# CS156 (Introduction to AI), Spring 2022

## Homework 4 submission


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**Any special notes or anything you would like to communicate to me about this homework submission goes in here.**

## References and sources

**List all your references and sources here. This includes all sites/discussion boards/blogs/posts/etc. where you grabbed some code examples.**

## Solution

#### Load libraries and set random number generator seed

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.svm import LinearSVC
from sklearn.svm import SVC
from sklearn.metrics import plot_confusion_matrix
from sklearn.model_selection import cross_val_score
```

In [2]:

```
np.random.seed(42)
```

#### Code the solution

### Part 1. Load the data from "homework4_input_data.csv" file

In [3]:

```
data = pd.read_csv('homework4_input_data.csv')
```

In [4]:

```
features = data.columns[1:3001]
X = np.array(data.loc[:,features])
Y = np.array(data['Class'])
```

```
X.shape, Y.shape, features
```

Out[4]:

```
((4336, 3000),
 (4336,),
 Index(['ASS1', 'SPX', 'C6orf141', 'SP5', 'SP6', 'ITGA8', 'ATP2A1', 'ATP2A3',
        'ITGA2', 'ITGA3',
        ...
        'SULT1B1', 'IKZF1', 'SLC14A1', 'TCEAL2', 'TCEAL7', 'TCEAL5', 'VCAN',
        'CDR1', 'KRBOX1', 'SELL'],
       dtype='object', length=3000))
```

In [5]:

```
data.head()
```

Out[5]:

| | id | ASS1 | SPX | C6orf141 | SP5 | SP6 | ITGA8 | ATP2A1 | ATP2A3 | ITGA2 | ... | IKZF1 | SLC14A1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | TCGA-AB-2828-03 | 3.935027 | 0.523329 | 0.0 | 0.000000 | 0.102277 | 2.686908 | 2.837357 | 7.444575 | 2.246715 | ... | 8.972232 | 1.560704 |
| **1** | TCGA-AB-2846-03 | 3.372801 | 0.000000 | 0.0 | 0.000000 | 0.116270 | 2.083429 | 5.567935 | 8.361999 | 3.626850 | ... | 8.662337 | 2.509522 |
| **2** | TCGA-AB-2870-03 | 4.198301 | 0.000000 | 0.0 | 0.000000 | 0.249176 | 1.546059 | 6.605116 | 9.138359 | 2.858430 | ... | 8.848274 | 3.137405 |
| **3** | TCGA-AB-2872-03 | 4.115014 | 0.000000 | 0.0 | 0.222018 | 0.632254 | 2.158989 | 6.858708 | 9.201254 | 2.295229 | ... | 7.730065 | 3.087055 |
| **4** | TCGA-AB-2881-03 | 3.662169 | 0.467823 | 0.0 | 0.000000 | 0.000000 | 1.183388 | 5.567935 | 9.040883 | 1.815837 | ... | 8.414421 | 2.683150 |

5 rows × 3002 columns

In [6]:

```
data.describe()
```

Out[6]:

| | ASS1 | SPX | C6orf141 | SP5 | SP6 | ITGA8 | ATP2A1 | ATP2A3 | ITGA2 |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 4336.000000 | 4336.000000 | 4336.000000 | 4336.000000 | 4336.000000 | 4336.000000 | 4336.000000 | 4336.000000 | 4336.000000 |
| **mean** | 6.493217 | 0.875979 | 2.547433 | 2.024070 | 2.788808 | 2.838891 | 2.413940 | 5.273215 | 4.531003 |
| **std** | 1.341540 | 1.322937 | 1.712000 | 1.442751 | 1.385994 | 1.147753 | 1.535475 | 1.570749 | 1.198838 |
| **min** | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 1.197540 |
| **25%** | 5.697111 | 0.000000 | 1.105780 | 0.999840 | 1.810114 | 2.055747 | 1.497904 | 4.215464 | 3.813267 |
| **50%** | 6.588478 | 0.279846 | 2.391468 | 1.710090 | 2.679240 | 2.630627 | 2.061542 | 5.211668 | 4.398703 |
| **75%** | 7.415357 | 1.159160 | 3.819411 | 2.976235 | 3.748897 | 3.439166 | 2.858414 | 6.405440 | 5.331706 |
| **max** | 10.753816 | 6.531445 | 8.714974 | 7.458509 | 7.685174 | 7.041480 | 10.548175 | 10.840692 | 8.464498 |

8 rows × 3000 columns

**Part 2. Produce a PCA plot of the input data, using the colors specified above.**

In [7]:

```
pca = PCA(n_components = 2)
X_reduced = np.array(pca.fit_transform(X))
print(X_reduced)
```

```
[[82.04598902 46.7130452 ]
 [76.72251477 37.9190887 ]
 [76.64320355 39.8676599 ]
 ...
 [-6.45313027 -2.46852613]
 [ 1.54972972  3.37494376]
 [ 9.11558797  9.49003632]]
```

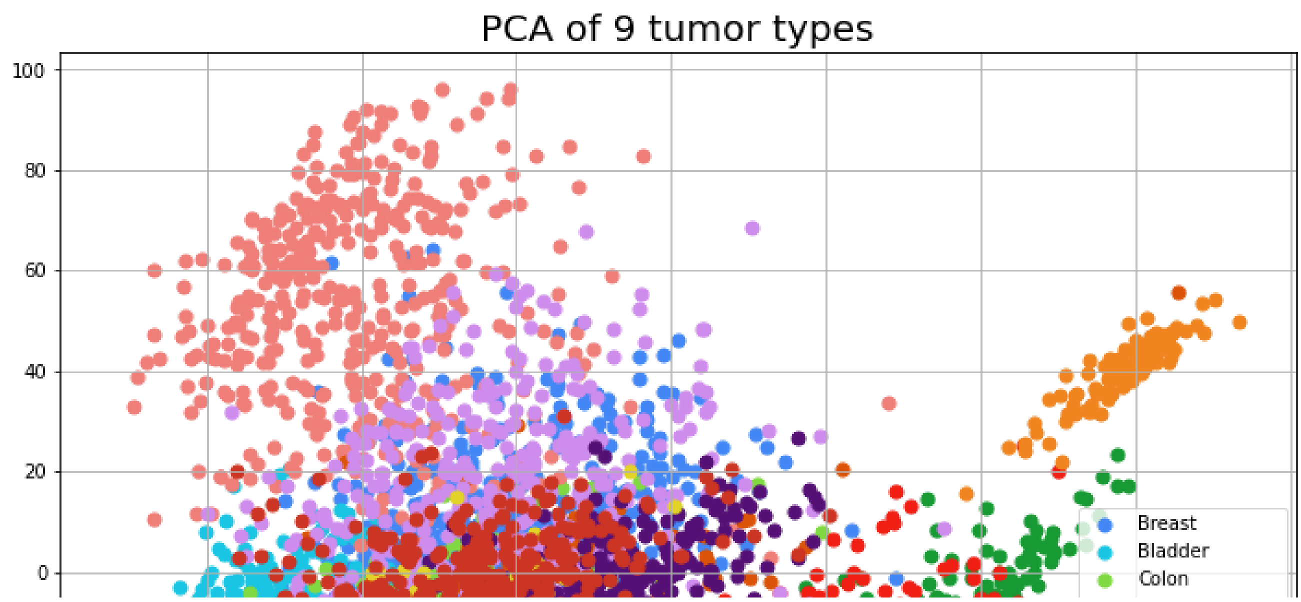
In [8]:

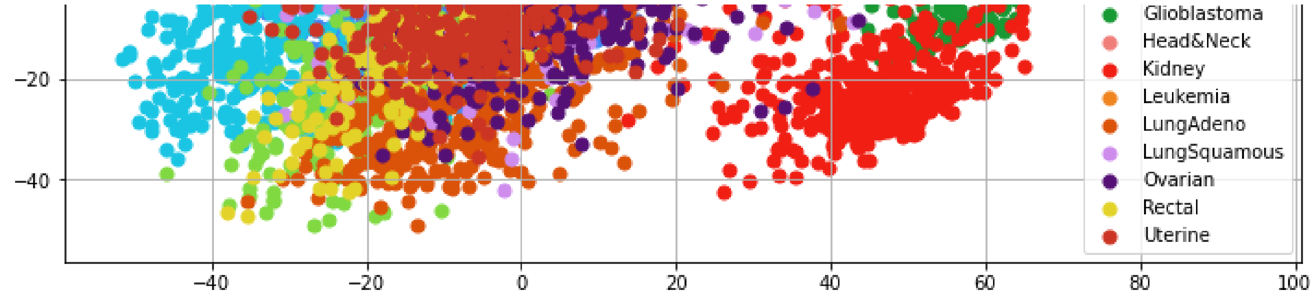
```
principalDf = pd.DataFrame(data = X_reduced, columns = ['principal component 1', 'principal component 2'])
finalDf = pd.concat([principalDf, data[['Class']]], axis = 1)
```

In [9]:

```
fig = plt.figure(figsize = (12,8))
ax = fig.add_subplot(1,1,1)
ax.set_title('PCA of 9 tumor types', fontsize = 20)
targets = ['Breast', 'Bladder', 'Colon', 'Glioblastoma', 'Head&Neck', 'Kidney', 'Leukemia', 'LungAdeno', 'LungSquamous', 'Ovarian',
           'Rectal', 'Uterine']
colors = ['#4287f5',
'#19c5e3',
'#80d941',
'#179933',
'#f07e78',
'#f01e13',
'#f0841f',
'#db5209',
'#ce8ced',
'#551075',
'#e3d329',
'#cc3423']

for target, color in zip(targets,colors):
    indicesToKeep = finalDf['Class'] == target
    ax.scatter(finalDf.loc[indicesToKeep, 'principal component 1']
               , finalDf.loc[indicesToKeep, 'principal component 2']
               , c = color
               , s = 50)
ax.legend(targets)
ax.grid()
```






### Part 3. Normalize the data using StandardScaler.

In [10]:

```
scaler = StandardScaler()
X_rescaled = scaler.fit_transform(X)
```

In [11]:

```
print(X_rescaled)
```

```
[[-1.90712548 -0.26659689 -1.48815802 ... -0.28717918 -1.48166105
   2.70287004]
 [-2.32626443 -0.66222355 -1.48815802 ... -0.07930675 -1.23869714
   3.01223639]
 [-1.71085564 -0.66222355 -1.48815802 ... -2.16692113 -1.48166105
   3.01739253]
 ...
 [ 0.95680383 -0.01256317 -0.3104437  ...  1.09636527  2.58748176
  -0.96701899]
 [ 1.43762043  0.31140135 -1.48815802 ... -0.14351678  0.11035555
  -0.41217216]
 [ 0.13807804 -0.01256317  1.53238206 ... -2.16692113 -0.60944949
  -1.33111116]]
```

### Part 4. Break the data into training anf test dataset

In [12]:

```
X_train, X_test, Y_train, Y_test = train_test_split(X_rescaled, Y, test_size=0.2, random
_state=0)
X_train.shape, Y_train.shape, X_test.shape, Y_test.shape
```

Out[12]:

```
((3468, 3000), (3468,), (868, 3000), (868,))
```

### Part 5. Define SVM model hyperparameters

In [13]:

```
model = SVC(kernel='rbf')
```

### Part 6. Report from 5-fold- cross-validation

In [19]:

```
scores = cross_val_score(model, X_train, Y_train, cv=5)
```

In [20]:

```
print('Individual cross validation accuracys: ',scores)
print('Mean cross validation accuracy: {:.2%}'.format(scores.mean()))
```

```
Individual coress-validation accuracies:  [0.95 0.95 0.97 0.96 0.96]
Mean cross validation accuracy: 95.85%
```

## Part 7. Train the final model on all the training data and assess model performance on the test set

In [16]:

```
model.fit(X_train,Y_train)
```

Out[16]:

```
SVC()
```

In [17]:

```
print('Accuracy of linear SVC on training set: {:.2%}'.format(model.score(X_train, Y_trai
n)))
print('Accuracy of linear SVC on test set: {:.2%}'.format(model.score(X_test, Y_test)))
```

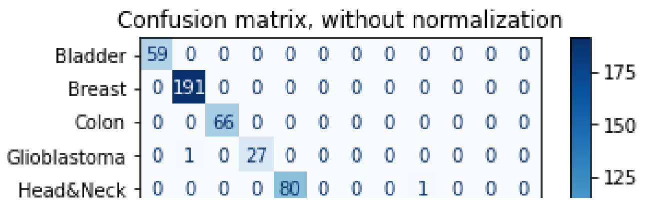
```
Accuracy of linear SVC on training set: 97.95%
Accuracy of linear SVC on test set: 95.85%
```

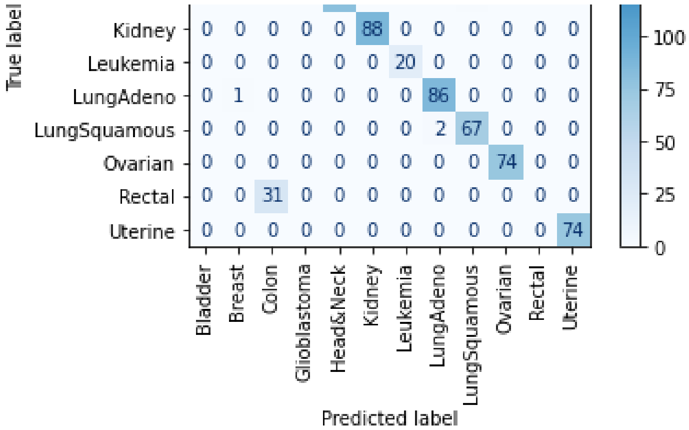
## Part 8. Plot two confusion matrices fot test set predictions

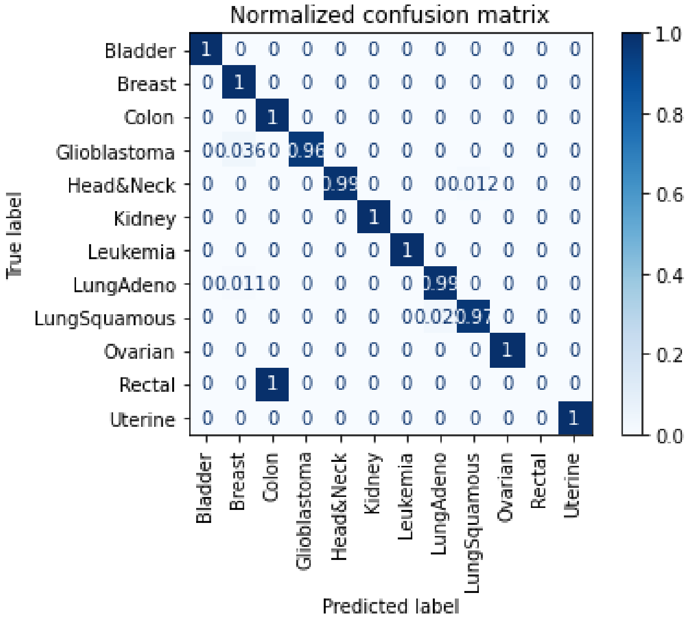
In [18]:

```
np.set_printoptions(precision=2)
titles_options = [("Confusion matrix, without normalization", None), ("Normalized confusi
on matrix", 'true')]
for title, normalize in titles_options:
    disp = plot_confusion_matrix(model, X_test, Y_test, cmap=plt.cm.Blues, normalize=nor
malize, xticks_rotation='vertical')
    disp.ax_.set_title(title)
    print(title)
    print(disp.confusion_matrix)
plt.show()
```

```
Confusion matrix, without normalization
[[ 59   0   0   0   0   0   0   0   0   0   0   0]
 [  0 191   0   0   0   0   0   0   0   0   0   0]
 [  0   0  66   0   0   0   0   0   0   0   0   0]
 [  0   1   0  27   0   0   0   0   0   0   0   0]
 [  0   0   0   0  80   0   0   0   1   0   0   0]
 [  0   0   0   0   0  88   0   0   0   0   0   0]
 [  0   0   0   0   0   0  20   0   0   0   0   0]
 [  0   1   0   0   0   0   0  86   0   0   0   0]
 [  0   0   0   0   0   0   0   2  67   0   0   0]
 [  0   0   0   0   0   0   0   0   0  74   0   0]
 [  0   0  31   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0  74]]
Normalized confusion matrix
[[1.   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.   1.   0.   0.   0.   0.   0.   0.   0.   0.   0.  ]
 [0.   0.04 0.   0.96 0.   0.   0.   0.   0.   0.   0.   0.  ]
 [0.   0.   0.   0.   0.99 0.   0.   0.   0.01 0.   0.   0.  ]
 [0.   0.   0.   0.   0.   1.   0.   0.   0.   0.   0.   0.  ]
 [0.   0.   0.   0.   0.   0.   1.   0.   0.   0.   0.   0.  ]
 [0.   0.01 0.   0.   0.   0.   0.   0.99 0.   0.   0.   0.  ]
 [0.   0.   0.   0.   0.   0.   0.   0.03 0.97 0.   0.   0.  ]
 [0.   0.   0.   0.   0.   0.   0.   0.   0.   1.   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.   1.  ]]
```






Normalized confusion matrix