In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.graph_objs as go
```

In [2]:

```
df = pd.read_csv('energydata_complete.csv')
```

In [3]:

```
df.head(4)
```

Out[3]:

	date	Appliances	lights	T1	RH_1	T2	RH_2	T3	RH_3	T4
0	2016-01-11 17:00:00	60	30	19.89	47.596667	19.2	44.790000	19.79	44.730000	19.000000
1	2016-01-11 17:10:00	60	30	19.89	46.693333	19.2	44.722500	19.79	44.790000	19.000000
2	2016-01-11 17:20:00	50	30	19.89	46.300000	19.2	44.626667	19.79	44.933333	18.926667
3	2016-01-11 17:30:00	50	40	19.89	46.066667	19.2	44.590000	19.79	45.000000	18.890000

4 rows × 29 columns

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19735 entries, 0 to 19734
Data columns (total 29 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   date         19735 non-null  object 
 1   Appliances   19735 non-null  int64  
 2   lights       19735 non-null  int64  
 3   T1           19735 non-null  float64
 4   RH_1         19735 non-null  float64
 5   T2           19735 non-null  float64
 6   RH_2         19735 non-null  float64
 7   T3           19735 non-null  float64
 8   RH_3         19735 non-null  float64
 9   T4           19735 non-null  float64
 10  RH_4         19735 non-null  float64
 11  T5           19735 non-null  float64
 12  RH_5         19735 non-null  float64
 13  T6           19735 non-null  float64
 14  RH_6         19735 non-null  float64
 15  T7           19735 non-null  float64
 16  RH_7         19735 non-null  float64
 17  T8           19735 non-null  float64
 18  RH_8         19735 non-null  float64
 19  T9           19735 non-null  float64
 20  RH_9         19735 non-null  float64
 21  T_out        19735 non-null  float64
 22  Press_mm_hg  19735 non-null  float64
 23  RH_out       19735 non-null  float64
 24  Windspeed    19735 non-null  float64
 25  Visibility   19735 non-null  float64
 26  Tdewpoint    19735 non-null  float64
 27  rv1          19735 non-null  float64
 28  rv2          19735 non-null  float64
dtypes: float64(26), int64(2), object(1)
memory usage: 4.4+ MB
```

In [5]:

```
df.columns
```

Out[5]:

```
Index(['date', 'Appliances', 'lights', 'T1', 'RH_1', 'T2', 'RH_2', 'T3',
       'RH_3', 'T4', 'RH_4', 'T5', 'RH_5', 'T6', 'RH_6', 'T7', 'RH_7', 'T8',
       'RH_8', 'T9', 'RH_9', 'T_out', 'Press_mm_hg', 'RH_out', 'Windspeed',
       'Visibility', 'Tdewpoint', 'rv1', 'rv2'],
      dtype='object')
```

In [6]:

```
df1 = df.rename(columns={'date':'date_time', 'Appliances':'a_energy', 'lights':'l_energ
                         'T1':'kitchen_temp', 'RH_1':'kitchen_hum', 'T2' : 'liv_temp',
                         'RH_2' : 'liv_hum', 'T3' : 'laun_temp', 'RH_3' : 'laun_hum',
                         'T4' : 'off_temp', 'RH_4' : 'off_hum', 'T5' : 'bath_temp',
                         'RH_5' : 'bath_hum', 'T6' : 'out_b_temp', 'RH_6' : 'out_b_hum
                         'T7' : 'iron_temp', 'RH_7' : 'iron_hum', 'T8' : 'teen_temp',
                         'RH_8' : 'teen_hum', 'T9' : 'par_temp', 'RH_9' : 'par_hum',
                         'T_out' : 'out_temp', 'Press_mm_hg' : 'out_press', 'RH_out' :
                         'Windspeed' : 'wind', 'Visibility' : 'visibility',
                         'Tdewpoint' : 'dew_point', 'rv1' : 'rv1', 'rv2' : 'rv2'} )
```

The a_energy and l_energy columns are the energy consumed by the appliances and lights respectively and are both in Wh (watt-hour). The temperature columns are all in degree Celsius and humidity columns are in %. The pressure column is in mmHg, the wind speed column is in meters per second, visibility is in kilometers, and Tdewpoint is in degree Celsius.

In [7]:

```
df1.head(2)
```

Out[7]:

	date_time	a_energy	l_energy	kitchen_temp	kitchen_hum	liv_temp	liv_hum	laun_temp	la
0	2016-01-11 17:00:00	60	30	19.89	47.596667	19.2	44.7900	19.79	
1	2016-01-11 17:10:00	60	30	19.89	46.693333	19.2	44.7225	19.79	

2 rows × 29 columns

In [8]:

```
df1.tail(2)
```

Out[8]:

	date_time	a_energy	l_energy	kitchen_temp	kitchen_hum	liv_temp	liv_hum	laun_t
19733	2016-05-27 17:50:00	420	10	25.5	46.99	25.414000	43.036000	26.89
19734	2016-05-27 18:00:00	430	10	25.5	46.60	25.264286	42.971429	26.82

2 rows × 29 columns

Looking at the date_time column, the collection of the data was from 11^{th} January 2016 to 27^{th} 2016 which is about 4.5 months.

In [9]:

```
df1.describe().T
```

Out[9]:

