Role of Artificial Intelligence in Industry 4.0 – Application to Indian Leather Industry

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Contents

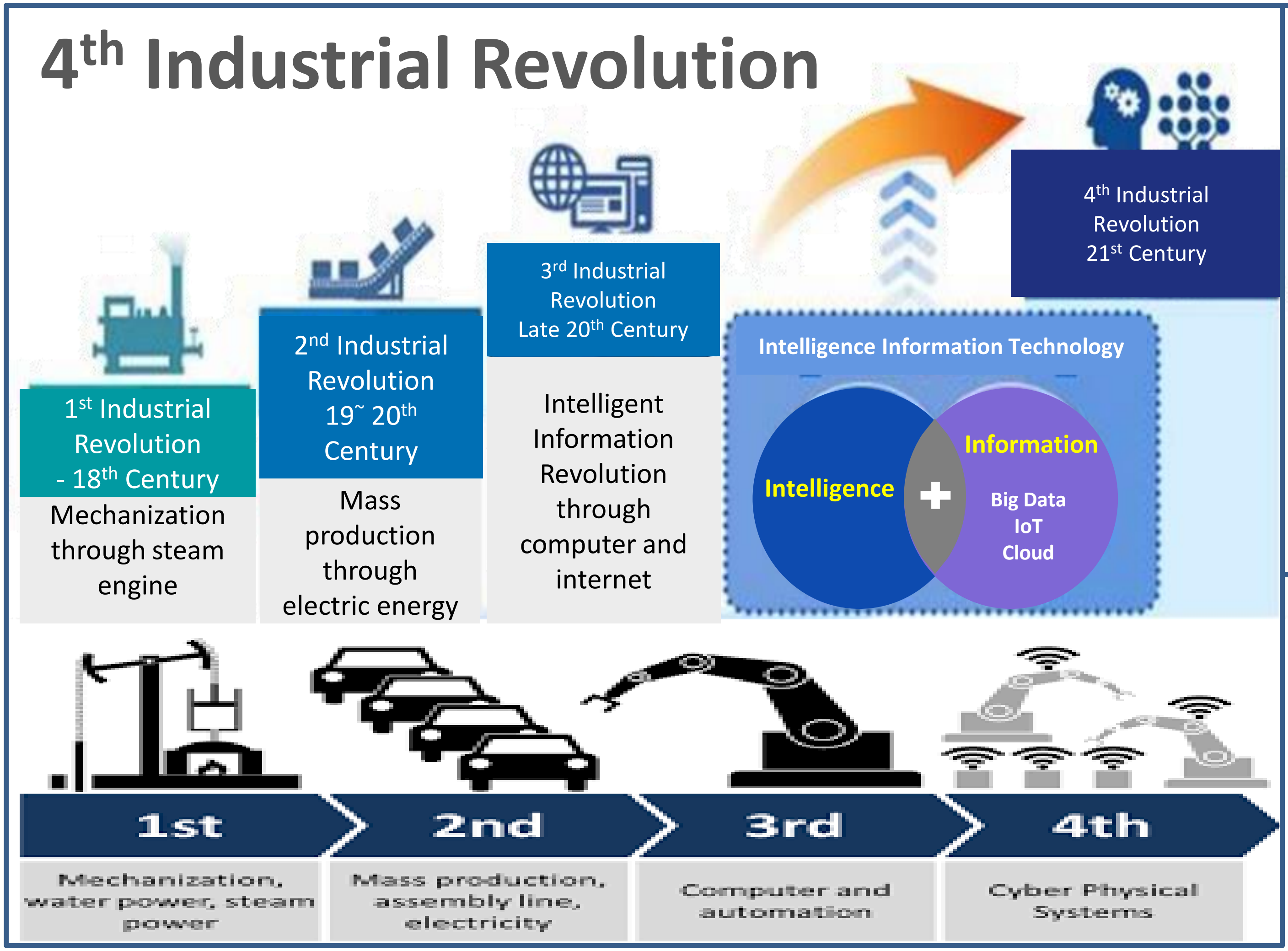
Digital India / Make-in-India Program

- Indian leather sector stands at USD 17.85 billion (Exports – USD 5.85 billion, Domestic Market – USD 12 billion) (2017-18).
- India accounts for 12.93% of the world's leather production of hides/skins.
- High Growth projected in the next five years.
- Indian leather industry has one of the youngest workforce with 55% of workforce below 35 years of age.
- India is the second largest producer of footwear and leather garments in the world.

WHY FDI

- Strong Raw Material Base: A strong base for raw materials – India is endowed with 20% of the world's cattle and buffalo and 11% of the world's goat and sheep population.
- India produces 2.5 billion sq. feet of leather, accounting for about 13% of global production.
- The Indian Leather Industry comprises of major segments namely Footwear, Finished Leather, Leather Goods, Leather Garments, Footwear Components and Saddlery and Harness. All these segments have high growth potential.
- Per capita consumption of footwear in India projected to increase upto 4 pairs and total domestic consumption is expected to reach upto 5 billion pairs by 2020.
- Great opportunity to set-up manufacturing facility of footwear components, considering increasing demand for fashion footwear in India.

The Advent of the 4th Industrial Revolution(IR) Age



4th Industrial Revolution

1st Industrial Revolution - 18th Century
Mechanization through steam engine

2nd Industrial Revolution 19~ 20th Century
Mass production through electric energy

3rd Industrial Revolution Late 20th Century
Intelligent Information Revolution through computer and internet

4th Industrial Revolution 21st Century

Intelligence Information Technology

1st Mechanization, water power, steam power

2nd Mass production, assembly line, electricity

3rd Computer and automation

4th Cyber Physical Systems

Components

Internet of Things

Cloud

Big data

Artificial Intelligence

Mobile

5G wireless network: 280 times faster than LTE and 70 times faster than 4G.

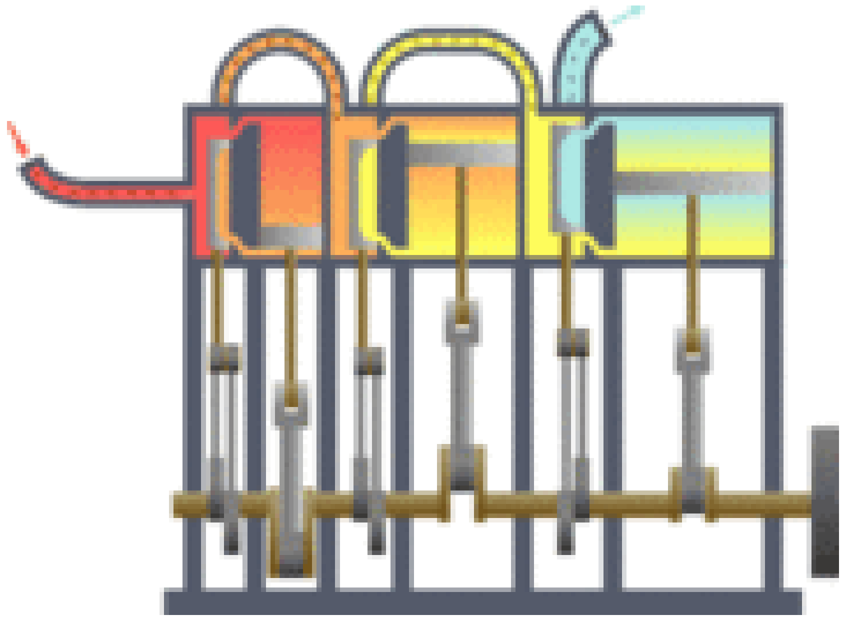
Phases of Industrial Revolutions

-- A Journey through ages

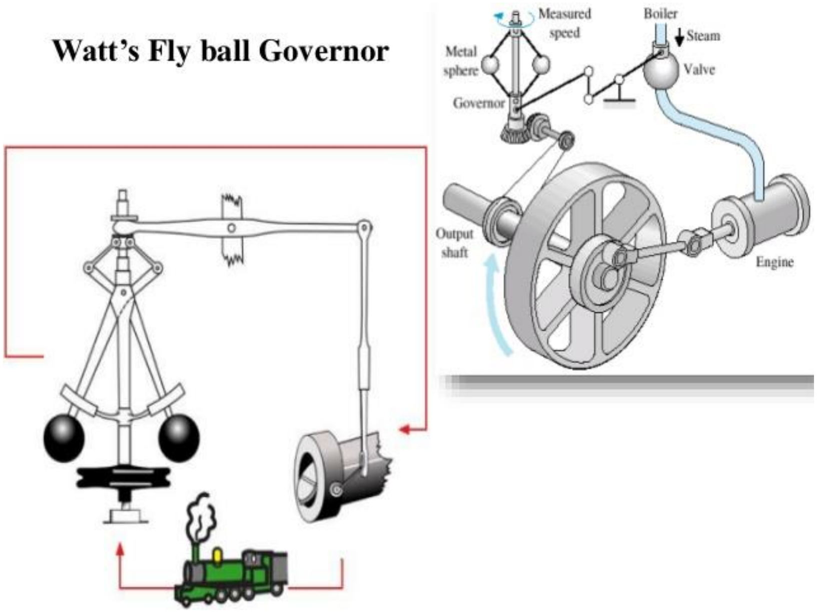
1. 1760 to 1840 - Ushered in Mechanical production; railways and steam engine ←Industry 1.0
2. 1870 to 1940 - Mass production; electricity and assembly line ←Industry 2.0
3. 1960 to 2010 - Computers; semi conductors, main frame computing, personal devices, internet ←Industry 3.0

Watt’s Flyball Governor

1788- Watt’s steam engine
Newcommen’s steam engine – a limited Success



Newcomen engines were successful in part because they were very safe to operate. Since the steam was under such low pressure (5 psi), there was no risk of a dangerous boiler explosion

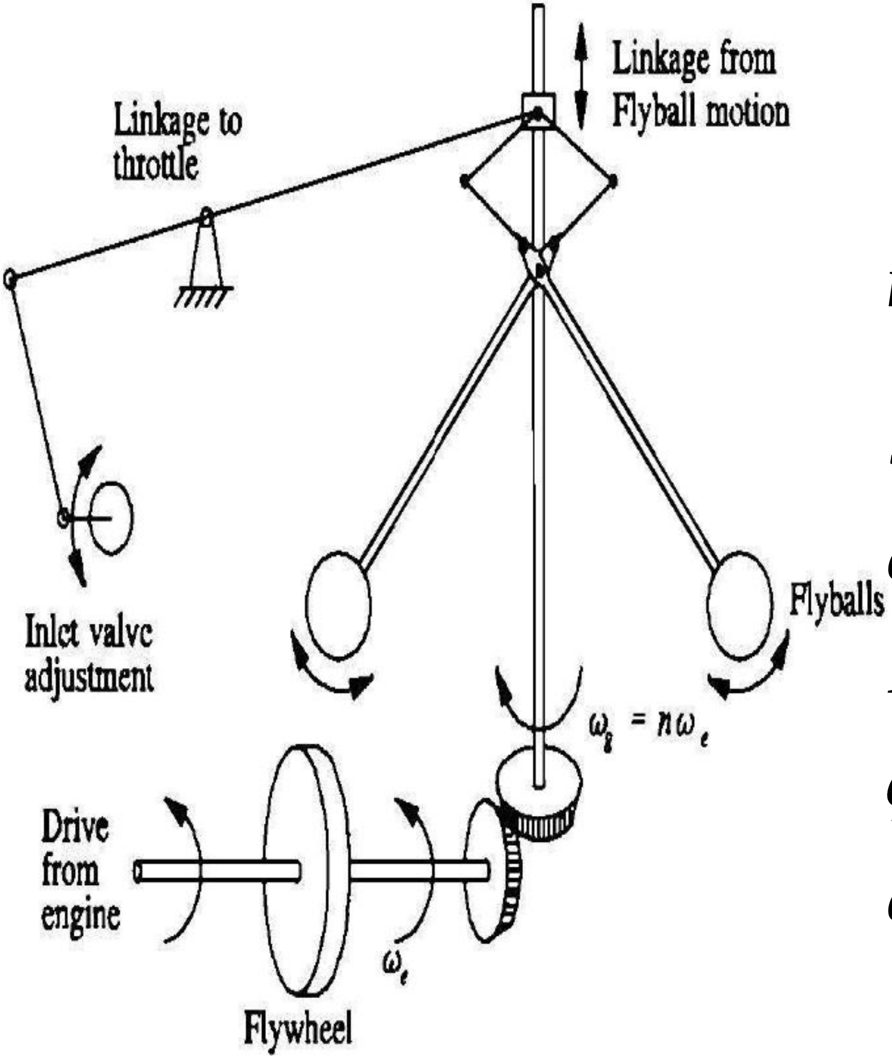


From 1832 Edinburg Encyclopedia

Power is supplied to the governor from the engine's output shaft by a belt connected to the flywheel. The governor is connected to a throttle valve that regulates the flow of steam supplying the prime mover. This in turn regulates amount of pressure acting on the piston. As the speed of the prime mover increases, the central spindle of the governor rotates at a faster rate and the kinetic energy of the balls increases. This allows the two masses on lever arms to move outwards and upwards against gravity. If the motion goes far enough, this motion causes the lever arms to pull down on a grooved collar, which moves a operating arm, which reduces the aperture of a throttle valve. The rate of working-fluid entering the cylinder is thus adjusted and the speed of the prime mover is settled in new position, preventing over-speeding or stalling the engine.

Analog - Devices

Mechanism



Watt’s governor
Analysis of James Clark Maxwell (1868)

$$ml\ddot{\phi} = l(m\omega_G^2 l\sin\phi\cos\phi - mg\sin\phi - b\dot{\phi})$$

$$J\dot{\omega}_E = k\cos\phi - T_L$$

$$\omega_G = n\omega_E$$

Linearization

$$\phi = \phi_0 + x \qquad x << 1$$

$$\omega_E = \omega_G + y \qquad y << 1$$

$$\dddot{y} + a_1\ddot{y} + a_2\dot{y} + a_3 y = 0$$

1885 Thermostat

- 1885 Albert Butz invented Damper Flapper

  -Bimetal Plate (Sensor/Control)

  -Motor to move the furnace damper

* Started a company that became Honeywell in 1927

1886

Damper Flapper

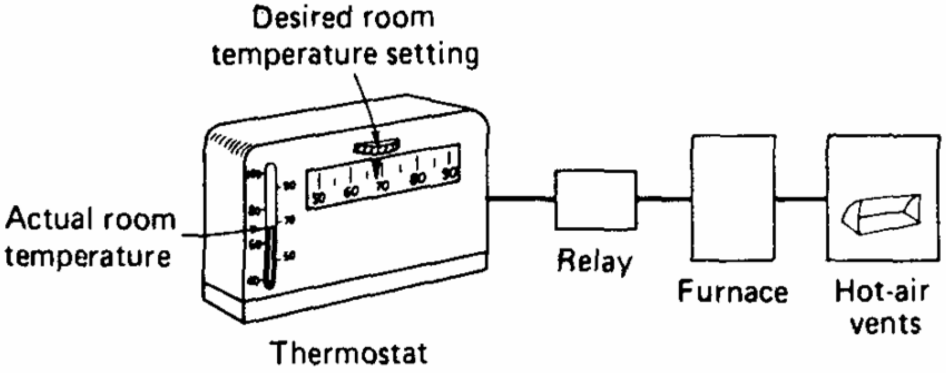
If room-temp is below set point

* Thermostat switching on makes the main motor shaft to turn one-half revolution opening the furnace's air damper.

If room-temp is above set point

- Thermostat switching off makes the motor to turn another half revolution, closing the damper and damping the fire

* On-off control based on threshold



Home heating control system.

Home heating loop

Analog - Devices

1930’s Feedback Amplifire

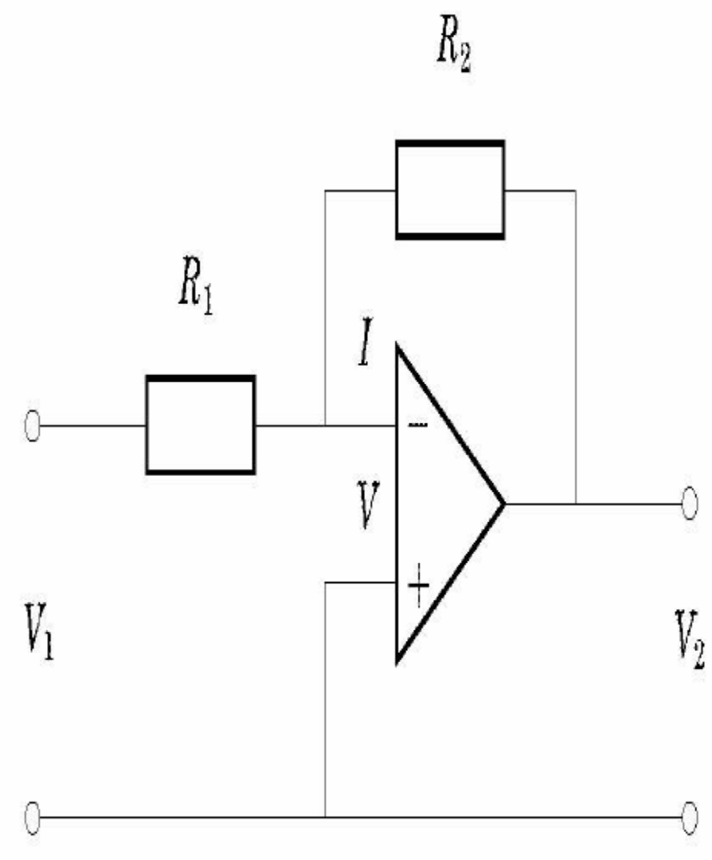
- Signal amplification in first telecom systems (telephone)

Analog vacuum tube amplifier technology

* Feedback concept

- Bode analysis of transients in amplifire in 1940

INPUT



$$\frac{V_1 - V}{R_1} = \frac{V - V_2}{R_2}$$

$$V_2 = GV$$

$$\frac{V_1}{V_2} = R_1\left[\frac{1}{R_2} - \frac{1}{G}\left(\frac{1}{R_1} + \frac{1}{R_2}\right)\right] = -\frac{R_1}{R_2}\left[1 - \frac{1}{G}\left(1 + \frac{R_2}{R_1}\right)\right]$$

1940-World War II Military Applications

- **Sperry Gyroscope Company – flight instruments – later bought by Honeywell to become Honeywell aerospace control business.**
- **Servosystem – gun pointing, ship steering, using gyro**
- **Norden bombsight – Honeywell's C-1 autopilot – over 110,000 manufactured. (also participated in Iraq war, 2003)**

* **Concepts – electromechanical feedback, PID control.**

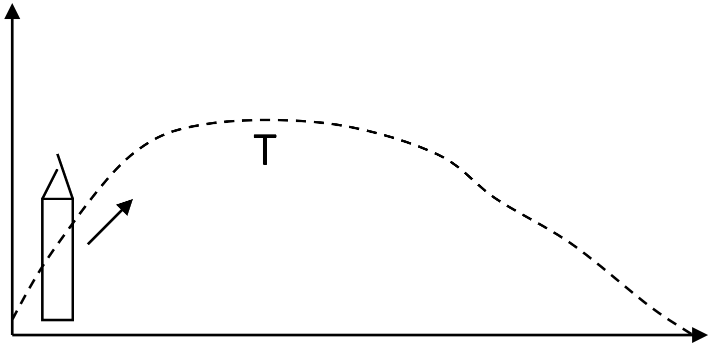
- **Nyquist, servomechanism, transfer function analysis –** System Stability

Since it was quite tiresome to fly an unstable aircraft (Right's Brother, 1905), there was strong motivation to find a mechanism that would stabilize an aircraft. Such a device, invented by Sperry, was based on the concept of feedback. Sperry used a gyro-stabilized pendulum to provide an indication of the vertical. He then arranged a feedback mechanism that would pull the stick to make the plane go up if it was pointing down and vice versa. The Sperry autopilot is the first use of feedback in aeronautical engineering.

1960's Rocket Science

- **SS-7 missile range control**

  – through the main engine cutoff time



Range: $r = F(\Delta V_x, \Delta V_y, \Delta x, \Delta y)$

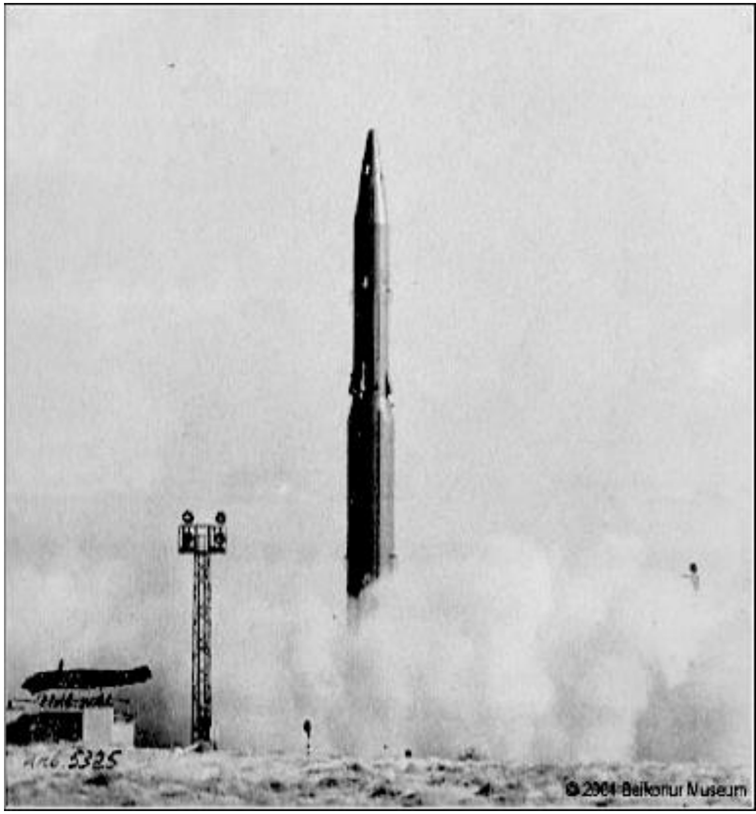
Range Error:

$$\delta r(t) = f_1 \Delta V_x(t) + f_2 \Delta V_y(t) + f_3 \Delta x(t) + f_4 \Delta y(t)$$

Algorithm:

Track $\delta r(t)$ **Cut the engine off at T when**

$\delta r(t)$**= 0**



USSR R-16/8K64/SS-7/Saddler
Copyright © 2001 RussianSpaceWeb.com
http://www.russianspaceweb.com/r16.html

MOTIVATION FOR AI

- Spurring AI-based innovation and establishing AI-ready infrastructure are necessary to prepare India's jobs and skills markets for an AI-based future and to secure its strategic interests -S. S. Vempati

- Recent advances in artificial intelligence (AI) are a wake-up call to policymakers in India.
- Industry 4.0, a German initiative, aims on optimization through AI and use of IoT, data analytics, additive manufacturing giving a shape of smart Industry. Cyber-physical systems monitor physical processes.

INDUSTRY – 4.0

Manufacturing Industry

Intelligent manufacturing

*Optimizes production
*Product Transactions

*Design
*Production
*Management
*Adv Information
*Integration of CPS

*smart sensors,
*adaptive decision-making models,
*advanced materials,
*intelligent devices
*data analytics

IoT-enabled manufacturing

*human-to-human
*human-to-machine
*machine-to-machine

Physical systems

Cloud manufacturing

Life cycle of Product
design
simulation
manufacturing
testing
maintenance
End-user's input
uses Barcode to control
Resource modeling &
modes of procurement

In leather processing, control and automation for recipes, heating, machining robotic vacuums, and remote monitoring can be achieved by IoT

Methods

(net-working & Data exchange)

Physical systems

- -electronic sensors
- -actuators
- -digital devices

Automatic identification smart objects

- - wireless
- - data analytics
- - machine learning

Internet-of-Things

Trans-disciplinary obj

- -cybernetics
- -mechanical engg,
- -mechatronics
- -design
- -Process science
- -manufacturing sys
- -comp sci

Control algorithms computation AI

Cyber-physical-sys

Cloud computing

- -on-demand self service
- -network access
- -resource pooling
- -rapid elasticity
- -measured service

Deploy Models:

public, private, community,hybrid

Delivery model:

- -software based
- -platform based
- -infrastructure

This tool helps in minimizing budget and data can be accessed easily. After water, electricity, gas and phone, cloud becomes the fifth utility for any industry.

Bigdata analytics

- -Volume of data
- -Variety of Data
- -Velocity of generatio of new data & analy
- -Value of data

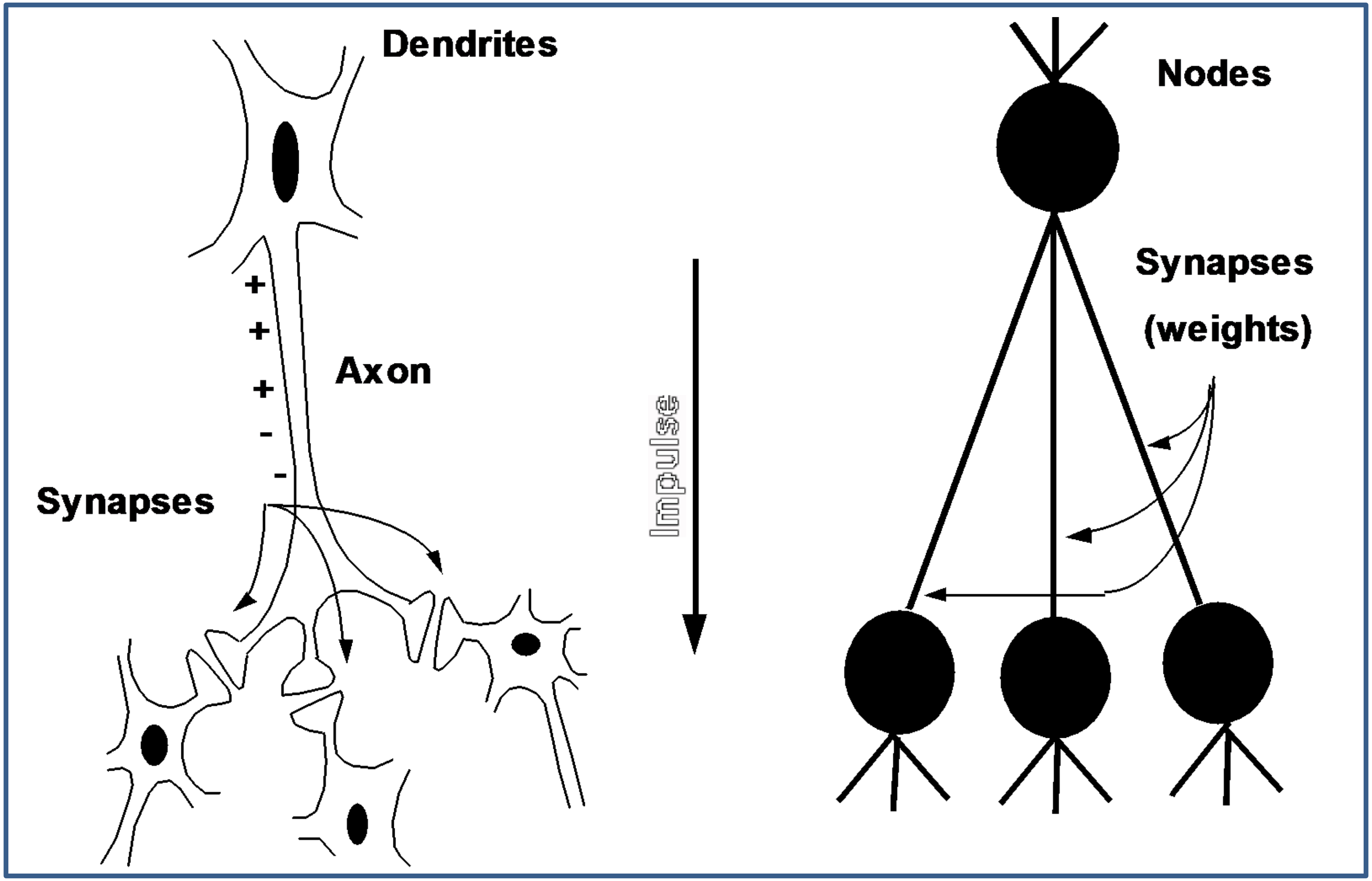
Works on:

- -Statistical modeling
- -Optimization

Provides:

process or product faults, threats in production systems, prediction of new issues in a production process

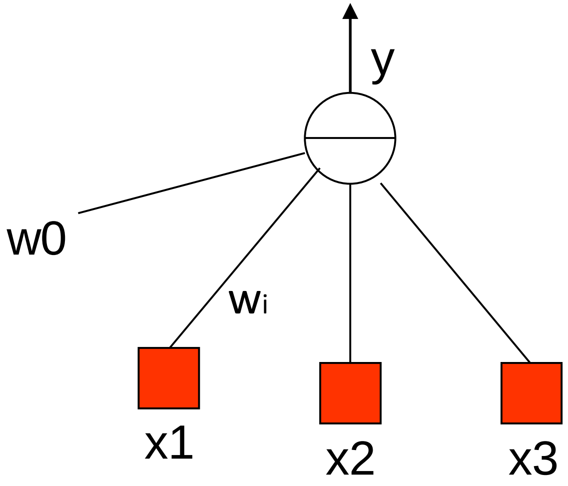
Biological Analogy



From Biological to Artificial Neurons

Behaviour of an artificial neural network to any particular input depends upon:

- structure of each node (activation function)
- structure of the network (architecture)
- weights on each of the connections
- Non linear, parameterized function with restricted output range

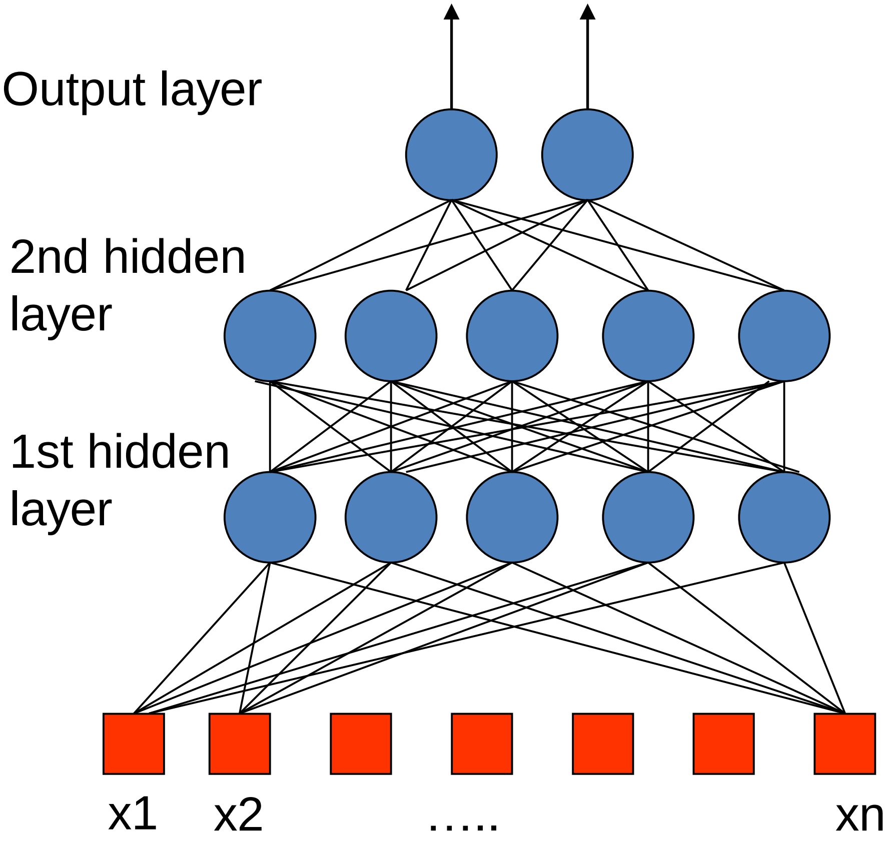


$$y = f\left(w_0 + \sum_{i=1}^{n-1} w_i x_i \right)$$

Neural Networks

- A mathematical model to solve engineering problems
  - Group of highly connected neurons to realize compositions of non linear functions
- Tasks
  - Classification
  - Discrimination
  - Estimation
- Types of networks
  - Feed forward Neural Networks
  - Recurrent Neural Networks
  - **Hebbian networks: reward 'good' paths, punish 'bad' paths**
  - **Bayesian – deals with probability: t**he distribution of the neural network parameters is learnt
  - Support Vector machine - the minimal representative subset of the available data is used to calculate the synaptic weights of the neurons

Feed Forward Neural Networks



- The information is propagated from the inputs to the outputs
- Computations of No non linear functions from n input variables by compositions of Nc algebraic functions
- Time has no role (NO cycle between outputs and inputs)

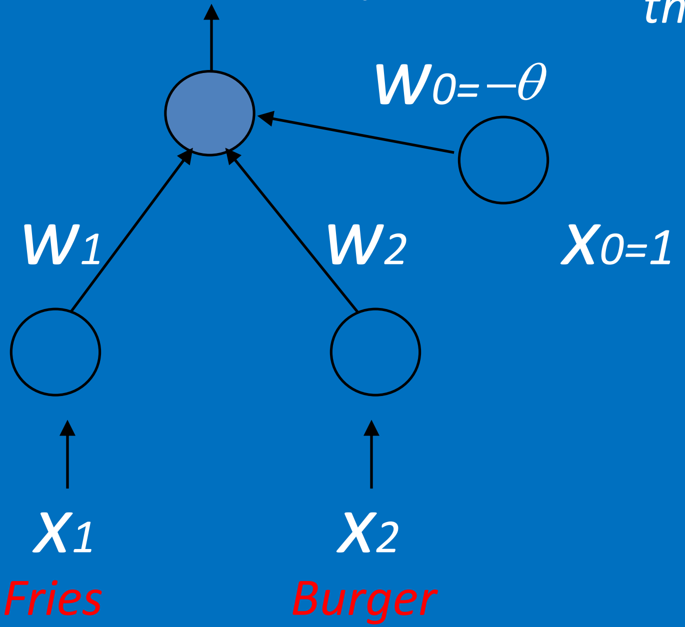
- 3 types of learning
  - The supervised learning
  - The unsupervised learning
  - Reinforcement Learning

Learning in a Simple Neuron

x_1	x_2	y
0	0	0
0	1	0
1	0	0
1	1	1

"Full Meal Deal"

$$y = f[\sum_{i=0}^{2} w_i x_i]$$



where f(a) is the step function, such that: $f(a)=1,\ a > 0$
$f(a)=0,\ a <= 0$

$$H = \{W \mid W \varepsilon R^{(n+1)}\}$$

The Back-propagation Algorithm

On-Line algorithm:

1. Initialize weights
2. Present a pattern and target output
3. Compute output : $o_j = f[\sum_{i=0}^{n} w_{ij} o_i]$
4. Update weights : $w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}$

where $\Delta w_{ij} = -\eta \frac{\delta E}{\delta w_{ij}}$

Repeat starting at 2 until acceptable level of error

Past Research & Literature

History of Artificial Neural Networks

- Creation:

  1890: William James - defined a neuronal process of learning

- Promising Technology:

  1943: McCulloch and Pitts - earliest mathematical models
  1954: Hebb and IBM research group - earliest simulations
  1958: Frank Rosenblatt - The Perceptron

- Disenchantment:

  1969: Minsky and Papert - perceptrons have severe limitations

- Re-emergence:

  1985: Multi-layer nets that use back-propagation
  1986: PDP Research Group - multi-disciplined approach
  1986: Rumelhart, Hinton + Williams present backpropagation
  1989: Tsividis: Neural Network on a chip

AI Development

- Artificial Intelligence (1950s) – Giving intelligence to machine
- Machine Learning (1980s) – realizing artificial intelligence (speech recognition, image recognition, playing go, dialogue)
- Deep Learning (2006) – for machine learning for higher prediction accuracy
  - A powerful class of machine learning model
  - Modern reincarnation of artificial neural network
  - Collection of simple, trainable mathematical functions

AI Development

- 1958: Rosenblatt’s **Perceptron** algorithm
- 1969: Minksky showed **Perceptron** could not solve the XOR problem, connectedness, parity.
- 1986: Rumelhart developed **Backpropagtion** algorithm to train neural network
- Mid 90’s: Cortes and Vapnik published paper on **Support Vector Machines**
- 2006: Hinton and Salakhutdinov proposed using **Restricted Blotzmann Machine** for pre-train Deep Neural Network

AI Development

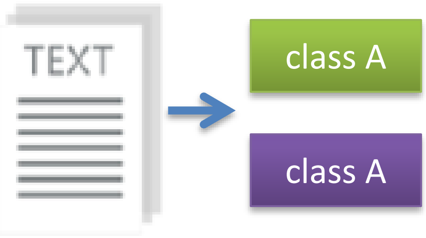
- 2007: Fei-Fei Li's ImageNet assembling a databse of 14 million labled images (Data drives learning)
- 2011: Micorsoft explored Speech recognition and IBM's Watson
- 2014: Google acquired DeepMind, combing deep learning and reinforcement learning
- 2016: DeepMind's AlphaGo defeated world champion Lee Sedol

Types of Learning

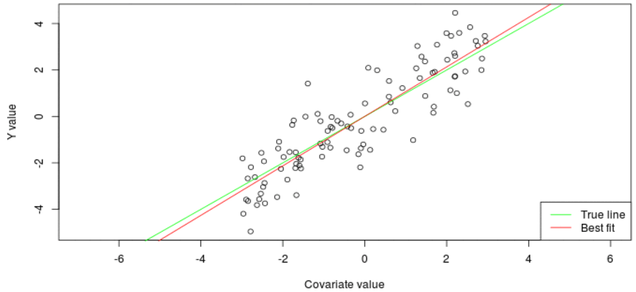
Supervised: Learning with a **labeled training** set
Example: email *classification* with already labeled emails

Unsupervised: Discover **patterns** in **unlabeled** data
Example: *cluster* similar documents based on text

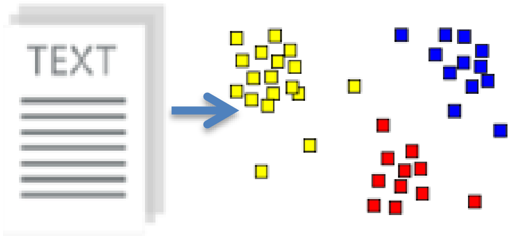
Reinforcement learning: learn to **act** based on **feedback/reward**
Example: learn to play Go, reward: *win or lose*



Classification



Regression

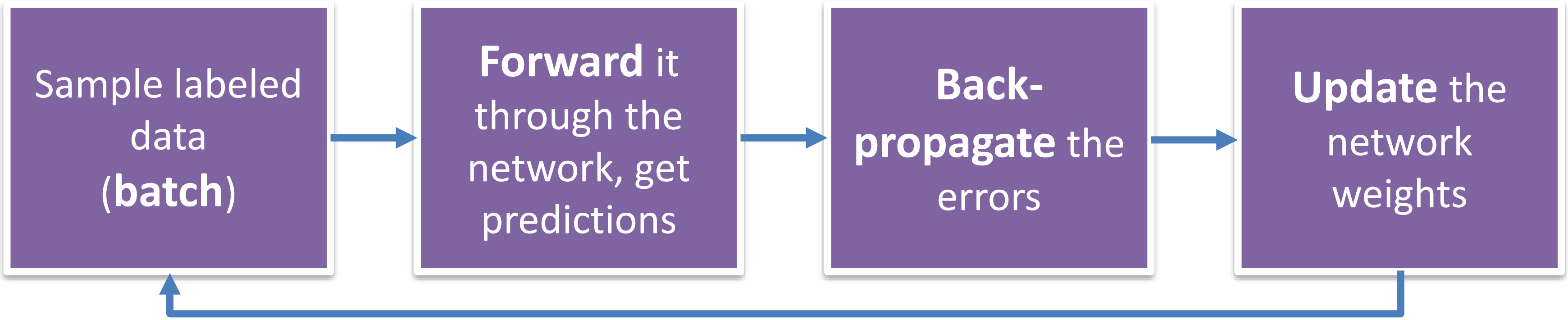


Clustering

Anomaly Detection
Sequence labeling
…

http://mbjoseph.github.io/2013/11/27/measure.html

Training



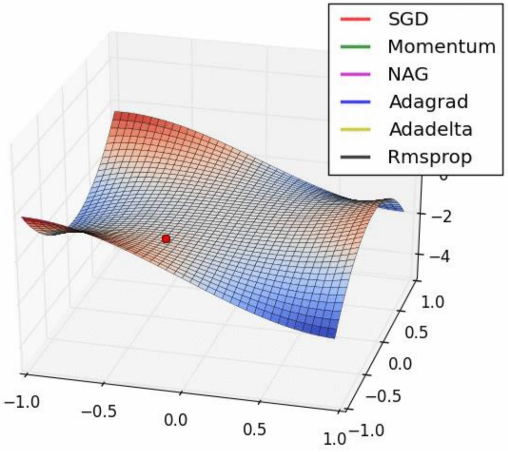
Sample labeled data (**batch**)

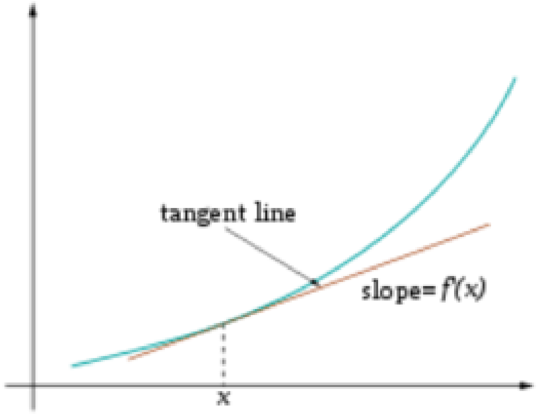
Forward it through the network, get predictions

Back-propagate the errors

Update the network weights

Optimize (min. or max.) **objective/cost function $J(\theta)$**
Generate **error signal** that measures difference between predictions and target values



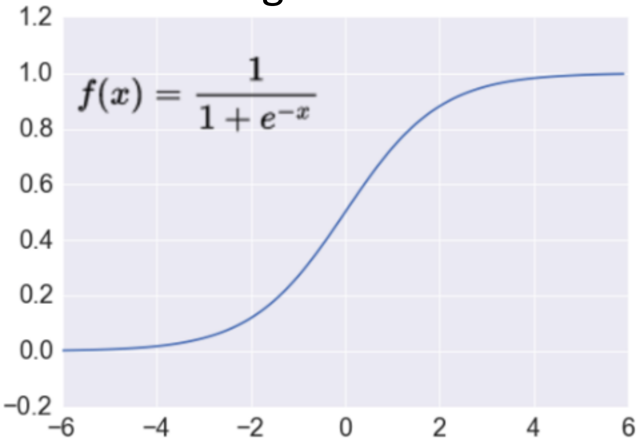


Use error signal to change the **weights** and get more accurate predictions
Subtracting a fraction of the **gradient** moves user towards the **(local) minimum of the cost function**

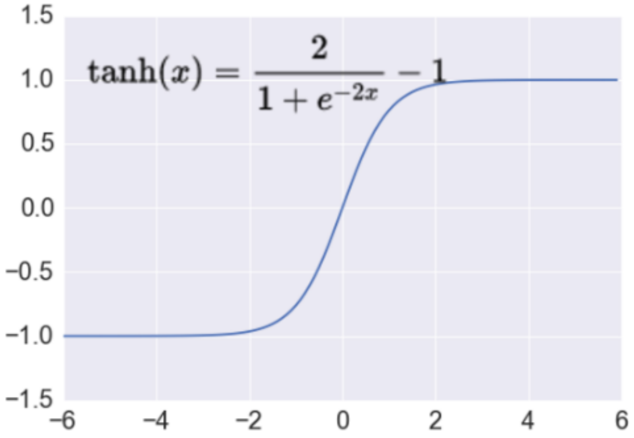
https://medium.com/@ramrajchandradevan/the-evolution-of-gradient-descend-optimization-algorithm-4106a6702d39

Activation : Functions

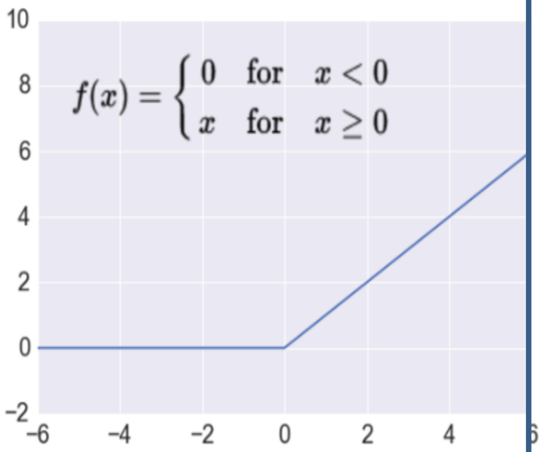
Sigmoid



tanh



Rectified Lin Unit



Most Deep Networks use ReLU nowadays

☐ Trains much **faster**
  - accelerates the convergence of SGD
  - due to linear, non-saturating form

☐ Less expensive operations
  - compared to sigmoid/tanh (exponentials etc.)
  - implemented by simply thresholding a matrix at zero

☐ More **expressive**

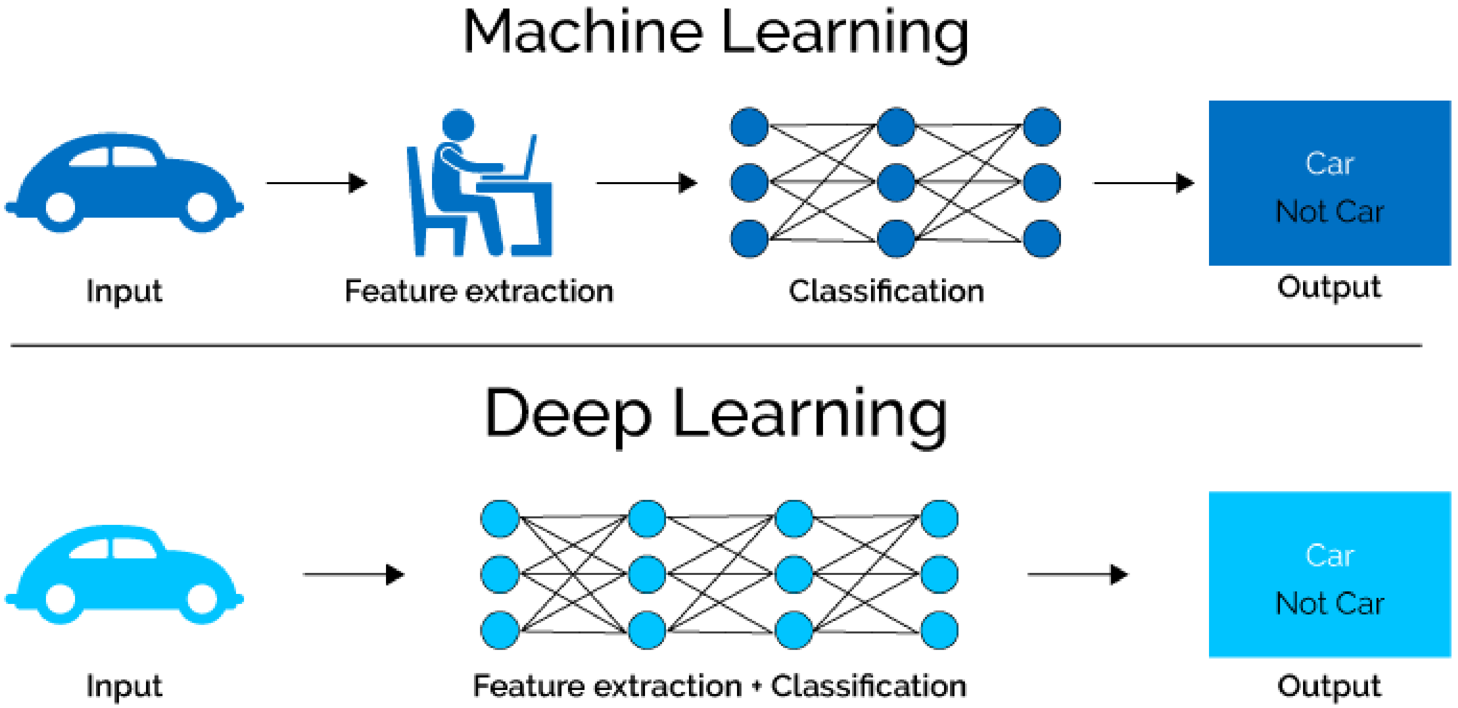
☐ Prevents the **gradient vanishing problem**

Machine /Deep Learning (DL)

A machine learning subfield of learning **representations** of data. Exceptional effective at **learning patterns**.

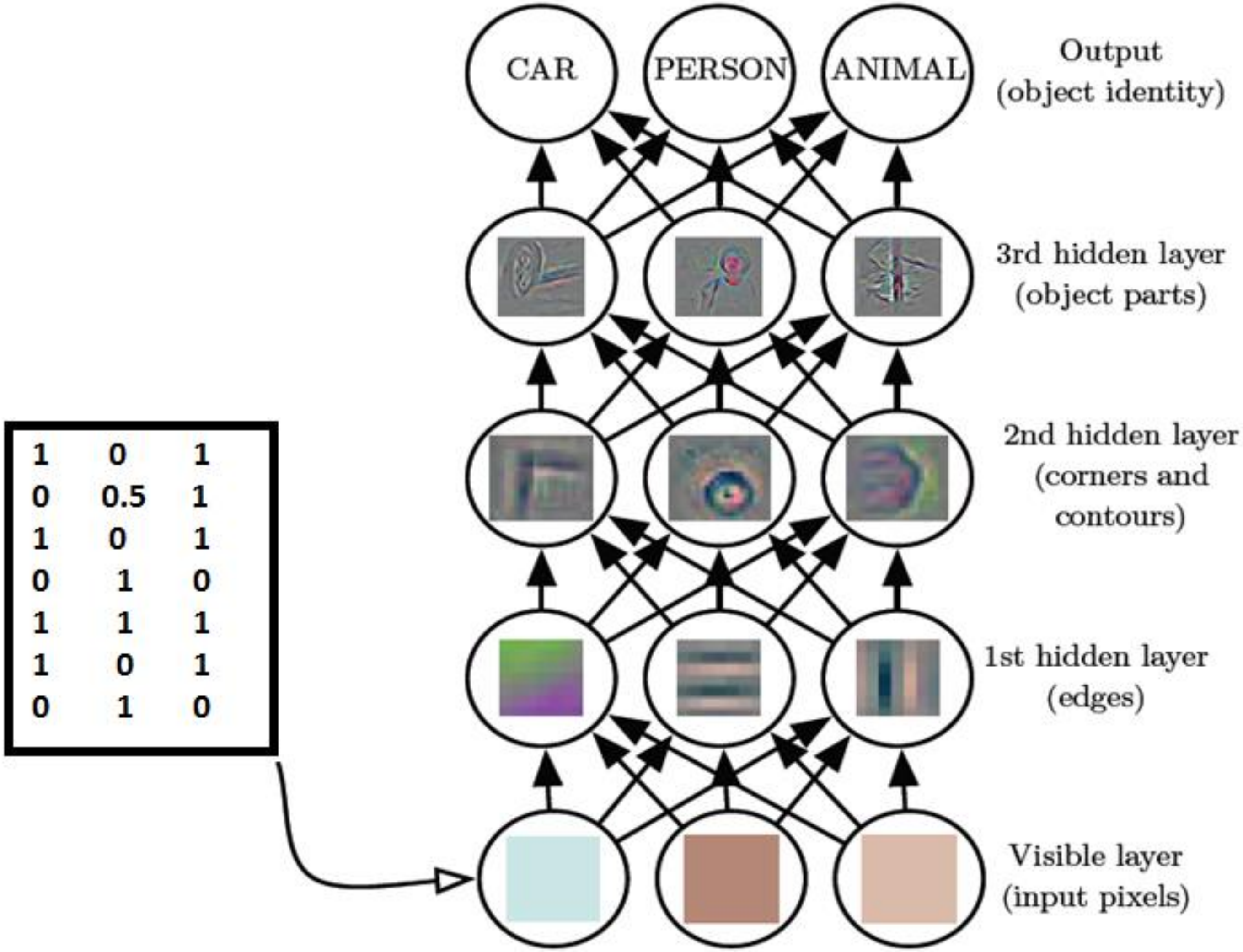
Deep learning algorithms attempt to learn (multiple levels of) representation by using a **hierarchy of multiple layers**

If you provide the system **tons of information**, it begins to understand it and respond in useful ways.



https://www.xenonstack.com/blog/static/public/uploads/media/machine-learning-vs-deep-learning.png

Deep Learning

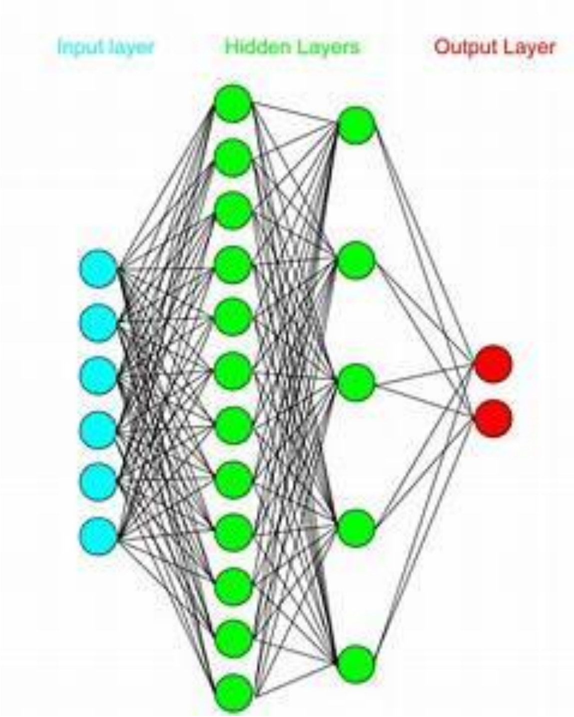


1	0	1
0	0.5	1
1	0	1
0	1	0
1	1	1
1	0	1
0	1	0

Neutral Network

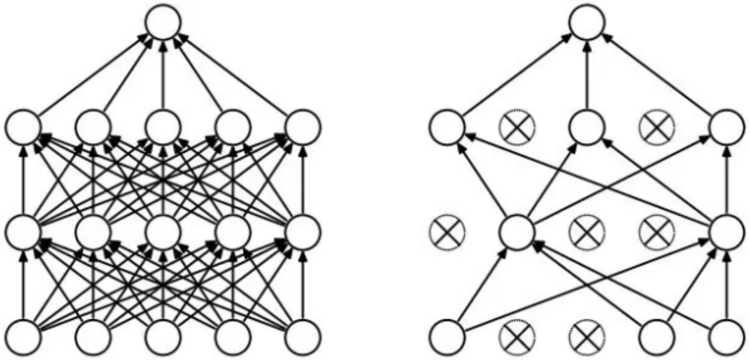
Big data (with large dataset)

- Deep Learning
  - Nonlinear activation function
  - Neuron could connect to every input
  - Multi-levels with millions neurons
  - Any function can be computed
- Types of Deep Learning
  - Deep Convolution
  - Deep Boltzman Machine
  - Recurrent Neural Net
  - New models and algorithms



Neural Network: pattern recognition or data classification

Regularization



Dropout

- Randomly drop units (along with their connections) during training
- Each unit retained with fixed probability p, independent of other units
- Hyper-parameter p to be chosen (tuned)

Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting." Journal of machine learning research (2014)

L2 = weight decay

- Regularization term that penalizes big weights, added to the objective
- Weight decay value determines how dominant regularization is during gradient computation
- Big weight decay coefficient → big penalty for big weights

$$J_{reg}(\theta) = J(\theta) + \lambda \sum_k \theta_k^2$$

Early-stopping

- Use validation error to decide when to stop training
- Stop when monitored quantity has not improved after n subsequent epochs
- n is called patience

Artificial Intelligence –
Deep Learning and its applications

- Information retrieval (search engines)
- Pattern recognition
- Audience targeting
- Sentiment analysis (based on written text)
- Personalization
- Automation
- Natural Language Processing
- Social media mining
- Organic search and content performance
- Brand and product differentiation

- Trend Prediction
- Recognition
- New Knowledge
- Making Sense
- Replacing Human

Data Centres

- Increase its energy efficiency by 15%
- 120 different variables (sensors, temperatue gauges, fans, windows…)

Artificial Intelligence – Deep Learning and its applications

- Language Translation
- Speech Recognition
- Generating Handwriting
- Face Recognition
- Autonomous Driving
- Generating Arts
- Imitating Famous Painters
- Generating Music
- Generating Photos

Power Systems

- Peak Load Forecast (e.g. Maximum Demand)
- Failure Prediction (e.g. Battery)
- Condition Monitoring (e.g. Partial Discharge)

Deep Learning Chemical Reaction: Reaction Predictor

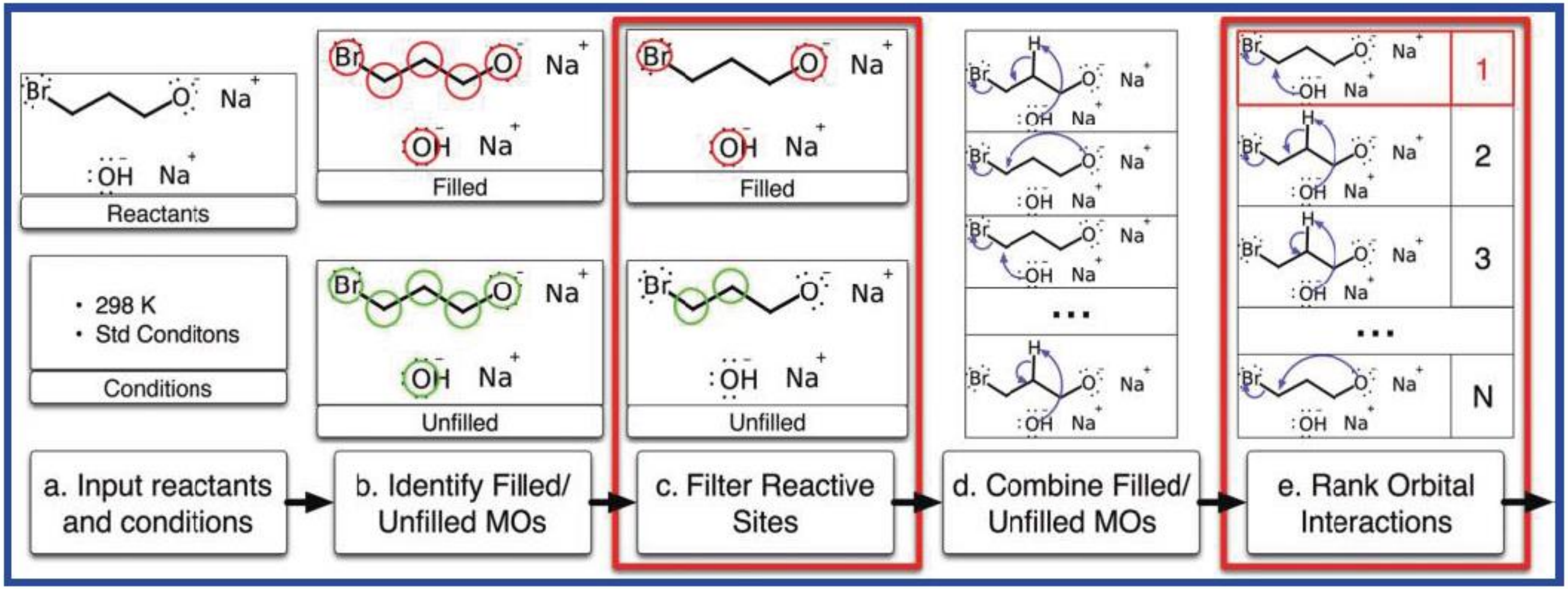
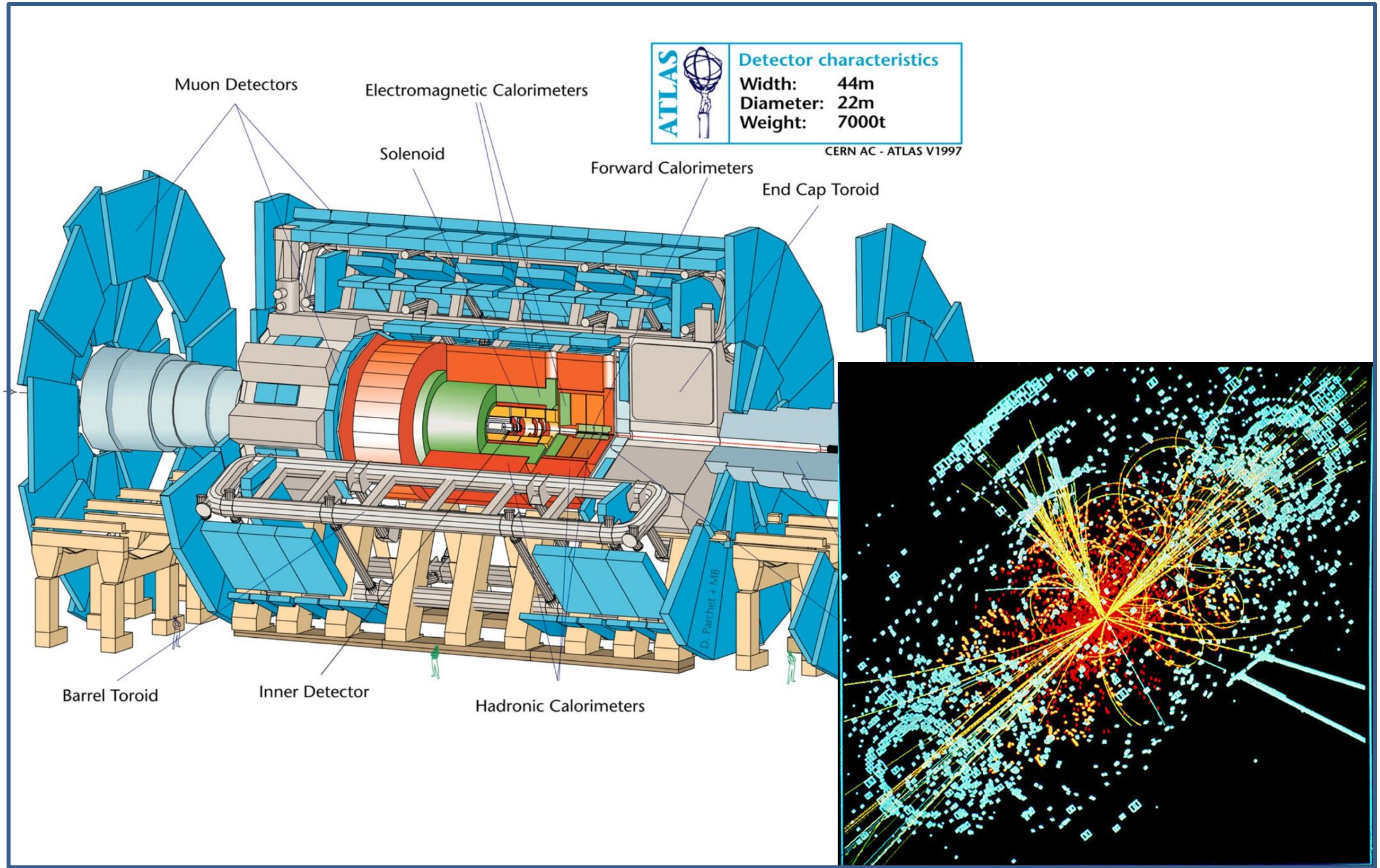


Figure 2. Overall reaction prediction framework: (a) A user inputs the reactants and conditions. (b) We identify potential electron donors and acceptors using coarse approximations of electron-filled and -unfilled MOs. (c) Highly sensitive reactive site classifiers are trained and used to filter out the vast majority of unreactive sites, pruning the space of potential reactions. (d) Reactions are enumerated by pairing filled and unfilled MOs. (e) A ranking model is trained and used to order the reactions, where the best ranking one or few represent the major products. The top-ranked product can be recursively chained to a new instance of the framework for multistep reaction prediction.

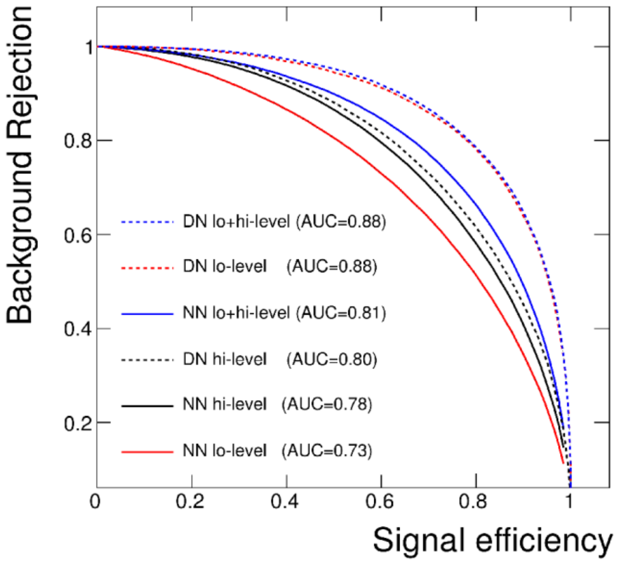
M. Kayala, C. Azencott, J. Chen, and P. Baldi. Learning to Predict Chemical Reactions. *Journal of Chemical Information and Modeling*, 51, 9, 2209–2222, (2011).

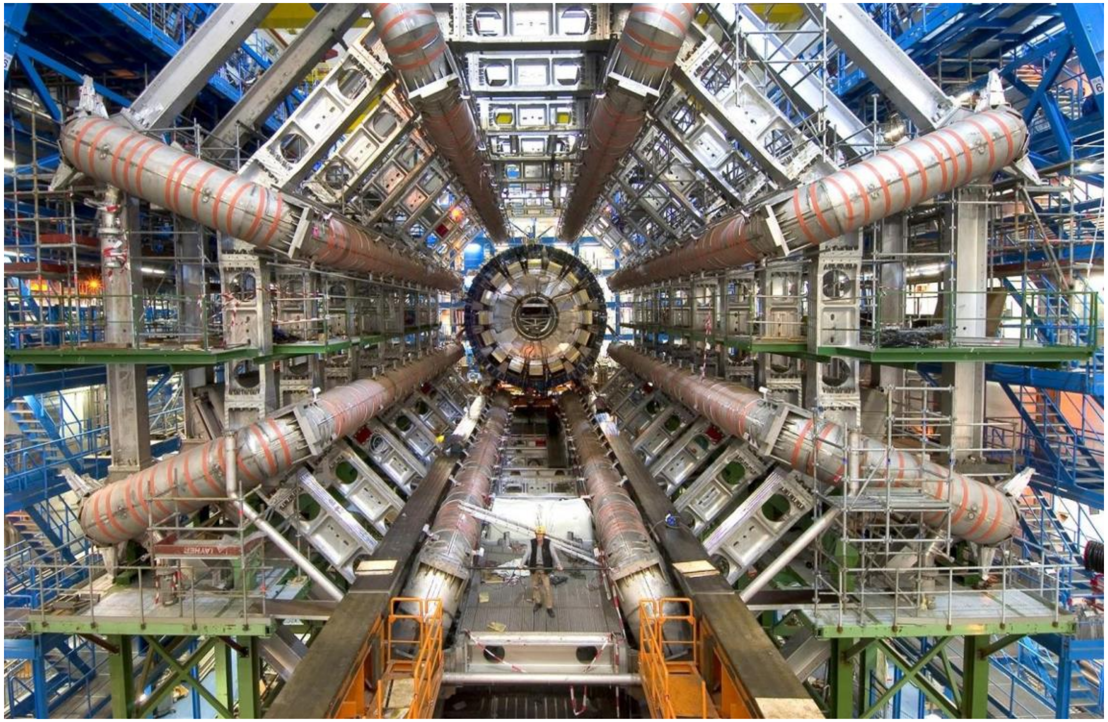
M. Kayala and P. Baldi. ReactionPredictor: Prediction of Complex Chemical Reactions at the Mechanistic Level Using Machine Learning. *Journal of Chemical Information and Modeling*, 52, 10, 2526–2540, (2012).

Deep Learning in Physics: Searching for Exotic Particles



Higgs Boson Detection

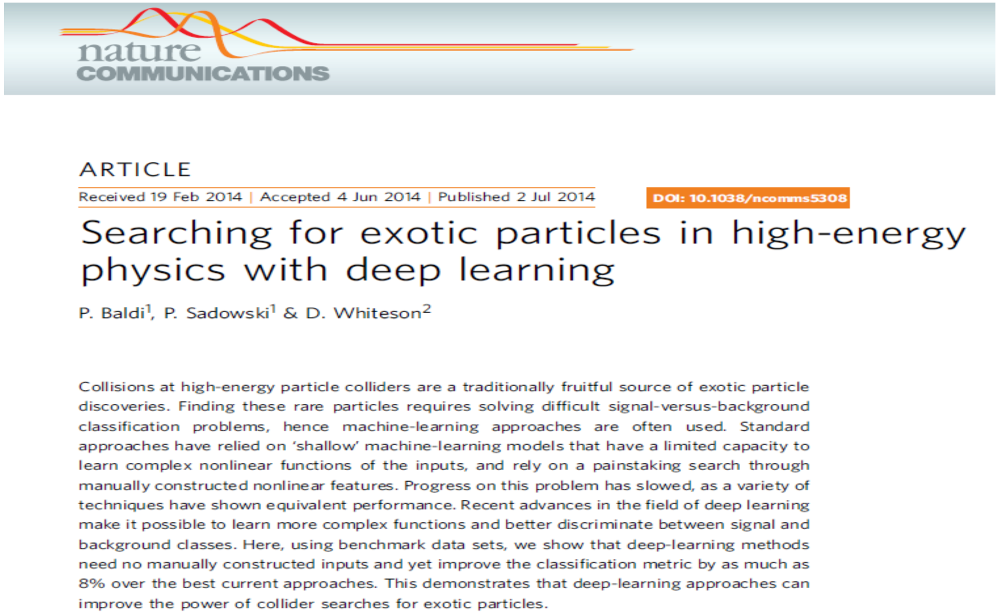




Receiver operating characteristics

Area under the curve

Deep network improves AUC by 8%



nature COMMUNICATIONS

ARTICLE

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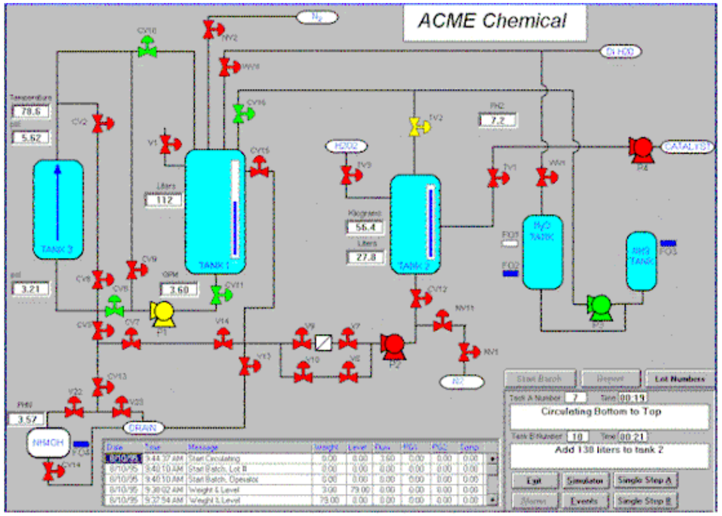
Searching for exotic particles in high-energy physics with deep learning

P. Baldi[1], P. Sadowski[1] & D. Whiteson[2]

Collisions at high-energy particle colliders are a traditionally fruitful source of exotic particle discoveries. Finding these rare particles requires solving difficult signal-versus-background classification problems, hence machine-learning approaches are often used. Standard approaches have relied on 'shallow' machine-learning models that have a limited capacity to learn complex nonlinear functions of the inputs, and rely on a painstaking search through manually constructed nonlinear features. Progress on this problem has slowed, as a variety of techniques have shown equivalent performance. Recent advances in the field of deep learning make it possible to learn more complex functions and better discriminate between signal and background classes. Here, using benchmark data sets, we show that deep-learning methods need no manually constructed inputs and yet improve the classification metric by as much as 8% over the best current approaches. This demonstrates that deep-learning approaches can improve the power of collider searches for exotic particles.

Some Examples



Tank A Number 7 Time 00:19

Circulating Bottom to Top

Tank B Number 10 Time 00:21

Add 130 liters to tank 2

Date	Time	Message	Weight	Level	Flow	PG1	PG2	Temp
8/10/95	9:44:37 AM	Start Circulating	0.00	0.00	3.60	0.00	0.00	0.00
8/10/95	9:40:10 AM	Start Batch, Lot B	0.00	0.00	0.00	0.00	0.00	0.00
8/10/95	9:40:10 AM	Start Batch, Operator	0.00	0.00	0.00	0.00	0.00	0.00
8/10/95	9:38:02 AM	Weight & Level	3.00	79.00	0.00	0.00	0.00	0.00
8/10/95	9:37:54 AM	Weight & Level	79.00	0.00	0.00	0.00	0.00	0.00

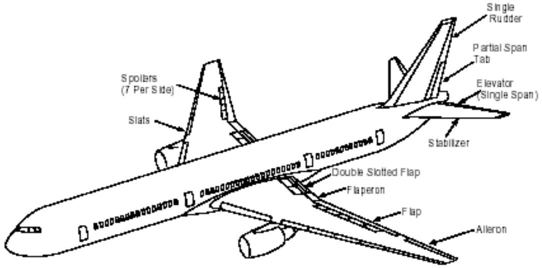
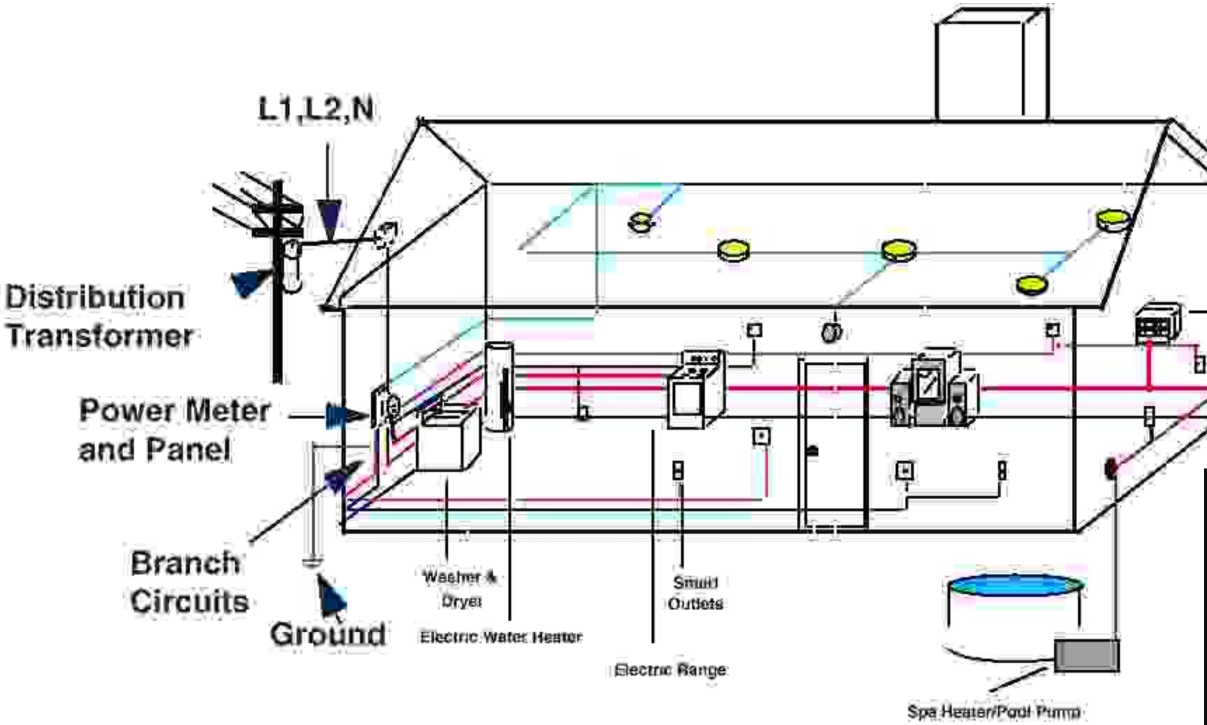


FIGURE 1 777 FLIGHT CONTROL SURFACES

Building Automation

basics: fire, intrusion, climate, energy management
HVAC = Heat, Ventilation and Cooling = air conditioning



visitors, meeting rooms, catering,….
low price tag

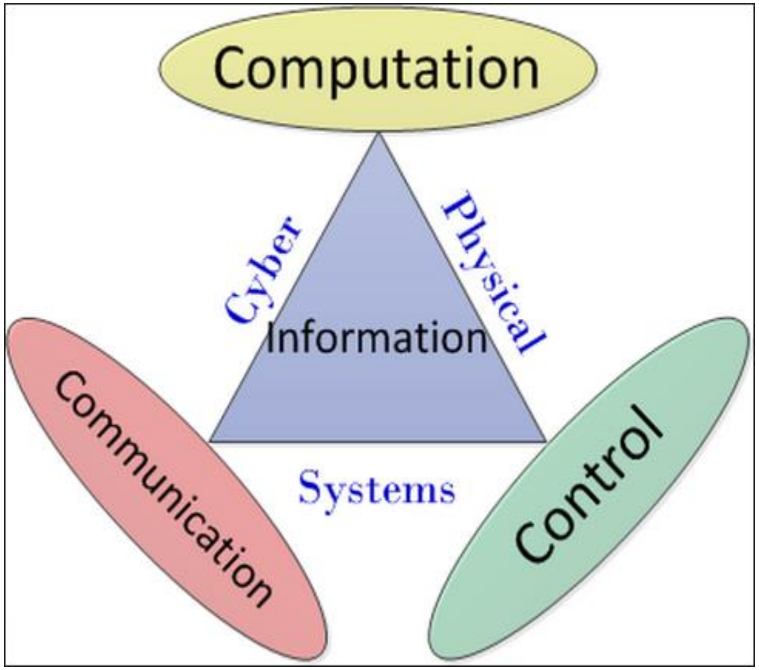
Instrumentation & Control Science has become Interdisciplinary

SMART MANUFACTURING

Smart leather is stain repellants and waterproofing agents that protect **leather.** It is a pH balanced formula that replenishes the essential, natural nutrients that keep natural **leather** soft and supple. When used on artificial **leather** surfaces, Smart Leather prevents fading and cracking.

- Builds on the Digital revolution
- Smaller & powerful sensors
- Machine Learning
- Ubiquitous internet
- Artificial Intelligence (AI)
- Labor & Energy Cost

Cyber Physical Systems



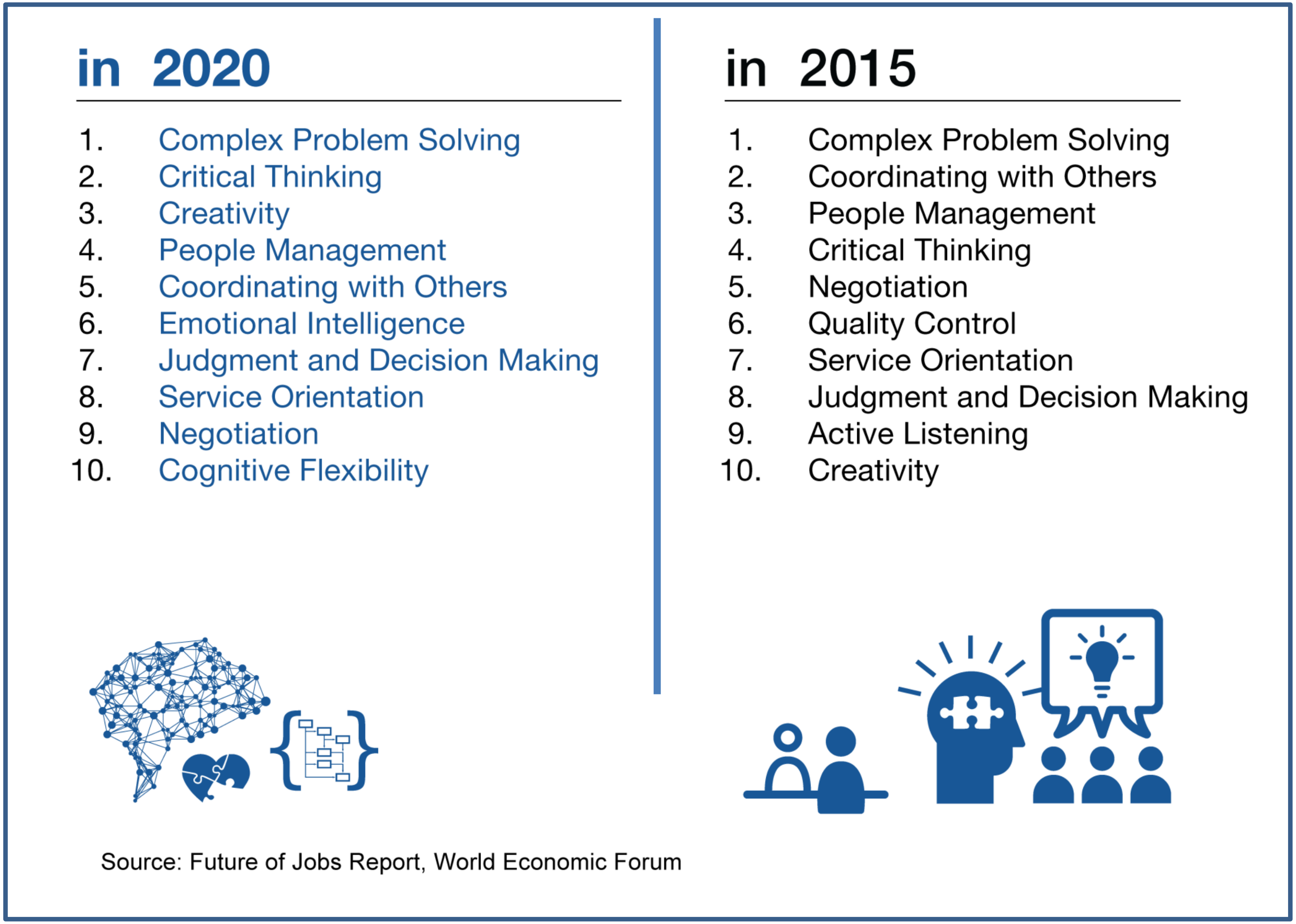
A **cyber-physical system** (**CPS**) is a system of collaborating computational elements controlling physical entities. CPS are physical and engineered systems whose operations are monitored, coordinated, controlled and integrated by a computing and communication core. They allow us to add capabilities to physical systems by merging computing and communication with physical processes. Physical systems and softwares are interconnected to exchange data through this mechanism. This system involves number of trans-disciplinary subjects such as cybernetics, mechanical engineering, mechatronics design and process science, manufacturing systems, and computer science

Industry 4.0

Six Design Principles

- **Interoperability**: the ability of **cyber-physical systems** (i.e. work piece carriers, assembly stations and products), humans and Smart Factories to connect and communicate with each other via the **Internet of Things** and the **Internet of Services**
- **Virtualization**: a virtual copy of the Smart Factory which is created by linking sensor data (from monitoring physical processes) with virtual plant models and simulation models
- **Decentralization**: the ability of **cyber-physical systems** within Smart Factories to make decisions on their own
- **Real-Time Capability**: the capability to collect and analyze data and provide the insights immediately
- **Service Orientation**: offering of services (of **cyber-physical systems**, humans and Smart Factories) via the **Internet of Services**
- **Modularity**: flexible adaptation of Smart Factories for changing requirements of individual modules

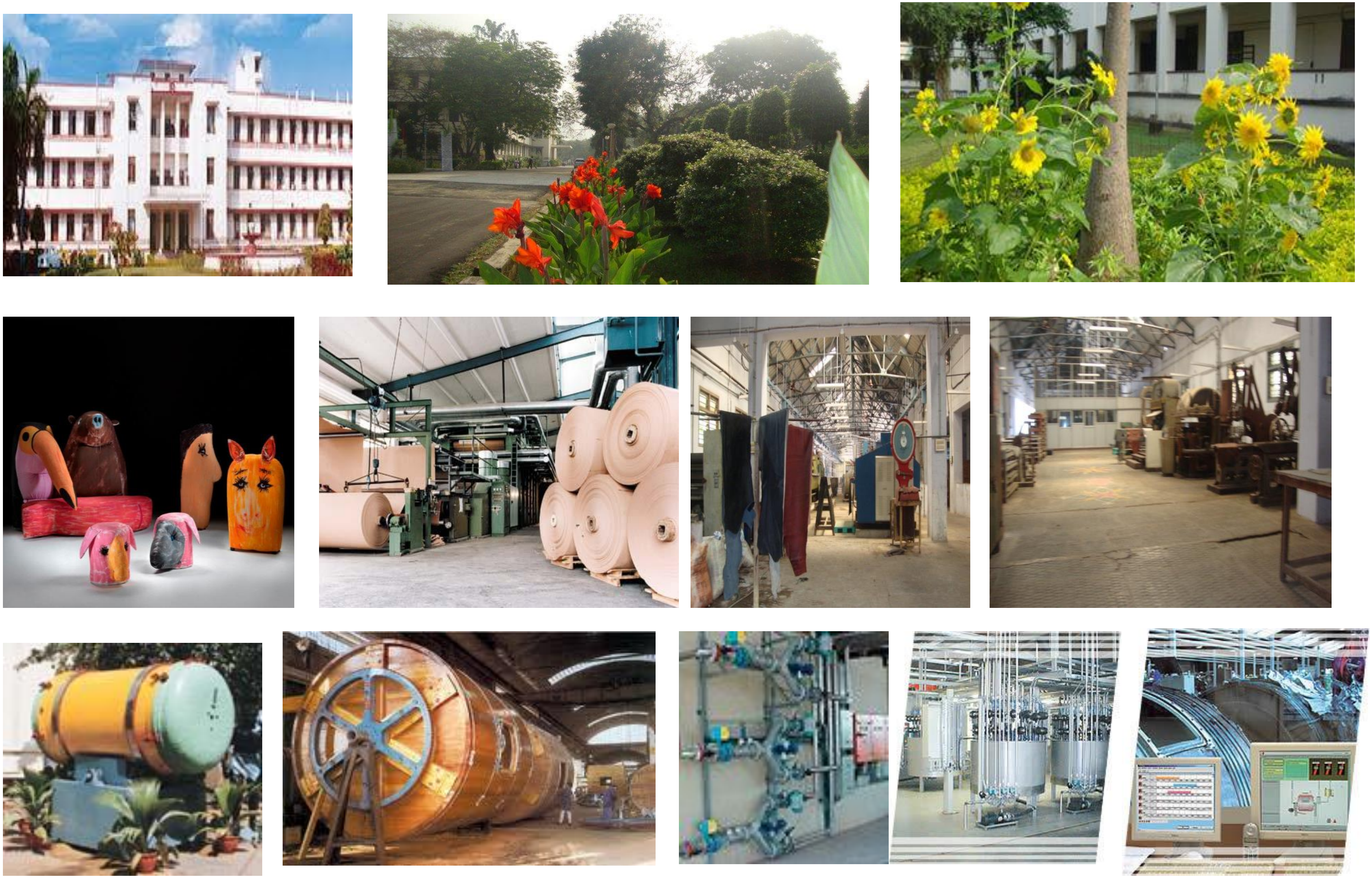
Top 10 Skills to be relevant in Industry 4.0



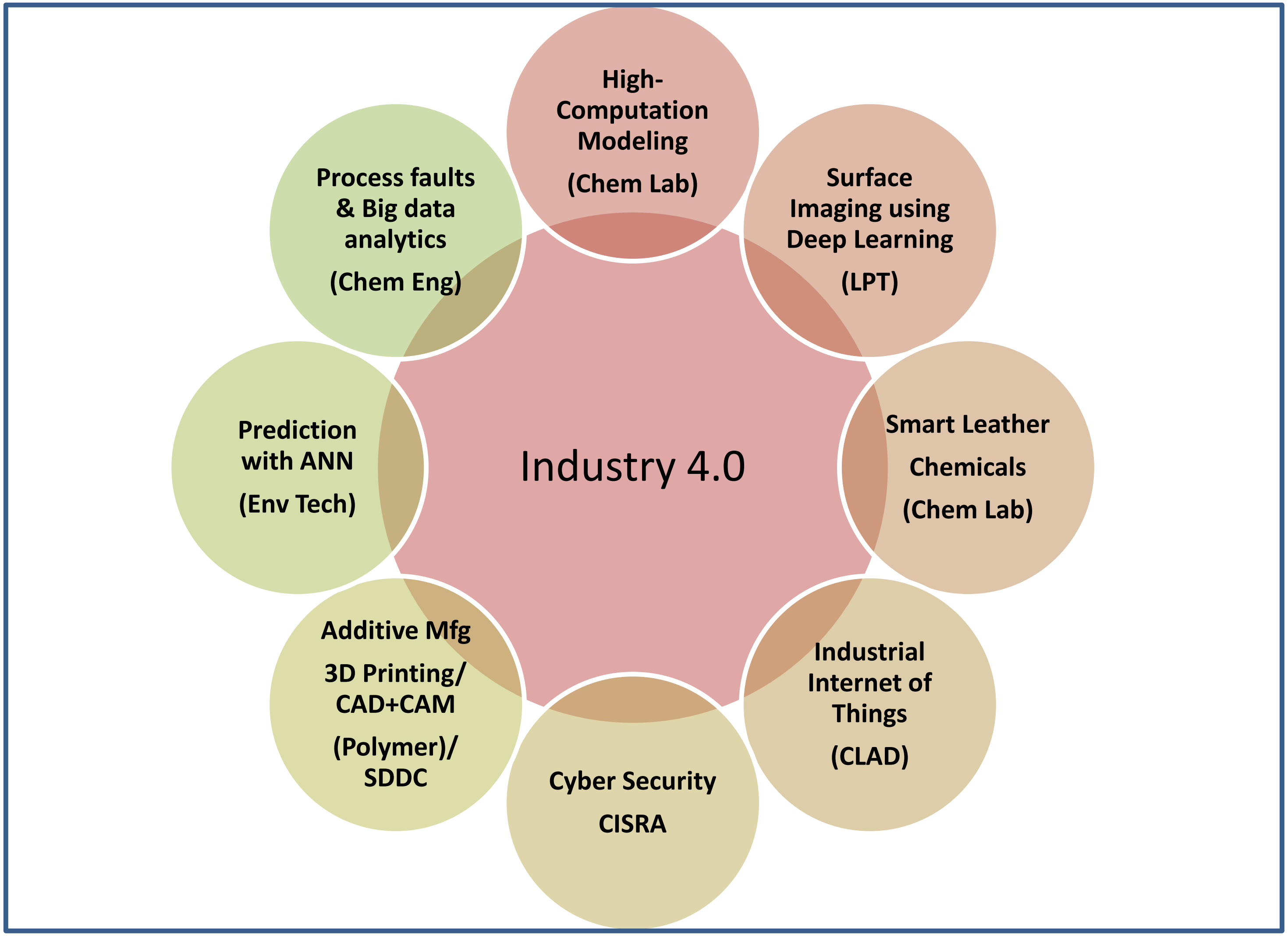
	in 2020		in 2015
1.	Complex Problem Solving	1.	Complex Problem Solving
2.	Critical Thinking	2.	Coordinating with Others
3.	Creativity	3.	People Management
4.	People Management	4.	Critical Thinking
5.	Coordinating with Others	5.	Negotiation
6.	Emotional Intelligence	6.	Quality Control
7.	Judgment and Decision Making	7.	Service Orientation
8.	Service Orientation	8.	Judgment and Decision Making
9.	Negotiation	9.	Active Listening
10.	Cognitive Flexibility	10.	Creativity

Source: Future of Jobs Report, World Economic Forum

CSIR-CENTRAL LEATHER RESEARCH INSTITUTE



AI at CSIR-CLRI



Industry 4.0

High-Computation Modeling
(Chem Lab)

Surface Imaging using Deep Learning
(LPT)

Smart Leather Chemicals
(Chem Lab)

Industrial Internet of Things
(CLAD)

Cyber Security
CISRA

Additive Mfg
3D Printing/ CAD+CAM
(Polymer)/ SDDC

Prediction with ANN
(Env Tech)

Process faults & Big data analytics
(Chem Eng)

Application of process control in tannery wet operations

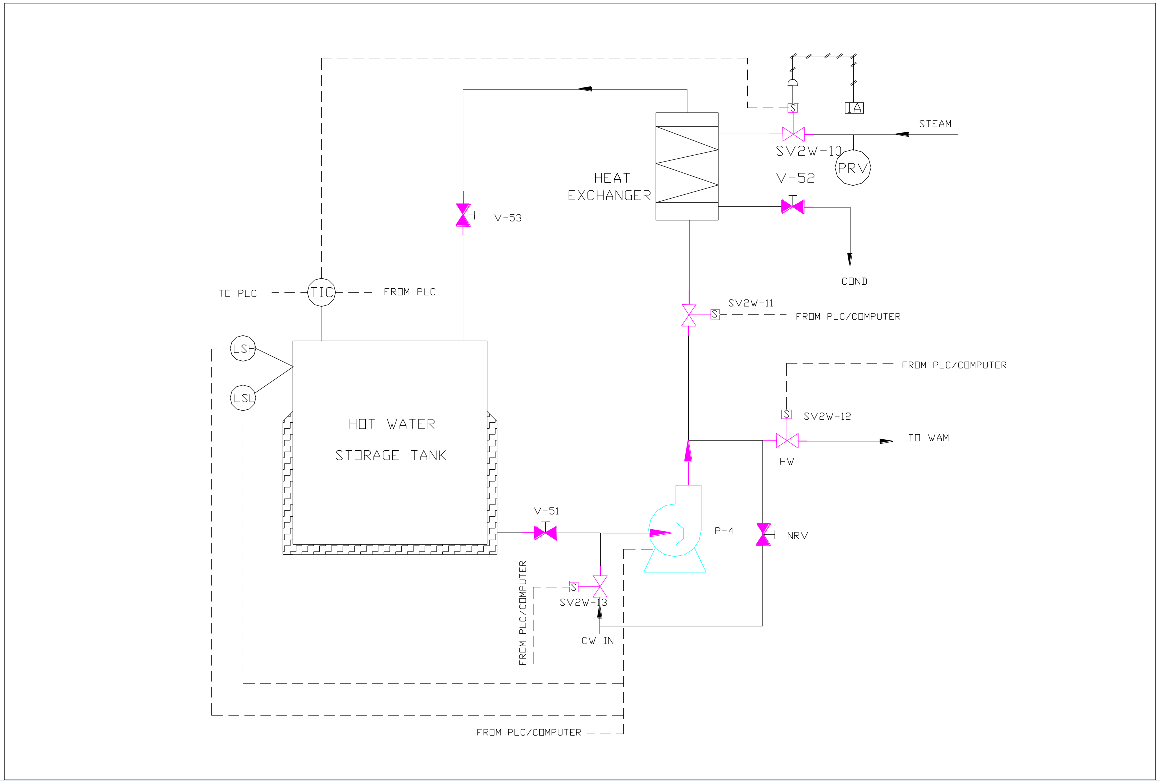
Implementation of cleaner production technology is essential for the sustained growth and development of Indian leather industry. Chemical engineering concepts are needed to minimize water usage, toxic chemical load in tannery waste, wastage of chemicals and to increase production capacity. Engineering inputs can give better & safe material handling, process control and provides environmentally cleaner and healthier working atmosphere

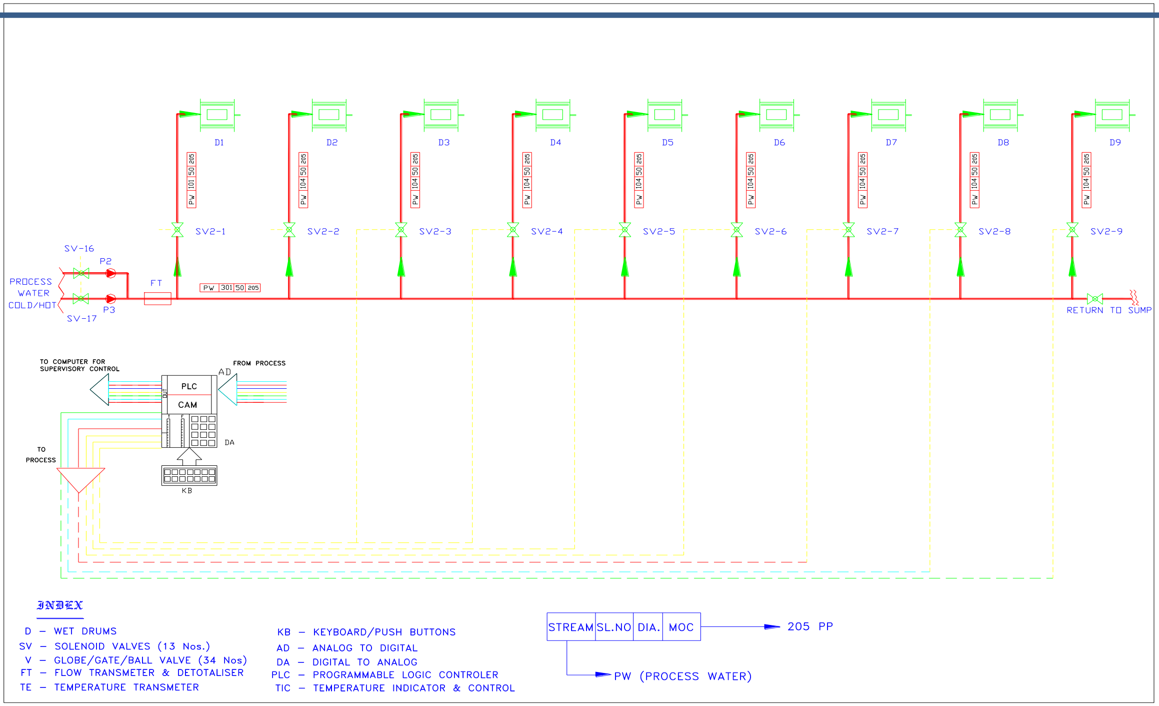
The entire process control operation is designed with following five modules:

a) Water addition module
b) Chemical preparation and dosing system
c) pH control and float recycle system
d) Drum rotation module
e) Odor reduction module

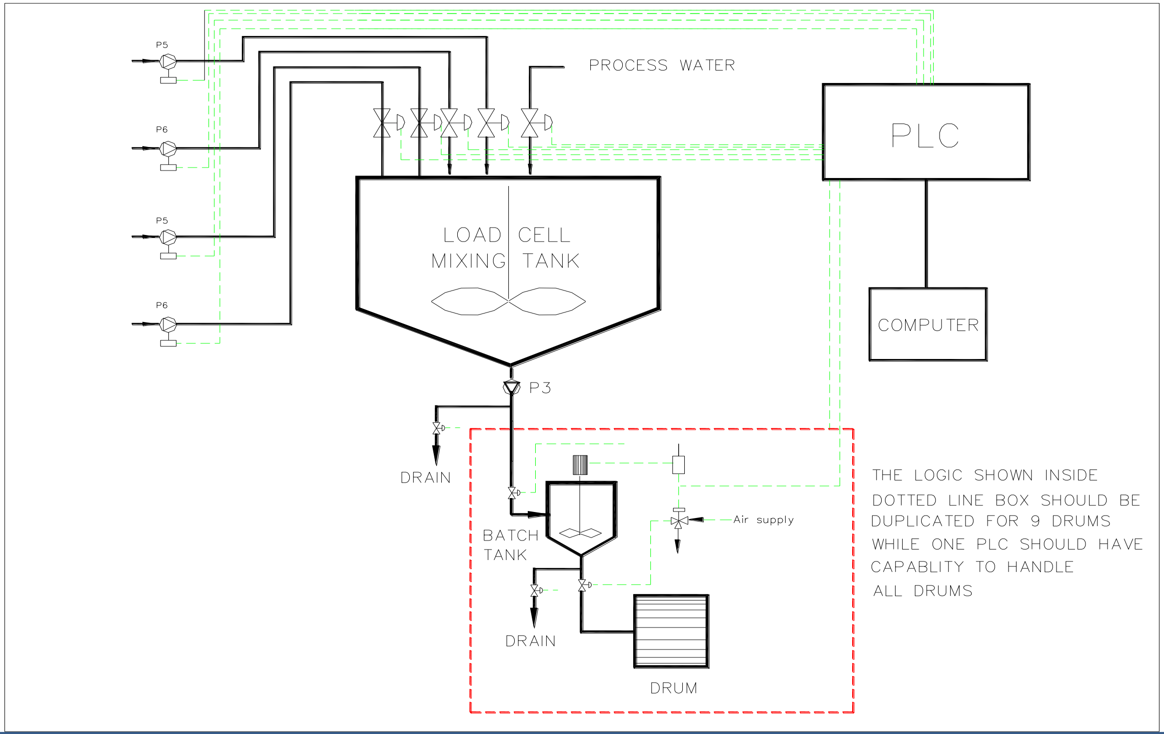
The proposed system is an integrated process computer with necessary field instrument and Programmable Logic Controller (PLC) connected in Distributed Control System (DCS) manner.

Water Addition Module (WAM): Hot/normal water is added in the drums as per process recipe. Water is also added in load cell tank for dilution of chemicals or is added to batch / bulk chemical tanks for ringing purpose. In case of hot water option, water is heated at 65 0C using steam in a heat exchanger. All the sequence of works are controlled by real time software for WAM through PC/PLC. The PC/PLC and field instruments/ controllers exchange data between them. Sequences and schedules of operation written using Laddar logic diagram are loaded into PC/PLC memory. The hot water storage tank is linked with the receiving units / equipments by header and branch pipelines as shown below. Based on the requirements of types of water hot/normal, water is added to respective drums through this module and pumps.





Chemical Dosing Module



pH Monitoring

Features of the CADS

- Recipe management (download parameters based on selected recipe)
- Monitor & Control of the process status
- Monitor & report operator’s intervention
- Time tagging of all functions
- Positioning of the drum in any position
- Speed control of the drum via variable frequency drives
- Control & Monitoring of the barrier & float & float temperature
- All color coded multiple level alarm functionality along with time tagging
- Interacts with Chemical feed and Water feed system
- Control with both manual & auto modes of all the drum operations
- Operate each drum independently & effectively
- Initiate each drum with any tanning operation
- De-initiate any of the initiated drum at any stage of the operation
- Option to extend any of the operation
- Wash the mixing tank, storage tanks independently
- Data logging and printing
- Digital indication of all process variables

Additional Features of the CADS / PLC system are

- Alarm : Audio-visual indications for the convenience of the operator
- Overall-Drum Status: Can be viewed on the custom graphic screens on the MMI
- Hard copies of the detail can be obtained
- Mimic panel board: to operate motors (MCB), pumps switches and AC/DC drives

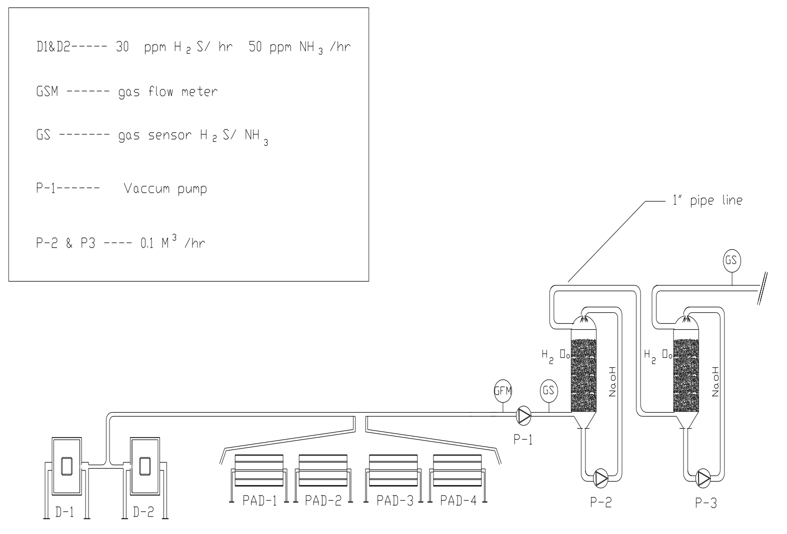
Odor Reduction

R&D work at CLRI

Sources & Effects

- **NH3, H2S, VOC, gases from degradation of putrescible materials in hides / skins**
- **These gases must be removed in order to maintain occupational safety, cleaner technology.**

VOC – 50 ppm
NH_3 – 30 ppm
H_2S - 20 ppm



Schematic P & I diagram for odor abatement

Different **methods of removal** of NH_3 and H_2S

a) Addition of Chemical Reagents

b) Passing Compressed Air

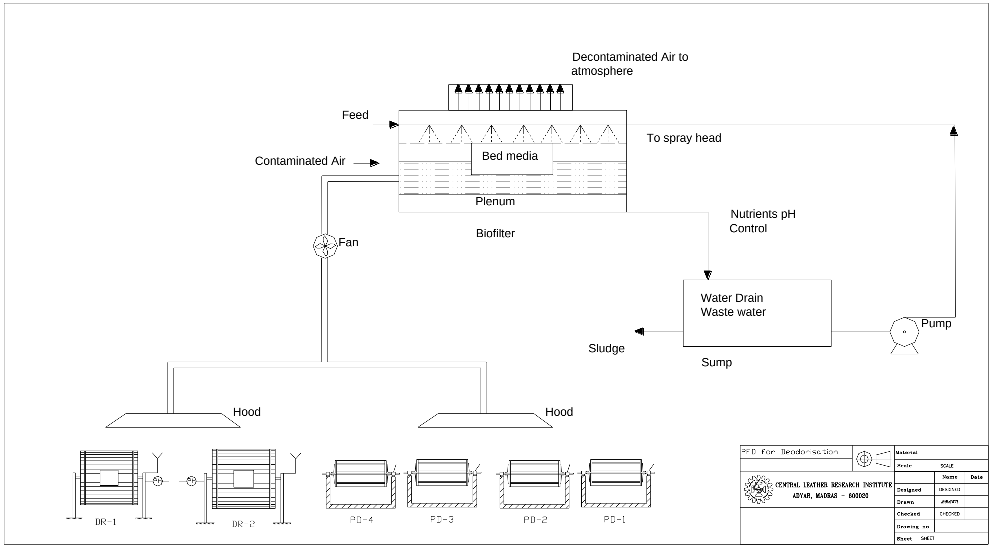
c) Ozone Oxidation

d) Passing air in counter current to liquor in a packed (activated carbon) bed

e) Biochemical and Biological methods

Odor Abatement BY Bio-Filter

R&D work at CLRI



Odor loading less than 1000 ppm

Removal efficiency 94%

Room size: 60 ft X 35 ft X 16 ft high.

Process: 2 Tanning Drums + 4 Paddles

Exhaust fan / Hoods

Microbial Feeding spray and pumps

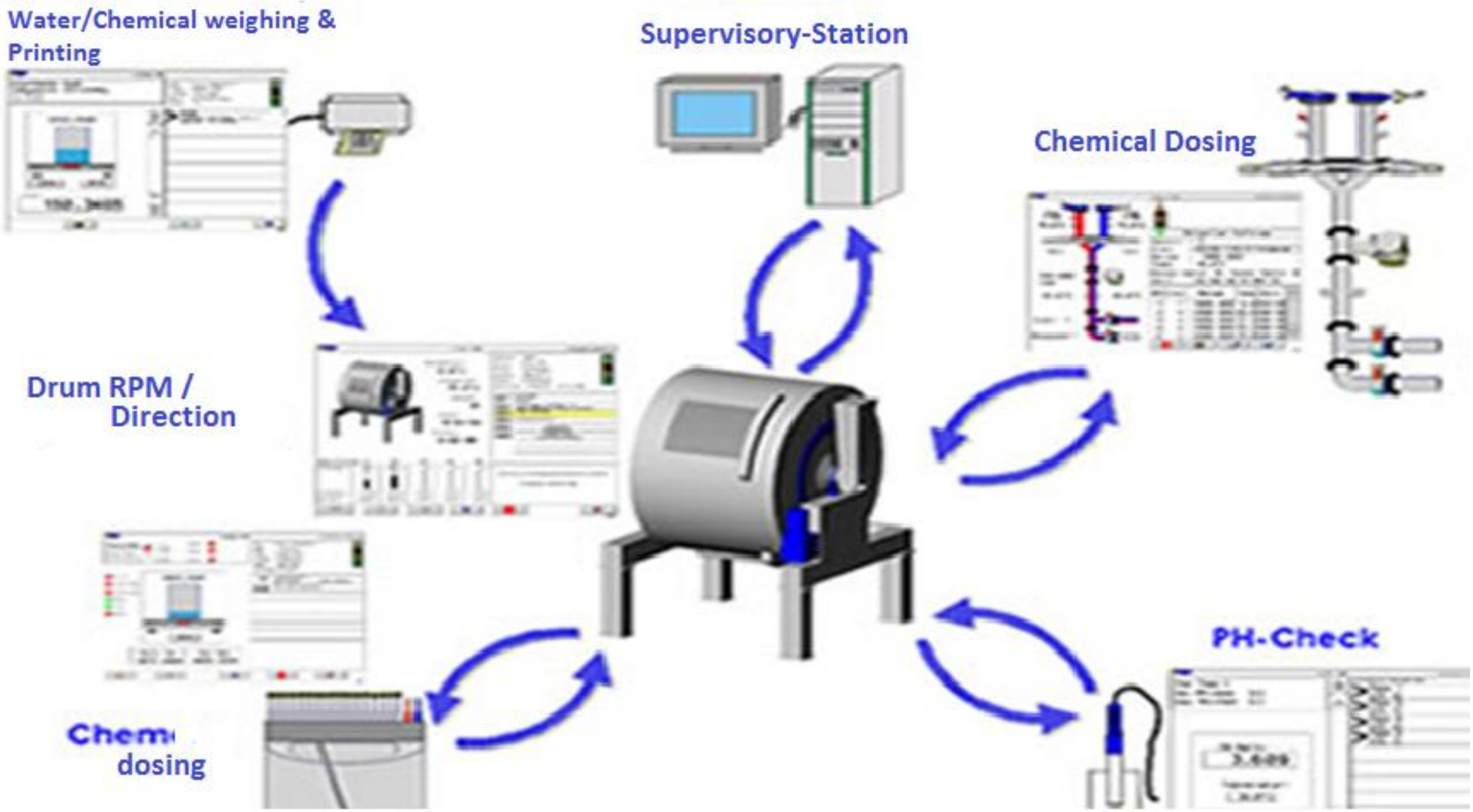
Recirculation pump

Continuous monitoring of odor gases / Olfactometer or Nasal ranger

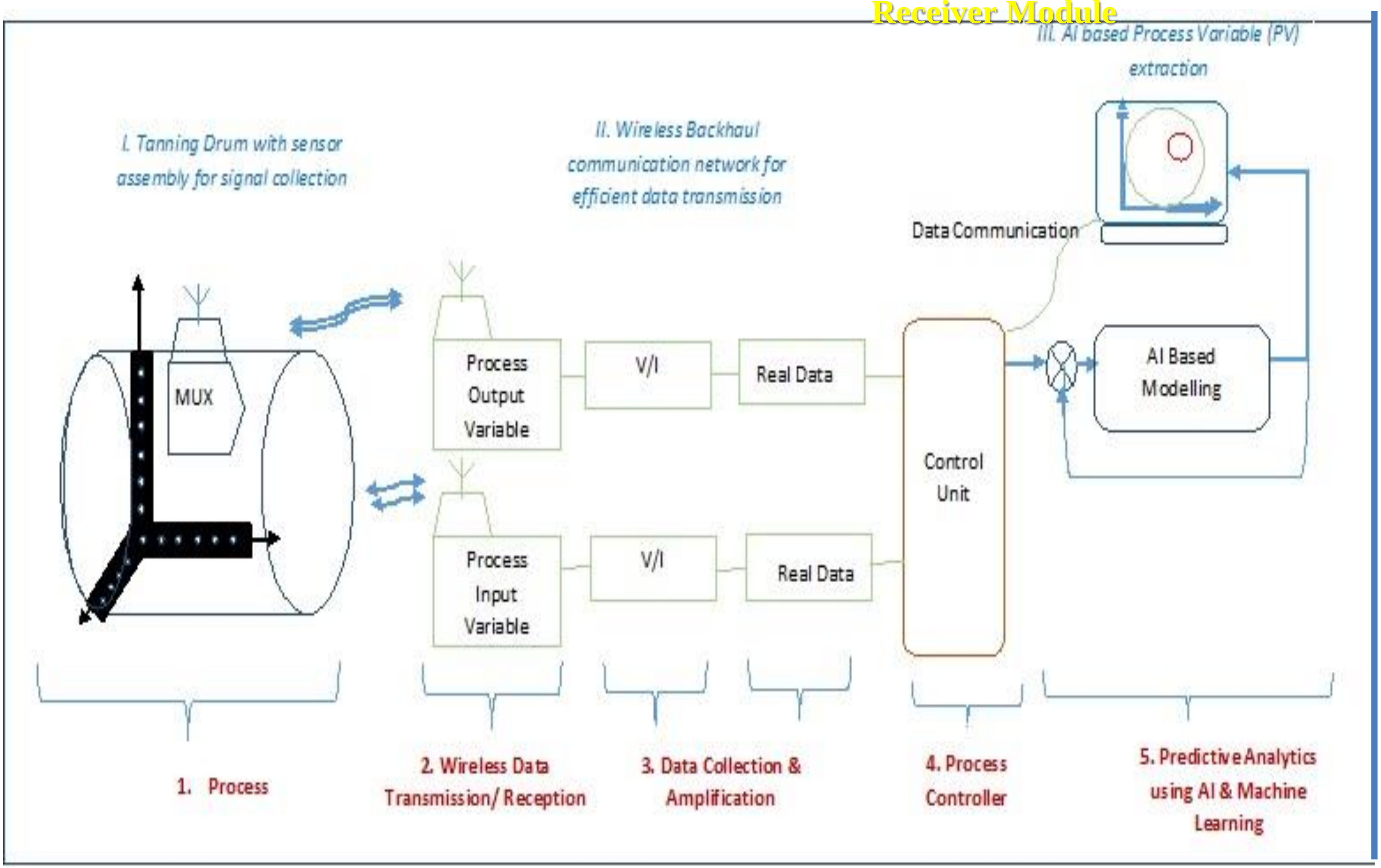
Implemented in M/s SA Abdul Azeez Tannery, Erode, TamilNadu

Adv in Chem Eng & Sci, 2(2), 2012, pp. 199-203.

Automatic Dosing : Process Control



SCHEME



AI based measurement of process variables

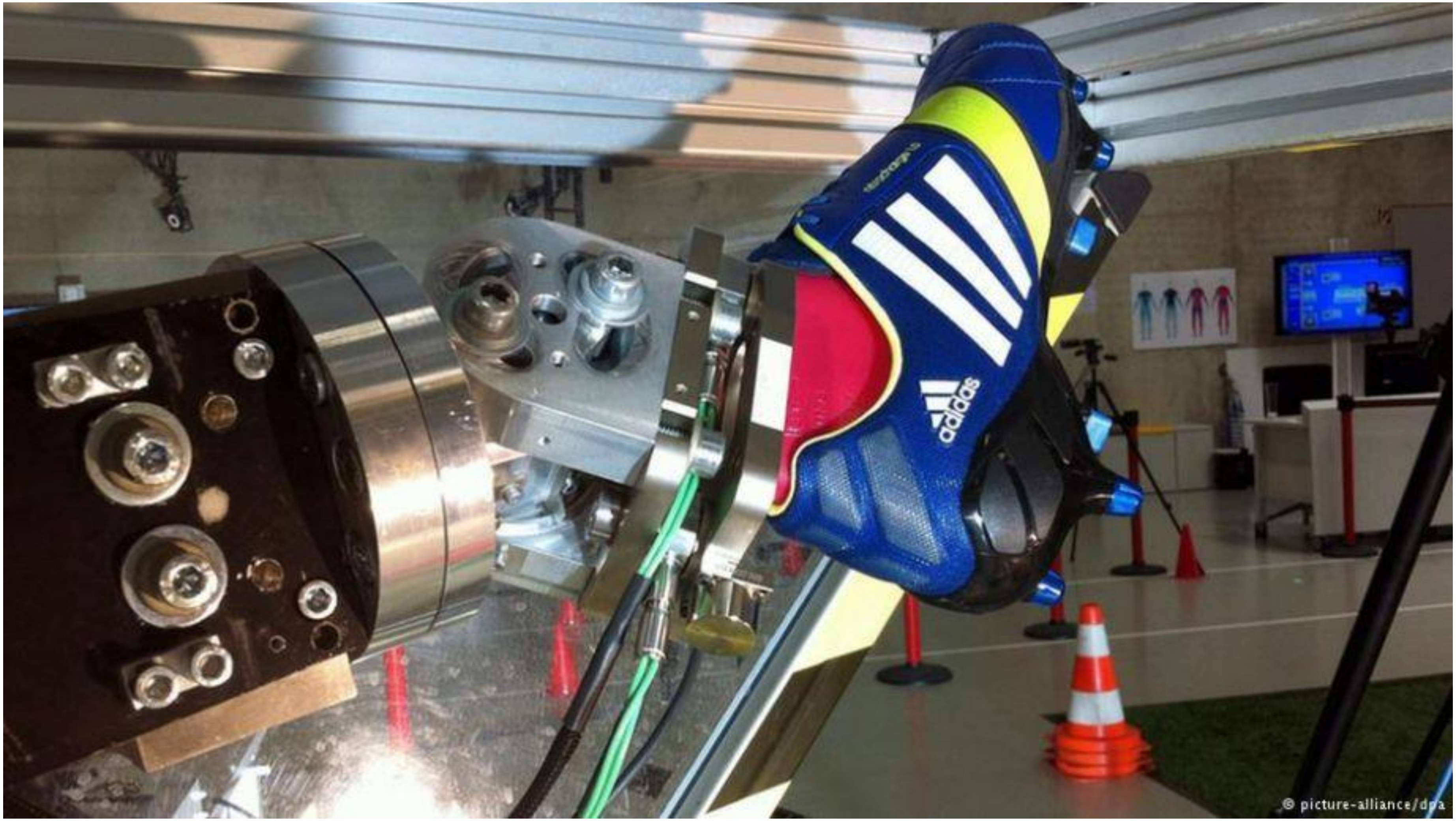
- **Achievement**: Indian Footwear, Leather & Accessories Development Programme (IFLADP), a special package for employment generation in leather and footwear sector has been launched in December 2017. The package involves implementation of Central Sector Scheme with an approved expenditure of INR 2600 Crore over the three financial years (i.e. 2017-18 to 2019-20)
- Two new branches of FDDI built in Patna and Hyderabad
- INR 1220.32 lakh has been sanctioned under Market Access Initiative scheme for marketing programmes and activities during FY 2017-18.
- 4.44 lakh people trained

Adidas : Speedfactory
Producing your own shoes

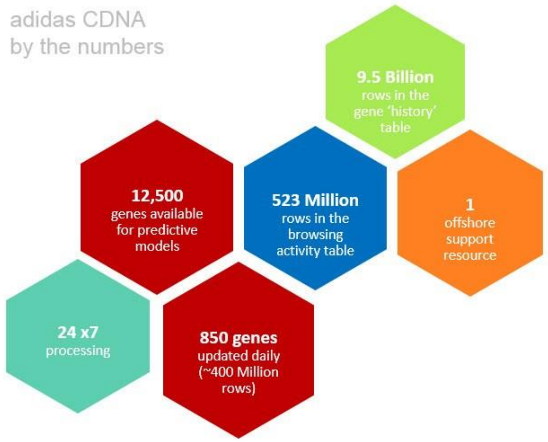
- The costumers can design their own short shoes using an App. Since the customer wants to receive his personalized product on the next day or faster, long logistic chains from low-wage countriesare no longer acceptable in the era of mass customization.
- Thus, Adidas decided to open various **"Speed Factories"** for personalized shoes in Germany close to the customer, using Cyber-physical production systems (CPPS).

Adidas is using robots to produce small-batch, local-market shoes

Shoemaker Adidas just rolled out the first of six local-market running shoes made in its so-called "Speedfactory" in Germany. The running shoe is designed for Londoners, and will be followed by five additional models created for markets like Paris, Los Angeles, and New York. It's an early step in a bold experiment by a global retailer to use time-saving robots to design small-batch collections, a departure from the mass production methods employed by global shoe and apparel brands. Adidas produces about 600 million pairs of shoes other apparel items per year. The brand relies on about a million factory workers in China and Vietnam. But as the shoe industry becomes more focused on hype-driven releases where scarcity and design play an important role in brand credibility, the old global manufacturing chain has become a hinderance. It typically takes Adidas a year or more to design, source, and deliver a shoe to market. Due to the economics of production, the brand must produce minimum batches of 50,000 or 100,000 shoes to make a profit next Adidas runners just might be made in America—by a robot. The shoemaker is building what it calls a "Speedfactory" in Atlanta this year. The factory features 74,000 square feet of robotic shoemaking capability. The factory has a capacity of 50,000 pairs of shoes a year

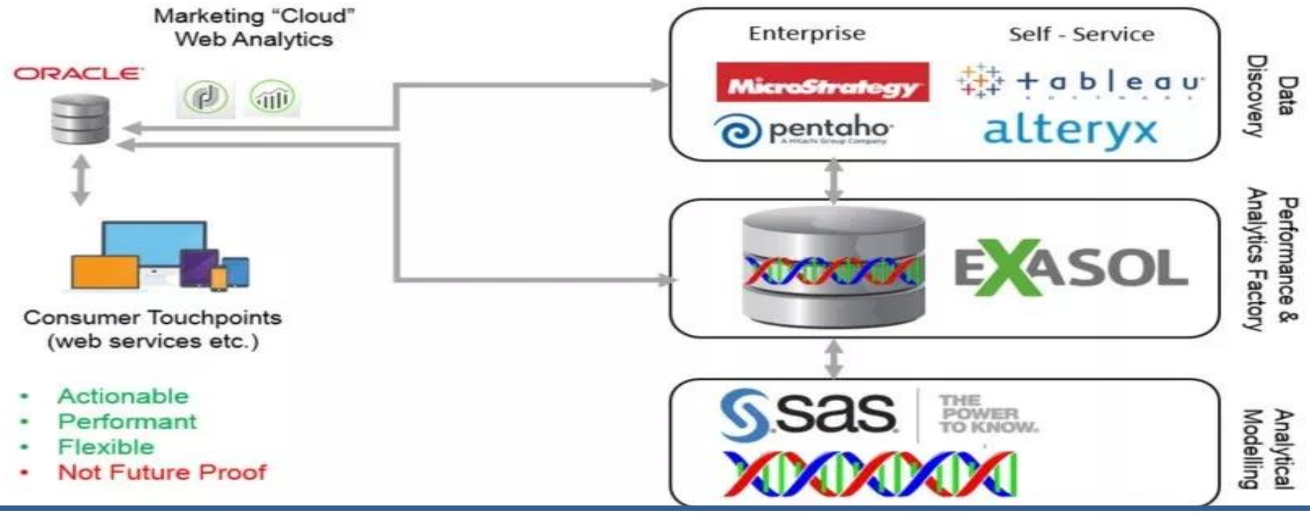


Adidas analytics technology was designed to understand what motivates consumers and drives decision-making. To facilitate this drive, data scientists at adidas created a Consumer DNA (CDNA) model consisting of re-useable, pre-fabricated analytics components to create a 360 degree Consumer View



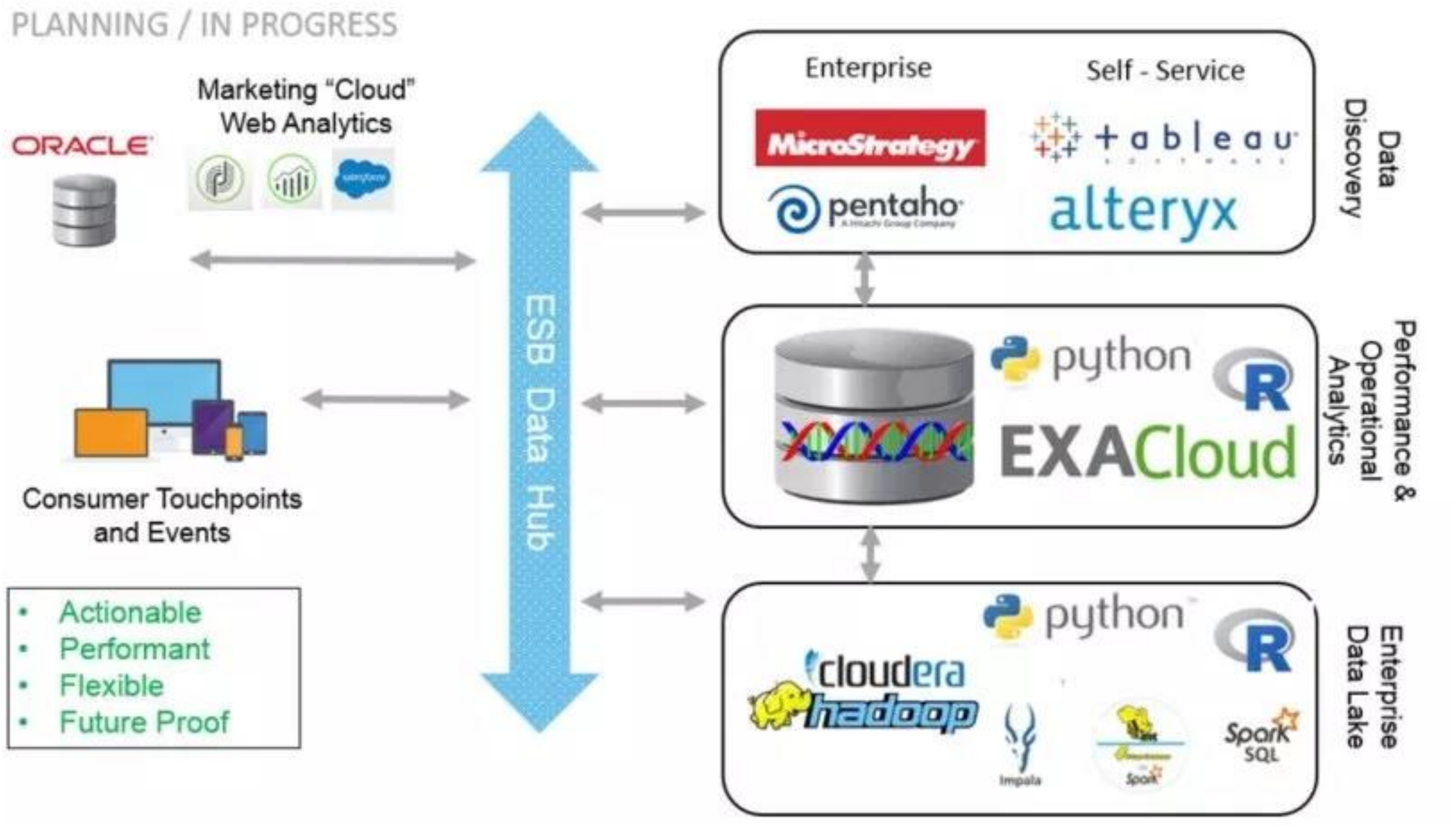
Director of Marketing intelligence (Adidas):

1. What do our digital consumers expect?
   --Personalization, understand me!
2. What are the key IT success factors enabling change?
   --Agility, speed, independence and data.
3. Do traditional IT processes and technologies match to the needs of the consumers?
   --Let‘s see



Cost effective
Analytic standards

The exports of leather and leather products for April-Jun 2018 have touched USD 1420 million. In order to compete in that global market, Indian leather industry has to gear-up through process automation and other requisites as to comply with industry 4.0 and to become at par with comparable qualities with optimal production as in other countries



Adidas :Adidas is using automation to bring manufacturing back to Europe

CDNA - footwear will be crafted with our individual anatomy and biomechanics as the foundation. The DNA concept leverages rapid manufacturing to create a shoe built not only to your foot contours, but also to how you move. By pairing data acquisition (A sensor shoe tracks your details as you do a test run.), user behavior (Are you running or doing cross-fit?), and rapid prototyping it creates a method of mass-tailoring products. Within hours you have a shoe tailored to your foot, your movement, and your style. Shoes should be built for the way you move.

The first step is to acquire the data that an individual's shoes will be based on. Each customer's feet are three dimensionally scanned. Then they put on a pair of special sensor shoes and go for a test run or walk. The sensors track their movement – footfall, pronation, balance, etc. – and combined with the scan and activity type create a usable database to build the new shoes around.

Algorithms are used to translate the data into form and the shoes start to come together. At this point, the customer is able to customize the materials, colors and textures of their shoe. Or they can save a shoe design in advance that can be combined with their foot data when they get to the store. Their design then goes to print, and as they shop the 3d printer creates their shoes

In the face of potential US tariffs on Chinese-made shoes, numerous world-famous shoe and handbag manufacturers are mulling over shifting sourcing to Vietnam

Smart leather is stain repellants and waterproofing agents that protect **leather.** It is a pH balanced formula that replenishes the essential, natural nutrients that keep natural **leather** soft and supple. When used on artificial **leather** surfaces, Smart Leather prevents fading and cracking.