Classification functions in sci-kit learn

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Machine Learning Practice

- In this week, we will study sklearn functionality for implementing classification algorithms.

- We will cover sklearn APIs for
  - Specific classification algorithms for least square classification, perceptron, and logistic regression classifier.
    - with regularization
    - multiclass, multilabel and multi-output setting
  - Various classification metrics.

- Cross validation and hyper parameter search for classification works exactly like how it works in regression setting.
  - However there are a couple of CV strategies that are specific to classification

Part I: sklearn API for classification

There are broadly two types of APIs based on their functionality:

Generic

- SGD classifier

Uses gradient descent for opt

Need to specify loss function

Specific

- Logistic regression
- Perceptron
- Ridge classifier (for LSC)
- K-nearest neighbours (KNNs)
- Support vector machines (SVMs)
- Naive Bayes

Specialized solvers for opt

All sklearn estimators for classification implement a few common methods for model training, prediction and evaluation.

Model training

```
fit(X, y[, coef_init, intercept_init, …])
```

Prediction

`predict(X)` predicts class label for samples

`decision_function(X)` predicts confidence score for samples.

Evaluation

```
score(X, y[, sample_weight])
```

Return the mean accuracy on the given test data and labels.

There a few common miscellaneous methods as follows:

`get_params([deep])`	gets parameter for this estimator.
`set_params(**params)`	sets the parameters of this estimator.
`densify()`	converts coefficient matrix to dense array format.
`sparsify()`	converts coefficient matrix to sparse format.

Now let's study how to implement different classifiers with sklearn APIs.

Let's start with implementation of least square classification (LSC) with RidgeClassifier API.

Ridge classifier

- RidgeClassifier is a classifier variant of the Ridge regressor.

Binary classification:

- classifier first converts binary targets to {-1, 1} and then treats the problem as a regression task, optimizing the objective of regressor:
  - minimize a penalized residual sum of squares
    - $\min_{\mathbf{w}} ||\mathbf{X}\mathbf{w} - \mathbf{y}||_2^2 + \alpha||\mathbf{w}||_2^2$
      - sklearn provides different solvers for this optimization
      - sklearn uses α to denote regularization rate
    - predicted class corresponds to the sign of the regressor's prediction

Multiclass classification:

- treated as multi-output regression
- predicted class corresponds to the output with the highest value

How to train a least square classifier?

Step 1: Instantiate a classification estimator without passing any arguments to it. This creates a ridge classifier object.

```
1 from sklearn.linear_model import RidgeClassifier
2 ridge_classifier = RidgeClassifier()
```

Step 2: Call fit method on ridge classifier object with training feature matrix and label vector as arguments.

Note: The model is fitted using X_train and y_train.

```
1 # Model training with feature matrix X_train and
2 # label vector or matrix y_train
3 ridge_classifier.fit(X_train, y_train)
```

How to set regularization rate in RidgeClassifier?

Set `alpha` to float value. The default value is 0.1.

```
1 from sklearn.linear_model import RidgeClassifier
2 ridge_classifier = RidgeClassifier(alpha=0.001)
```

- alpha should be positive.
- Larger alpha values specify stronger regularization.

How to solve optimization problem in RidgeClassifier?

Using one of the following solvers

`svd`	uses a Singular Value Decomposition of the feature matrix to compute the Ridge coefficients.
`cholesky`	uses `scipy.linalg.solve` function to obtain the closed-form solution
`sparse_cg`	uses the conjugate gradient solver of `scipy.sparse.linalg.cg` .
`lsqr`	uses the dedicated regularized least-squares routine `scipy.sparse.linalg.lsqr` and it is fastest.
`sag` , `saga`	uses a Stochastic Average Gradient descent iterative procedure 'saga' is unbiased and more flexible version of 'sag'
`lbfgs`	uses L-BFGS-B algorithm implemented in `scipy.optimize.minimize` . can be used only when coefficients are forced to be positive.

Uses of solver in RidgeClassifier

- For large scale data, use '`sparse_cg` ' solver.

- When both `n_samples` and `n_features` are large, use ‘`sag` ’ or ‘`saga`’ solvers.
  - Note that fast convergence is only guaranteed on features with approximately the same scale.

How to make RidgeClassifier select the solver automatically?

```
1 ridge_classifier = RidgeClassifier(solver=auto)
```

`auto`

chooses the solver automatically based on the type of data

```
1   if solver == 'auto':
2       if return_intercept:
3           # only sag supports fitting intercept directly
4           solver = "sag"
5       elif not sparse.issparse(X):
6           solver = "cholesky"
7       else:
8           solver = "sparse_cg"
```

Default choice for solver is **`auto`** .

Is intercept estimation necessary for RidgeClassifier?

If data is already centered, set fit_intercept as false, so that no intercept will be used in calculations.

Default:

```
1 ridge_classifier = RidgeClassifier(fit_intercept=True)
```

How to make predictions on new data samples?

Use `predict` method to predict class labels for samples

Step 1: Arrange data for prediction in a feature matrix of shape (#samples, #features) or in sparse matrix format.

Step 2: Call predict method on classifier object with feature matrix as an argument.

```
1 # Predict labels for feature matrix X_test
2 y_pred = ridge_classifier.predict(X_test)
```

Other classifiers also use the same predict method.

RidgeClassifierCV implements
RidgeClassifier with built-in cross validation.

Let's implement perceptron classifier with Perceptron API.

Perceptron classification

- It is a simple classification algorithm suitable for large-scale learning.

- Shares the same underlying implementation with `SGDClassifier`

```
Perceptron()
```

```
SGDClassifier(loss="perceptron", eta0=1,
learning_rate="constant", penalty=None)
```

Perceptron uses SGD for training.

How to implement perceptron classifier?

Step 1: Instantiate a Perceptron estimator without passing any arguments to it to create a classifier object.

```
1 from sklearn.linear_model import Perceptron
2 perceptron_classifier = Perceptron()
```

Step 2: Call fit method on perceptron estimator object with training feature matrix and label vector as arguments.

```
1 # Model training with feature matrix X_train and
2 # label vector or matrix y_train
3 perceptron_classifier.fit(X_train, y_train)
```

Perceptron can be further customized with the following parameters:

`penalty`
(default = 'l2')

`l1_ratio`
(default = 0.15)

`alpha`
(default = 0.0001)

`early_stopping`
(default = False)

`fit_intercept`
(default = True)

`max_iter`
(default = 1000)

`n_iter_no_change`
(default = 5)

`tol`
(default = 1e-3)

`eta0`
(default = 1)

`validation_fraction`
(default = 0.1)

- Perceptron classifier can be trained in an iterative manner with partial_fit method

- Perceptron classifier can be initialized to the weights of the previous run by specifying warm_start = True in the constructor.

Let's implement logistic regression classifier
with LogisticRegression API.

LogisticRegression API

- Implements logistic regression classifier, which is also known by a few different names like logit regression, maximum entropy classifier (maxent) and log-linear classifier.

$$\arg\min_{\mathbf{w},C} \text{ regularization penalty } + C \text{ cross entropy loss}$$

- This implementation can fit
  - binary classification
  - one-vs-rest (OVR)
  - multinomial logistic regression

- Provision for ℓ_1, ℓ_2 or elastic-net regularization

How to train a LogisticRegression classifier?

Step 1: Instantiate a classifier estimator without passing any arguments to it. This creates a logistic regression object.

```
1 from sklearn.linear_model import LogisticRegression
2 logit_classifier = LogisticRegression()
```

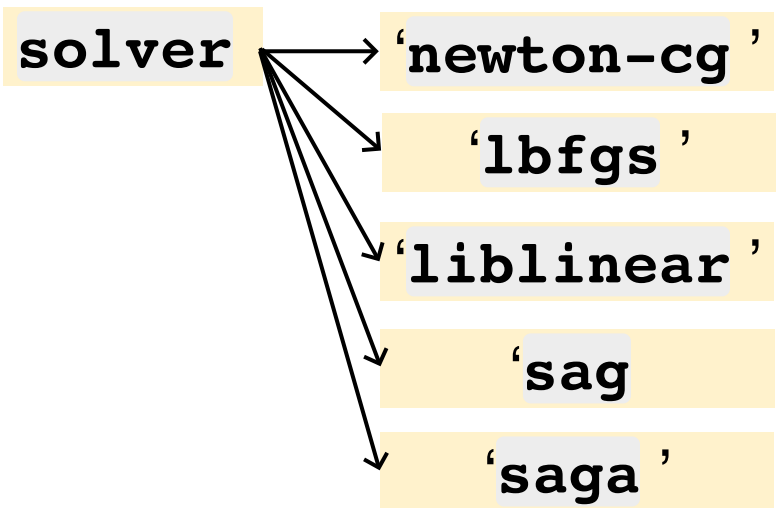
Step 2: Call fit method on logistic regression classifier object with training feature matrix and label vector as arguments

```
1 # Model training with feature matrix X_train and
2 # label vector or matrix y_train
3 logit_classifier.fit(X_train, y_train)
```

Logistic regression uses specific algorithms for solving the optimization problem in training. These algorithms are known as solvers.

The choice of the solver depends on the classification problem set up such as size of the dataset, number of features and labels.

How to select solvers for Logistic Regression classifier?



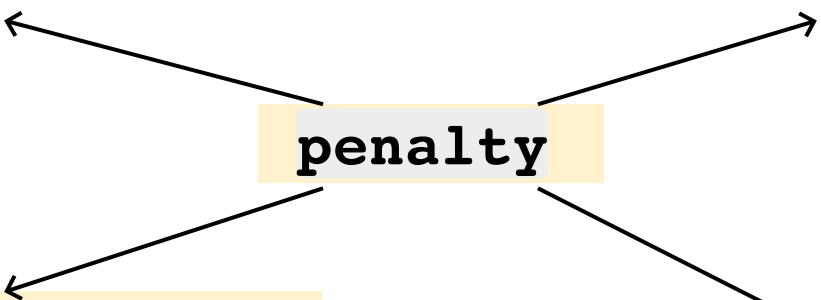
- For small datasets, 'liblinear' is a good choice, whereas 'sag' and 'saga ' are faster for large ones.
- For unscaled datasets, '`liblinear`', '`lbfgs`' and '`newton-cg` ' are robust.
- For multiclass problems, only '`newton-cg`', '`sag`', '`saga`' and '`lbfgs` ' handle multinomial loss.
- '`liblinear` ' is limited to one-versus-rest schemes

By default, logistic regression uses lbfgs solver.

```
1 logit_classifier = LogisticRegression(solver='lbfgs')
```

How to add regularization in Logistic Regression classifier?

- $l2$ - adds a L2 penalty term
- $l1$ - adds a L1 penalty term



- elasticnet - both L1 and L2 penalty terms are added
- none - no penalty is added

Regularization is applied by default because it improves numerical stability.

By default, it uses L2 penalty.

```
1 logit_classifier = LogisticRegression(penalty='l2')
```

- Not all the solvers supports all the penalties.
- Select appropriate solver for the desired penalty.
  - L2 penalty is supported by all solvers
  - L1 penalty is supported only by a few solvers.

Solver	Penalty
‘newton-cg ’	[‘l2’, ‘none’]
‘lbfgs ’	[‘l2’, ‘none’]
‘liblinear’	[‘l1’, ‘l2’]
‘sag’	[‘l2’, ‘none’]
‘saga ’	[‘elasticnet’, ‘l1’, ‘l2’, ‘none’]

How to control amount of regularization in logistic regression?

- sklearn implementation uses parameter C, which is inverse of regularization rate to control regularization.
- Recall

$$\arg\min_{\mathbf{w},C} \text{ regularization penalty } + C \text{ cross entropy loss}$$

- C is specified in the constructor and must be positive
  - Smaller value leads to stronger regularization.
  - Larger value leads to weaker regularization.

LogisticRegression classifier has a class_weight parameter in its constructor.

What purpose does it serve?

- Handles class imbalanace with differential class weights.
- Mistakes in a class are penalized by the class weight.
  - Higher value here would mean higher emphasis on the class.

This parameter is available in classifier estimators in sklearn.

Exercise: Read stack overflow discussion on this parameter.

LogisticRegressionCV implements logistic regression with in built cross validation support to find the best values of C and l1_ratio parameters according to the specified scoring attribute.

These classifiers can also be implemented with a generic SGDClassifier API by setting the loss parameter appropriately.

Let's study SGDClassifier API.

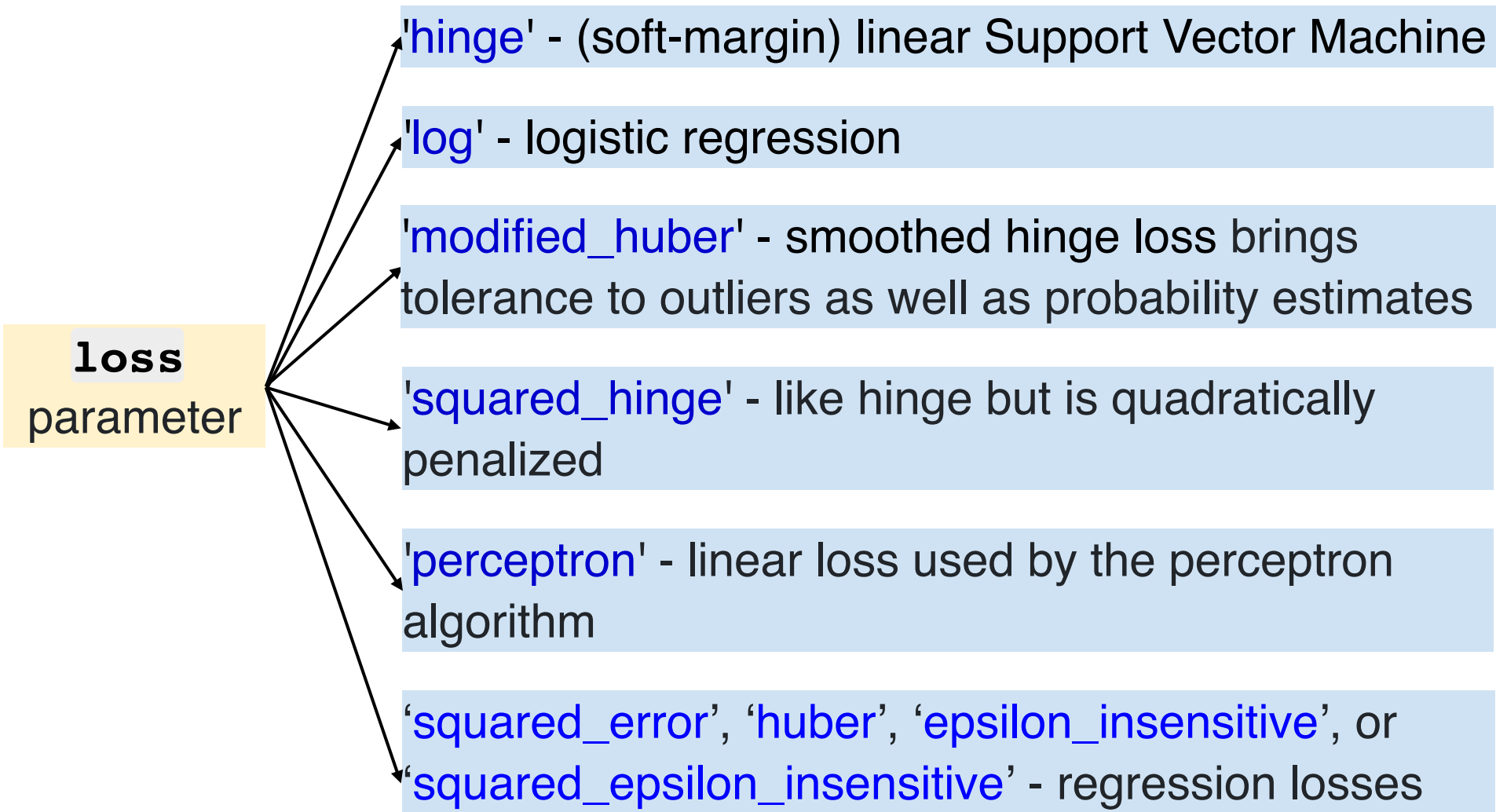
SGDClassifier

- **SGD** is a simple yet very efficient approach to fitting linear classifiers under convex loss functions

- This API uses SGD as an optimization technique and can be applied to build a variety of linear classifiers by adjusting the loss parameter.

- It supports multi-class classification by combining multiple binary classifiers in a "one versus all" (OVA) scheme.
- Easily scales up to large scale problems with more than 10^5 training examples and 10^5 features. It also works with sparse machine learning problems
  - Text classification and natural language processing

We need to set loss parameter appropriately to build train classifier of our interest with SGDClassifier



By default SGDClassifier uses hinge loss and hence trains linear support vector machine classifier.

- An instance of SGDClassifier might have an equivalent estimator in the scikit-learn API.

```
SGDClassifier(loss='log')
```

```
LogisticRegression(solver='sgd')
```

```
SGDClassifier(loss='hinge')
```

Linear Support vector machine

How does SGDClassifier work?

- SGDClassifier implements a plain stochastic gradient descent learning routine.
  - the gradient of the loss is estimated with one sample at a time and the model is updated along the way with a decreasing learning rate (or strength) schedule.

Advantages:

- Efficiency.
- Ease of implementation

Disadvantages:

- Requires a number of hyperparameters.
- Sensitive to feature scaling.

- It is important
  - to permute (shuffle) the training data before fitting the model.
  - to standardize the features.

How to use SGDClassifier for training a classifer?

Step 1: Instantiate a SGDClassifer estimator by setting appropriate loss parameter to define classifier of interest. By default it uses hinge loss, which is used for training linear support vector machine.

```
1 from sklearn.linear_model import SGDClassifier
2 SGD_classifier = SGDClassifier(loss='log')
```

Here we have used `log` loss that defines a logistic regression classifier.

Step 2: Call fit method on SGD classifier object with training feature matrix and label vector as arguments.

```
1 # Model training with feature matrix X_train and
2 # label vector or matrix y_train
3 SGD_classifier.fit(X_train, y_train)
```

How to perform regularization in SGD classifier?

- $l2$ - adds a L2 penalty term
- $l1$ - adds a L1 penalty term

penalty

- elasticnet - Convex combination of L2 and L1

`(1 - l1_ratio) * L2 + l1_ratio * L1`

(`l1_ratio` controls the convex combination of L1 and L2 penalty. default=0.15)

Default:

```
SGD_classifier = SGDClassifier(penalty='l2')
```

alpha

- Constant that multiplies the regularization term.
- Has float values and default = 0.0001

How to set maximum number of epochs for SGD Classifier?

The maximum number of passes over the training data (aka epochs) is an integer that can be set by the `max_iter` parameter.

```
1 SGD_classifier = SGDClassifier(max_iter=100)
```

Default:

`max_iter = 1000`

Some common parameters between SGDClassifier and SGDRegressor

`learning_rate`

- ‘constant’
- ‘optimal’
- ‘invscaling’
- ‘adaptive’

`warm_start`

- ‘True’
- ‘False’

`average`

- SGDClassifier also supports averaged SGD (ASGD)

Stopping criteria

- **`tol`**
- **`n_iter_no_change`**
- **`max_iter`**
- **`early_stopping`**
- **`validation_fraction`**

Summary

We learnt how to implement the following classifiers with sklearn APIs:

- Least square classification (RidgeClassifier)
- Perceptron (Perceptron)
- Logistic regression (LogisticRegression)

Alternatively we can use SGDClassifier with appropriate loss setting for implementing these classifiers:

- loss = `log` for logistic regression
- loss = `perceptron` for perceptron
- loss = `squared_error` for least square classification

Classification estimators implements a few common methods like fit, score, decision_function, and predict.

- These estimators can be readily used in multiclass setting.
- They support regularized loss function optimization.
- All classification estimators have ability to deal with class imbalance through class_weight parameter in the constructor.

Part II: Multi-learning classification set up

Let's extend these classifiers to multi-learning (multi-class, multi-label & multi-output) settings.

Basics of multiclass, multilabel and multioutput classification

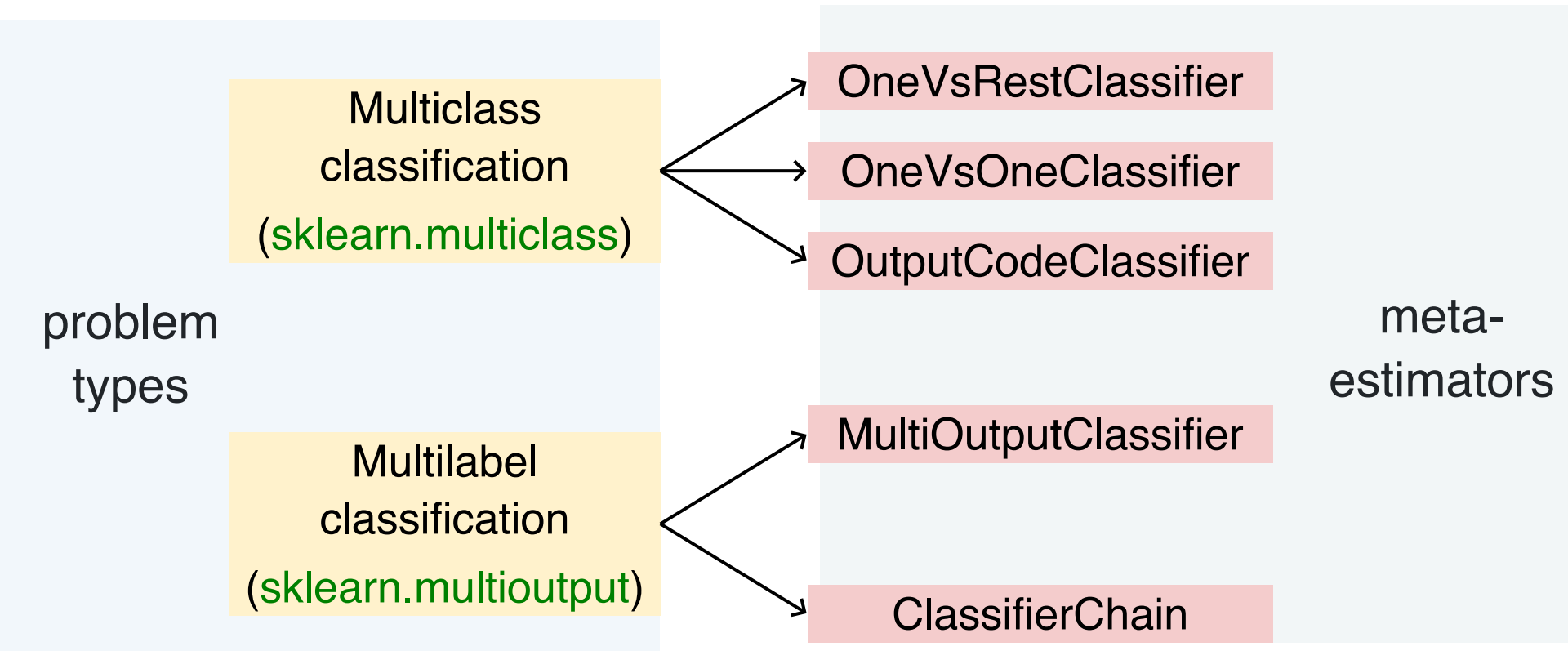
- Multiclass classification has exactly one output label and the total number of labels > 2.
- For more than one output, there are two types of classification models:

Multilabel	Multiclass multioutput
total #labels = 2	total #labels > 2

We will refer both these models as multi-label classification models, where # of output labels > 1.

Multiclass, multilabel, multioutput problems are referred to as multi-learning problems.

- sklearn provides a bunch of meta-estimators, which extend the functionality of base estimators to support multi-learning problems.
- The meta-estimators transform the multi-learning problem into a set of simpler problems and fit one estimator per problem.



- Many sklearn estimators have built-in support for multi-learning problems.
  - Meta-estimators are not needed for such estimators, however meta-estimators can be used in case we want to use these base estimators with strategies beyond the built-in ones.

Inherently multiclass	Multiclass as OVO	Multiclass as OVR	Multilabel

Inherently multiclass	LogisticRegression (multi_class = 'multinomial') LogisticRegressionCV (multi_class = 'multinomial') RidgeClassifier RidgeClassifierCV
Multiclass as OVR	LogisticRegression (multi_class = 'ovr') LogisticRegressionCV (multi_class = 'ovr') SGDClassifier Perceptron
Multilabel	RidgeClassifier RidgeClassifierCV

First we will study multiclass APIs in sklearn.

Multi-class classification

- Classification task with more than two classes.
- Each example is labeled with exactly one class

In Iris dataset,

- There are three class labels: setosa, versicolor and virginica.
- Each example has exactly one label of the three available class labels.
- Thus, this is an instance of a multi-class classification.

In MNIST digit recognition dataset,

- There are 10 class labels: 0, 1, 2, 3, 4, 5, 6, 7, 8, 9.
- Each example has exactly one label of the 10 available class labels.
- Thus, this is an instance of a multi-class classification.

How to represent class labels in multi-class setup?

- Each example is marked with a single label out of k labels. The shape of label vector is $(n, 1)$.
- Use LabelBinarizer transformation to convert the class label to multi-class format.

```
1 from sklearn.preprocessing import LabelBinarizer
2 y = np.array(['apple', 'pear', 'apple', 'orange'])
3 y_dense = LabelBinarizer().fit_transform(y)
```

- The resulting label vector has shape of (n, k).

```
[[1 0 0]
 [0 0 1]
 [1 0 0]
 [0 1 0]]
```

Let's say, you are given labels as part of the training set, how do we check if they are is suitable for multi-class classification?

- Use type_of_target to determine the type of the label.

```
from sklearn.utils.multiclass import type_of_target
type_of_target(y)
```

- In case, y is a vector with more than two discrete values, type_of_target returns multiclass.

type_of_target can determine different types
of multi-learning targets.

target_type	y
‘multiclass’	• contains more than two discrete values • not a sequence of sequences • 1d or a column vector
‘multiclass-multioutput’	• 2d array that contains more than two discrete values • not a sequence of sequences • dimensions are of size > 1
‘multilabel-indicator’	• label indicator matrix • an array of two dimensions with at least two columns, and at most 2 unique values.
‘unknown’	• array-like but none of the above, such as a 3d array, • sequence of sequences, or an array of non-sequence objects.

Examples

multiclass

```
>>> type_of_target([1, 0, 2])
'multiclass'
>>> type_of_target([1.0, 0.0, 3.0])
'multiclass'
>>> type_of_target(['a', 'b', 'c'])
'multiclass'
```

multiclass-multioutput

```
>>> type_of_target(np.array([[1, 2], [3, 1]]))
'multiclass-multioutput'
```

multilabel-indicator

```
type_of_target(np.array([[0, 1], [1, 1]]))
'multilabel-indicator'
>>> type_of_target([[1, 2]])
'multilabel-indicator'
```

Apart from these, there are three more types, type_of_target can determine targets corresponding to regression and binary classification.

- continuous - regression target
- continuous-multioutput - multi-output target
- binary - classification

All classifiers in scikit-learn perform multiclass classification out-of-the-box.

- Use sklearn.multiclass module only when you want to experiment with different multiclass strategies.
- Using different multi-class strategy than the one implemented by default may affect performance of classifier in terms of either generalization error or computational resource requirement.

What are different multi-class classification strategies implemented in sklearn?

- One-vs-all or one-vs-rest (OVR)
- One-vs-One (OVA)

- OVR is implemented by OneVsRestClassifier API.
- OVA is implemented by OneVsOneClassifier API.

OVR - OneVsRestClassifier

- Fits one classifier per class c - c vs not c.
- This approach is computationally efficient and requires only k classifiers.
- The resulting model is interpretable.

```
1 from sklearn.multiclass import OneVsRestClassifier
2 OneVsRestClassifier(LinearSVC(random_state=0)).fit(X, y)
```

- We need to supply estimator as an argument in the constructor.
- Support methods like other classifiers - fit, predict, predict_proba, partial_fit.

OneVsRest classifier also supports multilabel classification. We need to supply labels as indicator matrix of shape (n, k).

OVA - OneVsOneClassifier

- Fits one classifier per pair of classes. Total classifiers = $\binom{k}{2}$.
- Predicts class that receives maximum votes.
  - The tie among classes is broken by selecting the class with the highest aggregate classification confidence.

```
1 from sklearn.multiclass import OneVsOneClassifier
2 OneVsOneClassifier(LinearSVC(random_state=0)).fit(X, y)
```

- We need to supply estimator as an argument in the constructor.
- Support methods like other classifiers - fit, predict, predict_proba, partial_fit.

OneVsOne classifier processes subset of data at a time and is useful in cases where the classifier does not scale with the data.

What is the difference between OVR and OVA?

OneVsRestClassifier

- Fits one classifier per class.
- For each classifier, the class is fitted against all the other classes.

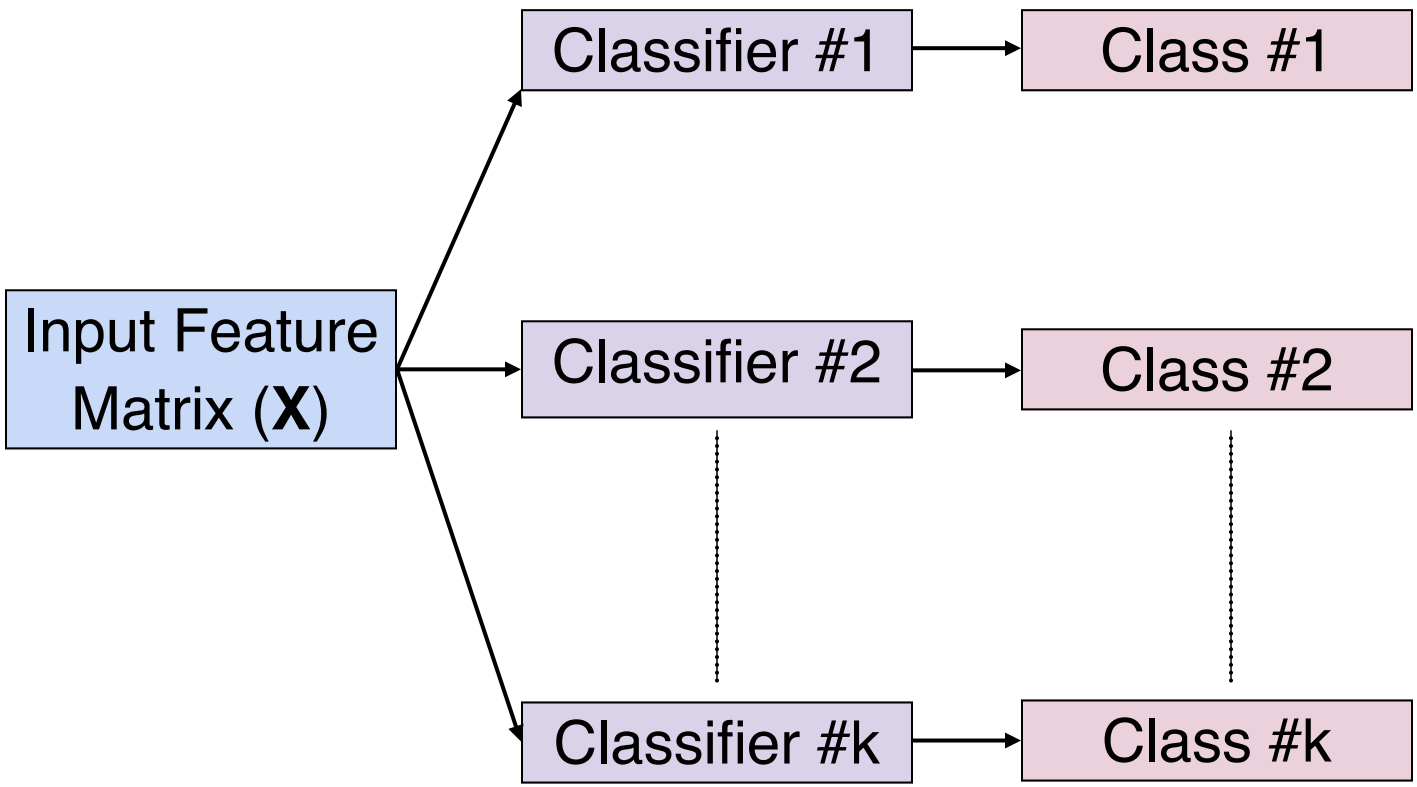
OneVsOneClassifier

- Fits one classifier per pair of classes.
- At prediction time, the class which received the most votes is selected.

Now we will learn how to perform multilabel and multi-output classification.

How MultiOutputClassifier works?

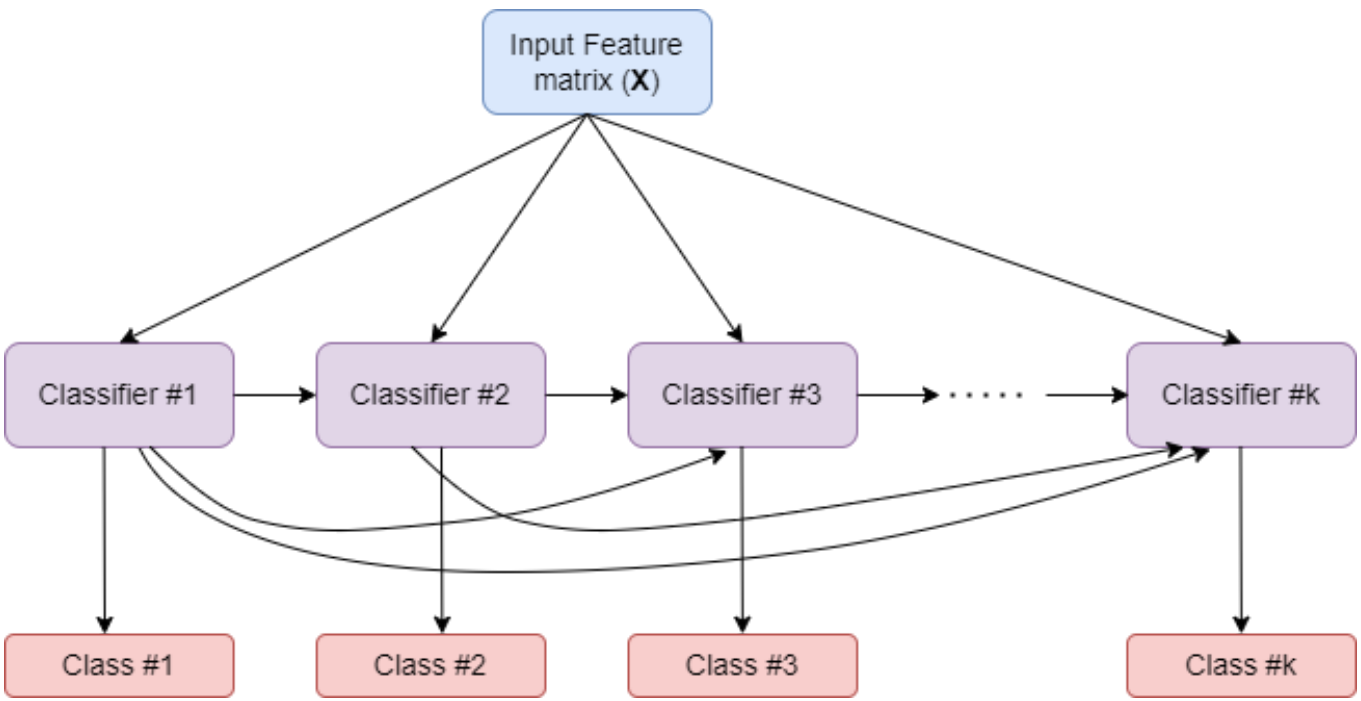
- Strategy consists of fitting one classifier per target.



- Allows multiple target variable classifications.

How ClassifierChain works?

- A multi-label model that arranges binary classifiers into a chain.
- Way of combining a number of binary classifiers into a single multi-label model.



Comparison of MultiOutputClassifier and ClassifierChain

MultiOutputClassifier	ClassifierChain
• Able to estimate a series of target functions that are trained on a single predictor matrix to predict a series of responses.	• Capable of exploiting correlations among targets.
• Allows multiple target variable classifications.	• For a multi-label classification problem with k classes, k binary classifiers are assigned an integer between 0 and $k-1$. • These integers define the order of models in the chain.

Summary

- Different types of multi-learning setups: multi-class, multi-label, multi-output.
- type_of_target to determine the nature of supplied labels.
- Meta-estimators:
  - multi-class: One-vs-rest, one-vs-one
  - multi-label: Classifier chain and multi-output classifier

Evaluating Classifiers

So far we learnt how to train classifiers for binary, multi-class and multi-label/output cases.

We will learn how to evaluate these classifiers with different scoring functions and with cross-validation.

We will also study how to set hyper-parameters for classifiers.

Many cross-validation and HPT methods discussed in the regression context are also applicable in classifiers.

- We will not repeat that discussion in this topic.
- Instead we will focus on only additional methods that are specific to classifiers.

Stratified cross validation iterators

There may be issues like class imbalance in classification, which tend to impact the cross validation folds.

The overall class distribution and the ones in folds may be different and this has implications in effective model training.

sklearn.model_selection module provides three stratified APIs to create folds such that the overall class distribution is replicated in individual folds.

sklearn.model_selection module provides the following three stratified APIs to create folds such that the overall class distribution is replicated in individual folds.

- StratifiedKFold
- RepeatedStratifiedKFold
- StratifiedShuffleSplit

Note: Folds obtained via StratifiedShuffleSplit may not be completely different.

LogisticRegressionCV

- Support in-build cross validation for optimizing hyperparameters
- The following are key parameters for HPT and cross validation

cv specifies cross validation iterator

scoring specifies scoring function to use for HPT

cs specifies regularization strengths to experiment with.

- Choosing the best hyper-parameters

refit = True

Scores averaged across folds, values corresponding to the best score are selected and final refit with these parameters

refit = False

the coefs, intercepts and C that correspond to the best scores across folds are averaged.

Now let's look at classification metrics implemented in sklearn.

Classification metrics

sklearn.metrics implements a bunch of classification scoring metrics based on true labels and predicted labels as inputs.

`accuracy_score` `balanced_accuracy_score`

`top_k_accuracy_score` `roc_auc_score`

`precision_score` `recall_score` `f1_score`

score(actual_labels, predicted_labels)

Confusion matrix

- `confusion_matrix` evaluates classification accuracy by computing the confusion matrix with each row corresponding to the true class.

```
1 from sklearn.metrics import confusion_matrix
2 confusion_matrix(y_true, y_predicted)
```

Example:

```
array([[2, 0, 0],
       [0, 0, 1],
       [1, 0, 2]])
```

Entry i, j in a confusion matrix

number of observations actually in group i, but predicted to be in group j.

Confusion matrix can be displayed with ConfusionMatrixDisplay API in sklearn.metrics.

- Confusion matrix

```
1 ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=clf.classes_)
```

- From estimators

```
1 ConfusionMatrixDisplay.from_estimator(clf, X_test, y_test)
```

- From predictions

```
1 ConfusionMatrixDisplay.from_predictions(y_test, y_pred)
```

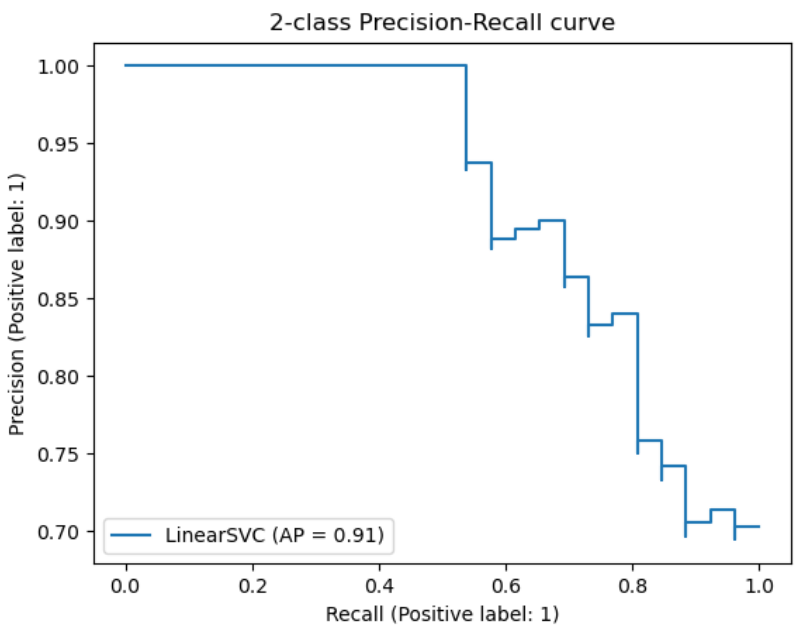
The `classification_report` function builds a text report showing the main classification metrics.

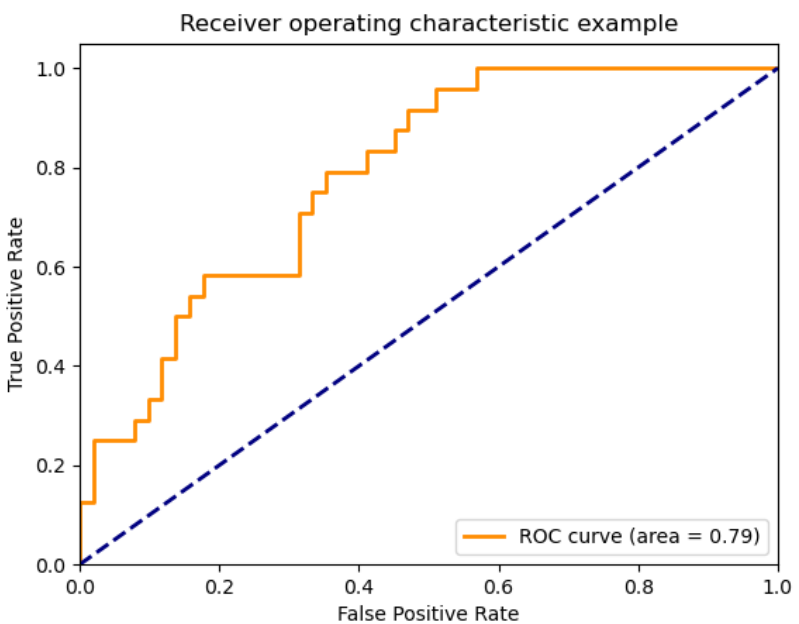
```
1 from sklearn.metrics import classification_report
2 print(classification_report(y_true, y_predicted))
```

	precision	recall	f1-score	support
class 0	0.67	1.00	0.80	2
class 1	0.00	0.00	0.00	1
class 2	1.00	0.50	0.67	2
accuracy			0.60	5
macro avg	0.56	0.50	0.49	5
weighted avg	0.67	0.60	0.59	5

Classifier Performance across probability thresholds

```
1 from sklearn.metrics import precision_recall_curve
2 precision, recall, thresholds = precision_recall_curve(y_true, y_predicted)
```






```
1 from sklearn.metrics import roc_curve
2 fpr, tpr, thresholds = metrics.roc_curve(y_true, y_scores, pos_label=2)
```

How to extend binary metric to multiclass or multilabel problems?

- Treat data as a collection of binary problems, one for each class.
- Then, average binary metric calculations across the set of classes.
  - Can be done using `average` parameter.

`macro`	calculates the mean of the binary metrics
`weighted`	computes the average of binary metrics in which each class's score is weighted by its presence in the true data sample.
`micro`	gives each sample-class pair an equal contribution to the overall metric
`samples`	calculates the metric over the true and predicted classes for each sample in the evaluation data, and returns their average
`None`	returns an array with the score for each class

Summary

- Classification specific cross validation iterator based on stratification.
- Classification metrics
- Extending binary metrics to multi-learning set up.