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Comparison of Individualized and Group-based Machine Learning Approaches to Predict Rate of Perceived Exertion of Professional Football Players

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Abstract—Monitoring fatigue in sport is critical to achieve elite performance and may benefit from machine learning techniques that are liable to predict changes in fatigue state. In this paper we present and compare different machine learning models to predict the Rate of Perceived Exertion (RPE) of training or game sessions for professional football (soccer) players. We compare different approaches to train predictive models in a supervised setting (regression) with a focus on individualized and group-based approaches, i.e. training a specific model for each player or predefined groups of players (full team or clusters defined using unsupervised learning). Both player-informed and player-agnostic models are compared in the group-based approach, i.e. providing or not player id as feature during training and inference. Compared models have been trained on real data collected during a full season of professional football players, and using among others, anthropometric, running activity, heart rate and weather data. The best results are obtained using a player-informed team-based approach with a Random Forest regressor (0.793 MAE, 1.033 RMSE). Results obtained are competitive with the best reported in the literature for this predictive task in elite Football players.

Index Terms—Machine Learning, Fatigue Prediction, RPE

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I. INTRODUCTION

Monitoring fatigue in sport is critical to achieve elite performance. This is particularly true for team sports in which players are engaged in long and demanding seasons, and therefore exposed to fatigue state potentially leading to decrease in performance or even injuries. Due to this context, many approaches have been studied to help sport teams leaders as well as physical trainers to monitor players’ fatigue state. Such monitoring is of particular interest to reduce risk of injury, but also to evaluate the potential impact of future training sessions, i.e. to quantify internal training loads and to improve players’ physical fitness. Among the different research endeavors under study, the use of predictive models taking advantage of data collected during training and competition is of particular interest. The aim of this research track is to develop predictive models that will be able, based on past data and perceived exertion assessments, to infer the fatigue state of a player, e.g. after a specific training session.

Among the different techniques that are commonly used to monitor fatigue, subjective measures of perceived exertion are often used in elite sport, e.g. team sports such as soccer [1]. The Rate of Perceived Exertion (RPE) is often used to enable athletes to subjectively quantify the perceived amount of effort experienced during a physical activity, i.e. how much the latter has been demanding. In this paper we study the use of machine learning approaches for automatic and non-subjective evaluations of RPE through predictive models. This is the

angle of study we will adopt in this paper, by evaluating how traditional machine learning models perform to predict RPE from several sources of data, e.g. data related to the players, and a training/game session. Our main contributions related to RPE prediction are listed below:

- Application and evaluation of several machine learning models to real-world data collected in a French elite soccer team. Insights related to data preparation and feature selection are discussed.
- Proposal and evaluation of 4 approaches to building predictors, evaluating the benefits of individualized (player-specific) predictors compared to group-based predictors, e.g. trained for the whole team of players. The impact of including a marker enabling player identification during training and inference building group-based predictors is also evaluated.

The paper is structured as follows. Section II introduces notions related to fatigue and RPE in sport, as well as prior works related to RPE prediction using machine learning. Section III describes the features that have been used as well as the proposed approaches for modelling predictors. Section IV introduces our experiments, including the dataset and its analysis, the evaluation protocol, and discusses the results we obtained. Section V concludes the paper.

II. STATE OF THE ART

A. *Fatigue and Rate of Perceived Exertion in sport*

Fatigue is a complex concept accepting different definitions in literature. In sport, it most often refers to exercise-induced fatigue, and in particular *motor performance fatigue* - also called muscle or neuromuscular fatigue - that can be quantified by a decrease of the (maximal) voluntary force that can be produced by the neuromuscular system in controlled conditions. Such fatigue is naturally dependent on several characteristics of the task (e.g. intensity, duration, weather) and of the athlete, e.g., age, fitness level. Aspects related to the perception of such a motor fatigue are also central to fully characterizing the notion of fatigue which is most often of interest in sport; to this end the notion of perceived motor fatigue relates to aspects referring to motivation, mood, effort perception [2]. More generally, works on fatigue monitoring will sometimes consider the notion of cognitive task-induced state fatigue which Behrens et al. define as a psychophysiological condition characterized by a decrease in motor or cognitive performance - i.e., motor or cognitive performance fatigue, respectively - and/or an increased perception of fatigue, i.e., perceived motor or cognitive fatigue [2]. In sport, fatigue is traditionally evaluated using different objective quantification techniques (e.g., blood lactate, muscle force, surface electromyography), but also using subjective evaluation such as RPE. A focus on RPE will be considered hereafter as this evaluation is popular in team sport environments and numerous studies consider this indicator to quantifying the notion of internal training load intrinsically related to the notion of perceived fatigue according to [3].

RPE scales have been developed to evaluate the level of perceived exertion according to cardiovascular (e.g., increased heart rate and breathing difficulty) and muscular (e.g., muscle exertion and pain) loads during a physical activity. Therefore, the RPE is based on the physical and mental sensations of the athlete considering, among others, his/her physical condition, general level of fatigue, effort management, as well as environmental conditions. The notion of RPE, even if it relates to the internal training load of an athlete, is therefore related to both notions of external and internal loads which are respectively, the amount of physical activity imposed to the athlete (e.g. running distance), and the physiological or psychological response induced by this activity (e.g. heart rate) [4]. RPE values are most often collected after physical activities enabling players to evaluate their level of exhaustion on a given scale dedicated to fatigue monitoring. Specific scales have been developed to this aim, one of the most popular being today the modified Borg Category-Ratio (CR10) which evaluates exertion from 0 to 10 (respectively referring to a resting state and a maximum effort) [5]. The intrinsic subjective nature of the RPE may however be misleading. Indeed, in some contexts, under or over evaluations of exertion can be observed, e.g. a player being somehow influenced by other players during rating, or not wanting to admit a peak of fatigue days or weeks before important dates in the season. In this context, automatic and non-subjective evaluations of RPE through predictive models may be of interest. This is the angle of study we will adopt in this paper, by evaluating how state of the art machine learning models perform to predict RPE from several sources of data, e.g. data related to the players, and a training/game session. A review of previous studies on RPE prediction using Machine Learning is proposed hereafter.

B. *Machine Learning for RPE prediction in sport*

In the last decade, several approaches have been studied for estimating the RPE of athletes using machine learning techniques, e.g. [6]–[9]. RPE prediction is to date traditionally modeled as a supervised machine learning problem, with works considering both modelling as regression or classification problems, e.g., [3], the former being the most popular approach. Models consider different input features related to data likely to inform on external and internal loads. Models therefore most often incorporate data related to global positioning systems (GPS) and accelerometers - enabling evaluation of locomotion-related production -, heart rate, weather conditions, and even sometimes answers to wellness questionnaires. Note however that the multitude of contexts of study (e.g. different sports, input features) and the fact that datasets are not publicly available due to obvious privacy and competitive reasons, make the comparison of results across studies difficult. Most contributions have so far focused on traditional machine learning techniques (e.g. linear models, Decision trees, Random Forest, SVM) with only a few contributions testing recent deep learning approaches [9]. Some examples of contributions illustrating the variety of

models that have been evaluated in the literature are presented hereafter.

Bartlett et al. [6] have been among the first to demonstrate that machine learning may outperform traditional methodologies to predict athlete response to training loads, in terms of RPE. To this end, the authors have compared predictive powers of traditional generalized estimating equations and multi-layer perceptron (MLP) in professional Australian football; best results were obtained using MLP (RMSE \simeq 1.24). They have also shown that, on their dataset, individualized modelling - designing a predictive model per athlete - achieves better performance than group modelling approaches - designing a single player-agnostic model for the whole team. In this same sport, Carrey et al. [3] have also proposed to study the use of machine learning approaches to predicting RPE with a focus on methods adapted to live estimation. Models considered explanatory variables of different natures, e.g., running metrics (distance, duration...), heart rate, acceleration. In their work, a random forest model using player-normalised running and heart rate variables achieved the best performance (RMSE \simeq 0.96); their results highlighted that running distances and speeds are among the strongest explanatory variables.

In soccer, Rossi et al. [7] have studied the relationship between RPE and the training load with machine learning models. Several traditional models (decision tree, random forest, SVM, logistic regression, k-NN non-parametric model) have been tested using features reflecting external and internal loads. Their best results obtained a RMSE slightly above 1, highlighting that training loads of the previous week most often have a strong effect on perceived exertion. Their results clearly support the use of machine learning as a valuable tool to help trainers and coaches in understanding individual responses to training loads in team sports. Marynowicz et al. [10] also proposed a detailed study on the use of decision tree as a white-box model for predicting RPE in soccer. They considered both global and individualized models. The best reported results were obtained using personalized models (RMSE around 0.755). Their results underlined the importance of features related to high-speed running distance during physical activity. Vallance et al. [8] have also evaluated the use of traditional machine learning techniques to predict RPE in professional soccer players (linear regression, decision trees, random forest, elastic net regression, XGBoost, k-NN). They achieved interesting results using random forest and XGBoost (RMSE \simeq 1), both models including several external load variables (derived from GPS and accelerometers), as well as internal load variables derived from past RPEs. Recently, Kim et al. [9] are among the first to have studied deep learning techniques for RPE prediction in soccer (among Korean elite soccer player). They have proposed FatigueNet, a model based on a Convolutional Neural Network combined with a Gated Recurrent Unit (CNN-GRU). Interestingly, compared to traditional machine learning approaches, FatigueNet only relies on players' movement data (raw time-series spatio-temporal data) instead of traditional handcrafted aggregated features. It however managed to achieve state-of-the-art performance for

the task of RPE prediction.

Putting aside the type of models used (traditional or deep learning models), the literature to date offers contradictory results regarding the benefits of using individualized models for predicting RPE. We therefore propose to contribute digging that question in this paper.

III. PROPOSED APPROACHES

We compare different approaches for building RPE predictors in the aim of evaluating the impact of player-specific information during model training and inference. Note that the studied approaches are model agnostic as they are not restricted to the choice of a specific machine learning model (e.g. Linear Regression, Random Forest, Multi-layer Perceptron or any recent Deep Learning model). In our context, a model can therefore be seen as a component of the general approaches we will compare. The notion of approach in our case refers to the methodology used to train a selected model, with potential repercussion on its practical application, e.g. an approach that requires a player id as input feature could be less resilient about team modifications.

The four approaches tested and compared in our study are summarized below. We stress in parenthesis if the approach has access to data enabling to explicitly distinguish a player during training and inference, e.g., with an id.

- 1) Player-specific predictor (Player-informed): predictors are individualized and have been obtained training models only considering labelled data that is specific to a given player, i.e. predictions for a specific player are made using a specific and dedicated model.
- 2) Player Cluster predictor (Player-agnostic): predictors have been obtained training models considering data of players sharing specific properties, i.e. predictions for a specific player are made using a specific model relevant for the corresponding player regarding a prior unsupervised clustering.
- 3) Team predictor (Player-informed): predictors have been obtained training models considering all players' data, including an input feature specifying the player id. This choice makes the model informed during both inference and prediction.
- 4) Team predictor (Player-agnostic): predictors are alike the Team predictors described above, except that the player's id is here not given during both training and inference.

All the predictors defined using these approaches use the same set of features, except for the player id that will only be considered in player-informed approaches (1 and 3). Details of each approach are presented next to the introduction of the set of features we have considered.

A. Set of features

This section describes the set of features that have been used to characterize an entry, i.e. the input features that will finally be considered for predicting the RPE for a given player in a specific physical activity. Features mostly correspond to domain-specific metrics computed to evaluate internal and

external loads. Some features correspond to metrics that are computed in specific “effort zones” that are defined regarding speed, or heart rate. Specific categorical features are one-hot encoded in practice.

1) *General and Anthropometric player features:*

- Player id that is encoded using one-hot encoding when it is used. This feature is the only one that will be used or excluded depending on the type of approach that will be studied.
- Position code, one-hot encoding defining the position of the player, e.g. goalkeeper, winger. We also consider a one-hot encoding of an additional feature defining the specific position of the player, e.g. right winger.
- Height weight ratio.
- Body mass index (BMI).
- Age code, this feature has not been one-hot encoded to enable models to take advantage of relative comparison.
- Team, one-hot encoding defining the team the player is a member of, i.e. first or second team.

2) *Physical activity features:*

Those features have mostly been obtained analyzing raw GPS and accelerometer data as well as meteo data captured during the physical activity requiring a prediction.

- Total distance covered during the running activity.
- Duration of the activity, i.e. duration of effort, as well as durations spent in the following 5 speed zones in kilometer per hour (km/h): below 3.6 km/h, in [0, 7.2[, [7.2, 14.4[, [14.4, 19.8[, [19.8, 25.2[, or above 25.2 km/h.
- Distances covered in the above-mentioned speed zones, e.g. sprint distance: the distance covered above 25.2 km/h.
- Number of accelerations that is computed using a proprietary Catapult™ device.
- PlayerLoad™, a Catapult™ metric, that reflects the number of accelerations across all directions during movement (based on the internal tri-axial accelerometer). SmoothLoad™, a metric related to PlayerLoad™, is also used.
- Metabolic power, a Catapult™ metrics that calculates the energy requirements for acceleration and deceleration events based on GPS data.
- Average heart rate and duration spent in specific heart rate zones, i.e. below 75 beats per minute, in [75, 125[, [125, 150[, [150, 160[, or above 160 beats per minute.
- Training period (am or pm), one-hot encoding.
- Weather data informing about pressure, wind, temperature, rain and humidity.

Prior to feature computation, data obtained from Catapult sensors, initially sampled at 10 Hz, have been down sampled at 2 Hz using rolling mean. Finally, normalization has been made on each feature using the Min-Max normalization approach, excluding categorical features (i.e. one-hot encoded). Note that we made the choice in this study not to incorporate information about prior RPEs as input feature, e.g. average of past 5 RPEs. This choice has been made to ease the use of the model when only limited data related to previous RPEs is available.

B. *Compared approaches*

1) *Player-specific predictor (Player-informed):* in this approach, a specific predictor is obtained for each player, i.e. each of those predictors is obtained only considering input features and RPE observations of a single player. The training phase therefore leads to producing one model per player. During testing, the evaluation is then made considering, for each test entry $x_i^{(j)}$, i.e. entry i associated to a the player id j , the appropriate model $pred_{\mathcal{D}(j)}$ to obtain the prediction $\hat{y}_{i(1)}^{(j)}$ that will be compared to the target value $y_i^{(j)}$ - subscript (1) refers to the approach' id.

$$\hat{y}_{i(1)}^{(j)} := pred_{\mathcal{D}(j)}(x_i^{(j)}) \quad (1)$$

Subscript $\mathcal{D}(j)$ stresses that the predictor has been trained only using labelled data of player j among the full training set \mathcal{D} .

2) *Player Cluster predictor (Player-agnostic):* this approach first assigns a single cluster id to each player. The technical approach we choose to build the clusters in practice will be discussed hereafter. Once the clusters are defined, a cluster-specific model is trained for each cluster. While training the predictor of a specific cluster, only observations related to players that are part of the corresponding cluster are considered. The predictions for the entries of a given player are then made considering the predictor learnt for the specific cluster the player is a member of. Formally:

$$\hat{y}_{i(2)}^{(j)} := pred_{\mathcal{D}[clust(k)]}(\bar{x}_i^{(j)}) \quad (2)$$

with $\bar{x}_i^{(j)}$ the $x_i^{(j)}$ vector representation without the player id feature encoding explicitly mentioning that we are dealing with player j ; $k = argmin_{l \in \{1, \dots, |C|\}} \|p_{(j)} - c_l\|_2$, C the set of centroids of all clusters, c_l the vector representation of centroid l , and $p_{(j)}$ the vector representation of player j .

Note that the choice has been made not to provide player id during inference. However, we choose to build clusters consider player-specific data captured during training/game sessions, as well as anthropometric data (no RPE value used, average values of features are used; i.e. $p_j := \frac{1}{|\mathcal{D}(j)|} \sum_{(x,y) \in \mathcal{D}(j)} \bar{x}$).

Clustering is made in an unsupervised way, using the traditional K-means algorithm, even if the global approach is *per se* not tight to this specific clustering algorithm.

3) *Player-informed Team predictor:* in this approach, a model is trained using the full training set \mathcal{D} , also considering the player id as input feature. During testing, the same predictor is therefore finally used to predict RPEs for all players specifying their corresponding ids during inference:

$$\hat{y}_{i(3)}^{(j)} := pred_{\mathcal{D}}(x_i^{(j)}) \quad (3)$$

4) *Player-agnostic Team predictor*: the models are trained adopting the same approach used to obtain the player-informed team predictors (3), except that, in this case, the player id feature encoding is not used. This enables us to obtain a single predictor for all players without restriction to player in \mathcal{D} .

$$\hat{y}_{i(4)}^{(j)} := \text{pred}_{\mathcal{D}}(\bar{x}_i^{(j)}) \quad (4)$$

IV. EXPERIMENTS

A. Dataset

The dataset used in this study is composed of data on physical activities collected during the 2022-2023 season on 33 French male professional football players. The full labelled dataset contains 5088 entries with a median of 169 observations per player (min: 32, max: 237, μ : 154.18, σ : 59.93). As mentioned in section III-A, each entry specifies values for a set of features related to external and internal loads, general information about the player, as well as a the corresponding RPE value using the modified Borg CR10 scale. RPEs have been collected right after the physical activity using the same protocol. Even if some data have been recorded during competition, most entries and in particular data related to external and internal loads and RPEs have been collected during training (e.g. small-sided games). Player’s motion data and heart rate have been recorded using a 10Hz GPS unit and the Catapult™ technology¹. Meteorological data have been gathered from Open-Meteo.² The dataset is not publicly available (restrictions due to privacy).

The distribution of RPE values in our dataset is characterized by a unimodal distribution centered around the middle of the scale; a peak between 4 and 6 clearly indicates that most of the training sessions were perceived as moderately intense by the players. Note that this distribution of RPEs, which reflects expectations, differs from the distribution observed in a similar dataset obtained in the Korean premier league [9] (right-skewed, majority of RPEs set to 3).

The analysis of the correlation between RPE and feature values has validated our choice of features - already studied in the literature. As an example, we observed that the distribution of heart rate monitored during sessions associated to high RPE is skewed towards higher values. This indicates that, intuitively, when players report high RPEs, their heart rate is also typically higher.

Note that entries with missing data have been excluded from the analysis (no use of imputation techniques). Statistics reported above have been computed after removal of those entries. Continuous variables have been normalized (Min-Max) and categorical variables have been encoded; details are provided in section III-A.

B. Evaluation protocol

A standard machine learning protocol was used in order to compare the different approaches. The performance of each

approach, considering all tested models, has been computed using an unstratified k-fold cross validation. Traditional regression metrics have been analyzed from which MAE and RMSE are reported. In the approach based on clusters, clustering is performed for each k-fold evaluation (iteration) to avoid test fold contamination during cluster computation. The number of clusters has been set to 3 through manual observations on training data.

All four approaches defined in Section III have been considered using a fixed set of machine learning models: Linear Regression, Random Forest Regressor, Ridge regression, Lasso, XGB as well as XGBRF. Implementations from Scikit-learn [11] and XGBoost³ Python packages have been used. Different hyperparameter values have been compared for several models, e.g. random forest regressors trained with 50, 75, 100 and 125 trees. No computing intensive hyperparameter tuning approach has however been used in addition to these predefined hyperparameter value configurations.

Performances of three naive baselines are also provided. Models named “*average*” refer to predictors set to fixed average RPE values, distinguishing Team, Cluster, and Player averages, depending on the set of training data used during estimation. The definition of these approaches is $\hat{y}_{i(average)}^{(j)} = \frac{1}{|\mathcal{D}'|} \sum_{(x,y) \in \mathcal{D}'} y$ with $\mathcal{D}' = \mathcal{D}$ for the Team average, $\mathcal{D}' = \mathcal{D}(j)$ for the player average, and $\mathcal{D}' = \mathcal{D}[clust(k)]$ for the player cluster dealing with a player who is part of cluster k .

C. Results and Discussion

Table I presents a selection of results focusing on average MAE and RMSE obtained through k-fold cross validation ($k = 3$). It reports the best results obtained using the four approaches we compared, independently from the underlying machine learning model (cf. Best per approach ranking). Comparative results of all the approaches fixing the model to a random forest regressor are also provided (cf. same model ranking). Finally, results using naive average baselines enable appreciating the level of performance reached by each approach.

The best results have been obtained using the team-based (group-based) player-informed approach using a single model for all players, that considers information about the player as input feature (by providing the player id, cf. section III-B3). Best results have always been obtained using a random forest regressor, with different numbers of trees, the best result being in our case obtained using 75 trees with a MAE of 0.793 ($\sigma = 0.017$) and a RMSE of 1.033 ($\sigma = 0.016$). Those results are significantly better than those obtained using naive baselines (MAE = 1.519) and are in line with the best results reported in the literature in terms of RPE prediction.

We note that the best performances obtained using the four different approaches are close, e.g. the weakest best performance is obtained by the individualized approach (i.e. player-specific model) that shows a moderate and in-practice insignificant loss of 0.073 MAE point (from 0.793 to 0.866).

¹<https://www.catapult.com>

²<https://open-meteo.com>

³<https://xgboost.readthedocs.io/en/stable/>

TABLE I
EXCERPT OF MEAN MAE AND RMSE RESULTS FOR SOME RPE
PREDICTION APPROACHES, USING K-FOLD CROSS VALIDATION ($k = 3$)

Approach ^a	Model	MAE μ	RMSE μ
<i>Best per approach ranking</i>			
(3) Team w/ player id	Random Forest (75 ^b)	0.793	1.033
(4) Team w/o player id	Random Forest (100)	0.796	1.037
(2) Player cluster	Random Forest (125)	0.819	1.077
(1) Player-specific	Random Forest (100)	0.866	1.143
<i>Same model ranking</i>			
(3) Team w/ player id	Random Forest (75)	0.793	1.033
(4) Team w/o player id	Random Forest (75)	0.801	1.046
(2) Player cluster	Random Forest (75)	0.821	1.078
(1) Player-specific	Random Forest (75)	0.866	1.144
<i>Baselines</i>			
(1) Player-specific	Average	1.519	1.819
(2) Player cluster	Average	1.557	1.890
(3,4) Team	Average	1.560	1.892

^aApproach id in parenthesis cf. section III-B, e.g. III-B3 for approach 3.
w/ with, w/o without.

^bNumber of trees.

Interestingly, focusing on subgroups of players sharing characteristics composed using an unsupervised learning clustering technique does not improve the results. This reduction of performance, like the one observed for individualized models, is most probably due to the reduction of data available for training predictors. In addition, adding the player id in team-based approaches does not induce significant changes in performance which can be explained by the importance played by the anthropometric features (e.g., BMI, age group...).

Regarding the influence of model choice setting a specific approach, the second-best result obtained using the team-based player-informed approach, but modifying the model, has been obtained using Ridge regression (alpha 0.75) with an MAE of 0.864 (-0.071 MAE point). This result stresses the importance of careful model selection despite the general model-agnostic nature of the approach. More generally, our result shows that all approaches are highly dependent on model selection.

Something that may have been overlooked in the literature our results underline is therefore that, beyond model selection in a specific setting (e.g. individualized approach), the global predictive approach (team-based, individualized, cluster-based...) may play an important role to achieving good predictive performances.

Numerous perspectives are offered to this work. It would first be interesting to evaluate these approaches using recent deep learning models that reduce the need of defining *ad hoc* aggregated features, e.g. FatigueNet [9]. It would also be relevant to explore other approaches to facilitate incorporating as much player-specific information as possible. Indeed, as we have seen, despite player-specific predictors suffering from limiting quantity of data available during training, they managed to obtain good performances overall (subject to proper model selection). A generic approach, like the one today traditionally considered in Deep learning, could be to study fine-tuning of a general predictor that would have been

pretrained using data related to a set of players (team or cluster of similar players). The two-step training approach would be as follows: 1) train a general predictor on the full or restricted but large part of the training set, and then 2) specialize it on the subset of data dedicated to a given player. This fine-tuning strategy would also ease the use of the approach when new players join the team.

Finally, our study deliberately considers that input features do not incorporate prior knowledge about past RPEs, even if this information could be very informative [8]. It could be interesting to incorporate such information into models, e.g. adding a feature averaging past 5 RPEs, or even for computing the clusters that would group players behaving similarly in terms of RPE assessment.

V. CONCLUSION

We have shown that Machine Learning can be used to accurately predict Rate of Perceived Exertion in Football Players (MAE \simeq 0.79). By comparing several supervised learning modelling of the problem, from individualized to group-based models, our results suggest that, considering the number of observations composing our labelled dataset (\simeq 5k), building a predictor at team-level and incorporating information about players through a player id feature is a pertinent approach.

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