Pattern & Anomaly Detection Lab

Experiment 11

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NOTE:

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"""
==========================================================================
Comparing anomaly detection algorithms for outlier detection on toy datasets
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This example shows characteristics of different anomaly detection algorithms
on 2D datasets. Datasets contain one or two modes (regions of high density)
to illustrate the ability of algorithms to cope with multimodal data.

For each dataset, 15% of samples are generated as random uniform noise. This
proportion is the value given to the nu parameter of the OneClassSVM and the
contamination parameter of the other outlier detection algorithms.
Decision boundaries between inliers and outliers are displayed in black
except for Local Outlier Factor (LOF) as it has no predict method to be applied
on new data when it is used for outlier detection.

The :class:`~sklearn.svm.OneClassSVM` is known to be sensitive to outliers and
thus does not perform very well for outlier detection. This estimator is best
suited for novelty detection when the training set is not contaminated by
outliers. That said, outlier detection in high-dimension, or without any
assumptions on the distribution of the inlying data is very challenging, and a
One-class SVM might give useful results in these situations depending on the
value of its hyperparameters.

The :class:`sklearn.linear_model.SGDOneClassSVM` is an implementation of the
One-Class SVM based on stochastic gradient descent (SGD). Combined with kernel
approximation, this estimator can be used to approximate the solution
of a kernelized :class:`sklearn.svm.OneClassSVM`. We note that, although not
identical, the decision boundaries of the
:class:`sklearn.linear_model.SGDOneClassSVM` and the ones of
:class:`sklearn.svm.OneClassSVM` are very similar. The main advantage of using
:class:`sklearn.linear_model.SGDOneClassSVM` is that it scales linearly with
the number of samples.

:class:`sklearn.covariance.EllipticEnvelope` assumes the data is Gaussian and
learns an ellipse. It thus degrades when the data is not unimodal. Notice
however that this estimator is robust to outliers.

:class:`~sklearn.ensemble.IsolationForest` and
:class:`~sklearn.neighbors.LocalOutlierFactor` seem to perform reasonably well
for multi-modal data sets. The advantage of
:class:`~sklearn.neighbors.LocalOutlierFactor` over the other estimators is
shown for the third data set, where the two modes have different densities.
This advantage is explained by the local aspect of LOF, meaning that it only
compares the score of abnormality of one sample with the scores of its
neighbors.

Finally, for the last data set, it is hard to say that one sample is more
abnormal than another sample as they are uniformly distributed in a
hypercube. Except for the :class:`~sklearn.svm.OneClassSVM` which overfits a
little, all estimators present decent solutions for this situation. In such a
case, it would be wise to look more closely at the scores of abnormality of
the samples as a good estimator should assign similar scores to all the
samples.

While these examples give some intuition about the algorithms, this
intuition might not apply to very high dimensional data.

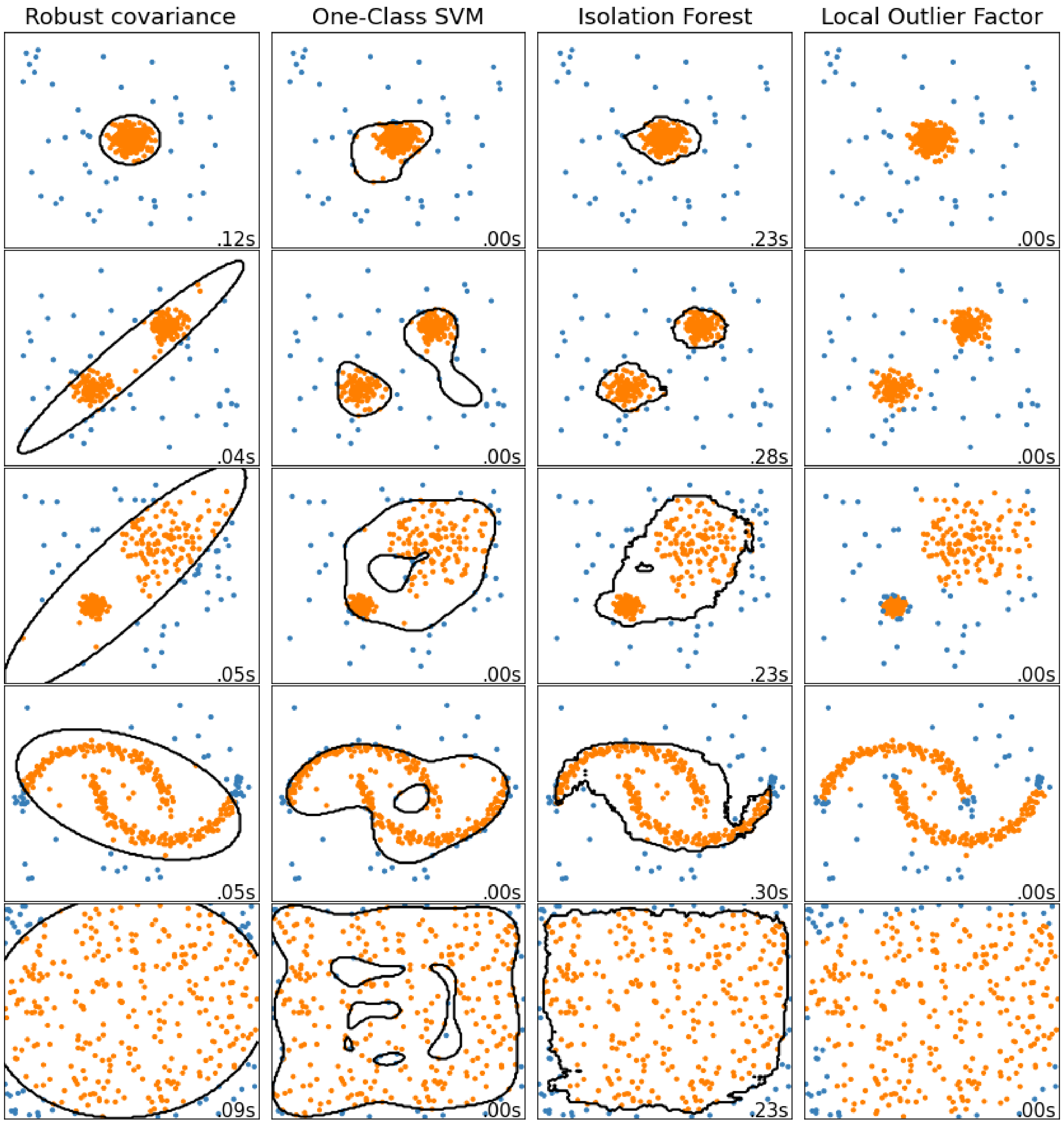
Finally, note that parameters of the models have been here handpicked but
that in practice they need to be adjusted. In the absence of labelled data,
the problem is completely unsupervised so model selection can be a challenge.
"""
```

CODE:

```python
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
#from sklearn.linear_model import SGDOneClassSVM
#from sklearn.kernel_approximation import Nystroem
#from sklearn.pipeline import make_pipeline

matplotlib.rcParams['contour.negative_linestyle'] = 'solid'

# Example settings
n_samples = 300
outliers_fraction = 0.15
n_outliers = int(outliers_fraction * n_samples)
n_inliers = n_samples - n_outliers

# define outlier/anomaly detection methods to be compared.
# the SGDOneClassSVM must be used in a pipeline with a kernel approximation
# to give similar results to the OneClassSVM
anomaly_algorithms = [
    ("Robust covariance", EllipticEnvelope(contamination=outliers_fraction)),
    ("One-Class SVM", svm.OneClassSVM(nu=outliers_fraction, kernel="rbf",
                                      gamma=0.1)),
    # ("One-Class SVM (SGD)", make_pipeline(
    #     Nystroem(gamma=0.1, random_state=42, n_components=150),
    #     SGDOneClassSVM(nu=outliers_fraction, shuffle=True,
    #                    fit_intercept=True, random_state=42, tol=1e-6)
    # )),
    ("Isolation Forest", IsolationForest(contamination=outliers_fraction,
                                         random_state=42)),
    ("Local Outlier Factor", LocalOutlierFactor(
        n_neighbors=35, 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)]

# 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)
```

```python
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

plt.show()
```

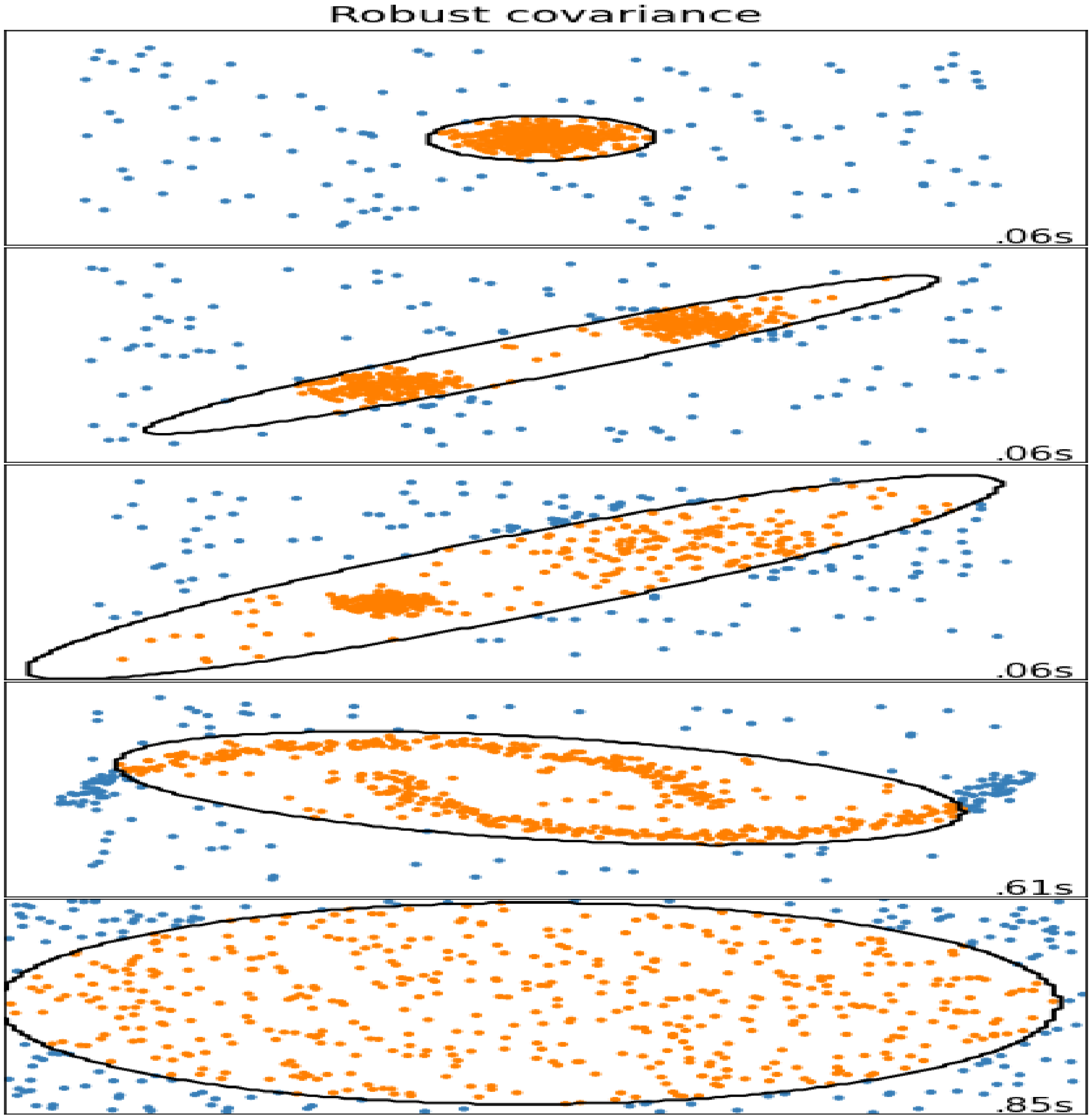
OUTPUT:



Robust covariance
One-Class SVM
Isolation Forest
Local Outlier Factor
.12s
.00s
.23s
.00s
.04s
.00s
.28s
.00s
.05s
.00s
.23s
.00s
.05s
.00s
.30s
.00s
.09s
.00s
.23s
.00s

CODE:
(Robust Covariance)

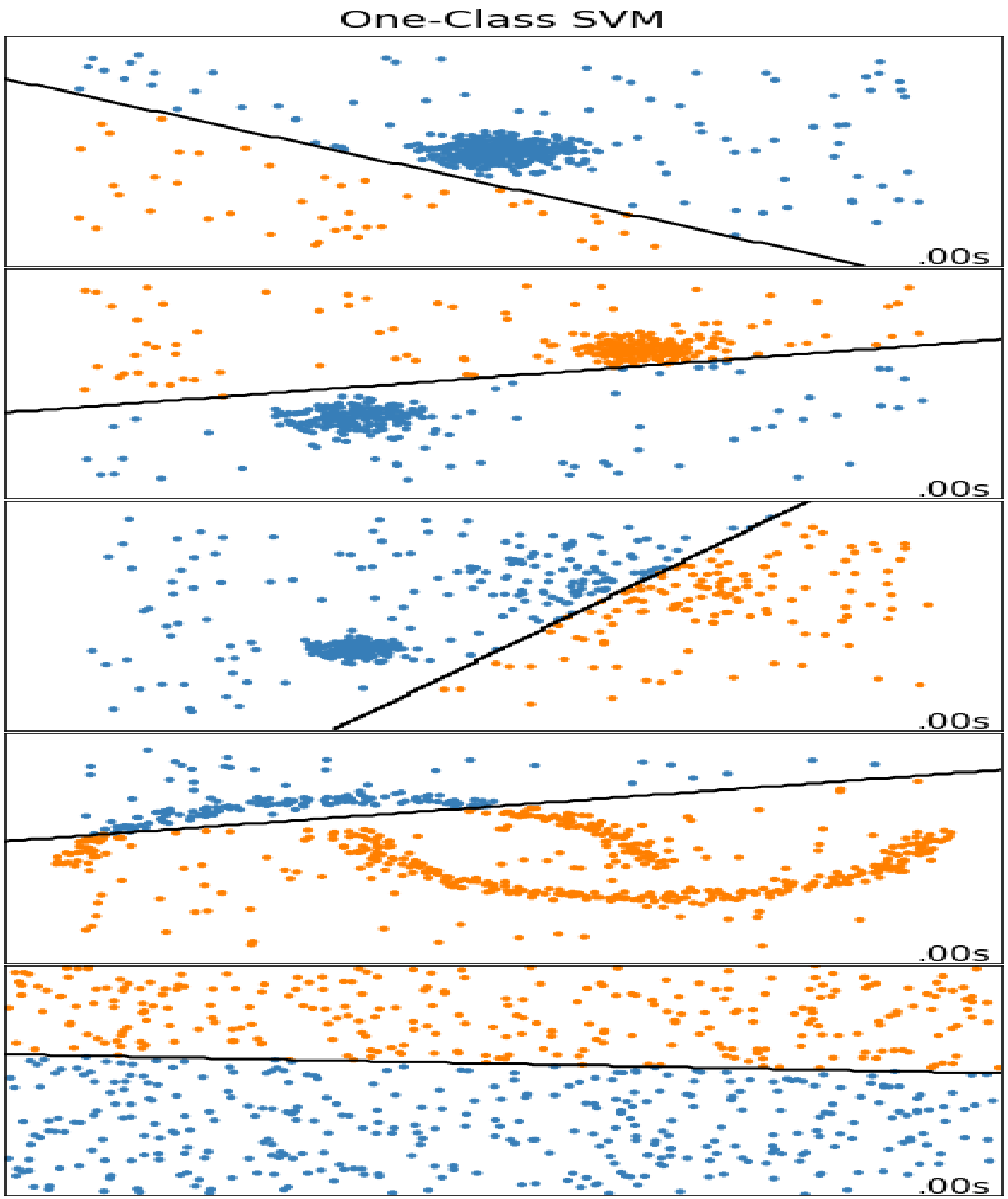
```python
#%%
matplotlib.rcParams['contour.negative_linestyle'] = 'solid'
n_samples = 500
outliers_fraction = 0.25
n_outliers = int(outliers_fraction * n_samples)
n_inliers = n_samples - n_outliers
anomaly_algorithms = [
    ("Robust covariance", EllipticEnvelope(store_precision=False,contamination=outliers_fraction,random_state=42))]
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)]
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
plt.show()
```



Robust covariance
.06s
.06s
.06s
.61s
.85s

CODE:
(One-Class SVM)

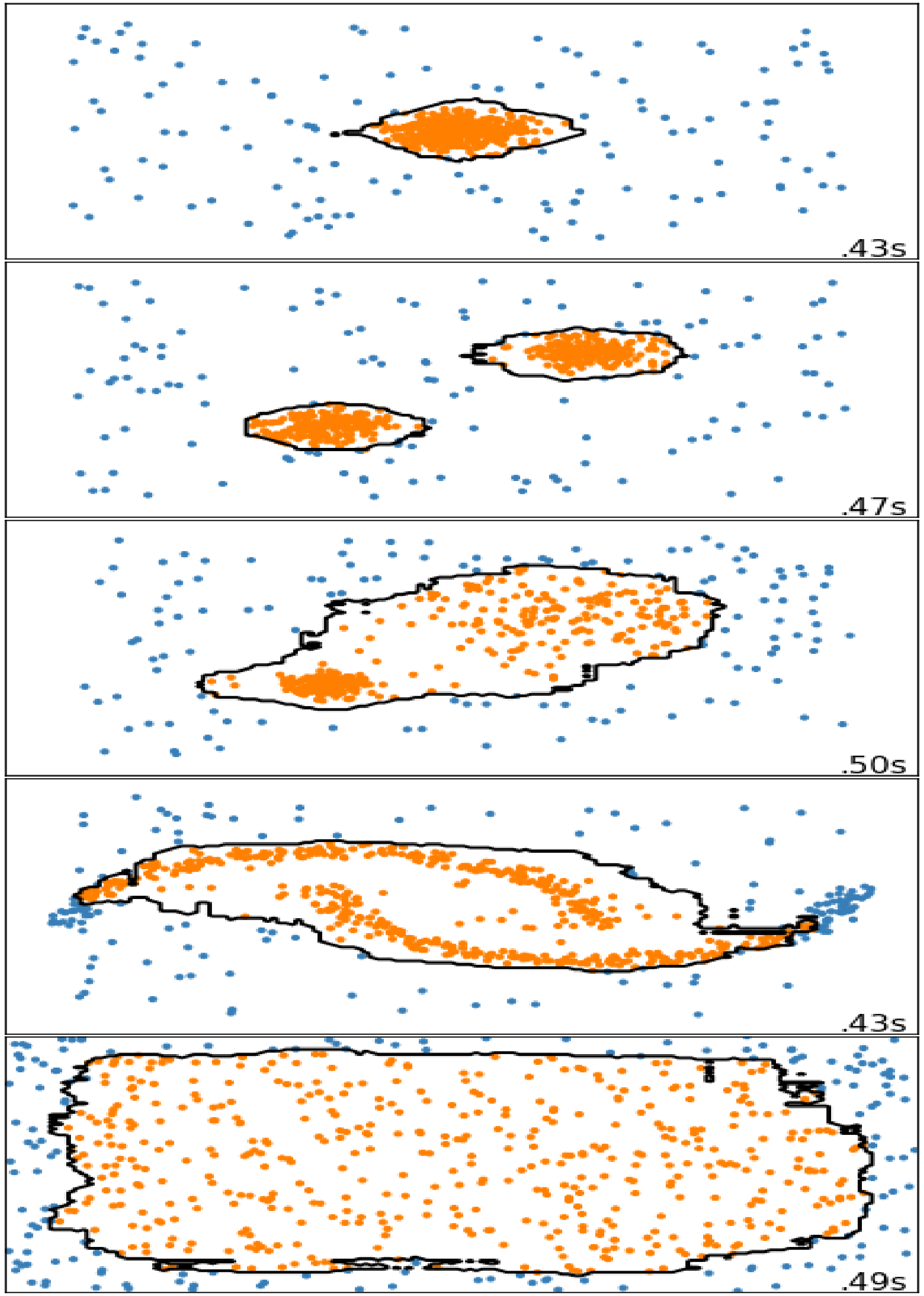
```python
#%%
matplotlib.rcParams['contour.negative_linestyle'] = 'solid'
n_samples = 500
outliers_fraction = 0.25
n_outliers = int(outliers_fraction * n_samples)
n_inliers = n_samples - n_outliers


anomaly_algorithms = [
    ("One-Class SVM", svm.OneClassSVM(nu=outliers_fraction, kernel="linear",degree=4,
              gamma=0.1)), ]
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)]
# 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
plt.show()
```


One-Class SVM
.00s
.00s
.00s
.00s
.00s

CODE:
(Isolation Forest)

```python
#%%
matplotlib.rcParams['contour.negative_linestyle'] = 'solid'
n_samples = 500
outliers_fraction = 0.25
n_outliers = int(outliers_fraction * n_samples)
n_inliers = n_samples - n_outliers
anomaly_algorithms = [ ("Isolation Forest", IsolationForest(contamination=outliers_fraction,bootstrap=True,
                                         random_state=42))]
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)]
# 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
plt.show()
#%%
```

Isolation Forest



CODE:
(Local Outlier Factor)

```python
#%%
matplotlib.rcParams['contour.negative_linestyle'] = 'solid'
n_samples = 500
outliers_fraction = 0.25
n_outliers = int(outliers_fraction * n_samples)
n_inliers = n_samples - n_outliers
anomaly_algorithms = [("Local Outlier Factor", LocalOutlierFactor(
        n_neighbors=5, algorithm='kd_tree',contamination=outliers_fraction))]
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)]
# 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
plt.show()
```

Local Outlier Factor