Problem 1: Time Series Forecasting (20 points) In this problem, we want to create time series model to predict monthly car sales for a company. Download the zip file for homework assignment #5, and use the CarSales dataset which is a standard univariate time series dataset consists of 108 months of car sales in Quebec 1960-1968. The first column is the date and the second is the number of sales.

In [1]:

```
#Import necessary packages to the Jupyter notebook
import pandas as pd
from pandas import read_csv
from matplotlib import pyplot
from pandas.plotting import autocorrelation_plot
from statsmodels.tsa.stattools import adfuller
from random import randrange
from statsmodels.tsa.seasonal import seasonal_decompose
from sklearn.linear_model import LinearRegression
import numpy as np

from pandas import DataFrame
from statsmodels.tsa.arima_model import ARIMA
from sklearn.metrics import mean_squared_error
from math import sqrt
filename ='Dataset5/CarSales.csv'
```

(a) Load time series data: Use read csv() function to load your time series datasets as a Series object, instead of DataFrame. Use the following arguments to the read csv() function to ensure the data is loaded as a Series.

In [2]:

```
pd1=pd.read_csv(filename,header=0,parse_dates=True,index_col=0,squeeze=True)
```

(b) Exploring time series data: Use the head() function to peek at the first 10 records of your data.

In [3]:

```
pd3=pd.read_csv(filename,parse_dates=True)
pd3.head(10)
```

Out[3]:

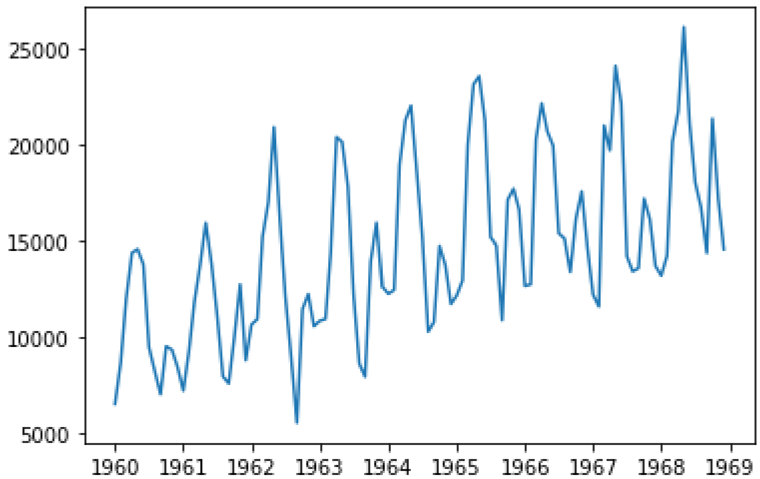
	Month	Sales
0	1960-01	6550
1	1960-02	8728
2	1960-03	12026
3	1960-04	14395
4	1960-05	14587
5	1960-06	13791
6	1960-07	9498
7	1960-08	8251
8	1960-09	7049
9	1960-10	9545

In [4]:
```
pd3.columns
```

Out[4]:
```
Index(['Month', 'Sales'], dtype='object')
```

(c) Line plot: Use the plotting functions(.plot() and .show()) from Matplotlib to visualize your Series of the monthly car sales dataset as a line plot.

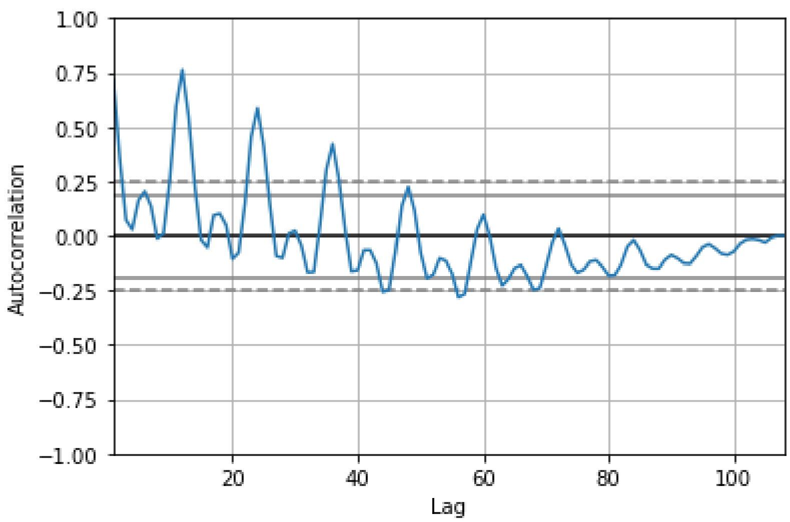
In [5]:
```
import matplotlib.pyplot as plt
plt.plot(pd1)
plt.show()
```



(d) Autocorrelation plot: Use Pandas plotting function autocorrelation plot() to create an autocorrelation plot for your series.

In [6]:
```
autocorrelation_plot(pd1)
```

Out[6]:
```
<AxesSubplot:xlabel='Lag', ylabel='Autocorrelation'>
```



(e) Stationarity in time series data: Use the adfuller() function from the Statsmodels library to perform Dickey-Fuller test to check if your time series is stationary or non-stationary. Interpret the results of the test.

In [7]:

```
# Augmented Dickey Fuller test
adfuller(pd1)
```

Out[7]:

```
(-1.223812766175286,
 0.663269104983286,
 12,
 95,
 {'1%': -3.5011373281819504,
  '5%': -2.8924800524857854,
  '10%': -2.5832749307479226},
 1671.1995896872572)
```

We see the p-value is greater then 0.05 so the series is non stationary

(f) Automatic time series decomposition: Use seasonal decompose() function from Statsmodels library. Specify your model as 'additive' and use the .plot() function to visualize the four resulting series. Interpret the results (Do you observe any trend; if yes, what kind of trend; Is there any seasonality in your data).

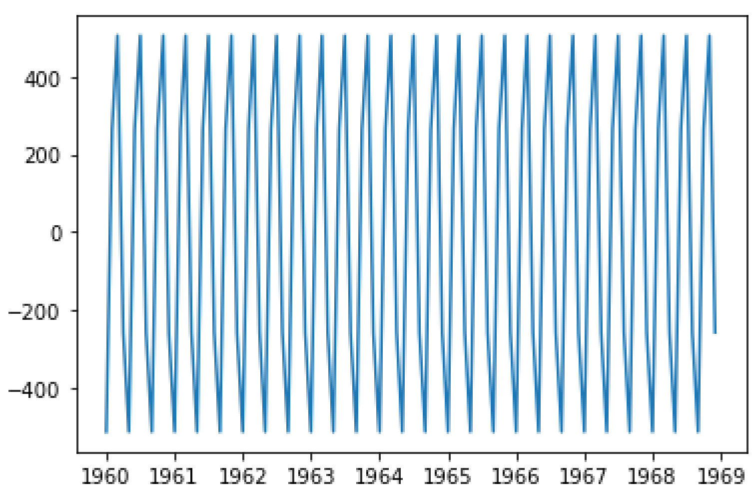
In [8]:

```
X=seasonal_decompose(pd1,period=4)
print(X.seasonal)
```

```
Month
1960-01-01   -513.270433
1960-02-01    264.806490
1960-03-01    505.965144
1960-04-01   -257.501202
1960-05-01   -513.270433
                 ...
1968-08-01   -257.501202
1968-09-01   -513.270433
1968-10-01    264.806490
1968-11-01    505.965144
1968-12-01   -257.501202
Name: seasonal, Length: 108, dtype: float64
```

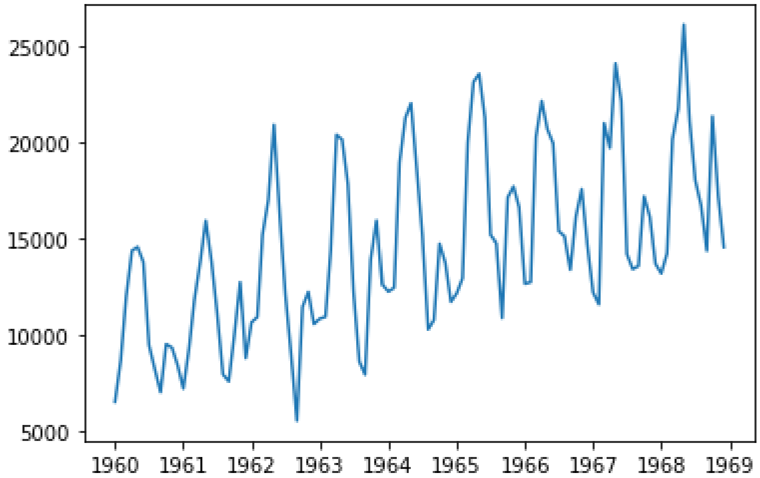
In [9]:

```
plt.plot(X.seasonal)
plt.show()
```



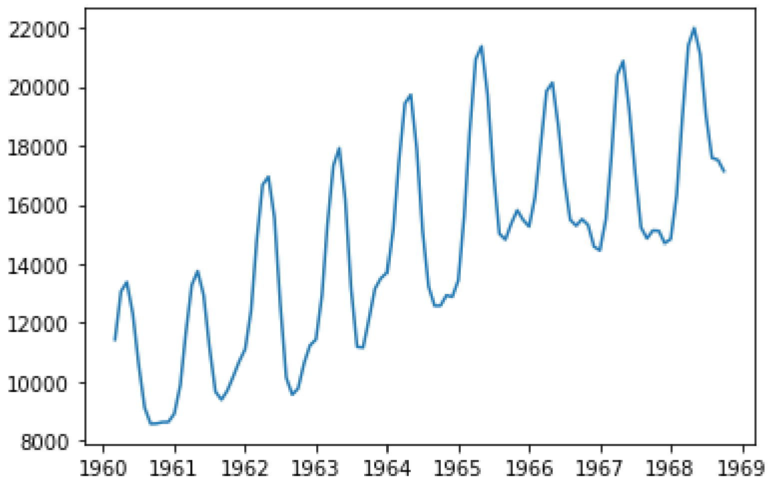
In [10]:

```
plt.plot(X.observed)
plt.show()
```



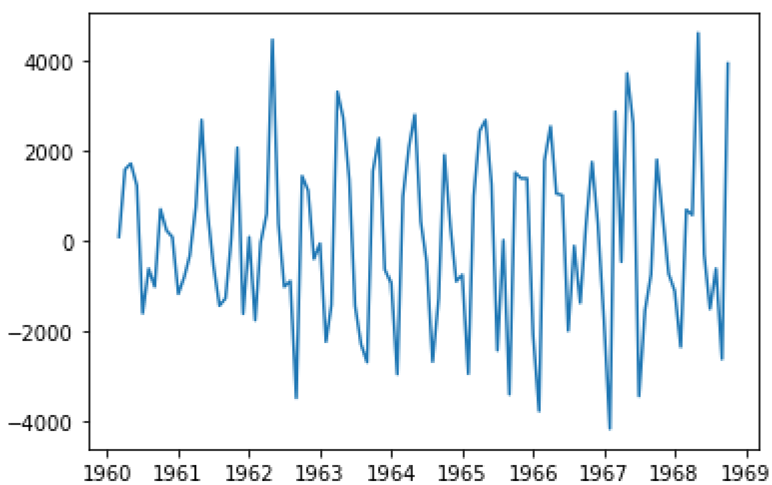
In [11]:

```
plt.plot(X.trend)
plt.show()
```



In [12]:

```
plt.plot(X.resid)
plt.show()
```



(g) Detrend by model fitting: Use a linear model to detrend your time series data:

i. Use the scikit-learn LinearRegression model to fit a linear model on your data.

ii. Use .predict() function to calculate the trend.

iii. Use .plot() and .show() functions to visualtize the trend and the series data on the same plot.

iv. Deterend your sereis by subtracting the trend values from the original values of the series, and plot the resulting detrented series in a separate plot.

In [13]:

```
X1=pd3['Month'].values.tolist()
fg=[]
c=1
for y in X1:
    fg.append(c)
    c+=1
pd3['count']=fg
X=pd3['count'].values.tolist()
y=pd3['Sales']
#pd3.head(5)
reg =LinearRegression().fit(np.array(X).reshape(-1,1), y)
reg.score(np.array(X).reshape(-1,1), y)
```

Out[13]:

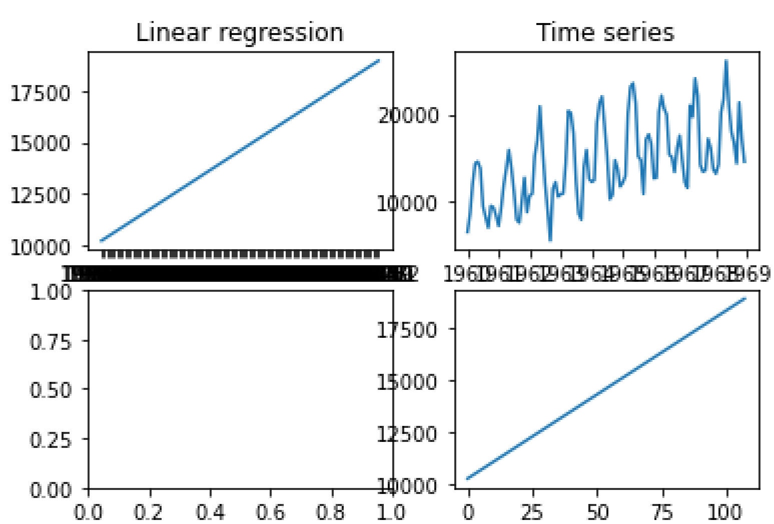
```
0.3158854329342885
```

In [14]:

```
Y2=reg.predict(np.array(X).reshape(-1,1))
import matplotlib.pyplot as plt

figure, axis = plt.subplots(2, 2)
axis[0, 0].plot(X1,Y2)
axis[0, 0].set_title("Linear regression")

# For Cosine Function
axis[0, 1].plot(pd1)
axis[0, 1].set_title("Time series")
plt.plot(Y2)
plt.show()
```



ARIMA with Python: To answer the questions for this part, you can take a look at the code from Lab Session 11. (5 points)

i. Extract the NumPy array of data values and split your data into train and test with a split of 70-30.

ii. Use the forecast() function to perform a one-step forecast using the model. Use the train set to fit the model, and generate a prediction for each element on the test set.

iii. Perform a rolling forecast by keeping track of all observations in a list called history that is seeded with the training data and to which new observations are appended each iteration; Print the prediction and expected value each iteration. To define your ARIMA model for this part use the ARIMA function from Statsmodels library, and pass in the parameters p=5, d=1, q=1.

iv. Calculate a final root mean squared error score (RMSE) for the predictions.

v. Create a line plot to show the expected values (blue) compared to the rolling forecast predictions (red).

In [15]:
```
import warnings
```

In [28]:
```
# split into train and test sets
size = int(len(pd3) * 0.66)
train, test = X[0:size], X[size:len(X)]
history = [x for x in train]
```

In [27]:
```
pd1.dropna(inplace=True)
```

model = ARIMA(history, order=(5,1,1)) # model_fit = model.fit() # output = model_fit.forecast() # prepare training dataset train_size = int(len(X) * 0.50) train, test = X[0:train_size], X[train_size:] history = [x for x in train]

In [29]:
```
# make prdictions
predictions = list()
# walk-forward validation
for t in range(len(test)):
    model = ARIMA(history, order=(5,1,1))
    model_fit = model.fit()
    output = model_fit.forecast()
    yhat = output[0]
    predictions.append(yhat)
    obs = test[t]
    history.append(obs)
    print('predicted=%f, expected=%f' % (yhat, obs))
```

```
---------------------------------------------------------------------------
LinAlgError                               Traceback (most recent call last)
C:\Users\SUMAMA~1\AppData\Local\Temp/ipykernel_59700/4132154632.py in <module>
      4 for t in range(len(test)):
      5     model = ARIMA(history, order=(5,1,1))
----> 6     model_fit = model.fit()
      7     output = model_fit.forecast()
      8     yhat = output[0]

~\anaconda3\lib\site-packages\statsmodels\tsa\arima_model.py in fit(self, start_params,
 trend, method, transparams, solver, maxiter, full_output, disp, callback, start_ar_lag
s, **kwargs)
```

```
   1226         r, order = 'F')
   1227         """
-> 1228         mlefit = super(ARIMA, self).fit(start_params, trend,
   1229                                         method, transparams, solver,
   1230                                         maxiter, full_output, disp,

~\anaconda3\lib\site-packages\statsmodels\tsa\arima_model.py in fit(self, start_params,
 trend, method, transparams, solver, maxiter, full_output, disp, callback, start_ar_lag
s, **kwargs)
   1025             kwargs.setdefault('m', 12)
   1026             kwargs.setdefault('approx_grad', True)
-> 1027         mlefit = super(ARMA, self).fit(start_params, method=solver,
   1028                                        maxiter=maxiter,
   1029                                        full_output=full_output, disp=disp,

~\anaconda3\lib\site-packages\statsmodels\base\model.py in fit(self, start_params, metho
d, maxiter, full_output, disp, fargs, callback, retall, skip_hessian, **kwargs)
    517         warn_convergence = kwargs.pop('warn_convergence', True)
    518         optimizer = Optimizer()
--> 519         xopt, retvals, optim_settings = optimizer._fit(f, score, start_params,
    520                                                        fargs, kwargs,
    521                                                        hessian=hess,

~\anaconda3\lib\site-packages\statsmodels\base\optimizer.py in _fit(self, objective, gra
dient, start_params, fargs, kwargs, hessian, method, maxiter, full_output, disp, callbac
k, retall)
    222
    223         func = fit_funcs[method]
--> 224         xopt, retvals = func(objective, gradient, start_params, fargs, kwargs,
    225                              disp=disp, maxiter=maxiter, callback=callback,
    226                              retall=retall, full_output=full_output,

~\anaconda3\lib\site-packages\statsmodels\base\optimizer.py in _fit_lbfgs(f, score, star
t_params, fargs, kwargs, disp, maxiter, callback, retall, full_output, hess)
    627         func = f
    628
--> 629     retvals = optimize.fmin_l_bfgs_b(func, start_params, maxiter=maxiter,
    630                                      callback=callback, args=fargs,
    631                                      bounds=bounds, disp=disp,

~\anaconda3\lib\site-packages\scipy\optimize\lbfgsb.py in fmin_l_bfgs_b(func, x0, fprim
e, args, approx_grad, bounds, m, factr, pgtol, epsilon, iprint, maxfun, maxiter, disp, c
allback, maxls)
    195             'maxls': maxls}
    196
--> 197     res = _minimize_lbfgsb(fun, x0, args=args, jac=jac, bounds=bounds,
    198                            **opts)
    199     d = {'grad': res['jac'],

~\anaconda3\lib\site-packages\scipy\optimize\lbfgsb.py in _minimize_lbfgsb(fun, x0, arg
s, jac, bounds, disp, maxcor, ftol, gtol, eps, maxfun, maxiter, iprint, callback, maxls,
finite_diff_rel_step, **unknown_options)
    304             iprint = disp
    305
--> 306     sf = _prepare_scalar_function(fun, x0, jac=jac, args=args, epsilon=eps,
    307                                   bounds=new_bounds,
    308                                   finite_diff_rel_step=finite_diff_rel_step)

~\anaconda3\lib\site-packages\scipy\optimize\optimize.py in _prepare_scalar_function(fu
n, x0, jac, args, bounds, epsilon, finite_diff_rel_step, hess)
```

```
    259     # ScalarFunction caches. Reuse of fun(x) during grad
    260     # calculation reduces overall function evaluations.
--> 261     sf = ScalarFunction(fun, x0, args, grad, hess,
    262                         finite_diff_rel_step, bounds, epsilon=epsilon)
    263

~\anaconda3\lib\site-packages\scipy\optimize\_differentiable_functions.py in __init__(self, fun, x0, args, grad, hess, finite_diff_rel_step, finite_diff_bounds, epsilon)
    138
    139         self._update_fun_impl = update_fun
--> 140         self._update_fun()
    141
    142         # Gradient evaluation

~\anaconda3\lib\site-packages\scipy\optimize\_differentiable_functions.py in _update_fun(self)
    231     def _update_fun(self):
    232         if not self.f_updated:
--> 233             self._update_fun_impl()
    234             self.f_updated = True
    235

~\anaconda3\lib\site-packages\scipy\optimize\_differentiable_functions.py in update_fun()
    135
    136         def update_fun():
--> 137             self.f = fun_wrapped(self.x)
    138
    139         self._update_fun_impl = update_fun

~\anaconda3\lib\site-packages\scipy\optimize\_differentiable_functions.py in fun_wrapped(x)
    132             # Overwriting results in undefined behaviour because
    133             # fun(self.x) will change self.x, with the two no longer linked.
--> 134             return fun(np.copy(x), *args)
    135
    136         def update_fun():

~\anaconda3\lib\site-packages\statsmodels\base\model.py in f(params, *args)
    499
    500         def f(params, *args):
--> 501             return -self.loglike(params, *args) / nobs
    502
    503         if method == 'newton':

~\anaconda3\lib\site-packages\statsmodels\tsa\arima_model.py in loglike(self, params, set_sigma2)
    839         method = self.method
    840         if method in ['mle', 'css-mle']:
--> 841             return self.loglike_kalman(params, set_sigma2)
    842         elif method == 'css':
    843             return self.loglike_css(params, set_sigma2)

~\anaconda3\lib\site-packages\statsmodels\tsa\arima_model.py in loglike_kalman(self, params, set_sigma2)
    849         Compute exact loglikelihood for ARMA(p,q) model by the Kalman Filter.
    850         """
--> 851         return KalmanFilter.loglike(params, self, set_sigma2)
    852
    853     def loglike_css(self, params, set_sigma2=True):
```

```
~\anaconda3\lib\site-packages\statsmodels\tsa\kalmanf\kalmanfilter.py in loglike(cls, params, arma_model, set_sigma2)
    216             paramsdtype) = cls._init_kalman_state(params, arma_model)
    217         if np.issubdtype(paramsdtype, np.float64):
--> 218             loglike, sigma2 = kalman_loglike.kalman_loglike_double(
    219                 y, k, k_ar, k_ma, k_lags, int(nobs),
    220                 Z_mat, R_mat, T_mat)

statsmodels\tsa\kalmanf\kalman_loglike.pyx in statsmodels.tsa.kalmanf.kalman_loglike.kalman_loglike_double()

statsmodels\tsa\kalmanf\kalman_loglike.pyx in statsmodels.tsa.kalmanf.kalman_loglike.kalman_filter_double()

<__array_function__ internals> in pinv(*args, **kwargs)

~\anaconda3\lib\site-packages\numpy\linalg\linalg.py in pinv(a, rcond, hermitian)
   2000         return wrap(res)
   2001     a = a.conjugate()
-> 2002     u, s, vt = svd(a, full_matrices=False, hermitian=hermitian)
   2003 
   2004     # discard small singular values

<__array_function__ internals> in svd(*args, **kwargs)

~\anaconda3\lib\site-packages\numpy\linalg\linalg.py in svd(a, full_matrices, compute_uv, hermitian)
   1658 
   1659         signature = 'D->DdD' if isComplexType(t) else 'd->ddd'
-> 1660         u, s, vh = gufunc(a, signature=signature, extobj=extobj)
   1661         u = u.astype(result_t, copy=False)
   1662         s = s.astype(_realType(result_t), copy=False)

~\anaconda3\lib\site-packages\numpy\linalg\linalg.py in _raise_linalgerror_svd_nonconvergence(err, flag)
     95 
     96 def _raise_linalgerror_svd_nonconvergence(err, flag):
---> 97     raise LinAlgError("SVD did not converge")
     98 
     99 def _raise_linalgerror_lstsq(err, flag):

LinAlgError: SVD did not converge
```

In [30]:

```python
import math
from sklearn.metrics import mean_squared_error

# evaluate forecasts
rmse = math.sqrt(mean_squared_error(test, predictions))
print("Test RMSE: {}".format(rmse))
# plot forecasts against actual outcomes
plt.plot(test)
plt.plot(predictions, color='red')
plt.show()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
C:\Users\SUMAMA~1\AppData\Local\Temp/ipykernel_59700/1095995198.py in <module>
      3 
```

```
      4 # evaluate forecasts
----> 5 rmse = math.sqrt(mean_squared_error(test, predictions))
      6 print("Test RMSE: {}".format(rmse))
      7 # plot forecasts against actual outcomes

~\anaconda3\lib\site-packages\sklearn\metrics\_regression.py in mean_squared_error(y_tru
e, y_pred, sample_weight, multioutput, squared)
    436     0.825...
    437     """
--> 438     y_type, y_true, y_pred, multioutput = _check_reg_targets(
    439         y_true, y_pred, multioutput
    440     )

~\anaconda3\lib\site-packages\sklearn\metrics\_regression.py in _check_reg_targets(y_tru
e, y_pred, multioutput, dtype)
     92         the dtype argument passed to check_array.
     93     """
---> 94     check_consistent_length(y_true, y_pred)
     95     y_true = check_array(y_true, ensure_2d=False, dtype=dtype)
     96     y_pred = check_array(y_pred, ensure_2d=False, dtype=dtype)

~\anaconda3\lib\site-packages\sklearn\utils\validation.py in check_consistent_length(*ar
rays)
    330     uniques = np.unique(lengths)
    331     if len(uniques) > 1:
--> 332         raise ValueError(
    333             "Found input variables with inconsistent numbers of samples: %r"
    334             % [int(l) for l in lengths]

ValueError: Found input variables with inconsistent numbers of samples: [37, 0]
```

In [ ]:

In [ ]:

Problem 2: Multilayer Perceptron for Binary Classification (15 points) In this problem you will create a classification neural network in Keras using the KerasClassifier wrapper. For this problem, from the zip file you downloaded for homework assignment #5, use the pima-indians-diabetes dataset. The objective of the dataset is to diagnostically predict whether or not a patient has diabetes, based on certain diagnostic measurements included in the dataset. Several constraints were placed on the selection of these instances from a larger database. In particular, all patients here are females at least 21 years old of Pima Indian heritage. The datasets consists of several medical predictor variables and one target variable. Predictor variables includes the number of pregnancies the patient has had, their BMI, insulin level, age, and so on.

!pip install tensorflow

In [31]:

```
import numpy as np
import tensorflow as tf
import random as python_random
# fix random seed for reproducibility
def reset_seeds ():
    np.random.seed ( 123 )
    python_random.seed ( 123 )
```

```
    tf.random.set_seed ( 1234 )
    reset_seeds ()
from numpy import loadtxt
from keras.models import Sequential
from keras.layers import Dense,InputLayer
from keras.wrappers. scikit_learn import KerasClassifier
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
import numpy
from pandas import read_csv
# Load the dataset
filename = "Dataset5/pima-indians-diabetes.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataset = read_csv ( filename , names = names )
# split into input (X) and output (y) variables
array = dataset . values
X = array [:,0:8]
y = array [:,8]
```

(a) Define your Keras model

In [32]:

```
def create_model():
    model = tf.keras.models.Sequential()
    model.add(tf.keras.layers.Dense(12,input_dim=8 ,activation='relu'))

# Now the model will take as input arrays of shape (None, 16)
# and output arrays of shape (None, 32).
# Note that after the first layer, you don't need to specify
# the size of the input anymore:
    model.add(tf.keras.layers.Dense(8,activation='relu'))
    model.add(tf.keras.layers.Dense(1, activation='sigmoid'))
    model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
    return model
#m1=create_model(X,y)
m2=KerasClassifier(build_fn=create_model,epochs=10,batch_size=16,verbose=0)
```

```
C:\Users\SUMAMA~1\AppData\Local\Temp/ipykernel_59700/291242446.py:14: DeprecationWarnin
g: KerasClassifier is deprecated, use Sci-Keras (https://github.com/adriangb/scikeras) i
nstead. See https://www.adriangb.com/scikeras/stable/migration.html for help migrating.
  m2=KerasClassifier(build_fn=create_model,epochs=10,batch_size=16,verbose=0)
```

In [33]:

```
print(m2)
```

```
<keras.wrappers.scikit_learn.KerasClassifier object at 0x0000027FB39876A0>
```

(b) Create model using KerasClassifier wrapper class: Wrap your deep learning model using KerasClassifier wrapper:

In [34]:

```
dict1={'epochs':[20,50,70],'batch_size':[16,32]}
clf = GridSearchCV(m2, dict1,cv=4)
'''
kfold=KFold(n_splits=4)
cv_results=cross_val_score(clf,X,y,cv=kfold,verbose=1)
'''
```

```
'\nkfold=KFold(n_splits=4)\ncv_results=cross_val_score(clf,X,y,cv=kfold,verbose=1)\n'
```

Out[34]:

(c) Evaluate model with cross-validation

In [35]:

```
fg=clf.fit(np.array(X),np.array(y))
```

In [36]:

```
for t in fg.cv_results_.keys():
    print(t,fg.cv_results_[t])
```

```
mean_fit_time [0.546287   0.97657204 1.24571913 0.35400623 0.5797956  0.83301556]
std_fit_time [0.04970124 0.06568983 0.08453245 0.00267233 0.01904517 0.07985517]
mean_score_time [0.08825666 0.08235198 0.07608241 0.07194698 0.072833   0.07362354]
std_score_time [0.00861939 0.00559923 0.00145848 0.00149754 0.00072484 0.00268758]
param_batch_size [16 16 16 32 32 32]
param_epochs [20 50 70 20 50 70]
params [{'batch_size': 16, 'epochs': 20}, {'batch_size': 16, 'epochs': 50}, {'batch_siz
e': 16, 'epochs': 70}, {'batch_size': 32, 'epochs': 20}, {'batch_size': 32, 'epochs': 5
0}, {'batch_size': 32, 'epochs': 70}]
split0_test_score [0.640625   0.703125   0.703125   0.60416669 0.66666669 0.69270831]
split1_test_score [0.67708331 0.69791669 0.63541669 0.58333331 0.66666669 0.671875  ]
split2_test_score [0.6875     0.79166669 0.76041669 0.60416669 0.671875   0.76041669]
split3_test_score [0.61458331 0.63541669 0.65104169 0.65625    0.65625    0.66666669]
mean_test_score [0.65494791 0.70703126 0.68750001 0.61197917 0.66536459 0.69791667]
std_test_score [0.02908634 0.0556555  0.0489971  0.02693771 0.00567565 0.03737683]
rank_test_score [5 1 3 6 4 2]
```

(d) Grid search parameters: Using GridSearchCV class, perform a grid search on the number of epochs [20,50,70], and the batch sizes of [5,10,20].

In [37]:

```
dict1={'epochs':[20,50,70],'batch_size':[16,32]}
clf = GridSearchCV(m2, dict1)
```

In [ ]:

```
```

Problem 3: CNN Model for Photo Classification (15 points) Define a simple CNN network and evaluate how well it performs on the problem of CIFAR-10 Photo Classification. CIFAR is an acronym that stands for the Canadian Institute For Advanced Research and the CIFAR-10 dataset was developed along with the CIFAR-100 dataset by researchers at the CIFAR institute. The dataset is comprised of 60,000 32×32 pixel color photographs of objects from 10 classes, such as frogs, birds, cats, ships, etc. Part of the code below loads the CIFAR-10 train and test dataset using the Keras API.

In [38]:

```
from keras.datasets import cifar10
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Dropout
from keras.layers import Flatten
from keras.constraints import maxnorm
from tensorflow.keras.optimizers import SGD
from keras.layers.convolutional import Conv2D
from keras.layers.convolutional import MaxPooling2D
from keras.utils import np_utils
from tensorflow.keras.utils import to_categorical
# Load data
```

```
( X_train,y_train),(X_test ,y_test)=cifar10.load_data ()
# normalize inputs from 0-255 to 0.0-1.0
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train = X_train / 255.0
X_test = X_test / 255.0
# one hot encode outputs
y_train = np_utils.to_categorical ( y_train )
y_test = np_utils.to_categorical ( y_test )
num_classes = y_test.shape [1]
```

(a) Create the CNN model: Use a structure with two convolutional layers followed by max pooling and a flattening out of the network to fully connected layers to make predictions.

(b) Compile the model: Compile your model with an SGD optimizer that uses learning rate schedule

In [39]:

```
from keras.layers import Input,Conv2D,MaxPooling2D,UpSampling2D,Flatten,Conv2DTranspose
from keras.models import Model, Sequential
from keras.layers.core import Dense, Dropout
from keras.layers.advanced_activations import LeakyReLU

def create_model():
    input1 = Input(shape=(32,32,3))
    first_conv = Conv2D(32,(3,3),activation='relu',padding='same')(input1)
    #sec_max=MaxPooling2D((2,2))(first_conv)
    first_conv=(BatchNormalization(momentum=0.8))(first_conv)
    first_conv=Dropout(rate=0.3)(first_conv) # apply 30% dropout to the next layer
    first_conv = Conv2D(32,(3,3),activation='relu',padding='same')(input1)
    #sec_max=MaxPooling2D((2,2))(first_conv)
    first_conv=Dropout(rate=0.3)(first_conv) # apply 30% dropout to the next layer
    first_conv=(BatchNormalization(momentum=0.8))(first_conv)
    sec_max=MaxPooling2D((2,2))(first_conv)
    flat = Flatten()(sec_max)
    dense1=Dense(512,activation='relu')(flat)
    dense2=Dense(10, activation='softmax')(dense1)
    model = Model(inputs=input1, outputs=dense2, name="classify_model")
    model.compile(loss='categorical_crossentropy',optimizer='sgd',metrics=['accuracy'])
    return model
mod1=create_model()
```

In [40]:

```
mod1.summary()
```

```
Model: "classify_model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 32, 32, 3)]       0

 conv2d_1 (Conv2D)           (None, 32, 32, 32)        896

 dropout_1 (Dropout)         (None, 32, 32, 32)        0

 batch_normalization_1 (Batc  (None, 32, 32, 32)       128
 hNormalization)

 max_pooling2d (MaxPooling2D  (None, 16, 16, 32)       0
 )
```

```
 flatten (Flatten)           (None, 8192)              0

 dense_75 (Dense)            (None, 512)               4194816

 dense_76 (Dense)            (None, 10)                5130

=================================================================
Total params: 4,200,970
Trainable params: 4,200,906
Non-trainable params: 64
_________________________________________________________________
```

(c) Fit the model

In [41]:

```python
mod1.fit(np.array(X_train),np.array(y_train),epochs=25,batch_size=32)
```

```
Epoch 1/25
1563/1563 [==============================] - 41s 26ms/step - loss: 1.4889 - accuracy: 0.
4745
Epoch 2/25
1563/1563 [==============================] - 44s 28ms/step - loss: 1.1374 - accuracy: 0.
5972
Epoch 3/25
1563/1563 [==============================] - 45s 29ms/step - loss: 0.9582 - accuracy: 0.
6645
Epoch 4/25
1563/1563 [==============================] - 45s 29ms/step - loss: 0.8135 - accuracy: 0.
7175
Epoch 5/25
1563/1563 [==============================] - 47s 30ms/step - loss: 0.6830 - accuracy: 0.
7607
Epoch 6/25
1563/1563 [==============================] - 48s 30ms/step - loss: 0.5622 - accuracy: 0.
8064
Epoch 7/25
1563/1563 [==============================] - 48s 30ms/step - loss: 0.4517 - accuracy: 0.
8450
Epoch 8/25
1563/1563 [==============================] - 45s 29ms/step - loss: 0.3550 - accuracy: 0.
8807
Epoch 9/25
1563/1563 [==============================] - 46s 29ms/step - loss: 0.2745 - accuracy: 0.
9090
Epoch 10/25
1563/1563 [==============================] - 55s 35ms/step - loss: 0.2117 - accuracy: 0.
9292
Epoch 11/25
1563/1563 [==============================] - 55s 35ms/step - loss: 0.1659 - accuracy: 0.
9459
Epoch 12/25
1563/1563 [==============================] - 56s 36ms/step - loss: 0.1325 - accuracy: 0.
9569
Epoch 13/25
1563/1563 [==============================] - 50s 32ms/step - loss: 0.1061 - accuracy: 0.
9676
Epoch 14/25
1563/1563 [==============================] - 43s 28ms/step - loss: 0.0867 - accuracy: 0.
9736
```

```
Epoch 15/25
1563/1563 [==============================] - 45s 29ms/step - loss: 0.0706 - accuracy: 0.
9790
Epoch 16/25
1563/1563 [==============================] - 46s 30ms/step - loss: 0.0657 - accuracy: 0.
9802
Epoch 17/25
1563/1563 [==============================] - 48s 31ms/step - loss: 0.0547 - accuracy: 0.
9841
Epoch 18/25
1563/1563 [==============================] - 44s 28ms/step - loss: 0.0500 - accuracy: 0.
9852
Epoch 19/25
1563/1563 [==============================] - 46s 29ms/step - loss: 0.0448 - accuracy: 0.
9870
Epoch 20/25
1563/1563 [==============================] - 47s 30ms/step - loss: 0.0360 - accuracy: 0.
9900
Epoch 21/25
1563/1563 [==============================] - 47s 30ms/step - loss: 0.0344 - accuracy: 0.
9898
Epoch 22/25
1563/1563 [==============================] - 50s 32ms/step - loss: 0.0299 - accuracy: 0.
9916
Epoch 23/25
1563/1563 [==============================] - 50s 32ms/step - loss: 0.0289 - accuracy: 0.
9918
Epoch 24/25
1563/1563 [==============================] - 50s 32ms/step - loss: 0.0253 - accuracy: 0.
9929
Epoch 25/25
1563/1563 [==============================] - 49s 31ms/step - loss: 0.0244 - accuracy: 0.
9933
```

Out[41]:

```
<keras.callbacks.History at 0x27fbcafee80>
```

(d) Evaluate the model

In [42]:

```
x=[1,-1,-1,-1,7]
f=np.array(x)
print(f)
print(np.gradient(f))
```

```
[ 1 -1 -1 -1  7]
[-2. -1.  0.  4.  8.]
```

In [ ]: