Assignment 1

Kaggle Competition

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1. Executive Summary

The primary objective of this project is to predict whether a college basketball player will be drafted to join the NBA league based on their statistics for the current season. This prediction task holds significant value for both sports commentators and fans, as it provides insights into the future prospects of aspiring players. We assess the model's performance using the AUROC (Area Under Receiver Operating Characteristic) score, a key benchmark for classification models. A higher AUROC score signifies a model's improved ability to accurately classify positive and negative examples, enhancing prediction accuracy.

However, we encountered some challenges during the experiments. The raw dataset presented challenges, primarily stemming from missing values (NA), which could potentially impact model training and results. Additionally, the choice of features and hyperparameters significantly influenced the AUROC scores, leading to a structured approach involving three experiments labeled A, B, and C. Each successive experiment builds upon the insights gained from the previous one.

After rigorous experimentation, the AdaBoost classifier model emerged as the top performer. It achieved an impressive AUROC score of 0.9886 on the testing set. This result was achieved by leveraging all available features and employing grid search to optimize hyperparameters, including learning_rate and n_estimators. The predictive power of this model will be harnessed for assessing the probability of player drafting in the test dataset.

This project underscores the value of machine learning in providing valuable insights into the world of basketball, benefiting analysts, enthusiasts, and the broader sports community.

2. Business Understanding

a. Business Use Cases

Project Scope: This project applies machine learning algorithms to address specific business use cases related to predicting the likelihood of a college basketball player being drafted into the NBA based on their statistics for the current season.

Challenges and Opportunities:

- Data Quality: The raw dataset posed challenges due to missing values (NA), potentially affecting the accuracy of model training and predictions. Addressing these data quality issues was a key motivation.

- Predictive Insights: The project offers valuable insights for various stakeholders, including sports commentators and fans, who are eager to assess the potential of college players and make predictions regarding their NBA draft prospects.

- AUROC Score Improvement: The project aims to improve the AUROC score, which measures the model's ability to distinguish positive and negative examples effectively. A higher AUROC score signifies enhanced prediction accuracy.

b. Key Objectives

Project Goals:

The primary objective is to predict the probability of a college basketball player being drafted into the NBA, leveraging machine learning algorithms. This prediction is crucial for assessing players' prospects.

Stakeholder Requirements:

Commentators require accurate predictions to provide informed insights and analysis during games and broadcasts. Also, fans are keen to follow the careers of college players and make informed speculations about their future in the NBA.

Addressing Stakeholder Requirements:

- Model Training: To address these requirements, a machine learning model is trained using a labeled training dataset that includes the 'drafted' feature.

- Model Comparison and Improvement: The project focuses on comparing and improving the AUROC scores of various machines learning algorithms, including the Adaboost classifier, Random Forest classifier, and Polynomial logistic regression. Different hyperparameters and feature selections are explored to enhance model performance.

- Prediction: After model training and selection, the best-performing model is utilized to predict the probability of drafting for players in the test dataset. This prediction serves as a valuable tool for sports commentators and fans to assess the potential of college basketball players in joining the NBA.

This project aligns the capabilities of machine learning algorithms with the needs of sports commentators and fans, providing accurate predictions and enhancing the overall understanding of player prospects in the NBA draft.

3. Data Understanding

The 'NBA Draft' dataset, sourced from Kaggle, comprises data on college basketball players' NBA draft prospects, as determined by their statistics for the current season. This dataset is divided into two subsets: the train dataset and the test dataset.

Train Dataset: The training dataset consists of 56,091 rows and 64 columns, including the target variable 'drafted,' which indicates whether a player was drafted into the NBA.

Test Dataset: The test dataset, used for predictions by the trained model, contains 4,970 rows and 63 columns (excluding the 'drafted' target variable).

