MagmaDNN 0.2 High-Performance Data Analytics for Manycore GPUs and CPUs

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3 PUBLICATIONS 0 CITATIONS

MagmaDNN 0.2

High-Performance Data Analytics for Manycore GPUs and CPUs

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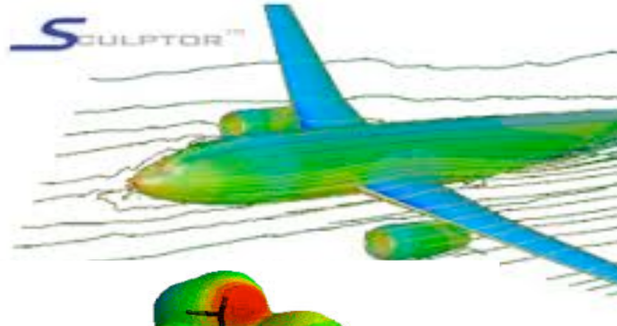
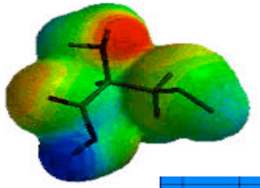
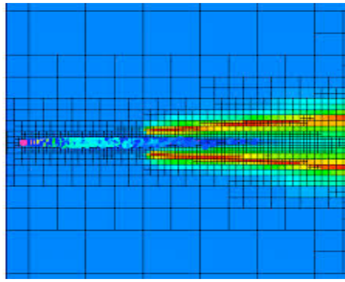
Dense Linear Algebra in Applications

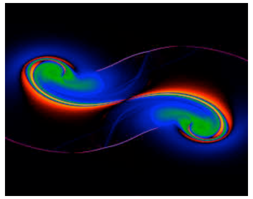
Dense Linear Algebra (DLA) is needed in a wide variety of science and engineering applications:

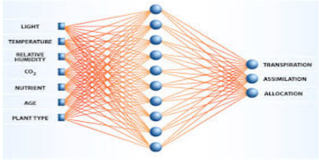
- **Linear systems:** Solve $Ax = b$
  - Computational electromagnetics, material science, applications using boundary integral equations, airflow past wings, fluid flow around ship and other offshore constructions, and many more
- **Least squares:** Find x to minimize $\| Ax - b \|$
  - Computational statistics (e.g., linear least squares or ordinary least squares), econometrics, control theory, signal processing, curve fitting, and many more
- **Eigenproblems:** Solve $Ax = \lambda x$
  - Computational chemistry, quantum mechanics, material science, face recognition, PCA, data-mining, marketing, Google Page Rank, spectral clustering, vibrational analysis, compression, and many more
- **SVD:** $A = U \Sigma V^*$ ($Au = \sigma v$ and $A^*v = \sigma u$)
  - Information retrieval, web search, signal processing, big data analytics, low rank matrix approximation, total least squares minimization, pseudo-inverse, and many more
- **Many variations depending on structure of A**
  - A can be symmetric, positive definite, tridiagonal, Hessenberg, banded, sparse with dense blocks, etc.
- **DLA is crucial to the development of sparse solvers**











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Provided in MAGMA 2.5

FEATURES AND SUPPORT

- MAGMA 2.5 FOR CUDA
- clMAGMA 1.4 FOR OpenCL
- MAGMA MIC 1.4 FOR Intel Xeon Phi

CUDA	OpenCL	Intel Xeon Phi	
●	●	●	Linear system solvers
●	●	●	Eigenvalue problem solvers
●	●		Auxiliary BLAS
●			Batched LA
●		●	Sparse LA
●	●	●	CPU/GPU Interface
●	●	●	Multiple precision support
● NEW			Mixed precision (including FP16)
●			Non-GPU-resident factorizations
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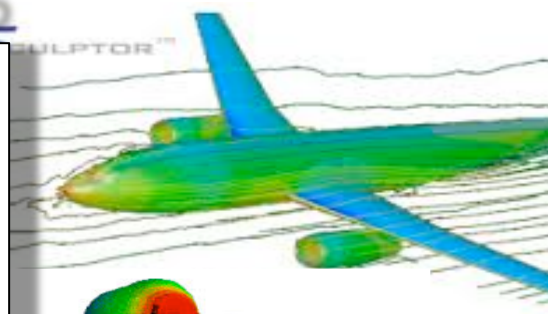
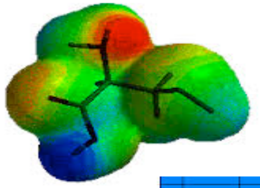
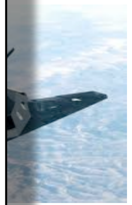
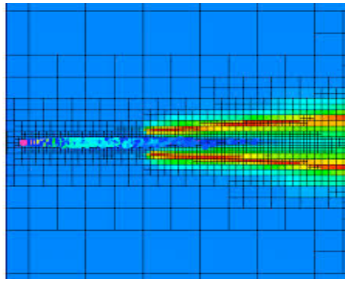
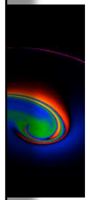
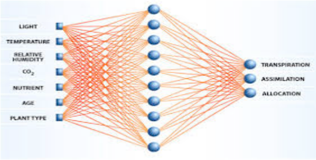












MAGMA

http://icl.cs.utk.edu/magma

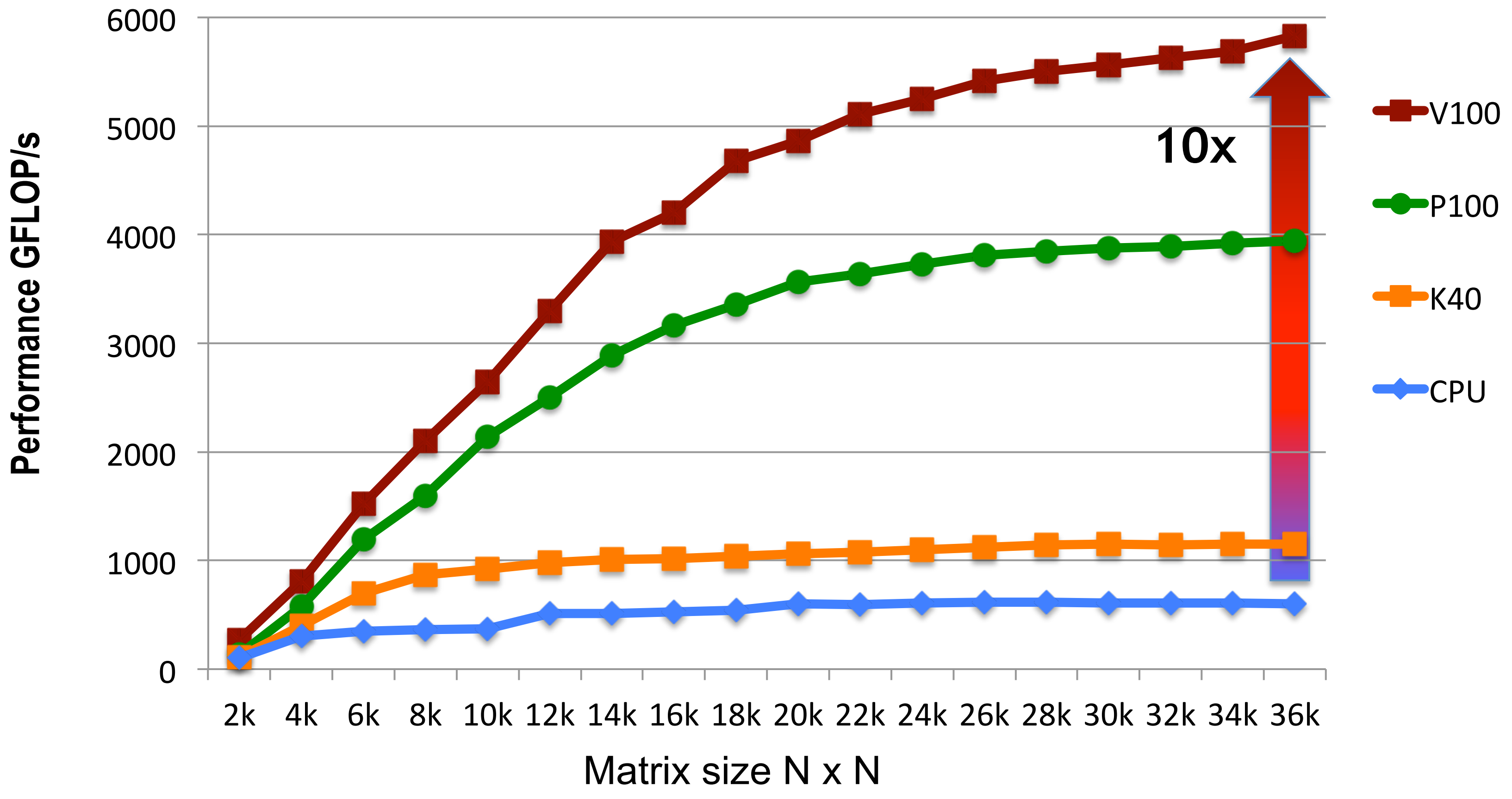
https://bitbucket.org/icl/magma

Why use GPUs in HPC?

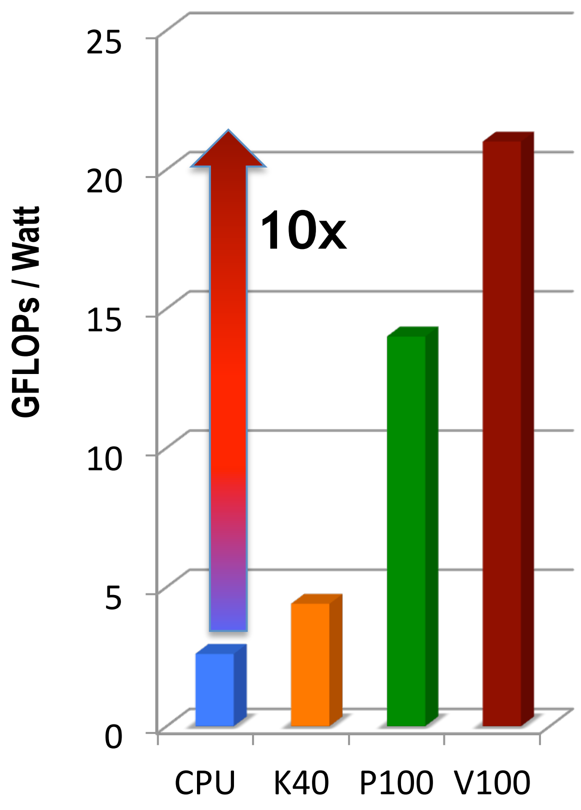
PERFORMANCE & ENERGY EFFICIENCY

MAGMA 2.5 LU factorization in double precision arithmetic

CPU Intel Xeon E5-2650 v3 (Haswell) 2x10 cores @ 2.30 GHz
K40 NVIDIA Kepler GPU 15 MP x 192 @ 0.88 GHz
P100 NVIDIA Pascal GPU 56 MP x 64 @ 1.19 GHz
V100 NVIDIA Volta GPU 80 MP x 64 @ 1.38 GHz



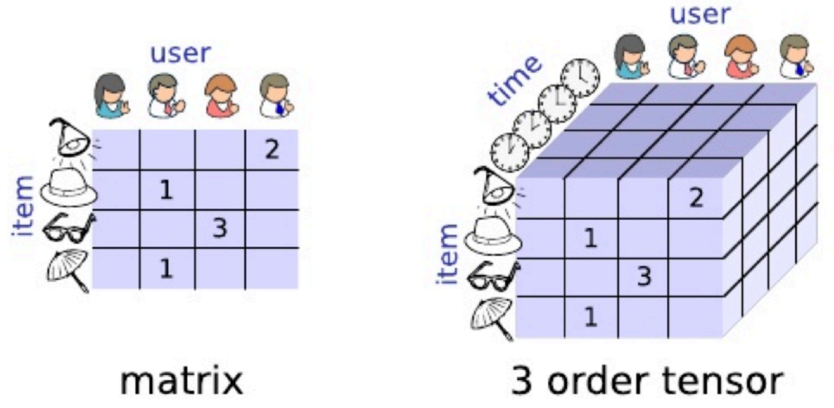
Energy efficiency
(under ~ the same power draw)



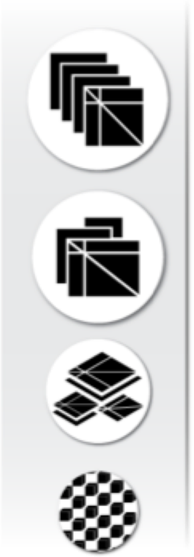
What about accelerated LA for Data Analytics?

- Traditional libraries like MAGMA can be used as backend to accelerate the LA computations in data analytics applications
- Need support for
  1) New data layouts, 2) Acceleration for small matrix computations, 3) Data analytics tools

Need data processing and analysis support for
Data that is multidimensional / relational



Small matrices, tensors, and batched computations



Fixed-size batches

Variable-size batches

Dynamic batches

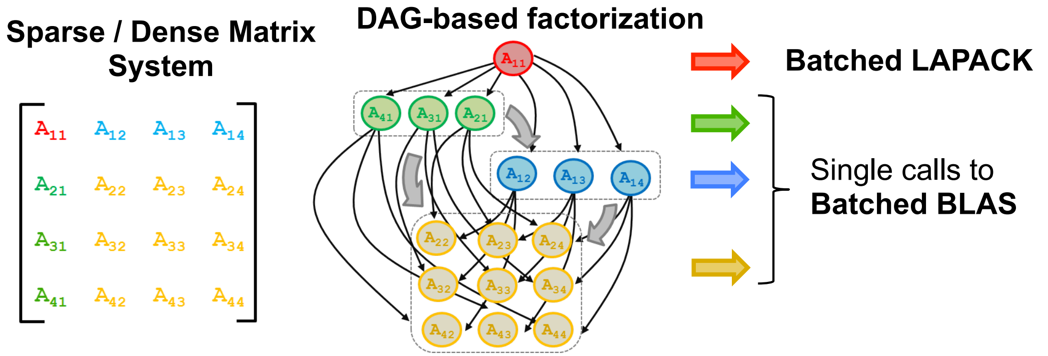
Tensors

Data Analytics and LA on many small matrices

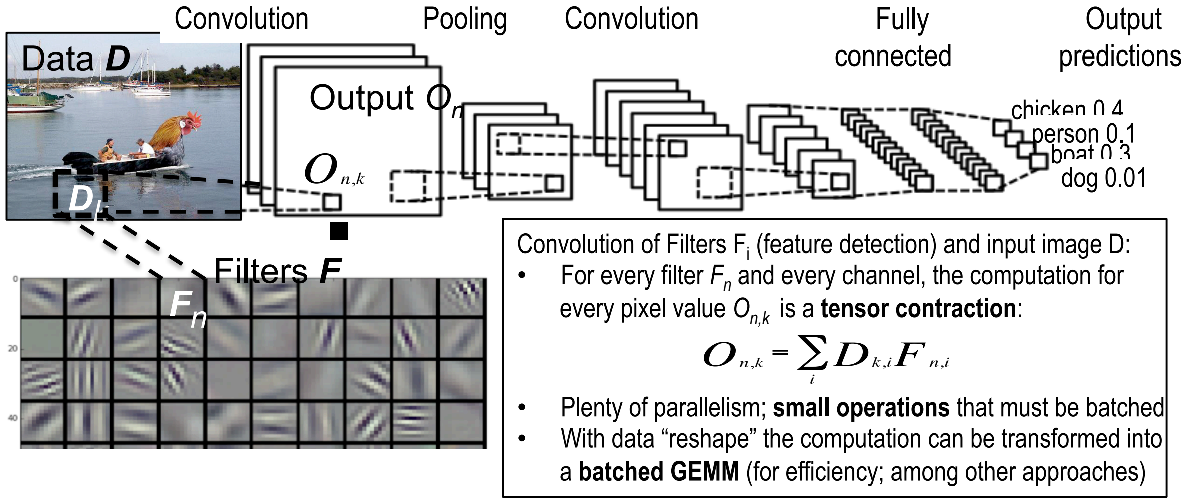
Data Analytics and associated with it Linear Algebra on small LA problems are needed in many applications:

- Machine learning,
- Data mining,
- High-order FEM,
- Numerical LA,
- Graph analysis,
- Neuroscience,
- Astrophysics,
- Quantum chemistry,
- Multi-physics problems,
- Signal processing, etc.

Sparse/Dense solvers & preconditioners



Machine learning



Applications using high-order FEM

- Matrix-free basis evaluation needs efficient tensor contractions,

$$C_{i1,i2,i3} = \sum_k A_{k,i1} B_{k,i2,i3}$$

- **Within ECP CEED Project,** designed MAGMA batched methods to split the computation in many small high-intensity GEMMs, grouped together (batched) for efficient execution:

Batch_{ $C_{i3} = A^T B_{i3}$, for range of i3 }

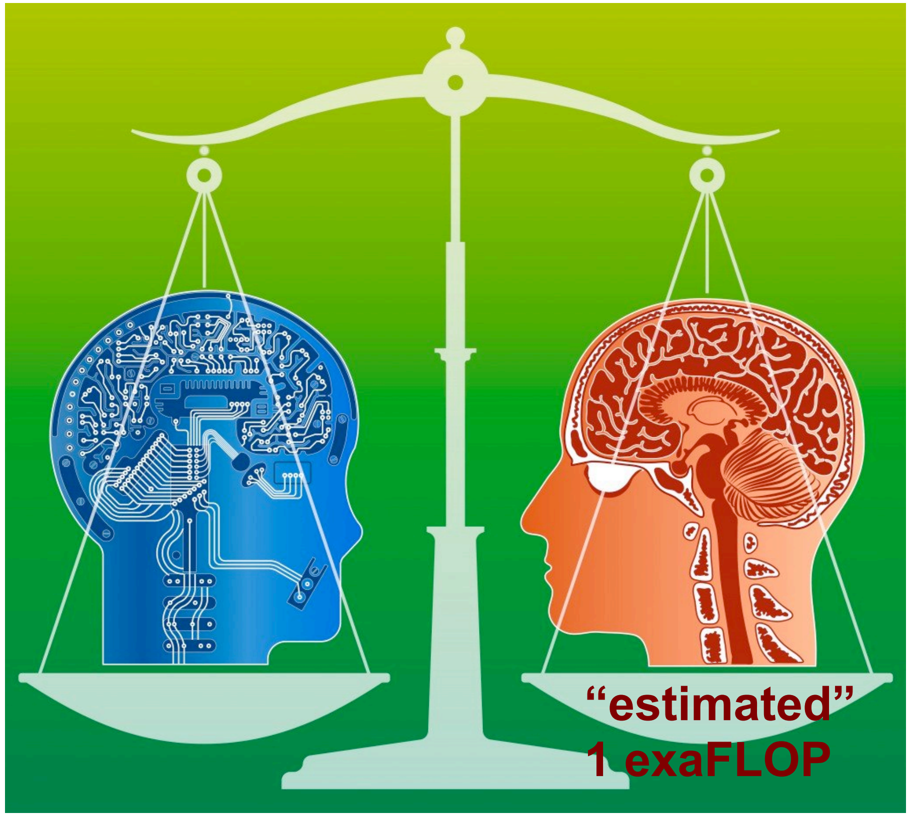
Machine learning / Artificial Intelligence

- Give computers the ability to “learn”

- Soon we may not have to program computers
  – We will train them instead !

See part of GTC’18 Keynote from NVIDIA CEO Jensen Huang
https://www.youtube.com/watch?v=oa__wkSmWUw

Human brain vs. supercomputer ?



https://www.scienceabc.com/humans/the-human-brain-vs-supercomputers-which-one-wins.html

MagmaDNN – Data Analytics Tool

- **MagmaDNN 0.2 – HP Data analytics and ML**
  GPU-accelerated numerical software using MAGMA as computational backend to accelerate its LA computations

- **Open source; looking for feedback and contributions**
  Started with students from REU/RECSEM program
  https://bitbucket.org/icl/magmadnn

Provided in MAGMA 2.5

FEATURES AND SUPPORT

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- **clMAGMA 1.4** FOR **OpenCL**
- **MAGMA MIC 1.4** FOR **Intel Xeon Phi**

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- **MagmaDNN 0.2 main functionalities**
  - Tensors and tensor operations
  - Deep learning primitives:
    Fully-connected layers, convolutional layers, pooling layers, activation layers, and output layers.
  - SGD back-propagation training
  - Established adapters for calling CuDNN
  - Winograd convolutions to accelerate CNNs
  - Mixed-precision (FP16-FP32) FFT
  - Hyperparameter optimization framework
  - MNIST and CIFAR-10 benchmarks using MagmaDNN
  - Performance comparisons, accuracy validations, etc. (w\ TensorFlow, Theano, and PyTorch)

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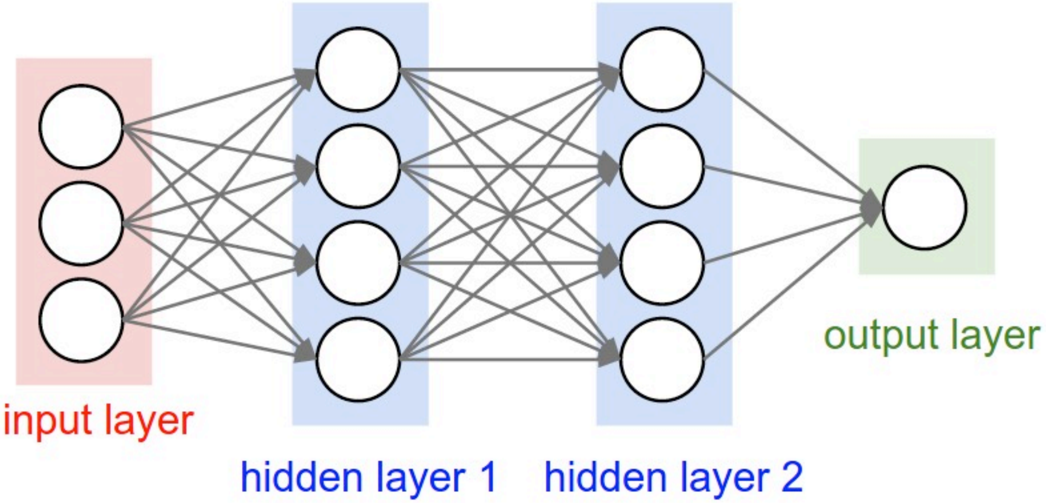
Fully connected layers with MagmaDNN

Fully-connected 3-layer Neural Network example



- **Data** (input, output, NN weights, etc.) **is** handled through **tensor abstractions**

```
// 2d tensor for n_images and n_features in the corresponding dimensions
Tensor<float> Images = Tensor<float>({n_images, n_features});
```

- **Support for various layers:**
  Fully connected (FCLayer), convolution, activation, flatten, pooling, input, output, etc. layers

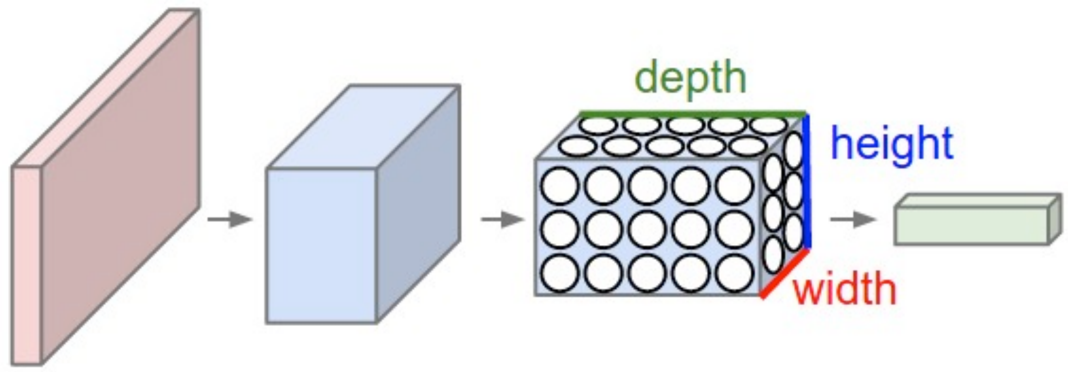
```
// Create layers for the network
FCLayer<float> *FC1             = new FCLayer<float>(&inputLayer, 128);
ActivationLayer<float> *actv1 = new ActivationLayer<float>(FC1, SIGMOID);
FCLayer<float> *FC2             = new FCLayer<float>(actv1, n_output_classes);
```

- **Support networks – composed of layers**

```
std::vector<Layer<float>*> vec_layer;
vec_layer.push_back(&inputLayer);
vec_layer.push_back(FC1);
vec_layer.push_back(actv1);
vec_layer.push_back(FC2);
…
```

Convolutional network layers

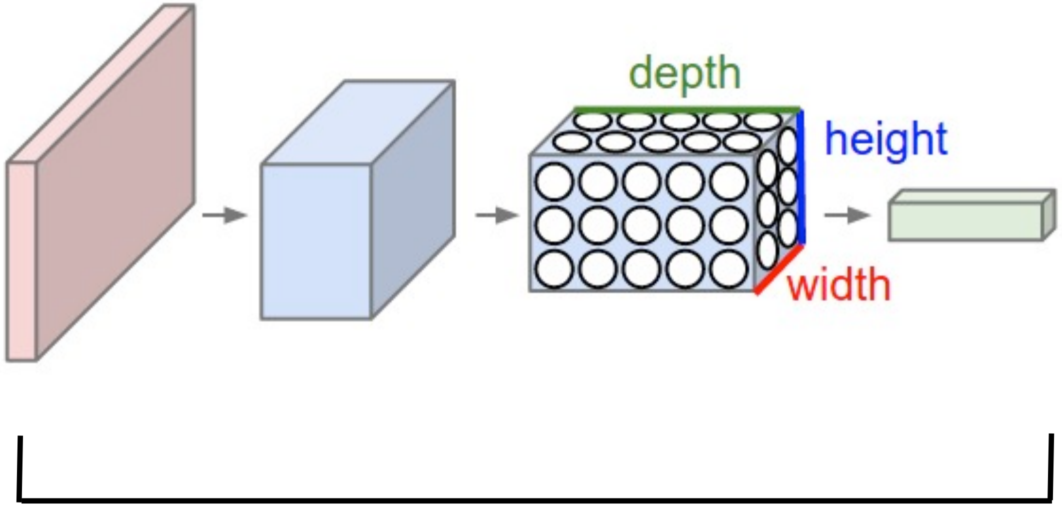
Convolution Network (ConvNet) example



- Layers are typically 3D volumes
- Handled through tensors
- Each layer transforms 3D tensor to 3D tensor
- Layers support the forward and backward pass algorithms for the training
- Support for optimization solvers (GD and derivatives)
  - Gradient Descent (GD)
  - Stochastic Gradient Descent (SGD)
  - Mini-Batch Gradient Descent (MB-GD)

How to accelerate on manycore GPU and CPUs?

Convolution Network (ConvNet) example



Require matrix-matrix products of various sizes, including batched GEMMs

- **Convolutions can be accelerated in various ways:**
  - **Unfold and GEMM**
  - **FFT**
  - **Winograd minimal filtering – reduction to batched GEMMs**

Fast Convolution				
Layer	m	n	k	M
1	12544	64	3	1
2	12544	64	64	1
3	12544	128	64	4
4	12544	128	128	4
5	6272	256	128	8
6	6272	256	256	8
7	6272	256	256	8
8	3136	512	256	16
9	3136	512	512	16
10	3136	512	512	16
11	784	512	512	16
12	784	512	512	16
13	784	512	512	16

- **Use autotuning to handle complexity of tuning**

Accelerating CNNs in MagmaDNN with FFT

- **Convolutions $D_{i,c}$ * $G_{k,c}$** of images $D_{i,c}$ and filers $G_{k,c}$ can be **accelerated through FFT,** as shown by the following equality, consequence of the convolution theorem:

$$D_{i,c} * G_{k,c} = FFT^{-1} \left[FFT(D_{i,c}) .* FFT(G_{k,c}) \right],$$

  where .* is the Hadamard (component-wise) product, following the '.*' Matlab notation

- Developed **mixed-precision (FP16-FP32) FFT** using the GPU's Tensor Cores (TC) acceleration
  - **Dynamic splitting to increase the FP16 accuracy, while using high-performance TC**

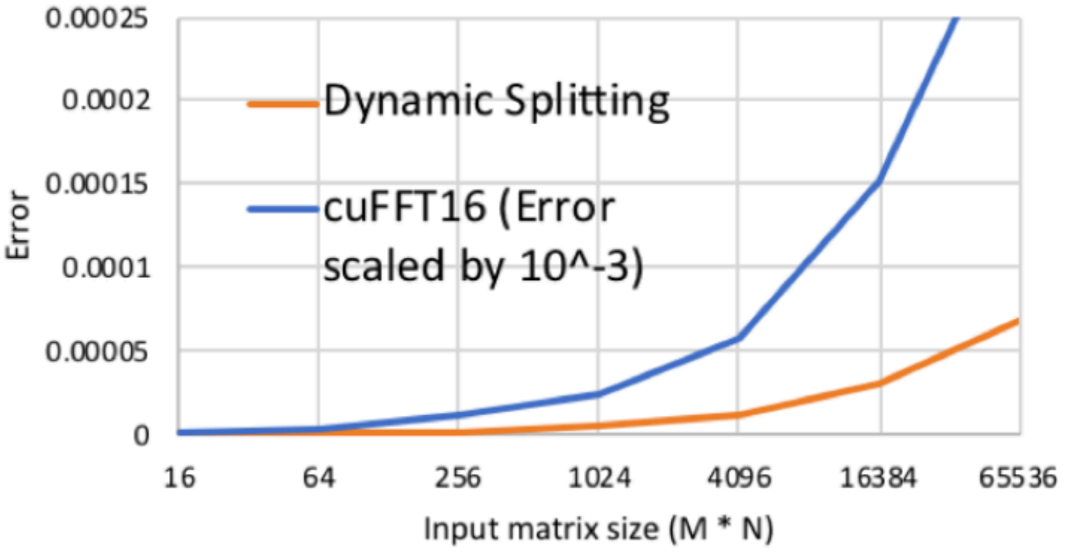
$$X_{FP32}(:) = s_1 \, X1_{FP16}(:) + s_2 \, X2_{FP16}(:)$$

[X1 X2] = FFT([X1 X2]   in FP16+ (e.g., go to radix 4, where the FFT matrix is exact in FP16)

$$FFT(X) \approx s_1 \, X1 + s_2 \, X2$$

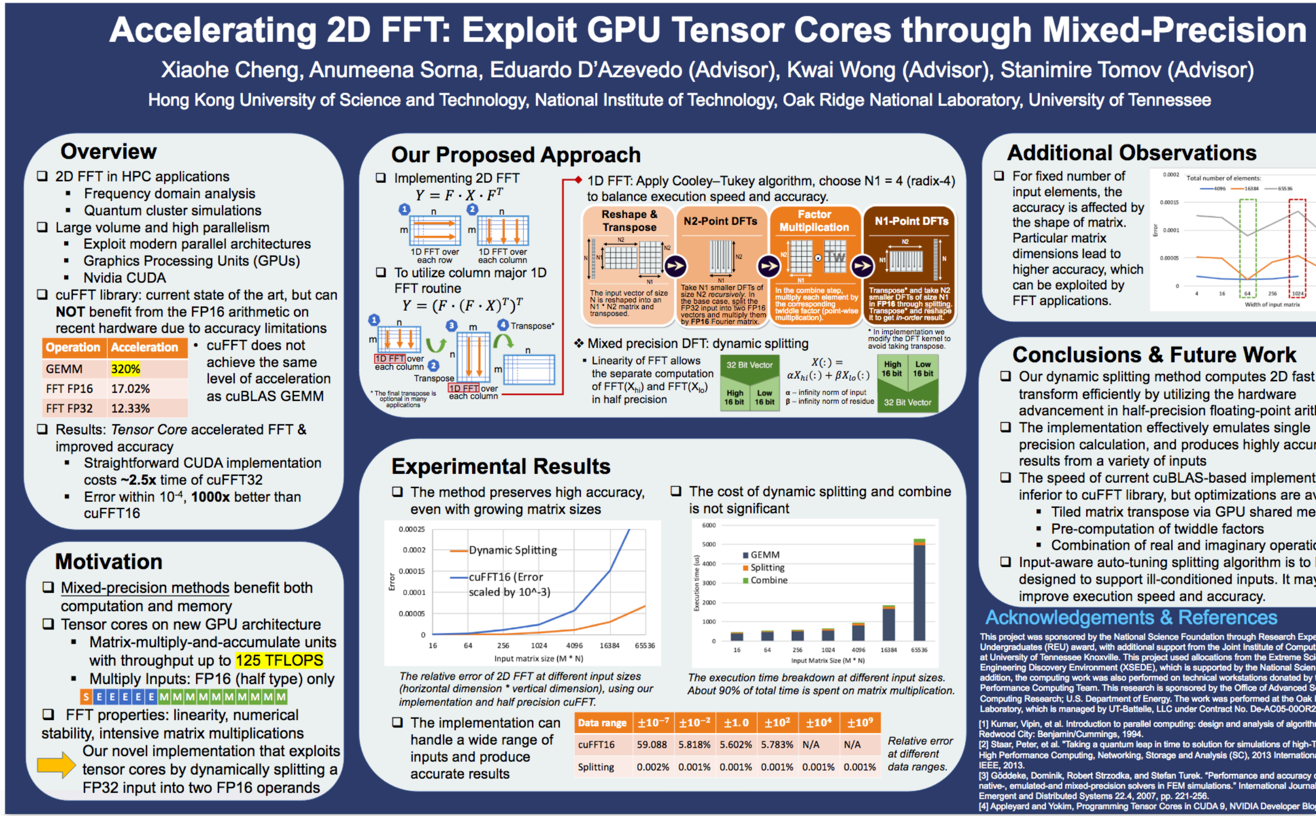
Accelerating CNNs with FFT

➢ **Accuracy of the mixed-precision (FP16-FP32) FFT**



Reference:
X. Cheng, A. Sorna , Ed D'Azevedo, K. Wong, S. Tomov, **"Accelerating 2D FFT: Exploit GPU Tensor Cores through Mixed-Precision,"** The International Conference for High Performance Computing, Networking, Storage, and Analysis (SC'18), ACM Student Research Poster, Dallas, TX, November 11-16, 2018.

https://icl.utk.edu/projectsfiles/magma/pubs/77-mixed-precision-FFT.pdf
https://www.jics.utk.edu/recsem-reu/recsem18



Accelerating CNNs with Winograd's minimal filtering algorithm

- **FFT Convolution is fast for large filters;**
  Typical filters are small, e.g., 3x3, where Winograds's algorithm has been successful;
  In 2D, convolution of tile D of size 4x4 with filter F of size 3x3 is computed as

  $$D * F = A^T \, [\, [\, G\, D\, G^T] \;.\!*\; [B^T\, D\, B]\,]\, A$$

  where B, G, and A are given on the right:

$$B^T = \begin{bmatrix} 1 & 0 & -1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & 1 & 0 & -1 \end{bmatrix}$$

$$G = \begin{bmatrix} 1 & 0 & 0 \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & -\frac{1}{2} & \frac{1}{2} \\ 0 & 0 & 1 \end{bmatrix}$$

$$A^T = \begin{bmatrix} 1 & 1 & 1 & 0 \\ 0 & 1 & -1 & -1 \end{bmatrix}$$

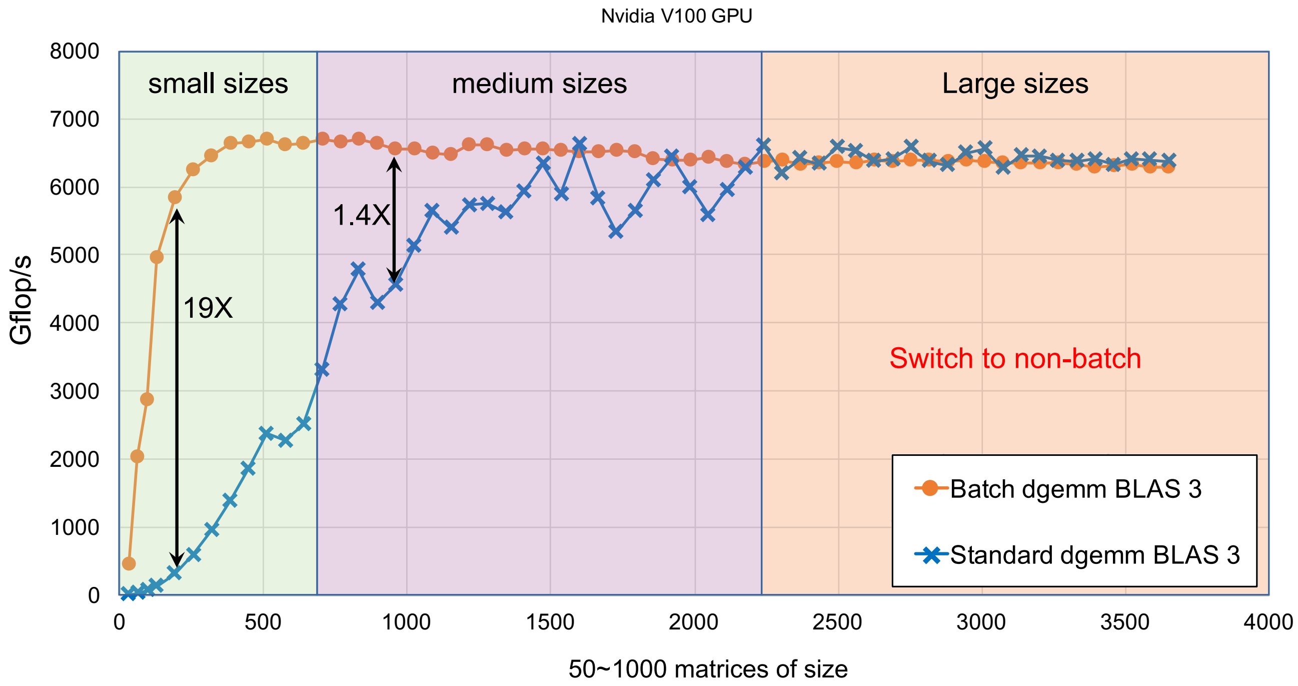
- Computing for a number of filters, sliding the tile over a batch of images, each with a number of channels, can be expressed as batched gemms, e.g.,

batch	m	n	k	
batch	**m**	**n**	**k**	**(sizes coming from VGG-16 CONVOLUTION LAYERS)**
16x64	12544	64	3	
16x64	**12544**	**64**	**64**	
16x16	12544	128	64	
16x16	**12544**	**128**	**128**	

…

How to implement fast batched DLA?

Problem sizes influence algorithms & optimization techniques

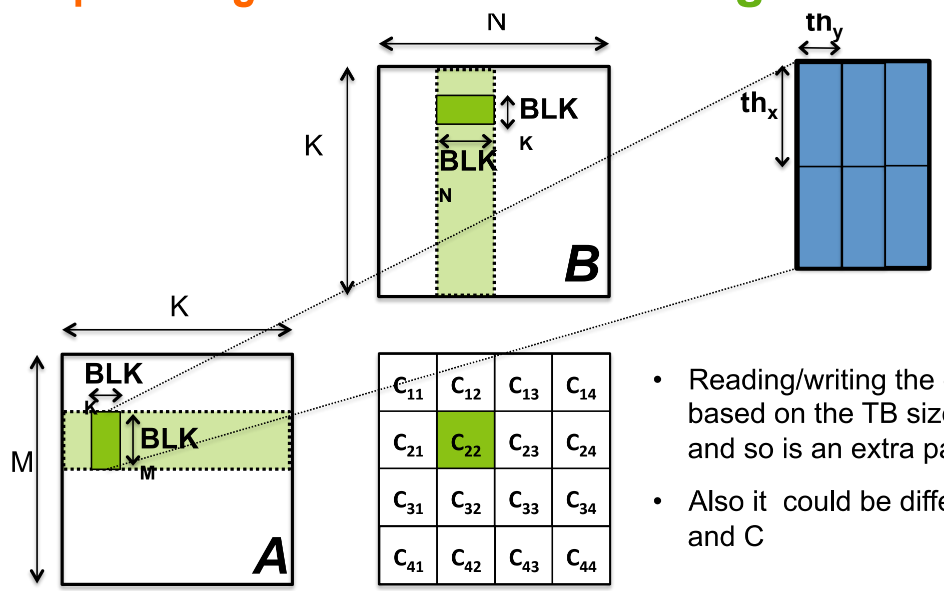


Matrix sizes (fixed) in the batch

Batch size 1,000 | Batch size 300 | Batch size 50

Kernels are designed various scenarios and parameterized for autotuning framework to find "best" performing kernels

Optimizing GEMM's: Kernel design



- Reading/writing the elements is based on the TB size (# threads) and so is an extra parameter.
- Also it could be different for A, B and C

Hyperparameter optimization framework

- **Hyperparameters are grouped in Model class**

```
// put in layers a sequence of predefined layers
std::vector<Layer<float>*> layers { &input_layer, FC1, actv1, FC2, output_layer };
// set some hyperparameters
Param p { learning_rate, weight_decay, batch_size, epochs };
Model model (p, &layers);

// train network model – arguments train data, train outcomes, verbose, accuracy, loss
model.fit(x_train, y_trian, false, accuracy, loss);
```

- **User can define a hyperparameter search space, e.g., start parameters, end, and step**

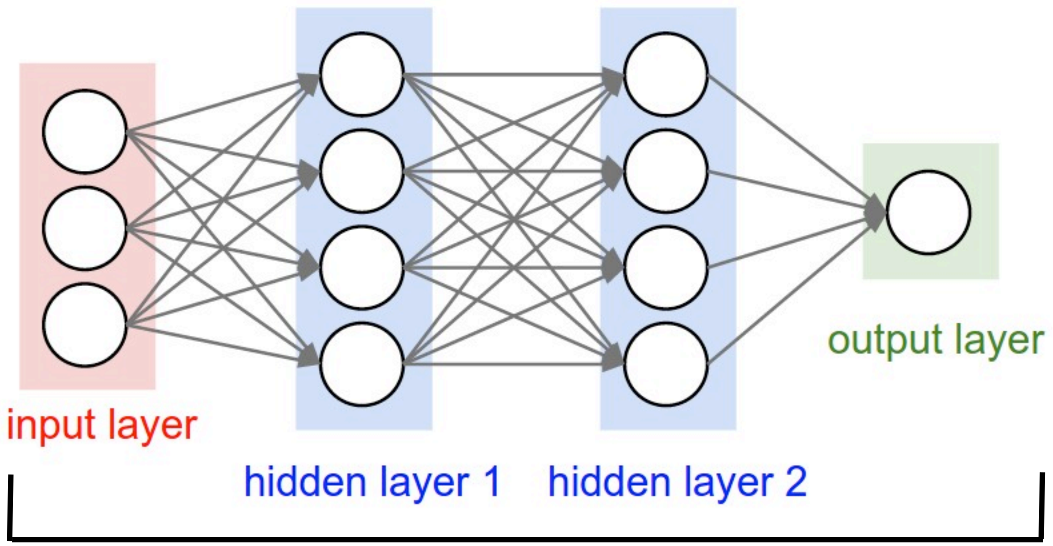
```
Param start  {  0.2,        0,  n_batch,       5 };
Param end    {  0.2,        1,  n_batch,       5 };
Param step   { 0.01,    0.01,         1,       1 };
Model model (start, &layers);
```

- **… and find optimal parameters via a grid_search function**

```
Param opt = grid_search(model, x_train, y_train, start, end, step, 5, -1, 5000, true);
```

MagmaDNN benchmarks and testing examples

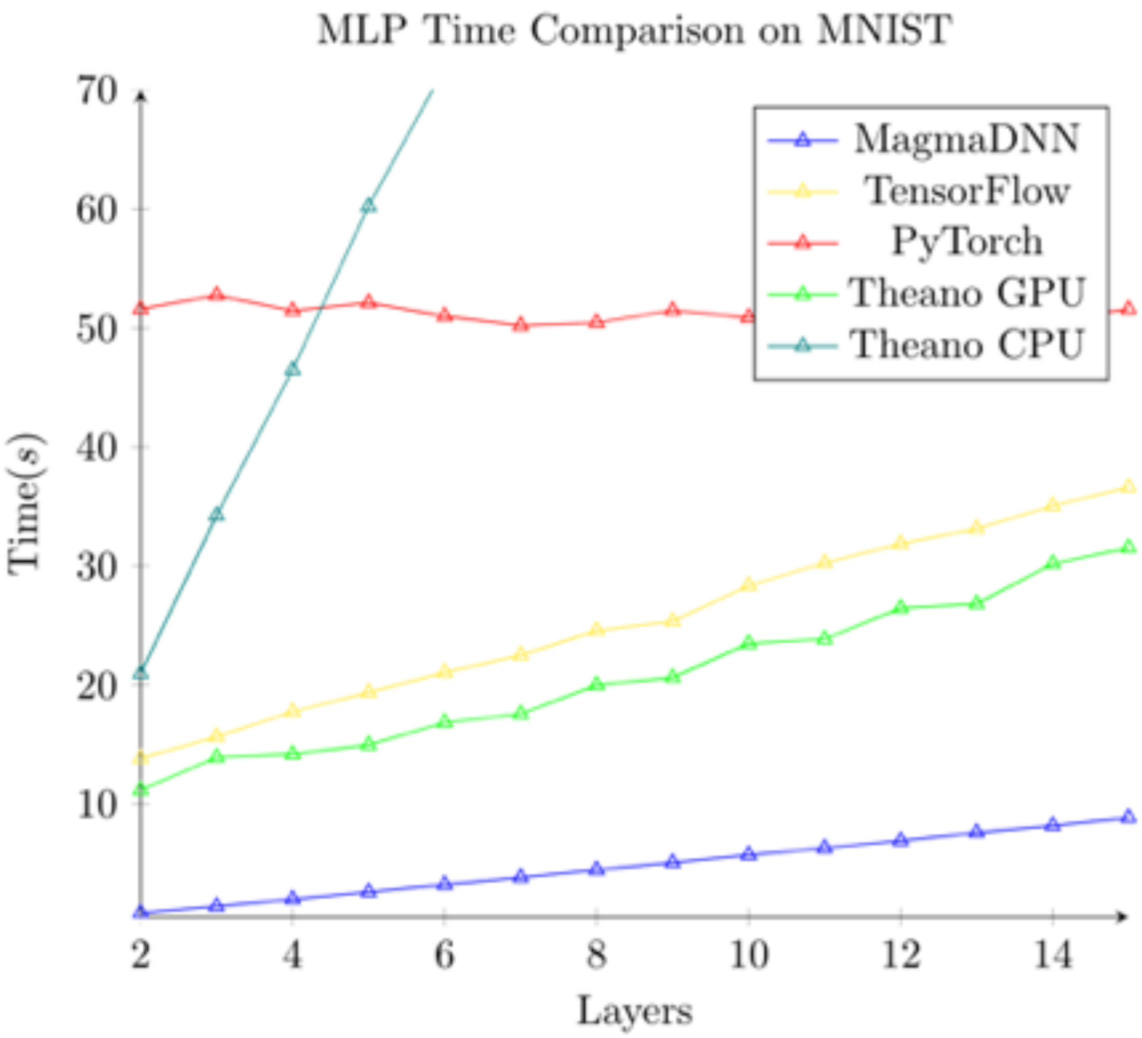
Fully-connected 3-layer Neural Network example



- The MNIST benchmark is a NN for recognizing handwritten numbers
- Input for the training are images of handwritten numbers and the labels indicating what are the numbers

- **MagmaDNN has testing/example drivers**
- **Example implementing the MNIST benchmark using MagmaDNN multilayer perceptron or a convolutional neural network**
- **CIFAR-10 benchmark using MagmaDNN**
- **Benchmarks for Wingrad and FFT**
- **Performance comparisons, accuracy validations, etc. (w\ TensorFlow, Theano, and PyTorch)**

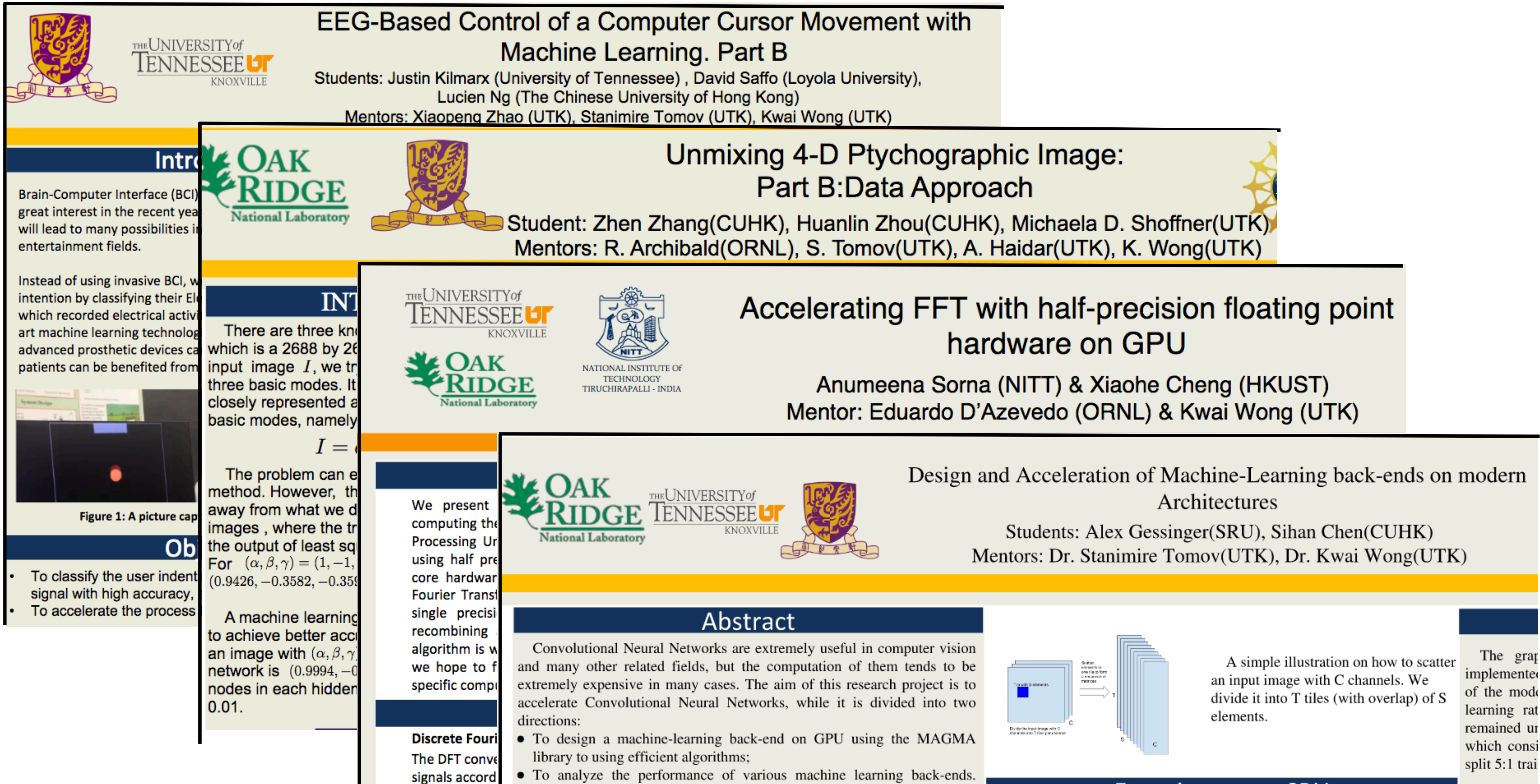
MagmaDNN performance benchmarks and validations



- MagmaDNN outperforms other popular deep learning libraries
- Compute time scales better than other libraries as models get larger

Parameter/Setting Name	Value
GPU	Nvidia 1050 Ti
CPU	Intel Xeon X5650 @ 2.67GHz x 12
OS	Ubuntu 16.04 LTS
Epochs	5
Batch Size	100
Learning Rate	0.2
Weight Decay	0.001
#Hidden Units / Layer	528

MagmaDNN benchmarks and testing examples …



Current work and Future directions

- **Performance portability and unified support on GPUs/CPUs**
  - C++ templates w/ polymorphic approach;
  - Parallel programming model based on CUDA, OpenMP task scheduling, and MAGMA APIs.
- **Hyperparameter optimization**
  - Critical for performance to provide optimizations that are application-specific;
  - A lot of work has been done (on certain BLAS kernels and the approach) but still need a simple framework to handle the entire library;
  - Current hyperparameter optimization tool must be further extended in functionalities
  - Add visualization and OpenDIEL to support ease of GPU deployment over large scale heterogeneous systems
- **Extend functionality, kernel designs, and algorithmic variants**
  - BLAS, Batched BLAS, architecture and energy-aware
  - New algorithms and building blocks, architecture and energy-aware
  - Randomization algorithms, e.g., for low-rank approximations, and applications
- **Use and integration with applications of interest (with ORNL collaborators)**
  - Brain-computer interface systems
  - Post-processing data from electron detectors for high-resolution microscopy studies (Unmixing 4-D Ptychographic Images)
  - Optimal cancer treatment strategies

Collaborators and Support

MAGMA team

http://icl.cs.utk.edu/magma

PLASMA team

http://icl.cs.utk.edu/plasma

Collaborating partners

University of Tennessee, Knoxville
Lawrence Livermore National Laboratory
University of California, Berkeley
University of Colorado, Denver
INRIA, France (StarPU team)
KAUST, Saudi Arabia