VSB TECHNICAL UNIVERSITY OF OSTRAVA | IT4INNOVATIONS NATIONAL SUPERCOMPUTING CENTER

Introduction to Deep Neural Networks

Georg Zitzlsberger georg.zitzlsberger@vsb.cz

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Development and Education

MINISTRY OF EDUCATION,
YOUTH AND SPORTS

Agenda

Introduction

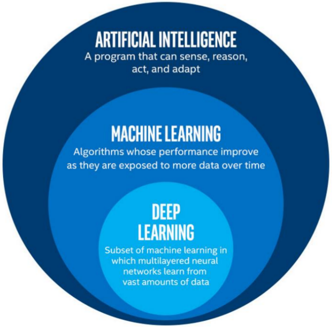
New Generation Silicon

Neuronal Networks

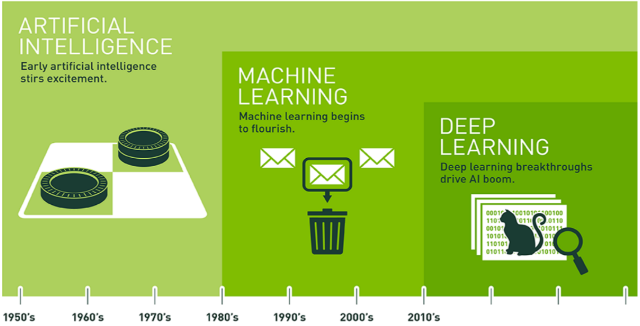
Optimizations for Inference

Summary

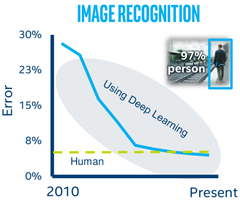
Introduction

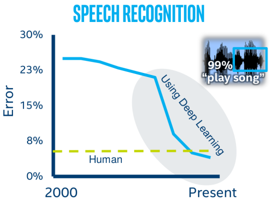


(Image: Intel)



(Image: NVIDIA)



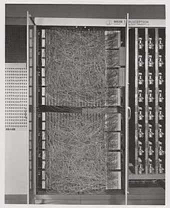


(Images: Intel)

History

Only very brief:

- 1950: Perceptron
  - By Frank Rosenblatt (funded by US Office of Naval Research)
  - 20x20 input photocells
  - Electro-mechanic
  - Not capable enough for multi-class patterns (only one layer)



(Image: Cornell Aeronautical Laboratory)

- First AI winter (1974-1980)
- 1989:
  Yann le Cun's *Theoretical Framework for Back-Propagation*
- Second AI winter (1987-1993)
- 2012:
  Dawn of Deep Neuronal Networks with *AlexNet*
- What's next? AI winter or Singularity?

Machine Learning: Feature Engineering

$N \times N$

$(f_1, f_2, \ldots, f_K)$

$K \ll N$

SVM
Random Forest
Naïve Bayes
Decision Trees
Logistic Regression
Ensemble methods

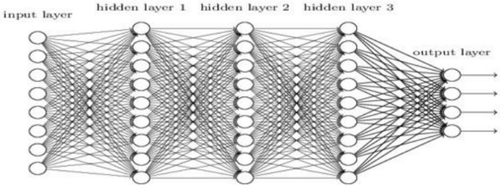
Arjun

!! Takes lot of time

(Image: Intel)

Deep Learning: Data Engineering

$N \times N$



Arjun

Features are discovered from data

Extract features at multiple levels of abstraction

Performance improves with more data

High degree of representational power

But old practices apply:
Data cleaning, Exploration, Data annotation, hyper-parameters, etc.

(Image: Intel)

Machine Learning vs. Deep Learning

- Pro Machine Learning (ML):
  - Best control over feature space
  - Preference if mathematical models exist that can be expressed directly
  - Guarantee of best solution (e.g. SVM with convex kernels)
  - Can work with less data
- Pro Deep Learning (DL):
  - Tackle complex problem spaces w/o feature engineering
  - Ensemble of networks possible
  - Allows to process large amounts of (i.i.d.) data
  - Easy to use across multiple nodes/GPUs

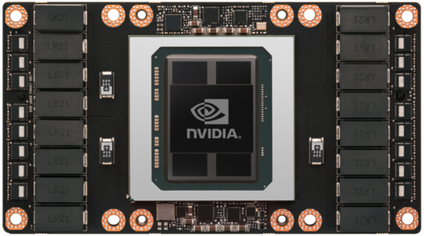
New Generation Silicon

(Image: NVIDIA)

Why now?

- Big Data:
  Large amounts of data are available
- Recent Deep Network Development:
  New Deep Learning methodologies evolved (2010 onwards)
- Hardware:
  Modern systems are fast enough and have the memory needed

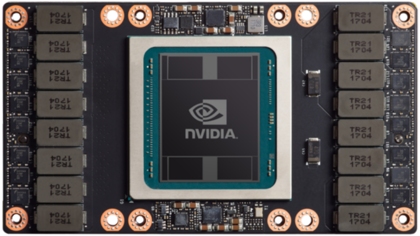
NVIDIA Tesla P100 (Pascal)



(Image: NVIDIA)

- Peak 4.7 TFLOPS (double precision), 9.3 TFLOPS (single precision), 18.7 (half precision)
- 12/16 GB HBM2 (CoWoS)
- Peak memory bandwidth: 549 GB/s (12 GB), 732 GB/s (16 GB)
- 3584 CUDA cores
- NVLink v1 (SXM) or PCIe x16 Gen3
- 300 (SXM) Watts, 250 Watts (PCIe)

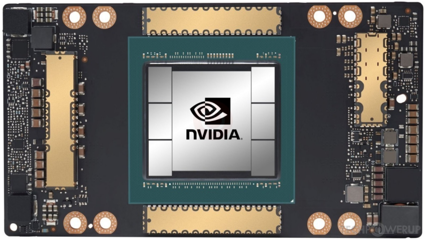
NVIDIA Tesla V100 (Volta)



(Image: NVIDIA)

- Peak 7.8 TFLOPS (double precision), 15.7 TFLOPS (single precision), 125 (half precision)
- Up to 125 “TensorTFLOPS” for Deep Learning
- 16/32 GB HBM2 (CoWoS)
- Peak 900 GB/s memory bandwidth
- 5120 CUDA cores + 620 Tensor Cores
- NVLink v2 (SXM) or PCIe x16 Gen3
- 300 (SXM) Watts, 250 (PCIe)

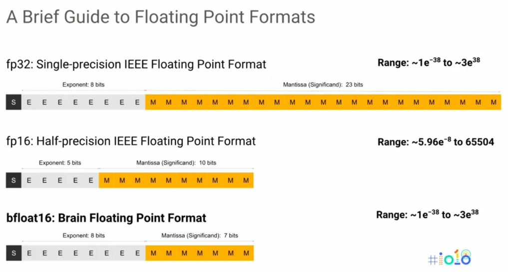
NVIDIA A100 (Ampere)



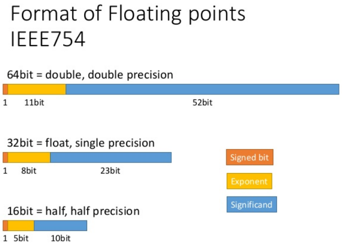
(Image: NVIDIA)

- Peak 9.7 TFLOPS (double precision), 19.5 TFLOPS (single precision), 312 (half precision)
- Up to 312 “TensorTFLOPS” for Deep Learning (624/1248 INT8/4)
- 40/80 GB HBM2 (CoWoS)
- Peak 1.6/2.0 TB/s memory bandwidth
- 6912 CUDA cores + 432 Tensor Cores
- NVLink v2 (SXM) or PCIe x16 Gen3
- 400 (SXM) Watts, 250 (PCIe)

Excursion: Floating Point Types



(Image: Google)

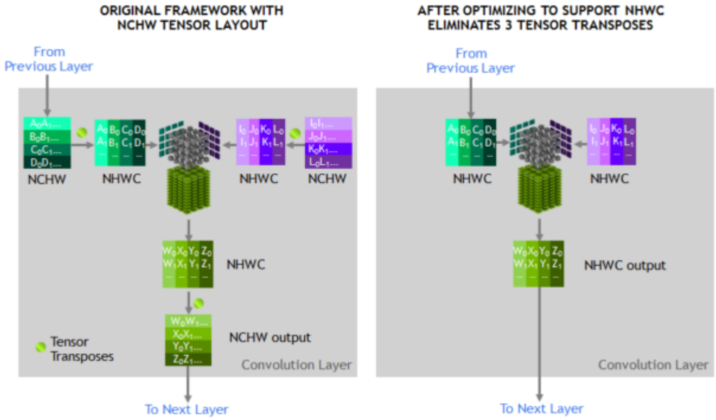


(Image: NVIDIA)

- FP32, FP16 and BFloat16[1] are of interest for Deep Learning (DL)
- FP64 is not common for DL but other Machine Learning algorithms
- Also integer types can be used (e.g. INT4, INT8)

[1] Note that we use the term "half precision" for FP16, which does not include BFloat16

NVIDIA Tesla V100 Tensor Cores



(Image: NVIDIA)

More information in the blog ▸ Volta Tensor Core GPU Achieves New AI Performance Milestones

NVIDIA Tesla T4 (Turing)

(Image: NVIDIA)

- Peak 8.1 TFLOPS (single precision)
- Up to 65 "TensorTFLOPS" for Deep Learning, 130/260 INT8/4 TOPS for inference
- 16 GB GDDR6
- Peak 300 GB/s memory bandwidth
- 2560 CUDA cores + 320 Tensor Cores
- PCIe x16 Gen3
- 70 Watts

NVIDIA Tesla Benchmarks

- **Single Precision (FP32):**

GPU	P100	V100	T4
Max. TFLOPS	9.32	14.02	8.07
FFT TFLOPS	1.51	2.30	0.66
GEMM TFLOPS	8.79	13.48	3.29
Theoretic Peak TFLOPS	9.3	15.7	8.1

- **Double Precision (FP64):**

GPU	P100	V100	T4
Max. TFLOPS	4.74	7.07	0.25
FFT TFLOPS	0.76	1.15	0.13
GEMM TFLOPS	4.26	5.92	0.25
Theoretic Peak TFLOPS	4.7	7.8	N/A

Results published at microway.com

Deep Learning Performance

GPU PERFORMANCE COMPARISON

	P100	V100	Ratio
DL Training	10 TFLOPS	120 TFLOPS	12x
DL Inferencing	21 TFLOPS	120 TFLOPS	6x
FP64/FP32	5/10 TFLOPS	7.5/15 TFLOPS	1.5x
HBM2 Bandwidth	720 GB/s	900 GB/s	1.2x
STREAM Triad Perf	557 GB/s	855 GB/s	1.5x
NVLink Bandwidth	160 GB/s	300 GB/s	1.9x
L2 Cache	4 MB	6 MB	1.5x
L1 Caches	1.3 MB	10 MB	7.7x

(Image: NVIDIA)

Heads-up:

- Real performance highly dependent on layers/operations used
- Uses half/mixed precision parameters that might or might not deliver the same/comparable model accuracy
- Assumes that the entire model and data fits into GPU memory

NVIDIA DGX

(Image: NVIDIA)

NVIDIA DGX-1:

- 8x V100 GPUs (also exists with P100 GPUs)
- Deep Learning: 1,000 TFLOPS (peak)
- CUDA cores: 40,960
- Tensor cores: 5,120
- Host system: 2x 20 core Intel E5-2698v4, 256 GB memory
- Power consumption: 3,500 Watts

NVIDIA DGX

(Image: NVIDIA)

NVIDIA DGX-2:

- 16x V100 GPUs
- Deep Learning: 2,000 TFLOPS (peak)
- CUDA cores: 81,920
- Tensor cores: 10,240
- Host system: 2x 24 core Intel Xeon Platinum 8168 Processor, 512 GB memory
- 12 NVSwitches (for NVLinks)
- Power consumption: 10,000 Watts

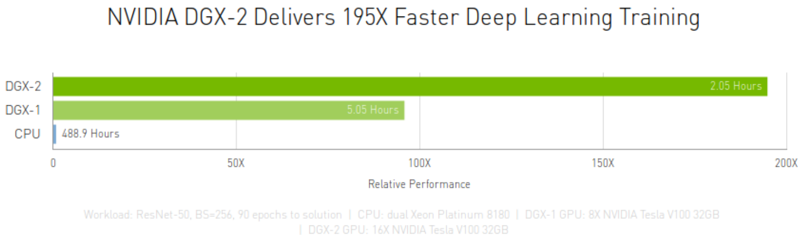
NVIDIA DGX

(Image: NVIDIA)

NVIDIA DGX A100:

- 8x A100 GPUs
- Deep Learning: 5,000 TFLOPS (peak)
- CUDA cores: 55,296
- Tensor cores: 3,456
- Host system: 2x 64 core AMD Rome 7742 Processor, 1 TB memory
- 8 NVSwitches (for NVLinks)
- Power consumption: 6,500 Watts

NVIDIA DGX-1 vs. DGX-2

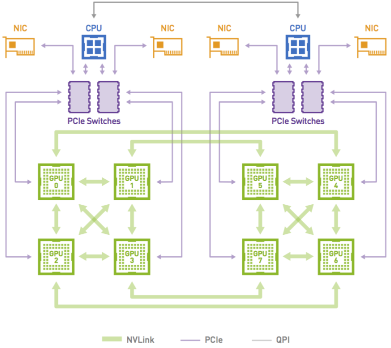


(Image: NVIDIA)

More benchmark results can be found at the ▸ NVIDIA Tesla Deep Learning Product Performance web page.

Also compare the official MLPerf results for training and inference ▸ here

NVLink

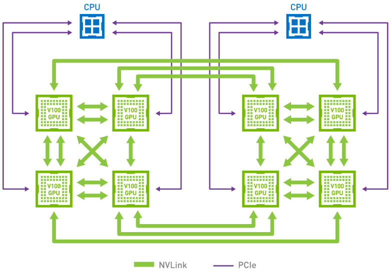


(Image: NVIDIA)

NVLink (v1):

- Tesla P100
- Hybrid Cube Mesh
- 4 links per GPU, 20 GB/s per direction/per NVLink (160 GB/s aggregated)

NVLink

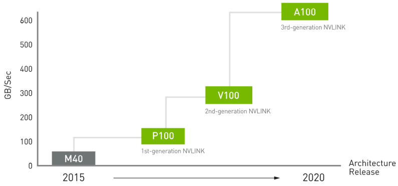


(Image: NVIDIA)

NVLink 2.0:

- Tesla V100
- Hybrid Cube Mesh (also switch configuration possible)
- 6 links per GPU, 25 GB/s per direction/per NVLink2 (300 GB/s aggregated)

NVLink



(Image: NVIDIA)

NVLink 3.0:

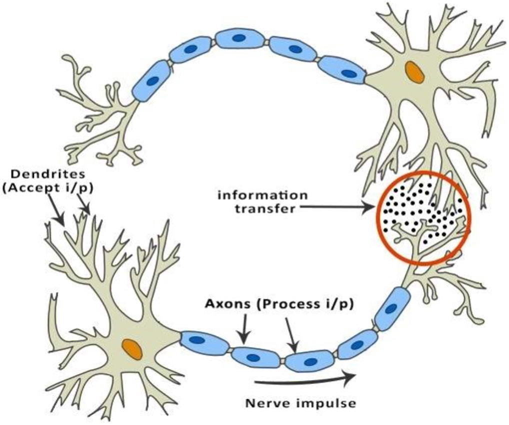
- ~~Tesla~~ A100
- Hybrid Cube Mesh (also switch configuration possible)
- 12 links per GPU, 25 GB/s per direction/per NVLink3 (600 GB/s aggregated)

CPU vs. GPU: Architectural Advantages

- Pro CPU:
  - More memory for larger models
  - Easier I/O and to set up
  - Some operations/layers can only be executed on the CPU (types or complexity)
- Pro GPU:
  - Very efficient if operations/layers are supported
  - Divide I/O and training between CPU and GPU
  - Best for deep networks (operations $\gg$ data ingestion)

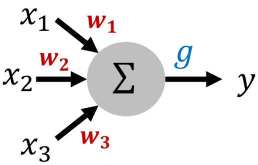
Neuronal Networks

Inspired by biology:



(Image: Intel)

Artificial Neuronal Networks



Input from unit j

$$y = g\left(\sum_j W_j x_j + b\right)$$

Output of unit

Linear weights

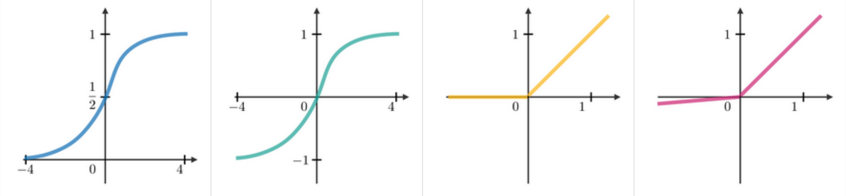
Bias unit

Activation Function

(Image: Intel)

Activation Function

Sigmoid	Tanh	ReLU	Leaky ReLU
$g(z) = \dfrac{1}{1+e^{-z}}$	$g(z) = \dfrac{e^z - e^{-z}}{e^z + e^{-z}}$	$g(z) = \max(0, z)$	$g(z) = \max(\epsilon z, z)$ with $\epsilon \ll 1$



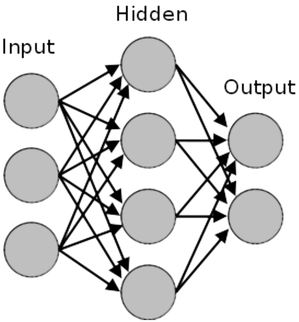
(Image: Afshine Amidi[2])

- Adds non-linearity
- ReLU is currently the most popular (est. 2010)

[2] https://stanford.edu/~shervine/teaching/cs-229/cheatsheet-deep-learning

Deep Neural Network

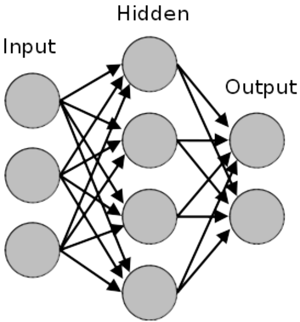
Example of a "Deep" Neural Network:



(Image: Intel)

- Layers can have different number of neurons
- Input and output formats can be arbitrary
- There can be multiple (hundreds) of hidden layers
- Typically output is combined with *softmax* function (probabilistic output)
- Example shows fully connected network, which is a special case

Deep Neural Network Operation

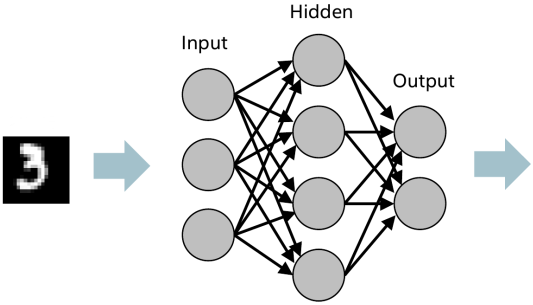


(Image: Intel)

1. Random weights
2. Get a random batch of training data
3. Forward propagation
4. Calculate cost (loss)
5. Backward propagation
6. Update weights and bias
7. Goto step 2.

Deep Neural Network: Forward Propagation

Example for one digit (image):



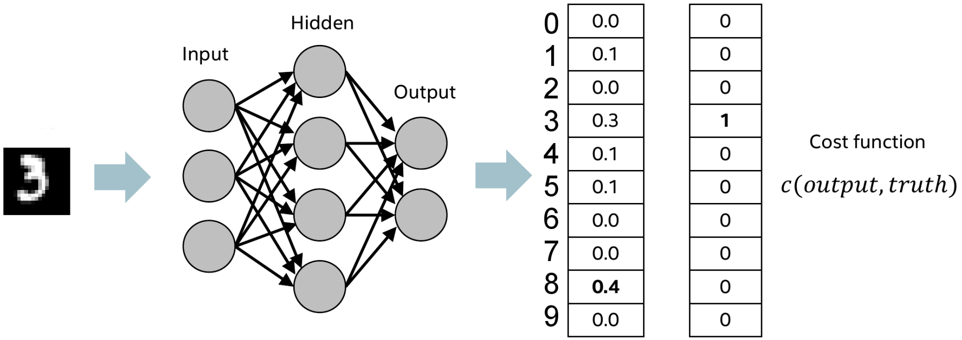
0	0.0
1	0.1
2	0.0
3	0.3
4	0.1
5	0.1
6	0.0
7	0.0
8	**0.4**
9	0.0

$$y = g\left(\sum_j W_j x_j + b\right)$$

(Image: Intel)

Deep Neural Network: Cost Function

Example of a cost (or loss) function:

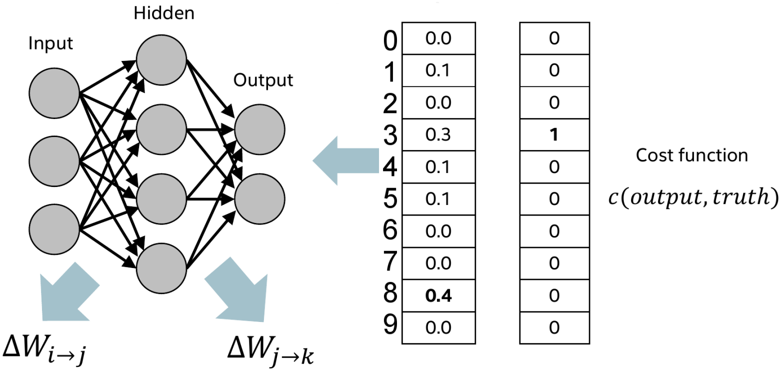


(Image: Intel)

- How far off are we from the ground truth?
- Example has labeled data (different if non-labeled data)

Deep Neural Network: Backward Propagation

How weights are updated:

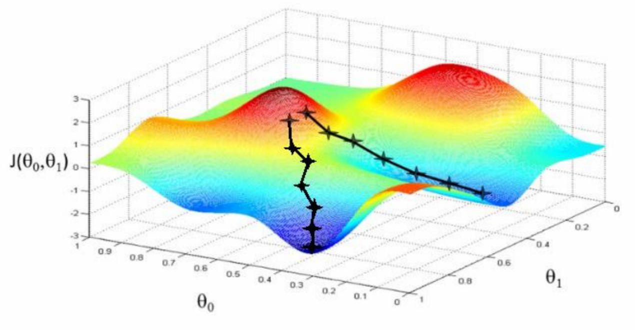


(Image: Intel)

- From back to front (problem: vanishing gradient for deep networks)
- Changes of the weights are usually dampened/controlled by a changing learning rate

Deep Neural Network: Stochastic Gradient Descent

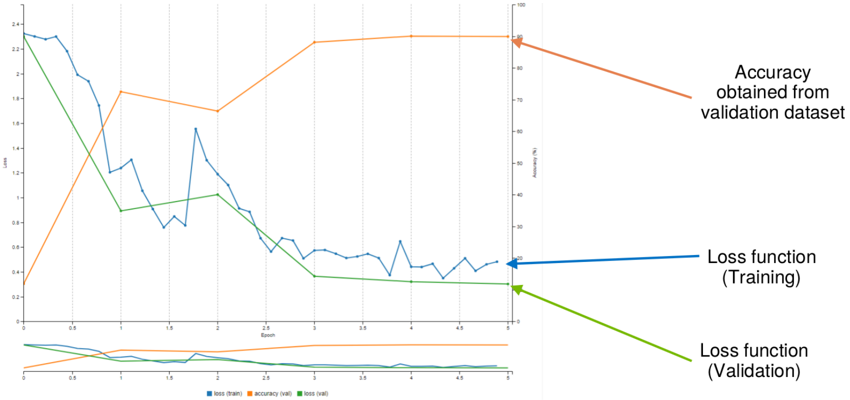
How to find the best weight updates:



(Image: Intel)

- Gradient descent methods, e.g.:
  - Stochastic Gradient Descent (SGD)
  - Adaptive Moment Estimation (ADAM)
- Example: only two weights (θ_1, θ_2) with cost in 3rd dimension
- Multiple (local) minima are possible

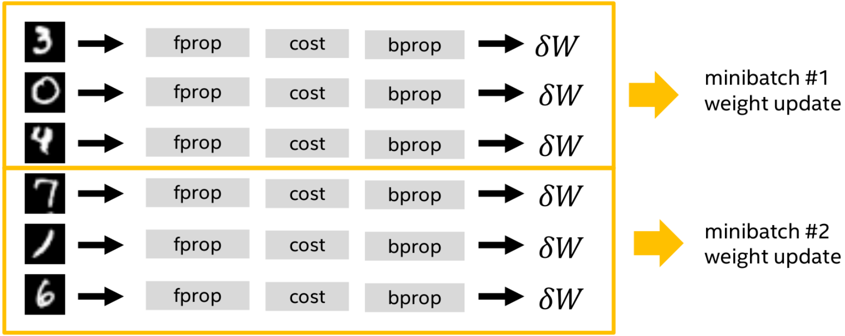
Training - Find the Best Weights



(Image: NVIDIA)

- Data sets separated into training, validation, and testing sets
- Training data set is repeatedly used for training (over epochs)
- Validation data: Track the performance of the network during training
- Testing data set: Final independent performance validation

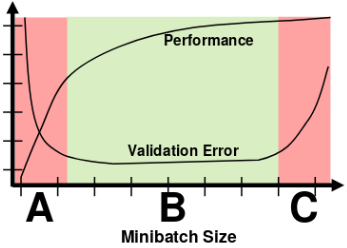
Excursion: Minibatch

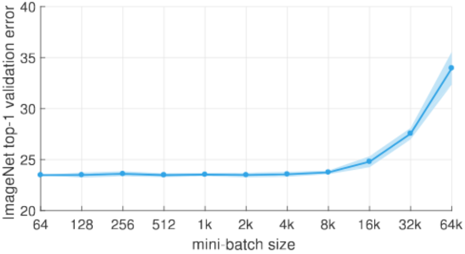


(Image: Intel)

- Back-propagation is very expensive compared to forward-propagation
- Group training data in batches (so-called *minibatch*) of size N
- $N = \frac{training_{size}}{\#_{batches}}$
- A *minibatch* allows parallel forward-propagation

Excursion: Minibatch Performance





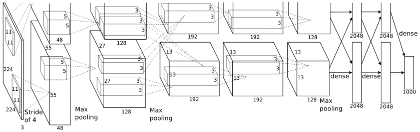
(Image: Ben-Nun, et al.)

- A higher mini-batch size increases performance
- **However:**
  - The larger the batch, the worse the training performance
  - The more memory is needed to store the parameters (problem for GPUs)
- Sweet spot needs to be found empirically

Deep Network Examples

AlexNet:

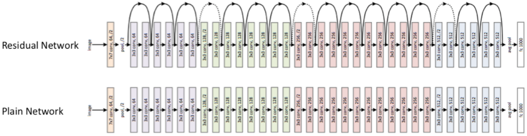
- Won ImageNet Challenge 2012
- 5 conv. + 3 fully connected layers
- 60 million parameters



(Image: Krizhevsky, et al.)

ResNet:

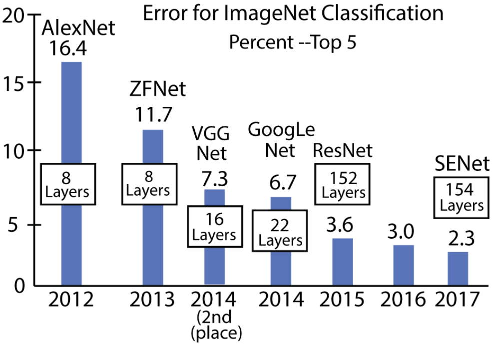
- Won ImageNet Challenge 2015
- Mitigates *vanishing gradient* problem
- 25 million parameters



(Image: He, et al.)

An overview of more can be found ▸ here

Image Classification Errors



(Image: principlesofdeeplearning.com)

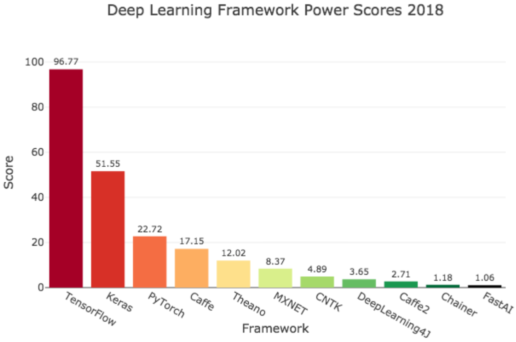
- Trend: More layers
- Error (performance) converges
- Ensemble networks were used last

Programming

How to "program" Deep Neural Networks is different:

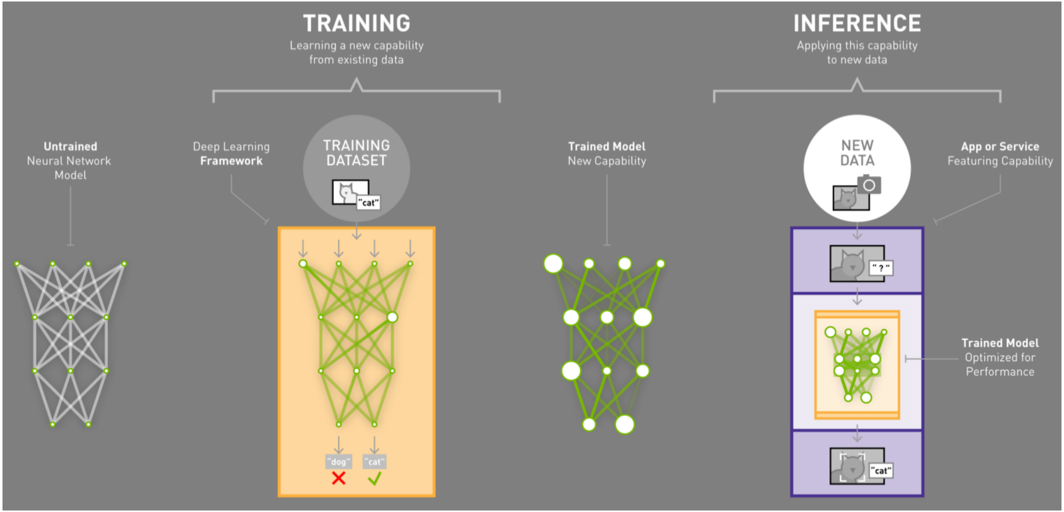
- In two phases:
  - Training (time consuming)
  - Inference (usage)
- High quality and quantity training (and validation/testing) data is needed
- Output is probabilistic
- Programming with frameworks:
  - TensorFlow
  - CNTK
  - Theano
  - PyTorch
  - Caffe{2}
  - ...

$\left.\begin{array}{l}\text{TensorFlow}\\ \text{CNTK}\\ \text{Theano}\end{array}\right\}$ Keras



(Image: keras.io)

Training vs. Inference



(Image: NVIDIA)

How to get Started?

Model Zoos make it easy to start:

- Use existing models
- Use pre-trained models for transfer learning

Model Zoo examples:

- Tensorflow: here
- PyTorch: here
- Caffe (BVLC): here
- ...

Pretrained models are also available (e.g. for object detection with Tensorflow)

Optimizations for Inference

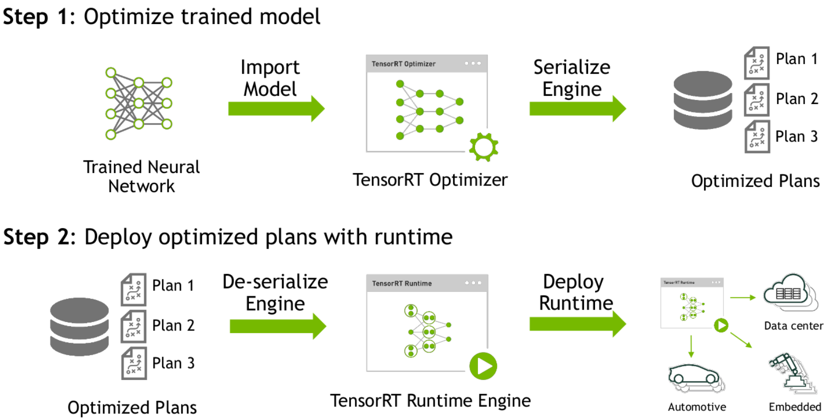
Training needs parallelism, but what about inference?

- Inference is the actual use of the network
- Inference only does forward propagation (weights are fixed)
- Trained networks can be optimized for inference:
  - Optimize away inactive neurons (due to drop-out)
  - Fuse layers and operations and remove redundancies
  - Optimize data structures
  - Optimize for different target architectures
  - Quantize (reduce precision of data types)
  - . . .

Optimizers exist:

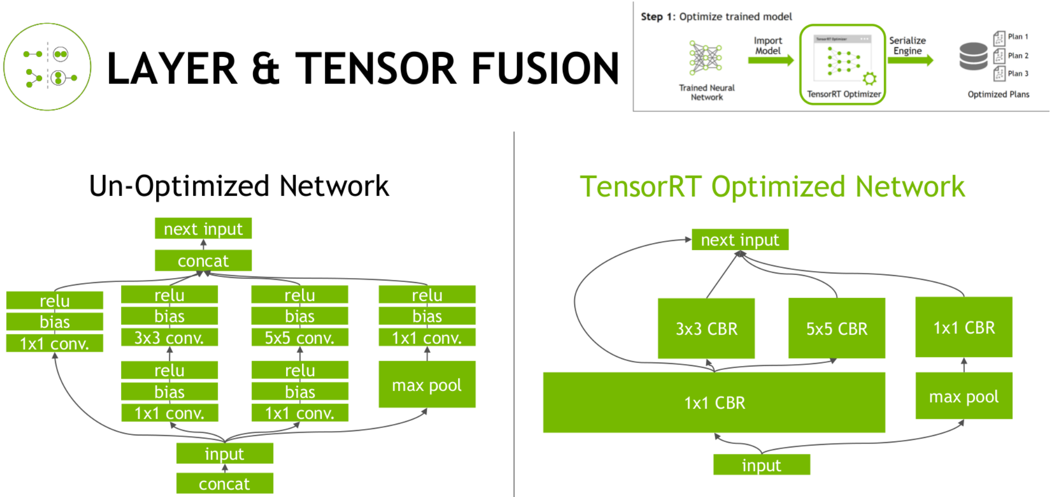
- TensorRT from NVIDIA ▸ TensorRT Documentation
- Intel Deep Learning Deployment Toolkit from ▸ Intel OpenVino
- Both support Open Neural Network Exchange (ONNX) format

Optimizations: NVIDIA TensorRT



(Image: NVIDIA)

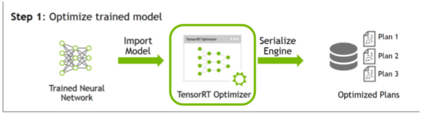
Optimizations: NVIDIA TensorRT



(Image: NVIDIA)

Optimizations: NVIDIA TensorRT

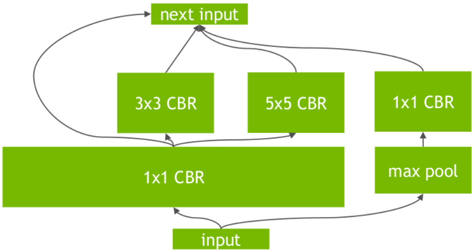
LAYER & TENSOR FUSION



- Vertical Fusion
- Horizonal Fusion
- Layer Elimination

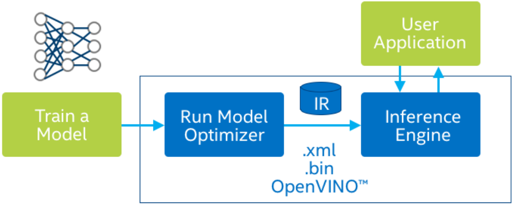
Network	Layers before	Layers after
VGG19	43	27
Inception V3	309	113
ResNet-152	670	159

TensorRT Optimized Network



(Image: NVIDIA)

Optimizations: Intel OpenVino



(Image: Intel)

- Model Optimizer:
  - Optimize for endpoint target device
  - Transform to intermediate representation (IR)
  - Validated with over 100 public models for Caffe, Tensorflow, MXNet and ONNX
- Inference Engine:
  - Execute different layers on different targets (parallelism)
  - Implement custom layers on a CPU

Summary

- Deep Neural Networks have shown and still show remarkable results
- Latest Hardware architecture improvements fuel DL further
- There are many DL frameworks for training and inference
- There are vendor specific extensions (Intel or NVIDIA)

Great State of the Art (academic) overview:

▸ Demystifying Parallel and Distributed Deep Learning: An In-Depth Concurrency Analysis

(Tal Ben-Nun and Torsten Hoefler)

VSB TECHNICAL UNIVERSITY OF OSTRAVA | IT4INNOVATIONS NATIONAL SUPERCOMPUTING CENTER

IT4Innovations National Supercomputing Center

VŠB – Technical University of Ostrava
Studentská 6231/1B
708 00 Ostrava-Poruba, Czech Republic
`www.it4i.cz`

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