Fast, Distributed Machine Learning for Python using H2O

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WHO AMI I

Lead, Customer Data Science @ H2O.ai

John Deere: Research, Software Product Development, High Tech Ventures

Lots of time dealing with data off of machines, equipment, satellites, weather, radar, hand sampled, and on.

Geospatial, temporal / time series data almost all from sensors.

Previously at startups and consulting (Red Sky Interactive, Nuforia, NetExplorer, Perot Systems, a few of my own)

Engineering & Management MIT
Physics Georgia Tech

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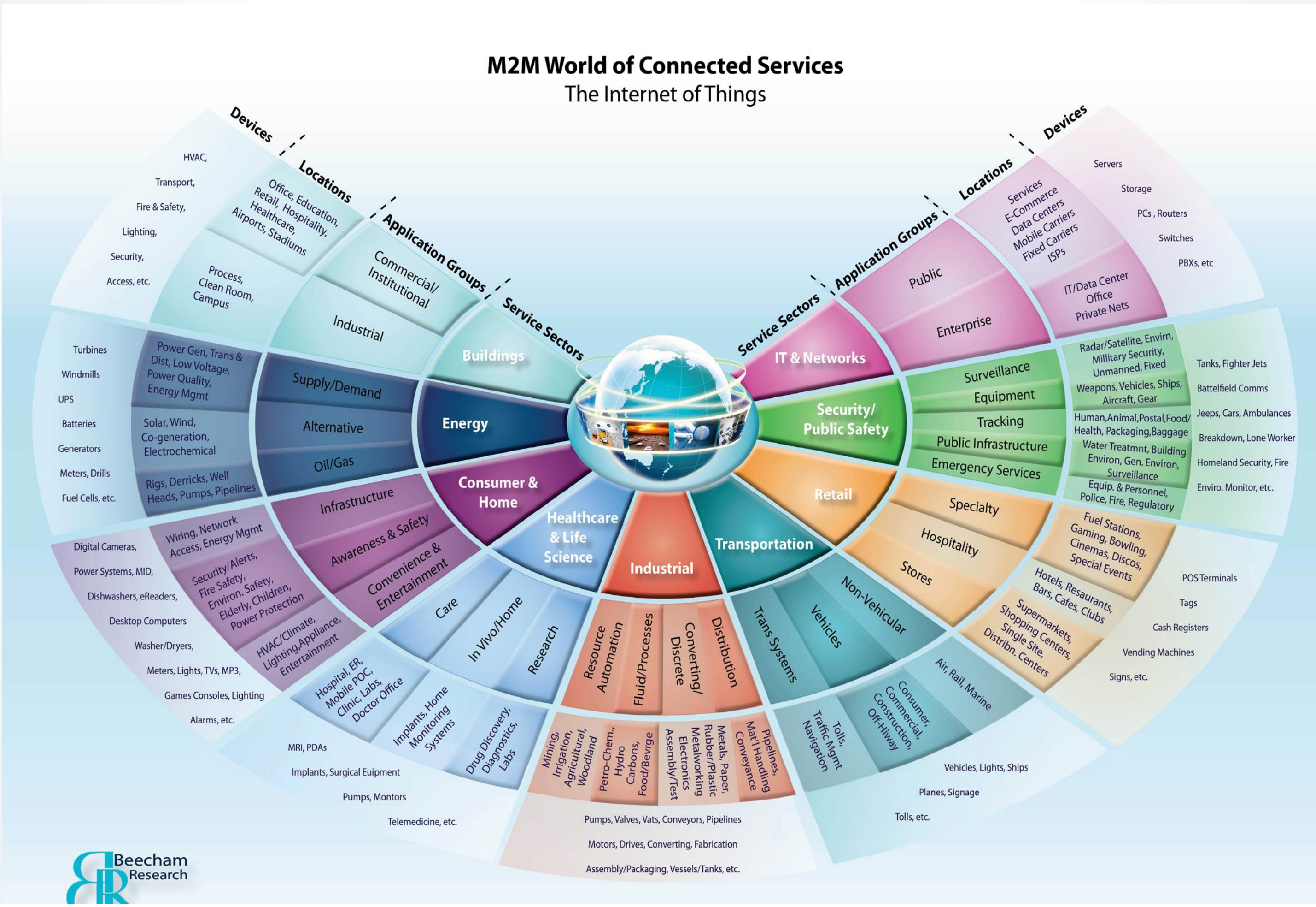
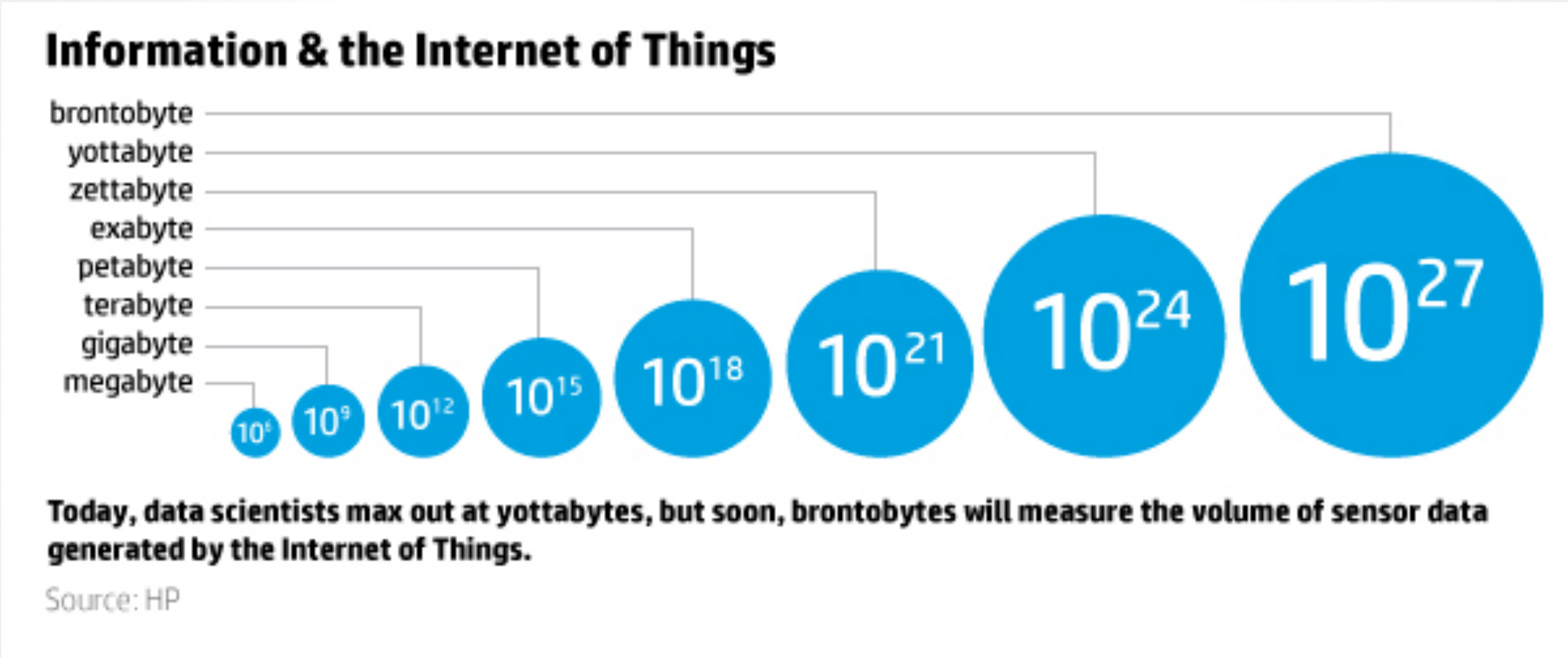
IF YOU ARE INTO DATA, THE IOT HAS IT

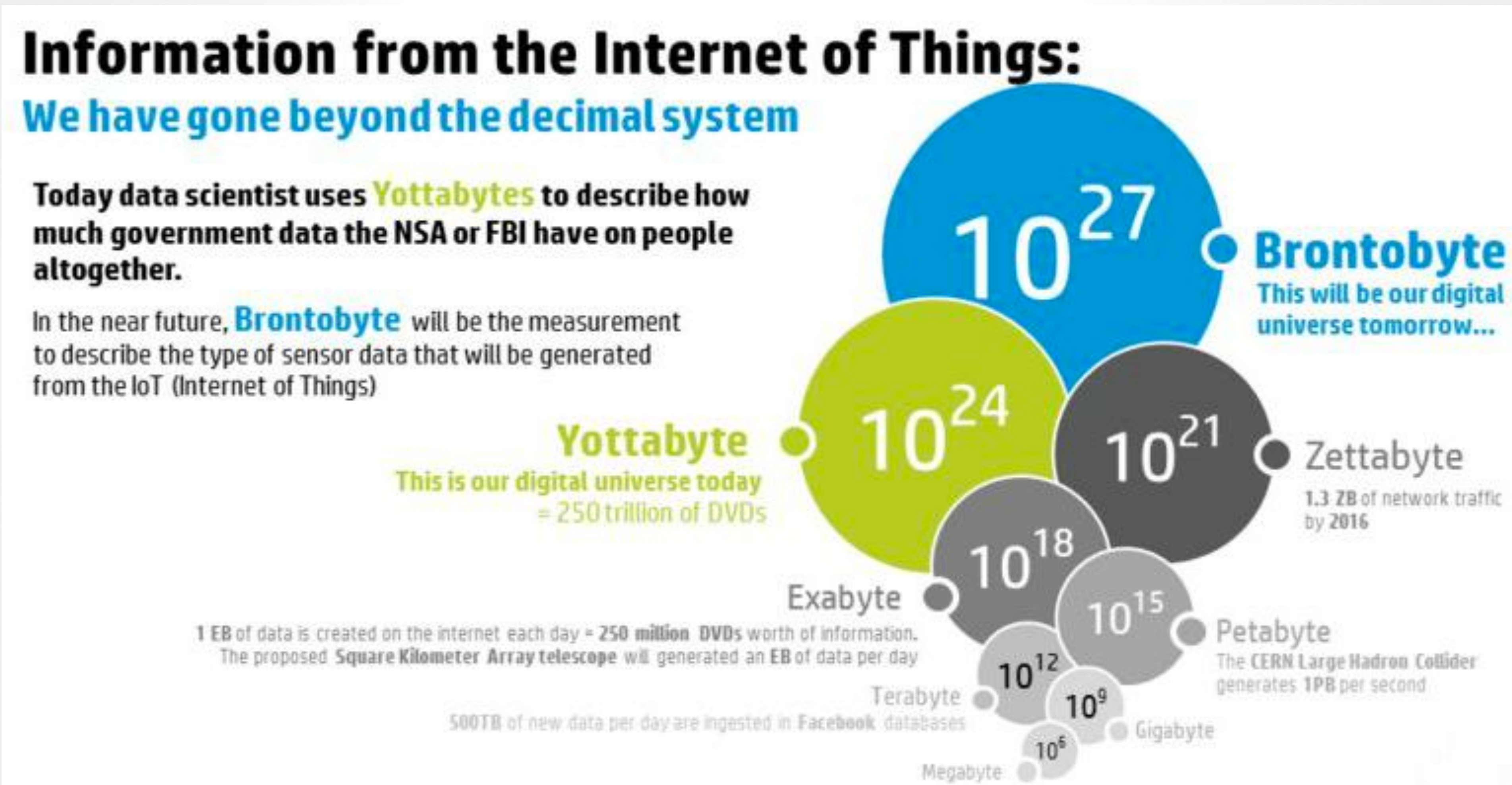


WHY THIS EXAMPLE?



GET READY FOR BRONTOBYTES!!

WOW, HOW BIG IS A BRONTOBYTE?



This much data will require a fast OODA loop

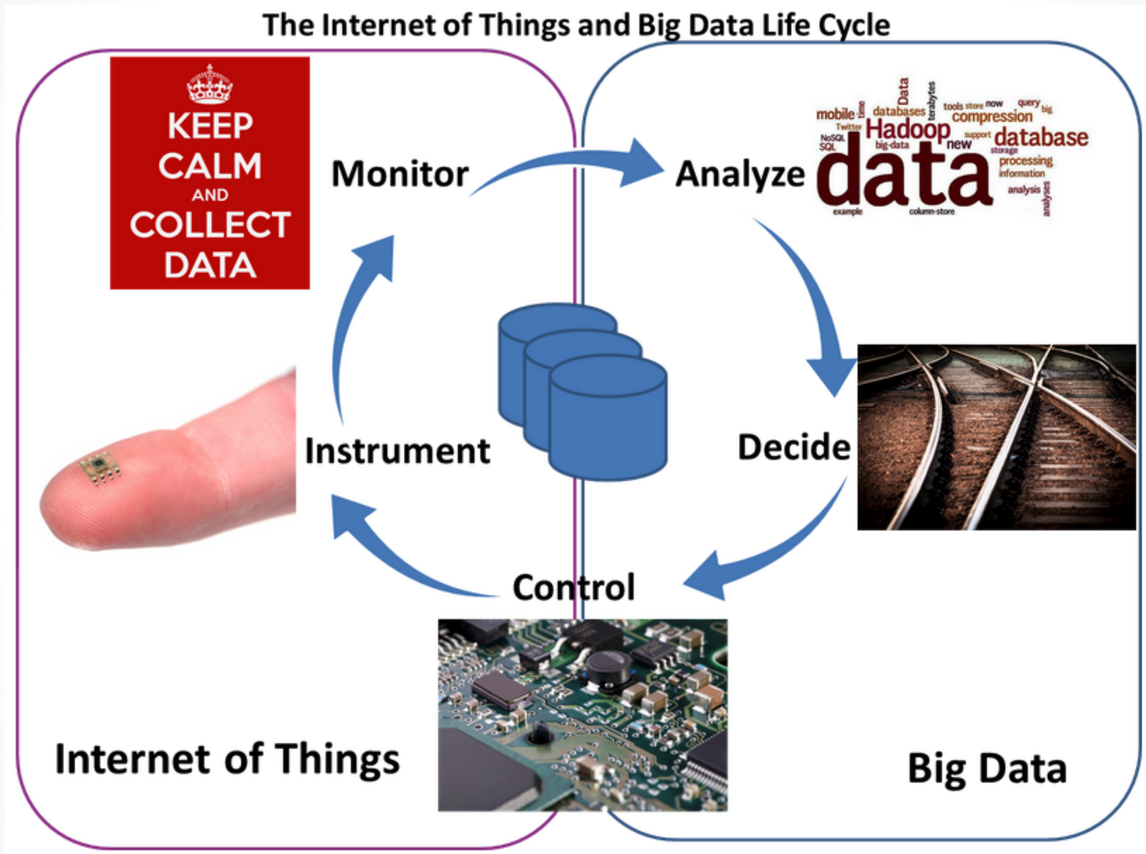


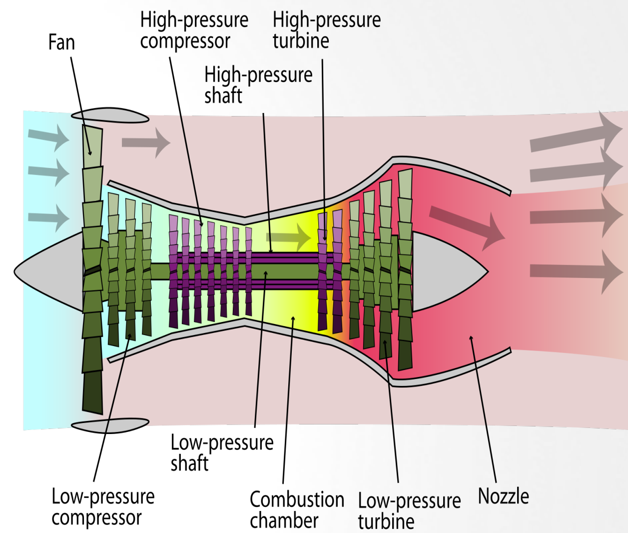
Image courtesy http://www.telecom-cloud.net/wp-content/uploads/2015/05/Screen-Shot-2015-05-27-at-3.51.47-PM.png

EXAMPLE FROM THE IOT

Domain: Prognostics and Health Management

Machine: Turbofan Jet Engines

Data Set: A. Saxena and K. Goebel (2008). "Turbofan Engine Degradation Simulation Data Set", NASA Ames Prognostics Data Repository



Predict Remaining Useful Life from Partial Life Runs

Six operating modes, two failure modes, manufacturing variability

Training: 249 jet engines run to failure

Test: 248 jet engines

LOADING DATA

```
train = h2o.upload_file("train_FD004.txt")
test  = h2o.upload_file("test_FD004.txt")
train.set_names(input_file_column_names);
test.set_names(input_file_column_names);
```

```
Parse Progress: [##################################################] 100%

Parse Progress: [##################################################] 100%
```

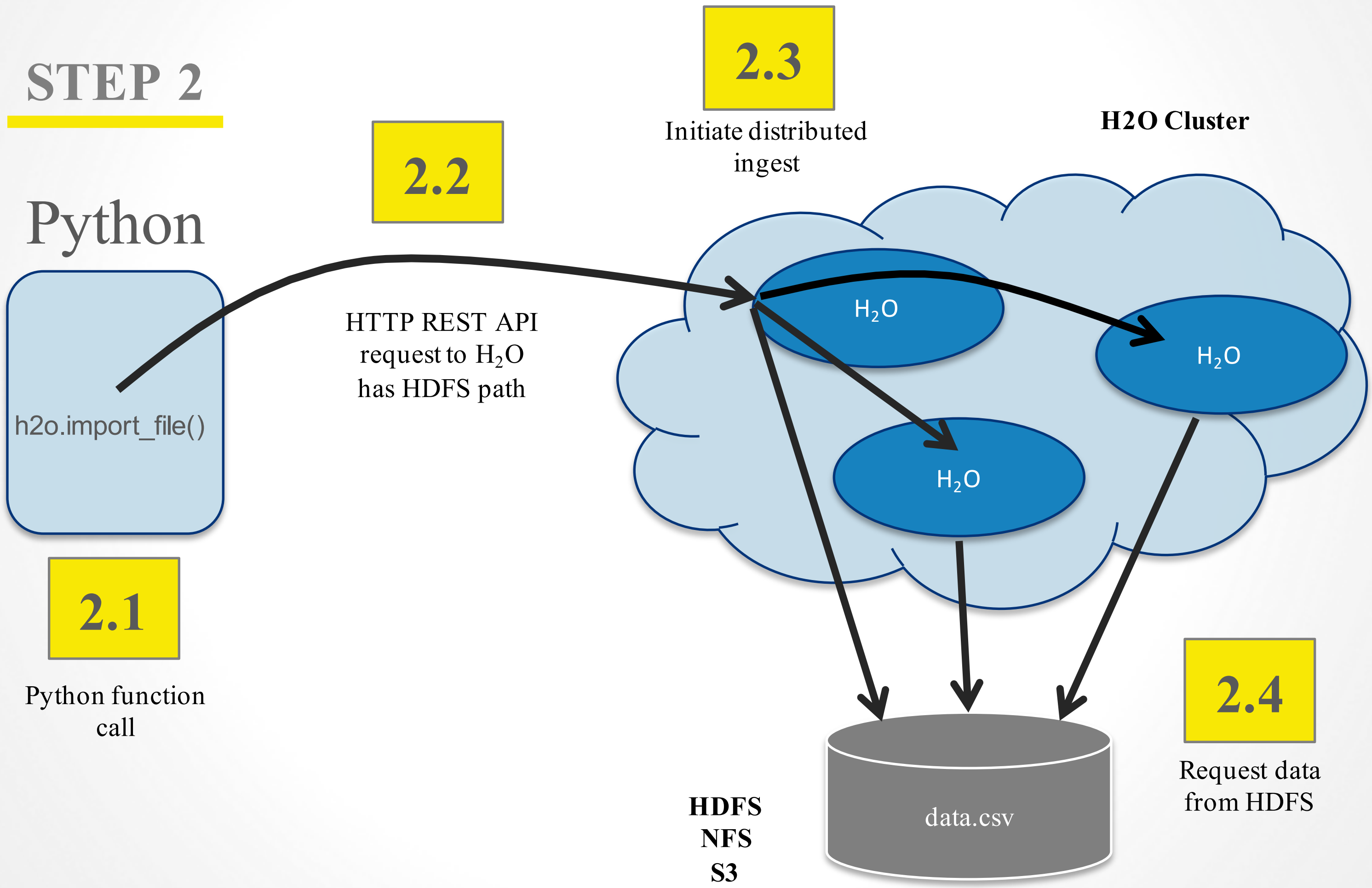
PYTHON (AND R) OBJECTS ARE PROXIES FOR BIG DATA

STEP 1

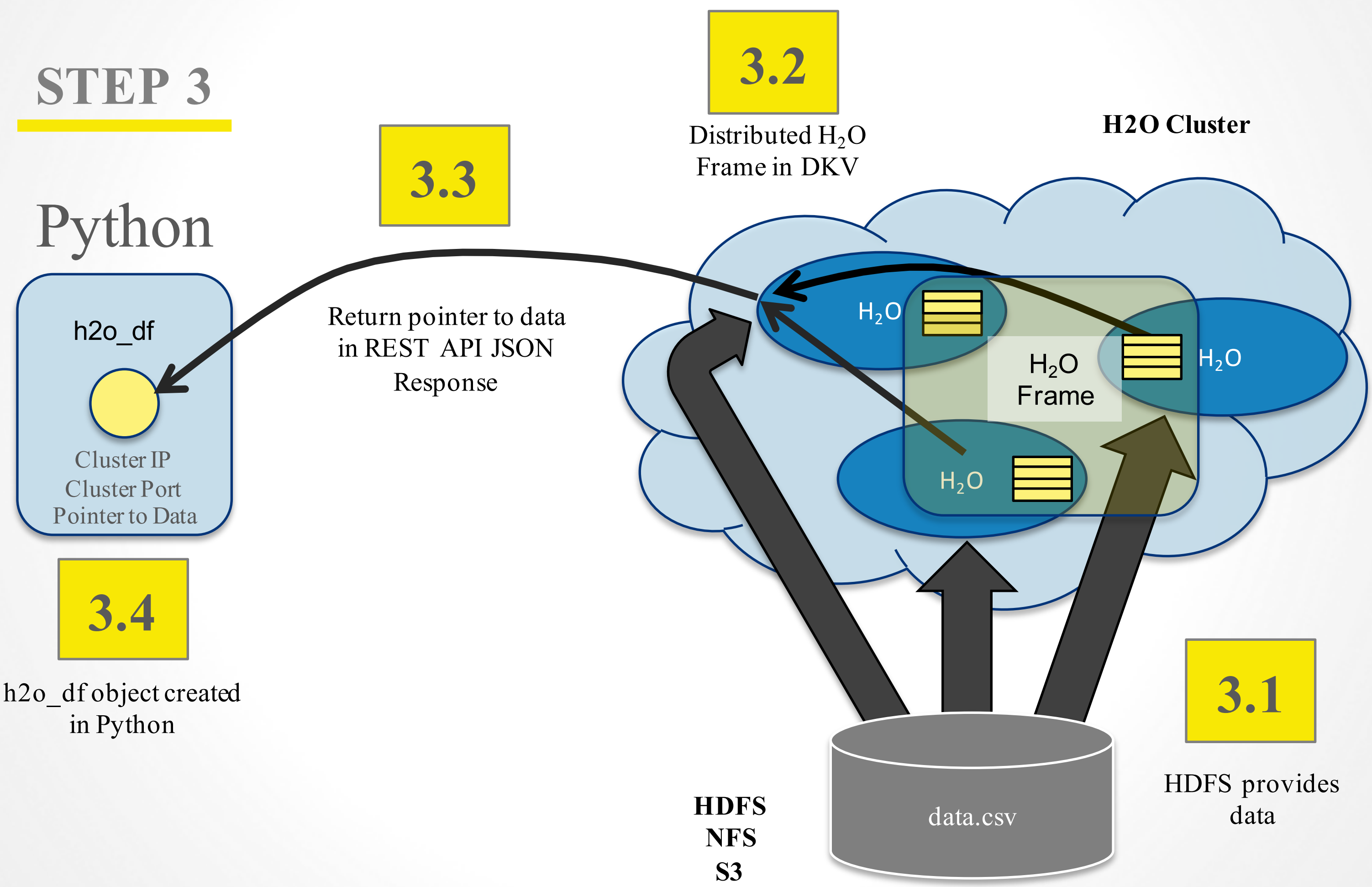
Python user

```
h2o_df = h2o.import_file("hdfs://path/to/data.csv")
```

PYTHON (AND R) OBJECTS ARE PROXIES FOR BIG DATA



PYTHON (AND R) OBJECTS ARE PROXIES FOR BIG DATA



SUMMARY STATISTICS

```
train.describe()
```

Rows:61,249 Cols:26

	UnitNumber	Cycle	OpSet1	OpSet2	OpSet3	SensorMeasure1	SensorMe
type	int	int	real	real	int	real	real
mins	1.0	1.0	0.0	0.0	60.0	445.0	535.48
mean	124.325180819	134.311417329	23.9998233424	0.571346890561	94.0315760257	472.882435468	579.42005
maxs	249.0	543.0	42.008	0.842	100.0	518.67	644.42
sigma	71.9953498537	89.7833894132	14.7807216523	0.310703444054	14.2519539188	26.4368316429	37.342646
zeros	0	0	162	4776	0	0	0
missing	0	0	0	0	0	0	0
0	1.0	1.0	42.0049	0.84	100.0	445.0	549.68
1	1.0	2.0	20.002	0.7002	100.0	491.19	606.07
2	1.0	3.0	42.0038	0.8409	100.0	445.0	548.95
3	1.0	4.0	42.0	0.84	100.0	445.0	548.7
4	1.0	5.0	25.0063	0.6207	60.0	462.54	536.1
5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

FEATURE ENGINEERING

```python
def add_remaining_useful_life(h2o_frame):
    grouped_by_unit = h2o_frame.group_by(by=["UnitNumber"])
    max_cycle = grouped_by_unit.max(col="Cycle").frame

    # Merge the max cycle back into the original frame
    result_frame = h2o_frame.merge(max_cycle)

    # Calculate remaining useful life for each row
    remaining_useful_life = result_frame["max_Cycle"] - \
                            result_frame["Cycle"]
    result_frame["RemainingUsefulLife"] = remaining_useful_life

    # drop the un-needed column
    result_frame = result_frame.drop("max_Cycle")
    return result_frame

train_with_predictor = add_remaining_useful_life(train)
```

Calculate Total Cycles For Each Unit

FEATURE ENGINEERING

```
def add_remaining_useful_life(h2o_frame):
    # Get the total number of cycles for each unit
    grouped_by_unit = h2o_frame.group_by(by=["UnitNumber"])
    max_cycle = grouped_by_unit.max(col="Cycle").frame

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    # drop the un-needed column
    result_frame = result_frame.drop("max_Cycle")
    return result_frame

train_with_predictor = add_remaining_useful_life(train)
```

Append To OriginalFrame

CREATE THE TARGET VARIABLE

```
def add_remaining_useful_life(h2o_frame):
    # Get the total number of cycles for each unit
    grouped_by_unit = h2o_frame.group_by(by=["UnitNumber"])
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    # drop the un-needed column
    result_frame = result_frame.drop("max_Cycle")
    return result_frame

train_with_predictor = add_remaining_useful_life(train)
```

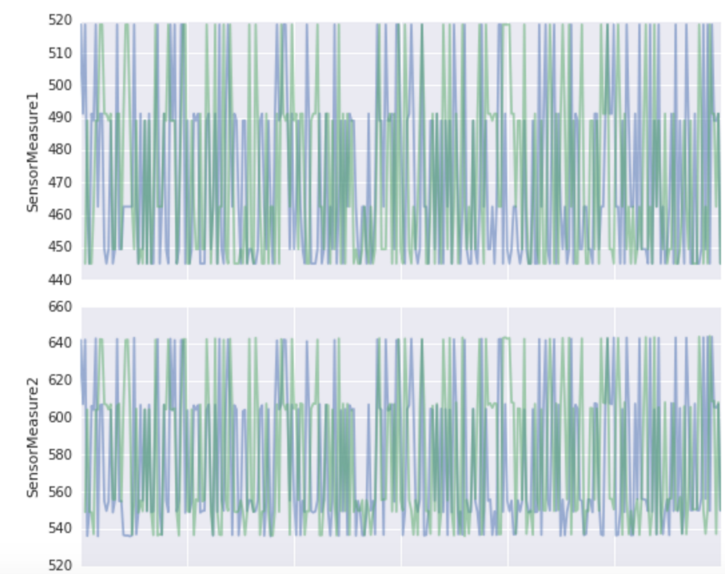
Create New Feature of Cycles Remaining

EXPLORATORY DATA ANALYSIS

```
sample_units = train_with_predictor["UnitNumber"] < 3
```

Boolean Indexing

```
g = sns.PairGrid(data=train_pd,
                 x_vars=dependent_var,
                 y_vars=sensor_measure_columns_names + \
                        operational_settings_columns_names,
                 hue="UnitNumber", size=3, aspect=2.5)
g = g.map(plt.plot, alpha=0.5)
g = g.set(xlim=(300,0))
g = g.add_legend()
```



EXPLORATORY DATA ANALYSIS

```
train_pd = train_with_predictor[sample_units].as_data_frame(
```

Sample the data to local memory

```
g = sns.PairGrid(data=train_pd,
                 x_vars=dependent_var,
                 y_vars=sensor_measure_columns_names + \
                        operational_settings_columns_names,
                 hue="UnitNumber", size=3, aspect=2.5)
g = g.map(plt.plot, alpha=0.5)
g = g.set(xlim=(300,0))
g = g.add_legend()
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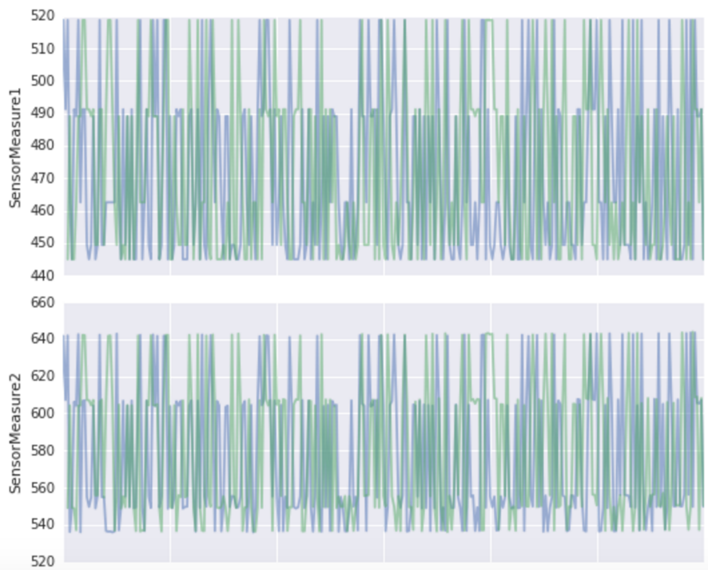

EXPLORATORY DATA ANALYSIS

```
sample_units = train_with_predictor["UnitNumber"] < 3
train_pd = train_with_predictor[sample_units] as data_fr
```

```
g = sns.PairGrid(data=train_pd,
                 x_vars=dependent_var,
                 y_vars=sensor_measure_columns_names + \
                        operational_settings_columns_names,
                 hue="UnitNumber", size=3, aspect=2.5)
g = g.map(plt.plot, alpha=0.5)
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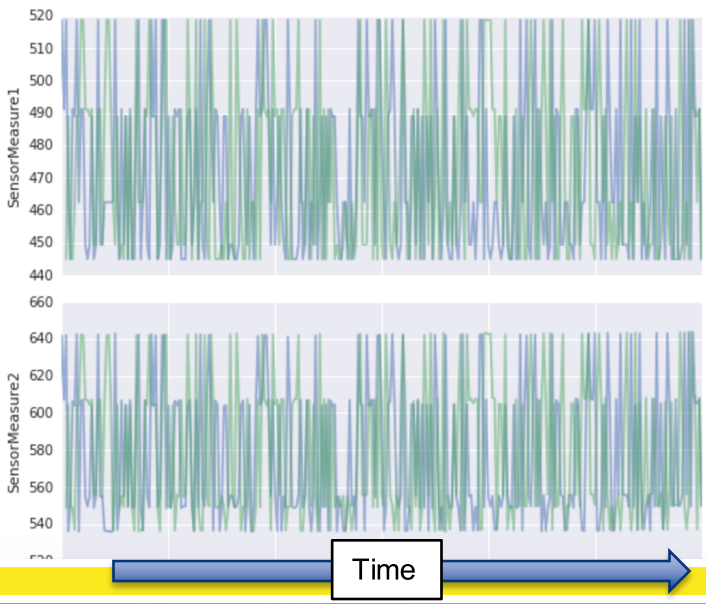


Zero Remaining Useful Life

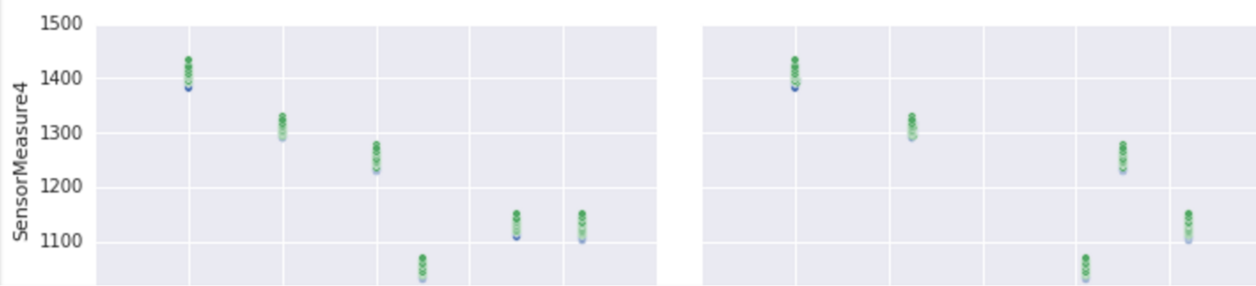
Use your favorite visualization tools

(Seaborn!)

Ugh, where are trends over time

MODEL BASED DATA ENRICHMENT

```python
g = sns.pairplot(data=train_pd,
                 x_vars=["OpSet1","OpSet2"],
                 y_vars=["SensorMeasure4", "SensorMeasure3",
                         "SensorMeasure9", "SensorMeasure8",
                         "SensorMeasure13", "SensorMeasure6"],
                 hue="UnitNumber", aspect=2)
```



Sensor measurements appear in clusters

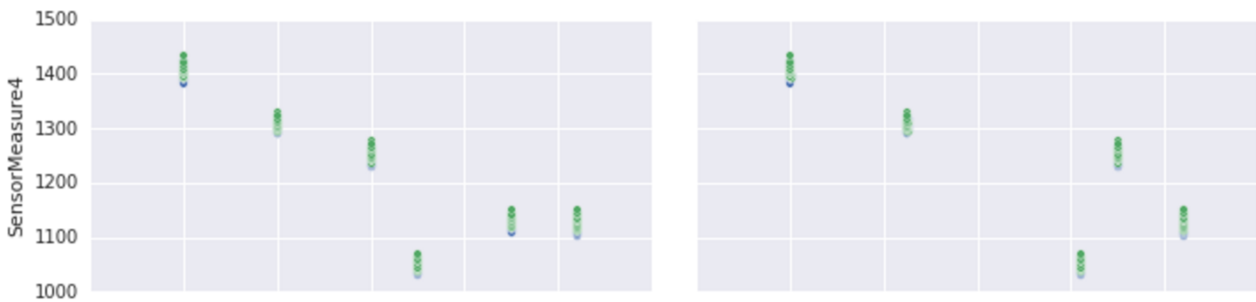
Corresponding to operating mode!

```python
from h2o.estimators.kmeans import H2OKMeansEstimator
```

```python
operating_mode_estimator = H2OKMeansEstimator(k=operating_modes)
operating_mode_estimator.train(x=operational_settings_columns_names,
                               training_frame=train_with_predictor)
```

FEATURE ENGINEERING

```
g = sns.pairplot(data=train_pd,
                 x_vars=["OpSet1","OpSet2"],
                 y_vars=["SensorMeasure4", "SensorMeasure3",
                         "SensorMeasure9", "SensorMeasure8",
                         "SensorMeasure13", "SensorMeasure6"],
                 hue="UnitNumber", aspect=2)
```




```
from h2o.estimators.kmeans import H2OKMeansEstimator
```

```
operating_mode_estimator = H2OKMeansEstimator(k=operating_modes)
operating_mode_estimator.train(x=operational_settings_columns_names,
                               training_frame=train_with_predictor)
```

Use H2O k-means to find cluster centers

FEATURE ENGINEERING

```
from h2o.estimators.kmeans import H2OKMeansEstimator
```

```
operating_mode_estimator = H2OKMeansEstimator(k=operating_r
operating_mode_estimator.train(x=operational_settings_colu
                               training_frame=train_with_pr
```

Enrich existing data with operating mode membership

```
def append_operating_mode(h2o_frame, estimator):
    operating_mode_labels = estimator.predict(h2o_frame)
    operating_mode_labels.set_names(operating_mode_column_name);
    operating_mode_labels = operating_mode_labels.asfactor()
    h2o_frame_augmented = h2o_frame.cbind(operating_mode_labels)
    return h2o_frame_augmented

train_augmented = append_operating_mode(train_with_predictor,operating_mode_estimator)
test_augmented = append_operating_mode(test,operating_mode_estimator)
```

MORE FEATURE ENGINEERING

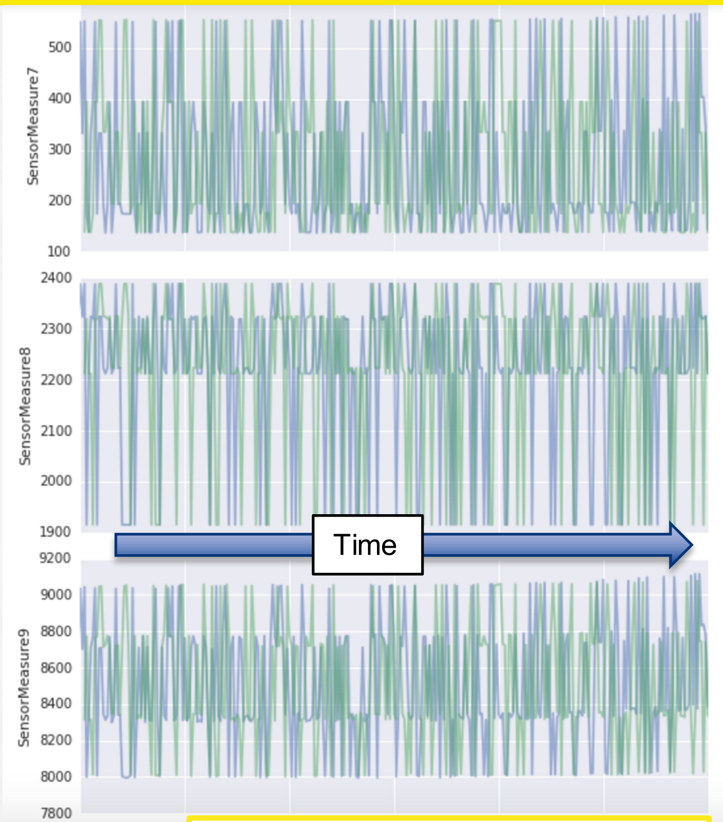
```
def standardize_by_operating_mode(train, test):
    t = train.group_by(operating_mode_column_name).\
        mean(sensor_measure_columns_names).\
        sd(sensor_measure_columns_names).frame

    s = train.merge(t)
    r = test.merge(t)
    standardize_measures_columns_names = []
    for sensor_measure_column_name in sensor_measure_columns_names:
        include_this_measure = True
        # if any of the operating modes shows 0 or NaN standard deviation,
        # do not standardize that sensor measure,
        # nor use it in the model building
        for i in range(0,operating_modes):
            stdev = t[t["OperatingMode"] == str(i),"sdev_"+sensor_measure_column_name][0,0]
            if stdev == 0.0:
                include_this_measure = False
                break
        if include_this_measure:
            new_column_name = "stdized_"+sensor_measure_column_name
            standardize_measures_columns_names.append(new_column_name)
            s[new_column_name] = ((s[sensor_measure_column_name]-
                                   s["mean_"+sensor_measure_column_name])/
                                   s["sdev_"+sensor_measure_column_name])
            r[new_column_name] = ((r[sensor_measure_column_name]-
                                   r["mean_"+sensor_measure_column_name])/
                                   r["sdev_"+sensor_measure_column_name])
    return (s,r,standardize_measures_columns_names)

train_stdized, test_stdized, standardized_measures_columns_names = \
    standardize_by_operating_mode(train_augmented, test_augmented)
```

For non-constant sensor measurements within an operating mode,

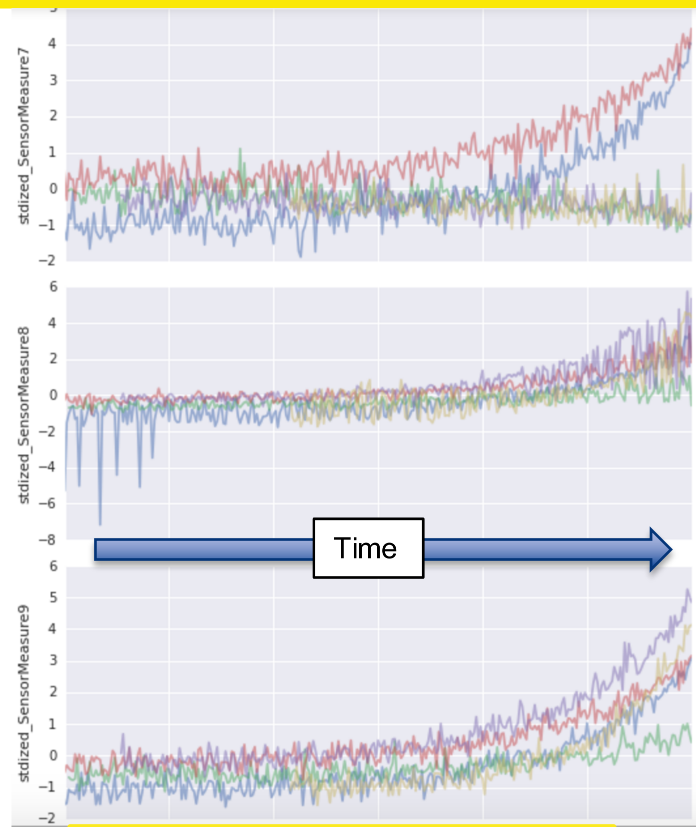
Standardize each sensor measurement by operating mode

Based on the training data

TRENDS OVER TIME!



Before
H2O Data Preparation



Ready for
H2O Learning

MODELING - SIMPLE

```python
from h2o.estimators.gbm import H2OGradientBoostingEstimator
```

```python
gbm_regressor = H2OGradientBoostingEstimator(distribution="gaussian",
                                             score_each_iteration=True,
                                             stopping_metric="MSE",
                                             stopping_tolerance=0.001,
                                             stopping_rounds=5)
gbm_regressor.train(x=independent_vars, y=dependent_var,
                    training_frame=train_final,
                    fold_column=fold_column_name)
```

Configure an Estimator

MODELING - SIMPLE

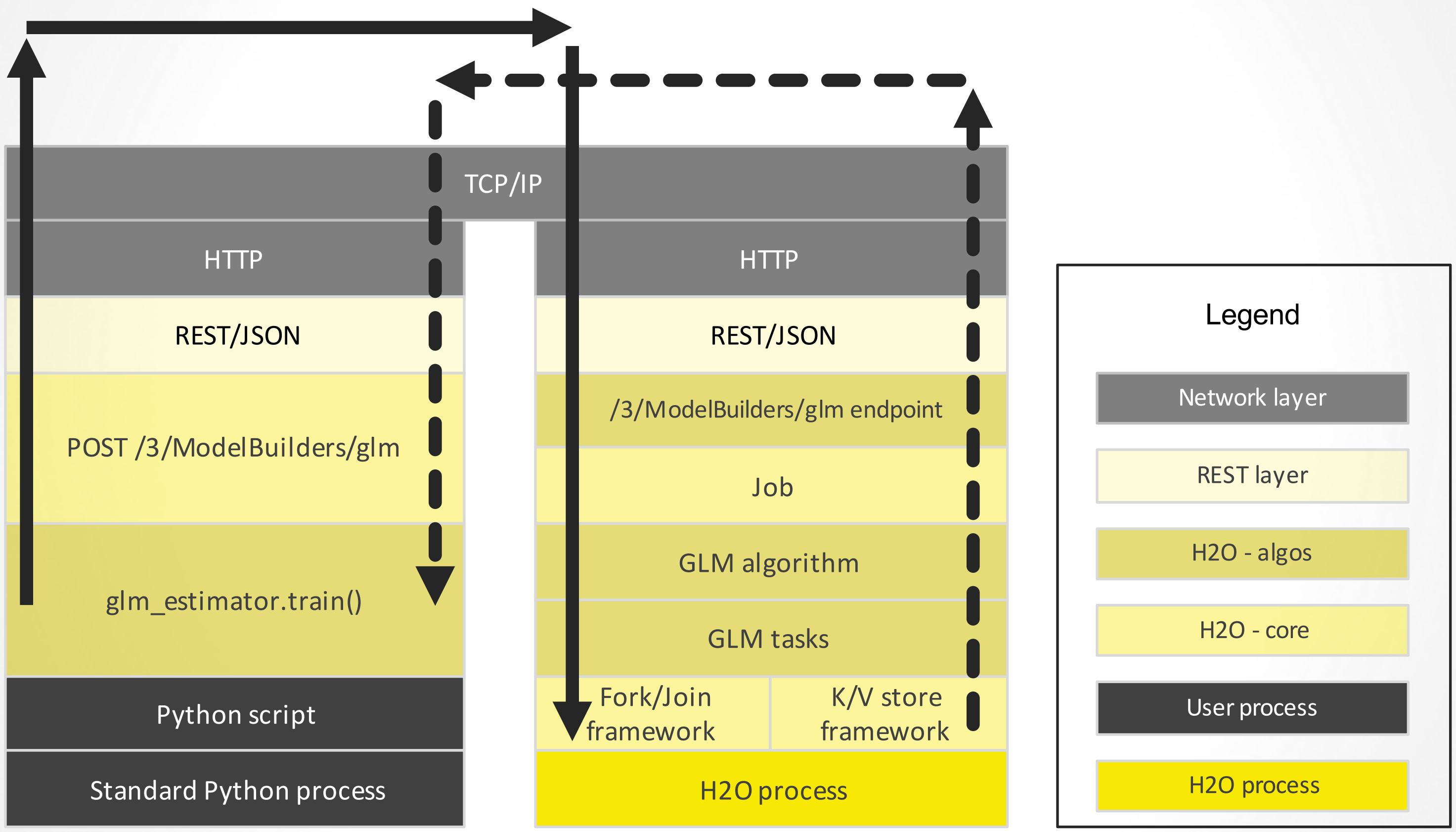
```
from h2o.estimators.gbm import H2OGradientBoostingEstimator
```

```
gbm_regressor = H2OGradientBoostingEstimator(distribution="gaussian",
                                             score_each_iteration=True,
                                             stopping_metric="MSE",
                                             stopping_tolerance=0.001,
```

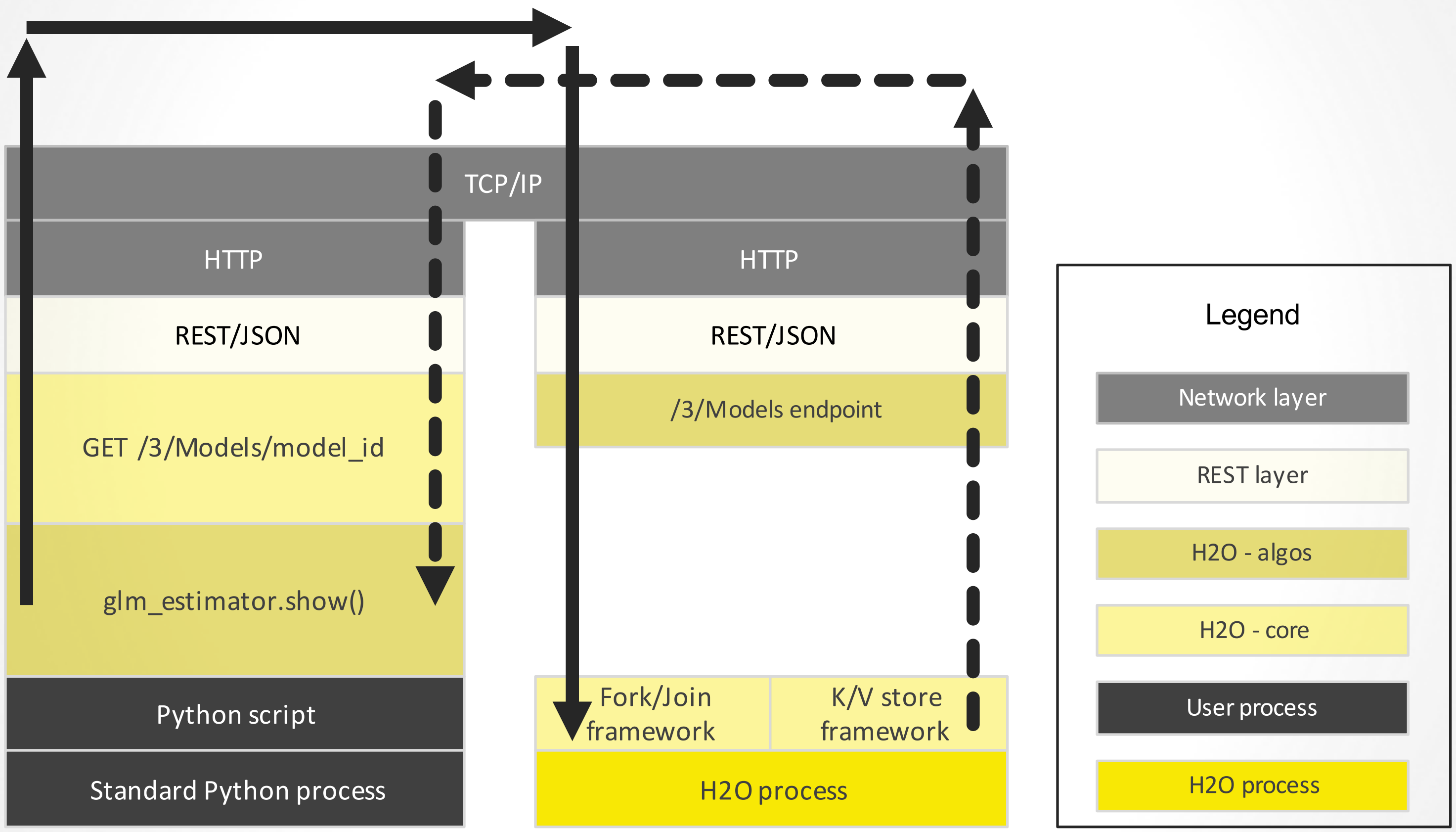
```
gbm_regressor.train(x=independent_vars, y=dependent_var,
                    training_frame=train_final,
                    fold_column=fold_column_name)
```

Train an Estimator

PYTHON SCRIPT STARTING H2O GLM



PYTHON SCRIPT STARTING H2O GLM



MODEL EVALUATION

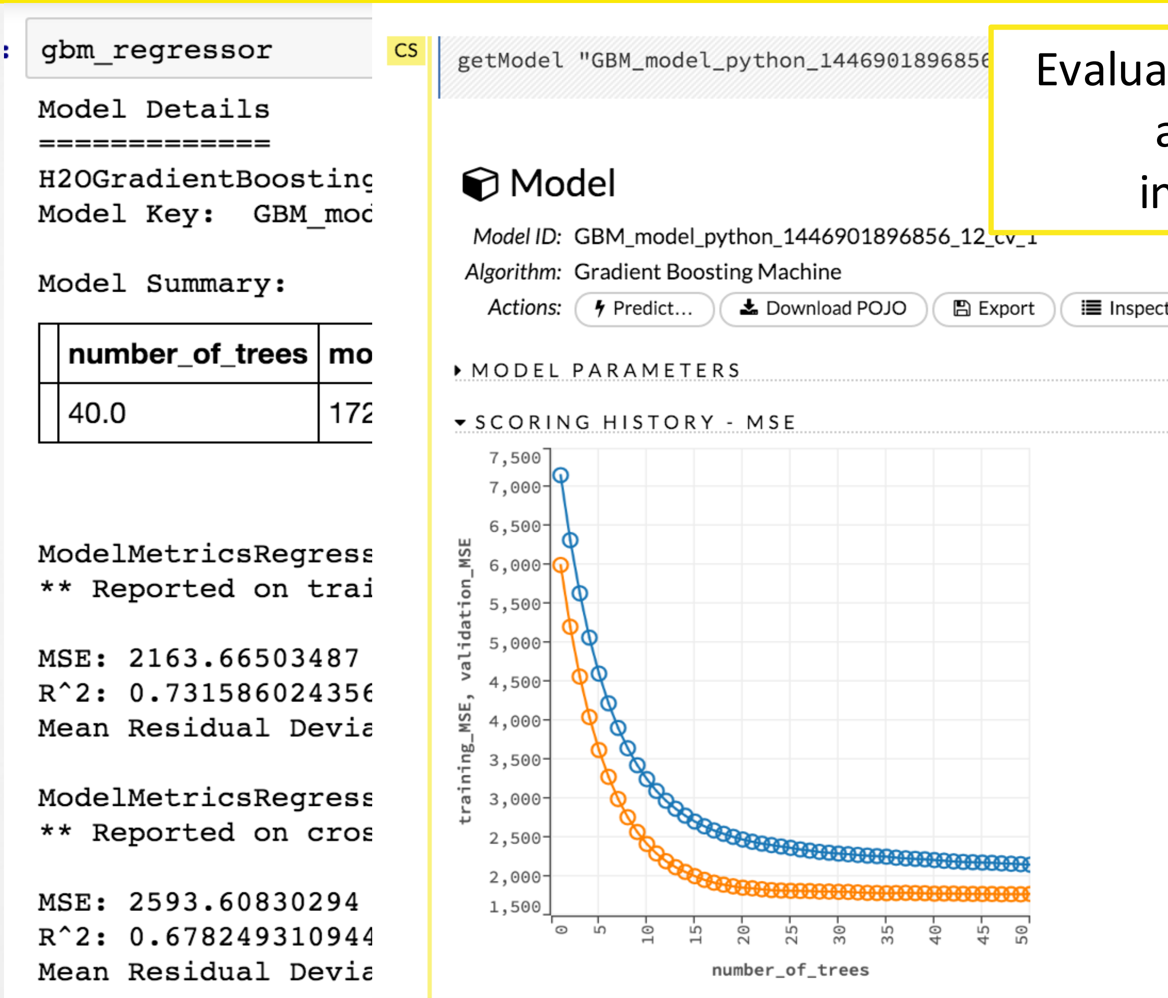
```
: gbm_regressor

Model Details
=============
H2OGradientBoostingEstimator :  Gradient Bo
Model Key:  GBM_model_python_1446901896856_

Model Summary:
```

	number_of_trees	model_size_in_bytes	min_depth
	40.0	17218.0	5.0

```
ModelMetricsRegression: gbm
** Reported on train data. **

MSE: 2163.66503487
R^2: 0.731586024356
Mean Residual Deviance: 2163.66503487

ModelMetricsRegression: gbm
** Reported on cross-validation data. **

MSE: 2593.60830294
R^2: 0.678249310944
Mean Residual Deviance: 2593.60830294
```

Evaluate Performance
at a glance
in Python

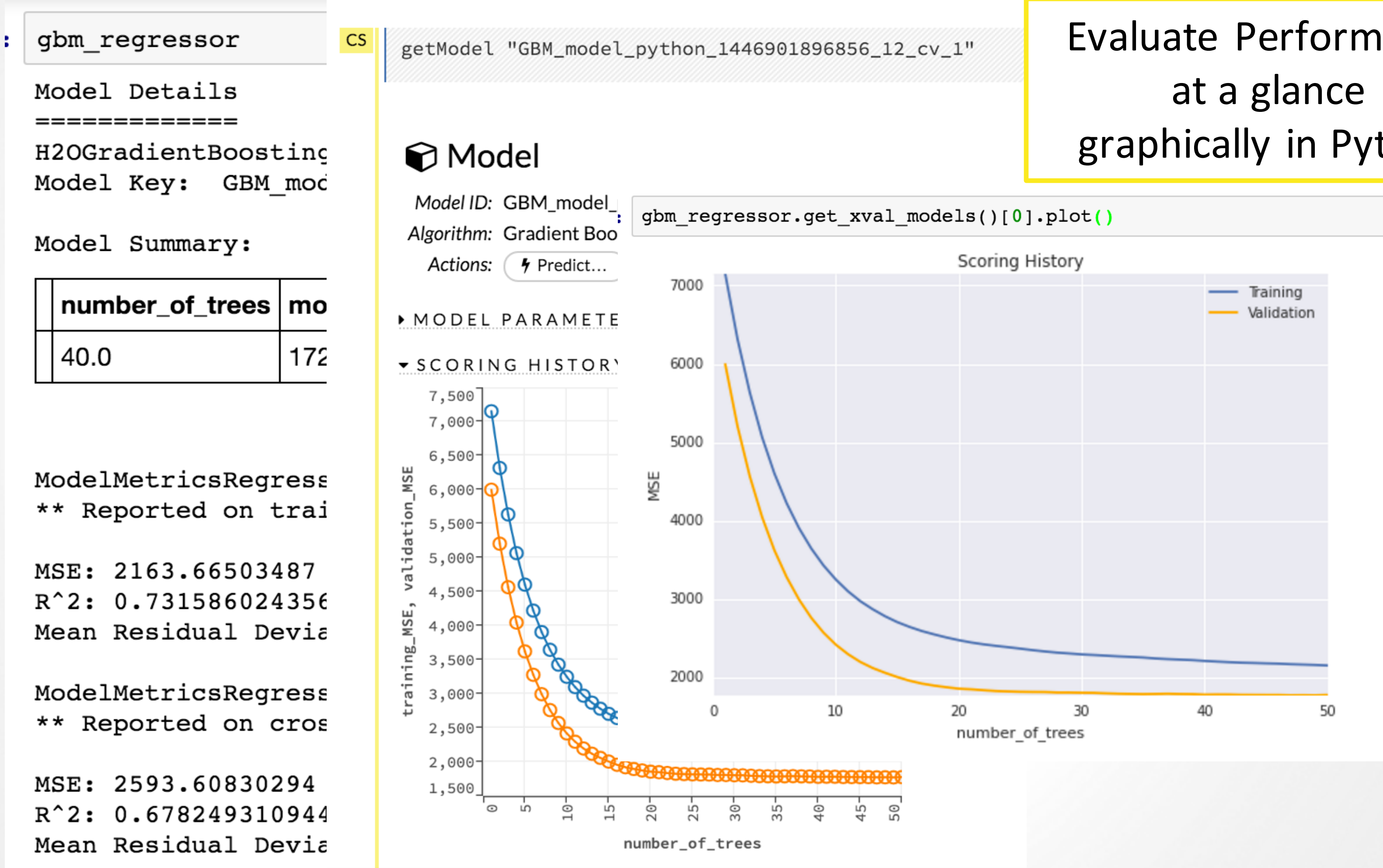
MODEL EVALUATION



Evaluate Performance at a glance in H2O Flow

MODEL EVALUATION

Evaluate Performance at a glance graphically in Python



CROSS VALIDATION

```
from h2o.grid.grid_search import H2OGridSearch

ntrees_opt = [1000]
max_depth_opt = [2, 5, 7]
learn_rate_opt = [0.01]
min_rows_opt = [5, 10, 15]
hyper_parameters = {"ntrees": ntrees_opt,
                    "max_depth":max_depth_opt,
                    "learn_rate":learn_rate_opt,
                    "min_rows": min_rows_opt}

gs = H2OGridSearch(gbm_regressor, hyper_params=hyper_parameters)

gs.train(x=independent_vars, y=dependent_var,
         training_frame=train_final,
         fold_column=fold_column_name)
```

Setup Hyperparameter Search Options

CROSS VALIDATION

```
from h2o.grid.grid_search import H2OGridSearch

ntrees_opt = [1000]
max_depth_opt = [2, 5, 7]
learn_rate_opt = [0.01]
min_rows_opt = [5, 10, 15]
hyper_parameters = {"ntrees": ntrees_opt,
                    "max_depth":max_depth_opt,
                    "learn_rate":learn_rate_opt,
                    "min_rows": min_rows_opt}
```

```
gs = H2OGridSearch(gbm_regressor, hyper_params=hyper_parameters)
```

```
gs.train(x=independent_vars, y=dependent_var,
         training_frame=train_final,
         fold_column=fold_column_name)
```

Configure
full full
grid search

CROSS VALIDATION

```
from h2o.grid.grid_search import H2OGridSearch

ntrees_opt = [1000]
max_depth_opt = [2, 5, 7]
learn_rate_opt = [0.01]
min_rows_opt = [5, 10, 15]
hyper_parameters = {"ntrees": ntrees_opt,
                    "max_depth":max_depth_opt,
                    "learn_rate":learn_rate_opt,
                    "min_rows": min_rows_opt}

gs = H2OGridSearch(gbm_regressor, hyper_params=hyper_parameters)
```

```
gs.train(x=independent_vars, y=dependent_var,
         training_frame=train_final,
         fold_column=fold_column_name)
```

Execute
grid search

CROSS VALIDATION

```
gs.train(x=independent_vars, y=dependent_var,
         training_frame=train_final,
         fold_column=fold_column_name)
```

```
gbm Grid Build Progress: [####################################
```

Evaluate results & model selection

```
gs.sort_by('mse', increasing=True)
```

```
Grid Search Results for H2OGradientBoostingEstimator:
```

Model Id	Hyperparameters: [learn_rate, ntrees, min_rows, max_depth]	mse
Grid_GBM_py_257_model_python_1446915311057_18_model_6	[0.01, 255, 5.0, 7]	1954.1
Grid_GBM_py_257_model_python_1446915311057_18_model_7	[0.01, 255, 10.0, 7]	1959.6
Grid_GBM_py_257_model_python_1446915311057_18_model_8	[0.01, 256, 15.0, 7]	1964.9
Grid_GBM_py_257_model_python_1446915311057_18_model_4	[0.01, 282, 10.0, 5]	2264.3
Grid_GBM_py_257_model_python_1446915311057_18_model_3	[0.01, 281, 5.0, 5]	2264.6

OPEN– SCIKIT PIPELINES

```
from h2o.transforms.decomposition import H2OPCA
from h2o.estimators.glm import H2OGeneralizedLinearEstimator
from h2o.model.regression import h2o_mean_squared_error
from sklearn.grid_search import RandomizedSearchCV
from sklearn.metrics.scorer import make_scorer
from sklearn.pipeline import Pipeline

pipeline = Pipeline([("pca", H2OPCA(k=2)),
                     ("glm", H2OGeneralizedLinearEstimator(family="gaussian"))])

params = {"pca__k":                  range(2,len(independent_vars)),
          "glm__alpha":              [0, 0.5, 1],
          "glm__lambda":             [1e-2, 3e-3, 1e-3, 3e-4, 1e-4]}

custom_cv = PreviouslyDefinedFold(train_final[fold_column_name])

random_search = RandomizedSearchCV(pipeline, params,
                                   n_iter=5,
                                   scoring=make_scorer(h2o_mean_squared_error),
                                   cv=custom_cv,
                                   random_state=42,
                                   n_jobs=1,refit=True)

random_search.fit(train_final[independent_vars], train_final[dependent_var])
```

Create Pipelines

Hyper-parameter Options

Cross validation strategy

Hyper-parameter Search Strategy

Fit

OPEN - POST PROCESSING

```
import pykalman as pyk

final_ensembled_preds = {}
pred_cols = [ name for name in predictions_df.columns if "predict" in name]
for unit in predictions_df.UnitNumber.unique():
    preds_for_unit = predictions_df[ predictions_df.UnitNumber == unit ]
    observations = preds_for_unit.as_matrix(pred_cols)
    initial_state_mean = np.array( [np.mean(observations[0]),-1] )
    kf = pyk.KalmanFilter(transition_matrices=a_transition_matrix,\
                          initial_state_mean=initial_state_mean,\
                          observation_covariance=r_observation_covariance,\
                          observation_matrices=h_observation_matrices,\
                          n_dim_state=n_dim_state, n_dim_obs=n_dim_obs)
    mean,_ = kf.filter(observations)
    final_ensembled_preds[unit] = mean
```

RESOURCES

- Download and go: http://www.h2o.ai/download
- Documentation: http://docs.h2o.ai/
- Booklets, Datasheet: http://www.h2o.ai/resources/
- Github: http://github.com/h2oai/
- Training: http://learn.h2o.ai/
  (Notebook is in this location)
- This presentation (look in 2016_01_16_DataDayTexas):
  https://github.com/h2oai/h2o-meetups/

THANK YOU