PRACTICAL - 5 & 6

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CLASS- AIML-1

GROUP- A

```
In [ ]:
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
df = pd.read_csv('/content/train.csv')
df
```

Out[]:

	label	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	pixel10	pixel11	pixel12	pixel13	pixel14	pixel1
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
564	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
565	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
566	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
567	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
568	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

569 rows × 785 columns

```
<u>+</u>
```

```
In [ ]:
```

```
df.shape
Out[]:
```

In []:

(569, 785)

```
df = df.fillna(0)
```

In []:

```
print(df.info())
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Columns: 785 entries, label to pixel783
dtypes: float64(88), int64(697)

```
memory usage: 3.4 MB
None
In [ ]:
df.columns
Out[]:
Index(['label', 'pixel0', 'pixel1', 'pixel2', 'pixel3', 'pixel4', 'pixel5',
         'pixel6', 'pixel7', 'pixel8',
        'pixel774', 'pixel775', 'pixel776', 'pixel777', 'pixel778', 'pixel779', 'pixel780', 'pixel781', 'pixel782', 'pixel783'],
       dtype='object', length=785)
In [ ]:
order = list(np.sort(df['label'].unique()))
print(order)
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
In [ ]:
num mean = df.groupby('label').mean()
num mean.head()
Out[]:
      pixel0 pixel1 pixel2 pixel3 pixel4 pixel5 pixel6 pixel7 pixel8 pixel9 pixel10 pixel11 pixel12 pixel13 pixel14 pixel15 pi
 label
         0.0
               0.0
                      0.0
                            0.0
                                   0.0
                                         0.0
                                                0.0
                                                      0.0
                                                             0.0
                                                                                                                0.0
    1
         0.0
               0.0
                      0.0
                            0.0
                                   0.0
                                         0.0
                                                0.0
                                                      0.0
                                                             0.0
                                                                   0.0
                                                                           0.0
                                                                                  0.0
                                                                                          0.0
                                                                                                 0.0
                                                                                                         0.0
                                                                                                                0.0
   2
         0.0
               0.0
                      0.0
                            0.0
                                   0.0
                                         0.0
                                               0.0
                                                      0.0
                                                             0.0
                                                                   0.0
                                                                           0.0
                                                                                  0.0
                                                                                          0.0
                                                                                                 0.0
                                                                                                         0.0
                                                                                                                0.0
    3
         0.0
               0.0
                      0.0
                            0.0
                                   0.0
                                         0.0
                                                0.0
                                                      0.0
                                                             0.0
                                                                   0.0
                                                                           0.0
                                                                                  0.0
                                                                                          0.0
                                                                                                 0.0
                                                                                                         0.0
                                                                                                                0.0
         0.0
               0.0
                      0.0
                            0.0
                                   0.0
                                         0.0
                                                0.0
                                                      0.0
                                                            0.0
                                                                   0.0
                                                                           0.0
                                                                                  0.0
                                                                                          0.0
                                                                                                 0.0
                                                                                                         0.0
                                                                                                                0.0
5 rows × 784 columns
4
                                                                                                                    F
In [ ]:
round(df.drop('label',axis = 1).mean(),2)
Out[]:
pixel0
              0.0
              0.0
pixel1
              0.0
pixel2
pixel3
              0.0
             0.0
pixel4
pixel779
            0.0
pixel780
              0.0
pixel781
              0.0
pixel782
             0.0
pixel783
             0.0
Length: 784, dtype: float64
In [ ]:
df = df.reset index()
In [ ]:
```

```
X = df.iloc[:,2:].values
y = df.iloc[:, 0].values
In [ ]:
X.shape
Out[]:
(569, 784)
In [ ]:
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X = sc.fit transform(X)
In [ ]:
from sklearn.model_selection import KFold
fold = KFold(n splits = 5, shuffle = True )
hyper_param = [{'gamma':[1e-2,1e-3,1e-4],
                 'C':[1,10,100,1000]}]
In [ ]:
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC
svc rbf = SVC(kernel = 'rbf')
model_cv = GridSearchCV(estimator = svc_rbf, param_grid = hyper_param , scoring = 'accuracy', cv =
fold , verbose = 1 , return_train_score= True)
model cv.fit(X,y)
Fitting 5 folds for each of 12 candidates, totalling 60 fits
[Parallel(n jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 60 out of 60 | elapsed: 2.3min finished
Out[]:
GridSearchCV(cv=KFold(n splits=5, random state=None, shuffle=True),
             error score=nan,
             estimator=SVC(C=1.0, break ties=False, cache size=200,
                            class weight=None, coef0=0.0,
                            decision_function_shape='ovr', degree=3,
                            gamma='scale', kernel='rbf', max iter=-1,
                            probability=False, random state=None, shrinking=True,
                            tol=0.001, verbose=False),
             iid='deprecated', n jobs=None,
             param_grid=[{'C': [1, 10, 100, 1000],
                           'gamma': [0.01, 0.001, 0.0001]}],
             pre dispatch='2*n jobs', refit=True, return train score=True,
             scoring='accuracy', verbose=1)
In [ ]:
cv_results = pd.DataFrame (model_cv.cv_results_)
cv_results
Out[]:
   mean_fit_time std_fit_time mean_score_time std_score_time param_C param_gamma
                                                                        params split0_test_score split1_test_sco
                                                                          {'C': 1,
       1.210020
                 0.028390
                               0.235375
                                            0.016800
                                                         1
                                                                   0.01 'gamma':
                                                                                                       0
                                                                          0.01}
```

1.181412

1

0.008549

0.239847

0.025961

{'C': 1,

0.001}

0.0

0

0.001 'gamma':

2	mean ₄ .184769	std ₀ .025793	mean_score_time	std_score_time	param_Ç	param_gamma	{'C': 1, ' params 'gamma	split0_test_score	split1_test_sco
							0.0001}		
3	1.183616	0.013374	0.219993	0.020165	10	0.01	{'C': 10, 'gamma': 0.01}	0.0	0
4	1.170103	0.014160	0.213069	0.012774	10	0.001	{'C': 10, 'gamma': 0.001}	0.0	0
5	1.193024	0.008776	0.208243	0.008646	10	0.0001	{'C': 10, 'gamma': 0.0001}	0.0	0
6	1.171226	0.007729	0.216625	0.016449	100	0.01	{'C': 100, 'gamma': 0.01}	0.0	0
7	1.162791	0.009975	0.214288	0.011952	100	0.001	{'C': 100, 'gamma': 0.001}	0.0	0
8	1.187706	0.004397	0.219455	0.012277	100	0.0001	{'C': 100, 'gamma': 0.0001}	0.0	0
9	1.228700	0.018532	0.261499	0.024407	1000	0.01	{'C': 1000, 'gamma': 0.01}	0.0	0
10	1.240289	0.033943	0.260133	0.026525	1000	0.001	{'C': 1000, 'gamma': 0.001}	0.0	0
11	1.211648	0.009252	0.225420	0.010397	1000	0.0001	{'C': 1000, 'gamma': 0.0001}	0.0	0
4									Þ

In []:

y_pred = model_cv.predict(X)

In []:

from sklearn.metrics import accuracy_score
print(accuracy_score(y,y_pred))

1.0

In []:

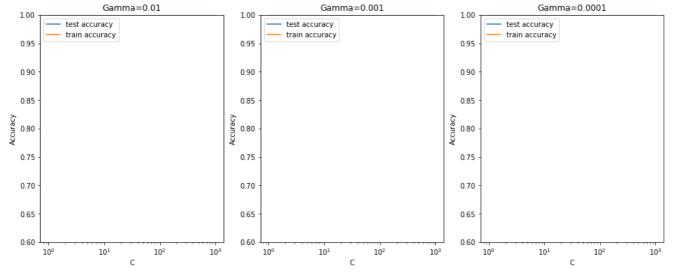
df2 = pd.read_csv('/content/sample_data/test.csv')
df2

Out[]:

	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	pixel10	pixel11	pixel12	pixel13	pixel14	pixel15	ķ
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
27995	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
27996	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
27997	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
27998	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
27999	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

20000 ----- -- 704 --!-----

```
# subplot 3/3
plt.subplot(133)
gamma_0001 = cv_results[cv_results['param_gamma']==0.0001]
plt.plot(gamma_0001["param_C"], gamma_0001["mean_test_score"])
plt.plot(gamma_0001["param_C"], gamma_0001["mean_train_score"])
plt.xlabel('C')
plt.xlabel('Accuracy')
plt.title("Gamma=0.0001")
plt.ylim([0.60, 1])
plt.legend(['test accuracy', 'train accuracy'], loc='upper left')
plt.xscale('log')
```



In []: