



ON ELO BASED PREDICTION MODELS FOR THE FIFA WORLD CUP 2018

Lorenz A. Gilch, Sebastian Müller

► To cite this version:

Lorenz A. Gilch, Sebastian Müller. ON ELO BASED PREDICTION MODELS FOR THE FIFA WORLD CUP 2018. 2018. hal-01807199

HAL Id: hal-01807199

<https://hal.science/hal-01807199>

Preprint submitted on 4 Jun 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

ON ELO BASED PREDICTION MODELS FOR THE FIFA WORLD CUP 2018

LORENZ A. GILCH AND SEBASTIAN MÜLLER

ABSTRACT. We propose an approach for the analysis and prediction of a football championship. It is based on Poisson regression models that include the Elo points of the teams as covariates and incorporates differences of team-specific effects. These models for the prediction of the FIFA World Cup 2018 are fitted on all football games on neutral ground of the participating teams since 2010. Based on these models for single matches we use Monte-Carlo simulations to estimate probabilities for reaching the different stages in the FIFA World Cup 2018 for all teams.

We propose two score functions for ordinal random variables that serve together with the rank probability score for the validation of our models with the results of the FIFA World Cups 2010 and 2014. All models favor Germany as the new FIFA World Champion.

All possible courses of the tournament and their probabilities are visualized using a single Sankey diagram.

1. INTRODUCTION

Football is a typical low-scoring game and games are frequently decided through single events in the game. These events may be extraordinary individual performances, individual errors, injuries, refereeing errors or just lucky coincidences. Moreover, during a tournament there are most of the time teams and players that are in exceptional shape and have a strong influence on the outcome of the tournament. One consequence is that every now and then alleged underdogs win tournaments and reputed favorites drop out already in the group phase.

The above effects are notoriously difficult to forecast. Despite this fact, every team has its strengths and weaknesses (e.g. defense and attack) and most of the results reflect the qualities of the teams. In order to model the random effects and the “deterministic” drift forecasts should be given in terms of probabilities.

Among football experts and fans alike there is mostly a consensus on the top favorites, e.g. Brazil, Germany, Spain, and more debate on possible underdogs. However, most of these predictions rely on subjective opinions and are not quantifiable. An additional difficulty is the complexity of the tournament, with billions of different outcomes, making it very difficult to obtain accurate guesses of the probabilities of certain events.

Date: June 4, 2018.

Key words and phrases. FIFA World Cup 2018; football; Poisson regression; score functions, visualization.

A series of statistical models have therefore been proposed in the literature for the prediction of football outcomes. They can be divided into two broad categories. The first one, the result-based model, models directly the probability of a game outcome (win/loss/draw), while the second one, the score-based model, focusses on the match score. We use the second approach since the match score is important in the group phase of the championship and it also implies a model for the first one.

There are several models for this purpose and most of them involve a Poisson model. The easiest model, Lee [19], assumes independence of the goals scored by each team and that each score can be modeled by a Poisson regression model. Bivariate Poisson models were proposed earlier by Maher [21] and extended by Dixon and Coles [10] and Karlis and Ntzoufras [16]. A short overview on different Poisson models and related models like generalised Poisson models or zero-inflated models are given in Zeileis et al. [23] and Chou and Steenhard [2]. Possible covariates for the above models may be divided into two major categories: those containing “prospective” informations and those containing “retrospective” informations. The first category contains other forecasts, especially bookmakers’ odds, see e.g. Leitner et al. [20, 24] and references therein. This approach relies on the fact that bookmakers have a strong economic incentive to rate the result correctly and that they can be seen as experts in the matter of the forecast of sport events. However, their forecast models remain undisclosed and rely on information that is not publicly available. The second category contains only historical data and no other forecasts. Since models based on the second category allow to explicitly model the influence of the covariates, we pursue this approach using regression models for the outcome of single matches. Since the FIFA World Cup 2018 is a more complex tournament, involving for instance effects such as group draws, e.g. see Deutsch [9], and dependences of the different matches, we use Monte-Carlo simulations to forecast the whole course of the tournament. For a more detailed summary on statistical modeling of major international football events we refer to Groll et al. [1] and references therein.

These days a lot of data on possible covariates for the forecast models is available. Groll et al. [1] performed a variable selection on various covariates and found that the three most significant retrospective covariates are the FIFA ranking followed by the number of Champions league and Euro league players of a team. We prefer to consider the Elo ranking instead of the FIFA ranking, since the calculation of the FIFA ranking changed over time and the Elo ranking is more widely used in football forecast models. See also Gásques and Royuela [13] for a recent discussion on this topic and a justification of the Elo ranking. At the time of our analysis the composition and the line ups of the teams have not been announced and hence the two other covariates are not available. This is one of the reasons that our models are solely based on the Elo points and matches of the participating teams on neutral ground since 2010. Our results show that, despite the simplicity of the models, the forecasts are conclusive and give together with the visualization, see Figure 4, a concise idea of the possible courses of the tournament.

We propose four models of Poisson regressions with increasing complexity. The validation of the models involve goodness of fit tests and analysis of residuals and AIC. Moreover, we validate the models on the FIFA Worldcups 2010 and 2014. This turned out to be a challenging task and the approach we propose here can only be considered as a first step.

A first difficulty is that every outcome of each single match is modeled as $G_A:G_B$, where G_A (resp. G_B) is the number of goals of team A (resp. of team B). To our knowledge there is no established score function for such kind of pairs of random variables. Even for the easier game outcome (win/loss/draw) there seems not to be a well established candidate for a good score function. However, the ranked probability skill score (RPS) is a natural and promising candidate; we refer to Constantinou et al. [5] for a discussion on this topic. So much the worse we forecast not only a single match but the course of the whole tournament. Even the most probable tournament outcome has a probability, very close to zero to be actually realized. Hence, deviations of the true tournament outcome from the model's most probable one are not only possible, but most likely. However, simulations of the tournament yield estimates of the probabilities for each team for reaching the different stages of the tournament. In this way we obtain for each team an ordinal random variable. For this variable we propose two new score functions and compare them to the RPS and the Brier score.

The models show a good fit and the score function on the validation on the FIFA World-cups 2010 and 2014 are very close to each other. This may be surprising since the actual probabilities that a given team wins the cup may be significantly different. However, all models favor Germany (followed by Brazil) to win the FIFA Worldcup 2018.

2. THE MODELS

Our models are based on the World Football Elo ratings of the teams. It is based on the Elo rating system, see Elo [11], but includes modifications to take various football-specific variables into account. The Elo ranking is published by the website [eloratings.net](http://www.eloratings.net). The Elo ratings as they were on 28 march 2018 for the top 5 nations (in this rating) are as follows:

Brazil	Germany	Spain	Argentina	France
2131	2092	2048	1985	1984

In the next sections we present several models in *increasing* complexity. They forecast the outcome of a match between teams A and B as $G_A : G_B$, where G_A (resp. G_B) is the number of goals scored by team A (resp. B). The models are based on Poisson regression models. In these models we assume (G_A, G_B) to be a bivariate Poisson distributed random variable; see Section 8 for a discussion on other underlying distributions for G_A and G_B . The distribution of (G_A, G_B) will depend on A and B , and the Elo rankings Elo_A and Elo_B of the two teams. The models are fitted using all matches of FIFA World Cup 2018 participating teams on *neutral* playground between 1.1.2010 and 31.12.2017; see Section 8 for a discussion why we dropped other games.

All models are key ingredients in order to simulate the whole tournament and to determine the likelihood of the success for each participant.

