```python
# -*- coding: utf-8 -*-
## Lecture 10 assessed exercises

# Packages
from pandas import Series, DataFrame
import pandas as pd
import numpy as np
import numpy.random as npr
import statsmodels.api as sm

from statsmodels.regression.linear_model import OLS
from statsmodels.tools import add_constant

# For this set of exercises we are going to use the prostate dataset and the diamonds
# dataset. Testing your functions with two different datasets should catch any error
# related to leaving the DataFrame names inside your function.
prostate = pd.read_csv('http://statweb.stanford.edu/~tibs/ElemStatLearn/datasets/prostate.data',
diamonds = pd.read_csv('diamonds.csv')
# Remove cathegorical data and take subset of diamonds dataset
dataA = prostate.drop('train',axis=1)
dataB = dataQ1b = diamonds.drop(['cut','color','clarity'],axis=1).iloc[:100,:]

# Let's fit some regression models and create a stepwise AIC function
# As we learnt in lectures to fit a regression model, we need to create a DataFrame X
# and Series y. X should contain the standardised version of all of the explanatory/
# exogenous variables and y should contain the standardised version of the response/
# endogenous variable. To fit the intercept, X must have an additional column of ones.

# Q1 Write a function to create X and y for a given DataFrame df. The function inputs are
# the DataFrame df and the label of the response/endogenous variable res_col. The function
# should return two objects, X and y (in that order), where X and why are both standardised
# and the column of ones is the first column of X.
# (You may assume that none of the variables are categorical)
def exercise1(df,res_col):
    X = df.drop(res_col,axis=1)
    X_std=(X-X.mean())/X.std()
    X_std.insert(0,'intercept',1)
    y_std=df[res_col]-df[res_col].mean()/df[res_col].std()
    return X_std,y_std
# Suggested tests
XA, yA = exercise1(dataA,'lpsa')
XB, yB = exercise1(dataB,'price')
# Things to check to ensure code is working correctly
# - XA and XB have the same number of rows and columns as dataA and dataB, respectively
# - the first column of XA and XB is entirely ones
# - yA and yB are Series with the same number of rows as dataA and dataB, respectively
# - the mean of each variable in XA, XB, yA and yB (apart from the intercept column)
# is close to zero (~10^(-16))
# - the std of each variable in XA, XB, yA and yB (apart from the intercept column)
# is 1

# Q2 Write a function that takes X and y as inputs and fits a linear regression model.
# The function should return the rsquared value rounded to 4 decimal places
def exercise2(X,y):
    mod = sm.OLS(y,X)
    res = mod.fit()
    return round(res.rsquared,4)
# Suggested tests
# Remember we can unpack a tuple to use as a set of inputs to a function. Here we unpack
# the tuple (X,y) returned by exercise1 to use as an input for exercise2
print(exercise2(*exercise1(dataA,'lpsa')))
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# Should give 0.6634
print(exercise2(*exercise1(dataB,'price')))
# Should give 0.9426


# AIC is the Akaike information criterion. It's designed to penalise models with
# lots of explanatory variables so that we pick models which fit the data well but
# aren't too complicated. In general, if you have two models fitted to the same data,
# the model with the lowest AIC is preferable. The AIC is given as part of the model
# summary with OLS

# The steps to run a forward selection AIC regression are:
# 1. Run a linear regression with just the intercept column. Get the AIC.
# 2. Add in the explanatory variables individually, run a linear regression for each one and det
#    how much they decreases the AIC
# 3. Find the variable with the biggest decrease in AIC and include it in your linear model
# 4. Repeat step 2-3 with this new linear model and remaining explanatory variables
# 5. Repeat this process until none of the remaining explanatory variables reduce the AIC
# The explanatory variables that have been included up to the stopping point are considered the
# variables that produce a good fit without overcomplicating the model.

# Q3 Write a function that performs the AIC algorithm for a given DataFrame X and Series y.
# The function should return the names of the columns used for the model that gives the lowest A
# This question is worth 2 marks
def exercise3(X,y):
    regr0=sm.OLS(y,X['intercept'])
    aic=regr0.fit().aic
    a=['intercept']
    col_name=[n for n in X.columns]
    col_name.remove('intercept')
    while True:
        aic0=[]
        for i in range(len(col_name)):
            b=a.copy()
            b.append(col_name[i])
            regr0=sm.OLS(y,X[b])
            aic0.append(regr0.fit().aic)
        if min(aic0)<aic:
            aic=min(aic0)
            a.append(col_name[np.argmin(aic0)])
            col_name.remove(col_name[np.argmin(aic0)])
        else:
            break
    return a
# Suggested tests
print(exercise3(*exercise1(dataA,'lpsa')))
# Should give ['intercept', 'lcavol', 'lweight', 'svi', 'lbph', 'age']
print(exercise3(*exercise1(dataB,'price')))
# Should give ['intercept', 'carat', 'z', 'x', 'y', 'table']
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