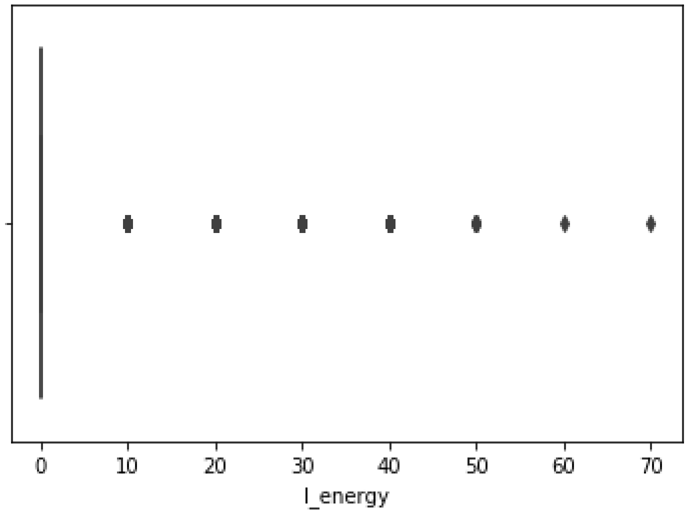
	count	mean	std	min	25%	50%	75%
a_energy	19735.0	97.694958	102.524891	10.000000	50.000000	60.000000	100.000000
l_energy	19735.0	3.801875	7.935988	0.000000	0.000000	0.000000	0.000000
kitchen_temp	19735.0	21.686571	1.606066	16.790000	20.760000	21.600000	22.600000
kitchen_hum	19735.0	40.259739	3.979299	27.023333	37.333333	39.656667	43.066667
liv_temp	19735.0	20.341219	2.192974	16.100000	18.790000	20.000000	21.500000
liv_hum	19735.0	40.420420	4.069813	20.463333	37.900000	40.500000	43.260000
laun_temp	19735.0	22.267611	2.006111	17.200000	20.790000	22.100000	23.290000
laun_hum	19735.0	39.242500	3.254576	28.766667	36.900000	38.530000	41.760000
off_temp	19735.0	20.855335	2.042884	15.100000	19.530000	20.666667	22.100000
off_hum	19735.0	39.026904	4.341321	27.660000	35.530000	38.400000	42.156667
bath_temp	19735.0	19.592106	1.844623	15.330000	18.277500	19.390000	20.619643
bath_hum	19735.0	50.949283	9.022034	29.815000	45.400000	49.090000	53.663333
out_b_temp	19735.0	7.910939	6.090347	-6.065000	3.626667	7.300000	11.256000
out_b_hum	19735.0	54.609083	31.149806	1.000000	30.025000	55.290000	83.226667
iron_temp	19735.0	20.267106	2.109993	15.390000	18.700000	20.033333	21.600000
iron_hum	19735.0	35.388200	5.114208	23.200000	31.500000	34.863333	39.000000
teen_temp	19735.0	22.029107	1.956162	16.306667	20.790000	22.100000	23.390000
teen_hum	19735.0	42.936165	5.224361	29.600000	39.066667	42.375000	46.536000
par_temp	19735.0	19.485828	2.014712	14.890000	18.000000	19.390000	20.600000
par_hum	19735.0	41.552401	4.151497	29.166667	38.500000	40.900000	44.338095
out_temp	19735.0	7.411665	5.317409	-5.000000	3.666667	6.916667	10.408333
out_press	19735.0	755.522602	7.399441	729.300000	750.933333	756.100000	760.933333
out_hum	19735.0	79.750418	14.901088	24.000000	70.333333	83.666667	91.666667
wind	19735.0	4.039752	2.451221	0.000000	2.000000	3.666667	5.500000
visibility	19735.0	38.330834	11.794719	1.000000	29.000000	40.000000	40.000000
dew_point	19735.0	3.760707	4.194648	-6.600000	0.900000	3.433333	6.566667
rv1	19735.0	24.988033	14.496634	0.005322	12.497889	24.897653	37.583769
rv2	19735.0	24.988033	14.496634	0.005322	12.497889	24.897653	37.583769

The a_energy column has a maximum value of 1,080, but the mean is around 97. This means that there are a few extreme values that might be outliers. The l_energy column has a 0 value for minimum, 25%, 50%, and 75%, and then has 70 as its maximum value. Something doesn't seem right here, so let's find out what doesn't seem right.

Analyzing the Light Energy(l_energy) Consumption column

In [10]:

```
1 light_box = sns.boxplot(df1.l_energy)
```



In [11]:

```
1 df1['l_energy'].value_counts()
```

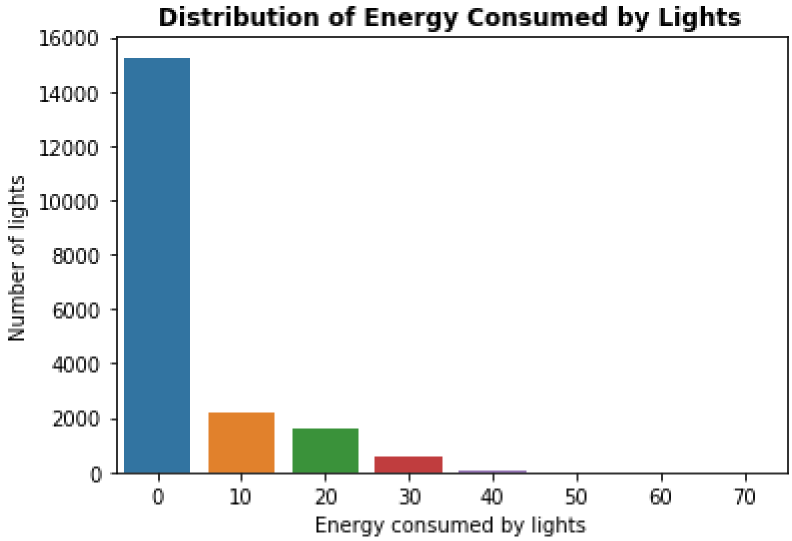
Out[11]:

```
0     15252
10     2212
20     1624
30      559
40       77
50        9
60        1
70        1
Name: l_energy, dtype: int64
```

From the preceding plot and the above output, we see the there are 8 unique values in the *l_energy* column with 0 as the highest.

In [12]:

```
lights = sns.barplot(x=df1['l_energy'].value_counts().index, y=df1['l_energy'].value_cc
lights.set_xlabel('Energy consumed by lights')
lights.set_ylabel('Number of lights')
lights.set_title("Distribution of Energy Consumed by Lights", weight='bold');
```



In [13]:

```
((df1.l_energy==0).sum()/df1.shape[0])*100
```

Out[13]:

```
77.28401317456296
```

77% of the instances in the l_energy column have 0 Wh. This renders the l_energy column quite useless because we can't possibly find any links between it and the other data. I'll get rid of this column.

In [14]:

```
new_df = df1
new_df.drop(columns=['l_energy'], inplace=True)
```

In [15]:

```
1 new_df.head(3)
```

Out[15]:

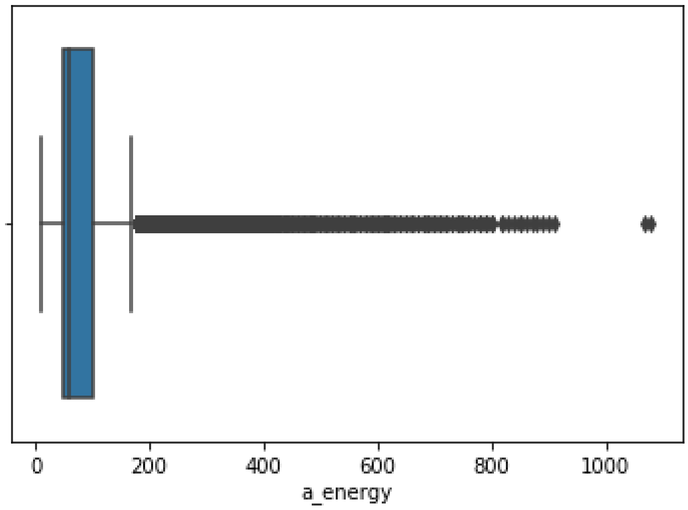
	date_time	a_energy	kitchen_temp	kitchen_hum	liv_temp	liv_hum	laun_temp	laun_hum
0	2016-01-11 17:00:00	60	19.89	47.596667	19.2	44.790000	19.79	44.730000
1	2016-01-11 17:10:00	60	19.89	46.693333	19.2	44.722500	19.79	44.790000
2	2016-01-11 17:20:00	50	19.89	46.300000	19.2	44.626667	19.79	44.933333

3 rows × 28 columns

Analyzing the Appliances Energy(a_energy) Consumption column

In [16]:

```
1 app_box = sns.boxplot(new_df.a_energy)
```



You can see that a majority of the values seem to lie between 50 Wh and 100 Wh. However, some values extend the upper bracket of 200 Wh and go beyond 1000 Wh. This seems odd. Check to see how many values extend above 200 Wh.

In [17]:

```
1 (new_df['a_energy']>200).sum()
```

Out[17]:

1916

In [18]:

```
((new_df['a_energy']>200).sum()/new_df.shape[0])*100
```

Out[18]:

```
9.708639473017481
```

In [19]:

```
(new_df['a_energy']>950).sum()
```

Out[19]:

```
2
```

In [20]:

```
((new_df['a_energy']>950).sum()/new_df.shape[0])*100
```

Out[20]:

```
0.010134279199391943
```

Only 0.01% of the instances have a_energy above 950 Wh, so deleting those 2 rows seems okay. However, close to 10% of the instances have a_energy above 200 Wh.

In [21]:

```
above_200_list = list(new_df.loc[(new_df['a_energy']>200)].index)
```

In [22]:

```
energy_df = new_df.drop(labels=above_200_list, axis=0)
```

In [23]:

```
energy_df.shape
```

Out[23]:

```
(17819, 28)
```

In [24]:

```
energy_df.describe().T
```

Out[24]:

	count	mean	std	min	25%	50%	75%
a_energy	17819.0	68.728324	31.378141	10.000000	50.000000	60.000000	80.000000
kitchen_temp	17819.0	21.687676	1.605252	16.790000	20.760000	21.600000	22.600000
kitchen_hum	17819.0	40.158323	3.933742	27.023333	37.260000	39.560000	42.900000
liv_temp	17819.0	20.294921	2.172435	16.100000	18.790000	19.926667	21.472333
liv_hum	17819.0	40.470961	4.062130	20.463333	37.930000	40.560000	43.326667
laun_temp	17819.0	22.230049	1.971209	17.200000	20.790000	22.100000	23.290000
laun_hum	17819.0	39.167393	3.223465	28.766667	36.826667	38.471429	41.590000
off_temp	17819.0	20.858577	2.048053	15.100000	19.566667	20.666667	22.100000
off_hum	17819.0	38.991000	4.324842	27.660000	35.500000	38.363333	42.090000
bath_temp	17819.0	19.607705	1.838655	15.330000	18.290000	19.390000	20.600000
bath_hum	17819.0	50.987044	9.009473	29.815000	45.400000	49.090000	53.826667
out_b_temp	17819.0	7.764725	6.031990	-6.065000	3.500000	7.160000	11.070714
out_b_hum	17819.0	54.917044	30.746291	1.000000	31.145000	55.290000	83.060000
iron_temp	17819.0	20.277619	2.102188	15.390000	18.700000	20.100000	21.600000
iron_hum	17819.0	35.435410	5.085182	23.290000	31.556905	34.900000	39.051865
teen_temp	17819.0	22.046567	1.963094	16.306667	20.823333	22.150000	23.390000
teen_hum	17819.0	43.019409	5.204613	29.600000	39.200000	42.453889	46.590000
par_temp	17819.0	19.502262	2.011673	14.890000	18.066667	19.390000	20.600000
par_hum	17819.0	41.556127	4.164766	29.166667	38.530000	40.863333	44.296667
out_temp	17819.0	7.315671	5.290522	-5.000000	3.533333	6.850000	10.333333
out_press	17819.0	755.559383	7.345043	729.366667	751.000000	756.100000	760.933333
out_hum	17819.0	80.236718	14.771215	24.000000	71.166667	84.333333	91.845238
wind	17819.0	3.975014	2.448213	0.000000	2.000000	3.500000	5.333333
visibility	17819.0	38.306600	11.951954	1.000000	29.000000	40.000000	40.000000
dew_point	17819.0	3.762120	4.186178	-6.600000	0.933333	3.433333	6.550000
rv1	17819.0	25.002765	14.519549	0.005322	12.461009	24.940753	37.660263
rv2	17819.0	25.002765	14.519549	0.005322	12.461009	24.940753	37.660263

FEATURE ENGINEERING

In [25]:

```
new_energy = energy_df.copy()
new_energy.head()
```

Out[25]:

	date_time	a_energy	kitchen_temp	kitchen_hum	liv_temp	liv_hum	laun_temp	laun_hum
0	2016-01-11 17:00:00	60	19.89	47.596667	19.2	44.790000	19.79	44.730000
1	2016-01-11 17:10:00	60	19.89	46.693333	19.2	44.722500	19.79	44.790000
2	2016-01-11 17:20:00	50	19.89	46.300000	19.2	44.626667	19.79	44.933333
3	2016-01-11 17:30:00	50	19.89	46.066667	19.2	44.590000	19.79	45.000000
4	2016-01-11 17:40:00	60	19.89	46.333333	19.2	44.530000	19.79	45.000000

5 rows × 28 columns

In [26]:

```
# I'll convert the date_time column of new_en into the DateTime format - %Y-%m-%d %H:%M
new_energy['date_time'] = pd.to_datetime(new_energy.date_time,
                                         format = '%Y-%m-%d %H:%M:%S')
```

In [27]:

```
new_energy.insert(loc = 1, column = 'month', value = new_energy.date_time.dt.month)
```

In [28]:

```
new_energy.insert(loc = 2, column = 'day', value = (new_energy.date_time.dt.dayofweek)+
```

In [29]:

```
new_energy.head(4)
```

Out[29]:

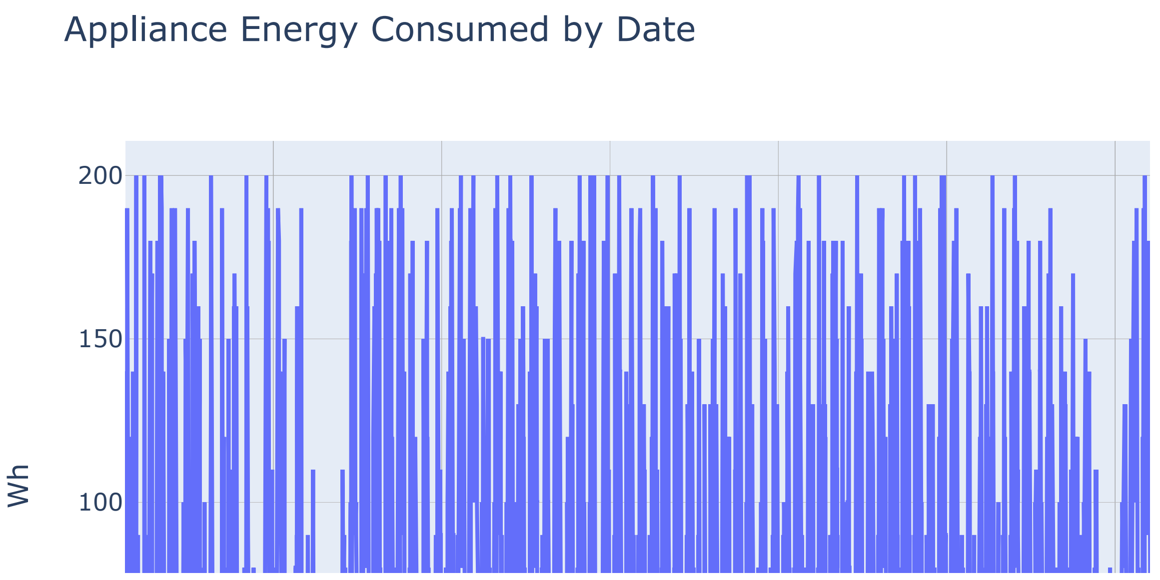
	date_time	month	day	a_energy	kitchen_temp	kitchen_hum	liv_temp	liv_hum	laun_ten
0	2016-01-11 17:00:00	1	1	60	19.89	47.596667	19.2	44.790000	19.1
1	2016-01-11 17:10:00	1	1	60	19.89	46.693333	19.2	44.722500	19.1
2	2016-01-11 17:20:00	1	1	50	19.89	46.300000	19.2	44.626667	19.1
3	2016-01-11 17:30:00	1	1	50	19.89	46.066667	19.2	44.590000	19.1

4 rows × 30 columns

Visualization

In [30]:

```
app_date = go.Scatter(x = new_energy.date_time, mode = "lines", y = new_energy.a_energy
layout = go.Layout(title = 'Appliance Energy Consumed by Date',
                   xaxis = dict(title='Date'), yaxis = dict(title='Wh'))
fig = go.Figure(data = [app_date], layout = layout)
fig.show()
```



The data seems quite evenly distributed; however, there is a dip in the energy consumed toward the end of January and the beginning of April. Let's check it out.

In [31]:

```
app_mon = new_energy.groupby(by = ['month'], as_index = False)['a_energy'].sum()
app_mon
```

Out[31]:

	month	a_energy
0	1	150060
1	2	258270
2	3	283190
3	4	274030
4	5	259120

In [32]:

```
app_mon.sort_values(by = 'a_energy', ascending = False)
```

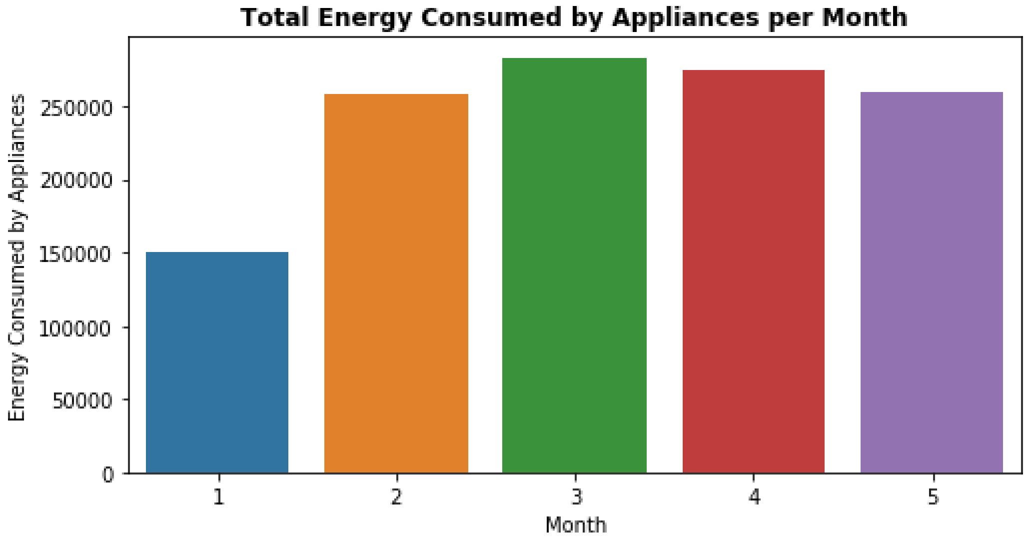
Out[32]:

	month	a_energy
2	3	283190
3	4	274030
4	5	259120
1	2	258270
0	1	150060

As you can see, March was the month during which the appliances consumed the most energy, and it was in January that they consumed the least. The difference between the energy consumed in January and February (the month during which the second least amount of energy was consumed) is approximately 100,000 Wh itself.

In [37]:

```
plt.subplots(figsize=(8,4))
am = sns.barplot(app_mon.month, app_mon.a_energy)
plt.xlabel('Month')
plt.ylabel('Energy Consumed by Appliances')
plt.title('Total Energy Consumed by Appliances per Month', weight='bold');
```



OBSERVING APPLIANCES ENERGY AND DAY

In [38]:

```
app_day =  new_energy.groupby(by = ['day'], as_index = False)['a_energy'].sum()
app_day
```

Out[38]:

	day	a_energy
0	1	161190
1	2	175930
2	3	191700
3	4	177830
4	5	161170
5	6	173640
6	7	183210

In [39]:

```
app_day.sort_values(by = 'a_energy', ascending = False)
```

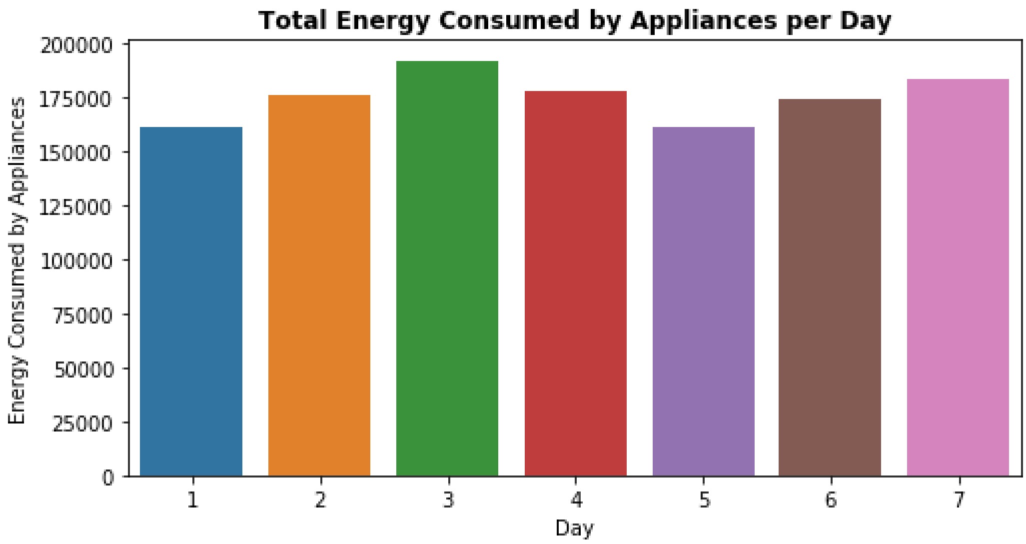
Out[39]:

	day	a_energy
2	3	191700
6	7	183210
3	4	177830
1	2	175930
5	6	173640
0	1	161190
4	5	161170

The perceding output indicates that Wednesdays were the days when the appliances consumed the most energy, which is a bit odd. The following day in the table is Sunday, which makes sense since people might be at home more. The day the least energy was consumed was Friday.

In [42]:

```
plt.subplots(figsize=(8,4))
am = sns.barplot(app_day.day, app_day.a_energy)
plt.xlabel('Day')
plt.ylabel('Energy Consumed by Appliances')
plt.title('Total Energy Consumed by Appliances per Day', weight='bold');
```



PLOTTING DISTRIBUTIONS OF THE TEMPERATURE COLUMNS

In [78]:

```
col_temp = ['kitchen_temp', 'liv_temp', 'laun_temp',
            'off_temp', 'bath_temp', 'out_b_temp',
            'iron_temp', 'teen_temp', 'par_temp']
```

In [79]:

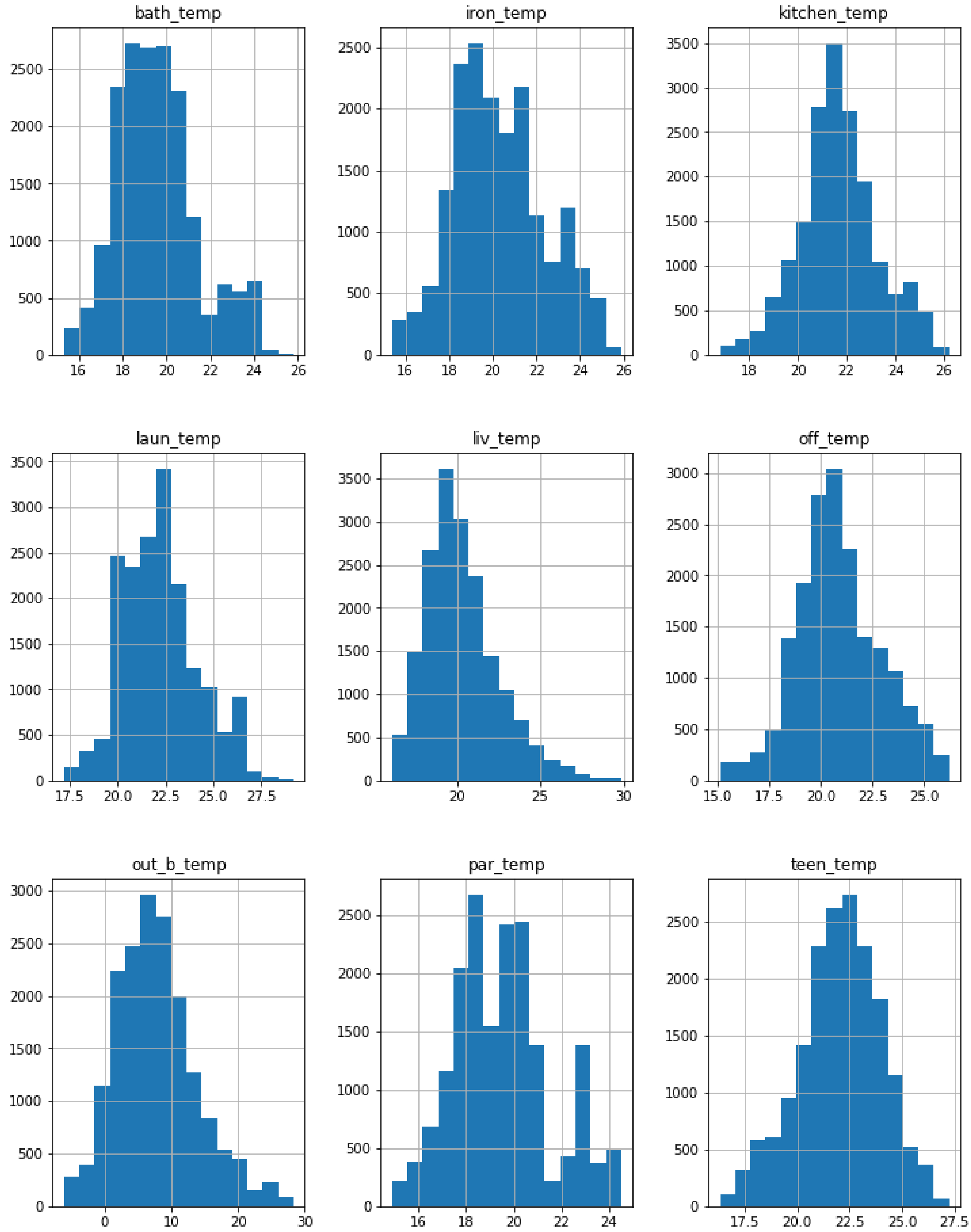
```
temp_df = new_energy[col_temp]
temp_df.head(3)
```

Out[79]:

	kitchen_temp	liv_temp	laun_temp	off_temp	bath_temp	out_b_temp	iron_temp	teen_tem
0	19.89	19.2	19.79	19.000000	17.166667	7.026667	17.2	18.
1	19.89	19.2	19.79	19.000000	17.166667	6.833333	17.2	18.
2	19.89	19.2	19.79	18.926667	17.166667	6.560000	17.2	18.

In [80]:

```
1 temp_df.hist(bins = 15, figsize = (12, 16));
```



All of these distributions seem to be following the normal distribution as they are spread across the scale with a few gradual surges in between. As you can see, there are no sudden rises or falls through the distribution and so we can conclude that the temperature data is not skewed.

PLOTTING DISTRIBUTIONS OF THE PRESSURE COLUMNS

In [71]:

```
c_ser = pd.Series(new_energy.columns)
```

In [73]:

```
hum_ser = pd.Series(c)
col_hum = list(hum_ser[hum_ser.str.contains('hum')])
```

In [76]:

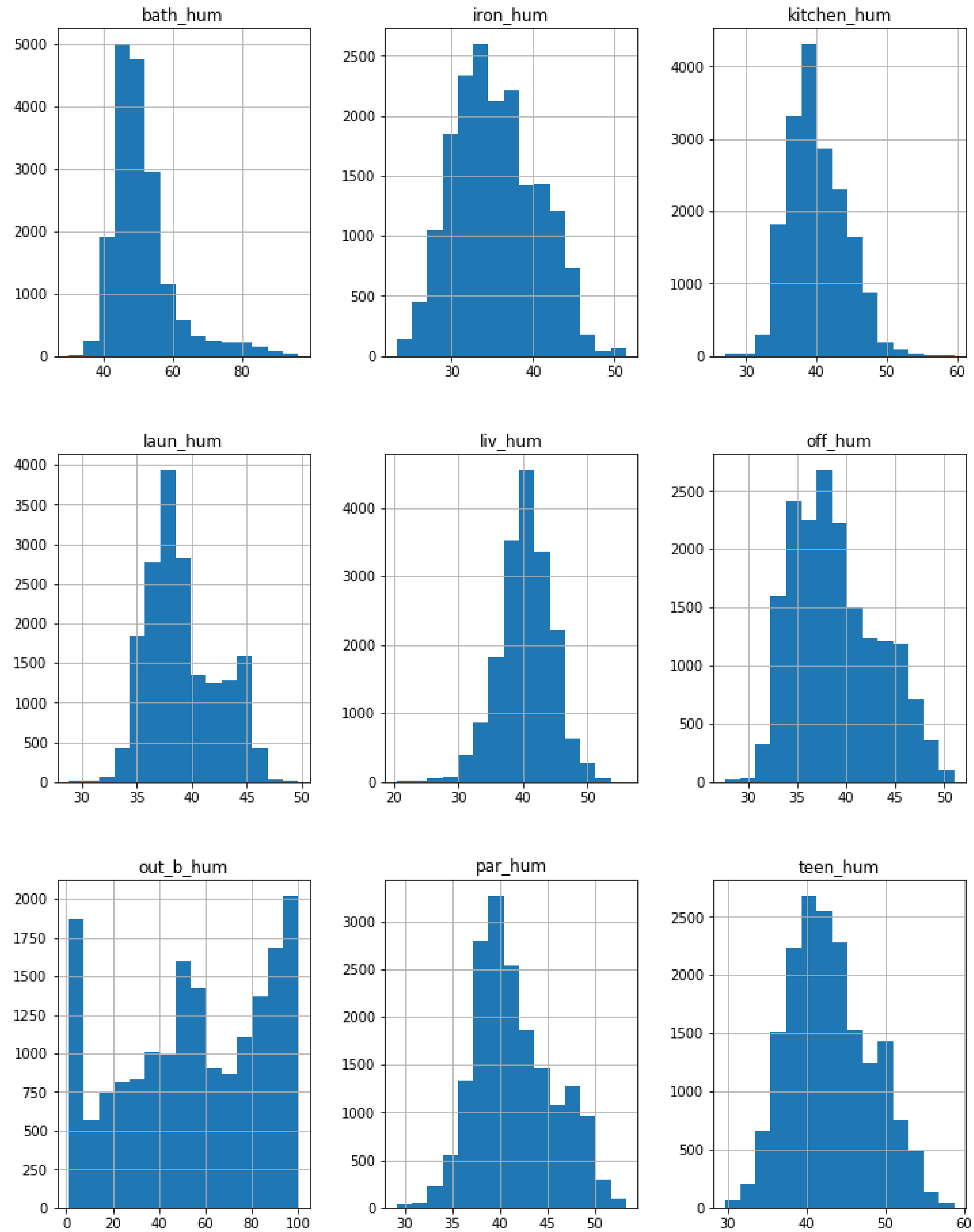
```
hum_df = new_energy[col_hum].drop(columns=['out_hum'], axis=1)
hum_df.head(3)
```

Out[76]:

	kitchen_hum	liv_hum	laun_hum	off_hum	bath_hum	out_b_hum	iron_hum	teen_hum
0	47.596667	44.790000	44.730000	45.566667	55.20	84.256667	41.626667	48.900000
1	46.693333	44.722500	44.790000	45.992500	55.20	84.063333	41.560000	48.863333
2	46.300000	44.626667	44.933333	45.890000	55.09	83.156667	41.433333	48.730000

In [77]:

```
hum_df.hist(bins = 15, figsize = (12, 16));
```



All the distributions except out_b_hum appear to be following the normal distribution. As you can see, the distribution of out_b_hum rises steeply at the extremes of the scale and the rest of the data points are spread unevenly across the x axis.

PLOTTING DISTRIBUTIONS OF THE WEATHER COLUMNS

In [81]:

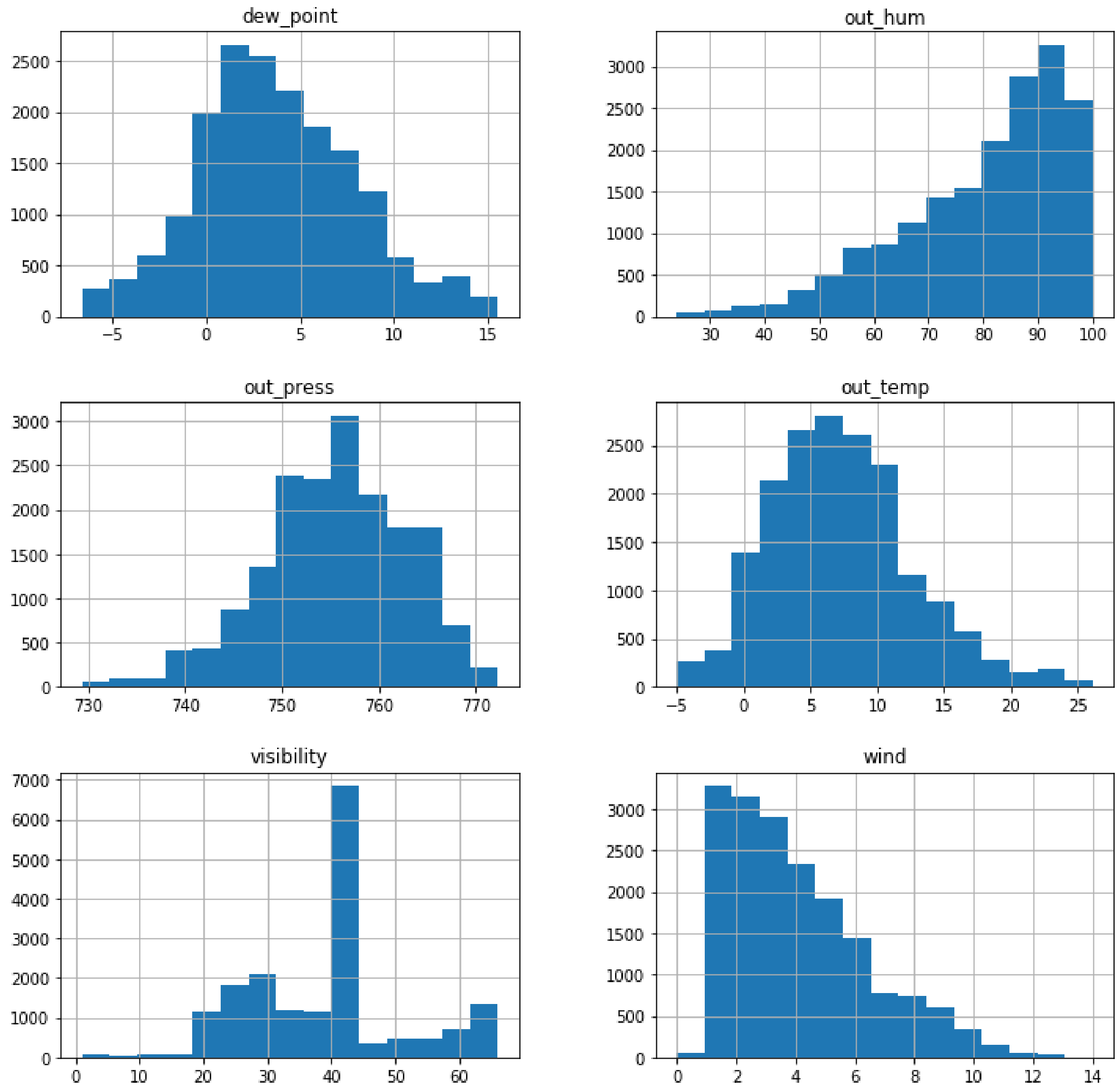
```
col_weather = ['out_temp', 'dew_point', 'out_hum', 'out_press', 'wind', 'visibility']
weather_df = new_energy[col_weather]
weather_df.head()
```

Out[81]:

	out_temp	dew_point	out_hum	out_press	wind	visibility
0	6.600000	5.3	92.0	733.5	7.000000	63.000000
1	6.483333	5.2	92.0	733.6	6.666667	59.166667
2	6.366667	5.1	92.0	733.7	6.333333	55.333333
3	6.250000	5.0	92.0	733.8	6.000000	51.500000
4	6.133333	4.9	92.0	733.9	5.666667	47.666667

In [83]:

```
weather_df.hist(bins = 15, figsize = (12, 12));
```



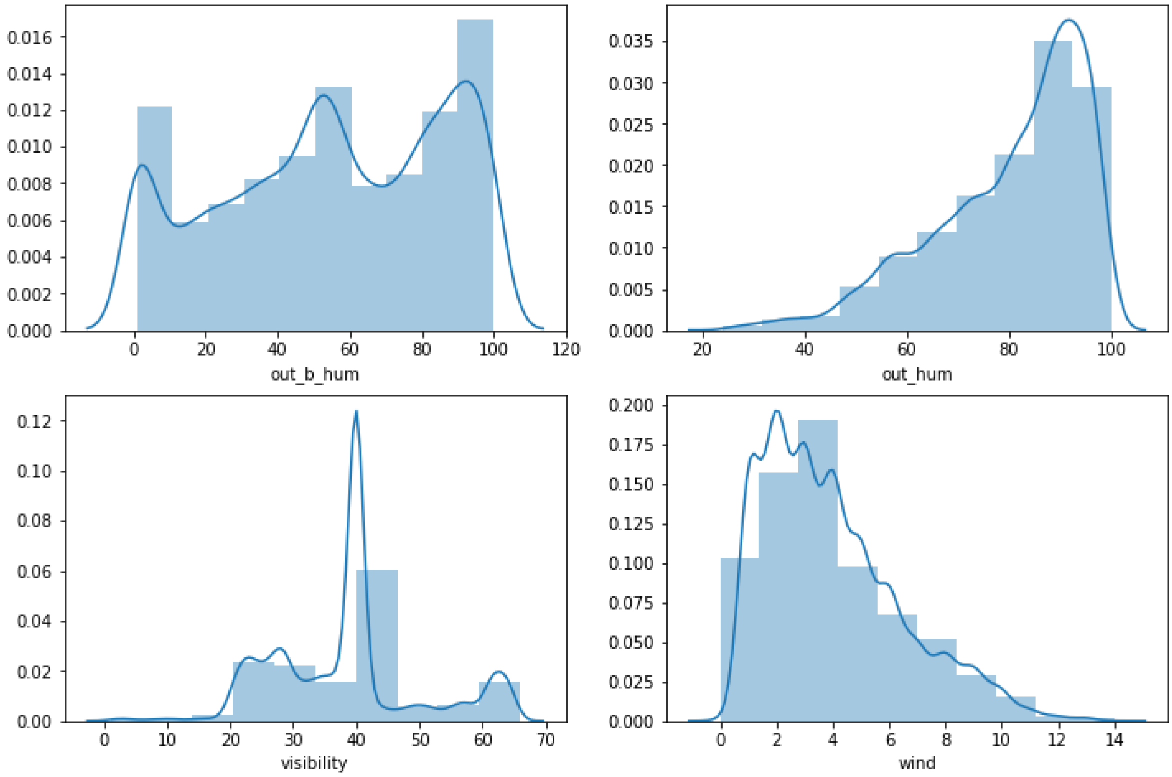
As you can see, three of these distributions are not normal: out_hum, visibility, and wind, as they

appear to show steep rises/falls through the plot. We need to find out the reason for this.

Plotting out_b, out_hum, visibility, and wind

In [84]:

```
f, ax = plt.subplots(2, 2, figsize = (12, 8))
obh = sns.distplot(hum_df["out_b_hum"], bins = 10, ax = ax[0][0])
oh = sns.distplot(weather_df["out_hum"], bins = 10, ax = ax[0][1])
vis = sns.distplot(weather_df["visibility"], bins = 10, ax = ax[1][0])
wind = sns.distplot(weather_df["wind"], bins = 10, ax = ax[1][1])
```



In [85]:

```
1 new_energy.corr()
```

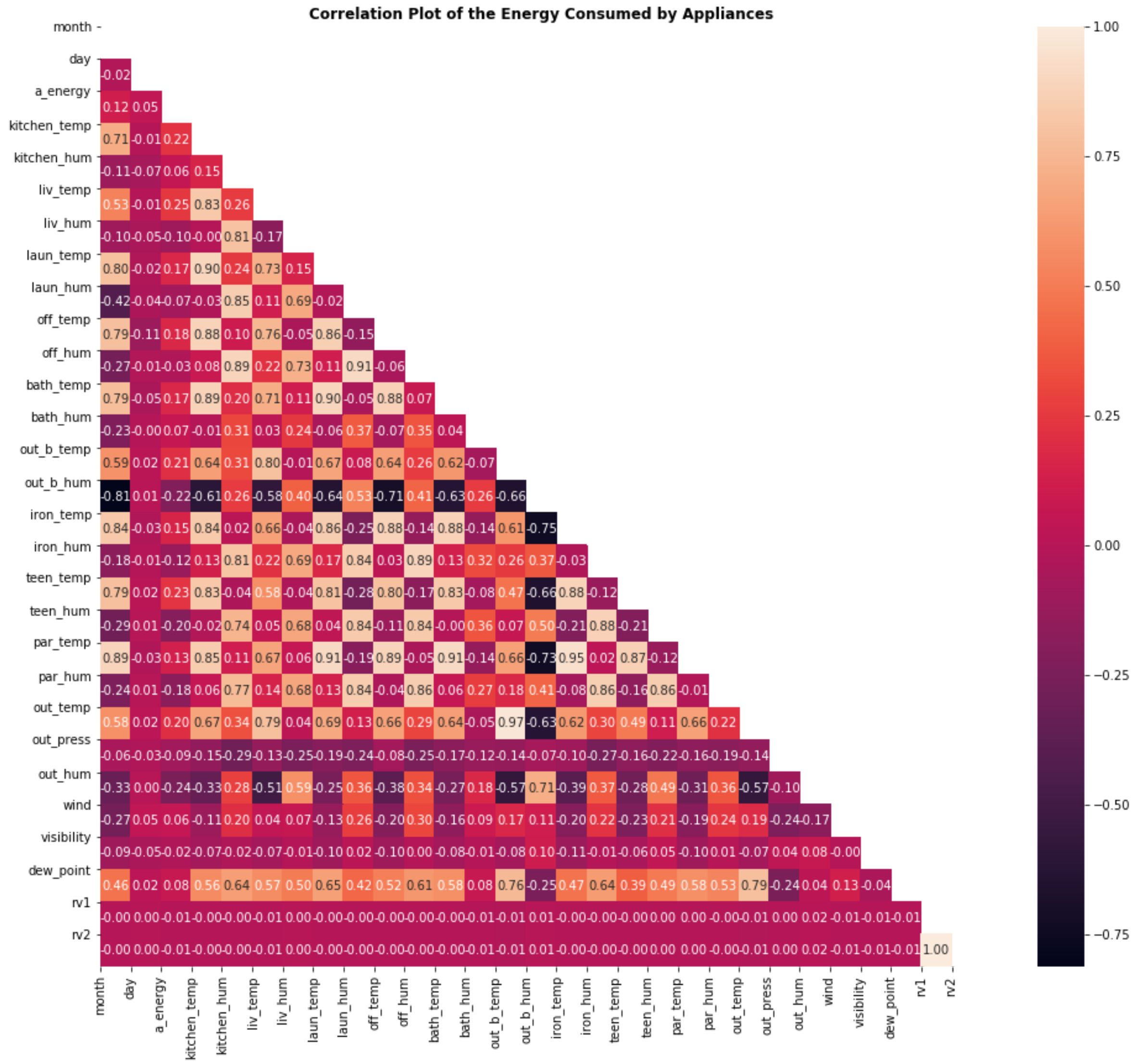
Out[85]:

	month	day	a_energy	kitchen_temp	kitchen_hum	liv_temp	liv_hum
month	1.000000	-0.016191	0.115125	0.708987	-0.106125	0.529894	-0.100761
day	-0.016191	1.000000	0.046149	-0.005030	-0.065452	-0.009717	-0.052663
a_energy	0.115125	0.046149	1.000000	0.222789	0.057062	0.246631	-0.100068
kitchen_temp	0.708987	-0.005030	0.222789	1.000000	0.153276	0.832574	-0.001788
kitchen_hum	-0.106125	-0.065452	0.057062	0.153276	1.000000	0.256966	0.805630
liv_temp	0.529894	-0.009717	0.246631	0.832574	0.256966	1.000000	-0.170334
liv_hum	-0.100761	-0.052663	-0.100068	-0.001788	0.805630	-0.170334	1.000000
laun_temp	0.799444	-0.023599	0.168179	0.896807	0.243160	0.725759	0.149026
laun_hum	-0.417525	-0.040370	-0.070810	-0.032696	0.853841	0.114513	0.688632
off_temp	0.794599	-0.108712	0.175203	0.880310	0.095862	0.758196	-0.045690
off_hum	-0.270533	-0.013330	-0.026794	0.082450	0.888905	0.218868	0.726219
bath_temp	0.786800	-0.053979	0.166719	0.886425	0.196119	0.713861	0.109408
bath_hum	-0.227631	-0.002937	0.065867	-0.007609	0.305407	0.034130	0.243451
out_b_temp	0.590502	0.018428	0.213271	0.642941	0.312131	0.797776	-0.009433
out_b_hum	-0.812664	0.011244	-0.217067	-0.612895	0.263262	-0.577933	0.396627
iron_temp	0.835467	-0.029212	0.153796	0.841692	0.019384	0.659617	-0.043039
iron_hum	-0.177165	-0.006247	-0.116821	0.125106	0.810108	0.219000	0.693278
teen_temp	0.788262	0.022484	0.234231	0.832059	-0.038402	0.577365	-0.040139
teen_hum	-0.288548	0.007751	-0.200369	-0.018868	0.741523	0.053026	0.680788
par_temp	0.889534	-0.033382	0.134592	0.847428	0.109708	0.670761	0.058399
par_hum	-0.236639	0.006655	-0.179340	0.059597	0.769947	0.143837	0.680281
out_temp	0.583420	0.022970	0.201174	0.671504	0.338990	0.788005	0.036581
out_press	-0.059009	-0.030739	-0.086890	-0.152250	-0.287800	-0.133151	-0.250262
out_hum	-0.329678	0.004130	-0.241227	-0.334571	0.283508	-0.508144	0.589211
wind	-0.270415	0.046082	0.059336	-0.106147	0.204454	0.044434	0.067913
visibility	-0.093734	-0.047817	-0.023696	-0.070878	-0.022641	-0.069253	-0.005566
dew_point	0.463486	0.024264	0.075059	0.564947	0.641620	0.574563	0.503367
rv1	-0.001082	0.003601	-0.009520	-0.003582	-0.002244	-0.007905	0.002685
rv2	-0.001082	0.003601	-0.009520	-0.003582	-0.002244	-0.007905	0.002685

29 rows × 29 columns

In [87]:

```
corr = new_energy.corr()
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
f, ax = plt.subplots(figsize=(16, 14))
sns.heatmap(corr, annot = True, fmt = ".2f", mask = mask)
plt.xticks(range(len(corr.columns)), corr.columns)
plt.yticks(range(len(corr.columns)), corr.columns)
plt.title("Correlation Plot of the Energy Consumed by Appliances", weight='bold')
plt.show()
```



In [ ]:

```
 
```