机器学习集成学习与模型融合！

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对比过kaggle比赛上面的top10的模型，除了深度学习以外的模型基本上都是集成学习的产物。集成学习可谓是上分大杀器，今天就跟大家分享在Kaggle或者阿里天池上面大杀四方的数据科学比赛利器---集成学习。

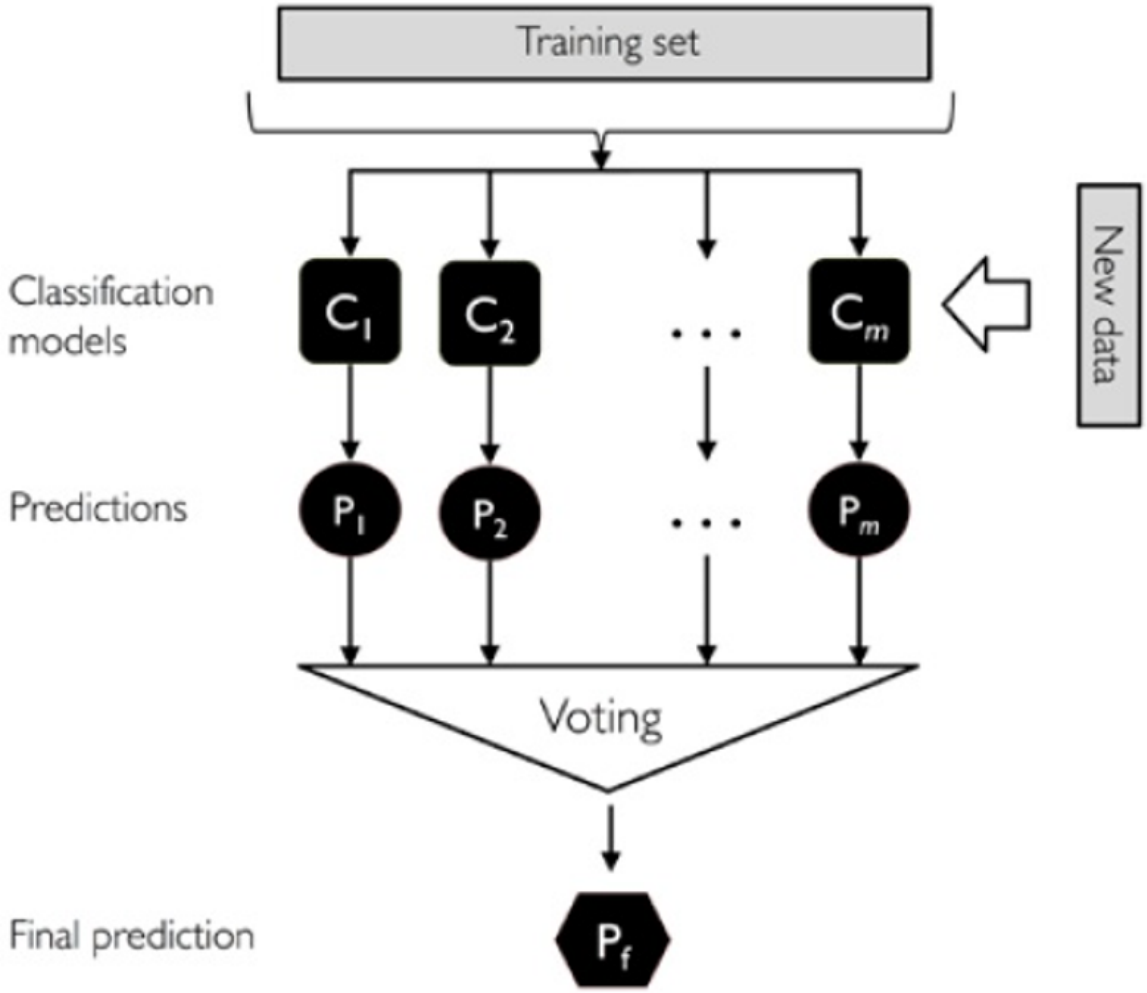
一、什么是集成学习

- 正所谓“三个臭皮匠赛过诸葛亮”的道理，在机器学习数据挖掘的工程项目中，使用单一决策的弱分类器显然不是一个明智的选择，因为各种分类器在设计的时候都有自己的优势和缺点，也就是说每个分类器都有自己工作偏向，那集成学习就是平衡各个分类器的优缺点，使得我们的分类任务完成的更加优秀。
- 在大多数情况下，这些基本模型本身的性能并不是非常好，这要么是因为它们具有较高的偏差（例如，低自由度模型），要么是因为他们的方差太大导致鲁棒性不强（例如，高自由度模型）。集成方法的思想是通过将这些弱学习器的偏差和/或方差结合起来，从而创建一个「强学习器」（或「集成模型」），从而获得更好的性能。

集成学习的方法：

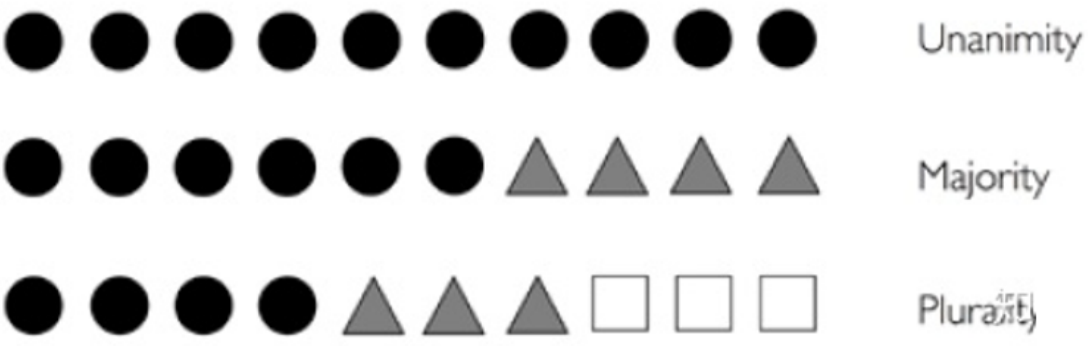
- 1. 基于投票思想的多数票机制的集成分类器(MajorityVoteClassifier)
- 2. 于bagging思想的套袋集成技术(BaggingClassifier)
- 3. 基于boosting思想的自适应增强方法(Adaboost)
- 4. 分层模型集成框架stacking(叠加算法)

二、基于投票思想的集成分类器



以上是多数投票的流程图：

- 分别训练n个弱分类器。
- 对每个弱分类器输出预测结果，并投票（如下图）
- 每个样本取投票数最多的那个预测为该样本最终分类预测。



加载相关库：

```
## 加载相关库
from sklearn.datasets import load_iris   # 加载数据
from sklearn.model_selection import train_test_split  # 切分训练集与测试集
```

```
from sklearn.preprocessing import StandardScaler  # 标准化数据
from sklearn.preprocessing import LabelEncoder   # 标签化分类变量
```

初步处理数据

```
## 初步处理数据
iris = load_iris()
X,y = iris.data[50:,[1,2]],iris.target[50:]
le = LabelEncoder()
y = le.fit_transform(y)
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.5,random_state=1,stratify=y)
```

我们使用训练集训练三种不同的分类器：逻辑回归 + 决策树 + k-近邻分类器

```
## 我们使用训练集训练三种不同的分类器：逻辑回归 + 决策树 + k-近邻分类器
from sklearn.model_selection import cross_val_score   # 10折交叉验证评价模型
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import Pipeline   # 管道简化工作流
clf1 = LogisticRegression(penalty='l2',C=0.001,random_state=1)
clf2 = DecisionTreeClassifier(max_depth=1,criterion='entropy',random_state=0)
clf3 = KNeighborsClassifier(n_neighbors=1,p=2,metric="minkowski")
pipe1 = Pipeline([['sc',StandardScaler()],['clf',clf1]])
pipe3 = Pipeline([['sc',StandardScaler()],['clf',clf3]])
clf_labels = ['Logistic regression','Decision tree','KNN']
print('10-folds cross validation :\n')
for clf,label in zip([pipe1,clf2,pipe3],clf_labels):
    scores = cross_val_score(estimator=clf,X=X_train,y=y_train,cv=10,scoring='roc_auc')
    print("ROC AUC: %0.2f(+/- %0.2f)[%s]"%(scores.mean(),scores.std(),label))
```

```
10-folds cross validation :

ROC AUC: 0.92(+/- 0.15)[Logistic regression]
ROC AUC: 0.87(+/- 0.18)[Decision tree]
ROC AUC: 0.85(+/- 0.13)[KNN]
```

我们使用MajorityVoteClassifier集成：

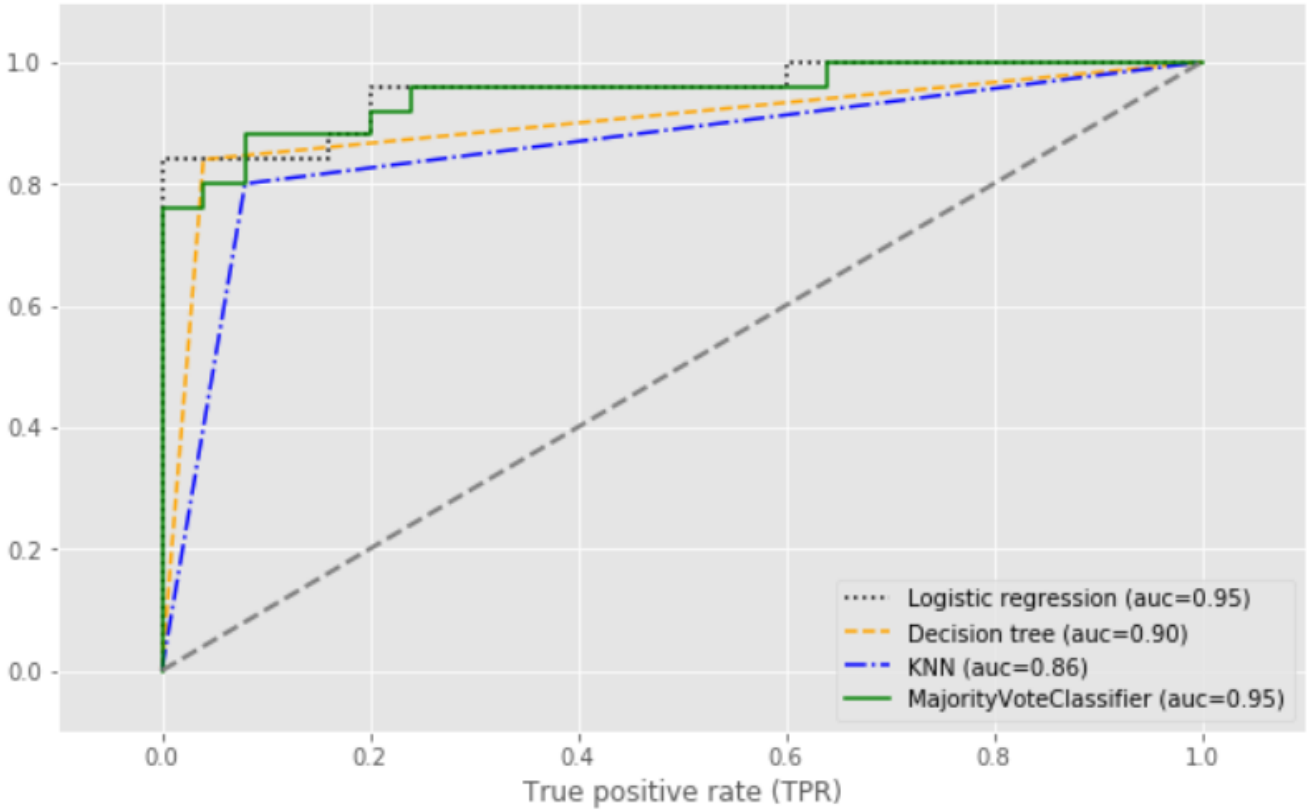
```
## 我们使用MajorityVoteClassifier集成：
from sklearn.ensemble import VotingClassifier
mv_clf = VotingClassifier(estimators=[('pipe1',pipe1),('clf2',clf2),('pipe3',pipe3)],voting='s
clf_labels += ['MajorityVoteClassifier']
all_clf = [pipe1,clf2,pipe3,mv_clf]
print('10-folds cross validation :\n')
for clf,label in zip(all_clf,clf_labels):
```

```
    scores = cross_val_score(estimator=clf,X=X_train,y=y_train,cv=10,scoring='roc_auc')
    print("ROC AUC: %0.2f(+/- %0.2f)[%s]"%(scores.mean(),scores.std(),label))
## 对比下面结果，可以得知多数投票方式的分类算法，抗差能力更强。
```

```
10-folds cross validation :

ROC AUC: 0.92(+/- 0.15)[Logistic regression]
ROC AUC: 0.87(+/- 0.18)[Decision tree]
ROC AUC: 0.85(+/- 0.13)[KNN]
ROC AUC: 0.98(+/- 0.05)[MajorityVoteClassifier]
```

使用ROC曲线评估集成分类器:

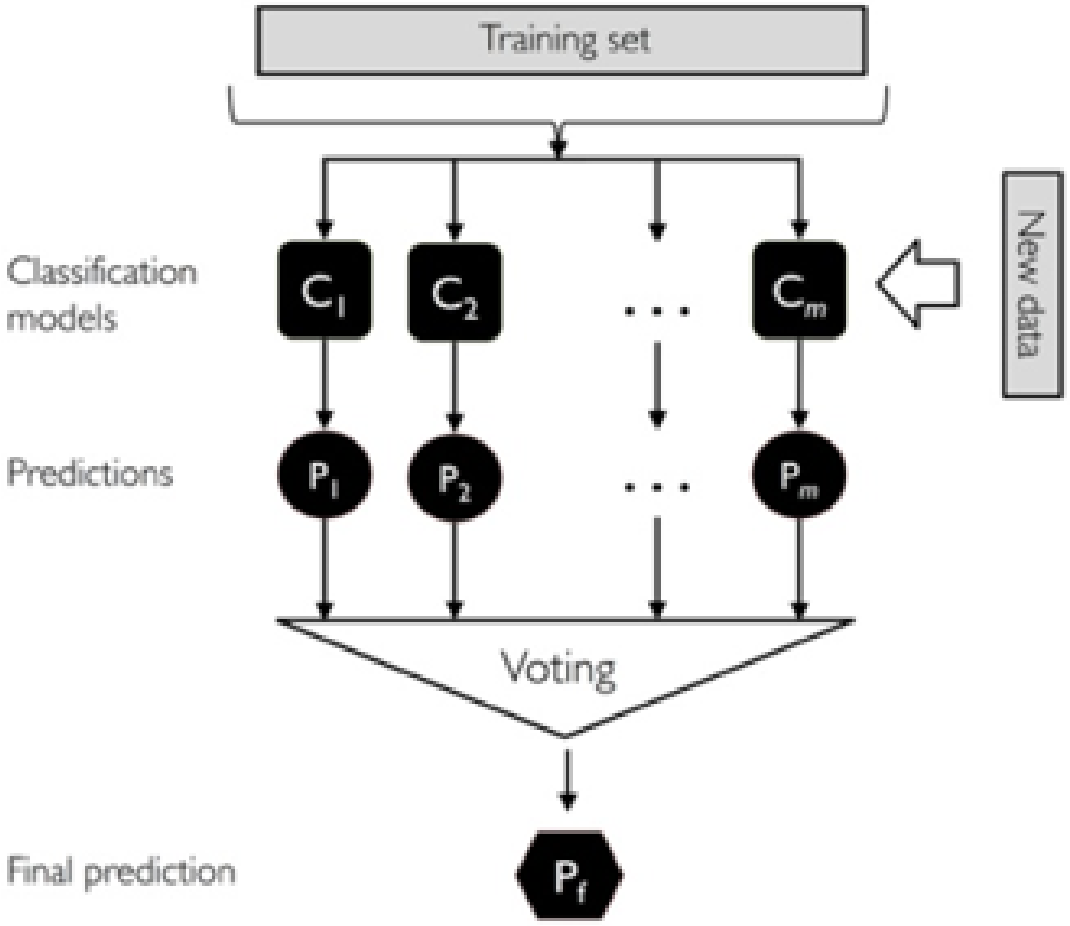
```
## 使用ROC曲线评估集成分类器
from sklearn.metrics import roc_curve
from sklearn.metrics import auc

colors = ['black','orange','blue','green']
linestyles = [':','--','-.','-']
plt.figure(figsize=(10,6))
for clf,label,clr,ls in zip(all_clf,clf_labels,colors,linestyles):
    y_pred = clf.fit(X_train,y_train).predict_proba(X_test)[:,1]
    fpr,tpr,trhresholds = roc_curve(y_true=y_test,y_score=y_pred)
    roc_auc = auc(x=fpr,y=tpr)
    plt.plot(fpr,tpr,color=clr,linestyle=ls,label='%s (auc=%0.2f)'%(label,roc_auc))
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],linestyle='--',color='gray',linewidth=2)
plt.xlim([-0.1,1.1])
plt.ylim([-0.1,1.1])
plt.xlabel('False positive rate (FPR)')
plt.xlabel('True positive rate (TPR)')
plt.show()
```



三、基于bagging思想的套袋集成技术

套袋方法是由柳.布莱曼在1994年的技术报告中首先提出并证明了套袋方法**可以提高不稳定模型的准确度的同时降低过拟合的程度(可降低方差)。**

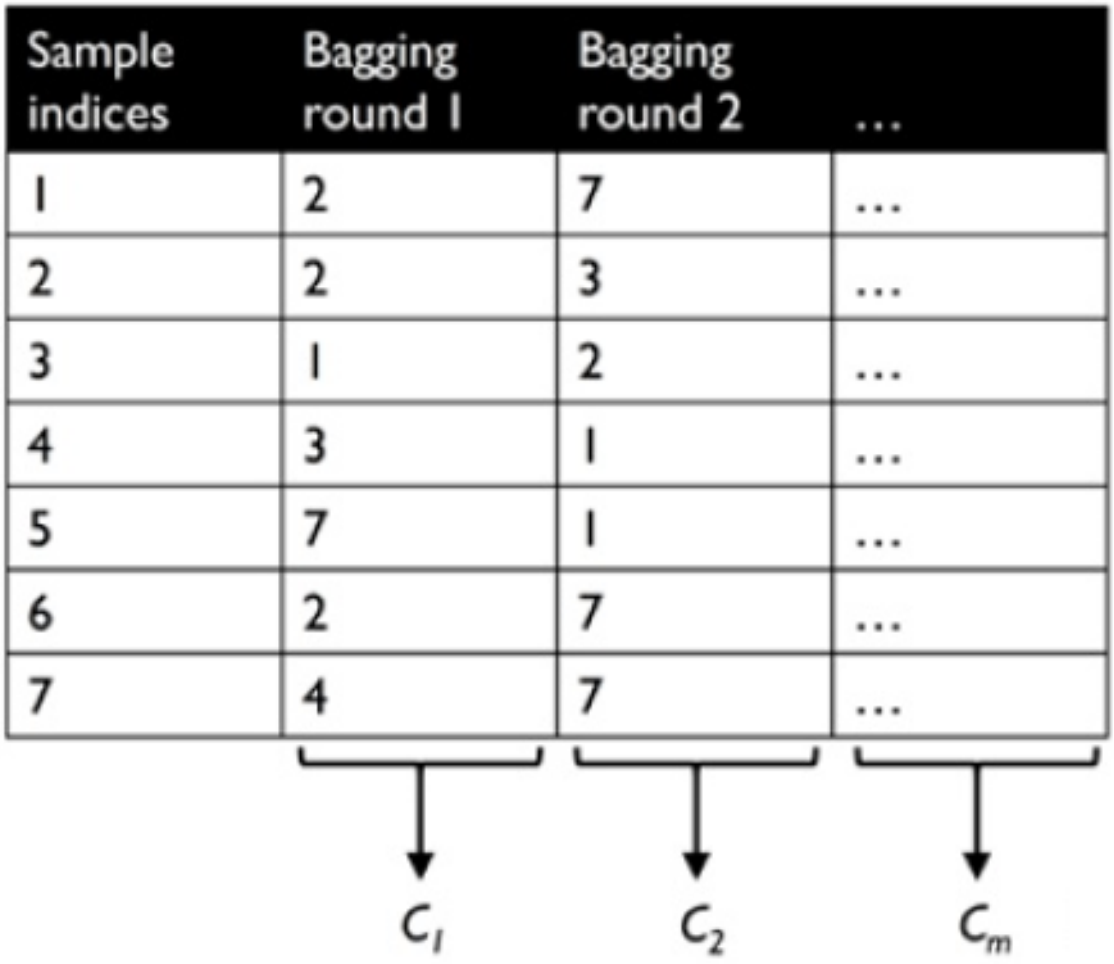
套袋方法的流程如下：



注意：套袋方法与投票方法的不同：

投票机制在训练每个分类器的时候都是用相同的全部样本，而Bagging方法则是使用全部样本的一个随机抽样，每个分类器都是使用不同的样本进行训练。其他都是跟投票方法一模一样！

- 对训练集随机采样
- 分别基于不同的样本集合训练n个弱分类器。
- 对每个弱分类器输出预测结果，并投票（如下图）
- 每个样本取投票数最多的那个预测为该样本最终分类预测。



我们使用葡萄酒数据集进行建模(数据处理):

```
## 我们使用葡萄酒数据集进行建模(数据处理)
df_wine = pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/wine/wine.dat
df_wine.columns = ['Class label', 'Alcohol','Malic acid', 'Ash','Alcalinity of ash','Magnesium
                   'Flavanoids', 'Nonflavanoid phenols','Proanthocyanins','Color intensity', '
df_wine = df_wine[df_wine['Class label'] != 1]  # drop 1 class
y = df_wine['Class label'].values
X = df_wine[['Alcohol','OD280/OD315 of diluted wines']].values
from sklearn.model_selection import train_test_split  # 切分训练集与测试集
from sklearn.preprocessing import LabelEncoder   # 标签化分类变量
le = LabelEncoder()
y = le.fit_transform(y)
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=1,stratify=y)
```

我们使用单一决策树分类:

```
## 我们使用单一决策树分类:
tree = DecisionTreeClassifier(criterion='entropy',random_state=1,max_depth=None)   #选择决策树为
from sklearn.metrics import accuracy_score
tree = tree.fit(X_train,y_train)
y_train_pred = tree.predict(X_train)
```

```
y_test_pred = tree.predict(X_test)
tree_train = accuracy_score(y_train,y_train_pred)
tree_test = accuracy_score(y_test,y_test_pred)
print('Decision tree train/test accuracies %.3f/%.3f' % (tree_train,tree_test))
```

我们使用BaggingClassifier分类：

```
## 我们使用BaggingClassifier分类：
from sklearn.ensemble import BaggingClassifier
tree = DecisionTreeClassifier(criterion='entropy',random_state=1,max_depth=None)   #选择决策树为
bag = BaggingClassifier(base_estimator=tree,n_estimators=500,max_samples=1.0,max_features=1.0,
                        bootstrap_features=False,n_jobs=1,random_state=1)
from sklearn.metrics import accuracy_score
bag = bag.fit(X_train,y_train)
y_train_pred = bag.predict(X_train)
y_test_pred = bag.predict(X_test)
bag_train = accuracy_score(y_train,y_train_pred)
bag_test = accuracy_score(y_test,y_test_pred)
print('Bagging train/test accuracies %.3f/%.3f' % (bag_train,bag_test))
```

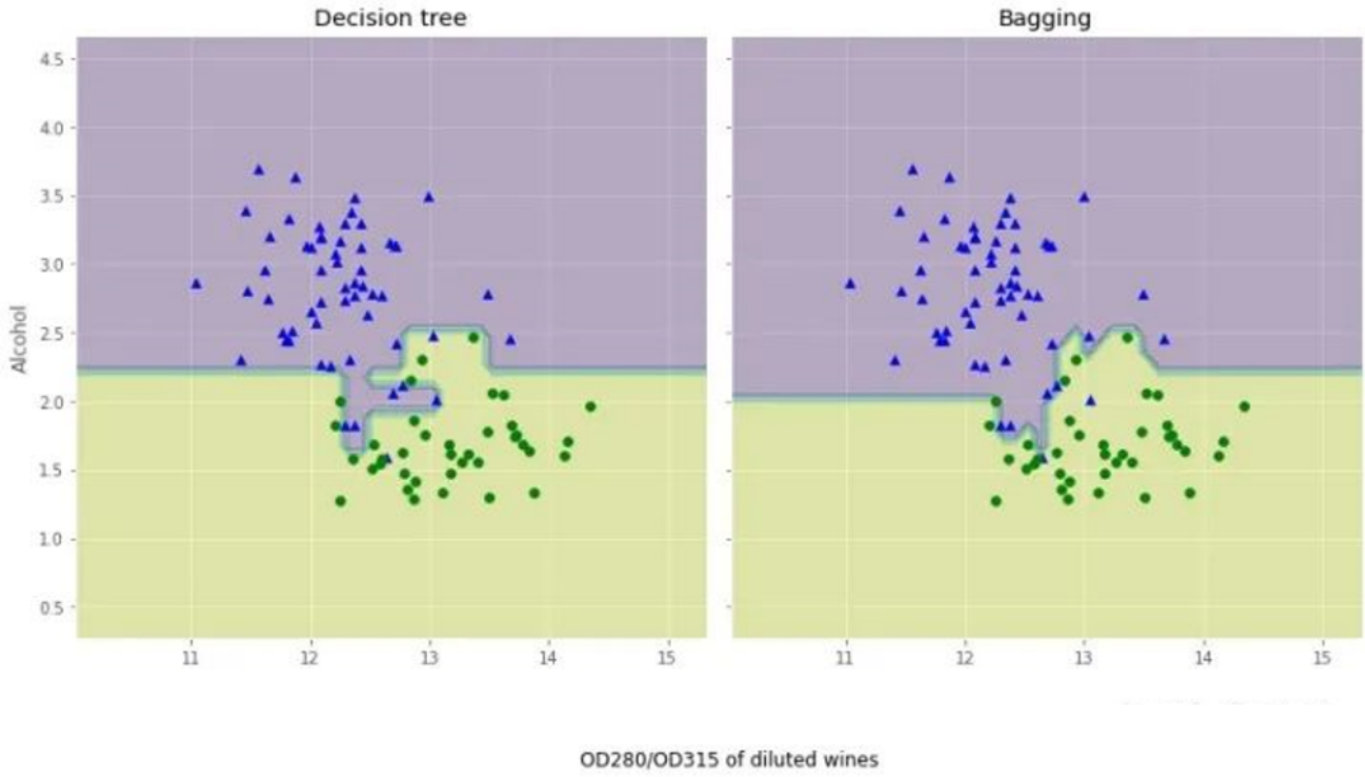
```
Bagging train/test accuracies 1.000/0.917
```

我们可以对比两个准确率，测试准确率较之决策树得到了显著的提高

我们来对比下这两个分类方法上的差异：

```
## 我们来对比下这两个分类方法上的差异
x_min = X_train[:, 0].min() - 1
x_max = X_train[:, 0].max() + 1
y_min = X_train[:, 1].min() - 1
y_max = X_train[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),np.arange(y_min, y_max, 0.1))
f, axarr = plt.subplots(nrows=1, ncols=2,sharex='col',sharey='row',figsize=(12, 6))
for idx, clf, tt in zip([0, 1],[tree, bag],['Decision tree', 'Bagging']):
    clf.fit(X_train, y_train)
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    axarr[idx].contourf(xx, yy, Z, alpha=0.3)
    axarr[idx].scatter(X_train[y_train==0, 0],X_train[y_train==0, 1],c='blue', marker='^')
    axarr[idx].scatter(X_train[y_train==1, 0],X_train[y_train==1, 1],c='green', marker='o')
    axarr[idx].set_title(tt)
axarr[0].set_ylabel('Alcohol', fontsize=12)
plt.tight_layout()
```

```
    plt.text(0, -0.2,s='OD280/OD315 of diluted wines',ha='center',va='center',fontsize=12,transfor
    plt.show()
```



从结果图看起来，三个节点深度的决策树分段线性决策边界在Bagging集成中看起来更加平滑。

四、基于boosting思想的自适应增强方法

Adaboost最初的想法是由Robert E. Schapire在1990年提出的，这个想法叫做自适应增强方法。

与Bagging相比，Boosting思想可以降低偏差。

原始的增强过程具体的实现如下：

- 1.从训练集D不放回抽取训练随机子集d_1来训练弱分类器C_1。
- 2.从训练集不放回抽取第二个训练随机子集d_2并把之前的分类错误样本的50%加入该子集来训练弱分类器C_2。
- 3.从训练集D中找出那些与C_1, C_2不一致的样本形成训练子集d_3来训练第三个弱分类器C_3。
- 4.通过多数票机制集成弱分类器C_1, C_2, C_3。

AdaBoost的具体步骤如下：

- 1.初始化一个权重w，其中$\sum_i w_i = 1$。
- 2.For j in m轮增强：
  - a.训练有权重的弱分类器：$C_j = train(X, y, w)$。
  - b.预测分类标签:$\hat{y} = predict(C_j, X)$。
  - c.计算权重错误率：$e = w * (\hat{y} \neq y)$。
  - d.计算系数：$\alpha_j = 0.5log\frac{1-e}{e}$。
  - e.更新权重：$w := x \times exp(-\alpha_j \times \hat{y} \times y)$。
  - f.归一化权重使其和为1：$w := w / \sum_i w_i$

如更新权重如下图：

Index	x	y	Weights	$\hat{y}$(x <= 3.0)?	Correct?	Updated weights
1	1.0	1	0.1	1	Yes	0.072
2	2.0	1	0.1	1	Yes	0.072
3	3.0	1	0.1	1	Yes	0.072
4	4.0	-1	0.1	-1	Yes	0.072
5	5.0	-1	0.1	-1	Yes	0.072
6	6.0	-1	0.1	-1	Yes	0.072
7	7.0	1	0.1	-1	No	0.167
8	8.0	1	0.1	-1	No	0.167
9	9.0	1	0.1	-1	No	0.167
10	10.0	-1	0.1	-1	Yes	0.072

我们用单一决策树建模：

```
## 我们用单一决策树建模：
from sklearn.ensemble import AdaBoostClassifier
tree = DecisionTreeClassifier(criterion='entropy',random_state=1,max_depth=1)
from sklearn.metrics import accuracy_score
tree = tree.fit(X_train,y_train)
y_train_pred = tree.predict(X_train)
y_test_pred = tree.predict(X_test)
tree_train = accuracy_score(y_train,y_train_pred)
tree_test = accuracy_score(y_test,y_test_pred)
print('Decision tree train/test accuracies %.3f/%.3f' % (tree_train,tree_test))
```

```
Decision tree train/test accuracies 0.916/0.875
```

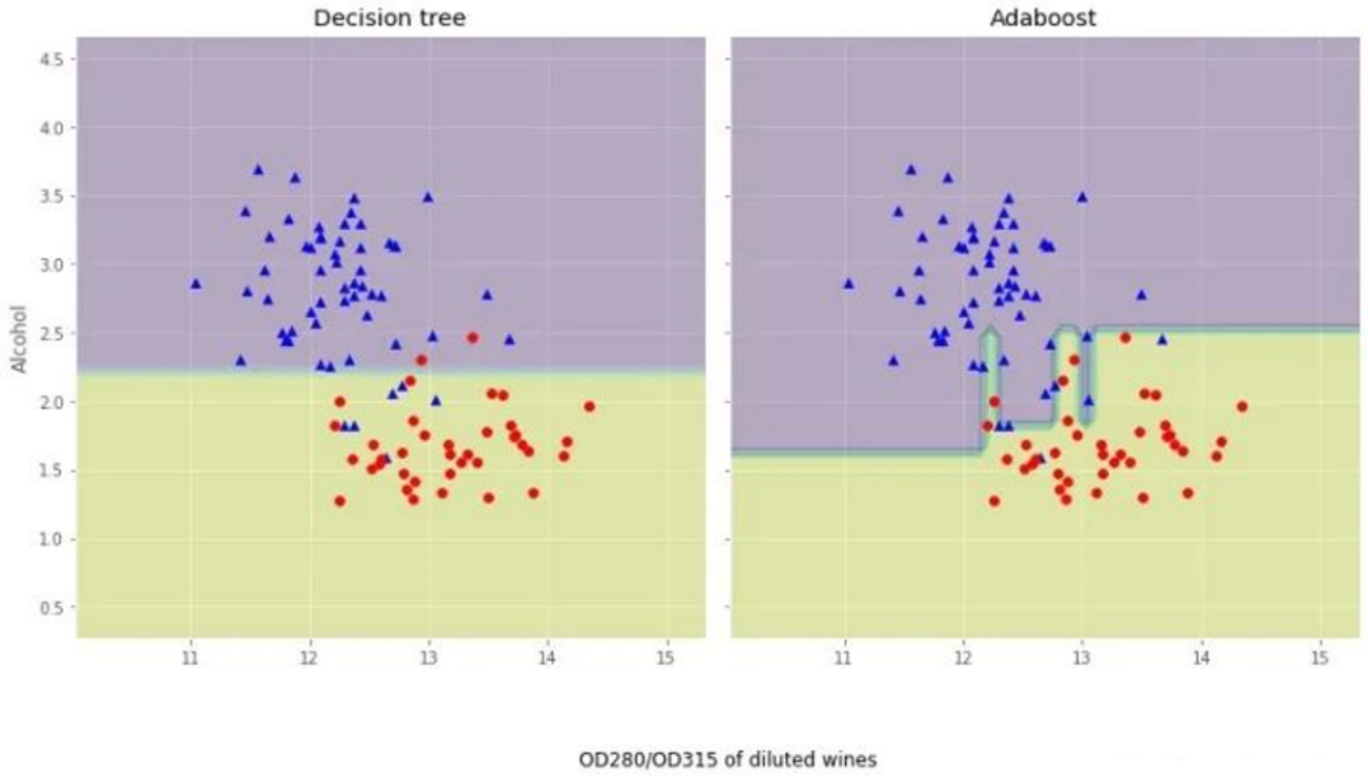
我们使用Adaboost集成建模：

```
## 我们使用Adaboost集成建模：
ada = AdaBoostClassifier(base_estimator=tree,n_estimators=500,learning_rate=0.1,random_state=1
ada = ada.fit(X_train,y_train)
y_train_pred = ada.predict(X_train)
y_test_pred = ada.predict(X_test)
ada_train = accuracy_score(y_train,y_train_pred)
ada_test = accuracy_score(y_test,y_test_pred)
print('Adaboost train/test accuracies %.3f/%.3f' % (ada_train,ada_test))
```

```
Adaboost train/test accuracies 1.000/0.917
```

我们观察下Adaboost与决策树的异同：

```
## 我们观察下Adaboost与决策树的异同
x_min = X_train[:, 0].min() - 1
x_max = X_train[:, 0].max() + 1
y_min = X_train[:, 1].min() - 1
y_max = X_train[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),np.arange(y_min, y_max, 0.1))
f, axarr = plt.subplots(nrows=1, ncols=2,sharex='col',sharey='row',figsize=(12, 6))
for idx, clf, tt in zip([0, 1],[tree, ada],['Decision tree', 'Adaboost']):
    clf.fit(X_train, y_train)
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    axarr[idx].contourf(xx, yy, Z, alpha=0.3)
    axarr[idx].scatter(X_train[y_train==0, 0],X_train[y_train==0, 1],c='blue', marker='^')
    axarr[idx].scatter(X_train[y_train==1, 0],X_train[y_train==1, 1],c='red', marker='o')
    axarr[idx].set_title(tt)
axarr[0].set_ylabel('Alcohol', fontsize=12)
plt.tight_layout()
plt.text(0, -0.2,s='OD280/OD315 of diluted wines',ha='center',va='center',fontsize=12,transfor
plt.show()
```

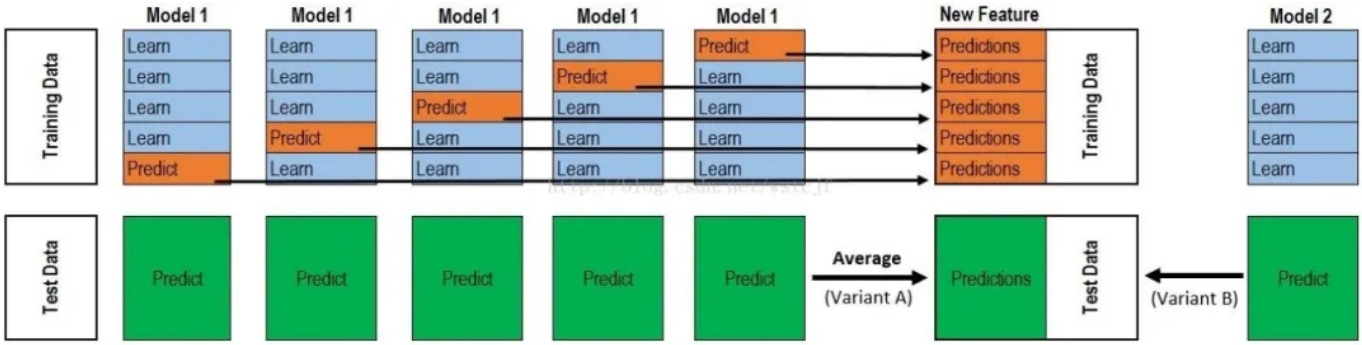


从结果图看起来，Adaboost决策边界比单层决策树复杂得多！

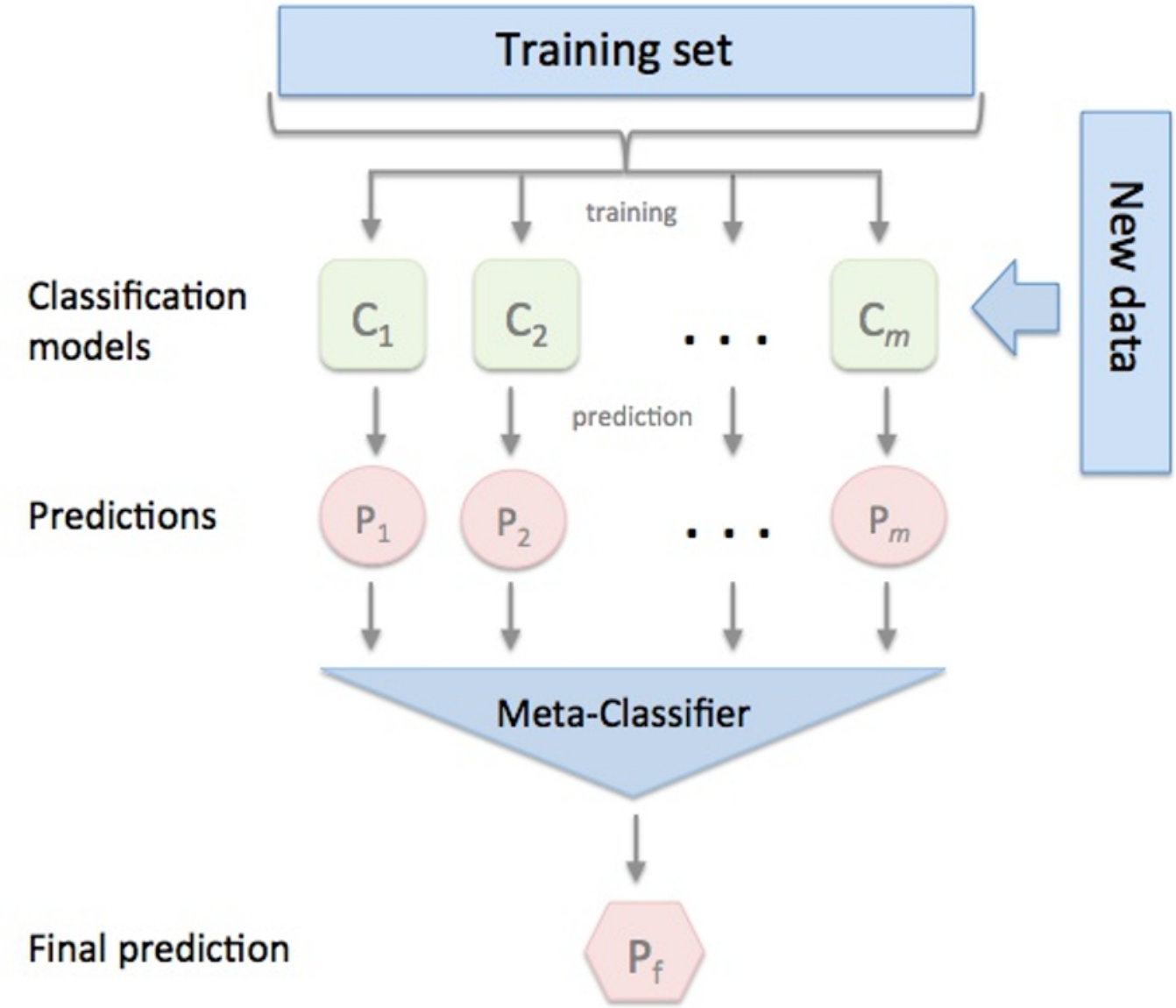
五、分层模型集成框架stacking（叠加算法）

Stacking集成算法可以理解为一个两层的集成，第一层含有一个分类器，把预测的结果(元特征)提供给第二层， 而第二层的分类器通常是逻辑回归，他把一层分类器的结果当做特征做拟合输出预测结果。

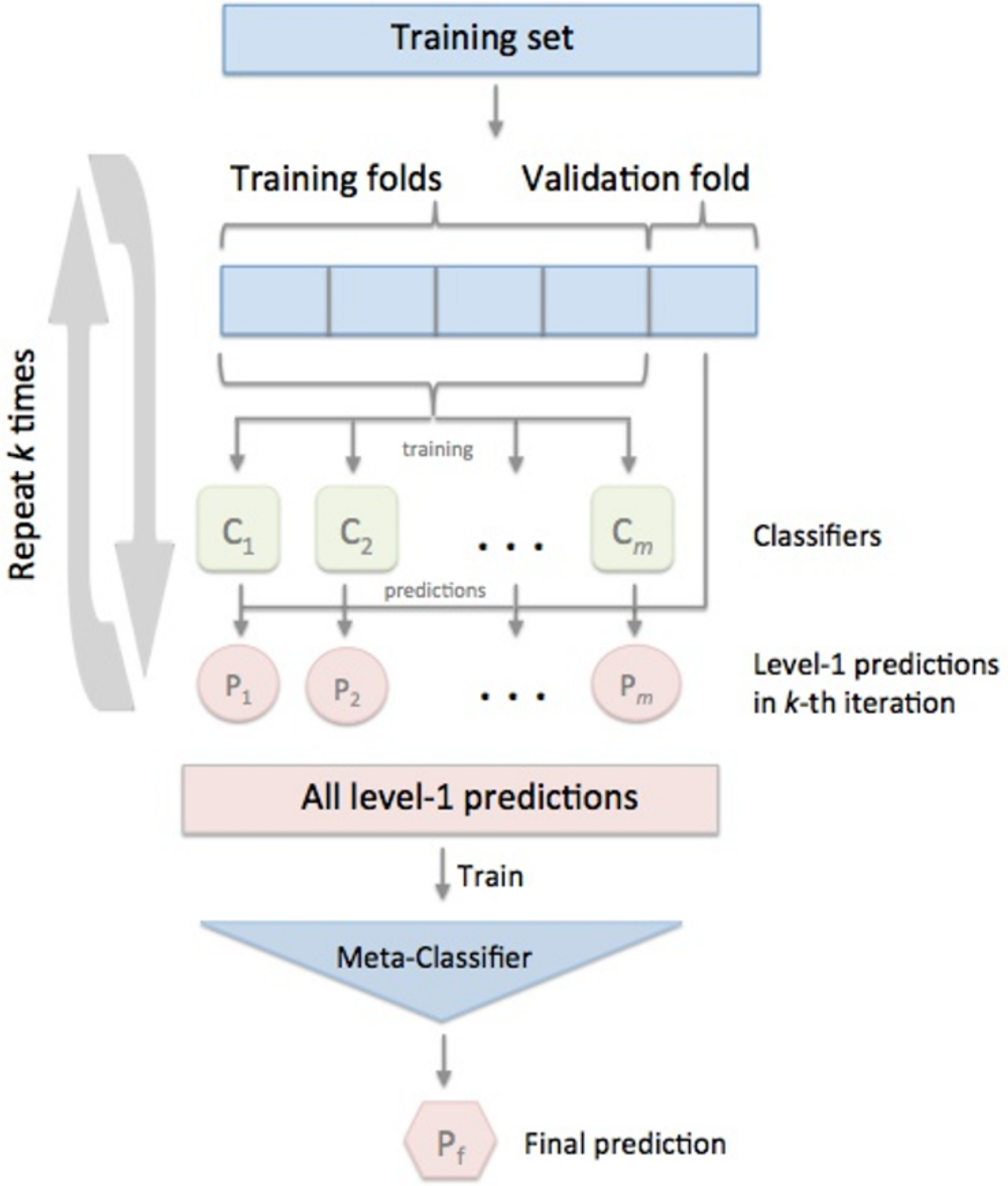
过程如下图:



标准的Stacking，也叫Blending如下图:



但是，标准的Stacking会导致信息泄露，所以推荐以下Satcking算法：



由于目前sklearn没有Stacking相关的类，因此我们使用mlxtend库！！！！

详细代码内容查看：

http://rasbt.github.io/mlxtend/user_guide/classifier/StackingClassifier/

http://rasbt.github.io/mlxtend/user_guide/classifier/StackingCVClassifier/

1. 简单堆叠3折CV分类：

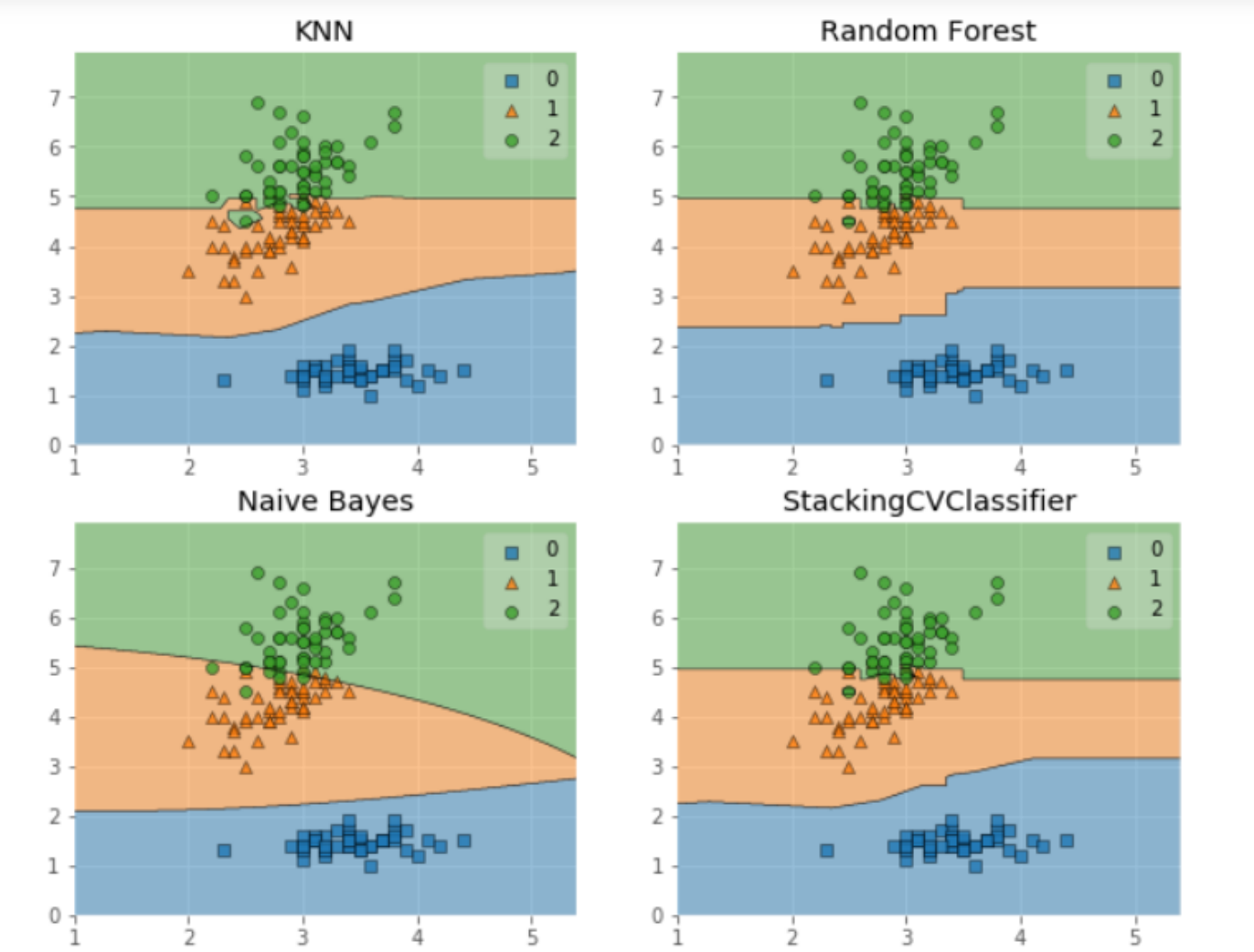
```
## 1. 简单堆叠3折CV分类
from sklearn import datasets

iris = datasets.load_iris()
X, y = iris.data[:, 1:3], iris.target
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from mlxtend.classifier import StackingCVClassifier

RANDOM_SEED = 42

clf1 = KNeighborsClassifier(n_neighbors=1)
clf2 = RandomForestClassifier(random_state=RANDOM_SEED)
clf3 = GaussianNB()
lr = LogisticRegression()

# Starting from v0.16.0, StackingCVRegressor supports
# `random_state` to get deterministic result.
sclf = StackingCVClassifier(classifiers=[clf1, clf2, clf3],  # 第一层分类器
                            meta_classifier=lr,   # 第二层分类器
                            random_state=RANDOM_SEED)

print('3-fold cross validation:\n')

for clf, label in zip([clf1, clf2, clf3, sclf], ['KNN', 'Random Forest', 'Naive Bayes','Stacki
    scores = cross_val_score(clf, X, y, cv=3, scoring='accuracy')
    print("Accuracy: %0.2f (+/- %0.2f) [%s]" % (scores.mean(), scores.std(), label))
```

```
3-fold cross validation:

Accuracy: 0.91 (+/- 0.01) [KNN]
Accuracy: 0.95 (+/- 0.01) [Random Forest]
Accuracy: 0.91 (+/- 0.02) [Naive Bayes]
Accuracy: 0.93 (+/- 0.02) [StackingClassifier]
```

我们画出决策边界：

```
## 我们画出决策边界
from mlxtend.plotting import plot_decision_regions
import matplotlib.gridspec as gridspec
import itertools

gs = gridspec.GridSpec(2, 2)
fig = plt.figure(figsize=(10,8))
for clf, lab, grd in zip([clf1, clf2, clf3, sclf],
```

```
                          ['KNN',
                           'Random Forest',
                           'Naive Bayes',
                           'StackingCVClassifier'],
                           itertools.product([0, 1], repeat=2)):
    clf.fit(X, y)
    ax = plt.subplot(gs[grd[0], grd[1]])
    fig = plot_decision_regions(X=X, y=y, clf=clf)
    plt.title(lab)
plt.show()
```



2.使用概率作为元特征:

```
## 2.使用概率作为元特征
clf1 = KNeighborsClassifier(n_neighbors=1)
clf2 = RandomForestClassifier(random_state=1)
clf3 = GaussianNB()
lr = LogisticRegression()

sclf = StackingCVClassifier(classifiers=[clf1, clf2, clf3],
                            use_probas=True,
                            meta_classifier=lr,
                            random_state=42)
```

```
print('3-fold cross validation:\n')

for clf, label in zip([clf1, clf2, clf3, sclf],
                      ['KNN',
                       'Random Forest',
                       'Naive Bayes',
                       'StackingClassifier']):

    scores = cross_val_score(clf, X, y,
                                              cv=3, scoring='accuracy')
    print("Accuracy: %0.2f (+/- %0.2f) [%s]"
          % (scores.mean(), scores.std(), label))
```

```
3-fold cross validation:

Accuracy: 0.91 (+/- 0.01) [KNN]
Accuracy: 0.95 (+/- 0.01) [Random Forest]
Accuracy: 0.91 (+/- 0.02) [Naive Bayes]
Accuracy: 0.95 (+/- 0.02) [StackingClassifier]
```

3. 堆叠5折CV分类与网格搜索(结合网格搜索调参优化):

```
## 3. 堆叠5折CV分类与网格搜索(结合网格搜索调参优化)
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from mlxtend.classifier import StackingCVClassifier

# Initializing models

clf1 = KNeighborsClassifier(n_neighbors=1)
clf2 = RandomForestClassifier(random_state=RANDOM_SEED)
clf3 = GaussianNB()
lr = LogisticRegression()

sclf = StackingCVClassifier(classifiers=[clf1, clf2, clf3],
                            meta_classifier=lr,
                            random_state=42)

params = {'kneighborsclassifier__n_neighbors': [1, 5],
          'randomforestclassifier__n_estimators': [10, 50],
          'meta_classifier__C': [0.1, 10.0]}

grid = GridSearchCV(estimator=sclf,
                    param_grid=params,
                    cv=5,
                    refit=True)
grid.fit(X, y)

cv_keys = ('mean_test_score', 'std_test_score', 'params')
```

```
for r, _ in enumerate(grid.cv_results_['mean_test_score']):
    print("%0.3f +/- %0.2f %r"
          % (grid.cv_results_[cv_keys[0]][r],
             grid.cv_results_[cv_keys[1]][r] / 2.0,
             grid.cv_results_[cv_keys[2]][r]))

print('Best parameters: %s' % grid.best_params_)
print('Accuracy: %.2f' % grid.best_score_)
```

```
0.947 +/- 0.03 {'kneighborsclassifier__n_neighbors': 1, 'meta_classifier__C': 0.1, 'randomforestclassifier__n_estimators': 10}
0.933 +/- 0.02 {'kneighborsclassifier__n_neighbors': 1, 'meta_classifier__C': 0.1, 'randomforestclassifier__n_estimators': 50}
0.940 +/- 0.02 {'kneighborsclassifier__n_neighbors': 1, 'meta_classifier__C': 10.0, 'randomforestclassifier__n_estimators': 10}
0.940 +/- 0.02 {'kneighborsclassifier__n_neighbors': 1, 'meta_classifier__C': 10.0, 'randomforestclassifier__n_estimators': 50}
0.953 +/- 0.02 {'kneighborsclassifier__n_neighbors': 5, 'meta_classifier__C': 0.1, 'randomforestclassifier__n_estimators': 10}
0.953 +/- 0.02 {'kneighborsclassifier__n_neighbors': 5, 'meta_classifier__C': 0.1, 'randomforestclassifier__n_estimators': 50}
0.953 +/- 0.02 {'kneighborsclassifier__n_neighbors': 5, 'meta_classifier__C': 10.0, 'randomforestclassifier__n_estimators': 10}
0.953 +/- 0.02 {'kneighborsclassifier__n_neighbors': 5, 'meta_classifier__C': 10.0, 'randomforestclassifier__n_estimators': 50}
Best parameters: {'kneighborsclassifier__n_neighbors': 5, 'meta_classifier__C': 0.1, 'randomforestclassifier__n_estimators': 10}
Accuracy: 0.95
```

如果我们打算多次使用回归算法，我们要做的就是在参数网格中添加一个附加的数字后缀，如下所示：

```
## 如果我们打算多次使用回归算法，我们要做的就是在参数网格中添加一个附加的数字后缀，如下所示：
from sklearn.model_selection import GridSearchCV

# Initializing models

clf1 = KNeighborsClassifier(n_neighbors=1)
clf2 = RandomForestClassifier(random_state=RANDOM_SEED)
clf3 = GaussianNB()
lr = LogisticRegression()

sclf = StackingCVClassifier(classifiers=[clf1, clf1, clf2, clf3],
                            meta_classifier=lr,
                            random_state=RANDOM_SEED)

params = {'kneighborsclassifier-1__n_neighbors': [1, 5],
          'kneighborsclassifier-2__n_neighbors': [1, 5],
          'randomforestclassifier__n_estimators': [10, 50],
          'meta_classifier__C': [0.1, 10.0]}

grid = GridSearchCV(estimator=sclf,
                    param_grid=params,
                    cv=5,
                    refit=True)
grid.fit(X, y)

cv_keys = ('mean_test_score', 'std_test_score', 'params')

for r, _ in enumerate(grid.cv_results_['mean_test_score']):
    print("%0.3f +/- %0.2f %r"
          % (grid.cv_results_[cv_keys[0]][r],
             grid.cv_results_[cv_keys[1]][r] / 2.0,
             grid.cv_results_[cv_keys[2]][r]))
```

```
print('Best parameters: %s' % grid.best_params_)
print('Accuracy: %.2f' % grid.best_score_)
```

```
0.940 +/- 0.02 {'kneighborsclassifier-1__n_neighbors': 1, 'kneighborsclassifier-2__n_neighbors': 1, 'meta_classifier__C': 0.1, 'randomforest
classifier__n_estimators': 10}
0.940 +/- 0.02 {'kneighborsclassifier-1__n_neighbors': 1, 'kneighborsclassifier-2__n_neighbors': 1, 'meta_classifier__C': 0.1, 'randomforest
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0.953 +/- 0.02 {'kneighborsclassifier-1__n_neighbors': 5, 'kneighborsclassifier-2__n_neighbors': 5, 'meta_classifier__C': 0.1, 'randomforest
classifier__n_estimators': 10}
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classifier__n_estimators': 50}
0.953 +/- 0.02 {'kneighborsclassifier-1__n_neighbors': 5, 'kneighborsclassifier-2__n_neighbors': 5, 'meta_classifier__C': 10.0, 'randomfores
tclassifier__n_estimators': 10}
0.953 +/- 0.02 {'kneighborsclassifier-1__n_neighbors': 5, 'kneighborsclassifier-2__n_neighbors': 5, 'meta_classifier__C': 10.0, 'randomfores
tclassifier__n_estimators': 50}
Best parameters: {'kneighborsclassifier-1__n_neighbors': 1, 'kneighborsclassifier-2__n_neighbors': 5, 'meta_classifier__C': 0.1, 'randomfore
stclassifier__n_estimators': 10}
Accuracy: 0.96
```

4.在不同特征子集上运行的分类器的堆叠：

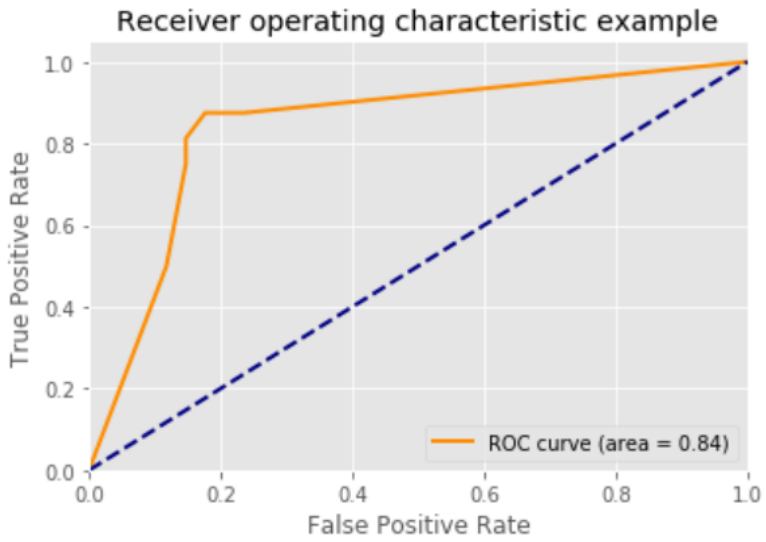
```
## 4.在不同特征子集上运行的分类器的堆叠
###不同的1级分类器可以适合训练数据集中的不同特征子集。以下示例说明了如何使用scikit-learn管道和ColumnSel
from sklearn.datasets import load_iris
from mlxtend.classifier import StackingCVClassifier
from mlxtend.feature_selection import ColumnSelector
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import LogisticRegression

iris = load_iris()
X = iris.data
y = iris.target

pipe1 = make_pipeline(ColumnSelector(cols=(0, 2)),  # 选择第0,2列
                      LogisticRegression())
pipe2 = make_pipeline(ColumnSelector(cols=(1, 2, 3)),  # 选择第1,2,3列
                      LogisticRegression())

sclf = StackingCVClassifier(classifiers=[pipe1, pipe2],
                            meta_classifier=LogisticRegression(),
                            random_state=42)

sclf.fit(X, y)
```

```
StackingCVClassifier(classifiers=[Pipeline(memory=None,
                                           steps=[('columnselector',
                                                   ColumnSelector(cols=(0, 2),
                                                                  drop_axis=False)),
                                                  ('logisticregression',
                                                   LogisticRegression(C=1.0,
                                                                      class_weight=None,
                                                                      dual=False,
                                                                      fit_intercept=True,
                                                                      intercept_scaling=1,
                                                                      l1_ratio=None,
                                                                      max_iter=100,
                                                                      multi_class='auto',
                                                                      n_jobs=None,
                                                                      penalty='l2',
                                                                      random_state=None,
                                                                      solver='lbfgs',
                                                                      tol=0.0...
                                                   fit_intercept=True,
                                                   intercept_scaling=1,
                                                   l1_ratio=None,
                                                   max_iter=100,
                                                   multi_class='auto',
                                                   n_jobs=None,
                                                   penalty='l2',
                                                   random_state=None,
                                                   solver='lbfgs',
                                                   tol=0.0001, verbose=0,
                                                   warm_start=False),
                           n_jobs=None, pre_dispatch='2*n_jobs', random_state=42,
                           shuffle=True, store_train_meta_features=False,
                           stratify=True, use_clones=True,
                           use_features_in_secondary=False, use_probas=False,
                           verbose=0)
```

5.ROC曲线 decision_function：

```
## 5.ROC曲线 decision_function
### 像其他scikit-learn分类器一样，它StackingCVClassifier具有decision_function可用于绘制ROC曲线的方法
### 请注意，decision_function期望并要求元分类器实现decision_function。
from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from mlxtend.classifier import StackingCVClassifier
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import train_test_split
from sklearn import datasets
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier

iris = datasets.load_iris()
X, y = iris.data[:, [0, 1]], iris.target

# Binarize the output
y = label_binarize(y, classes=[0, 1, 2])
n_classes = y.shape[1]

RANDOM_SEED = 42

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.33, random_state=RANDOM_SEED)
```

```
clf1 =  LogisticRegression()
clf2 = RandomForestClassifier(random_state=RANDOM_SEED)
clf3 = SVC(random_state=RANDOM_SEED)
lr = LogisticRegression()

sclf = StackingCVClassifier(classifiers=[clf1, clf2, clf3],
                            meta_classifier=lr)

# Learn to predict each class against the other
classifier = OneVsRestClassifier(sclf)
y_score = classifier.fit(X_train, y_train).decision_function(X_test)

# Compute ROC curve and ROC area for each class
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test[:, i], y_score[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
fpr["micro"], tpr["micro"], _ = roc_curve(y_test.ravel(), y_score.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

plt.figure()
lw = 2
plt.plot(fpr[2], tpr[2], color='darkorange',
         lw=lw, label='ROC curve (area = %0.2f)' % roc_auc[2])
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```



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