



Plan

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I. Dataset SkillCraft Description

- The dataset used in this project is the SkillCraft1 master table dataset from UCI machine learning repository. It aggregates screen movements into screen-fixations using a Salvucci & Goldberg (2000) dispersion-threshold algorithm, and defined Perception Action Cycles (PACs) as fixations with at least one action.
- In simple words, they actually tried to find the league of players based on their screen movement when playing the game.

Date

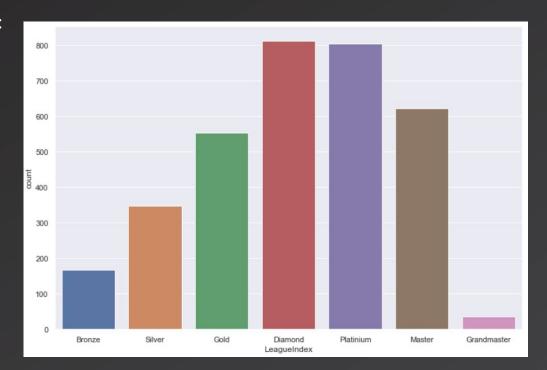
I. Data Analyzing

After analyzing our Dataset , we came up with these caracteristics :

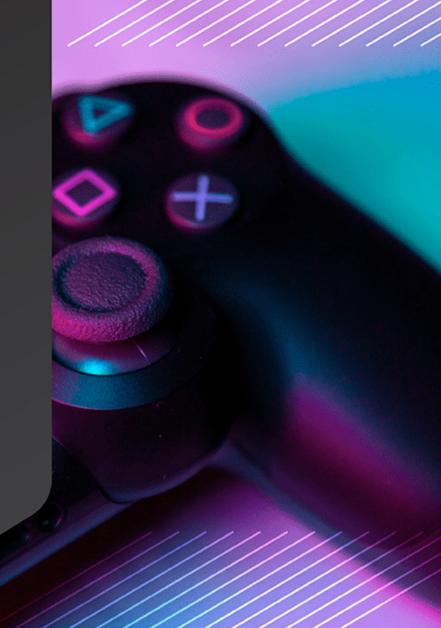
Dimensions: 3395 rows × 20 columns

Target : LeagueIndex

Partitions of Data :



We have 7 classes in the league there is not the professionel leagues as mentioned in the dataset description and as we can see the Data varries a lot in this Dataset, and this is a little bit concerning in fitting models later as we can have an underfitted models.



- As you can see there is a huge correlation between different features, so we had to clean our dataset, I can't spoil you but it did make a difference in improving the scores.
- Cor(gameid,leagueindex)=0.025
- Cor(age,leagueindex)=-0.13
- Cor(actioninPAC,leagueindex)=0.14
- Cor(complexabilitiesused, leagueindex)=0.16
- Cor(uniqueunitmade, leagueindex)=0.15
- Cor(complexunitmade, leagueindex)=0.17
- Cor(Totalhours, leagueindex) = 0.024

GameID	1	0.025	0.089	-0.025	0.0042	0.076	0.07	0.064	0.081	0.022	0.0099	0.036	-0.066	-0.043	0.039	0.031	-0.015	0.029	-0.018	0.0041
LeagueIndex	0.025	1	-0.13	0.22	0.024		0.43	0.49	0.32	0.27	0.21	0.59	-0.54	-0.66	0.14	0.23	0.31	0.15	0.17	0.16
Age	0.089	-0.13	1	-0.18	-0.017	-0.21	-0.13	-0.1	0.015	0.043	-0.02	-0.2	0.11	0.24	-0.046	-0.024	-0.092	0.023	-0.08	-0.066
HoursPerWeek	-0.025	0.22	-0.18	1	0.024	0.25	0.21	0.16	0.07	0.084	0.049	0.17	-0.13	-0.19	0.095	0.065	0.051	0.039	0.059	0.075
TotalHours	0.0042	0.024	-0.017	0.024	1	0.073	0.082	0.042	0.0093	0.00087	0.0077	0.04	-0.021	-0.036	0.011	0.02	0.015 -	0.0024	-0.0072	40.0063
APM	0.076		-0.21	0.25	0.073		0.81	0.53	0.34	0.22	0.31		-0.57	-0.72	0.4	0.24	0.38	0.12	0.16	0.14
SelectByHotkeys	0.07	0.43	-0.13	0.21	0.082	0.81	1	0.45	0.27	0.13	0.11	0.36	-0.27	-0.39	0.17	0.097	0.16	0.028	0.065	0.064
AssignToHotkeys	0.064	0.49	-0.1	0.16	0.042	0.53	0.45	1	0.4	0.21	0.15	0.45	-0.38		0.092	0.2	0.2	0.15	0.17	0.17
UniqueHotkeys	0.081	0.32	0.015	0.07	0.0093	0.34	0.27	0.4	1	0.15	0.12	0.35	-0.22	-0.3	-0.022	0.27	0.11	0.23	0.12	0.11
MinimapAttacks	0.022	0.27	0.043	0.084	0.00087	0.22	0.13	0.21	0.15	1	0.22	0.14	-0.21	-0.17	0.13	0.16	0.082	0.13	0.052	0.042
MinimapRightClicks	0.0099	0.21	-0.02	0.049	0.0077	0.31	0.11	0.15	0.12	0.22	1	0.14	-0.24	-0.22	0.32	0.17	0.21	0.15	0.098	0.096
NumberOfPACs	0.036	0.59	-0.2	0.17	0.04		0.36	0.45	0.35	0.14	0.14		-0.49	-0.82	-0.24	0.47	0.28	0.32	0.2	0.18
GapBetweenPACs	-0.066		0.11	-0.13	-0.021	-0.57	-0.27	-0.38	-0.22	-0.21	-0.24		1	0.68	-0.31	-0.095	-0.24	-0.09	-0.083	-0.092
ActionLatency	-0.043	-0.66	0.24	-0.19	-0.036	-0.72	-0.39	-0.46	-0.3	-0.17	-0.22	-0.82	0.68	1	-0.11	-0.35	-0.31	-0.22	-0.2	-0.19
ActionsInPAC	0.039	0.14	-0.046	0.095	0.011	0.4	0.17	0.092	-0.022	0.13	0.32	-0.24	-0.31	-0.11	1	-0.16	0.25	-0.13	0.054	0.053
TotalMapExplored	0.031	0.23	-0.024	0.065	0.02	0.24	0.097	0.2	0.27	0.16	0.17	0.47	-0.095	-0.35	-0.16	1	0.13	0.58	0.31	0.25
WorkersMade	-0.015	0.31	-0.092	0.051	0.015	0.38	0.16	0.2	0.11	0.082	0.21	0.28	-0.24	-0.31	0.25	0.13	1	0.11	0.2	0.1
UniqueUnitsMade	0.029	0.15	0.023	0.039	-0.0024	0.12	0.028	0.15	0.23	0.13	0.15	0.32	-0.09	-0.22	-0.13	0.58	0.11	1	0.38	0.29
ComplexUnitsMade	-0.018	0.17	-0.08	0.059	-0.0072	0.16	0.065	0.17	0.12	0.052	0.098	0.2	-0.083	-0.2	0.054	0.31	0.2	0.38	1	0.62
ComplexAbilitiesUsed	0.0041	0.16	-0.066	0.075	-0.0063	0.14	0.064	0.17	0.11	0.042	0.096	0.18	-0.092	-0.19	0.053	0.25	0.1	0.29	0.62	1
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Date

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- 0.75

- 0.50

- 0.25

- 0.00

- -0.25

- -0 50

- -0.7

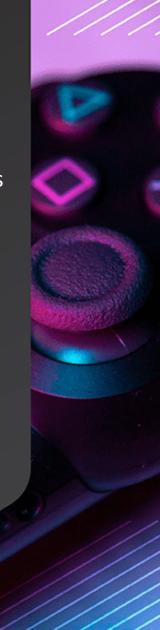
I. Data Cleaning

- First of all, we noticed that there is some rows with '?' Inside witch we think its some corrupted data, so we had to remove them.
- Then we searched for missing values, we hadn't found anything.
- There is 3 features that have an object type that will make it difficult

for the work so we had to change

them to 'integer'

Out[6]:	GameID	int64
	LeagueIndex	int64
	Age	object
	HoursPerWeek	object
	TotalHours	object
	APM	float64
	SelectByHotkeys	float64
	AssignToHotkeys	float64
	UniqueHotkeys	int64
	MinimapAttacks	float64
	MinimapRightClicks	float64
	NumberOfPACs	float64
	GapBetweenPACs	float64
	ActionLatency	float64
	ActionsInPAC	float64
	TotalMapExplored	int64
	WorkersMade	float64
	UniqueUnitsMade	int64
	ComplexUnitsMade	float64
	ComplexAbilitiesUsed	float64



Its time to remove the unwanted features: "GameID","LeagueIndex","Age","TotalHours","ActionsInPAC", Our dataset is clean and ready for some work .

I. Fitting models

1. Logistic regression :

We began our journey with logestic regression since it's the easiest one to come to mind and our target is categorical.

After implementing and fiting the model we had a score of 0.38 we thought that this score is too low so we tried cross-validation since it can give better results and we chose our fold number to be equal to 5 (its actually the default one it gives normally the best results):

model_0 = LogisticRegressionCV(cv=5).fit(x_train, y_train)

and at last we got a score of 0.417

This score is actually very casual in such a dataset because of the variation of the distribution of the data that we saw before .



1. Naive Bayes:

We re going to use now the naive bayes model, there's actually different techniques but we chose the gaussian method since it's the most fit for our data, and we got 0.34,

We didn't actually stop their we did the cross-validation since we could get better results and it was the case , we got 0.37 .

We couldn't plot anything with these two methods since we don't have variables to play with , so we tried the random forest method .



1. Random forest:

Its random forest turn , so we tried to implement the algorithm with random paremeters :

clf2 = RandomForestClassifier(n_estimators = 240, random_state = 123)

We got **0.41** its quiet good, but we wanted to go even further, we tried the grid search, it's a function that finds the best parameters for a model, but unfortunately we got only **0.39** because we didn't play with the random because it takes too much time for a single one and days if we do it 100 time.

This the graph of repeated testing on Random forest with different parameters :

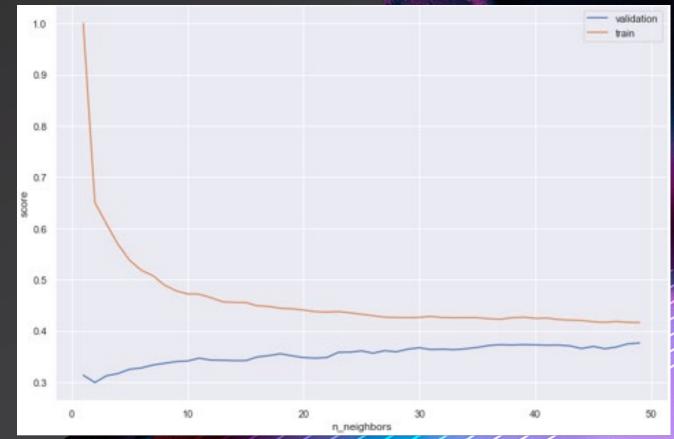
The graph is like that because of the lack of data in the dataset!.



1. KNN:

Finally we went with our last hope KNN (k-nearest neighbors) to get the best scores, but sadly we got only 0.38 when k equal to 28, and we got the same result with the grid search .

This is the graph of the algorith when k varies from 1 to 50, as you can see the score is rising very slowly towards the 0.4 and this is due to the repartition of data in the Dataset.



I. Models comparisons

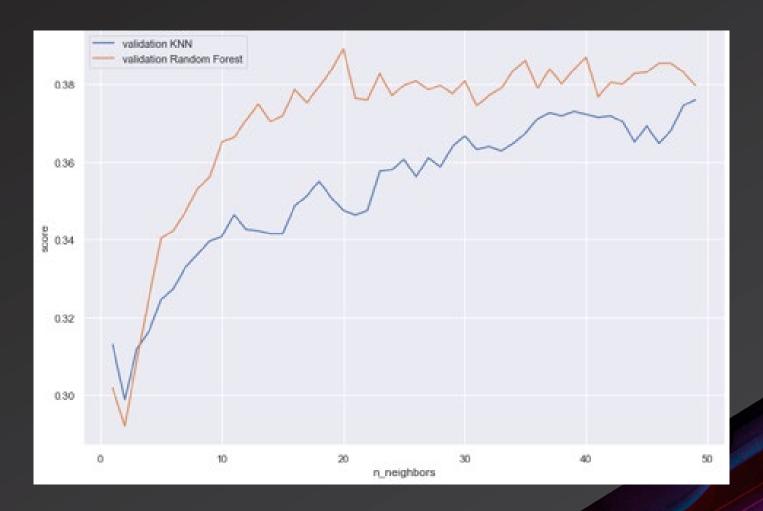
We now will compare all the models that we've done in this table :

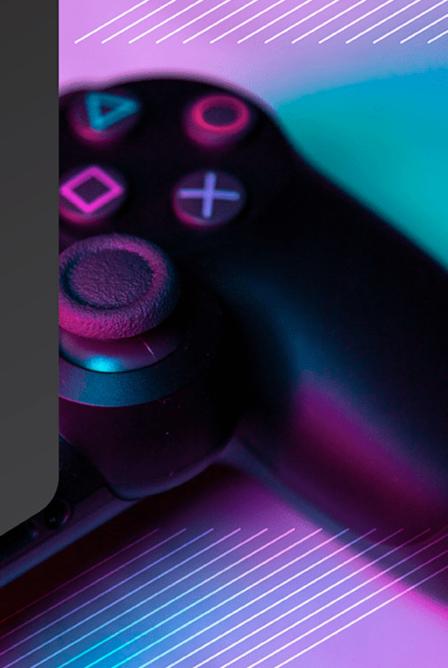
Logest	ic regression	Naive	bayes	Randon	n Forest	KNN			
normal	Cross- validation	Gaussian	Cross- validation	Random parameters	Grid search	normal	Grid search		
0.38	0.417	0.34	0.37	0.410	0.39	0.38	0.38		

The best score is with the logestic regression with the cross-validation, but we can see that it has similar score with the random forest, but we took the simpler and no time costing one which is the logestic regression.



This is a comparison graph between Random Forest and KNN which we can observe that random forest is better than KNN





I. Casting results on Flusk

welcome to the Skillcraft predictor enter the hours per week: enter the action per minute: enter the Number of unit or building selections made using hotkeys per timestamp: enter the Number of units or buildings assigned to hotkeys per timestamp: enter the Number of unique hotkeys used per timestamp : enter the Number of attack actions on minimap per timestamp: enter the number of right-clicks on minimap per timestamp: enter the Number of PACs per timestamp: enter the Mean duration in milliseconds between PACs: enter the Mean latency from the onset of a PACs to their first action in milliseconds enter the number of 24x24 game coordinate grids viewed by the player per timestamp: enter the Number of SCVs, drones, and probes trained per timestamp:

predict

We have created a flask application that it contains a form which has the features that the person need to fill in order to have his league level as showed in the two pictures.





I. conclusions

After analysing the dataset and implementiing different algorithms, and with the scores that we got, we can say that the dataset is lacking for some data, all models are underfitted, if you remember there is some classes with almost no data in them, we suggest that we remove that class "7" and make a fusion with the class "6" and the class "1" with the class "2", so we get better predictions and results, or they can update the dataset with more information that will give it the push that it needs.

