CHAPTER -1

INTRODUCTION

A smart meter is an electronic device that records consumption of electric energy in intervals of an hour or less and communicates that information at least daily back to the utility for monitoring and billing.
Smart meters enable two-way communication between the meter and the central system.

Todays smart meters are increasingly used in worldwide for the ability of providing timely reading, automating metering without customer promises, producing fine-grained data, and more. Smart meters collect energy consumption data at a time interval, usually every 15 minutes or hourly. Smart meter data analytics system is an ICT-based platform for analyzing the collected meter readings, which nowadays has become an indispensable part for utilities running smart grid.

Smart meter data analytics can help utilities better understand customer consumption patterns, provision energy supply to peak demand, detect energy theft, and provide personalized feedback to customers. Also, government can make the decision for future smart grid development based on analytic results. For customers, smart meter data analytics can help them better understand their own energy consumption, save energy, and reduce their bills. Smart meter analytics thus is seen so important that the market has been growing rapidly, which is expected to reach over four billion dollar by year 2020 [19].

Various algorithms for smart meter data analytics have been proposed, mainly in the smart grid literature, such as the ones for electricity consumption prediction, consumption profile extractions, clustering similar consumers, and personalized feedback to consumers on how to adjust their habits and reduce their bills. Nevertheless, there has been lacking smart meter analytics applications in reality until in the recent that some database vendors starts to offer smart meter analytics software, e.g., SAP and Oracle/Data Raker. So did several startups in this area, e.g., C3Energy.com and OPower.com. Furthermore, some utilities such as California's PG&E4 also start to provide on-line portals where customers can view their electricity consumption and compare it with their neighbourhood's average. However, these systems and tools focus on simple aggregation and simple ways of visualizing consumption.

The details of their implementations are not disclosed. It is unclear on how to build a practical and scalable analytics system to handling smart meter data, which are characterized by big volume and big velocity.

In this paper we present a software platform for streamlining smart meter data analytics. This platform is built based on our benchmark work for smart meter data analytics technologies , and extended from our prototype smart meter data analytics system, *SMAS* .

This platform aims at providing a solution for facilitating the whole process of smart meter data analytics, including data ingestion, data transformation, loading, analyzing, and visualization. Utilities or customers can get the final information through these stages.

We adopt a hybrid architecture in the system design, in which the primary building blocks consist of Spark and Hive in the data processing layer, and PostgreSQL with MADlib [18] in the analytics layer. The design considers the support for high performance analytics queries, i.e., through RDBMS, and the support for big data analytics, i.e., through Spark and Hive. We decouple the system architecture into three layers, including data ingestion layer, processing layer, and analytics layer, which make it easy for users' implementation and extension.

Smart meter data goes through the three layers from data sources to be presented in a web portal. The processing layer is an open platform that can integrate various user-defined processing units, such as the units for data transformation, data anonymization, and anormal data detection. While, the analytics layer is also open to the extension of different analytics algorithms.

The analytics layer currently supports multiple types of algorithms, including time-series analytics at different temporal aggregations (e.g., hourly, daily, or weekly), load dis-aggregation, consumption pattern discovery, segmentation, forecasting and consumer feedback. Consequently, in this paper we make the following contributions: 1) we propose a hybrid architecture of combining the best of different technologies for streamlining smart meter data analytics; 2) we implement the open data platform that can be easily extended by using different data processing units and analtyics algorithms; and 3) we implement smart meter data analytics system of supporting both supply- and demand-side analytics, which can help utilities better to manage energy supply and help consumers save energy.

The rest of this paper is structured as follows. Section 2 summarizes the related work; Section 3 presents the design principles of the system; Section 4 gives an overview of the system; Section 5 and 6 present data processing layer and analytics layer of the system, respectively; Section 7 concludes the paper with directions for future work.

Figure 1.1

CHAPTER 2

SMART METER

A **smart meter** is an electronic device that records consumption of electric energy in intervals of an hour or less and communicates that information at least daily back to the utility for monitoring and billing.

OVERVIEW:-

Smart meters enable two-way communication between the meter and the central system. Unlike home energy monitors, smart meters can gather data for remote reporting. Such an advanced metering infrastructure (AMI) differs from traditional automatic meter reading (AMR) in that it enables two-way communications with the meter. Communications from the meter to the network can be done via fixed wired connections (such as power line communications) or via wireless.

In using wireless, one can opt for cellular communications (which can be expensive), Wi-Fi (readily available), wireless ad hoc networks over Wi-FI, wireless mesh networks, low power long range wireless (LORA), ZigBee (low power low data rate wireless), Wi-SUN (Smart Utility Networks), etc.

The term *Smart Meter* often refers to an electricity meter, but it also may mean a device measuring natural gas or water consumption.

Similar meters, usually referred to as interval or time-of-use meters, have existed for years, but "Smart Meters" usually involve real-time or near real-time sensors, power outage notification, and power quality monitoring. These additional features are more than simple automated meter reading (AMR). They are similar in many respects to Advanced Metering Infrastructure (AMI) meters. Interval and time-of-use meters historically have been installed to measure commercial and industrial customers, but may not have automatic reading.

Research by Which?, the UK consumer group, showed that as many as one in three confuse smart meters with energy monitors, also known as in-home display monitors.

The roll-out of smart meters is one strategy for energy savings. While energy suppliers in the UK could save around £300 million a year from their introduction, consumer benefits will depend on people actively changing their energy use. For example, time of use tariffs offering lower rates at off-peak times, and selling electricity back to the grid with net metering, may also benefit consumers.

The installed base of smart meters in Europe at the end of 2008 was about 39 million units, according to analyst firm Berg

Insight. Globally, Pike Research found that smart meter shipments were 17.4 million units for the first quarter of 2011. Visiongain has determined that the value of the global smart meter market will reach $7bn in 2012.

Smart meters may be part of a *smart grid*, but alone, they do not constitute a smart grid.

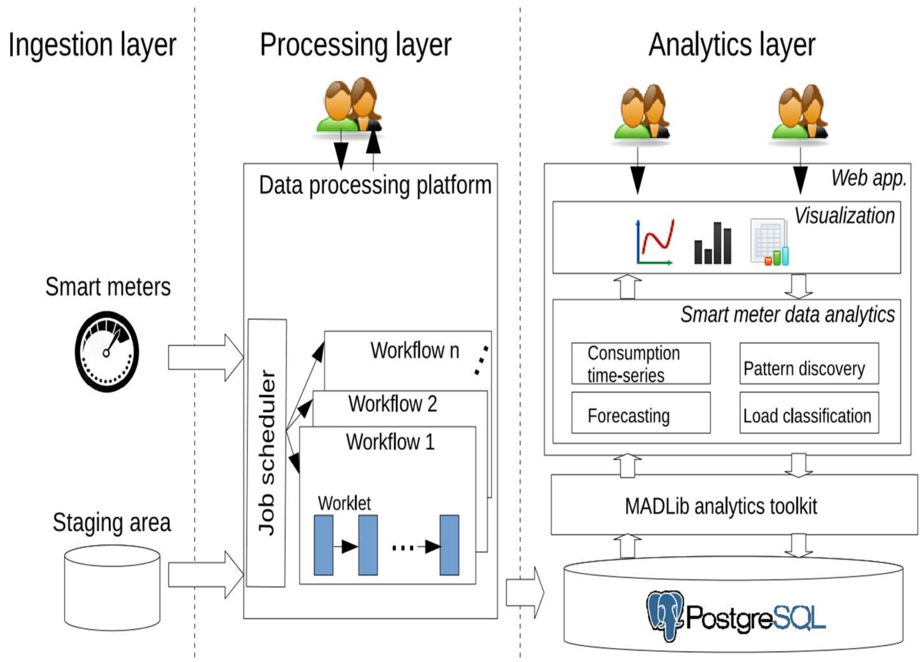

Fig.2.1 The system architecture of smart meter data analytics system

HISTORY:-

In 1972, Theodore George "Ted" Paraskevakos, while working with Boeing in Huntsville, Alabama, developed a sensor monitoring system that used digital transmission for security, fire, and medical alarm systems as well as meter reading capabilities. This technology was a spin-off from the automatic telephone line identification system, now known as Caller ID.

In 1974, Paraskevakos was awarded a U.S. patent for this technology. In 1977, he launched Metretek, Inc.[7], which developed and produced the first fully automated, commercially available remote meter reading and load management system. Since this system was developed pre-Internet, Metretek utilized the IBM series 1 mini-computer. For this approach, Paraskevakos and Metretek were awarded multiple patents.

PURPOSE:-

Since the inception of electricity deregulation and market-driven pricing throughout the world, utilities have been looking for a means to match consumption with generation. Traditional electrical and gas meters only measure total consumption, and so provide no information of when the energy was consumed at each metered site. Smart meters provide a way of measuring this site-specific information, allowing utility companies to introduce different prices for consumption based on the time of day and the season.

Utility companies propose that from a consumer perspective, smart metering offers potential benefits to householders. These include, a) an end to estimated bills, which are a major source of complaints for many customers b) a tool to help consumers better manage their energy purchases - stating that smart meters with a display outside their homes could provide up-to-date information on gas and electricity consumption and in doing so help people to manage their energy use and reduce their energy bills. Electricity pricing usually peaks at certain predictable times of the day and the season. In particular, if generation is constrained, prices can rise if power from other jurisdictions or more costly generation is brought online.

Proponents assert that billing customers at a higher rate for peak times will encourage consumers to adjust their consumption habits to be more responsive to market prices and assert further, that regulatory and market design agencies hope these "price signals" could delay the construction of additional generation or at least the purchase of energy from higher priced sources, thereby controlling the steady and rapid increase of electricity prices. There are some concerns, however, that low income and vulnerable consumers may not benefit from intraday time-of-use tariffs.

An academic study based on existing trials showed that homeowners' electricity consumption on average is reduced by approximately 3-5%.

IMPLEMENTATION EXAMPLE:-

The American Council for an Energy-Efficient Economy reviewed more than 36 different residential smart metering and feedback programmes internationally. This is the most extensive study of its kind (as of January 2011).

Their conclusion was: “To realise potential feedback-induced savings, advanced meters [smart meters] must be used in conjunction with in-home (or on-line) displays and well-designed programmes that successfully inform, engage, empower and motivate people."

There are near universal calls from both the energy industry and consumer groups for a national social marketing campaign to help raise awareness of smart metering and give customers the information and support they need to become more energy efficient, and what changes they must make to realize the potential of proposed smart meters.

Australia

In 2004, the Essential Services Commission of Victoria, Australia (ESC) released its changes to the Electricity Customer Metering Code and Procedure to implement its decision to mandate interval meters for 2.6 million Victorian electricity customers.

The ESC's Final Paper titled "Mandatory Rollout of Interval Meters for Electricity Customers" foreshadowed the changes to be implemented and contained the rollout timetable requiring interval meters to be installed for all small businesses and residences. The rollout commenced in mid-2009 and was completed at the end of 2013.

The Commonwealth issued a Joint Communiqué at the Council of Australian Governments meeting in Canberra on 10 February 2006 committing all governments to the progressive rollout of smart metering technology from 2007.

In 2009 the Victorian Auditor General undertook a review of the program and found that there were "significant inadequacies" in advice to government and that project governance "has not been appropriate".

Meters installed in Victoria have been deployed with limited smart functionality that is being increased over time. 30-minute interval data is available, remote cut-off and start-up energization is available, and the Home Area Network will be available for households in 2012.

In May 2010 it was reported that the program was expected to cost $500 million more than originally estimated by proponents, with a total cost of $1.6 billion.

In November 2010 the Victorian Labor Party was voted out of state government. The incoming coalition stated that the meter program would be reviewed and the Auditor General's recommendations implemented, specifically commenting on program governance, customer data protection, and cost recovery. In January 2011 the Energy Minister, Michael O'Brien, said he was not ruling out a suspension of the program. This review, delivered in December 2012 endorsed the continuation of the roll out, with minor changes.

The Victorian Government after initially halting the planned implementation of Time-of-Use tariffs for general consumers has now allowed their introduction from mid-2013.

As shown in the chart below, Victorian metering charges increased by approximately $60 per meter per year after the introduction of AMI cost recovery from customers in 2010 and a projected increase to 125.73 by 2016-2017.

By mid-July 2013, the first Smart Meter In-Home Displays were being made available to Victorian consumers. At the beginning of 2014 there were three approved Smart Meter In-Home Displays directly available to consumers.

Annual meter charge increases with smart meter costs in 2010 and projections to 2017 ($)

Distributor	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2015**	**20162017**
SP AusNet	177.49	177.49	177.49	177.49	177.49	86.1	93.83	101.02	108.75	117.08	126.04
Unite	6.	6.	6.	6.	6.	69	89	99	10	11	12

d Energy Distribution	60	60	60	60	60	.21	.18	.57	7.62	6.33	5.73
Jemena Electricity Networks	12.87	12.87	12.87	12.87	12.87	134.63	136.7	155.84	159.86	162.34	164.88

Citipower	15.20	15.20	15.20	15.20	15.20	104.79	108.4	93.38	95.26	97.17	99.13
Powercor	17.20	17.20	17.20	17.20	17.20	96.67	105.35	92.72	93.91	95.12	96.34

Canada

The Ontario Energy Board in Ontario, Canada has worked to define the technology and develop the regulatory framework for its implementation. The Government of Ontario set a target of deploying smart meters to 800,000 homes and small businesses (i.e. small "general service" customers under 50 kW demand) by the end of 2007, which was surpassed, and throughout the province by the end of 2010. Notably, the addition of smart meters to the grid in Ontario has been financed, in part, by the Green Energy Act 2009 and the resulting tariff known as the Global Adjustment. This fee has played a major role in financing additional investments in the grid, such as smart meters and new high capacity transmission lines.

Canada has implemented Itron smart meters to most of its customers by the end of 2012.

Smart meter installations have been associated with several fires in Canada but these were probably caused by preexisting problems unrelated to the meters. BC Hydro maintains that "the risk of a smart meter installation causing an electrical problem is extremely low" and will assist homeowners if repairs are necessary for a safe installation.

In November 2011, the Union of British Columbia Municipalities voted in favour of a moratorium to temporarily suspend smart meter installations. The provincial government insists that installations will proceed, based on global standards. As of May 2012, 39 municipalities in British Columbia have passed motions opposing the installation of smart meters. The utility company, BC Hydro, is not legally obliged to abide by these city decisions. In September 2013 BC Hydro announced the "Meter Choices Program" which allows customers to keep their old meter or have a smart meter with the radio off. Both options have an additional monthly negative option fee in the range of $20–$33 per month, depending on specifics.

Marijuana grow-ops are a major illicit industry in British Columbia. The installation of smart meters is part of BC Hydro's electricity theft reduction program.

VIEW OF SMART METER:-

Figure 2.2:- Smart Meter

CHAPTER-3

SMART METER APPLICATIONS

1- Electric:-

Fig:3.1-Electric Smart Meter

Smart 'electric meters are electronic devices that track and record customers' home electricity use. Electric utilities have been replacing old, analog meters that are read manually once a month with new, digital smart meters that automatically capture information about electricity consumption and transmit it back to electric companies.

Smart meters can provide quick, accurate measurements of electricity use without the need for estimated monthly bills or visits from meter readers.

On the other hand, there are some concerns that smart meters can and do collect unnecessary information about hourly electricity use, thus violating users' privacy.

Smart meters offer the following benefits and challenges to electric utilities, customers, and the environment:

Advantages of Electric Smart Meters

Smart meters can **benefit the electric company** by...

- Eliminating manual meter reading
- Monitoring the electric system more quickly
- Making it possible to use power resources more efficiently
- Providing real-time data useful for balancing electric loads and reducing power outages (blackouts)
- Enabling dynamic pricing (raising or lowering the cost of electricity based on demand)
- Avoiding the capital expense of building new power plants
- Helping to optimize income with existing resources

After the electric company has fully installed its advanced metering infrastructure, smart meters can **benefit the electricity customer** by...

- Offering more detailed feedback on energy use
- Enabling them to adjust their habits to lower electric bills
- Reducing blackouts and system-wide electric failures

Smart meters can ultimately **benefit the environment** by...

- Preventing the need for new power plants that would produce pollution
- Curbing greenhouse gas emissions from existing power plants
- Reducing pollution from vehicles driven by meter readers

Disadvantages of Smart Meters

All technology has its advantages and drawbacks; while smart meters have their benefits, they also present challenges to electric utilities and customers. The vast majority of these drawbacks, however, are short term. Once the system has been set up and training is complete, smart meters can be very helpful to both electricity providers and consumers.

Smart meters present these **challenges and costs to the electric company**...

- Transitioning to new technology and processes
- Managing public reaction and customer acceptance of the new meters

- Making a long-term financial commitment to the new metering technology and related software
- Managing and storing vast quantities of metering data
- Ensuring the security of metering data

Smart meters pose these **challenges to consumers**...

- Verifying that the new meter is accurate
- Protecting the privacy of their personal data
- Paying additional fees for the new meter

Other disadvantages include the reality that smart meters put human meter readers out of work; to date, hundreds of individuals have lost their jobs. In addition, while it was anticipated that that smart meters would save consumers money, consumers rarely check their complex meters and thus are unable to make energy consumption changes.

.2-WATER:-

Fig-3.2- Water Smart Meter

Many cities across Michigan are installing or have installed smart water meters, and like smart electric meters, smart water meters are making many people ill. Smart water meters are almost always located inside the home, filling the home with nearly continuous radiofrequency emissions.

For instance, one man in Inkster had his blood-sugar and blood pressure levels skyrocket after the smart water meter was installed. He wasn't aware of the installation, and neither he nor his doctor could understand why his levels had suddenly changed so dramatically. Months later, he learned about smart meters, and his doctor told him this was a likely cause of the sudden changes.

Smart water meters, like smart electric meters, are continuously broadcasting RF waves. For example, the Neptune E-coder R900i transmits data to the utility every 14 seconds! Why, we might ask, does *anyone*—individual, government, or business—need to know 14-second water-usage intervals? It seems to be another case of "just because we can collect it, we will." This meter has been installed in Romulus and other Michigan cities. See a YouTube video of smart water meter transmissions.

The meters use frequency-hopping spectrums, which further harm health. Ninety-six days of historical data can be retrieved directly from the meter and then downloaded.

The Neptune meter can force water-use restrictions by day on individual customers .

Fig-3.3 Water Consumption Graph

3-GAS METER:-

Fig-3.4- Gas Smart Meter

A smart meter is a new kind of gas and electricity meter that can digitally send meter readings to your energy supplier for more accurate energy bills. Smart meters come with in home displays, so you can better understand your energy usage. Every home in Britain will have been offered a smart meter from their supplier by 2020

Smart Meter are progressively substituting existing meters, and are a helpful tool for our customers to keep on top of energy bills.

Smart meters work with a smart energy monitor, that you can place anywhere in your home, to show how much energy you're using and an indication of how much it's costing you, in pounds & pence. You can view both your gas and electricity consumption. So you can see how much it is costing to boil the kettle or leave the heating on at night, and when you can really see how much you're using, you can start to make small changes to use less and save money on your bills.

Smart meters are gas and electricity meters that make your life easier.

- They’ll automatically send us your meter readings, so you don’t have to.
- They come with a smart energy monitor that shows you how much energy you are using in pounds and pence.

- You’ll be able to access the British Gas interactive online tool to see how you’re using your energy.
- Pay As You Go customers can top up anywhere using our app, online, over the phone or in a shop and you can view your balance on your smart energy monitor.

4-HEAT ALLOCATION:-

Fig:3.5- Heat Allocation Meter

Heat is measured with heat allocation meters or **heat meters**. Heat meters are used to measure the physical flow of energy used for heating, for example in apartments with underfloor heating systems. The installation of heat meters can also be recommended for metering the energy consumption of different user groups in one building (e.g. shops and apartments).

We install state-of-the-art heat meters which allow accurate heat metering according to standards. Depending on the use of the heat meters, we offer electrical or ultrasound heat meters available as heat or hybrid meters.

All our heat meters can also be upgraded with modular radio technology. With this technology, all measured data are automatically sent to our data centre via a secure radio net.

CHAPTER-4

MACHINE LEARNING

Machine learning is the subfield of computer science that, according to Arthur Samuel in 1959, gives "computers the ability to learn without being explicitly programmed." Evolved from the study of pattern recognition and computational learning theory in artificial intelligence, machine learning explores the study and construction of algorithms that can learn from and make predictions on data – such algorithms overcome following strictly static program instructions by making data-driven predictions or decisions, through building a model from sample inputs.

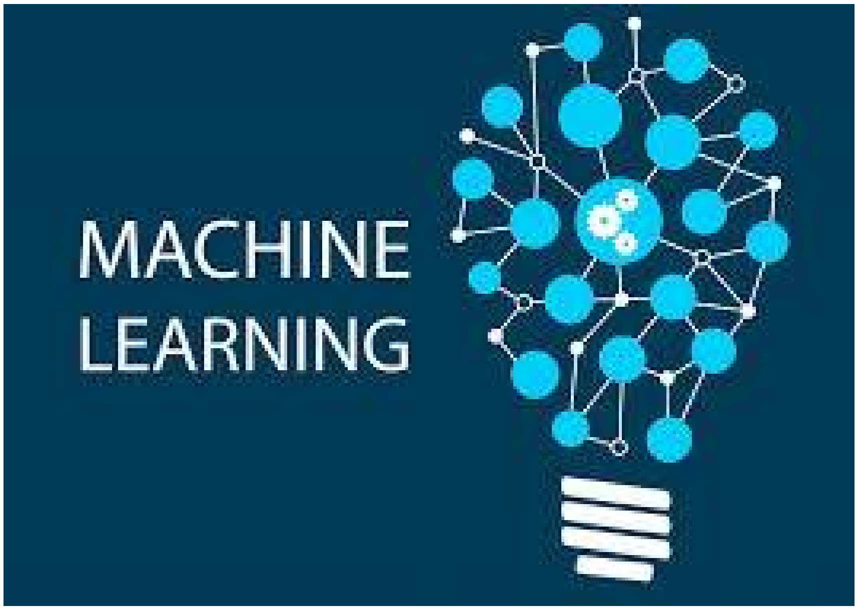

Fig:4.1- Machine Learning(1)

Machine learning is employed in a range of computing tasks where designing and programming explicit algorithms with good performance is difficult or infeasible; example applications include email filtering, detection of network intruders or malicious insiders working towards a data breach, optical character recognition (OCR), learning to rank, and computer vision.

Machine learning is closely related to (and often overlaps with) computational statistics, which also focuses on prediction-making through the use of computers. It has strong ties to mathematical optimization, which delivers methods, theory and application domains to the field. Machine learning is sometimes conflated with data mining, where the latter subfield focuses more on exploratory data analysis and is known as unsupervised learning.

Machine learning can also be unsupervised and be used to learn and establish baseline behavioral profiles for various entities and then used to find meaningful anomalies.

Within the field of data analytics, machine learning is a method used to devise complex models and algorithms that lend themselves to prediction; in commercial use, this is known as predictive analytics. These analytical models allow researchers, data scientists, engineers, and analysts to "produce reliable, repeatable decisions and results" and uncover "hidden insights" through learning from historical relationships and trends in the data.

As of 2016, machine learning is a buzzword, and according to the Gartner hype cycle of 2016, at its peak of inflated expectations. Effective machine learning is difficult because finding patterns is hard and often not enough training data is available; as a result, machine-learning programs often fail to deliver.

THEORY:-

A core objective of a learner is to generalize from its experience. Generalization in this context is the ability of a learning machine to perform accurately on new, unseen examples/tasks after having experienced a learning data set. The training examples come from some generally unknown probability distribution (considered representative of the space of occurrences) and the learner has to build a general model about this space that enables it to produce sufficiently accurate predictions in new cases.

The computational analysis of machine learning algorithms and their performance is a branch of theoretical computer science known as computational learning theory. Because training sets are finite and the future is uncertain, learning theory usually does not yield guarantees of the performance of algorithms. Instead, probabilistic bounds on the performance are quite common. The bias–variance decomposition is one way to quantify generalization error.