The dataset encompasses 7 categorical features and 57 numeric features, each contributing to the predictive power of the model. Below, you will find a list of these features and their respective descriptions.

feature	name	description
1	team	Name of team
2	conf	Name of conference
3	GP	Games played
4	Min_per	Player's percentage of available team minutes played
5	ORtg	ORtg - Offensive Rating (available since the 1977-78 season in the NBA); for players it is points produced per 100 posessions, while for teams it is points scored per 100 possessions. This rating was developed by Dean Olive
6	usg	Usg% - Usage Percentage (available since the 1977-78 season in the NBA); the formula is 100 * ((FGA + 0.44 * FTA + TOV) * (Tm MP / 5)) / (MP * (Tm FGA + 0.44 * Tm FTA + Tm TOV)). Usage percentage is an estimate of the
7	eFG	eFG% - Effective Field Goal Percentage; the formula is (FG + 0.5 * 3P) / FGA. This statistic adjusts for the fact that a 3-point field goal is worth one more point than a 2-point field goal. For example, suppose Player A goes 4 f
8	TS_per	TS% - True Shooting Percentage; the formula is PTS / (2 * TSA). True shooting percentage is a measure of shooting efficiency that takes into account field goals, 3-point field goals, and free throws.
9	ORB_per	ORB% - Offensive Rebound Percentage (available since the 1970-71 season in the NBA); the formula is 100 * (ORB * (Tm MP / 5)) / (MP * (Tm ORB + Opp DRB)). Offensive rebound percentage is an estimate of the percentag
10	DRB_per	DRB% - Defensive Rebound Percentage (available since the 1970-71 season in the NBA); the formula is 100 * (DRB * (Tm MP / 5)) / (MP * (Tm DRB + Opp ORB)). Defensive rebound percentage is an estimate of the percentag
11	AST_per	AST% - Assist Percentage (available since the 1964-65 season in the NBA); the formula is 100 * AST / (((MP / (Tm MP / 5)) * Tm FG) - FG). Assist percentage is an estimate of the percentage of teammate field goals a player a
12	TO_per	TOV% - Turnover Percentage (available since the 1977-78 season in the NBA); the formula is 100 * TOV / (FGA + 0.44 * FTA + TOV). Turnover percentage is an estimate of turnovers per 100 plays.
13	FTM	Free Throws
14	FTA	Free Throw Attempts
15	FT_per	Free Throw Percentage; the formula is FTM / FTA.
16	twoPM	2P - 2-Point Field Goals
17	twoPA	2PA - 2-Point Field Goal Attempts
18	twoP_per	2P% - 2-Point Field Goal Percentage; the formula is 2P / 2PA.
19	TPM	3P - 3-Point Field Goals (available since the 1979-80 season in the NBA)
20	TPA	3PA - 3-Point Field Goal Attempts (available since the 1979-80 season in the NBA)
21	TP_per	3P% - 3-Point Field Goal Percentage (available since the 1979-80 season in the NBA); the formula is 3P / 3PA.
22	blk_per	BLK% - Block Percentage (available since the 1973-74 season in the NBA); the formula is 100 * (BLK * (Tm MP / 5)) / (MP * (Opp FGA - Opp 3PA)). Block percentage is an estimate of the percentage of opponent two-point fie
23	stl_per	STL% - Steal Percentage (available since the 1973-74 season in the NBA); the formula is 100 * (STL * (Tm MP / 5)) / (MP * Opp Poss). Steal Percentage is an estimate of the percentage of opponent possessions that end with
27	ftr	
28	yr	Student's year of study: `Fr` for freshmen, `So` for sophomores, `Jr` for juniors, `Sr` for seniors
29	ht	Height of student
30	num	Player's number
31	porpag	Points Over Replacement Per Adjusted Game
32	adjoe	AdjO – Adjusted offensive efficiency – An estimate of the offensive efficiency (points scored per 100 possessions) a team would have against the average D-I defense.
33	pfr	
34	year	Season's year
35	type	Type of metrics displayed: `All` for all types, `C` for conference`, `NC` for non-conference, `PC` for pre-conference tour, `R` for regular season, `P` for post-season, `T` for NCAA
36	Rec_Rank	Recruiting rank i.e. what the player was ranked as a recruit coming out of high school
37	ast_tov	Ratio Assists against Turnovers
38	rimmade	Shots made at or near the rim
39	rimmade_rimmiss	Sum of Shots made at or near the rim and Shots missed
40	midmade	Two point shots that were not made at or near the rim
41	midmade_midmiss	Sum of Two point shots that were not made at or near the rim and Shots missed
42	rim_ratio	Ratio between Shots made at or near the rim against Shots missed
43	mid_ratio	Ratio between Two point shots that were not made at or near the rim and Shots missed
44	dunksmade	Dunks made
45	dunksmiss_dunksmade	Sum of Dunks made and Dunks missed
46	dunks_ratio	Ratio between Dunks made and Dunks missed
47	pick	Order of NBA draft
48	drtg	DRtg - Defensive Rating (available since the 1973-74 season in the NBA); for players and teams it is points allowed per 100 posessions. This rating was developed by Dean Oliver, author of Basketball on Paper. Please see th
49	adrtg	Adjusted DRtg
50	dporpag	Asdjusted porpag
54	stops	Stops - Stops; Dean Oliver's measure of individual defensive stops. Please see the article Calculating Individual Offensive and Defensive Ratings for more information.
55	bpm	BPM - Estimate the player's contribution in points above league average per 100 possessions played
56	obpm	Offensive BPM
57	dbpm	Defensive BPM
58	gbpm	BPM 2.0
59	mp	MP - Minutes Played (available since the 1951-52 season)
60	ogbpm	Offensive BPM 2.0
61	dgbpm	Defensive BPM 2.0
62	oreb	ORB - Offensive Rebounds (available since the 1973-74 season in the NBA)
63	dreb	DRB - Defensive Rebounds (available since the 1973-74 season in the NBA)
64	treb	TRB - Total Rebounds (available since the 1950-51 season)
65	ast	AST - Assists
66	stl	STL - Steals (available since the 1973-74 season in the NBA)
67	blk	BLK - Blocks (available since the 1973-74 season in the NBA)
68	pts	PTS - Points
69	player_id	Unique identifier of player
70	drafted	Target - Was the player drafted at the end of the season

Figure 1 The table of the dataset description

In preparation for this project, an exploratory data analysis (EDA) was conducted to gain insights into the dataset's characteristics. EDA allows for the visualization and understanding of trends, distributions, and potential correlations among features. This process aids in selecting relevant variables and optimizing the model-building process.

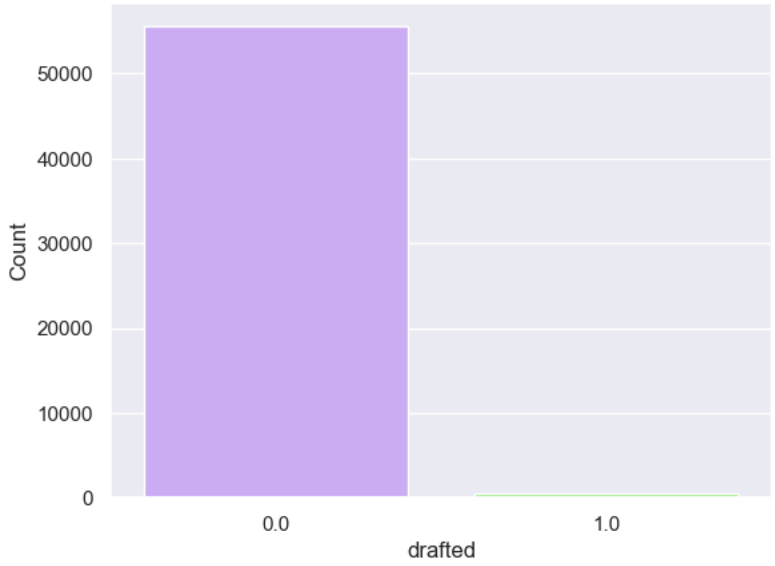


Figure 2 The bar chart indicates whether a player was drafted into the NBA or not.

It can be seen obviously that the target variable, drafted, is imbalanced. In this case, we have a significantly higher number of players who are not drafted compared to those that are drafted. This can lead to a bias in the model towards predicting that a player is not drafted. We may use the Over-sampling Technique (SMOTE) to address this issue.

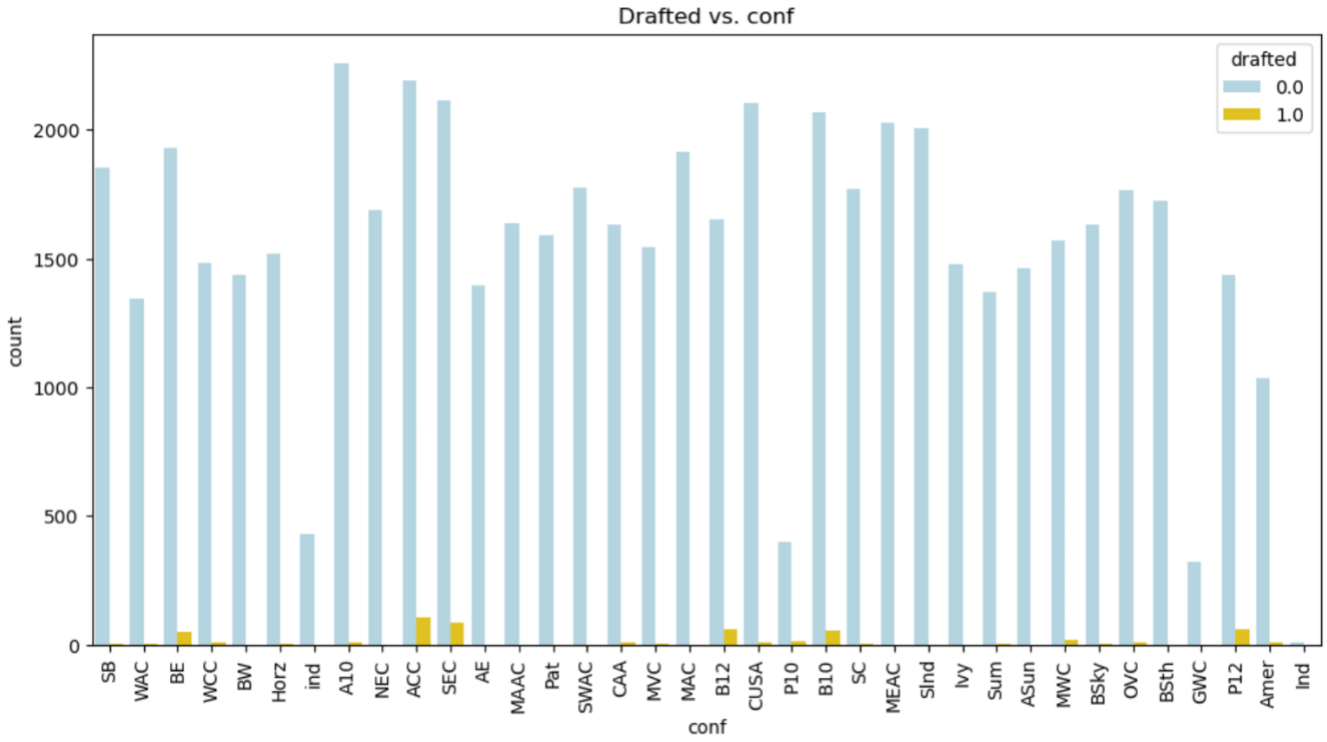


Figure 3 The bar chart of Name of conference vs drafted.

It is evident that the majority of players in the conference were not drafted. However, there are some significant yellow bars in the chart, indicating drafted players in the ACC and SEC.

4. Data Preparation

Pre-processing data:

1. Load two dataset by reading CSV. file. The train.csv dataset used for training the model and the test.csv dataset which is not contain the drafted feature will be used for predicting probability in the final result.

2. Clean NA:

- Check NA

```
pick           54705
Rec_Rank       39055
dunks_ratio    30793
mid_ratio       9688
rim_ratio       9464
               ...
porpag             0
adjoe              0
pfr                0
year               0
drafted            0
Length: 64, dtype: int64
```

After sorting all the features, 'pick,' 'Rec_rank,' and 'dunks_ratio' have a high number of missing values, which is above 10k. We will drop these variables since they could potentially lead to inaccurate outcomes. However, dunks_ratio seems to be significant for the player to be drafted. There are some patterns to be relevant to this feature.

- Missing value pattern

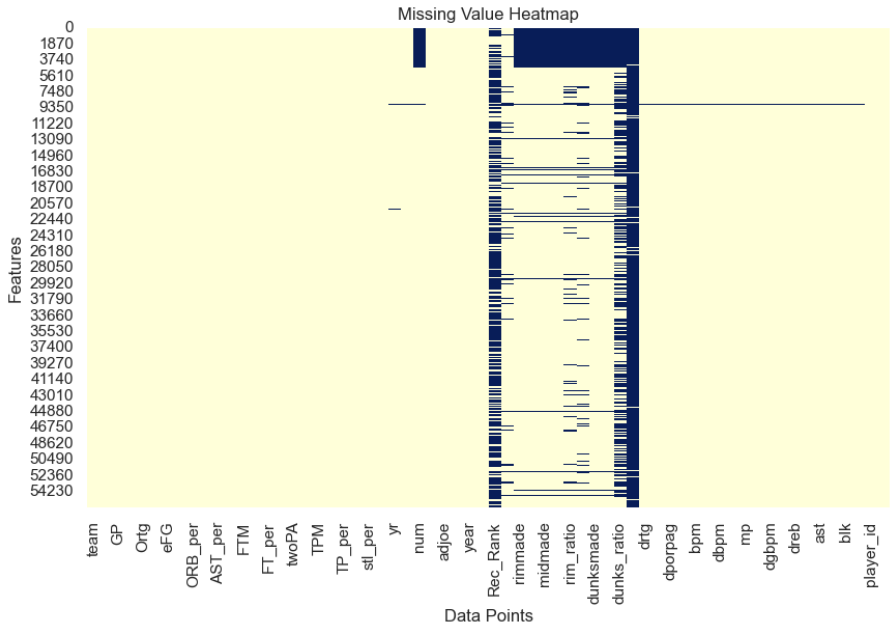


Figure 4 The missing value Heatmap

It's evident that 'rimmade,' 'rimmade_rimmiss,' 'midmade,' 'midmade_midmiss,' 'dunksmade,' and 'dunksmiss_dunksmade' share the same number of missing values. This is because the data contained in these features starts from the season year 2010.

- Clean data

First, we will drop features with more than 10,000 missing values and then replace missing values with zero in columns with missing data for the year 2009. We will also drop irrelevant features (e.g., 'num' and 'ht') with respect to the target variable and impute missing numeric values with the mean and missing categorical values with the mode.

Feature engineering:

1. Label encoding the categorical features including yr, type, team, player_id, and conf.

2. Scale data with StandardScaler

3. using Synthetic Minority Over-sampling Technique (SMOTE) since the 'drafted' is imbalanced. The new balance is 55,555 for each drafted and not drafted.

4. Split data into train, validation, and test set with ratio 80:20.

5. Modeling

With binary classification as the target variable, we will train the first dataset containing the target variable using a different models, hyperparameters, and features selection. This will allow us to assess the AUROC scores of the training, validation, and test sets. Subsequently, we will employ the best trained model to predict the probability of being drafted for the second (test) dataset, which does not contain the target variable. This project divided into three experiments, including A, B, and C.

a. Experiment A

In this experiment, we will train the first dataset containing the target variable using a **logistic regression classifier with polynomial features**. This will enable us to assess the AUROC scores for the training, validation, and test sets in comparison to the baseline models.

The hyperparameters were selected using a random forest classifier and the Variance Inflation Factor (VIF). The final feature set, denoted as 'X,' comprises four features: 'adjoe,' 'rimmade,' 'dunks_ratio,' and 'adrtg.' Additionally, we addressed the issue of imbalanced data by employing SMOTE during the feature engineering process.

b. Experiment B

In this experiment, we will train the dataset using an **AdaBoost classifier with hyperparameter tuning.** The goal is to improve the AUROC scores on the training, validation, and test sets by exploring various hyperparameters.

To facilitate a comparison with the best model from the previous experiment, we will train the AdaBoost classifier on the same feature selection and dataset split used in the previous experiment.

c. Experiment C

In this experiment, we will train and compare the models of **Polynomial Logistic Regression, AdaBoost, and Random Forest classifiers using grid search**. The objective is to enhance the AUROC scores on the validation and test sets by experimenting with different models.

To improve the AUROC score, we will explore a new feature selection, which includes all the features from the dataset after dropping and cleaning NA values.

The hyperparameters used after grid search are as follows:

1. LogisticRegression(random_state=42)

2. AdaBoostClassifier(learning_rate=0.1, n_estimators=200, random_state=42)

3.RandomForestClassifier(max_depth=10,min_samples_leaf=2,min_samples_split=5, random_state=42)

6. Evaluation

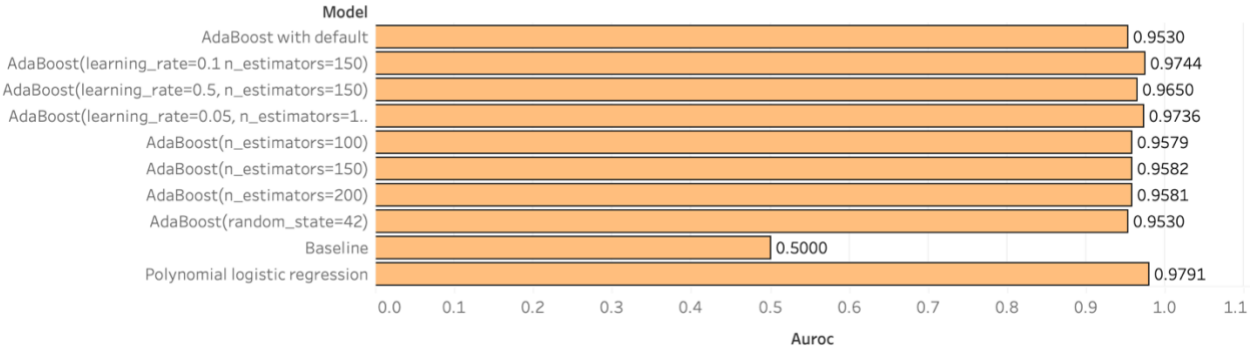
a. Evaluation Metrics

AUROC Score

The AUROC measures model accuracy in predicting NBA draft prospects, making it a key metric for our project's success. Its flexibility, balanced assessment, and ability to facilitate model comparison make it a suitable and relevant metric for evaluating the project's success in achieving this goal.

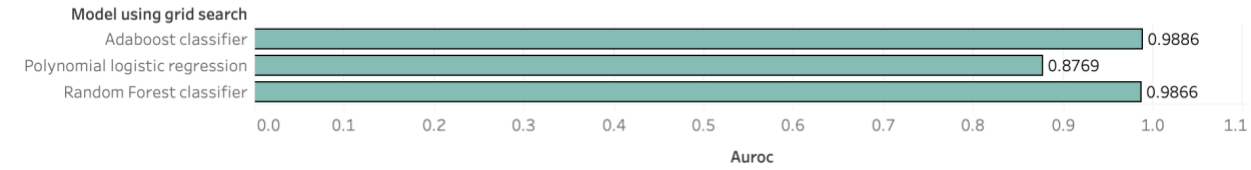
b. Results and Analysis

The bar chart of AUROC scores on experiments A and B



The bar chart above represents the AUROC scores of three models: the baseline, Polynomial Logistic Regression, and Adaboost with hyperparameter tuning. It is evident that **Polynomial Logistic Regression** achieves the highest score at 0.9791487117335488.

The bar chart of AUROC scores on experiments C



The bar chart above displays the AUROC scores for the AdaBoost classifier, Polynomial Logistic Regression, and Random Forest classifier using grid search. Notably, Random Forest and AdaBoost classifiers exhibit nearly identical AUROC scores of 0.98. However, **the AdaBoost classifier** outperforms the Random Forest model significantly, achieving a score of 0.9885671963371937 on the testing set, whereas the Random Forest scores 0.9866246970105036. This demonstrates the superiority of boosting over bagging in this context.

In conclusion, training **the AdaBoost classifier with hyperparameters learning_rate=0.1, n_estimators=200, and random_state=42,** using all available features, yielded the highest AUROC score. We will utilize this trained model to predict the probability of being drafted in the test dataset.

c. Business Impact and Benefits

The AdaBoost classifier, with its optimized parameters, significantly improves the accuracy of predicting NBA draft prospects. This positive impact is evident through the availability of the result_C.csv file, which allows sports commentators and fans to assess a player's likelihood of being drafted into the NBA, enhancing their engagement and predictions. The model's superiority over bagging techniques reinforces its value in this context.

d. Data Privacy and Ethical Concerns

1. Data Privacy Implications:

Sensitive Information: The dataset used for this project likely contains sensitive information about individuals, particularly college basketball players. This includes their performance statistics and potentially other personal details. Sharing or using this information without proper consent or anonymization could raise data privacy concerns.

2. Ethical Concerns:

Informed Consent: Ethical concerns arise if the data used in this project was collected without proper informed consent from the individuals involved. If players' data was used without their knowledge or consent, it raises ethical questions regarding data usage.

Fair and Unbiased Models: There is an ethical responsibility to ensure that the predictive models are fair and unbiased. Any biases present in the data or model can result in unfair treatment or discrimination.

3. Data Privacy and Ethical Considerations:

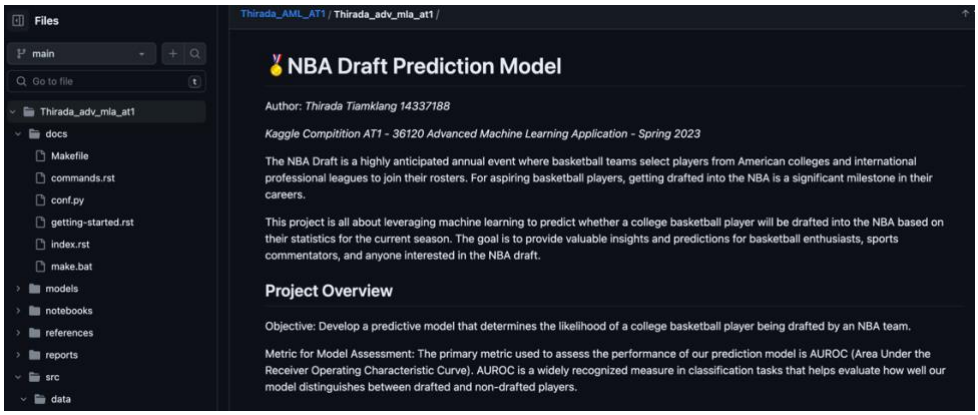
Data Anonymization: Steps should be taken to anonymize the data, removing any personally identifiable information to protect the privacy of individuals.

Consent and Transparency: If possible, ensure that the data used for this project was collected with proper consent and transparent information sharing practices. Inform individuals about the purpose of data collection and how their data will be used.

7. Deployment

Deployment Process:

The deployment of the best-performing models has been streamlined and is available through the '.joblib' files, which are located in the 'models/' directory. You can access these files in the GitHub repository here.



Real-World Implementation:

To apply the model in real-world scenarios, follow these steps:

1. Predicting on Test Data: To predict the probability of college basketball players being drafted into the NBA using the test dataset, refer to the 'result_C.csv' file. It contains the predictions based on the trained models.

2. Predicting on New Data: If you have new or current data and wish to make predictions, you can use the provided script (e.g., 'predict.py'). This script is designed to load the pre-trained models and is ready to predict the likelihood of college players being drafted into the NBA.

Recommendations:

1. Regularly monitor model performance in the real-world context and be prepared to fine-tune or update the model as needed.

2. Document the deployment process, including instructions for users, as provided in the README.md file in the GitHub repository, to facilitate ease of use and understanding.

3. Encourage user feedback to identify any issues or improvements in the deployment process and the predictions made by the model.

8. Conclusion

In summary, this project has yielded valuable insights and outcomes for predicting the likelihood of college basketball players being drafted into the NBA. Key findings include:

- The AdaBoost model, configured with 'learning_rate=0.1,' 'n_estimators=200,' and 'random_state=42,' demonstrated outstanding performance on the testing set, achieving an AUROC score of 0.9886.

- This model's accuracy in predicting draft prospects makes it a valuable tool for sports broadcasters and fans seeking real-time insights into current season results.

The project has succeeded in achieving its goals, particularly in building a predictive model that enhances our ability to assess NBA draft prospects accurately. It meets the requirements of stakeholders, contributing to more informed predictions in the world of basketball.

Future Work and Recommendations:

- Model Updates: Continual updates to the model using new data can further enhance accuracy.

- Real-Time Deployment: Consider deploying the model in real-time applications for immediate predictions during the NBA season.

- Enhanced User Experience: Improve user interfaces and accessibility for sports broadcasters and enthusiasts.

Overall, the success of this project paves the way for more accurate predictions and deeper engagement in the world of college basketball and the NBA. The continuous evolution of this model promises even more accurate assessments in the future.

9. References

So, A. (2023). *36120_AdvMLA-Lab1_Exercise2-Solutions.ipynb*. https://colab.research.google.com/drive/15OZMUMwUBoAmtrfuzJaEhF1Ta8XkCmQZ?authuser=1#scrollTo=Pw_LqGuGC9Oz

So, A. (2023). *36120_AdvMLA-Lab1_Exercise3-Solutions.ipynb*. https://colab.research.google.com/drive/1sHbkg8n7cU_GSm4AB7oKKIzFjJvobBxK?authuser=1#scrollTo=Bc10AnKyW23U