Deep Learning for NAS

Real-time Hazard Precursor Identification

Presented to: ATIEC 2016

By: Dr. Nancy Grady & Dr. Philip Reiner, SAIC

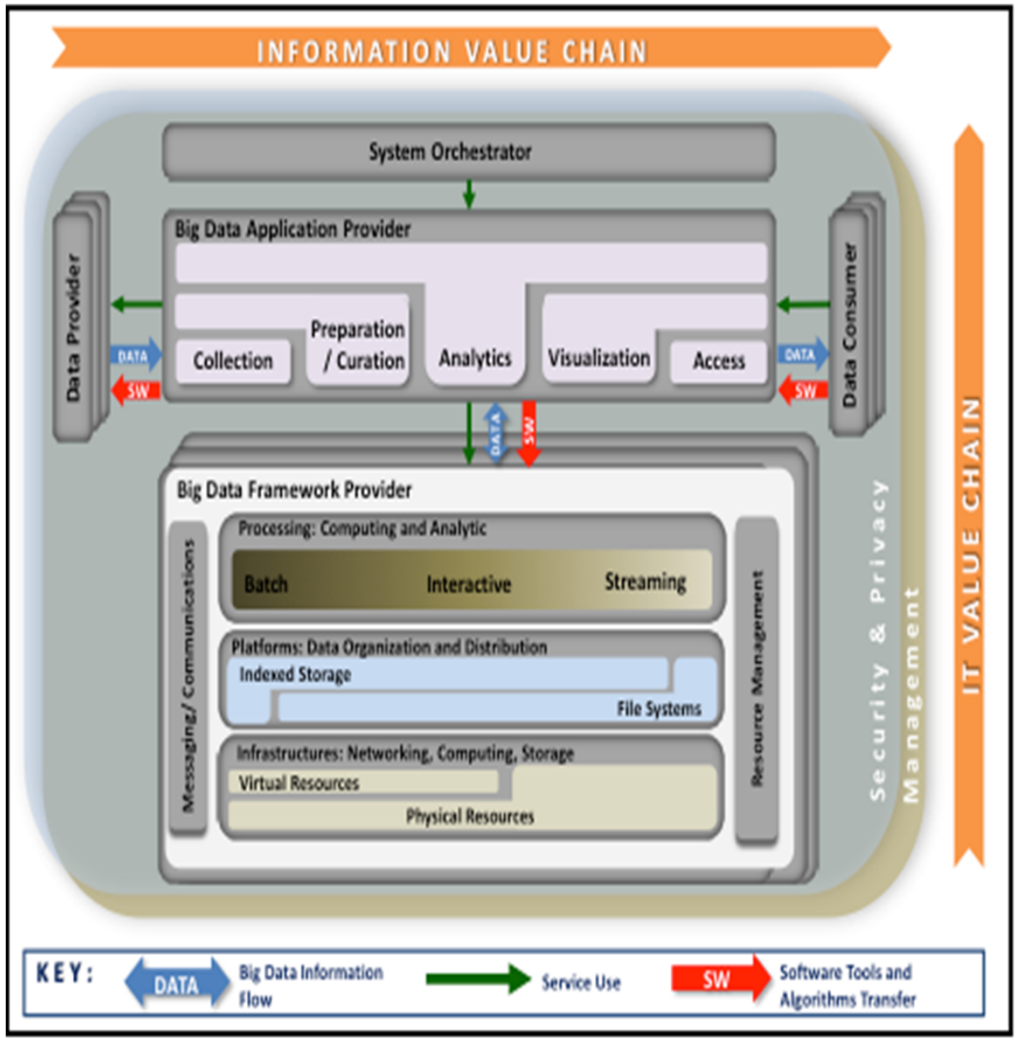
Date: September 21, 2016

Aviation Information World – Forecasting the Future

Deep Learning for NAS

- **Big Data**
- **Data Science**
- **Big Data Analytics Trends**
- **Deep Learning Technique**
- **NAS Application**

NIST Big Data Reference Architecture



Big Data consists of

extensive datasets

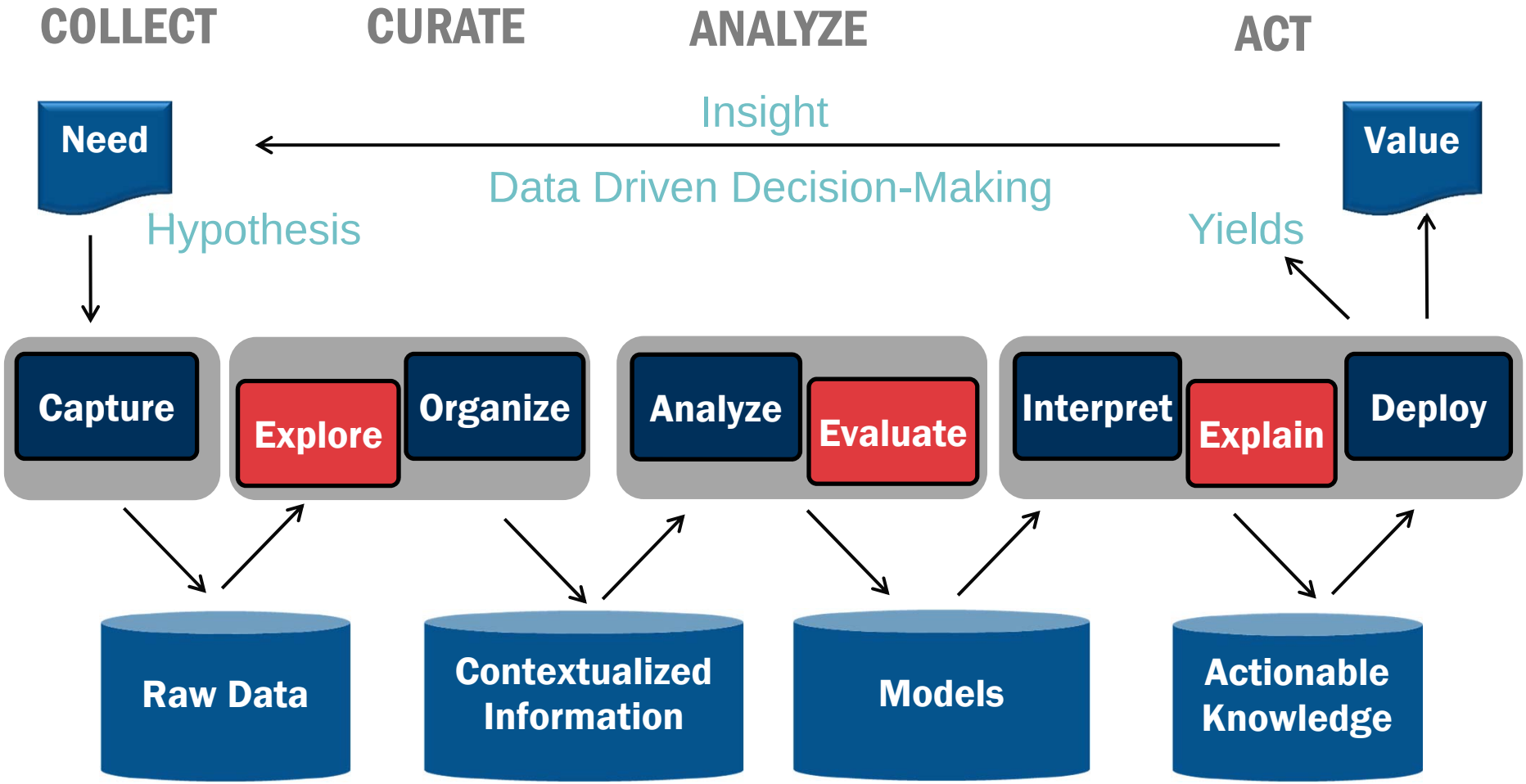
that require a

scalable architecture

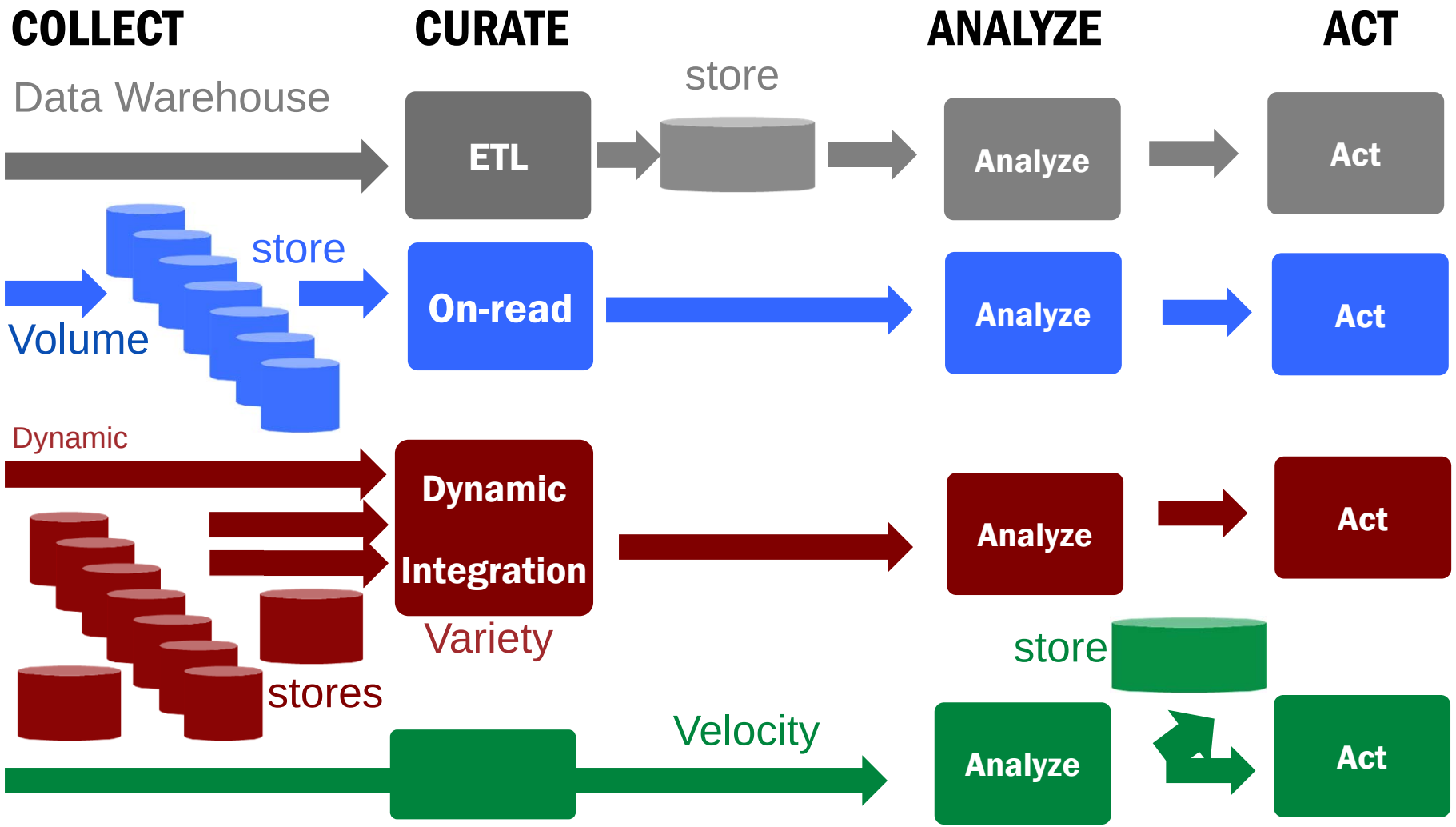
for efficient storage, manipulation, and analysis.

https://www.nist.gov/el/cyber-physical-systems/big-data-pwg

Application Layer—Data Science



Why only 3 V's


COLLECT
CURATE
ANALYZE
ACT
Data Warehouse
ETL
store
Analyze
Act
store
Volume
On-read
Analyze
Act
Dynamic
Dynamic
Integration
Variety
Analyze
Act
stores
store
Velocity
Analyze
Act

Now: Internet of Things

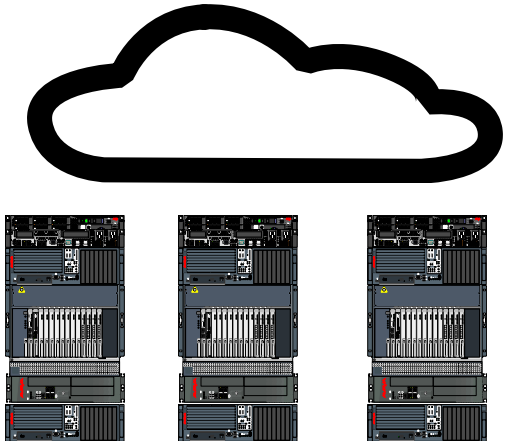
Multi-tiered Architecture

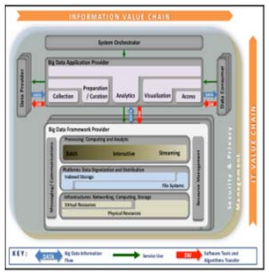
Sensors

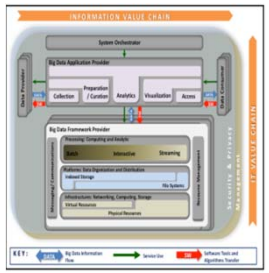
Fog/Local

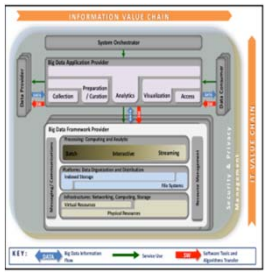
Fabric/Regional

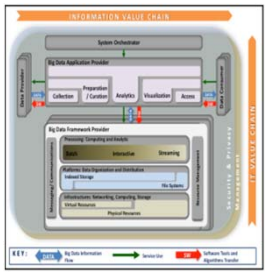
Data Lake/National



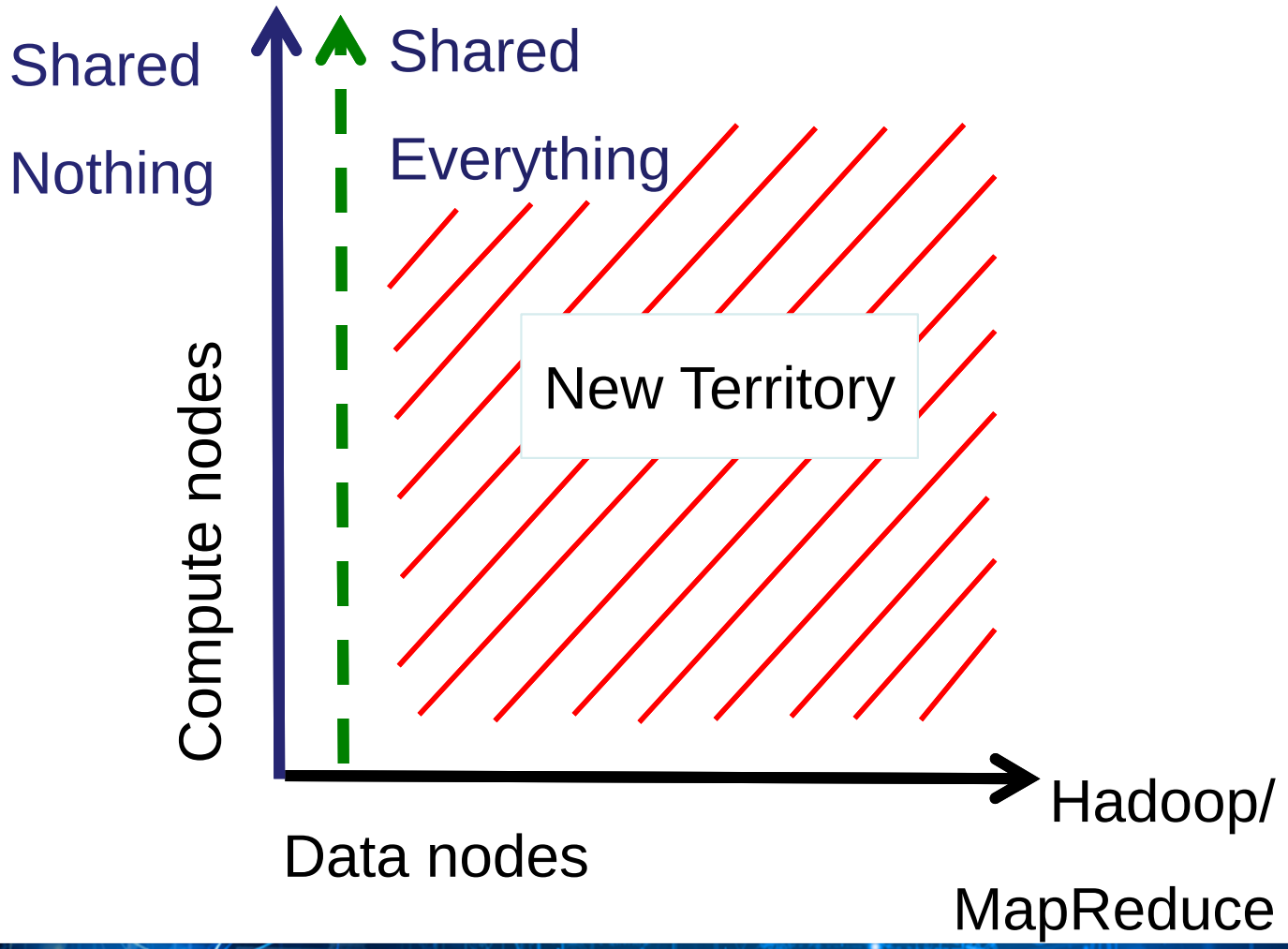








lew: Compute vs. Data Intensive



lew Computing Trends

Compute-intensive parallel computing

Data-intensive parallel computing

Data Centers and Data Lakes

CPU and GPU

Data Mining and Data Science

Network for sharing vs. distributed computing

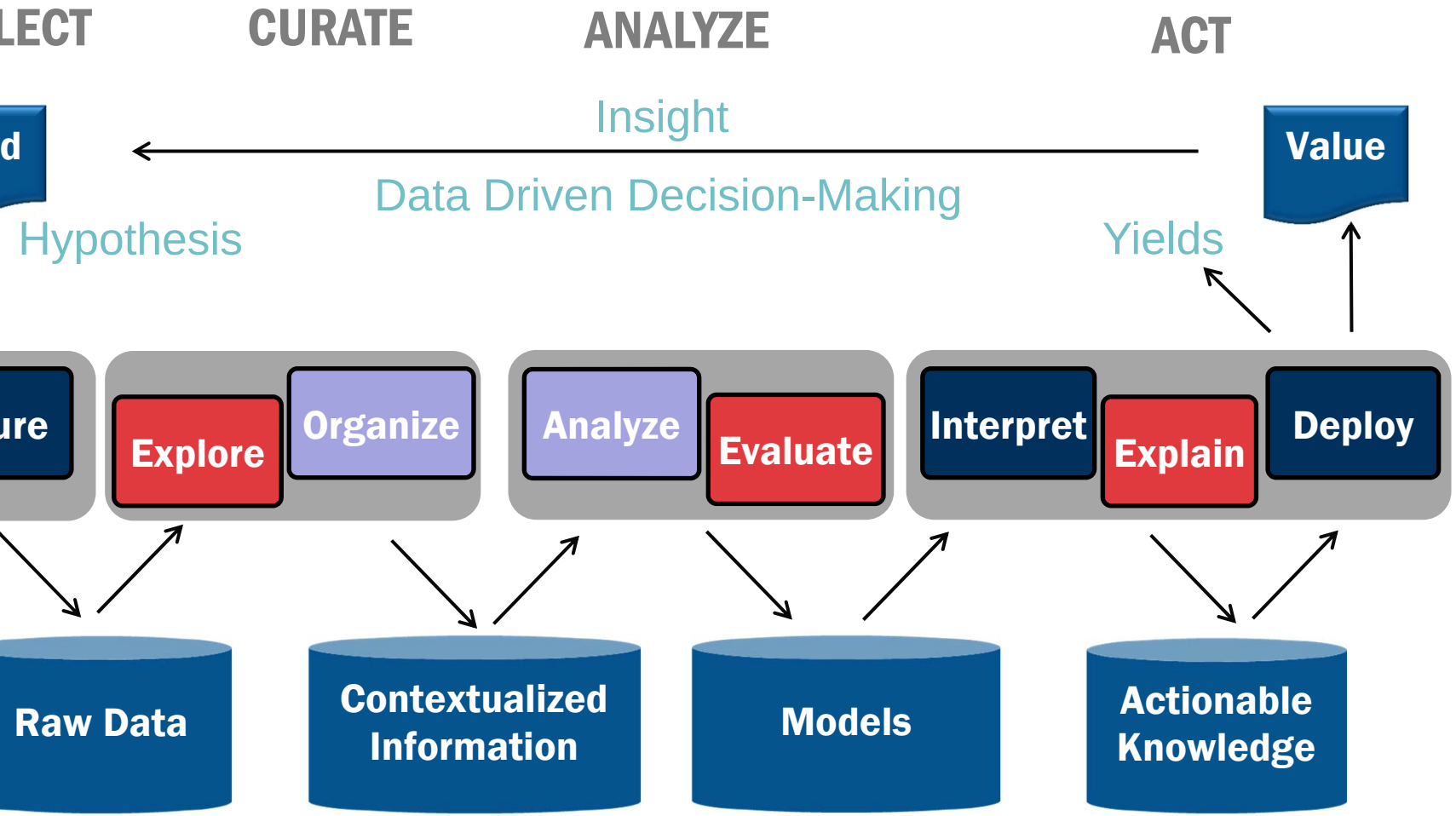
Distributed Analytics

Cloud and Micro-services

Network Effect

lodeling Implication

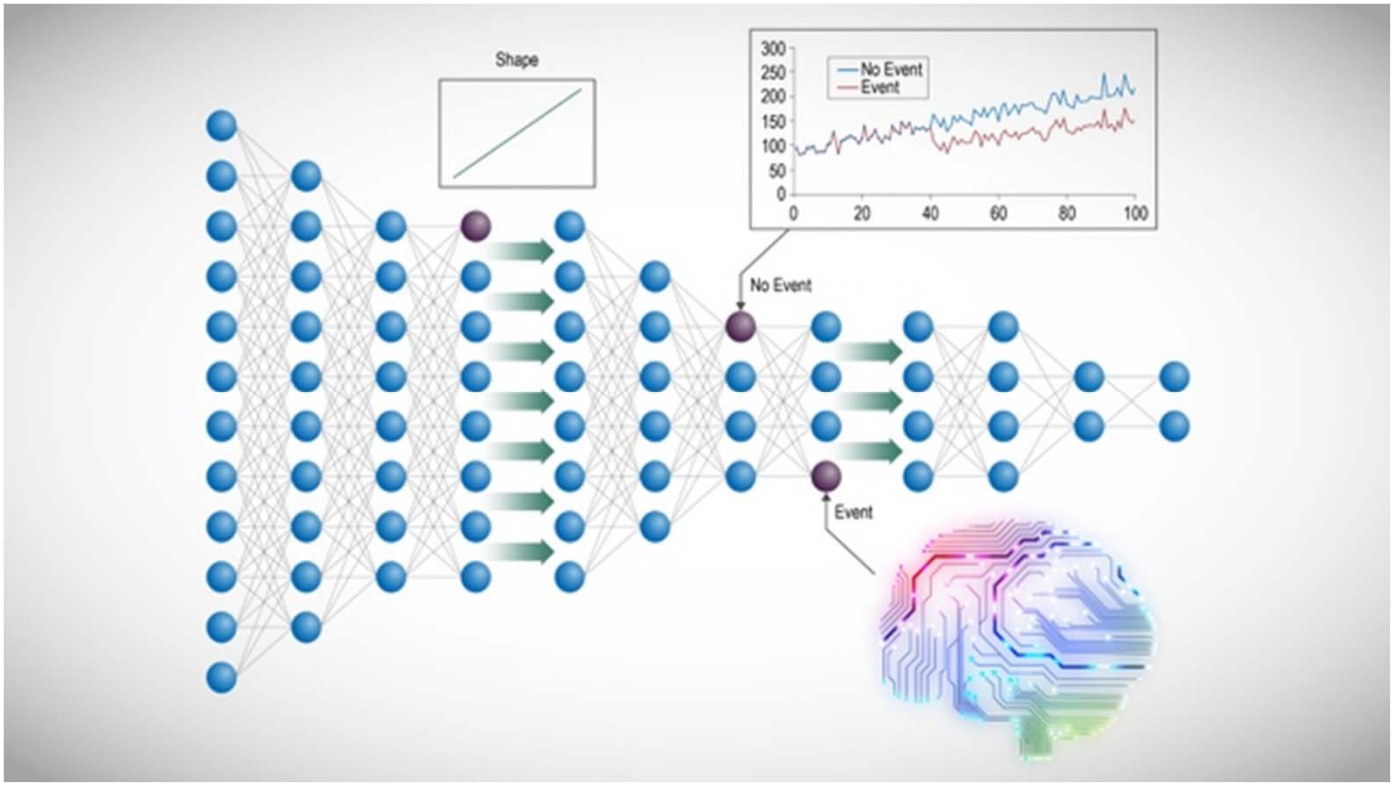
eature Extraction and Analysis



lo-Feature-Extraction Analysis

- **Involves direct learning from data**
- **Unsupervised for automated feature extraction**
- **Combines supervised and unsupervised**

ake a Cue From Neurobiology



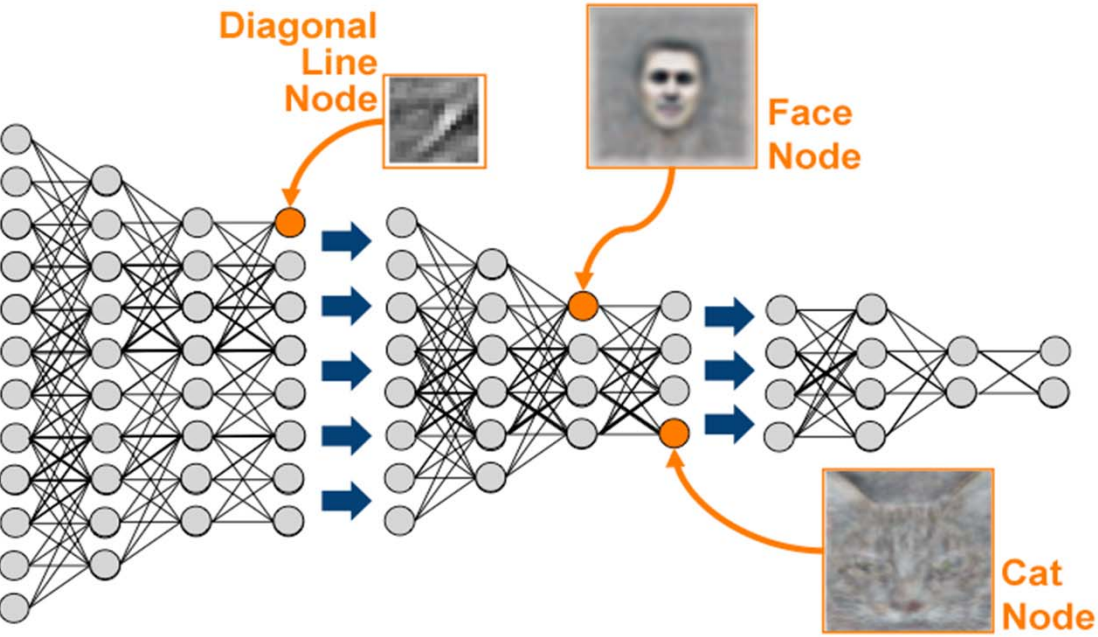
Mimic the Brain

eep Learning

rm gained popularity in 2007

nch of machine learning based on a set of algorithms that attempt to model

n-level abstractions in data by using a deep graph with multiple processing layers



- **Since 1980**
- **GPU computing**
- **Distributed computing**
- **Distributed memory**
- **Large-scale storage**

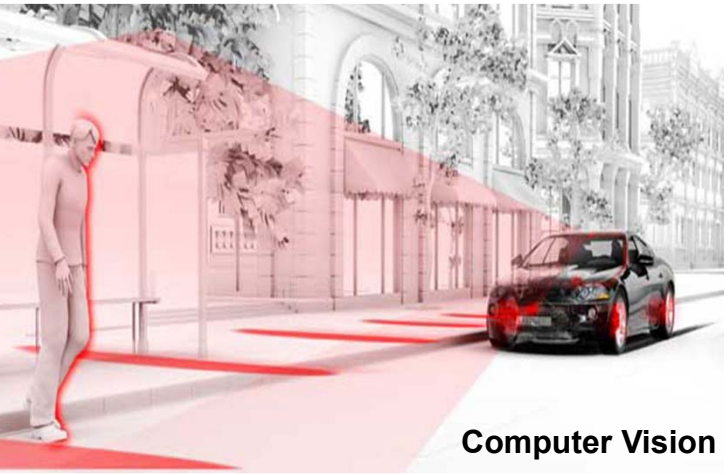
•Google's deep network that automatically created image filters for recognizing faces and cats.

’s Not Your Father’s Neural Network

ject Recognition

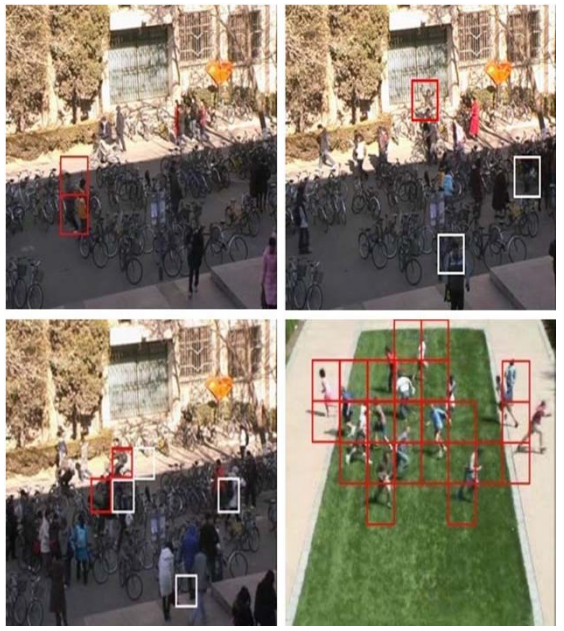
Object Classification

Language Translation



Computer Vision

Anomaly Detection



Deep Learning for NAS

Sensor Analytics

– Failure prediction

Trajectory Analysis

– Identification of hazard features

Component Failure Prediction

Sensor data from component

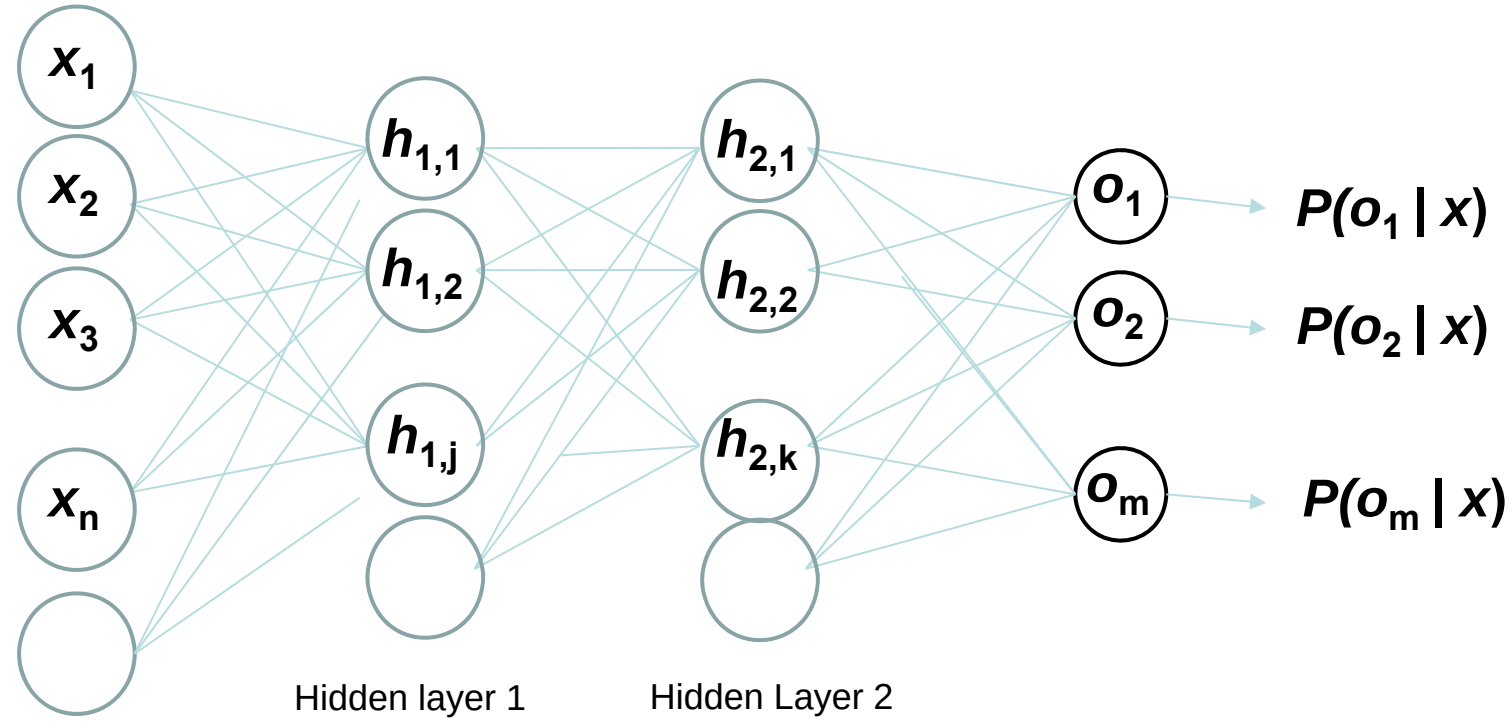
- Past data where failures have occurred
- Currently running data

Model learns from past data

- Features
- Relationships between features and fault classification

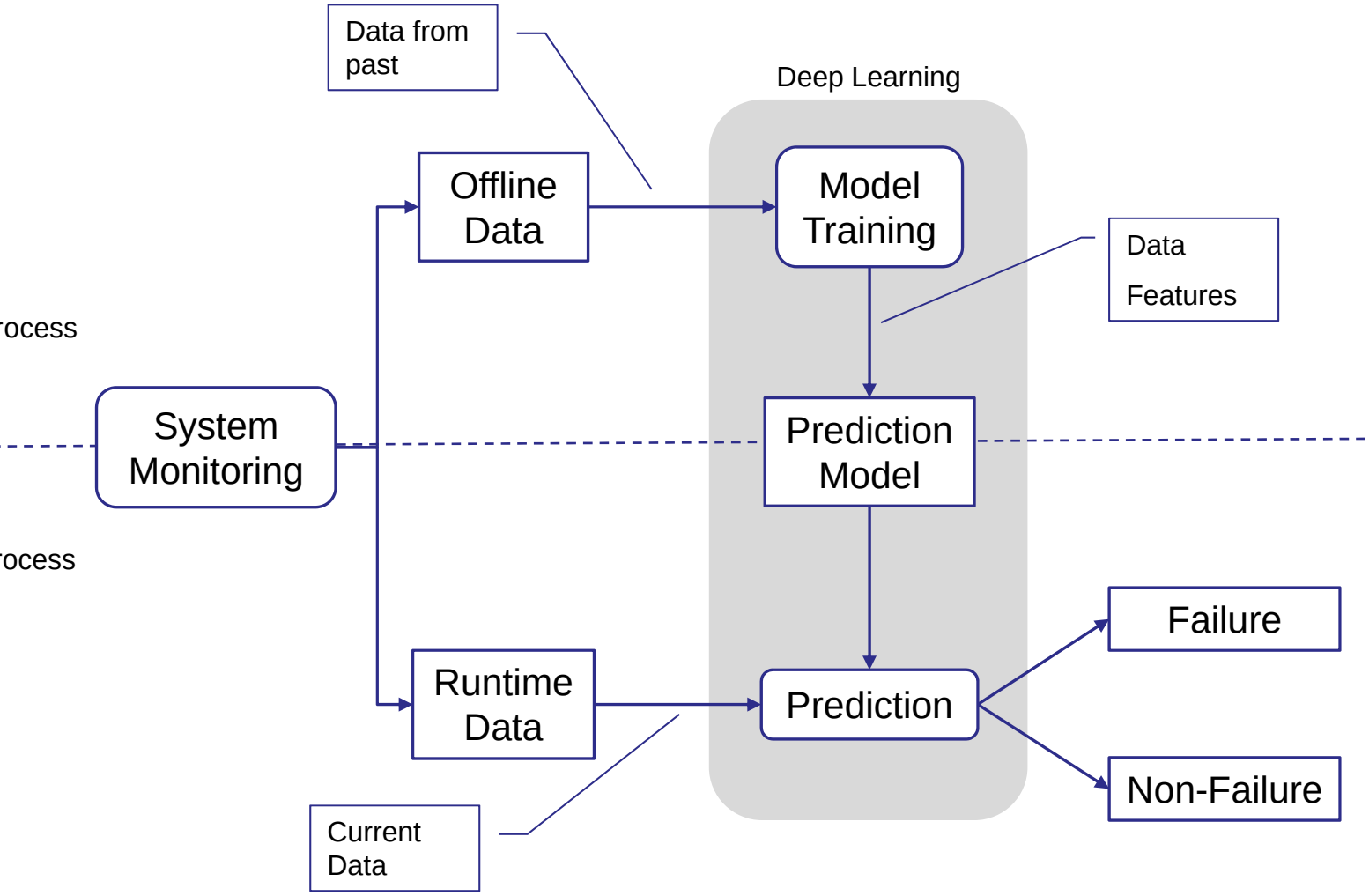
Component Failure Prediction

eep Learning Use Case



ta Layer **Feature Extraction Layers** **Classification Layer**

Component Failure Prediction



ypes of Deep Learning

From Neural Network Origins

- Torch, Theano, Caffe
- Supervised and/or unsupervised

From Neurological Origins

- Numenta Hierarchical Temporal Memory
- Continual Learning

luPIC Approach

umenta Platform for Intelligent Computing

- Continuous online learning
- Temporal and spatial patterns
- Real-time streaming data
- Prediction and modeling
- Anomaly detection
- Hierarchical temporal memory

http://numenta.com/biological-and-machine-intelligence/

Use Case: Trajectory Anomalies

uPIC HTM

Learning directly from observations

Neuroscience-based pattern recognition

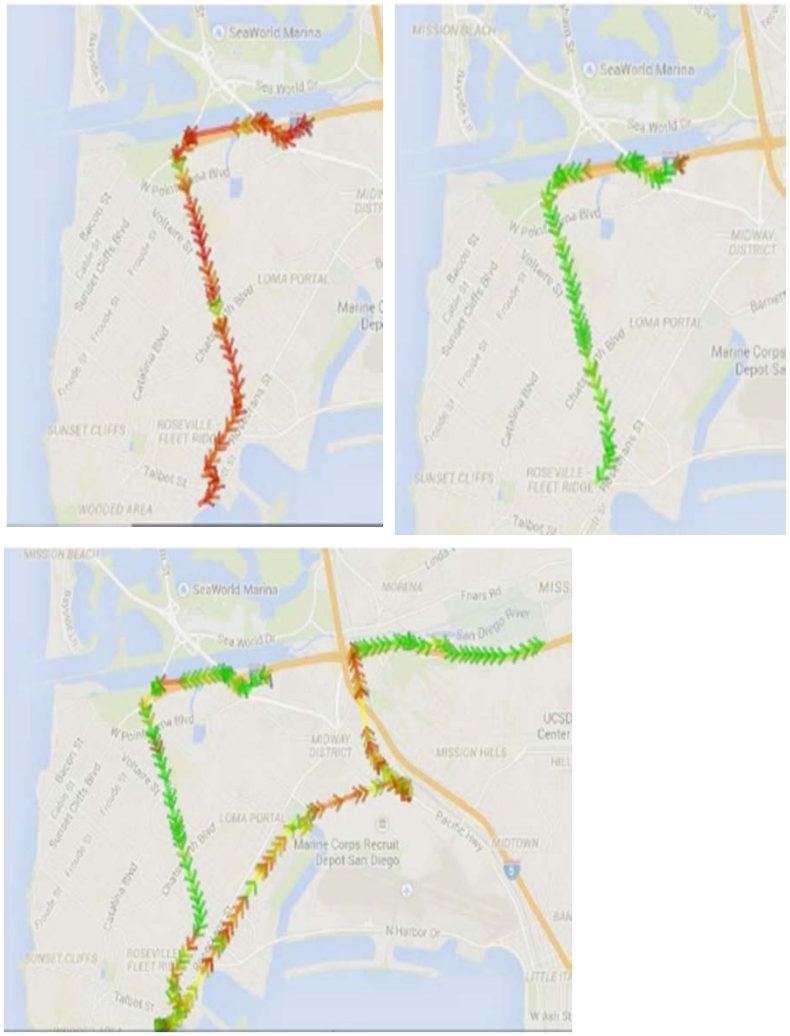
- Learning, as the brain learns
- Good for pattern recognition

Continuous learning

- Not constrained to train-test-live
- Accommodates drift

Anomaly detection

- In space and time



ummary

Separation of model-building and model-scoring

Competition between data sharing and sharing analytics results

Alternate method for learning from data

- Without feature extraction

Competition between physics-based models and unsupervised learning

Questions/Comments?

nancy.w.grady@saic.com
philip.d.reiner@saic.com