In [14]:
```
import numpy as np # linear algebra
import pandas as pd # data processing
import matplotlib.pyplot as plt
from pandas import datetime
import seaborn as sns
%matplotlib inline

from sklearn.cluster import KMeans
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
```

```
<ipython-input-14-500d58bfe76b>:4: FutureWarning: The pandas.datetime class is deprecated and will be removed from pand
as in a future version. Import from datetime module instead.
  from pandas import datetime
```

In [ ]:

Dataset Loading

In [2]:
```
def function_transpose(file):
    data=pd.read_csv(file)
    data=data.T
    return data

file = 'weather_daily_darksky.csv'
function_transpose(file)
```

Out[2]:

temperatureMax	Year	11.96	8.59	10.33	8.07	8.22	7.97	13.19	8.32	9.82	...
0	temperatureMax	11.96	8.59	10.33	8.07	8.22	7.97	13.19	8.32	9.82	...
1	temperatureMaxTime	2011-11-11 23:00:00	2011-12-11 14:00:00	2011-12-27 02:00:00	2011-12-02 23:00:00	2011-12-24 23:00:00	2011-12-15 14:00:00	2011-11-19 14:00:00	2011-11-16 23:00:00	2011-12-12 23:00:00	...
2	windBearing	123	198	225	232	252	234	117	117	221	...
3	icon	fog	partly-cloudy-day	partly-cloudy-day	wind	partly-cloudy-night	wind	fog	fog	wind	...
4	dewPoint	9.4	4.49	5.47	3.69	2.79	2.41	8.12	5.58	4.1	...
5	temperatureMinTime	2011-11-11 07:00:00	2011-12-11 01:00:00	2011-12-27 23:00:00	2011-12-02 07:00:00	2011-12-24 07:00:00	2011-12-15 00:00:00	2011-11-19 23:00:00	2011-11-16 07:00:00	2011-12-12 07:00:00	...
6	cloudCover	0.79	0.56	0.85	0.32	0.37	0.42	0.26	0.81	0.38	...
7	windSpeed	3.88	3.94	3.54	3	4.46	4.71	2.37	2.36	5.02	...
8	pressure	1016.08	1007.71	1032.76	1012.12	1028.17	996.75	1016.8	1017.4	1002.47	...
9	apparentTemperatureMinTime	2011-11-11 07:00:00	2011-12-11 02:00:00	2011-12-27 22:00:00	2011-12-02 07:00:00	2011-12-24 07:00:00	2011-12-15 00:00:00	2011-11-19 08:00:00	2011-11-16 04:00:00	2011-12-12 08:00:00	...
10	apparentTemperatureHigh	10.87	5.62	10.33	5.33	5.02	4.25	13.19	6.64	5.18	...
11	precipType	rain	rain	rain	rain	rain	rain	rain	rain	rain	...
12	visibility	3.3	12.09	13.39	11.89	13.16	12.79	6.63	3.69	12.05	...
13	humidity	0.95	0.88	0.74	0.87	0.8	0.77	0.92	0.93	0.84	...
14	apparentTemperatureHighTime	2011-11-11 19:00:00	2011-12-11 19:00:00	2011-12-27 14:00:00	2011-12-02 12:00:00	2011-12-24 15:00:00	2011-12-15 14:00:00	2011-11-19 14:00:00	2011-11-16 14:00:00	2011-12-12 16:00:00	...
15	apparentTemperatureLow	10.87	-0.64	5.52	3.26	4.37	-2.58	4.76	4.68	2.71	...
16	apparentTemperatureMax	11.96	5.72	10.33	5.33	5.32	4.38	13.19	7.14	5.94	...
17	uvIndex	1	1	0	1	1	1	1	1	1	...
18	time	2011-11-11 00:00:00	2011-12-11 00:00:00	2011-12-27 00:00:00	2011-12-02 00:00:00	2011-12-24 00:00:00	2011-12-15 00:00:00	2011-11-19 00:00:00	2011-11-16 00:00:00	2011-12-12 00:00:00	...
19	sunsetTime	2011-11-11 16:19:21	2011-12-11 15:52:53	2011-12-27 15:57:56	2011-12-02 15:56:17	2011-12-24 15:55:55	2011-12-15 15:52:48	2011-11-19 16:08:22	2011-11-16 16:12:12	2011-12-12 15:52:47	...
20	temperatureLow	10.87	3.09	8.03	6.33	7.45	1.8	4.76	6.93	6.88	...
21	temperatureMin	8.85	2.48	8.03	2.56	3.17	4.08	7.48	5.19	3.09	...
22	temperatureHigh	10.87	8.59	10.33	7.36	7.93	7.97	13.19	8.18	8.53	...
23	sunriseTime	2011-11-11 07:12:14	2011-12-11 07:57:02	2011-12-27 08:07:06	2011-12-02 07:46:09	2011-12-24 08:06:15	2011-12-15 08:00:46	2011-11-19 07:26:03	2011-11-16 07:20:57	2011-12-12 07:58:02	...
24	temperatureHighTime	2011-11-11 19:00:00	2011-12-11 14:00:00	2011-12-27 14:00:00	2011-12-02 12:00:00	2011-12-24 15:00:00	2011-12-15 14:00:00	2011-11-19 14:00:00	2011-11-16 14:00:00	2011-12-12 19:00:00	...
25	uvIndexTime	2011-11-11 11:00:00	2011-12-11 12:00:00	2011-12-27 00:00:00	2011-12-02 10:00:00	2011-12-24 13:00:00	2011-12-15 11:00:00	2011-11-19 10:00:00	2011-11-16 11:00:00	2011-12-12 11:00:00	...
26	summary	Foggy until afternoon.	Partly cloudy throughout the day.	Mostly cloudy throughout the day.	Partly cloudy throughout the day and breezy ov...	Mostly cloudy throughout the day.	Partly cloudy throughout the day and breezy in...	Foggy starting in the evening.	Foggy starting in the evening.	Partly cloudy throughout the day and breezy st...	...
27	temperatureLowTime	2011-11-11 19:00:00	2011-12-12 07:00:00	2011-12-27 23:00:00	2011-12-02 19:00:00	2011-12-24 19:00:00	2011-12-16 08:00:00	2011-11-20 08:00:00	2011-11-16 19:00:00	2011-12-13 08:00:00	...
28	apparentTemperatureMin	6.48	0.11	5.59	0.46	-0.51	1.07	5.98	2.93	-0.64	...
29	apparentTemperatureMaxTime	2011-11-11 23:00:00	2011-12-11 20:00:00	2011-12-27 02:00:00	2011-12-02 12:00:00	2011-12-24 23:00:00	2011-12-15 21:00:00	2011-11-19 14:00:00	2011-11-16 23:00:00	2011-12-12 23:00:00	...
30	apparentTemperatureLowTime	2011-11-11 19:00:00	2011-12-12 08:00:00	2011-12-28 00:00:00	2011-12-02 19:00:00	2011-12-24 20:00:00	2011-12-16 08:00:00	2011-11-20 08:00:00	2011-11-16 19:00:00	2011-12-13 08:00:00	...

31 rows × 883 columns

In [7]:
```
weather = pd.read_csv('weather_daily_darksky.csv')
energy = pd.read_csv('energy.csv')
```

Dataset Preprocessing

In [8]:
```
"""
The number of homes for which energy data was obtained on different days is vary throughout the dataset.
This might lead to the incorrect conclusion that the energy for a certain day is high when the data was
only obtained for a larger number of residences. Each day's house count will be examined.
"""

housecount = energy.groupby('day')[['LCLid']].nunique()
```

Data Normalization

In [9]:
```
"""
Because data collection across homes is uneven, we'll use energy per household as our prediction objective rather than
 energy alone.
This is an optional step because we can also anticipate the total amount of energy used by each home. However, there ar
e a lot of
unique homes for which we'll have to repeat the procedure, and our ultimate objective is to anticipate aggregate consum
ption, not household consumption.
"""

energy = energy.groupby('day')[['energy_sum']].sum()
energy = energy.merge(housecount, on = ['day'])
energy = energy.reset_index()
energy.count()
```

Out[9]:
```
day           829
energy_sum    829
LCLid         829
dtype: int64
```

In [10]:
```
energy.day = pd.to_datetime(energy.day,format='%Y-%m-%d').dt.date
energy['avg_energy'] =  energy['energy_sum']/energy['LCLid']
print("Starting Point of Data at Day Level",min(energy.day))
print("Ending Point of Data at Day Level",max(energy.day))
```

```
Starting Point of Data at Day Level 2011-11-23
Ending Point of Data at Day Level 2014-02-28
```

In [11]:
```
weather['day']=  pd.to_datetime(weather['time']) # day is given as timestamp
weather['day']=  pd.to_datetime(weather['day'],format='%Y%m%d').dt.date
# selecting numeric variables
weather = weather[['temperatureMax', 'windBearing', 'dewPoint', 'cloudCover', 'windSpeed',
       'pressure', 'apparentTemperatureHigh', 'visibility', 'humidity',
       'apparentTemperatureLow', 'apparentTemperatureMax', 'uvIndex',
       'temperatureLow', 'temperatureMin', 'temperatureHigh',
       'apparentTemperatureMin', 'moonPhase','day']]
weather = weather.dropna()
```

Relationship of weather condition with electricity consumption

In [12]:
```
weather_energy =  energy.merge(weather,on='day')
weather_energy.head(2)
```

Out[12]:

	day	energy_sum	LCLid	avg_energy	temperatureMax	windBearing	dewPoint	cloudCover	windSpeed	pressure	...	visibility	humidity	appa
0	2011-11-23	90.385	13	6.952692	10.36	229	6.29	0.36	2.04	1027.12	...	8.06	0.93	
1	2011-11-24	213.412	25	8.536480	12.93	204	8.56	0.41	4.04	1027.22	...	10.64	0.89	

2 rows × 21 columns

Correlation between Weather Variables and Energy Consumption

- Energy has high positive correlation with humidity and high negative correlation with temperature.
- Dew Point, UV Index display multicollinearity with Temperature, hence discarded
- Cloud Cover and Visibility display multicollinearity with Humidity, hence discarded
- Pressure and Moon Phase have minimal correlation with Energy, hence discarded
- Wind Speed has low correlation with energy but does not show multicollinearity

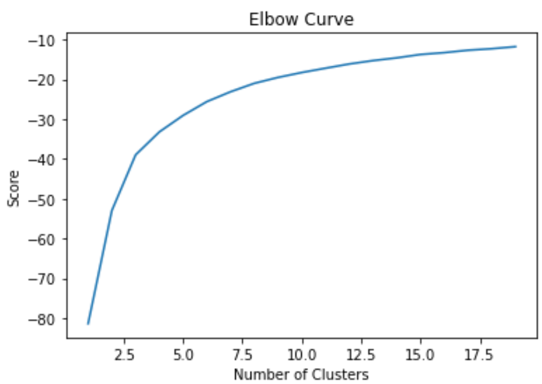
Clustering

In [16]:
```
"""
There are a lot of variables in meteorological data, and not all of them are relevant.
We'll try to make weather clusters to see if we can come up with a day's weather based
on granular weather data like temperature and precipitation.
"""

#scaling
scaler = MinMaxScaler()
weather_scaled = scaler.fit_transform(weather_energy[['temperatureMax','humidity','windSpeed']])

# optimum K
Nc = range(1, 20)
kmeans = [KMeans(n_clusters=i) for i in Nc]
kmeans

score = [kmeans[i].fit(weather_scaled).score(weather_scaled) for i in range(len(kmeans))]
score
plt.plot(Nc,score)
plt.xlabel('Number of Clusters')
plt.ylabel('Score')
plt.title('Elbow Curve')
plt.show()
```

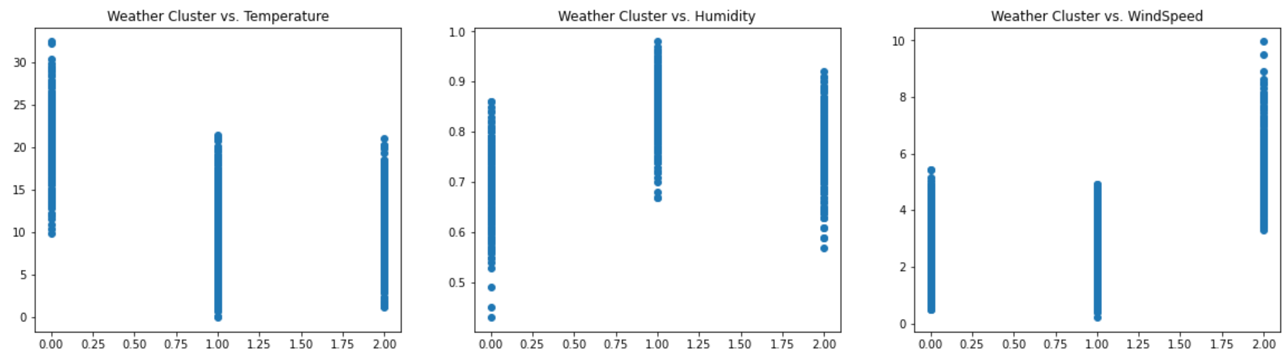


In [17]:
```
kmeans = KMeans(n_clusters=3, max_iter=600, algorithm = 'auto')
kmeans.fit(weather_scaled)
weather_energy['weather_cluster'] = kmeans.labels_
```

In [18]:

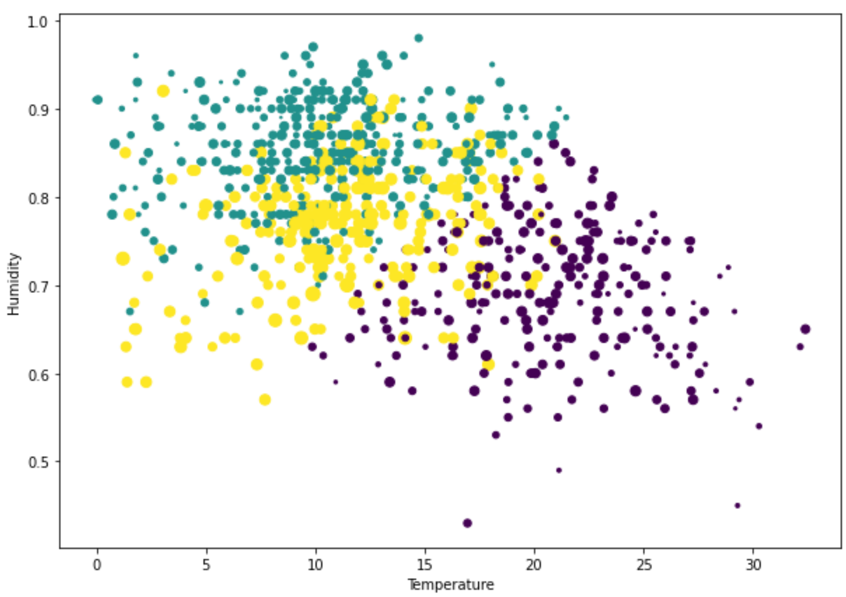
```
# Cluster Relationships with weather variables
plt.figure(figsize=(20,5))
plt.subplot(1, 3, 1)
plt.scatter(weather_energy.weather_cluster,weather_energy.temperatureMax)
plt.title('Weather Cluster vs. Temperature')
plt.subplot(1, 3, 2)
plt.scatter(weather_energy.weather_cluster,weather_energy.humidity)
plt.title('Weather Cluster vs. Humidity')
plt.subplot(1, 3, 3)
plt.scatter(weather_energy.weather_cluster,weather_energy.windSpeed)
plt.title('Weather Cluster vs. WindSpeed')

plt.show()
# put this in a loop
```



