ALGORITHM ANOMALY DETECTION



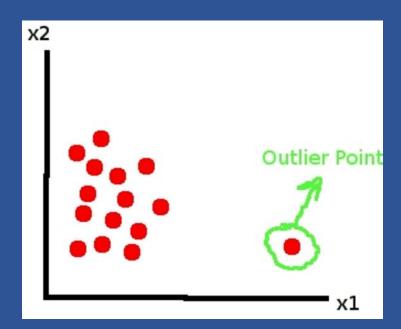
In this session

- Anomaly Detection
- One-Class SVM Algorithm
- PCA-Based Algorithm
- Data set
- Data attribute
- Experiment Steps

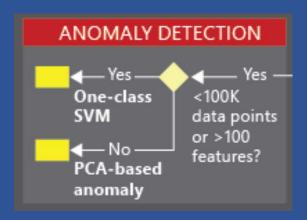
Anomaly Detection

Anomaly Detection

- Credit card fraud, transaction, medical, text etc.
- Also referred to as outliers, novelties, noise, deviations and exceptions
- The data consists of 'normal' applications and 'risky' applications
- Risky transactions = anomalous



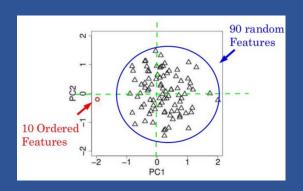
Algorithm Anomaly detection One-Class SVM



One-Class SVM

- SVM = Support Vector Model
- Supervised learning models
- Analyze data and recognize patterns
- Have a lot of "normal" data and not many cases of the anomalies
- Use with Train Anomaly Detection Model
- The train data set contain all or mostly normal cases.

Algorithm Anomaly detection PCA-Based

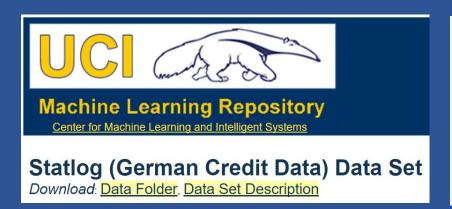


PCA-Based Anomaly Detection module

- Principal Component Analysis (PCA)
- Use when easy to obtain training data from one class
- One class = acceptable transactions
- Use when difficult to obtain sufficient samples of the targeted anomalies
- Detect fraudulent transaction
- You might not have enough examples of fraud to train the mode
- But have many examples of good transactions

Algorithm Anomaly detection Data set

https://archive.ics.uci.edu/ml/datasets/Statlog+(German+Credit+Data)



Quelle:

Professor Dr. Hans Hofmann Institut für Statistik und "Okonometrie Universit "in Hamburg FB Wirtschaftswissenschaften Von-Melle-Park 5 2000 Hamburg 13

German credit dataset

- Credit card application
- 1000 instances (rows)
- Attributes = 20 (7 numerical, 13 categorical)
- Label 1 = normal, 2 = risky

Data attribute

```
A11 6 A34 A43 1169 A65 A75 4 A93 A101 4 A121 67 A143 A152 2 A173 1 A192 A201 1 A12 48 A32 A43 5951 A61 A73 2 A92 A101 2 A121 22 A143 A152 1 A173 1 A191 A201 2 A14 12 A34 A46 2096 A61 A74 2 A93 A101 3 A121 49 A143 A152 1 A172 2 A191 A201 1 A11 42 A32 A42 7882 A61 A74 2 A93 A103 4 A122 45 A143 A153 1 A173 2 A191 A201 1 A11 24 A33 A40 4870 A61 A73 3 A93 A101 4 A124 53 A143 A153 2 A173 2 A191 A201 2 A14 36 A32 A46 9055 A65 A73 2 A93 A101 4 A124 35 A143 A153 1 A172 2 A192 A201 1 A14 24 A32 A42 2835 A63 A75 3 A93 A101 4 A122 53 A143 A152 1 A173 1 A191 A201 1
```

Attribute: Account status, month, credit history, propose, amount, saving, employ since, installment rate, sex ...

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Attribute 9: (qualitative)

Personal status and sex

A91 : male : divorced/separated

A92 : female : divorced/separated/married

A93 : male : single

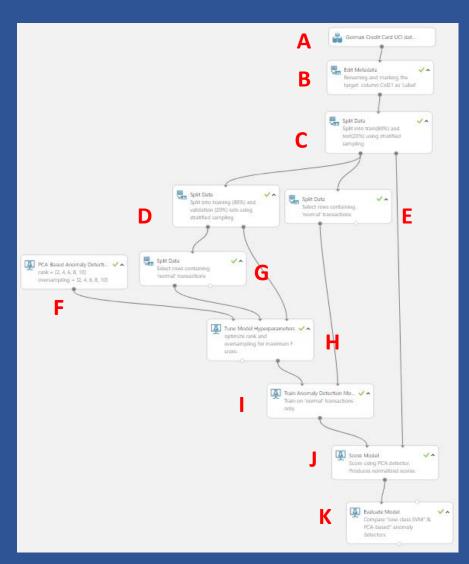
A94 : male : married/widowed

A95 : female : single
```

Experiment Steps

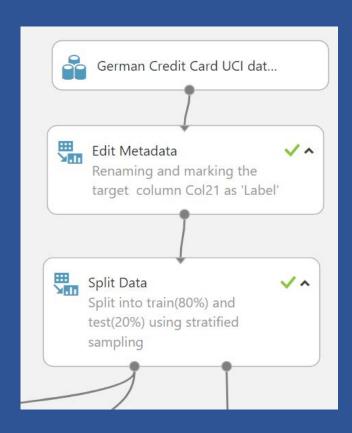
Experiment steps

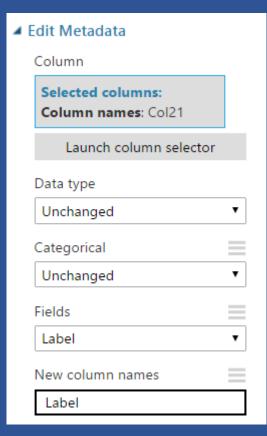
- 1. Import data set
- 2. Edit metadata
- 3. Split data for training
- 4. Split data for Score
- 5. Add PCA Base method
- 6. Add Tune Model Hyper parameters
- 7. Add Train Anomaly Detection Model
- 8. Add Score model
- 9. Add Evaluate Model



Experiment Steps

- A. Import data set
- B. Edit metadata
- C. Split data for training





■ Split Data
Splitting mode
Split Rows ▼
Fraction of rows in the fir \equiv
0.75
Randomized split
Random seed
0
Stratified split
True ▼
Stratification key column
Selected columns: Column names: Label
Column Hames. Laber

Experiment Steps

Add 4 Split data models and PCA Based

D ■ Split Data ■ Split Data ■ Split Data Splitting mode Splitting mode Splitting mode Split Rows Regular Expression Regular Expression Fraction of rows in the fir... Regular expression Regular expression 0.75 \"Label" ^1 \"Label" ^1 Randomized split Random seed Stratified split True Stratification key column Selected columns: Column names: Label Launch column selector

Experiment Steps

Training mode

• Single Parameter: If you know how you want to configure the model, you can provide a specific set of values as arguments. You might have learned these values by experimentation or received them as guidance.

• Parameter Range: If you are not sure of the best parameters, you can find the optimal parameters by specifying multiple values and using a parameter sweep to find the optimal

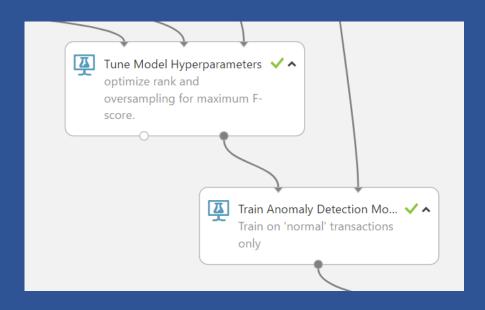
configuration.

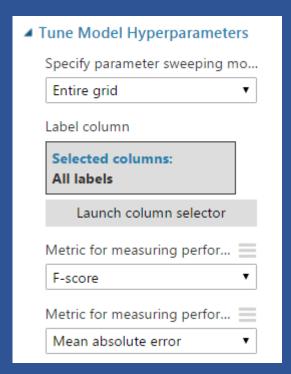
PCA-Based Anomaly Detecti...
rank = [2, 4, 6, 8, 10]
oversampling = [2, 4, 6, 8, 10]

■ PCA-Based Anomaly Detection
Training mode
Parameter Range ▼
Range for number of PCA c
Use Range Builder
2, 4, 6, 8, 10
2, 4, 0, 0, 10
Range for the oversampling
Range for the oversampling

Experiment Steps

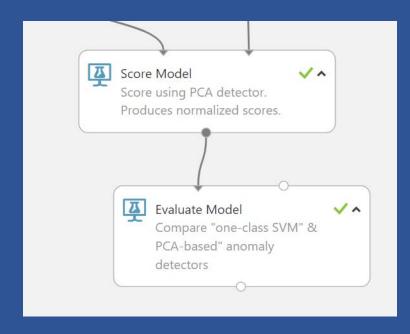
- H. Add Tune Model Hyperparameters
- I. Add Train Anomaly Detection Model

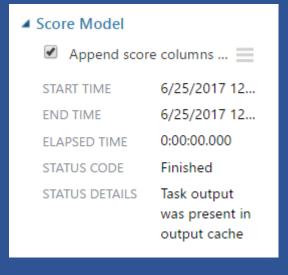




Experiment Steps

- J. Add Score Model
- K. Add Evaluate Model

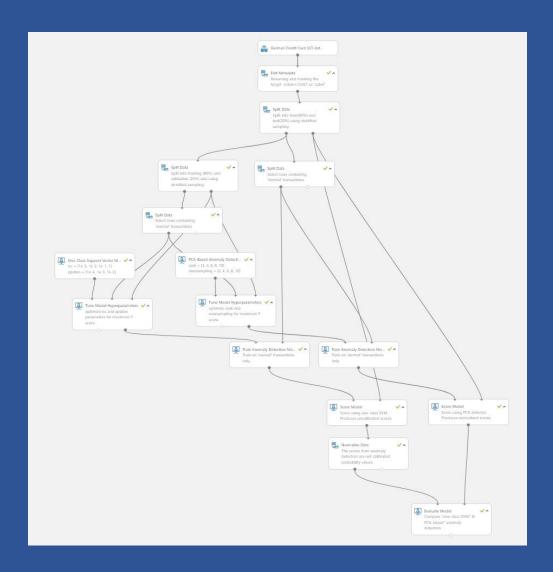




Compare two anomaly algorithm

Compare One-Class Support Vector Machine with PCA-Based Anomaly Detection

https://gallery.cortanaintelligence.com/ Experiment/Anomaly-compare



More Information

PCA-Based Anomaly Detection

https://msdn.microsoft.com/en-us/library/azure/dn913102.aspx

This Experiment

https://gallery.cortanaintelligence.com/Experiment/Anomaly-Detection-9

Anomaly compare

https://gallery.cortanaintelligence.com/Experiment/Anomaly-compare