Introduction

Business objective: Prediction the buying price of a car given :

- Maintenance
- Number of doors
- Lug Boot Size
- Safety
- Class Value

Assumptions:

- `Higher comfort` - luggage boot size, number of doors & people, safety; `higher pricing` (positive correlation)
- `Higher class`; `higher pricing` (positive correlation)

Table content

In [1]:

```
import pandas as pd
from pandas.plotting import scatter_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
%matplotlib inline
```

In [2]:

```
import warnings
warnings.filterwarnings('ignore')
```

1. Loading the data

In [3]:

```
ATTRIBUTES = ['buying', 'maint', 'doors', 'persons', 'lug_boot',
'safety', 'class']
```

In [4]:
```
data = pd.read_csv("data/car.data", names=ATTRIBUTES)
```

2. Discoverng and visualizing the data to gain insights

In [5]:
```
data.head(10)
```

Out[5]:

	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
5	vhigh	vhigh	2	2	med	high	unacc
6	vhigh	vhigh	2	2	big	low	unacc
7	vhigh	vhigh	2	2	big	med	unacc
8	vhigh	vhigh	2	2	big	high	unacc
9	vhigh	vhigh	2	4	small	low	unacc

The attributes are Ordinal (Categorical)

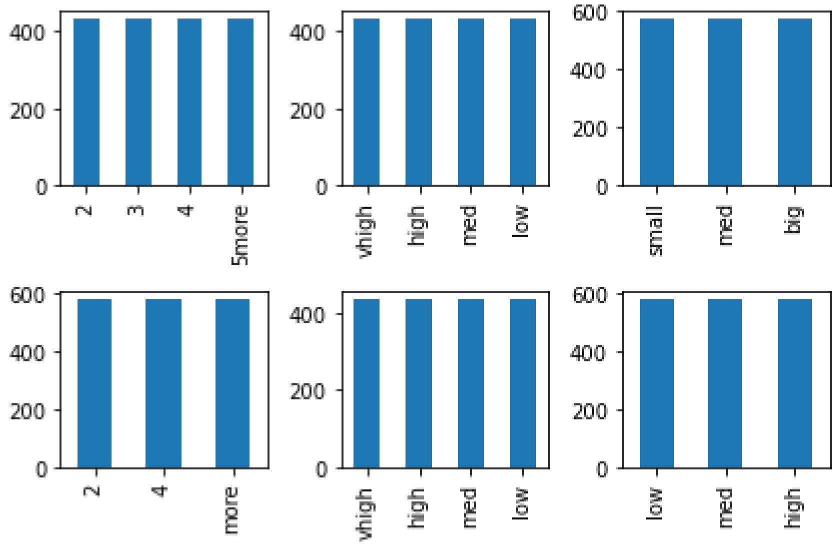
In [6]:
```
for i in data.columns:
    print("{} attribute has {} values".format(i,data[i].unique()))
```

```
buying attribute has ['vhigh' 'high' 'med' 'low'] values
maint attribute has ['vhigh' 'high' 'med' 'low'] values
doors attribute has ['2' '3' '4' '5more'] values
persons attribute has ['2' '4' 'more'] values
lug_boot attribute has ['small' 'med' 'big'] values
safety attribute has ['low' 'med' 'high'] values
class attribute has ['unacc' 'acc' 'vgood' 'good'] values
```

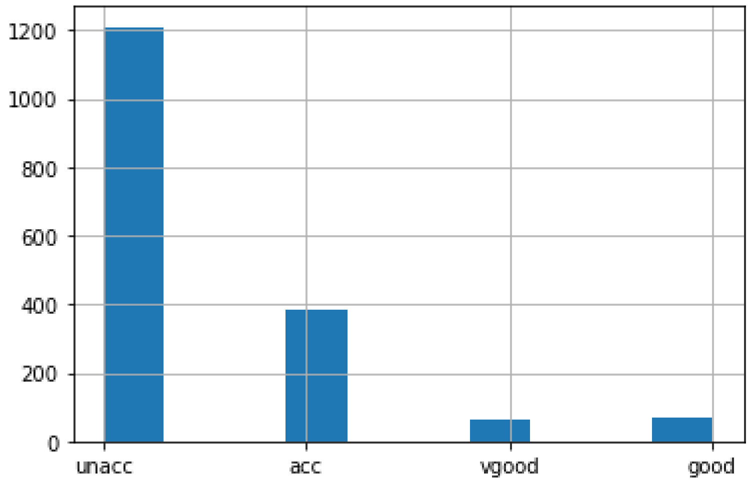
The strata (subgroups) are well-distributed (that's rare) except for the `class` attribute.

In [7]:
```
fig, axes = plt.subplots(nrows=2, ncols=3)


data['buying'].value_counts().plot(kind='bar', ax=axes[0,1])
data['maint'].value_counts().plot(kind='bar', ax=axes[1,1])
data['doors'].value_counts().plot(kind='bar', ax=axes[0,0])
data['persons'].value_counts().plot(kind='bar', ax=axes[1,0])
data['lug_boot'].value_counts().plot(kind='bar', ax=axes[0,2])
data['safety'].value_counts().plot(kind='bar', ax=axes[1,2])
```

```
fig.tight_layout() # Or equivalently,  "plt.tight_layout()"

plt.show()
```



In [8]:
```
data['class'].hist()
plt.show()
```



In [9]:
```
data.describe()
```

Out[9]:

	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	vhigh	vhigh	2	2	small	low	unacc
freq	432	432	432	576	576	576	1210

Nice! There is no null value in the dataset.

In [10]:
```
data.info()
```

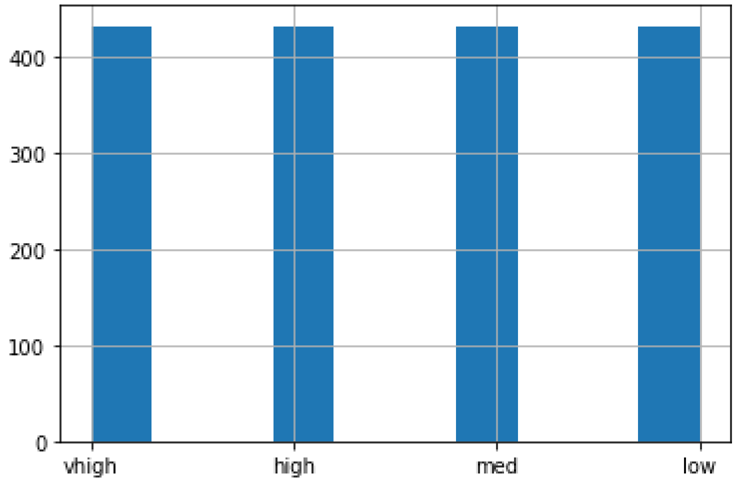
```
<class 'pandas.core.frame.DataFrame'>
```

```
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
```

In [11]:

```
data['buying'].hist()
```

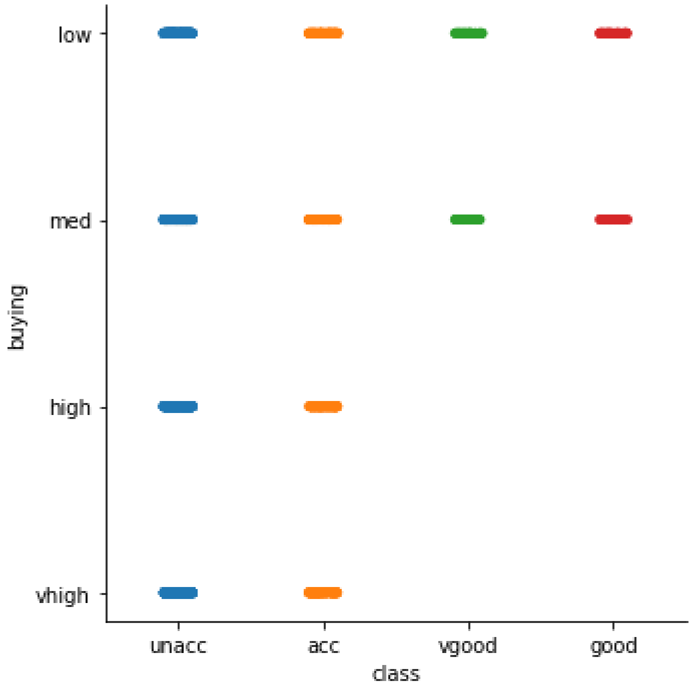
Out[11]: <AxesSubplot:>



Negative correlation between `class` and `buying`

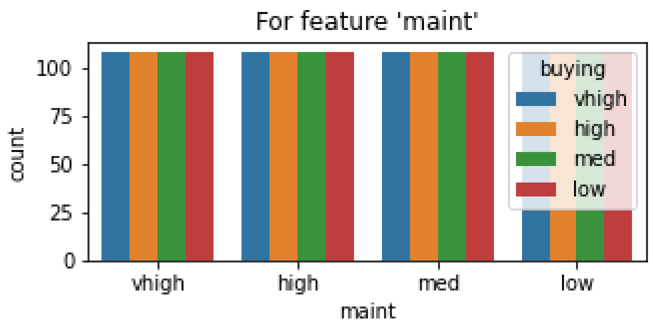
In [12]:

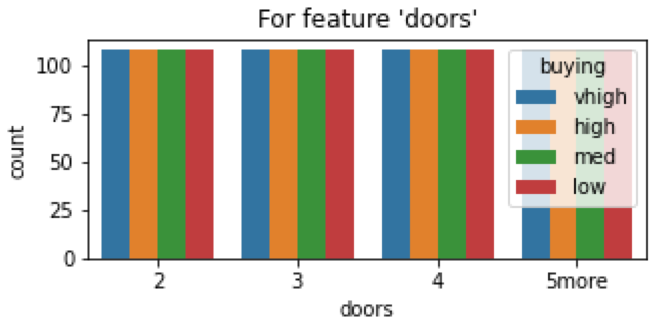
```
sns.catplot(x="class", y="buying", data=data)
plt.show()
```

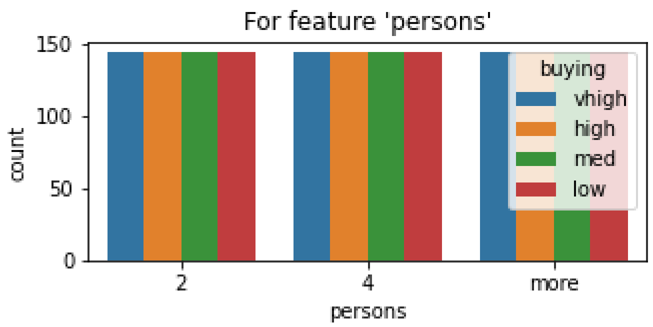


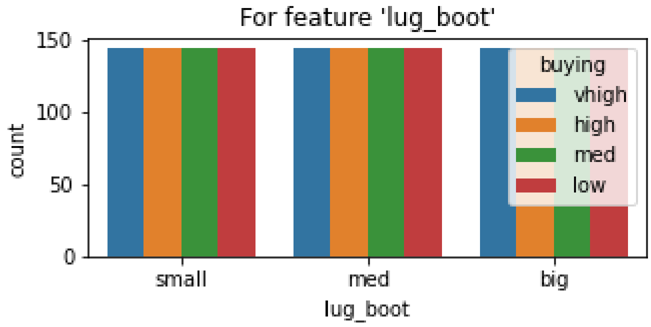
Visualizing the distribution of `buying` across attributes

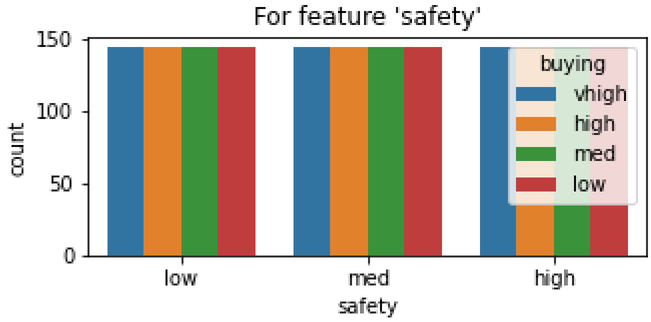
In [13]:
```
for i in data.columns[1:]:
    plt.figure(figsize=(5,2))
    plt.title("For feature '%s'"%i)
    sns.countplot(data[i],hue=data['buying'])
```

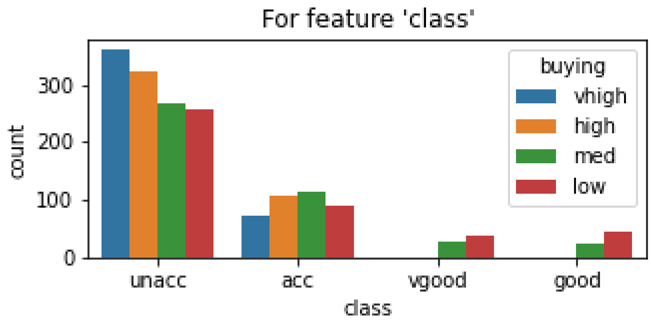












`vhigh` and `high` buying price are associated with only `unacc` and `acc` classes.

From the EDA on the data we observe that there is no need to handle missing values, feature scaling, outliers handling and so on.

3. Preparing the data for Machine Learning Algorithms

Performing ordinal encoding since they give better measure of the distance between different categories of an ordinal attribute

In [14]:

```
# ordinal mapping of the attributes
buying_mapping = {"vhigh": 3, "high": 2, "med": 1, 'low': 0}
maint_mapping = {"vhigh": 3, "high": 2, "med": 1, 'low': 0}
lug_boot_mapping = {"small": 0, "med": 1, "big": 2}
safety_mapping = {"low": 0, "med": 1, "high": 2}
class_mapping = {"unacc": 0, "acc": 1, "good": 2, "vgood": 3}
doors_mapping = {"2": 0, "3": 1, "4": 2, "5more": 3}
persons_mapping = {"2": 0, "3": 1, "more": 2}
```

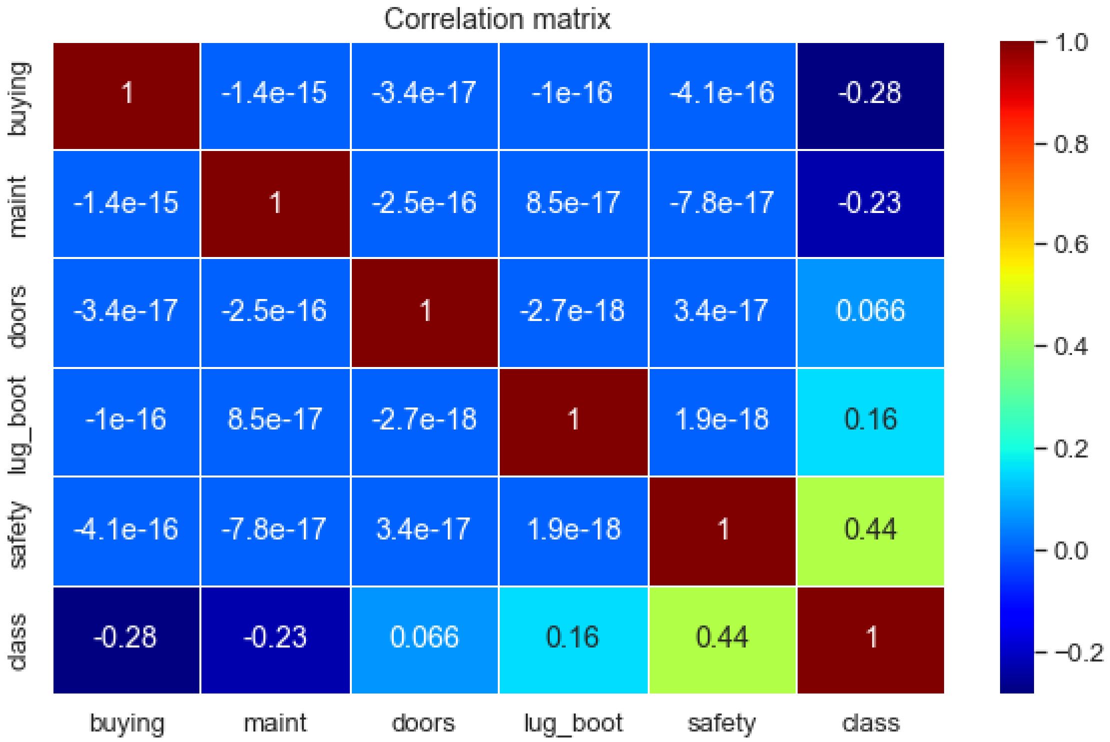
In [15]:

```
# mapping the categories to the respective ordinal value for each
attribute
trans_data = data.replace({"buying": buying_mapping})
trans_data = trans_data.replace({"maint": maint_mapping})
```

```
trans_data = trans_data.replace({"lug_boot": lug_boot_mapping})
trans_data = trans_data.replace({"safety": safety_mapping})
trans_data = trans_data.replace({"class": class_mapping})
trans_data = trans_data.replace({"persons": persons_mapping})
trans_data = trans_data.replace({"doors": doors_mapping})
```

Now we have the data in numeric format let's create the correlation matrix.

In [16]:
```
plt.figure(figsize=(10,6))
sns.set(font_scale=1.2)
sns.heatmap(trans_data.corr(),annot=True,
cmap='jet',linewidth=0.5)
plt.title('Correlation matrix');
```



`class` and `maint` are highly correlated (negatively)

`buying` and `class` are highly correlated (negatively)

Testing the initial assumption

Let's look at the correlation matrix again:

In [17]:
```
corr_matrix = trans_data.corr()
corr_matrix['buying'].sort_values(ascending=False)
```

Out[17]:
```
buying      1.000000e+00
doors      -3.433468e-17
lug_boot   -1.045866e-16
safety     -4.082114e-16
maint      -1.356939e-15
```

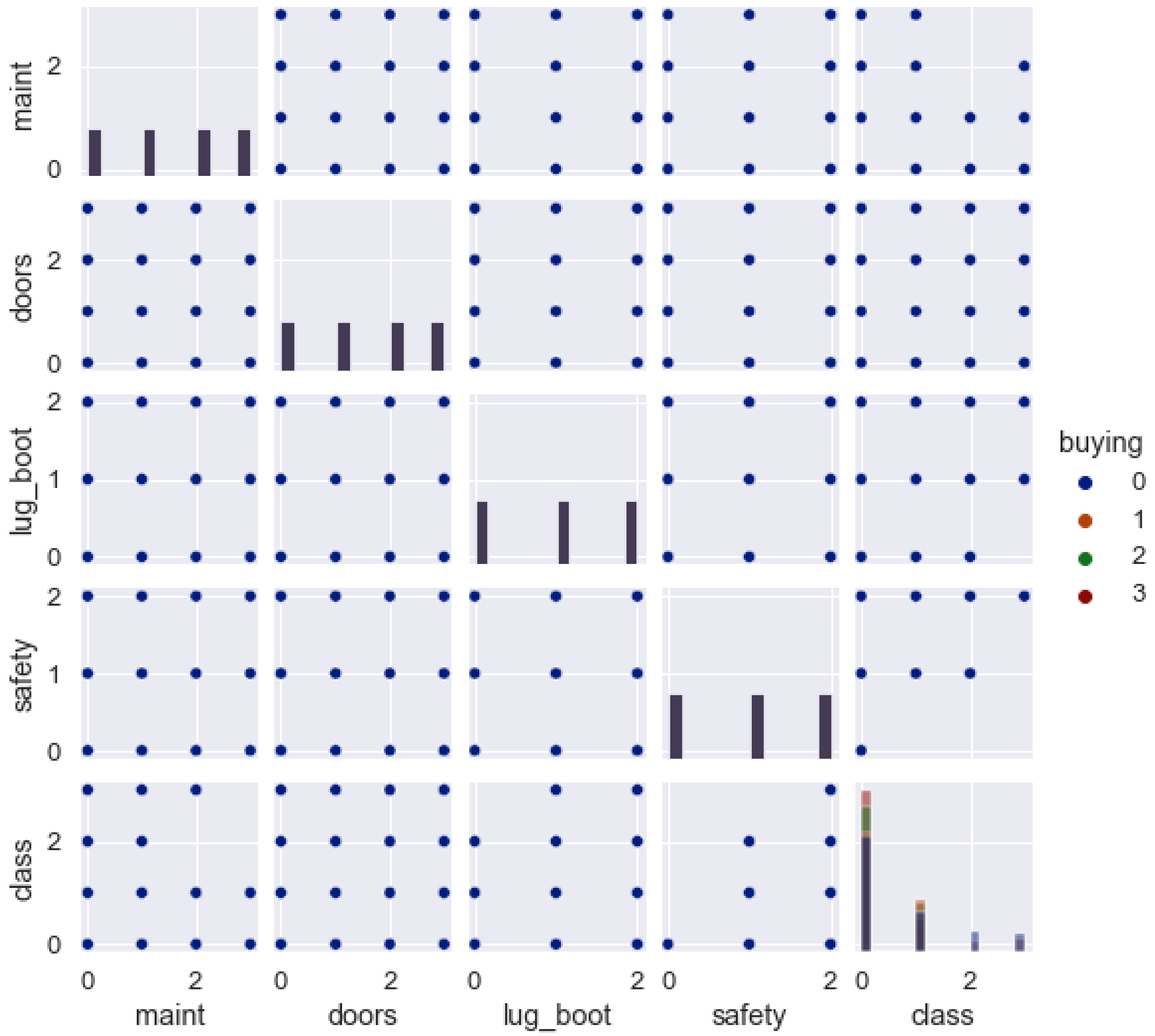
```
class      -2.827504e-01
Name: buying, dtype: float64
```

Attributes are negatively correlated with the `buying` attribute

> This makes the initial assumptions regarding positive correlation between buying and {doors, lug_boot, safety, persons } FALSE.

Let's look into the distribution of ***buying*** categories on other attributes

In [18]:
```
sns.pairplot(trans_data, hue="buying", diag_kind="hist",
height=1.5, palette="dark")
plt.show()
```



Splitting the data into training and testing

In [22]:
```
from sklearn.model_selection import train_test_split
```

In [23]:
```
X = trans_data.drop(['buying'], axis = 1)
y = trans_data['buying']
```

Following general convention - 80% training and 20% testing data, with random shuffling to prevent any potential selection bias

In [24]:
```
# train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, shuffle=True, random_state=42)

# train_set['class'].value_counts()/len(train_set)
# test_set['class'].value_counts()/len(train_set)
```

4. Training, evaluating and error analysis on the training set

In [25]:
```
# models
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeRegressor
from sklearn.neural_network import MLPClassifier
from sklearn import tree

# ensemble models
from sklearn.ensemble import RandomForestClassifier

# metrics
# from sklearn.metrics import log_loss
from sklearn.model_selection import cross_val_score,
learning_curve, GridSearchCV
from sklearn.metrics import confusion_matrix, mean_squared_error,
\
mean_absolute_error, classification_report, precision_score,
recall_score, f1_score,\
matthews_corrcoef, cohen_kappa_score, roc_auc_score
```

In [26]:
```
# good to test on various metrics for the multi-classification
task
def cal_metrics(y_test, y_pred):
    print(classification_report(y_test, y_pred))
    print('Recall: %.3f' % recall_score(y_test, y_pred,
average='micro'))
    print('F1: %.3f' % f1_score(y_test, y_pred, average='micro'))
    print("matthews_corrcoef: %.3f" % matthews_corrcoef(y_test,
y_pred))
    print("cohen_kappa_score: %.3f" % cohen_kappa_score(y_test,
y_pred))
```

```
    print("Mean squared error (MSE): %.3f" % 
mean_squared_error(y_test, y_pred))
    print("Mean absolute error (MAE): %.3f" % 
mean_absolute_error(y_test, y_pred))

# confusion matrix for error analysis
def create_confusion_matrix(y_test, y_pred, model_type):
    # Plot confusion matrix.
    cm_matrix = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(4,4))
    sns.set(font_scale=1.4)
    sns.heatmap(cm_matrix, annot=True, cbar=True, 
cmap='jet',linewidth=0.5,fmt="d")
    plt.ylabel('True Label')
    plt.xlabel('Predicted Label')
    plt.title('Confusion Matrix for {}'.format(model_type));
```

4.1. Logistic Regression

In [27]:
```
# Initialize a Logistic Regression classifier.
logreg = LogisticRegression(solver='saga', multi_class='auto', 
random_state=42, n_jobs=-1)
logreg.fit(X_train, y_train)

# cross validation evaluation
logreg_cv = cross_val_score(logreg, X_train, y_train, cv=20)
```

In [28]:
```
# CV Accuracy
print('CV Accuracy: %.3f' % logreg_cv.mean())
```

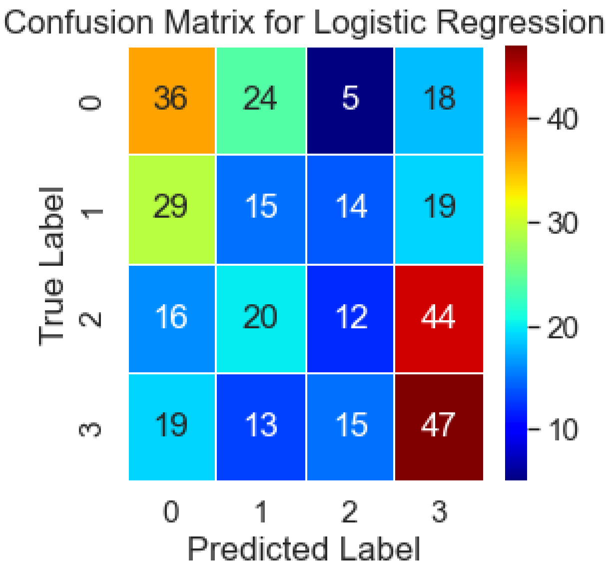
```
CV Accuracy: 0.328
```

Predictions and error analysis

In [29]:
```
logreg_pred = logreg.predict(X_test)
cal_metrics(y_test, logreg_pred)
print('\n')
create_confusion_matrix(y_test, logreg_pred, "Logistic 
Regression")
```

```
              precision    recall  f1-score   support

           0       0.36      0.43      0.39        83
           1       0.21      0.19      0.20        77
           2       0.26      0.13      0.17        92
```

```
           3       0.37      0.50      0.42        94

    accuracy                           0.32       346
   macro avg       0.30      0.31      0.30       346
weighted avg       0.30      0.32      0.30       346

Recall: 0.318
F1: 0.318
matthews_corrcoef: 0.091
cohen_kappa_score: 0.089
Mean squared error (MSE): 1.997
Mean absolute error (MAE): 1.049
```



4.2. Logistic Regression - Grid Search

In [192…

```python
# Hyperparameters to be checked.
parameters = {'C':[0.0001,0.001, 0.01, 1, 0.1, 10, 100, 1000],
              'penalty':['none','l2'],
              'solver':['lbfgs','sag','saga','newton-cg']
             }

# Logistic Regression classifier.
default_logreg=LogisticRegression(multi_class='auto',
random_state=42, n_jobs=-1)

# GridSearchCV estimator.
gs_logreg = GridSearchCV(default_logreg, parameters, cv=10,
verbose=1)

# Train the GridSearchCV estimator and search for the best
parameters.
gs_logreg.fit(X_train,y_train)
```

```
Fitting 10 folds for each of 64 candidates, totalling 640 fits
```

Out[192…

```
GridSearchCV(cv=10, estimator=LogisticRegression(n_jobs=-1, random_state=42),
             param_grid={'C': [0.0001, 0.001, 0.01, 1, 0.1, 10, 100, 1000],
                         'penalty': ['none', 'l2'],
                         'solver': ['lbfgs', 'sag', 'saga', 'newton-cg']},
             verbose=1)
```

In [200…

```python
# Best parameters.
print("Best Logistic Regression Parameters:
{}".format(gs_logreg.best_params_))

# Cross validation accuracy for the best parameters.
print('CV accuracy: %0.3f' % gs_logreg.best_score_)

# Accuracy: 1 is perfect prediction.
print('Accuracy: %0.3f' % (gs_logreg.score(X_test, y_test)))
```

```
Best Logistic Regression Parameters: {'C': 0.1, 'penalty': 'l2', 'solver': 'lb
fgs'}
CV accuracy: 0.329
Accuracy: 0.327
```

4.3. K-Nearest Neighbours

In [60]:

```python
# Initialize a decision tree estimator.
knn = KNeighborsClassifier(n_jobs=-1, n_neighbors=300)
# Train the estimator.
knn.fit(X_train, y_train)

# cross validation evaluation
knn_cv = cross_val_score(knn, X_train, y_train, cv=20)
```

In [62]:

```python
# CV Accuracy
print('CV Accuracy: %.3f' % knn_cv.mean())
```

```
CV Accuracy: 0.313
```

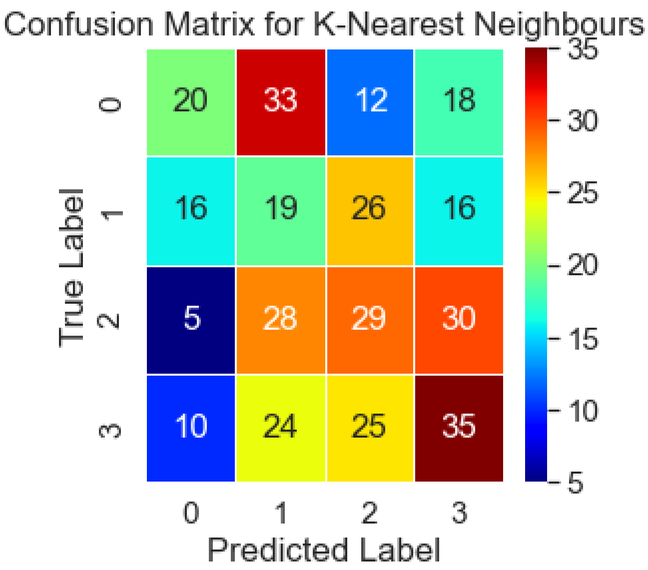
Predictions and error analysis

In [64]:

```python
knn_pred = knn.predict(X_test)
cal_metrics(y_test, knn_pred)
print('\n')
create_confusion_matrix(y_test, knn_pred, "K-Nearest Neighbours")
```

```
              precision    recall  f1-score   support

           0       0.39      0.24      0.30        83
           1       0.18      0.25      0.21        77
```

```
           2       0.32      0.32      0.32        92
           3       0.35      0.37      0.36        94

    accuracy                           0.30       346
   macro avg       0.31      0.29      0.30       346
weighted avg       0.31      0.30      0.30       346

Recall: 0.298
F1: 0.298
matthews_corrcoef: 0.063
cohen_kappa_score: 0.063
Mean squared error (MSE): 1.844
Mean absolute error (MAE): 1.029
```



4.4. Decision Trees

In [85]:
```
# Initialize a decision tree estimator.
tr = tree.DecisionTreeClassifier(max_depth=4, criterion='entropy',
random_state=42)
# Train the estimator.
tr.fit(X_train, y_train)

# cross validation evaluation
tr_cv = cross_val_score(tr, X_train, y_train, cv=20)
```

In [86]:
```
# CV Accuracy
print('CV Accuracy: %.3f' % tr_cv.mean())
```

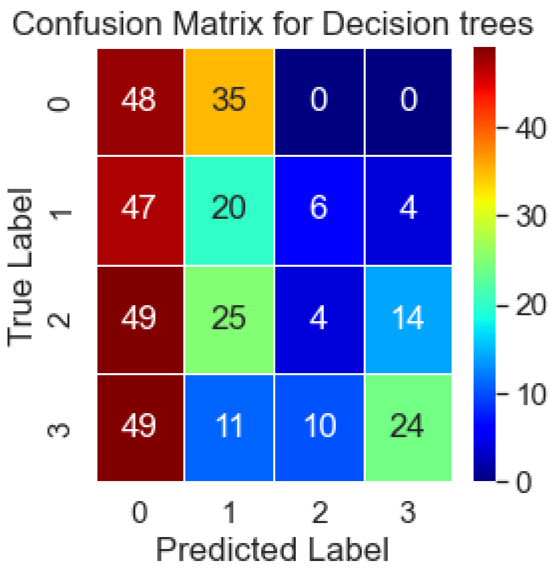
```
CV Accuracy: 0.311
```

Predictions and error analysis

In [88]:
```
tr_pred = tr.predict(X_test)
cal_metrics(y_test, tr_pred)
```

```
print('\n')
create_confusion_matrix(y_test, tr_pred, "Decision trees")
```

```
              precision    recall  f1-score   support

           0       0.25      0.58      0.35        83
           1       0.22      0.26      0.24        77
           2       0.20      0.04      0.07        92
           3       0.57      0.26      0.35        94

    accuracy                           0.28       346
   macro avg       0.31      0.28      0.25       346
weighted avg       0.32      0.28      0.25       346

Recall: 0.277
F1: 0.277
matthews_corrcoef: 0.055
cohen_kappa_score: 0.048
Mean squared error (MSE): 2.410
Mean absolute error (MAE): 1.191
```



4.5. Decision Trees - Grid Search

In [195…

```
# Hyperparameters to be checked.
parameters = {'criterion':['gini','entropy'],
              'max_depth':
[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20]
             }

# Default Decision tree estimator.
default_tr = tree.DecisionTreeClassifier(random_state=42)

# GridSearchCV estimator.
gs_tree = GridSearchCV(default_tr, parameters, cv=10,
```

```
n_jobs=-1,verbose=1)

# Train the GridSearchCV estimator and search for the best
parameters.
gs_tree.fit(X_train,y_train)
```

```
Fitting 10 folds for each of 40 candidates, totalling 400 fits
```

Out[195…

```
GridSearchCV(cv=10, estimator=DecisionTreeClassifier(random_state=42),
             n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,
                                       13, 14, 15, 16, 17, 18, 19, 20]},
             verbose=1)
```

In [199…

```
# Best parameters.
print("Best Decision Tree Parameters:
{}".format(gs_tree.best_params_))

# Cross validation accuracy for the best parameters.
print('CV accuracy: %0.3f' % gs_tree.best_score_)

# Accuracy: 1 is perfect prediction.
print('Accuracy: %0.3f' % (gs_tree.score(X_test, y_test)))
```

```
Best Decision Tree Parameters: {'criterion': 'entropy', 'max_depth': 3}
CV accuracy: 0.321
Accuracy: 0.298
```

4.6. Multi Layered Perceptron

In [93]:

```
mlp = MLPClassifier(hidden_layer_sizes=(10), max_iter=100,
random_state=42, shuffle=True, verbose=False)
mlp.fit(X_train, y_train)

# cross validation evaluation
mlp_cv = cross_val_score(mlp, X_train, y_train, cv=20)
```

In [94]:

```
# CV Accuracy
print('CV Accuracy: %.3f' % mlp_cv.mean())
```

```
CV Accuracy: 0.321
```

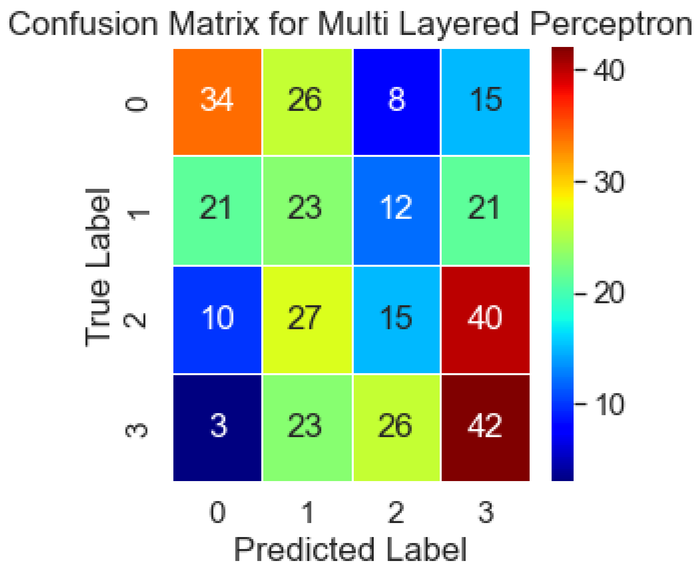
Predictions and error analysis

In [96]:

```
mlp_pred = mlp.predict(X_test)
cal_metrics(y_test, mlp_pred)
print('\n')
```

```
create_confusion_matrix(y_test, mlp_pred, "Multi Layered
Perceptron")
```

```
              precision    recall  f1-score   support

           0       0.50      0.41      0.45        83
           1       0.23      0.30      0.26        77
           2       0.25      0.16      0.20        92
           3       0.36      0.45      0.40        94

    accuracy                           0.33       346
   macro avg       0.33      0.33      0.33       346
weighted avg       0.33      0.33      0.33       346

Recall: 0.329
F1: 0.329
matthews_corrcoef: 0.107
cohen_kappa_score: 0.106
Mean squared error (MSE): 1.624
Mean absolute error (MAE): 0.954
```



4.7. Multi Layered Perceptron - Grid Search

In [ ]:

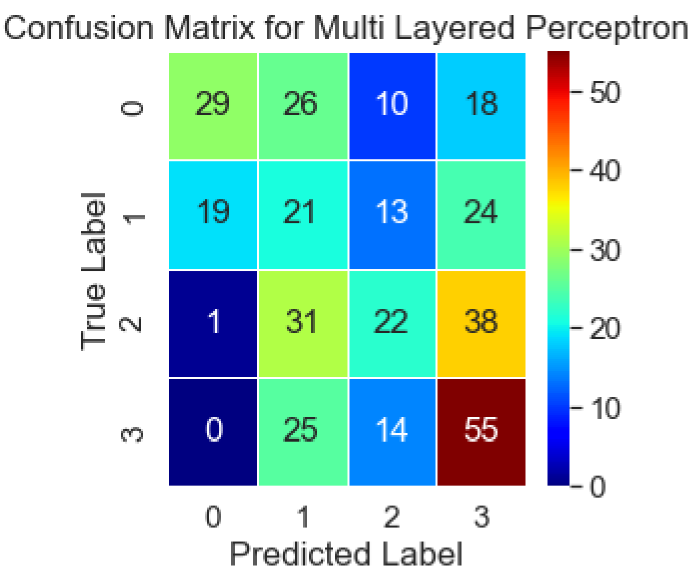
```
# Hyperparameters to be checked.
parameters = {'activation':['logistic','tanh','relu'],
              'solver': ['lbfgs','adam','sgd'],
              'alpha':10.0 ** -np.arange(1,3),
              'hidden_layer_sizes':[(5),(100),(3),(4),(3,1),
(5,3)]}

# MLP estimator.
default_mlp = MLPClassifier(random_state=42)

# GridSearchCV estimator.
```

```
gs_mlp = GridSearchCV(default_mlp, parameters, cv=10,
n_jobs=-1,verbose=1)

# Train the GridSearchCV estimator and search for the best
parameters.
gs_mlp.fit(X_train,y_train)
```

In [198…

```
gs_mlp_pred = gs_mlp.predict(X_test)
cal_metrics(y_test, gs_mlp_pred)
print('\n')
create_confusion_matrix(y_test, gs_mlp_pred, "Multi Layered
Perceptron")
```

```
              precision    recall  f1-score   support

           0       0.59      0.35      0.44        83
           1       0.20      0.27      0.23        77
           2       0.37      0.24      0.29        92
           3       0.41      0.59      0.48        94

    accuracy                           0.37       346
   macro avg       0.39      0.36      0.36       346
weighted avg       0.40      0.37      0.37       346

Recall: 0.367
F1: 0.367
matthews_corrcoef: 0.158
cohen_kappa_score: 0.154
Mean squared error (MSE): 1.569
Mean absolute error (MAE): 0.910
```



In [190…

```
# Best parameters.
print("Best MLP Parameters: {}".format(gs_mlp.best_params_))
```

```
# Cross validation accuracy for the best parameters.
print('CV accuracy: %0.3f' % gs_mlp.best_score_)

# Accuracy: 1 is perfect prediction.
print('Accuracy: %0.3f' % (gs_mlp.score(X_test,y_test)))
```

```
Best MLP Parameters: {'activation': 'logistic', 'alpha': 0.01, 'hidden_layer_s
izes': (3, 1), 'solver': 'lbfgs'}
CV accuracy: 0.353
Accuracy: 0.367
```

4.8. Ensembling - Random Forest

In [182…

```
# Initialize a Random Forest classifier.
rfc = RandomForestClassifier(n_jobs=-1,
                             min_samples_leaf=2,
                             max_depth=4,
                             n_estimators=10,
                             min_samples_split=5,
                             random_state=51)
rfc.fit(X_train, y_train)

# cross validation evaluation
rfc_cv = cross_val_score(rfc, X_train, y_train, cv=20)
```

In [183…

```
# CV Accuracy
print('CV Accuracy: %.3f' % rfc_cv.mean())
```

```
CV Accuracy: 0.319
```

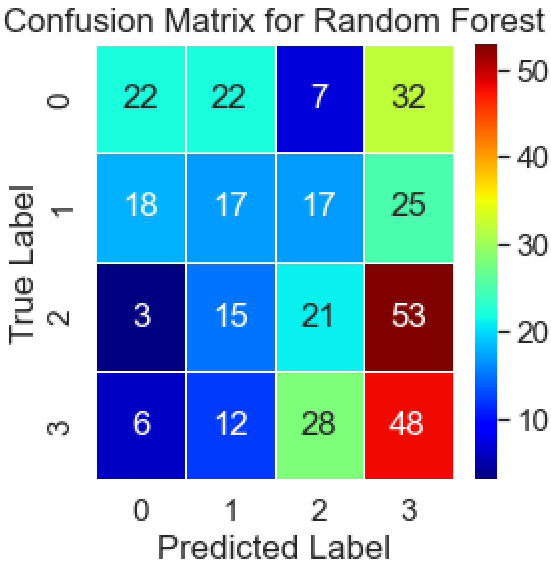
Predictions and error analysis

In [184…

```
rfc_pred = rfc.predict(X_test)
cal_metrics(y_test, rfc_pred)
print('\n')
create_confusion_matrix(y_test, rfc_pred, "Random Forest")
```

```
              precision    recall  f1-score   support

           0       0.45      0.27      0.33        83
           1       0.26      0.22      0.24        77
           2       0.29      0.23      0.25        92
           3       0.30      0.51      0.38        94

    accuracy                           0.31       346
   macro avg       0.32      0.31      0.30       346
weighted avg       0.32      0.31      0.30       346
```

```
Recall: 0.312
F1: 0.312
matthews_corrcoef: 0.077
cohen_kappa_score: 0.075
Mean squared error (MSE): 1.974
Mean absolute error (MAE): 1.043
```



5. Selecting the best model

Neural network (Multi Layered perceptron) with Grid Search performed the best among other machine learning models tested.

```
With parameters: {'activation': 'logistic', 'alpha': 0.01,
'hidden_layer_sizes': (3, 1), 'solver': 'lbfgs'}
CV accuracy: 0.353
Accuracy: 0.367
```

6. Conclusions: Presenting solutions

With data analysis and modelling I have following conclusions:

1. The best model with `36.7%` performs far worse than the random chance (50% accuracy). Such models are NOT suitable for a business use case. Rather a data-driven approach needs to be applied rather than focusing on a model-driven approach i.e. finding the best model.

2. Clearly, with `36.7%` accuracy the model didn't converge to an optimal loss.

3. Error analysis with confusion matrix refects random guessing across the `buying price` categories.

4. The data failed my assumptions of the correlations. While my assumptions might be flawed but I believe that help from an expert in the required field can help curate the

data.

5. The data already has fewer features and even if I dropped the least important feature or correlated ones, then also the accuracy was reduced by around $1-2\%$. So, dropping a feature is not an option to reduce variance in a model.
6. Collecting other features (attributes) and scaling data can be helpful.