分类问题

```
import sklearn
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt

## 读取数据
datapath = ""
data = pd.read_csv(datapath + "ionosphere_data.csv")

## data processing
data.replace({"column_a":{True:1,False:0},"column_b":
{True:1,False:0},"column_ai":{'g':1,'b':0}},inplace=True)

data.head()
```

	col_a	col_b	col_c	col_d	col_e	col_f	...	col_ah	col_ai
0	1	0	0.995	-0.059	0.852	0.023	...	-0.453	1
1	1	0	1.000	-0.188	0.930	-0.361	...	-0.025	0
2	1	0	1.000	-0.034	1.000	0.005	...	-0.382	1
3	1	0	1.000	-0.451	1.000	1.000	...	1.000	0
4	1	0	1.000	-0.024	0.941	0.065	...	-0.657	1

5 rows × 35 columns

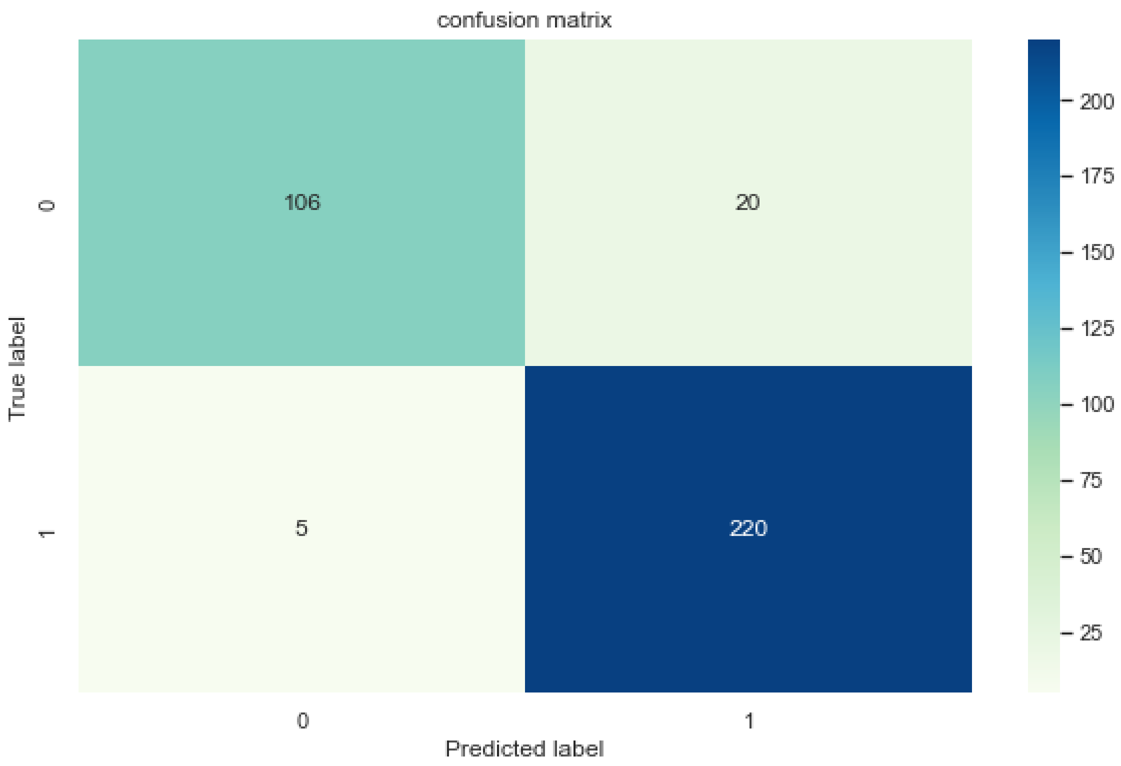
```
# 将x属性和y属性分开
y = data['column_ai'].copy()
x = data.drop('column_ai', axis=1)
```

SVM模型

```
from sklearn.model_selection import KFold
from sklearn.metrics import mean_squared_error as MSE
from math import sqrt
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import LinearSVR
from sklearn.svm import SVC
```

```python
# 10折交叉验证
k_fold = KFold(n_splits=10,shuffle=True,random_state=42)

# SVM模型
predict = []
true = []

for train_index, test_index in k_fold.split(x):
    train_x, test_x = x.iloc[train_index], x.iloc[test_index]
    train_y, test_y = y[train_index], y[test_index]

    SVCModel = SVC()
    SVCModel = SVCModel.fit(train_x,train_y)
    pred_y = SVCModel.predict(test_x)
    predict.extend(pred_y)
    true.extend(test_y)

from sklearn.metrics import accuracy_score, precision_score, recall_score,
f1_score, roc_auc_score
print("RMSE:",sqrt(MSE(predict,true)))
print("Accuracy:",accuracy_score(true,predict))
print("Precision:",precision_score(true,predict,average='micro'))
print("Recall:",recall_score(true,predict,average='micro'))
print("F1:",f1_score(true,predict,average='micro'))
# print(true)
# print(predict)
print("AUC:",roc_auc_score(true,predict,multi_class='ovo'))

# 数据可视化
sns.set()
f,ax=plt.subplots(figsize=(10,6))
C=confusion_matrix(true, predict, labels=[0, 1])
sns.heatmap(C,annot=True,ax=ax,cmap=plt.cm.GnBu,fmt='g') #热力图

ax.set_title('confusion matrix') #标题
ax.set_xlabel('Predicted label') #x轴
ax.set_ylabel('True label') #y轴
```

```
RMSE: 0.2668802563418119
Accuracy: 0.9287749287749287
Precision: 0.9287749287749287
Recall: 0.9287749287749287
F1: 0.9287749287749287
AUC: 0.9095238095238095
```