2.1. Independent Poisson regression model. In this model we assume both G_A and G_B to be independent Poisson distributed variables with rates $\lambda_{A|B}$ and $\lambda_{B|A}$. We estimate the Poisson rates $\lambda_{A|B}$ and $\lambda_{B|A}$ via Poisson regression with the Elo scores of A and B as

covariates. Poisson regression models are performed for every team in order to incorporate team specific strengths (attack and defense). The rates are calculated as follows:

- (1) The first step models the number of goals \tilde{G}_A scored by team A playing against a team with a given Elo score $\text{Elo} = \text{Elo}_B$. The random variable \tilde{G}_A is modeled as a Poisson distribution with parameter μ_A . The parameter μ_A as a function of the Elo rating Elo_O of the opponent O is given as

$$\log \mu_A(\text{Elo}_O) = \alpha_0 + \alpha_1 \cdot \text{Elo}_O, \quad (2.1)$$

where α_0 and α_1 are obtained via Poisson regression.

- (2) Teams of similar Elo scores may have different strengths in attack and defense. To take this effect into account we model the number of goals team B receives against a team of Elo score $\text{Elo} = \text{Elo}_A$ using a Poisson distribution with parameter ν_B . The parameter ν_B as a function of the Elo rating Elo_O is given as

$$\log \nu_B(\text{Elo}_O) = \beta_0 + \beta_1 \cdot \text{Elo}_O, \quad (2.2)$$

where the parameters β_0 and β_1 are obtained via Poisson regression.

- (3) Team A shall in average score $\mu_A(\text{Elo}_B)$ goals against team B , but team B shall have $\nu_B(\text{Elo}_A)$ goals against. As these two values rarely coincide we model the numbers of goals G_A as a Poisson distribution with parameter

$$\lambda = \lambda_{A|B} = \frac{\mu_A(\text{Elo}_B) + \nu_B(\text{Elo}_A)}{2}.$$

Analogously, we obtain

$$\lambda_{B|A} = \frac{\mu_B(\text{Elo}_A) + \nu_A(\text{Elo}_B)}{2}.$$

For each team, the regression parameters $\alpha_0, \alpha_1, \beta_0$ and β_1 are estimated. The match A versus B is then simulated using two independent Poisson random variables G_A and G_B with rates $\lambda_{A|B}$ and $\lambda_{B|A}$.

2.1.1. Regression plots. As two examples of interest, we sketch in Figure 1 the results of the regression in (2.1) for Germany and Brazil. The dots show the observed data (i.e., number of scored goals on the y -axis in dependence of the opponent's strength on the x -axis) and the line is the estimated mean depending on the opponent's Elo strength.

Analogously, Figure 2 sketches the regression in (2.2) for Germany and Brazil. The dots show the observed data (i.e., the number of goals against) and the line is the estimated mean for the number of goals against.

2.1.2. Goodness of fit test. We check goodness of fit of the Poisson regressions in (2.1) and (2.2) for all participating teams. For each team \mathbf{T} we calculate the following χ^2 -statistic from the list of matches:

$$\chi_{\mathbf{T}} = \sum_{i=1}^{n_{\mathbf{T}}} \frac{(x_i - \hat{\mu}_i)^2}{\hat{\mu}_i},$$

where $n_{\mathbf{T}}$ is the number of matches of team \mathbf{T} , x_i is the number of scored goals of team \mathbf{T} in match i and $\hat{\mu}_i$ is the estimated Poisson regression mean.

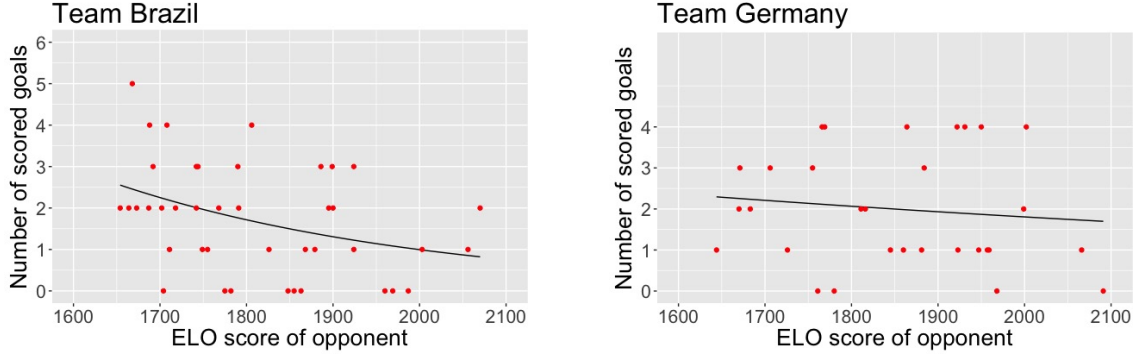


FIGURE 1. Plots for the number of goals scored by Brazil and Germany in regression (2.1).

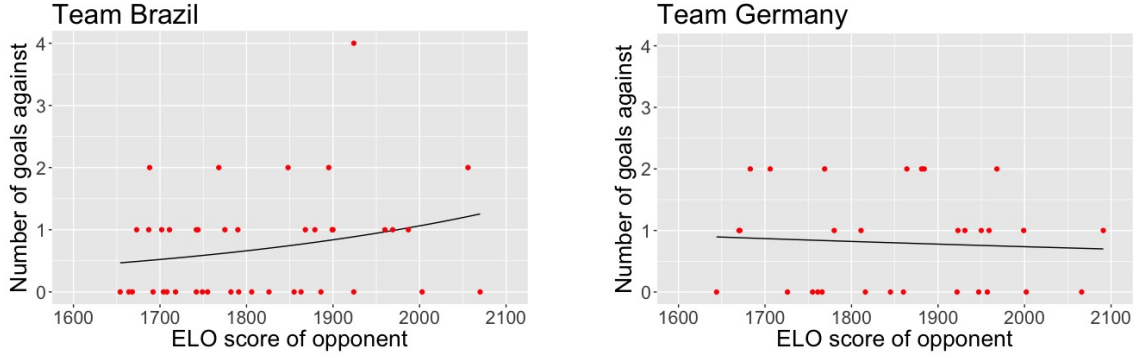


FIGURE 2. Plots for the number of goals against for Brazil and Germany in regression (2.2).

We observe that most teams have a good fit, except some teams of less impact and France. We have found out that the bad fit of France is also a consequence of the bad and chaotic performance during the World Cup 2010. Therefore, we considered only French matches after 01.01.2012 but have also taken the matches of the EURO 2016 (held in France) into account when fitting the parameters of France. As an consequence the regression plots in Figure 3 promise an acceptable fit. The p -values for the top 5 teams are given in Table 1. We remark that without the specific adaption for France we would get a p -value of 0.0011 for France.

Team	Brazil	Germany	Spain	Argentina	France
p-value	0.56	0.39	0.40	0.14	0.03

TABLE 1. Goodness of fit test for the independent Poisson regression model defined in Section 2.1 for the top five teams.

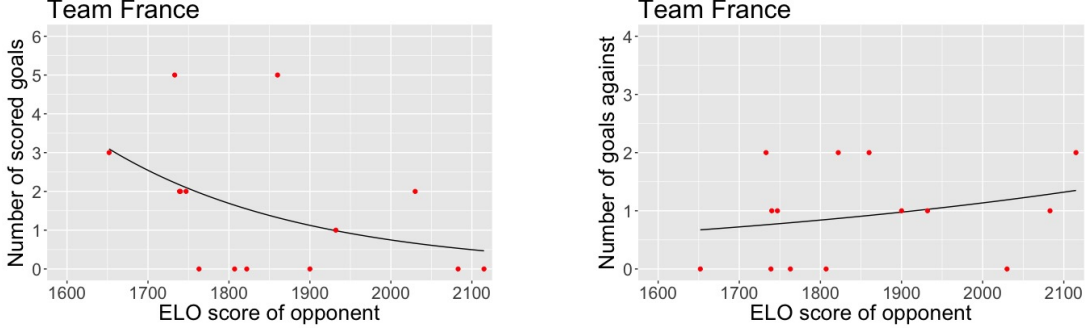


FIGURE 3. Regression plots of France for the number of goals scored and goals against in regressions (2.1) and (2.2).

