SPORT ANALYTICS

Fall 2019 Presentation

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Context

2660
Games to analyze (38 matches per team per season, 7 seasons)

71
Predictors for each game (including fouls, corners, cards, ...)

505
Players from 20 different teams (65.2% of whom are not from the UK)

£8.39B
Total cumulated market value of PL teams for season 18/19

Objectives of the project

The project core objective is to **predict** the result of English Premier League soccer games as well as the **final rankings** at the end of a season.

We will rely on a Bayesian approach to establish **team rankings** and develop a **predictive model** on top of it to generate a win, draw and loss probability for a given game.

Benefits of the project

Team Management: Optimize team training program to ensure perfect fit for key decisional games and determine when to substitute the B team

Club-level decisions: Better quantify the market value of a scouted player and shape the club's willingness to pay by estimating the impact of the acquisition

Betting strategy: Provide probabilities estimation for gamblers willing to increase their chances over the teams they support

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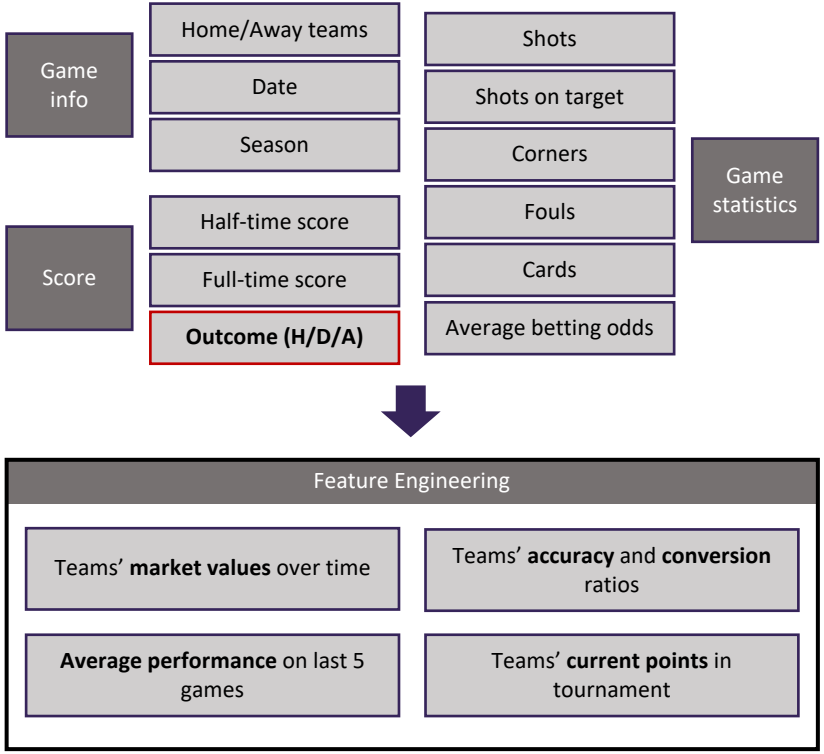
Discovering the data



Methodology

1

The first step of our approach will consist in establishing **team rankings** for each season in our data, that we can further reuse for game/season outcome prediction as we did in class.

For each season, we aggregate previous seasons' data to form a **prior** estimator and then use a **Bayesian approach** to formulate an estimation of the **posterior ranking**.

We then use this to compare the **performance of different models** with home and/or away advantage at predicting games outcomes.

2

In parallel to this, we build additional **intensive features** aiming at capturing more accurately **momentum** in one team's performance: past 5 games averaged shot accuracy, shot conversion, etc.

Once data is cleaned and normalized, we try different **supervised-learning models** to predict probabilities of win/draw/loss for each game, and choose the best performing one.

We then incorporate rankings and predictions from the Bayesian approach to the model, as well as teams' **market value** at game time.

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3. Bayesian approach for team rankings

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1. Simple rating model with Home advantage for each season

Year	RMSE
2013	1.486
2014	1.589
2015	1.470
2016	1.518
2017	1.558
2018	1.871

2018 Rankings			
1	Man City	11	Man United
2	Liverpool	12	West Ham
3	Chelsea	13	Bournemouth
4	Arsenal	14	Newcastle
5	Tottenham	15	Southampton
6	Wolves	16	Crystal Palace
7	Watford	17	Burnley
8	Leicester	18	Fulham
9	Brighton	19	Huddersfield
10	Everton	20	Cardiff

We try to predict the **outcome of each game** using teams' **ratings**, obtained by **minimizing the RMSE** on all game predictions.

2. Bayesian prior on past seasons to account for macro trends

Games	Test
380	304

Model test (4,3)	Model SR	Model Bayes
RMSE	47.3%	46.1%
Model SR		.3%
Model Bayes	99.7%	

We add a term for **Bayesian mean reversion** based on all previous seasons of data.

3. Simulation over many games to estimate current season ratings

Win league: **rank 1** in points

Champions league qualify: **top 4** in points

Relegated: rank **>= 18** in points

Team	Win League	Champions	Relegation
Man City	52.5%	99.1%	0.0%
Liverpool	37.0%	98.4%	0.0%
Chelsea	7.3%	84.4%	0.0%
Arsenal	2.1%	59.7%	0.0%
Tottenham	1.1%	45.1%	0.0%

We perform a **simulation** of 1000 trials for 3 probabilities: **winning** the league, **qualifying** for UCL and being **relegated**.

4. Predict season final rankings & create a feature from this rating

2019 Rankings			
1	Liverpool	11	Burnley
2	Leicester	12	Crystal Palace
3	Man City	13	Bournemouth
4	Chelsea	14	Brighton
5	Tottenham	15	Newcastle
6	Man United	16	Everton
7	Sheffield United	17	West Ham
8	Wolves	18	Southampton
9	Arsenal	19	Norwich
10	Aston Villa	20	Watford

We use the ratings obtained with this training phase to **predict outcomes** for the current season's **games** & **final rankings**.

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4. Feature engineering & selection

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Web scrapping

Cut-off date: Nov 15, 2019 Show

#	Club	Current value
1	Manchester City	£1.15bn
2	Liverpool FC	£965.48m
3	Chelsea FC	£726.30m
4	Tottenham Hotspur	£886.50m
5	Arsenal FC	£621.68m
6	Manchester United	£677.93m

Teams' market value on 11/15/19

Feature selection

- We want to keep only **intensive features** that will be available to predict future outcomes.
- We get rid of features related to **fair-play** (ie fouls, cards, etc.) and **game facts** (corners, free-kicks, etc.).
- We also keep the **average odds provided by betting websites** at the time of a game.

Feature Engineering

1. Filling in for teams without market value

For each season, some teams do not have market value because they just got promoted/relegated.

We tried filling the missing values with
- Average
- Median
- **Minimum value** (worked best)

2. Adding conversion & accuracy features

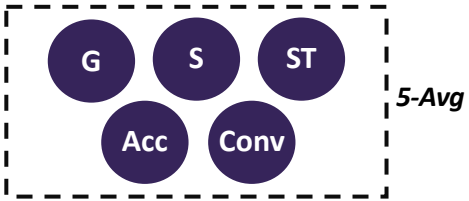
Creating **ratio features** better fitted and scaled to **comparing performance between teams**: goal conversion and shot accuracy.

$$\text{Accuracy} = \frac{\#\text{ Shots on target}}{\#\text{ Shots}}$$

$$\text{Conversion} = \frac{\#\text{ Goals}}{\#\text{ Shots}}$$

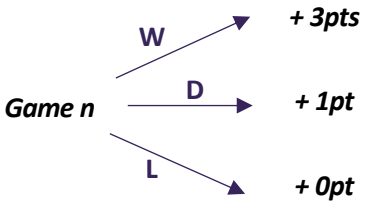
3. Creating momentum features

We build features aiming at capturing the team's **momentum** based on its **last 5 games** (with a minimum of 2 games played in the season).



4. Championship points counter

To determine **final season** rankings, we implement a **point counter** to track the number of points after every game played by a team.



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Model

1 Logistic Regression → **2 Random Forest**

Description

The **logistic regression** is the equivalent of a linear regression for when the variable to predict falls into **categorical buckets** (ie is not continuous).

Here, we use all previous features to predict the *RESULT* dependent variable which has **multiple classes**: Win / Draw / Loss.

Logistic regression is a **simple and interpretable model** and its results are easy to convert into applicable **business decisions**.

The random forest is a more complex classifier made of **decision trees** where **the features are randomly sampled,** and which outputs the **most frequently predicted class** among all trees.

This model is more likely to accurately extend its predictions to **new teams** in the league and will work better if one of the 3 **classes** is less represented.

Random forests **combine** multiple hypothesis to form a better one and **generalize** better to new data.

Results

73%	Of game outcomes well predicted on **training** seasons (2012/13 to 2017-18)	**77%**	On **training** seasons	**80%** On **training** seasons
52%	Of game outcomes well predicted on the **test** season (2018/19)	**55%**	On **test** season	**60%** On **test** season

With Bayesian ratings

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1 Naive Strategy

- For **each match** of the season bet $1 on the **predicted outcome.**
- The money made is based on the **true odds** of the match.

We bet **$1** on **all 360 games**

Expected return: **$232**

ROI: +64.4%

2 Odd-based Strategy

- Hypothesis that the **inverse of the odd** is their probability.
- If our max probability is **higher than the odd's** max probability, we bet $1 on our prediction.

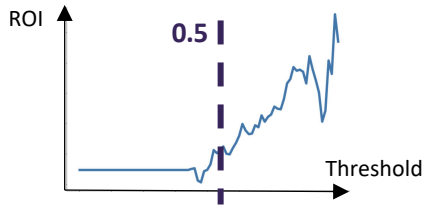
We bet **$1** on **only 142 games**

Expected return: **$95**

ROI: +66.9%

3 Threshold-based strategy

- If the **highest prediction probability is above a threshold,** we place a bet.
- We bet on **each outcome** by placing a regular amount (eg $1 per betting)



ROI: +75.9%

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Thank you for your attention!

Any questions?

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