In [ ]:

Great Energy Predictor III

In this competition, you'll develop accurate models of metered building energy usage in the following areas: chilled water, electric, hot water, and steam meters. The data comes from over 1,000 buildings over a three-year timeframe. With better estimates of these energy-saving investments, large scale investors and financial institutions will be more inclined to invest in this area to enable progress in building efficiencies.

https://www.kaggle.com/c/ashrae-energy-prediction/overview/description (https://www.kaggle.com/c/ashrae-energy-prediction/overview/description)

Evaluation Metric

The evaluation metric for this competition is Root Mean Squared Logarithmic Error.

The RMSLE is calculated as

ϵ=1n∑i=1n(log(pi+1)−log(ai+1))2−−−−−−−−−−−−−−−−−−−−−−−−−√ Where:

ϵ is the RMSLE value (score) n is the total number of observations in the (public/private) data set, pi is your prediction of target, and ai is the actual target for i. log(x) is the natural logarithm of x Note that not all rows will necessarily be scored.

library

In [1]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import os
for dirname, _, filenames in os.walk('/data/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

In [47]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import gc

# matplotlib and seaborn for plotting
import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns
import matplotlib.patches as patches

from plotly import tools, subplots
import plotly.offline as py
py.init_notebook_mode(connected=True)
import plotly.graph_objs as go
import plotly.express as px
pd.set_option('max_columns', 150)

py.init_notebook_mode(connected=True)
from plotly.offline import init_notebook_mode, iplot
init_notebook_mode(connected=True)
import plotly.graph_objs as go

# matplotlib and seaborn for plotting
import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns
import matplotlib.patches as patches
from scipy import stats
from scipy.stats import skew

import os,random, math, psutil, pickle

from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import mean_squared_error
import lightgbm as lgb
from sklearn.model_selection import KFold, StratifiedKFold
from tqdm import tqdm
```

In [ ]:
```
print(os.listdir("../input/ashrae-energy-prediction/"))
```

In [4]:
```
%%time
root = '../input/ashrae-energy-prediction/'
train_df = pd.read_csv(root + 'train.csv')
train_df["timestamp"] = pd.to_datetime(train_df["timestamp"], format='%Y-%m-%d
%H:%M:%S')

weather_train_df = pd.read_csv(root + 'weather_train.csv')
test_df = pd.read_csv(root + 'test.csv')
weather_test_df = pd.read_csv(root + 'weather_test.csv')
building_meta_df = pd.read_csv(root + 'building_metadata.csv')
sample_submission = pd.read_csv(root + 'sample_submission.csv')
```

```
CPU times: user 41.9 s, sys: 6.39 s, total: 48.3 s
Wall time: 48.4 s
```

In [5]:
```
print('Size of train_df data', train_df.shape)
print('Size of weather_train_df data', weather_train_df.shape)
print('Size of weather_test_df data', weather_test_df.shape)
print('Size of building_meta_df data', building_meta_df.shape)
```

```
Size of train_df data (20216100, 4)
Size of weather_train_df data (139773, 9)
Size of weather_test_df data (277243, 9)
Size of building_meta_df data (1449, 6)
```

Reducing mmory size

In [6]:
```
## Function to reduce the DF size
def reduce_mem_usage(df, verbose=True):
    numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
    start_mem = df.memory_usage().sum() / 1024**2
    for col in df.columns:
        col_type = df[col].dtypes
        if col_type in numerics:
            c_min = df[col].min()
            c_max = df[col].max()
            if str(col_type)[:3] == 'int':
                if c_min > np.iinfo(np.int8).min and c_max < np.iinfo(np.int8)
.max:
                    df[col] = df[col].astype(np.int8)
                elif c_min > np.iinfo(np.int16).min and c_max < np.iinfo(np.in
t16).max:
                    df[col] = df[col].astype(np.int16)
                elif c_min > np.iinfo(np.int32).min and c_max < np.iinfo(np.in
t32).max:
                    df[col] = df[col].astype(np.int32)
                elif c_min > np.iinfo(np.int64).min and c_max < np.iinfo(np.in
t64).max:
                    df[col] = df[col].astype(np.int64)
            else:
                if c_min > np.finfo(np.float16).min and c_max < np.finfo(np.fl
oat16).max:
                    df[col] = df[col].astype(np.float16)
                elif c_min > np.finfo(np.float32).min and c_max < np.finfo(np.
float32).max:
                    df[col] = df[col].astype(np.float32)
                else:
                    df[col] = df[col].astype(np.float64)
    end_mem = df.memory_usage().sum() / 1024**2
    if verbose: print('Mem. usage decreased to {:5.2f} Mb ({:.1f}% reduction)'
.format(end_mem, 100 * (start_mem - end_mem) / start_mem))
    return df
```

In [7]:
```
## REducing memory
train_df = reduce_mem_usage(train_df)
test_df = reduce_mem_usage(test_df)

weather_train_df = reduce_mem_usage(weather_train_df)
weather_test_df = reduce_mem_usage(weather_test_df)
building_meta_df = reduce_mem_usage(building_meta_df)
```

```
Mem. usage decreased to 289.19 Mb (53.1% reduction)
Mem. usage decreased to 596.49 Mb (53.1% reduction)
Mem. usage decreased to  3.07 Mb (68.1% reduction)
Mem. usage decreased to  6.08 Mb (68.1% reduction)
Mem. usage decreased to  0.03 Mb (60.3% reduction)
```

It is necessary that after using this code, carefully check the output results for each column.

preparing Building DF and Weather DF

In [8]:
```
train_df['timestamp'] = pd.to_datetime(train_df['timestamp'])
test_df['timestamp'] = pd.to_datetime(test_df['timestamp'])

weather_train_df['timestamp'] = pd.to_datetime(weather_train_df['timestamp'])
weather_test_df['timestamp'] = pd.to_datetime(weather_test_df['timestamp'])

building_meta_df['primary_use'] = building_meta_df['primary_use'].astype('cate
gory')
```

In [9]:
```
temp_df = train_df[['building_id']]
temp_df = temp_df.merge(building_meta_df, on=['building_id'], how='left')
del temp_df['building_id']
train_df = pd.concat([train_df, temp_df], axis=1)

temp_df = test_df[['building_id']]
temp_df = temp_df.merge(building_meta_df, on=['building_id'], how='left')

del temp_df['building_id']
test_df = pd.concat([test_df, temp_df], axis=1)
del temp_df, building_meta_df
```

In [10]:
```
temp_df = train_df[['site_id','timestamp']]
temp_df = temp_df.merge(weather_train_df, on=['site_id','timestamp'], how='lef
t')

del temp_df['site_id'], temp_df['timestamp']
train_df = pd.concat([train_df, temp_df], axis=1)

temp_df = test_df[['site_id','timestamp']]
temp_df = temp_df.merge(weather_test_df, on=['site_id','timestamp'], how='lef
t')

del temp_df['site_id'], temp_df['timestamp']
test_df = pd.concat([test_df, temp_df], axis=1)

del temp_df, weather_train_df, weather_test_df
```

In [11]:
```
train_df.to_pickle('train_df.pkl')
test_df.to_pickle('test_df.pkl')

del train_df, test_df
gc.collect()
```

Out[11]:
```
0
```

In [17]:
```
train_df = pd.read_pickle('train_df.pkl')
test_df = pd.read_pickle('test_df.pkl')
```

Encoding variables

In [18]:
```
# Convert wind direction into categorical feature. We can split 360 degrees in
to 16-wind compass rose.
# See this: https://en.wikipedia.org/wiki/Points_of_the_compass#16-wind_compas
s_rose
def degToCompass(num):
    val=int((num/22.5))
    arr=[i for i in range(0,16)]
    return arr[(val % 16)]
```

In [19]:
```
le = LabelEncoder()

train_df['primary_use'] = le.fit_transform(train_df['primary_use']).astype(np.
int8)

test_df['primary_use'] = le.fit_transform(test_df['primary_use']).astype(np.in
t8)
```

In [21]:
```
train_df.head()
```

Out[21]:

	building_id	meter	timestamp	meter_reading	site_id	primary_use	square_feet	year_built	fl
0	0	0	2016-01-01	0.0	0	0	7432	2008.0	
1	1	0	2016-01-01	0.0	0	0	2720	2004.0	
2	2	0	2016-01-01	0.0	0	0	5376	1991.0	
3	3	0	2016-01-01	0.0	0	0	23685	2002.0	
4	4	0	2016-01-01	0.0	0	0	116607	1975.0	

In [20]:
```
train_df['age'] = train_df['year_built'].max() - train_df['year_built'] + 1
test_df['age'] = test_df['year_built'].max() - test_df['year_built'] + 1
```

Feature Selection

In [23]:
```
def average_imputation(df, column_name):
    imputation = df.groupby(['timestamp'])[column_name].mean()

    df.loc[df[column_name].isnull(), column_name] = df[df[column_name].isnull
()][[column_name]].apply(lambda x: imputation[df['timestamp'][x.index]].values
)
    del imputation
    return df
```

In [24]:
```
train_df = average_imputation(train_df, 'wind_speed')
train_df = average_imputation(train_df, 'wind_direction')

beaufort = [(0, 0, 0.3), (1, 0.3, 1.6), (2, 1.6, 3.4), (3, 3.4, 5.5), (4, 5.5,
8), (5, 8, 10.8), (6, 10.8, 13.9),
          (7, 13.9, 17.2), (8, 17.2, 20.8), (9, 20.8, 24.5), (10, 24.5, 28.5),
(11, 28.5, 33), (12, 33, 200)]

for item in beaufort:
    train_df.loc[(train_df['wind_speed']>=item[1]) & (train_df['wind_speed']<i
tem[2]), 'beaufort_scale'] = item[0]

train_df['wind_direction'] = train_df['wind_direction'].apply(degToCompass)
train_df['beaufort_scale'] = train_df['beaufort_scale'].astype(np.uint8)
train_df["wind_direction"] = train_df['wind_direction'].astype(np.uint8)
train_df["meter"] = train_df['meter'].astype(np.uint8)
train_df["site_id"] = train_df['site_id'].astype(np.uint8)


test_df = average_imputation(test_df, 'wind_speed')
test_df = average_imputation(test_df, 'wind_direction')

for item in beaufort:
    test_df.loc[(test_df['wind_speed']>=item[1]) & (test_df['wind_speed']<item
[2]), 'beaufort_scale'] = item[0]

