

Applying Machine Learning using H2O.
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Security Scientist



Overview

- Introduction to H2O
- H2O architecture
- Agenda
- Problem Definition
- Setup of H2O
- Data Analysis
- Results



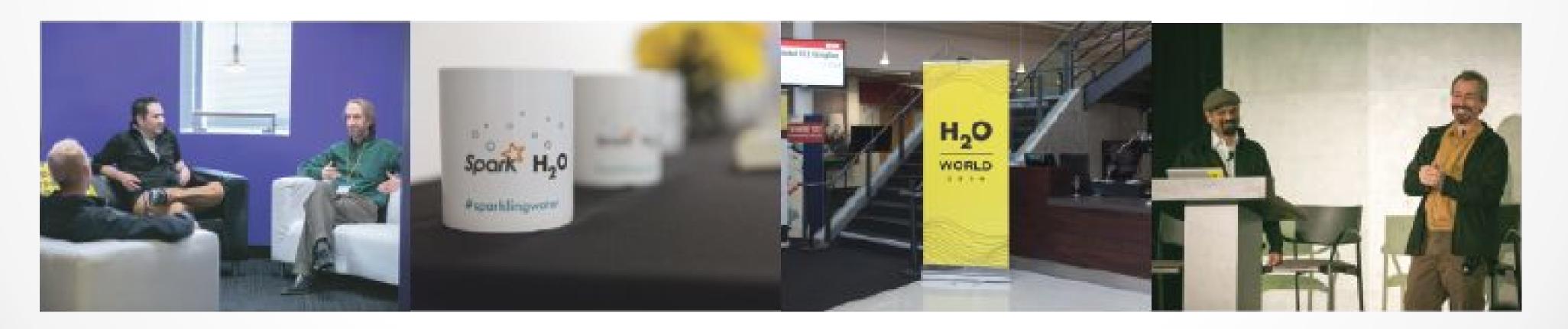
Company Overview

Company

- Team: 80. Founded in 2012, Mountain View, CA
- Stanford Math & Systems Engineers

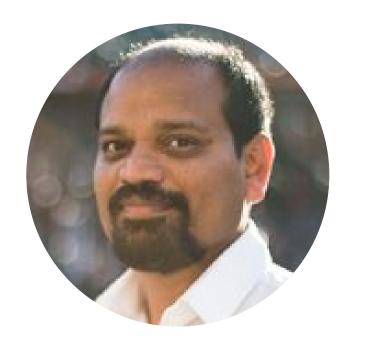
Product

- Open Source Leader in Machine & Deep learning
- Ease of Use and Smarter Applications
- R, Python, Spark & Hadoop Interfaces
- Expanding Predictions to Mass Analyst markets





Executive Team



Sri Satish Ambati
CEO & Co-founder

DataStax



Tom Kraljevic
VP of Engineering

Abrizio, Intel



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Chief Architect

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Trevor Hastie Stephen Boyd Rob Tibshirani



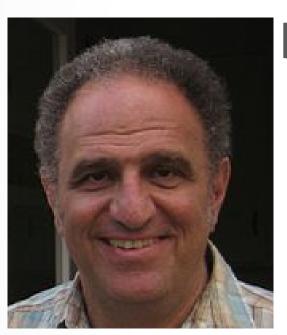


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Dr. Trevor Hastie

- PhD in Statistics, Stanford University
- John A. Overdeck Professor of Mathematics, Stanford University
- Co-author, The Elements of Statistical Learning: Prediction, Inference and Data Mining
- Co-author, Generalized Additive Models
- 108,404 citations (via Google Scholar)



Dr. Rob Tibshirani

- PhD in Statistics, Stanford University
- Professor of Statistics and Health Research and Policy, Stanford University
- COPPS Presidents' Award recipient
- Co-author, The Elements of Statistical Learning: Prediction, Inference and Data Mining
- Author, Regression Shrinkage and Selection via the Lasso
- Co-author, An Introduction to the Bootstrap



Dr. Stephen Boyd

- PhD in Electrical Engineering and Computer Science, UC Berkeley
- Professor of Electrical Engineering and Computer Science, Stanford University
- Co-author, Convex Optimization
- Co-author, Linear Matrix Inequalities in System and Control Theory
- Co-author, Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers

What is H20?

Math Platform

Open source in-memory prediction engine

- Parallelized and distributed algorithms making the most use out of multithreaded systems
- GLM, Random Forest, GBM, PCA, etc.

API

Easy to use and adopt

- Written in Java perfect for Java Programmers
- REST API (JSON) drives H2O from R, Python, Excel, Tableau

Big Data

More data? Or better models? BOTH

- Use all of your data model without down sampling
- Run a simple GLM or a more complex GBM to find the best fit for the data
- More Data + Better Models = Better Predictions



Algorithms on H2O

Supervised Learning

Statistical Analysis

Ensembles

Deep Neural Networks

- Generalized Linear Models: Binomial,
 Gaussian, Gamma, Poisson and Tweedie
- Naïve Bayes
- Distributed Random Forest: Classification or regression models
- Gradient Boosting Machine: Produces an ensemble of decision trees with increasing refined approximations
- Deep learning: Create multi-layer feed forward neural networks starting with an input layer followed by multiple layers of nonlinear transformations

Algorithms on H2O

Unsupervised Learning

Clustering

 K-means: Partitions observations into k clusters/groups of the same spatial size

Dimensionality Reduction

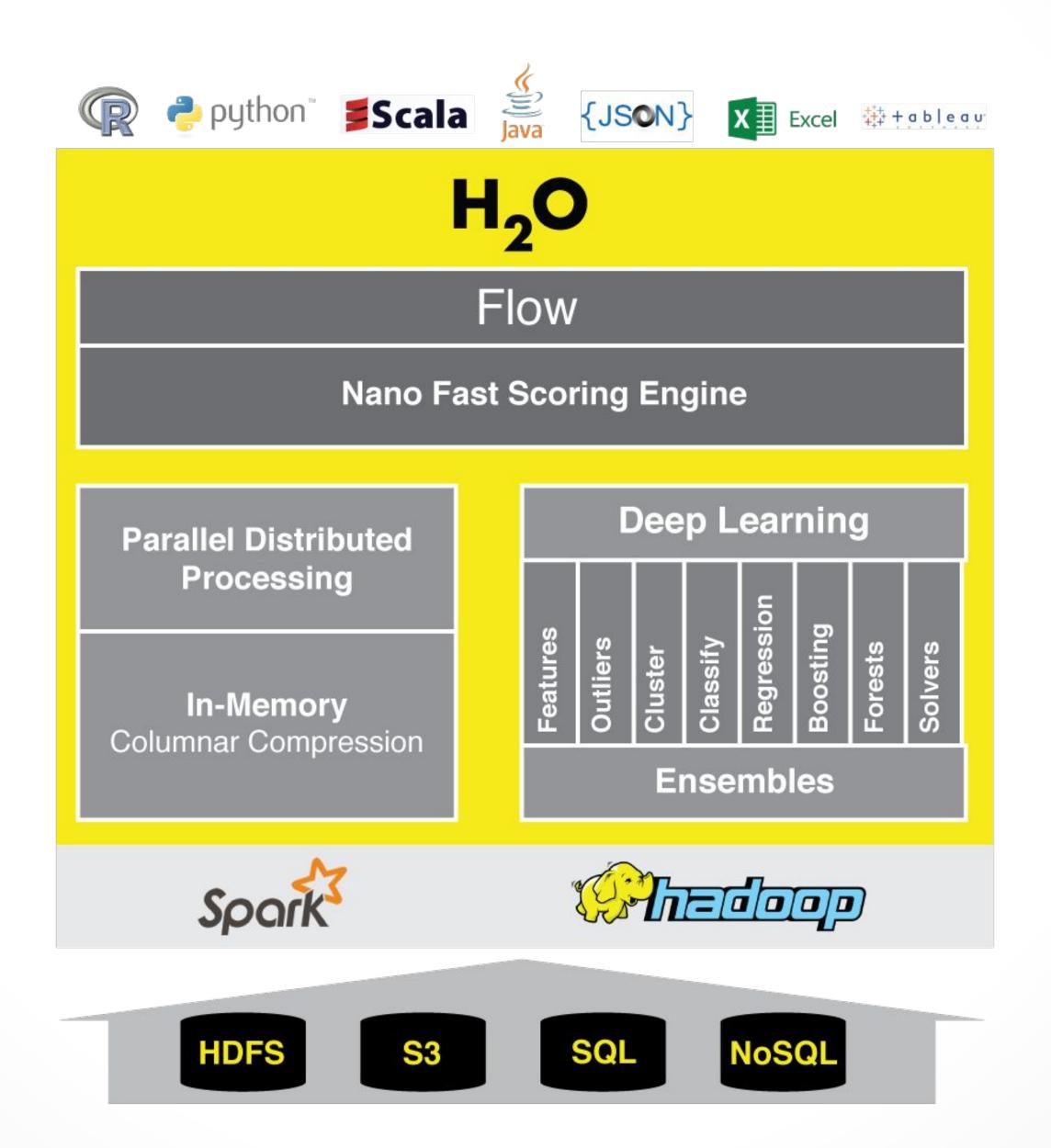
 Principal Component Analysis: Linearly transforms correlated variables to independent components

Anomaly Detection

 Autoencoders: Find outliers using a nonlinear dimensionality reduction using deep learning



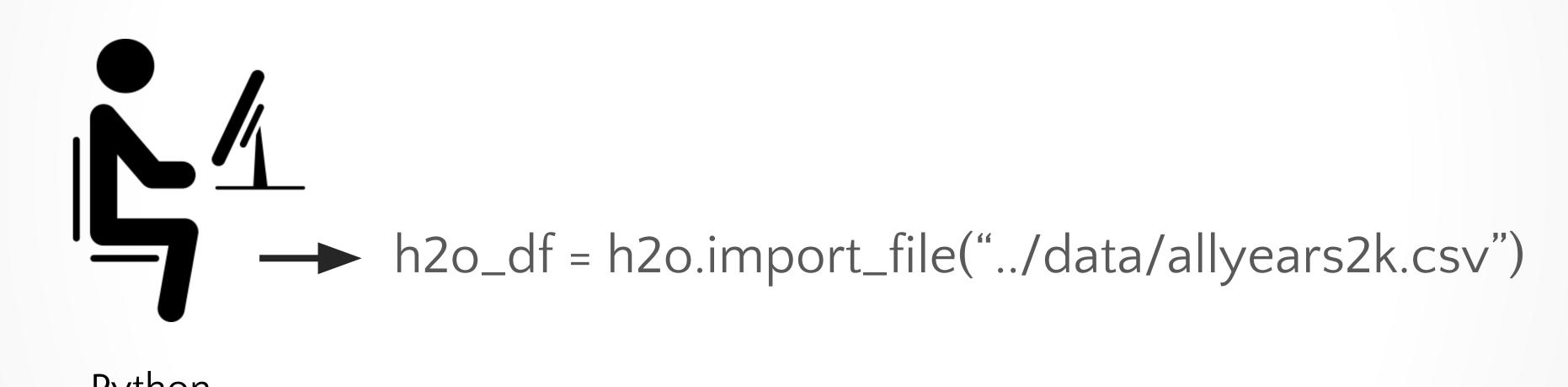
Accuracy with Speed and Scale



Machine Intelligence

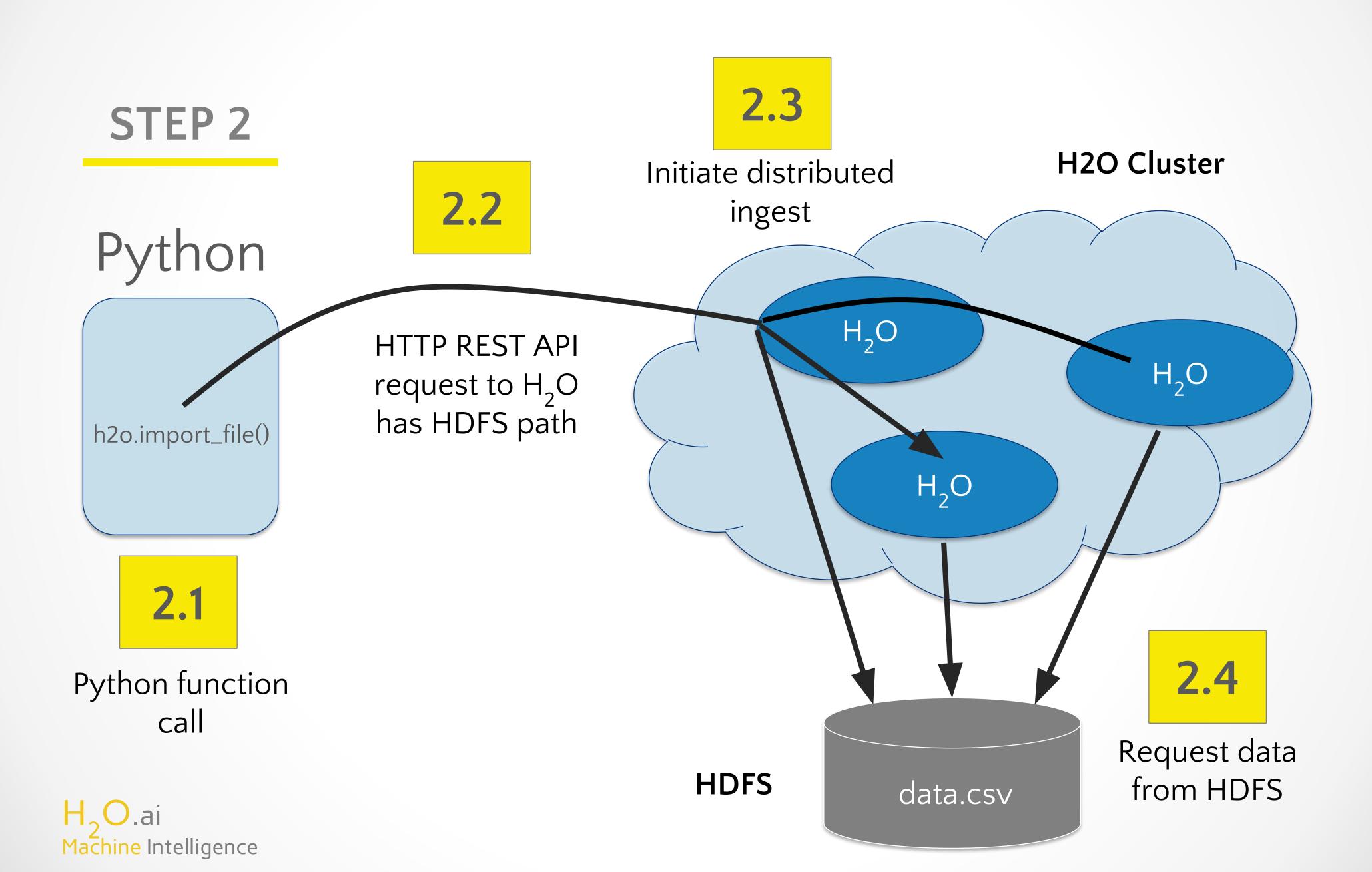
Reading Data into H2O with Python

STEP 1

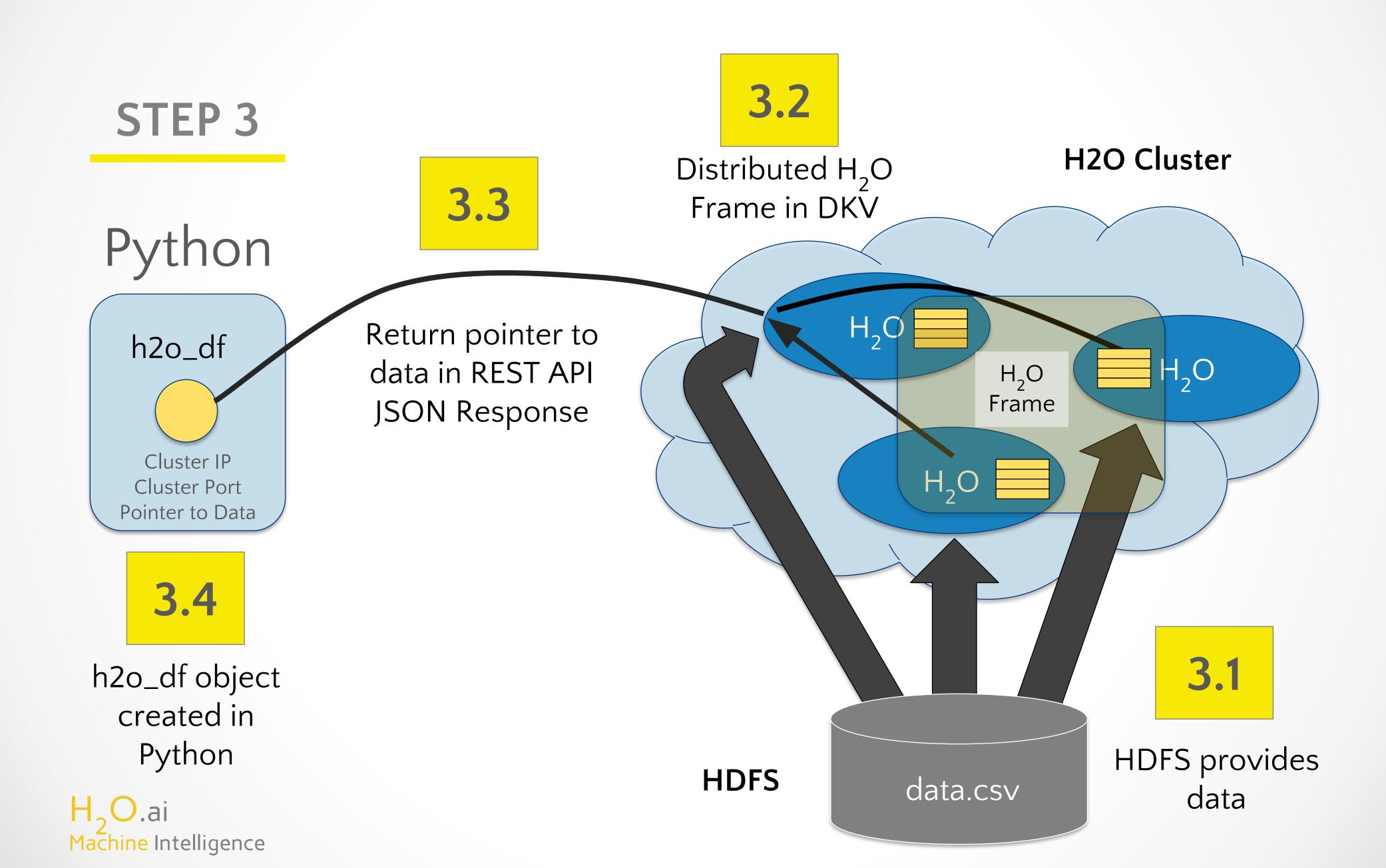


Python user

Reading Data from HDFS into H2O with Python



Reading Data from HDFS into H2O with Python



Agenda

- Understand the architecture of H2O
- Use H2O with Python through the REST API.
- Shape the data for analysis
- Model the data
- Read the results



Problem Definition

Sorting a large pool of system event logs by their source.



Problem Breakdown

- Every small and large company stores aggregated system event logs.
- Log storage is cheap and almost a requirement for compliance.
- Identifying source of logs from aggregated system logs is tough due to multiple devices, and networks.
- Breaking down these logs into their respective source bins is important for security event analysis.
- We use machine learning to show how this can be done.



Sample Data

- <30>Feb 23 10:02:24 10.14.3.101 dhcpd[10039]: balanced pool 81df410 10.6.28.0/23 total 495 free 278 backup 186 Its 46 max-misbal 70
- <166>2016-02-23T13:02:24.363Z server1.example.com **Vpxa**: [42764B90 verbose 'VpxaHalCnxHostagent' opID=WFU-e1f63e34] [WaitForUpdatesDone] Received callback
- <166>2016-02-23T13:02:24.363Z server1.example.com Vpxa: [42764B90 verbose 'hostdvm'
- opID=WFU-e1f63e34] [VpxaHalVmHostagent] 4357: GuestInfo changed 'guest.disk'
- <30>Feb 23 10:02:24 10.0.2.108 dhcpd[2331]: DHCPACK to 10.0.0.58 (4c:34:88:fa:f9:a1) via eth2
- <30>Feb 23 10:02:24 10.0.2.108 dhcpd[2331]: DHCPACK to 10.0.0.58 (4c:34:88:fa:f9:a1) via eth2



Study of Logs

- The logs have a data format
- There are IP addresses in the logs
- There are also MAC addresses in the logs
- Logs from same source have the same word(s). Hence, similar sized words.
- Prival or Priority value is a valuable information to identify if the event is coming from a system daemon or other sources.
- Prival also tells us the facility and severity of the source. (Refer RFC 5424)



Features

- Priority Value
- Date Format
- Number of Characters
- Number of IP addresses
- Number of MAC addresses
- Fraction of dictionary words by size.



Labeling

Supervised approach

Requires model to understand response



Labeling Example

```
my_dict = {
  'rsa.ims.authn':'securid.txt',
        '\%ASA' :'ciscoasa.txt',
        '\[acc\]':'bigip-vpn.txt',
   'from\ssensor':'airmagnet.txt',
   'CPPM\_':'arubanetworks.txt',
        'Vpxa' :'vmware.txt',
        'SecureSphere' :'waf.txt'
     }
}
```



Data for Modeling



Acknowledgements

- Hanif Zachary, CapitalOne
- Avni Wadhwa, H2O.ai
- Mark Chan, H2O.ai



Thank You
Questions?

