19075153_O'Leary_PartB2

September 11, 2021

[1]:

```
# Feature Extraction with Univariate Statistical Tests (Chi-squared for␣
 ↪classification)
import pandas
import numpy as np
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.feature_selection import RFE
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score
from sklearn.decomposition import PCA
```

1 Data pre-processing performed

[2]:

```
# load data
path = "Autism-Screening-Child-Data Plus Description/Autism-Child-Data.arff"
from scipy.io.arff import loadarff
raw_data = loadarff(path)
df_data = pandas.DataFrame(raw_data[0])

# Remove the b'' from the data
str_df = df_data.select_dtypes([np.object])
str_df = str_df.stack().str.decode('utf-8').unstack()
for col in str_df:
    df_data[col] = str_df[col]

# Make the whole lot categorical
list_of_columns = df_data.columns
df_data[list_of_columns] = df_data[list_of_columns].apply(lambda col:pandas.
 ↪Categorical(col).codes)

# Remove all rows with negative values
df_data = df_data[(df_data >= 0).all(1)]
```

```python
# split the data to X and y
X = df_data.loc[:, df_data.columns != 'result']
Y = df_data.iloc[:, 17]
#with pandas.option_context('display.max_rows', None, 'display.max_columns',␣
↪None):
#    print(df_data)
df_data
```

```
<ipython-input-2-b56ce8af1f47>:8: DeprecationWarning: `np.object` is a
deprecated alias for the builtin `object`. To silence this warning, use `object`
by itself. Doing this will not modify any behavior and is safe.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  str_df = df_data.select_dtypes([np.object])
```

[2]:

```
     A1_Score  A2_Score  A3_Score  A4_Score  A5_Score  A6_Score  A7_Score  \
0           1         1         0         0         1         1         0
1           1         1         0         0         1         1         0
2           1         1         0         0         0         1         1
3           0         1         0         0         1         1         0
4           1         1         1         1         1         1         1
..        …       …       …       …       …       …       …
287         1         1         1         1         1         1         1
288         1         0         0         0         1         0         1
289         1         0         1         1         1         1         1
290         1         1         1         0         1         1         1
291         0         0         1         0         1         0         1

     A8_Score  A9_Score  A10_Score  …  gender  ethnicity  jundice  austim  \
0           1         0          0  …       1          6        0       0
1           1         0          0  …       1          5        0       0
2           1         0          0  …       1          0        0       0
3           0         0          1  …       0          0        1       0
4           1         1          1  …       1          6        1       0
..        …       …        …  …  …     …       …      …
287         1         1          1  …       0         10        1       1
288         0         0          1  …       0         10        1       1
289         0         0          1  …       1          4        0       0
290         1         1          1  …       1          8        0       0
291         0         0          0  …       0          8        0       0

     contry_of_res  used_app_before  result  age_desc  relation  Class/ASD
0               24                0       5         0         2          0
1               24                0       5         0         2          0
2               24                1       5         0         0          0
3               24                0       4         0         0          0
4               51                0      10         0         2          1
```

```
..                …           …    …      …      …       …
287              50           0   10      0      2          1
288               3           0    4      0      2          0
289               8           0    7      0      2          1
290              18           0    9      0      2          1
291              18           0    3      0      2          0

[288 rows x 21 columns]
```

2 Feature selection

[3]:
```
# generate model and get accuracy
def get_accuracy(target_train, target_test, predicted_test, predicted_train):
    clf = MLPClassifier(activation='logistic', solver='sgd',␣
 ↪learning_rate_init=0.1, alpha=1e-5, hidden_layer_sizes=(5, 2),␣
 ↪random_state=1,max_iter=2000)
    clf.fit(predicted_train, np.ravel(target_train, order='C'))
    predictions = clf.predict(predicted_test)
    return accuracy_score(target_test, predictions)

pred_train, pred_test, tar_train, tar_test = train_test_split(X, Y, test_size=.
 ↪3, random_state=4)
print("Accuracy score of our model without feature selection : %.2f" %␣
 ↪get_accuracy(tar_train, tar_test, pred_test, pred_train))

# feature extraction
test = SelectKBest(score_func=chi2, k=5)
fit = test.fit(X, Y)
# summarize scores
np.set_printoptions(precision=3)
print(fit.scores_)
features = fit.transform(X)
# summarize selected features
print(features[0:5, :],"summerize features")
print()
# Now apply only the K most significant features according to the chi square␣
 ↪method
pred_features = features[:, 0:5]
pred_train, pred_test, tar_train, tar_test = train_test_split(pred_features, Y,␣
 ↪test_size=.3, random_state=2)
print("Accuracy score of our model with chi square feature selection : %.2f" %␣
 ↪get_accuracy(tar_train, tar_test, pred_test,pred_train))
print()

## Feature Importance with Extra Trees Classifier
from sklearn.feature_selection import SelectFromModel
```

```
# Feature Extraction with RFE
model = LogisticRegression()  # Logistic regression is the Wrapper classifier␣
 ↪here
rfe = RFE(model, 5)
fit = rfe.fit(X, Y)
## summarize components
#print("Num Features: %d" % (fit.n_features_))
#print("Selected Features: %s" % (fit.support_))
#print("Feature Ranking: %s" % (fit.ranking_))
## Now apply only the K most significant features according to the RFE feature␣
 ↪selection method
features = fit.transform(X)
pred_features = features[:, 0:5]
pred_train, pred_test, tar_train, tar_test = train_test_split(pred_features, Y,␣
 ↪test_size=.3, random_state=2)
print("Accuracy score of our model with RFE selection : %.2f" %␣
 ↪get_accuracy(tar_train, tar_test, pred_test,pred_train))
print()

## Feature Extraction with PCA
## feature extraction
pca = PCA(n_components=5)
fit = pca.fit(X)
features = fit.transform(X)
## summarize components
#print("Explained Variance: %s" % (fit.explained_variance_ratio_))
#print(fit.components_)
## Now apply only the K most significant faetures (components) according to the␣
 ↪PCA feature selection method
#features = fit.transform(X)
pred_features = features[:, 0:5]
pred_train, pred_test, tar_train, tar_test = train_test_split(pred_features, Y,␣
 ↪test_size=.3, random_state=2)
print("Accuracy score of our model with PCA selection : %.2f" %␣
 ↪get_accuracy(tar_train, tar_test, pred_test,pred_train))
print()

## Feature Importance with Extra Trees Classifier
from sklearn.ensemble import ExtraTreesClassifier
## feature extraction
model = ExtraTreesClassifier(max_depth=3,min_samples_leaf=2)
fit = model.fit(X, Y)
print(model.feature_importances_)
print()
t = SelectFromModel(fit, prefit=True)
features = t.transform(X)
```

```
pred_features = features[:, 0:5]
pred_train, pred_test, tar_train, tar_test = train_test_split(pred_features, Y,␣
 ↪test_size=.3, random_state=2)
print("Accuracy score of our model with Extra Trees selection : %.2f" %␣
 ↪get_accuracy(tar_train, tar_test, pred_test, pred_train))
print()
```

```
Accuracy score of our model without feature selection : 0.05
[ 20.321  22.921  21.164  51.545  18.469  33.979  18.496  43.588  56.682
  20.841  26.617   1.917  56.078   5.255   5.473 121.11    1.619     nan
   4.792 149.   ]
[[ 0  0  6 24  0]
 [ 0  0  5 24  0]
 [ 0  0  0 24  0]
 [ 0  0  0 24  0]
 [ 1  1  6 51  1]] summerize features

Accuracy score of our model with chi square feature selection : 0.15


/home/bernard/anaconda3/lib/python3.8/site-
packages/sklearn/utils/validation.py:70: FutureWarning: Pass
n_features_to_select=5 as keyword args. From version 1.0 (renaming of 0.25)
passing these as positional arguments will result in an error
  warnings.warn(f"Pass {args_msg} as keyword args. From version "
/home/bernard/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:763: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
/home/bernard/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:763: ConvergenceWarning: lbfgs failed
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  n_iter_i = _check_optimize_result(
/home/bernard/anaconda3/lib/python3.8/site-
```

```
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packages/sklearn/linear_model/_logistic.py:763: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

```
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    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
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packages/sklearn/linear_model/_logistic.py:763: ConvergenceWarning: lbfgs failed
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    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
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    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
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    https://scikit-learn.org/stable/modules/preprocessing.html
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    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
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packages/sklearn/linear_model/_logistic.py:763: ConvergenceWarning: lbfgs failed
to converge (status=1):
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Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
```

```
regression
  n_iter_i = _check_optimize_result(
/home/bernard/anaconda3/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:763: ConvergenceWarning: lbfgs failed
to converge (status=1):
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    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```
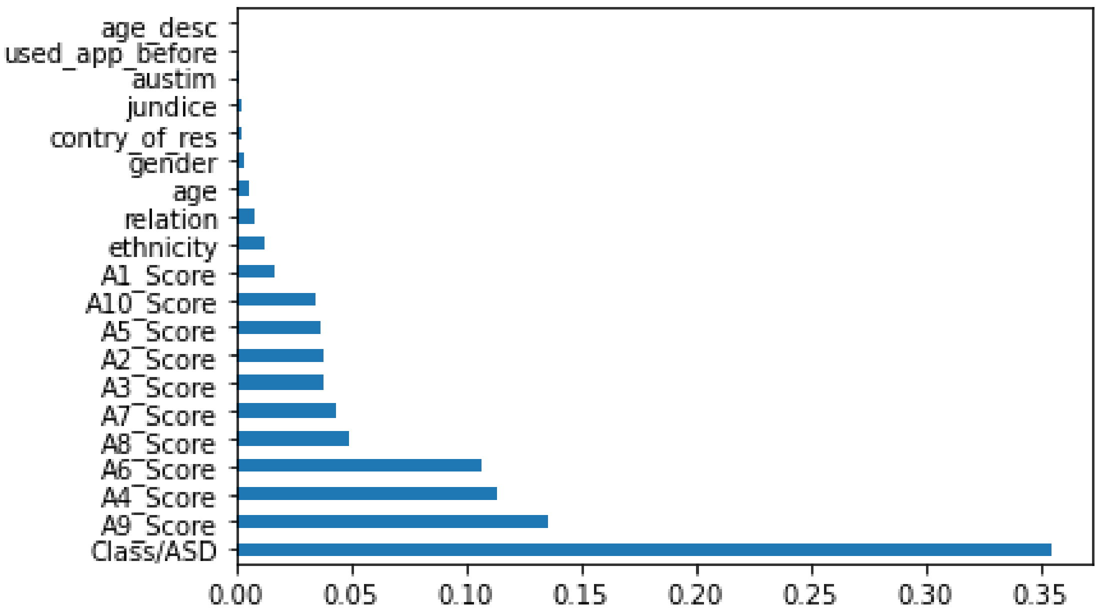

```
Accuracy score of our model with RFE selection : 0.15

Accuracy score of our model with PCA selection : 0.15

[0.026 0.036 0.053 0.115 0.043 0.091 0.04  0.059 0.133 0.038 0.008 0.003
 0.007 0.002 0.002 0.003 0.001 0.    0.01  0.329]

Accuracy score of our model with Extra Trees selection : 0.15
```

3 Get five most important features

[4]:

```
from sklearn.ensemble import ExtraTreesClassifier
import matplotlib.pyplot as plt

# Get the average of the list
def Average(lst):
    return sum(lst) / len(lst)

## feature extraction
model = ExtraTreesClassifier(max_depth=3,min_samples_leaf=2)
fit = model.fit(X, Y)
print(model.feature_importances_)
print()
feat_importances = pandas.Series(model.feature_importances_, index=X.columns)
feat_importances.nlargest(20).plot(kind='barh')

t = SelectFromModel(fit, prefit=True)
features = t.transform(X)
pred_features = features[:, 0:5]
pred_train, pred_test, tar_train, tar_test = train_test_split(pred_features, Y,␣
 ↪test_size=.3, random_state=4)
```

```
[0.017 0.038 0.038 0.114 0.036 0.107 0.043 0.049 0.136 0.035 0.006 0.004
 0.012 0.002 0.001 0.002 0.    0.    0.008 0.355]
```

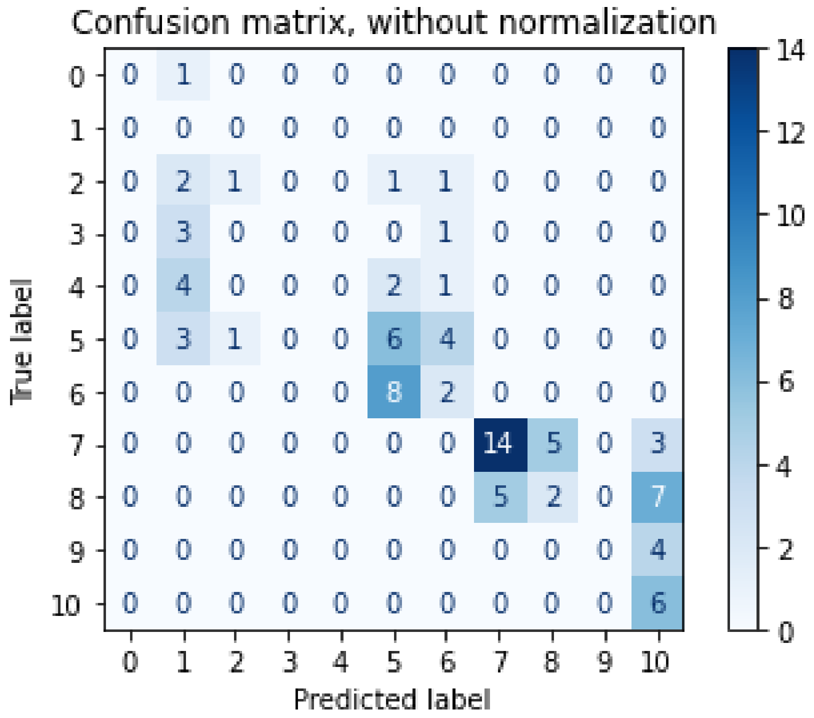


4 Naive Bayes Model

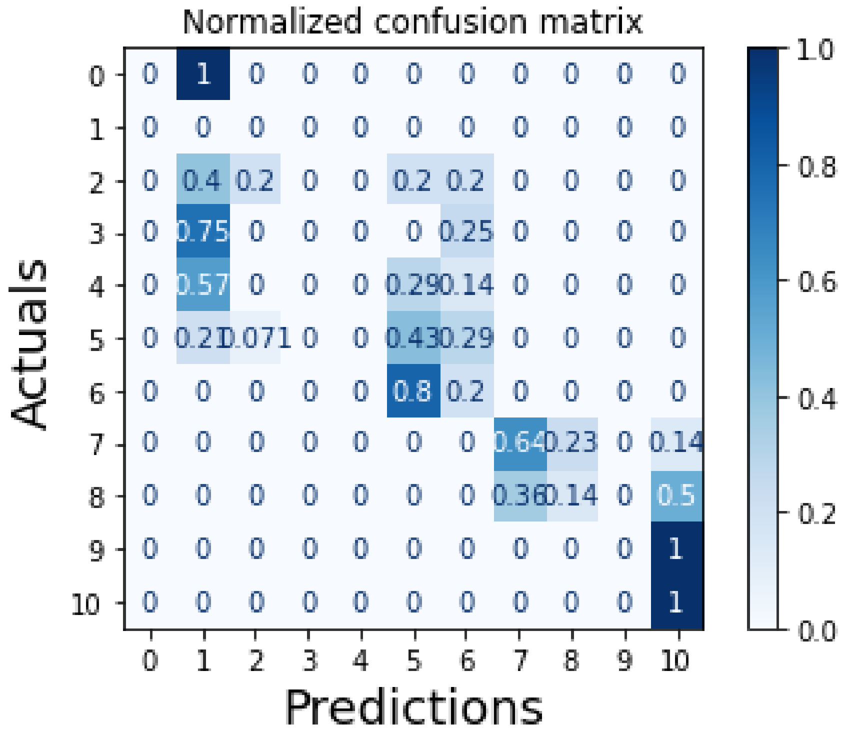
[5]:

```
from sklearn.model_selection import KFold
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import precision_score, recall_score, auc, roc_curve

from sklearn import svm, datasets
from sklearn.model_selection import train_test_split
from sklearn.metrics import plot_confusion_matrix

gnb = GaussianNB() #suitable for numeric features
gnb.fit(pred_train, np.ravel(tar_train,order='C'))
kf = KFold(n_splits=10)
gnb.fit(pred_train, tar_train)

# Plot non-normalized confusion matrix
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
for title, normalize in titles_options:
    disp = plot_confusion_matrix(gnb, pred_test, tar_test,
                                 #display_labels=['yes','no'],
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
    disp.ax_.set_title(title)

    print(title)
    print(disp.confusion_matrix)

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.show()

# Print accuracy
print(Average(cross_val_score(gnb, pred_train, tar_train, cv=kf, scoring='accuracy')))
```

```
Confusion matrix, without normalization
[[ 0  1  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0]
 [ 0  2  1  0  0  1  1  0  0  0  0]
 [ 0  3  0  0  0  0  1  0  0  0  0]
 [ 0  4  0  0  0  2  1  0  0  0  0]
 [ 0  3  1  0  0  6  4  0  0  0  0]
 [ 0  0  0  0  0  8  2  0  0  0  0]
 [ 0  0  0  0  0  0  0 14  5  0  3]
 [ 0  0  0  0  0  0  0  5  2  0  7]
 [ 0  0  0  0  0  0  0  0  0  0  4]
 [ 0  0  0  0  0  0  0  0  0  0  6]]
Normalized confusion matrix
[[0.    1.    0.    0.    0.    0.    0.    0.    0.    0.    0.   ]
 [0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.   ]
 [0.    0.4   0.2   0.    0.    0.2   0.2   0.    0.    0.    0.   ]
 [0.    0.75  0.    0.    0.    0.    0.25  0.    0.    0.    0.   ]
 [0.    0.571 0.    0.    0.    0.286 0.143 0.    0.    0.    0.   ]
 [0.    0.214 0.071 0.    0.    0.429 0.286 0.    0.    0.    0.   ]
 [0.    0.    0.    0.    0.    0.8   0.2   0.    0.    0.    0.   ]
 [0.    0.    0.    0.    0.    0.    0.    0.636 0.227 0.    0.136]
 [0.    0.    0.    0.    0.    0.    0.    0.357 0.143 0.    0.5  ]
 [0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    1.   ]
 [0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    1.   ]]
```



	0	1	2	3	4	5	6	7	8	9	10
0	0	1	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0
2	0	2	1	0	0	1	1	0	0	0	0
3	0	3	0	0	0	0	1	0	0	0	0
4	0	4	0	0	0	2	1	0	0	0	0
5	0	3	1	0	0	6	4	0	0	0	0
6	0	0	0	0	0	8	2	0	0	0	0
7	0	0	0	0	0	0	0	14	5	0	3
8	0	0	0	0	0	0	0	5	2	0	7
9	0	0	0	0	0	0	0	0	0	0	4
10	0	0	0	0	0	0	0	0	0	0	6



	0	1	2	3	4	5	6	7	8	9	10
0	0	1	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0
2	0	0.4	0.2	0	0	0.2	0.2	0	0	0	0
3	0	0.75	0	0	0	0	0.25	0	0	0	0
4	0	0.57	0	0	0	0.29	0.14	0	0	0	0
5	0	0.21	0.071	0	0	0.43	0.29	0	0	0	0
6	0	0	0	0	0	0.8	0.2	0	0	0	0
7	0	0	0	0	0	0	0	0.64	0.23	0	0.14
8	0	0	0	0	0	0	0	0.36	0.14	0	0.5
9	0	0	0	0	0	0	0	0	0	0	1
10	0	0	0	0	0	0	0	0	0	0	1

```
0.35261904761904767
```

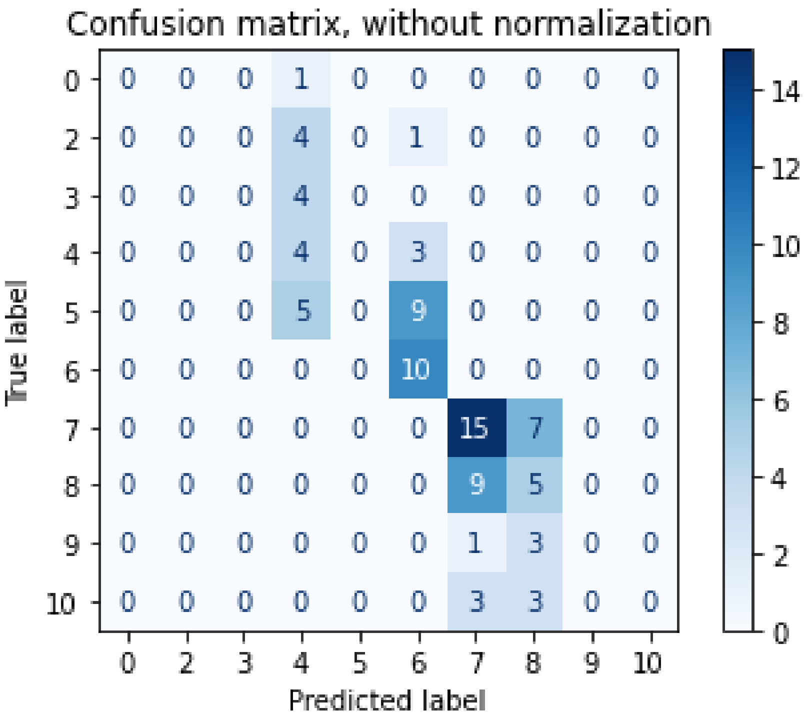
5 Decision Tree Classifier Model

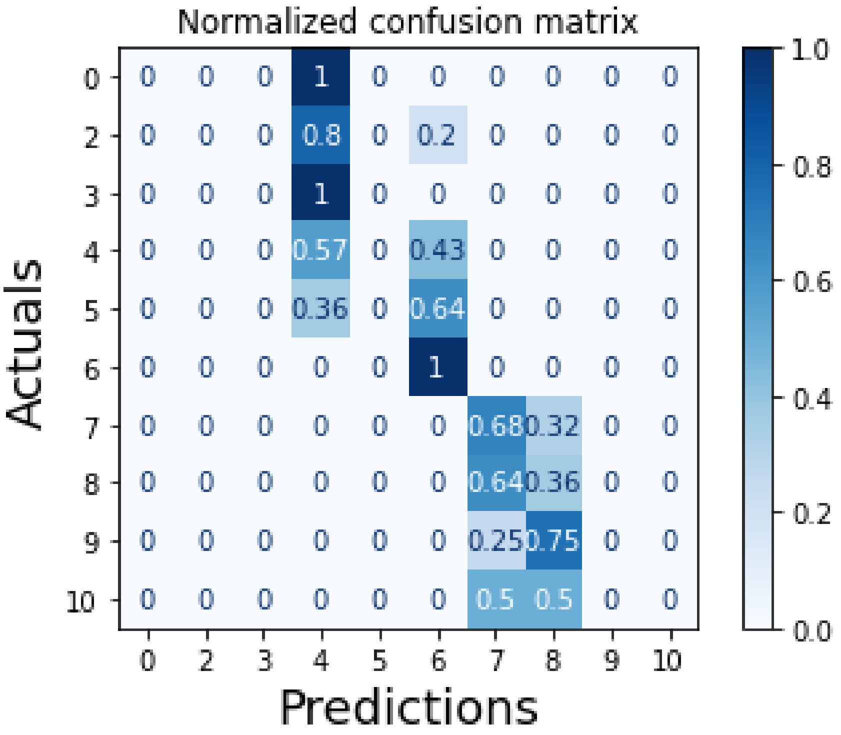
[6]:

```python
from sklearn.tree import DecisionTreeClassifier
import numpy as np
import matplotlib.pyplot as plt

from sklearn import svm, datasets
from sklearn.model_selection import train_test_split
from sklearn.metrics import plot_confusion_matrix

# Reset the train/test-split
pred_train, pred_test, tar_train, tar_test = train_test_split(X, Y, test_size=.
 ↪3, random_state=4)

# Train the DTC
dt = DecisionTreeClassifier(min_samples_leaf=0.2, min_samples_split=0.3)
kf = KFold(n_splits=10)
dt.fit(pred_train, tar_train)
train_pred = dt.predict(pred_train)

# Plot non-normalized confusion matrix
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
for title, normalize in titles_options:
    disp = plot_confusion_matrix(dt, pred_test, tar_test,
                                 #display_labels=['yes','no'],
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
    disp.ax_.set_title(title)

    print(title)
    print(disp.confusion_matrix)

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.show()

# print acccuracy
print(Average(cross_val_score(dt, pred_train, tar_train, cv=kf,␣
 ↪scoring='accuracy')))


# get importance
print(dt.feature_importances_)
print()
```

```python
feat_importances = pandas.Series(dt.feature_importances_, index=X.columns)
feat_importances.nlargest(20).plot(kind='barh')
```

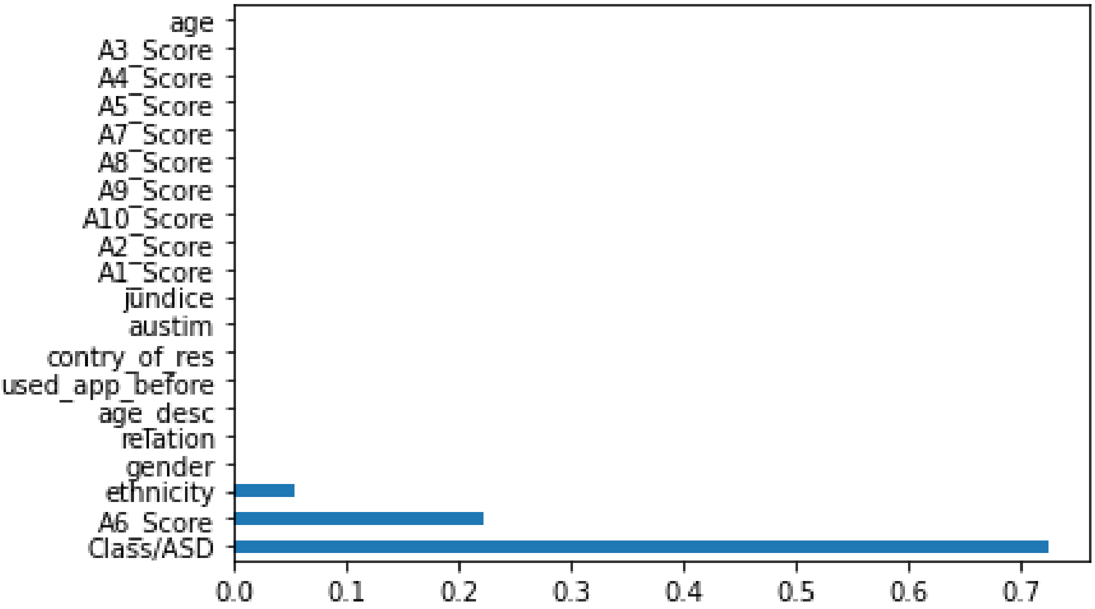
```
Confusion matrix, without normalization
[[ 0  0  0  1  0  0  0  0  0  0]
 [ 0  0  0  4  0  1  0  0  0  0]
 [ 0  0  0  4  0  0  0  0  0  0]
 [ 0  0  0  4  0  3  0  0  0  0]
 [ 0  0  0  5  0  9  0  0  0  0]
 [ 0  0  0  0  0 10  0  0  0  0]
 [ 0  0  0  0  0  0 15  7  0  0]
 [ 0  0  0  0  0  0  9  5  0  0]
 [ 0  0  0  0  0  0  1  3  0  0]
 [ 0  0  0  0  0  0  3  3  0  0]]
Normalized confusion matrix
[[0.    0.    0.    1.    0.    0.    0.    0.    0.    0.   ]
 [0.    0.    0.    0.8   0.    0.2   0.    0.    0.    0.   ]
 [0.    0.    0.    1.    0.    0.    0.    0.    0.    0.   ]
 [0.    0.    0.    0.571 0.    0.429 0.    0.    0.    0.   ]
 [0.    0.    0.    0.357 0.    0.643 0.    0.    0.    0.   ]
 [0.    0.    0.    0.    0.    1.    0.    0.    0.    0.   ]
 [0.    0.    0.    0.    0.    0.    0.682 0.318 0.    0.   ]
 [0.    0.    0.    0.    0.    0.    0.643 0.357 0.    0.   ]
 [0.    0.    0.    0.    0.    0.    0.25  0.75  0.    0.   ]
 [0.    0.    0.    0.    0.    0.    0.5   0.5   0.    0.   ]]
```





```
0.27809523809523806
[0.    0.    0.    0.    0.    0.223 0.    0.    0.    0.    0.    0.
 0.054 0.    0.    0.    0.    0.    0.    0.723]
```

[6]: <AxesSubplot:>


age
A3_Score
A4_Score
A5_Score
A7_Score
A8_Score
A9_Score
A10_Score
A2_Score
A1_Score
jundice
austim
contry_of_res
used_app_before
age_desc
relation
gender
ethnicity
A6_Score
Class/ASD
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7

```
[ ]:
```