Open data analysis to predict the results of the League of Legends World Championship

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Abstract

League of Legends (LoL) is a MOBA which has become the online computer game with more active users in the world. In League of Legends, players assume the role of an unseen "summoner" that controls a "champion" with unique abilities and battle against a team of other players. Each team usually consists of five players and the main goal is to destroy the opposing team's "nexus", a structure which lies at the heart of a base protected by defensive structures ("turrets") situated along the three streets or lanes that constitute the map. There are currently 138 champions in League of Legends (by October 2017) which are classified in different types or classes which generally determine what part of the map the champions gravitates towards during the early game. There is the top-lane player, the mid-lane player, two bot-lane players which play together, and the player who heads to the "jungle", the areas of the map that lie between the three mentioned lanes.

This game also has the most solid competitive structure between all the e-sports (the League of Legends competitive scene moves more money than the European basketball League), and the sports betting sites are starting to offer services in this fields.

The aim of our project is to predict some of the results of the 2017 World Championship, the biggest event in the e-sports, using open data resources from different APIs. To do it, we will use the data of the different professional players and teams which compete in the World Championship, and the data of the different champions that they can play, and we will develop a logistic regression model to predict the results of the knock-out stage (quarter-finals, semi-finals and final) using data from the group stage.

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Contents

1 Overview

(Josep) “Com una intro”:

- Tornar a dir que lo important per nosaltres és el fet que és un joc on competeixen 2 equips amb 5 jugados cadascun i amb 5 rols (que es corresponen normalment amb un conjunt de campions particulars) per cadascun d’aquests rols.
- Game patches/updates, items + champs + patch —>meta game
- Worlds –> patch 7.18, Meta –> supports and adcs
- també necesitem que es comenti aqui breu ment que existeixen lligues, per classificar com de bons son els jugadors: bronze ,plata, or platino diamante master aspirante

Popularity of e-sports is on the up and up, what started as a hobby is becoming a big industry which is starting to move a huge amount of money. 2017 Legue of Legends World’s Championship final was seen by 75 millions, and it filled the Olympic stadium of Beijing known as the "Bird Nest" (80,000 people). E-sports in Europe are already moving more money than the Euroleague of basketball. It already exists a solid base of supporters, teams and players and at the same time other industries are taking advantage of this new trend.

News paper Marca recently started a section on e-sports in its on-line version, the first TV channel devoted to e-sports has already been launched in some Nordic and Baltic countries (esports TV from the company ESL), lots of companies are already selling merchandise from the different e-sport’s starts and finally, sports betting houses are starting to accept bets in e-sports.

Our aim in this project is to build a simple model that can predict better than humans the result of a match in e-sports using open data. We will focus in the MOBA League of Legends, the game with more active players in the world, and specifically in the League of Legends World’s Championship, the biggest e-sport event nowadays. We will try to predict the knock-out stage of the tournament (quarterfinals, semifinals and the final) using the data from the previously played games (region-qualifier stage and groups stage). Now we will briefly explain how works a match of League of Legends and the major facts that must be taken into account in our opinion in order to build a model.

League of Legends is a game were two teams of 5 players[1] face each other in a field called the "Summoner’s Rift" using a champion. Each team has a base and the team who breaks the enemy’s base wins the game. Since there are 5 players playing, and there are more than a hundred of champions to pick, it seems impossible to make a model using the data available (there are not many profesional games data), due to the complexity of the game.

However, each player plays as a specific role: Top-laner, mid-laner, adc, support or jungle. Each role has its specific function which determines a group of champions that can be played in that role. Then, despite there are more than a hundred different champions, each one can only play as 1/2 roles, which reduces the amount of champions that each player can chose (professional players always play as the same role).

Moreover, there is another factor that reduces the complexity of the game: the metagame. Metagame is a term use in e-sports and computer games in general, and it is the more effective strategy of

[1]When we say player we refer to the person who is physically playing, not the character that he is using. Players are physic persons, champions the virtual characters they use to play

playing a certain game. In the case of League of Legends, it means that some champions are more powerful than others. Every two weeks, Riot, the company that owns League of Legends adds a patch, trying to balance the power between their champions. However having more than a hundred champions balanced between them is almost impossible, and in every match some champions are more powerful than others, and some roles become more relevant than others. Since professional players only play champions that are in the metagame, this reduces even more the amount of champions played.

That is why we will try to model professional League of Legends matches, because despite there is less data than on the amateur games, the matches are less complex. We will collect data to estimate the skill of each player individually, the power of each champion in the patch that the World Championship is held (patch 7.18), and we will also take into account in which team each player plays, and in which side of the field the team plays. With all this variables we will do a logistic regression, and we will try to predict the outcome of the games of the knock-out stage, in the case that we already know which champions will be picked by each player (since it is possible to bet after the players have picked, it should not be a problem to consider that we have this information). Then we will compare our effectiveness with the mean of all the humans that participated in the "pick'em", a League of Legend's World Championship pool where almost all the League of Legends players participated.

Section 3 is devoted to explain the data sources and tools that have been used to develop and implement the model that is explained in Section 2, and whose results are presented in Section 4. Finally, Section 6 is devoted to summarize legal and ethical issues about the sources we have made use of and in Section 7 we discuss limitations and possible extensions of our model, and alternatives. The GitHub repository containing the all code and data files used can be found here: `https://github.com/dsalgador/LeagueOfLegends_Project`. During the report we will be citing the names of the files.

2 Problem statement and mathematical modelling

Before the League of Legends Worlds tournament starts, some matches are played between the candidate teams that come from each continent (region?) in order to select the 16 teams that will participate. Then the tournament consists in two main stages:

- The first one is the **group stage**, where the participant teams are divided in four groups of four teams that compete between them. The two teams of each group with larger number of wins are classified and go to the next main stage.
- The second main stage starts with **quarter-finals**, where the classified teams that were ranked in first position are paired randomly with another team that was ranked in second position to compete against each other. The winners of each pair is classified to play in the **semifinals** (2 groups of 2 teams), and then the two winner teams from the semifinals play against each other in the **final**. In the final and the semifinals "the best of five matches" criteria is followed.

Our goal is to develop a mathematical model able to predict the results quarter-finals, semifinals and the final of the 2017 Worlds championship by means of a model that require information available strictly before the second main stage of the tournament starts.

The model we propose consists of a binary logistic regression, since it is a technique that is well suited for examining the relationship between a categorical response variable Y, such as it is "winning"

($Y = 1$) or "losing" ($Y = 0$) a particular match, and one or more categorical or continuous predictor variables X_1,..., X_n, [1, 2, 3]

The magnitude of interest is the probability $p = P(Y = 1)$ (resp. $1 - p = P(Y = 0)$) that a team wins (resp. loses) a particular match, and the logistic regression model is written as

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n, \tag{2.1}$$

where β_i are constant coefficients to be determined. Then, assuming that these coefficients have been determined numerically using predefined algorithms that we do not discuss here, and given some observational data $(x_1, ..., x_n)$ of the predictor variables of a particular match and a particular team of this match, the predicted probability that the selected team wins is given by:

$$p = \frac{1}{1 + e^{-z}}, \text{ where } z = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n. \tag{2.2}$$

The predictor variables we consider for our base model are the following:

Categorical variables

A k-levels categorical variable X_i leads to $k - 1$ predictor variables $X_{i,1}, ..., X_{i,k-1}$ for the model equation (2.1) (see for instance [4]), and in our case we consider

a) A N-levels categorical variable X_1 representing **the team**, where N is the total number of teams that participate in the classification stage (N = 24 in 2017). One of the teams (lets call it T_0) is chosen as a kind of "origin" and then we have $N - 1$ predictor Variables $X_{1,1}, X_{1,2}, ..., X_{1,N-1}$ associated to the other teams T_1,..., T_{N-1}, defined as follows:

$$X_{1,i} = \begin{cases} 1 & \text{if the team in consideration is } T_i \\ 0 & \text{otherwise} \end{cases}$$

These variables are supposed to account for the "power" of the team. For instance, it is well-known that Korean teams usually are pretty much good than European or American teams.

b) A two levels variable X_2: The **side of the map** where the team in consideration plays, denoted by BLUE or RED, and mathematically modelled as $X_2 = 0$ if BLUE and $X_2 = 0$ if RED. This variable is supposed to account for the possible advantage of playing in one part of the map or the other.

Continuous variables

Our base model starts by considering a total of 10 continuous variables:

c) Five continuous predictor variables $X_{3,j}$, $j = 1, ..., 5$ (referred to Top, Jungler, Mid, Adc and Support), whose values are between 0 and 1, and account for the **average matchup win rate of a champion**, that is played in a given position by the team in consideration and against a given enemy champion from the same position [2]. These variables are supposed to account for the *metagame* of the patch where the tournament is being played, i.e. to account for the fact that there are champions that are more over powered than others.

[2]The average is done among all "ranked" matches that have been played in Platinum or higher leagues during the patch of interest.

d) Another five continuous predictor variables $X_{4,j}$, $j = 1, ..., 5$ (referred to Top, Jungler, Mid, Adc and Support), whose values are also between 0 and 1, and account for the **win rate that a given player has with the champion that is playing with** during the match in consideration. In this case, these variables are supposed to account for "how good is a particular player with a particular champion".

With all these variables already defined, we can write our binary logistic regression model equation as follows:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \sum_{i=1}^{N-1} \beta_{1,i} X_{1,i} + \beta_2 X_2 + \sum_{j=3}^{4} \sum_{i=1}^{5} \beta_{j,i} X_{j,i}, \tag{2.3}$$

where p is the probability that the team in consideration wins the match. Similarly, we can consider an expression for finding p such as in equation (2.2).

In order to compute values for the β coefficients we need *train data* coming from all the matches played before quarter-finals in a well structured format and containing values for all the predictor variables that appear in (2.3). The following table illustrates how the train data of a single match should look like:

```
 result         team  side topwr_champ jngwr_champ midwr_champ adcwr_
   champ
1      1     Team WE  Blue         0.5          0.5         0.49
   0.5
2      0 Lyon Gaming  Red          0.5          0.5         0.51
   0.5
  supwr_champ topwr_player jngwr_player midwr_player adcwr_player
1        0.53          0.58          0.60          0.66          0.62
2        0.47          0.55          0.78          0.50          0.00
  supwr_player
1          1.0
2          0.6
```

Figure 2.1

In the above example, the teams of the considered match are Team WE (winner) and Lyon Gaming (loser).

Therefore, for each match we need two rows of data, one for each team, where the fields (columns) are: the result of the match with respect to the team (1 if wins 0, if loses), the name of the team, the matchup champion win rate for each position (top, mid, jungle, adc and support, respectively), and the player win rate with the specific champion that is playing (again for each position). In principle this model is open to be extended, in the sense that we could add more predictor variables; for instance, we would want to consider the KDA (which is the number of kills plus assistances divided by the number of deaths) of each player playing a particular champion, so that we would have five additional predictor variables, lets call them $X_{5,k}$, $k = 1, ..., 5$.

In the next Section we explain how we have obtained and manipulated data from different sources so that we have been able to have well structured train data set containing the information from all matches played before the group stage of the tournament.

Similarly the *test data* is built using the necessary data coming from the quarter-final, semifinal and final matches.

3 Data life-cycle

3.1 Data collection

3.1.1 Player data: scraping a web page with python

From `lol.gamepedia.com` we have obtained `players_info.json`. This file contains data about the performance of the different players in their World Championship appearances (incorrecte). For every player we extract from the web a list with the champions he has used, the games he has won and lost with said champion and their KDA performance (Kill, Death, Assist).

In order to do so, we have used Scrapy as the framework for extracting the information. We have developed `spider_xpath.py`, a simple spider that is run throughout all the websites of the players in the World Championship and gets the data from a table by accessing it through its Xpath. When running the spider through the terminal we choose to create a json file with all the extracted data.

3.1.2 Champion data: querying an API

Static champion data From `ddragon.leagueoflegends.com` we have obtained a `champ_info.json` file containing all the static data from any of the champions released before patch 7.19 (see [5]). In this case the patch is not that important since we are using this data just to have a list of the champion names and ids (which are static, specific and non-consecutive integers that characterize a particular champion). Thus, there is a bijective relation between champion names and ids. This is important for when we manipulate the `champion_matchups_patch7_21.json` data set where champions are identified with the id number and not by the name (string).

Dynamic champion (and player related) data To obtain the average matchup win rates of each champion we have made use of the `champion.gg` API (see [6]). The particular query URL we have used to obtain a `champion_matchups_patch7_21.json` file containing a lot of champion matchup information is:

`http://api.champion.gg/v2/champions?&champData=matchups&limit=200&api_key=<api_key>`,

where the field `<api_key>` has to be replaced by a valid API key that one has to ask for by registering in the API web page.

This project was started when the current game patch was the 7.21. At champion.gg the data is updated to the current patch (almost) every two weeks, and the data from the previous patches is replaced by the current one. In order to be strictly according to our model, the data we would need would be that from the patch 7.18. Since it was already deleted, we will instead use that from patch 7.21.

3.1.3 Match data: using already processed open data

A very important data source that we need to train and test our logistic regression model is that consisting of data from each match played in the Worlds championship. We have obtained this data set from [8] in .xlsx format and we have then converted it to .csv format via a online converter [9]. The corresponding file containing this data is called `2017_WorldsMatchData_all.csv`. The original

data can be publicly accessed through `lolesports.com`, [8].

3.2 Data cleaning and manipulation

In this section we explain how we have manipulated the raw data files already mentioned in section 3.1, in order to build the train and test datasets that will allow us to define and check our theoretical model numerically. All the code files used to do so are written in R language and can be found in the GitHub repository we already mentioned in Section 1.

3.2.1 Player data

Once the file `players_info.json` is read in R, we convert it to a data table format which at the end, after some simple data manipulation, consists of four columns and about 2700 rows. The full code can be found in the file `PlayerChampionWinrates.R`. The second column consists of the player names repeated as many times as the number of different champions for which there is information related to the player in consideration. The first column contains champion names, the third contains win rates of a given player with a given champion, and similarly in the fourth column there is de KDA.

Then using this data table we have coded a function `winrate_player(champ_name, player_name )` that given a champion name and a player name returns the win rate of this player with this champion. Similarly, using this auxiliary function we have build a function `winrate_teamplayers(team_champs, team_players)` that given an array `team_champs` containing the champion names (and respecting the position order: Top, Jungler, Mid, Adc and Support) and an array `team_players` containing the player names of that team (again respecting the position order), it returns an array of win rates associated to each player and the associated champion that he is playing.

```
#Example
Input:
team_champs = c("Trundle", "Sejuani", "Orianna", "Twitch",  "Janna")
team_players = c("Huni",  "Blank", "Faker", "Bang",  "Wolf")
round(winrate_teamplayers(team_champs, team_players),2)

Output:
[1] 0.67 0.60 0.66 0.79 0.50
```

If there is some combination of player name and champion for which there is no available data, we have decided to return a neutral win rate value, i.e. 0.5.

3.2.2 Champion data

Using the `champ_info.json` and `champion_matchups_patch7_21.json` data files, we have coded a script in R (the `MatchupChampionWinrates.R` file) where for each position (Top, Jungler, Mid, Adc and Support) it is build a matrix $P = (p_{id_i,id_j})$ that has as column and row labels the ids of the champions that are played in that position, and such that the component P_{id_i,id_j} contains the average win rate of the champion with $id = id_i$ when it plays against the champion with $id = id_j$. In the cases where $id_i = id_j$ (for instance if the two adc players are playing the same champion),

the win rate is set to 0.5. However, in official matches like the ones in the Worlds championship it is not possible that two players, regardless of the team, play the same champion.

For convenience we have build two functions that allow us to convert champion names to ids and ids to champion names.

Once we have an "average matchup win rate" matrix for each of the five positions, we have build a function `winrate_pair(champion1, champion2, POSITION)` that returns the average matchup win rate of `champion1` when plays against `champion2` in the position `POSITION`. Then, by using this auxiliary function, we have coded another function `winrate_match(team1, team2)` that given the champion names of the champions played by `team1` (an array of champion names, respecting the position order: Top, Jungler, Mid, Adc and Support) and the associated champion names to `team2` it returns an array of average matchup win rates for each of the five positions and in the order that we have been considering so far.

```
#Example:
Input:
team1= c("Tryndamere","Lee Sin", "Yasuo", "Miss Fortune", "Leona")
team2 = c("Dr. Mundo", "Xin Zhao", "Taliyah", "Lucian", "Janna" )
winrate_match(team1, team2)

Output:
[1] 0.4971 0.4331 0.4979 0.5519 0.4895
```

If there is some combination of champion names and position for which there is no available data, we have decided to return a neutral win rate value, i.e. 0.5.

To sum up, with this code implementations we are now able to obtain values for the predictor variables $X_{4,j}$, $j = 1, ..., 5$, assuming that we previously know the champions that are played in each team and in a given match.

3.2.3 Match data: building the train and test datasets

Using the `2017_WorldsMatchData_all.csv` file and the functions and data sets explained in the last two sections we have implemented a script in R (`Match_TrainAndTest_data.R`) that, given a set of matches from `2017_WorldsMatchData_all.csv`, generates a table whose columns and rows gather information about each match as we showed in Figure 2.1. That is, for each match in the set of matches of interest, two rows (as seen in Figure 2.1 for one match) are generated and included in the final table. In this way we have created the train data set file `train_data.csv` containing information of matches played before the quarter-finals, and the test data set file `test_data.csv` containing the information of the matches that we want to predict using our model (i.e., those from quarter-finals, semifinals and the final).

3.3 Data analysis and statistical tools

In this section we familiarize with the base model we have developed formally in Section 2 and present the main statistical tools that will serve us to improve it. Otherwise noted, for statistical purposes (tests), we will work always with a significance level $\alpha = 0.05$ (i.e., with 95% confidence level).

3.3.1 Model fitting

First of all we have to use some `train` data (initially that from `train_data.csv`) to estimate the model coefficients β_i numerically. We can do this in `R` with the predefined `glm` function as follows:

`model <-glm(result ~ .,family=binomial(link='logit'),data=train)`,

where `result` is the column of the data set `train` that contains 0 and 1 that represent wins and loses. At this point `model` contains numerical estimations for each of the β_i coefficients.

It is interesting to consider confidence intervals for each of these coefficients. The following command allows us to create a table with a first column containing the estimated β_i values and two additional columns which are the left and the right bound of a 95% confidence interval:

`round(cbind( coef(model), confint.default(model)) ,1)` (the output is found in Appendix A.1, listing 2).

We are dealing with a total of 30 β_i coefficients and it is quite probable that some of them are insignificant or inappropriate to obtain high prediction accuracies.

A useful way to rate the relevance of a predictor variable consists in performing a χ^2 ANOVA test:

`anova(model, test="Chisq")`

```
Model: binomial, link: logit
Response: result
Terms added sequentially (first to last)

             Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                         179     249.53
team         23   56.992       156     192.54 0.0001027 ***
side          1    1.053       155     191.49 0.3048675
topwr_champ   1    3.234       154     188.25 0.0721285 .
jngwr_champ   1    2.543       153     185.71 0.1107626
midwr_champ   1   10.664       152     175.05 0.0010923 **
adcwr_champ   1    1.028       151     174.02 0.3106769
supwr_champ   1    0.314       150     173.71 0.5750306
topwr_player  1   19.489       149     154.22 1.012e-05 ***
jngwr_player  1   13.724       148     140.49 0.0002117 ***
midwr_player  1   15.925       147     124.57 6.589e-05 ***
adcwr_player  1   13.828       146     110.74 0.0002003 ***
supwr_player  1   28.648       145      82.09 8.680e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Listing 1: Analysis of Deviance Table for the Base model (Model v1)

The difference between the null deviance and the residual deviance shows how our model is doing against the null model (a model with only the intercept). The wider this gap, the better. Analysing the table we can see the drop in deviance when adding each variable one at a time. Adding `team`, and the five "`positionwr_player`" predictors significantly reduces the residual deviance. The other variables seem to improve the model less, even though `midwr_champ` has a low p-value. A large p-value here indicates that the model without the variable explains more or less the same amount of variation, [3].

Another useful tool to asses the significance of predictor variables is the so called Wald test. "*A wald test is used to evaluate the statistical significance of each coefficient in the model and is calculated by taking the ratio of the square of the regression coefficient to the square of the standard error of the coefficient. The idea is to test the hypothesis that the coefficient of an independent variable in the model is significantly different from zero. If the test fails to reject the null hypothesis, this suggests that removing the variable from the model will not substantially harm the fit of that model*", [1].

If we test the overall effect of team names (i.e. the `team` predictor variable) executing the following code line `wald.test(b = coef(model), Sigma = vcov(model), Terms = 2:24)`, we obtain a p-value equal to $0.37 \gg 0.05$.

```
Wald test (teams):
----------
Chi-squared test:
X2 = 24.6, df = 23, P(> X2) = 0.37
```

Therefore, we do not reject the null hypothesis that the overall effect of the `team` predictor coefficients is not significant, so that we accept that the β coefficients of team names, as a whole, are statistically insignificant and equal to zero. Note that if we perform a Wald test for each team name individually, one can see that there are some teams that are statistically significant, but the majority are not[3] and, as a whole, we have seen that there is no statistical significance.

Similarly, by testing the `side` variable, `wald.test(b = coef(model), Sigma = vcov(model), Terms = 25)`, we conclude that the `side` of the map where a team is playing is not significant at all (note that the p-value is almost 1).

```
Wald test (side):
----------
Chi-squared test:
X2 = 1e-04, df = 1, P(> X2) = 0.99
```

About the the overall effect of the "`positionwr_champion`" predictors, we can say that is quite significant, since `wald.test(b = coef(model), Sigma = vcov(model), Terms = 26:30)` gives

```
Wald test ("positionwr_champion"):
----------
Chi-squared test:
X2 = 22.2, df = 5, P(> X2) = 0.00049
```

but in fact the only significant predictor is `midwr_champion`, because `wald.test(b = coef(model), Sigma = vcov(model), Terms = c(26,27,29,30))` gives

[3]For the majority of team names 0 belongs to the 95% confidence interval of the associated β coefficient.

```
Wald test ("positionwr_champion" except midwr_champion):
----------
Chi-squared test:
X2 = 5.4, df = 4, P(> X2) = 0.25
```

Finally if we test the overall effect of the "positionwr_player" predictors we see that it is statistically significant:

```
wald.test(b = coef(model), Sigma = vcov(model), Terms = 31:35)
```

```
Wald test ("positionwr_player"):
----------
Chi-squared test:
X2 = 22.2, df = 5, P(> X2) = 0.00049
```

Moreover, if we test each of these predictors individually, the p-values obtained are always smaller than $0.02 \leq 0.05$, which mean that each of these predictors are statistically significant.

3.3.2 Assessing the predictive ability of the model

Now we would like to see how the behaviour of the model when predicting y_i (win or lose of a given match i) on a new set of `test` data. By setting the parameter type='response', R will output the estimated probabilities in the form of $P(y_i = 1|x)$, where $x = (x_1, ..., x_n)$ are the observed values of the predictor variables of the match. In fact, in our case, each two consecutive rows of the `test` data correspond to one match. Thus, for each match i, we have two output predicted probabilities $P\left(y_i^{(1)} = 1|x\right)$ and $P\left(y_i^{(2)} = 1|x\right)$, where the superscript indicates the team.

Our decision boundary must satisfy that $y_i^{(1)} = 1$ (resp. $y_i^{(2)} = 1$) if and only if $y_i^{(2)} = 0$ (resp. $y_i^{(1)} = 0$). Thus, for each pair of rows that correspond to the same match, we have to decide which team should have won according to the model predictions. To do so we consider the following criteria:

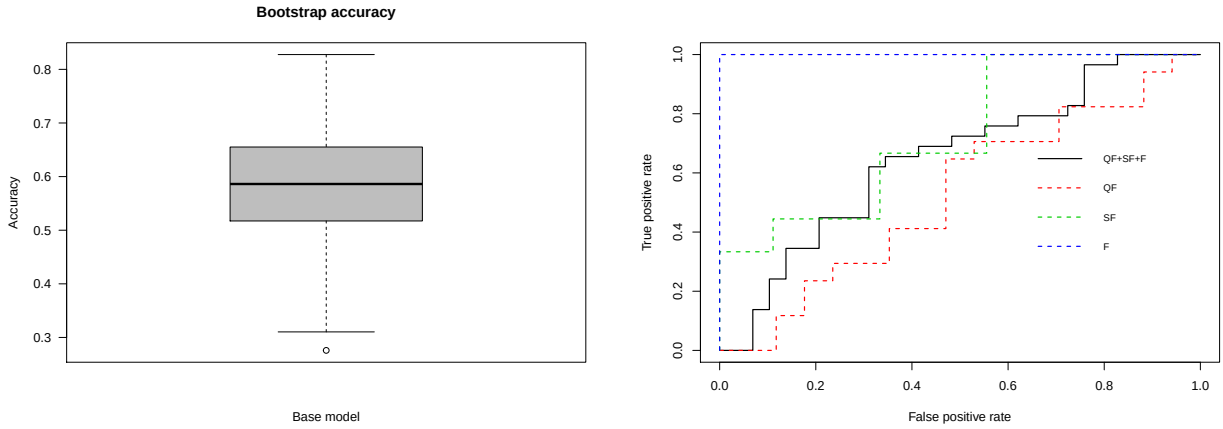
- If $P\left(y_i^{(1)} = 1|x\right) < P\left(y_i^{(2)} = 1|x\right)$, then $y_i^{(2)} = 1$, $y_i^{(1)} = 0$,
- otherwise $y_i^{(2)} = 0$, $y_i^{(1)} = 1$.

```
fitted.results <- predict(model,newdata=test,type='response')
num_results <- length(fitted.results)
for(i in seq(1,num_results, 2) ){
      fitted.results[i] <- ifelse(fitted.results[i]>fitted.results[i+1],1,0)
      fitted.results[i+1] <- abs(fitted.results[i]-1)
    }
```

Then we can compute the accuracy of the model by comparing the predicted results with the real results:

```
misClasificError <- mean(fitted.results != test$result) #proportion of failures
print(paste('Accuracy',1-misClasificError)) #proportion of right predictions
```

If we use as `test` data set the whole file `test_data.csv`, the model accuracy is: 0.586. In order to obtain some confidence interval for the accuracy, we can perform a bootstrap procedure (see `Bootstraping_accuracy.R`) where one takes a different `test` data at each bootstrap iteration obtained by sampling the original `test` data with replacement. In our case we have to be careful when sampling, since the data observations (rows) are paired.



(a) (b)

Figure 3.1: (a) Box plot of the bootstrap sample of model accuracies (1000 iterations). (b) ROC curves for the base model with respect to the whole knockout stage (black line), quarter finals (red dashed line), semi finals (green dashed line) and the finals (blue dashed line).

After bootstrapping 1000 times, using the quantile method we obtain the following 95% confidence interval: $[0.41, 0.76]$. In Figure 3.1a we have a box plot of the bootstrap sample of accuracies.

Now we would like to compare the accuracy of our model with the average accuracy of the Worlds pick'em performance made by real League of Legends players. The pick'em data set has been obtained by copy-pasting the table that is found in the knockout stage window from [11]. By doing some simple calculations (which can be found at the beginning of the file `BinaryLogitRegression.R`) we obtain that the mean accuracy of all the people that have taken the knockout stage pick'em is: 0.558. Since the model accuracy is 0.586, we cannot reject the null hypothesis that the model accuracy and the mean pick'em accuracy are equal. For this reason, in Section 4 we will try to improve the performance of our base model by eliminating irrelevant or bad predictor variables.

As a last step, we are going to plot the ROC (receiving operating characteristic) curve and calculate the AUC (area under that curve) which are typical performance measurements for a binary classifier, [3]. The ROC is a curve is constructed by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. That is, *using the proportion of positive data points that are correctly considered as positive and the proportion of negative data points that are mistakenly considered as positive, we generate a graphic that shows the trade off between the rate at which you can correctly predict something with the rate of incorrectly predicting something*, [1].

The AUC metric ranges from 0.5 to 1. As a rule of thumb, a model with good predictive ability should have an AUC closer to 1 (1 is ideal) than to 0.5, [3]. Values above 0.8 indicate that the model does a good job in discriminating between two categories which comprise our target variable, [1]. In Figure 3.1b we have plotted the ROC curves for the whole knockout stage pick'em (black line), together with the ROC curves for the separate phases QF (quarter finals), SF (semi finals) and F (finals). We can see that the ROC curve corresponding to the finals is the unity (the ideal case), which means that the model behaves perfectly when predicting the results of the finals' matches.

4 Model variations and results

In the last section 3.3 we analysed the numerical results obtained for our base model and introduced the basic tools to asses the goodness of a logistic regression model and its predictor variables. We saw that the base model is quite unsatisfactory, and for this reason we will now consider some variations of the current model (we call it Model v1).

The first change we consider is to remove the `team` predictor variable from all computations (i.e., from the `train` data used to build the model), since we saw that the overall effect of it is not significant by means of a Wald test. We call this variation Model v2. The fact that the overall effect of the `team` variable is not significant, does not mean that if we eliminate it from he model, then the predictability (for example accuracy) will not change at all. In fact, there were some team names whose β coefficients were quite significant. However, since the number of teams is quite large (24) compared with the total amount of match data available (90 matches), it is quite probable that the effect of adding the `team` variable to the model harms its predictability. We will see that this is what in fact happens.

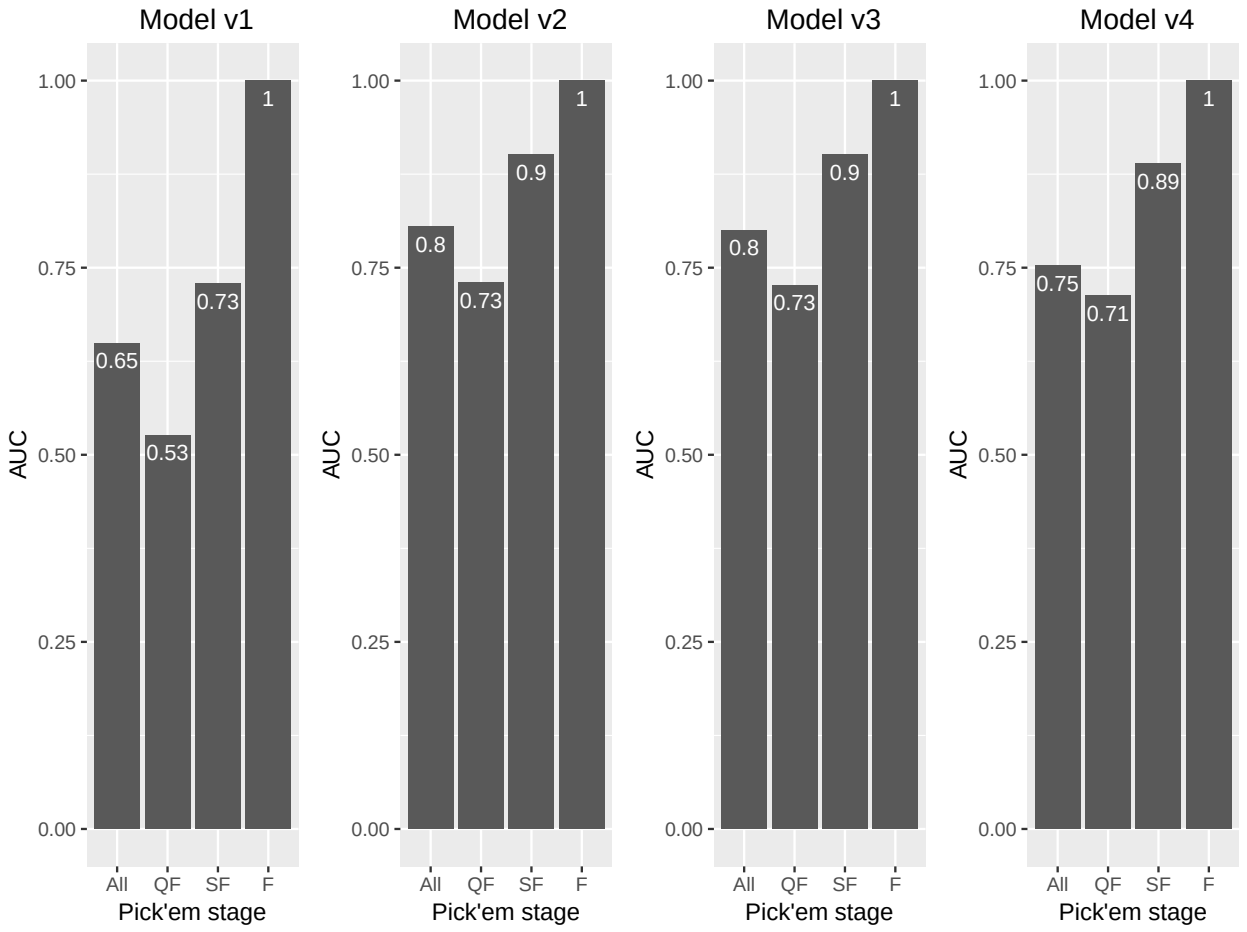


Figure 4.1: AUC values for the four model variations (or versions). Overall performance of the model (All), quarter finals (QF), semi finals (SF) and finals (F).

The second change we consider is to remove the `side` predictor variable from the model. The corresponding Wald test we discussed in section 3.3.1 told us that this variable was very insignificant (the p-value was almost 1). We call this variation Model v3. We will quantitatively check the fact

that the importance of the `side` variable in Model v2 is very low.

Finally, we have considered to remove the champion matchup win rates (i.e., the "`positionwr_champion`" predictor variables), for two main reasons:

1) First, we can see (see the outputs from Appendix A.1) that there are statistical evidences of the fact that the β coefficients associated to some of the champion matchup win rate variables (in our case `jngwr_champion` and `topwr_champion`) are negative. If we remember equation (2.2), this would imply that the higher the matchup champion win rate for the top or jungle position, the smaller the probability of winning the match. This clearly makes no sense for our model so we decide to remove at least these two variables from the model.

2) Second, since the champion matchup win rate dataset corresponds to the game patch 7.21, with a delay of about 6 weeks with respect to the Worlds patch (7.18), and we are aware of the fact that the metagame have changed quite since then, we consider a model where we also remove the other three variables (`midwr_champion`, `adcwr_champion`, `supwr_champion`), although they are (statistically) positive.

We call it Model v4.

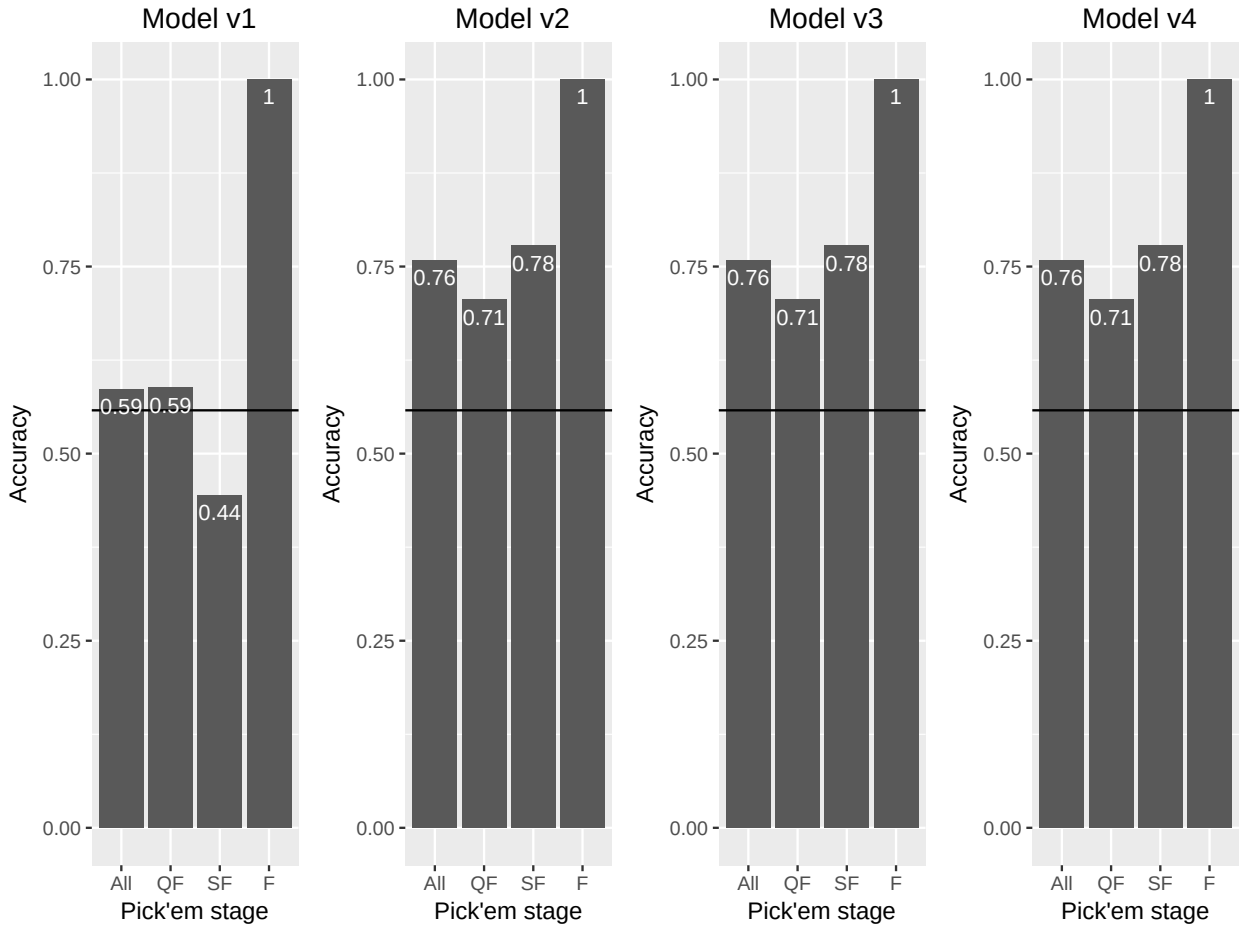


Figure 4.2: Model accuracies for the four model variations (or versions). Overall accuracy of the model (All), quarter finals (QF), semi finals (SF) and finals (F). The horizontal black line represents the mean accuracy threshold given by the mean pick'em performance of all participants.

In Figure 4.1 we have displayed a bar chart for each model to represent the AUC values corresponding to the overall knockout stage (All = QF+SF+F), the quarter finals (QF) stage, the semi finals (SF) stage and the finals (F). Similarly, in Figure 4.2 there are the corresponding bar charts for the accuracy of the model when predicting the results of every stage we already mentioned.

The most significant result we can extract from these bar charts is that when we remove the `team` variable from the base model (to obtain Model v2), the AUC of every single stage and the overall stage, increases between 0.15 and 0.2 units. Similarly, the prediction accuracy of the base model for the overall stage, the quarter finals and the semifinals, increases significantly so that they surpass the "mean pick'em accuracy" (black horizontal line) threshold in about 0.2 units.

When the `side` variable is removed (Model v3), the change in the AUC values is negligible if we only consider the first two significant digits; this is consistent with the fact that a Wald test for this predictor has a p-value very close to 1. The same applies for the accuracy, where no changes are observed.

Similarly, if we remove from the model the predictor variables "`positionwr _champion`" (Model v4), the accuracy of the model with respect to each stage remains unchanged again, but the AUC for the overall stage, the quarter finals and the semi finals decreases between 0.01 and 0.05 units.

In Figure 4.3 we show a table that contains means, variances and 95% confidence intervals for the overall accuracies of each model, obtained via a bootstrap procedure (1000 iterations) as we commented in Section 3.3.2. The information of this table can be understood graphically by looking at the box plot that is on the right. Again we confirm the fact that the important change that makes the base model improve significantly is removing the `team` predictor variable. The other changes that lead to Model v3 and Model v4 are almost equivalent to Model v2 with regard to accuracy.

