## Walchand College of Engineering, Sangli Department of CSE

Seminar on "Scaling Up Machine Learning and Deep Learning: Parallel Approach with CUDA and OpenMP"

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#### Research Area

Research Area: Applying High Performance Computing / Parallel Computing

to Machine Learning Algorithms.

► Paper Title: Accelerating nearest neighbour partitioning neural network

classifier based on CUDA.

Authors: Lin Wang, Ajith Abraham, Meihui Li

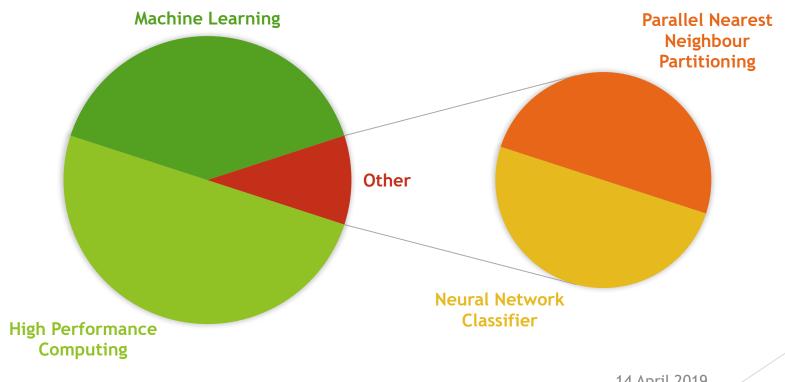
Publisher: Elsevier

Journal : Engineering Applications of Artificial Intelligence

Publication Year: 2018

## **Technology**

#### **WORKING DISTRIBUTION**



# Why Machine Learning with High Performance Computing?

- Numerical analysis formed backbone for supercomputing devices over the decades.
- Recently scientists have begun experimenting with understanding complex systems using
  - Machine Learning predictive models
  - Deep Neural Network
  - With Parallel Computing

Trained by virtually unlimited datasets produced globally.

► HPC can improve accuracy, accelerate time to solution and significantly reduce costs.

## Literature Survey

- Anderson, D., Coupland, S., Parallelisation of fuzzy inference on a graphics processor unit using the compute unified device architecture. Recent. Progr. Med. 85 (3), 160-165, 2008.
- ▶ Jang, H., Park, A., Jung, K., Neural network implementation using cuda and openmp. In: Digital Image Computing: Techniques and Applications. pp. 155-161, 2008.
- Wang, L., Yang, B., Chen, Y., Improving particle swarm optimization using multilayer searching strategy. Inform. Sci. 274 (8), 70-94, 2014.
- Wang, L., Yang, B., Chen, Y., Abraham, A., Sun, H., Chen, Z., Wang, H., Improvement of neural network classifier using floating centroids. Knowl. Inf. Syst. 31 (3), 433-454, 2012.

## Literature Survey: Floating Centroid Method

#### Fixed Centroids

- In traditional Neural Network, features of centroids are fixed.
- In mapping of samples, fixed centroids reduces possibilities of finding optimal solution.

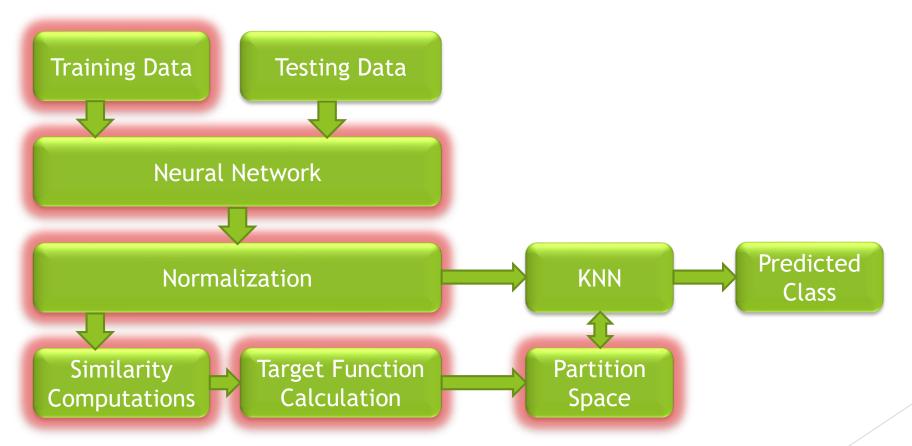
#### Floating Centroid Method

- In partition space, centroid is point. The proposed approach introduces many floating centroids.
- FCMs are spread throughout partition space, and obtained by using K-Means algorithms.

## Limitations of FCM

- Cannot yield flexible decision boundaries.
- Problem overcomes by Neural Network Partitioning.

# Literature Survey: Particle Swarm Optimization



## Methodology

Sample Mapping Normalization Similarity Computations Target Function Calculation

## Sample Mapping in Parallel

In CUDA, data transmission takes place between CPU and GPU

Original samples → Global Memory
Information of Neural Network → Shared Memory

Data Divided as  $\Rightarrow$   $|S^{i}| = \begin{cases} \frac{|S|}{threadcount}, & i < threadcount \\ |S|mod \left[ \frac{|S|}{threadcount} \right], & i = threadcount \end{cases}$ 

## Sample Mapping in Parallel

```
tx \rightarrow identity of thread block
Value of identity of particle \rightarrow particleid = \frac{tx}{threadcount}
```

The value of identity of thread in each neural network  $\rightarrow$ 

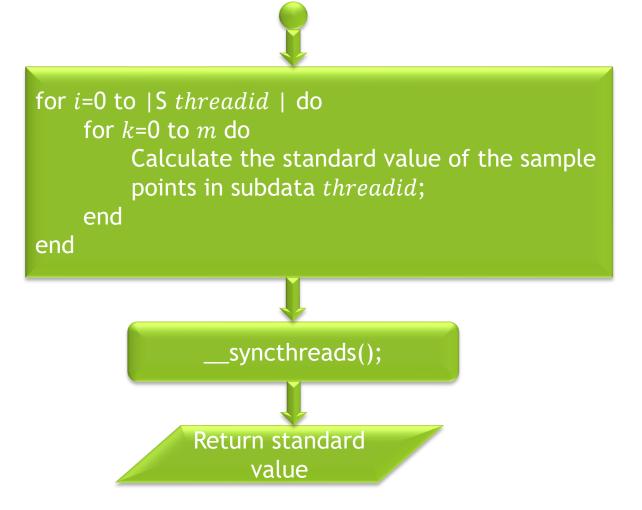
threadid = tx mod thread count

Evaluation of sample is executed parallelly by tasks  $\{T^1, T^2, ..., T^{threadnum}\}$  are allocated to the *threadnum* parallel thread in one block. Then mapped samples stored in global memory.

#### Normalization in Parallel

Set the value of mean and standard deviation of subdata threadid to 0 for i=0 to |S| threadid |S|for j=0 to |S| do Calculate the average value and standard deviation of each sample in subdata threadid; end end \_syncthreads();

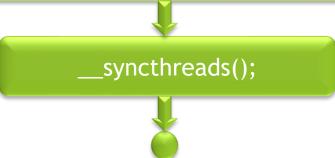
#### Normalization in Parallel



## Similarity Computation in Parallel

$$d = |x| \frac{1 - e^{-|x|/2}}{|x| + |x| \cdot e^{-|x|/2}}$$

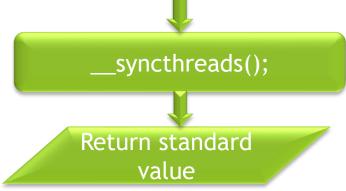
```
for i=0 to |S threadid | do
for j=0 to m do
Calculate d use formula in subdata
threadid; Obtain the values by the
normalized points into a hypersphere;
end
end
```



## Similarity Computation in Parallel



```
for i=0 to |S threadid | do
    for j=0 to |S| do
        Calculate the distance D between two points with
        Euclidean Distance in subdata threadid;
        if threadid:=j then
            The value of SimilarityArray<sub>threadid,j</sub> is 2;
        else
            The value of SimilarityArray<sub>threadid,j</sub> is 2-D;
        end
end
```



## Target Function Calculation in Parallel

```
F = \omega(x_i)(S_{nonself}(x_i) - \alpha S_{self}(x_i))
\alpha \rightarrow \text{adjustment coefficient}
S_{nonself}(x_i) \rightarrow \text{Sum of similarities between } x_i \text{ and samples in other classes}
S_{self}(x_i) \rightarrow \text{sum of similarities between } x_i \text{ and samples in same class}
S_{self}(x_i) \rightarrow \text{sum of similarities between } x_i \text{ and samples in same class}
S_{self}(x_i) \rightarrow \text{sum of similarities between } x_i \text{ and samples in same class}
```

- ► Host side → weight of each sample is calculated
- ▶ Device side → data is transmitted to and stored in array weight
- Each thread calculates each subdata in array *SimilarityArray*
- Each sample is divided into **self-class** and **nonself-class** according to similarity
- $\triangleright$  Each thread calculates value of  $S_{self}$  and  $S_{nonself}$  in parallel

## Implementation: Environment

CPU: Intel i7 4<sup>th</sup> Gen.

- $\rightarrow$  CPU Cores  $\rightarrow$  8
- ► CPU Clock → 3.40 GHz
- ► L3 Cache → 8 MB

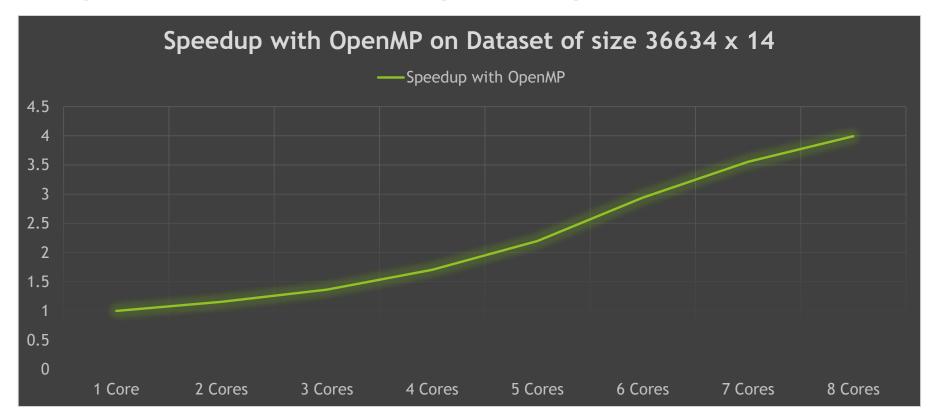
GPU: NVIDIA GeForce GT740

- ► CUDA Cores  $\rightarrow$  384
- ► Graphics Clock → 993 MHz
- ► Memory → 2048 MB DDR3

## **Implementation**

- C++ Serial program for Normalization of Data
- C++ Parallel program for Normalization of Data using OpenMP
- C++ Parallel program for Normalization of Data using CUDA on NVIDIA's GPU

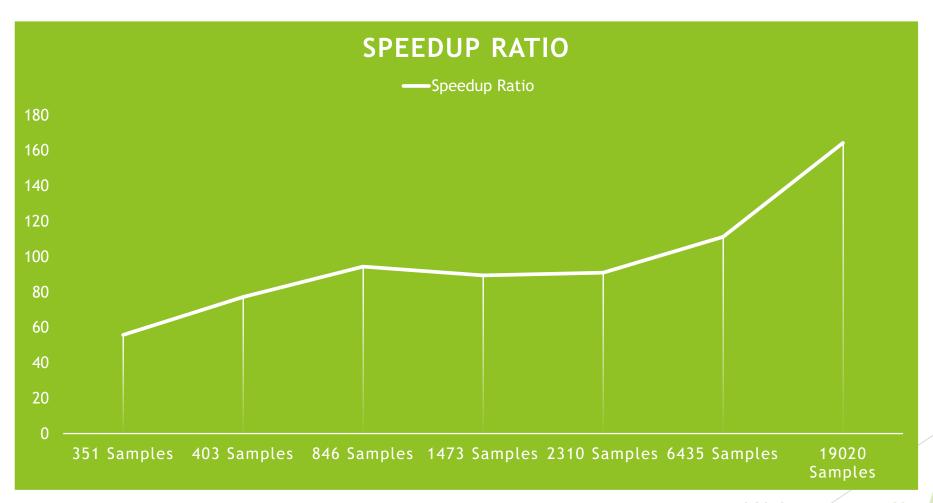
### Implementation: Speedup vs. Cores



- $\diamond$  Average Time Required to CUDA Program for Execution  $\rightarrow$  1085 microsec.
- ❖ Speedup GPU vs CPU → 7.9253

- Experiment
  - ► C / C++ programing environment and Linux Operating System
  - NVIDIA's high performance Tesla K10 GPU
    - ▶ 8 SMs each consisting 192 SPs
    - ► SP's clock frequency → 750 MHz
    - ► In each block  $\rightarrow$  65,536 registers
    - ► Each Multiprocessor → Thousands of CUDA cores
- 10-Fold Cross-Validation
  - ▶ Dataset divided into 10 subsets
  - One is used for testing
  - Remaining are used for training
  - ▶ Then average performance reported

Dataset	Size	NNP Seconds	PNNP Seconds	Speedup Ratio
IONOSPHERE	351 x 34	1283	23	55.78
UKM	403 x 5	1158	15	77.2
VEHICLE	846 x 18	6230	66	94.39
CMC	1473 x 9	19583	219	89.42
SEGMENT	2310 x 19	71198	783	90.93
SATELLITE	6435 x 36	578905	5178	111.8
MAGIC	19020 x 10	8177290	49773	164.29



	Traditional (Wang et al., 2017)	SoftMax (Wang et al., 2017)	ECOC (Wang et al., 2017)	FCM (Wang et al., 2017)	PNNP
IONOSPHERE	86.18(±6.42)	N/A	N/A	93.44(±5.43)	93.59(±1.63)
PARKINSONS	83.12(±16.57)	N/A	N/A	76.75(±17.39)	85.52(±9.07)
HABERMAN	59.42(±8.02)	N/A	N/A	55.93(±9.61)	66.79(±5.73)
UKM	92.73(±5.03)	85.22(±14.79)	93.26(±2.98)	96.11(±2.03)	97.64(±2.01)
VEHICLE	81.88(±2.14)	83.28(±2.19)	80.10(±3.12)	78.54(±4.17)	83.19(±2.24)
CMC	50.84(±4.88)	50.49(±2.89)	49.28(±3.16)	52.83(±2.55)	$53.08(\pm 2.5)$
SEGMENT	96.66(±1.79)	96.55(±1.40)	96.16(±1.37)	95.72(±1.69)	$96.92(\pm0.90)$
VC	72.50(±5.72)	79.98(±6.31)	73.59(±9.61)	81.21(±7.77)	83.02(±6.68)
SEEDS	93.32(±6.01)	92.85(±7.15)	94.26(±7.43)	95.18(±5.08)	96.16(±3.06)
WINE	97.85(±3.69)	98.33(±3.77)	97.78(±2.88)	98.88(±2.36)	99.49(±1.62)

#### Conclusion

- ► To speedup the training process of NNP, particularly for large dataset, we proposed parallel NNP based on NVIDIA's CUDA framework.
- $\rightarrow$  At CPU Side  $\rightarrow$  Main optimization algorithm performed in serial.
- At GPU Side → NNP Neural Network Classifier is evaluated parallelly on multiple blocks and all subtasks are performed parallelly using threads.
- ▶ PNNP not only increases speed but also improves measurements.
- ▶ PNNP yields promising that it is able to solve real world problems.
- In the future, PNNP can be used in medical image analysis and bioinformatics with referenced to big data.

#### References

- Anderson, D., Coupland, S., Parallelisation of fuzzy inference on a graphics processor unit using the compute unified device architecture. Recent. Progr. Med. 85 (3), 160-165, 2008.
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## Thank You!