Introduction to H2O
And
Sparkling Water

SETTING UP QWIKLABS

Qwiklabs Instructions

1. Go to: https://h2oai.qwiklab.com/
2. Click “Join” in upper right hand corner to create an account
   - If you have already done a Qwiklabs you can click “Sign In”
3. Go to the “Catalog” view
4. Click on the lab: “H2O and Sparkling Water Workshop”
5. Click Start Lab
6. Enter License

H2O Training

1. Introduction to ML and H2O
2. H2O Auto Machine Learning
3. H2O Feature Engineering
4. Sparkling Water

Introduction:

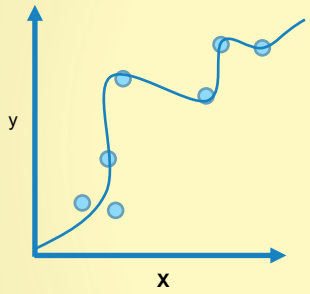
INTRODUCTION TO MACHINE LEARNING

What is Machine Learning?

- Set of statistical and optimization tools to model data
  - Supervised Learning
  - Unsupervised Learning
- Focus on “production analytics”
  - Reducing need for
    - Sampling
    - Periodic revision of models
    - Subjective priors
    - Hand coding models in a production language

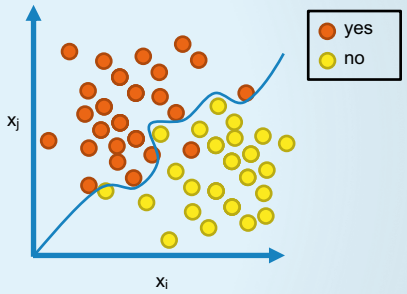
Supervised Learning

Regression:
How much will a customers spend?



H_2O algos:
Penalized Linear Models
Random Forest
Gradient Boosting
Neural Networks
Stacked Ensembles

Classification:
Will a customer make a purchase? Yes or No



H_2O algos:
Penalized Linear Models
Naïve Bayes
Random Forest
Gradient Boosting
Neural Networks
Stacked Ensembles

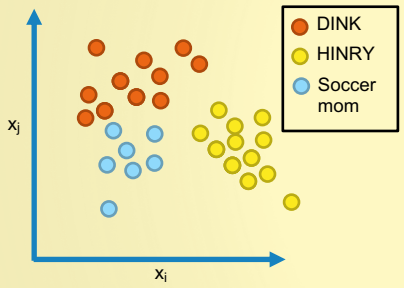
Stacked Ensembles

$$\left[y \right] \approx \left[\hat{y}_l \right] = f_l \left(\left[x_1 \dots x_p \right] \right) \qquad \left[y \right] \approx g \left(\left[\hat{y}_1 \dots \hat{y}_L \right] \right)$$

- Engineer original feature set
- Train L models using strong learners (GLM, RF, GBM, …)
- Control overfitting using k-fold CV
- Stack these predicted values to form new feature set
- Train metalearner on stacked predictions

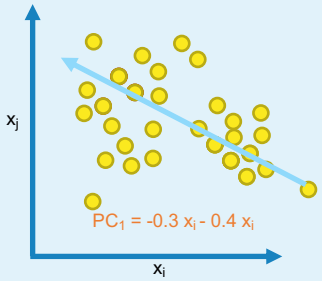
Unsupervised Learning

Clustering:
Grouping rows – e.g. creating groups of similar customers



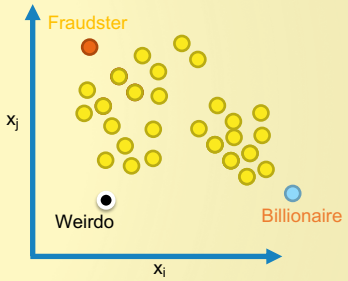
H_2O algos:
k – means

Feature extraction:
Grouping columns – Create a small number of new representative dimensions



H_2O algos:
Principal components
Generalized low rank models
Autoencoders
Word2Vec

Anomaly detection:
Detecting outlying rows - Finding high-value, fraudulent, or weird customers



H_2O algos:
Principal components
Generalized low rank models
Autoencoders

H_2O.ai

Introduction:

INTRODUCTION TO H2O

H2O Machine Learning Methods

Supervised Learning

Statistical Analysis

- **Penalized Linear Models**: Super-fast, super-scalable, and interpretable
- **CoxPH:** Cox Proportional Hazards Survival Analysis
- **Naïve Bayes:** Straightforward linear classifier

Decision Tree Ensembles

- **Distributed Random Forest**: Easy-to-use tree-bagging ensembles
- **Gradient Boosting Machine**: Highly tunable tree-boosting ensembles
- **eXtreme Gradient Boosting**: Popular XGBoost algorithm in H2O

Stacking

- **Stacked Ensemble**: Combine multiple types of models for better predictions

AutoML

- **Automatic Machine Learning**: Automated exploration of supervised learning approaches

Unsupervised Learning

Clustering

- **K-means**: Partitions observations into similar groups; automatically detects number of groups

Dimensionality Reduction

- **Principal Component Analysis**: Transforms correlated variables to independent components
- **Generalized Low Rank Models:** Extends the idea of PCA to handle arbitrary data consisting of numerical, Boolean, categorical, and missing data

Aggregator

- **Aggregator:** Efficient, advanced sampling that creates smaller data sets from larger data sets

Neural Networks

Multilayer Perceptron

Deep Learning

- **Deep neural networks**: Multi-layer feed-forward neural networks for standard data mining tasks
- **Convolutional neural networks:** Sophisticated architectures for pattern recognition in images, sound, and text

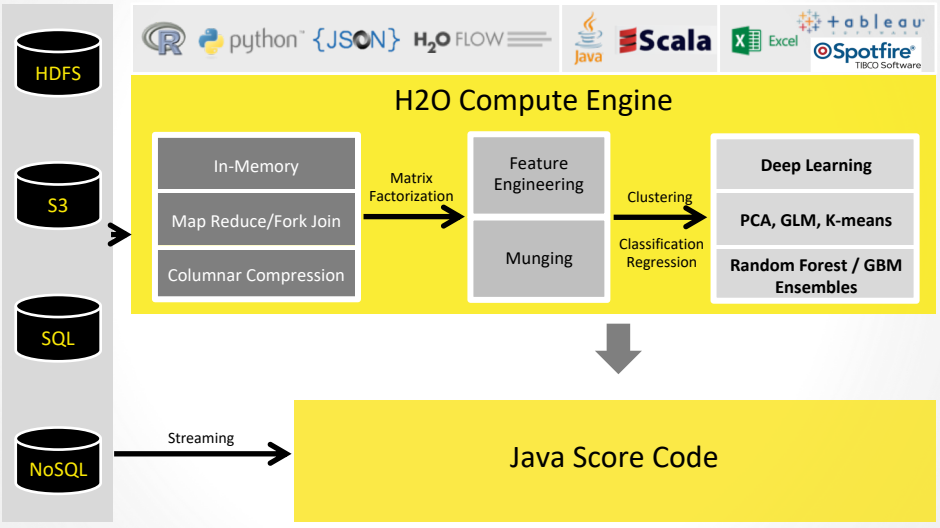
Anomaly Detection

Term Embeddings

- **Autoencoders**: Find outliers using a nonlinear dimensionality reduction technique
- **Word2vec:** Generate context-sensitive numerical representations of a large text corpus

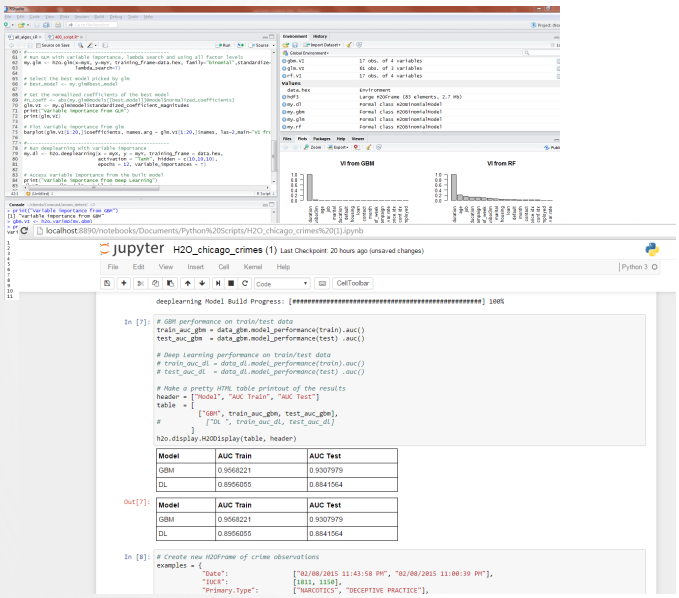
H2O.ai

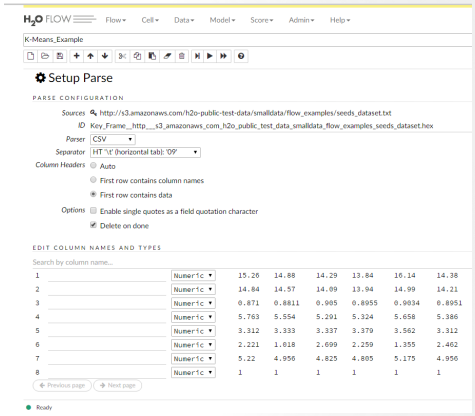
Data and Client Agnostic



H2O.ai

R, Python and Flow





R Interface Overview

Action	R	H2O
Reading data	`read_csv(data_path)`	`h2o.importFile(data_path)`
Summarizing data	`summary(data_frame)`	`h2o.summary(h2o_frame)`
Summary statistics	`mean(data_frame[["x"]])`	`h2o.mean(h2o_frame)`
Combining rows	`rbind(data_frame1, data_frame2)`	`h2o.rbind(h2o_frame1, h2o_frame2)`
Combining columns	`cbind(data_frame1, data_frame2)`	`h2o.cbind(h2o_frame1, h2o_frame2)`
Data selection	`data_frame[,]`	`h2o_frame[,]`
Transforming columns	`log(data_frame[,"x"])` `sqrt(data_frame[,"x"])`	`log(h2o_frame[,"x"])` `sqrt(h2o_frame[,"x"])`
Building Random Forest	`model = randomForest(y ~ x, data_frame)`	`model = h2o.randomForest(x, y, train_frame)`
Model Prediction	`predict(model, data_frame)`	`h2o.predict(model, h2o_frame)`
Model Metrics	`performance(model)` `auc(model)`	`metrics = model.model_performance(frame)` `h2o.auc(model)`

Python Interface Overview

Action	Pandas or scikit-learn	H2O
Reading data	`pandas.read_csv(data_path)`	`h2o.import_file(data_path)`
Summarizing data	`pandas_frame.describe()`	`h2o_frame.describe()`
Summary statistics	`pandas_frame.mean()`	`h2o_frame.mean()`
Combining rows	`pandas.concat(list[frame1,frame2])`	`h2o_frame.rbind(h2o_frame2)`
Combining columns	`pandas.concat(list[frame1,frame2],axis = 1)`	`h2o_frame.cbind(h2o_frame2)`
Data selection	`pandas_frame[:, :]`	`h2o_frame[:, :]`
Transforming columns	`np.log(pandas_frame[x])` `np.sqrt(pandas_frame[x])`	`h2o_frame[x].log()` `h2o_frame[x].sqrt()`
Building Random Forest	`model = RandomForestClassifier(n_estimators = 100)` `model = model.fit(x_frame, y_frame)`	`model = H2ORandomForestClassifier(n_trees = 100)` `model = model.train(x, y, train_frame)`
Model Prediction	`model.predict`	`model.predict`
Model Metrics	`metrics.auc`	`metrics = model.model_performance(frame)` `metrics.auc()`

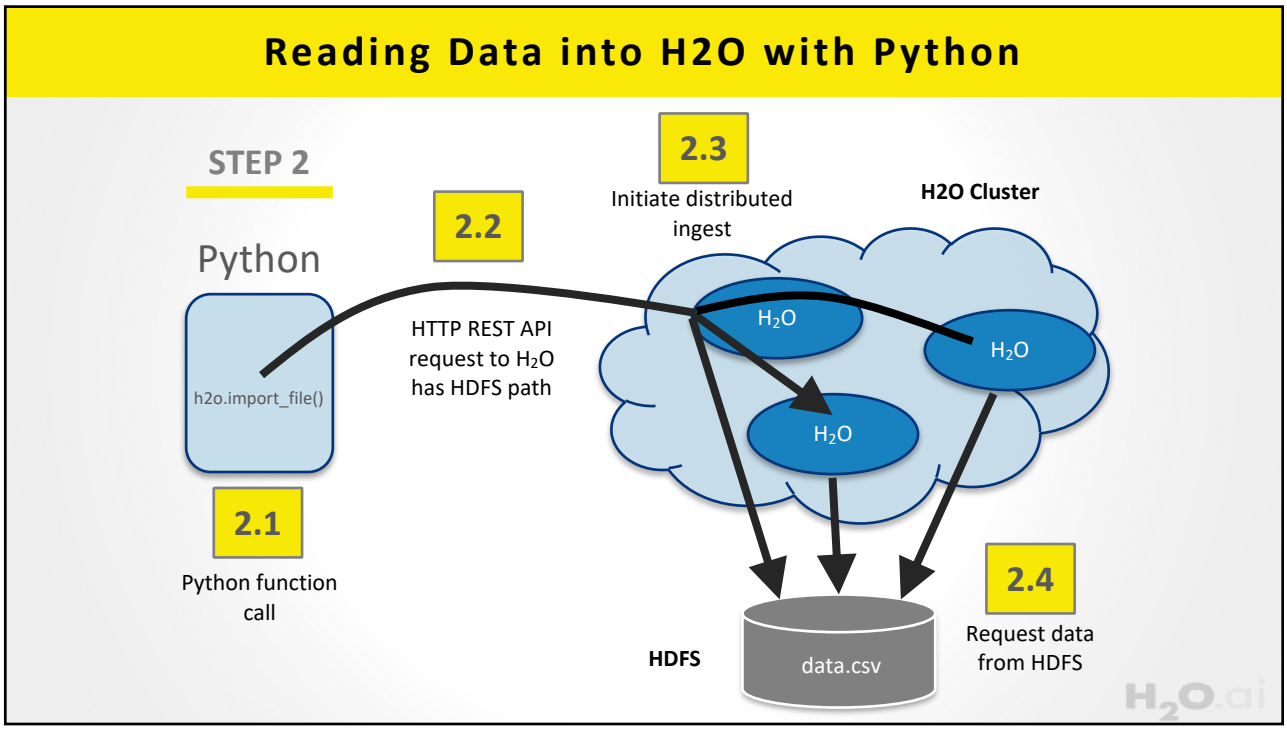
Reading Data into H2O with Python

STEP 1

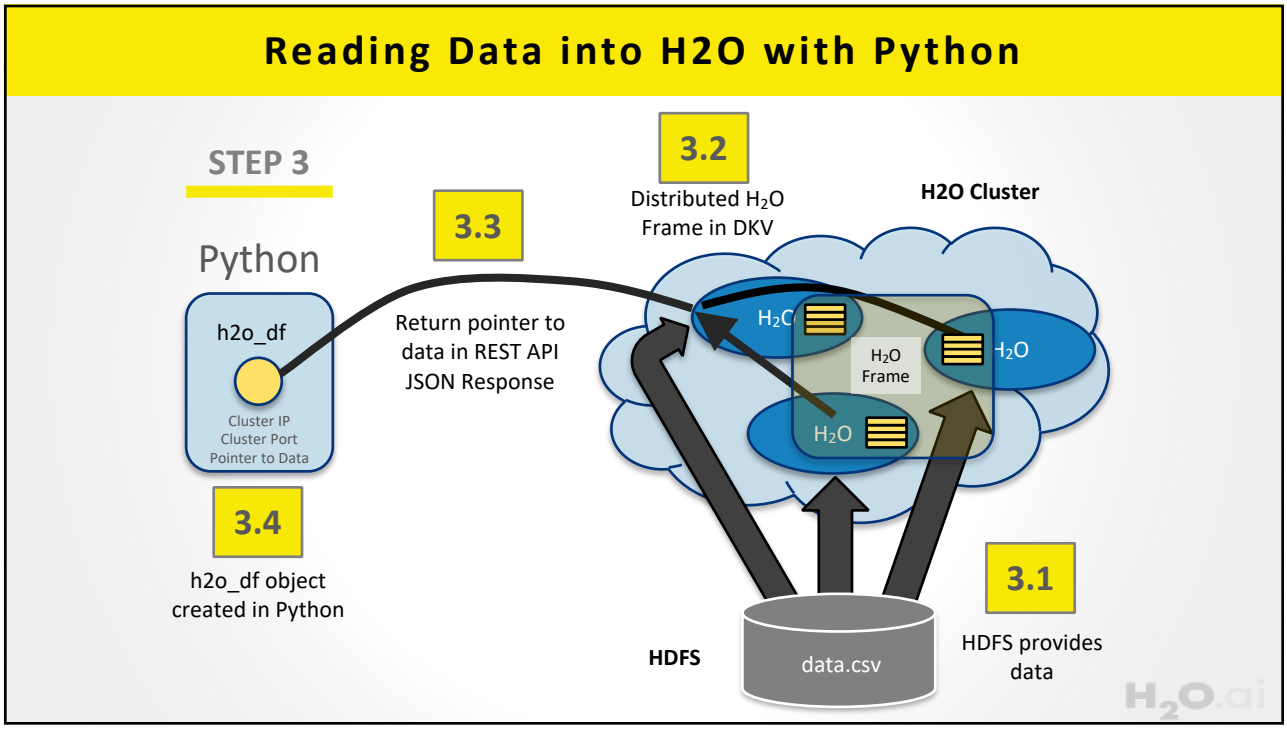
Python user

h2o_df = h2o.import_file("../data/allyears2k.csv")

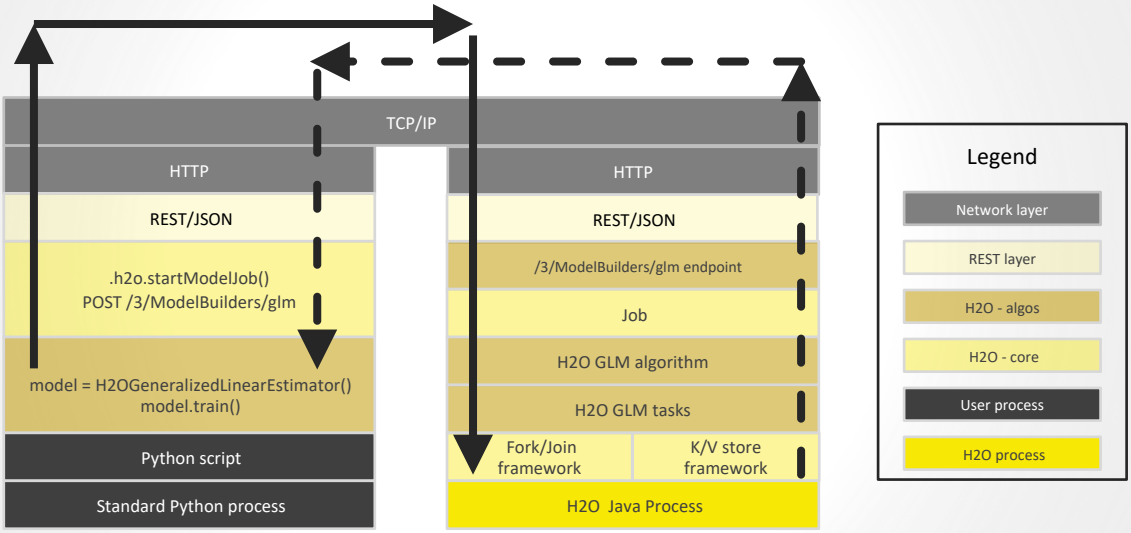
Reading Data into H2O with Python



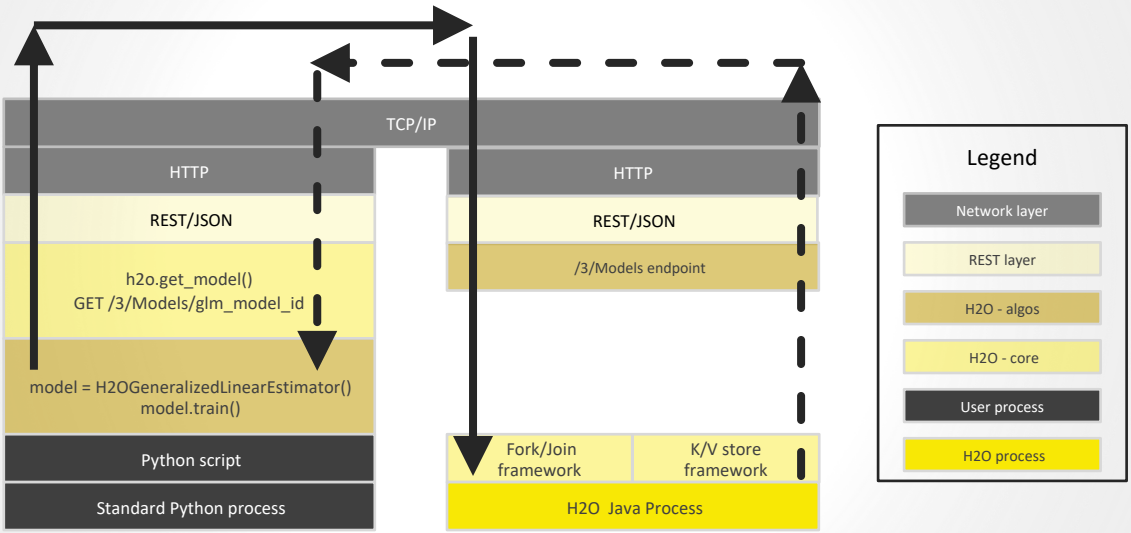
Reading Data into H2O with Python



Training GLM from Python



Retrieving GLM Result from Python



H2O Training

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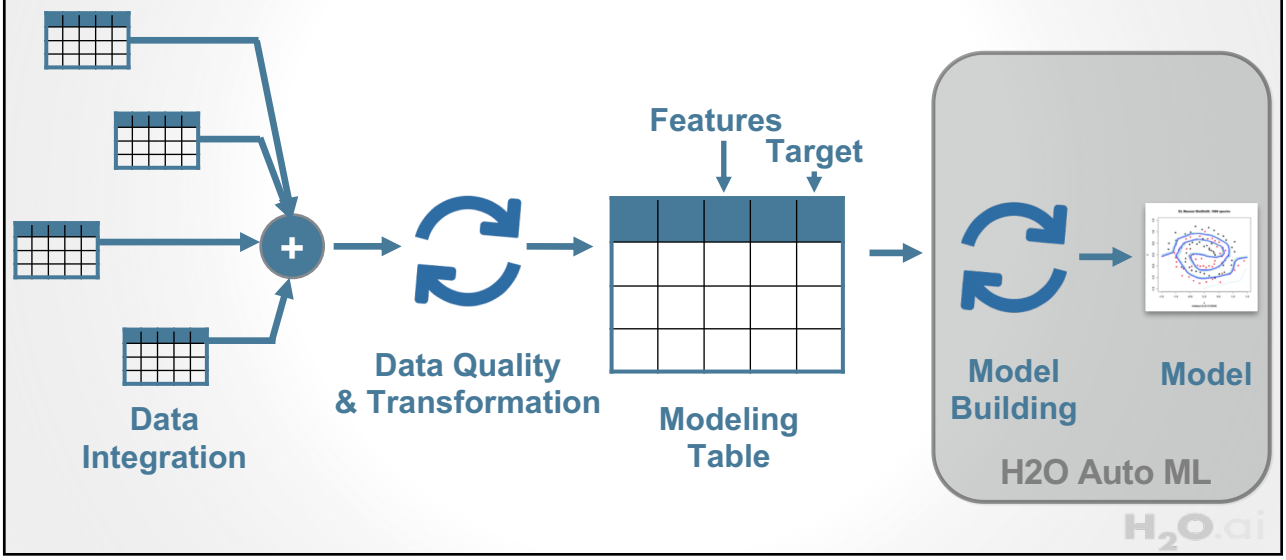
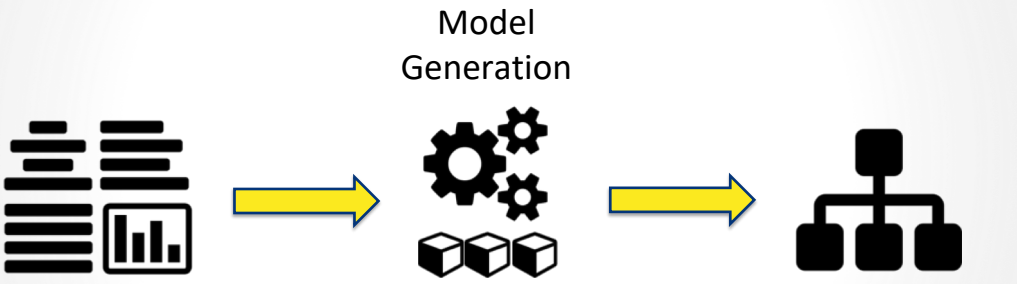
4. Sparkling Water

H2O Auto ML in Typical Enterprise Workflow



H2O Auto ML Pipeline



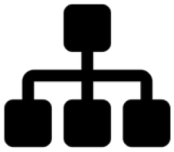
H2O AutoML Light Data Preparation

- Impute missing data
- Standardize numeric features
- One-hot encode categorical features

H2O AutoML Model Generation

- Explore multiple algorithms
  - GLMs, Random Forests, GBMs, Deep Neural Networks
- Perform random grid search over hyper-parameter space
- Use early stopping rules for models and grids

H2O AutoML Stacked Ensemble Creation



- Stacked ensembles of all models
- Stacked ensembles of best model for each algorithm

H2OAutoML R Syntax

```
h2o.automl(x, y,
           training_frame,
           validation_frame = NULL,
           leaderboard_frame = NULL,
           nfolds = 5,
           fold_column = NULL,
           weights_column = NULL,
           max_runtime_secs = 3600,
           max_models = NULL,
           stopping_metric = c("AUTO", "deviance", "logloss", "MSE",
             "RMSE", "MAE", "RMSLE", "AUC", "lift_top_group",
             "misclassification", "mean_per_class_error"),
           stopping_tolerance = NULL,
           stopping_rounds = 3,
           seed = NULL,
           project_name = NULL,
           exclude_algos = NULL)
```

H2OAutoML Python Syntax

```
# Set up automatic machine learning experiment
aml = H2OAutoML(nfolds = 5, max_runtime_secs = 3600, max_models = None,
                stopping_metric = 'AUTO', stopping_tolerance = None,
                stopping_rounds = 3, seed = None, project_name = None,
                exclude_algos = None)
```

```
# Train models
aml.train(x = None, y = None, training_frame = None, fold_column = None,
          weights_column = None, validation_frame = None,
          leaderboard_frame = None)
```

Case Study: Lending Club Dataset

https://github.com/h2oai/h2o-tutorials/blob/master/training/h2o_3_hands_on/automl/lending_club_automl.ipynb

- Loan data from 2007 up until 2015 including rejected applications and accepted applications.
- Of the 500k accepted applicants about 160k loans have either been completely paid off or defaulted.
- There are about 4 million applicants in the rejected loans dataset.
- **Use Case 1**: Predict the likelihood of a user defaulting based on the information supplied when applying for a loan.
- **Use Case 2**: Determine the interest rate Lending Club would have offered the user based on the information supplied when applying for a loan.
- Full Data: https://www.kaggle.com/wendykan/lending-club-loan-data
- H2O Subset: https://s3.amazonaws.com/h2o-public-test-data/bigdata/laptop/lending-club/loan.csv

Case Study: Lending Club Dataset

	Column Name	Description	Unit	Role
1	loan_amnt	Requested loan amount	US dollars	Predictor
2	term	Longest term length	Months	Predictor
✱	**int_term**	**Recommended interest rate**	**Rate**	**Response**
4	emp_length	Employment length	Years	Predictor
5	home_ownership	Housing status	Categorical	Predictor
6	annual_inc	Annual income	US dollars	Predictor
7	purpose	Purpose for the loan	Categorical	Predictor
8	addr_state	State of residence	Categorical	Predictor
9	dti	Debt to income ratio	Percent	Predictor
10	delinq_2yrs	Number of delinquencies in the past 2 years	Count	Predictor
11	revol_util	Revolving credit line utilized	Percent	Predictor
12	total_acc	Number of active accounts	Count	Predictor
⇨	**bad_loan**	**Bad loan indicator**	**Boolean**	**Response**
14	longest_credit_length	Age of oldest active account	Years	Predictor
15	verification_status	Income verification status	Boolean	Predictor

Case Study: Auto ML of Lending Club Dataset

```r
# Load package and connect to cluster
library(h2o)
h2o.init(max_mem_size = "6g")

# Import data and manage data types
train_path <- "https://raw.githubusercontent.com/h2oai/app-consumer-loan/master/data/loan.csv"
train <- h2o.importFile(train_path, destination_frame = "loan_train")
train["bad loan"] = h2o.asfactor(train["bad loan"])

# Set target and predictor variables
y <- "bad_loan"
x <- h2o.colnames(train)
x <- setdiff(x, c (y, "int rate"))

# Use Auto ML to train models
aml <- h2o.automl(x = x, y = y, training_frame = train, max_runtime_secs = 300)
```

Case Study: Auto ML of Lending Club Dataset

```python
# Load package and connect to cluster
import h2o
h2o.init(max_mem_size = "6g")

# Import data and manage data types
train_path = "https://raw.githubusercontent.com/h2oai/app-consumer-loan/master/data/loan.csv"
train = h2o.import_file(train_path, destination_frame = "loan_train")
train["bad loan"] = train["bad loan"].asfactor()

# Set target and predictor variables
y = "bad_loan"
x = train.col_names
x.remove(y)
x.remove("int rate")

# Use Auto ML to train models
from h2o.automl import H2OAutoML
aml = H2OAutoML(max_runtime_secs = 300)
aml.train(x = x, y = y, training_frame = train)
```

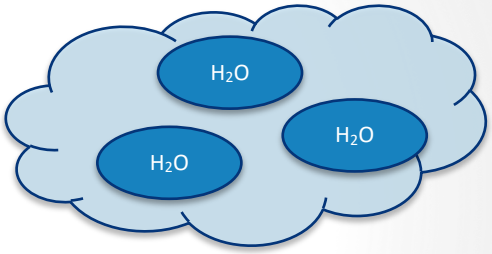
Operationalizing Machine Learning:

PRODUCTIONALIZING MODELS

Productionalizing Models

Immediate Action

- H2O Real-Time (RT) Scoring
  - POJO/MOJO + JRE
  - *Feature engineering not included*



Later Action

- H2O Off-Line (Batch) Scoring
  - H2O Cluster
  - *Feature engineering supported*

R Syntax H2O Scoring

```
# Save Real-Time Scoring Code
h2o.download_pojo(model, path = NULL, get_jar = TRUE, jar_name = "")

h2o.download_mojo(model, path = getwd(), get_genmodel_jar = FALSE,
                  genmodel_name = "")
```

```
# Save / Load Batch Scoring Model
h2o.saveModel(object, path = "", force = FALSE)
model <- h2o.loadModel(path)

# Batch Scoring
h2o.predict(model, newdata, ...)
```

Python Syntax H2O Scoring

```
# Save Real-Time Scoring Code
model.download_pojo(path = u'', get_genmodel_jar = False, genmodel_name = u'')

model.download_mojo(path = u'', get_genmodel_jar = False, genmodel_name = u'')
```

```
# Save / Load Batch Scoring Model
h2o.save_model(model, path = u'', force = False)
model = h2o.load_model(path)

# Batch Scoring
model.predict(test_data, custom_metric = None, custom_metric_func = None)
```

Java Syntax H2O Real-Time Scoring

```
import java.io.*;
import hex.genmodel.easy.RowData;
import hex.genmodel.easy.EasyPredictModelWrapper;
import hex.genmodel.easy.prediction.*;

public class main {
  private static String modelClassName = "model_pojo";
  public static void main(String[] args) throws Exception {
    hex.genmodel.GenModel rawModel;
    rawModel = (hex.genmodel.GenModel)
                  Class.forName(modelClassName).newInstance();
    EasyPredictModelWrapper model = new EasyPredictModelWrapper(rawModel);
    RowData row = new RowData();
    BinomialModelPrediction p = model.predictBinomial(row);
  }
}
```

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H2O Data Munging

- Data Transfer
- H2OFrame Attributes
- Data Column Types
- Row & Columns Selection
- Categorical Data Operations
- Filters & Logical Operations
- Missing Data Handling
- Summary & Aggregation
- Numeric Data Summaries
- Numeric Data Transformations
- Date/Time Manipulations
- String Munging
- Joins Between Two H2OFrames
- Histogram of Numeric Columns

Data Transfer between Python and H2O

`h2o.H2OFrame`

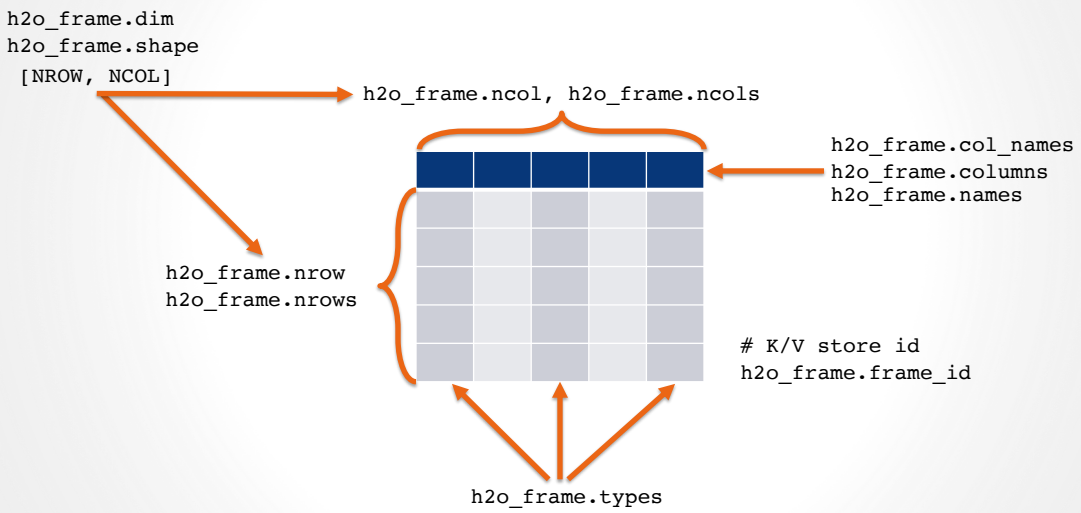
- Turns python pandas frame into an H2OFrame
- Saves dataframe to CSV and then performs `h2o.upload()` to H2O cluster

`h2o.as_list` OR `h2o_frame.as_data_frame`

- Turns H2OFrame to lists of list or pandas frame
- Downloads the H2OFrame locally and will parse with pandas if use_pandas is set to True

Note: Be mindful of `h2o.as_list`, it is difficult to fit a large H2OFrame into a Python session

H2OFrame Attributes



H2O Column Types

Enum

data[x].asfactor()

Used to convert given variable to an enumerated type variable

(booleans are coded as enum)

Numeric

data[x].asnumeric()

Used to convert given variable to an numeric variable

Dates

data[x].year()

Convert the entries of an H2OFrame object from milliseconds to years, indexed starting from 1900.

data[x].month()

Converts the entries of an H2OFrame object from milliseconds to months (on a 1 to 12 scale).

String

data[x].ascharacter()

Used to convert given variable to an string type variable

H2OFrame Example

```
1 import h2o
2 h2o.init()
3 data_path = "https://s3.amazonaws.com/h2o-public-test-data/smalldata/census_income/adult_data.csv"
4 census_data = h2o.import_file(data_path, destination_frame = "census_init")
```

```
Parse progress: |████████████████████████████████████████████████████████| 100%
```

```
1 print(census_data.types)
```

```
{'age': 'int',
 'workclass': 'enum',
 'fnlwgt': 'int',
 'education': 'enum',
 'education-num': 'int',
 'marital-status': 'enum',
 'occupation': 'enum',
 'relationship': 'enum',
 'race': 'enum',
 'sex': 'enum',
 'capital-gain': 'int',
 'capital-loss': 'int',
 'hours-per-week': 'int',
 'native-country': 'enum',
 'income': 'enum'}
```


H2OFrame Example

```
1 census_data[0:5].summary() # census_data[0:5].describe()
```

	age	workclass	fnlwgt	education	education-num
type	int	enum	int	enum	int
mins	17.0		12285.0		1.0
mean	38.581646755321145		189778.36651208595		10.080679340315212
maxs	90.0		1484705.0		16.0
sigma	13.640432553581354		105549.97769702227		2.5727203320673966
zeros	0		0		0
missing	0	1836	0	0	0
0	39.0	State-gov	77516.0	Bachelors	13.0
1	50.0	Self-emp-not-inc	83311.0	Bachelors	13.0
2	38.0	Private	215646.0	HS-grad	9.0
3	53.0	Private	234721.0	11th	7.0

Row & Column Selection

Pandas-like convention for slicing and dicing data

(0-based indexes)

Extracting a single column

- `h2o_frame["x"] # column name x`
- `h2o_frame[2]  # 3rd col`
- `h2o_frame[-2]  # 2nd col from end`
- `h2o_frame[:, -1] # Last column`

Filtering rows

- `h2o_frame[0:5, :]`
- `h2o_frame[h2o_frame["x"] > 1, :]`

Extracting multiple columns

- `h2o_frame[["x","y","z"]]`
- `h2o_frame[[1, 5, 6]]`

Filtering rows for select columns

```
h2o_frame[0:50, [1,2,3]]

med = h2o_frame["a"].median()
h2o_frame[h2o_frame["a"] > med, "z"]
```

Filters & Logical Operations

- Logical Operators
  - `h2o_frame[x].logical_negation()`
  - `h2o_frame[x] & h2o_frame[y]`
  - `h2o_frame[x] | h2o_frame[y]`
- Comparison Operators
  - `h2o_frame[x] {==, !=, <, <=, >=, >} value`
  - `h2o_frame[x] {==, !=, <, <=, >=, >} h2o_frame[y]`
- Logical Data Summaries
  - `h2o_frame[x].all()  # includes NAs`
  - `h2o_frame[x].any()  # includes NAs`
  - `h2o_frame[x].any_na_rm() # disregards NAs`

Filters & Logical Operations

```
test.ifelse(yes, no)
```

Arguments

`test`	A logical description of the condition to be met (>, <, =, etc…)
`yes`	The value to return if the condition is TRUE.
`no`	The value to return if the condition is FALSE.

Equivalent to `[y if t else n for t,y,n in zip(self,yes,no)]`

Note: Only numeric values can be tested, and only numeric results can be returned.

Categorical Data Operations

- Metadata
  - `h2o_frame[x].categories()`
  - `h2o_frame[x].levels()`
  - `h2o_frame[x].nlevels()`
- Categorical Data Manipulation
  - `h2o_frame.relevel(y)`
  - `h2o_frame.set_level(level)`
  - `h2o_frame.set_levels(levels)`

Data Selection Example

```
1 tech_support_income = census_data[census_data["occupation"] == "Tech-support", "income"]
2 print(type(tech_support_income))
```

```
<class 'h2o.frame.H2OFrame'>
```

```
1 print(tech_support_income.table())
```

```
income   Count
 <=50K     645
  >50K     283
```


Missing Data Handling

- Missing Data Code
  - None
- Missing Data Filtering
  - h2o_frame.filter_na_cols(frac=0.2)
  - h2o_frame.na_omit()
- Missing Data Replacement
  - h2o_frame.impute(…)
  - H2OGeneralizedLowRankEstimator
- Missing Data Inclusion
  - h2o_frame.insert_missing_values(fraction=0.1, seed=None)
- Missing Data Summaries
  - h2o_frame.nacnt()

Missing Data Handling

```
h2o_frame.impute(column = 0, method = c("mean", "median",
"mode"), combine_method c("interpolate","average", "lo", "hi"),
by = NULL, groupByFrame = NULL, values = NULL)
```

Arguments

h2o_frame	The dataset containing the column to impute.
column	The column to impute.
method	"mean" replaces NAs with the column mean; "median" replaces NAs with the column median; "mode" replaces with the most common factor (for factor columns only)
combine_method	If method is "median", then choose how to combine quantiles on even sample sizes. This parameter is ignored in all other cases
by	Group by columns
groupByFrame	Impute the column col with this pre-computed grouped frame.
values	A vector of impute values (one per column). NaN indicates to skip the column

Missing Data Handling

```
1 nacnts = dict(zip(census_data.col_names, census_data.nacnt()))
2 print(dict((k, int(v)) for (k, v) in nacnts.items() if v > 0))
```

```
{'workclass': 1836, 'occupation': 1843, 'native-country': 583}
```

```
1 codes = census_data["native-country"].asnumeric()
2 levels = census_data["native-country"].levels()[0]
3 levels.append("Unknown")
4
5 census_data["native-country-clean"] = h2o.H2OFrame.ifelse(codes != None, codes, len(levels))
6 census_data["native-country-clean"] = census_data["native-country-clean"].asfactor()
7 census_data["native-country-clean"] = census_data["native-country-clean"].set_levels(levels)
8
9 print((census_data["native-country-clean"] == "Unknown").table())
```

native-country-clean	Count
0	31978
1	583

Summary & Aggregation

```
h2o_frame[x].table(dense = TRUE)
```

Arguments

h2o_frame	An H2OFrame object with at least one column
x	Column name
dense	A logical for dense representation, which lists only non-zero counts, 1 combination per row. Set to FALSE to expand counts across all combinations.

Value: Returns a tabulated H2OFrame Object

Summary & Aggregation

```
h2o.group_by(data, by, ..., gb.control =
list(na.methods = NULL, col.names = NULL))
```

Arguments

data	an H2OFrame object.
by	a list of column names
gb.control	a list of how to handle NA values in the dataset as well as how to name output columns
. . .	Any supported aggregated function: `mean, min, max, sum, sd, nrow`

Numeric Data Summaries

- h2o_frame[x].cor(y=None, na_rm=False, use=None)
- h2o_frame[x].kurtosis(na_rm=False)
- h2o_frame[x].max()
- h2o_frame[x].mean(skipna=False)
- h2o_frame[x].median(na_rm=False)
- h2o_frame[x].min()
- h2o_frame[x].prod(na_rm=False)
- h2o_frame[x].quantile(…)
- h2o_frame[x].sd(na_rm=False)
- h2o_frame[x].skewness(na_rm=False)
- h2o_frame[x].sum(skipna=True)
- h2o_frame[x].var(y=None, na_rm=False, use=None)

Group By Aggregation

```
1 grouped_data = census_data[["occupation", "education-num"]].group_by(["occupation"])
2 stats = grouped_data.count(na = "ignore").median(na = "ignore").mean(na = "ignore").sd(na = "ignore")
3 stats.get_frame()
```

occupation	nrow	median_education-num	mean_education-num	sdev_education-num
	0	9	9.25339	2.60279
Adm-clerical	3770	10	10.1135	1.69805
Armed-Forces	9	9	10.1111	2.02759
Craft-repair	4099	9	9.11076	2.03865
Exec-managerial	4066	12	11.4491	2.14321
Farming-fishing	994	9	8.60865	2.75607
Handlers-cleaners	1370	9	8.51022	2.20338
Machine-op-inspct	2002	9	8.48751	2.28528
Other-service	3295	9	8.77967	2.29966
Priv-house-serv	149	9	7.36242	3.11104

Cross-Validated Mean Target Encoding

(Feature Engineering Sneak Peak)

```
def mean_target_encoding(data, x, y, fold_column):
    grouped_data = data[[x, fold_column, y]].group_by([x, fold_column])
    grouped_data.sum(na = "ignore").count(na = "ignore")
    df = grouped_data.get_frame().as_data_frame()
    df_list = []
    nfold = int(data[fold_column].max()) + 1
    for j in range(0, nfold):
        te_x = "te_{}".format(x)
        sum_y = "sum_{}".format(y)
        oof = df.loc[df[fold_column] != j, [x, sum_y, "nrow"]]
        stats = oof.groupby([x]).sum()
        stats[x] = stats.index
        stats[fold_column] = j
        stats[te_x] = stats[sum_y] / stats["nrow"]
        df_list.append(stats[[x, fold_column, te_x]])
    return h2o.H2OFrame(pd.concat(df_list))
```

Numeric Data Transformations

- h2o_frame[x].abs()
- h2o_frame[x].acos()
- h2o_frame[x].acosh()
- h2o_frame[x].asin()
- h2o_frame[x].asinh()
- h2o_frame[x].atan()
- h2o_frame[x].atanh()
- h2o_frame[x].ceil()
- h2o_frame[x].cos()
- h2o_frame[x].cosh()
- h2o_frame[x].cospi()
- h2o_frame[x].cut(breaks, …)
- h2o_frame[x].digamma()
- h2o_frame[x].exp()
- h2o_frame[x].expm1()
- h2o_frame[x].floor()
- h2o_frame[x].gamma()
- h2o_frame[x].lgamma()
- h2o_frame[x].log()
- h2o_frame[x].log10()
- h2o_frame[x].log1p()
- h2o_frame[x].log2()
- h2o_frame[x].round(digits=0)
- h2o_frame[x].scale(center=True, scale=True)
- h2o_frame[x].sign()
- h2o_frame[x].signif(digits=6)
- h2o_frame[x].sin()
- h2o_frame[x].sinh()
- h2o_frame[x].sinpi()
- h2o_frame[x].sqrt()
- h2o_frame[x].tan()
- h2o_frame[x].tanh()
- h2o_frame[x].tanpi()
- h2o_frame[x].trigamma()
- h2o_frame[x].trunc()

Numeric Data Transformations

Transformation for skewed data with positive and negative values

pseudoLog10(x) = asinh(x/2) / log(10)

```
1  import math
2
3  def pseudo_log10(x):
4      return math.asinh(x / 2) / math.log(10)
5
6  print("pseudo_log10(\261{}) = \261{:0.6f}".format(100000, pseudo_log10(100000)))
7  print("pseudo_log10(\261{})  = \261{:0.6f}".format(10000, pseudo_log10(10000)))
8  print("pseudo_log10(\261{})   = \261{:0.6f}".format(1000, pseudo_log10(1000)))
9  print("pseudo_log10(\261{})    = \261{:0.6f}".format(100, pseudo_log10(100)))
10 print("pseudo_log10(\261{})     = \261{:0.6f}".format(10, pseudo_log10(10)))
11 print("pseudo_log10(\261{})      = \261{:0.6f}".format(1, pseudo_log10(1)))
12 print("pseudo_log10({})       = {}".format(0, pseudo_log10(0)))
```

```
pseudo_log10(±100000) = ±5.000000
pseudo_log10(±10000)  = ±4.000000
pseudo_log10(±1000)   = ±3.000000
pseudo_log10(±100)    = ±2.000043
pseudo_log10(±10)     = ±1.004279
pseudo_log10(±1)      = ±0.208988
pseudo_log10(0)       = 0.0
```


Numeric Data Transformations

```
1  import numpy as np
2  breaks = np.linspace(10, 90, 9).tolist()
3  census_data["age_group"] = census_data["age"].cut(breaks)
4
5  census_data["log1p_capital-gain"] = census_data["capital-gain"].log1p()
6  census_data["log1p_capital-loss"] = census_data["capital-loss"].log1p()
7  print(census_data["age_group"].table())
```

age_group	Count
(10.0,20.0]	2410
(20.0,30.0]	8162
(30.0,40.0]	8546
(40.0,50.0]	6983
(50.0,60.0]	4128
(60.0,70.0]	1792
(70.0,80.0]	441
(80.0,90.0]	99

Date/Time Manipulations

- Date/Time Creation
  - `h2o_frame[x].as_date(format)`
- Date Extraction
  - `h2o_frame[x].day()`
  - `h2o_frame[x].dayOfWeek()`
  - `h2o_frame[x].month()`
  - `h2o_frame[x].week()`
  - `h2o_frame[x].year()`
- Time Extraction
  - `h2o_frame[x].hour()`
  - `h2o_frame[x].minute()`
  - `h2o_frame[x].second()`

String Munging

- String Matching
  - `h2o_frame[x].countmatches()`
  - `h2o_frame[x].grep()`
  - `h2o_frame[x].match()`
- Substitute pattern match
  - `h2o_frame[x].gsub() # Replace all occurrences`
  - `h2o_frame[x].sub()  # Replace first occurrence`
- String Cleaning
  - `h2o_frame[x].substring()`
  - `h2o_frame[x].strsplit()`
  - `h2o_frame[x].trim()`
  - `h2o_frame[x].lstrip()`
  - `h2o_frame[x].rstrip()`

Joins Between Two H2OFrames

```
h2o_frame.merge(other, all_x=False, all_y=False, by_x=None,
                by_y=None, method='auto')
```

Arguments

h2o_frame	left/self data set in the join.
other	right/other data set in the join.
all_x	If True, include all rows from the left/self frame.
all_y	If True, include all rows from the right/other frame.
by_x	list of columns in the left/self frame to use as a merge key.
by_y	list of columns in the right/other frame to use as a merge key.
method	string representing the merge method, one of auto(default), radix or hash.

Joins Between Two H2OFrames

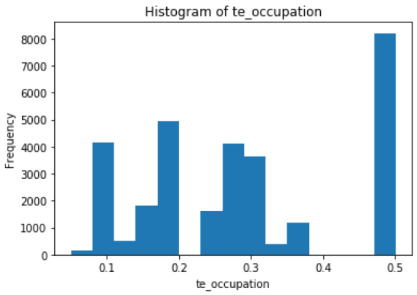
```
1 census_data["cv_fold"] = census_data.kfold_column(n_folds = 5, seed = 123)
2 census_data["high_income"] = census_data["income"] == ">50K"
3 te_occupation = mean_target_encoding(census_data, x = "occupation", y = "high_income",
                                       fold_column = "cv_fold")
```

```
Parse progress: |████████████████████████████████████████████████████████| 100%
```

```
1 census_data = census_data.merge(te_occupation, all_x = True)
```

Histogram of Numeric Columns

```
1 import matplotlib.pyplot as plt
2 %matplotlib inline
3
4 import warnings
5 import matplotlib.cbook
6 warnings.filterwarnings("ignore", category = matplotlib.cbook.mplDeprecation)
7
8 census_data["te_occupation"].hist()
```



Case Study: Lending Club Dataset

- Loan data from 2007 up until 2015 including rejected applications and accepted applications.
- Of the 500k accepted applicants about 160k loans have either been completely paid off or defaulted.
- There are about 4 million applicants in the rejected loans dataset.
- **Use Case 1**: Predict the likelihood of a user defaulting based on the information supplied when applying for a loan.
- **Use Case 2**: Determine the interest rate Lending Club would have offered the user based on the information supplied when applying for a loan.
- Full Data: https://www.kaggle.com/wendykan/lending-club-loan-data
- H2O Subset: https://s3.amazonaws.com/h2o-public-test-data/bigdata/laptop/lending-club/loan.csv

Case Study: Lending Club Dataset

	Column Name	Description	Unit	Role
1	loan_amnt	Requested loan amount	US dollars	Predictor
2	term	Longest term length	Months	Predictor
3	**int_term**	**Recommended interest rate**	**Rate**	**Response**
4	emp_length	Employment length	Years	Predictor
5	home_ownership	Housing status	Categorical	Predictor
6	annual_inc	Annual income	US dollars	Predictor
7	purpose	Purpose for the loan	Categorical	Predictor
8	addr_state	State of residence	Categorical	Predictor
9	dti	Debt to income ratio	Percent	Predictor
10	delinq_2yrs	Number of delinquencies in the past 2 years	Count	Predictor
11	revol_util	Revolving credit line utilized	Percent	Predictor
12	total_acc	Number of active accounts	Count	Predictor
13	**bad_loan**	**Bad loan indicator**	**Boolean**	**Response**
14	longest_credit_length	Age of oldest active account	Years	Predictor
15	verification_status	Income verification status	Boolean	Predictor

Case Study: Lending Club Dataset

Predictor Column Name	Transformation
loan_amnt	Manage high and low amounts
term	Recode as 0/1 binary
emp_length	Create missing value indicator
home_ownership	Combine categories
annual_inc	Manage high and low annual incomes
purpose	Cross-Validated Mean Target Encoding
addr_state	Cross-Validated Mean Target Encoding
dti	Manage high and low debt-to-income ratios
delinq_2yrs	Manage high and low delinquency counts
revol_util	Manage high and low utilization
total_acc	Manage high and low number of accounts
longest_credit_length	Manage high and low credit lengths
verification_status	Recode as 0/1 binary

H2O Training

1. Introduction to ML and H2O
2. H2O Auto Machine Learning
3. H2O Feature Engineering
4. Sparkling Water

H2O.ai

SPARKLING WATER

Why use Sparkling Water?

Spark Cluster — Leverage Spark Cluster

- Launch H2O-3 Machine Learning Engine on top of your Spark Cluster

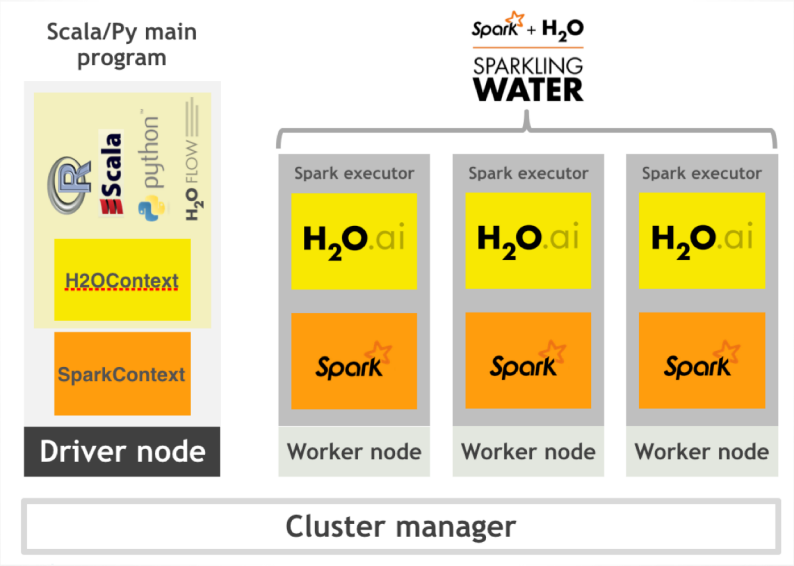
Spark Data Munging — Leverage Spark Data Munging Functionality

- Transparent integration of H2O with Spark ecosystem
- Transparent use of H2O data structures and algorithms with Spark API

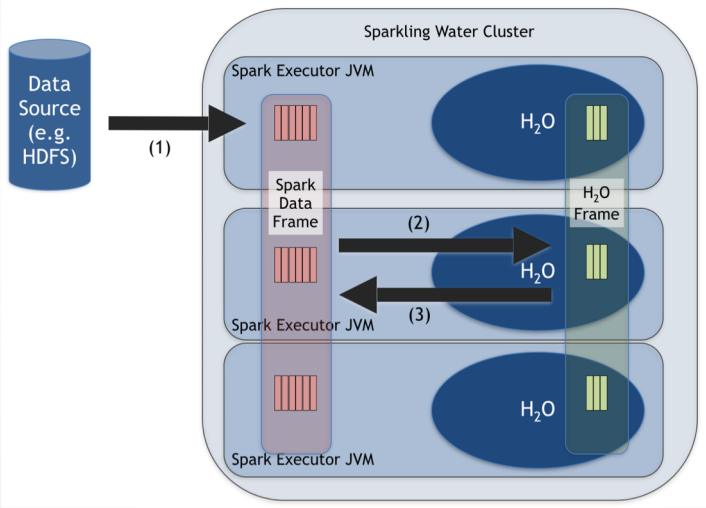
Spark Pipelines — Leverage Spark Pipelines

- Incorporate H2O-3 models into existing Spark pipelines
- Excels in existing Spark workflows requiring advanced Machine Learning algorithms

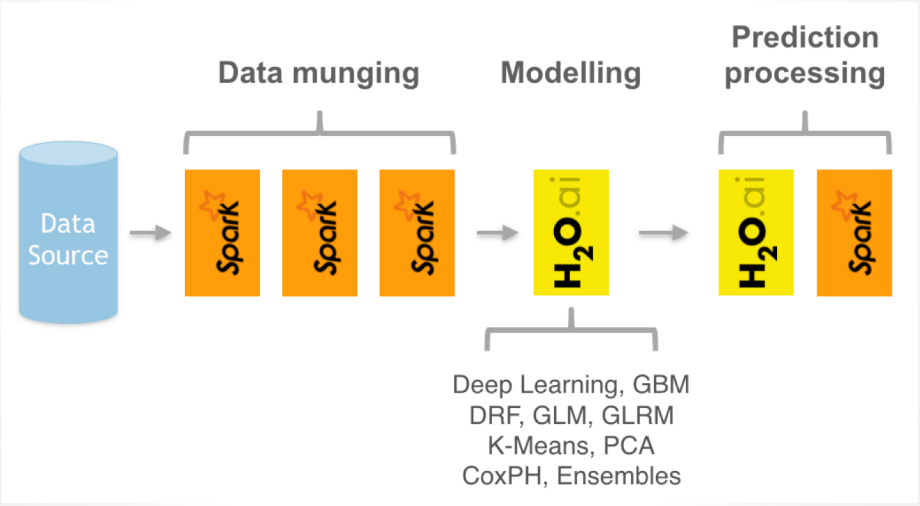
High Level Architecture



Sparkling Water Data Management



Use Case



Sparkling Water Data Conversion Functions

- Converting an H2OFrame into an RDD[T]

  `def asRDD[A <: Product: TypeTag: ClassTag](fr : H2OFrame) : RDD[A]`

- Converting an H2OFrame into a DataFrame

  `def asDataFrame(fr : H2OFrame)(implicit sqlContext: SQLContext) : DataFrame`

- Converting an RDD[T] into an H2OFrame

  `def asH2OFrame[A <: Product : TypeTag](rdd : RDD[A], frameName: Option[String]) : H2OFrame`

- Converting a DataFrame into an H2OFrame

  `def asH2OFrame(rdd : DataFrame, frameName: Option[String]) : H2OFrame`

Washington State Cannabis Sales

https://github.com/h2oai/h2o-tutorials/blob/master/training/sparkling_water_hands_on/time_series/WA_Cannabis_Sales_Daily.ipynb

- Washington State Cannabis Sales
  - Contains: daily sales metrics for different organizations in Washington state
  - Date Range: 2015-11-08 to 2017-03-04
  - Reference: https://data.lcb.wa.gov/dataset/Dashboard-Usable-Sales-w-Weight-Daily/9wz2-qma2
- Questions to answer:
  1. How many previous weeks influence cannabis sales?
  2. What days exhibit unusual sales?
  3. Do stores in counties that voted to legalize marijuana behave differently that those that didn't?

Washington State Cannabis Sales

Column Name	Description
SalesDate	Sales date
Organization	Organization name
County	County name
City	City name
SalesPrice	Transaction sales price
Freq	Number of times transaction occurred

Online Resources

- H2O Tutorials and Training Material
  - https://github.com/h2oai/h2o-tutorials
  - https://github.com/h2oai/h2o-tutorials/tree/master/training/lending_club_exercise
  - https://github.com/h2oai/app-consumer-loan
- Datasets
  - https://s3.amazonaws.com/h2o-public-test-data/bigdata/laptop
  - https://s3.amazonaws.com/h2o-public-test-data/bigdata/laptop/lending-club/loan.csv