test_df['wind_direction'] = test_df['wind_direction'].apply(degToCompass)
test_df['wind_direction'] = test_df['wind_direction'].apply(degToCompass)
test_df['beaufort_scale'] = test_df['beaufort_scale'].astype(np.uint8)
test_df["wind_direction"] = test_df['wind_direction'].astype(np.uint8)
test_df["meter"] = test_df['meter'].astype(np.uint8)
test_df["site_id"] = test_df['site_id'].astype(np.uint8)
```

Feature Engineering

In [26]:
```
###Datetime Features
```

In [27]:
```
train_df['month_datetime'] = train_df['timestamp'].dt.month.astype(np.int8)
train_df['weekofyear_datetime'] = train_df['timestamp'].dt.weekofyear.astype(n
p.int8)
train_df['dayofyear_datetime'] = train_df['timestamp'].dt.dayofyear.astype(np.
int16)

train_df['hour_datetime'] = train_df['timestamp'].dt.hour.astype(np.int8)
train_df['day_week'] = train_df['timestamp'].dt.dayofweek.astype(np.int8)
train_df['day_month_datetime'] = train_df['timestamp'].dt.day.astype(np.int8)
train_df['week_month_datetime'] = train_df['timestamp'].dt.day/7
train_df['week_month_datetime'] = train_df['week_month_datetime'].apply(lambda
x: math.ceil(x)).astype(np.int8)


test_df['month_datetime'] = test_df['timestamp'].dt.month.astype(np.int8)
test_df['weekofyear_datetime'] = test_df['timestamp'].dt.weekofyear.astype(np.
int8)
test_df['dayofyear_datetime'] = test_df['timestamp'].dt.dayofyear.astype(np.in
t16)

test_df['hour_datetime'] = test_df['timestamp'].dt.hour.astype(np.int8)
test_df['day_week'] = test_df['timestamp'].dt.dayofweek.astype(np.int8)
test_df['day_month_datetime'] = test_df['timestamp'].dt.day.astype(np.int8)
test_df['week_month_datetime'] = test_df['timestamp'].dt.day/7
test_df['week_month_datetime'] = test_df['week_month_datetime'].apply(lambda x
: math.ceil(x)).astype(np.int8)
```

In [28]:
```
train_df.head()
```

Out[28]:

	building_id	meter	timestamp	meter_reading	site_id	primary_use	square_feet	year_built	fl
0	0	0	2016-01-01	0.0	0	0	7432	2008.0	
1	1	0	2016-01-01	0.0	0	0	2720	2004.0	
2	2	0	2016-01-01	0.0	0	0	5376	1991.0	
3	3	0	2016-01-01	0.0	0	0	23685	2002.0	
4	4	0	2016-01-01	0.0	0	0	116607	1975.0	

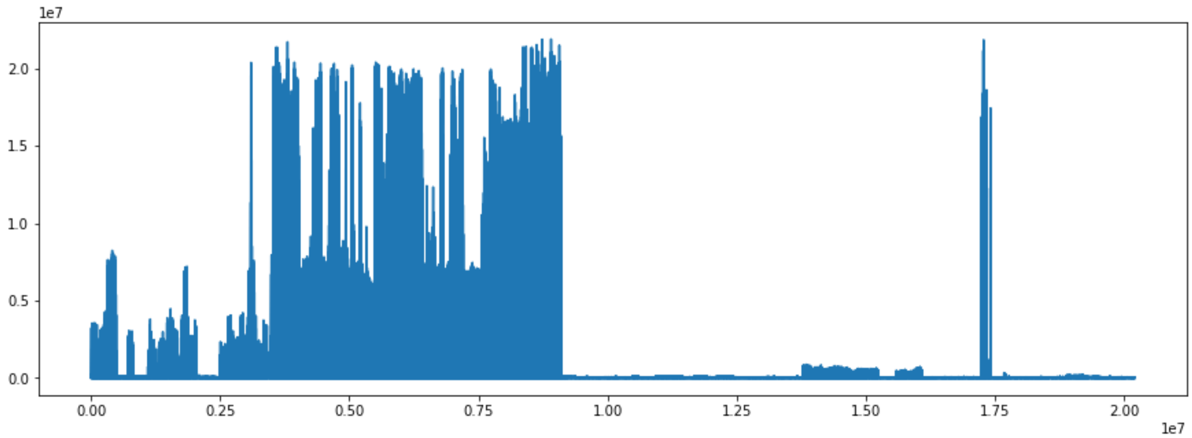
In [29]:
```
train_df.columns.values
```

Out[29]:
```
array(['building_id', 'meter', 'timestamp', 'meter_reading', 'site_id',
       'primary_use', 'square_feet', 'year_built', 'floor_count',
       'air_temperature', 'cloud_coverage', 'dew_temperature',
       'precip_depth_1_hr', 'sea_level_pressure', 'wind_direction',
       'wind_speed', 'age', 'beaufort_scale', 'month_datetime',
       'weekofyear_datetime', 'dayofyear_datetime', 'hour_datetime',
       'day_week', 'day_month_datetime', 'week_month_datetime'],
      dtype=object)
```

Exploratory Data Analysis

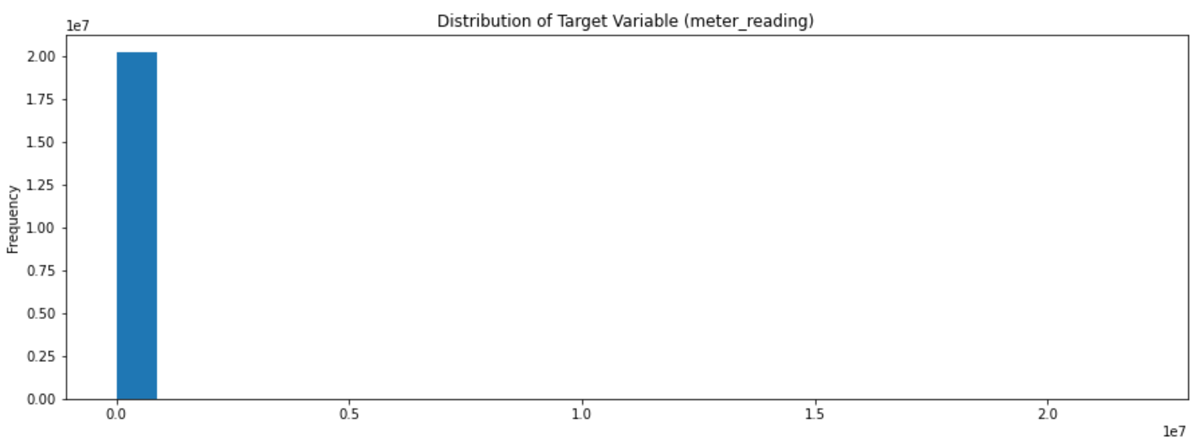
In [31]:
```
plt.figure(figsize = (15,5))
train_df['meter_reading'].plot()
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3cd69af610>



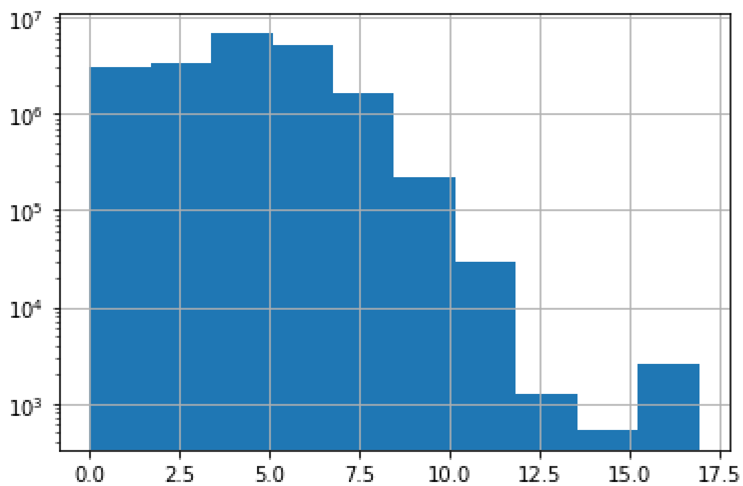
The target is meter_reading - Energy consumption in kWh (or equivalent). Note that this is real data with measurement error, which we expect will impose a baseline level of modeling error.

In [32]:
```
train_df['meter_reading'].plot(kind='hist',
                               bins=25,
                               figsize=(15, 5),
                              title='Distribution of Target Variable (meter_readi
ng)')
plt.show()
```



In [33]:
```
#Target's log-log histogram:
ax = np.log1p(train_df['meter_reading']).hist()
ax.set_yscale('log')
train_df.meter_reading.describe()
```

Out[33]:
```
count    2.021610e+07
mean     1.988706e+03
std      1.532159e+05
min      0.000000e+00
25%      1.830000e+01
50%      7.877500e+01
75%      2.679840e+02
max      2.190470e+07
Name: meter_reading, dtype: float64
```



Handling Missing Values

In [35]:
```
# checking missing data
total = train_df.isnull().sum().sort_values(ascending = False)
percent = (train_df.isnull().sum()/train_df.isnull().count()*100).sort_values(
ascending = False)
missing__train_data  = pd.concat([total, percent], axis=1, keys=['Total', 'Per
cent'])
missing__train_data.head(10)
```

Out[35]:

	Total	Percent
floor_count	16709167	82.652772
age	12127645	59.990033
year_built	12127645	59.990033
cloud_coverage	8825365	43.655131
precip_depth_1_hr	3749023	18.544739
sea_level_pressure	1231669	6.092515
dew_temperature	100140	0.495348
air_temperature	96658	0.478124
meter	0	0.000000
timestamp	0	0.000000

In [39]:
```
!pip install quilt
import missingno as msno
```

```
Requirement already satisfied: quilt in /opt/conda/lib/python3.7/site-package
s (2.9.15)
Requirement already satisfied: appdirs>=1.4.0 in /opt/conda/lib/python3.7/sit
e-packages (from quilt) (1.4.3)
Requirement already satisfied: packaging>=16.8 in /opt/conda/lib/python3.7/si
te-packages (from quilt) (20.1)
Requirement already satisfied: pyarrow>=0.9.0 in /opt/conda/lib/python3.7/sit
e-packages (from quilt) (0.16.0)
Requirement already satisfied: requests>=2.12.4 in /opt/conda/lib/python3.7/s
ite-packages (from quilt) (2.23.0)
Requirement already satisfied: xlrd>=1.0.0 in /opt/conda/lib/python3.7/site-p
ackages (from quilt) (1.2.0)
Requirement already satisfied: numpy>=1.14.0 in /opt/conda/lib/python3.7/site
-packages (from quilt) (1.18.5)
Requirement already satisfied: pandas>=0.21.0 in /opt/conda/lib/python3.7/sit
e-packages (from quilt) (1.0.3)
Requirement already satisfied: tqdm>=4.11.2 in /opt/conda/lib/python3.7/site-
packages (from quilt) (4.45.0)
Requirement already satisfied: future>=0.16.0 in /opt/conda/lib/python3.7/sit
e-packages (from quilt) (0.18.2)
Requirement already satisfied: six>=1.10.0 in /opt/conda/lib/python3.7/site-p
ackages (from quilt) (1.14.0)
Requirement already satisfied: pyyaml>=3.12 in /opt/conda/lib/python3.7/site-
packages (from quilt) (5.3.1)
Requirement already satisfied: pyparsing>=2.0.2 in /opt/conda/lib/python3.7/s
ite-packages (from packaging>=16.8->quilt) (2.4.7)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /op
t/conda/lib/python3.7/site-packages (from requests>=2.12.4->quilt) (1.24.3)
Requirement already satisfied: chardet<4,>=3.0.2 in /opt/conda/lib/python3.7/
site-packages (from requests>=2.12.4->quilt) (3.0.4)
Requirement already satisfied: certifi>=2017.4.17 in /opt/conda/lib/python3.
7/site-packages (from requests>=2.12.4->quilt) (2020.6.20)
Requirement already satisfied: idna<3,>=2.5 in /opt/conda/lib/python3.7/site-
packages (from requests>=2.12.4->quilt) (2.9)
Requirement already satisfied: pytz>=2017.2 in /opt/conda/lib/python3.7/site-
packages (from pandas>=0.21.0->quilt) (2019.3)
Requirement already satisfied: python-dateutil>=2.6.1 in /opt/conda/lib/pytho
n3.7/site-packages (from pandas>=0.21.0->quilt) (2.8.1)
```

In [38]:
```
!pip install --upgrade pip
```

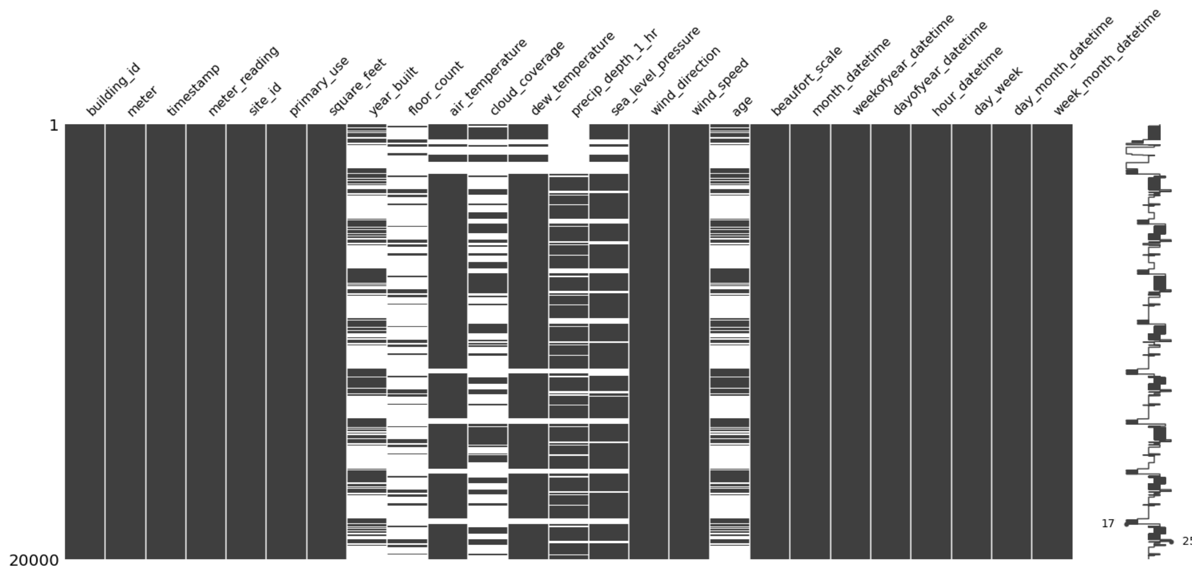
```
Collecting pip
  Downloading pip-20.2.1-py2.py3-none-any.whl (1.5 MB)
     |████████████████████████████████| 1.5 MB 402 kB/s eta 0:00:01
Installing collected packages: pip
  Attempting uninstall: pip
    Found existing installation: pip 20.1.1
    Uninstalling pip-20.1.1:
      Successfully uninstalled pip-20.1.1
Successfully installed pip-20.2.1
```

Nullity Matrix

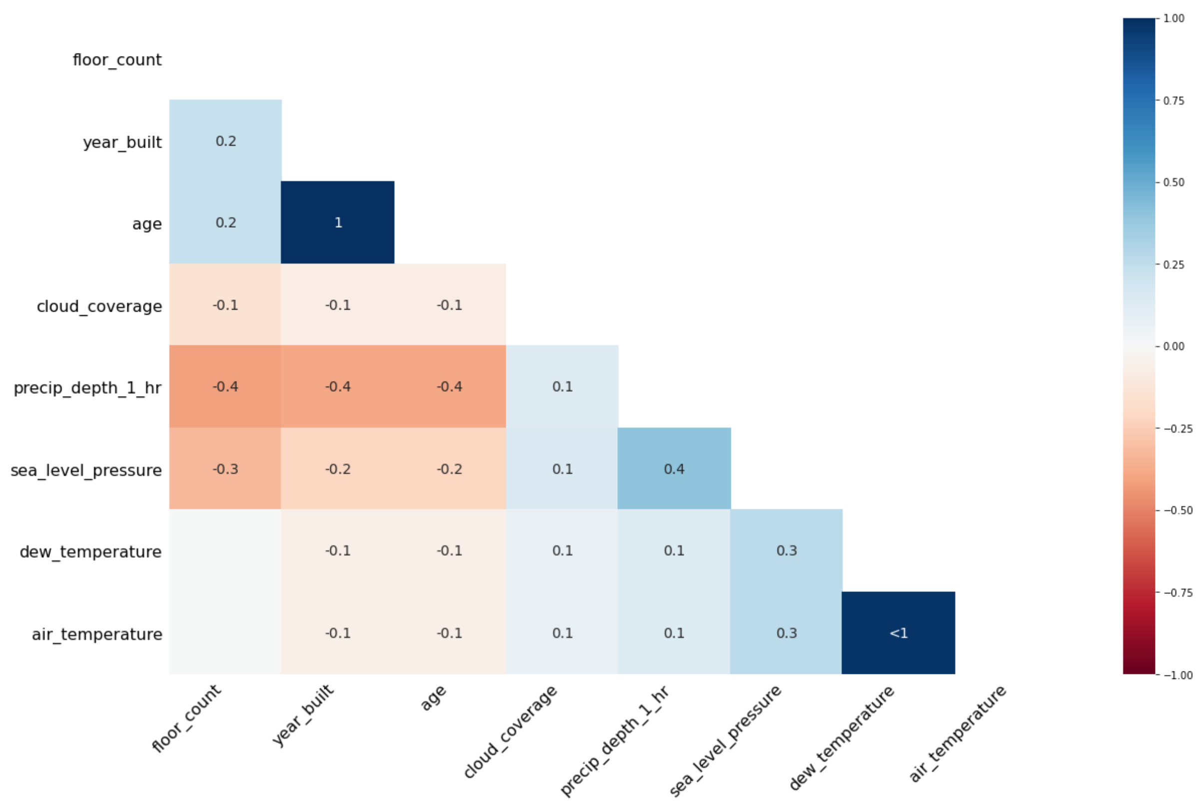
The msno.matrix nullity matrix is a data-dense display which lets you quickly visually analyse data completion.

In [40]:
```
msno.matrix(train_df.head(20000))
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d0b68b390>



In [41]:
```
#Heat map
a = msno.heatmap(train_df, sort='ascending')
```



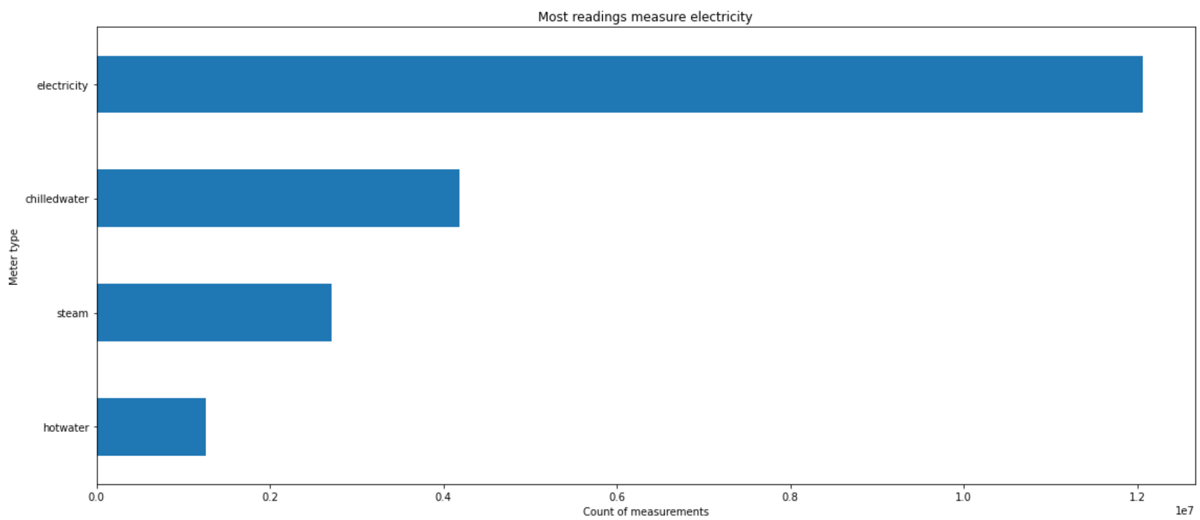
Manually dealing with missing values will often improve model performance.

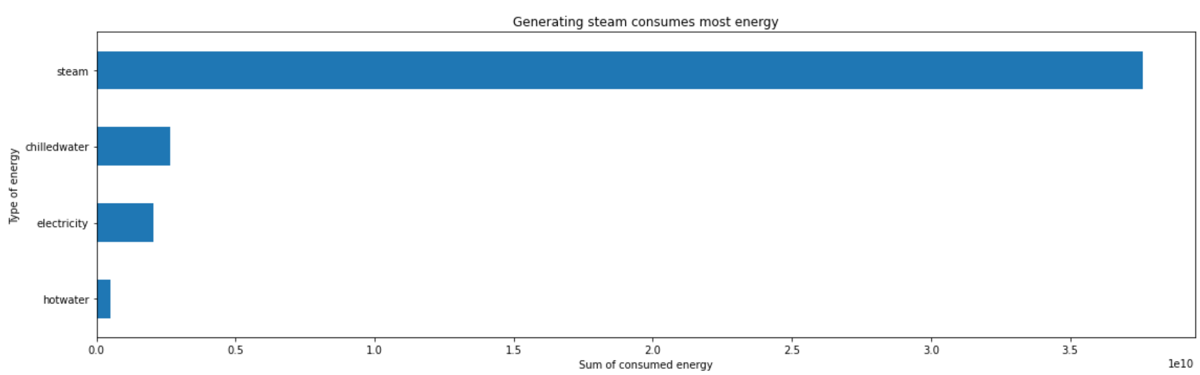
Our approach we input fillNaN = -999 just for the 4 features with most missing values.

In [42]:
```
train_df['floor_count'] = train_df['floor_count'].fillna(-999).astype(np.int16
)
test_df['floor_count'] = test_df['floor_count'].fillna(-999).astype(np.int16)

train_df['year_built'] = train_df['year_built'].fillna(-999).astype(np.int16)
test_df['year_built'] = test_df['year_built'].fillna(-999).astype(np.int16)

train_df['age'] = train_df['age'].fillna(-999).astype(np.int16)
test_df['age'] = test_df['age'].fillna(-999).astype(np.int16)

train_df['cloud_coverage'] = train_df['cloud_coverage'].fillna(-999).astype(np
.int16)
test_df['cloud_coverage'] = test_df['cloud_coverage'].fillna(-999).astype(np.i
nt16)
```

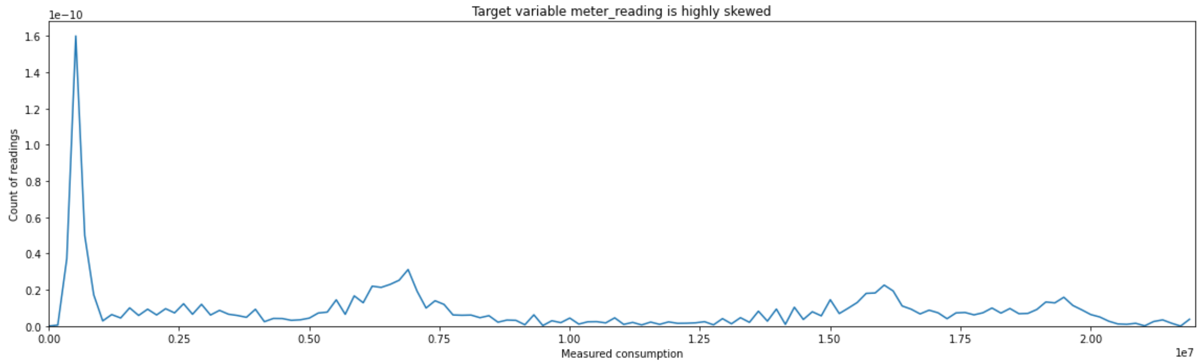
In [43]:
```
#Outlier Analysis
#https://www.kaggle.com/chmaxx/ashrae-eda-and-visualization-wip
```

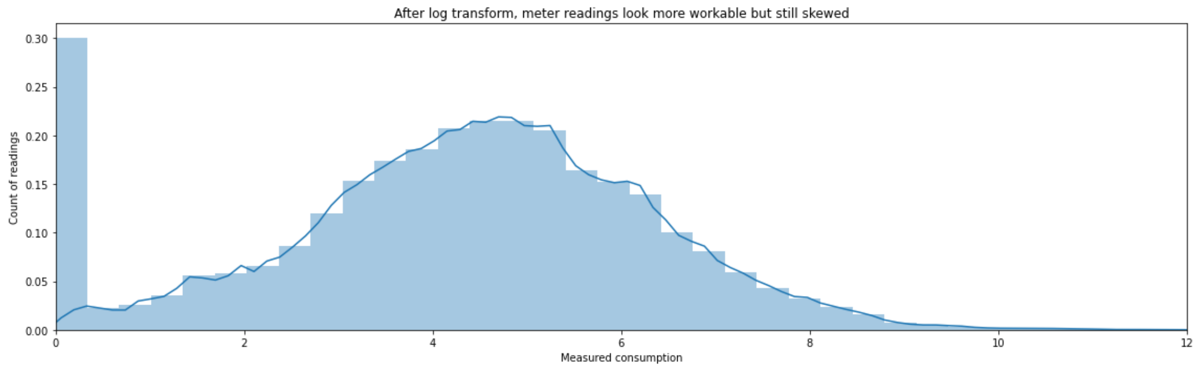
In [44]:
```
energy_types_dict = {0: "electricity", 1: "chilledwater", 2: "steam", 3: "hotw
ater"}
energy_types      = ['electricity', 'chilledwater', 'steam', 'hotwater']

plt.figure(figsize=(16,7))
tmp_df = train_df.meter.value_counts()
tmp_df.index = energy_types
tmp_df.sort_values().plot(kind="barh")
plt.title(f"Most readings measure electricity")
plt.xlabel("Count of measurements")
plt.ylabel(f"Meter type")
plt.tight_layout()
plt.show()

plt.figure(figsize=(16,5))
tmp_df = train_df.groupby("meter").meter_reading.sum()
tmp_df.index = energy_types
tmp_df.sort_values().plot(kind="barh")
plt.title(f"Generating steam consumes most energy")
plt.xlabel("Sum of consumed energy")
plt.ylabel(f"Type of energy")
plt.tight_layout()
plt.show()
```

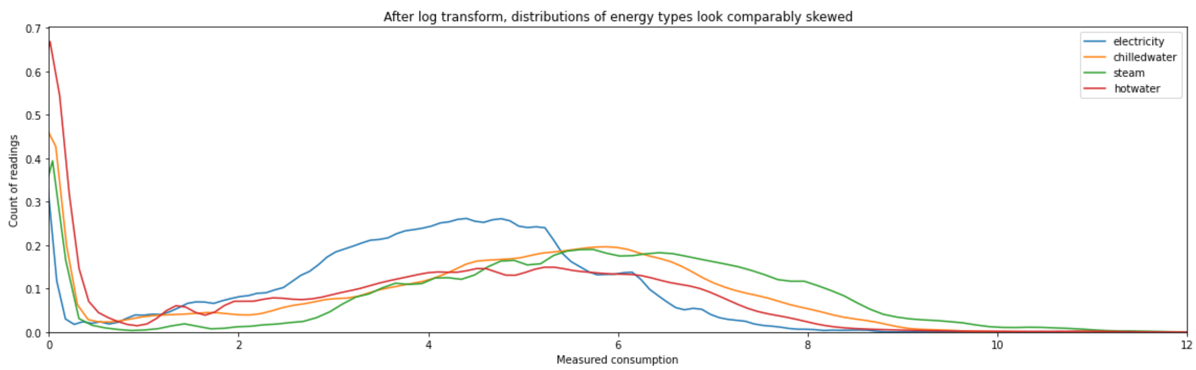




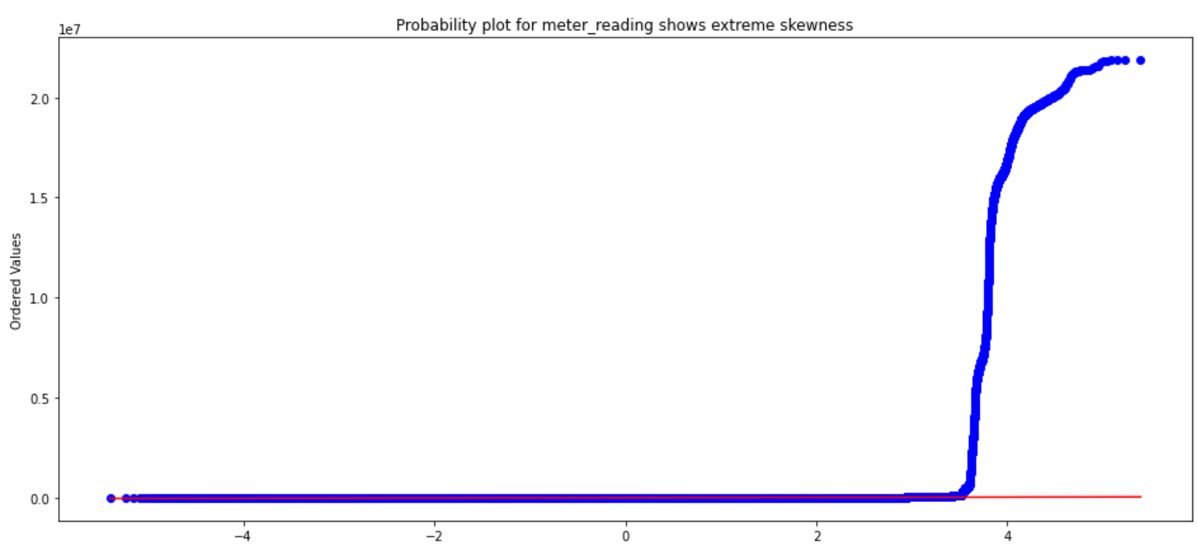
In [45]:
```
plt.figure(figsize=(16,5))
sns.distplot(train_df.meter_reading, hist=False)
plt.title(f"Target variable meter_reading is highly skewed")
plt.ylabel("Count of readings")
plt.xlabel(f"Measured consumption")
plt.xlim(0, train_df.meter_reading.max() + 100_000)
plt.tight_layout()
plt.show()

plt.figure(figsize=(16,5))
sns.distplot(np.log1p(train_df.meter_reading))
plt.title(f"After log transform, meter readings look more workable but still s
kewed")
plt.ylabel("Count of readings")
plt.xlabel(f"Measured consumption")
plt.xlim(0, 12)
plt.tight_layout()
plt.show()

plt.figure(figsize=(16,5))
for idx in range(0,4):
    sns.distplot(np.log1p(train_df[train_df.meter==idx].meter_reading), hist=F
alse, label=energy_types[idx])
plt.title(f"After log transform, distributions of energy types look comparably
skewed")
plt.ylabel("Count of readings")
plt.xlabel(f"Measured consumption")
plt.legend()
plt.xlim(0, 12)
plt.tight_layout()
plt.show()
```



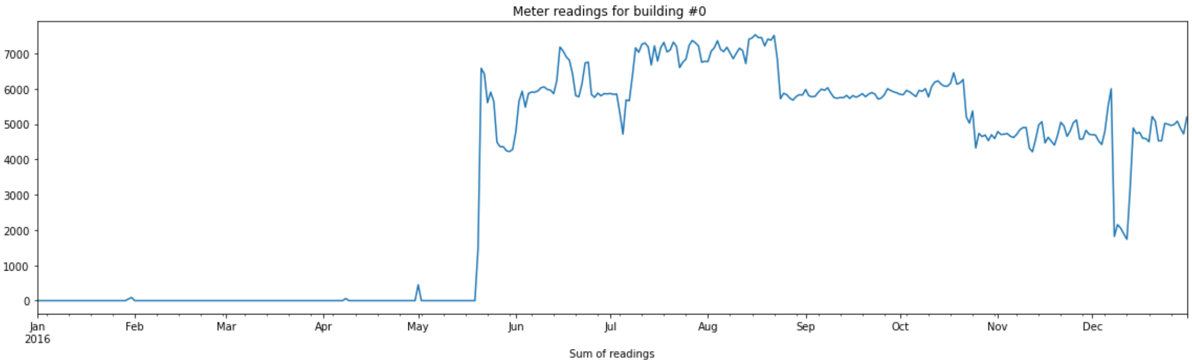


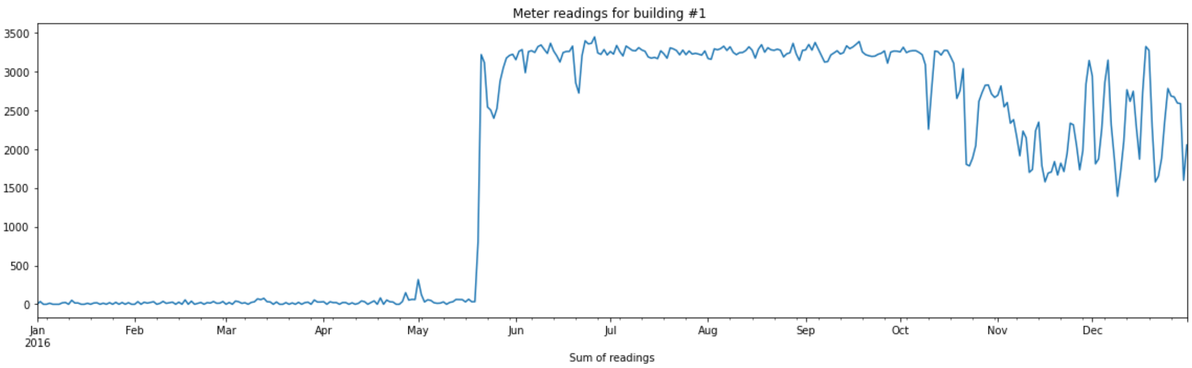


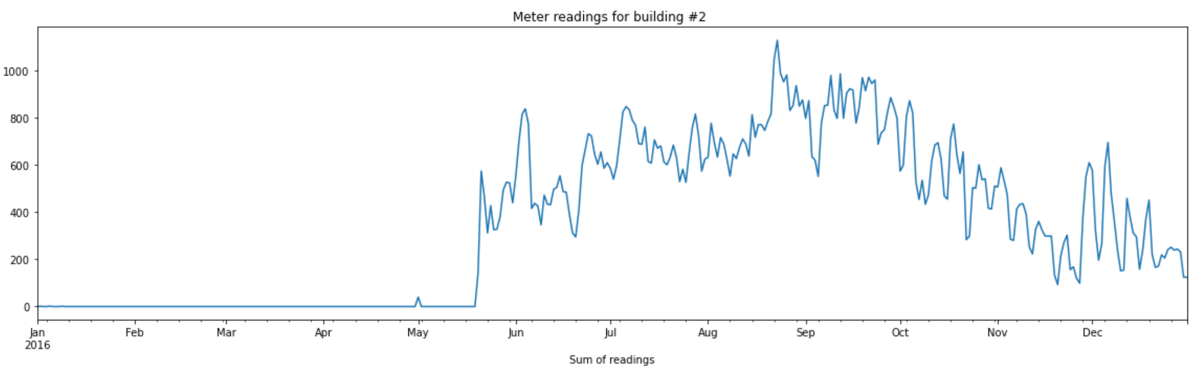
In [48]:
```
plt.figure(figsize=(16,7))
_ = stats.probplot(train_df['meter_reading'], plot=plt)
plt.title("Probability plot for meter_reading shows extreme skewness")
plt.show()
```

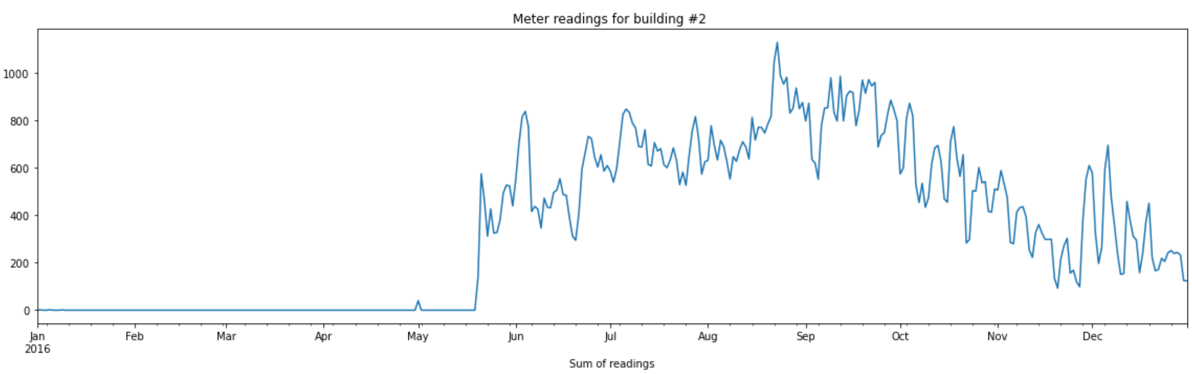


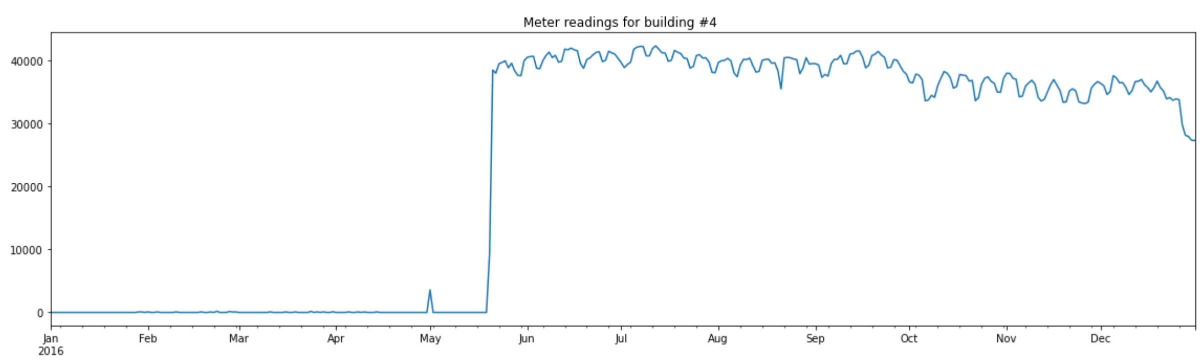
In [49]:
```
#Meter readings for first 10 buildings [ 1,2,3,4,5,6,7,8,9,10]
for bldg_id in [0, 1, 2, 2, 4,5, 6,7,8,9,10]:
    plt.figure(figsize=(16,5))
    tmp_df = train_df[train_df.building_id == bldg_id].copy()
    tmp_df.set_index("timestamp", inplace=True)
    tmp_df.resample("D").meter_reading.sum().plot()
    plt.title(f"Meter readings for building #{bldg_id} ")
    plt.xlabel("Sum of readings")
    plt.tight_layout()
    plt.show()
```

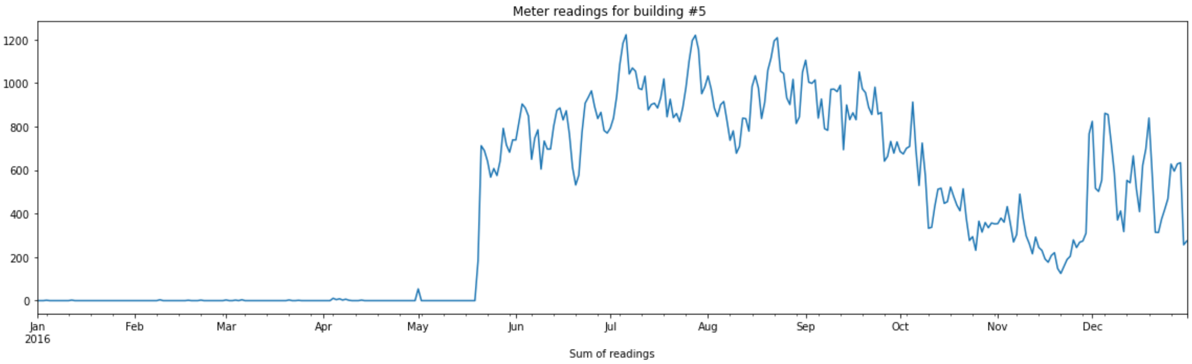

Meter readings for building #0
7000
6000
5000
4000
3000
2000
1000
0
Jan
2016
