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A Model for Using Machine Learning Algorithms to Analyse Consumer Behaviour

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ABSTRACT_ The importance of the machine learning algorithm has increased due to their forecasting accuracy. Due to an unanticipated customer situation, it is exceedingly challenging to estimate a customer's performance. For the same objective, numerous algorithms have been created. Three Bays algorithms, including AODE, Naive Bayes, and AODEsr, have been examined and analysed in this article. We used the WEKA tool to implement these methods and created a new model with greater accuracy than the one previously used. We have worked to eliminate noise and mistake in the data during development, but we also need to filter the information. The new filtered data will receive Wj weight as a result of this operation. The error may be identified as E (j, k), Where j _ J, or it may be assumed to be an error. K depends on the purpose. Similarly, another function can be used to define noise. N = E + W.

1.INTRODUCTION

Artificial intelligence includes machine learning, in which we teach a machine to predict the desired value. The machine learns the defined pattern when we define some rules or patterns during training. Therefore, input data for machine learning is generated using knowledge that has been recorded in a database. We need to construct an algorithm and pattern to collect the necessary information because we are building our system to forecast or extract pertinent information from the incoming data set. Following the construction of the algorithm and pattern in these two steps, the machine may perform the following tasks:

2.LITERATURE SURVEY

[1] Webb, G.I., Boughton, J., Wang, Z.: Not so naive bayes: Aggregating one-dependence estimators. Machine Learning 58, 5– 24 (2005) zbMATHCrossRefGoogle Scholar

Of numerous proposals to improve the accuracy of naive Bayes by weakening its attribute independence assumption, both LBR and Super-Parent TAN have demonstrated remarkable error performance. However, both techniques obtain this

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outcome at a considerable computational cost. We present a new approach to weakening the attribute independence assumption by averaging all of a constrained class of classifiers. In extensive experiments this technique delivers comparable prediction accuracy to LBR and Super-Parent TAN with substantially improved computational efficiency at test time relative to the former and at training time relative to the latter. The new algorithm is shown to have low variance and is suited to incremental learning.

[2] Chen S., Martinez A.M., Webb G.I. (2014) Highly Scalable Attribute Selection for Averaged One-Dependence Estimators. In: Tseng V.S., Ho T.B., Zhou ZH., Chen A.L.P., Kao HY. (eds)Advances in Knowledge Discovery and Data Mining. PAKDD 2014. Lecture Notes in Computer Science, vol 8444. Springer, Cham.

Averaged One-Dependence Estimators (AODE) is a popular and effective approach to Bayesian learning. In this paper, a new attribute selection approach is proposed for AODE. It can search in a large model space, while it requires only a single extra pass through the training data, resulting in a computationally efficient two-pass learning algorithm. The experimental results indicate that the new technique significantly reduces AODE's bias at the cost of a modest increase in training time. Its low bias and computational efficiency make it an attractive algorithm for learning from big data.

[3] Witten, I.H., Frank, E.: Data mining-Practical Machine Learning Tools and Techniques with Java Implementation. Morgan Kaufmann, San Francisco (2000), http://prdownloads.sourceforge.net/weka/datasets-UCI.jar Google Scholar

NB(naive Bayes) is a probabilistic classification model, which is based on the attribute independence assumption. However, in many real-world data mining applications, this assumption is often violated. Responding to this fact, researchers have made a substantial amount of effort to improve NB's accuracy by weakening its attribute independence assumption. For a recent example, Webb et al.[1] propose a model called Averaged One-Dependence Estimators, simply AODE, which weakens the attribute independence assumption by averaging all models from a restricted class of one-dependence classifiers. Motivated by their work, we believe that assigning different weights to these one-dependence classifiers can result in significant improvement. Based on this belief, we present an improved algorithm called Weightily Averaged One-Dependence Estimators, simply WAODE. We experimentally tested our algorithm in Weka system[2], using the whole 36 UCI data sets[3]

selected by Weka[2], and compared it to NB, SBC[4], TAN[5], NBTree[6], and AODE[1]. The experimental results show that WAODE significantly outperforms all the other algorithms used to compare.

[4] Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations

Smartphones have become the ultimate 'personal' computer, yet despite this, general-purpose data mining and knowledge discovery tools for mobile devices are surprisingly rare. DataLearner is a new data mining application designed specifically for Android devices that imports the Weka data mining engine and augments it with algorithms developed by Charles Sturt University. Moreover, DataLearner can be expanded with additional algorithms. Combined, DataLearner delivers 40 classification, clustering and association rule mining algorithms for model training and evaluation without need for cloud computing resources or network connectivity. It provides the same classification accuracy as PCs and laptops, while doing so with acceptable processing speed and consuming negligible battery life. With its ability to provide easy-to-use data mining on a phone-size screen, DataLearner is a new portable, self-contained data mining tool for remote, personalised and educational applications alike. DataLearner features four elements – this paper, the app available on Google Play, the GPL3-licensed source code on GitHub and a short video on YouTube.

3.PROPOSED SYSTEM

Digital marketers are given the tools they need to make wise, forward-thinking decisions via predictive marketing, which combines robust prediction models with advancements in automation, visualisation, and user experience. Since businesses have always sought to foretell their future, they now have access to a limitless amount of data. Being proactive rather than reactive is key. Customer behaviour prediction analyses patterns of customer behaviour to forecast how comparable customers would act in similar situations. is concerned with developing a mathematical construct to represent the typical customer behaviour patterns in order to forecast how comparable customers would act in similar situations. Customer behaviour models can be used to forecast what a group of customers will do in response to a specific marketing action because they are often based on data mining of customer data. Most of the customers in the group will behave as anticipated by the model if the model is correct and the market agrees.

3.1 IMPLEMENTATION

When implementing a model for predicting consumer behavior using machine learning, you can organize your code into different modules or components to improve modularity, readability, and maintainability. Here are some suggested modules that you can consider:

Data collection module: This module is responsible for collecting and retrieving the relevant data needed for training and prediction. It can include functions or classes to fetch data from various sources, such as databases, APIs, or file systems.

Data preprocessing module: This module handles the cleaning and preprocessing of the collected data. It can contain functions or classes for tasks like data cleaning, handling missing values, feature scaling, feature encoding, and data splitting into training and testing sets.

Feature engineering module: This module focuses on creating and transforming features to improve the performance of the model. It can include functions or classes for tasks like feature extraction, feature selection, feature normalization, or any other techniques specific to your domain.

Model selection module: This module deals with selecting the appropriate machine learning algorithm for your prediction task. It can include functions or classes to compare and evaluate different models, perform hyperparameter tuning, and save or load trained models.

Model training module: This module is responsible for training the selected machine learning model using the preprocessed data. It can include functions or classes to fit the model to the training data, perform cross-validation, and evaluate the model's performance.

4.RESULTS AND DISCUSSION

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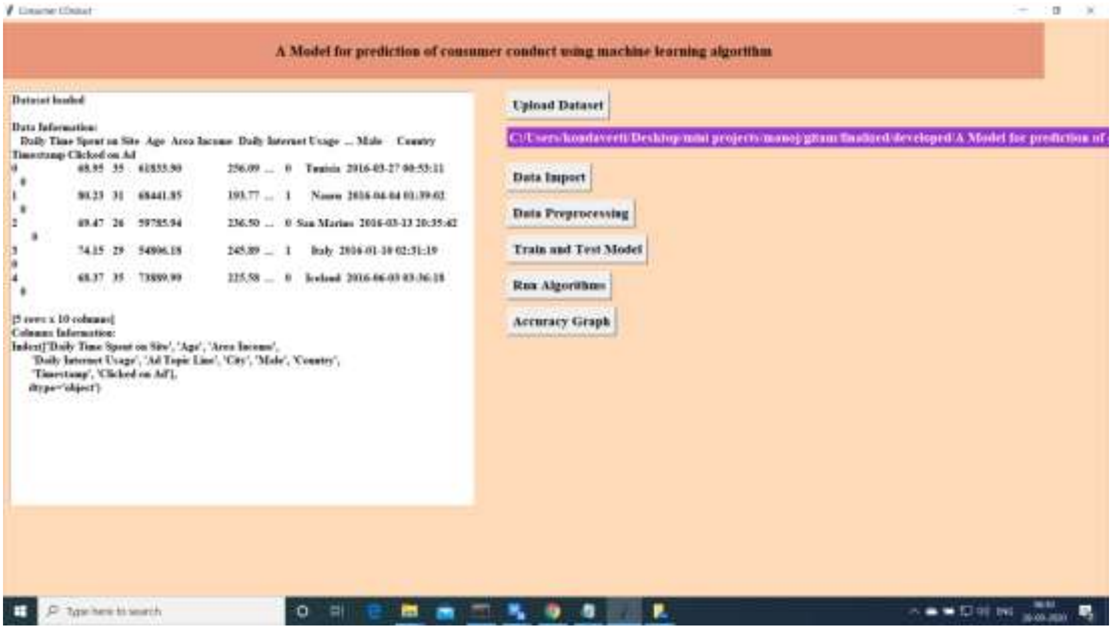

Fig 1;Upload the data and read the basic data information will be shown on the screen

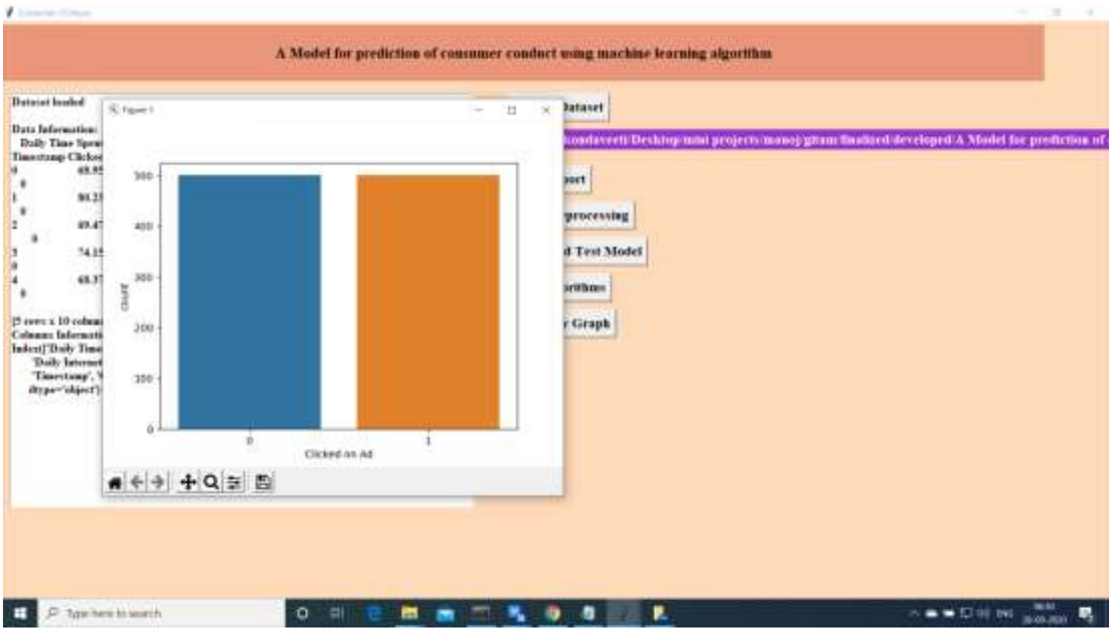

Fig 2: Graph

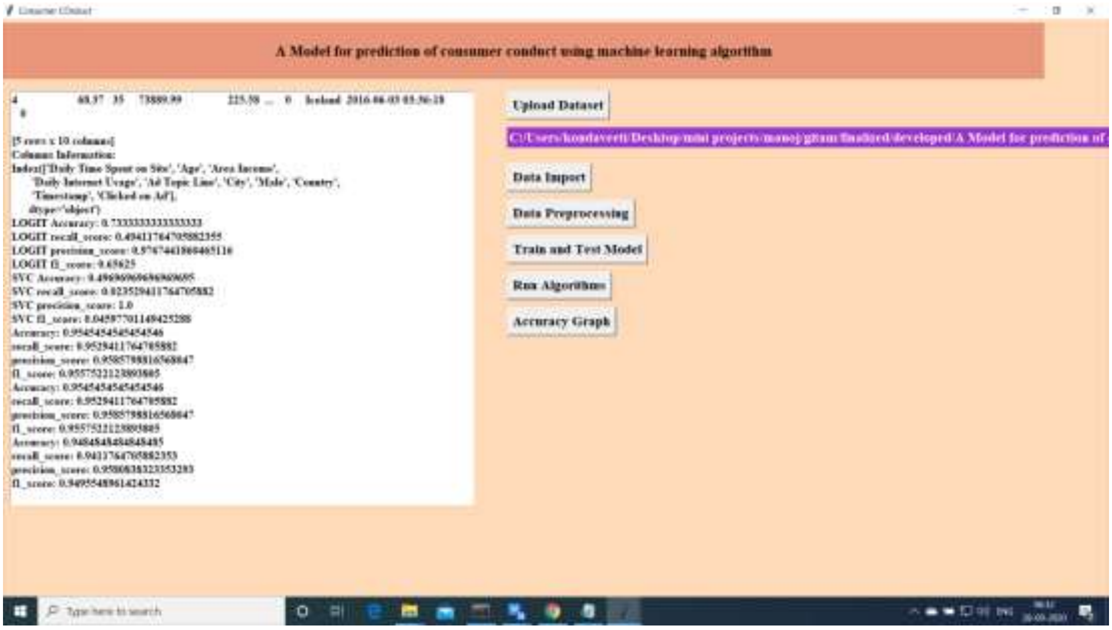

FIG 3:Algorithms Accuracy

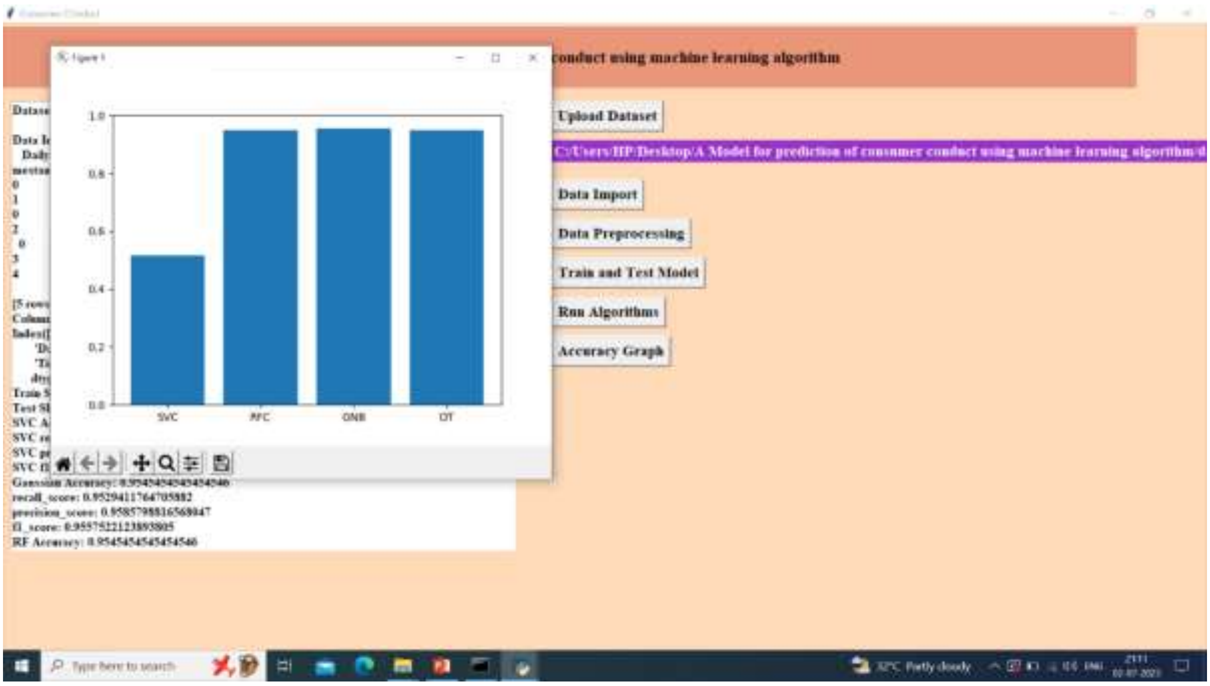

Fig 3:Accuracy graphs

4.CONLUSION

The results of the observations show that the proposed algorithm is more accurate than the previous algorithms , AODE, and AODEsr. Compared to AODE and AODEsr, it takes a lot less training time. The fact that the method described in this paper is a complicated one-dimensional model and not equal to high-dimensional data is useful in highlighting this.

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