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Master thesis

Master thesis

Prediction of Soccer Penalty Kicks

using a Discrete Choice Model

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List of Abbreviations

alt.	alternative
db	database
max	maximum
m	meter
MNL	Multinomial Logit Model
prob.	probability

List of Symbols

ASC_i	alternative specific constant of alternative i
B	alternative-specific boundary
β_{im}	factor of characteristic m for alternative i
C	choice
ϵ_{it}	error term/bias considering alternative i and penalty-taker t
DC	alternative 5: DC (Down Center)[3]
DL	alternative 4: DL (Down Left)[3]
DR	alternative 6: DR (Down Right)[3]
i	alternative i
Pr_i	probability of choosing alternative i
S_{mt}	"value of mth characteristic for"[1] penalty-taker t
TC	alternative 2: TC (Top Center)[3]
TL	alternative 1: TL (Top Left)[3]
TR	alternative 3: TR (Top Right)[3]
t	decision maker respectively penalty-taker
U_{it}	utility of alternative i for penalty-taker t
V_{it}	utility estimated by analyst
$V(S_t)$	utility estimated by analyst based on characteristics of penalty-taker t
$V(X_i)$	utility estimated by analyst based on attributes of alternative i
X_{ki}	"value of attribute k for alternative i"[2]
γ_k	factor of attribute k

[1] Koppelman & Bhat (2006, p.23)

[2] Koppelman & Bhat (2006, p.20)

[3] The numbers of the alternatives are important for understanding the "R" files and the "Excel" files. In this written report the numbers are used for the variable "la_i".

1 Introduction

The penalty kick in soccer is a huge chance to score a goal. Dalton et al. (2015, p.815-827) show that teams obtaining a penalty in a match, have a high chance of winning (52%) and a clearly smaller chance of losing (18%) the match. Moreover, they ascertain, if the penalty is successful, the chance of winning rises up to 61%. If the penalty is not successful, this chance can be reduced up to 29%. Furthermore, if a knockout match is tied after 120 minutes, the winner of the match is determined in a penalty shootout. From these facts, we can conclude that the penalty has an important role in soccer.

In this thesis, we try to predict the behavior of the penalty-taker and, thus, the shot direction of the penalty. Predicting the shot direction of a penalty is often done in soccer matches, especially in penalty shootouts. One very famous example is the German goalkeeper Jens Lehmann at the World Cup quarterfinal penalty shootout against Argentina 2006, where he was obviously looking on his sheet of paper. He was always able to dive to the correct side, which helps him to save two penalties. Another famous example is the match in the Europa League Final 2021 between FC Villareal and Manchester United. The goalkeeper David de Gea got a sheet of paper with the strong foot of the penalty-taker and a prediction of the shot direction. In this case, only 3 out of 10 shots were predicted correctly, de Gea was not able to save any of the penalties and so they lost the match.

At this example we can see, how difficult it can be to predict the correct shot direction. In this thesis, we show our collection of over 2300 penalties of all top competitions in the world. We want to use this data to estimate a discrete choice model regarding the behavior of the penalty-taker. From the estimated model, we derive the probabilities of the different shot directions and so we try to predict which shot direction is chosen. During the research, we are considering the question "where does the penalty-taker most likely shoots the ball?". Furthermore, we are regarding "which variables are useful to predict the shot direction?" Finally, we investigate "how can we use our estimated probabilities to derive a suited prediction method?". The structure of the paper is organized as follows. We start explaining the current problem. In the succeeding section, we give an overview of the most important literature, describe the composition of the data and analyze the data shortly. Afterwards, we introduce the mathematical model, and we show the estimation

process. This is followed by the presentation of the main results. We finish by giving a short conclusion.

2   Problem Description

In this thesis, we consider the penalty kicks in soccer. We display the situation in figure 1. The penalty-taker shoots the ball from the penalty spot (11 meters away from the goal) to the goal, whereby only the goalkeeper is allowed to save this shot. The goalkeeper has to stay on or behind the goal-line at the moment of the shot. Since 1997, the goalkeeper can move laterally on his goal-line, which makes the penalty more complex (see Dalton et al. (2015, p.815-827)). After a change in rule in June 2019, the goalkeeper now just needs to stay with at least one foot on or behind the goal-line, the other foot can be placed before. We only have penalties shot after 1997 in our database. For all official rules regarding the penalty kick, we refer to the website "https://www.theifab.com/de/laws/latest/the-penalty-kick/". Neglecting any rule violations, a penalty has three possible outcomes. If the ball is shoot into the goal, the outcome is a "Goal". When the goalkeeper prevents that the ball is shoot into the goal, the penalty is "saved". If the ball is not shoot into the goal, but the goalkeeper did not save it, the penalty is "missed".

Figure 1: Penalty situation
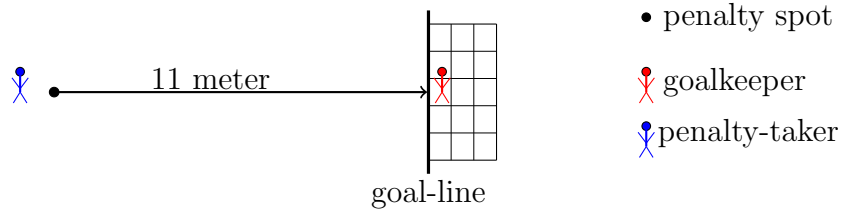
In this thesis, we handle two main tasks. The first task is to collect and prepare suitable data of penalties. Since high quality data is difficult to get and can be expensive, we decide to create our own collection of penalties. For that, we first investigate the current literature and try to find potential variables influencing the shot performance and behavior. In the next step, we collect penalty data using different sources, especially regarding the potential variables identified by the literature review and some self-identified variables. Both processes, we describe in more detail in the next section.

The second task is to estimate a discrete choice model of the penalty-taker's

behavior. For a goalkeeper to save a penalty, it is crucial to know, where the penalty-taker wants to shoot the ball. Since the penalty-taker has a lot of different possibilities to shoot the ball, predicting the correct direction can get a difficult task. In our model, we assume that the penalty-taker has six different alternatives to shoot on the goal, which we show in figure 2. We divide the goal one time horizontally into flat and high shots. Furthermore, we divide the goal two times vertically, so the penalty-taker can decide to shoot to his left, to the center or to his right. In this thesis, regarding the penalty shot directions and the movements of the goalkeeper, we are always considering the point of view of the penalty-taker. The possibility of shooting beside the goal or just hitting the goalpost or the crossbar are included in the alternatives. For example, shots like the points x1 and x2 belong to the alternative TL. These shots are "missed". Shots are also missed, if the ball hits the goalpoast/crossbar and afterwards bounces from the goalkeeper into the goal. Furthermore, figure 2 shows the measures of a goal. From the ground to the crossbar the goal measures 2.44 m and between the goalposts it measures 7.32 m.

Figure 2: Soccer goal with the considered alternatives
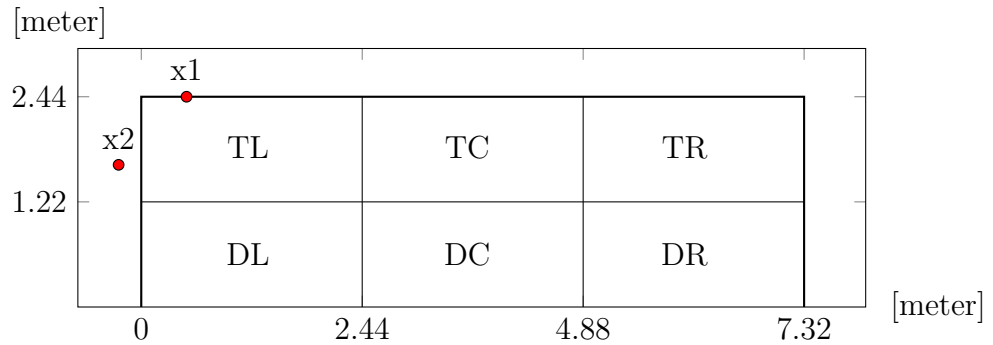
3 Data Collection, Preparation and Analysis

In the following section, we present our collected data and show how we find potential interesting variables, from which sources we compile the data and how we prepare it to ensure high quality. Furthermore, we shortly analyze the data regarding the most important statistics.

3.1 Literature Review

The literature review shall give an overview and help to detect interesting and potential variables of predicting the behavior of the penalty-taker. A possible

partition of the investigations of penalty kicks in the literature is just considering in-match penalties (see e.g. Horn et al. (2020, p.139-155)) and penalty shootouts (see e.g. Hughes & Wells (2002, p.55-72), Krumer (2020, 101578)). In his research, Krumer (2020,101578) ascertains that the teams playing in a higher league than their opponent have a greater chance of winning the penalty shootout. Inspired from this research, in this thesis, we consider being the favored team (respectively the underdog) as potential influencing variable for shooting a penalty.

Buzzacchi & Pedrini (2014, p.1067-1080) state that the behavior of the penalty-takers is rational and, under specific circumstances, it can not always be recognized. Furthermore, they mention that high quality players are easier to predict since they are more often shooting to their preferred direction/their natural side. The natural side is for a right-footed penalty-taker the left side of the goal, and for a left-footed penalty-taker the right side of the goal. Regarding the high quality players, Baumann et al. (2011, p.81-105) present the same result, too. In this thesis, we especially consider high quality players and regard the footedness (i.e. strong foot of player) of the penalty-taker.

A time-depending performance analysis of penalty kicks is made by Almeida et al. (2016, p.508-522). They divide the match into three thirds of half an hour and could find differences in performance regarding these parts. We conclude that the point in time can be decisive and a variable of interest.

With increasing minutes played, the players also get more fatigue. The fatigue as potential influencing factor on the performance is analyzed by Jordet et al. (2007, p.121-129). Overall, fatigue has a small influence on the performance. More interesting is the detection of these authors that stress, indicated by the importance of the match, has a negative influence on the performance of the penalty-taker. Consequently, we will test the importance of a match as a potential influencing variable.

For maximizing success, the penalty-taker should shoot the ball with a high accuracy. The accuracy is already influenced by the pure presence of a goalkeeper (see Navarro et al. (2011, p.921-929)). The same counts, when the goalkeeper is moving (see Wood & Wilson (2010, p.937-946)). Based on these assumptions, Lidor et al. (2012, p.375-389) show the occurrence of misleading strategies (e.g. standing off-center), which help the goalkeeper to influence the penalty-taker to shoot in the goalkeeper's wanted direction.

Already, Chiappori et al. (2002, p.1138-1151) mention that the behavior of the penalty-taker probably depends on the behavior of the goalkeeper. This is also valid, when the penalty-taker is using a so-called keeper-dependent strategy (see Noel et al. 2015, p.1-10). Using this strategy, the penalty-taker reacts to the movements of the goalkeeper, which potentially lead to a change of the previous desired shot direction. Overall, we conclude that the movement and position of the goalkeeper are possible variables influencing the penalty-taker. Thus, we include these in our data collection.

A further research regarding the goalkeeper was done by Müller et al. (2018, p.128-134). They show that a goalkeeper with a high reputation influences the shot performance of a penalty-taker negatively and is observed taller than a low reputation goalkeeper. Further potential influencing factors of the performance of a penalty kick (in penalty shootouts) are analyzed by Noel et al. (2014, p.51-62). They investigate for example the jersey color and the experience. Even though not all factors are relevant for success, we still consider some of them as potential variable for predicting the shot direction.

Even if most researchers mentioned rather consider the performance of the penalty kick, the mentioned variables possibly influence the shot direction, too. Overall, we are able to derive several ideas from the literature regarding potential variables.

3.2 Collecting and Preparing of Data and Variables

For collecting the data, we use a lot of different sources. This enables a high quality, because the information of the different sources could be compared and consequently checked for correctness. A list of all used sources can be found in the appendix. The database comprises 2358 penalties. The following table gives a short overview of the different competitions and the years/seasons which can be found in our database.

Table 1: Competitions in database

competition	*year/season*
German "Bundesliga"	2018/19, 2019/20, 2020/21
"DFB-Pokal"	2018/19, 2019/20, 2020/21
World Cup	2006, 2010, 2014, 2018
European Championship	2008, 2012, 2016, 2021

The database contains the penalties (in-match and shootout) of all German "Bundesliga" clubs of the seasons mentioned, including the competitions "DFB-Pokal", "Europa League" and "Champions League". Furthermore, we collect the penalties of the opponents of the Bundesliga clubs in a penalty shootout, too. Moreover, the database contains all penalties (in-match and shootout) of the World Cup and European Championship of the last 15 years. Last but not least, almost all penalties of several (high quality) players e.g. Ronaldo and Messi we include in the database. The full list of all players, which we investigate, can be found in the appendix. The choice of the single players is rather random and hardly under some specific conditions. We try to find both very good penalty-takers and rather bad penalty-takers. The main factors are to investigate famous players, from which almost all penalties can be considered. Moreover, regarding the choice of the penalty-taker, we try to balance between right-footed and left-footed players and between the different player positions.

The data for the single penalties we mainly derive from "www.transfermarkt.de". On this website there is for every player a detailed list of all shot penalties. Each penalty is linked to the match, where the penalty was shot and from there we derive the main data like minute, scoreline, goalkeeper etcetera. The website "www.kicker.de" we use to check and confirm the presented information. The shot directions, we mainly get by video analyzing via the platforms "YouTube.com" and "dailymotion.com", where the highlights of the single matches containing the penalties are uploaded. There are a lot of different uploaders, the most used are: "DAZN", "Bild" and the official channels of the clubs and competitions. This kind of data is free available, nevertheless, it is licensed, and so we can guarantee to have the correct data. For almost all penalties, we use a video analysis, which mostly shows the entire penalty from at least two different camera perspectives. In just a few cases, we estimate the shot direction by using pictures and reports e.g. from "www.kicker.de".

For that few cases, we have no information concerning the movement and the position of the goalkeeper during the run-up of the penalty-taker, which is needed for several variables. Furthermore, we do the video analyze manually by a human and not by a computer. Considering the shot direction and the position of the goalkeeper, we are limited and just do estimates. Consequently, we can not guarantee to have perfectly correct data. Nevertheless, we are convinced to have high quality and suited data.

We derive the data manually, which should not but can lead to small errors, which simultaneously is a limitation of our model estimation. We periodically check the data for correctness, considering typing errors etcetera. Moreover, we try to avoid errors by preparing the data using the software Excel and RStudio. In the following, we present some potential errors, which we fixed:

– check age, e.g. age not under 16 or over 45

– check height of goalkeeper, e.g. not under 1.7 m and not over 2.2 m

– check same goalkeeper has always same height

– check same player/goalkeeper always gets the same name

– check no redundant penalty

– check dates, e.g. no penalty before 2000 or after 2021

– check actual result

– check whether number of goals/fails of an individual player is correct.

Furthermore, we video analyzed all penalties at least three times, always on a different day, to minimize errors especially regarding the shot direction.

Considering our identified variables, we always have at least 90 penalties, including the single values of each variable. This should help to avoid overfitting. The full list of all variables, shortly explained, we present in the tables 11-16 in the appendix.

3.3   Data Analysis

In the following section, we present a short general analysis of the data and then focus on analyzing the success rate of the penalties. We especially consider the single alternatives mentioned in the problem description. We refrain from analyzing each variable in detail, since we want to avoid making an analysis of an irrelevant variable.

The database consists of 2358 penalties shot by 485 different players. These penalty-takers are in average rounded 27 years old, whereby the youngest player is 16 and the oldest is 40. All in all, we have 1421 penalties shot by a striker, 698 penalties shot by a midfielder, 237 penalties shot by a defender and two penalties shot by a goalkeeper. We consider 1834 in-match penalties and 524 penalties shot in a penalty shootout.

The goalkeeper stands in 92.2% of the penalties in the center of the goal. Standing at the left (3.42%) or right (4.36%) side has almost the same probability and overall,

it is relative unusual. In rounded one third of the cases (33.7 %) the goalkeeper is moving during the run-up of the penalty-taker. The average height of the goalkeepers amounts to a rounded 1.90 m, whereby the range is between 1.76 m and 2.03 m. The penalties result in 1873 cases to a goal (79.43 %), 351 times the ball is saved by the goalkeeper (14.89 %) and 134 times the penalty-taker misses the goal (5.68 %).

Figure 3: Probabilities of alternatives chosen in database

9.84 %	5.6 %	8.99 %	24.43 %
37.23 %	6.83 %	31.51 %	75.57 %
47.07 %	12.43 %	40.5 %	

In figure 3, we show the probabilities of the penalties shot to the different alternatives. The most penalties are shots in the down corners, whereby the ball has shot more often to the down left corner (37.23 %). The next most probable chosen alternatives are the top corners, whereby again the left corner is more often chosen than the right corner. Overall, the penalty-takers shot the ball in a rounded three-quarters rather flat to the goal.

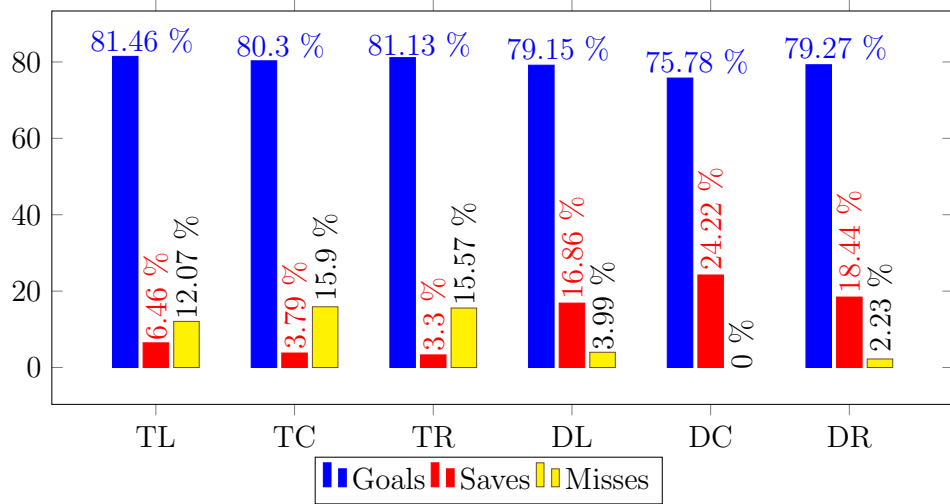Figure 4: Probability of goal,save and miss of each alternative

Figure 4 shows the single percentages of goals, saves and misses regarding the single alternatives. In all cases, shooting a goal is the most probable. The highest probability of shooting a goal is given by shooting the ball to one of the top corners, since these corners the goalkeeper can not cover completely. The probabilities

amount to 81.46% for the left top corner and 81.13% for the right top corner. Another clear observation is that the shots to the top of the goal have a higher chance of being missed than being saved. Reasons are that high shots can be shoot over and beside the goal, but therefor, the goalkeeper has a relative small coverage to save those. The opposite is valid for flat shots, where the save rate is clearly higher than the miss rate. Considering these shots, the goalkeeper has a relative high coverage. The ball can not be shoot under the goal, thus, flat shots can only be missed by shooting beside the goal. That is why DC has a miss probability of 0%, since it is not possible. However, DC has the highest probability of being saved.

In the literature review, we mentioned a "natural side" of the penalty-taker, depending on their strong foot. In the following, we analyze this phenomenon by considering left-footed and right-footed penalty-takers. We display a comparison in figure 5. In our database, we have 579 penalties shot by a left-footed player and 1779 penalties shot by a right-footed player.

Figure 5: Comparison left-footed and right-footed penalty-takers

left-footed				right-footed		
7.25 %	3.45 %	14.33 %		10.68 %	6.3 %	7.25 %
29.88 %	6.75 %	38.34 %		39.63 %	6.86 %	29.28 %
37.13 %	10.2 %	52.67 %		50.31 %	13.16 %	36.53 %

Regarding our database, we are able to confirm the phenomenon. It is clearly to observe that left-footed players more likely shoot to their right side. Vice versa, we can see that right-footed players more likely shoot to their left side. Both shoot over the half of their penalties to their "natural side"

Whether the ball has shot rather flat or rather high is not affected by this phenomena. Equally to the general analysis from figure 3, we can ascertain that the shots are in circa three-quarter of the cases rather flat. Interesting to observe is that, given a left-footed penalty-taker has shot to the top of the goal, shooting to their natural side is not only the most probable alternative, it is more probable than the other two alternatives together (14.33% > 10.7%). Comparatively, for right-footed players shooting to the top, the natural side is admittedly the most probable, but not more likely than the other two alternatives together (10.68% < 13.55%).

4 Model Estimation and Results

4.1 Mathematical Model

In the following section, we present the model. The assumptions and the model are based on the general model for discrete choice models made by Koppelman & Bhat (2006, p.14-60). We will consider a utility-based model, whereby we assume that the decision maker chooses (C) the alternative which is giving him the highest utility U. The choice is unique, since the utility values differ clearly among the alternatives.

$$C = \{i | U_{it} = max(U_{it})\} \tag{1}$$

$$U_{it} = V_{it} + \epsilon_{it} \tag{2}$$

The utility U_{it}, we calculate for each single alternative i given the decision maker t. It is comprised by two parts. The first part is the utility estimated by the analyst based on his observations. The second part is the utility, which is not observable and so not measurable for the analyst. This part is known as error term. It is used to include all factors into the model which otherwise would not be in the model. The observable part of the utility is calculated by the addition of three parts:

$$V_{it} = V(S_t) + V(X_i) + V(S_t + X_i). \tag{3}$$

The variable $V(S_t)$ is the observable utility based on the characteristics of the decision maker t. We will call it in this thesis character-based utility. For the model estimation, we calculate this part as follows.

$$V(S_t) = \beta_{i0} \cdot ASC_i + \sum_{m=1}^{M} \beta_{im} \cdot S_{mt} \tag{4}$$

The first term of the equation 4 represents the specific preference regarding the single alternatives. This is called bias and is always calculated related to one reference alternative. The value ASC_i is constant for each single alternative. The β_{i0} is a factor of how strong the bias contributes to the utility of the single alternatives.

The second term is the sum of the weighted single characteristics of the decision maker. The S_{mt} is "the value of the mth characteristic for individual t" (ebd.:23), which is equal for each alternative. The β_{im} is the factor determining how strong the mth characteristic contributes to the utility of the alternative i, and it can be for each alternative different. For the model estimation, it is important to mention

that we will estimate each β_{im} to one reference alternative, which will get a constant value of $\beta_{im} = 0$.

The second term of equation 3, $V(X_i)$, is the observable utility based on the attributes of the alternative i. In this thesis, we will call it alternative-based utility. We calculate it as follows:

$$V(X_i) = \sum_{k}^{K} \gamma_k \cdot X_{ki} \tag{5}$$

The γ_k is the factor determining how strong the attribute contributes to the utility of the single alternatives, which is equal for each alternative. The X_{ki} is "the value of attribute k for alternative i" (ebd.:20), which can have for each alternative a different value. If there is a reasoning why we could assume that the factor γ_k should not be the same for all alternatives, this is possible by introducing a second γ for the attribute k. For an example, we refer to Koppelman & Bhat (2006, p.20f).

The last term of equation 3 is the utility based on the interactions of the attributes and characteristics of alternative i and decision maker t. The interaction of both is in our model only observable by the variable "$perc_i$". This variable considers for the single decision maker with which percentage he has previously chosen the single alternatives. Furthermore, in our model, we consider two different attributes of the alternatives. These are the save rate "$SRGK_i$" and the missing probability "$MPGK_i$" (explanations in the appendix). All other variables considered are characteristics of the decision maker respectively of the considered match, but not alternative specialized.

Based on the utility functions, we want to derive with which probability the single alternatives are chosen. Therefor, we need three assumptions, which helps us to define a so-called multinomial logit model. We firstly assume that the error components (equation 2) are "extreme value or Gumbel distributed"(ebd.:26). Furthermore, the "error components are identically and independently distributed across alternatives"(ebd.:26) and they are "identically and independently distributed across observations" (ebd.:26). These assumptions help us to calculate the probability of each single alternative based on the observed utility values of all alternatives.

$$Pr(i) = \frac{exp(V_i)}{\sum_{j=i}^{J} exp(V_j)} \qquad \forall i \in J \tag{6}$$

The probabilities, we calculate by the exponential function of the observable utility of alternative i: $exp(V_i)$. This we divide by the sum of the exponential function of the observable utility of all alternatives including alternative i, too. This automatically leads to the property that an increasing probability of choosing alternative i is reducing the probabilities of choosing one of the other alternatives.

4.2 Estimation Process

In this section, we present the estimation process of the model. We do the estimation of the model with the software R. We use the package apollo, which is designed for the estimation and application of choice models. We especially refer to Hess & Palma (2021, p.1-206), which give a detailed explanation of all possible functions using apollo. Furthermore, we inherit the example codes given from these authors and apply them to our problem. The tests we execute during the process are made in apollo, too. For the theoretical-based knowledge of these tests, we refer to Koppelman & Bhat (2006 (p.82ff)).

We start making a pre-estimation analysis of our database. Regarding an analyzed variable, the choice analysis of apollo records three values:

– the mean value of the variable, when the alternative is chosen,

– the mean value of the variable, when the alternative is not chosen,

– and a two-sample t-test, which compares these means.

The higher the t-value, the more significant is the difference between the two means. If the t-value is higher than 1.96, we have a 95 % confidence that the values are significant different from each other. We show an example in table 2.

