Machine Learning Engineer Nanodegree

Capstone Proposal

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I. Definition

Project Overview

In this project, it will be analysed a dataset containing data on NBA Players game stats from 1980 to 2017. One goal of this project is to find the set of features that best describes a player position.

The original dataset for this project has been taken from this repository at Kaggle (https://www.kaggle.com/drgilermo/nba-players-stats/data), which in turn has scrapped it from Basketball-reference (https://www.basketball-reference.com).

A model will be trained to predict player positions based on their stats for that set of features. This model could be used by NBA trainers to rethink his players' position having into consideration their last year stats. Some players, when they get older, move their playing position to more interior roles, to compensate the loss of velocity.

Machine learning has been previously used to make sports predictions. In the following link (https://www.sciencedirect.com/science/article/pii/S2210832717301485), it can be found a critical survey of the literature on ML for sports result prediction, focusing on the use of neural networks (NN) for this problem.

Problem Statement

The problem to be solved is to predict which position should be playing a NBA player based on his stats. It is usual that players as they get older, they move slower and it is needed to change their playing position to more interior roles. Being able to predict when that change is needed can save both the trainer's and the player's season!

Our problem corresponds to what is known as a Multi-Class Classification (https://en.wikipedia.org/wiki/Multiclass_classification) problem. The model has to predict a discrete number of labels, i.e., point guard, small guard, center...

The dataset mentioned in the previous section will be used as input of an unsupervised learning algorithm which, making use of principal component analysis, will return which features best describe a player position.

The features selected by the previous algorithm will be used as input features, using the player game position as the label to train a supervised learning algorithm.

The supervised learning algorithm will be trained with only the 80% of the dataset. The remaining 20% will be used to test the model and ensure that it can successfully predict a player's position based on his benchmark. The predictions and the labels of the testing set will be compared, and the model accuracy will be calculated using the following formula:

```
def categorical_accuracy(y_true, y_pred):
  return K.cast(K.equal(K.argmax(y_true, axis=-1), K.argmax(y_pred, axis=-1)), K.floatx())
```

`categorical_accuracy` checks to see if the index of the maximal true value is equal to the index of the maximal predicted value.

In the *data exploration section* it can be seen that the classes are balanced. That characteristic of our dataset will let us use the accuracy of the predictions to evaluate the performance of this project solution.

Whenever an NBA trainer would like to reconsider the position of any of his team players, he will only need to enter the player stats corresponding to the features previously mentioned as input to the model, and it will return the players' predicted position.

Technical Requirements

This project has been developed in Python 3.6.5 (https://www.python.org/downloads/release/python-365/), on a Jupyter Notebook (http://jupyter.org/), by making use of the following libraries:

- IPython (https://ipython.org/)
- Keras (http://keras.io/)
- Matplotlib (https://matplotlib.org/)
- NumPy (http://www.numpy.org/)
- pandas (https://pandas.pydata.org/)
- TensorFlow (http://tensorflow.org/)
- scikit-learn (http://scikit-learn.org/)

For the benefit of the reader, a functional description has been added prior to each code section. Nevertheless, some basic Python (https://www.python.org/) and Machine Learning (https://en.wikipedia.org/wiki/Machine_learning) is recommended for a complete understanding of the project.

II. Analysis

Data Exploration

As previously mentioned, the original dataset for this project has been taken from this repository at Kaggle (https://www.kaggle.com/drgilermo/nba-players-stats/data), which in turn has scrapped it from Basketball-reference (https://www.basketball-reference.com).

The dataset consists on 18609 samples. Each sample contains the following information:

Field	Description	Type
Year	Season	Numeric
Age	Age	Numeric
G	Games	Numeric
MP	Minutes played	Numeric
FG	Field goals	Numeric
FGA	Field goal attempts	Numeric
3P	3-point field goals	Numeric
3PA	3-point field goal attempts	Numeric
2P	2-point field goals	Numeric
2PA	2-point field goal attempts	Numeric
FT	Free throws	Numeric
FTA	Free throw attempts	Numeric
ORB	Offensive rebounds	Numeric
DRB	Defensive rebounds	Numeric
TRB	Total rebounds	Numeric
AST	Assists	Numeric
STL	Steals	Numeric
BLK	Blocks	Numeric
TOV	Turnovers	Numeric
PF	Personal fouls	Numeric
PTS	Points	Numeric
Pos	Position	String

Please notice that the last column (`Pos`, the player's position) corresponds to the feature we would like our model to predict based on the values of the other features.

In the table below it can be seen the different values that the `Pos` feature can contain, its description, and the number of samples per value.

Value	Description	# samples
C	Center	3737
PF	Power forward	3919
PG	Poing guard	3737
SF	Small forward	3547
SG	Shooting guard	3669

For your reference I have copied below the first eleven records of the dataset in both plain text and table formats:

Sample data in plain text:

```
Year,Age,G,MP,FG,FGA,3P,3PA,2P,2PA,FT,FTA,ORB,DRB,TRB,AST,STL,BLK,TOV,PF,PTS,Pos
1980,32,82,3143,835,1383,0,1,835,1382,364,476,190,696,886,371,81,280,297,216,2034,C
1980,25,67,1222,153,318,0,1,153,317,56,82,62,129,191,87,35,12,39,118,362,PF
1980,25,75,2168,465,875,0,2,465,873,188,236,158,451,609,322,108,55,218,237,1118,C
1980,31,80,2864,383,794,4,18,379,776,361,435,59,138,197,671,106,10,242,218,1131,PG
1980,31,26,560,27,60,0,0,27,60,32,50,29,86,115,40,12,15,27,66,86,C 1980,28,20,180,16,35,1,1,15,34,5,13,6,22,28,26,7,4,11,18,38,SG
1980,22,67,726,122,271,0,0,122,271,68,101,71,126,197,28,21,54,79,116,312,PF
1980,25,82,2438,545,1101,16,47,529,1054,171,227,240,398,638,159,90,36,133,197,1277,SF
1980,28,77,2330,384,760,1,3,383,757,139,209,192,264,456,279,85,49,189,268,908,SF
1980,27,20,287,24,60,0,0,24,60,16,32,34,43,77,18,5,12,18,52,64,PF
```

Same sample data in table format:

Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS	Pos
1980	32	82	3143	835	1383	0	1	835	1382	364	476	190	696	886	371	81	280	297	216	2034	C

Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS	Pos
1980	25	67	1222	153	318	0	1	153	317	56	82	62	129	191	87	35	12	39	118	362	PF
1980	25	75	2168	465	875	0	2	465	873	188	236	158	451	609	322	108	55	218	237	1118	C
1980	31	80	2864	383	794	4	18	379	776	361	435	59	138	197	671	106	10	242	218	1131	PG
1980	31	26	560	27	60	0	0	27	60	32	50	29	86	115	40	12	15	27	66	86	C
1980	28	20	180	16	35	1	1	15	34	5	13	6	22	28	26	7	4	11	18	38	SG
1980	22	67	726	122	271	0	0	122	271	68	101	71	126	197	28	21	54	79	116	312	PF
1980	25	82	2438	545	1101	16	47	529	1054	171	227	240	398	638	159	90	36	133	197	1277	SF
1980	28	77	2330	384	760	1	3	383	757	139	209	192	264	456	279	85	49	189	268	908	SF
1980	27	20	287	24	60	0	0	24	60	16	32	34	43	77	18	5	12	18	52	64	PF

Below, it can be observed a statistical description of the dataset:

	Year	Age	G	MP	FG	FGA	3P
count	18609.000000	18609.000000	18609.000000	18609.000000	18609.000000	18609.000000	18609.000000
mean	2000.208931	26.838412	49.933903	1170.126337	186.599172	404.127465	22.303348
std	10.708379	4.000733	26.551748	923.422603	181.545157	378.867873	38.655701
min	1980.000000	18.000000	1.000000	1.000000	0.000000	1.000000	0.000000
25%	1991.000000	24.000000	26.000000	321.000000	37.000000	89.000000	0.000000
50%	2001.000000	26.000000	55.000000	996.000000	131.000000	294.000000	3.000000
75%	2010.000000	30.000000	75.000000	1906.000000	287.000000	624.000000	27.000000
max	2017.000000	44.000000	85.000000	3533.000000	1098.000000	2279.000000	402.000000

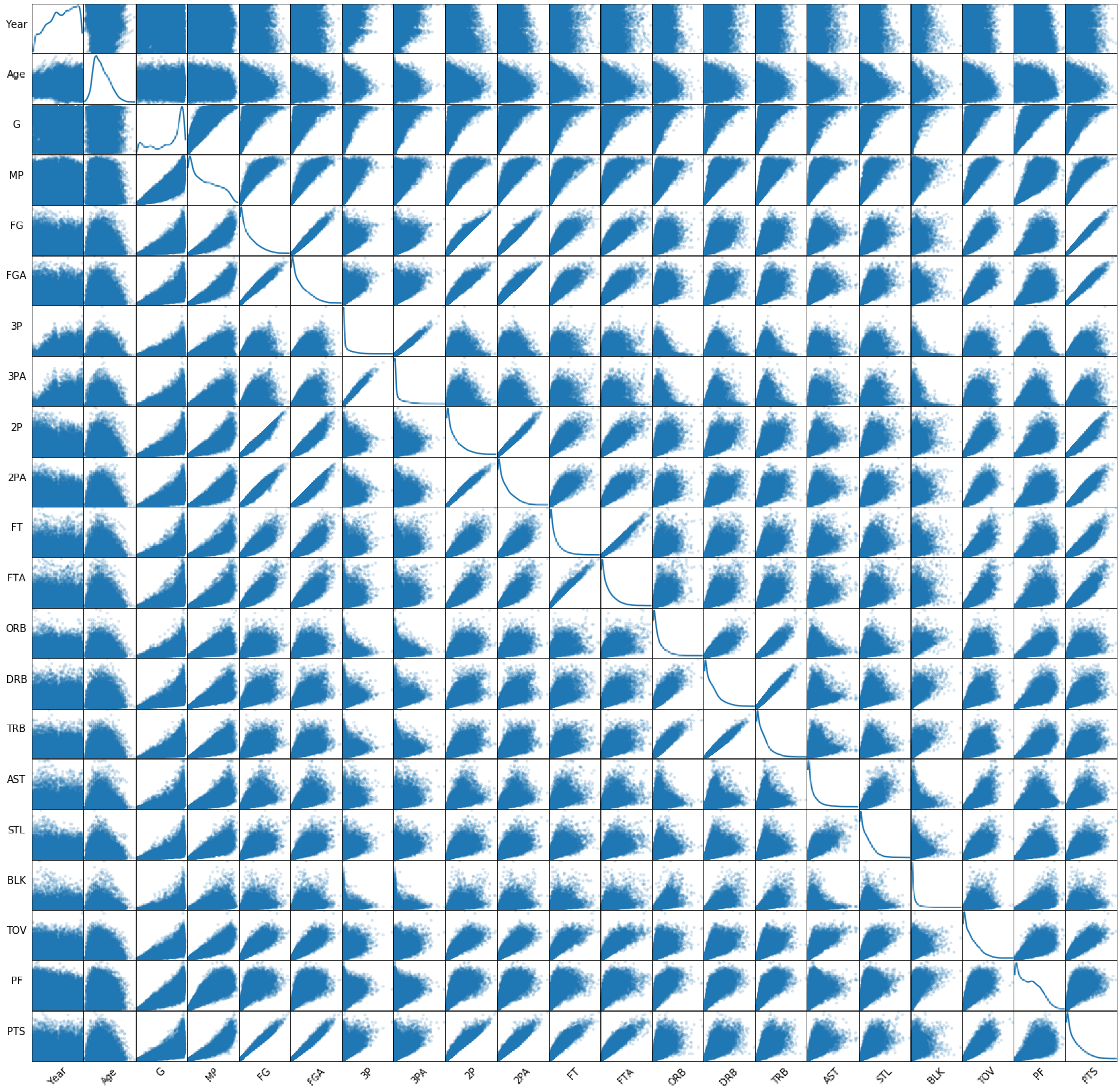
	3PA	2P	2PA	FT	FTA	ORB	DRB
count	18609.000000	18609.000000	18609.000000	18609.000000	18609.000000	18609.000000	18609.000000
mean	63.839271	164.295825	340.288194	94.324735	125.244183	60.674674	144.947767
std	102.679571	168.188121	335.619645	107.571363	137.384324	66.152039	142.418313
min	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	31.000000	71.000000	16.000000	23.000000	12.000000	33.000000
50%	12.000000	109.000000	235.000000	56.000000	78.000000	36.000000	105.000000
75%	84.000000	248.000000	513.000000	136.000000	182.000000	89.000000	211.000000
max	886.000000	1086.000000	2213.000000	833.000000	972.000000	573.000000	1007.000000

	TRB	AST	STL	BLK	TOV	PF	PTS
count	18609.000000	18609.000000	18609.000000	18609.000000	18609.000000	18609.00000	18609.000000
mean	205.622441	111.459348	39.056747	24.396152	73.112741	109.07405	489.826428
std	202.929588	137.760783	37.890003	36.654134	66.652526	80.87030	480.208673
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000	0.000000
25%	47.000000	17.000000	9.000000	3.000000	18.000000	36.00000	98.000000
50%	146.000000	62.000000	29.000000	11.000000	55.000000	100.00000	341.000000
75%	297.000000	153.000000	59.000000	30.000000	111.000000	170.00000	756.000000
max	1530.000000	1164.000000	301.000000	456.000000	464.000000	386.00000	3041.000000

Exploratory Visualization

To get a better understanding of the dataset, I have constructed a scatter matrix of each of the features present in the data. If a feature is relevant for the dataset, then the scatter matrix below may not show any correlation between that feature and the others. Conversely, if you believe that feature is not relevant for identifying the player's position on the court, the scatter matrix might show a correlation between that feature and another feature in the data.

Please notice that, in the picture below, both axis (horizontal and vertical) contain all the features in the dataset.



It can be observed above that some features present a huge correlation between them. For instance, both *defensive rebounds (DRB)* and *offensive rebounds (ORB)* correlate with *total rebounds (TRB)*. The same thing happens with some other features like *2-point field goals (2P)* and *2-point field goal attempts (2PA)*.

Principal Component Analysis (PCA) will take advantage of the correlation existing between some features in the dataset. By making use of PCA and feature reduction, we will also be lowering the impact of the curse of dimensionality (https://en.wikipedia.org/wiki/Curse_of_dimensionality).

Algorithms and Techniques

The following techniques will be applied to complete the project goal:

- Unsupervised learning (https://en.wikipedia.org/wiki/Unsupervised_learning) will be used to find the set of features that best describes a player position. Principal component analysis (PCA) (https://en.wikipedia.org/wiki/Principal_component_analysis) will help conclude the underlying structure of the dataset. PCA uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called **principal components**. This transformation is defined in such a way that the first principal component has the largest possible variance and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. PCA is sensitive to the relative scaling of the original variables. The features that best describe a player position will be selected as the input to the supervised learning algorithm. The label will be the player position.
- Supervised learning (https://en.wikipedia.org/wiki/Supervised_learning) will be used to train a model that predicts player positions based on their stats. A decision tree classifier (https://medium.com/machine-learning-101/chapter-3-decision-trees-theory-e7398adac567) will be trained for that purpose. A decision tree is a flowchart-like structure in which each internal node represents a "test" on an attribute (e.g. whether a coin flip comes up heads or tails), each branch represents the outcome of the test, and each leaf node represents a class label (decision taken after computing all attributes). The paths from root to leaf represent classification rules. The parameters of the tree will be optimized by cross-validated grid-search over a parameter grid. ShuffleSplit cross-validation technique will be used when training the model. The model performance will be validated against the testing set. The higher the accuracy is the more likely the model will be to be used by NBA trainers.

As a final bonus, the benchmark neural network model will also be trained with the new features set, to compare the performance of both neural networks, before and after having selected a subset of features using **principal component analysis**.

Please notice that, in this project, the models will always be trained with the 80% of the dataset and tested with the remaining 20%.

In this project, I have chosed to train our solution with a *decision tree classifier* just for illustrative purposes. Before taking this project to a production environment, I would have trained the date not only with a decision tree classifier, but also with other algorithms such as support vector machines for multiclass classification (http://scikit-learn.org/stable/modules/svm.html#multi-class-classification), naive bayes classifiers (https://en.wikipedia.org/wiki/Naive_Bayes_classifier), and a more complex neural network than the used to benchmark the model. More information about multiclass classification can be found here (https://en.wikipedia.org/wiki/Multiclass_classification).

Benchmark Model

Our solution will be benchmarked against a simple neural network consisting on three fully connected dense layers.

The accuracy of the benchmark model and the new model will be compared. The objective is to discern if the combination of feature selection and hiperparameter tunning on decision trees can outperform a basic neural network approach.

It is important to notice that all the dataset features will be used and none of them (but the labels) have been preprocessed at this moment.

The accuracy of our benchmark model is around 21%, which is almost the same than the accuracy obtained by a model which randomly selects the players position (20% is the probability of randomly selecting the correct player position between 5 possible values).

This model was selected because its probability out of the box is quite similar to the random player position selection, and, once the data has been preprocessed and a new set of features selected, it will show the correctness of our actions and decisions alongside the project.

Evaluation Metrics

In the *data exploration* section it can be seen that the classes are balanced. That characteristic of our dataset will let us use the accuracy of the predictions to evaluate the performance of this project solution.

III. Methodology

Data Preprocessing

Some basic data preprocessing has been performed to our dataset prior to use it:

- The number of features in the original dataset has been reduced from 52 to 22, to trying to reduce the impact of the curse of dimensionality (https://en.wikipedia.org/wiki/Curse_of_dimensionality). The fields removed from the original dataset were the name of the players and the fields that can be easily calculated by the combination of other fields (i.e., the percentage of success 2 point shots).
- The rows with an empty value in any of the features have been removed, to have a consistent set of features. In order to select and remove these rows, Microsoft Excel (https://products.office.com/en-US/excel) was used. This action could have been done in Python (and that would be my option chosen if the dataset was subject to change frequently or if the result of this project were going to be used in real life), but in our case, I considered that the most straightforward and cost-effective solution was to filter these rows with Excel. While performing this action in Excel, I also got a better understanding of the dataset. After removing the rows with empty value, the number of registers in our dataset decreased from 24691 to 18609.

In our dataset, the basketball player position (https://en.wikipedia.org/wiki/Basketball_positions) can be found within column `Pos`. Please find below its possible values:

Value	Description
C	Center
PF	Power forward
PG	Poing guard
SF	Small forward
SG	Shooting guard

A good representation for categorical data (https://en.wikipedia.org/wiki/Categorical_variable) is the one hot (https://en.wikipedia.org/wiki/One-hot) codification. The `Pos` column will be one-hot encoded to facilitate its treatment.

Please find below the value of the labels, once they have been one-hot encoded.

Value	Description	One-hot encoding
C	Center	[1 0 0 0 0]
PF	Power forward	[0 1 0 0 0]
PG	Poing guard	[0 0 1 0 0]
SF	Small forward	[0 0 0 1 0]
SG	Shooting guard	[0 0 0 0 1]

Implementation

This project has been developed in Python 3.6.5 (https://www.python.org/downloads/release/python-365/), on a Jupyter Notebook (http://jupyter.org/), by making use of the following libraries:

- IPython (https://ipython.org/)
- Keras (http://keras.io/)
- Matplotlib (https://matplotlib.org/)
- NumPy (http://www.numpy.org/)
- pandas (https://pandas.pydata.org/)
- TensorFlow (http://tensorflow.org/)
- scikit-learn (http://scikit-learn.org/)

As the first step in our project, a **random seed** (https://en.wikipedia.org/wiki/Random_seed) will be set for both numpy and tensorflow. This is done for reproducibility purposes (https://machinelearningmastery.com/reproducible-results-neural-networks-keras/). This step is quite important, because random numbers are used to initiallize weights in most of the machine learning algorithms. The *random seed* is used to initialize a pseudorandom number generator, and using always the same seed will make it possible to obtain the same random weights at each execution.

The next step will be to load the NBA stats (https://www.kaggle.com/drgilermo/nba-players-stats/data) dataset. The _pandas read*csv* method has been used to load the csv file containing the dataset.

The `Pos` feature (used as the label of our dataset), has been one-hot encoded using the *sklearnt LabelBinarizer* class.

After having loaded the dataset, it will be split into labels and features (https://stackoverflow.com/questions/40898019/what-is-the-difference-between-a-feature-and-a-label). The `Pos` column (the label to predict) will be one-hot encoded to facilitate its treatment. To split the dataset into *X_train, X_test, y_train, y_test* subsets, the _train_test*split* method from the *sklearnt* library has been used. 80% of the data has been allocated into the {X_train, y_train} sets and the remaining 20% into the {X_test, y_test} sets.

At that moment, a basic neural network with three fully connected dense layers will be used as the benchmark model. This model will be trained with the 80% of the dataset and tested with the remaining 20%.

This basic neural network consists on three fully connected *dense layers* (https://keras.io/layers/core/#dense), with relu activation (https://keras.io/activations/#relu) in the first two layers and a softmax activation (https://keras.io/activations/#softmax) in the last layer. Dropout (https://keras.io/layers/core/#dropout) has not been used. The loss function is 'categorical_crossentropy' and 'Adam' has been selected as the optimizer. Ten epochs were used to train the network and a learning rate of 0.001 was used.

As mentioned before, the rationale behind selecting this network architecture and parameters is to test the dataset against a simple neural network which might be improved in the future.

It is important to notice that all the dataset features will be used and none of them (but the labels) have been preprocessed at this moment.

The accuracy of our benchmark model is around 21%.

With the intention to outperform the accuracy obtained by our benchmark model, the following techniques will be used in this project:

Outlier detection and removal (https://en.wikipedia.org/wiki/Anomaly_detection):

Detecting outliers in the data is extremely important in the data preprocessing step of any analysis.

The presence of outliers can often skew results which take into consideration these data points. There are many "rules of thumb" for what constitutes an outlier in a dataset.

The Tukey's Method (http://datapigtechnologies.com/blog/index.php/highlighting-outliers-in-your-data-with-the-tukey-method/) has been used in this project for identifying outliers. An outlier step is calculated as 1.5 times the interquartile range (IQR). A data point with a feature that is beyond an outlier step outside of the IQR for that feature is considered abnormal.

The 10% of the data has been selected as the Q1 percentile and the 90% of the data as the Q3 percentile.

Below, it can be observed the outliners per feature identified after applying the method described above. They have been removed from our dataset.

In [19]:

```
Data points considered outliers for the feature '3P':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
6075	1995	27	80	3069	509	1198	199	555	310	643	156	214	117	276	393	616	200	26	242	164	1373
6285	1995	29	82	3091	438	1031	199	548	239	483	206	282	104	271	375	340	96	38	105	155	1281
6421	1995	29	80	2725	419	1062	217	611	202	451	168	228	34	185	219	411	92	4	160	257	1223
6526	1996	28	81	2893	455	1123	231	623	224	500	127	170	110	222	332	478	212	17	188	151	1268
6784	1996	28	79	2846	530	1281	257	678	273	603	180	224	116	263	379	212	113	38	166	212	1497
6881	1996	30	81	2946	611	1368	225	515	386	853	425	491	54	215	269	255	125	19	220	233	1872
6915	1996	27	82	3041	491	1117	267	628	224	489	182	222	63	246	309	243	90	29	122	169	1431
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
18229	2017	27	81	2947	674	1533	262	756	412	777	746	881	95	564	659	906	120	37	464	215	2356
18341	2017	26	75	2694	661	1488	214	578	447	910	488	545	46	322	368	439	68	20	197	152	2024
18470	2017	32	78	2198	396	890	201	468	195	422	180	202	11	160	171	110	55	13	98	125	1173
18531	2017	27	76	2569	682	1473	245	646	437	827	590	649	43	162	205	449	70	13	210	167	2199
18536	2017	26	78	2649	644	1376	268	647	376	729	186	218	49	236	285	160	66	40	128	139	1742
18563	2017	26	79	2739	643	1449	240	602	403	847	304	359	45	263	308	435	85	22	168	119	1830
18572	2017	28	81	2802	824	1941	200	583	624	1358	710	840	137	727	864	840	133	31	438	190	2558

67 rows × 21 columns

```
Data points considered outliers for the feature '3PA':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
4236	1991	28	66	2346	560	1421	167	564	393	857	465	529	58	198	256	693	147	6	240	162	1752
6075	1995	27	80	3069	509	1198	199	555	310	643	156	214	117	276	393	616	200	26	242	164	1373
6285	1995	29	82	3091	438	1031	199	548	239	483	206	282	104	271	375	340	96	38	105	155	1281
6421	1995	29	80	2725	419	1062	217	611	202	451	168	228	34	185	219	411	92	4	160	257	1223
6526	1996	28	81	2893	455	1123	231	623	224	500	127	170	110	222	332	478	212	17	188	151	1268
6784	1996	28	79	2846	530	1281	257	678	273	603	180	224	116	263	379	212	113	38	166	212	1497
6915	1996	27	82	3041	491	1117	267	628	224	489	182	222	63	246	309	243	90	29	122	169	1431
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
18213	2017	28	75	2323	412	1016	246	661	166	355	147	175	29	172	201	188	48	40	121	150	1217
18229	2017	27	81	2947	674	1533	262	756	412	777	746	881	95	564	659	906	120	37	464	215	2356
18341	2017	26	75	2694	661	1488	214	578	447	910	488	545	46	322	368	439	68	20	197	152	2024
18531	2017	27	76	2569	682	1473	245	646	437	827	590	649	43	162	205	449	70	13	210	167	2199
18536	2017	26	78	2649	644	1376	268	647	376	729	186	218	49	236	285	160	66	40	128	139	1742
18563	2017	26	79	2739	643	1449	240	602	403	847	304	359	45	263	308	435	85	22	168	119	1830
18572	2017	28	81	2802	824	1941	200	583	624	1358	710	840	137	727	864	840	133	31	438	190	2558

47 rows × 21 columns

```
Data points considered outliers for the feature '2P':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
2717	1987	23	82	3281	1098	2279	12	66	1086	2213	833	972	166	264	430	377	236	125	272	237	3041
3114	1988	24	82	3311	1069	1998	7	53	1062	1945	723	860	139	310	449	485	259	131	252	270	2868

```
Data points considered outliers for the feature '2PA':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
2717	1987	23	82	3281	1098	2279	12	66	1086	2213	833	972	166	264	430	377	236	125	272	237	3041

```
Data points considered outliers for the feature 'FT':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
420	1981	24	80	3417	909	1627	2	7	907	1620	632	784	192	317	509	322	109	18	282	245	2452
565	1981	25	80	3245	806	1545	1	3	805	1542	609	804	474	706	1180	141	83	150	308	223	2222
787	1982	25	81	3222	904	1586	1	3	903	1583	648	818	231	283	514	324	95	14	299	252	2457
938	1982	26	81	3398	945	1822	0	6	945	1816	630	827	558	630	1188	142	76	125	294	208	2520
1308	1983	27	78	2922	654	1305	0	1	654	1304	600	788	445	749	1194	101	89	157	264	206	1908
1536	1984	27	79	2984	802	1438	1	4	801	1434	813	946	179	269	448	310	61	4	263	201	2418
1975	1985	21	82	3144	837	1625	9	52	828	1573	630	746	167	367	534	481	196	69	291	285	2313
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
15804	2013	24	81	3119	731	1433	139	334	592	1099	679	750	46	594	640	374	116	105	280	143	2280
15861	2013	23	78	2985	585	1337	179	486	406	851	674	792	62	317	379	455	142	38	295	178	2023
16395	2014	25	81	3122	849	1688	192	491	657	1197	703	805	58	540	598	445	103	59	285	174	2593
17058	2015	25	81	2981	647	1470	208	555	439	915	715	824	75	384	459	565	154	60	321	208	2217
17652	2016	26	82	3125	710	1617	236	657	474	960	720	837	63	438	501	612	139	51	374	229	2376
18229	2017	27	81	2947	674	1533	262	756	412	777	746	881	95	564	659	906	120	37	464	215	2356
18572	2017	28	81	2802	824	1941	200	583	624	1358	710	840	137	727	864	840	133	31	438	190	2558

50 rows × 21 columns

```
Data points considered outliers for the feature 'FTA':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
214	1980	24	82	3140	778	1549	0	6	778	1543	563	783	573	617	1190	147	80	107	300	210	2119
420	1981	24	80	3417	909	1627	2	7	907	1620	632	784	192	317	509	322	109	18	282	245	2452
565	1981	25	80	3245	806	1545	1	3	805	1542	609	804	474	706	1180	141	83	150	308	223	2222
787	1982	25	81	3222	904	1586	1	3	903	1583	648	818	231	283	514	324	95	14	299	252	2457
938	1982	26	81	3398	945	1822	0	6	945	1816	630	827	558	630	1188	142	76	125	294	208	2520
1308	1983	27	78	2922	654	1305	0	1	654	1304	600	788	445	749	1194	101	89	157	264	206	1908
1536	1984	27	79	2984	802	1438	1	4	801	1434	813	946	179	269	448	310	61	4	263	201	2418
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
14795	2011	25	78	2935	619	1044	0	7	619	1037	546	916	309	789	1098	107	107	186	279	258	1784
15861	2013	23	78	2985	585	1337	179	486	406	851	674	792	62	317	379	455	142	38	295	178	2023
16395	2014	25	81	3122	849	1688	192	491	657	1197	703	805	58	540	598	445	103	59	285	174	2593
17058	2015	25	81	2981	647	1470	208	555	439	915	715	824	75	384	459	565	154	60	321	208	2217
17652	2016	26	82	3125	710	1617	236	657	474	960	720	837	63	438	501	612	139	51	374	229	2376
18229	2017	27	81	2947	674	1533	262	756	412	777	746	881	95	564	659	906	120	37	464	215	2356
18572	2017	28	81	2802	824	1941	200	583	624	1358	710	840	137	727	864	840	133	31	438	190	2558

53 rows × 21 columns

```
Data points considered outliers for the feature 'ORB':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
214	1980	24	82	3140	778	1549	0	6	778	1543	563	783	573	617	1190	147	80	107	300	210	2119
565	1981	25	80	3245	806	1545	1	3	805	1542	609	804	474	706	1180	141	83	150	308	223	2222
660	1981	23	82	2578	304	594	0	0	304	594	177	301	433	561	994	93	70	63	146	316	785
938	1982	26	81	3398	945	1822	0	6	945	1816	630	827	558	630	1188	142	76	125	294	208	2520
1308	1983	27	78	2922	654	1305	0	1	654	1304	600	788	445	749	1194	101	89	157	264	206	1908
2041	1985	22	82	2914	677	1258	0	0	677	1258	338	551	440	534	974	111	99	220	234	344	1692
2095	1985	27	80	2497	366	690	0	0	366	690	155	256	405	464	869	96	78	54	160	285	887
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
7981	1998	36	80	2856	155	360	4	23	151	337	61	111	421	780	1201	230	47	18	147	238	375
8117	1998	29	65	2343	321	645	0	4	321	641	195	293	443	440	883	67	45	49	95	236	837
9711	2002	22	80	3020	532	1010	0	0	532	1010	389	524	396	529	925	191	80	163	173	254	1453
16391	2014	20	81	2619	479	769	0	2	479	767	137	328	440	631	1071	35	101	131	110	273	1095
16981	2015	21	82	2502	494	961	0	2	494	959	142	365	437	667	1104	55	73	153	120	285	1130
17124	2015	26	82	2820	379	534	1	4	378	530	187	471	397	829	1226	61	81	183	109	245	946
17583	2016	22	81	2666	552	1060	2	6	550	1054	208	586	395	803	1198	67	119	112	155	245	1314

18 rows × 21 columns

