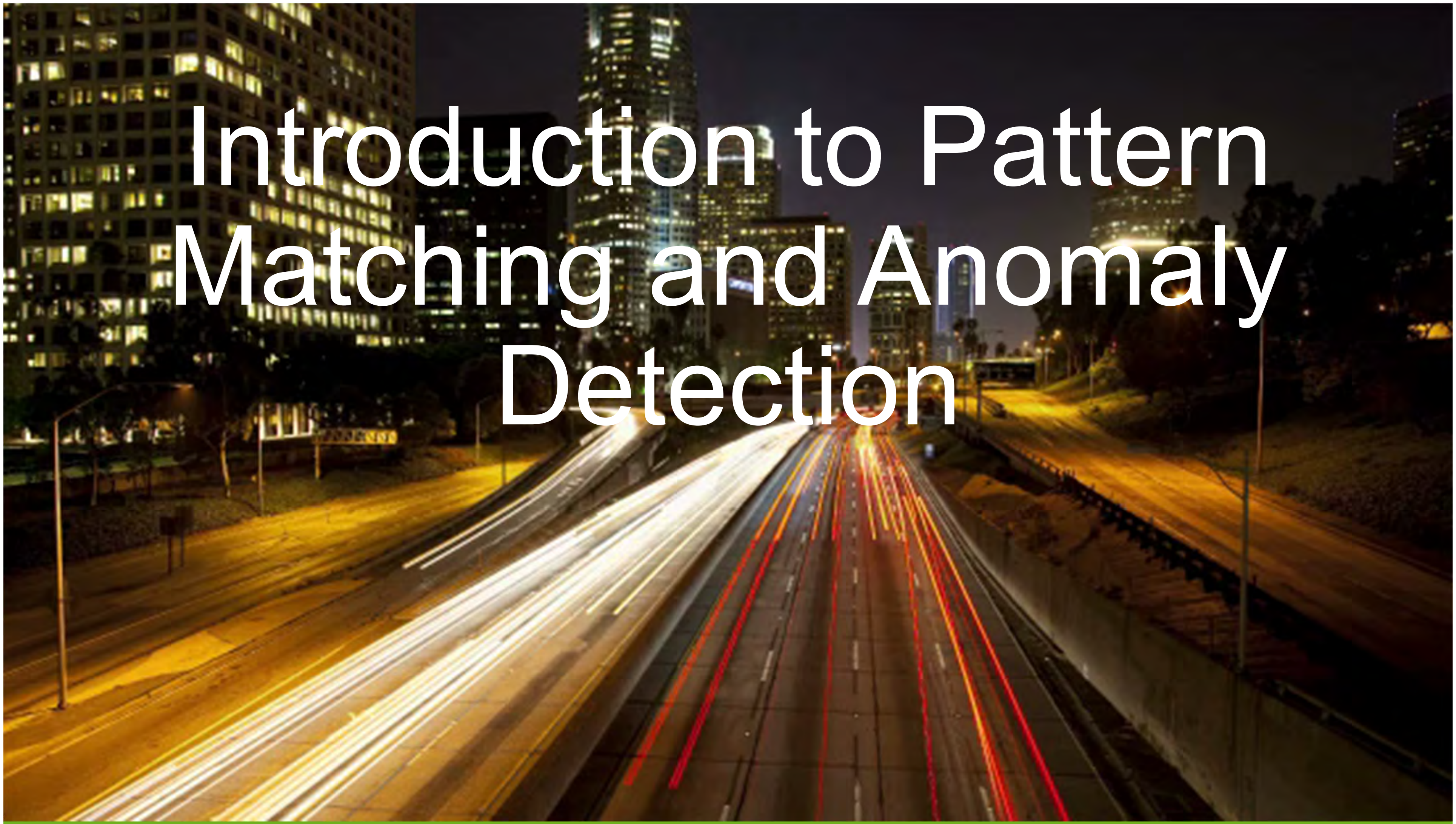


Introduction to Pattern Matching and Anomaly Detection

Version 1.0

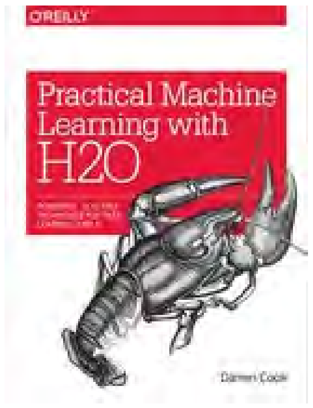
Programme

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 - 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

Support Metrics

- H2O supports a number of metrics, ways to measure a model's usefulness.
- Before we get into parameters it is worth taking a look at them because when we talk about "scoring a model" we mean evaluating on one of these metrics.

http://h2o-release.s3.amazonaws.com/h2o/master/3484/docs-website/h2o-py/docs/modeling.html#h2odeeplearningestimator



Practical Machine Learning with H2O

Regression	Classification
RMSE - The square root of MSE. If your response variable units are dollars, the units of MSE is dollars-squared, but RMSE is back into dollars	**Misclassification** - This is the overall error, the number shown in the bottom right of a confusion matrix. If it got 1 of 20 wrong in class A, 1 of 50 wrong in class B, and 2 of 30 wrong in class C, it got 4 wrong in total out of 100, so the misclassification is 4, or 4%.
MAE - Mean Absolute Error. Following on from the MSE example, a guess of 1,4,3 has absolute errors of 1, so the MAE is 1. But 2,3,6 has absolute errors of 0,0,2 so the MAE is 0.667. As with RMSE, the units are the same as your response variable.	**Mean_per_class_error** - The right column in a confusion matrix has an error rate for each class. This is the average of them, so for the preceding example it is the mean of 1/20, 1/50, and 2/30, which is 4.556%. If your classes are balanced (exactly the same size) it is identical to misclassification.
R2 - R-squared, also written as R^2, and also known as the coefficient of determination. This used to be available as a choice for stopping_metric, but has fallen out of favor	**Logloss** (default) - The H2O algorithms don't just guess the category, they give a probability for the answer being each category. The confidence assigned to the correct category is used to calculate logloss (and MSE). Logloss disproportionately punishes low numbers, which is another way of saying having high confidence in the wrong answer is a bad thing.
RMSLE - The catchy abbreviation of Root Mean Squared Logarithmic Error. Prefer this to RMSE if an under-prediction is worse than an over-prediction.	**MSE** - Mean Squared Error. The error is the distance from 1.0 of the probability it suggested. So assume we have three classes, A, B, and C, and your model guesses A with 0.91, B with 0.07, and C with 0.02. If the correct answer was A the error (before being squared) is 0.09, if it is B 0.93, and if C it is 0.98.
	AUC - Area Under Curve

Model Evaluation

Threshold Metrics	Ranking Metrics	Probabilistic Metrics
Threshold metrics are those that **quantify the classification prediction errors.** That is, they are designed to summarize the fraction, ratio, or rate of when a predicted class does not match the expected class in a holdout dataset.	Rank metrics are more concerned with evaluating classifiers based on how effective they are at separating classes. These metrics require that a classifier predicts a score or a probability of class membership. From this score, different thresholds can be applied to test the effectiveness of classifiers. Those models that maintain a good score across a range of thresholds will have good class separation and will be ranked higher	designed specifically to quantify the uncertainty in a classifier's predictions. These are useful for problems where we are less interested in incorrect vs. correct class predictions and more interested in the uncertainty the model has in predictions and penalizing those predictions that are wrong but highly confident.

Threshold Metrics

- Used when we want a model to minimize the number of errors
- Classification Accuracy

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions}$$

- Classification Error

$$Error = \frac{Incorrect\ Predictions}{Total\ Predictions}$$

- universally inappropriate for imbalanced classification

Threshold Metrics

- Sensitivity-Specificity Metrics
  - Sensitivity refers to the true positive rate and
  - summarizes how well the positive class was predicted.

$$Sensitivity = \frac{TruePositive}{TruePositive + FalseNegative}$$

  - Specificity is the complement to sensitivity, or the true negative rate, and
  - Summarizes how well the negative class was predicted.

$$Specificity = \frac{TrueNegative}{FalsePositive + TrueNegative}$$

Threshold Metrics

- Precision-Recall Metrics
  - Precision summarizes the fraction of examples assigned the positive class that belong to the positive class.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

  - Recall summarizes how well the positive class was predicted and is the same calculation as sensitivity

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

Threshold Metrics

- Precision
  - Consider a dataset with a 1:100 minority to majority ratio, with 100 minority examples and 10,000 majority class examples.
  - A model makes predictions and predicts 120 examples as belonging to the minority class, 90 of which are correct, and 30 of which are incorrect.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

Precision = 90/(90+30) = 90/120 = 0.75

It does not comment on how many real positive class examples were predicted as belonging to the negative class, so-called false negatives.

sklearn.metrics.precision score API:
https://scikit-learn.org/stable/modules/generated/sklearn.metrics.precision_score.html

Threshold Metrics

- Recall
  - Consider a dataset with a 1:100 minority to majority ratio, with 100 minority examples and 10,000 majority class examples.
  - A model makes predictions and predicts 90 of the positive class predictions correctly and 10 incorrectly.

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

Recall = 90/(90+10) = 90/100 = 0.90

sklearn.metrics.recall score API.
https://scikit-learn.org/stable/modules/generated/sklearn.metrics.recall_score.html

Threshold Metrics

- Precision vs Recall
  - Maximizing precision will minimize the number false positive errors,
  - Maximizing the recall will minimize the number of false negative errors.

Precision: Appropriate when minimizing false positives is the focus.

Recall: Appropriate when minimizing false negatives is the focus.

Threshold Metrics

- F-Measure
  - F-measure provides a way to combine both precision and recall into a single measure that captures both properties..

$$F_{measure} = \frac{(2) \text{ x } Precision \text{ x } Recall}{Precision + \ Recall}$$

  - sometimes called the F-score or the F1-measure
  - might be the most common metric used on imbalanced classification problems.

