

Advance Monthly Sales for Retail and Food Services Units: Millions of Dollars. <https://fred.stlouisfed.org/series/RSCCASN>. Prediction and forecasting using Recurrent Neural Network(RNN).Tensorflow and keras

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
df=pd.read_csv(r'C:\Users\chumj\Downloads\RSCCASN.csv',index_col='DATE',parse_dates=True)
df.columns=['Sales']
```

In [3]:

```
df.head(3)
```

Out[3]:

Sales	
DATE	
1992-01-01	6938
1992-02-01	7524
1992-03-01	8475

In [4]:

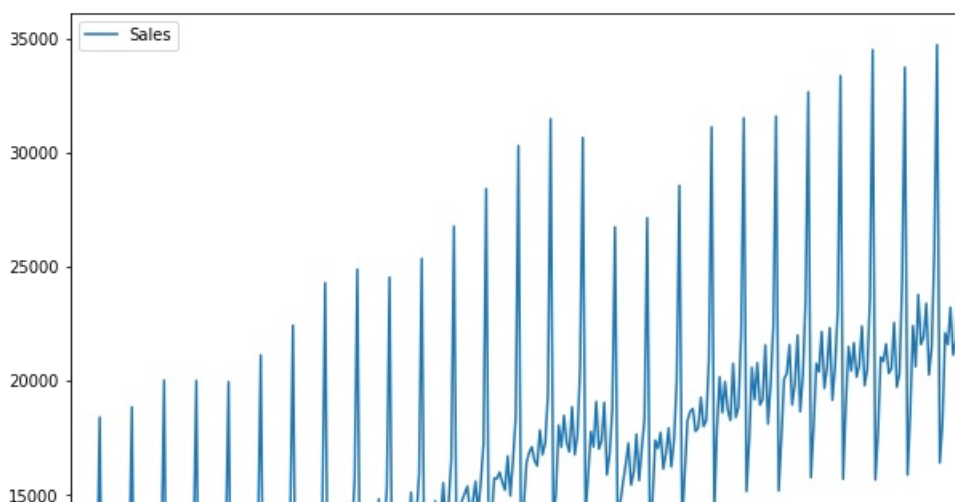
```
df.tail(3)
```

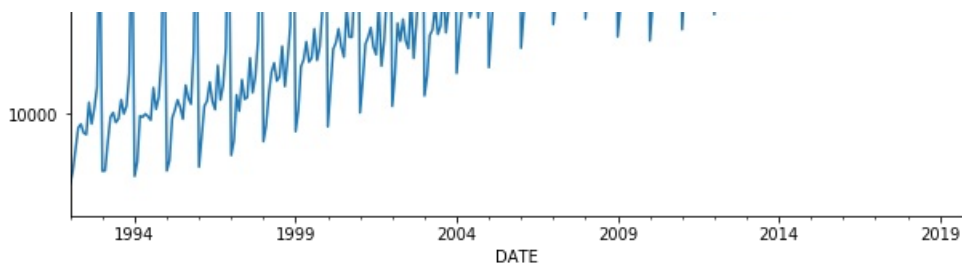
Out[4]:

Sales	
DATE	
2019-08-01	23791
2019-09-01	19695
2019-10-01	21113

In [5]:

```
df.plot(figsize=(10,8));
```





In [6]:

```
len(df)
```

Out[6]:

334

In [7]:

```
#lets take 2years or 24months for our test set
test_size=24
test_index=len(df)-test_size
test_index
```

Out[7]:

310

In [8]:

```
#splitting our data to train and test dataset
train=df.iloc[:310]
test=df.iloc[310:]
```

In [9]:

```
#Scaling and transforming our dataset.
from sklearn.preprocessing import MinMaxScaler
```

In [10]:

```
scaler=MinMaxScaler()
```

In [11]:

```
scaler_train=scaler.fit_transform(train)
scaler_test=scaler.transform(test)
```

In [12]:

```
# fit our data into Timeseries Generator
from tensorflow.keras.preprocessing.sequence import TimeseriesGenerator
```

In [13]:

```
length=12
batch_size=1
generator=TimeseriesGenerator(scaler_train,scaler_train,length=length,batch_size=batch_size)
```

In [14]:

```
#lets take a look at what the first batch and 5 batches look like
X,y=generator[0]
```

In [15]:

```
X
```

Out[15]:

```
array([[0.          ],
       [0.02127505],
       [0.05580163],
       [0.08942056],
       [0.09512053],
       [0.08146965],
       [0.07860151],
       [0.12979233],
       [0.09566512],
       [0.1203892 ],
       [0.15426227],
       [0.41595266]])
```

In [16]:

```
len(X[0])
```

Out[16]:

```
12
```

In []:

In [17]:

```
X
```

Out[17]:

```
array([[0.          ],
       [0.02127505],
       [0.05580163],
       [0.08942056],
       [0.09512053],
       [0.08146965],
       [0.07860151],
       [0.12979233],
       [0.09566512],
       [0.1203892 ],
       [0.15426227],
       [0.41595266]])
```

In [18]:

```
y
```

Out[18]:

```
array([[0.02047633]])
```

In [19]:

```
scaler_train
```

Out[19]:

```
array([[0.          ],
       [0.02127505],
       [0.05580163],
       [0.08942056],
       [0.09512053],
       [0.08146965],
       [0.07860151],
```

[0.12979233],
[0.09566512],
[0.1203892],
[0.15426227],
[0.41595266],
[0.02047633],
[0.02127505],
[0.06636654],
[0.10633895],
[0.11345484],
[0.09791606],
[0.10368864],
[0.13396747],
[0.11163956],
[0.12372931],
[0.17506535],
[0.43265079],
[0.0124165],
[0.03499855],
[0.10829945],
[0.10641156],
[0.11149434],
[0.10728289],
[0.10154662],
[0.1531731],
[0.11904589],
[0.13767064],
[0.19663085],
[0.47480395],
[0.02105722],
[0.03714058],
[0.10445106],
[0.11726692],
[0.13367703],
[0.12209556],
[0.10332559],
[0.1570578],
[0.13694453],
[0.12710572],
[0.21104415],
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[0.02708394],
[0.07453529],
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[0.16217688],
[0.13128086],
[0.11850131],
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[0.13378594],
[0.15654952],
[0.21554604],
[0.47218995],
[0.04559977],
[0.06887162],
[0.14166425],
[0.11592361],
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[0.13491141],
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[0.17052716],
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[0.06760093],
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[0.17742521],
[0.19245571],
[0.16384694],
[0.17045455],
[0.21903137],
[0.15524252],
[0.19772001],
[0.25108917],
[0.56200988]

[0.00200000],
[0.08346645],
[0.11737584],
[0.18671943],
[0.19779262],
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[0.19394423],
[0.20051554],
[0.2467325],
[0.19673976],
[0.21819634],
[0.27973424],
[0.62982864],
[0.09109062],
[0.15364508],
[0.21431165],
[0.22458612],
[0.24676881],
[0.21837787],
[0.20193146],
[0.27853616],
[0.23369881],
[0.23348098],
[0.31720157],
[0.65121261],
[0.11334592],
[0.16381063],
[0.2225167],
[0.23322684],
[0.24865669],
[0.21772437],
[0.20556201],
[0.28608771],
[0.18755446],
[0.22799884],
[0.30547488],
[0.63883241],
[0.12365669],
[0.17397618],
[0.25555475],
[0.22716381],
[0.26183561],
[0.22770839],
[0.21547342],
[0.29679785],
[0.19993465],
[0.25660761],
[0.32576968],
[0.66845774],
[0.14035725],
[0.17150741],
[0.23649434],
[0.24517136],
[0.28289283],
[0.23809178],
[0.25108917],
[0.31164682],
[0.24066947],
[0.27820941],
[0.34915045],
[0.71964856],
[0.17615452],
[0.23257334],
[0.28398199],
[0.29480105],
[0.30645513],
[0.26499419],
[0.28060558],
[0.31404299],
[0.26452222],
[0.31338949],
[0.37365669],
[0.77940749],
[0.18544874],
[0.2519605],
[0.31908946],
[0.31839965],
[0.32860151]

[0.32990151],
[0.31299012],
[0.30060993],
[0.35430584],
[0.2912431],
[0.3474804],
[0.4162068],
[0.84729887],
[0.21619954],
[0.27359861],
[0.34301481],
[0.35978798],
[0.36904589],
[0.34733517],
[0.3389849],
[0.39551263],
[0.35684723],
[0.37449172],
[0.45211298],
[0.89035725],
[0.25373947],
[0.29549085],
[0.40324572],
[0.36879175],
[0.4188208],
[0.37579872],
[0.36105867],
[0.43247168],
[0.35677462],
[0.38759802],
[0.49419111],
[0.86033256],
[0.26267064],
[0.32449898],
[0.39326169],
[0.36904589],
[0.44096718],
[0.36556056],
[0.37870317],
[0.43940604],
[0.32471682],
[0.35790009],
[0.42905896],
[0.71841417],
[0.23413448],
[0.28122277],
[0.31313535],
[0.34123584],
[0.37489108],
[0.30845193],
[0.32925501],
[0.38912286],
[0.31556782],
[0.36723061],
[0.41366541],
[0.733009],
[0.22792623],
[0.2860151],
[0.37946558],
[0.36683125],
[0.39170055],
[0.33401104],
[0.35957014],
[0.39881644],
[0.33742376],
[0.3802643],
[0.47433198],
[0.78445396],
[0.24560703],
[0.32649579],
[0.41076096],
[0.42510166],
[0.42960354],
[0.39373366],
[0.39932472],
[0.44746587],
[0.40157566],
[0.41096000]


```
#creating the model
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,LSTM
#Number of features, just one
n_features=1
```

In [21]:

```
model=Sequential()
```

In [22]:

```
model.add(LSTM(100,activation='relu',input_shape=(length,n_features)))
model.add(Dense(1))
model.compile(optimizer='adam',loss='mse')
model.summary()
```

WARNING:tensorflow:From C:\Users\chumj\Anaconda3\Ben\lib\site-packages\tensorflow\python\ops\init_ops.py:1251: calling VarianceScaling.__init__ (from tensorflow.python.ops.init_ops) with dtype is deprecated and will be removed in a future version. Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 100)	40800
dense (Dense)	(None, 1)	101

=====
 Total params: 40,901
 Trainable params: 40,901
 Non-trainable params: 0
 =====

In [23]:

```
# implementing early stopping
from tensorflow.keras.callbacks import EarlyStopping
```

In [24]:

```
early_stop=EarlyStopping(monitor='val_loss',patience=2)
validation_generator=TimeseriesGenerator(scaler_test,scaler_test,length=length,batch_size=1)
```

In [25]:

```
model.fit_generator(generator,epochs=15,validation_data=validation_generator,callbacks=[early_stop])
```

Epoch 1/15
 WARNING:tensorflow:From C:\Users\chumj\Anaconda3\Ben\lib\site-packages\tensorflow\python\ops\math_grad.py:1250: add_dispatch_support.<locals>.wrapper (from tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version. Instructions for updating:
 Use tf.where in 2.0, which has the same broadcast rule as np.where
 298/298 [=====] - 8s 26ms/step - loss: 0.0248 - val_loss: 0.0328
 Epoch 2/15
 298/298 [=====] - 5s 17ms/step - loss: 0.0188 - val_loss: 0.0223
 Epoch 3/15
 298/298 [=====] - 7s 23ms/step - loss: 0.0154 - val_loss: 0.0194
