FINAL REPORT ON PREDICTION MODELS OF A COLLEGE BASKETBALL PLAYER BEING DRAFTED TO JOIN THE NBA LEAGUE

Subject Name: Advanced Machine Learning Applications

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1. BUSINESS UNDERSTANDING

Determine business objectives:

The NBA (National Basketball Association) draft is an annual event in which teams select players from their American colleges as well as international professional leagues to join their rosters. Specifically, the teams that performed the worst in the previous are given the first chances to pick new players for their teams for the next season.

This project is a Kaggle competition and aims to build a machine learning model which can generate the probability of being drafted for each player. The data scientist is required to submit their prediction probability to Kaggle and can see how accurate their outcomes are by watching the accuracy score in the Leaderboard. To do this, a number of machine learning models will be used. Ultimately, the best model with the most accurate probability will be selected.

The results of this project is important to both the teams and the players. Apparently, an accurate model will help improve the performance of the team and accelerate its ranking in the league. Likewise, for the player, if the pick proves to be a good fit, it will be a great beginning of their NBA career.

Determine data mining goals:

From a technical data mining perspective, this project is expected to generate a clean and reliable data input with different data preparation steps. In order to achieve that, it is important to check whether the dataset has any duplicated records. In addition, in case of missing values, the data scientist needs to decide whether to remove those records or to fill them with a suitable method. Another essential step is to ensure the dataset is free of outliers, which can be done by investigating the descriptive statistics of the dataset. It is also noticeable that the provided dataset is heavily biased towards target value 0, i.e. not being drafted. The data scientist needs to decide a suitable technique to handle this matter during the data preparation process.

Produce project plan:

For phase 2 (Data Understanding), phase 3 (Data Preparation), phase 4 (Modeling), and phase 5 (Evaluation), Python Jupyter Notebook or any Python IDE is the required coding tool to perform the data wrangling tasks. In phase 6 (Deployment), a Python Flask Application could be created and then deployed on Streamlit or Heroku to run a web application. This helps anyone with or without IT technical expertise can utilize it easily.

2. DATA UNDERSTANDING

There are training and testing datasets provided for the prediction task. The datasets contains information about the players and their past performance metrics.

In the training dataset, there are 64 columns, including 63 feature columns and 01 target column. However, in the testing dataset, there is no target column provided. There are 56,091 and 4,970 rows in the training and testing datasets respectively.

Column	Description
team	Name of team
conf	Name of conference
GP	Games played
Min_per	Player's percentage of available team minutes played
ORtg	ORtg - Offensive Rating (available since the 1977-78 season in the NBA)
usg	Usg% - Usage Percentage (available since the 1977-78 season in the NBA)
eFG	eFG% - Effective Field Goal Percentage; the formula is (FG + 0.5 * 3P) / FGA
TS_per	TS% - True Shooting Percentage; the formula is PTS / (2 * TSA)
ORB_per	ORB% - Offensive Rebound Percentage (available since the 1970-71 season in the NBA)
DRB_per	DRB% - Defensive Rebound Percentage (available since the 1970-71 season in the NBA)
AST_per	AST% - Assist Percentage (available since the 1964-65 season in the NBA)
TO_per	TOV% - Turnover Percentage (available since the 1977-78 season in the NBA)
FTM	Free Throws
FTA	Free Throw Attempts
FT_per	Free Throw Percentage; the formula is FTM / FTA.
twoPM	2P - 2-Point Field Goals
twoPA	2PA - 2-Point Field Goal Attempts
twoP_per	2P% - 2-Point Field Goal Percentage; the formula is 2P / 2PA.
TPM	3P - 3-Point Field Goals (available since the 1979-80 season in the NBA)
TPA	3PA - 3-Point Field Goal Attempts (available since the 1979-80 season in the NBA)

TP_per	3P% - 3-Point Field Goal Percentage (available since the 1979-80 season in the NBA)
blk_per	BLK% - Block Percentage (available since the 1973-74 season in the NBA)
stl_per	STL% - Steal Percentage (available since the 1973-74 season in the NBA)
ftr	
yr	Student's year of study: `Fr` for freshmen, `So` for sophomores, `Jr` for juniors, `Sr` for seniors
ht	Height of student
num	Player's number
porpag	Points Over Replacement Per Adjusted Game
adjoe	AdjO – Adjusted offensive efficiency
pfr	
year	Season's year
type	Type of metrics displayed
Rec_Rank	Recruiting rank i.e. what the player was ranked as a recruit coming out of high school
ast_tov	Ratio Assists against Turnover
rimmade	Shots made at or near the rim
rimmade_rimmiss	Sum of Shots made at or near the rim and Shots missed
midmade	Two point shots that were not made at or near the rim
midmade_midmiss	Sum of Two point shots that were not made at or near the rim and Shots missed
rim_ratio	Ratio between Shots made at or near the rim against Shots missed
mid_ratio	Ratio between Two point shots that were not made at or near the rim and Shots missed
dunksmade	Dunks made
dunksmiss_dunksmade	Sum of Dunks made and Dunks missed
dunks_ratio	Ratio between Dunks made and Dunks missed
pick	Order of NBA draft
drtg	DRtg - Defensive Rating (available since the 1973-74 season in the NBA)
adrtg	Adjusted DRtg
dporpag	Adjusted porpag
stops	Stops - Stops; Dean Oliver's measure of individual defensive stops
bpm	BPM - Estimate the player's contribution in points above league average per 100 possessions played

obpm	Offensive BPM
Offensive BPM	Defensive BPM
gbpm	BPM 2.0
mp	MP - Minutes Played (available since the 1951-52 season)
ogbpm	Offensive BPM 2.0
dgbpm	Defensive BPM 2.0
oreb	ORB - Offensive Rebounds (available since the 1973-74 season in the NBA
dreb	DRB - Defensive Rebounds (available since the 1973-74 season in the NBA)
treb	TRB - Total Rebounds (available since the 1950-51 season)
ast	AST - Assists
stl	STL - Steals (available since the 1973-74 season in the NBA)
blk	BLK - Blocks (available since the 1973-74 season in the NBA)
pts	PTS - Points
player_id	Unique identifier of player
drafted	Target - Was the player drafted at the end of the season

There are a number of columns that have missing values. These missing values were replaced with the mean value of that column. Compared to the dropping method, when applying this ffill method, data was not wasted and could be effectively used to train the model.

It was also noted that the distribution of target values is heavily imbalanced, in which value 0 accounting for more than 99% (Figure 1). In this project, we will address this issue with an oversampling method called SMOTE to balance the datasets.

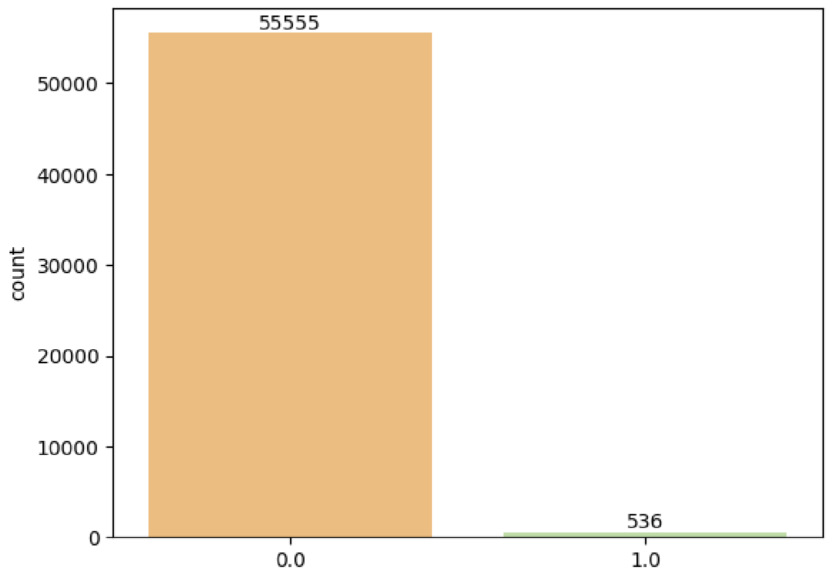


Figure 1 – depicts imbalanced distribution of target values

3. DATA PREPARATION

To clean the datasets, below steps were performed:

