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Pattern Recognition: Possible Research Areas and Issues

Jayashree Rajesh Prasad

Department of Computer Engineering, Sinhgad College of Engineering, University of Pune,
Pune, Mahaashtra 411048, India

Abstract - Pattern recognition is a tough problem for computers, although humans are wired for it. Pattern recognition is becoming increasingly important in the age of automation and information handling and retrieval. This paper reviews possible application areas of Pattern recognition. Author covers various sub-disciplines of pattern recognition based on learning methods, such as supervised, unsupervised, semi-supervised learning and key research areas such as grammar induction. Novel solutions to these possible problems could be well deployed for character recognition, speech analysis, man and machine diagnostics, person identification, industrial inspection and so on. The paper concludes with brief discussion on open issues that need to be addressed by future researchers.

Keywords - *Anomaly detection, Classification, Clustering, Dimensionality reduction, Grammar induction, Feature learning, Supervised, unsupervised learning*.

1. Introduction

Pattern recognition is the branch of artificial intelligence that enables a machine to recognize a “pattern” or “regularity” of a fixed structure in data. To do this we need to “teach” machine i.e. to train the machine by labeling the data. This description of pattern recognition makes it synonymous to “Machine learning”. Interestingly, it is a fact that the two fields can rarely be separated. In most cases, these two fields go hand in hand.

When pattern are recognized using a “labeled data” it is termed as “Supervised learning” i.e. data is described (labels) and category (class) is known. While on the other hand, if the data is “unlabelled” it is termed as “Un-Supervised learning” i.e. the category or class is unknown at the time of learning. Similar to machine learning, other related terms to Pattern recognition are data mining and knowledge discovery in databases as they largely overlap in their scope. Furthermore, Pattern recognition has its origins in artificial intelligence as stated above, and the term is popular in the context of computer vision and image processing. Pattern recognition focuses on formalizing, explaining and visualizing the pattern whereas machine learning traditionally focuses on maximizing the recognition rates. However all of these domains have evolved substantially from their roots in artificial intelligence, engineering and statistics; and have become increasingly similar by integrating developments and ideas from each other.

2. Pattern Recognition Domain: Possible Problem Areas

Pattern recognition is the human ability to see regularities in observations.

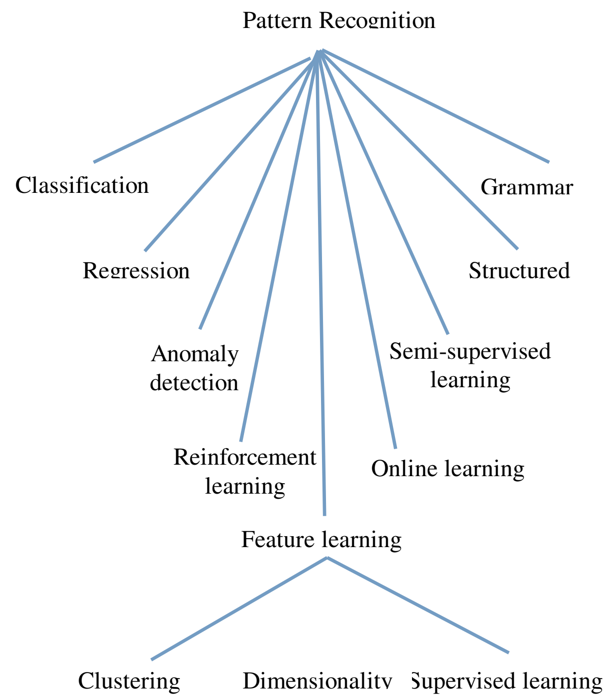

Fig.1. Research areas in pattern recognition domain

From the early development of computers, scientists and engineers tried to imitate this ability by mechanical means, either partially or in its entirety. This analysis focuses on the pattern recognition research aiming at the development of automatic systems as discussed above. We will especially deal with the possibilities of these systems to learn from sets of patterns.

