hw4

May 10, 2021

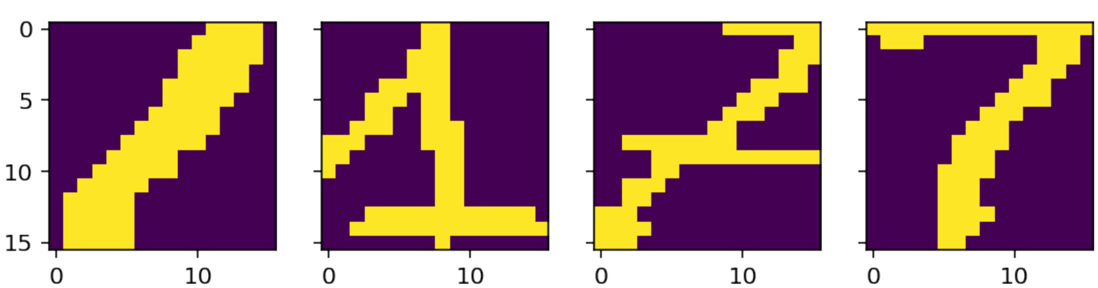
[110]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
%matplotlib inline
%config InlineBackend.figure_format = 'retina'
import warnings
warnings.filterwarnings('ignore')
```

[111]:
```
path = os.getcwd()
train = pd.read_csv(path+"/digits_train.csv")
test = pd.read_csv(path+"/digits_test.csv")
```

[112]:
```
def plotDigit(k,dat):
    f = np.reshape(np.array(dat.loc[k][0:256]),[-1,16])
    print("row: "+str(k)+"| digit: "+str(dat.loc[k][256]))
    return f
fig ,(ax1,ax2,ax3,ax4) = plt.subplots(1,4,sharey = True ,figsize = (8,2))
ax1.imshow(plotDigit(8,train))
ax2.imshow(plotDigit(53,train))
ax3.imshow(plotDigit(151,train))
ax4.imshow(plotDigit(622,train))
```

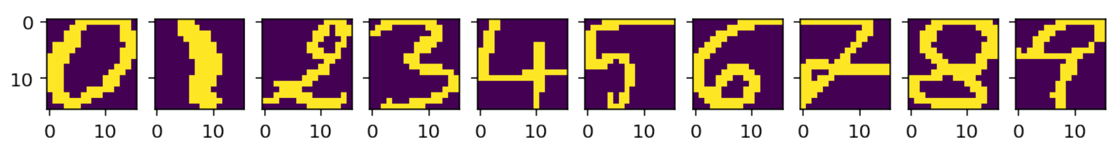
```
row: 8| digit: 1
row: 53| digit: 1
row: 151| digit: 7
row: 622| digit: 7
```

[112]:
```
<matplotlib.image.AxesImage at 0x7f91d8a10fd0>
```



[113]:
```
numbers = np.unique(train["digit"])
fig ,axs = plt.subplots(1,10,sharey = True ,figsize = (10,3))
for j in numbers:
    q = 8
    dataj = train[train['digit'] == j].iloc[q,:]
    print(train[train['digit'] == j].index[q])
    fj = np.reshape(dataj[:256].values.flatten(),[-1,16])
    axs[j].imshow(fj)
```

```
76
56
91
99
96
78
80
98
139
85
```



1 .

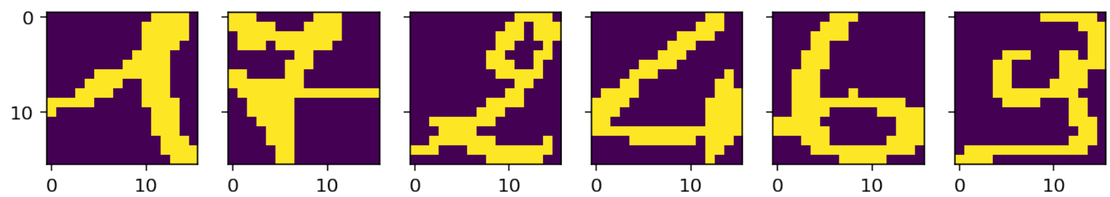
1.1 .

[114]:
```
fuzzys = [[1,47],[7,49],[2,91],[4,102],[6,89],[9,178]]
fig ,axs = plt.subplots(1,6,sharey = True ,figsize = (10,3))
j=0
for t in fuzzys:

    q = t[1]
    dataj = train.iloc[q,:]
    fj = np.reshape(dataj[:256].values.flatten(),[-1,16])
    axs[j].imshow(fj)
    j+=1
    print("The number is: ",str(t[0]))
```

```
The number is:  1
The number is:  7
```

```
The number is:  2
The number is:  4
The number is:  6
The number is:  9
```



1.2 .

[115]:
```python
from sklearn.linear_model import LogisticRegression as LR
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
```

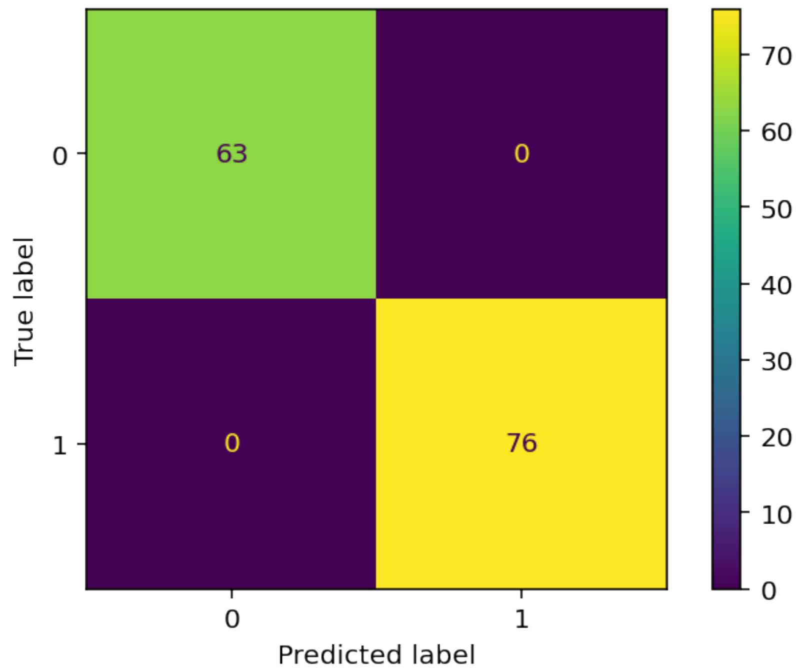
[116]:
```python
# classificaton 1 and 7
X = train[(train['digit'] == 1) | (train["digit"] == 7)]
y= X.digit.map(lambda x: 1 if x ==1  else 0)
X = X.drop(["digit"],axis=1)
```

[117]:
```python
clf = LR()
clf.fit(X,y)
clf.score(X,y)
```

[117]:
```
1.0
```

[118]:
```python
train_matrix = confusion_matrix(y, clf.predict(X),labels = [0,1])
disp = ConfusionMatrixDisplay(confusion_matrix=train_matrix,
                              display_labels=clf.classes_)
disp.plot()
```

[118]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f91d87e9c10>
```



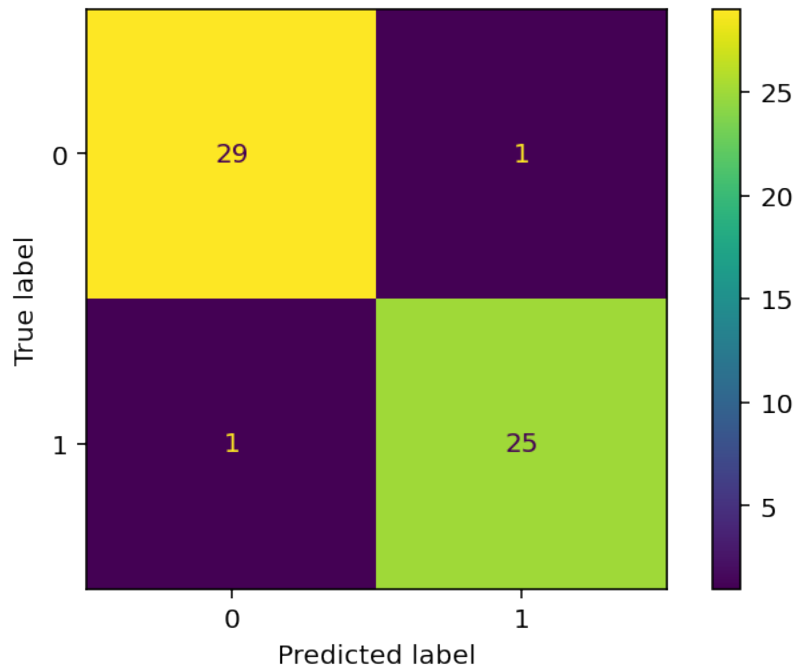
[119]:
```
testX=  test[(test['digit'] == 1) | (test["digit"] == 7)]
testy= testX.digit.map(lambda x: 1 if x ==1  else 0)
testX = testX.drop(["digit"],axis=1)
```

[120]:
```
clf.score(testX,testy)
```

[120]: 0.9642857142857143

[121]:
```
test_matrix = confusion_matrix(testy,clf.predict(testX),labels = [0,1])
disp = ConfusionMatrixDisplay(confusion_matrix=test_matrix,
                              display_labels=clf.classes_)
disp.plot()
```

[121]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f91d9343070>

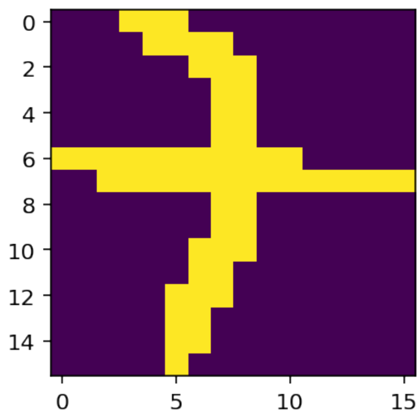
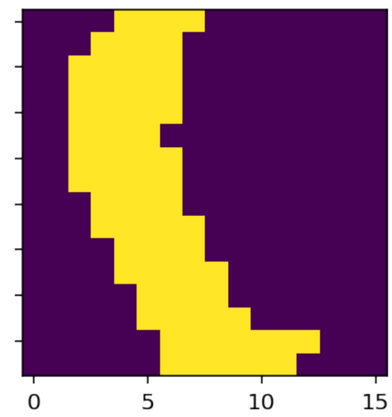


1.2.1 In the training set, all the numbers are correctly classified. In the test set, only 2 predictions are wrong. A picture that is actually 1 is predicted to be 7, and a 7 is predicted to be 1

[122]:
```
result = (clf.predict(testX) == testy)
wrong = result[result==0].index.values
```

[123]:
```
fig ,axs = plt.subplots(1,2,sharey = True ,figsize = (10,3))
j=0
for t in wrong:
    dataj = test.iloc[t,:]
    fj = np.reshape(dataj[:256].values.flatten(),[-1,16])
    axs[j].imshow(fj)
    print("The figure is: ",test.iloc[t,-1],"and the prediction is false.")
    j+=1
```

```
The figure is:  7 and the prediction is false.
The figure is:  1 and the prediction is false.
```

2 .

2.1 .

[124]:
```
multi_clf = LR(multi_class = 'ovr',max_iter=1000)
```

In the LogisticRegression function in sklearn, the optional parameters "ovr" and "multinomial" for multi-class problems. For the "ovr" type and the class mentioned in the class, select a base class to compare with other classes, and "multinomial" is to take any pair .For comparison, the number of operations is more and the correct rate is higher

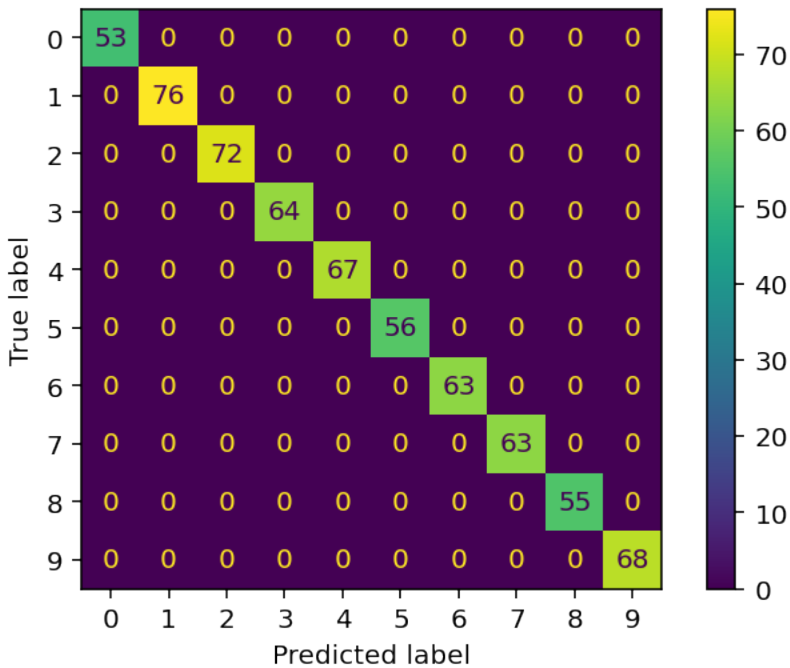
[125]:
```
trainX = train.iloc[:,:-1]
trainY = train.iloc[:,-1]
testX = test.iloc[:,:-1]
testY = test.iloc[:,-1]
```

[126]:
```
multi_clf.fit(trainX,trainY)
```

[126]:
```
LogisticRegression(max_iter=1000, multi_class='ovr')
```

[127]:
```
train_matrix = confusion_matrix(trainY, multi_clf.predict(trainX),labels =␣
 ↪multi_clf.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=train_matrix,
                              display_labels=multi_clf.classes_)
disp.plot()
```

[127]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f91d8a3beb0>
```

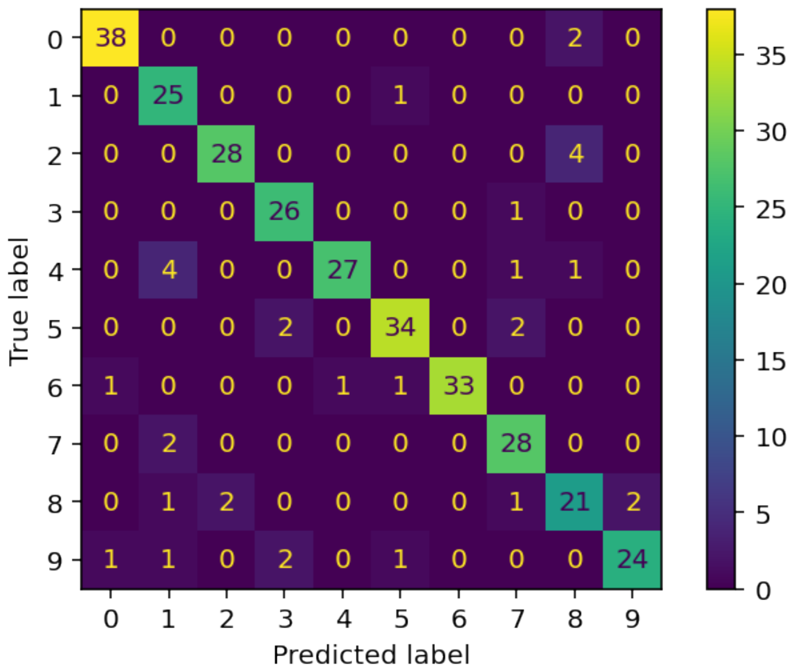


Observing the confusion matrix of the training set, we can find that the model can correctly classify all images on the training set, and there is a phenomenon of perfect seperation.

2.2 .

[128]:
```
test_matrix = confusion_matrix(testY, multi_clf.predict(testX),labels =␣
 ↪multi_clf.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=test_matrix,
                              display_labels=multi_clf.classes_)
disp.plot()
```

[128]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f91d86f2400>



Observing the confusion matrix of the test set, we can find that the classifier is relatively inaccurate in predicting 2, 4, 8, and 9, while it is more accurate in predicting 1-7, which is contrary to guessing.

2.3 .

[129]:
```
print("The accuracy on the test set is :{:.4f}".format(multi_clf.
 ↪score(testX,testY)))
```

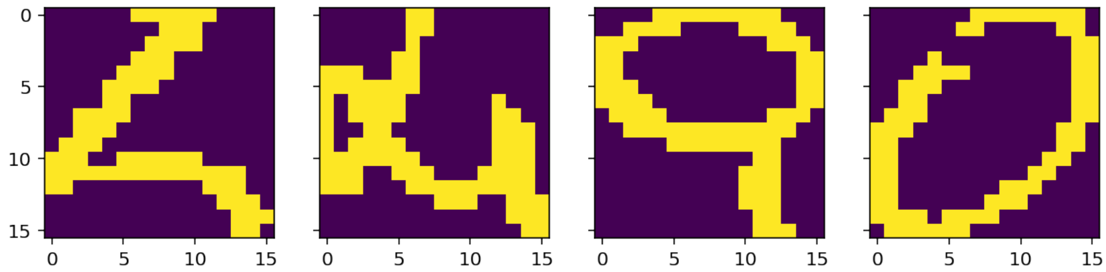
```
The accuracy on the test set is :0.8931
```

[130]:
```
result = (multi_clf.predict(testX) == testY)
wrong = result[result==0].index.values
```

[131]:
```
fig ,axs = plt.subplots(1,4,sharey = True ,figsize = (10,3))
j=0
for i in range(4):
    t = wrong[i]+1
    dataj = test.iloc[t,:]
    fj = np.reshape(dataj[:256].values.flatten(),[-1,16])
    axs[j].imshow(fj)
    print("The figure is: ",test.iloc[t,-1],"and the prediction is false.")
    j+=1
```

```
The figure is:  4 and the prediction is false.
```

```
The figure is:  4 and the prediction is false.
The figure is:  9 and the prediction is false.
The figure is:  0 and the prediction is false.
```



3 .

3.1 .

[132]:
```python
from sklearn.model_selection import GridSearchCV
```

[133]:
```python
parameters = {'penalty':['l2'], 'solver':['lbfgs'],'multi_class':
 ↪['multinomial'],'C':[10**x for x in range(-3,12)]}
svc = LR()
clf = GridSearchCV(svc, parameters,cv=10,scoring='accuracy')
clf.fit(trainX,trainY)
%time
```

```
CPU times: user 7 µs, sys: 23 µs, total: 30 µs
Wall time: 7.87 µs
```

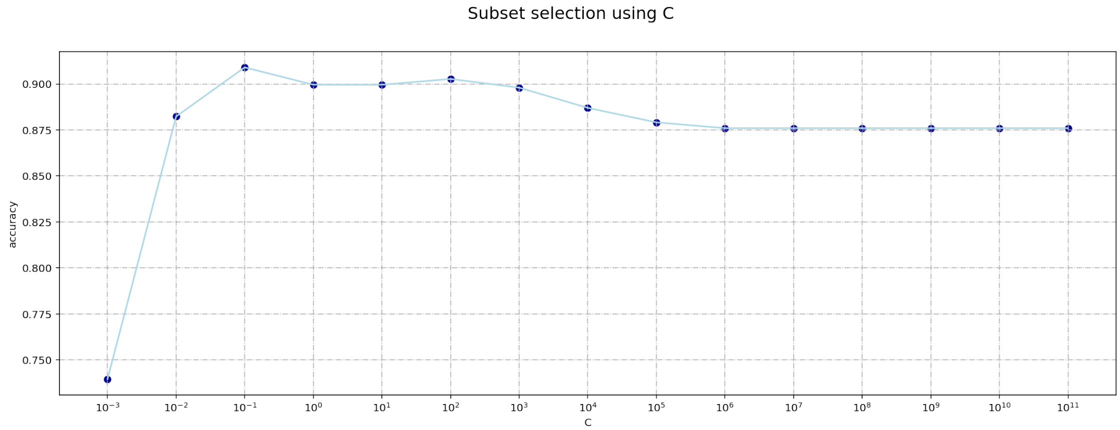
[134]:
```python
df_results = pd.DataFrame({'c':clf.cv_results_["param_C"].data,'accuracy':clf.
 ↪cv_results_["mean_test_score"].data})
```

[135]:
```python
df_results = df_results.dropna(how = "any")
```

[136]:
```python
fig = plt.figure(figsize = (18,6))
v = 'accuracy'
ax = fig.subplots(1, 1)

ax.grid(True, linestyle='-.')
ax.set_xscale('log')
ax.set_xticks([10**x for x in range(-3,12)])
ax.plot(df_results['c'],df_results[v], color = 'lightblue')
ax.scatter(df_results['c'],df_results[v], color = 'darkblue')
ax.set_xlabel('C')
ax.set_ylabel(v)
```

```
fig.suptitle('Subset selection using ' + "C", fontsize = 16)
plt.show()
print("The best C_(min) is 0.1")
```




```
The best C_(min) is 0.1
```

[137]:
```
clf.best_params_
```

[137]: `{'C': 0.1, 'multi_class': 'multinomial', 'penalty': 'l2', 'solver': 'lbfgs'}`

[138]:
```
best_clf = LR(penalty='l2',C=0.
↪1,multi_class='multinomial',max_iter=1000,solver='lbfgs')
best_clf.fit(trainX,trainY)
```

[138]: `LogisticRegression(C=0.1, max_iter=1000, multi_class='multinomial')`

3.2 3-2

[139]:
```
print('The accuracy on train set : {:.4f}'.format(best_clf.
↪score(trainX,trainY)))
```

```
The accuracy on train set : 0.9890
```

[140]:
```
print('The accuracy on test set : {:.4f}'.format(best_clf.score(testX,testY)))
```

```
The accuracy on test set : 0.8868
```

3.3 3-3

[141]:
```
print("The number of coefficients that are estimated as zero :",(abs(best_clf.
↪coef_) < 1e-2).sum())
```

```
# print("The number of coefficients that are not estimated as zero :",(best_clf.
↪coef_ > 1e-5).sum())
```

```
The number of coefficients that are estimated as zero : 203
```

It can be found that the number of coefficients estimated to be 0 is similar to the number of non-zeros, so it is in line with the expectation. Lasso regression is regularized. The gradient obtained during gradient descent only has two values of 1 and -1, so the step size is updated each time It is moving forward steadily; the regularization gradient of Ridge regression will decrease as it approaches the lowest point, and when it approaches the minimum, its gradient will also become smaller, so it will not really become 0, so Ridge's better effect.

4 .

[142]:
```
from sklearn.decomposition import PCA

pca = PCA(n_components=30)
pca.fit(trainX)
pca_X = pca.transform(trainX)
```

[143]:
```
import warnings
warnings.filterwarnings('ignore')
parameters = {'penalty':['l2'], 'solver':['lbfgs'],'multi_class':
↪['multinomial'],'C':[10**x for x in range(-3,12)]}
logr = LR()
clf = GridSearchCV(logr, parameters,cv=10,scoring='accuracy')
clf.fit(pca_X,trainY)
%time
```

```
CPU times: user 2 µs, sys: 1e+03 ns, total: 3 µs
Wall time: 6.91 µs
```

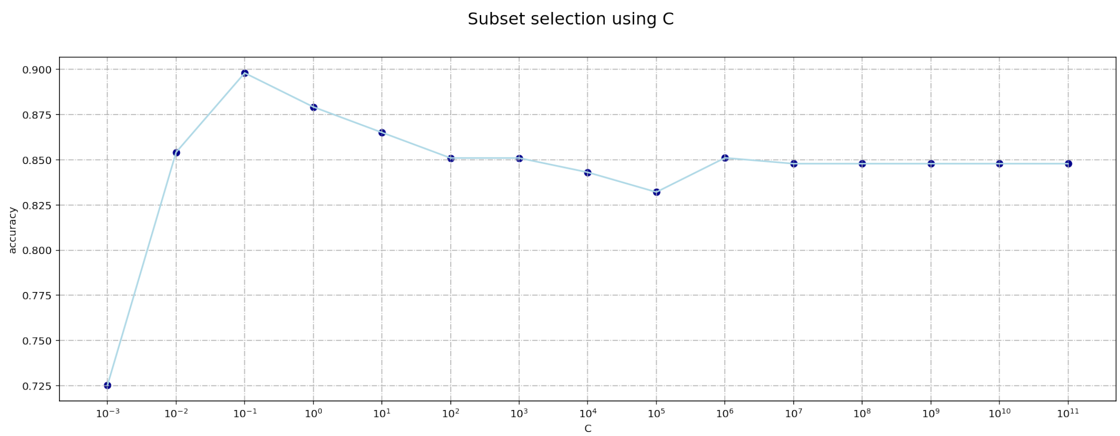
[144]:
```
df_results = pd.DataFrame({'c':clf.cv_results_["param_C"].data,'accuracy':clf.
↪cv_results_["mean_test_score"].data})
```

[145]:
```
df_results = df_results.dropna(how = "any")
```

[146]:
```
fig = plt.figure(figsize = (18,6))
v = 'accuracy'
ax = fig.subplots(1, 1)

ax.grid(True, linestyle='-.')
ax.set_xscale('log')
ax.set_xticks([10**x for x in range(-3,12)])
ax.plot(df_results['c'],df_results[v], color = 'lightblue')
ax.scatter(df_results['c'],df_results[v], color = 'darkblue')
```

```
ax.set_xlabel('C')
ax.set_ylabel(v)
fig.suptitle('Subset selection using ' + "C", fontsize = 16)
plt.show()
print("The best C_(min) is 0.1")
```




```
The best C_(min) is 0.1
```

[147]:
```
clf.best_params_
```

[147]:
```
{'C': 0.1, 'multi_class': 'multinomial', 'penalty': 'l2', 'solver': 'lbfgs'}
```

[148]:
```
best_clf = LR(penalty='l2',C=0.
 ↪1,multi_class='multinomial',max_iter=1000,solver='lbfgs')
best_clf.fit(pca_X,trainY)
```

[148]:
```
LogisticRegression(C=0.1, max_iter=1000, multi_class='multinomial')
```

[149]:
```
print('The accuracy on train set : {:.4f}'.format(best_clf.score(pca_X,trainY)))
```

```
The accuracy on train set : 0.9435
```

[150]:
```
pca_test_X = pca.transform(testX)
```

[151]:
```
print('The accuracy on test set : {:.4f}'.format(best_clf.
 ↪score(pca_test_X,testY)))
```

```
The accuracy on test set : 0.8616
```

The accuracy of the X-trained model processed by pca has decreased on both the training set and the test set, but it has dropped more on the training set.

4.1 .

[152]:
```
from sklearn.decomposition import PCA

pca = PCA(n_components=50)
pca.fit(trainX)
pca_X = pca.transform(trainX)
```

[153]:
```
import warnings
warnings.filterwarnings('ignore')
parameters = {'penalty':['l2'], 'solver':['lbfgs'],'multi_class':
↪['multinomial'],'C':[10**x for x in range(-3,12)]}
logr = LR()
clf = GridSearchCV(logr, parameters,cv=10,scoring='accuracy')
clf.fit(pca_X,trainY)
```

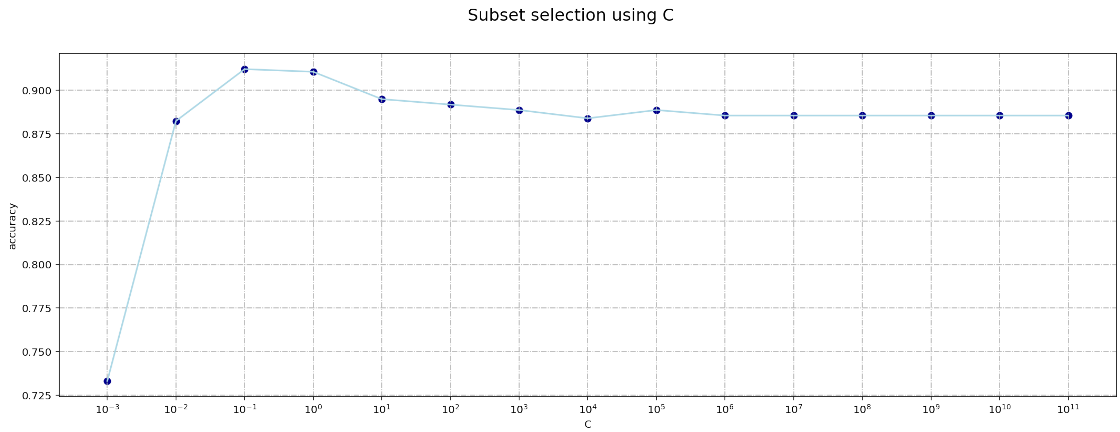
[153]:
```
GridSearchCV(cv=10, estimator=LogisticRegression(),
             param_grid={'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000,
                               100000, 1000000, 10000000, 100000000, 1000000000,
                               10000000000, 100000000000],
                         'multi_class': ['multinomial'], 'penalty': ['l2'],
                         'solver': ['lbfgs']},
             scoring='accuracy')
```

[154]:
```
df_results = pd.DataFrame({'c':clf.cv_results_["param_C"].data,'accuracy':clf.
↪cv_results_["mean_test_score"].data})
```

[155]:
```
df_results = df_results.dropna(how = "any")
```

[156]:
```
fig = plt.figure(figsize = (18,6))
v = 'accuracy'
ax = fig.subplots(1, 1)

ax.grid(True, linestyle='-.')
ax.set_xscale('log')
ax.set_xticks([10**x for x in range(-3,12)])
ax.plot(df_results['c'],df_results[v], color = 'lightblue')
ax.scatter(df_results['c'],df_results[v], color = 'darkblue')
ax.set_xlabel('C')
ax.set_ylabel(v)
fig.suptitle('Subset selection using ' + "C", fontsize = 16)
plt.show()
print("The best C_(min) is 0.1")
```




```
The best C_(min) is 0.1
```

[157]:
```
clf.best_params_
```

[157]:
```
{'C': 0.1, 'multi_class': 'multinomial', 'penalty': 'l2', 'solver': 'lbfgs'}
```

[158]:
```
best_clf = LR(penalty='l2',C=0.
 ↪1,multi_class='multinomial',max_iter=1000,solver='lbfgs')
best_clf.fit(pca_X,trainY)
```

[158]:
```
LogisticRegression(C=0.1, max_iter=1000, multi_class='multinomial')
```

[159]:
```
print('The accuracy on train set : {:.4f}'.format(best_clf.score(pca_X,trainY)))
```

```
The accuracy on train set : 0.9717
```

[160]:
```
pca_test_X = pca.transform(testX)
```

[161]:
```
print('The accuracy on test set : {:.4f}'.format(best_clf.
 ↪score(pca_test_X,testY)))
```

```
The accuracy on test set : 0.8994
```

After using 50 principal components, the accuracy on the training set is reduced, but it is higher than the accuracy on the test set, and the model is better than the original.

[ ]:
```

```