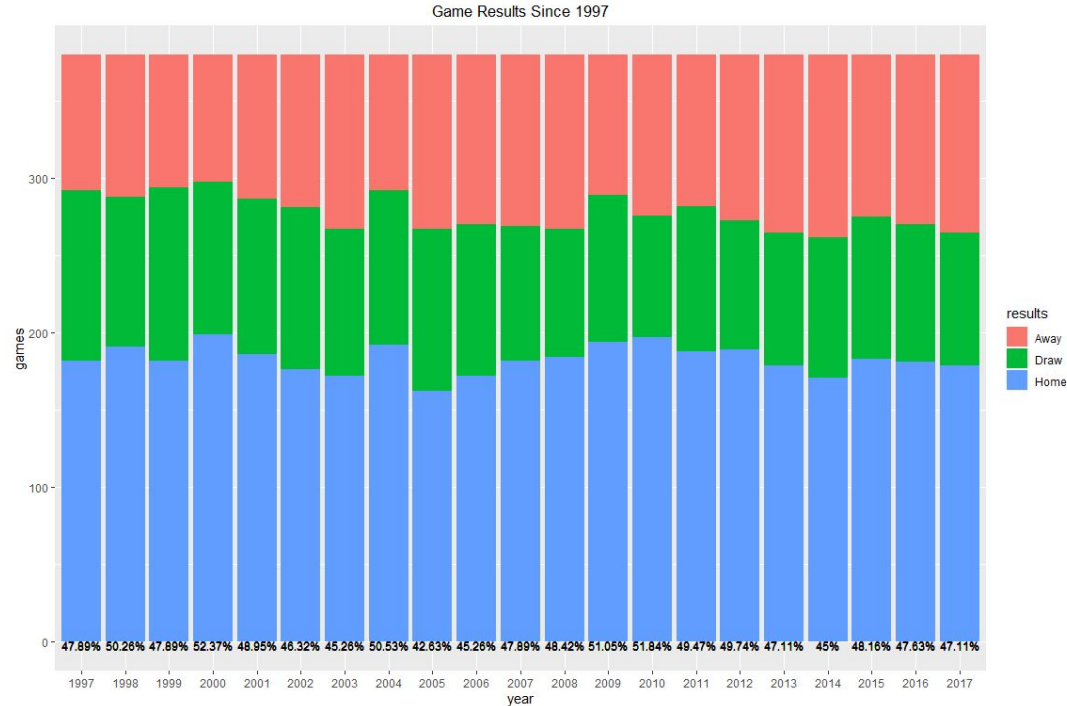


Histogram of Score Difference



# Results Proportion

- If there's no home advantage, the proportion of home win/draw/away win would be the same
- Home win ~48%
- Home Advantage confirmed!



# Approach 1 - Model Set-up

- Home team win follows a binomial distribution, with parameter of home team winning probability
- Home team win probability is defined by the equation with parameter of team abilities (home and away) and home advantage factor
- Team abilities is  $e$  to the power of  $\log(\text{ability})$ , which follows a normal distribution, with parameter of performance variation; home advantage follows a uniform distribution
- Performance variation follows a uniform distribution

$\text{performance\_variation} \sim \text{dunif}(0,2)$

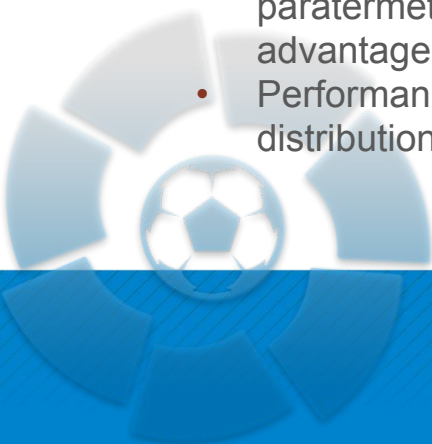
$\text{home\_advantage} \sim \text{dunif}(1,1.5)$

$\log(\text{ability}) \sim \text{dnorm}(0,1/\text{performance\_variation}^2)$

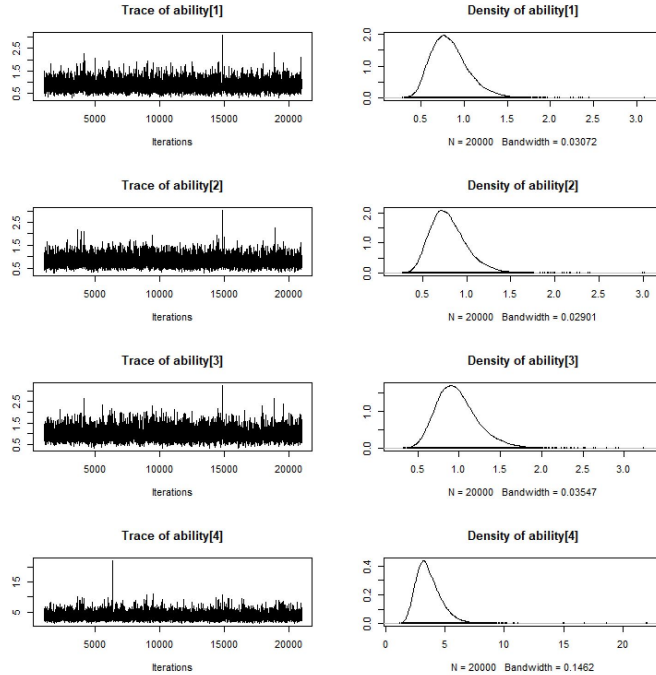
$\text{ability}[i] \sim \exp(\log(\text{ability}))$

$\text{prob}[i] = \frac{\text{ability}(\text{home}[i]) * \text{home\_advantage}}{\text{ability}(\text{home}[i]) * \text{home\_advantage} + \text{ability}(\text{away}[i])}$

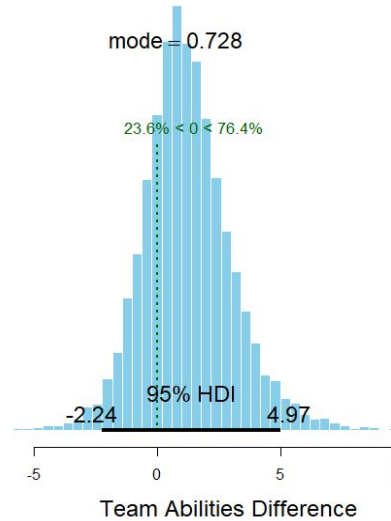
$y_i (\text{home win}) \sim \text{dbin}(\text{prob}[i], 1)$



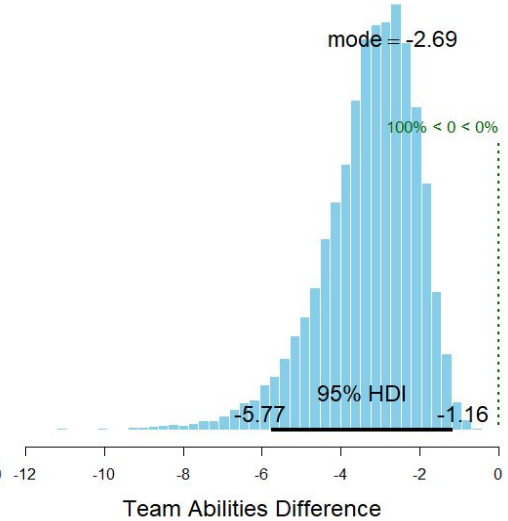
# Approach 1 - Team Comparison



Barcelona - Real Madrid 2015-2017



Espanol - Real Madrid 2015-2017



# Approach 1 - Prediction

Season 2017, 380 games total

How should we bet?

