



CERN openlab Machine Learning and
Data Analytics Workshop

April 29th, 2016

Machine Learning and Data Analytics at Cisco

At the edge and core of the network

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Overview on...

- ❖ Platform for Network Data Analytics
- ❖ Deep Learning for Visual Analytics
- ❖ Data Fusion for Edge Computing
- ❖ Self-Learning Networks

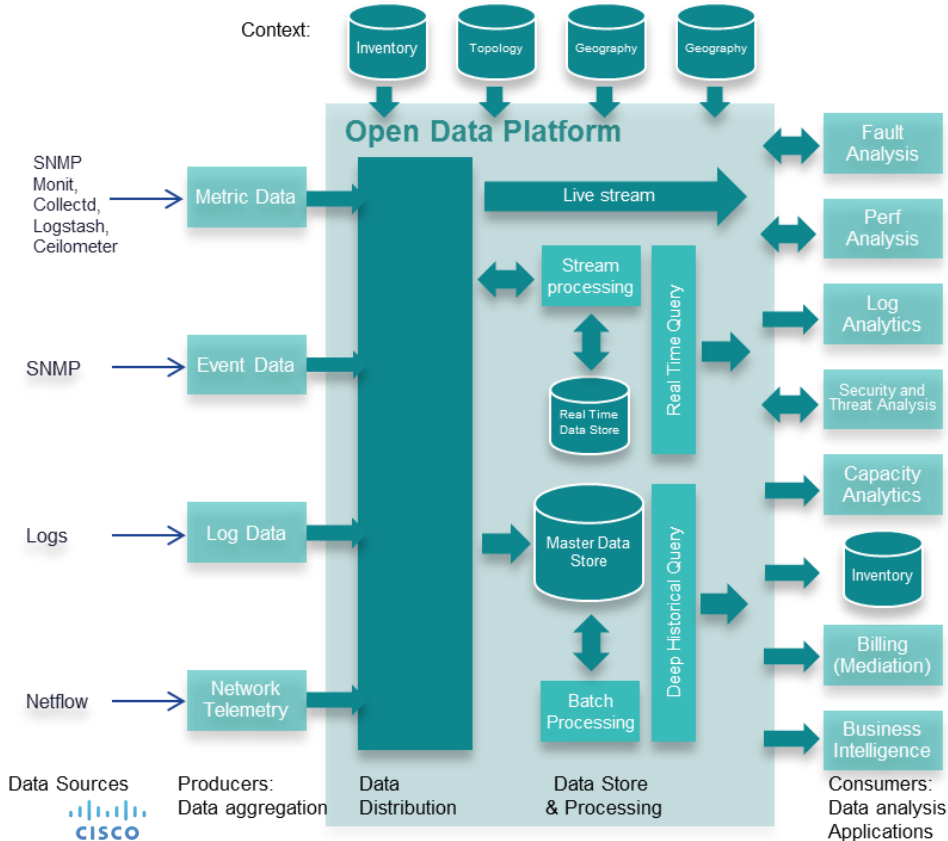
PaNDA

Platform for Network Data Analytics

Problem statement

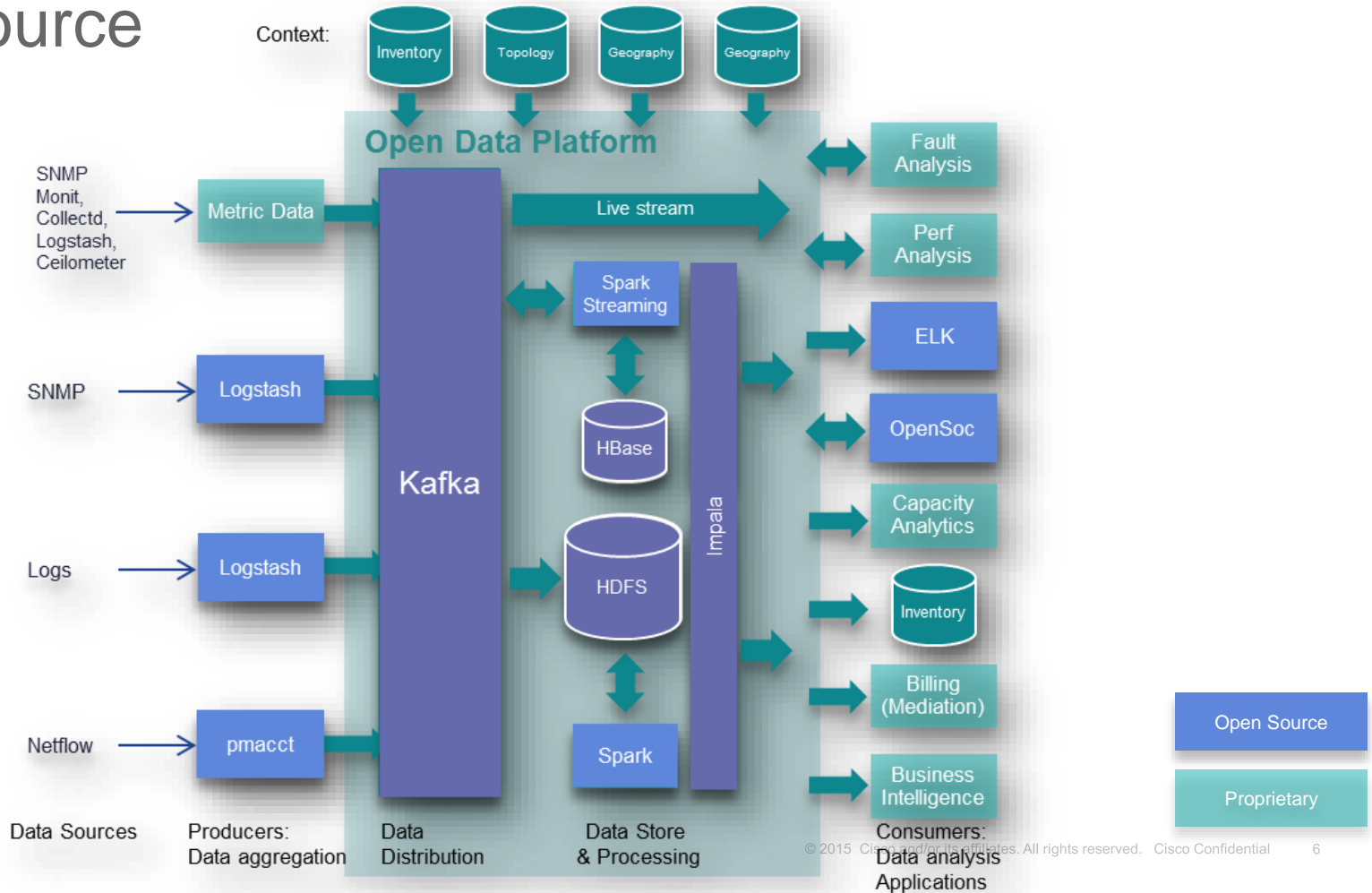
- ❑ NFV (network function virtualisation), SDN & IoT = dynamic, scalable and service-assured infrastructures on which to deploy
- ❑ These service topologies generate large quantities of system log, network flow and telemetry data
- ❑ Reduce the operational complexity for SP&Enterprise customers
 - Low-order : “Do I have service-impacting issues?”
 - Mid-order : “Will I have any service-impacting issues”
 - High-order : “Automate the control of my services”
- ❑ This, alongside existing workflows, tools and SLA’s, drives the need for an open, scalable analytics platform

Platform



- ❑ Lambda-based architecture: (batch + streaming)
- ❑ Collect data once : allow any analysis application to mine any data source
- ❑ Extensible : enable the rapid deployment of analysis functions
- ❑ Streaming (online) & batch (offline) machine intelligence
- ❑ Leverage the continual innovation in open-source data and ML community
- ❑ Contribute our work back to this community

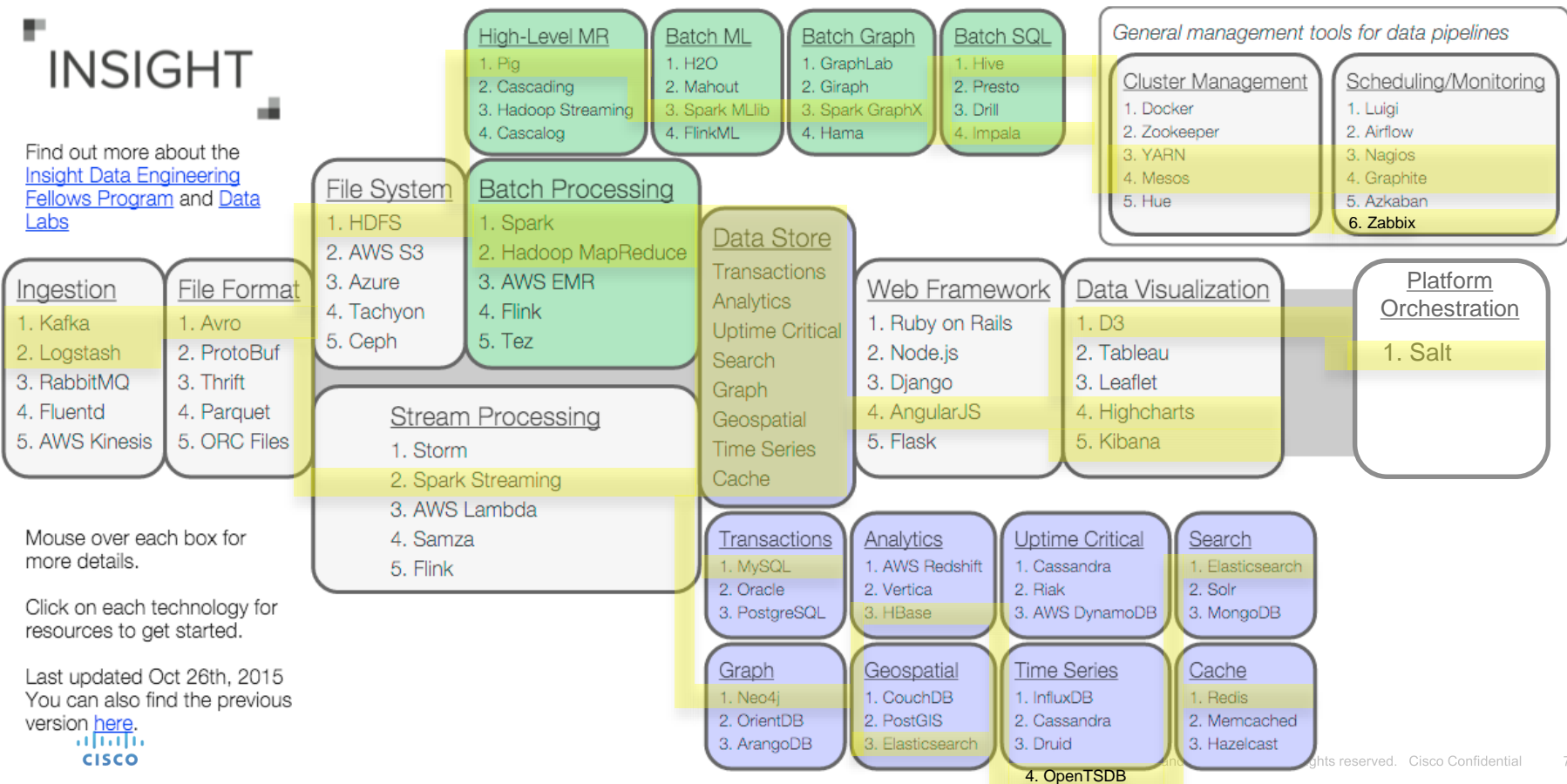
Open-source



Technology map

INSIGHT

Find out more about the [Insight Data Engineering Fellows Program](#) and [Data Labs](#)



Mouse over each box for more details.

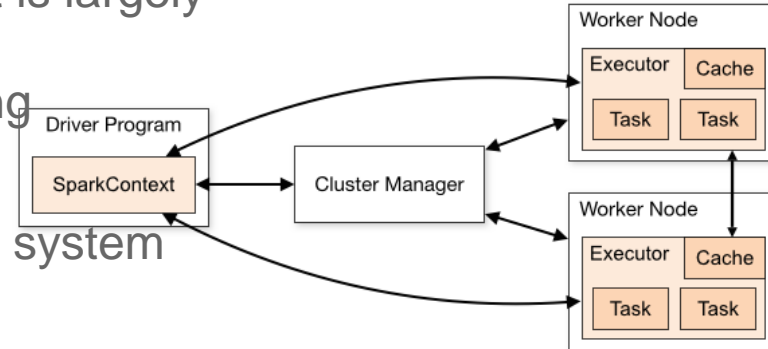
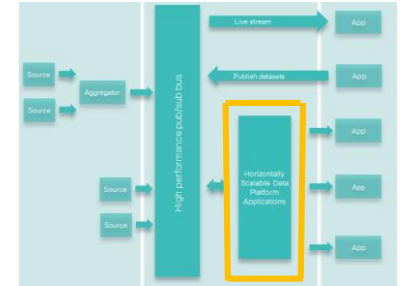
Click on each technology for resources to get started.

Last updated Oct 26th, 2015
You can also find the previous version [here](#).



Massively-parallel batch processing

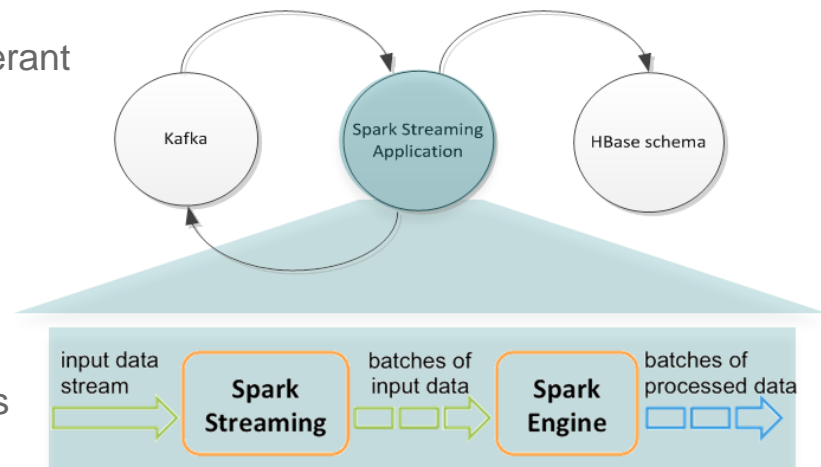
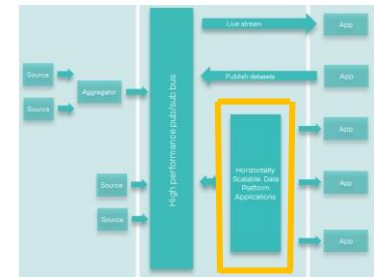
- ❑ Support for applications that deliver computations over very large datasets with highly heterogeneous structure
 - Addresses data volume & variety
- ❑ **Apache Spark** (spark.apache.org)
 - Framework and engine for distributed, large scale data processing
 - Many times faster than MapReduce, which it is largely replacing in industry
 - Also provides engine behind Spark Streaming
- ❑ **HDFS** (hadoop.apache.org)
 - Fault tolerant and self-healing distributed file system
 - Large-scale data processing workloads
 - Focus on scalability, flexibility and throughput



Proven deployments of >100PB

Stream processing

- ❑ Support for applications that need to deliver computations over data in near real time (e.g. 1s)
 - Addresses data velocity
- ❑ **Apache Spark Streaming** (spark.apache.org)
 - Framework and engine for distributed, scalable fault-tolerant streaming applications
 - Micro-batch orientation
 - Consume/produce to/from Kafka
- ❑ **Apache HBase** (hbase.apache.org)
 - ❑ Distributed, scalable data store
 - ❑ Designed for fast, random access to very large data sets
 - ❑ e.g. billions of rows and millions of columns
 - ❑ Persists results of streaming computation in optimized schema



Platform management

The screenshot displays the PaNDA Data Platform management interface. The top navigation bar includes the Cisco logo, version information (PaNDA 0.1.106 [devnet]), and navigation links for Home, Metrics View, and panda.cisco.com.

PaNDA Data Platform

Data Distribution

- Kafka** (Last update: 1 minute)
Select rate: Mean rate ▾
avro.events: 278.17678 Bytes/s → 385.29245 Bytes/s →
avro.kso.metrics: 411.39536 Bytes/s → 453.06867 Bytes/s →
- Zookeeper** (Last update: 1 minute)

Data Processing

- Stream**
 - Spark Streaming** (Last update: 1 minute)
- Batch**
 - Spark** (Last update: 1 minute)
 - Oozie** (Last update: 1 minute)
- Yarn** (Last update: 1 minute)
 - Used Memory: 5GB/24GB
 - Used vCores: 5/24

Data Storage

- HBase** (Last update: 1 minute)
- Hive metastore** (Last update: 1 minute)
- HDFS** (Last update: 1 minute)

Query

- Impala** (Last update: 1 minute)

Explore

- Zeppelin**

Metrics

- OpenTSDB**
- Grafana**

Applications

- Deployment Manager** (Last update: 1 minute)
 - devoteam-swo-spark-st... 1.0.0
 - sampleKSOapp
 - spark-streaming-to-hbase-exempl...
 - weatherLogger

Console

- Backend**
 - Metric Logger

HDFS Metrics Table

Metric	Value
Used Capacity	74.5GB/252.3GB
JVM Heap Used	274 MB
Total No. of Files	26,917
Live Datanodes	3
Dead Datanodes	0



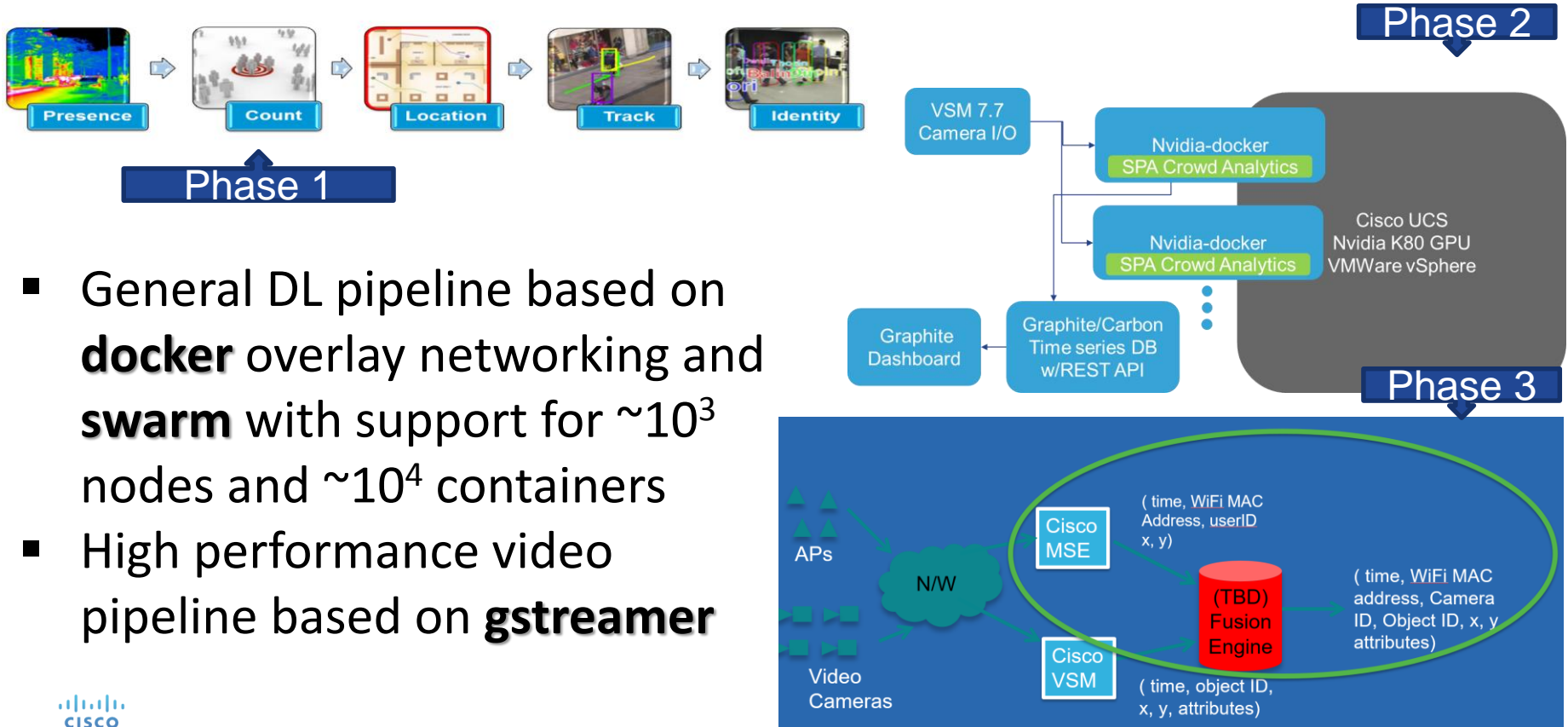
panda.cisco.com

Deep Learning for Visual Analytics

Spatial Predictive Analytics: Problem to solve

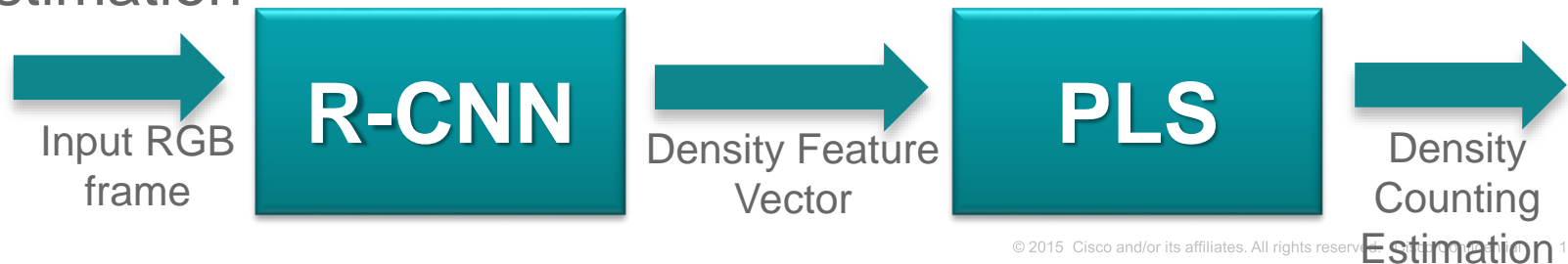
- ❑ Cisco customers ask for accurate people counting, location, tracking, and more advanced crowd analytics
- ❑ There are already practical solutions for the sparse target case but **not** for the dense target case
- ❑ Outstanding crowd analytics using only CV for real-world PoC is difficult. Clutter and occlusions add even more complexities.

Spatial Predictive Analytics Overview



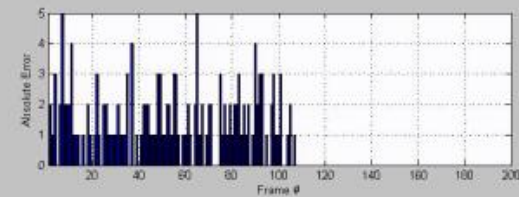
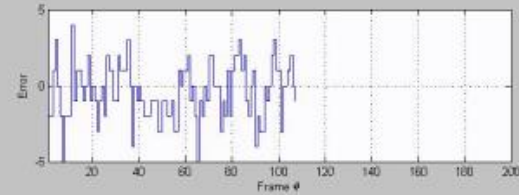
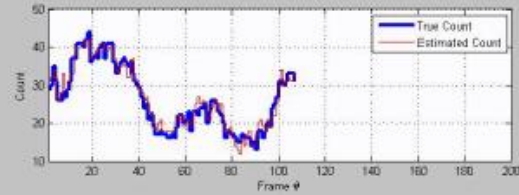
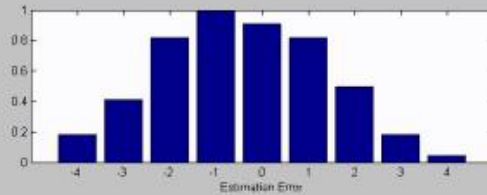
Spatial Predictive Analytics – Crowd Counting

- We aim at counting individuals in crowded environments
- Traditionally the number of people in region of interest is inferred by (1) person-counting sensors, (2) special purpose top view cameras
- We use Region-based Convolutional architecture (R-CNN) and multivariate regression (PLS) for density counting estimation



	MAE	MSE
Chen 2 (BMVC2012)	3.59	19.0
Chen 3 (CVPR2013)	3.43	17.7
PLS (with original HLAC)	3.82	22.3
SVR (with proposed feature)	3.41	18.5
Proposed method	1.8	7.5

http://www.eecs.qmul.ac.uk/~ccloy/downloads/mall_dataset.html



Spatial Predictive Analytics – multi-tracking

- We aim at tracking multiple person once localized in a frame
 1. estimate the spatio-temporal position of each person in each frame using a DL pipeline: CNN (GoogLeNet)+LSTM
 2. assign UIDs to formed trajectories: Kalman filter + Jonker-Volgenant to solve the assignment problem



Training

□ Ground-Truth generation is a pain

□ **Transfer Learning** : use previously trained model to perform inductive learning

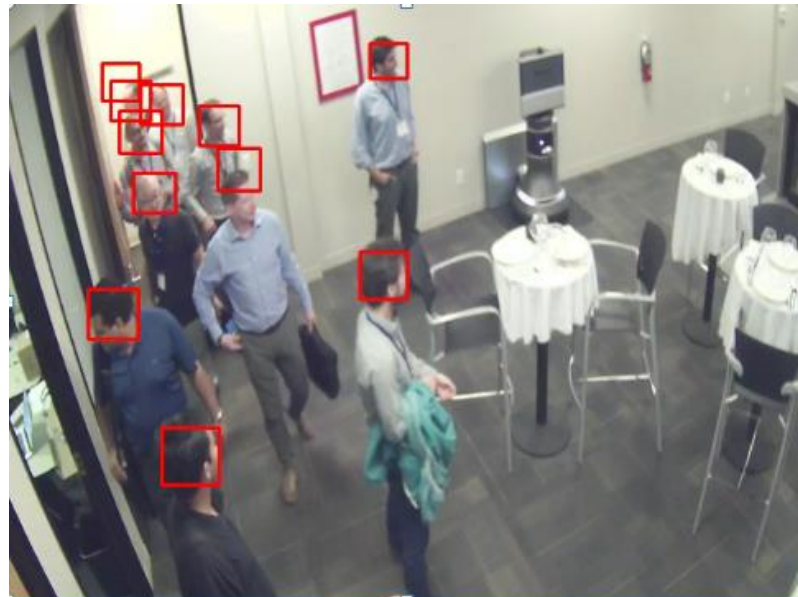
□ **Semi-supervised learning** : partially labelled dataset reduces the training iterations and improves accuracy

Spatial Predictive Analytics -- Location

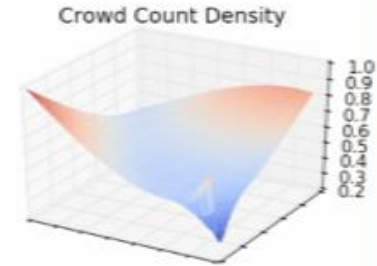
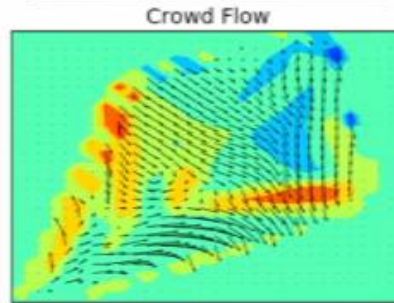
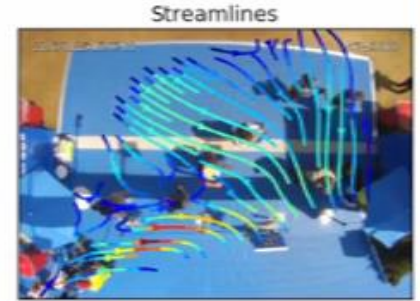
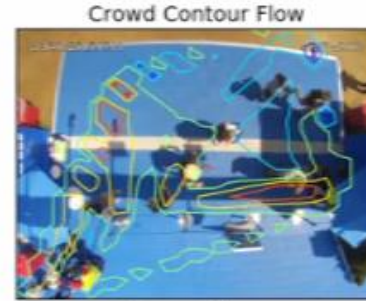
Open Source Retail Mall Dataset



Cisco Lab in San Jose



Spatial Predictive Analytics -- Tracking



Near field DL pipeline

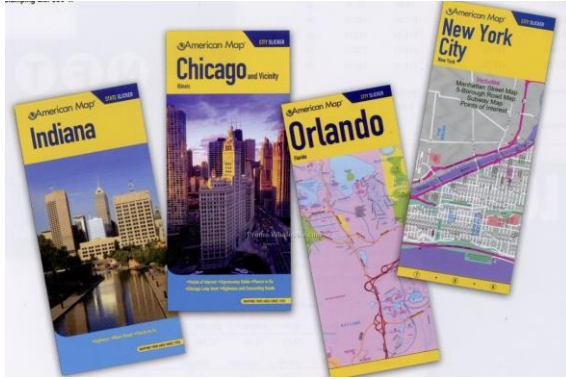


Far field DL pipeline



Data Fusion for Edge Computing

Evolution of location use-cases



Healthcare

Asset management & wayfinding

Retail

Engage shopper in aisle & deliver proximity-based offers

Museum

Enabling the Digital docent

Office
cisco

Wayfinding & workspace optimization

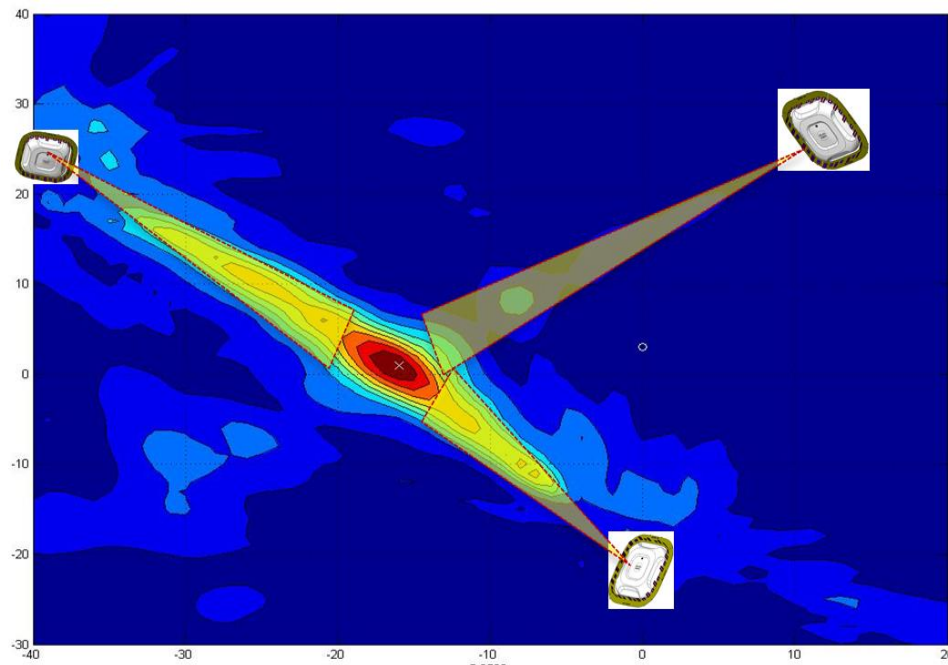
Technology – network based location

□ State of the art:

- 5-7m accuracy
 - Multi-lateration on WiFi Client based on RSSI at multiple APs

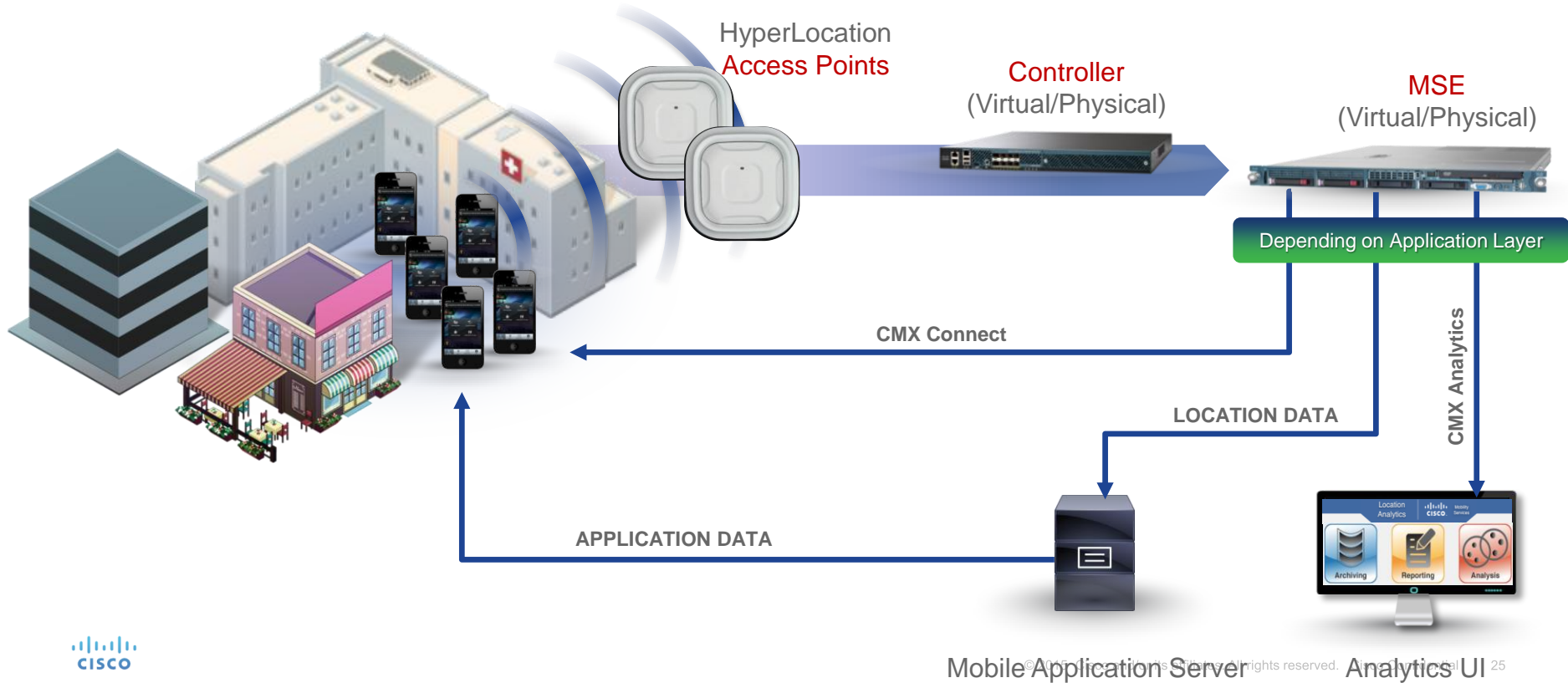
□ Cisco-Hyperlocation:

- 1m accuracy
 - Increase accuracy & reliability
 - AP connected clients
 - Add Angle-of-Arrival in addition to RSSI



How Hyperlocation Works

Built on Cisco Unified Access

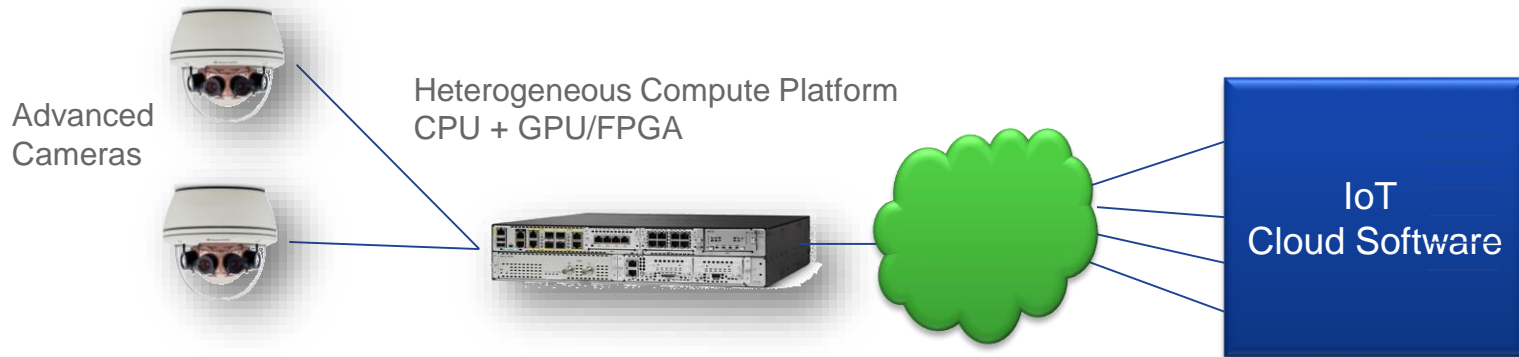


Machine Learning from End Point to Cloud

An intersection of technology and trends:

- Recent **camera sensor technologies** offer advanced capabilities
- Advanced cameras + **analytics create powerful IoT sensors**
- Visual analytics and data fusion **fit naturally into the fog architecture**

The industry is moving towards **scalable, flexible, distributed analytics platforms**



Cisco Data Center Portfolio and NVidia

- **Virtual workstation for high-end graphics applications**

- Cisco UCS C240 M4 Rack servers
 - Support NVIDIA GRID 1.0 and 2.0 with K1/K2 and M60 cards
 - Support for Magma ExpressBox for higher density
- Cisco UCS B200 M4 Blade servers
 - Recently introduced NVIDIA M6 MXM support on Blade server



- **Cisco HyperFlex –2nd generation HyperConverged platform**

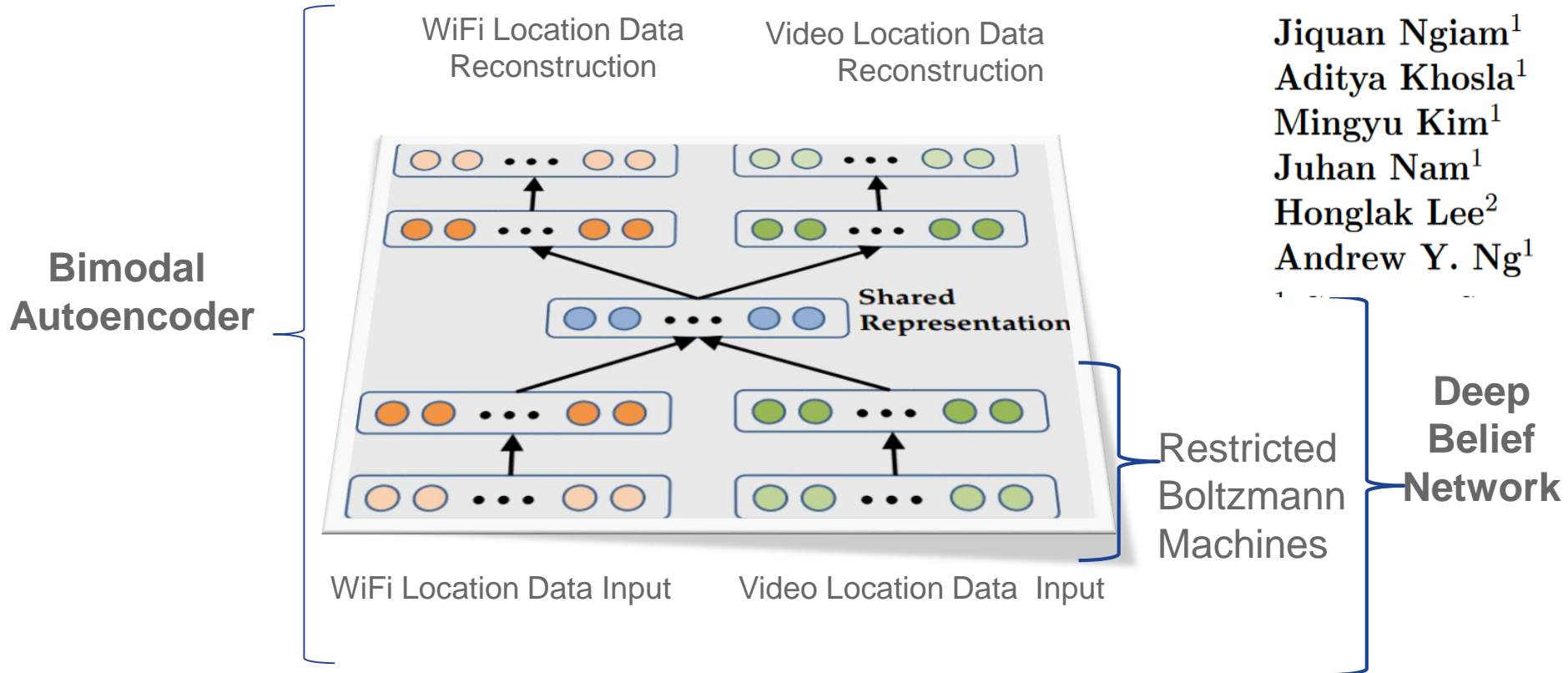
- Phase 1: K1/K2 support
- Phase 2: M6/M60 support



- **Deep Learning and HPC**

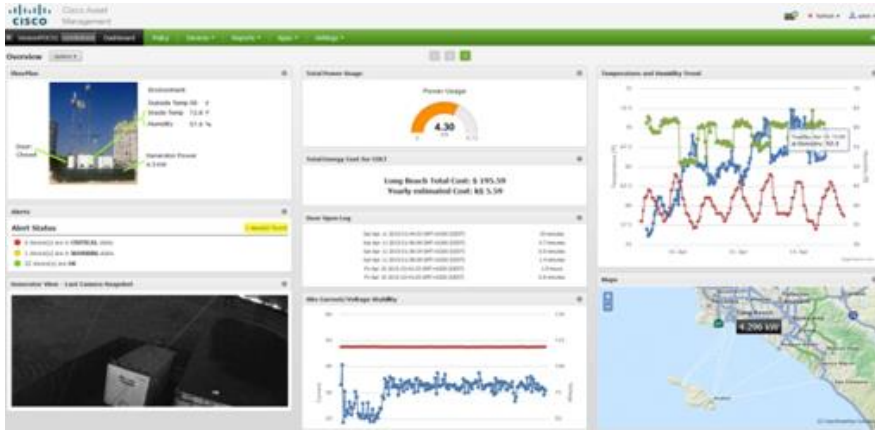
- Cisco UCS C240 Rack servers with TESLA K80

WiFi / Video Data Fusion

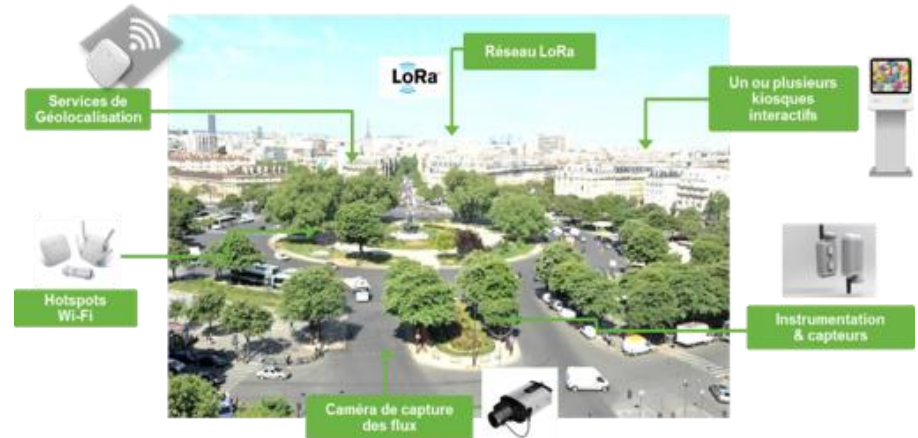


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Smart Cities: Innovative pilot proposed by the City of Paris



1. Optimization of energy management in public buildings



2. Better Understanding of the public space


 CDP, MERAKI wifi, CMX, LoRaWAN, cameras, video analytics, Energy / Asset Management















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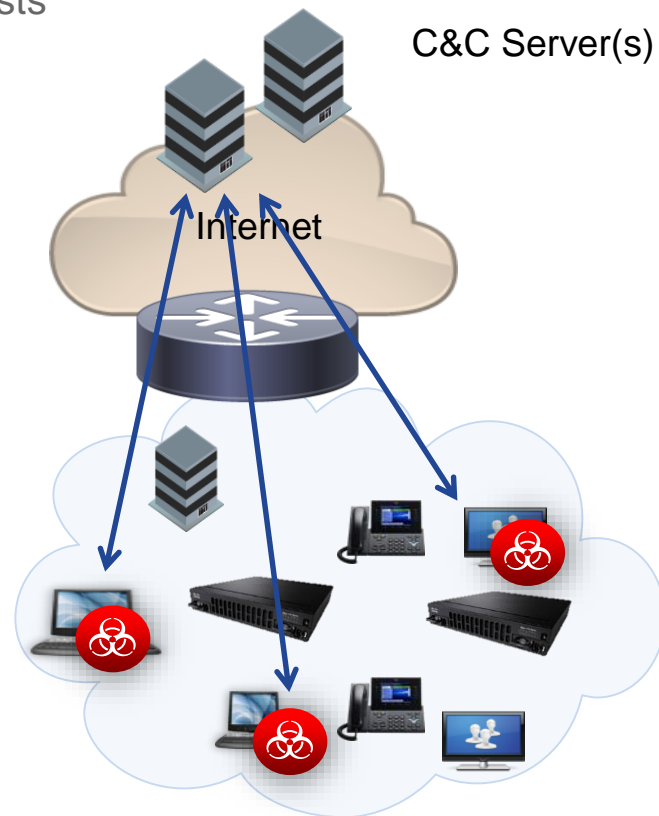
Self-Learning Networks

What Self Learning Networks is About ...

- SLN is fundamentally a **hyper-distributed analytics** platform at the edge
- Putting together analytics and networking
 - Goldmine of untouched data on networking gear (**sensing**)
 - Network **learns** and **computes** models **on premise** (**analytics**)
 - The Network adapts, modifies its behavior (**control**)
- SLN *for* Security: attacks are incredibly sophisticated and targeted, ex-filtration of data being a major concern, requiring a next-generation approach.
- True Technology disruption

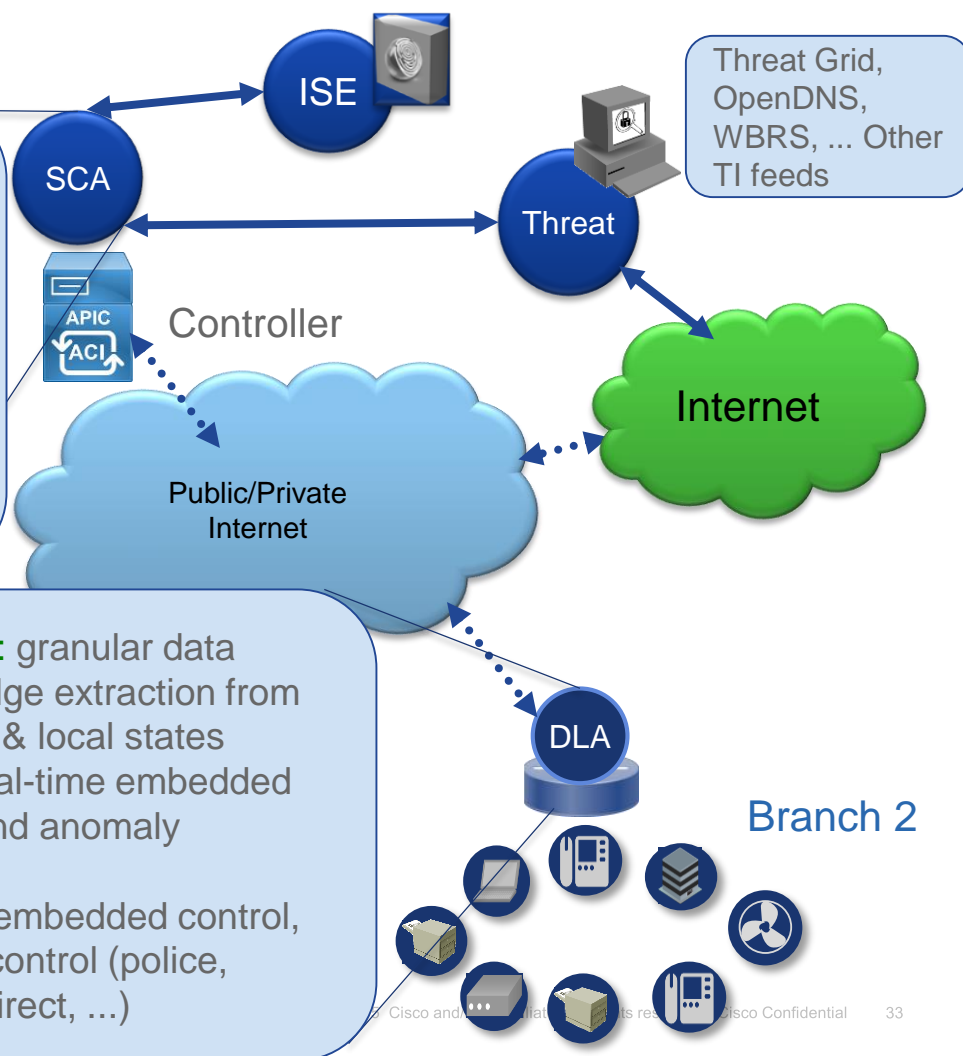
Botnets and Data Ex-Filtration Techniques

- Size can range from thousands to millions of compromised hosts
- Botnet can cause DDoS & other malicious traffic (spam, ...) to originate from the inside of the corporate network
- C&C (C2) servers become increasingly evasive
 - Fast Flux Service Networks (FFSN), single or double Flux
 - DGA-based malware (Domain Generation Algorithms)
 - DNS/NTP Tunneling
 - Peer-to-Peer (P2P) protocols
 - Anonymized services (Tor)
 - Steganography, potentially combined with Cryptography
 - Social media updates or email messages
 - Mixed protocols
 - Timing Channels



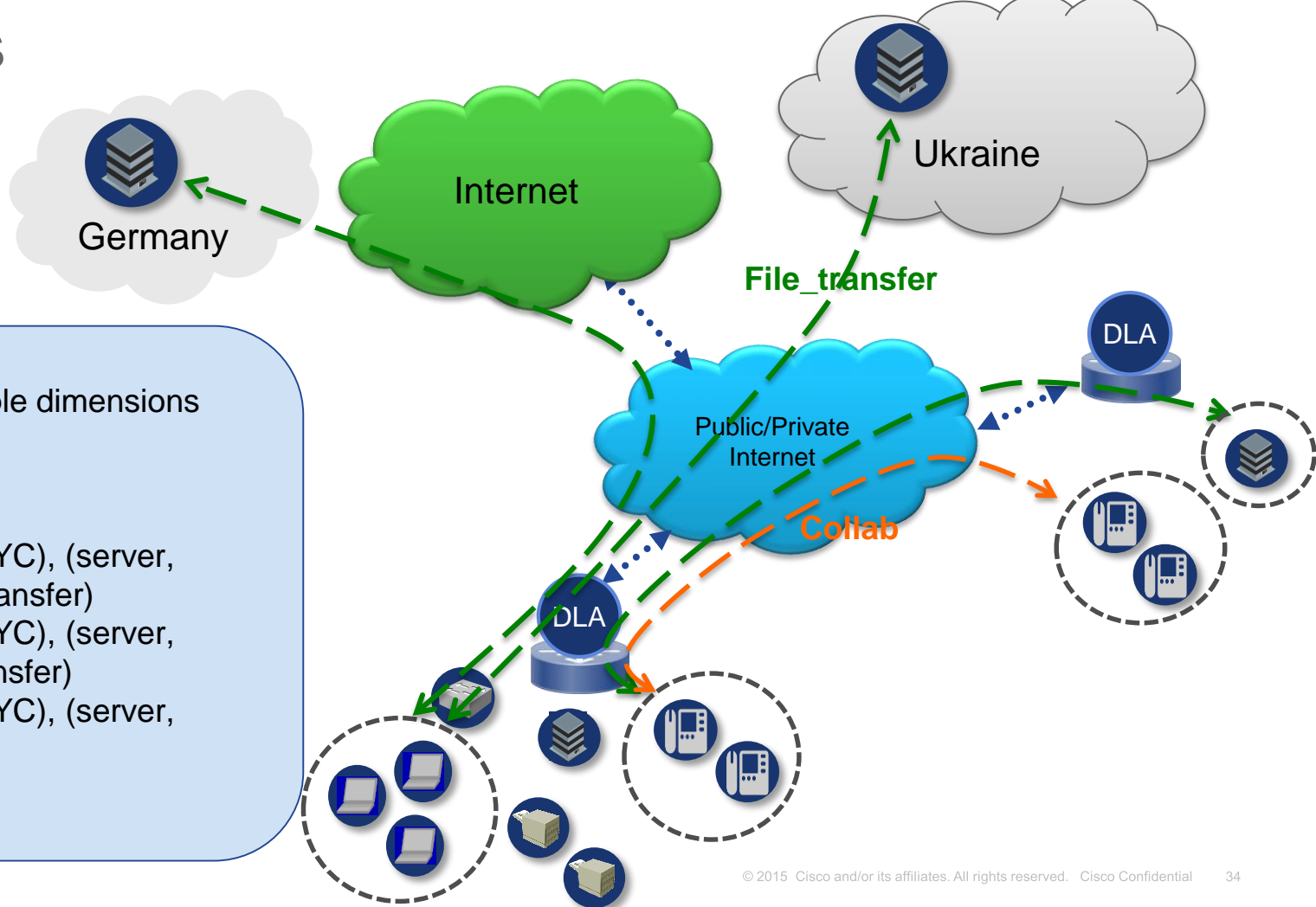
SLN Architecture

- **Orchestration of Distributed Learning Agents (DLAs)**
 - Advanced Visualization of anomalies
 - Centralized policy for mitigation
 - Interaction with other security components.
 - North bound API to SIEM/Database (e.g.Splunk) using CEF/CIM format
- **Evaluation of anomaly relevance**



- **Sensing (knowledge):** granular data collection with knowledge extraction from control and data plane & local states
- **Machine Learning:** real-time embedded behavioral modeling and anomaly detection
- **Control:** autonomous embedded control, advanced networking control (police, shaper, recoloring, redirect, ...)

ML Models



Models use multiple dimensions and hierarchy

Example:

M1: {(windows; NYC), (server, Germany), File_transfer}

M2: {(windows; NYC), (server, Ukraine), File_transfer}

M3: {(windows; NYC), (server, Germany), Shell}

....