```
Bootstrap (mean and variance) accuracies and 95%
confidence intervals (quantile and standard methods)

     Mean Variance 2.5%(q) 97.5%(q) 2.5%(s) 97.5%(s)
v1  0.590  0.00898   0.414    0.759   0.404    0.776
v2  0.762  0.00646   0.586    0.897   0.604    0.919
v3  0.759  0.00628   0.586    0.897   0.604    0.915
v4  0.756  0.00634   0.586    0.897   0.600    0.912
```

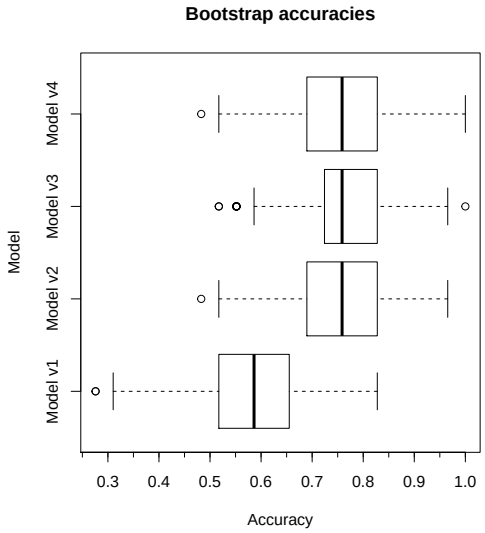


Figure 4.3: On the left, table of means, variances and confidence intervals for the bootstrap accuracy samples for each model. Two kind of confidence intervals are considered: using the quantile method (q) and using the standard method (s). On the right, we have a box plot associated to the bootstrap accuracy samples

As one may have already noticed, both the AUC and the accuracy with respect to the finals stage (F) is equal to 1 regardless of the model variation we consider. Thus, from the very beginning, each of our model variants predict that Samsung Galaxy (SSG) won the three game matches played (3-0) against SK Telecom T1 (SKT). This must be considered a quite surprising and positive result,

because since 2013, SKT has won three World Championships including the last two back to back.

"*They have never lost a best of five at Worlds and have far and away the most experienced and proven player of all time anchoring their mid lane. Until proven otherwise, it's likely best to assume that SKT will win whatever series they are playing. But this one won't be easy.*

The only other team to have won worlds in that time span is Samsung Galaxy, who have played better than SKT in the Knockout Stage of this tournament. Not only that, but Samsung are likely the best team in the world right now at reading their opponent's strengths and countering them, something SKT has already proven vulnerable to at Worlds 2017.

In the quarterfinals, Samsung took down Longzhu Gaming, a team widely considered to be the best in the world at the time, in a quick 3-0 [...]" [13].

Therefore, in principle both teams seemed to be equally stronger and candidates to win the 2017 Worlds Championship, but our model has been able to realize that SSG was, in fact, stronger. However, lets analyse in a bit more detail how are our models are distinguishing SKT and SSG.

In Figure 4.4 we have plotted, for each match played in the finals stage, the difference between the predicted probability that SSG wins the match and the predicted probability that SKT wins the match, i.e., P(SSG wins) - P(SKT wins), as a function of the model variation (v1, v2, v3 and v4). This probability increment is a measure directly proportional to "how well is the model distinguishing the winner of the match".

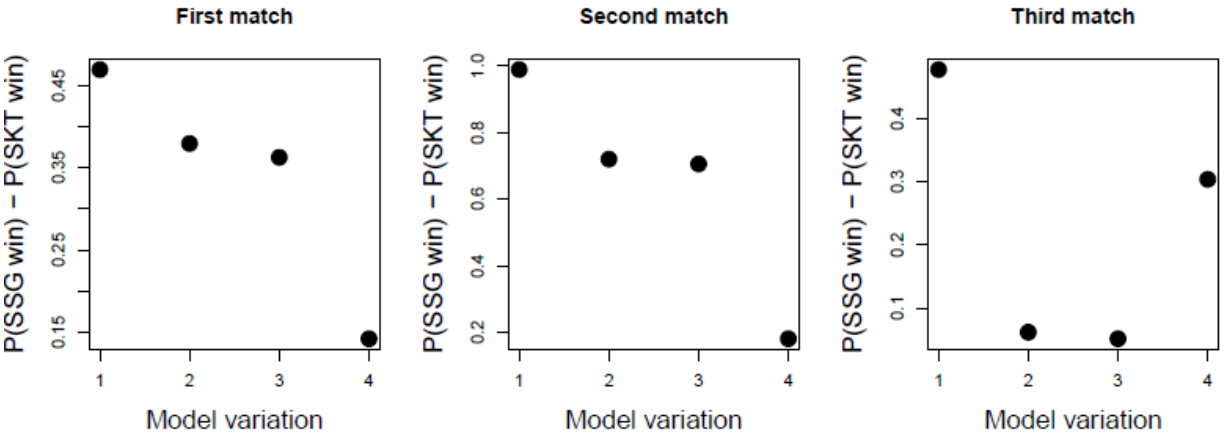


Figure 4.4

We can see that as the model version increase, or equivalently, as the number of model predictor variables decrease, the distinguishability of the winner significantly decreases. We could analyse this for all the matches of the knockout stage, but our purpose is just to show that although the AUC values and accuracies from models v2, v3 and v4 are very similar, in general this is not true for *distinguishability*.

Thus, we should do a balance between the AUC values, the accuracy and the *distinguishablity* (among other possible quantities) to decide which model is better.

Taking into account all the results and observations we have done so far, and the fact that the matchup champion data we use (patch 7.21) corresponds to a quite different metagame from the one that was played during the tournament (patch 7.18), we believe that **the best model version would be the one that considers both the champion matchup win rates and the player's champion win rates**. We expect that the model coefficients for the champion matchups would have been all positive if we could have accessed to data from patch 7.18. Moreover, we don't reject the possibility of including the `side` variable predictor, since it could be an important predictor during the next tournament patches.

To end with this section we would like to discuss about the relative importance of individual predictors in the models v2 and v4. This can be done by looking at the absolute value of the t-statistic for each model parameter [1]. In R we can do it by executing the command `varImp(model)`.

The results for Model v2 and Model v4 predictors are shown in Figures 4.5 and 4.6, respectively.

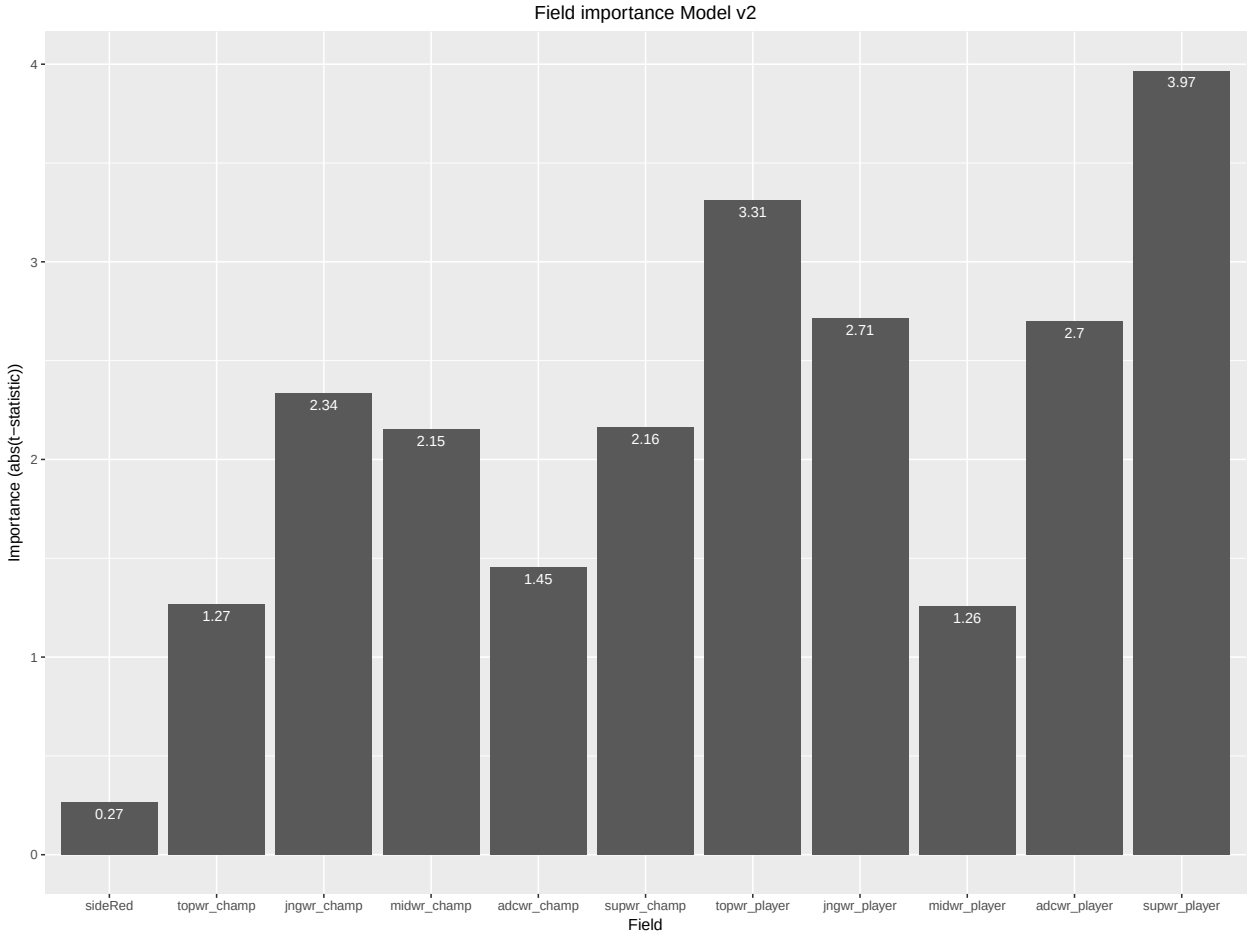


Figure 4.5: Importance of each predictor variable from Model v2

Regarding to Model v2, we don't take care about the `topwr_champion` and `jngwr_champion` predictors since they are negative and doesn't make sense for us.

Now we point out the following observations regarding Model v2:

- As we expected, the importance of the `side` variable is insignificant (0.27).
- For each `position` (top, jng, mid, adc and sup), the importance of the predictor variables

"positionwr_player" is larger than the importance of the "positionwr_champion" predictor variables. This means that, according to our model, "how good is a player with a particular champion" is more important than "how good is a particular champion in the current metagame". However, we have to be careful with this last affirmation, since we are working with data from a different patch and the results could vary.

- The outstanding position (both for the metagame and the goodness of the player) is the Support and the worst is the Midlaner. We can say that the other three positions are almost equally important. The fact that the mid position seems to be the less important one is an argument in favour of the fact that SKT was less likely to win. As we commented before in the text, SKT has probably the current best League of Legends player in the World (Faker) whose main position is mid.

Finally we discuss about the importance of the predictors from Model v4 (Figure 4.6).

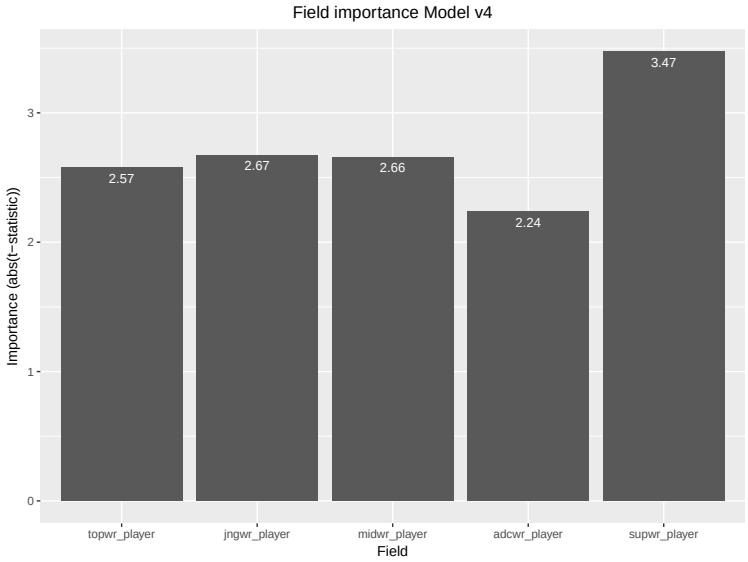


Figure 4.6: Importance of each predictor variable from Model v4

Whereas the top, jungle, mid and adc positions have approximately the same importance, as it happened in Model v2, the importance of the support position outstands quite significantly with respect to the other positions. This result is quite in agreement with the fact that the metagame from the 2017 Worlds Championship was dominated by the role of Adcs and Supports.

5 Conclusions

(Josep? quan estigui tot lo altre fet, es deixa per lo últim)

6 Legal and ethical issues

(Josep/sergi?)

7 Limitations and future work

Limitations

- In order to use our model to make predictions in future World Championships we need to know, a priori, which champions will select each team. As it is the model right now, it would be useful to bet in real time and just before each match starts.
- We have been discussing about the hypothetical negative effect of using "metagame-related" data from a different game patch on the predictability and the model interpretations (importance of predictor variables and so on). Thus, it would be good, whenever possible, to avoid using data from a patch that does not correspond to that in the tournament.
- alguna altra idea?

Future work

- Instead of using the `team` predictor variables which is a categorical variable of dimensions 24, it could be better to use a similar categorical variable but with smaller dimension. An option would be to consider a predictor variable that says from which region comes a particular team (Europe, America, Korea,...).
- Since we have seen that the most important predictor variables are those related with "how good is a player", a viable extension of the model that would probably improve the accuracy, would be to add new predictor variables related to players. To begin with, we could include the average KDA ratio of each player with a given champion. Another option would be to consider one predictor variable associated to each player and related to the "ranking position" as professional players.
- If we wanted to make predictions just before a knockout stage starts, we would not know which champions would play every single player in every single match, so all the "win rate - related" predictor variables would be useless. A solution to deal with this problem would be, for instance, to consider the average win rate of each player with the most played champions; to account for the metagame, we could use an average champion win rate obtained by averaging the win rate of the most played champions by a given player.

  An alternative that would maintain the model as it is right now would be, for example, to consider the top five champions of each player and then simulate all possible permutations of matchups (or a part of them, since this number of permutations will be very large) between one team and the other, and estimate which of the two teams in consideration is more likely to win (i.e., which team wins a higher number of matches from the sample obtained by doing the mentioned permutation procedure).

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[13] *The 2017 Worlds finals between SKT and Samsung Galaxy will be all about adapting*, by Austen Goslin.https://www.riftherald.com/lol-worlds/2017/11/3/16603216/lol-worlds-finals-2017-skt-ssg-preview

A Code outputs

A.1 Models' β coefficients and confidence intervals

Listing 2: Model β coefficients of the base model (v1)

```
                                  2.5 % 97.5 %
(Intercept)                -57.4   -95.6  -19.1
teamCloud9                   5.9     2.1    9.8
teamDire Wolves              0.7    -4.1    5.4
teamEDward Gaming            0.5    -3.9    4.9
teamFenerbahce Esports       2.5    -1.3    6.4
teamFlash Wolves            -2.4    -9.9    5.2
teamFnatic                   3.0    -0.6    6.6
teamG2 Esports               6.8     2.0   11.6
teamGambit Esports         -17.3 -4533.7 4499.1
teamGigabyte Marines         9.0     2.2   15.8
teamHong Kong Attitude       5.2     0.7    9.7
teamImmortals                1.5    -3.1    6.1
teamKaos Latin Gamers        3.0    -2.8    8.8
teamLongzhu Gaming          21.8 -4044.3 4088.0
teamLyon Gaming              5.0    -0.7   10.7
teamMisfits                  9.1     3.8   14.3
teamRampage                  0.4 -5721.8 5722.6
teamRoyal Never Give Up      4.5     0.4    8.7
teamSamsung Galaxy           1.1    -3.0    5.3
teamSK Telecom T1            2.2    -2.6    7.0
teamTeam oNe Esports         3.3    -2.7    9.4
teamTeam SoloMid             4.8     0.3    9.3
teamTeam WE                  8.6     3.4   13.9
teamYoung Generation        12.4     5.8   18.9
sideRed                      0.0    -1.3    1.3
topwr_champ                -13.3   -35.7    9.1
jngwr_champ                -16.5   -43.6   10.5
midwr_champ                 24.3     5.4   43.2
adcwr_champ                 32.9   -20.6   86.4
supwr_champ                 18.0    -9.8   45.9
topwr_player                11.8     2.7   20.8
jngwr_player                 5.5     1.7    9.3
midwr_player                 6.8     0.8   12.9
adcwr_player                15.5     5.9   25.1
supwr_player                12.9     6.1   19.6
```

Listing 3: Model β coefficients of Model v2

```
                   2.5 % 97.5 %
(Intercept)  -21.3 -44.0    0.1
sideRed       -0.1  -0.9    0.7
topwr_champ   -8.8 -23.0    4.4
```

```
jngwr_champ   -20.5 -38.5   -3.9
midwr_champ    10.3   1.3   20.2
adcwr_champ    24.2  -8.1   57.6
supwr_champ    15.8   1.8   30.6
topwr_player    5.4   2.4    8.8
jngwr_player    2.8   0.9    4.9
midwr_player    1.7  -0.9    4.5
adcwr_player    4.0   1.3    7.2
supwr_player    5.0   2.6    7.6
```

Listing 4: Model β coefficients of Model v3

```
                    2.5 % 97.5 %
(Intercept)   -20.9 -43.3    0.3
topwr_champ    -8.8 -23.0    4.3
jngwr_champ   -20.7 -38.7   -4.2
midwr_champ    10.4   1.4   20.3
adcwr_champ    23.4  -8.4   56.2
supwr_champ    15.7   1.7   30.5
topwr_player    5.4   2.4    8.8
jngwr_player    2.8   0.9    4.9
midwr_player    1.8  -0.8    4.6
adcwr_player    4.0   1.3    7.2
supwr_player    5.0   2.7    7.6
```

Listing 5: Model β coefficients of Model v4

```
                  2.5 % 97.5 %
(Intercept)   -9.4 -12.9   -6.5
topwr_player   3.8   1.1    6.8
jngwr_player   2.5   0.7    4.4
midwr_player   3.3   1.0    5.9
adcwr_player   2.9   0.5    5.7
supwr_player   3.9   1.8    6.2
```

A.2 ANOVA tests for each model

Listing 6: ANOVA test for Model v2

```
Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                          179     249.53
side          1    1.424       178     248.11 0.2327296
topwr_champ   1    0.535       177     247.57 0.4643226
jngwr_champ   1    4.457       176     243.12 0.0347515 *
midwr_champ   1    4.727       175     238.39 0.0296887 *
adcwr_champ   1    1.077       174     237.31 0.2994692
supwr_champ   1    1.477       173     235.84 0.2243128
topwr_player  1   33.530       172     202.31 7.019e-09 ***
```

```
jngwr_player   1    14.276        171      188.03 0.0001578 ***
midwr_player   1    11.671        170      176.36 0.0006348 ***
adcwr_player   1     8.534        169      167.82 0.0034857 **
supwr_player   1    19.434        168      148.39 1.041e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Listing 7: ANOVA test for Model v3

```
             Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                         179     249.53
topwr_champ   1    0.494        178     249.04 0.4820141
jngwr_champ   1    4.724        177     244.31 0.0297513 *
midwr_champ   1    4.942        176     239.37 0.0262176 *
adcwr_champ   1    0.715        175     238.66 0.3979253
supwr_champ   1    1.516        174     237.14 0.2182490
topwr_player  1   33.501        173     203.64 7.121e-09 ***
jngwr_player  1   14.493        172     189.15 0.0001407 ***
midwr_player  1   12.084        171     177.06 0.0005085 ***
adcwr_player  1    8.982        170     168.08 0.0027259 **
supwr_player  1   19.621        169     148.46 9.445e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Listing 8: ANOVA test for Model v4

```
             Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                         179     249.53
topwr_player  1   26.319        178     223.22 2.895e-07 ***
jngwr_player  1   14.093        177     209.12 0.0001740 ***
midwr_player  1   19.938        176     189.18 8.000e-06 ***
adcwr_player  1    5.722        175     183.46 0.0167535 *
supwr_player  1   14.282        174     169.18 0.0001574 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

B Additional plots

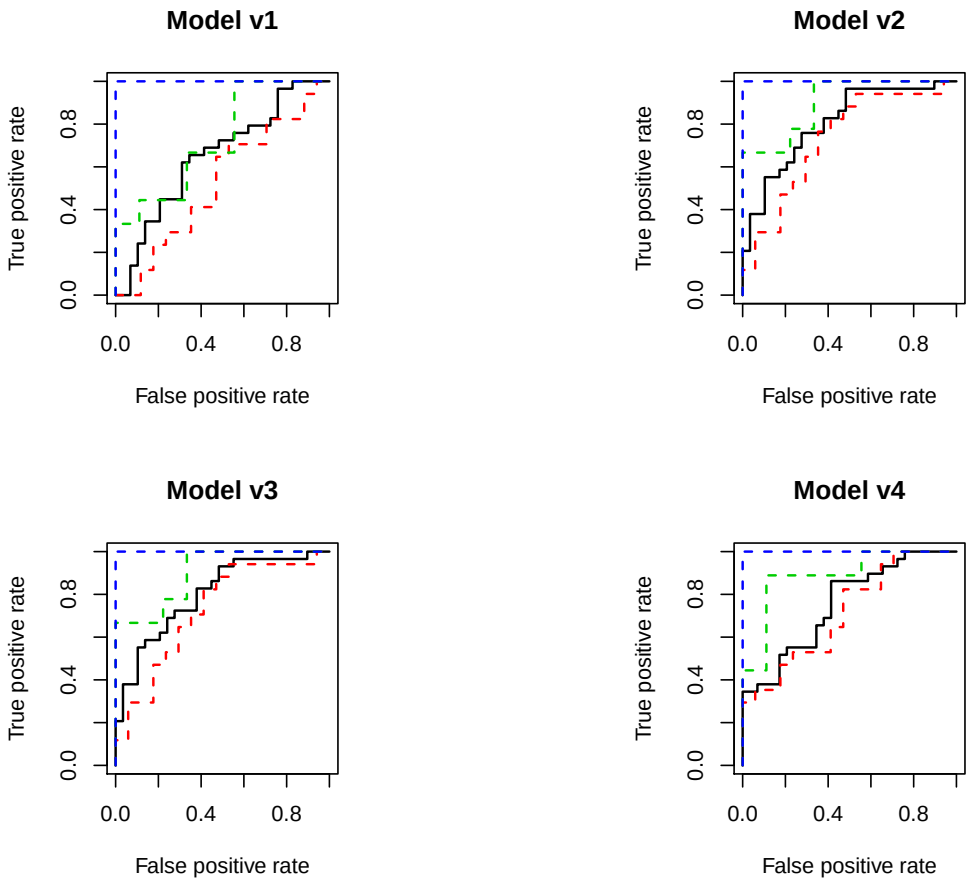

Figure B.1: ROC curves for the four models considered in the text, with respect to the whole knockout stage (black line), quarter finals (red dashed line), semi finals (green dashed line) and the finals (blue dashed line).