analysis-2

May 11, 2020

1 Analysis and Transformation

[1]:
```
%load_ext watermark
```

[2]:
```
%watermark -v -m -p numpy,seaborn,matplotlib,pandas,sklearn -g
```

```
CPython 3.7.3
IPython 7.9.0

numpy 1.18.1
seaborn 0.9.0
matplotlib 3.1.1
pandas 1.0.3
sklearn 0.22.1

compiler   : GCC 7.3.0
system     : Linux
release    : 4.4.0-18362-Microsoft
machine    : x86_64
processor  : x86_64
CPU cores  : 8
interpreter: 64bit
Git hash   : 4fff44c59f50549026bcfcfbc5b596537f00cee7
```

```
/home/hades/anaconda3/envs/test101/lib/python3.7/site-
packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is
deprecated. Use the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

[3]:
```
from matplotlib import pyplot as plt
%matplotlib inline
```

[4]:
```
import seaborn as sns
```

[5]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
```

```
from sklearn.preprocessing import StandardScaler, MinMaxScaler, normalize
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.dummy import DummyClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import f1_score, precision_score, accuracy_score,␣
 ↪recall_score, confusion_matrix, classification_report
```

[6]:
```
SEED = 61
np.random.randome = SEED
```

[7]:
```
df = pd.read_csv('../datasets/train.csv')
```

[8]:
```
mainTest = pd.read_csv('../datasets/test.csv')
```

[9]:
```
df.columns
```

[9]:
```
Index(['blueWardsPlaced', 'blueWardsDestroyed', 'blueFirstBlood', 'blueKills',
       'blueDeaths', 'blueAssists', 'blueDragons', 'blueHeralds',
       'blueTowersDestroyed', 'blueTotalGold', 'blueAvgLevel',
       'blueTotalExperience', 'blueTotalMinionsKilled',
       'blueTotalJungleMinionsKilled', 'redWardsPlaced', 'redWardsDestroyed',
       'redAssists', 'redDragons', 'redHeralds', 'redTowersDestroyed',
       'redTotalGold', 'redAvgLevel', 'redTotalExperience',
       'redTotalMinionsKilled', 'redTotalJungleMinionsKilled', 'blueWins'],
      dtype='object')
```

1.0.1 PreScaling Data

[10]:
```
X = df.loc[:, ~df.columns.isin(['blueFirstBlood', 'blueWins'])]
y = df['blueWins']
firstBld = df['blueFirstBlood']
```

[11]:
```
X1 = mainTest.loc[:, ~mainTest.columns.isin(['blueFirstBlood', 'blueWins'])]
y1 = mainTest['blueWins']
firstBld1 = mainTest['blueFirstBlood']
```

[12]:
```
X.columns
```

[12]:
```
Index(['blueWardsPlaced', 'blueWardsDestroyed', 'blueKills', 'blueDeaths',
       'blueAssists', 'blueDragons', 'blueHeralds', 'blueTowersDestroyed',
       'blueTotalGold', 'blueAvgLevel', 'blueTotalExperience',
```

```
       'blueTotalMinionsKilled', 'blueTotalJungleMinionsKilled',
       'redWardsPlaced', 'redWardsDestroyed', 'redAssists', 'redDragons',
       'redHeralds', 'redTowersDestroyed', 'redTotalGold', 'redAvgLevel',
       'redTotalExperience', 'redTotalMinionsKilled',
       'redTotalJungleMinionsKilled'],
      dtype='object')
```

[13]:
```
ss = StandardScaler()
mm = MinMaxScaler()
```

[14]:
```
Xstd = ss.fit_transform(X)
Xmm = mm.fit_transform(X)
```

[15]:
```
df_ss = pd.DataFrame(Xstd, columns=X.columns)
df_mm = pd.DataFrame(Xmm, columns=X.columns)
```

[16]:
```
df_ss = pd.concat([df_ss, firstBld], axis=1)
df_mm = pd.concat([df_mm, firstBld], axis=1)
```

[17]:
```
ss1 = StandardScaler()
mm1 = MinMaxScaler()

test_ss = ss1.fit_transform(X1)
test_mm = mm1.fit_transform(X1)

test_ss = pd.DataFrame(test_ss, columns=X1.columns)
test_mm = pd.DataFrame(test_mm, columns=X1.columns)

test_ss = pd.concat([test_ss, firstBld1], axis=1)
test_mm = pd.concat([test_mm, firstBld1], axis=1)
```

1.1 Unscaled Data

[18]:
```
steps = {
    'dummy': [('dummy', DummyClassifier())],
    'svc': [('svc', SVC())],
    'log': [('log', LogisticRegression())],
    'rmf': [('rmf', RandomForestClassifier())],
    'knn': [('knn', KNeighborsClassifier())],
    'tree': [('tree', DecisionTreeClassifier())]
}
```

[19]:
```
X_train, X_test, y_train, y_test = train_test_split(df.loc[:, df.columns!
↪='blueWins'], df['blueWins'], test_size=0.3, stratify=df['blueWins'],␣
↪random_state=SEED)
```

[20]:
```
print('Labels counts in y:', np.bincount(df['blueWins']))
print('Labels counts in y_train:', np.bincount(y_train))
print('Labels counts in y_test:', np.bincount(y_test))
```

```
Labels counts in y: [3464 3451]
Labels counts in y_train: [2425 2415]
Labels counts in y_test: [1039 1036]
```

[21]:
```
pipe = {}
for key in steps.keys():
    pipe[key] = Pipeline(steps[key])
    pipe[key].fit(X_train, y_train)
    print('[{}] Classification accuracy without selecting features: {:.3f}'
      .format(key, pipe[key].score(X_test, y_test)))
```

```
[dummy] Classification accuracy without selecting features: 0.506
```

```
/home/hades/anaconda3/envs/test101/lib/python3.7/site-
packages/sklearn/dummy.py:132: FutureWarning: The default value of strategy will
change from stratified to prior in 0.24.
  "stratified to prior in 0.24.", FutureWarning)
```

```
[svc] Classification accuracy without selecting features: 0.727
[log] Classification accuracy without selecting features: 0.727
[rmf] Classification accuracy without selecting features: 0.727
[knn] Classification accuracy without selecting features: 0.695
[tree] Classification accuracy without selecting features: 0.637
```

1.1.1 Standard Scaled Data

[22]:
```
X_train, X_test, y_train, y_test = train_test_split(df_ss, y, test_size=0.3,␣
↪stratify=y, random_state=SEED)
```

[23]:
```
print('Labels counts in y:', np.bincount(df['blueWins']))
print('Labels counts in y_train:', np.bincount(y_train))
print('Labels counts in y_test:', np.bincount(y_test))
```

```
Labels counts in y: [3464 3451]
Labels counts in y_train: [2425 2415]
Labels counts in y_test: [1039 1036]
```

[24]:
```
steps = {
    'dummy': [('dummy', DummyClassifier())],
    'svc': [('svc', SVC())],
    'log': [('log', LogisticRegression())],
    'rmf': [('rmf', RandomForestClassifier())],
```

```
    'knn': [('knn', KNeighborsClassifier())],
    'tree': [('tree', DecisionTreeClassifier())]
}
```

[25]:
```
sspipe = {}
for key in steps.keys():
    sspipe[key] = Pipeline(steps[key])
    sspipe[key].fit(X_train, y_train)
    print('[{}] Classification accuracy without selecting features: {:.3f}'
      .format(key, sspipe[key].score(X_test, y_test)))
```

```
[dummy] Classification accuracy without selecting features: 0.493
```

```
/home/hades/anaconda3/envs/test101/lib/python3.7/site-
packages/sklearn/dummy.py:132: FutureWarning: The default value of strategy will
change from stratified to prior in 0.24.
  "stratified to prior in 0.24.", FutureWarning)
```

```
[svc] Classification accuracy without selecting features: 0.727
[log] Classification accuracy without selecting features: 0.734
[rmf] Classification accuracy without selecting features: 0.721
[knn] Classification accuracy without selecting features: 0.686
[tree] Classification accuracy without selecting features: 0.628
```

1.1.2 MinMax

[26]:
```
steps = {
    'dummy': [('dummy', DummyClassifier())],
    'svc': [('svc', SVC())],
    'log': [('log', LogisticRegression())],
    'rmf': [('rmf', RandomForestClassifier())],
    'knn': [('knn', KNeighborsClassifier())],
    'tree': [('tree', DecisionTreeClassifier())]
}
```

[27]:
```
X_train, X_test, y_train, y_test = train_test_split(df_mm, y, test_size=0.3,␣
 ↪stratify=y, random_state=SEED)
```

[28]:
```
print('Labels counts in y:', np.bincount(y))
print('Labels counts in y_train:', np.bincount(y_train))
print('Labels counts in y_test:', np.bincount(y_test))
```

```
Labels counts in y: [3464 3451]
Labels counts in y_train: [2425 2415]
Labels counts in y_test: [1039 1036]
```

[29]:
```
mmpipe = {}
for key in steps.keys():
    mmpipe[key] = Pipeline(steps[key])
    mmpipe[key].fit(X_train, y_train)
    print('[{}] Classification accuracy without selecting features: {:.3f}'
      .format(key, mmpipe[key].score(X_test, y_test)))
```

```
[dummy] Classification accuracy without selecting features: 0.502
```

```
/home/hades/anaconda3/envs/test101/lib/python3.7/site-
packages/sklearn/dummy.py:132: FutureWarning: The default value of strategy will
change from stratified to prior in 0.24.
  "stratified to prior in 0.24.", FutureWarning)
```

```
[svc] Classification accuracy without selecting features: 0.735
[log] Classification accuracy without selecting features: 0.739
[rmf] Classification accuracy without selecting features: 0.723
[knn] Classification accuracy without selecting features: 0.678
[tree] Classification accuracy without selecting features: 0.629
```