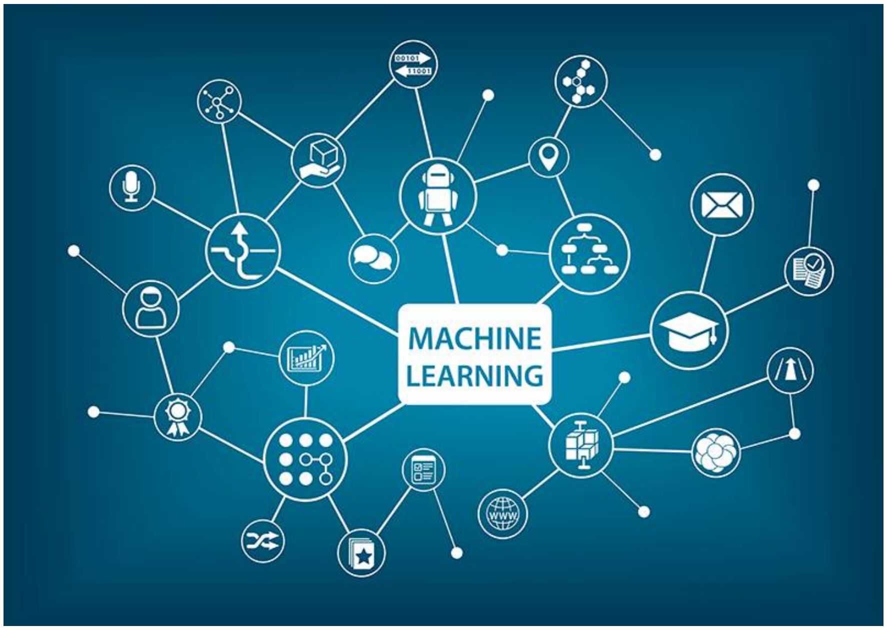

Fig:4.2- Machine Learning(2)

For the best performance in the context of generalization, the complexity of the hypothesis should match the complexity of the function underlying the data. If the hypothesis is less complex than the function, then the model has underfit the data. If the complexity of the model is increased in response, then the training error decreases. But if the hypothesis is too complex, then the model is subject to overfitting and generalization will be poorer.

In addition to performance bounds, computational learning theorists study the time complexity and feasibility of learning. In computational learning theory, a computation is considered feasible if it can be done in polynomial time. There are two kinds of time complexity results. Positive results show that a certain class of functions can be learned in polynomial time. Negative results show that certain classes cannot be learned in polynomial time.

HISTORY AND RELATIONSHIP TO OTHER FIELD:-

As a scientific endeavour, machine learning grew out of the quest for artificial intelligence. Already in the early days of AI as an academic discipline, some researchers were interested in having machines learn from data. They attempted to approach the problem with various symbolic methods, as well as what were then termed "neural networks"; these were mostly perceptrons and other models that were later found to be reinventions of the generalized linear models of statistics. Probabilistic reasoning was also employed, especially in automated medical diagnosis.

However, an increasing emphasis on the logical, knowledge-based approach caused a rift between AI and machine learning. Probabilistic systems were plagued by theoretical and practical problems of data acquisition and representation. By 1980, expert systems had come to dominate AI, and statistics was out of favor. Work on symbolic/knowledge-based learning did continue within AI, leading to inductive logic programming, but the more statistical line of research was now outside the field of AI proper, in pattern recognition and information retrieval.

Neural networks research had been abandoned by AI and computer science around the same time. This line, too, was continued outside the AI/CS field, as "connectionism", by researchers from other disciplines including Hopfield, Rumelhart and Hinton. Their main success came in the mid-1980s with the reinvention of backpropagation.

Machine learning, reorganized as a separate field, started to flourish in the 1990s. The field changed its goal from achieving artificial intelligence to tackling solvable problems of a practical nature. It shifted focus away from the symbolic approaches it had inherited from AI, and toward methods and models borrowed from statistics and probability theory. It also benefited from the increasing availability of digitized information, and the possibility to distribute that via the Internet.

Machine learning and data mining often employ the same methods and overlap significantly, but while machine learning focuses on prediction, based on *known* properties learned from the training data, data mining focuses on the discovery of (previously) *unknown* properties in the data (this is the analysis step of Knowledge Discovery in Databases).

Data mining uses many machine learning methods, but with different goals; on the other hand, machine learning also employs data mining methods as "unsupervised learning" or as a preprocessing step to improve learner accuracy. Much of the confusion between these two research communities (which do often have separate conferences and separate journals, ECML PKDD being a major exception) comes from the basic assumptions they work with: in machine learning, performance is usually evaluated with respect to the ability to *reproduce known* knowledge, while in Knowledge Discovery and Data Mining (KDD) the key task is the discovery of previously *unknown* knowledge.

Evaluated with respect to known knowledge, an uninformed (unsupervised) method will easily be outperformed by other supervised methods, while in a typical KDD task, supervised methods cannot be used due to the unavailability of training data.

Machine learning also has intimate ties to optimization: many learning problems are formulated as minimization of some loss function on a training set of examples. Loss functions express the discrepancy between the predictions of the model being trained and the actual problem instances (for example, in classification, one wants to assign a label to instances, and models are trained to correctly predict the pre-assigned labels of a set of examples).

The difference between the two fields arises from the goal of generalization: while optimization algorithms can minimize the loss on a training set, machine learning is concerned with minimizing the loss on unseen samples.

Relation to statistics

Machine learning and statistics are closely related fields. According to Michael I. Jordan, the ideas of machine learning, from methodological principles to theoretical tools, have had a long pre-history in statistics. He also suggested the term data science as a placeholder to call the overall field.

Leo Breiman distinguished two statistical modelling paradigms: data model and algorithmic model wherein 'algorithmic model' means more or less the machine learning algorithms like Random forest.

Some statisticians have adopted methods from machine learning, leading to a combined field that they call *statistical learning*.

APPLICATION:-

Applications for machine learning include:

- Adaptive websites
- Affective computing
- Bioinformatics
- Brain-machine interfaces
- Cheminformatics
- Classifying DNA sequences
- Computational anatomy
- Computer vision, including object recognition

- Detecting credit card fraud
- Game playing
- Information retrieval
- Internet fraud detection
- Linguistics
- Marketing
- Machine learning control
- Machine perception
- Medical diagnosis
- Natural language processing
- Natural language understanding
- Optimization and metaheuristic
- Online advertising
- Recommender systems
- Robot locomotion
- Search engines
- Sentiment analysis (or opinion mining)
- Sequence mining
- Software engineering
- Speech and handwriting recognition
- Financial market analysis
- Structural health monitoring
- Syntactic pattern recognition
- User behavior analytics
- Translation

In 2006, the online movie company Netflix held the first "Netflix Prize" competition to find a program to better predict user preferences and improve the accuracy on its existing Cinematch movie recommendation algorithm by at least 10%.

A joint team made up of researchers from AT&T Labs-Research in collaboration with the teams Big Chaos and Pragmatic Theory built an ensemble model to win the Grand Prize in 2009 for $1 million. Shortly after the prize was awarded, Netflix realized that viewers' ratings were not the best indicators of their viewing patterns ("everything is a recommendation") and they changed their recommendation engine accordingly.

In2012,co-founder of Sun Microsystems Vinod Khosla predicted that 80% of medical doctors jobs would be lost in the next two decades to automated machine learning medical diagnostic software.

In 2014, it has been reported that a machine learning algorithm has been applied in Art History to study fine art paintings, and that it may have revealed previously unrecognized influences between artists.

CHAPTER-5

CONCLUSION

A smart meter is an electronic device that records consumption of electric energy in intervals of an hour or less and communicates that information at least daily back to the utility for monitoring and billing.

Smart meters enable two-way communication between the meter and the central system.

More accurate bills Smart meters mean the end of estimated bills, the end of having to remember to provide meter readings and/or have a stranger come into your home to read your meter.

Better understanding of your usage With the smart meter display, you can see the direct impact your habits and lifestyle have on your bill. This is particularly useful to prepayment meter customers, who can better track how their usage impacts their available credit. By making your energy usage easier to understand, you can make smarter decisions to save energy and money, including feeling more confident switching energy supplier.

Smart Meters will transport us into a new era of energy delivery and enhanced customer service, including the ability to support:

Expanded product options - Your Retail Electric Provider (REP) may offer new, innovative price plans such as time-of-use rates and pre-paid metering.

Home Area Network (HAN) - Over time, you'll be able to remotely control 'smart' appliances like your thermostat at your home or business through the Internet.

In-home monitors - These devices that may be sold at retailers or through your REP, will provide you with immediate feedback from your Smart Meter and REP, including your current and past electricity information.

CHAPTER-6

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