

# Machine Learning with Python and H2O

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<http://h2o.ai/resources/>

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Machine Learning with Python and H2O  
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# Introduction

This documentation describes how to use H2O from Python. More information on H2O's system and algorithms (as well as complete Python user documentation) is available at the H2O website at <http://docs.h2o.ai>.

H2O Python uses a REST API to connect to H2O. To use H2O in Python or launch H2O from Python, specify the IP address and port number of the H2O instance in the Python environment. Datasets are not directly transmitted through the REST API. Instead, commands (for example, importing a dataset at specified HDFS location) are sent either through the browser or the REST API to perform the specified task.

The dataset is then assigned an identifier that is used as a reference in commands to the web server. After one prepares the dataset for modeling by defining significant data and removing insignificant data, H2O is used to create a model representing the results of the data analysis. These models are assigned IDs that are used as references in commands.

Depending on the size of your data, H2O can run on your desktop or scale using multiple nodes with Hadoop, an EC2 cluster, or Spark. Hadoop is a scalable open-source file system that uses clusters for distributed storage and dataset processing. H2O nodes run as JVM invocations on Hadoop nodes. For performance reasons, we recommend that you do not run an H2O node on the same hardware as the Hadoop NameNode.

H2O helps Python users make the leap from single machine based processing to large-scale distributed environments. Hadoop lets H2O users scale their data processing capabilities based on their current needs. Using H2O, Python, and Hadoop, you can create a complete end-to-end data analysis solution.

This document describes the four steps of data analysis with H2O:

1. installing H2O
2. preparing your data for modeling
3. creating a model using simple but powerful machine learning algorithms
4. scoring your models

## What is H2O?

H2O.ai is focused on bringing AI to businesses through software. Its flagship product is H2O, the leading open source platform that makes it easy for financial services, insurance companies, and healthcare companies to deploy AI and deep learning to solve complex problems. More than 9,000 organizations and 80,000+ data scientists depend on H2O for critical applications like predictive maintenance and operational intelligence. The company – which was recently named to the CB Insights AI 100 – is used by 169 Fortune 500 enterprises, including 8 of the world's 10 largest banks, 7 of the 10 largest insurance companies, and 4 of the top 10 healthcare companies. Notable customers include Capital One, Progressive Insurance, Transamerica, Comcast, Nielsen Catalina Solutions, Macy's, Walgreens, and Kaiser Permanente.

Using in-memory compression, H2O handles billions of data rows in-memory, even with a small cluster. To make it easier for non-engineers to create complete analytic workflows, H2O's platform includes interfaces for R, Python, Scala, Java, JSON, and CoffeeScript/JavaScript, as well as a built-in web interface, Flow. H2O is designed to run in standalone mode, on Hadoop, or within a Spark Cluster, and typically deploys within minutes.

H2O includes many common machine learning algorithms, such as generalized linear modeling (linear regression, logistic regression, etc.), Naïve Bayes, principal components analysis, k-means clustering, and word2vec. H2O implements best-in-class algorithms at scale, such as distributed random forest, gradient boosting, and deep learning. H2O also includes a Stacked Ensembles method, which finds the optimal combination of a collection of prediction algorithms using a process known as "stacking." With H2O, customers can build thousands of models and compare the results to get the best predictions.

H2O is nurturing a grassroots movement of physicists, mathematicians, and computer scientists to herald the new wave of discovery with data science by collaborating closely with academic researchers and industrial data scientists. Stanford university giants Stephen Boyd, Trevor Hastie, and Rob Tibshirani advise the H2O team on building scalable machine learning algorithms. And with hundreds of meetups over the past several years, H2O continues to remain a word-of-mouth phenomenon.

### Try it out

- Download H2O directly at <http://h2o.ai/download>.
- Install H2O's R package from CRAN at <https://cran.r-project.org/web/packages/h2o/>.

- Install the Python package from PyPI at <https://pypi.python.org/pypi/h2o/>.

### Join the community

- To learn about our training sessions, hackathons, and product updates, visit <http://h2o.ai>.
- To learn about our meetups, visit <https://www.meetup.com/topics/h2o/all/>.
- Have questions? Post them on Stack Overflow using the **h2o** tag at <http://stackoverflow.com/questions/tagged/h2o>.
- Have a Google account (such as Gmail or Google+)? Join the open source community forum at <https://groups.google.com/d/forum/h2ostream>.
- Join the chat at <https://gitter.im/h2oai/h2o-3>.

## Example Code

Python code for the examples in this document is located here:

[https://github.com/h2oai/h2o-3/tree/master/h2o-docs/src/booklets/v2\\_2015/source/Python\\_Vignette\\_code\\_examples](https://github.com/h2oai/h2o-3/tree/master/h2o-docs/src/booklets/v2_2015/source/Python_Vignette_code_examples)

## Citation

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## Installation

H2O requires Java; if you do not already have Java installed, install it from <https://java.com/en/download/> before installing H2O.

The easiest way to directly install H2O is via a Python package.

## Installation in Python

To load a recent H2O package from PyPI, run:

```
pip install h2o
```

To download the latest stable H2O-3 build from the H2O download page:

1. Go to <http://h2o.ai/download>.
2. Choose the latest stable H2O-3 build.
3. Click the "Install in Python" tab.
4. Copy and paste the commands into your Python session.

After H2O is installed, verify the installation:

```
1 import h2o
2
3 # Start H2O on your local machine
4 h2o.init()
5
6 # Get help
7 help(h2o.estimators.glm.H2OGeneralizedLinearEstimator)
8 help(h2o.estimators.gbm.H2OGradientBoostingEstimator)
9
10 # Show a demo
11 h2o.demo("glm")
12 h2o.demo("gbm")
```

## Data Preparation

The next sections of the booklet demonstrate the Python interface using examples, which include short snippets of code and the resulting output.

In H2O, these operations all occur distributed and in parallel and can be used on very large datasets. More information about the Python interface to H2O can be found at [docs.h2o.ai](http://docs.h2o.ai).

Typically, we import and start H2O on the same machine as the running Python process:

```
1 import h2o
2 h2o.init()
```

To connect to an established H2O cluster (in a multi-node Hadoop environment, for example):

```
1 h2o.init(ip="123.45.67.89", port=54321)
```

To create an H2OFrame object from a Python tuple:

```

1 df = h2o.H2OFrame(zip(*((1, 2, 3), ('a', 'b', 'c'), (0.1, 0.2, 0.3))))
2
3 # View the H2OFrame
4 df
5
6 #   C1  C2   C3
7 # --- --- ---
8 #   1  a   0.1
9 #   2  b   0.2
10 #   3  c   0.3
11 #
12 # [3 rows x 3 columns]

```

To create an H2OFrame object from a Python list:

```

1 df = h2o.H2OFrame(zip(*[[1, 2, 3], ['a', 'b', 'c'], [0.1, 0.2, 0.3]]))
2
3 # View the H2OFrame
4 df
5
6 #   C1  C2   C3
7 # --- --- ---
8 #   1  a   0.1
9 #   2  b   0.2
10 #   3  c   0.3
11 #
12 # [3 rows x 3 columns]

```

To create an H2OFrame object from `collections.OrderedDict` or a Python dict:

```

1 df = h2o.H2OFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'c'], 'C': [0.1, 0.2, 0.3]})
2
3 # View the H2OFrame
4 df
5
6 #   A    C  B
7 # --- --- ---
8 #   1  0.1 a
9 #   2  0.2 b
10 #   3  0.3 c
11 #
12 # [3 rows x 3 columns]

```

To create an H2OFrame object from a Python dict and specify the column types:

```

1 df2 = h2o.H2OFrame.from_python({'A': [1, 2, 3],
2                                 'B': ['a', 'a', 'b'],
3                                 'C': ['hello', 'all', 'world'],
4                                 'D': ['12MAR2015:11:00:00', '13MAR2015
5                                       :12:00:00', '14MAR2015:13:00:00']},
6                                 column_types=['numeric', 'enum', 'string', '
7                                 time'])

```



```

8 df2
9
10 #   A   C   B   D
11 # --- ---- - - - -
12 #   1 hello a   1.42618e+12
13 #   2 all  a   1.42627e+12
14 #   3 world b   1.42636e+12
15 #
16 # [3 rows x 4 columns]

```

To display the column types:

```

1 df2.types
2 # {u'A': u'numeric', u'B': u'string', u'C': u'enum', u'D': u'time'}

```

## Viewing Data

To display the top and bottom of an H2OFrame:

```

1 import numpy as np
2 df = h2o.H2OFrame.from_python(np.random.randn(100,4).tolist(), column_names=
3     list('ABCD'))
4 # View top 10 rows of the H2OFrame
5 df.head()
6
7 #           A           B           C           D
8 # -----
9 # -0.613035  -0.425327  -1.92774  -2.1201
10 # -1.26552  -0.241526  -0.0445104  1.90628
11 #  0.763851  0.0391609  -0.500049  0.355561
12 # -1.24842  0.912686  -0.61146  1.94607
13 #  2.1058  -1.83995  0.453875  -1.69911
14 #  1.7635  0.573736  -0.309663  -1.51131
15 # -0.781973  0.051883  -0.403075  0.569406
16 #  1.40085  1.91999  0.514212  -1.47146
17 # -0.746025  -0.632182  1.27455  -1.35006
18 # -1.12065  0.374212  0.232229  -0.602646
19 #
20 # [10 rows x 4 columns]
21
22 # View bottom 5 rows of the H2OFrame
23 df.tail(5)
24
25 #           A           B           C           D
26 # -----
27 #  1.00098  -1.43183  -0.322068  0.374401
28 #  1.16553  -1.23383  -1.71742  1.01035
29 # -1.62351  -1.13907  2.1242  -0.275453
30 # -0.479005  -0.0048988  0.224583  0.219037
31 # -0.74103  1.13485  0.732951  1.70306
32 #
33 # [5 rows x 4 columns]

```

To display the column names:

```
1 df.columns
2 # [u'A', u'B', u'C', u'D']
```

To display compression information, distribution (in multi-machine clusters), and summary statistics of your data:

```
1 df.describe()
2
3 # Rows: 100 Cols: 4
4 #
5 # Chunk compression summary:
6 # chunk_type      chunkname      count      count_%      size      size_%
7 # -----
8 # 64-bit Reals      C8D          4          100          3.4 KB    100
9 #
10 # Frame distribution summary:
11 #              size      #_rows      #_chunks_per_col      #_chunks
12 # -----
13 # 127.0.0.1:54321  3.4 KB    100          1                      4
14 # mean              3.4 KB    100          1                      4
15 # min                3.4 KB    100          1                      4
16 # max                3.4 KB    100          1                      4
17 # stddev              0 B       0            0                      0
18 # total              3.4 KB    100          1                      4
19 #
20 #              A              B              C              D
21 # -----
22 # type            real            real            real            real
23 # mins            -2.49822       -2.37446       -2.45977       -3.48247
24 # mean            -0.01062       -0.23159       0.11423        -0.16228
25 # maxs            2.59380        1.91998        3.13014        2.39057
26 # sigma           1.04354        0.90576        0.96133        1.02608
27 # zeros           0              0              0              0
28 # missing         0              0              0              0
```

## Selection

To select a single column by name, resulting in an H2OFrame:

```
1 df['A']
2
3 #              A
4 # -----
5 # -0.613035
6 # -1.265520
7 #  0.763851
8 # -1.248425
9 #  2.105805
10 #  1.763502
11 # -0.781973
12 #  1.400853
13 # -0.746025
14 # -1.120648
15 #
16 # [100 rows x 1 column]
```

To select a single column by index, resulting in an H2OFrame:

```

1 df[1]
2
3 #           B
4 # -----
5 # -0.425327
6 # -0.241526
7 #  0.039161
8 #  0.912686
9 # -1.839950
10 #  0.573736
11 #  0.051883
12 #  1.919987
13 # -0.632182
14 #  0.374212
15 #
16 # [100 rows x 1 column]

```

To select multiple columns by name, resulting in an H2OFrame:

```

1 df[['B', 'C']]
2
3 #           B           C
4 # -----
5 # -0.425327 -1.927737
6 # -0.241526 -0.044510
7 #  0.039161 -0.500049
8 #  0.912686 -0.611460
9 # -1.839950  0.453875
10 #  0.573736 -0.309663
11 #  0.051883 -0.403075
12 #  1.919987  0.514212
13 # -0.632182  1.274552
14 #  0.374212  0.232229
15 #
16 # [100 rows x 2 columns]

```

To select multiple columns by index, resulting in an H2OFrame:

```

1 df[0:2]
2
3 #           A           B
4 # -----
5 # -0.613035 -0.425327
6 # -1.265520 -0.241526
7 #  0.763851  0.039161
8 # -1.248425  0.912686
9 #  2.105805 -1.839950
10 #  1.763502  0.573736
11 # -0.781973  0.051883
12 #  1.400853  1.919987
13 # -0.746025 -0.632182
14 # -1.120648  0.374212
15 #
16 # [100 rows x 2 columns]

```

To select multiple rows by slicing, resulting in an H2OFrame:

**Note** By default, H2OFrame selection is for columns, so to slice by rows and get all columns, be explicit about selecting all columns:

```

1 df[2:7, :]
2
3 #           A           B           C           D
4 # -----
5 #  1.31828    0.316926    0.970535    0.218061
6 # -0.18547    0.207064    1.3229     -0.432614
7 # -0.424018  -1.72759     0.356871    0.206214
8 #  1.3377     1.10761    -0.280443    0.0964197
9 # -0.385682  0.190449     0.760816    1.92447
10 #
11 # [5 rows x 4 columns]
```

To select rows based on specific criteria, use Boolean masking:

```

1 df2[ df2["B"] == "a", :]
2
3 #   A   C   B           D
4 # --- ---- ---
5 #  1 hello a  1.42618e+12
6 #  2 all  a  1.42627e+12
7 #
8 # [2 rows x 4 columns]
```

## Missing Data

The H2O parser can handle many different representations of missing data types, including '' (blank), 'NA', and None (Python). They are all displayed as nan in Python.

To create an H2OFrame from Python with missing elements:

```

1 df3 = h2o.H2OFrame.from_python(
2     {'A': [1, 2, 3, None, ''],
3      'B': ['a', 'a', 'b', 'NA', 'NA'],
4      'C': ['hello', 'all', 'world', None, None],
5      'D': ['12MAR2015:11:00:00', None,
6           '13MAR2015:12:00:00', None,
7           '14MAR2015:13:00:00']},
8     column_types=['numeric', 'enum', 'string', 'time'])
```

To determine which rows are missing data for a given column ('1' indicates missing):

```

1 df3["A"].isna()
2
3 #   C1
4 # ----
5 #   0
6 #   0
```

```

7 # 0
8 # 1
9 # 1
10 #
11 # [5 rows x 1 column]

```

To change all missing values in a column to a different value:

```
1 df3[df3["A"].isna(), "A"] = 5
```

To determine the location of all missing data in an H2OFrame:

```

1 df3.isna()
2
3 # C1 C2 C3 C4
4 # --- --- --- ---
5 # 0 0 0 0
6 # 0 0 0 1
7 # 0 0 0 0
8 # 0 0 0 1
9 # 0 0 0 0
10 #
11 # [5 rows x 4 columns]

```

## Operations

When performing a descriptive statistic on an entire H2OFrame, missing data is generally excluded and the operation is only performed on the columns of the appropriate data type:

```

1 df4 = h2o.H2OFrame.from_python(
2     {'A': [1, 2, 3, None, ''],
3      'B': ['a', 'a', 'b', 'NA', 'NA'],
4      'C': ['hello', 'all', 'world', None, None],
5      'D': ['12MAR2015:11:00:00', None,
6           '13MAR2015:12:00:00', None,
7           '14MAR2015:13:00:00']},
8     column_types=['numeric', 'enum', 'string', 'time'])
9
10 df4.mean(na_rm=True)
11 # [2.0, nan, nan, nan]

```

When performing a descriptive statistic on a single column of an H2OFrame, missing data is generally *not* excluded:

```

1 df4["A"].mean()
2 # [nan]
3
4 df4["A"].mean(na_rm=True)
5 # [2.0]

```

In both examples, a native Python object is returned (list and float respectively in these examples).