Ranking Metrics

- Rank metrics are more concerned with evaluating classifiers based on how effective they are at separating classes.
- These metrics require that a classifier predicts a score or a probability of class membership.
- Those models that maintain a good score across a range of thresholds will have good class separation and will be ranked higher

Ranking Metrics

- Receiver Operating Characteristic (ROC Curve)
  - Summarizes a field of study for analyzing binary classifiers based on their ability to discriminate classes
  - A ROC curve is a diagnostic plot for summarizing the behavior of a model by calculating the false positive rate and true positive rate for a set of predictions by the model under different thresholds.
  - The true positive rate is the recall or sensitivity.

$$TruePositiveRate = \frac{TruePositive}{TruePositive + FalseNegative}$$

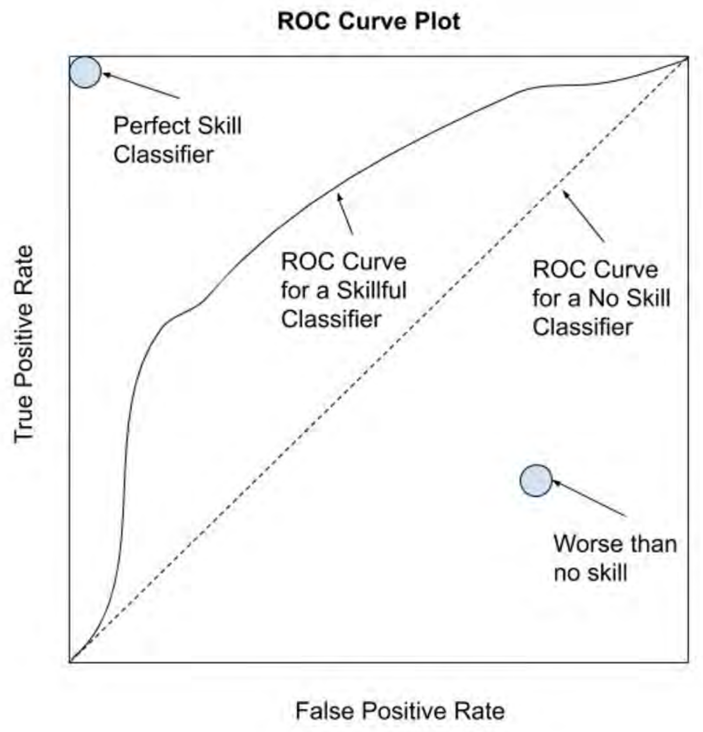
  - The false positive rate is calculated as

$$FalsePositiveRate = \frac{FalsePositive}{FalsePositive + TrueNegative}$$

It is a popular diagnostic tool for classifiers on balanced and imbalanced binary prediction problems alike because it is not biased to the majority or minority class

Ranking Metrics

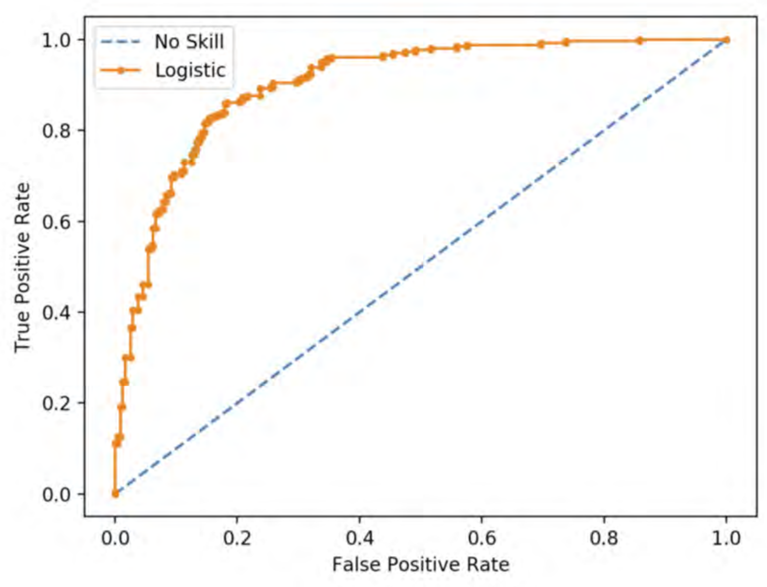
- Receiver Operating Characteristic (ROC Curve)
  - Each threshold is a point on the plot and the points are connected to form a curve. A classifier that has no skill (e.g. predicts the majority class under all thresholds) will be represented by a diagonal line from the bottom left to the top right. Any points below this line have worse than no skill. A perfect model will be a point in the top left of the plot.



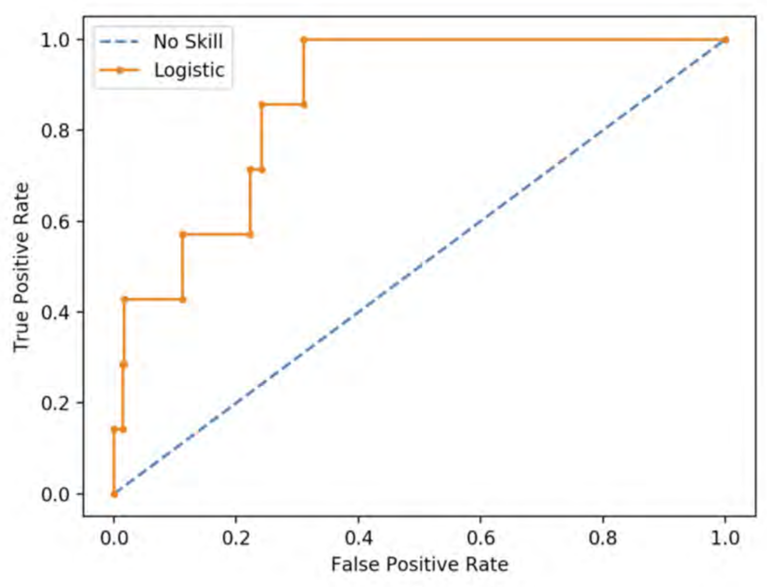
A no skill classier will have a score of 0.5, whereas a perfect classier will have a score of 1.0.

sklearn.metrics.roc curve API https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html

ROC



Balanced Dataset



Imbalanced Dataset

Ranking Metrics

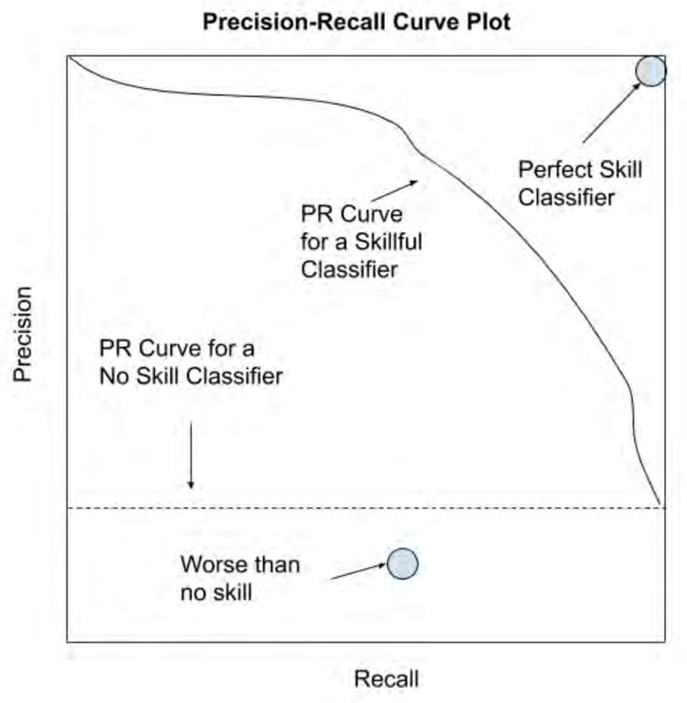
- ROC AUC
  - the area under the curve can be calculated to give a single score for a classier model across all threshold values.
  - The score is a value between 0.0 and 1.0, with 1.0 indicating a perfect classifier.

For imbalanced classification with a severe skew and few examples of the minority class, the ROC AUC can be misleading.
This is because a small number of correct or incorrect predictions can result in a large change in the ROC Curve or ROC AUC score.

sklearn.metrics.roc auc score API
https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_auc_score.html

Ranking Metrics

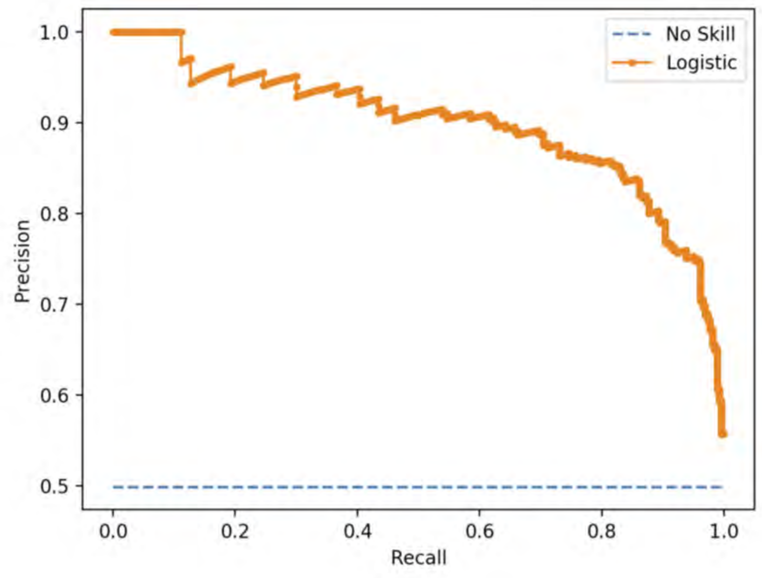
- Precision-Recall curve
  - ROC AUC can be optimistic under a severe class imbalance, especially when the number of examples in the minority class is small.
  - An alternative to the ROC Curve is the precision-recall curve that can be used in a similar way, although focuses on the performance of the classifier on the minority class.

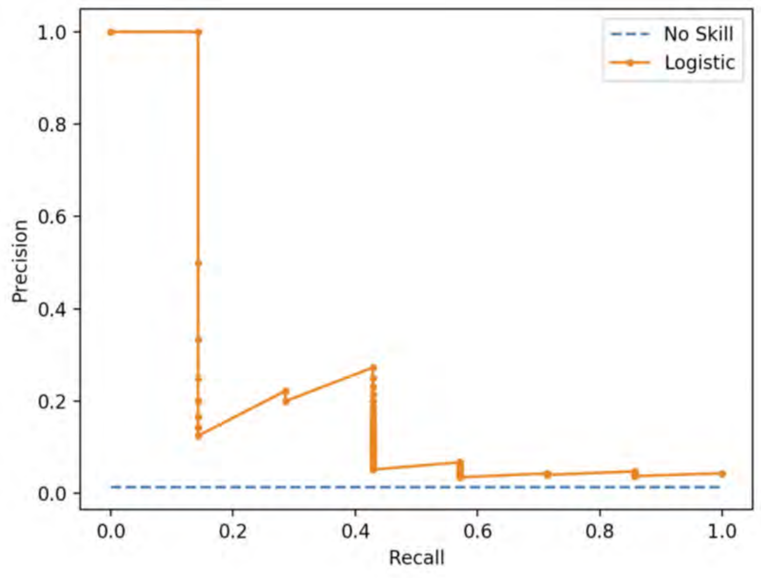


A no-skill classifier will be a horizontal line on the plot with a precision that is proportional to the number of positive examples in the dataset.

For a balanced dataset this will be 0.5. A perfect classier is represented by a point in the top right.

PR Curve





Balanced Dataset

Imbalanced Dataset

Ranking Metrics

- Precision-Recall curve
  - Like the ROC Curve, the Precision-Recall Curve is a helpful diagnostic tool for evaluating a single classifier but challenging for comparing classifiers.
  - like the ROC AUC, we can calculate the area under the curve as a score and use that score to compare classifiers.
  - In this case, the focus on the minority class makes the Precision-Recall AUC more useful for imbalanced classification problems.
  - The Precision-Recall AUC score can be calculated using the auc() function in scikit-learn, taking the precision and recall values as arguments.

sklearn.metrics.precision recall curve API:
https://scikit-learn.org/stable/modules/generated/sklearn.metrics.precision_recall_curve.html

sklearn.metrics.auc API:
https://scikit-learn.org/stable/modules/generated/sklearn.metrics.auc.html

Probabilistic Metrics

- designed specifically to quantify the uncertainty in a classifier’s predictions
- useful for problems where we are less interested in incorrect vs. correct class predictions and more interested in the uncertainty the model has in predictions and penalizing those predictions that are wrong but highly confident.

Probabilistic Metrics

- Log Loss (cross-entropy)

$$LogLoss = -((1 - y) \text{ x } \log(1 \ - yhat) + y \text{ x } \log(yhat)$$

  - The score can be generalized to multiple classes by simply adding the terms

$$LogLoss = -\sum^{cEC} y_c \text{ x } \log(yhatc)$$

  - This generalization is also known as **cross-entropy**
  - summarizes the average difference between two probability distributions.
  - **A perfect classifier has a log loss of 0.0, with worse values being positive up to infinity**

sklearn.metrics.log loss API.
https://scikit-learn.org/stable/modules/generated/sklearn.metrics.log_loss.html

Probabilistic Metrics

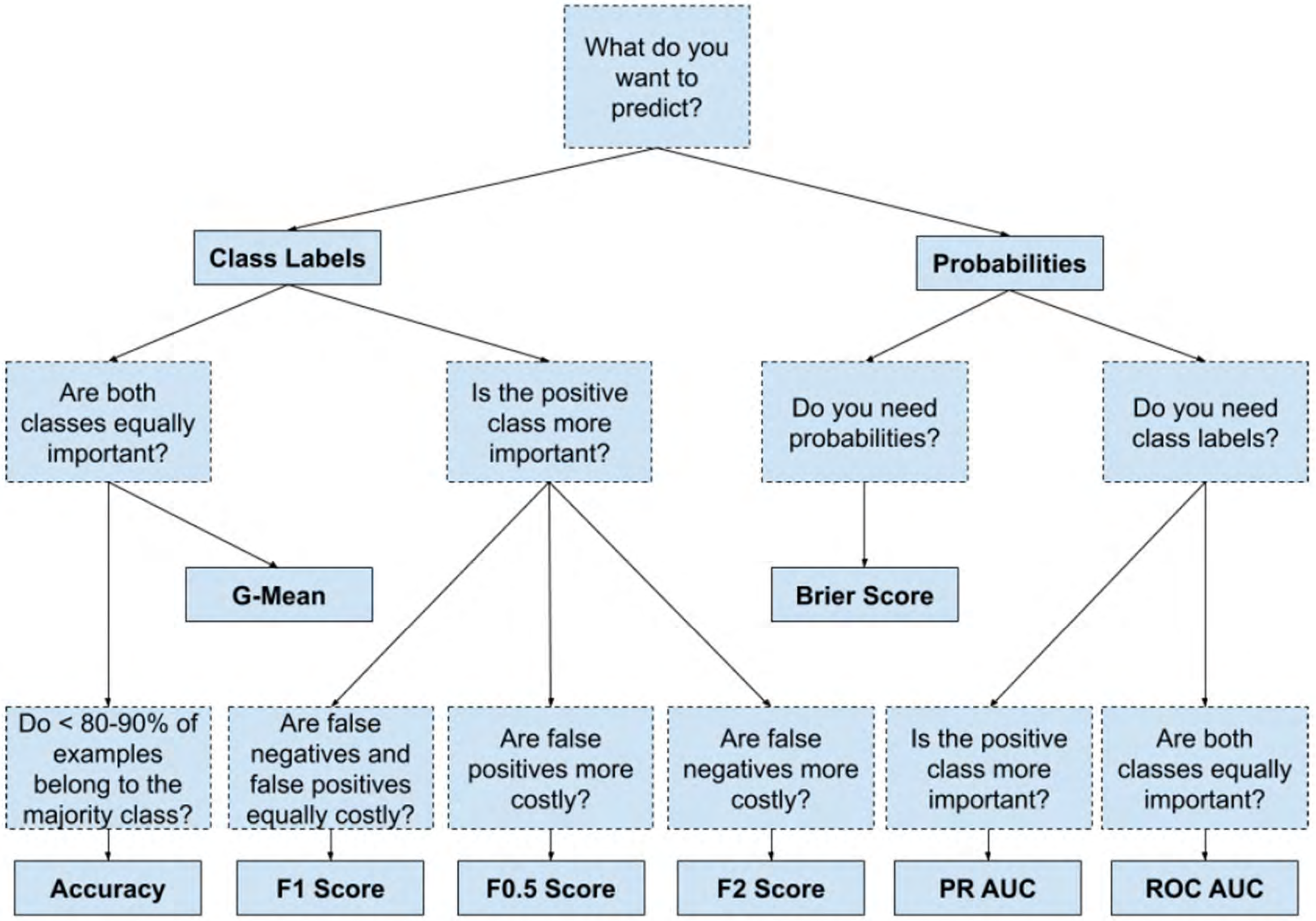
- Brier score
  - The benefit of the Brier score is that it is focused on the **positive class**, which for imbalanced classification is the minority class.
  - This makes it more preferable than log loss, which is focused on the entire probability distribution.
  - The score can be generalized to multiple classes by simply adding the terms

$$LogLoss = \frac{1}{n} \times \sum_{i=1}^{n} (yhat_2 - y_2)^2$$

  - A perfect classifier has a Brier score of 0.0.
  - Although popular for balanced classification problems, probability scoring methods are less widely used for classification problems with a skewed class distribution

sklearn.metrics.brier score loss API.
https://scikit-learn.org/stable/modules/generated/sklearn.metrics.brier_score_loss.html

Choose an Evaluation Metric


What do you want to predict?
Class Labels
Probabilities
Are both classes equally important?
Is the positive class more important?
Do you need probabilities?
Do you need class labels?
G-Mean
Brier Score
Do < 80-90% of examples belong to the majority class?
Are false negatives and false positives equally costly?
Are false positives more costly?
Are false negatives more costly?
Is the positive class more important?
Are both classes equally important?
Accuracy
F1 Score
F0.5 Score
F2 Score
PR AUC
ROC AUC

How to choose a metric for imbalanced classification

Further Reading

- Precision and recall, Wikipedia
  - https://en.wikipedia.org/wiki/Precision_and_recall
- Sensitivity and specicity, Wikipedia
  - https://en.wikipedia.org/wiki/Sensitivity_and_specificity
- Receiver operating characteristic, Wikipedia
  - https://en.wikipedia.org/wiki/Receiver_operating_characteristic
- Cross entropy, Wikipedia
  - https://en.wikipedia.org/wiki/Cross_entropy
- Brier score, Wikipedia
  - https://en.wikipedia.org/wiki/Brier_score
- Scikit-learn Metrics and scoring
  - https://scikit-learn.org/stable/modules/model_evaluation.html#scoring-parameter

Common Parameters

- The Essentials
  - **x** – Which fields in training_frame to learn from
  - **y** – Which fields in training_frame should be learned (response variable)
  - **training_frame** – the data set to train from
  - **ignore_const_cost** –Defaults to true, meaning if all values in a column are the same value, then ignore that column.
- Effort
  - **epochs** - The amount of training cycles a deep learning algorithm should do
  - **seed** - An integer to control random number generation, which allows you to get exactly the same model if you run the algorithm again. If using deep learning, you also need to set reproducible.
  - **reproducible** - If true, then deep learning will run on a single thread. This takes away the random element, but of course means it will train more slowly. Set this if also setting a seed, don't set it if not.
- Scoring and Validation
  - **validation_frame** - The (handle to the H2O) data set to validate against

Deep learning has a large number of additional scoring parameters. Check H2O documentation

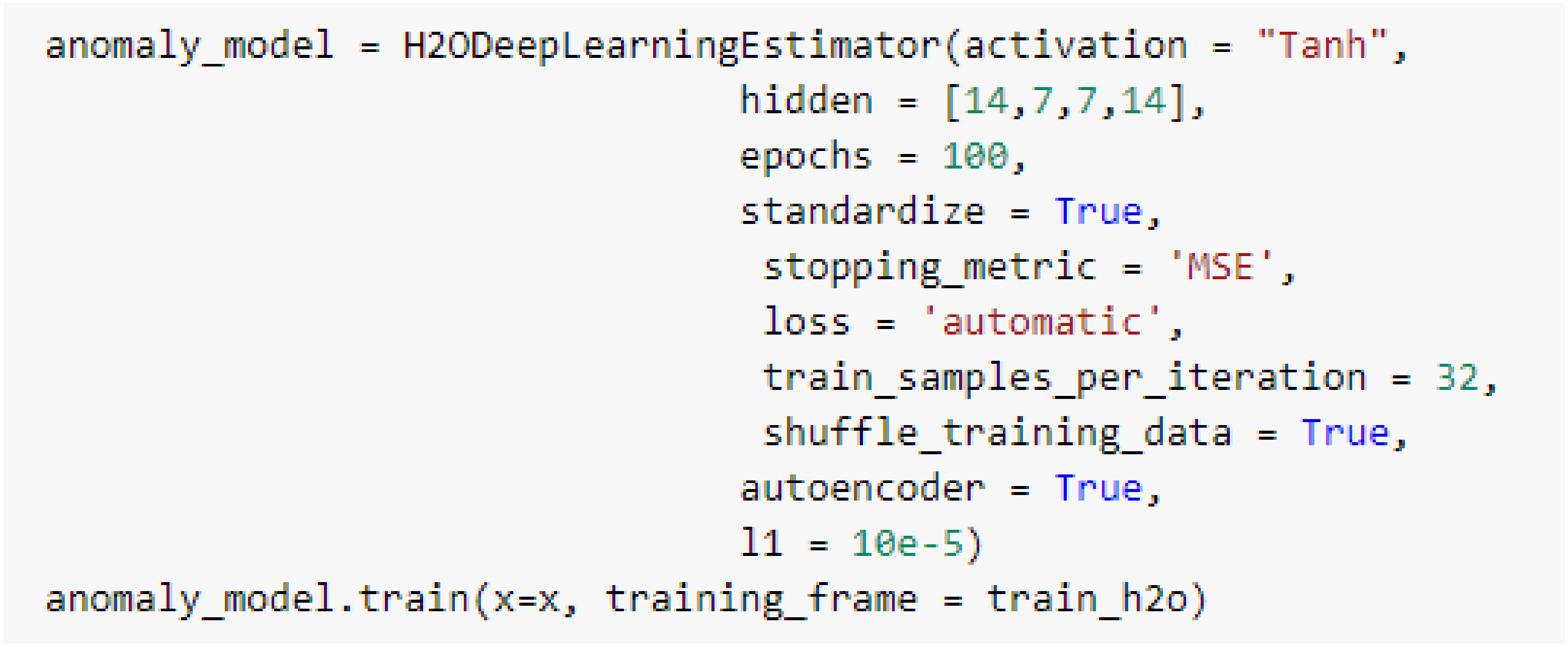
Common Parameters

- Early Stopping
  - **stopping_metric** - How to decide if the model is improving or not.
  - **stopping_tolerance** - Stop if it (your metric of choice) has not improved by at least this much
- Checkpoints
- Cross-Validation
- Data Weighting
- Sampling, Generalizing
- Regression
  - **loss** - Certain distributions (gaussian, laplace, huber) allow you to choose a loss function. The default choices for those three being: “Quadratic,” “Absolute,” “Huber.” The final possible value is “CrossEntropy,” which is for classification. Give the default of “Automatic” unless you have a good reason not to. You cannot define your own loss function.
- Output Control

Common Parameters

- Deep Learning
  - **shuffle_training_data** - Defaults to false. If true then training data is randomly sorted
  - **autoencoder** - Defaults to false (meaning to do supervised learning). Set this to true if auto-encoding. Usually you should set activation to Tanh at the same time.
  - **l1** - L1 regularization. Also known as lasso regularization. Defaults to 0, and typical values to try are 0.0001 or smaller.
  - **train_samples_per_iteration** - This controls how many training rows (samples) to use per iteration; an iteration can be thought of as when the model is scored. It is an integer, and normally you will use one of the following three special values. –2 is the default, and lets H2O decide
  - **activation** – Recitifer (default), Tanh (for autoencoder) or Maxout. Three other type with dropout not discussed here)
  - **hidden** - Hidden layer sizes. The default is 200,200, meaning there will be two hidden layers, with 200 neurons in each layer. If you give 60,40,20 then you will have three hidden layers, with 60 in the first, 40 in the second, and 20 in the third.

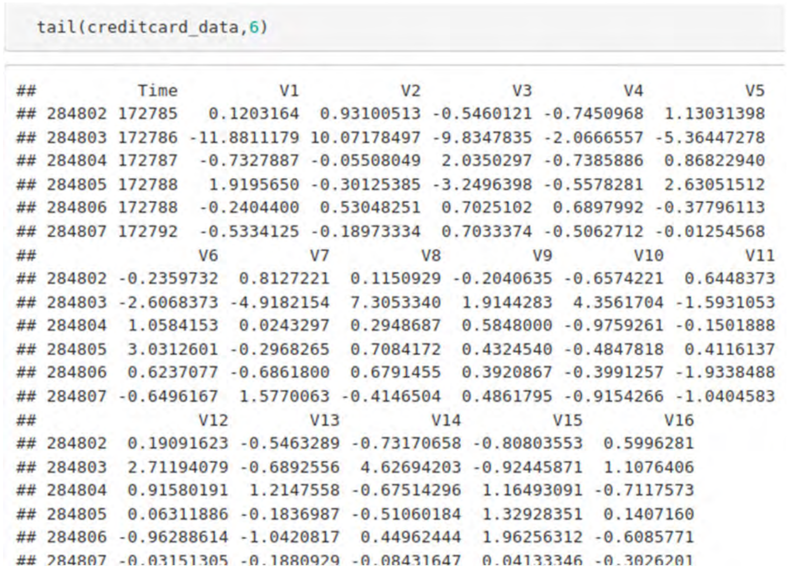
H2ODeepLearningEstimator



```
anomaly_model = H2ODeepLearningEstimator(activation = "Tanh",
                                         hidden = [14,7,7,14],
                                         epochs = 100,
                                         standardize = True,
                                          stopping_metric = 'MSE',
                                          loss = 'automatic',
                                          train_samples_per_iteration = 32,
                                          shuffle_training_data = True,
                                         autoencoder = True,
                                         l1 = 10e-5)
anomaly_model.train(x=x, training_frame = train_h2o)
```

Activity 11 – Credit Fraud

- Credit Card Fraud with H2O (Autoencoder)



```
tail(creditcard_data,6)
```

```
##          Time         V1          V2         V3         V4          V5
## 284802 172785   0.1203164  0.93100513 -0.5460121 -0.7450968  1.13031398
## 284803 172786 -11.8811179 10.07178497 -9.8347835 -2.0666557 -5.36447278
## 284804 172787  -0.7327887 -0.05508049  2.0350297 -0.7385886  0.86822940
## 284805 172788   1.9195650 -0.30125385 -3.2496398 -0.5578281  2.63051512
## 284806 172788  -0.2404400  0.53048251  0.7025102  0.6897992 -0.37796113
## 284807 172792  -0.5334125 -0.18973334  0.7033374 -0.5062712 -0.01254568
##                V6         V7         V8         V9        V10        V11
## 284802 -0.2359732  0.8127221  0.1150929 -0.2040635 -0.6574221  0.6448373
## 284803 -2.6068373 -4.9182154  7.3053340  1.9144283  4.3561704 -1.5931053
## 284804  1.0584153  0.0243297  0.2948687  0.5848000 -0.9759261 -0.1501888
## 284805  3.0312601 -0.2968265  0.7084172  0.4324540 -0.4847818  0.4116137
## 284806  0.6237077 -0.6861800  0.6791455  0.3920867 -0.3991257 -1.9338488
## 284807 -0.6496167  1.5770063 -0.4146504  0.4861795 -0.9154266 -1.0404583
##                V12        V13         V14         V15        V16
## 284802  0.19091623 -0.5463289 -0.73170658 -0.80803553  0.5996281
## 284803  2.71194079 -0.6892556  4.62694203 -0.92445871  1.1076406
## 284804  0.91580191  1.2147558 -0.67514296  1.16493091 -0.7117573
## 284805  0.06311886 -0.1836987 -0.51060184  1.32928351  0.1407160
## 284806 -0.96288614 -1.0420817  0.44962444  1.96256312 -0.6085771
## 284807 -0.03151305 -0.1880929 -0.08431647  0.04133346 -0.3026201
```

Exercises:

Increase the number of layers

Increase the number of neurons per layer

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

15 mins

Step 2:
Work through the activities

Individual Activity

30 mins

Isolation Forest

- A tree-based anomaly detection algorithm
- It is based on modelling the normal data in such a way to isolate anomalies that are both few in number and different in the feature space
    - our proposed method takes advantage of two anomalies' quantitative properties: i) they are the minority consisting of fewer instances and ii) they have attribute-values that are very different from those of normal instances. - Isolation Forest, 2008
- Tree structures are created to isolate anomalies.
- The result is that isolated examples have a relatively short depth in the trees, whereas normal data is less isolated and has a greater depth in the trees

Example - Mutant Fish

Each fisherman first picks a random feature to judge the samples. E.g. Length of the fish, circumference of the fish, or the proportion of its tail fin to its overall length.

Then picks a random value between the known min and max values of the corresponding measurement for the native species and splits all the fish accordingly (all fish with the relevant measurement equal to or bigger than the picked value go right, and every thing else goes left, for example)

The fisherman repeats the entire process over and over again until every single fish has been partitioned and a “tree” of fish has been created.

The resulting trees of the entire group of fishermen represent an isolation forest.

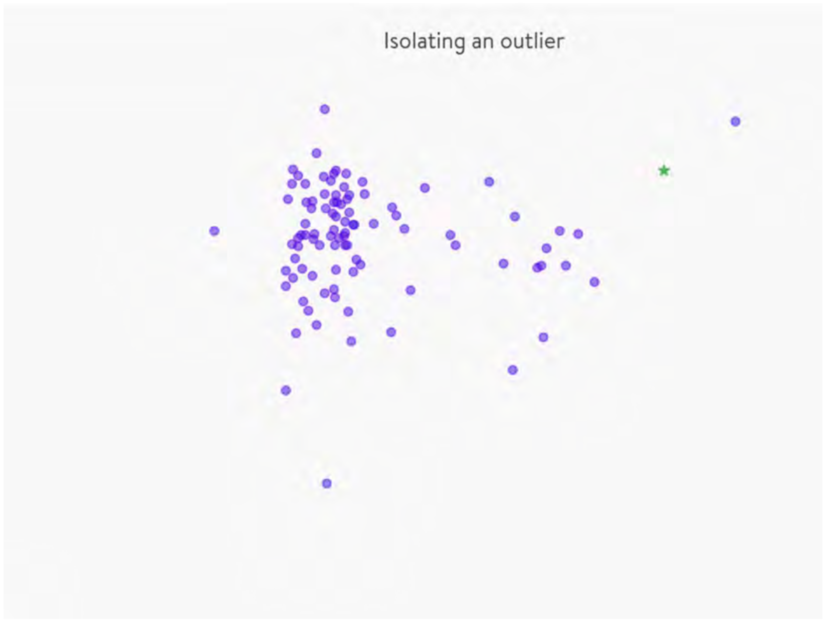
Procedure

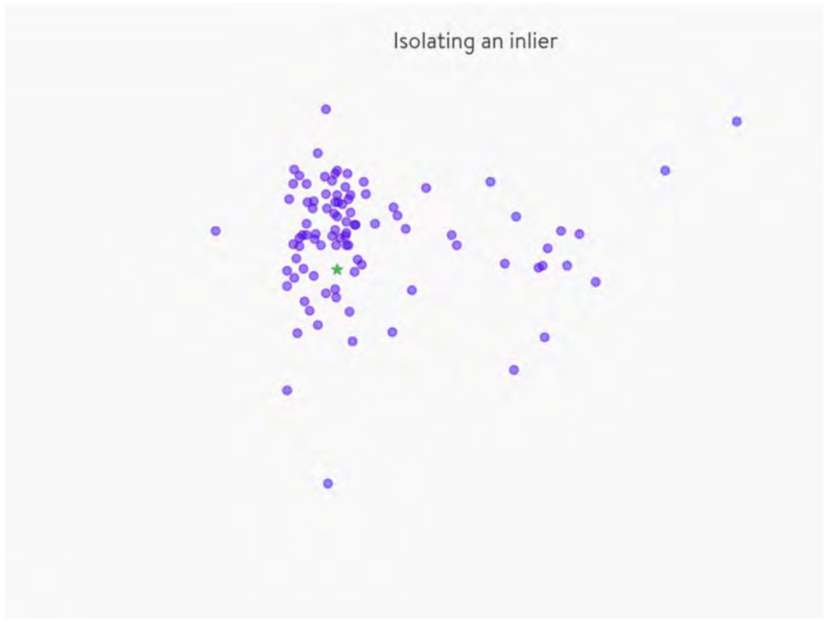
- How do we separate each point? The simple procedure is as follows for each point of the data set:
    1. Select the point to isolate.
    2. For each feature, set the range to isolate between the minimum and the maximum.
    3. Choose a feature randomly.
    4. Pick a value that's in the range, again randomly:
        1. If the chosen value keeps the point *above*, switch the *minimum* of the range of the feature to the value.
        2. If the chosen value keeps the point *below*, switch the *maximum* of the range of the feature to the value.
    5. Repeat steps 3 & 4 until the point is isolated. That is, until the point is the only one which is inside the range for all features.
    6. Count how many times you've had to repeat steps 3 & 4. We call this quantity the **isolation number.**

The algorithm claims that a point is an outlier if it doesn't have to repeat the steps 3 & 4 several times.

https://quantdare.com/isolation-forest-algorithm/

An illustration

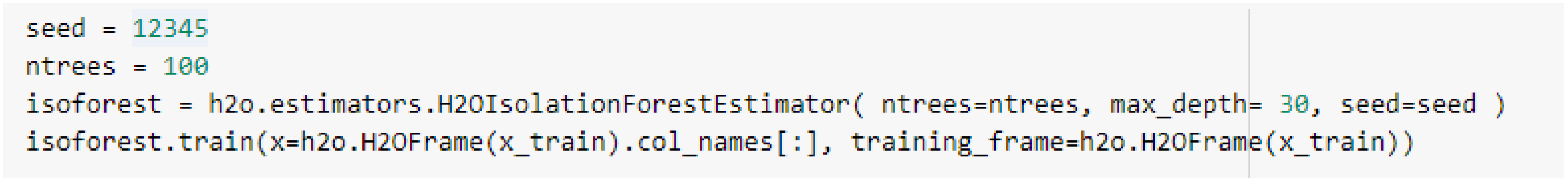




For inliers, the algorithm has to be repeated 15 times. Meanwhile, the outlier’s isolation number is 8. **Isolating an outlier means fewer loops than an inlier**.

H2OIsolationForestEstimator

- Builds an Isolation Forest model. Isolation Forest algorithm samples the training frame and in each iteration builds a tree that partitions the space of the sample observations until it isolates each observation. Length of the path from root to a leaf node of the resulting tree is used to calculate the anomaly score. Anomalies are easier to isolate and their average tree path is expected to be shorter than paths of regular observations.



```
seed = 12345
ntrees = 100
isoforest = h2o.estimators.H2OIsolationForestEstimator( ntrees=ntrees, max_depth= 30, seed=seed )
isoforest.train(x=h2o.H2OFrame(x_train).col_names[:], training_frame=h2o.H2OFrame(x_train))
```

Metrics

- Precision-Recall Metrics
  - Precision summarizes the fraction of examples assigned the positive class that belong to the positive class.

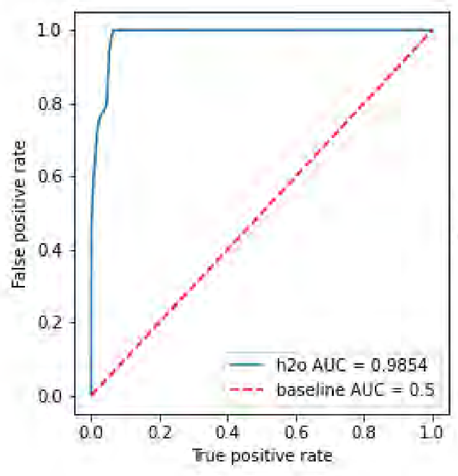
$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

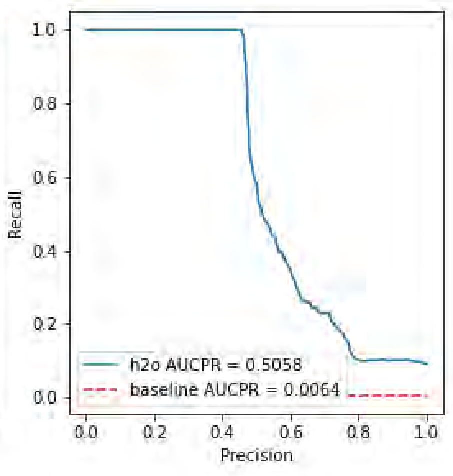
  - Recall summarizes how well the positive class was predicted and is the same calculation as sensitivity

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

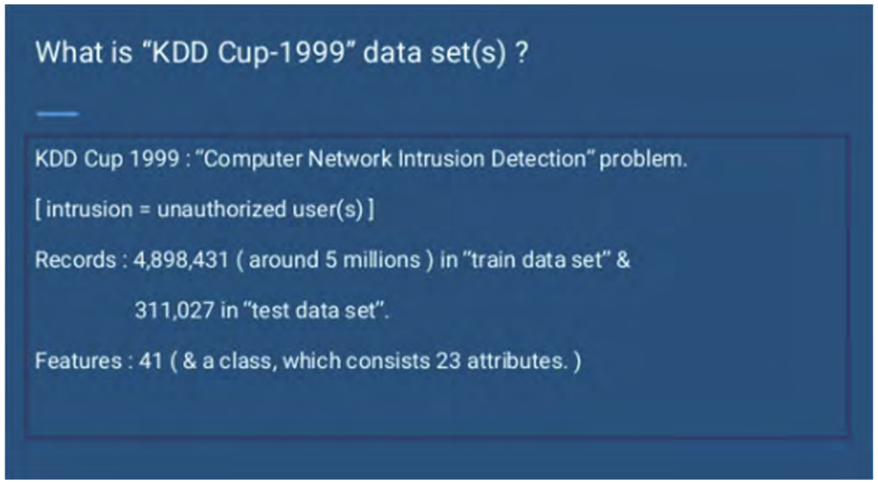
Metrics

- Area Under the Receiver Operating Characteristic Curve (AUC)
  - a metric evaluating how well a binary classification model distinguishes true positives from false positives. The perfect AUC score is 1; the baseline score of a random guessing is 0.5
- Area under the Precision-Recall Curve (AUCPR)
  - A metric evaluating the precision recall trade-off of a binary classification using different thresholds of the continuous prediction score. The perfect AUCPR score is 1; the baseline score is the relative count of the positive class.





Activity 12 – Intrusion Detection



What is "KDD Cup-1999" data set(s) ?

KDD Cup 1999 : "Computer Network Intrusion Detection" problem.

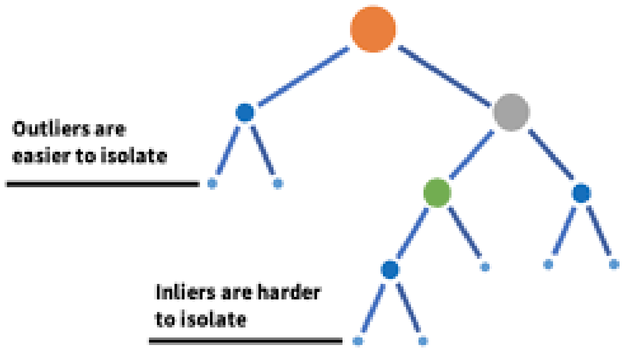
[intrusion = unauthorized user(s)]

Records : 4,898,431 (around 5 millions) in "train data set" &

311,027 in "test data set".

Features : 41 (& a class, which consists 23 attributes.)

Exercises:
- Change the no of trees
- Change the max depth



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

20 mins

Step 2:
- Do on your own

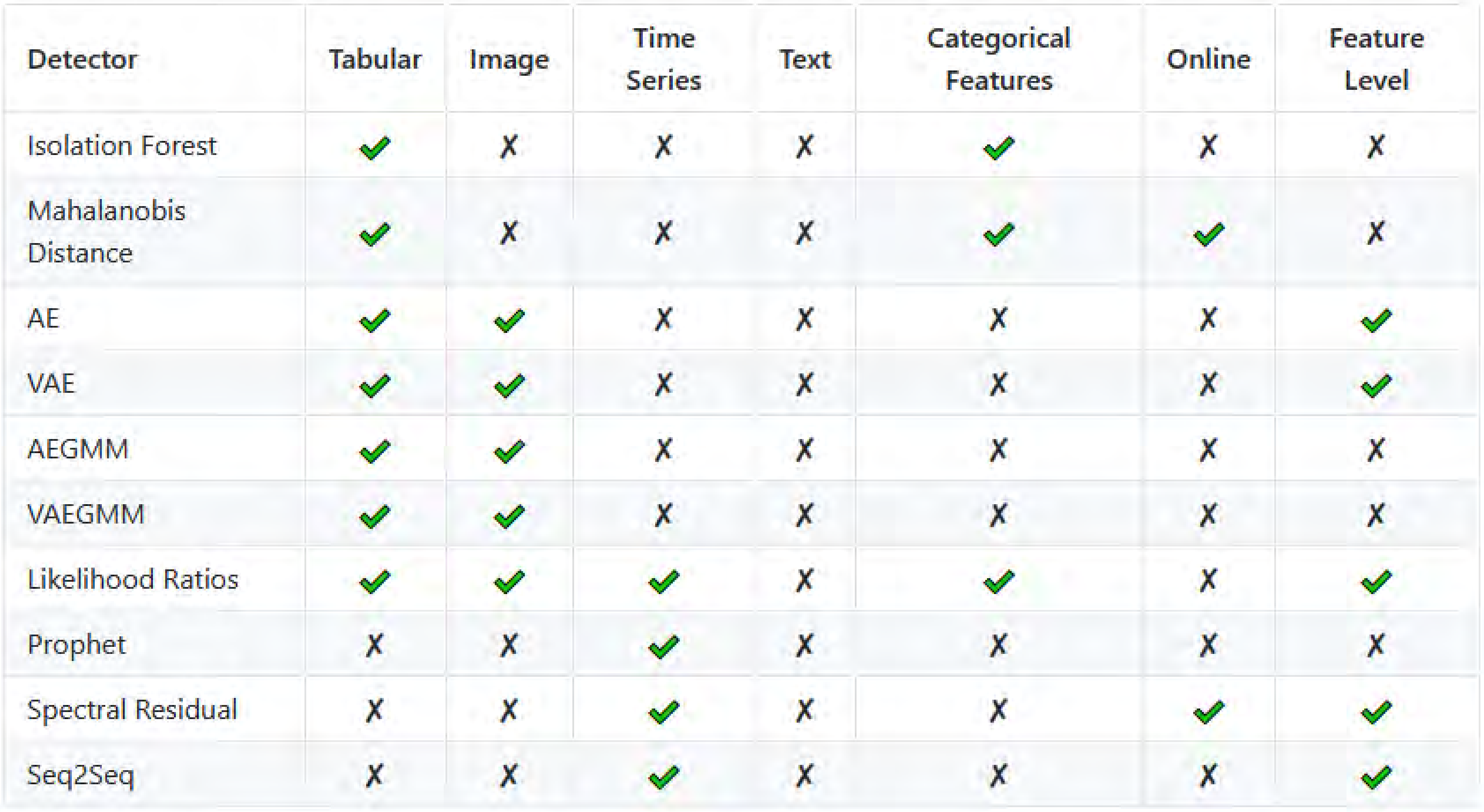
Individual Activity

30 mins

Alibi-detect

- an open source Python library for outlier, adversarial and drift detection, that includes a variety of powerful algorithms and techniques.
- It also supports various types of data, such as tabular, time series and image.
- **Outlier Detection Algorithms**
  - Isolation Forest
  - Mahalanobis Distance
  - Autoencoder (AE)
  - Variational Autoencoder (VAE)
  - Autoencoding Gaussian Mixture Model (AEGMM)
  - Variational Autoencoding Gaussian Mixture Model (VAEGMM)
  - Likelihood Ratios
  - Prophet Time Series Outlier Detector
  - Spectral Residual
  - Sequence-to-Sequence (Seq2Seq)

Outlier Detection Algorithms



Detector	Tabular	Image	Time Series	Text	Categorical Features	Online	Feature Level
Isolation Forest	✓	✗	✗	✗	✓	✗	✗
Mahalanobis Distance	✓	✗	✗	✗	✓	✓	✗
AE	✓	✓	✗	✗	✗	✗	✓
VAE	✓	✓	✗	✗	✗	✗	✓
AEGMM	✓	✓	✗	✗	✗	✗	✗
VAEGMM	✓	✓	✗	✗	✗	✗	✗
Likelihood Ratios	✓	✓	✓	✗	✓	✗	✓
Prophet	✗	✗	✓	✗	✗	✗	✗
Spectral Residual	✗	✗	✓	✗	✗	✓	✓
Seq2Seq	✗	✗	✓	✗	✗	✗	✓

Suggested use for each algorithm included in the Alibi Detect library

Threshold Metrics

- F-Measure
  - F-measure provides a way to combine both precision and recall into a single measure that captures both properties..

$$F_{measure} = \frac{(2) \text{ x } Precicion \text{ x } Recall}{Precicion + \ Recall}$$

  - sometimes called the F-score or the F1-measure
  - might be the most common metric used on imbalanced classification problems.

Threshold Metrics

- Consider a binary classification dataset with 1:100 minority to majority ratio, with 100 minority examples and 10,000 majority class examples
- Consider a model that predicts 150 examples for the positive class, 95 are correct (true positives), meaning five were missed (false negatives) and 55 are incorrect (false positives).

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

= 95/(95+55) = 0.633

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

= 95 / (95+5) = 0.95

Threshold Metrics

$$F_{measure} = \frac{2\ \times\ Precision\ \times Recall}{Precision + Recall}$$

$$= \frac{2\ \times 0.633 + 0.95}{0.633 + 0.95}$$

$$= 0.759$$

sklearn.metrics.f1 score API.
https://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html

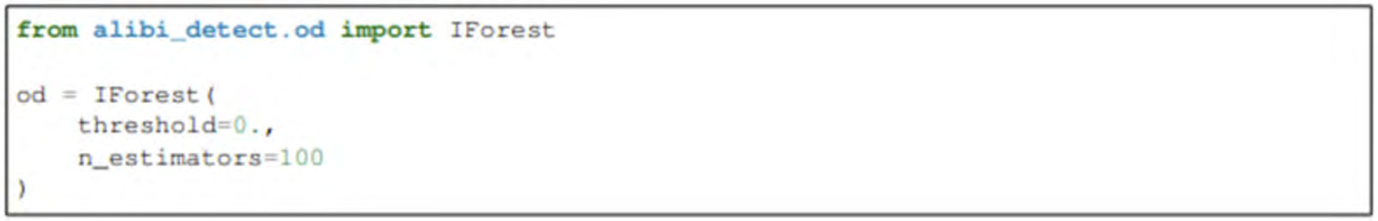
Getting Started

- Import alibi_detect
- Prepare data for training
- Initialise a detector
- Train the detector or load from file (od.fit() or load_dector())
- Make predictions (od.predict())

The predictions are returned in a dictionary with as keys meta and data. meta contains the detector's metadata while data is in itself a dictionary with the actual predictions. It has either is_outlier, is_adversarial or is_drift (filled with 0's and 1's) as well as optional instance_score, feature_score or p_value as keys with numpy arrays as values

IForest

- Parameters:
  - threshold: threshold value for the outlier score above which the instance is flagged as an outlier.
  - n_estimators: number of base estimators in the ensemble. Defaults to 100.
  - max_samples: number of samples to draw from the training data to train each base estimator. If int, draw max_samples samples. If float, draw max_samples times number of features samples. If ‘auto’, max_samples = min(256, number of samples).
  - max_features: number of features to draw from the training data to train each base estimator. If int, draw max_features features. If float, draw max_features times number of features features.
  - bootstrap: whether to fit individual trees on random subsets of the training data, sampled with replacement.
  - n_jobs: number of jobs to run in parallel for fit and predict.
  - data_type: can specify data type added to metadata. E.g. ‘tabular’ or ‘image’.



```
from alibi_detect.od import IForest

od = IForest(
    threshold=0.,
    n_estimators=100
)
```

IForest

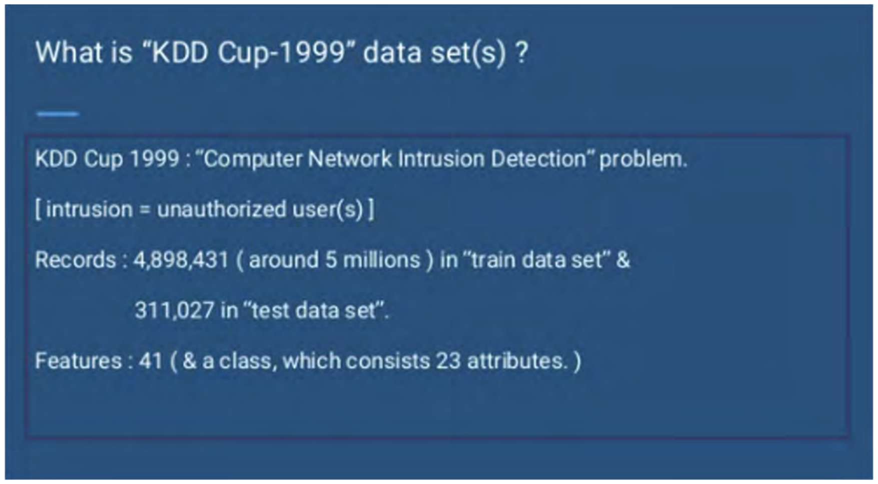
- We then need to train the outlier detector.
  - X: training batch as a numpy array.
  - sample_weight: array with shape (batch size,) used to assign different weights to each instance during training. Defaults to None.

```
od.fit(
    X_train
)
```

- It is often hard to find a good threshold value. If we have a batch of normal and outlier data and we know approximately the percentage of normal data in the batch, we can infer a suitable threshold:

```
od.infer_threshold(
    X,
    threshold_perc=95
)
```

Activity 12 – Network Intrusion



What is “KDD Cup-1999” data set(s) ?

KDD Cup 1999 : “Computer Network Intrusion Detection” problem.

[intrusion = unauthorized user(s)]

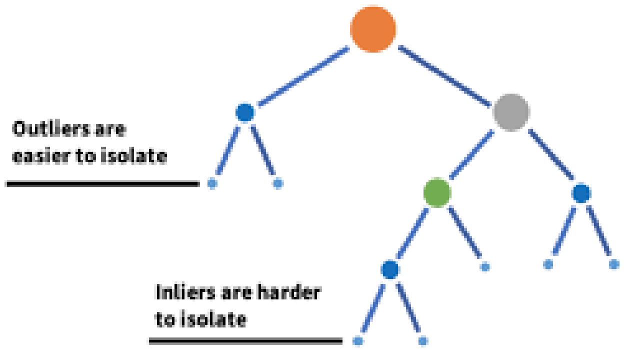
Records : 4,898,431 (around 5 millions) in “train data set” &

311,027 in “test data set”.

Features : 41 (& a class, which consists 23 attributes.)

Exercises:

- Change the no base estimators
- Change the max_samples and max_features



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

20 mins

Step 2:
- Do on your own

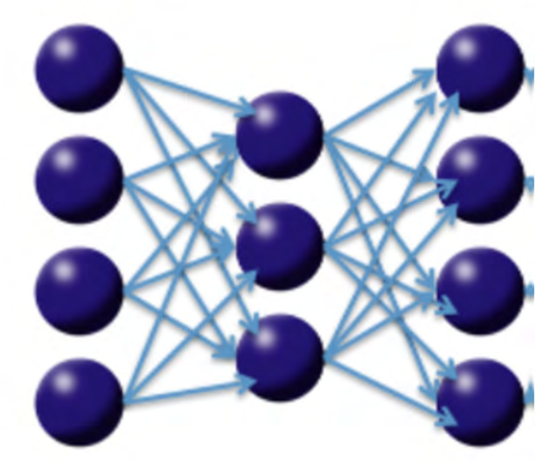
Optional Activity

30 mins

Autoencoders

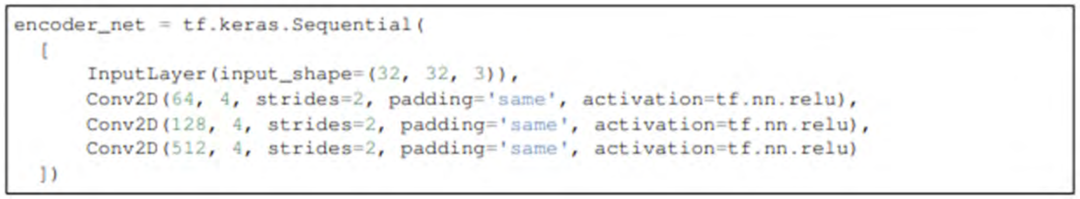
- Approach AD using a semi-supervised learning
  - Identify a set of data that represents the normal distribution. Non anomaly.
  - Learn what "normal" means from this training dataset. The trained model will provide a sort of metric in its mathematical definition; i.e. a function mapping every point 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)



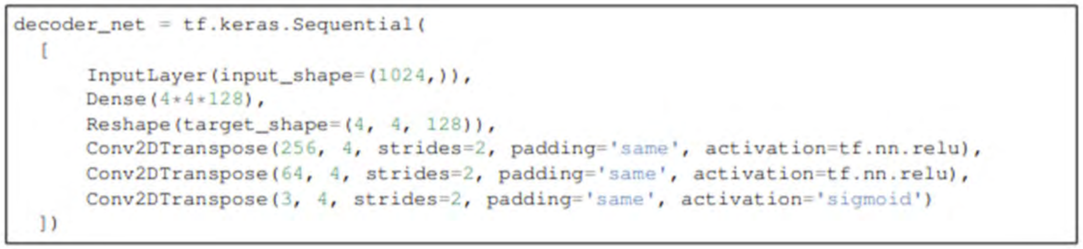
Usage

- Parameters:
  - threshold: threshold value above which the instance is flagged as an outlier.
  - encoder_net: tf.keras.Sequential instance containing the encoder network. Example:



```
encoder_net = tf.keras.Sequential(
  [
      InputLayer(input_shape=(32, 32, 3)),
      Conv2D(64, 4, strides=2, padding='same', activation=tf.nn.relu),
      Conv2D(128, 4, strides=2, padding='same', activation=tf.nn.relu),
      Conv2D(512, 4, strides=2, padding='same', activation=tf.nn.relu)
  ])
```

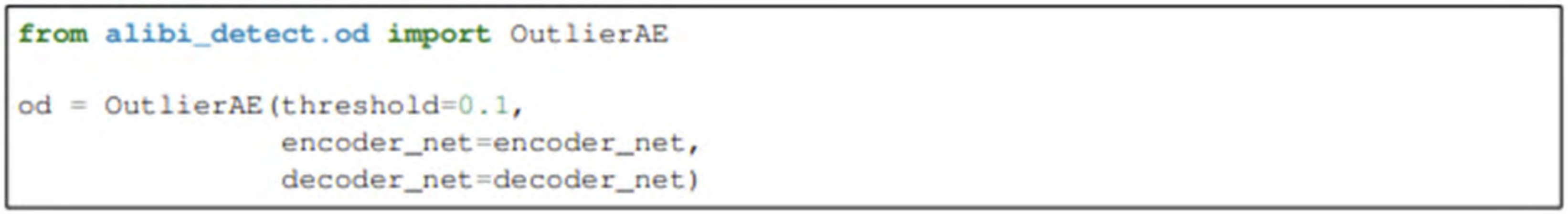
  - decoder_net: tf.keras.Sequential instance containing the decoder network. Example:



```
decoder_net = tf.keras.Sequential(
  [
      InputLayer(input_shape=(1024,)),
      Dense(4*4*128),
      Reshape(target_shape=(4, 4, 128)),
      Conv2DTranspose(256, 4, strides=2, padding='same', activation=tf.nn.relu),
      Conv2DTranspose(64, 4, strides=2, padding='same', activation=tf.nn.relu),
      Conv2DTranspose(3, 4, strides=2, padding='same', activation='sigmoid')
  ])
```

  - ae: instead of using a separate encoder and decoder, the AE can also be passed as a tf.keras.Model.
  - data_type: can specify data type added to metadata. E.g. ‘tabular’ or ‘image’.

Usage

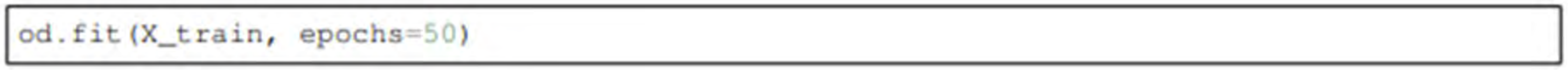


```
from alibi_detect.od import OutlierAE

od = OutlierAE(threshold=0.1,
               encoder_net=encoder_net,
               decoder_net=decoder_net)
```

Train

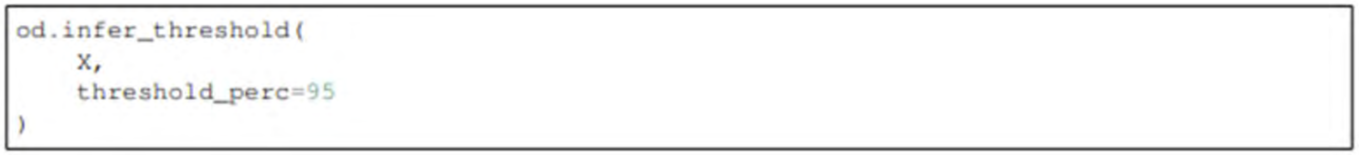
- We then need to train the outlier detector. The following parameters can be specified:
  - **X**: training batch as a numpy array of preferably normal data.
  - **loss_fn**: loss function used for training. Defaults to the Mean Squared Error loss.
  - **optimizer**: optimizer used for training. Defaults to Adam with learning rate 1e-3.
  - **epochs**: number of training epochs.
  - **batch_size**: batch size used during training.
  - **verbose**: boolean whether to print training progress.
  - **log_metric**: additional metrics whose progress will be displayed if verbose equals True.



```
od.fit(X_train, epochs=50)
```

Train

- It is often hard to find a good threshold value. If we have a batch of normal and outlier data and we know approximately the percentage of normal data in the batch, we can infer a suitable threshold:



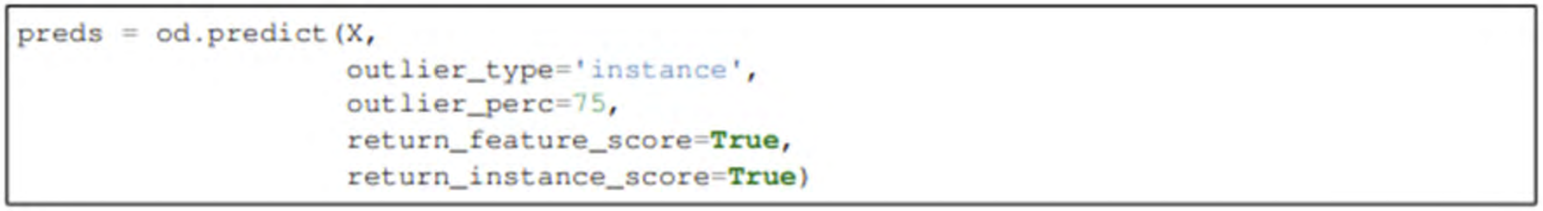
```
od.infer_threshold(
    X,
    threshold_perc=95
)
```

Detect

- We detect outliers by simply calling predict on a batch of instances X. Detection can be customized via the following parameters:
  - **outlier_type**: either ‘instance’ or ‘feature’. If the outlier type equals ‘instance’, the outlier score at the instance level will be used to classify the instance as an outlier or not. If ‘feature’ is selected, outlier detection happens at the feature level (e.g. by pixel in images).
  - **outlier_perc**: percentage of the sorted (descending) feature level outlier scores. We might for instance want to flag an image as an outlier if at least 20% of the pixel values are on average above the threshold. In this case, we set outlier_perc to 20. The default value is 100 (using all the features).
  - **return_feature_score**: boolean whether to return the feature level outlier scores.
  - **return_instance_score**: boolean whether to return the instance level outlier scores

Detect

- The **prediction** takes the form of a dictionary with meta and data keys. meta contains the detector’s metadata while data is also a dictionary which contains the actual predictions stored in the following keys:
  - **is_outlier**: boolean whether instances or features are above the threshold and therefore outliers. If outlier_type equals ‘instance’, then the array is of shape (batch size,). If it equals ‘feature’, then the array is of shape (batch size, instance shape).
  - **feature_score**: contains feature level scores if return_feature_score equals True.
  - **instance_score**: contains instance level scores if return_instance_score equals True

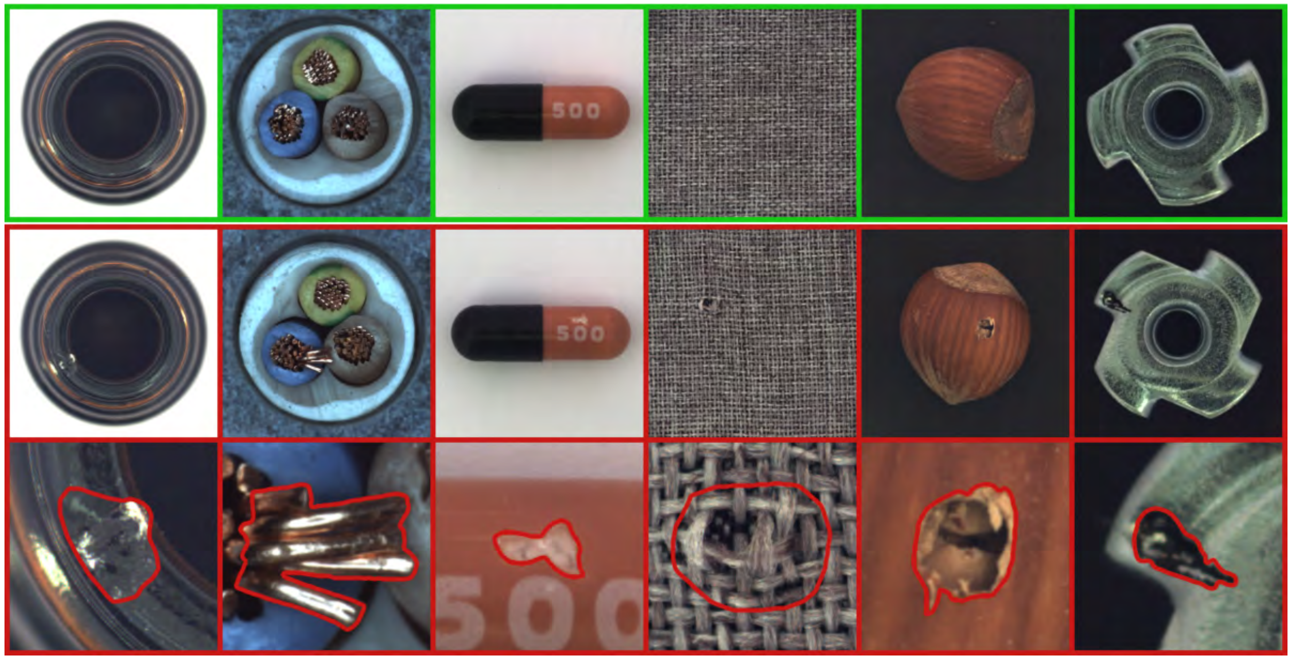


```
preds = od.predict(X,
                   outlier_type='instance',
                   outlier_perc=75,
                   return_feature_score=True,
                   return_instance_score=True)
```

OFFICIAL (CLOSED) \ NON-SENSITIVE

The MVTec AD Data Set

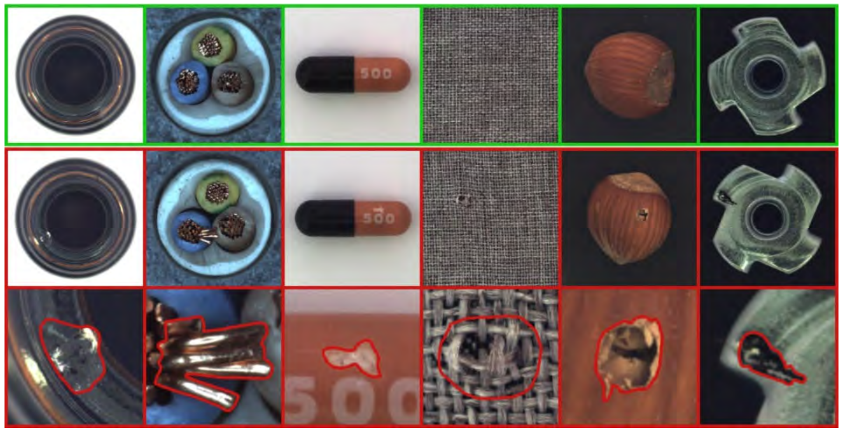
- Testing the accuracy of an outlier detection model in real-world conditions can be challenging, as the number and properties of the outliers in a data set, are typically unknown to us.
- We can overcome this obstacle by training and testing our models on a data set that was specifically created for this purpose

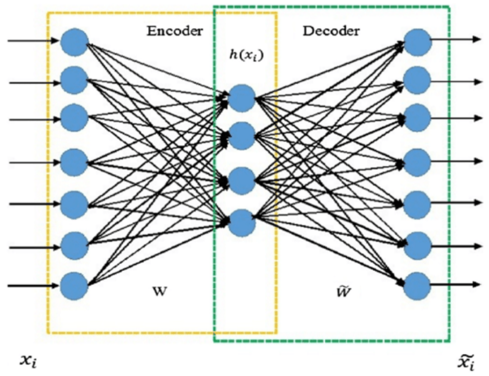


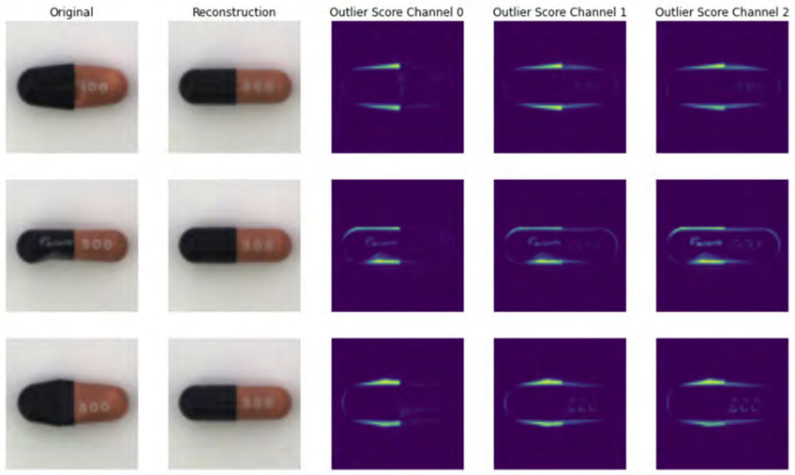
The MVTec AD Data Set

- The MVTec AD data set contains thousands of high-resolution images, and is suitable for testing and **benchmarking image outlier methods**, with a focus on quality control in industrial manufacturing.
- The data set is comprised of 15 categories of images, such as carpet, leather, transistor, screw etc.
- The training set for each category includes normal images only, while the test set has both normal images and outliers with various defects.
- For additional information about the dataset and the benchmarking results for various outlier detection algorithms, you can refer to the associated research paper

Activity 13 – MVTec







Exercises:

- Change the decoder and decoder design

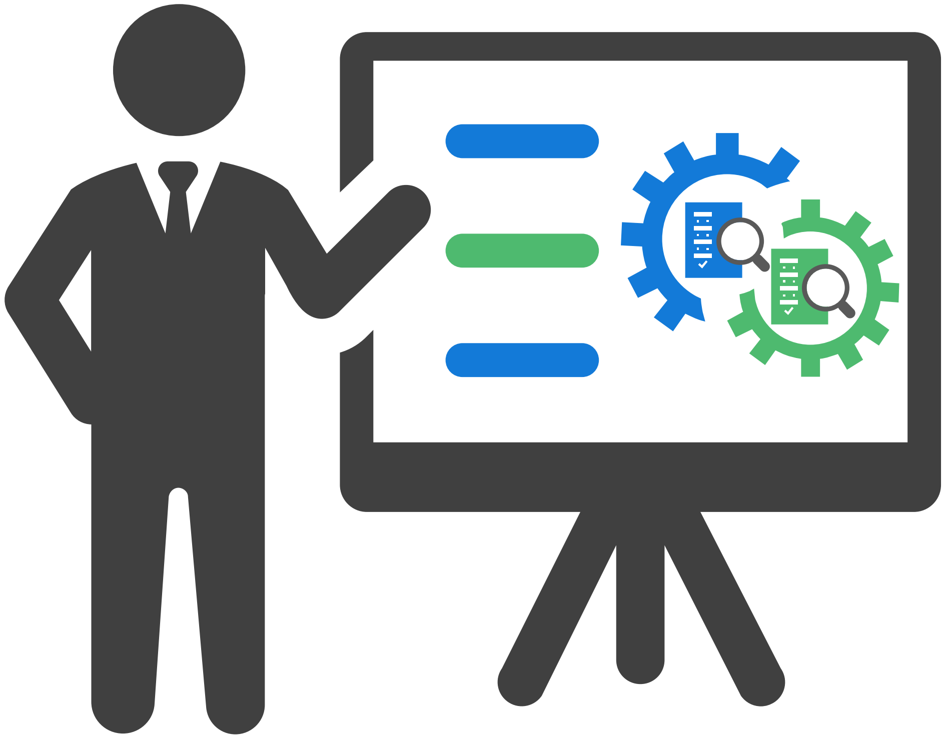
Step 1:
Watch and listen to the instructor's demonstration

20 mins

Step 2:
- Do on your own

Individial Activity

30 mins



Summary

Email
seow_khee_wei@rp.edu.sg

Telegram
@kwseow

Source code:

Thank you