ABOUT THE AUTHORS

Dr. T. Arumuga Maria Devi, B.E., M.Tech., Ph.D., Received B.E degree in Electronics & Communication Engineering from Manonmaniam Sundaranar University, Trinelveli, Tamil Nadu, India in 2003. Completed M.Tech degree in computer & Information Technology from Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India in 2005. Received Ph.D Degree in Information Technology Computer Science and Engineering from Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India in 2012. She is the Assistant Professor of Centre for Information Technology and Engineering , ManonmaniamSundaranar University, Tirunelveli since 2005.

Mrs. Ajitha S Raj, M.C.A., M.Phil., Research Scholar,Centre for Information Technology and Engineering , manonmaniam Sundaranar University, Trinelveli and presently working as Assistant Professor, Department of Computer Science, Women's Christian College, Nagercoil, Tamil Nadu, India. She has nine years of teaching experience and also serving as a Committee member of Eco Club. She has attended 30 FDP's, 10 Workshops and more than 50 seminars and webinars.

Mr. A. Chockalingam, B.Tech., M.Tech., is a Researcher and Assistant Professor in Centre for Information Technology and Engineering, Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India.He has three years of teaching experience and five years of Research experience in areas like Data Analytics, Deep Learning, Machine Learning and Artificial Neural Networks. He has contributed in a research project "Automatic License Plate Recognition" granted by Centre for Development of Advanced Computing (C-DAC), Trivandrum, India.He has completed '4' edX Verified Certifications in Data Analytics and Cyber Security domains.

Mrs. Sunitha S, M.Sc., (Ph.D), presently working as Assistant Professor & IQAC Member, Department of Computer Science, Women's Christian College, Nagercoil, Tamil Nadu, India. She has Thirteen years of teaching experience and also serving as a Committee member in SCMI, Fine Arts Club, Counselling Cell, Art Culture and Heritage Club. She has published 3 research articles in Scopus, 2 in UGC care and 2 in International journals. She has presented 2 papers in International and National level respectively. She has attended 33 FDP's, 10 Workshops and more than 60 seminars and webinars.

Mrs.S.Gnana Sophia,M.Sc.,M.Phil.,(PhD).,presently working as Assistant Professor, Department of Computer Applications, Scott Christian College (Autonomous),Nagercoil, Tamil Nadu, India. She has 21 years of experience. She has been researching Machine Learning, Cloud Computing, Big Data and Computer Networks. She has published 13 research articles in Scopus, Web of Science, UGC care and open-access journals. She has presentedseven papers at various National and International conferences. She has attended five seminars and workshops.

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Dr.T.Arumuga Maria Devi
Assistant Professor,
Centre for Information Technology and Engineering,
Manonmaniam Sundaranar University,
Tirunelveli, Tamil Nadu, India

Mrs.Ajitha S Raj,
Assistant Professor,
Department of Computer Science, Women's Christian College,
Nagercoil, Tamil Nadu, India. Researcher, Centre for Information Technology and Engineering, Manonmaniam Sundaranar University,
Tirunelveli, Tamil Nadu, India

Mr.A.Chockalingam
Assistant Professor (T) & Researcher,
Centre for Information Technology and Engineering,
Manonmaniam Sundaranar University,
Tirunelveli, Tamilnadu, India.

Mrs.S.Sunitha
Assistant Professor, Department of Computer Science,
Women's Christian College, Nagercoil,
Tamil Nadu, India

Mrs.S.Gnana Sophia
Assistant Professor,
Department of Computer Applications,
Scott Christian College (Autonomous), Nagercoil,
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CONTENTS

CHAPTER 1

MACHINE LEARNING

1.1 INTRODUCTION

The term "machine learning" was coined in the 1950s by Arthur Samuel, an Artificial Intelligence pioneer who created the first self-learning system for playing checkers. He noticed that the more he played, the better the system performed.

Machine learning has truly taken off in recent years, thanks to advances in statistics and computer science, as well as better datasets and the growth of neural networks.

Machine learning is now everywhere, whether you realise it or not - automated translation, image recognition, voice search technology, self-driving cars, and more.

Machine learning (ML) is an artificial intelligence (AI) branch that allows computers to "self-learn" from training data and improve over time without being explicitly programmed. Machine learning algorithms can detect and learn from data patterns to make their own predictions. In a nutshell, machine learning algorithms and models learn by doing.

A computer engineer writes a series of instructions that instruct a computer on how to transform input data into the desired output in traditional programming. The majority of instructions follow an IF-THEN structure: when certain conditions are met, the programme performs a specific action.

Machine learning, on the other hand, is a computer-assisted process that allows machines to solve problems with little or no human intervention and take action based on previous observations.

While the terms artificial intelligence and machine learning are frequently used interchangeably, they are not the same thing. Machine learning is a subset of AI that enables intelligent systems to autonomously learn new things from data. AI is the broader concept - machines making decisions, learning new skills, and solving problems in a similar way to humans.

Instead of programming machine learning algorithms to perform tasks, you can feed them examples of labelled data (known as training data), which allows them to automatically make calculations, process data, and identify patterns.

Machine learning can be applied to massive amounts of data and performs far better than humans. It can help you save time and money on tasks and analyses such as resolving customer pain points to improve customer satisfaction, automating support tickets, and mining data from internal and external sources.

To comprehend how machine learning works, you must first investigate various machine learning methods and algorithms, which are essentially sets of rules that machines use to make decisions. The five most common and widely used types of machine learning are listed below:

1.1.1 Supervised Learning

Based on labelled training data, supervised learning algorithms and models make predictions. Each training sample contains an input as well as the desired output. When determining the labels for unseen data, a supervised learning algorithm analyses the sample data and makes an inference - basically, an educated guess.

CHAPTER 2

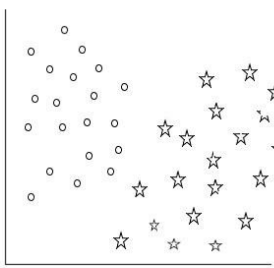
THE KNN CLASSIFICATION ALGORITHM ASSIGNS

2.0 What exactly is KNN?

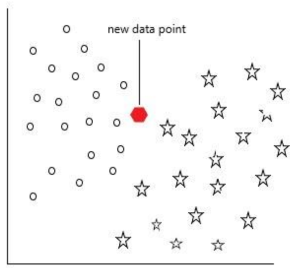
The KNN classification algorithm assigns a data point to the category that is most common among its neighbours. If a datapoint is surrounded mostly by a specific type of data point, say "Red dots," it is very likely that the datapoint under consideration is also a red dot.

The 'K' in KNN represents the number of nearest neighbours considered in the voting process to determine the majority.

Consider two data points: 1) a circle and 2) a star.



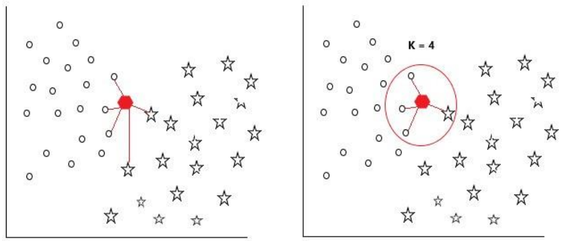
Conside two data points
1) Circle 2) Star



There is a new data point and wanted to predict whether that new point belongs to circle or start data points

Suppose, if we want to test the new data point and predict whether it belongs to a circle or star category?

OK, how do we predict or classify the new data point?



Finding the datapoints which is nearest to the new data points by using distance measures

Let's assume K = 4. New data points is identified by the majority of votes from its four neighbours. Here three points are circle out of four nearest datapoints. Hence, the new data point belongs to circle class.

To begin, we must calculate the distance between the new data points and the nearest data points using similarity measures. Distance between two data points is what similarity measures are. There are various distance measurements available. Popular ones include the Euclidean, Manhattan, Minkowski, and Hamming distance methods. The Euclidean distance is commonly used. For category variables, the Hamming distance is used.

Then, in the preceding example, we must determine who the neighbours are. Let us suppose K = 4. The new data points are then classified based on the majority of votes cast by their four neighbours. The new data point is a circle because three of its four neighbours are circles.

The K-NN algorithm operates in this manner.

CHAPTER 3

INTRODUCTION OF DEEP LEARNING

3.1 INTELLIGENCE

See Intellect for the human capacity for reasoning and understanding. Human intelligence may be found at the following link: human intelligence. See Intelligence for further information (disambiguation).

Intelligence has been defined in various ways, including the capacity for abstraction, logic, understanding, self-awareness, learning, emotional knowledge, reasoning, planning, creativity, critical thinking, and problem- solving. It may be defined more broadly as the ability to perceive or infer information and retain it as knowledge for adaptive actions within an environment or context.

Although intelligence is most often studied in humans, it has also been observed in non-human animals and plants, despite debate about whether some of these life forms demonstrate intelligence. Artificial intelligence refers to intelligence in computers or other machines.

The term "intelligence" comes from the Latin nouns intelligentia or intellctus, which come from the verb intelligere, which means "to understand or perceive." In the Middle Ages, intellectus became a scholarly technical term for understanding and a translation of the Greek philosophical term nous. This phrase, however, was firmly associated with teleological scholasticism's philosophical and cosmological theories, including theories of soul immortality and the concept of the active intellect (also known as the active intelligence). This method of nature study was vehemently opposed by early modern philosophers such as Francis Bacon, Thomas Hobbes, John Locke, and David Hume, who all favoured "understanding" (rather than "intellectus" or "intelligence") in their English philosophical writings. For example, Hobbes cited "intellectus intelligit," translated in English as "the understanding understandeth," as a classic illustration of a logical absurdity in his Latin De Corpore. As a result, the term "intelligence" has become less prevalent in English-language philosophy. However, it has since been adopted (with the scholastic theories that it now entails) in more recent psychology.

The concept of "intelligence" is debatable, with differing abilities on what it entails and whether it is measurable. Some psychologists have proposed the following definitions:

From "Mainstream Science on Intelligence," a Wall Street Journal op-ed declaration signed by fifty-two researchers (out of a total of 131 asked to sign):

A broad mental ability includes the ability to reason, plan, solve problems, think abstractly, absorb complicated concepts, learn fast, and learn from experience, among other things. It is more than just book knowledge, a certain academic competence, or test-taking ability. Rather, it indicates a larger and deeper understanding of our surroundings—"catching on," "making sense," or "figuring out" what to do.

Intelligence: Knowns and Unknowns (1995), a study produced by the American Psychological Association's Board of Scientific Affairs:

Individuals vary in their ability to comprehend complicated concepts, adapt efficiently to their surroundings,

CHAPTER 4

MACHINE LEARNING TYPES

4.1 INTRODUCTION

A type of AI called "machine learning" enables a machine to automatically learn from data, improve performance based on prior experiences, and make predictions. A collection of algorithms used in machine learning work on vast amounts of data. These algorithms are given data to train them. After training, they develop a model and carry out a certain job.

1. Supervised Machine Learning
2. Unsupervised Machine Learning
3. Semi-Supervised Machine Learning
4. Reinforcement Learning

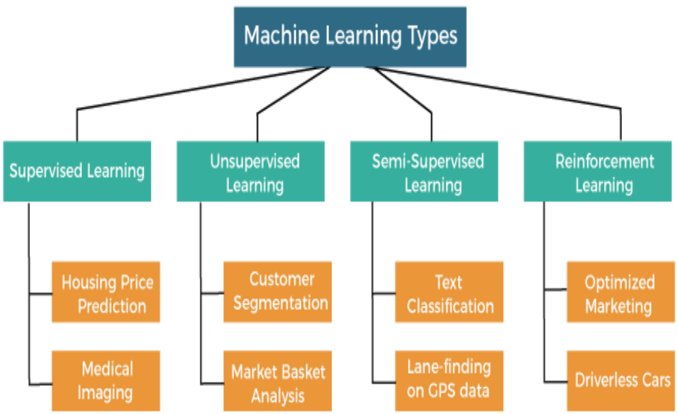


Fig 4.1 Machine Learning Types

In this topic, we will provide a detailed description of the types of Machine Learning along with their respective algorithms:

4.2 SUPERVISED MACHINE LEARNING

Supervised machine learning, as its name suggests,Is based on supervision. We train the machines using the "labelled" dataset in the supervised learning approach. Then the machine predicts the output based on the training. Here, the labelled data indicates which inputs have already been mapped to which output. A more accurate machine would be that we first train the machine with the input and related output. Then we ask it to predict the output using the test dataset.

Let's use an example to understand supervised learning. Suppose we have a dataset of images of cats and dogs as input. Therefore, in order for the machine to understand the images, we must first train it to do so. This training will include teaching it about the size and shape of a dog's tail, the shape of a cat's eyes, their colour, and their height (dogs are higher than cats). After training, we input a cat image and ask the machine to identify the object and predict the output. The machine is now well-trained, so it will examine the object's features, including height, shape, colour, eyes, ears, tail, and so on, and find that it is a cat. As a result, it will be classified as a cat. This is the process the machine uses to recognise the objects in supervised learning.

To map the input variable (x) with the output variable is the primary goal of the supervised learning approach (y). Risk assessment, fraud detection, spam filtering, and other practical supervised learning applications include these.

Supervised Machine Learning Categories

CHAPTER 5

INTRODUCTION TO TIME SERIES ANALYSIS

5.1 INTRODUCTION

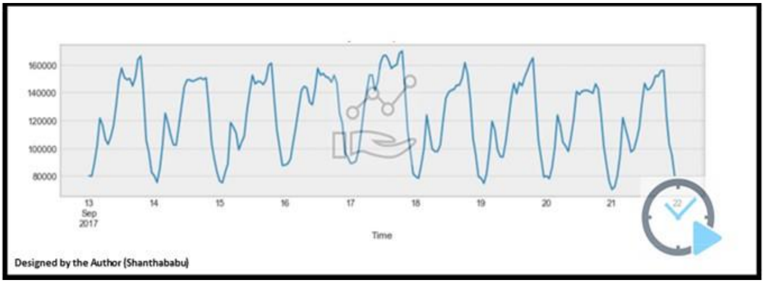


Fig 5.1 Time Series Analysis

Synopsis of Time Series Analysis

- A Time-Series represents a series of time-based orders. It would be Years, Months, Weeks, Days, Horus, Minutes, and Seconds
- A time series is an observation from the sequence of discrete-time of successive intervals.
- A time series is a running chart.
- The time variable/feature is the independent variable and supports the target variable to predict the results.
- Time Series Analysis (TSA) is used in different fields for time-based predictions – like Weather Forecasting, Financial, Signal processing,
- Engineering domain – Control Systems, Communications Systems.

- Since TSA involves producing the set of information in a particular sequence, it distinguishes it from spatial and other analyses.
- We could predict the future using AR, MA, ARMA, and ARIMA models.

Studying the features of the response variable concerning time, as the independent variable, is done via time series analysis. Utilizing the time variable as a point of reference, one might estimate the target variable in the interest of predicting or forecasting. TSA Objectives, Assumptions, and Components will be covered in depth in this article (stationary, and Non-stationary). Along with the TSA algorithm and specific Python usage cases. What is Time Series Analysis Definition If you see, there are many more definitions for TSA. But make it simple.

A time series is nothing but a sequence of various data points that occurred in a successive order for a given period

Objectives

- To understand how time series works, what factors affect a certain variable(s) at different time points.
- Time series analysis will provide the consequences and insights of the given dataset's features that change over time.
- Supporting to derive the predicting the future values of the time series variable.
- Assumptions There is one and the only assumption that is “stationary”, which means that the origin of time, does not affect the properties of the process under the statistical factor.

CHAPTER 6

DATA CLEANUP, CHARACTERISTICS AND FEATURE SELECTION

6.1 DATA CLEANSING

Real-world data includes a range of gaps, noise, and irregularities. Ensure sure the data can be usefully evaluated before beginning any statistical analysis. Data cleaning often takes the longest to complete during data analysis. However, this up-front expenditure is required since the dependability of model outputs directly depends on the quality of the data. Although various machine learning projects call for different data cleaning procedures, the following particular activities are often meant when "data cleansing" is used.

Cleaning Missing Values

Many machine learning techniques do not support data with missing Many machine learning values do not handle missing value data. We must first understand why some data are missing to address this. Missing values often happen because there is no information provided, however there are other situations that might result in data gaps as well. When data is retrieved and combined from many sources, for instance, selecting the wrong data types for attributes might result in data loss.

Finding patterns in missing data is one technique to identify into missing values. For instance, it may be clear that only male respondents are asked specific survey questions if female respondents' replies to such questions are absent. Two loan documents that have the same ID might serve as another example. If all of the values in the second record are empty except "Market Price," the second record is probably only updating the market price of the first record.

After the early review of missing data is over, we may set thinking about how to address the issue. Ignoring the records with missing values is the simplest method to deal with them. This approach isn't always workable, however. If the dataset has a significant number of missing values, removing them altogether can leave behind data that isn't a good representation of the starting population. In such instance, an appropriater course of action is to impute missing values with reasonable values rather than filtering out pertinent rows or attributes.

The most common value or a newly constructed "unknown" category is often used for categorical variables to impute missing values. The mean or median values for numeric variables may be used to fill up the gaps left by missing values. There are other, more sophisticated values to deal with missing values, such as listwise deletion for erasing rows with missing data and multiple imputations for dealing with.

Reducing Noise in Data

“Erroneous values and outliers are called "noise" in data. Noise is an inevitable issue that may be brought on by various things, including human error in data input, technological issues, and many more. Noisy data hurts model performance, making its identification and elimination crucial to the data cleaning.

The two main forms of noise in data are attribute noise and

CHAPTER 7

ENSEMBLE MODEL DEVELOPMENT

7.1 ENSEMBLE LEARNING

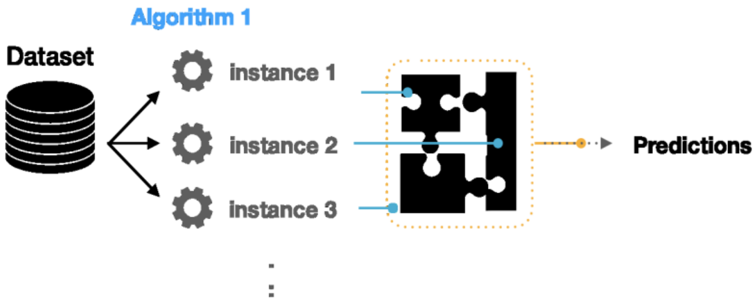


Fig 7.1 Aggregated Predictions Using Multiple Weak Learners of the Same Algorithm

When building ensemble models, we're not only focusing on the algorithm's variance. For instance, we could build multiple C45 models where each model learns a specific pattern specialized in predicting any given thing. Models we can use to obtain a meta-model are called weak learners. In this ensemble learning architecture, the inputs are passed to each weak learner while collecting their predictions. We can use the combined prediction to build a final ensemble model.

One important thing to mention is that weak learners can map features with variant decision boundaries differently.

7.2 ENSEMBLE ALGORITHM

A single algorithm may not make the ideal prediction for a certain data set. Machine learning algorithms have certain limits, and challenging a model with great accuracy is difficult. We can increase the accuracy overall if we create and merge numerous models. After that, we combine the output from each model with the following two goals to implement the combination of models

1. Reducing the model error
2. Maintaining the model's generalization

You can implement such aggregation using different techniques, sometimes referred to as meta-algorithms.

