First data insight

Basic infos

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
```

In [2]:
```
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
pd.set_option('display.max_columns', 100)
```

In [3]:
```
from sklearn.preprocessing import MinMaxScaler
import folium
```

In [4]:
```
input_dir = os.path.join('..', 'input')
output_dir = os.path.join('..', 'output')
print(os.listdir(input_dir))
```

```
['input_training_ssnsrY0.csv', 'Screenshot from 2019-05-28 10-48-59.png', 'inp
ut_test_cdKcI0e.csv', 'vacances-scolaires.csv', 'jours_feries_seuls.csv', 'BCM
_custom_metric.py', 'output_training_Uf11I9I.csv']
```

In [5]:
```
# each id is unique so we can use this column as index
df = pd.read_csv(os.path.join(input_dir, 'input_training_ssnsrY0.csv'), index_c
df.iloc[23:26]
```

Out[5]:

ID	timestamp	temp_1	temp_2	mean_national_temp	humidity_1	humidity_2	loc_1	loc_2
23	2016-11-01T23:00:00.0	10.8	NaN	11.1	87.0	NaN	(50.633, 3.067)	(43.530, 5.447)
24	2016-11-02T00:00:00.0	10.8	NaN	11.1	86.0	NaN	(50.633, 3.067)	(43.530, 5.447)
25	2016-11-02T01:00:00.0	10.5	NaN	11.0	81.0	NaN	(50.633, 3.067)	(43.530, 5.447)

In [6]:
```
df_out = pd.read_csv(os.path.join('..', 'input', 'output_training_Uf11I9I.csv')
df_out.head()
```

Out[6]:

ID	consumption_1	consumption_2
0	100	93
1	101	94
2	100	96
3	101	95
4	100	100

In [7]:
```
df.shape, df_out.shape
```

Out[7]:
```
((8760, 14), (8760, 2))
```

In [8]:
```
df.info()
```

```
&lt;class 'pandas.core.frame.DataFrame'&gt;
Int64Index: 8760 entries, 0 to 8759
Data columns (total 14 columns):
timestamp                  8760 non-null object
temp_1                     8589 non-null float64
temp_2                     8429 non-null float64
mean_national_temp         8760 non-null float64
humidity_1                 8589 non-null float64
humidity_2                 8428 non-null float64
loc_1                      8760 non-null object
loc_2                      8760 non-null object
loc_secondary_1            8760 non-null object
loc_secondary_2            8760 non-null object
loc_secondary_3            8760 non-null object
consumption_secondary_1    8760 non-null int64
consumption_secondary_2    8760 non-null int64
consumption_secondary_3    8760 non-null int64
dtypes: float64(5), int64(3), object(6)
memory usage: 1.0+ MB
```

Missing or irrelevant values

In [9]:
```
df.isnull().sum()
```

Out[9]:
```
timestamp                    0
temp_1                     171
temp_2                     331
mean_national_temp           0
humidity_1                 171
humidity_2                 332
loc_1                        0
loc_2                        0
loc_secondary_1              0
loc_secondary_2              0
loc_secondary_3              0
consumption_secondary_1      0
consumption_secondary_2      0
consumption_secondary_3      0
dtype: int64
```

In [10]:
```
df.duplicated().sum()
```

Out[10]:
```
0
```

In [11]:
```
#sns.pairplot(df_viz.select_dtypes(['int64', 'float64']))# apply(pd.Series.num
```

Transforming time informations

In [12]:
```
def transform_datetime_infos(data_frame):
    data_frame['datetime'] = pd.to_datetime(data_frame['timestamp'])
    data_frame['month'] = data_frame['datetime'].dt.month
    data_frame['week of year'] = data_frame['datetime'].dt.weekofyear
    data_frame['day of year'] = data_frame['datetime'].dt.dayofyear
    data_frame['day'] = data_frame['datetime'].dt.weekday_name
    data_frame['hour'] = data_frame['datetime'].dt.hour

    # for merging purposes
    data_frame['date'] = data_frame['datetime'].dt.strftime('%Y-%m-%d')

    return data_frame
```

In [13]:
```
df = transform_datetime_infos(df)
df.head(3)
```

Out[13]:

ID	timestamp	temp_1	temp_2	mean_national_temp	humidity_1	humidity_2	loc_1	loc_2
0	2016-11-01T00:00:00.0	8.3	NaN	11.1	95.0	NaN	(50.633, 3.067)	(43.530, 5.447)
1	2016-11-01T01:00:00.0	8.0	NaN	11.1	98.0	NaN	(50.633, 3.067)	(43.530, 5.447)
2	2016-11-01T02:00:00.0	6.8	NaN	11.0	97.0	NaN	(50.633, 3.067)	(43.530, 5.447)

Considered sites

In [14]:
```
# Number of unique classes in each object column # Check the nb of sites
df.select_dtypes('object').apply(pd.Series.nunique, axis=0)
```

Out[14]:
```
timestamp            8759
loc_1                   1
loc_2                   1
loc_secondary_1         1
loc_secondary_2         1
loc_secondary_3         1
day                     7
date                  365
dtype: int64
```

In [15]:
```
for i in ['loc_1', 'loc_2', 'loc_secondary_1', 'loc_secondary_2', 'loc_secondar
    print('site : ', i, 'coordinates : ', df[i][0])
```

```
site :  loc_1 coordinates :  (50.633, 3.067)
site :  loc_2 coordinates :  (43.530, 5.447)
site :  loc_secondary_1 coordinates :  (44.838, -0.579)
site :  loc_secondary_2 coordinates :  (47.478, -0.563)
site :  loc_secondary_3 coordinates :  (48.867, 2.333)
```

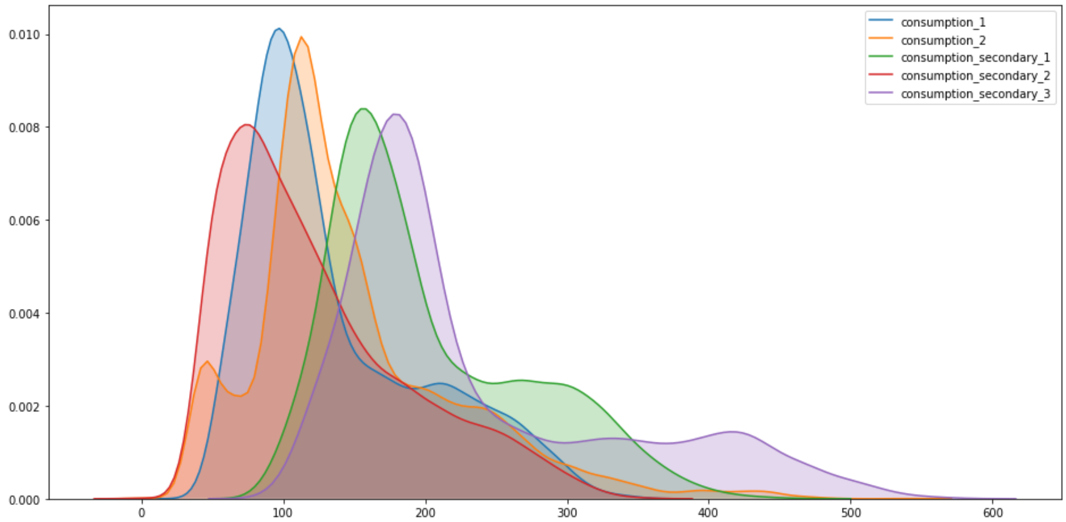
In [16]:
```
# Create a map centered at the given latitude and longitude
france_map = folium.Map(location=[47,1], zoom_start=6)

# Add markers with labels
for i in ['loc_1', 'loc_2', 'loc_secondary_1', 'loc_secondary_2', 'loc_secondar
    temp_str = df[i][0].strip('(').strip(')').strip(' ')
    temp_str1, temp_str2 = temp_str.split(', ')
    folium.Marker([float(temp_str1), float(temp_str2)], popup=None, tooltip=i).

# Display the map
display(france_map)
```

- loc_1 is in the north near Lille.
- loc_1 is in the south east near Marseille.
- loc_secondary_1 is in the south west near Bordeaux.
- loc_secondary_2 is in the west near Le Mans.
- loc_secondary_3 is in the north near Paris.

Exploratory Data Analysis

Distribution of consumption

In [17]:
```python
plt.figure(figsize=(16, 8))
sns.kdeplot(df_out['consumption_1'], shade=True) #, label = 'consumption_1')
sns.kdeplot(df_out['consumption_2'], shade=True) #, label = 'consumption_2')
sns.kdeplot(df['consumption_secondary_1'], shade=True) #, label = 'consumption_
sns.kdeplot(df['consumption_secondary_2'], shade=True) #, label = 'consumption_
sns.kdeplot(df['consumption_secondary_3'], shade=True) #, label = 'consumption_
plt.show()
```

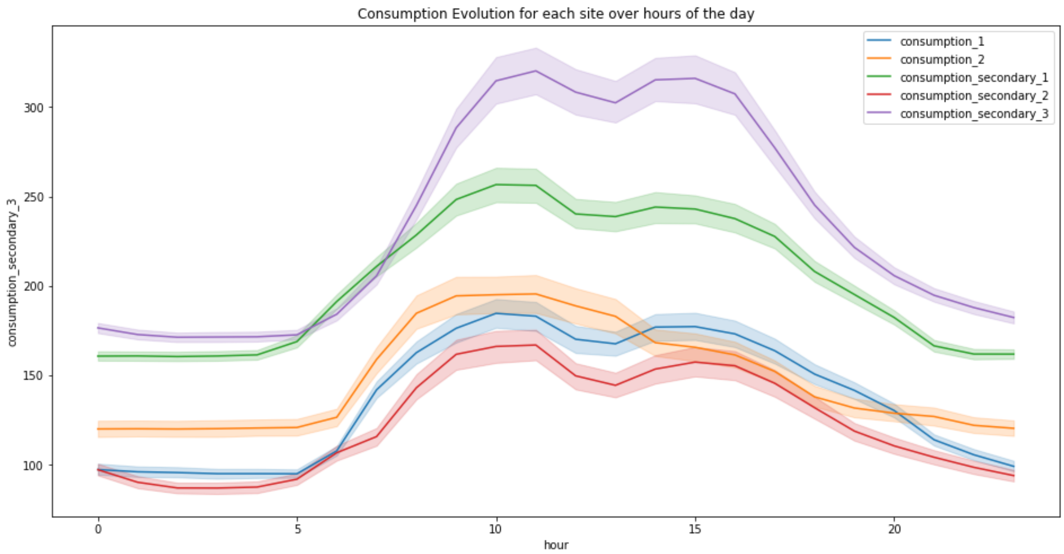


Consumption variation during time

In [18]:
```python
df.groupby(['hour'])['consumption_secondary_1'].mean().values
```

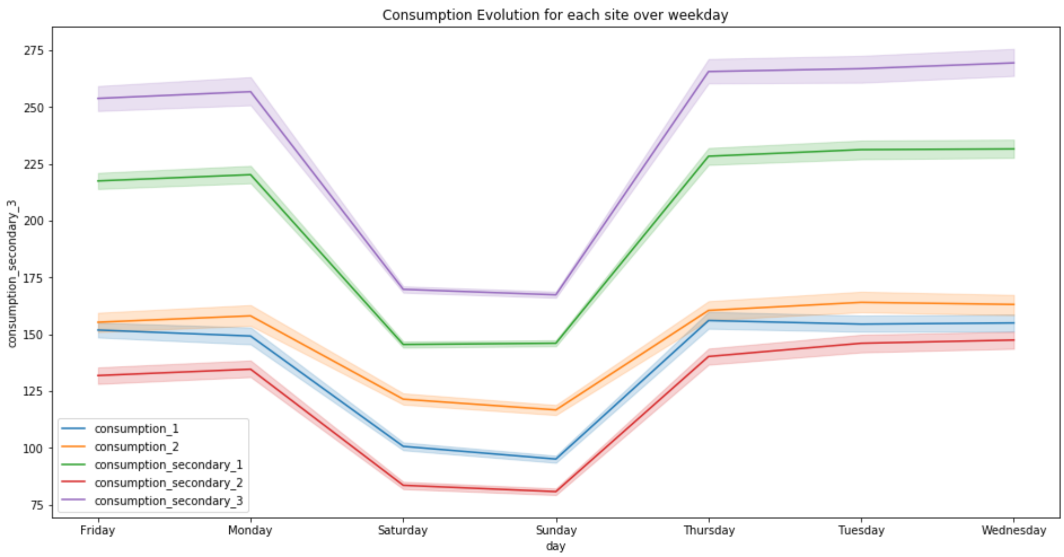
Out[18]:
```
array([160.77534247, 160.8739726 , 160.5260274 , 160.83835616,
       161.46027397, 168.88767123, 191.30136986, 210.9369863 ,
       228.49863014, 248.32328767, 256.64657534, 256.21369863,
       240.23287671, 238.76438356, 244.09041096, 242.99178082,
       237.61643836, 227.66027397, 208.08767123, 195.21917808,
       182.35068493, 166.50958904, 161.92054795, 161.87671233])
```

In [19]:
```
df_viz = pd.concat((df, df_out), axis=1)
plt.figure(figsize=(16, 8))
plt.title("Consumption Evolution for each site over hours of the day")
for c in ['consumption_1', 'consumption_2', 'consumption_secondary_1', 'consump
    sns.lineplot(x="hour", y=c, data=df_viz, label=c)
plt.show()
```



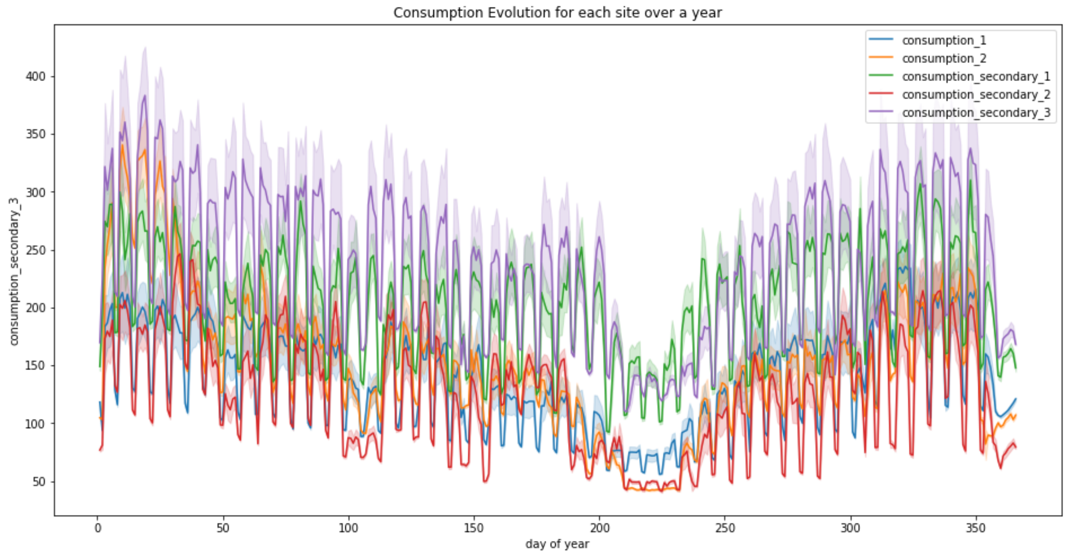
The graph above clearly shows that the electricity consumption is higher during working hours of the day.

In [20]:
```
plt.figure(figsize=(16, 8))
plt.title("Consumption Evolution for each site over weekday")
for c in ['consumption_1', 'consumption_2', 'consumption_secondary_1', 'consump
    sns.lineplot(x="day", y=c, data=df_viz, label=c)
plt.show()
```



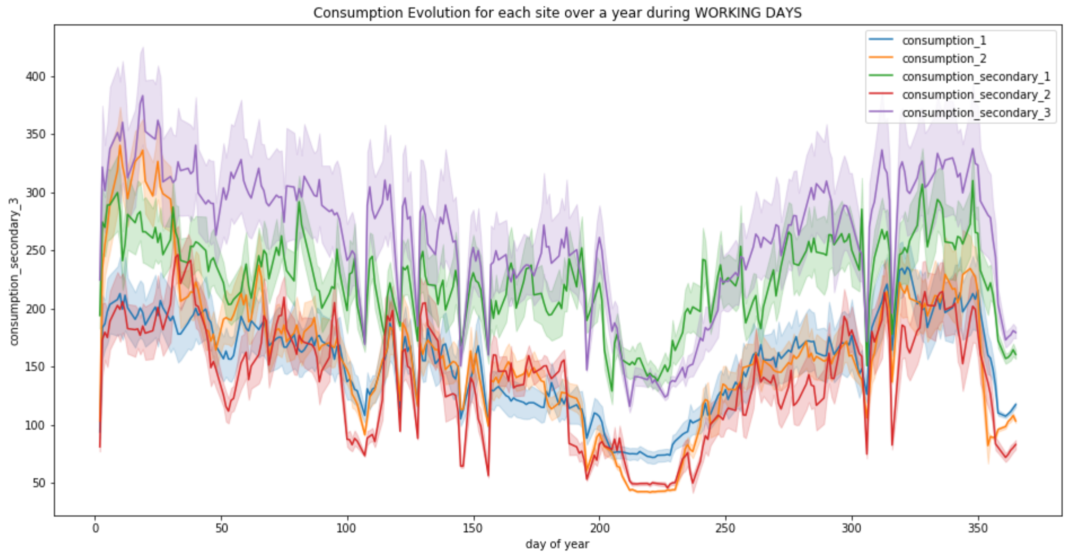
The consumption is lower during the week-end. So we can deduce that those sites are not housings.

In [21]:
```
plt.figure(figsize=(16, 8))
plt.title("Consumption Evolution for each site over a year")
for c in ['consumption_1', 'consumption_2', 'consumption_secondary_1', 'consump
    sns.lineplot(x="day of year", y=c, data=df_viz, label=c)
plt.show()
```

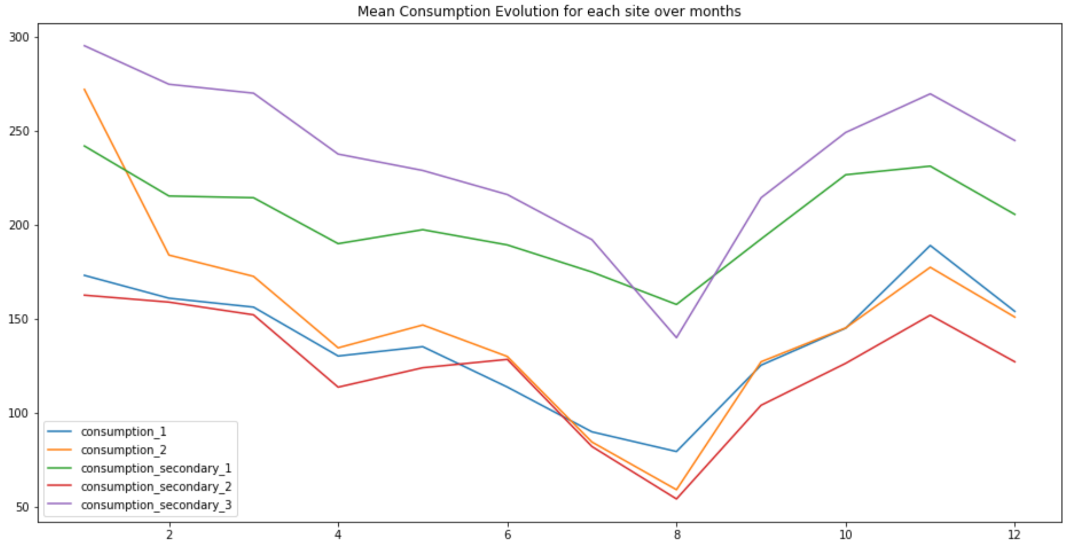


We can see that globally the mean consumption decreases until the summer, then increases until the end of the year.

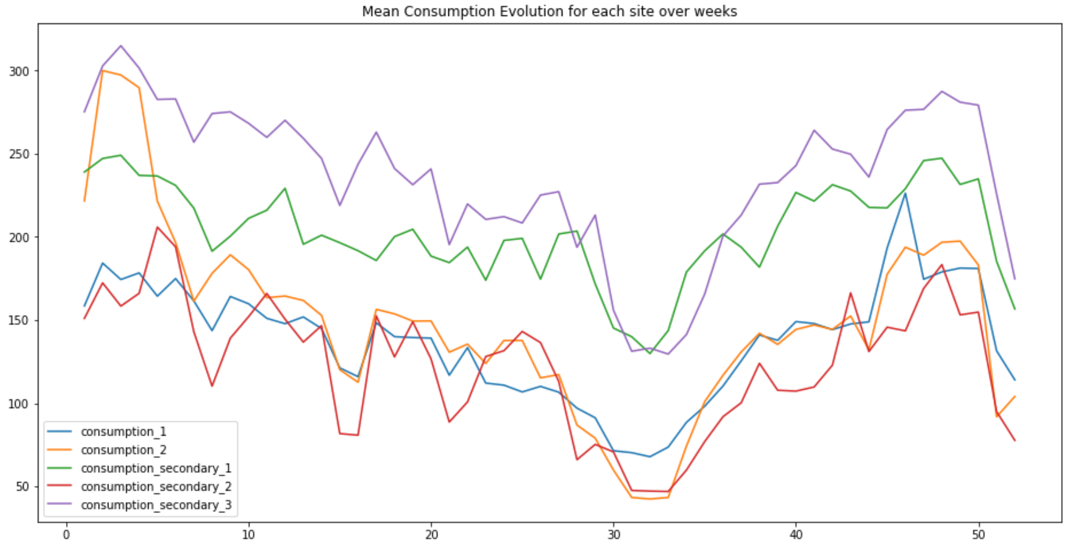
In [22]:
```
plt.figure(figsize=(16, 8))
plt.title("Consumption Evolution for each site over a year during WORKING DAYS'
for c in ['consumption_1', 'consumption_2', 'consumption_secondary_1', 'consump
    sns.lineplot(x="day of year", y=c, data=df_viz[~df_viz['day'].isin(['Saturc
plt.show()
```



In [23]:
```
plt.figure(figsize=(16, 8))
plt.title("Mean Consumption Evolution for each site over months")
for c in ['consumption_1', 'consumption_2', 'consumption_secondary_1', 'consump
    sns.lineplot(data=df_viz.groupby(['month'])[c].mean(), label=c)
plt.show()
```

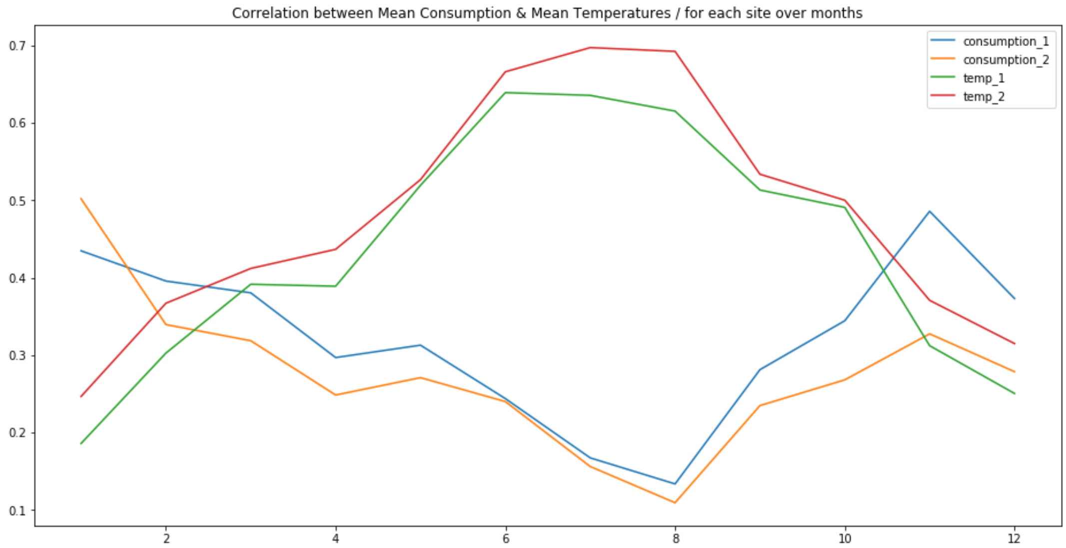


In [24]:
```
plt.figure(figsize=(16, 8))
plt.title("Mean Consumption Evolution for each site over weeks")
for c in ['consumption_1', 'consumption_2', 'consumption_secondary_1', 'consump
    sns.lineplot(data=df_viz.groupby(['week of year'])[c].mean(), label=c)
plt.show()
```



In [25]:
```
temp_consumption_cols = ['consumption_1', 'consumption_2', 'temp_1', 'temp_2']
df_viz[temp_consumption_cols] = MinMaxScaler().fit_transform(df_viz[temp_consun

plt.figure(figsize=(16, 8))
plt.title("Correlation between Mean Consumption & Mean Temperatures / for each
for c in temp_consumption_cols:
    sns.lineplot(data=df_viz.groupby(['month'])[c].mean(), label=c)
plt.show()
```

```
/home/sunflowa/Anaconda/lib/python3.7/site-packages/sklearn/preprocessing/dat
a.py:334: DataConversionWarning: Data with input dtype int64, float64 were all
converted to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
```



Electricity consumption and temperatures seem to be negatively correlated.

Features Engineering

Special dates - non working days "Jours fériés"

(credits: Antoine Augusti https://github.com/AntoineAugusti/jours-feries-france (https://github.com/AntoineAugusti/jours-feries-france))

In [26]:
```
jf = pd.read_csv(os.path.join(input_dir, 'jours_feries_seuls.csv')).drop(columr
# the date column is kept as a string for merging purposes
jf['est_jour_ferie'] = jf['est_jour_ferie'].astype('int')
jf.tail()
```

Out[26]:

	date	est_jour_ferie
1102	2050-07-14	1
1103	2050-08-15	1
1104	2050-11-01	1
1105	2050-11-11	1
1106	2050-12-25	1

In [27]:
```
if est_jour_ferie.unique()
```
Out[27]:
```
array([1])
```

Holidays

(credits: Antoine Augusti https://www.data.gouv.fr/fr/datasets/vacances-scolaires-par-zones/ (https://www.data.gouv.fr/fr/datasets/vacances-scolaires-par-zones/))

In [28]:
```
holidays = pd.read_csv(os.path.join(input_dir, 'vacances-scolaires.csv')).drop(
# the date column is kept as a string for merging purposes
for col in ['vacances_zone_a', 'vacances_zone_b', 'vacances_zone_c']:
    holidays[col] = holidays[col].astype('int')
holidays.tail()
```
Out[28]:

	date	vacances_zone_a	vacances_zone_b	vacances_zone_c
11318	2020-12-27	0	0	0
11319	2020-12-28	0	0	0
11320	2020-12-29	0	0	0
11321	2020-12-30	0	0	0
11322	2020-12-31	0	0	0

Sunlight hours

work in progress, more to come in the next days...stay tuned :)

Merging all infos

In [29]:
```
def merge_infos(data_frame):
    data_frame = pd.merge(data_frame, holidays, on='date', how='left')
    data_frame = pd.merge(data_frame, jf, on='date', how='left')
    return data_frame
```
In [30]:
```
df = merge_infos(df)
df.vacances_zone_a.value_counts()/24
```
Out[30]:
```
0    243.958333
1    121.041667
Name: vacances_zone_a, dtype: float64
```
In [31]:
```
df.est_jour_ferie.value_counts()/24
```
Out[31]:
```
1.0    11.0
Name: est_jour_ferie, dtype: float64
```

Cleaning Data

In [32]:
```
def cleaning_data(data_frame):

    # The Nan values of the column "est_jour_ferie" correspond to working days
    # because in the dataset merged with, there is only non working days
    data_frame['est_jour_ferie'] = data_frame['est_jour_ferie'].fillna(0)

    # At first, missing values in the temperatures and humidity columns are rep
    # later another approach with open data of means of the corresponding month
    for c in ['temp_1', 'temp_2', 'humidity_1', 'humidity_2']:
        data_frame[c] = data_frame[c].fillna(data_frame[c].median())

    return data_frame
```

In [33]:
```
df = cleaning_data(df)
df.isnull().sum()
```

Out[33]:
```
timestamp                 0
temp_1                    0
temp_2                    0
mean_national_temp        0
humidity_1                0
humidity_2                0
loc_1                     0
loc_2                     0
loc_secondary_1           0
loc_secondary_2           0
loc_secondary_3           0
consumption_secondary_1   0
consumption_secondary_2   0
consumption_secondary_3   0
datetime                  0
month                     0
week of year              0
day of year               0
day                       0
hour                      0
date                      0
vacances_zone_a           0
vacances_zone_b           0
vacances_zone_c           0
est_jour_ferie            0
dtype: int64
```

In [34]:
```
df.head()
```

Out[34]:

	timestamp	temp_1	temp_2	mean_national_temp	humidity_1	humidity_2	loc_1	loc_2
0	2016-11-01T00:00:00.0	8.3	14.5	11.1	95.0	65.0	(50.633, 3.067)	(43.530, 5.447)
1	2016-11-01T01:00:00.0	8.0	14.5	11.1	98.0	65.0	(50.633, 3.067)	(43.530, 5.447)
2	2016-11-01T02:00:00.0	6.8	14.5	11.0	97.0	65.0	(50.633, 3.067)	(43.530, 5.447)
3	2016-11-01T03:00:00.0	7.5	14.5	10.9	99.0	65.0	(50.633, 3.067)	(43.530, 5.447)
4	2016-11-01T04:00:00.0	6.1	14.5	10.8	98.0	65.0	(50.633, 3.067)	(43.530, 5.447)

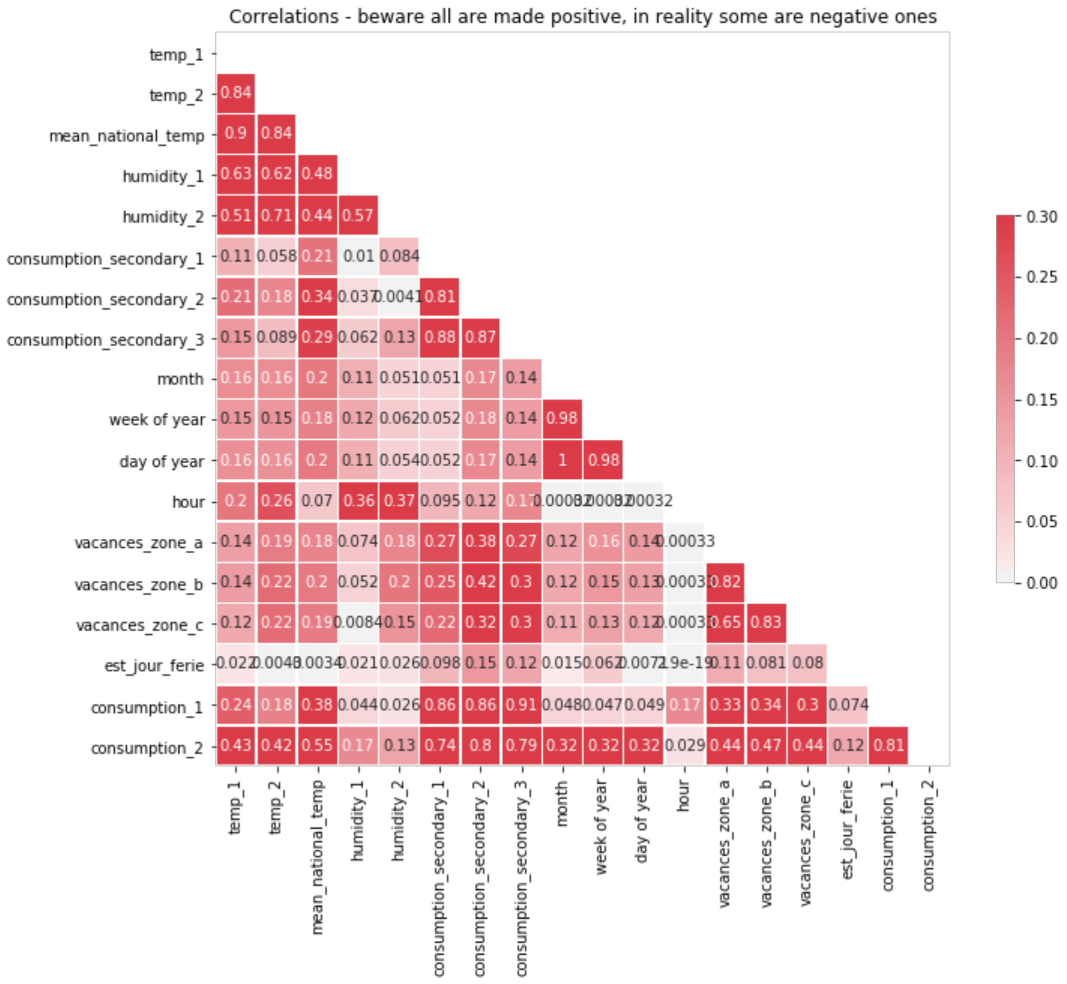
Correlations

In [35]:
```
# after dummies
# sns.pairplot(df_viz.select_dtypes(['int64', 'float64']))# apply(pd.Series.nu
```

In [36]:
```
df_viz = pd.concat((df, df_out), axis=1)
corr = df_viz.corr()

# makes all correlations positive for the heatmap
corr = np.sqrt(corr * corr)
```

In [37]:
```
# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
plt.title('Correlations - beware all are made positive, in reality some are neg
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}, annot=True)
```

Out[37]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f0389be4b00>`



There medium correlations between weather informations. The given sites have also positively correlated consumption, this makes sense because all sites are housings. The targets seem to be weakly correlated with time infos...

Comparison between X_train & X_test

In [38]:
```
X_test = pd.read_csv(os.path.join(input_dir, 'input_test_cdKcI0e.csv'), index_c
X_test.iloc[23:26]
```

Out[38]:

ID	timestamp	temp_1	temp_2	mean_national_temp	humidity_1	humidity_2	loc_1	loc_
8783	2017-11-01T23:00:00.0	9.0	9.0	9.4	78.0	95.0	(50.633, 3.067)	(43.53(5.447
8784	2017-11-02T00:00:00.0	8.8	8.6	9.4	79.0	95.0	(50.633, 3.067)	(43.53(5.447
8785	2017-11-02T01:00:00.0	7.6	8.8	9.4	82.0	96.0	(50.633, 3.067)	(43.53(5.447

In [39]:
```
df.shape, X_test.shape
```

Out[39]: ((8760, 25), (8736, 14))

There are 24 lines (hours) more wich correspond to one day, because 2016 was a leap year

In [40]:
```
X_test.iloc[[0, -1]]
```

Out[40]:

ID	timestamp	temp_1	temp_2	mean_national_temp	humidity_1	humidity_2	loc_1	loc
8760	2017-11-01T00:00:00.0	6.5	7.1	8.8	91.0	82.0	(50.633, 3.067)	(43.5: 5.44
17495	2018-10-30T23:00:00.0	7.5	11.2	6.7	85.0	77.0	(50.633, 3.067)	(43.5: 5.44

In [41]:
```
df.iloc[[0, -1]]
```

Out[41]:

	timestamp	temp_1	temp_2	mean_national_temp	humidity_1	humidity_2	loc_1	loc_
0	2016-11-01T00:00:00.0	8.3	14.5	11.1	95.0	65.0	(50.633, 3.067)	(43.53(5.447
8759	2017-10-31T23:00:00.0	7.0	7.9	8.8	90.0	78.0	(50.633, 3.067)	(43.53(5.447

There is a difference in the length of the two dataframes X_train & X_test

Data preparation

In [42]:
```
feat_to_drop = [
'timestamp',
'loc_1',
'loc_2',
'loc_secondary_1',
'loc_secondary_2',
'loc_secondary_3',
'datetime',
'date']
```

In [43]:
```
feat_to_scale = [
'temp_1',
'temp_2',
'mean_national_temp',
'humidity_1',
'humidity_2',
'consumption_secondary_1',
'consumption_secondary_2',
'consumption_secondary_3']
```

In [44]:
```
feat_to_dummies = [
'day',
'month',
'week of year',
#'day of year',
'hour']
```

Side note : let's try to run models without dummification of day of year

In [45]:
```
def prepare_feat_df(data_frame):
    data_frame = data_frame.drop(columns=feat_to_drop)
    data_frame[feat_to_scale] = MinMaxScaler().fit_transform(data_frame[feat_to
    data_frame = pd.get_dummies(data=data_frame, columns=feat_to_dummies, drop_
    return data_frame
```

In [46]:
```
df = prepare_feat_df(df)
df.head(2)
```

```
/home/sunflowa/Anaconda/lib/python3.7/site-packages/sklearn/preprocessing/dat
a.py:334: DataConversionWarning: Data with input dtype int64, float64 were all
converted to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
```

Out[46]:

	temp_1	temp_2	mean_national_temp	humidity_1	humidity_2	consumption_secondary_1	consumptio
0	0.356234	0.466667	0.428571	0.936709	0.609195	0.155263	
1	0.348601	0.466667	0.428571	0.974684	0.609195	0.150000	

2 rows × 104 columns

Data Preparation

In [47]:
```
def prepare_data(input_file_name, output_file_name1, output_file_name2):
    data_frame = pd.read_csv(os.path.join(input_dir, input_file_name), index_cc

    data_frame = transform_datetime_infos(data_frame)
    data_frame = merge_infos(data_frame)
    data_frame = cleaning_data(data_frame)
    data_frame = prepare_feat_df(data_frame)

    df_1 = data_frame.drop(columns=['temp_2', 'humidity_2'])
    df_2 = data_frame.drop(columns=['temp_1', 'humidity_1'])

    df_1.to_csv(os.path.join(output_dir, output_file_name1), index=False)
    df_2.to_csv(os.path.join(output_dir, output_file_name2), index=False)

    #return df_1, df_2
```

In [48]:
```
prepare_data('input_training_ssnsrY0.csv', 'X_train_1.csv', 'X_train_2.csv')
prepare_data('input_test_cdKcI0e.csv', 'X_test_1.csv', 'X_test_2.csv')
```

```
/home/sunflowa/Anaconda/lib/python3.7/site-packages/sklearn/preprocessing/dat
a.py:334: DataConversionWarning: Data with input dtype int64, float64 were all
converted to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
/home/sunflowa/Anaconda/lib/python3.7/site-packages/sklearn/preprocessing/dat
a.py:334: DataConversionWarning: Data with input dtype int64, float64 were all
converted to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
```

In [55]:
```
pd.read_csv(os.path.join(output_dir, 'X_train_1.csv')).head()
```

Out[55]:

	temp_1	mean_national_temp	humidity_1	consumption_secondary_1	consumption_secondary_2	consu
0	0.356234	0.428571	0.936709	0.155263	0.208451	
1	0.348601	0.428571	0.974684	0.150000	0.169014	
2	0.318066	0.425249	0.962025	0.152632	0.169014	
3	0.335878	0.421927	0.987342	0.144737	0.169014	
4	0.300254	0.418605	0.974684	0.184211	0.169014	

5 rows × 102 columns

In [73]:
```
df_out['consumption_1'].to_csv(os.path.join('..', 'output', 'y_train_1.csv'), i
df_out['consumption_2'].to_csv(os.path.join('..', 'output', 'y_train_2.csv'), i
```

Conclusion

In this first part, we've made an exploration of the data, thus you can see :

- how the weather (and particularly the temperature) could influence the electricity consumption. And the other correlations.
- how cyclic time infos are, and how the consumption vary depending on the hour of the day, the day of the week and the week of the year Then we've have cleaned and prepared the datasets that will be used in the following part by the machine learning models.