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Predicting NBA All-Stars



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Background



What is our project?

NBA All-Star Selection

- Every February, 24 players are chosen for the NBA All-Star Game.
- Players are divided into Eastern and Western Conference.
- Selection is based on voting: 50% fan vote, 25% current player vote, and 25% by NBA representatives

Research Question & Method

- Can we predict which players will be named all-stars before the voting process?
- Focus: Analyze data from the 2010-2023 seasons.
- Use player statistics to build a predictive model for all-star designation.

Goals & Impact

- Determine the most influential stats for all-star selection.
- Help fans make more informed votes.
- Provide players with insights into the stats they need to excel in for potential selection.

Description of Dataset

We gathered data from stats.nba.com and basketball-reference.com. Our dataset includes player statistics from 2010–2023 and identifies whether a player was named an All-Star. This data was collected by web scraping using Python to retrieve 68 attributes from each player, including points, rebounds, assists, and other performance metrics. One limitation of our dataset we would like to point out is that not many players are all-stars in the nba causing our dataset to be heavily skewed.

68

Number of Attributes

7190

Total Instances

538

Number of players who were all-stars

Notable Initial Attributes

GP: Games Played

W: Wins

L: Losses

MIN: Average minutes played a game

PTS: Average points a game

FGM: Field Goals Made on average– Any shot or tap in besides a free throw.

FGA: Field Goals Attempted - the number of field goals attempted by the player on average.

FG_PCT: Field Goal Percentage - the percentage of field goals made by the player on average.

FG3M: Three Pointers Made - the number of three pointers made by the player on average.

FG3_PCT: Three Pointer Percentage - the percentage of three pointers made by the player on average.

FT_PCT: Free Throw Percentage - the percentage of free throws made by the player on average .

OREB: Offensive Rebounds per game - the number of offensive rebounds grabbed by the player on average .

DREB: Defensive Rebounds per game - the number of defensive rebounds grabbed by the player on average .

AST: Assists - the number of assists passed by the player on average .

TOV: Turnovers - the number of turnovers caused by the player on average .

STL: Steals - the number of steals forced by the player on average .

BLK: Blocks - the number of shots blocked by the player on average .

PF: Personal Fouls - the number of personal fouls committed by the player on average .

NBA_FANTASY_POINTS: The number of fantasy points generated by the player on average.

DD2: Double-Doubles - the number of games in which a player achieves double digits in two statistical categories

TD3: Triple-Doubles - the number of games in which a player achieves double digits in three statistical categories

PLUS_MINUS: The point differential when a player is on the court.

And our class is:

All_Star_Selection: Whether or not player was named All-Star

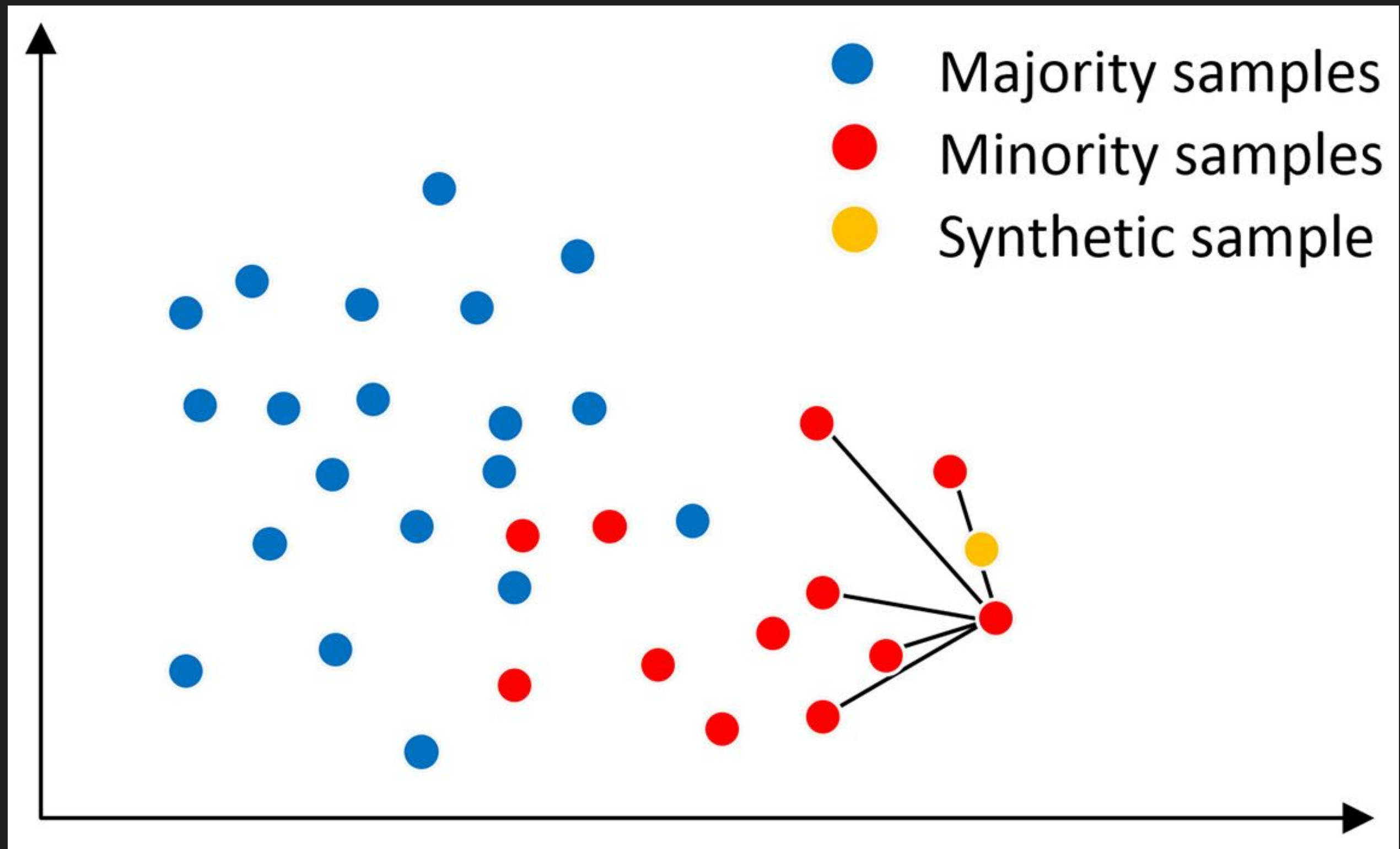
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Preprocessing



