In [1]:

```
import pandas as pd
import tensorflow as tf
import keras
from keras import Sequential
import matplotlib.pyplot as plt
import seaborn as sns
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.
testing is deprecated. Use the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

In [1]:

```

```

In [2]:

```
df=pd.read_csv('YESBANK.csv',usecols=['Open','High','Low','Close','Volume'])
train=df.head(400)
test=df.tail(89)
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 89 entries, 400 to 488
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Open    88 non-null     float64
 1   High    88 non-null     float64
 2   Low     88 non-null     float64
 3   Close   88 non-null     float64
 4   Volume  88 non-null     float64
dtypes: float64(5)
memory usage: 3.6 KB
```

In [3]:

```
train
```

Out[3]:

	Open	High	Low	Close	Volume
0	334.0	338.500000	328.000000	333.899994	470267.0
1	336.0	343.750000	331.250000	342.500000	653618.0
2	350.0	356.500000	333.100006	340.250000	2419109.0
3	348.0	352.000000	339.250000	348.299988	1659646.0
4	349.0	358.000000	349.000000	355.250000	663569.0
...	...	...	...	...	...
395	65.0	65.199997	58.049999	59.500000	14885233.0
396	59.0	59.299999	55.000000	57.349998	19171338.0
397	58.0	60.900002	55.549999	59.500000	19148813.0
398	59.5	62.250000	57.650002	58.799999	12946414.0
399	58.0	60.200001	57.299999	59.450001	9047280.0

400 rows × 5 columns

In [4]:

```
label_train=train.pop('Close')
label_test=test.pop('Close')
```

In [5]:

```
label_train
```

Out[5]:

```
0      333.899994
1      342.500000
2      340.250000
3      348.299988
4      355.250000
          ...
395     59.500000
396     57.349998
397     59.500000
398     58.799999
399     59.450001
Name: Close, Length: 400, dtype: float64
```

In [6]:

```
train_stats=train.describe().T
train_stats
```

Out[6]:

	count	mean	std	min	25%	50%	75%	max
Open	400.0	2.453318e+02	9.472542e+01	56.299999	178.412502	2.382750e+02	3.333375e+02	3.974500e+02
High	400.0	2.498312e+02	9.525151e+01	59.299999	181.787506	2.462000e+02	3.379125e+02	4.040000e+02
Low	400.0	2.393314e+02	9.443892e+01	53.150002	171.337502	2.329500e+02	3.299125e+02	3.927000e+02
Volume	400.0	4.108042e+06	4.388718e+06	211556.000000	771410.500000	2.821196e+06	5.674854e+06	2.579198e+07

In [7]:

```
def norm(x):
  return (x-train_stats['mean'])/train_stats['std']
train=norm(train)
test=norm(test)
```

In [8]:

```
def build_model():

  #sigmoid
  #relu-rectified linear unit


  model=Sequential([
                        keras.layers.Dense(64,activation='relu',input_shape=[len(train.keys())]),
                        keras.layers.Dense(64,activation='relu'),
                        keras.layers.Dense(1)
  ])
  optimizer=tf.keras.optimizers.RMSprop(0.001)  #RMSprop
  model.compile(loss='mse',optimizer=optimizer,metrics=['mse','mae'])

  return model
```

In [9]:

```
model=build_model()
```

In [10]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 64)                320
_________________________________________________________________
dense_1 (Dense)              (None, 64)                4160
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 65
=================================================================
Total params: 4,545
Trainable params: 4,545
Non-trainable params: 0
_________________________________________________________________
```

In [11]:

```
obj=model.fit(
    train,label_train,epochs=10,validation_split=0.4,
)
```

```
Epoch 1/10
8/8 [==============================] - 0s 23ms/step - loss: 93255.9453 - mse: 93255.9453 - mae: 297.
3993 - val_loss: 30809.1250 - val_mse: 30809.1250 - val_mae: 162.3454
Epoch 2/10
8/8 [==============================] - 0s 3ms/step - loss: 92714.9766 - mse: 92714.9766 - mae: 296.5
499 - val_loss: 30623.2598 - val_mse: 30623.2598 - val_mae: 161.6139
Epoch 3/10
8/8 [==============================] - 0s 3ms/step - loss: 92171.7891 - mse: 92171.7891 - mae: 295.6
946 - val_loss: 30399.9219 - val_mse: 30399.9219 - val_mae: 160.7282
Epoch 4/10
8/8 [==============================] - 0s 3ms/step - loss: 91573.9141 - mse: 91573.9141 - mae: 294.7
407 - val_loss: 30129.6621 - val_mse: 30129.6621 - val_mae: 159.6413
Epoch 5/10
8/8 [==============================] - 0s 3ms/step - loss: 90862.5547 - mse: 90862.5547 - mae: 293.6
036 - val_loss: 29806.2500 - val_mse: 29806.2500 - val_mae: 158.3374
Epoch 6/10
8/8 [==============================] - 0s 3ms/step - loss: 89993.7422 - mse: 89993.7422 - mae: 292.2
064 - val_loss: 29451.8223 - val_mse: 29451.8223 - val_mae: 156.8982
Epoch 7/10
8/8 [==============================] - 0s 3ms/step - loss: 88983.2578 - mse: 88983.2578 - mae: 290.5
697 - val_loss: 28999.6660 - val_mse: 28999.6660 - val_mae: 154.9934
Epoch 8/10
8/8 [==============================] - 0s 3ms/step - loss: 87826.9297 - mse: 87826.9297 - mae: 288.6
814 - val_loss: 28506.4180 - val_mse: 28506.4180 - val_mae: 152.8965
Epoch 9/10
8/8 [==============================] - 0s 3ms/step - loss: 86457.1641 - mse: 86457.1641 - mae: 286.4
395 - val_loss: 27953.9531 - val_mse: 27953.9531 - val_mae: 150.4889
Epoch 10/10
8/8 [==============================] - 0s 3ms/step - loss: 84895.0703 - mse: 84895.0703 - mae: 283.8
573 - val_loss: 27354.1816 - val_mse: 27354.1816 - val_mae: 147.8241
```

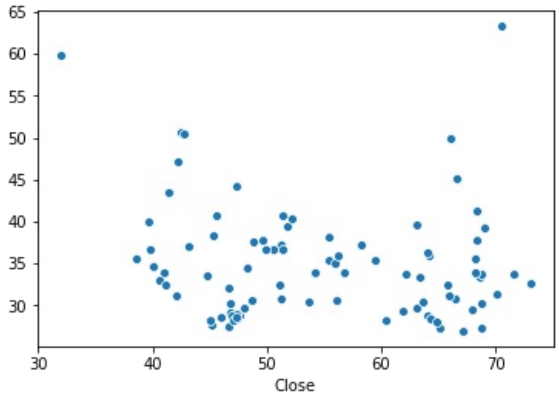
In [12]:

```
test_predictions= model.predict(test).flatten()

sns.scatterplot(label_test,test_predictions)
```

Out[12]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f96e150ce48>
```



In [13]:

```
test_predictions
```

Out[13]:

```
array([29.39704 , 28.305233, 29.70388 , 33.74158 , 29.563684, 33.454544,
       26.955334, 27.328016, 28.738953, 33.961212, 38.149166, 35.35934 ,
       30.541504, 30.361244, 32.51153 , 37.62358 , 43.493996, 59.78089 ,
       50.601208, 47.25449 , 40.691864, 37.116516, 33.87306 , 40.057037,
       34.738686, 32.948013, 32.47511 , 44.200924, 40.786064, 39.36667 ,
       37.256966, 34.44162 , 40.435196,       nan, 37.197037, 33.902557,
       63.29755 , 45.19217 , 50.00143 , 37.719322, 33.65449 , 30.866213,
       39.228096, 32.690117, 35.56397 , 30.314556, 27.271626, 31.221296,
       35.98253 , 32.51911 , 28.47357 , 27.98981 , 30.44498 , 33.349064,
       33.970833, 31.31995 , 41.25096 , 36.35713 , 35.374218, 39.715652,
       33.761513, 34.97998 , 36.000008, 36.603485, 50.497444, 38.36283 ,
       32.063896, 30.2429  , 28.765583, 29.09685 , 36.596283, 36.6391  ,
       37.793686, 30.849037, 30.656227, 29.635784, 28.962076, 28.825327,
       27.570229, 28.43608 , 28.157   , 27.698849, 28.23877 , 28.634398,
       28.64354 , 33.525043, 31.2596  , 35.570393, 36.611984],
      dtype=float32)
```

In [15]:

```
pd.DataFrame(test_predictions[0:100],label_test[0:100])
```

Out[15]:

	0
Close	
61.900002	29.397039
60.400002	28.305233
63.099998	29.703880
71.599998	33.741581
67.949997	29.563684
...	...
47.299999	28.643539
44.799999	33.525043
42.099998	31.259600
38.549999	35.570393
39.799999	36.611984

89 rows × 1 columns

In [16]:

```
#Making a new prediction
import numpy as np

new=pd.DataFrame(np.array([334,310,350,986887])) #new data for prediction

train_stats=new.describe().T

#send data to norm function
new=norm(new).to_numpy().reshape(-1,4)


model.predict(new)
```

Out[16]:

```
array([[12.335249]], dtype=float32)
```