#### Various GBM Performance Topics

Damien Soukhavong (Laurae)
SAP BI / Data Science Consultant, Planeum

Budapest BI Forum November 2019

#### Laurae (Damien)



Laurae's Data Science & Design curated posts

Editor of Imploding Gradients and Data Science & Design

5 Following 887 Followers · 🎳





#### Damien (Laurae)

@Laurae\_Cht

Laurae's. Creating & Designing wizard for Data Science in general

Paris, France

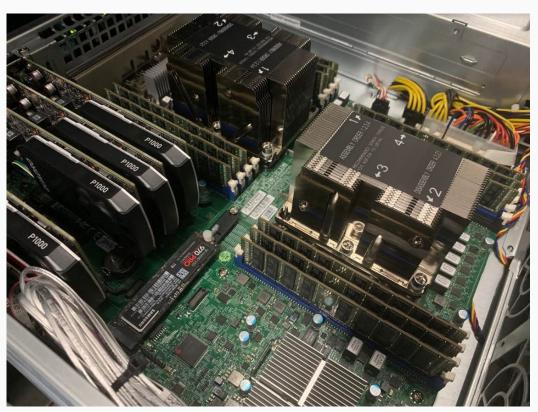
95 Following 368 Followers

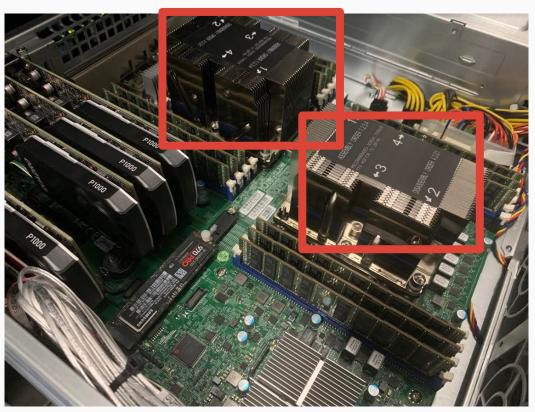
Disclaimer:

I am not representing my employer (Planeum) in this talk

results etc. mentioned in this talk

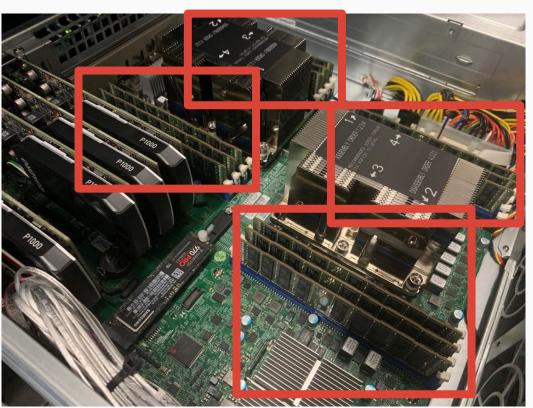
I cannot confirm nor deny if Planeum is using any of the methods, tools,





CPU: 2x Dual Xeon 6154

- 36 cores / 72 threads, 400W
- All turbo 3.7 GHz (if AVX256/512)

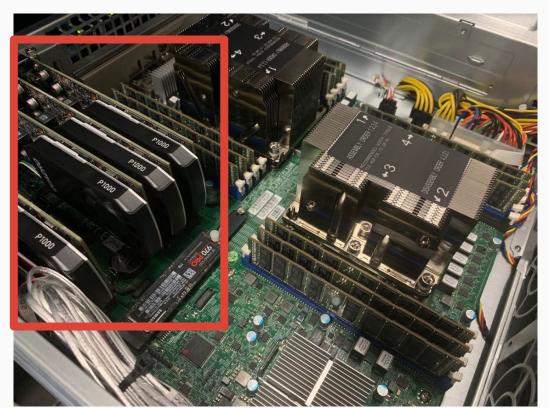


CPU: 2x Dual Xeon 6154

- 36 cores / 72 threads, 400W
- All turbo 3.7 GHz (if AVX256/512)

RAM: 768 GB RAM

- 12x 32 GB RAM
- DDR4 2666 MHz



CPU: 2x Dual Xeon 6154

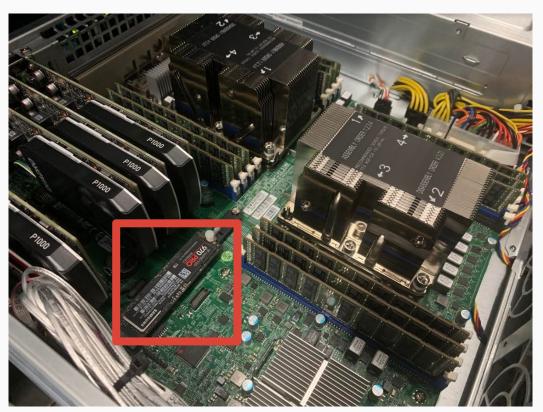
- 36 cores / 72 threads, 400W
- All turbo 3.7 GHz (if AVX256/512)

RAM: 768 GB RAM

- 12x 32 GB RAM
- DDR4 2666 MHz

#### GPU: 4x NVIDIA PNY Quadro P1000

- Equivalent of NVIDIA 1050
- Low Profile HHHL: Half Height Half Length
- 4 GB RAM



CPU: 2x Dual Xeon 6154

- 36 cores / 72 threads, 400W
- All turbo 3.7 GHz (if AVX256/512)