1) Drop the `type`, `player_id`, `Rec_Rank`, `dunks_ratio`, `pick` columns:

   - Column `type`: There is only one value in this column, which is 'all'. Hence there is no need to keep this column.
   - Column `player_id`: This column does not play any role in the prediction task.
   - Columns `Rec_Rank`, `dunks_ratio`, `pick`: These columns contain missing values > 50% of the total values

2) Column `num`:
   - Replace any non-numeric values with NaN values
3) Apply **LabelEncoder** technique to categorical columns to convert them into numerical values, including `team`, `conf`, `yr`
4) **Fill missing values** in the dataframe with their mean values
5) Apply **SMOTE** oversampling technique to address the imbalanced dataset
6) **Feature elimination with correlation matrix** to select the most relevant features of the dataset
7) **Scale data**:
   - Apply StandardScaler method on X_train, X_val, X_test
8) **Split the dataset**:
   - As the testing dataset had no target column, we could not use this dataset to evaluate performance of the models. Therefore, it is essential to split the training dataset into training and validation sets with the test size of 20%
   - Split X_data and y_data → X_train, X_val, y_train, y_val with test size of 20%

4. MODELING

There are a total of 3 experiments implemented to find out the best performing one.

1) Logistic Regression Classifier
   - No feature selection performed
   - No SMOTE oversampling technique performed
   - Train Model with default hyperparameters
2) Adaboost Classifier
   - Feature selection performed with Correlation Matrix Heatmap
   - SMOTE oversampling technique performed
   - Train Model with Default Hyperparameters
   - Improve Model Performance with Hyperparameter Tuning
     - Hyperparameter Tuning with learning_rate=0.05
3) RandomForest

- Feature selection performed with Correlation Matrix Heatmap
- SMOTE oversampling technique performed
- Train RandomForest Model with Default Hyperparameter
- Improve Model Performance with Hyperparameter Tuning
    - n_estimators Hyperparameter
    - max_depth Hyperparameter
    - min_samples_leaf Hyperparameter
    - max_features Hyperparameter

5. EVALUATION

The AUROC scores were used to evaluate model performances. After conducting 3 models, RandomForest model with default hyperparameters proved to be the most effective machine learning model amongst the other ones as it is able to generate predictions having highest recall score compared to the actual values, and with minimal overfitting. Its AUROC scores on the training and validation datasets are 1.0 and 0.999873430745366 respectively.

Experiment 1 (Logistic Regression Classifier)		
Train model with default hyperparameters	Training	0.9891360804890494
	Validation	0.9874001668651553

Experiment 2 (Adaboost Classifier)		
Train model with default hyperparameters	Training	0.9965191666385046
	Validation	0.9958602138308584
Train model with learning_rate=0.05	Training	0.9965191666385046
	Validation	0.9958602138308584

Experiment 3 (RandomForest Classifier)		
Train model with default hyperparameters	Training	1.0
	Validation	0.9998734307453669
Train model with n_estimators=90	Training	1.0
	Validation	0.999869927420505
Train model with n_estimators=90, max_depth=30	Training	0.9999965275615045
	Validation	0.9996575246817134

Train model with n_estimators=90, max_depth=18	Training	0.9994360241472875
	Validation	0.9987519901315267
Train model with n_estimators=90, max_depth=18, min_samples_leaf=2	Training	0.9995628033374554
	Validation	0.9988653520539349
Train model with n_estimators=90, max_depth=18, min_samples_leaf=6, max_features=12	Training	0.9991857853148767
	Validation	0.9983015638064566

Figure 2 and Figure 3 illustrate the AUC Curve on traning and validation datasets of the RandomForest model with default hyperparameters.

Figure 2

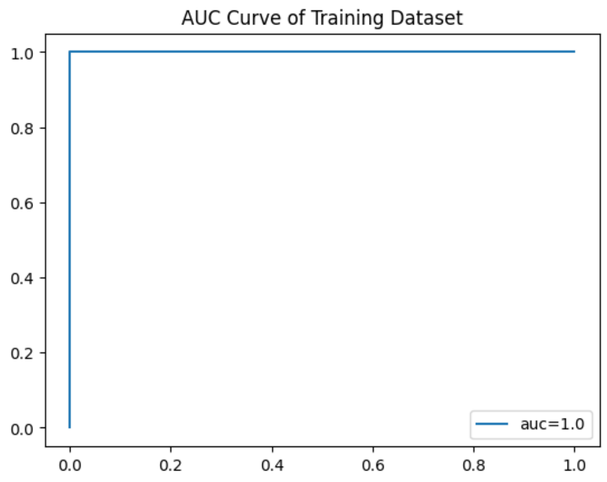
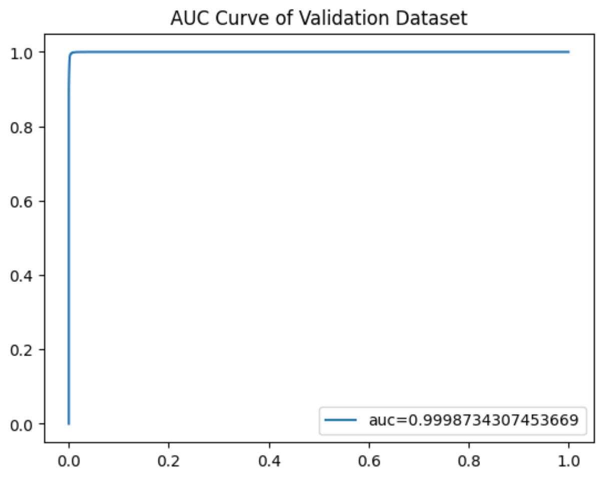


Figure 3



From the best model, feature importance was calculated (Figure 4). The 3 most important features are Points Over Replacement Per Adjusted Game (porpag), adjusted porpag, and player's estimated contribution in points above league average per 100 possessions played.

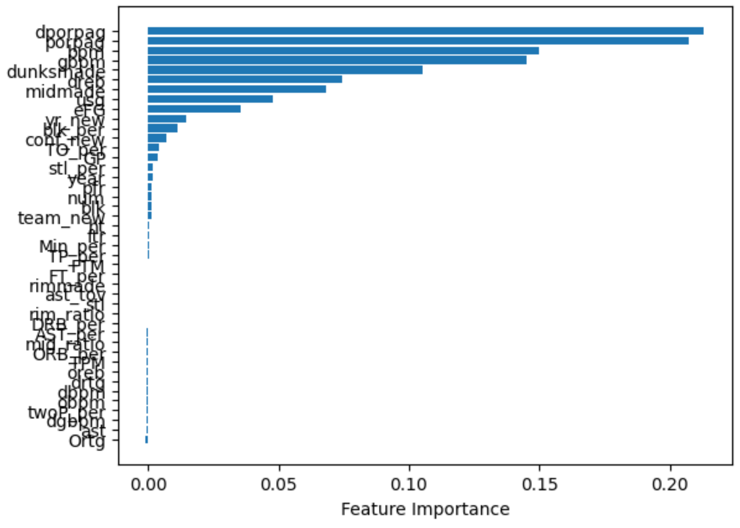


Figure 4 – illustrates feature importance of the best model

6. DEPLOYMENT

When it comes to deployment, it is critical to ensure not only the effectiveness but also the efficiency of the model are achieved. In other words, the model needs to produce accurate predictions, and be optimized in terms of execution speed as well, especially when the size of the dataset is built up over time.

As the end users normally do not have technical knowledge or applications to run the machine learning model, it is essential to build an web app with questionnaires covering all important factors as the data input. Python Flask App and Streamlit or Heroku are suggested solutions to build this web app. When the end users click the 'Submit' button on the web app, the back-end system will run the model and generate the predictions accordingly. As regards to maintenance and monitoring of the deployment, it is essential for machine learning engineers to frequently update the data and retrain the model when needed.

This project contains little to none potential data privacy risk as there is no sensitive or personal information in the dataset.