CSCE 438/838: Internet of Things

Machine Learning for IoT

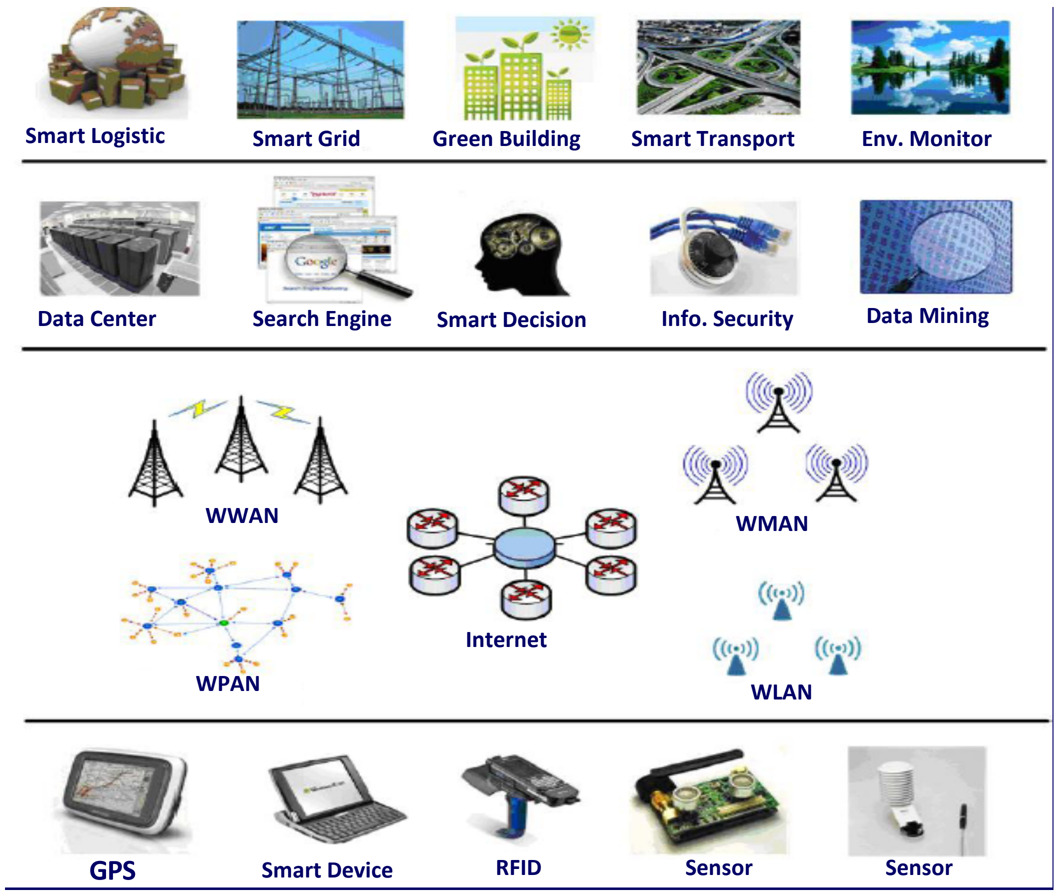
Many Devices and Huge Amount of Data

- Device Management
  - Number of devices in IoT is extremely large
  - Connection between them and with the sinks over very large distances
  - Connectivity of devices is very important
  - Very large collected data must be managed efficiently
- Device Diversity and Interoperability
  - Many products from many different companies
- Integration of Data from Multiple Sources
  - Large amounts of data will be collected from different sources such as sensors, mobile devices, etc
  - Interpretation of these data is challenging
- Scale, Data Volume, and Performance
  - Big Data Problem (how to handle and analyze the data)
- Flexibility and Evolution of Applications
  - New use cases and new business models

Bottomline

- Diverse IoT applications: Health, transportation, smart home, smart city, agriculture, education, etc.
- Main element: Intelligent learning mechanism for
  - Prediction (i.e., regression, classification, and clustering),
  - Data mining
  - Pattern recognition
  - Data analytics in general

4-Layer Model for IoT



Integrated Application

Information Processing

Network Construction

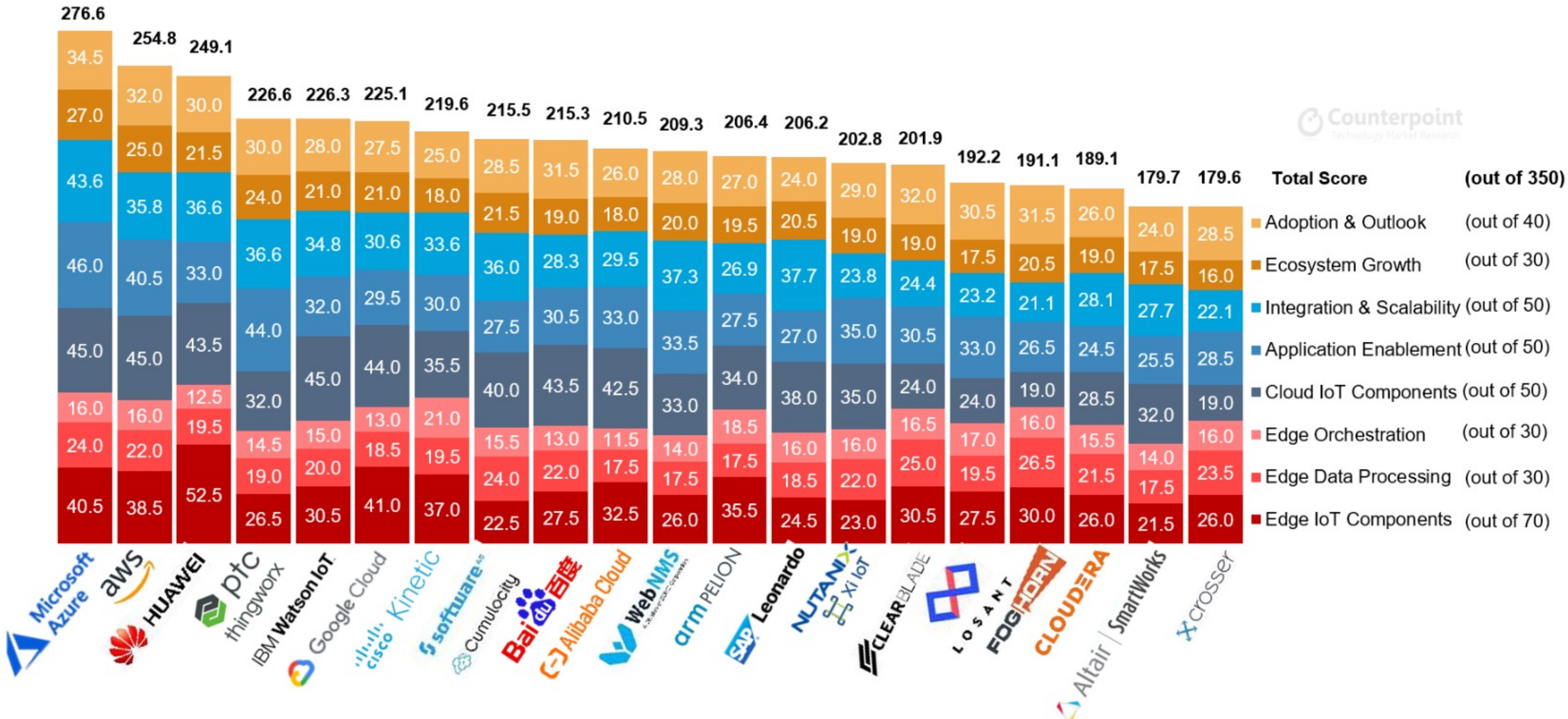
Sensing and Identification

Information Processing

- Edge Computing
  - Pre-processing and pre analytics of IoT data
  - Located at the IoT site (on-prem)
  - Large IoT data needs to be processed before sending to cloud
  - Connectivity constraints
  - Privacy and security constraints
  - Federated learning
- Cloud Analytics and Data Centers
  - ML/DL
  - Data storage
  - Device management

IoT Cloud Platforms

- Microsoft Azure IoT
- Amazon Web Services IoT
- Google Cloud IoT
- ThingWorx (PTC)
- Huawei IoT
- IBM Watson IoT
- Alibaba IoT
- Ayla IoT Platform
- Bosch IoT
- Cisco IoT Cloud Connect
- Artik (Samsung) IoT
- HP IoT
- Many more…



Source: https://virtualizationreview.com/articles/2020/05/29/cloud-iot-report.aspx

IoT Cloud Services

- Device software
  - RTOS
- Device management
  - Connection, HTTP/MQTT, security, device health
- Analytics
  - Event detection, edge analytics, stream analytics, ML/DL, data collection/storage

Types of IoT Analytics

Prescriptive analytics

- Descriptive – insight into what has happened
- Predictive – forecast what will happen

Spatial analytics

- Geospatial analytics with IoT data
- Find hidden patterns

Streaming analytics

- Real-time data processing
- Time critical or limited storage

Time series analytics

- Infer trends
- E.g., health, weather

Big IoT Data

- Big Data vs IoT Data
  - Large-scale streaming data – continuous streaming of data
  - Heterogeneous data – data from various IoT devices
  - Time and space correlation – IoT data is inherently tied to time and space
  - High noise data – Sensor errors, device errors, communication errors
- Need fast and streaming data analytics
  - Can you deliver and store *all* IoT data for postprocessing?
- Characterized by 6Vs

6Vs of IoT Data

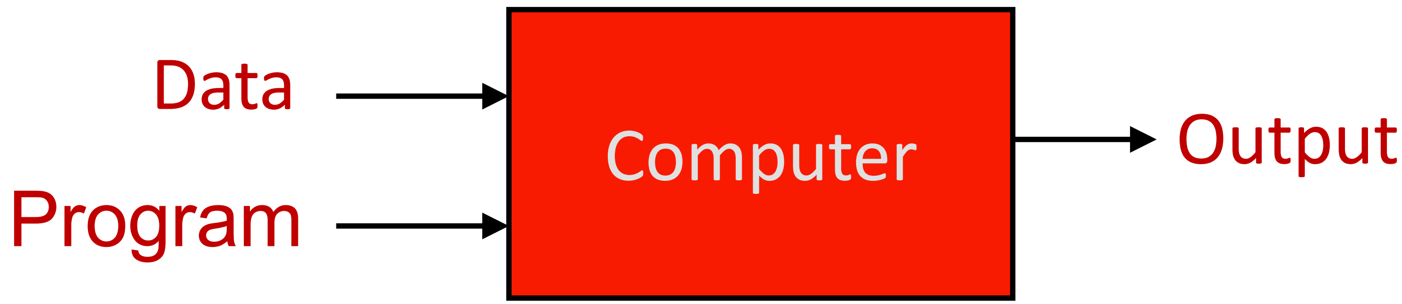
- Volume: Very large data
- Velocity: Continuous data production – streaming analytics
- Variety: Text, audio, video, sensory data, etc
- Veracity: Quality, consistency, and trustworthiness of the data – IoT and crowd-sensing data.
- Variability: Different rates of data flow – event-based sensing in IoT
- Value: Is data useful? – Age of information in IoT (medical vital sign vs temperature for weather)

From Data to Inference

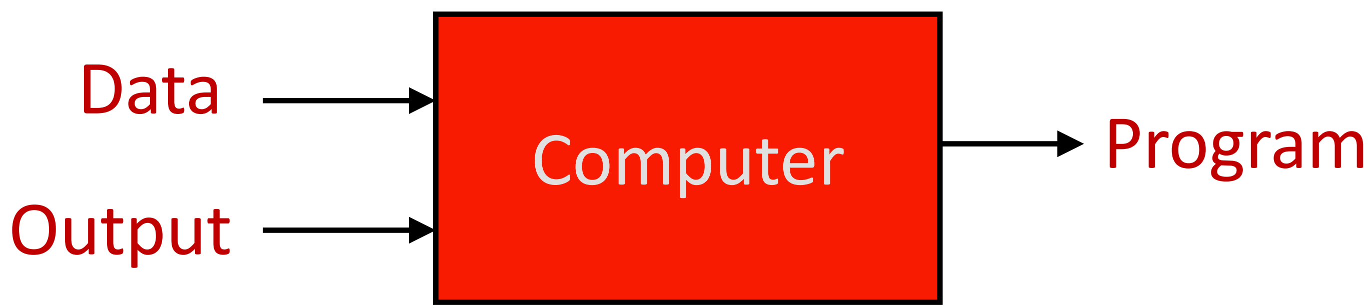
- Machine Learning = Data + Features + Algorithms
- Data
  - Manual – less error prone, not scalable
  - Automatic – error prone, IoT
- Features/Parameters
  - ML Network models look for these variables
  - Data and feature gives patterns
  - Feature engineering – create new features from existing ones – linchpin of modern ML
- Algorithms
  - Precision, performance, size
- Garbage in – garbage out

MACHINE LEARNING BASICS

- Traditional Programming

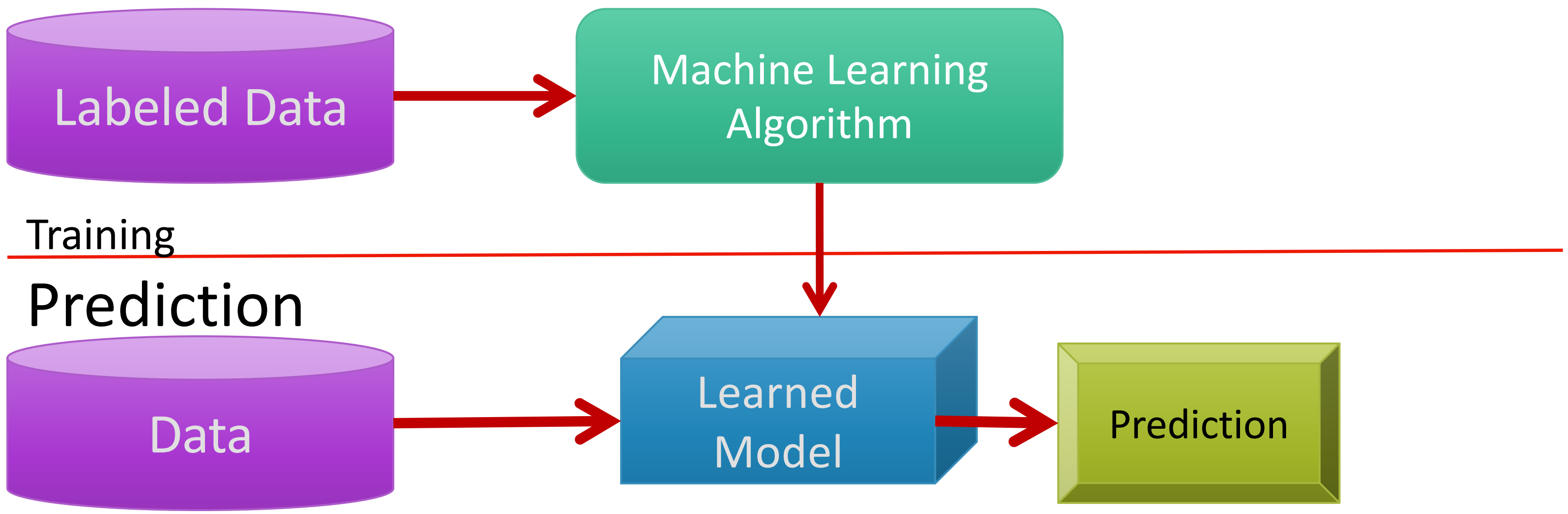


- Machine Learning

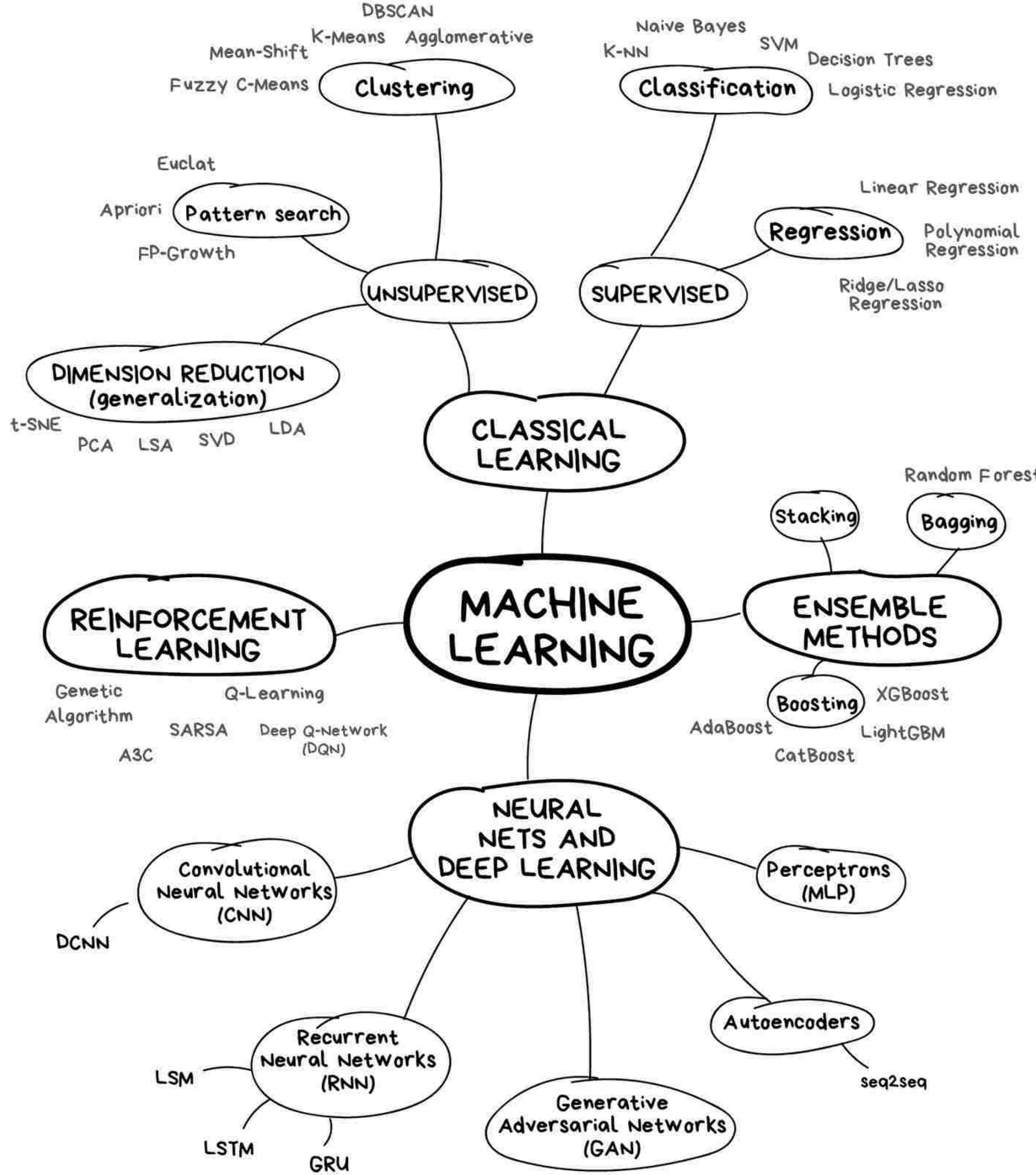


MACHINE LEARNING BASICS

- Machine learning gives computers/machines the ability to learn without being explicitly programmed



- It consists of methods that can learn from and make predictions on data
- Labeled Data: Supervised Learning;   Unlabeled Data: Unsupervised Learning


DBSCAN
K-Means
Agglomerative
Mean-Shift
Fuzzy C-Means
Clustering
Naive Bayes
SVM
K-NN
Decision Trees
Classification
Logistic Regression
Euclat
Apriori
Pattern search
FP-Growth
Linear Regression
Regression
Polynomial Regression
Ridge/Lasso Regression
UNSUPERVISED
SUPERVISED
DIMENSION REDUCTION (generalization)
t-SNE
PCA
LSA
SVD
LDA
CLASSICAL LEARNING
Random Forest
Stacking
Bagging
REINFORCEMENT LEARNING
MACHINE LEARNING
ENSEMBLE METHODS
Genetic Algorithm
Q-Learning
SARSA
Deep Q-Network (DQN)
A3C
Boosting
XGBoost
AdaBoost
LightGBM
CatBoost
NEURAL NETS AND DEEP LEARNING
Convolutional Neural Networks (CNN)
DCNN
Perceptrons (MLP)
Autoencoders
seq2seq
Recurrent Neural Networks (RNN)
LSM
LSTM
GRU
Generative Adversarial Networks (GAN)

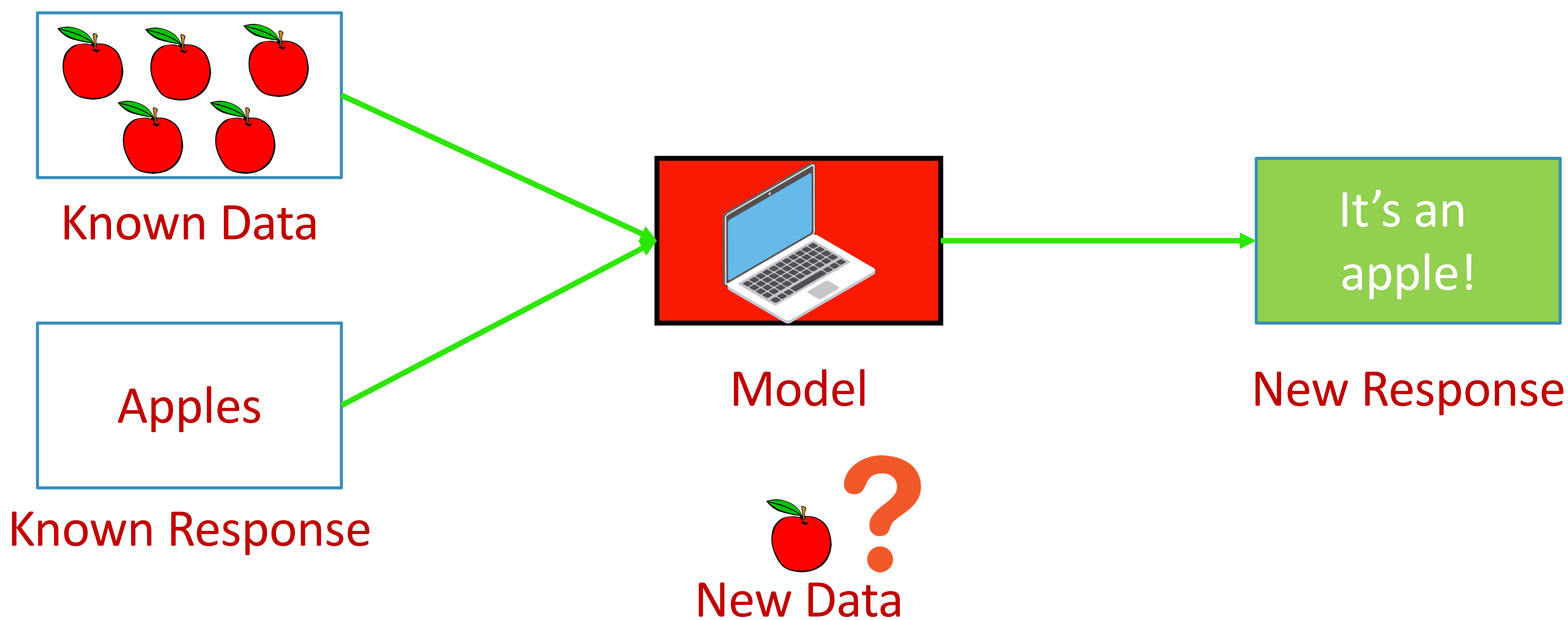
Main Categories of ML

- A ML algorithm takes a training set to learn a model
- Three main categories of learning: Supervised, Unsupervised, Reinforcement
- 1. Supervised (Inductive) Learning
  - Training set: Input vectors and labels - appropriate target vectors
  - Simple data, clear features
  - Training data includes desired outputs
- 2. Unsupervised Learning
  - No labels are required for the training set
  - Training data does not include desired outputs
- 3. Reinforcement Learning
  - No data but have an environment to interact with
  - Learn the appropriate action(s) to be taken for a given situation in order to maximize payoff
  - Rewards from sequence of actions

Supervised Learning

- Objective: Learn how to predict the appropriate output vector for a given input vector
  - Applications: Target labels consist of a finite number of discrete categories are known as classification tasks. (Classes are pre-defined; Mixed input; ML classifies them)
  - Cases: Target labels are composed of one or more continuous variables are known as regression tasks.

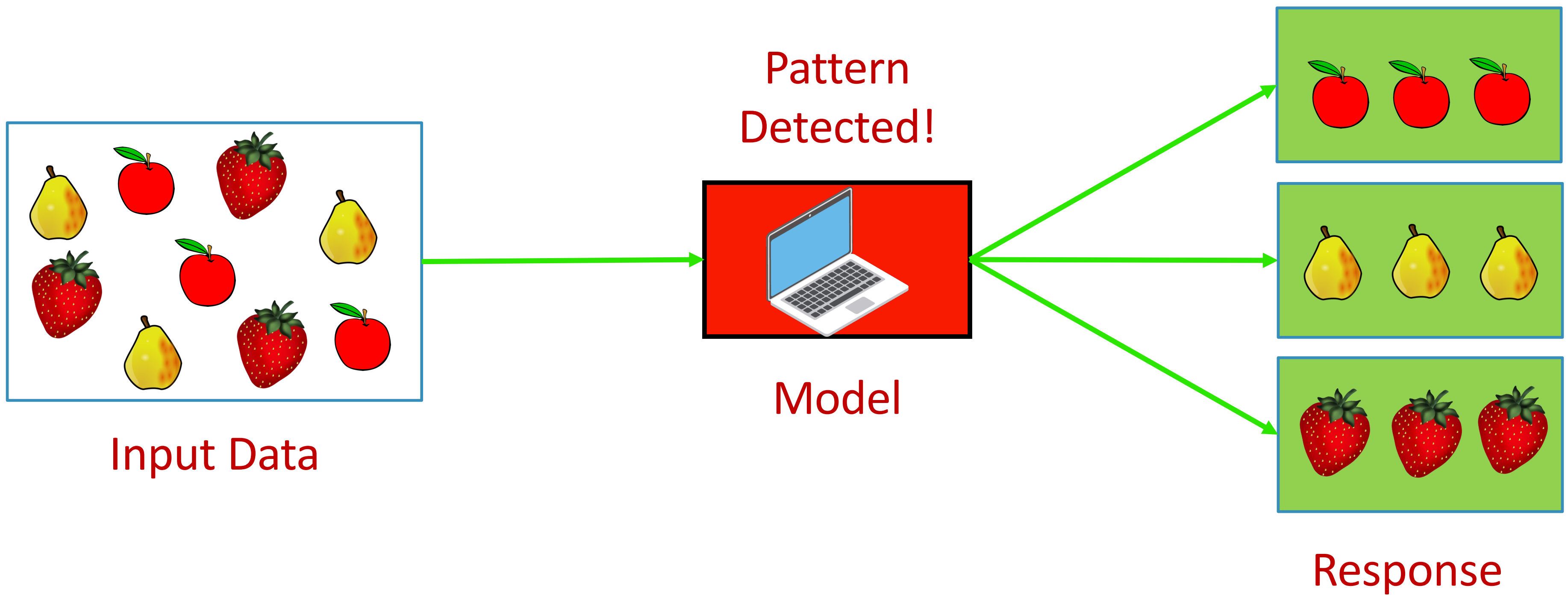
Supervised Learning Example



Unsupervised Learning

- Objective: Difficult to define!
- Identify sensible clusters of similar samples within the input data, known as clustering. (Classes are not defined; ML clusters similar data)
- Discover a useful internal representation of the input data by preprocessing the original input variable in order to transfer it into a new variable space.
- Preprocessing stage: Improve the result of the subsequent machine learning algorithm and is named feature extraction.

Unsupervised Learning: Clustering Example

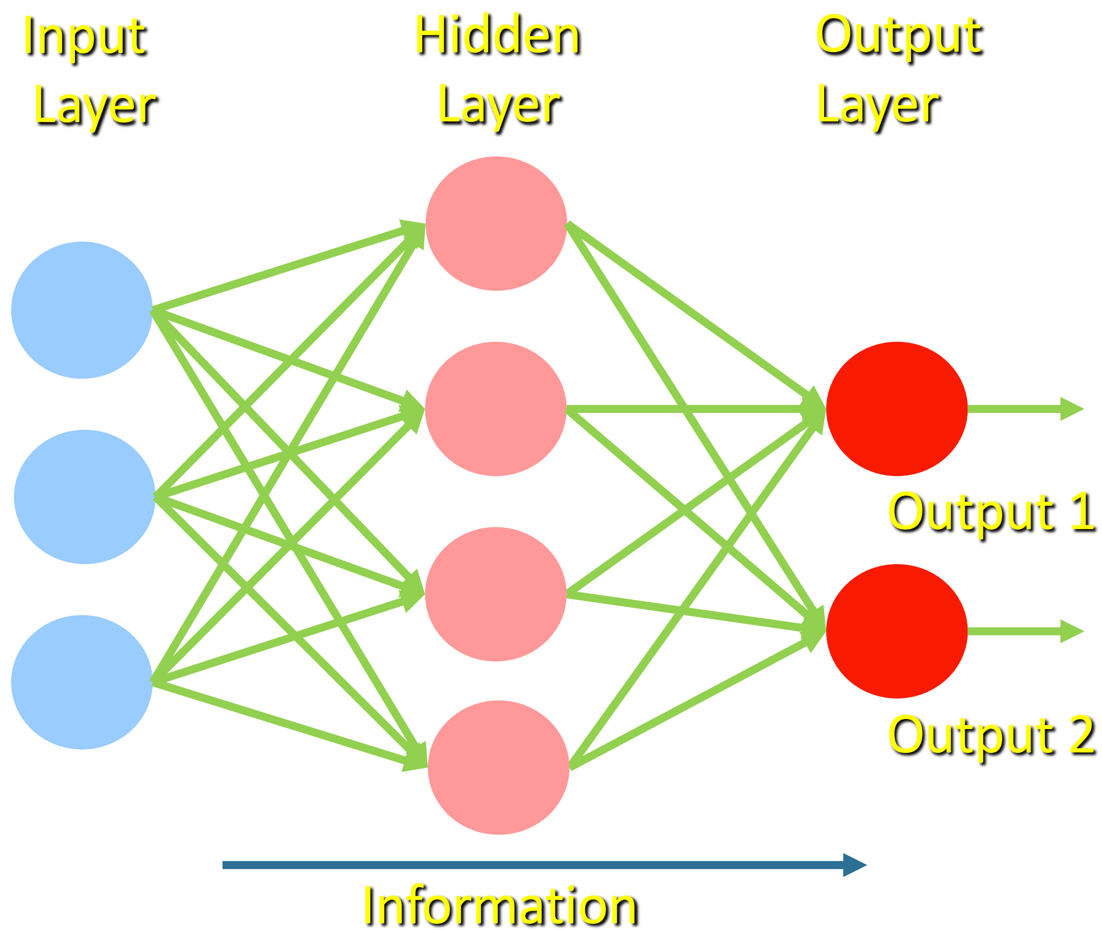


Neural Networks

- Biologically-inspired programming paradigm which enables a computer to learn from observational data
- It is modelled after the human brain and the nervous system.
  - Process information much more like the brain than a serial computer
- 2 most important properties
  - Highly parallel
  - Learning
- It is based on very simple principles but shows very complex behaviors
- Basis for Deep Learning

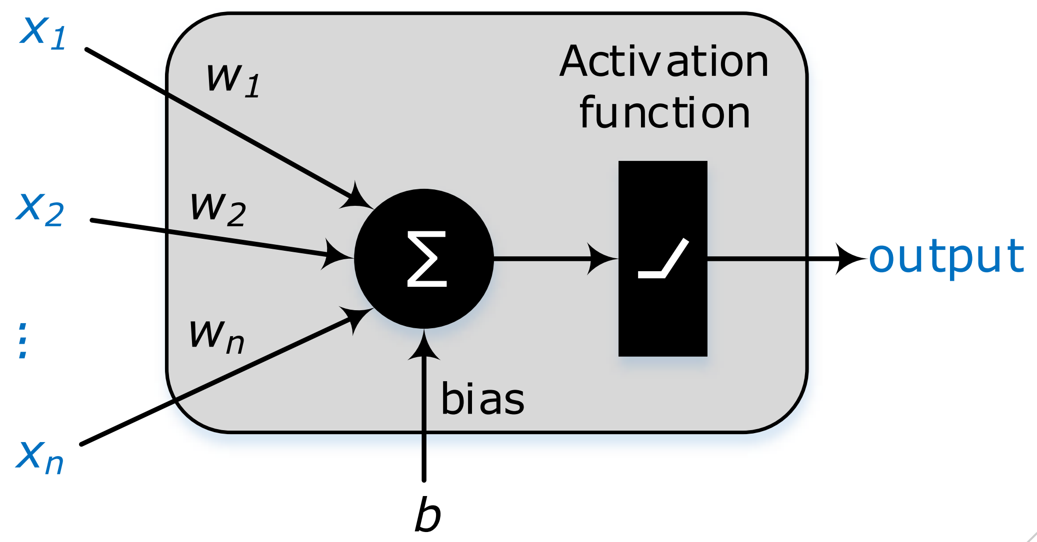
Neural Networks: Feedforward Neural Network

- Input Nodes
  - Provide information from the outside world to the network and are together referred to as the "Input Layer".
- Hidden Nodes
  - No direct connection with the outside world (hence the name "hidden").
  - Perform computations and transfer information from the input nodes to the output nodes
  - A collection of hidden nodes forms a "Hidden Layer"
  - While a feedforward network will only have a single input layer and a single output layer, it can have zero or multiple hidden Layers
- Output Nodes
  - Output Layer – responsible for computations and transferring information from the network to the outside world



Perceptron

- Artificial analog to neurons
- Connects one layer (inputs) to the next (output)
- Activation functions: Step, sigmoid, linear, hyperbolic tangent, rectified linear unit (ReLU)
- Training = Choosing weights and bias – backpropagation based on a loss function

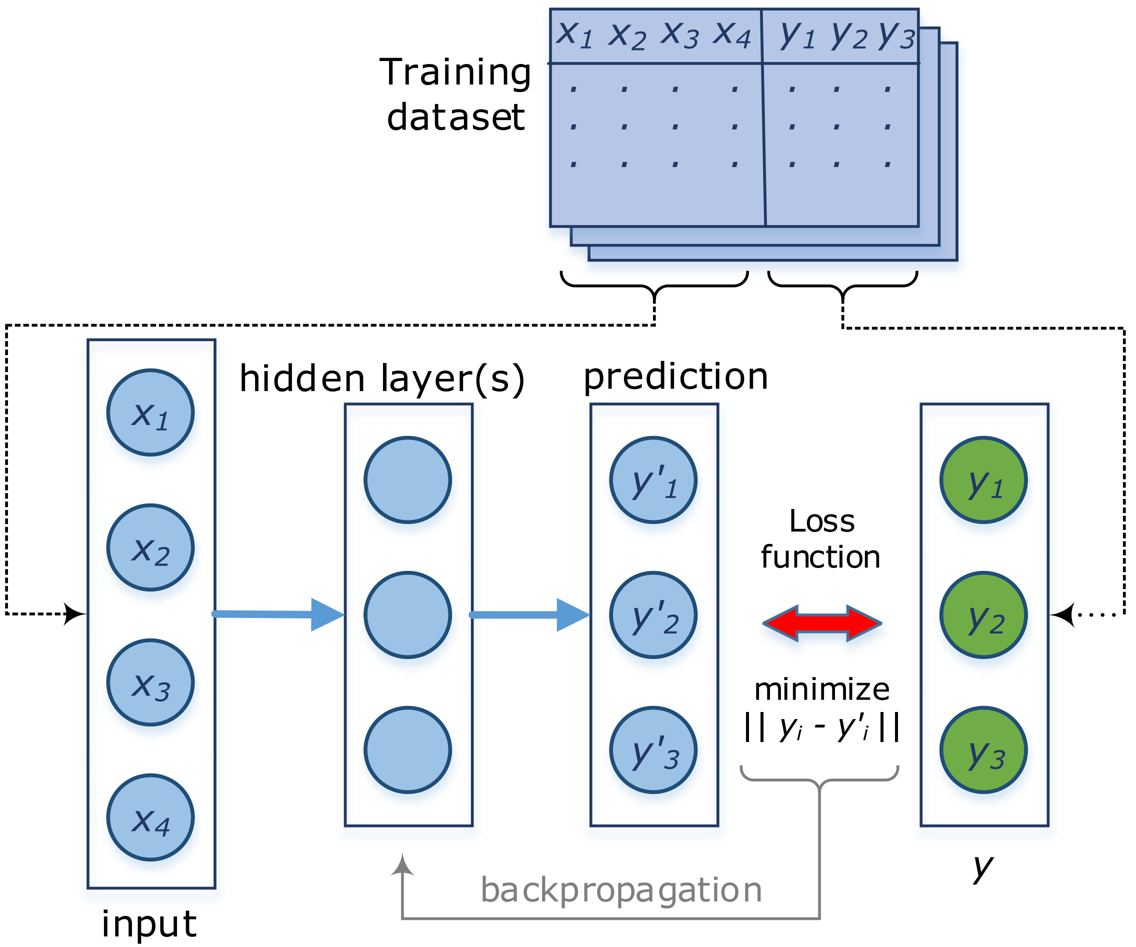


M. Mohammadi, et.al., ``Deep Learning for IoT Big Data and Streaming Analytics: A Survey,'' IEEE Communications Surveys and Tutorials, vol. 20, no. 4, 2018

Deep Learning

- Modern method of building, training, and using neural networks
- A new architecture
- Learn data representations with multiple levels of abstractions using a training set
- Data – complex and large
- Features – unclear
- Algorithms – architecture
- Deep = >2
- Why it works – 🤷‍♂️

Deep Learning



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Deep Learning Architectures

- Generative ~ unsupervised
- Discriminative ~ supervised
- Hybrid

Deep Learning Architectures

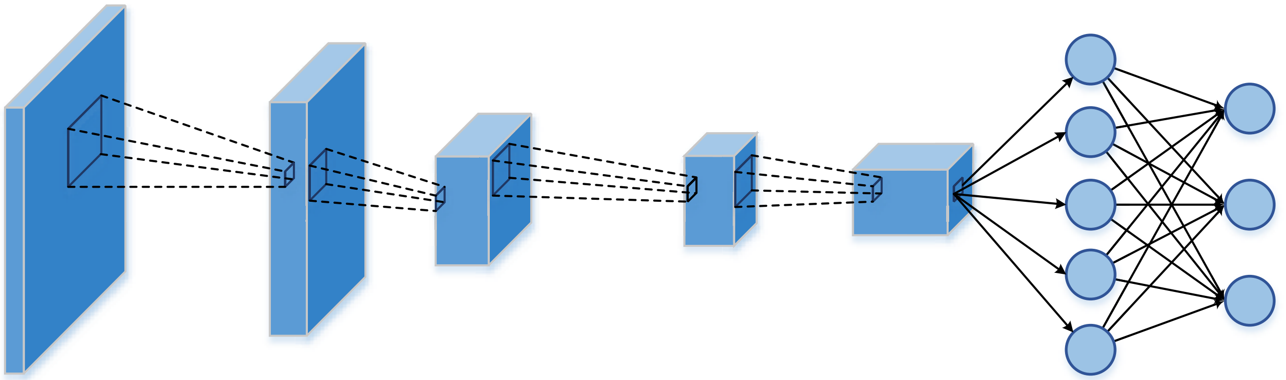
- Convolutional Neural Networks (CNNs) – 2D images
- Recurrent Neural Networks (RNNs) – Time-series
- Long Short Term Memory (LSTM) – Time-series
- Autoencoders (AEs) – Feature extraction
- Variational Autoencoders (VAEs) – Scarce labels
- Generative Adversarial Networks (GANs) – two networks
- Restricted Boltzmann Machine (RBMs) – Classification
- Deep Belief Network (DBNs) – Hierarchical features
- Ladder Networks – Noisy data

Which DNN architectures have you used so far?

Total Results: 18

Deep Learning Architectures

- **Convolutional Neural Networks (CNNs)**



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Joint DL

- Deep Reinforcement Learning
  - Combines reinforcement learning with DNNs
  - Localization
- Transfer Learning
  - Transfer trained model from one domain to another
  - IoT – relieves data needs
- Online learning with DL
  - Streaming analytics vs batch learning
  - Evolve trained model with new data

Deep Learning in IoT

- Image recognition
  - Waymo, Tesla
- Speech/Voice recognition
  - Alexa, Siri
- Indoor Localization
  - Inputs: Vision, visible light communication, infrared, ultrasound, WiFi, RFID, ultrawide band, Bluetooth
- Physiological and Psychological State Detection
  - Wearables
  - Smart homes, smart cars, video games, education, rehabilitation and health support, sports, and industrial manufacturing
- Security and Privacy
  - For DL, by DL
- Applications
  - Smart home, smart city, energy, ITS, healthcare, agriculture, education, industry, government, sports, retail

Service	AE	CNN	DBN	LSTM	RBM	RNN
Image Recognition	✅	✅	✅	✅		✅
Voice/Speech Recognition		✅	✅		✅	✅
Physiological & Psychological Detection	✅	✅	✅	✅		✅
Localization	✅	✅		✅	✅	
Privacy & Security		✅	✅			

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SUMMARY OF DEEP LEARNING MODELS & IoT APPLICATIONS

Model	Category	Learning Model	Typical input data	Characteristics	Sample IoT Applications
AE	Generative	Unsupervised	Various	• Suitable for feature extraction, dimensionality reduction • Same number of input and output units • The output reconstructs input data • Works with unlabeled data	• Machinery fault diagnosis • Emotion recognition
RNN	Discriminative	Supervised	Serial, time-series	• Processes sequences of data through internal memory • Useful in IoT applications with time-dependent data	• Identify movement patterns • Behavior detection
RBM	Generative	Unsupervised, Supervised	Various	• Suitable for feature extraction, dimensionality reduction, and classification • Expensive training procedure	• Indoor localization • Energy consumption prediction

Autoencoder (AE)
Recurrent Neural Network (RNN)
Restricted Boltzmann Machine (RBM)

SUMMARY OF DEEP LEARNING MODELS & IoT APPLICATIONS

Model	Category	Learning Model	Typical input data	Characteristics	Sample IoT Applications
DBN	Generative	Unsupervised, Supervised	Various	• Suitable for hierarchical features discovery • Greedy training of the network layer by layer	• Fault detection classification • Security threat identification
LSTM	Discriminative	Supervised	Serial, time-series, long time dependent data	• Good performance with data of long time lag • Access to memory cell is protected by gates	• Human activity recognition • Mobility prediction
CNN	Discriminative	Supervised	2-D (image, sound, etc.)	• Convolution layers take biggest part of computations • Less connection compared to DNNs. • Needs a large training dataset for visual tasks.	• Plant disease detection • Traffic sign detection

Deep Belief Network (DBN)
Long Short Term Memory (LSTM)
Convolutional Neural Network (CNN)

SUMMARY OF DEEP LEARNING MODELS & IoT APPLICATIONS

Model	Category	Learning Model	Typical input data	Characteristics	Sample IoT Applications
VAE	Generative	Semi-supervised	Various	• A class of Auto-encoders • Suitable for scarcity of labeled data	• Intrusion detection • Failure detection
GAN	Hybrid	Semi-supervised	Various	• Suitable for noisy data • Composed of two networks: a generator and a discriminator	• Localization wayfinding • Image to text
Ladder Net	Hybrid	Semi-supervised	Various	• Suitable for noisy data • Composed of three networks: two encoders and one decoder	• Face recognition • Authentication

Variational Autoencoder (VAE)
Generative Adversarial Network (GAN)
Ladder Network

Research trends and open issues

- Challenge 1. IoT Data Characteristics
- High quality information is required since the quality directly effects the accuracy of knowledge extraction.
- IoT data characteristics:
  - High volume
  - Fast velocity
  - Variety of data
  - Consists mostly of raw data
  - Distributed nature
- Solution: Semantic technologies
  - Enhance the abstraction of IoT data through annotation algorithms
  - Require further effort to overcome its velocity and volume

Research trends and open issues

- Challenge 2. IoT Applications

- Each application has its own unique features.
- IoT Applications require:
  - Privacy of collected personal or business data is highly critical
  - Network security and data encryption

- If security is ignored in the design and implementation, an infected network of IoT devices can lead to a crisis.

Research trends and open issues

- Challenge 3. IoT Data Analytics Algorithms

- According to the characteristic of smart data, analytics algorithms should be able to handle big data.
- Algorithms must be able to analyze
  - Data coming from a variety of sources
  - In real time

- Solution: Deep learning algorithms can reach high accuracy if they have enough data and time
  - Cons:
    - They can be easily influenced by noisy smart data.
    - Neural network based algorithms lack interpretation (Data scientist cannot understand the reasons for the model results)
    - Semi-supervised algorithms, which model a small amount of labeled data with a large amount of unlabeled data can assist

RESEARCH CHALLENGES: Scalability

- Massive increase in number of devices connected
- Need to provide reliable coverage
- Increased number of devices per base station
- Increased number of handoffs
- Can be solved by adopting W-SDN/NFV & Fog/Edge Computing

RESEARCH CHALLENGES: Processing and Storage

- Handle data generated by 50 billion devices
  - Convert data into actionable knowledge
  - Not handled efficiently by cloud/big data
- Move cloud services to edge of the network
  - Fog computing
- Reduce data to be stored
  - Intelligent compression by exploiting redundancy

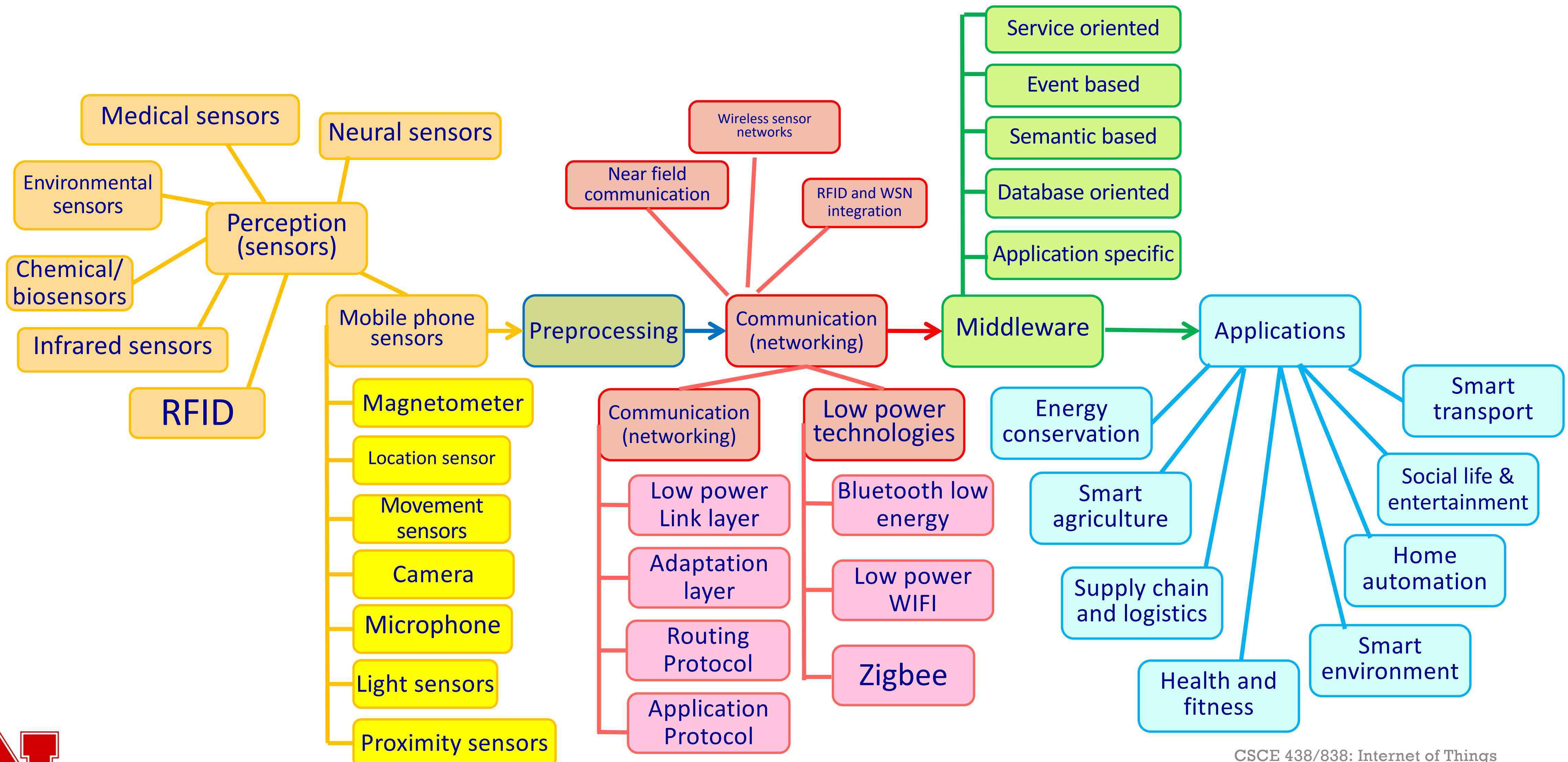
FURTHER RESEARCH CHALLENGE: Energy Harvesting in IoT

- How do you power stand-alone IoT devices and do so at a low cost? Batteries?
- Cost of maintaining, replacing and discarding billions of batteries would be astronomical (not to mention the enormity of the human labor issue)
- How can we scavenge energy from IoT device's environment?
- Energy harvesting techniques use power generating elements to convert light (solar), heat (thermoelectric), vibration (piezoelectric), or RF energy (such as that emitted from cellphone towers)
- Design of Batteryless IoTs

CHALLENGE: Standardization

- IoT devices by different vendors use different standards and interfaces
  - Incompatible across vendors, causes vendor lock-in
- Standardization required to maintain interoperability
- Standard should support wide variety of sensors
- Interfaces to cloud servers also needs to be standardized

Research Directions in IoT Overview



Which concept was the most intriguing? (one word)

distributed-computing
distributed computing
cloud fog
cloud-functions
efficiency data

Total Results: 0

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