Applied Machine Learning Final Project

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Introduction

In this project, we aim to write 2 classification algorithms

- Logistic Regression
- K Nearest Neighbors

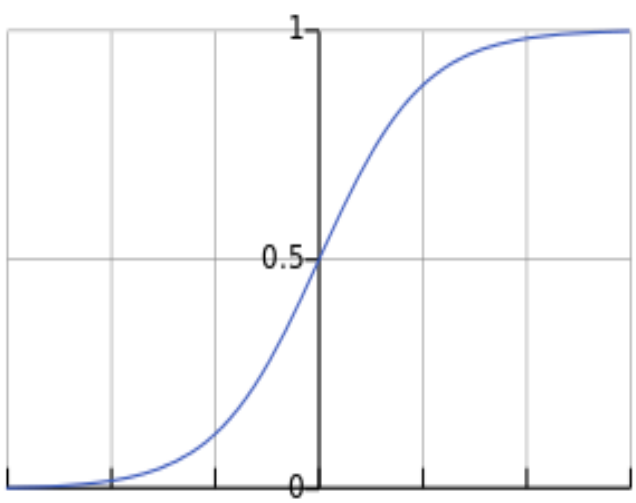
and apply them to two different datasets to evaluate their performance. We will first discuss about the Logistic Regression Algorithm and its performance on the Prima India Diabetes Dataset in classifying the patients who have diabetes from the other patients who do not have diabetes. Then we will discuss about the K Nearest Neighbors Algorithm implementation and its use in classifying the Iris dataset taken from UCI database. The Algorithm tries to classify the Iris dataset into 3 different types based on their features.

Logistic Regression

Logistic Regression is a very commonly used linear classification problem. It is mostly used for binary classification. Logistic Regression is named after the logistic function which is at the core of the working of logistic Regression. The logistic function is given as:

$$f(x) = \frac{1}{(1+e^{-x})}$$

It can be plotted as:



The value of a logistic function always lies between 0 and 1 and we can use this property to do binary classification very easily. The output value of the logistic function less than 0.5 are rounded off to 0 and those greater than 0.5 are rounded off to 1.
We have also used the stochastic gradient descent method to find the optimal weights for each attribute so that the error in prediction is minimized. While performing the Stochastic Gradient Descent algorithm, each instance is shown to the model one at a time. The model makes a prediction on the instance and the error is calculated. The model is updated to reduce the error on the next prediction.

Pima Indians Diabetes Data Set

https://archive.ics.uci.edu/ml/datasets/Pima+Indians+Diabetes

The Pima Indians Diabetes Data Set contains details about female patients, all 21 years old or above, of the Pima Indian Heritage. The task is to predict if a person will suffer from diabetes given her medical details.

There are 9 attributes in the data set. Attributes 1 to 8 are the attributes containing the various medical details. The 9^{th} attribute is the class variable which denotes if a person has diabetes or not. Class variable 0 denotes that the person does not have diabetes and Class variable 1 denotes that a person has diabetes. All the attributes are numeric.

The details of the attributes, in sequence, are as follows:

1. Number of times pregnant
2. Plasma glucose concentration a 2 hours in an oral glucose tolerance test
3. Diastolic blood pressure (mm Hg)
4. Triceps skin fold thickness (mm)
5. 2-Hour serum insulin (mu U/ml)
6. Body mass index (weight in kg/(height in m)^2)
7. Diabetes pedigree function
8. Age (years)
9. Class variable (0 or 1)

Results after running the algorithm on the dataset

We ran the code by varying the parameters i.e. number of iterations and learning rate.

For iterations =100 and rate = 0.1

	Run 1	Run 2	Run 3	Run 4	Run 5
Accuracy	79.130	74.782	76.521	77.826	75.217
True positive	40	45	44	47	54
True Negative	142	127	132	132	119
False Negative	39	46	42	36	35
False Positive	9	12	12	15	22

For iterations =200 and rate = 0.2

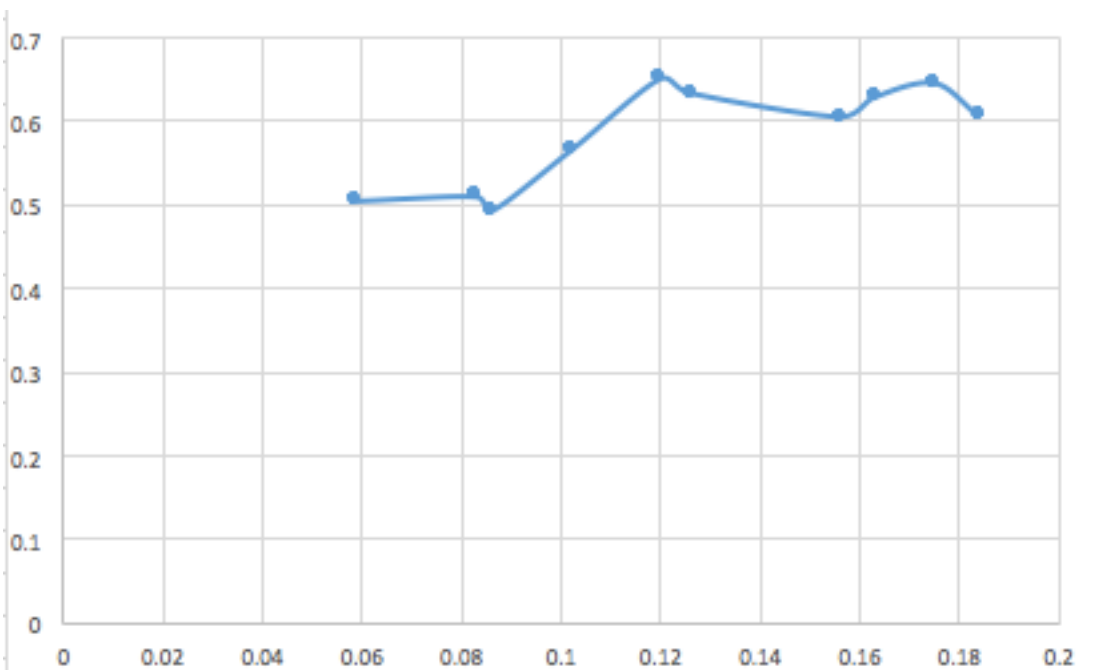
	Run 1	Run 2	Run 3	Run 4	Run 5
Accuracy	75.652	73.913	76.086	79.130	74.782
True positive	56	51	53	58	55
True Negative	118	119	122	124	117
False Negative	33	33	29	31	41
False Positive	23	27	26	17	17

Average Accuracy = 76.30

For the 10 runs the True positive Rate and False Positive Rate are summarized in the following table:

False Positive Rate	True Positive Rate
0.059	0.506
0.083	0.511
0.086	0.494
0.102	0.566
0.12	0.651
0.126	0.634
0.156	0.606
0.163	0.629
0.175	0.646
0.184	0.607

ROC



Area Under the Curve = 0.073

Weka Output

=== Run information ===

Scheme: weka.classifiers.functions.Logistic -R 1.0E-8 -M -1 -num-decimal-places 4
Relation: Diabetes_Weka
Instances: 767
Attributes: 9
              1
              95
              60
              18
              58
              23.9
              0.26
              22
              No
Test mode: 10-fold cross-validation

=== Classifier model (full training set) ===

Logistic Regression with ridge parameter of 1.0E-8
Coefficients...

	Class
Variable	No
1	-0.1231
95	-0.0351
60	0.0133
18	-0.0006
58	0.0012
23.9	-0.0896
0.26	-0.9442
22	-0.0148
Intercept	8.3981

Odds Ratios...

	Class
Variable	No
1	0.8842
95	0.9655
60	1.0134
18	0.9994
58	1.0012
23.9	0.9143
0.26	0.389
22	0.9853

Time taken to build model: 0.04 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	594	77.4446 %
Incorrectly Classified Instances	173	22.5554 %
Kappa statistic	0.4773	
Mean absolute error	0.3105	
Root mean squared error	0.3966	
Relative absolute error	68.2638 %	
Root relative squared error	83.1913 %	
Total Number of Instances	767	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.886	0.433	0.792	0.886	0.836	0.485	0.829	0.889	No
	0.567	0.114	0.727	0.567	0.637	0.485	0.829	0.710	Yes
Weighted Avg.	0.774	0.322	0.769	0.774	0.767	0.485	0.829	0.827	

=== Confusion Matrix ===

a	b	<-- classified as
442	57	a = No
116	152	b = Yes

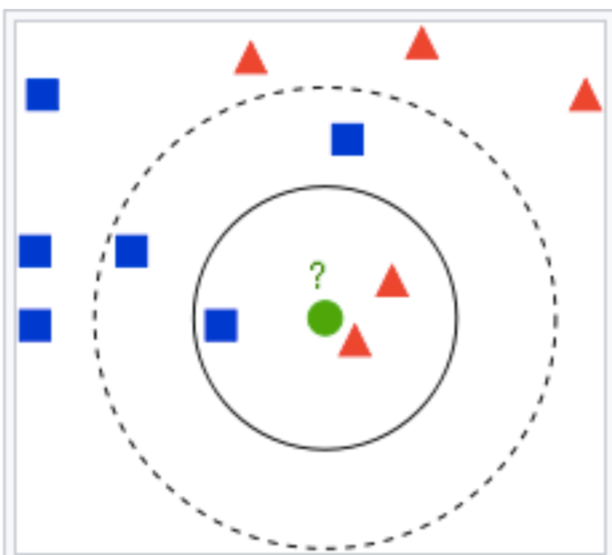
About the code

We have implemented Logistic Regression along with Stochastic Batch Gradient Descent optimization. The weights assigned to the attributes are updated according to an equation so that the error in prediction on the training set is minimized after each iteration. A learning rate parameter has been used in the update equation to control the updates of the weights. Normalization of the attributes has also been done in the code. In the initial runs without normalization of the data set, the accuracy was coming to be very low. After normalizing the data (each attribute between 0 to 1), the accuracy of the predictions has increased sufficiently.

Improvements in the code

The logic for cross validation by splitting the dataset into a number of folds will be added. Currently, cross validation is being done manually by altering the input data set.
The logic for Batch Gradient Descent needs to be added in the code base. This way we can check which optimization method works better on a particular data set – stochastic or batch.

K Nearest Neighbors



(Is the circle similar to the triangles or the square? KNN will tell.)

The K Nearest Neighbors algorithm is mostly used for classification of data (although it can be used for regression also). This algorithm is very use to interpret and depends on the similarity between two points to make a prediction. The similarity is usually found out by calculating the distance between two instances.

The K Nearest Neighbors algorithm will use the total training set as its model. When a new example is provided to it, it will scan through the entire training set to find the most similar instances and assign the majority of the class variable that is most prevalent in those instances to the new unseen instance.

Distance between points is used as the scale to find out similarity between the instances. In our case, we are using Euclidian distance as the measure. KNN is a lazy algorithm as it does not build a model till a prediction is required. As it uses the entire training dataset as its model, it can be expensive on resources also.

Iris Data set

https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data

This is a dataset containing the details of the flower of the Iris plant. The data set contains 150 instances. There are 3 classes in the dataset. Each instance has 4 attributes regarding the measurement of the Iris flower. The attribute details are as follows:

1. sepal length in cm
2. sepal width in cm
3. petal length in cm
4. petal width in cm
5. class:
    a. Iris Setosa
    b. Iris Versicolour
    c. Iris Virginica

All the attributes are numeric in nature. The dataset is not skewed. All the 3 classes are evenly distributed.

Results after running the algorithm on the dataset

The following table shows the Accuracy of the algorithm in 10 test runs:

Run	Accuracy
1	62.22
2	75.55
3	75.55
4	88.88
5	95.55
6	88.88
7	97.77
8	86.66
9	95.55
10	86.66

Average Accuracy = 85.327

About the code

The code implementation depends on finding the distance between a new unseen instance from all other instances in the training dataset. We use Euclidian distance as the measure in our algorithm. After the distance is found, we pick up the 'K' instances in the training data set which are closer to the unseen instance. Finally, the majority of the class value of the nearest instances is assigned to the unseen instance as its class value.

Improvements in the code

The code needs to be further modified to allow for n-fold cross validation. Currently, the same is being done by randomly sampling the dataset to choose random test set and training set Data normalization needs to be included into the algorithm. Normalization might increase the accuracy of the model.

Conclusion

In this project, we have used two different classification algorithms running on two different data sets. The Logistic Regression algorithm does the job of binary linear classification whereas K Nearest Neighbor Algorithm performs multiclass classification algorithm with ease. In our experiments, the KNN algorithm performs better than the Logistic regression, but this is the case when they are run on 2 different data sets. The KNN algorithm is sensitive towards the training data set. Accuracy changes significantly if the training data set changes.

References

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2. https://en.wikipedia.org/wiki/Logistic_function
3. https://en.wikipedia.org/wiki/Receiver_operating_characteristic
4. Programming collective intelligence by Toby Segaran