

M32

_Xarxa_walkforard_normalitzat_multivariate2tempmin_presiopostaclo walkforward augment

December 21, 2019

1 Xarxa neuronal

```
In [1]: import pandas as pd
import numpy as np
from pandas import datetime
from matplotlib import pyplot as plt

import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM

from keras.optimizers import SGD
from sklearn.model_selection import StratifiedKFold
from scipy.stats import uniform as sp_rand
from scipy.stats import randint
from time import time
from sklearn import preprocessing
```

Using TensorFlow backend.

1.1 Consum diari total multivariate one-step

```
In [2]: daily=pd.read_csv('C:/Users/Laura/Desktop/Smart meters London/workspace R/Dades netes/1
daily.head(5)
```

```
Out[2]:
```

	date	apparentTemperatureMax	apparentTemperatureMin	sunsetTimeHour	\
0	2014-02-08	5.67	2.19	17	
1	2013-12-24	11.93	2.68	15	
2	2012-11-01	11.46	0.85	16	
3	2014-02-05	5.86	1.03	16	

4	2012-04-17		10.01		2.76	19
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	weekday	season	cloudCover	humidity	visibility	month	dewPoint	\
0	6	winter	0.47	0.77	11.20	2	3.99	
1	2	winter	0.40	0.81	10.86	12	5.42	
2	4	autumn	0.44	0.85	12.54	11	5.06	
3	3	winter	0.73	0.77	10.91	2	4.06	
4	2	spring	0.60	0.87	11.86	4	5.74	

	pressure	energy_sum
0	979.25	11.569300
1	979.52	11.981672
2	979.63	10.781689
3	982.20	11.415105
4	982.22	10.617443

```
In [3]: #Ens quedem amb date i energy_sum, ordenem valors per data i resetejem index
daily_dia=daily[['date','energy_sum','apparentTemperatureMax','apparentTemperatureMin']
daily_dia.head(5)
```

```
Out[3]:
```

	index	date	energy_sum	apparentTemperatureMax	\
0	735	2011-11-23	6.952692	10.36	
1	736	2011-11-24	8.536480	12.93	
2	682	2011-11-25	9.499781	13.03	
3	713	2011-11-26	10.267707	12.96	
4	609	2011-11-27	10.850805	13.54	

	apparentTemperatureMin	humidity	pressure	sunsetTimeHour	cloudCover
0	2.18	0.93	1027.12	16	0.36
1	7.01	0.89	1027.22	16	0.41
2	4.84	0.79	1024.47	16	0.48
3	4.69	0.81	1025.80	16	0.44
4	2.94	0.72	1021.11	16	0.42

```
In [18]: plt.plot(daily_dia.energy_sum )
```

```
Out[18]: [<matplotlib.lines.Line2D at 0x1d48d92d710>]
```



```
In [4]: daily_dia['t-1']=daily_dia['energy_sum'].shift(1)
daily_dia['t-2']=daily_dia['energy_sum'].shift(2)
daily_dia['t-3']=daily_dia['energy_sum'].shift(3)
daily_dia['t-4']=daily_dia['energy_sum'].shift(4)
daily_dia['t-5']=daily_dia['energy_sum'].shift(5)
daily_dia['t-6']=daily_dia['energy_sum'].shift(6)
daily_dia['t-7']=daily_dia['energy_sum'].shift(7)
daily_dia['t-8']=daily_dia['energy_sum'].shift(8)
daily_dia['t-9']=daily_dia['energy_sum'].shift(9)
daily_dia['t-10']=daily_dia['energy_sum'].shift(10)
daily_dia['t-11']=daily_dia['energy_sum'].shift(11)
daily_dia['t-12']=daily_dia['energy_sum'].shift(12)
daily_dia['t-13']=daily_dia['energy_sum'].shift(13)
daily_dia['t-14']=daily_dia['energy_sum'].shift(14)

daily_dia['temp(t-1)']=daily_dia['apparentTemperatureMax'].shift(1)
daily_dia['temp(t-2)']=daily_dia['apparentTemperatureMax'].shift(2)
daily_dia['temp(t-3)']=daily_dia['apparentTemperatureMax'].shift(3)
daily_dia['temp(t-4)']=daily_dia['apparentTemperatureMax'].shift(4)
daily_dia['temp(t-5)']=daily_dia['apparentTemperatureMax'].shift(5)
daily_dia['temp(t-6)']=daily_dia['apparentTemperatureMax'].shift(6)
daily_dia['temp(t-7)']=daily_dia['apparentTemperatureMax'].shift(7)
daily_dia['temp(t-8)']=daily_dia['apparentTemperatureMax'].shift(8)
daily_dia['temp(t-9)']=daily_dia['apparentTemperatureMax'].shift(9)
daily_dia['temp(t-10)']=daily_dia['apparentTemperatureMax'].shift(10)
daily_dia['temp(t-11)']=daily_dia['apparentTemperatureMax'].shift(11)
```

```
daily_dia['temp(t-12)']=daily_dia['apparentTemperatureMax'].shift(12)
daily_dia['temp(t-13)']=daily_dia['apparentTemperatureMax'].shift(13)
daily_dia['temp(t-14)']=daily_dia['apparentTemperatureMax'].shift(14)
```

```
daily_dia['tempmin(t-1)']=daily_dia['apparentTemperatureMin'].shift(1)
daily_dia['tempmin(t-2)']=daily_dia['apparentTemperatureMin'].shift(2)
daily_dia['tempmin(t-3)']=daily_dia['apparentTemperatureMin'].shift(3)
daily_dia['tempmin(t-4)']=daily_dia['apparentTemperatureMin'].shift(4)
daily_dia['tempmin(t-5)']=daily_dia['apparentTemperatureMin'].shift(5)
daily_dia['tempmin(t-6)']=daily_dia['apparentTemperatureMin'].shift(6)
daily_dia['tempmin(t-7)']=daily_dia['apparentTemperatureMin'].shift(7)
daily_dia['tempmin(t-8)']=daily_dia['apparentTemperatureMin'].shift(8)
daily_dia['tempmin(t-9)']=daily_dia['apparentTemperatureMin'].shift(9)
daily_dia['tempmin(t-10)']=daily_dia['apparentTemperatureMin'].shift(10)
daily_dia['tempmin(t-11)']=daily_dia['apparentTemperatureMin'].shift(11)
daily_dia['tempmin(t-12)']=daily_dia['apparentTemperatureMin'].shift(12)
daily_dia['tempmin(t-13)']=daily_dia['apparentTemperatureMin'].shift(13)
daily_dia['tempmin(t-14)']=daily_dia['apparentTemperatureMin'].shift(14)
```

```
daily_dia['humidity(t-1)']=daily_dia['humidity'].shift(1)
daily_dia['humidity(t-2)']=daily_dia['humidity'].shift(2)
daily_dia['humidity(t-3)']=daily_dia['humidity'].shift(3)
daily_dia['humidity(t-4)']=daily_dia['humidity'].shift(4)
daily_dia['humidity(t-5)']=daily_dia['humidity'].shift(5)
daily_dia['humidity(t-6)']=daily_dia['humidity'].shift(6)
daily_dia['humidity(t-7)']=daily_dia['humidity'].shift(7)
daily_dia['humidity(t-8)']=daily_dia['humidity'].shift(8)
daily_dia['humidity(t-9)']=daily_dia['humidity'].shift(9)
daily_dia['humidity(t-10)']=daily_dia['humidity'].shift(10)
daily_dia['humidity(t-11)']=daily_dia['humidity'].shift(11)
daily_dia['humidity(t-12)']=daily_dia['humidity'].shift(12)
daily_dia['humidity(t-13)']=daily_dia['humidity'].shift(13)
daily_dia['humidity(t-14)']=daily_dia['humidity'].shift(14)
```

```
daily_dia['pres(t-1)']=daily_dia['pressure'].shift(1)
daily_dia['pres(t-2)']=daily_dia['pressure'].shift(2)
daily_dia['pres(t-3)']=daily_dia['pressure'].shift(3)
daily_dia['pres(t-4)']=daily_dia['pressure'].shift(4)
daily_dia['pres(t-5)']=daily_dia['pressure'].shift(5)
daily_dia['pres(t-6)']=daily_dia['pressure'].shift(6)
daily_dia['pres(t-7)']=daily_dia['pressure'].shift(7)
daily_dia['pres(t-8)']=daily_dia['pressure'].shift(8)
daily_dia['pres(t-9)']=daily_dia['pressure'].shift(9)
daily_dia['pres(t-10)']=daily_dia['pressure'].shift(10)
daily_dia['pres(t-11)']=daily_dia['pressure'].shift(11)
daily_dia['pres(t-12)']=daily_dia['pressure'].shift(12)
daily_dia['pres(t-13)']=daily_dia['pressure'].shift(13)
daily_dia['pres(t-14)']=daily_dia['pressure'].shift(14)
```

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daily_dia['sun(t-1)']=daily_dia['sunsetTimeHour'].shift(1)
daily_dia['sun(t-2)']=daily_dia['sunsetTimeHour'].shift(2)
daily_dia['sun(t-3)']=daily_dia['sunsetTimeHour'].shift(3)
daily_dia['sun(t-4)']=daily_dia['sunsetTimeHour'].shift(4)
daily_dia['sun(t-5)']=daily_dia['sunsetTimeHour'].shift(5)
daily_dia['sun(t-6)']=daily_dia['sunsetTimeHour'].shift(6)
daily_dia['sun(t-7)']=daily_dia['sunsetTimeHour'].shift(7)
daily_dia['sun(t-8)']=daily_dia['sunsetTimeHour'].shift(8)
daily_dia['sun(t-9)']=daily_dia['sunsetTimeHour'].shift(9)
daily_dia['sun(t-10)']=daily_dia['sunsetTimeHour'].shift(10)
daily_dia['sun(t-11)']=daily_dia['sunsetTimeHour'].shift(11)
daily_dia['sun(t-12)']=daily_dia['sunsetTimeHour'].shift(12)
daily_dia['sun(t-13)']=daily_dia['sunsetTimeHour'].shift(13)
daily_dia['sun(t-14)']=daily_dia['sunsetTimeHour'].shift(14)

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daily_dia['cloudCover(t-1)']=daily_dia['cloudCover'].shift(1)
daily_dia['cloudCover(t-2)']=daily_dia['cloudCover'].shift(2)
daily_dia['cloudCover(t-3)']=daily_dia['cloudCover'].shift(3)
daily_dia['cloudCover(t-4)']=daily_dia['cloudCover'].shift(4)
daily_dia['cloudCover(t-5)']=daily_dia['cloudCover'].shift(5)
daily_dia['cloudCover(t-6)']=daily_dia['cloudCover'].shift(6)
daily_dia['cloudCover(t-7)']=daily_dia['cloudCover'].shift(7)
daily_dia['cloudCover(t-8)']=daily_dia['cloudCover'].shift(8)
daily_dia['cloudCover(t-9)']=daily_dia['cloudCover'].shift(9)
daily_dia['cloudCover(t-10)']=daily_dia['cloudCover'].shift(10)
daily_dia['cloudCover(t-11)']=daily_dia['cloudCover'].shift(11)
daily_dia['cloudCover(t-12)']=daily_dia['cloudCover'].shift(12)
daily_dia['cloudCover(t-13)']=daily_dia['cloudCover'].shift(13)
daily_dia['cloudCover(t-14)']=daily_dia['cloudCover'].shift(14)

```

daily_dia

```

Out[4]:
   index  date  energy_sum  apparentTemperatureMax  \
0      735  2011-11-23    6.952692                10.36
1      736  2011-11-24    8.536480                12.93
2      682  2011-11-25    9.499781                13.03
3      713  2011-11-26   10.267707                12.96
4      609  2011-11-27   10.850805                13.54
5      641  2011-11-28    9.103382                12.58
6      265  2011-11-29    9.274873                13.47
7      571  2011-11-30    8.813513                11.87
8      199  2011-12-01    9.227707                12.15
9      338  2011-12-02   10.145910                 5.33
10     131  2011-12-03   10.780273                11.42
11     100  2011-12-04   12.163127                 6.66

```

12	176	2011-12-05	10.609714	3.13
13	203	2011-12-06	11.673417	3.77
14	240	2011-12-07	10.889362	5.14
15	299	2011-12-08	11.525150	12.89
16	294	2011-12-09	11.759837	3.99
17	455	2011-12-10	12.633801	3.14
18	215	2011-12-11	13.749174	5.72
19	115	2011-12-12	11.951958	5.94
20	22	2011-12-13	11.957446	12.08
21	45	2011-12-14	12.392776	2.88
22	59	2011-12-15	12.307079	4.38
23	11	2011-12-16	13.376080	0.99
24	228	2011-12-17	13.511968	1.72
25	478	2011-12-18	14.732271	1.98
26	412	2011-12-19	13.774471	4.02
27	433	2011-12-20	12.709106	4.98
28	524	2011-12-21	12.148570	12.14
29	689	2011-12-22	11.839403	12.14
..
800	41	2014-01-29	11.800777	2.53
801	105	2014-01-30	11.685169	5.86
802	80	2014-01-31	11.857957	5.27
803	21	2014-02-01	11.710582	6.86
804	163	2014-02-02	12.078164	6.48
805	135	2014-02-03	11.280011	4.59
806	60	2014-02-04	11.095584	5.63
807	3	2014-02-05	11.415105	5.86
808	18	2014-02-06	11.445403	7.34
809	14	2014-02-07	10.972318	8.44
810	0	2014-02-08	11.569300	5.67
811	7	2014-02-09	12.202967	3.91
812	35	2014-02-10	11.264175	7.07
813	57	2014-02-11	11.452649	4.06
814	44	2014-02-12	11.679099	4.73
815	33	2014-02-13	11.285737	3.42
816	23	2014-02-14	11.816914	12.02
817	13	2014-02-15	11.490470	5.79
818	187	2014-02-16	11.582159	7.88
819	218	2014-02-17	10.979566	10.67
820	235	2014-02-18	10.781898	10.13
821	322	2014-02-19	10.674624	10.13
822	101	2014-02-20	10.573835	12.50
823	129	2014-02-21	10.518126	10.15
824	248	2014-02-22	10.776242	11.63
825	285	2014-02-23	11.480411	11.94
826	158	2014-02-24	10.411403	14.23
827	95	2014-02-25	10.294997	11.43
828	360	2014-02-26	10.202945	11.29

829 197 2014-02-27 10.356350 10.31

	apparentTemperatureMin	humidity	pressure	sunsetTimeHour	cloudCover	\
0	2.18	0.93	1027.12	16	0.36	
1	7.01	0.89	1027.22	16	0.41	
2	4.84	0.79	1024.47	16	0.48	
3	4.69	0.81	1025.80	16	0.44	
4	2.94	0.72	1021.11	16	0.42	
5	1.31	0.86	1022.80	15	0.56	
6	3.39	0.82	1009.70	15	0.60	
7	3.34	0.78	1019.43	15	0.31	
8	5.29	0.82	1007.12	15	0.57	
9	0.46	0.87	1012.12	15	0.32	
10	4.71	0.79	1003.55	15	0.54	
11	1.03	0.82	1001.15	15	0.36	
12	-1.69	0.77	1006.01	15	0.20	
13	-1.61	0.83	1007.32	15	0.34	
14	0.94	0.68	1008.76	15	0.29	
15	0.63	0.81	1010.84	15	0.53	
16	-1.42	0.71	1010.60	15	0.15	
17	-3.42	0.81	1015.58	15	0.17	
18	0.11	0.88	1007.71	15	0.56	
19	-0.64	0.84	1002.47	15	0.38	
20	0.22	0.75	990.27	15	0.42	
21	0.78	0.79	994.48	15	0.36	
22	1.07	0.77	996.75	15	0.42	
23	-2.65	0.88	988.10	15	0.70	
24	-3.56	0.86	1008.46	15	0.37	
25	-4.12	0.84	1016.37	15	0.22	
26	-3.67	0.94	1014.39	15	0.47	
27	1.68	0.81	1015.09	15	0.48	
28	3.84	0.94	1017.91	15	0.67	
29	5.37	0.87	1024.71	15	0.38	
..	
800	0.18	0.90	993.99	16	0.93	
801	0.61	0.91	1001.76	16	0.81	
802	0.29	0.91	998.51	16	0.73	
803	1.10	0.76	990.08	16	0.19	
804	3.21	0.72	1005.39	16	0.22	
805	1.96	0.79	1003.89	16	0.47	
806	1.12	0.75	996.87	16	0.42	
807	1.03	0.77	982.20	16	0.73	
808	1.96	0.82	989.90	16	0.67	
809	-0.86	0.79	988.77	17	0.63	
810	2.19	0.77	979.25	17	0.47	
811	1.38	0.66	984.71	17	0.52	
812	0.89	0.84	992.84	17	0.55	
813	-0.57	0.76	996.66	17	0.41	

814	-1.20	0.75	994.27	17	0.59
815	0.05	0.68	992.43	17	0.36
816	0.45	0.81	990.31	17	0.67
817	1.77	0.69	988.63	17	0.35
818	-1.03	0.76	1006.70	17	0.13
819	2.84	0.83	1007.80	17	0.56
820	3.83	0.87	1008.67	17	0.57
821	2.65	0.87	1011.57	17	0.64
822	3.95	0.84	1001.54	17	0.61
823	0.19	0.72	1003.42	17	0.22
824	1.59	0.71	1009.09	17	0.25
825	5.53	0.76	1010.37	17	0.66
826	5.52	0.74	1005.19	17	0.50
827	3.89	0.78	1000.65	17	0.62
828	1.67	0.73	1012.73	17	0.26
829	1.41	0.74	1007.02	17	0.32

	t-1	...	cloudCover(t-5)	cloudCover(t-6)	cloudCover(t-7)	\
0	NaN	...	NaN	NaN	NaN	
1	6.952692	...	NaN	NaN	NaN	
2	8.536480	...	NaN	NaN	NaN	
3	9.499781	...	NaN	NaN	NaN	
4	10.267707	...	NaN	NaN	NaN	
5	10.850805	...	0.36	NaN	NaN	
6	9.103382	...	0.41	0.36	NaN	
7	9.274873	...	0.48	0.41	0.36	
8	8.813513	...	0.44	0.48	0.41	
9	9.227707	...	0.42	0.44	0.48	
10	10.145910	...	0.56	0.42	0.44	
11	10.780273	...	0.60	0.56	0.42	
12	12.163127	...	0.31	0.60	0.56	
13	10.609714	...	0.57	0.31	0.60	
14	11.673417	...	0.32	0.57	0.31	
15	10.889362	...	0.54	0.32	0.57	
16	11.525150	...	0.36	0.54	0.32	
17	11.759837	...	0.20	0.36	0.54	
18	12.633801	...	0.34	0.20	0.36	
19	13.749174	...	0.29	0.34	0.20	
20	11.951958	...	0.53	0.29	0.34	
21	11.957446	...	0.15	0.53	0.29	
22	12.392776	...	0.17	0.15	0.53	
23	12.307079	...	0.56	0.17	0.15	
24	13.376080	...	0.38	0.56	0.17	
25	13.511968	...	0.42	0.38	0.56	
26	14.732271	...	0.36	0.42	0.38	
27	13.774471	...	0.42	0.36	0.42	
28	12.709106	...	0.70	0.42	0.36	
29	12.148570	...	0.37	0.70	0.42	

...
800	11.344805	...	0.54	0.32
801	11.800777	...	0.44	0.54
802	11.685169	...	0.40	0.44
803	11.857957	...	0.38	0.40
804	11.710582	...	0.61	0.38
805	12.078164	...	0.93	0.61
806	11.280011	...	0.81	0.93
807	11.095584	...	0.73	0.81
808	11.415105	...	0.19	0.73
809	11.445403	...	0.22	0.19
810	10.972318	...	0.47	0.22
811	11.569300	...	0.42	0.47
812	12.202967	...	0.73	0.42
813	11.264175	...	0.67	0.73
814	11.452649	...	0.63	0.67
815	11.679099	...	0.47	0.63
816	11.285737	...	0.52	0.47
817	11.816914	...	0.55	0.52
818	11.490470	...	0.41	0.55
819	11.582159	...	0.59	0.41
820	10.979566	...	0.36	0.59
821	10.781898	...	0.67	0.36
822	10.674624	...	0.35	0.67
823	10.573835	...	0.13	0.35
824	10.518126	...	0.56	0.13
825	10.776242	...	0.57	0.56
826	11.480411	...	0.64	0.57
827	10.411403	...	0.61	0.64
828	10.294997	...	0.22	0.61
829	10.202945	...	0.25	0.22

	cloudCover(t-8)	cloudCover(t-9)	cloudCover(t-10)	cloudCover(t-11) \
0	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN
5	NaN	NaN	NaN	NaN
6	NaN	NaN	NaN	NaN
7	NaN	NaN	NaN	NaN
8	0.36	NaN	NaN	NaN
9	0.41	0.36	NaN	NaN
10	0.48	0.41	0.36	NaN
11	0.44	0.48	0.41	0.36
12	0.42	0.44	0.48	0.41
13	0.56	0.42	0.44	0.48
14	0.60	0.56	0.42	0.44

15	0.31	0.60	0.56	0.42
16	0.57	0.31	0.60	0.56
17	0.32	0.57	0.31	0.60
18	0.54	0.32	0.57	0.31
19	0.36	0.54	0.32	0.57
20	0.20	0.36	0.54	0.32
21	0.34	0.20	0.36	0.54
22	0.29	0.34	0.20	0.36
23	0.53	0.29	0.34	0.20
24	0.15	0.53	0.29	0.34
25	0.17	0.15	0.53	0.29
26	0.56	0.17	0.15	0.53
27	0.38	0.56	0.17	0.15
28	0.42	0.38	0.56	0.17
29	0.36	0.42	0.38	0.56
..
800	0.37	0.17	0.33	0.35
801	0.69	0.37	0.17	0.33
802	0.32	0.69	0.37	0.17
803	0.54	0.32	0.69	0.37
804	0.44	0.54	0.32	0.69
805	0.40	0.44	0.54	0.32
806	0.38	0.40	0.44	0.54
807	0.61	0.38	0.40	0.44
808	0.93	0.61	0.38	0.40
809	0.81	0.93	0.61	0.38
810	0.73	0.81	0.93	0.61
811	0.19	0.73	0.81	0.93
812	0.22	0.19	0.73	0.81
813	0.47	0.22	0.19	0.73
814	0.42	0.47	0.22	0.19
815	0.73	0.42	0.47	0.22
816	0.67	0.73	0.42	0.47
817	0.63	0.67	0.73	0.42
818	0.47	0.63	0.67	0.73
819	0.52	0.47	0.63	0.67
820	0.55	0.52	0.47	0.63
821	0.41	0.55	0.52	0.47
822	0.59	0.41	0.55	0.52
823	0.36	0.59	0.41	0.55
824	0.67	0.36	0.59	0.41
825	0.35	0.67	0.36	0.59
826	0.13	0.35	0.67	0.36
827	0.56	0.13	0.35	0.67
828	0.57	0.56	0.13	0.35
829	0.64	0.57	0.56	0.13

cloudCover(t-12) cloudCover(t-13) cloudCover(t-14)

0	NaN	NaN	NaN
1	NaN	NaN	NaN
2	NaN	NaN	NaN
3	NaN	NaN	NaN
4	NaN	NaN	NaN
5	NaN	NaN	NaN
6	NaN	NaN	NaN
7	NaN	NaN	NaN
8	NaN	NaN	NaN
9	NaN	NaN	NaN
10	NaN	NaN	NaN
11	NaN	NaN	NaN
12	0.36	NaN	NaN
13	0.41	0.36	NaN
14	0.48	0.41	0.36
15	0.44	0.48	0.41
16	0.42	0.44	0.48
17	0.56	0.42	0.44
18	0.60	0.56	0.42
19	0.31	0.60	0.56
20	0.57	0.31	0.60
21	0.32	0.57	0.31
22	0.54	0.32	0.57
23	0.36	0.54	0.32
24	0.20	0.36	0.54
25	0.34	0.20	0.36
26	0.29	0.34	0.20
27	0.53	0.29	0.34
28	0.15	0.53	0.29
29	0.17	0.15	0.53
..
800	0.47	0.58	0.77
801	0.35	0.47	0.58
802	0.33	0.35	0.47
803	0.17	0.33	0.35
804	0.37	0.17	0.33
805	0.69	0.37	0.17
806	0.32	0.69	0.37
807	0.54	0.32	0.69
808	0.44	0.54	0.32
809	0.40	0.44	0.54
810	0.38	0.40	0.44
811	0.61	0.38	0.40
812	0.93	0.61	0.38
813	0.81	0.93	0.61
814	0.73	0.81	0.93
815	0.19	0.73	0.81
816	0.22	0.19	0.73

817	0.47	0.22	0.19
818	0.42	0.47	0.22
819	0.73	0.42	0.47
820	0.67	0.73	0.42
821	0.63	0.67	0.73
822	0.47	0.63	0.67
823	0.52	0.47	0.63
824	0.55	0.52	0.47
825	0.41	0.55	0.52
826	0.59	0.41	0.55
827	0.36	0.59	0.41
828	0.67	0.36	0.59
829	0.35	0.67	0.36

[830 rows x 107 columns]

```
In [5]: #Ens quedem amb energies i temperatures
#No agafem apparent temperature max ja que quan fem la predicció representa que no ho
daily_dia=daily_dia.drop(['index','date','apparentTemperatureMax','apparentTemperatureMin'])
daily_dia.head(5)
```

```
Out [5]:
```

	energy_sum	t-1	t-2	t-3	t-4	t-5	t-6	t-7	t-8	\
0	6.952692	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	8.536480	6.952692	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
2	9.499781	8.536480	6.952692	NaN	NaN	NaN	NaN	NaN	NaN	
3	10.267707	9.499781	8.536480	6.952692	NaN	NaN	NaN	NaN	NaN	
4	10.850805	10.267707	9.499781	8.536480	6.952692	NaN	NaN	NaN	NaN	

	t-9	...	cloudCover(t-5)	cloudCover(t-6)	cloudCover(t-7)	\
0	NaN	...	NaN	NaN	NaN	
1	NaN	...	NaN	NaN	NaN	
2	NaN	...	NaN	NaN	NaN	
3	NaN	...	NaN	NaN	NaN	
4	NaN	...	NaN	NaN	NaN	

	cloudCover(t-8)	cloudCover(t-9)	cloudCover(t-10)	cloudCover(t-11)	\
0	NaN	NaN	NaN	NaN	
1	NaN	NaN	NaN	NaN	
2	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	

	cloudCover(t-12)	cloudCover(t-13)	cloudCover(t-14)
0	NaN	NaN	NaN
1	NaN	NaN	NaN
2	NaN	NaN	NaN
3	NaN	NaN	NaN
4	NaN	NaN	NaN

[5 rows x 99 columns]

In [6]: *#Eliminem les 14 primeres files ja que contenen NaN (valors buits)*

```
daily_dia=daily_dia.drop([0,1,2,3,4,5,6,7,8,9,10,11,12,13])
daily_dia.head(5)
```

```
Out[6]:
```

	energy_sum	t-1	t-2	t-3	t-4	t-5	\
14	10.889362	11.673417	10.609714	12.163127	10.780273	10.145910	
15	11.525150	10.889362	11.673417	10.609714	12.163127	10.780273	
16	11.759837	11.525150	10.889362	11.673417	10.609714	12.163127	
17	12.633801	11.759837	11.525150	10.889362	11.673417	10.609714	
18	13.749174	12.633801	11.759837	11.525150	10.889362	11.673417	

	t-6	t-7	t-8	t-9	...	cloudCover(t-5)	\
14	9.227707	8.813513	9.274873	9.103382	...	0.32	
15	10.145910	9.227707	8.813513	9.274873	...	0.54	
16	10.780273	10.145910	9.227707	8.813513	...	0.36	
17	12.163127	10.780273	10.145910	9.227707	...	0.20	
18	10.609714	12.163127	10.780273	10.145910	...	0.34	

	cloudCover(t-6)	cloudCover(t-7)	cloudCover(t-8)	cloudCover(t-9)	\
14	0.57	0.31	0.60	0.56	
15	0.32	0.57	0.31	0.60	
16	0.54	0.32	0.57	0.31	
17	0.36	0.54	0.32	0.57	
18	0.20	0.36	0.54	0.32	

	cloudCover(t-10)	cloudCover(t-11)	cloudCover(t-12)	cloudCover(t-13)	\
14	0.42	0.44	0.48	0.41	
15	0.56	0.42	0.44	0.48	
16	0.60	0.56	0.42	0.44	
17	0.31	0.60	0.56	0.42	
18	0.57	0.31	0.60	0.56	

	cloudCover(t-14)
14	0.36
15	0.41
16	0.48
17	0.44
18	0.42

[5 rows x 99 columns]

In [7]: len(daily_dia)

Out[7]: 816

```

In [7]: #normalitzem
        scaler=preprocessing.MinMaxScaler(feature_range=(0, 1))
        daily_dia_norm=scaler.fit_transform(daily_dia)

In [8]: #Seleccionem dades per test i train
        y_daily=daily_dia_norm[:,0]
        X_daily=daily_dia_norm[:,1:99]

        #y_daily=daily_dia['energy_sum']
        #X_daily=daily_dia.drop(['energy_sum'], axis='columns')

        #Reshape de [samples,timesteps] a [samples,timesteps,features]

        #Enlloc de 14 features en son 7 de una feature i 7 duna altre
        X_daily=np.reshape(X_daily, (X_daily.shape[0], 14,7))

In [37]: # definim model
         import tensorflow as tf
         model =Sequential()
         model.add(LSTM(50, activation='relu', input_shape=(14, 7)))
         model.add(Dense(1))
         model.compile(optimizer='adam', loss='mse', metrics=['accuracy'])

In [38]: import math
         from sklearn.metrics import mean_squared_error

         #Walk forward per test i train
         minim=100
         n_train=465
         lenght=len(daily_dia)

         llista_evaluate=list()
         llista_prediccions=list()
         llista_predittrain=list()
         llista_scores=list()
         llista_scoretrain=list()
         sumScores=0

         for i in range(n_train,lenght):
             #minim=minim+1
             X_train,X_test= X_daily[minim:i],X_daily[i:i+1]
             y_train,y_test= y_daily[minim:i],y_daily[i:i+1]

             #fem fit al model
             model.fit(X_train, y_train, epochs=50, verbose=0)

```

```

#mostrem score per cada model
score=model.evaluate(X_test,y_test,verbose=0)
llista_evaluate.append(score)

#Predim per cadascun
preditest=model.predict(X_test)
llista_prediccions.append(preditest)

preditrain=model.predict(X_train)
llista_preditrain.append(preditrain)

trainScore = math.sqrt(mean_squared_error(y_train, predictrain))
llista_scoretrain.append(trainScore )

testScore = math.sqrt(mean_squared_error(y_test, predictest))
llista_scores.append(testScore)

sumScores=sumScores+testScore

```

```

In [39]: #Dividim la suma de scores de test entre el nombre de prediccions per obtenir la mitja
sumScores/(length-n_train)

```

```

Out[39]: 0.03896499394834957

```

```

In [40]: llista_scores

```

```

Out[40]: [0.027064353965038812,
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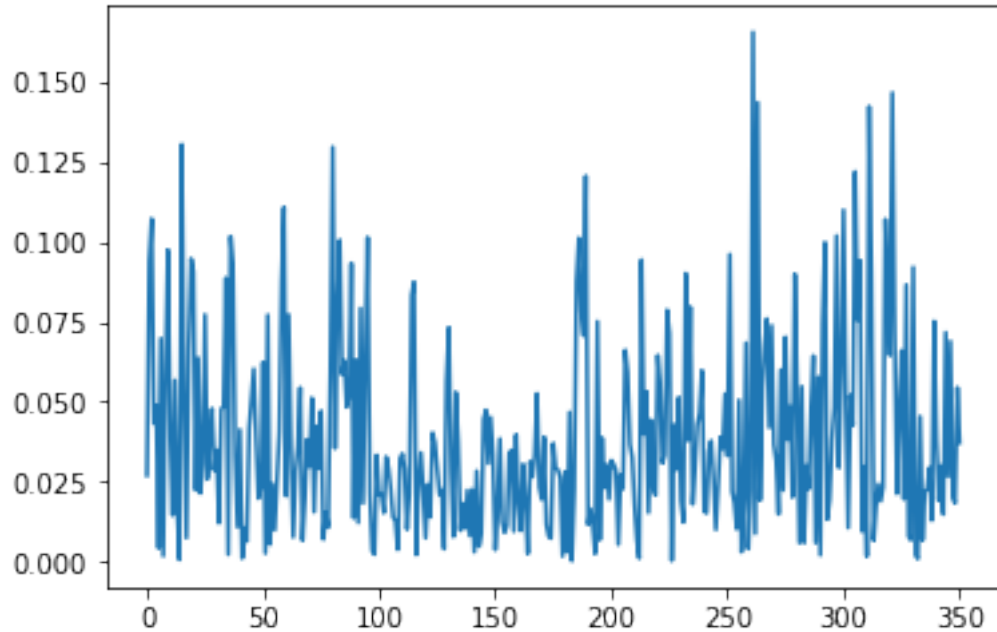
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```

```
In [41]: plt.plot(llista_scores)
```

```
Out[41]: [<matplotlib.lines.Line2D at 0x1a04d733320>]
```



```
In [42]: predis=list()
```

```
for i in range(len(llista_prediccions)):
    predi=llista_prediccions[i].tolist()
    predis.append(predi)
```

```
predis=np.reshape(predis, (351) )
```

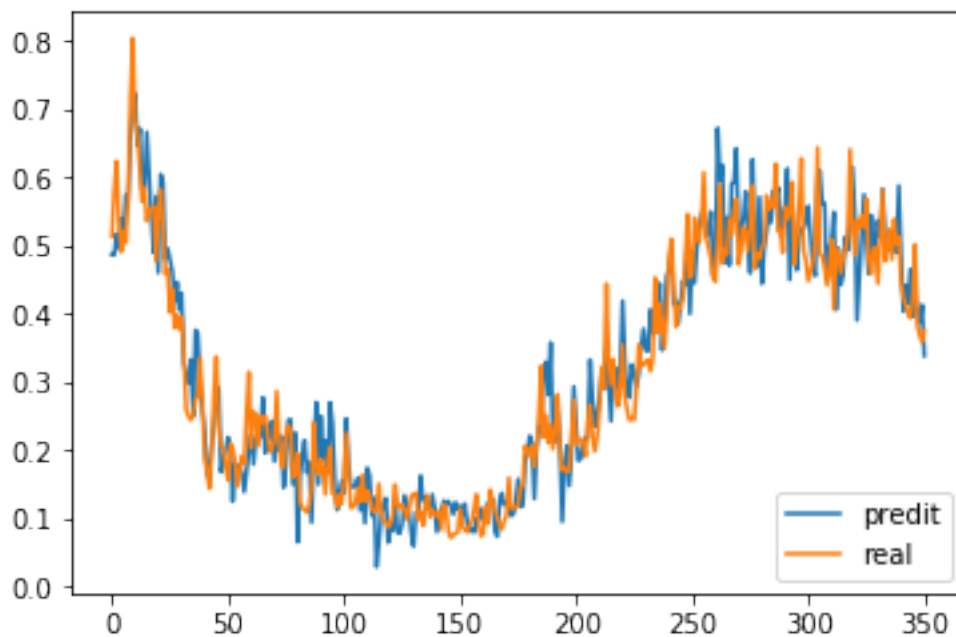
```
predis
```

```
Out[42]: array([0.48699713, 0.48676774, 0.51716542, 0.49600911, 0.54029763,
 0.51777875, 0.5742355 , 0.5657962 , 0.66042817, 0.70724785,
 0.72343707, 0.64755476, 0.67193705, 0.58285552, 0.58487988,
 0.66686213, 0.60431701, 0.54470837, 0.490437 , 0.57247365,
 0.46056879, 0.60479426, 0.59348065, 0.48041299, 0.49629569,
 0.47982019, 0.46280327, 0.41806811, 0.44676274, 0.40656191,
 0.43071666, 0.32908025, 0.30814552, 0.29863706, 0.3332963 ,
 0.2501823 , 0.37637937, 0.37197903, 0.30265522, 0.25963277,
 0.22852692, 0.16821918, 0.15509966, 0.20633014, 0.24165235,
 0.28608492, 0.2919313 , 0.16881558, 0.181638 , 0.19865561,
 0.21906665, 0.20718105, 0.12544179, 0.17945635, 0.17157894,
 0.17914721, 0.16607034, 0.13932523, 0.16787675, 0.20423251,
 0.22438326, 0.17986342, 0.21804518, 0.2143428 , 0.22146648,
 0.27758881, 0.19630975, 0.21993351, 0.21803914, 0.2432313 ,
 0.18400207, 0.23566052, 0.19964528, 0.22066386, 0.14591384,
 0.17696291, 0.24425967, 0.2455239 , 0.15035421, 0.2257154 ,
```

0.06574841, 0.16099371, 0.19264741, 0.21474609, 0.16772552,
0.18242726, 0.09459981, 0.1891131 , 0.27051008, 0.15036741,
0.25052387, 0.18593995, 0.21490425, 0.16738737, 0.27002141,
0.23928742, 0.15767816, 0.11292589, 0.13762036, 0.15541591,
0.13801977, 0.24657248, 0.17513099, 0.14876255, 0.14629719,
0.14702827, 0.15935282, 0.11198847, 0.16060866, 0.09352303,
0.17439535, 0.16365653, 0.10424846, 0.13065346, 0.02935756,
0.06347919, 0.10703397, 0.12176796, 0.12991665, 0.06516924,
0.08479591, 0.08226133, 0.13568765, 0.0799329 , 0.07825409,
0.09208369, 0.13398644, 0.12161953, 0.11027543, 0.07800231,
0.05968272, 0.10906009, 0.10736556, 0.16294266, 0.12742712,
0.130959 , 0.11604123, 0.11304548, 0.13529068, 0.11660736,
0.08051929, 0.10782572, 0.1123731 , 0.12596738, 0.12187562,
0.12547465, 0.11925471, 0.10643664, 0.12387718, 0.1133403 ,
0.11869159, 0.10399313, 0.12189528, 0.09312184, 0.08137608,
0.08544514, 0.08004674, 0.10061142, 0.10116102, 0.11468896,
0.09611782, 0.10796475, 0.12328875, 0.12374292, 0.12868099,
0.08177561, 0.07396029, 0.12512615, 0.13723727, 0.12008739,
0.12397441, 0.12071019, 0.10393211, 0.10715125, 0.12369666,
0.1578899 , 0.11730075, 0.11919221, 0.18047924, 0.1991984 ,
0.22134048, 0.20977587, 0.12930053, 0.20514479, 0.23445615,
0.23640174, 0.32045275, 0.32974762, 0.28174126, 0.35814488,
0.21399468, 0.21312493, 0.27028316, 0.20695886, 0.0956361 ,
0.1821658 , 0.20683663, 0.14845395, 0.19383737, 0.29346925,
0.23904204, 0.18510336, 0.18809114, 0.20580178, 0.21869153,
0.21879135, 0.33284876, 0.27804109, 0.23556232, 0.2505908 ,
0.27520037, 0.31542408, 0.29009819, 0.35010254, 0.29985943,
0.24313113, 0.3178823 , 0.321628 , 0.28832459, 0.31485313,
0.41935873, 0.33353943, 0.29032943, 0.27790213, 0.32581306,
0.31628543, 0.29385886, 0.31217974, 0.35194942, 0.37812188,
0.34756845, 0.34546629, 0.40646183, 0.37176251, 0.37335581,
0.39034182, 0.44475618, 0.34705168, 0.39602071, 0.45542872,
0.4664644 , 0.49464133, 0.41428363, 0.41938695, 0.38563102,
0.41843387, 0.44849551, 0.44213036, 0.5110867 , 0.40050775,
0.49182519, 0.44519687, 0.49685907, 0.52359152, 0.54450071,
0.55693281, 0.51462781, 0.51719248, 0.54994726, 0.45815611,
0.47016343, 0.672629 , 0.59802908, 0.61815816, 0.47505081,
0.54181433, 0.47142583, 0.59156889, 0.59328181, 0.6425975 ,
0.5097909 , 0.52186614, 0.54208249, 0.57969505, 0.5142681 ,
0.46014887, 0.62675095, 0.51559663, 0.46914056, 0.57138669,
0.44465962, 0.49672627, 0.51885599, 0.54726541, 0.53481466,
0.5805493 , 0.57222313, 0.58568764, 0.51601702, 0.54816186,
0.55900455, 0.61344212, 0.45042944, 0.5802508 , 0.49242586,
0.46441841, 0.51099473, 0.52624744, 0.52313673, 0.53718853,
0.5585869 , 0.51086301, 0.46494856, 0.45621204, 0.60115027,
0.61058062, 0.56083596, 0.56281072, 0.45208114, 0.49343076,
0.507294 , 0.54949027, 0.40652612, 0.49619997, 0.44282025,
0.45726439, 0.51287067, 0.49395606, 0.53432155, 0.61580688,


```
0.55106628, 0.39107519, 0.45356375, 0.52254504, 0.57516283,
0.50248778, 0.45967597, 0.54524708, 0.48643833, 0.50468165,
0.53696871, 0.51381791, 0.5834887 , 0.52298808, 0.49180874,
0.50185966, 0.5027231 , 0.50990415, 0.4898102 , 0.58820927,
0.48375666, 0.40450656, 0.44175917, 0.41533515, 0.46584964,
0.39635286, 0.4328137 , 0.40251318, 0.38767135, 0.41346294,
0.33888587])
```

```
In [43]: ##Mostrem
plt.plot(predis, label="predit")
plt.plot(y_daily[n_train:lenght], label="real")
plt.legend(loc="lower right")
plt.show()
```



```
In [44]: #Creem un dataset amb format (nombre prediccions,17) per tornar les prediccions i els
#El necessitem d'aquesta mida encara que només volguem passar 2 variables ja que al fe
#per fer la inversa necessitem 17 variables
#Com que només en tenim 2, les ajuntem al dataset inicial i ens quedem amb 15 variabl
#Obtenint un dataset amb 15 variables aleatòries i les 2 variables que ens interessen
```

```
prova=daily_dia.iloc[n_train:lenght]
prova
#len(predis)
#lenght-n_train
prova['predi']=predis
```

```
prova['y']=y_daily[n_train:lenght]
prova=prova.drop(['energy_sum','t-1'], axis=1)
prova
```

```
prova=prova[['predi','y','t-2','t-3','t-4','t-5','t-6','t-7','t-8','t-9','t-10','t-11']]
prova
```

c:\users\laura\appdata\local\programs\python\python37\lib\site-packages\ipykernel_launcher.py:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: <http://pandas.pydata.org/pandas-docs/stable/indexing.html>
if sys.path[0] == '':
c:\users\laura\appdata\local\programs\python\python37\lib\site-packages\ipykernel_launcher.py:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: <http://pandas.pydata.org/pandas-docs/stable/indexing.html>
del sys.path[0]

```
Out[44]:
```

	predi	y	t-2	t-3	t-4	t-5	\
479	0.486997	0.514061	12.119938	12.852295	13.106773	12.823073	
480	0.486768	0.580609	11.786082	12.119938	12.852295	13.106773	
481	0.517165	0.624326	11.590859	11.786082	12.119938	12.852295	
482	0.496009	0.539280	12.186487	11.590859	11.786082	12.119938	
483	0.540298	0.491355	12.577783	12.186487	11.590859	11.786082	
484	0.517779	0.522145	11.816573	12.577783	12.186487	11.590859	
485	0.574235	0.504442	11.387627	11.816573	12.577783	12.186487	
486	0.565796	0.567725	11.663214	11.387627	11.816573	12.577783	
487	0.660428	0.719460	11.504756	11.663214	11.387627	11.816573	
488	0.707248	0.804631	12.071173	11.504756	11.663214	11.387627	
489	0.723437	0.684716	13.429271	12.071173	11.504756	11.663214	
490	0.647555	0.662177	14.191591	13.429271	12.071173	11.504756	
491	0.671937	0.615194	13.118295	14.191591	13.429271	12.071173	
492	0.582856	0.565466	12.916559	13.118295	14.191591	13.429271	
493	0.584880	0.585646	12.496044	12.916559	13.118295	14.191591	
494	0.666862	0.536523	12.050954	12.496044	12.916559	13.118295	
495	0.604317	0.552256	12.231576	12.050954	12.496044	12.916559	
496	0.544708	0.552256	11.791904	12.231576	12.050954	12.496044	
497	0.490437	0.557809	11.932721	11.791904	12.231576	12.050954	
498	0.572474	0.477794	11.932721	11.932721	11.791904	12.231576	
499	0.460569	0.551195	11.982423	11.932721	11.932721	11.791904	
500	0.604794	0.582339	11.266252	11.982423	11.932721	11.932721	
501	0.593481	0.529772	11.923226	11.266252	11.982423	11.932721	
502	0.480413	0.458904	12.201972	11.923226	11.266252	11.982423	
503	0.496296	0.465733	11.731479	12.201972	11.923226	11.266252	
504	0.479820	0.402622	11.097177	11.731479	12.201972	11.923226	

505	0.462803	0.436918	11.158295	11.097177	11.731479	12.201972
506	0.418068	0.380048	10.593420	11.158295	11.097177	11.731479
507	0.446763	0.398860	10.900388	10.593420	11.158295	11.097177
508	0.406562	0.377916	10.391372	10.900388	10.593420	11.158295
..
800	0.391075	0.537515	11.753871	12.729659	11.620778	11.409880
801	0.453564	0.524598	11.344805	11.753871	12.729659	11.620778
802	0.522545	0.543903	11.800777	11.344805	11.753871	12.729659
803	0.575163	0.527438	11.685169	11.800777	11.344805	11.753871
804	0.502488	0.568506	11.857957	11.685169	11.800777	11.344805
805	0.459676	0.479332	11.710582	11.857957	11.685169	11.800777
806	0.545247	0.458726	12.078164	11.710582	11.857957	11.685169
807	0.486438	0.494425	11.280011	12.078164	11.710582	11.857957
808	0.504682	0.497810	11.095584	11.280011	12.078164	11.710582
809	0.536969	0.444954	11.415105	11.095584	11.280011	12.078164
810	0.513818	0.511653	11.445403	11.415105	11.095584	11.280011
811	0.583489	0.582450	10.972318	11.445403	11.415105	11.095584
812	0.522988	0.477562	11.569300	10.972318	11.445403	11.415105
813	0.491809	0.498620	12.202967	11.569300	10.972318	11.445403
814	0.501860	0.523920	11.264175	12.202967	11.569300	10.972318
815	0.502723	0.479971	11.452649	11.264175	12.202967	11.569300
816	0.509904	0.539318	11.679099	11.452649	11.264175	12.202967
817	0.489810	0.502845	11.285737	11.679099	11.452649	11.264175
818	0.588209	0.513089	11.816914	11.285737	11.679099	11.452649
819	0.483757	0.445764	11.490470	11.816914	11.285737	11.679099
820	0.404507	0.423680	11.582159	11.490470	11.816914	11.285737
821	0.441759	0.411694	10.979566	11.582159	11.490470	11.816914
822	0.415335	0.400434	10.781898	10.979566	11.582159	11.490470
823	0.465850	0.394209	10.674624	10.781898	10.979566	11.582159
824	0.396353	0.423048	10.573835	10.674624	10.781898	10.979566
825	0.432814	0.501722	10.518126	10.573835	10.674624	10.781898
826	0.402513	0.382286	10.776242	10.518126	10.573835	10.674624
827	0.387671	0.369280	11.480411	10.776242	10.518126	10.573835
828	0.413463	0.358995	10.411403	11.480411	10.776242	10.518126
829	0.338886	0.376135	10.294997	10.411403	11.480411	10.776242

	t-6	t-7	t-8	t-9	...	cloudCover(t-5)	\
479	11.559878	10.930170	10.889469	10.675248	...	0.81	
480	12.823073	11.559878	10.930170	10.889469	...	0.60	
481	13.106773	12.823073	11.559878	10.930170	...	0.54	
482	12.852295	13.106773	12.823073	11.559878	...	0.37	
483	12.119938	12.852295	13.106773	12.823073	...	0.27	
484	11.786082	12.119938	12.852295	13.106773	...	0.65	
485	11.590859	11.786082	12.119938	12.852295	...	0.69	
486	12.186487	11.590859	11.786082	12.119938	...	0.64	
487	12.577783	12.186487	11.590859	11.786082	...	0.50	
488	11.816573	12.577783	12.186487	11.590859	...	0.59	
489	11.387627	11.816573	12.577783	12.186487	...	0.78	

490	11.663214	11.387627	11.816573	12.577783	...	0.61
491	11.504756	11.663214	11.387627	11.816573	...	0.69
492	12.071173	11.504756	11.663214	11.387627	...	0.85
493	13.429271	12.071173	11.504756	11.663214	...	0.83
494	14.191591	13.429271	12.071173	11.504756	...	0.68
495	13.118295	14.191591	13.429271	12.071173	...	0.69
496	12.916559	13.118295	14.191591	13.429271	...	0.48
497	12.496044	12.916559	13.118295	14.191591	...	0.50
498	12.050954	12.496044	12.916559	13.118295	...	0.59
499	12.231576	12.050954	12.496044	12.916559	...	0.66
500	11.791904	12.231576	12.050954	12.496044	...	0.57
501	11.932721	11.791904	12.231576	12.050954	...	0.40
502	11.932721	11.932721	11.791904	12.231576	...	0.20
503	11.982423	11.932721	11.932721	11.791904	...	0.45
504	11.266252	11.982423	11.932721	11.932721	...	0.55
505	11.923226	11.266252	11.982423	11.932721	...	0.63
506	12.201972	11.923226	11.266252	11.982423	...	0.23
507	11.731479	12.201972	11.923226	11.266252	...	0.40
508	11.097177	11.731479	12.201972	11.923226	...	0.36
..
800	11.300414	11.109560	11.370601	11.430883	...	0.54
801	11.409880	11.300414	11.109560	11.370601	...	0.44
802	11.620778	11.409880	11.300414	11.109560	...	0.40
803	12.729659	11.620778	11.409880	11.300414	...	0.38
804	11.753871	12.729659	11.620778	11.409880	...	0.61
805	11.344805	11.753871	12.729659	11.620778	...	0.93
806	11.800777	11.344805	11.753871	12.729659	...	0.81
807	11.685169	11.800777	11.344805	11.753871	...	0.73
808	11.857957	11.685169	11.800777	11.344805	...	0.19
809	11.710582	11.857957	11.685169	11.800777	...	0.22
810	12.078164	11.710582	11.857957	11.685169	...	0.47
811	11.280011	12.078164	11.710582	11.857957	...	0.42
812	11.095584	11.280011	12.078164	11.710582	...	0.73
813	11.415105	11.095584	11.280011	12.078164	...	0.67
814	11.445403	11.415105	11.095584	11.280011	...	0.63
815	10.972318	11.445403	11.415105	11.095584	...	0.47
816	11.569300	10.972318	11.445403	11.415105	...	0.52
817	12.202967	11.569300	10.972318	11.445403	...	0.55
818	11.264175	12.202967	11.569300	10.972318	...	0.41
819	11.452649	11.264175	12.202967	11.569300	...	0.59
820	11.679099	11.452649	11.264175	12.202967	...	0.36
821	11.285737	11.679099	11.452649	11.264175	...	0.67
822	11.816914	11.285737	11.679099	11.452649	...	0.35
823	11.490470	11.816914	11.285737	11.679099	...	0.13
824	11.582159	11.490470	11.816914	11.285737	...	0.56
825	10.979566	11.582159	11.490470	11.816914	...	0.57
826	10.781898	10.979566	11.582159	11.490470	...	0.64
827	10.674624	10.781898	10.979566	11.582159	...	0.61

828	10.573835	10.674624	10.781898	10.979566	...	0.22
829	10.518126	10.573835	10.674624	10.781898	...	0.25

	cloudCover(t-6)	cloudCover(t-7)	cloudCover(t-8)	cloudCover(t-9)	\
479	0.84	0.83	0.68	0.17	
480	0.81	0.84	0.83	0.68	
481	0.60	0.81	0.84	0.83	
482	0.54	0.60	0.81	0.84	
483	0.37	0.54	0.60	0.81	
484	0.27	0.37	0.54	0.60	
485	0.65	0.27	0.37	0.54	
486	0.69	0.65	0.27	0.37	
487	0.64	0.69	0.65	0.27	
488	0.50	0.64	0.69	0.65	
489	0.59	0.50	0.64	0.69	
490	0.78	0.59	0.50	0.64	
491	0.61	0.78	0.59	0.50	
492	0.69	0.61	0.78	0.59	
493	0.85	0.69	0.61	0.78	
494	0.83	0.85	0.69	0.61	
495	0.68	0.83	0.85	0.69	
496	0.69	0.68	0.83	0.85	
497	0.48	0.69	0.68	0.83	
498	0.50	0.48	0.69	0.68	
499	0.59	0.50	0.48	0.69	
500	0.66	0.59	0.50	0.48	
501	0.57	0.66	0.59	0.50	
502	0.40	0.57	0.66	0.59	
503	0.20	0.40	0.57	0.66	
504	0.45	0.20	0.40	0.57	
505	0.55	0.45	0.20	0.40	
506	0.63	0.55	0.45	0.20	
507	0.23	0.63	0.55	0.45	
508	0.40	0.23	0.63	0.55	
..	
800	0.32	0.69	0.37	0.17	
801	0.54	0.32	0.69	0.37	
802	0.44	0.54	0.32	0.69	
803	0.40	0.44	0.54	0.32	
804	0.38	0.40	0.44	0.54	
805	0.61	0.38	0.40	0.44	
806	0.93	0.61	0.38	0.40	
807	0.81	0.93	0.61	0.38	
808	0.73	0.81	0.93	0.61	
809	0.19	0.73	0.81	0.93	
810	0.22	0.19	0.73	0.81	
811	0.47	0.22	0.19	0.73	
812	0.42	0.47	0.22	0.19	

813	0.73	0.42	0.47	0.22
814	0.67	0.73	0.42	0.47
815	0.63	0.67	0.73	0.42
816	0.47	0.63	0.67	0.73
817	0.52	0.47	0.63	0.67
818	0.55	0.52	0.47	0.63
819	0.41	0.55	0.52	0.47
820	0.59	0.41	0.55	0.52
821	0.36	0.59	0.41	0.55
822	0.67	0.36	0.59	0.41
823	0.35	0.67	0.36	0.59
824	0.13	0.35	0.67	0.36
825	0.56	0.13	0.35	0.67
826	0.57	0.56	0.13	0.35
827	0.64	0.57	0.56	0.13
828	0.61	0.64	0.57	0.56
829	0.22	0.61	0.64	0.57

	cloudCover(t-10)	cloudCover(t-11)	cloudCover(t-12)	cloudCover(t-13)	\
479	0.12	0.27	0.58	0.66	
480	0.17	0.12	0.27	0.58	
481	0.68	0.17	0.12	0.27	
482	0.83	0.68	0.17	0.12	
483	0.84	0.83	0.68	0.17	
484	0.81	0.84	0.83	0.68	
485	0.60	0.81	0.84	0.83	
486	0.54	0.60	0.81	0.84	
487	0.37	0.54	0.60	0.81	
488	0.27	0.37	0.54	0.60	
489	0.65	0.27	0.37	0.54	
490	0.69	0.65	0.27	0.37	
491	0.64	0.69	0.65	0.27	
492	0.50	0.64	0.69	0.65	
493	0.59	0.50	0.64	0.69	
494	0.78	0.59	0.50	0.64	
495	0.61	0.78	0.59	0.50	
496	0.69	0.61	0.78	0.59	
497	0.85	0.69	0.61	0.78	
498	0.83	0.85	0.69	0.61	
499	0.68	0.83	0.85	0.69	
500	0.69	0.68	0.83	0.85	
501	0.48	0.69	0.68	0.83	
502	0.50	0.48	0.69	0.68	
503	0.59	0.50	0.48	0.69	
504	0.66	0.59	0.50	0.48	
505	0.57	0.66	0.59	0.50	
506	0.40	0.57	0.66	0.59	
507	0.20	0.40	0.57	0.66	

508	0.45	0.20	0.40	0.57
...
800	0.33	0.35	0.47	0.58
801	0.17	0.33	0.35	0.47
802	0.37	0.17	0.33	0.35
803	0.69	0.37	0.17	0.33
804	0.32	0.69	0.37	0.17
805	0.54	0.32	0.69	0.37
806	0.44	0.54	0.32	0.69
807	0.40	0.44	0.54	0.32
808	0.38	0.40	0.44	0.54
809	0.61	0.38	0.40	0.44
810	0.93	0.61	0.38	0.40
811	0.81	0.93	0.61	0.38
812	0.73	0.81	0.93	0.61
813	0.19	0.73	0.81	0.93
814	0.22	0.19	0.73	0.81
815	0.47	0.22	0.19	0.73
816	0.42	0.47	0.22	0.19
817	0.73	0.42	0.47	0.22
818	0.67	0.73	0.42	0.47
819	0.63	0.67	0.73	0.42
820	0.47	0.63	0.67	0.73
821	0.52	0.47	0.63	0.67
822	0.55	0.52	0.47	0.63
823	0.41	0.55	0.52	0.47
824	0.59	0.41	0.55	0.52
825	0.36	0.59	0.41	0.55
826	0.67	0.36	0.59	0.41
827	0.35	0.67	0.36	0.59
828	0.13	0.35	0.67	0.36
829	0.56	0.13	0.35	0.67

	cloudCover(t-14)
479	0.83
480	0.66
481	0.58
482	0.27
483	0.12
484	0.17
485	0.68
486	0.83
487	0.84
488	0.81
489	0.60
490	0.54
491	0.37
492	0.27

493	0.65
494	0.69
495	0.64
496	0.50
497	0.59
498	0.78
499	0.61
500	0.69
501	0.85
502	0.83
503	0.68
504	0.69
505	0.48
506	0.50
507	0.59
508	0.66
..	...
800	0.77
801	0.58
802	0.47
803	0.35
804	0.33
805	0.17
806	0.37
807	0.69
808	0.32
809	0.54
810	0.44
811	0.40
812	0.38
813	0.61
814	0.93
815	0.81
816	0.73
817	0.19
818	0.22
819	0.47
820	0.42
821	0.73
822	0.67
823	0.63
824	0.47
825	0.52
826	0.55
827	0.41
828	0.59
829	0.36

[351 rows x 99 columns]

In [45]: *# Convert predictions back to normal values*

```
predi = scaler.inverse_transform(prova)
print(predi)
print(predi[0][0])
print(predi[0][1])
```

#Les variables en posició 0 i 1 són predicció i y respectivament

```
[[ 11.34862043  11.59085917 115.46893021 ...  0.58          0.66
   0.83          ]
 [ 11.3465673   12.18648691 112.48075791 ...  0.27          0.58
   0.66          ]
 [ 11.61864091  12.57778255 110.7334244  ...  0.12          0.27
   0.58          ]
 ...
 [ 10.45960788  10.2949966  109.74485905 ...  0.36          0.59
   0.41          ]
 [ 10.69045474  10.20294532 100.17673598 ...  0.67          0.36
   0.59          ]
 [ 10.02295483  10.3563499   99.13484299 ...  0.35          0.67
   0.36          ]]
11.348620434048419
11.590859170709699
```

In [46]: *#Fem una llista amb les prediccions i una llista amb y(valor real)*

```
listpredi=list()
for i in range(len(predi)):
    listpredi.append(predi[i][0])
listpredi

listy=list()
for i in range(len(predi)):
    listy.append(predi[i][1])
listy
```

Out[46]: [11.590859170709699,
12.186486909458,
12.5777825527296,
11.816572589134799,
11.3876267050719,
11.6632140210701,
11.5047561338867,
12.071172692490801,
13.4292708131623,

14.1915913964734,
13.1182948122023,
12.916559451200099,
12.4960441531868,
12.050954318124699,
12.231575736212301,
11.7919036962847,
11.9327208888355,
11.9327208888355,
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11.923225859637402,
12.2019722473821,
11.7314792668086,
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10.593420449120199,
10.900387923175302,
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10.531617352131999,
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9.44901226100687,
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8.506098960360191,
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8.77842514832838,
9.525847240364241,
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9.06303884040141,
8.84434200802974,
8.79350297401487,
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8.86870556311186,
8.80253695803389,
8.645489666170171,
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8.50373096231614,
8.7022052143203,

8.60023035333333,
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9.80834829610728,
8.81359064611515,
9.290409387781711,
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9.15104978517621,
9.23372603556509,
9.019062861238579,
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8.82453115537314,
8.90278416695295,
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8.03627886081334,

8.103375796384409,
8.29101761577961,
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8.248033919715139,
8.19504650277517,
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7.99750949821328,
8.339931338431152,
7.96851749430023,
7.8650527002635,
7.84724430656879,
7.770923626787059,
7.81593541751083,
7.9428796842026,
8.32997890363534,
8.0665576486624,
8.023428248794731,
8.07288736129215,
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7.8767767942362,
8.01356375908834,
8.19377346364493,
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7.959776351171141,
7.91322415390285,
7.98315031223294,
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9.116968037282302,
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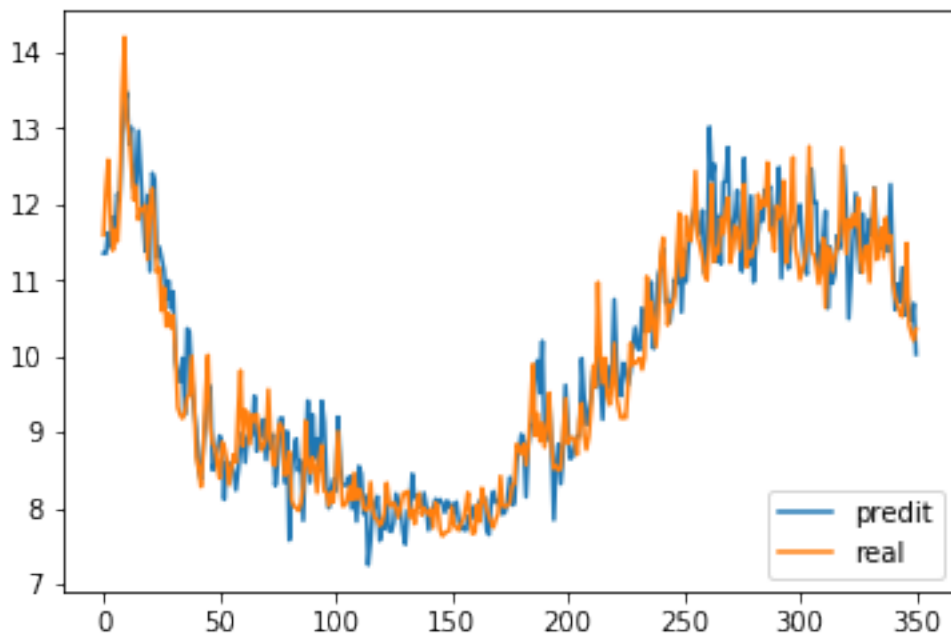
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8.76896484119116,
8.94084204544581,
9.29505780576148,
9.8737308507775,
9.597023808870972,
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9.47103368658325,
9.360215124264,
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9.92981667575583,
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11.490469615202198,
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10.6746236023562,
10.573835396803801,
10.5181264982014,


```
10.7762421096284,  
11.480410763265299,  
10.411403084521401,  
10.294996596876901,  
10.202945322371301,  
10.3563498993587]
```

```
In [47]: ##Mostrem  
plt.plot(listpredi, label="predit")  
plt.plot(listy, label="real")  
plt.legend(loc="lower right")  
plt.show()
```



```
In [48]: print(listy[300])  
         print(listpredi[300])  
  
         print(listy[300]-listpredi[300])  
         (listy[300]-listpredi[300])/listy[300]
```

```
11.0061509800784  
11.989382632338454  
-0.9832316522600539
```

```
Out [48]: -0.08933474145863934
```

```

In [49]: llista_errors=list()
         llista_errorsabs=list()
         llista_errorsres=list()

         for i in range(len(listpredi)):
             valor=listy[i]-listpredi[i]
             valorabs=math.fabs(valor)
             valorrespecte=valorabs/listy[i]
             llista_errors.append(valor)
             llista_errorsabs.append(valorabs)
             llista_errorsres.append(valorrespecte)

```

```

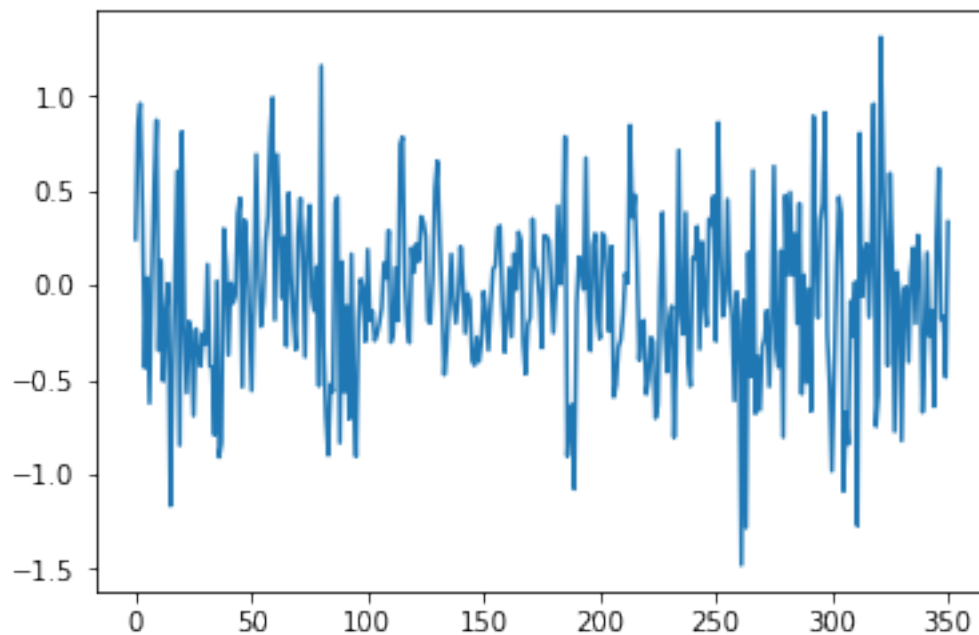
In [50]: plt.plot(llista_errors)

```

```

Out[50]: [<matplotlib.lines.Line2D at 0x1a0504bac50>]

```



```

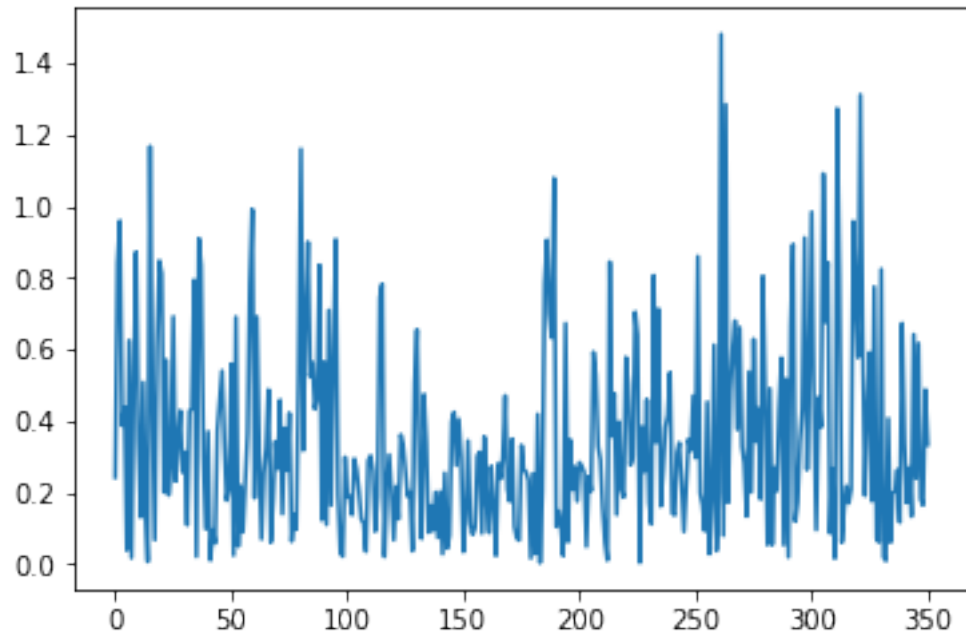
In [51]: plt.plot(llista_errorsabs)

```

```

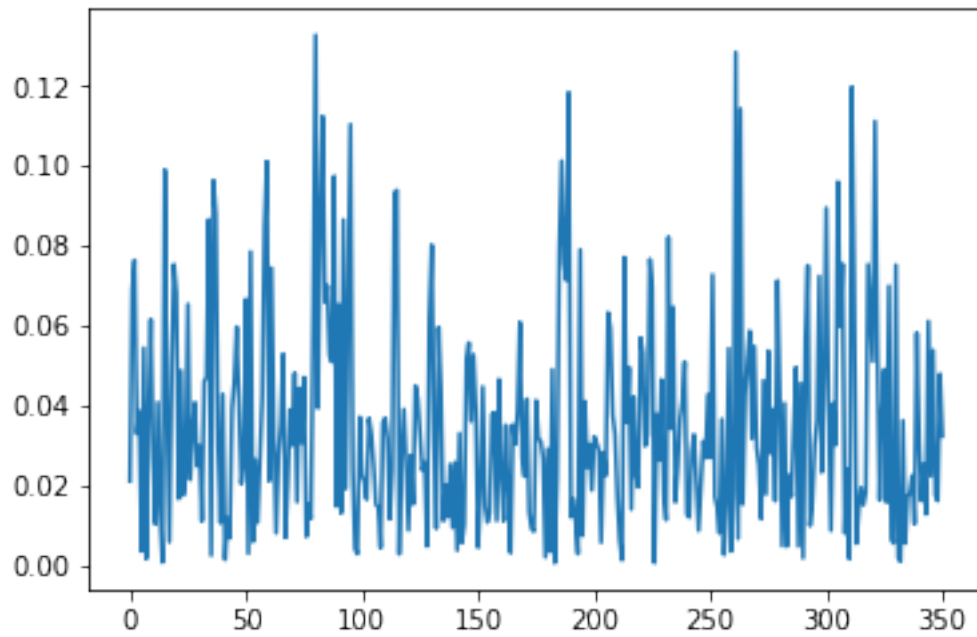
Out[51]: [<matplotlib.lines.Line2D at 0x1a0505210f0>]

```



```
In [52]: plt.plot(llista_errorsres)
```

```
Out[52]: [<matplotlib.lines.Line2D at 0x1a050585198>]
```



```
In [53]: sum(llista_errorsres)/(len(llista_errorsres))
```

```
Out[53]: 0.03529540168381798
```

```
In [ ]:
```