H2O Machine Learning & Deep Learning London Workshop



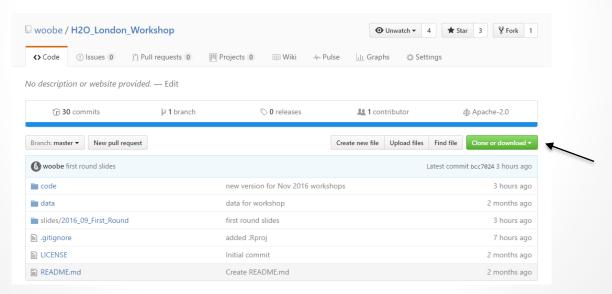
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Data Science for IoT Meetup Barclays Eagle Venture Labs 21st & 24th November, 2016

Download Data & Code for Workshop

Please go to

bit.ly/h2o_iot_workshop1

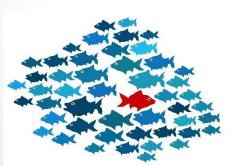


Example 2: Anomaly Detection

Anomaly (Outlier) Detection

Definition

 Identification of items, events or observations which do not conform to an expected pattern or other items in a dataset.

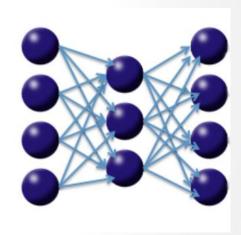


Use Cases

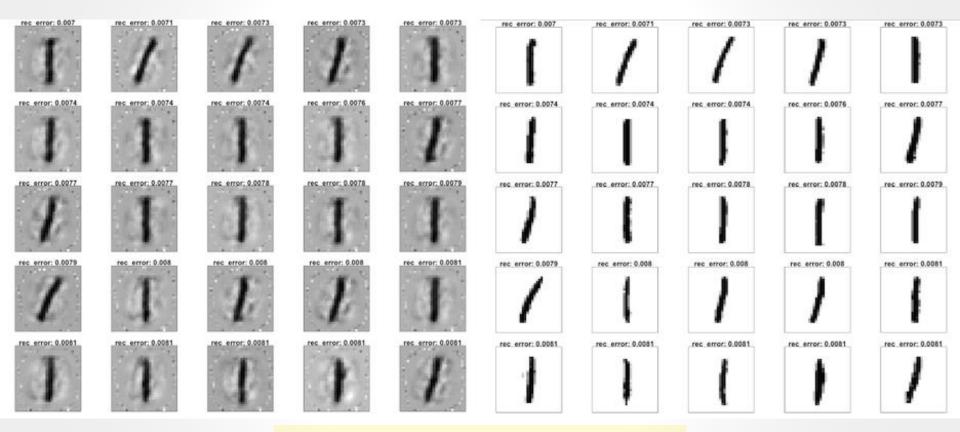
- Bank Fraud
- MonitoringManufacturing Lines
- Machine Learning
 - Separate dataset and build different models

Deep Autoencoder for Anomaly Detection

- Consider the following three-layer neural network with one hidden layer and the same number of input neurons (features) as output neurons.
- The loss function is the mean squared error (MSE) between the input and the output. Hence, the network is forced to learn the identity via a nonlinear, reduced representation of the original data.
 - e.g. High MSE = potential outliers
- Such an algorithm is called a deep autoencoder.

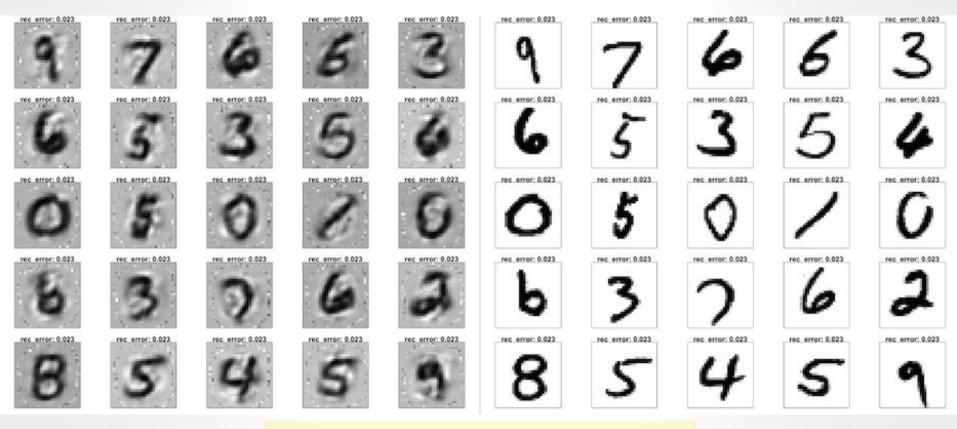


MNIST Example - The Good Ones

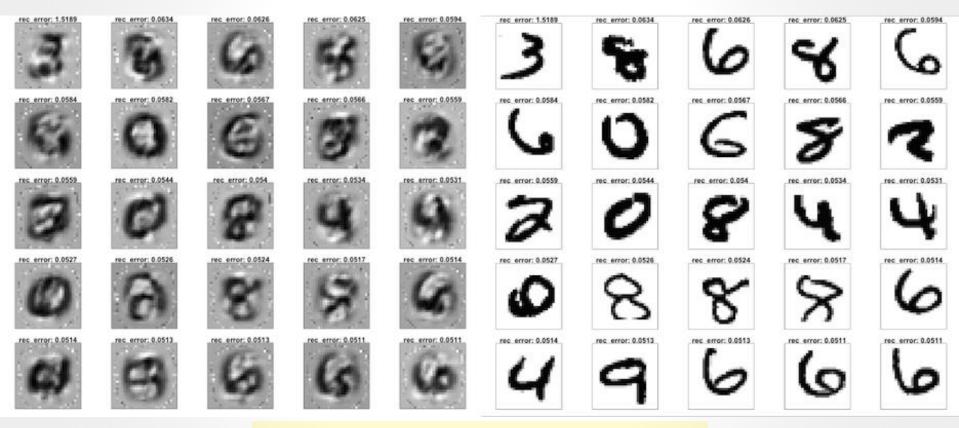


Samples with Low Mean Squared Error (MSE)

MNIST Example - The Bad Ones



MNIST Example - The Ugly Ones



use_case_2_anomaly_detection.R

```
# Step 8: Using Deep Learning for Anomaly Detection
    # Start and connect to a local H2O cluster
    library(h2o)
    h2o.init(nthreads = -1)
 8
    # Import data from a local CSV file
    mtcar <- read.csv("./data/auto_design.csv")</pre>
    mtcar$gear <- as.factor(mtcar$gear)</pre>
    mtcar$carb <- as.factor(mtcar$carb)</pre>
    mtcar$cvl <- as.factor(mtcar$cvl)</pre>
    mtcar$vs <- as.factor(mtcar$vs)
    mtcar$am <- as.factor(mtcar$am)
    mtcar$ID <- 1:nrow(mtcar)</pre>
17
    # Print it out
    print(mtcar)
20
    # Convert R data frame into H2O data frame
    h2o_mtcar <- as.h2o(mtcar)
```

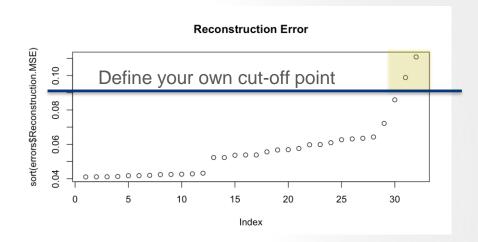
```
> print(mtcar)
                  X mpa cvl disp
           Mazda RX4 21.0 6 160.0 110
                                      3.90
                                            2.620
       Mazda RX4 Wag 21.0 6 160.0 110
                                     3.90
                                             2.875
                                                    17.02 0 1
          Datsun 710 22.8 4 108.0
                                      3.85
                                             2.320
      Hornet 4 Drive 21.4 6 258.0 110 3.08
                                            3.215
                                                    19.44 1
    Hornet Sportabout 18.7 8 360.0 175
                                     3.15
                                            3.440
                                                    17.02 0
             Valiant 18.1 6 225.0 105
                                     2.76
                                             3.460
                                                    20.22 1 0
          Duster 360 14.3 8 360.0 245
                                      3.21
                                             3.570
                         4 146.7 62 3.69
                                             3.190
            Merc 230 22.8 4 140.8
                                  95 3.92
                                            3.150
                         6 167.6 123 3.92
                         6 167.6 210 800.00 900.000 1000.00
          Merc 450SE 16.4
                         8 275.8 180
                                            4.070
          Merc 450SL 17.3 8 275.8 180
                                     3.07
                                            3.730
         Merc 450SLC 15.2 8 275.8 180
                                      3.07
                                            3.780
15 Cadillac Fleetwood 10.4 8 472.0 205
                                     2.93
                                            5.250
                                                    17.98 0 0
                                                                      4 15
16 Lincoln Continental 10.4 8 460.0 215
                                      3.00
                                            5.424
                                                    17.82 0
                                                                      4 16
    Chrysler Imperial 14.7 8 440.0 230 3.23
                                            5.345
                                                                      4 17
            Figt 128 32.4 4 780.0 2100 400.00 200.000
19
         Honda Civic 80.4 10 75.7 100 4.93
20
       Toyota Corolla 33.9 4 71.1 65
                                     4.22
                                            1.835
                                                                      1 20
21
       Toyota Corona 21.5 4 120.1 97 3.70
                                            2.465
                                                                      1 21
     Dodge Challenger 15.5 8 318.0 150 2.76
                                            3.520
                                                    16.87 0 0
                                                                      2 22
23
         AMC Javelin 15.2 8 304.0 150 3.15
                                            3.435
                                                    17.30 0 0
                                                                      2 23
24
          Camaro Z28 13.3 8 350.0 245
                                      3.73
                                             3.840
                                                                      4 24
     Pontiac Firebird 19.2 8 400.0 175
                                     3.08
                                            3.845
26
           Fiat X1-9 27.3 4 79.0 66 4.08
                                            1.935
                                                    18.90 1 1
                                                                      1 26
27
       Porsche 914-2 26.0 4 120.3 91 4.43
                                            2.140
                                                                      2 27
        Lotus Europa 30.4 4 95.1 113 3.77 1.513
28
                                                                      2 28
       Ford Pantera L 15.8 8 351.0 264 4.22 3.170
        Ferrari Dino 19.7 6 900.0 700 3.62 200.770
                                                                      6 30
31
       Maserati Bora 15.0 8 301.0 335 3.54 3.570
                                                                      8 31
32
          Volvo 142E 21.4 4 121.0 109 4.11 2.780
```

use_case_2_anomaly_detection.R

Build a Deep Autoencoder

```
# Training an unsupervised deep neural network with autoencoder
28
29
    # Use a bigger DNN
    model \leftarrow h2o.deeplearning(x = 1:10,
31
                              training_frame = h2o_mtcar,
32
                              autoencoder = TRUE.
                              activation = "RectifierWithDropout",
33
34
                              hidden = c(50, 50, 50),
35
                              epochs = 100)
36
    # Calculate reconstruction errors (MSE)
    errors <- h2o.anomaly(model, h2o_mtcar, per_feature = FALSE)
    print(errors)
    errors <- as.data.frame(errors)
                                           Look at the MSE
41
    # Plot
    plot(sort(errors$Reconstruction.MSE), main = "Reconstruction Error")
44
    # Outliers (define 0.09 as the cut-off point)
    row_outliers <- which(errors > 0.09) # based on plot above
    mtcar[row_outliers.]
```

Define cut-off



Outliers identified

Thanks!

- Organisers & Contributors Slides & Code
 - Ajit Jaokar
 - Sibanjan Das

- **Key Resources**
 - o docs.h2o.ai
 - o github.com/h2oai/h2omeetups

- - o bit.ly/ h2o_iot_workshop1

- Contact
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 - o github.com/woobe