Data Mining project report

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`https://github.com/nikodallanoce/DataMiningProject`

Abstract

The report shows all the tasks considered during the project, from data understanding to time series analysis. The aim of the report is to explain what we did during our work while giving reasons about our choices and the results obtained.

Contents

1 Data understanding and preparation

We focused our work on the matches dataset that contains tennis matches played in many tournaments across the world over the last five years, it includes both male and female players and has 186.129 records and 49 features. We decided not to do any cleaning or integration on the male and female datasets since they were only used to get the sex for each player.

1.1 Data understanding

The data understanding task focuses on analyzing the dataset and its integration by removing duplicated values, fixing missing values and solving the possible outliers.

1.1.1 Data semantics

In this phase we focused on understanding the meaning of each feature inside the dataset.

- **tourney_id**: it's a *string* that uniquely identifies each tournament. It is mainly composed by two parts separated by a dash "-", where the first one indicates the year when the tournament was played and the second one refers to the tournament identifier, i.e. '2018-W-WITF-EGY-03A-2018'. The dataset contains some null value for this feature (only for the last tournament), while it has 4853 unique values.
- **tourney_name**: it's a *string* that represent the name of the tournament and it's not unique because the name of the tournament is usually the same over the years. It has some missing values only in the last part of the dataset.
- **surface**: it indicates the surface where the matches took place. It's a categorical attribute which its possible values are: hard, clay, grass and carpet. Only few matches are missing this feature.
- **draw_size**: it's a *float* that indicates the number of players in a tournament.
- **tourney_level**: it's a *string* indicates whether the tournament is for male or female players and also its level (mastr, ATP500, ATP1000 etc.). Has some missing values in the last part of the dataset just like for the tourney_id.
- **tourney_date**: it's the date when the match took place. In the dataset it's a *float* in the form YYYYMMDD. To use it as real date, a parsing to a date type is needed. Missing values are present only in the last part of the dataset.
- **match_number**: it's a *float* number that represents the match number in a tournament. Due to its meaning, it should be parsed to an integer.
- **winner_id**: it's a *float* representing the id of the match winner. It's unique for players with the same gender, while the same id can appear for a male player and for a female player as well, since they play in different tours (ATP and WTA).

- **winner_entry**: it's a *string* that indicates how a player joined the tournament. There are a lot of missing values for this feature.
- **winner_hand**: it's a *string* representing the winner player's favourite hand. Its possible values are 'U' for unknown, 'R' for right and 'L' for left. Actually there are also null values, but they can be treated as unknown.
- **winner_ht and loser_ht**: *float* representing the winner player's height. There are a lot of missing values for this field that can not be inferred by other records where this it's filled.
- **winner_ioc and loser_ioc**: a 3-character *string* representing the player's nationality. Some of them have been written using different standards. For instance, a German player is present both as 'GER' and as 'DEU'. Also, some players appear with more than one nationality because they switched it during the last years.
- **winner_age and loser_age**: a *float* that indicates the age of the winner. The decimal part represents the percentage of the days days left to the birthday. Some of these values are missing in the dataset, but few of them can be precisely inferred.
- **best_of**: a *float* indicating the number of set for a match. We parse it to an integer.
- **round**: the match round (e.g. F stands for final and SF for semifinal).
- **minutes**: indicates how much a match lasted. It's a *float* that we converted to an integer.
- **w_ace and l_ace**: number of aces (valid serve won, first or second, not touched by the opposing player). It's a *float*, but it should be an integer.
- **w_df and l_df**: number of double faults committed by the player (more specifically the number of invalid second serves). It's a *float* converted to int.
- **w_svpt and l_svpt**: this may be confusing, it isn't the number of points obtained after a player's serve but the number of serves done by the player (the former is referred on specialised sites as serve points won).
- **w_1stIn and l_2stIn**: number of valid first serve by the player.
- **w_1stWon and l_1stWon**: number of points won after a valid first serve by the player.
- **w_2ndWon and l_2ndWon**: number of points won after a valid second serve by the player, be aware that a point lost after a second serve could be a double fault (this means that the second serve wasn't valid).
- **w_SvGms and l_SvGms**: number of games (not points) where the player was serving.
- **w_bpSaved and l_bpSaved**: number of breakpoints (the player is a point from losing a game where he's serving) saved (the player serving won the point).

- **w_bpFaced and l_bpFaced**: number of breakpoints that the player faced (see previous feature).
- **w_rank and l_rank**: the player's rank, in tennis points are awarded based on the performance at each tournament.
- **w_rank_points and l_rank_points**: the player's ranking points.
- **tourney_revenue**: the tourney revenue coming from ticket sales etc. It isn't the prize of the tournament (which would have been more interesting for a player analysis).
- **tourney_spectators**: number of spectators of the entire tournament.

1.1.2 Type casting

In this dataset, most of the features have an incorrect data type. We parse the tourney_date from float to pandas date type. Furthermore, every float attribute has been parsed to integer except for the winner/loser age and the tourney_revenue.

1.1.3 Dropping useless matches

There are many matches without any statistics, highlighted in Figure 1. Such matches are from minor tournaments and the players who played in them don't have many matches in the dataset, we decided to drop them.

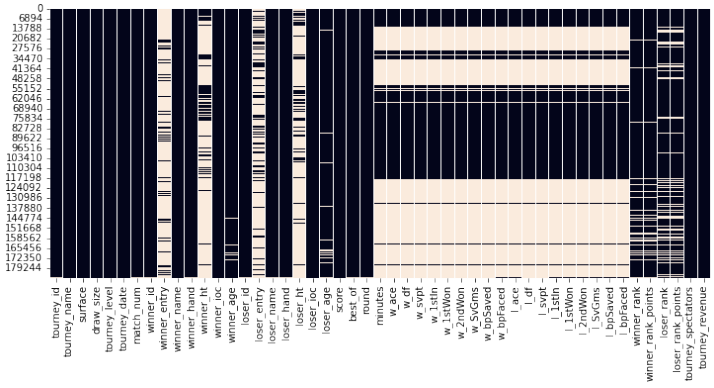


Figure 1: The missing values heatmap.

Furthermore, starting from line n. 186073 to the end, we found a block of records that is a copy of some matches of the Taipei tournament, but with some field left empty. Having noticed this, we dropped this useless part of the dataset.

1.1.4 Dropping useless features:

For our purpose, an analysis of the players, some features are not interesting or straight useless, so we decided to drop them. We don't need the **tourney name**, since we don't differentiate

between the tournaments (masters atp, ATP1000 etc.), moreover we already have the **tourney id** and **date**.

The **draw size** is useless for the players and the **tourney level** can't be used to differentiate between men and women, since the latter can play the same kind of tournaments of the former. For what concerns **match num**, it's a progressive number for the matches of a tournament, sometimes is totally arbitrary, we don't need it.

Winner entry (and **loser entry**) is a string that shows if the player qualified by a wildcard, as a lucky loser etc., it's not a very useful attribute since no site lists them, moreover is the feature with the most missing values.

The last features we dropped are **tourney revenue** and **tourney spectators**, the former is the amount of revenue generated by the tournament and not the winner prize which would have been really interesting. The latter is the amount of spectators of the entire tournament, not match to match, so we can't retrieve information about how famous the players involved in a certain match are or if they can play better under more pressure.

1.1.5 Dropping duplicates

We found that the matches dataset has 302 duplicated records. Due to the domain of this dataset, these duplicates are useless, so we dropped them.

1.1.6 Data integration

The data integration task consists in solving the various issues found in the dataset by filling the missing values, where it's possible, and fixing the various problems that may arise (e.g.: players with two hands preferred or with more than one ioc).

Player id and name In our analysis, we found that there are three players ('Guy Stokman', 'Giuseppe Tresca', 'Kuan Yi Lee') that appear in the dataset with more than one id associated. Moreover, there's only one player with an actual homonym (Kuan Yi Lee), one is a male (id: 134120) and the other one is female (id: 221745), but we discovered that the actual name of the male player is Kuan-Yi, so we changed his name to differentiate between the two players. For what concerns the other two players, we assigned them their last id.

Deepening the analysis, we found that ids are shared only between a male and female player and this is allowed since different tours exist (ATP and WTA) for each sex, so we don't need to apply any change, moreover we won't work with ids so this won't affect our analysis.

Surface We found that the "surface" feature has some null values. Moreover, the number of tournaments without a surface are 42 while the number of matches without a surface are 117. In order to solve this problem, for those tournaments that lack the surface we can retrieve it if at least one match of the same tournament has it. Unluckily there are no tournaments for which we could retrieve the surface (all of them are from the Davis or Federation cup, where the surface changes from event to event), so we chose to sample such values from the distribution of the surfaces.

Winner/loser hand We have to manage the missing values for both "winner_hand" and "loser_hand". To do this, we checked if the value is missing only for a particular player or if he/she never has the hand defined and, in this case, we assign it to him/her. After this step, however, the missing values are still present, but since the domain of this feature is 'U', 'L', 'R', we can safely treat null values as 'U'. The players with unknown hand are 1840. Among them, we retrieved the actual preferred hand for one player, Amina Anshba, who is left-handed.

Winner/loser height This feature contains missing values too, so we addressed this problem as before, looking for those players that have a known height somewhere in the dataset. A deeper analysis show us that 'David Goffin' has two heights registered: 180 cm and 163 cm. Since his real height is the first one, we fixed it in in all occurrences in which he appears.

Winner/loser ioc Since there are no missing values for this feature, we only needed to check if there are players with more than one ioc. Since we dropped records and players that have played too few matches, we haven't found players with more than one ioc. In the original dataset, instead, it happens. Anyway, we found that the player called 'Xinmu Zhou', has 'UNK' nationality, but he is Chinese actually, so we assign him 'CHN'. Lastly, we discovered that, sometimes, the acronyms of the nations are wrong, since some of them don't follow the international standard (e.g.: GRE for Greece instead of GRC, or TPE for Taiwan instead of TWN) or have both at the same time (e.g.: DEU and GER for Germany), so we fixed them, at least the ones we found.

Winner/loser age There are 58 players with unknown age. Among them there are only two players whose age can be inferred from the other information inside the dataset, we fixed the missing ages during the data preparation task.

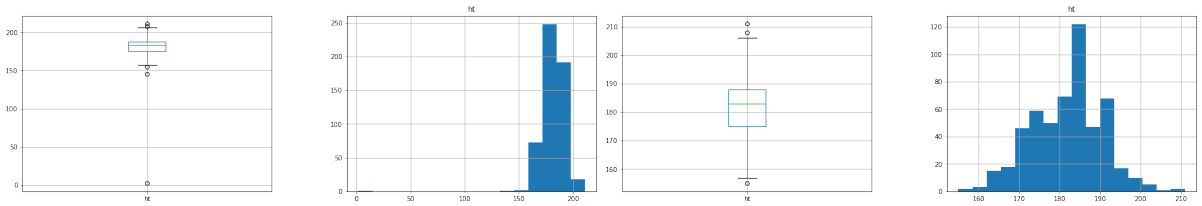
Winner/loser rank This information is missing for those players that played only few matches. We fixed the missing values with the last tournament rank for each player (or the next if not present) that already had a rank. For those without rank we assumed they didn't have any points so we assigned them the maximum rank found in the dataset.

Winner/loser rank points Same work as for the rank feature, instead this time we assign the minimum value for those players without any rank points (they are the same we found during the rank integration).

1.1.7 Outlier detection

Given that all the feature distribution are Gaussian or half normal, to analyze outliers we must first compute the first quartile, the third quartile, the median and the interquartile for each feature. Then we compute the lower bound $L = Q1 - 1.5 * IQR$ and the upper bound $U = Q1 + 1.5 * IQR$ for each feature. In case some numerical data was less or greater than the lower or upper bound respectively, we can identify an outlier. For half-normal distribution we don't consider the lower bound. In case of an outlier that can be fixed with a real value, we did it. In this way we found, for example, two players that have too low height and, in fact, these

data were wrong. We fixed it with the players' real height. Whereas high values correspond to those players that are actually tall. We have applied this analysis for every numerical feature.



(a) Before detection (b) After detection

Figure 2: An example of a feature's distribution after dealing with outliers.

1.1.8 Correlations

We plotted the correlation matrix in order to visualize whether there are correlations between the features. In Figure 3, the more the color is red the more the features are correlated.

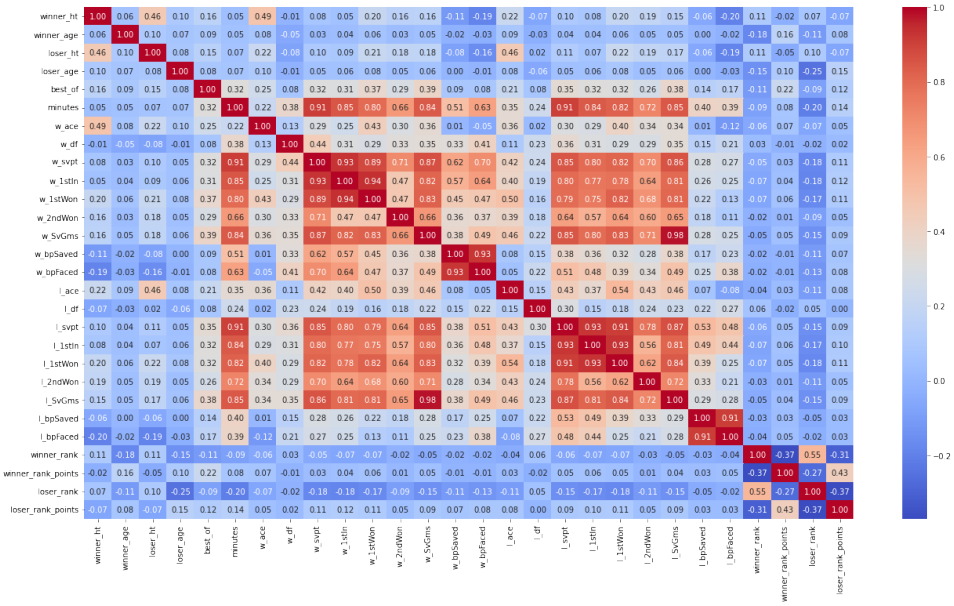


Figure 3: Correlation matrix of the tennis matches dataset.

After looking at the correlation matrix we dropped the minutes feature since we deemed it as useless after doing a huge help during the outlier detection by showing "inusual matches".

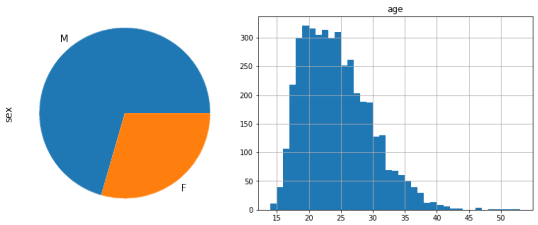
1.2 Data preparation

In this section we focus on describing how we built our new dataset, cleaned and composed by some new features derived by the original ones.

1.2.1 Building the player's profile

The purpose of data preparation is building a profile that will feed the clustering analysis, as a starting point we decided to build such profile from the features we had from the matches dataset.

Sex First of all, when we started building our new dataset, we assigned the sex to each player inside tennis_matches using the female_players and male_players datasets. Some players of the tennis_matches dataset were not found in the "sex" dataset due to spelling errors in their name, but we solved this problem by looking online.



(a) Sex distribution (b) Age distribution

Figure 4: Sex and age distribution

Age Since we are doing a "current" analysis, we assign to each one of the players the last age they appear in the original dataset. Some of them have an unknown one, we had to sample it.

Ioc This was the easiest one since we didn't have to deal with missing values.

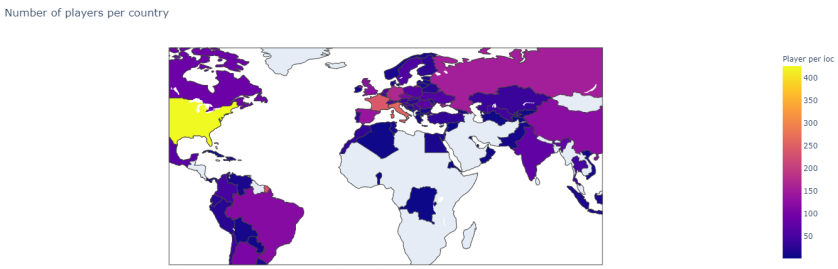


Figure 5: IOC distribution

Height We solved the issue of having many players without an height by sampling their height from the distributions based on countries and sex where this was possible, otherwise we assigned them the mean height of their respective sex.

Hand Just like for the ioc we just needed to assign the hand to the players since the missing values were already dealt with.

Wins and losses We calculated the total matches won or lost by the player and also how many matches they won on a specific surface.

Tournaments won We calculated the tournaments won by the player by looking at how many times he appeared in a final as the winner.

Surfaces We inserted the amount of wins by a player for each surface he/she played on, moreover we dropped all the statistics (percentage of win and number of wins) about the matches played on carpet since such surface is no more allowed by the international federation.

Statistics, rank and rank points For each player we calculated all the statistics coming from the cleaned matches dataset, futhermore we assigned at each player their rank and rank points, eliminating from the dataframe those that played less than ten matches.

1.2.2 Building new features

Having inserted the features coming from the cleaned matches dataset, it was time to look at the correlations between those features, we saw that many of those were many highly-correlated, so we decided to build new ones from them, such as [*num_matches, p_wins, p_w_Hard, p_w_Clay, p_w_Grass, mean_ace and p_aces, mean_double_faults and p_double_faults, mean_1st_in and p_1st_in, mean_1st_won and p_1st_won, mean_2nd_won and p_2nd_won, mean_bp_saved and p_bp_saved, mean_bp_faced, mean_sv_games, mean_sv_points*]

Categorical features We built categorical attributes that split players by age, height and rank ranges.

We then dropped the features that were too high correlated with another one or we deemed useless for the players analysis (n_matches, mean_aces, mean_sv_games, mean_double_faults). After adding the new derived features, we checked that they were not correlated each other by calculating again the correlation matrix, as showed in Figure 6.

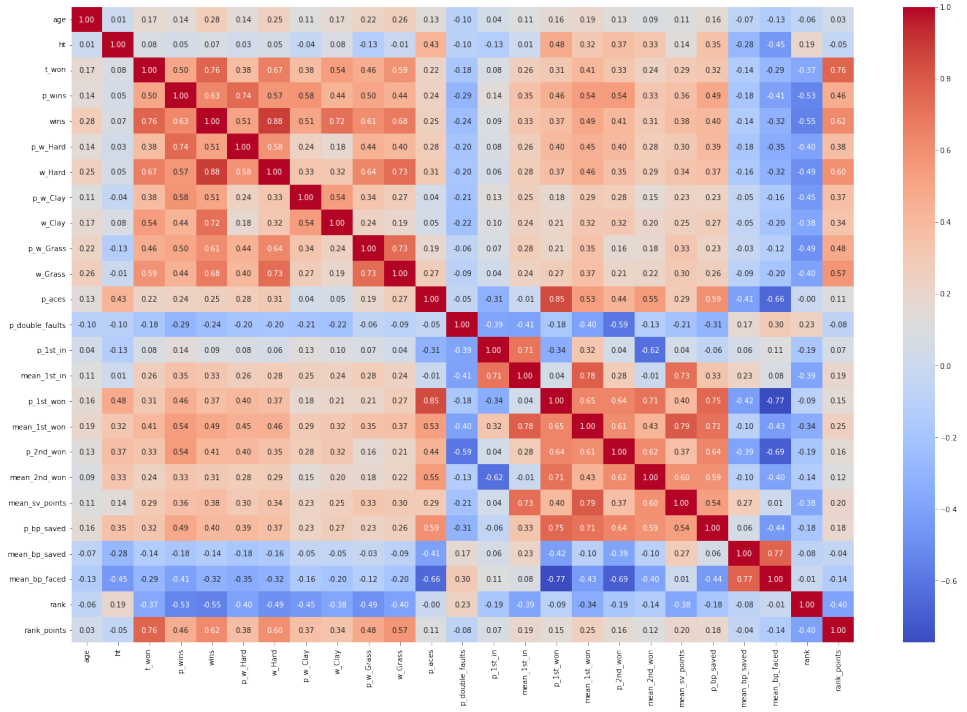


Figure 6: Correlation matrix of the new dataset with the features we added.

2 Clustering analysis

2.1 Preprocessing

In order to let the cluster algorithms work, we had to preprocess the data. Initially we tried to use the MinMax scaler, but we saw that K-Means wasn't working well. Due to that, we decided to normalize such features with their z-score by using the scikit-learn StandardScaler method.

2.2 K-Means

2.2.1 Feature selection

In order to apply K-Means, we selected only some features to avoid the *curse of dimensionality*, the chosen features are the ones **that best differentiate strong players from weak ones**. We have also tried the PCA (principal components' analysis) approach to understand the most relevant features, but the results, obtained by the K-Means on these features, were not satisfying in terms of silhouette score. After several experiments, we obtained the best result choosing as parameters the number of tourney won (*t_won*), the percentage of wins (*p_wins*) and the rank (*rank*) of each player. We also tried different set of features (percentage of wins on each surface and statics) which we also explored with the k-means algorithm, but the explanation of the results it's not easy for someone who isn't fond of tennis, so we decided to work mainly with the three features listed before.

2.2.2 Choosing the best K

The choice of the parameter k in the k-means approach is crucial since it identifies the number of clusters resulting from the algorithm's execution, but before choosing the best k we let the algorithm work for twenty times and then we analyzed the indicators in Figure 8. We choose $k = 3$ by following the informal elbow rule for the SSE graph in Figure 7, moreover we wanted an high value for the silhoutte score and a low one for the Davies-Bouldin score as we can see for $k = 3$ on Figure 8.

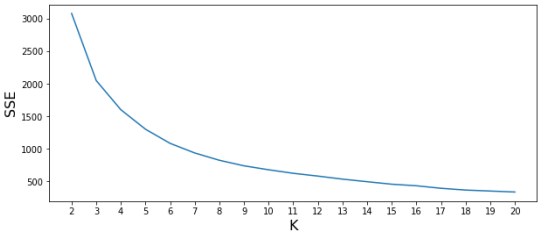
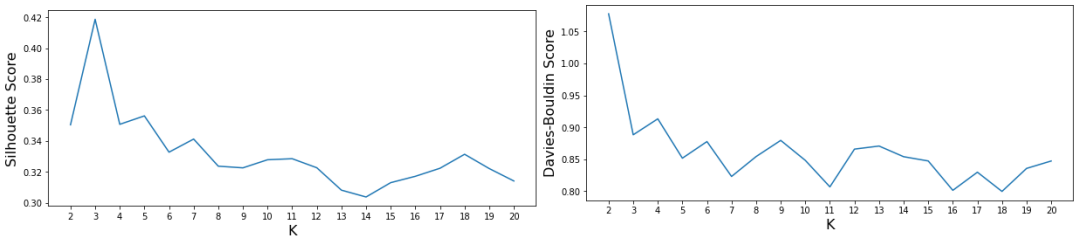


Figure 7: K-Means SSE over K clusters.



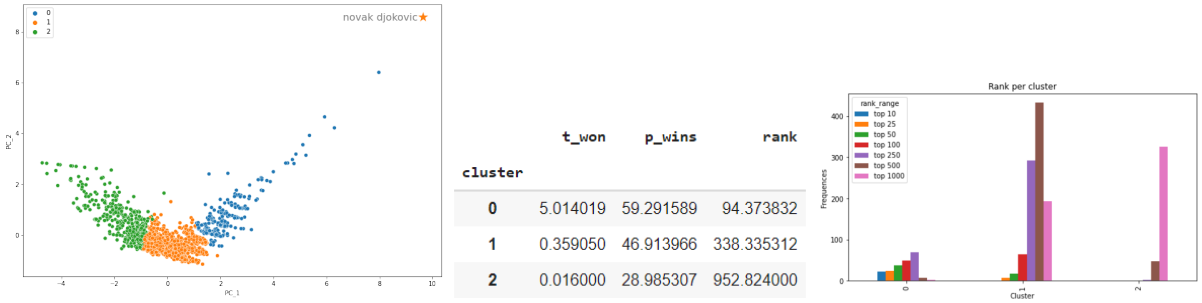
(a) K-Means silohuette score

(b) K-Means Davies-Bouldin Score

Figure 8: K-Means metrics over k clusters.

2.2.3 Cluster analysis

We applied the PCA on the previously chosen features to analyze the K-means results, then we showed the scatterplot of the first two principal components. As we can see in Figure 9, the players are divided from left to right by their skills: the weak ones, the average ones and the strong ones. The points on the top right correspond to the top tennis players, such as Djokovic, Nadal and Zverev; we have highlighted Novak Djokovic, the player with rank 1, in the plot to better show the distribution of the players by strength. We have noticed that some players with a high rank are in cluster 0, this is probably due to the fact that they have a high win rate or have won some minor tournaments.



cluster	t_won	p_wins	rank
0	5.014019	59.291589	94.373832
1	0.359050	46.913966	338.335312
2	0.016000	28.985307	952.824000

Figure 9: The 3 clusters obtained using K-Means and statistics of the features for each cluster.

2.3 DBScan

We decided to work with the dataframe used in the k-means analysis (the one with "t_won", "p_wins", "rank"), since we think that it better describes who are the best players and those who aren't.

2.3.1 Determining eps and min points

The distance between data points is computed using the Euclidean metric, and for selecting the best eps and min_samples values we first performed a grid search whose results can be found on the notebook. From the results we chose $min\_samples = 8$ and by looking at Figure 10 we chose $eps = 0.55$ since it's the value at which the graph's curvature is the highest. The silhouette score is equal to 0.6208

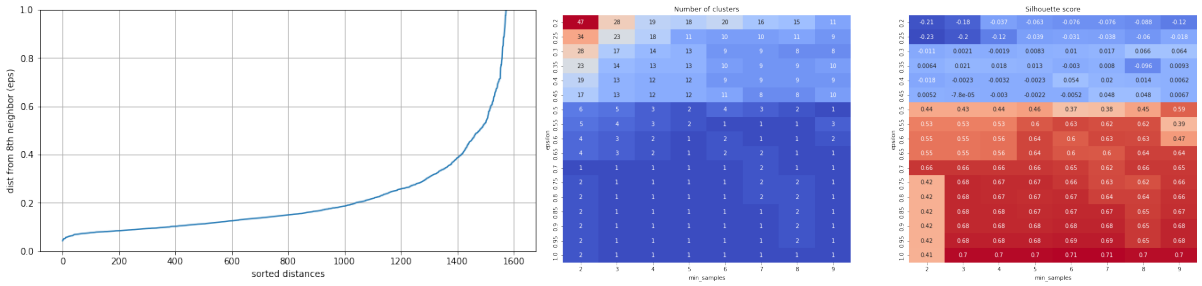
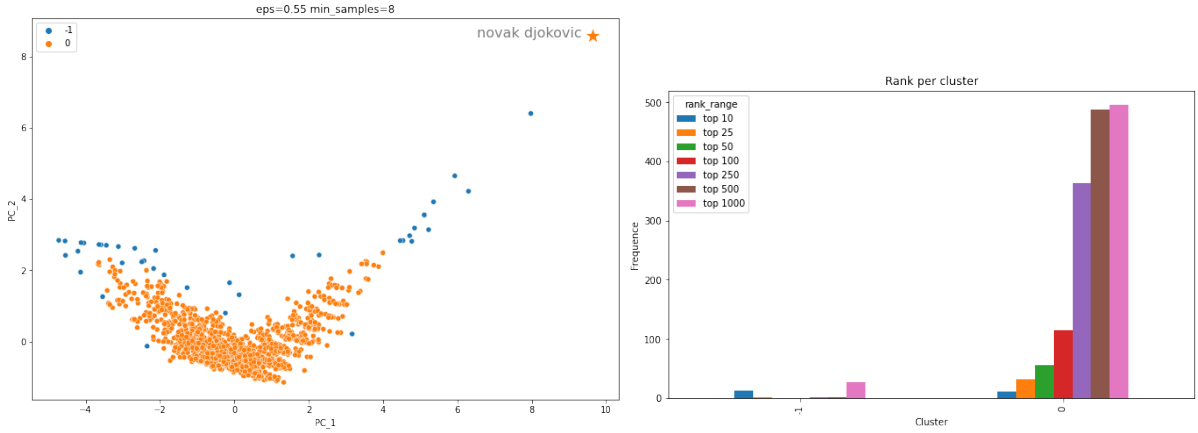


Figure 10: DBScan: determining eps and min_samples

2.3.2 Cluster analysis

Analyzing the clusters obtained by the DBScan method (Figure 11), we've seen that there is a single large cluster (the orange one) and the blue points referring to the outliers (or noise). In the outliers' cluster there are the players at the extremes: those who have won very few matches and the strongest players in the world, respectively on the left and right side of the main cluster. There are also outliers in the center of the plot, representing players who have won some minor tournaments despite not being among the strongest ones.



(a) Clusters generated by applying DBScan, plotted along the 2 P.C.

(b) Distribution of players' ranks per cluster

Figure 11: DBScan: cluster analysis.

2.4 Hierachical Clustering

The analysis of the hierarchical clustering has been conducted using the same set of attributes of the previous algorithms, in order to get results comparable in terms of indicators and properties among the approaches.

2.4.1 Distance methods

Like we did with the other clustering algorithms, we used the Euclidean metric to compute the distance between the pairs of points. We have tried several types of agglomerative clustering that differ by the merging criterion of the clusters like min, max, average and ward. In the hierarchical clustering approach, we have not assumed any particular number of clusters: any desired number of clusters can be obtained by 'cutting' the dendrogram at the proper level.

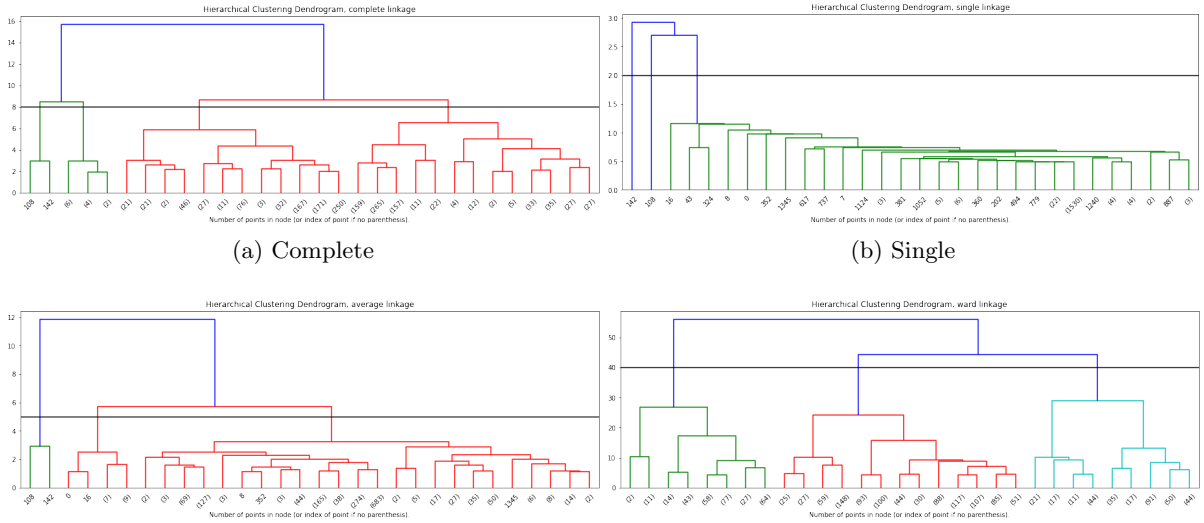
2.4.2 Comparing dendrograms

Cut threshold The "best cut" of the dendrograms is a cut that passes from the longest vertical segment not interrupted by horizontal lines. Anyway we avoided to choose a cut that would have produced too unbalanced clusters.

Method	**cluster id : its dimension**	**Silhouette**
Complete	0: 759, 1: 12, 2: 827, 3: 2	0.3082
Single	0: 1598, 1: 1, 2: 1	0.8013
Average	0: 1580, 1: 2, 2: 18	0.6485
Ward	0: 330, 1: 296, 2: 974	0.3756

Even if the silhouette is pretty good using the single and average methods, we can't say the same thing looking at the dendrograms, since the clusters are unbalanced, and as a consequence,

most of the points fall into one big cluster. The only exceptions in this behaviour is produced by applying the Ward method, that produced an almost balanced clusters closer to the K-Means one, as shown in Figure 13.



(a) Complete

(b) Single

(c) Average

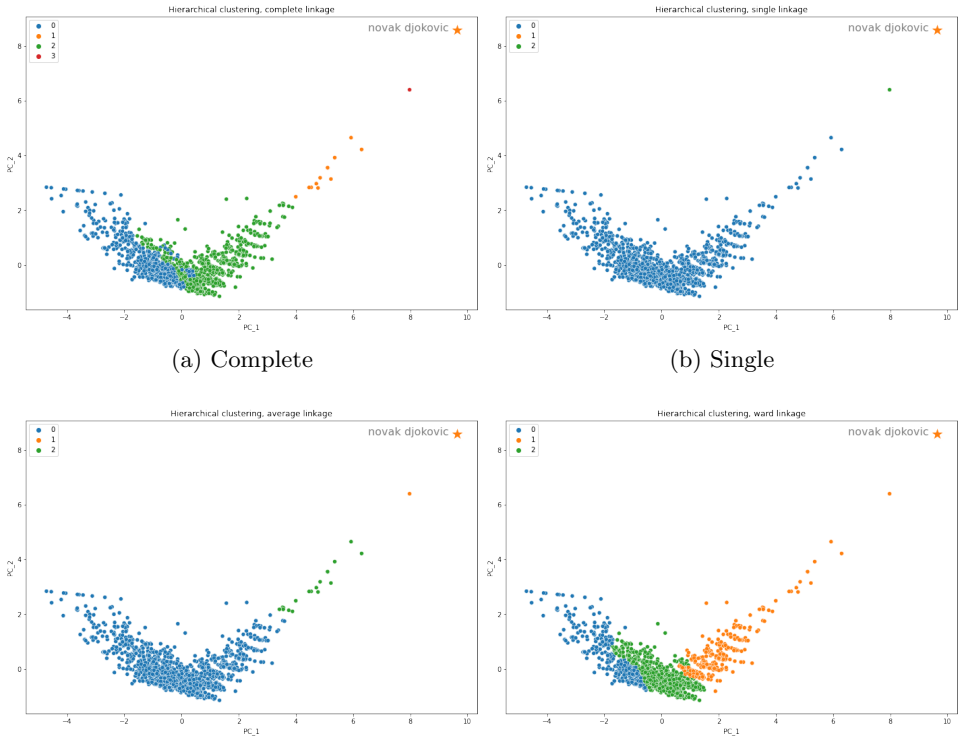
(d) Ward

Figure 12: Hierarchical clustering methods comparison: dendrograms.

2.4.3 Comparing clusters

By looking at the pcas plot from Figure 13, we can define the hierarchical clusterings with complete and ward linkage as the best ones among the four methods. The single linkage was the worst one since it created two cluster with one player each (Djokivic and Nadal which are the best overall players), meanwhile the average one separated the extremely strong players (again Djokivic and Nadal) from the strong ones (green cluster) and the average or weak ones (blue cluster).

The only approaches that didn't have such drastic separation were the complete and ward linkages, which is why we considered them as the best among the four approaches.



(a) Complete (b) Single

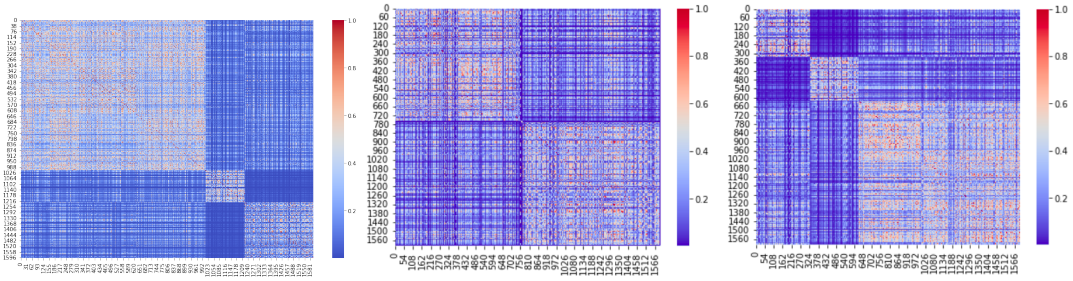
(c) Average (d) Ward

Figure 13: Hierarchical clustering: plotting along the PCAs.

2.5 Validation by external measures

We computed the *similarity matrix* S given a particular clustering. To obtain this matrix, the indices are sorted according to the labels of the clusters and the component $S(i, j)$ is equal to $e^{-d(i,j)}$, where $d(i, j)$ is the euclidean distance between the points i and j. If we have well-separated clusters, then the similarity matrix should be roughly block-diagonal.

We also computed the entropy of each feature per cluster: a low entropy score of each attribute indicates a more predictable and less uncertain trend within the clusters.



(a) Similarity Kmeans (b) Similarity Complete (c) Similarity Ward

	t_won	p_wins	rank	total	cluster
0	1.22241	5.96804	6.4523	13.642740	0
1	1.24287	5.02835	5.16675	11.437966	1
2	0.926832	5.31888	5.58171	11.827420	2

(d) Entropy Kmeans

	t_won	p_wins	rank	total	cluster
0	1.29796	5.92966	6.27411	13.501734	0
1	1.09861	2.48491	2.48491	6.068426	1
2	1.04161	5.75331	6.17364	12.968556	2
3	0	0.693147	0.693147	1.386294	3

(e) Entropy Complete

	t_won	p_wins	rank	total	cluster
0	1.40096	5.47581	5.62733	12.504099	0
1	1.293	5.29267	5.54986	12.135523	1
2	1.03742	5.83546	6.29367	13.166547	2

(f) Entropy Ward

	t_won	p_wins	rank	total	cluster
0	1.17746	6.17805	6.57116	13.926668	0
1	0	0	0	0.000000	1
2	0	0	0	0.000000	2

(g) Entropy Single

	t_won	p_wins	rank	total	cluster
0	1.16622	6.16747	6.56644	13.900121	0
1	0.693147	0.693147	0.693147	2.079442	1
2	1.41687	2.89037	2.89037	7.197613	2

(h) Entropy Average

Figure 14: Similarity matrices and Entropy of attributes per cluster for each method

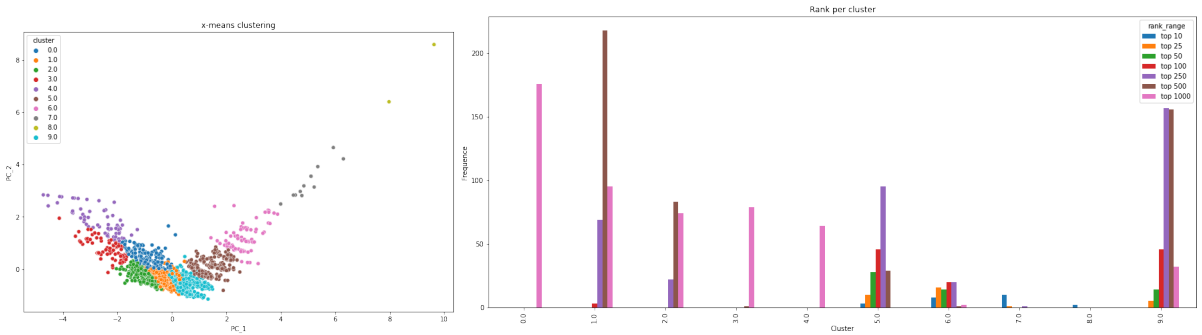
2.6 Other clustering approaches explored

For the final work on clustering we went to explore two more approaches from the pyclustering 1[2] package as suggested by the professor, our choice fell on X-Means and SOM soft-clustering.

2.6.1 X-Means

From the pyclustering package documentation: X-means clustering method starts with the assumption of having a minimum number of clusters, and then dynamically increases them. X-means uses specified splitting criterion to control the process of splitting clusters.

This approach is different from the previous ones we tried, since it doesn't need to know beforehand the number of clusters, but it starts with a pre-determined amount and then splits them into smaller ones. The results change from one try to another, but we've seen that this approach usually worked better for our dataframe.



(a) Clusters generated by X-Means

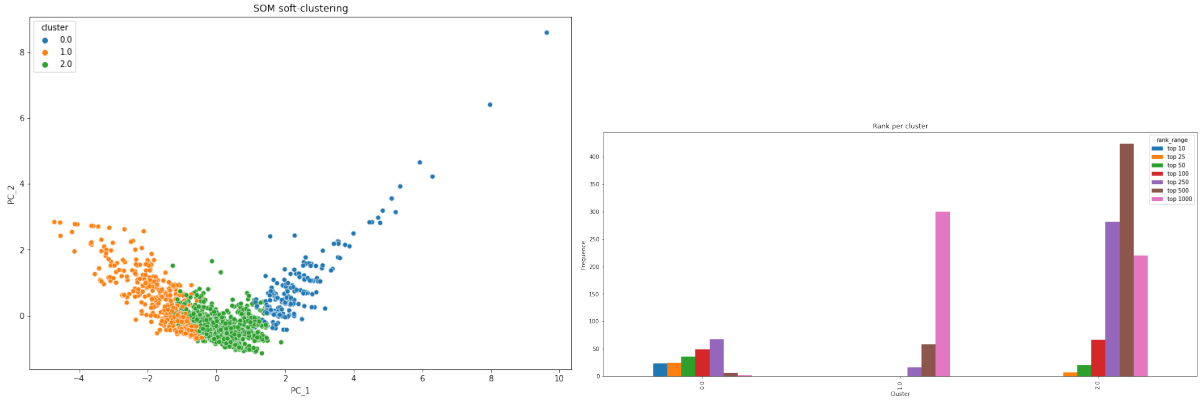
(b) Distribution of players' ranks per cluster

Figure 15: X-Means: pca and analysis.

By looking at Figure 15 we can see that X-Means separated better the players by their skills than our previous attempts, so we think that it did the best job among everything we tried.

2.6.2 SOM Soft-Clustering

From the pyclustering package documentation: this algorithm uses an amount of clusters that should be allocated as the size of a SOM map. The captured objects by the neurons are clusters. We expected the pyclustering library to provide us a way to plot the SOM lattice but this wasn't the case, so we went, as always, with the pca just like the other approaches. For the choice of k we did the same work as K-Means and we found that the best choice was for $k = 3$ but we couldn't calculate in any way the SSE since the implementation by the library doesn't come with a way to obtain the cluster centroids, so we only considered the Silhoutte and Davies-Bouldin scores.



(a) Clusters generated by SOMsc

(b) Distribution of players' ranks per cluster

Figure 16: SOM soft-clusering: plot along PCAs and analysis.

The results obtained, which can be seen on Figure 16, are similar to the ones obtained by k-means, so we think we don't need to explain anything more about this approach.

3 Predictive Analysis

3.1 Data Preparation

Our goal is to classify the players in two categories: 'strong' players and the 'weak' players. To do this, we started from the dataframe of the players used in the clustering phase and we labeled them in the two aforementioned classes, exploiting the rank of each player. We decided that the players whose rank fall in a category that is top 5, top 10, top 25, top 50 or top 100 are labelled as strong, thus, all the others as 'weak'. For the male players, we also label as 'strong' the one whose rank is 'top 250'.

Furthermore, we removed some features that we considered irrelevant, such as the players' hand obtained previously through a sampling process and the win rates on different surfaces, but keeping the average number of wins for each surface. Furthermore, we also didn't care about the players' nationality because it's useless for the classification purpose (a player's nationality can't determine his actual strength).

Finally, we removed the rank range, ranking points and ranking, to ensure that the classifier doesn't learn our labeling strategy.

The classification was done by dividing the male players from the female ones, this means that there are some models trained using the 'male' data set that work only with the male players data and other ones that work with the female one. Initially, we conducted the classification analysis by using our entire dataset which is made by both male and female players, the latter are present in minority, about 32% of the entire data set. By doing in this way the classification metrics were good, but this happened due to the fact that our data set is imbalanced with respect to the players' sex. In fact, we tried to build two test sets based on the players' sex and we discovered that the classification models worked well on the 'male' set, while their performance dropped down on the 'female' set. For this reason, we present our analysis for this section by keeping male and female players separated.

3.2 Imbalanced data

Our labeling strategy carried out an imbalanced data set, which is likely to happen in competitive sports. The problem is that the classifiers trained on imbalanced data sets can perform bad as they tend to overfit towards the majority class. In our case, the male dataset has a distribution of the 'strong' and 'weak' players which is circa 74% and 26% respectively, totalling 1102 players. The female data set is also imbalanced to the 'weak' class, having a 76/24 percentage distribution, totalling 498 players. To overcome this problems we exploited the SMOTE approach for over-sampling the minority class combined with an under-sampling on the majority class. In this way, the distribution of the players is 55% for the 'weak' class and 45% for the 'strong' one.

3.3 Classification methods

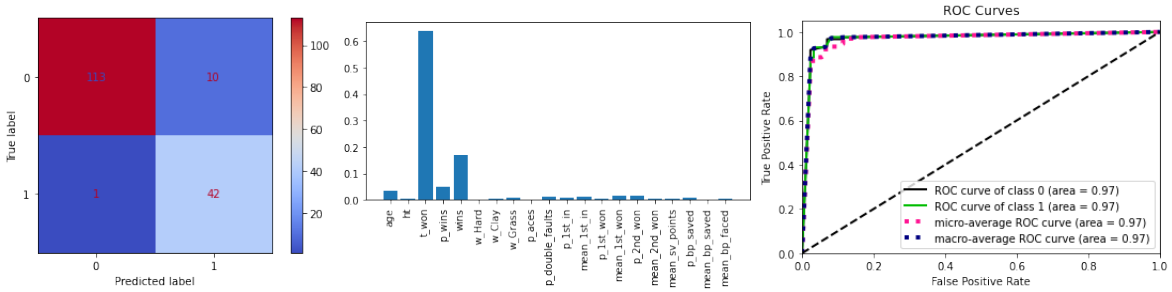
Before applying any of the following classification algorithms, we splitted the dataset into development and test sets, the latter consisting of 15% of the original data set. Furthermore we used the StandardScaler algorithm from the scikit-learn library to standardize our data.

The following results have been obtained by exploiting the best parameters carried out by the K-Fold cross validation, with K equal to 4, comparing the results by measuring the accuracy score between the K folds. For the lack of space, we will only show the graphical results for the male players, whereas in subsection 3.4 we study the performance obtained by our models in both the male and female data set.

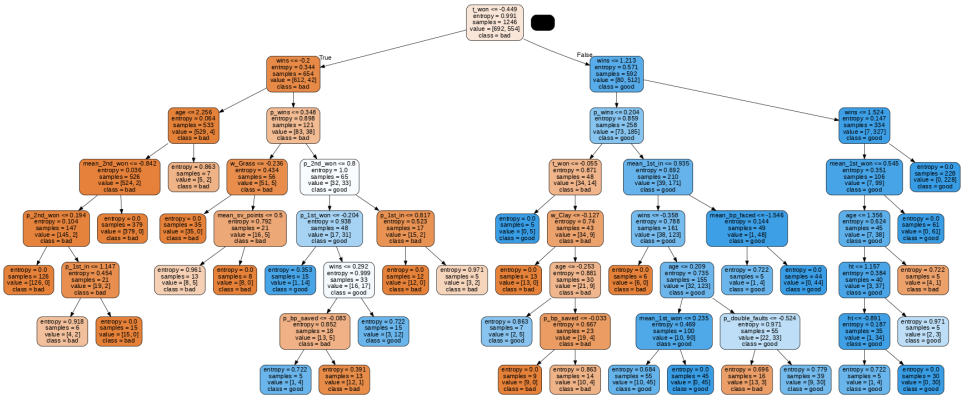
Evaluation In order to evaluate the goodness of our models, we'll show classification metrics like accuracy, precision, recall and F1 score. The miss-classified patterns can be numerically viewed by using the confusion matrix (label 0 for 'weak', 1 for 'strong') and graphically by plotting the ROC curve. Finally, we'll show the "global" weight that each feature had in the classification of the tennis players for those models that offer this capability. Talking about the test set, it is made up of imbalanced data, having the same distribution as the original dataset, thus it's without any sampling strategy applied. This means that any of the following algorithms should beat the dummy classifier.

3.3.1 Decision tree

Decision tree is a classification method which produces interpretable results. It's not one of the best algorithms we tested, but, anyway, its performances are pretty good.



(a) Confusion matrix (b) Features importance (c) ROC curve

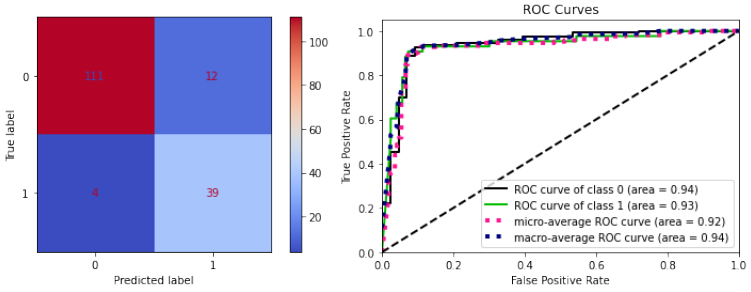


(d) Decion tree splitting

Figure 17: Results for the Decision Tree classifier

3.3.2 Naive Bayes

The Naive Bayes classifier is a "probabilistic classifier" based on applying Bayes' theorem with strong (naïve) independence assumptions between the features.

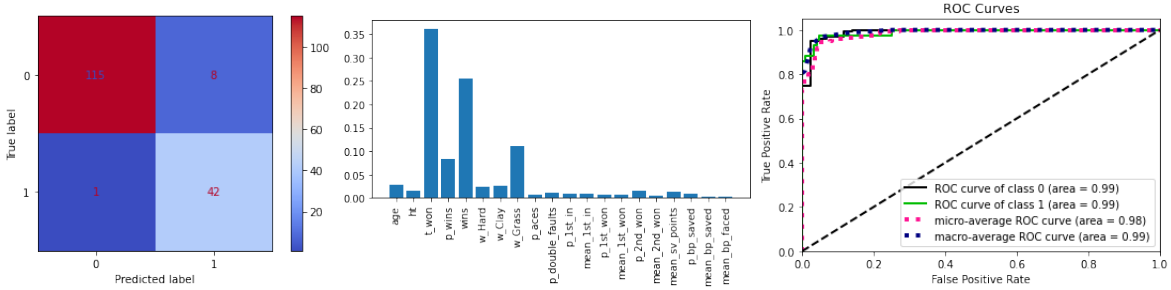


(a) Confusion matrix (b) ROC curve

Figure 18: Results for the Naive Bayes classifier

3.3.3 Random forest

It's an ensemble method specifically designed for decision trees, it combines the predictions made by multiple decision trees and outputs the class that is the mode of the class' output by individual trees.

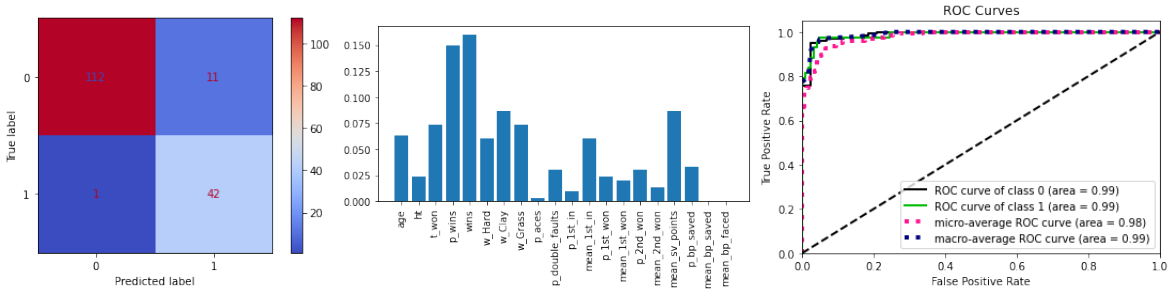


(a) Confusion matrix (b) Features importance (c) ROC curve

Figure 19: Results for the Random Forest classifier

3.3.4 Adaptive boosting (AdaBoost)

It can be used as ensembler of based classifiers to improve performance. The output of the base learning algorithms ('weak learners') is combined into a weighted sum that represents the final output of the boosted classifier. AdaBoost is adaptive in the sense that subsequent weak learners are tweaked in favor of those instances misclassified by previous classifiers.

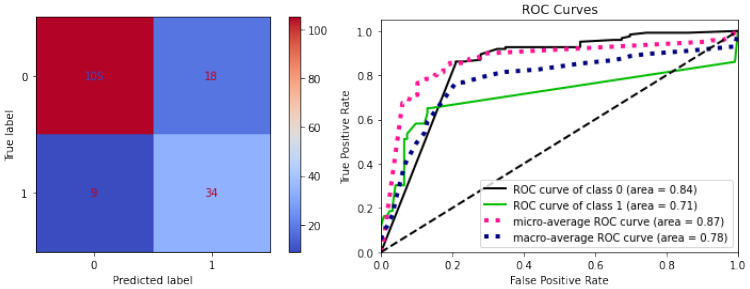


(a) Confusion matrix (b) Features importance (c) ROC curve

Figure 20: Results for the AdaBoost classifier

3.3.5 Rule based

The rule-based classifier is a classification scheme that makes use of IF-THEN rules for class prediction.

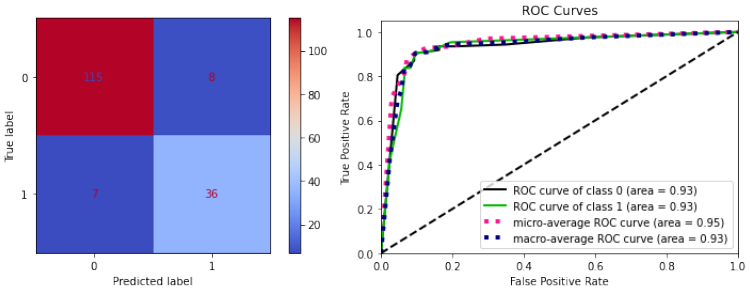


(a) Confusion matrix (b) ROC curve

Figure 21: Results for the Rule Based classifier

3.3.6 K-nearest neighbors (KNN)

The KNN is an instance based classifier, it uses class labels of nearest neighbors to determine the class label of unknown records.

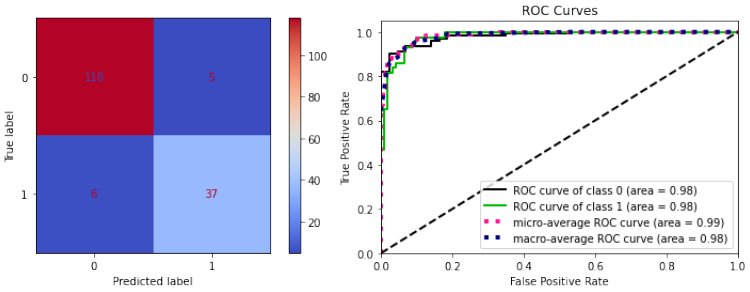


(a) Confusion matrix (b) ROC curve

Figure 22: Results for the KNN classifier

3.3.7 Support-vector machine (SVM)

SVM is a robust classifier based on statistical learning frameworks, it maps training examples to points in space to maximise the width of the gap between the two categories. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

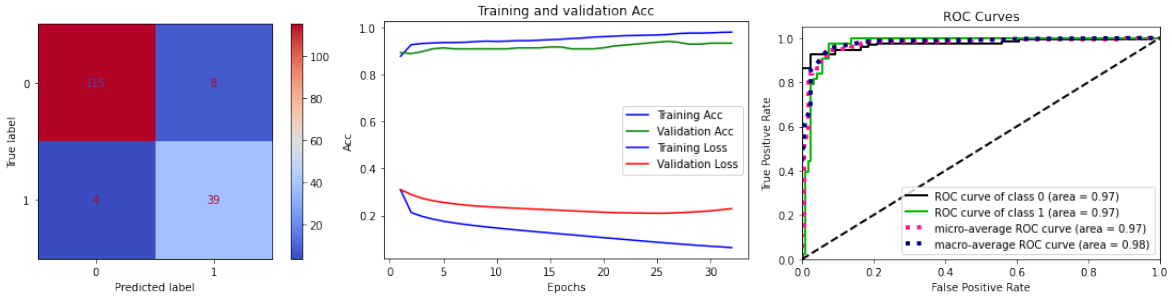


(a) Confusion matrix (b) ROC curve

Figure 23: Results for the SVM classifier

3.3.8 Neural network

We developed a FF neural network made up of two hidden layers whose neurons are 'activated' by the elu function and a softmax on the output layer. To ensure the generalization capability, we use the dropout technique and the layer normalization, to stabilize the training phase. In the end, we used the categorical cross entropy as loss function and early stopping to avoid overfitting.

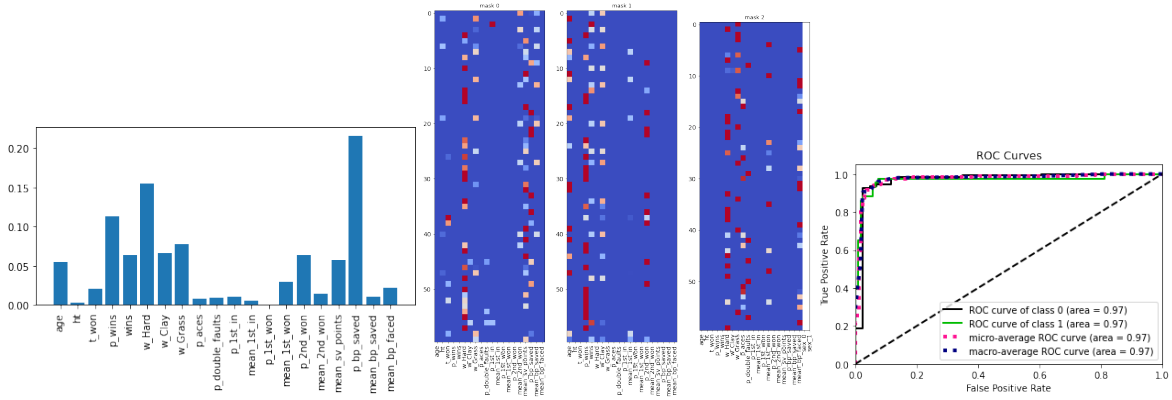


(a) Confusion matrix (b) Learning curve (c) ROC curve

Figure 24: Results for the Neural Network classifier

3.3.9 TabNet

TabNet [1] is a novel high-performance and interpretable canonical deep tabular data learning architecture. TabNet uses sequential attention to choose which features to reason from at each decision step, enabling interpretability and more efficient learning as the learning capacity is used for the most salient features.



(a) Global feature importance (b) Local feature importance (c) ROC curve

Figure 25: Results for the Tab Net classifier

3.4 Comparison

In this section we show how the aforementioned algorithms performed in both the female and male datasets. In Table 1 and Table 2 we reported the performances in percentages. For each numerical entry, the first number is referred to the 'weak' class and the second one to the 'strong' class. In general, there wasn't a model that performed well in both the two data set as AdaBoost obtained the best performance on the female data set, whereas Random Forest in the male one. Based on the average *accuracy* metric on the *k folds validation set*, we can assert that AdaBoost was the best model overall, which is a good result because it also provides the

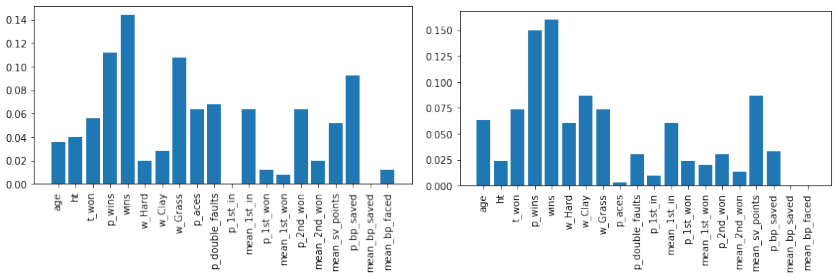
importance of each feature. For this reason, we also compared the feature importance that this model associates to the male players with respect to the female players, as shown in Figure 26.

Female players classification								
Model	**Training**				**Test**			
	Prec.	Rec.	F1	Acc.	Prec.	Rec.	F1	Acc.
Decision Tree	95/89	91/94	93/91	92	96/62	82/89	89/73	84
Naive Bayes	91/84	86/90	89/87	88	96/62	82/89	89/73	84
Random Forest	100/97	98/100	99/98	99	95/75	91/83	93/79	89
AdaBoost	100/100	100/100	100/100	100	95/83	95/83	95/83	92
Rule Based	90/93	95/87	92/90	91	91/48	74/78	82/60	75
KNN	95/86	88/95	91/90	91	94/68	88/83	91/75	87
SVM	100/95	96/100	98/97	97	95/75	91/83	93/79	89
Neural Network	92/87	89/91	91/89	90	98/71	88/94	93/81	89
TabNet	97/85	86/97	91/91	91	93/70	89/78	91/74	87

Table 1: A comparison between the performance of the algorithms employed to classify the female players.

Male players classification								
Model	**Training**				**Test**			
	Prec.	Rec.	F1	Acc.	Prec.	Rec.	F1	Acc.
Decision Tree	97/95	96/96	96/96	96	99/81	92/98	95/88	93
Naive Bayes	94/88	89/92	92/90	91	97/76	90/91	93/83	90
Random Forest	100/97	98/100	99/99	99	99/84	93/98	96/90	95
AdaBoost	95/91	93/94	94/93	93	99/79	91/98	95/88	93
Rule Based	95/93	95/94	95/94	94	92/65	85/79	89/72	84
KNN	96/94	95/95	96/95	95	92/82	93/84	94/83	91
SVM	100/97	98/99	99/98	98	95/88	96/86	96/87	93
Neural Network	93/92	94/91	93/92	93	98/85	94/95	96/90	95
TabNet	94/88	90/93	92/90	91	97/85	94/93	96/89	94

Table 2: A comparison between the performance of the algorithms employed to classify the male players.



(a) Features importance for female (b) Features importance for male

Figure 26: Features importance to classify a player based on its sex.

4 Time Series Analysis

We decided to do task 4.1 as last part of the project which expected us to find groups of similar cities given their temperature trends. Figure 27 shows the initial dataset and the modified one, the latter, built with the pivot method from pandas, was the one we worked on during our analysis. The resulting dataframe now has the cities as indexes and the temperature records as values, so it made our task easier.

	AverageTemperature	AverageTemperatureUncertainty	City	Country	Latitude	Longitude	time
1813	27.685	0.267	Abidjan	Côte D'Ivoire	5.63N	3.23W	2000-02-01
1814	29.061	0.224	Abidjan	Côte D'Ivoire	5.63N	3.23W	2000-03-01
1815	28.162	0.478	Abidjan	Côte D'Ivoire	5.63N	3.23W	2000-04-01
1816	27.547	0.509	Abidjan	Côte D'Ivoire	5.63N	3.23W	2000-05-01
1817	25.812	0.231	Abidjan	Côte D'Ivoire	5.63N	3.23W	2000-06-01
...	...	...	...	...	...	...	...
239128	18.459	0.374	Xian	China	34.56N	108.97E	2009-09-01
239129	14.195	0.163	Xian	China	34.56N	108.97E	2009-10-01
239130	2.916	0.675	Xian	China	34.56N	108.97E	2009-11-01
239131	-0.712	0.259	Xian	China	34.56N	108.97E	2009-12-01
239132	-0.237	0.554	Xian	China	34.56N	108.97E	2010-01-01

(a) Initial dataset

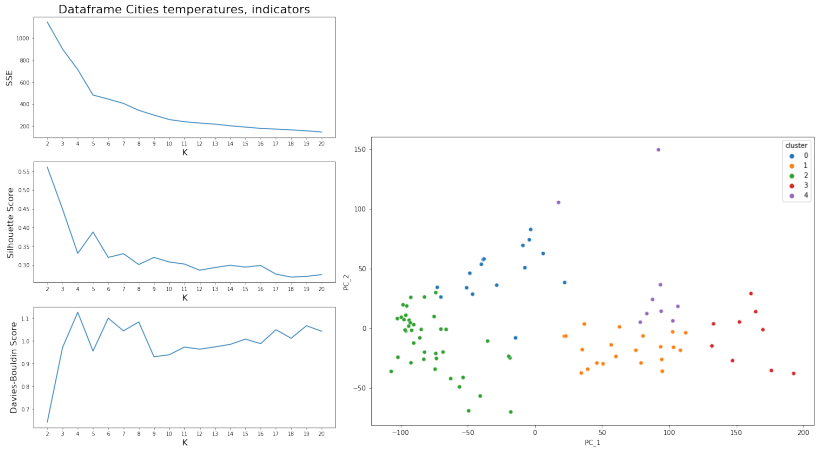
time	2000-02-01	2000-03-01	2000-04-01	2000-05-01	2000-06-01	2000-07-01	2000-08-01	2000-09-01	2000-10-01	2000-11-01	2000-12-01	2001-01-01	2001-02-01	2001-03-01	2001-04-01	2001-05-01	2001-06-01	2001-07-01	2001-08-01	2001-09-01	2001-10-01
City																					
Abidjan	27.685	29.061	28.162	27.547	25.812	24.870	24.884	25.405	26.074	27.315	26.929	26.920	28.234	28.706	27.702	27.653	25.940	24.841	24.280	24.797	26.278
Addis Abeba	19.183	20.230	20.398	19.977	18.254	17.109	16.944	17.542	17.113	17.741	17.013	17.454	18.864	20.043	20.233	19.908	17.978	17.011	17.152	17.867	18.047
Ahmadabad	21.246	26.565	32.275	32.847	32.490	28.678	28.616	29.087	29.285	25.577	21.785	19.770	22.438	27.198	31.034	33.358	30.717	27.730	27.893	29.490	29.073
Aleppo	6.832	10.421	17.743	22.240	27.781	31.957	29.873	25.877	18.846	13.380	7.636	7.306	8.787	14.904	17.666	21.191	27.922	30.727	30.330	26.419	20.153
Alexandria	14.300	15.266	19.556	21.828	24.619	27.091	26.930	25.939	22.842	20.524	16.460	15.312	15.403	18.834	19.709	22.533	24.652	27.094	28.246	26.963	23.599
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
Tokyo	1.765	5.709	11.155	17.261	20.396	25.214	25.843	22.005	15.197	9.572	4.245	0.573	2.519	6.038	12.373	17.246	20.659	26.326	24.092	20.184	14.846
Toronto	-4.177	2.675	4.968	13.068	17.095	18.296	18.522	14.296	9.723	1.849	-8.854	-5.783	-5.604	-2.592	6.434	13.708	17.972	19.042	20.842	14.547	8.854
Umm Durman	24.991	27.506	32.774	34.786	34.795	32.279	31.233	31.790	30.641	27.746	23.539	22.502	24.995	29.504	33.552	34.729	33.332	31.398	30.242	32.027	31.831
Wuhan	5.842	13.016	17.898	23.914	26.511	30.222	28.404	24.146	17.993	10.449	7.588	5.061	7.204	12.875	16.768	23.488	26.109	30.729	27.718	25.359	19.310
Xian	0.943	8.997	13.714	20.568	22.387	25.578	22.517	17.823	11.116	4.095	1.265	-1.249	2.649	8.873	12.072	19.679	23.561	26.094	23.148	17.400	12.659

(b) The organized dataset

Figure 27: Time series dataset before and after using the pivot method from pandas.

4.1 Shape-based clustering

We used the k-means clustering from the tslearn package to find those similar groups of cities and in order to choose the best values of k (the number of clusters) we based our choice, as seen during the clustering task, on the SSE, silhouette and Davies-Bouldin scores. Afterwards, we took the best k value and we used it to do the final clustering on the cities dataframe.



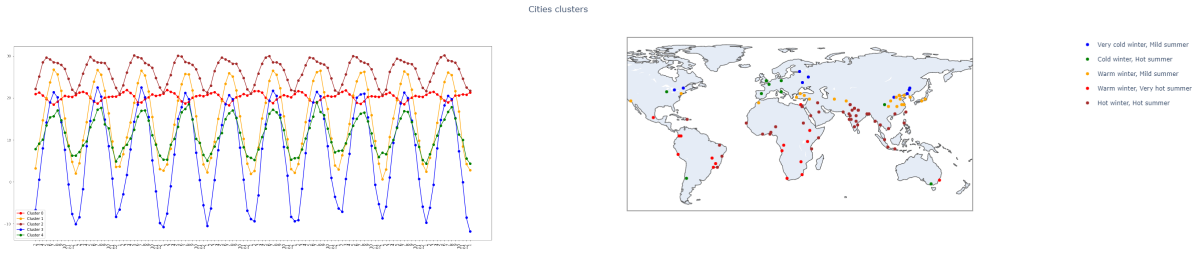
(a) Scores

(b) The plot with k=5

Figure 28: Scores for each value of k and clustering with the best k value.

As Figure 28 on the left shows, by using the elbow rule and by looking at the other two values we took 5 as the best value for k and the final clustering analysis is shown on Figure 28 on the right end.

The cities are, therefore, separated in five different cluster in accordance to their temperature trends: *warm winter and very hot summer*, *cold winter and hot summer*, *very hot winter and very hot summer*, *warm winter and mild summer* and lastly *very cold winter and mild summer*. We then plotted those temperature trends on a graph in order to compare them between each other, the cities were, instead, plotted on a map according to the cluster they belong to.



(a) Cluster trends

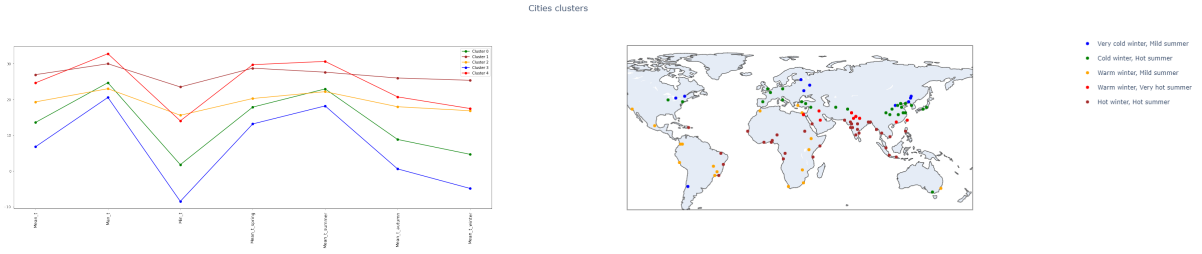
(b) Cluster map

Figure 29: Temperature trends for each cluster and the map with the cities plotted with respect to the cluster they belong to.

The map in Figure 29 shows that cities in similar clusters are somewhat at the same latitude (which is something that we expected).

4.2 Feature-based clustering

As final clustering analysis on the time series, we decided to try the feature-based approach by defining new features from the ones we had and by doing the same work that we did for the shape-based clustering. The features we built were based on the mean temperatures for each season (keep in mind that seasons are different in the two hemispheres) and then we inserted the mean, max and min temperatures recorded for each city.



(a) Cluster trends

(b) Cluster map

Figure 30: Statistics for each cluster (our newly defined features) and the map with the cities plotted with respect to the cluster they belong to.

The results are pretty similar with respect to the shape-based approach since not many cities were classified in very different clusters.

References

[1] Sercan O. Arik and Tomas Pfister. Tabnet: Attentive interpretable tabular learning, 2020.

[2] Andrei Novikov. PyClustering: Data mining library. *Journal of Open Source Software*, 4(36):1230, apr 2019.