1.1.3 Conclusion on First Run

Logistic Regression seems to pull ahead with scaled or unscaled data

Accuracy Score Table

	Dummy	SVC	Logistic	RandomForest	KNN	DecisionTree
UnScaled	52.4%	72.7%	72.7%	72.5%	69.5%	63.2%
Standard Scaler	49.5%	72.7%	73.4%	71.6%	68.6%	62.6%
MinMax Scale	49.4%	73.5%	73.9%	72.1%	67.8%	63.0%

Feature Importance with random Forests

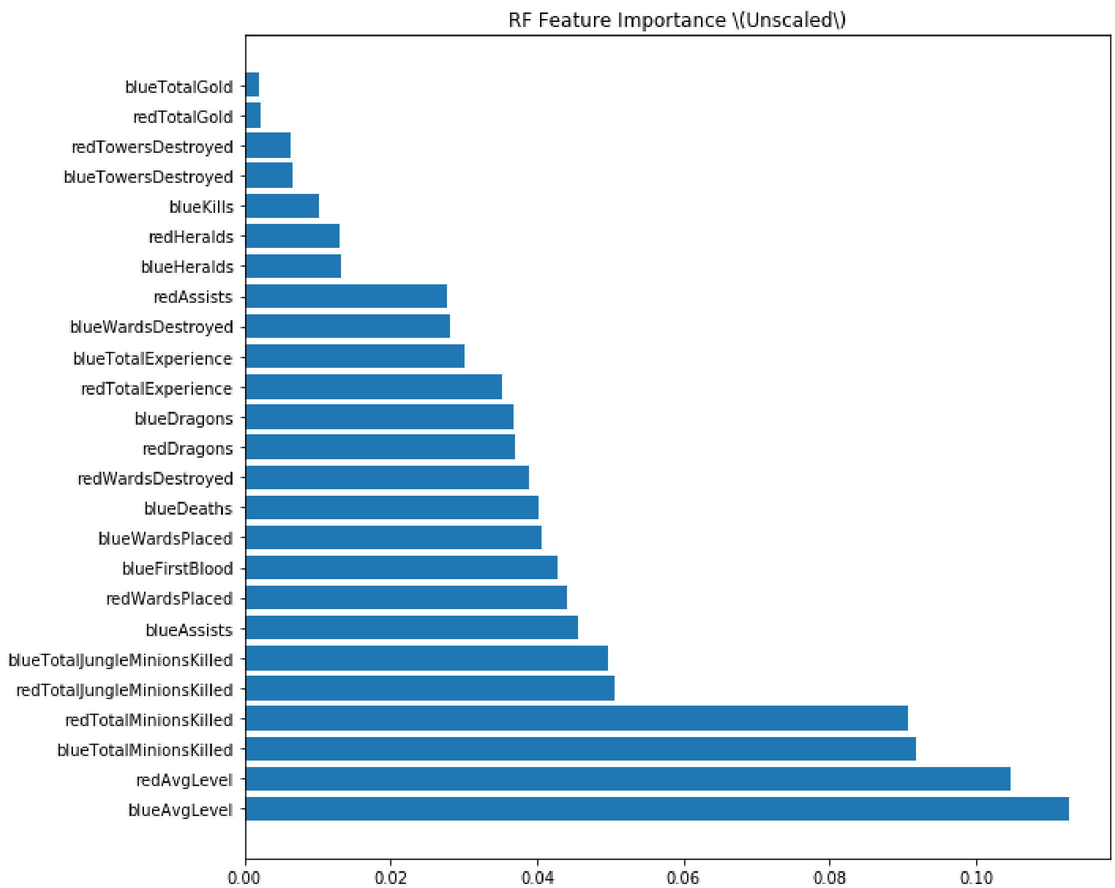
[30]:
```
def featureImp(importance, title):
    cols = X_train.columns
    collen = len(cols)
    indices = np.argsort(importance)[::-1]
#     print(len(importance))
#     print(len(indices))
#     print(collen)
#     for ind in range(collen):
# #         print(ind)
#         print("%2d) %-*s %f" % (ind + 1, 30, cols[indices[ind]],␣
 ↪importance[indices[ind]]))
#         print(ind)
#         print('{} title {}'.format(ind, cols[ind]))
    y_ticks = np.arange(0, collen)
```

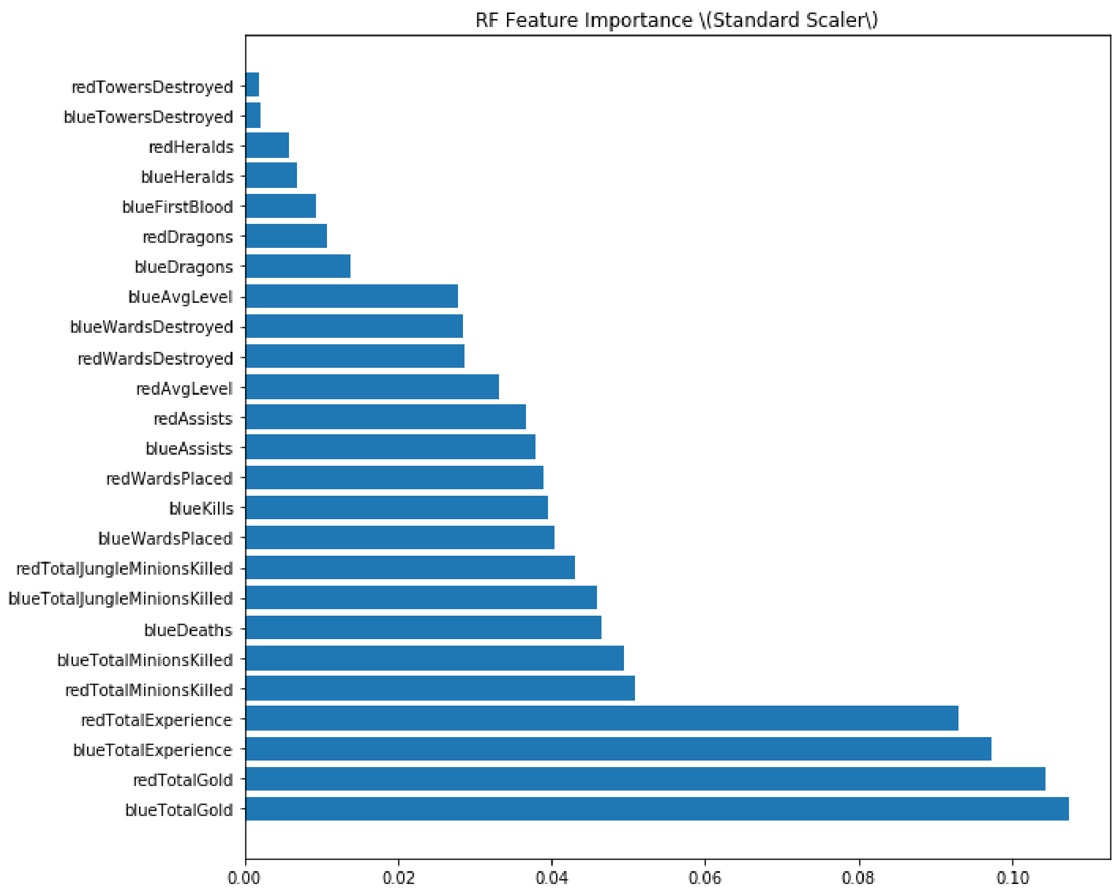
```
    fig, ax = plt.subplots(figsize=(10, 8))
    ax.barh(y_ticks, importance[indices])
    ax.set_yticklabels(cols[indices])
    ax.set_yticks(y_ticks)
    ax.set_title(title)
    fig.tight_layout()
    plt.show()
#     print(indices)
#     plt.figure(figsize= (10,5))
#     print(cols[indices])
#     plt.title('Feature Importance')

#     plt.barh(range(collen), importance[indices], align='center')

#     plt.yticks(range(collen), cols[indices], rotation=0)

#     plt.ylim([-1, len(cols)])

#     plt.tight_layout()
#     plt.show()
```

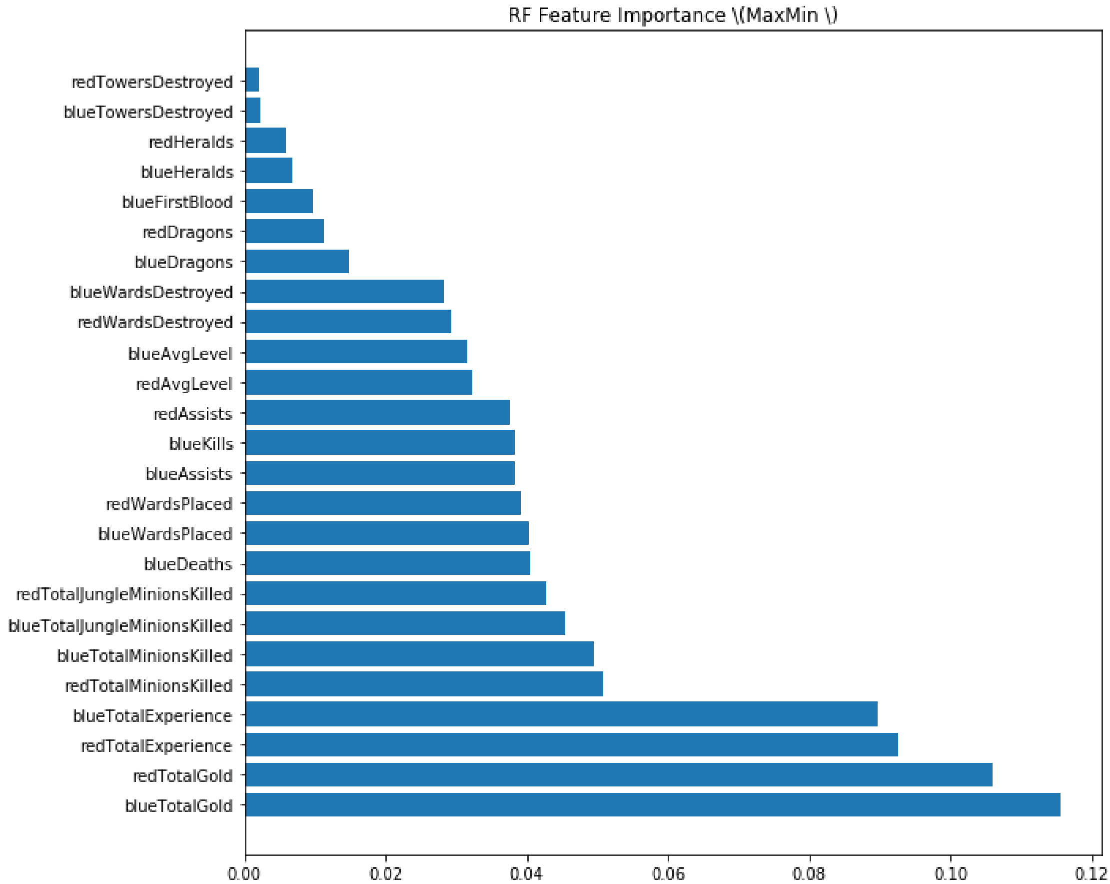
[31]:
```
feature_importances = np.column_stack((pipe['rmf']['rmf'].feature_importances_,␣
↪sspipe['rmf']['rmf'].feature_importances_, mmpipe['rmf']['rmf'].
↪feature_importances_))
```

[32]:
```
featuredf = pd.DataFrame(feature_importances, columns=['Unscaled',␣
↪'StandardScaler', 'MinMax'])
```

[33]:
```
# Unscaled Data
# print(X.columns)
featureImp(pipe['rmf']['rmf'].feature_importances_, 'RF Feature Importance␣
↪\(Unscaled\)')
featureImp(sspipe['rmf']['rmf'].feature_importances_, 'RF Feature Importance␣
↪\(Standard Scaler\)')
featureImp(mmpipe['rmf']['rmf'].feature_importances_, 'RF Feature Importance␣
↪\(MaxMin \)')
```


RF Feature Importance \(Unscaled\)
blueTotalGold
redTotalGold
redTowersDestroyed
blueTowersDestroyed
blueKills
redHeralds
blueHeralds
redAssists
blueWardsDestroyed
blueTotalExperience
redTotalExperience
blueDragons
redDragons
redWardsDestroyed
blueDeaths
blueWardsPlaced
blueFirstBlood
redWardsPlaced
blueAssists
blueTotalJungleMinionsKilled
redTotalJungleMinionsKilled
redTotalMinionsKilled
blueTotalMinionsKilled
redAvgLevel
blueAvgLevel
0.00
0.02
0.04
0.06
0.08
0.10


RF Feature Importance \(Standard Scaler\)
redTowersDestroyed
blueTowersDestroyed
redHeralds
blueHeralds
blueFirstBlood
redDragons
blueDragons
blueAvgLevel
blueWardsDestroyed
redWardsDestroyed
redAvgLevel
redAssists
blueAssists
redWardsPlaced
blueKills
blueWardsPlaced
redTotalJungleMinionsKilled
blueTotalJungleMinionsKilled
blueDeaths
blueTotalMinionsKilled
redTotalMinionsKilled
redTotalExperience
blueTotalExperience
redTotalGold
blueTotalGold
0.00
0.02
0.04
0.06
0.08
0.10



1.2 Testing on Test Data

[34]:
```
# df.loc[:, df.columns!='blueWins'], df['blueWins']
for key in pipe.keys():
    print('[{}] Classification accuracy without selecting features: {:.3f}'
      .format(key, pipe[key].score(mainTest.loc[:, mainTest.columns !=␣
 ↪'blueWins'], mainTest['blueWins'])))
```

```
[dummy] Classification accuracy without selecting features: 0.510
[svc] Classification accuracy without selecting features: 0.737
[log] Classification accuracy without selecting features: 0.738
[rmf] Classification accuracy without selecting features: 0.731
[knn] Classification accuracy without selecting features: 0.680
[tree] Classification accuracy without selecting features: 0.626
```

[35]:
```
for key in sspipe.keys():
    print('[{}] Classification accuracy without selecting features: {:.3f}'
      .format(key, sspipe[key].score(test_ss, y1)))
```

```
[dummy] Classification accuracy without selecting features: 0.502
[svc] Classification accuracy without selecting features: 0.730
[log] Classification accuracy without selecting features: 0.733
[rmf] Classification accuracy without selecting features: 0.732
[knn] Classification accuracy without selecting features: 0.684
[tree] Classification accuracy without selecting features: 0.629
```

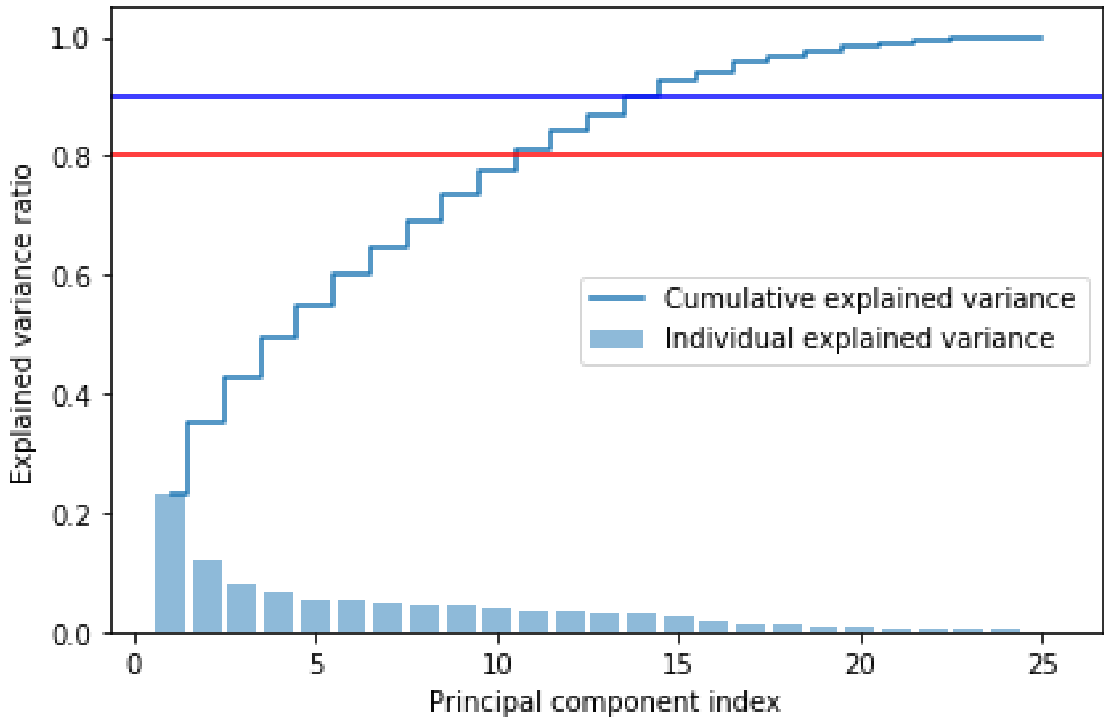
[36]:
```
for key in mmpipe.keys():
    print('[{}] Classification accuracy without selecting features: {:.3f}'
      .format(key, mmpipe[key].score(test_mm, y1)))
```

```
[dummy] Classification accuracy without selecting features: 0.495
[svc] Classification accuracy without selecting features: 0.717
[log] Classification accuracy without selecting features: 0.711
[rmf] Classification accuracy without selecting features: 0.709
[knn] Classification accuracy without selecting features: 0.682
[tree] Classification accuracy without selecting features: 0.621
```

1.3 PCA

[37]:
```
X_train, X_test, y_train, y_test = train_test_split(df_ss, y, test_size=0.3,␣
 ↪stratify=y, random_state=SEED)
```

[38]:
```
cov_mat = np.cov(X_train.T)
eigen_vals, eigen_vecs = np.linalg.eig(cov_mat)

tot = sum(eigen_vals)
var_exp = [(i / tot) for i in sorted(eigen_vals, reverse=True)]
cum_var_exp = np.cumsum(var_exp)
plt.bar(range(1,26), var_exp, alpha=0.5, align='center', label='Individual␣
 ↪explained variance')
plt.step(range(1,26), cum_var_exp, where='mid', label='Cumulative explained␣
 ↪variance')
plt.ylabel('Explained variance ratio')
plt.xlabel('Principal component index')
plt.legend(loc='best')
plt.axhline(y=0.8, color='r', linestyle='-')
plt.axhline(y=0.9, color='b', linestyle='-')
plt.tight_layout()
plt.show()
```



To explain 80% variance of the data more than 10 components are required. And to explain 90% it requires 14 components.

[39]:
```
# Make a list of (eigenvalue, eigenvector) tuples
eigen_pairs = [(np.abs(eigen_vals[i]), eigen_vecs[:, i]) for i in␣
↪range(len(eigen_vals))]

# Sort the (eigenvalue, eigenvector) tuples from high to low
eigen_pairs.sort(key=lambda k: k[0], reverse=True)

w = np.hstack((eigen_pairs[0][1][:, np.newaxis], eigen_pairs[1][1][:, np.
↪newaxis]))
```

[40]:
```
X_train_pca = X_train.dot(w)
```

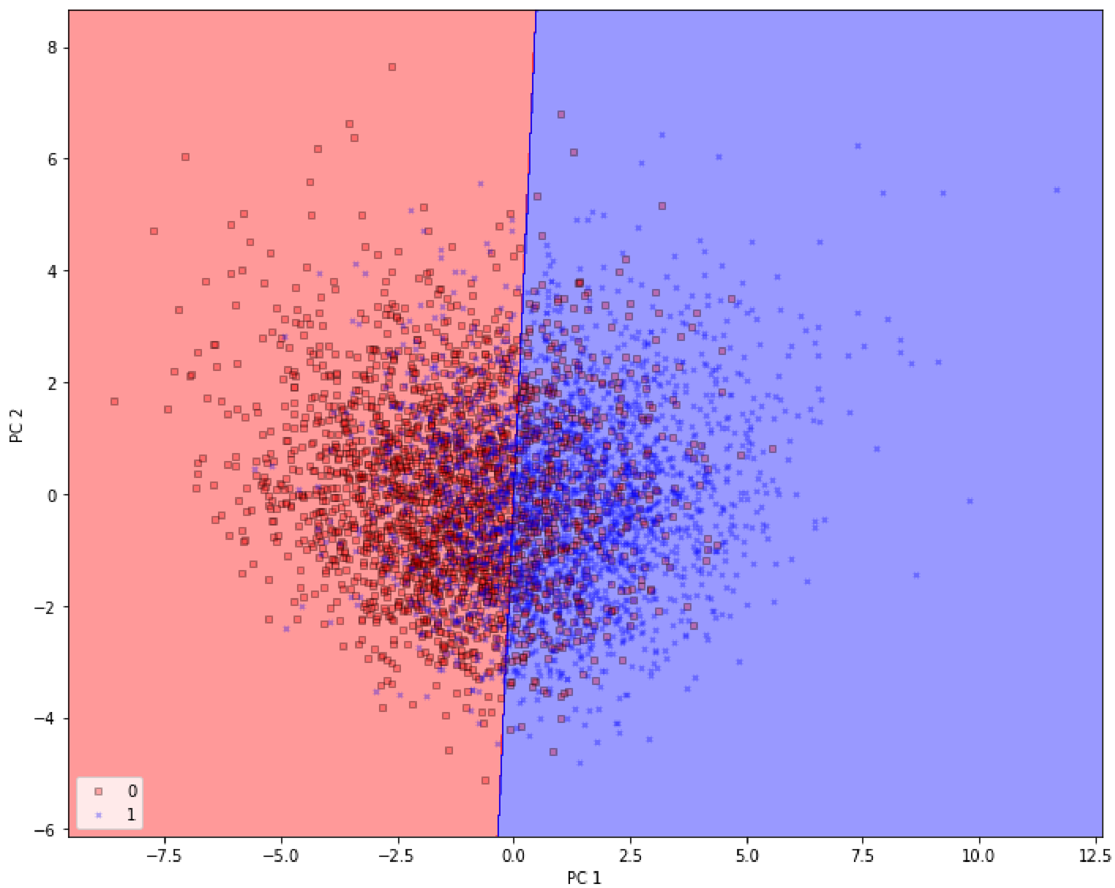
[41]:
```
# colors = ['r', 'b']

# markers = [ 'o', 'x']

# plt.figure(figsize=(15,10))
# for l, c, m in zip(np.unique(y_train), colors, markers):
#         plt.scatter(X_train_pca[y_train==l, 0], X_train_pca[y_train==l, 1],␣
↪c=c, label=l, marker=m, s=7, alpha=0.3)
```

```
# plt.xlabel('PC 1')
# plt.ylabel('PC 2')
# plt.legend(loc='lower left')
# plt.tight_layout()
# plt.show()
```

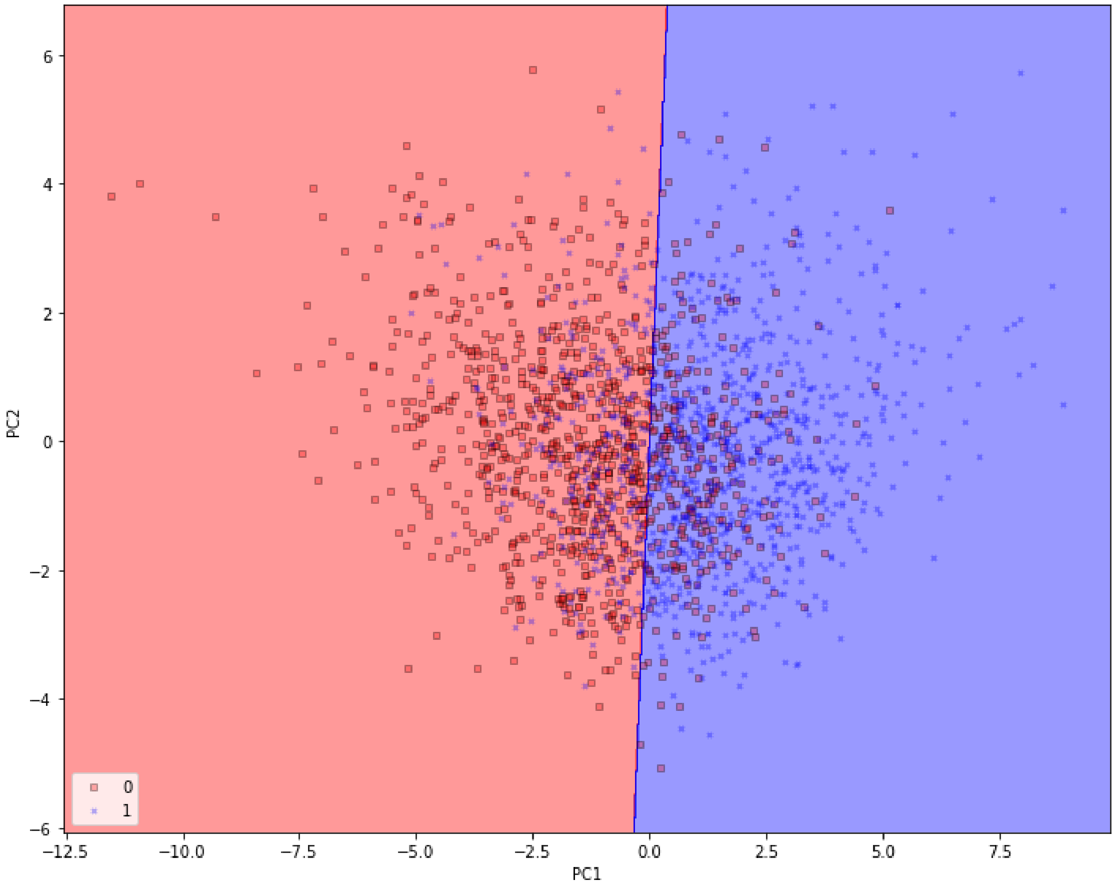
[42]:
```
from matplotlib.colors import ListedColormap
def plot_decision_regions(X, y, classifier, resolution=0.02):

    # setup marker generator and color map
    markers = ('s', 'x', 'o', '^', 'v')
    colors = ('red', 'blue', 'lightgreen', 'gray', 'cyan')
    cmap = ListedColormap(colors[:len(np.unique(y))])

    # plot the decision surface
    x1_min, x1_max = X[:, 0].min() - 1, X[:, 0].max() + 1
    x2_min, x2_max = X[:, 1].min() - 1, X[:, 1].max() + 1
    xx1, xx2 = np.meshgrid(np.arange(x1_min, x1_max, resolution),
                           np.arange(x2_min, x2_max, resolution))
    Z = classifier.predict(np.array([xx1.ravel(), xx2.ravel()]).T)
    Z = Z.reshape(xx1.shape)
    plt.contourf(xx1, xx2, Z, alpha=0.4, cmap=cmap)
    plt.xlim(xx1.min(), xx1.max())
    plt.ylim(xx2.min(), xx2.max())

    # plot examples by class
    for idx, cl in enumerate(np.unique(y)):
        plt.scatter(x=X[y == cl, 0],
                    y=X[y == cl, 1],
                    alpha=0.3,
                    color=cmap(idx),
                    edgecolor='black',
                    marker=markers[idx],
                    label=cl, s= 10)
```

[43]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.decomposition import PCA

# initializing the PCA transformer and
# logistic regression estimator:
pca = PCA(n_components=2)
lr = LogisticRegression(random_state=42)

# dimensionality reduction:
X_train_pca = pca.fit_transform(X_train)
X_test_pca = pca.transform(X_test)
# fitting the logistic regression model on the reduced dataset:
```

```
lr.fit(X_train_pca, y_train)

plt.figure(figsize=(10,8))
plot_decision_regions(X_train_pca, y_train, classifier=lr)

plt.xlabel('PC 1')
plt.ylabel('PC 2')
plt.legend(loc='lower left')
plt.tight_layout()
plt.show()
```



[44]:
```
plt.figure(figsize=(10,8))
plot_decision_regions(X_test_pca, y_test, classifier=lr)
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.legend(loc='lower left')
plt.tight_layout()
plt.show()
```



1.4 Classification LDA

[45]:
```
np.set_printoptions(precision=4)
X_train_std = X_train.to_numpy()
mean_vecs = []
for label in range(0,2):
    mean_vecs.append(np.mean(X_train_std[y_train==label], axis=0))
    print('MV %s: %s\n' %(label, mean_vecs[label-1]))
```

```
MV 0: [-0.0092 -0.0436 -0.3158  0.3389 -0.2464 -0.2089 -0.0716 -0.1228 -0.3965
 -0.3349 -0.3758 -0.2267 -0.1229  0.0273  0.0569  0.283   0.2013  0.0723
  0.0875  0.407   0.358   0.3838  0.208   0.1155  0.4033]

MV 1: [-0.0092 -0.0436 -0.3158  0.3389 -0.2464 -0.2089 -0.0716 -0.1228 -0.3965
 -0.3349 -0.3758 -0.2267 -0.1229  0.0273  0.0569  0.283   0.2013  0.0723
  0.0875  0.407   0.358   0.3838  0.208   0.1155  0.4033]
```

[46]:
```
d = 25 # number of features

S_W = np.zeros((d, d))
for label, mv in zip(range(0, 2), mean_vecs):
    class_scatter = np.zeros((d, d))

for row in X_train_std[y_train == label]:
    row, mv = row.reshape(d, 1), mv.reshape(d, 1)
    class_scatter += (row - mv).dot((row - mv).T)
    S_W += class_scatter

print('Within-class scatter matrix: %sx%s' % ( S_W.shape[0], S_W.shape[1]))
```

```
Within-class scatter matrix: 25x25
```

[47]:
```
 print('Class label distribution: %s'
       % np.bincount(y_train))
```

```
Class label distribution: [2425 2415]
```

[48]:
```
d = 25 # number of features

S_W = np.zeros((d, d))

for label,mv in zip(range(0, 2), mean_vecs):
    class_scatter = np.cov(X_train_std[y_train==label].T)
    S_W += class_scatter

print('Scaled within-class scatter matrix: %sx%s'
        % (S_W.shape[0], S_W.shape[1]))
```

```
Scaled within-class scatter matrix: 25x25
```

[49]:
```
mean_overall = np.mean(X_train_std, axis=0)

d = 25 # number of features

S_B = np.zeros((d, d))

for i, mean_vec in enumerate(mean_vecs):
    n = X_train_std[y_train == i + 1, :].shape[0]
    mean_vec = mean_vec.reshape(d, 1) # make column vector
    mean_overall = mean_overall.reshape(d, 1)
    S_B += n * (mean_vec - mean_overall).dot(
    (mean_vec - mean_overall).T)
print('Between-class scatter matrix: %sx%s' % (S_B.shape[0], S_B.shape[1]))
```

```
Between-class scatter matrix: 25x25
```

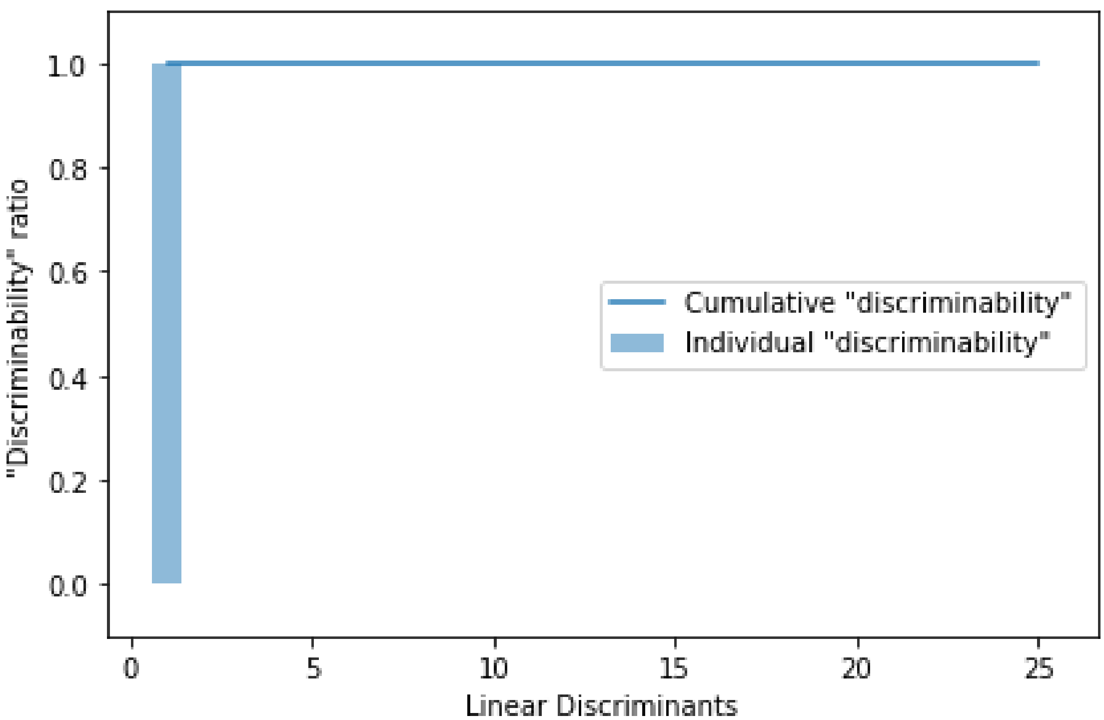
```
[50]: eigen_vals, eigen_vecs = np.linalg.eig(np.linalg.inv(S_W).dot(S_B))
```

```
[51]: eigen_pairs = [(np.abs(eigen_vals[i]), eigen_vecs[:,i]) for i in␣
       ↪range(len(eigen_vals))]

      eigen_pairs = sorted(eigen_pairs, key=lambda k: k[0], reverse=True)

      print('Eigenvalues in descending order:\n')

      for eigen_val in eigen_pairs:
          print(eigen_val[0])
```

```
Eigenvalues in descending order:

455.3388166988832
1.0092435301874656e-12
8.261360329677005e-13
8.261360329677005e-13
6.772193461018064e-13
2.9574204786819156e-13
2.9574204786819156e-13
1.9792573614703075e-13
1.8652311656745798e-13
1.8652311656745798e-13
1.118969669196991e-13
1.118969669196991e-13
8.070745640211005e-14
8.070745640211005e-14
5.638589159112176e-14
5.638589159112176e-14
3.9423048620396975e-14
3.9423048620396975e-14
2.3007749937386383e-14
9.15130715035284e-15
6.232082538961704e-15
6.232082538961704e-15
2.476444962510234e-15
1.991264087950623e-15
0.0
```

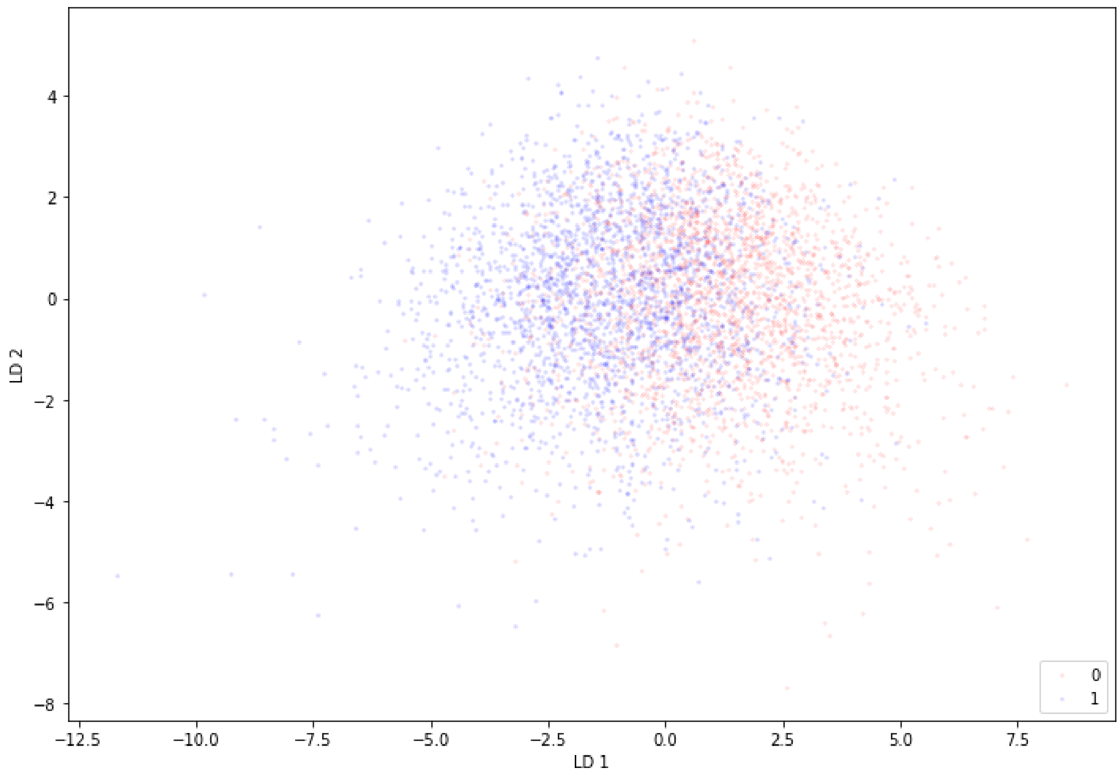
```
[52]: tot = sum(eigen_vals.real)

      discr = [(i / tot) for i in sorted(eigen_vals.real, reverse=True)]

      cum_discr = np.cumsum(discr)
      plt.bar(range(1, 26), discr, alpha=0.5, align='center', label='Individual␣
       ↪"discriminability"')
```

```
plt.step(range(1, 26), cum_discr, where='mid', label='Cumulative␣
↪"discriminability"')

plt.ylabel('"Discriminability" ratio')

plt.xlabel('Linear Discriminants')

plt.ylim([-0.1, 1.1])

plt.legend(loc='best')

plt.tight_layout()

plt.show()
```



[53]:
```
X_train_lda = X_train_std.dot(w)

colors = ['r', 'b']
markers = ['x', 'o']

plt.figure(figsize=(10,7))
```

```
for l, c, m in zip(np.unique(y_train), colors, markers):
     plt.scatter(X_train_lda[y_train==l, 0], X_train_lda[y_train==l, 1] * (-1),
    c=c, label=l, marker=m, s=3, alpha=0.1)

plt.xlabel('LD 1')
plt.ylabel('LD 2')
plt.legend(loc='lower right')
plt.tight_layout()
plt.show()
```



[54]:
```
from sklearn.base import BaseEstimator
from sklearn.base import ClassifierMixin
from sklearn.preprocessing import LabelEncoder
from sklearn.base import clone
from sklearn.pipeline import _name_estimators
import numpy as np
import operator
class MajorityVoteClassifier(BaseEstimator,
                             ClassifierMixin):
    """ A majority vote ensemble classifier

    Parameters
```

```python
    ----------
    classifiers : array-like, shape = [n_classifiers]
      Different classifiers for the ensemble

    vote : str, {'classlabel', 'probability'}
      Default: 'classlabel'
      If 'classlabel' the prediction is based on
      the argmax of class labels. Else if
      'probability', the argmax of the sum of
      probabilities is used to predict the class label
      (recommended for calibrated classifiers).

    weights : array-like, shape = [n_classifiers]
      Optional, default: None
      If a list of `int` or `float` values are
      provided, the classifiers are weighted by
      importance; Uses uniform weights if `weights=None`.

    """
    def __init__(self, classifiers,
                 vote='classlabel', weights=None):

        self.classifiers = classifiers
        self.named_classifiers = {key: value for
                                  key, value in
                                  _name_estimators(classifiers)}
        self.vote = vote
        self.weights = weights

    def fit(self, X, y):
        """ Fit classifiers.

        Parameters
        ----------
        X : {array-like, sparse matrix},
            shape = [n_examples, n_features]
            Matrix of training examples.

        y : array-like, shape = [n_examples]
            Vector of target class labels.

        Returns
        -------
        self : object

        """
        if self.vote not in ('probability', 'classlabel'):
```

```
            raise ValueError("vote must be 'probability'"
                             "or 'classlabel'; got (vote=%r)"
                             % self.vote)
        if self.weights and len(self.weights) != len(self.classifiers):
            raise ValueError("Number of classifiers and weights"
                             "must be equal; got %d weights,"
                             "%d classifiers"
                             % (len(self.weights),
                             len(self.classifiers)))
        # Use LabelEncoder to ensure class labels start
        # with 0, which is important for np.argmax
        # call in self.predict
        self.lablenc_ = LabelEncoder()
        self.lablenc_.fit(y)
        self.classes_ = self.lablenc_.classes_
        self.classifiers_ = []
        for clf in self.classifiers:
            fitted_clf = clone(clf).fit(X,
                               self.lablenc_.transform(y))
            self.classifiers_.append(fitted_clf)
        return self

    def predict(self, X):
        """ Predict class labels for X.

        Parameters
        ----------
        X : {array-like, sparse matrix},
            Shape = [n_examples, n_features]
            Matrix of training examples.

        Returns
        ----------
        maj_vote : array-like, shape = [n_examples]
            Predicted class labels.

        """
        if self.vote == 'probability':
            maj_vote = np.argmax(self.predict_proba(X), axis=1)
        else: # 'classlabel' vote

            # Collect results from clf.predict calls
            predictions = np.asarray([clf.predict(X)
                                      for clf in
                                      self.classifiers_]).T

            maj_vote = np.apply_along_axis(lambda x: np.argmax(
```

```
                                          np.bincount(x,
                                          weights=self.weights)),
                                          axis=1,
                                          arr=predictions)
        maj_vote = self.lablenc_.inverse_transform(maj_vote)
        return maj_vote

    def predict_proba(self, X):
        """ Predict class probabilities for X.

        Parameters
        ----------
        X : {array-like, sparse matrix},
            shape = [n_examples, n_features]
            Training vectors, where
            n_examples is the number of examples and
            n_features is the number of features.

        Returns
        ----------
        avg_proba : array-like,
            shape = [n_examples, n_classes]
            Weighted average probability for
            each class per example.

        """
        probas = np.asarray([clf.predict_proba(X)
                             for clf in self.classifiers_])
        avg_proba = np.average(probas, axis=0,
                               weights=self.weights)
        return avg_proba

    def get_params(self, deep=True):
        """ Get classifier parameter names for GridSearch"""
        if not deep:
            return super(MajorityVoteClassifier,
                         self).get_params(deep=False)
        else:
            out = self.named_classifiers.copy()
            for name, step in self.named_classifiers.items():
                for key, value in step.get_params(
                        deep=True).items():
                    out['%s__%s' % (name, key)] = value
            return out
```

[55]:

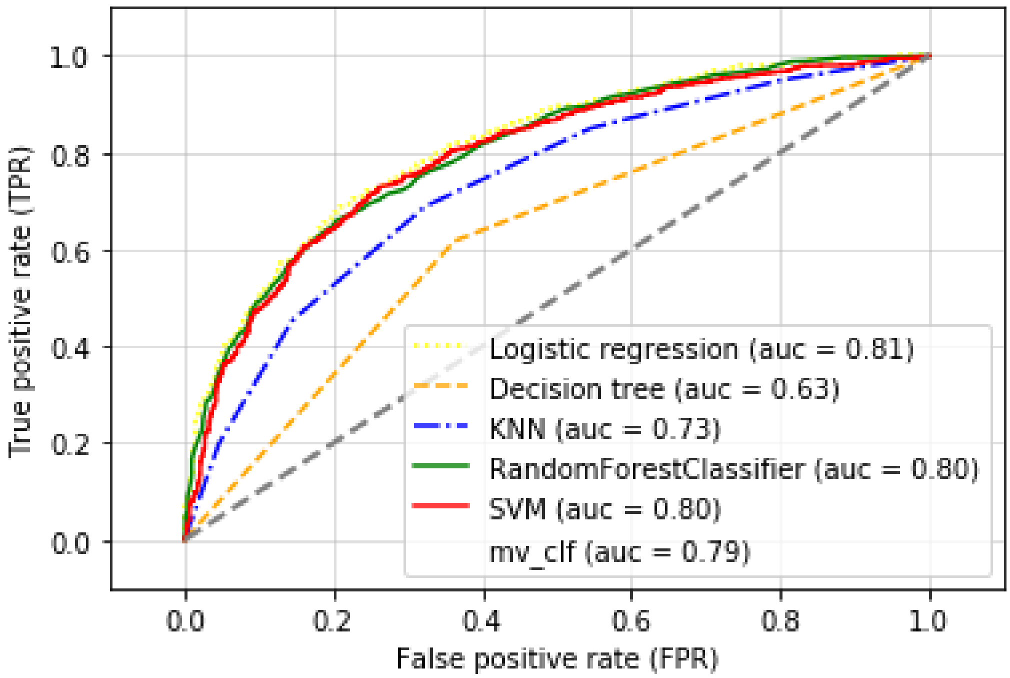
```
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import Pipeline
```

```python
clf1 = LogisticRegression(random_state=42)
clf2 = DecisionTreeClassifier(random_state=42)
clf3 = KNeighborsClassifier()
clf4 = RandomForestClassifier(random_state=42)
clf5 = SVC(random_state=42, probability = True)

pipe1 = Pipeline([['sc', StandardScaler()], ['clf', clf1]])
pipe3 = Pipeline([['sc', StandardScaler()], ['clf', clf3]])
pipe5 = Pipeline([['sc', StandardScaler()], ['clf', clf5]])
mv_clf = MajorityVoteClassifier(classifiers=[pipe1, clf2, pipe3, clf4, pipe5])

clf_labels = ['Logistic regression', 'Decision tree', 'KNN',␣
↪'RandomForestClassifier', 'SVM', 'mv_clf']

print('10-fold cross validation:\n')
for clf, label in zip([pipe1, clf2, pipe3, clf4, pipe5, mv_clf], clf_labels):
    scores = cross_val_score(estimator=clf, X=X_train, y=y_train, cv=10,␣
↪scoring='roc_auc')
    print("ROC AUC: %0.2f (+/- %0.2f) [%s]"
          % (scores.mean(), scores.std(), label))
```

```
10-fold cross validation:

ROC AUC: 0.80 (+/- 0.02) [Logistic regression]
ROC AUC: 0.62 (+/- 0.02) [Decision tree]
ROC AUC: 0.73 (+/- 0.02) [KNN]
ROC AUC: 0.79 (+/- 0.02) [RandomForestClassifier]
ROC AUC: 0.78 (+/- 0.02) [SVM]
ROC AUC: 0.78 (+/- 0.02) [mv_clf]
```

[56]:
```python
from sklearn.metrics import roc_curve
from sklearn.metrics import auc

colors = ['yellow', 'orange', 'b', 'green', 'r', 'black']
all_clf = [pipe1, clf2, pipe3, clf4, pipe5, mv_clf]
linestyles = [':', '--', '-.', '-', 'solid', '']


for clf, label, clr, ls \
    in zip(all_clf, clf_labels, colors, linestyles):
    # assuming the label of the positive class is 1
    y_pred = clf.fit(X_train, y_train).predict_proba(X_test)[:, 1]
    fpr, tpr, thresholds = roc_curve(y_true=y_test, y_score=y_pred)
    roc_auc = auc(x=fpr, y=tpr)
    plt.plot(fpr, tpr, color=clr, linestyle=ls, label='%s (auc = %0.2f)' %␣
↪(label, roc_auc))
```

```
plt.legend(loc='lower right')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray', linewidth=2)
plt.xlim([-0.1, 1.1])
plt.ylim([-0.1, 1.1])
plt.grid(alpha=0.5)
plt.xlabel('False positive rate (FPR)')
plt.ylabel('True positive rate (TPR)')
plt.show()
```



[67]:
```
from sklearn.model_selection import GridSearchCV

lr = LogisticRegression(random_state=42, C = 1)

param_grid = {'C': [0.001, 0.1, 10, 100.0]}

lr_cv = GridSearchCV(lr, param_grid, cv=10)
lr_cv.fit(X_train, y_train)

print(lr_cv.best_params_)
print(lr_cv.best_score_)
```

```
{'C': 0.1}
0.7303719008264464
```

[68]:
```
param_grid = {'n_neighbors': np.arange(1,25)}

knn = KNeighborsClassifier()
knn_cv = GridSearchCV(knn, param_grid, cv=10)

knn_cv.fit(X_train,y_train)
print(knn_cv.best_params_)
print(knn_cv.best_score_)
```

```
{'n_neighbors': 24}
0.7039256198347108
```

[69]:
```
from sklearn.pipeline import make_pipeline

pipe_lr = make_pipeline(PCA(n_components=2),
                        LogisticRegression(random_state=42, solver='lbfgs'))
pipe_lr.fit(X_train, y_train)
y_pred = pipe_lr.predict(X_test)
print('Test Accuracy: %.3f' % pipe_lr.score(X_test, y_test))
```

```
Test Accuracy: 0.728
```

[70]:
```
pipe_svc = make_pipeline(SVC(random_state=42))

param_range = [0.0001, 0.001, 0.01, 0.1, 1.0, 10.0, 100.0, 1000.0]

param_grid = [{'svc__C': param_range, 'svc__kernel': ['linear']},
              {'svc__C': param_range,'svc__gamma': param_range,'svc__kernel':␣
 ↪['rbf']}]

gs = GridSearchCV(estimator=pipe_svc, param_grid=param_grid,␣
 ↪scoring='accuracy',cv=10,refit=True,n_jobs=-1)

gs = gs.fit(X_train, y_train)
print(gs.best_score_)
print(gs.best_params_)
```

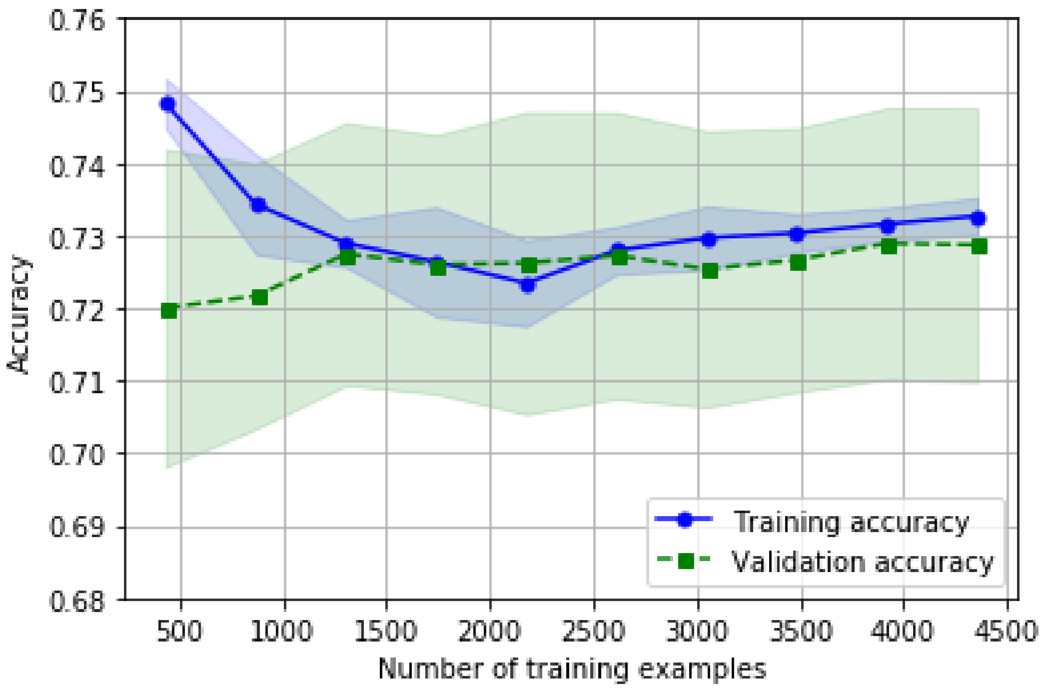
```
0.7276859504132231
{'svc__C': 10.0, 'svc__kernel': 'linear'}
```

[71]:
```
from sklearn.naive_bayes import GaussianNB

gaus = Gaussmake_pipelinegaus.fit(X_train, y_train)

ypred = gaus.predict(X_test)

# get the accuracy score
```

```
acc_nb = accuracy_score(ypred, y_test)
print(acc_nb)
```

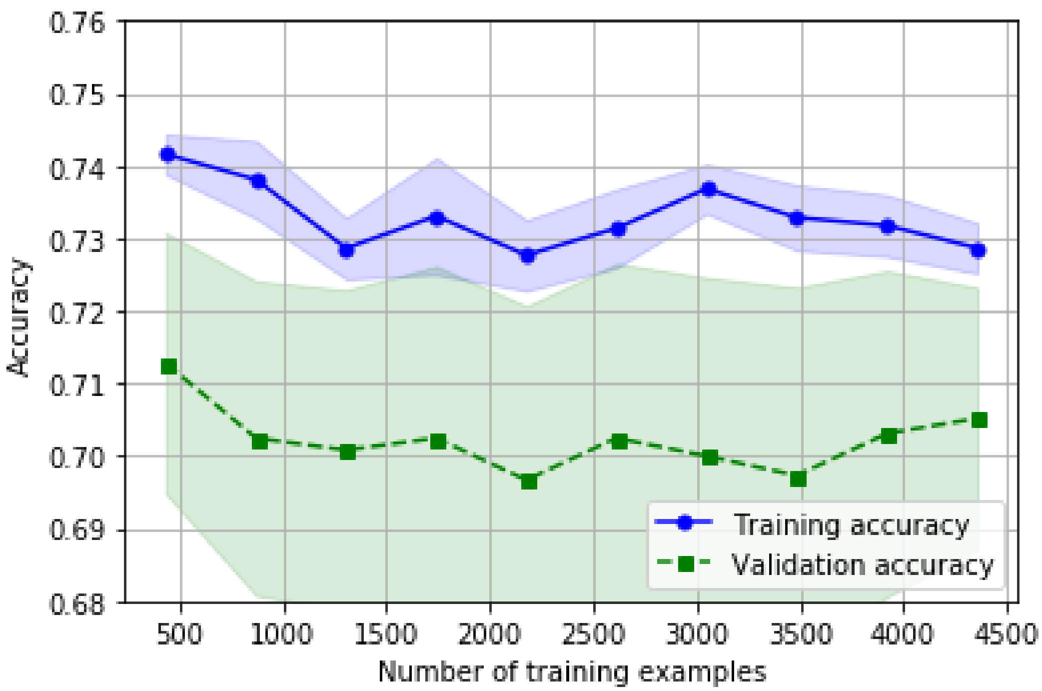
0.7253012048192771

[61]:
```
from sklearn.model_selection import learning_curve

pipe_lr = make_pipeline(LogisticRegression(random_state= 42, C=0.1))



train_sizes, train_scores, test_scores =␣
↪learning_curve(estimator=pipe_lr,X=X_train,
                                    y=y_train, train_sizes=np.linspace(0.1, 1.
↪0, 10), cv=10, n_jobs=1)

train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

plt.plot(train_sizes, train_mean, color='blue', marker='o', markersize=5,␣
↪label='Training accuracy')
plt.fill_between(train_sizes,train_mean + train_std, train_mean -␣
↪train_std,alpha=0.15, color='blue')

plt.plot(train_sizes, test_mean,color='green', linestyle='--', marker='s',␣
↪markersize=5,label='Validation accuracy')

plt.fill_between(train_sizes, test_mean + test_std, test_mean - test_std,␣
↪alpha=0.15, color='green')

plt.grid()

plt.xlabel('Number of training examples')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
plt.ylim([0.68, 0.76])
plt.show()
```



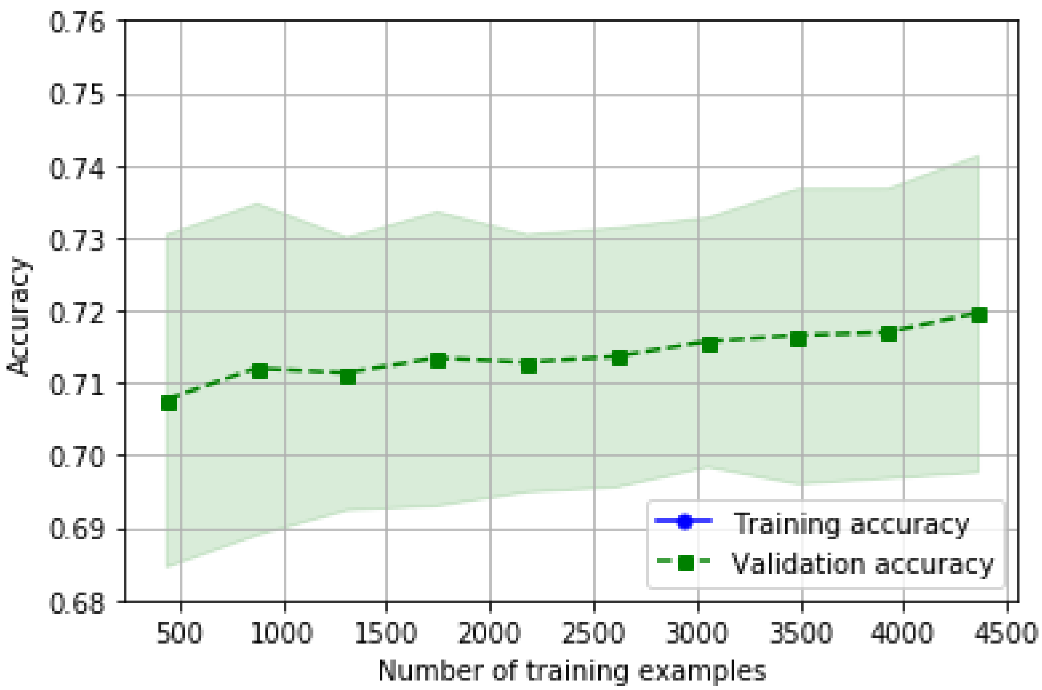
[62]:
```
pipe_knn = make_pipeline(KNeighborsClassifier(n_neighbors=23))


train_sizes, train_scores, test_scores =␣
 ↪learning_curve(estimator=pipe_knn,X=X_train,
                                    y=y_train, train_sizes=np.linspace(0.1, 1.
 ↪0, 10), cv=10, n_jobs=1)

train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

plt.plot(train_sizes, train_mean, color='blue', marker='o', markersize=5,␣
 ↪label='Training accuracy')
plt.fill_between(train_sizes,train_mean + train_std, train_mean -␣
 ↪train_std,alpha=0.15, color='blue')

plt.plot(train_sizes, test_mean,color='green', linestyle='--', marker='s',␣
 ↪markersize=5,label='Validation accuracy')

plt.fill_between(train_sizes, test_mean + test_std, test_mean - test_std,␣
 ↪alpha=0.15, color='green')
```

```
plt.grid()

plt.xlabel('Number of training examples')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
plt.ylim([0.68, 0.76])
plt.show()
```



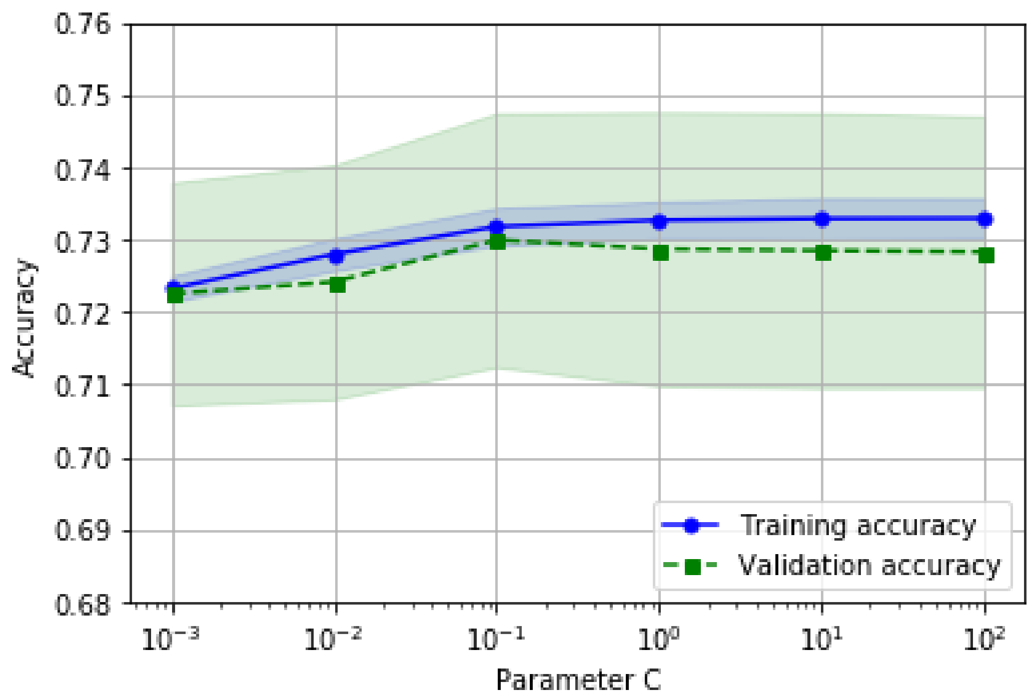
[63]:
```
svm_lr = make_pipeline(SVC(random_state= 42, C=100.0))



train_sizes, train_scores, test_scores = learning_curve(estimator=svm_lr,␣
 ↪X=X_train,
                                        y=y_train, train_sizes=np.linspace(0.1, 1.
 ↪0, 10), cv=10, n_jobs=1)

train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

plt.plot(train_sizes, train_mean, color='blue', marker='o', markersize=5,␣
 ↪label='Training accuracy')
```

```
plt.fill_between(train_sizes,train_mean + train_std, train_mean -␣
 ↪train_std,alpha=0.15, color='blue')

plt.plot(train_sizes, test_mean,color='green', linestyle='--', marker='s',␣
 ↪markersize=5,label='Validation accuracy')

plt.fill_between(train_sizes, test_mean + test_std, test_mean - test_std,␣
 ↪alpha=0.15, color='green')

plt.grid()

plt.xlabel('Number of training examples')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
plt.ylim([0.68, 0.76])
plt.show()
```



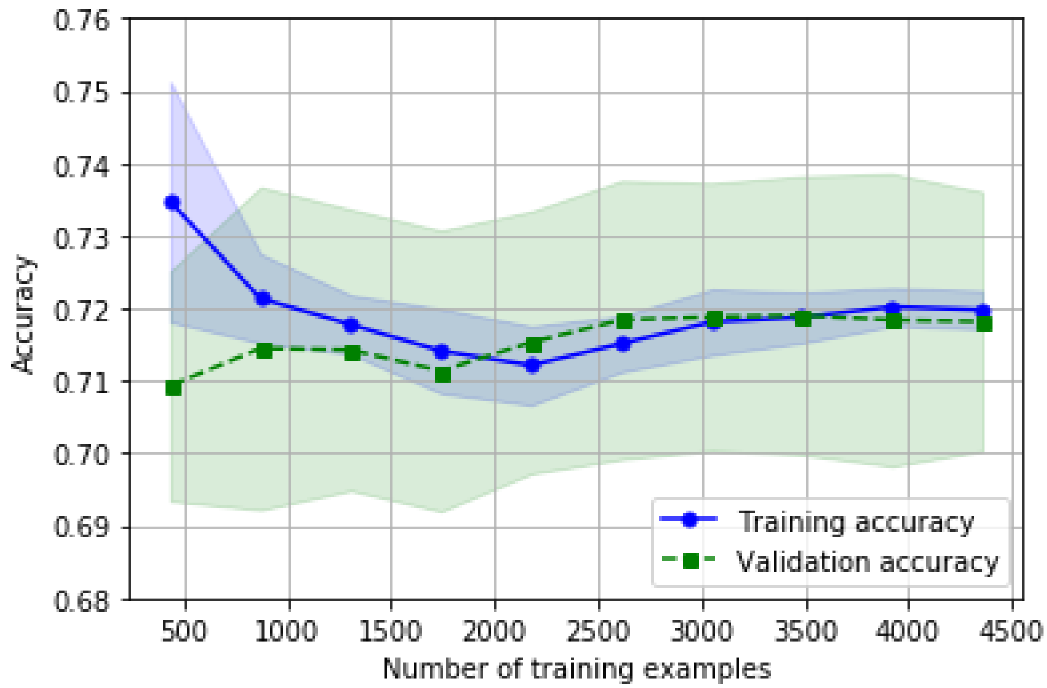
[64]:
```
from sklearn.model_selection import validation_curve

param_range = [0.001, 0.01, 0.1, 1.0, 10.0, 100.0]
train_scores, test_scores = validation_curve(estimator=pipe_lr,X=X_train,
                            y=y_train, param_name='logisticregression__C',␣
 ↪param_range=param_range,cv=10)
```

```
train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

plt.plot(param_range, train_mean, color='blue', marker='o',markersize=5,␣
 ↪label='Training accuracy')
plt.fill_between(param_range, train_mean + train_std,train_mean - train_std,␣
 ↪alpha=0.15, color='blue')

plt.plot(param_range, test_mean,  color='green', linestyle='--', marker='s',␣
 ↪markersize=5,label='Validation accuracy')

plt.fill_between(param_range, test_mean + test_std, test_mean - test_std,␣
 ↪alpha=0.15, color='green')

plt.grid()
plt.xscale('log')
plt.legend(loc='lower right')
plt.xlabel('Parameter C')
plt.ylabel('Accuracy')
plt.ylim([0.68, 0.76])
plt.show()
```



[72]:

```
pipe_gaus = make_pipeline(GaussianNB())


train_sizes, train_scores, test_scores =␣
↪learning_curve(estimator=pipe_gaus,X=X_train,
                                    y=y_train, train_sizes=np.linspace(0.1, 1.
↪0, 10), cv=10, n_jobs=1)

train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)
test_mean = np.mean(test_scores, axis=1)
test_std = np.std(test_scores, axis=1)

plt.plot(train_sizes, train_mean, color='blue', marker='o', markersize=5,␣
↪label='Training accuracy')
plt.fill_between(train_sizes,train_mean + train_std, train_mean -␣
↪train_std,alpha=0.15, color='blue')

plt.plot(train_sizes, test_mean,color='green', linestyle='--', marker='s',␣
↪markersize=5,label='Validation accuracy')

plt.fill_between(train_sizes, test_mean + test_std, test_mean - test_std,␣
↪alpha=0.15, color='green')

plt.grid()

plt.xlabel('Number of training examples')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
plt.ylim([0.68, 0.76])
plt.show()
```



[75]:
```
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import Pipeline
from sklearn.ensemble import VotingClassifier

clf1 = LogisticRegression(random_state=42, C=0.1) # Optimal Logistic Regression
clf2 = GaussianNB()
# clf4 = RandomForestClassifier(random_state=42)
clf5 = SVC(random_state=42, probability = True, C=100.0, kernel='linear')

voting_clf = VotingClassifier(estimators=[('lr', clf1), ('gaussian', clf2),␣
 ↪('svc', clf5)])

voting_clf.fit(X_train, y_train)
print('Accuracty : {}'.format(voting_clf.score(X_test, y_test)))
# print("ROC AUC: %0.2f (+/- %0.2f) [%s]"
#         % (scores.mean(), scores.std(), label))
```

```
Accuracty : 0.7330120481927711
```

1.4.1 Using Real Test Set

[78]:
```
y_test_pred = voting_clf.predict(test_ss)
print('Accuracy :  {}'.format(accuracy_score(y1, y_test_pred)))
```

```
Accuracy :  0.7365047233468286
```

[ ]:
```
```