

Prediction of Soccer Penalty Kicks using R

Group 1

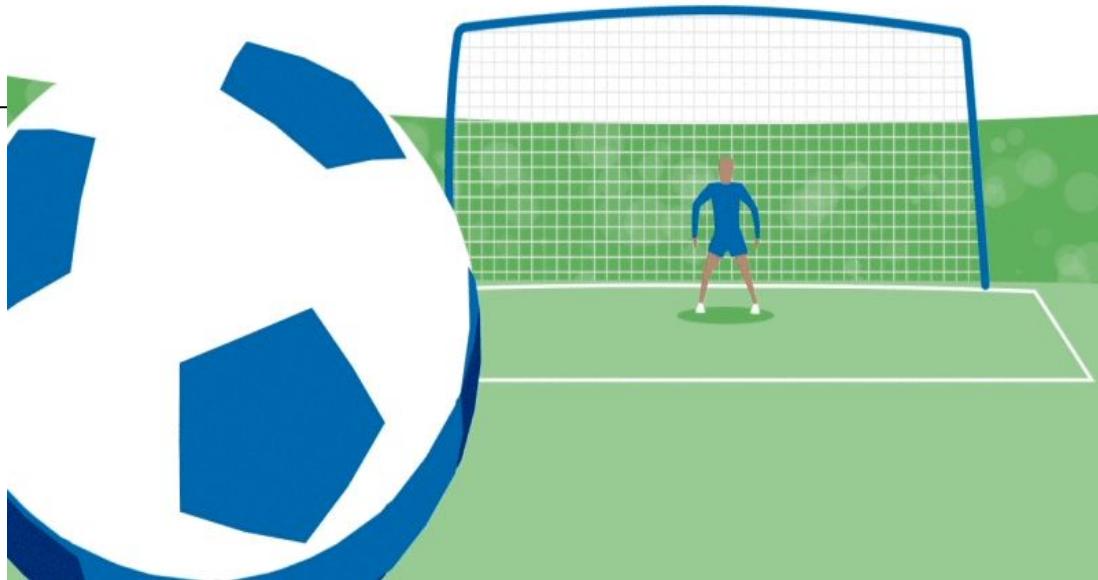
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Analytics Project SoSe 2022
Prof. Dr. Sven Müller
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Introduction



IMPORTANCE OF PENALTIES IN FOOTBALL

50%

Probability of winning a
match

52%

Probability of winning a
match when the team has a
ingame penalty

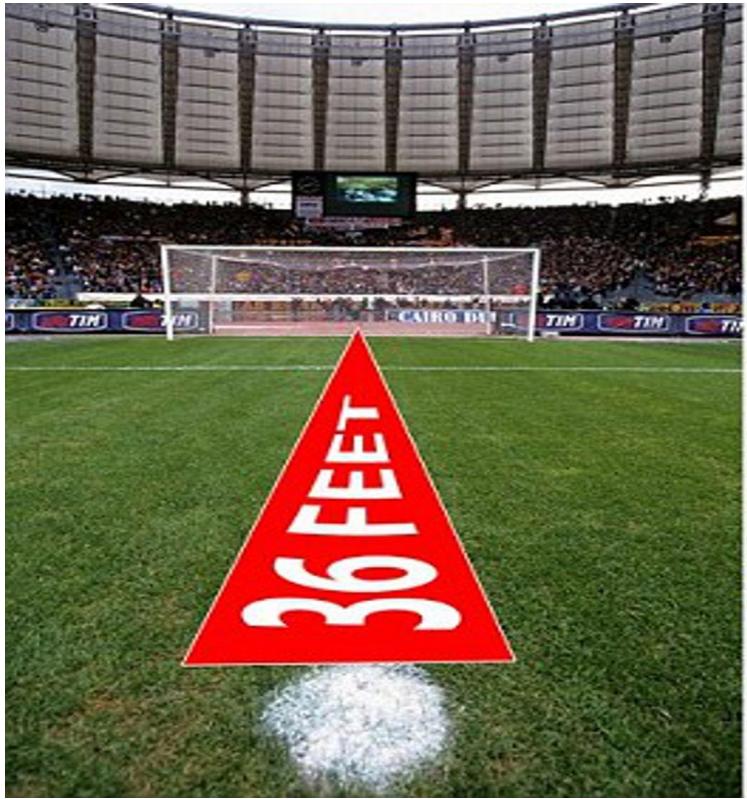
61%

Probability of winning a
match when the team has a
ingame penalty and scores it

[1]

IMPORTANCE OF PENALTIES IN FOOTBALL

SCIENCE OF A PENALTY SHOOTOUT

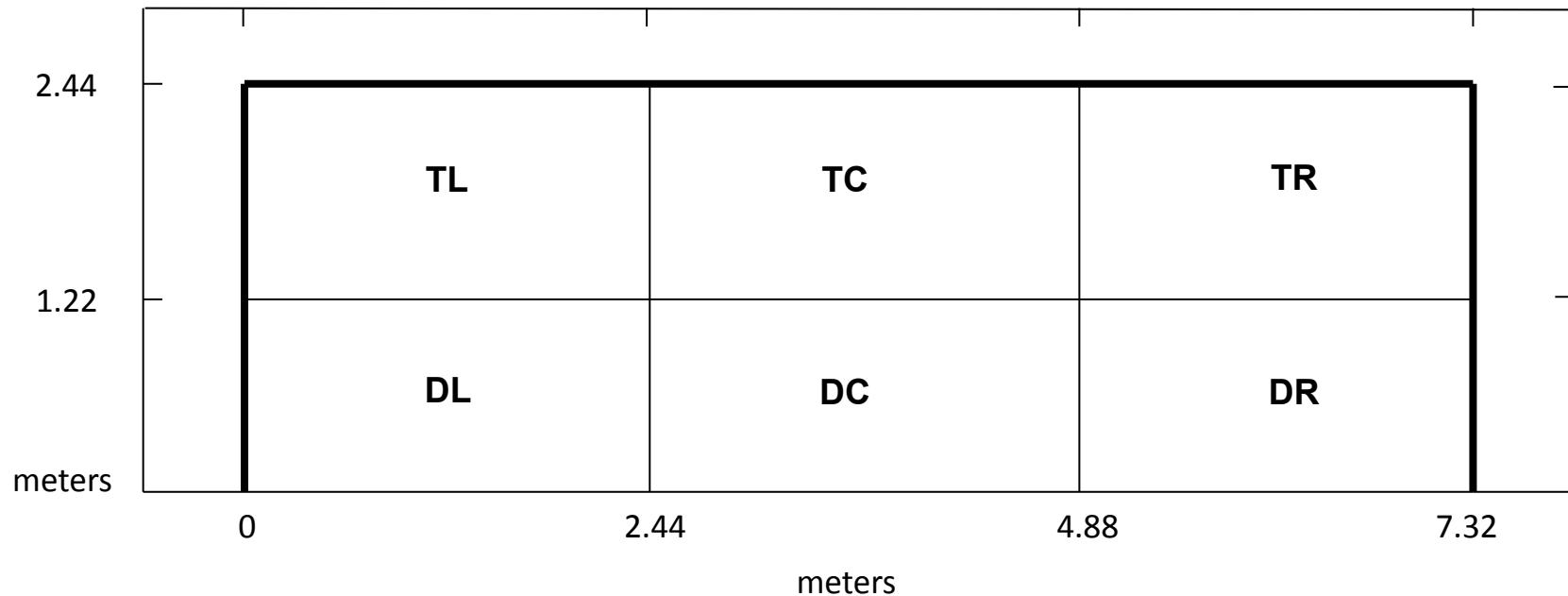


AGENDA

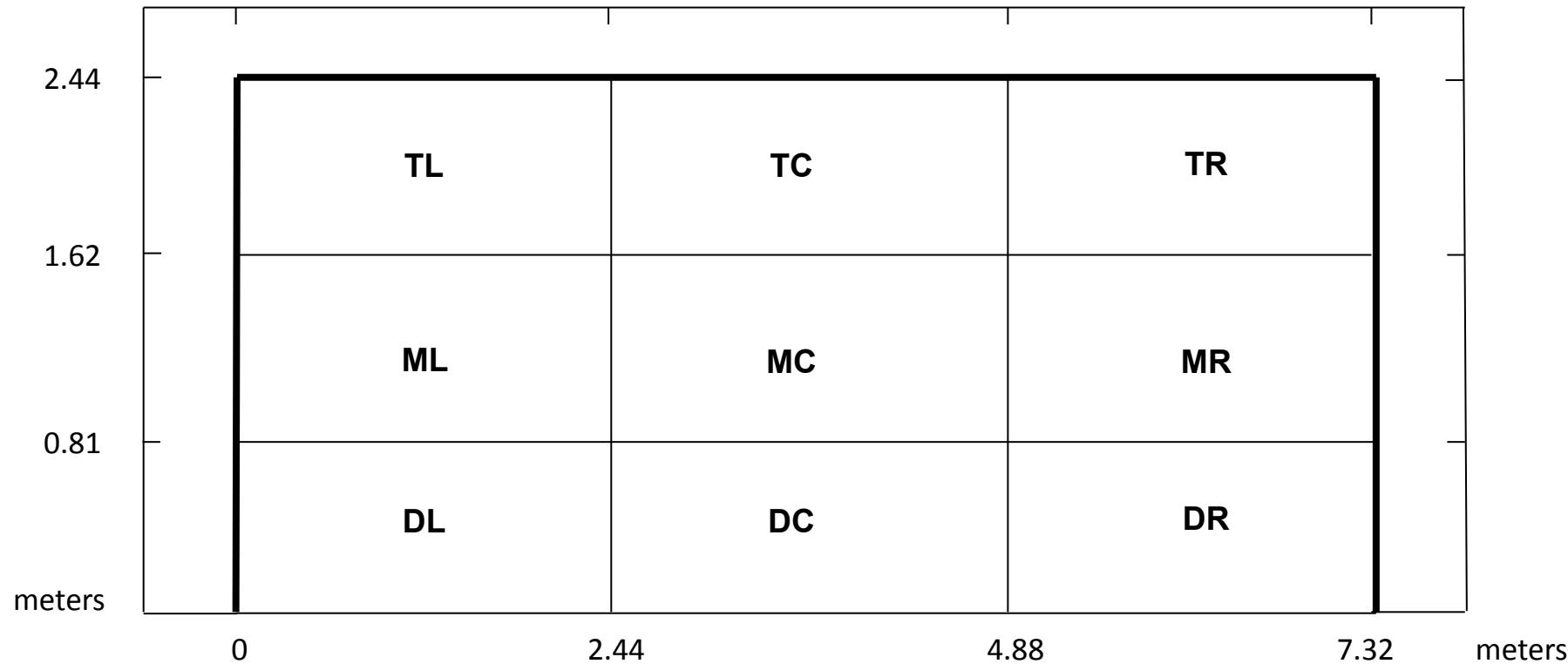
- Deep Dive into the Alternatives
- Data Analysis
- Methodology
- Model Estimation
- IIA Verification of the models
- Analysis based on Literature Findings
- Model Performance on Unseen Data
- Prediction Results
- Comparing 6-alt and 9-alt Model
- Conclusion

DEEP DIVING INTO ALTERNATIVES

6 ALTERNATIVE MODEL

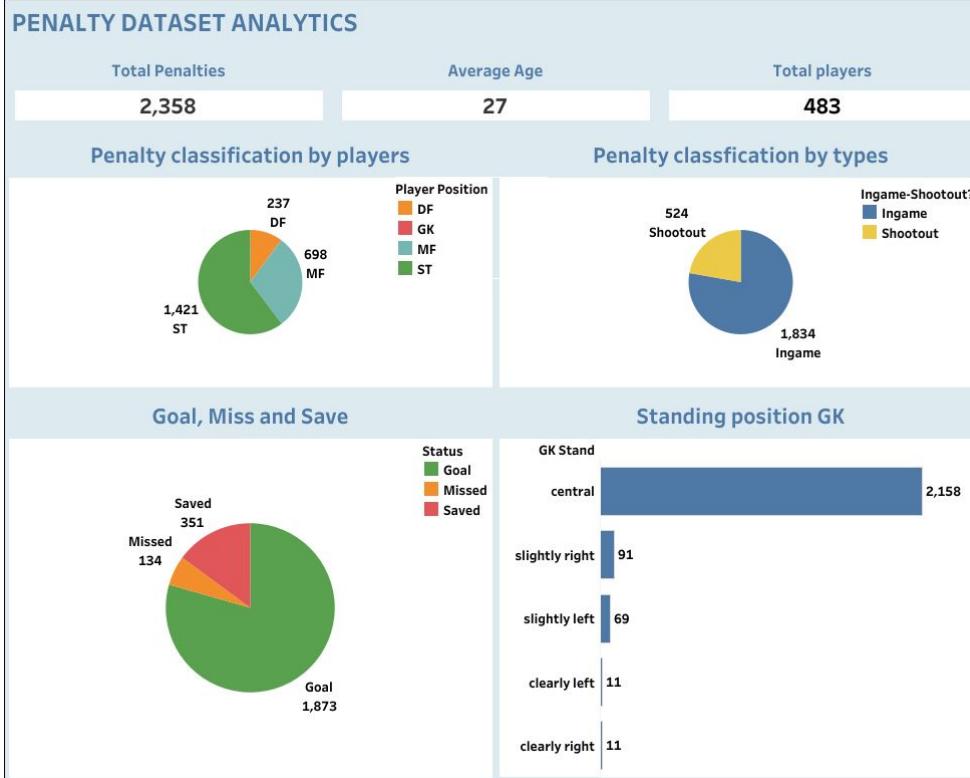


9 ALTERNATIVE MODEL

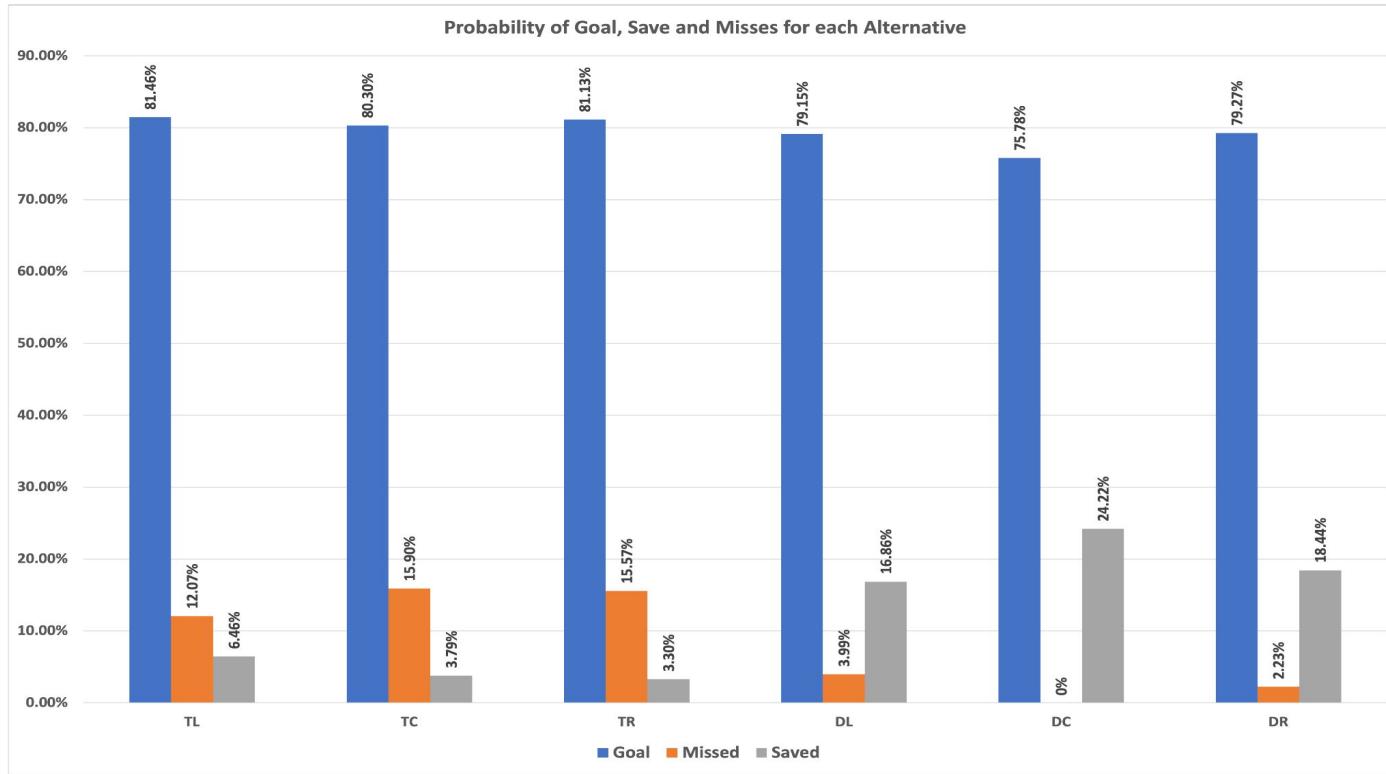


DATA ANALYSIS

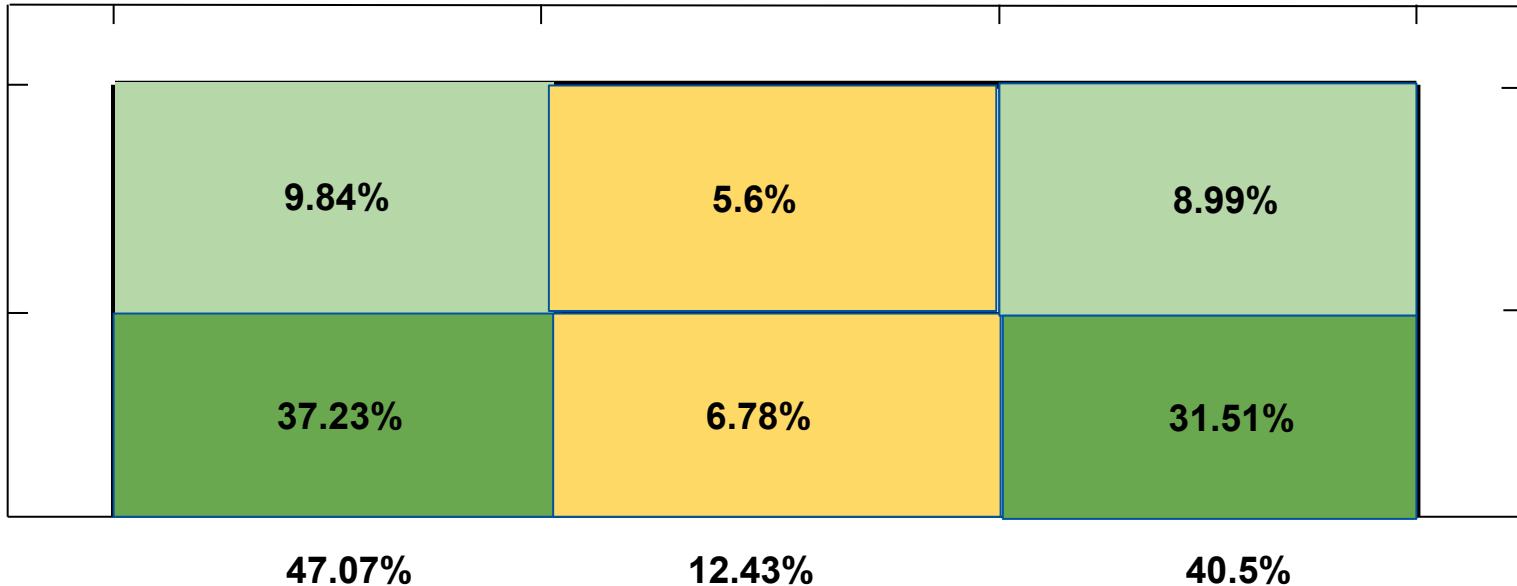
DATA ANALYSIS DASHBOARD



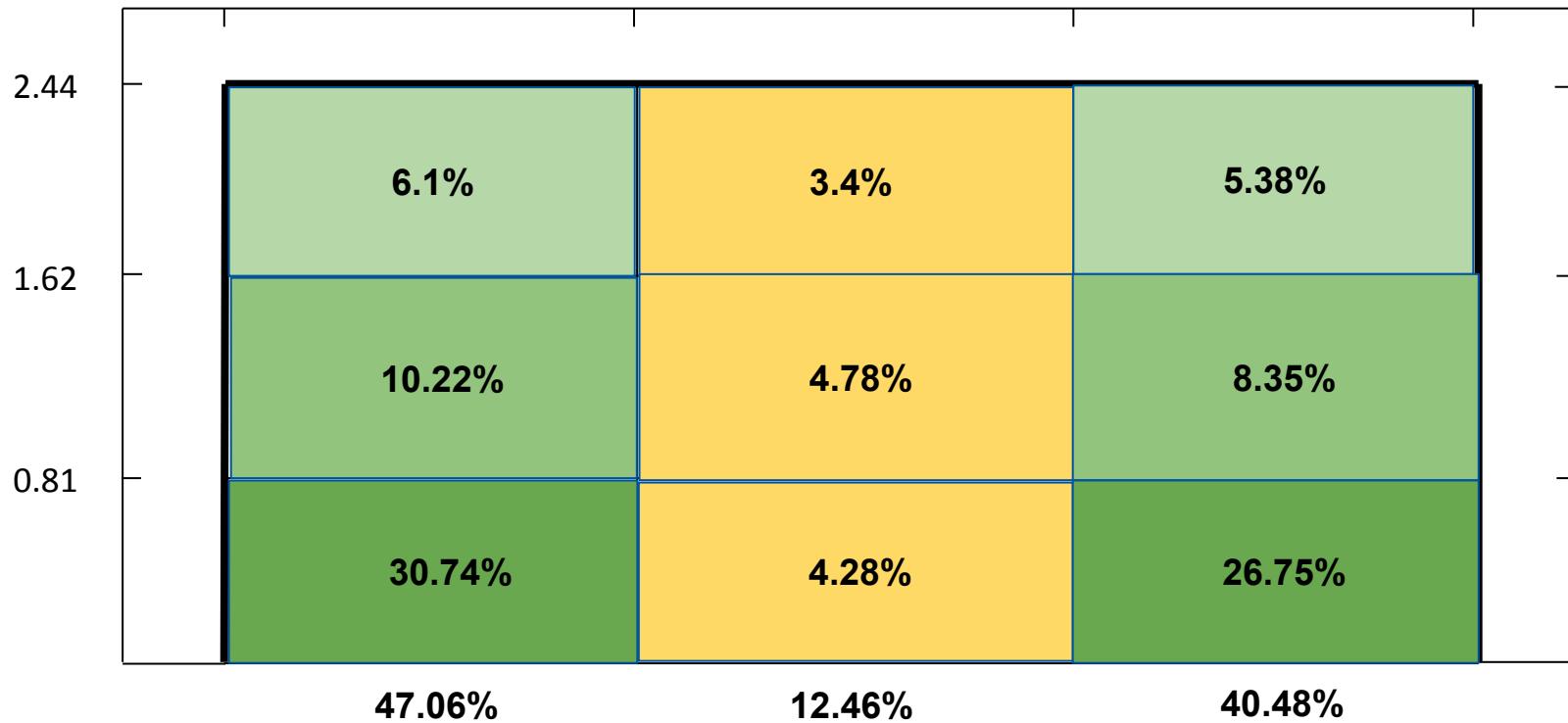
PROBABILITY OF 'GOAL', 'SAVE' AND 'MISS' FOR EACH ALTERNATIVE



Probability of a goal for a 6 alternative model



Probability of a goal for a 9 alternative model



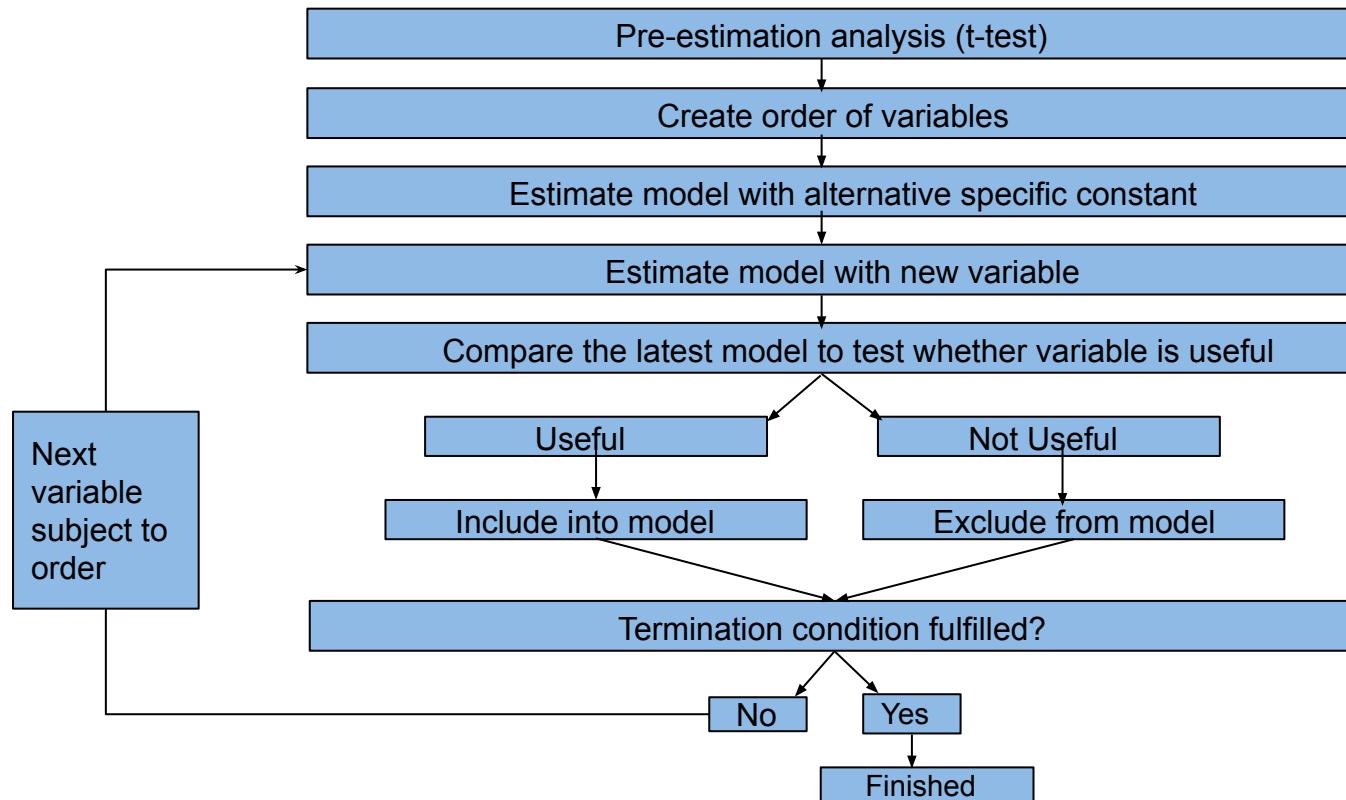
Data Dictionary

Variable	Description	Values
Date	Range of dates for the matches	Int Ex: 2004-2021
Player	Names of the Penalty Takers	String Ex: Aguero
Nation	Nationality of the penalty takers	String Ex: France
Player Position	Refers to the position which the player takes on the field	String : DF(Defender)/GK(Goalkeeper)/MF(Midfielder)/ST(Striker)
Player Foot	Whether the player is left footed or right footed	String : L(Left)/R(Right)
Age	Age of the players throughout different championships over the years (Age of a single player v. Int: 16 to 40	
Age in groups	Age of the players in designated age groups	String:Under21, 21-33, Over33
GK(Goalkeeper)	Names of the Goalkeepers	String Ex: Buffon
Great GK?	Whether Goalkeeper is great	Boolean:Yes/No
GK already saved one	Whether Goalkeeper was successful in saving the goal	Boolean:Yes/No
Height of GK	Recorded heights of all goalkeepers (in cms)	Int: 176 to 203 (cms)
Height of GK (Grouped)	Recorded heights of all goalkeepers in designated groups	String:Under183, 183-196, Over196
Team	Clubs/National Teams that players belong to	String: Ex: Manchester City
Club/National Team	Whether players belong to a club or a national team for the games	String: Club/National Team
Table Position	Team standings	String: Upper/Middle/Bottom
Opponent	Opponent Team	String Ex: Real Madrid
Opponent Table position	Opponent Team standings	String: Upper/Middle/Bottom
Location(H-A-N)	Whether the match venue for the team is at home,away or neither	String: H(Home)/A(Away)/N(Neutral)
Round Number	Number for each round	String: Ex: Quarter-Final, Final
Competition	The name of the different football leagues /tournaments played	String: Ex: League, UCL
Special match?	Whether the match is a special match (For ex. world cup final)	Boolean:Yes/No

https://docs.google.com/spreadsheets/d/1RMvy-auTaM4igd7T6o49wOnpvPrP5qmbVs5BTxbBy_Y/edit#gid=0

METHODOLOGY

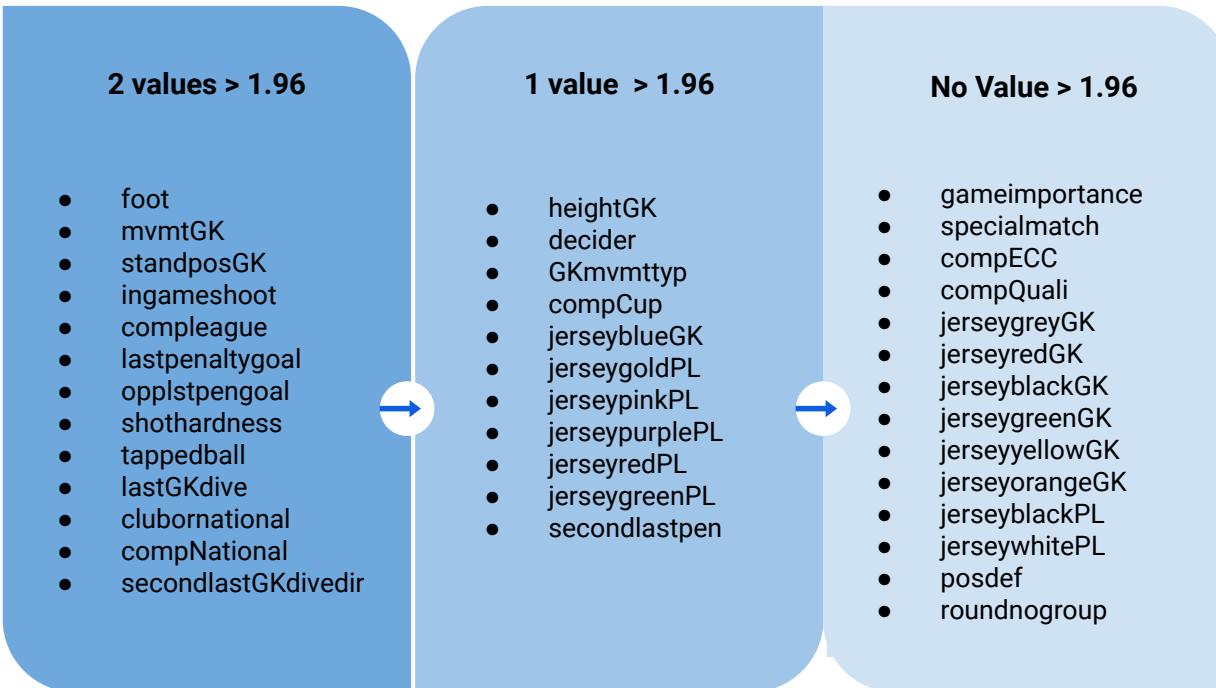
Steps involved



Pre-estimation analysis (t-test)

Explanators	TL	TC	TR	DL	DC	DR
Explanator 1 (foot_cat), mean when alt is chosen:	0.82	0.85	0.61	0.80	0.76	0.70
Explanator 1 (foot_cat), mean when alt is not chosen:	0.75	0.75	0.77	0.73	0.75	0.78
Explanator 1 (foot_cat), t-test (mean if chosen - mean if not chosen)	2.65	3.05	-4.61	4.35	0.10	-3.94

Create order of variables



MODEL ESTIMATION

Multinomial Logit Model

Logit Model is a mathematical model used to estimate the probability of an event occurring (choice) having been given some previous data.

Multinomial Logit Model is a classification method that generalizes logistic regression and is best suited for :

- Modelling multiclass problems, i.e. with more than two possible discrete outcomes.
- Useful when the dependent variable in question is nominal.

$$\begin{aligned} U_{nC} &= V_{nC} + \epsilon_{nC} & = \beta_0 + \beta_1 TC_{nC} + \epsilon_{nC} \\ U_{nT} &= V_{nT} + \epsilon_{nT} & = \beta_2 + \beta_1 TC_{nT} + \epsilon_{nT} \\ U_{nB} &= V_{nB} + \epsilon_{nB} & = \beta_1 TC_{nB} + \epsilon_{nB} \end{aligned}$$

$$P_n(C | \{C, T, B\}) = \frac{e^{\mu V_{nC}}}{e^{\mu V_{nC}} + e^{\mu V_{nT}} + e^{\mu V_{nB}}}$$

For every model,



1 Utility Equation

$$V(TL) = ASC_{TL}$$

$$V(TC) = ASC_{TC}$$

$$V(TR) = ASC_{TR}$$

$$V(DL) = ASC_{DL}$$

$$V(DC) = ASC_{DC}$$

$$V(DR) = ASC_{DR}$$

Estimate model with alternative specific constant

2 Log likelihood values

LL(start)	-4224.97
LL(0)	-4224.97
LL(C)	-3586.82
LL(final)	-3586.82
Rho-square (0)	0.15
Adj.Rho-square (0)	0.15
Rho-square (c)	0.00
Adj.Rho-square (c)	0.00
AIC	7183.63
BIC	7212.46

Estimate model with alternative specific constant

3 Estimates, Standard error and t-ratio

Alternatives	Estimate	s.e.	t.rat.(0)	Rob.s.e.	Rob.t.rat.(0)
asc_TL	0.37	0.10	3.56	0.10	3.56
asc_TC	-0.20	0.12	-1.69	0.12	-1.69
asc_TR	0.28	0.10	2.63	0.10	2.63
asc_DL	1.70	0.09	19.79	0.09	19.78
asc_DC	0.00	0.00	0.00	0.00	0.00
asc_DR	1.53	0.09	17.59	0.09	17.59

1 Utility Equation

$$V(TL) = ASC_{TL} + \beta_{foot_{TL}} * foot_cat$$

$$V(TC) = ASC_{TC} + \beta_{foot_{TC}} * foot_cat$$

$$V(TR) = ASC_{TR} + \beta_{foot_{TR}} * foot_cat$$

$$V(DL) = ASC_{DL} + \beta_{foot_{DL}} * foot_cat$$

$$V(DC) = ASC_{DC} + \beta_{foot_{DC}} * foot_cat$$

$$V(DR) = ASC_{DR} + \beta_{foot_{DR}} * foot_cat$$

2 Log likelihood values

LL(start)	-4224.97
LL(0)	-4224.97
LL(C)	-3586.82
LL(final)	-3558.25
Rho-square (0)	0.16
Adj.Rho-square (0)	0.16
Rho-square (c)	0.01
Adj.Rho-square (c)	0.01
AIC	7136.49
BIC	7194.15

Estimate model with new variable

3

Estimates, Standard error and t-ratio

Alternatives	Estimate	s.e.	t.rat.(0)	Rob.s.e.	Rob.t.rat.(0)
asc_TL	0.07	0.22	0.33	0.22	0.33
asc_TC	-0.67	0.28	-2.43	0.28	-2.43
asc_TR	0.76	0.19	3.89	0.19	3.89
asc_DL	1.49	0.18	8.40	0.18	8.40
asc_DC	0.00	0.00	0.00	0.00	0.00
asc_DR	1.74	0.17	10.02	0.17	10.01
b_foot1	0.37	0.25	1.47	0.25	1.47
b_foot2	0.58	0.30	1.91	0.30	1.91
b_foot3	-0.70	0.23	-3.02	0.23	-3.02
b_foot4	0.26	0.20	1.31	0.20	1.31
b_foot5	0.00	0.00	0.00	0.00	0.00
b_foot6	-0.29	0.20	-1.43	0.20	-1.43

Compare the latest model to test whether variable is useful

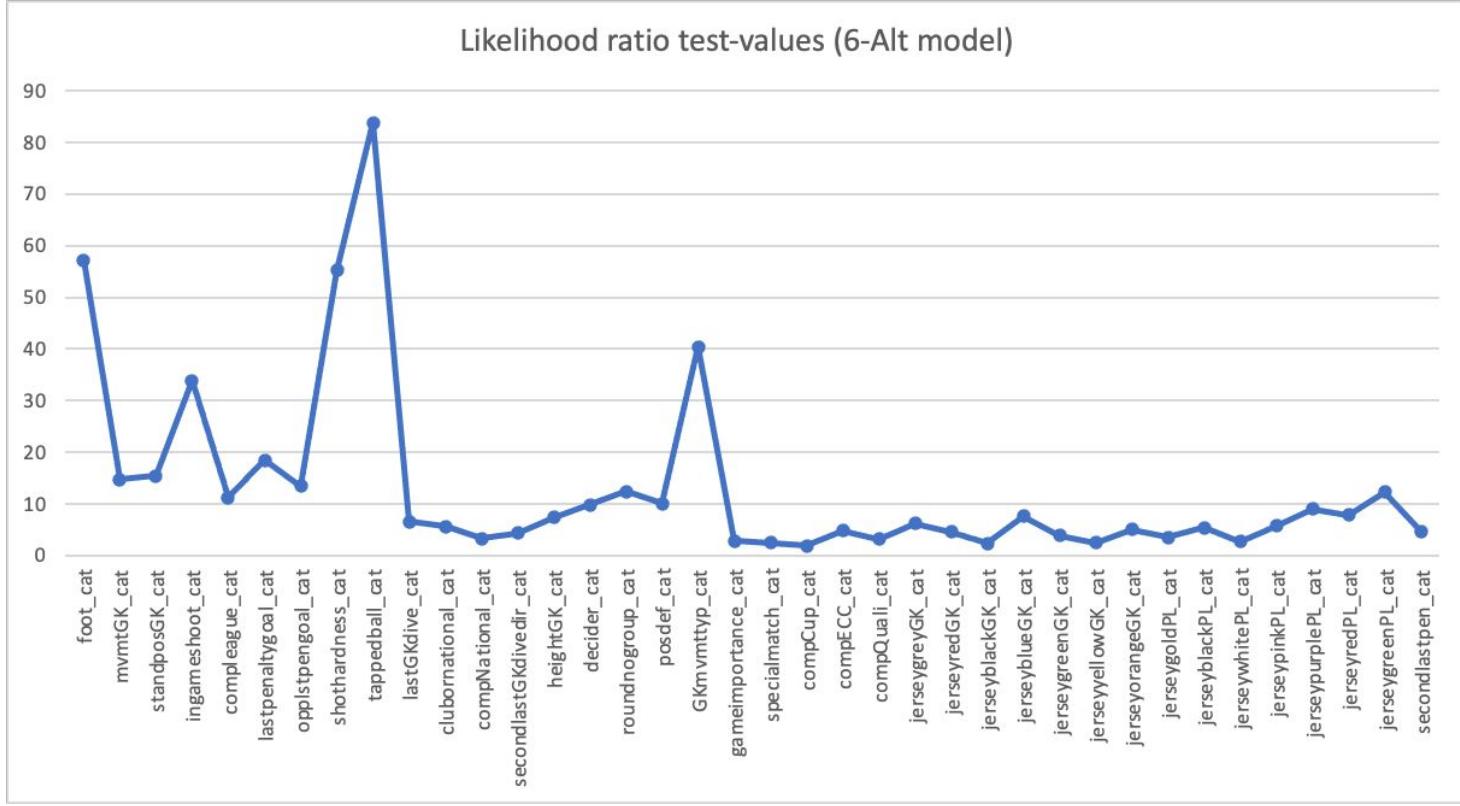
Model	LL	par
Null model	-3586.82	5
Model with foot	-3558.24	10
Difference	28.58	5

Level of confidence number of restrictions	90%	95%	99%
1	2.71	3.84	6.63
2	4.61	5.99	11.34
5	9.24	11.07	15.09

[1]

Likelihood ratio test-value:	57.16
Degrees of freedom:	5
Likelihood ratio test p-value:	4.69E-11

Feature extraction graph analysis (6 Alt model)



Data Dictionary for 6 Alt model

Variable	Equivalent feature variable	Description
foot_cat	Foot	strong foot of penalty-taker. Coding; 0: Left, 1: Right
mvmtGK_cat	moveGK	movement of goalkeeper during run-up of penalty-taker. Coding; 0: no/null, 1: movement to left , 2: jumping left and right, 2: jumping on spot, 2: step forward, 3: movement to right
standposGK_cat	GKS	standing position of goalkeeper during penalty kick. Coding; 1: clearly or slightly left, 2: central, 3:clearly or slightly right, 0/NA: not available
ingameshoot_cat	Ingso	whether penalty is shot in-match or in a penalty shootout. Coding; 0: Ingame, 1: shootout
compleague_cat	Competition	whether team of penalty-taker is playing in a "league" match or not. Coding; 0: no, 1: yes
lastpenaltygoal_cat	lpgb	whether last penalty of penalty-taker was a goal, missed or saved . Coding; 1: 'missed' or 'saved', 2: 'goal'
opplstpengoal_cat	Solsbgopponent	whether last shot penalty of the opponent of the penalty-taker in a penalty shootout was a goal, missed or saved. Coding; 1: 'goal', 2: 'missed', 0:'saved'
shothardness_cat	Shothardness	whether the penalty shot by the penalty-taker is classified as strong/normal/weak. Coding; 1:'strong', 2:'normal', 3:'weak'
tappedball_cat	tappedtheball	whether the goalkeeper tapped the ball during the penalty shootout. Coding; 1:yes,0:'no'
roundnogroup_cat	rnoGroup	whether team of penalty-taker is playing in a group stage match or not. Coding; 0: no, 1: yes
GKmvmttyp_cat	nmovGK	whether goalkeeper is moving when the penalty is hit by penalty-taker. Coding; 0/NA: not available, 1: moving, 2: still

Final 6 Alt Model after Feature Selection

2 Log likelihood values

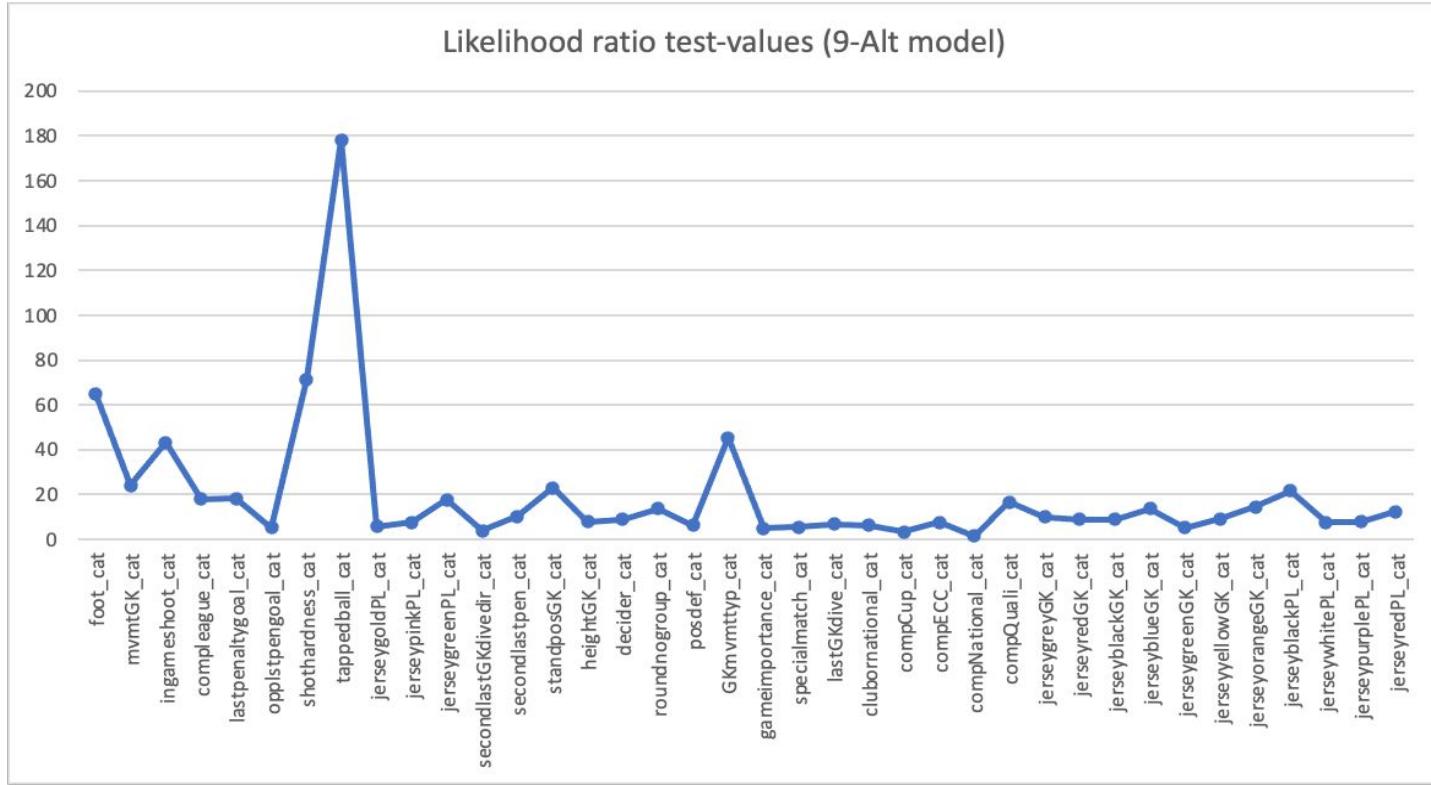
LL(start)	-4224.97
LL(0)	-4224.97
LL(C)	-3586.82
LL(final)	-3395.11
Rho-square (0)	0.1964
Adj.Rho-square (0)	0.181
Rho-square (c)	0.0534
Adj.Rho-square (c)	0.0353
AIC	6920.21
BIC	7294.97

FINAL MODEL AFTER FEATURE SELECTION (6 ALT)

	Estimate	s.e.	t.rat.(0)	Rob.s.e.	Rob.t.rat.(0)
asc_TL	0.44	1.18	0.37	1.08	0.41
asc_TC	0.14	1.30	0.11	1.49	0.10
asc_TR	1.67	1.15	1.46	1.09	1.54
asc_DL	1.71	0.97	1.76	0.96	1.78
asc_DC	0.00	NA	NA	NA	NA
asc_DR	3.28	0.96	3.42	0.92	3.58
b_foot1	0.39	0.25	1.55	0.25	1.56
b_foot2	0.61	0.31	1.97	0.31	1.98
b_foot3	-0.73	0.24	-3.09	0.23	-3.10
b_foot4	0.31	0.21	1.53	0.20	1.54
b_foot5	0.00	NA	NA	NA	NA
b_foot6	-0.27	0.20	-1.34	0.20	-1.35
b_mvmtGK1	0.08	0.22	0.38	0.22	0.39
b_mvmtGK2	-0.07	0.25	-0.27	0.27	-0.25
b_mvmtGK3	0.14	0.22	0.62	0.22	0.62
b_mvmtGK4	0.34	0.18	1.87	0.19	1.81
b_mvmtGK5	0.00	NA	NA	NA	NA
b_mvmtGK6	-0.31	0.19	-1.62	0.19	-1.58

<https://docs.google.com/spreadsheets/d/1b5zdbrU7qKk0EHTXGprB9SEaf3VgbvDyuCBwCRmo8aQ/edit?usp=sharing>

Feature extraction graph analysis (9 Alt model)

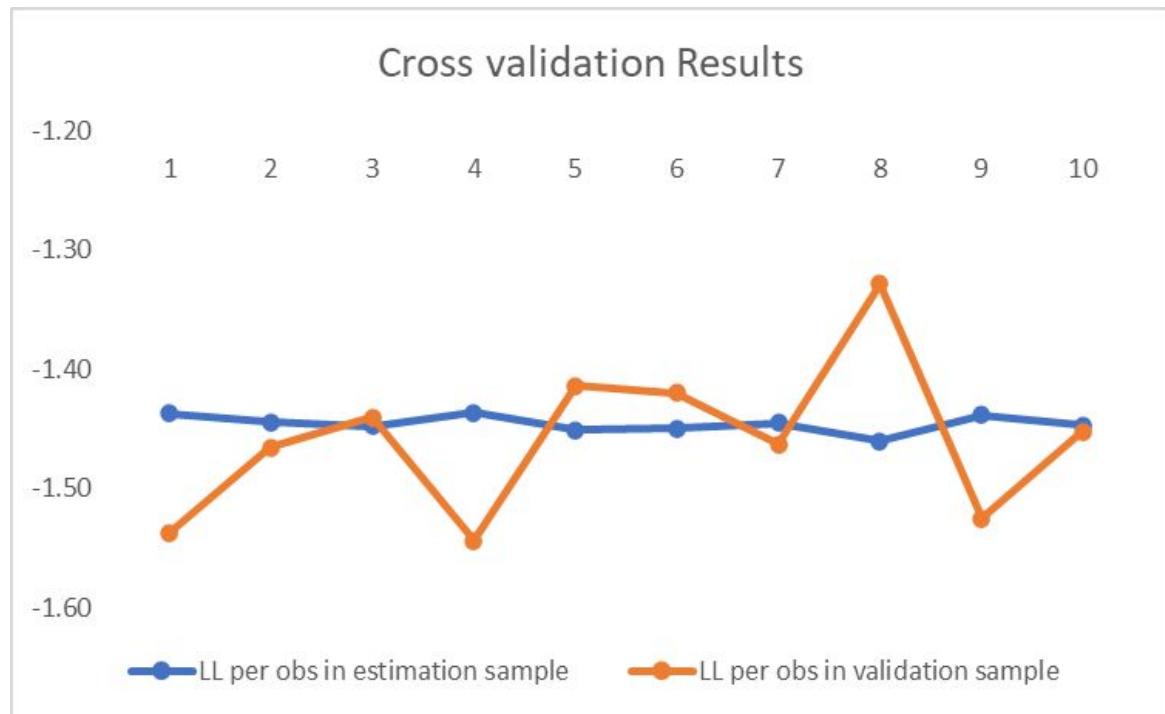


Data Dictionary for 9 Alt model

Variable	Equivalent feature variable	Description
foot_cat	Foot	strong foot of penalty-taker. Coding; 0: Left, 1: Right
mvmtGK_cat	moveGK	movement of goalkeeper during run-up of penalty-taker. Coding; 0: no/null, 1: movement to left , 2: jumping left and right, 2: jumping on spot, 2: step forward, 3: movement to right
ingameshoot_cat	Ingso	whether penalty is shot in-match or in a penalty shootout. Coding; 0: Ingame, 1: shootout
comleague_cat	Competition	whether team of penalty-taker is playing in a "league" match or not. Coding; 0: no, 1: yes
lastpenaltygoal_cat	lpg	whether last penalty of penalty-taker was a goal, missed or saved . Coding; 1: 'missed' or 'saved', 2: 'goal'
shothardness_cat	Shothardness	whether the penalty shot by the penalty-taker is classified as strong/normal/weak. Coding; 1:'strong', 2:'normal', 3:'weak'
tappedball_cat	tappedtheball	whether the goalkeeper tapped the ball during the penalty shootout. Coding; 1:'yes',0:'no'
standposGK_cat	GKS	standing position of goalkeeper during penalty kick. Coding; 1: clearly or slightly left, 2: central, 3:clearly or slightly right, 0/NA: not available
GKmvmttyp_cat	nmovGK	whether goalkeeper is moving when the penalty is hit by penalty-taker. Coding; 0/NA: not available, 1: moving, 2: still
compQuali_cat	Competition	whether team of penalty-taker is playing in a qualification match or not

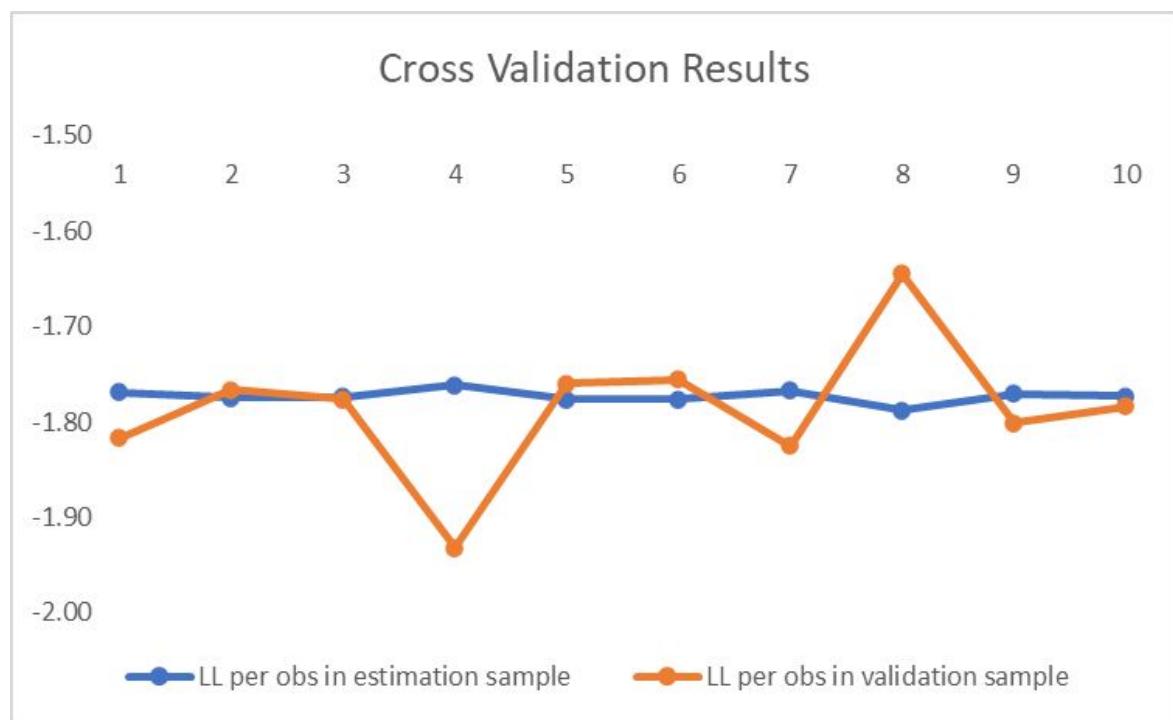
Cross Validation results of the final model (6 alt)

Estimation Sample (LL per observation)	Validation Sample (LL per observation)
-1.44	-1.54
-1.44	-1.47
-1.45	-1.44
-1.44	-1.54
-1.45	-1.41
-1.45	-1.42
-1.45	-1.46
-1.46	-1.33
-1.44	-1.53
-1.45	-1.45



Cross Validation results of the final model (9 alt)

Estimation Sample (LL per observation)	Validation Sample (LL per observation)
-1.77	-1.82
-1.77	-1.77
-1.77	-1.78
-1.76	-1.93
-1.78	-1.76
-1.78	-1.76
-1.77	-1.83
-1.79	-1.64
-1.77	-1.80
-1.77	-1.78

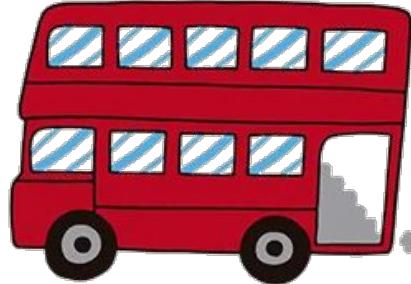


IIA VERIFICATION

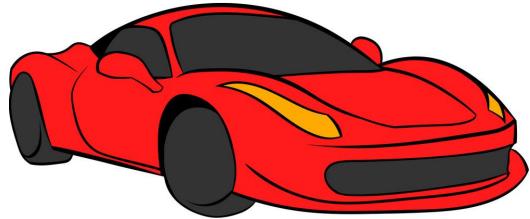
Independence of Irrelevant Alternatives (IIA)

Independence of irrelevant alternatives is the property stating that any item added to the set of choices will decrease all other items' likelihood by an equal fraction.

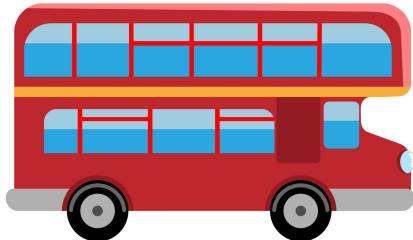
Red Bus - Blue Bus Paradox



Independence of Irrelevant Alternatives (IIA)



$$U_{car} = \beta_{TT} + \epsilon_{car}$$



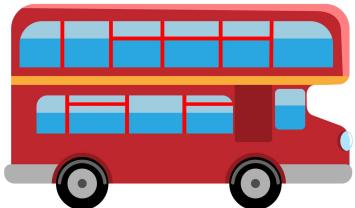
$$U_{bus} = \beta_{TT} + \epsilon_{bus}$$

$$P(car|car, bus) = \left(e^{\beta_{TT}} / (e^{\beta_{TT}} + e^{\beta_{TT}}) \right)$$

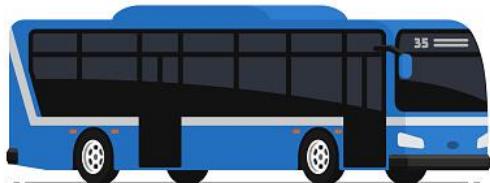
Independence of Irrelevant Alternatives (IIA)



$$U_{car} = \beta_{TT} + \epsilon_{car}$$



$$U_{bluebus} = \beta_{TT} + \epsilon_{bluebus}$$



$$U_{redbus} = \beta_{TT} + \epsilon_{redbus}$$

$$P(car|car, bluebus, redbus) = \left(e^{\beta_{TT}} / (e^{\beta_{TT}} + e^{\beta_{TT}} + e^{\beta_{TT}}) \right)$$

IIA for the 6 Alt model

b_foot1	0.36886	0.2508	1.4706	0.2509	1.4703
b_foot2	0.58231	0.3046	1.3119	0.3046	1.9114
b_foot3	-0.69392	0.2316	-3.0204	0.2316	-3.0197
b_foot4	0.26442	0.2026	1.3053	0.2026	1.305
b_foot5	0	0	0	0	0
b_foot6	-0.28742	0.2007	-1.4324	0.2007	-1.4321

Model without TC alternative

Alternative	Estimate	standard error	t.rat.	Rob.s.e.	Rob.t.rat.	T Ratio calcul.	IIA verific.
asc_TL	0.07416	0.2224	0.3335	0.2224	0.3334		
asc_TR	0.75529	0.1941	3.8905	0.1942	3.8896		
asc_DL	1.48974	0.1773	8.4042	0.1773	8.4022		
asc_DC	0	0	0	0	0		
asc_DR	1.73913	0.1736	10.0165	0.1737	10.0142		
b_foot1	0.36885	0.2508	1.4706	0.2509	1.4703	-3.98724E-05	IIA holds
b_foot3	-0.69349	0.2316	-3.0203	0.2317	-3.0196	0.000129534	IIA holds
b_foot4	0.26444	0.2026	1.3054	0.2026	1.3051	9.87167E-05	IIA holds
b_foot5	0	0	0	0	0		
b_foot6	-0.28739	0.2007	-1.4323	0.2007	-1.432	0.000149477	IIA holds

Model without DL alternative

Alternative	Estimate	standard error	t.rat.	Rob.s.e.	Rob.t.rat.	T Ratio calcul.	IIA verific.
asc_TL	0.07411	0.2224	0.3333	0.2225	0.3332		
asc_TC	-0.66783	0.275	-2.4282	0.2751	-2.4274		
asc_TR	0.75529	0.1941	3.8905	0.1942	3.8892		
asc_DC	0	0	0	0	0		
asc_DR	1.73912	0.1736	10.0165	0.1737	10.0131		
b_foot1	0.36889	0.2508	1.4707	0.2509	1.4703	0.000119617	IIA holds
b_foot2	0.58231	0.3046	1.3119	0.3047	1.9112	0	IIA holds
b_foot3	-0.69349	0.2316	-3.0203	0.2317	-3.0183	0.000129534	IIA holds
b_foot5	0	0	0	0	0		
b_foot6	-0.28739	0.2007	-1.4323	0.2007	-1.4318	0.000149477	IIA holds

Model without DR alternative

Alternative	Estimate	standard error	t.rat.	Rob.s.e.	Rob.t.rat.	T Ratio calcul.	IIA verific.
asc_TL	0.07415	0.2224	0.3334	0.2224	0.3333		
asc_TC	-0.66776	0.275	-2.428	0.2751	-2.4272		

b_foot3	-0.69395	0.2316	-3.02	0.2317	-3.0193	8.63558E-05	IIA holds
b_foot4	0.26445	0.2026	1.3056	0.2026	1.3051	0.000148075	IIA holds
b_foot5	0	0	0	0	0	0	
b_foot6	-0.2874	0.2007	-1.4322	0.2007	-1.4319	0.000149477	IIA holds

Model without TR alternative

Alternative	Estimate	standard error	t.rat.(0)	Rob.s.e.	Rob.t.rat.(0)	T Ratio calcul.	IIA verific.
asc_TL	0.0741	0.2224	0.3332	0.2224	0.3331		
asc_TC	-0.66781	0.275	-2.4281	0.2751	-2.4276		
asc_DL	1.48973	0.1773	8.4042	0.1773	8.4022		
asc_DC	0	0	0	0	0		
asc_DR	1.73912	0.1736	10.0165	0.1737	10.0142		
b_foot1	0.36891	0.2508	1.4708	0.2509	1.4705	0.000199362	IIA holds
b_foot2	0.58229	0.3046	1.3118	0.3046	1.9114	-6.58539E-05	IIA holds
b_foot4	0.26445	0.2026	1.3054	0.2026	1.3051	0.000148075	IIA holds
b_foot5	0	0	0	0	0	0	
b_foot6	-0.28739	0.2007	-1.4322	0.2007	-1.4319	0.000149477	IIA holds

Model without DC alternative

Alternative	Estimate	standard error	t.rat.(0)	Rob.s.e.	Rob.t.rat.(0)	T Ratio calcul.	IIA verific.
asc_TL	0.7421	0.2717	2.7315	0.2717	2.731		
asc_TC	0	0	0	0	0		
asc_TR	1.423	0.2491	5.7128	0.2491	5.7116		
asc_DL	2.1575	0.2362	9.1352	0.2362	9.1334		
asc_DR	2.4069	0.2335	10.3098	0.2335	10.3077		
b_foot1	-0.2135	0.2966	-0.7197	0.2967	-0.7196	-1.963452451	IIA does not hold
b_foot2	0	0	0	0	0	0	
b_foot3	-1.2817	0.2806	-4.568	0.2806	-4.567	-2.074768354	IIA does not hold
b_foot4	-0.3178	0.2571	-1.2357	0.2572	-1.2355	-2.264566317	IIA does not hold
b_foot6	-0.8696	0.2556	-3.4017	0.2557	-3.401	-2.277699531	IIA does not hold

[https://docs.google.com/spreadsheets/d/1pLtpulP6GrOXdavZPqDZorn-hLZQ0U
BZGNJmUKFvHs/edit#gid=1519839050](https://docs.google.com/spreadsheets/d/1pLtpulP6GrOXdavZPqDZorn-hLZQ0U
BZGNJmUKFvHs/edit#gid=1519839050)

IIA for the 9 alt model

9 Alt model with all alts						
Alternatives	Estimate	standard error	t.rat.(0)	Rob.s.e.	Rob.t.rat.	
b_foot1	0.30	0.34	0.89	0.34	0.89	
b_foot2	0.27	0.40	0.68	0.40	0.68	
b_foot3	-1.16	0.30	-3.86	0.30	-3.86	
b_foot4	-0.91	0.28	-3.22	0.28	-3.22	
b_foot5	0.00	0.00	0.00	0.00	0.00	
b_foot6	-0.15	0.29	-0.52	0.29	-0.52	
b_foot7	-0.06	0.26	-0.24	0.26	-0.24	
b_foot8	-0.41	0.33	-1.22	0.33	-1.22	
b_foot9	-0.54	0.26	-2.10	0.26	-2.10	

Without TL						
Alternatives	Estimate	standard error	t.rat.(0)	Rob.s.e.	Rob.t.rat.	T Ratio calculat.
b_foot2	0.27	0.40	0.68	0.40	0.68	-0.00055836
b_foot3	-1.16	0.30	-3.87	0.30	-3.86	-6.6357E-05
b_foot4	-0.15	0.29	-0.52	0.29	-0.52	2.643475251
b_foot5	0.00	0.00	0.00	0.00	0.00	IIA holds
b_foot6	-0.91	0.28	-3.22	0.28	-3.22	-2.691046881
b_foot7	-0.06	0.26	-0.24	0.26	-0.24	0.000231214
b_foot8	-0.41	0.33	-1.23	0.33	-1.22	-0.00027084
b_foot9	-0.54	0.26	-2.10	0.26	-2.10	0.000310438

Without TC						
Alternatives	Estimate	standard error	t.rat.(0)	Rob.s.e.	Rob.t.rat.(0)	T Ratio calculat.
b_foot1	0.30	0.34	0.89	0.34	0.89	-2.95683E-05
b_foot3	-1.16	0.30	-3.87	0.30	-3.86	-0.000165893
b_foot4	-0.15	0.29	-0.52	0.29	-0.52	2.643406023
b_foot5	0.00	0.00	0.00	0.00	0.00	IIA holds
b_foot6	-0.91	0.28	-3.22	0.28	-3.22	-2.69123123
b_foot7	-0.06	0.26	-0.24	0.26	-0.24	-3.85356E-05
b_foot8	-0.41	0.33	-1.22	0.33	-1.22	-6.01866E-05
b_foot9	-0.54	0.26	-2.10	0.26	-2.10	7.76096E-05

Without TR						
Alternatives	Estimate	standard error	t.rat.(0)	Rob.s.e.	Rob.t.rat.(0)	T Ratio calculat.
b_foot1	0.30	0.34	0.89	0.34	0.89	-0.000680071
b_foot2	0.27	0.40	0.68	0.40	0.68	-0.000505306
b_foot4	-0.15	0.29	-0.52	0.29	-0.52	2.643094496
b_foot5	0.00	0.00	0.00	0.00	0.00	IIA holds
b_foot6	-0.91	0.28	-3.22	0.28	-3.22	-2.691857596
b_foot7	-0.06	0.26	-0.24	0.26	-0.24	-0.000423892
b_foot8	-0.41	0.33	-1.23	0.33	-1.22	-0.000541679
b_foot9	-0.54	0.26	-2.10	0.26	-2.10	-0.000349243

<https://docs.google.com/spreadsheets/d/19mOWqOyM3ci1NoxCAGz6wBLBYMArRKHrT9BqqxT1pmw/edit#gid=1826902422>

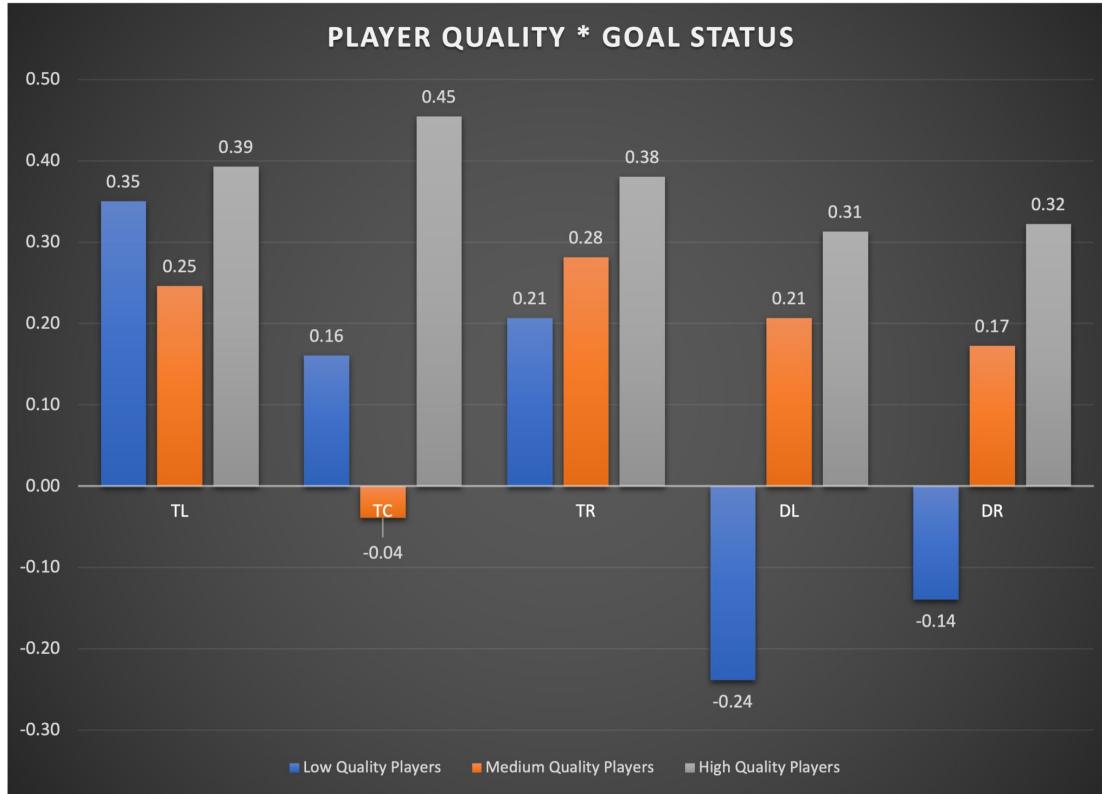
ANALYSIS BASED ON LITERATURE FINDINGS

PLAYER QUALITY ANALYSIS

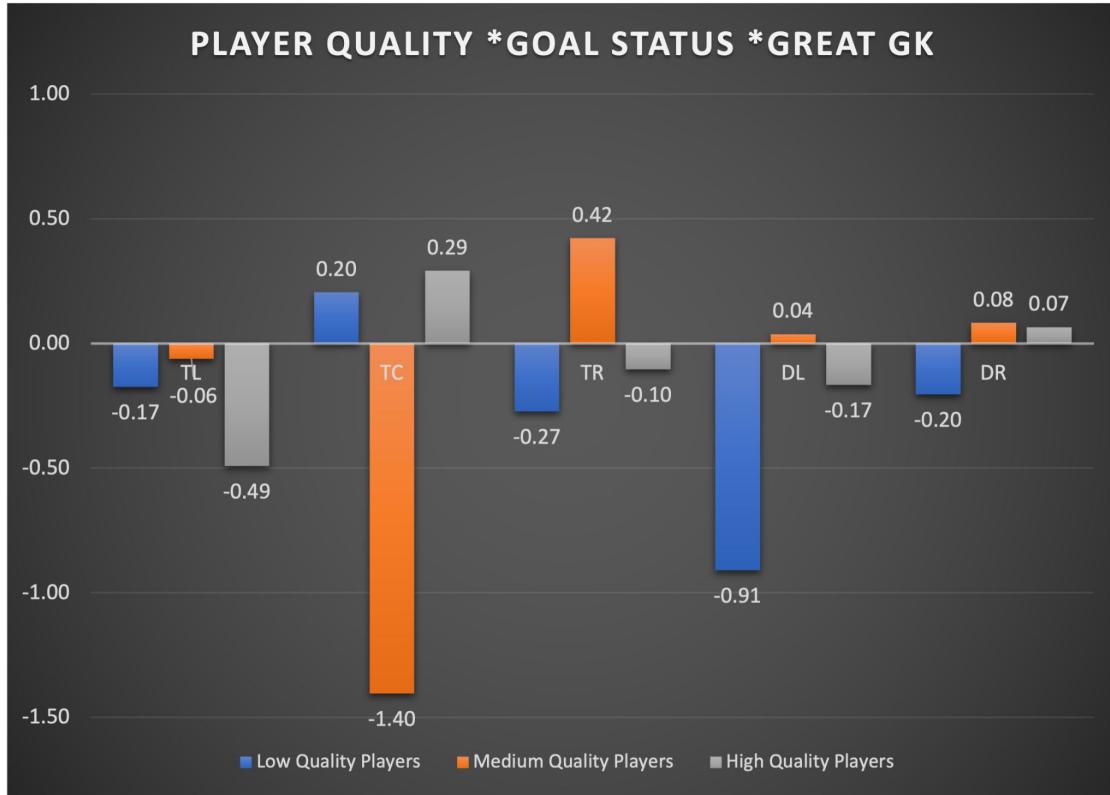


**OR= Overall Rating

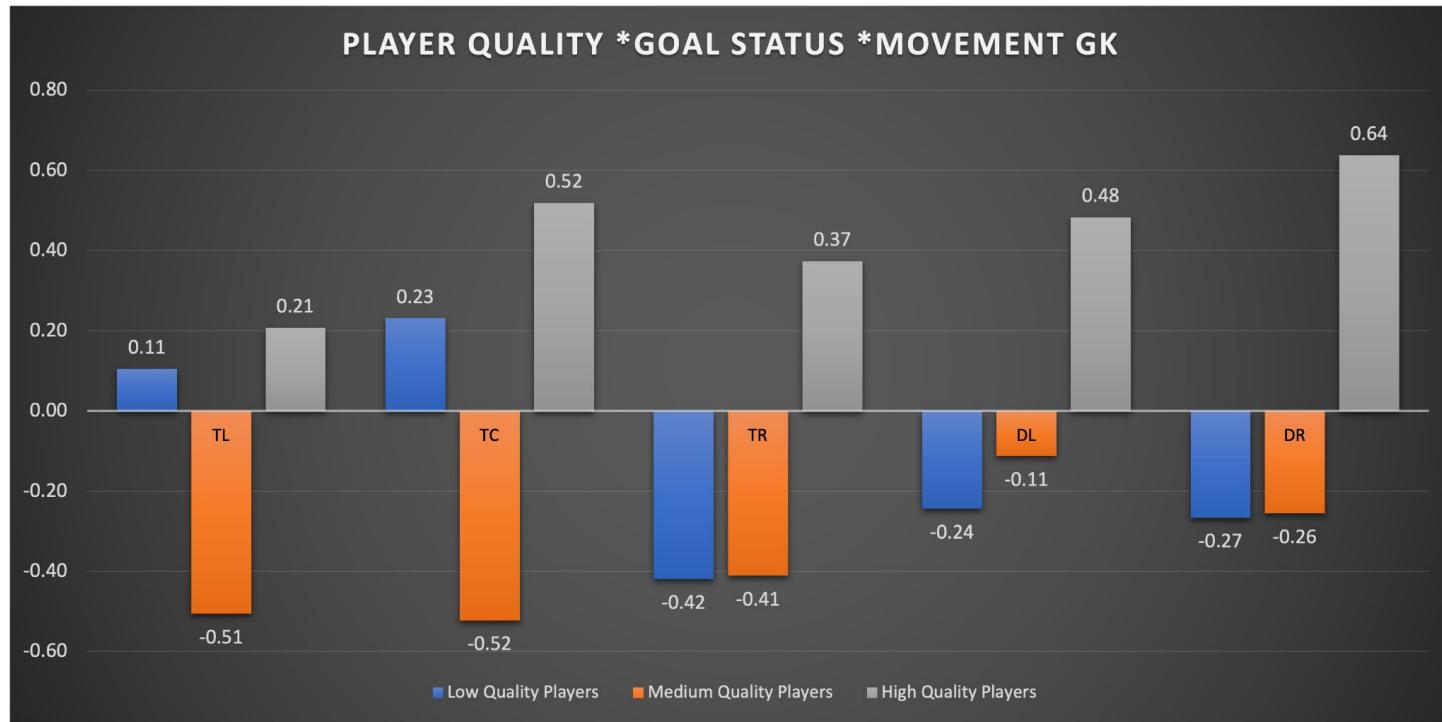
MODEL 1



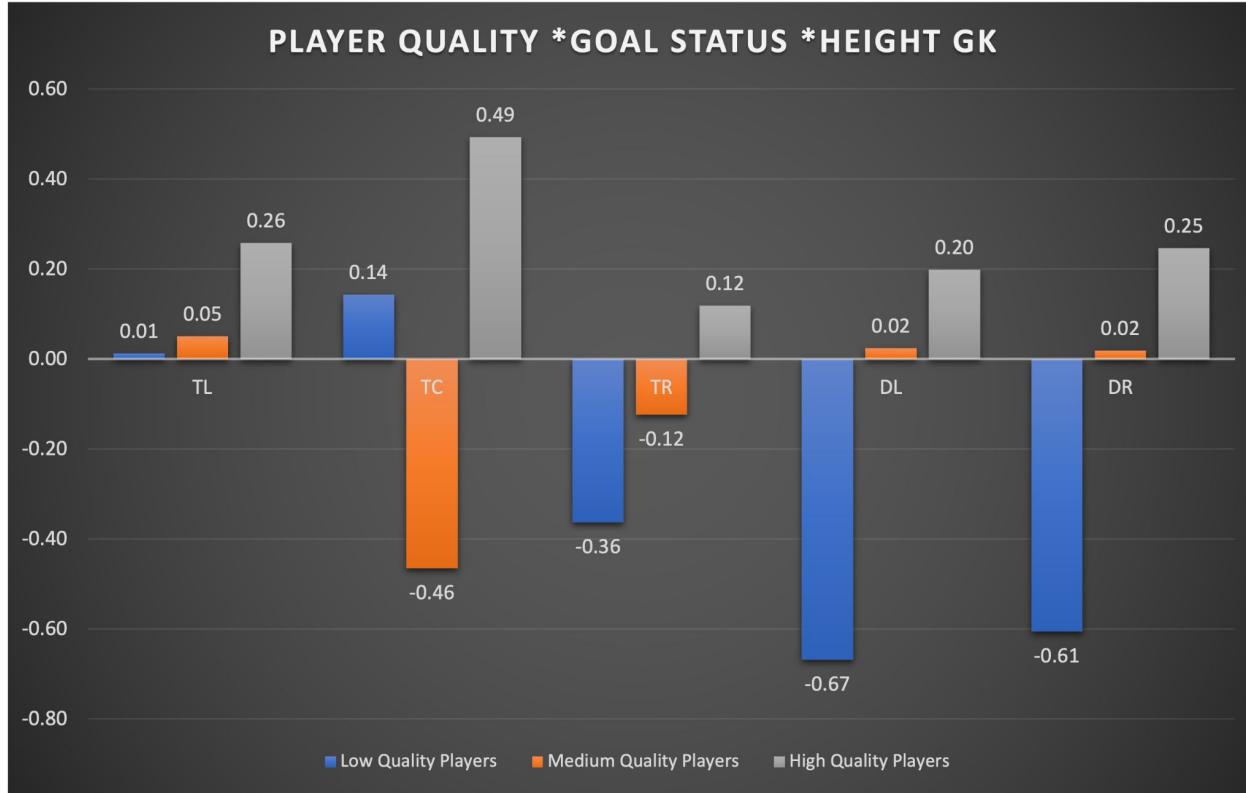
MODEL 2



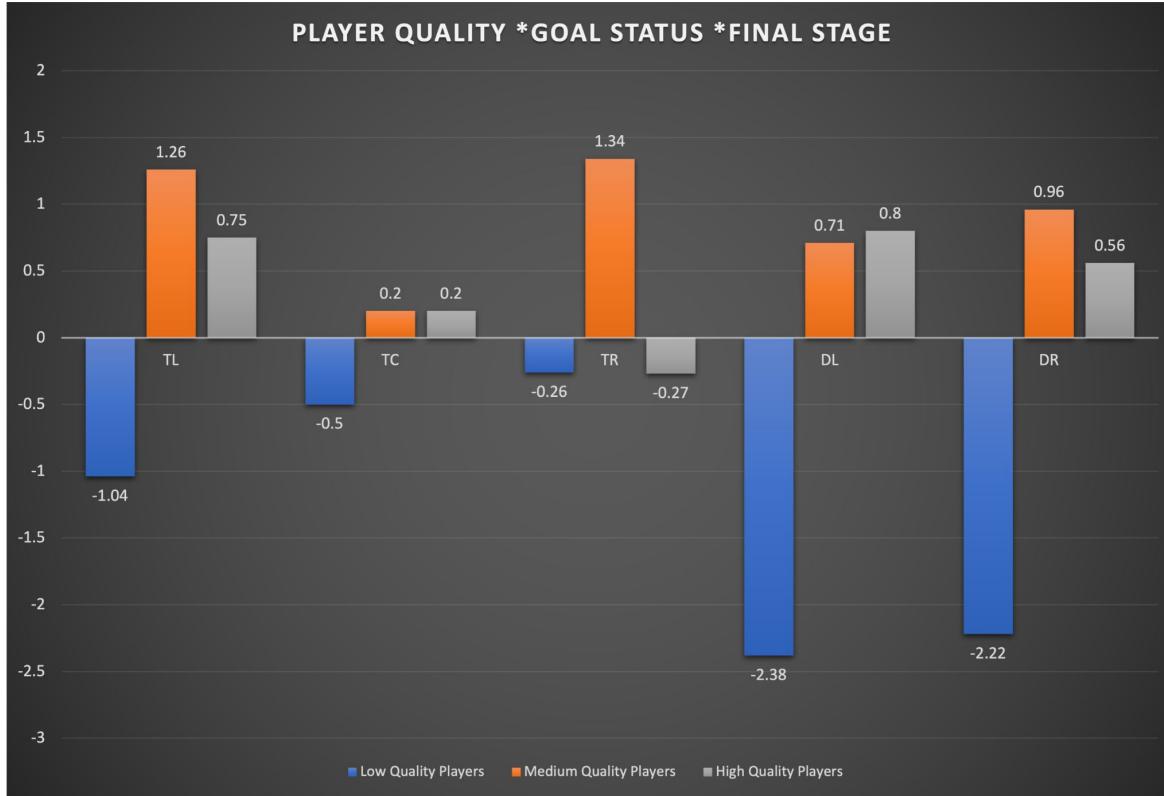
MODEL 3



MODEL 4



MODEL 5



MODEL PERFORMANCE ON UNSEEN DATA

Test Data 6 alt (Penalties Happened in Last 2 Years)

D	playerid	name	TL	TC	TR	DL	DC	DR	chosen	predicted by the model	original value	Value Matches or not?
1	14	Alberto More	0.05	0.00	0.06	0.70	0.06	0.13	0.13 DL	DR		FALSE
2	355	Rashford	0.15	0.04	0.08	0.37	0.05	0.31	0.37 DL	DL		TRUE
3	327	Parejo	0.15	0.02	0.06	0.29	0.05	0.43	0.29 DR	DL		FALSE
4	89	Cavani	0.20	0.01	0.03	0.52	0.05	0.18	0.52 DL	DL		TRUE
5	172	Gomez	0.15	0.04	0.08	0.37	0.05	0.31	0.05 DL	DC		FALSE
6	151	Fred	0.08	0.01	0.25	0.35	0.04	0.27	0.27 DL	DR		FALSE
7	15	Albiol	0.15	0.04	0.08	0.37	0.05	0.31	0.31 DL	DR		FALSE
8	20	Alonso	0.10	0.07	0.12	0.43	0.05	0.23	0.43 DL	DL		TRUE
9	265	Lewandowski	0.16	0.05	0.05	0.22	0.05	0.47	0.47 DR	DR		TRUE
10	11	Alaba	0.08	0.01	0.27	0.35	0.04	0.25	0.25 DL	DL		TRUE
11	213	Hummels	0.19	0.01	0.03	0.61	0.04	0.11	0.61 DL	DL		TRUE
12	242	Kessie	0.06	0.13	0.19	0.35	0.10	0.17	0.19 DL	TR		FALSE
13	56	Berardi	0.06	0.01	0.14	0.65	0.08	0.06	0.01 DL	TC		FALSE
14	293	Messi	0.09	0.01	0.41	0.37	0.04	0.08	0.41 TR	TR		TRUE
15	367	Ronaldo	0.08	0.03	0.13	0.47	0.11	0.18	0.03 DL	TC		FALSE
16	419	Suarez	0.04	0.18	0.12	0.20	0.10	0.36	0.36 DR	DR		TRUE
17	Dalot		0.15	0.04	0.08	0.37	0.05	0.31	0.08 DL	TR		FALSE
18	Milner		0.16	0.02	0.57	0.08	0.06	0.10	0.57 TR	TR		TRUE
19	Thiago		0.18	0.06	0.08	0.19	0.08	0.41	0.19 DR	DL		FALSE
20	Reece James		0.17	0.01	0.09	0.63	0.04	0.06	0.01 DL	TC		FALSE
21	Firmino		0.05	0.00	0.05	0.77	0.04	0.09	0.05 DL	TL		FALSE
22	Dembélé		0.17	0.04	0.14	0.27	0.09	0.29	0.29 DR	DR		TRUE
23	Pjanić		0.07	0.00	0.04	0.78	0.06	0.05	0.78 DL	DL		TRUE
24	puig		0.12	0.04	0.27	0.32	0.07	0.19	0.19 DL	DR		FALSE
25	Veretout		0.02	0.02	0.03	0.31	0.15	0.46	0.31 DR	DL		FALSE

https://docs.google.com/spreadsheets/d/1_lj8VKUD6tf0TTfI7POaCD2v1qirb7wZLXQAO8yBTI/edit#gid=0

Test Data 9 alt (Penalties Happened in Last 2 Years)

ID	playerid	name	TL	TC	TR	ML	MC	MR	DL	DC	DR	chosen	Predicted by the Model	Original Value	Value Match or not ?
1	14	Alberto Moreni	0	0	0	0.05	0.02	0.31	0.03	0.11	0.48	0.48 DR	DR	TRUE	
2	355	Rashford	0.12	0.03	0.08	0.01	0.02	0.11	0.35	0.05	0.22	0.35 DL	DL	TRUE	
3	327	Parejo	0.13	0.01	0.05	0.02	0.01	0.13	0.25	0.06	0.34	0.25 DL	DL	TRUE	
4	89	Cavani	0.13	0.01	0.04	0.03	0.01	0.11	0.11	0.07	0.48	0.48 DR	DR	TRUE	
5	172	Gomez	0.35	0.03	0.08	0.01	0.02	0.11	0.12	0.05	0.22	0.35 TL	TL	TRUE	
6	151	Fred	0.04	0.01	0.16	0.02	0	0.3	0.27	0.04	0.15	0.15 DL	DR	FALSE	
7	15	Albiol	0.12	0.03	0.08	0.01	0.02	0.11	0.35	0.05	0.22	0.22 DL	DR	FALSE	
8	20	Alonso	0.08	0.03	0.21	0.01	0.02	0.18	0.2	0.08	0.19	0.21 TR	DL	FALSE	
9	265	Lewandowski	0.14	0.03	0.06	0.03	0.01	0.15	0.1	0.08	0.4	0.4 DR	DR	TRUE	
10	11	Alaba	0.04	0.01	0.16	0.02	0	0.3	0.27	0.04	0.15	0.16 DL	TR	FALSE	
11	213	Hummels	0.11	0.01	0.04	0.03	0	0.11	0.57	0.06	0.06	0.57 DL	DL	TRUE	
12	242	Kessie	0.05	0.12	0.07	0.04	0.22	0.04	0.31	0.03	0.12	0.07 DL	TR	FALSE	
13	56	Berardi	0.54	0.01	0.05	0.19	0.01	0.11	0.02	0.05	0.03	0.01 TL	TC	FALSE	
14	293	Messi	0.05	0.01	0.32	0.03	0	0.29	0.22	0.03	0.04	0.32 TR	TR	TRUE	
15	367	Ronaldo	0.07	0.05	0.03	0.15	0.03	0.39	0.09	0.05	0.15	0.05 MR	MR	TRUE	
16	419	Suarez	0.04	0.15	0.3	0.03	0.19	0.03	0.18	0.04	0.04	0.04 TR	DR	FALSE	
17	293	Messi	0.05	0.01	0.22	0.32	0	0.29	0.01	0.03	0.04	0.32 ML	ML	TRUE	
19	89	Cavani	0.13	0.01	0.04	0.48	0.01	0.11	0.03	0.07	0.11	0.48 ML	ML	TRUE	
18	Reece James	0.12	0.01	0.07	0.04	0.01	0.14	0.55	0.04	0.03	0.14 DL	MR	FALSE		
20	Dalot	0.12	0.03	0.08	0.01	0.02	0.11	0.22	0.05	0.35	0.02 DR	MC	FALSE		
21	Jesus	0.11	0.03	0.06	0.03	0.01	0.48	0.15	0.07	0.06	0.15 MR	MR	TRUE		
22	Dalot	0.12	0.03	0.08	0.01	0.02	0.11	0.35	0.05	0.22	0.08 DL	TR	FALSE		
23	Milner	0.48	0.03	0.06	0.03	0.01	0.15	0.11	0.07	0.06	0.06 TL	TR	FALSE		
24	Thiago	0.14	0.03	0.07	0	0.07	0.04	0.17	0.06	0.42	0.17 DR	DL	FALSE		
25	Reece James	0.12	0.55	0.07	0.04	0.01	0.14	0.03	0.04	0.03	0.01 TC	TC	TRUE		
26	Firmino	0	0	0	0.06	0.02	0.22	0.59	0.07	0.03	0 DL	TR	FALSE		
27	Dembélé	0.14	0.04	0.08	0.01	0.03	0.1	0.24	0.07	0.3	0.3 DR	DR	TRUE		
28	Pjanic	0	0	0	0.06	0.02	0.17	0.62	0.09	0.03	0.62 DL	DL	TRUE		
29	pug	0.11	0.05	0.2	0.01	0.03	0.13	0.3	0.05	0.12	0.12 TR	DR	FALSE		
30	Veretout	0	0	0	0.12	0.07	0.09	0.25	0.07	0.4	0.25 DL	DL	TRUE		

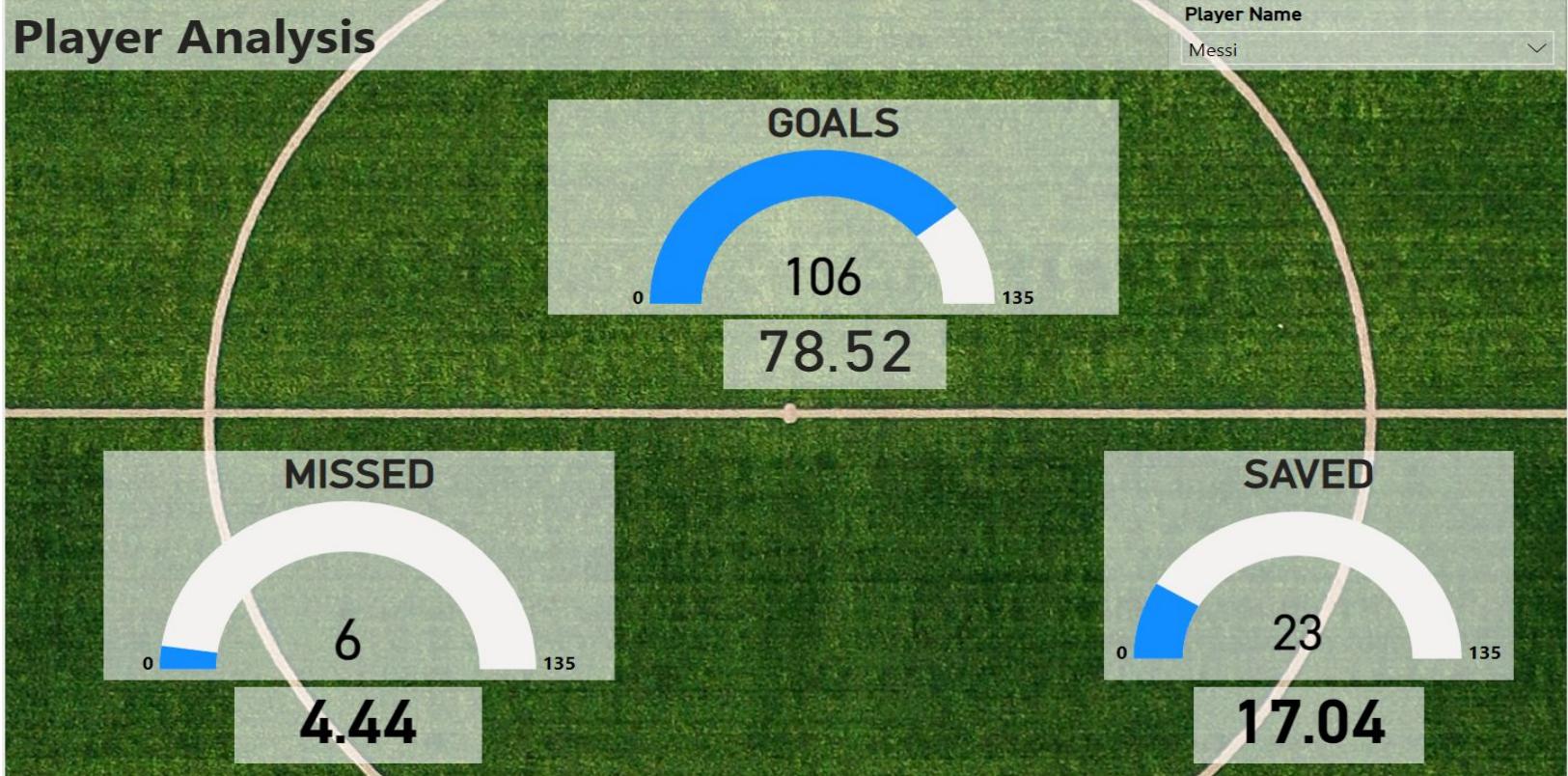
https://docs.google.com/spreadsheets/d/1Ac6OIKYKOy9Jp9qYH1r8QIN1JTbwQjiV_2nCxRwubhA/edit#gid=0

PREDICTION RESULTS

PREDICTION RESULTS



PREDICTION RESULTS



CHOOSING BETWEEN 6 ALT AND 9 ALT MODEL

Ockham's Razor (Law of Parsimony)

The cyclic multiverse has multiple branes - each a universe - that collided, causing Big Bangs. The universes bounce back and pass through time, until they are pulled back together and again collide, destroying the old contents and creating them anew.

God did it.

[1]

Conclusion

- Two models were proposed namely, the 6-alt & 9-alt model
- After performing the data & pre-estimation analysis, we were able to extract 12 variables out of 42 for 6-alt model using the LR test
- Similarly, for 9-alt model, we were able to extract 10 variables out of 42
- From the results of Cross-Validation for 6-alt & 9-alt model, we observed that the difference between the 'LL per Observation' for Estimation and Validation Samples is quite small
- We saw that the IIA was holding for both 6-alt & 9-alt models
- Literature findings proved to be quite successful as we were able to observe the influences clearly
- Model performance on unseen data was favourable to an extent
- Direction of the penalty-taker shot was identified by the interactive Power BI dashboard
- 6-alt model was chosen between the two models which were initially proposed

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