Better than Deep Learning: Gradient Boosting Machines (GBM) - 2019 edition

Szilard Pafka, PhD
Chief Scientist, Epoch

LA West R Meetup, Santa Monica
May 2019

Edit profile

Szilard [Deeper than Deep Learning]

@DataScienceLA

physics PhD, chief (data) scientist, meetup organizer, datascience.la, (visiting) professor, machine learning benchmarks 🇺🇸🇭🇺🇪🇺

Santa Monica, California linkedin.com/in/szilard

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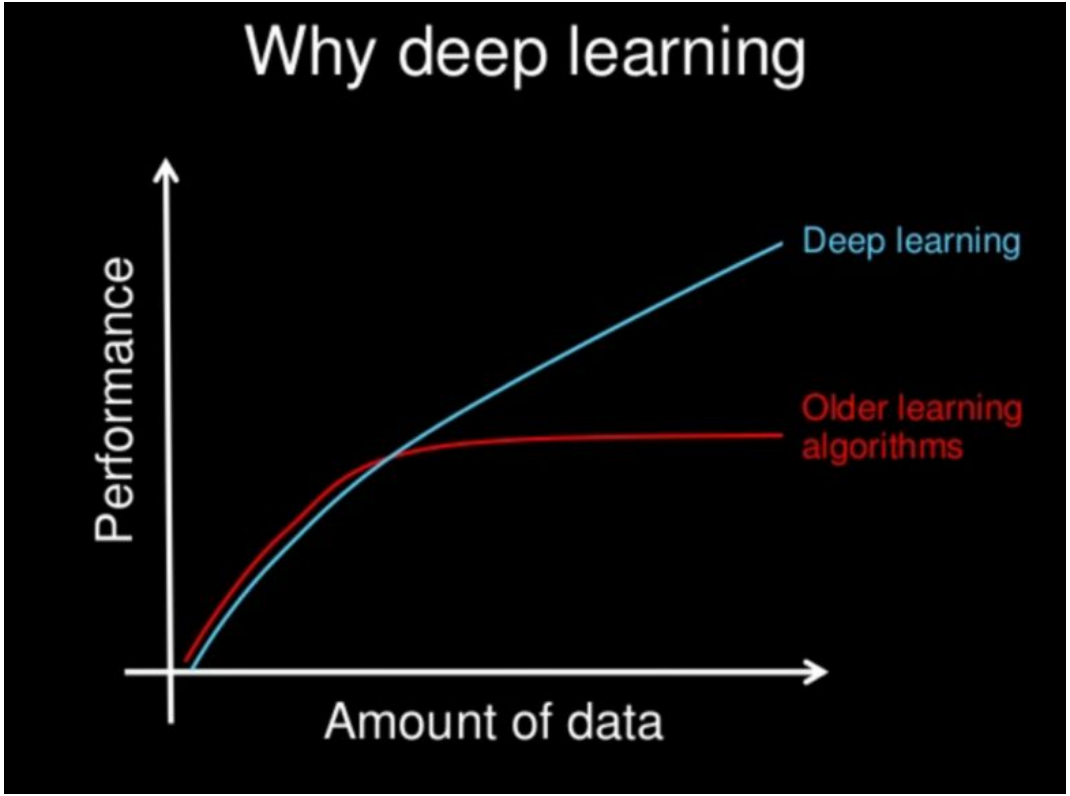
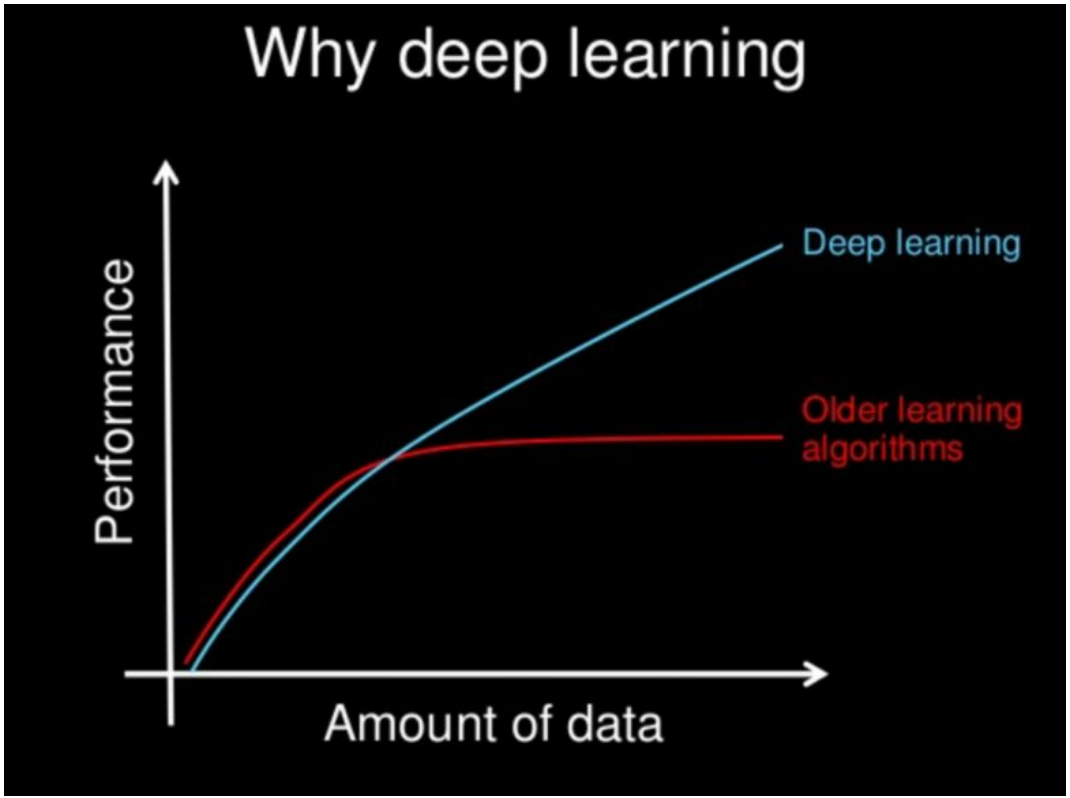
I am not representing my employer (Epoch) in this talk

I cannot confirm nor deny if Epoch is using any of the methods, tools, results etc. mentioned in this talk



Source: Andrew Ng



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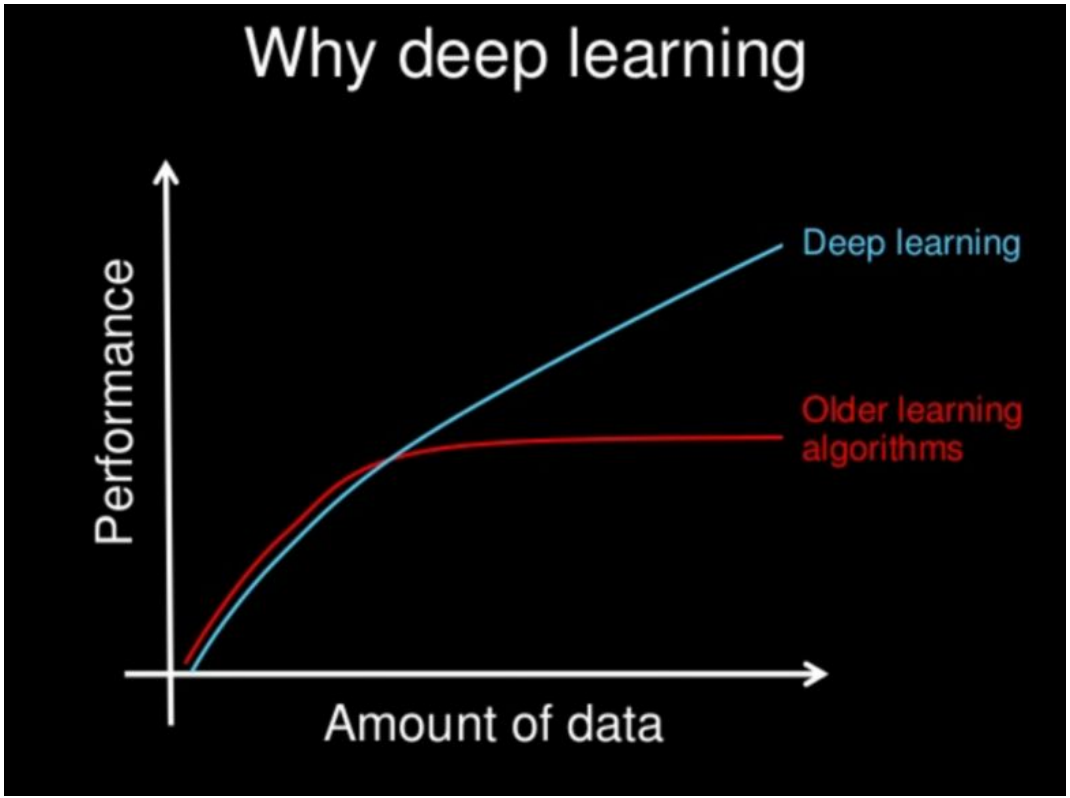

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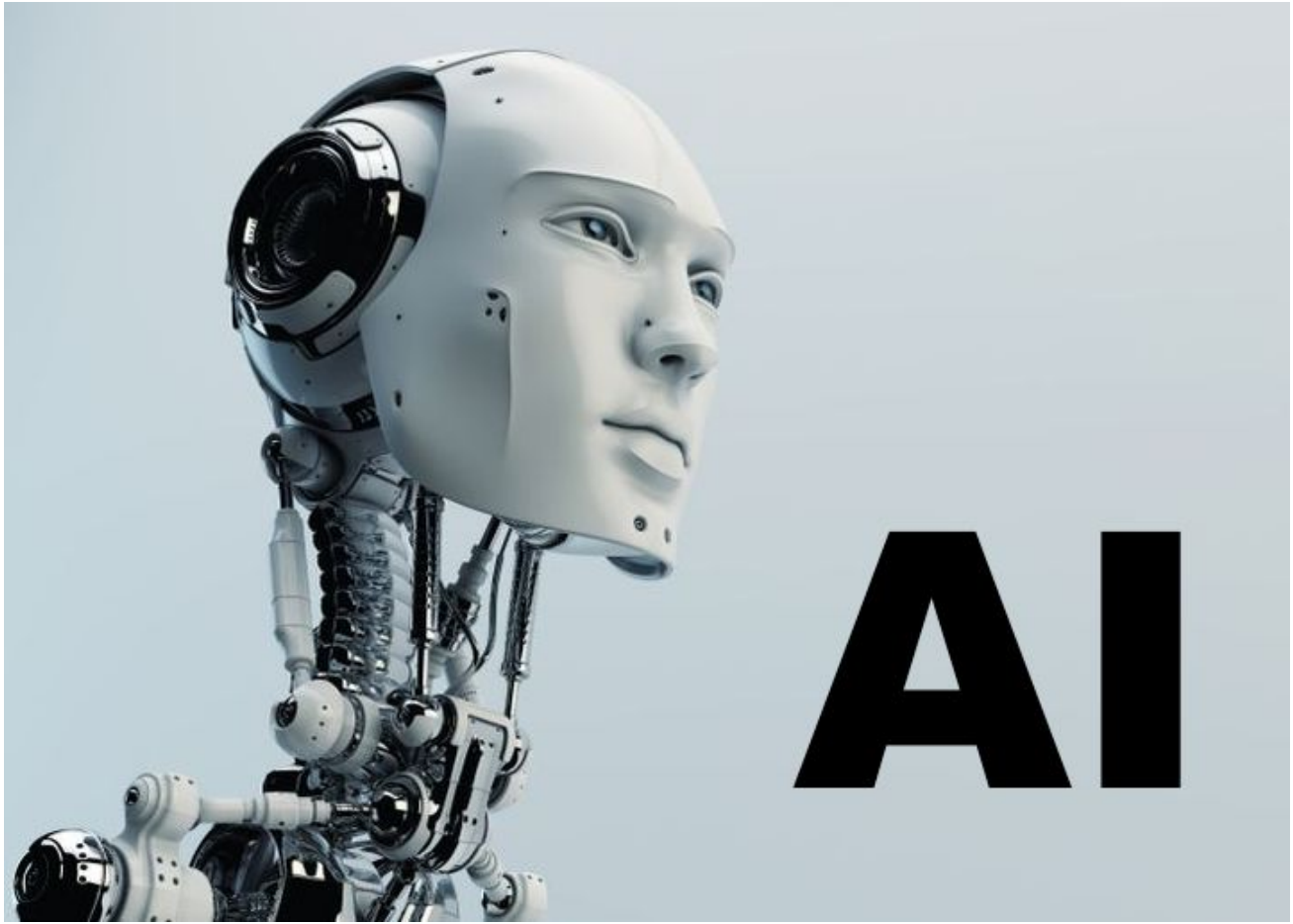
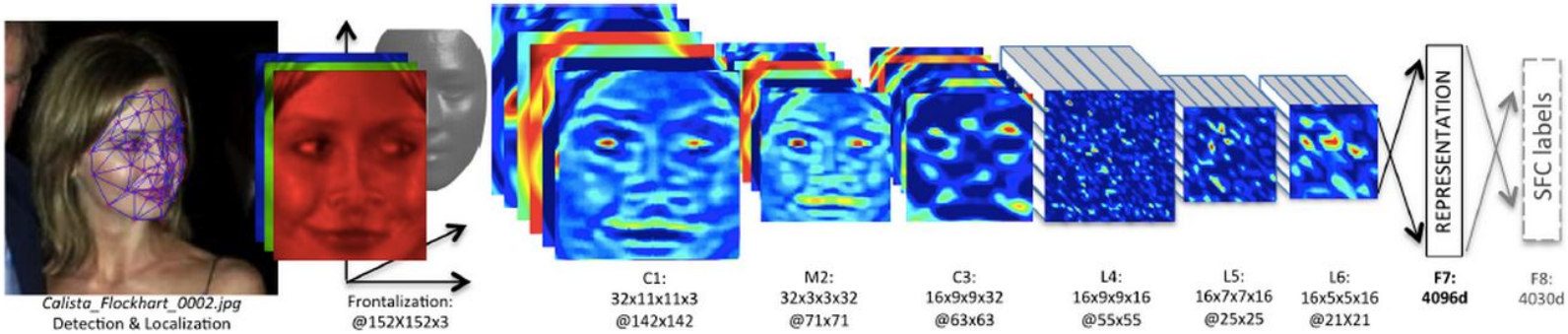
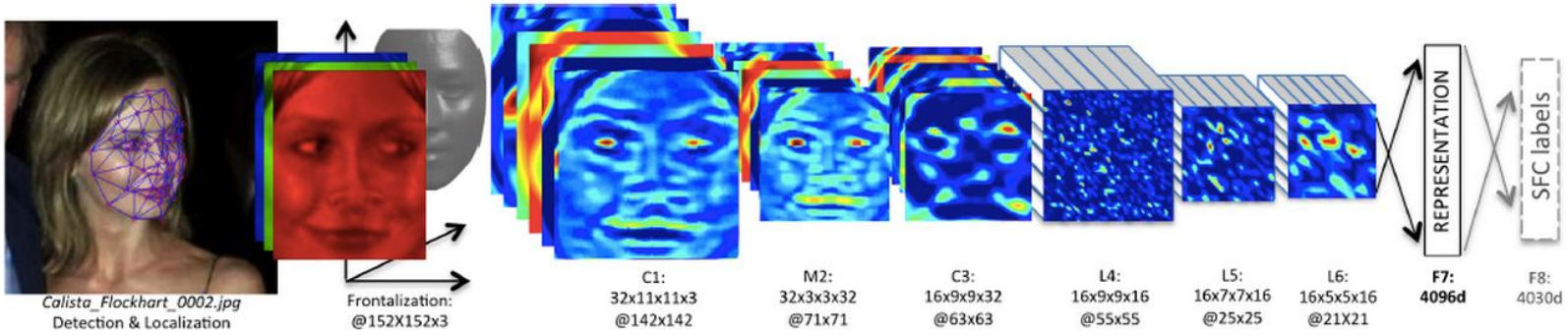

AI


Calista_Flockhart_0002.jpg
Detection & Localization
Frontalization:
@152X152x3
C1:
32x11x11x3
@142x142
M2:
32x3x3x32
@71x71
C3:
16x9x9x32
@63x63
L4:
16x9x9x16
@55x55
L5:
16x7x7x16
@25x25
L6:
16x5x5x16
@21X21
F7:
4096d
REPRESENTATION
SFC labels
F8:
4030d


Calista_Flockhart_0002.jpg
Detection & Localization
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16x5x5x16
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F8:
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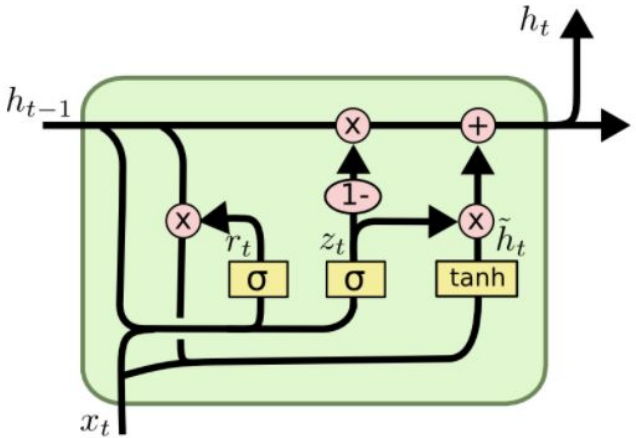
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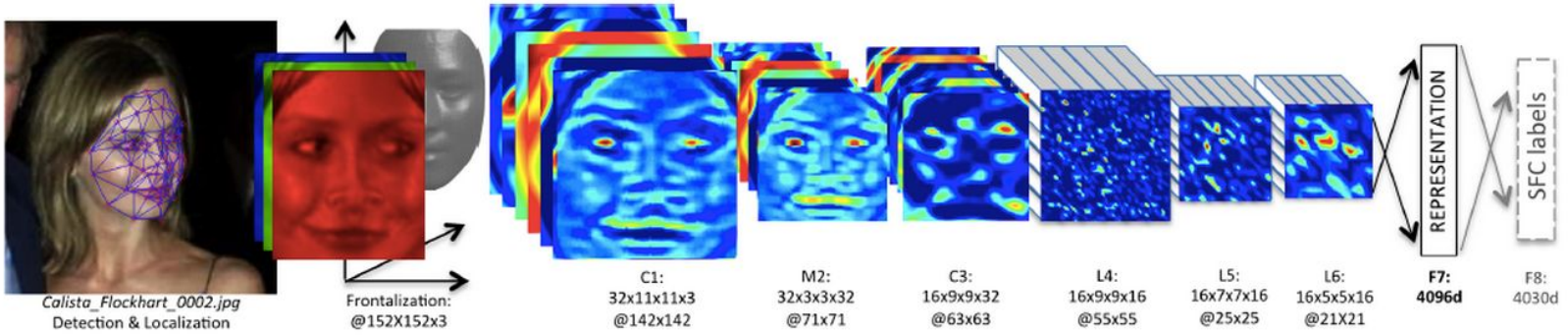
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Detection & Localization
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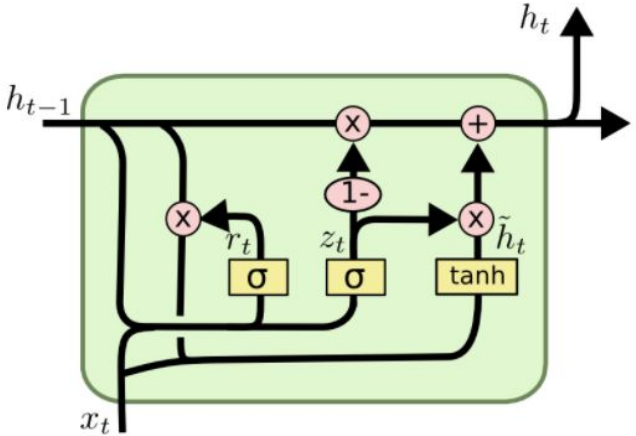
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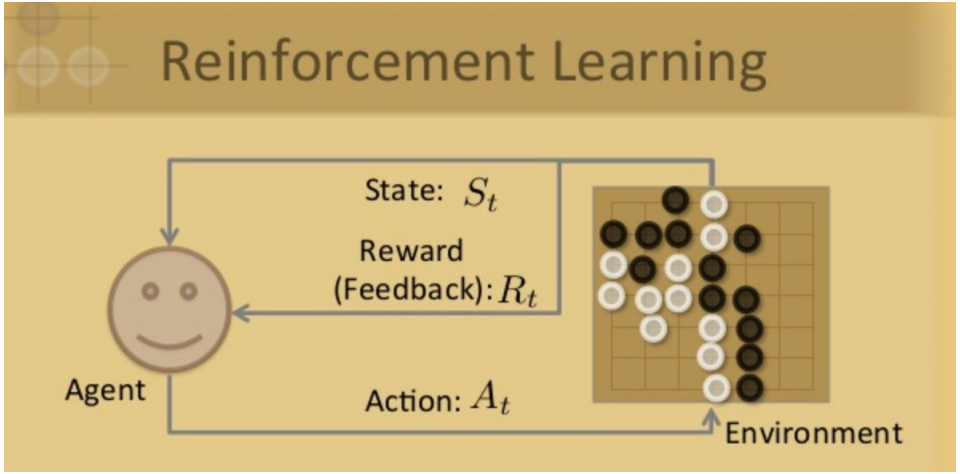
Reinforcement Learning
State: S_t
Reward
(Feedback): R_t
Agent
Action: A_t
Environment

Source: https://twitter.com/iamdevloper/


FRAUD
FRAUD


710
POOR
GOOD


marketing
client
delivering
customers
profit
solution
concept
creating
relationships
techniques
profitable
society
activities
goal
goods
communicating
satisfaction
focus
build
contribute
brand
value
offer
strategy
business
activity
strong
long term
management
development
organization


FRAUD
FRAUD


710
POOR
GOOD


marketing
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profit
solution
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goal
goods
communicating
satisfaction
build
contribute
strategy
brand
value
offer
business
activity
strong
management
development
organization

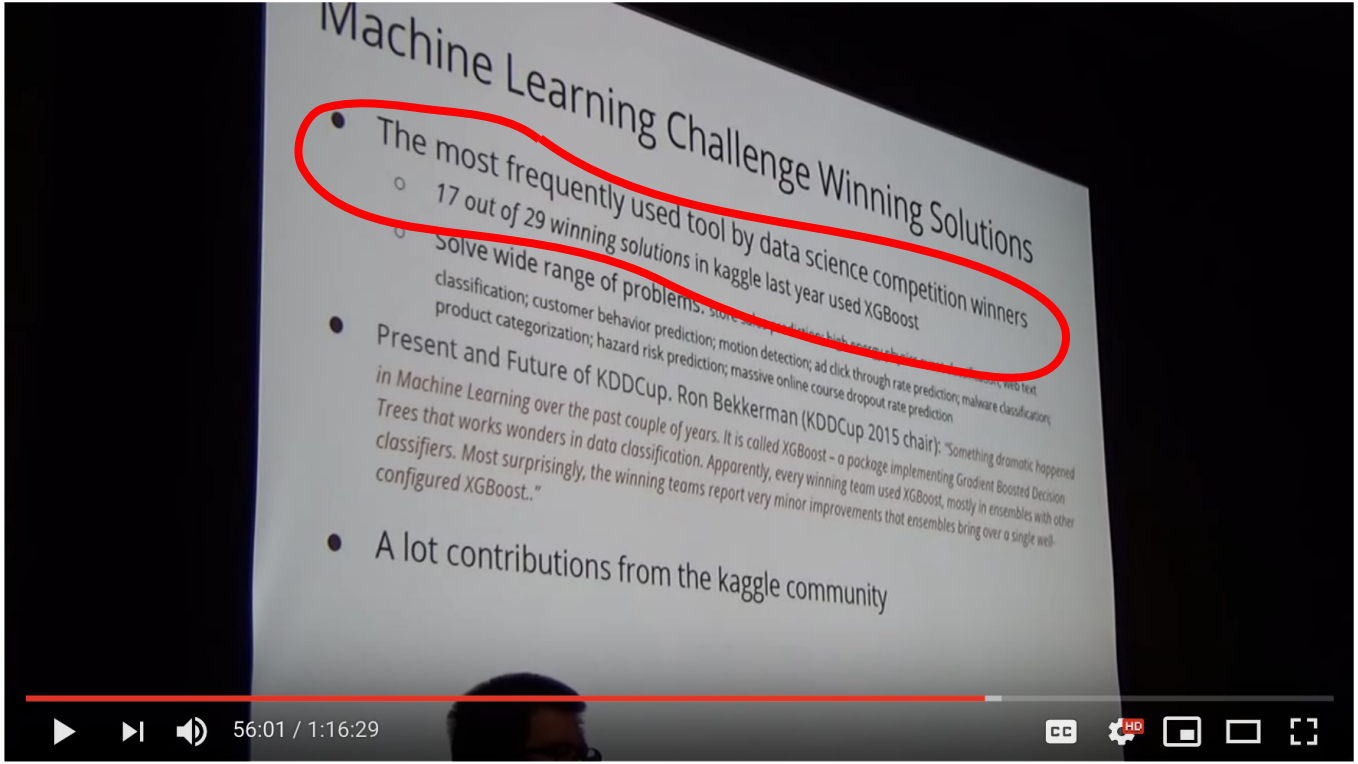
Params	AUC	Time (s)	Epochs
default: `activation = "Rectifier", hidden = c(200,200)`	73.1	270	1.8
`hidden = c(50,50,50,50), input_dropout_ratio = 0.2`	73.2	140	2.7
`hidden = c(50,50,50,50)`	73.2	110	1.9
`hidden = c(20,20)`			
`hidden = c(20)`			

szilard commented Nov 27, 2015

Trying to see if DL can match RF/GBM in accuracy on the airline dataset (wh
years 2005-2006, while validation and test sets sampled disjunctly from 20(
kept categorical artificially and are intentionally not encoded as ordinal varia
structure of business datasets).

`RectifierWithDropout, c(200,200,20(`			
`ADADELTA rho = 0.95, epsilon = 1e-(`			
`rho = 0.999, epsilon = 1e-08`	73.3	270	1.9
`adaptive = FALSE` default: `rate = 0.005, decay = 1, momentum = 0`	73.0	340	1.1
`rate = 0.001, momentum = 0.5 / 1e5 / 0.99`	73.2	410	0.7
`rate = 0.01, momentum = 0.5 / 1e5 / 0.99`	73.3	280	0.9
`rate = 0.01, rate_annealing = 1e-05, momentum = 0.5 / 1e5 / 0.99`	73.5	360	1
`rate = 0.01, rate_annealing = 1e-04, momentum = 0.5 / 1e5 / 0.99`	72.7	3700	8.7
`rate = 0.01, rate_annealing = 1e-05, momentum = 0.5 / 1e5 / 0.9`	73.4	350	0.9

kaggle



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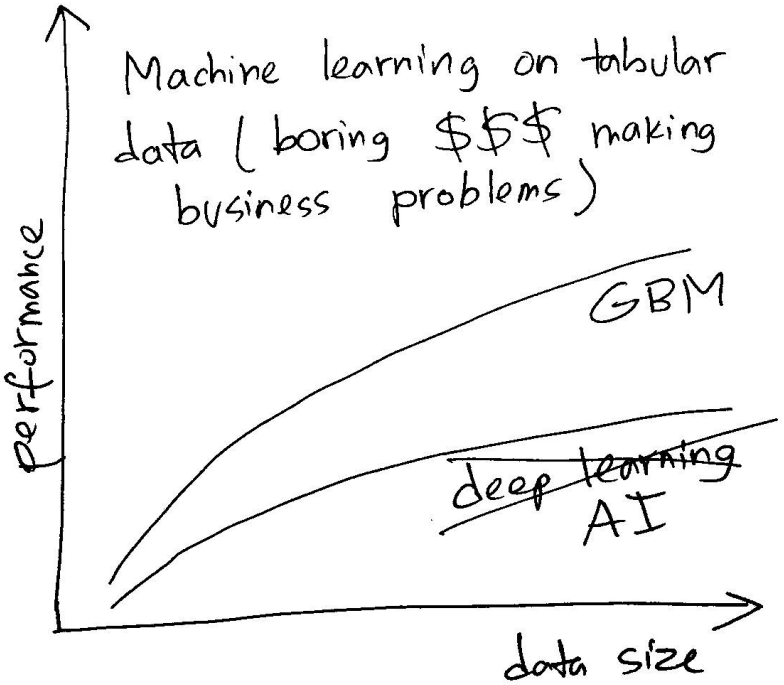
Szilard [Deeper than Deep Learning] @DataScienceLA · 2 Nov 2016

Can anyone **beat** GBMs with deep learning (ahem, AI) on the airline dataset (or generally tabular/business data)? github.com/szilard/benchm…



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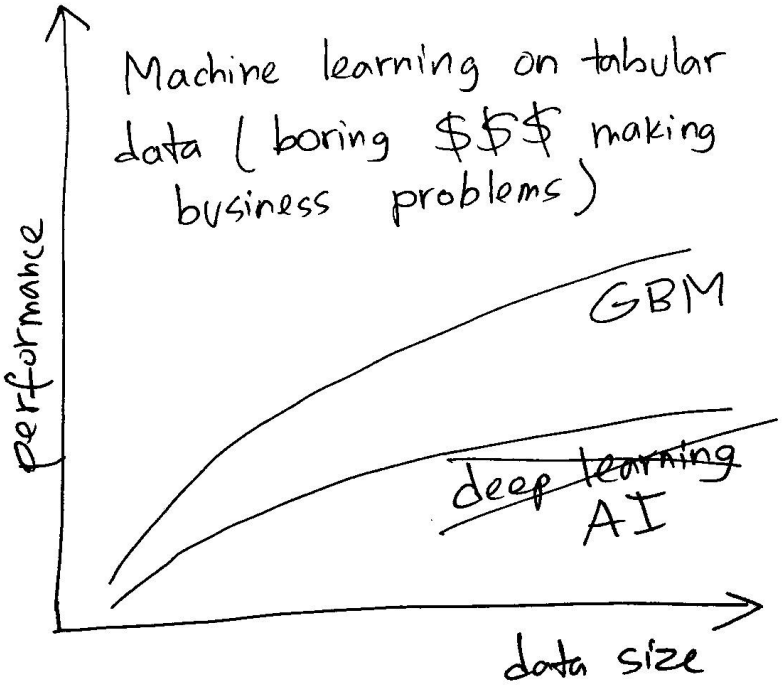

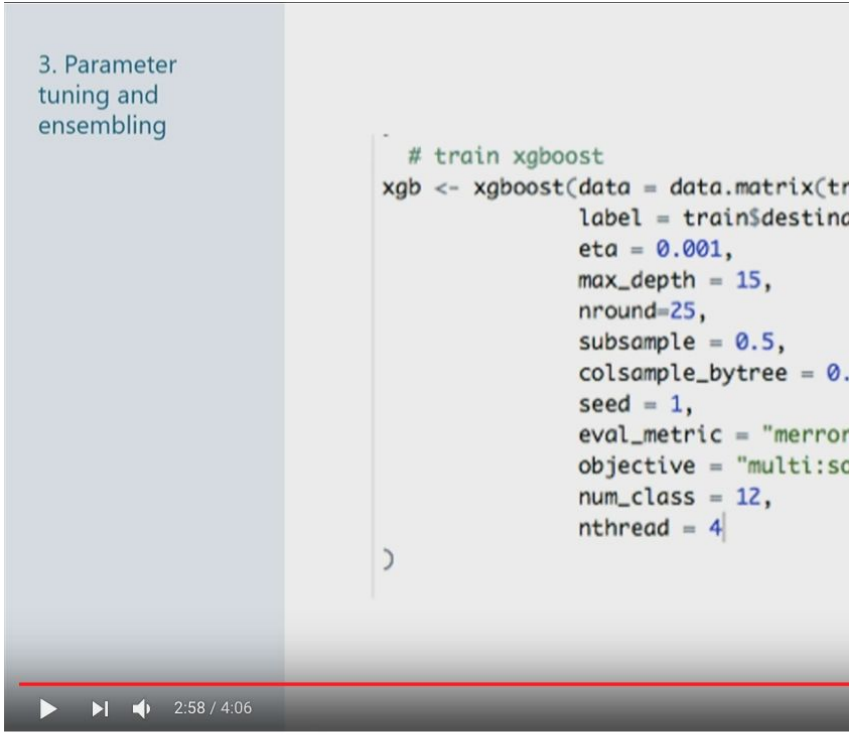

What Kaggle has learned from almost a million data scientists - Anthony Goldbloom

18,153 views

O'Reilly

Published on May 25, 2017

MODEL	1ST	2ND
BST-DT	0.580	0.228
RF	0.390	0.525
BAG-DT	0.030	0.232
SVM	0.000	0.008
ANN	0.000	0.007
KNN	0.000	0.000
BST-STMP	0.000	0.000
DT	0.000	0.000
LOGREG	0.000	0.000
NB	0.000	0.000

AVG	1ST	2ND
RF	0.727	0.207
ANN	0.053	0.172
BSTDT	0.059	0.228
SVM	0.043	0.195
LR	0.089	0.132
BAGDT	0.002	0.012
KNN	0.023	0.045
BSTST	0.004	0.009
PRC	0	0
NB	0	0

An Empirical Comparison of Supervised Learning Algorithms

http://www.cs.cornell.edu/~alexn/papers/empirical.icml06.pdf

An Empirical Evaluation of Supervised Learning in High Dimensions

http://lowrank.net/nikos/pubs/empirical.pdf

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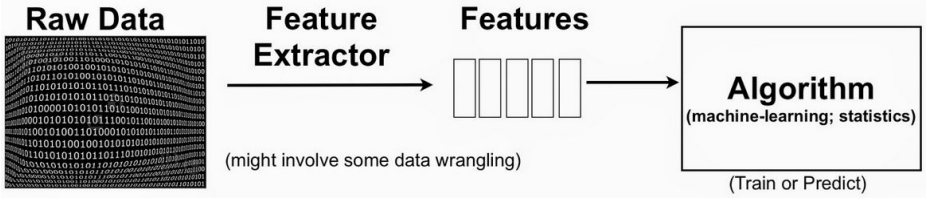
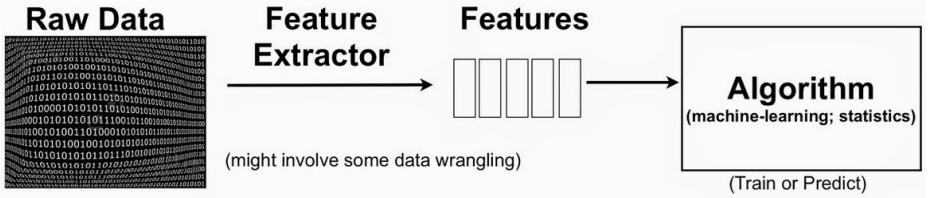

Raw Data
Feature Extractor
Features
Algorithm
(machine-learning; statistics)
(might involve some data wrangling)
(Train or Predict)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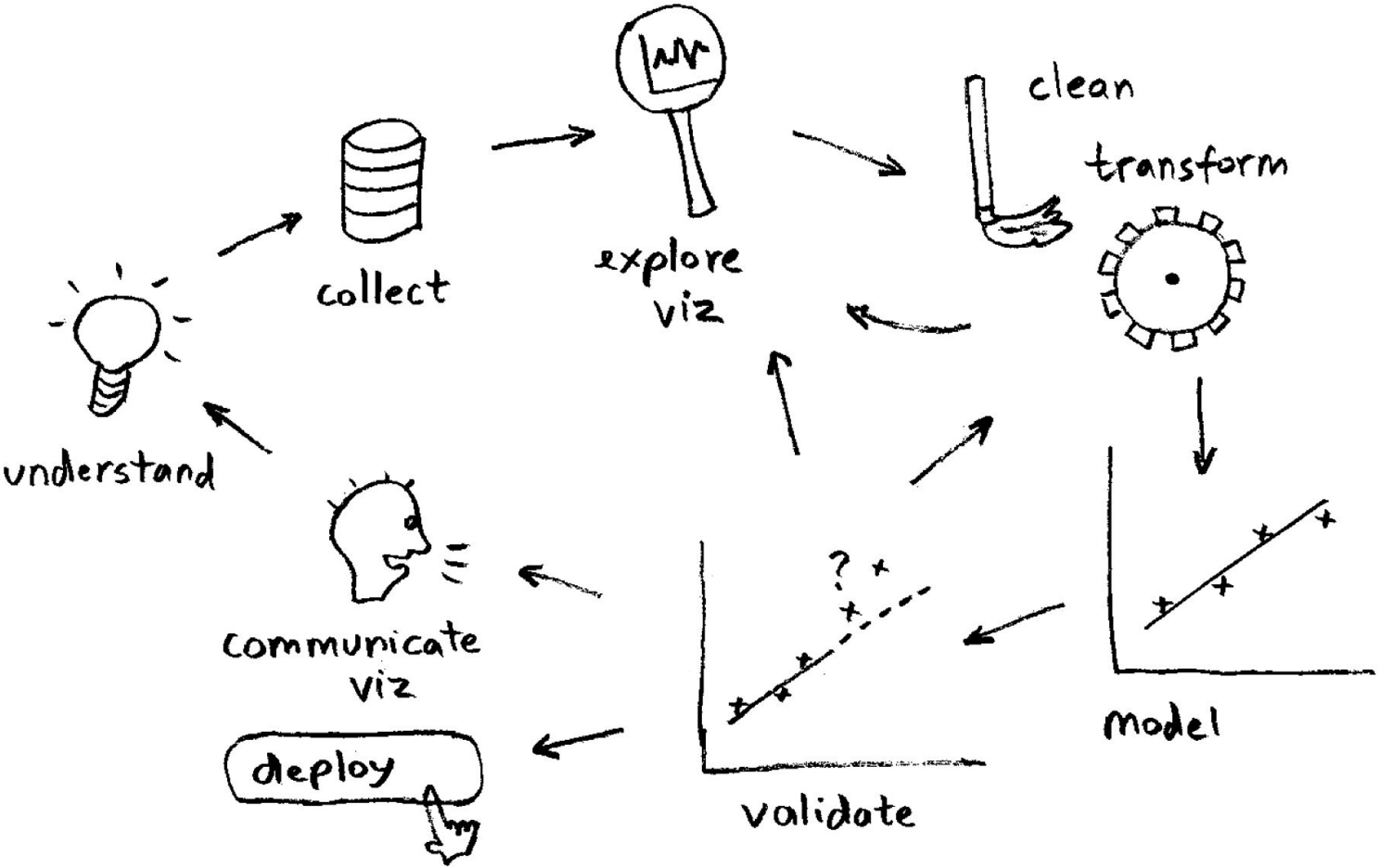
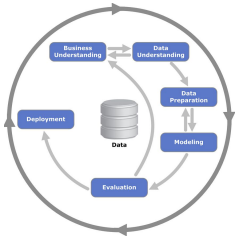
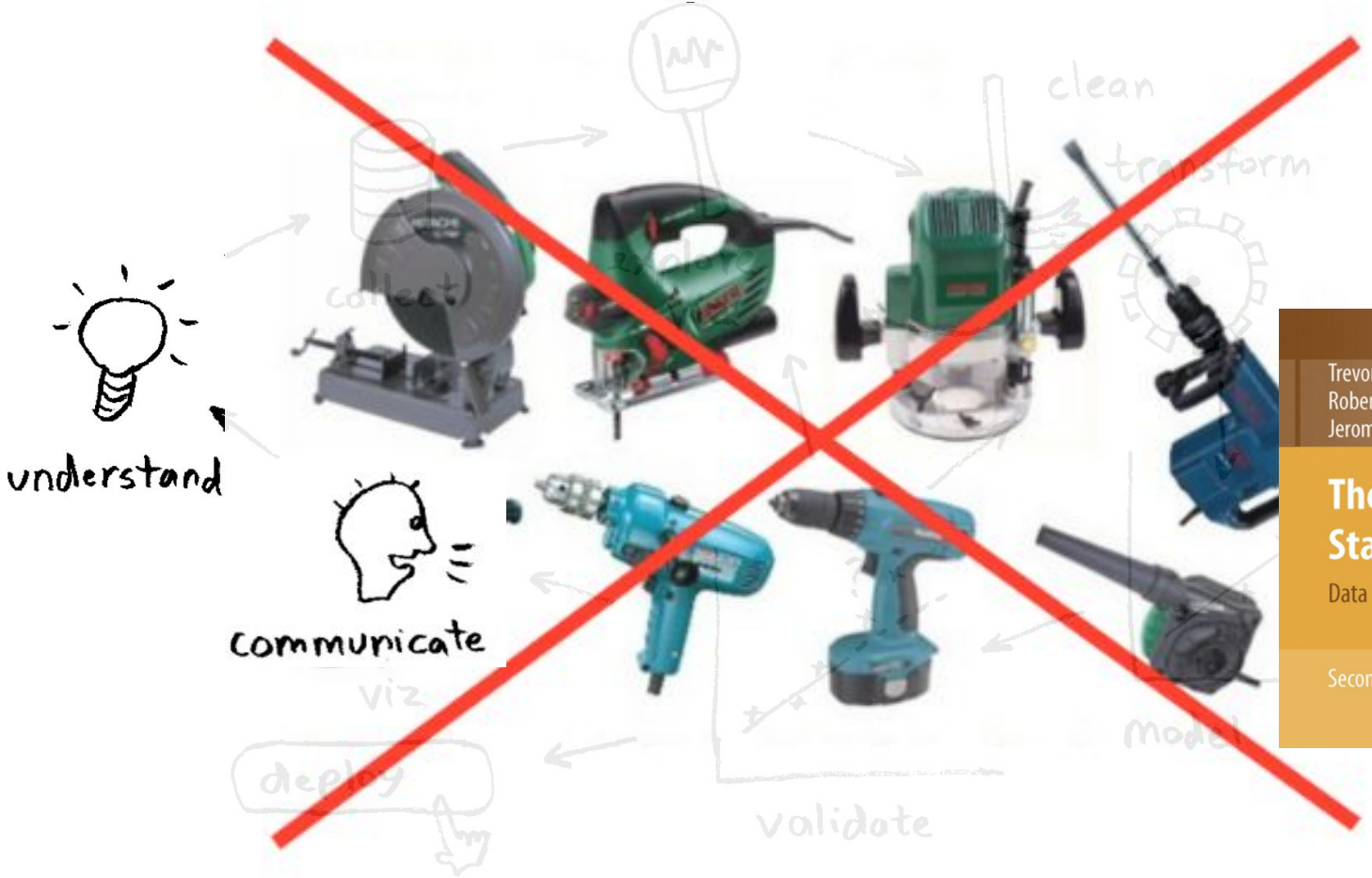

clean
transform
explore
viz
collect
understand
communicate
viz
deploy
validate
model


Business Understanding
Data Understanding
Data Preparation
Modeling
Evaluation
Deployment
Data

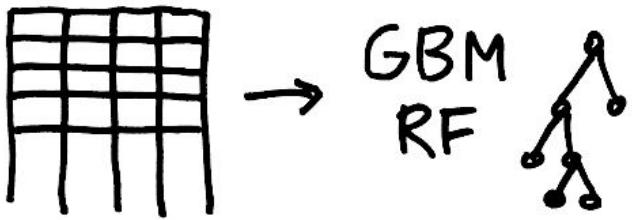


Trevor Hastie
Robert Tibshirani
Jerome Friedman

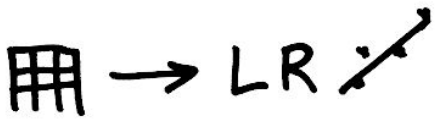
The Elements of Statistical Learning

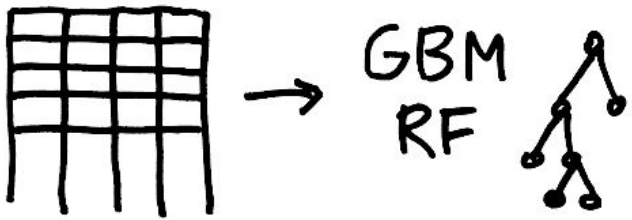
Data Mining, Inference, and Prediction

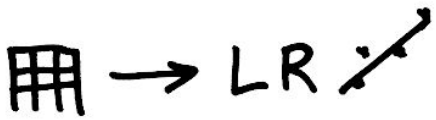
Second Edition


GBM
RF


GBM
RF


LR


GBM
RF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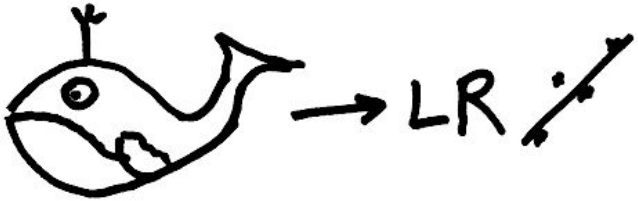
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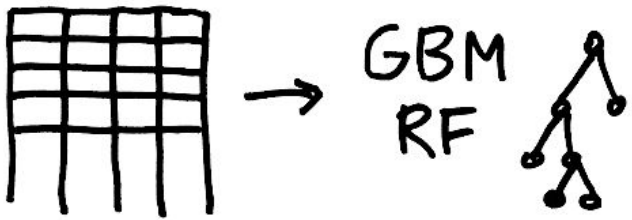
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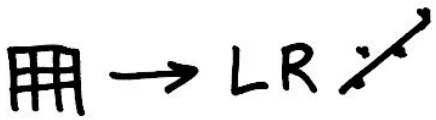
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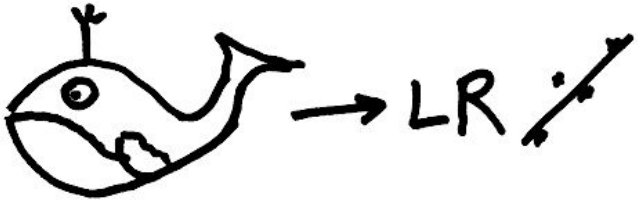
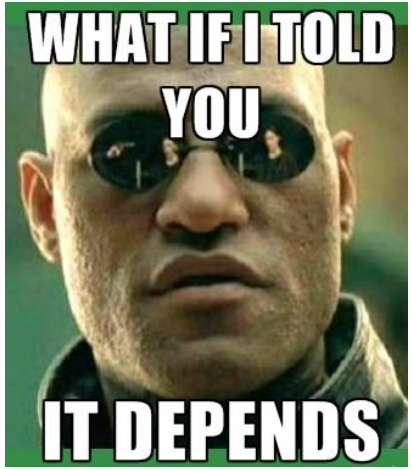
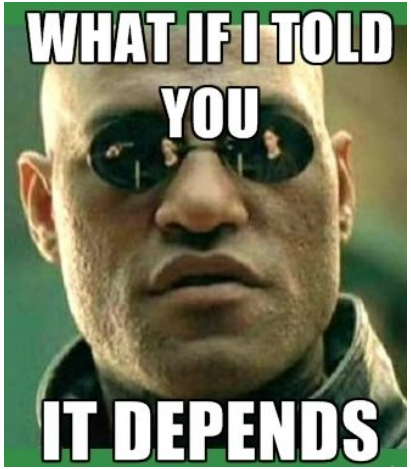

LR


DL


WHAT IF I TOLD YOU
IT DEPENDS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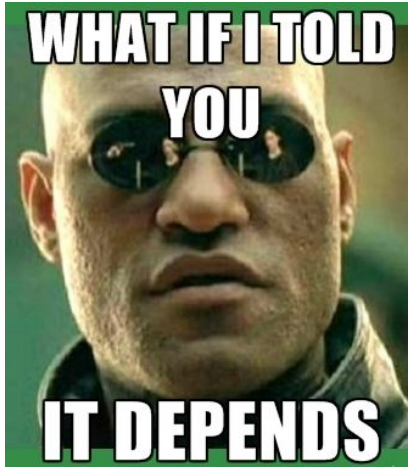
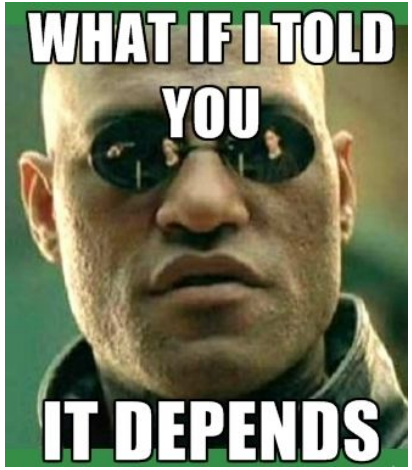
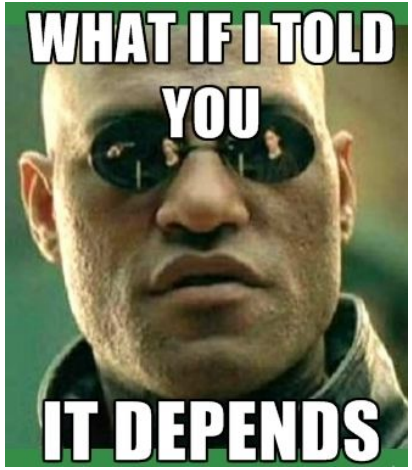


Hyperparameter tuning

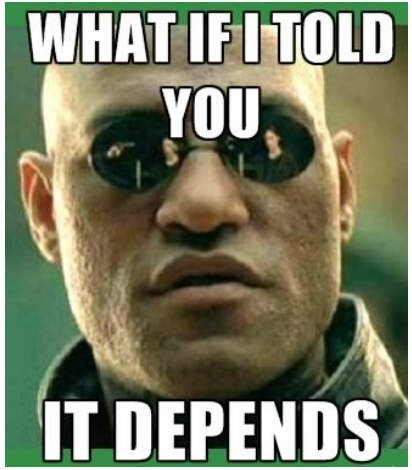


Hyperparameter tuning



Hyperparameter tuning

Features



Hyperparameter tuning

Features

BLACK BOX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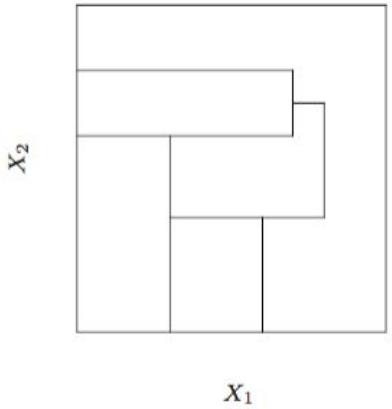
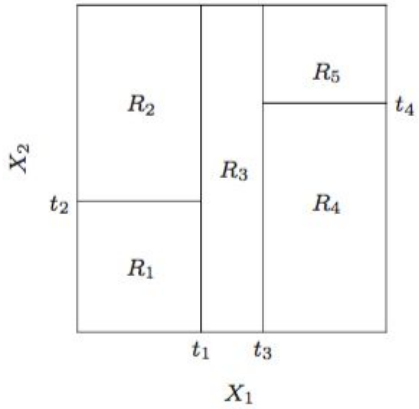
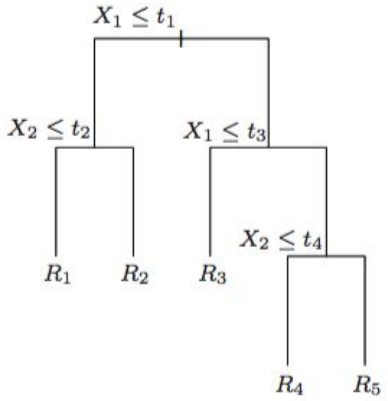
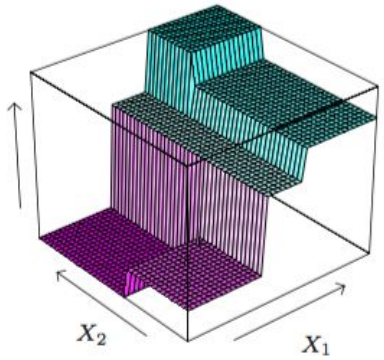
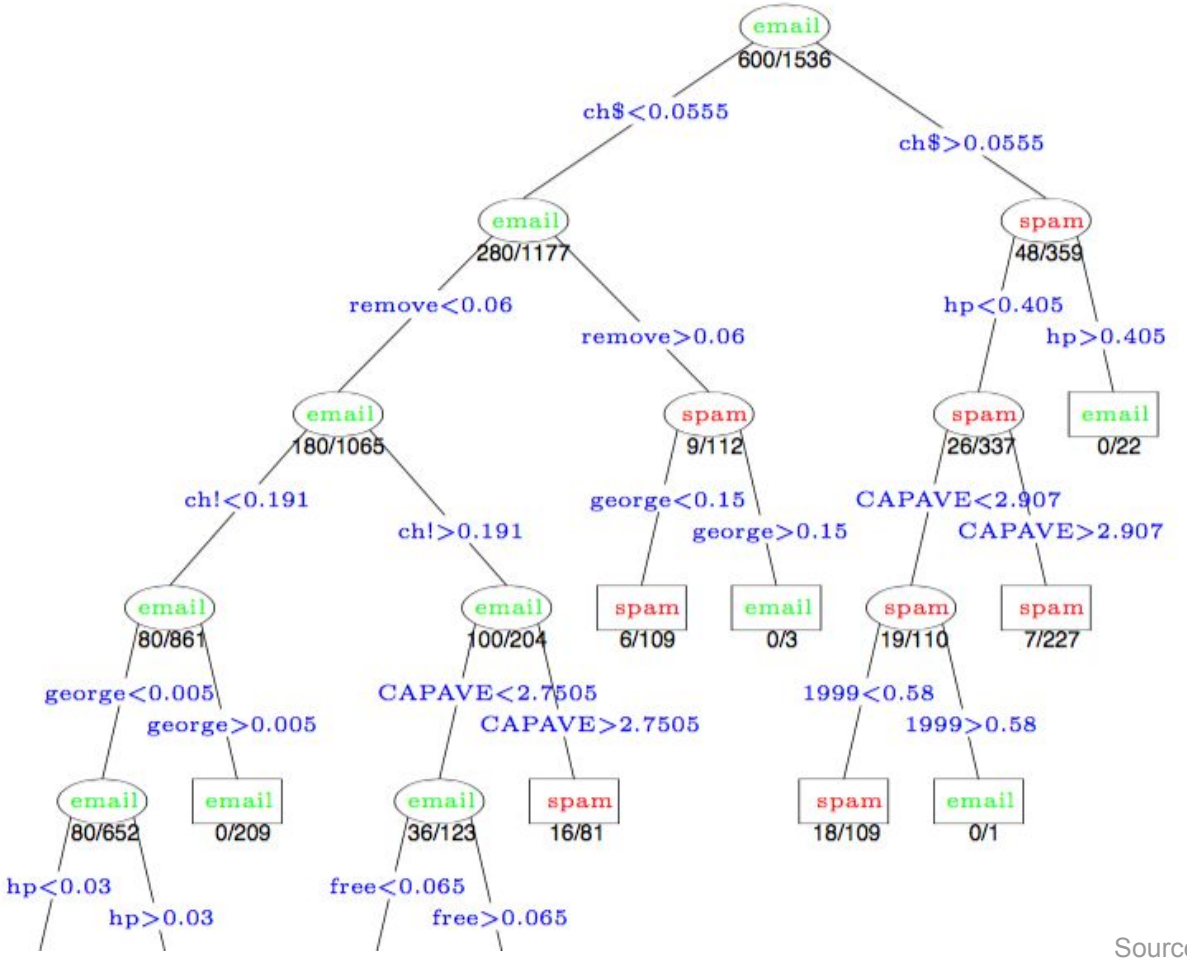








Source: Hastie etal, ESL 2ed



Source: Hastie etal, ESL 2ed

Algorithm 10.1 *AdaBoost.M1.*

1. Initialize the observation weights $w_i = 1/N,\ i = 1, 2, \ldots, N$.
2. For $m = 1$ to M:
   (a) Fit a classifier $G_m(x)$ to the training data using weights w_i.
   (b) Compute
   $$\text{err}_m = \frac{\sum_{i=1}^{N} w_i I(y_i \neq G_m(x_i))}{\sum_{i=1}^{N} w_i}.$$
   (c) Compute $\alpha_m = \log((1 - \text{err}_m)/\text{err}_m)$.
   (d) Set $w_i \leftarrow w_i \cdot \exp[\alpha_m \cdot I(y_i \neq G_m(x_i))],\ i = 1, 2, \ldots, N$.
3. Output $G(x) = \text{sign}\left[\sum_{m=1}^{M} \alpha_m G_m(x)\right]$.

Source: Hastie etal, ESL 2ed

Algorithm 10.3 *Gradient Tree Boosting Algorithm.*

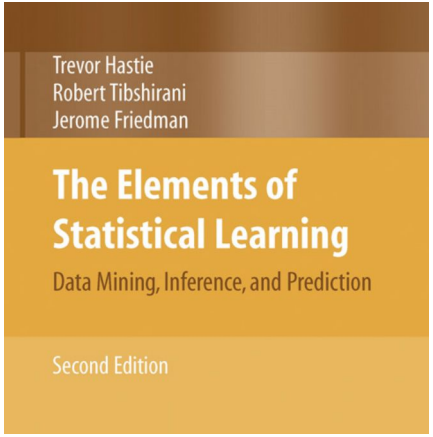
1. Initialize $f_0(x) = \arg\min_\gamma \sum_{i=1}^{N} L(y_i, \gamma)$.
2. For $m = 1$ to M:
   (a) For $i = 1, 2, \ldots, N$ compute

$$r_{im} = -\left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]_{f=f_{m-1}}.$$

   (b) Fit a regression tree to the targets r_{im} giving terminal regions R_{jm}, $j = 1, 2, \ldots, J_m$.
   (c) For $j = 1, 2, \ldots, J_m$ compute

$$\gamma_{jm} = \arg\min_\gamma \sum_{x_i \in R_{jm}} L\left(y_i, f_{m-1}(x_i) + \gamma\right).$$

   (d) Update $f_m(x) = f_{m-1}(x) + \sum_{j=1}^{J_m} \gamma_{jm} I(x \in R_{jm})$.
3. Output $\hat{f}(x) = f_M(x)$.



Source: Hastie etal, ESL 2ed

- R packages
- Python scikit-learn
- Vowpal Wabbit
- H2O
- xgboost
- Spark MLlib
- a few others

open source

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Meetup

open source

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Meetup

stackoverflow

open source

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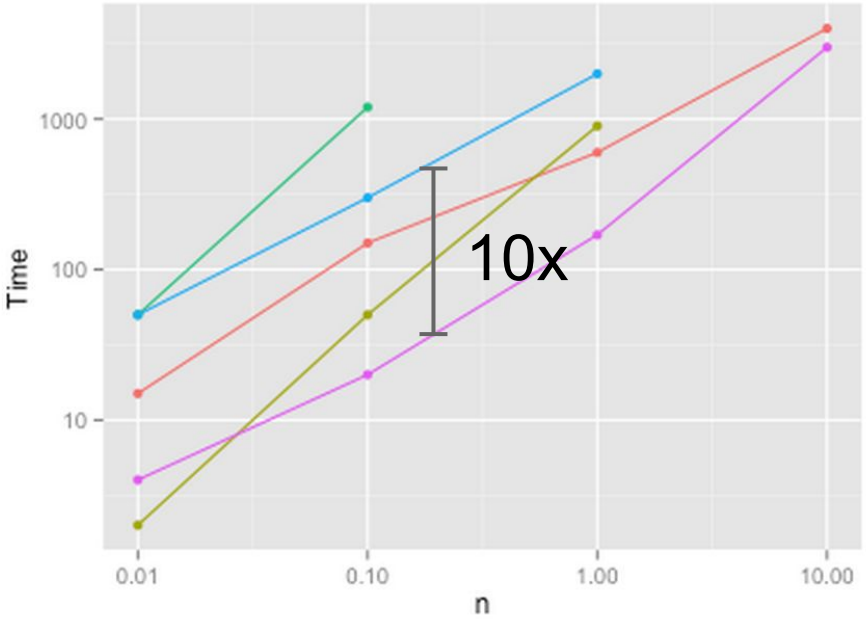
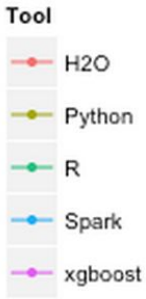
- a few others

szilard / benchm-ml

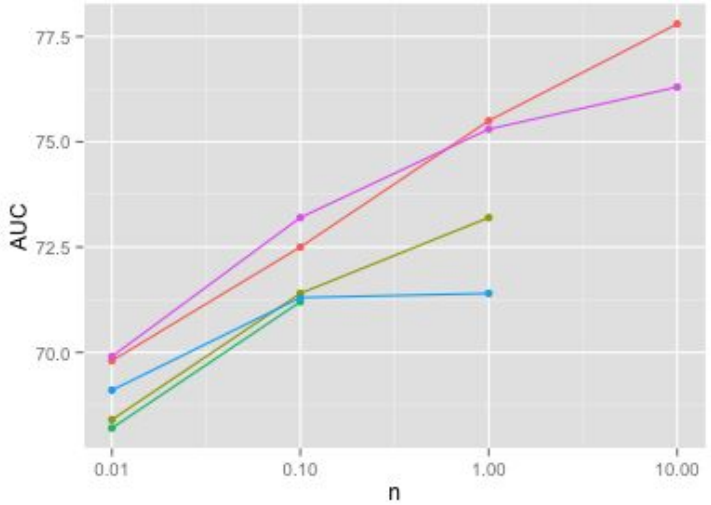
★ Star 1,203

Simple/limited/incomplete benchmark





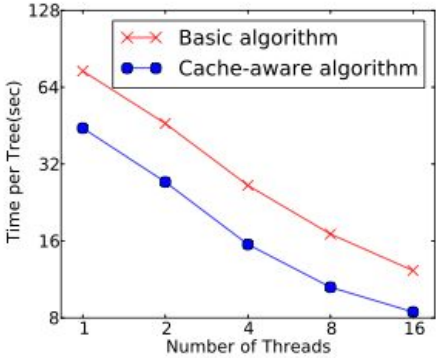
szilard / **benchm-ml**



arXiv.org > cs > arXiv:1603.02754

Computer Science > Learning

XGBoost: A Scalable Tree Boosting System

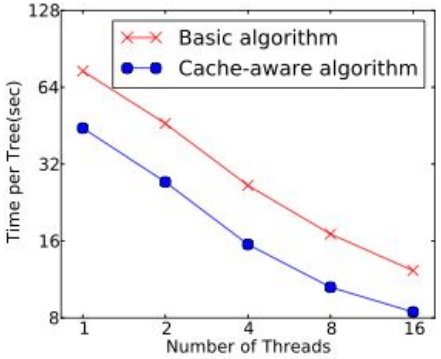


H2O.ai

arXiv.org > cs > arXiv:1603.02754

Computer Science > Learning

XGBoost: A Scalable Tree Boosting System



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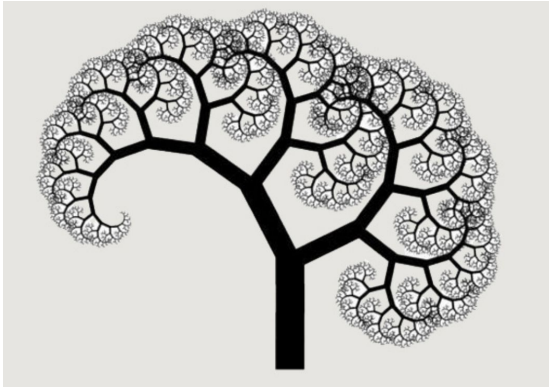

Microsoft / LightGBM

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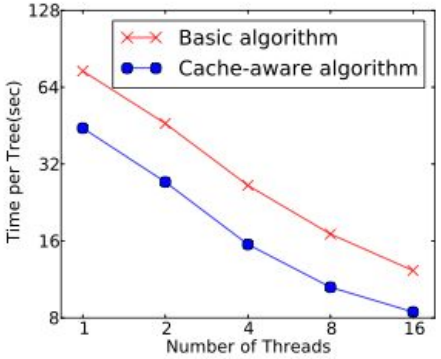
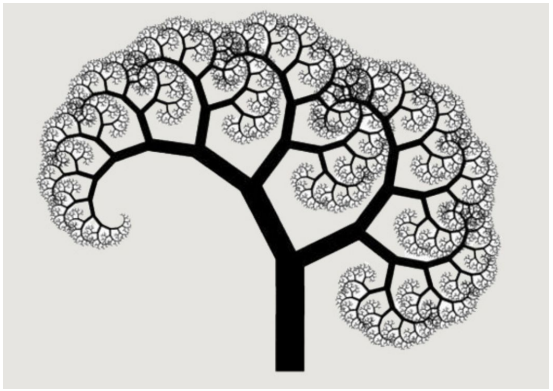
XGBoost: A Scalable Tree Boosting System



H2O.ai



Microsoft / LightGBM

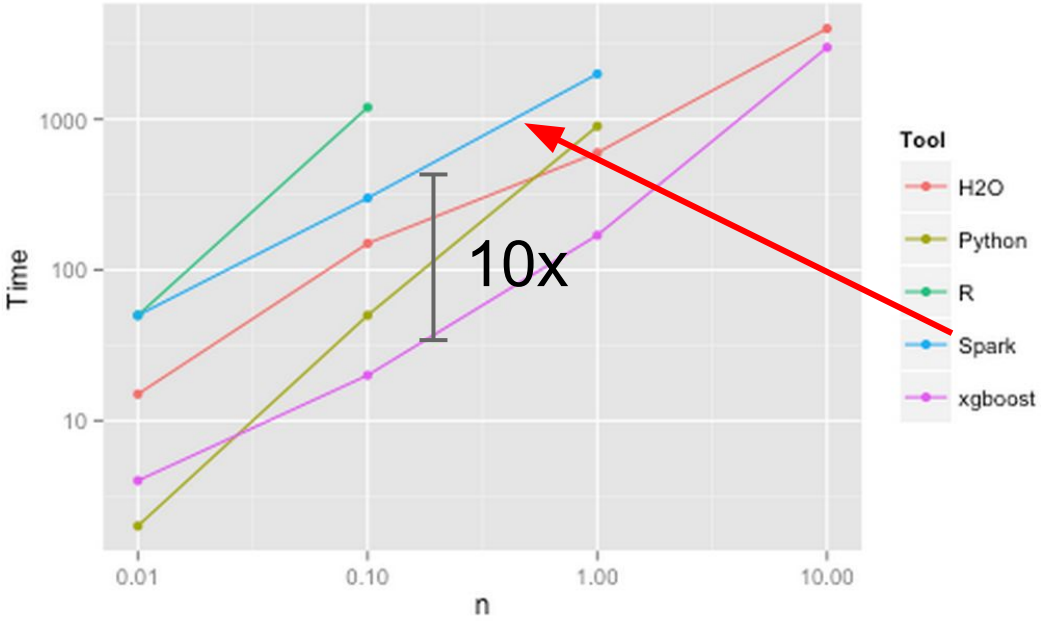
https://cran.r-project.org/web/pa

xgboost: Extreme Gradient Boosting

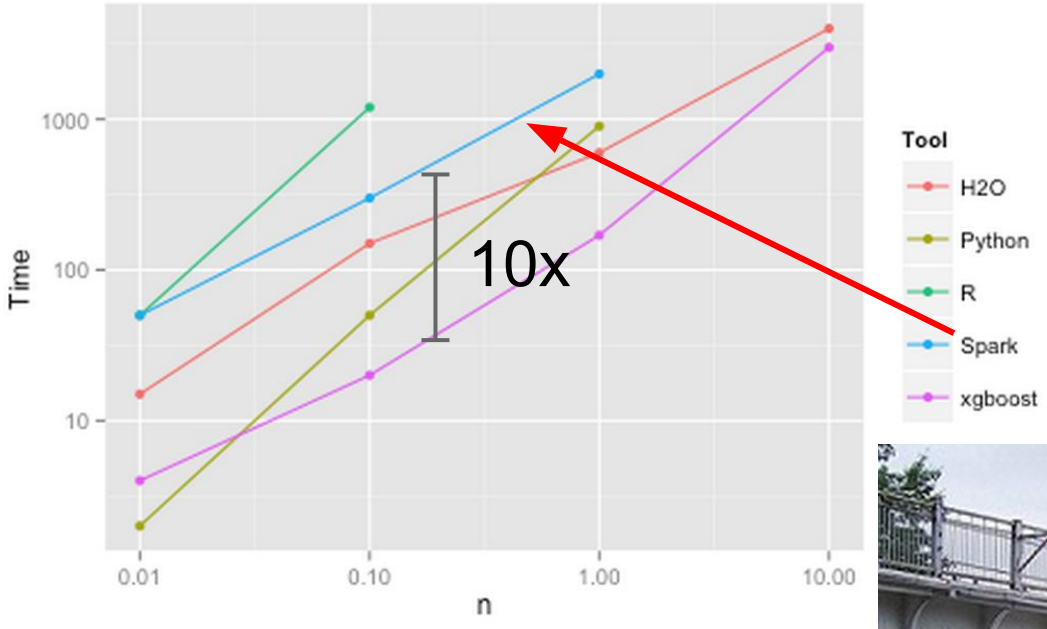
https://cran.r-project.org/

h2o: R Interface for H2O

PyData



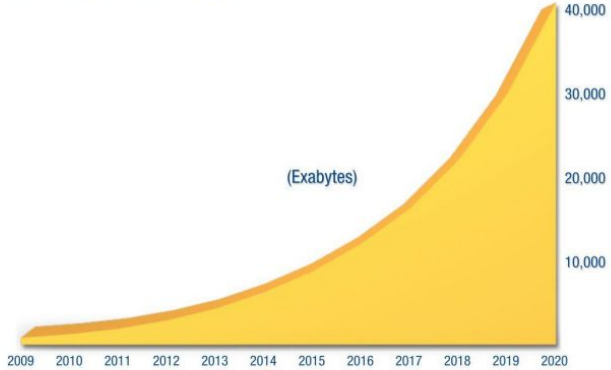
szilard / **benchm-ml**



szilard / **benchm-ml**

Figure 1

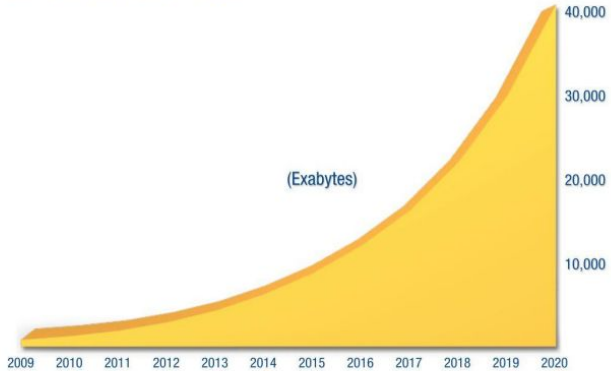
The Digital Universe: 50-fold Growth from the Beginning of 2010 to the End of 2020



Source: IDC's Digital Universe Study, sponsored by EMC, December 2012

Figure 1

The Digital Universe: 50-fold Growth from the Beginning of 2010 to the End of 2020



Source: IDC's Digital Universe Study, sponsored by EMC, December 2012

Hadley Wickham
@hadleywickham

Following

"It takes a big man to admit his data is small" — @jcheng

Figure 1

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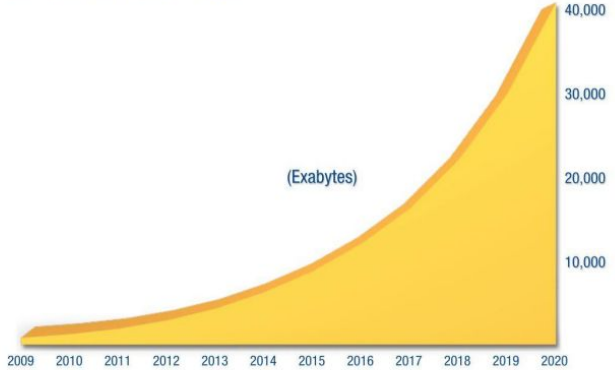

Source: IDC's Digital Universe Study, sponsored by EMC, December 2012

Hadley Wickham
@hadleywickham

Following

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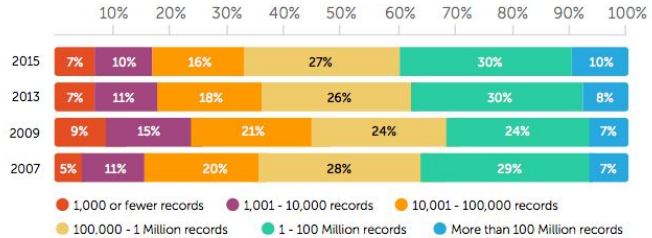
TYPICAL SIZE OF DATASETS



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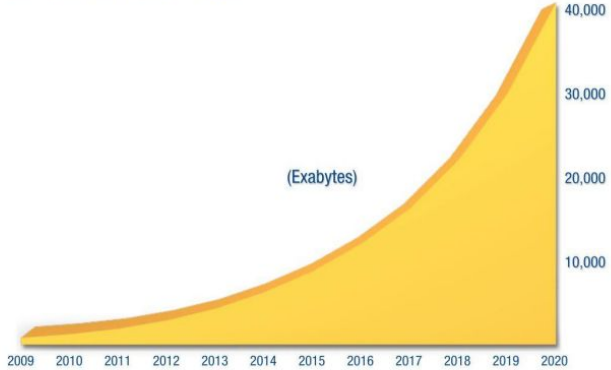

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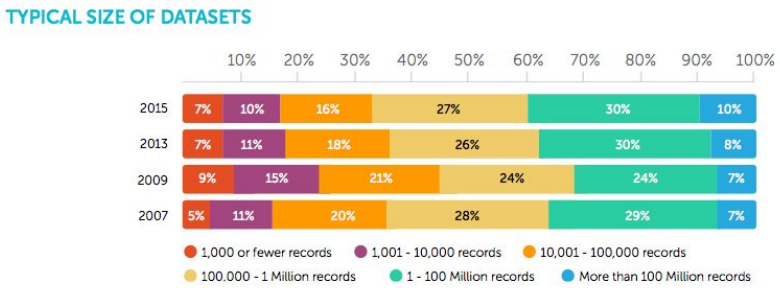

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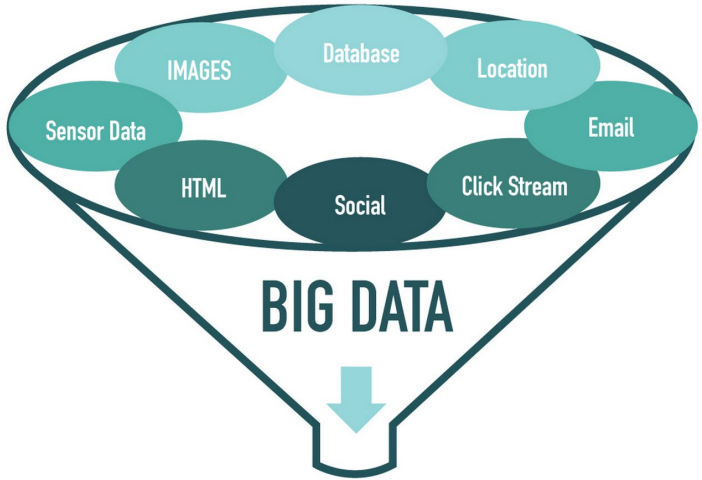
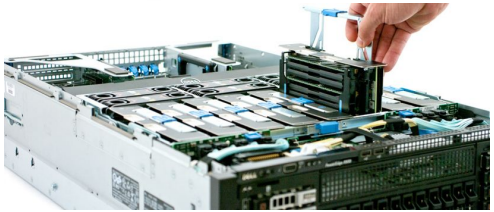




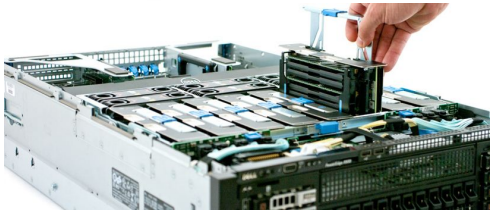
Kingston Technology Value RAM 128GB Kit (4x32GB) 2133MHz DDR4 ECC Reg CL15 (KVR21R15D4K4/128)

by Kingston Technology

Be the first to review this item

Was: ~~$743.99~~

Price: $743.96 & **FREE Shipping**. Details



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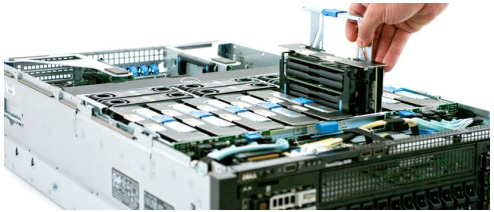
amazon web services

Model	vCPU	Mem (GiB)
r3.8xlarge	32	244
x1e.32xlarge	128	3,904
u-12tb1.metal	448	12 (TiB)



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Szilard @DataScienceLA · 18 Nov 2015

Big RAM is eating #bigdata: datasets for analytics grew 20% /yr (last decade @kdnuggets), RAM EC2 grew 50% /yr

Szilard @DataScienceLA · Aug 3

I wish my #machinelearning worked... ("both" is not a choice 😀) #bigdata #datascience #rstats #pydata cc @h2o @databricks @cloudera @kaggle

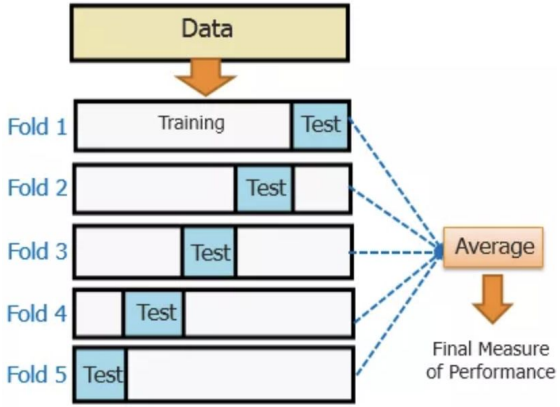
10% on 10x bigger data

70% 10x faster

20% I don't care about either

104 votes • Final results


16


Data
Fold 1
Training
Test
Fold 2
Test
Fold 3
Test
Fold 4
Test
Fold 5
Test
Average
Final Measure
of Performance


Hyperparameter
tuning

szilard / GBM-perf

```
git clone https://github.com/szi
cd GBM-perf/cpu
sudo docker build -t gbmperf_cpu
sudo docker run --rm gbmperf_cpu
```

r4.8xlarge (32 cores, but run on physical cores only/no hyperthreading) with software as of

Tool	Time[s] 100K	Time[s] 1M	Time[s] 10M	AUC 1M	AUC 10M
h2o	16	20	100	0.762	0.776
xgboost	3.8	12	78	0.749	0.755
lightgbm	**2.4**	**5.2**	42	0.764	0.774
catboost	5.4	50	490	0.740	0.744

szilard / GBM-perf

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lightgbm	**2.4**	**5.2**	42	0.764	0.774
catboost	5.4	50	490	0.740	0.744

p3.2xlarge (1 GPU, Tesla V100) with software as of 2019-04-29:

Tool	Time[s] 100K	Time[s] 1M	Time[s] 10M	AUC 1M	AUC 10M
h2o xgboost	9	14	60	0.749	0.756
xgboost	**2.4**	**4.8**	**13**	0.750	0.756
lightgbm	10	16	67	0.766	0.774
catboost	3.9	10	135	0.742	0.750

100M records and RAM usage

CPU (m5.12xlarge):

Tool	time [s]	AUC	RAM train [GB]
h2o	520	0.775	8
xgboost	510	0.751	15
lightgbm	**310**	0.774	**5**
catboost	3360	0.723 ?!	140

100M records and RAM usage

CPU (m5.12xlarge):

Tool	time [s]	AUC	RAM train [GB]
h2o	520	0.775	8
xgboost	510	0.751	15
lightgbm	**310**	0.774	**5**
catboost	3360	0.723 ?!	140

GPU (Tesla V100):

Tool	time [s]	AUC	GPU mem [GB]	extra RAM [GB]
h2o xgboost	270	0.755	4	30
xgboost	**80**	0.756	6	**0**
lightgbm	400	0.774	3	6
catboost	crash (OOM)		>16	14

```
## exporting model for scoring

h2o.download_mojo(md_rf, path = "./h2o")
```

GitHub Gist Search...

szilard / h2o_scoring.R

```
## building prediction service

# (need jetty-runner.jar ROOT.war from Steam)
java -jar jetty-runner.jar ROOT.war

curl -X POST --form mojo=@h2o_RF.zip --form jar=@h2o-genmodel.jar \
             localhost:8080/makewar > h2o_RF_MOJO.war
```

H2O.ai

```
## exporting model for scoring

h2o.download_mojo(md_rf, path = "./h2o")
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GitHub Gist Search...

szilard / h2o_scoring.R

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## building prediction service

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curl -X POST --form mojo=@h2o_RF.zip --form jar=@h2o-genmodel.jar \
             localhost:8080/makewar > h2o_RF_MOJO.war
```
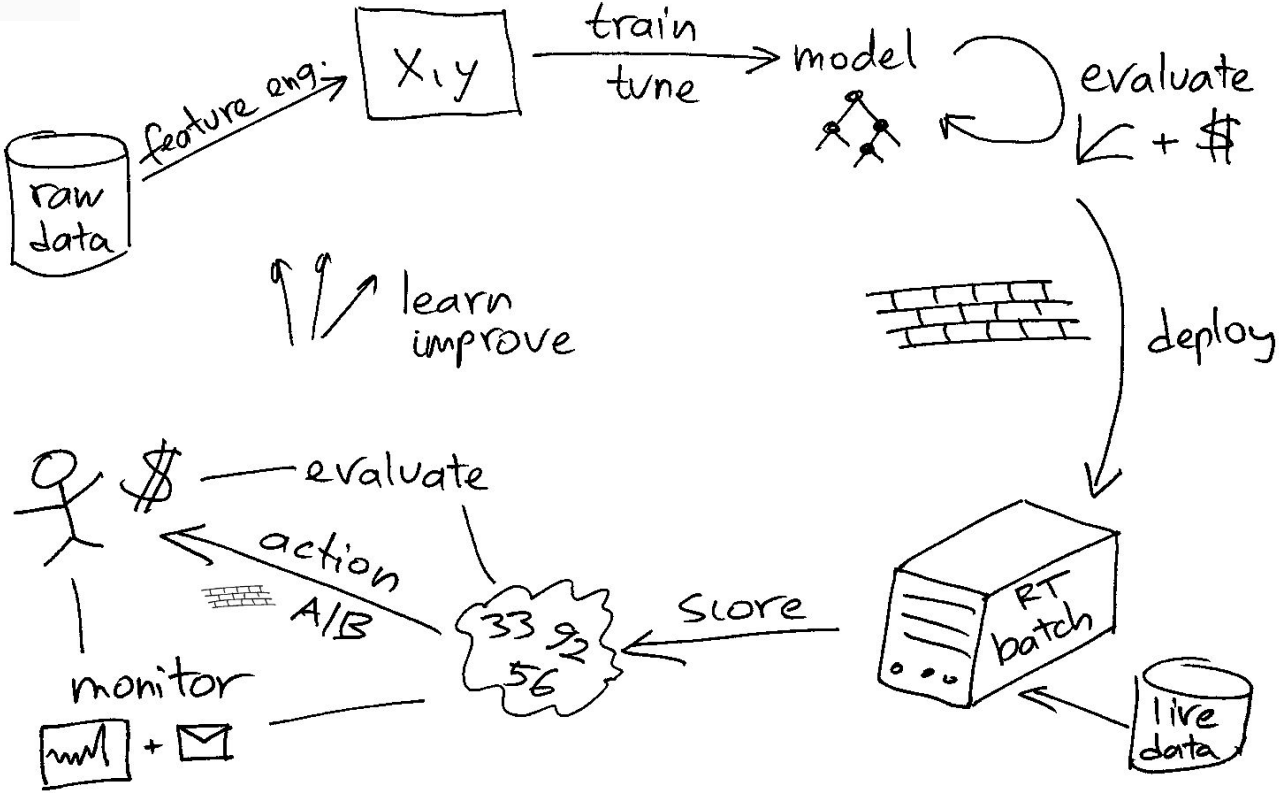

```
## run prediction service

java -jar jetty-runner.jar --port 20000 h2o_RF_MOJO.war
```

H2O.ai

```
## score via REST API

time curl "http://localhost:20000/predict?Month=c-8&DayofMonth=c-21&Day
# (fast scoring needs JVM to warm up with a few requests)
```

szilard / **ml-prod**



Spark 2.4.2 as of 2019-05-05

size	time lgbm [s]	time spark [s]	ratio
100K	2.4	1020	425
1M	5.2	1380	265
10M	42	8390	200

Spark 2.4.2 as of 2019-05-05

size	time lgbm [s]	time spark [s]	ratio
100K	2.4	1020	425
1M	5.2	1380	265
10M	42	8390	200

		100M			10M		
trees	depth	time [s]	AUC	RAM [GB]	time [s]	AUC	RAM [GB]
1	1	1150	0.634	620	70	0.635	110
1	10	1350	0.712	620	90	0.712	112
10	10	7850	0.731	780	830	0.731	125
100	10	crash OOM		>960 (OOM)	8390	0.755	230

Spark 2.4.2 as of 2019-05-05

size	time lgbm [s]	time spark [s]	ratio
100K	2.4	1020	425
1M	5.2	1380	265
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		100M			10M		
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lightgbm 5GB RAM usage

Spark 2.4.2 as of 2019-05-05

size	time lgbm [s]	time spark [s]	ratio
100K	2.4	1020	425
1M			
10M			

		100M		
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1	1	1150	0.634	620
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10	10	7850	0.731	780
100	10	crash OOM		>960 (OOM)

lightgbm 5GB RAM usage

Spark 10 trees, depth 10:

size	system	nodes	cores	partitions	time [s]	AUC	RAM [GB]	total RAM [GB]
10M	local	r4.8xl	32	32	830	0.731	125	240
10M	Cluster_1	r4.8xl	32	64	1180	0.731	73	240
10M	Cluster_10	r4.8xl	320	320 (m)	330	0.73		2400
100M	local	x1e.8xl	32		7850	0.731	780	960
100M	Cluster_10	r4.8xl	320	585	1825	0.731	10*72	2400

Spark 10 trees, depth 10:

size	system	nodes	cores	partitions	time [s]	AUC	RAM [GB]	total RAM [GB]
10M	local	r4.8xl	32	32	830	0.731	125	240
10M	Cluster_1	r4.8xl	32	64	1180	0.731	73	240
10M	Cluster_10	r4.8xl	320	320 (m)	330	0.73		2400
100M	local	x1e.8xl	32		7850	0.731	780	960
100M	Cluster_10	r4.8xl	320	585	1825	0.731	10*72	2400

Spark 10 trees, depth 10:

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10M	Cluster_10	r4.8xl	320	320 (m)	330	0.73		2400
100M	local	x1e.8xl	32		7850	0.731	780	960
100M	Cluster_10	r4.8xl	320	585	1825	0.731	10*72	2400

Spark 10 trees, depth 10:

size	system	nodes	cores	partitions	time [s]	AUC	RAM [GB]	total RAM [GB]
10M	local	r4.8xl	32	32	830	0.731	125	240
10M	Cluster_1	r4.8xl	32	64	1180	0.731	73	240
10M	Cluster_10	r4.8xl	320	320 (m)	330	0.73		2400
100M	local	x1e.8xl	32		7850	0.731	780	960
100M	Cluster_10	r4.8xl	320	585	1825	0.731	10*72	2400

lib	size	hw	cores	time [s]	AUC	RAM [GB]	total RAM [GB]
lightgbm	10M	c5.2xl	1 (m)	29	0.743		16
xgboost	10M	c5.2xl	1 (m)	38	0.726		16
xgboost	10M	i5-5200U	1 (m)	71	0.726	6	8
lightgbm	10M	r4.8xl	16 (m)	7	0.743	4	240
lightgbm	100M	r4.8xl	16 (m)	60	0.743	13(d)+5	240

xgboost/lightgbm: 100 trees runtime is <10x 10 trees, RAM = 10 trees
Spark: 100 trees runtime = 10x 10 trees, RAM > 10 trees

Spark 10 trees, depth 10:

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10M	Cluster_1	r4.8xl	32	64	1180	0.731	73	240
10M	Cluster_10	r4.8xl	320	320 (m)	330	0.73		2400
100M	local	x1e.8xl	32		7850	0.731	780	960
100M	Cluster_10	r4.8xl	320	585	1825	0.731	10*72	2400

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xgboost	10M	i5-5200U	1 (m)	71	0.726	6	8
lightgbm	10M	r4.8xl	16 (m)	7	0.743	4	240
lightgbm	100M	r4.8xl	16 (m)	60	0.743	13(d)+5	240

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10M	Cluster_1	r4.8xl	32	64	1180	0.731	73	240
10M	Cluster_10	r4.8xl	320	320 (m)	330	0.73		2400
100M	local	x1e.8xl	32		7850			
100M	Cluster_10	r4.8xl	320	585	1825			

dmlc XGBoost

lib	size	hw	cores	time [s]	AUC
lightgbm	10M	c5.2xl	1 (m)	29	0.743
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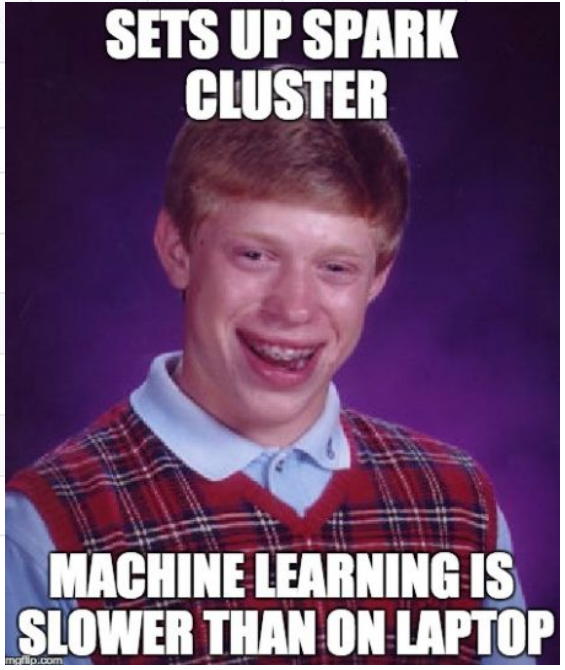
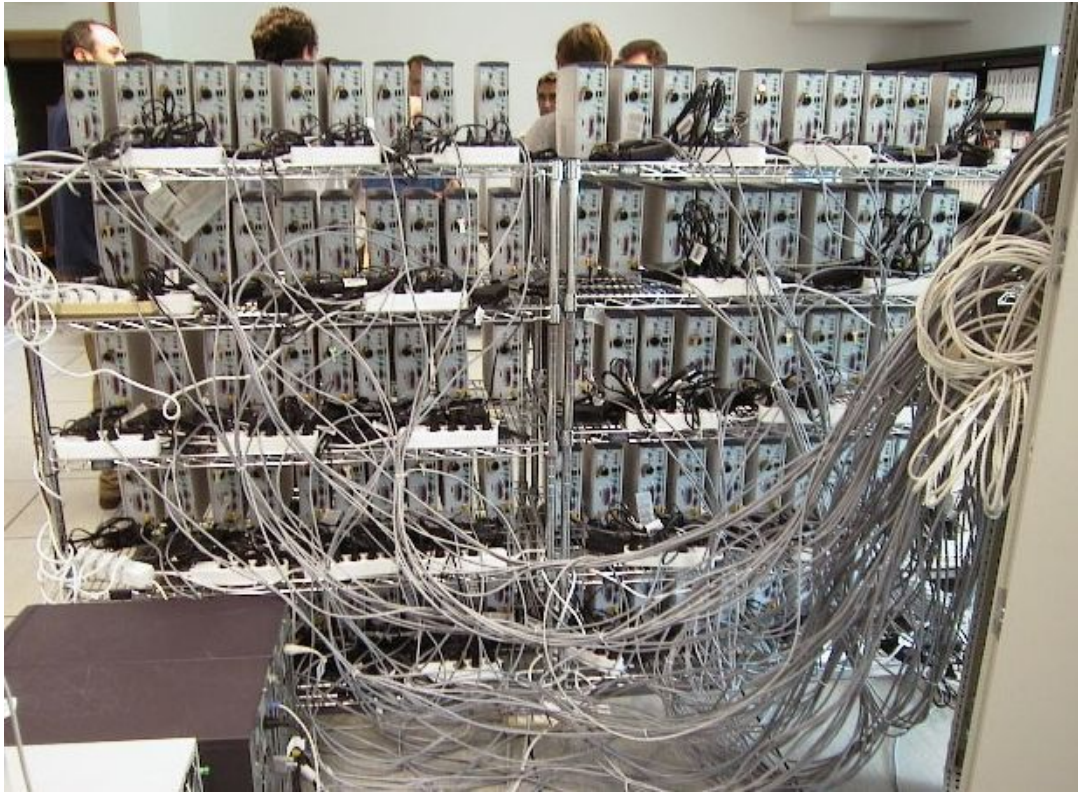
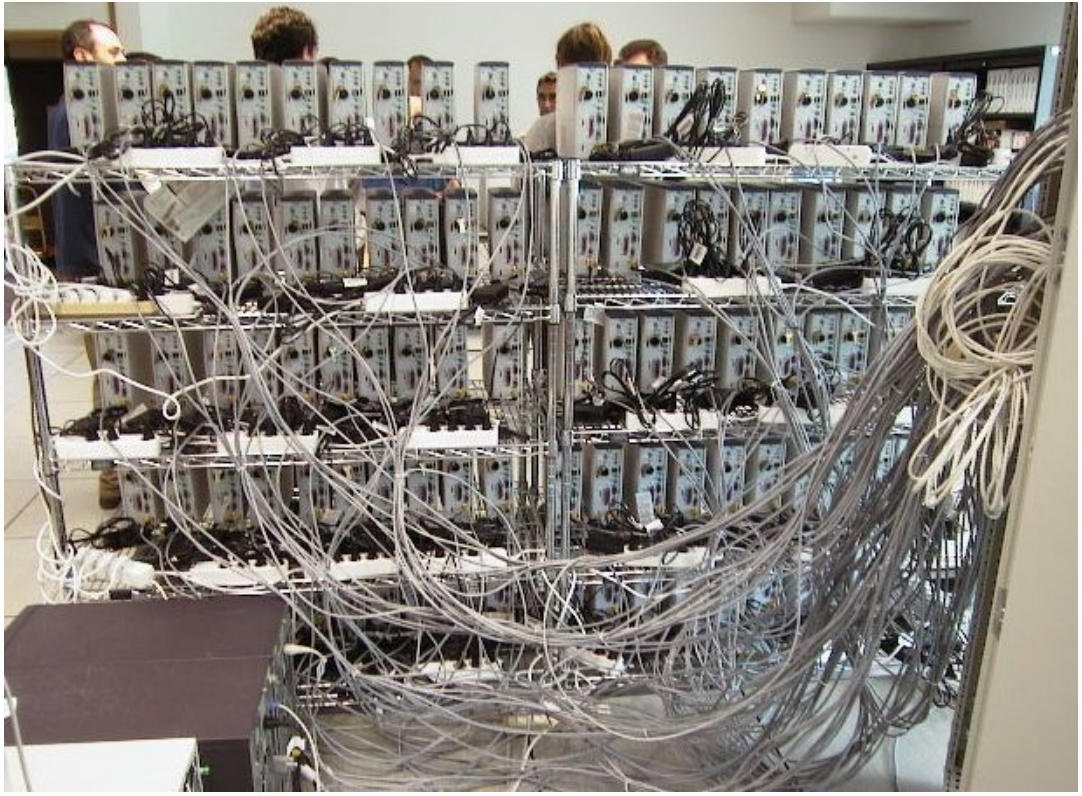
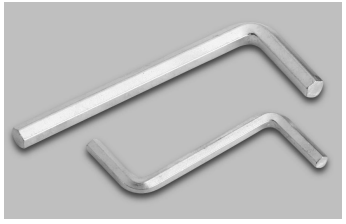
lightgbm	100M	r4.8xl	16 (m)	60	0.743

xgboost/lightgbm: 100 trees runtime is <10x 10 trees, RAM = 10 trees
Spark: 100 trees runtime = 10x 10 trees, RAM > 10 trees







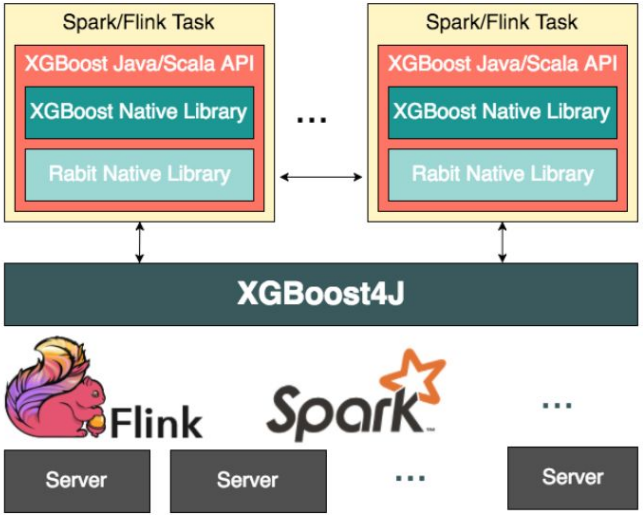


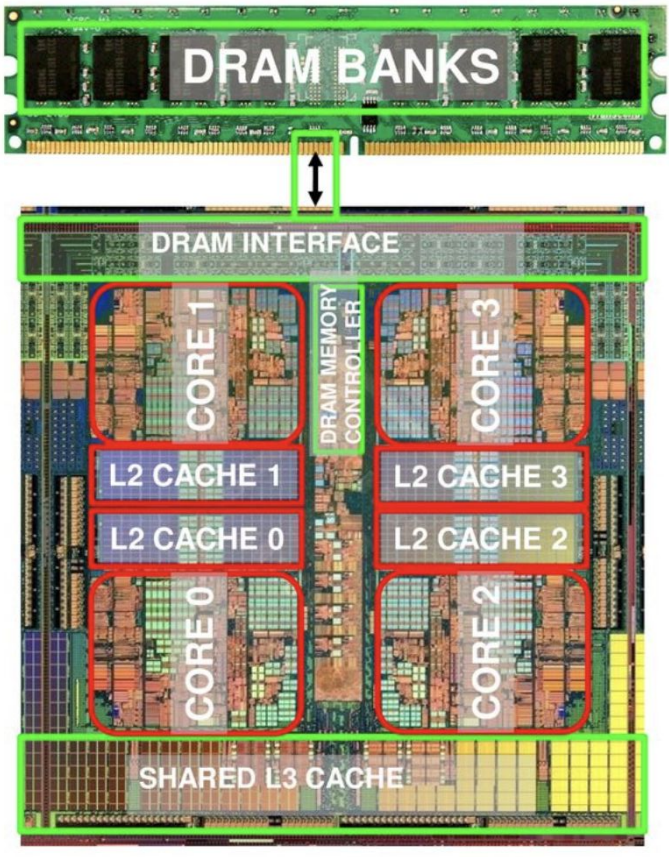

SYSTEM FAILURE


Spark

Spark + H_2O

SPARKLING WATER




DRAM BANKS
DRAM INTERFACE
CORE 1
DRAM MEMORY CONTROLLER
CORE 3
L2 CACHE 1
L2 CACHE 3
L2 CACHE 0
L2 CACHE 2
CORE 0
CORE 2
SHARED L3 CACHE

CORE 0
L2 CACHE 0
L2 CACHE 1
CORE 1
SHARED L3 CACHE
DRAM INTERFACE
DRAM MEMORY CONTROLLER
DRAM BANKS
CORE 2
L2 CACHE 2
L2 CACHE 3
CORE 3

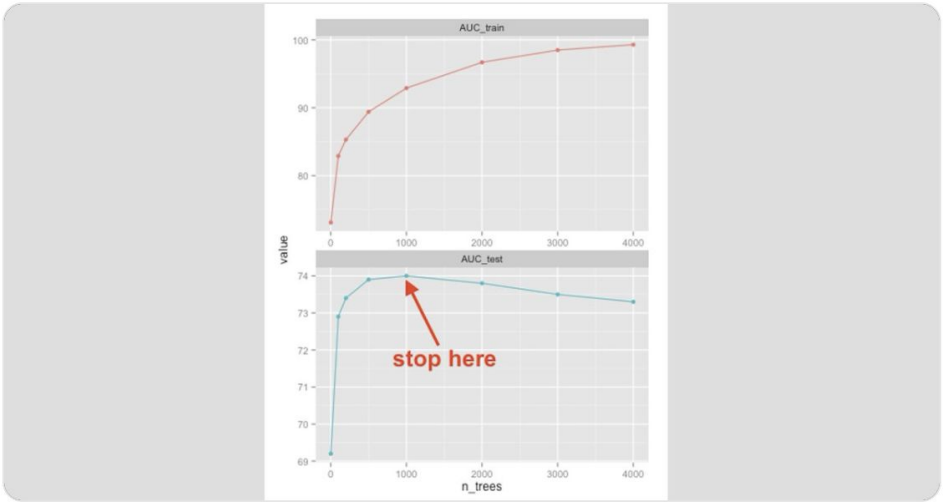
PCI Express 3.0 Host Interface
GigaThread Engine
Memory Controller
GPC
Raster Engine
TPC
PolyMorph Engine
SM
RT CORE
L2 Cache
High-Speed Hub
NVLink – Two x8 Links

```r
## read CSV (e.g. data.table::fread) or get data from database (SQL connector)
## do one-hot-encoding of categorical variables (e.g. Matrix::sparse.model.matrix)

## special optimized data structure
dxgb_train <- xgb.DMatrix(data = X_train, label = y_train)

## TRAIN
md <- xgb.train(data = dxgb_train,
                objective = "binary:logistic",
                nround = 100, max_depth = 10, eta = 0.1,
                tree_method = "hist")

## SCORE
yhat <- predict(md, newdata = X_test)

## evaluation (score distribution, ROC curve, AUC etc.)
```

```
h2o.gbm(x, y, training_frame, model_id, checkpoint, ignore_const_cols = TRUE,
  distribution = c("AUTO", "gaussian", "bernoulli", "multinomial", "poisson",
  "gamma", "tweedie", "laplace", "quantile", "huber"), quantile_alpha = 0.5,
  tweedie_power = 1.5, huber_alpha = 0.9, ntrees = 50, max_depth = 5,
  min_rows = 10, learn_rate = 0.1, learn_rate_annealing = 1,
  sample_rate = 1, sample_rate_per_class, col_sample_rate = 1,
  col_sample_rate_change_per_level = 1, col_sample_rate_per_tree = 1,
  nbins = 20, nbins_top_level = 1024, nbins_cats = 1024,
  validation_frame = NULL, balance_classes = FALSE, class_sampling_factors,
  max_after_balance_size = 5, seed, build_tree_one_node = FALSE,
  nfolds = 0, fold_column = NULL, fold_assignment = c("AUTO", "Random",
  "Modulo", "Stratified"), keep_cross_validation_predictions = FALSE,
  keep_cross_validation_fold_assignment = FALSE,
  score_each_iteration = FALSE, score_tree_interval = 0,
  stopping_rounds = 0, stopping_metric = c("AUTO", "deviance", "logloss",
  "MSE", "AUC", "misclassification", "mean_per_class_error"),
  stopping_tolerance = 0.001, max_runtime_secs = 0, offset_column = NULL,
  weights_column = NULL, min_split_improvement = 1e-05,
  histogram_type = c("AUTO", "UniformAdaptive", "Random", "QuantilesGlobal",
  "RoundRobin"), max_abs_leafnode_pred, pred_noise_bandwidth = 0,
  categorical_encoding = c("AUTO", "Enum", "OneHotInternal", "OneHotExplicit",
  "Binary", "Eigen"))
```

Szilard [Deeper than Deep Learning]
@DataScienceLA

GBM/GBDT tip of the day: If it's not using early stopping, it's crap. 😬😬😬 (early stopping: checking accuracy metric on a validation set and stopping when it starts deteriorating by X) If not, you are either overfitting or wasting CPU/training time (or both). Don't do either!



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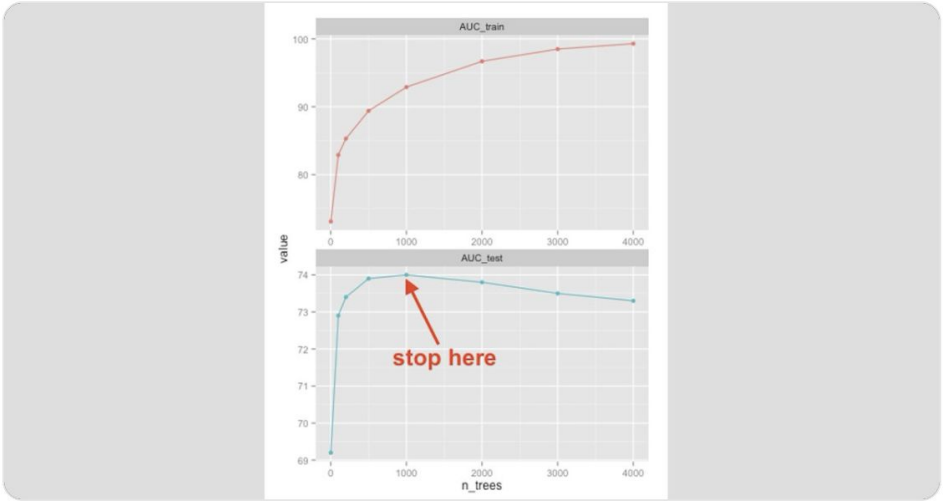


Szilard [Deeper than Deep Learning]
@DataScienceLA

in all 3 top GBM implementations (#xgboost, #lightgbm, #h2oai) all you have to do (for early stopping) is to set a few params in the training function

```
md <- xgb.train(data = dxgb_train,
+             objective = "binary:logistic",
+             max_depth = 10, eta = 0.1,
+             nround = 10000, early_stopping_rounds = 10, watchlist = list(valid=dxgb_valid),
+             tree_method = "hist")

[1]     valid-error:0.207010
Will train until valid_error hasn't improved in 10 rounds.

[2]     valid-error:0.203230
[3]     valid-error:0.202950
[4]     valid-error:0.202810
[5]     valid-error:0.202550
[6]     valid-error:0.202380
[7]     valid-error:0.202410
[8]     valid-error:0.202380
....
[113]   valid-error:0.197940
[114]   valid-error:0.197960
[115]   valid-error:0.197940
[116]   valid-error:0.197950
[117]   valid-error:0.197820
Stopping. Best iteration:
[107]   valid-error:0.197750
```

blog.h2o.ai/2016/06/h2o-gbm-tuning-tutorial-for-r/

Arno Candel in GBM, R, Technical, Tutorials | June 16, 2016

H2O GBM Tuning Tutorial for R

In this tutorial, we show how to build a well-tuned H2O GBM model for a supervised classification task. and use a small dataset to allow you to reproduce these results in a few minutes on a laptop. This script ca dreds of GBs large and H2O clusters with dozens of compute nodes.

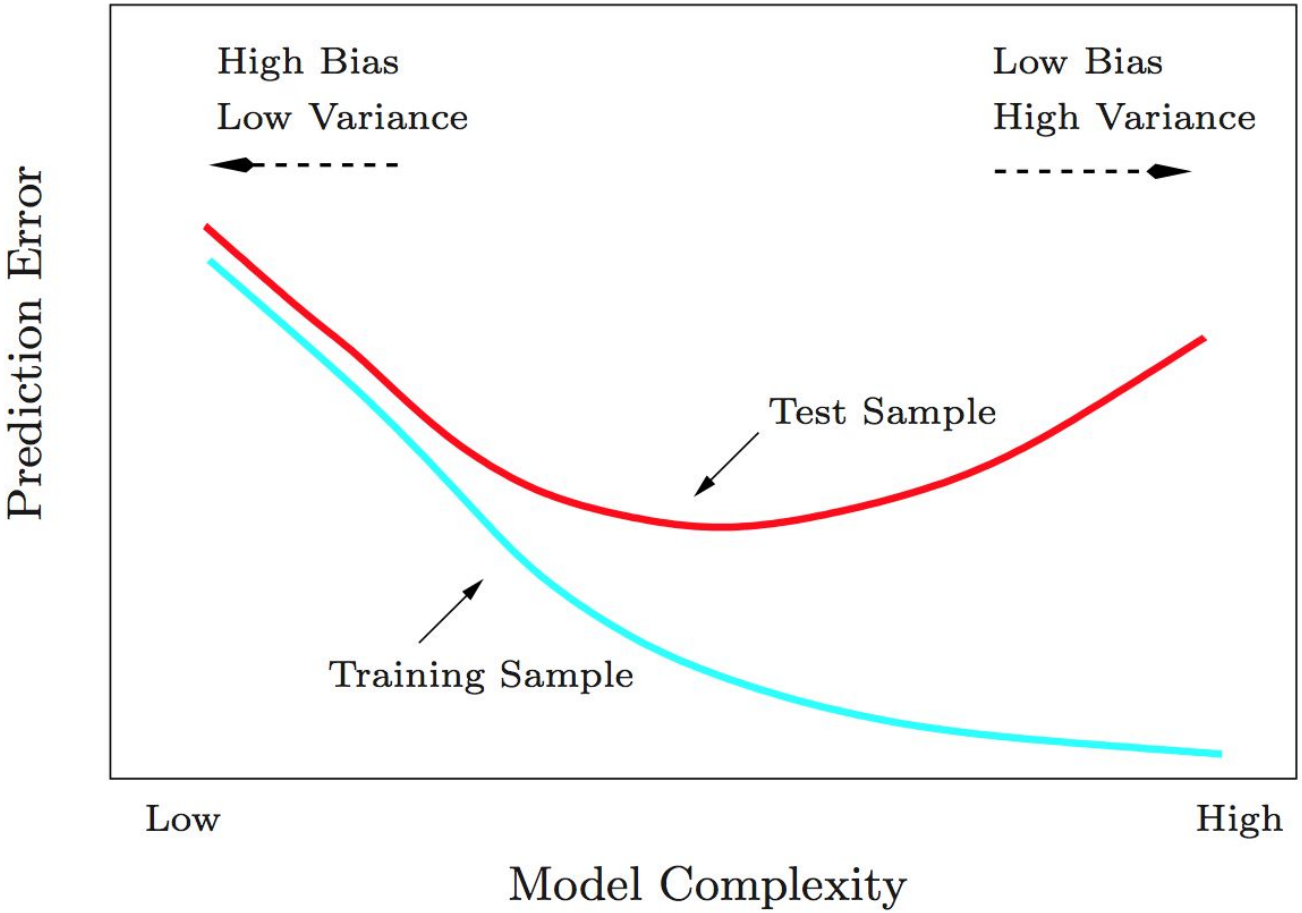
machinelearningmastery.com/configure-gradient-boosting-algorithm/

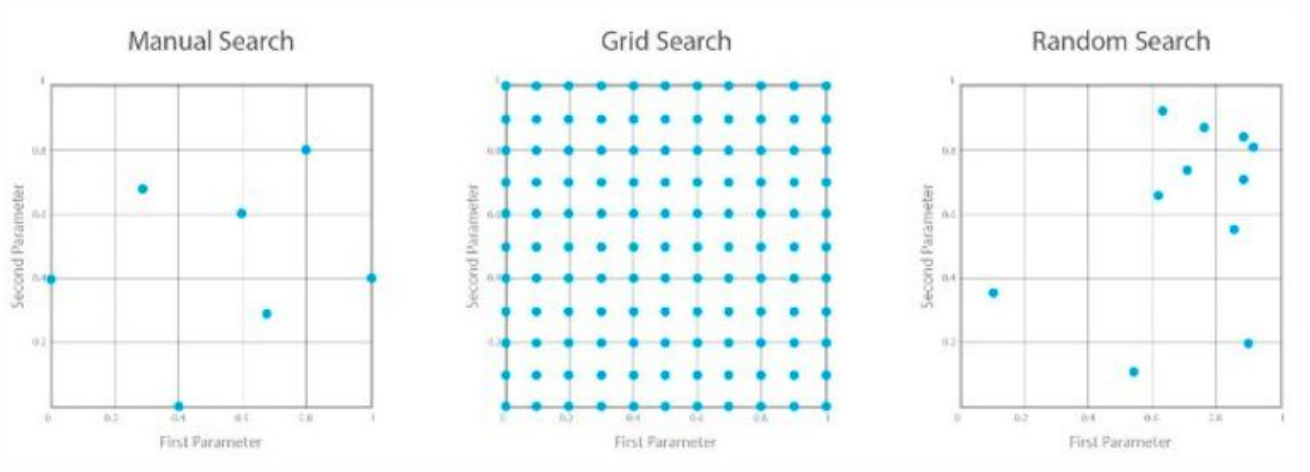
Start Here

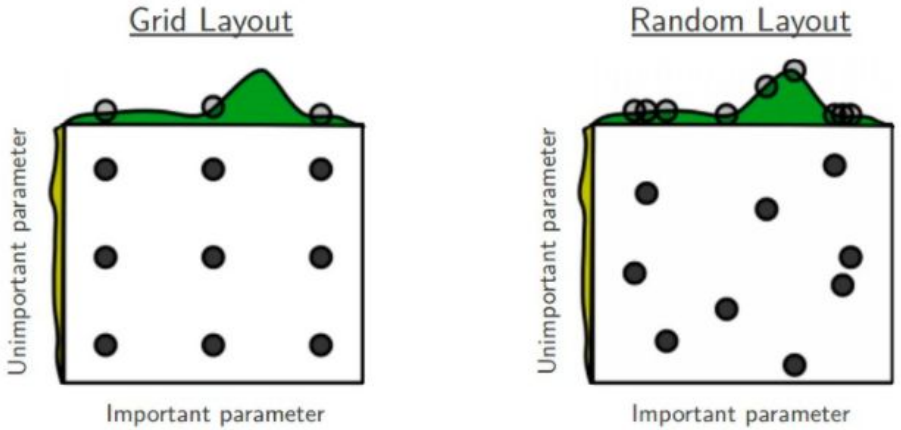
Search...

How to Configure the Gradient Boosting Algorithm

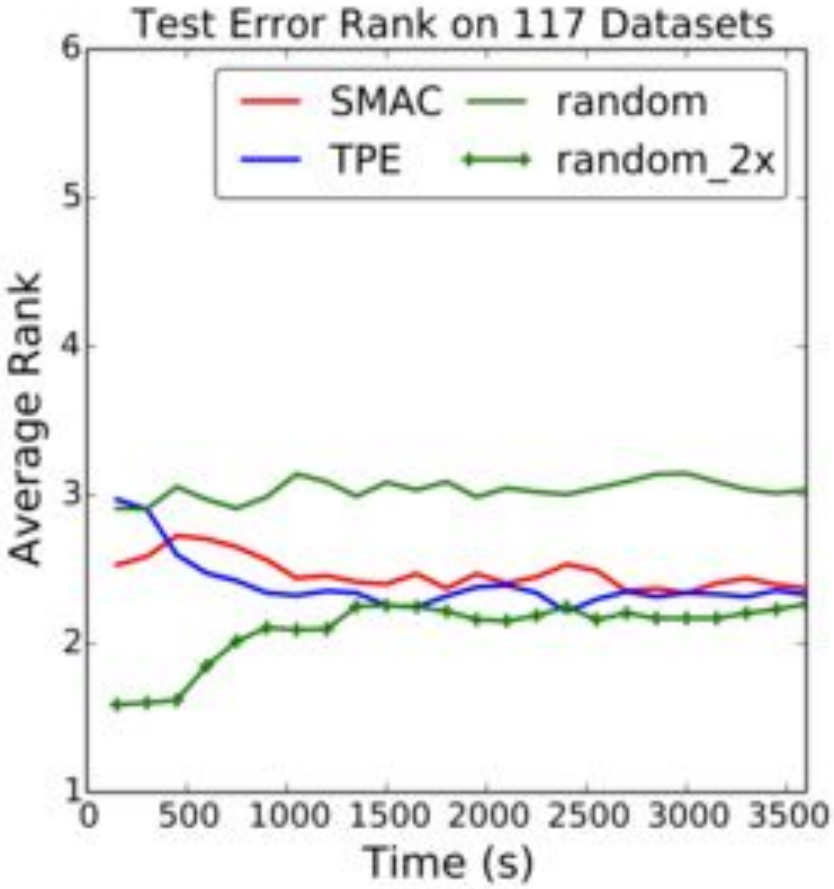
by **Jason Brownlee** on September 12, 2016 in **XGBoost**


High Bias
Low Variance
Low Bias
High Variance
Prediction Error
Test Sample
Training Sample
Low
High
Model Complexity





http://www.jmlr.org/papers/volume13/bergstra12a/bergstra12a.pdf

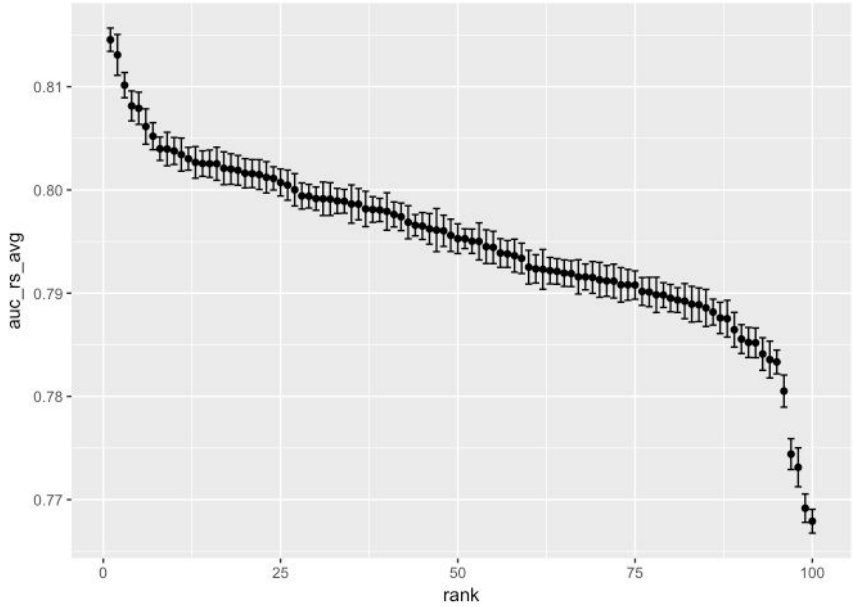


- Gaussian Processes (GP)
- Tree of Parzen Estimators (TPE)
- Sequential Model-based Algorithm Configuration (SMAC)

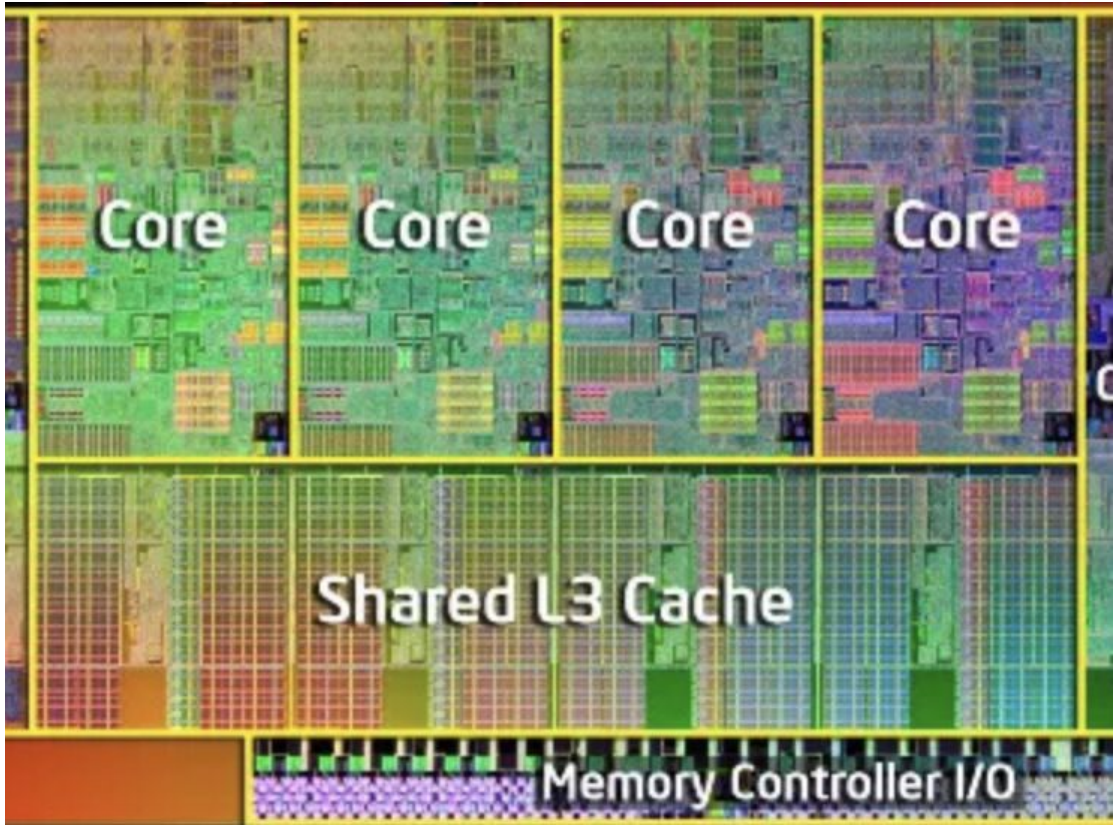
http://www.argmin.net/2016/06/20/hypertuning/

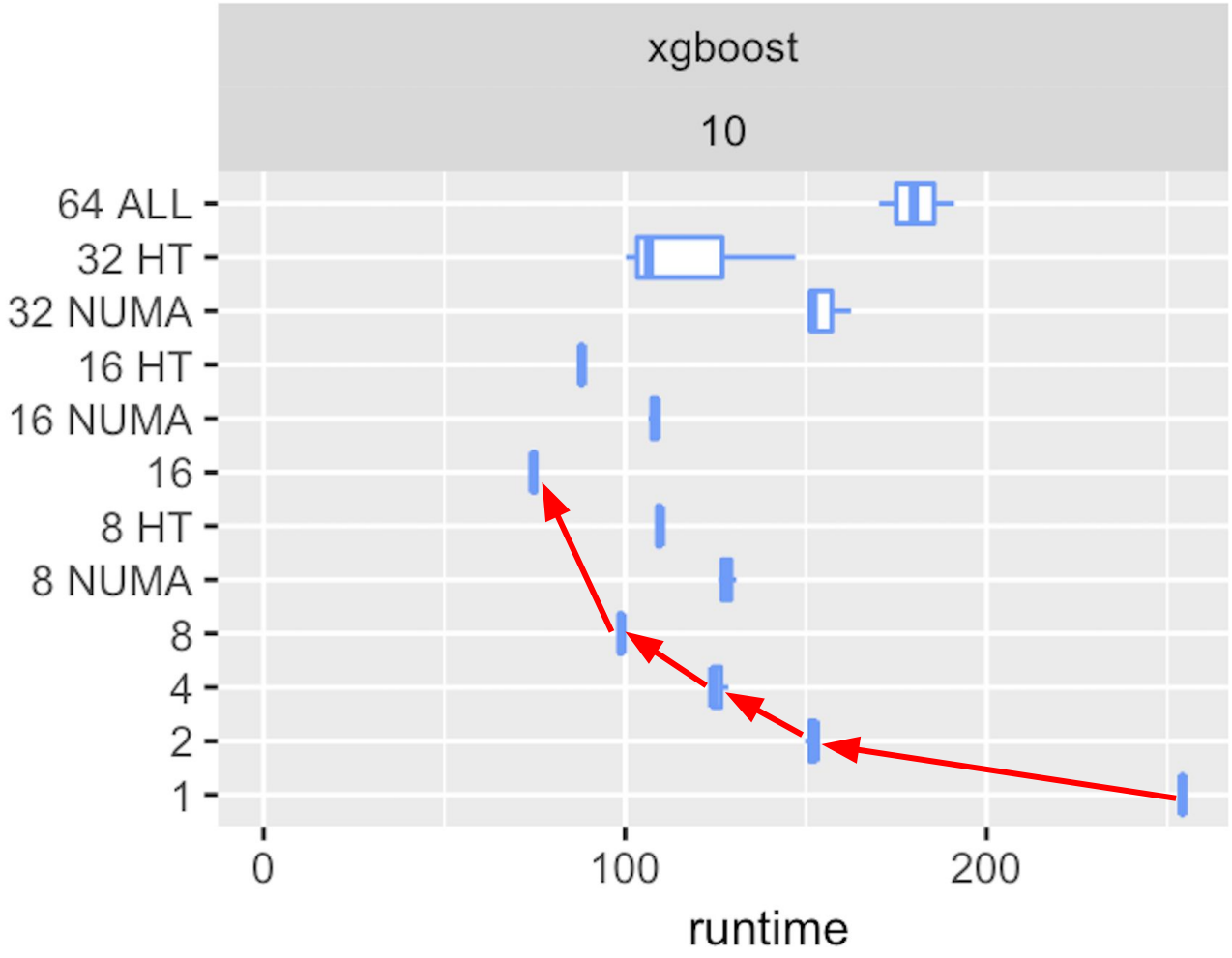
szilard / GBM-tune

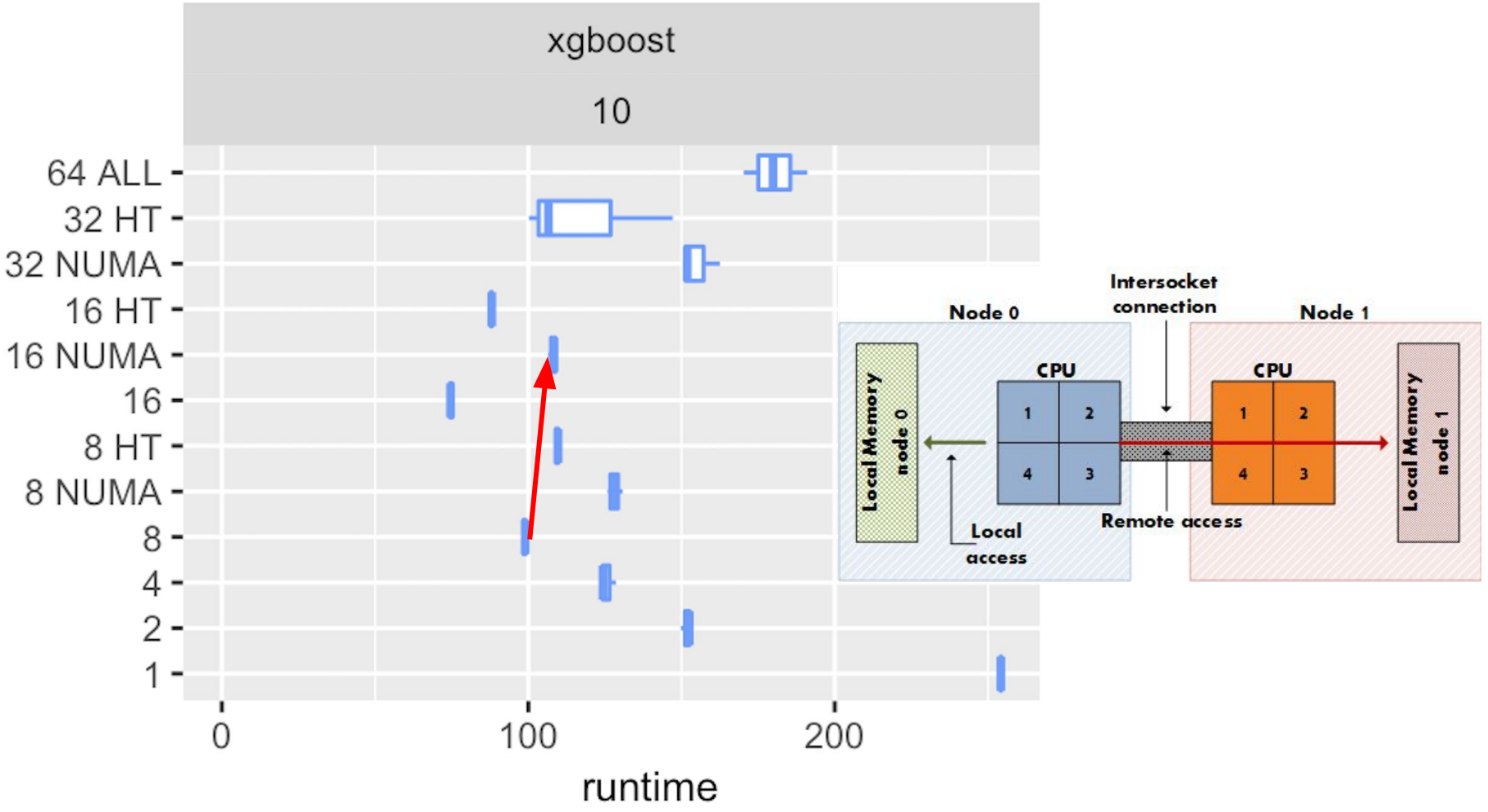
```
n_random <- 100      ## TODO: 1000?

params_grid <- expand.grid(                    # default
  num_leaves = c(100,200,500,1000,2000,5000),  # 31 (was 127)
  learning_rate = c(0.01,0.03,0.1),            # 0.1
  min_data_in_leaf = c(5,10,20,50),            # 20 (was 100)
  feature_fraction = c(0.6,0.8,1),             # 1
  bagging_fraction = c(0.4,0.6,0.8,1),         # 1
  lambda_l1 = c(0,0,0,0, 0.01, 0.1, 0.3),      # 0
  lambda_l2 = c(0,0,0,0, 0.01, 0.1, 0.3)       # 0
## TODO:
  ## min_sum_hessian_in_leaf
  ## min_gain_to_split
  ## max_bin
  ## min_data_in_bin
)
```

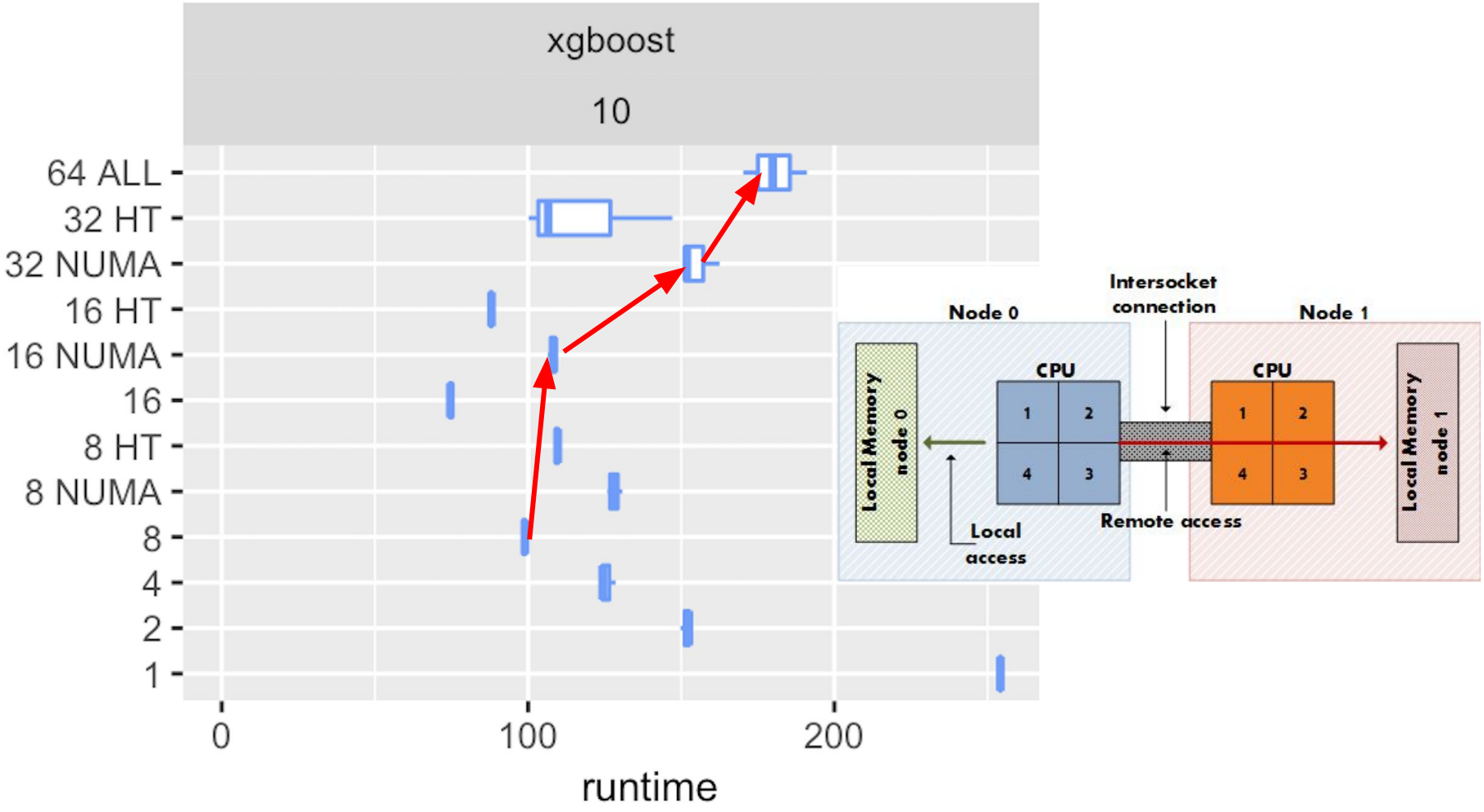


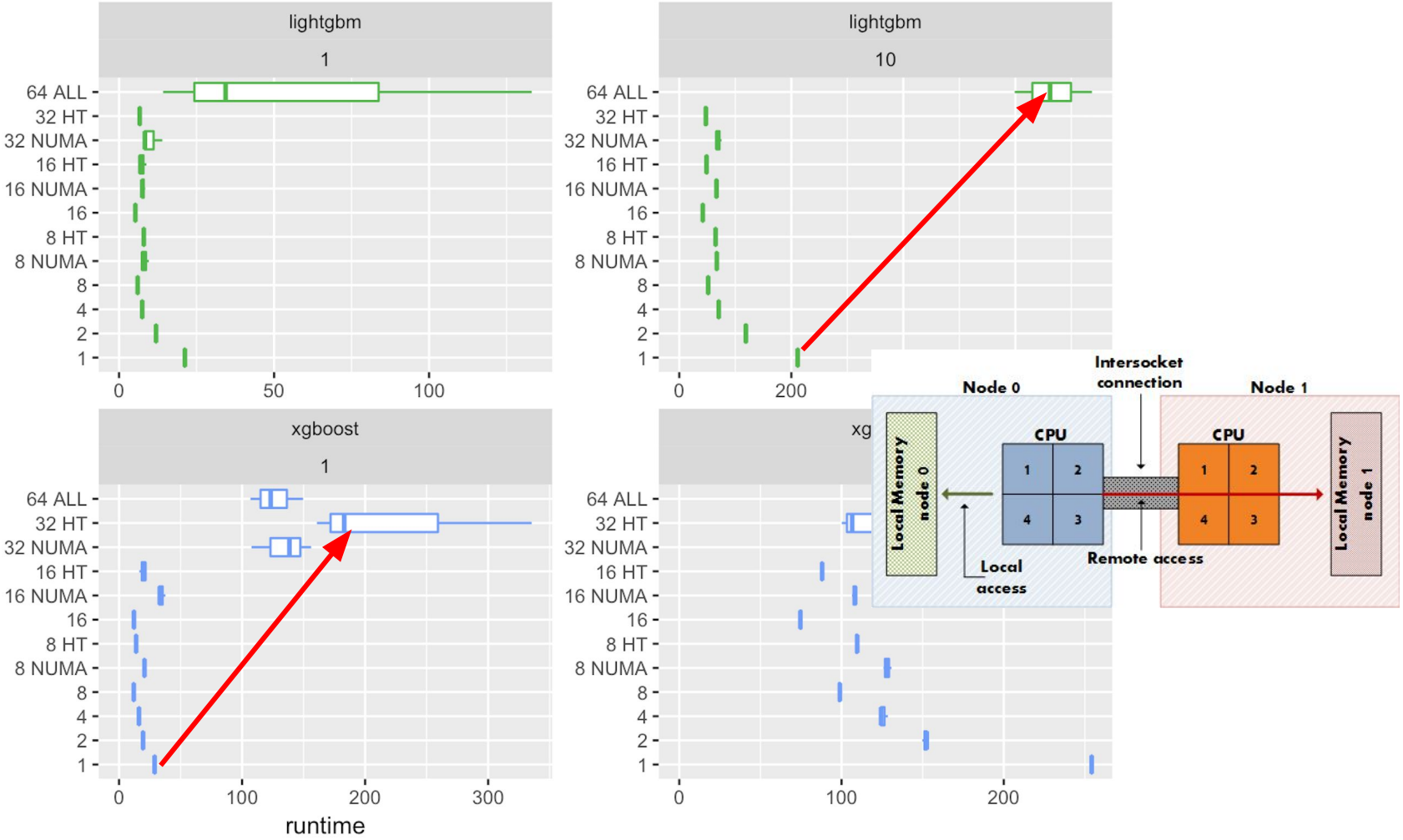
	num_leaves	learning_rate	min_data_in_leaf	feature_fraction
1	1000	0.03	5	0.8
2	1000	0.03	5	0.8
3	500	0.01	10	0.8
4	5000	0.01	5	0.8
5	500	0.01	10	0.8
6	5000	0.01	10	0.8
7	1000	0.10	20	0.8
8	5000	0.01	10	0.8
9	500	0.10	20	0.8
10	500	0.01	5	0.6

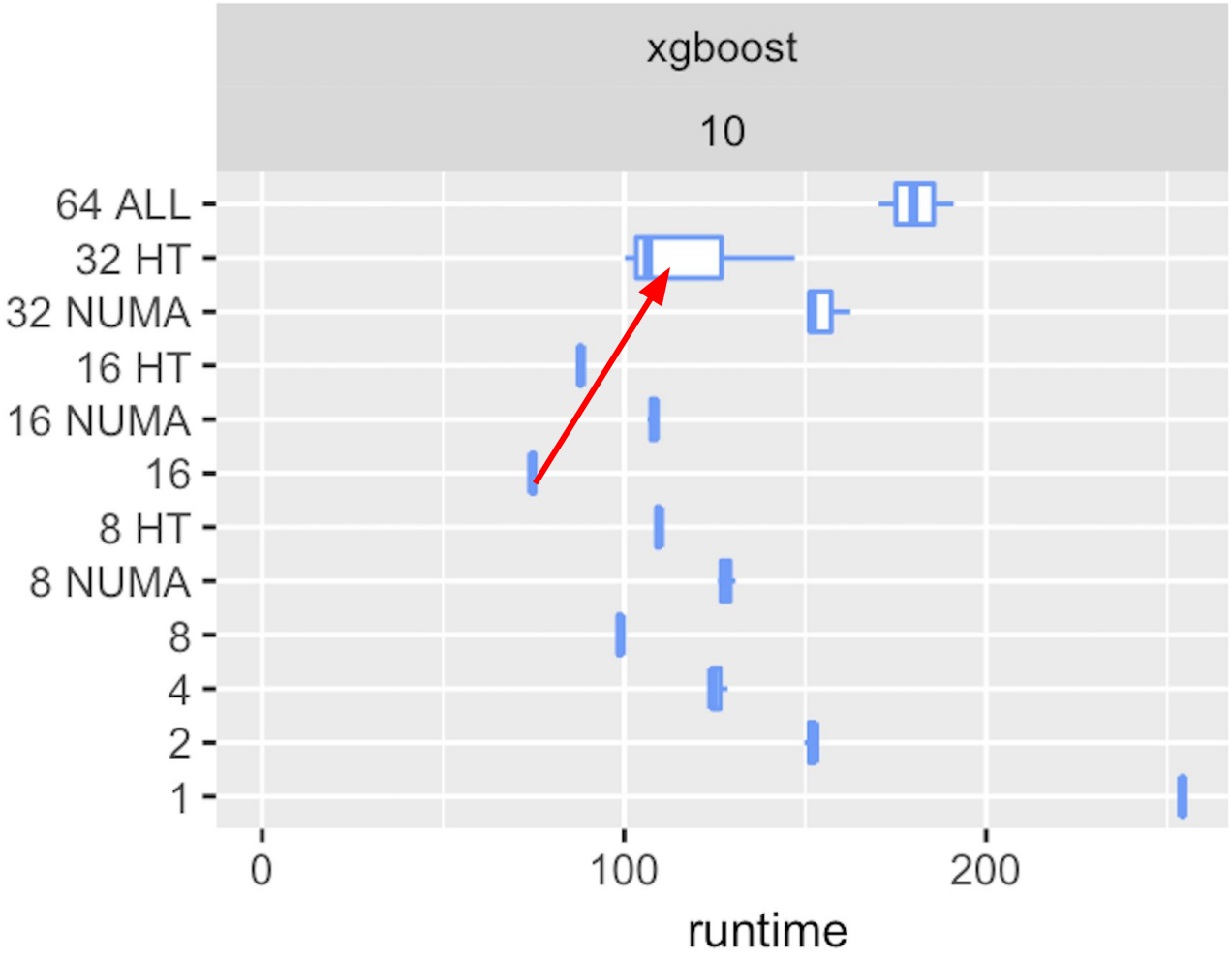

Core
Core
Core
Core
Shared L3 Cache
Memory Controller I/O

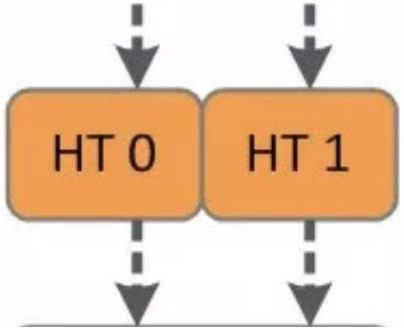

xgboost
10
64 ALL
32 HT
32 NUMA
16 HT
16 NUMA
16
8 HT
8 NUMA
8
4
2
1
0
100
200
runtime


xgboost
10
64 ALL
32 HT
32 NUMA
16 HT
16 NUMA
16
8 HT
8 NUMA
8
4
2
1
0
100
200
runtime
Node 0
Intersocket connection
Node 1
Local Memory node 0
CPU
1
2
4
3
CPU
1
2
4
3
Local Memory node 1
Local access
Remote access


xgboost
10
64 ALL
32 HT
32 NUMA
16 HT
16 NUMA
16
8 HT
8 NUMA
8
4
2
1
0
100
200
runtime
Node 0
Intersocket connection
Node 1
CPU
CPU
Local Memory node 0
Local Memory node 1
1
2
4
3
1
2
4
3
Local access
Remote access


lightgbm
1
lightgbm
10
xgboost
1
64 ALL
32 HT
32 NUMA
16 HT
16 NUMA
16
8 HT
8 NUMA
8
4
2
1
0
50
100
200
300
runtime
Intersocket connection
Node 0
Node 1
CPU
Local Memory node 0
Local Memory node 1
Local access
Remote access


xgboost
10
64 ALL
32 HT
32 NUMA
16 HT
16 NUMA
16
8 HT
8 NUMA
8
4
2
1
0
100
200
runtime


HT 0
HT 1

szilard / ml-x1

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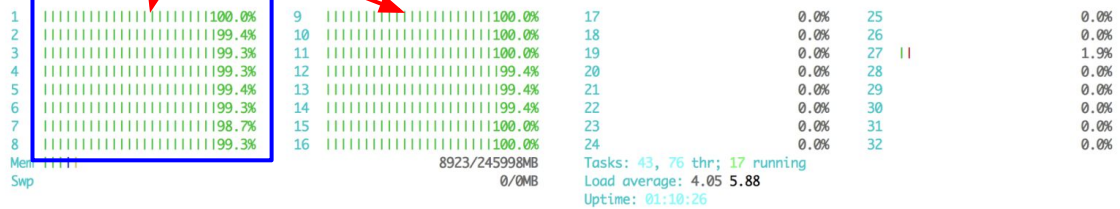
xgboost CPU % usage patterns #1

Open **szilard** opened this issue on Nov 6, 2016 · 4 comments

szilard commented on Nov 6, 2016 • edited

r3.8xlarge: CPU1 0-7 (and 16-23 hyperthread pairs), CPU2 8-15

```
taskset -c 0-7 Rscript xgb.R 8 &
taskset -c 8-15 Rscript xgb.R 8
```



szilard / ml-x1

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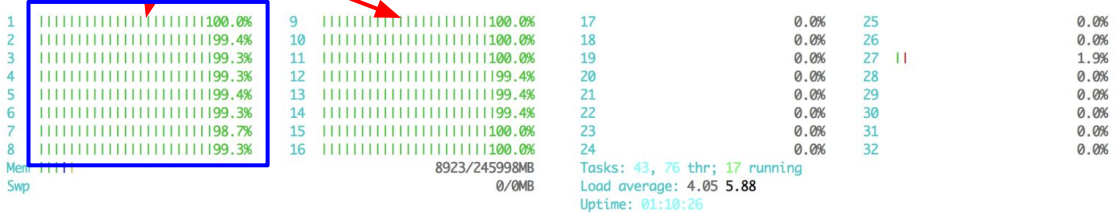
CV/hyperparam search:

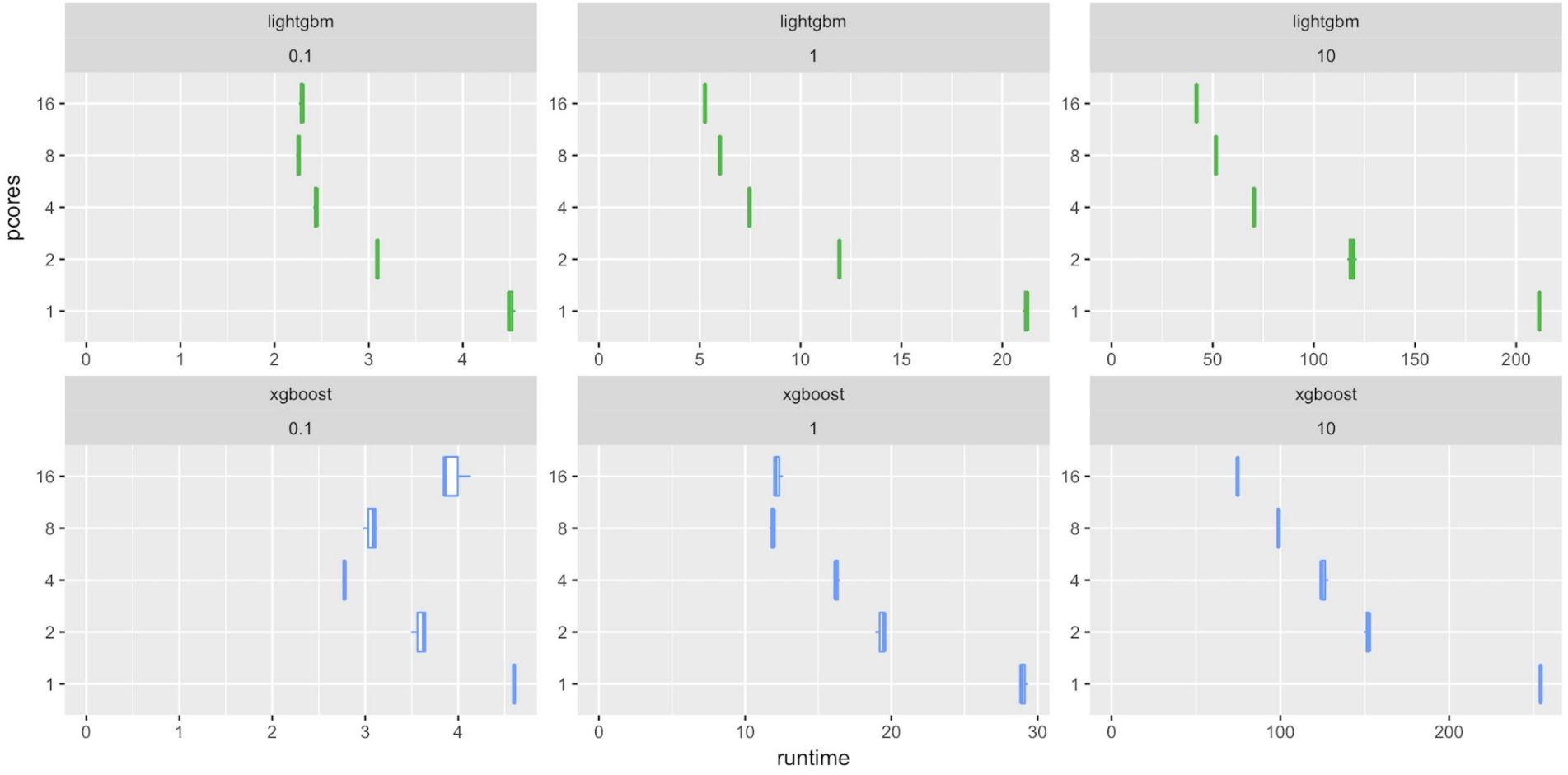
Option 1: run sequentially on 32 cores, takes 64sec/fold

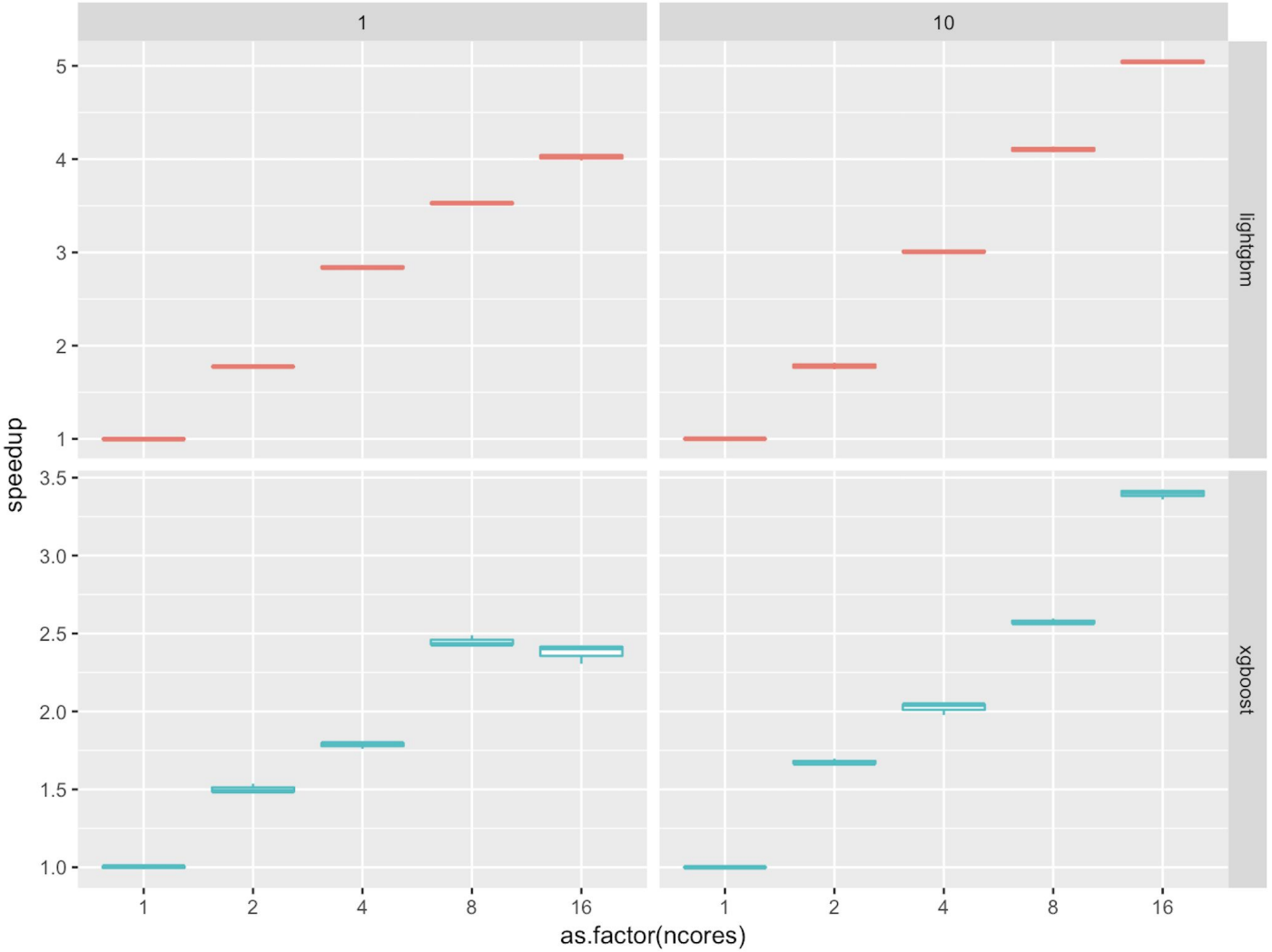
Option2: run 2 folds at a time pinned to cores 0-7 and 8-15, takes 35sec

So Opt2 is 3.6x faster than Opt1.

```
taskset -c 0-7 Rscript xgb.R 8 &
taskset -c 8-15 Rscript xgb.R 8
```




lightgbm
0.1
lightgbm
1
lightgbm
10
xgboost
0.1
xgboost
1
xgboost
10
pcores
16
8
4
2
1
0
1
2
3
4
0
5
10
15
20
0
50
100
150
200
0
10
20
30
0
100
200
runtime


1
10
lightgbm
xgboost
speedup
5
4
3
2
1
3.5
3.0
2.5
2.0
1.5
1.0
1
2
4
8
16
as.factor(ncores)

Laurae2 / **ml-perf**

szilard commented 7 hours ago • edited

I will include this (simplified results for xgboost CPU) in my talks (with credit to **@Laurae2**):

Parallel Threads	Model Threads	Models	Seconds / Model
1	1	25	11.39
9	1	50	1.46
18	1	100	0.78
35	1	250	0.49
70	1	500	0.43
1	1	50	11.4
1	9	50	6.6
1	18	50	6.6
1	35	50	25
1	70	50	165

(for easy ref: 2 socket system with 18+18HT cores each socket, total 72 cores; 0.1m dataset; 500 trees, depth 6, learn rate 0.05)

Laurae2 / **ml-perf**

Szilard [Deeper than Deep Learning]
@DataScienceLA

Replying to @rquintino

If you have lots of models to train (or hyperparam values to try etc.) and fixed hardware resources the best (least wall time/most throughput) is actually running 1 model/CPU core (quite unsexy, huh?) see here github.com/szilard/GBM-pe … (joint work but mostly by @Laurae_Cht)

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	gbm (R pkg)	xgboost	lightgbm	h2o
easy R install	cran	cran	linux OK	java+cran
maintained	retired	yes	yes	yes
preprocessing	not needed	1-hot	1-hot/categ int	not needed
new cats scoring	yes	no	no	yes
early stopping	no	yes	yes	yes
speed (CPU)	1 core	ok	fastest	slow (small data)
GPU supported	no	yes	yes	via xgboost
speed GPU	NA	fastest	ok/slow	indirectly/slower
REST scoring	no	no	no	yes
other algos	no	RF	RF	RF/GLM/NN
best for	teaching/historic	Kaggle	Kaggle	prod/real-time

Recommendations

If you **don't have a GPU, lightgbm** (CPU) trains the fastest.

If you **have a GPU, xgboost** (GPU) is also very fast (and depending on the data, your hardware etc. often faster than the above mentioned lightgbm on CPU).

If you consider deployment, **h2o has the best ways to deploy** as a real-time (fast scoring) application.

Note, however, there are a lot more other criteria to consider when you choose which tool to use.

szilard / **GBM-perf**

Szilard @DataScienceLA · Apr 23

What algo do you use the most for supervised learning?

33% lin/logistic regression

56% random forest/GBM

4% shallow neural nets

7% deep learning

57 votes • Final results

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Szilard
@DataScienceLA

Friday fun: what's your favorite gradient boosting machine (GBM) library?

58% xgboost

16% lightgbm

24% h2o

2% spark mllib

127 votes • Final results

3:21 PM - 11 May 2018

Szilard
@DataScienceLA

Friday fun: what's your favorite gradient boosting machine (GBM) library?

58% xgboost

16% lightgbm

24% h2o

2% spark mllib

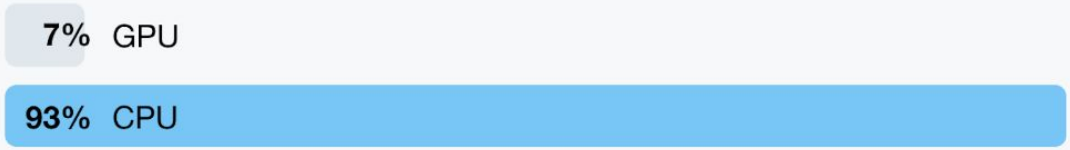
no-one is using this crap

127 votes • Final results

3:21 PM - 11 May 2018

Szilard @DataScienceLA · May 16 (2018)

If you are using gradient boosting machines(GBM), are you running it (training) on GPUs or CPUs?



55 votes • Final results

Szilard @DataScienceLA · May 16 (2018)

If you are using gradient boosting machines(GBM), are you running it (training) on GPUs or CPUs?

7% GPU

93% CPU

55 votes • Final results

Szilard [Deeper than Deep Learning]
@DataScienceLA

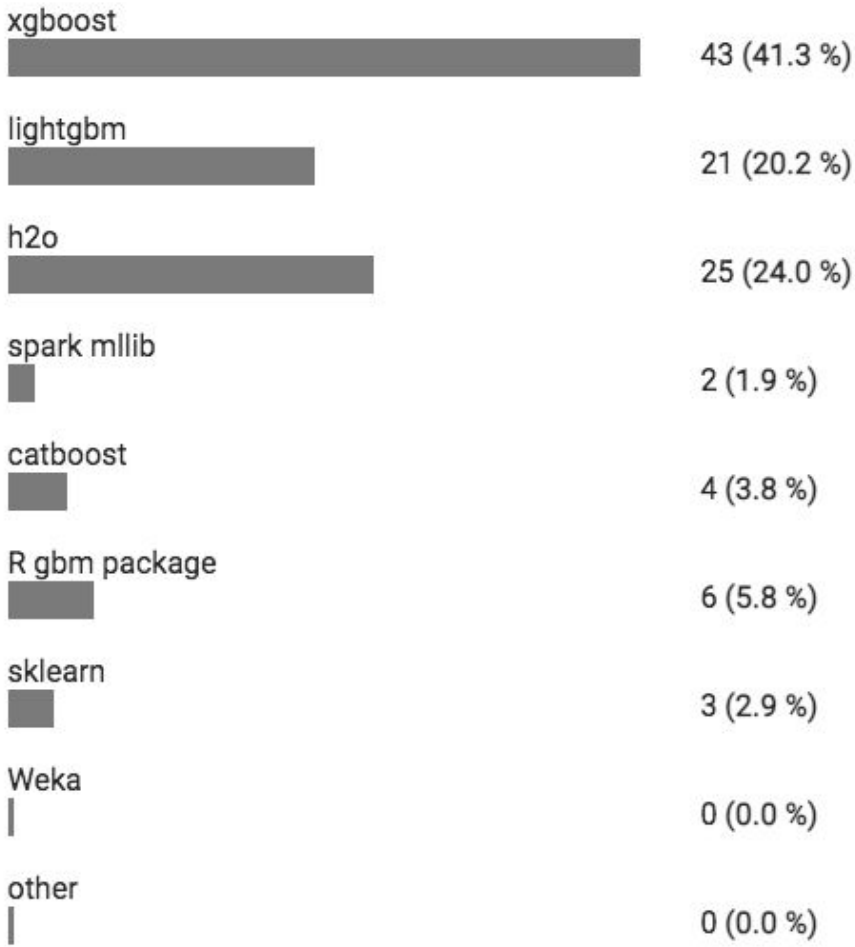
If you are using gradient boosting machines (GBM)/boosted trees (GBDT) are you using (training) them most often on the CPU or a GPU? #xgboost #lightgbm #h2oai #catboost #apachespark #mllib #sklearn

86% CPU

14% GPU

69 votes • Final results

11:39 AM - 4 May 2019



104 people have already voted
You have already answered this poll

show the configuration of this Ferendum

Winning Solution of KaggleDays 2019 Competition in San Francisco

Source: https://www.linkedin.com/pulse/winning-solution-kaggledays-2019-competition-san-francisco-mark-peng/

Winning Solution of KaggleDays 2019 Competition in San Francisco

During the first two to three hours of the competition, we focused on exploratory data analysis (EDA). We first analyzed the distributions of raw features between train and test

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For model training, LightGBM is chosen as the baseline model for doing quick experiments on raw and engineered features. It turned out that our engineered features improved AUC in

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Based on the LightGBM baseline notebook, I created other notebooks for Xgboost, Logistic Regression, Random Forests and Extra Trees models. To save some time, I ran Random

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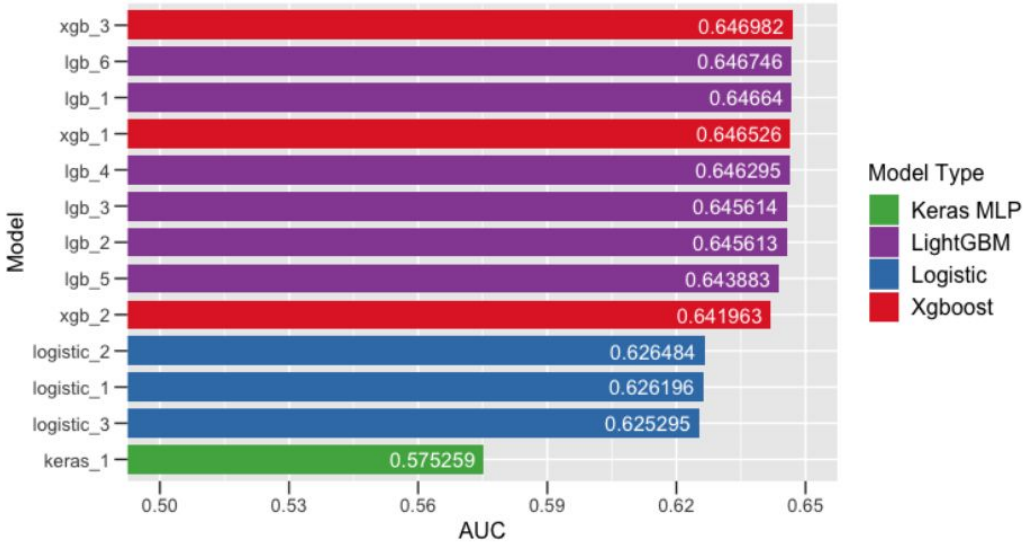

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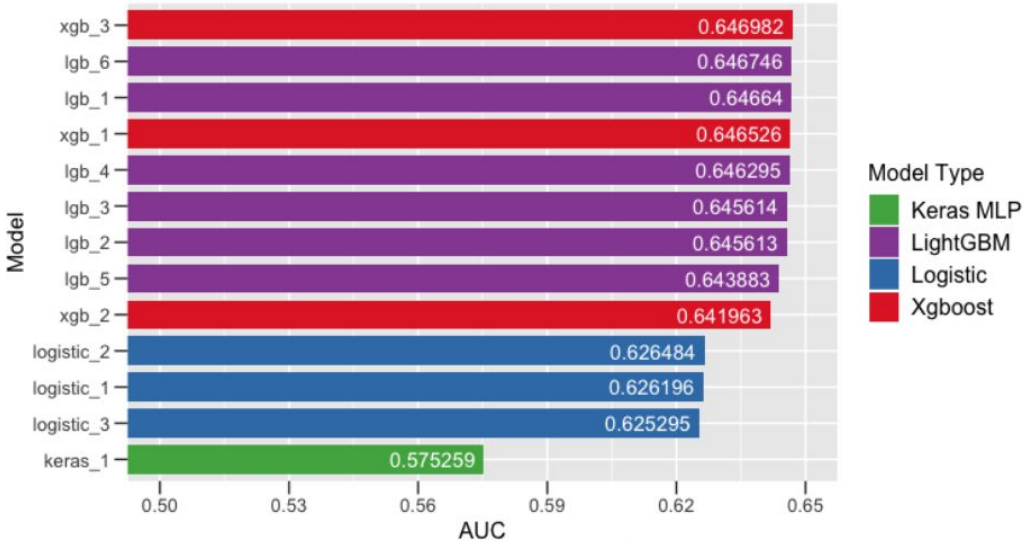

For blending and stacking, we looked for diverse models that perform relatively well, but are not highly correlated with each other. Xgboost and LightGBM had very similar

Source: https://www.linkedin.com/pulse/winning-solution-kaggledays-2019-competition-san-francisco-mark-peng/


TABULAR DATA YOU HAVE
GBM USE YOU MUST

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szilard / teach-ML-CEU-master-bizanalytics

szilard / GBM-perf

szilard / ML-scoring

szilard / GBM-tune

GitHubGist Search...

szilard / GBM-multicore


szilard / h2o_scoring.R

szilard / GBM-workshop


szilard / ML_with_H2O.R

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