car_evaluation

July 3, 2021

To Do 1. Predict the condition of a vehicle based on its features. 2. Plot the most important features. 3. Train multiple classifiers and compare the accuracy. 4. Evaluate the XGBoost model with K-fold cross-validation.

[14]:

```
#import libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

[15]:

```
#import the data
raw_data = pd.read_csv('car_evaluation.csv')
```

[17]:

```
raw_data
```

[17]:

```
     buying  maint  doors persons lug_boot safety  class
0     vhigh  vhigh      2       2    small    low  unacc
1     vhigh  vhigh      2       2    small    med  unacc
2     vhigh  vhigh      2       2    small   high  unacc
3     vhigh  vhigh      2       2      med    low  unacc
4     vhigh  vhigh      2       2      med    med  unacc
…       …     …      …      …        …      …      …
1723    low    low  5more    more      med    med   good
1724    low    low  5more    more      med   high  vgood
1725    low    low  5more    more      big    low  unacc
1726    low    low  5more    more      big    med   good
1727    low    low  5more    more      big   high  vgood

[1728 rows x 7 columns]
```

[31]:

```
raw_data.shape
```

[31]:

```
(1728, 7)
```

1 EDA

[19]:

```
#Chect the dataset info
raw_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1728 entries, 0 to 1727
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   buying    1728 non-null   object
 1   maint     1728 non-null   object
 2   doors     1728 non-null   object
 3   persons   1728 non-null   object
 4   lug_boot  1728 non-null   object
 5   safety    1728 non-null   object
 6   class     1728 non-null   object
dtypes: object(7)
memory usage: 94.6+ KB
```

[21]:

```
raw_data.describe()
```

[21]:

```
       buying maint doors persons lug_boot safety  class
count    1728  1728  1728    1728     1728   1728   1728
unique      4     4     4       3        3      3      4
top      high  high     2       2    small   high  unacc
freq      432   432   432     576      576    576   1210
```

[22]:

```
raw_data.isnull().sum()
```

[22]:

```
buying      0
maint       0
doors       0
persons     0
lug_boot    0
safety      0
class       0
dtype: int64
```

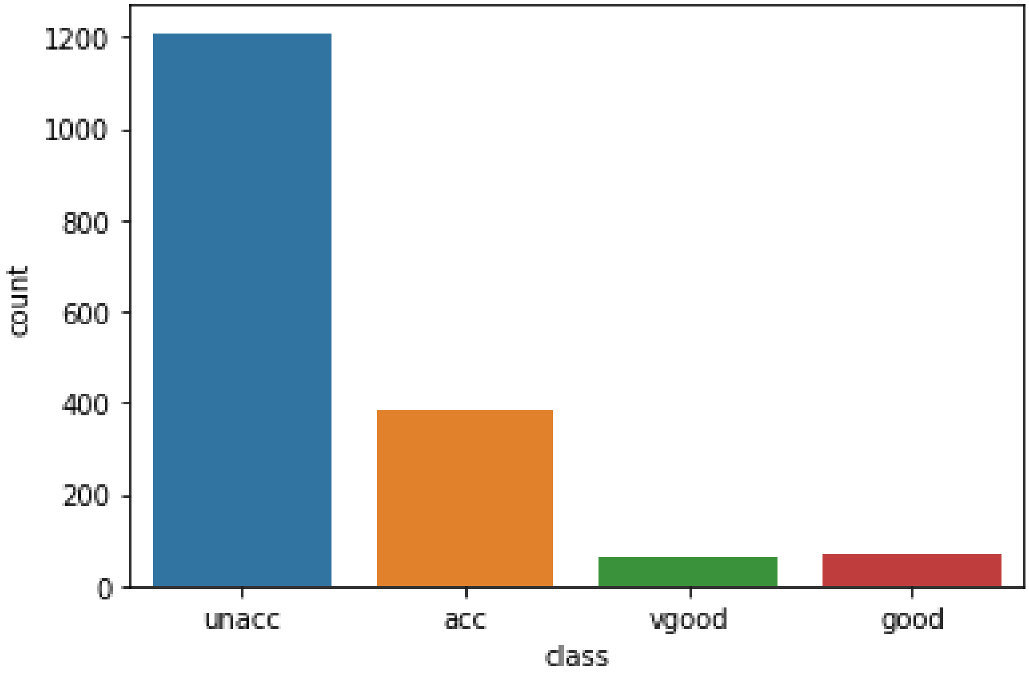
[38]:

```
#check for unique values of each column

#raw_data['safety'].unique()
#raw_data['class'].unique()

for i in raw_data.columns:
    print(raw_data[i].unique())
```

```
['vhigh' 'high' 'med' 'low']
['vhigh' 'high' 'med' 'low']
['2' '3' '4' '5more']
['2' '4' 'more']
['small' 'med' 'big']
['low' 'med' 'high']
['unacc' 'acc' 'vgood' 'good']
```

[47]:
```
#plot the column "class" distribution
sns.countplot(raw_data['class'])
```

[47]:
```
<AxesSubplot:xlabel='class', ylabel='count'>
```



the dataset is highly unbalance.

[49]:
```
#create dummies

#here we are going to use LabelEncoder(the categorical variable are comparable).

from sklearn.preprocessing import LabelEncoder
```

[50]:
```
le = LabelEncoder()
```

[54]:
```
data = raw_data
#transform all columns
```

```
for i in raw_data.columns:
    data[i] = le.fit_transform(raw_data[i])
```

[55]:

```
data
```

[55]:

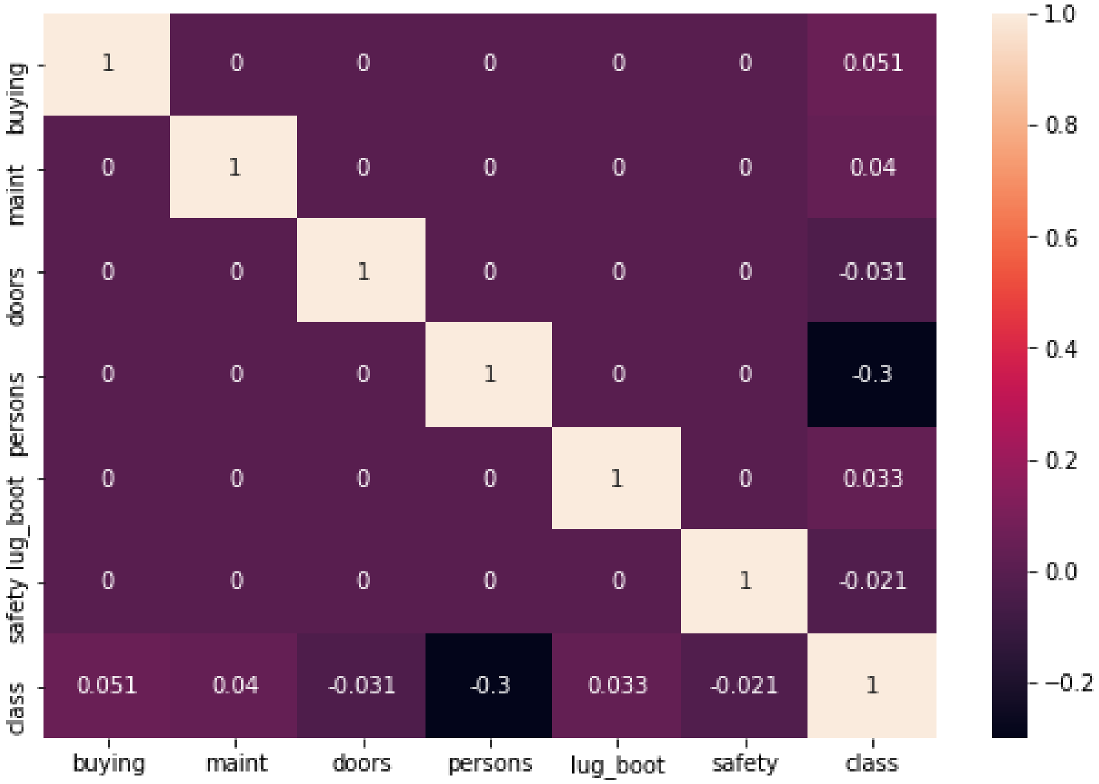
```
      buying  maint  doors  persons  lug_boot  safety  class
0          3      3      0        0         2       1      2
1          3      3      0        0         2       2      2
2          3      3      0        0         2       0      2
3          3      3      0        0         1       1      2
4          3      3      0        0         1       2      2
…       …     …     …      …       …      …     …
1723       1      1      3        2         1       2      1
1724       1      1      3        2         1       0      3
1725       1      1      3        2         0       1      2
1726       1      1      3        2         0       2      1
1727       1      1      3        2         0       0      3

[1728 rows x 7 columns]
```

[60]:

```
#plot the Correlation matrix
fig=plt.figure(figsize=(9,6))
sns.heatmap(data.corr(), annot=True)
```

[60]:

```
<AxesSubplot:>
```



[ ]:

```

```

2 Model Selection¶

[67]:

```
X = data.drop(['class'], axis=1)
y = data['class']
```

[67]:

```
       buying  maint  doors  persons  lug_boot  safety
0           3      3      0        0         2       1
1           3      3      0        0         2       2
2           3      3      0        0         2       0
3           3      3      0        0         1       1
4           3      3      0        0         1       2
…        …    …     …      …       …       …
1723        1      1      3        2         1       2
1724        1      1      3        2         1       0
1725        1      1      3        2         0       1
1726        1      1      3        2         0       2
1727        1      1      3        2         0       0
```

```
[1728 rows x 6 columns]
```

[82]:

```
#split the dataset
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report
from sklearn.model_selection import cross_val_score
from sklearn.neighbors import KNeighborsClassifier



X_train, X_test, y_train, y_test = train_test_split(X, y , test_size=0.3,␣
 ↪random_state=10)
```

2.0.1 1. Logistic Regression¶

[72]:

```
from sklearn.linear_model import LogisticRegression
logis_reg = LogisticRegression()
```

[76]:

```
logis_reg.fit(X_train, y_train)
y_predict = logis_reg.predict(X_test)

accuracy_score(y_predict, y_test)
```

[76]:

```
0.6955684007707129
```

[77]:

```
confusion_matrix(y_predict, y_test)
```

[77]:

```
array([[ 19,   3,  30,   8],
       [  0,   0,   0,   0],
       [ 78,  18, 339,  14],
       [  5,   0,   2,   3]])
```

[84]:

```
print(classification_report(y_predict, y_test))
```

```
              precision    recall  f1-score   support

           0       0.19      0.32      0.23        60
           1       0.00      0.00      0.00         0
           2       0.91      0.76      0.83       449
           3       0.12      0.30      0.17        10

    accuracy                           0.70       519
   macro avg       0.31      0.34      0.31       519
weighted avg       0.81      0.70      0.75       519
```

2.0.2 2. KNN Classifier

[85]:

```python
knn = KNeighborsClassifier(n_jobs=-1)
```

[92]:

```python
knn.fit(X_train, y_train)
y_predict = knn.predict(X_test)
accuracy_score(y_predict,y_test)
```

[92]:

```
0.9267822736030829
```

[89]:

```python
knn.score(X_test,y_test)
```

[89]:

```
0.9267822736030829
```

[93]:

```python
print(classification_report(y_predict, y_test))
```

```
              precision    recall  f1-score   support

           0       0.82      0.85      0.84        99
           1       0.62      0.81      0.70        16
           2       0.99      0.95      0.97       388
           3       0.64      1.00      0.78        16

    accuracy                           0.93       519
   macro avg       0.77      0.90      0.82       519
weighted avg       0.94      0.93      0.93       519
```

2.0.3 3.Random Forests Classifie

[108]:

```python
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(n_jobs=-1,random_state=10)
```

[97]:

```python
rfc.fit(X_train, y_train)
print(rfc.score(X_test, y_test))
```

```
0.9807321772639692
```

2.0.4 4.XGBoost

[109]:

```python
from xgboost import XGBClassifier
from sklearn import model_selection

xgb = XGBClassifier()
```

[117]:

```
seed = 7
num_trees = 50

kfold = model_selection.KFold(n_splits=10, random_state=seed)
model = XGBClassifier(n_estimators=num_trees,random_state=seed)

results = cross_val_score(model,X_train,y_train, cv=kfold)
```

[127]:

```
acc = results.mean()*100

print(f'With XGBoost the accuracy is: {acc:.2f}% .')
```

```
With XGBoost the accuracy is: 98.10% .
```

[ ]:

```

```