RAM: 768 GB RAM

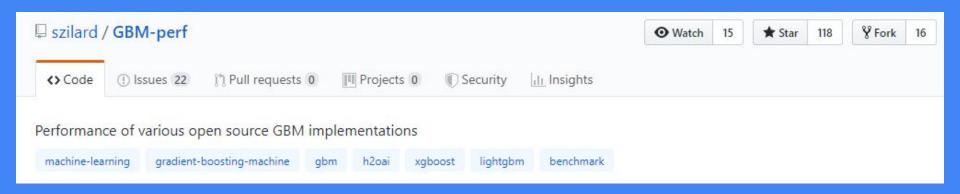
- 12x 32 GB RAM
- DDR4 2666 MHz

GPU: 4x NVIDIA PNY Quadro P1000

- Equivalent of NVIDIA 1050
- Low Profile HHHL: Half Height Half Length
- 4 GB RAM

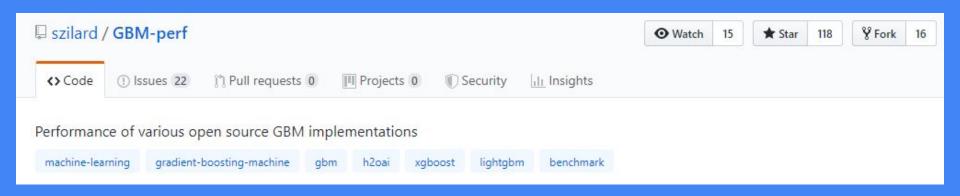
Drive: Samsung 970 Pro (NVMe)

- 1 GB RAM
- 36 GB SLC cache

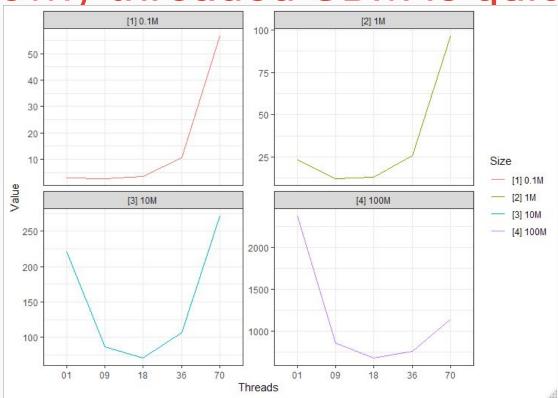


Data: <a href="https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt">https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt</a>

# Lowly threaded GBM is quick xgboost



Data: <a href="https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt">https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt</a>



```
ggplot2::ggplot(
    data.frame(
        Size = rep(c("[1] 0.1M", "[2] 1M", "[3] 10M", "[4] 100M"), each = \frac{5}{100},
        Threads = rep(c("01", "09", "18", "36", "70"), 4),
        Value = c(3.062, 2.735, 3.407, 10.515, 56.710,
                  23.293, 12.254, 12.929, 25.980, 96.465,
                  220.200, 86.092, 70.121, 106.479, 271.683,
                  2373.128, 858.772, 675.223, 756.661, 1142.271)),
  ggplot2::aes(x = Threads,
               y = Value,
               group = Size,
               color = Size)) +
  ggplot2::facet_wrap(~ Size,
                       scales = "free_y") +
  ggplot2::geom_line() +
  ggplot2::theme_bw()
```

Size	1 Thread	9 Threads	18 Threads	36 Threads	70 Threads
0.1M	3.062	2.735	3.407	10.515	56.710
1M	23.293	12.524	12.929	25.980	96.465
10M	220.200	86.092	70.121	106.479	271.683
100M	2373.128	858.772	675.223	756.661	1142.271

Comparison unit: seconds

Size	1 Thread	9 Threads	18 Threads	36 Threads	70 Threads
0.1M	1x	1.12x	0.89x	0.29x	0.05x
1M	1x	1.86x	1.80x	0.90x	0.24x
10M	1x	2.56x	3.14x	2.07x	0.81x
100M	1x	2.76x	3.51x	3.14x	2.08x

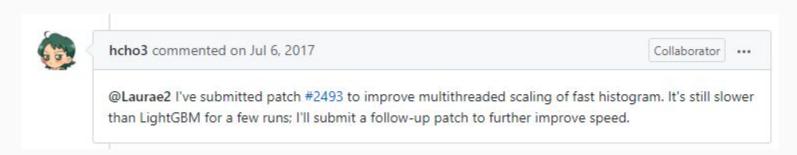
Comparison unit: 1 model thread speed

Size	1 Thread	9 Threads	18 Threads	36 Threads	70 Threads
0.1M	1x	1.12x	0.89x	0.29x	0.05x
1M	1x	1.86x	1.80x	0.90x	0.24x
10M	1x	2.56x	3.14x	2.07x	0.81x
100M	1x	2.76x	3.51x	3.14x	2.08x

Comparison unit: 1 model thread speed

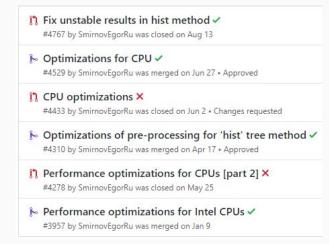
- xgboost has difficulties to scale (even on a log scale)
- Poor threading leads to slow training times
- Large data (100M) does not benefit from using lot of threads

xgboost hist, CPU



Sponsored(?) by





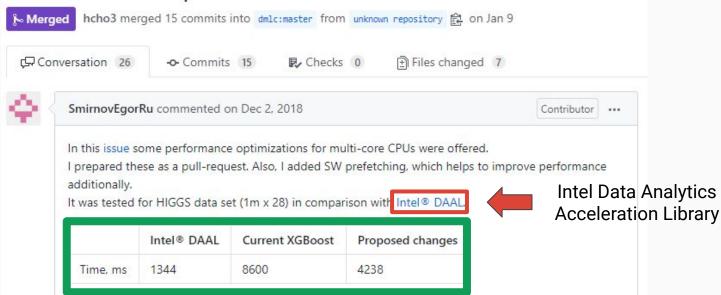
#### Mixed bag of results:

- Sometimes faster
- Sometimes significantly slower

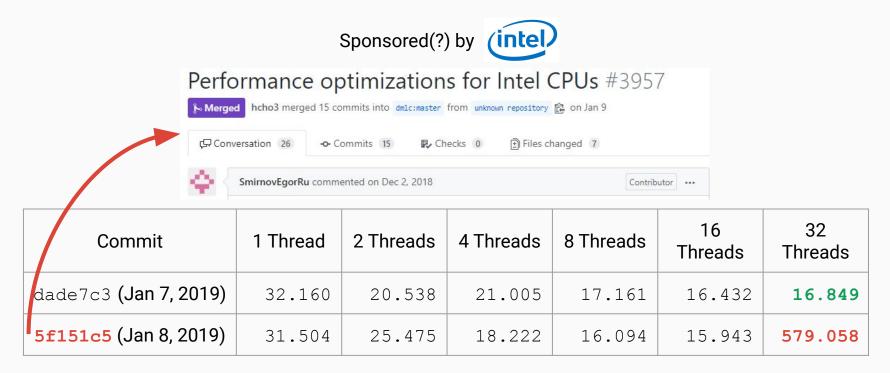
xgboost hist, CPU

Sponsored(?) by (intel)

#### Performance optimizations for Intel CPUs #3957



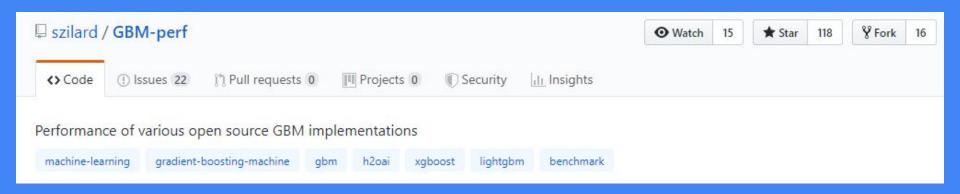




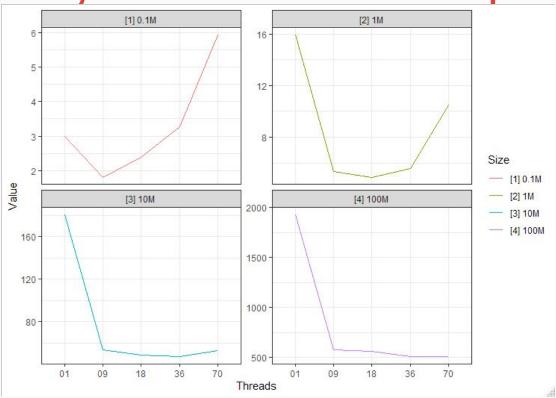
New multithreaded scaling behavior depends on the dataset

xgboost hist, CPU

# Lowly threaded GBM is quick LightGBM



Data: https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt



LightGBM, CPU

```
ggplot2::ggplot(
    data.frame(
        Size = rep(c("[1] 0.1M", "[2] 1M", "[3] 10M", "[4] 100M"), each = \frac{5}{100},
        Threads = rep(c("01", "09", "18", "36", "70"), 4),
        Value = c(2.983, 1.801, 2.389, 3.266, 5.943,
                  15.919, 5.363, 4.891, 5.568, 10.487,
                  180.748, 53.689, 48.620, 47.033, 53.234,
                  1930.816, 578.734, 560.296, 507.580, 507.627)),
  ggplot2::aes(x = Threads,
               y = Value,
               group = Size,
               color = Size)) +
  ggplot2::facet_wrap(~ Size,
                       scales = "free_y") +
  ggplot2::geom_line() +
  ggplot2::theme_bw()
```

Size	1 Thread	9 Threads	18 Threads	36 Threads	70 Threads
0.1M	2.983	1.801	2.389	3.266	5.943
1M	15.919	5.363	4.891	5.568	10.487
10M	180.748	53.689	48.260	47.033	53.234
100M	1930.816	578.834	560.296	507.580	507.627

Comparison unit: seconds

LightGBM, CPU

Size	1 Thread	9 Threads	18 Threads	36 Threads	70 Threads
0.1M	1x	1.66x	1.25x	0.91x	0.50x
1M	1x	2.97x	3.25x	2.86x	1.52x
10M	1x	3.37x	3.75x	3.84x	3.40x
100M	1x	3.34x	3.45x	3.80x	3.80x

Comparison unit: 1 model thread speed

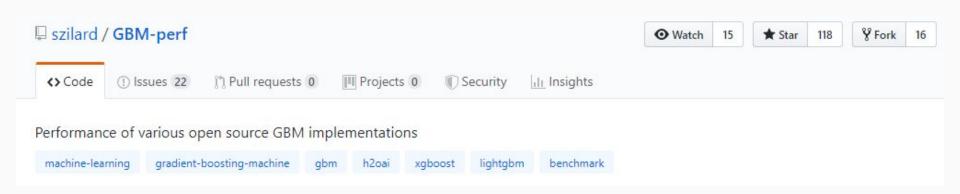
Size	1 Thread	9 Threads	18 Threads	36 Threads	70 Threads
0.1M	1x	1.66x	1.25x	0.91x	0.50x
1M	1x	2.97x	3.25x	2.86x	1.52x
10M	1x	3.37x	3.75x	3.84x	3.40x
100M	1x	3.34x	3.45x	3.80x	3.80x

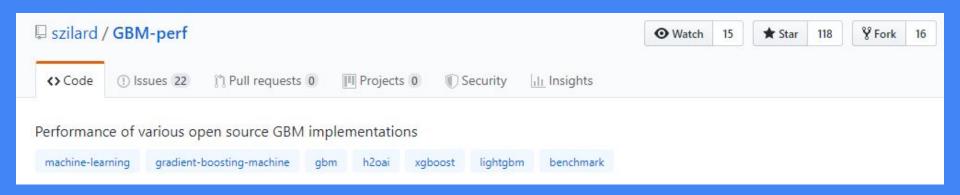
Comparison unit: 1 model thread speed

- LightGBM scales okay-ish with the number of threads
- Good threading makes scaling easy to predict
- Large data (100M) benefits a bit from using lot of threads

LightGBM, CPU

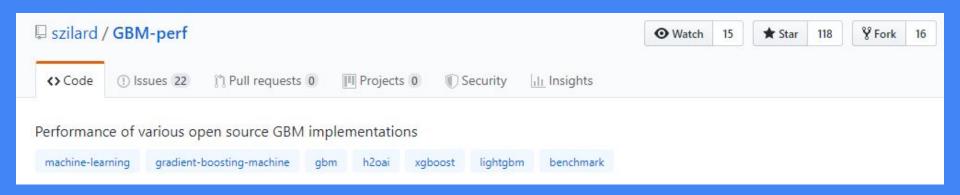
See more: <a href="https://github.com/szilard/GBM-perf">https://github.com/szilard/GBM-perf</a>





Data: <a href="https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt">https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt</a>

# Weak GPU for GBM is quick xgboost



Data: <a href="https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt">https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt</a>

	0.1M	1M	10M	100M
CPU (Best)	2.735	12.524	70.121	675.223
Quadro P1000	17.529	38.528	103.154	CRASH
GPU Perf. (%)	15.6%	32.5%	67.9%	N/A

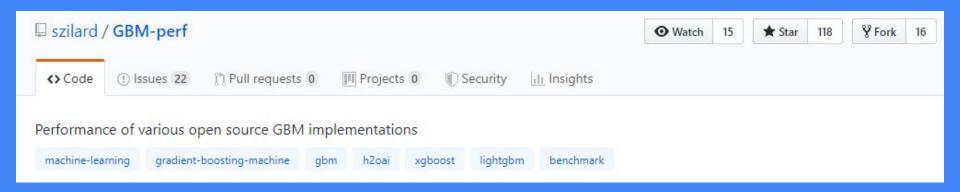
N.B: Dual Xeon 6154 (~\$7,000) vs Quadro P1000 (~\$400)

Very high GPU usage (can be better using better GPU)

Comparison unit: seconds

xgboost hist, GPU

# Weak GPU for GBM is quick LightGBM



Data: https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt

	0.1M	1M	10M	100M
CPU (Best)	1.801	4.891	47.033	507.580
Quadro P1000	18.345	22.179	62.929	396.233
GPU Perf. (%)	9.8%	22.1%	74.7%	128.1%

N.B: Dual Xeon 6154 (~\$7,000) vs Quadro P1000 (~\$400)

Very low GPU usage (you can use many in parallel!)

Comparison unit: seconds

LightGBM, GPU

#### **Very low GPU usage for LightGBM?**

#### Example using R:

- To train 10x LightGBM models in parallel
- On Airline 10M dataset

Only ~50% GPU usage, if GPU had more RAM, it could train 20 in parallel without any potential compute bottleneck

IVI	IA-SMI	418.56	6	Driver	Version: 418.56	CUDA	Versio	on: 10.1
GPU Fan	Name Temp	Perf		tence-M age/Cap				Uncorr. ECC Compute M.
0 34%	Quadro 35C	P1000		Off / N/A	000000000:3B:00.0 0 4017MiB / 4040M		48%	N/A Default
1 34%	Quadro 17C	P1000 P8		Off / N/A	00000000:86:00.0 0 17MiB / 4040M		0%	N/A Defaul
2 34%	Quadro 18C	P1000 P8		Off / N/A	00000000:AF:00.0 0 17MiB / 4040M		0%	N/A Default
3 34%	Quadro 18C	P1000 P8		Off / N/A	00000000:D8:00.0 0 17MiB / 4040M		0%	N// Default
GPU		PID	Туре	Process	s name			GPU Memory Usage
GPU								Usage
GPU	13			/usr/lo	ocal/lib64/R/bin/exe			GPU Memory Usage 333MiE
GPU 0	13 13	473	C	/usr/lo		c/R		Usage ====================================
GPU  0 0	13 13 13	473 487	C C	/usr/lo /usr/lo /usr/lo	ocal/lib64/R/bin/exe	c/R c/R		Usage ====================================
GPU  0 0 0 0	13 13 13 13 13	473 487 501 515 532	C C C C	/usr/lo /usr/lo /usr/lo /usr/lo /usr/lo	cal/lib64/R/bin/exe cal/lib64/R/bin/exe cal/lib64/R/bin/exe cal/lib64/R/bin/exe cal/lib64/R/bin/exe	c/R c/R c/R c/R		Usage ====================================
GPU  0 0 0 0 0	13 13 13 13 13 13	473 487 501 515 532 549	C C C C	/usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo	ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe	c/R c/R c/R c/R c/R		Usage 333Mif 333Mif 333Mif 333Mif 333Mif 333Mif
GPU  0 0 0 0 0	13 13 13 13 13 13 13	473 487 501 515 532 549 563	00000	/usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo	ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe	c/R c/R c/R c/R c/R		Usage 333Mii 333Mii 333Mii 333Mii 333Mii 333Mii 333Mii
GPU 0 0 0 0 0 0	13 13 13 13 13 13 13 13	473 487 501 515 532 549 563 577	000000	/usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo	ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe	c/R c/R c/R c/R c/R c/R		Usage 333MiE
GPU 0 0 0 0 0 0	13 13 13 13 13 13 13 13 13 13	473 487 501 515 532 549 563 577		/usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo	ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe	c/R c/R c/R c/R c/R c/R c/R		Usage  333Mil 333Mil 333Mil 333Mil 333Mil 333Mil 333Mil 333Mil 333Mil
GPU 0 0 0 0 0 0	13 13 13 13 13 13 13 13 13 13	473 487 501 515 532 549 563 577	000000	/usr/lo/	ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe ocal/lib64/R/bin/exe	c/R c/R c/R c/R c/R c/R c/R c/R c/R		Usage 333Mil 333Mil 333Mil 333Mil 333Mil 333Mil 333Mil 333Mil 333Mil

xgboost

LightGBM

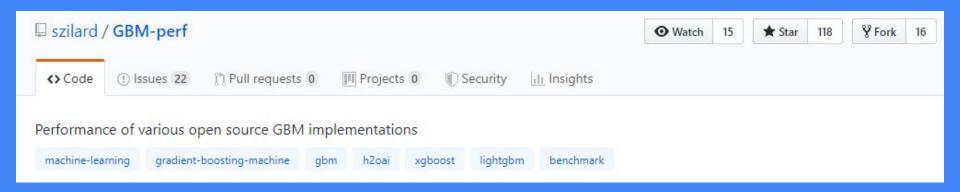
NVID	IA-SMI	418.56	5	Driver	Version:	418.	56	CUDA Versio	on: 10.1
GPU Fan	Name Temp	Perf		tence-M  age/Cap			Disp.A ory-Usage		Uncorr. ECC Compute M.
0 34%	Quadro 27C	P1000 P0	N/A	Off   / N/A			00.0 Off 4040MiB	+=======     98%	N/A Default
1 34%	Quadro 17C	P1000 P8	N/A	Off   / N/A			00.0 Off 4040MiB	   0%	N/A Default
2 34%	Quadro 18C	P1000 P8	N/A	Off   / N/A		EB /	00.0 Off 4040MiB	0%	N/A Default
3 34%	Quadro 18C	P1000 P8	N/A				00.0 Off 4040MiB	0%	N/A Default
Proc	esses:	PID	Туре	Process	name			÷	GPU Memory Usage
Θ	======	===== 079	 C		=======	1/R/h	in/exec/R		1109MiB
0	23	096 113	C	/usr/lo	cal/lib64	1/R/b	in/exec/R in/exec/R in/exec/R		1109MiB 1109MiB 1109MiB

MATD	IA-SMI	418.56		DITAGE	Version: 418.	. 50	toph versi	
GPU Fan	Name Temp	Perf		tence-M  age/Cap	Memo	ry-Usage	GPU-Util	Uncorr. ECC Compute M.
==== 0 34%	Quadro 35C			Off   / N/A	00000000:3B: 4017MiB /	:00.0 Off		N/A
1 34%	Quadro 17C	P1000 P8	N/A	Off   / N/A	00000000:86: 17MiB /		0%	N/A Default
2 34%	Quadro 18C	P1000 P8	N/A	Off   / N/A	00000000:AF: 17MiB /	00.0 Off 4040MiB	0%	N/A Default
3	Quadro			Off	00000000:D8:	:00.0 Off		N/A
34%	18C	P8	N/A	/ N/A	17MiB /	4040MiB	0% +	Default
	esses:		N/A Type	/ N/A   Process		4040MiB	1 0%	
Proc	esses:		Type C	Process				GPU Memory Usage 333MiE
Proc GPU ====	esses: ======= 13 13	PID ====== 473 487	Type C C	Process /usr/lo	name ======= cal/lib64/R/t	oin/exec/R		GPU Memory Usage 333MiE 333MiE
Proc GPU ==== 0 0	esses: ======= 13 13 13	PID ====== 473 487 501	Type C C	Process  /usr/lo /usr/lo /usr/lo	name ======= cal/lib64/R/t cal/lib64/R/t	======= pin/exec/R pin/exec/R		GPU Memory Usage 333MiE 333MiE 333MiE
Proc GPU 0 0	esses: ======= 13 13 13	PID ====== 473 487 501 515	Type C C C	Process /usr/lo /usr/lo /usr/lo	name ======= cal/lib64/R/t cal/lib64/R/t cal/lib64/R/t	====== pin/exec/R pin/exec/R pin/exec/R		GPU Memory Usage 333MiE 333MiE 333MiE 333MiE
Proc GPU 9 0	esses: ======= 13 13 13 13 13	PID ====== 473 487 501 515 532	Type C C C C	Process /usr/lo /usr/lo /usr/lo /usr/lo	name ========= cal/lib64/R/b cal/lib64/R/b cal/lib64/R/b cal/lib64/R/b	====== pin/exec/R pin/exec/R pin/exec/R pin/exec/R		GPU Memory Usage 333Mii 333Mii 333Mii 333Mii 333Mii
Proc GPU ==== 0 0 0 0	esses: ======= 13 13 13 13 13	PID ====== 473 487 501 515 532 549	Type C C C C	Process /usr/lo /usr/lo /usr/lo /usr/lo	name ========= cal/lib64/R/t cal/lib64/R/t cal/lib64/R/t cal/lib64/R/t	oin/exec/R pin/exec/R pin/exec/R pin/exec/R pin/exec/R		GPU Memory Usage 333Mii 333Mii 333Mii 333Mii 333Mii 333Mii
Proc GPU 9 0	esses: 13 13 13 13 13 13 13	PID ====== 473 487 501 515 532	Type C C C C	Process /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo	name ========= cal/lib64/R/b cal/lib64/R/b cal/lib64/R/b cal/lib64/R/b	Din/exec/R Din/exec/R Din/exec/R Din/exec/R Din/exec/R Din/exec/R		GPU Memory Usage 333MiE 333MiE 333MiE 333MiE 333MiE 333MiE 333MiE
Proc GPU 9 9 9 9	esses:  13 13 13 13 13 13 13 13 13 13 13 13	PID ====== 473 487 501 515 532 549 563 577 594	Type C C C C C C C	Process  /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo	name ====================================	pin/exec/R pin/exec/R pin/exec/R pin/exec/R pin/exec/R pin/exec/R pin/exec/R		GPU Memory Usage 333Mii 333Mii 333Mii 333Mii 333Mii 333Mii 333Mii
GPU ==== 0 0 0 0 0 0 0	esses: 13 13 13 13 13 13 13 13 13	PID ====== 473 487 501 515 532 549 563 577	Type C C C C C C	Process  /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo /usr/lo	name ====================================	Din/exec/R Din/exec/R Din/exec/R Din/exec/R Din/exec/R Din/exec/R Din/exec/R Din/exec/R		GPU Memory Usage 333MiE 333MiE

N.B: xgboost uses 100% GPU for 1 model... no benefits from parallel training (applies to my NVIDIA Quadro P1000 which is not a powerful GPU)

LightGBM, GPU

# Multi GPU xgboost



Data: <a href="https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt">https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt</a>

#### Multi GPU xgboost

	0.1M	1M	10M	100M
CPU (Best)	2.735	12.524	70.121	675.223
Quadro P1000	17.529	38.528	103.154	CRASH
4 Quadro P1000	18.838	36.877	64.994	232.947
4 GPU Perf. (%)	14.5%	34.0%	107.9%	289.9%

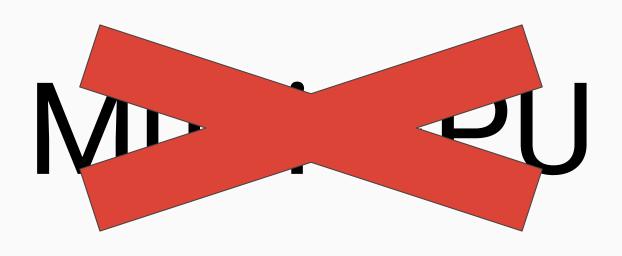
N.B: Dual Xeon 6154 (~\$7,000) vs Quadro P1000 (~\$400) vs 4 Quadro P1000 (~\$1,600)

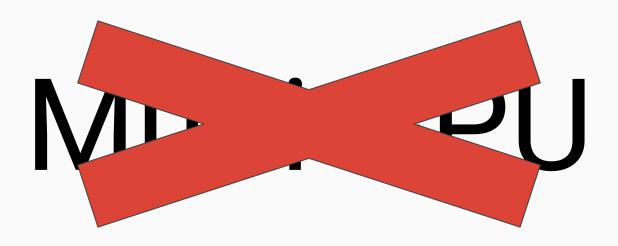
Comparison unit: seconds

Multi GPU xgboost requires NCCL = only for Linux

xgboost hist, GPU

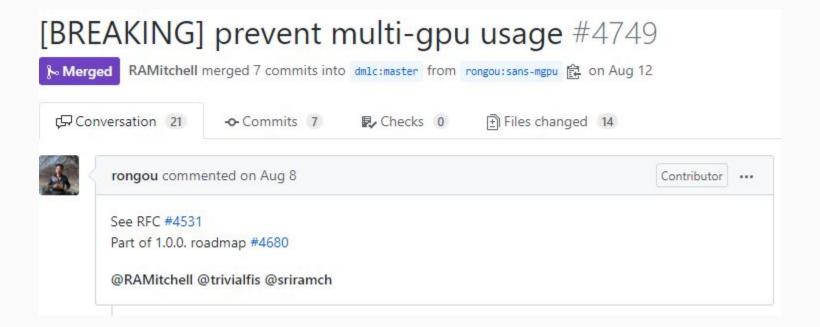
# Multi GPU

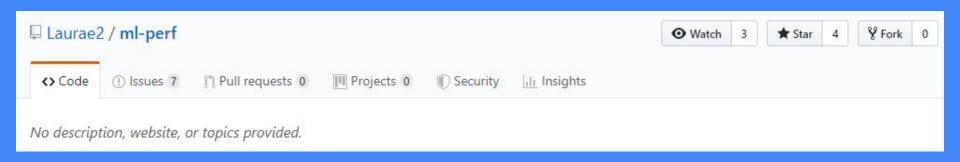




If you want to use xgboost with multiple GPU, use a commit before August 12, 2019.

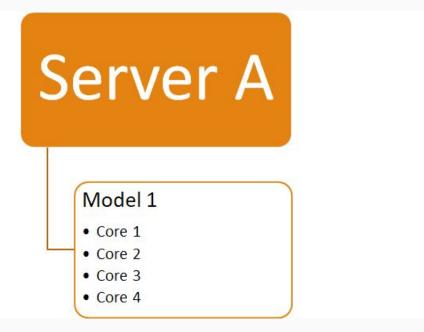
### Multi GPU xgboost





Data: <a href="https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt">https://github.com/szilard/benchm-ml/blob/master/0-init/2-gendata.txt</a>

Sequential Parallel training "Train each model using all cores"

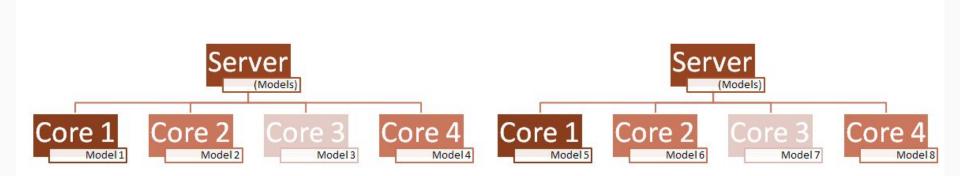


### Server A Model 2 Core 1 Core 2 Core 3 Core 4

Parallel Threads	Model Threads	Seconds / model	
1	1	11.383	
1	9	6.565	
1	18	6.481	
1	35	24.601	
1	70	165.947	

How to not use parallelism correctly (when data is small)

Parallel Sequential training "Train each model using 1 core"



Parallel Threads	Model Threads	Seconds / model (Model)	Seconds / model (Model -> Parallel)	Performance Boost
1	1	11.383	11.389	1x
1	9	6.565	1.456	4.51x
1	18	6.481	0.782	8.29x
1	35	24.601	0.489	50.31x
1	70	165.947	0.428	387.73x

Parallel Threads	Model Threads	Seconds / model (Model)	Seconds / model (Model -> Parallel)	Performance Boost
1	1	11.383	11.389	1x
1	9	6.565	1.456	4.51x
1	18	6.481	0.782	8.29x
1	35	24.601	0.489	50.31x
1	70	165.947	0.428	387.73x

#### Drawbacks:

- Really fully uses all hardware resources
- Might hit RAM bandwidth limitations
- Might hit L1 / L2 / L3 cache limitations
- Optional: pin process to maximize performance

**Fastest vs Slowest** 

xgboost hist, CPU

See more: <a href="https://github.com/Laurae2/ml-perf">https://github.com/Laurae2/ml-perf</a>



#### For single model training:

- Use very high frequency CPUs
- Favor desktop CPUs over server CPUs
- Favor CPU overclocking
- Favor recent CPU generations
- Does not need many CPU cores
- Hyperthreading may not help



Call for contribution: improve multi-core CPU performance New issue of 'hist' #3810 hcho3 opened this issue on Oct 19, 2018 · 34 comments hcho3 commented on Oct 19, 2018 • edited -Collaborator Assignees No one assigned It is about time to tackle the elephant in the room: performance on multi-core CPUs. Labels **Description of Problem** status: help wanted type: roadmap Currently, the hist tree-growing algorithm (tree\_method=hist) scales poorly on multi-core CPUs: for some datasets, performance deteriorates as the number of threads is increased. This issue was Projects discovered by @Laurae2's Gradient Boosting Benchmark (GitHub repo).

#### For sequential model training:

- Use very high frequency CPUs
- Favor desktop CPUs over server CPUs
- Favor CPU overclocking
- Favor recent CPU generations
- Does not need many CPU cores
- Hyperthreading may not help
- Favors large tasks

#### For parallel model training:

- Use (very) high frequency CPUs
- Favor server CPUs over desktop CPUs
- Favor recent CPU generations
- Need many CPU cores
- Hyperthreading should help (+20~40% performance)
- Favors short tasks







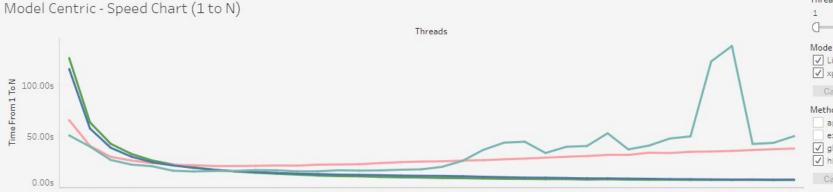
is much better than



for training GBMs (in general)

Model Centric - 1 to N iterations | Model Centric - 0 to N iterations | Memory Centric - 1 to N iterati... | Memory Centric - 0 to N iterati...

#### Model Centric - 1 to N iterations

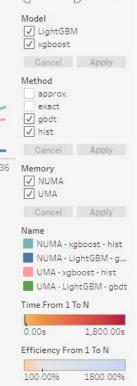


Model Centric - Speed Data (1 to N)

	Me	mory / Mo	del / Metl	nod	
	NU	MA	UMA		
	xgboost	LightGBM	xgboost	LightGBM	
Threads	hist	gbdt	hist	gbdt	
Grand Total	35.82s	17.29s	29.28s	17.20s	
1	50.82s	115.34s	65.67s	125.93s	
2	40.02s	57.65s	40.70s	63.64s	
3	27.00s	38.88s	30.07s	42.72s	
4	22.48s	30.22s	26.43s	32.88s	
5	20.87s	24.75s	23.98s	26.50s	
6	16.56s	21.68s	22.21s	22.56s	

#### Model Centric - Efficiency Data (1 to N)

	Memory / Model / Method				
	NUI	MA	UMA		
Threads	xgboost hist	LightGBM gbdt	xgboost hist	LightGBM gbdt	
Grand Total	195.93%	975.06%	238.03%	1166.29%	
1	100.00%	100.00%	100.00%	100.00%	
2	126.99%	200.09%	161.34%	197.89%	
3	188.24%	296.67%	218.41%	294.77%	
4	226.03%	381.67%	248.45%	382.99%	
5	243.45%	465.96%	273.80%	475.17%	
6	306.94%	532.00%	295.64%	558.12%	
7	321.71%	596.66%	300.79%	638.18%	
ρ	212 //7%	663 79%	211 79%	719 22%	



Threads

36



Parallelism and scaling on CPU:

"slow" by today's standards

the fastest GBMs

	xgboost (exact)	xgboost (hist)	LightGBM
Inherent Parallelism (C++)	Row	Row	Column

Parallelism and scaling on CPU:

"slow" by today's standards

the fastest GBMs

	xgboost (exact)	xgboost (hist)	LightGBM
Inherent Parallelism (C++)	Row	Row	Column
Scaling with more rows*	Excellent	Poor	Good

\* Use more rows on dataset

Parallelism and scaling on CPU:

"slow" by today's standards

the fastest GBMs

	xgboost (exact)	xgboost (hist)	LightGBM
Inherent Parallelism (C++)	Row	Row	Column
Scaling with more rows*	Excellent	Poor	Good
Scaling with more columns**	Good	Poor	Good

<sup>\*</sup> Use more rows on dataset

<sup>\*\*</sup> Use more columns on dataset

Parallelism and scaling on CPU:

"slow" by today's standards

the fastest GBMs

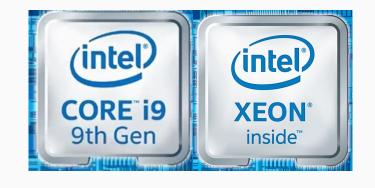
	xgboost (exact)	xgboost (hist)	LightGBM
Inherent Parallelism (C++)	Row	Row	Column
Scaling with more rows*	Excellent	Poor	Good
Scaling with more columns**	Good	Poor	Good
Scaling of models***	Excellent	Excellent	Excellent

<sup>\*</sup> Use more rows on dataset

<sup>\*\*</sup> Use more columns on dataset

<sup>\*\*\*</sup> Train models in parallel instead of sequentially

## Need speed?



## Need speed?



### Use GPU\*

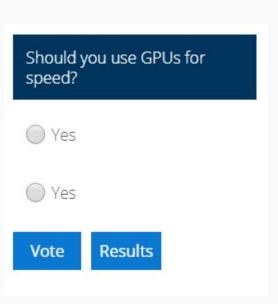
\*with enough RAM to fit dataset in memory (and must not care about non-reproducible results)

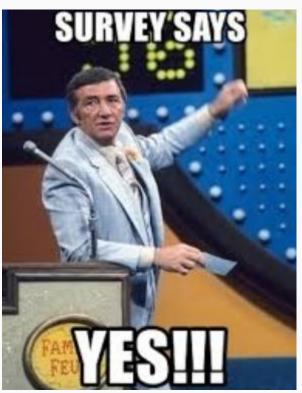


Use GPU\*



Use GPU\*





#### Learn hyperparameters:

https://sites.google.com/view/lauraepp/parameters (especially the most impactful)

Туре	+	Category	+	Parameter	+	xgboost	+	:
LightGBM	+	Major Impact	~	Minor Impact	<b>v</b>	Search		
I - 86 / 86								< >
	Para	ameter		Parameter name:	Number of T	broada		
Number of Threads				Parameter mame.	Nullibel of I	Illedus		
Learning rate				Type of parameter	: Model			
Number of Iterations				. ype or parameter				
Number of Trees				Category of param	neter: Genera	al		
Early Stopping								
Verbosity								
Debugging Verbosity				xgboost name: nth				
Missing Values				LightGBM name: n	um_threads			
Maximum Depth								
Maximum Leaves				Range: [1, ∞[				
Row Sampling				Major Impact: Trai				
Row Sampling Seed				Minor Impact: RAN	vi Usage			
Row Sampling Frequen	CV							
Column Sampling by Tr				Description: Numb	or of throad	s using for training	modele	
Column Sampling by Le				Description. Num	Dei Oi tilleau	s using for training	models.	
Column Sampling Seed				Behavior				
L1 Regularization				Larger is usually b	ottor			
L2 Regularization				Typical: number of				
L2 Bias Regularization							maller data has reverse b	anafite
L2 Categorical Regulari	zation			rips. larger data b	chem nom	nore timedas, but s	maner data mas reverse i	ochemo.
Categorical Smoothing								
Loss Regularization								
Hessian Regularization				xgboost Specific				
Minimum Data per Leaf							inear) as long as the data	
Histogram Binning							poorly (parabola) to wel	I (nearly linear) as long
Histogram Binning (Cat	egorical)			as the dataset is la			-ul. (u-l-ala) +- (11 /-	
Histogram Size						xgboost scales po	orly (parabola) to well (r	learly linear) as long as
Histogram Sample Con	struction			the dataset is larg		f throada in var-	a a bin a	
Histogram Bin Construc	tion			Defaults to NULL, tr	ie number o	f threads in your ma	acnine.	
Matrix Data Type				LiebtODM Coif-				
Sparse Threshold				LightGBM Specific		10121 01 10	and the second of the second	



dsoukhavong@gmail.com



twitter.com/@Laurae\_Cht



github.com/Laurae2



medium.com/@Laurae2