2.1. Classification

Classification in machine learning or statistical pattern recognition is the problem of identifying to which of a set of classes (categories) a new observation belongs, on the basis of a training set of data containing observations (or instances) whose category membership is known. An algorithm that implements classification is known as a classifier. The term "classifier" is nothing but the mathematical function implemented by a classification algorithm that maps input data to a category.

Supervised classification is one of the tasks most frequently carried out by so-called Intelligent Systems. Thus, a large number of techniques have been developed based on Artificial Intelligence (Logic-based techniques, Perceptron-based techniques) and Statistics (Bayesian Networks, Instance-based techniques). The goal of supervised learning is to build a concise model of the distribution of class labels in terms of predictor features. The resulting classifier is then used to assign class labels to the testing instances where the values of the predictor features are known, but the value of the class label is unknown. A paper describes various classification algorithms and the recent attempt for improving classification accuracy—ensembles of classifier [1].

2.2. Clustering

The activity of grouping a set of objects is termed as cluster analysis or clustering. The objects in a cluster are similar to each other than to those in other groups (clusters). Few common applications lie in data mining, statistical data analysis machine learning, pattern recognition, image analysis, information retrieval, and bioinformatics.

Cluster technique refers to a task to solve a problem rather than a specific algorithm. This task is performed by various algorithms that differ significantly in their notion of what constitutes a cluster and how to efficiently find them. Popular notions of clusters include groups with small distances among the cluster members, dense areas of the data space, intervals or particular statistical distributions. Clustering problem therefore can be viewed as a multi-objective optimization problem. The appropriate clustering algorithm and parameter settings (including values such as the distance function to use, a density threshold or the number of expected clusters) depend on the individual data set and intended use of the results. Cluster analysis is an iterative process of knowledge discovery or interactive multi-objective optimization that involves trial and failure. The data preprocessing and model parameters are often modified until the result achieves the desired properties.

Clustering is a typical method of grouping data points in an unsupervised learning environment. The performance of most clustering algorithms is dependent on the accurate estimate of the cluster number, which is always unknown in the real applications. A new parametric approach is presented, which starts with an estimate of the local distribution and efficiently avoids pre-assuming the cluster number. This clustering program is applied to both artificial and benchmark data classification and its performance is proven better than the well-known k-means algorithm [2].

2.3. Regression

In statistics, regression technique is used to estimate relationship among variables. The popular relationship analyzed using regression is between a dependent variable and one or more independent variables. It is especially useful while analyzing how the typical value of the dependent variable (or 'criterion variable') changes when any one of the independent variables is varied, while the other independent variables are held fixed.

Popular applications of Regression analysis include prediction and forecasting, where its use has substantial overlap with the field of machine learning. Linear regression and ordinary least squares regression are mainly used for this purpose.

A novel approach of face identification by formulating the pattern recognition problem in terms of linear regression is presented [3]. Using a fundamental concept that patterns from a single-object class lie on a linear subspace, we develop a linear model representing a probe image as a linear combination of class-specific galleries. The inverse problem is solved using the least-squares method and the decision is ruled in favor of the class with the minimum reconstruction error. Authors [3] proposed Linear Regression Classification (LRC) algorithm falls in the category of nearest subspace classification. The algorithm is extensively evaluated on several standard databases under a number of exemplary evaluation protocols reported in the face recognition literature. A comparative study with state-of-the-art algorithms clearly reflects the efficacy of the proposed approach. For the problem of contiguous occlusion, a Modular LRC approach, introducing a novel Distance-based Evidence Fusion (DEF) algorithm is presented. The methodology found achieving the best results ever reported for the challenging problem of occlusion.

2.4. Anomaly Detection

Pattern recognition could be uniquely applied to anomaly detection (or outlier detection). It aims to identify the items, events or observations which do not conform to an expected pattern or other items in a dataset. Some typical scenarios for this could be a *Bank fraud* where the anomalous items will translate to some kind of problem such, a structural defect, medical problem or finding errors in text.

There are three important ways to anomaly detection.

Unsupervised anomaly detection- detects anomalies in an unlabeled test data set.
Supervised anomaly detection- detects anomalies in a labeled test data that has been labeled as "normal" and "abnormal".
Semi-supervised anomaly detection constructs a model representing normal behavior from a given *normal* training data set, and then tests the likelihood of a test instance to be generated by the learnt model.

A framework for anomaly detection in crowded scene is found [4]. The three properties such as joint modeling appearance and dynamics of the scene, the ability to detect, then temporal and spatial abnormalities have been effectively utilized. Temporal anomalies are equated to events of low-probability, while spatial anomalies are handled using discriminant saliency. This technique [4] is shown to outperform various states of art anomaly detection techniques.

Association rules As stated above machine learning, data mining and pattern recognition are found interrelated in many applications using association rule learning. Interesting relations between variables in large databases are discovered in databases using different measures of interestingness. Based on the concept of strong rules, the association rules for discovering regularities between products in large-scale transaction data recorded by point-of-sale (POS) systems in supermarkets are introduced.

For example, the rule: **{Bread, veggies} => {Sandwich}** found in the sales data of a supermarket would indicate that if a customer buys onions and potatoes together, he or she is likely to also buy butter or cheese. Such information can be used as the basis for decisions about marketing activities such as, e.g., promotional pricing or product placements. In addition to the above example from market basket analysis association rules are employed today in many application areas including Web usage mining, intrusion detection, Continuous production, and bioinformatics. In contrast with sequence mining, association rule learning typically does not consider the order of items either within a transaction or across transactions.

A paper presents QUANTMINER, a mining quantitative association rules system [5]. This system is based on a genetic algorithm that dynamically discovers “good” intervals in association rules by optimizing both. The experiments on real and artificial databases have shown the usefulness of QUANTMINER as an interactive, exploratory data mining tool.

2.5 Reinforcement Learning

Reinforcement learning is a specialized domain of machine learning inspired by cognitive science. This domain deals with how software agents ought to take *actions* in an *environment* so as to maximize some notion of cumulative *reward*. This research problem, due to its generality, is studied in many other disciplines, such as game theory, control theory, operations research, information theory, simulation-based optimization, statistics, and genetic algorithms.

Reinforcement learning differs from supervised learning in that correct input/output pairs are never presented, nor sub-optimal actions explicitly corrected. Further, it emphasizes on on-line performance, which involves finding a balance between exploration and.

Current computer vision systems whose basic methodology is open-loop or filter type typically use image segmentation followed by object recognition algorithms. These systems are not robust for most real-world applications. In contrast, the system presented here achieves robust performance by using reinforcement learning to induce a mapping from input images to corresponding segmentation parameters. This is accomplished by using the confidence level of model matching as a reinforcement signal for a team of learning automata to search for segmentation parameters during training. The use of the recognition algorithm as part of the evaluation function for image segmentation [6] gives rise to significant improvement of the system performance by automatic generation of recognition strategies. The system is verified through experiments on sequences of indoor and outdoor color images with varying external conditions.

2.6 Structured Prediction

Umbrella activity for supervised learning techniques is structured prediction or structured (output) learning. To represent a sentence in English into syntactic form, a parse tree is used. This is a typical natural language problem.

Probabilistic graphical models are a large class of structured prediction models. Popular models that are used to solve structural prediction problems in bioinformatics, natural language processing, speech recognition, and computer vision are Bayesian networks and random fields. are popularly used to solve structured prediction problems in a wide variety of application domains However some other algorithms and models for structured prediction include inductive logic programming, structured Support Vector Machines (SVMs), Markov logic networks and constrained conditional models.

Structured prediction models are typically trained by means of observed data in which the true prediction value is used to adjust model parameters as in case of supervised learning techniques. Due to the complexity of the model and the interrelations of predicted variables the process of prediction using a trained model and of training itself is often computationally infeasible and approximate inference and learning methods are used.

A major part of natural language processing now depends on the use of text data to build linguistic analyzers. Various statistical, computational approaches to modeling linguistic structure are considered [7]. Authors seek to unify across many approaches and many kinds of linguistic structures. Assuming a basic understanding of natural language processing and/or machine learning, the gap between the two fields is bridged. Approaches to decoding (i.e., carrying out linguistic structure prediction) and supervised and unsupervised learning of models that predict discrete structures as outputs are the focus. Authors [7] survey natural language processing problems to which these methods are being applied, and address related topics in probabilistic inference, optimization, and experimental methodology

2.7 Feature Learning

Pattern recognition problems involve feature learning or representation learning that includes a set of techniques in machine learning that learn a convert "raw" inputs to a representation that can be effectively exploited in a supervised learning task such as classification. Feature learning algorithms are classified as either unsupervised or supervised, and include auto-encoders, dictionary learning, matrix factorization, restricted Boltzmann machines and various forms of clustering. Multilayer neural networks are most commonly used for feature learning, since they learn a representation of their input at the hidden layers which is subsequently used for classification or regression at the output layer, and feature learning is an integral part of deep learning, to the point that the two are sometimes considered synonyms. On the other hand, kernel methods such as the support vector machine do not perform feature *learning*; instead compute a fixed transformation of their inputs by means of a kernel function. When the feature learning can be performed in an unsupervised way, it enables a form of semi-supervised learning where first, features are learned from an unlabeled dataset, which are then employed to improve performance in a supervised setting with labeled data.

The optimal coding hypothesis proposes that the human visual system has adapted to the statistical properties of the environment by the use of relatively simple optimality criteria. A paper [8] presents a discussion how the properties of different models of image coding, i.e. sparseness, decoration and statistical independence are related to each other. Authors further propose to evaluate the different models by variable performance measures. Authors analyze the classification performance on image of handwritten digits. Application of SPARSENET algorithm to derive a local filter basis is found. The images in the database are filtered and dimensionality is reduced. A support vector machine is trained on a training set to classify the digits and report results obtained on a separate test set. The authors claim to achieve good results as compared to all methods that do not use data-specific knowledge.

2.8 Online learning

An interesting application of pattern recognition for the task of "Stock-market prediction can be found using online machine learning is a model of induction that learns one instance at a time. The goal in on-line learning is to predict labels for instances. The idea is to describe the instances for the current conditions of the stock market, and an online algorithm predicts tomorrow's value of a particular stock. The key defining characteristic of on-line learning is that soon after the prediction is made, the true label of the instance is discovered. This information can then be used to refine the prediction hypothesis used by the algorithm. The goal of the algorithm is to make predictions that are close to the true labels.

2.9 Semi-Supervised Learning

Another important field of interest is semi-supervised learning. It is a learning standard that deals with the study of how computers and natural systems such as human beings acquire knowledge in the presence of both labeled and unlabeled data. Semi–supervised learning based methods are preferred when compared to the supervised and unsupervised learning because of the improved performance shown by the semi-supervised approaches in the presence of large volumes of data. Labels are very hard to attain while unlabeled data are surplus, therefore semi-supervised learning is a noble indication to shrink human labor and improve accuracy. There has been a large spectrum of ideas on semi-supervised learning. A survey of some popular approaches to semi-supervised learning is presented [9] It is found that learning of labeled data is expensive and hard to obtain. On the other hand unlabeled data is comparatively easy to gather. Semi-supervised learning can be used to classify the unlabeled data and also it can be used to develop better classifiers. Semi-supervised learning needs less human labor and gives a better performance than the unsupervised and supervised counterparts. Because of this advantage semi-supervised learning is of great interest in theory as well as in practice.

2.10 Grammar Induction

A process of formal grammar learning popularly known as syntactic pattern recognition is nothing but the process in machine learning.. The grammar is a collection of *re-write rules* or *productions* or alternatively as a finite state machine or automaton of some kind from a set of observations, thus constructing a model which accounts for the characteristics of the observed objects. More generally, grammatical inference is that branch of machine learning where the instance space consists of discrete combinatorial objects such as strings, trees and graphs. There is enormous literature available on learning different types of grammar and automata, under various different learning models and using various different methodologies.

Research in the field of Natural Language Processing has been emerged due to highly complex natural language and grammar. This NLP research is mainly in the area of investigating solutions for automating grammar generation and updating process. Large numbers of algorithms for inference of context free grammar are available in literature. Survey of the methodologies for inferring context-free grammars from examples is presented [10] Some of the most relevant existing grammatical inference methods for natural language are described and classified according to the kind of presentation i.e. text or informant and the type of information, i.e. supervised, unsupervised or semi supervised. The state of art strategies for evaluation and comparison of different grammar methods is presented [10] The readers are provided with introduction to major concepts and current approaches in Natural Language research.

There are still more possible problem domains in pattern recognition. However we limit this review to brief coverage of these issues.

2.11 Supervised Learning (classification • regression)

The best-known supervised techniques are reviewed in details [11]. These approaches include:

- Decision trees
- Ensembles (Bagging, Boosting, Random forest)
- *k*-NN
- Linear regression
- Naive Bayes
- Neural networks
- Logistic regression
- Perceptron
- Support vector machine (SVM)

The key question when dealing with ML classification is not whether a learning algorithm is superior to others, but under which conditions a particular method can significantly outperform others on a given application problem. Meta-learning is moving in this direction, trying to find functions that map datasets to algorithm performance. Typical characteristics of learning that decide performance are:

- the number of instances,
- the proportion of categorical attributes,
- the proportion of missing values,
- the entropy of classes, etc.

After a better understanding of the strengths and limitations of each method, the possibility of integrating two or more algorithms together to solve a problem should be investigated. The objective is to utilize the strengths of one method to complement the weaknesses of another. If we are only interested in the best possible classification accuracy, it might be difficult or impossible to find a single classifier that performs as well as a good ensemble of classifiers. Despite the obvious advantages, ensemble methods have following disadvantages:

- Increased storage as a direct consequence of the requirement that all component classifiers, instead of a single classifier, need to be stored after training. The total storage depends on the size of each component classifier itself and the size of the ensemble (number of classifiers in the ensemble).
- The second weakness is increased computation because in order to classify an input query, all component classifiers (instead of a single classifier) must be processed.
- Decreased comprehensibility. With involvement of multiple classifiers in decision-making, it is more difficult for non-expert users to perceive the underlying reasoning process leading to a decision.

2.12 Clustering

Clustering is a typical method of grouping data points in an unsupervised learning environment. The performance of most clustering algorithms is dependent on the accurate estimate of the cluster number, which is always unknown in the real applications. The domain of pattern recognition is enriched by various clustering techniques. The clustering problem is defined as a problem of classifying a group of data points into a number of clusters without any prior knowledge about data structure, to produce a concise representation of the data. It is a fundamental means for multivariate data analysis widely used in numerous applications, especially in pattern recognition. Clustering techniques have been investigated extensively for decades. The existing approaches to data clustering include:

- BIRCH
- Hierarchical
- *k*-means
- Expectation-maximization (EM)
- DBSCAN
- OPTICS
- Mean-shift

The problem of clustering the signal data can be decomposed into two sub problems:
Extraction of the seed clusters – Cluster Growth program
¨ merging of clusters with a similar distribution of data – Cluster Merge program [12, 13].

2.13 Dimensionality Reduction

Data collection and storage capabilities advancements during the past decades have led to an information overload in most sciences. Researchers in diversified fields, face larger and larger observations and simulations on a daily basis. Such datasets, in contrast with smaller, more traditional datasets that have been studied extensively in the past, present new challenges in data analysis. Conventional statistical methods fail because of the increase in the number of observations, but mostly because of the increase in the number of variables associated with each observation. The dimension of the data is the number of variables that are measured on each observation.

High-dimensional datasets suffer with many mathematical challenges as well as some opportunities, and are bound to give rise to new theoretical developments [14]. One of the problems with high-dimensional datasets is that, in many cases, not all the measured variables are “important” for understanding the underlying phenomena of interest. Certain computationally expensive novel methods construct predictive models with high accuracy from high-dimensional data, it is still of interest in many applications to reduce the dimension of the original data prior to any modelling of the data. Most commonly used approaches to dimensionality reduction include:

- Factor analysis
- CCA
- ICA
- LDA
- NMF
- PCA
- t-SNE

For high-dimensional datasets (i.e. with number of dimensions more than 10), dimension reduction is usually performed prior to applying a K-nearest neighbors algorithm (k-NN) in order to avoid the effects of the curse of dimensionality.

Feature extraction and dimension reduction can be combined in one step using principal component analysis (PCA), linear discriminant analysis (LDA), or canonical correlation analysis (CCA) techniques as a pre-processing step followed by clustering by K-NN on feature vectors in reduced-dimension space. In machine learning this process is also called low-dimensional embedding.

For very-high-dimensional datasets (e.g. when performing similarity search on live video streams, DNA data or high-dimensional Time series) running a fast approximate K-NN search using locality sensitive hashing, "random projections", "sketches" or other high-dimensional similarity search techniques from the VLDB toolbox might be the only feasible option [14].

3. Conclusions

The area of pattern recognition has developed itself into a mature engineering field with many practical applications. This increased applicability, together with the development of sensors and computer resources, leads to new research areas and rises new questions. The domain analysis of this field and the relevant literature review finds many old (commonly observed) and new (emerging) open issues that need to be addressed by future researchers in the field. Some of the problems analyzed below may be solved either by a better understanding of their causes or by novel and better procedures [15]. Many emerging applications of pattern recognition involve complicated high-dimensional pattern spaces, small amounts of data-per-dimension, low signal-to-noise ratio, poorly specified statistical distributions and anomalous statistical outliers. In some cases these difficulties are compounded by distributed data collection requirements that impose constraints on data integration and decentralized decision making. This credits both challenges and possible solutions in several applications areas. The research in the field of character recognition has addressed many of these issues [16, 17, 18, 19 and 20].

Pattern recognition is a human activity that we try to imitate by mechanical means. There are no physical laws that assign observations to classes. It is the human consciousness that groups observations together. The human process of learning patterns from examples may follow along the lines of trial and error. Estimating probabilities, especially in multi-variate situations is not very intuitive for majority of people. Moreover, the large amount of examples needed to build a reliable classifier by statistical means is much larger than it is available for human learning. In human recognition, proximities based on relations between objects seem to come before features are searched and may be, thereby, more fundamental. Above study shows that the study of dissimilarities, distances and domain based classifiers are of great interest. I think that the use of dissimilarities for representation, generalization and evaluation constitute the most intriguing issues in pattern recognition.

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Jayashree Rajesh Prasad

Jayashree Rajesh Prasad graduated in Computer Science and Engineering from North Maharashtra University in 1996 and completed M.E. in Computer Engineering from Pune University in 2004. She pursued Ph.D. in Computer Science and engineering from Swami Ramananda Tirtha University, Nanded in 2014. She has a research project "Conversion of Gujrati Script to Speech", funded by BCUD (University of Pune) to her credit. She works with Sinhgad College of Engineering, Pune. Her research interests are in the field of Soft Computing, pattern recognition and image processing. She is Life member of Computer Society of India, Life Member of Indian Society for Technical Education, Member of IAENG (International Association of Engineers) and Member of IACSIT (International Association of Computer Science and Information Technology).