Machine Learning Engineer Nanodegree

Capstone Project

Chess (King-Rook vs. King)

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I. Definition

Project overview

Rook endgames are the most common type of endgames there is in the game of chess. These endgames take place in about in 50% of all the games. The main idea is checkmate of black king with white king and white rook. This should be done in less than 16 steps.

Chess endgames are complex domains which are enumerable. The game theoretic values stored denote whether or not positions are won for either side, or include also depth of wins (number of moves).

The relevant paper related to this M. Bain. "Learning optimal chess strategies", ILP 92: ICOT TM-1182, S. Muggleton, Institute for New Generation Computer Technology, Tokyo, Japan. [Web Link] .

Problem Statement:

The main aim of my project is to predict the outcome of the king-rook vs. king endgame. For this I selected the dataset from UCI (https://archive.ics.uci.edu/ml/datasets/Chess+%28King-Rook+vs.+King%29) So my goal is to predict the outcome of the game whether the white king will win the game in less than 16 moves or not. Here I am using classification models to find the f score of each model and select the model which will have high f score. Here the input parameter is given in the form of training data.

The tasks involved in it are:

1. Download the data
2. Cleaning the data and removing the null data points, duplicated data rows.
3. Visualizing the data.

4. Split the data and train and test which classifier performs good on the dataset based on the evaluation metric we have chosen.
5. Choose the best classifier that gives the best accuracy scores.

Metrics:

Here I will use f score as evaluation metric because my model has imbalanced instances for all classes present. Hence we prefer f score over accuracy. I will be predicting the f score for the selected model.

We need to get a high f score than the benchmark model.

For evaluating the f score we have the following formula:

$$F1 = 2 \times \frac{Precision * Recall}{Precision + Recall}$$

We also have formulas for precision and recall as follows:

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$= \frac{True\ Positive}{Total\ Predicted\ Positive}$$

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$F1 = 2 \times \frac{Precision * Recall}{Precision + Recall}$$

True Positives: are the values which are correctly predicted as positives.

True Negatives: are the values which are correctly classified as negatives.

False Positives: are the values which are wrongly classified as positives. These are also type-1 errors.

False Negatives: are the values which are wrongly classified as negatives. These are also called as type-2 errors.

II. Analysis

Data Exploration

The dataset will comprise of multivariate data. Here the dataset will have categorical values and integer values. There will be total of 28056 instances, and the total number of attributes is 6. The dataset here is a multivariate.

For the best result we will split the data into training set and testing set. On a whole we will assign 70% of the data to training set and 30% of the data to testing set.

Attribute information:

White king file (column)

White king rank (row)

White rook file

White rook rank

Black king file

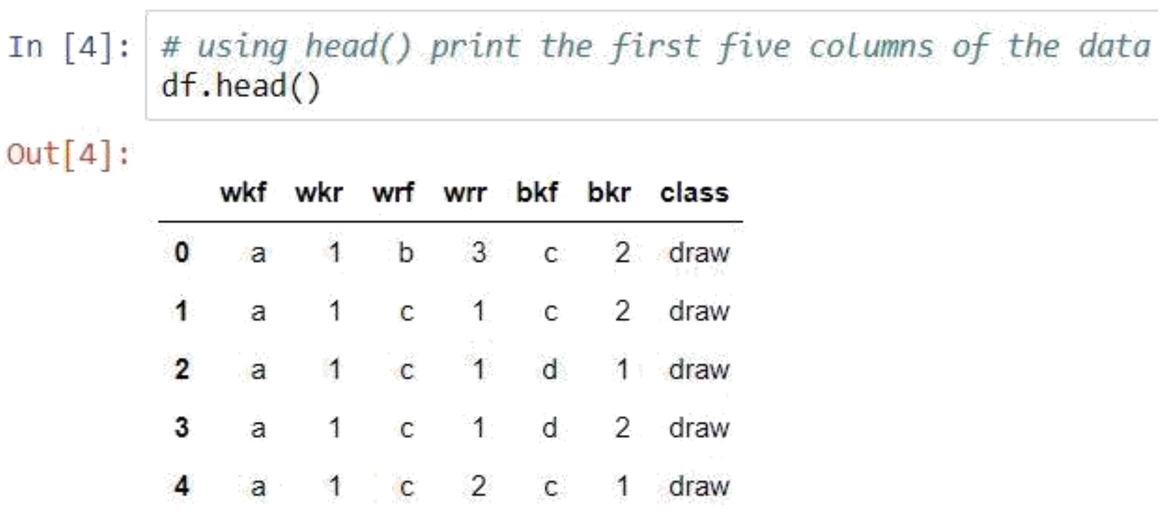
Black king rank

Optimal depth-of-win for white in 0 to 16 moves otherwise drawn {Draw, 0,1,2...16 }

The number of examples for each class labels is as follows:

Fourteen	4553
Thirteen	4194
Twelve	3597
Eleven	2854
Draw	2796
Fifteen	2166
Ten	1985
Nine	1712
Eight	1433
Seven	683
Six	592
Five	471
Sixteen	390
Two	246
Four	198
Three	81
One	78
Zero	27

The head of the data is as follows:

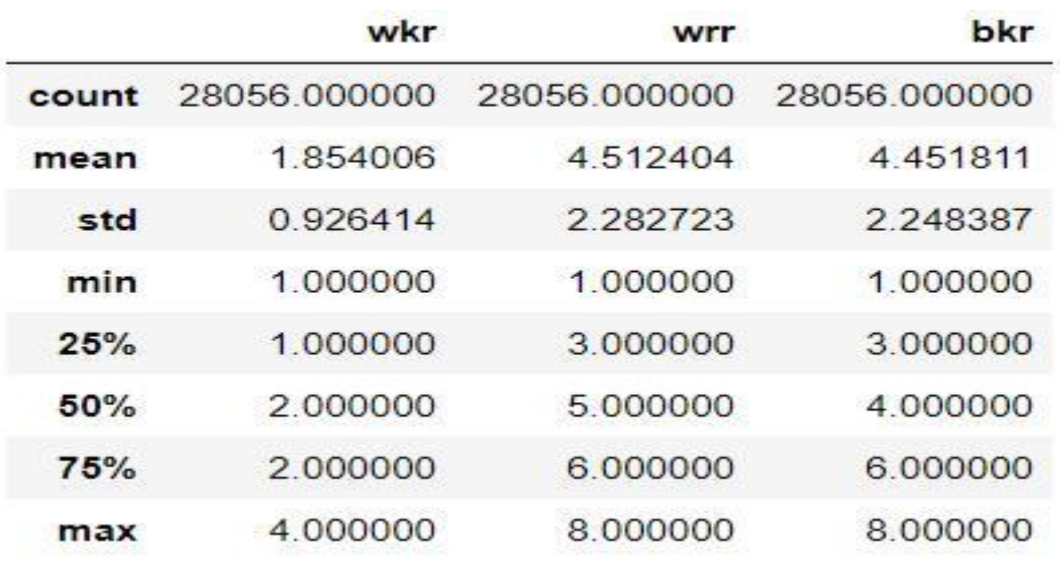


```
In [4]: # using head() print the first five columns of the data
        df.head()

Out[4]:
```

	wkf	wkr	wrf	wrr	bkf	bkr	class
0	a	1	b	3	c	2	draw
1	a	1	c	1	c	2	draw
2	a	1	c	1	d	1	draw
3	a	1	c	1	d	2	draw
4	a	1	c	2	c	1	draw

The statistical information regarding the dataset is as follows



	wkr	wrr	bkr
count	28056.000000	28056.000000	28056.000000
mean	1.854006	4.512404	4.451811
std	0.926414	2.282723	2.248387
min	1.000000	1.000000	1.000000
25%	1.000000	3.000000	3.000000
50%	2.000000	5.000000	4.000000
75%	2.000000	6.000000	6.000000
max	4.000000	8.000000	8.000000

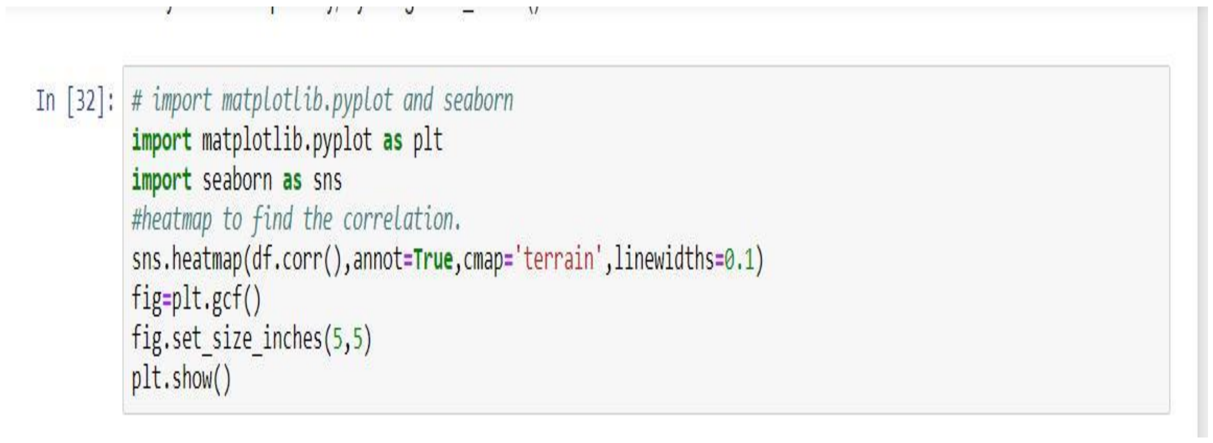
Exploratory Visualization

Heat map:

The heat map is a 2-D representation of data in which values are represented by colours. A simple heat map provides the immediate visual summary of information. More elaborate heat maps allow the user to understand complex data.

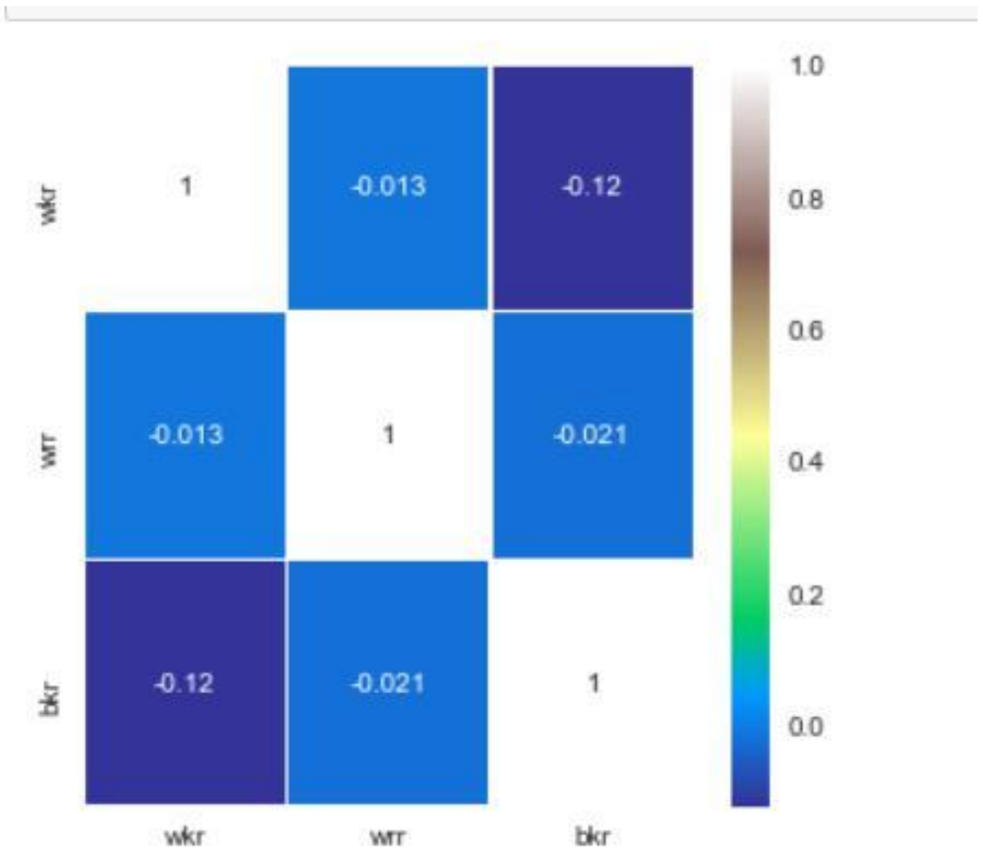
Here we will know the correlation the attributes like wkr (white king rank), wrr (white rook rank), bkr (Black king rank)

By using the below code we will generate the heat map between the attributes and try to deduce the correlation between the attributes. We will use the following code to do so.



```
In [32]: # import matplotlib.pyplot and seaborn
         import matplotlib.pyplot as plt
         import seaborn as sns
         #heatmap to find the correlation.
         sns.heatmap(df.corr(),annot=True,cmap='terrain',linewidths=0.1)
         fig=plt.gcf()
         fig.set_size_inches(5,5)
         plt.show()
```

By executing the above code we get the following heat map:



(For a more clear heat map refer to the Code shown in the above that was executed in the project)

From the above heat map we can clearly say that there is no much correlation between the attributes.

Algorithms and techniques:

Here mainly we will use three algorithms.

1. Decision Tree.(Benchmark Model)
2. Random Forest.
3. Support Vector Machine.

Decision Tree:

Decision Tree algorithm belongs to the family of supervised learning algorithms. Unlike other supervised learning algorithms, decision tree algorithm can be used for solving regression and classification problems too. The general motive of using Decision Tree is to create a training model which can use to predict class or value of target variables by learning decision rules inferred from prior data(training data).

The understanding level of Decision Trees algorithm is so easy compared with other classification algorithms. The decision tree algorithm tries to solve the problem, by using tree representation. Each internal node of the tree corresponds to an attribute, and each leaf node corresponds to a class label.

Advantages:

- Decision Trees are easy to explain. It results in a set of rules.
- It follows the same approach as humans generally follow while making decisions.
- Interpretation of a complex Decision Tree model can be simplified by its visualizations. Even a naive person can understand logic.
- The Number of hyper-parameters to be tuned is almost null..

Disadvantages:

- There is a high probability of overfitting in Decision Tree.
- Generally, it gives low prediction accuracy for a dataset as compared to other machine learning algorithms.
- Information gain in a decision tree with categorical variables gives a biased response for attributes with greater no. of categories.

- Calculations can become complex when there are many class labels.

Parameters:

class sklearn.tree.DecisionTreeClassifier(criterion='gini', splitter='best', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features=None, random_state=None, max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, class_weight=None, presort=False)

Random Forest:

Tree models are known to be high variance, low bias models. In consequence, they are prone to over fit the training data. This is catchy if we recapitulate what a tree model does if we do not prune it or introduce early stopping criteria like a minimum number of instances per leaf node. Well, it tries to split the data along the features until the instances are pure regarding the value of the target feature, there are no data left, or there are no features left to spit the dataset on. If one of the above holds true, we grow a leaf node. The consequence is that the tree model is grown to the maximal depth and therewith tries to reshape the training data as precise as possible which can easily lead to over fitting. Another drawback of classical tree models like the (ID3 or CART) is that they are relatively unstable. This instability can lead to the situation that a small change in the composition of the dataset leads to a completely different tree model.

Parameters:

Class sklearn.ensemble.RandomForestClassifier (n_estimators='warn', criterion='gini', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=None, random_state=None, verbose=0, warm_start=False, class_weight=None

Advantages:

1. Reduction in over fitting: by averaging several trees, there is a significantly lower risk of over fitting.
2. Less variance: By using multiple trees, you reduce the chance of stumbling across a classifier that doesn't perform well because of the relationship between the train and test data.

Disadvantages:

1. It takes more time to train samples.

Support vector machine (svm):

The objective of the support vector machine algorithm is to find a hyper plane in an N-dimensional space (N — the number of features) that distinctly classifies the data points.

To separate the two classes of data points, there are many possible hyper planes that could be chosen. Our objective is to find a plane that has the maximum margin, i.e. the maximum distance between data points of both classes. Maximizing the margin distance provides some reinforcement so that future data points can be classified with more confidence.

Advantages:

SVM's are very good when we have no idea on the data. Works well with even unstructured and semi structured data like text, Images and trees. The kernel trick is real strength of SVM. With an appropriate kernel function, we can solve any complex problem. Unlike in neural networks, SVM is not solved for local optima. It scales relatively well to high dimensional data. SVM models have generalization in practice; the risk of over fitting is less in SVM.

Disadvantages:

Choosing a good kernel function is not easy. Long training time for large datasets. Difficult to understand and interpret the final model, variable weights and individual impact. Since the final model is not so easy to see, we can not do small calibrations to the model hence it's tough to incorporate our business logic.

Parameters:

class sklearn.svm.**SVC**(*C=1.0*, *kernel='rbf'*, *degree=3*, *gamma='auto_deprecated'*, *coef0=0.0*, *shrinking=True*, *probability=False*, *tol=0.001*, *cache_size=200*, *class_weight=None*, *verbose=False*, *max_iter=-1*, *decision_function_shape='ovr'*, *random_state=None*) ¶

Benchmark Model:

For this problem we will choose Decision Tree model as the benchmark model.

By applying this Decision Tree model we achieved an f score of 0.601 that is 60.1%.

Now we will try and achieve better f score than this model by using the above mentioned classification models.

III. Methodology

<u>Data Pre-processing:</u>

In this step we will pre process the data. Data pre-processing is considered to be the first and foremost step that is to be done before starting any process. We will read the data by using read_csv. Then we will know the shape of the data. After that we will know the unique class attributes by using unique (). And by using the info () we will know the information of the attributes. Then we will check whether there are any null values by using isnull ().

LabelEncoder can be used to normalize labels. We will import LabelEncoder from sklearn.preprocessing we will also use fit_transform(y) for Fit label encoder and return encoded labels. After doing that we will use le.transform () for Transform labels to normalized encoding.

After that we will divide the whole data into training and testing data. We will assign 70% of the data to the training data and the remaining 30% of the data into testing data. We will do this by using train_test_split from sklearn.model_selection.

<u>Implementation</u>

Out of the chosen algorithms we will first take Random Forest classification model. We will take a classifier and fit the training data. After that we will predict that by using predict (X_train). Now we will predict the f score of the testing data by using f1_score(y_test, pred). By doing so for the Logistic regression which is the benchmark will give us the f score of 0.601.

We will now choose the algorithm which will give us the better score than the benchmark model out of Random Forest and SVM.

By following the same procedure above that is fitting, predicting and finding the f score we will get the f score as below.

Random Forest: 0.737

SVM: 0.654

From the above reports Random Forest seems to be performing well.

Complications:

While building the Random Forest Classifier I faced a complication while tuning the parameters. Firstly we should come to a conclusion about the parameters we are going to tune. Then by varying the range of values of the chosen parameter we should be able to get the parameter value which gives us the better f score than the unturned value. So it is complicated to choose the parameter that is to be tuned in this case n_estimator.

Refinement

I found out random forest as the best classifier out of the chosen classifiers. Now we will perform tuning of random forest classifier in order to achieve the better f score. For this we will use GridSearchCV.

For doing refinement we will just tune the parameter. Here we will assign n_estimators=[450,500] and 'criterion': ['gini', 'entropy']. Now will find out the new f score. The new f score will be 0.7400. This tuned f score will be a little bit more than the untuned f score.

IV. Result

Model evaluation and validation

The final model we have chosen is tuned random forest which gave us more F score that is 0.7400. In order to achieve this f score we assigned n_estimators=[450,500] and 'criterion': ['gini', 'entropy'] but without using the n_estimators and criterion we achieved the f score of only 0.737 which is a bit less than the tuned value. Here we can say that the solution is reasonable because we are getting much more less f score while using other models.

The final model that is tuned random forest has been tested with various inputs to evaluate whether the model generalises well. This model is also robust enough for the given problem. We can say this by testing it over different random sates. Here we used the random sates 1,2,3 and obtained nearly same f score for each model and the mean f score is equal to the f score when random sate is 1. From this we can say that Small changes in the training data will not affect the results greatly. So the results found from this model can be trusted.

Justification

My final model's solution is better than the benchmark model.

	Tuned random forest	Benchmark model
F score	0.7400	0.601

From the above we can conclude that the results for the final model are stronger than the benchmark model.

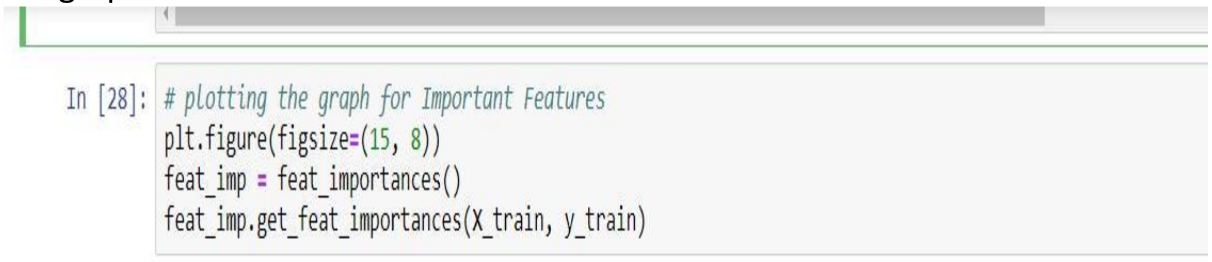
Hence we can say that tuned random forest provides the significant to solve the problem of predicting the outcome of the endgame King-Rook vs. King.

V. Conclusion

Free-form Visualization

After studying the data and applying all the classification models we can visualize the following. We try to find out the important features in the model. For this we will be using feature_importances_

We will plot the important features according to their rank by using the bar graph.

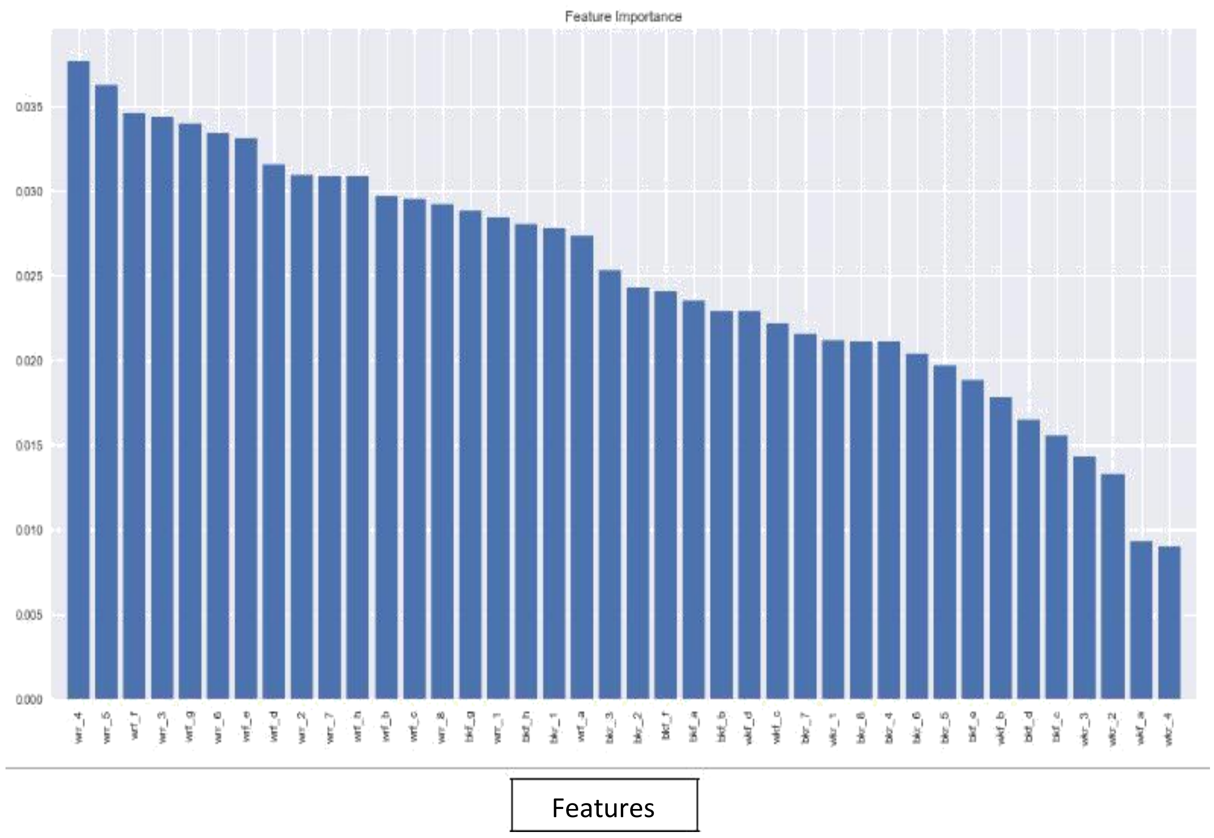


```
In [28]: # plotting the graph for Important Features
         plt.figure(figsize=(15, 8))
         feat_imp = feat_importances()
         feat_imp.get_feat_importances(X_train, y_train)
```

We will plot the graph by using the above code. We can find this in the coding section.

By plotting the bar diagram with features on x-axis and their importance on y-axis we will get the below bar diagram showing the ranks of the features according to their importance.

Plot for the feature importance



From the above graph we conclude the important features according to their rank that is wrr_4 is the most important feature and wkr_4 is the least important feature.

Reflection:

1. I have learnt how to visualize and understand the data.
2. I have learnt that the data cleaning place a very vital role in data analytics.
3. Removing the data features which are not necessary in evaluating model is very important.
4. I got to know how to use the best technique for the data using appropriate ways
5. I got to know how to tune the parameters in order to achieve the best score.
6. On a whole I learnt how to graph a dataset and applying cleaning techniques on it and to fit the best techniques to get best score.

Improvement:

The process which i have followed can be improved to classify not only for the King-Rook vs. King Endgame. This can also be applied for the all the other endgames in chess like King-Rook vs. King-Pawn end game. This model is a part of my researching in Endgames. This application can be taken to next level with the many more applications. As we can say that there has never been an end in the machine learning there will be many more models to learn. By taking the more amount of dataset which consists the information about all the endgames in chess this can be more and more be generalized to all the endgames in the chess.