ANALYSIS ON APPLICATIONS OF MACHINE LEARNING AND AUXILIARY TUMOR TREATMENT IN THE PROCESS OF MEDICAL RESOURCE ALLOCATION

Attanti Brahmendra Charan[1], Om Sai Madala[2]

[1,2]*Student in Computer Science and Engineering at JNTUH COLLEGE OF ENGINEERING HYDERABAD*

---***---

ABSTRACT: In the last decade, machine learning has become very interesting, driven by cheaper computing power and costly storage—so that growing numbers of data can be saved, processed, and analyzed effectively. Enhanced algorithms are designed and used to identify hidden insights and correlations between non-human data elements in broad datasets. These insights help companies to better decide and optimize key indicators of interest. Machine learning is becoming more common because of the agnostic use of learning algorithms. The paper presents several machineries and auxiliary tumor processes to assign health resources and proposes some new ways to use these resources at the time of artificial intelligence to make human life part of this process and explore the good conditions which are shared by both the medical and computer industries.

Keywords: Machine learning, AI, Medical resource, Healthcare.

1. INTRODUCTION

With the ongoing digitalization of medical data and data from advanced medical equipment provided to us by the patient, we are becoming widespread with large volumes of patient data. One common outcome of the information revolution is the daunting task of data understanding and interpretation. It is not only overwhelming to gain the sense of such a vast data collection; manual tools and techniques that can be a slow and tedious process are often impossible to use. There is a great need for data-driven approaches to computer science to help the understanding of the data. Such approaches can be used to analyze the medical information for patients and doctors to better decide critical health information. Both industry and academia now start to invest heavily in the application of data science technologies to support medical data analysis. The amount of data generated in medicine will grow quickly and in future years, data science will play an important role.

The growing impact of digital treatment on diagnostics and the handling of diseases shortly has an increasing impact on daily life and Artificial Intelligence (AI) and Machine Training (ML). Tech advances in AI and ML have opened the way for self-contained tools to diagnose disease using big data sets to address the future challenges of human disease detection, particularly in cancer, early. ML is an AI subset that develops Neural-Network algorithms for a machine to learn and solve problems such as the brain of humans[1, 2]. Deep Learning is, in turn, a subset of ML which imitates the ability of the human brain for processing images, objects, languages, drug-detection improvements, precision upgrades, diagnostics, and human decision making. It can also work and propose an output without human monitoring[3]. DL can use the Artificial Network (ANN) to imitate human neuronal architecture, including medical imaging, and is composed of inputs, outputs, and various hidden multistage networks that improve the processing power of machine learning; (Fig. 1).

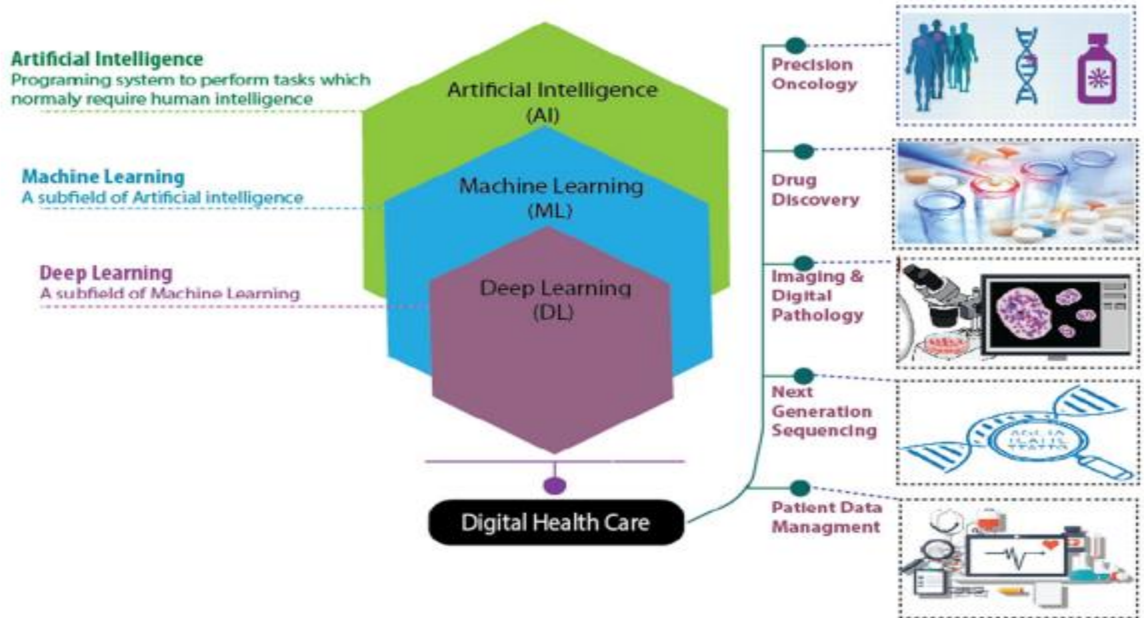

Fig. 1 Digital health and oncology applications for AI, ML, and DL to solve health problems and predict the optimal result of treatment

In leaps and limits, AI increases. The clinical oncology research is now focused more on cancer molecular onset by decoding the complex biological architecture of the proliferation of cancer cells. The objective is to address the existing scenario in millions of relevant big data and computational biology of the increasing number of deaths from cancer in the world[6]. The use of AI in clinical decision-making should also increase the chances for early diagnosis and disease prediction in the form of NGS sequences and high-resolution imaging techniques. It would also lead to the introduction of new biomarkers for diagnosing cancer, the design of new personalized drugs, and the provision of treatment strategies through the generation and use of bioinformatics.

2. SOURCES OF HEALTHCARE DATA

There are at least three data areas in the health sector that can be helped almost instantly by data science technologies:

Hospital Claims Data

In hospitals throughout the country, millions and millions of patients are treated every year. Data science technologies may contribute to understanding trends of visits to hospitals, diseases, injuries, and effective methods of mitigating visits, population trends, and disease prevention based on the models of prediction. Understanding hospital information will also assist providers in making informed decisions on ways to improve the quality of care.

Patient's Clinical Data

Clinical information is the results of laboratories, user data, medical photos, correlating and classifying medical notes to improve support for clinical decisions (understanding health and wellness of patients and manifestations of diseases). Adding data from various sources makes it possible for medical professionals to see an overview. Increased population rates predict that clinical data will only grow quickly and therefore, as is mainly the case nowadays, virtually impossible, based on manual analysis.

Trial Data for Research & Development

A growing number of studies are being conducted around the globe to understand diseases and mechanisms for coping with them. Large quantities of rich data sets are collected to apply techniques of data analysis to detect insights, relationships, and associations in the data.

3. APPLICATIONS OF MACHINE LEARNING IN MEDICAL CARE

A. Assisted tumor diagnosis

ML has been studied with the development of medical technology and Artificial Intelligence for tumor prevention, follow-up treatment, etc. Currently, a relevant study is important in breast, lung, and skin cancer. Researchers continue to promote other cancer research.

For example, SVM is a common method to use for taking treatments for breast cancer, dividing the tumor into benign and malignant, and mapping them into multi-dimensional spaces, to relieve complex analysis in a relatively simple, two-dimensional environment. It always selects the best hyperplane for splitting these data. CHEN et al.[1] found that the specific characteristics of cancer nests, cancer cell density, and stem cell structure are of particular importance with respect to nuclear information in the pathogenesis of breast cancers by data mining on the 1150 chromosome image of SVM Chen, and others. The use of super hacking using 3121 breast tissues in the joint kernel to compensate for the semi-anticipating diagnosis breach from low to high. In large databases, braincases, 88.1% retrieval accuracy, and 91.3% rating accuracy were recorded in the 16.6m query time. Jaworek[3] has suggested a more accurate method to differentiate between melanoma in the field of skin cancer. He used Dermoscopic to pre-process images of skin to remove pieces not linked to symptoms of the skin. Then he segments and extracts images with color characteristics. He used co-occurrence rendering of gray-level texture matrix, meanwhile. The level of skin cancer was assessed and its precision reached 92%.

B. Applications in medical imaging

At present, when medical resources are limited, most people are unable to satisfy the effectiveness of the medical imaging test and the relevant results. It means ML will greatly reduce manpower and enhance efficiency when used in medical imaging. Medical professionals in the areas of CT segmentation, RIM analysis, and other medical pictures have favored ML over the past several years.

Zhu[4] in his article suggests that the artificial neural network algorithm can be used to determine benign and malevolent thyroid nodules aboutprojects ultrasound detection. A total of 618 patients and 689 thyroid nodules, no history of thyroid disease, no nose radiation history, or ultrasound examinations. The Vascular features Doppler of each nodule have been built up by the neural system with the use of 0 and 1, respectively, to indicate the good quality of the neural nodule and the malignant system after morphology, margin, echo, inner combination, calcification, hail sign, color. There were 561 nodules in the study, which reduced the previous six unique and related qualities, to prevent excess training.

4. METHODOLOGY

Machine learning – neural networks and deep learning

Machine learning is a data fitting and 'learning' scan statistical technique for data training models. One of the most popular forms of AI is machine learning. In the Deloitte 2018 survey of 1,100 US managers whose organizations were already employees of AI, 63 percent of the companies surveyed employed machine learning in their enterprises.

1. There are many versions and a wide range of techniques at the heart of AI approaches. Precision medicine – which protocols are likely to be effective based on a vast range of patient attributes and the therapeutic context – is the most common application of traditional machine learning for healthcare.

2. The great majority of applications of machine learning and precision medicine demand a training data set which is known as a supervised study for the outcomes variable (e.g. onset of diseases). A more complex type of machine training is the neural network, a technology that has been well-established in health research since the 1960s for several years 3 and that is used to determine if a patient has a particular disease for categorization purposes. It views problems in terms of variables or 'features' associating input with outputs in inputs, outputs, and weights. The way neurons process signals have been likened but the analogy with the function of the brain is relatively weak.

The methylation method

The methylating classifier was initially trained to sort medulloblastomas into subtypes by a consortium of dozens of scientists. In the end, the team led by Germany increased the effort to cover 100 or so known central nervous system cancers. The researchers made the classification available online when the initial results were published in March 2018. Other scientists can upload methylation profiles and learn in a matter of minutes what type of cancer suits. They get a trust score that shows what the result is likely to be right. Every month about 1,000 such profiles are uploaded, says Andreas von Deimling, who was one of the project leading neuropathologists at the German Cancer Research Centre.

Although the New York State endorsed the use of the test by Langone, the website notes that the classifier remains a clinically validated tool for research. Initially, the classifier was performed on about 2,800 tumor samples, but the number has grown to around 60,000 since the Website was operational. "It is much greater than the entire lifetime of a single pathologist," says von Deimling. "With this system now we find new entities which no pathologist has ever defined with the sheer number of tumors." The system compares the data with its tumor list and puts the profile in a group, but cancer receives little confidence if it is not fully matched. Pathologists examine samples with low scores and assign them to a new group and retrain the classifier if they have at least seven with the same methylation profiles. Around 150 different cancer entities now are recognized by the classifier.

Hospital error rates could be reduced if the computer can find those cancer types. In the initial study, 12 percent of brain tumors were misdiagnosed by pathologists. The algorithm showed Snuderl says NYU has 12% to 14% of its patients with similar error rates. "This is not a small number of people who could simply benefit from the right diagnosis," says Snyder.

Profiling methylation is costly — usually only large cancer research centers. Thus, scientists expect to identify subtypes by simple biomarkers. If, for example, they can discover differences that are visible by looking under a microscope at the stained tissue, many hospitals that do not have the resources to profile the methylation can make the same level of diagnostic sorting available. "If you first have a correct grouping, you can only develop these markers," says von Deimling.

Getting it right

It can also be difficult to correctly diagnose cancers elsewhere in the body. It may be difficult to find out whether a person has prostate cancer and whether that cancer is aggressive enough or just to be monitored.

Although the majority of prostate cancers are diagnosed with biopsies from standard sites, this can result in a lack of real cancer. A more recent approach is using MRI imagery to combine various types of MRI scans. Using MRI imagery is a new approach. But highly trained radiologists don't always agree about the images, and even less experienced people are unfamiliar. "Achieving a certain level of radiology expertise, particularly in this diagnosis of prostate cancer MRI, requires a great deal of training," says Kyung Hyun Sung, a radiologist from the University of California, Los Angeles. The University has a radiologist's reading program and is a leading center in the treatment of prostate cancer with experts with 10 years of or more experience. This is not the rule, however. "Community hospitals in their ranks don't have this training or expertise," Sung says.

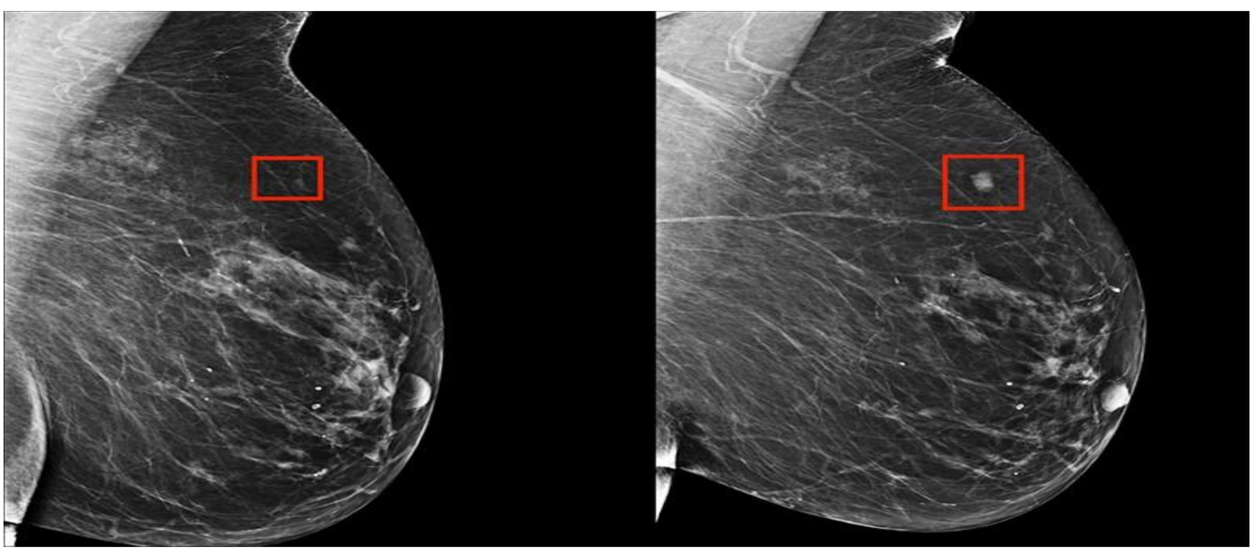

Figure 2: Four years (left) before a woman developed an AI system for the potential breast tumor (right).

Sung creates an AI system called FocalNet to help physicians classify prostate cancer better with those hospitals in mind. Sung and colleagues collected around 400 preoperative MRI scan from persons who would have been operated on to remove their prostate to train the program. Researchers supplied the FocalNet scans together with the Gleason rating of the tumor, a malignancy rating that was determined by pathologists who analyzed the tissue after removal of the prostate. The system then searched for patterns in the MRI scans, which correspond to pathology.

5. RESULTS AND DISCUSSION

All of the points are a hyperplane that minimizes the cost function so that the data points can be connected to the best possible level.

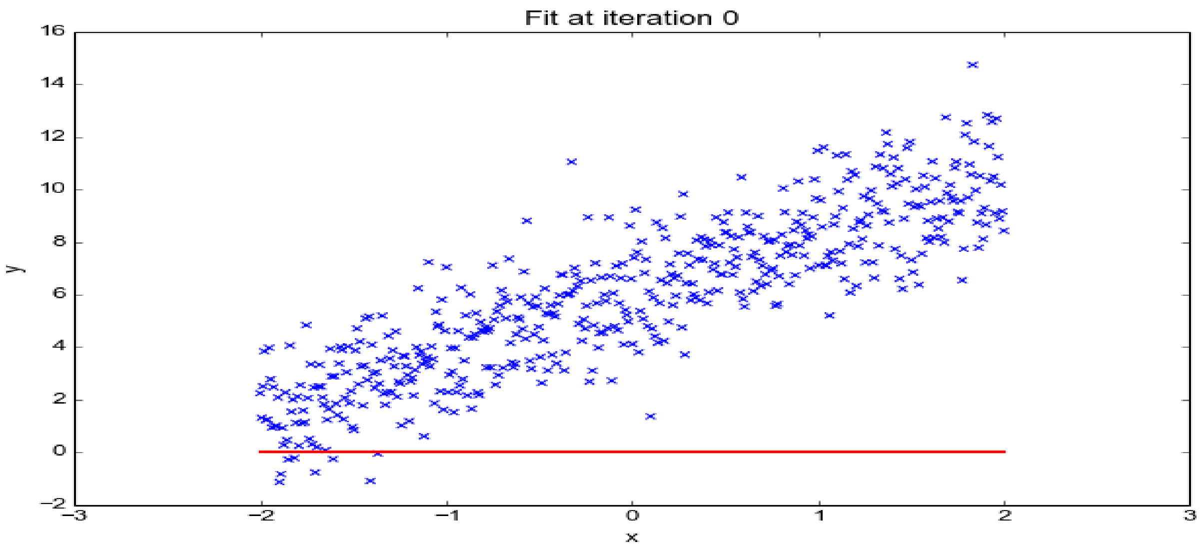

Figure 3: Linear regression to improve the relationship

It begins with a random line without a correlation, which through a gradient descent reaffirms the optimum relationship.

The Gradient Descent algorithm is used for regression. By changing model parameters, this algorithm reduces the cost function.

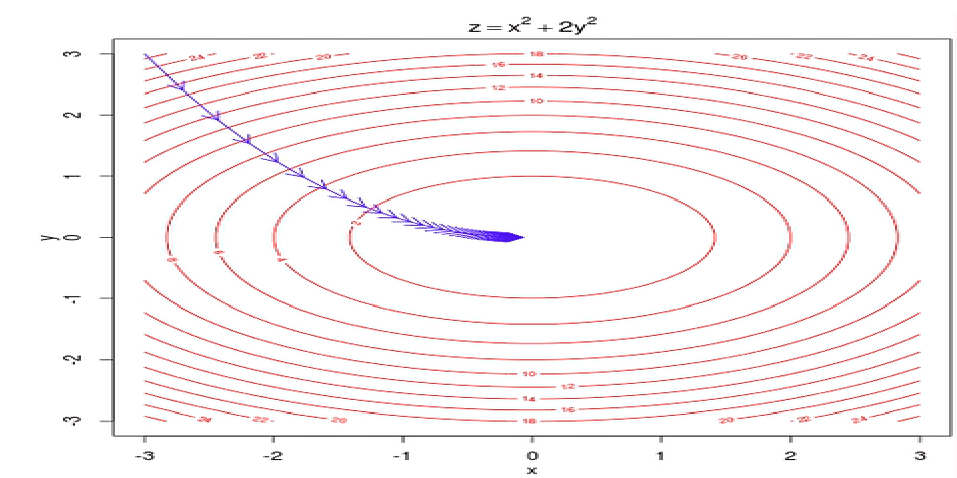

Figure 4: Think about the descents as you go down a hill to the lowest point.

In the meantime, the results are more accurate, as the decreasing gradient reduces the cost function down and down. That is how the regression helps to make your model more accurate to fit the data.

Classification Categorizes Data Points Into Groups

Supervised learning models can do more than simple regress. One of ML's most important duties is classification. Classification algorithms establish boundaries between data points that classify them as a group, according to their properties, which correspond to the model parameters.

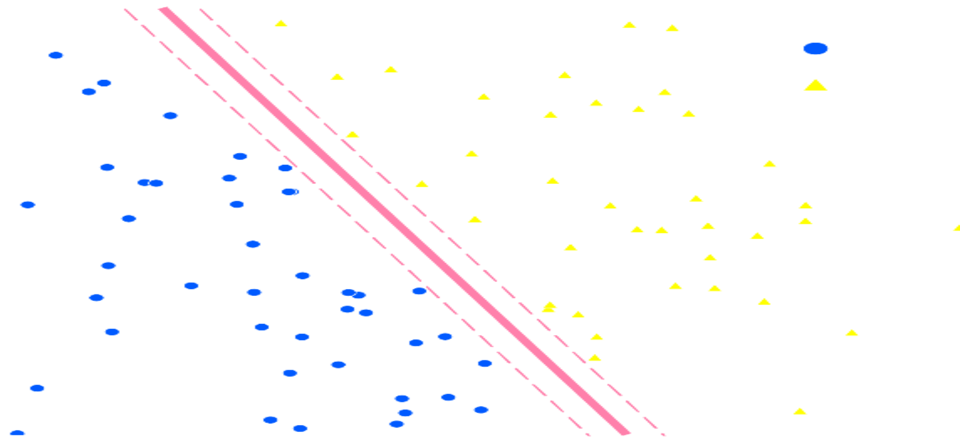

Figure 5: Either sheep or goat is classified by data points.

Data points are classified as sheep or goats in this model. This is subject to the average daily temperature depending on their steps.

A process called logistic regression creates the boundary of the classes. The boundary does not depend on the data is an important fact to remember. Do you recall the cost function? Surprise! is also used in the ranking.

Figure 6: regression to find the best possible fit to the data

Similarly, regression is used to find the best fit of data in the classification.

CONCLUSION

This article discusses the main methods of machine learning. After understanding the history and current application of medical machine learning, this article summarizes several representative applications. The typical concepts and algorithms are summed up. Operation, chemo, and radiotherapy are no doubt that for many years to come will remain the standard cancer therapy but, at the same time, the scientific population is increasingly interested in further maturing the current clinical strategies for cancer. Input and assistance from computing are a true reality for the future clinical environment and lead to a major technological revolution that can be used for the prevention and real-time diagnosis of human health issues. AI avoids fatigue, cultural and moral convictions, and emotional problems. Excellent decisions and continuous improvement with artificial neural networks and DL would quickly assist physicians in their diagnosis and cancer exploration. The capacity for processing an extensive amount of information and data is limited to natural people.

REFERENCES

[1] G. Eason, B. Noble, and I.N. Sneddon, “On certain integrals of Lipschitz-Hankel type involving products of Bessel functions,” Phil. Trans. Roy. Soc. London, vol. A247, pp. 529-551, April 1955. (references)

[2] Jiang M, Zhang S, Huang J, et al. Scalable histopathological image analysis via supervised hashing with multiple features[J]. Medical Image Analysis, 2016, 34:3-12.

[3] Joanna J K, Pawel K . Automatic Classification of Specific Melanocytic Lesions Using Artificial Intelligence[J]. BioMed Research International, 2016, 2016:1-17.

[4] Lu-Cheng, Zhu,Yun-Liang, Ye,Wen-Hua, Luo,Meng, Su,Hang-Ping, Wei,Xue-Bang, Zhang,Juan, Wei,Chang-Lin, Zou.A model to discriminate malignant from benign thyroid nodules using an artificial neural network.[J].PloS one,2013,8(12):e82211.

[5] Huang W C , Chang C P . Automatic Nasal Tumor Detection by grey prediction and Fuzzy C-Means clustering[C]// IEEE International Conference on Systems. IEEE, 2006.M. Young, The Technical Writer’s Handbook. Mill Valley, CA: University Science, 1989.

[6] Sarraf S, Tofighi G . Classification of Alzheimer's Disease using fMRI Data and Deep Learning Convolutional Neural Networks[J]. 2016.

[7] Dou Q , Chen H , Yu L , et al. Automatic Detection of Cerebral Microbleeds from MR Images via 3D Convolutional Neural Networks[J]. IEEE Transactions on Medical Imaging, 2016:1-1.

[8] Pang-ning Tan, Michael Steinbach, Vipin Kumar, Introduction to data mining, Beijing: Posts & Telecom Press, 2011

[9] Xue-Hu WANG, Study Liver Segmentation Method from CT Images based on Deformation Optimization and Sparse Statistics[D]. Beijing Institute of Technology, 2015.

[10] Yu Q, Jiang T , Zhou A , et al. Computer-aided diagnosis of malignant or benign thyroid nodes based on ultrasound images[J]. European Archives of Oto-Rhino-Laryngology, 2017, 274(7):2891- 2897.

[11] Pedro Domingos, The Master Algorithm: How the Quest for the Ultimate Learning Machine Will Remake Our World, ISBN-10: 0465065708, 2015.

[12] Bayesian Analysis. (2015, January 28). http://www.britannica.com/EBchecked/topic/56811/Bay es ian-analysis.

[13] Triola M. F. Bayes Theorem. Retrieved September 16, 2014 from http://faculty.washington.edu/tamre/BayesTheorem.pdf

[14] Belavkin, R. “Feed-Forward Neural Networks” http://www.eis.mdx.ac.uk/staffpages/rvb/teaching/BIS32 2 6/hand11.pdf

[15] David E. Rumelhart (Author), James L. McClelland (Author), PDP Research Group Parallel Distributed Processing, ISBN-10: 026268053X, 1987.