147

148

149

Student Number: 231012

1. Introduction

The task required for this binary class experiment involves the training of data to assess for ability to remember its contents. The solution to be presented involves a method of machine learning to correctly label a confidence rating of either 1 (for total confidence/ability to remember), 0.66 for partial ability or 0 not memorable. This report will discuss in part, pre-processing techniques, methods/models needed and finally the data obtained from classification techniques implemented.

2. Methodology

Due to the nature of the project, there are a set number of methods that could be used and implemented for this task. The most optimal solution is one in which the level of accuracy retrieved, is at its highest. The first of these methods is the usage of a Naïve Bayes (NB) Classifier, which utilizes the Bayes' Theorem to statistically train/build models to predict on probability [1]. In addition to this, other models like the use of a multi-layer perceptron [MLP], could prove to be invaluable. These networks integrate a method of generating an output through methods like backpropagation. Whilst a simplistic concept, the idea of generating an output by working backwards throughout a network in a nonlinear approach has proven to be particularly successful [2].

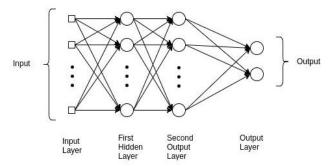


Figure 1: An example of a Multilayer Perceptron [3]

As seen in figure 1 as the name suggests, multiple hidden and output layers comprise of the metaphorical "meat" of the MLP. To be able to train this MLP, supervised training would have to occur, whereby forward propagation would take place, and then go backwards to assess if the end output resolves back into put. Overall, MLP structures are known to be especially effective at producing high

accuracy ratings. Finally, the use of a Logistic Regression (LR) Modeling tool will play a big role in this task. LR modeling is a form of statistical analysis that can create predictions from a trained dataset. This is achieved through the usage of functions like that of sigmoidal relationships. This refers to an activation function that assists with non-linear values and makes a judgement on what to pass as an output [4]. LR modeling usually begins by defining, non-linear (but not restricted to it), boundaries which are then connected to a probability within the 162 classifier. Furthermore, there are other certain events 163 within a LR model that need to be accounted for, for 164 example, Cross – Entropy (CE). CE within LR models, 165 tends to represent the loss function, generally as a form of 166 declaring the difference between level of uncertainty that a 167 model has, and its realistic probability score. The general 168 rule of thumb with LR modeling, is to reduce the CE 169 function as much as possible to achieve the highest 170 accuracy ratings.

150

151

152

153

154

155

156

157

158

159

171

172

173

174

181

182

183

187

188

189

190

191

192

193

194

195

196

197

198

199

3. Pre-Processing

Pre-processing refers to a state of normalization or data 175 preparation for a set of procedures. This the state of this 176 task, pre-processing has been used to investigate which sections of the training back can be procured to retrieve as optimal accuracy ratings as possible. To begin, an aspect of attempting to gain best results possible, is by removing points of weakness or delicacy. Since low confident data is rated from X>0.66, it would be ideal to remove anything that classifies as being X, thus providing a strong set of accurate predictions for a classifier to learn from. Once this process is complete, comparisons between GIST and CNN extraction methods need to occur. Implementing data from both these features tools, a level of importance 186 indicator was retrieved.



Figure 2: GIST (Lower) and CNN (Top) Importance ratings.

Figure 2 shows that the GIST feature extractions are relatively more of significance and would be beneficial to use for greater accuracy, since there was better outlook on object recognition and scene-based classification [5].

The training set used within this project, also had instances of missing information, as commonly seen by "NaN".

To combat this dilemma, all these points of Anomaly had to be addressed through data imputation. This technique is best suited for these scenarios whereby missing information must be replaced using a substitute value approximate to pre-existing data. This results in a complete and concise data matrix to create accurate predicts with, because of SimpleInputer, a package by scikit.

Finally, the most important part is using the newly formatted data for the purpose of training and learning. Since currently there is no total confidence in understanding which model is superior in this task, a set of training data will be implemented to test 5 different sets of data.

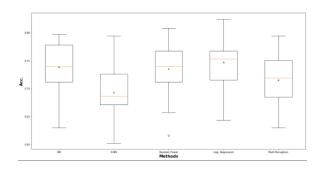


Figure 3: (From L to R) NB, K-NN, Random Forest & LR

```
NB: 0.739152 (0.044049)
K-NN : 0.693533 (0.044018)
Random Forest : 0.735505 (0.046478)
Logi. Regression: 0.747797 (0.040121)
Multi Perceptron: 0.715864 (0.045373)
```

Figure 4: Accuracy Values of classifiers

After the 5 different tests on different classifier methods, it is quite apparent that the LR Classification (as seen in figure 3 & 4) has a better accuracy score of 0.747797, with a better overall average. This was a result that was to be expected in some degree, as LR is a statistical analysis tool with a strong emphasis on memorization of objects/scenes, with strong cases of working effectively in cases of binary values. This means that for proper implementation, the LR will be the main subject of attempting to create a set of accurate predictions.

4. Results

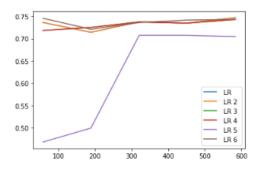


Figure 5: LR Learning Curve

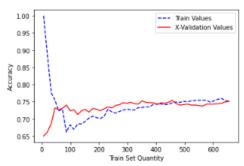


Figure 6: Learning curve of accuracy vs data-size

5. Discussion

Based on the data collected from the results, the LR 281 worked quite effectively when it came to accurate 282 predictions. Figure 5 shows that highest confidence rating 283 to be around 0.750987, When examining figure 6, this is 284 only more apparent as cross-validation averages overall 285 accuracy just above the 0.75 mark. To potentially increase 286 these values in a future experiment, it would be ideal to 287 have a pre-existing dataset of values, instead of having to 288 rely on external tools like data imputation. Furthermore, 289 by further increasing the dataset, it may mean that the LR model would have a better amount of information collected to be tested against and hence, performs a lot more precisely.

300		350
301	References	351
302	[1] Ranganathan, S., Gribskov, M., Nakai, K. and Schönbach, C.,	352
303	2019. Encyclopedia of bioinformatics and computational	353
304	biology. 1st ed. pp.403-404.	354
305		355
306	[2] Chauvin, Y. and Rumelhart, D., 2009. Back propagation.	356
307	New York: Psychology Press, pp.1-7.	357
308	[3] Peixoto, F., 2020. A Simple Overview of Multilayer	358
309	Perceptron (MLP) Deep Learning. [online] Analytics Vidhya.	359
310	Available at:	360
311	https://www.analyticsvidhya.com/blog/2020/12/mlp-multilayer-	361
312	perceptron-simple-overview/	362
313	[4] Koment D. 2021 Interdesting to Legistic Recognition	363
314	[4] Kumawat, D., 2021. Introduction to Logistic Regression - Sigmoid Function, Code Explanation Analytics Steps. [online]	364
315	Analyticssteps.com. Available at:	365
316	https://www.analyticssteps.com/blogs/introduction-logistic-	366
317	regression-sigmoid-function-code-explanation	367
318		368
319	[5] J. Yin, H. Li and X. Jia, "Crater Detection Based on Gist	369
320	Features," in <i>IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing</i> , vol. 8, no. 1, pp. 23-29, Jan.	370
321	2015	371
322		372
323		373
324		374
325		375
326		376
327		377
328		378
329		379
330		380
331		381
332		382
333		383
334		384
335		385
336		386
337		387
338		388
339		389
340		390
341		391
342		392
343		393
344		394
345		395
346		396
347		397
348		398
349		399