IJCSE International Journal of Computer Sciences and Engineering Open Access
Review Paper Volume4, Issue-8 E-ISSN: 2347-2693

Analysis on Machine Learning Techniques

S . Parvathavardhini[1*] and Dr .S . Manju[2]

[2]Dept of Computer Science,
Sri Ramakrishna College of Arts and Science for Women, India

Available online at: www.ijcseonline.org

Received: 22/Jun/2016 Revised: 10/Jul/2016 Accepted: 16/Aug/2016 Published: 31/Aug/2016

Abstract-*Machine learning* is the self-driven technology. It is the science of getting computers to act without being explicitly programmed. Machine learning refers to self-improving algorithms, explores the study and construction of algorithms that can learn from and make predictions on data. These are predefined processes conforming to specific rules, performed by a computer can be applied to any learning task and it is flexible and it don't need a programmer or human expert.Machine learning algorithms are common in web applications that we use every day and have a growing relevance to enterprise applications. Two of the most widely adopted machine learning methods are supervised learning and unsupervised learning. While many machine learning algorithms have been around for a long time, the ability to automatically apply complex mathematical calculations to big data – over and over, faster and faster is a recent development.

Keywords: Data mining, Artificial Intelligence, Neural Networks and Machine learning

I. INTRODUCTION:

Machine learning is a method of data analysis that automates analytical model building. Using algorithms that iteratively learn from data, machine learning allows computers to find hidden insights without being explicitly programmed where to look.Machine learning is used to reproduce known patterns and knowledge, automatically apply that to other data, and then automatically apply those results to decision making and actions. Machine learning is closely related to computational statistics; a discipline that aims at the design of algorithms for implementing statistical methods on computers. It has strong ties to mathematical optimization, which delivers methods, theory and application domains to the field. Machine learning is employed in a range of computing tasks where designing and programming explicit algorithms is infeasible. Eg applications include spam filtering.

Machine Learning is concerned with the design and development of algorithms. Machine Learning research is focusing on Learning and recognizing complex patterns and to make intellectual decisions based on data. In the field of Machine Learning, algorithms are organized on the expected outcomes. Reinforcement Learning is a type of Machine Learning algorithm, which gains knowledge based on the observation of environment. The outcome of the environment is rewards. The main advantage of Reinforcement Learning is that, it provides most successful rewards even when the environment is too large or cannot be shortly described[23].The machine learning method "unsupervised learning" or "learning without a teacher" is generically associated with the idea of using a collection of observation X1,..., Xn sampled from a distribution p(X) to describe properties of p(X). This definition is extremely generic, and could describe, for example, any procedure of descriptive statistics.Unsupervised learning methods are used in bioinformatics for sequence analysis and genetic clustering; in data mining for sequence and pattern mining; in medical imaging for image segmentation; and in computer vision for object recognition. One of the approaches in unsupervised learning is the method of moments. In the method of moments, the unknown parameters (of interest) in the model are related to the moments of one or more random variables, and thus, these unknown parameters can be estimated given the moments. The moments are usually estimated from samples in an empirical way. The basic moments are first and second order moments. For a random vector, the first order moment is the mean vector, and the second order moment is thecovariance matrix.Higher order moments are usually represented using tensors which are the generalization of matrices to higher orders as multi-dimensional array.The most common unsupervised learning method is cluster analysis, which is used for exploratory data analysis to find hidden patterns or grouping in data. The clusters are modeled using a measure of similarity which is defined upon metrics such as Euclidean or probabilistic distance. Most machine learning – about 70 percent – is supervised learning. Unsupervised learning accounts for 10 to 20 percent. Semi-supervised and reinforcement learning are two other technologies that are sometimes used.

Machine learning is sometimes conflated with data mining, although that focuses more on exploratory data analysis.Machine learning and pattern recognition can be viewed as two facets of the same field.When employed in industrial contexts, machine learning methods may be referred to as predictive analytics or predictive modelling. Supervised learning algorithms are trained using labeled examples, such as an input where the desired output is known. For example, a piece of equipment could have data points labeled either "F" (failed) or "R" (runs). The learning algorithm receives a set of inputs along with the corresponding correct outputs, and the algorithm learns by comparing its actual output with correct outputs to find errors. It then modifies the model accordingly. Through methods like classification, regression, prediction and gradient boosting, supervised learning uses patterns to predict the values of the label on additional unlabeled data. Supervised learning is commonly used in applications where historical data predicts likely future events. For example, it can anticipate when credit card transactions are likely to be fraudulent or which insurance customer is likely to file a claim. Machine learning is used to reproduce known patterns and knowledge, automatically apply that to other data, and then automatically apply those results to decision making and actions.Reinforcement learning is often used for robotics, gaming and navigation. With reinforcement learning, the algorithm discovers through trial and error which actions yield the greatest rewards. This type of learning has three primary components: the agent (the learner or decision maker), the environment (everything the agent interacts with) and actions (what the agent can do). The objective is for the agent to choose actions that maximize the expected reward over a given amount of time. The agent will reach the goal much faster by following a good policy. So the goal in reinforcement learning is to learn the best policy.This analysis mainly focuses on Unsupervised Learning,Supervised Learning,Neural networks ,Artificial intelligence and Reinforcement learning associated with Machine learning.

II.REVIEW:

Semisupervised Learning:

In classification, semisupervised learning usually involves a large amount of unlabeled data with only a small number of labeled data. This imposes a great challenge in that it is difficult to achieve good classification performance through labeled data alone. To leverage unlabeled data for enhancing classification, this article introduces a large margin semisupervised learning method within the framework of regularization, based on an efficient margin loss for unlabeled data, which seeks efficient extraction of the information from unlabeled data for estimating the Bayes decision boundary for classification. For implementation, an iterative scheme is derived through conditional expectations.Finally, theoretical and numerical analyses are conducted, in addition to an application to gene function prediction. They suggest that the proposed method enables to recover the performance of its supervised counterpart based on complete data in rates of convergence, when possible. Our specific focus is predicting functional categories defined by the MIPS, a multifunctional classification schem. For simplicity, we examine two functional categories,namely "transcriptional control" and "mitochondrion", with 334 and 346 annotated genes, respectively.The goal is to predict gene functional categories for genes annotated within these two categoriesby training our semisupervised classifier on expression profiles of genes, where some genes are treated as if their functions are unknown to mimic the semisupervised scenario in complete dataset[17].

This analysis presents a novel semi-supervised method that employs a learning paradigm which we call structural learning. The idea is to find "what good classifiers are like" by learning from thousands of automatically generated auxiliary classification problems on unlabeled data. By doing so, the common predictive structure shared by the multiple classification problems can be discovered,which can then be used to improve performance on the target problem. The method produces performance higher than the previous best results on CoNLL'00 syntacticchunking and CoNLL'03 named entity chunking. Our goal has been to develop a general learning framework for reliably using unlabeled data to improve performance irrespective of the amount of labeled data available. It is exactly this important and difficult problem that we tackle here. We present two general strategies for generating useful auxiliary problems: one in a completely unsupervised fashion, and the other in a partiallysupervised fashion. The key idea is to create auxiliary problems automatically from unlabeled data so that predictive structures can be learned from that data. In practice,it is desirable to create as many auxiliary problems as possible, as long as there is some reason to believe in their relevancy to the task. This is because the risk is relatively minor while the potential gain from relevant problems is large[32].

The semi-supervised learning problem is then formulated in terms of a Gaussian random field on this graph, the mean of which is characterized in terms of harmonic functions. Active learning is performed on top of the semisupervised learning scheme by greedily selecting queries from the unlabeled data to minimize the estimated expected classification error (risk); in the case of Gaussian fields the risk is efficiently computed using matrix methods. We propose to perform active learning with the Gaussian random field model by greedily selecting queries from the unlabeled data to minimize the risk of the harmonic energy minimization function. The risk is the estimated generalization error of the Bayes classifier, and can be

efficiently computed with matrix methods.We present experimental results on synthetic data,handwritten digit recognition, and text classification tasks. The active learning scheme requires a much smaller number of queries to achieve high accuracy compared with random query selection. We have proposed an approach to active learning which is tightly coupled with semi-supervised learning using Gaussian fields and harmonic functions. The algorithm selects queries to minimize an approximation to the expected generalization error. Experiments on text categorization and handwritten digit recognition indicate that the active learning algorithm can be highly effective[48].

The goal of our work here is to propose a simple semisupervised learning method that consistently provides accuracy improvements, that is robust across many problem domains without meta-parameter tuning, and scalable to extremely large unlabeled data set sizes.This paper presents expectation regularization (XR), a new method for semi-supervised learning with exponential-family parametric models. Many exponential-family models such as logistic regression and multi-class maximum entropy classifiers are optimized by maximizing the conditional log-likelihood of the true labels given the input features. XR augments this objective function by adding a second term that encourages model predictions on unlabeled data to match certain designer-provided expectations. In particular, the XR term minimizes the KL-divergence between feature/label expectations predicted by the model and human-provided feature/label expectation priors. In this paper we empirically explore one important special case termed label regularization, in which the human provides a label prior distribution, and the XR term encourages the optimization procedure to find parameters that predict a similar label distribution on the unlabeled examples. Appropriate label distributions are often easily provided by human prior knowledge; alternatively they can be obtained from the limited labeled data, from which they can be estimated far more accurately than sparse input feature distributions[11].

In this analysis,we investigate a more common case of semi-supervised learning for imbalanced sentiment classification. In particular, various random subspaces are dynamically generated to deal with the imbalanced class distribution problem. Evaluation across four domains shows the effectiveness of our approach.. This paper employs the co-training technique in semi-supervised learning for imbalanced sentiment classification.In particular, different views are generated from random subspaces. Balanced sentiment classification. We first adopt under-sampling to generate multiple sets of balanced initial training data and then propose a novel semi-supervised learning method based on random subspace generation which dynamically generates various subspaces in the iteration process to guarantee enough variation among the involved classifiers. Evaluation shows that our semi-supervised method can successfully make use of the unlabeled data and that dynamic subspace generation significantly outperforms traditional static subspace generation.To the best of our knowledge, this is the first work that systematically addresses the imbalanced class distribution problem in sentiment classification, especially under semi-supervised learning[37].

This analysis reviews key ideas in this literature. The performance and behavior of various S3VM algorithms is studied together, under a common experimental setting. The aim of this paper is to provide a review of optimization techniques for semi-supervised SVMs and to bring different implementations, and various aspects of their empirical performance,under a common experimental setting. A problem in performing a Newton optimization with a non-convex optimization function is that the step might not be a descent direction because the Hessian is not necessarily positive definite. To avoid this problem, we use the Levenberg-Marquardt algorithm .Roughly speaking, this algorithm is the same as Newton minimization, but a large enough ridge is added to the Hessian such that it becomes positive definite. When practical S3VM implementations fail to give good results on a problem, one might suspectthat either: (a) the cluster assumption does not hold; or, (b) the cluster assumption holds but local minima problems are severe; or, (c) the S3VM objective function is unable to implement the cluster assumption. We began our empirical study by benchmarking current S3VM implementations against a global optimizer. Our results narrowed the cause for performanceloss down to suboptimal local minima, and established a correlation between generalization performanceand the S3VM objective function. For problems where the cluster assumption is true, we expect the S3VM objective to indeed be an appropriate quantity to minimize. Due to non-convexity however, this minimization is not completely straightforward—an assortment of optimization techniques have been brought to bear on this problem with varying degrees of success. In this paper,we have reviewed these techniques and studied them empirically, taking several subtle differences into account. In a neutral experimental protocol, we were unable to identify any single technique as being consistently superior to another in terms of generalization performance. We believe better methods are still needed to optimize the S3VM objective function[29].

In this analysis, we show that S3VMs, with knowledge of the means of the class labels of the unlabeled data, is closely related to the supervised SVM with known labels on all the unlabeled data. This motivates us to first estimate the label means of the unlabeled data.Two versions of the *meanS3VM*, which work by maximizing the margin between the label means,are proposed. The first one is based on multiple kernel learning, while the second one is based on alternating optimization. Experiments show that both of the

proposed algorithms achieve highly competitive and sometimes even the best performance as compared to the state-of-the-art semi-supervised learners. Moreover, they are more efficient than existing S3VMs. we propose in this paper a new approach which works by first estimating the label means of the unlabeled data. We show that the semi-supervised SVM with known label means of unlabeled data is closely related to the supervised SVM that has access to all the labels of the unlabeled examples. Based on this observation, we propose two algorithms that maximize the margin between the label means of the unlabeled data. Experiments on a broad range of data sets show that, in comparison with state-of-the-art semi-supervised learning methods, both of our proposed algorithms achieve highly competitive or sometimes even thebest performance, and are much faster to train[51].

In this we extend ELMs for both semi-supervised and unsupervised tasks based on the manifold regularization, thus greatly expanding the applicability of ELMs. The key advantages of the proposed algorithms are 1) both the semi-supervised ELM(SS-ELM) and the unsupervised ELM (US-ELM) exhibit the learning capability and computational efficiency of ELMs; 2) both algorithms naturally handle multi-class classification or multi-cluster clustering; and 3) both algorithms are *inductive* and can handle unseen data at test time directly. Moreover, it is shown in this paper that all the supervised, semi-supervised and unsupervised ELMs can actually be put into a unified framework.This provides new perspectives for understanding the mechanism of *random feature mapping*, which is the key concept in ELM theory. Empirical study on a wide range of data sets demonstrates that the proposed algorithms are competitive with state-of-the-art semi-supervised or unsupervised learning algorithms in terms of accuracy and efficiency. One of the most successful algorithms for training SLFNs is the support vector machines (SVMs) which is a maximal margin classifier derived under the framework of structural risk minimization (SRM). The dual problem of SVMs is a quadratic programming and can be solved conveniently. Due to its simplicity and stable generalization performance, SVMs have been widely studied and applied to various domains. In this paper, we have proposed two algorithms, SSELM and US-ELM, to extend the traditional ELMs for semi-supervised and unsupervised learning tasks, respectively.Compared to existing semi-supervised ELM algorithms, the proposed SS-ELM maintains almost all the advantages of ELMs, such as the remarkable training efficiency and direct implementation for multi-class classification problems. On a variety of data sets, SS-ELM consistently outperformed pure supervised learning algorithms such as SVMs and ELMs when auxiliary unlabeled data are available. It also led to competitive results with several state-of-the-art semi-supervised learning algorithms, and it required significantly less training time on multi-class classification problems. With respect to the unsupervised learning algorithm US-ELM, to the best of our knowledge, it is the first extension of ELMs for embedding and clustering based on the spectral techniques.We have evaluated US-ELM on a wide range of real world clustering tasks. Experimental results demonstrate that USELM gives favorable performance compared to state-of-the-art clustering algorithms. These two extensions of ELMs for semisupervised and unsupervised learning are expected to greatly expand the applicability of ELMs, and provide new insights into the extreme learning paradigm[10].

The analysis have shown that semi-supervised novelty detection reduces to Neyman-Pearson classification.This allows us to leverage known performance guarantees for NP classification algorithms, and to import practical algorithms. We have applied techniques from statistical learning theory, such as uniform deviation inequalities, to establish distribution free performance guarantees for SSND, as well as a distribution free lower bound and universally consistent estimator for p, and test for $p = 0$.Our approach optimally adapts to the unknown novelty distribution, unlike inductive approaches,which operate as if novelties are uniformly distributed. We also introduced a hybrid method that has the properties of SSND when $p > 0$, and effectively reverts to the inductive method when $p = 0$.Our analysis strongly suggests that in novelty detection, unlike traditional binary classification,unlabeled data are essential for attaining optimal performance in terms of tight bounds, consistency,and rates of convergence. In an extensive experimental study, we found that the advantages of our approach are most pronounced for high dimensional data. Our analysis and experiments confirm some challenges that seem to be intrinsic to the SSND problem. In particular, SSND is more difficult for smaller p. Furthermore, estimating the novelty proportion p can become arbitrarily difficult as the nominal and novel distributions become increasingly similar.Our methodology also provides general solutions to two well-studied problems in hypothesis testing. First, our lower bound on p translates immediately to a test for $p = 0$, which amounts to a distribution-free solution to the two-sample problem. Second, we also show that SSND provides a powerful generalization of standard multiple testing[12].

We present a method for utilizing unannotated sentences to improve a semantic parser which maps natural language (NL) sentences into their formal meaning representations(MRs). Given NL sentences annotated with their MRs, the initial supervised semantic parser learns the mapping by training Support Vector Machine(SVM) classifiers for every production in the MR grammar. Our new method applies the learned semantic parser to the unannotated sentences and collects unlabeled examples which are then used to retrain the classifiers using a variant of *transductive* SVMs. Experimental results show the improvements obtained over the purely supervised parser,

particularly when the annotated training set is small. This paper has presented a semi-supervised approach to semantic parsing. Our method utilizes unannotated sentences during training by extracting unlabeled examples for the SVMclassifiers it uses to perform semantic parsing. These classifiers are then retrained using transductive SVMs. Experimental results demonstrated that this exploitation of unlabeled data significantly improved the accuracy of the resulting parsers when only limited supervised data was provided[33].

Supervised learning:

This study presents results of a large-scale empirical comparison of ten supervised learning algorithms using eight performance criteria. The results depend on the choice of problems and metrics. What impact might selecting other problems, or evaluating performance on other metrics, have on the results? For example, neural nets perform well on allmetrics on 10 of 11 problems, but perform poorly on COD. If we hadn't included the COD problem, neural nets would move up 1-2 places in the rankings.To help evaluate the impact of the choice of problems and metrics we performed a bootstrap analysis. We randomly select a bootstrap sample (sampling withreplacement) from the original 11 problems. For this sample of problems we then randomly select a boot-strap sample of 8 metrics from the original 8 metrics(again sampling with replacement). For this bootstrapsample of problems and metrics we rank the ten algorithms by mean performance across the sampled problems and metrics (and the 5 folds). This bootstrap sampling is repeated 1000 times, yielding 1000 potentially different rankings of the learning methods. With excellent performance on all eight metrics, calibrated boosted trees were the best learning algorithm overall. Random forests are close second, followed by uncalibrated bagged trees, calibrated SVMs, and uncalibrated neural nets. The models that performed poorest were naive bayes, logistic regression, decision trees, and boosted stumps. Although some methods clearly perform better or worse than other methods on average, there is significant variability across the problems and metrics[31].

Although a user can get started with RTextTools in less than ten steps, many more options are available that help to remove noise, refine trained models, and ultimately improve accuracy. If you want more control over your data, please refer to the documentation bundled with the package. Moreover, there is hope that the package will become increasingly useful and flexible over time as advanced users develop add-on functions. RTextTools was designed to make machine learning accessible by providing a start-to-finish product in less than 10 steps. After installing RTextTools, the initial step is to generate a document term matrix. Second, a container object is created, which holds all the objects needed for further analysis. Third, users can use up to nine algorithms to train their data.Fourth, the data are classified. Fifth, the classification is summarized. Sixth, functions are available for performance evaluation. Seventh, ensemble agreement is conducted. Eighth, users can cross-validate their data. Finally, users write their data to a spreadsheet, allowing for further manual coding if required[44].

This explores and identifies the use of different learning algorithms for classifying spam messages from e-mail. A comparative analysis among the algorithms has also been presented. The data set was separated into two parts, one part is used as training data set to produce the prediction model, and the other part is used as test data set to test the accuracy of our model. The Training data set contains feature values as well asclassification of each record. Testing is done by 10-fold cross validation method. Thus through this paper a comprehensive analysis of various classifiers using different software tools viz. WEKA,RapidMiner was implemented on a common dataset. The results were compared based on a fore mentioned evaluation criteria. The study revealed that the same classifier performed dissimilarly when run on the same dataset but using different software tools. Some of those classifiers to different software tools for one would expect the classifiers to be consistent as the test was done on the same dataset. Classifier like LDA is a good example. However some classifiers like NB and Simple Logistic performs well. But when it is compared with MLP it seems not to be better. Thus from all perspectives MLP were top performers in all cases and thus can be deemed consistent.Further it is observed that for this dataset the error rate irrespective of the classifier for MLP yielded excellent error
rates compared to other algorithms[9].

The goal of this analysis is to study the impact of natural clustering according to expert domain knowledge on DR for supervised learning (SL) in the area of antibiotic resistance.We compare several data-mining strategies that apply DR by means of feature extraction or feature selection with subsequent SL on microbiological data. The results of our study show that local DR within natural clusters may result in better representation for SL in comparison with the global DR on the whole data. For some problem domains a feature subset may be useful in a subspace of the instance space, and at the same time, it may be useless or even misleading in another subspace. In such a situation, it might be difficult or even impossible to remove irrelevant and/or redundant features and leave only the useful ones using global FS. However, if it is possible to find local homogeneous subspaces of the instance space, then there might be better chances to apply FS successfully. For FE, the decision whether to proceed globally over the entire instance space or locally in different subspaces is also one of the key issues. It can be demonstrated that despite being globally high dimensional and sparse, data distributions in

some subareas of the instance space are often low dimensional and dense, for example, in physical movement systems . The results of our study show that natural clustering is an effective approach that facilitates local DR and that the proper selection of a DR technique within each natural cluster enables to get higher predictive accuracy (on average) in comparison with the global SL with or without DR. DR is an effective approach to data reduction aimed at focusing on relevant features and improving the quality of data representation. We experimentally compared and showed the benefits of local and global DR (by means of FS and FE) for subsequent SL. In this paper, we applied the natural clustering approach using contextual features (constructed with the help of domain experts) to split a real-world clinical data set into more homogeneous clusters to use DR and SL locally.The results of our experiments demonstrate that the proper selection of a local DR technique can lead to the increase of predictive accuracy in comparison with the global classification with or without DR. The amount of features extracted or selected is always smaller for local than global DR. This shows the usefulness of natural clustering in coping with data heterogeneity and high dimensionality[26].

In this study,a filter method that directly aimsto select the optimal set of features for a general performance measure of interest has been developed. This approach uses the Bayes error with respect to the given performance measure as the criterion for feature selection and applies a greedy algorithm to optimize this criterion. We demonstrate application of this method to a variety of learning problems involving different performance measures. Experiments suggest the proposed approach is competitive with several state-of-the-art methods. We have developed a Bayes optimal filter method for feature selection with supervised learning considering general performance measures, and provided instantiations of our method for a variety of learning problems and performance measures. Experiments demonstrate that our approach is competitive with many state-of-the-art methods. While our focus has been on problems with binary labels, our approach easily generalizes to multiclass settings[34].

In this novel framework for estimating margin-based risks using only unlabeled data has been developed.We shows that it performs well in practice on several different datasets. We derived a theoretical basis by casting it as a maximum likelihood problem for Gaussian mixture model followed by plug-in estimation. Remarkably, the theory states that assuming normality of f_(X) and a known p(Y) we are able to estimate the risk R(θ) without a single labeled example. That is the risk estimate converges to the true risk as the number of unlabeled data increase. Moreover,using uniform convergence arguments it is possible to show that the proposed training algorithm converges to the optimal classifier as $n \rightarrow \infty$ without any labels[19].

This research is related to the study of the existing classification algorithm and their comparative in terms of speed, accuracy, scalability and other issues which in turn would help other researchers in studying the existing algorithms as well as developing innovative algorithms for applications or requirements which are not available.This work concentrated on the comparative study of some very well known classification algorithms like Decision Tree Induction, Baysian Network, Neural Network, K-nearest neighbours and Support Vector Machine. A comparative study would definitely bring out the advantages and disadvantages of one method over the other. This would provide the guideline for interesting research issues which in turn help other researchers in developing innovative algorithms for applications or requirements which are not available. In this paper the comparison of the most well known classification algorithms like decision trees, neural network, Bayesian network, nearest neighbour and support vector machine has been done in detail. The aim behind this study was to learn their key ideas and find the current research issues, which can help other researchers as well as students who are doing an advanced course on classification. The comparative study had shown that each algorithm has its own set of advantages and disadvantages as well as its own area of implementation. None of the algorithm can satisfy all the criteria. One can investigate a classifier which can be built by an integration of two or more classifier by combining their strength[13].

This study, focus attention on the methods which are being used for supervised learning. This study will contribute to new researchers for getting up-to-date knowledge about supervised ML approaches. Due to scope of this paper, it is very difficult to discuss the strength and weaknesses of each algorithm of ML. The selection of algorithm in ML is mainly depends on task nature. The performance of SVM and Neural Networks is better when dealing with multidimensions and continuous features. While logic-based systems tend to perform better when dealing with discrete/categorical features. For neural network models and SVMs, a large sample size is required in order to achieve its maximum prediction accuracy whereas NB may need a relatively small dataset[14].

The analysis presents a new learning approach for pattern classification applications involving imbalanced data sets. In this approach, a clustering technique is employed to resample the original training set into a smaller set of representative training exemplars, represented by weighted cluster centers and their target outputs. Based on the proposed learning approach, four training algorithms are derived for feed-forward neural networks.These algorithms are implemented and tested on three benchmark data sets. Experimental results show that with the proposed learning approach, it is possible to design networks to tackle the class

imbalance problem,without compromising the overall classification performance[27].

The problem addressed in this study is machine learning in an intelligent environment. The intelligent environment is a computer system that executes a number of services according to perceptual information on user actions or activity. As we know, user behavior changes in the course of time. The automatic adaptation of system (re)actions according to changing user needs is seen as machine learning process.We need information in the form of feedback on executed system services in order to guide the learning process[26].

Reinforcement learning:

The central issues of reinforcement learning, including trading, exploration and exploitation, establishing the foundations of the field via Markov decision theory, learning from delayed reinforcement, constructing empirical models to accelerate learning, making use of generalization and hierarchy, and coping with hidden state. It concludes with a survey of some implemented systems and an assessment of the practical utility of current methods for reinforcement learning[21]. Creative thinking provide ways to many technical ideas, were new innovations will come to existence. For a single problem there can be numerous innovative solutions, it is very important to make evaluation and selection of ideas to achieve better results[22].

Reinforcement Learning techniques allow an agent to become competent simply by exploring its environment and observing the resulting percepts and rewards, gradually converging on estimates of the value of actions or states that allow it to behave optimally. In this Learning there is no requirement for a skilled human to provide training examples. Secondly, the exploration process allows the agent to become competent in areas of the state space that are seldom visited by human experts and for which no training examples may be available[25].

In this reinforcement learning approach for mapping natural language instructions to sequences of executable actions has been presented. We assume access to a reward function that defines the quality of the executed actions. During training, the learner repeatedly constructs action sequences for a set of documents, executes those actions, and observes the resulting reward. We use a policy gradient algorithm to estimate the parameters of a log-linear model for action selection. We apply our method to interpret instructions in two domains windows troubleshooting guides and game tutorials. Our results demonstrate that this method can rival supervised learning techniques while requiring few or or no annotated training examples. To apply our algorithm to the Windows domain, we use the Win32 application programming interface to simulate human interactions with the user interface, and to gather environment state information. The operating system environment is hosted within a virtual machine,allowing us to rapidly save and reset system state snapshots. For the puzzle game domain, we replicated the game with an implementation that facilitates automatic play. For evaluation, we compare the results to manually constructed sequences of actions. We measure the number of correct actions, sentences, and documents. An action is correct if it matches the annotations in terms of command and parameters. A sentence is correct if all of its actions are correctly identified, and analogously for documents.11 Statistical significance is measured with the sign test. In this paper, we presented a reinforcement learning approach for inducing a mapping between instructions and actions. This approach is able to use environment-based rewards, such as task completion, to learn to analyze text. We showed that having access to a suitable reward function can significantly reduce the need for annotations[5].

Reinforcement learning is generally a hard problem and many of its challenges are particularly apparent in the robotics setting. As the states and actions of most robots are inherently continuous, we are forced to consider the resolution at which they are represented. We must decide how fine grained the control is that we require over the robot, whether we employ discretization or function approximation, and what time step we establish.we have reviewed a large variety of problems and associated solutions within robot reinforcement learning. In this section, we will take a complementary approach and discuss one task in detail that has previously been studied. This ball-in-a-cup task due to its relative simplicity can serve as an example to highlight some of the challenges and methods that were discussed earlier. We do not claim that the method presented is the best or only way to address the presented problem; instead, our goal is to provide a case study that shows design decisions which can lead to successful robotic reinforcement learning.We have surveyed the state of the art in robot reinforcement learning for both general reinforcement learning audiences and robotics researchers to provide possibly valuable insight into successful techniques and approaches. From this overview, it is clear that using reinforcement learning in the domain of robotics is not yet a straightforward undertaking but rather requires a certain amount of skill. Hence, in this section, we highlight several open questions faced by the robotic reinforcement learning community in order to make progress towards “off-the-shelf” approaches as well as a few current practical challenges. Finally, we try to summarize several key lessons from robotic reinforcement learning for the general reinforcement learning community[16].

In this initial results from a computational study of intrinsically motivated reinforcement learning aimed at allowing arti- ficial agents to construct and extend

hierarchies of reusable skills that are needed for competent autonomy has been presented.One of the key aspects of the Playroom example was that intrinsic reward was generated only by unexpected salient events. But this is only one of the simplest possibilities and has many limitations. It cannot account for what makes many forms of exploration and manipulation "interesting." In the future, we intend to implement computational analogs of other forms of intrinsic motivation as suggested in the psychological, statistical, and neuroscience literatures. Despite the "toy" nature of this domain, these results are among the most sophisticated we have seen involving intrinsically motivated learning. Moreover, they were achieved quite directly by combining a collection of existing RL algorithms for learning options and option-models with a simple notion of intrinsic reward. The idea of intrinsic motivation for artificial agents is certainly not new, but we hope to have shown that the elaboration of the formal RL framework in the direction we have pursued, together with the use of recentlydeveloped hierarchical RL algorithms, provides a fruitful basis for developing competently autonomous agents[36].

The first large-scale empirical application of reinforcement learning to the important problem of optimized trade execution in modern financial markets. Our experiments are based on 1.5 years of millisecond time-scale limit order data from NASDAQ, and demonstrate the promise of reinforcement learning methods to market microstructure problems. Our learning algorithm introduces and exploits a natural "low-impact" factorization of the state space. In this paper, we report on the first extensive empirical application of reinforcement learning (RL) to the problem of optimized execution using large-scale NASDAQ market microstructure data sets. We begin our presentation of empirical results with a brief discussion of how our choice of stock, volume, and execution horizon affects the RL performance across all state space representations. All other factors kept constant, the following facts hold (and are worth keeping in mind going forward): 1. NVDA is the least liquid stock, and thus is the most expensive to trade; QCOM is the most liquid and the cheapest to trade. 2. Trading larger orders is always more costly than trading smaller ones. 3. Having less time to execute a trade results in higher costs. In simplest terms: one has to accept the largest price concession when he is selling a large number of shares of NVIDIA in the short amount of time[52].

This analysis explores a very simple agent design method called Q-decomposition, wherein a complex agent is built from simpler subagents. Each subagent has its own reward function and runs its own reinforcement learning process. It supplies to a central arbitrator the Q-values for each possible action. The arbitrator selects an action maximizing the sum of Q-values from all the subagents. This approach has advantages over designs in which subagents recommend actions. It also has the property that if each subagent runs the Sarsa reinforcement learning algorithm to learn its local Q-function, then a globally optimal policy is achieved. In some cases, this form of agent decomposition allows the local Q-functions to be expressed by muchreduced state and action spaces. These results are illustrated in two domains that require effective coordination of behaviors. Consider the problem of allocating resources in a commercial fishery. A commercial fishing fleet wishes to maximize the aggregate discounted value of its catch over time, which requires that it show at least some concern for the sustainability of the fish population. Individual fishermen, however, may choose to act selfishly and maximize their own profit, assuming that others in the fleet will reduce their catch for the viability of the fishery. If all fishermen follow the selfish policy, the result is a "tragedy of the commons": fish stocks collapse and the fishery dries up. In treating only local Q learning and local Sarsa, this paper has evaluated two points in the continuum of possible representations[41].

The analysis on the first deep learning model to successfully learn control policies directly from high-dimensional sensory input using reinforcement learning. The model is a convolutional neural network, trained with a variant of Q-learning, whose input is raw pixels and whose output is a value function estimating future rewards. We apply our method to seven Atari 2600 games from the Arcade Learning Environment, with no adjustment of the architecture or learning algorithm. We find that it outperforms all previous approaches on six of the games and surpasses a human expert on three of them. This paper demonstrates that a convolutional neural network can overcome these challenges to learn successful control policies from raw video data in complex RL environments. The network is trained with a variant of the Q-learning algorithm, with stochastic gradient descent to update the weights. To alleviate the problems of correlated data and non-stationary distributions, we use an experience replay mechanism which randomly samples previous transitions, and thereby smooths the training distribution over many past behaviors. This paper introduced a new deep learning model for reinforcement learning, and demonstrated its ability to master difficult control policies for Atari 2600 computer games, using only raw pixels as input. We also presented a variant of online Q-learning that combines stochastic minibatch updates with experience replay memory to ease the training of deep networks for RL. Our approach gave state-of-the-art results in six of the seven games it was tested on, with no adjustment of the architecture or hyperparameters[48].

In thsis analysis propose to use Reinforcement Learning for building an intelligent tutoring system to teach autistic students, who can't communicate well with others. In reinforcement learning, a policy is updated for taking appropriate action to teach the student. The main advantage of using reinforcement learning is that, it eliminates the need

for encoding pedagogical rules. Various issues in using reinforcement learning for intelligent tutoring systems are discussed in this paper.We are now concentrating on improving the present ITS using the hierarchical framework . In a hierarchical framework, entire knowledge base is divided into lessons and each lesson is divided into different categories. The RL agent has to learn two policies, one for picking a lesson and the other for picking a categories within the lesson, which is expected to improve the performance of the ITS. We have developed an ITS to teach pattern classification problem. In our case, pattern classification problem is that the student has to classify the pattern (question) given to him. This problem is selected for validating the approach using ANNs, though this is not directly relevant to teaching children. Appropriate question banks should be developed to teach human students. In pattern classification problem, the knowledge base contains two dimensional patterns from four classes, A, B, C and D. The classes are selected in such a way that if a random action is selected, the probability of selecting the pattern from class A is more than from the other classes. The target output for ANN is a four dimensional vector, for example, [1 0 0 0] is the target for class A, [0 1 0 0] is for class B, and so on. On-line training and testing have been performed on the ANN. The response (output) of ANN is classified into correct (1) and wrong (0) answers. For example, if the target of training question is [0 0 1 0] and if the third output of the ANN is higher than all other outputs then the response is considered as correct, else wrong. The summary of the ANN's response for past 300 questions and the history of responses for past 50 questions are considered for a state of the ANN[39].

In this a learning algorithm for deterministic OO-MDPs and prove a polynomial bound on its sample complexity has been introduced. We illustrate the performance gains of our representation and algorithm in the wellknown Taxi domain, plus a real-life videogame. In this paper, we propose an extension to the standard MDP formalism, which we call Object-Oriented MDPs (OOMDPs), and present an efficient learning algorithm for deterministic OO-MDPs. We claim that this object-based approach is a natural way of viewing and describing many real-life domains that enables multiple opportunities for generalization. There are many ways of incorporating objects into models for learning and decision making—this paper explores one particular approach as a first attempt to understand the issues that arise. To present and test our approach, we first provide benchmark experiments in the well-known Taxi domain. We further demonstrate its applicability by designing an agent that can solve an interesting problem in the real-life videogame Pitfall.

The problem of learning the transition dynamics of an OO-MDP has polynomial sample complexity in the KWIK setting have been shown,when by sample we only refer to the cases where an effect is observed. We introduced OO-MDPs, an object-oriented representation for reinforcement-learning problems that provides a natural way of modeling a broad set of domains, while enabling generalization. We presented DOORMAX, a learning algorithm for deterministic OO-MDPs that not only outperforms state-of-the-art algorithms for factored-state representations, but also scales very nicely with respect to the size of the state space, as long as transition dynamics between objects do not change. We presented bounds for learning transition dynamics of determinstic OO-MDPs in the KWIK framework[6].

In this analysis to what extent the action selection process can be automated by current state-of-the-art reinforcement learning methods for dialogue management has been assessed. In examining the strengths and weaknesses of these methods with respect to practical deployment, we discuss the challenges that need to be overcome before these methods can become commonplace in deployed systems. The evaluation of reinforcement learning techniques for spoken dialogue systems has mostly centered on user simulation. Ever since researchers began examining reinforcement learning for dialogue management, they have realized that obtaining data to learn a policy would be problematic . Because it is impractical, timeconsuming and burdensome to have a SDS explore all different types of actions with real users, the idea was to learn a generative model of the user so that user actions could be simulated in response to system actions. With good user modeling, a SDS could be rapidly prototyped and evaluated. Although this line of research is very promising and would greatly benefit practical deployment, the challenge of making sure that the user model truly reflects what real users are likely to do, which oftentimes is dependent on very subtle aspects of the dialogue design and task domain, is a daunting task. In this paper, we investigated reinforcement learning methods that utilize a fully or partially observable MDP for dialogue management. We assessed the strengths and weaknesses of these methods with respect to practical deployment and discussed challenges that need to be overcome before these methods can become commonplace in deployed systems. Finally, we compared the primary strength of these methods against its primary weakness and concluded that the current state-of-the-art is not quite ready for practical deployment[43].

Artificial intelligence:

One conclusion of the analysis is that classifier performance is often measured in terms of classification accuracy, e.g., with cross-validation tests.Some methods were found to be general in the way that they can be used to evaluate any classifier (regardless of which algorithm was used to generate it) or any algorithm (regardless of the structure or representation of the classifiers it generates),while other

methods only are applicable to a certain algorithm or representation of the classifier.Learning is a complex process as lot of decisions are made and also it depends from machine to machine and from algorithm to algorithm, how to understands a particular problem and on understanding the problem how it responds to it. Some of the issues make a complex situation for the machine to respond and react. These problems not only make problem complex it also affects the learning process of the machine. As the machine is dependent on what it perceives, the perception module of the machine should also focus on different types of challengesand environment which it will face, as different input can produce different outputs and the most appropriate and optimize output should be considered by the machine. The question of how to measure the performance of learning algorithms and classifiers has been investigated. This is a complex question with many aspects to consider. The thesis resolves some issues, e.g., by analyzing current evaluation methods and the metrics by which they measure performance,and by defining a formal framework used to describe the methods in a uniform and structured way. One out of ten evaluation methods was graphical, i.e., the method does not work like a function returning a performance score as output, but rather the user has to analyze a visualization of classifier performance.The applicability of measure-based evaluation for measuring classifier performance has also been investigated and we provide empirical experiment results that strengthen earlier published theoretical arguments for using measure-based evaluation.. Since time is often of essence when evaluating, e.g., if the evaluation method is used as a fitness function for a genetic algorithm, we have analyzed measure-based evaluation in terms of the time consumed to evaluate different classifiers. The conclusion is that the evaluation of lazy learners is slower than for eager learners, as opposed to cross-validation tests. Additionally, we have presented a method for measuring the impact that learning algorithm parameter tuning has on classifier performance using quality attributes. The results indicate that parameter tuning is often more important than the choice of algorithm. Quantitative support is provided to the assertion that some algorithms are more robust than others with respect to parameter configuration[2].

This analysis describes a new instance-based learning algorithm called the Boundary Forest (BF) algorithm, that can be used for supervised and unsupervised learning. The algorithm builds a forest of trees whose nodes store previously seen examples. It can be shown data points one at a time and updates itself incrementally, hence it is naturally online. Few instance-based algorithms have this property while being simultaneously fast, which the BF is. This is crucial for applications where one needs to respond to input data in real time. The number of children of each node is not set beforehand but obtained from the training procedure, which makes the algorithm very flexible with regards to what data manifolds it can learn. We test its generalization performance and speed on a range of benchmark datasets and detail in which settings it outperforms the state of the art. Empirically we find that training time scales as $O(DNlog(N))$ and testing as $O(Dlog(N))$, where D is the dimensionality and N the amount of data.We have described and studied a novel online learning algorithm with empirical $Nlog(N)$ training and $log(N)$ querying scaling with the amount of data N, and similar performance to $k-NN$.The speed of this algorithm makes it appropriate for applications such as real-time machine learning, and metriclearning[7].

The purpose of this analysis is to present the conceptual framework of well known Supervised and Unsupervised learning algorithms in pattern classification scenario and to discuss the efficiency of these models in an education industry as a sample study. In any ANN model that is used for classification problem, the principle is learning from observation. As the objective of the paper is to observe the pattern classification properties of those two algorithms, we developed Supervised ANN and Unsupervised ANN for the problem mentioned above. A Data set consists of 10 important attributes that are observed as qualification to pursue Master of Computer Applications (MCA), by a university/institution is taken. These attributes explains, the students' academic scores, priori mathematics knowledge, score of eligibility test conducted by the university. Three classes of groups are discovered by the input observation. Following sections presents the structural design of ANN models, their training process and observed results of those learning ANN model. We found out that though the error back-propagation supervised learning algorithm is very efficient for many non- linear real time problems, in the case of student classification KSOM – the unsupervised model performs efficiently than the supervised learning algorithm[35].

Neural networks:

In most networks, the principle of learning a network is based on minimizing the gradient of error. Therefore it is assumed that a network has a minimum error at the end of learning process but it is not always happened like this. Sometimes because of the largeness of the domain of changes of the input network signal, the activity function of some neurons will be saturated and at last the output of these categories of neurons will be fixed in their border amount. It can make a same situation for the next layers of neurons. With continuing this situation, the network will be in a stable mode. In this case the output of neurons will be fixed and continuing learning is not useful because the network is trapped at a minimum position as a cure we can teach the neurons activity function gradient like links weight. Among neurons activity functions sigmoid function (one directed & two directed) has the most application, therefore for studying the mathematical form of the network[53].

The MNIST handwritten digit dataset is generally considered as a well-studied problem, which offers the ability to ensure that new algorithms produce sensible results when compared to the many other techniques that have been benchmarked.The stochasticity introduced by the standout network successfully removes hidden units that are unnecessary for good performance and that hinder performance. When evaluated on the MNIST and NORB datasets, we found that our method achieves lower classification error rates than other feature learning methods, including standard dropout, denoising auto-encoders, and restricted Boltzmann machines.We trained a shallow one hidden layer auto-encoder on MNIST using the approximate learning algorithm. We can visualize the effect of the standout network by showing the units that output low dropout probability for one class but not others. The standout network learns that some hidden units are important for one class and tends to keep those. These hidden units are more likely to be dropped when the input comes from a different class.By inspecting the weights from auto-encoders regularized by dropout and standout, we find that the standout auto-encoder weights are sharper than those learnt using dropout, which may be consistent with the improved performance on classification tasks. Our results demonstrate that the proposed use of standout networks can significantly improve performanceof feature-learning methods. Further,results provide additional support for the 'regularization by noise' hypothesis that has been used to regularize other deep architectures, including RBMs and denoising auto-encoders, and in dropout[53].

The main aim is to explore the recent applications of Neural Networks and Artificial Intelligence and provides an overview of the field, where the AI & ANN"s are used and discusses the critical role of AI & NN played in different areas. Unsupervised learning is much more important then supervised learning since it likely to be much more common in the brain then supervised learning. The kind of learning is determined by the way in which the changes to network parameters have done. An activation function Φ (.) performs a mathematical operation on the outputs of neuron Vk. The activation functions are selected according to the types of problem to be solved by the network. The basic problem of behavior understanding is the target motion trajectory analysis. The goal of NLP is "to accomplish human-like language processing". The choice of the word processing is very deliberate, and should not be replaced with Understanding. Robotics is one field within artificial intelligence. The term "artificial intelligence" is defined as systems that combine sophisticated hardware and software with elaborate databases and knowledge-based processing models to demonstrate characteristics of effective human decision making. It involves mechanical, usually computer-controlled, devices to perform tasks that require extreme precision or tedious or hazardous work by people. Traditional Robotics uses Artificial Intelligence planning techniques to program robot behaviors and works toward robots as technical devices that have to be developed and controlled by a human engineer.

The Autonomous Robotics approach suggests that robots could develop and control themselves autonomously. These robots are able to adapt to both uncertain and incomplete information in constantly changing environments. It lets a simulated evolution process develop adaptive robots. The most intriguing use of robotics, however, is one that Mitsubishi just recently created. They have demonstrated robotic fish running AI programs, and swim around in the water. In fact, they look so real that only a close examination of the fish will reveal their robotic eyes .Two of the many research projects of the MIT Artificial Intelligence department include an artificial humanoid called Cog and his baby brother Kismet. What the researchers learn while putting the robots together will be shared to speed up development. Once finished, Cog will have everything except legs, whereas Kismet has only a 3·6-kilogram head that can display a wide variety of emotions. Kismet is an autonomous robot designed for social interactions with humans and is part of the larger Cog Project. This project focuses not on robot-robot interactions, but rather on the construction of robots that engage in meaningful social exchanges with humans .The goals of most robotic research projects is the advancement of abilities in one or more of the following technological areas Artificial intelligence, effectors and mobility, sensor detection and especially robotic vision, and control systems.Currently the most common trajectory analysis methods focus on the geometric characteristics of the whole trajectory and neglect the semantic information related to the common sub-trajectories . Here the task is all about the modeling or creating representation of object behaviors using detailed, learnt statistical models. A statistically based model of object trajectories is presented which is learnt from the observation of long image sequences[18].

The Forgy's algorithm is a method of unsupervised learning and classification using mirroring neural networks and forgy's clustering technique. In the implementation of Forgy's algorithm, initial seed points are selected in such a way that they are distant enough to be perfectly grouped into different categories. Thus a new method of unsupervised learning is formulated and demonstrated in this paper. This method gave impressive results when applied to classification of different image patterns.To improve the performance of Forgy's clustering technique as applied to our application, we set a threshold distance between randomly selected initial seed points.This threshold made the randomly selected seed points sufficiently far apart as to make Forgy's technique cluster the input patterns perfectly.The results of the algorithm over three different input patterns were encouraging. This can be extended to an architecture wherein the network will not only classify an

input image pattern but it can also learn and classify any new pattern which is not one of the trained patterns.In this a new instance-based learning algorithm called the Boundary Forest (BF) algorithm, that can be used for supervised and unsupervised learning. The algorithm builds a forest of trees whose nodes store previously seen examples. It can be shown data points one at a time and updates itself incrementally, hence it is naturally online. The main claim we substantiate in this section is that the BF as a classification or regression algorithm has accuracy comparable to the K-nearest neighbors (K-NN) algorithm on real datasets, with a fraction of the computational time,while maintaining the desirable property of learning incrementally.Since the traversal of the BF is dictated by the metric, the algorithm relies on metric comparisons being informative.Thus, if certain features are much more important than others, BF, like other metric-based methods will performpoorly, unless one can identify or learn a good metric. The main advantage of BFs is the ability to quickly train on and respond to arbitrarily large numbers of examples (because of logarithmic scaling) as would be obtained in an online streaming scenario. To our knowledge, these properties are unique to BFs as compared with other approximate nearest neighbor schemes. On the other hand,online R-kd is faster to train since it only does single feature comparisons at each node in the trees, however since it uses less informative decisions than metric comparisons it ends up searching a large portion of the previously seen data points, which makes it slower to test. The speed of this algorithm makes it appropriate for applications such as real-time machine learning, and metric learning[8].

With increasing complexity in the environment and the agent, this approach fails to scale well as the space requirements become prohibitive.In this to investigate an alternative implementation in which we use an arti_cial neural network as a function approximator and eliminate the need for an explicit table and to analysis the practical limitations of using tables as well as the viability of using artificial neural networks to approximate the utility in place of using tables. The core of the entire q-learning algorithm revolves around the premise of a reward scheme. In order for q-learning to function correctly, it is imperative that the robot be able to determine the approximate value of an action immediately after performing the action. A successful reward scheme for the light finding task is one that awards the robot for getting closer to areas of brighter light thus implicitly motivating the robot to fnd the light. In order to achieve this, we allowed the robot to wander around in the environment until is appeared to have learned a successful approach to the problem. The results also show that the more complex the environment gets, the better the neural net implementation does over the q-table implementation. We anticipate that the difference between the two approaches in the complex environment might only become apparent after more than 30000 learning iterations. The results also show that in simpler environments in which the state-action space is containable, a neural network implementation of q-learning is not the best approach and a traditional q-table implementation is probably better[40].

The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well. This paper gives overview of Artificial Neural Network, working & training of ANN. It also explain the application and advantages of ANN. In this paper we discussed about the Artificial neural network, working of ANN. Also training phases of an ANN. There are various advantages of ANN over conventional approaches. Depending on the nature of the application and the strength of the internal data patterns you can generally expect a network to train quite well. This applies to problems where the relationships may be quite dynamic or non-linear. ANNs provide an analytical alternative to conventional techniques which are often limited by strict assumptions of normality, linearity, variable independence etc. Because an ANN can capture many kinds of relationships it allows the user to quickly and relatively easily model phenomena which otherwise may have been very difficult or imposible to explain otherwise. Today, neural networks discussions are occurring everywhere. Their promise seems very bright as nature itself is the proof that this kind of thing works[38].

This study explores about the different techniques for application of Neural networks and discussed their present limitations and scope for future research in neural networks. In a similar manner, ANN's are usually formed from many hundreds or thousands of simple processing units, connected in parallel and feeding forward in several layers. In a biological neural network, the memory is believed to be stored in the strength of interconnections between the layers of neurons. Using neural network terminology, the strength or influence of an interconnection is known as its weight. ANN borrows from this theory and utilizes variable inter-connections weights between layers of simulated neurons This paper presents a brief survey on various techniques for application of artificial neural networks and the different learning in neural networks, such as supervised, unsupervised, reinforced and competitive learning it also analysis the major advantages and their drawbacks. In order to find out the perfect, efficient solutions for artificial neural networks has been widely studied and found[1].

Unsupervised learning:

The techniques presented in this open the door to many new applications of disease progression modeling.When paired with visualization tools, clinicians could use these models to better understand the evolution of chronic illnesses, optimize treatments, and design clinical guidelines. Our empirical study focused on the problem of discovering a single disease progression model for COPD. Thus,we constrained the continuous-time Markov model to allow only forward transitions[47].

Two issues involved in developing an automated feature subset selection algorithm for unlabeled data: the need for finding the number of clusters in conjunction with feature selection, and the need for normalizing the bias of feature selection criteria with respectto dimension. We explore the feature selection problem and these issues through FSSEM (Feature Subset Selection using Expectation-Maximization (EM) clustering) and through two different performance criteria for evaluating candidate feature subsets: scatter separability and maximum likelihood. We present proofs on the dimensionality biases of these feature criteria, and present a cross-projection normalization scheme that can be applied to any criterion to ameliorate these biases. Experiments have shown the need for feature selection, the need for addressing these two issues,and the effectiveness of our proposed solutions. the issues involved in developing automated feature subset selection algorithms for unsupervised learning. By unsupervised learning we mean unsupervised classification,or clustering. Cluster analysis is the process of finding "natural" groupings by grouping "similar"objects together. The problem is that not all featuresare important. Some of the features may be redundant, some may be irrelevant, and some can even misguide clustering results. In addition, reducing the number of features increases comprehensibilityand ameliorates the problem that some unsupervised learning algorithms break down with high dimensional data. In this investigates the wrapper framework through FSSEM introduced in. Here, the term "EM clustering" refers to the expectation-maximization (EM) algorithm applied to estimating the maximum likelihood parameters of a finite Gaussian mixture. Although we apply the wrapper approach to EM clustering,the framework presented in this paper can be applied to any clustering method. FSSEM serves as an example. We present this paper such that applying a different clustering algorithm or feature selection criteria would only require replacing the corresponding clustering or feature criterion.The issues we have encountered and solutions presented are applicable to any feature subset wrapper approach.Depending on one's application, one may choose to apply a more appropriate search method, clustering and feature selection criteria[15].

The intuitive EM algorithm still applies, but with a gradient-based M-step familiar from discriminative training of logistic regression models.This technique is applied to part-of-speech induction, grammar induction, word alignment,and word segmentation, incorporating a few linguistically-motivated features into the standard generative model for each task.These feature-enhanced models each out perform their basic counterparts by a substantial margin, and even compete with and surpass more complex state-of-the-art models. Word alignment is a core machine learning component of statistical machine translation systems,and one of the few NLP tasks that is dominantly solved using unsupervised techniques. The purpose of word alignment models is to induce a correspondence between the words of a sentence andthe words of its translation. The feature-enhanced model, trained using the direct gradient approach, achieves an accuracy of 63.0 for English, and an accuracy of 53.6 for Chinese. To our knowledge, our method for featurebased dependency parse induction outperforms all existing methods that make the same set of conditional independence assumptions as the DMV.The analysis shown that simple, locally normalized models can effectively incorporate features into unsupervisedmodels. These enriched models can be easily optimized using standard NLP building blocks. Beyond the four tasks explored in this paper—POS tagging, DMV grammar induction,word alignment, and word segmentation—the method can be applied to many other tasks, for example grounded semantics, unsupervised PCFG induction,document clustering, and anaphora resolution[42].

In this unsupervised method for learning a hierarchy of sparse feature detectors that are invariant to small shifts and distortions. The resulting feature extractor consists of multiple convolution filters, followed by a pointwise sigmoid non-linearity, and a feature-pooling layer that computes the max of each filter output within adjacent windows. A second level of larger and more invariant features is obtained by training the same algorithm on patches of features from the first level. While the resulting architecture is similar to convolutional networks, the layer-wise unsupervised training procedure alleviates the over-parameterization problems that plague purely supervised learning procedures, and yields good performance with very few labeled training samples. We have presented an unsupervised method for learning sparse hierarchical features that are locally shift invariant. A simple learning algorithm was proposed to learn the parameters,level by level. We applied this method to extract features for a multi-stage Hubel-Wiesel type architecture. The model was trained on two different recognition tasks. Stateof-art accuracy was achieved on handwritten digits from the MNIST dataset, and near state-of-the-art accuracy was obtained on Caltech 101. Our system is in its first generation,and we expect its accuracy on Caltech-101 to improve significantly as we gain experience with the method. Improvements could be obtained through pooling over scale,and through using position-dependent filters instead of convolutional filters. More importantly, as new datasets with more training

samples will become available, we expect our learning-based methodology to improve in comparison to other methods that rely less on learning.The contribution of this work lies in the definition of a principled method for learning the parameters of an invariant feature extractor. It is widely applicable to situations where purely supervised learning would over-fit for lack of labeled training data[24].

Consider the problem of building highlevel,class-specific feature detectors from only unlabeled data.To train this network using model parallelism and asynchronous SGD on a cluster with 1,000 machine for three days. Contrary to what appears to be a widely-held intuition, our experimental results reveal that it is possible to train a face detector without having to label images as containing a face or not. Control experiments show that this feature detector is robust not only to translation but also to scaling and out-of-plane rotation. We also find that the same network is sensitive to other high-level concepts such as cat faces and human bodies.Starting with these learned features, we trained our network to obtain 15.8% accuracyin recognizing 22,000 object categories from ImageNet, a leap of 70% relative improvementover the previous state-of-the-art. The training dataset is constructed by sampling frames from 10 million YouTube videos. To avoid duplicates,each video contributes only one image to the dataset.Each example is a color image with 200x200 pixels. To train the model,model parallelism have been implemented by distributing the local weights W1, W2 and H to different machines. A single instance of the model partitions the neurons and weights out across 169 machines(where each machine had 16 CPU cores). A set of machines that collectively make up a single copy of the model is referred to as a "model replica." We have built a software framework called DistBelief that manages all the necessary communication between the different machines within a model replica, so that users of the framework merely need to write the desired upwards and downwards computation functions for the neurons in the model, and don't have to deal with the low-level communication of data across machines.We further scaled up the training by implementing asynchronous SGD using multiple replicas of the coremodel. In our training, at every step of SGD, the gradient is computed on a minibatch of 100 examples. Network have been trained on a cluster with 1,000 machines for three days. The analysis of the learned representations in recognizing faces ("the face detector") have been shown and present control experiments to understand invariance properties of the face detector[30].

In the OCC approach three problem areas have been demostrated: clustering, feature learning and online facility location.We evaluate our methods via large-scale experiments in a cluster computing environment. In this paper a third approach, optimistic concurrency control (OCC) which offers the performance gains of the coordination-free approach while at the same time ensuring a serializable execution and preserving the theoretical properties of the serial algorithm. Like the coordinationfree approach, OCC exploits the infrequency of data-corrupting operations. However, instead of allowing occasional data-corruption, OCC detects data-corrupting operations and applies correcting computation. As a consequence, OCC automatically ensures correctness, and the analysis is only necessary to guarantee optimal scaling performance. In this paper we have shown how optimistic concurrency control can be usefully employed in the design of distributed machine learning algorithms. As opposed to previous approaches, this preserves correctness, in most cases at a small cost. We established the equivalence of our distributed OCC DPmeans, OFL and BP-means algorithms to their serial counterparts, thus preserving their theoretical properties. In particular, the strong approximation guarantees of serial OFL translate immediately to the distributed algorithm. Our theoretical analysis ensures OCC DP-means achieves high parallelism without sacrificing correctness. We implemented and evaluated all three OCC algorithms on a distributed computing platform and demonstrate strong scalability in practice.We believe that there is much more to do in this vein. Indeed, machine learning algorithms have many properties that distinguish them from classical database operations and may allow going beyond the classic formulation of OCC. In particular we may be able to partially or probabilistically accept non-serializable operations in a way that preserves underlying algorithm invariants. Laws of large numbers and concentration theorems may provide tools for designing such operations. Moreover, the conflict detection mechanism can be treated as a control knob, allowing us to softly switch between stable, theoretically sound algorithms and potentially faster coordination-free algorithms[49].

In this unsupervised clustering based analysis towards very large datasets for analysis towards health insurance dataset for their preferences towards health insurance products for intelligent decision making. The weak tool has been considered for the purpose of analysis and test results. The WEKA ("Waikato Environment for Knowledge Analysis") tool is used for Data mining. Data mining finds valuable information hidden in large volumes of data. Weka is a collection of machine learning algorithms for data mining tasks, written in Java and it contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. The key features of Weka are it is open source and platform independent. Simple k-means algorithm is applied on Health Insurance data set for cluster formation and subsequent analysis to predict customer preferences towards health insurance. Analysis of policyholders behavior enables companies to improve support of their policy holder oriented processes, which aims to improve the overall performance of the health insurance company. Unsupervised data mining methodology has a tremendous contribution for researchers to extract the hidden

knowledge and information .customer segmentation generated by clustering based model will add value by enabling target appropriate products to different consumers. The research described in this paper also identified gender based preferences towards health insurance policies in addition other attributes[4].

The analysis summarizes the formulation of the fully-automatic web-extraction problem,our clustering approach, and our results on a set of experiments This paper describes a new approach to data extraction from the web. Our approach uses unsupervised learning to analyze the structure of a site and its pages, with the objective of extracting and structuring the data on the site,so that the data can be transformed into a webfeed . Consider the task of creating a web site for current weather conditions in U.S. cities. We might start by defining a relational database table with the current weather for all the cities, one row per city. Next, we might write a script to generate an HTML page for each row of the table. At this point, we have a set of pages that contain information from a single relational database table and are similarly formatted.We will call such a set of pages a page type. A key algorithmic problem is how to cluster the pages and data, given that the experts are heterogeneous and identify very different types of structure. This is a common problem in AI, and is analogous to the problem of combining syntax,semantics and pragmatics for natural language understanding.To address this, our experts output their observations using a common representation. In this scheme, all experts produce "hints" indicating that two items should be in the same cluster. The clustering process then uses a probabilistic model of the hint-generation process to rate alternative clusterings. Unsupervised web-site extraction is a new challenge in making the web machine-understandable. In this paper, we have presented our formulation of the problem and our approach based on multiple heterogeneous experts.We believe our preliminary experiments demonstrate the broad potential of our approach. By using multiple experts,each capable of discovering a basic type of structure, we are able to piece together clues which in turn lead us to the relational data underlying the site[3].

A method for training an off-line handwriting recognition system in an unsupervised manner is presented.For an isolated word recognition task, we are able to bootstrap the system without any annotated data. We then retrain the system using the best hypothesis from a previous recognition pass in an iterative fashion. Our approach relies only on a prior language model and does not depend on an explici segmentation of words into characters. The resulting system shows a promising performance on a standard dataset in comparison to a system trained in a supervised fashion for the same amount of training data. The performance of the unsupervised-trained system in comparison to the supervised-trained one is promising.It must be noted that the unsupervised training procedure cannot outperform the supervised one for the same amount of training data, because the presence of annotations is always an unbeatable advantage. In fact we did not try to beat the supervised system but wanted to demonstrate that it is possible to train a good system in an unsupervised manner.An interesting result is that the difference in error rates is much bigger on the training set than on the validation. This is because the supervised-trained system has the tendency to overfit the training data. The system trained using our method has the capability to generalize well. Successfully predicting the length of the word is a crucial aspect of training a system in an unsupervised manner. This is a clear advantage of HMMs which have the property that the length of one character (in number of frames) is enforced in a probabilistic sense by the length of the HMM model (in number of states). Predicting a priori a most probable word of a correct length can be seen as a best joint a priori prediction of all separate characters. Successively it means that on each character position we will predict the most frequent character. During the estimation of system parameters the means will tend towards correct characters.That is why the system is able to converge into the right direction.Another reason behind the use of HMMs is their relative speed. In our experiments we needed at least 20 iterations to obtain reasonable results, which means that this training procedure takes 20 times longer than the standard procedure of supervised training. Such a long execution time may prove prohibitive with other methods. Our system is a pure HMM system, yet it has been shown that an HMM system can be improved by using neural networks or system combination . The systems proposed by A2iA, UPV and ParisTech were combinations of different classifiers including recurrent neural networks and HMMs. TUM used a system based solely on a multi-dimensional neural network. The systems from IRISA and SIEMENS were based on a single HMM with the sliding window approach[25].

In this a new method for editing speech related facial motions is presented. Our method uses an unsupervised learning technique, Independent Component Analysis (ICA), to extract a set of meaningful parameters without any annotation of the data. With ICA, we are able to solve a blind source separation problem and describe the original data as a linear combination of two sources. One source captures content (speech) and the other captures style(emotion). By manipulating the independent components we can edit the motions in intuitive ways. In this paper we address the problem of editing recorded facial motion. Editing motion capture data is an important problem, since without the ability to edit recorded motion we can only replay the recorded data. In this paper we propose an unsupervised learning technique,based on Independent Component Analysis (ICA),that splits the recorded motions into linear mixtures of statistically independent sources. These sources, called independent

components, offer a compact representation of the data with clear semantics. The lack of structure or model underlying the recorded data makes it really hard to edit. In contrast, the decomposition we propose provides a meaningful parameterization of the original data that is suitable for editing. The technique is automatic and does not require annotating the data. In this paper we propose an unsupervised learning technique based on Independent Component Analysis. With ICA we extract meaningful parameters from recorded facial motions.Our method provides a representation of the data that has a number of important features. First this representation has much more intuitive semantics than the original data. Each independent component can be associated with a clear meaning.These components can be edited separately. Second it is significantly more compact; 6 independent components instead of the original motion data that has 327 parameters(i.e. three euclidian coordinates for each of the 109 markers).But perhaps the most intriguing contribution of this paper is to show that facial motions should lend themselves so easily to a linear decomposition, despite the complexity of the associated control system (the brain) and of the mechanisms responsible for these motions. Our results shows that ICA can be used to decompose speechrelated facial motion into meaningful components[50].

In this paper we are using multiple dataset where some of them are existing dataset and some of them are new dataset. For the implementation of SentiWordNet we use java Netbeans IDE. Here we are using multiple dataset. Aspect-level sentiment analysis generates sentiment profile. Feature identification and selection is most important task of opinion mining. There is more than one name for the same aspects. For example someone use “story of the book is good” or someone use “the storyline of the book is fantastic” but meaning of story and storyline is same. Sentiment classification is the most widely studied and research topic nowadays. Basically there are two techniques for Sentiment analysis. First one is a supervised learning technique which is based on machine learning classifiers. It uses training on labelled data before they can be applied to the actual sentiment classification task. Naïve Bayesian, Support Vector Machines (SVM), maximum entropy etc. are existing supervised learning methods can be readily applied to sentiment classification. Several numbers of papers mentioning “sentiment analysis” focus on the specific application of classifying review as to their polarity.The Second technique is based on lexicon which is also called unsupervised learning technique.It performs classification based on some fixed syntactic patterns that are likely to be used to express opinions. It classifies the document using semantic orientation or sentiment dictionary for computing sentiment polarity of a text. SOPMI-IR [Semantic Orientation - Pointwise Mutual Information-Information Retrieval] algorithm is another unsupervised approach, which uses the mutual occurrence frequency of selected words to compute the sentiment polarity. Hence also identify same synonym of the different aspects and design an aspect matrix.We implemented all the existing dataset. Also we have design new dataset for mobile. For this we collect reviews from Amazon.com websites and implemented it with both scheme SWN(AAC) and SWN(AAAVC). Here we present the example of mobile Samsung Galaxy S5-Wireless on selected aspects of a review. Both sentiment profiles of this phone defines positive results with many aspects. Opinion mining become popular research area due to the increasing number of internet users, social media etc.Here we have work on aspect level analysis using SentiWordNet. The method used here is very simple and domain independent. In this paper we present our experiment with reviews which generate great result[45].

III.DISCUSSION:

The goal of semi-supervised learning is to understand how combining labeled and unlabeled data may change the learning behavior, and design algorithms that take advantage of such a combination. Semi-supervised learning is of great interest in machine learning and data mining because it can use readily available unlabeled data to improve supervised learning tasks when the labeled data are scarce or expensive.Semi-supervised learning also shows potential as a quantitative tool to understand human category learning, where most of the input is self-evidently unlabeled. One of the challenges that arise in reinforcement learning and not in other kinds of learning is the trade-off between exploration and exploitation. To obtain a lot of reward, a reinforcement learning agent must prefer actions that it has tried in the past and found to be effective in producing reward. But to discover such actions, it has to try actions that it has not selected before. The agent has to *exploit* what it already knows in order to obtain reward, but it also has to *explore* in order to make better action selections in the future. This is an important kind of learning, but alone it is not adequate for learning from interaction. In interactive problems it is often impractical to obtain examples of desired behavior that are both correct and representative of all the situations in which the agent has to act. In uncharted territory--where one would expect learning to be most beneficial--an agent must be able to learn from its own experience.Whereas the aim of supervised, machine learning is to build a model that makes predictions based on evidence in the presence of uncertainty. As adaptive algorithms identify patterns in data, a computer "learns" from the observations. he central scientific goal of AI is to understand the principles that make intelligent behavior possible in natural or artificial systems. This is done by the analysis of natural and artificial agents,formulating and testing hypotheses about what it takes to construct intelligent agents; and designing, building, and experimenting with computational systems that perform tasks commonly viewed as requiring intelligence. Neural networks take a different approach to problem solving than

that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem. That restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve. But computers would be so much more useful if they could do things that we don't exactly know how to do.Unsupervised methods now provide a sometimes-superior, and broadly usable, alternative to established methods, especially for problems that haven't been solved neatly by supervised machine learning or non-machine learning approaches.When we need large amount of data and language understanding and image identification, application that involves detecting patterns and extracting salient information from noisy environments it is appropriate to use unsupervised learning. sometimes a rules-based approach just isn't the best way to go, for instance in trying to automate the process of making sense of social postings, where there's no boundary on discussion, volumes are huge, participants are hugely diverse, many languages and lots of slang and irregular language and cultural reference are in play, and new topics arise constantly. For sources with these sorts of characteristics, machine learning may outperform both established automated methods and human analyses.

IV.CONCLUSION:

The paper describes different methodologies and techniques associated with machine learning. Unsupervised methods provide a sometimes-superior, and broadly usable, alternative to established methods, especially for problems that haven't been solved neatly by supervised machine learning or non-machine learning approaches.And it also gives an overview of different clustering algorithms used in large data sets. However unsupervised learning also encompasses many other techniques that seek to summarize and explain key features of the data. This integrated technique of clustering and classification gives a promising classification results with utmost accuracy rate and robustness.Then describes about the general working behaviour, and the methodologies followed on these approaches and the parameters which used in these algorithms with large data sets.

REFERENCES:

[1] Abdullahi Uwaisu Muhammad, Abdullahi Garba Musa, Kamaluddeen Ibrahim Yarima," Survey on Training Neural Networks ", International Journal of Advanced Research in Computer Science and Software Engineering.

[2] Anish Talwar, Yogesh Kumar," Machine Learning: An artificial intelligence methodology", International Journal Of Engineering And Computer Science ISSN:23197242.

[3] Bora Gaze,Steven Minton," Overview of AutoFeed: An Unsupervised Learning System for GeneratingWebfeeds", Fetch Technologies 2041 Rosecrans Ave.El Segundo, California, USA.

[4] S.Balaji, Dr.S.K.Srivatsa," Unsupervised Learning in Large Datasets for Intelligent Decision Making", International Journal of Scientific and Research Publications, Volume 2, Issue 9, September 2012 1 ISSN 2250-3153.

[5] S.R.K. Branavan, Harr Chen, Luke S. Zettlemoyer, Regina Barzilay," Reinforcement Learning for Mapping Instructions to Actions", Computer Science and Artificial Intelligence Laboratory.

[6] Carlos Diuk, Andre Cohen, Michael L. Littman," An Object-Oriented Representation for Efficient Reinforcement Learning", RL3 Laboratory, Department of Computer Science, Rutgers University, Piscataway, NJ USA.

[7] Charles Mathy, Nate Derbinsky, Jose Bento, Jonathan Rosenthal, Jonathan Yedidia," The Boundary Forest Algorithm for Online Supervised and Unsupervised Learning", Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence.

[8] Dasika Ratna Deepthi, G.R.Aditya Krishna, K. Eswaran,"Automatic pattern classification by unsupervised learning using dimensionality reduction of data with mirroring neural networks".

[9] R.Deepa Lakshmi, N.Radha," Supervised Learning Approach for Spam Classification Analysis using Data Mining Tools", (IJCSE) International Journal on Computer Science and Engineering Vol. 02, No. 08, 2010, 2760-2766.

[10] Gao Huang, Shiji Song, Jatinder N. D. Gupta, and Cheng Wu," Semi-supervised and unsupervised extreme learning machines", IEEE transactions on cybernetics.

[11] Gideon S. Mann, Andrew McCallum," Simple, Robust, Scalable Semi-supervised Learning via Expectation Regularization", Proceedings of the 24 th International Conference on Machine Learning, Corvallis, OR, 2007. Copyright 2007 by the author(s)/owner(s).

[12] Gilles Blanchard, Gyemin Lee Clayton Scott," Semi-Supervised Novelty Detection", Journal of Machine Learning Research 11 (2010) 2973-3009.

[13] Hetal Bhavsar, Amit Ganatra," A Comparative Study of Training Algorithms for Supervised Machine Learning", International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-2, Issue-4, September 2012.

[14] Iqbal Muhammad, Zhu Yan," Supervised machine learning approaches: a survey", ictact journal on soft computing, april 2015, volume: 05, issue: 03.

[15] Jennifer G. Dy, Carla E. Brodley," Feature Selection for Unsupervised Learning", Journal of Machine Learning Research 5 (2004) 845–889.

[16] Jens Kober, J. Andrew Bagnell, Jan Peters," Reinforcement Learning in Robotics: A Survey", Kober IJRR 2013.

[17] Junhui Wang, Xiaotong Shen, Wei Pan," On Efficient Large Margin Semisupervised Learning: Method and

Theory", Journal of Machine Learning Research 10 (2009) 719-742.

[18] Koushal Kumar, Gour Sundar Mitra Thakur," Advanced Applications of Neural Networks and Artificial Intelligence: A Review", I.J. Information Technology and Computer Science, 2012, 6, 57-68.

[19] Krishnakumar Balasubramanian, Pinar Donmez, Guy Lebanon," Unsupervised Supervised Learning II: Margin-Based Classification without Labels", Proceedings of the 14th International Conference on Artificial Intelligence and Statistics (AISTATS) 2011, Fort Lauderdale, FL, USA. Volume 15 of JMLR: W&CP 15. Copyright 2011 by the authors.

[20] Lei Jimmy Ba, Brendan Frey," Adaptive dropout for training deep neural networks", Advances in Neural Information Processing Systems.

[21] Leslie Pack Kaelbling, Michael L. Littman, Andrew W. Moore," Reinforcement Learning: A Survey", Journal of Artificial Intelligence Research 4 (1996) 237-285.

[22] Manju.S, M.Punithavalli,"Neural network-based ideation learning for intelligent agents: e-brainstorming with privacy preferences",International Journal of Computational Vision and Robotics,Vol. 5, No. 3, 2015.

[23] Manju.S, M. Punithavalli, "An Analysis of Q-Learning Algorithms with Strategies of Reward Function, International Journal on Computer Science and Engineering",ISSN : 0975-3397 Vol. 3 No. 2 Feb 2011.

[24] Marc'Aurelio Ranzato, Fu-Jie Huang, Y-Lan Boureau, Yann LeCun,"Unsupervised Learning of Invariant Feature Hierarchies with Applications to Object Recognition".

[25] Michał Kozielski, Malte Nuhn, Patrick Doetsch, Hermann Ney," Towards Unsupervised Learning for Handwriting Recognition", Human Language Technology and Pattern Recognition Group.

[26] Mykola Pechenizkiy, Alexey Tsymbal, and Seppo Puuronen," Local Dimensionality Reduction and Supervised Learning Within Natural Clusters for Biomedical Data Analysis",IEEE transactions on information technology in biomedicine, vol. 10, no. 3, july 2006.

[27] G. Nguyen, A. Bouzerdoum & S. Lam. Phung, "A supervised learning approach for imbalanced data sets," in International Conference on Pattern Recognition, 2008, pp. 1-4.

[28] Oliver Brdiczka, Patrick Reignier & James L. Crowley," Supervised Learning of an Abstract Context Model for an Intelligent Environment", Grenoble, october 2005 Joint sOc-EUSAI conference.

[29] Olivier Chapelle, Vikas Sindhwani, Sathiya S. Keerthi," Optimization Techniques for Semi-Supervised Support Vector Machines", Journal of Machine Learning Research 9 (2008) 203-233.

[30] Quoc V,Marc'Aurelio Ranzato,Rajat Monga,Matthieu Devin,Kai Chen,Greg S. Corrado,Jeff Dean,Andrew Y. Ng," Building High-level Features Using Large Scale Unsupervised Learning", Proceedings of the 29 th International Conference on Machine Learning, Edinburgh, Scotland, UK, 2012.

[31] Rich Caruana,Alexandru Niculescu-Mizil," An Empirical Comparison of Supervised Learning Algorithms", Proceedings of the 23 rd International Con-ference on Machine Learning, Pittsburgh, PA, 2006.

[32] Rie Kubota Ando, Tong Zhang," A High-Performance Semi-Supervised Learning Method for Text Chunking", IBM T.J. Watson Research Center Yorktown Heights, NY 10598, U.S.A.

[33] Rohit J. Kate and Raymond J. Mooney," Semi-Supervised Learning for Semantic Parsing using Support Vector Machines", In Proceedings of the Human Language Technology Conference of the North American Chapter of the Association for Computational Linguistics, Short Papers (NAACL/HLT-2007), pp. 81-84, Rochester, NY, April 2007.

[34] Saneem Ahmed C.G,Harikrishna Narasimhan,Shivani Agarwal,"Bayes Optimal Feature Selection for Supervised Learning with General Performance Measures".

[35] R. Sathya, Annamma Abraham," Comparison of Supervised and Unsupervised Learning Algorithms for Pattern Classification", (IJARAI) International Journal of Advanced Research in Artificial Intelligence, Vol. 2, No. 2, 2013.

[36] Satinder Singh, Andrew G. Barto, Nuttapong Chentanez," Intrinsically Motivated Reinforcement Learning", NSF grant CCF 0432027 and by a grant from DARPA's IPTO program.

[37] Shoushan Li, Zhongqing Wang, Guodong Zhou, Sophia Yat Mei Lee," Semi-Supervised Learning for Imbalanced Sentiment Classification", Proceedings of the Twenty-Second International Joint Conference on Artificial Intelligence.

[38] Ms. Sonali. B. Maind, Ms. Priyanka Wankar," Research Paper on Basic of Artificial Neural Network", International Journal on Recent and Innovation Trends in Computing and Communication, ISSN: 2321-8169.

[39] B. H. Sreenivasa Sarma, B. Ravindran," Intelligent Tutoring Systems using Reinforcement Learning to teach Autistic Students".

[40] Steve Dini ,Mark Serrano," Combining Q-Learning with Artificial Neural Networks in an Adaptive Light Seeking Robot", International Joint Conference on Neural Networks.

[41] Stuart Russell, Andrew L. Zimdars,"Q-Decomposition for Reinforcement Learning Agents", Computer Science Division, University of California, Berkeley, Berkeley CA 94720-1776 USA.

[42] Taylor Berg-Kirkpatrick, Alexandre Bouchard-Cot, John DeNero,Dan Klein," Painless Unsupervised Learning with Features", Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the ACL.

[43] Tim Paek," Reinforcement Learning for Spoken Dialogue Systems: Comparing Strengths and Weaknesses for Practical Deployment", Microsoft Research One Microsoft Way, Redmond, WA 98052.

[44] Timothy P. Jurka, Loren Collingwood, Amber E. Boydstun, Emiliano Grossman, and Wouter van Atteveldt," RTextTools: A Supervised Learning Package for Text Classification" ,The R Journal Vol.5/1 June ISSN 2073-4859.
[45] Vibha Soni, Meenakshi R Patel," Unsupervised Opinion Mining From Text Reviews Using SentiWordNet", International Journal of Computer Trends and Technology (IJCTT) – volume 11 number 5 – May 2014.
[46] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra ,Martin Riedmiller," Playing Atari with Deep Reinforcement Learning", DeepMind Technologies.
[47] Xiang Wang, David Sontag, Fei Wang,"Unsupervised Learning of Disease Progression Models", KDD'14, August 24–27, 2014, New York, NY, USA.
[48] Xiaojin Zhu, John Lafferty, Zoubin Ghahramani," Combining Active Learning and Semi-Supervised Learning Using Gaussian Fields and Harmonic Functions", Proceedings of the ICML-2003 Workshop on The Continuum from Labeled to Unlabeled Data, Washington DC, 2003.
[49] Xinghao Pan, Joseph Gonzalez,Stefanie Jegelka,Tamara Broderick, Michael I. Jordan, "Optimistic Concurrency Control for Distributed Unsupervised Learning".
[50] Yong Cao, Petros Faloutsos, Frédéric Pighin," Unsupervised Learning for Speech Motion Editing", Eurographics/SIGGRAPH Symposium on Computer Animation (2003).
[51] Yu-Feng Li, James T. Kwok, Zhi-Hua Zhou," Semi-Supervised Learning Using Label Mean," Proceedings of the 26 th International Conference on Machine Learning", Montreal, Canada, 2009. Copyright 2009 by the author(s)/owner(s).
[52] Yuriy Nevmyvaka, Yi Feng, Michael Kearns," Reinforcement Learning for Optimized Trade Execution", Proceedings of the 23 rd International Conference on Machine Learning, Pittsburgh, PA, 2006.
[53] M.Subba Rao, Dr.B.Eswara Reddy," Comparative Analysis of Pattern Recognition Methods: An Overview", Indian Journal of Computer Science and Engineering, Vol. 2 No. 3 Jun-Jul 2011.