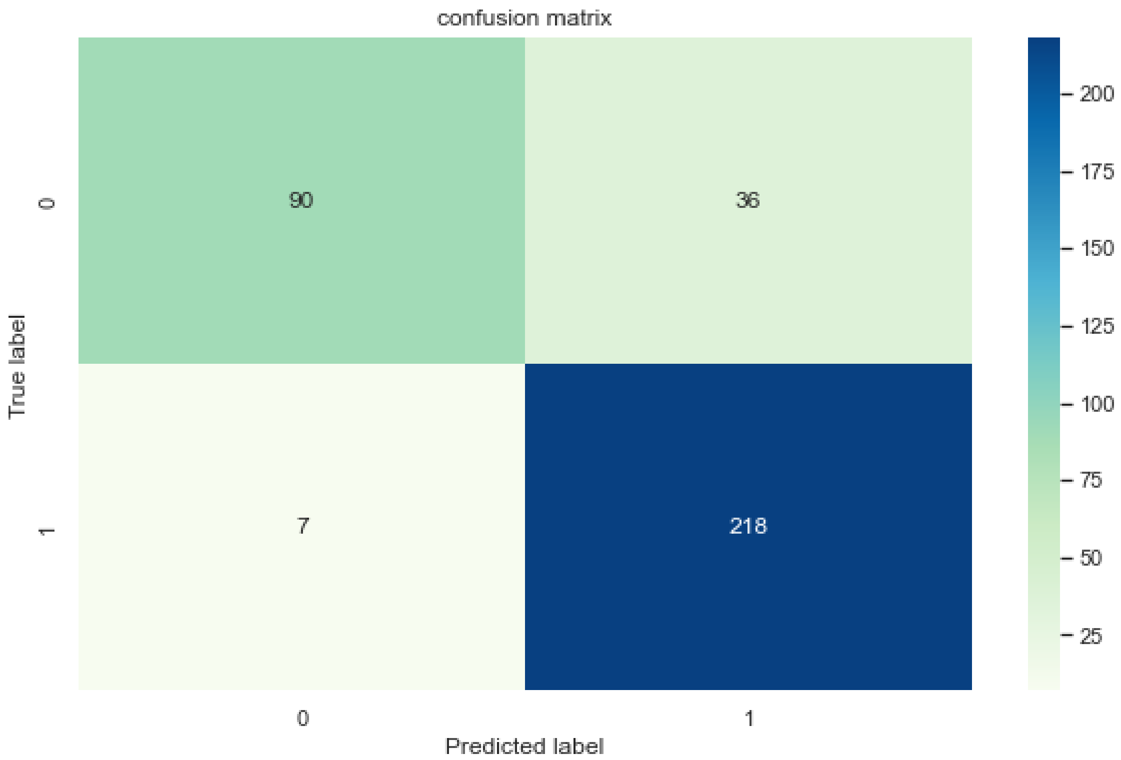


Logistic回归

```
from sklearn.model_selection import KFold
from sklearn.metrics import mean_squared_error as MSE
from math import sqrt
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression

# 10折交叉验证
k_fold = KFold(n_splits=10,shuffle=True,random_state=42)

predict = []
true = []

for train_index, test_index in k_fold.split(x):
    train_x, test_x = x.iloc[train_index], x.iloc[test_index]
    train_y, test_y = y[train_index], y[test_index]

    Model  = LogisticRegression(random_state=42)
    Model  = Model.fit(train_x,train_y)
    pred_y = Model.predict(test_x)
    predict.extend(pred_y)
    true.extend(test_y)

from sklearn.metrics import accuracy_score, precision_score, recall_score,
f1_score, roc_auc_score
print("RMSE:",sqrt(MSE(predict,true)))
print("Accuracy:",accuracy_score(true,predict))
print("Precision:",precision_score(true,predict,average='micro'))
```

```
print("Recall:",recall_score(true,predict,average='micro'))
print("F1:",f1_score(true,predict,average='micro'))
# print(true)
# print(predict)
print("AUC:",roc_auc_score(true,predict,multi_class='ovo'))

# 数据可视化
sns.set()
f,ax=plt.subplots(figsize=(10,6))
C=confusion_matrix(true, predict, labels=[0, 1])
sns.heatmap(C,annot=True,ax=ax,cmap=plt.cm.GnBu,fmt='g') #热力图

ax.set_title('confusion matrix') #标题
ax.set_xlabel('Predicted label') #x轴
ax.set_ylabel('True label') #y轴
```

```
RMSE: 0.35001017486227815
Accuracy: 0.8774928774928775
Precision: 0.8774928774928775
Recall: 0.8774928774928775
F1: 0.8774928774928775
AUC: 0.8415873015873017
```

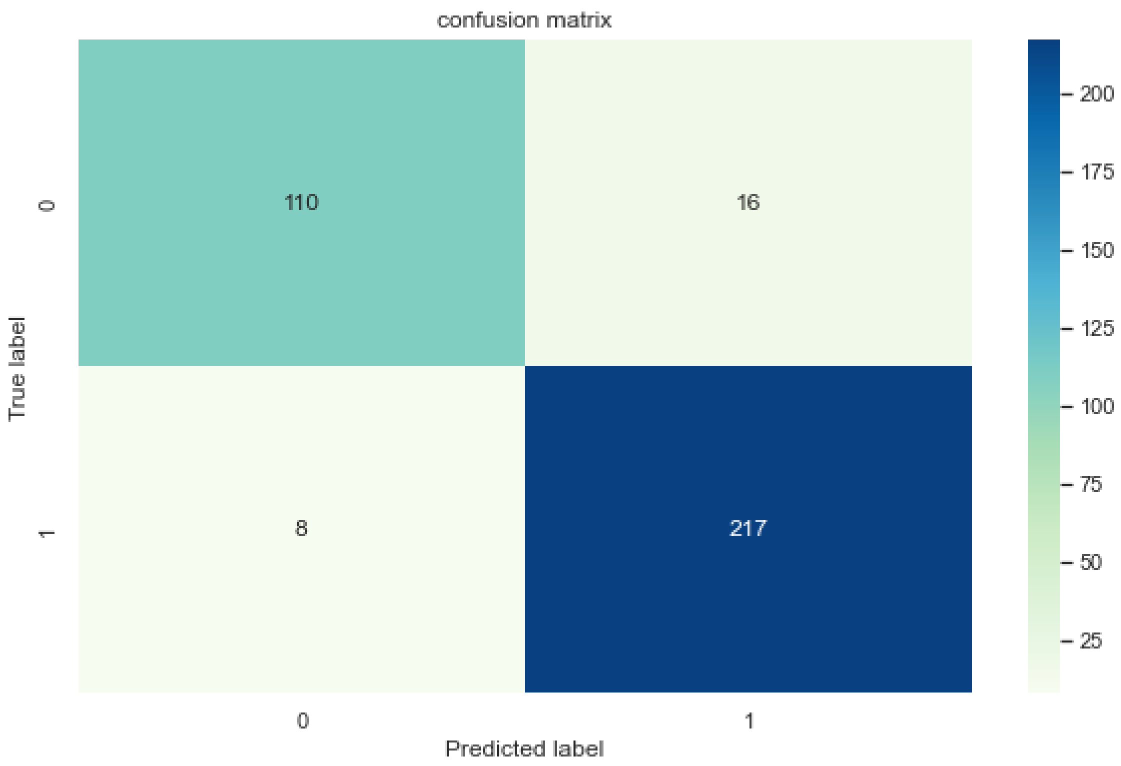


随机森林

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import KFold
from sklearn.metrics import mean_squared_error as MSE
```

```python
from math import sqrt

# 10折交叉验证
k_fold = KFold(n_splits=10,shuffle=True,random_state=42)

predict = []
true = []

# 随机森林模型
Model = RandomForestClassifier(random_state=42)

for train_index, test_index in k_fold.split(x):
    train_x, test_x = x.iloc[train_index], x.iloc[test_index]
    train_y, test_y = y[train_index], y[test_index]

    Model = Model.fit(train_x,train_y)
    pred_y = Model.predict(test_x)
    predict.extend(pred_y)
    true.extend(test_y)

from sklearn.metrics import accuracy_score, precision_score, recall_score,
f1_score, roc_auc_score
print("RMSE:",sqrt(MSE(predict,true)))
print("Accuracy:",accuracy_score(true,predict))
print("Precision:",precision_score(true,predict,average='micro'))
print("Recall:",recall_score(true,predict,average='micro'))
print("F1:",f1_score(true,predict,average='micro'))
# print(true)
# print(predict)
print("AUC:",roc_auc_score(true,predict,multi_class='ovo'))

# 数据可视化
sns.set()
f,ax=plt.subplots(figsize=(10,6))
C=confusion_matrix(true, predict, labels=[0, 1])
sns.heatmap(C,annot=True,ax=ax,cmap=plt.cm.GnBu,fmt='g') #热力图

ax.set_title('confusion matrix') #标题
ax.set_xlabel('Predicted label') #x轴
ax.set_ylabel('True label') #y轴
```

```
RMSE: 0.2614881801842454
Accuracy: 0.9316239316239316
Precision: 0.9316239316239316
Recall: 0.9316239316239316
F1: 0.9316239316239316
AUC: 0.9187301587301587
```

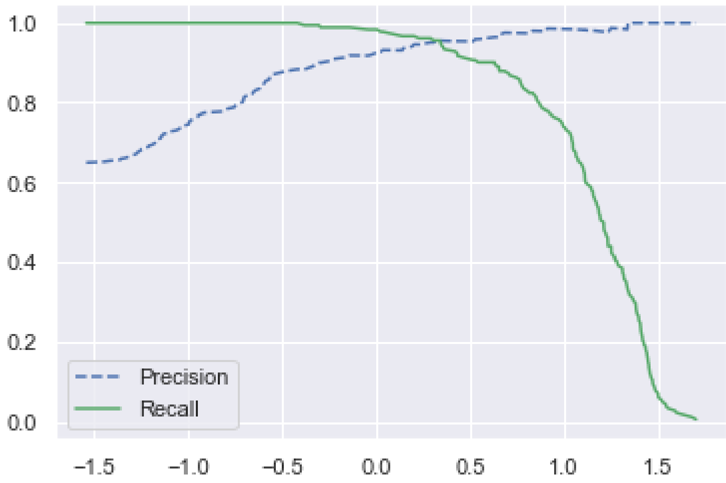


训练SVM分类器

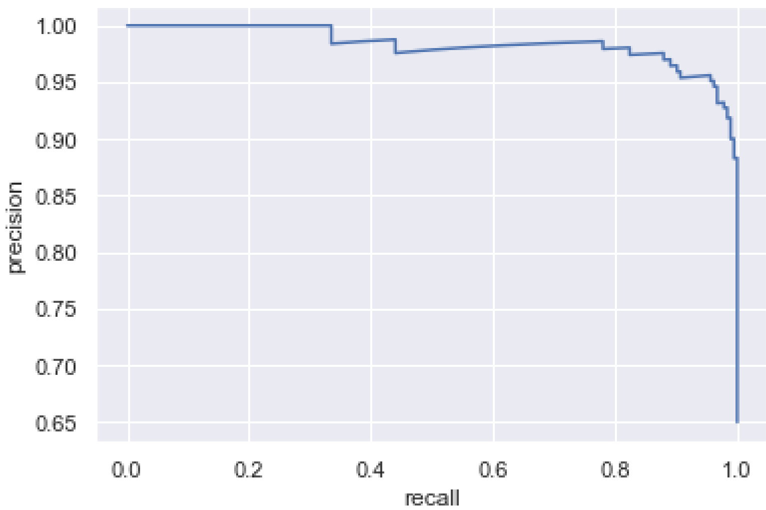
```
from sklearn.model_selection import cross_val_predict
from sklearn.model_selection import train_test_split

train_set, test_set = train_test_split(data, test_size=0.2, random_state=42)
y_train = train_set['column_ai'].copy()
x_train = train_set.drop('column_ai', axis=1)
y_test = test_set['column_ai'].copy()
x_test = test_set.drop('column_ai', axis=1)

svc_clf = SVC(random_state=42)
svc_clf.fit(x_train, y_train)
y_scores = cross_val_predict(svc_clf, x_train, y_train, cv=10,
method="decision_function")
```

```
from sklearn.metrics import precision_recall_curve
precisions, recalls, thresholds = precision_recall_curve(y_train, y_scores)
```

```
# 绘制精确率和召回率相对于阈值的函数图
import matplotlib.pyplot as plt
def plot_precision_recall_vs_threshold(precisions, recalls, thresholds):
    plt.plot(thresholds, precisions[:-1], "b--", label="Precision")
    plt.plot(thresholds, recalls[:-1], "g-", label="Recall")
    plt.legend()
plot_precision_recall_vs_threshold(precisions, recalls, thresholds)
plt.show()
```




```
# 绘制精确率和召回率函数图
plt.plot(recalls, precisions)
plt.xlabel("recall")
plt.ylabel("precision")
```




```
# 精确度选择为95%
threshold_95_precision = thresholds[np.argmax(precisions >= 0.95)]
y_train_pred_95 = (y_scores >= threshold_95_precision)
```

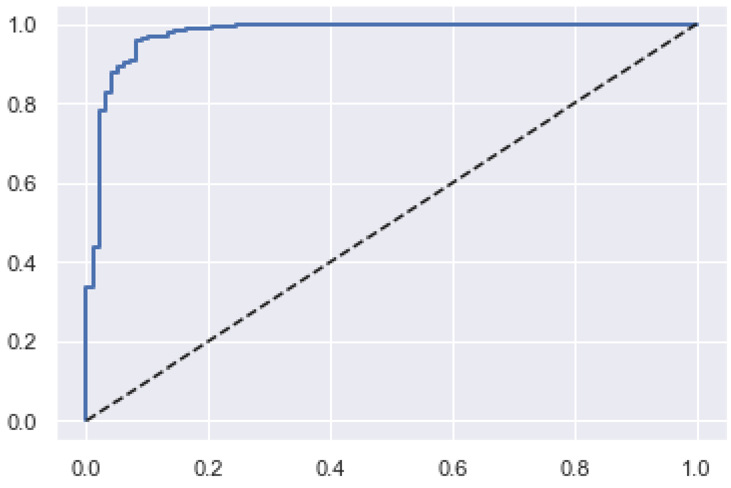
```
from sklearn.metrics import precision_score, recall_score
precision_score(y_train, y_train_pred_95)
```

```
0.9510869565217391
```

```
recall_score(y_train, y_train_pred_95)
```

```
0.9615384615384616
```

```
from sklearn.metrics import roc_curve

fpr, tpr, thresholds = roc_curve(y_train, y_scores)
def plot_roc_curve(fpr, tpr, label=None):
    plt.plot(fpr, tpr, linewidth=2, label=label)
    plt.plot([0, 1], [0, 1], 'k--') # Dashed diagonal
plot_roc_curve(fpr, tpr)
plt.show()
```



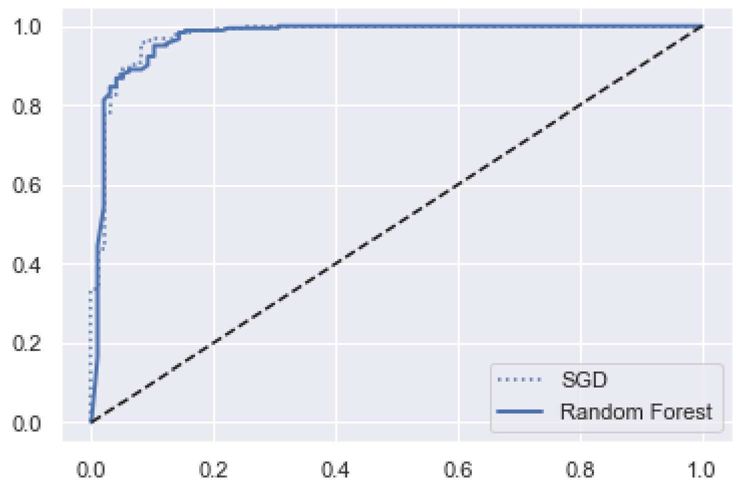

```
from sklearn.metrics import roc_auc_score
roc_auc_score(y_train, y_scores)
```

```
0.9760596546310831
```

```
# 随机森林分类器
from sklearn.ensemble import RandomForestClassifier
forest_clf = RandomForestClassifier(random_state=42)
y_probas_forest = cross_val_predict(forest_clf, x_train, y_train, cv=3,
method="predict_proba")
```

```
y_scores_forest = y_probas_forest[:, 1]
fpr_forest, tpr_forest, thresholds_forest = roc_curve(y_train,y_scores_forest)
```

```
plt.plot(fpr, tpr, "b:", label="SGD")
plot_roc_curve(fpr_forest, tpr_forest, "Random Forest")
plt.legend(loc="lower right")
plt.show()
```



实验总结与体会

在解决回归预测问题或分类预测问题时，需要先对数据集进行数据处理，清洗异常数据和缺失数据。然后对数据进行可视化分析，选择较为适合的预测模型进行回归或分类。

当数据样本量较小时可以使用交叉验证优化模型，再通过调整相关参数或阈值选择较优模型。

对于一个机器学习模型，需要通过相关文档查阅各参数的使用方法和优化结构，调整模型参数。

对于预测得到的实验结果，可以通过对误差数据进行数据分析，优化初始模型结构。