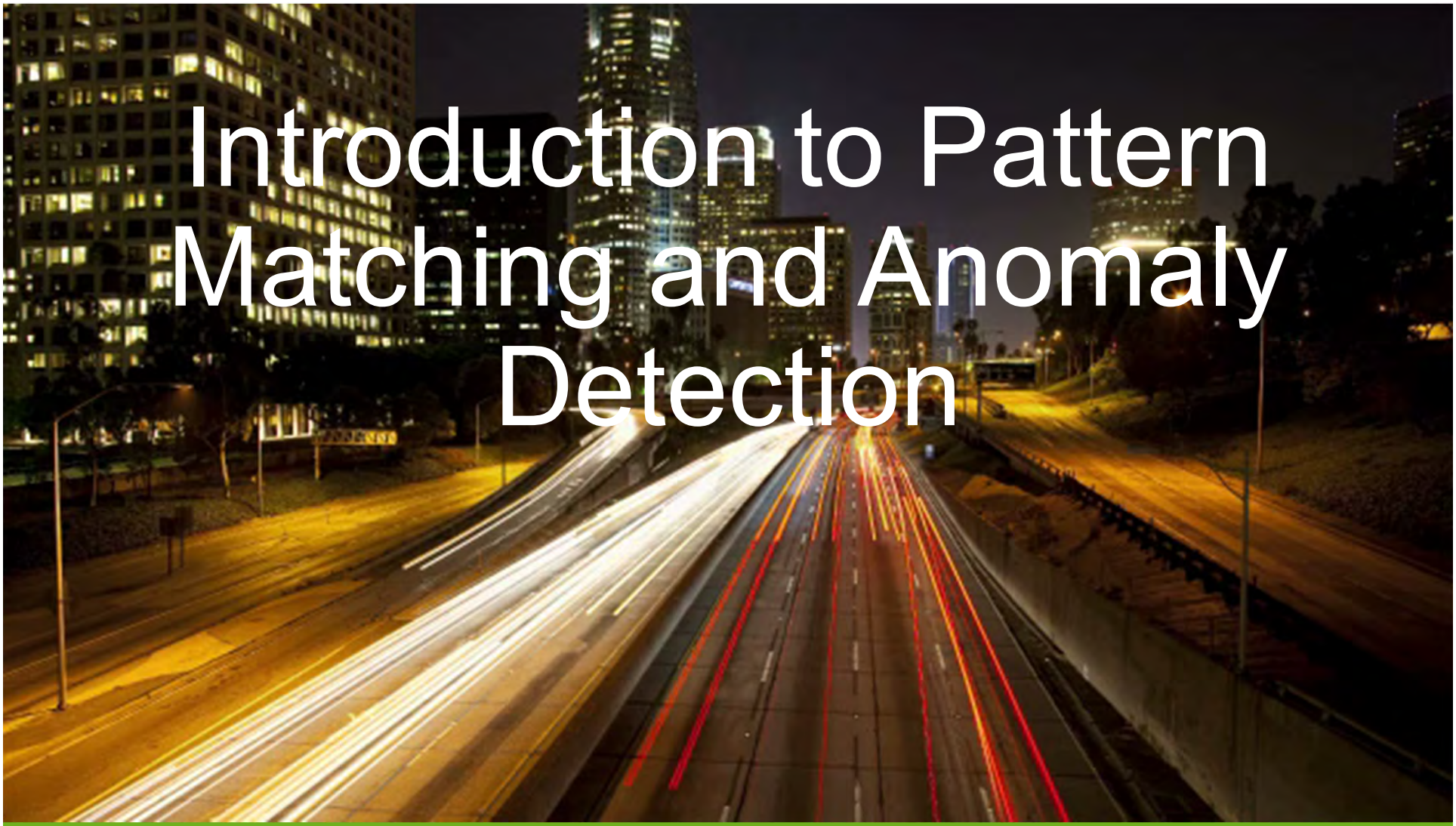
REPUBLIC POLYTECHNIC
DISCOVER. TRANSFORM. ACHIEVE



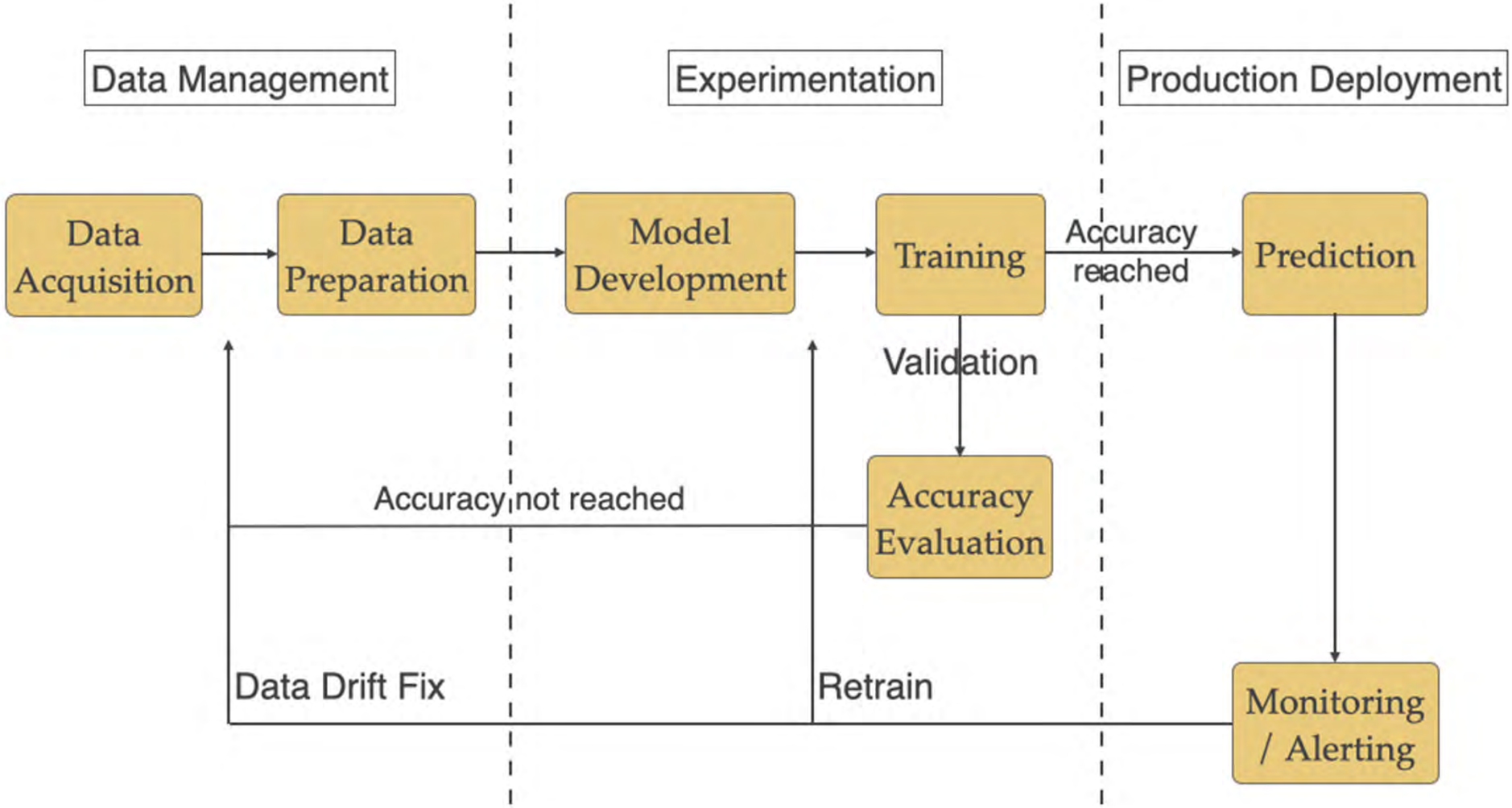
Introduction to Pattern Matching and Anomaly Detection

Version 1.0

Programme

Day 1	Introduction to Pattern Recognition and their techniques Activity – KNN & K-Means (iris) Common Python Lib - Numpy Activity - Numpy	Common Python Lib – Pandas, matplotlib, Scikit-learn Activity – Pandas, Matplotlib, Scikit-learn
Day 2	Data gathering to prepare for training and testing data Activity – Data Cleaning Use low-pass filter and simple moving average to detect abnormalities Activity – Simple Anomaly Detector	Introduction to anomaly detection and their techniques Introduction to H2O Activity - IRIS, MNIST, Fashion MNIST
Day 3	Activity – Credit card fraud with H2O/Isolation forest Activity – Intrusion detection system	Introduction to Alibi-Detect Activity – Intrusion detection system Activity – Image anomaly detection (MVTec)

Machine Learning workflow



Ref: https://towardsdatascience.com/challenges-deploying-machine-learning-models-to-production-ded3f9009cb3

Data Preparation

- Data can be gathered from many sources and the quality of the data may not be ‘clean’
- Data preparation involves the following
  - Data Cleaning
  - Segmentation of Data for Training, Validation and Testing
- Data scientist will be spending most of the time in data preparation

After the Cleansing

Similarity to data cleansing, we need to clean up the data as the situation when it is gathered may not ideal

Data Cleaning

- Data that are gathered are usually far from ideal as there may be:
  - Incorrect Data Format (e.g. Date should be ivy/mmm/did)
  - Missing Data
  - Incorrect Data Type (e.g. Data is numeric but a string value is given)
  - Data Duplication
  - …. Etc.

It is a tedious tasks that need to be done

https://idatassist.com/avoid-inaccurate-conclusions-through-data-cleaning/

WHY IS IT IMPORTANT!

- Poor data could lead to wrong classification
- When there is wrong classification of data, it will lead to wrong predication and outcome.
- Wrong predication and outcome will be ‘costly’ to the organization

For example, the Land Transport Authority may like to investigate the public transport usage. If the data is not clean, LTA may not have the wrong conclusion and prediction.

Data Cleaning

- In Data Science (e.g. Data Analytics, AI), it will require large amount of data and manually cleaning of these data will be impossible
- Tools like Python will be able to automate the process of cleaning the data based on ‘rules’
- The data will be manipulated based the rules set in the programmed

Explanation to the Data Cleaning Programme

```
# Scenario 1
# This programme is to clean the data from the input file
import pandas as pd
import numpy as np

#Example
df = pd.read_csv('Data/dirty_data.csv')

#Create a duplicate for d
df_Ex1= df.copy()

# Rule 1
# This sets of routines will null all non-numeric values from the individual columns
df_Ex1['floor_size'] = pd.to_numeric(df_Ex1['floor_size'], errors="coerce")

# Scenario 1 Exercise 1: Add the codes required to null all
# ........ COMPLETE CODE ------------
#-------------------------------------


# Computer the means
df_mean=df_Ex1.mean()

# Rule 2
# This set of rountes are to convert null value to the mean value of the columns
df_Ex1.loc[df_Ex1['floor_size'].isnull(),'floor_size'] = df_mean['floor_size']

# Scenario 1 Exercise 2: Add the
# ........ COMPLETE CODE ------------
#-------------------------------------

#Save to CSV file
df_Ex1.to_csv('Data/clean_data_scenario1.csv')
```

Creating a duplicate of the dataframe df
Changes made to df_Ex1 will not change the values of df1

This step will nullify ALL non-numeric or blank values for a particular column

Remember the loc function
df.loc(row, column)

Boolean function that will return the index of row that meet the condition

Save DataFrame to a csv file

Explanation to the Data Cleaning Programme

```
# Scenario 2
# This programme is to clean the data from the input file
import pandas as pd
import numpy as np

#Example
df = pd.read_csv('Data/dirty_data.csv')

#Create a duplicate for dataframe df
df_Ex2 = df.copy()

df_Ex2a = df_Ex2.drop(df_Ex2[df_Ex2['median_income'].str.isalpha()== True].index)
#Complete the cod
# Add the requi    odes for the rest of the columns
```

Drop the rows from the DataFrame

Function that check whether the value is characters

Writing the Data Cleaning Programme

Scenario 1

- Rules for cleaning the data
  - Ensure that all non-numeric characters are nullified
  - Ensure that all nullified values are given the mean values of the respective columns

Scenario 2

- Rules for cleaning the data
  - Remove rows where there are non-numeric value
  - Ensure that all nullified values are given the mean values of the respective columns

Data Preparation for building the model

- Machine Learning will require a model to perform prediction
- The model used are usually statistical algorithms that will perform the ‘prediction’
- Prediction are based on the probability of the data point that matches certain criterion

The last step in Data Preparation

- After the data are ‘cleaned’, it is important that the data split into the following datasets
  - Training
  - Validation
  - Test

  Note in some case. validation is known as the test and test is known as the holding datasets
- It is important to note that the data are randomly split into the respective datasets (Training, Validation and Test)

Purpose of the Respective Datasets

- Training
  - Training datasets are used for training the models. For each data that passed through the model, it will ‘refine’ the model.
- Validation
  - Validation datasets are used for the checking the model.
- Testing
  - Test datasets plays the similar role as the validation datasets but it is to ensure that the model best fit the hypothesis

Normal Ratio of splitting the data:

Training :70% Validation 20% Testing : 10%

Note this ratio is able to change based on requirements

Example of Data Splitting Programme

- Ratio of Training : Validation: Test is 70:20:10

```
df = pd.read_csv('../Data/out/clean_data_scenario1.csv')

#Create a duplicate for dataframe df
df_Example= df.copy()

train, validate, test = np.split(df_Example.sample(frac=1), [int(.7*len(df_Example)), int(.9*len(df_Example))])
```

Split location in the array

Activity 6

- 3 cleaning exercises
  - non-numeric characters are set to null
  - non-numeric characters are dropped
  - Splitting the data for training and testing.

Step 1:
Watch and listen to the instructor's demonstration

15 mins

Step 2:
Work through the activities

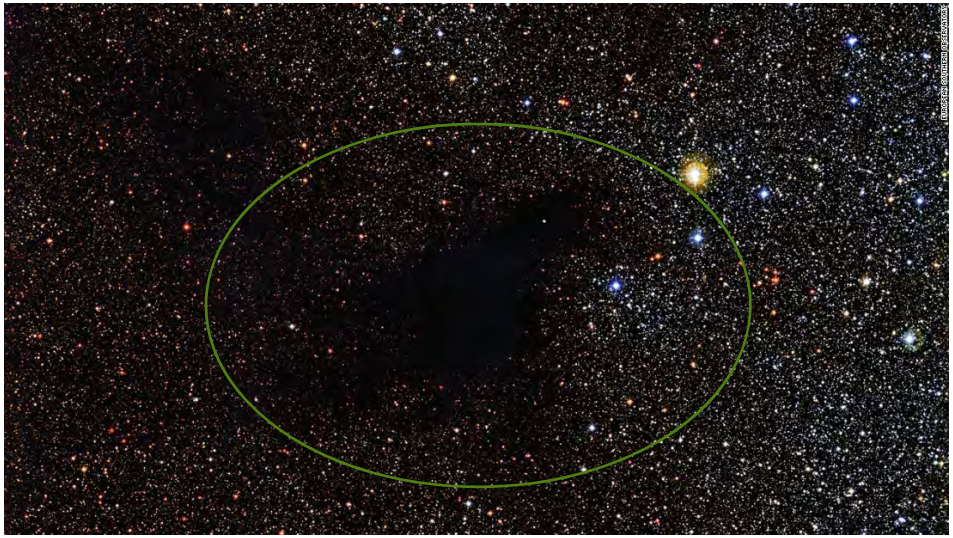
Individual Activity

30 mins

Anomalies

- What are anomalies?
  - It is a series of events that does not conform to the expected patterns or outcomes

Where is the anomaly in this picture?



Machine Learning Algorithm can be used to detect such anomalies

Type of Anomalies

- Point Anomalies
  - A single instance of data that is too far from the rest
- Contextual Anomalies
  - Anomalies are more context specific and is common in time series data
- Collective Anomalies
  - A set of data instances collectively that collectively determines anomalies (e.g. High processing time + High Network traffic = Potential Cyber attack)

Machine Learning Anomalies Detection Techniques

- Density-Based Anomaly Detection
  - It is based on the K-nearest neighbors algorithm
  - It is based on assumption that the normal data points occur near a dense neighborhood. Any data points are far away are consider as anomalies.
- Clustered-Based Anomaly Detection
  - Based on the k-means algorithms to detect anomalies in unsupervised learning
  - Data points that belong to a clusters are determined by the distance from the centroids of the cluster. Data points are outside these groups are considered as anomalies

Machine Learning Anomalies Detection Techniques

- **Moving Average (Low Pass filter) using Discrete Linear Convolution**
  - Convolution is a mathematical operation that is performed on two function to produce the third function
- It is uses a time-series to analyze the data and detect the anomalies in the data
- Moving average extract trends of a time series
- In the presence of outlier, it will affect the moving averages
- It will attempt to filter high value data and allow only low values to pass through

Disadvantage of Moving Average (Low-pass filter)

- There are many ways in which an anomaly occurring in a time series may be defined.
- For detecting anomalous sub-sequences, the exact length of the subsequence is often unknown.
- Performances of many anomaly detection algorithms are **highly susceptible** to noise in the time series data, since differentiating anomalies from noise is a challenging task.
- Time series in real applications are usually long and as the length increases the computational complexity also increases.

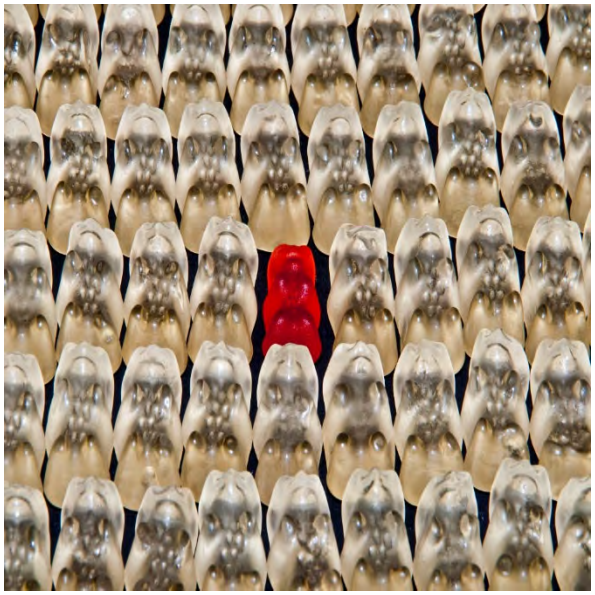
Pre-briefing for writing Low Pass filter Programme

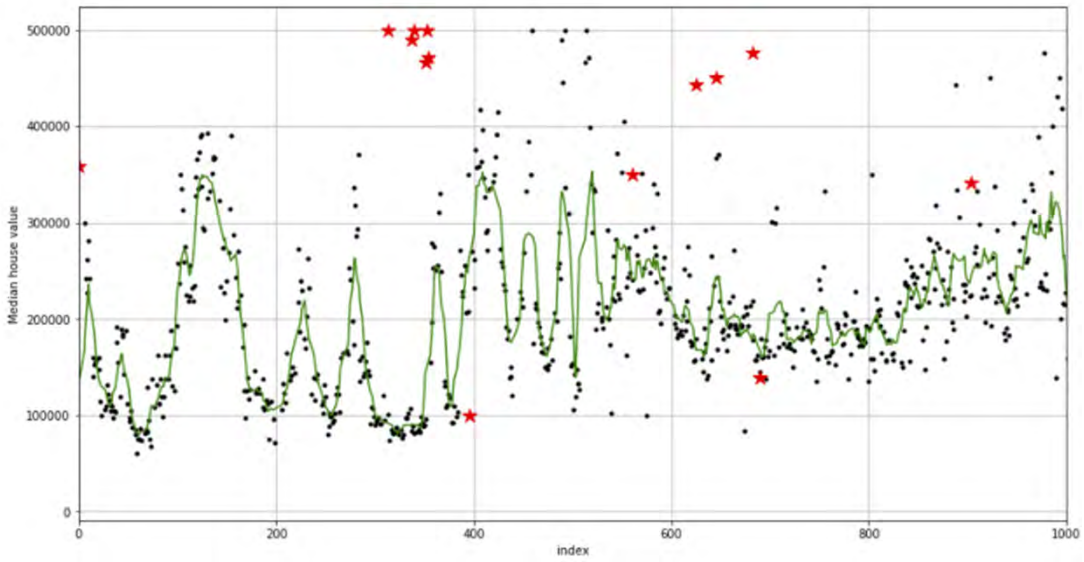
- The following are key functions in the programme:
  - moving_average
  - explain_anomalies
  - explain_anomalies_rolling_std
  - plot_results

- You need not make changes to the function

- The partial code given will explain what need to be done

Activity 7 - Low pass filter detector





Exercise

Develop a low pass filter detector using the sunspot dataset (sunspot.csv)

Step 1:

Watch and listen to the instructor's demonstration

10 mins

Step 2:

- Do on your own

Optional Activity

30 mins

H2O

- What is H2O?
  - Open-source, rich analytics platform that provides both machine learning algorithms and high-performance parallel computing abstractions.
  - Built around a Java Virtual Machine optimized for in-memory processing of distributed data collections.
  - Platform can be used via web-based UI or via languages such as Python, R, Java, Scala, and JSON in a REST API.
  - After loading into H2O, data is represented in an H2O frame.

Advantages of H2O

- Can run locally or deployed in a cluster on top of Spark or Hadoop MapReduce.
  - Scalability
- Why we choose H2O?
  - It provides a built-in class, H2OAutoEncoderEstimator, that we use for unsupervised learning.
  - Ease of use
    - Well-suited for curious users who want to learn and experiment
  - Reliability
    - Good fit for enterprise environments that care about production aspects

Installation

- Pre-requisites
  - Python 2.7 or Python 3.5
  - pip, Python's package manager
  - Java platform (JDK) 9
- Test H2O

```
python
import h2o
h2o.init()
```

```
Connecting to H2O server at http://127.0.0.1:54321... successful.
--------------------------  ------------------------------
H2O cluster uptime:         05 secs
H2O cluster version:        3.16.0.4
H2O cluster version age:    10 hours and 20 minutes
H2O cluster name:           H2O_from_python_student_q8gvwl
H2O cluster total nodes:    1
H2O cluster free memory:    477.1 Mb
H2O cluster total cores:    1
H2O cluster allowed cores:  1
H2O cluster status:         accepting new members, healthy
H2O connection url:         http://127.0.0.1:54321
H2O connection proxy:
H2O internal security:      False
H2O API Extensions:         AutoML, Algos, Core V3, Core V4
Python version:             2.7.6 final
--------------------------  ------------------------------
>>>
```

