

SDA: Software-Defined Accelerator for Large-Scale DNN Systems

Jian Ouyang,¹ Shiding Lin,¹ Wei Qi, ¹ Yong Wang, ¹ Bo Yu, ¹
Song Jiang,²

¹Baidu, Inc. ²Wayne State University



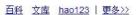


Introduction of Baidu

- A dominant Internet company in China
 - ~US\$80 Billion market value
 - 600M+ users
 - Exploiting internet markets of Brazil, Southeast Asia and Middle east Asia
- Main Services
 - PC search and mobile search
 - 70%+ market share in China
 - LBS(local base service)
 - 50%+ market share
 - On-line trips
 - QUNR[subsidiary company], US\$3 billions market value
 - Video,
 - Top 1 mobile video in China
 - Personal cloud storage
 - 100M+ users, the largest in China
 - APPs store, image and speech
- Baidu is a technology-driven company
 - Tens of data centers, hundreds of thousands of servers
 - Over one thousand PetaByte data (LOG, UGC, Webpages, etc.)









DNN in Baidu

- DNN has been deployed to accelerate many critical services at Baidu
 - Speech recognition
 - Reduce 25%+ error ratio compared to the GMM (Gaussian Mixture Model) method
 - Image
 - Image search, OCR, face recognition
 - Ads
 - Web page search
 - LBS/NLP(Natural Language Processing)
- What is DNN (deep neural network or deep learning)
 - DNN is a multi-layer neural network.
 - DNN uses usually an unsupervised and unfeatured machine learning method.
 - Regression and classification
 - Pattern recognition, function fitting or more
 - Often better than shallow learning (SVM(Support Vector Machine), Logistics Regression, etc.)
 - Unlabeled features
 - Stronger representation ability
 - Often demands more compute power
 - Need to train much more parameters
 - Need to leverage big training data to achieve better results



Outline

- Overview of the DNN algorithm and system
- Challenges on building large-scale DNN system
- Our solution: SDA (Software-Defined Accelerator)
 - Design goals
 - Design and implementation
 - Performance evaluation
- Conclusions



Overview of DNN algorithm

Single neuron structure

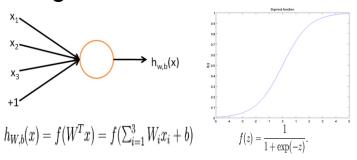
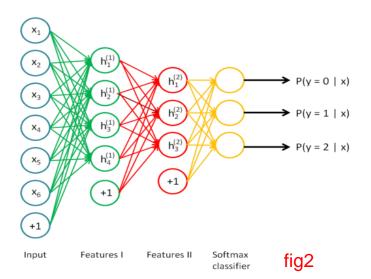


fig1

Multiple neurons and layers



Back-propagation training

```
For each input vector

// forward , for input layer to output layer

O_i=f(W_i * O_i-1)

// backward, for output layer to input layer

delta_i = O_i+1 * (1-O_i) * (W_i * delta_i+1)

//update weight ,for input layer to output layer

W_i = W_i + n* delta_i*O_i-1

Almost matrix multiplications and additions

Complexity is O(3*E*S*L*N³)

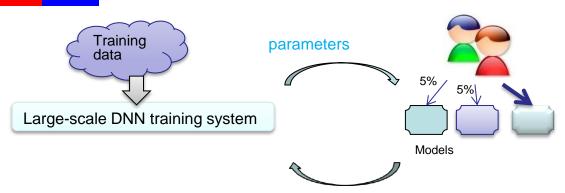
E: epoch number; S: size of data set; L: layers number; N: size of weight
```

- Online-prediction
 - Only forward stage

Online-prediction Complexity: O(V*L*N²) V: input vector number L: layer number N: size of weight matrix

N=2048,L=8,V=16 for typical applications, computation of each input vector is ~1GOP, and almost consumes 33ms in latest X86 CPU core.

Overview of DNN system



Off-line training

- Scale
 - 10~100TB training data
 - 10M~100B parameters
- workload type
 - Compute intensive
 - Communication intensive
 - Difficult to scale out
- Cluster type
 - Medium size (~100)
 - GPU and IB

On-line prediction

- Scale
 - 10M~B users
 - 100M~10B requests/day
- Workload type
 - Compute intensive
 - Less communication
 - Easy to scale out
- Cluster type
 - Large scale(K~10K)
 - CPU (AVX/SSE) and 10GE



Challenges on Existing Large-scale DNN system

- DNN training system
 - Scale: ~100 servers due to algorithm and hardware limitations
 - Speed: training time from days to months
 - Cost: many machines demanded by a large number of applications
- DNN prediction
 - Cost: 1K~10K servers for one service
 - Speed: latency of seconds for large models
- Cost and speed are critical for both training and prediction
 - GPU
 - High cost
 - High power and high space consumption
 - Higher demand on data center cooling, power supply, and space utilization
 - CPU
 - Medium cost and power consumption
 - Low speed
- Are any other solutions?



Challenges of large DNN system

- Other solutions
 - ASIC
 - High NRE
 - Long design period, not suitable for fast iteration in Internet companies
 - FPGA
 - Low power
 - Less than 40W
 - Low cost
 - Hundreds of dollars
 - Hardware reconfigurable
- Is FPGA suitable for DNN system ?



Challenges of large DNN system

- FPGA's challenges
 - Developing time
 - Internet applications need very fast iteration
 - Floating point ALU
 - Training and some predictions require floating point
 - Memory bandwidth
 - Lower than GPU and CPU
- Our Approach
 - SDA: Software-Defined Accelerator



SDA Design Goals

- Supports major workloads
 - Floating point: training and prediction
- Acceptable performance
 - 400Gflops, higher than 16core x86 server
- Low cost
 - Medium-end FPGA
- Not require changes of existent data center environments
 - Low power: less than 30w of total power
 - Half-height, half-length, and one slot thickness
- Support fast iteration
 - Software-Defined



Designs and implementations

- Hardware board design
- Architecture
- Hardware and software interface



Design – Hardware Board

Specifications

- Xilinx K7 480t
- 2 DDR3 channels, 4GB
- PCIE 2.0x8



Size

- Half-height, half-length and one slot thickness
- Can be plugged into any types of 2U and 1U servers.

Power

- Supplied by the PCIE slot
- Peak power of board less than 30w



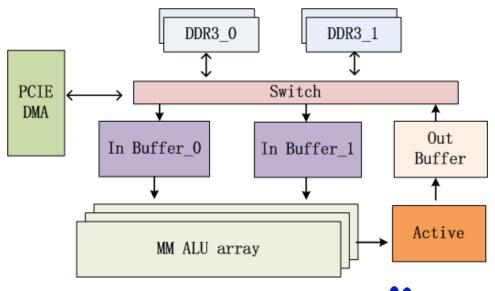
Design - Architecture

- Major functions
 - Floating point matrix multiplication
 - Floating point active functions
- Challenges of matrix multiplications
 - The numbers of floating point MUL and ADD
 - Data locality
 - Scalability for FPGAs of different sizes
- Challenges of active functions
 - Tens of different active functions
 - Reconfigurable on-line within milliseconds



Design - Architecture

- Customized FP MUL and ADD
 - About 50% resource reduction compared to standard IPs
- Leverage BRAM for data locality
 - Buffer 2x512x512 tile of matrix
- Scalable ALU
 - Each for a 32x32 tile



Design - architecture

- Software-defined active functions
 - Support tens of active functions: sigmod, tanh, softsign...
 - Implemented by lookup table and linear fitting
 - Reconfigure the table by user-space API
- Evaluations
 - 1-e5 ~1-e6 precision
 - Can be reconfigured within 10us



Design - Software/hardware Interface

- Computation APIs
 - Similar to CUBLAS
 - Memory copy: host to device and device to host
 - Matrix MUL
 - Matrix MUL with active function
- Reconfiguration API
 - Reconfigure active functions



Evaluations

- Setup
 - HOST
 - Intel E5620v2x2, 2.4GHz, 16 cores
 - 128GB memory
 - 2.6.32 Linux Kernel, MKL 11.0
 - SDA
 - Xilinx K7-480t
 - 2x2GB DDR3 on-board memory, with ECC, 72bit, 1066MHz
 - PCIE 2.0x8
 - GPU
 - One type server-class GPU
 - Two independent devices. The following evaluation leverages one device.

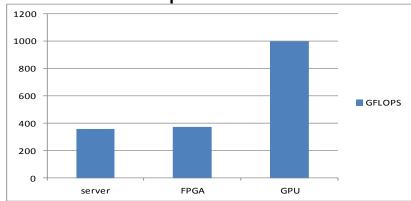


Evaluations-Micro Benchmark

- SDA implementation
 - 300MHz, 640 ADDs and 640 MULs

	LUT	DSP	REG	BRAM
Resource utilization	70%	100%	37%	75%

- Peak performance
 - Matrix multiplication : MxNxK=2048x2048x2048



power

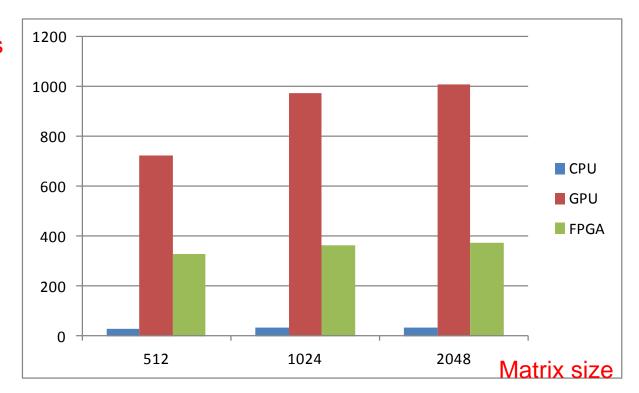
	CPU	FPGA	GPU
Gflops/W	4	12.6	8.5



Evaluations-Micro Benchmark

- M=N=K, matrix multiplication
 - CPU leverages one core, GPU is one device
 - M=512,1024 and 2048

Gfops





Evaluations: On-line Prediction Workload

- Input batch size is small
 - Batch size: the number of input vector
 - Typical batch size is 8 or 16
- Typical layer is 8
- The size of hidden layer is several hundreds to several thousands
 - Depending on applications, practical tuning and training time
- Workload1
 - Batch size=8, layer=8, hidden layer size=512
 - Thread number is 1~64, test the request/s
- Workload2
 - Batch size=8, layer=8, hidden layer size=2048
 - Thread number is 1~32, test the request/s



Evaluations: On-line Prediction Workload

- Batch size=8, layer=8
- Workload1
 - Weight matrix size=512
 - FPGA is 4.1x than GPU
 - FPGA is 3x than CPU

Workload2

- Weight matrix size=2048
- FPGA is 2.5x than GPU
- FPGA is 3.5x than CPU

Conclusions

- FPGA can merge the small requests to improve performance
- Throughput in Req/s of FPGA scales better

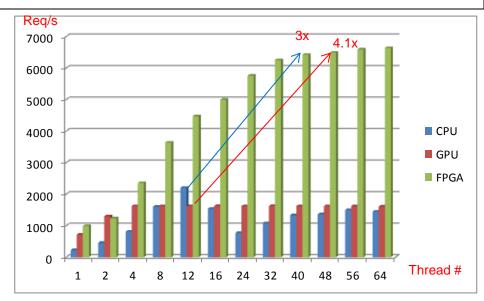


Fig a:workload1

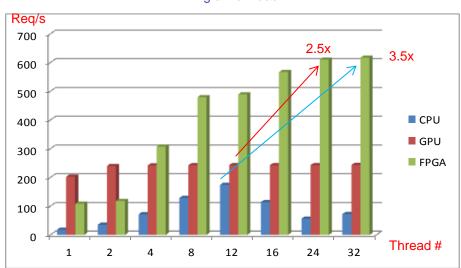


Fig b: workload2

The features of SDA

- Software-defined
 - Reconfigure active functions by user-space API
 - Support very fast iteration of internet services
- Combine small requests to big one
 - Improve the QPS while batch size is small
 - The batch size of real workload is small
- CUBLAS-compatible APIs
 - Easy to use



Conclusions

- SDA: Software-Defined Accelerator
 - Reconfigure active functions by user-space APIs
 - Provide higher performance in the DNN prediction system than GPU and CPU server
 - Leverage mid-end FPGA to achieve about 380Gflops
 - 10~20w power in real production system
 - Can be deployed in any types of servers
 - Demonstrate that FPGA is a good choice for large-scale DNN systems

