MLDB Presentation
SLIDE: Sub-LInear Deep Learning Engine

Beidi Chen Tharun Medini James Farwell Sameh Gobriel
Charlie Tai Anshumali Shrivastava

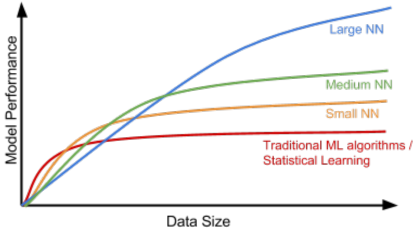
June 17, 2020

Overview

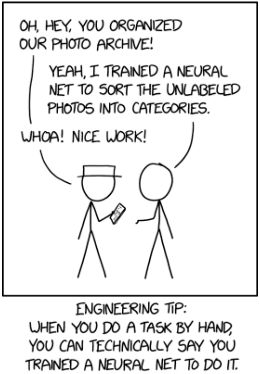
1. Motivation
   - Existing Approaches
   - Problem Setting
2. Contributions
3. Locality Sensitive Hashing
   - Sampling Approach to LSH
   - Additional LSH tricks
4. Implementation
5. Results

Motivation

Era of Deep Learning



(a) Model Performance wrt Dataset size



(b) Fun xkcd comic

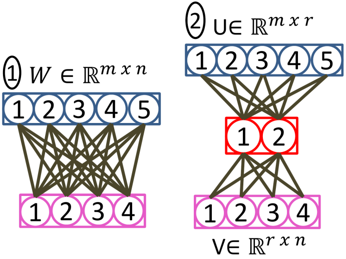
Trends

- Large datasets $\rightarrow$ More Data
- Big models (Eg, 17B parameter NLP models)
- Improvements in optimizations and gradient descent
- Matrix multiplication is a computational bottleneck
- Many approaches exists such as GPUs

Existing Approaches

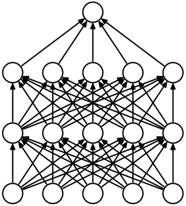
Low Rank structure

- $W \in \mathbb{R}^{m \times n}$ is weight matrix
- W has a low-rank structure $W = UV$
- $U \in \mathbb{R}^{m \times r}$ and $V \in \mathbb{R}^{r \times n}$, where $r \ll \min(m, n)$
- Equivalent representation with I activation function is better
- $\mathcal{O}(mn)$ becomes $\mathcal{O}(mr + rn)$
- Better storage of parameters as well
- But still needs dense gradient update, cannot parallelise asynchronously

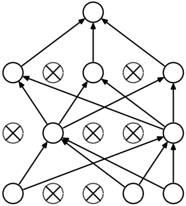


Dropout and Sparsity

- Well known regularization method for Neural Networks
- With probability p neurons in each layer is turned off
- Used during training to ensure model generalizes
- Sparsity above 50% tends to begin hurting performance



(a) Standard Neural Net



(b) After applying dropout.

Adaptive Dropout

- p is chosen adaptively based on activation of neurons in a layer
- And perform forward and backward propagation only on the active neurons in each layer
- Reduces the number of neurons to compute in each layer
- RELU is sparse in nature and filters negative activations
- [Ba and Frey, 2013] use a Bernoulli distribution proportional to activation of each neuron
- Still requires computing all activations to identify active neurons

Problem Setting

Sampling Problem

- Each layer has N time-varying sampling weights
- Weights a function of activations of neurons, $w_1^t, w_2^t, \ldots, w_N^t$
- At each time t, we need to sample x_i with probability w_i^t
- Sampling cost is $\mathcal{O}(N)$ for each time step t

Sampling Problem

- Each layer has N time-varying sampling weights
- Weights a function of activations of neurons, $w_1^t, w_2^t, \ldots, w_N^t$
- At each time t, we need to sample x_i with probability w_i^t
- Sampling cost is $\mathcal{O}(N)$ for each time step t

Problem

Can we efficiently sample the neurons in a layer to find the active neurons given the input to the layer?

Contributions

Main Contributions

[Chen et al., 2020] Contributions

- C++ OpenMP implementation for "standard" CPU
- Sparsity inspired, LSH based backpropagation algorithm
- Rigorous evaluation with TensorFlow(TF)-GPU and CPU
- Further optimizations using Hugepages and SIMD instructions

Main Contributions

[Chen et al., 2020] Contributions

- C++ OpenMP implementation for "standard" CPU
- Sparsity inspired, LSH based backpropagation algorithm
- Rigorous evaluation with TensorFlow(TF)-GPU and CPU
- Further optimizations using Hugepages and SIMD instructions

[Spring and Shrivastava, 2017] Contributions

- LSH and hash tables based identification of active neurons
- Sparse gradient updates in backpropagation
- Gains in computations using Asynchronous SGD (ASGD)

Locality Sensitive Hashing

LSH Family

Definition: LSH Famiy

A family $\mathcal{H}$ is called (S_0, cS_0, p_1, p_2) -sensitive if for any two points $x, y \in \mathbb{R}^D$ and h chosen uniformly from $\mathcal{H}$ satisfies the following:

- if $\text{Sim}(x, y) \geq S_0$ then $\Pr(h(x) = h(y)) \geq p_1$
- if $\text{Sim}(x, y) \leq cS_0$ then $\Pr(h(x) = h(y)) \leq p_2$

- For approx nearest neighbour search, $p_1 > p_2$ and $c < 1$
- $\Pr_{\mathcal{H}}(h(x)h(y)) \propto \text{Sim}(x, y)$ is sufficient for $\mathcal{H}$ to be a LSH family
- A LSH family is sufficient to solve nearest-neighbour search in sub-linear time
- There is a preprocessing and query phase

LSH Preprocessing phase

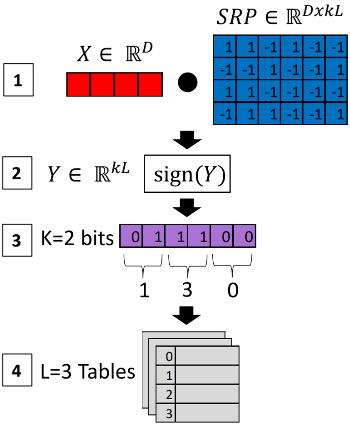


Figure 1: Locality Sensitive Hashing: (1) Compute the projection using a signed, random matrix $\mathcal{R}^{D \times kL}$ and the item $x \in \mathcal{R}^D$. (2) Generate a bit from the sign of each entry in the projection $\mathcal{R}^{kL}$ (3) From the kL bits, we create L integer fingerprints with k bits per fingerprint. (4) Add the item x into each hash table using the corresponding integer key

LSH query phase

- Now, given a query Q, we first compute the K hashes for each table
- Then we retrieve all the elements in the corresponding bucket of that table
- The union of all the elements from the L buckets is the candidate set
- for nearest-neighbour we then further filter the candidate set to get the possible answers
- K reduces false positives and L decreases false negatives
- An item x is in the candidate set with probability $1 - (1 - p^K)^L$
- Here $p \propto \text{Sim}(Q, x)$

Sampling Approach to LSH

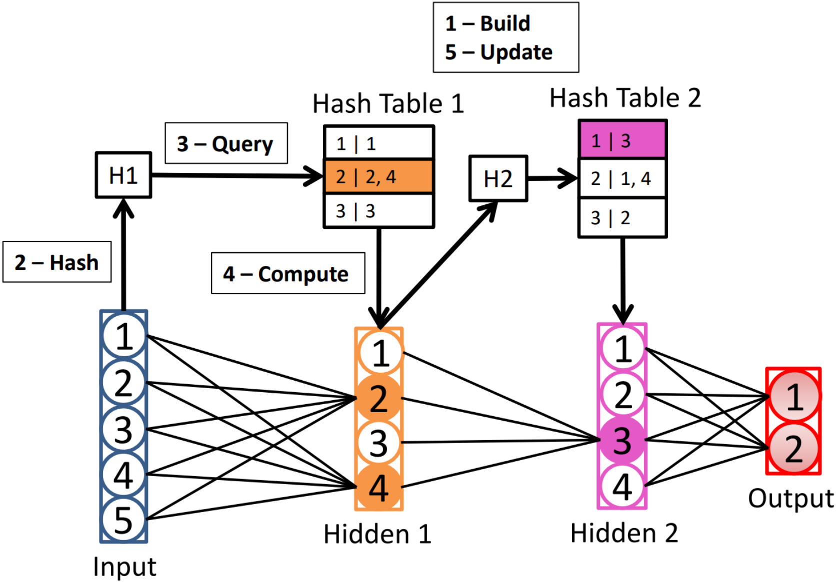
Hashing-Based Sampling

- Essentially LSH samples, in sub-linear time, elements with probability $1 - (1 - p^K)^L$
- Therefore, we can use the candidate set returned by LSH as the result of an adaptive sampling algorithm

Intuition

- Consider a node i with weight w_i and an input x
- Activation is monotonic function of $w_i^T \cdot x$
- Finding the active neurons is searching each w_i and finding the ones with largest inner product
- Can do this efficiently using LSH and hash tables

Intuition



1 – Build
5 – Update
Hash Table 1
Hash Table 2
3 – Query
H1
1 | 1
2 | 2, 4
3 | 3
H2
1 | 3
2 | 1, 4
3 | 2
2 – Hash
4 – Compute
1
2
3
4
5
Input
Hidden 1
Hidden 2
Output

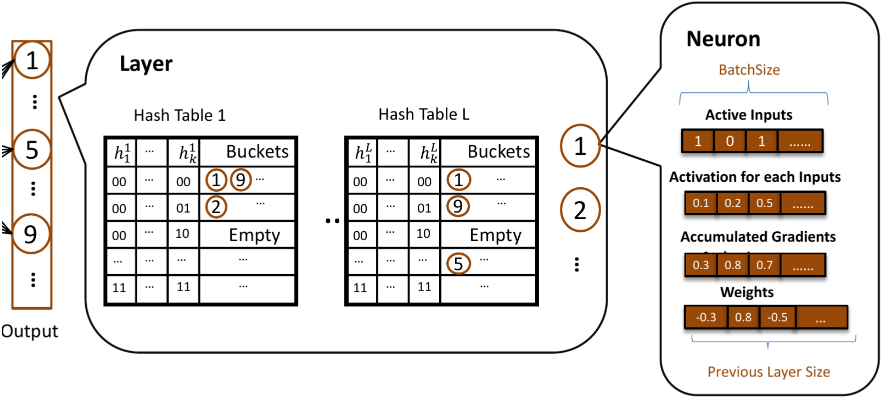
Additional LSH tricks

LSH tricks

1. Hashing inner products
   - Maximum Inner Product Search (MIPS): $p = \text{argmax}_{x \in \mathcal{S}} \, q^T x$
   - Nearest neighbour search (NNS): $p = \text{argmin}_{x \in \mathcal{S}} \, \|q - x\|_2^2$
   - Equivalent if norm of every element $x \in \mathcal{S}$ is constant. This is not the case for neural network weights.
   - In regular LSH, $\Pr[h(x) = h(x)] = 1$ is closest neighbour for query x
   - [Shrivastava and Li, 2014] proposes using an asymmetric transformation to solve MIPS using LSH
2. Large L for good estimates in vanilla LSH
   - [Lv et al., 2007] proposes Multi-probe LSH which reduces number of tables
   - When querying, probe nearby buckets as well
   - Do this by flipping a few bits in the hash for that table

Implementation

LSH Implementation



Overview of Implementation

- Each batch is processed in parallel using simple OpenMP
- Only active neurons take part in forward and backpropagation
- The output softmax is also computed only on active neurons
- After gradients are updates the hash tables are updated
- Can use Simhash or Densified Winner Take All (DWTA) hash families

Benefits

- Highly sparse active set, as small 5% of all neurons
- Each update is computationally efficient
- Gradient updates are sparse $\rightarrow$ parallel ASGD
- Can choose different sampling

Results

Results

SWITCH TO OTHER SLIDES

Questions or Comments

Ba, L. J. and Frey, B. (2013).
Adaptive dropout for training deep neural networks.
In *Proceedings of the 26th International Conference on Neural Information Processing Systems - Volume 2*, NIPS'13, page 3084–3092, Red Hook, NY, USA. Curran Associates Inc.

Chen, B., Medini, T., Farwell, J., gobriel, s., Tai, C., and Shrivastava, A. (2020).
Slide : In defense of smart algorithms over hardware acceleration for large-scale deep learning systems.
In *Proceedings of Machine Learning and Systems 2020*, pages 291–306.

Lv, Q., Josephson, W., Wang, Z., Charikar, M., and Li, K. (2007).
Multi-probe lsh: efficient indexing for high-dimensional similarity search.
In *Proceedings of the 33rd international conference on Very large data bases*, pages 950–961.

Shrivastava, A. and Li, P. (2014).

Asymmetric lsh (alsh) for sublinear time maximum inner product search (mips).
In *Advances in Neural Information Processing Systems*, pages 2321–2329.

Spring, R. and Shrivastava, A. (2017).
Scalable and sustainable deep learning via randomized hashing.
In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '17, page 445–454, New York, NY, USA. Association for Computing Machinery.