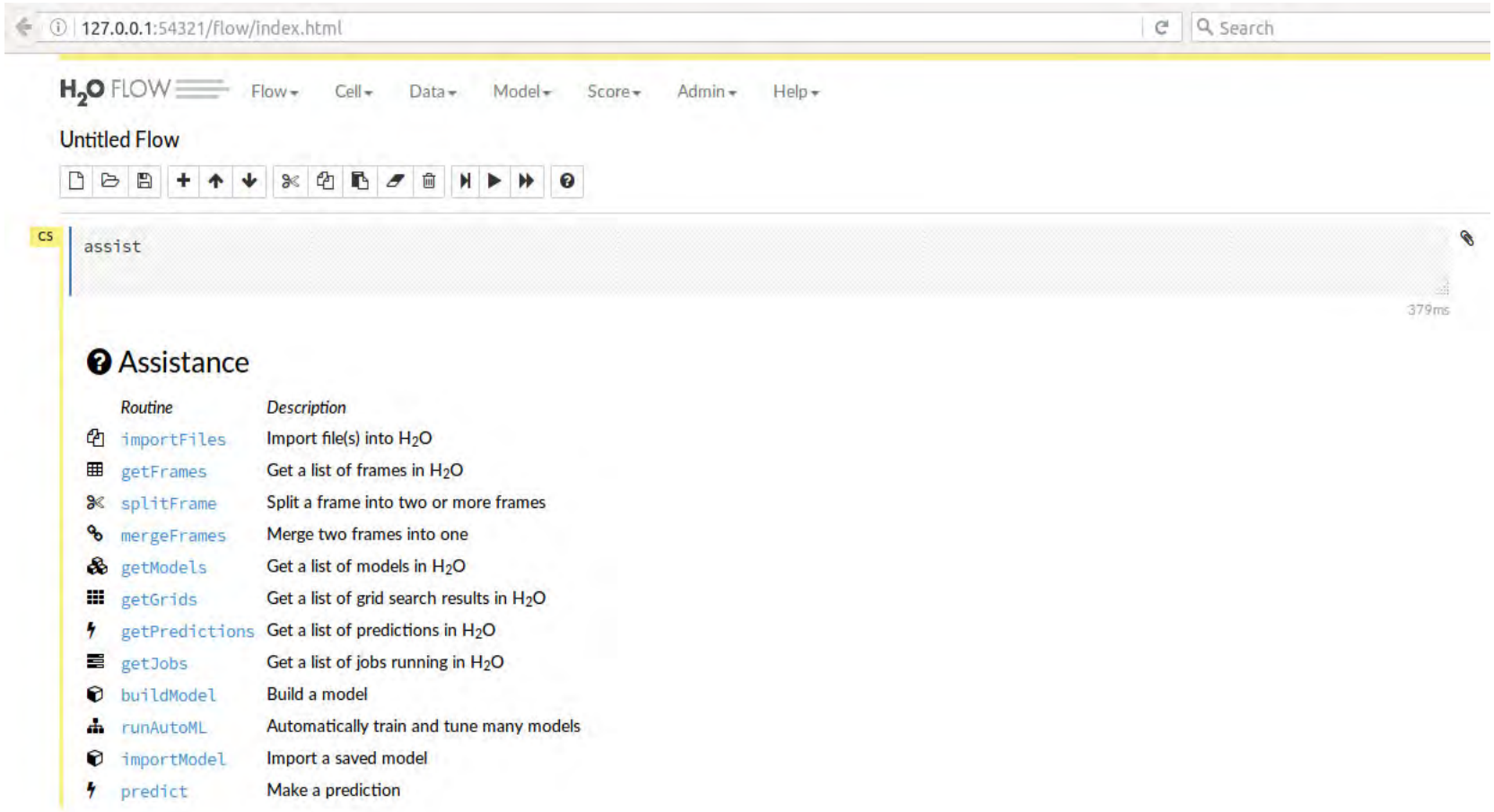
Installation

colab

▾ Setup and init H2O

```
[ ]  ! apt-get install default-jre
     ! java -version
     ! pip install h2o
     import h2o
```

H2O GUI (Flow)


127.0.0.1:54321/flow/index.html
Search
H2O FLOW
Flow
Cell
Data
Model
Score
Admin
Help
Untitled Flow
CS
assist
379ms
Assistance
Routine
Description
importFiles
Import file(s) into H2O
getFrames
Get a list of frames in H2O
splitFrame
Split a frame into two or more frames
mergeFrames
Merge two frames into one
getModels
Get a list of models in H2O
getGrids
Get a list of grid search results in H2O
getPredictions
Get a list of predictions in H2O
getJobs
Get a list of jobs running in H2O
buildModel
Build a model
runAutoML
Automatically train and tune many models
importModel
Import a saved model
predict
Make a prediction

Getting Started

- Import and initialise module
  - **h2o.init** : ConnecttoarunningH2OinstanceusingallCPUsonthehost.
- Data preparation
  - **h2o.importFile:** Import a file into H2O from a server-side path, and parse it.
  - **h2o.splitFrame**: Split an existing H2O dataset according to user-specified ratios
  - .**insert_missing_values()** – Replaces a user-specified fraction of entries in an H2O dataset with missing values.
- Define and train model
  - **H2ORandomForestEstimator(), H2ODeepLearningEstimator**()
  - .**train** – train the model
- Evaluate model
  - Use **scikit-learn**, **score_history**(), **model_performance**(), **confusion_matrix**()
- Predict
  - .**predict**()
- Load & save model
  - h2o.**save_model**(), h2o.**load_model**()

Estimators

- Supervised
  - Cox Proportional Hazards
  - Neural Networks
  - Distributed Random Forest (DRF)
  - Generalised Linear Model (GLM)
  - Generalised Additive Models (GAM)
  - Gradient Booting Machine (GBM)
  - Naïve Bayes Classifer
  - RuleFit
  - Stacked Ensembles
  - Support Vector Machine (SVM)
  - XGBoost
- Unsupervised
  - Aggregator
  - Generalised Low Rank Models (GLRM)
  - Isolation Forest
  - K-Means Clustering
  - Principal Component Analysis

Supervised Algorithms

- Cox Proportional Hazards
  - most widely used approach for modeling time to event data
- **Deep Learning (Neural Networks)**
  - based on a multi-layer feedforward artificial neural network that is trained with stochastic gradient descent using back-propagation.
- **Distributed Random Forest(DRF)**
  - powerful classification and regression tool. When given a set of data, DRF generates a forest of classification or regression trees, rather than a single classification or regression tree. (https://docs.h2o.ai/h2o/latest-stable/h2o-docs/data-science/drf.html)
- **Generalised Linear Model (GLM)**
  - estimate regression models for outcomes following exponential distributions. Includes Gaussian, Poisson and Binomial regression (classification) etc.(https://docs.h2o.ai/h2o/latest-stable/h2o-docs/data-science/glm.html)
- Generalized Additive Models (GAM)
  - a GLM in which the linear predictor depends linearly on predictor variables and smooth functions of predictor variables.

Supervised Algorithms

- **Gradient Boosting Machine (GBM)**
  - a forward learning ensemble method. The guiding heuristic is that good predictive results can be obtained through increasingly refined approximations (for Regression and Classification) (https://docs.h2o.ai/h2o/latest-stable/h2o-docs/data-science/gbm.html)
- Naïve Bayes Classifier
  - a classification algorithm that relies on strong assumptions of the independence of covariates in applying Bayes Theorem. The Naïve Bayes classifier assumes independence between predictor variables conditional on the response, and a Gaussian distribution of numeric predictors with mean and standard deviation computed from the training dataset.
- RuleFit
  - combines tree ensembles and linear models to take advantage of both methods: the accuracy of a tree ensemble and the interpretability of a linear model. (https://docs.h2o.ai/h2o/latest-stable/h2o-docs/data-science/rulefit.html)

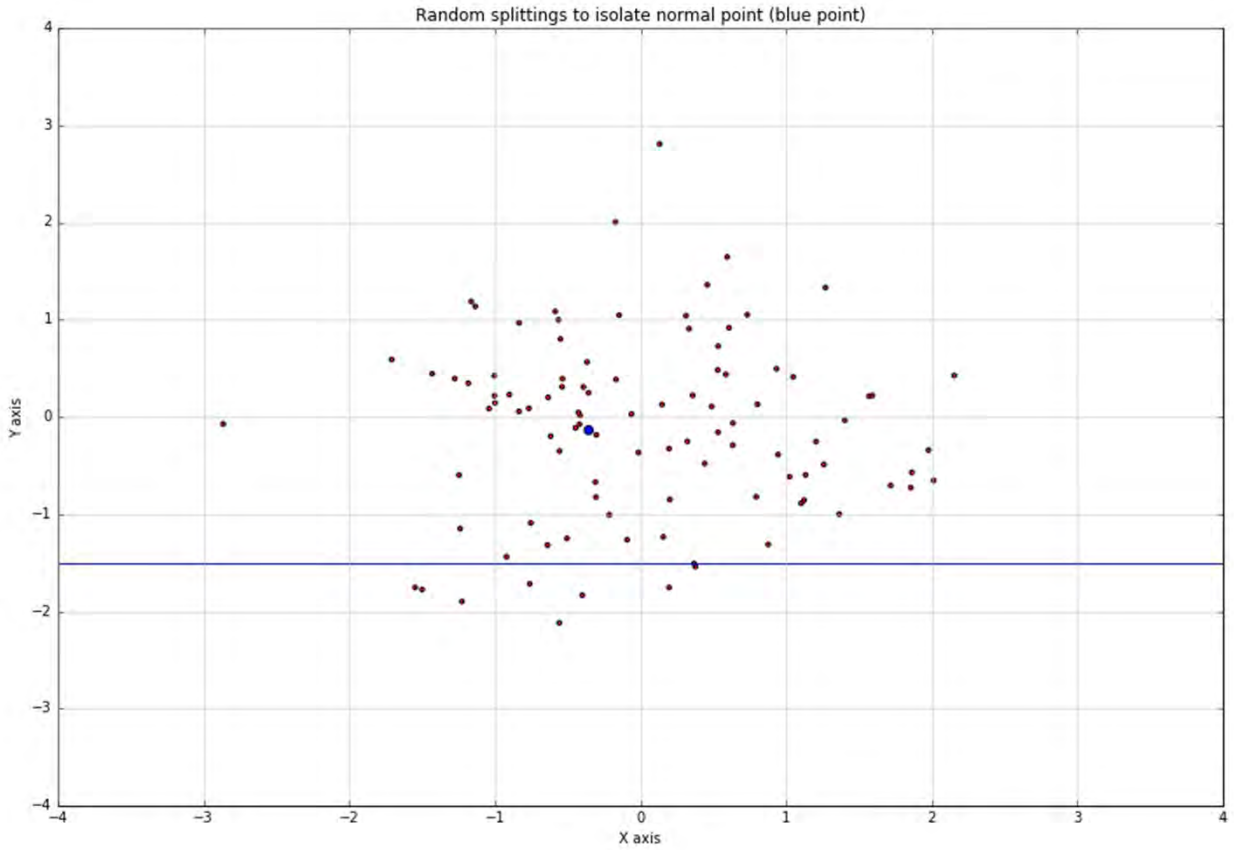
Supervised Algorithms

- Stacked Ensembles
  - use multiple learning algorithms to obtain better predictive performance than could be obtained from any of the constituent learning algorithms. (https://docs.h2o.ai/h2o/latest-stable/h2o-docs/data-science/stacked-ensembles.html)
- Support Vector Machine (SVM)
  - A supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. (https://docs.h2o.ai/h2o/latest-stable/h2o-docs/data-science/svm.html)
- **XGBoost**
  - A supervised learning algorithm that implements a process called boosting to yield accurate models. Boosting refers to the ensemble learning technique of building many models sequentially, with each new model attempting to correct for the deficiencies in the previous model. (https://docs.h2o.ai/h2o/latest-stable/h2o-docs/data-science/xgboost.html)

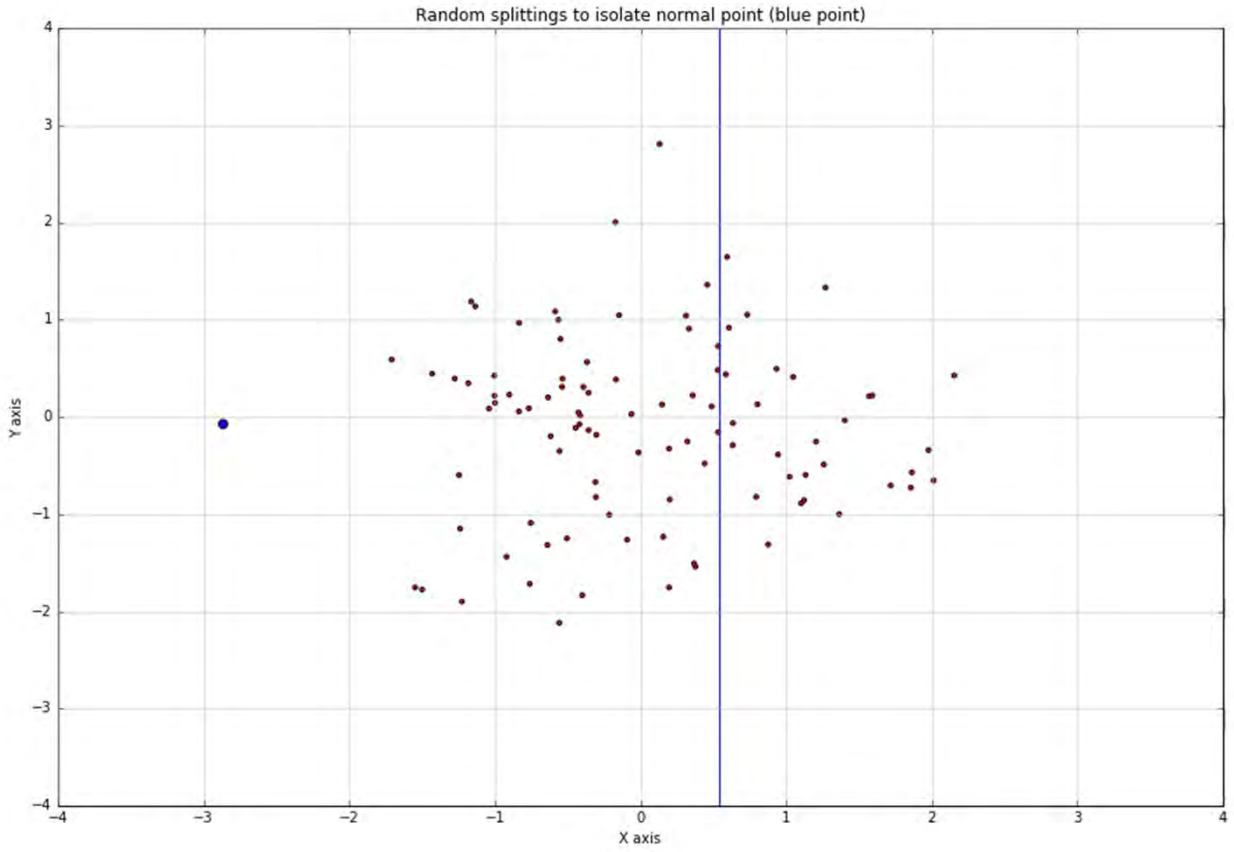
Unsupervised Algorithms

- Aggregator
  - clustering-based method for reducing a numerical/categorical dataset into a dataset with fewer rows. (http://docs.h2o.ai/h2o/latest-stable/h2o-docs/data-science/aggregator.html)
- Generalised Low Rank Models (GLRM)
  - an algorithm for dimensionality reduction of a dataset.
- **Isolation Forest**
  - similar in principle to Random Forest and is built on the basis of decision trees. Isolation Forest, however, identifies anomalies or outliers rather than profiling normal data points. Isolation Forest isolates observations by randomly selecting a feature and then randomly selecting a split value between the maximum and minimum values of that selected feature. This split depends on how long it takes to separate the points.

Isolation normal



Isolation abnormal



Unsupervised Algorithms

- **K-Means Clustering**
  - a form of unsupervised learning that tries to find structures in the data without using any labels or target values. Clustering partitions a set of observations into separate groupings such that an observation in a given group is more similar to another observation in the same group than to another observation in a different group.
- Principal Component Analysis
  - closely related to Principal Components Regression. The algorithm is carried out on a set of possibly collinear features and performs a transformation to produce a new set of uncorrelated features.
  - PCA is commonly used to model without regularization or perform **dimensionality reduction**. It can also be useful to carry out as a preprocessing step before distance-based algorithms such as K-Means since PCA guarantees that all dimensions of a manifold are orthogonal.

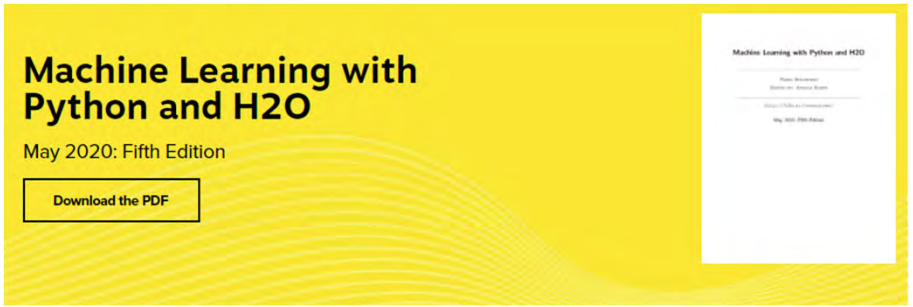
AutoML

- easy-to-use interface which automates the process of training a large selection of candidate models.
- a simple wrapper function that **performs a large number of modeling-related tasks that would typically require many lines of code**, and by freeing up their time to focus on other aspects of the data science pipeline tasks such as data-preprocessing, feature engineering and model deployment.

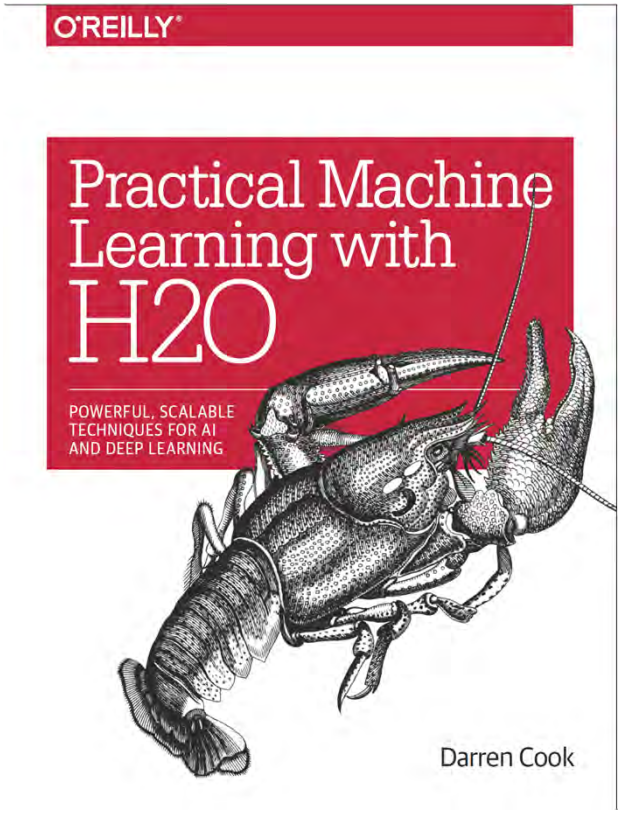
Resources

- H2OFrame Pandas DataFrame cheat sheet https://github.com/h2oai/h2o-3/blob/master/h2o-docs/src/cheatsheets/Python_H2OFrame_PandasDataFrame_Parity.md
- h2o cheat sheet : https://ugoproto.github.io/ugo_r_doc/pdf/h2o.pdf

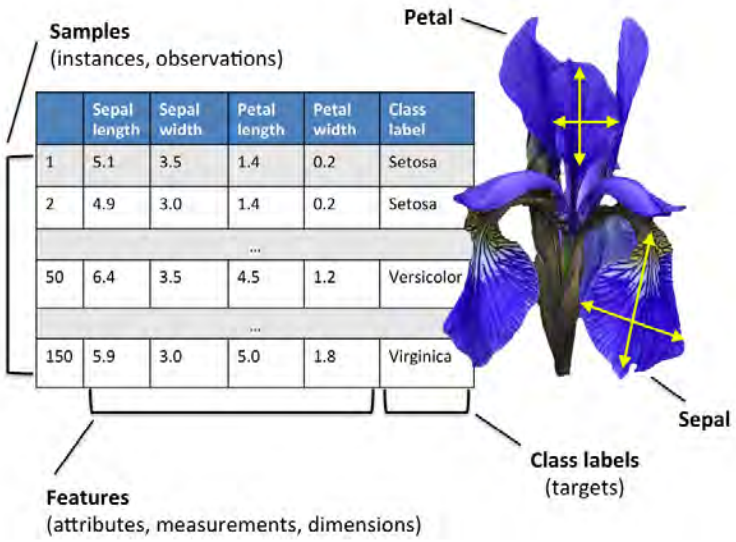
https://www.h2o.ai/resources/booklet/deep-learning-with-h2o/



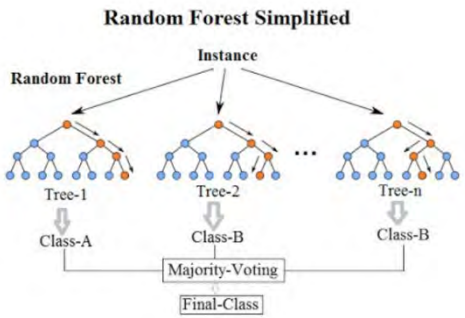
https://www.h2o.ai/resources/booklet/deep-learning-with-h2o/



Activity 8 – H2O IRIS



	Sepal length	Sepal width	Petal length	Petal width	Class label
1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3.0	1.4	0.2	Setosa
...					
50	6.4	3.5	4.5	1.2	Versicolor
...					
150	5.9	3.0	5.0	1.8	Virginica



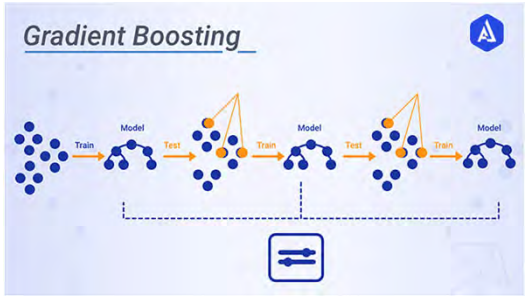


Image credits: Principal Component Analysis by Sebastian Raschka

Exercise

Use another supervised learning algorithm from H2O documentation to perform the classification

http://docs.h2o.ai/h2o/latest-stable/h2o-docs/data-science.html#supervised

Step 1:
Watch and listen to the instructor's demonstration

15 mins

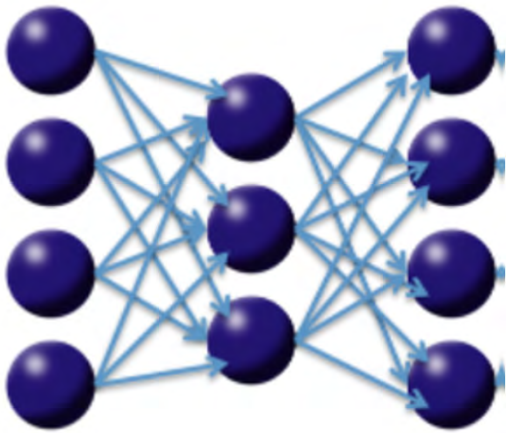
Step 2:
- Do on your own

Individual Activity

30 mins

Autoencoders

- Approach AD using a semi-supervised learning
  - Identify a set of data that represents the normal distribution. Non anomaly.
  - **Learn what "normal" means** from this training dataset. The trained model will provide a sort of metric in its mathematical definition; i.e. a function mapping every point to a real number representing the distance from another point representing the normal distribution.
- By selecting the right **threshold**, we can achieve the desired trade-off between precision (fewer false alarms) and recall (fewer missed detections)
- Robust to noise
- Uses MSE as the loss function
- Reconstruct based on intermediate representations that minimize the training error. We learn those compression functions from the training set so that a normal pint is very likely to be reconstructed correctly, but **an outlier would have a higher reconstruction error** (the mean squared error between the original point and the reconstructed one)



auto-encoders to identify anomalies

- Dataset: MNIST digit anomaly recognition
- We are NOT predicting which number each image represents BUT identifying badly written digit images.
- We are doing unsupervised learning as we are discarding the column containing the label (the digit).

Lab worksheet

- Step 1: Import data from H2O repository

```
train_with_label = h2o.import_file("http://h2o-public-test-data.s3.amazonaws.com/bigdata/laptop/mnist/train.csv.gz")
test_with_label = h2o.import_file("http://h2o-public-test-data.s3.amazonaws.com/bigdata/laptop/mnist/test.csv.gz")
```

- Step 2: Partition into train and test

```
predictors = list(range(0,784))
train = train_with_label[predictors]
test = test_with_label[predictors]
```

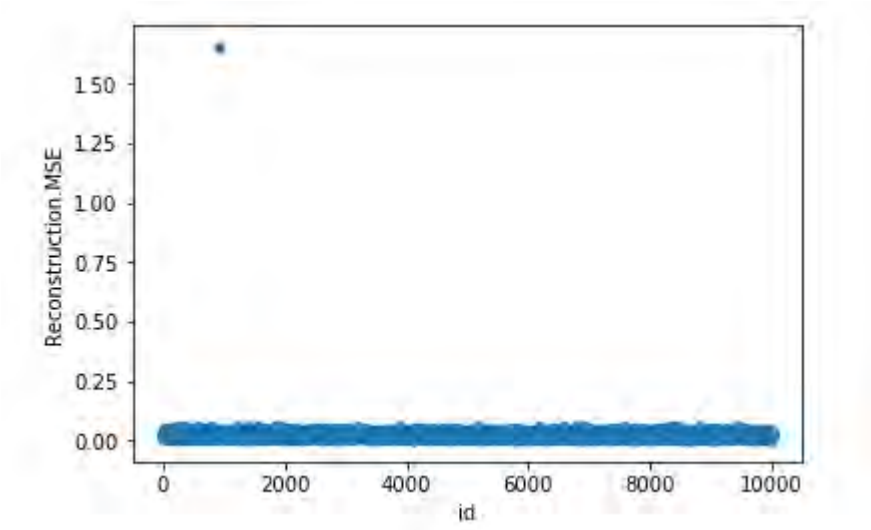
- Step 3: Create auto-encoder model

```
from h2o.estimators.deeplearning import H2OAutoEncoderEstimator
model = H2OAutoEncoderEstimator(activation="Tanh", hidden=[20], ignore_const_cols=False, epochs=1)
model.train(x=predictors,training_frame=train)
```

- Step 4: Calculate reconstruction error

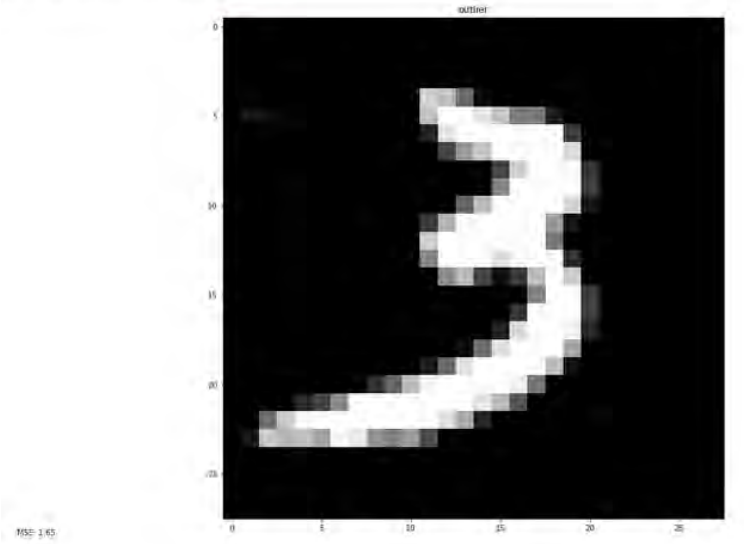
```
test_rec_error = model.anomaly(test)
```

- Step 5: Create scatter plot of reconstruction error

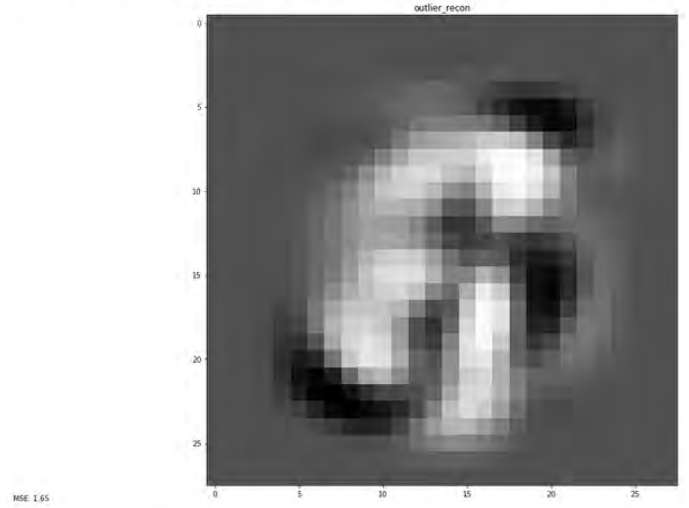


- Step 6: Plot original outlier and its reconstructed version

```
plot_digit(outlier,'outlier')
```

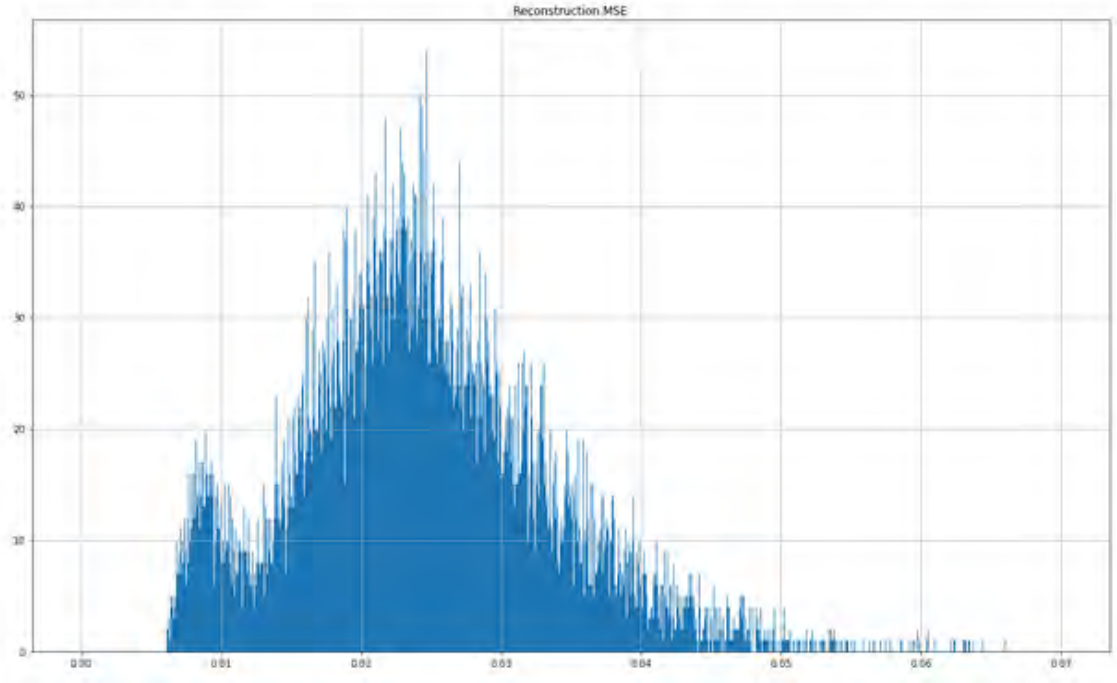



```
plot_digit(outlier_recon,'outlier_recon')
```



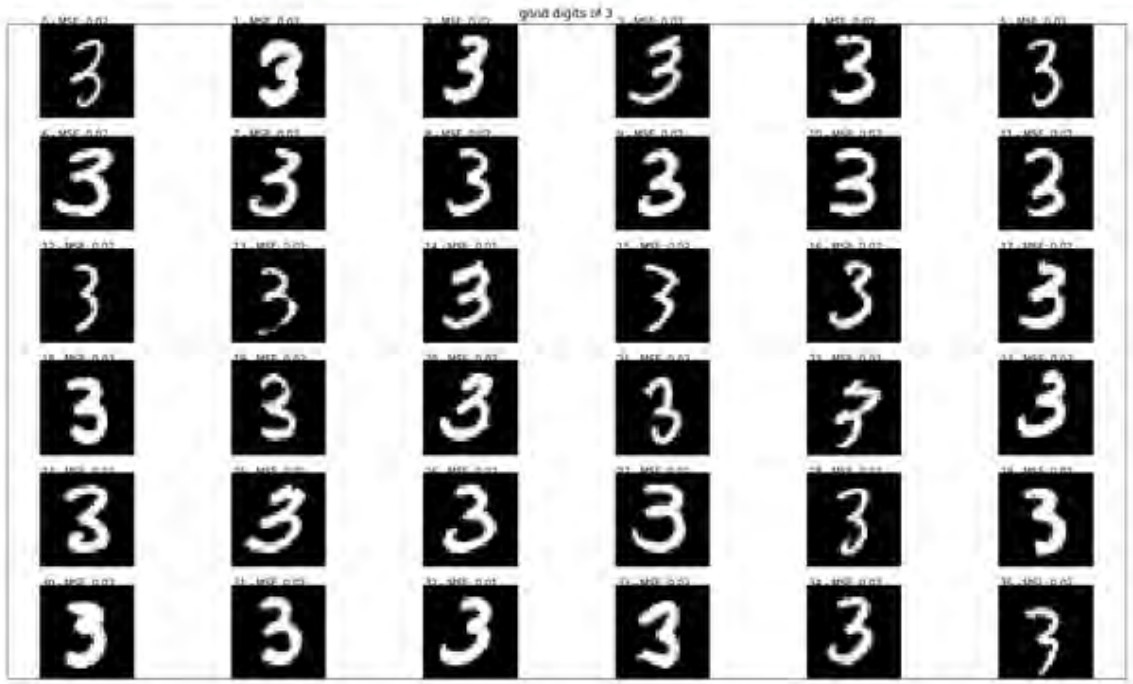
- Step 7: Plot error distribution of the remaining points

```
In [133]: test_rec_error.as_data_frame().hist(bins=1000,range=[0.0,0.07])
Out[133]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0xada78eec>]],
          dtype=object)
```



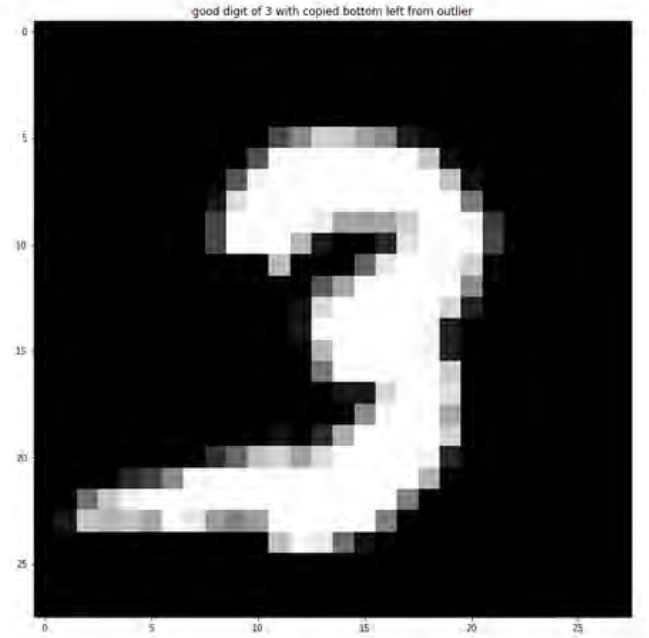
- Step 8: Visualize good digits of number three

```
In [204]: plot_multi_digits(digits_of_3, 6, 6, "good digits of 3")
          #plot_multi_digits(model.predict(digits_of_3[predictors]).cbind(digits_of_3[
```

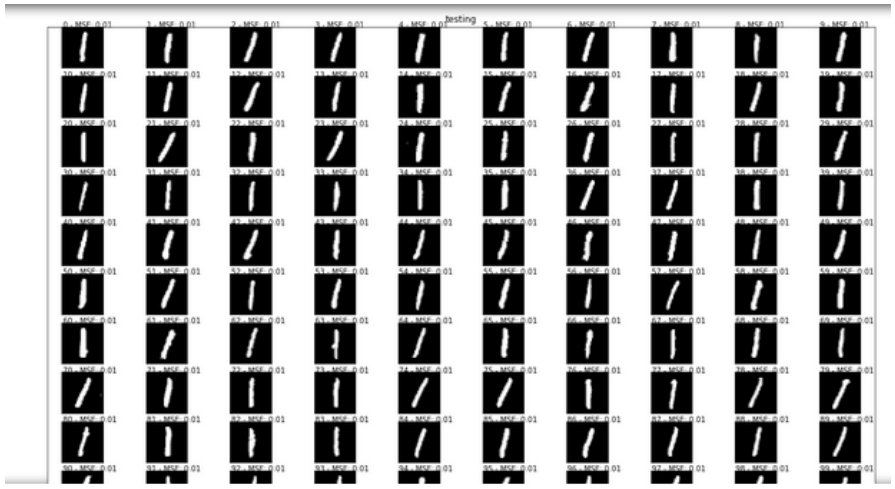


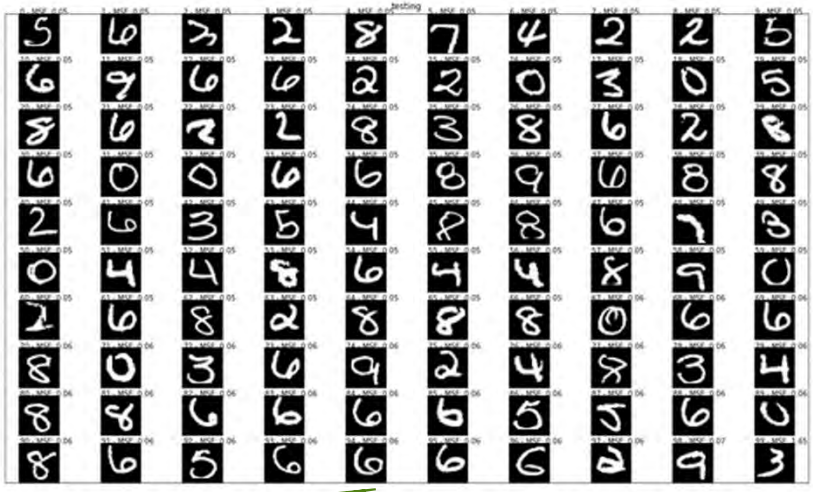
- Step 9: Visualize reconstructed version of the good digits of number three

```
In [196]: plot_digit(good_digit_of_3, 'good digit of 3 with copied bottom left from ou
```



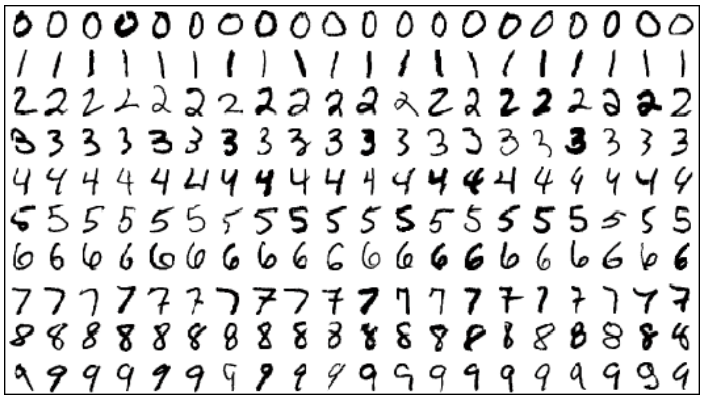
- Step 10: Manual inspection of bottom 100 (good) digits and 100 (ugly) digits

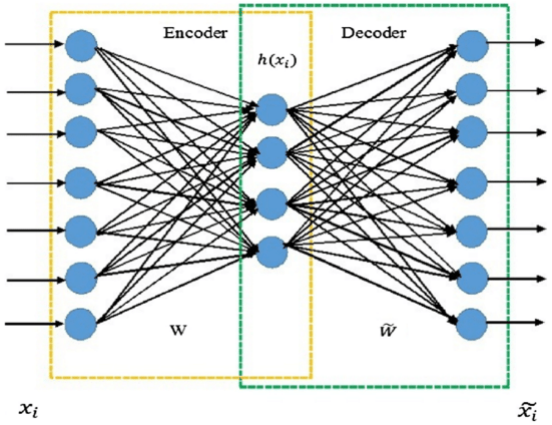




Viola! Indeed, the ugly digits represent the anomalies.

Activity 10 – H2O MNIST





Exercise

Fashion MNIST

Fashion-MNIST is a dataset of Zalando's article images—consisting of a training set of 60,000 examples and a test set of 10,000 examples. Each example is a 28x28 grayscale image, associated with a label from 10 classes. Fashion-MNIST to serve as a direct ***drop-in replacement for the original MNIST*** dataset for benchmarking machine learning algorithms. It shares the same image size and structure of training and testing splits.

*** Use fashion-mnist_test.csv and fashion-mnist-train.csv provided**

Step 1:
Watch and listen to the instructor's demonstration

20 mins

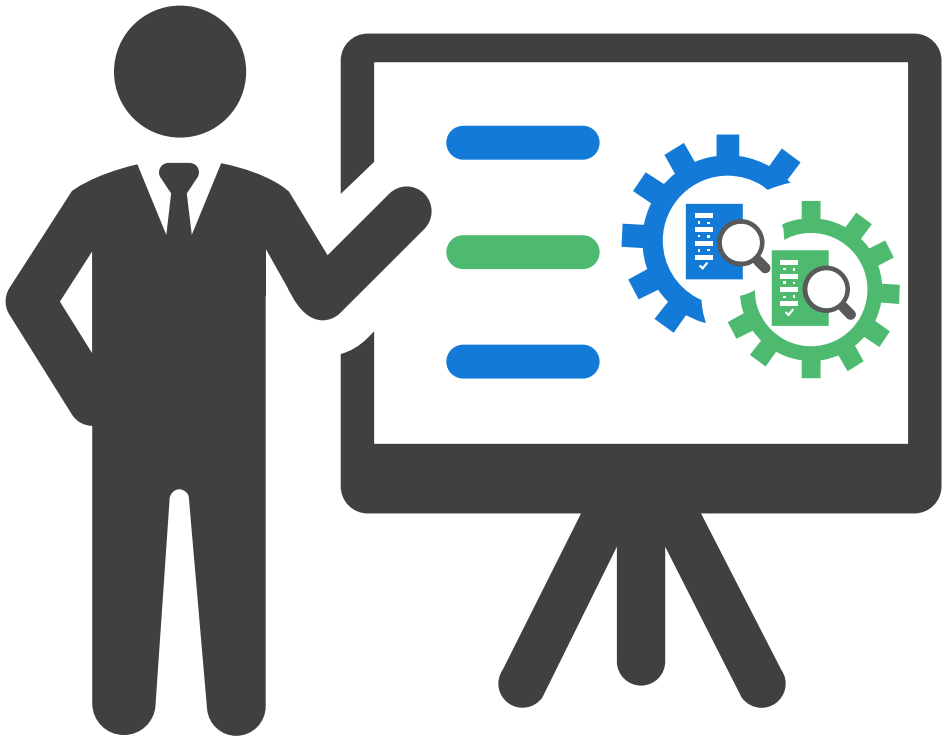
Step 2:
- Do on your own

Optional Activity

30 mins

Slide 50

S1 Seow, 12/19/2020



Summary

- Data gathering to prepare for training and testing data
- Use low-pass filter and simple moving average to detect abnormalities
- Introduction to anomaly detection and their techniques
- Introduction to H2O
- Supervised and unsupervised learning with Iris, MNIST, Fashion MNIST

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Source code: