Get moving with CMC FPGA/GPU Cluster

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CMC MICROSYSTEMS

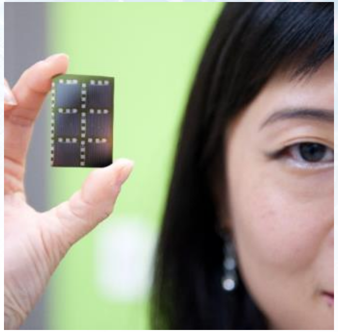
Agenda

- CMC Microsystems
- AI ML and DL: basic concepts
- CMC Cloud FPGA/GPU Cluster
  - HW architecture
  - SW Stack
- End-to-end Deep Learning platform
- Use Case : CNN architecture and training implementation using Caffe
- Live Demo
  - Training on Tesla V100 GPU
  - Inference on Alveo FPGA
- Q&A

CMC Microsystems

Lowering barriers to technology adoption

CMC Microsystems



The services provided by CMC are essential for the research and training required to advance the digital economy:

Industry 4.0, autonomous vehicles, big data, Internet of Things (IoT), cyber defence and security, 5G, quantum computing, artificial intelligence (AI)

Academic and Industrial Users

> Not for profit – federally incorporated 1984

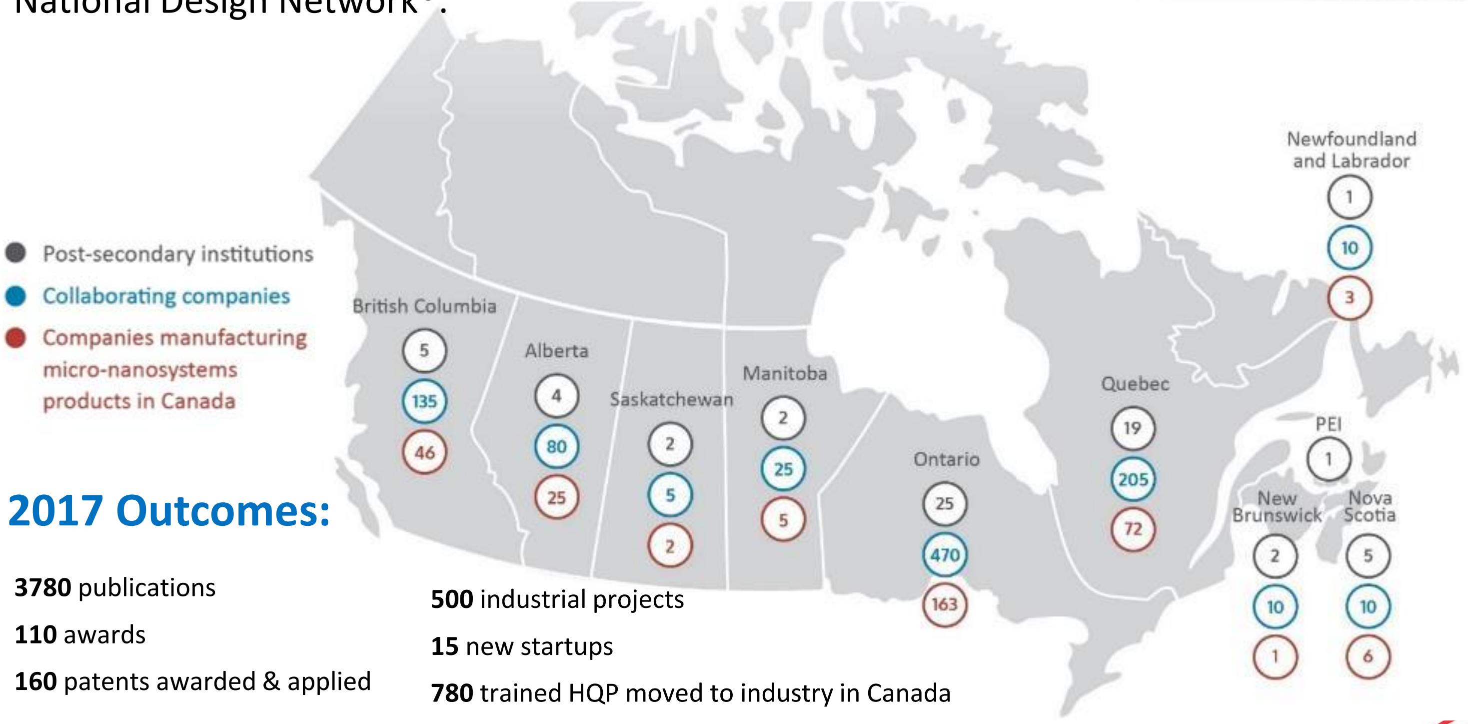
> Manages Canada's National Design Network®

> Delivers micro-nano innovation capabilities

CMC

Canada’s National Design Network®

A Canada-wide collaboration between **66** universities/colleges to connect **10,000** academic participants with **950** companies to design, make and test micro-nanosystem prototypes. CMC Microsystems manages Canada’s National Design Network®.



Annually:

1200 connected professors

4200 researchers on professors’ teams

5700 users of computer aided design tools

300 physical prototypes

80 test equipment loan items otherwise unaffordable to users

2017 Outcomes:

3780 publications

110 awards

160 patents awarded & applied

500 industrial projects

15 new startups

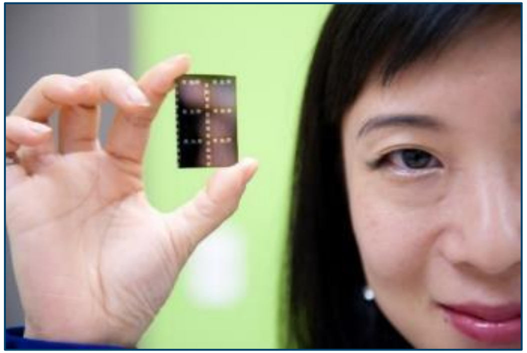
780 trained HQP moved to industry in Canada

CMC

Lowering Barriers to Technology Adoption

CMC delivers key services to increase researchers' and companies' innovation capability in Canada:

- ➢ Design tools (software)
- ➢ Fabrication services to create working prototypes
- ➢ Equipment and services for prototype testing
- ➢ Platform technologies
- ➢ Training, support, networking
- ➢ Technology plan and roadmap

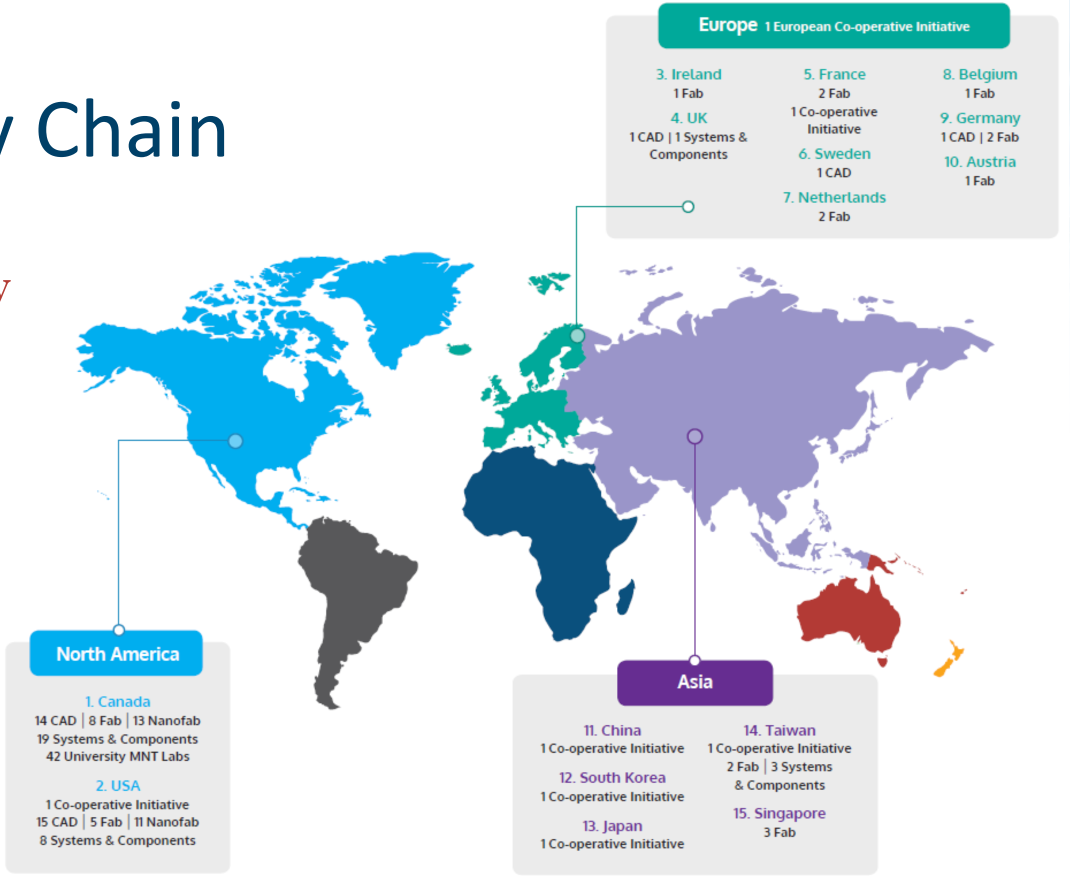


CMC

Industrial Supply Chain

CNDN - Engaging strategically in Canada and worldwide

Global partnerships to support research excellence in Canada



info@cmc.ca

Discover, Collaborate, Connect

Make CMC your partner on the path to R&D and commercialization

> Industrial Supply Chain - *engaging strategically*

> R&D collaborations - *accelerating projects*

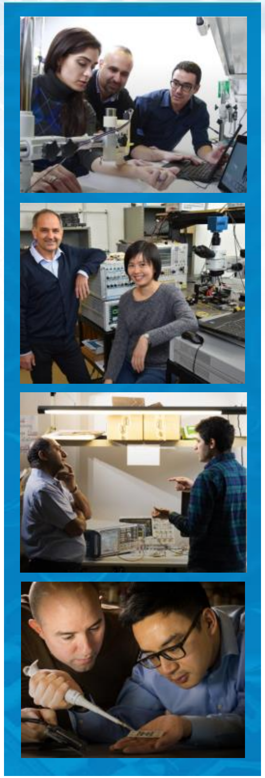
> Services for emerging processes and products - *connecting to early adopters*

> SponsorChip - *enhancing your research efforts*

Products & services: keeping researchers at the leading edge

> CAD - FAB - LAB - and more…

> Visit: www.cmc.ca/SuccessStories



From idea to manufacturable prototype

CAD

State-of-the-art environments for successful design

- Selection of high-performance Computer Aided Design (CAD) tools and design environments
- Available via desktop or through CMC Cloud
- User guides, application notes, training materials and courses

CMC.ca/CAD

FAB

Services for making working prototypes

- Multi-project wafer services with affordable access to foundries worldwide
- Fabrication and travel assistance to prototype at a university-based lab
- Value-added packaging and assembly services
- In-house expertise for first-time-right prototypes

CMC.ca/FAB

LAB

Device validation to system demonstration

- Access to platform-based microsystems design and prototyping environments
- Access to test equipment on loan
- Access to contract engineering services

CMC.ca/LAB

CAD

State-of-the-art environments for successful design | www.cmc.ca/CAD

CAD

Over 500 CAD tools and modules

Over 5000 individual users annually

PDK, training, support

AND MORE…

FAB

Services for making working prototypes | www.cmc.ca/FAB

25

multi-project wafer services available through nine foundries worldwide, offering industrial-scale manufacturing

Global supply chain

> Advanced technology access to **microelectronics, photonics, optoelectronics, MEMS, microfluidics, and embedded systems technology** including TSMC, GlobalFoundries, AMF, IBM, and STMicroelectronics.

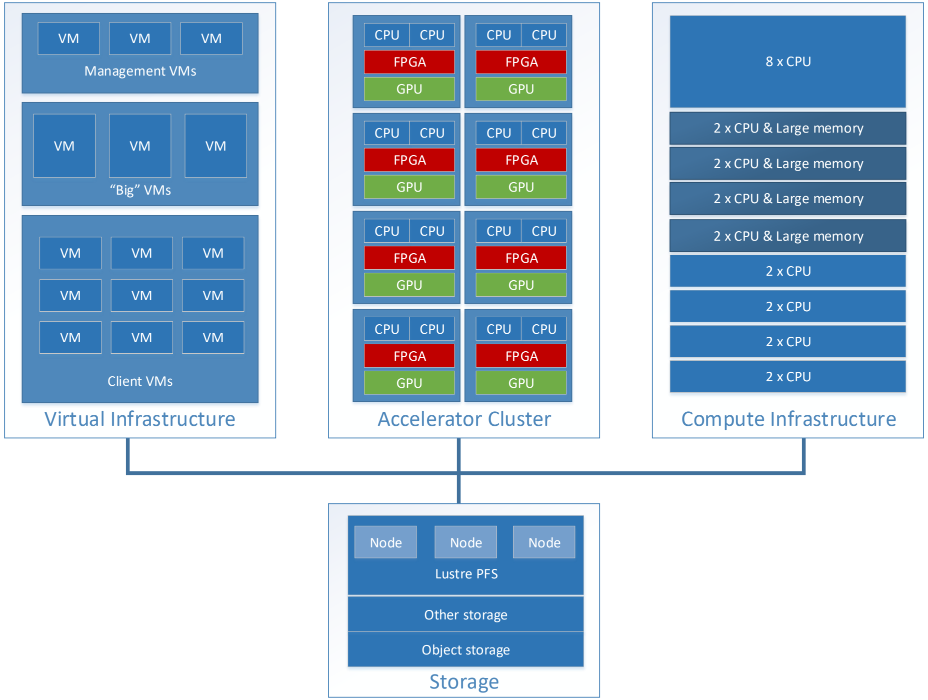
> CMC is channel partner for GlobalFoundries in North America.

AND MORE…

LAB

Device validation to system demonstration | www.cmc.ca/LAB

CMC Cloud:
Unified Architecture

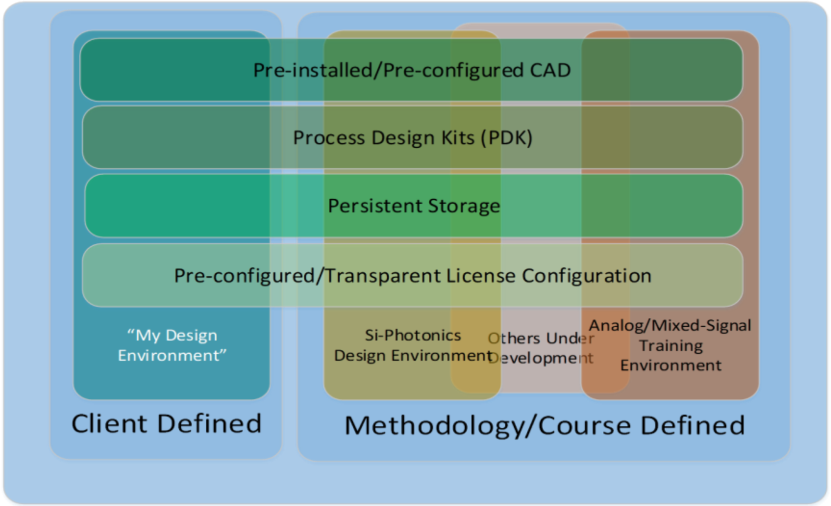


Seamless Transition Between Environments

- **CAD** - Design using CMC Cloud desktop
- **FAB** - Simulate on the CAD Compute cluster
- **LAB** - Prototype on the FPGA+GPU cluster

CMC Cloud: Design Environments

CMC Cloud provides researchers with secure, high-performance, remotely accessible EDA resources for design of advanced microsystems and nanotechnologies.



No local CAD server available?

- Complex design tools (e.g. Cadence, Mentor, Synopsys), scripts and licensing pre-configured and ready

High quality server infrastructure

- Enterprise grade server infrastructure being using to run the tools in CMC Cloud

Time from concept to using tools

- After you discover you need to use a tool, with CMC Cloud you can be fully utilizing the tools within minutes

Immediate access to design flows

- Design flows are **developed** and **supported** by CMC engineers

www.cmc.ca/CMCCloud

CMC Cloud “mini”-HPC Cluster for CAD

Speed up your simulations

- CMC engineers provide assistance in utilizing the infrastructure as well as domain knowledge on utilizing HPC infrastructure
- Documentation/reference designs available for ANSYS, COMSOL, Xilinx and more
- Uniform array available in standard and large memory configurations

CAD Compute Cluster – *8 nodes*

- Dual 16-core 2.1-.3.7 GHz CPU
- 4 nodes each with 384GB RAM
- 4 nodes each with 768GB RAM
- 300GB local storage
- 100Gb EDR node interconnect / 10GbE storage

CMC Cloud FPGA/GPU Cluster

- CPUs, GPUs and FPGAs in pre-validated cluster to scale heterogenous computing workloads
  - Machine learning training and inference (e.g. CNN for object detection, speech recognition)
  - Video Processing / Transcoding, Financial Computing, Database analytics, Networking
  - Quantum chemistry, molecular dynamics, climate and weather, Genomics
  - RISC-V Accelerators in Open Source Cloud Computing

Cluster HW

FPGA/GPU cluster Specifications

Cluster Configuration

Environment	Description	# Nodes
Accel - Cerebro	2 Alveo FPGA U200	3
Accel - Genisys	2 V100 GPUs	3
Accel - Synergy	1 Alveo FPGA U200 1 V100 GPU	2

1 Node Specifications

Dual 12 core 3.0 GHz CPU
192 GB RAM
300 GB local storage
100 Gb EDR node interconnect
10 GbE storage network

Research in the public cloud

CMC Microsystems offers members of the Cadence® University Software Program access to leading-edge technology through the Cadence Cloud Passport program

Cloud Passport:

> Cadence in public cloud

> Fully configured and installed:
on-demand, continuous software updates, zero admin costs

> Access high-performance design lab anywhere

Related CMC Services:

> Training courses, webinars, and documentation

> PDKs from CMC suppliers

> CMC's fabrication services (DRC and MPW)

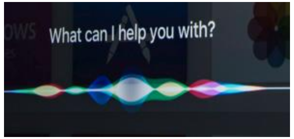
> Cadence license management

AI ML and DL

AI: Area of Specialization

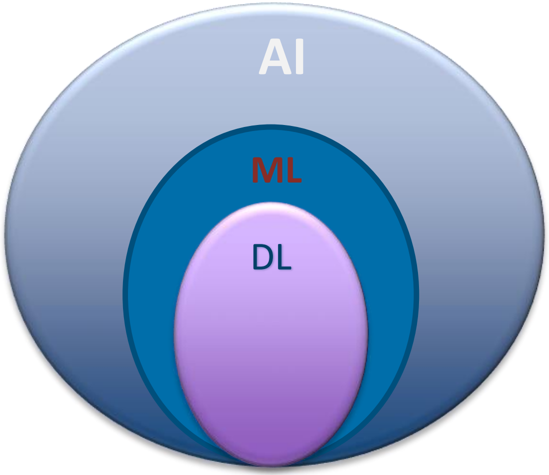
- Transforming almost every business
- Exploding ecosystem of tools, making it more accessible to even non-experts
- Area of Specialization
  - Gaming
  - Natural Language Processing
  - Computer Vision
  - Robotics
  - Autonomous Cars
  - …



AI and Machine Learning

AI: The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages. *–Source oxfordreference.com*



- **AI: Artificial Intelligence**
  - Sense, reason, act and adapt
- ML: Machine Learning
  - Algorithms that improve as they are exposed to data over time
- DL: Deep Learning
  - Multilayered neural networks learn from vast amounts of data
- **DL Training:**
  Using a set of training sample data to determine the optimal weights of the artificial neurons in a DNN.
- **DL Inference:**
  - Analyzing specific data using a previously trained DNN.

Source: What's the Difference Between Artificial Intelligence (AI), Machine Learning, and Deep Learning? by Glenn Evan Touger

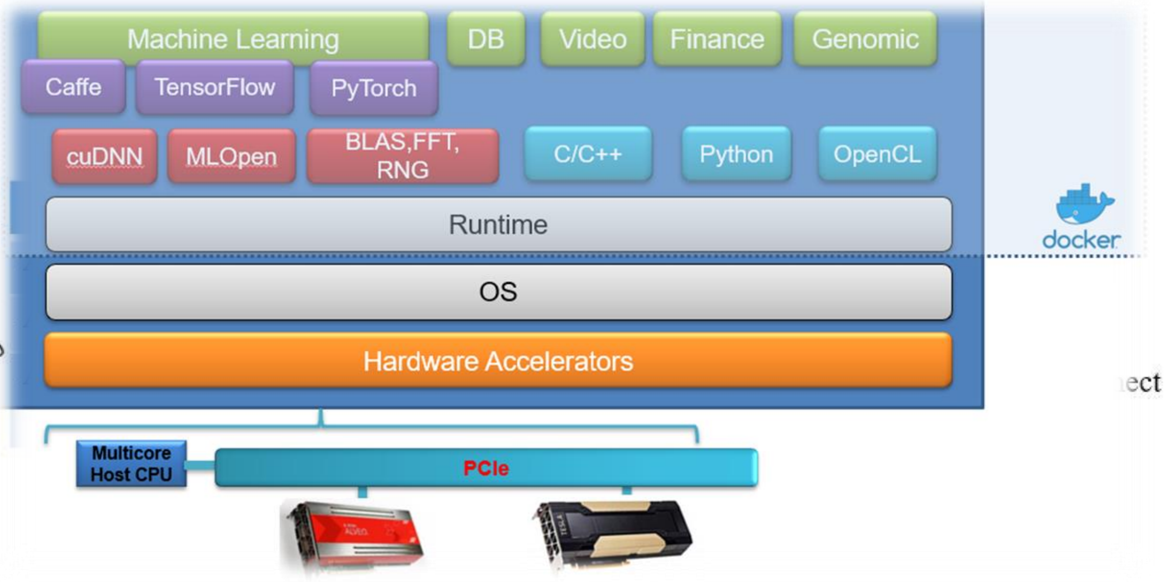
- After a neural **network** is trained, it is deployed to run **inference**:
  - to classify, recognize, and process new inputs.

Rise in popularity of deep learning

- Key enablers:
  - Greater availability of large data sets, containing more training examples
  - Availability and Efficient use of accelerators such as GPUs, FPGAs and custom hardware such as Tensor Processor to train deep learning models
  - New ML techniques (Deep Neaural Networks) and Open source machine learning flow, as well as ML libraries

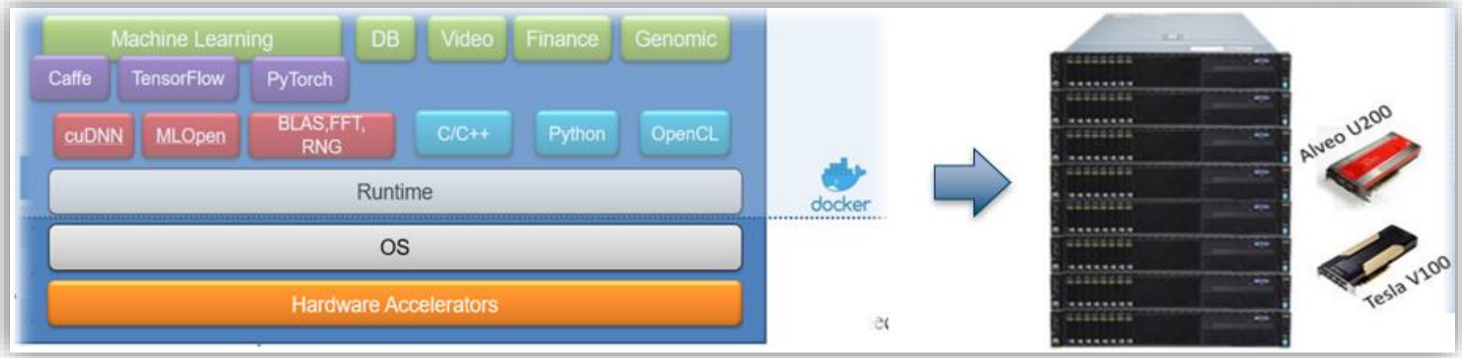
FPGA/GPU cluster HW and SW Specifications

CMC Cloud FPGA/GPU Cluster



Machine Learning
DB
Video
Finance
Genomic
Caffe
TensorFlow
PyTorch
cuDNN
MLOpen
BLAS,FFT, RNG
C/C++
Python
OpenCL
Runtime
docker
OS
Hardware Accelerators

Alveo U200
Tesla V100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Alveo U200
Tesla V100

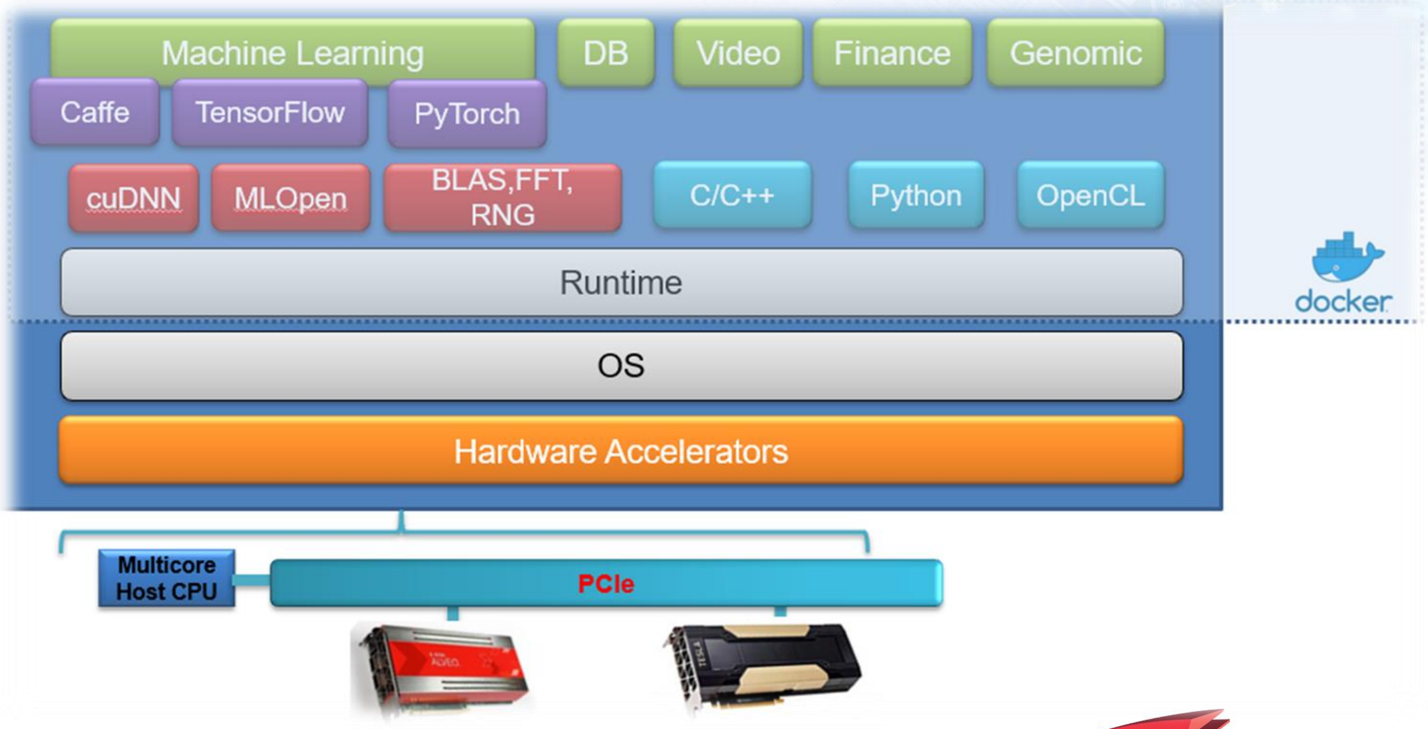
Software stack for the FPGA/GPU cluster

Applications

ML Framework

Middleware,
Tools and Libraries

Hardware



End-to-end Deep Learning platform

Desktop

1

Prototype

FPGA/GPU cluster

2

Training

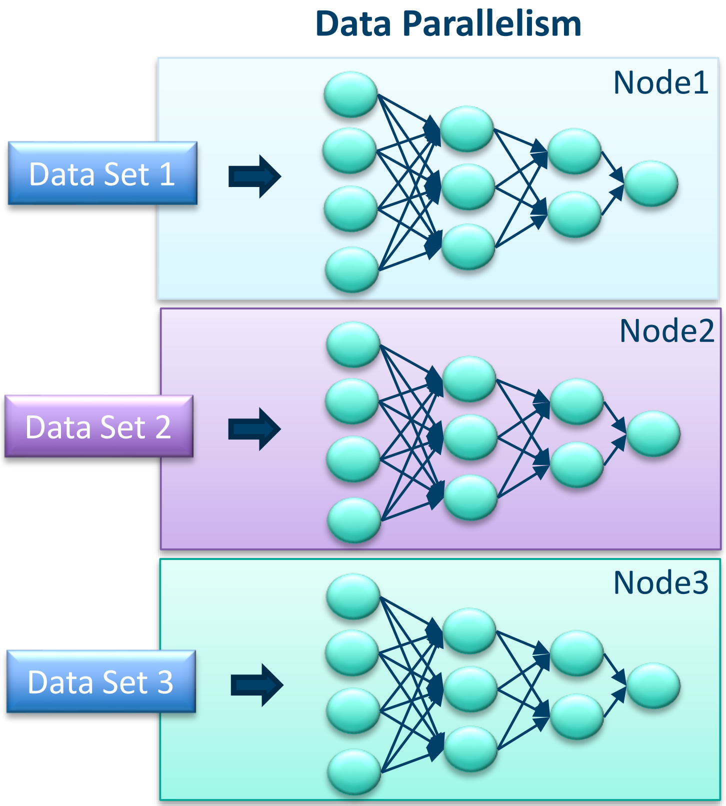
FPGA/GPU cluster

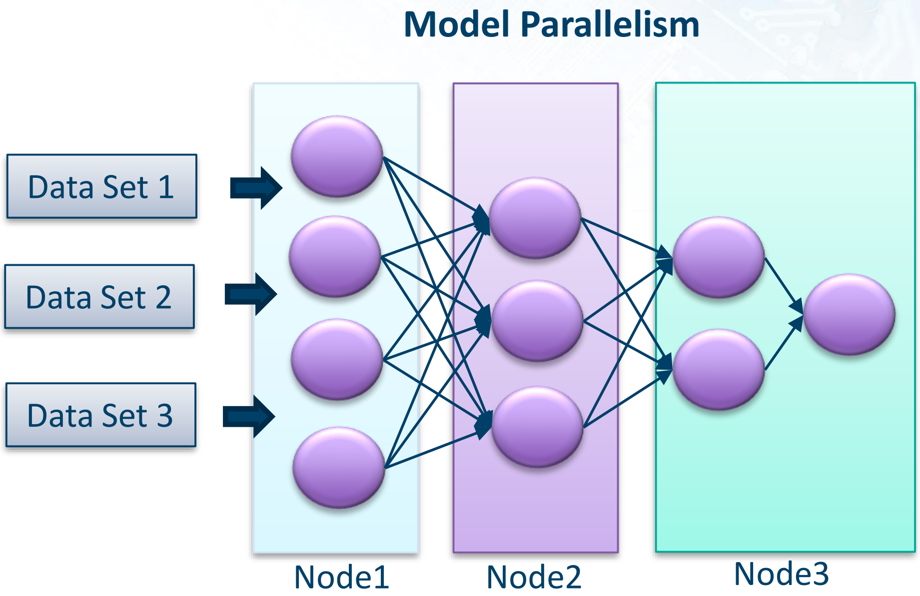
Embedded System

3

Inference

Scale-out for Training and Inference





Cluster HW

Cluster Configuration

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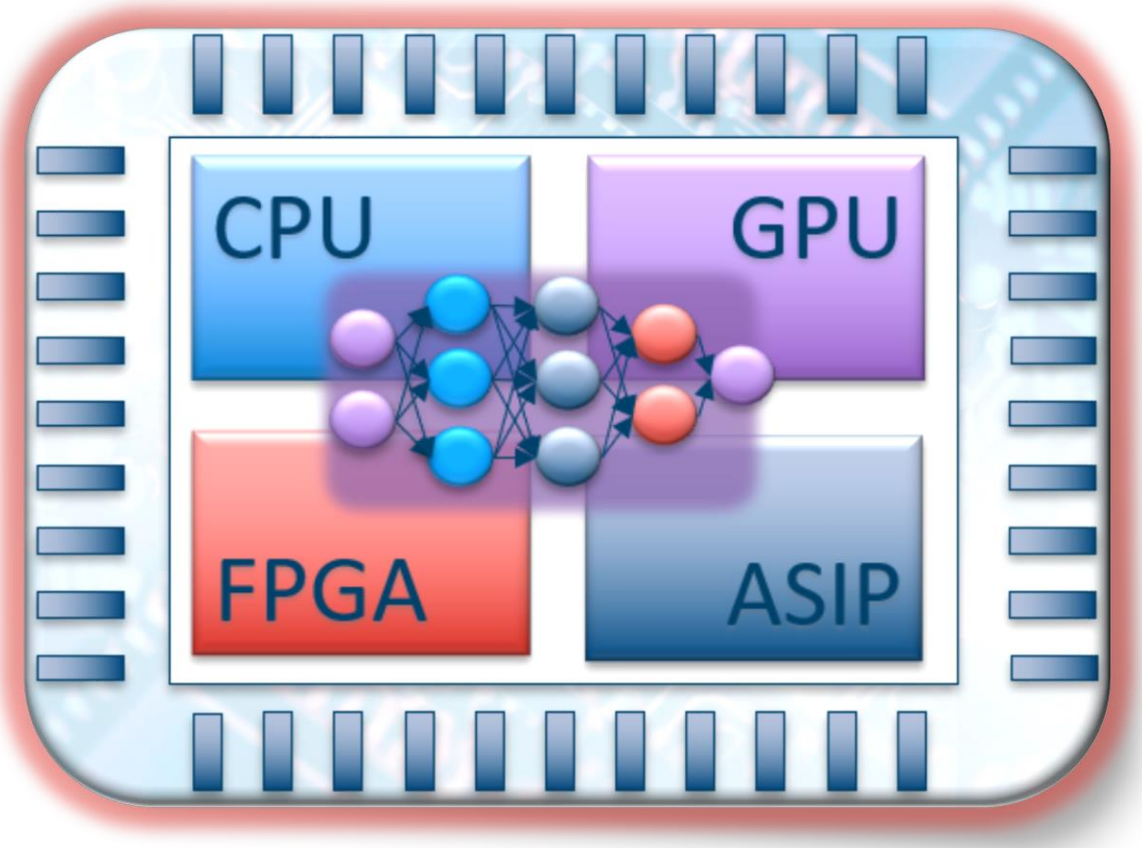
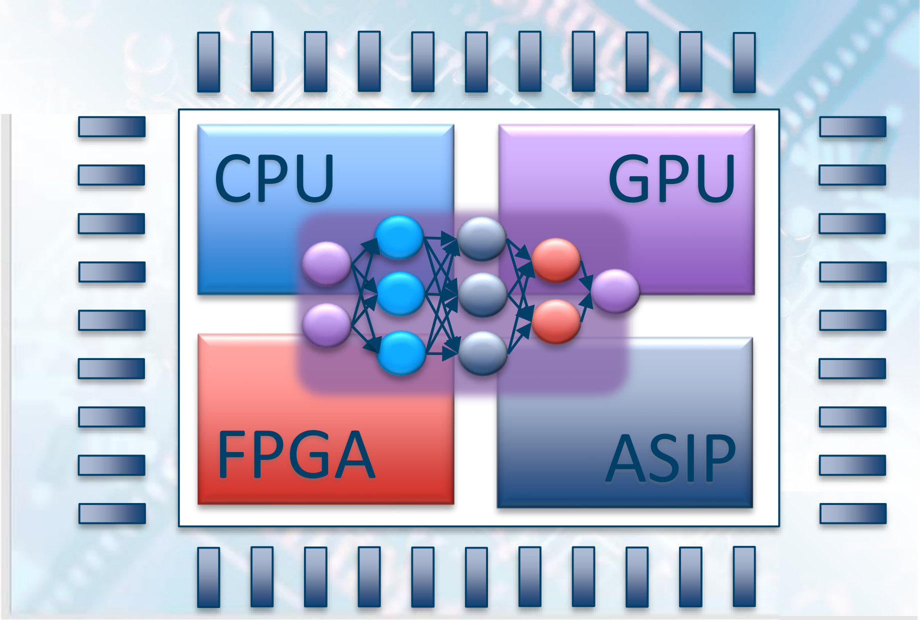
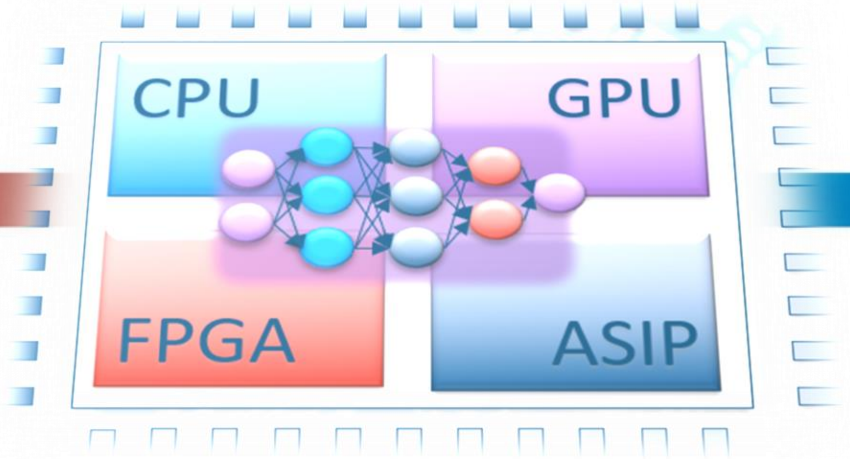
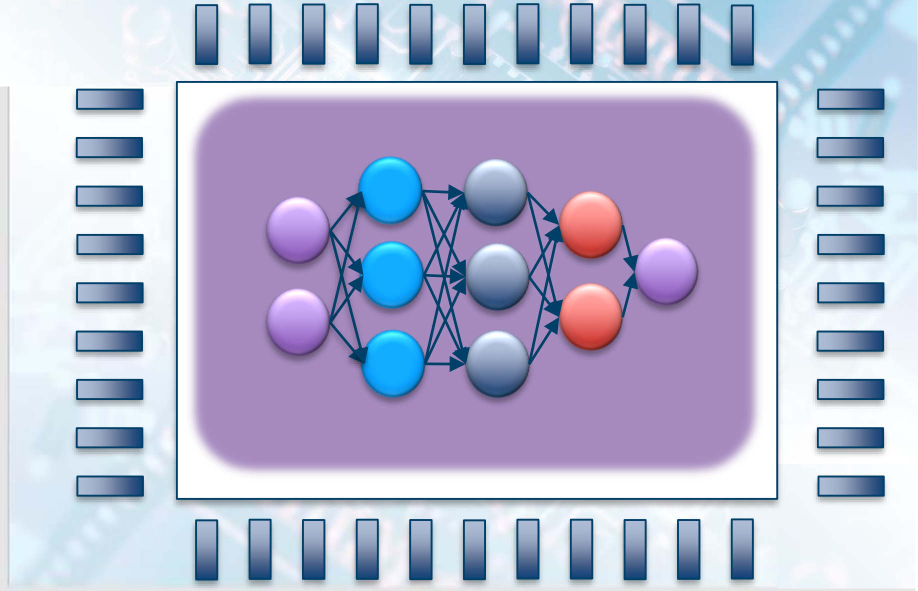

CPU
GPU
FPGA
ASIP


CPU
GPU
FPGA
ASIP


CPU
GPU
FPGA
ASIP



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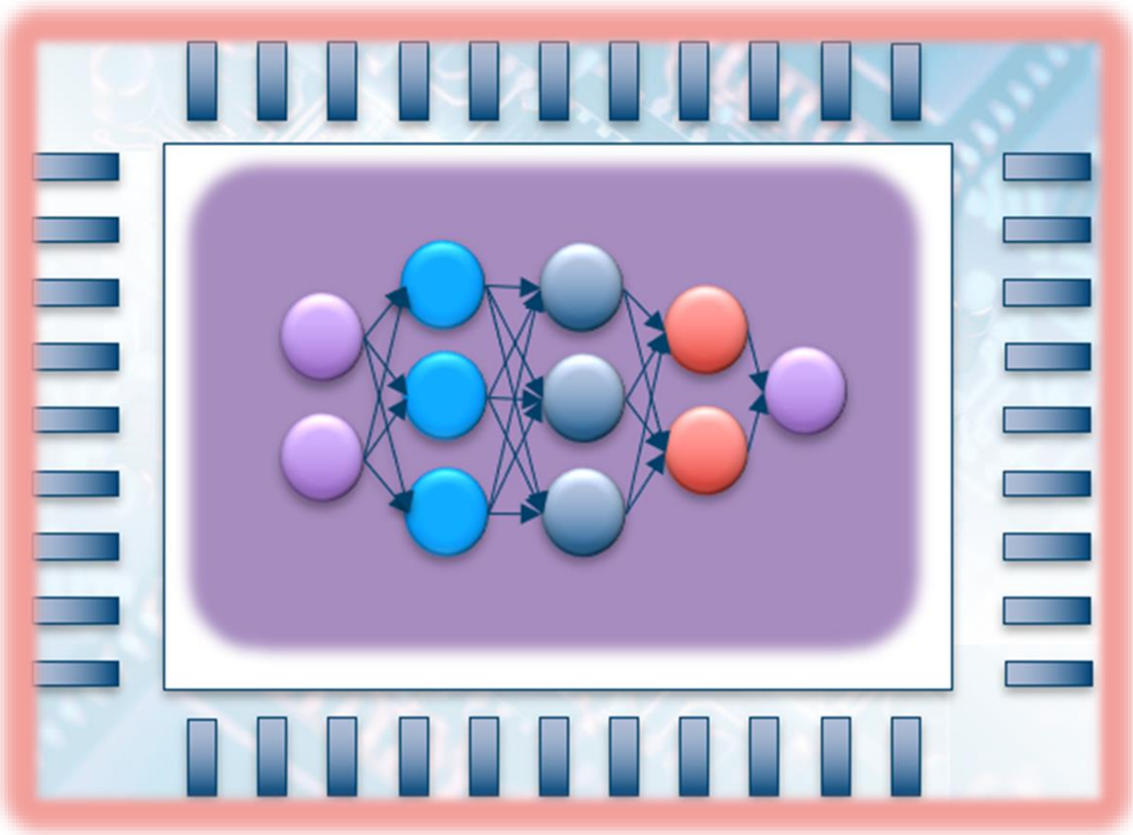
AI SoC

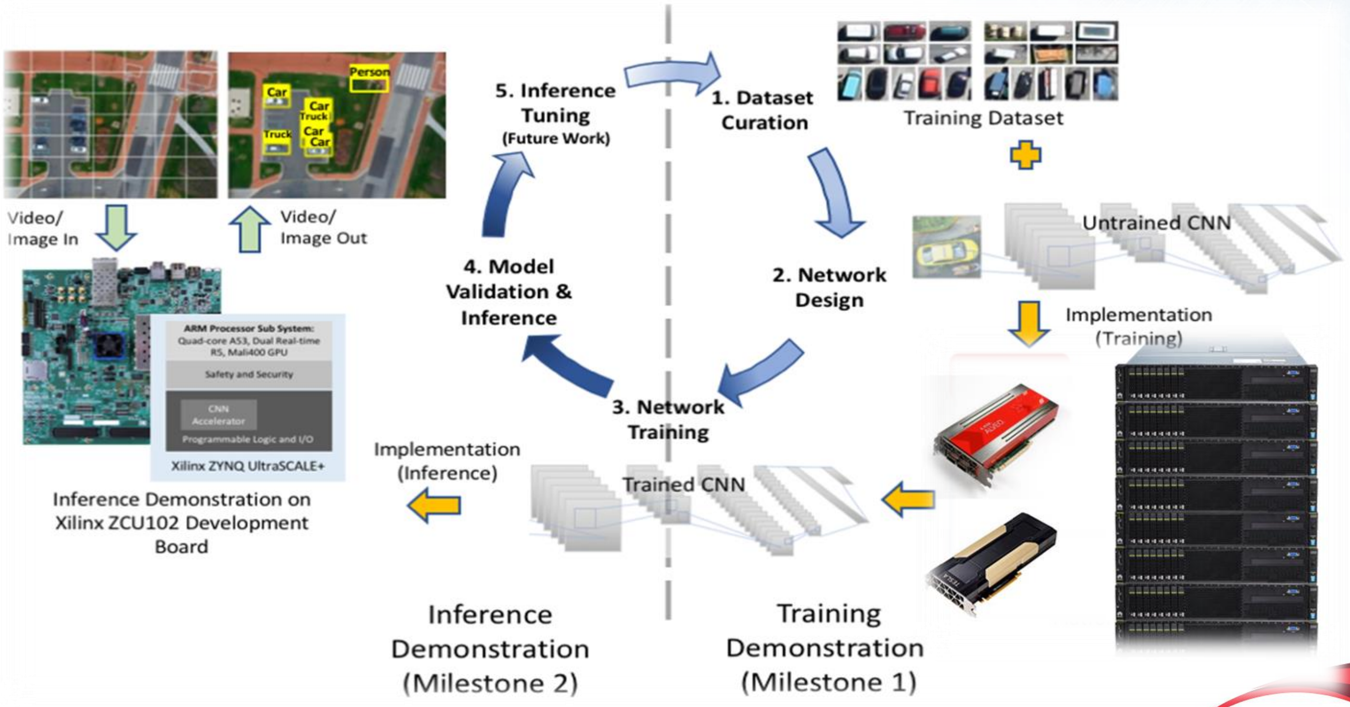


End-to-end Deep Learning platform

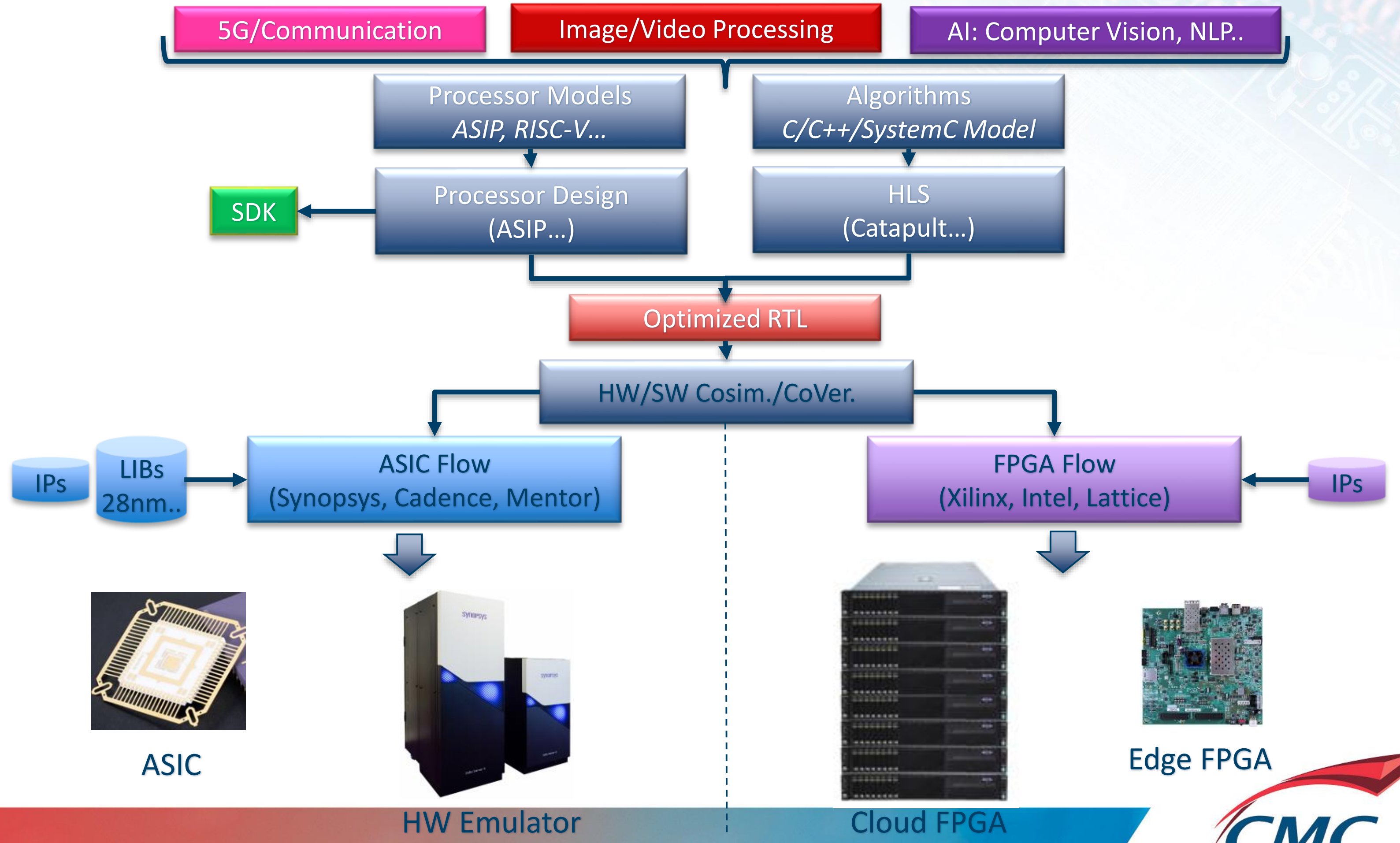
Use case

Innovation for Defence Excellence and Security (IDEaS)

A Novel Platform of Artificial Intelligence-based Object Detection, Classification and Tracking Using Heterogeneous Computing Architectures.



A Unified Design Flow for Advanced Computing Platforms

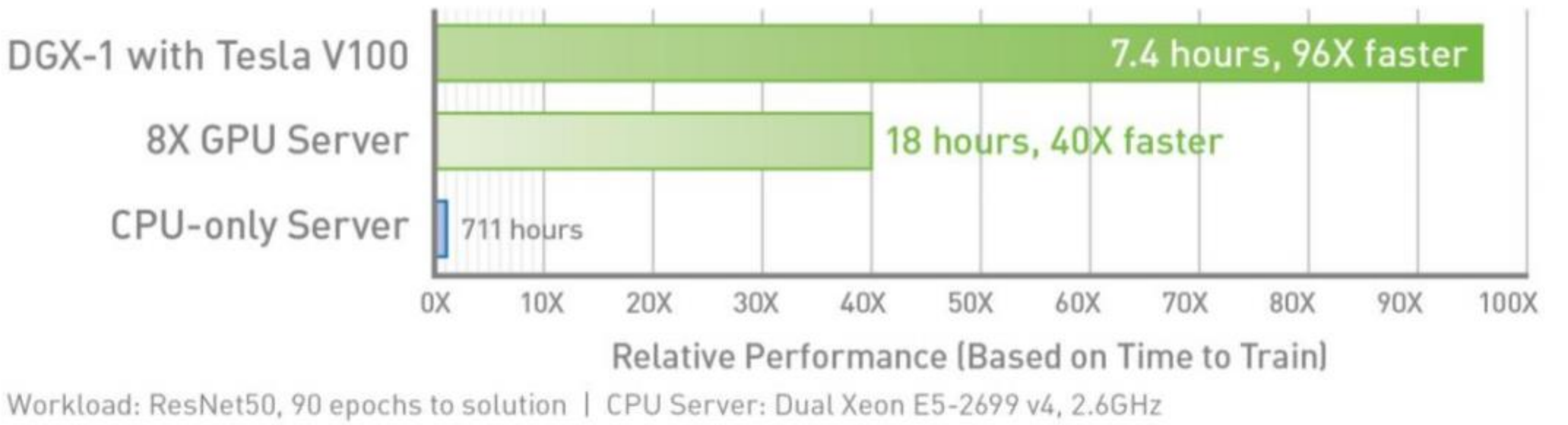


Alveo workloads acceleration

AREA	PARTNER WORKLOAD	ALVEO ACCELERATION VS CPU
Database Search and Analytics	BlackLynx Unstructured Data Elasticsearch	90X
Financial Computing	Maxeler Value-at-Risk (VAR) Calculation	89X
Machine Learning	Xilinx Real-Time Machine Learning Inference	20X
Video Processing / Transcoding	NGCodec HEVC Video Encoding	12X
Genomics	Falcon Computing Genome Sequencing	10X

Ref. Product Brief Xilinx Alveo U200 & U250

Tesla V100 Acceleration



Ref. NVIDIA TESLA V100 GPU ARCHITECTURE

CAFFE Framework

Basic concepts

Caffe features
Data pre-processing and management

$CAFFE_ROOT/build/tools

Data ingest formats

- LevelDB, LMDB database
- HDF5
- Image files

Pre-processing tools

- LevelDB/LMDB creation from raw images
- Generation of the Mean-image
- Training and validation set creation with shuffling

Data transformations

- Image cropping, resizing, scaling and mirroring
- Mean subtraction

Caffe features
Deep Learning model definition

- Protobuf model format:
  - Developed by Google
  - Method of serializing structured data
  - Human readable
  - Used to define network architecture and training parameters
  - No coding required!

```
layer {
  name: "conv2"
  type: "Convolution"
  bottom: “data"
  top: "conv2"
param {
    lr_mult: 2
    decay_mult: 0
  }
  convolution_param {
    num_output: 256
    pad: 2
    kernel_size: 5
    group: 2
    weight_filler {
      type: "gaussian"
      std: 0.01
    }
    bias_filler {
      type: "constant"
      value: 1
 }
}
 }
```

Caffe features
Deep Learning model definition

Loss functions:
- Classification
  - Softmax
  - Hinge loss
- Linear regression
  - Euclidean loss
- Attributes/multiclassification
  - Sigmoid cross entropy loss
- and more…

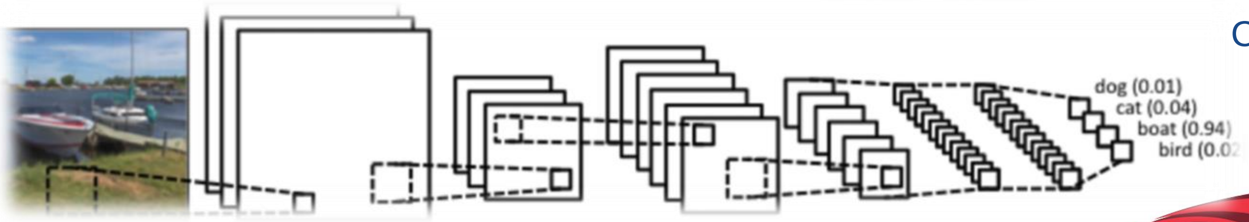
Available layer types:
- Convolution
- Pooling
- Normalization
- Data…

Activation functions:
- ReLU
- Sigmoid
- Tanh
- and more…

Feature Extraction
- Convolution
- Pooling (Max, Average…)
- Activation (ReLu…)

Classification
- Fully-connected network
- Matrix multiply

Image



Class IDs. Prob.

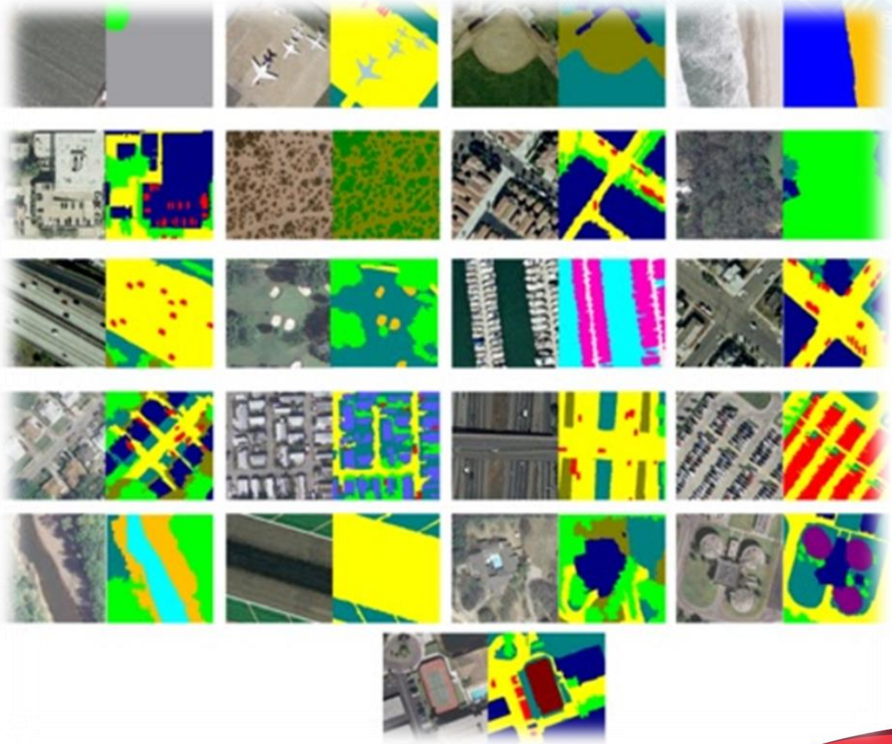
CAFFE Framework

Use Case : CNN architecture and training implementation

DLRSD dataset

2100 images 256x256 pixels, 21 class labels

- agricultural
- airplane
- baseballdiamond
- beach
- buildings
- chaparral
- denseresidential
- forest
- freeway
- golfcourse
- harbor
- intersection
- mediumresidential
- mobilehomepark
- overpass
- parkinglot
- river
- runway
- sparseresidential
- storagetanks
- tenniscourt



Step 1 - Data preparation

Objective: Create a training and validation databases (from DLRSD dataset) that can be ingested by CAFFE.

We created two scripts to perform this step:

Script 1: ***prepair_images.py***

> copy all images from DLRSD directories to one destination directory,

> creates ***train.txt*** and ***val.txt*** required for the training and validation theses text files provide for each image file its class.

Script 2: ***create_dataset_lmdb.sh***

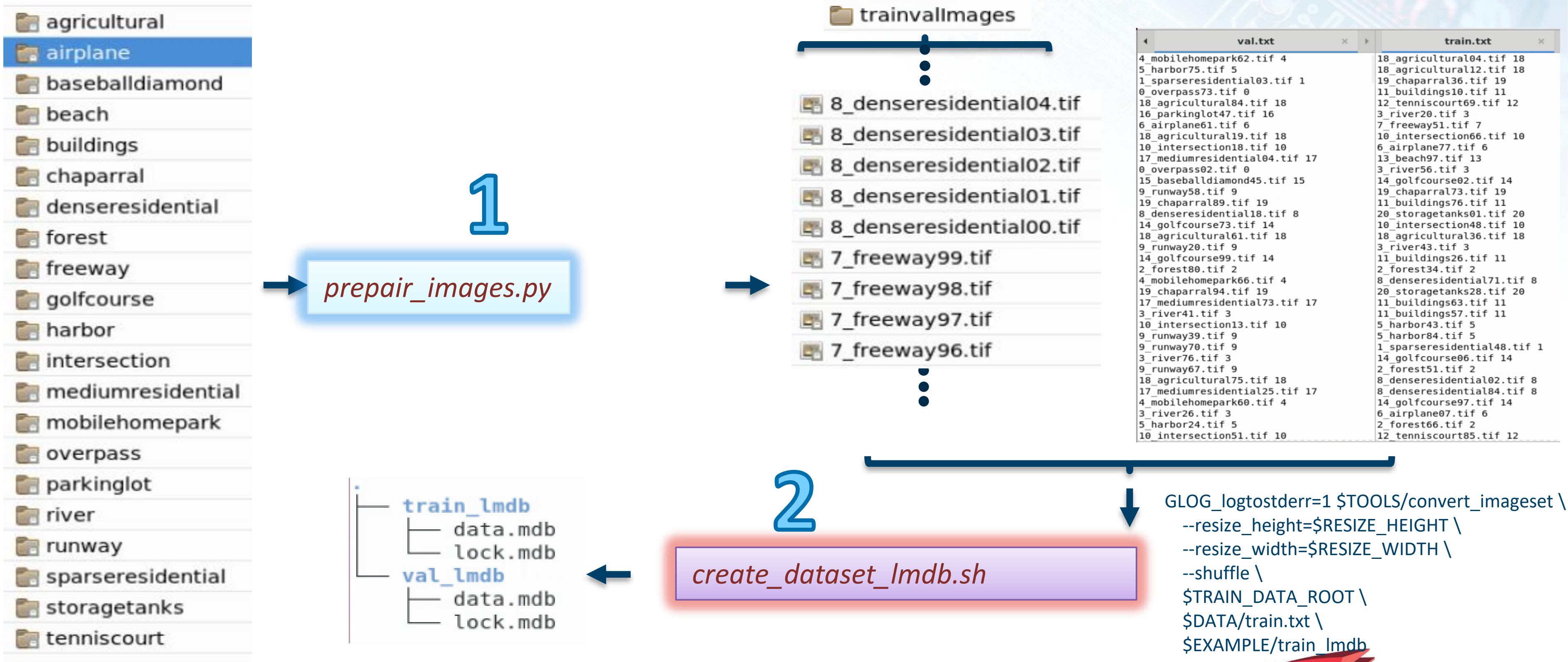
> resizes all images in the dataset to 227x227 resolution,

> creates ***train_lmdb*** as well as ***val_lmdb*** required for training and validation,

An additional step in the data preparation is the creation of the mean image *mean.binaryproto* using *make_mean.sh* which is provided by CAFFE.

CMC

Step 1 - Data preparation



Step 2 - Model definition

- Select a CNN architecture and define its parameters in a configuration file ***caffenet_train_val_1.prototxt.***
- In this demo, we will use the ***bvlc_reference_caffenet*** model, which is a replication of ***AlexNet***.
- In order to fit this model with the requirement of this project, we need to perform the following modifications:
  - Update the path for input training data, input validation data as well as the path to the mean image.
  - Update the outputs of the fully connected layer "fc8" from 1000 to 21.

Step 2 - Model definition

caffenet_train_val_1.prototxt

1

Change the path for input data and mean image

```
name: "CaffeNet"
layer {
  name: "data"
  type: "Data"
  top: "data"
  top: "label"
  include {
    phase: TRAIN
  }
  transform_param {
    mirror: true
    crop_size: 227
    mean_file: "/home/ideas/.local/install/caffe/cmcideas_dev0/mean.binaryproto"
  }
  data_param {
    source: "/home/ideas/.local/install/caffe/cmcideas_dev0/outlmdb/train_lmdb"
    batch_size: 50
    backend: LMDB
  }
}
layer {
  name: "data"
  type: "Data"
  top: "data"
  top: "label"
  include {
    phase: TEST
  }
  transform_param {
    mirror: false
    crop_size: 227
    mean_file: "/home/ideas/.local/install/caffe/cmcideas_dev0/mean.binaryproto"
  }
  data_param {
    source: "/home/ideas/.local/install/caffe/cmcideas_dev0/outlmdb/val_lmdb"
    batch_size: 20
    backend: LMDB
  }
}
```

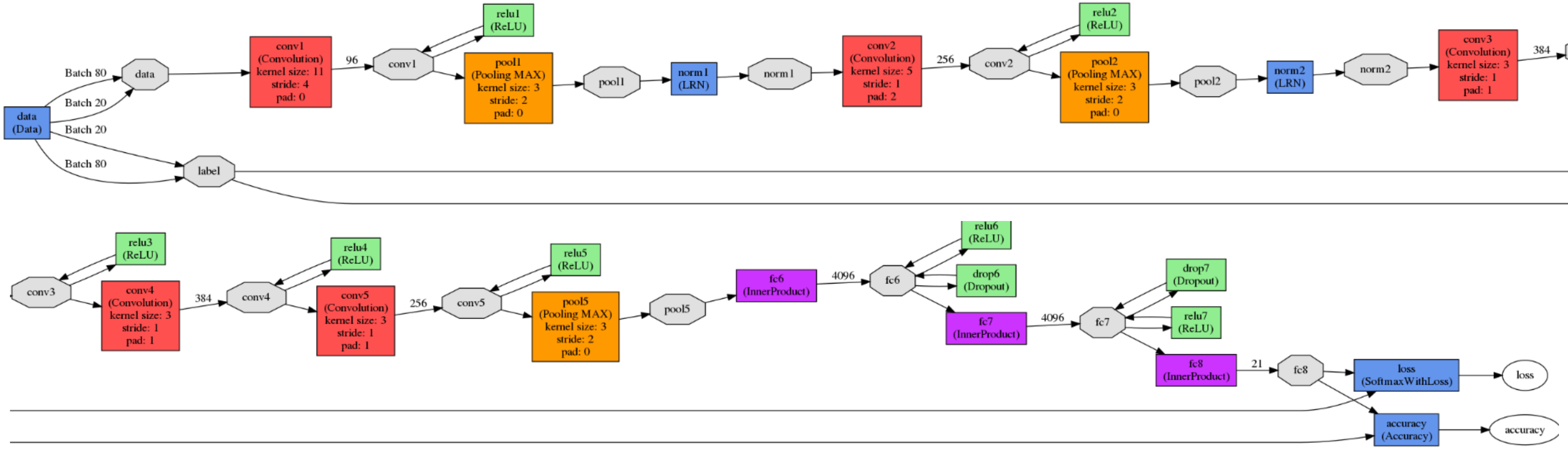
2

Change the number of outputs from 1000 to 21

```
  type: "InnerProduct"
  bottom: "fc7"
  top: "fc8"
  param {
    lr_mult: 1
    decay_mult: 1
  }
  param {
    lr_mult: 2
    decay_mult: 0
  }
  inner_product_param {
    num_output: 21
    weight_filler {
      type: "gaussian"
      std: 0.01
    }
    bias_filler {
      type: "constant"
      value: 0
    }
  }
}
layer {
  name: "accuracy"
  type: "Accuracy"
  bottom: "fc8"
  bottom: "label"
  top: "accuracy"
  include {
    phase: TEST
  }
}
layer {
  name: "loss"
  type: "SoftmaxWithLoss"
  bottom: "fc8"
  bottom: "label"
  top: "loss"
```

Step 2 - Model definition printing the model

> python /home/ideas/.local/install/caffe/ python/draw_net.py /home/ideas/.local/install/caffe/cmcideas_dev0/*caffenet_train_val_1.prototxt* /home/ideas/.local/install/caffe/cmcideas_dev0/caffe_model_1.png



Step 3 - Solver definition

- The solver provide parameters to perform model optimisation and guide the training and testing process.
- The content of *solver_1.prototxt* is as follow:

```
net: "/home/ideas/.local/install/caffe/cmcideas_dev0/caffenet_train_val_1.prototxt"
test_iter: 400
test_interval: 500
base_lr: 0.001
lr_policy: "step"
gamma: 0.1
stepsize: 5000
display: 20
max_iter: 10000
momentum: 0.9
weight_decay: 0.0005
snapshot: 2000
snapshot_prefix: "/home/ideas/.local/install/caffe/cmcideas_dev0/caffe_model_1"
solver_mode: GPU
```

Step 4 - Model training

At this step, we are ready to train the model by executing the following CAFFE command from the terminal:

>caffe train solver /home/ideas/.local/install/caffe/cmcideas_dev0/solver_1.prototxt 2>&1 | tee /home/ideas/.local/install/caffe/cmcideas_dev0/train.log

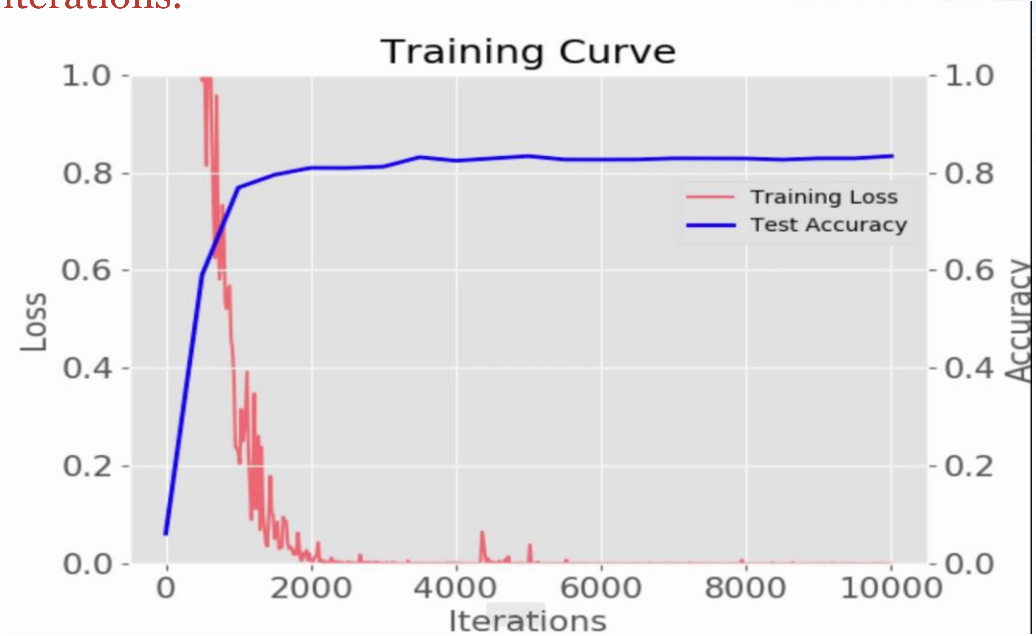
train.log

```
I0205 11:13:50.180753 23320 sgd_solver.cpp:105] Iteration 3900, lr = 0.001
I0205 11:13:50.365981 23326 data_layer.cpp:73] Restarting data prefetching from start.
I0205 11:13:53.088064 23320 solver.cpp:218] Iteration 3920 (6.87914 iter/s, 2.90734s/20 iters), loss = 5.28497e-05
I0205 11:13:53.088107 23320 solver.cpp:237]     Train net output #0: loss = 5.27813e-05 (* 1 = 5.27813e-05 loss)
I0205 11:13:53.088116 23320 sgd_solver.cpp:105] Iteration 3920, lr = 0.001
I0205 11:13:53.418174 23326 data_layer.cpp:73] Restarting data prefetching from start.
I0205 11:13:55.995802 23320 solver.cpp:218] Iteration 3940 (6.87827 iter/s, 2.90771s/20 iters), loss = 0.000599943
I0205 11:13:55.995854 23320 solver.cpp:237]     Train net output #0: loss = 0.000599875 (* 1 = 0.000599875 loss)
I0205 11:13:55.995863 23320 sgd_solver.cpp:105] Iteration 3940, lr = 0.001
I0205 11:13:56.472354 23326 data_layer.cpp:73] Restarting data prefetching from start.
I0205 11:13:58.904565 23320 solver.cpp:218] Iteration 3960 (6.876 iter/s, 2.90867s/20 iters), loss = 0.000147462
I0205 11:13:58.904662 23320 solver.cpp:237]     Train net output #0: loss = 0.000147394 (* 1 = 0.000147394 loss)
I0205 11:13:58.904672 23320 sgd_solver.cpp:105] Iteration 3960, lr = 0.001
I0205 11:13:59.525619 23326 data_layer.cpp:73] Restarting data prefetching from start.
I0205 11:14:01.812296 23320 solver.cpp:218] Iteration 3980 (6.87841 iter/s, 2.90765s/20 iters), loss = 0.000356035
I0205 11:14:01.812355 23320 solver.cpp:237]     Train net output #0: loss = 0.000355967 (* 1 = 0.000355967 loss)
I0205 11:14:01.812364 23320 sgd_solver.cpp:105] Iteration 3980, lr = 0.001
I0205 11:14:02.579222 23326 data_layer.cpp:73] Restarting data prefetching from start.
I0205 11:14:04.524401 23320 solver.cpp:447] Snapshotting to binary proto file /home/ideas/.local/install/caffe/cmcideas_dev0/
caffe_model_1_iter_4000.caffemodel
```

>python /home/ideas/.local/install/caffe/cmcideas_dev0/plot_learning_curve.py /home/ideas/.local/install/caffe/cmcideas_dev0/train.log /home/ideas/.local/install/caffe/cmcideas_dev0/learning_curve.png

Training result

Figure depicts the resulting learning curve, which is a plot of the training loss and test accuracy as a function of the number of iterations.



- We observe from this figure that the model achieved a validation accuracy of **~85%,** and it stopped improving after **4000** iterations.

Transfer Learning

- Issues:
  - CNNs require large datasets and a lot of time to train.
  - Some CNNs could take up to 3-4 weeks to train.
- Solution: Transfer learning.
- Concept: Instead of training the network from scratch, transfer learning trains an already trained model on a different dataset.
  - Fine-tune the trained model:
    - Train the trained model on the new dataset by continuing the backpropagation.
    - We can either fine-tune the whole network or freeze some of its layers.

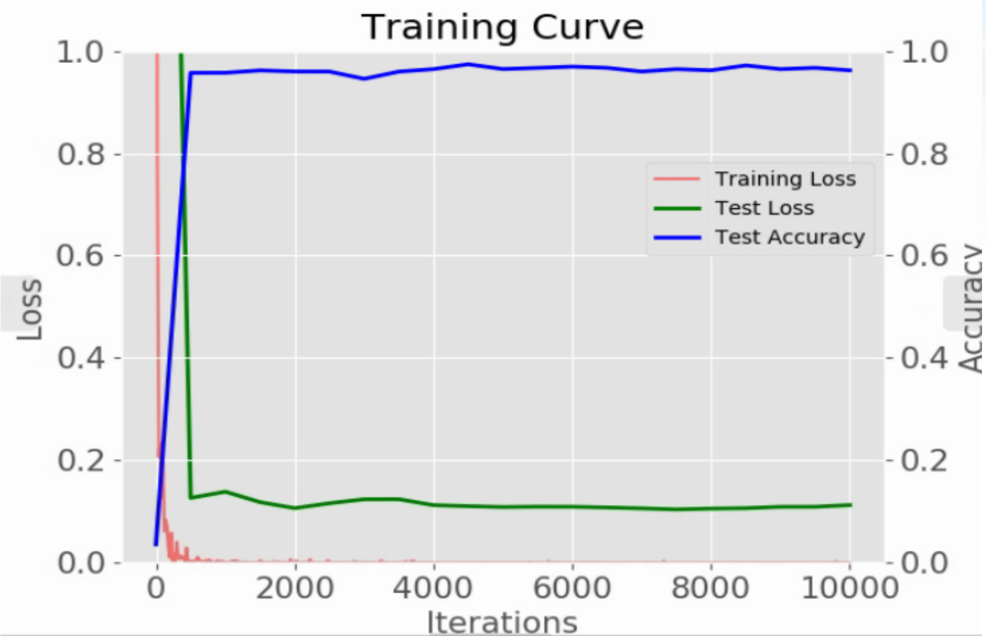
Model Training with Transfer Learning

- After defining the model and the solver, we can start training the model by executing the command below.
- Note that we can pass the trained model's weights by using the argument --weights

```
> caffe train --solver=/home/ideas/.local/install/caffe/cmcideas_dev0/solver_1.prototxt --weights /home/ideas/.local/install/caffe/models/bvlc_reference_caffenet/bvlc_reference_caffenet.caffemodel 2>&1 | tee /home/ideas/.local/install/caffe/cmcideas_dev0/train.log
```

Training result

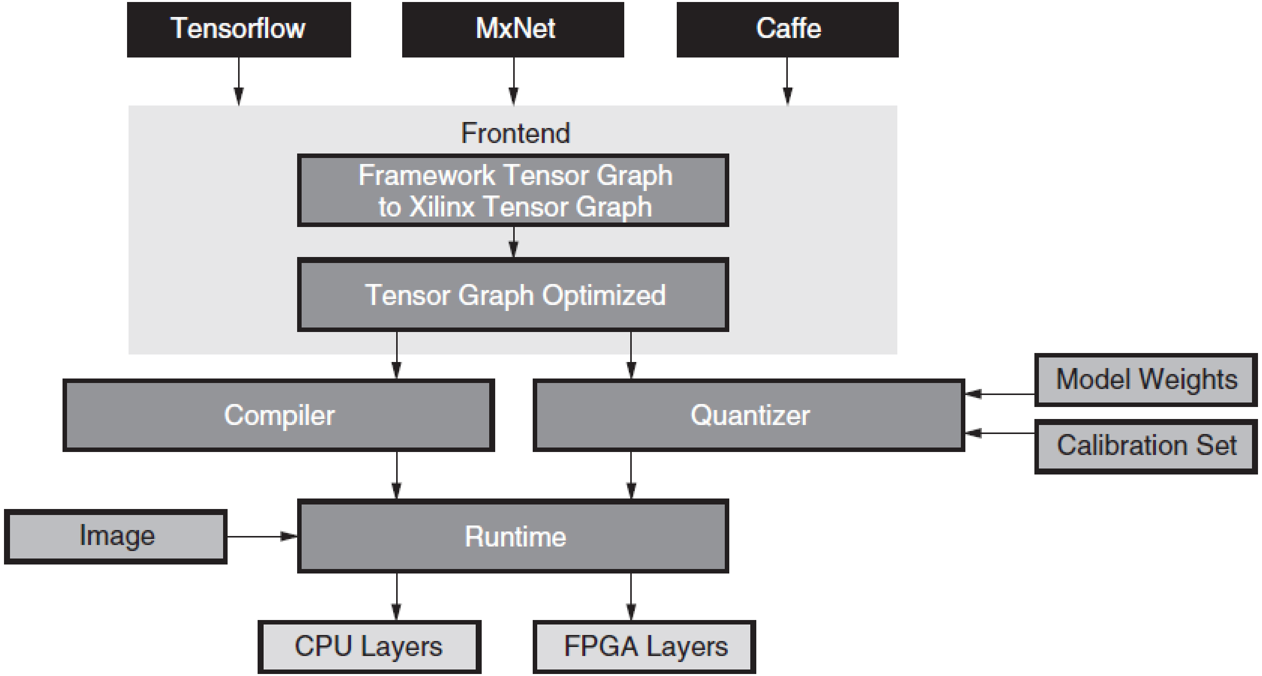
This figure depicts the resulting learning curve, which is a plot of the training loss and test accuracy as a function of the number of iterations.



- We observe from this figure that the model achieved a validation accuracy of **~98%,** and it stopped improving after **1000** iterations.

Live Demo

xfDNN Software Stack Overview



Ref. Accelerating DNNs with Xilinx Alveo Accelerator Cards

Thank you

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