```
import seaborn as sns
 In [4]:
          from sklearn.datasets import load_boston
          X, y = load_boston(return_X_y=True)
          feature_names = load_boston().feature_names
          data = pd.DataFrame(X, columns=feature_names)
          data['MEDV'] = y
         C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning: Function load_boston is deprecated; `load_boston` is deprecated in
         1.0 and will be removed in 1.2.
             The Boston housing prices dataset has an ethical problem. You can refer to
             the documentation of this function for further details.
             The scikit-learn maintainers therefore strongly discourage the use of this
             dataset unless the purpose of the code is to study and educate about
             ethical issues in data science and machine learning.
             In this special case, you can fetch the dataset from the original
             source::
                 import pandas as pd
                 import numpy as np
                 data_url = "http://lib.stat.cmu.edu/datasets/boston"
                 raw_df = pd.read_csv(data_url, sep="\s+", skiprows=22, header=None)
                 data = np.hstack([raw_df.values[::2, :], raw_df.values[1::2, :2]])
                 target = raw_df.values[1::2, 2]
             Alternative datasets include the California housing dataset (i.e.
             :func:`~sklearn.datasets.fetch_california_housing`) and the Ames housing
             dataset. You can load the datasets as follows::
                  from sklearn.datasets import fetch_california_housing
                 housing = fetch_california_housing()
             for the California housing dataset and::
                 from sklearn.datasets import fetch_openml
                 housing = fetch_openml(name="house_prices", as_frame=True)
             for the Ames housing dataset.
           warnings.warn(msg, category=FutureWarning)
 In [5]:
          # compute pearson's r
          target_correlation = data.corr()[['MEDV']]
          # we only care about the target variable
          plt.figure(figsize=(7,5))
          sns.heatmap(target_correlation, annot=True, cmap=plt.cm.Reds)
          plt.show()
                                                              1.0
            CRIM -
                                   -0.39
                                   0.36
             ΖN
                                                              0.8
                                   -0.48
           INDUS
                                                              0.6
                                   0.18
           CHAS
                                   -0.43
            NOX
                                                              0.4
             RM:
                                   0.7
                                   -0.38
                                                              - 0.2
            AGE
             DIS
                                                              - 0.0
                                   -0.38
            RAD
                                   -0.47
            TAX
                                                              - -0.2
                                   -0.51
          PTRATIO
                                                              -0.4
           LSTAT
                                   -0.74
                                                              - -0.6
           MEDV
                                   MEDV
          sns.heatmap(data.corr().loc[['RM', 'PTRATIO', 'LSTAT'], ['RM', 'PTRATIO', 'LSTAT']], annot=True, cmap=plt.cm.Reds)
          plt.show()
                                                   - 1.0
                                                   - 0.8
                            -0.36
                                        -0.61
          RΜ
                                                   - 0.6
                                                   - 0.4
                -0.36
                                                   - 0.2
                                                   - 0.0
                                                   - -0.2
                -0.61
                                                   -0.4
                                                   - -0.6
                           PTRATIO
                                       LSTAT
                 RM
 In [7]:
          #Linear Discriminant Analysis
          import pandas as pd
          import numpy as np
          from sklearn.linear_model import LogisticRegression
          from sklearn.preprocessing import LabelEncoder
          from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
          from sklearn.model_selection import StratifiedKFold, cross_val_score
          from sklearn.pipeline import Pipeline
In [8]:
          df = pd.read_csv('cancer.csv').iloc[:,1:-1]
          X = df.drop(['diagnosis'], axis=1)
          le = LabelEncoder()
          y = le.fit_transform(df.diagnosis)
          labels = le.classes_
In [9]:
          steps = [('lda', LinearDiscriminantAnalysis()), ('m', LogisticRegression(C=10))]
          model = Pipeline(steps=steps)
In [10]:
          # evaluate model
          cv = StratifiedKFold(n_splits=5)
          n_scores_lda = cross_val_score(model, X, y, scoring='f1_macro', cv=cv, n_jobs=-1)
          model = LogisticRegression(C=10)
          n_scores = cross_val_score(model, X, y, scoring='f1_macro', cv=cv, n_jobs=-1)
In [11]:
          # report performance
          print('f1-score (macro)\n')
          print('With LDA: %.2f' % np.mean(n_scores_lda))
          print('Without LDA: %.2f' % np.mean(n_scores))
         f1-score (macro)
         With LDA: 0.97
         Without LDA: 0.93
In [12]:
          # ANOVA
          from sklearn.feature_selection import f_classif, SelectKBest
          fs = SelectKBest(score_func=f_classif, k=5)
          X_{new} = fs.fit(X, y)
In [19]:
          from sklearn.model_selection import StratifiedKFold, GridSearch
          from sklearn.pipeline import Pipeline
          from sklearn.linear_model import LinearRegression
          cv = StratifiedKFold(n_splits=5)
          pipeline = Pipeline(steps=[('anova',fs), ('lr', LinearRegression(solver='liblinear'))])
          params = {['anova_k']: [i+1 for i in range(X.shape[1])]}
          search = GridSearchCV(pipeline, params, scoring='accuracy', n_jobs=-1, cv=cv)
          results = search.fit(X, y)
          print('Best k: %s' % results.best_params_)
                                                    Traceback (most recent call last)
         <ipython-input-19-8b97af7e48d4> in <module>
          ----> 1 from sklearn.model_selection import StratifiedKFold, GridSearch
               2 from sklearn.pipeline import Pipeline
               3 from sklearn.linear_model import LinearRegression
               4 cv = StratifiedKFold(n_splits=5)
               5 pipeline = Pipeline(steps=[('anova', fs), ('lr', LinearRegression(solver='liblinear'))])
         ImportError: cannot import name 'GridSearch' from 'sklearn.model_selection' (C:\ProgramData\Anaconda3\lib\site-packages\sklearn\model_selection\__init__.py)
In [22]:
          \#\chi^2 Chi-squared tests
          from sklearn.feature_selection import chi2, SelectKBest
          loan = pd.read_csv('loan_data_set.csv')
          loan = loan.drop('Loan_ID', axis=1) # irrelevant feature
In [23]:
          #Transform the numerical feature into categorical feature
          loan['Loan_Amount_Term'] = loan['Loan_Amount_Term'].astype('object')
          loan['Credit_History'] = loan['Credit_History'].astype('object')
In [24]:
          #Dropping all the null value
          loan.dropna(inplace = True)
In [25]:
          #Retrieve all the categorical columns except the target
          categorical_columns = loan.select_dtypes(exclude='number').drop('Loan_Status', axis=1).columns
          X = loan[categorical_columns].apply(LabelEncoder().fit_transform)
          y = LabelEncoder().fit_transform(loan['Loan_Status'])
          fs = SelectKBest(score_func=chi2, k=5)
          X_kbest = fs.fit_transform(X, y)
In [26]:
          X_kbest
Out[26]: array([[1, 1, 0, 0, 1],
                 [1, 0, 0, 1, 1],
                 [1, 0, 1, 0, 1],
                 [1, 1, 0, 0, 1],
                 [1, 2, 0, 0, 1],
                 [0, 0, 0, 1, 0]])
```

In [3]:

#Pearson's Correlation
import pandas as pd

import matplotlib.pyplot as plt