Knowledge Structure Infusion for Classification in Supervised Learning in Data Mining

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Abstract

Nowadays classifications in supervised learning are getting significant in the domain of data mining due to the frequent applications obtained for the society. However the research community finds the difficulty in tackling supervised learning. The main aim (objective, goal, result of this paper is to achieve a simple layout for the knowledge structure for an effective class room (learning platform) in order to meet the learning outcome of classifications in supervised learning. the construction is carefully made after surveys & reviews throughout the branches of **bharath university** and obtained the knowledge structural model .this model is finally evaluated for its performance and result are presented.

Keywords: Regression, Classification, Ontology, Knowledge Structure, Reinforcement, Machine Learning

1. Introduction

In this section presents the supervised learning is the machine learning task of learning a function that maps an input to an output based on example input-output pairs. A supervised learning algorithm analyzes, the training data and produces an inferred function.Supervised and Unsupervised Machine Learning Algorithms. The majority of practical machine learning uses supervised learning.

Supervised learning is where you have input variables (x) and an output variable (Y) and you use an algorithm to learn the mapping function from the input to the output.

$$Y = f(X)$$

The goal is to approximate the mapping function so well that when you have new input data (x) that you can predict the output variables (Y) for that data.

It is called supervised learning because the process of an algorithm learning from the training dataset can be thought of as a teacher supervising the learning process. We know the correct answers, the algorithm iteratively makes predictions on the training data and is corrected by the teacher. Learning stops when the algorithm achieves an acceptable level of performance.Supervised learning problems can be further grouped into regression and classification problems.

Some popular examples of supervised machine learning algorithms are:

- Linear regression for regression problems.
- Random forest for classification and regression problems.
- Support vector machines for classification problems.

In section two presents the related works around machine learning in order to link the relevance of our work. The section three describes the terms and methods in order to enhance the readability of the research work. The section four presents the main experiments applied for main approach and the results are presented in the section five with concluding remarks.

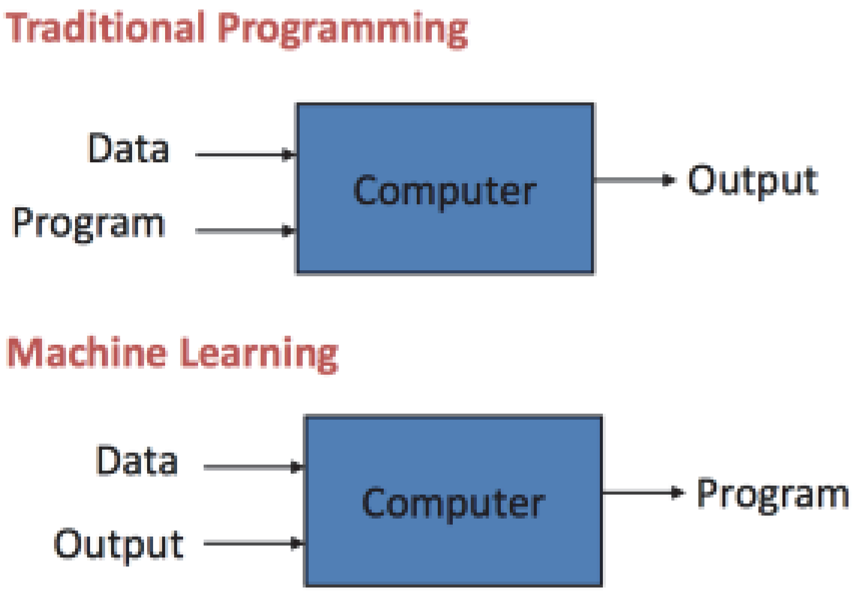

Fig.1 Machine Learning Vs Traditional Programming

2. Related works

In this section presents on the related works of the machine learning in supervised algorithms by using the optimization of an unknown black-box function and invoke algorithms developed for such problems. A good choice is Bayesian optimization [1], which has been shown to outperform other state of the art global optimization algorithms on a number of challenging optimization benchmark functions [2]. For continuous functions, Bayesian optimization typically works by assuming the unknown function was sampled from a Gaussian process and maintains a posterior distribution for this function as observations are made or, in our case, as the results of running learning algorithm experiments with different hyperparameters are observed. To pick the hyperparameters of the next experiment, one can optimize the expected improvement (EI) [1] over the current best result or the Gaussian process upper confidence bound (UCB)[3]. EI and UCB have been shown to be efficient in the number of function evaluations required to find the global optimum of many multimodal black-box functions [4, 3]. [7] have developed sequential model-based optimization strategies for the configuration of satisfiability and mixed integer programming solvers using random forests. The machine learning algorithms we consider, however, warrant a fully Bayesian treatment as their expensive nature necessitates minimizing the number of evaluations. Bayesian optimization strategies have also been used to tune the parameters of Markov chain Monte Carlo algorithms [8]. Recently, Bergstra et al. [5] have explored various strategies for optimizing the hyperparameters of machine learning algorithms. They demonstrated that grid search strategies are inferior to random search [9],

3. Terms and Methods

In this section the terms and methods for supervised learning classifications are described in simple form as follows. The terms are introduced from the conceptual level and methods are selected to emphasis the proof of existence of terminology for supervised learning classifications.

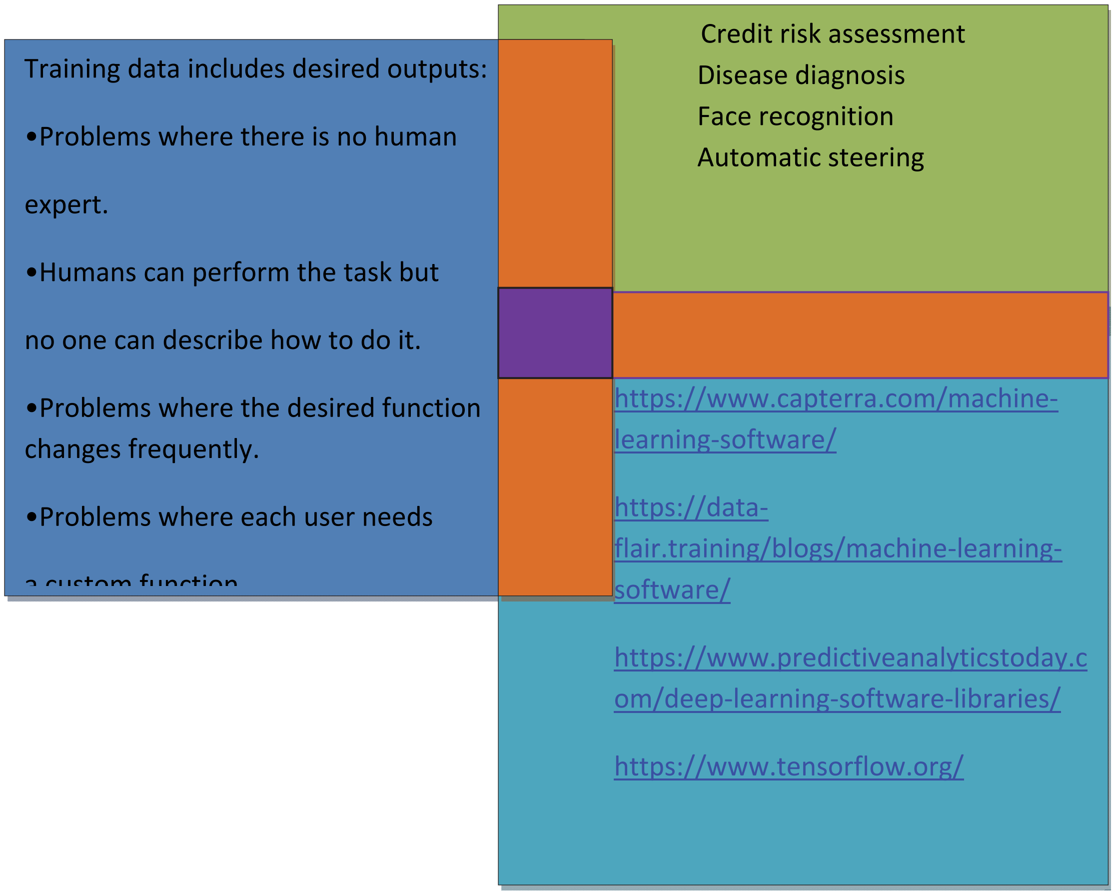

Fig 2. Architecture Diagram

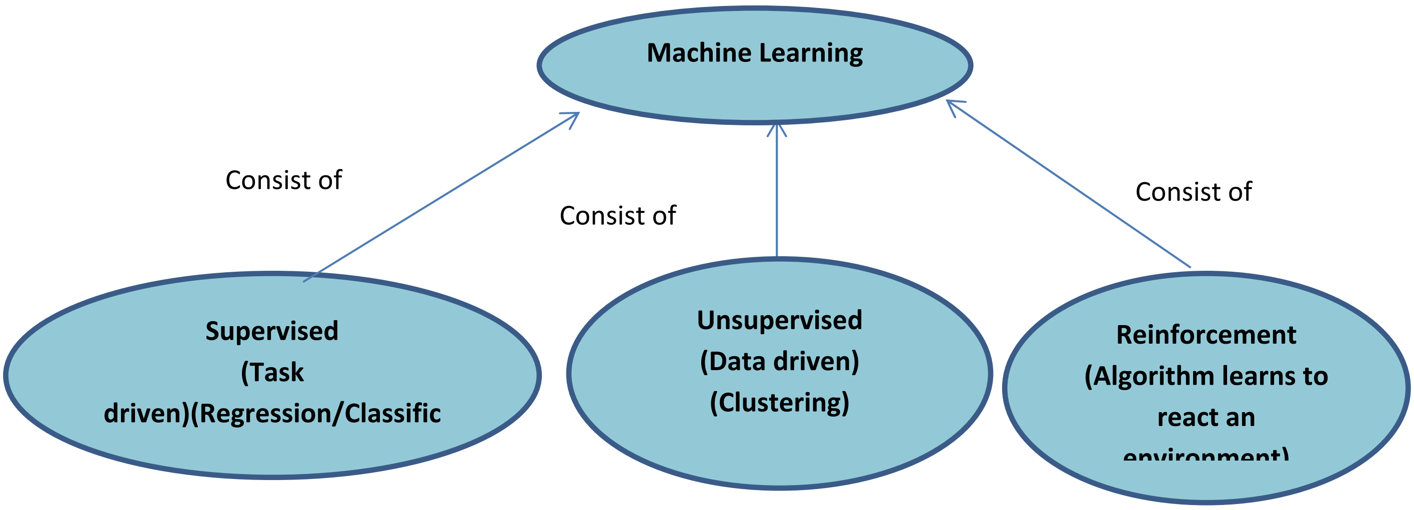

Fig: 3 Ontology for Machine Learning

The above diagram represents the ontology for Machine Learning.

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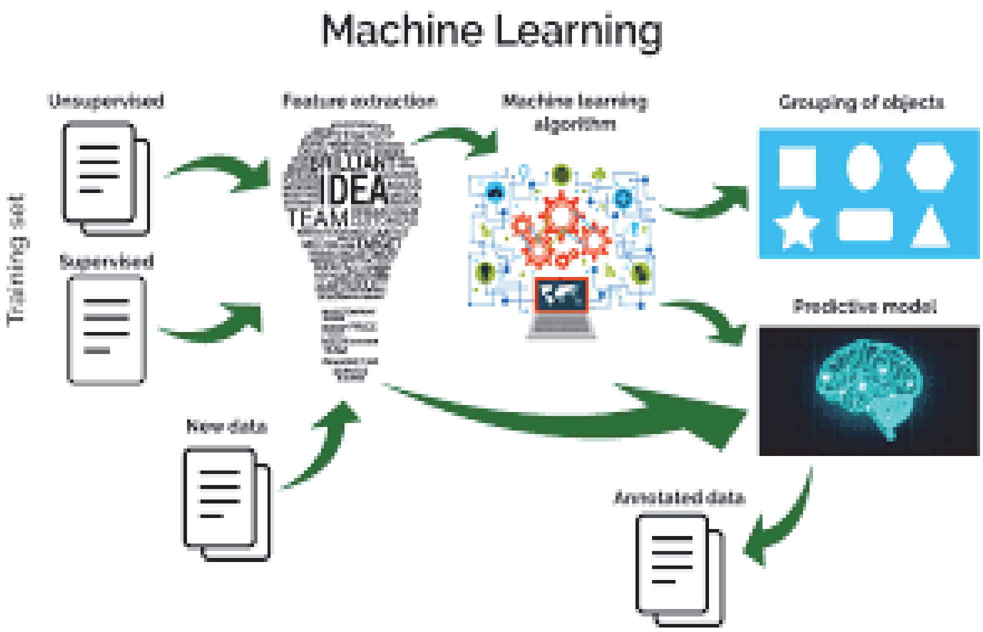

Fig: 4 Overview of conceptual elements

The above diagram represents the conceptual elements of the machine learning.

4. Methodology for Application of Machine Learning in Supervised Learning

The recent development in instruction Technology for Education has shown various methods for effective learning. Preparation of knowledge structure of supervised learning classifications for using inside a class room must be evaluated for its design and contents. The framework shown in the fig2.architecture diagram contains three components. The focus concept is treated with three levels namely with three levels familiarity scale, (which can be dealt as reading assignment or self study through the internet search engines), threshold concepts (which are mandatory learning task inside the class room or library or in the form of project based or mini projects) and list of pointers in the web space namely the uniform resource location.

5. Experimental Setup

The experiments based on our selection of topic in the domain of interest were carried out. This had been implemented with appropriate approvals from authorities in the university. Since the knowledge structure is part of activities of the teacher's pedagogy style, getting permissions happened to be cleared quickly as well automatically. Few classes were selected for internal assessment and these tools were applied to check the feasibility and the correctness of the approaches. The following table shows the difference in the performance.

Table 1.Comparison of KS –(N) with Non KS approaches

S.No	Class	Branch	with KS	Without KS
1	II A	IT	98%	83%
2	II B	IT	92%	80%
3	III A	CSE	90%	75%
4	III B	CSE	83%	73%
5	III C	CSE	70%	65%
6	IIA	CSE	58%	51%
7	IIB	CSE	56%	52%
8	IIIC	IT	83%	79%

The above table clearly makes us to understand the following observations. The foremost observation is the KS approach demonstrates the other approaches. The last row values are inferior due to the learning style of the students in the class as well as difficulty level inherently hidden in the some of the parts of supervised learning.

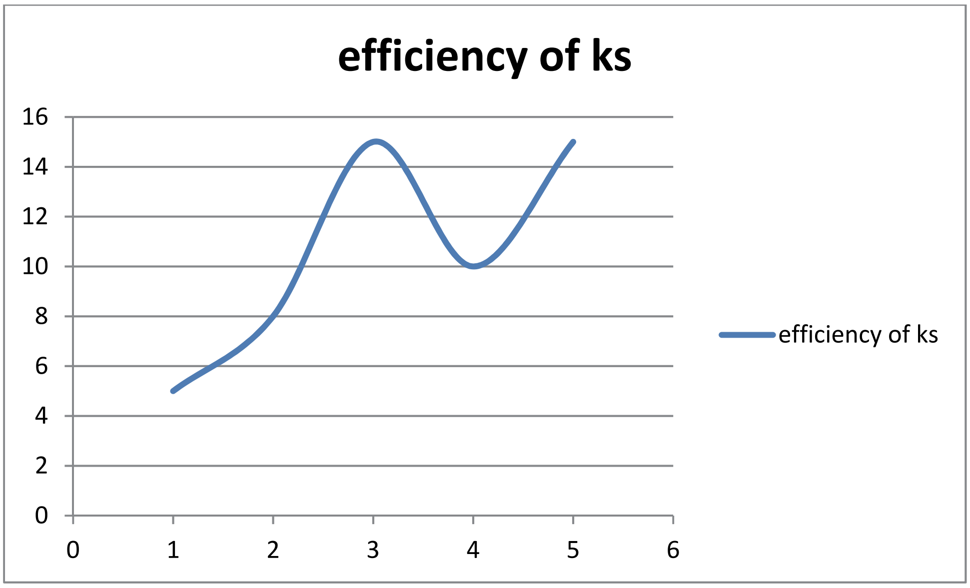

Fig.5 Efficiency of knowledge structure

In fig.5 the efficiency of depicted by the difference in the approaches and it demonstrate the performance appreciably. The maximum efficiency is found for approach in the range of 14% to 15%.

6. Conclusions

The spectrum of methods followed traditionally yields much variation and not of any lifted advantages. However our novel approach based knowledge structure mapping into the syllabus contents yield better results as demonstrated by our experiments

7. Acknowledgement

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