SVM_Luxottica_dataset

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1 Machine Learning LAB 2: SUPPORT VECTOR MACHINES

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The notebook contains some simple tasks to be performed with **SUPPORT VECTOR MACHINES (SVM)**. Complete all the **required code sections** and **answer to all the questions**.

1.0.1 IMPORTANT for the evaluation score:

1. **Read carefully all cells** and **follow the instructions**
2. **Re-run all the code from the beginning** to obtain the results for the final version of your notebook, since this is the way we will do it before evaluating your notebooks.
3. Make sure to fill the code in the appropriate places **without modifying the template**, otherwise you risk breaking later cells.
4. Please **submit the jupyter notebook file (.ipynb)**, do not submit python scripts (.py) or plain text files. **Make sure that it runs fine with the restat&run all command**.
5. **Answer the questions in the appropriate cells**, not in the ones where the question is presented.

2 Weather Classification with Support Vector Machines

In this notebook we are going to explore the use of Support Vector Machines (SVM) for weather classification. We will use a dataset collected using the Luxottica iSee glasses, similarly to the previous laboratory. The dataset corresponds to 8 hours of atmospherical data recordings sampled every 3 seconds.

The dataset labels are the following:

ID	Label
0	Sunny
1	Rain
2	Cloudy
3	Mostly Clear

Place your **name** and **ID number** (matricola) in the cell below. Also recall to **save the file as Surname_Name_LAB2.ipynb**, failure to do so will incur in a **lower grade**.

Student name: Tommaso Bergamasco **ID Number**: 2052409

[1]:
```
#load the required packages
%matplotlib inline

import numpy as np
import scipy as sp
from matplotlib import pyplot as plt

import sklearn
from sklearn.datasets import fetch_openml
from sklearn.neural_network import MLPClassifier
from sklearn.decomposition import PCA
import sklearn.metrics as skm
```

[2]:
```
# helper function to load the dataset
def load_dataset(path):
    with np.load(path) as data:
        x, y = data["x"], data["y"]

        # normalize data
        x -= x.mean(axis=0)
        x /= x.std(axis=0)

    return x, y
```

2.1 A) Hyper-parameter search

TO DO (A.0): Set the random **seed** using your **ID**. If you need to change it for testing add a constant explicitly, eg.: 1234567 + 1

[3]:
```
# fix your ID ("numero di matricola") and the seed for random generator
# as usual you can try different seeds by adding a constant to the number:
# ID = 1234567 + X
ID = 2052409
np.random.seed(ID)
```

Before proceding to the training steps, we **load the dataset and split it** in training and test set (while the **training** set is **typically larger**, here we set the number of training samples to 1000 and 4000 for the test data). The **split** is **performed after applying a random permutation** to the dataset, such permutation will **depend on the seed** you set above. **DO NOT CHANGE THE PRE-WRITTEN CODE UNLESS OTHERWISE SPECIFIED**

[4]:
```
X, y = load_dataset("data/lux.npz")
print(X.shape, y.shape)
```

```
(15099, 3) (15099,)
```

[5]:
```
# The task is quite easy, let's add noise to make it more challenging!
```

```
# You can try without noise (comment the next 2 lines, easy task), with the␣
 ↪suggested amount of noise,
# or play with the suggested amount of noise

noise = np.random.normal(0,0.1,X.shape)
X=X+noise
```

TO DO (A.1): Divide the **data into training and test set** (for this part use 1000 samples in the **first** set, 4000 in the **second** one). Make sure that each label is present at least 10 times in training. If it is not, then keep adding permutations to the initial data until this happens.

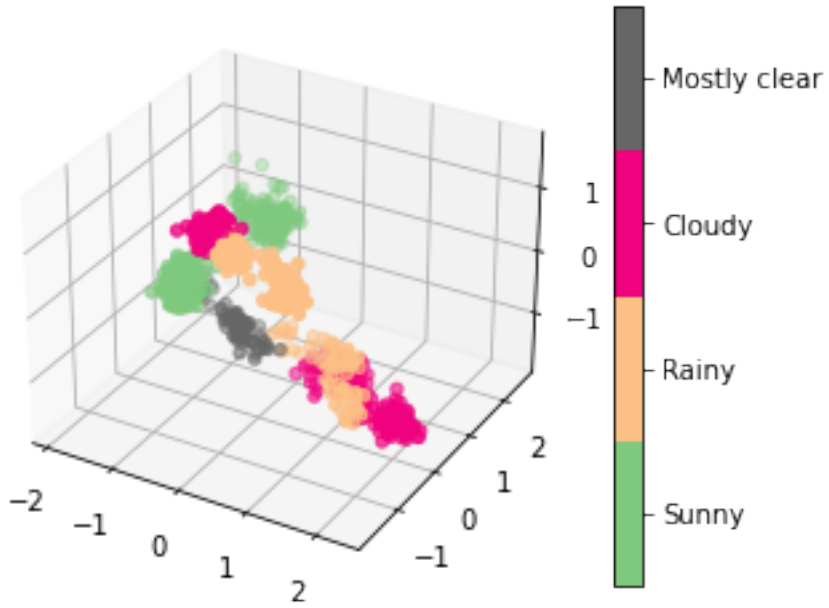
[6]:
```
while True:
    #random permute the data and split into training and test taking the first␣
 ↪1000
    #data samples as training and 4000 samples as test
    permutation = np.random.permutation(X.shape[0]) # ADD YOUR CODE HERE

    X = X[permutation] # ADD YOUR CODE HERE
    y = y[permutation] # ADD YOUR CODE HERE

    m_training = 1000
    m_test = 4000

    X_train = X[:m_training] # ADD YOUR CODE HERE
    X_test = X[m_training:m_training+m_test] # ADD YOUR CODE HERE
    y_train = y[:m_training] # ADD YOUR CODE HERE
    y_test = y[m_training:m_training+m_test] # ADD YOUR CODE HERE

    print("X_train shape:", X_train.shape,"X_test shape:", X_test.
 ↪shape,"||","y_train shape:",  y_train.shape,"y_test shape:", y_test.shape)

    labels, freqs = np.unique(y_train, return_counts=True) # ADD YOUR CODE HERE.
 ↪ Hint: use np.unique()
    print("Labels in training dataset: ", labels)
    print("Frequencies in training dataset: ", freqs)
    at_least_10 = True
    for i in freqs:
        if i < 10:
            at_least_10 = False
    if at_least_10 == True:
        print('Training data are Representative of the entire data set --> OK!')
        break
```

```
X_train shape: (1000, 3) X_test shape: (4000, 3) || y_train shape: (1000,)
y_test shape: (4000,)
Labels in training dataset:  [0. 1. 2. 3.]
Frequencies in training dataset:  [387 180 364  69]
```

```
Training data are Representative of the entire data set --> OK!
```

[7]:
```
#function for plotting a image and printing the corresponding label
def plot_input(X_matrix, labels):
    fig = plt.figure()
    ax = fig.add_subplot(projection="3d")
    cmap = plt.cm.get_cmap('Accent', 4)
    im = ax.scatter(X_matrix[:,0], X_matrix[:,1], X_matrix[:,2], c=labels,␣
 ↪cmap=cmap)
    im.set_clim(-0.5, 3.5)
    cbar=fig.colorbar(im, ticks=[0,1,2,3], orientation='vertical', cmap=cmap)
    cbar.ax.set_yticklabels(['Sunny', 'Rainy','Cloudy', 'Mostly clear'])
```

[8]:
```
#let's try the plotting function
plot_input(X_train,y_train)
```



TO DO (A.2): Use a SVM classfier with cross validation to pick a model. Use a 4-fold cross-validation. Let's start with a Linear kernel.

[9]:
```
#import SVC
from sklearn.svm import SVC
#import for Cross-Validation
from sklearn.model_selection import GridSearchCV

# parameters for linear SVM
parameters = {'C': [ 0.01, 0.1, 1, 10]}
```

```
#train linear SVM
linear_SVM = SVC(kernel='linear') # ADD YOUR CODE
clf = GridSearchCV(linear_SVM, parameters, return_train_score=True)
clf.fit(X_train, y_train)

print('RESULTS FOR LINEAR KERNEL')

print("Best parameters set found:")
best_parameters = clf.best_params_ # ADD YOUR CODE
print(best_parameters)

print("Score with best parameters:")
best_score = clf.best_score_
print(best_score)

print("All scores on the grid:")
results = clf.cv_results_
all_scores = results['mean_test_score']
print(all_scores)
# ADD YOUR CODE
```

```
RESULTS FOR LINEAR KERNEL
Best parameters set found:
{'C': 10}
Score with best parameters:
0.893
All scores on the grid:
[0.747 0.876 0.888 0.893]
```

TO DO (A.3): Pick a model for the Polynomial kernel with degree=2.

[10]:
```
# parameters for poly with degree 2 kernel
parameters = {'C': [0.01, 0.1, 1],'gamma':[0.01,0.1,1.]}

#run SVM with poly of degree 2 kernel
poly2_SVM = SVC(kernel='poly', degree = 2) # ADD YOUR CODE
clf = GridSearchCV(poly2_SVM, parameters, return_train_score=True)
clf.fit(X_train, y_train)

# ADD YOUR CODE

print ('RESULTS FOR POLY DEGREE=2 KERNEL')

print("Best parameters set found:")
best_parameters = clf.best_params_
print(best_parameters)
# ADD YOUR CODE
```

```
print("Score with best parameters:")
best_score = clf.best_score_
print(best_score)
# ADD YOUR CODE

print("\nAll scores on the grid:")
results = clf.cv_results_
all_scores = results['mean_test_score']
print(all_scores)
# ADD YOUR CODE
```

```
RESULTS FOR POLY DEGREE=2 KERNEL
Best parameters set found:
{'C': 1, 'gamma': 1.0}
Score with best parameters:
0.9410000000000001

All scores on the grid:
[0.387 0.387 0.839 0.387 0.752 0.937 0.387 0.839 0.941]
```

TO DO (A.4): Now let's try a higher degree for the polynomial kernel (e.g., 3rd degree).

[11]:
```
# parameters for poly with higher degree kernel
parameters = {'C': [0.01, 0.1, 1],'gamma':[0.01,0.1, 1]}

#run SVM with poly of higher degree kernel
degree = 3
poly3_SVM = SVC(kernel='poly', degree = 3) # ADD YOUR CODE
clf = GridSearchCV(poly3_SVM, parameters, return_train_score=True)
clf.fit(X_train, y_train)


# ADD YOUR CODE

print ('RESULTS FOR POLY DEGREE=', degree, ' KERNEL')

print("Best parameters set found:")
best_parameters = clf.best_params_
print(best_parameters)
# ADD YOUR CODE

print("Score with best parameters:")
best_score = clf.best_score_
print(best_score)
# ADD YOUR CODE

print("\nAll scores on the grid:")
```

```
results = clf.cv_results_
all_scores = results['mean_test_score']
print(all_scores)
# ADD YOUR CODE
```

```
RESULTS FOR POLY DEGREE= 3  KERNEL
Best parameters set found:
{'C': 1, 'gamma': 1}
Score with best parameters:
0.924

All scores on the grid:
[0.387 0.387 0.84  0.387 0.498 0.909 0.387 0.765 0.924]
```

TO DO (A.5): Pick a model for the Radial Basis Function kernel:

[12]:
```
# parameters for rbf SVM
parameters = {'C': [0.1, 1, 10, 100],'gamma':[0.001, 0.01, 0.1,1]}

#run SVM with rbf kernel

# ADD YOUR CODE
rbf_SVM = SVC(kernel='rbf') # ADD YOUR CODE
clf = GridSearchCV(rbf_SVM, parameters, return_train_score=True)
clf.fit(X_train, y_train)
print ('RESULTS FOR rbf KERNEL')

print("Best parameters set found:")
best_parameters = clf.best_params_
print(best_parameters)
# ADD YOUR CODE

print("Score with best parameters:")
best_score = clf.best_score_
print(best_score)
# ADD YOUR CODE

print("\nAll scores on the grid:")
results = clf.cv_results_
all_scores = results['mean_test_score']
print(all_scores)
# ADD YOUR CODE
```

```
RESULTS FOR rbf KERNEL
Best parameters set found:
{'C': 10, 'gamma': 1}
Score with best parameters:
0.99
```

```
All scores on the grid:
[0.387 0.573 0.837 0.948 0.572 0.795 0.945 0.986 0.785 0.889 0.989 0.99
 0.881 0.971 0.987 0.985]
```

TO DO (A.Q1) [Answer the following] What do you observe when using RBF and polynomial kernels on this dataset ?

```
**ANSWER A.Q1**:<br>
```

- Observe that the polynomial kernel with degree 2 performs better than the polynomial with degree 3. This means that the second one is probably overfitting the training data since it has higher modelling capabilities.
- The best results are given by the rbf kernel. This is probably due to the fact that it takes into account the influence of the neighbours, which is useful in this case since we can notice in the data (look at cell #8) regions of low-variance (namely points very close to each other).

TO DO (A.6): Report here the best SVM kernel and parameters

[13]:
```
#get training and test error for the best SVM model from CV
best_SVM = SVC(kernel='rbf', C=10, gamma=0.1) # USE YOUR OPTIMAL PARAMETERS
best_SVM.fit(X_train, y_train)

# ADD YOUR CODE
# (error is 1 - sum.score)
training_error = 1 - best_SVM.score(X_train, y_train) # ADD YOUR CODE
test_error = 1 - best_SVM.score(X_test, y_test) # ADD YOUR CODE
print ("Best SVM training error: %f" % training_error)
print ("Best SVM test error: %f" % test_error)
```

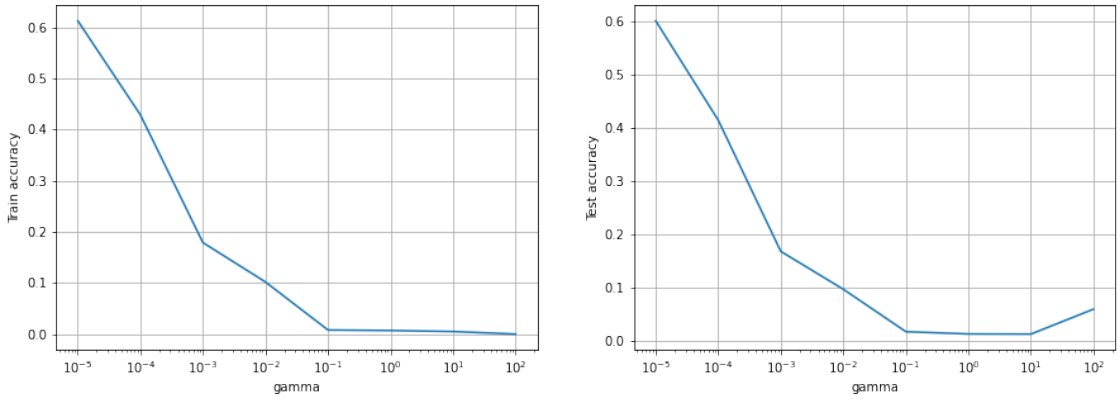
```
Best SVM training error: 0.008000
Best SVM test error: 0.018000
```

TO DO (A.7): Analyze how the gamma parameter (inversely proportional to standard deviation of Gaussian Kernel) impact the performances of the classifier

[14]:
```
#Test with different values of gamma

gamma_values = np.logspace(-5,2,8)
print(gamma_values)
# use rbf kernel and C=1
train_acc_list, test_acc_list = [], []


# ADD YOUR CODE TO TRAIN THE SVM MULTIPLE TIMES WITH THE DIFFERENT VALUES OF␣
 ↪GAMMA
# PLACE THE TRAIN AND TEST ACCURACY FOR EACH TEST IN THE TRAIN AND TEST␣
 ↪ACCURACY LISTS
for g in gamma_values:
    SVM = SVC(kernel='rbf', C=10, gamma=g)
```

```
    SVM.fit(X_train, y_train)
    training_error = 1 - SVM.score(X_train, y_train)
    test_error = 1 - SVM.score(X_test, y_test)
    train_acc_list.append(training_error)
    test_acc_list.append(test_error)

# Plot
fig, ax = plt.subplots(1,2, figsize=(15,5))

ax[0].plot(gamma_values, train_acc_list)
ax[0].set_xscale('log')
ax[0].set_xlabel('gamma')
ax[0].set_ylabel('Train accuracy')
ax[0].grid(True)

ax[1].plot(gamma_values, test_acc_list)
ax[1].set_xscale('log')
ax[1].set_xlabel('gamma')
ax[1].set_ylabel('Test accuracy')
ax[1].grid(True)

plt.show()
```

```
[1.e-05 1.e-04 1.e-03 1.e-02 1.e-01 1.e+00 1.e+01 1.e+02]
```



2.2 B) More data

Now let's do the same but using more data points for training.

TO DO (B.0): Choose a higher number of data points (e.g. x = 10000) for training data depending on your computing capability.

[15]:
```
X = X[permutation]
y = y[permutation]

m_training = 10000 # ADD YOUR CODE: adjust depending on the capabilities of␣
 ↪your PC

X_train, X_test = X[:m_training], X[m_training:]
y_train, y_test = y[:m_training], y[m_training:]

labels, freqs = np.unique(y_train, return_counts=True) # ADD YOUR CODE
print("Labels in training dataset: ", labels)
print("Frequencies in training dataset: ", freqs)

# initialize support variables for boundaries visualization
granularity = 25
x_max = np.abs(X).max()
x_range = np.linspace(-x_max, x_max, granularity)
x_grid = np.stack(np.meshgrid(x_range, x_range, x_range)).reshape(3, -1).T
```

```
Labels in training dataset:  [0. 1. 2. 3.]
Frequencies in training dataset:  [4033 1669 3670  628]
```

TO DO (B.1): Let's try to use SVM with parameters obtained from the best model for $m_{training} = 10000$. Since it may take a long time to run, you can decide to just let it run for some time and stop it if it does not complete. If you decide to do this, report it in the TO DO (C.Q1) cell below.

[16]:
```
#get training and test error for the best SVM model from CV

# ADD YOUR CODE
rbf_SVM.fit(X_train, y_train)
training_error = 1 - rbf_SVM.score(X_train, y_train)
test_error = 1 - rbf_SVM.score(X_test, y_test)

print ("Best SVM training error: %f" % training_error)
print ("Best SVM test error: %f" % test_error)
```

```
Best SVM training error: 0.014000
Best SVM test error: 0.009610
```

TO DO (B.2): Just for comparison, let's also use logistic regression (without regularization, i.e. with C very large).

[17]:
```
from sklearn import linear_model

# ADD YOUR CODE
lr = linear_model.LogisticRegression(C=1e5)
lr.fit(X_train, y_train)
pred_train = lr.predict(X_train)
```

```
pred_test = lr.predict(X_test)

training_error = 1 - lr.score(X_train, y_train)
test_error = 1 - lr.score(X_test, y_test)

print ("Best logistic regression training error: %f" % training_error)
print ("Best logistic regression test error: %f" % test_error)
```

```
Best logistic regression training error: 0.116300
Best logistic regression test error: 0.104334
```

TO DO (B.3): Try logistic regression with regularization (use C=1)

[18]:
```
# ADD YOUR CODE
regL2 = linear_model.LogisticRegression(C=1)
regL2.fit(X_train, y_train)

training_error = 1 - regL2.score(X_train, y_train)
test_error = 1 - regL2.score(X_test, y_test)


print ("Best regularized logistic regression training error: %f" %␣
 ↪training_error)
print ("Best regularized logistic regression test error: %f" % test_error)
```

```
Best regularized logistic regression training error: 0.116600
Best regularized logistic regression test error: 0.103746
```

3 C) Boundaries Visualization

Now let us compare the shape of classification boundaries.

TO DO (C.0): Use the SVM, logistic regression (with and without regularization) to predict on the test set X_test.

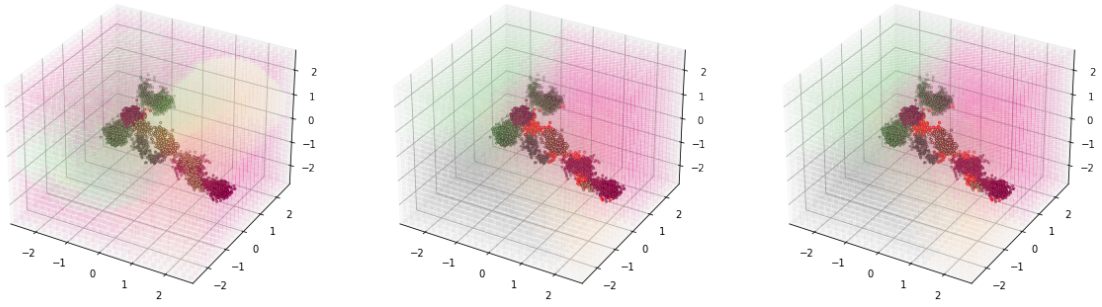
[19]:
```
rbf_SVM_test = rbf_SVM.predict(X_test) # ADD YOUR CODE
lr_test = lr.predict(X_test) # ADD YOUR CODE
regL2_test = regL2.predict(X_test) # ADD YOUR CODE
```

We constructed a grid of all possible combinations of input values, we now use it to extract the classification boundaries of the three classifiers by having them predict on each input.

[20]:
```
rbf_SVM_grid = rbf_SVM.predict(x_grid)
lr_grid = lr.predict(x_grid)
regL2_grid = regL2.predict(x_grid)

rbf_SVM_m = y_test == rbf_SVM_test
lr_m = y_test == lr_test
regL2_m = y_test == lr_test
```

```
fig = plt.figure(figsize=(20,36))
ax1 = fig.add_subplot(1, 3, 1, projection="3d")
ax2 = fig.add_subplot(1, 3, 2, projection="3d")
ax3 = fig.add_subplot(1, 3, 3, projection="3d")

ax1.scatter(x_grid[:,0], x_grid[:,1], x_grid[:,2], c=rbf_SVM_grid, linewidth=0,␣
 ↪marker="s", alpha=.05,cmap='Accent')
ax2.scatter(x_grid[:,0], x_grid[:,1], x_grid[:,2], c=lr_grid, linewidth=0,␣
 ↪marker="s", alpha=.05,cmap='Accent')
ax3.scatter(x_grid[:,0], x_grid[:,1], x_grid[:,2], c=regL2_grid, linewidth=0,␣
 ↪marker="s", alpha=.05,cmap='Accent')

ax1.scatter(X_test[rbf_SVM_m,0], X_test[rbf_SVM_m,1], X_test[rbf_SVM_m,2],␣
 ↪c=y_test[rbf_SVM_m], linewidth=.5, edgecolor="k", marker=".",cmap='Accent')
ax1.scatter(X_test[~rbf_SVM_m,0], X_test[~rbf_SVM_m,1], X_test[~rbf_SVM_m,2],␣
 ↪c=y_test[~rbf_SVM_m], linewidth=1, edgecolor="r", marker=".",cmap='Accent')
ax1.set_xlim([-x_max, x_max])
ax1.set_ylim([-x_max, x_max])
ax1.set_zlim([-x_max, x_max])

ax2.scatter(X_test[lr_m,0], X_test[lr_m,1], X_test[lr_m,2], c=y_test[lr_m],␣
 ↪linewidth=.5, edgecolor="k", marker=".",cmap='Accent')
ax2.scatter(X_test[~lr_m,0], X_test[~lr_m,1], X_test[~lr_m,2], c=y_test[~lr_m],␣
 ↪linewidth=1, edgecolor="r", marker=".",cmap='Accent')
ax2.set_xlim([-x_max, x_max])
ax2.set_ylim([-x_max, x_max])
ax2.set_zlim([-x_max, x_max])

ax3.scatter(X_test[regL2_m,0], X_test[regL2_m,1], X_test[regL2_m,2],␣
 ↪c=y_test[regL2_m], linewidth=.5, edgecolor="k", marker=".",cmap='Accent')
ax3.scatter(X_test[~regL2_m,0], X_test[~regL2_m,1], X_test[~regL2_m,2],␣
 ↪c=y_test[~regL2_m], linewidth=1, edgecolor="r", marker=".",cmap='Accent')
ax3.set_xlim([-x_max, x_max])
ax3.set_ylim([-x_max, x_max])
ax3.set_zlim([-x_max, x_max])
```

[20]: (-2.696344710670878, 2.696344710670878)



TO DO (C.Q1) [Answer the following] Compare and discuss: - the results from SVM with m=600 and with m=10000 (or whatever value you set) training data points. If you stopped the SVM, include such aspect in your comparison. - the results of SVM and of Logistic Regression

ANSWER C.Q1:

- We can note that the SVM over 10000 samples has higher training error but lower generalization error, which is a desirable effect and is due to the fact that when increasing the training set size we decrease the effect of overfitting.
- The SVM performs definitely better than the logistic regression, this is probably due to the "geometric nature" of the data distribution. Note also that the regularized logistic regression performs better than the simple logistic regression which is a self explanatory behaviour.

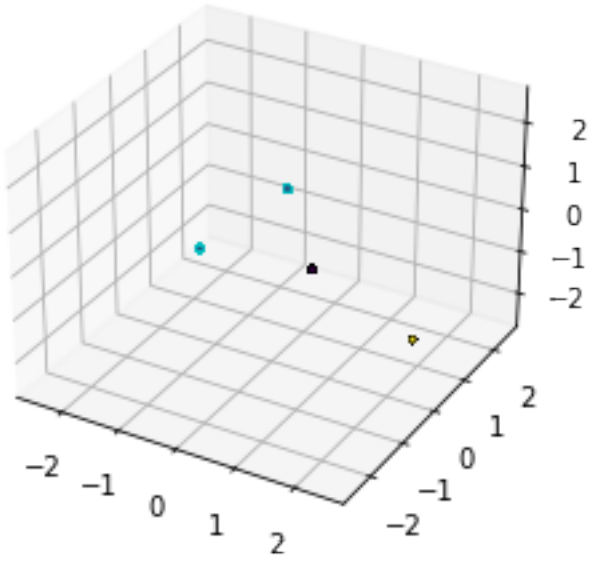
TO DO (C.1): Change the code below to highlight the samples classified **correctly by SVM** and **wrongly by logistic regression**.

[21]:
```
fig = plt.figure()
ax = fig.add_subplot(projection="3d")
print(y_test.shape, rbf_SVM_test.shape, y_test.shape)

mask = [0]*y_test.shape[0] # ADD YOUR CODE
for i in range(y_test.shape[0]):
    if (y_test[i] == rbf_SVM_test[i]) and (y_test[i]!=lr_test[i]):
        mask[i] = 1
mask = np.array(mask)
print('The plot is wrong, I dont understand why')

ax.scatter(X_test[mask,0], X_test[mask,1], X_test[mask,2], c=y_test[mask],␣
 ↪linewidth=1, edgecolor="c", marker=".")
ax.scatter(X_test[~mask,0], X_test[~mask,1], X_test[~mask,2], c=y_test[~mask],␣
 ↪linewidth=.5, edgecolor="k", marker=".")
ax.set_xlim([-x_max, x_max])
ax.set_ylim([-x_max, x_max])
ax.set_zlim([-x_max, x_max])
```

```
(5099,) (5099,) (5099,)
```

The plot is wrong, I dont understand why

[21]: (-2.696344710670878, 2.696344710670878)



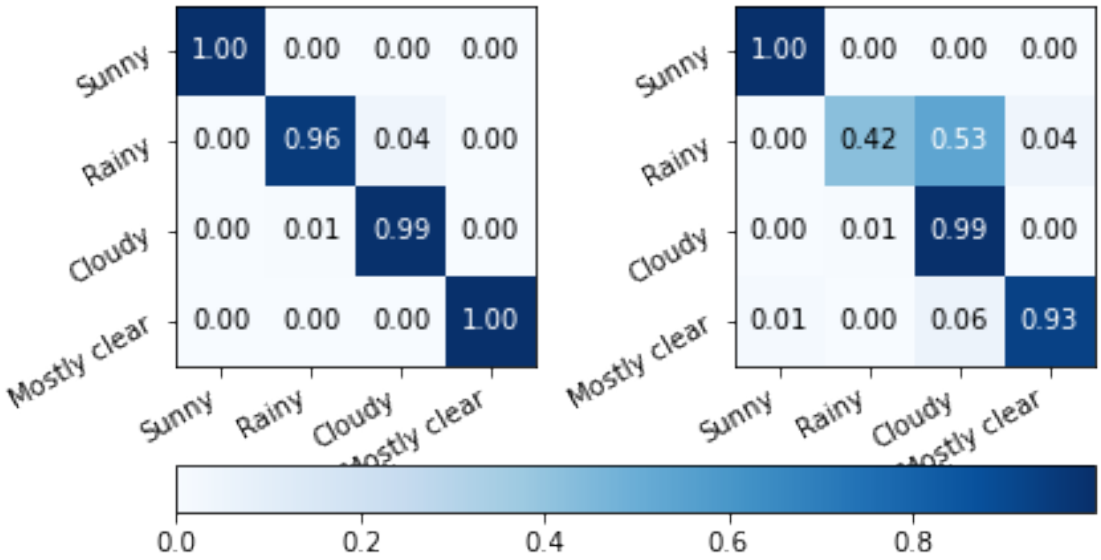
TO DO (C.2): Plot the confusion matrix for the SVM classifier and for logistic regression. The confusion matrix has one column for each predicted label and one row for each true label. It shows for each class in the corresponding row how many samples belonging to that class gets each possible output label. Notice that the diagonal contains the correctly classified samples, while the other cells correspond to errors. You can obtain it with the sklearn.metrics.confusion_matrix function (see the documentation). You can also print also the normalized confusion matrix.

[22]:
```
np.set_printoptions(precision=2, suppress=True) # for better aligned printing␣
 ↪of confusion matrix use floatmode='fixed'

u, counts = np.unique(y_test, return_counts=True)
print("Labels and frequencies in test set: ", counts)

confusion_SVM = sklearn.metrics.confusion_matrix(y_test, rbf_SVM_test) # ADD␣
 ↪YOUR CODE
print("\n Confusion matrix SVM  \n \n", confusion_SVM)
print("\n Confusion matrix SVM (normalized)   \n \n", confusion_SVM /counts[:
 ↪,None] )

confusion_LR = sklearn.metrics.confusion_matrix(y_test, lr_test) # ADD YOUR CODE
print("\n Confusion matrix LR  \n \n", confusion_LR)
print("\n Confusion matrix LR (normalized)   \n \n", confusion_LR /counts[:
 ↪,None] )
```

```
Labels and frequencies in test set:  [2085  859 1853  302]

 Confusion matrix SVM

 [[2085    0    0    0]
 [   0  824   34    1]
 [   0   14 1839    0]
 [   0    0    0  302]]

 Confusion matrix SVM (normalized)

 [[1.   0.   0.   0.  ]
 [0.   0.96 0.04 0.  ]
 [0.   0.01 0.99 0.  ]
 [0.   0.   0.   1.  ]]

 Confusion matrix LR

 [[2080    0    4    1]
 [   1  364  459   35]
 [   0   10 1842    1]
 [   4    0   17  281]]

 Confusion matrix LR (normalized)

 [[1.   0.   0.   0.  ]
 [0.   0.42 0.53 0.04]
 [0.   0.01 0.99 0.  ]
 [0.01 0.   0.06 0.93]]
```

[23]:
```
fig, axs = plt.subplots(1, 2)

for idx, conf in enumerate([confusion_SVM, confusion_LR]):

    im = axs[idx].imshow(conf /counts[:,None],␣
 ↪cmap="Blues",interpolation='nearest')
    axs[idx].set_xticks([0,1,2,3])
    axs[idx].set_yticks([0,1,2,3])
    axs[idx].set_xticklabels(['Sunny', 'Rainy','Cloudy', 'Mostly␣
 ↪clear'],ha="right",rotation=30)
    axs[idx].set_yticklabels(['Sunny', 'Rainy','Cloudy', 'Mostly␣
 ↪clear'],ha="right",rotation=30)
    cm = conf /counts[:,None]
    fmt = '.2f'
    thresh = cm.max() / 2.
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
```

```
            axs[idx].text(j, i, format(cm[i, j], fmt),
            ha="center", va="center",
            color="white" if cm[i, j] > thresh else "black")

fig.tight_layout()
fig.colorbar(im, ax=axs[:], location='bottom')
plt.show()
```



TO DO (C.Q2) [Answer the following] Have a look at the confusion matrices and comment on the obtained accuracies. Why some classes have lower accuracies and others an higher one ? Make some guesses on the possible causes.

ANSWER C.Q2:

- As we already seen before the SVM performs better than logistic regression.
- Anyway both models have the biggest problems when classifying a rainy weather which is (in particular for LR) classified many times as cloudy. This is of course due to the similarity and partial superposition of the 2 states. Note also that the cloudy data points are divided in 2 separate "clusters" and rainy points seem to present the higher variance among all classes (see the first 3d plot) which makes the classification task harder.
- In general note that the classes that tend to be confused are the most "similar ones".

[ ]: