Automated recommending machine learning algorithms

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ABSTRACT

There are numerous steps involved in creation of a machine learning model. Essentially, computer scientists create algorithms that learn or "learn" from data that contains information about the situation that you want the model to analyze, with the idea being that the model will be able to perform a better analysis when it gets access to more data. For example, In cases like economics, you can train a model to predict market behavior . . . and in society, you can train models to predict social trends.

These steps can be divided into three broad categories: selecting relevant features, using the correct classifier and tuning hyperparameters. All of these steps are challenging and time consuming. So, In this study, we have created a process which empirically ranks and evaluates classifiers and helps the users in choosing the right methodology.

This paper is an extension of the paper "Accurate multi-criteria decision making methodology for recommending machine learning algorithms" [1]. The given Methodology used human input for making decisions at key points. We have eliminated the use of said "experts" and made the whole process automated.

KEYWORDS

Algorithm recommendation, classification , Multi-Criteria Decision Making, Ranking Classifiers

INTRODUCTION

Machine Learning is useful in a variety of real-life problems. The algorithm for these problems is selected manually by Data experts. The algorithm selected by the expert might be sub-optimal due to various reasons such as lack of knowledge etc. Experts usually have huge monetary costs to the business which makes the selection all the more difficult.

We assume that the data given to us is already preprocessed. This means following steps have already been performed:

- Cleaning data: Taking messy, disparate sources of information, understanding the context, and transforming the data into a single, organized table at the appropriate level of detail or aggregation, which can then be used for machine learning.
- Formulating the problem: Understanding the true business need, properly posing the right data science question, and gathering the appropriate data for the machine learning problem.

Choices in Machine Learning is a true issue in different spaces, for example, information mining business, information obtaining and thinking, research and numerous others territories . Huge business firms and exploration establishments enlist AI specialists, for example, experts, information investigators and information specialists to dissect the business information for various kinds of key arranging. For the most part, specialists pick fitting AI algorithms utilizing their heuristic information about the area furthermore, the accessible arrangement calculations. The heuristics-based algorithms determination is a hazardous task and once in a while bring about determination of a problematic presentation algorithms. The reasons may incorporate need of the total information about the area application, i.e., the datasets have distinctive characteristic attributes, and the up-and-comer classifiers have various abilities and qualities. This procedure become additional difficult when the choice of best classifier depends on numerous measures under exacting conditions and requirements.

As per the notable "no free lunch" hypothesis, no machine learning calculation performs well on all sort of learning issues. Be that as it may, it tends to be made conceivable to gauge the choice of a reasonable AI calculation for an application close by. This choice procedure of the classifiers is an application subordinate errand, since it has been hypothetically and experimentally demonstrated that no AI calculation is all around predominant on all datasets because of the various qualities and highlights of the space information.

So, Using a process which automatically decides the best algorithm for your dataset will have huge benefits. Hence, we have created a multi criteria decision making methodology to select the best classifier. We have used "Fuzzy Analytical Hierarchical Processing" [2] based methods to estimate relative weights for evaluation metrics. Further, classifiers are ranked based on Relative Closeness Score. The paper follows the following steps:

- A model is created for the selecting the best possible classifier from among a dataset of training examples.
- This model contains:
  - Metadata of the training datasets
  - Best classification algorithms for the training datasets
- Logistic Regression is used to predict the suitable algorithm whenever a new dataset is given.

LITERATURE SURVEY

Assigning Weight manually to features is a hard task by different such as SIM(Soares, Costa, Brazdil, 2000) , MBE (Andersson, Davidsson, LindÃĺn, 1999). The difference is dimensonality between evaluation and feature set is hard to determine.(Zavadskas, Zakarevicius, Antucheviciene, 2006). We can use some normalization techniques to overcome this issue.

There are plenty of other methods to evaluate classifiers. Some methods use single criteria such as accuracy (Aha, 1992; Alexandros Melanie, 2001; Brodley, 1993; Gama Brazdil, 1995; Lindner Studer, 1999; Smith, Woo, Ciesielski, Ibrahim, 2002) or a combination of criterions such as accuracy and time (Ali Smith-Miles, 2006; Brazdil, Soares, Da Costa, 2003; Lim, Loh, Shih, 2000) and on the basis of sensitivity, precision, F-score, and area under the curve (AUC) is presented in (Romero, Olmo, Ventura, 2013). Each machine learning algorithm performs differently on different datasets. Some algorithms focuses on maximizing accuracy while ignoring other criterias (A. A. Freitas, 2006)

The most commonly used criteria for algorithms evaluation are the adjusted ratio of ratio (ARR) (Brazdil, et al., 2003) and performance of algorithm (PAlg) on dataset (Song, Wang, Wang, 2012), which use accuracy and time. Reif et al., (Reif, Shafait, Goldstein, Breuel, Dengel, 2014) used root mean squared error (RMSE) and Pearson product-moment correlation coefficient (PMCC) (Gayen, 1951) for the evaluation and recommendation of the best classification algorithm.

METHODS AND PROCEDURES

In this section, first we define a set of general guidelines and then describe the methodology for evaluating classification algorithms on the basis of multiple evaluation criteria.

Guidelines for algorithm Training

For recreating this specific algorithm, a sequence of essential tasks need to be performed. To efficiently perform these tasks, a set of guidelines is presented as follows:

- **Goal and target definition**: depicts the last objective, its comparing destinations and the related requirements to accomplish the goals. For instance, the determination of ideal execution grouping calculation for multi-class issues. In this announcement, objective G is the "determination of ideal execution grouping calculation" and the worldwide imperative C is "multi-class issues". The relating targets against this objective can be, e.g., accuracy, Big O complexity, and consistency
- **Extracting internal properties of dataset**: Every Dataset has some intrinsic properties such as no. of categorical variables, amount of data etc. These properties can be taken as non target variables which can be used to predict the best algorithm.

  The best algorithm will be a combination of the target properties with the intrinsic properties. The inputs from Dataset can be used as the training data. We will build models using these classes and decide which model to use for data selection. This works when the difference in training and testing datasets have a small amount of variance. On the other hand, when the difference in training and testing datasets have high variance, the algorithm performs poorly.[5]
- Computing the best classifier for each dataset.
  - Finding out different QMM scores for each Dataset-Algorithm pair.
  - Computing Relative Closeness Score for each algorithm which will be used to rank the algorithms.
  - Filling the best algorithm in the internal dataset properties.
- Each classifier has a number of parameters which are configured to control its performance on the training set. Each classifier has a unique set of parameters that can be manipulated to create a personalization that best suits the case that is being tested.

In the next sections, we have elaborated on the methodologies given above.

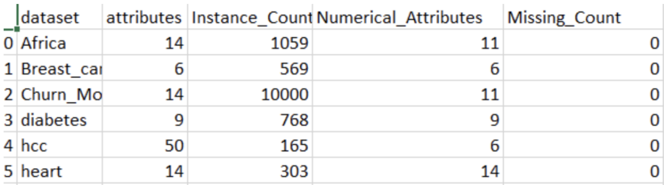
Extracting internal properties of dataset

Metadata is created using the following features of the dataset:Total Attributes,Total Instance Count,Total Numerical Attributes,Total Missing Count etc. We will use this metadata to differentiate between datasets.

Algorithm 1: Procedure Of Extracting Metadata

```
Input: Multiple Datasets
Output: A new Dataset containing meta properties of given datasets
$MetadataDataset$ = [ ]
for every Dataset d do
    $propertiesDataset$ = extractProperties(d)
    $MetadataDataset$.append($propertiesDataset$)
return MetadataDataset
```

The results for a few datasets can be seen below.



	dataset	attributes	Instance_Count	Numerical_Attributes	Missing_Count
0	Africa	14	1059	11	0
1	Breast_cai	6	569	6	0
2	Churn_Mo	14	10000	11	0
3	diabetes	9	768	9	0
4	hcc	50	165	6	0
5	heart	14	303	14	0

Example of Metadata

Selecting Best Algorithm for Training Datasets

Six classification algorithms are used to create this model : K Nearest Neighbours,Naive Bayes Classifier,Support Vector Machine,Decision Trees,Logistic Regression,Linear Discriminant Analysis.For each of the above algorithms, the following metrics are stored for each dataset : Accuracy,F-Score,Cohen Kappa Score,CPU-Training Time,CPU-testing Time.

Fuzzy AHP is used to assign weights to each of the above metrics.Normalised performance matrix is made and relative closeness is calculated .According to relative closeness, rank is calculated for each algorithm for each dataset.

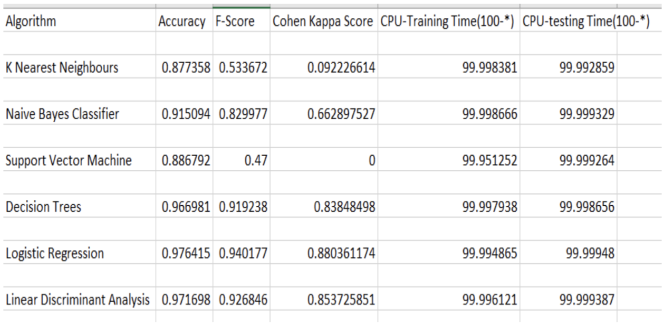
Algorithm 2: Procedure Of Selecting Algorithm

```
Input: Dataset d
Output: Ranking of Algorithms for that particular dataset
$RCValues$ = [ ]
for every Algorithm a do
    a.fit(d) // Training Algorithm a on Dataset d
    matrix = a.scores() // Get Different scores such as Accuracy , F1-score , Testing Time etc.
    RC = getRC(matrix) // Get RC value from the score
    $RCValues$.append[$RC$ , a]
rank = rankAlgorithms(RCValues)
return rank
```

Let’s look at all the functions used in the algorithm one by one.

- **fit**: A classic function used in almost all machine learning libraries.
- **scores**: This method is used to calculate different scores determined suitable for judging an algorithm. The scores include Accuracy, F-Score, CPU Training Time etc.

- **getRC**: Relative Closeness score is defined as the closeness of the algorithm to the ideal algorithm. It has been discussed extensively in the next module.
- **rankAlgorithm**: A simple sort is performed on RCScore and the algorithm with the highest RCScore is deemed suitable for the given dataset.



Algorithm	Accuracy	F-Score	Cohen Kappa Score	CPU-Training Time(100-*)	CPU-testing Time(100-*)
K Nearest Neighbours	0.877358	0.533672	0.092226614	99.998381	99.992859
Naive Bayes Classifier	0.915094	0.829977	0.662897527	99.998666	99.999329
Support Vector Machine	0.886792	0.47	0	99.951252	99.999264
Decision Trees	0.966981	0.919238	0.83848498	99.997938	99.998656
Logistic Regression	0.976415	0.940177	0.880361174	99.994865	99.99948
Linear Discriminant Analysis	0.971698	0.926846	0.853725851	99.996121	99.999387

Results for African Banking Crisis Dataset

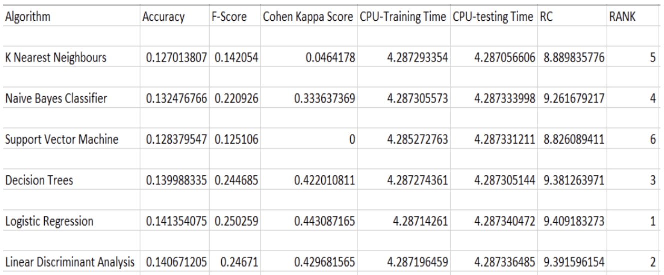
Computing RC Score

State of the art ranking algorithms are based on the combined score of the multiple evaluation matrix. Our thought is to test the candidate algorithm and rank them according to the score of their relative closeness. We are inspired by the consistency and ranking capacity of TOPSIS decision-making system with multi-criteria methods(Garcia-Cascales Lamata, 2012; Tzeng Huang, 2011). The steps for generating RC Score are given below:

Algorithm 3: Computing RC Score

```
Input: S - m*n matrix containing performance results of the given algorithm
Output: R - n*1 (single column) matrix of the relative closeness score
S = $S_{ij}$    // where $S_{ij}$ represents value of algorithm i for evaluation metric j
$r_{ij}$ = $S_{ij}/\sqrt(\sum_{i=1}^{n} S_{ij}^2)$    // Normalize performance matrix
$PIS_i^+$ = $\sqrt(\sum i = 1^m (v_{ij} - v_j^+)^2)$    // Positive Ideal Solution
$NIS_i^-$ = $\sqrt(\sum i = 1^m (v_{ij} - v_j^-)^2)$    // Negative Ideal Solution
RC = $PIS_i/(PIS_i$ + $NIS_i)$ for each i    // Computing relative closeness with ideal algorithms
return RC
```

We have computed RC Scores for the African banking crisis dataset. The results are shown below:



Algorithm	Accuracy	F-Score	Cohen Kappa Score	CPU-Training Time	CPU-testing Time	RC	RANK
K Nearest Neighbours	0.127013807	0.142054	0.0464178	4.287293354	4.287056606	8.889835776	5
Naive Bayes Classifier	0.132476766	0.220926	0.333637369	4.287305573	4.287333998	9.261679217	4
Support Vector Machine	0.128379547	0.125106	0	4.285272763	4.287331211	8.826089411	6
Decision Trees	0.139988335	0.244685	0.422010811	4.287274361	4.287305144	9.381263971	3
Logistic Regression	0.141354075	0.250259	0.443087165	4.28714261	4.287340472	9.409183273	1
Linear Discriminant Analysis	0.140671205	0.24671	0.429681565	4.287196459	4.287336485	9.391596154	2

Normalised performance matrix with **Relative closeness** and **Ranks** from African Banking crisis dataset

Predicting Algorithms for New Datasets

After Getting the best Algorithms, this turns into a simple Classification problem. We have used logistic regression to classify which algorithm works best on the input dataset.

DATASETS

We have used 8 real world datasets including Spectra evolution during coating(2014) and using 27 classification algorithms. We have described the datasets and their attributes below:

- Diabetes Dataset: We have to predict whether the patient has diabetes or not. We have features such as Pregnency, Glucose, BloodPressure, Skin Thickness, Insulin , BMI.
- Breast Cancer Dataset: It contains feature mean radius, mean texture, mean perimeter, mean area, smoothness and we have to predict whether it's cancerous or not.
- Churn Modelling Dataset: This dataset is used to predict the probablity of an customer leaving (churning) the company. It contains features CreditScore,Geograpgy,Gender,Age,IsActiveMember and we have predict their probablity of leaving.
- Heart Risk Dataset: It contains features Age, Sex, Rest Blood Pressure, Cholestrol, Rest ECG etc and we have to predict whether the person has a serious risk ailment or not.
- Ramen Ratings Datasets: We had the brand name, variety, style and country and we have to determine the rating of the ramen noodles.

OBSERVATIONS

A few key Observations made are mentioned below:

Pros

- The algorithms that decides the best classifier, if the expert input is automated, are highly reliable and considers all the factors that can be the decision-making criteria for the best classifier selection.
- The Weka classifiers used for comparison to select the best one out of them is completely reliable and accurate.

Cons

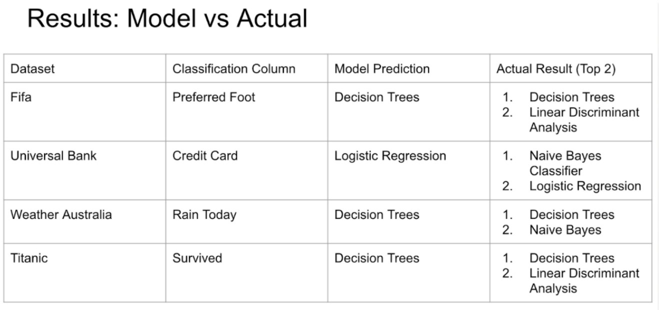
- The methodology given in that research paper require human(experts) intervention at key points of the procedure.
- The algorithms developed by them to get the best classifier for dataset are completely based on the input given by the experts, which is highly ambiguous
- The ranking methodology is used by them is highly complex, which again depends on the criteria decided by the experts.

EXPERIMENTS

One common point in all the cons is the human intervention. So, our focus was to convert the human provided inputs to machine provided inputs. To automate this process multiple multi-criteria decision-making analysis is done to determine the best input that was earlier being provided by the expert. The key input provided by the experts were the weights to different metrics that were being used to determine the best classifier. To get those best set of weights we used Fuzzy AHP as our procedure to get those weights. Fuzzy AHP is one of the best multi-criteria decision-making procedure to get the best set of weights. The procedure to determine the best set of weights is provided in the methodologies section. This process was run multiple times on same set of datasets, till the set of weights being used were not able to give the best results for the classifier selection.

RESULTS

We performed the experiments on 35 most commonly used multi-class classification algorithms, shown in Table below. For convinience, we have shown only 4 rows below. These algorithms belong to six heterogeneous families of classifiers including: probabilistic learners, functions-based learners, decision trees learners, rules-based learners, meta-learners, and miscellaneous learners. The meta-classifiers, i.e., Adaboost M1, Randomspace, and Voting are used with REPTree as the base classifier. Similarly, Dagging and Stacking are used with NaÃŕve Bayes as the base classifier.



Results: Model vs Actual

Dataset	Classification Column	Model Prediction	Actual Result (Top 2)
Fifa	Preferred Foot	Decision Trees	1. Decision Trees 2. Linear Discriminant Analysis
Universal Bank	Credit Card	Logistic Regression	1. Naive Bayes Classifier 2. Logistic Regression
Weather Australia	Rain Today	Decision Trees	1. Decision Trees 2. Naive Bayes
Titanic	Survived	Decision Trees	1. Decision Trees 2. Linear Discriminant Analysis

Accuracy

To estimate accuracy level of the proposed method, average Spearman's rank correlation coefficient is computed for all the datasets.

The weights used for generating the recommended ranking are: Wgt.Avg.F-score (0.69520), CPUTimeTraining (0.05067), CPUTimeTesting (0.10097), and Consistency (0.15315). In the second step, ideal rankings for all the datasets are generated by taking average of the weighted sum of the normalized values of these evaluation metrics.

The average Rank is very close to 1 which demonstrates the correctness of our methodology. It accurately ranks the algorithms and thus assists experts in the selection of accurate algorithms under the specified criteria. The statistical significance test of Spearman's rank correlation coefficient shows that the value is statistically significant at the level of 0.5, because the average correlation value is far greater than the critical value of the correlation, i.e., 0.231.

Consistency and senstivity Analysis

In multi-criteria decision making, the choice and number or weights of the criteria affect the final recommended ranking [6]. It has already been proven that any tinkering in criteria or weights results in change in final recommended ranking [7]. Decision Makers often don't agree with the ranks generated hence we have removed them altogether [8].

In our case, the scope of sensitivity analysis is limited to the change in relative weights of criteria. We change the weight of each criterion, i.e., Wgt.Avg.F-score, CPUTimeTesting, CPUTimeTraining and Consistency, one at a time, and compute the SpearmanâĂ§s rank correlation coefficient value to see how the proposed method behaves with the changed weights. For the criteria Wgt.Avg.F-score, CPUTimeTesting, CPUTimeTraining and Consistency, the results generated by the proposed methodology using weights (0.70,0.05,0.10,0.15).

The performance results of the proposed method are significantly better than the results of the PAlg and ARR under the three different setup: all (k=35) algorithms, top k=5 algorithms and top k=3 algorithms. Similar interpretation can be made for PAlg method. However, this method produces ranks for the algorithms (with k=35) on the ADA Agnostic dataset, which is statistically insignificant with respect to the ideal ranking. Similarly, the results of ARR method are significantly poor as compared to the proposed methods under all the conditions of k=35, k=5 and k=3.

FURTHER WORK

We can use techniques such as Bayesian Optimization for hyperparameter tuning of all models. Although, being more time consuming, this will ensure that we get the best model in the end. Model can be further enhanced to recommend algorithms for different kinds of datasets not only binary classification datasets.Different techniques of similarity measuring can be used instead of cosine and euclidean for best results.

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