Table 2: Example pre-estimation analysis

Alt.	mean for "foot" if chosen	mean for "foot" if not chosen	t-test for difference
TL	0.819	0.7474	-2.65
TC	0.8485	0.7489	.3.05
TR	0.6085	0.7689	4.61
DL	0.803	0.7257	-4.35
DC	0.7578	0.7542	-0.1
DR	0.7012	0.7789	3.94

Regarding the example, we can observe that the variable "foot" has a very high t-value for almost all alternatives. Thus, it is very probable that this variable has a high influence on the choice of the alternatives.

We do the pre-estimation analysis for all possible character-based variables. In this process, we separate these variables into two lists whether they have for at least two alternatives a t-value of over 1.96 or not. Variables fulfilling this condition have a higher chance of being important for the model. Furthermore, we create an order of the variables according to the t-values, starting with the variable with the highest average t-value. This order rather should give an orientation, which variables are more likely to have an influence on the choice of the alternatives, but it should not claim, that a variable A has a greater influence than a variable B.

The next step is to start estimating the model. Firstly, we only use the alternative specific constants (ASC) of each single alternative. As reference alternative, we always use the alternative DC. This is valid for all character-based variables, too. The estimated model is then our latest model.

After finish estimating, we add one character-based variable to our model according to our created order. Afterwards, we compare the "new" model including the added variable with the latest model and use a likelihood ratio test to check whether the variable should be excluded from the model. The hypothesis to test is whether both models are equal. For the test, we consider the critical chi-square values. Since we have six alternatives, from which one is the reference alternative, we have a degree of freedom/number of added restrictions of five. If the likelihood ratio test value is higher than 9.24 (90 % confidence), we reject the hypothesis. Thus, we will include the variable in the model and update our latest model. If not, this variable is excluded and the latest model stays the same. This process we repeat until every variable from the first list is checked.

Afterwards, we will implement the variables $SRGK_i$, $MPGK_i$ and $perc_i$ step by step into the model. These variables we test by using a likelihood ratio test, too. We again decide by using the chi-square values, but different to the character-based variables, the number of added restrictions is not necessarily five. If we consider the same factor for each alternative, this number is equal to one. In the subsection "Estimation results", we will mention the number of restrictions, we use for testing the single variables.

Even though on our second list of character-based variables we only have probably unimportant variables, we still check all of them. This, we do after checking the alternative-based variables, and we do the same process as for the other character-based variables. If there are no variables left to be checked, we are finished.

We choose this approach, because we want to have firstly some variables in the model included, of which we feel certain that they will be in the model (e.g. footedness of penalty-taker). We believe that this is building a good basis, from which we then can make good decisions whether further variables are useful or not. The whole estimation process is summarized shortly in the following figure.

Figure 6: Estimation process
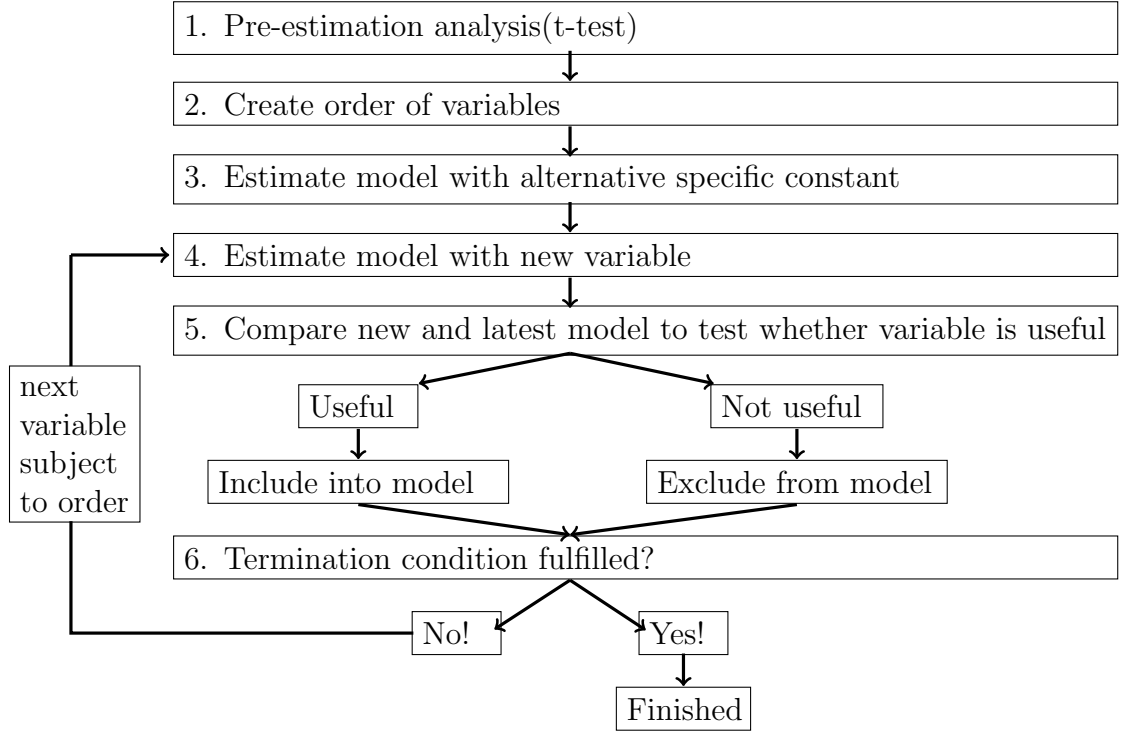
4.3 Estimation Results

In the following, we use the described method to estimate the model. We start explaining the method shortly at one iteration. After this, we show the main results considering the estimated probabilities, different predictions methods and a possible extension of the model.

We start by making the pre-estimation analysis. We detect that the variables "foot", "moveGK" and "GKS" have the highest likelihood of being important for the model. After estimating the model with the alternative specific constants, we start adding step by step the single variables. The first variable we want to include is "foot". By doing the likelihood ratio test to determine whether we should exclude "foot", we get a likelihood-ratio test value of 57.16. As mentioned, the number of restrictions is in this case equal to five. We are to rounded 100 % confident to reject the hypothesis

and include "foot" into our model. This, we can derive from the chi-quadrat values for the different confidence-levels, which we show in the following table.

Table 3: Chi-quadrat table

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

We continue this procedure for all variables on the first list. If the test-value for a variable is at least higher than the 90 % confidence level, we are including it into the model. The test-values of the variables which we identified as more likely to be important, we show in the following table.

Table 4: Likelihood ratio test-values of character-based variables

variable	test-value	include in model?	variable	test-value	include in model?
moveGK	14.08	✓	tup	8.44	✗
GKS	14.46	✓	obot	8.5	✗
IngSo	34.3	✓	Mins3	6.52	✗
comLea	11.06	✓	Mint3	5.18	✗
comNTC	2.24	✗	la_3	11.32	✓
ClubNT	4.16	✗	la_6	12.62	✓
HeiGK	10.78	✓	st	4.86	✗
Imp	2.3	✗	rnoLS	5.38	✗
Dec	10.24	✓	Stlsbg	4.3	✗
lpbg	18.78	✓	SlGKd	1.06	✗
lGKd	4.72	✗	Solsbg	9.54	✓

The variables with a "✓", we will include into the model. Thus, we include additionally to whether the penalty-taker is left-footed or right-footed ("foot"), whether the match where the penalty is taken, is a "league" match or not ("comLea") and whether the penalty is shot in a penalty shootout or in-match ("IngSo"). Furthermore, regarding a penalty shootout, the fact whether the opponent's last penalty was a goal or not influences the penalty-taker ("Solsbg"). Considering the goalkeeper, his movements during the run-up of the penalty-taker, for instance stepping respectively leaning to a specific side or jumping on spot, are included ("moveGK") as well as his standing position during the run-up ("GKS") and his height (HeiGK). A further big influence is given by the previously shot penalty of the penalty-taker. Especially when the last penalty was shot either to TR or DR ("la_3", "la_6") is giving a clue for the next shot direction as well as the fact whether the last penalty was a goal or not ("lpbg"). Last but not least, the fact whether the

penalty is a "Decider", we include into our model ("Dec").

As a next step, we test which alternative-based variables we will include into the model. We start testing the variable "$SRGK_i$". In the first estimation, by using the same factor for all alternatives, we got a positive value for the factor. Since we assume that the save-rate should get a negative value, since in our opinion it reduces the utility for an alternative, we estimate a factor for each single alternative. For the variable "$MPGK_i$" the same counts theoretically, too. Finally, we include the variables "$SRGK_{TL}$" and "$SRGK_{TR}$", since these have a negative factor and fulfill the likelihood-ratio test condition. Furthermore, we include the variable "$perc_i$". The other alternative-based variables are excluded from the model. This we conclude by considering the test-values of these variables, which we show in the following table. These test-values, we compare with the corresponding values from table 3. For the variable "$MPGK_i$", we have by testing an individual factor for each alternative five instead of six restrictions, since the alternative DC has no missing probability and so "$MPGK_{DC}$" has no influence on the model.

Table 5: Likelihood ratio test-values of alternative-based variables

variable	number of added restrictions	test-value	include in model?
"$perc_i$"	1	6.66	✓
"$SRGK_i$"	2	7.16	✓
"$MPGK_i$"	1	0.02	✗
"$MPGK_i$"	5	5.8	✗

We continue by processing the remaining variables. From these, we include the variable "rnoGroup", which contains the information whether the penalty has shot in a group stage match or not. Furthermore, we include the variable "def", giving the information whether the penalty-taker is a defender or not. Last but not least, the variable "nmovGK" is in our model, which is a further variable considering the movement of the goalkeeper. This variable differs between the goalkeeper is moving or not, but it does not specify the movements, since this is already covered by the variable "moveGK". All other variables like the jersey color, the minute of play, the importance of the game etcetera, we detect as ineffective for predicting. In the following table, we show the final estimations for the different factors of the included variables.

Table 6: Factors of single utility functions

Alt.	TL	TC	TR	DL	DC	DR
ASC_i	2.875	0.297	5.355	0.196	0	2.682
β_{foot_i}	0.431	0.8033	-0.592	0.376	0	-0.216
β_{moveGK_i}	-0.062	-0.131	0.027	0.4	0	-0.325
β_{GKS_i}	0.241	0.019	-0.589	-0.162	0	-0.138
β_{IngSo_i}	-0.214	-0.306	0.851	0.4521	0	0.231
β_{comL_i}	-0.696	-0.484	-0.124	-0.15	0	-0.07
β_{HGK_i}	0.048	0.019	0.016	-0.015	0	0.028
β_{dec_i}	0.358	-1.37	0.487	0.066	0	0.193
β_{lp_i}	0.076	-0.577	-0.16	-0.173	0	0.17
β_{latr_i}	0.45	0.95	1.026	0.679	0	0.538
β_{ladr_i}	-0.191	0.049	-0.421	0.094	0	-0.226
β_{sr_i}	-57.185	0	-134.346	0	0	0
β_{perc}	0.333	0.333	0.333	0.333	0.333	0.333
β_{rnog_i}	-0.612	-0.969	0.288	-0.3	0	-0.232
β_{solsbg_i}	0.104	-0.6	-0.371	-0.437	0	-0.265
β_{nmovGK_i}	0.01	-0.475	0.222	0.61	0	-0.744
β_{def_i}	0.437	1.376	0.645	0.678	0	0.52

Since "DC" is the reference alternative, it has for almost all factors a value of 0. If a factor of a character-based variable has for an alternative a negative sign, this means the variable has a negative utility for this alternative, compared to the reference alternative DC. For example, considering the variable foot, which is for a right-footed player equal to "1" and for a left-footed player equal to "0", the right sided alternatives DR and TR have a negative factor, since right-footed players prefer shooting to the left side. Consequently, the left sided alternatives DL and TL have a positive factor for this variable. Overall, we can use the factors to derive the utility of the respective variables to the single alternatives.

For the alternative-based variables, we do not consider a reference alternative. Consequently, for these variables, a negative factor means negative utility and a positive factor means positive utility. The following equations show, exemplarily for the alternative TL, how we construct the utility functions.

$$
\begin{aligned}
V(TL) = {} & ASC_{TL} + \beta_{foot_{TL}} \cdot foot + \beta_{moveGK_{TL}} \cdot moveGK + \beta_{GKS_{TL}} \cdot GKS \\
& + \beta_{IngSo_{TL}} \cdot IngSo + \beta_{comL_{TL}} \cdot comLea + \beta_{HGK_{TL}} \cdot HeiGK + \beta_{dec_{TL}} \cdot Dec \\
& + \beta_{lp_{TL}} \cdot lpbg + \beta_{latr_{TL}} \cdot la_3 + \beta_{ladr_{TL}} \cdot la_6 + \beta_{sr_{TL}} \cdot SRGK_{TL} + \beta_{perc} \cdot perc_{TL} \\
& + \beta_{rnog_{TL}} \cdot rnoGroup + \beta_{solsbg_{TL}} \cdot Solsbg + \beta_{nmovGK_{TL}} \cdot nmovGK + \beta_{def_{TL}} \cdot def
\end{aligned}
$$

$$V(TL) = 2.875 + 0.431 \cdot foot - 0.062 \cdot moveGK + 0.241 \cdot GKS$$
$$- 0.214 \cdot IngSo - 0.696 \cdot comLea + 0.048 \cdot HeiGK + 0.358 \cdot Dec$$
$$+ 0.076 \cdot lpbg + 0.45 \cdot la_3 - 0.191 \cdot la_6 - 57.185 \cdot SRGK_{TL} + 0.333 \cdot perc_{TL}$$
$$- 0.612 \cdot rnoGroup + 0.104 \cdot Solsbg + 0.01 \cdot nmovGK + 0.437 \cdot def$$

The other utility functions are construct on the same way. We can use these utility functions to calculate the probabilities for each single alternative given the penalty (conditions). As mentioned, we do this by using the R package apollo. Afterwards, we use the probabilities to predict the shot direction, using two different methods. We predict each single penalty in our database. The prediction results, also considering some single players, we show in the following.

Figure 7: Comparison of estimated probabilities

avg. estimated probability			avg. estimated probability when chosen		
9.84%	5.6%	8.99%	12.03%	7.47%	12.1%
37.23%	6.83%	31.51%	39.55%	7.52%	33.84%

We first show in figure 7 on the left side the average probabilities of each single alternative estimated by our model. Comparing this to figure 3, we can observe that the average probabilities are exactly like the probabilities of our database. On the right side, we show the estimated average probabilities of the single alternatives, in the case they are chosen by the penalty-takers. Comparing these to the left side, we can observe that our models estimates these probabilities for all alternatives clearly higher. This is especially valid for the shots to the right or to the left, for which the increase is at least 2.19 %. Consequently, our model is able to recognize some patterns and variables increasing the utility of the single alternatives.

In the next step, we give an analysis of some single players. The figure 8 shows the estimated average probabilities for each alternative of the players Griezmann, Dybala, Suarez and Ramos.

Figure 8: Estimated average probabilities of different penalty-takers
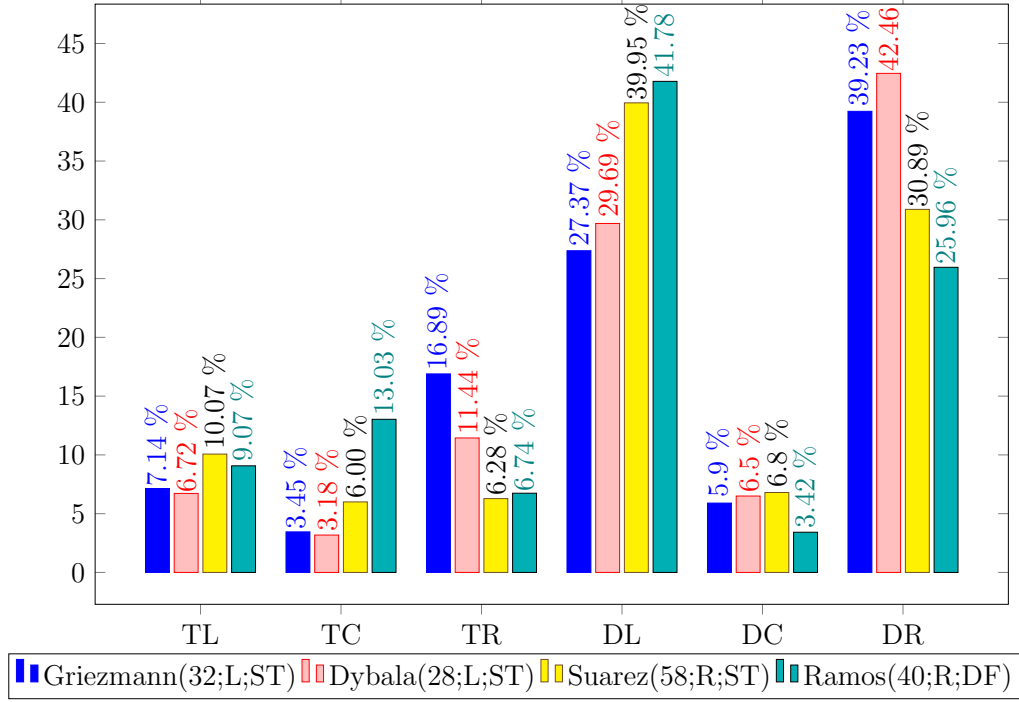
In brackets, we show the number of penalties in the database, the strong foot and the position of the single players. We can clearly observe that our model differs extremely between left-footed and right-footed players. For Griezmann and Dybala our model estimates a clearly higher probability to shoot to the right of the goal than for Suarez and Ramos and vice versa, for Suarez and Ramos our model estimates a higher probability to shoot to the left. Furthermore, we can observe that the players Griezmann and Dybala, which have the same position and the same strong foot, have also relative similar estimated probabilities. Nevertheless, the probabilities are especially for the alternatives DL, DR and TR not equal, so the model differentiates between these two players.

Considering the example, the player Ramos has the biggest estimated average probability for the alternative TC, which is more than twice as high as for the other players. The reason for that is, that this player more often shoots to that direction (30 % in db). Our model is able to recognize this, cause of using the variable "$perc_i$". The same accounts for the player Griezmann, who more often shoots to the right upper corner (31.25% in db), and so he gets a relative high estimated average probability for this alternative. Nevertheless, our model just rarely predicts these alternatives as the alternative with the highest probability, which we show in the following.

4.4 Prediction Results

We first start by using the prediction method according to our mathematical model. The alternative with the highest utility, meaning the alternative with the highest probability, is our prediction. Overall, using this method we are able to predict 42.24 % of the penalties correctly and vice versa 57.76 % incorrect. This is clearly better than predicting for each penalty it will be shot to "DL", the alternative with the highest probability, which would give us a prediction rate of 37.23 % correct predictions. Additionally, we show in table 7 how often in the database the single alternatives are chosen, how often the alternatives have according to our model the highest probability and how often in that case the ball was shot to that direction.

Table 7: Numbers of choice considering the alternatives

alt.	times chosen (db)	times highest probability	times chosen by penalty-taker when highest probability
TL	232	12	5
TC	132	1	0
TR	212	20	7
DL	878	1606	678
DC	161	0	-
DR	743	719	306

As an example, when our model predicts "DR", it is in 42.56% of the cases correctly. Our models rarely predicts a shot to the top of the goal (33 times). Furthermore, shooting to the center of the goal has only one time the highest probability using our model. This is clearly dominated by the alternatives DL and DR, which is obvious, since these alternatives are the most chosen. However, if a penalty-taker knows that a goalkeeper is behaving according to our prediction method, he just would shoot to the center of the goal and has a great chance to score a goal. Since this scenario would make our model ineffective, we create a further prediction method.

According to this method, we calculate for each alternative the difference of the estimated probability (Pr_i) and the estimated average probability ($\overline{Pr_i}$). We then choose the alternative with the maximum difference. This alternative has the highest increase in probability respectively utility. For this method, the same assumptions and equations are valid as we presented in the mathematical model (section 4.1). We only change the assumption, which alternative we choose (equation 1).

$$C = \{i|(Pr_i - \overline{Pr_i}) = max(Pr_i - \overline{Pr_i})\} \tag{7}$$

An example for the method, regarding a random penalty, we show in the next table.

Table 8: Example second prediction method

alternative	TL	TC	TR	DL	DC	DR
estimated prob.	0.128	0.043	0.203	0.24	0.074	0.3116
avg. prob.	0.098	0.056	0.09	0.372	0.068	0.3151
increase in prob.	0.03	-0.013	0.113	-0.132	0.006	-0.0035

In the example, TR has the highest increase in probability and DR has the highest overall probability. Consequently, we predict TR instead of DR. The advantage of this method is that we predict all alternatives frequently. We choose 62 times DC and 177 times TC, which is clearly more than one time. Our prediction is 805 times DL, which is almost the half compared to the first method. Furthermore, we predict 663 times DR, 377 times TL and 274 times TR. We can observe that this distribution is clearly more balanced, and more similar to the quantity the alternatives are chosen in the database. The disadvantage of the method is a low prediction rate of 33.59 %, which is almost 9 % less compared to the first method.

Consequently, a combination of both methods could be interesting. On the one hand, this would enable a relative high prediction rate. On the other hand, each alternative would be predicted sometimes. A possible method for this is to predict using the second method if and only if the probability increase is greater than a specific boundary. As example, we use an alternative-specific boundary (B), calculated for each alternative by the maximum estimated probability ($max(Pr_i)$) reduced by the average estimated probability ($\overline{Pr_i}$) and this result divided by 2.5. We got this boundary via testing.

$$B = \frac{max(Pr_i) - \overline{Pr_i}}{2.5} \tag{8}$$

Using the combined methods and this boundary, we are predicting in 40.63 % of the cases correctly. This is a strong increase compared to the second method. We predict 57 times DC, 16 times TC, 97 times TL and 29 times TR. Compared to the numbers of table 12, we clearly more often predict these rather unusual alternatives. Overall, we need to weigh up, which requirements we want to have for our predictions and choose according to these requirements a suited method.

Last but not least, we shortly investigate the prediction rate of penalty-taker that have only one shot in our database and those that have at least five penalties, using the first prediction method only. We present this in the following table, whereby we always show the average prediction rate of all penalty-takers with the according number of penalties in our database.

Table 9: Prediction rate of penalty-takers with different number of penalties

number of penalties	1	5-9	10-29	30-49	50 or more
perc. correct	35.49%	37,76%	42.36%	46.63%	43.95%

We observe that the prediction rate of 35.49 % for penalty-takers with only one penalty is relative small. The higher the number of considered penalties for a single player, the higher is the prediction rate. The only exception is for penalty-takers with over 50 penalties, for which we still have a relative high prediction rate. Since we can observe more penalties and several variables in our model consider the previously shot penalties of a penalty-taker, the increase in prediction rate by an increasing number of penalties considered, is reasonable. Consequently, if we want to predict the behavior of a penalty-taker, we should collect as much penalty-data of that player as we can. Nevertheless, even for the penalty-takers for which we collect a lot of data, we predict on average under 50% correctly, thus less than a half. Concluding, we can state that predicting the shot direction is a difficult task.

As a potential extension of our model, we consider building a nested multinomial logit model. A detailed description of this model is given by Koppelman & Bhat (p.157f). The main advantage of this model is to avoid the independence of irrelevant alternative's assumption we make by the multinomial logit model. Therefor, we build nests/subgroups of alternatives, which are relative similar to each other. We regard building the nests by separating the goal vertically into left (TL and DL), center (TC and DC) and right (TR and DR). We assume that the most influencing variables are the same as for the normal MNL. Furthermore, we assume that the utility functions are almost the same. The only difference is that the alternatives belonging to the same nest, we decide to have the same (β-) factor of the variable "foot".

Overall, this extension gives no observable improvement to the normal model. The prediction rate using the highest utility method is 41.86 %, which is very similar to our normal MNL. The "problem" of predicting the rather unusual alternatives infrequently, we have by using this nested model, too. Important to state is that the nested variant is computational expensive, and we reach the maximum number of iterations the software is in our case able to execute. Consequently, we are not able to fully investigate this kind of model and stop further investigations.

5 Conclusion

Summarizing, we present a discrete choice model which can help to predict the behavior of a penalty-taker in soccer. Using our model, we can answer the questions arose in the beginning of this thesis. In this thesis, we first showed how we derive suitable, high-quality data of overall 2358 different penalties. This process includes to find possible factors influencing the decision, where to shoot the ball. Collecting and preparing the data are further steps in this process.

Afterwards, we described the way we want to estimate a suited model, and we then presented our results. All in all, the footedness of the penalty-taker and the previous behavior by penalties (especially considering the last penalty) are the main influencing variables of predicting the behavior. Regarding the goalkeeper, the position in the goal and the movement, both during the run-up to the penalty, have a big impact on the penalty-taker. The height of the goalkeeper influences the penalty-taker, too. Moreover, we show that the kind of competition, e.g. a league match, can help to predict. Last but not least, the behavior of the penalty-taker can differ when a penalty is shot in a penalty shootout.

Using our model, we derive the probabilities where a penalty-taker most likely shoots a penalty. Moreover, we compare the estimated probabilities of different players to display how our models differs between different and relative equal types of penalty-taker. We further show how to predict the shot direction using our model. There we present two methods, where one has a higher accuracy, but only one time predicts for the goalkeeper to stay in the center. The other one has a clearly lower accuracy, but we predict each shot direction frequently. Furthermore, we show that the more penalty data we have for a specific penalty-taker, mostly the better we are able to predict him.

All in all, we can state that predicting the behavior of a penalty-taker is very difficult. Regarding that some penalty-takers observe the movement of the goalkeeper shows that the penalty-takers are able to make their decision where to shoot the ball in just a few seconds. Consequently, a penalty-taker is able to change his desired shot direction during his run-up, which is a possible reason why predicting gets hard.

For future research, we could search for different methods to predict the shot direction using our model respectively our calculated probabilities. Moreover, we could investigate whether we find further variables influencing the behavior of the

penalty-taker significantly. Generally, the main limitations of our data is that it is video analyzed manually by a human, which never can be as accurate as when this is done by a computer. Using technology could give further improvements and gives the possibility to investigate further factors like the velocity of the ball or the posture and the line of gaze of the penalty-taker, too.

Moreover, the investigations considering the nested multinomial logit model could be continued. The number of different nests is very high, even though not all potential pairs of alternatives seem to be logically reasonable. Nevertheless, the nested models have advantages, for which further investigations can be interesting.

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References Data Sources

Table 10: List of data sources

area	source
sources regarding player and match facts	www.transfermarkt.de; www.kicker.de; www.sport.de; www.bundesliga.de; www.spox.com; www.fifa.com; www.ran.de; www.sky.de; www.torwart.de; www.eplreview.com; www.iffhs.com; www.weltfussball.de; www.fussballdaten.de
video sources (publisher)[4]	Sportschau.de; Bild.de; Dazn; Sportbild.de; Bundesliga.de; Sky.Sport; DFB.de; official YouTube channels of: (publisher mentioned before; Serie A ; LaLiga Santander; Ligue 1; Premier League; Sky Sport HD; RptimaoTV; Manchester United; Tottenham Hotspurs; AC Milan; FC Bayern München; FC Barcelona; Real Madrid; Liverpool FC; Inter Mailand; SSC Neapel; Paris St.Germain; Lazio Rom; Juventus Turin; Athletico Madrid; AS Rom; FC Porto; Sporting Lissabon; Sport TV; VSPORTS; Sportstudio; Uefa.com; FIFATV; Copa America; CAF TV); YouTube; Dailymotion; VSPORTS

[4] During working and writing on the thesis, some videos used for collecting the data got unavailable online.

Table 11: Variable description I

Variable	Description
ppos	penalty-taker's position. Coding; 0: Goalkeeper, 1: Defender, 2: Midfielder, 3: Striker. The same player has always the same position, even if in a match where the player shoots a penalty he plays on another position. For wingers we decide in the individual case whether striker or midfielder
def	whether penalty-taker is defender or not. Coding; 0:no, 1:yes
mf	whether penalty-taker is midfielder or not. Coding; 0:no, 1:yes
st	whether penalty-taker is striker or not. Coding; 0:no, 1:yes
foot	strong foot of penalty-taker. Coding; 0: Left, 1: Right
Age	Age of penalty-taker, coding type. Coding; 1: age<21, 2: 22, 3: 23, 4: 24, 5: 25, 6: 26, 7: 27, 8: 28, 9: 29, 10: 30, 11: 31, 12: 32, 13: 33, 14: age>33
RepGK	Goalkeeper with great Reputation. Coding; 0: no, 1: yes. Chosen Goalkeeper: Alisson, Barthez, Bravo, Buffon, Carrasso, Casillas, Cech, Consigli, Costil, Courtois, Diego Alves, Donnarumma, Fährmann, Handanovic, Hart, Jimenez, Julio Cesar, Krul, Lloris, Navas, Neuer, Oblak, Rafael, Schmeichel, Simon, Sirigu, Subasic, Szczesny, ter Stegen, Viviano, choice based on article[5] and the choice of the world's best goalkeeper done by the FIFA and IFHHS
HeiGK	Height of Goalkeeper [in cm]. Coding; 1: height<183, 2: 183, 3: 184, 4: 185, 5: 186, 6: 187, 7: 188, 8: 189, 9: 190, 10: 191, 11: 191, 12: 193, 13: 194, 14: 195, 15: 196, 16: height>196
tpos	table position of club of penalty-taker. Coding; 0/NA: no table position available, 1: upper, 2: middle, 3: bottom. upper: approx. upper third of the table ; middle: approx. second third of the table; bottom: approx. down third of the table
tup	whether team of penalty-taker is on a upper place of the table or not. Coding; 0/NA: not available, 1: no, 2: yes
tmid	whether team of penalty-taker is on a middle place of the table or not. Coding; 0/NA: not available, 1: no, 2: yes
tbot	whether team of penalty-taker is on a bottom place of the table or not. Coding; 0/NA: not available, 1: no, 2: yes
otpos	table position of opponent of penalty-taker. Coding; 0/NA: no table position available, 1: upper, 2: middle, 3: bottom. same structure as for "tpos"
oup	whether opponent of penalty-taker is on a upper place of the table or not. Coding; 0/NA: not available, 1: no, 2: yes
omid	whether opponent of penalty-taker is on a middle place of the table or not. Coding; 0/NA: not available, 1: no, 2: yes
obot	whether opponent of penalty-taker is on a bottom place of the table or not. Coding; 0/NA: not available, 1: no, 2: yes

[5] https://www.spox.com/de/sport/fussball/international/1912/Diashows/gehaltene-elfmeter-seit-2010/elfmeterkiller-des-jahrzehnts-dieser-keeper-hielten-die-meisten-elfmeter.html

Table 12: Variable description II

Variable	Description
fav	being favourite or underdog in a match based on league and table position. 1: underdog, 2: same level, 3: slightly favourite, 4: one league higher, 5: two or more leagues higher. As "slightly favourite" we define matches against teams playing in the same league, but the team of the penalty-taker is at least 10 places better in the table than the opponent. This is not valid for matches before the 6th matchday of a season. These matches we assume to have no favourite. A team is an "underdog" if its opponent plays in a higher conference or the opponent is a "slightly favourite". For national teams we derive being a favourite by regarding the official Fifa World Ranking, rank difference 1-30 = no favourite, rank difference 31-60 = slighlty favourite/underdog, rank difference 60-120 is like one league difference, rank difference 120 or higher is like two leagues difference
favU	whether team of penalty-taker is the underdog before kickoff or not. Coding; 0: no, 1: yes
favF	whether team of penalty-taker is the favourite (including fav=3v4v5) before kickoff or not. Coding; 0: no, 1: yes
loc	location of match. Coding; 1: Home, 2: Neutral, 3: Away
locH	whether team of penalty-taker is playing at home or not. Coding; 0: no, 1: yes
locN	whether team of penalty-taker is playing on neutral location or not. Coding; 0: no, 1: yes
locA	whether team of penalty-taker is playing away or not. Coding; 0: no, 1: yes
rnoGroup	whether team of penalty-taker is playing in a group stage match or not. Coding; 0: no, 1: yes
rko	whether team of penalty-taker is playing in a "Last sixteen", in a quarter-final, in a semi-final or final match or not. Coding; 0: no, 1: yes
IngSo	whether penalty is shot in-match or in a penalty shootout. Coding; 0: Ingame, 1: shootout
Min	Minute when penalty given. Coding; 0/NA: shootout/not available, 1: Minute < 16, 2: 15 < Minute < 31, 3: 30 < Minute < 46, 4: 45 < Minute < 61, 5: 60 <Minute < 76 & 90 < Minute < 106, 6: 75 < Minute < 90 & 105 < Minute < 120, 7: Minute = 90 & Minute = 120
Minf3	whether penalty is in the first thirty minutes of match. Coding; 0/NA: not available, 1: no, 2: yes
Mins3	whether penalty is in the second thirty minutes of match. Coding; 0/NA: not available, 1: no, 2: yes
Mint3	whether penalty is in the third thirty minutes of match or in the overtime (not including the 90th and 120th minute). Coding; 0/NA: not available, 1: no, 2: yes
Min90	whether penalty is in the 90th or 120th minute. Coding; 0/NA: not available, 1: no, 2: yes

Table 13: Variable description III

Variable	Description
Imp	Importance of match. Coding; 1: unimportant, 2: normal, 3: important. is derived for each match individually and is determined slightly subjectively. As rule of thumb: each match played in the league, the first three rounds of each "cup" or each match during a group stage have a "normal" importance. Friendly games and the last matchdays of a season or group stage, where the team is not able to win or lose a place in the table are defined as "unimportant". "important": League matches can be important if it is a special match (e.g. against a rival) or if the match is within the last ten matchdays of a season and the team is playing against a direct opponent in the table. Especially matches of the last three matchdays of a season, when a team is playing against relegation or for a place qualifying to the "Champions League" or "Europa League", can be determined as "important", even though the opponent is no direct competition. For each competition using a knockout system, we define each match played in the round of the last sixteen, quarter final, semi final and the final as "important". The importance of qualifications matches we assess depending on three factors: team is already qualified → unimportant , normal qualification match → "normal" importance, qualification match in ko-system or last possible match to qualify → important.
Dec	whether penalty is deciding (based on short time remaining). Coding; 0: no, 1: yes. A "Decider" is in an ingame-match a penalty shot in the 90th minute, which would change the actual result crucially to a draw or to a lead, in case of the penalty is scored. Potential additional time is not investigated for this, meaning the "Decider" is not necessarily the last action of a match and further goals can be scored even after a "Decider". Regarding penalty shootouts there are two cases defining a "Decider". The first case is when the penalty-taker scores the penalty his team is winning the match. The second case is when the penalty-taker is not scoring the penalty, his team is losing the match.
SpecM	whether match is a special match. Coding; 0: no, 1: yes. Based on the opponent team. As Special Match we define matches against the top teams of each league, international top teams, the top national teams and each match known as "derby"[6], where a team is playing against his rival. Teams with * we assume to be international top teams, the rest are top teams of their league, List: FC Bayern München(*), Borussia Dortmund ,Atletico Madrid, FC Barcelona(*), Real Madrid(*), Benfica Lissabon, Sporting Lissabon, Juventus Turin(*), Manchester City(*), Manchester United(*), Liverpool FC(*), Chelsea London, Italy, France, Spain, Germany, Portugal, Brazil, Argentina, England, Netherlands

[6] list of rivals/derbys derived from the video game Football Manager 2021; Developer: Sports Interactive, Publisher: Sega, licenses of overall 29 leagues

Table 14: Variable description IV

Variable	*Description*
iLdbb	actual result when penalty is taken (lead, draw, in behind). Coding; 1: behind by 3 or more (goals), 2: behind by 2, 3: behind by 1; 4: draw, 5: in lead by 1, 6: in lead by 2 or more
bb2	whether team of penalty-taker is actually in deficit by two or more goals. Coding; 0: no, 1: yes
bb1	whether team of penalty-taker is actually in deficit by one goal. Coding; 0: no, 1: yes
d0	whether actual result is a draw. Coding; 0: no, 1 :yes
il1	whether team of penalty-taker is actually in lead by one goal. Coding; 0: no, 1: yes
il2	whether team of penalty-taker is actually in lead by two or more goals. Coding; 0: no, 1: yes
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
moveGK	movement of goalkeeper during run-up of penalty-taker. Coding; 0/NA: not moving/not available, 1: movement to left (including step or jumping to the left and if the goalkeeper's posture is leaned to the left; left from the point of view of the penalty-taker), 2: jumping left and right, 2: jumping on spot, 2: step forward (all get "2", because of not going to a specific side, but goalkeeper is moving), 3: movement to right (it counts the same as for left),
nmovGK	whether goalkeeper is moving during run-up of penalty-taker or not. Coding; 0/NA: not available (18 times in database), 1: moving, 2: not moving.
cjGrey	whether jersey color of goalkeeper is grey or not. Coding; 0: no, 1: yes
cjBlack	whether jersey color of goalkeeper is black or not. Coding; 0: no, 1: yes
cjBlue	whether jersey color of goalkeeper is blue or not. Coding; 0: no, 1: yes
cjGreen	whether jersey color of goalkeeper is green or not. Coding; 0: no, 1: yes
cjYellow	whether jersey color of goalkeeper is yellow or not. Coding; 0: no, 1: yes
cjOrange	whether jersey color of goalkeeper is orange or not. Coding; 0: no, 1: yes
cjRed	whether jersey color of goalkeeper is red or not. Coding; 0: no, 1: yes

Table 15: Variable description V

Variable	Description
ClubNT	shooting penalty for Club or National team. Coding; 0: Club, 1: National team
comLea	whether team of penalty-taker is playing in a "league" match or not. Coding; 0: no, 1: yes
comCup	whether team of penalty-taker is playing in a "cup" match or not. Coding; 0: no, 1: yes
comECC	whether team of penalty-taker is playing in a "Champions League" or "Europa League" match or not. Coding; 0: no, 1: yes
comQuali	whether team of penalty-taker is playing in a qualification match or not. Coding; 0: no, 1: yes
comNTC	whether team of penalty-taker is playing in a "World Cup", "European Championship" or "Copa-America" match or not. Coding; 0: no, 1: yes
la_i	whether last alternative chosen was alternative i or not. Coding; 0/NA: not available, 1: no, 2: yes
lpbg	whether last penalty of penalty-taker was a goal or not. Coding; 0/NA: not available, 1: no, 2: yes
lGKd	goalkeepers dive at last shot penalty. Coding; 1: Left, 2: Center, 3: Right, 0/NA: not available
tlpmon	time since last penalty in month. Coding; 1: 0 month, 2: 1 month, 3: 2 month, 4: 3 month, 5: 4 month, 6: 5 month, 7: 6-12 months, 8: 13-24 months, 9: more than 24 months, 0/NA: not available

Table 16: Variable description VI

$Variable$	$Description$
Stlsbg	whether last shot penalty of the team of the penalty-taker in a penalty shootout was a goal or not. Coding; 0/NA: not available, 1: no, 2: yes
SlGKd	(opposing) goalkeeper's dive at the last penalty of the team of the penalty-taker in a penalty shootout. Coding; 1: Left, 2: Center, 3: Right, 0/NA: not available
Solsbg	whether last shot penalty of the opponent of the penalty-taker in a penalty shootout was a goal or not. Coding; 0/NA: not available, 1: no, 2: yes
$perc_i$	percentage of all previous shot penalties chosen alternative i
$MPGK_i$	probability of shooting the penalty not onto the goal when the ball is shot to alternative i. based on the data set and the (average) height of the goalkeeper [in meter] [7]. formula: $MPGKi = MP_i \cdot (1 + (HeiGK - \overline{HeiGK})$; where MP_i is the miss probability of alternative i and $\overline{HeiGK}$ is the average goalkeeper height, which amounts to 1.90 m.
$SRGK_i$	probability of goalkeeper saving the penalty when the ball is shot to alternative i. based on the data set and the (average) height of the goalkeeper [in meter] [7]. formula: $SRGKi = SR_i \cdot (1 + (HeiGK - \overline{HeiGK}))$; where SR_i is the save probability of alternative i and $\overline{HeiGK}$ is the average goalkeeper height, which amounts to 1.90 m.

[7] Considering our database, we detect that the percentages of Saves and Misses are for goalkeeper, who are taller than the average goalkeeper, higher than for goalkeeper, who are smaller than the average goalkeeper. That is why we include the height into the variables $MPGK_i$ and $SRGK_i$. A further advantage is that now the values are more different for the single penalties.

Table 17: List of players considered

playerposition	player
striker	Agüero, Cavani, Dybala, Griezmann, Haaland, Ibrahimovic, Immobile[10], Kane[10], Lewandowski, Lukaku, Martial, Mbappe, Messi[11], Niang, Oyarzabal, Rashford, Ronaldo, Salah, (Andre) Silva, Suarez, Vardy, Waris
midfielder	Bentaleb, Fekir, Fernandes, Gündogan, Havertz, Hofmann[9], James Rodriguez, Jorginho, Kessie, Ljajic, Modric[8], Müller[9], Parejo, Saul Niguez, Stindl, Vidal
defender	Bensebaini, Brosinski[9], Halstenberg[9], Hummels, Kolarov, Ramos, Telles, Wendell

[8] not all penalties of the player could be found
[9] not all penalties of these players could be video analyzed
[10] some penalties are excluded, since penalty-taker slips during shot
[11] penalty of Messi against Celta Vigo, 14.02.16: Messi is just passing forward, this penalty is excluded from the database

We do not consider penalties, which need to be repeated, since mostly either the goalkeeper or the penalty-taker have created a not allowed advantage for themself. Furthermore, like point [10], we do no consider penalties, where the penalty-taker slips during shot, since the desired shot direction can not be derived with certainty.

I declare that I have authored this thesis independently, that I have not used other than the declared sources / resources, and that I have explicitly marked all material which has been quoted either literally or by content from the used sources.
I declare that this thesis submitted for consideration, or any abridgment thereof, was not used for any other degree seeking purpose.
Magdeburg, 20th September 2021