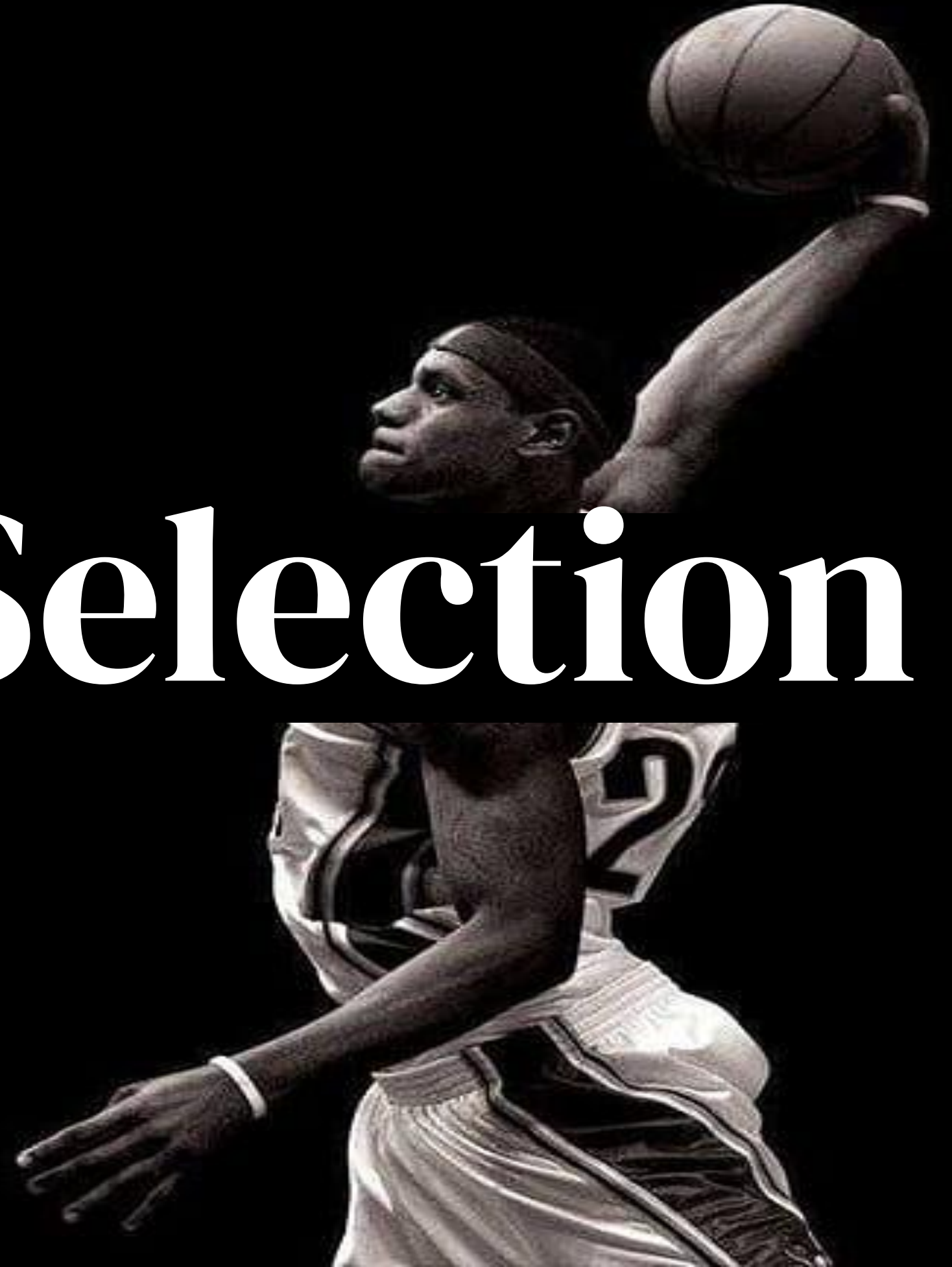
Preprocessing

- Missing Attributes
 - No missing values; comprehensive data source.
- Unrelated Attributes
 - We removed irrelevant attributes such as Player ID, Player Name, Nickname, Fantasy Rank, etc.
- Derived Attributes
 - We removed calculated attributes such as Win PCT, FT PCT, etc.
- SMOTE
 - We addressed the class imbalance mentioned in a previous slide by using SMOTE (Synthetic Minority Oversampling Technique)
 - Achieved a ratio of 2152 all-stars to 8804 instances (24%).



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Attribute Selection



Attribute Selection Methods

CoorelationAttributeEval

This calculates the Pearson correlation coefficient between each feature and the class.

CfsSubsetEval

CfsSubsetEval works by evaluating the degree of redundancy among features associated with the class. It selects features that are highly correlated with the target variable but not correlated with each other.

Set chosen by us

Using our own prior knowledge we select attributes we believe to be the most correlated with all-star selection

OneRAttributeEval

OneRAttributeEval in WEKA evaluates attributes by creating one-rule classifiers based on each attribute and measuring their classification error rates.

InfoGainAttributeEval

InfoGainAttributeEval determines how well a given attribute separates the training examples according to their class labels. The higher the ranking means the attribute is more informative for classification.

CorrelationAttributeEval

Cutoff Value of 0.02, 12 attributes

```
Attribute Evaluator (supervised, Class (nominal): 54 All_Star_Selection):
Correlation Ranking Filter
Ranked attributes:
0.062185    1 AGE
0.05316    21 PLUS_MINUS
0.050227   50 PLUS_MINUS_RANK
0.031603    26 W_RANK
0.031529    45 BLK_RANK
0.025575    37 FTA_RANK
0.024148     2 W
0.023675    28 W_PCT_RANK
0.023367    38 FT_PCT_RANK
0.022805    39 OREB_RANK
0.021037    44 STL_RANK
0.0207      40 DREB_RANK
0.019931    41 REB_RANK
0.019801    15 STL
0.019262    35 FG3_PCT_RANK
0.018113    36 FTM_RANK
0.017732     5 FGM
0.015941    20 PTS
0.014166    53 TD3_RANK
0.013723    13 AST
0.013652     6 FGA
0.012685    47 PF_RANK
0.012499    46 BLKA_RANK
0.012222    14 TOV
0.011615    10 FTA
0.011351    25 GP_RANK
0.010839    49 PTS_RANK
0.010758    30 FGM_RANK
0.010091    51 NBA_FANTASY_PTS_RANK
0.009865    34 FG3A_RANK
0.009652    48 PFD_RANK
0.009615    17 BLKA
0.009125    24 TD3
0.008928    22 NBA_FANTASY_PTS
0.00881     27 L_RANK
0.008561     9 FTM
0.008532    31 FGA_RANK
0.008373    33 FG3M_RANK
0.008026    32 FG_PCT_RANK
0.007851    52 DD2_RANK
0.007505    23 DD2
0.005311    43 TOV_RANK
0.005166     7 FG3M
0.005092    18 PF
0.00505     16 BLK
0.004934     3 L
0.004608    42 AST_RANK
0.003905    11 OREB
0.003639    19 PFD
0.003425    12 DREB
0.002834     4 MIN
0.001585     8 FG3A
0.000618    29 MIN_RANK

Selected attributes: 1,21,50,26,45,37,2,28,38,39,44,40,41,15,35,36,5,20,53,13,6,47,46,14,10,25,49,30,51,34,48,17,24,22,27,9,31,33,32,52,23,43,7,18,16,3,42,11,19,12,4,8,29 : 53
```

CfsSubsetEval

9 Attributes

```
NBA_FANTASY_PTS
DD2
TD3
GP_RANK
W_RANK
L_RANK
W_PCT_RANK
MIN_RANK
FGM_RANK
FGA_RANK
FG_PCT_RANK
FG3M_RANK
FG3A_RANK
FG3_PCT_RANK
FTM_RANK
FTA_RANK
FT_PCT_RANK
OREB_RANK
DREB_RANK
REB_RANK
AST_RANK
TOV_RANK
STL_RANK
BLK_RANK
BLKA_RANK
PF_RANK
PFD_RANK
PTS_RANK
PLUS_MINUS_RANK
NBA_FANTASY_PTS_RANK
DD2_RANK
TD3_RANK
All_Star_Selection
Evaluation mode:      evaluate on all training data

=== Attribute Selection on all input data ===

Search Method:
  Greedy Stepwise (forwards).
  Start set: no attributes
  Merit of best subset found:      0.294

Attribute Subset Evaluator (supervised, Class (nominal): 54 All_Star_Selection):
  CFS Subset Evaluator
  Including locally predictive attributes

Selected attributes: 1,7,11,14,15,16,17,21,53 : 9
  AGE
  FG3M
  OREB
  TOV
  STL
  BLK
  BLKA
  PLUS_MINUS
  TD3_RANK
```


InfoGainAttributeEval

Cutoff Value of 0.2, 12 attributes

Information Gain Ranking Filter

Ranked attributes:

0.42707	1	AGE
0.3909	53	TD3_RANK
0.38878	11	OREB
0.37236	14	TOV
0.3652	15	STL
0.36494	17	BLKA
0.35663	7	FG3M
0.32901	16	BLK
0.28443	19	PFD
0.255	9	FTM
0.24841	10	FTA
0.23932	52	DD2_RANK
0.14831	23	DD2
0.10132	8	FG3A
0.02734	2	W
0.02479	24	TD3
0.0242	6	FGA
0.00982	21	PLUS_MINUS
0.00907	3	L
0.00875	25	GP_RANK
0.00813	28	W_PCT_RANK
0.00805	35	FG3_PCT_RANK
0.00793	50	PLUS_MINUS_RANK
0.0071	38	FT_PCT_RANK
0.00661	27	L_RANK
0.00511	34	FG3A_RANK
0.0043	45	BLK_RANK
0.00422	44	STL_RANK
0.0034	29	MIN_RANK
0.00318	47	PF_RANK
0.00312	5	FGM
0.00298	26	W_RANK
0.00289	33	FG3M_RANK
0.00275	31	FGA_RANK
0.00266	37	FTA_RANK
0.00212	36	FTM_RANK
0.00209	39	OREB_RANK
0.00196	46	BLKA_RANK
0.0019	42	AST_RANK
0.0018	40	DREB_RANK
0	49	PTS_RANK
0	4	MIN
0	41	REB_RANK
0	43	TOV_RANK
0	48	PFD_RANK
0	22	NBA_FANTASY_PTS
0	20	PTS
0	18	PF
0	30	FGM_RANK
0	32	FG_PCT_RANK
0	12	DREB
0	13	AST
0	51	NBA_FANTASY_PTS_RANK

Selected attributes: 1,53,11,14,15,17,7,16,19,9,10,52,23,8,2,24,6,21,3,25,28,35,50,38,27,34,45,44,29,47,5,26,33,31,37,36,39,46,42,40,49,4,41,43,48,22,20,18,30,32,12,13,51 : 53

OneRAtributeEval

Cutoff Value of 90.8, 11 attributes

Minimum bucket size for OneR: 6

Ranked attributes:

92.48069	3	L
92.34439	2	W
92.26488	1	AGE
91.87869	18	PF
91.28805	12	DREB
91.12903	19	PFD
91.10632	11	OREB
90.90186	21	PLUS_MINUS
90.90186	8	FG3A
90.8905	14	TOV
90.811	53	TD3_RANK
90.62926	10	FTA
90.62926	5	FGM
90.59518	15	STL
90.51567	7	FG3M
90.36801	13	AST
90.27715	9	FTM
89.91368	17	BLKA
89.56156	16	BLK
88.43707	52	DD2_RANK
87.92594	6	FGA
86.21081	20	PTS
83.83689	23	DD2
81.07678	26	W_RANK
81.00863	27	L_RANK
80.57701	4	MIN
79.72512	22	NBA_FANTASY_PTS
79.57746	25	GP_RANK
77.38528	49	PTS_RANK
77.36256	35	FG3_PCT_RANK
77.28305	37	FTA_RANK
77.24898	41	REB_RANK
77.16947	34	FG3A_RANK
77.05588	43	TOV_RANK
76.99909	42	AST_RANK
76.99909	39	OREB_RANK
76.93094	48	PFD_RANK
76.93094	44	STL_RANK
76.93094	31	FGA_RANK
76.91958	45	BLK_RANK
76.89687	51	NBA_FANTASY_PTS_RANK
76.88551	36	FTM_RANK
76.88551	33	FG3M_RANK
76.87415	32	FG_PCT_RANK
76.85143	50	PLUS_MINUS_RANK
76.82871	38	FT_PCT_RANK
76.806	46	BLKA_RANK
76.71513	30	FGM_RANK
76.70377	29	MIN_RANK
76.70377	40	DREB_RANK
76.56747	24	TD3
76.56747	47	PF_RANK
76.28351	28	W_PCT_RANK

Selected attributes: 3,2,1,18,12,19,11,21,8,14,53,10,5,15,7,13,9,17,16,52,6,20,23,26,27,4,22,25,49,35,37,41,34,43,42,39,48,44,31,45,51,36,33,32,50,38,46,30,29,40,24,47,28 : 53

Set chosen by us

- Based on our NBA knowledge and player performance insight we chose:
 - W
 - FGM
 - PLUS_MINUS
 - PLUS_MINUS_RANK
 - BLK
 - STL
 - AST
 - FG3M
 - MIN

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Classification



Different Classifiers Used

Naive Bayes

A probabilistic classifier that assumes the presence of each feature is independent of the other features.

OneR

A simple, rule-based classifier that generates one rule for each predictor and selects the one that performs the best.

J48

A decision tree algorithm that splits the data based on attribute values. It creates tree-structures that can handle both categorical and continuous data.

Logistic

A statistical model used for binary classification. It assumes a linear relationship between the independent variable and the log odds of the dependent variable.

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Results



Results

Accuracy	NaiveBayes	J48	OneR	Logistic
CorrelationAttrib	75.4824	91.1464	92.395	76.6175
CfsSubsetEval	76.6175	90.1249	92.5085	76.6175
InfoGainAttribute	76.6175	89.8978	92.5085	76.6175
OneRAttributeEv	76.6175	90.2384	92.395	76.6175
Our Chosen At	76.6175	88.8763	92.395	76.6175
TP Rate	NaiveBayes	J48	OneR	Logistic
CorrelationAttrib	0.019	0.66	0.675	0
CfsSubsetEval	0	0.684	0.68	0
InfoGainAttribute	0	0.675	0.68	0
OneRAttributeEv	0	0.68	0.675	0
Our Chosen At	0	0.621	0.675	0
ROC Area	NaiveBayes	J48	OneR	Logistic
CorrelationAttrib	0.55	0.842	0.837	0.522
CfsSubsetEval	0.585	0.831	0.84	0.549
InfoGainAttribute	0.546	0.826	0.84	0.501
OneRAttributeEv	0.574	0.866	0.837	0.539
Our Chosen At	0.562	0.796	0.837	0.536

Accuracy

Five Highest Accuracies:

- 1.CfsSubsetEval with OneR Classification - 92.5085%
- 1.InfoGainAttributeEval with OneR Classification - 92.5085%
- 2.CorrelationAttributeEval with OneR Classification - 92.395%
- 2.OneRAttributeEval with OneR Classification - 92.395%
- 2.Our Chosen Attributes with OneR Classification - 92.395%

TP Rate*

Five Highest True Positive Rates:

- 1.CfsSubsetEval with J48 Classification - 0.684
- 2.CfsSubsetEval with OneR Classification - 0.68
- 2.InfoGainAttributeEval with OneR Classification - 0.68
- 2.OneRAttributeEval with J48 Classification - 0.68
5. InfoGainAttributeEval with J48 Classification - 0.675

ROC Area

Five Highest ROC Areas:

- 1.OneRAttributeEval with J48 Classification - 0.866**
- 2.CorrelationAttributeEval with J48 Classification - 0.842**
- 3.CfsSubsetEval with OneR Classification - 0.84**
- 3.InfoGainAttributeEval with OneR Classification - 0.84**
- 5.Our Chosen Attributes with One R Classification - 0.837**

Best Performing Model:

CfsSubsetEval with J48 Classification

- Highest TP Rate
- Strong Accuracy and ROC Area

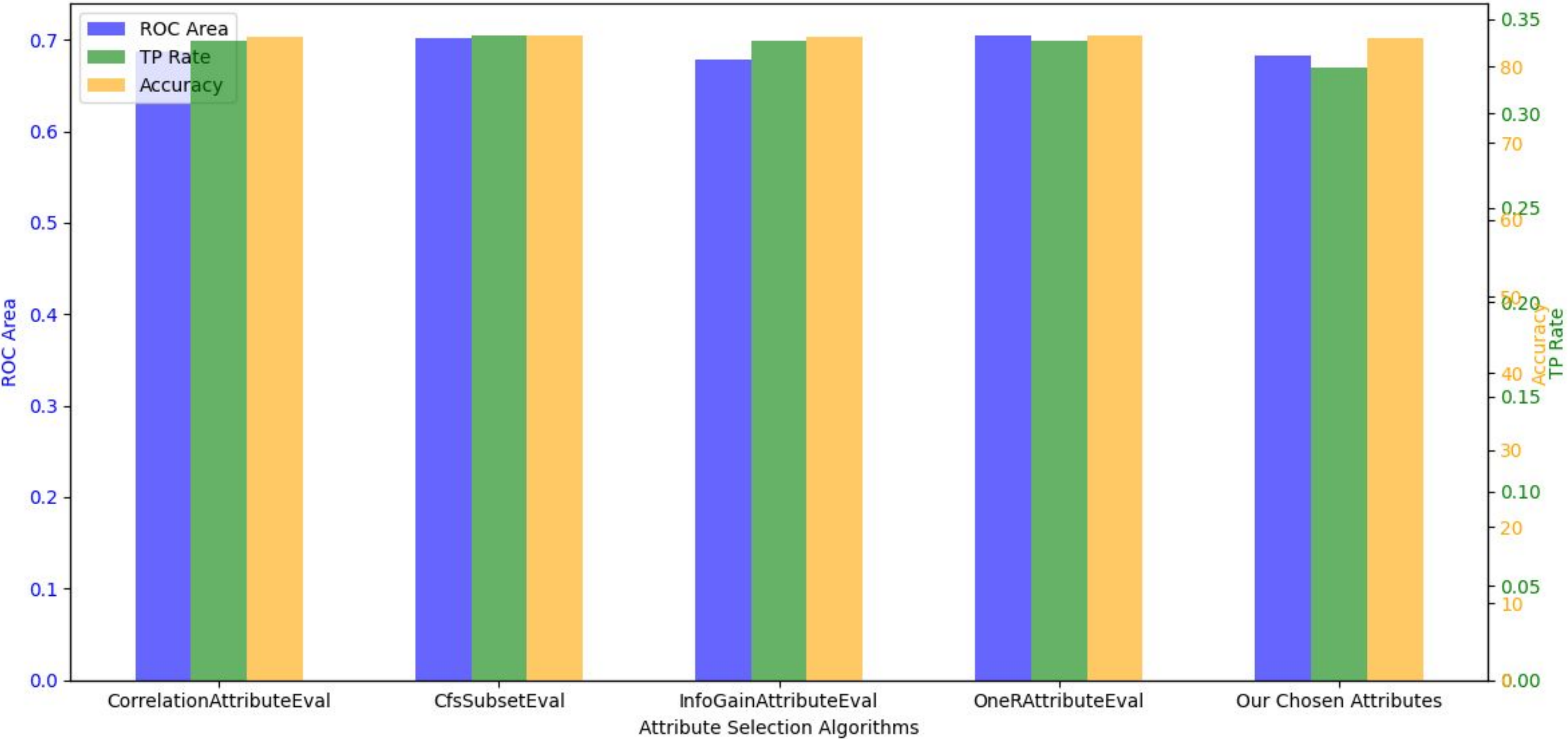
Confusion Matrix

		Classified	
Actual	Class 1	653	22
	Class 2	65	141

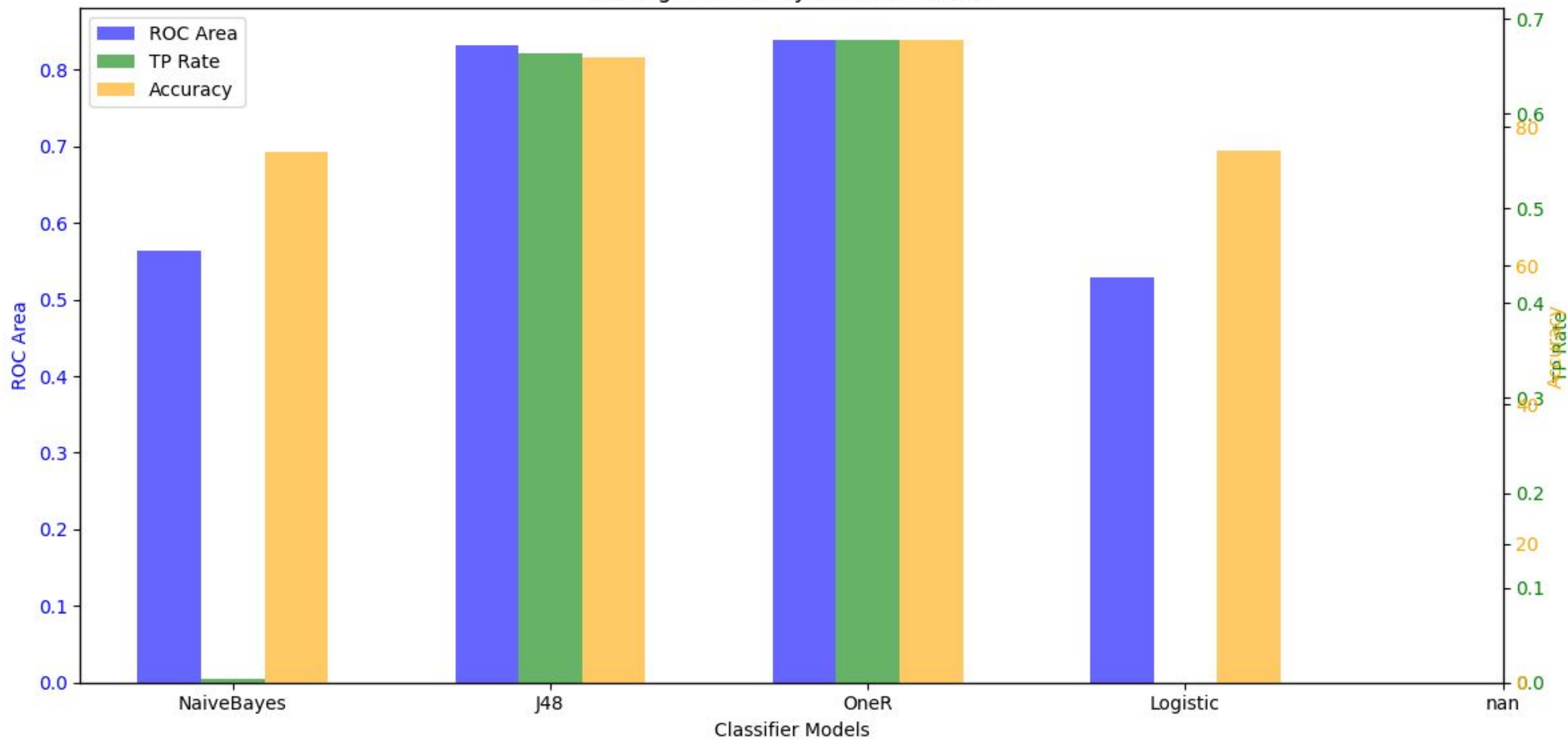


Analysis

Average Metrics by Attribute Selection Algorithm



Average Metrics by Classifier Model



Key Findings

- High performance of OneR
 - The OneR classification model consistently performs well across all attribute evaluation methods
- Poor performance of NaiveBayes and Logistic Regression
 - both are bad with imbalanced data (not to mention feature independence)
- J48's TP Rate
 - J48 shows superior performance in TP rate despite not leading in accuracy
- ROC Area Consistency
 - Models like OneR and J48 maintain a high ROC Area showing they are quite effective despite accuracy or TP rates

Key Findings

- Attributes selected by OneR
 - OneR picked either Age or Wins for the rule, showing that these are the two most applicable attributes for attribute selection

Why?

Future Outlook

- Look at advanced performance metrics, not just “traditional” statistics
- Gather data prior to 2010
- Use other attribute selection algorithms and classifier models (maybe even a deep learning algorithm)
- Possibly expand to MVP selection, All NBA teams, ROTY, DPOY, OPOY
- Explain why wins are so important

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Thank you