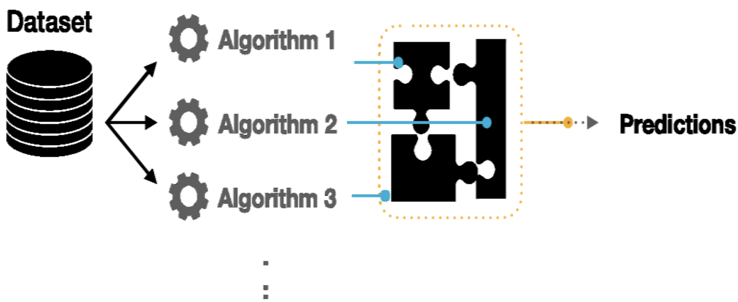


Fig 7.2 Diversifying the Model Predictions Using Multiple Algorithms

7.3 TYPES OF ENSEMBLE MODELING TECHNIQUES

1. Bagging
2. Boosting
3. Stacking
4. Blending

CHAPTER 8

LAYER PERCEPTRONS AND ACTIVATION FUNCTIONS

8.1 SINGLE LAYER PERCEPTRON

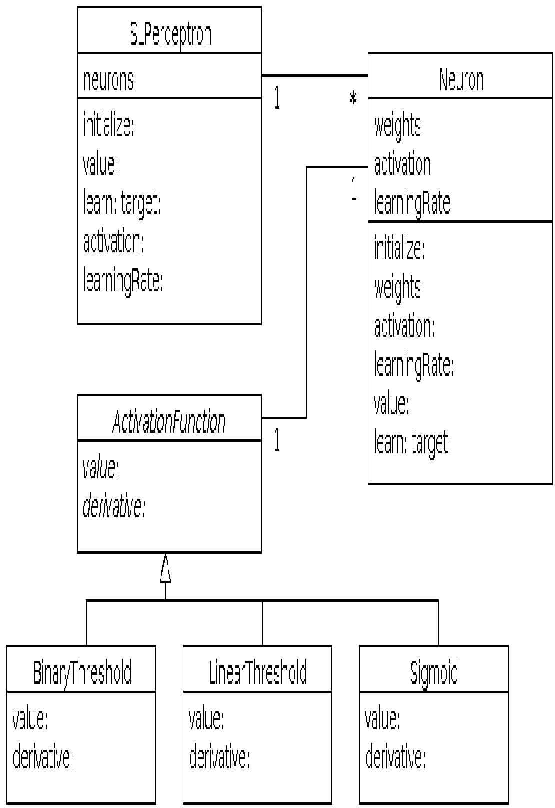
A thorough but condensed explanation of perceptrons and the many activation mechanisms

Fig 8.1 Single Layer Perceptron

A feed-forward network based on a threshold transfer function is known as a single layer perceptron (SLP). SLP is the most basic type of artificial neural network. It can only categorise situations that can be separated into two networks linearly using a binary goal. Equations called activation functions are used to control a neural network's output. The function, which is activated to every neuron in the network, decides whether or not to activate each neuron based on whether or not its input is important for the prediction made by the model.

8.1.1 Work Flow of Single Layer Perceptron

Linear classifier, or algorithm that divides input into two categories along a straight line, is what a perceptron is. A feature vector x is typically multiplied by weights w and added to a bias b as the input



ACRONYMS

1-bit SGD - 1-bit Stochastic Gradient Descent (1-bit SGD) ACE - Alternating conditional expectation (ACE) algorithm BLEU - Bilingual Evaluation Understudy (BLEU)
BPMF - Bayesian Probabilistic Matrix Factorization (BPMF) BPTT - Backpropagation Through Time (BPTT)
BRNN - Bidirectional Recurrent Neural Network (BRNN) CAE - Contractive autoencoder (CAE)
CBOW - Continuous-Bag-of-Words (CBOW) CMMs - Conditional Markov Models (CMMs) CNN - Convolutional Neural Networks (CNN) CRFs - Conditional Random Fields (CRFs)
CTC - Connectionist Temporal Classification (CTC) CTR - Collaborative Topic Regression (CTR)
DCGAN - Deep Convolutional Generative Adversarial Network (DCGAN) DE - Differential Evolution (DE)
ELU - Exponential Linear Unit (ELU)
EM - Expectation-maximization (EM) algorithm
F1 Score - Harmonic Precision-Recall Mean (F1 Score) FFT - Fast Fourier transform (FFT)
FST - Finite-state transducer (FST)
GAM - Generalized additive model (GAM) GAN - Generative Adversarial Network (GAN) GAP - Global Average Pooling (GAP)
GMM - Gaussian mixture model (GMM)
Global Vectors - GloVe (Global Vectors) embeddings
HDP - Hierarchical Dirichlet process (HDP) HMMs - Hidden Markov Models (HMMs)

KL - Kullback-Leibler (KL) divergence LDA - Latent Dirichlet allocation (LDA) LDA - Linear discriminant analysis (LDA)
LDADE - Latent Dirichlet Allocation Differential Evolution (LDADE) LSA - Latent semantic analysis (LSA)
LSI - Latent Semantic Indexing (LSI) LSTM - Long Short-Term Memory (LSTM) LTR - Learning To Rank (LTR)
MAP - Maximum A Posteriori (MAP) Estimation
MCMC - Markov Chain Monte Carlo (MCMC)
MDL - Minimum description length (MDL) principle
MDRNN - Multidimensional recurrent neural network (MDRNN) MLE - Maximum Likelihood Estimation (MLE)
MRR - Mean Reciprocal Rank (MRR) NER - Named Entity Recognition (NER)
NERQ - Named Entity Recognition in Query (NERQ) NFL - No Free Lunch (NFL) theorem
NTM - Neural Turing Machine (NTM)
PACO - Poisson Additive Co-Clustering (PACO) PCA - Principal Component Analysis (PCA)
PLSI - Probabilistic Latent Semantic Indexing (PLSI) PMF - Probabilistic Matrix Factorization (PMF)
PMI - Pointwise Mutual Information (PMI) POS - Part-of-Speech (POS) Tagging
PPMI - Positive Pointwise Mutual Information (PPMI) PYTM - Pitman-Yor Topic Modeling (PYTM)
RF - Random Forest (RF)
RL - Reinforcement Learning (RL)
RLFM - Regression based latent factors (RLFM)
RNNLM - Recurrent Neural Network Language Model (RNNLM) ROC - Receiver Operating Characteristic (ROC)
ReLU - Rectified Linear Unit (ReLU) SBM - Stochastic block model (SBM)

SBO - Structured Bayesian optimization (SBO) SBSE - Search-based software engineering (SBSE) SCH - Stochastic convex hull (SCH)
SGD - Stochastic Gradient Descent (SGD)
SGVB - Stochastic Gradient Variational Bayes (SGVB) SMBO - Sequential Model-Based Optimization (SMBO) SSVM - Smooth support vector machine (SSVM)
SVD - Singular Value Decomposition (SVD) SVM - Support Vector Machine (SVM)
TGAN - Temporal Generative Adversarial Network (TGAN) TRPO - Trust Region Policy Optimization (TRPO)
VAE - Variational Autoencoder (VAE)
VQ-VAE - Vector-Quantized Variational Autoencoders (VQ-VAE)
WFST - Weighted finite-state transducer (WFST)
audio - Bit transparency (audio) convolution - Filter (convolution) convolution - Kernel (convolution) convolution - Padding (convolution) convolution - Sobel filter (convolution) convolution - Stride (convolution) disambiguation - Facet (disambiguation)
hLDA - Hierarchical Latent Dirichlet allocation (hLDA)
i.i.d - Independent and Identically Distributed (i.i.d)
intersection over union - Jaccard index (intersection over union) object detection algorithm - YOLO (object detection algorithm) object detection algorithm - YOLO9000 (object detection algorithm) object detection algorithm - YOLOv2 (object detection algorithm) seq2seq - Sequence to Sequence Learning (seq2seq)
visualization tool - Facet (visualization tool)

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For Full Book Contact

Dr.T.Arumuga Maria Devi

Assistant Professor,

Centre for Information Technology and Engineering,

Manonmaniam Sundaranar University,

Tirunelveli, Tamil Nadu, India

Email : deviececit@gmail.com
Email : arumugamariadevi@msuniv.ac.in
Mobile : +91 8667899606