Random Forest Classification Model

Premier League Win-Loss Prediction
Seasons 2016 - 2019

Project Team

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Project Goal

- Make accurate predictions about Premier League game Win-Loss based on historical game statistics using Machine Learning Model

Objectives

- Research available sources of historical soccer game data
- Download data in standardized format
- Clean the data
- Select model features
- Select prediction variable
- Transform data into format to fit machine learning model

Objectives cont'd

- Select prediction model
- Train and test the model
- Evaluate prediction performance of the model
- Fine-tune model hyper-parameters to improve model prediction
- Evaluate results
- Conclusions

Resources

- Data source: RapidAPI
- Data: Premier League Seasons 2016 - 2019
- Data format: CSV
- Dataset type: detailed fixture game stats by season game
- Dataset size: approx. 1.4 mil. rows by 33 columns

Machine Learning Model

- Model selected: Balanced Random Forest Classifier (BRF)
- Reduces overfitting
- Proven performer in classification prediction problems
- Works with categorical and continuous values
- Uses Ensemble Learning technique (many weak learners strong together)

Base BRF Model Features and Prediction

- Total features in dataset: 32
- 100 Trees Balanced Random Forest
- Train data: seasons 2016-2018
- Test data: season 2019
- Prediction: h_result (Win-Loss)

Base BRF Model Confusion Matrix

- 100 Trees
- 32 Features

	Predicted 0	Predicted 1
Actual 0	48	57
Actual 1	51	34

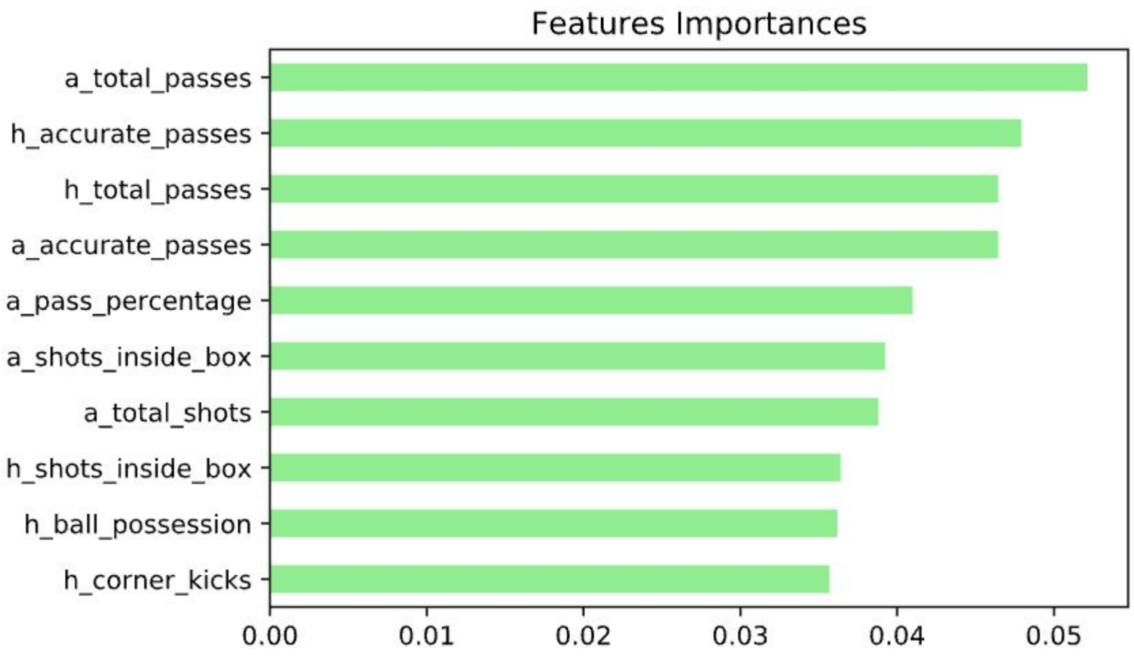
Base BRF Model Accuracy

```
Balanced Accuracy Score : 0.42857142857142855
```

Base BRF Classification Report

	pre	rec	spe	f1	geo	iba	sup
0	0.48	0.46	0.40	0.47	0.43	0.18	105
1	0.37	0.40	0.46	0.39	0.43	0.18	85
avg / total	0.44	0.43	0.43	0.43	0.43	0.18	190

Most Important Features



Fine-Tuned BRF Model Features and Prediction

- Total features in dataset: 6 most important from Base BRF
- 128 Trees BRF (higher number (500) did not add to accuracy)
- Features selected for the base model:
  - `h_accurate_passes`
  - `h_total_passes`
  - `h_pass_percentage`
  - `h_ball_possession`
  - `h_total_shots`
  - `h_fouls`
- Prediction: h_result (Win-Loss)

Fine-Tuned BRF Model Features and Prediction

- Dropped Season 2019 because of insufficient data
- Train data 2016-2017
- Test data: 2018

Modified BRF Model Accuracy

```
Balanced Accuracy Score : 0.6418001610261251
```

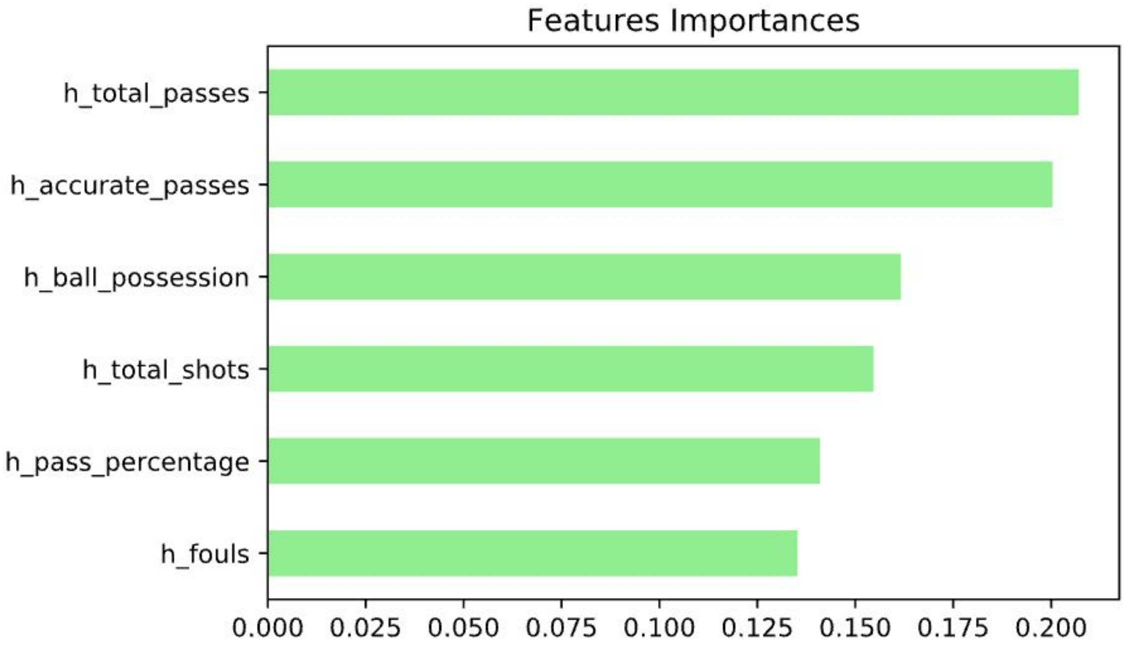
Confusion Matrix

	Predicted 0	Predicted 1
Actual 0	129	70
Actual 1	66	115

Classification Report

	f1-score	precision	recall	support
0	0.654822	0.661538	0.648241	199.000000
1	0.628415	0.621622	0.635359	181.000000
accuracy	0.642105	0.642105	0.642105	0.642105
macro avg	0.641619	0.641580	0.641800	380.000000
weighted avg	0.642244	0.642525	0.642105	380.000000

Most Important Features



Alternative Classification Models

- Easy Ensemble Classifier
- SMOTEENN Model

Easy Ensemble Classifier Accuracy Score

```
Balanced Accuracy Score : 0.608900857880563
```

Easy Ensemble Classification Report

Classification Report

	pre	rec	spe	f1	geo	iba	sup
0	0.62	0.64	0.57	0.63	0.61	0.37	199
1	0.59	0.57	0.64	0.58	0.61	0.37	181
avg / total	0.61	0.61	0.61	0.61	0.61	0.37	380

SMOTEENN Model Accuracy Score

SMOTEEN Balanced Accuracy Score = 0.4908381687442739

SMOTEENN Classification Report

	pre	rec	spe	f1	geo	iba	sup
0	0.52	0.52	0.46	0.52	0.49	0.24	199
1	0.47	0.46	0.52	0.47	0.49	0.24	181
avg / total	0.49	0.49	0.49	0.49	0.49	0.24	380

Conclusions

- Random Forest best performing classification model
- Fine-tuning hyper-parameter improved significantly prediction ability of the Base BRF model
- Longer data history would potentially improve model score
- Alternative classification models underperformed BRF model

Conclusions cont’d

- Overall accuracy of Modified BRF model (0.64) puts prediction odds in our favor
- BRF model could benefit from more data history to potentially further improve accuracy