assignment 12

May 18, 2021

0.1 Task 12.1

Load the data from 'Petroleum to phase dataset', a dataset collecting a set of field measurements and theoretical values about how oil may flow within pipes, depending on several geometrical and environmental values (e.g., inclination of the pipe, geometry of the pipe, temperature of the fluid, etc.).

The problem is actually a classification problem, where:

- the inputs are the geometrical and environmental values mentioned above
- the outputs are different flow regimes. The following acronyms indicate the various classes, that should be intended as "types of flow regimes":
  - B = bubble,
  - I = intermittent,
  - C = churn,
  - A = annular,
  - DB = disperse bubble,
  - M = mist,
  - SS = stratified smooth,
  - SW = stratified wavy

As a task, execute the code below and familiarize with the results.

[4]:
```
# import the normal stuff
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# import necessary stuff from sklearn
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score

# set the default parameters for the figures
plt.rcParams['figure.figsize'] = [10, 5]
plt.rcParams['font.size'] = 16
```

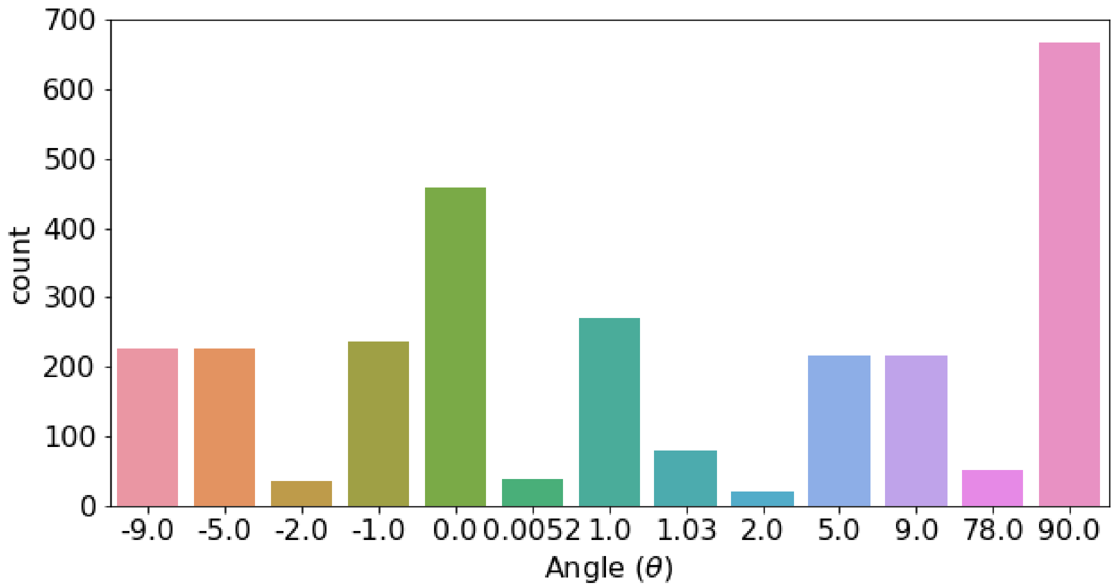
[5]:
```python
# read the part of the dataset that refers to the field measurements
data = pd.read_csv('./Petroleum2PhaseData/Petroleum2PhaseData.csv', sep=';')

# visualize the data, so to see if everything is where it should be
"""
structure of the table:
- "Class_id" = "Class_name" = output class
  (note that these two fields are actually equivalent,
   with "Class_name" being one of the acronyms listed above)

- all the other columns: the various geometrical and
  environmental values mentioned above = input features
"""
data.head()
```

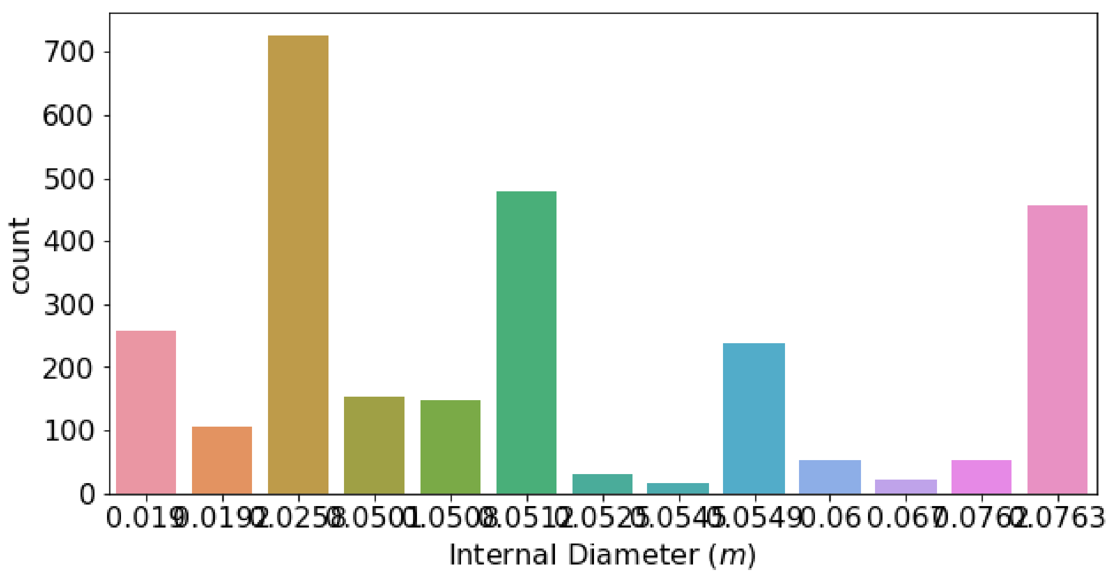
[5]:
```
   Class_id Class_name       Vsl       Vsg      ID  Roughness  Ang  Density_L  \
0         2         SS  0.029427  0.087232  0.0258          0  0.0      860.0
1         5          I  0.057772  0.086743  0.0258          0  0.0      860.0
2         5          I  0.119709  0.086256  0.0258          0  0.0      860.0
3         5          I  0.210969  0.084695  0.0258          0  0.0      860.0
4         5          I  0.361904  0.085076  0.0258          0  0.0      860.0

   Density_G  Visc_L   Visc_G     ST      P     T
0      4.134   0.007  0.00001  0.032  350.0  22.0
1      4.134   0.007  0.00001  0.032  350.0  22.0
2      4.134   0.007  0.00001  0.032  350.0  22.0
3      4.134   0.007  0.00001  0.032  350.0  22.0
4      4.134   0.007  0.00001  0.032  350.0  22.0
```

[6]:
```python
"""
Checking the unbalancedness on the inputs

Note: one of the features, "Ang" (i.e., the inclination
of the pipe in degrees), has the peculiarity of inducing
a slightly unbalanced dataset, as shown in the first plot below.
The same for the internal diameter.

Something similar may be verified for the other variables,
if wished
"""

# plot how many samples there exist for each value of the Ang variable
plt.figure()
sns.countplot(x = 'Ang', data = data)
plt.xlabel(r'Angle ($\theta$)')
```

```
# plot how many samples there exist for each value of the internal diameter␣
↪variable
plt.figure()
sns.countplot(x = 'ID', data = data)
plt.xlabel(r'Internal Diameter ($m$)')
```

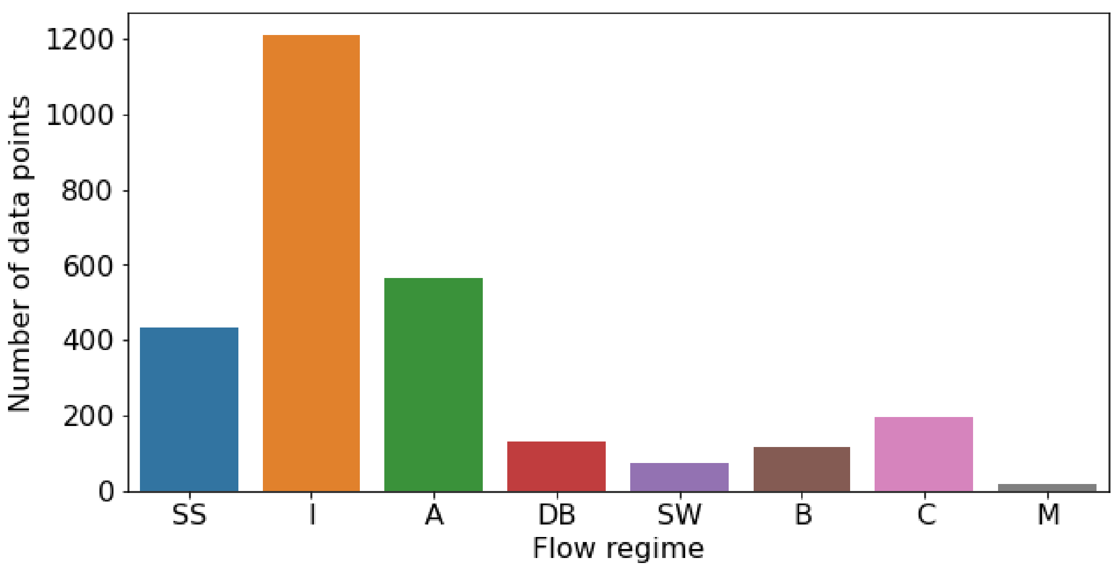
[6]: Text(0.5, 0, 'Internal Diameter (m)')





[7]:
```python
"""
Checking the unbalancedness on the outputs

The dataset is such that some classes are much
more represented than the other ones. This is an issue,
as said in the course. For a nice recap of what problems
one may encounter in this situation, see

https://towardsdatascience.com/
↪handling-imbalanced-datasets-in-machine-learning-7a0e84220f28
"""
plt.figure()
sns.countplot(x='Class_name', data=data)
plt.xlabel("Flow regime")
plt.ylabel("Number of data points")
```

[7]:
```
Text(0, 0.5, 'Number of data points')
```



0.2 Task 12.2

Comment what you expect this unbalancedness will cause when, later on, we will use some pre-made algorithms for classifying test data from this dataset.
The class imbalance might cause classifiers to classify a disproportionate amount of I, A and SS given a balanced test set. It can also fail to classify classes with few datapoints, such as M and SW, because it hasnt been exposed to as many members of those classes.

0.3 Task 12.3

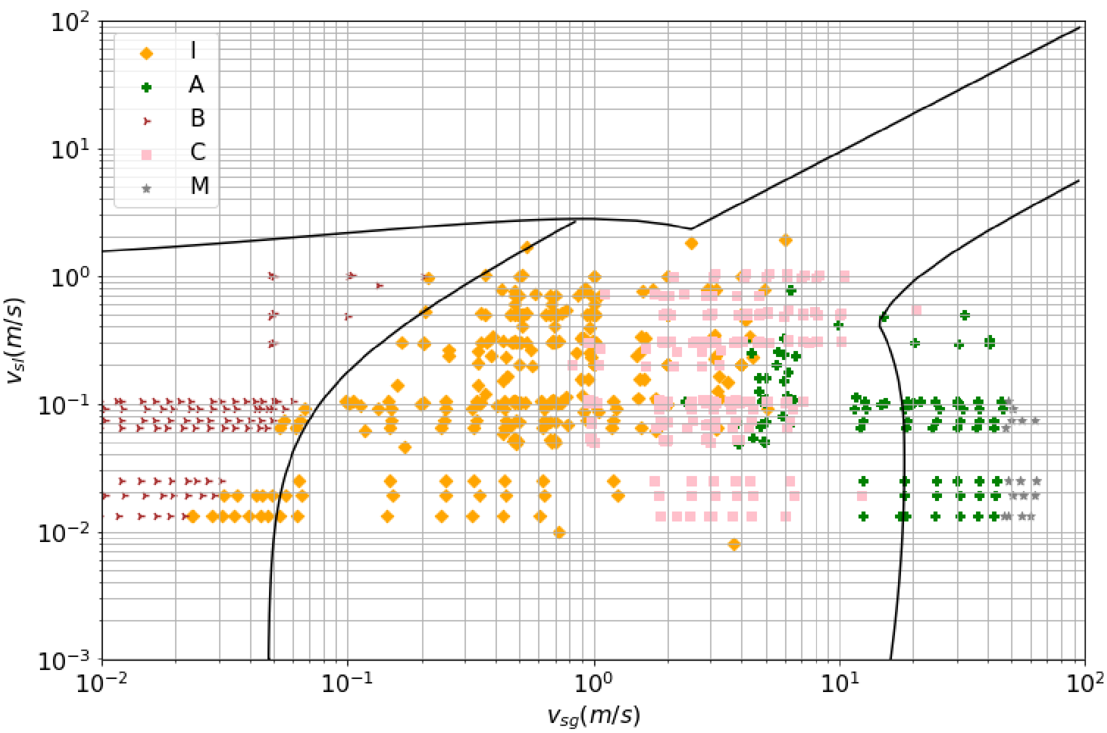
Load the part of data from the 'Petroleum to phase dataset' relative to the theoretical values about how oil may flow within pipes, depending on several geometrical and environmental values. This data corresponds to some boundaries on the inputs space that define opportune regions where the flows should nominally be of certain types. These boundaries will be then compared later on against the field measurements that we loaded above.

[8]:
```
# load the theoretical data relative to horizontally placed pipes
h_annular = pd.read_csv('./Petroleum2PhaseData/DecisionBoundaries/horizontal/
 ↪annular.txt',    sep='\t').values
h_bf = pd.read_csv('./Petroleum2PhaseData/DecisionBoundaries/horizontal/bf.
 ↪txt',         sep='\t').values
h_db = pd.read_csv('./Petroleum2PhaseData/DecisionBoundaries/horizontal/db.
 ↪txt',         sep='\t').values
h_stratified = pd.read_csv('./Petroleum2PhaseData/DecisionBoundaries/horizontal/
 ↪stratified.txt', sep='\t').values
h_wavy = pd.read_csv('./Petroleum2PhaseData/DecisionBoundaries/horizontal/wavy.
 ↪txt',       sep='\t').values

# load the theoretical data relative to vertically placed pipes
v_annular = pd.read_csv('./Petroleum2PhaseData/DecisionBoundaries/vertical/
 ↪annular.txt',      sep='\t').values
v_bf = pd.read_csv('./Petroleum2PhaseData/DecisionBoundaries/vertical/bf.txt', ␣
 ↪         sep='\t').values
v_db = pd.read_csv('./Petroleum2PhaseData/DecisionBoundaries/vertical/db.txt', ␣
 ↪         sep='\t').values
```

[9]:
```
# to compare the measured data against the theoretical
# boundaries, select only the measurements relative to vertically placed pipes
vertical = data['Ang'] > 89
v_data = data[vertical]

# actually through selecting only a subset of measurements
# we do not get anymore all the classes represented
print(v_data['Class_name'].unique())

# for readability -- assign the various samples to individual variables
I = v_data.loc[v_data['Class_name'] == 'I']
A = v_data.loc[v_data['Class_name'] == 'A']
B = v_data.loc[v_data['Class_name'] == 'B']
C = v_data.loc[v_data['Class_name'] == 'C']
M = v_data.loc[v_data['Class_name'] == 'M']
```

```
['I' 'A' 'B' 'C' 'M']
```

[18]:
```python
# initialize the plot
f = plt.figure(figsize = (12, 8))

# draw the theoretical boundaries with some black lines
plt.plot(v_annular[:,0], v_annular[:,1], color='black')
plt.plot(v_bf[:, 0], v_bf[:, 1], color='black')
plt.plot(v_db[:, 0], v_db[:, 1], color='black')

# draw what has been measured in the field
i = plt.scatter(I['Vsg'], I['Vsl'], marker='D', color='orange')
a = plt.scatter(A['Vsg'], A['Vsl'], marker='P', color='green')
b = plt.scatter(B['Vsg'], B['Vsl'], marker='4', color='brown')
c = plt.scatter(C['Vsg'], C['Vsl'], marker='s', color='pink')
m = plt.scatter(M['Vsg'], M['Vsl'], marker='*', color='grey')

# ancillary settings
plt.xscale('log')
plt.yscale('log')
plt.axis([0.01, 100, 0.01, 100])
plt.xticks([0.01, 0.1, 1, 10, 100])
plt.yticks([0.001, 0.01, 0.1, 1, 10, 100])
plt.grid(True, which="both")
plt.legend((i, a, b, c, m), ('I', 'A', 'B', 'C', 'M'))
plt.xlabel(r'$v_{sg}(m/s)$')
plt.ylabel(r'$v_{sl}(m/s)$')
plt.show()
```



0.4 Task 12.4

Comment the results visualized by the figure above, focusing on: - comparing the theoretical vs. the measured data, - using this comparison to motivate whether one should try to see whether instead of the theoretical boundaries one should use a data driven approach.

From the theoretical boundaries that are drawn in black we see that they fail to capture the actual measured data in many cases, especially for I and A. Almost every member of classes B and M are contained within the theoretical borders. This holds for C as well, but the theoretical boundaries do not give a way of separating C and I. A data driven approach seems appropriate for this dataset.

0.5 Task 12.5

Run the code below, that loads the dataset in a way that is convenient for applying the classification algorithms in the sklearn package.

[11]:
```
# for readability, give the classical names to the variables
Y = data['Class_id'].values
X = data[['Vsl', 'Vsg', 'Ang', 'Density_L', 'Density_G', 'Visc_L', 'Visc_G',␣
 ↪'ST']].values

# scale also the X data, so to avoid scaling issues. See also
# https://towardsai.net/p/data-science/
 ↪how-when-and-why-should-you-normalize-standardize-rescale-your-data-3f083def38ff
scaler = StandardScaler()
X = scaler.fit_transform(X)

# divide also the dataset in training and test sets
X_train, \
X_test,  \
y_train, \
y_test   = train_test_split(X, Y, test_size=0.2, random_state=1)

# DEBUG
print("training set size = {}\ntest set size     = {}".format(X_train.size,␣
 ↪X_test.size))
```

```
training set size = 17536
test set size     = 4392
```

[12]:
```
"""
Ancillary function that plots a confusion matrix in a nice way.
Normalization can be applied by setting `normalize=True`
"""

from sklearn.metrics import confusion_matrix
```

```python
import itertools
def plot_confusion_matrix(cm,       # the actual matrix
                          classes,
                          normalize = False,
                          title     = 'Confusion matrix',
                          cmap      = plt.cm.Blues ):

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    plt.figure()
    plt.imshow(cm, interpolation='nearest', cmap=cmap)

    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.1f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color = "white" if cm[i, j] > thresh else "black")

    plt.ylabel('true label')
    plt.xlabel('predicted label')
    plt.title(title)
    plt.colorbar()
    plt.tight_layout()
```

0.6 Task 12.6 - Logistic Regression

Complete the code below, that implements a logistic regression algorithm.

[76]:
```python
# load the right package
from sklearn.linear_model import LogisticRegression

# allocate the object that will perform the regression
lr = LogisticRegression(solver='lbfgs',
                        multi_class='auto',
                        max_iter=10000,
                        penalty='none')

# do the actual learning
lr.fit(X_train, y_train)
```

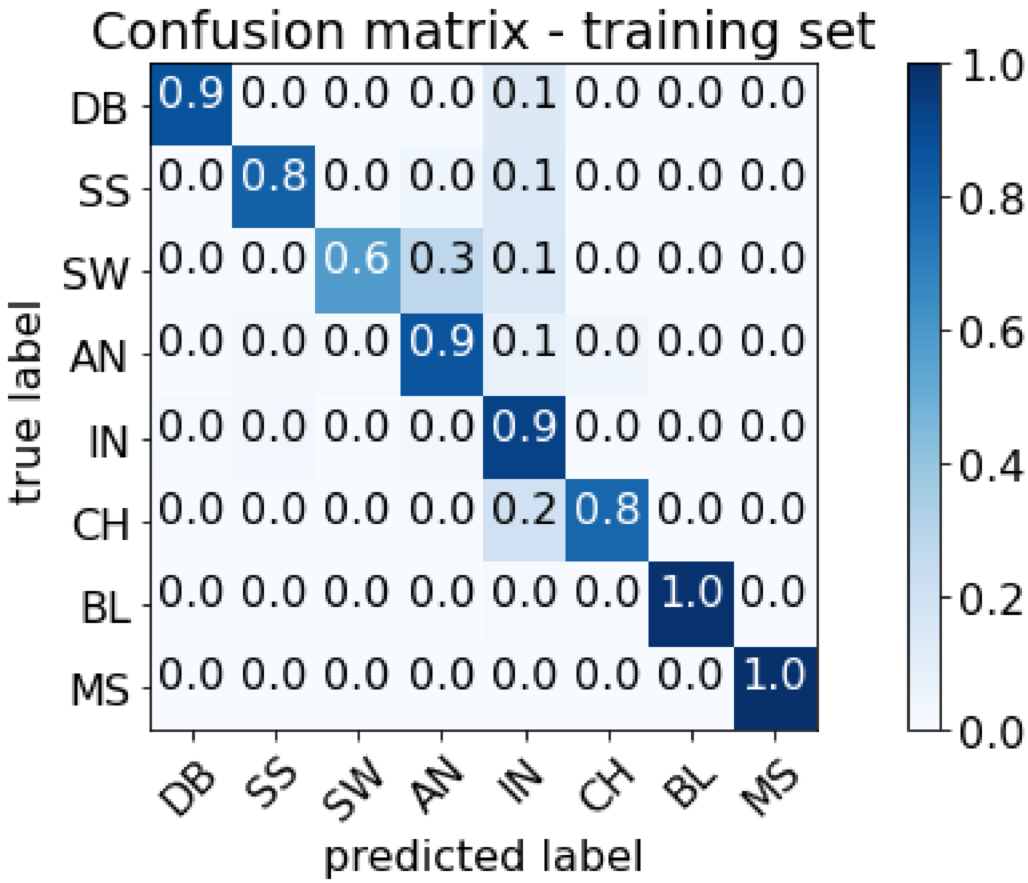
[76]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=10000,
                   multi_class='auto', n_jobs=None, penalty='none',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

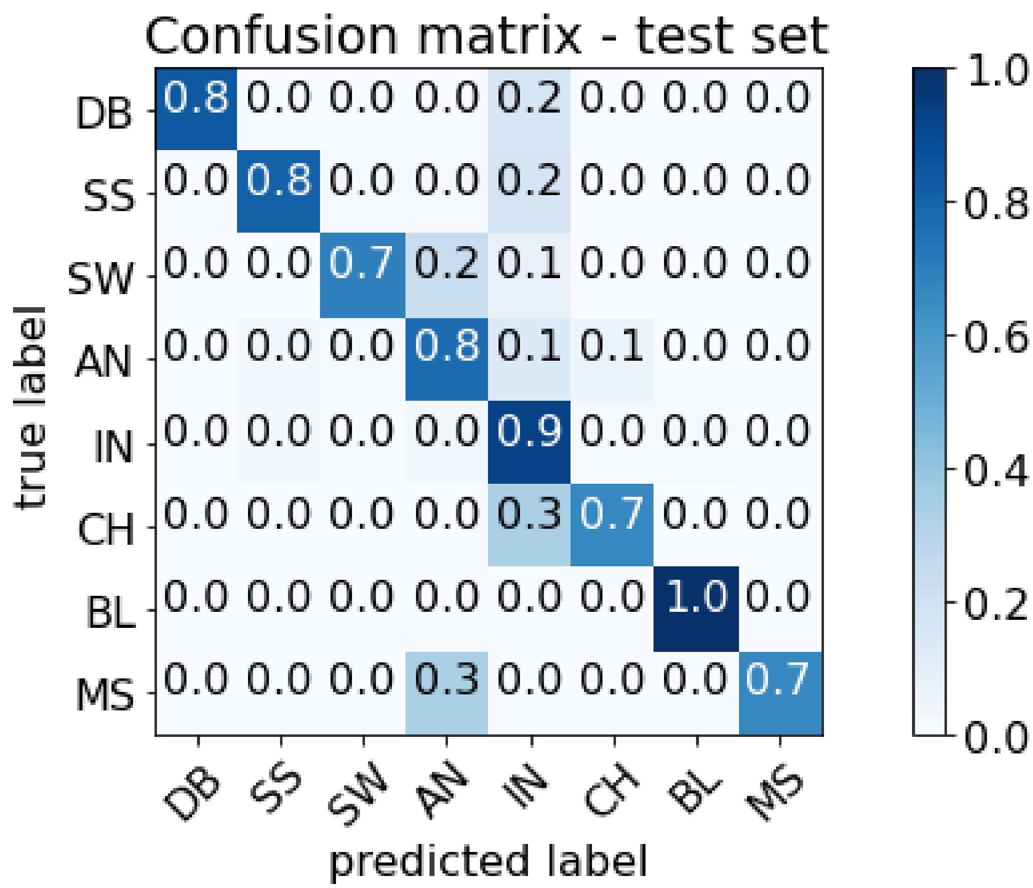
[78]:

```
# compute the performance indexes on the training and test sets
y_lr_predict_train = lr.predict(X_train)
y_lr_predict_test  = lr.predict(X_test)
#
accuracy_LR_train = accuracy_score(y_train, y_lr_predict_train)
accuracy_LR_test  = accuracy_score(y_test,  y_lr_predict_test)

# DEBUG
print("accuracy of logistic regression\n - on the training set: {}\n - on the␣
 ↪test set:     {}".format(accuracy_LR_train, accuracy_LR_test))

# compute the confusion matrices on the training and test sets
cm_train = confusion_matrix(y_train, y_lr_predict_train)
cm_test  = confusion_matrix(y_test,  y_lr_predict_test)

# for readability
classes = ['DB', 'SS', 'SW', 'AN', 'IN', 'CH', 'BL', 'MS']

# plot the confusion matrices
plot_confusion_matrix(cm_train,
                      classes,
                      normalize=True, # try both "True" and "False"!
                      title='Confusion matrix - training set')
#
plot_confusion_matrix(cm_test,
                      classes,
                      normalize=True, # try both "True" and "False"!
                      title='Confusion matrix - test set')
```

```
accuracy of logistic regression
 - on the training set: 0.8763686131386861
 - on the test set:     0.8506375227686703
```



Confusion matrix - training set
true label
predicted label
DB
SS
SW
AN
IN
CH
BL
MS
0.9 0.0 0.0 0.0 0.1 0.0 0.0 0.0
0.0 0.8 0.0 0.0 0.1 0.0 0.0 0.0
0.0 0.0 0.6 0.3 0.1 0.0 0.0 0.0
0.0 0.0 0.0 0.9 0.1 0.0 0.0 0.0
0.0 0.0 0.0 0.0 0.9 0.0 0.0 0.0
0.0 0.0 0.0 0.0 0.2 0.8 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 1.0
1.0
0.8
0.6
0.4
0.2
0.0



0.7 Task 12.7

Comment the performance indexes and confusion matrices above, and state whether you think there may be overfitting / underfitting phenomena.

Accuracy scores from the train set vs from the test set suggests that there is a slight overfitting to the training data. However, the overfitting is marginal and expected, having an accuracy difference of just over 2%.

Confusion matrices shows that the algorithm has comparable performance on the test as to the training set, but with worse classification power when predicting MS, where it confuses MS for AN in 30% of test cases. The rest of the confusion matrix entries vary slightly, but with no surprising amounts. This again suggests slight overfitting to the test set, but especially on the MS class.

0.8 Task 12.8 - Random Forests

Complete the code below, that implements a random forest classification algorithm.

[169]:
```
# import the necessary packages
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
```

```
# allocate the object that will perform the classification
rfc = RandomForestClassifier()

# setup the parameters for the grid-search
grid_param = {
    'n_estimators': [100, 300, 500, 800, 1000],
    'criterion': ['gini', 'entropy'],
    'bootstrap': [False],
    'max_depth': [5, 8, 12, 15]
}

# construct an object that will take care of training
# the classifier while exhaustively searching for the
# best parameters values in a grid search fashion
gd_rfc = GridSearchCV(estimator=rfc,
                      param_grid=grid_param,
                      scoring='accuracy',
                      cv=5,
                      n_jobs=-1)

# launch the actual training & grid search
gd_rfc.fit(X_train, y_train)

# DEBUG
print("Best parameters found by GridSearchCV:")
print(gd_rfc.best_params_)
print("Best performance index found by GridSearchCV:")
print(gd_rfc.best_score_)
```

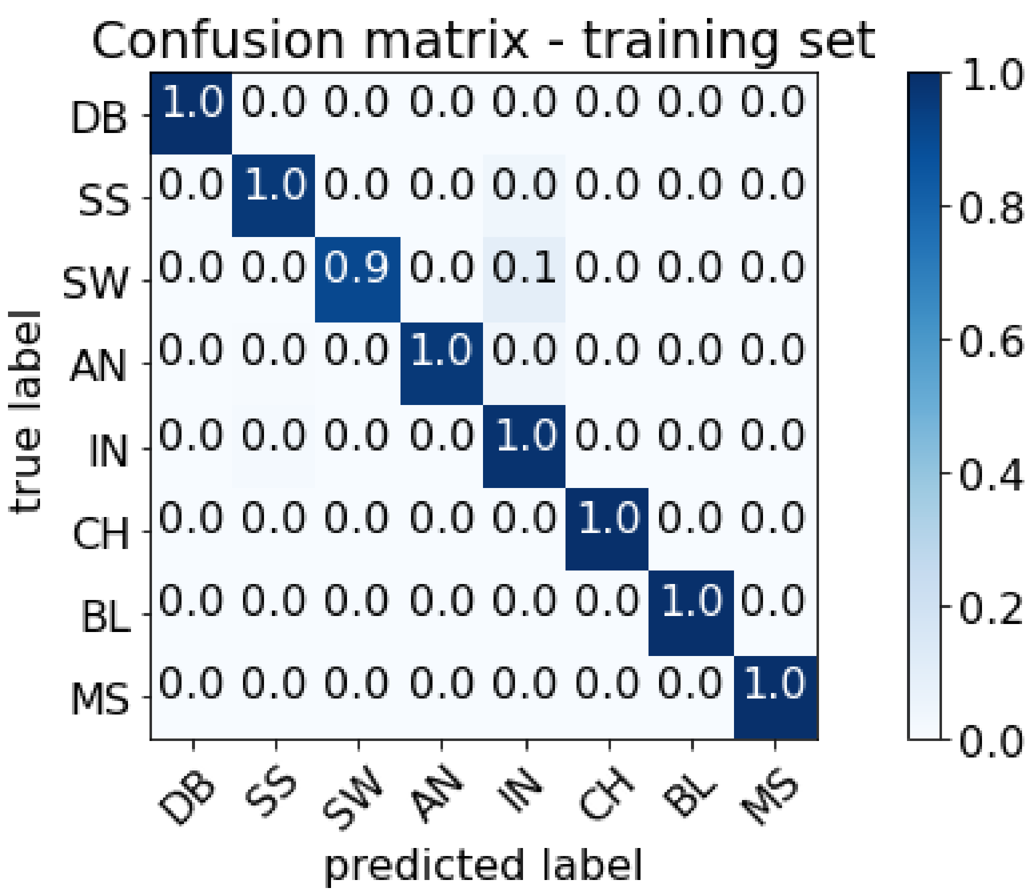
```
Best parameters found by GridSearchCV:
{'bootstrap': False, 'criterion': 'entropy', 'max_depth': 12, 'n_estimators':
1000}
Best performance index found by GridSearchCV:
0.9183459710217285
```

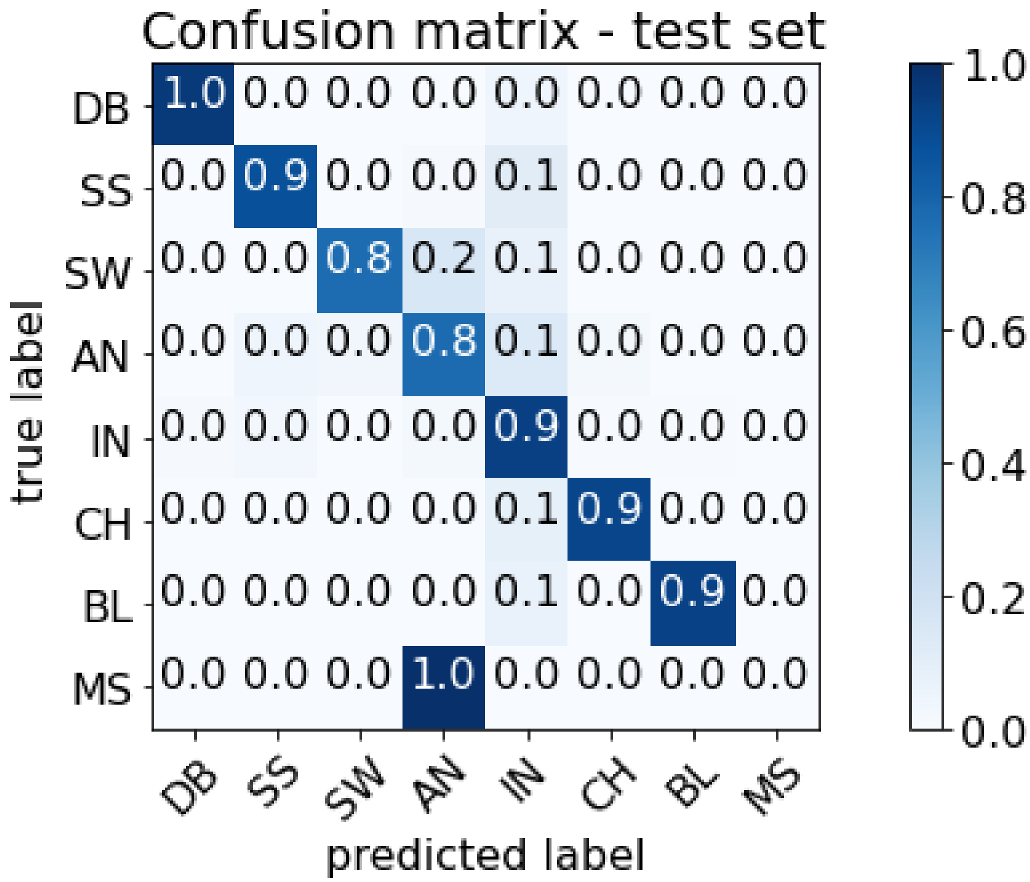
[170]:

```
# compute the performance indexes on the training and test sets
y_rfc_predict_train = gd_rfc.predict(X_train)
y_rfc_predict_test  = gd_rfc.predict(X_test)
#
accuracy_RFC_train = accuracy_score(y_train, y_rfc_predict_train)
accuracy_RFC_test  = accuracy_score(y_test,  y_rfc_predict_test)

# DEBUG
print("accuracy of random forests:\n - on the training set: {}\n - on the test␣
 ↪set:     {}".format(accuracy_RFC_train, accuracy_RFC_test))
```

```python
# compute the confusion matrices on the training and test sets
cm_train = confusion_matrix(y_train, y_rfc_predict_train)
cm_test  = confusion_matrix(y_test,  y_rfc_predict_test)

# for readability
classes = ['DB', 'SS', 'SW', 'AN', 'IN', 'CH', 'BL', 'MS']

# plot the confusion matrices
plot_confusion_matrix(cm_train,
                      classes,
                      normalize=True, # try both "True" and "False"!
                      title='Confusion matrix - training set')
#
plot_confusion_matrix(cm_test,
                      classes,
                      normalize=True, # try both "True" and "False"!
                      title='Confusion matrix - test set')
```

```
accuracy of random forests:
 - on the training set: 0.9781021897810219
 - on the test set:     0.8816029143897997
```





0.9 Task 12.9

As in Task 12.7, comment the performance indexes and confusion matrices above, and state whether you think there may be overfitting / underfitting phenomena. Compare moreover the various performance of the random forest again the logistic regressor, and draw your conclusions.
From the accuracy numbers we notice that the training set classifications have a much higher performance than the test set classifications. This suggests that there is overfitting present. Notice from the test classification confusion matrix that the algorithm completely fails to correctly predict MS, where it confuses it for AN in all test cases. When comparing the rfc to the logistic regressor we notice a greater amount of overfitting in the rfc, but with the bonus of overall increased accuracy. Accuracy decay was more even over all categories in the logistic regressor, compared to rfc, where we generally observe high classification accuracies across categories except for MS. It is possible that fitting the rfc to all other categories than MS and fitting another classifier to MS would give a much improved overall testing accuracy when used as an ensemble.

0.10 Task 12.10 - SVC

Complete the code below, that implements a support vector classification algorithm.

[160]:
```
# import the relative package
from sklearn.svm import SVC

# allocate the object that will eventually learn the classification rule
svc = SVC(C=2000, # small amount of regularization
          kernel='rbf',
          #degree=3, # Rbf ignores this
          gamma='scale',
          #coef0=0,
          shrinking=True,
          probability=False, # Dont need predict proba
          tol=1e-4,
          #cache_size=200,
          verbose=True,
          max_iter=100000,
          decision_function_shape='ovo')

# do the actual training
svc.fit(X_train, y_train)
```

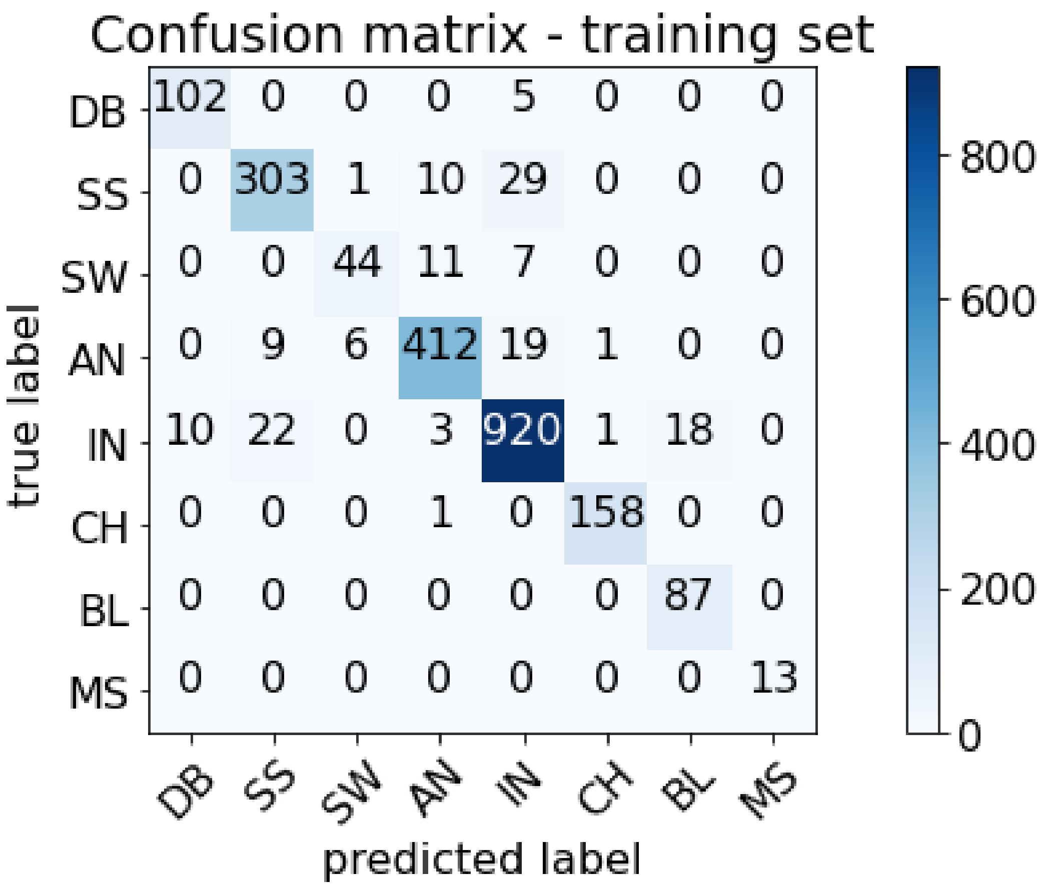
```
[LibSVM]
```

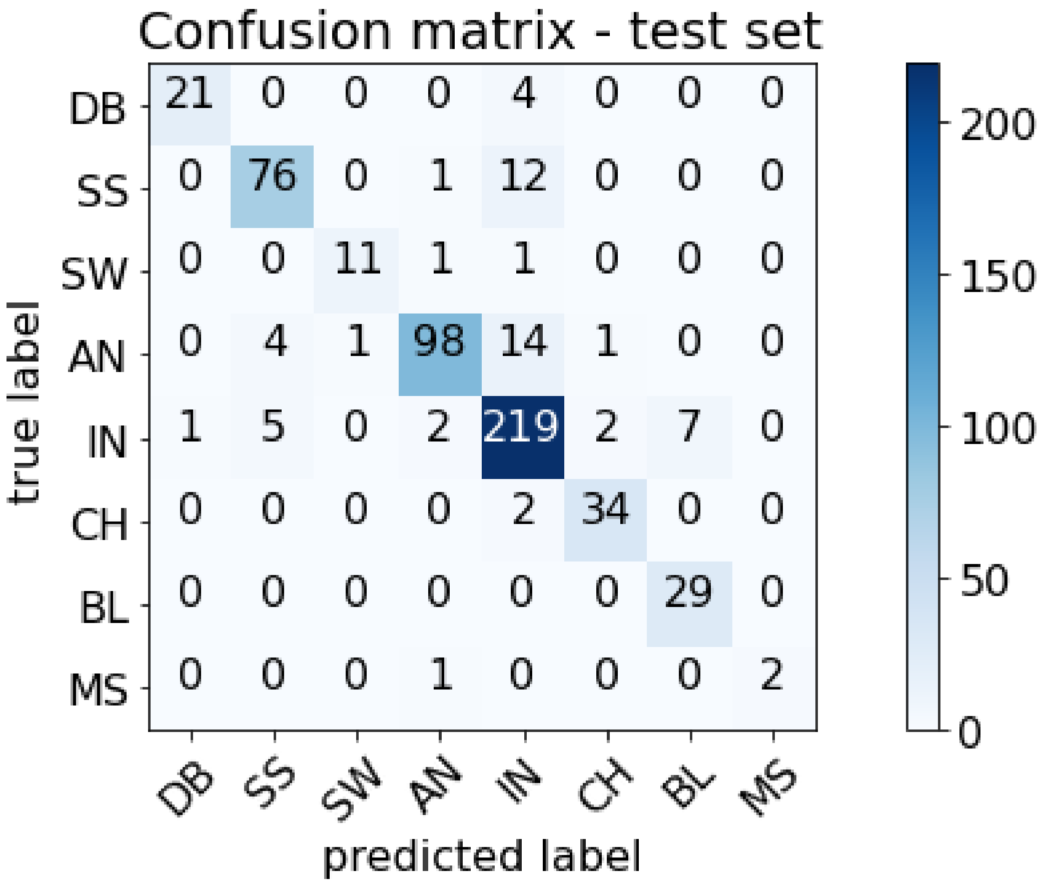
[160]:
```
SVC(C=2000, break_ties=False, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovo', degree=3, gamma='scale', kernel='rbf',
    max_iter=100000, probability=False, random_state=None, shrinking=True,
    tol=0.0001, verbose=True)
```

[161]:
```
# compute the performance indexes on the training and test sets
y_svc_predict_train = svc.predict(X_train)
y_svc_predict_test  = svc.predict(X_test)
#
accuracy_SVC_train = accuracy_score(y_train, y_svc_predict_train)
accuracy_SVC_test  = accuracy_score(y_test,  y_svc_predict_test)

# DEBUG
print("accuracy of SVCs:\n - on the training set: {}\n - on the test set: ␣
 ↪{}".format(accuracy_SVC_train, accuracy_SVC_test))

# compute the confusion matrices on the training and test sets
cm_train = confusion_matrix(y_train, y_svc_predict_train)
cm_test  = confusion_matrix(y_test,  y_svc_predict_test)

# for readability
classes = ['DB', 'SS', 'SW', 'AN', 'IN', 'CH', 'BL', 'MS']
```

```python
# plot the confusion matrices
plot_confusion_matrix(cm_train,
                      classes,
                      normalize=False, # try both "True" and "False"!
                      title='Confusion matrix - training set')
#
plot_confusion_matrix(cm_test,
                      classes,
                      normalize=False, # try both "True" and "False"!
                      title='Confusion matrix - test set')
```

```
accuracy of SVCs:
 - on the training set: 0.9302007299270073
 - on the test set:     0.8925318761384335
```





0.11 Task 12.11

As in Task 12.7 and 12.9, comment the performance indexes and confusion matrices above, and state whether you think there may be overfitting / underfitting phenomena. Compare moreover the various performance of the SVC against the random forest and logistic regressor ones, and draw your conclusions.

SVC seems to be a good combination of random forest and logistic regressor as the overfitting is minimal but the accuracy is on par with or even better than random forest classifier. SVC is the best classifier choice for this dataset.

```
[ ]:
```