NO₂

November 30, 2017

```
In [1]: import numpy as np
        import pandas as pd
        import os
        import matplotlib.pyplot as plt
In [2]: os.listdir('data')
Out[2]: ['AllNO2_QH.csv',
         'AllPM_QH.csv',
         'Env_QH.csv',
         'GradientTemp_15minDataSet.csv',
         'micro_sud3.pkl',
         'micro_sud3_normalized.pkl',
         'Patm_15minDataSet.csv',
         'pickles']
In [3]: df = pd.read_pickle('data/micro_sud3_normalized.pkl')
        df = df.reset_index()
        df.head(100)
Out[3]:
            index
                                         PM_ref
                                                  PM_6182
                                                            PM_6179
                                                                      PM_617B
                                   date
        0
               15
                   2017-09-28 14:00:00
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               16
                                           9.6 -1.108262 -1.085060 -1.121956
                   2017-09-28 14:15:00
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                   2017-09-28 14:30:00
                                           10.3 -1.178505 -1.169515 -1.257077
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                                            9.4 -1.137530 -1.000606 -1.206407
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                                           10.7 -1.166798 -1.164236 -1.138846
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                   2017-09-28 15:15:00
                                           10.7 -1.166798 -1.201185 -1.037506
                  2017-09-28 15:30:00
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                                           9.6 -1.078994 -1.169515 -1.007948
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               22 2017-09-28 15:45:00
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               23 2017-09-28 16:00:00
                                            9.8 -1.043872 -1.095617 -0.910830
        9
               24 2017-09-28 16:15:00
                                            8.9 -1.043872 -1.042833 -1.181072
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                                           10.1 -0.920945 -0.784192 -1.029061
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                                           10.7 -0.862409 -0.842254 -0.969945
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                                           12.0 -0.932653 -0.778913 -0.915052
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                                           12.3 -0.903385 -0.905595 -0.817934
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   -1.101652 -1.071229 -1.128278
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       98 0.850022 -0.053093 -0.593641 -0.106285 3.041287
       99 0.708021 0.110146 -0.538849 -0.106285 7.031051
        [100 rows x 18 columns]
In [4]: df = df[['date', 'NO2_ref', 'NO2_61FD', 'NO2_61FO', \
                'NO2_61EF', 'temp', 'rh', 'tgrad', 'pressure', 'pluvio']]
```

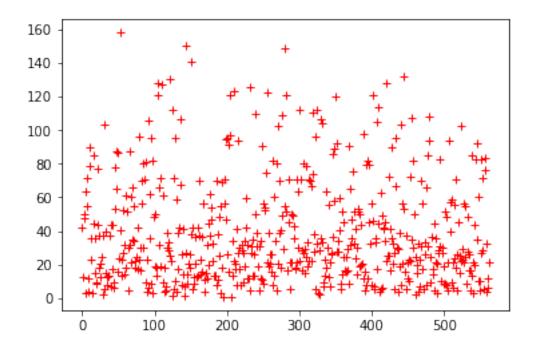
1 Premier modèle: simple DNN

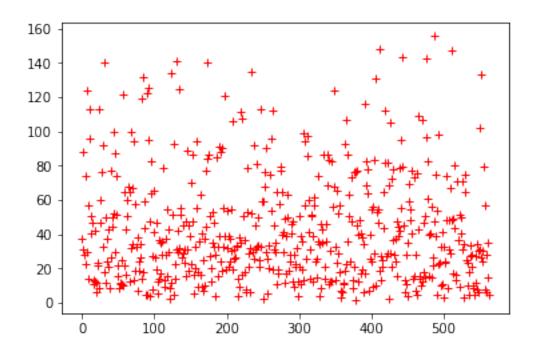
```
In [5]: from keras.models import Sequential
    from keras.layers import Dense
    from keras.callbacks import EarlyStopping

def baseline_model(dense_size, input_dim, loss='mean_squared_error', optimizer='adam')
    # create model
    model = Sequential()
    model.add(Dense(dense_size, input_dim=input_dim, kernel_initializer='normal', actimodel.add(Dense(1, kernel_initializer='normal'))
    # Compile model
    model.compile(loss=loss, optimizer=optimizer)
    model.summary()
    return model
```

Using TensorFlow backend.

```
In [6]: df = df.reindex(np.random.permutation(df.index))
        def split_dataframe(dataframe, percent):
            nb_rows = int(np.floor(percent * len(dataframe)))
            return dataframe[:nb_rows], dataframe[nb_rows:]
        def dataframe_to_xy(df):
            return (np.array(df[['NO2_61FD', 'NO2_61F0', 'NO2_61EF', 'temp', 'rh',\
                                 'tgrad', 'pressure', 'pluvio']]),\
                    np.array(df['NO2_ref']))
        df_train, df_test = split_dataframe(df, 0.5)
        df_valid, df_test = split_dataframe(df_test, 0.5)
        X_train, y_train = dataframe_to_xy(df_train)
        X_valid, y_valid = dataframe_to_xy(df_valid)
        X_test, y_test = dataframe_to_xy(df_test)
In [7]: plt.plot(y_train, '+r')
        plt.show()
        plt.plot(y_valid, '+r')
        plt.show()
        plt.plot(y_test, '+r')
        plt.show()
         175
         150
         125
         100
          75
          50
          25
           0
                        200
                                  400
                                            600
                                                     800
                                                               1000
```





```
Layer (type)
     Output Shape
          Param #
______
     (None, 32)
dense_1 (Dense)
          288
-----
dense 2 (Dense)
     (None, 1)
          33
______
Total params: 321
Trainable params: 321
Non-trainable params: 0
Train on 1126 samples, validate on 563 samples
Epoch 1/5000
Epoch 2/5000
Epoch 3/5000
Epoch 4/5000
Epoch 5/5000
Epoch 6/5000
Epoch 7/5000
Epoch 8/5000
Epoch 9/5000
Epoch 10/5000
Epoch 11/5000
Epoch 12/5000
Epoch 13/5000
Epoch 14/5000
Epoch 15/5000
Epoch 16/5000
Epoch 17/5000
Epoch 18/5000
```

Enach 10/5000									
Epoch 19/5000		٥-	60		J	124 1025		1 1	264 E10
1126/1126 [====================================	_	US	62us/step	_	loss:	434.4035	_	vai_loss:	304.518
Epoch 20/5000		0	40 / 1		,	440 4007			044 5504
1126/1126 [====================================	_	US	49us/step	_	loss:	410.1337	_	val_loss:	344.5599
Epoch 21/5000		_	47 / .		-	000 5700			000 000
1126/1126 [====================================	-	0s	47us/step	-	loss:	390.5729	-	val_loss:	328.3883
Epoch 22/5000		_			_				
1126/1126 [====================================	-	0s	48us/step	-	loss:	374.7627	-	val_loss:	315.467
Epoch 23/5000									
1126/1126 [====================================	-	0s	49us/step	-	loss:	360.3925	-	val_loss:	303.3226
Epoch 24/5000									
1126/1126 [=======]	-	0s	45us/step	-	loss:	347.1892	-	val_loss:	292.4300
Epoch 25/5000									
1126/1126 [=======]	-	0s	48us/step	-	loss:	334.9128	-	<pre>val_loss:</pre>	281.6309
Epoch 26/5000									
1126/1126 [===========]	-	0s	51us/step	-	loss:	322.5714	-	<pre>val_loss:</pre>	271.1792
Epoch 27/5000									
1126/1126 [====================================	-	0s	50us/step	-	loss:	310.3080	-	<pre>val_loss:</pre>	261.1138
Epoch 28/5000									
1126/1126 [=========]	-	0s	47us/step	-	loss:	298.0337	-	<pre>val_loss:</pre>	251.6564
Epoch 29/5000									
1126/1126 [===========]	-	0s	52us/step	-	loss:	286.2926	-	<pre>val_loss:</pre>	241.708
Epoch 30/5000			_						
1126/1126 [====================================	-	0s	49us/step	_	loss:	274.0643	-	val_loss:	231.1999
Epoch 31/5000			_						
1126/1126 [====================================	-	0s	50us/step	_	loss:	261.2273	-	val_loss:	221.8276
Epoch 32/5000			-					_	
1126/1126 [====================================	-	0s	48us/step	_	loss:	249.3111	_	val_loss:	212.228
Epoch 33/5000			•					_	
1126/1126 [====================================	_	0s	50us/step	_	loss:	237.6641	_	val loss:	203.360
Epoch 34/5000								_	
1126/1126 [====================================	_	0s	49us/step	_	loss:	226.3875	_	val loss:	194.8508
Epoch 35/5000			. 1					_	
1126/1126 [====================================	_	0s	50us/step	_	loss:	216.4259	_	val loss:	187.380
Epoch 36/5000			<u>.</u>					<u>-</u>	
1126/1126 [====================================	_	0s	52us/step	_	loss:	206.8391	_	val loss:	180.5998
Epoch 37/5000			, _F						
1126/1126 [====================================	_	0s	51us/step	_	loss:	198.3697	_	val loss:	174.1484
Epoch 38/5000		• •	oras, reep						_, _, _,
1126/1126 [====================================	_	0s	50us/step	_	loss:	190.2108	_	val loss:	168.1269
Epoch 39/5000		• •	oraz, zrep						
1126/1126 [====================================	_	۸e	47119/sten	_	1088.	182 6863	_	val logg.	162 8869
Epoch 40/5000		OB	1, 40, 20eh		1000.	102.000		, ar_1000.	102.000
1126/1126 [====================================	_	Λα	47119/stan	_	1088.	176 1663	_	val logg.	158 0801
Epoch 41/5000		OB	11 ab/ b cep		TOBB.	110.1000		, at_topp.	100.0092
1126/1126 [====================================	_	Λα	19119/stan	_	1000.	169 7631	_	wal loce.	153 4351
Epoch 42/5000		GO	Tomp, preh		TOSS.	100.7001		, ατ ⁻ τουυ.	100.400
1126/1126 [====================================	_	Λα	16119/etan	_	1000.	164 0514	_	wal loce.	149 563
1120/1120 [OB	rous, sceb		TODD.	10-1.0014		vur_1088.	140.000.

Epoch 43/5000									
1126/1126 [====================================	_	۸e	17112/stan	_	loggi	158 8700	_	wal logg.	145 858
Epoch 44/5000		US	Ti day a cep		TOSS.	100.0799		vai_ioss.	140.000
1126/1126 [====================================	_	٥q	51us/sten	_	1088.	154 1968	_	val logg.	142 2461
Epoch 45/5000		O.D.	orab, btop		TODD.	101.1000		var_1055.	112.2100
1126/1126 [====================================	_	0s	51us/step	_	loss:	149.7311	_	val loss:	139.393
Epoch 46/5000		O.D.	orab, btop		TODD.	110.7011		var_1055.	100.000
1126/1126 [====================================	_	0s	49us/step	_	loss:	145.8988	_	val loss:	136.424
Epoch 47/5000			, <u>-</u>						
1126/1126 [====================================	_	0s	52us/step	_	loss:	142.1967	_	val loss:	133.9994
Epoch 48/5000			-					_	
1126/1126 [====================================	_	0s	50us/step	_	loss:	139.0513	_	val_loss:	131.783
Epoch 49/5000			_						
1126/1126 [========]	-	0s	48us/step	-	loss:	136.0343	-	val_loss:	129.7454
Epoch 50/5000									
1126/1126 [============]	-	0s	48us/step	-	loss:	133.2760	-	val_loss:	127.3062
Epoch 51/5000									
1126/1126 [=======]	-	0s	49us/step	-	loss:	130.8140	-	<pre>val_loss:</pre>	125.5816
Epoch 52/5000									
1126/1126 [====================================	-	0s	46us/step	-	loss:	128.7272	-	val_loss:	123.840
Epoch 53/5000									
1126/1126 [====================================	-	0s	48us/step	-	loss:	126.5977	-	val_loss:	122.1814
Epoch 54/5000		_			_				
1126/1126 [====================================	-	0s	49us/step	-	loss:	124.9579	_	val_loss:	120.8459
Epoch 55/5000		_			_				
1126/1126 [====================================	-	0s	48us/step	_	loss:	123.2888	_	val_loss:	119.6220
Epoch 56/5000		^	40 / .		7	404 7540			440 040
1126/1126 [====================================	_	US	48us/step	_	loss:	121.7510	_	val_loss:	118.3136
Epoch 57/5000 1126/1126 [====================================		٥٥	15:10 /aton		1	100 4017]]	117 046
Epoch 58/5000	_	US	45us/step	_	TOSS:	120.4017	_	vai_ioss:	117.2404
1126/1126 [====================================	_	Λe	10ug/gton	_	logge	110 2/17/	_	wal loss:	116 5379
Epoch 59/5000		US	Tous/scep		TOSS.	113.2414		var_ross.	110.5572
1126/1126 [====================================	_	0s	50us/sten	_	loss	118 1796	_	val loss.	115 5154
Epoch 60/5000		O.D	coub, bucp		TODD.	110.1100		var_1000.	110.010
1126/1126 [====================================	_	0s	48us/step	_	loss:	117.1929	_	val loss:	114.7570
Epoch 61/5000									
1126/1126 [====================================	_	0s	47us/step	_	loss:	116.2677	_	val_loss:	113.930
Epoch 62/5000			•					_	
1126/1126 [====================================	_	0s	51us/step	_	loss:	115.5200	_	val_loss:	113.423
Epoch 63/5000									
1126/1126 [=======]	-	0s	47us/step	-	loss:	114.6976	_	<pre>val_loss:</pre>	112.7728
Epoch 64/5000									
1126/1126 [====================================	-	0s	45us/step	-	loss:	113.9036	-	<pre>val_loss:</pre>	112.2018
Epoch 65/5000									
1126/1126 [=======]	-	0s	49us/step	-	loss:	113.3173	-	<pre>val_loss:</pre>	111.3092
Epoch 66/5000									
1126/1126 [====================================	-	0s	49us/step	-	loss:	112.6448	-	val_loss:	111.675

Epoch 67/5000									
1126/1126 [====================================	_	٥q	45us/sten	_	1088.	112 1339	_	val logg.	110 8356
Epoch 68/5000		V.S	40us/scep		1055.	112.1000		vai_1055.	110.0000
1126/1126 [====================================	_	٥q	51us/sten	_	1088.	111 5857	_	val logg.	110 427
Epoch 69/5000		O.D.	orab, btop		TODD.	111.0001		var_robb.	110.121
1126/1126 [====================================	_	0s	48us/sten	_	loss	111 2429	_	val loss:	109 732
Epoch 70/5000		O.D.	rous, stop		TODD.	111.2120		var_robb.	100.102
1126/1126 [========]	_	0s	42us/step	_	loss:	110.6758	_	val loss:	109.448
Epoch 71/5000		•••	1245, 200p						1001110
1126/1126 [=========]	_	0s	46us/step	_	loss:	110.3384	_	val loss:	109.1534
Epoch 72/5000								_	
1126/1126 [====================================	-	0s	44us/step	_	loss:	110.0463	_	val_loss:	108.692
Epoch 73/5000			-					_	
1126/1126 [====================================	-	0s	48us/step	-	loss:	109.6243	-	<pre>val_loss:</pre>	108.523
Epoch 74/5000									
1126/1126 [==========]	-	0s	48us/step	-	loss:	109.2389	-	<pre>val_loss:</pre>	108.0040
Epoch 75/5000									
1126/1126 [===========]	-	0s	40us/step	-	loss:	108.9889	-	<pre>val_loss:</pre>	107.6430
Epoch 76/5000									
1126/1126 [=======]	-	0s	32us/step	-	loss:	108.7005	-	<pre>val_loss:</pre>	107.501
Epoch 77/5000									
1126/1126 [=======]	-	0s	44us/step	-	loss:	108.5178	-	val_loss:	107.373
Epoch 78/5000									
1126/1126 [====================================	-	0s	45us/step	-	loss:	108.2708	-	val_loss:	106.965
Epoch 79/5000									
1126/1126 [====================================	-	0s	53us/step	-	loss:	108.3069	-	val_loss:	106.955
Epoch 80/5000		_			_				
1126/1126 [====================================	-	0s	43us/step	-	loss:	108.0226	-	val_loss:	106.8576
Epoch 81/5000		^	40 / 1		7	407 7067			400 750
1126/1126 [====================================	_	US	48us/step	_	loss:	107.7967	_	val_loss:	106.7560
Epoch 82/5000		0-	10/		1	107 5401		1]	106 204
1126/1126 [====================================	_	US	49us/step	_	TOSS:	107.5421	_	vai_ioss:	100.3044
Epoch 83/5000 1126/1126 [====================================	_	٥٥	E0119/9+02	_	loggi	107 50/5		l logg.	106 072
Epoch 84/5000		US	sous/step	_	1088.	107.3043		vai_ioss.	100.073
1126/1126 [====================================	_	۸e	4511g/gten	_	loggi	107 2228	_	wal logg.	105 9090
Epoch 85/5000		OB	Tous, scep		1055.	107.2220		vai_1055.	100.505
1126/1126 [====================================	_	0s	59us/sten	_	loss:	107.1244	_	val loss:	105.959
Epoch 86/5000		Ů.	ocas, scop		1000.	10111211		, ur_1022.	100.000
1126/1126 [========]	_	0s	47us/step	_	loss:	106.8920	_	val loss:	105.4604
Epoch 87/5000									
1126/1126 [=========]	_	0s	43us/step	_	loss:	106.8475	_	val loss:	105.4398
Epoch 88/5000			,r						
1126/1126 [=========]	-	0s	45us/step	_	loss:	106.6759	_	val_loss:	105.557
Epoch 89/5000			•					-	
1126/1126 [====================================	-	0s	51us/step	-	loss:	106.7223	-	val_loss:	105.2194
Epoch 90/5000			-						
1126/1126 [=======]	-	0s	41us/step	-	loss:	106.5891	-	<pre>val_loss:</pre>	105.208

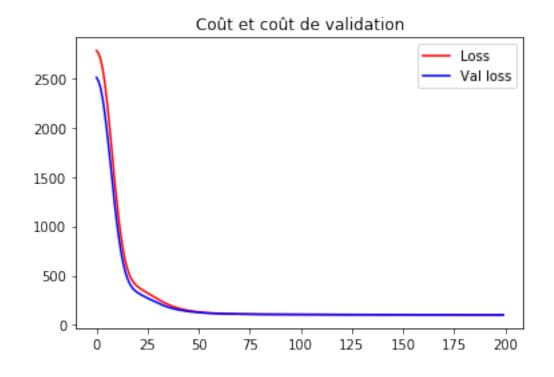
```
Epoch 91/5000
Epoch 92/5000
Epoch 93/5000
Epoch 94/5000
Epoch 95/5000
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Epoch 112/5000
Epoch 113/5000
Epoch 114/5000
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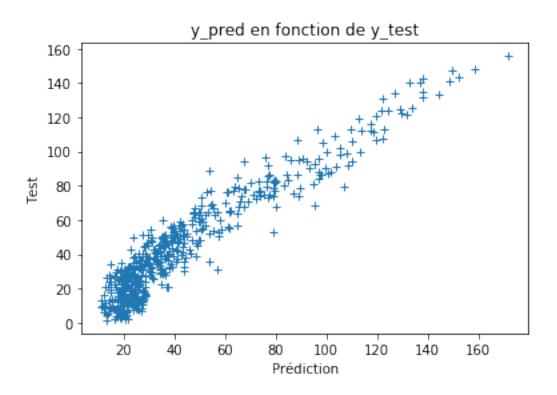
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Epoch 115/5000
Epoch 116/5000
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Epoch 187/5000
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Epoch 195/5000
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Epoch 197/5000
Epoch 198/5000
Epoch 199/5000
Epoch 200/5000
Epoch 00200: early stopping
In [9]: y_pred = model.predict(X_test)
  plt.title('Coût et coût de validation')
  line1,=plt.plot(history.history['loss'], label="Loss", linestyle='-', color='r')
  line2,=plt.plot(history.history['val_loss'], label="Val loss", linestyle='-', color='b
  first_legend = plt.legend(handles=[line1, line2], loc=1)
  plt.show()
  plt.title('y_pred en fonction de y_test')
  plt.plot(y_pred[:], y_test[:], '+')
  plt.ylabel('Test')
  plt.xlabel('Prédiction')
  plt.show()
```





1.1 DNN 2 Couches

In [10]: from keras.layers import SimpleRNN

```
df = pd.read_pickle('data/micro_sud3_normalized.pkl')
       df = df[['date', 'NO2_ref', 'NO2_61FD', 'NO2_61F0', \
             'NO2_61EF', 'temp', 'rh', 'tgrad', 'pressure', 'pluvio']]
       df = df.reset_index()
       df_train, df_test = split_dataframe(df, 0.5)
       df_valid, df_test = split_dataframe(df_test, 0.5)
       X_train, y_train = dataframe_to_xy(df_train)
       X_valid, y_valid = dataframe_to_xy(df_valid)
       X_test, y_test = dataframe_to_xy(df_test)
       def simple_rnn_model(nb_units, dense_size, loss='mean_squared_error', optimizer='adam
          model = Sequential()
          model.add(Dense(dense_size, input_dim=dense_size, kernel_initializer='normal', ac
          model.add(Dense(dense_size//2, kernel_initializer='normal', activation='relu'))
          model.add(Dense(1, kernel_initializer='normal'))
          model.compile(loss=loss, optimizer=optimizer)
          model.summary()
          return model
       model = simple_rnn_model(32, X_train.shape[1])
Layer (type)
            Output Shape Param #
______
dense_3 (Dense)
                     (None, 8)
dense_4 (Dense)
                      (None, 4)
                                           36
              (None, 1) 5
dense_5 (Dense)
______
Total params: 113
Trainable params: 113
Non-trainable params: 0
______
In [11]: early_stopping = EarlyStopping(monitor='val_loss', verbose=1, mode='auto', patience=1
       history = model.fit(X_train, y_train, batch_size=32, epochs=5000, validation_data=(X_
Train on 1126 samples, validate on 563 samples
Epoch 1/5000
Epoch 2/5000
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Epoch 3/5000
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Epoch 26/5000
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Epoch 98/5000

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Epoch 128/5000
Epoch 129/5000
Epoch 130/5000
Epoch 131/5000
Epoch 132/5000
Epoch 133/5000
Epoch 134/5000
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Epoch 142/5000
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Epoch 144/5000
Epoch 145/5000
Epoch 146/5000
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Epoch 147/5000
Epoch 148/5000
Epoch 149/5000
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Epoch 169/5000
Epoch 170/5000
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Epoch 171/5000
Epoch 172/5000
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Epoch 191/5000
Epoch 192/5000
Epoch 193/5000
```

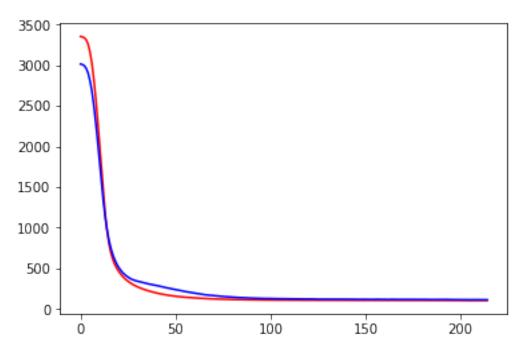
Epoch 194/5000

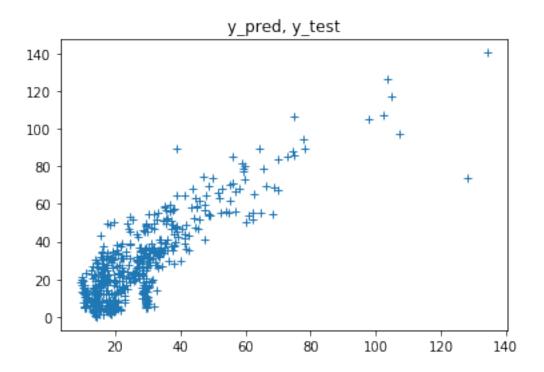
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Epoch 195/5000
Epoch 196/5000
Epoch 197/5000
Epoch 198/5000
Epoch 199/5000
Epoch 200/5000
Epoch 201/5000
Epoch 202/5000
Epoch 203/5000
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Epoch 208/5000
Epoch 209/5000
Epoch 210/5000
Epoch 211/5000
Epoch 212/5000
Epoch 213/5000
Epoch 214/5000
Epoch 215/5000
Epoch 00215: early stopping
```

```
plt.plot(history.history['val_loss'], 'b-')
plt.show()

plt.title('y_pred, y_test')

plt.plot(y_pred[:], y_test[:], '+')
plt.show()
percent_high_detected = np.sum(y_pred.reshape((len(y_pred), )) > 20) / np.sum(y_test.reprint(percent_high_detected))
```





1.11627906977

In []: