A RANDOM GOSSIP BMUF PROCESS FOR NEURAL LANGUAGE MODELING

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Delivered by Dr. Yiheng Huang
Introduction: Background

Deep Learning

Machine Learning

Deep Learning

DNN

CNN

LSTM

Computer Vision

Speech Recognition

Natural Language Processing
As data size and model complexity increase, one essential challenge is to leverage between scaling the learning procedure and handling big data.

Distributed Learning Algorithms are necessities in industrial practices.
Introduction: Centralized vs. Decentralized

System Structure Classification

Centralized (left): Parameter-Server (red node) included vs. Decentralized (right): Parameter-Server excluded

<table>
<thead>
<tr>
<th>Structure</th>
<th>Features</th>
<th>Drawbacks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Centralized</td>
<td>The parameter-server: • collects/distributes variables (or gradients) from all worker nodes • controls the learning process</td>
<td>• Communication speed with the parameter-server is the bottleneck of the training process</td>
</tr>
<tr>
<td>Decentralized</td>
<td>• Collect/Distribute variables (or gradients) by peer-to-peer communication</td>
<td>• Poor accuracy performance compared with Centralized structure</td>
</tr>
</tbody>
</table>
Related Works:

- **Centralized methods:**
  - Downpour SGD[8]: utilizes thousands of machines to train various deep machines with an asynchronous SGD (ASGD) procedure
  - Hogwild ASGD[9]; EASGD[10]
  - Model Average[12,13] and its derivatives like Blockwise Model Update Filtering (BMUF)[14]:
    - (1) models are updated independently on their own computing nodes
    - (2) the global average without/with momentum item is used to synchronize the models accordingly every a few iterations

- **Decentralized:**
  - Gossip[19]: recursively, each node fetches the parameters of another node, and then compute the average between that and the local model to update itself.

Our method, gossip-BMUF, is mainly inspired by BMUF and gossip
Model Average (MA)

Recursively, all nodes update as follow:

① Models are identical on all nodes after latest loop
② Each node updates its local model independently by local data, and then a local move vector (blue arrow) is accessible on each node
③ A global move vector (red arrow) is computed by averaging all local move vectors, and the initial model is updated by the global move vector to obtain the new model
Under mild assumptions, the MA estimator will asymptotically approach the optimal but with a bias term that is proportional to the number of nodes.

Assume $\theta^k$ is the parameter for worker $k$, then $\theta_t = [(\theta^1_t)^T, \cdots, (\theta^n_t)^T]^T$ is the concatenated parameter vector for all workers at time $t$. Also note $\theta,1 = [\theta^T, \cdots, \theta^T]^T$ is the optimal parameters to be estimated.

**Theorem** Let $f$ be a $m$-strongly convex function with $L$-lipschitz gradients. Assume that we can sample gradients $g = \nabla f(\theta_t; X_i) + \xi_i$. with additive noise with zero mean $\mathbb{E}[\xi_i] = 0$ and bounded variance $\mathbb{E}[\xi_i^T \xi_i] \leq \sigma^2$. Then, running the MA algorithm, with constant step size $0 < \alpha < \frac{2}{m+L}$, the expected sum of squares convergence of the local parameters to the optimal is bounded by

$$\mathbb{E}[|\theta_t - \theta_*|^2] \leq \left(1 - 2\alpha \cdot \frac{mL}{m + L}\right)^t |\theta_0 - \theta_*| + n \frac{m + L}{2mL} \alpha \sigma^2$$

converge to zero as $t$ grows

bias term, grows linearly with number of node: $n$

* Learn the proof in our paper
BMUF: a derivative of MA

Blockwise Model Update Filtering (BMUF)

In BMUF, the *momentum*-like process is introduced.
We note *block momentum, block learning rate and synchronization period* by $\eta$, $\xi$ and $T$ respectively; for a model at time $t$ and on rank $k$, $\theta^k$, function *LocalMoveVector*($t, k$) stands for its local update information of that time and rank. Then BMUF optimizes the model from time $t$ to $t+T$ as follow:

\[
\begin{align*}
\theta^{k}_{t+T} &\leftarrow \omega_g + \sum_{i=0}^{T-1} \text{LocalMoveVector}(t+i,k) \\
\bar{\theta}_{t+T} &\leftarrow (\sum_{k=1}^{n} \theta^{k}_{t+T}) / n \\
G &\leftarrow \bar{\theta}_{t+T} - \omega_g \\
\Delta &\leftarrow \eta \Delta + \xi G \quad (0 \leq \eta < 1, \xi > 0) \\
\omega &\leftarrow \omega + \Delta
\end{align*}
\]

\[
\begin{cases}
\omega_g \leftarrow \omega \text{ if Classic Block Momentum (CBM)} \\
\omega_g \leftarrow \omega + \eta \Delta \text{ if Nesterov Block Momentum (NBM)}
\end{cases}
\]

\[
\theta^{k}_{t+T} \leftarrow \omega_g
\]
BMUF: from Centralized to Decentralized

• BMUF is centralized and requires global communication: an *all-reduce* process. Problems occur since:
  • Communication latency is considerable when number of nodes grows

• gossip-BMUF, with *gossip* process introduced, is in decentralized style and benefits from:
  • Communication effort is significantly reduced as only local communications are needed

We further optimize BMUF by introducing gossip-like process
The *gossip* process described in [19] acts as follow:

1. **Initial model**
2. **Intermediate model**
3. **New model**

- **Node**
- **Local update**
- **Random sampling from another node (gossip)**
- **Averaging**
Our randomness in *gossip* process, however, is more complex.

Ring Topology: each node only samples its neighbors instead of all other nodes.

For each node (like the red one), only $p$ nodes on its right and left are connected and could be sampled, called neighbors (the blue ones). $p$ is considered *symmetric degree*.

(Above: 8-node ring topology with 2 symmetric degree)

Model Split: split the model into multiple components:

- component 1
- component 2
- ...
- component $m-1$
- component $m$

For models of each rank, the model $\theta$ is split into $m$ components: $\theta = [\theta_1^T, \ldots, \theta_m^T]^T$. 
With a $n$-node, $p$-symmetric topology, the whole model parameter $\theta$ is split into $m$ components: $\theta = [\theta_1^T, \ldots, \theta_m^T]^T$, and the training dataset $D$ is evenly split into $n$ partitions: $D = \bigcup D_k = 1 \ldots n$.

To implement Gossip-BMUF, hyper-parameter setting and additional variable initialization are necessary for each worker $k$:

- **Require**: initial model $\theta_0$
- **Require**: components of the model $\theta = [\theta_1^T, \ldots, \theta_m^T]^T$
- **Require**: slots $\Delta^k$, $\omega^k$, $G^k$, with the same shape as $\theta$
- **Require**: training data with labels $D$
- **Require**: synchronous period $H_i$ for each component $\theta_i$
- **Require**: number of gossip neighbors $q \leq 2p$
- **Require**: momentum $\eta$ and block learning rate $\zeta$
- **Require**: learning rate $\alpha_t$
gossip-BMUF training Process on worker k

1. \( \theta_0^k \leftarrow \theta_0, \ \omega^k \leftarrow \theta_0, \ \Delta^k \leftarrow 0, \ G^k \leftarrow 0 \)
2. For for \( i = 1, \cdots, T \) do
3. sample a mini-batch from \( D_t^k \) and calculate the gradients \( g_t^k \)
4. for \( i = 1, \cdots, m \) parallel do
5. \( \theta_{i,t}^k \leftarrow \theta_{i,t-1}^k - \alpha_t \cdot g_{i,t}^k \)
6. if \( t \mod H_i = 0 \) then
7. randomly choose \( q \) neighbors \( k_1 \cdots, k_q \)
8. \( \overline{\theta}_{i,t}^k \leftarrow \frac{1}{q+1} \left( \theta_{i,t}^k + \sum_{1 \leq j \leq q} \theta_{i,t}^{kj} \right) \)
9. if Gossip-BMUF then
10. \( G_i^k \leftarrow \overline{\theta}_{i,t}^k - \theta_{i,t-H_i}^k \)
11. \( \Delta_i^k \leftarrow \eta \Delta_i^k + \zeta G_i^k \)
12. \( \omega_i^k \leftarrow \omega_i^k + \Delta_i^k \)
13. \( \theta_{i,t}^k \leftarrow \omega_i^k + \eta \Delta_i^k \) (Nesterov)
14. else if Gossip-MA then
15. \( \theta_{i,t}^k \leftarrow \overline{\theta}_{i,t}^k \)
16. end if
17. end if
18. end for
19. end for
20. return \( \theta = \frac{1}{n} \sum_{k=1}^{n} \theta_i^k \)
A Gossip process is independently random:
- on different nodes;
- for different components of the model;
- in different iterations where synchronization conducts.
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  • on different nodes;
  • for different components of the model;
  • in different iterations where synchronization conducts

* Different colors of blocks indicate different ranks

Gossip Process: Our Modified Version

Averaging

\[ \overline{\theta_{p,t}^k} \]

\[ \overline{\theta_{p',t}^k} \]
A *Gossip* process is independently random:

- on different nodes;
- for different components of the model;
- in different iterations where synchronization conducts

*Different colors of blocks indicate different ranks*
Two things to highlight in Gossip-BMUF

Full Sampling: Gossip process would degrade if all neighbors are sampled

Gossip process would degraded to local process if all neighbors are sampled, as no randomness is introduced. (Above: local process(left), gossip process(right). Blue node means being sampled)

Synchronization Period: different components may have different synchronization period

component 1
component 2
...
component m

Synchronization Period $H_1$
Synchronization Period $H_2$
...
...
Synchronization Period $H_m$
Experiments and Results: Experiment Setting

Platform
- 2 identical MPI-based HPC machine learning platforms with 16 Nvidia Tesla M40 in total
- Implemented by TensorFlow equipped with Horovod*

Task and Dataset:
- Language Modeling Task
- wiki-text-103: 0.1B tokens; Gutenberg: 0.13B tokens

Model Configuration
- A standard, 1-layer LSTM structure and a projection layer is chosen, with adaptive-softmax trick adopted.
- Set block learning rate and momentum to 1.0 and 0.9 respectively
- The whole model is split into groups:
  - Embeddings are evenly split into 8 shards;
  - LSTM weights form one group;
  - LSTMP weights form another group;
  - Head weights in adaptive-softmax form one group;
  - Weights of each tails in adaptive-softmax form their individual groups.
- Learn more details about our language model setting and optimization strategy in our paper

* An internal modified version of Horovod that contains the implementation of Gossip process
Experiments and Results: Explanation of Experiments

Explanation of Experiments:

• We use Parentheses “()” to note the synchronization period:
  • (8) means: all variables are synchronized every 8 iterations
  • (16, 128) means: all variables except the embedding tables are synchronized every 16 iterations, while the embedding tables are synchronized every 128 iterations.

• We use curly braces “{}” to note the integer pairs of symmetric degree and number of gossip neighbors like \{p, q\}
  • For gossip-BMUF / gossip-MA, we choose \{1, 1\}, \{2, 2\}, \{3, 2\} for 4 / 8 / 16 GPUs respectively.
  • For local-BMUF / local-MA, we choose \{1, 2\}, \{2, 4\}, \{3, 6\} for 4 / 8 / 16 GPUs respectively.
  • We empirically recommend to choose \(p = \log_2(n) - 1\) where \(n\) is the number of nodes
## Experiments and Results: Experimental Results on wiki-text-103

### wiki-text-103 Results

<table>
<thead>
<tr>
<th>Method-period</th>
<th>GPUs</th>
<th>Test ppl</th>
<th>Period</th>
<th>GPUs</th>
<th>Test ppl</th>
</tr>
</thead>
<tbody>
<tr>
<td>MA-(8)</td>
<td>4</td>
<td>55.1</td>
<td>(16,128)</td>
<td>8</td>
<td>64.1</td>
</tr>
<tr>
<td>BMUF-NBM-(8)</td>
<td>4</td>
<td>50.7</td>
<td>(16,128)</td>
<td>8</td>
<td>50.3</td>
</tr>
<tr>
<td>local-BMUF-(8)</td>
<td>4</td>
<td>51.0</td>
<td>(16,128)</td>
<td>8</td>
<td>50.4</td>
</tr>
<tr>
<td>gossip-BMUF-(8)</td>
<td>4</td>
<td><strong>48.4</strong></td>
<td>(16,128)</td>
<td>8</td>
<td><strong>49.0</strong></td>
</tr>
<tr>
<td>MA-(16,128)</td>
<td>4</td>
<td>54.3</td>
<td>(16,128)</td>
<td>16</td>
<td>80.5</td>
</tr>
<tr>
<td>BMUF-NBM-(16,128)</td>
<td>4</td>
<td>51.1</td>
<td>(16,128)</td>
<td>16</td>
<td>50.5</td>
</tr>
<tr>
<td>local-BMUF-(16,128)</td>
<td>4</td>
<td>51.5</td>
<td>(16,128)</td>
<td>16</td>
<td>50.6</td>
</tr>
<tr>
<td>gossip-BMUF-(16,128)</td>
<td>4</td>
<td><strong>48.5</strong></td>
<td>(16,128)</td>
<td>16</td>
<td><strong>49.3</strong></td>
</tr>
<tr>
<td>single-GPU baseline</td>
<td></td>
<td>49.3</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Method-GPUs</th>
<th>period</th>
<th>Speedups</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gossip-BMUF-4</td>
<td>(16,128)</td>
<td>3.42X*</td>
</tr>
<tr>
<td>Gossip-BMUF-8</td>
<td>(16,128)</td>
<td>6.32X*</td>
</tr>
<tr>
<td>BMUF-4</td>
<td>(16,128)</td>
<td>3.20X</td>
</tr>
<tr>
<td>BMUF-8</td>
<td>(16,128)</td>
<td>5.47X</td>
</tr>
</tbody>
</table>

* These results are obtained by our further optimization, differing from initial results in our paper.
### Gutenberg Results

<table>
<thead>
<tr>
<th>method-period</th>
<th>GPUs</th>
<th>test ppl</th>
</tr>
</thead>
<tbody>
<tr>
<td>MA-(16,128)</td>
<td>4/8/16</td>
<td>158.0/178.9/211.1</td>
</tr>
<tr>
<td>BMUF-NBM-(16,128)</td>
<td>4/8/16</td>
<td>156.3/152.6/146.3</td>
</tr>
<tr>
<td>local-BMUF-(16,128)</td>
<td>4/8/16</td>
<td>156.1/153.8/148.0</td>
</tr>
<tr>
<td>gossip-BMUF-(16,128)</td>
<td>4/8/16</td>
<td>149.4/148.4/146.1</td>
</tr>
<tr>
<td>single-GPU baseline</td>
<td></td>
<td>144.6</td>
</tr>
</tbody>
</table>

### Observations:

- gossip-BMUF consistently outperform other methods, and even achieve better results than single-GPU baseline on wiki-text-103 dataset.
- The performance degradation of MA is very significant when the number of GPUs is large.
- Local-BMUF has a slightly worse performance than BMUF-NBM, which indicates that the randomly selected neighbors are the key success in gossip-BMUF.
Observation:

- The training curves of gossip-BMUF is very similar to that of single-GPU baseline
- The training curves of BMUF-NBM fluctuates more fiercely than that of gossip-BMUF
- The training curves of BMUF and local-BMUF indicate that the over-fitting might already happen
Conclusion

Combine gossip process (modified) with BMUF: gossip-BMUF

Features of gossip-BMUF

- Decentralized style:
  - Adopt more flexible topology
- Robustness:
  - The training can continue even several nodes get stuck
- Accuracy:
  - Consistently better performance than other competitors on two benchmarks
- Speedup:
  - Considerable speed improvement, as no global communication needed
- Randomness:
  - The random collection of neighbor components are the key success of our algorithm
- Over-fitting reduction:
  - Best approximation of single-GPU baseline and less over-fitting observed compared with BMUF

Gossip-BMUF: randomly samples neighbors and act in a BMUF-like process
(Above: BMUF(left), gossip(right))
Future Work Perspective

- Experimentally evaluate our method on other deep machines
- Statistical Analysis on gossip-BMUF

Gossip-BMUF

- CNN
- Transformer
- ...

Gossip-BMUF

- Convergence Speed
- Convergence Bound
- ...

⋯
Thanks for Listening!