2.1.3. *Deviance analysis.* First, we calculate the null and residual deviances for each team for the regression in (2.1). Table 2 shows the deviance values and the p -values for the residual deviance for the top five teams in the current Elo ranking. Although several of the p -values are low, they are still acceptable.

Team	Null deviance	Residual deviance	p-value
Brazil	65.03	50.04	0.21
Germany	41.83	34.99	0.20
Spain	54.83	38.89	0.26
Argentina	59.65	47.19	0.10
France	30.08	25.66	0.019

TABLE 2. Deviance analysis for the top five teams in regressions (2.1)

The deviances and the p -values for the regression in (2.2) are given in Table 3.

Team	Null deviance	Residual deviance	p-value
Brazil	48.06	45.98	0.35
Germany	31.69	31.48	0.34
Spain	49.65	46.93	0.07
Argentina	52.49	51.68	0.04
France	14.81	13.50	0.41

TABLE 3. Deviance analysis for the top five teams in regressions (2.2)

2.2. Bivariate Poisson regression model. The possible weakness of the previous model is that the number of goals G_A and G_B are realized independently and the fits in Tables 2 and 3 are not overwhelming. In this section we make a bivariate Poisson regression approach. First, recall the definition of a *bivariate Poisson* distribution: let X_1, X_2, X_0 be *independent* Poisson distributed random variables with rates $\lambda_1, \lambda_2, \lambda_0$. Define $Y_1 =$

$X_1 + X_0$ and $Y_2 = X_2 + X_0$. Then (Y_1, Y_2) is *bivariate* Poisson distributed with parameters $(\lambda_1, \lambda_2, \lambda_0)$. In particular, Y_i is Poisson distributed with rate $\lambda_i + \lambda_0$ and $\text{Cov}(Y_1, Y_2) = \lambda_0$.

The plan is to model (G_A, G_B) as a bivariate Poisson distributed random vector for every couple A, B separately (in order to keep each participants individual strengths). The main idea is two perform one regression over all matches of team A and to estimate the average number of goals of team A and its opponent in terms of his Elo strength Elo_B . Then we perform another regression over all matches of team B and estimate the expected number of goals of B and the average goals against of B when playing against a team of Elo rank Elo_A . Hereby, we use the same notation as in Section 2.1 with $\mu_{\mathbf{T}}$ being the Poisson rate for the average of scored goals of any team \mathbf{T} , while $\nu_{\mathbf{T}}$ is the average number of goals against of team \mathbf{T} . The model uses the following regression approach.

- (1) For each World Cup participating team \mathbf{T} , we estimate the parameters $(\lambda_1, \lambda_2, \lambda_0) = (\mu_{\mathbf{T}}, \nu_{\mathbf{T}}, \tau_{\mathbf{T}})$ from the viewpoint of team \mathbf{T} , where we only take matches of team \mathbf{T} on neutral playground into account. The parameters shall depend on the Elo strength $\text{Elo}_{\mathbf{O}}$ of an opponent team \mathbf{O} . To this end, we use the following Poisson regression model:

$$\begin{aligned} \log \mu_{\mathbf{T}}(\text{Elo}_{\mathbf{O}}) &= \alpha_{1,0} + \alpha_{1,1} \text{Elo}_{\mathbf{O}}, \\ \log \nu_{\mathbf{T}}(\text{Elo}_{\mathbf{O}}) &= \alpha_{2,0} + \alpha_{2,1} \text{Elo}_{\mathbf{O}}, \\ \log \tau_{\mathbf{T}}(\text{Elo}_{\mathbf{O}}) &= \alpha_{3,0} \end{aligned} \tag{2.3}$$

That is, the estimated expected number of scored goals of team \mathbf{T} against a team of Elo strength $\text{Elo}_{\mathbf{O}}$ is given by $\mu_{\mathbf{T}}(\text{Elo}_{\mathbf{O}}) + \tau_{\mathbf{T}}$, while the estimated expected number of scored goals of a team with Elo score $\text{Elo}_{\mathbf{O}}$ against \mathbf{T} is given by $\nu_{\mathbf{T}}(\text{Elo}_{\mathbf{O}}) + \tau_{\mathbf{T}}$.

- (2) In order to estimate the Poisson rates $(\lambda_1, \lambda_2, \lambda_0)$ for the match result (G_A, G_B) we can use the regression coefficients both of A and B in the following way: λ_1 may be estimated either by considering all matches of team A and calculating $\mu_A(\text{Elo}_B)$ or by considering all matches of team B and calculating $\nu_B(\text{Elo}_A)$, which corresponds to the goals against of team B (that is, the number of scored goals of team A against B). Therefore, we estimate λ_1 as the mean of $\mu_A(\text{Elo}_B)$ and $\nu_B(\text{Elo}_A)$. Analogously, we estimate λ_2 as the mean of $\mu_B(\text{Elo}_A)$ and $\nu_A(\text{Elo}_B)$ and λ_0 also as the mean of the covariances τ_A and τ_B . That is,

$$\begin{aligned} \lambda_1 &= \frac{\mu_A(\text{Elo}_B) + \nu_B(\text{Elo}_A)}{2}, \\ \lambda_2 &= \frac{\mu_B(\text{Elo}_A) + \nu_A(\text{Elo}_B)}{2}, \\ \lambda_0 &= \frac{\tau_A(\text{Elo}_B) + \tau_B(\text{Elo}_A)}{2}, \end{aligned}$$

- (3) Finally, we assume that (G_A, G_B) is bivariate Poisson distributed with parameters $(\lambda_1, \lambda_2, \lambda_0)$.

Remark: In (2.3) we estimate $\tau_{\mathbf{T}}$ to be a constant for each team. Of course, one can also let $\tau_{\mathbf{T}}$ depend on the opponent's Elo score $\text{Elo}_{\mathbf{O}}$, that is,

$$\log \tau_{\mathbf{T}}(\text{Elo}_{\mathbf{O}}) = \alpha_{3,0} + \alpha_{3,1} \text{Elo}_{\mathbf{O}}.$$

Calculations, however show that the AIC increases by adding the covariate $\text{Elo}_{\mathbf{O}}$ for most of the teams. The same observation is made if we add $\text{Elo}_{\mathbf{T}}$ as an additional covariate.

2.3. Bivariate Poisson regression with diagonal inflation. We consider the previous model with additional diagonal inflation. Such models are quite useful when one expects diagonal combinations with higher probabilities than the ones fitted under a bivariate Poisson model. In particular, it has been observed earlier, e.g. see [16, 17], that the number of draws is in some situation larger than those predicted by a simple bivariate Poisson model. We inflate the diagonal with probability p . The inflation is given by the vector $(\theta_0, \theta_1, \theta_2)$ that describes the probability of the match results 0:0, 1:1 and 2:2. We compare the AIC of the diagonal inflated model with the non-inflated model, see Table 4 for the five top teams. The values of the inflation probability are close to zero. Despite the fact that the AIC decreases for almost all teams we do not believe that the inflated model improves the forecast. This observation is also supported by the results in Tables 7 and 10.

Team	p	θ_0	θ_1	θ_2	AIC inflated	AIC not inflated
Brazil	0.01	0.00	0.00	1.00	251.56	257.40
Germany	0.01	0.00	0.00	1.00	186.19	192.18
Spain	0.00	0.00	0.00	1.00	215.06	221.06
Argentina	0.02	0.00	0.00	1.00	230.97	236.56
France	0.03	1.00	0.00	0.00	93.53	99.46

TABLE 4. Diagonal inflated bivariate Poisson regression for the top five teams.

2.4. Nested Poisson regression model. We now present another *dependent* Poisson regression approach. The Poisson rates $\lambda_{A|B}$ and $\lambda_{B|A}$ are now determined as follows:

- (1) We always assume that A has higher Elo score than B . This assumption can be justified, since usually the better team dominates the weaker team's tactics. Moreover the number of goals the stronger team scores has an impact on the number of goals of the weaker team. For example, if team A scores 5 goals it is more likely that B scores also 1 or 2 goals, because the defense of team A lacks in concentration due to the expected victory. If the stronger team A scores only 1 goal, it is more likely that B scores no or just one goal, since team A focusses more on the defence and secures the victory.
- (2) The Poisson rate for G_A is determined as in Section 2.1 before by

$$\lambda_{A|B} = \frac{\mu_A(\text{Elo}_B) + \nu_B(\text{Elo}_A)}{2},$$

which is obtained via Poisson regression.

- (3) The number of goals G_B scored by B is assumed to depend on the Elo score $E_A = \text{Elo}_A$ and additionally on the outcome of G_A . More precisely, G_B is modeled as a Poisson distribution with parameter $\lambda_B(E_A, G_A)$ satisfying

$$\log \lambda_B(E_A, G_A) = \gamma_0 + \gamma_1 \cdot E_A + \gamma_2 \cdot G_A. \quad (2.4)$$

Once again, the parameters $\gamma_0, \gamma_1, \gamma_2$ are obtained by Poisson regression. Hence,

$$\lambda_{B|A} = \lambda_B(E_A, G_A).$$

- (4) The result of the match A versus B is simulated by realizing G_A first and then realizing G_B in dependence of the realization of G_A .

This approach may also be justified through the definition of conditional probabilities:

$$\mathbb{P}[G_A = i, G_B = j] = \mathbb{P}[G_A = i] \cdot \mathbb{P}[G_B = j \mid G_A = i] \quad \forall i, j \in \mathbb{N}_0.$$

We are not aware of other validation methods for this model than the validation on historical data. Tables 7 and 10 indicate that this model may indeed have the best fit.

3. SCORE FUNCTIONS

In the following we want to compare the predictions with actual results of the two previous FIFA World Cups. For this purpose, we introduce the following notation. For a team \mathbf{T} we define:

$$\text{result}(\mathbf{T}) = \begin{cases} 1, & \text{if } \mathbf{T} \text{ was FIFA World Cup winner,} \\ 2, & \text{if } \mathbf{T} \text{ lost the final,} \\ 3, & \text{if } \mathbf{T} \text{ dropped out in semifinal,} \\ 4, & \text{if } \mathbf{T} \text{ dropped out in quarterfinal,} \\ 5, & \text{if } \mathbf{T} \text{ dropped out in round of last 16,} \\ 6, & \text{if } \mathbf{T} \text{ dropped out in round robin.} \end{cases}$$

For example, in 2014 we have $\text{result}(\text{Germany}) = 1$, $\text{result}(\text{Argentina}) = 2$, $\text{result}(\text{Brazil}) = 3$ or $\text{result}(\text{Italy}) = 6$. We consider the variable result as a ordinal variable, since for instance predicting Germany to drop out in round robin should be penalized more than predicting that Germany loses the final. We choose a linear scaling, i.e. the values 1, 2, 3, 4, 5, 6, since there is always one match between the different rounds. Score functions for ordinal variables are, to the best of our knowledge, not well studied. We refer to [5] for a discussion on this topic. We propose two new score functions and compare them with the Brier score and the Rank-Probability-Score (RPS). For each model, the simulation leads to a probability distribution given by $p_j(\mathbf{T}) = \mathbb{P}[\text{result}(\mathbf{T}) = j]$, $j \in \{1, \dots, 6\}$, for the result of each team \mathbf{T} . The following score functions measure and compare the forecasts with the real outcome.

- (1) **Maximum-Likelihood-Score:** The error of team \mathbf{T} is defined as

$$\text{error}_1(\mathbf{T}) = \left| \text{result}(\mathbf{T}) - \underset{i=1, \dots, 6}{\operatorname{argmax}} p_i(\mathbf{T}) \right|.$$

The total error score is given by summing up the errors of all World Cup participating teams:

$$E_1 = \sum_{\mathbf{T}} \text{error}_1(\mathbf{T}).$$

(2) **Weighted differences:** The error of team \mathbf{T} is defined as

$$\text{error}_2(\mathbf{T}) = \sum_{j=1}^6 p_j(\mathbf{T}) |j - \text{result}(\mathbf{T})|.$$

The total error score is given by

$$E_2 = \sum_{\mathbf{T}} \text{error}_2(\mathbf{T}).$$

(3) **Brier Score:** The error of team \mathbf{T} is defined as

$$\text{error}(\mathbf{T})_3 = \sum_{j=1}^6 (p_j(\mathbf{T}) - \mathbb{1}_{[\text{result}(\mathbf{T})=j]})^2.$$

The total error score is given by

$$BS = \sum_{\mathbf{T}} \text{error}_3(\mathbf{T}).$$

(4) **Rank-Probability-Score (RPS):** The error of team \mathbf{T} is defined as

$$\text{error}_4(\mathbf{T}) = \frac{1}{5} \sum_{i=1}^5 \left(\sum_{j=1}^i p_j(\mathbf{T}) - \mathbb{1}_{[\text{result}(\mathbf{T})=j]} \right)^2.$$

The total error score is given by

$$RPS = \sum_{\mathbf{T}} \text{error}_4(\mathbf{T}).$$

We note that the dependence of the different outcomes of the teams penalizes exceptional outcomes as underdogs wins and early drop outs of favorites.

4. VALIDATION OF MODELS ON FIFA WORLD CUP 2014 RESULTS

In this section we test the different models from the previous section on the FIFA World Cup 2014 data. For this purpose, we take into account all matches between 01.01.2002 and the beginning of the tournament of all participants on *neutral playground*. We remark that it was necessary to take historical match data up to 12 years before the tournament due to lack of enough matches for reasonable fits (e.g, the regression for Belgium matches was not satisfying). We simulate the whole tournament according to the FIFA rules, that is, at the end of the group stage the final group table is evaluated according to the FIFA rules (except Fair-Play criterion). Additional, after each game the Elo scores of the teams are updated. Furthermore, the score of a match which goes into extra time is simulated with the same Poisson rates as for a match of 90 minutes but with rates divided by 3 (extra time is 30 minutes = 90 minutes / 3). For each model 100.000 simulations are performed.

The simulation results are given in the following form. For each team we estimate the probability that the team reaches a certain round or wins the tournament. For instance,

Team	World Champion	Final	Semi	Quarter	R16	Prelim. Round
Brazil	20.30	30.30	40.30	54.80	86.10	13.90

means that Brazil wins the cup with a probability of 20.30%, reaches the final with probability 30.30%, the semifinals with probability 40.30% etc. The last column gives the probability to drop out in the group phase. For each team we mark in bold type the round where the team actually dropped out. Results for independent Poisson regression and the nested regression model may be found in Tables 5 and 6. The tables for the other models can be found in Appendix 10.1.

	Team	World Champion	Final	Semi	Final	R16	Prelim. Round
1	Spain	21.80	32.50	42.20	58.40	88.40	11.60
2	Brazil	20.30	30.30	40.30	54.80	86.10	13.90
3	Germany	11.90	23.80	51.20	69.70	85.20	14.80
4	Netherlands	7.70	14.60	23.10	37.50	71.50	28.50
5	Portugal	5.50	12.90	30.10	48.10	67.90	32.10
6	Argentina	5.10	13.90	36.90	65.60	92.10	7.90
7	England	4.10	9.40	17.20	43.30	69.20	30.80
8	Uruguay	3.80	8.50	15.90	40.10	66.70	33.30
9	Italy	2.20	5.20	10.40	28.10	52.20	47.80
10	Russia	2.10	5.70	15.30	29.30	73.80	26.20
11	Colombia	1.90	4.70	9.80	27.80	59.20	40.80
12	France	1.90	4.70	12.10	28.50	57.80	42.20

TABLE 5. FIFA World Cup 2014 prediction via independent Poisson regression

	Team	World Champion	Final	Semi	Quarter	R16	Prelim. Round
1	Brazil	20.00	28.50	36.80	51.40	81.30	18.70
2	Spain	16.70	26.20	35.10	51.50	85.10	14.90
3	Germany	13.50	25.10	51.10	67.60	84.50	15.50
4	Netherlands	8.80	15.90	24.80	40.10	74.10	25.90
5	Argentina	8.10	19.30	44.00	71.50	92.90	7.10
6	Uruguay	6.00	12.20	21.80	47.60	73.20	26.80
7	England	4.20	9.50	18.00	43.70	69.60	30.40
8	Russia	3.20	7.70	17.80	32.70	70.90	29.10
9	Portugal	2.70	8.20	21.70	38.60	58.20	41.80
10	Colombia	2.00	4.90	10.20	27.40	61.10	38.90

TABLE 6. FIFA World Cup 2014 prediction via nested Poisson regression

The Elo ratings as they were on 11 june 2014 for the top 5 nations (in this rating) are as follows:

Brazil	Spain	Germany	Argentina	Netherlands
2113	2086	2046	1989	1959

We clearly see that the forecasts correspond roughly to the Elo ranking, but the different modeling of team specific strengths changes the ordering of the teams slightly. Moreover, certain probabilities differ significantly in the different models. For example, Spain wins the cup with probability 21.80% in the independent regression model but only with probability 16.70% in the nested regression model. We also see that the early drop out of Italy was not so surprising after all.

In Table 7 we compare the different models by calculating the different scores from Section 3. The nested Poisson regression scores best for the E_1 score, Brier score and RPS. The E_2 score favors slightly the bivariate model.

Models	E_1	E_2	Brier	RPS
Independent Poisson regression	26	34.65	22.10	5.48
Nested Poisson regression	25	34.32	21.89	5.42
Bivariate Poisson regression	28	34.16	22.33	5.52
Diagonal Inflated Bivariate Poisson regression	26	34.68	22.13	5.48

TABLE 7. Scores for the FIFA World Cup 2014 simulations

5. VALIDATION OF MODELS ON FIFA WORLD CUP 2010 RESULTS

The simulations for the FIFA World Cup 2010 are done as in the previous section, but using data between 01.01.2000 and the beginning of the championship.

Results for the independent regression model and the nested regression model are given in Tables 8 and 9. The tables for the other models can be found in Appendix 10.2.

	Team	World Champion	Final	Semi	Quarter	R16	Prelim. Round
1	Brazil	25.50	34.10	45.10	61.60	78.60	21.40
2	Netherlands	15.00	24.40	36.40	67.30	87.70	12.30
3	Spain	11.20	23.00	32.90	49.80	90.90	9.10
4	England	7.80	15.50	34.30	57.80	85.10	14.90
5	Portugal	5.80	13.40	22.70	38.60	69.10	30.90
6	Italy	4.80	11.20	19.90	48.40	86.90	13.10
7	France	4.80	9.00	18.00	31.50	58.40	41.60
8	Argentina	3.50	10.50	28.70	51.80	86.60	13.40
9	Uruguay	3.30	6.80	15.20	28.80	55.80	44.20
10	South Korea	2.70	5.40	11.40	22.40	45.20	54.80
11	Germany	2.30	9.80	33.60	64.80	93.00	7.00

TABLE 8. FIFA World Cup 2010 prediction via independent Poisson regression

	Team	World Champion	Final	Semi	Quarter	R16	Prelim. Round
1	Brazil	19.70	27.60	38.40	54.90	69.30	30.70
2	Spain	14.70	26.80	36.80	51.80	94.40	5.60
3	Netherlands	14.60	23.90	37.30	65.10	87.60	12.40
4	England	7.00	14.60	32.80	57.80	86.20	13.80
5	Uruguay	6.40	11.70	21.50	36.60	62.90	37.10
6	France	4.70	8.70	16.20	28.50	52.30	47.70
7	Portugal	4.30	10.10	18.40	32.20	60.50	39.50
8	Italy	4.00	9.80	19.70	50.90	89.80	10.20
9	South Korea	3.90	7.10	13.20	25.50	52.40	47.60
10	Argentina	3.70	9.80	26.50	48.00	84.20	15.80

TABLE 9. FIFA World Cup 2010 prediction via nested Poisson regression

The Elo ratings as they were on 11 june 2010 for the top 5 nations (in this rating) are as follows:

Brazil	Spain	Netherlands	England	Germany
2087	2085	2016	1975	1929

The early drop out of Brazil may be unlikely at first sight, but at second sight seems not so surprising since they lost against the Netherlands in the quarter final. The forecast of Germany becoming world champion is remarkably low in all models. This reflects the influence of the course of the tournament since Germany played against England in R16, Argentina in the quarters and Spain in the semi finals. Interesting to note that the early drop out of France had already a high probability. Knowing this “le fiasco de Knysna” may have been avoided.

The error scores for the World Cup 2010 tournament are given in Table 10. Again the nested Poisson regression scores best, now even for all four score functions.

Models	E_1	E_2	Brier	RPS
Independent Poisson regression	25	30.97	17.97	5.05
Nested Poisson regression	24	30.50	17.51	4.93
Bivariate Poisson regression	25	33.04	17.97	4.99
Diagonal Inflated Bivariate Poisson regression	25	31.49	17.96	5.08

TABLE 10. Scores for FIFA World Cup 2010

Remarks: In order to avoid a degenerate behaviour and a bad fit of our models we had to do the following adaptations:

- For the nested Poisson regression model for Slovenia only matches against other participants were used.
- For the bivariate Poisson regression model for Germany, we have taken into account also the matches of Germany during the World Cup 2006 (held in Germany).

- The matches of Serbia include also the matches of former “Yugoslavia” and “Serbia and Montenegro” before the year 2006, in which Serbia started its own national team.

6. WORLD CUP 2018 SIMULATIONS

We simulate the whole tournament 100.000 times for each model as described in Section 4. The models are fitted on matches of all participants on neutral ground since 01.01.2010. For France we consider only matches after 01.01.2012 and include also the matches of the EURO 2016; compare with Section 2.1.2. The results are presented in Tables 11, 12, 13 and 14. The regression models coincide in the order of the first four favorites for the cup. In particular, they favor Germany and not Brazil. However, single probabilities may be quite different. For instance, Germany is estimated to win the cup with 26.00% in the independent Poisson regression model and with 30.50% in the nested Poisson regression model. The circumstance that all models do favor Germany and not Brazil may depend on team specific effects and the following fact. If both Germany and Brazil win their group they will meet only in the final. Now, if Germany reaches the final it more likely won against stronger teams and therefore is likely to have higher Elo ranking in the final than Brazil. This underlines the importance of the dynamic Elo updating in the simulations.

	Team	World Champion	Final	Semi	Quarter	R16	Prelim. Round
1	Germany	26.00	36.50	52.10	68.80	92.50	7.40
2	Brazil	13.20	26.00	41.00	57.70	88.30	11.70
3	Spain	11.20	21.30	41.50	68.60	84.90	15.30
4	Argentina	9.20	16.70	31.90	53.60	84.50	15.50
5	Colombia	7.00	13.20	24.10	49.70	75.10	24.90
6	Portugal	5.90	13.30	28.80	53.80	73.90	26.20
7	France	5.30	12.40	26.00	46.60	79.70	20.30
8	Peru	4.30	9.20	19.00	35.80	67.70	32.30
9	Belgium	3.60	9.40	19.50	48.20	85.40	14.80
10	Poland	2.80	6.30	13.70	33.20	59.80	40.20

TABLE 11. World Cup 2018 prediction via independent Poisson regression

	Team	World Champion	Final	Semi	Quarter	R16	Prelim. Round
1	Germany	30.50	41.80	57.70	74.30	92.10	7.90
2	Brazil	18.30	33.60	46.20	61.90	93.20	6.70
3	Spain	13.90	24.80	47.50	70.80	90.00	10.10
4	Argentina	8.30	16.20	32.30	57.10	86.20	13.80
5	Colombia	4.30	9.40	19.30	45.00	73.40	26.60
6	Portugal	3.90	11.00	27.40	52.00	75.90	24.10
7	France	3.40	10.10	25.10	46.70	78.90	21.20
8	Belgium	3.00	8.70	18.70	50.40	83.10	16.80
9	Russia	2.80	5.30	10.40	21.50	49.00	51.00
10	England	2.60	6.70	15.30	43.60	75.80	24.40

TABLE 12. World Cup 2018 prediction via nested Poisson regression

	Team	World Champion	Final	Semi	Quarter	R16	Prelim. Round
1	Germany	26.90	37.30	52.30	70.70	93.20	6.80
2	Brazil	13.00	26.00	40.10	59.80	89.70	10.30
3	Spain	11.20	21.20	41.70	69.20	86.20	13.90
4	Argentina	9.60	17.30	33.60	56.30	88.20	11.90
5	Colombia	8.40	15.30	27.80	59.10	82.20	17.80
6	France	5.20	12.60	27.90	49.20	81.80	18.30
7	Portugal	5.20	13.00	28.90	53.70	76.00	24.10
8	Belgium	3.90	10.60	22.40	55.90	89.70	10.40
9	Peru	3.90	8.80	19.00	36.00	68.50	31.40
10	England	2.10	4.90	11.70	31.40	76.70	23.20

TABLE 13. World Cup 2018 prediction via bivariate Poisson regression

	Team	World Champion	Final	Semi	Quarter	R16	Prelim. Round
1	Germany	25.80	36.10	51.00	68.70	91.40	8.60
2	Brazil	12.30	24.30	38.50	57.00	89.60	10.30
3	Spain	11.20	20.90	40.40	66.60	85.70	14.30
4	Argentina	9.60	17.20	33.00	55.00	86.70	13.10
5	Colombia	7.60	14.10	26.30	55.50	81.00	18.90
6	Portugal	5.20	12.40	27.60	51.70	75.60	24.30
7	France	5.00	11.60	24.80	44.30	75.40	24.60
8	Belgium	3.90	10.50	21.90	53.90	87.10	12.90
9	Peru	3.70	8.50	18.20	35.20	67.50	32.50
10	England	2.20	4.60	10.00	26.40	59.30	40.70

TABLE 14. World Cup 2018 prediction via diagonal inflated Poisson regression

7. SANKEY

We present the simulation results of the nested Poisson regression model in a Sankey diagram, see Figure 4. The width of the edges correspond to the probabilities of reaching stages in the tournament.

8. DISCUSSION

In this section we want to give some quick discussion about the used Poisson models and related models. Of course, the Poisson models we used are not the only natural candidates for modeling football matches. Multiplicative mixtures may lead to overdispersion. Thus, it is desirable to use models having a variance function which is flexible enough to deal with overdispersion and underdispersion. One natural model for this is the *generalised Poisson model*, which was suggested by Consul [8]. We omit the details but remark that this distribution has an additional parameter φ which allows to model the variance as λ/φ^2 ; for more details on generalised Poisson regression we refer to Stekler [22] and Erhard [12]. Estimations of φ by generalised Poisson regression lead to the observation that φ is close to 1 for the most important teams. Therefore, no additional gain is given by the use of the generalised Poisson model.

Another related candidate for the simulation of football matches is given by the *negative binomial distribution*, where also another parameter comes into play to allow a better fit. However, the same observations as in the case of the generalised Poisson model can be made, that is, the estimates of the additional parameter lead to a model which is almost just a simple Poisson model. We refer to Joe and Zhu [15] for a detailed comparison of generalized Poisson distribution and negative Binomial distribution.

A potential problem may rely in the fact that there are not sufficiently many matches for each team during the last eight years. This relies, in particular, on the fact that we considered only matches on *neutral* playground. Of course, it is possible to include also matches from the qualifier rounds for the international tournaments. We followed this approach and, in order to weight home advantages/away disadvantages, we introduced another categorical covariate L for the “home advantage” which lead to the following regression model extending (2.1) and (2.2):

$$\begin{aligned}\log \mu_A(\text{Elo}_{\mathbf{O}}) &= \alpha_0 + \alpha_1 \cdot \text{Elo}_{\mathbf{O}} + \alpha_2 \cdot L, \\ \log \nu_B(\text{Elo}_{\mathbf{O}}) &= \beta_0 + \beta_1 \cdot \text{Elo}_{\mathbf{O}} + \beta_2 \cdot L,\end{aligned}$$

where $L = 1$ if A plays at home, $L = -1$ if B plays at home, and $L = 0$ if the match is on neutral playground.

Using this regression approach leads, however, to effects that hide the team’s real strength in tournaments. In numbers, almost every team has then a probability between 2% and 6% of winning the World Cup, which obviously makes no sense. This in turn leads to the conclusion that matches during championships behave different than typical matches in the qualifier round.

We did not study the robustness of our models rigorously. However, we observed that the regressions models tend to be rather sensitive to the choices of matches. In particular, we

had to adapt the time range of historical match data before each of the different World Cup simulations for 2010, 2014 and 2018. Although 8 years seem to be a quite reasonable time range, it did not lead to satisfying regression parameters for the World Cup 2010 and 2014 simulations. This explains why we had to take different time ranges for each World Cup under consideration. We refer to Karlis and Ntzoufras [18] for a detailed discussion on robustness. We note that the model is sensitive to changes of the Elo points during the tournament. Simulations where the Elo points are not updated during the tournament lead to quite different probabilities (up to 5 percent points) and clearly favor the stronger teams. In particular, this shows that the dynamic Elo updating models the effect of alleged underdogs having a good run.

There have been attempts to improve the Elo rating. For instance, Constantinou and Fenton [6] propose a dynamic rating that takes into account the relative ability between adversaries. In [6] it is shown that this rating outperforms in certain cases models based solely on Elo scores. We also refer to Constantinou and Fenton [4, 7] and references therein for more details on Bayesian models for forecasting football matches outcomes and to Hirotsu and Mike Wright [14] for Markov models of team specific characteristics. The models above are in our opinion more appropriate for short term forecasts. As in our case we are interested in long term forecasts, random effects are of considerable influence, and we suspect that more sophisticated models do not a priori improve the quality of the forecast. It goes without saying that a more intensive study on which data is relevant for (longtime) football forecasts is needed, e.g. see Constantinou and Fenton [3].

Measuring the accuracy of any forecasting model is a critical part of its validation. In the absence of an agreed and appropriate type of scoring rule it is rather difficult to reach a consensus about whether a model is sufficiently “good” or which of several different models is “best”. Our results show that the four scoring rules under considerations agree on the “best” model. With the relentless increase in football forecasting sports events and tournaments it will become more and more important to use effective scoring rules for ordinal variables. Although we are not suggesting (neither are convinced) that our proposed scoring rules E_1 and E_2 and the RPS are the only valid candidates for such a scoring rule, we have shown that they mostly, at least in our setting, give the same result on which model is “best”.

9. CONCLUSION

Several team-specific Poisson regression models for the number of goals in football matches facing each other in international tournament matches are studied and compared. They all include the Elo points of the teams as covariates and use all FIFA matches of the teams since 2010 as underlying data. The fitted models were used for Monte-Carlo simulations of the FIFA Worldcup 2018. According to these simulations, Germany (followed by Brazil) turns out to be the top favorite for winning the title. Besides, for every team probabilities of reaching the different stages of the cup are calculated.

A major part of the statistical novelty of the presented work lies in the introduction of two new score functions for ordinal variables as well as the construction of the nested regression model. This model outperforms previous studied models, that use (inflated)

bivariate Poisson regression, when tested on the previous FIFA World Cups 2010 and 2014.

We propose a weighted visualization of the course of the tournament using a large Sankey diagram. It enables experts and fans to obtain at a glance a quantified estimation of all kind of possible events.

10. APPENDIX

10.1. FIFA World Cup 2014 simulations. We present the tables of the forecast for the FIFA World Cup 2014 simulations using the bivariate Poisson regression model and the diagonal inflated bivariate Poisson regression model. Each model was simulated 100.000 times.

	Team	World Champion	Final	Semi	Quarter	R16	Prelim. Round
1	Spain	24.70	35.80	46.00	60.30	89.90	10.10
2	Brazil	21.00	31.20	41.50	54.90	86.90	13.10
3	Germany	11.80	24.20	52.40	70.40	85.70	14.30
4	Netherlands	7.80	15.00	23.70	37.70	72.50	27.50
5	Portugal	5.30	12.90	30.80	48.50	68.00	32.00
6	Argentina	4.80	13.90	38.00	68.10	93.80	6.20
7	Uruguay	3.60	8.30	15.80	41.20	67.50	32.50
8	England	3.00	8.00	15.00	44.70	70.60	29.40
9	Russia	2.20	6.30	16.90	32.60	79.60	20.40
10	Italy	2.10	4.90	9.90	27.20	50.80	49.20
11	Colombia	1.80	4.50	9.50	27.40	59.50	40.50
12	France	1.70	4.30	11.60	28.50	58.30	41.70

TABLE 15. FIFA World Cup 2014 prediction via bivariate Poisson regression

	Team	World Champion	Final	Semi	Quarter	R16	Prelim. Round
1	Spain	20.70	31.40	43.30	57.60	88.00	12.00
2	Brazil	20.40	30.80	41.30	54.90	86.60	13.40
3	Germany	11.70	24.10	51.50	69.60	85.40	14.60
4	Netherlands	7.80	14.80	23.50	37.30	71.30	28.70
5	Argentina	7.70	16.80	38.00	67.60	93.70	6.30
6	Portugal	5.50	12.90	30.40	48.20	68.10	31.90
7	Uruguay	3.70	8.50	16.30	41.30	67.00	33.00
8	England	3.40	8.40	16.00	44.80	69.50	30.50
9	Russia	2.50	6.40	16.40	31.80	78.30	21.70
10	Colombia	1.80	4.50	9.60	27.70	59.90	40.10
11	France	1.80	4.30	11.80	28.60	58.80	41.20
12	Italy	1.70	4.20	9.20	25.80	48.80	51.20

TABLE 16. FIFA World Cup 2014 prediction via diagonal inflated bivariate Poisson regression

10.2. FIFA World Cup 2010 simulations. We present the tables of the forecast for the FIFA World Cup 2010 simulations using the bivariate Poisson regression model and the diagonal inflated bivariate Poisson regression model. Each model was simulated 100.000 times.

	Team	World Champion	Final	Semi	Quarter	R16	Prelim. Round
1	Brazil	24.60	33.20	43.90	60.90	77.30	22.70
2	Netherlands	15.10	24.40	35.90	65.20	89.10	10.90
3	Spain	12.00	24.60	35.10	52.70	93.20	6.80
4	England	6.60	13.50	30.20	50.10	77.40	22.60
5	Italy	5.20	11.60	20.60	47.90	85.00	15.00
6	Portugal	4.80	11.80	20.50	35.90	68.10	31.90
7	France	4.50	8.60	17.60	31.40	58.60	41.40
8	Germany	3.80	12.20	37.00	64.50	93.00	7.00
9	Argentina	3.60	10.40	28.30	52.60	87.40	12.60
10	Uruguay	3.20	6.70	15.20	29.20	56.40	43.60

TABLE 17. World Cup 2010 prediction via bivariate Poisson regression

	Team	World Champion	Final	Semi	Quarter	R16	Prelim. Round
1	Brazil	23.20	31.40	42.00	58.30	76.70	23.30
2	Netherlands	14.60	23.80	35.60	64.20	87.90	12.10
3	Spain	8.40	17.70	29.10	44.70	83.80	16.20
4	England	7.10	14.20	30.90	51.20	77.80	22.20
5	Germany	5.80	15.60	36.90	64.10	92.60	7.40
6	Portugal	5.30	12.50	21.90	38.20	68.00	32.00
7	Italy	5.30	11.70	21.30	47.50	84.70	15.30
8	France	4.60	8.60	17.40	31.40	58.50	41.50
9	Argentina	4.50	11.50	27.90	52.20	87.20	12.80
10	Uruguay	3.30	6.90	15.10	29.20	56.20	43.80

TABLE 18. World Cup 2010 prediction via diagonal inflated bivariate Poisson regression