In [19]:

```
fig, ax1 = plt.subplots(figsize = (10,7))
ax1.scatter(weather_energy.temperatureMax,
            weather_energy.humidity,
            s = weather_energy.windSpeed*10,
            c = weather_energy.weather_cluster)
ax1.set_xlabel('Temperature')
ax1.set_ylabel('Humidity')
plt.show()
```



In [21]:

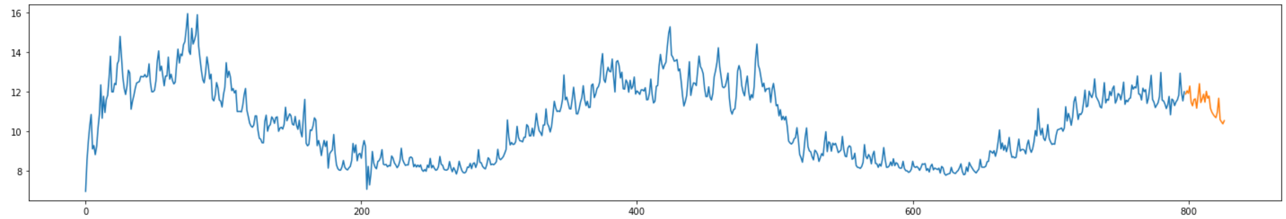
```
holiday = pd.read_csv('holidays.csv')
holiday['Bank holidays'] = pd.to_datetime(holiday['Bank holidays'],format='%Y-%m-%d').dt.date
weather_energy = weather_energy.merge(holiday, left_on = 'day',right_on = 'Bank holidays',how = 'left')
weather_energy['holiday_ind'] = np.where(weather_energy['Bank holidays'].isna(),0,1)
```

Fitting

In [22]:
```
model_data = weather_energy[['avg_energy','weather_cluster','holiday_ind']]
# train = model_data.iloc[0:round(len(model_data)*0.90)]
# test = model_data.iloc[len(train)-1:]
train = model_data.iloc[0:(len(model_data)-30)]
test = model_data.iloc[len(train):(len(model_data)-1)]
```

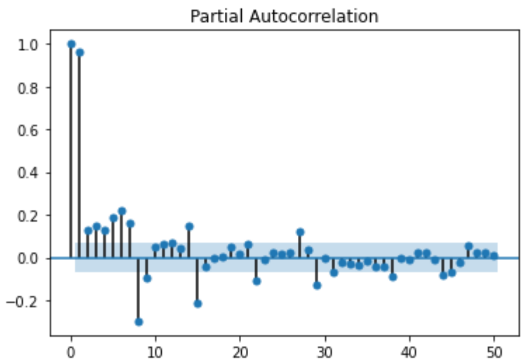
In [23]:
```
train['avg_energy'].plot(figsize=(25,4))
test['avg_energy'].plot(figsize=(25,4))
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x19e2ffee910>



In [25]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

plot_pacf(train.avg_energy,lags=50)
plt.show()
```



Autocorrelation plot shows gradual decay while Partial AutoCorrelation shows that there is a sharp drop after 1st lag. This means that most of the higher-order autocorrelations are effectively explained by the k = 1 lag. Therefore, the series displays AR 'signature'

Prediction

In [29]:
```
import statsmodels.api as sm

endog = train['avg_energy']
exog = sm.add_constant(train[['weather_cluster','holiday_ind']])

mod = sm.tsa.statespace.SARIMAX(endog=endog, exog=exog, order=(7,1,1),seasonal_order=(1,1, 0, 12),trend='c')
model_fit = mod.fit()
model_fit.summary()
```

Out[29]:

SARIMAX Results

Dep. Variable:	avg_energy	**No. Observations:**	798
Model:	SARIMAX(7, 1, 1)x(1, 1, [], 12)	**Log Likelihood**	-649.414
Date:	Mon, 16 May 2022	**AIC**	1326.828
Time:	00:24:22	**BIC**	1392.148
Sample:	0	**HQIC**	1351.943
	- 798		
Covariance Type:	opg		

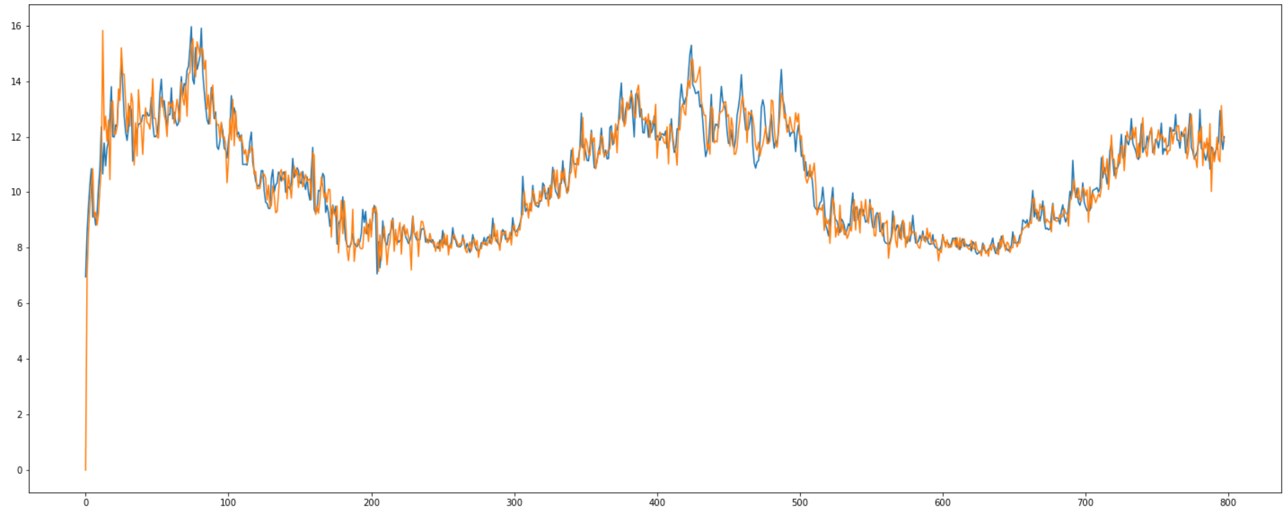
	coef	std err	z	P>|z|	[0.025	0.975]
intercept	-0.0065	0.017	-0.382	0.703	-0.040	0.027
const	-2.999e-08	2.73e-10	-110.007	0.000	-3.05e-08	-2.95e-08
weather_cluster	-0.0039	0.025	-0.156	0.876	-0.053	0.045
holiday_ind	-0.0348	0.088	-0.395	0.693	-0.207	0.138
ar.L1	-0.0019	0.087	-0.022	0.983	-0.172	0.168
ar.L2	-0.1547	0.032	-4.853	0.000	-0.217	-0.092
ar.L3	-0.1434	0.039	-3.711	0.000	-0.219	-0.068
ar.L4	-0.1512	0.038	-3.982	0.000	-0.226	-0.077
ar.L5	-0.1635	0.040	-4.097	0.000	-0.242	-0.085
ar.L6	0.0083	0.037	0.226	0.821	-0.063	0.080
ar.L7	0.3528	0.028	12.407	0.000	0.297	0.409
ma.L1	-0.1840	0.092	-2.007	0.045	-0.364	-0.004
ar.S.L12	-0.4832	0.033	-14.843	0.000	-0.547	-0.419
sigma2	0.3041	0.013	24.075	0.000	0.279	0.329

Ljung-Box (Q):	221.13	**Jarque-Bera (JB):**	45.40
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.53	**Skew:**	-0.16
Prob(H) (two-sided):	0.00	**Kurtosis:**	4.13

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 3.51e+17. Standard errors may be unstable.

In [32]:
```python
#Model fit

train['avg_energy'].plot(figsize=(25,10))
model_fit.fittedvalues.plot()
plt.show()
```



In [40]:
```python
# prediction

predict = model_fit.predict(start = len(train),end = len(train)+len(test)-1,
                            exog = sm.add_constant(test[['weather_cluster','holiday_ind']]))
test['predicted'] = predict.values
test.tail(5)
```

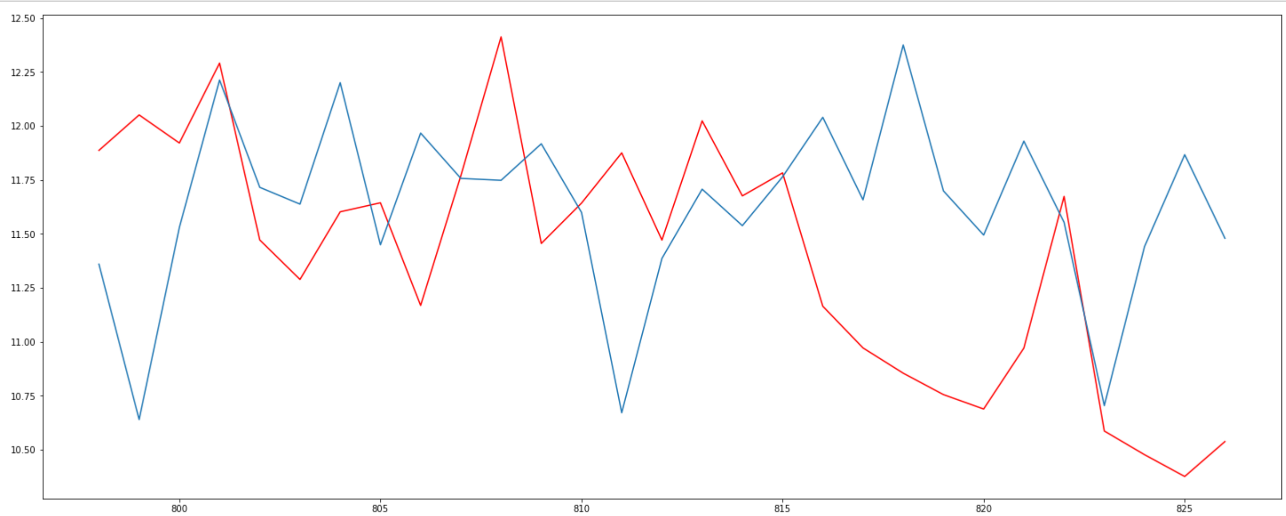
```
<ipython-input-40-ed90cde52d8b>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a
-view-versus-a-copy
  test['predicted'] = predict.values
```

Out[40]:

	avg_energy	weather_cluster	holiday_ind	predicted
822	11.673756	2	0	11.553517
823	10.586235	2	0	10.703869
824	10.476498	2	0	11.440806
825	10.375366	2	0	11.867154
826	10.537250	2	0	11.479704

In [43]:
```python
plt.figure(figsize=(6,6))
test['avg_energy'].plot(figsize=(25,10),color = 'red')
test['predicted'].plot()
plt.show()
```



In [ ]: