



Machine Learning and Deep Learning for IIOT

Chanchal Chatterjee, Dell EMC
Reston, March 22 2016





Goals of the Meeting

- Provide insights on methods and systems for machine learning and deep learning.
- Provide machine/deep learning use cases for IIOT.
- Provide architectures and frameworks for machine/deep learning for IIOT.





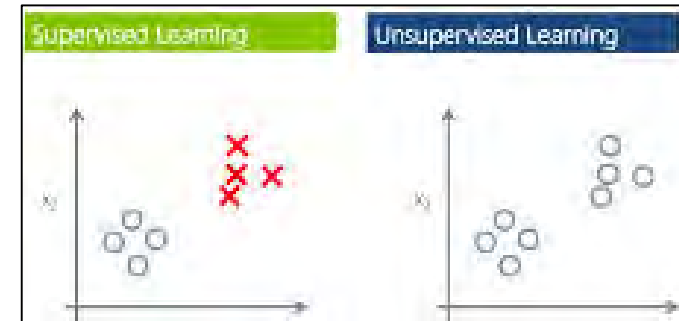
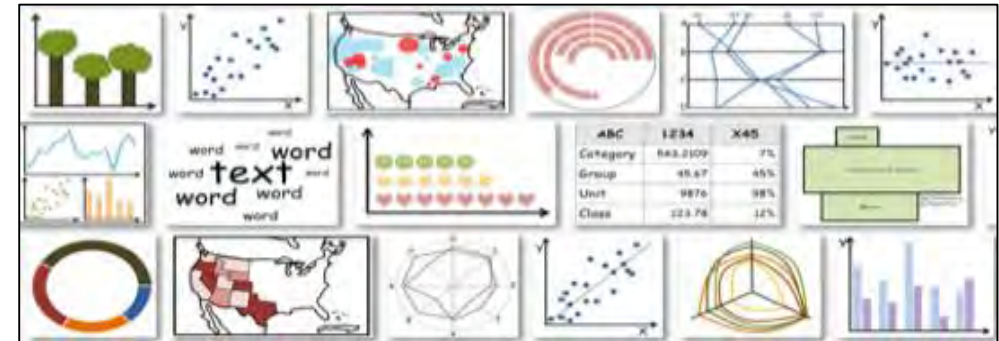
Machine Learning & Deep Learning – Confusing, Eh!





Machine Learning and Deep Learning Dependencies

- Types of Data
- Types of Learning
- Types of Algorithms



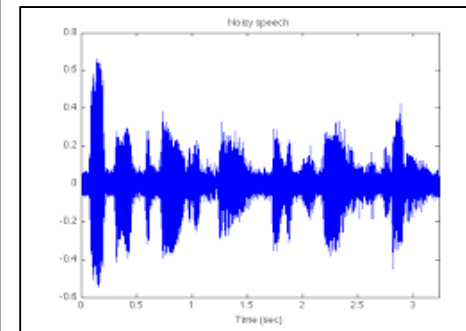
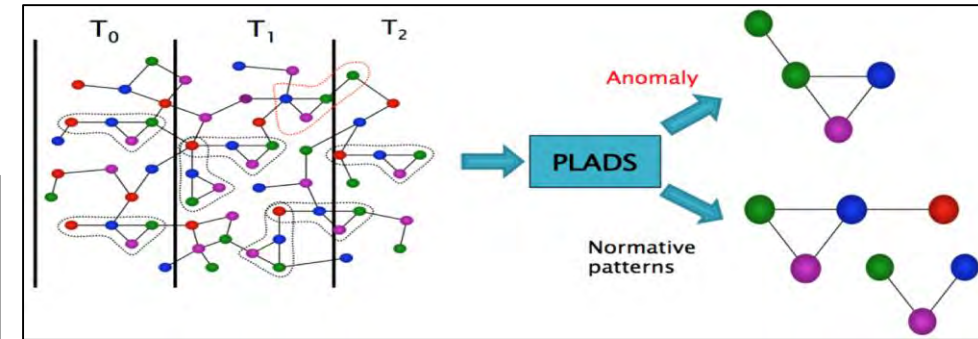
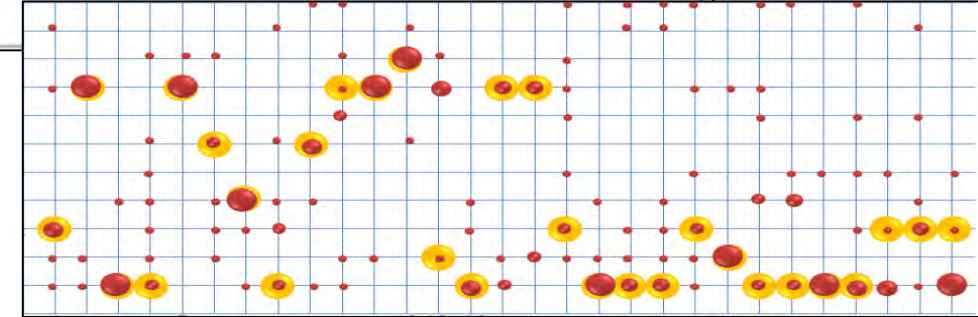
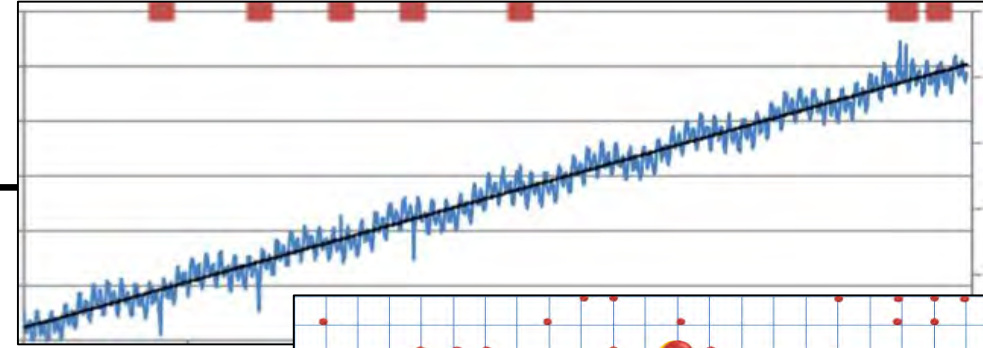
Types of Data