 Epoch 4/15
 298/298 [=====] - 7s 23ms/step - loss: 0.0094 - val_loss: 0.0061
 Epoch 5/15
 298/298 [=====] - 6s 21ms/step - loss: 0.0040 - val_loss: 8.9834e-04
 Epoch 6/15
 298/298 [=====] - 5s 17ms/step - loss: 0.0027 - val_loss: 0.0015
 Epoch 7/15
 298/298 [=====] - 6s 20ms/step - loss: 0.0024 - val_loss: 7.7742e-04
 Epoch 8/15
 298/298 [=====] - 5s 17ms/step - loss: 0.0021 - val_loss: 0.0023

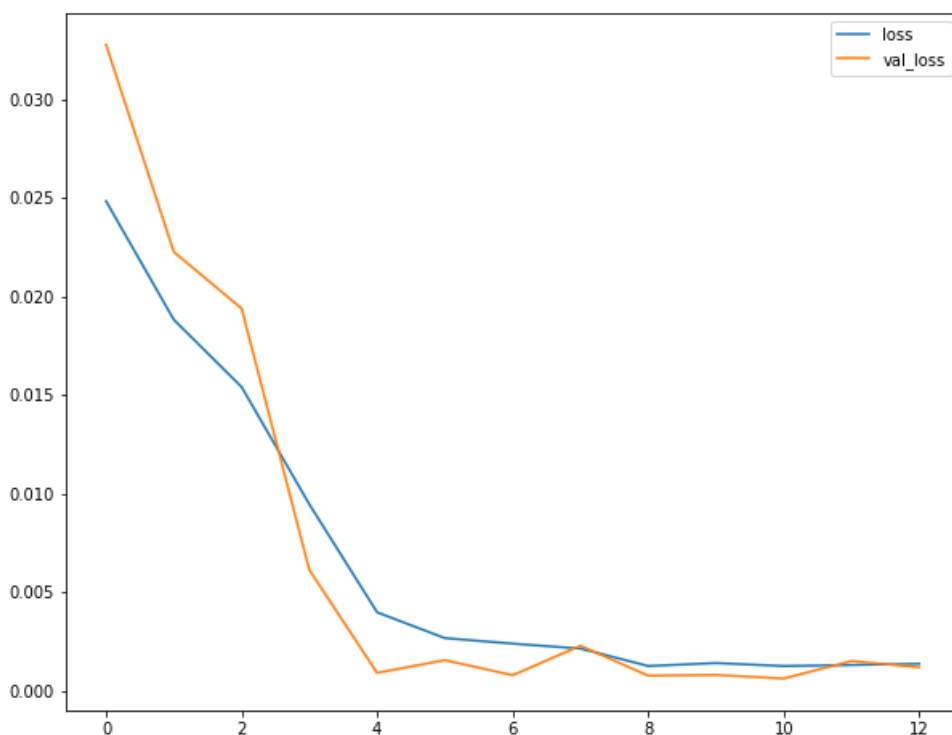

```
Epoch 9/15
298/298 [=====] - 7s 22ms/step - loss: 0.0012 - val_loss: 7.5629e-04 0s -
loss
Epoch 10/15
298/298 [=====] - 5s 18ms/step - loss: 0.0014 - val_loss: 7.8937e-04
Epoch 11/15
298/298 [=====] - 5s 18ms/step - loss: 0.0012 - val_loss: 6.1079e-04
Epoch 12/15
298/298 [=====] - 5s 18ms/step - loss: 0.0013 - val_loss: 0.0015
Epoch 13/15
298/298 [=====] - 5s 18ms/step - loss: 0.0014 - val_loss: 0.0012
```

Out[25]:

<tensorflow.python.keras.callbacks.History at 0x28a369ad708>

In [48]:

```
#visualise the losses
loss=pd.DataFrame(model.history.history)
loss.plot(figsize=(10,8));
```



In [56]:

```
import numpy as np
```

In [57]:

```
test_predictions = []

first_eval_batch = scaler_train[-length:]
current_batch = first_eval_batch.reshape((1, length, n_features))

for i in range(len(test)):

    # get prediction 1 time stamp ahead ([0] is for grabbing just the number instead of [array])
    current_pred = model.predict(current_batch)[0]

    # store prediction
    test_predictions.append(current_pred)

    # update batch to now include prediction and drop first value
    current_batch = np.append(current_batch[:,1:,:], [[current_pred]],axis=1)
```

In [58]:

```
true_predictions=scaler.inverse_transform(test_predictions)
```

In [59]:

```
test['predictions']=true_predictions
```

In [60]:

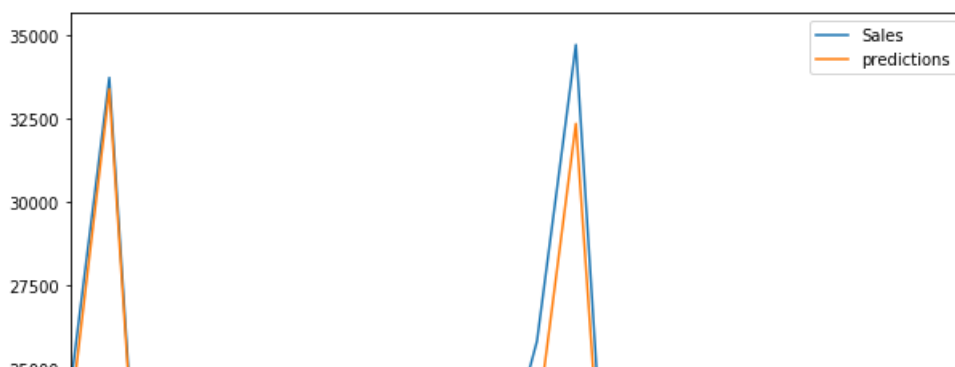
```
test
```

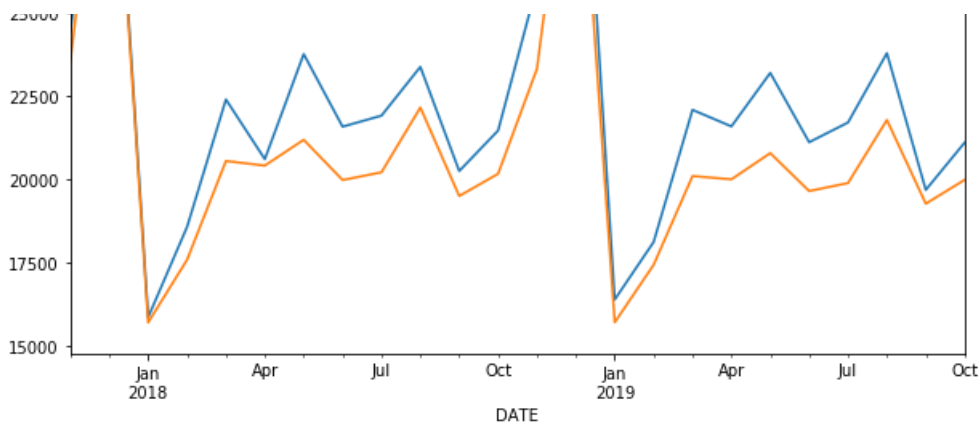
Out[60]:

	Sales	predictions
DATE		
2017-11-01	24438	23555.788689
2017-12-01	33720	33377.917974
2018-01-01	15881	15722.589042
2018-02-01	18585	17600.460015
2018-03-01	22404	20560.135283
2018-04-01	20616	20423.109054
2018-05-01	23764	21196.342269
2018-06-01	21589	19990.039942
2018-07-01	21919	20222.103814
2018-08-01	23381	22162.364584
2018-09-01	20260	19511.344946
2018-10-01	21473	20177.742079
2018-11-01	25831	23323.929214
2018-12-01	34706	32344.163607
2019-01-01	16410	15728.320392
2019-02-01	18134	17449.799049
2019-03-01	22093	20109.957491
2019-04-01	21597	20011.268595
2019-05-01	23200	20796.300248
2019-06-01	21123	19659.816638
2019-07-01	21714	19899.947250
2019-08-01	23791	21789.923670
2019-09-01	19695	19281.816757
2019-10-01	21113	19996.963203

In [61]:

```
test.plot(figsize=(10,8));
```





In [62]:

```
from sklearn import metrics
```

In [77]:

```
print('MSE:',metrics.mean_squared_error(test['Sales'],test['predictions']))
print('\n')

print('RMSE:',np.sqrt(metrics.mean_squared_error(test['Sales'],test['predictions'])))
```

MSE: 2373022.710653571

RMSE: 1540.4618497884233

In [78]:

```
test['Sales'].mean()
```

Out[78]:

22393.208333333332

In [79]:

```
#After satisfied with our model is time to do some forecast.
All_scaler=MinMaxScaler()
```

In [80]:

```
Ful_scaled=All_scaler.fit_transform(df)
```

In [81]:

```
length=12
generator=TimeseriesGenerator(Ful_scaled,Ful_scaled,length=length,batch_size=1)
```

In [83]:

```
model=Sequential()
model.add(LSTM(100,activation='relu',input_shape=(length,n_features)))
model.add(Dense(1))
model.compile(optimizer='adam',loss='mse')
model.fit_generator(generator,epochs=7)
```

Epoch 1/7
322/322 [=====] - 8s 24ms/step - loss: 0.0231
Epoch 2/7
322/322 [=====] - 5s 16ms/step - loss: 0.0184
Epoch 3/7
322/322 [=====] - 7s 21ms/step - loss: 0.0144

```
Epoch 4/7
322/322 [=====] - 5s 16ms/step - loss: 0.0084
Epoch 5/7
322/322 [=====] - 5s 16ms/step - loss: 0.0038
Epoch 6/7
322/322 [=====] - 7s 22ms/step - loss: 0.0030
Epoch 7/7
322/322 [=====] - 6s 17ms/step - loss: 0.0018
```

Out[83]:

```
<tensorflow.python.keras.callbacks.History at 0x28a3c28e048>
```

In [88]:

```
forecast = []
periods=24 # use whatever forcast length you want
first_eval_batch =Ful_scaled [-length:]
current_batch = first_eval_batch.reshape((1, length, n_features))

for i in range(len(test)):

    # get prediction 1 time stamp ahead ([0] is for grabbing just the number instead of [array])
    current_pred = model.predict(current_batch)[0]

    # store prediction
    forecast.append(current_pred)

    # update batch to now include prediction and drop first value
    current_batch = np.append(current_batch[:,1:,:], [[current_pred]],axis=1)
```

In [89]:

```
forecast=scaler.inverse_transform(forecast)
```

In [90]:

```
df
```

Out[90]:

Sales	
DATE	
1992-01-01	6938
1992-02-01	7524
1992-03-01	8475
1992-04-01	9401
1992-05-01	9558
...	...
2019-06-01	21123
2019-07-01	21714
2019-08-01	23791
2019-09-01	19695
2019-10-01	21113

334 rows × 1 columns

In [91]:

```
forecast
```

Out[91]:

```
array([[27287.74988222],
       [35895.22197247],
```

```
[17885.01721287],
[19663.67310905],
[23243.72971058],
[22932.90861177],
[24427.70587492],
[22784.30722189],
[23420.12593365],
[25275.22172546],
[21975.50220251],
[23408.46950626],
[29236.13813686],
[37680.00488091],
[19352.97678328],
[21319.72801542],
[24739.22143412],
[24567.55509377],
[26022.72542906],
[24648.1896615 ],
[25374.49836826],
[27148.12065792],
[24390.21158075],
[25910.30657482]])
```

In [92]:

```
forecast_index=pd.date_range(start='2019-10-01',periods=periods,freq='MS')
```

In [93]:

```
forecast_index
```

Out[93]:

```
DatetimeIndex(['2019-10-01', '2019-11-01', '2019-12-01', '2020-01-01',
                '2020-02-01', '2020-03-01', '2020-04-01', '2020-05-01',
                '2020-06-01', '2020-07-01', '2020-08-01', '2020-09-01',
                '2020-10-01', '2020-11-01', '2020-12-01', '2021-01-01',
                '2021-02-01', '2021-03-01', '2021-04-01', '2021-05-01',
                '2021-06-01', '2021-07-01', '2021-08-01', '2021-09-01'],
              dtype='datetime64[ns]', freq='MS')
```

In [94]:

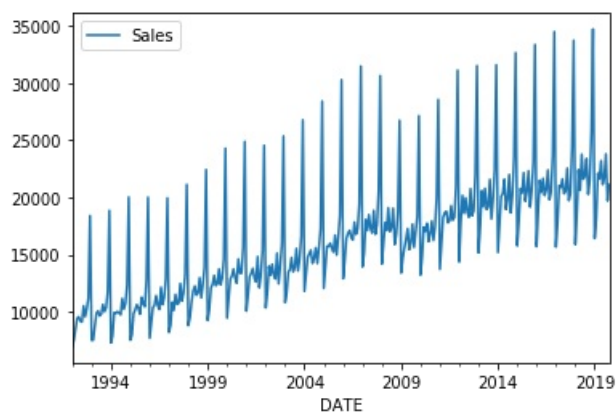
```
forecast_df=pd.DataFrame(data=forecast,index=forecast_index,columns=['forecast'])
```

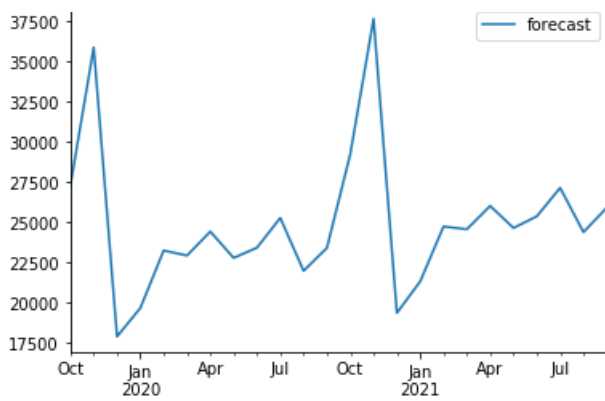
In [95]:

```
df.plot()
forecast_df.plot()
```

Out[95]:

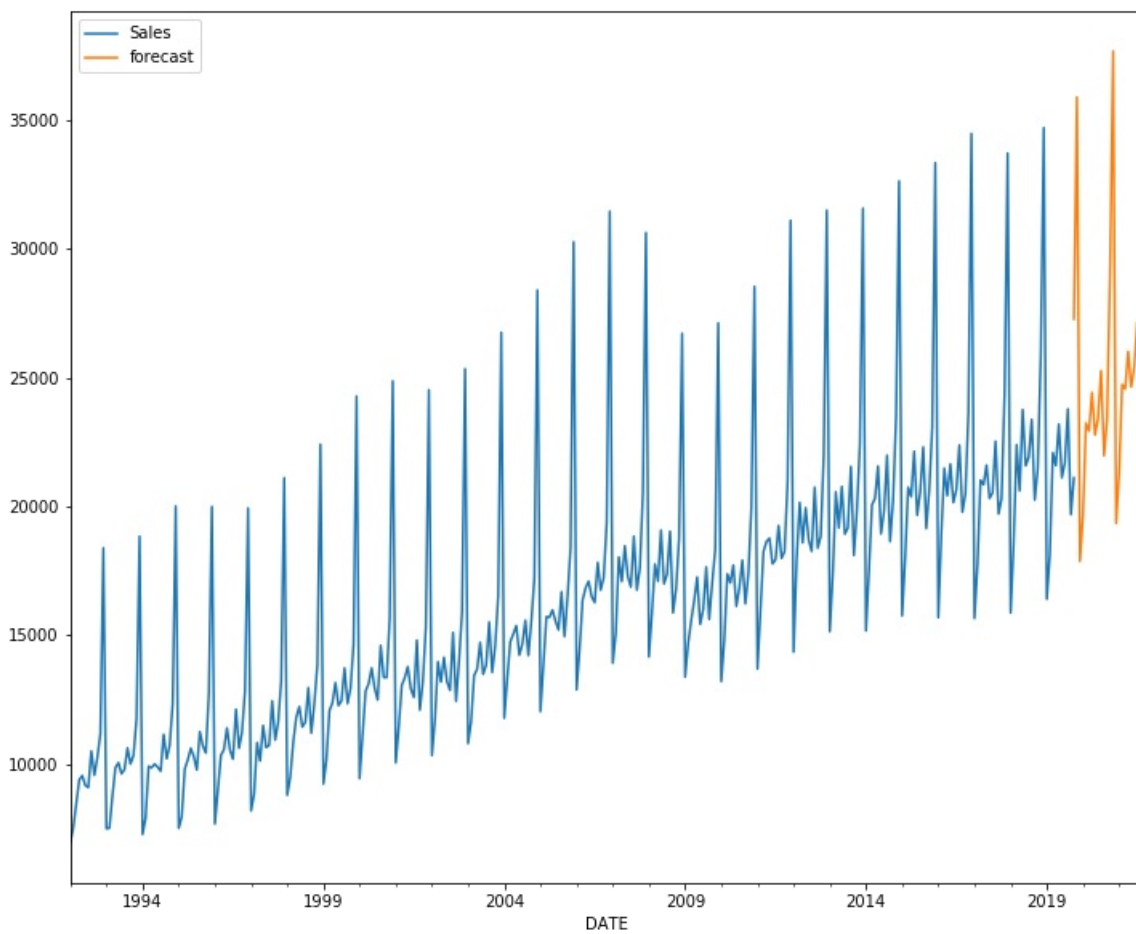
<matplotlib.axes._subplots.AxesSubplot at 0x28a3c563708>





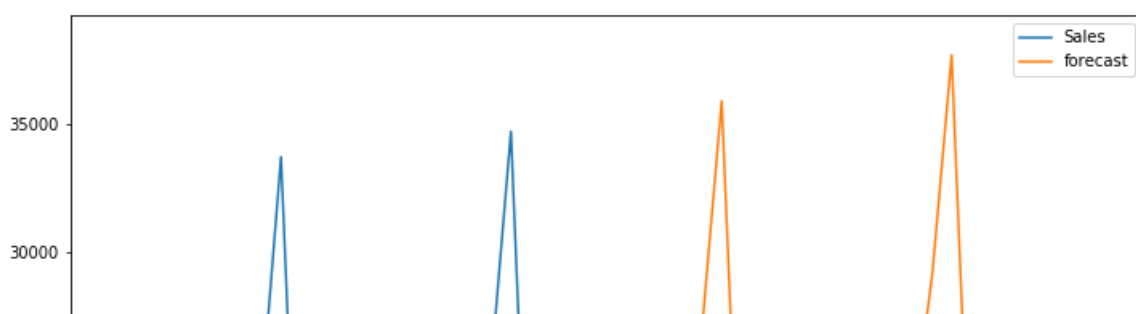
In [97]:

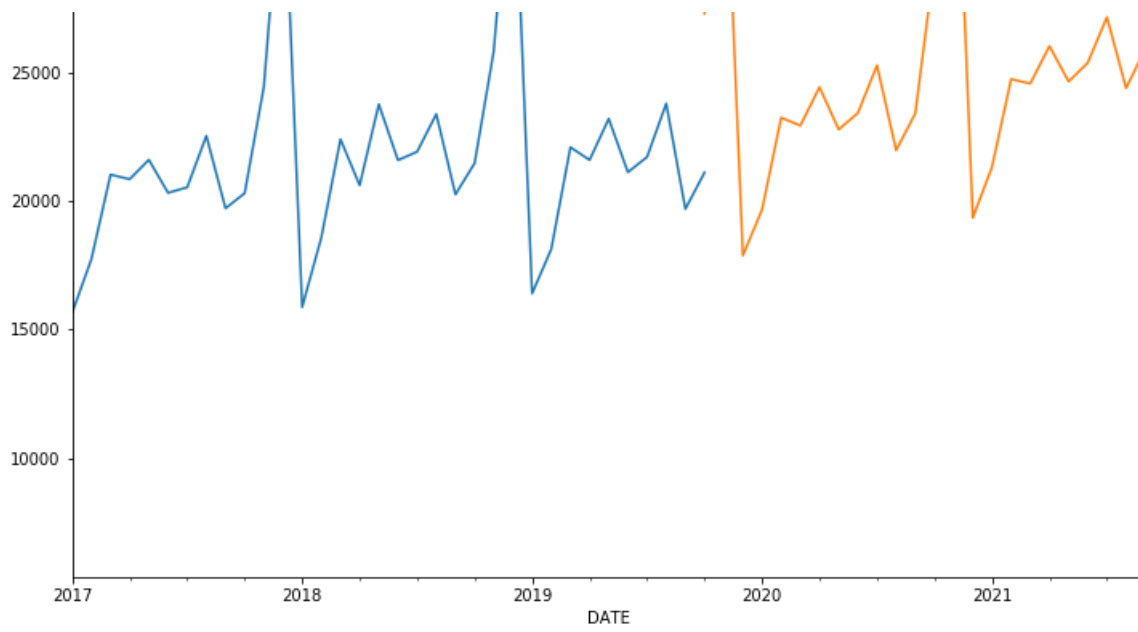
```
ax=df.plot(figsize=(12,10))
forecast_df.plot(ax=ax,figsize=(12,10));
```



In [99]:

```
ax=df.plot(figsize=(12,10))
forecast_df.plot(ax=ax,figsize=(12,10))
plt.xlim('2017-01-01','2021-09-01');
```





In []: