Support Vector Machines

Support vector machines (SVM) are a set of supervised learning methods used for *classification*, *regressions*, and *outliers detection*.

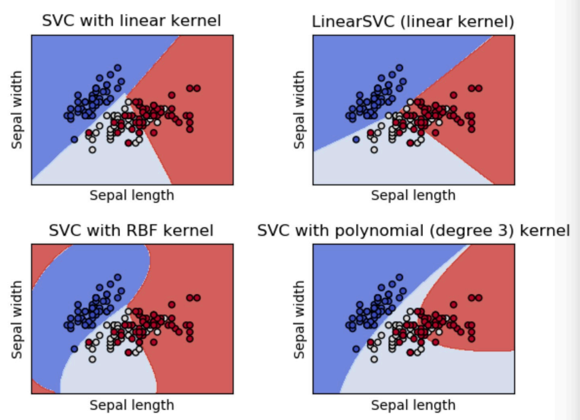
Advantage

- Effective in high dimensional spaces
- Effective in cases where # of dimensions is greater than # of samples
- Use a subset of training points in decision function (support vectors) so that can be memory efficient
- Versatile

Disadvantage

- Overfitting
- Do not provide probabilities estimates (calculated using five-fold cross validation)

Classification



`SVC`, `NuSVC`, and `LinearSVC` can perform multi-class classification on a dataset.

- `SVC` and `NuSVC` are similar
- `LinearSVC` is another implementation for the case of a linear kernel (does not accept the keyword `kernel`, assumed to be linear)
- All take as input two arrays
  - An array `X` of size `[n_samples, n_features]` from training samples
  - An array `y` of class labels (strings or integers) of size `[n_samples]`

```
>>> from sklearn import svm
>>> X = [[0, 0], [1, 1]]
>>> y = [0, 1]
>>> clf = svm.SVC()
>>> clf.fit(X, y)
SVC(C=1.0, cache_size=200,
class_weight=None, coef0=0.0, decision_-
function_shape='ovr', degree=3, gam-
ma='auto', kernel='rbf', max_iter=-1,
probability=False, random_state=None,
shrinking=True, tol=0.001, verbose=False)
```

After being fitted, the model can then be used to predict new values:

```
>>> clf.predict([[2., 2.]])
array([1])
```

Multi-class Classification

- `SVC` and `NuSVC` implement the 'one-against-one' approach for multi-class classification
- If `n_class` is the # of class, then `n_class * (n_class - 1) / 2` classifiers are constructed and each one trains data from two classes
- `decision_function_shape` options allows to aggregate the results of the 'one-against-one' classifiers to a decision function of shape `(n_samples, n_classes)`

```
>>> X = [[0], [1], [2], [3]]
>>> Y = [0, 1, 2, 3]
>>> clf = svm.SVC(decision_func-
tion_shape='ovo')
>>> clf.fit(X, Y)
SVC(C=1.0, cache_size=200,
class_weight=None, coef0=0.0,
```

```
    decision_function_shape='ovo', degree=3, gamma='auto', kernel='rbf', max_iter=-1, probability=False, random_state=None, shrinking=True, tol=0.001, verbose=False)
>>> dec = clf.decision_function([[1]])
>>> dec.shape[1] # 4 classes: 4*3/2 = 6
6
>>> clf.decision_function_shape = "ovr"
>>> dec = clf.decision_function([[1]])
>>> dec.shape[1] # 4 classes
4
```

- `LinearSVC` implements 'one-vs-the-rest' multi-class strategy (training `n_class` models)
- If there are two classes, only one class is trained

```
>>> lin_clf = svm.LinearSVC()
>>> lin_clf.fit(X, Y)
LinearSVC(C=1.0, class_weight=None,
dual=True, fit_intercept=True,
     intercept_scaling=1,
loss='squared_hinge', max_iter=1000,
     multi_class='ovr', penalty='l2',
random_state=None, tol=0.0001, verbose=0)
>>> dec = lin_clf.decision_function([[1]])
>>> dec.shape[1]
4
```

Scores and Probabilities

- `SCV` method `decision_function` gives per-class scores for each sample
- When the constructor option `probability` is set to `True`, class membership probability estimates are enabled

Unbalanced Problems

- Keywords `class_weigth` and `sample_weight` can be used in problems where it is desired to give more importance to certain classes or certain individual samples
- `SVC` implement a keyword `class_weigth` in the `fit` method (a dictionary of the form `{class_label: value}`, where the value is a floating point number > 0 that sets the parameter `C` of `class_label` to `C * value`
- `SVC`, `NuSVC`, `SVR`, `NuSVR`, and `OneClassSVM` implement also weights for individual samples in the method `fit` keyword `sample_weight` (parameter `C` for the i-th example to `C * weight[i]`)

```
sklearn.svm.SVC
```

```
class sklearn.svm.SVC(C=1.0, kernel='rbf', degree=3, gamma='auto', coef0=0.0, shrinking=True, probability=False, tol=0.001, cache_size=200, class_weight=None, verbose=False, max_iter=-1, decision_function_shape='ovr', random_state=None)
```

Kernel: string, optional (default='rbf')

- One of 'linear', 'poly', 'rbf', 'sigmoid', 'precomputed' or a callable

C: float, optional (default=1.0)

- Penalty parameter C of the error term
- Controls the tradeoff between smooth decision boundary and classifying training points correctly
- Straight forward may be a better choice

Large C value means getting more points correct

Gamma: float, optional (default='auto')

- Kernel coefficient for 'rbf', 'poly', and 'sigmoid'. If gamma is 'auto' then `1/n_features` will be used instead
- Defines how far the influence of a single training example reaches

Low gamma value means every point has a far reach, and low gamma value means every point has a close reach

Overfitting

- Stop overfitting (tuning parameters)
  - C
  - Gamma
  - Kernel