```
Data points considered outliers for the feature 'DRB':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
243	1980	30	81	2860	443	799	0	2	443	797	196	273	352	864	1216	233	45	37	257	259	1082
5017	1992	30	82	3301	342	635	32	101	310	534	84	140	523	1007	1530	191	68	70	140	248	800
5940	1994	32	79	2989	156	292	5	24	151	268	53	102	453	914	1367	184	52	32	138	229	370
8958	2000	33	82	2984	322	573	0	0	322	573	298	421	304	853	1157	105	27	269	174	248	942
10291	2003	26	82	3321	743	1481	20	71	723	1410	377	502	244	858	1102	495	113	129	229	199	1883
10804	2004	27	82	3231	804	1611	11	43	793	1568	368	465	245	894	1139	409	120	178	212	202	1987
11378	2005	28	82	3121	683	1360	6	25	677	1335	445	549	247	861	1108	466	121	112	222	207	1817
13051	2008	22	82	3088	583	974	0	4	583	970	529	897	279	882	1161	110	74	176	263	274	1695

```
Data points considered outliers for the feature 'TRB':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
5017	1992	30	82	3301	342	635	32	101	310	534	84	140	523	1007	1530	191	68	70	140	248	800
5109	1992	29	81	2962	591	1224	6	37	585	1187	292	363	418	840	1258	173	72	54	197	223	1480
5940	1994	32	79	2989	156	292	5	24	151	268	53	102	453	914	1367	184	52	32	138	229	370

```
Data points considered outliers for the feature 'AST':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
272	1980	24	82	3060	502	1063	27	110	475	953	223	338	151	388	539	832	265	35	359	260	1254
621	1981	30	81	2577	446	859	3	12	443	847	191	247	35	89	124	734	110	10	251	257	1086
877	1982	22	78	2991	556	1036	6	29	550	1007	329	433	252	499	751	743	208	34	286	223	1447
961	1982	23	79	2294	309	667	1	21	308	646	122	182	62	213	275	762	163	12	175	254	741
1247	1983	23	79	2907	511	933	0	21	511	912	304	380	214	469	683	829	176	47	301	200	1326
1330	1983	24	77	2552	394	841	5	22	389	819	148	199	65	212	277	753	194	32	226	247	941
1578	1984	29	81	2768	439	904	2	17	437	887	192	234	56	174	230	748	215	13	172	155	1072
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
17866	2016	30	74	2420	515	1114	122	329	393	785	294	328	39	271	310	738	152	13	194	185	1446
17899	2016	29	72	2537	355	782	62	170	293	612	87	150	77	358	435	839	141	10	278	175	859
17986	2016	25	77	2784	572	1349	115	328	457	1021	272	344	42	337	379	789	145	59	318	159	1531
17995	2016	27	80	2750	656	1444	101	341	555	1103	465	573	145	481	626	834	163	20	342	200	1878
18229	2017	27	81	2947	674	1533	262	756	412	777	746	881	95	564	659	906	120	37	464	215	2356
18564	2017	26	78	2836	647	1435	89	272	558	1163	422	527	58	268	326	831	157	49	323	151	1805
18572	2017	28	81	2802	824	1941	200	583	624	1358	710	840	137	727	864	840	133	31	438	190	2558

103 rows × 21 columns

```
Data points considered outliers for the feature 'STL':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
272	1980	24	82	3060	502	1063	27	110	475	953	223	338	151	388	539	832	265	35	359	260	1254
631	1981	25	79	3175	523	1116	23	102	500	1014	224	338	173	372	545	627	232	35	302	258	1293
2028	1985	26	82	2689	416	910	25	89	391	821	189	248	94	284	378	816	229	18	236	247	1046
2062	1985	29	82	3127	690	1470	29	115	661	1355	240	313	156	301	457	669	243	22	249	277	1649
2444	1986	23	82	2878	562	1093	8	29	554	1064	260	327	184	332	516	448	301	40	256	296	1392
2717	1987	23	82	3281	1098	2279	12	66	1086	2213	833	972	166	264	430	377	236	125	272	237	3041
2816	1987	24	81	2697	589	1264	13	48	576	1216	244	324	186	238	424	421	260	35	243	264	1435
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4557	1991	28	81	2598	438	904	23	63	415	841	199	263	191	268	459	444	246	16	212	273	1098
4600	1991	28	82	3103	496	978	58	168	438	810	363	434	46	191	237	1164	234	16	298	233	1413
5059	1992	29	82	3002	453	939	83	204	370	735	308	366	68	202	270	1126	244	22	286	234	1297
5106	1992	25	79	2750	404	824	8	33	396	791	372	427	73	209	282	647	233	22	240	262	1188
6357	1995	29	79	3014	634	1320	109	316	525	1004	315	440	175	464	639	409	232	89	271	238	1692
6839	1996	27	81	3162	618	1276	98	299	520	977	229	306	104	235	339	608	231	19	260	221	1563
10351	2003	27	82	3485	804	1940	84	303	720	1637	570	736	68	276	344	454	225	13	286	149	2262

20 rows × 21 columns

```
Data points considered outliers for the feature 'BLK':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
0	1980	32	82	3143	835	1383	0	1	835	1382	364	476	190	696	886	371	81	280	297	216	2034
58	1980	28	72	1366	97	244	0	1	97	243	39	62	164	246	410	82	23	162	68	191	233
137	1980	34	81	3183	761	1677	3	13	758	1664	334	478	269	627	896	129	62	189	215	309	1859
158	1980	31	81	2119	248	543	0	1	248	542	89	126	192	410	602	173	53	258	199	312	585
167	1980	29	80	2771	232	532	0	2	232	530	124	178	219	731	950	164	43	162	218	298	588
265	1980	24	82	2349	296	566	0	2	296	564	139	167	124	436	560	131	45	162	103	283	731
281	1980	24	82	2123	287	514	0	0	287	514	157	220	283	491	774	76	54	244	99	322	731
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
17124	2015	26	82	2820	379	534	1	4	378	530	187	471	397	829	1226	61	81	183	109	245	946
17738	2016	27	77	2598	357	508	0	1	357	507	266	619	267	792	1059	90	51	177	107	207	980
17996	2016	26	73	2125	413	682	0	0	413	682	214	329	238	627	865	30	44	269	137	201	1040
18141	2017	23	75	2708	770	1527	40	134	730	1393	519	647	174	712	886	157	94	167	181	168	2099
18208	2017	24	81	2744	413	624	0	1	413	623	311	476	314	721	1035	97	49	214	148	246	1137
18548	2017	20	81	2541	444	869	40	115	404	754	245	303	139	448	587	106	74	173	105	262	1173
18575	2017	27	77	2513	542	973	0	0	542	973	225	358	293	795	1088	57	56	161	154	226	1309

260 rows × 21 columns

```
Data points considered outliers for the feature 'TOV':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
18229	2017	27	81	2947	674	1533	262	756	412	777	746	881	95	564	659	906	120	37	464	215	2356
18572	2017	28	81	2802	824	1941	200	583	624	1358	710	840	137	727	864	840	133	31	438	190	2558

```
Data points considered outliers for the feature 'PTS':
```

	Year	Age	G	MP	FG	FGA	3P	3PA	2P	2PA	FT	FTA	ORB	DRB	TRB	AST	STL	BLK	TOV	PF	PTS
2717	1987	23	82	3281	1098	2279	12	66	1086	2213	833	972	166	264	430	377	236	125	272	237	3041

Unsupervised learning (https://en.wikipedia.org/wiki/Unsupervised_learning):

Unsupervised learning will be used to find the set of features that best describes a player position. Principal component analysis (PCA) (https://en.wikipedia.org/wiki/Principal_component_analysis) will help conclude the underlying structure of the dataset. The features that best describe a player position will be selected as the input to the supervised learning algorithm. The label will be the player position.

The *PCA* class from *sklearn* has been used to perform principal component analysis. The dataset employed to fit the model is the one resulting of the outliers removal from our previously manually preprocessed dataset).

The *PCA transform* method will be used to obtain the reduced features set. We have chosen 8 as the number of components requested having into consideration that the PCA analysis concluded that the eight first components explain the 99.79% of the data. A visual explanation of this fact can be found below, at the *free-form visualization* section.

Supervised learning (https://en.wikipedia.org/wiki/Supervised_learning):

Supervised learning will be used to train a model that predicts player positions based on their stats. A decision tree classifier (https://medium.com/machine-learning-101/chapter-3-decision-trees-theory-e7398adac567) will be trained for that purpose. The parameters of the tree will be optimized by cross-validated grid-search over a parameter grid. ShuffleSplit cross-validation technique will be used when training the model. The model performance will be validated against the testing set. The higher the accuracy is, the more likely the model will be to be used by NBA trainers.

Finally, the benchmark neural network model will also be trained with the new features set, to compare the performance of both neural networks, before and after having selected a subset of features using **principal component analysis**.

Refinement

In order to improve our model, the following refinements where performed:

- The *criterion* parameter of the decision tree classifier was automatically selected by cross-validated grid-search over the two possible options 'entropy' and 'gini'. 'Entropy' was selected as the most performant criteria (there is about a 7% difference between using 'entropy and 'gini').
- The _max*depth* parameter of the decision tree classifier was also automatically selected by cross-validated grid-search. It was determined that setting this parameter to 'None' is more performant than choosing between a depth between 1 and 60.
- The Q1 and Q3 percentile values were selected by trial and error. It where initially set to 25% and 75% initially, changing in steps of 5% to the selected values. Using Q1=10% and Q3=90% increased the final model performance in around 5%.
- A different number of components have been trying when fitting the data through [PCA transformation (http://setosa.io/ev/principal-component-analysis/)](http://setosa.io/ev/principal-component-analysis/). From a range of 6 to 10, the most performant value was setting the _n_components value to 8.

When testing the model without performing any refinements (with default values), the obtained accuracy was a 44%. Changing the *criterion* parameter increased its accuracy to 46%. With the change of the percentiles from {Q1=25%, Q3=75%} to {Q1=10%, Q3=90%}, the final accuracy of our model reached the 53.25%.

IV. Results

Model Evaluation and Validation

Once applied outliers detection and removal, reduced the number of features to 8, and trained the decision tree classifier with the optimal parameters explained in the *Refinement* section above, the accuracy of our model is a 53.25%.

At the beginning of the project, the benchmark model got an accuracy of around 21%.

The new model result gets a 32.25% increase in accuracy with respect to the benchmark model, which can be considered good having into consideration that the models used in this project do not have high complexity and are almost 'out of the box' solutions.

It is also worth mentioning that if the benchmark model is trained and tested with the same dataset that the decision tree classifier (the one without outliers and with a reduced number of features, its accuracy increases to a 47.38%.

It could be concluded that these results make sense. Using optimal parameters for the decision tree classifier, reducing the dimensionality, and removing outliers use to be good practices to increase the performance of machine learning solutions.

Finally, please notice that to make this results are reproducible, the TensorFlow and Numpy seed have been set to 23 and 32 respectively.

To test the robustness of our model, it has also been trained with the following seed values: {45, 128, 256}, obtaining the same performance for the decission tree classifier (53.25%) and similar results for the final neural network, obtaining an accuracy between the 58.3% and the 61,3%. In addition to this, when optimizing the model, ShuffleSplit cross-validation has been used to randomly sample the entire dataset during each iteration.

Justification

As mentioned above, our final model gets a 53.25% accuracy. It can be considered a low percentage by some researchers. I may agree with them, but there are other aspects to be considered when evaluating these results:

- This is a first approach to the problem. An *Out of the box* algorithm (decision tree classifier) has been used to illustrate the steps needed to solve this problem.
- At the end of the project, an `improved_final_model` has been added to proof that better results can be obtained with a slightly more complex model. In this case, adding a couple of dropout layers and changing the units of the original neural network increases the performance to a 60.9%.

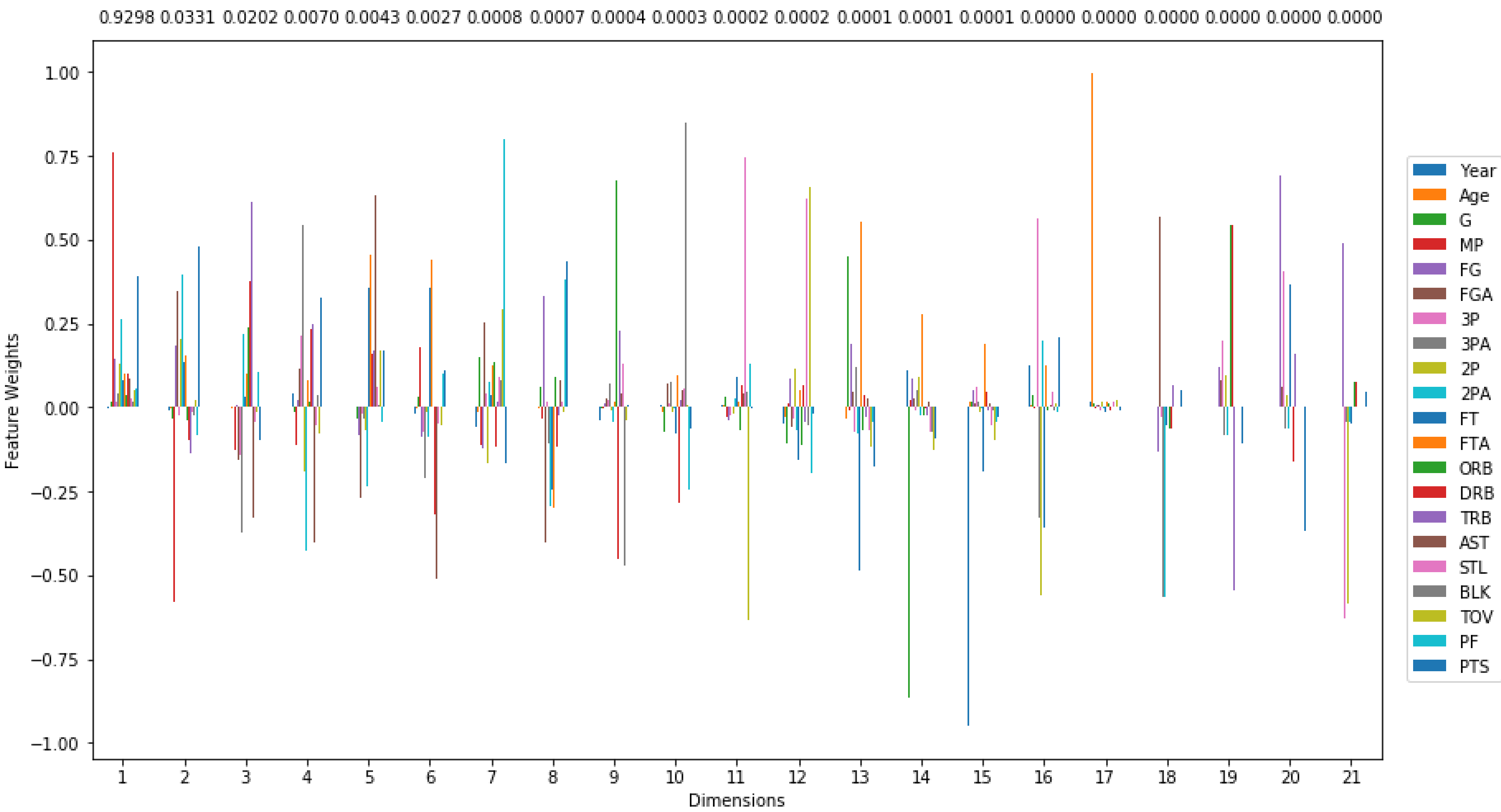
Could the problem be considered as solved? I would not say it is solved, but it is a good start. With the existing results, the model could be used to assist the trainer in the decision-making process, but I would not recommend its use to select the team players positions without human supervision.

V. Conclusion

Free-form visualization

I think it is worth visualizing the PCA results to discover which dimensions about the data best maximize the variance of features involved. Note that a component (dimension) from PCA can be considered a new "feature" of the space. However, it is a composition of the original features present in the data.

The graph below detail the feature weights, the dimensions of the 'new features', the original feature names and, at the top of the graph, the explained variance per component.



It can be seen that the 1st component explains the 92.98% of the data, and the eight first component explain the 99.79% of the data. That's the reason why these components have been used to train our final model.

Reflection

Facing this project has been a very challenging and rewarding experience.

It has let me combine different machine learning techniques, reaching a result which, even it is not optimal, motivates me to keep on improving the project in the near future.

Choosing a *not conventional* project has been the most difficult part of this project. I think I have risked a lot when I decided not to select a more frequently used topic as image classification or time series prediction. Joining all the techniques together to produce consistent results has also involved significant effort.

As a brief summary, I have followed the next steps to complete this project:

- Navigate through different datasets at Kaggle (http://kaggle.com/) until finding the NBA players stats dataset (https://www.kaggle.com/drgilermo/nba-players-stats/data) that I have used in this project. I am a formar basketball player (not a professional but neither a bad player) so this subject was very attractive to me.
- Manually inspect the data to have a better understanding of the dataset and performing some preprocess of it, such as removing features that could be easily calculated from others and removing records without all the features fulfilled.
- Once loaded the dataset into pandas, the dataset stats showed that the classes are balanced. That characteristic of our dataset has let me use the accuracy of the predictions to evaluate the performance of this project solution.
- The labels to predict has been one-hot encoded from character to binary vectors. This has been done to facilitate its treatment.
- A basic neural network has been trained before performing any additional preprocessing of the dataset. A 21% accuracy has been obtained by this model. This accuracy is very similar to the one which would have obtained a model with randomly selects the player position. This is a good starting point, to evaluate how our proposed solution (and even the benchmark model) might improve this result once the following techniques are applied.
- Outliers has been removed from the dataset. The Q1 percentile has been set to 10% and the Q3 to 90%. Different values were tried, from {Q1=25%, Q3=75} to our chosen parameters {Q1=10%, Q3=90%}
- Principal component analysis has been performed to reduce the number of features, and therefore trying to avoid the curse of dimensionality effects. After analyzing the PCA results, it was decided to use eight first components, because the explain 99.79% of the data.
- Once reduced the number of features from 22 to 8, our target classifier algorithm, a decission tree algorithm, has been tuned by cross-validated grid-search over a parameter grid. ShuffleSplit cross-validation technique has been used to train the model. The model performance has been validated against the testing set. The resulting model has obtained a 53.25% accuracy, which is significantly better than our initial benchmark.
- As a bonus, the original benchmark model has been retrained and tested this time with the same dataset that the decision tree classifier (the one without outliers and with a reduced number of features). Its accuracy has increased from 21% to 47.38%.
- Finally, and with the intention to prove that better results can be achieved from this project without too much effort, a slightly improved version of the benchmark model has been trained, obtaining a 60.9% accuracy. The only modifications performed in this new model has been the addition of a couple of Droupt layers and to increase the number of units in the dense layers.

I must confess that I am pleased with having been able to preprocess the dataset, removing its outliers, reducing its dimensionality, optimizing the parameters of an out of the box model and improving by three times the benchmark model accuracy.

Improvement

I think it is fair to conclude that there is still some room to improve the solution to the proposed problem.

I would focus the efforts in two different aspects:

- Firstly, I would try to add some more preprocessing to the dataset, probably by scaling the feature using some non-linear method such as applying the natural logarithm. If that were not be good enough, I would consider using a Box-Cox test (http://scipy.github.io/devdocs/generated/scipy.stats.boxcox.html), which calculates the best power transformation of the data that reduces skewness.
- In addition to that, a custom model based on a more complex neural network might be used to improve the results accuracy.

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