Modeling-set: 200

Predicting-set: 180

$P_{\text{pred}} > 0.6$ , we bet the home team win  
prediction accuracy : 70 %

$P_{\text{pred}} > 0.7$ , we bet the home team win  
prediction accuracy : 82.61 %





# Interesting Findings





















## Rank alignment and mismatch

### Reasons:

1. Strong teams are really dominating, thus easier to predict
2. Many factors that could impact the game results, such as referee decisions, core player injury, weather conditions, especially for teams with very close abilities
3. Limited data at hand, we can't include other factors into our model

La Liga 2017-2018 final rank

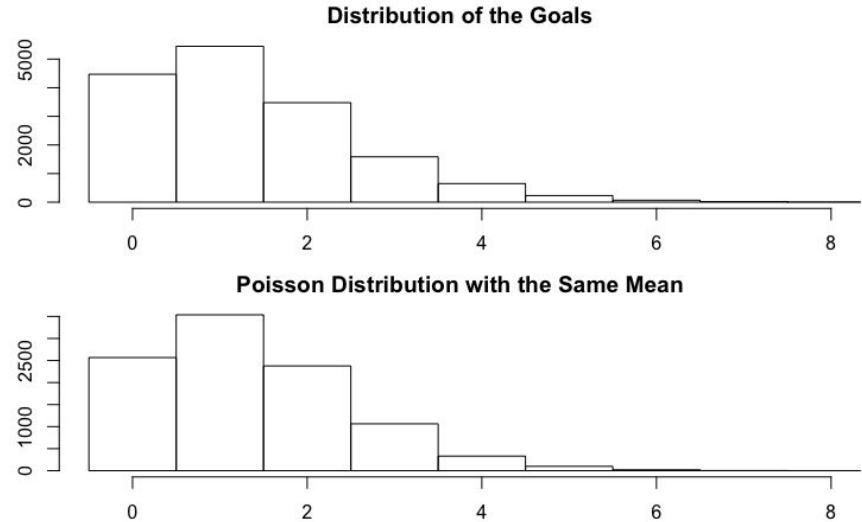
Predicted team abilities rank

Club	MP	W	D	L	GF	GA	GD	Pts	ability avg	rank	
1  Barcelona	38	28	9	1	99	29	70	93	Barcelona	5.1342212	1
2  Atlético Madrid	38	23	10	5	58	22	36	79	Atletico de Madrid	2.3655118	2
3  Real Madrid	38	22	10	6	94	44	50	76	Real Madrid	1.9297434	3
4  Valencia	38	22	7	9	65	38	27	73	Valencia	1.9251803	4
5  Villarreal	38	18	7	13	57	50	7	61	Villarreal	1.4372378	5
6  Real Betis	38	18	6	14	60	61	-1	60	Girona	1.2799012	6
7  Sevilla	38	17	7	14	49	58	-9	58	Getafe	1.2415454	7
8  Getafe CF	38	15	10	13	42	33	9	55	Sevilla	1.0836440	8
9  Eibar	38	14	9	15	44	50	-6	51	Atletico de Bilbao	1.0830023	9
10  Girona	38	14	9	15	50	59	-9	51	Espanol	1.0716992	10
11  Espanyol	38	12	13	13	36	42	-6	49	Betis	0.9622172	11
12  Real Sociedad	38	14	7	17	66	59	7	49	Celta de Vigo	0.9267895	12
13  Celta Vigo	38	13	10	15	59	60	-1	49	Leganes	0.9198342	13
14  Alavés	38	15	2	21	40	50	-10	47	Eibar	0.9014992	14
15  Levante	38	11	13	14	44	58	-14	46	Levante	0.8103701	15
16  Ath. Bilbao	38	10	13	15	41	49	-8	43	Real Sociedad	0.8012979	16
17  Leganes	38	12	7	19	34	51	-17	43	Deportivo	0.7144869	17
18  Deportivo	38	6	11	21	38	76	-38	29	Alaves	0.6030408	18
19  Las Palmas	38	5	7	26	24	74	-50	22	Las Palmas	0.5290823	19
20  Málaga	38	5	5	28	24	61	-37	20	Malaga	0.4477355	20



# Approach 2 - Model Set-up

- In ideal poisson distribution, all football matches are about the same length, both teams have a lot of chances to score, and each team has the same probability of scoring a goal.
- In reality, if the teams are all the same, the game is meaningless, and the distribution of real data also prove it.



# Approach 2 - Model 1 Set-up

The skill of one team minus another can predict the result of the game.

$$Goals \sim \text{Poisson}(\lambda)$$

$$\log(\lambda) = \text{baseline} + \text{skill}_i - \text{skill}_j$$

The baseline is assumed that both teams are equally good:

$$HomeGoals_{i,j} \sim \text{Poisson}(\lambda_{\text{home},i,j})$$

$$AwayGoals_{i,j} \sim \text{Poisson}(\lambda_{\text{away},i,j})$$

$$\log(\lambda_{\text{home},i,j}) = \text{baseline} + \text{skill}_i - \text{skill}_j$$

$$\log(\lambda_{\text{away},i,j}) = \text{baseline} + \text{skill}_j - \text{skill}_i$$

The prior distribution of baseline and skills is set as follows:

$$\text{baseline} \sim \text{Normal}(0, 4^2)$$

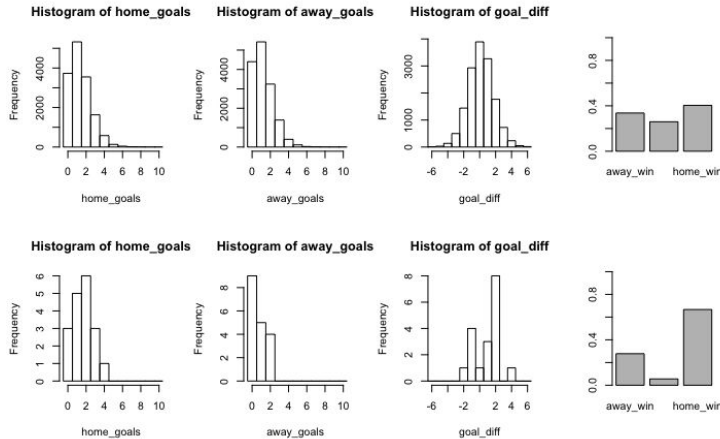
$$\text{skill}_{1\dots n} \sim \text{Normal}(\mu_{\text{teams}}, \sigma_{\text{teams}}^2)$$

$$\mu_{\text{teams}} \sim \text{Normal}(0, 4^2)$$

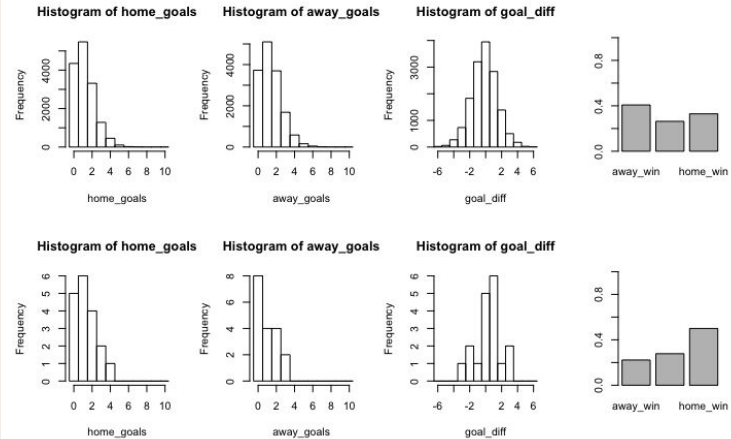
$$\sigma_{\text{teams}} \sim \text{Uniform}(0, 3)$$

# Approach 2 - Model 1 Evaluation

Valencia home to Sevilla away:



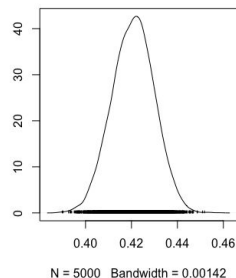
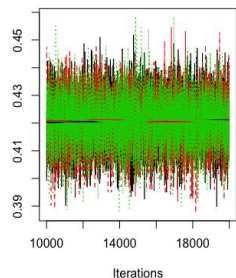
Sevilla home to Valencia away:



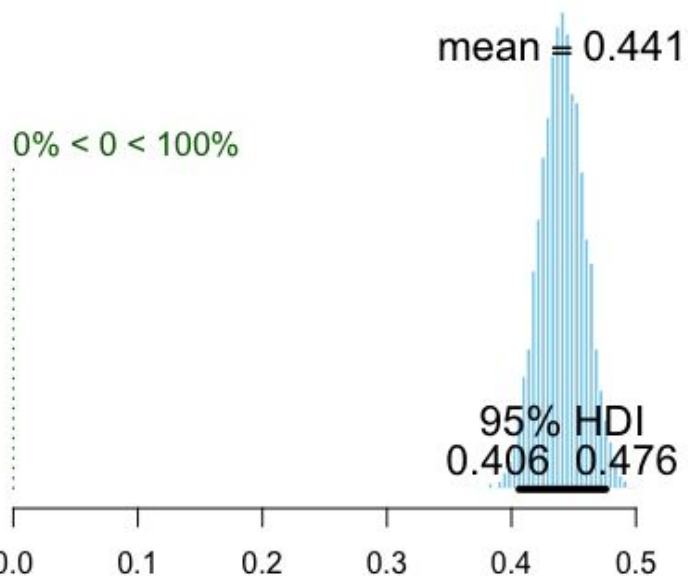
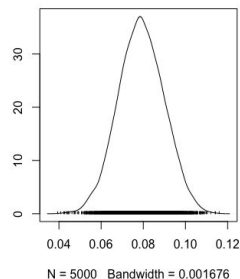
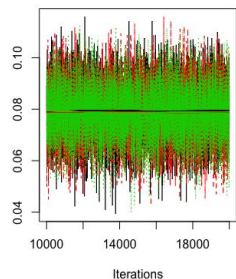
To predict the goal of Valencia and Sevilla. We can check the following barplot for different home cases. The first row in the figure shows the simulation and the second row shows the historical data.

# Approach 2 - Model Updating

Home  
Baseline



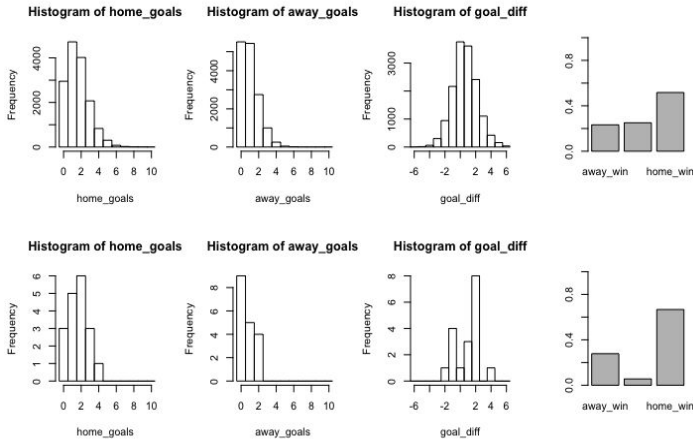
Away  
Baseline



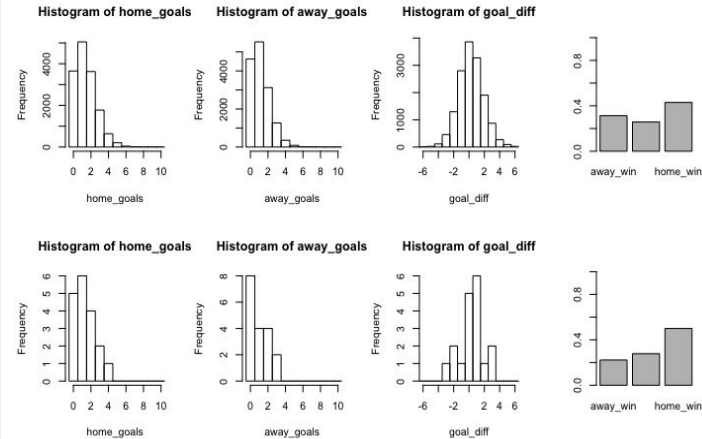
Home advantage in number of goals

# Approach 2 - Model 2 Evaluation

Valencia home to Sevilla away:



Sevilla home to Valencia away:

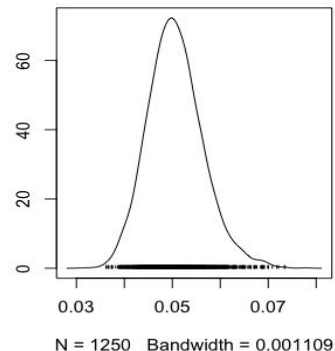
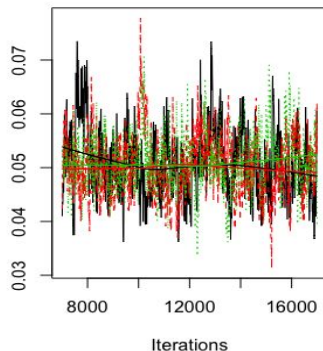


To predict the goal of Valencia and Sevilla. We can check the following barplot for different home cases. The first row in the figure shows the simulation and the second row shows the historical data.

# Approach 2 - Model Updating

The original assumption is that every team has the same skill level in every year, but it's not real. Team performs differently year to year. For fixing this part, we modify the model to include the year-to-year variability in team skills:

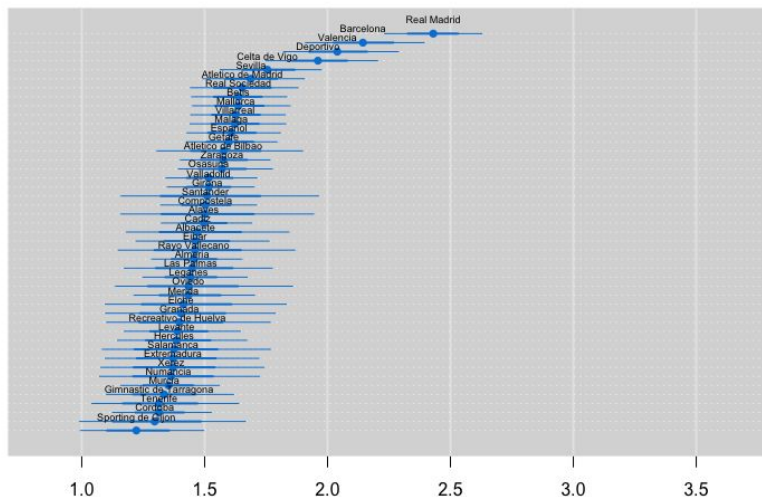
$$skill_{t+1} \sim \text{Normal}(skill_t, \sigma_{year}^2)$$



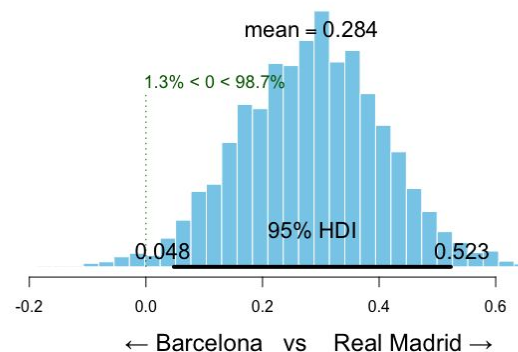


# Approach 2 - Model 3 Evaluation

Ranking plot based on Model 3:



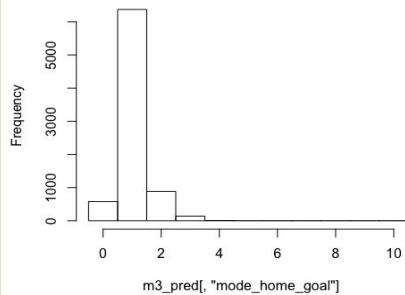
Team skills of Real Madrid - Team skills of Barcelona:



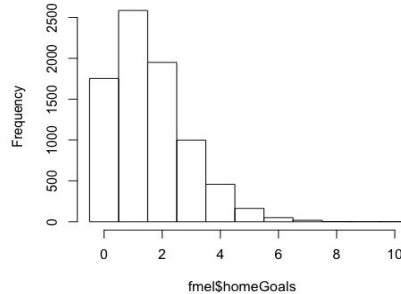
# Approach 2 - Prediction

- 1 home goal has the highest probability.
- Prediction accuracy: 0.3310777.
- Mean square error : 1.464646.

Histogram of m3\_pred[, "mode\_home\_goal"]

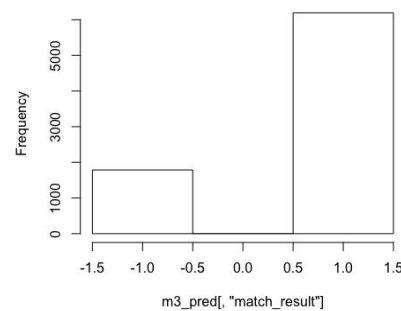


Histogram of fme1\$homeGoals

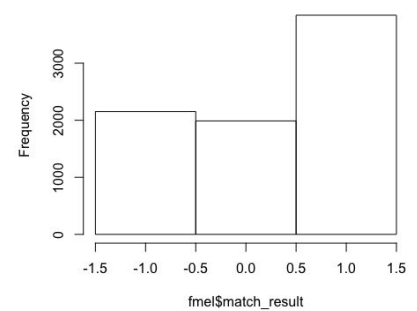


- Prediction of win or lose.
- Prediction accuracy: 0.5358396.

Histogram of m3\_pred[, "match\_result"]



Histogram of fme1\$match\_result



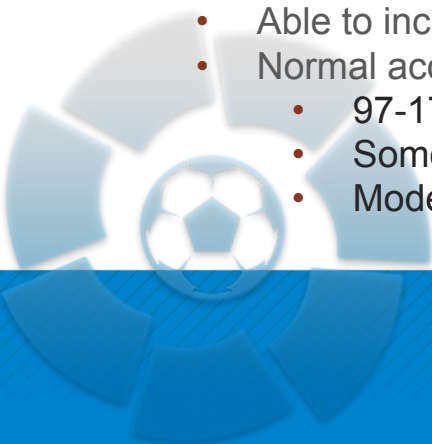
# Analysis of Two Approaches

## Approach 1

- Good Accuracy
- Missed goal information
  - 6:1 home win - 2:1 home win
- Other outcomes are not included

## Approach 2

- Able to include all game outcomes
- Normal accuracy
  - 97-17, there will be many roster changes
  - Some teams good at attacking, while some teams good at defending
  - Modelling goals rather than “ability to win”



# Conclusion

## Summary

- Many factors can affect the results of football games, game results prediction is hard
- Demonstrated 2 relatively straightforward approaches
  - Home win - Binomial
  - Goals - Poisson

## Future Work

- Get more data, include other factors into model
- More complicated model, or combine the power of our 2 approaches





# Reference

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