Experiment 11

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Different Anomaly Detection Algorithms on 2D Dataset

Importing required libraries

In [1]:
```
import time
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
from sklearn import svm
from sklearn.datasets import make_moons, make_blobs
from sklearn.covariance import EllipticEnvelope
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor
```

Data

for this experiment we have use make_moons, make_blobs datsets which are already in sklearn.datasets

sklearn.datasets.make_blobs(n_samples=100, n_features=2, *, centers=None, cluster_std=1.0, center_box=(- 10.0, 10.0), shuffle=True, random_state=None, return_centers=False) Generate isotropic Gaussian blobs for clustering.

sklearn.datasets.make_moons(n_samples=100, *, shuffle=True, noise=None, random_state=None) Make two interleaving half circles. A simple toy dataset to visualize clustering and classification algorithms.

Preprocessing & Visualization

for this experiment we do not need preprocessing as we need to visualize different anomaly detection algorithms

Model Building

Covariance Matrix

This metric assesses how many standard deviations σ away x_i is from μ, thereby being dimensionless. An extreme observation has a large distance from the center of a distribution. It is useful in predictive maintenance as it enables finding unusual behavior of a system; upcoming down-times and malfunction can be targeted and identified, which is particularly important since finding faults in equipment, machines, and devices early can reduce the extent of the damage.

sklearn.covariance.EllipticEnvelope(*, store_precision=True, assume_centered=False, support_fraction=None, contamination=0.1, random_state=None)

One Class SVM

One Class SVM mode is trained in only one class, referred to as the normal class. The model learns all the features and patterns of the normal class . When a new observation is introduced to the model, then based on its learning, the One Class SVM detects if the new observation deviates from the normal behaviour then it classifies it as an oulier else the new observation will identified as an inlier. One Class SVM is based on Support Vector Machines where the binary classes are separated by a non-linear hyper plane

sklearn.svm.OneClassSVM(*, kernel='rbf', degree=3, gamma='scale', coef0=0.0, tol=0.001, nu=0.5, shrinking=True, cache_size=200, verbose=False, max_iter=- 1)

Local Outlier Factor

Local outlier factor (LOF) is an algorithm used for Unsupervised outlier detection. It produces an anomaly score that represents data points which are outliers in the data set. It does this by measuring the local density deviation of a given data point with respect to the data points near it.

class sklearn.neighbors.LocalOutlierFactor(n_neighbors=20, *, algorithm='auto', leaf_size=30, metric='minkowski', p=2, metric_params=None, contamination='auto', novelty=False, n_jobs=None)

Isolation Forest

Isolation Forest is based on the Decision Tree algorithm. It isolates the outliers by randomly selecting a feature from the given set of features and then randomly selecting a split value between the max and min values of that feature. This random partitioning of features will produce shorter paths in trees for the anomalous data points, thus distinguishing them from the rest of the data.

sklearn.ensemble.IsolationForest(*, n_estimators=100, max_samples='auto', contamination='auto', max_features=1.0, bootstrap=False, n_jobs=None, random_state=None, verbose=0, warm_start=False)

Compile & Train

Altering the hyperparameters to see the effect of the hyperparameter on the working of the algorithm

In [2]:
```
matplotlib.rcParams['contour.negative_linestyle'] = 'solid'
n_samples = 300
outliers_fraction = 0.15
n_outliers = int(outliers_fraction * n_samples)
n_inliers = n_samples - n_outliers
anomaly_algorithms = [
    ("Robust covariance", EllipticEnvelope(contamination=outliers_fraction)),
    ("One-Class SVM", svm.OneClassSVM(nu=outliers_fraction, kernel="poly",
                                      gamma=0.1)),
    ("Isolation Forest", IsolationForest(contamination=outliers_fraction,
                                         random_state=42)),
    ("Local Outlier Factor", LocalOutlierFactor(
        n_neighbors=35, algorithm='auto',contamination=outliers_fraction))]

# Define datasets
blobs_params = dict(random_state=0, n_samples=n_inliers, n_features=2)
datasets = [
    make_blobs(centers=[[0, 0], [0, 0]], cluster_std=0.5,
               **blobs_params)[0],
    make_blobs(centers=[[2, 2], [-2, -2]], cluster_std=[0.5, 0.5],
               **blobs_params)[0],
    make_blobs(centers=[[2, 2], [-2, -2]], cluster_std=[1.5, .3],
               **blobs_params)[0],
    4. * (make_moons(n_samples=n_samples, noise=.05, random_state=0)[0] -
          np.array([0.5, 0.25])),
    14. * (np.random.RandomState(42).rand(n_samples, 2) - 0.5)]
matplotlib.rcParams['contour.negative_linestyle'] = 'solid'
# Compare given classifiers under given settings
xx, yy = np.meshgrid(np.linspace(-7, 7, 150),
                     np.linspace(-7, 7, 150))

plt.figure(figsize=(len(anomaly_algorithms) * 2 + 4, 12.5))
plt.subplots_adjust(left=.02, right=.98, bottom=.001, top=.96, wspace=.05,
                    hspace=.01)

plot_num = 1
rng = np.random.RandomState(42)

for i_dataset, X in enumerate(datasets):
    # Add outliers
    X = np.concatenate([X, rng.uniform(low=-6, high=6, size=(n_outliers, 2))],
                       axis=0)

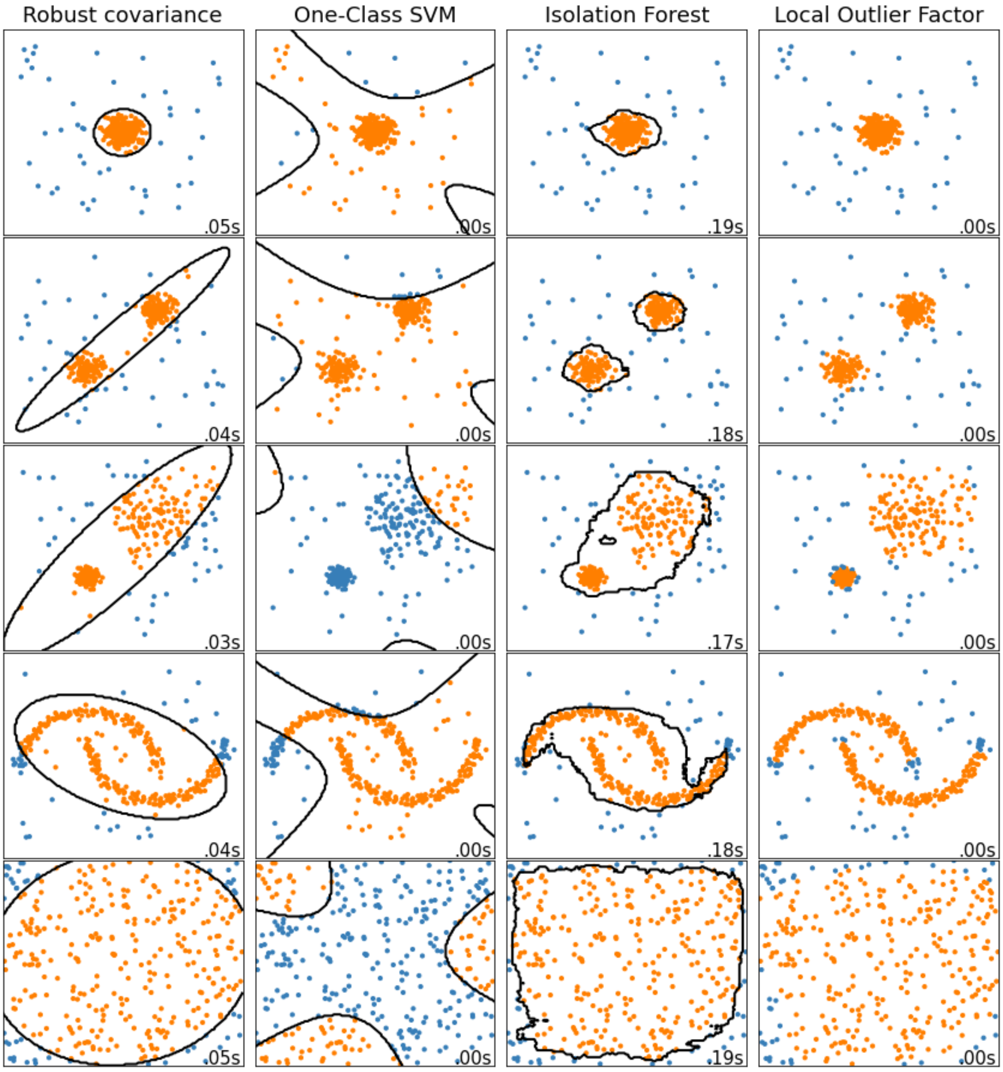
    for name, algorithm in anomaly_algorithms:
        t0 = time.time()
        algorithm.fit(X)
        t1 = time.time()
        plt.subplot(len(datasets), len(anomaly_algorithms), plot_num)
        if i_dataset == 0:
            plt.title(name, size=18)

        # fit the data and tag outliers
        if name == "Local Outlier Factor":
            y_pred = algorithm.fit_predict(X)
        else:
            y_pred = algorithm.fit(X).predict(X)

        # plot the levels lines and the points
        if name != "Local Outlier Factor":  # LOF does not implement predict
            Z = algorithm.predict(np.c_[xx.ravel(), yy.ravel()])
            Z = Z.reshape(xx.shape)
            plt.contour(xx, yy, Z, levels=[0], linewidths=2, colors='black')

        colors = np.array(['#377eb8', '#ff7f00'])
        plt.scatter(X[:, 0], X[:, 1], s=10, color=colors[(y_pred + 1) // 2])

        plt.xlim(-7, 7)
        plt.ylim(-7, 7)
        plt.xticks(())
        plt.yticks(())
        plt.text(.99, .01, ('%.2fs' % (t1 - t0)).lstrip('0'),
                 transform=plt.gca().transAxes, size=15,
                 horizontalalignment='right')
        plot_num += 1
```



Robust covariance
One-Class SVM
Isolation Forest
Local Outlier Factor
.05s
.00s
.19s
.00s
.04s
.00s
.18s
.00s
.03s
.00s
.17s
.00s
.04s
.00s
.18s
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.19s
.00s

In [3]:
```
matplotlib.rcParams['contour.negative_linestyle'] = 'solid'
n_samples = 300
outliers_fraction = 0.15
n_outliers = int(outliers_fraction * n_samples)
n_inliers = n_samples - n_outliers
anomaly_algorithms = [
    ("Robust covariance", EllipticEnvelope(contamination=outliers_fraction)),
    ("One-Class SVM", svm.OneClassSVM(nu=outliers_fraction, kernel="rbf",
                                      gamma=0.5)),
    ("Isolation Forest", IsolationForest(contamination=outliers_fraction,
                                         random_state=42)),
    ("Local Outlier Factor", LocalOutlierFactor(
        n_neighbors=15,algorithm='ball_tree', contamination=outliers_fraction))]

# Define datasets
blobs_params = dict(random_state=0, n_samples=n_inliers, n_features=2)
datasets = [
    make_blobs(centers=[[0, 0], [0, 0]], cluster_std=0.5,
               **blobs_params)[0],
    make_blobs(centers=[[2, 2], [-2, -2]], cluster_std=[0.5, 0.5],
               **blobs_params)[0],
    make_blobs(centers=[[2, 2], [-2, -2]], cluster_std=[1.5, .3],
               **blobs_params)[0],
    4. * (make_moons(n_samples=n_samples, noise=.05, random_state=0)[0] -
          np.array([0.5, 0.25])),
    14. * (np.random.RandomState(42).rand(n_samples, 2) - 0.5)]
matplotlib.rcParams['contour.negative_linestyle'] = 'solid'
# Compare given classifiers under given settings
xx, yy = np.meshgrid(np.linspace(-7, 7, 150),
                     np.linspace(-7, 7, 150))

plt.figure(figsize=(len(anomaly_algorithms) * 2 + 4, 12.5))
plt.subplots_adjust(left=.02, right=.98, bottom=.001, top=.96, wspace=.05,
                    hspace=.01)

plot_num = 1
rng = np.random.RandomState(42)

for i_dataset, X in enumerate(datasets):
    # Add outliers
    X = np.concatenate([X, rng.uniform(low=-6, high=6, size=(n_outliers, 2))],
                       axis=0)

    for name, algorithm in anomaly_algorithms:
        t0 = time.time()
        algorithm.fit(X)
        t1 = time.time()
        plt.subplot(len(datasets), len(anomaly_algorithms), plot_num)
        if i_dataset == 0:
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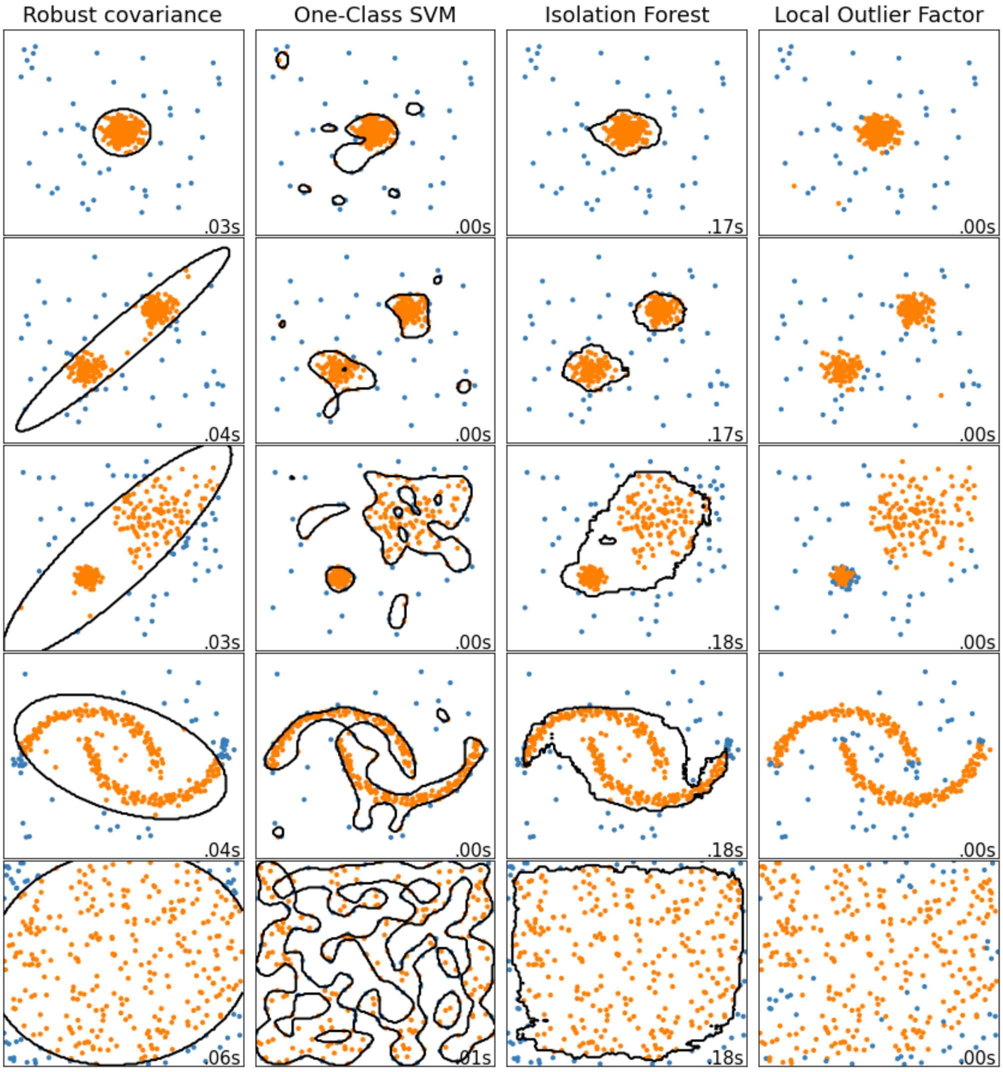
        # fit the data and tag outliers
        if name == "Local Outlier Factor":
            y_pred = algorithm.fit_predict(X)
        else:
            y_pred = algorithm.fit(X).predict(X)

        # plot the levels lines and the points
        if name != "Local Outlier Factor":  # LOF does not implement predict
            Z = algorithm.predict(np.c_[xx.ravel(), yy.ravel()])
            Z = Z.reshape(xx.shape)
            plt.contour(xx, yy, Z, levels=[0], linewidths=2, colors='black')

        colors = np.array(['#377eb8', '#ff7f00'])
        plt.scatter(X[:, 0], X[:, 1], s=10, color=colors[(y_pred + 1) // 2])

        plt.xlim(-7, 7)
        plt.ylim(-7, 7)
        plt.xticks(())
        plt.yticks(())
        plt.text(.99, .01, ('%.2fs' % (t1 - t0)).lstrip('0'),
                 transform=plt.gca().transAxes, size=15,
                 horizontalalignment='right')
        plot_num += 1
```


Robust covariance
One-Class SVM
Isolation Forest
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.03s
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.00s
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.00s
.04s
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.18s
.00s
.06s
.01s
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In [4]:
```
matplotlib.rcParams['contour.negative_linestyle'] = 'solid'
n_samples = 300
outliers_fraction = 0.15
n_outliers = int(outliers_fraction * n_samples)
n_inliers = n_samples - n_outliers
anomaly_algorithms = [
    ("Robust covariance", EllipticEnvelope(contamination=outliers_fraction)),
    ("One-Class SVM", svm.OneClassSVM(nu=outliers_fraction, kernel="linear",
                                      gamma=0.75)),
    ("Isolation Forest", IsolationForest(contamination=outliers_fraction,
                                         random_state=0)),
    ("Local Outlier Factor", LocalOutlierFactor(
        n_neighbors=50,algorithm='kd_tree', contamination=outliers_fraction))]

# Define datasets
blobs_params = dict(random_state=0, n_samples=n_inliers, n_features=2)
datasets = [
    make_blobs(centers=[[0, 0], [0, 0]], cluster_std=0.5,
               **blobs_params)[0],
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matplotlib.rcParams['contour.negative_linestyle'] = 'solid'
# Compare given classifiers under given settings
xx, yy = np.meshgrid(np.linspace(-7, 7, 150),
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plt.figure(figsize=(len(anomaly_algorithms) * 2 + 4, 12.5))
plt.subplots_adjust(left=.02, right=.98, bottom=.001, top=.96, wspace=.05,
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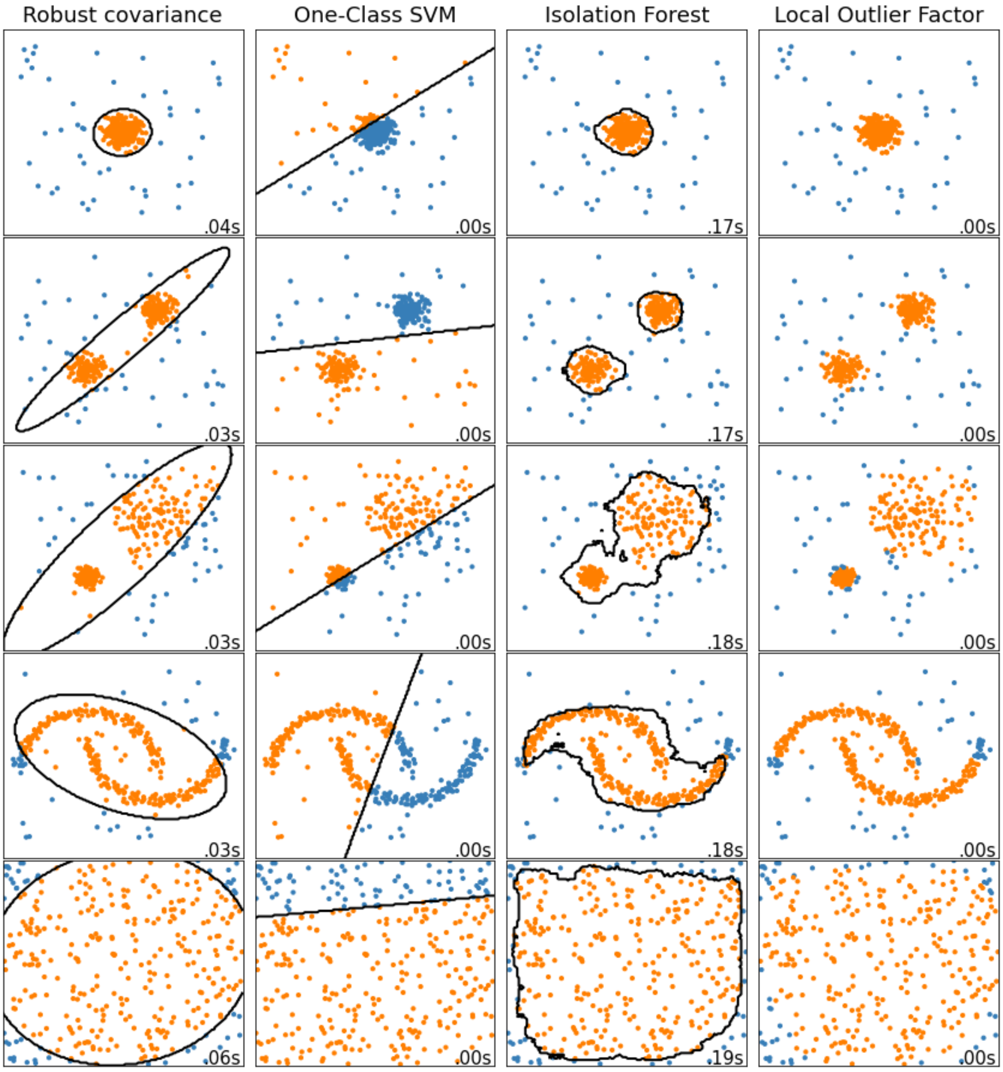

Result

By this experiment i came to know the working of different anomaly detection algorithms and how they differ from each other in working and in time perspective how they find anomaly

In [ ]: