from google.colab import drive drive.mount('/content/drive/')%cd /content/drive/My Drive/TimeSeriesForecasting

Web Traffic Forecasting : DL Modeling

In [3]:

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

from tqdm import tqdm
import pandas as pd
import numpy as np
from tqdm import tqdm
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
import joblib

from sklearn.preprocessing import StandardScaler

import tensorflow as tf
import gc
from tensorflow.keras.backend import clear_session
from tensorflow.keras.models import model_from_json

from tensorflow.keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import RandomizedSearchCV

from tensorflow.keras.layers import Dense, concatenate, Activation, BatchNormalization
from tensorflow.keras.layers import Input, Flatten, LSTM
from tensorflow.keras.layers import Dropout, Conv1D, MaxPooling1D
from tensorflow.keras import Model, Sequential

from tensorflow.keras import optimizers
from tensorflow.keras.models import model_from_json
```

Loading Actual Train Data

In [4]:

```
complete_train = pd.read_csv('./train_2.csv')

complete_train['Site']      = complete_train['Page'].map(lambda x:x.split('_')[-3])
complete_train['Site_Name'] = complete_train['Site'].map(lambda x:x.split('.')[1])
complete_train['Language']  = complete_train['Site'].map(lambda x:x.split('.')[0])
complete_train['Access']    = complete_train['Page'].map(lambda x:x.split('_')[-2])
complete_train['Agent']     = complete_train['Page'].map(lambda x:x.split('_')[-1])

from sklearn.preprocessing import LabelEncoder
label = LabelEncoder()

complete_train['Site_OHE'] = label.fit_transform(complete_train['Site_Name']).tolist()
print("Site Encoded using     : ", label.classes_)

complete_train['Lang_OHE'] = label.fit_transform(complete_train['Language']).tolist()
print("Language Encoded using : ", label.classes_)

complete_train['Access_OHE'] = label.fit_transform(complete_train['Access']).tolist()
print("Access Encoded using   : ", label.classes_)

complete_train['Agent_OHE'] = label.fit_transform(complete_train['Agent']).tolist()
print("Agent Encoded using    : ", label.classes_)

complete_train.drop(['Site', 'Site_Name', 'Language', 'Access', 'Agent'], axis=1, inpla
ce=True)
complete_train = complete_train.fillna(0)
#complete_train.to_csv('./Transformed_train_2.csv', index=False)


#test_dates
from datetime import date, timedelta

#end of the train is Sep 20, 2017 and data to e
start = date(2017,9,11)
end   = date(2017,11,13)
no_days = end - start
test_days = [ (start+timedelta(days=x)).strftime('%Y-%m-%d') for x in range(no_days.day
s+1) ]
print("\n\nTest Data to run from {0} upto {1}".format(test_days[0], test_days[-1]))
```

```
Site Encoded using     :  ['mediawiki' 'wikimedia' 'wikipedia']
Language Encoded using :  ['commons' 'de' 'en' 'es' 'fr' 'ja' 'ru' 'www'
'zh']
Access Encoded using   :  ['all-access' 'desktop' 'mobile-web']
Agent Encoded using    :  ['all-agents' 'spider']


Test Data to run from 2017-09-11 upto 2017-11-13
```

Loading Page-Key file

In [5]:

```
page_key = pd.read_csv('./key_2.csv')
page_key.head()
```

Out[5]:

	Page	Id
0	007_スペクター_ja.wikipedia.org_all-access_all-agen...	0b293039387a
1	007_スペクター_ja.wikipedia.org_all-access_all-agen...	7114389dd824
2	007_スペクター_ja.wikipedia.org_all-access_all-agen...	057b02ff1f09
3	007_スペクター_ja.wikipedia.org_all-access_all-agen...	bd2aca21caa3
4	007_スペクター_ja.wikipedia.org_all-access_all-agen...	c0effb42cdd5

Loading Train Data

In [6]:

```
#Load data
train = pd.read_csv('./train_data.csv')
test  = pd.read_csv('./test_data.csv')
```

In [7]:

```
non_date_cols = [ x for x in train.columns.tolist() if x.endswith('_OHE') ]
date_cols = [ x for x in train.columns.tolist() if x not in non_date_cols ]
```

In [8]:

```
X_timeseries  = train[date_cols]
X_pagedata    = train[non_date_cols]
observed      = X_timeseries.iloc[:, -1]
pagename_X_te = test[non_date_cols]
```

Metric for evaluation

In [9]:

```
def smape(ytr, ypr):
    ytr += np.log1p(0.0001)
    numerator   = np.abs(ypr - ytr)
    #print(numerator)
    denominator = (np.abs(ytr) + np.abs(ypr))
    #print(denominator)
    return (200/len(ytr) * np.sum( numerator / denominator ))


def tf_smape(ytr, ypr):
    return tf.py_function(smape, (ytr, ypr), tf.double)


def rmse(ytr, ypr):
    from math import sqrt
    from sklearn.metrics import mean_squared_error
    return sqrt(mean_squared_error(ytr, ypr))


def tf_rmse(ytr, ypr):
    return tf.py_function(rmse, (ytr, ypr), tf.double)
```

In [10]:

```
#parameters
lagged_window = [7, 30, 90, 365]
batch = 256
epoch = 20
models = dict()
```

In [11]:

```
from tensorflow.keras.callbacks import EarlyStopping
dl_stopping = EarlyStopping(monitor='tf_smape', patience=3)

deep_epoch = 150
```

[1] Deep Learning Models

[1.1] Simple DNN

In [20]:

```
def dense_model(shape, print_summary=False):
  """
  Model returns simple Deep Neural Network for given data, given input params
  """
  model = Sequential()
  model.add(Dense(512, activation='relu', input_shape=(shape, )))
  model.add(Dense(128, activation='relu'))
  model.add(Dense(64, activation='relu'))
  model.add(Dense(8, activation='relu'))
  model.add(Dense(1))
  model.compile(loss='mean_squared_error', optimizer='adam', metrics=[tf_smape])
  if print_summary:
      model.summary()
  return model
```

[1.1.1] Hyper Parameter Tuning

In [ ]:

```
error = list()
for lag in lagged_window:
  clear_session()
  print("**** Running for Lag = ",lag)
  X = np.log1p(X_timeseries.iloc[:,-lag-1:-1])
  #X = X_timeseries.iloc[:,-lag-1:-1]
  observed = X_timeseries.iloc[:,-1]
  Y = np.log1p(X_timeseries.iloc[:,-1])
  #Y = X_timeseries.iloc[:,-1]
  #print("Dataset shape is ",X.shape)
  model = dense_model(lag)
  model.fit(X, Y, batch_size=batch, epochs=epoch, verbose=0)
  predicted = np.ceil(np.expm1(model.predict(X)))
  #predicted = np.ceil(model.predict(X))
  predicted = np.array(predicted).reshape((X.shape[0]))
  cv_smape = smape(observed, predicted)
  error.append([cv_smape, lag])
  print("SMAPE = {0} for lag = {1}".format(cv_smape, lag))

index         = np.argmin([ x[0] for x in error ])
best_window   = error[index][1]
best_cv_smape = error[index][0]

print("\n\nBest Values are : \n",best_window, "\n", "Best SMAPE on CV data is ",best_cv
_smape)
```

```
**** Running for Lag =  7
SMAPE = 33.00412664190798 for lag = 7
**** Running for Lag =  30
SMAPE = 33.479609194460465 for lag = 30
**** Running for Lag =  90
SMAPE = 31.717767144881265 for lag = 90
**** Running for Lag =  365
SMAPE = 32.75959930484306 for lag = 365


Best Values are :
 90
 Best SMAPE on CV data is  31.717767144881265
```

[1.1.2] Fitting Model with Best Window

In [21]:

```
best_window = 90
print("Model is trained and found to have : ")
print("Best Window = ",best_window)
print("\n\n")
gc.collect()
X = np.log1p(X_timeseries.iloc[:,-best_window-1:-1])
Y = np.log1p(X_timeseries.iloc[:,-1])

#fitting model with best parameters
model = dense_model(best_window, print_summary=True)
model.fit(X, Y, batch_size=batch, epochs=epoch, verbose=1)

#save the model weights
my_model = model.to_json()
with open("copy_dnn_model.json", "w") as json_file:
  json_file.write(my_model)
model.save_weights("copy_dnn_model_weights.h5")
```

```
Model is trained and found to have :
Best Window =  90



Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 512)               46592
_________________________________________________________________
dense_1 (Dense)              (None, 128)               65664
_________________________________________________________________
dense_2 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_3 (Dense)              (None, 8)                 520
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 9
=================================================================
Total params: 121,041
Trainable params: 121,041
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
567/567 [==============================] - 4s 7ms/step - loss: 0.3479 - tf
_smape: 18.5284
Epoch 2/20
567/567 [==============================] - 4s 7ms/step - loss: 0.2060 - tf
_smape: 17.2852
Epoch 3/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1880 - tf
_smape: 16.9578
Epoch 4/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1783 - tf
_smape: 16.7330
Epoch 5/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1778 - tf
_smape: 16.7006
Epoch 6/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1711 - tf
_smape: 16.4924
Epoch 7/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1733 - tf
_smape: 16.4948
Epoch 8/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1691 - tf
_smape: 16.3811
Epoch 9/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1706 - tf
_smape: 16.3822
Epoch 10/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1653 - tf
_smape: 16.2543
Epoch 11/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1635 - tf
_smape: 16.1833
Epoch 12/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1621 - tf
_smape: 16.1338
Epoch 13/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1618 - tf
```

```
_smape: 16.0896
Epoch 14/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1629 - tf
_smape: 16.1612
Epoch 15/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1576 - tf
_smape: 15.9910
Epoch 16/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1561 - tf
_smape: 15.9508
Epoch 17/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1556 - tf
_smape: 15.9177
Epoch 18/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1555 - tf
_smape: 15.9109
Epoch 19/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1562 - tf
_smape: 15.9481
Epoch 20/20
567/567 [==============================] - 4s 7ms/step - loss: 0.1554 - tf
_smape: 15.9336
```

[1.1.3] CV data Analysis

In [ ]:

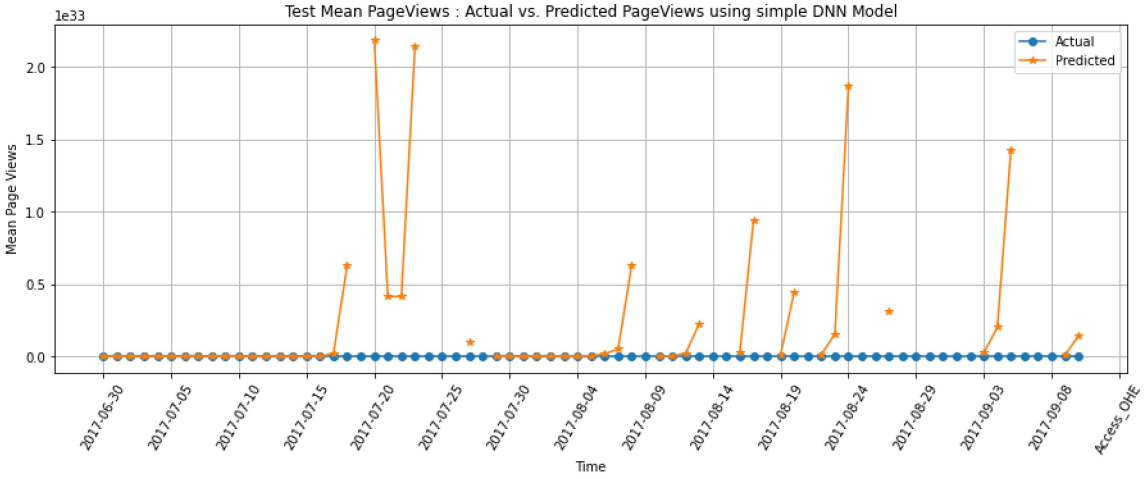
```
#history of values
history = X_timeseries.iloc[:, -best_window:]
gc.collect()
clear_session()
#testing the model on test data
test_data = pd.DataFrame()
test_cols = test.columns.tolist()
for col in tqdm(test_cols[:-4]):
  X = np.log1p(history.iloc[:,-best_window:])
  #X = history.iloc[:,-best_window:]
  predict = np.ceil(np.expm1(model.predict(X)))
  #predict = np.ceil(model.predict(X))
  predict = np.array(predict).reshape((X.shape[0]))
  test_data[col] = predict
  history[col]   = predict

#checking SMAPE on forecasted and actual CV values
cv_smape = np.mean(smape(test.iloc[:,:-4], test_data))
print("\nSMAPE on CV data = ",cv_smape)
models['DNN Model'] = [best_window, cv_smape]
```

```
100%|██████████| 73/73 [04:32<00:00,  3.73s/it]

SMAPE on CV data =  52.22553137457099
```

[1.1.4] CV SMAPE Performance

In [ ]:

```
#plot for mean of actual test and predicted test
plt.figure(figsize=(15, 5))
plt.title('Test Mean PageViews : Actual vs. Predicted PageViews using simple DNN Model'
)
actual_mean = test.iloc[:, :-4].mean(axis=0)
pred_mean   = test_data.mean(axis=0)

xtick_labels = [ x for x in enumerate(test_cols) if x[0]%5==0 ]
xtick_loc    = [ x[0] for x in xtick_labels ]
xtick_label  = [ x[1] for x in xtick_labels ]
b1 = plt.plot(actual_mean, marker="o")
b2 = plt.plot(pred_mean, marker="*")
plt.xlabel('Time')
plt.ylabel('Mean Page Views')
plt.grid()
plt.legend([b1[0], b2[0]], ['Actual', 'Predicted'])
plt.xticks(xtick_loc, xtick_label, rotation=60)
plt.show()
```



[1.2] Simple LSTM

In [28]:

```
def lstm(shape, print_summary=False):
    """
    simple 2 layered LSTM model for data. Returns the compiled model with
    passed parameters.
    """
    model = Sequential()
    model.add(LSTM(16, activation='relu', return_sequences=True, input_shape=(shape, 1
)))
    model.add(LSTM(16, activation='relu'))
    model.add(Dropout(0.20))
    #model.add(Flatten())
    model.add(Dense(1))
    model.compile(loss='mean_squared_error', optimizer='adam', metrics=[tf_smape])
    if print_summary:
        model.summary()
    return model
```

[1.2.1] Hyper Parameter Tuning

In [4]:

```
gc.collect()
error = list()
for lag in lagged_window:
  clear_session()
  print("**** Running for Lag=",lag)
  X = np.log1p(X_timeseries.iloc[:,-lag-1:-1])
  #X = X_timeseries.iloc[:,-lag-1:-1]
  r, c  = X.shape
  X = np.array(X).reshape((r, c, 1))
  Y = np.log1p(X_timeseries.iloc[:,-1])
  observed = X_timeseries.iloc[:, -1]
  #Y = X_timeseries.iloc[:,-1]
  #print("Dataset shape is ",X.shape)
  model = lstm(lag)
  model.fit(X, Y, batch_size=batch, epochs=epoch, verbose=1)
  predicted = np.ceil(np.expm1(model.predict(X)))
  #predicted = np.ceil(model.predict(X))
  predicted = np.array(predicted).reshape((X.shape[0]))
  #tr_smape = smape(Y, predicted)
  cv_smape = np.mean(smape(observed, predicted))
  print("SMAPE for Lag=%d is %f"%(lag, cv_smape))
  error.append([cv_smape, lag])

index         = np.argmin([ x[0] for x in error ])
best_window   = error[index][1]
best_cv_smape = error[index][0]

print("\n\nBest Values are : \n",best_window, "\n", best_cv_smape)
```

```
**** Running for Lag= 7
SMAPE for Lag=7 is 33.978622
**** Running for Lag= 30
SMAPE for Lag=30 is 33.208534
**** Running for Lag= 90
SMAPE for Lag=90 is 77.149977
**** Running for Lag= 365
SMAPE for Lag=90 is nan


Best Values are :
 30
 33.20853431493801
```

[1.2.2] Fitting Model with Best Window

In [5]:

```
print("Model is trained and found to have : ")
print("Best Window = ",best_window)
print("\n\n")

#fiting model with best parameters
X = np.log1p(X_timeseries.iloc[:,-best_window-1:-1])
#X = X_timeseries.iloc[:,-best_window-1:-1]
r, c = X.shape
X = np.array(X).reshape((r, c, 1))
Y = np.log1p(X_timeseries.iloc[:,-1])
#Y = X_timeseries.iloc[:,-1]

#fitting model wth best parameters
clear_session()
model = lstm(best_window, print_summary=True)
model.fit(X, Y, batch_size=batch, epochs=epoch, verbose=1)

#save the model weights
my_model = model.to_json()
with open("copy_lstm_model.json", "w") as json_file:
  json_file.write(my_model)
model.save_weights("copy_lstm_model_weights.h5")
```

```
Model is trained and found to have :
Best Window =  30



_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 30, 16)            1152
_________________________________________________________________
lstm_1 (LSTM)                (None, 16)                2112
_________________________________________________________________
dropout (Dropout)            (None, 16)                0
_________________________________________________________________
dense (Dense)                (None, 1)                 17
=================================================================
Total params: 3,281
Trainable params: 3,281
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
145063/145063 [==============================] - 35s 244us/sample - loss:
1.7801 - tf_smape: 32.7476
Epoch 2/20
145063/145063 [==============================] - 36s 248us/sample - loss:
1.0008 - tf_smape: 25.9185 - loss: 1.
Epoch 3/20
145063/145063 [==============================] - 35s 243us/sample - loss:
0.8892 - tf_smape: 24.9882
Epoch 4/20
145063/145063 [==============================] - 36s 248us/sample - loss:
0.8249 - tf_smape: 24.1920
Epoch 5/20
145063/145063 [==============================] - 36s 251us/sample - loss:
0.7478 - tf_smape: 23.3956
Epoch 6/20
145063/145063 [==============================] - 36s 248us/sample - loss:
0.6780 - tf_smape: 22.6881 - loss: 0.6787 - tf_smape: 22
Epoch 7/20
145063/145063 [==============================] - 36s 251us/sample - loss:
0.6254 - tf_smape: 22.1257
Epoch 8/20
145063/145063 [==============================] - 37s 255us/sample - loss:
0.5648 - tf_smape: 21.6160
Epoch 9/20
145063/145063 [==============================] - 37s 255us/sample - loss:
0.5224 - tf_smape: 21.2912
Epoch 10/20
145063/145063 [==============================] - 37s 253us/sample - loss:
0.4743 - tf_smape: 20.8531
Epoch 11/20
145063/145063 [==============================] - 37s 256us/sample - loss:
0.4483 - tf_smape: 20.6893
Epoch 12/20
145063/145063 [==============================] - 37s 255us/sample - loss:
0.4233 - tf_smape: 20.5420 - loss: 0.4232 - t
Epoch 13/20
145063/145063 [==============================] - 38s 264us/sample - loss:
0.4109 - tf_smape: 20.4978
Epoch 14/20
145063/145063 [==============================] - 36s 251us/sample - loss:
```

```
0.3983 - tf_smape: 20.5042
Epoch 15/20
145063/145063 [==============================] - 37s 254us/sample - loss:
0.3879 - tf_smape: 20.4735
Epoch 16/20
145063/145063 [==============================] - 37s 252us/sample - loss:
0.3892 - tf_smape: 20.5422
Epoch 17/20
145063/145063 [==============================] - 38s 263us/sample - loss:
0.3910 - tf_smape: 20.6383 - loss - ETA: 4s - loss
Epoch 18/20
145063/145063 [==============================] - 38s 261us/sample - loss:
0.3800 - tf_smape: 20.5794
Epoch 19/20
145063/145063 [==============================] - 37s 257us/sample - loss:
0.3776 - tf_smape: 20.6055
Epoch 20/20
145063/145063 [==============================] - 36s 248us/sample - loss:
0.3776 - tf_smape: 20.5790
```

[1.2.3] CV data Analysis

In [2]:

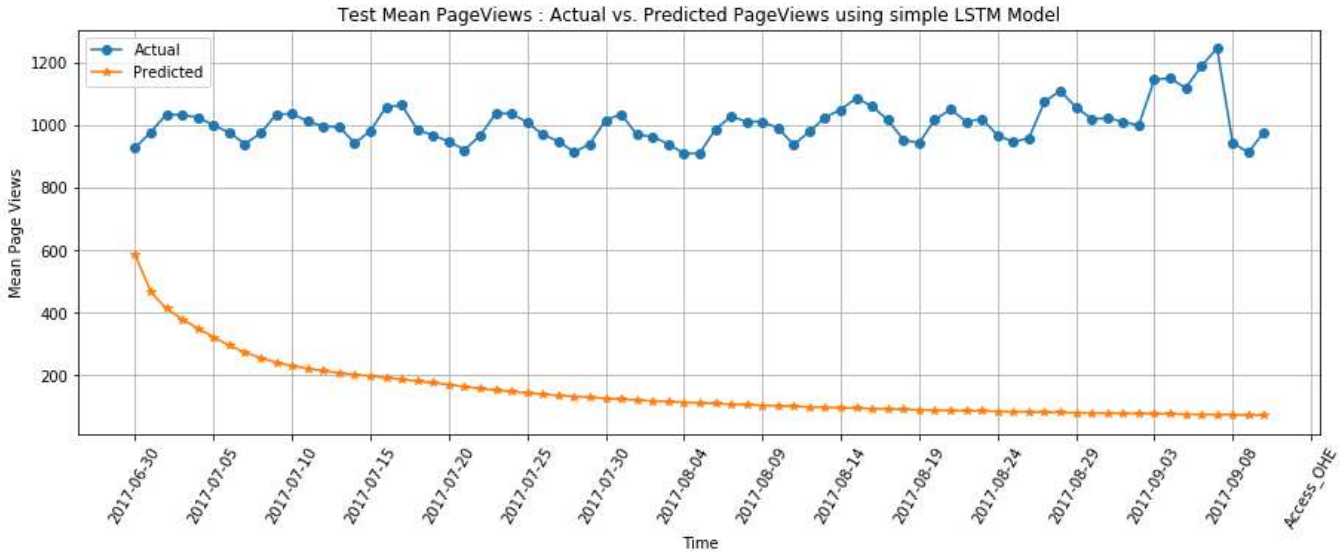
```
#history of values
history = X_timeseries.iloc[:, -best_window:]
gc.collect()
#testing the model on test data
test_data = pd.DataFrame()
test_cols = test.columns.tolist()
for col in tqdm(test_cols[:-4]):
  clear_session()
  X = np.log1p(history.iloc[:,-best_window:])
  #X = history.iloc[:,-best_window:]
  r, c = X.shape
  X = np.array(X).reshape((r, c, 1))
  predict = np.ceil(np.expm1(model.predict(X)))
  #predict = np.ceil(model.predict(X))
  predict = np.array(predict).reshape((X.shape[0]))
  test_data[col] = predict
  history[col]   = predict

#checking SMAPE on forecasted and actual CV values
cv_smape = np.mean(smape(test.iloc[:,:-4], test_data))
print("\nSMAPE on CV data = ",cv_smape)
models['LSTM Model'] = [best_window, cv_smape]
```

```
SMAPE on CV data =  94.2299259028066
```

[1.2.4] CV SMAPE Performance

In [ ]:

```
#plot for mean of actual test and predicted test
plt.figure(figsize=(15, 5))
plt.title('Test Mean PageViews : Actual vs. Predicted PageViews using simple LSTM Mode
l')
actual_mean = test.iloc[:, :-4].mean(axis=0)
pred_mean   = test_data.mean(axis=0)

xtick_labels = [ x for x in enumerate(test_cols) if x[0]%5==0 ]
xtick_loc    = [ x[0] for x in xtick_labels ]
xtick_label  = [ x[1] for x in xtick_labels ]
b1 = plt.plot(actual_mean, marker="o")
b2 = plt.plot(pred_mean, marker="*")
plt.xlabel('Time')
plt.ylabel('Mean Page Views')
plt.grid()
plt.legend([b1[0], b2[0]], ['Actual', 'Predicted'])
plt.xticks(xtick_loc, xtick_label, rotation=60)
plt.show()
```



[1.3] CNN Model

In [29]:

```
def cnn_model(shape, print_summary=False):
  """
  function that takes paramter and returns simple CNN model
  """
  model = Sequential()
  #adding convolution layer
  model.add(Conv1D(filters=128, kernel_size=2, activation='relu', \
                   kernel_initializer = 'he_uniform', input_shape=(shape, 1)))
  model.add(Conv1D(filters=128, kernel_size=2, activation='relu', \
                   kernel_initializer = 'he_uniform'))
  model.add(MaxPooling1D(pool_size=3))
  #flatten the model output
  model.add(Flatten())
  #add Dense layers
  model.add(Dense(32, activation='relu'))
  model.add(Dense(1))
  #compile model with loss and metrics
  model.compile(loss='mean_squared_error', optimizer='adam', metrics=[tf_smape])
  #return model and Print is necessary
  if print_summary:
    model.summary()
  return model
```

[1.3.1] Hyper Parameter Tuning

In [ ]:

```
gc.collect()
error = list()
for lag in lagged_window:
  print("**** Running for Lag=",lag)
  clear_session()
  X = np.log1p(X_timeseries.iloc[:,-lag-1:-1])
  #X = X_timeseries.iloc[:,-lag-1:-1]
  r, c  = X.shape
  X = np.array(X).reshape((r, c, 1))
  Y = np.log1p(X_timeseries.iloc[:,-1])
  #Y = X_timeseries.iloc[:,-1]
  observed = X_timeseries.iloc[:, -1]
  #print("Dataset shape is ",X.shape)
  model = cnn_model(lag)
  model.fit(X, Y, batch_size=batch, epochs=epoch, verbose=0)
  predicted = np.ceil(np.expm1(model.predict(X)))
  #predicted = np.ceil(model.predict(X))
  predicted = np.array(predicted).reshape((X.shape[0]))
  #tr_smape = smape(Y, predicted)
  cv_smape = np.mean(smape(observed, predicted))
  error.append([cv_smape, lag])
  print("SMAPE = {0} for Lag = {1}".format(cv_smape, lag))
index         = np.argmin([ x[0] for x in error ])
best_window   = error[index][1]
best_cv_smape = error[index][0]

print("\n\nBest Values are : \n",best_window, "\n", "Best SMAPE on CV data is ",best_cv
_smape)
```

```
**** Running for Lag= 7
SMAPE = 36.903023985148906 for Lag = 7
**** Running for Lag= 30
SMAPE = 37.92718723119423 for Lag = 30
**** Running for Lag= 90
SMAPE = 33.94058462715518 for Lag = 90
**** Running for Lag= 365
SMAPE = 45.45721823042916 for Lag = 365


Best Values are :
 90
 Best SMAPE on CV data is  33.94058462715518
```

[1.3.2] Fitting Model with Best Window

In [ ]:

```
#best_window = 30
print("Model is trained and found to have : ")
print("Best Window = "    ,best_window)
print("\n\n")
gc.collect()

X = np.log1p(X_timeseries.iloc[:,-best_window-1:-1])
#X = X_timeseries.iloc[:,-best_window-1:-1]
r, c = X.shape
X = np.array(X).reshape((r, c, 1))
Y = np.log1p(X_timeseries.iloc[:,-1])
#Y = X_timeseries.iloc[:,-1]

#fitting model wth best parameters
model = cnn_model(best_window, print_summary=True)
model.fit(X, Y, batch_size=batch, epochs=epoch, verbose=1)

#save the model weights
my_model = model.to_json()
with open("copy_cnn_model.json", "w") as json_file:
  json_file.write(my_model)
model.save_weights("copy_cnn_model_weights.h5")
```

```
Model is trained and found to have :
Best Window =  90



Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_2 (Conv1D)            (None, 89, 128)           384
_________________________________________________________________
conv1d_3 (Conv1D)            (None, 88, 128)           32896
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 29, 128)           0
_________________________________________________________________
flatten_1 (Flatten)          (None, 3712)              0
_________________________________________________________________
dense_2 (Dense)              (None, 32)                118816
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 33
=================================================================
Total params: 152,129
Trainable params: 152,129
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
567/567 [==============================] - 76s 135ms/step - loss: 25.8401
- tf_smape: 177.4318
Epoch 2/20
567/567 [==============================] - 76s 135ms/step - loss: 13.7947
- tf_smape: 103.5658
Epoch 3/20
567/567 [==============================] - 77s 135ms/step - loss: 0.2625 -
tf_smape: 17.8155
Epoch 4/20
567/567 [==============================] - 76s 135ms/step - loss: 0.2227 -
tf_smape: 17.3939
Epoch 5/20
567/567 [==============================] - 77s 136ms/step - loss: 0.2115 -
tf_smape: 17.2064
Epoch 6/20
567/567 [==============================] - 77s 135ms/step - loss: 0.2075 -
tf_smape: 17.1612
Epoch 7/20
567/567 [==============================] - 76s 135ms/step - loss: 0.2055 -
tf_smape: 17.1461
Epoch 8/20
567/567 [==============================] - 76s 134ms/step - loss: 0.2001 -
tf_smape: 16.9979
Epoch 9/20
567/567 [==============================] - 78s 137ms/step - loss: 0.1971 -
tf_smape: 16.9304
Epoch 10/20
567/567 [==============================] - 79s 140ms/step - loss: 0.1974 -
tf_smape: 16.9231
Epoch 11/20
567/567 [==============================] - 77s 137ms/step - loss: 0.1955 -
tf_smape: 16.8685
Epoch 12/20
567/567 [==============================] - 77s 136ms/step - loss: 0.1933 -
tf_smape: 16.8296
```

```
Epoch 13/20
567/567 [==============================] - 77s 135ms/step - loss: 0.1932 -
tf_smape: 16.8252
Epoch 14/20
567/567 [==============================] - 77s 136ms/step - loss: 0.1950 -
tf_smape: 16.8795
Epoch 15/20
567/567 [==============================] - 76s 135ms/step - loss: 0.1905 -
tf_smape: 16.7339
Epoch 16/20
567/567 [==============================] - 76s 135ms/step - loss: 0.1924 -
tf_smape: 16.8101
Epoch 17/20
567/567 [==============================] - 77s 136ms/step - loss: 0.1906 -
tf_smape: 16.7771
Epoch 18/20
567/567 [==============================] - 77s 135ms/step - loss: 0.1898 -
tf_smape: 16.7510
Epoch 19/20
567/567 [==============================] - 76s 135ms/step - loss: 0.1894 -
tf_smape: 16.7464
Epoch 20/20
567/567 [==============================] - 75s 133ms/step - loss: 0.1891 -
tf_smape: 16.7529
```

[1.3.3] CV data Analysis

In [ ]:

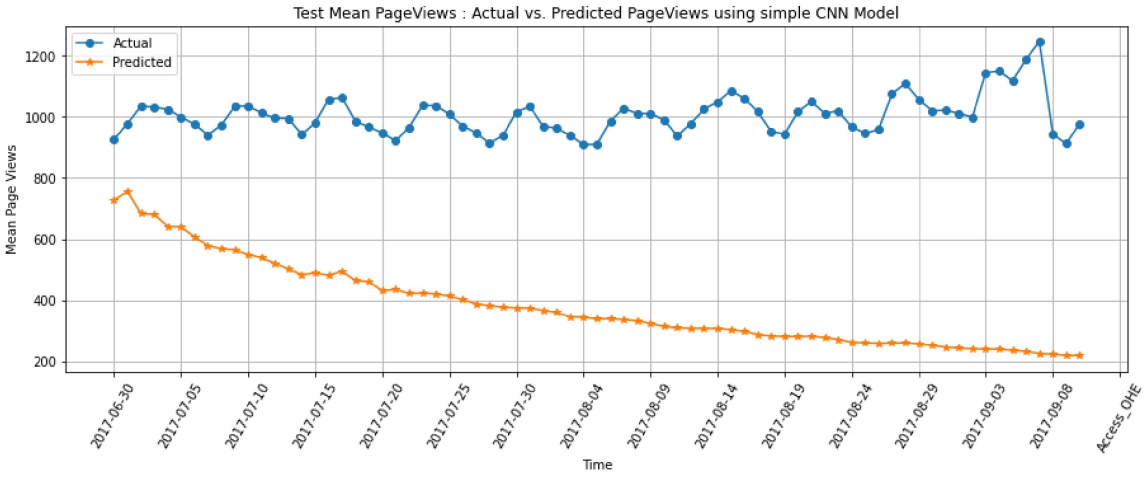
```
#history of values
history = X_timeseries.iloc[:, -best_window:]

#testing the model on test data
test_data = pd.DataFrame()
test_cols = test.columns.tolist()
for col in tqdm(test_cols[:-4]):
  clear_session()
  X = np.log1p(history.iloc[:,-best_window:])
  #X = history.iloc[:,-best_window:]
  r, c = X.shape
  X = np.array(X).reshape((r, c, 1))
  predict = np.ceil(np.expm1(model.predict(X)))
  #predict = np.ceil(model.predict(X))
  predict = np.array(predict).reshape((X.shape[0]))
  test_data[col] = predict
  history[col]   = predict

#checking SMAPE on forecasted and actual CV values
cv_smape = np.mean(smape(test.iloc[:,:-4], test_data))
print("\nSMAPE on CV data = ",cv_smape)
models['CNN Model'] = [best_window, cv_smape]
```

```
100%|██████████| 73/73 [34:32<00:00, 28.39s/it]

SMAPE on CV data =  57.822529574117574
```

[1.3.4] CV SMAPE Performance

In [ ]:

```
#plot for mean of actual test and predicted test
plt.figure(figsize=(15, 5))
plt.title('Test Mean PageViews : Actual vs. Predicted PageViews using simple CNN Model'
)
actual_mean = test.iloc[:, :-4].mean(axis=0)
pred_mean   = test_data.mean(axis=0)

xtick_labels = [ x for x in enumerate(test_cols) if x[0]%5==0 ]
xtick_loc    = [ x[0] for x in xtick_labels ]
xtick_label  = [ x[1] for x in xtick_labels ]
b1 = plt.plot(actual_mean, marker="o")
b2 = plt.plot(pred_mean, marker="*")
plt.xlabel('Time')
plt.ylabel('Mean Page Views')
plt.grid()
plt.legend([b1[0], b2[0]], ['Actual', 'Predicted'])
plt.xticks(xtick_loc, xtick_label, rotation=60)
plt.show()
```



[1.4] CNN-LSTM

In [30]:

```
def cnn_lstm_model(shape, print_summary=False):
    model = Sequential()
    #adding convolution layer
    model.add(Conv1D(filters=128, kernel_size=2, activation='relu', \
                     kernel_initializer = 'he_uniform', input_shape=(shape, 1)))
    model.add(Conv1D(filters=128, kernel_size=2, activation='relu', \
                     kernel_initializer = 'he_uniform'))
    model.add(MaxPooling1D(pool_size=3))
    #model.add(Flatten())
    #adding LSTM layer
    model.add(LSTM(128, activation='relu', return_sequences=True))
    model.add(LSTM(128, activation='relu'))
    #flatten the model output
    #model.add(Flatten())
    #add Dense layers
    #model.add(Dense(128, activation='relu'))
    model.add(Dense(64, activation='relu'))
    model.add(Dropout(0.20))
    model.add(Dense(8, activation='relu'))
    model.add(Dropout(0.20))
    model.add(Dense(1))

    #compile model with loss and metrics
    model.compile(loss='mean_squared_error', optimizer='adam', metrics=[tf_smape])
    #return model and Print is necessary
    if print_summary:
      model.summary()
    return model
```

[1.4.1] Hyper Parameter Tuning

In [3]:

```
gc.collect()
error = list()
for lag in lagged_window:
  clear_session()
  print("**** Running for Lag=",lag)
  X = np.log1p(X_timeseries.iloc[:,-lag-1:-1])
  #X = X_timeseries.iloc[:,-lag-1:-1]
  r, c  = X.shape
  X = np.array(X).reshape((r, c, 1))
  Y = np.log1p(X_timeseries.iloc[:,-1])
  observed = X_timeseries.iloc[:,-1]
  #Y = X_timeseries.iloc[:,-1]
  #print("Dataset shape is ",X.shape)
  model = cnn_lstm_model(lag)
  model.fit(X, Y, batch_size=batch, epochs=epoch, verbose=1)
  predicted = np.ceil(np.expm1(model.predict(X)))
  #predicted = np.ceil(model.predict(X))
  predicted = np.array(predicted).reshape((X.shape[0]))
  #tr_smape = smape(Y, predicted)
  cv_smape = np.mean(smape(observed, predicted))
  error.append([cv_smape, lag])
  print("SMAPE = {0} for Lag = {1}".format(cv_smape, lag))

index         = np.argmin([ x[0] for x in error ])
best_window   = error[index][1]
best_cv_smape = error[index][0]

print("\n\nBest Values are : \n",best_window, "\n", "Best SMAPE on CV data is ",best_cv
_smape)
```

```
**** Running for Lag= 7
SMAPE = 39.37963930453302 for Lag = 7
**** Running for Lag= 30
SMAPE = 40.214171562408254 for Lag = 30
**** Running for Lag= 90
SMAPE = 125.42138458837948 for Lag = 90
**** Running for Lag= 365
SMAPE = nan for Lag = 365


Best Values are :
 7
 Best SMAPE on CV data is 39.37963930453302
```

[1.4.2] Fitting Model with Best Window

In [ ]:

```
best_window = 7
print("Model is trained and found to have : ")
print("Best Window = ",best_window)
print("\n\n")
gc.collect()
X = np.log1p(X_timeseries.iloc[:,-best_window-1:-1])
#X = X_timeseries.iloc[:,-best_window-1:-1
r, c = X.shape
X = np.array(X).reshape((r, c, 1))
Y = np.log1p(X_timeseries.iloc[:,-1])
#Y = X_timeseries.iloc[:,-1]

#fitting model wth best parameters
model = cnn_lstm_model(best_window, print_summary=True)
model.fit(X, Y, batch_size=batch, epochs=epoch, verbose=1)

#save the model weights
my_model = model.to_json()
with open("copy_cnn_lstm_model.json", "w") as json_file:
  json_file.write(my_model)
model.save_weights("copy_cnn_lstm_model_weights.h5")
```

```
Model is trained and found to have :
Best Window =  7



Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d (Conv1D)              (None, 6, 128)            384
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 5, 128)            32896
_________________________________________________________________
max_pooling1d (MaxPooling1D) (None, 1, 128)            0
_________________________________________________________________
lstm (LSTM)                  (None, 1, 128)            131584
_________________________________________________________________
lstm_1 (LSTM)                (None, 128)               131584
_________________________________________________________________
dense (Dense)                (None, 64)                8256
_________________________________________________________________
dropout (Dropout)            (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 8)                 520
_________________________________________________________________
dropout_1 (Dropout)          (None, 8)                 0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 9
=================================================================
Total params: 305,233
Trainable params: 305,233
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
567/567 [==============================] - 15s 27ms/step - loss: 2.7432 -
tf_smape: 39.3032
Epoch 2/20
567/567 [==============================] - 15s 26ms/step - loss: 2.1506 -
tf_smape: 34.5698
Epoch 3/20
567/567 [==============================] - 15s 27ms/step - loss: 1.8659 -
tf_smape: 31.9813
Epoch 4/20
567/567 [==============================] - 15s 27ms/step - loss: 1.5962 -
tf_smape: 29.7126
Epoch 5/20
567/567 [==============================] - 15s 26ms/step - loss: 1.3745 -
tf_smape: 27.8663
Epoch 6/20
567/567 [==============================] - 15s 26ms/step - loss: 1.1821 -
tf_smape: 26.3996
Epoch 7/20
567/567 [==============================] - 15s 26ms/step - loss: 1.0382 -
tf_smape: 25.3538
Epoch 8/20
567/567 [==============================] - 15s 26ms/step - loss: 0.9084 -
tf_smape: 24.5452
Epoch 9/20
567/567 [==============================] - 15s 26ms/step - loss: 0.8081 -
tf_smape: 23.9284
Epoch 10/20
```

```
567/567 [==============================] - 15s 26ms/step - loss: 0.7348 -
tf_smape: 23.4781
Epoch 11/20
567/567 [==============================] - 15s 27ms/step - loss: 0.6804 -
tf_smape: 23.2343
Epoch 12/20
567/567 [==============================] - 15s 27ms/step - loss: 0.6440 -
tf_smape: 23.1066
Epoch 13/20
567/567 [==============================] - 15s 26ms/step - loss: 0.6227 -
tf_smape: 23.1369
Epoch 14/20
567/567 [==============================] - 15s 27ms/step - loss: 0.5995 -
tf_smape: 22.9819
Epoch 15/20
567/567 [==============================] - 15s 27ms/step - loss: 0.5932 -
tf_smape: 23.0784
Epoch 16/20
567/567 [==============================] - 15s 26ms/step - loss: 0.5899 -
tf_smape: 23.0904
Epoch 17/20
567/567 [==============================] - 16s 28ms/step - loss: 0.5859 -
tf_smape: 23.1269
Epoch 18/20
567/567 [==============================] - 15s 27ms/step - loss: 0.5886 -
tf_smape: 23.1906
Epoch 19/20
567/567 [==============================] - 15s 26ms/step - loss: 0.5760 -
tf_smape: 23.1008
Epoch 20/20
567/567 [==============================] - 15s 26ms/step - loss: 0.5762 -
tf_smape: 23.0964
```

[1.4.3] CV data Analysis

In [ ]:

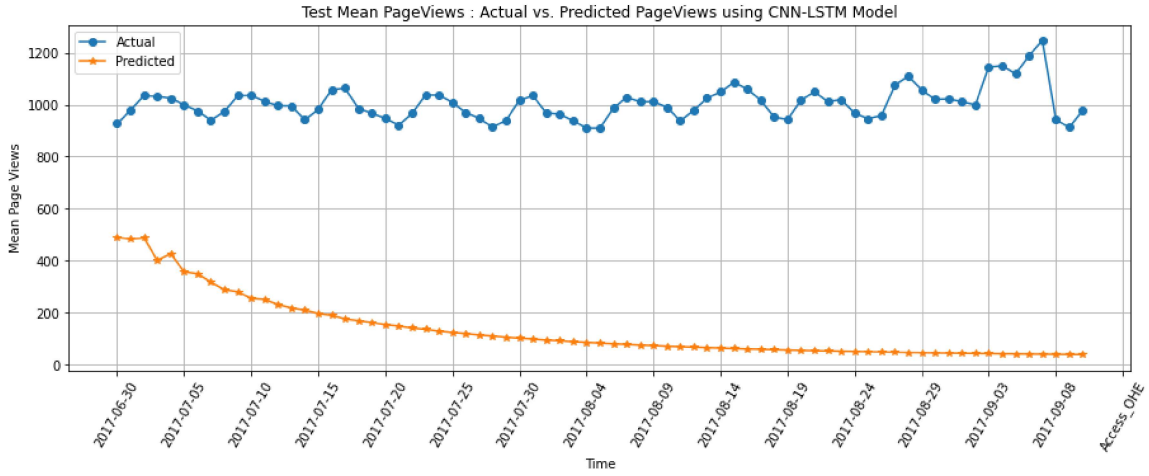
```
#history of values
history = X_timeseries.iloc[:, -best_window:]

gc.collect()
#testing the model on test data
test_data = pd.DataFrame()
test_cols = test.columns.tolist()
for col in tqdm(test_cols[:-4]):
  clear_session()
  X = np.log1p(history.iloc[:,-best_window:])
  #X = history.iloc[:,-best_window:]
  r, c = X.shape
  X = np.array(X).reshape((r, c, 1))
  predict = np.ceil(np.expm1(model.predict(X, batch_size=batch, use_multiprocessing=Tru
e)))
  #predict = np.ceil(model.predict(X))
  predict = np.array(predict).reshape((X.shape[0]))
  test_data[col] = predict
  history[col]   = predict

#checking SMAPE on forecasted and actual CV values
cv_smape = np.mean(smape(test.iloc[:,:-4], test_data))
print("\nSMAPE on CV data = ",cv_smape)
models['CNN-LSTM Model'] = [best_window, cv_smape]
```

```
100%|██████████| 73/73 [05:00<00:00,  4.12s/it]

SMAPE on CV data =  97.02710490172983
```

[1.4.4] CV SMAPE Performance

In [ ]:

```
#plot for mean of actual test and predicted test
plt.figure(figsize=(15, 5))
plt.title('Test Mean PageViews : Actual vs. Predicted PageViews using CNN-LSTM Model')
actual_mean = test.iloc[:, :-4].mean(axis=0)
pred_mean   = test_data.mean(axis=0)

xtick_labels = [ x for x in enumerate(test_cols) if x[0]%5==0 ]
xtick_loc    = [ x[0] for x in xtick_labels ]
xtick_label  = [ x[1] for x in xtick_labels ]
b1 = plt.plot(actual_mean, marker="o")
b2 = plt.plot(pred_mean, marker="*")
plt.xlabel('Time')
plt.ylabel('Mean Page Views')
plt.grid()
plt.legend([b1[0], b2[0]], ['Actual', 'Predicted'])
plt.xticks(xtick_loc, xtick_label, rotation=60)
plt.show()
```



[2] Conclusion : Model Performance

In [8]:

```
from prettytable import PrettyTable
dl_models = PrettyTable(['Model', 'Best Window', 'CV performance'])

for k, v in models.items():
  dl_models.add_row([k, v[0], round(v[1], 4)])

print(dl_models)
```

```
+----------------+-------------+----------------+
|     Model      | Best Window | CV performance |
+----------------+-------------+----------------+
|   DNN Model    |      90     |    52.2255     |
|   LSTM Model   |      30     |    84.4969     |
|   CNN Model    |      90     |    57.8225     |
| CNN-LSTM Model |      7      |    97.0271     |
+----------------+-------------+----------------+
```

From above, we can see that Models, DNN, CNN and LSTM gives least SMAPE with CV data.

We will prepare the test forecasting of these models as well as increase the layers of the LSTM and CNN models to check if they perform better or not

[3] On Test Data

In [ ]:

```
models = dict()
```

[3.1] Test Data Analysis : DNN Model

In [ ]:

```
#load the model weights
with open('copy_dnn_model.json', 'r') as f:
    model = model_from_json(f.read())
# Load weights into the new model
model.load_weights('copy_dnn_model_weights.h5')
```

In [22]:

```
best_window = 90
print("DNN Model is trained and found to have Best_Window of %d"%best_window)

past_data_cols = complete_train.columns.tolist()[-best_window-5:]
past_data_cols.insert(0, 'Page')

past_data = complete_train[past_data_cols]
#past_data.head()

#getting date columns and non_date columns
date_cols = [ x for x in past_data.columns.tolist() if '-' in x ]
non_date  = [ x for x in past_data.columns.tolist() if x not in date_cols and x != 'Pag
e' ]

#separating the ata into series of PageViews and Site features
timeseries_X = complete_train[date_cols]
```

```
DNN Model is trained and found to have Best_Window of 90
```

In [23]:

```
X = np.log1p(timeseries_X.iloc[:,:-1])
#X = X_timeseries.iloc[:,-best_window-1:-1]
r, c = X.shape
X = np.array(X).reshape((r, c, 1))
Y = np.log1p(timeseries_X.iloc[:,-1])
#Y = X_timeseries.iloc[:,-1]

#from tensorflow.keras.models import model_from_json
#with open('complex_lstm_model.json', 'r') as f:
#    model = model_from_json(f.read())
## Load weights into the new model
#model.load_weights('complex_lstm_model_weights.h5')
model.summary()

#model.fit(X, Y, batch_size=batch, epochs=epoch, verbose=1)
```

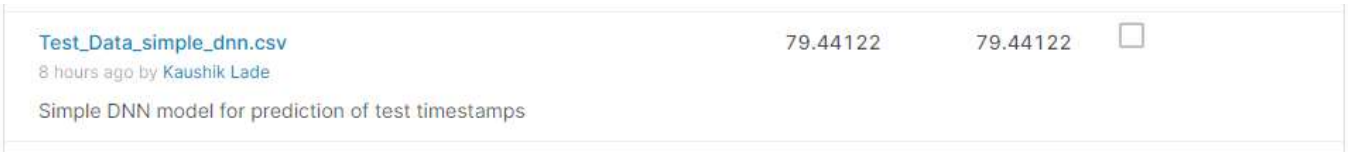
```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 512)               46592
_________________________________________________________________
dense_1 (Dense)              (None, 128)               65664
_________________________________________________________________
dense_2 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_3 (Dense)              (None, 8)                 520
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 9
=================================================================
Total params: 121,041
Trainable params: 121,041
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```
model_test = pd.DataFrame()
model_test['Page'] = complete_train.Page.values
#print(past_data.shape)
for test_index in range(len(test_days)):
    #clear_session()
    print("Remaining are %d"%(len(test_days)-test_index+1))
    #print(history.shape)
    X = np.log1p(timeseries_X.iloc[:,-best_window:])
    r, c = X.shape
    #X = np.array(X).reshape((r, c, 1))
    #X_lagged = np.hstack((X_pagename_te, X))
    predicted = np.ceil(np.expm1(model.predict(X)))
    model_test[test_days[test_index]]   = predicted
    timeseries_X[test_days[test_index]] = predicted
```

In [26]:

```
f = open('simple_dnn_Page_Count.csv', 'w')
f.write('Page|Visits'+'\n')
for col in model_test.iloc[:,-62:].columns.tolist():
  test_data = model_test[['Page',col]]
  pageviews = [ str(int(x)) for x in test_data.iloc[:,-1] ]
  pagename  = [ x+'_'+test_data.columns.tolist()[-1] for x in test_data.iloc[:,0] ]
  page_view = list(zip(pagename,pageviews))
  #writing it into file
  for line in page_view:
    n, c = line
    f.write(n+'|'+c)
    f.write('\n')
test_data_final = pd.read_csv('./simple_dnn_Page_Count.csv', sep='|')

#saving the final file
page_key.merge(test_data_final, how='left', on='Page')[['Id', 'Visits']].fillna(0).to_c
sv('./Test_Data_simple_dnn.csv', index=False)
```



In [ ]:

```
models['DNN Model'] = [best_window, cv_smape, 79.44122]
```

[3.2] Test Data Analysis : CNN Model

In [34]:

```
best_window = 90
print("CNN Model is trained and found to have Best_Window of %d"%best_window)


past_data_cols = complete_train.columns.tolist()[-best_window-5:]
past_data_cols.insert(0, 'Page')

past_data = complete_train[past_data_cols]
#past_data.head()

#getting date columns and non_date columns
date_cols = [ x for x in past_data.columns.tolist() if '-' in x ]
non_date  = [ x for x in past_data.columns.tolist() if x not in date_cols and x != 'Pag
e' ]

#separating the ata into series of PageViews and Site features
pagename_X   = complete_train[non_date]
timeseries_X = complete_train[date_cols]
```

```
CNN Model is trained and found to have Best_Window of 90
```

In [36]:

```
X = np.log1p(timeseries_X.iloc[:,-best_window-1:-1])
#X = X_timeseries.iloc[:,-best_window-1:-1]
r, c = X.shape
X = np.array(X).reshape((r, c, 1))
Y = np.log1p(timeseries_X.iloc[:,-1])
#Y = X_timeseries.iloc[:,-1]

from tensorflow.keras.models import model_from_json
with open('copy_cnn_model.json', 'r') as f:
    model = model_from_json(f.read())
# Load weights into the new model
model.load_weights('copy_cnn_model_weights.h5')
model.summary()

#model.fit(X, Y, batch_size=batch, epochs=epoch, verbose=1)
```

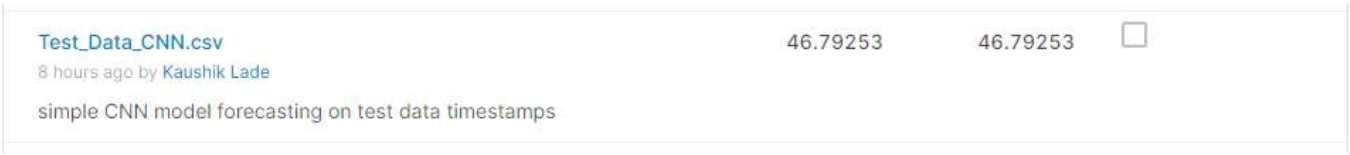
```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_2 (Conv1D)            (None, 89, 128)           384
_________________________________________________________________
conv1d_3 (Conv1D)            (None, 88, 128)           32896
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 29, 128)           0
_________________________________________________________________
flatten_1 (Flatten)          (None, 3712)              0
_________________________________________________________________
dense_2 (Dense)              (None, 32)                118816
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 33
=================================================================
Total params: 152,129
Trainable params: 152,129
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```
model_test = pd.DataFrame()
model_test['Page'] = complete_train.Page.values
#print(past_data.shape)
for test_index in range(len(test_days)):
    #clear_session()
    print("Remaining are %d"%(len(test_days)-test_index+1))
    #print(history.shape)
    X = np.log1p(timeseries_X.iloc[:,-best_window:])
    r, c = X.shape
    X = np.array(X).reshape((r, c, 1))
    #X_lagged = np.hstack((X_pagename_te, X))
    predicted = np.ceil(np.expm1(model.predict(X)))
    model_test[test_days[test_index]]   = predicted
    timeseries_X[test_days[test_index]] = predicted
```

In [43]:

```
f = open('CNN_Page_Count.csv', 'w')
f.write('Page|Visits'+'\n')
for col in model_test.iloc[:,-62:].columns.tolist():
  test_data = model_test[['Page',col]]
  pageviews = [ str(int(x)) for x in test_data.iloc[:,-1] ]
  pagename  = [ x+'_'+test_data.columns.tolist()[-1] for x in test_data.iloc[:,0] ]
  page_view = list(zip(pagename,pageviews))
  #writing it into file
  for line in page_view:
    n, c = line
    f.write(n+'|'+c)
    f.write('\n')
test_data_final = pd.read_csv('./CNN_Page_Count.csv', sep='|')

#saving the final file
page_key.merge(test_data_final, how='left', on='Page')[['Id', 'Visits']].fillna(0).to_c
sv('./Test_Data_CNN.csv', index=False)
```



In [ ]:

```
models['CNN Model'] = [best_window, cv_smape, 46.79253]
```

[3.3] Test Data Analysis : LSTM Model

In [12]:

```
best_window = 30
print("LSTM Model is trained and found to have Best_Window of %d"%best_window)


past_data_cols = complete_train.columns.tolist()[-best_window-5:]
past_data_cols.insert(0, 'Page')

past_data = complete_train[past_data_cols]
#past_data.head()

#getting date columns and non_date columns
date_cols = [ x for x in past_data.columns.tolist() if '-' in x ]
non_date  = [ x for x in past_data.columns.tolist() if x not in date_cols and x != 'Pag
e' ]

#separating the ata into series of PageViews and Site features
pagename_X   = complete_train[non_date]
timeseries_X = complete_train[date_cols]
```

```
LSTM Model is trained and found to have Best_Window of 30
```

In [13]:

```
X = np.log1p(timeseries_X.iloc[:,:-1])
#X = X_timeseries.iloc[:,-best_window-1:-1]
r, c = X.shape
X = np.array(X).reshape((r, c, 1))
Y = np.log1p(timeseries_X.iloc[:,-1])
#Y = X_timeseries.iloc[:,-1]

#fitting model wth best parameters
#model = lstm(best_window, print_summary=True)

from tensorflow.keras.models import model_from_json
with open('copy_lstm_model.json', 'r') as f:
    model = model_from_json(f.read())
# Load weights into the new model
model.load_weights('copy_lstm_model_weights.h5')
model.summary()

#model.fit(X, Y, batch_size=batch, epochs=epoch, verbose=1)
```

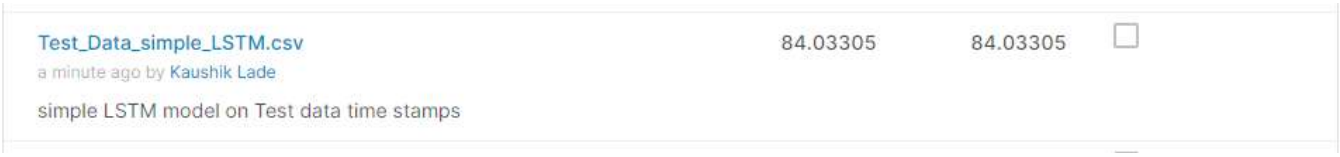
```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 30, 16)            1152
_________________________________________________________________
lstm_1 (LSTM)                (None, 16)                2112
_________________________________________________________________
dropout (Dropout)            (None, 16)                0
_________________________________________________________________
dense (Dense)                (None, 1)                 17
=================================================================
Total params: 3,281
Trainable params: 3,281
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```
model_test = pd.DataFrame()
model_test['Page'] = complete_train.Page.values
#print(past_data.shape)
for test_index in range(len(test_days)):
    #clear_session()
    print("Remaining are %d"%(len(test_days)-test_index+1))
    #print(history.shape)
    X = np.log1p(timeseries_X.iloc[:,-best_window:])
    r, c = X.shape
    X = np.array(X).reshape((r, c, 1))
    #X_lagged = np.hstack((X_pagename_te, X))
    predicted = np.ceil(np.expm1(model.predict(X)))
    model_test[test_days[test_index]]   = predicted
    timeseries_X[test_days[test_index]] = predicted
```

In [15]:

```
f = open('simple_LSTM_Page_Count.csv', 'w')
f.write('Page|Visits'+'\n')
for col in model_test.iloc[:,-62:].columns.tolist():
  test_data = model_test[['Page',col]]
  pageviews = [ str(int(x)) for x in test_data.iloc[:,-1] ]
  pagename  = [ x+'_'+test_data.columns.tolist()[-1] for x in test_data.iloc[:,0] ]
  page_view = list(zip(pagename,pageviews))
  #writing it into file
  for line in page_view:
    n, c = line
    f.write(n+'|'+c)
    f.write('\n')
test_data_final = pd.read_csv('./simple_LSTM_Page_Count.csv', sep='|')

#saving the final file
page_key.merge(test_data_final, how='left', on='Page')[['Id', 'Visits']].fillna(0).to_c
sv('./Test_Data_simple_LSTM.csv', index=False)
```



In [ ]:

```
models['LSTM Model'] = [ best_window, cv_smape, 84.03305]
```

[4] Increasing the complexity of DL Models

[4.1] Complex LSTM Model

In [ ]:

```
clear_session()
```

In [ ]:

```
def complex_lstm(shape, print_summary=False):
    """
    simple 2 layered LSTM model for data. Returns the compiled model with
    passed parameters.
    """
    model = Sequential()
    model.add(LSTM(128, activation='relu', return_sequences=True, input_shape=(shape, 1
)))
    model.add(LSTM(128, activation='relu', return_sequences=True))
    model.add(Dropout(0.20))
    #model.add(LSTM(64, activation='tanh', return_sequences=True))
    model.add(LSTM(64, activation='relu'))
    model.add(Dropout(0.20))
    #model.add(Flatten())
    #model.add(Dense(16, activation='relu'))
    #model.add(Dropout(0.5))
    #model.add(Dense(8, activation='relu'))
    #model.add(Dropout(0.5))
    model.add(Dense(1))
    model.compile(loss='mean_squared_error', optimizer='adam', metrics=[tf_smape])
    if print_summary:
        model.summary()
    return model
```

[4.1.1] Hyper Parameter Tuning

In [47]:

```
gc.collect()
error = list()
for lag in sorted(lagged_window, reverse=True):
  clear_session()
  print("**** Running for Lag=",lag)
  X = np.log1p(X_timeseries.iloc[:,-lag-1:-1])
  #X = X_timeseries.iloc[:,-lag-1:-1]
  r, c  = X.shape
  X = np.array(X).reshape((r, c, 1))
  Y = np.log1p(X_timeseries.iloc[:,-1])
  observed = X_timeseries.iloc[:, -1]
  #Y = X_timeseries.iloc[:,-1]
  #print("Dataset shape is ",X.shape)
  model = complex_lstm(lag, print_summary=False)
  model.fit(X, Y, batch_size=batch, epochs=deep_epoch, verbose=1, \
            callbacks=[dl_stopping])
  predicted = np.ceil(np.expm1(model.predict(X)))
  #predicted = np.ceil(model.predict(X))
  predicted = np.array(predicted).reshape((X.shape[0]))
  #tr_smape = smape(Y, predicted)
  cv_smape = np.mean(smape(observed, predicted))
  print("SMAPE for Lag=%d is %f"%(lag, cv_smape))
  error.append([cv_smape, lag])

index         = np.argmin([ x[0] for x in error ])
best_window   = error[index][1]
best_cv_smape = error[index][0]

print("\n\nBest Values are : \n",best_window, "\n", best_cv_smape)
```

```
**** Running for Lag= 7
SMAPE for Lag=7 is 31.909865
**** Running for Lag= 30
SMAPE for Lag=30 is 33.070041
**** Running for Lag= 90
SMAPE for Lag=90 is 39.066548
**** Running for Lag= 365
SMAPE for Lag=365 is nan
```

[4.1.2] Fitting model with Best Window

In [39]:

```
print("Model is trained and found to have : ")
print("Best Window = ",best_window)
print("\n\n")

#fiting model with best parameters
X = np.log1p(X_timeseries.iloc[:,-best_window-1:-1])
#X = X_timeseries.iloc[:,-best_window-1:-1]
r, c = X.shape
X = np.array(X).reshape((r, c, 1))
Y = np.log1p(X_timeseries.iloc[:,-1])
#Y = X_timeseries.iloc[:,-1]

#fitting model wth best parameters
clear_session()
model = complex_lstm(best_window, print_summary=True)
model.fit(X, Y, batch_size=batch, epochs=deep_epoch, \
          verbose=1, callbacks=[dl_stopping])

#save the model weights
my_model = model.to_json()
with open("complex_lstm_model.json", "w") as json_file:
  json_file.write(my_model)
model.save_weights("complex_lstm_model_weights.h5")
```

```
Model is trained and found to have :
Best Window =  7



Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 7, 128)            66560
_________________________________________________________________
lstm_1 (LSTM)                (None, 7, 128)            131584
_________________________________________________________________
dropout (Dropout)            (None, 7, 128)            0
_________________________________________________________________
lstm_2 (LSTM)                (None, 64)                49408
_________________________________________________________________
dropout_1 (Dropout)          (None, 64)                0
_________________________________________________________________
dense (Dense)                (None, 8)                 520
_________________________________________________________________
dropout_2 (Dropout)          (None, 8)                 0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 9
=================================================================
Total params: 248,081
Trainable params: 248,081
Non-trainable params: 0
_________________________________________________________________
Epoch 1/150
567/567 [==============================] - 54s 96ms/step - loss: 2.9923 -
tf_smape: 41.4516
Epoch 2/150
567/567 [==============================] - 55s 98ms/step - loss: 2.1058 -
tf_smape: 34.6045
Epoch 3/150
567/567 [==============================] - 55s 96ms/step - loss: 1.8631 -
tf_smape: 32.2406
Epoch 4/150
567/567 [==============================] - 54s 96ms/step - loss: 1.6138 -
tf_smape: 29.9833
Epoch 5/150
567/567 [==============================] - 54s 95ms/step - loss: 1.3862 -
tf_smape: 28.0773
Epoch 6/150
567/567 [==============================] - 55s 96ms/step - loss: 1.1779 -
tf_smape: 26.4863
Epoch 7/150
567/567 [==============================] - 54s 95ms/step - loss: 1.0227 -
tf_smape: 25.2855
Epoch 8/150
567/567 [==============================] - 54s 95ms/step - loss: 0.8877 -
tf_smape: 24.3836
Epoch 9/150
567/567 [==============================] - 56s 99ms/step - loss: 0.7844 -
tf_smape: 23.6706
Epoch 10/150
567/567 [==============================] - 56s 98ms/step - loss: 0.6987 -
tf_smape: 23.1408
Epoch 11/150
567/567 [==============================] - 56s 99ms/step - loss: 0.6427 -
```

```
tf_smape: 22.8360
Epoch 12/150
567/567 [==============================] - 57s 100ms/step - loss: 0.5988 -
tf_smape: 22.6008
Epoch 13/150
567/567 [==============================] - 56s 98ms/step - loss: 0.5743 -
tf_smape: 22.5213
Epoch 14/150
567/567 [==============================] - 55s 98ms/step - loss: 0.5550 -
tf_smape: 22.5485
Epoch 15/150
567/567 [==============================] - 57s 100ms/step - loss: 0.5465 -
tf_smape: 22.5774
Epoch 16/150
567/567 [==============================] - 58s 102ms/step - loss: 0.5395 -
tf_smape: 22.5988
```

[4.1.3] CV data Analysis

In [ ]:

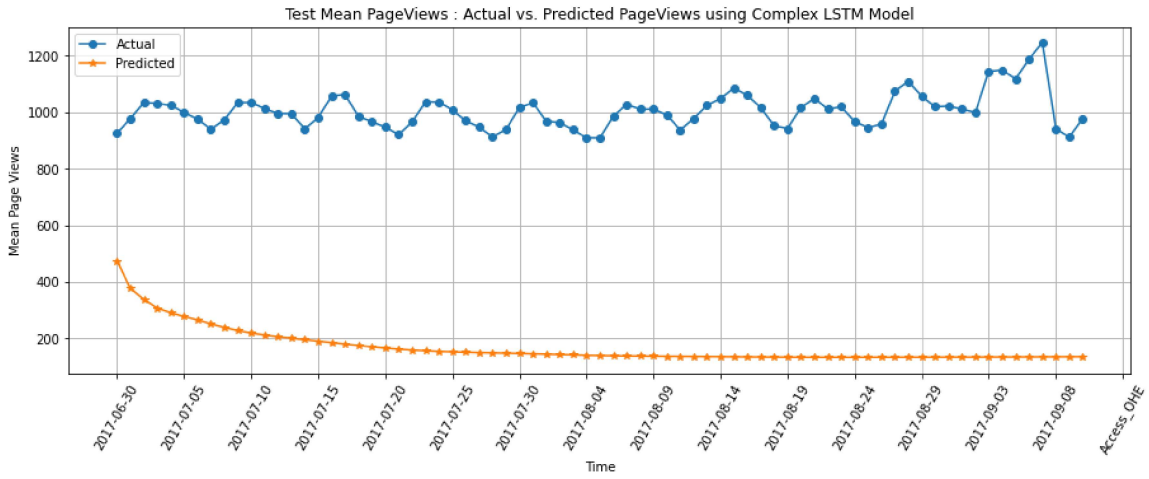
```
#history of values
history = X_timeseries.iloc[:, -best_window:]
gc.collect()
#testing the model on test data
test_data = pd.DataFrame()
test_cols = test.columns.tolist()
for col in (test_cols[:-4]):
  clear_session()
  X = np.log1p(history.iloc[:,-best_window:])
  #X = history.iloc[:,-best_window:]
  r, c = X.shape
  X = np.array(X).reshape((r, c, 1))
  predict = np.ceil(np.expm1(model.predict(X, use_multiprocessing=True)))
  #predict = np.ceil(model.predict(X))
  predict = np.array(predict).reshape((X.shape[0]))
  test_data[col] = predict
  history[col]   = predict

#checking SMAPE on forecasted and actual CV values
cv_smape = np.mean(smape(test.iloc[:,:-4], test_data))
print("\nSMAPE on CV data = ",cv_smape)
models['LSTM Model'] = [best_window, cv_smape]
```

```
SMAPE on CV data =  91.03182489986288
```

[4.1.4] CV SMAPE Performance

In [ ]:

```
#plot for mean of actual test and predicted test
plt.figure(figsize=(15, 5))
plt.title('Test Mean PageViews : Actual vs. Predicted PageViews using Complex LSTM Mode
l')
actual_mean = test.iloc[:, :-4].mean(axis=0)
pred_mean   = test_data.mean(axis=0)

xtick_labels = [ x for x in enumerate(test_cols) if x[0]%5==0 ]
xtick_loc    = [ x[0] for x in xtick_labels ]
xtick_label  = [ x[1] for x in xtick_labels ]
b1 = plt.plot(actual_mean, marker="o")
b2 = plt.plot(pred_mean, marker="*")
plt.xlabel('Time')
plt.ylabel('Mean Page Views')
plt.grid()
plt.legend([b1[0], b2[0]], ['Actual', 'Predicted'])
plt.xticks(xtick_loc, xtick_label, rotation=60)
plt.show()
```



[4.1.5] On Test Data

In [48]:

```
#Load the model weights
with open('complex_lstm_model.json', 'r') as f:
    model = model_from_json(f.read())
# Load weights into the new model
model.load_weights('complex_lstm_model_weights.h5')
```

In [49]:

```
best_window = 7
print("LSTM Model is trained and found to have Best_Window of %d"%best_window)

past_data_cols = complete_train.columns.tolist()[-best_window-5:]
past_data_cols.insert(0, 'Page')

past_data = complete_train[past_data_cols]
#past_data.head()

#getting date columns and non_date columns
date_cols = [ x for x in past_data.columns.tolist() if '-' in x ]
non_date  = [ x for x in past_data.columns.tolist() if x not in date_cols and x != 'Pag
e' ]

#separating the ata into series of PageViews and Site features
timeseries_X = complete_train[date_cols]
```

```
LSTM Model is trained and found to have Best_Window of 7
```

In [50]:

```
X = np.log1p(timeseries_X.iloc[:,:-1])
#X = X_timeseries.iloc[:,-best_window-1:-1]
r, c = X.shape
X = np.array(X).reshape((r, c, 1))
Y = np.log1p(timeseries_X.iloc[:,-1])
#Y = X_timeseries.iloc[:,-1]

from tensorflow.keras.models import model_from_json
with open('complex_lstm_model.json', 'r') as f:
    model = model_from_json(f.read())
# Load weights into the new model
model.load_weights('complex_lstm_model_weights.h5')
model.summary()

#model.fit(X, Y, batch_size=batch, epochs=epoch, verbose=1)
```

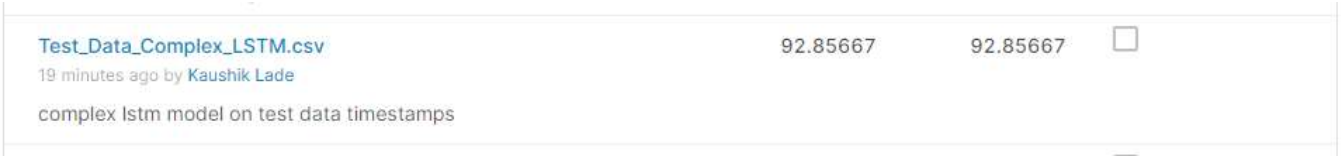
```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 7, 128)            66560
_________________________________________________________________
lstm_1 (LSTM)                (None, 7, 128)            131584
_________________________________________________________________
dropout (Dropout)            (None, 7, 128)            0
_________________________________________________________________
lstm_2 (LSTM)                (None, 64)                49408
_________________________________________________________________
dropout_1 (Dropout)          (None, 64)                0
_________________________________________________________________
dense (Dense)                (None, 8)                 520
_________________________________________________________________
dropout_2 (Dropout)          (None, 8)                 0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 9
=================================================================
Total params: 248,081
Trainable params: 248,081
Non-trainable params: 0
_________________________________________________________________
```

In [ ]:

```
model_test = pd.DataFrame()
model_test['Page'] = complete_train.Page.values
#print(past_data.shape)
for test_index in range(len(test_days)):
    #clear_session()
    print("Remaining are %d"%(len(test_days)-test_index+1))
    #print(history.shape)
    X = np.log1p(timeseries_X.iloc[:,-best_window:])
    r, c = X.shape
    X = np.array(X).reshape((r, c, 1))
    #X_lagged = np.hstack((X_pagename_te, X))
    predicted = np.ceil(np.expm1(model.predict(X)))
    model_test[test_days[test_index]]   = predicted
    timeseries_X[test_days[test_index]] = predicted
```

In [52]:

```
f = open('Complex_LSTM_Page_Count.csv', 'w')
f.write('Page|Visits'+'\n')
for col in model_test.iloc[:,-62:].columns.tolist():
  test_data = model_test[['Page',col]]
  pageviews = [ str(int(x)) for x in test_data.iloc[:,-1] ]
  pagename  = [ x+'_'+test_data.columns.tolist()[-1] for x in test_data.iloc[:,0] ]
  page_view = list(zip(pagename,pageviews))
  #writing it into file
  for line in page_view:
    n, c = line
    f.write(n+'|'+c)
    f.write('\n')
test_data_final = pd.read_csv('./Complex_LSTM_Page_Count.csv', sep='|')

#saving the final file
page_key.merge(test_data_final, how='left', on='Page')[['Id', 'Visits']].fillna(0).to_c
sv('./Test_Data_Complex_LSTM.csv', index=False)
```



In [ ]:

```
models['Complex LSTM Models'] = [best_window, cv_smape, 92.85667 ]
```

[4.2] Complex CNN Model

In [ ]:

```
def complex_cnn_model(shape, print_summary=False):
  """
  function that takes paramter and returns simple CNN model
  """
  model = Sequential()
  #first layer of CNN Models
  model.add(Conv1D(filters=32, kernel_size=2, padding='same', \
                   activation='relu', kernel_initializer = 'he_uniform', \
                   input_shape=(shape, 1)))
  model.add(Conv1D(filters=32, kernel_size=2, padding='same', \
                   activation='relu', kernel_initializer = 'he_uniform'))
  model.add(MaxPooling1D(pool_size=2))
  #second layer of CNN Models
  model.add(Conv1D(filters=32, kernel_size=2, padding='same', \
                   activation='relu', kernel_initializer = 'he_uniform'))
  model.add(Conv1D(filters=32, kernel_size=2, \
                   activation='relu', kernel_initializer = 'he_uniform'))
  model.add(MaxPooling1D(pool_size=2))
  #flatten the model output
  model.add(Flatten())
  #add Dense layers
  #model.add(Dense(16, activation='relu'))
  #model.add(Dropout(0.5))
  #model.add(Dense(16, activation='relu'))
  #model.add(Dropout(0.5))
  model.add(Dense(32, activation='relu'))
  model.add(Dense(1))
  #compile model with loss and metrics
  model.compile(loss='mean_squared_error', optimizer='adam', metrics=[tf_smape])
  #return model and Print is necessary
  if print_summary:
    model.summary()
  return model
```

[4.2.1] Hyper Parameter Tuning

In [40]:

```
gc.collect()
error = list()
for lag in sorted(lagged_window, reverse=True):
  print("**** Running for Lag=",lag)
  clear_session()
  X = np.log1p(X_timeseries.iloc[:,-lag-1:-1])
  #X = X_timeseries.iloc[:,-lag-1:-1]
  r, c  = X.shape
  X = np.array(X).reshape((r, c, 1))
  Y = np.log1p(X_timeseries.iloc[:,-1])
  #Y = X_timeseries.iloc[:,-1]
  observed = X_timeseries.iloc[:, -1]
  #print("Dataset shape is ",X.shape)
  model = complex_cnn_model(lag)
  model.fit(X, Y, batch_size=batch, epochs=deep_epoch, \
            verbose=1, callbacks=[dl_stopping])
  predicted = np.ceil(np.expm1(model.predict(X)))
  #predicted = np.ceil(model.predict(X))
  predicted = np.array(predicted).reshape((X.shape[0]))
  #tr_smape = smape(Y, predicted)
  cv_smape = np.mean(smape(observed, predicted))
  error.append([cv_smape, lag])
  print("SMAPE = {0} for Lag = {1}".format(cv_smape, lag))
index         = np.argmin([ x[0] for x in error ])
best_window   = error[index][1]
best_cv_smape = error[index][0]

print("\n\nBest Values are : \n",best_window, "\n", "Best SMAPE on CV data is ",best_cv
_smape)
a = gc.collect()
```

```
**** Running for Lag= 365
SMAPE = 32.53622030907409 for Lag = 365
**** Running for Lag= 90
SMAPE = 32.08136539761829 for Lag = 90
**** Running for Lag= 30
SMAPE = 32.14619961091478 for Lag = 30
**** Running for Lag= 7
SMAPE = 33.407790513449505 for Lag = 7


Best Values are :
 90
 Best SMAPE on CV data is  32.08136539761829
```

[4.2.2] Fitting model with Best Window

In [41]:

```
print("Model is trained and found to have : ")
print("Best Window = "    ,best_window)
print("\n\n")
gc.collect()

X = np.log1p(X_timeseries.iloc[:,-best_window-1:-1])
#X = X_timeseries.iloc[:,-best_window-1:-1]
r, c = X.shape
X = np.array(X).reshape((r, c, 1))
Y = np.log1p(X_timeseries.iloc[:,-1])
#Y = X_timeseries.iloc[:,-1]

#fitting model wth best parameters
model = complex_cnn_model(best_window, print_summary=True)
model.fit(X, Y, batch_size=batch, epochs=deep_epoch, \
          verbose=1, callbacks=[dl_stopping])

#save the model weights
my_model = model.to_json()
with open("complex_cnn_model.json", "w") as json_file:
  json_file.write(my_model)
model.save_weights("complex_cnn_model_weights.h5")
```

```
Model is trained and found to have :
Best Window =  90



Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_4 (Conv1D)            (None, 90, 32)            96
_________________________________________________________________
conv1d_5 (Conv1D)            (None, 90, 32)            2080
_________________________________________________________________
max_pooling1d_2 (MaxPooling1 (None, 45, 32)            0
_________________________________________________________________
conv1d_6 (Conv1D)            (None, 45, 32)            2080
_________________________________________________________________
conv1d_7 (Conv1D)            (None, 44, 32)            2080
_________________________________________________________________
max_pooling1d_3 (MaxPooling1 (None, 22, 32)            0
_________________________________________________________________
flatten_1 (Flatten)          (None, 704)               0
_________________________________________________________________
dense_2 (Dense)              (None, 32)                22560
_________________________________________________________________
dropout_1 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 33
=================================================================
Total params: 28,929
Trainable params: 28,929
Non-trainable params: 0
_________________________________________________________________
Epoch 1/150
567/567 [==============================] - 27s 47ms/step - loss: 1.9216 -
tf_smape: 28.4065
Epoch 2/150
567/567 [==============================] - 27s 47ms/step - loss: 0.8692 -
tf_smape: 25.5200
Epoch 3/150
567/567 [==============================] - 27s 47ms/step - loss: 0.8264 -
tf_smape: 24.9001
Epoch 4/150
567/567 [==============================] - 27s 47ms/step - loss: 0.7800 -
tf_smape: 24.2549
Epoch 5/150
567/567 [==============================] - 27s 48ms/step - loss: 0.7202 -
tf_smape: 23.5559
Epoch 6/150
567/567 [==============================] - 28s 50ms/step - loss: 0.6374 -
tf_smape: 22.5629
Epoch 7/150
567/567 [==============================] - 27s 47ms/step - loss: 0.5750 -
tf_smape: 21.8597
Epoch 8/150
567/567 [==============================] - 26s 47ms/step - loss: 0.5414 -
tf_smape: 21.4353
Epoch 9/150
567/567 [==============================] - 26s 47ms/step - loss: 0.4997 -
tf_smape: 21.0345
Epoch 10/150
```

```
567/567 [==============================] - 26s 46ms/step - loss: 0.4599 -
tf_smape: 20.6538
Epoch 11/150
567/567 [==============================] - 27s 47ms/step - loss: 0.4304 -
tf_smape: 20.3406
Epoch 12/150
567/567 [==============================] - 27s 47ms/step - loss: 0.3986 -
tf_smape: 20.0242
Epoch 13/150
567/567 [==============================] - 27s 47ms/step - loss: 0.3654 -
tf_smape: 19.6867
Epoch 14/150
567/567 [==============================] - 27s 47ms/step - loss: 0.3353 -
tf_smape: 19.3645
Epoch 15/150
567/567 [==============================] - 27s 47ms/step - loss: 0.3166 -
tf_smape: 19.2250
Epoch 16/150
567/567 [==============================] - 27s 48ms/step - loss: 0.3086 -
tf_smape: 19.1484
Epoch 17/150
567/567 [==============================] - 26s 46ms/step - loss: 0.2965 -
tf_smape: 18.9966
Epoch 18/150
567/567 [==============================] - 27s 47ms/step - loss: 0.2870 -
tf_smape: 18.9205
Epoch 19/150
567/567 [==============================] - 26s 45ms/step - loss: 0.2846 -
tf_smape: 18.9639
Epoch 20/150
567/567 [==============================] - 26s 46ms/step - loss: 0.2772 -
tf_smape: 18.8664
Epoch 21/150
567/567 [==============================] - 26s 45ms/step - loss: 0.2734 -
tf_smape: 18.8964
Epoch 22/150
567/567 [==============================] - 28s 49ms/step - loss: 0.2680 -
tf_smape: 18.7886
Epoch 23/150
567/567 [==============================] - 27s 48ms/step - loss: 0.2691 -
tf_smape: 18.8025
Epoch 24/150
567/567 [==============================] - 27s 47ms/step - loss: 0.2623 -
tf_smape: 18.7619
Epoch 25/150
567/567 [==============================] - 27s 47ms/step - loss: 0.2609 -
tf_smape: 18.7916
Epoch 26/150
567/567 [==============================] - 27s 47ms/step - loss: 0.2579 -
tf_smape: 18.7707
Epoch 27/150
567/567 [==============================] - 27s 47ms/step - loss: 0.2583 -
tf_smape: 18.8764
```

[4.2.3] CV data Analysis

In [42]:

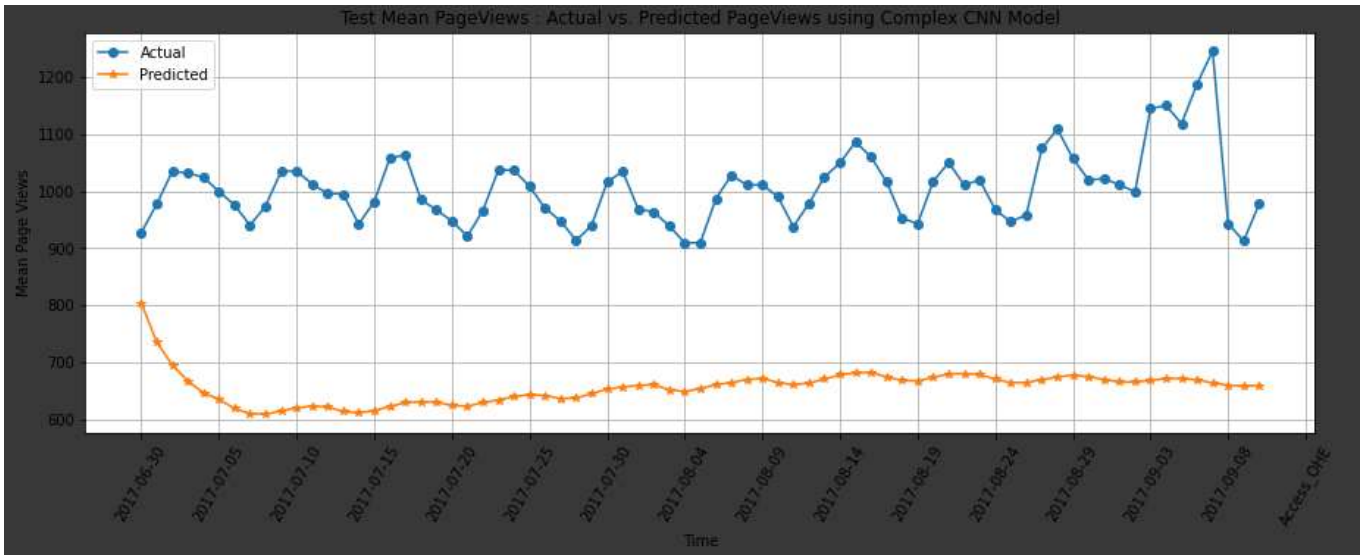
```
with open('complex_cnn_model.json', 'r') as f:
    model = model_from_json(f.read())
# Load weights into the new model
model.load_weights('complex_cnn_model_weights.h5')

gc.collect()
#history of values
history = X_timeseries.iloc[:, -best_window:]

#testing the model on test data
test_data = pd.DataFrame()
test_cols = test.columns.tolist()
for col in (test_cols[:-4]):
  clear_session()
  X = np.log1p(history.iloc[:,-best_window:])
  #X = history.iloc[:,-best_window:]
  r, c = X.shape
  X = np.array(X).reshape((r, c, 1))
  predict = np.ceil(np.expm1(model.predict(X)))
  #predict = np.ceil(model.predict(X))
  predict = np.array(predict).reshape((X.shape[0]))
  test_data[col] = predict
  history[col]   = predict

#checking SMAPE on forecasted and actual CV values
cv_smape = np.mean(smape(test.iloc[:,:-4], test_data))
print("\nSMAPE on CV data = ",cv_smape)
models['CNN Model'] = [best_window, cv_smape]
```

```
100%|██████████| 73/73 [17:14<00:00, 14.17s/it]

SMAPE on CV data =  55.56740122259976
```

[4.2.4] CV SMAPE Performance

In [ ]:

```
#plot for mean of actual test and predicted test
plt.figure(figsize=(15, 5))
plt.title('Test Mean PageViews : Actual vs. Predicted PageViews using Complex CNN Mode
l')
actual_mean = test.iloc[:, :-4].mean(axis=0)
pred_mean   = test_data.mean(axis=0)

xtick_labels = [ x for x in enumerate(test_cols) if x[0]%5==0 ]
xtick_loc    = [ x[0] for x in xtick_labels ]
xtick_label  = [ x[1] for x in xtick_labels ]
b1 = plt.plot(actual_mean, marker="o")
b2 = plt.plot(pred_mean, marker="*")
plt.xlabel('Time')
plt.ylabel('Mean Page Views')
plt.grid()
plt.legend([b1[0], b2[0]], ['Actual', 'Predicted'])
plt.xticks(xtick_loc, xtick_label, rotation=60)
plt.show()
```



[4.2.5] On Test Data

In [ ]:

```
best_window = 90
print("LSTM Model is trained and found to have Best_Window of %d"%best_window)

past_data_cols = complete_train.columns.tolist()[-best_window-5:]
past_data_cols.insert(0, 'Page')

past_data = complete_train[past_data_cols]
#past_data.head()

#getting date columns and non_date columns
date_cols = [ x for x in past_data.columns.tolist() if '-' in x ]
non_date  = [ x for x in past_data.columns.tolist() if x not in date_cols and x != 'Pag
e' ]

#separating the ata into series of PageViews and Site features
timeseries_X = complete_train[date_cols]
```

```
LSTM Model is trained and found to have Best_Window of 90
```

In [ ]:

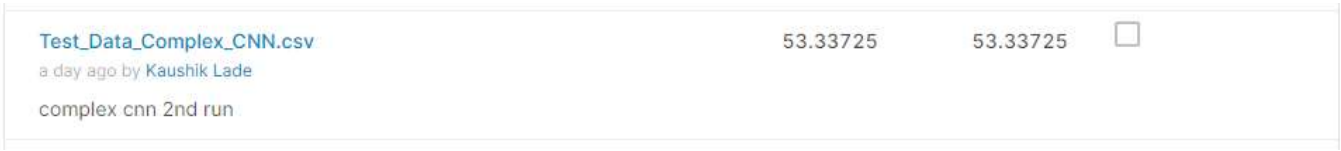
```
X = np.log1p(timeseries_X.iloc[:,:-1])
#X = X_timeseries.iloc[:,-best_window-1:-1]
r, c = X.shape
X = np.array(X).reshape((r, c, 1))
Y = np.log1p(timeseries_X.iloc[:,-1])
#Y = X_timeseries.iloc[:,-1]

from tensorflow.keras.models import model_from_json
with open('complex_cnn_model.json', 'r') as f:
    model = model_from_json(f.read())
# Load weights into the new model
model.load_weights('complex_cnn_model_weights.h5')
#model.summary()
#model.fit(X, Y, batch_size=batch, epochs=epoch, verbose=1)
```

In [ ]:

```
model_test = pd.DataFrame()
model_test['Page'] = complete_train.Page.values
#print(past_data.shape)
for test_index in range(len(test_days)):
    clear_session()
    #print("Remaining are %d"%(len(test_days)-test_index+1))
    #print(history.shape)
    X = np.log1p(timeseries_X.iloc[:,-best_window:])
    r, c = X.shape
    X = np.array(X).reshape((r, c, 1))
    #X_lagged = np.hstack((X_pagename_te, X))
    predicted = np.ceil(np.expm1(model.predict(X, batch_size=batch)))
    model_test[test_days[test_index]]   = predicted
    timeseries_X[test_days[test_index]] = predicted
```

In [ ]:

```
f = open('Complex_CNN_Page_Count.csv', 'w')
f.write('Page|Visits'+'\n')
for col in model_test.iloc[:,-62:].columns.tolist():
  test_data = model_test[['Page',col]]
  test_data = test_data.replace([np.inf, -np.inf], 0)
  pageviews = [ str(int(x)) for x in test_data.iloc[:,-1] ]
  pagename  = [ x+'_'+test_data.columns.tolist()[-1] for x in test_data.iloc[:,0] ]
  page_view = list(zip(pagename,pageviews))
  #writing it into file
  for line in page_view:
    n, c = line
    f.write(n+'|'+c)
    f.write('\n')
test_data_final = pd.read_csv('./Complex_CNN_Page_Count.csv', sep='|')

#saving the final file
page_key.merge(test_data_final, how='left', on='Page')[['Id', 'Visits']].fillna(0).to_c
sv('./Test_Data_Complex_CNN.csv', index=False)
```



In [ ]:

```
models['Complex CNN'] = [best_window, cv_smape, 53.33725]
```

[5] Conclusion

In [18]:

```
from prettytable import PrettyTable
dl_models = PrettyTable(['Model', 'Best Window', 'CV performance', 'Test Performance'])

for k, v in models.items():
    dl_models.add_row([k, v[0], round(v[1], 4)
    , v[2]])

print(dl_models)
```

```
+--------------------+-------------+----------------+------------------+
|       Model        | Best Window | CV performance | Test Performance |
+--------------------+-------------+----------------+------------------+
|     DNN Model      |      90     |    52.2255     |     79.44122     |
|     CNN Model      |      90     |    57.8225     |     46.7953      |
|     LSTM Model     |      30     |    84.4969     |     84.03305     |
| Complex LSTM Model |      7      |    91.0318     |     92.85667     |
| Complex CNN Model  |      90     |    55.5674     |     53.33725     |
+--------------------+-------------+----------------+------------------+
```

By building simple Deep NN models with simple sequence information of the data, we can get pretty good results of forecasting.

Modeling is done with

- Deep MLP
- Simple LSTM
- Simple CNN
- Combined CNN-LSTM Model
- Complex LSTM
- Complex CNN

Out of these, we get best results with simple and 2 layered CNN models on CV data.

Comparing the model performances after increasing their complexity, i.e. by adding extra layers, we observed that the models performance slightly decreases, but the same can be maintained with the hyper-parameter tuning of each individual layers.