When applying functions to each column of the data, an H2OFrame containing the means of each column is returned:

```

1 df5 = h2o.H2OFrame.from_python(np.random.randn(100,4).tolist(), column_names=
2   list('ABCD'))
3
4 df5.apply(lambda x: x.mean(na_rm=True))
5
6 # H2OFrame:
7 #           A           B           C           D
8 # -----
9 # 0.0304506  0.0334168  -0.0374976  0.0520486
10 #
11 # [1 row x 4 columns]

```

When applying functions to each row of the data, an H2OFrame containing the sum of all columns is returned:

```

1 df5.apply(lambda row: row.sum(), axis=1)
2
3 # H2OFrame:
4 #           C1
5 # -----
6 # -0.388512
7 #  1.67669
8 # -2.56216
9 # -0.277616
10 #  1.13655
11 # -0.575992
12 # -3.49258
13 #  0.776883
14 # -0.778604
15 #  2.30617
16 #
17 # [100 rows x 1 column]

```

H2O provides many methods for histogramming and discretizing data. Here is an example using the `hist` method on a single data frame:

```

1 df6 = h2o.H2OFrame.from_python(np.random.randn(100,1).tolist())
2
3 df6.hist(plot=False)
4
5 # Parse Progress: [#####] 100%
6 #   breaks      counts      mids_true      mids      density
7 # -----
8 # -1.51121         nan         nan         nan         0
9 # -0.868339         9      -1.07704     -1.18977     0.139997
10 # -0.225468        12      -0.73561     -0.546904    0.186663
11 #  0.417403        18      -0.413093     0.0959675    0.279994
12 #  1.06027         26      -0.10108     0.738839     0.404436
13 #  1.70315         22       0.214337     1.38171     0.342215
14 #  2.34602         7       0.607727     2.02458     0.108887
15 #  2.98889         6       0.860969     2.66745     0.0933313
16 #
17 # [8 rows x 5 columns]

```

H2O includes a set of string processing methods in the H2OFrame class that make it easy to operate on each element in an H2OFrame.

To determine the number of times a string is contained in each element:

```

1 df7 = h2o.H2OFrame.from_python(['Hello', 'World', 'Welcome', 'To', 'H2O', '
  World'])
2
3 # View the H2OFrame
4 df7
5
6 # C1      C2      C3      C4      C5      C6
7 # ----  ----  ----  ----  ----  ----
8 # Hello World Welcome To H2O World
9 #
10 # [1 row x 6 columns]
11
12 # Find how many times "l" appears in each string
13 df7.countmatches('l')
14
15 # C1      C2      C3      C4      C5      C6
16 # ----  ----  ----  ----  ----  ----
17 # 2      1      1      0      0      1
18 #
19 # [1 row x 6 columns]

```

To replace the first occurrence of 'l' (lower case letter) with 'x' and return a new H2OFrame:

```

1 df7.sub('l','x')
2
3 # C1      C2      C3      C4      C5      C6
4 # ----  ----  ----  ----  ----  ----
5 # Hexlo Worxd Wexcome To H2O Worxd

```

For global substitution, use `gsub`. Both `sub` and `gsub` support regular expressions.

To split strings based on a regular expression:

```

1 df7.strsplit('(l)+')
2
3 # C1      C2      C3      C4      C5      C6      C7      C8      C9      C10
4 # ----  ----  ----  ----  ----  ----  ----  ----  ----  ----
5 # He   o   Wor  d   We   come To   H2O   Wor  d
6 #
7 # [1 row x 10 columns]

```

## Merging

To combine two H2OFrames together by appending one as rows and return a new H2OFrame:

```

1 # Create a frame of random numbers w/ 100 rows
2 df8 = h2o.H2OFrame.from_python(np.random.randn(100,4).tolist(), column_names=
   list('ABCD'))
3
4 # Create a second frame of random numbers w/ 100 rows
5 df9 = h2o.H2OFrame.from_python(np.random.randn(100,4).tolist(), column_names=
   list('ABCD'))
6
7 # Combine the two frames, adding the rows from df9 to df8
8 df8.rbind(df9)
9
10 #
11 # ----- A ----- B ----- C ----- D -----
12 # 1.11442 1.31272 0.250418 1.73182
13 # -1.61876 0.428622 -1.16684 -0.032936
14 # 0.637249 -0.48904 1.55848 0.669266
15 # 0.00355574 -0.40736 -0.979222 -0.395017
16 # 0.218243 -0.154004 -0.219537 -0.750664
17 # -0.047789 0.306318 0.557441 -0.319108
18 # -1.45013 -0.614564 0.472257 -0.456181
19 # -0.594333 -0.435832 -0.0257311 0.548708
20 # 0.571215 -1.22759 -2.01855 -0.491638
21 # -0.697252 -0.864301 -0.542508 -0.152953
22 #
23 # [200 rows x 4 columns]
```

For successful row binding, the column names and column types between the two H2OFrames must match. To combine two H2O frames together by appending one as columns and return a new H2OFrame:

```

1 df8.cbind(df9)
2
3 #
4 # ----- A ----- B ----- C ----- D ----- A0 ----- B0 ----- C0 ----- D0 -----
5 # -0.09 0.944 0.160 0.271 -0.351 1.66 -2.32 -0.86
6 # -0.95 0.669 0.664 1.535 -0.633 -1.78 0.32 1.27
7 # 0.17 0.657 0.970 -0.419 -1.413 -0.51 0.64 -1.25
8 # 0.58 -0.516 -1.598 -1.346 0.711 1.09 0.05 0.63
9 # 1.04 -0.281 -0.411 0.959 -0.009 -0.47 0.41 -0.52
10 # 0.49 0.170 0.124 -0.170 -0.722 -0.79 -0.91 -2.09
11 # 1.42 -0.409 -0.525 2.155 -0.841 -0.19 0.13 0.63
12 # 0.94 1.192 -1.075 0.017 0.167 0.54 0.52 1.42
13 # -0.53 0.777 -1.090 -2.237 -0.693 0.24 -0.56 1.45
14 # 0.34 -0.456 -1.220 -0.456 -0.315 1.10 1.38 -0.05
15 #
16 # [100 rows x 8 columns]
```



H2O also supports merging two frames together by matching column names:

```

1 df10 = h2o.H2OFrame.from_python( {
2     'A': ['Hello', 'World', 'Welcome', 'To', 'H2O', 'World'],
3     'n': [0,1,2,3,4,5] } )
4
5 # Create a single-column, 100-row frame
6 # Include random integers from 0-5
7 df11 = h2o.H2OFrame.from_python(np.random.randint(0,6,(100,1)), column_names=
8     list('n'))
9
10 # Combine column "n" from both datasets
11 df11.merge(df10)
12
13 #      n A
14 # --- -----
15 #    2 Welcome
16 #    5 World
17 #    4 H2O
18 #    2 Welcome
19 #    3 To
20 #    3 To
21 #    1 World
22 #    1 World
23 #    3 To
24 #    1 World
25 # [100 rows x 2 columns]

```

## Grouping

"Grouping" refers to the following process:

- splitting the data into groups based on some criteria
- applying a function to each group independently
- combining the results into an H2OFrame

To group and then apply a function to the results:

```

1 df12 = h2o.H2OFrame(
2     {'A': ['foo', 'bar', 'foo', 'bar', 'foo', 'bar', 'foo', 'foo'],
3      'B': ['one', 'one', 'two', 'three', 'two', 'two', 'one', 'three'],
4      'C': np.random.randn(8).tolist(),
5      'D': np.random.randn(8).tolist()})
6
7 # View the H2OFrame
8 df12
9
10 #      A          C      B          D
11 # --- -----
12 # foo -0.710095  one    0.253189
13 # bar -0.165891  one   -0.433233
14 # foo -1.51996  two    1.12321
15 # bar  2.25083  three  0.512449
16 # foo -0.618324  two    1.35158
17 # bar  0.0817828 two    0.00830419

```

```

18 # foo 0.634827 one 1.25897
19 # foo 0.879319 three 1.48051
20 #
21 # [8 rows x 4 columns]
22
23 df12.group_by('A').sum().frame
24
25 # A      sum_C      sum_B      sum_D
26 # --- -----
27 # bar 2.16672      3 0.0875206
28 # foo -1.33424      5 5.46746
29 #
30 # [2 rows x 4 columns]

```

To group by multiple columns and then apply a function:

```

1 df13 = df12.group_by(['A', 'B']).sum().frame
2
3 # View the H2OFrame
4 df13
5
6 # A      B      sum_C      sum_D
7 # --- -----
8 # bar one -0.165891 -0.433233
9 # bar three 2.25083 0.512449
10 # bar two 0.0817828 0.00830419
11 # foo one -0.0752683 1.51216
12 # foo three 0.879319 1.48051
13 # foo two -2.13829 2.47479
14 #
15 # [6 rows x 4 columns]

```

Use merge to join the results into the original H2OFrame:

```

1 df12.merge(df13)
2
3 # A      B      C      D      sum_C      sum_D
4 # --- -----
5 # foo one -0.710095 0.253189 -0.0752683 1.51216
6 # bar one -0.165891 -0.433233 -0.165891 -0.433233
7 # foo two -1.51996 1.12321 -2.13829 2.47479
8 # bar three 2.25083 0.512449 2.25083 0.512449
9 # foo two -0.618324 1.35158 -2.13829 2.47479
10 # bar two 0.0817828 0.00830419 0.0817828 0.00830419
11 # foo one 0.634827 1.25897 -0.0752683 1.51216
12 # foo three 0.879319 1.48051 0.879319 1.48051
13 #
14 # [8 rows by 6 columns]

```

## Using Date and Time Data

H2O has powerful features for ingesting and feature engineering using time data. Internally, H2O stores time information as an integer of the number of milliseconds since the epoch.

To ingest time data natively, use one of the supported time input formats:

```

1 df14 = h2o.H2OFrame.from_python(
2     {'D': ['18OCT2015:11:00:00',
3         '19OCT2015:12:00:00',
4         '20OCT2015:13:00:00']},
5     column_types=['time'])
6
7 df14.types
8 # {u'D': u'time'}
```

To display the day of the month:

```

1 df14['D'].day()
2
3 # D
4 # ---
5 # 18
6 # 19
7 # 20
```

To display the day of the week:

```

1 df14['D'].dayOfWeek()
2
3 # D
4 # ---
5 # Sun
6 # Mon
7 # Tue
```

## Categoricals

H2O handles categorical (also known as enumerated or factor) values in an H2OFrame. This is significant because categorical columns have specific treatments in each of the machine learning algorithms.

Using 'df12' from above, H2O imports columns A and B as categorical/enumerated/factor types:

```

1 df12.types
2 # {u'A': u'enum', u'C': u'real', u'B': u'enum', u'D': u'real'}
```

To determine if any column is a categorical/enumerated/factor type:

```

1 df12.anyfactor()
2 # True
```

To view the categorical levels in a single column:

```

1 df12["A"].levels()
2 # ['bar', 'foo']
```

To create categorical interaction features:

```

1 df12.interaction(['A','B'], pairwise=False, max_factors=3, min_occurrence=1)
2
3 # A_B
4 # -----
5 # foo_one
6 # bar_one
7 # foo_two
8 # other
9 # foo_two
10 # other
11 # foo_one
12 # other
13 #
14 # [8 rows x 1 column]
```

To retain the most common categories and set the remaining categories to a common 'Other' category and create an interaction of a categorical column with itself:

```

1 bb_df = df12.interaction(['B','B'], pairwise=False, max_factors=2,
2 min_occurrence=1)
3
4 # View H2OFrame
5 bb_df
6
7 # B_B
8 # ----
9 # one
10 # one
11 # two
12 # other
13 # two
14 # one
15 # other
16 #
17 # [8 rows x 1 column]
```

These can then be added as a new column on the original dataframe:

```

1 df15 = df12.cbind(bb_df)
2
3 # View H2OFrame
4 df15
5
6 # A C B D B_B
7 # --- ----- ---- -
8 # foo -0.809171 one 1.79059 one
9 # bar 0.216644 one 2.88524 one
10 # foo -0.033664 two 0.61205 two
11 # bar 0.985545 three 0.357742 other
12 # foo -2.15563 two 0.0456449 two
13 # bar -0.0170454 two -1.33625 two
14 # foo 1.32524 one 0.308092 one
15 # foo -0.546305 three -0.92675 other
16 #
17 # [8 rows x 5 columns]
```

## Loading and Saving Data

In addition to loading data from Python objects, H2O can load data directly from:

- disk
- network file systems (NFS, S3)
- distributed file systems (HDFS)
- HTTP addresses

H2O currently supports the following file types:

- |                         |        |
|-------------------------|--------|
| • CSV (delimited) files | • ARFF |
| • ORC                   | • XLS  |
| • SVMLite               | • XLSX |
| • Parquet               | • AVRO |

To load data from the same machine running H2O:

```
1 df = h2o.upload_file("/pathToFile/fileName")
```

To load data from the machine(s) running H2O to the machine running Python:

```
1 df = h2o.import_file("/pathToFile/fileName")
```

To save an H2OFrame on the machine running H2O:

```
1 h2o.export_file(df, "/pathToFile/fileName")
```

To save an H2OFrame on the machine running Python:

```
1 h2o.download_csv(df, "/pathToFile/fileName")
```

## Machine Learning

The following sections describe some common model types and features.

### Modeling

The following section describes the features and functions of some common models available in H2O. For more information about running these models in

Python using H2O, refer to the documentation on the H2O.ai website or to the booklets on specific models.

H2O supports the following models:

- Deep Learning
- Naïve Bayes
- Principal Components Analysis (PCA)
- K-means
- Stacked Ensembles
- XGBoost
- Generalized Linear Models (GLM)
- Gradient Boosting Machine (GBM)
- Generalized Low Rank Model (GLRM)
- Distributed Random Forest (DRF)
- Word2vec

The list continues to grow, so check [www.h2o.ai](http://www.h2o.ai) to see the latest additions.

## Supervised Learning

**Generalized Linear Models (GLM):** Provides flexible generalization of ordinary linear regression for response variables with error distribution models other than a Gaussian (normal) distribution. GLM unifies various other statistical models, including Poisson, linear, logistic, and others when using  $\ell_1$  and  $\ell_2$  regularization.

**Distributed Random Forest:** Averages multiple decision trees, each created on different random samples of rows and columns. It is easy to use, non-linear, and provides feedback on the importance of each predictor in the model, making it one of the most robust algorithms for noisy data.

**Gradient Boosting Machine (GBM):** Produces a prediction model in the form of an ensemble of weak prediction models. It builds the model in a stage-wise fashion and is generalized by allowing an arbitrary differentiable loss function. It is one of the most powerful methods available today.

**Deep Learning:** Models high-level abstractions in data by using non-linear transformations in a layer-by-layer method. Deep learning is an example of supervised learning, which can use unlabeled data that other algorithms cannot.

**Naïve Bayes:** Generates a probabilistic classifier that assumes the value of a particular feature is unrelated to the presence or absence of any other feature, given the class variable. It is often used in text categorization.

**Stacked Ensembles:** Using multiple models built from different algorithms, Stacked Ensembles finds the optimal combination of a collection of prediction algorithms using a process known as "stacking."

**XGBoost:** XGBoost is an optimized gradient boosting library that implements machine learning algorithms under the Gradient Boosting Machine (GBM) framework. For many problems, XGBoost is the one of the best GBM frameworks today. In other cases, the H2O GBM algorithm comes out on top. Both implementations are available on the H2O platform.

## Unsupervised Learning

**K-Means:** Reveals groups or clusters of data points for segmentation. It clusters observations into  $k$ -number of points with the nearest mean.

**Principal Component Analysis (PCA):** The algorithm is carried out on a set of possibly collinear features and performs a transformation to produce a new set of uncorrelated features.

**Generalized Low Rank Model (GLRM):** The method reconstructs missing values and identifies important features in heterogeneous data. It also recognizes a number of interpretations of low rank factors, which allows clustering of examples or of features.

**Anomaly Detection:** Identifies the outliers in your data by invoking the deep learning autoencoder, a powerful pattern recognition model.

## Miscellaneous

**Word2vec:** Takes a text corpus as an input and produces the word vectors as output. The result is an H2O Word2vec model that can be exported as a binary model or as a MOJO.

## Running Models

This section describes how to run the following model types:

- Gradient Boosting Machine (GBM)
- Generalized Linear Models (GLM)
- K-means
- Principal Components Analysis (PCA)

This section also shows how to generate predictions.

## Gradient Boosting Machine (GBM)

To generate gradient boosting machine models for creating forward-learning ensembles, use `H2OGradientBoostingEstimator`.

The construction of the estimator defines the parameters of the estimator and the call to `H2OGradientBoostingEstimator.train` trains the estimator on the specified data. This pattern is common for each of the H2O algorithms.

```

1 In [1]: import h2o
2
3 In [2]: h2o.init()
4
5 Checking whether there is an H2O instance running at http://localhost:54321
6 ..... not found.
7 Attempting to start a local H2O server...
8   Java Version: java version "1.8.0_25"; Java(TM) SE Runtime Environment (
9     build 1.8.0_25-b17); Java HotSpot(TM) 64-Bit Server VM (build 25.25-
10    b02, mixed mode)
11   Starting server from /usr/local/h2o_jar/h2o.jar
12   Ice root: /var/folders/yl/cq5nhky53hjcl9wrqxt39kz80000gn/T/tmpHpRzVe
13   JVM stdout: /var/folders/yl/cq5nhky53hjcl9wrqxt39kz80000gn/T/tmpHpRzVe/
14     h2o_techwriter_started_from_python.out
15   JVM stderr: /var/folders/yl/cq5nhky53hjcl9wrqxt39kz80000gn/T/tmpHpRzVe/
16     h2o_techwriter_started_from_python.err
17   Server is running at http://127.0.0.1:54321
18 Connecting to H2O server at http://127.0.0.1:54321 ... successful.
19
20 In [3]: from h2o.estimators.gbm import H2OGradientBoostingEstimator
21
22 In [4]: iris_data_path = "http://h2o-public-test-data.s3.amazonaws.com/
23     smallldata/iris/iris.csv" # load demonstration data
24
25 In [5]: iris_df = h2o.import_file(path=iris_data_path)
26
27 Parse Progress: [#####] 100%
28
29 In [6]: iris_df.describe()
30 Rows:150 Cols:5
31
32 Chunk compression summary:
33 chunktype chunkname count count_% size size_%
34 -----
35 1-Byte Int C1 1 20 218B 18.890
36 1-Byte Flt C2 4 80 936B 81.109
37
38 Frame distribution summary:
39 size rows chunks/col chunks
40 -----
41 127.0.0.1:54321 1.1KB 150 1 5
42 mean 1.1KB 150 1 5
43 min 1.1KB 150 1 5
44 max 1.1KB 150 1 5
45 stddev 0 B 0 0 0
46 total 1.1 KB 150 1 5
47
48 C1 C2 C3 C4 C5
49 -----
50 type real real real real enum

```



```

45 mins      4.3          2.0          1.0          0.1          0.0
46 mean     5.843333333333  3.054        3.75866666667  1.19866666667  NaN
47 maxs     7.9          4.4          6.9          2.5          2.0
48 sigma    0.828066127978  0.433594311362  1.76442041995  0.763160741701  NaN
49 zeros    0            0            0            0            50
50 missing  0            0            0            0            0
51
52
53 In [7]: gbm_regressor = H2OGradientBoostingEstimator(distribution="gaussian",
      ntrees=10, max_depth=3, min_rows=2, learn_rate="0.2")
54
55 In [8]: gbm_regressor.train(x=range(1,iris_df.ncol), y=0, training_frame=
      iris_df)
56
57 gbm Model Build Progress: [#####] 100%
58
59 In [9]: gbm_regressor
60 Out[9]: Model Details
61 =====
62 H2OGradientBoostingEstimator: Gradient Boosting Machine
63 Model Key: GBM_model_python_1446220160417_2
64
65 Model Summary:
66   number_of_trees      |          10
67   model_size_in_bytes  |         1535
68   min_depth            |           3
69   max_depth            |           3
70   mean_depth           |           3
71   min_leaves           |           7
72   max_leaves           |           8
73   mean_leaves          |          7.8
74
75 ModelMetricsRegression: gbm
76 ** Reported on train data. **
77
78 MSE: 0.0706936802293
79 RMSE: 0.265882831769
80 MAE: 0.219981056849
81 RMSLE: 0.0391855537448
82 Mean Residual Deviance: 0.0706936802293
83
84 Scoring History:
85   timestamp          duration    number_of_trees    training_MSE
86   training_deviance
87   -----
88   2015-10-30 08:50:00  0.121 sec    1          0.472445
89   2015-10-30 08:50:00  0.151 sec    2          0.334868
90   2015-10-30 08:50:00  0.162 sec    3          0.242847
91   2015-10-30 08:50:00  0.175 sec    4          0.184128
92   2015-10-30 08:50:00  0.187 sec    5          0.14365
93   2015-10-30 08:50:00  0.197 sec    6          0.116814
94   2015-10-30 08:50:00  0.208 sec    7          0.0992098
95   2015-10-30 08:50:00  0.219 sec    8          0.0864125

```

```

95      2015-10-30 08:50:00 0.229 sec  9          0.077629
96      2015-10-30 08:50:00 0.238 sec  10         0.0706937
97
98 Variable Importances:
99 variable      relative_importance      scaled_importance      percentage
100 -----
101 C3             227.562                    1                      0.894699
102 C2             15.1912                   0.0667563             0.0597268
103 C5             9.50362                   0.0417627             0.037365
104 C4             2.08799                   0.00917544            0.00820926
    
```

To generate a classification model that uses labels,  
use `distribution="multinomial"`:

```

1 In [10]: gbm_classifier = H2OGradientBoostingEstimator(distribution="
2           multinomial", ntrees=10, max_depth=3, min_rows=2, learn_rate="0.2")
3
4 In [11]: gbm_classifier.train(x=range(0,iris_df.ncol-1), y=iris_df.ncol-1,
5           training_frame=iris_df)
6
7 gbm Model Build Progress: [#####] 100%
8
9 In [12]: gbm_classifier
10 Out[12]: Model Details
11 =====
12 H2OGradientBoostingEstimator : Gradient Boosting Machine
13 Model Key:  GBM_model_python_1446220160417_4
14
15 Model Summary:
16
17   number_of_trees      model_size_in_bytes      min_depth      max_depth
18   mean_depth      min_leaves      max_leaves      mean_leaves
19 --- -----
20
21   30             3933            1            3
22   2.93333            2            8            5.86667
23
24 ModelMetricsMultinomial: gbm
25 ** Reported on train data. **
26
27 MSE: 0.00976685303214
28 RMSE: 0.0988273900907
29 LogLoss: 0.0782480973696
30 Mean Per-Class Error: 0.00666666666667
31 Confusion Matrix: vertical: actual; across: predicted
32
33 Iris-setosa      Iris-versicolor      Iris-virginica      Error      Rate
34 -----
35 50              0                    0                0          0 / 50
36 0               49                    1                0.02       1 / 50
37 0               0                    50               0          0 / 50
38 50              49                    51               0.00666667 1 / 150
39
40 Top-3 Hit Ratios:
41 k      hit_ratio
42 --- -----
43 1      0.993333
44 2      1
45 3      1
    
```

```

41 Scoring History:
42
43   timestamp                duration    number_of_trees    training_MSE
44   training_logloss        training_classification_error
45 -----
46 2015-10-30 08:51:52    0.047 sec    1                0.282326
47   0.758411                0.0266667
48 2015-10-30 08:51:52    0.068 sec    2                0.179214
49   0.550506                0.0266667
50 2015-10-30 08:51:52    0.086 sec    3                0.114954
51   0.412173                0.0266667
52 2015-10-30 08:51:52    0.100 sec    4                0.0744726
53   0.313539                0.02
54 2015-10-30 08:51:52    0.112 sec    5                0.0498319
55   0.243514                0.02
56 2015-10-30 08:51:52    0.131 sec    6                0.0340885
57   0.19091                0.00666667
58 2015-10-30 08:51:52    0.143 sec    7                0.0241071
59   0.151394                0.00666667
60 2015-10-30 08:51:52    0.153 sec    8                0.017606
61   0.120882                0.00666667
62 2015-10-30 08:51:52    0.165 sec    9                0.0131024
63   0.0975897                0.00666667
64 2015-10-30 08:51:52    0.180 sec    10               0.00976685
65   0.0782481                0.00666667
66
67 Variable Importances:
68 variable    relative_importance    scaled_importance    percentage
69 -----
70 C4          192.761                1                    0.774374
71 C3          54.0381                0.280338             0.217086
72 C1          1.35271                0.00701757           0.00543422
73 C2          0.773032                0.00401032           0.00310549

```

## Generalized Linear Models (GLM)

Generalized linear models (GLM) are some of the most commonly-used models for many types of data analysis use cases. While some data can be analyzed using linear models, linear models may not be as accurate if the variables are more complex. For example, if the dependent variable has a non-continuous distribution or if the effect of the predictors is not linear, generalized linear models will produce more accurate results than linear models.

Generalized Linear Models (GLM) estimate regression models for outcomes following exponential distributions in general. In addition to the Gaussian (i.e. normal) distribution, these include Poisson, binomial, gamma and Tweedie distributions. Each serves a different purpose and, depending on distribution and link function choice, it can be used either for prediction or classification.

H2O's GLM algorithm fits the generalized linear model with elastic net penalties. The model fitting computation is distributed, extremely fast, and scales extremely

well for models with a limited number ( $\sim$  low thousands) of predictors with non-zero coefficients.

The algorithm can compute models for a single value of a penalty argument or the full regularization path, similar to `glmnet`. It can compute Gaussian (linear), logistic, Poisson, and gamma regression models. To generate a generalized linear model for developing linear models for exponential distributions, use `H2OGeneralizedLinearEstimator`. You can apply regularization to the model by adjusting the `lambda` and `alpha` parameters.

```

1 In [13]: from h2o.estimators.glm import H2OGeneralizedLinearEstimator
2
3 In [14]: prostate_data_path = "http://h2o-public-test-data.s3.amazonaws.com/
4         smalldata/prostate/prostate.csv"
5
6 In [15]: prostate_df = h2o.import_file(path=prostate_data_path)
7
8 Parse Progress: [#####] 100%
9
10 In [16]: prostate_df["RACE"] = prostate_df["RACE"].asfactor()
11
12 In [17]: prostate_df.describe()
13 Rows:380 Cols:9
14
15 Chunk compression summary:
16
17 chunk_type    chunk_name                count    count_percentage    size
18   size_percentage
19 -----
20 CBS           Bits                                1         11.1111              118 B
21   1.39381
22 C1N           1-Byte Integers (w/o NAs)           5         55.5556              2.2 KB
23   26.4588
24 C2           2-Byte Integers                     1         11.1111              828 B
25   9.7803
26 CUD           Unique Reals                         1         11.1111              2.1 KB
27   25.6556
28 C8D           64-bit Reals                        1         11.1111              3.0 KB
29   36.7116
30
31 Frame distribution summary:
32
33 size    number_of_rows    number_of_chunks_per_column
34   number_of_chunks
35 -----
36 127.0.0.1:54321  8.3 KB  380                1                9
37 mean            8.3 KB  380                1                9
38 min             8.3 KB  380                1                9
39 max             8.3 KB  380                1                9
40 stddev          0 B     0                  0                0
41 total           8.3 KB  380                1                9
42
43
44 In [18]: glm_classifier = H2OGeneralizedLinearEstimator(family="binomial",
45               nfolds=10, alpha=0.5)
46
47 In [19]: glm_classifier.train(x=["AGE", "RACE", "PSA", "DCAPS"], y="CAPSULE",
48               training_frame=prostate_df)

```

```

38
39 glm Model Build Progress: [#####] 100%
40
41 In [20]: glm_classifier
42 Out[20]: Model Details
43 =====
44 H2OGeneralizedLinearEstimator : Generalized Linear Model
45 Model Key: GLM_model_python_1446220160417_6
46
47 GLM Model: summary
48
49     family    link    regularization
50     number_of_predictors_total    number_of_active_predictors
51     number_of_iterations    training_frame
52 -----
53
54     binomial  logit    Elastic Net (alpha = 0.5, lambda = 3.251E-4 ) 6
55                                     6
56                                     py_3
57
58 ModelMetricsBinomialGLM: glm
59 ** Reported on train data. **
60
61 MSE: 0.202442565125
62 RMSE: 0.449936178947
63 LogLoss: 0.591121990582
64 Null degrees of freedom: 379
65 Residual degrees of freedom: 374
66 Null deviance: 512.288840185
67 Residual deviance: 449.252712842
68 AIC: 461.252712842
69 AUC: 0.718954248366
70 Gini: 0.437908496732
71
72 Confusion Matrix (Act/Pred) for max f1 @ threshold = 0.282384349078:
73
74     0    1    Error    Rate
75 -----
76 0    80   147   0.6476   (147.0/227.0)
77 1    19   134   0.1242   (19.0/153.0)
78 Total 99   281   0.4368   (166.0/380.0)
79
80 Maximum Metrics: Maximum metrics at their respective thresholds
81
82 metric                threshold    value    idx
83 -----
84 max f1                0.282384    0.617849    276
85 max f2                0.198777    0.77823    360
86 max f0point5         0.415125    0.636672    108
87 max accuracy         0.415125    0.705263    108
88 max precision        0.998613    1    0
89 max recall           0.198777    1    360
90 max specificity       0.998613    1    0
91 max absolute_mcc     0.415125    0.369123    108
92 max min_per_class_accuracy 0.332648    0.656388    175
93 max mean_per_class_accuracy 0.377454    0.67326    123
94
95 Gains/Lift Table: Avg response rate: 40.26 %
96
97 ModelMetricsBinomialGLM: glm
98 ** Reported on cross-validation data. **
99

```

```

94 MSE: 0.209698776592
95 RMSE: 0.457928789871
96 LogLoss: 0.610086165597
97 Null degrees of freedom: 379
98 Residual degrees of freedom: 374
99 Null deviance: 513.330704712
100 Residual deviance: 463.665485854
101 AIC: 475.665485854
102 AUC: 0.688203622124
103 Gini: 0.376407244249
104 Confusion Matrix (Act/Pred) for max f1 @ threshold = 0.339885371023:
105   0    1  Error  Rate
106 -----
107 0    154  73  0.3216  (73.0/227.0)
108 1     53 100  0.3464  (53.0/153.0)
109 Total 207 173 0.3316  (126.0/380.0)
110 Maximum Metrics: Maximum metrics at their respective thresholds
111
112 metric                threshold      value      idx
113 -----
114 max f1                 0.339885   0.613497  172
115 max f2                 0.172551   0.773509  376
116 max f0point5          0.419649   0.615251  105
117 max accuracy          0.447491   0.692105  93
118 max precision          0.998767   1          0
119 max recall             0.172551   1          376
120 max specificity        0.998767   1          0
121 max absolute_mcc       0.419649   0.338849  105
122 max min_per_class_accuracy 0.339885   0.653595  172
123 max mean_per_class_accuracy 0.339885   0.666004  172
124 Gains/Lift Table: Avg response rate: 40.26 %
125
126
127 Scoring History:
128   timestamp                duration      iteration      log_likelihood      objective
129   -----
130   2016-08-25 12:54:20  0.000 sec  0          256.144
131   0.674064
132   2016-08-25 12:54:20  0.055 sec  1          226.961
133   0.597573
134   2016-08-25 12:54:20  0.092 sec  2          224.728
135   0.591813
136   2016-08-25 12:54:20  0.125 sec  3          224.627
137   0.591578
138   2016-08-25 12:54:20  0.157 sec  4          224.626
139   0.591578

```

## K-means

To generate a K-means model for data characterization, use `h2o.kmeans()`. This algorithm does not require a dependent variable.

```

1 In [21]: from h2o.estimators.kmeans import H2OKMeansEstimator
2
3 In [22]: cluster_estimator = H2OKMeansEstimator(k=3)
4
5 In [23]: cluster_estimator.train(x=[0,1,2,3], training_frame=iris_df)

```

```

6
7 kmeans Model Build Progress: [#####] 100%
8
9 In [24]: cluster_estimator
10 Out[24]: Model Details
11 =====
12 H2OKMeansEstimator : K-means
13 Model Key: K-means_model_python_1446220160417_8
14
15 Model Summary:
16   number_of_rows  number_of_clusters  number_of_categorical_columns
17   number_of_iterations  within_cluster_sum_of_squares
18   total_sum_of_squares  between_cluster_sum_of_squares
19 -----
20 -----
21 150                3                190.757                0
22   4                                405.243                596
23
24 ModelMetricsClustering: kmeans
25 ** Reported on train data. **
26
27 MSE: NaN
28 RMSE: NaN
29 Total Within Cluster Sum of Square Error: 190.756926265
30 Total Sum of Square Error to Grand Mean: 596.0
31 Between Cluster Sum of Square Error: 405.243073735
32
33 Centroid Statistics:
34   centroid  size  within_cluster_sum_of_squares
35 -----
36 1          96  149.733
37 2          32  17.292
38 3          22  23.7318
39
40 Scoring History:
41   timestamp  duration  iteration  avg_change_of_std_centroids
42   within_cluster_sum_of_squares
43 -----
44 2016-08-25 13:03:36 0.005 sec 0  nan
45   385.505
46 2016-08-25 13:03:36 0.029 sec 1  1.37093
47   173.769
48 2016-08-25 13:03:36 0.029 sec 2  0.184617
49   141.623
50 2016-08-25 13:03:36 0.030 sec 3  0.00705735
51   140.355
52 2016-08-25 13:03:36 0.030 sec 4  0.00122272
53   140.162
54 2016-08-25 13:03:36 0.031 sec 5  0.000263918
55   140.072
56 2016-08-25 13:03:36 0.031 sec 6  0.000306555
57   140.026

```

## Principal Components Analysis (PCA)

To map a set of variables onto a subspace using linear transformations, use `H2OPrincipalComponentAnalysisEstimator`. This is the first step in Principal Components Regression.

```

1 In [25]: from h2o.estimators.pca import
          H2OPrincipalComponentAnalysisEstimator
2
3 In [26]: pca_decomp = H2OPrincipalComponentAnalysisEstimator(k=2, transform="
          NONE", pca_method="Power", impute_missing=True)
4
5 In [27]: pca_decomp.train(x=range(0,4), training_frame=iris_df)
6
7 pca Model Build Progress: [#####] 100%
8
9 In [28]: pca_decomp
10 Out[28]: Model Details
11 =====
12 H2OPCA : Principal Component Analysis
13 Model Key: PCA_model_python_1446220160417_10
14
15 ModelMetricsPCA: pca
16 ** Reported on train data. **
17
18 MSE: NaN
19 RMSE: NaN
20
21 Scoring History from Power SVD:
22 timestamp          duration    iterations    err
23 -----
24 2018-01-18 08:35:44 0.002 sec    0          29.6462    1
25 2018-01-18 08:35:44 0.002 sec    1          0.733806   1
26 2018-01-18 08:35:44 0.002 sec    2          0.0249718  1
27 2018-01-18 08:35:44 0.002 sec    3          0.000851969 1
28 2018-01-18 08:35:44 0.002 sec    4          2.90753e-05 1
29 2018-01-18 08:35:44 0.002 sec    5          1.3487e-06  1
30 2018-01-18 08:35:44 0.002 sec    6          nan         1
31 2018-01-18 08:35:44 0.003 sec    7          1.02322    2
32 2018-01-18 08:35:44 0.003 sec    8          0.0445794  2
33 2018-01-18 08:35:44 0.003 sec    9          0.00164307 2
34 2018-01-18 08:35:44 0.003 sec   10          6.27379e-05 2
35 2018-01-18 08:35:44 0.003 sec   11          2.40329e-06 2
36 2018-01-18 08:35:44 0.003 sec   12          9.88431e-08 2
37 2018-01-18 08:35:44 0.003 sec   13          nan         2
38 <bound method H2OPrincipalComponentAnalysisEstimator.train of >
39
40 In [29]: pred = pca_decomp.predict(iris_df)
41
42 pca prediction progress: [#####] 100%
43
44 In [30]: pred.head() # Projection results
45 Out[30]:
46      PC1      PC2
47 -----
48 -5.9122  2.30344
49 -5.57208 1.97383
50 -5.44648 2.09653
51 -5.43602 1.87168

```



```

52 -5.87507 2.32935
53 -6.47699 2.32553
54 -5.51543 2.07156
55 -5.85042 2.14948
56 -5.15851 1.77643
57 -5.64458 1.99191

```

## Grid Search

H2O supports grid search across hyperparameters:

```

1 In [32]: ntrees_opt = [5, 10, 15]
2
3 In [33]: max_depth_opt = [2, 3, 4]
4
5 In [34]: learn_rate_opt = [0.1, 0.2]
6
7 In [35]: hyper_parameters = {"ntrees": ntrees_opt, "max_depth":max_depth_opt,
8     "learn_rate":learn_rate_opt}
9
10 In [36]: from h2o.grid.grid_search import H2OGridSearch
11
12 In [37]: gs = H2OGridSearch(H2OGradientBoostingEstimator(distribution="
13     multinomial"), hyper_params=hyper_parameters)
14
15 In [38]: gs.train(x=range(0,iris_df.ncol-1), y=iris_df.ncol-1, training_frame
16     =iris_df, nfolds=10)
17
18 gbm Grid Build Progress: [#####] 100%
19
20 In [39]: print gs.sort_by('logloss', increasing=True)
21
22 Grid Search Results:
23 Model Id                                Hyperparameters: ['learn_rate', 'ntrees', '
24     max_depth']      logloss
25 -----
26 -----
27 Grid_GBM_model_1446220160417_30  ['0.2, 15, 4']
28                                     0.05105
29 Grid_GBM_model_1446220160417_27  ['0.2, 15, 3']
30                                     0.0551088
31 Grid_GBM_model_1446220160417_24  ['0.2, 15, 2']
32                                     0.0697714
33 Grid_GBM_model_1446220160417_29  ['0.2, 10, 4']
34                                     0.103064
35 Grid_GBM_model_1446220160417_26  ['0.2, 10, 3']
36                                     0.106232
37 Grid_GBM_model_1446220160417_23  ['0.2, 10, 2']
38                                     0.120161
39 Grid_GBM_model_1446220160417_21  ['0.1, 15, 4']
40                                     0.170086
41 Grid_GBM_model_1446220160417_18  ['0.1, 15, 3']
42                                     0.171218
43 Grid_GBM_model_1446220160417_15  ['0.1, 15, 2']
44                                     0.181186
45 Grid_GBM_model_1446220160417_28  ['0.2, 5, 4']
46                                     0.275788
47 Grid_GBM_model_1446220160417_25  ['0.2, 5, 3']
48                                     0.27708

```

33	Grid_GBM_model_1446220160417_22	['0.2, 5, 2']	0.280413
34	Grid_GBM_model_1446220160417_20	['0.1, 10, 4']	0.28759
35	Grid_GBM_model_1446220160417_17	['0.1, 10, 3']	0.288293
36	Grid_GBM_model_1446220160417_14	['0.1, 10, 2']	0.292993
37	Grid_GBM_model_1446220160417_16	['0.1, 5, 3']	0.520591
38	Grid_GBM_model_1446220160417_19	['0.1, 5, 4']	0.520697
39	Grid_GBM_model_1446220160417_13	['0.1, 5, 2']	0.524777

## Integration with scikit-learn

The H2O Python client can be used within scikit-learn pipelines and cross-validation searches. This extends the capabilities of both H2O and scikit-learn. Note that the `sklearn` and `scipy` packages are required to use the H2O Python client with scikit-learn.

## Pipelines

To create a scikit-learn style pipeline using H2O transformers and estimators:

```

1 In [41]: from h2o.transforms.preprocessing import H2OScaler
2
3 In [42]: from sklearn.pipeline import Pipeline
4
5 In [44]: # Turn off h2o progress bars
6
7 In [45]: h2o.__PROGRESS_BAR__=False
8
9 In [46]: h2o.no_progress()
10
11 In [47]: # build transformation pipeline using sklearn's Pipeline and H2O
           transforms
12
13 In [48]: pipeline = Pipeline([("standardize", H2OScaler()),
14     ....:                      ("pca", H2OPrincipalComponentAnalysisEstimator(k=2)
15     ....:                      ("gbm", H2OGradientBoostingEstimator(distribution="
           multinomial")))]
16
17 In [49]: pipeline.fit(iris_df[:4],iris_df[4])
18 Out[49]: Model Details
19 =====
20 H2OPCA : Principal Component Analysis
21 Model Key: PCA_model_python_1446220160417_32
22
23 Importance of components:
24 -----
25
```

```

26 Standard deviation      3.22082  0.34891
27 Proportion of Variance 0.984534 0.0115538
28 Cumulative Proportion 0.984534 0.996088
29
30
31 ModelMetricsPCA: pca
32 ** Reported on train data. **
33
34 MSE: NaN
35 RMSE: NaN
36 Model Details
37 =====
38 H2OGradientBoostingEstimator : Gradient Boosting Machine
39 Model Key: GBM_model_python_1446220160417_34
40
41 Model Summary:
42   number_of_trees  number_of_internal_trees  model_size_in_bytes
43   min_depth      max_depth      mean_depth      min_leaves      max_leaves
44   mean_leaves
45 -----
46   50              150              4.84              2              28170              13              1
47   9.97333
48
49 ModelMetricsMultinomial: gbm
50 ** Reported on train data. **
51
52 MSE: 0.00162796447355
53 RMSE: 0.0403480417561
54 LogLoss: 0.0152718656454
55 Mean Per-Class Error: 0.0
56 Confusion Matrix: vertical: actual; across: predicted
57
58 Iris-setosa      Iris-versicolor      Iris-virginica      Error      Rate
59 -----
60 50              0                    0                    0          0 / 50
61 0               50                   0                    0          0 / 50
62 0               0                    50                   0          0 / 50
63 50              50                   50                   0          0 / 150
64
65 Top-3 Hit Ratios:
66 k      hit_ratio
67 ---  -----
68 1      1
69 2      1
70 3      1
71
72 Scoring History:
73   timestamp      duration      number_of_trees      training_rmse
74   training_logloss      training_classification_error
75 -----
76 2016-08-25 13:50:21  0.006 sec  0.0          0.666666666667
77   1.09861228867      0.66
78 2016-08-25 13:50:21  0.077 sec  1.0          0.603019288754
79   0.924249463924      0.04
80 2016-08-25 13:50:21  0.096 sec  2.0          0.545137025745
81   0.788619346614      0.04

```

```

76      2016-08-25 13:50:21 0.110 sec  3.0          0.492902188607
          0.679995476522      0.04
77      2016-08-25 13:50:21 0.123 sec  4.0          0.446151758168
          0.591313596193      0.04
78 --- --- --- --- --- ---
79      2016-08-25 13:50:21 0.419 sec  46.0         0.0489303232171
          0.0192767805328      0.0
80      2016-08-25 13:50:21 0.424 sec  47.0         0.0462779490149
          0.0180720396825      0.0
81      2016-08-25 13:50:21 0.429 sec  48.0         0.0444689238255
          0.0171428314531      0.0
82      2016-08-25 13:50:21 0.434 sec  49.0         0.0423442541538
          0.0161938230172      0.0
83      2016-08-25 13:50:21 0.438 sec  50.0         0.0403480417561
          0.0152718656454      0.0
84
85 Variable Importances:
86 variable      relative_importance      scaled_importance      percentage
87 -----
88 PC1            448.958                1                0.982184
89 PC2            8.1438                0.0181393        0.0178162
90 Pipeline(steps=[('standardize', <h2o.transforms.preprocessing.H2OScaler
          object at 0x1088c6a50>), ('pca', ), ('gbm', )])

```

## Randomized Grid Search

To create a scikit-learn style hyperparameter grid search using k-fold cross validation:

```

1 In [57]: from sklearn.model_selection import RandomizedSearchCV
2
3 In [58]: from h2o.cross_validation import H2OKFold
4
5 In [59]: from h2o.model.regression import h2o_r2_score
6
7 In [60]: from sklearn.metrics.scorer import make_scorer
8
9 # Parameters to test
10 In [61]: params = {"standardize_center": [True, False],
11     ....:          "standardize_scale": [True, False],
12     ....:          "pca_k": [2, 3],
13     ....:          "gbm_ntrees": [10, 20],
14     ....:          "gbm_max_depth": [1, 2, 3],
15     ....:          "gbm_learn_rate": [0.1, 0.2]}
16
17 In [62]: custom_cv = H2OKFold(iris_df, n_folds=5, seed=42)
18
19 In [63]: pipeline = Pipeline([("standardize", H2OScaler()),
20     ....:                      ("pca", H2OPrincipalComponentAnalysisEstimator(
21     ....:                          k=2)),
22     ....:                      ("gbm", H2OGradientBoostingEstimator(
23     ....:                          distribution="gaussian"))])
24
25 In [64]: random_search = RandomizedSearchCV(pipeline, params,
26     ....:                                   n_iter=5,
27     ....:                                   scoring=make_scorer(h2o_r2_score),
28     ....:                                   cv=custom_cv,

```

```

27     ....:                                     random_state=42,
28     ....:                                     n_jobs=1)
29 In [65]: random_search.fit(iris_df[1:], iris_df[0])
30 Out [65]:
31 RandomizedSearchCV(cv=<h2o.cross_validation.H2OKFold instance at 0x10ba413d0
32 >,
33     error_score='raise',
34     estimator=Pipeline(steps=[('standardize', <h2o.transforms.
35     preprocessing.H2OScaler object at 0x10c0f18d0>), ('pca', ), ('
36     gbm', )]),
37     fit_params={}, iid=True, n_iter=5, n_jobs=1,
38     param_distributions={'pca__k': [2, 3], 'gbm__ntrees': [10, 20], '
39     standardize__scale': [True, False], 'gbm__max_depth': [1, 2,
40     3], 'standardize__center': [True, False], 'gbm__learn_rate':
41     [0.1, 0.2]},
42     pre_dispatch='2*n_jobs', random_state=42, refit=True,
43     scoring=make_scorer(h2o_r2_score), verbose=0)
44
45 In [66]: print random_search.best_estimator_
46 Model Details
47 =====
48 H2OPCA : Principal Component Analysis
49 Model Key: PCA_model_python_1446220160417_136
50
51 Importance of components:
52
53 -----
54          pc1          pc2          pc3
55 -----
56 Standard deviation    9.6974    0.091905    0.031356
57 Proportion of Variance 0.9999    8.98098e-05    1.04541e-05
58 Cumulative Proportion 0.9999    0.99999    1
59
60 ModelMetricsPCA: pca
61 ** Reported on train data. **
62
63 MSE: NaN
64 RMSE: NaN
65 Model Details
66 =====
67 H2OGradientBoostingEstimator : Gradient Boosting Machine
68 Model Key: GBM_model_python_1446220160417_138
69
70 Model Summary:
71
72   number_of_trees  number_of_internal_trees  model_size_in_bytes
73   min_depth      max_depth      mean_depth  min_leaves  max_leaves
74   mean_leaves
75 -----
76
77   -----
78
79   20              3              20              3              5              2958              8              3
80
81   6.85
82
83 ModelMetricsRegression: gbm
84 ** Reported on train data. **
85
86 RMSE: 0.193906262445
87 MAE: 0.155086582663
88 RMSLE: NaN
89 Mean Residual Deviance: 0.0375996386155
90 Scoring History:
91
92

```

```

77      timestamp          duration    number_of_trees    training_rmse
78      training_mse      training_deviance
79      -----
80      2016-08-25 13:58:15 0.000 sec  0.0          0.683404046309
81      0.569341466973    0.467041090512
82      2016-08-25 13:58:15 0.002 sec  1.0          0.571086656306
83      0.469106400643    0.326139969011
84      2016-08-25 13:58:15 0.003 sec  2.0          0.483508601652
85      0.395952082872    0.233780567872
86      2016-08-25 13:58:15 0.004 sec  3.0          0.414549015095
87      0.339981133963    0.171850885916
88      2016-08-25 13:58:15 0.005 sec  4.0          0.362852508373
89      0.298212416346    0.131661942833
90      ---
91      2016-08-25 13:58:15 0.017 sec  16.0         0.204549491682
92      0.164292158112    0.0418404945473
93      2016-08-25 13:58:15 0.018 sec  17.0         0.201762323368
94      0.162030458841    0.0407080351307
95      2016-08-25 13:58:15 0.019 sec  18.0         0.199709571992
96      0.160735480674    0.0398839131454
97      2016-08-25 13:58:15 0.019 sec  19.0         0.196739590066
98      0.158067452484    0.0387064662994
99      2016-08-25 13:58:15 0.020 sec  20.0         0.193906262445
100     0.155086582663    0.0375996386155
101
102     Variable Importances:
103     variable      relative_importance    scaled_importance    percentage
104     -----
105     PC1           160.092                1                    0.894701
106     PC3           14.8175                0.0925562           0.08281
107     PC2           4.0241                 0.0251361           0.0224893
108
109     Pipeline(steps=[('standardize', <h2o.transforms.preprocessing.H2OScaler
110     object at 0x10c1679d0>), ('pca', ), ('gbm', )])

```

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