Machine Learning: Design, Development and Augmented Intelligence

David White
Virtuoso R&D
September, 2017

cadence®

Three Challenges Facing EDA

Design Challenges That Are Faced Today

- ✓ **EDA wrestles with many Data Driven problems**
- ✓ Need to provide answers quickly, design-time solutions
- ✓ Heavy degree of automation needed
- ✓ What-if analysis to explore alternative solutions faster

Scale

- Larger designs
- More rules and restrictions
- More data (simulation, extraction, shapes, techfiles)

Complexity

- More complicated silicon technologies (FinFET)
- More complicated design and electrical rules
- More interactions between chip, package and board
- Thermal related impact between devices and wires

Productivity

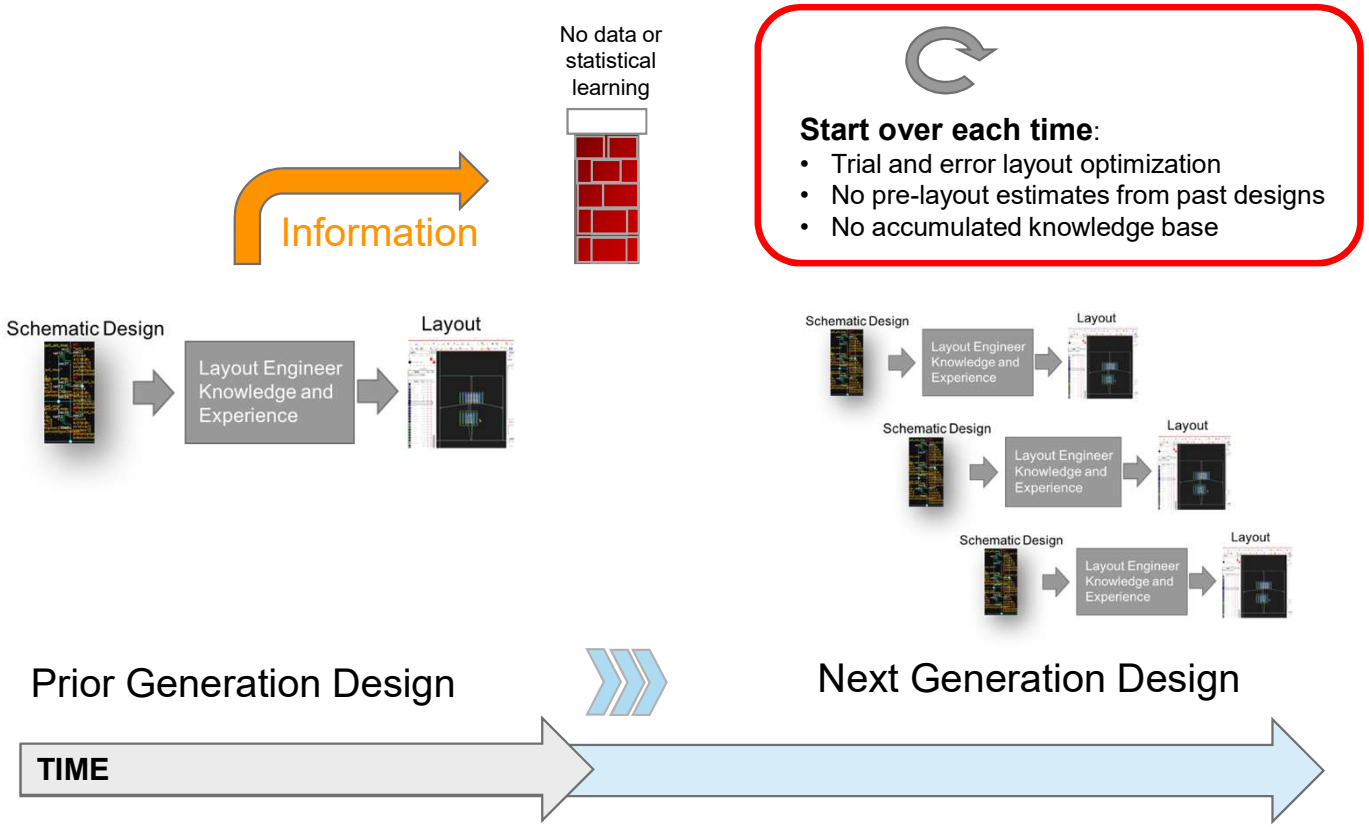
- More Uncertainty leads to re-design and missed schedules
- Limited number of capable, trained design and layout engineers
- Larger Complexity and Scale… more activities in same schedule

One impacts the others

cadence

ML Based Layout Generation for Chip Design

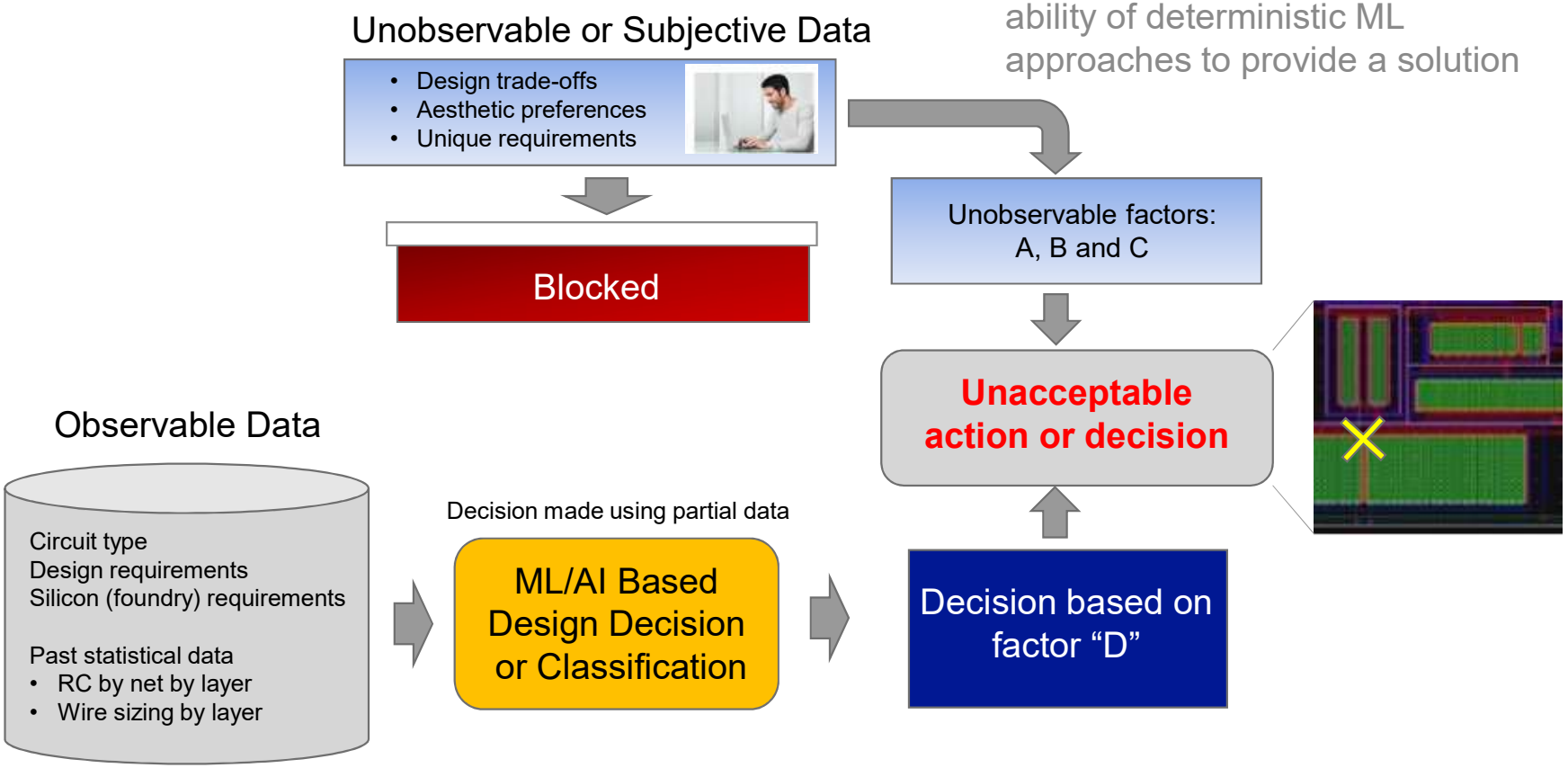
Today



Complexity of ML Based Design Decisions

Using Past Data for Future Design

Unobservable factors limit the ability of deterministic ML approaches to provide a solution



Why is This Problem So Difficult

- Decision processes like CAD/EDA systems are uncertain
- Environmental factors and circumstances that influence a user's decisions may be unobservable such as design intent or preferences
- Often process is dynamic… decision V may rely on prior decisions Q, R and S
- Often useful features that are observable but not labeled, requiring feature extraction or feature selection
- Cumulative effects yield uncertainty and that leads to error

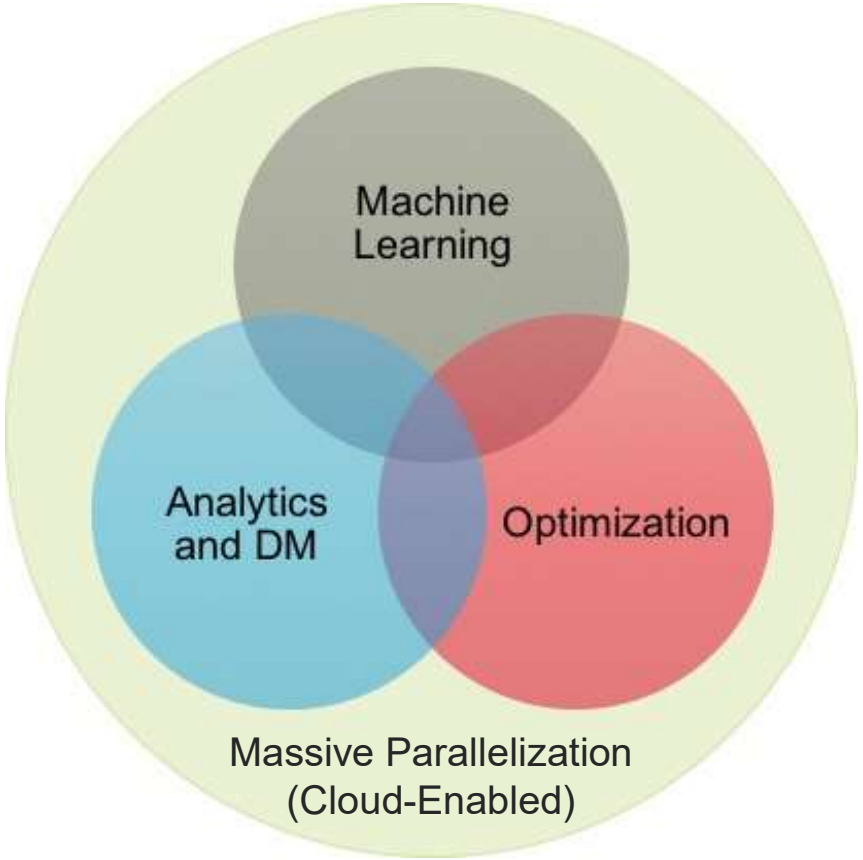
Potential Solution: Augmented Intelligence

Intelligent Systems Framework

Four Powerful Tools for Intelligent Design Solutions

Data Driven Problems Require More Intelligent Solutions

- Scale: more data needs to be processed in a shorter period of time
- Complexity: data driven machine learning models and analytics can capture complicated relationships
- Productivity: more analysis and verification during design, ensuring correct by construction and intent maintained throughout



Intelligent Solutions Apply to:

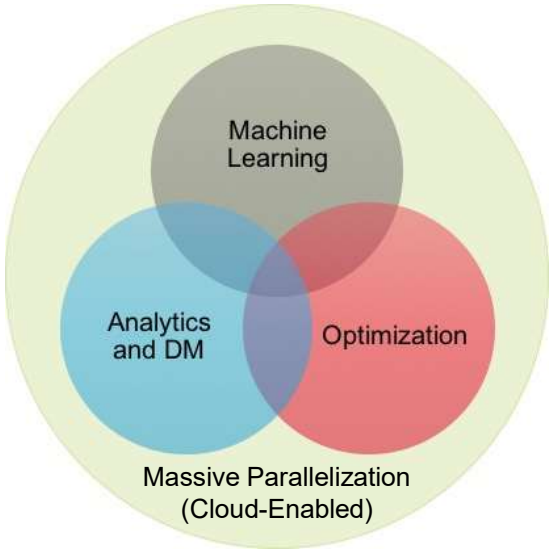
- Embedded Mobile
- IoT
- Cloud-based Services
- Scheduling/Logistics
- Transportation
- Finance

…and yes, CAD Systems

Design and Development of Intelligent Solutions

Data Driven Problems Require More Intelligent Solutions

How do we create software solutions from these tools



Steps in Producing Intelligent Solutions

Data Preparation

- Filter
- Label
- Augment
- Reduce
- Partition

Model Based Inference

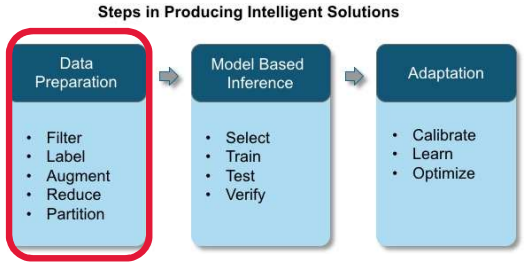
- Select
- Train
- Test
- Verify

Adaptation

- Calibrate
- Learn
- Optimize

Phase 1: Data Preparation

Data Driven Problems Require More Intelligent Solutions



Data Preparation

Filter

Goal:
Improve signal to noise

Examples:
- Bandpass
- Kalman Filter
- Wavelet
- FFT
- Wiener

Augment

Goal:
Create a more uniform set of data and remove bias

Examples:
- Normalize
- Pad
- Scale
- Rotate
- Threshold

Label

Goal:
Organize data for training and analysis

Examples:
- Tagging
- Clustering
- Hierarchical clustering
- Co-localization

Reduce

Goal:
Reduce dimensionality of input space with feature selection or extraction

Examples:
- PCA/KPCA
- LDA/GDA
- Wavelets
- Auto encoder

Partition

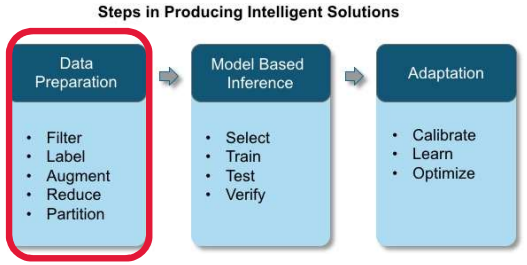
Goal:
Properly assess the quality and robustness of a predictive model

Examples:
- Training
- Testing
- Validation
- Verification
- K-fold CV

cadence

Phase 1: Data Preparation

Data Driven Problems Require More Intelligent Solutions



Data Preparation

Filter

Goal:
Improve signal to noise

Examples:
- Bandpass
- Kalman Filter
- Wavelet
- FFT
- Wiener

Augment

Goal:
Create a more uniform set of data and remove bias

Examples:
- Normalize
- Pad
- Scale
- Rotate
- Threshold

Label

Goal:
Organize data for training and analysis

Examples:
- Tagging
- Clustering
- Hierarchical clustering
- Co-localization

Reduce

Goal:
Reduce dimensionality of input space with feature selection or extraction

Examples:
- PCA/KPCA
- LDA/GDA
- Wavelets
- Auto encoder

Partition

Goal:
Properly assess the quality and robustness of a predictive model

Examples:
- Training
- Testing
- Validation
- Verification
- K-fold CV

cadence

Output of CNN Based Image Analysis

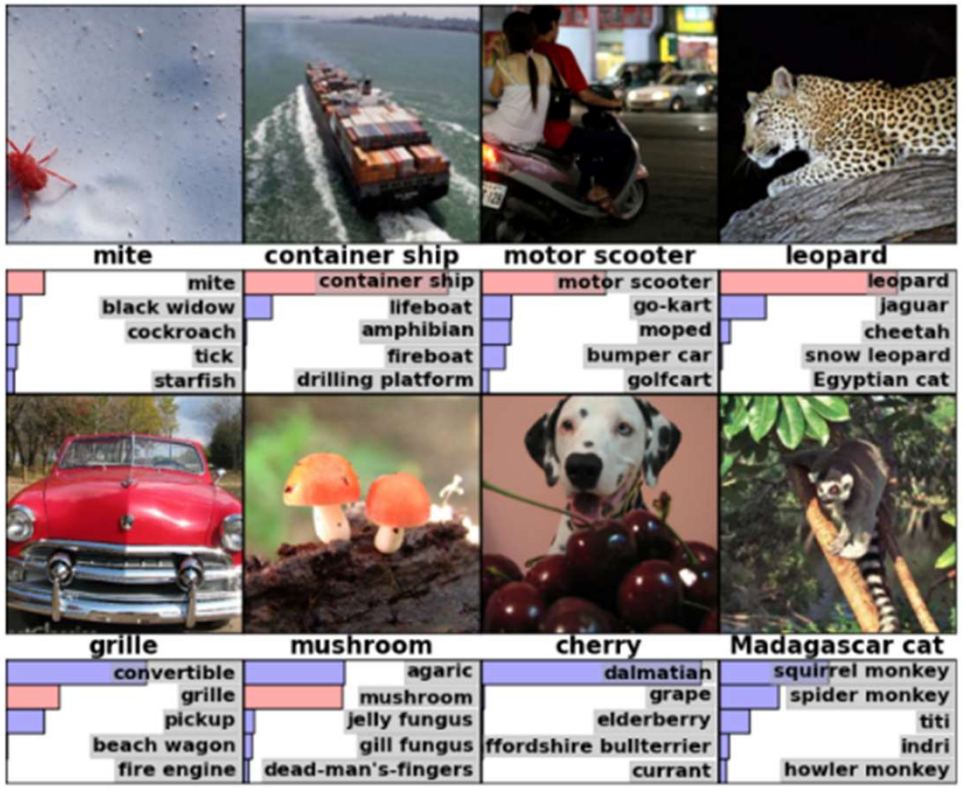
How you label and structure your training set heavily impacts results

Famous Example:

These results illustrate cases where the selection of the training data and label is important

Right Classification

Wrong Classification



The car is a convertible and has a grille, which is correct?

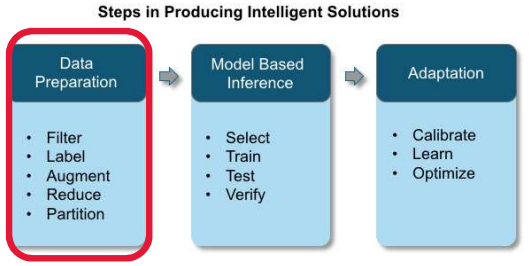
The photo is labeled as cherries but there's a Dalmatian in background

Farabet, Couprie, Najman, LeCun, "Scene Parsing with Multiscale Feature Learning, Purity Trees, and Optimal Covers", ICML 2012

cadence

Phase 1: Data Preparation

Data Driven Problems Require More Intelligent Solutions



Data Preparation

Filter

Goal:
Improve signal to noise

Examples:
- Bandpass
- Kalman Filter
- Wavelet
- FFT
- Wiener

Augment

Goal:
Create a more uniform set of data and remove bias

Examples:
- Normalize
- Pad
- Scale
- Rotate
- Threshold

Label

Goal:
Organize data for training and analysis

Examples:
- Tagging
- Clustering
- Hierarchical clustering
- Co-localization

Reduce

Goal:
Reduce dimensionality of input space with feature selection or extraction

Examples:
- PCA/KPCA
- LDA/GDA
- Wavelets
- Auto encoder

Partition

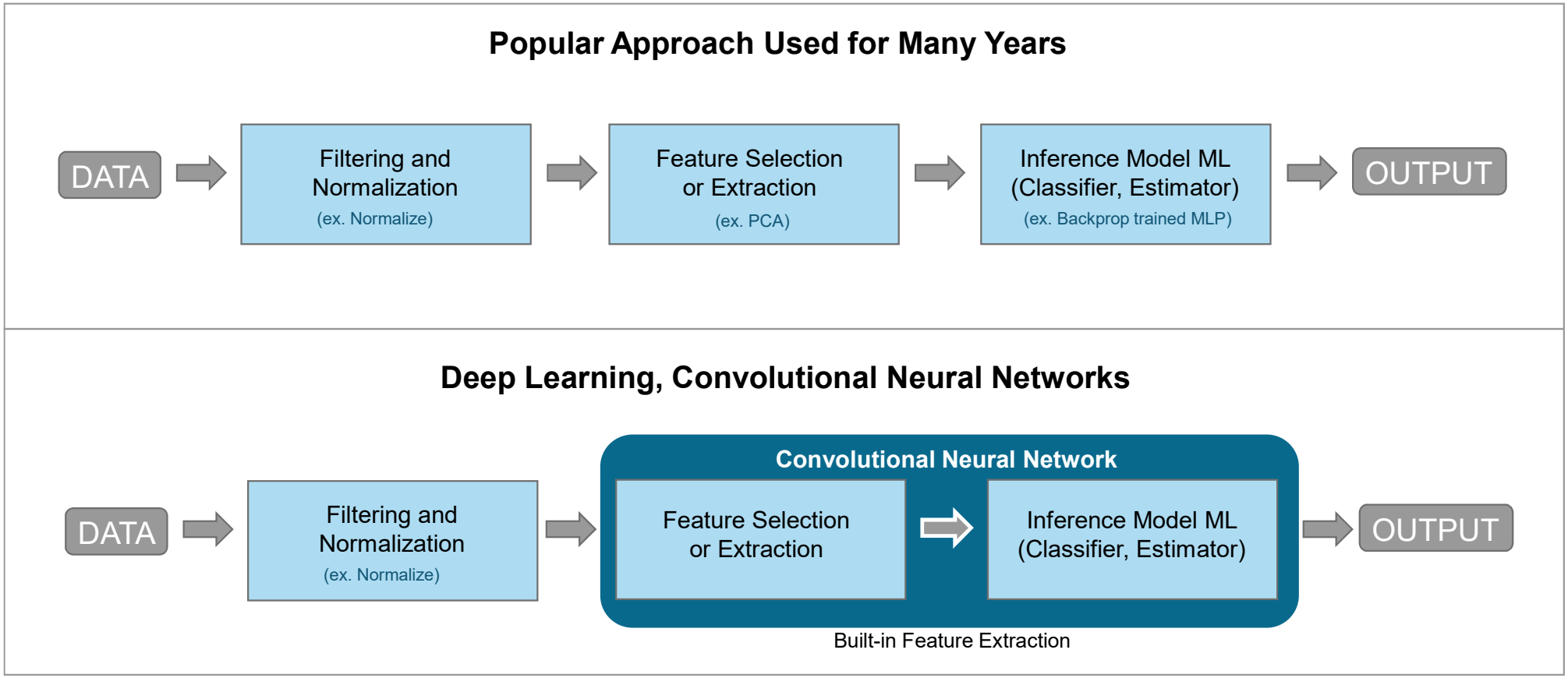
Goal:
Properly assess the quality and robustness of a predictive model

Examples:
- Training
- Testing
- Validation
- Verification
- K-fold CV

cadence

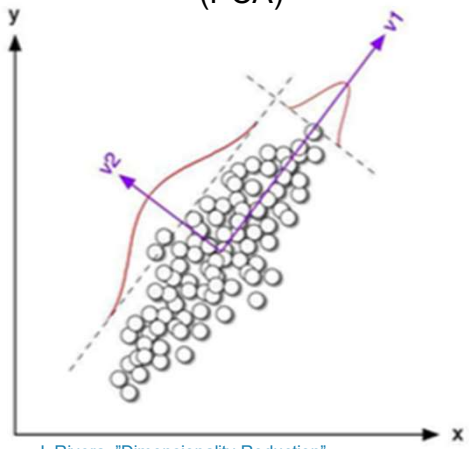
So How to Handle Large Dimensional Data

Feature Extraction and Dimensionality Reduction



Feature Extraction

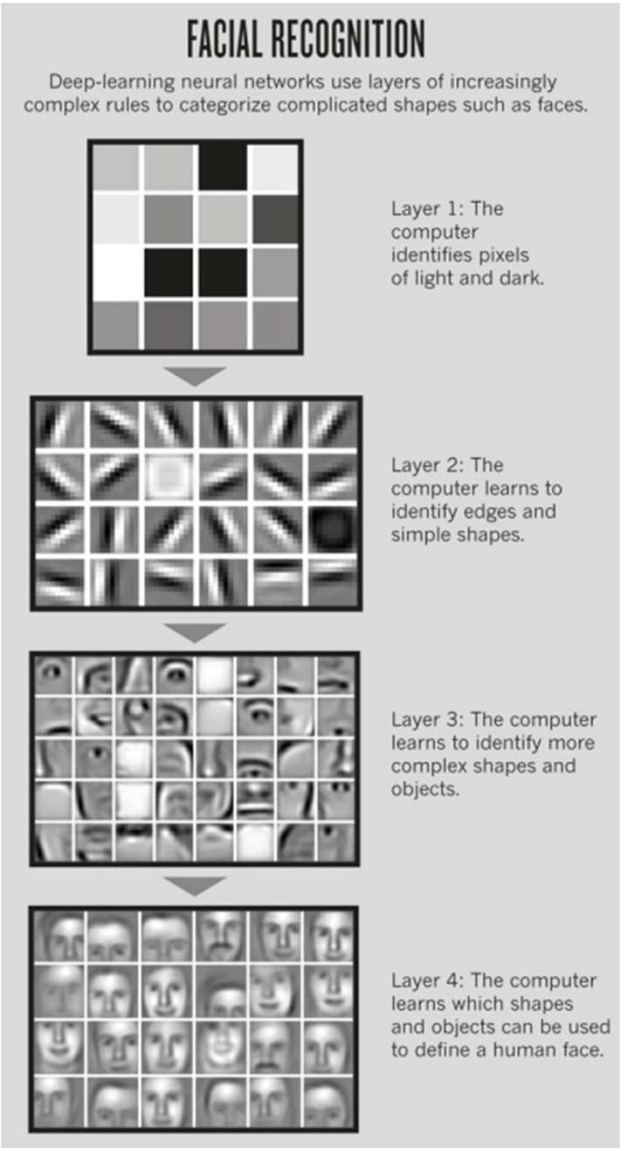
Principal Component Analysis (PCA)



J. Rivera, "Dimensionality Reduction", Course Notes, MAS 622J, 2010

- Data sampled from two variables (x,y)
- Can we reduce this to one variable?
- Find eigenvectors (v1,v2) of covariance matrix
- Observe that most of variance is captured by v1
- Multiply original x,y data onto 1st eigenvector (v1)
- New basis reduces dimension from 2 to 1

Different extremes of feature extraction



Deep Learning

Deep Learning (CNN) has Feature Extraction Built-in to Training

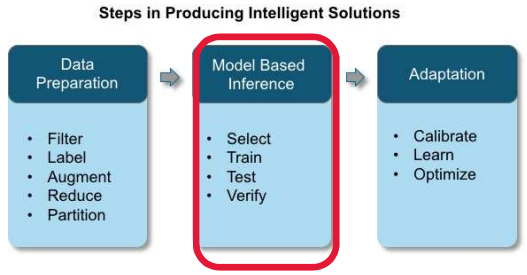
More on that later

Lee, H., et. Al, Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations , Proceedings of the 26th International Conference on Machine Learning, Montreal, Canada, 2009.

cadence

Phase 2: Model Based Inference

Data Driven Problems Require More Intelligent Solutions



Model Based Inference

Select

Goal:
Choose the right algorithm, architecture and parameters

Examples:
- Algorithms
- Architecture
- Parameters

Train

Goal:
Create an accurate model from data

Examples:
- Convergence
- Learning rate
- Momentum
- Dropout
- Regularization
- Boosting

Test

Goal:
Test and validation to ensure a robust and high quality model

Examples:
- Cross Validation
- K-fold CV
- LOO CV
- Hypothesis Test

Verify

Goal:
Verification of model within environment to ensure robustness

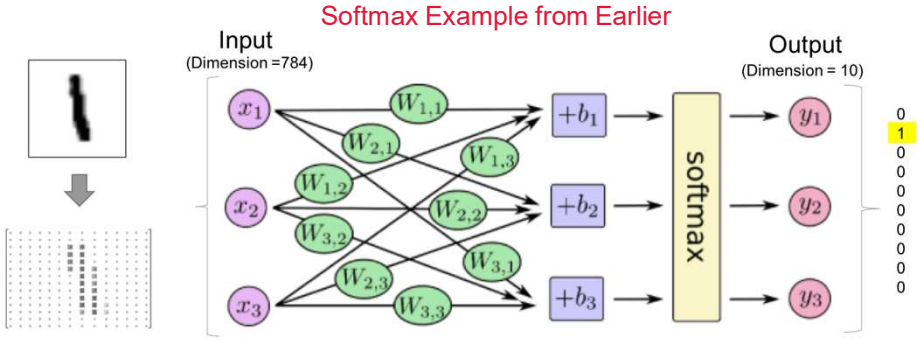
Examples:
- Perturbation
- Noise injection
- Environmental
- Quantization
- Stress tests

What is Deep Learning?

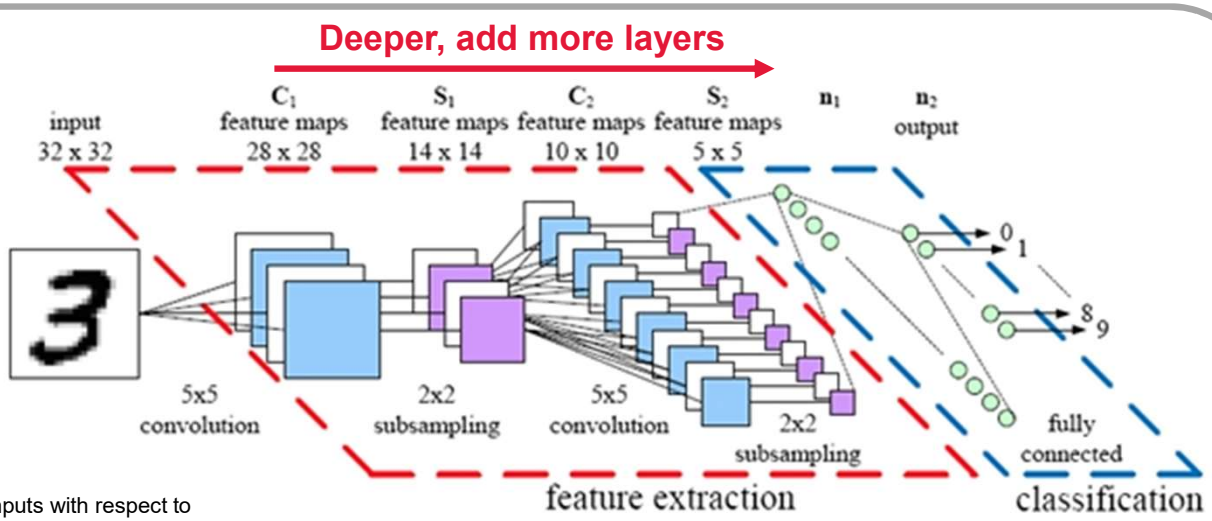
Deep refers to more layers

"Shallow Learning"
Softmax Neural Network

Softmax Example from Earlier



"Deep Learning"
Convolutional
Neural Network



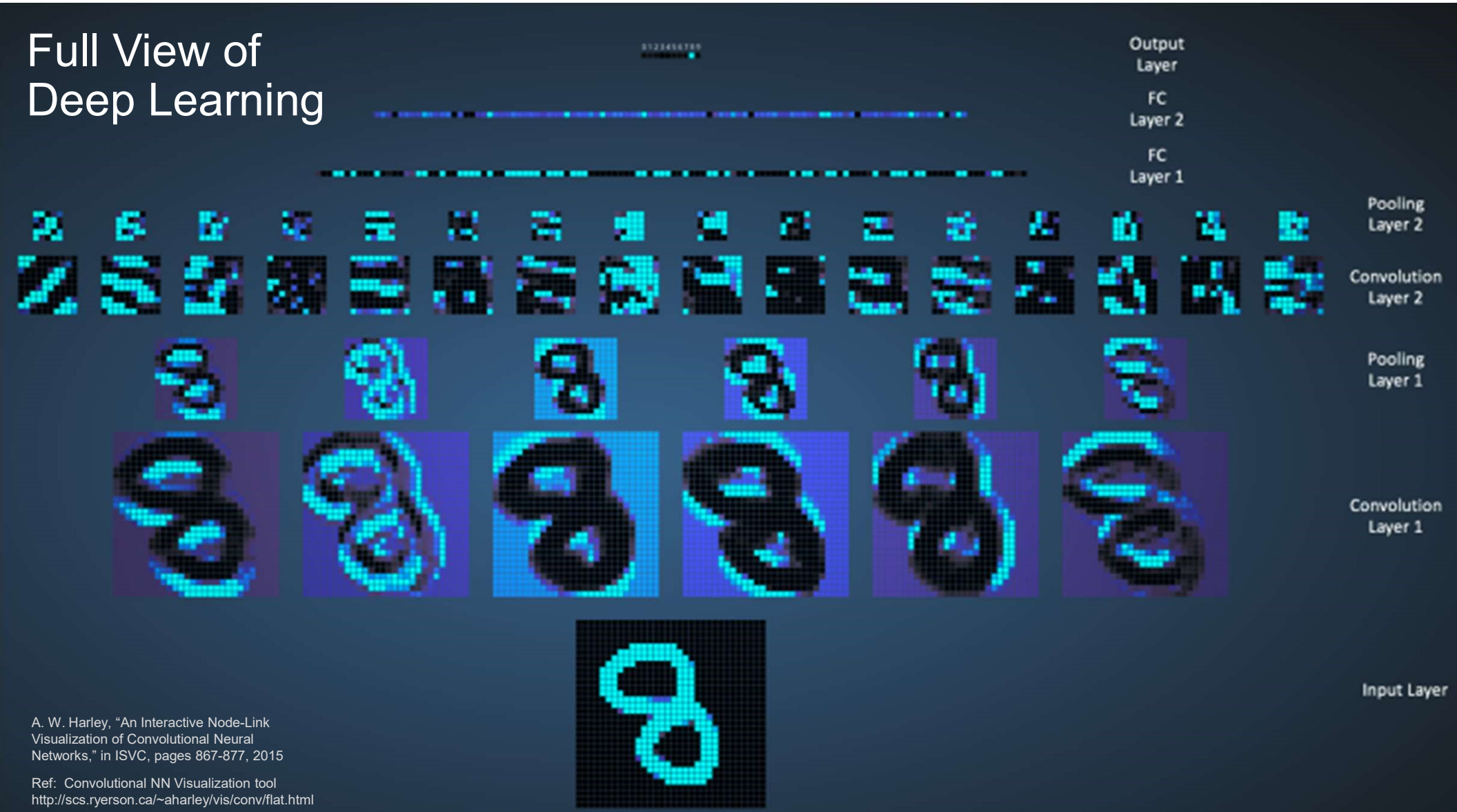
Localization of inputs with respect to inputs (pixels) through convolution

Reference: Tensor Flow Machine Learning Tutorial, Google-TensorFlow, https://www.tensorflow.org/versions/r0.9/tutorials/mnist/beginners/index.html

From: Efficient mapping of the training of Convolutional Neural Networks to a CUDA-based cluster, http://parse.ele.tue.nl/education/cluster2

cadence

Full View of Deep Learning

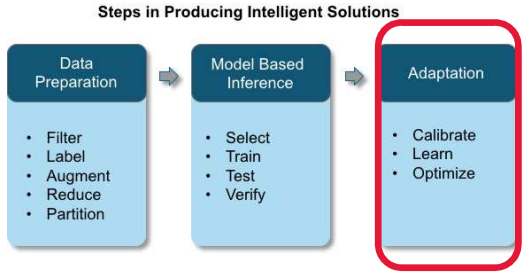


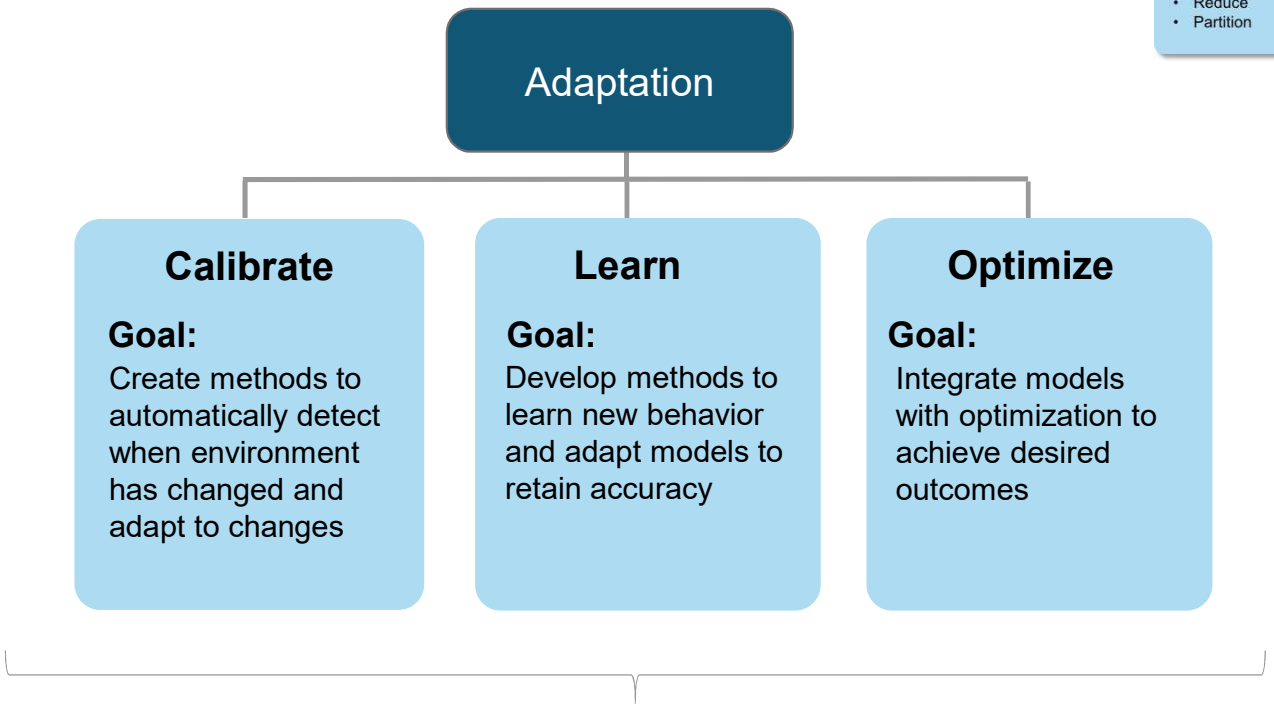
A. W. Harley, "An Interactive Node-Link Visualization of Convolutional Neural Networks," in ISVC, pages 867-877, 2015

Ref: Convolutional NN Visualization tool
http://scs.ryerson.ca/~aharley/vis/conv/flat.html

Phase 3: Adaptation

Data Driven Problems Require More Intelligent Solutions



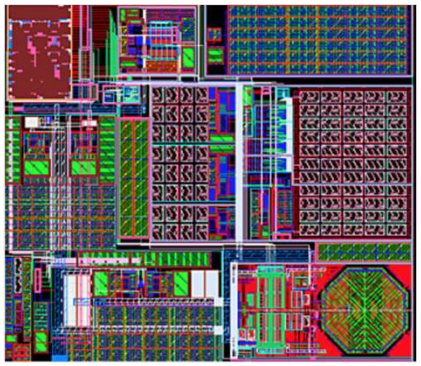


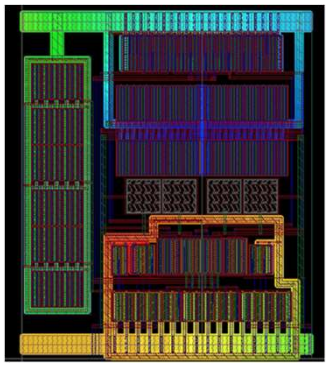
Augmented Intelligence:
Augment knowledge of the expert user using machine learning to recommend correct actions across sequential decisions in uncertain environments

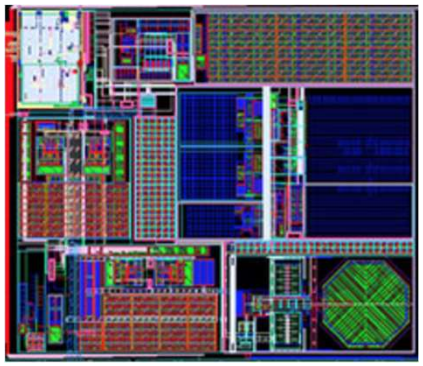
EDA Applications

Applications for Machine Learning in EDA

- Fast Models for Parasitic Extraction
- Hotspot Detection in Layout
- Place and Route
- Macro-models for Circuit Simulation







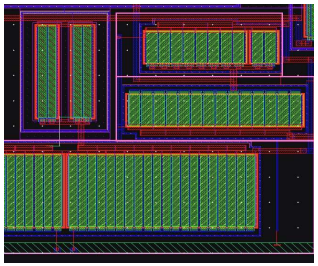
cadence

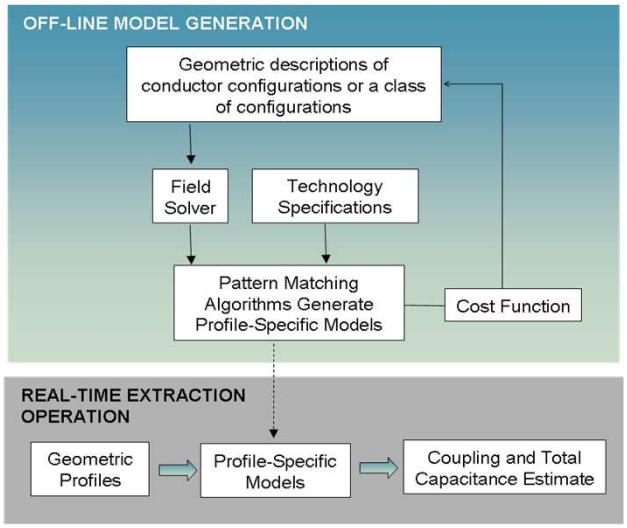
Machine Learning Used in Virtuoso EAD to Estimate In-Design Capacitance

Top part is done during tech-file creation at foundry

Incremental layout changes are made

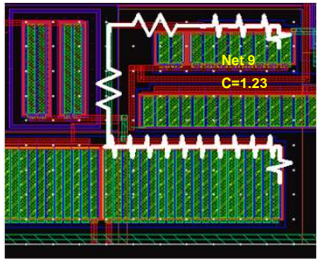
Canvas view



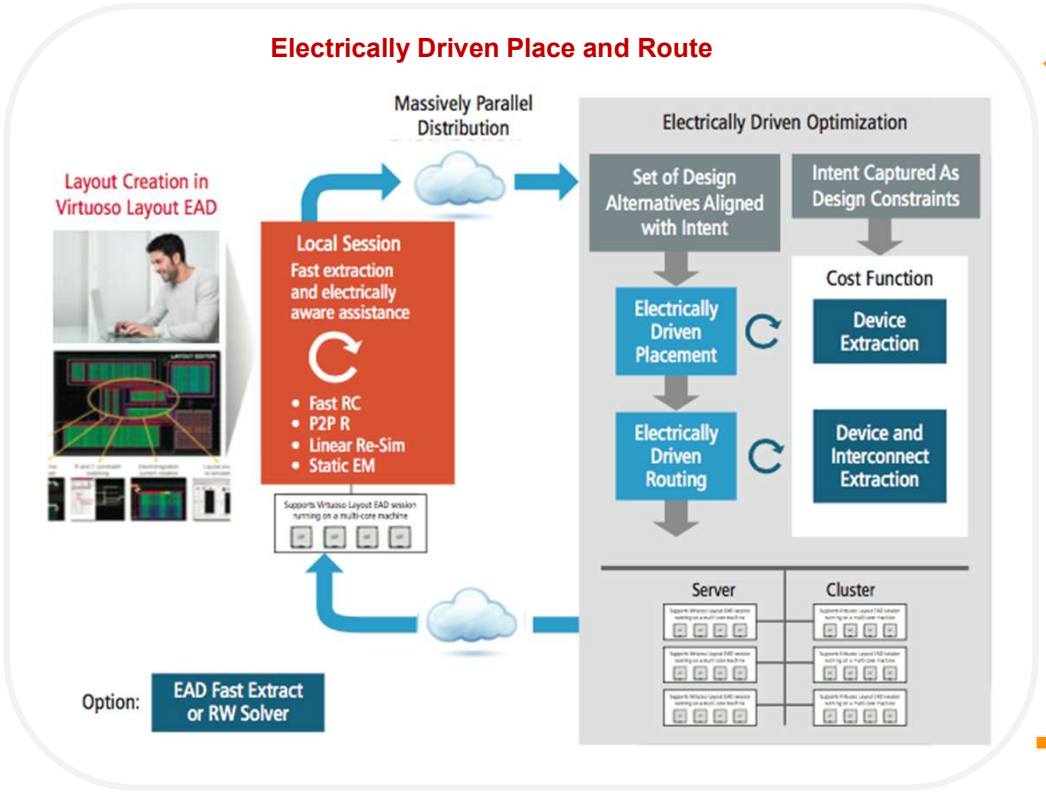


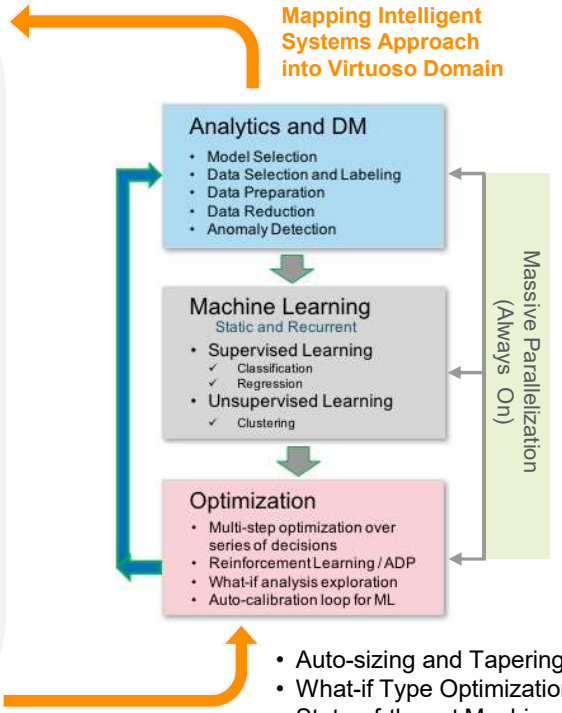
Extracted C parasitics estimated in real-time as each incremental change is made

Canvas view



Augmented Intelligence for Virtuoso





- Auto-sizing and Tapering of Wires
- What-if Type Optimization Across Corners
- State-of-the-art Machine Learning
- Combines Analytics, Machine Learning and Optimization with Massively Parallel Frameworks

Thank you!

QUESTIONS ?


cadence®