Scalability of Predictive Modeling Algorithms Master's thesis presentation

Ing. Tomáš Frýda

Supervisor: Ing. Pavel Kordík, Ph.D.

Scalability of Predictive Modeling Algorithms

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Base Models Ensembles Evolution

H2C

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Motivation

- Model selection usually does not depend solely on predictive performance
- I took in to account time, which gives me two basic use cases:
 - Good enough model trained using limited computational resources

- Highly accurate model trained using as much computational resources as needed
- Make FAKE GAME usable on big data

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FAKE GAME

- Originally created for small data
- Base models
 - Decision tree, KNN, etc
 - Regression models
- Ensembles
 - Bagging
 - Boosting
 - Stacking, Cascade Correlation, ...
- Genetic programming-based ensemble creation

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Base Models

regression models

- linear
- polynomial
- sigmoid
- ▶ sine, . . .
- regression models are used as discriminant functions for classification
- decision trees
- k-NN

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Ensembles

- Arbitrating¹
- Bagging
- Boosting
- Cascade Generalization
- Cascading¹
- Delegating¹
- Stacking

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¹used only for classification

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Evolution

Genetic programming used for evolving templates that can be expanded to hierarchical ensembles

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- framework for distributed machine learning based on MapReduce
- support for preprocessing and data manipulation
- RESTful API used by various language bindings (R, Python, ...)

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Overview

Machine Learning algorithms included in H2O:

- Deep Learning
- Distributed Random Forest
- Gradient Boosting Machines
- Generalized Linear Model
- Naïve Bayes
- K-Means
- PCA
- GLRM
- ▶ ...

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Architecture

- in-memory MapReduce
- uses distributed key-value storage
- tries to keep related data in the same or nearby node in order to minimize network usage
- columns are compressed and lazily decompressed just in time of usage in CPU registers
- parallel data load

See more at http://blog.h20.ai/2014/03/h2o-architecture/

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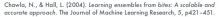
How are decision trees built in H2O?

Implementation #1

Build independent trees per machine local data

- RVotes approach
- Each node builds a subset of forest





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Fast - trees are independent and can be built in parallel

O Data have to fit into memory

Possible accuracy decrease if each node can see only subset of data

Oxdata

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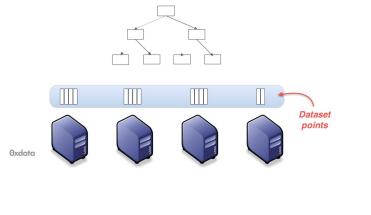
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Build a distributed tree over all data



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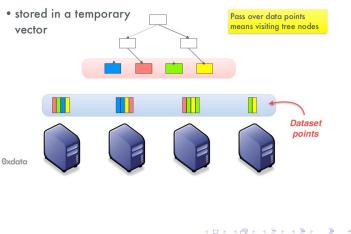
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Each data point has assigned a tree node



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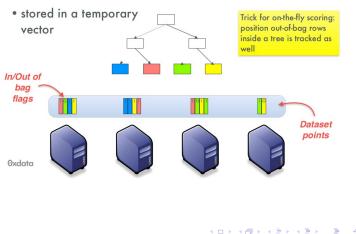
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Each data point has in/out of bag flag



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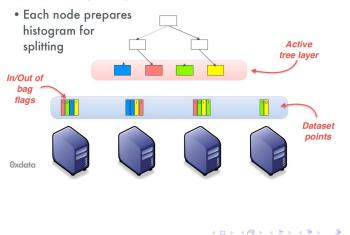
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Tree is built per layer



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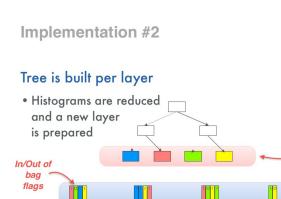
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Active tree layer

Dataset points

Exact solution - no decrease of accuracy

Elegant solution merging tree building and OOB scoring

More data transfers to exchange histograms

Can produce huge trees (since tree size depends on data)

0xdata

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Python

import h2o h2o.init() $data = h2o.import_file($ path="data.csv") # Create test/train split s = data ["Year"]. runif() train = data[s <= 0.75] test = data [s > 0.75]*#* Create an estimator dl=H2ODeepLearningEstimator(hidden = [10, 10],epochs = 5. balance_classes=True) # Train an estimator dl.train(x=mvX.

```
y=myY,
training_frame=train,
validation_frame=test)
```

R library ("h2o") h2o.init() dt <- h2o.importFile(</pre> path = "data.csv") # Create test/train split **dt**.**split** <- h2o.splitFrame(data = dt. ratios = 0.75) train <- **dt**.**split** [[1]] test <- dt.split [[2]] # Create an estimator and # train it dl <- h2o.deeplearning(x = mvX. v = mvY. $training_{-}frame = train$, validation_frame = test, hidden= $\mathbf{c}(10, 10)$

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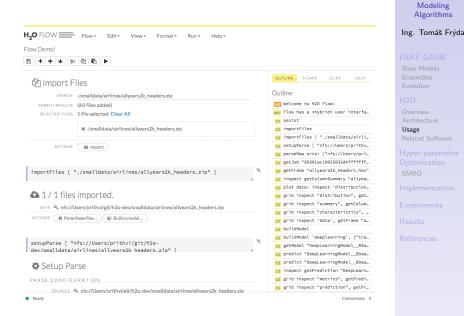
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H2O Flow



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Scalability of

Predictive

H2O Flow

H,O FLOW Flow - Edit - View - Format - Run -Heln v Flow Demo! B + + + × 2 B > OUTLINE FLOWS Setup Parse Outline Welcome to H2O Flow! SOURCES & nfs://Users/prithvi/git/h2o-dev/smalldata/airlines/allyears2k headers.zip MD Flow has a *hybrid* user interfa... DESTINATION KEY allvears2k headers.hex cs assist PARSER CSV + cs importFiles SEPARATOR .: '44' cs importFiles ["./smalldata/airli... COLUMN HEADERS () Auto cs setupParse ["nfs://Users/prithv... First row contains column names cs parseRaw srcs: ["nfs://Users/pri... First row contains data cs getJob "\$0301ac10025832d4fffffff... cs getFrame "allvears2k.headers.hex" OPTIONS Enable single quotes as a field quotation character cs inspect getColumnSummary "allyea... Delete on done cs plot data: inspect 'distribution..

DATA PREVIEW

Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	Arı
1987	10	14	3	741	730	912
1987	10	15	4	729	730	903
1987	10	17	6	741	730	918
1987	10	18	7	729	730	847
1987	10	19	1	749	730	922
1987	10	21	3	728	730	848
1987	10	22	4	728	730	852
1987	10	23	5	731	730	902

Ready

cs grid inspect "distribution", get. cs grid inspect "summary", getColum.. cs grid inspect "characteristics", ... cs grid inspect 'data', getFrame "a., cs buildModel cs buildModel 'deeplearning', {"tra.. cs getModel "DeepLearningModel 89a. cs predict "DeepLearningModel___89aa... cs predict "DeepLearningModel__89aa.. cs inspect getPrediction "DeepLearn.

cs grid inspect "metrics", getPredi... cs grid inspect "prediction", getPr...

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H₂O Flow

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Flow Demo!

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getFrame "allyears2k_headers.hex"

allyears2k_headers.hex

ACTIONS: 🔳 V	iew Data	🕞 Bu	ild Model	9 Predi	ct		III Inspect	
LABEL	MISSING	ZEROS	PINES NINES	MIN	MAX	MEAN		
Year				1987	2008	1997.5	6.34436090:	
Month				1	10	1.409090909090909092	1.87471137134	
DayofMonth				1	31	14.601073263904679	9.1757904258	
DayOfWeek				1	7	3.820614852880986	1.905013119:	
DepTime	1086	1086		1	2400	1345.8466613820758	465.34089912	
CRSDepTime		569			2359	1313.2228614307153	476.25113999;	
ArrTime	1195	1195		1	2400	1504.6341303788888	484.34748790	
CRSArrTime		569			2359	1485.2891673109282	492.75043412	
UniqueCarrier		724			9	6.935490472508982	2.051212270	
FlightNum				1	3949	818.8429896766565	777.4043691	
TailNum	32	34			3500	2376.097506030128	1168.7593115	
ActualElapsedTime	1195	1195		16	475	124.81452913540424	73.97444166(
CRSElapsedTime	13	13		17	437	125.0215626066189	73.401594630	
AirTime	16649	16649		14	402	114.31611109078268	69.63632951!	
ArrDelay	1195	2709		-63	475	9.317111936984317	29.8402219624	
DepDelay	1086	7479		-16	473	10.007390655600112	26.438809042	
Origin		59			131	61.183000591204696	37.644115210	
Dest		172			133	78.55259447905772	33.9300703;	
Distance	35	35		11	3365	730.1821905650502	578.43800823	
TaxiIn	16026	16649			128	5.381368059530624	4.20197993	
TaxiOut	16024	16581			254	14.16863418473206	9.9050857472	
Cancelled		42892			1	0 024694165264450407	0.1551931413	

OU	TLINE FLOWS CLIPS HELP
Out	tline
H1	Welcome to H2O Flow!
MD	Flow has a *hybrid* user interfa
CS	assist
CS	importFiles
CS	importFiles ["./smalldata/airli…
CS	setupParse ["nfs://Users/prithv…
CS	parseRaw srcs: ["nfs://Users/pri…
CS	getJob "\$0301ac10025832d4fffffff
CS	getFrame "allyears2k_headers.hex"
CS	inspect getColumnSummary "allyea…
CS	
CS	grid inspect "distribution", get…
CS	grid inspect "summary", getColun
CS	grid inspect "characteristics",
CS	grid inspect 'data', getFrame "a
CS	buildModel
CS	buildModel 'deeplearning', {"tra…
CS	getModel "DeepLearningModel89a…
CS	predict "DeepLearningModel89aa…
CS	predict "DeepLearningModel89aa
CS	
CS	
CS	grid inspect "prediction", getPr

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H2O Flow

CS

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getModel "DeepLearr	ingModel89aaf0804	239efe2521844cddcbb417e"	OUTLINE FLOWS CLIPS HELI		
😭 Model			Outline H1 Welcome to H2O Flow!		
	ngModel_89aaf0804239	efe2521844cddcbb417e	MD Flow has a *hybrid* user interf		
ALGORITHM: deeplearnin			cs assist		
ACTIONS: / Predict	은 Clone this model	Inspect	cs importFiles		
		V Show all parameters	cs setupParse ["nfs://Users/prith		
PARAMETER	VALUE	DESCRIPTION	CS parseRaw srcs: ["nfs://Users/pr		
TRAINING_FRAME	allyears2k_headers.hex	Training frame	CS getJob "\$8301ac16025832d4ffffff		
RESPONSE_COLUMN	IsDepDelayed	Response column	<pre>cs getFrame "allyears2k_headers.he</pre>		
DO_CLASSIFICATION	true	Convert the response column to an enum	CS inspect getColumnSummary "allye		
		(forcing a classification instead of a regression)	CS plot data: inspect 'distributio		
		if needed.	cs grid inspect "distribution", ge		
MAX_AFTER_BALANCE_SIZE	Infinity	Maximum relative size of the training data after	CS grid inspect "summary", getColl CS grid inspect "characteristics".		
		balancing class counts (can be less than 1.0)	cs grid inspect 'data', getFrame '		
SEED	881048674552106414	Seed for random numbers (affects sampling) -	cs buildModel		
		Note: only reproducible when running single threaded	cs buildModel 'deeplearning', {"tr		
	MeanSquare	Loss function	<pre>cs bartahobet deeptearning, { cr cs getModel "DeepLearningModel89</pre>		
MAX_AFTER_BALANCE_SIZE		Maximum relative size of the training data after	cs predict "DeepLearningModel89a		
		balancing class counts (can be less than 1.0)	cs predict "DeepLearningModel89a		
REPLICATE_TRAINING_DATA	false	Replicate the entire training dataset onto every	cs inspect getPrediction "DeepLear		
		node for faster training on small datasets	cs grid inspect "metrics", getPred		
			cs grid inspect "prediction", getP		

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H₂O Flow

H_O FLOW Flow - Edit - View - Format - Run -

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Flow Demo!

CS

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grid inspect "metrics", getPredictions model: "DeepLearningModel___89aaf0804239efe2521844cddcbb417e", frame: "allvears2k headers.hex" metrics Metrics for the selected predictions

CRITERIA	THRESHOLD	F1	F 2	FOPOINTS	ACCURACY	ERROR	PRECISION
maximum F1		0.68857443	0.8468044	0.5801671	0.525058	0.47494203	0.525058
maximum F2		0.68857443	0.8468044	0.5801671	0.525058	0.47494203	0.525058
maximum F0point5		0.68857443	0.8468044	0.5801671	0.525058	0.47494203	0.525058
maximum Accuracy		0.68857443	0.8468044	0.5801671	0.525058	0.47494203	0.525058
maximum Precision	0.0014023929	0.0063889488	0.004002683	0.015820755	0.47662467	0.52337533	1
maximum Recall		0.68857443	0.8468044	0.5801671	0.525058	0.47494203	0.525058
maximum Specificity	0.0014023929	0.0063889488	0.004002683	0.015820755	0.47662467	0.52337533	1
maximum absolute MCC	0.00034111855	0.37031785	0.3361132	0.4122729	0.43464914	0.56535083	0.44595584
minimizing max per class Error	0.00029882442	0.45200276	0.44506764	0.4591574	0.43910593	0.5608941	0.46405438

OUTLINE	FLOWS	CLIPS	HELP
Outline			
		F1	
	ome to H2O		
	has a *hyt	orid* user	interfa
cs assi			
	rtFiles		
CS impo	rtFiles ['	./smalldat	a/airli…
cs setu	pParse ["r	nfs://Users	/prithv…
cs pars	eRaw srcs:	["nfs://Us	ers/pri…
CS get3	ob "\$0301ad	10025832d4	fffffff
CS getF	rame "allye	ars2k_head	ers.hex"
cs insp	ect getColu	unnSummary	"allyea…
CS plot	data: insp	ect 'distr	ibution
cs grid	inspect "d	istributio	n", get…
cs grid	inspect "s	summary", g	etColum
cs grid	inspect "d	haracteris	tics", …
cs grid	inspect 'd	iata', getF	rame "a…
cs buil	dModel		
CS buil	dModel 'dee	plearning'	, {"tra…
CS getM	odel "Deepl	.earningNod	el89a…
cs pred	ict "DeepLe	arningMode	l89aa
cs pred	ict "DeepLe	arningMode	l89aa
cs insp	ect getPred	diction "De	epLearn
cs grid	inspect "r	netrics", g	etPredi…
cs grid	inspect "p	rediction"	, getPr…

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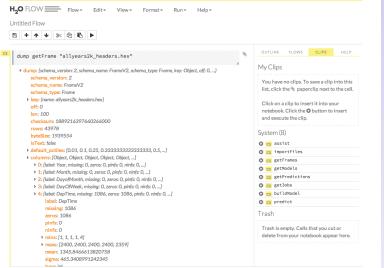
Usage

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H2O Flow



Readv

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Related Software

Sparkling Water

- Deep Water
- Steam H2O deployment

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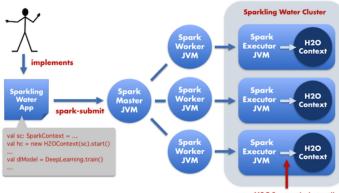
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Sparkling Water



new H2OContext(sc).start()

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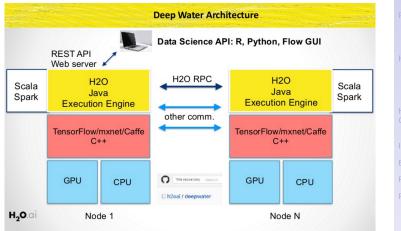
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Deep Water



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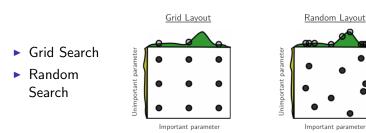
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Hyper-Parameter Optimization



Bayesian optimization (SMAC)

Scalability of Predictive Modeling Algorithms

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Sequential Model-based Bayesian Optimization (SMBO)

- 1. evaluate random configuration and add it to the probabilistic model
- select promising configuration based on probabilistic model using an acquisition function²
- 3. evaluate the configuration
- 4. add the new configuration to the probabilistic model
- 5. go to step 2

²usually Expected Improvement $EI(x) = E(\max\{0, f_{t+1}(x) - f(x^+)\}|M_t)$

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Instances of SMBO

- Gaussian Process based SMBO
 - no obvious way how to deal with categorical parameters
- Tree-structured Parzen Estimator (TPE)
- Sequential Model-based Algorithm Configuration (SMAC)
- Hyperband

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Tree-structured Parzen Estimator

$$p(x|y) = \begin{cases} l(x) & \text{if } y < y^* \\ g(x) & \text{if } y \ge y^* \end{cases}$$

▶ easy to sample space of promising values
 ▶ El is proportional to (γ + g(x)/l(x)(1 - γ))⁻¹

 y^* is chosen as some quantile (e.g., $p(y < y^*) = 0.15 = \gamma$)

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Sequential Model-based Algorithm Configuration

- based upon ROAR an racing optimization algorithm
- uses random forest as a probabilistic model
- usage of random forest makes it easy to use user-defined cost metric
- configuration to be evaluated is selected by following process
 - 1. take 10 best previously seen configurations
 - initialize local search (using one-exchange neighbourhood for categorical, and four random neighbours for numerical variables)
 - 3. merge resulting 10 best configurations with 10 000 randomly sampled configurations
 - 4. sort by their El
 - 5. interleave with uniformly sampled configurations

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Hyperband

- SMBO with enhanced selection and evaluation phase
- uses information from training phase of a model that is being optimized and eventually stops it if it doesn't converge well ⇒ explores more space using the same amount of resources
- iteratively discards the worse half of evaluated configurations

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Implementation

- integration of FAKE GAME into H2O framework
- creation of benchmarking environment
 - written in Python
 - supports
 - all supervised machine learning algorithms in H2O
 - H2O Ensemble (implemented in R, based on SuperLearner package)
 - Hyper-Parameter optimization using Random Search and SMAC

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configurable using YAML and Python

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Experiments

- 2 datasets with binomial response class
 - Higgs
 - Airline 4 different scenarios
- ▶ 20+ models benchmarked on each of 5 scenarios
- Hyper-Parameter optimization on each dataset

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Overview of Results

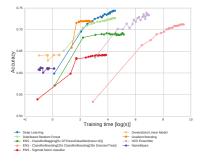


Figure: Higgs dataset

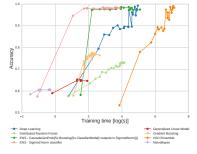


Figure: Airline – predicting IsDepDelayed

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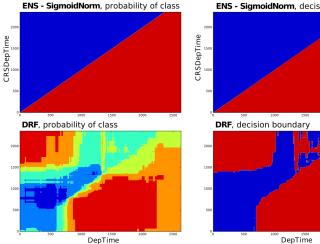
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Decision Boundary on Airline dataset



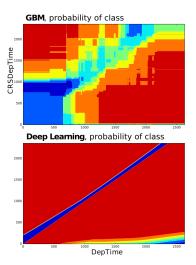
ENS - SigmoidNorm, decision boundary

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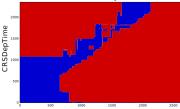
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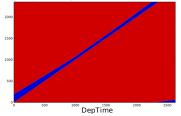
Decision Boundary on Airline dataset







Deep Learning, decision boundary



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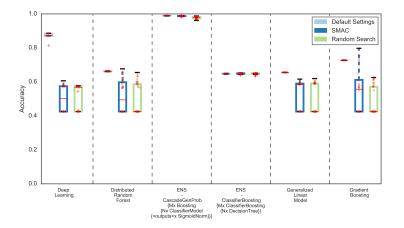
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Conclusion

- Successfully integrated FAKE GAME into H2O and created benchmarking environment
- Experiments took over 2000 hours (wall clock), used 12 CPUs and 16 GiB of RAM
- Experiments show that
 - newly integrated FAKE GAME can find better models than those previously present in H2O
 - H2O's auto-tuning yields good results by default
- Results of those experiments were submitted, as part of an article, to be published in Machine Learning

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0xdata,

https://www.slideshare.net/Oxdata/rf-brighttalk https://www.slideshare.net/Oxdata/ deep-water-gpu-deep-learning-for-h2o-arno-candel

J. Bergstra, R. Bardenet, Y. Bengio, and B. Kégl, "Algorithms for Hyper-Parameter Optimization," Adv. Neural Inf. Process. Syst., pp. 2546–2554, 2011.

F. Hutter, H. H. Hoos, and K. Leyton-Brown, "Sequential model-based optimization for general algorithm configuration",

Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 6683 LNCS, pp. 507–523, 2011.



L. Li, K. Jamieson, G. DeSalvo, A. Rostamizadeh, and A. Talwalkar,

"Efficient Hyperparameter Optimization and Infinitely Many Armed Bandits,"

arXiv Prepr., 2016.

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