KNN classification Algorithm in Machine Learning

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Abstract

The k-Nearest Neighbour (KNN) algorithm is an advanced but productive machine learning algorithm. It is active in divisions and regression. However, it is widely used in segregation forecast. KNN combines data into clusters or sort and disassemble the newly added data based similar to its previously trained data. Input assigned to an intimate class nearby neighbours. Although KNN works well, it has a lot weakness. This paper highlights the KNN method once its modified versions found in the previous version research. These varieties remove the weakness of KNN also provided a very efficient method .

Key Words

I. Introduction

K-Nearest-Neighbours (KNN) is a non-parameter, simple but effective method of differentiation in most cases [1]. In order for the data record to be split, its closest neighbours are retrieved, and this creates a t. The majority of voting between local data records is usually used to determine the split in two or without considering distance-based estimates. However, to use KNN we need to select the correct value of k, and the success of the split depends largely on this value. In a sense, the KNN method is biased by k. There are many ways to choose the value of k, but the simplest is to use the algorithm multiple times with different values of k and choose the one that works best. In order for KNN not to rely heavily on the choice of k, Wang [2] proposed considers more sets of nearby neighbours than one set of k neighbours. The proposed layout is based on contextual possibilities, and the idea is to combine support for multiple sets of adjacent neighbours of different categories to provide a more reliable support value, better reflecting the actual t-class. However, in its basic form the path is slower, requiring O (n2) to separate the new one.

II. ABOUT THE PROPOSED WORK

2.1 Literature Survey

The main idea of k-NN is based on calculating the distances between the testes, and samples of training data to identify their closest neighbours. The tested sample was then given to a class of its immediate neighbour.

In k-NN, the value of k represents the number of nearby neighbours. This value is the main determining factor of this divider because of the k value that determines how many neighbours influence the division. If k = 1 a new data object is simply assigned to its nearest neighbour category. Neighbours are drawn from a training data collection material where the correct distinction is already known. K-NN works naturally with numerical data. Various numerical methods such as Euclidean, Manhattan, Minkowsky, City-block, and Chebyshev range have been used. Among these, the Euclidean is the most widely used distance function by k-NN.

The main steps of the k-NN algorithm:

1.Determine the number of nearby neighbours (values K).

2.Calculate the distance between the test sample and all training samples.

3.Sort a distance and determine the nearest neighbours based on the minimum K-th range.

4.Gather categories of nearby neighbours.

5.Use the simple majority of the nearby neighbours category as the guessing value of a new data object

According to [21], the k-NN class can be used to classify new data objects using only their distance to labelled samples. However, other activities consider any matric or non-matric steps used with this separator: several studies have been performed to test k-NN phase using different matric and non-matric steps such as subjects presented .

2.2 Proposed Work

This work is a follow-up study based on our previous data reduction study (DR) . The advantage of DR is that raw data and reduced data can be represented in both hyper relationships. A high-level relationship can be made into a complete Boolean algebra in a natural way, so any unique hyper tuples (unique) hyper tuples can be found, such as downgrades. The test result shows that DR can achieve a relatively low reduction rate while maintaining the accuracy of its components. However, it slows down in your basic type of construction, as more time is spent trying to integrate what is possible. this problem . Hart proposed a simple computerized local search method such as Condensed Nearest Neighbour (CNN) by reducing the number of stored patterns and keeping only a small set of training set to separate. The basic premise is that the patterns in the training set may be very similar and some do not add further information and thus are discarded. Gate has proposed a Reduced Near Neighbourhood Act (RNN) which aims to reduce the small set of savings after using CNN. It simply removes those features from the set that will not cause the error. Alp Aydin investigated other voting systems for multiple students to improve class accuracy, and Kubat et al [8] looked at how to select three subgroups of models that, when used as 1-NN sub classifiers, each often made a mistake. in a different area of the model area. Easy voting and fixing many failures of each sub classifiers. The experimental results of those approaches to other public data sets were reported in [9]. Build a model by getting a set of representatives with additional information from training data based on the principle of similarity. Created representatives can be identified as regions in the information area and will be used for additional classification.

KNN is a state-of-the-art learning method, which stores all training data for classification. Being a lazy learner is a barrier to many programs such as dynamic web mines of a large repository. One way to improve its efficiency is to find other representatives who will represent all the training data to be segmented, namely to build a learning learning model from the training database and use this model (representatives) to differentiate. There are many algorithms available such as decision trees or neural networks designed to build such a model. One of the testing standards for different algorithms is their effectiveness. Since kNN is a simple but effective method of segmentation and convincing as one of Reuters' s most effective ways to split text, it encourages us to build a kNN model to improve its efficiency while maintaining the accuracy of its segmentation. Figure 1, a training

data set consisting of 36 two-dimensional data {square, circle} is distributed in a two-dimensional data space.Fig. 1. Distribution of data points. Figure 2. The first representative obtained.If we use the Euclidean range as our measurement of similarities, it is clear that many data points with the same category label are closer to the average distance in most localities. In each local region, the central data point looks at Figure 2Sim (di), Num (di) = 9di

for example, for additional information such as Num (di) - the number of data pointing between the local region and the Sim (di) - the similarity of the remote data point within the local region to di, may be the appropriate representative of that area. region. If we take these representatives as a model to represent the entire training database, it will significantly reduce the number of data points to be categorized, thereby improving its efficiency. Obviously, if a new data point is covered by a representative it will be separated by a label label of its representative. If not, we calculate the point of the new data point to each approx. boundaries and take the proximal boundary of each proxy as a data point, and then divide the new data point with the KNN spirit. of the same class. Based on these localities, the largest local area (called the largest area) can be found in each cycle. This vast global area can be seen as a representative of all the data points compiled by it. For datapoints that are not covered by any representatives, we repeat the above function until all data points are covered by the selected representatives. Obviously, we do not need to choose a particular k of our method in the model building process, the amount of data covered by the representative may be considered appropriate k but it varies from different representatives. The k is automatically generated in the model building process. Moreover, using a list of selected representatives as a partition model not only reduces the amount of partition data, and greatly improves its efficiency. According to this point of view, our proposed approach overcomes these two inherited deficiencies in the KNN path.

D must be a collection of tuples known data in class {d1, d2,…, dn}. Di∈D may be a document represented in the vector type of space di = <wi1, wi2,…, wim>, where wijcould be the standard TF-IDF presentation for weight representation in text separation as an example. For general practice from now on, we use the term ‘data tuple’ to represent all types of data in different applications in this paper to avoid limiting our algorithm to other applications. And the term ‘similarity rate’ can be any measure of similarity as Euclidean distance or Cosine similarity only if it is suitable for practical use. To simplify, from now on, we use the Euclidean range as the default equation measure to define the following algorithms.) Set 'separate' tag for all copies of data. (3) For each 'uncollected' data copy, locate the largest locality that includes the largest number of neighbors with the same category. (4) Find tuple di data with the largest land Neighbour Ni for all the neighbourhoods, create a representative for <Cls (di), Sim (di), Num (di), Rep (di)> M to represent all copies of the data covered by Ni, and then set to 'collect' the mark of all copies of the data covered by Ni. until all data is copied. The training database is set to 'collect'. (6) Model M contains all the representatives collected from the above learning process. In the algorithm above, M represents the created model. Representative <Cls (di), Sim (di), Num (di), Rep (di)> respectively represents the di class label, the lowest similarity of di between copies of data covered by Ni; the number of data obtained by Ni, and the representation of the di itself. In step (4), if there are more than one neighborhood with the same large number of neighbors, we select the minimum number of Sim (di), i.e.. with a large quantity, as a representative.The classification algorithm is defined as follows: (1) For dt of new data to be separated, calculate its similarity with all the representatives in model M. (2) If dt is only one compound. representing <Cls (dj), Sim (dj), Num (dj), Rep (dj)>, i.e. the Euclidean distance of dt to dj is smaller than Sim (dj), dt is classified as category of dj. (3) If the dt is composed of at least two representatives with a different category, divide the dt as the representative category by the largest Num (dj) number, i.e.. neighbour collects the largest number of copies of the data in the training database. di represent equal to the Euclidean range of di to dt remove Sim (di) .To improve the accuracy of the KNN Model sections, we have used two different pruning methods in our KNN Model. Another option is to remove the representatives from Model M which includes only a few copies of the data and the relevant data copies covered by these representatives in the training database, and then model again from the updated training database. The second method is to change the 3rd step in the model construction

algorithm to allow the cover of each large r area (so-called degree of error tolerance) copies of data with different categories in the same category in this neighbourhood. This modification includes the work of pruning in the model construction process. Test results will be reported in the next section.

III. CONCLUSION AND FUTURE WORK

In this paper we have presented a novel solution to address o KNN shortcomings. In order to overcome the problems of low performance and reliance on k, we select a few representatives in the training database for more information to represent the entire training database. In each proxy selection we use a complete but different k determined by the data set itself to remove the k dependence without user intervention. Test results conducted on six community databases show that the KNN Model is the most competitive way to differentiate. The accuracy of the categories in the six public databases compared to C5.0 and KNN. And KNN Model significantly reduced the number of copies of data in the final model specification by a reduction rate of 90.41% on average. It would be a good substitute for KNN in many applications such as dynamic web mines for large repositories. Further research is needed to improve the accuracy of separate data sets outside the representative regions.

We plan to continue our research by taking hyperplanes into consideration which will further reduce the computational cost. Also we are working on more effective feature weighting algorithm to give proper weights to categorical features.

IV. ACKNOWLEDGEMENT

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