- **Structured Data**

- Time Series
- Events
- Graph

- **Unstructured Data**

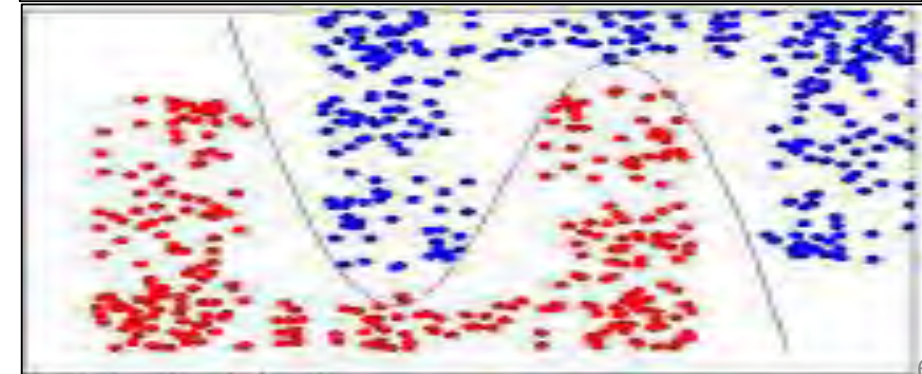
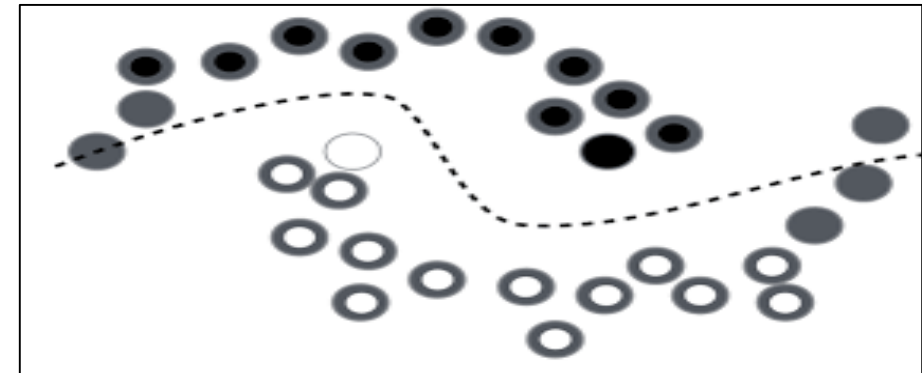
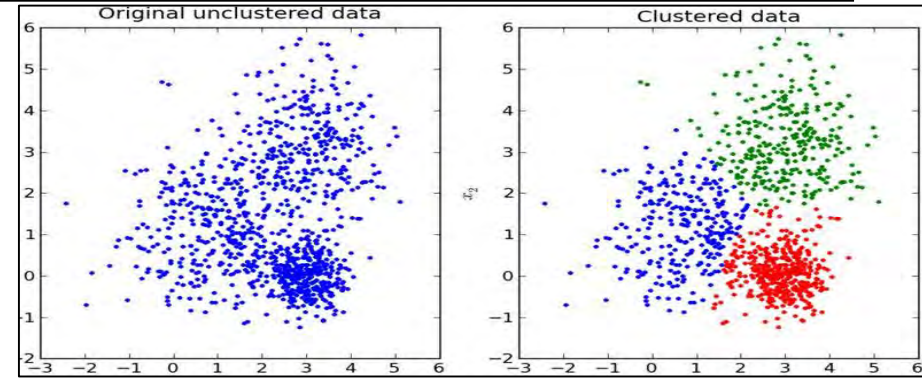
- Video/Images
- Voice
- Text





Types of Learning

- **Un-Supervised**
 - Do not require training data
 - Assume normal instances far more frequent than anomalies
- **Semi-Supervised**
 - Training data has labeled instances for only the normal class
 - Assume normal instances far more frequent than anomalies
- **Supervised**





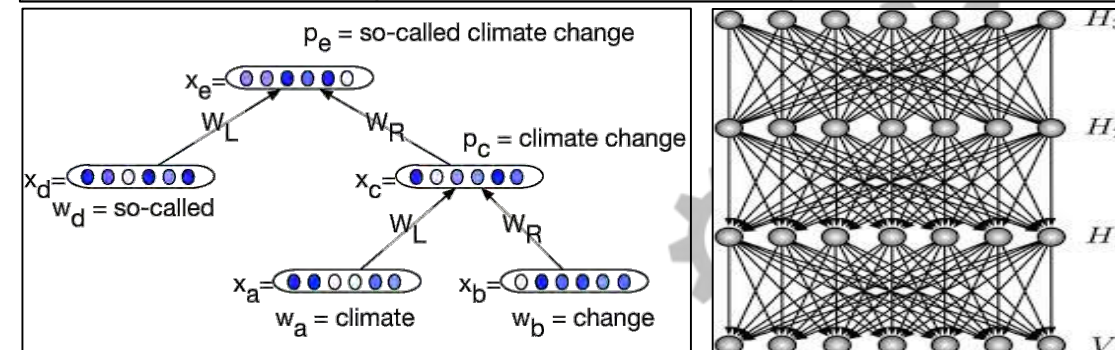
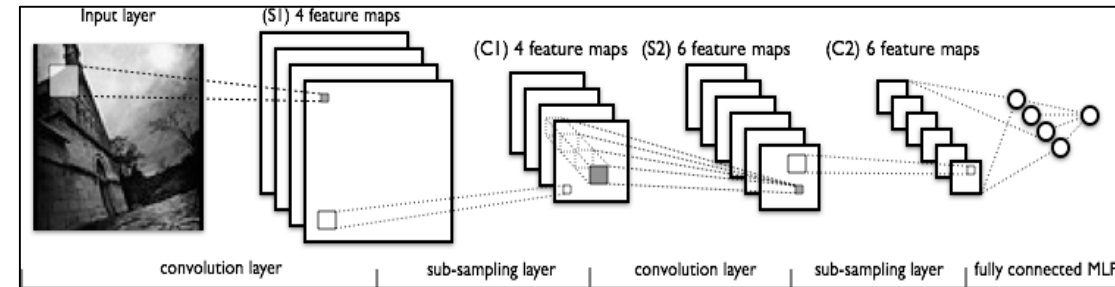
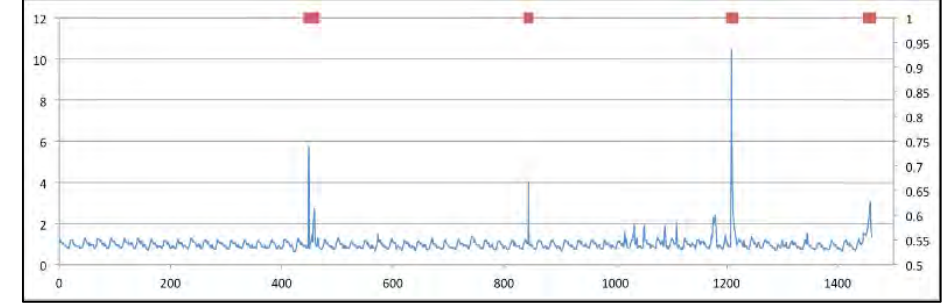
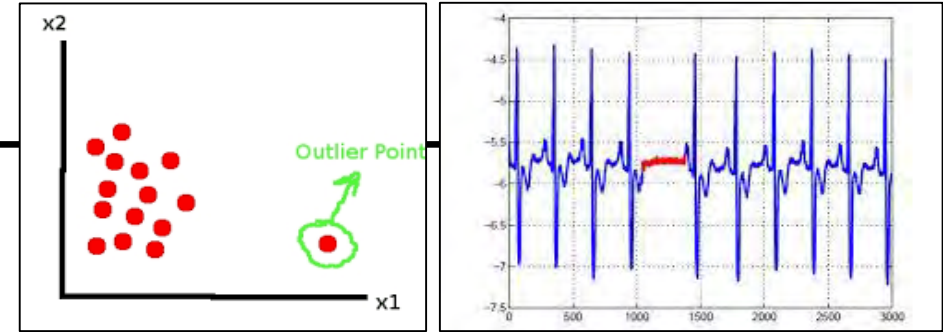
Types of Algorithms

ML: Machine Learning

- Anomaly Detection
- Trends, Predictions & Forecasting
- Association & Grouping

DL: Deep Learning

- Ladder Network
- Convolutional Neural Network
- Recurrent Neural Network
- Deep Belief Networks





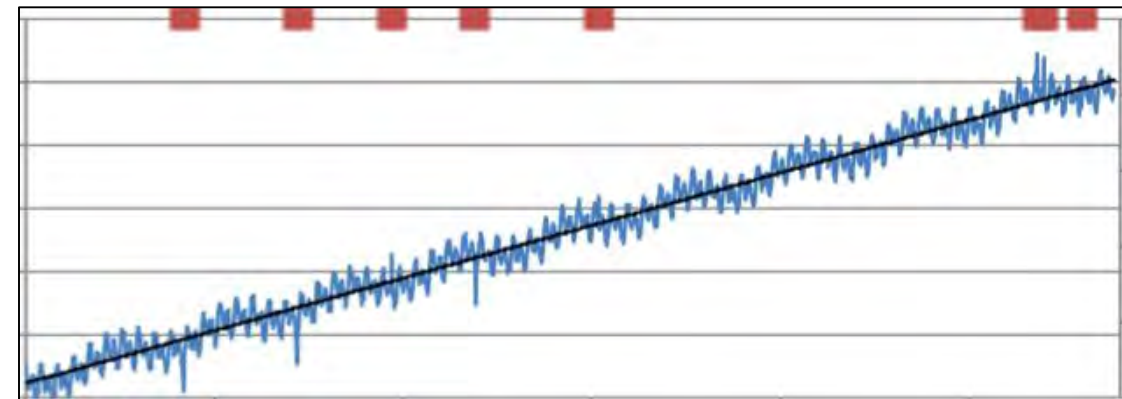
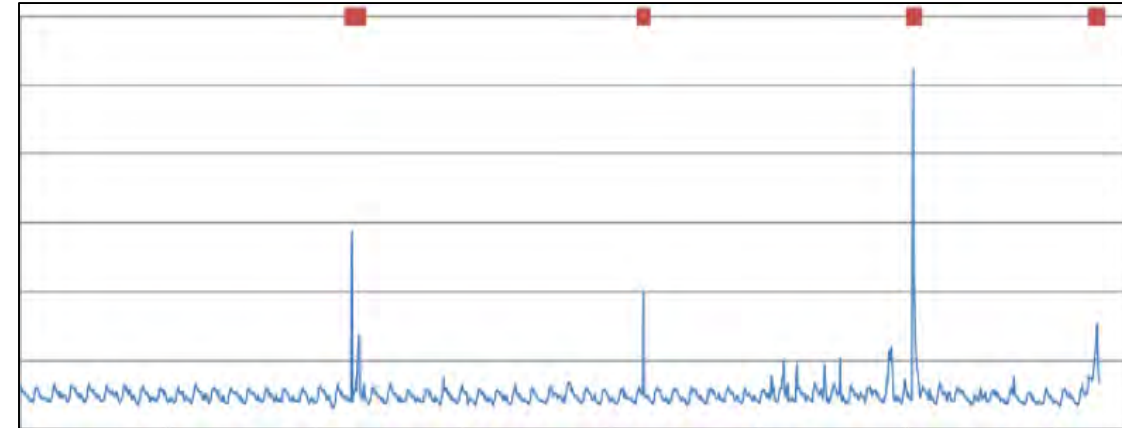
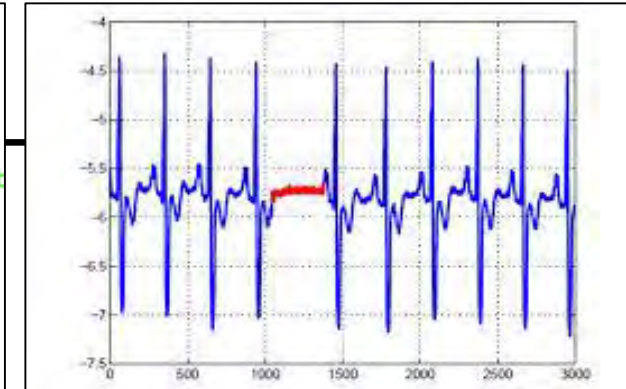
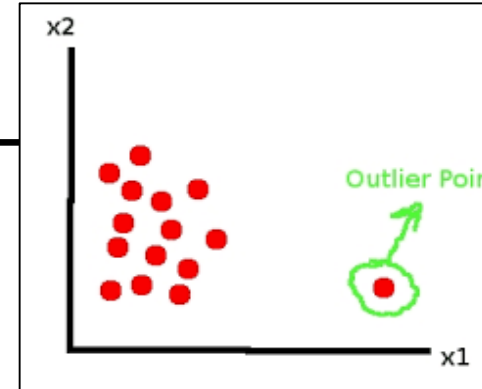
Some Details





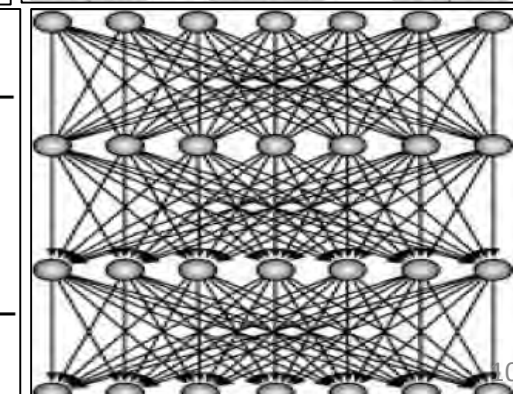
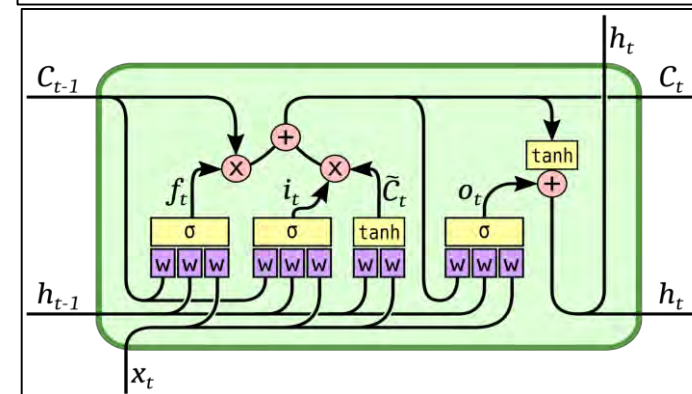
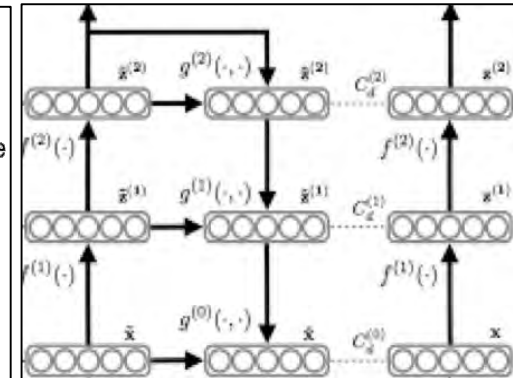
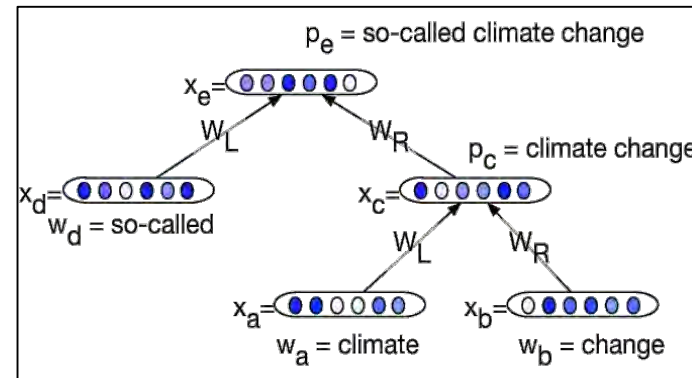
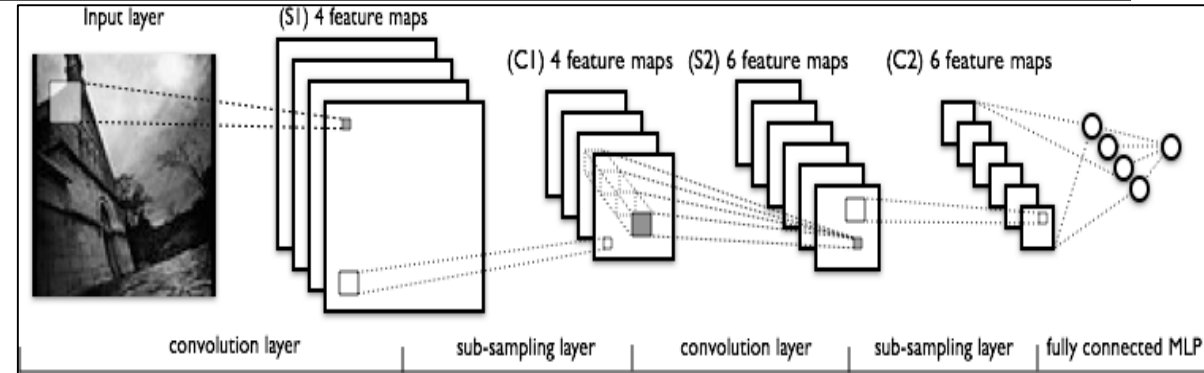
Machine Learning

- **Anomaly Detection**
 - Point Anomaly
 - Contextual Anomaly
 - Collective Anomaly
 - Graph Anomaly
- **Trends, Predictions & Forecasting**
- **Associations & Grouping**

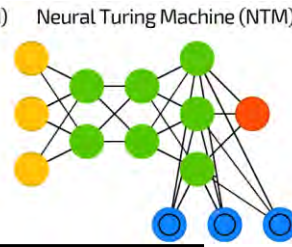
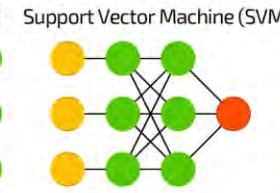
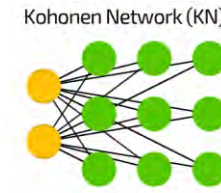
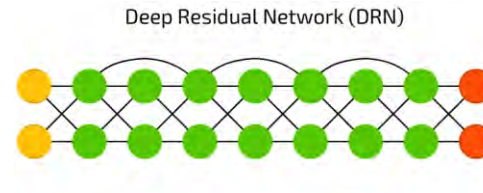


Deep Learning

- **Ladder Network**
- **Convolutional NN (CNN)**
- **Recurrent NN (RNN)**
 - Recurrent Recursive NN (R^2NN)
 - Long Short Term Memory (LSTM)
- **Deep Belief Networks (DBM)**
 - Restricted Boltzmann Machine (RBM)



Deep Learning Networks



Source: <http://www.asimovinstitute.org/neural-network-zoo/>

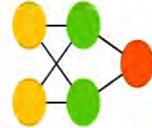
- Backfed Input Cell
- Input Cell
- Noisy Input Cell
- Hidden Cell
- Probabilistic Hidden Cell
- Spiking Hidden Cell
- Output Cell
- Match Input Output Cell
- Recurrent Cell
- Memory Cell
- Different Memory Cell
- Kernel
- Convolution or Pool

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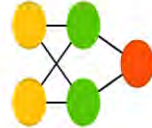
Perceptron (P)



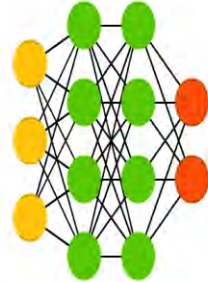
Feed Forward (FF)



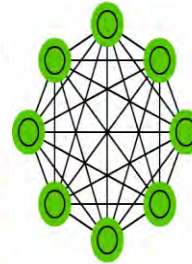
Radial Basis Network (RBF)



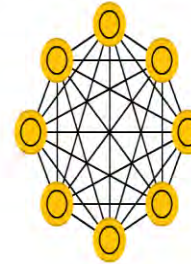
Deep Feed Forward (DFF)



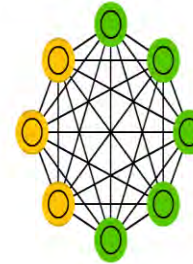
Markov Chain (MC)



Hopfield Network (HN)



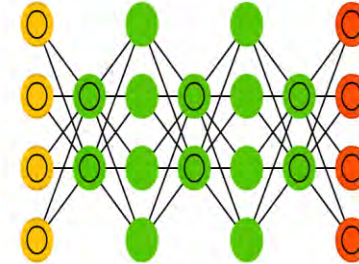
Boltzmann Machine (BM)



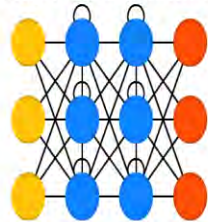
Restricted BM (RBM)



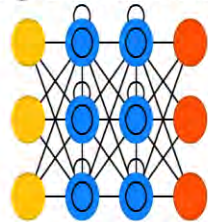
Deep Belief Network (DBN)



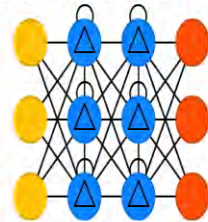
Recurrent Neural Network (RNN)



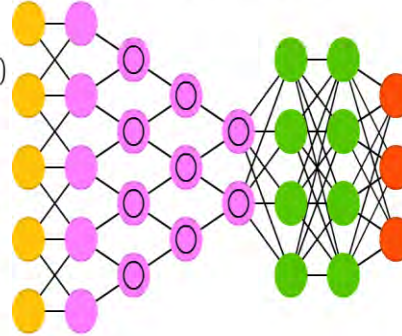
Long / Short Term Memory (LSTM)



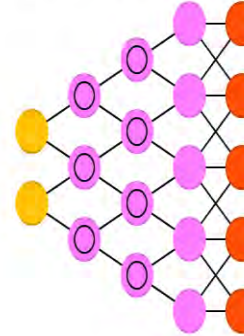
Gated Recurrent Unit (GRU)



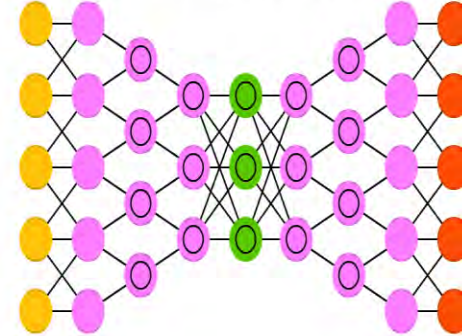
Deep Convolutional Network (DCN)



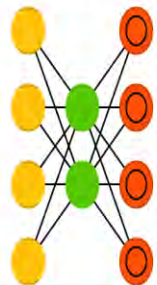
Deconvolutional Network (DN)



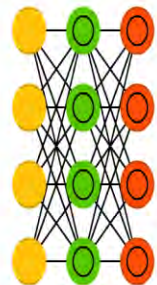
Deep Convolutional Inverse Graphics Network (DCIGN)



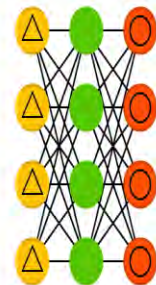
Auto Encoder (AE)



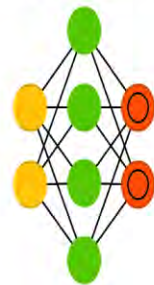
Variational AE (VAE)



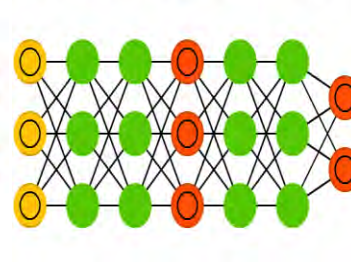
Denosing AE (DAE)



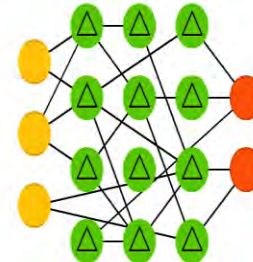
Sparse AE (SAE)



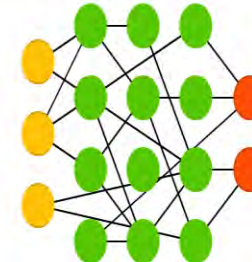
Generative Adversarial Network (GAN)



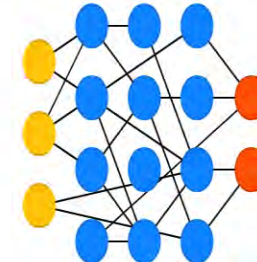
Liquid State Machine (LSM)



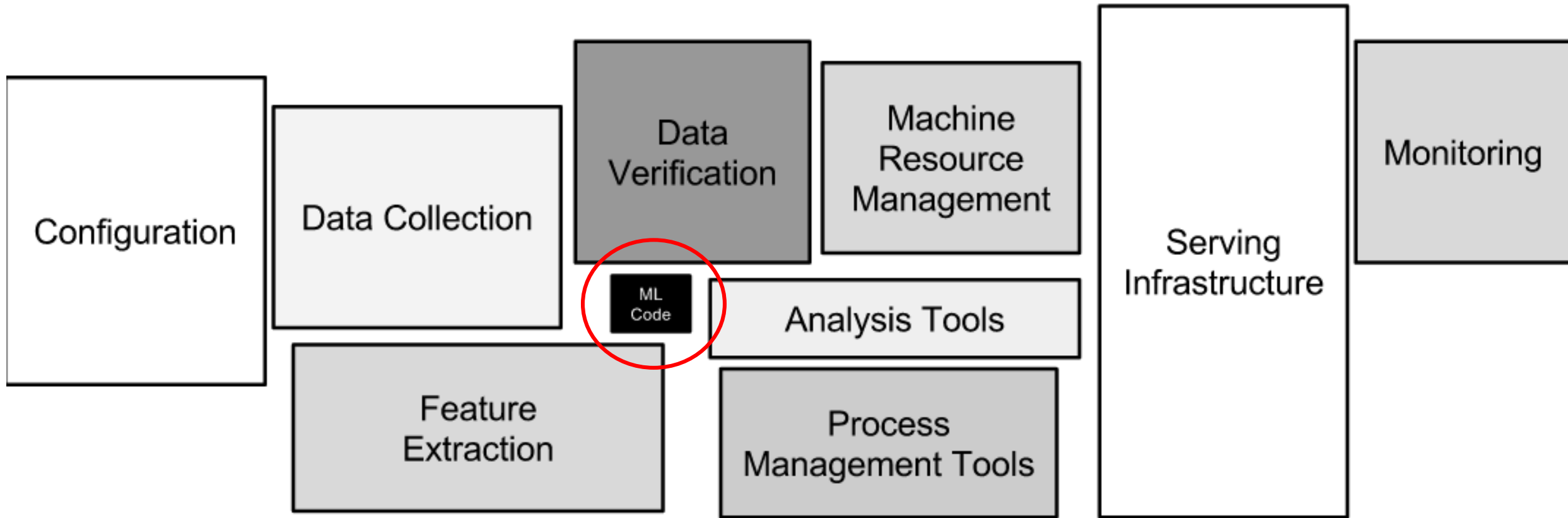
Extreme Learning Machine (ELM)



Echo State Network (ESN)



Small Fraction of Real-World ML Systems Have ML Code



From Hidden Technical Debt in Machine Learning Systems
Scully et al, NIPS 2016





Manufacturing IoT Use Cases

Use Cases	Drivers	Challenges
<ul style="list-style-type: none">• Predictive maintenance• Process optimization• Warehouse/supply chain optimization• Remote asset maintenance and control• Product lifecycle monitoring• Integrated plant management• Product-as-a-service	<ul style="list-style-type: none">• Increase yield/asset utilization• New revenue streams• Operational efficiencies• Increased worker satisfaction/safety• Eco-sustainability	<ul style="list-style-type: none">• Low latencies• Data security• Interoperability between diverse sets of equipment (typically with their own proprietary control system and data interchange standard)• Rapid interpretation of large volumes of data• Reliable indoor/outdoor coverage in harsh environments• Connectivity across different access technologies

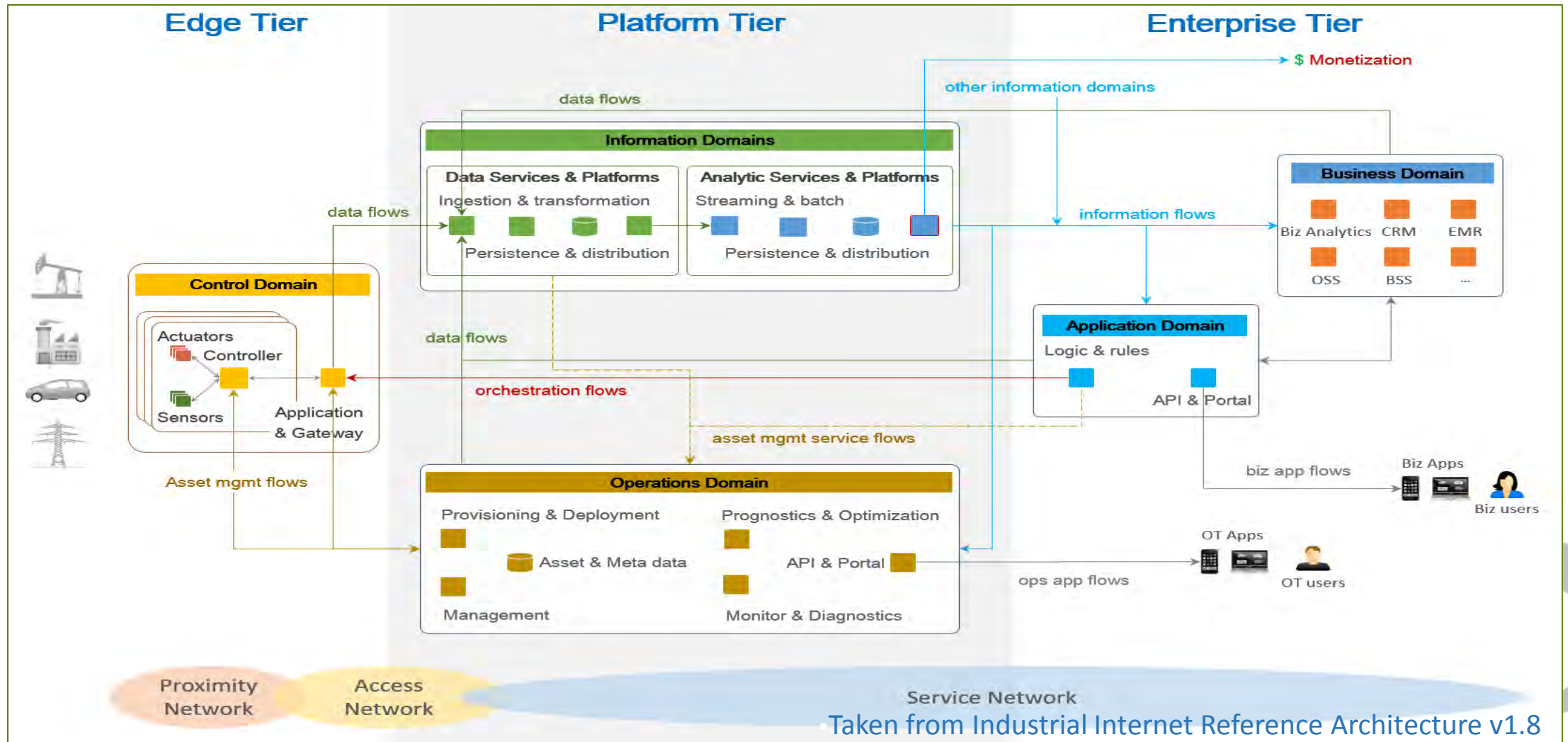
Source: SDx Central IoT Infrastructure Report 2017



IIoT Architectures

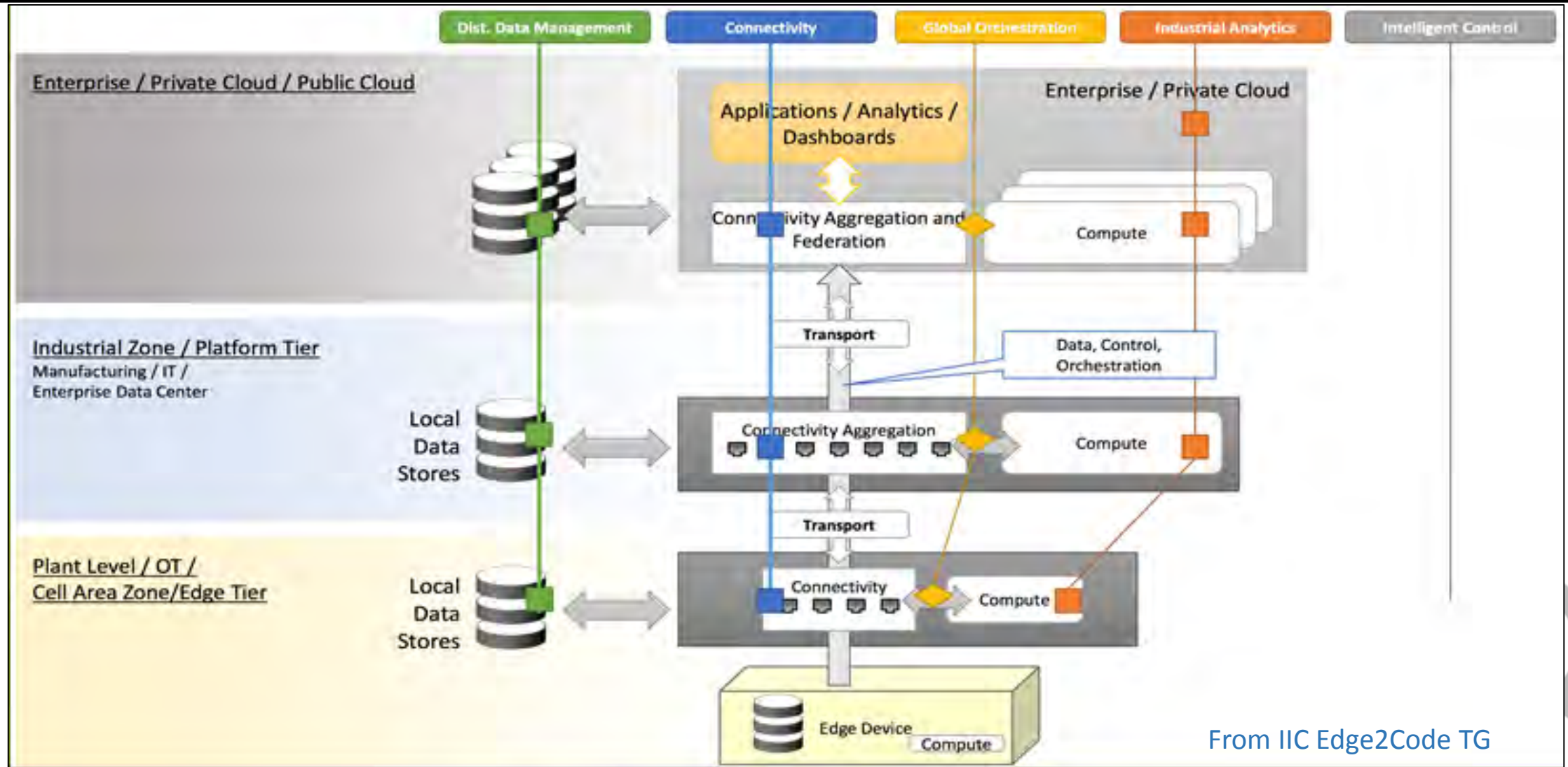


Three Tier Deployment Model





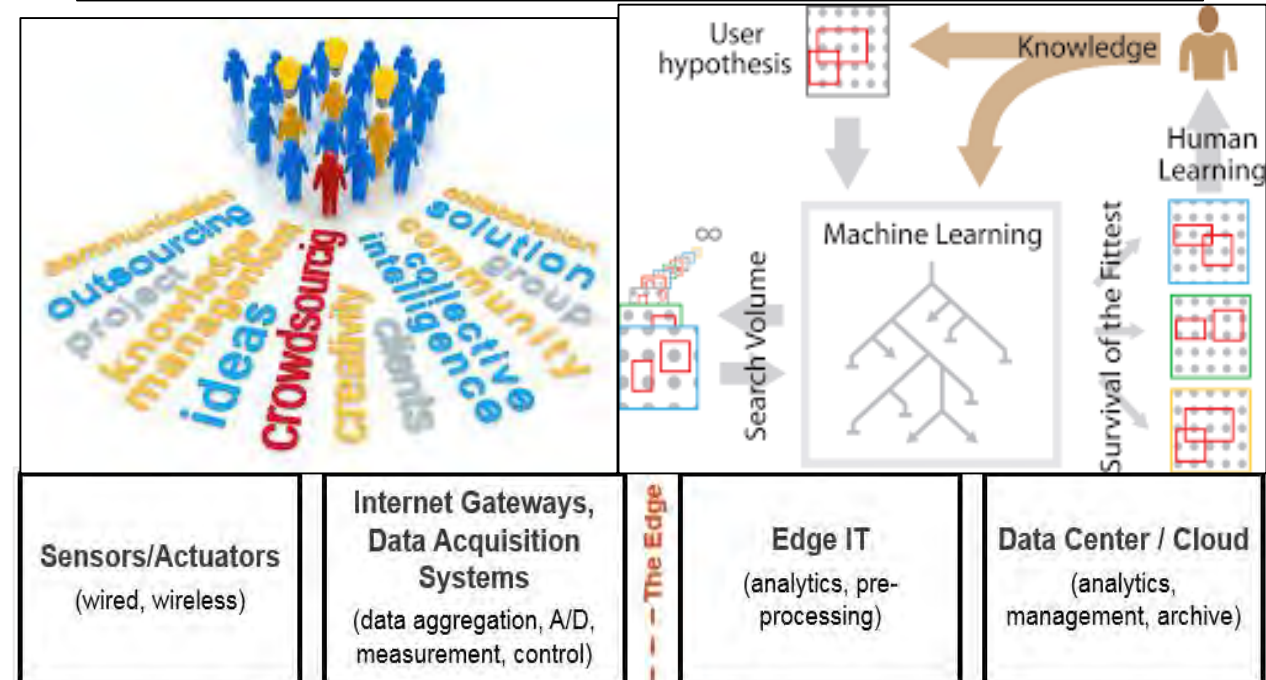
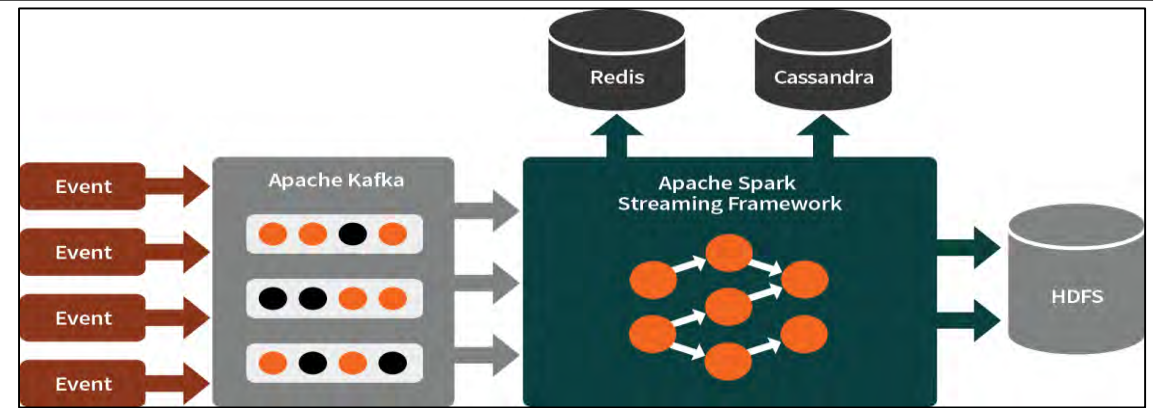
Edge2Core Crosscutting Functions



From IIC Edge2Code TG

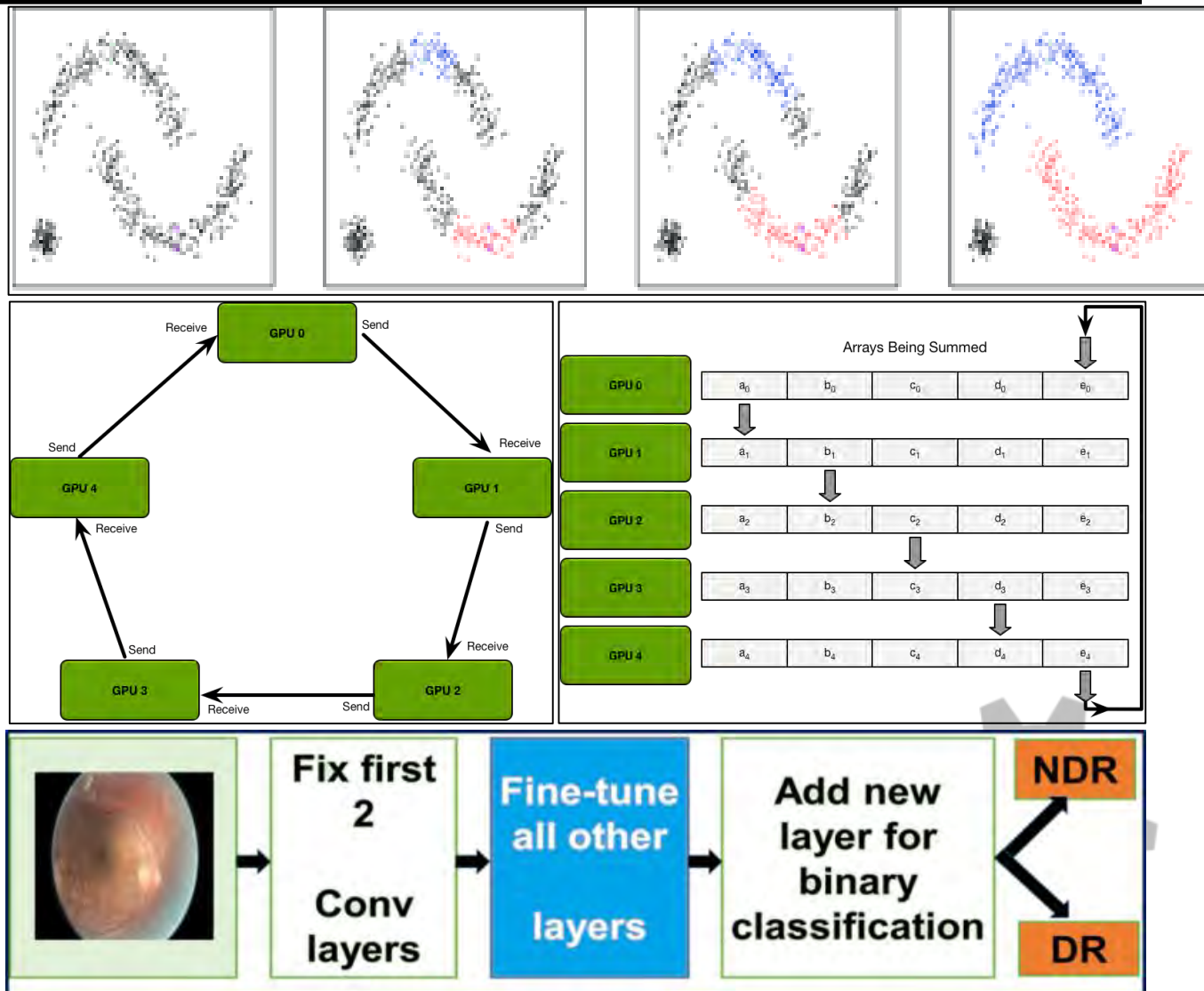
IIOT Analytics Implementation Challenges

- How to Combine Streaming and Batch Processing Frameworks
- How to Introduce Human Domain Knowledge
 - NLP, Reinforced Learn, ...
- How to Distribute Processing and Data at the Tiers



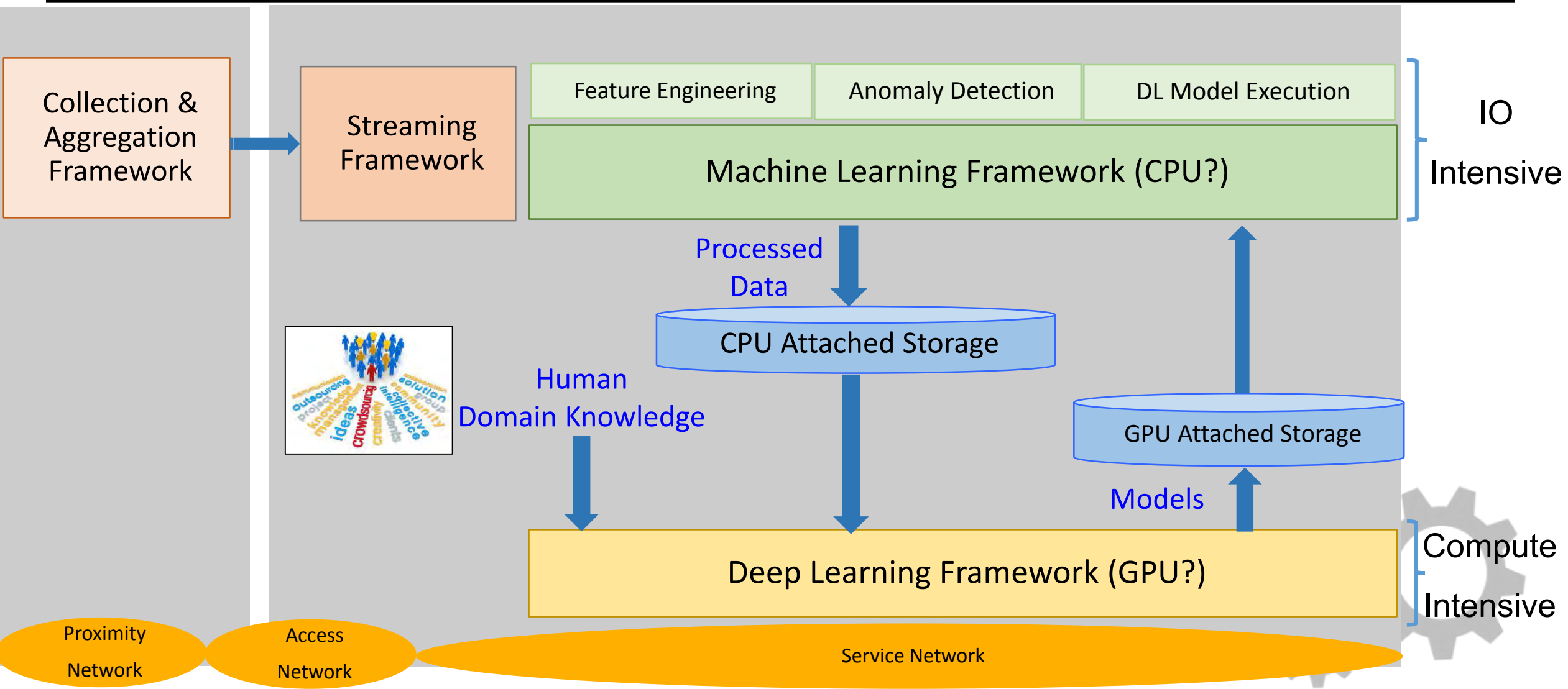
IIOT Analytics Implementation Challenges

- How to train DL with Unlabeled data using Algorithms & Domain knowledge
- How to scale DL into multiple nodes
- How to tune DL Nws
 - architecture, parameters





IIoT End to End Frameworks





Open Source Frameworks for ML and DL

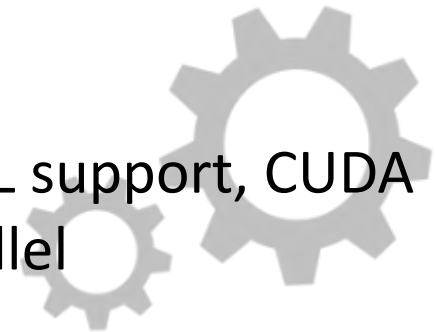




Deep Learning Frameworks

- Apache SINGA
- Brainstorm
- Caffe
- Chainer
- CNTK (Microsoft)
- DL4J
- DMLC
- Fbcunn (Facebook)
- Lasagne
- Minerva
- Mocha.jl (Julia)
- MXnet
- Neon (Nervana)
- Purine
- Tensorflow (Google)
- Theano
- Torch
- Warp-CTC (Baidu)
- Brain (Javascript)
- Cudamat
- Deep Learning Framework (Intel)
- Deepnet
- Hebel
- Infer.NET
- Keras
- Leaf
- MLPNeuralNet
- Neural Network Toolbox (MatLab)
- Neuraltalk
- Neurolab
- OpenDeep
- PyBrain
- Swift-AI
- VELES (Samsung)

Each differ on – Licensing, Language implemented, OpenMP Support, OpenCL support, CUDA support, Various networks implemented, Pretrained model support and parallel implementations





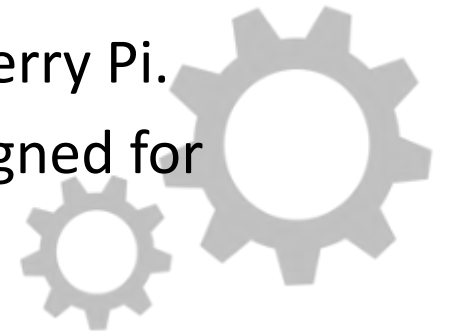
Deep Learning Frameworks

Software	Software license	Platform	<u>OpenMP</u> support	<u>OpenCL</u> support	<u>CUDA</u> support	<u>Recurrent nets</u>	<u>Convolutional nets</u>	<u>RBM/DBNs</u>
<u>TensorFlow</u>	<u>Apache 2.0</u>	<u>Linux, Mac OS X, Windows</u>	No	On roadmap	Yes	Yes	Yes	Yes
<u>Caffe</u>	<u>BSD 2-Clause License</u>	<u>Linux, Mac OS X, unoffl Android, Windows</u>	No	3 rd party implementation	Yes	Yes	Yes	No
<u>Keras</u>	<u>MIT license</u>	<u>Linux, Mac OS X, Windows</u>	Only if <u>Theano</u> backend	Under dev for <u>Theano</u> backend	Yes	Yes	Yes	Yes
<u>Deeplearning4j</u>	<u>Apache 2.0</u>	<u>Linux, Mac OS X, Windows, Android (Cross-platform)</u>	Yes	On roadmap	Yes	Yes	Yes	Yes
<u>MXNet</u>	<u>Apache 2.0</u>	<u>Linux, Mac OS X, Windows, AWS, Android iOS, JavaScript</u>	Yes	On roadmap	Yes	Yes	Yes	Yes
<u>Theano</u>	<u>BSD license</u>	<u>Cross-platform</u>	Yes	Under development	Yes	Yes	Yes	Yes
<u>Facebook Torch</u>	<u>BSD License</u>	<u>Linux, Mac OS X, Windows, Android, iOS</u>	Yes	3 rd party implementations	Yes	Yes	Yes	Yes



TensorFlow for Deep Learning

- Open source library for Machine Learning and Deep Learning by Google.
- Supports CUDA, CNN, RNN and DBN. Distributed TensorFlow offers flexibility to scale up to hundreds of GPUs, train models with a huge number of parameters.
- Has a well documented Python API, less documented C++ and Java APIs.
- Uses XLA, JIT, AOT, and other compilation techniques to minimize execution time and maximize computing resources.
- TensorBoard – Visualize TensorFlow graphs, monitor training performance, and explore how models represent data.
- Layers, Estimators, and Canned Estimators for defining models.
- Keras DL framework can be used in Tensorflow. DeepMind also uses TensorFlow.
- TensorFlow models can be deployed in iOS and Android apps, and Raspberry Pi.
- TensorFlow Serving, a flexible, high-performance ML serving system designed for production environments.
- TensorFlow has a toolkit of ML algorithms.





Apache Spark for Streaming and Machine Learning

- Open source library for SQL, Streaming, ML and Graph in a distributed cluster.
- Provides APIs for Scala, Java, Python and R.
- DAG execution engine supports acyclic data flow and in-memory computing.
- Runs on Hadoop, Mesos, standalone, or in the cloud. It can access diverse data sources including HDFS, Cassandra, HBase, Hive, and S3.
- Supports standalone (native Spark cluster), Hadoop YARN, or Apache Mesos.
- Spark Streaming has support built-in to consume from Kafka, Flume, Twitter, ZeroMQ, Kinesis, and TCP/IP sockets.
- Spark MLlib simplifies large scale machine learning pipelines, including:
 - Summary statistics, correlations, stratified sampling, hypothesis testing, random data generation[16]
 - Classification and regression: support vector machines, logistic regression, linear regression, decision trees, naive Bayes
 - Collaborative filtering techniques including alternating least squares (ALS)
 - Cluster analysis methods including k-means, and Latent Dirichlet Allocation (LDA)
 - Dimensionality reduction techniques: singular value decomposition (SVD), and principal component analysis (PCA)
 - Feature extraction and transformation functions
 - Optimization algorithms such as stochastic gradient descent, limited-memory BFGS (L-BFGS)
- GraphX is a distributed graph processing framework.





THANK YOU

