When was used MSE measurement and when cross_entropy(log loss)?

While corss entropy measures the classifications performances whose outputs are probability between 0 and 1, MSE(mean square error) measures the regression preformace.

When is softmax activation function used?

Softmax activation function is used for multiclass classification predicting class membership probabilities of output layer which classes are mutually exclusive.

What is difference betwenn incremental learning and batch learning?

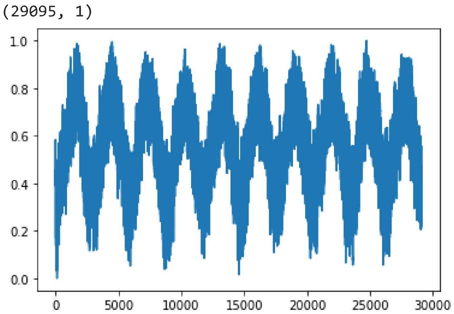
While in incremental learning the learning algorithm and its weights are updated by one training data, in batch learning they are update by average of multiple training data feedback, providing faster speed on algorithm.Each learning method is apropriate for various problems.For example, batch learning is applied for systems only have new data every week, but in case of every minute data changing, incremental learning is more suitable.In addtion incremental learning will be efficient if machine learning's memory not enough for huge data.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.layers.experimental import preprocessing
import tensorflow as tf
from tensorflow.keras.utils import timeseries_dataset_from_array
from sklearn.model_selection import train_test_split
from keras.models import Sequential
from keras.layers import Dense


tmps_df = pd.read_excel('/content/drive/MyDrive/Temperature.xlsx')
dataset = np.array(tmps_df['دما'])
print("total number = {}".format(len(dataset)))
```

```
total number = 29095
```

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
print(scaler.fit(dataset.reshape(-1,1)))

print(scaler.data_max_)

normed_dataset = scaler.transform(dataset.reshape(-1,1))
plt.plot(normed_dataset)
print(normed_dataset.shape)
```

```
MinMaxScaler(copy=True, feature_range=(0, 1))
[41.7]
(29095, 1)
```



Data before normalization

```

plt.plot(dataset)
```

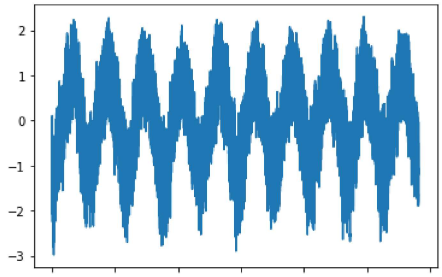
```
[<matplotlib.lines.Line2D at 0x7f4fbc886950>]
```

```python

normalizer = preprocessing.Normalization(axis=None)
normalizer.adapt(dataset)
normed_dataset = normalizer(dataset)
```

Data after normalization

```python
plt.plot(normed_dataset)
```

```
[<matplotlib.lines.Line2D at 0x7f4fbcd55e90>]
```




```python

def prepare_timeseries(dataset, window_size, sequence_stride, sampling_rate=1):
  time_series = timeseries_dataset_from_array(
      dataset[:-sequence_stride], dataset[window_size:], window_size, sequence_stride=1, sampling_rate=1, batch_size=len(dataset), shuffle=True
  )
  return time_series.get_single_element()

window_sizes = [3, 5, 10]

time_series = prepare_timeseries(normed_dataset.flatten(), window_size=window_sizes[0], sequence_stride=1, sampling_rate=1)
x1, y1 = time_series
x1train, x1test = tf.split(x1, [ int(0.7*len(x1)), len(x1) - int(0.7*len(x1))] )
y1train, y1test = tf.split(y1, [ int(0.7*len(y1)), len(y1) - int(0.7*len(y1))] )

print("with winodw size={} train data{}={}".format(3, 1,x1train.shape))
print("with winodw size={} test data{}={}\n\n".format(3, 1,x1test.shape))

time_series = prepare_timeseries(normed_dataset.flatten(), window_size=window_sizes[1], sequence_stride=1, sampling_rate=1)
x2, y2 = time_series
x2train, x2test = tf.split(x2, [  int(0.7*len(x2)), len(x2) - int(0.7*len(x2))] )
y2train, y2test = tf.split(y2, [  int(0.7*len(y2)), len(y2) - int(0.7*len(y2))] )
print("with winodw size={} train data{}={}".format(3, 2,x2train.shape))
print("with winodw size={} test data{}={}\n\n".format(3, 2,x2test.shape))

time_series = prepare_timeseries(normed_dataset.flatten(), window_size=window_sizes[2], sequence_stride=1, sampling_rate=1)
x3, y3 = time_series
x3train, x3test = tf.split(x3, [  int(0.7*len(x3)), len(x3) - int(0.7*len(x3)) ] )
y3train, y3test = tf.split(y3, [ int(0.7*len(y3)), len(y3) - int(0.7*len(y3))] )
print("with winodw size={} train data{}={}".format(3, 3,x3train.shape))
print("with winodw size={} test data{}={}\n\n".format(3, 3, x3test.shape))


```

```
with winodw size=3 train data1=(20364, 3)
with winodw size=3 test data1=(8728, 3)


with winodw size=3 train data2=(20363, 5)
with winodw size=3 test data2=(8727, 5)


with winodw size=3 train data3=(20359, 10)
with winodw size=3 test data3=(8726, 10)
```

Window size = 3

```python

model1 = Sequential()
model1.add(Dense(8, activation='relu'))

optimizer = tf.keras.optimizers.Adam(learning_rate=0.01)
model1.add(Dense(1,))

model1.compile(loss='mean_squared_error',optimizer=optimizer)
model1.build(input_shape=(1,window_sizes[0]))
model1.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (1, 8)                    32
```

```
dense_1 (Dense)              (1, 1)                    9
=================================================================
Total params: 41
Trainable params: 41
Non-trainable params: 0
_________________________________________________________________
```

```
history = model1.fit(x1train, y1train, validation_split=0.3, epochs=20, shuffle=True, verbose=1)
```

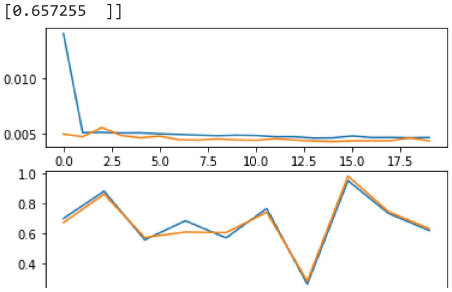
```
Epoch 1/20
446/446 [==============================] - 2s 2ms/step - loss: 0.0140 - val_loss: 0.0050
Epoch 2/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0051 - val_loss: 0.0047
Epoch 3/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0051 - val_loss: 0.0056
Epoch 4/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0051 - val_loss: 0.0049
Epoch 5/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0051 - val_loss: 0.0046
Epoch 6/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0050 - val_loss: 0.0048
Epoch 7/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0049 - val_loss: 0.0045
Epoch 8/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0049 - val_loss: 0.0044
Epoch 9/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0048 - val_loss: 0.0045
Epoch 10/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0049 - val_loss: 0.0045
Epoch 11/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0049 - val_loss: 0.0044
Epoch 12/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0047 - val_loss: 0.0046
Epoch 13/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0047 - val_loss: 0.0044
Epoch 14/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0046 - val_loss: 0.0044
Epoch 15/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0046 - val_loss: 0.0043
Epoch 16/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0048 - val_loss: 0.0044
Epoch 17/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0047 - val_loss: 0.0044
Epoch 18/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0047 - val_loss: 0.0044
Epoch 19/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0046 - val_loss: 0.0046
Epoch 20/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0047 - val_loss: 0.0044
```

```
model1.evaluate(x1test,y1test)
```

```
273/273 [==============================] - 0s 998us/step - loss: 0.0045
0.004452623426914215
```

```
plt.subplot(2, 1, 1)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])

plt.subplot(2, 1, 2)
predicts = model1.predict(x1test)
plt.plot(predicts[:10])
plt.plot(y1test[:10])
print(predicts)
```

```
[[0.6981483 ]
 [0.8803155 ]
 [0.55555564]
 ...
 [0.28835797]
 [0.8523818 ]
 [0.657255  ]]
```



Window_size 5 In this part i wlil ilustrate how plaining the netwrok structure results in bad result although the window size increased

```
model2 = Sequential()
# model2.add(Dense(8, activation='relu'))

optimizer = tf.keras.optimizers.Adam(learning_rate=0.01)
model2.add(Dense(1,))

```

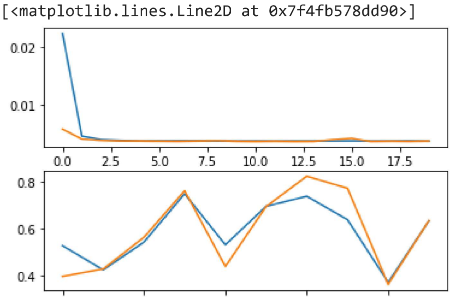
```
model2.compile(loss='mean_squared_error',optimizer=optimizer)
model2.build(input_shape=(1,window_sizes[1]))
model2.summary()
history = model2.fit(x2train, y2train, validation_split=0.3, epochs=20, shuffle=True, verbose=1)
model2.evaluate(x2test,y2test)
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_2 (Dense)              (1, 1)                    6
=================================================================
Total params: 6
Trainable params: 6
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0224 - val_loss: 0.0057
Epoch 2/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0045 - val_loss: 0.0039
Epoch 3/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0038 - val_loss: 0.0037
Epoch 4/20
446/446 [==============================] - 1s 1ms/step - loss: 0.0037 - val_loss: 0.0036
Epoch 5/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0036 - val_loss: 0.0036
Epoch 6/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0036 - val_loss: 0.0035
Epoch 7/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0036 - val_loss: 0.0035
Epoch 8/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0036 - val_loss: 0.0036
Epoch 9/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0036 - val_loss: 0.0037
Epoch 10/20
446/446 [==============================] - 1s 1ms/step - loss: 0.0036 - val_loss: 0.0035
Epoch 11/20
446/446 [==============================] - 1s 1ms/step - loss: 0.0036 - val_loss: 0.0035
Epoch 12/20
446/446 [==============================] - 1s 1ms/step - loss: 0.0036 - val_loss: 0.0035
Epoch 13/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0036 - val_loss: 0.0035
Epoch 14/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0036 - val_loss: 0.0035
Epoch 15/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0036 - val_loss: 0.0038
Epoch 16/20
446/446 [==============================] - 1s 1ms/step - loss: 0.0036 - val_loss: 0.0041
Epoch 17/20
446/446 [==============================] - 1s 1ms/step - loss: 0.0036 - val_loss: 0.0035
Epoch 18/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0036 - val_loss: 0.0035
Epoch 19/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0036 - val_loss: 0.0035
Epoch 20/20
446/446 [==============================] - 1s 1ms/step - loss: 0.0036 - val_loss: 0.0036
273/273 [==============================] - 0s 1ms/step - loss: 0.0035
0.003546466352418065
```

Predicts

```
plt.subplot(2, 1, 1)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])

plt.subplot(2, 1, 2)
predicts = model2.predict(x2test)
plt.plot(predicts[:10])
plt.plot(y2test[:10])
```

```
[<matplotlib.lines.Line2D at 0x7f4fb578dd90>]
```



Window size 10

```
model3 = Sequential()
# model3.add(Dense(8, activation='relu'))

optimizer = tf.keras.optimizers.Adam(learning_rate=0.01)
model3.add(Dense(1,))

model3.compile(loss='mean_squared_error',optimizer=optimizer)
model3.build(input_shape=(1,window_sizes[2]))
```

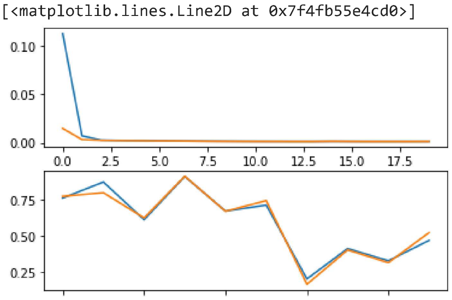
```
model3.summary()
history = model3.fit(x3train, y3train, validation_split=0.3, epochs=20, shuffle=True, verbose=1)
model3.evaluate(x3test,y3test)
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_3 (Dense)              (1, 1)                    11        
=================================================================
Total params: 11
Trainable params: 11
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
446/446 [==============================] - 1s 2ms/step - loss: 0.1127 - val_loss: 0.0148
Epoch 2/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0071 - val_loss: 0.0032
Epoch 3/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0027 - val_loss: 0.0024
Epoch 4/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0023 - val_loss: 0.0022
Epoch 5/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0021 - val_loss: 0.0020
Epoch 6/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0019 - val_loss: 0.0018
Epoch 7/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0018 - val_loss: 0.0018
Epoch 8/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0017 - val_loss: 0.0016
Epoch 9/20
446/446 [==============================] - 1s 1ms/step - loss: 0.0016 - val_loss: 0.0014
Epoch 10/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0015 - val_loss: 0.0013
Epoch 11/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0014 - val_loss: 0.0012
Epoch 12/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0013 - val_loss: 0.0012
Epoch 13/20
446/446 [==============================] - 1s 1ms/step - loss: 0.0013 - val_loss: 0.0012
Epoch 14/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0013 - val_loss: 0.0012
Epoch 15/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0014 - val_loss: 0.0014
Epoch 16/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0013 - val_loss: 0.0012
Epoch 17/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0013 - val_loss: 0.0011
Epoch 18/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0013 - val_loss: 0.0012
Epoch 19/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0013 - val_loss: 0.0012
Epoch 20/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0013 - val_loss: 0.0012
273/273 [==============================] - 0s 1ms/step - loss: 0.0013
0.0012868698686361313
```

The line graph provided shows that as window become bigger model can learn more.

```
plt.subplot(2, 1, 1)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])

plt.subplot(2, 1, 2)
predicts = model3.predict(x3test)
plt.plot(predicts[:10])
plt.plot(y3test[:10])
```

```
[<matplotlib.lines.Line2D at 0x7f4fb55e4cd0>]
```



lets change the activation function for window size 5

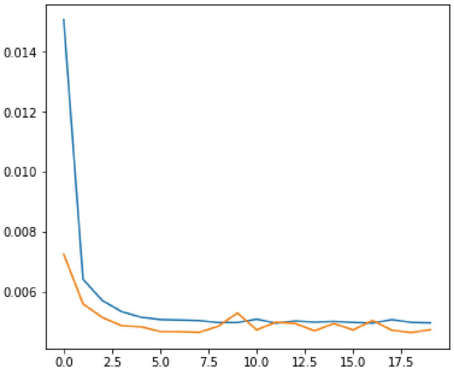
```
model4 = Sequential()
model4.add(Dense(2, activation='sigmoid'))

optimizer = tf.keras.optimizers.Adam(learning_rate=0.01)
model4.add(Dense(1,))

model4.compile(loss='mean_squared_error',optimizer=optimizer)
model4.build(input_shape=(1,window_sizes[0]))
model4.summary()
history = model4.fit(x1train, y1train, validation_split=0.3, epochs=20, shuffle=True, verbose=1)
```

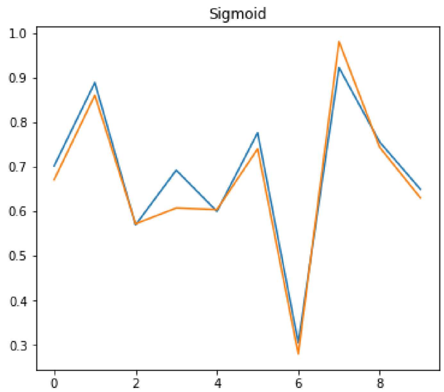
```
model4.evaluate(x1test,y1test)
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (1, 2)                    8
_________________________________________________________________
dense_5 (Dense)              (1, 1)                    3
=================================================================
Total params: 11
Trainable params: 11
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0151 - val_loss: 0.0073
Epoch 2/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0064 - val_loss: 0.0056
Epoch 3/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0057 - val_loss: 0.0052
Epoch 4/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0053 - val_loss: 0.0049
Epoch 5/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0052 - val_loss: 0.0048
Epoch 6/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0051 - val_loss: 0.0047
Epoch 7/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0051 - val_loss: 0.0047
Epoch 8/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0050 - val_loss: 0.0047
Epoch 9/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0050 - val_loss: 0.0049
Epoch 10/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0050 - val_loss: 0.0053
Epoch 11/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0051 - val_loss: 0.0047
Epoch 12/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0050 - val_loss: 0.0050
Epoch 13/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0050 - val_loss: 0.0049
Epoch 14/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0050 - val_loss: 0.0047
Epoch 15/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0050 - val_loss: 0.0049
Epoch 16/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0050 - val_loss: 0.0047
Epoch 17/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0050 - val_loss: 0.0051
Epoch 18/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0051 - val_loss: 0.0047
Epoch 19/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0050 - val_loss: 0.0046
Epoch 20/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0050 - val_loss: 0.0047
273/273 [==============================] - 0s 1ms/step - loss: 0.0049
0.004926361609250307
```

The line gaph ilustrates with sigmoid function model did not work as well as relu function model which is a linear function.As a result the linear regression does not work effectively with non-linear functions.

```
plt.subplot(3, 1, 1)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])

plt.subplot(3, 1, 2)
predicts = model4.predict(x1test)
plt.title('Sigmoid')
plt.plot(predicts[:10])
plt.plot(y1test[:10])

plt.subplot(3, 1, 3)
predicts = model1.predict(x1test)
plt.title('Relu')
plt.plot(predicts[:10])
plt.plot(y1test[:10])

plt.subplots_adjust( top=3.5)

```





lets change the learning rate

```
model5 = Sequential()
model5.add(Dense(2, activation='relu'))

optimizer = tf.keras.optimizers.Adam(learning_rate=0.1)
model5.add(Dense(1,))

model5.compile(loss='mean_squared_error',optimizer=optimizer)
model5.build(input_shape=(1,window_sizes[0]))
model5.summary()
history = model5.fit(x1train, y1train, validation_split=0.3, epochs=20, shuffle=True, verbose=1)
model5.evaluate(x1test,y1test)
```

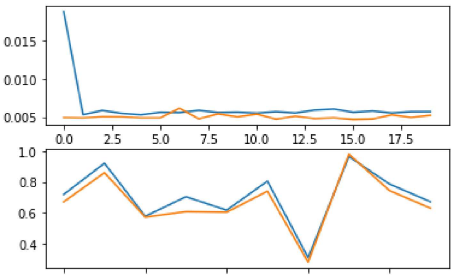
```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_6 (Dense)              (1, 2)                    8
_________________________________________________________________
dense_7 (Dense)              (1, 1)                    3
=================================================================
Total params: 11
Trainable params: 11
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0188 - val_loss: 0.0049
Epoch 2/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0053 - val_loss: 0.0049
Epoch 3/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0059 - val_loss: 0.0050
Epoch 4/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0055 - val_loss: 0.0050
Epoch 5/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0053 - val_loss: 0.0049
Epoch 6/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0056 - val_loss: 0.0049
Epoch 7/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0056 - val_loss: 0.0062
Epoch 8/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0059 - val_loss: 0.0048
Epoch 9/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0056 - val_loss: 0.0054
Epoch 10/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0056 - val_loss: 0.0050
Epoch 11/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0055 - val_loss: 0.0054
Epoch 12/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0057 - val_loss: 0.0047
Epoch 13/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0055 - val_loss: 0.0051
Epoch 14/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0059 - val_loss: 0.0048
Epoch 15/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0061 - val_loss: 0.0049
Epoch 16/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0056 - val_loss: 0.0047
Epoch 17/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0058 - val_loss: 0.0047
```

```
Epoch 18/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0055 - val_loss: 0.0053
Epoch 19/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0057 - val_loss: 0.0049
Epoch 20/20
446/446 [==============================] - 1s 2ms/step - loss: 0.0057 - val_loss: 0.0052
273/273 [==============================] - 0s 1ms/step - loss: 0.0054
0.005379165057092905
```

it is evident that with bigger learning rate model works worse.

```
plt.subplot(2, 1, 1)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])

plt.subplot(2, 1, 2)
predicts = model5.predict(x1test)
plt.plot(predicts[:10])
plt.plot(y1test[:10])
```

```
[<matplotlib.lines.Line2D at 0x7f4fae70eed0>]
```



lets change the loss function

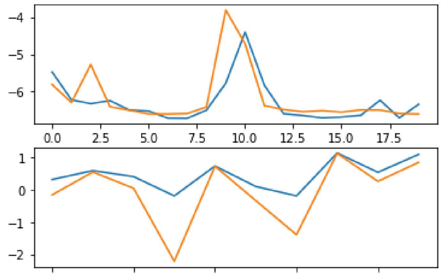
```
model6 = Sequential()
model6.add(Dense(2, activation='relu'))

optimizer = tf.keras.optimizers.Adam(learning_rate=0.01)
model6.add(Dense(1,))

model6.compile(loss='binary_crossentropy',optimizer=optimizer)
model6.build(input_shape=(1,window_sizes[0]))
model6.summary()
history = model6.fit(x1train, y1train, validation_split=0.3, epochs=20, shuffle=True, verbose=1)
model6.evaluate(x1test,y1test)
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_8 (Dense)              (1, 2)                    8
_________________________________________________________________
dense_9 (Dense)              (1, 1)                    3
=================================================================
Total params: 11
Trainable params: 11
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 2/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 3/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 4/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 5/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 6/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 7/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 8/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 9/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 10/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 11/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 12/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 13/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 14/20
446/446 [==============================] - 1s 2ms/step - loss: 8.7085 - val_loss: 8.6599
Epoch 15/20
272/446 [=================>...........] - ETA: 0s - loss: 8.7270
```

```
plt.subplot(2, 1, 1)
plt.plot(history.history['loss'])
```

```
plt.plot(history.history['val_loss'])

plt.subplot(2, 1, 2)
predicts = model6.predict(x1test)
plt.plot(predicts[:10])
plt.plot(y1test[:10])
```

```
[<matplotlib.lines.Line2D at 0x7fb9d4f084d0>]
```



conclusion

1.linear activation functions are more apropriate for linear regression problems

2.As learning rate are become excessively big optimization algorithm could not find the best solution.

3.probablity loss functions are not suitable for regression problems.

4.As layers in model increase overfitting occured.

5.The most important point if window size increase, training model can learn better.