Artificial Neural Networks (ANN) and K Nearest Neighbors (KNN)

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Introduction

As part of this binary classification project Artificial Neural Networks (ANN) and K Nearest Neighbors were implemented in Python and Google colab using the SGEMM GPU kernel performance data set from UCI Machine Learning repository -> Dataset and on the Rain in Australia dataset from Kaggle -> Dataset2 . The project involved data pre-processing, data visualization, algorithm application, prediction and experimenting with different parameters like Number of hidden layers, Neurons, Activation Functions, Optimizer, Batch size, epoch, K, etc.

Dataset Description

Dataset1 - SGEMM GPU:

- The First dataset contains 241600 observations and 18 variables with no missing values.
- There are 18 variables, the first 14 are parameters upon which we will train our model. The first 10 parameters are ordinal with 4 levels, the next 4 are binary and last 4 variables are 4 different run times for the SGEMM GPU
- The description for the independent variables is given in the dataset link.
- The dataset was divided into train and test with a 70:30 split.
- For dependent variable 'avg' was created using average of the 4 run times provided which tells
 us the average running time for matrix-matrix product of the four runs. For classification the
 dependent variable 'avg' was converted into a binary variable using median as the threshold.
 (High/Low)

Dataset2:

- This Dataset contains 142193 observations with 24 variables
- Here the Target variable is Rain Tomorrow, we need to predict if it will rain tomorrow or not.
- It is given that Risk_MM variable is a very good predictor of the outcome and is dropped.
- Variables with more than 35% missing values were dropped and Last observation carried forward LOCF was used to impute the remaining missing values

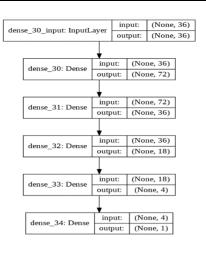
Artificial Neural Networks

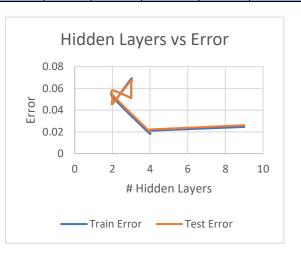
Dataset-1:

Tanh =	Sigmoid =	Relu =	Adam =	SGD	SoftMax =
Т	S	R	Α	=SG	SX

Dataset1										
Model #	No of Hidden Layers	Neurons in each Hidden layer	Activation Function in Each Layer (Hidden & Output Layer)	Optimizer	Batch Size	Epoch	Loss	Train Error	Test Error	Training Time
1	2	4,4	R,R,S	Α	10	5	0.1221	0.05162	0.052	207
2	2	4,4	R,R,S	Α	20	5	0.1231	0.0508	0.0515	130
3	2	4,4	R,R,S	Α	100	5	0.116	0.0492	0.0498	30
4	2	4,4	R,R,S	Α	10	10	0.1094	0.0456	0.0456	517
5	4	4,4,4,4	R,R,R,R,S	Α	10	5	0.6934	0.4999	0.5005	318
6	4	4,4,4,4	R,R,R,R,S	Α	100	10	0.6931	0.4999	0.5005	70
7	3	4,4,4	R,R,R,S	Α	10	5	0.1838	0.0689	0.0674	278
8	3	4,4,4	R,R,R,S	Α	50	5	0.174	0.0651	0.0647	61
9	3	4,4,4	R,R,T,S	Α	10	5	0.1219	0.0514	0.0509	292
10	3	4,4,4	R,R,T,S	SG	10	5	0.1242	0.0513	0.0509	216
11	2	4,2	R,T,S	SG	10	5	0.1397	0.0581	0.0584	205
12	2	4,2	R,T,S	Α	10	5	0.1241	0.0522	0.0542	269
13	4	72,36,18,4	R,T,T,T,S	Α	10	5	0.0469	0.0181	0.0201	289
14	4	72,36,18,4	R,T,R,T,S	Α	10	5	0.0509	0.0208	0.0221	292
15	5	36,36,18,18,4,1	R,T,S,S,T,S	Α	10	5	0.0539	0.0218	0.023	303
16	9	36,32,28,24,20,16,12,8,4	R,T,T,T,T,S,S,T,S	Α	10	5	0.0602	0.0245	0.0261	401





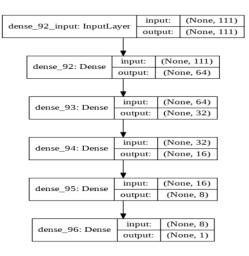


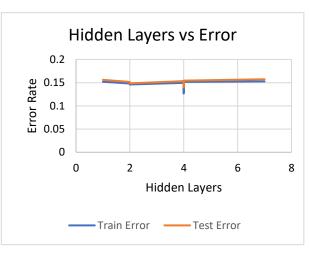
From this experiment we saw that Adam (RMSProp + Momentum) and SGD(Stochastic Gradient Descent) optimizer gave similar results. We got the best result when we used a 4 hidden layer neural network with Relu and Tanh activation functions with decreasing number of neurons. We also observed lowest loss for this result. Increasing the complexity of neural network by increasing number of hidden layers decrease the train and test error but it started increasing again with high number of hidden layers .

Dataset-2:

Dataset2										
Model #	No of Hidden Layers	Neurons in each Hidden layer	Activation Function in Each Layer (Hidden & Output Layer)	Optimizer	Batch Size	Epoch	Loss	Train Error	Test Error	Training Time
1	2	4,4	R,R,S	Α	10	5	0.3455	0.1482	0.1516	70
2	2	4,4	R,R,S	Α	20	5	0.3426	0.1473	0.1489	40
3	2	4,4	R,R,S	Α	100	5	0.3398	0.146	0.1484	20
4	4	4,4,4,4	R,R,R,R,S	Α	10	5	0.3526	0.1495	0.1532	78
5	4	64,32,16,8	R,R,R,R,S	Α	10	5	0.3092	0.1309	0.1429	83
6	4	64,32,16,8	R,T,T,R,S	Α	10	5	0.3064	0.1308	0.1418	82
7	4	64,32,16,8	R,S,S,R,S	Α	10	5	0.3102	0.1328	0.1409	82
8	4	64,32,16,8	R,S,S,R,S	SG	10	5	0.2983	0.127	0.1399	75
9	4	64,32,16,8	R,S,S,R,SX	SG	10	20	11.84	0.7771	0.7731	320
10	4	64,32,16,8	T,T,T,T,S	SG	10	20	0.3309	0.14	0.1455	300
11	4	64,64,64	T,T,T,T,S	SG	10	5	0.3581	0.1517	0.1544	78
12	1	64	T,S	SG	10	5	0.3571	0.1519	0.1562	70
13	11	100,90,80,70,60,50,40,30,20,10,5	T,T,T,T,T,S,S,T,T,T,T,S	SG	10	5	0.5307	0.223	0.223	95
14	7	200,100,100,100,75,50,25	т,т,т,т,т,т,х,	SG	10	5	0.3617	0.1527	0.1573	96







From this experiment we got the best result when we used a 4 Hidden layer neural network with decreasing number of neurons, Relu and Sigmoid Activation functions and SG optimizer. The Training and Testing Error remains very similar for different neural networks.

K Nearest Neighbors (KNN)

We have used PyCaret library in python to implement KNN. For initial models we have used Minkowski metric for Dataset1 and Dataset2. Minkowski distance is a generalization of both the Euclidean distance and the Manhattan distance and hence can be a good fit for our model. Using Pycaret we have created tuned and calibrated models for KNN. We have used a 2 fold cross validation for all the models.

Dataset-1:

Train and Test Errors Respectively

1)KNN

			Accuracy	AUC	Recall	Prec.	F1	Kappa
		0	0.9499	0.9863	0.9381	0.9608	0.9493	0.8998
		1	0.9494	0.9862	0.9367	0.9612	0.9488	0.8989
		Mean	0.9497	0.9862	0.9374	0.9610	0.9490	0.8994
		SD	0.0002	0.0001	0.0007	0.0002	0.0003	0.0005
		Model	Accuracy	ALIC	Recall	Drec	F1	Карра
_		Wouei	Accuracy	700	Recail	FIEC.	- ' '	Карра
0	K Neighbors	Classifier	0.9655	0.9932	0.9517	0.9787	0.965	0.931

2)Tuned KNN

		A	ccuracy	AUC	Recall	Prec.	F1	Карра
		0	0.9594	0.9935	0.9401	0.9779	0.9586	0.9188
		1	0.9576	0.9931	0.9388	0.9754	0.9568	0.9152
	1	Mean	0.9585	0.9933	0.9394	0.9766	0.9577	0.9170
		SD	0.0009	0.0002	0.0006	0.0012	0.0009	0.0018
		Model	Accura	cy AU	C Recal	I Prec.	F1	Kappa
0	K Neighbors	Classifier	0.96	69 0.996	5 0.949	0.9879	0.9683	0.9379

4) Calibrated Isotonic KNN

		Accuracy	AUC	Recall	Prec.	F1	Kappa
	0	0.9511	0.9905	0.9254	0.9756	0.9498	0.9023
	1	0.9500	0.9904	0.9239	0.9747	0.9486	0.8999
	Mean	0.9505	0.9904	0.9247	0.9751	0.9492	0.9011
	SD	0.0006	0.0001	0.0008	0.0004	0.0006	0.0012
	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa
0	Calibrated Classifier C V	0.9651	0.9943	0.9633	0.9668	0.965	0.9302



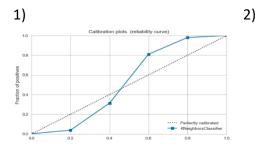
cv=2, method='isotonic')

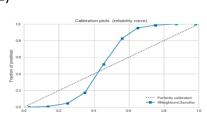
3) Calibrated KNN (Platt sigmoid)

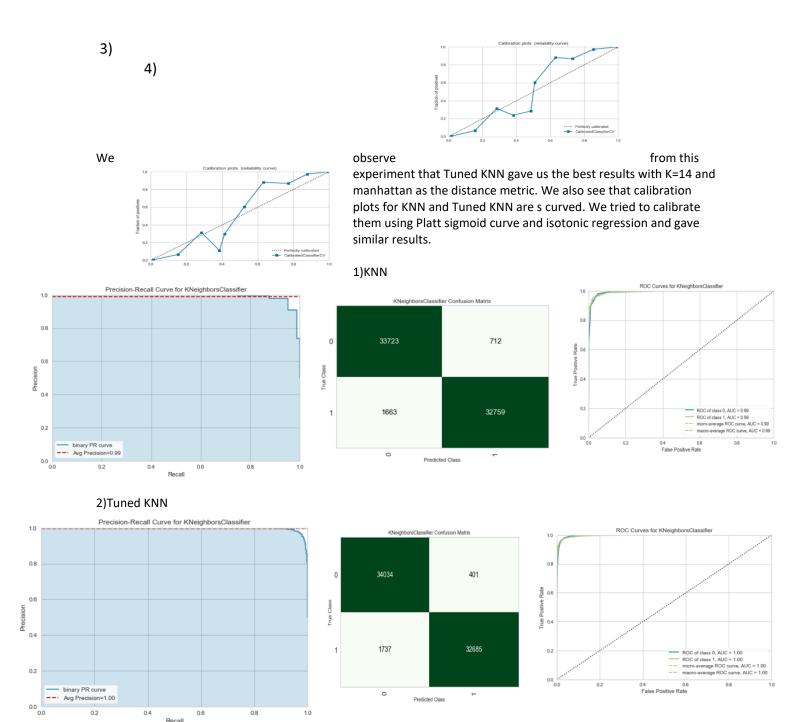
		Accuracy	AUC	Recall	Prec.	F1	Kappa
	0	0.9551	0.9905	0.9552	0.9550	0.9551	0.9102
	1	0.9529	0.9903	0.9539	0.9519	0.9529	0.9057
Me	ean	0.9540	0.9904	0.9546	0.9535	0.9540	0.9080
	SD	0.0011	0.0001	0.0006	0.0015	0.0011	0.0022

	NOGE	Accuracy	AUC	Recall	FIEC.	- 11	Kappa	
0	Calibrated Classifier C V	0.9651	0.9943	0.9633	0.9668	0.965	0.9302	

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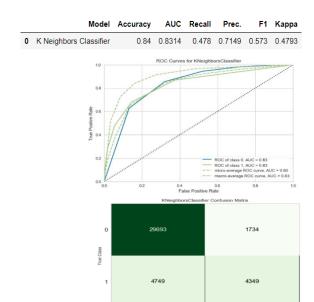
We ran all model comparison to see which model performed best. We can see that CatBoostClassifier gives best training accuracy. We need to apply on test data to see if overfitting is not taking place. A 2 fold cross validation has been applied to all models.

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa
0	CatBoost Classifier	0.9839	0.999	0.9785	0.9893	0.9838	0.9678
1	Decision Tree Classifier	0.9834	0.9834	0.9841	0.9827	0.9834	0.9668
2	Extra Trees Classifier	0.9823	0.9984	0.9757	0.9888	0.9822	0.9646
3	Random Forest Classifier	0.9722	0.996	0.9571	0.9869	0.9718	0.9444
4	Light Gradient Boosting Machine	0.9672	0.996	0.9485	0.9853	0.9666	0.9344
5	K Neighbors Classifier	0.9497	0.9862	0.9374	0.961	0.949	0.8994
6	Gradient Boosting Classifier	0.9122	0.9614	0.8919	0.9297	0.9104	0.8244
7	Extreme Gradient Boosting	0.908	0.9604	0.8895	0.9236	0.9062	0.816
8	SVM - Linear Kernel	0.839	0	0.8359	0.841	0.8385	0.6779
9	Logistic Regression	0.8227	0.8842	0.8211	0.8237	0.8224	0.6454
10	Ridge Classifier	0.8226	0	0.8155	0.8271	0.8213	0.6451
11	Linear Discriminant Analysis	0.8226	0.8832	0.8156	0.8271	0.8213	0.6451
12	Ada Boost Classifier	0.8005	0.8765	0.8202	0.7891	0.8044	0.6011
13	Naive Bayes	0.7876	0.8244	0.7371	0.8198	0.7763	0.5752
14	Quadratic Discriminant Analysis	0.6809	0.7299	0.711	0.6706	0.6902	0.3617

Dataset-2:

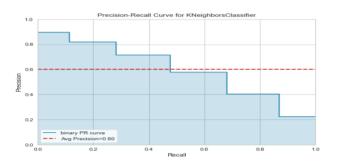
1)KNN

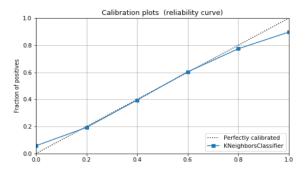
		Accuracy	AUC	Recall	Prec.	F1	Kappa
	0	0.8352	0.8181	0.4565	0.7053	0.5543	0.4588
	1	0.8331	0.8175	0.4482	0.7006	0.5467	0.4504
	Mean	0.8342	0.8178	0.4523	0.7030	0.5505	0.4546
	SD	0.0010	0.0003	0.0041	0.0024	0.0038	0.0042

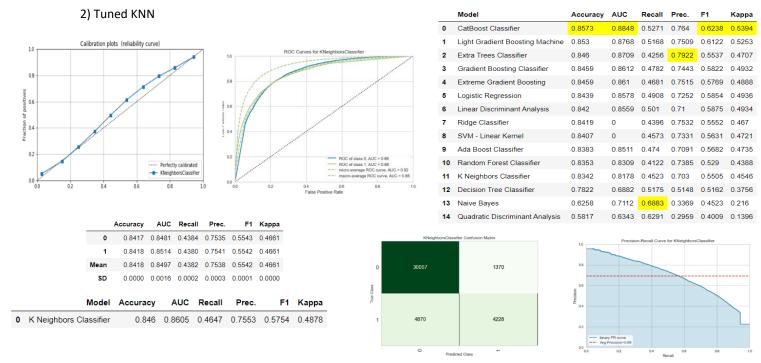


1 print(knn)

print(tuned_knn)







We can see from this experiment that on dataset

2 the Tuned KNN performed better as compared to KNN. Both are very well calibrated and so we don't need to do any calibration. The Tuned KNN used Euclidean distance with K=10. We also KNN performance when compared to other algorithms and again see that CatBoost performs Best.

Comparison of Both Algorithms:

Dataset 1 - ANN Performed Best, Accuracy was the Measure and it is a balanced dataset.

Dataset 2 - ANN Performed Best,

KNN took lot of time to train as compared to ANN, which provided higher accuracy in lesser time. This is because KNN takes more time when features are more. So when we dummy our variables the cost of computation is higher for KNN.

We can improve performance in Dataset2 by using synthetic sampling like SMOTE, ADASYN as it is imbalanced.