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Sum of readings

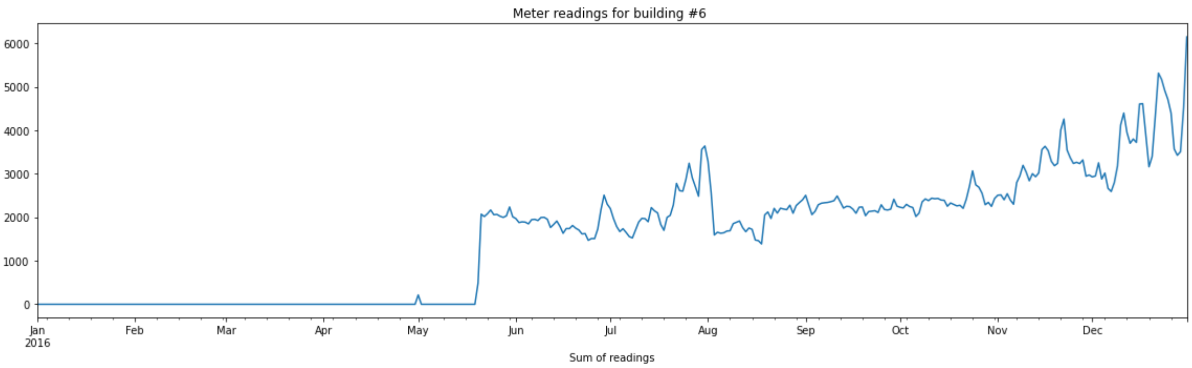

Meter readings for building #1
3500
3000
2500
2000
1500
1000
500
0
Jan
2016
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Sum of readings

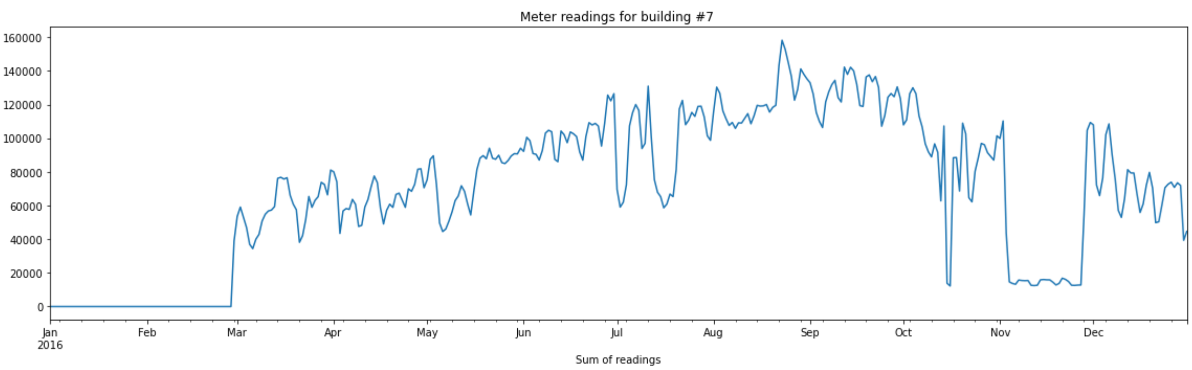

Meter readings for building #2
1000
800
600
400
200
0
Jan
2016
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Sum of readings

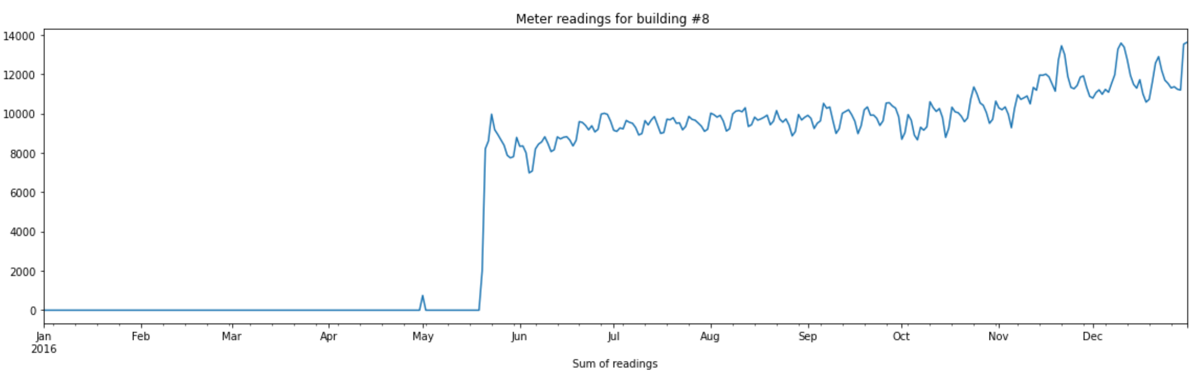

Meter readings for building #2
1000
800
600
400
200
0
Jan
2016
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Sum of readings

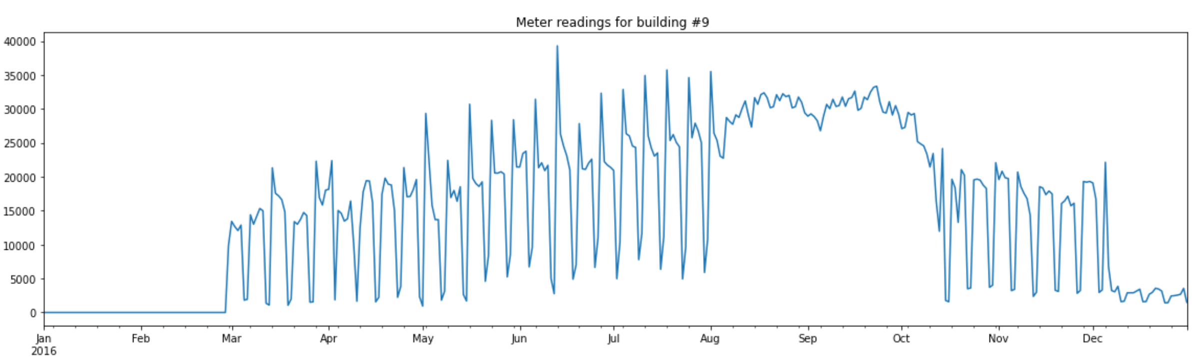

Meter readings for building #4
40000
30000
20000
10000
0
Jan
2016
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Sum of readings

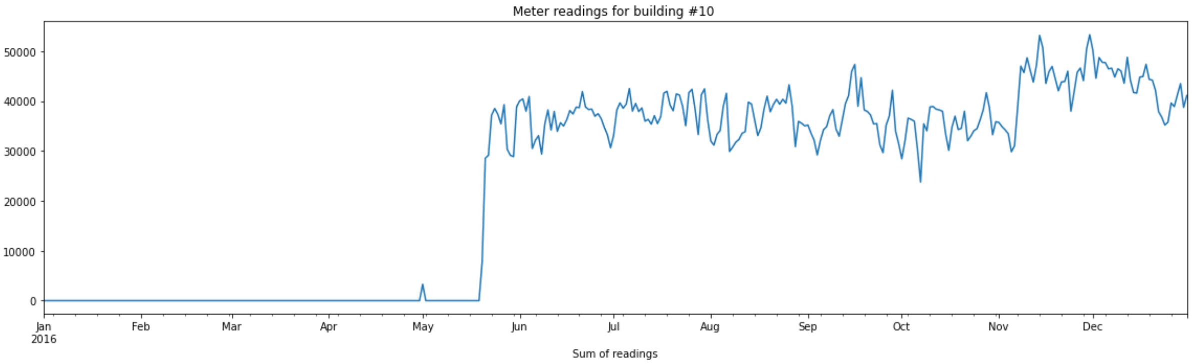

Meter readings for building #5
Sum of readings


Meter readings for building #6
Sum of readings

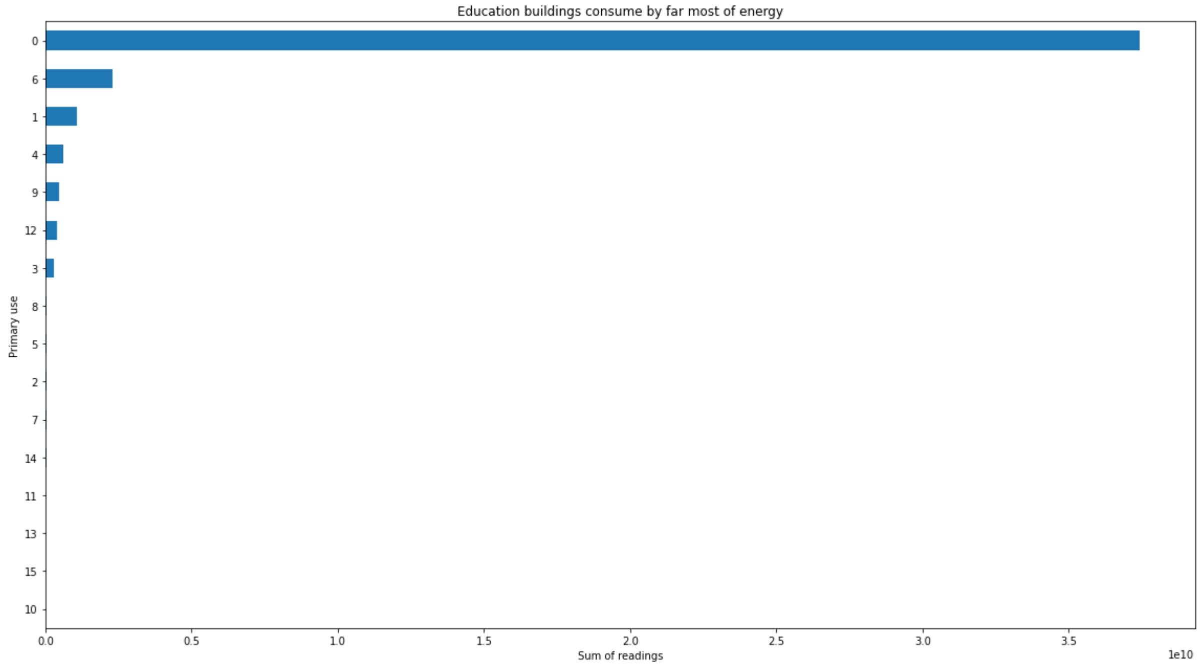

Meter readings for building #7
Sum of readings

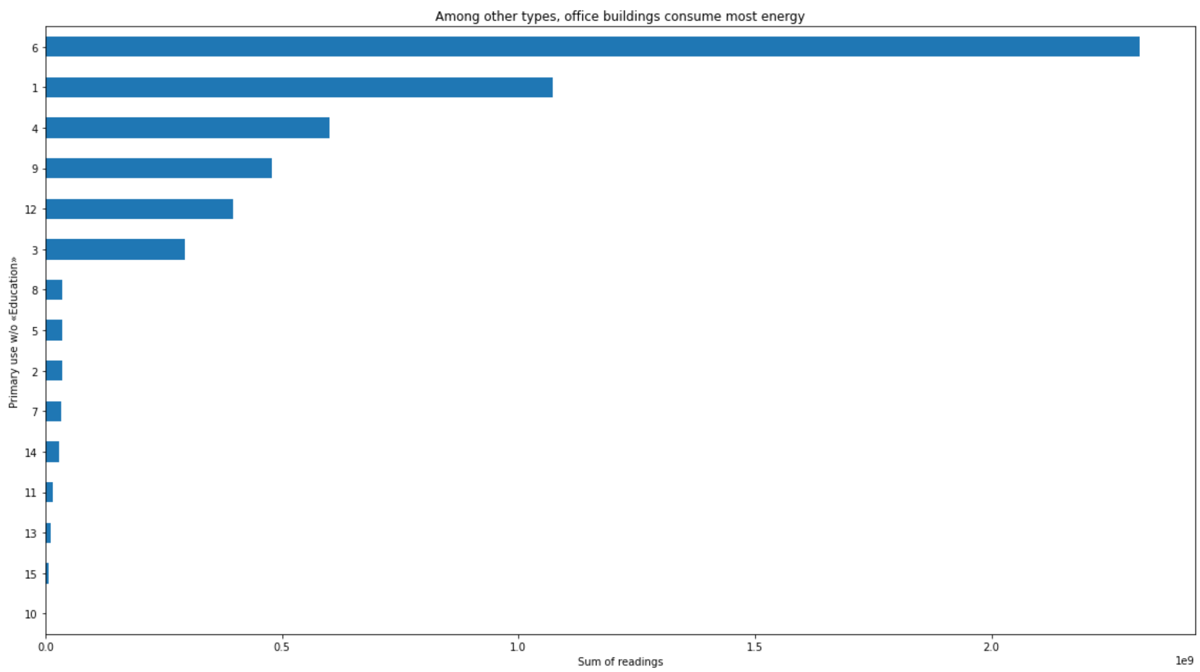

Meter readings for building #8
Sum of readings


Meter readings for building #9
Sum of readings


Meter readings for building #10
50000
40000
30000
20000
10000
0
Jan
2016
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Sum of readings

In [50]:
```
temp_df = train_df.groupby("primary_use").meter_reading.sum().sort_values()

plt.figure(figsize=(16,9))
temp_df.plot(kind="barh")
plt.title(f"Education buildings consume by far most of energy")
plt.xlabel("Sum of readings")
plt.ylabel(f"Primary use")
plt.tight_layout()
plt.show()

plt.figure(figsize=(16,9))
temp_df[:-1].plot(kind="barh")
plt.title(f"Among other types, office buildings consume most energy")
plt.xlabel("Sum of readings")
plt.ylabel(f"Primary use w/o «Education»")
plt.tight_layout()
plt.show()
```

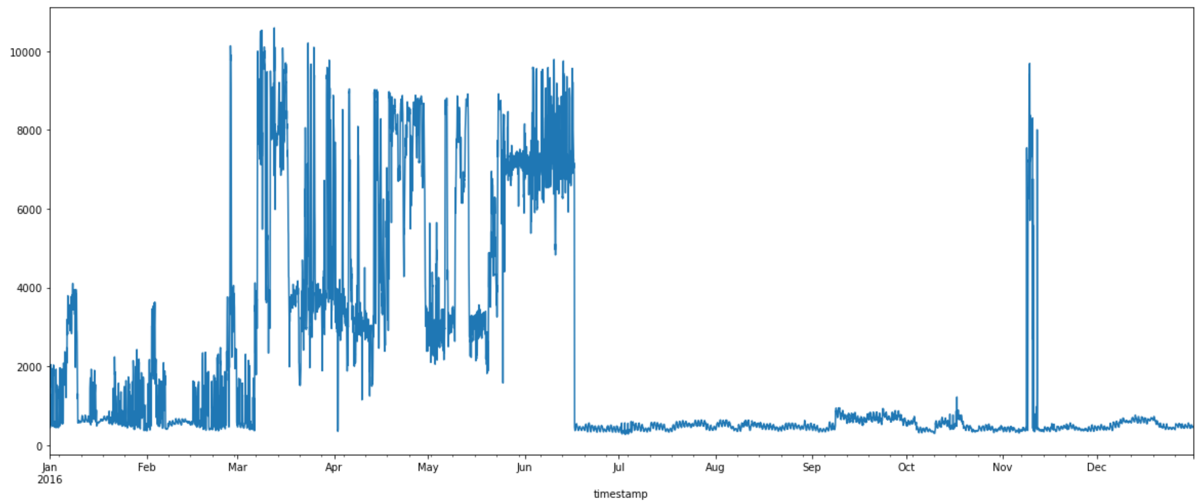




Outlier Distribution

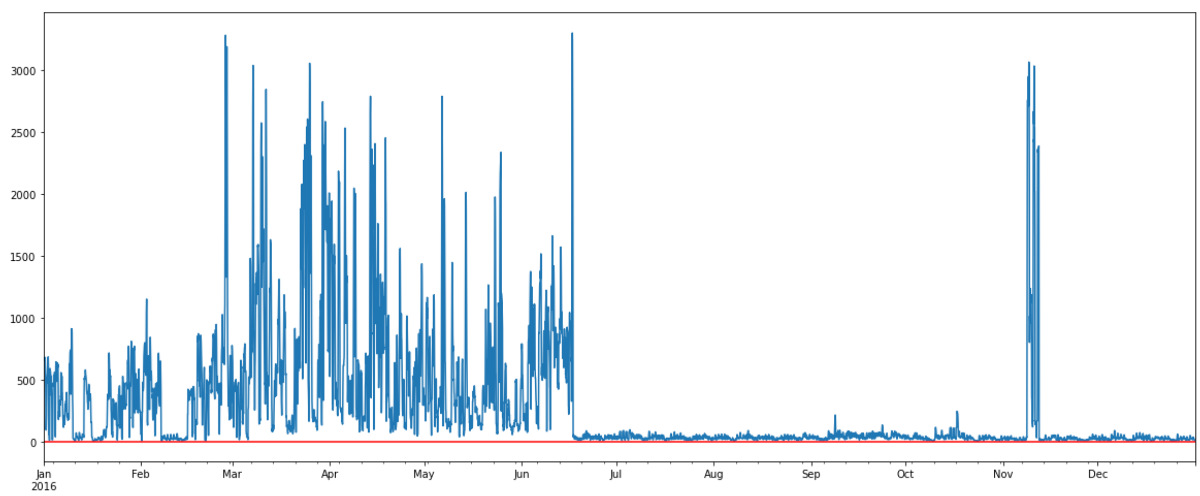
In [52]:
```
y_mean_time = train_df.groupby('timestamp').meter_reading.mean()
y_mean_time.plot(figsize=(20, 8))
```

Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3ccd05f050>



In [53]:
```
y_mean_time.rolling(window=10).std().plot(figsize=(20, 8))
plt.axhline(y=0.009, color='red')
plt.axvspan(0, 905, color='green', alpha=0.1)
plt.axvspan(906, 1505, color='red', alpha=0.1)
```

Out[53]: <matplotlib.patches.Polygon at 0x7f3cccd71950>



In [54]:
```
#https://www.kaggle.com/juanmah/ashrae-outliers
daily_train = train_df
daily_train['date'] = daily_train['timestamp'].dt.date
daily_train = daily_train.groupby(['date', 'building_id', 'meter']).sum()
daily_train

daily_train_agg = daily_train.groupby(['date', 'meter']).agg(['sum', 'mean',
'idxmax', 'max'])
daily_train_agg = daily_train_agg.reset_index()
level_0 = daily_train_agg.columns.droplevel(0)
level_1 = daily_train_agg.columns.droplevel(1)
level_0 = ['' if x == '' else '-' + x for x in level_0]
daily_train_agg.columns = level_1 + level_0
daily_train_agg.rename_axis(None, axis=1)
daily_train_agg.head()
```

Out[54]:

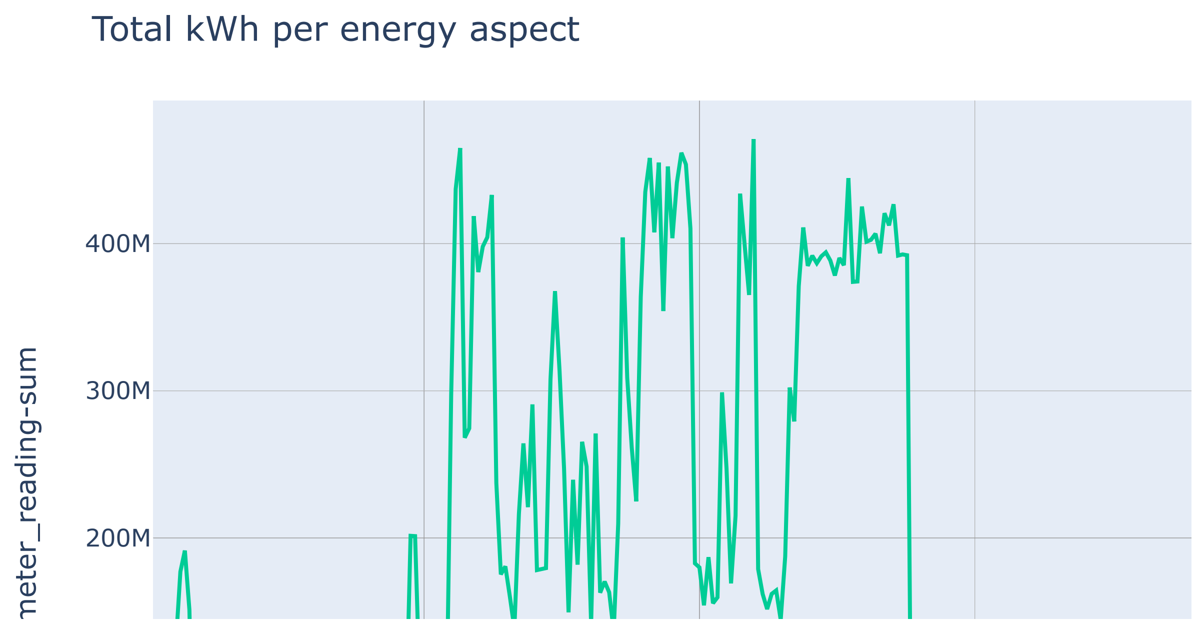
	date	meter	meter_reading-sum	meter_reading-mean	meter_reading-idxmax	meter_reading-max	site_id-sum	si
0	2016-01-01	0	4.219648e+06	3037.903076	(2016-01-01, 803, 0)	1.160372e+05	228225.0	164.3(
1	2016-01-01	0	4.219648e+06	3037.903076	(2016-01-01, 803, 0)	1.160372e+05	228225.0	164.3(
2	2016-01-01	1	1.412169e+06	3090.084961	(2016-01-01, 1289, 1)	1.042116e+05	107738.0	235.7!
3	2016-01-01	1	1.412169e+06	3090.084961	(2016-01-01, 1289, 1)	1.042116e+05	107738.0	235.7!
4	2016-01-01	2	6.873201e+07	218891.734375	(2016-01-01, 1099, 2)	5.095080e+07	87728.0	279.3!

In [55]:
```
#Aggregate the data for buildings
daily_train_agg = daily_train.groupby(['date', 'meter']).agg(['sum', 'mean',
'idxmax', 'max'])
daily_train_agg = daily_train_agg.reset_index()
level_0 = daily_train_agg.columns.droplevel(0)
level_1 = daily_train_agg.columns.droplevel(1)
level_0 = ['' if x == '' else '-' + x for x in level_0]
daily_train_agg.columns = level_1 + level_0
daily_train_agg.rename_axis(None, axis=1)
daily_train_agg.head()
```

Out[55]:

	date	meter	meter_reading-sum	meter_reading-mean	meter_reading-idxmax	meter_reading-max	site_id-sum	si
0	2016-01-01	0	4.219648e+06	3037.903076	(2016-01-01, 803, 0)	1.160372e+05	228225.0	164.3
1	2016-01-01	0	4.219648e+06	3037.903076	(2016-01-01, 803, 0)	1.160372e+05	228225.0	164.3
2	2016-01-01	1	1.412169e+06	3090.084961	(2016-01-01, 1289, 1)	1.042116e+05	107738.0	235.7
3	2016-01-01	1	1.412169e+06	3090.084961	(2016-01-01, 1289, 1)	1.042116e+05	107738.0	235.7
4	2016-01-01	2	6.873201e+07	218891.734375	(2016-01-01, 1099, 2)	5.095080e+07	87728.0	279.3

In [56]:
```
fig_total = px.line(daily_train_agg, x='date', y='meter_reading-sum', color='m
eter', render_mode='svg')
fig_total.update_layout(title='Total kWh per energy aspect')
fig_total.show()
```



The sum for each energy aspect, shows some aberrant values.

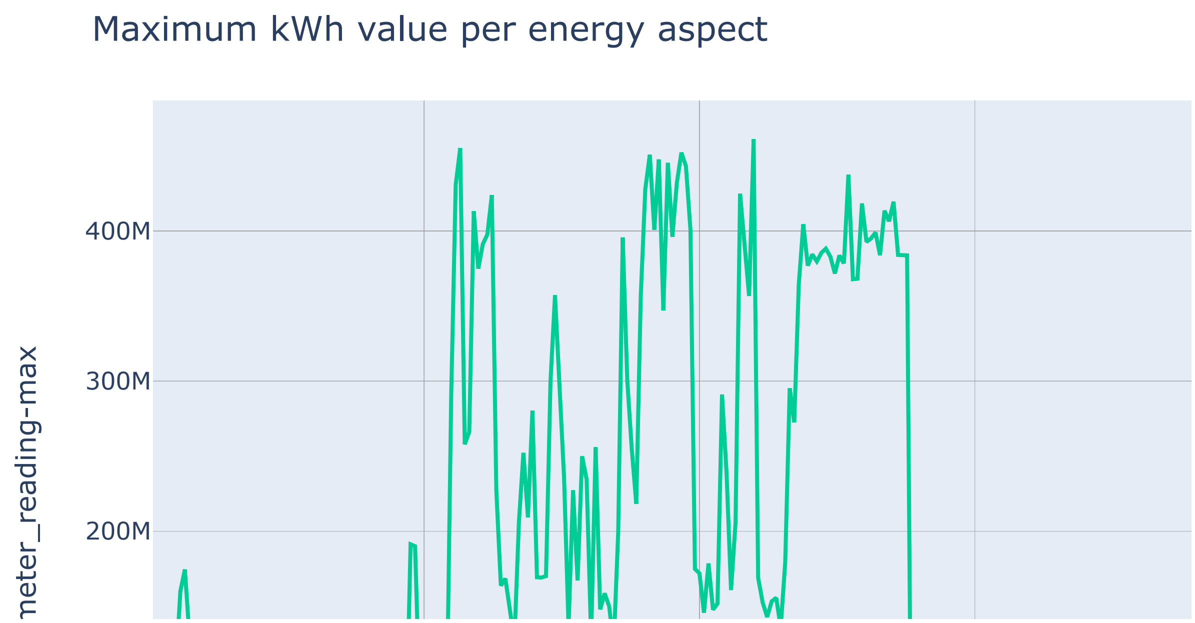
meter=0 Eletricity

meter=1 Chilledwater

meter=2 Steam

meter=3 Hotwater

In [57]:
```
fig_maximum = px.line(daily_train_agg, x='date', y='meter_reading-max', color=
'meter', render_mode='svg')
fig_maximum.update_layout(title='Maximum kWh value per energy aspect')
fig_maximum.show()
```



In [58]:
```
daily_train_agg['building_id_max'] = [x[1] for x in daily_train_agg['meter_rea
ding-idxmax']]
daily_train_agg.head()
```

Out[58]:

	date	meter	meter_reading-sum	meter_reading-mean	meter_reading-idxmax	meter_reading-max	site_id-sum	si
0	2016-01-01	0	4.219648e+06	3037.903076	(2016-01-01, 803, 0)	1.160372e+05	228225.0	164.3
1	2016-01-01	0	4.219648e+06	3037.903076	(2016-01-01, 803, 0)	1.160372e+05	228225.0	164.3
2	2016-01-01	1	1.412169e+06	3090.084961	(2016-01-01, 1289, 1)	1.042116e+05	107738.0	235.7
3	2016-01-01	1	1.412169e+06	3090.084961	(2016-01-01, 1289, 1)	1.042116e+05	107738.0	235.7
4	2016-01-01	2	6.873201e+07	218891.734375	(2016-01-01, 1099, 2)	5.095080e+07	87728.0	279.3

Modeling

Data preparation

In [59]:
```
del train_df["timestamp"], test_df["timestamp"]
categoricals = ["site_id", "building_id", "primary_use",  "meter",  "wind_dire
ction"] #"hour", "weekday",
drop_cols = ["sea_level_pressure", "wind_speed"]

numericals = ["square_feet", "year_built", "air_temperature", "cloud_coverage"
,
              "dew_temperature", 'precip_depth_1_hr', 'floor_count', 'beaufort
_scale']

feat_cols = categoricals + numericals
```

In [60]:
```
target = np.log1p(train_df["meter_reading"])

del train_df["meter_reading"]

train_df = train_df.drop(drop_cols, axis = 1)
```

Modeling simple LGBM

In [61]:
```
#simple k-fold cross validation
```

In [62]:
```
params = {
            'boosting_type': 'gbdt',
            'objective': 'regression',
            'metric': {'rmse'},
            'subsample_freq': 1,
            'learning_rate': 0.3,
            'bagging_freq': 5,
            'num_leaves': 330,
            'feature_fraction': 0.9,
            'lambda_l1': 1,
            'lambda_l2': 1
            }

folds = 5
seed = 666
shuffle = False
kf = KFold(n_splits=folds, shuffle=shuffle, random_state=seed)

models = []
for train_index, val_index in kf.split(train_df[feat_cols], train_df['building
_id']):
    train_X = train_df[feat_cols].iloc[train_index]
    val_X = train_df[feat_cols].iloc[val_index]
    train_y = target.iloc[train_index]
    val_y = target.iloc[val_index]
    lgb_train = lgb.Dataset(train_X, train_y, categorical_feature=categoricals
)
    lgb_eval = lgb.Dataset(val_X, val_y, categorical_feature=categoricals)
    gbm = lgb.train(params,
                lgb_train,
                num_boost_round=500,
                valid_sets=(lgb_train, lgb_eval),
                early_stopping_rounds=50,
                verbose_eval = 50)
    models.append(gbm)
```

```
/opt/conda/lib/python3.7/site-packages/sklearn/model_selection/_split.py:297:
FutureWarning:

Setting a random_state has no effect since shuffle is False. This will raise
an error in 0.24. You should leave random_state to its default (None), or set
shuffle=True.

/opt/conda/lib/python3.7/site-packages/lightgbm/basic.py:1291: UserWarning:

Using categorical_feature in Dataset.


Training until validation scores don't improve for 50 rounds
[50]    training's rmse: 0.94896        valid_1's rmse: 1.2666
Early stopping, best iteration is:
[34]    training's rmse: 0.968494       valid_1's rmse: 1.26259
Training until validation scores don't improve for 50 rounds
[50]    training's rmse: 0.927933       valid_1's rmse: 1.28531
Early stopping, best iteration is:
[18]    training's rmse: 0.990694       valid_1's rmse: 1.2734
Training until validation scores don't improve for 50 rounds
[50]    training's rmse: 0.966793       valid_1's rmse: 1.09942
Early stopping, best iteration is:
[21]    training's rmse: 1.01445        valid_1's rmse: 1.09383
Training until validation scores don't improve for 50 rounds
[50]    training's rmse: 0.940128       valid_1's rmse: 1.21763
Early stopping, best iteration is:
[19]    training's rmse: 0.999754       valid_1's rmse: 1.20817
Training until validation scores don't improve for 50 rounds
[50]    training's rmse: 0.907018       valid_1's rmse: 1.46948
Early stopping, best iteration is:
[7]     training's rmse: 1.08182        valid_1's rmse: 1.40598
```

In [63]:
```
test_df = test_df[feat_cols]
```

In [2]:
```
import numpy as np
i=0
res=[]
step_size = 50000
for j in tqdm(range(int(np.ceil(test_df.shape[0]/50000)))):
    res.append(np.expm1(sum([model.predict(test_df.iloc[i:i+step_size]) for mo
del in models])/folds))
    i+=step_size
```

In [65]:
```
res = np.concatenate(res)
```

In [66]:
```
#Submission
```

In [67]:
```
sample_submission['meter_reading'] = res
sample_submission.loc[sample_submission['meter_reading']<0, 'meter_reading'] =
0
```

In [4]:
```
import pandas as pd
sample_submission= pd.read_csv("submission.csv")
```

In [5]:
```
sample_submission.head()
#sample_submission.to_csv('submission.csv', index=False)
```

Out[5]:

	row_id	meter_reading
0	0	17.550667
1	1	10.552085
2	2	2.316952
3	3	14.207939
4	4	25.399353

In [ ]: