Neural Network on CUDA

Restricted Boltzmann Machine

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Outline

● Restricted Boltzmann Machine background
● CUDA Implementation
  – Matrix Library
  – Random Number Generator
  – Sigmoid Function
● Results
● Discussion
Background

- Neural networks is a computational paradigm that is inspired by biological nervous systems.
- Based on the idea of having lots of simple computational units, called nodes, that maps an input to an output.
- Interesting behaviour emerges from massive networks of interconnected nodes.
Background

• Artificial neural networks are capable of learning
  • Given a data set, automated learning rules can be applied to achieve a desired behaviour
• Artificial neural networks are applied to a growing number of applications
  • Pattern classification
  • Computer vision
  • Signal processing
RBM Theory
RBM Theory

Visible Layer

Binary state \{0,1\}

\( v_i \)
RBM Theory

Visible Layer

Hidden Layer

Binary state {0, 1}
RBM Theory

Hidden Layer

visible layer

\[ v_i \]

\[ h_j \]

Connections/Weights

\[ w_{i,j} \]

\[ \in \mathbb{R} \]
RBM Theory
Alternating Gibbs Sampling
RBM Theory

Alternating Gibbs Sampling

Load data vector in visible layer
RBM Theory

Alternating Gibbs Sampling

\[ E_j = \sum_j w_{i,j} v_i \]

Generate energies
RBM Theory

Alternating Gibbs Sampling

\[ h_j = f(E_j) \]

Determine node state through transfer function
RBM Theory

Alternating Gibbs Sampling

Determine node state through transfer function
RBM Theory

Alternating Gibbs Sampling

Determine node state through transfer function
RBM Theory

Alternating Gibbs Sampling

Reconstruct visible nodes
RBM Theory

Alternating Gibbs Sampling

\[ E_i = \sum_i w_{i,j} h_j \]

\[ v_i = f(E_i) \]

Reconstruct visible nodes
RBM Theory

Alternating Gibbs Sampling

Reconstruct visible nodes
RBM Theory

Alternating Gibbs Sampling

Update weights (simplified)
RBM Theory

Alternating Gibbs Sampling

\[ w_{i,j} = w_{i,j} \pm \epsilon v_i h_j \]

Update weights (simplified)
RBM Theory

Alternating Gibbs Sampling

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Update weights (simplified)
RBM Theory

Alternating Gibbs Sampling

Repeat cycle
CUDA Implementation

- The project was divided into three kernels
  - Matrix Operations
  - Random Number Generation
  - Sigmoid Function
Matrix Operations

- Node states, energies and weights can be represented as matrices
- Computation is dominated by matrix operations
- Matrix libraries were based on the examples in the SDK
  - Additional optimization was achieved
  - Extra care was used to ensure coalesced memory calls and bank conflicts were avoided
Matrix Addition

\[ C = \epsilon (A + B) \]
Matrix Addition

\[ C = \varepsilon(A + B) \]
Matrix Addition

\[ C = \varepsilon (A + B) \]
Matrix Transpose

\[ B = A^T \]
Matrix Transpose

\[ B = A^T \]
Matrix Transpose

\[ B = A^T \]
Matrix Multiply

C = BA
Matrix Multiply

\[ C = BA \]
Matrix Multiply

$C = BA$
Matrix Multiply

\[ C = BA \]
Matrix Multiply

\[ C = BA \]
Random Number Generator

- **Mersenne Twister**
  - **Pros**
    - Uses bitwise operations
    - Long period \(2^{19937}-1\)
    - High dimensional equidistribution
    - Efficient memory usage
  - **Cons**
    - Iterative
    - Insecure – after N outputs, it’s predictable
CUDA Implementation

- Launch many Mersenne twisters simultaneously
  - \texttt{MT\_RNG\_COUNT=threads*blocks}
- Initialization computes of per-thread configuration
  - \texttt{dcmt0.4} library
    - Can be time consuming
Sigmoid Function

\[ P(t) = \frac{1}{1 + e^{-t}}. \]

- Road blocks
  - Number Representation
    - Fixed point
    - Floating point
  - Approximations
  - Input and Output are floats
- 100% parallel: one-to-one data-to-output map
Sigmoid Implementations

- Native floating point function
- Broken line approximation (9 segments)
- Second order approximation
- Precalculated texture (256 values)
Results

- Software baseline
  - Optimized Sequential C++ code
  - Compiled with g++ version 4.1.2
    - Flags = -O3
  - 2.83GHz Intel Core2 Quad core, 6MB L2 Cache
  - 4GB DDR2 RAM

- CUDA implementation
  - GTX280
Results

- **RBM Properties**
  - 512 Nodes in Visible Layer
  - 512 Nodes in Hidden Layer
  - 256k Single-Precision Floating Point Weights

- **Metrics**
  - Performance Ratio
  - Error rate was not measured
    - Different random number implementations = different results
Results

Computation Time

<table>
<thead>
<tr>
<th>Type</th>
<th>Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Addition</td>
<td>0.9305</td>
</tr>
<tr>
<td>Transpose</td>
<td>1.19045</td>
</tr>
<tr>
<td>Multiply</td>
<td>1.50</td>
</tr>
<tr>
<td>256k Rand</td>
<td>6.02</td>
</tr>
<tr>
<td>24M Rand</td>
<td>540.89</td>
</tr>
<tr>
<td>Float</td>
<td>2158.36</td>
</tr>
<tr>
<td>Texture</td>
<td>3.10</td>
</tr>
<tr>
<td>Lin. Approx</td>
<td>1.92</td>
</tr>
<tr>
<td>2nd Order</td>
<td>1.92</td>
</tr>
<tr>
<td>RBM Total</td>
<td>25661.60</td>
</tr>
</tbody>
</table>
Results

GPU vs CPU Speed-up

<table>
<thead>
<tr>
<th>Type</th>
<th>Speed-up</th>
</tr>
</thead>
<tbody>
<tr>
<td>Addition</td>
<td>17.19</td>
</tr>
<tr>
<td>Transpose</td>
<td>2.66</td>
</tr>
<tr>
<td>Multiply</td>
<td>166.4</td>
</tr>
<tr>
<td>256k Rand</td>
<td>10.26</td>
</tr>
<tr>
<td>24M Rand</td>
<td>66.09</td>
</tr>
<tr>
<td>Float</td>
<td>1199.33</td>
</tr>
<tr>
<td>Texture</td>
<td>696.99</td>
</tr>
<tr>
<td>Lin. Approx</td>
<td>1123.68</td>
</tr>
<tr>
<td>2nd Order</td>
<td>1122.81</td>
</tr>
<tr>
<td>RBM Total</td>
<td>65.83</td>
</tr>
</tbody>
</table>
Discussion

• End Result program is much more efficient

• Programming evidence
  – >25 individual hours of debugging code
  – Memcpy in/out produces different results!
  – Adding dummy Memcpy changes behaviour!
  – One/Two consecutive prints change behaviour!
  – Removed compiler optimizations
  – Peppered code with cudaThreadSynchronize()
  – Conclusion: parallelization bugs by compiler
Conclusion

- CUDA implementations is well suited for Neural Network applications
  - 65 fold speed up was achieved for 512x512 network
- The CUDA language could be more mature and bug-free
- Further optimization still could be drawn from profiling and integrating code
Performance

• For 262144 numbers
  – Compared to CPU implementation of MT
    • ~10.26x speed up
  – Compared to optimized RNG on CPU
    • ~1.67x speed up

• For 24 million numbers
  – Compared to CPU implementation of MT
    • ~66.09x speed up
  – Compared to optimized RNG on CPU
    • ~11.19x speed up
## Sigmoid Performance

<table>
<thead>
<tr>
<th>Method</th>
<th>Time (CUDA)</th>
<th>Speed-up</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPU</td>
<td>2158.36</td>
<td>N/A</td>
</tr>
<tr>
<td>Float</td>
<td>1.7996</td>
<td>1199.33</td>
</tr>
<tr>
<td>Texture</td>
<td>3.0967</td>
<td>696.99</td>
</tr>
<tr>
<td>Linear Approximation</td>
<td>1.9208</td>
<td>1123.68</td>
</tr>
<tr>
<td>Second Order</td>
<td>1.9223</td>
<td>1122.81</td>
</tr>
</tbody>
</table>

- Native `__expf()` is the fastest method
- Texture slowest
- Normalized to 1000 kernel calls
- Sigmoid of 24M numbers