REFERENCES

- [1] Groll Andreas, Schauburger Gunther, and Tutz Gerhard. Prediction of major international soccer tournaments based on team-specific regularized Poisson regression: An application to the FIFA World Cup 2014. *Journal of Quantitative Analysis in Sports*, 11(2):97–115, June 2015.
- [2] N.-T. Chou and D. Steenhard. Bivariate count data regression models – a SAS[®] macro program. *SAS Global Forum 2011 - Paper 355-2011*, pages 1–10, 2011.
- [3] Anthony Constantinou and Norman Fenton. Towards smart-data: Improving predictive accuracy in long-term football team performance. *Knowledge-Based Systems*, 124:93 – 104, 2017.
- [4] Anthony C. Constantinou, Norman E. Fenton, and Martin Neil. pi-football: A Bayesian network model for forecasting association football match outcomes. *Knowledge-Based Systems*, 36:322 – 339, 2012.
- [5] Anthony Costa Constantinou and Norman Elliott Fenton. Solving the problem of inadequate scoring rules for assessing probabilistic football forecast models. *Journal of Quantitative Analysis in Sports*, 8(1):NA–NA, 2012.
- [6] Anthony Costa Constantinou and Norman Elliott Fenton. Determining the level of ability of football teams by dynamic ratings based on the relative discrepancies in scores between adversaries. *Journal of Quantitative Analysis in Sports*, 9(1):37–50, 2013.
- [7] Anthony Costa Constantinou, Norman Elliott Fenton, and Martin Neil. Profiting from an inefficient association football gambling market: Prediction, risk and uncertainty using Bayesian networks. *Knowledge-Based Systems*, 50:60 – 86, 2013.
- [8] P.C. Consul. *Generalized Poisson distributions : properties and applications*. Statistics, textbooks and monographs v. 99. New York, M. Dekker, 1989.
- [9] Roland C. Deutsch. Looking back at South Africa: Analyzing and reviewing the 2010 FIFA world cup. *CHANCE*, 24(2):15–23, 2011.
- [10] Mark J. Dixon and Stuart G. Coles. Modelling association football scores and inefficiencies in the football betting market. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 46(2):265–280, 1997.
- [11] Arpad E. Elo. *The rating of chessplayers, past and present*. Arco Pub., New York, 1978.
- [12] V. Erhardt. Verallgemeinerte Poisson und Nullenueberschuss – Regressionsmodelle mit regressiertem Erwartungswert, Dispersions- und Nullenueberschuss-Parameter und eine Anwendung zur Patentmodellierung. Master’s thesis, Technical University of Munich, 2006.
- [13] Roberto Gásques and Vicente Royuela. The determinants of international football success: A panel data analysis of the elo rating*. *Social Science Quarterly*, 97(2):125–141, 2016.
- [14] Nobuyoshi Hirotsu and Mike Wright. An evaluation of characteristics of teams in association football by using a Markov process model. *Journal of the Royal Statistical Society. Series D (The Statistician)*, 52(4):591–602, 2003.
- [15] Harry Joe and Rong Zhu. Generalized Poisson distribution: the property of mixture of Poisson and comparison with negative binomial distribution. *Biometrical Journal*, 47(2):219–229, 2005.
- [16] Dimitris Karlis and Ioannis Ntzoufras. Analysis of sports data by using bivariate Poisson models. *Journal of the Royal Statistical Society. Series D (The Statistician)*, 52(3):381–393, 2003.
- [17] Dimitris Karlis and Ioannis Ntzoufras. Bivariate Poisson and Diagonal Inflated Bivariate Poisson Regression Models in R. *Journal of Statistical Software*, 14(i10), 2005.
- [18] Dimitris Karlis and Ioannis Ntzoufras. Robust fitting of football prediction models. *IMA Journal of Management Mathematics*, 22(2):171–182, 2011.
- [19] Alan J. Lee. Modeling scores in the Premier League: Is Manchester United really the best? *CHANCE*, 10(1):15–19, 1997.
- [20] Christoph Leitner, Achim Zeileis, and Kurt Hornik. Forecasting sports tournaments by ratings of (prob)abilities: A comparison for the EURO 2008. *International Journal of Forecasting*, 26(3):471 – 481, 2010. Sports Forecasting.
- [21] M. J. Maher. Modelling association football scores. *Statistica Neerlandica*, 36(3):109–118, 1982.
- [22] D. Stekeler. Verallgemeinerte Poissonregression und daraus abgeleitete zero-inflated und zero-hurdle Regressionsmodelle. Master’s thesis, Technical University of Munich, 2004.

- [23] Achim Zeileis, Christian Kleiber, and Simon Jackman. Regression models for count data in r. *Journal of Statistical Software, Articles*, 27(8):1–25, 2008.
- [24] Achim Zeileis, Christoph Leitner, and Kurt Hornik. History repeating: Spain beats Germany in the EURO 2012 final. Working Papers in Economics and Statistics 2012-09, University of Innsbruck, Innsbruck, 2012.

LORENZ A. GILCH, UNIVERSITÄT PASSAU, INNSTRASSE 33, 94032 PASSAU, GERMANY

SEBASTIAN MUELLER, AIX MARSEILLE UNIVERSITÉ, CNRS CENTRALE MARSEILLE, I2M, UMR 7373, 13453 MARSEILLE, FRANCE

E-mail address: `gilch@TUGraz.at`, `sebastian.muller@univ-amu.fr`

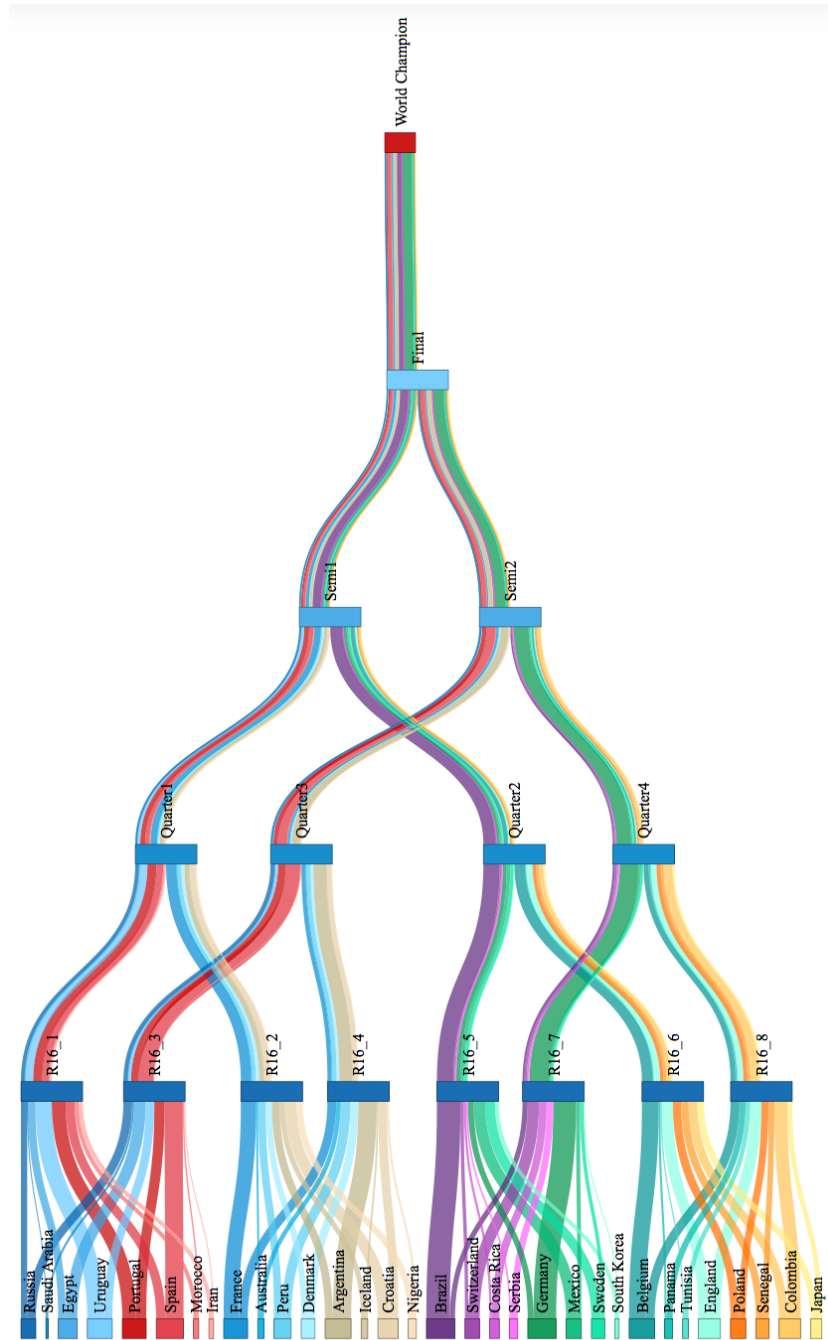


FIGURE 4. Sankey presentation of the forecast of the FIFA Worldcup 2018 based on 100.000 simulations of the nested regression model.