In [1]:
```
import numpy as np
import pandas as pd
import os, warnings, math
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from sklearn.preprocessing import LabelEncoder
from IPython.display import set_matplotlib_formats
set_matplotlib_formats('pdf','svg')

warnings.filterwarnings("ignore")
```

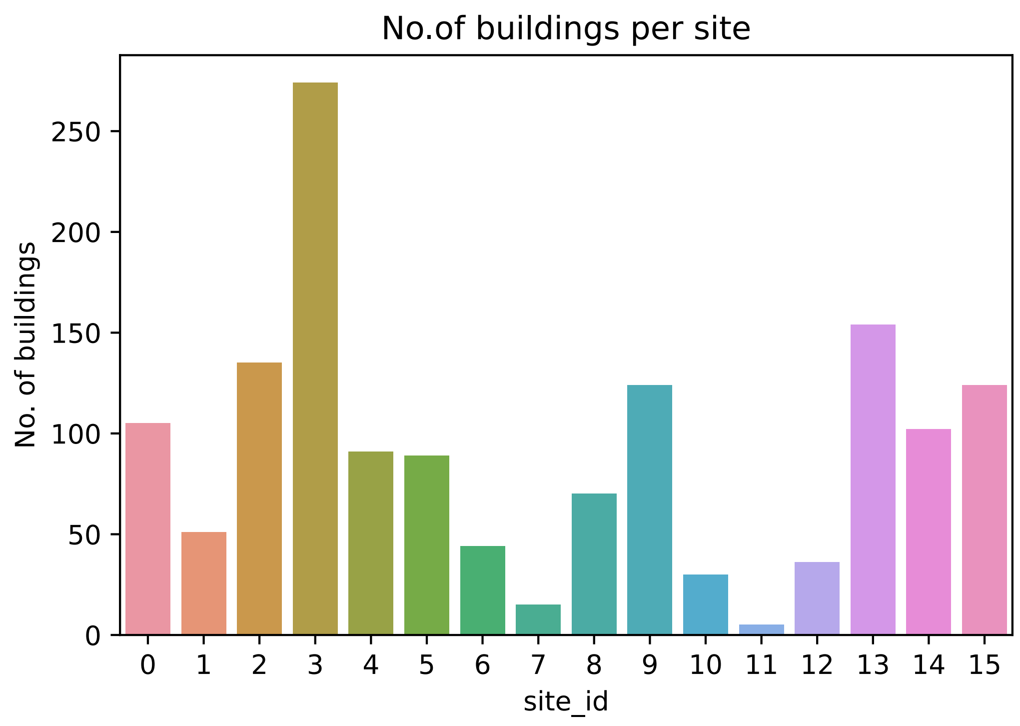
Building Metadata

In [2]:
```
building_df = pd.read_csv("../data/building_metadata.csv")
building_df.head()
```

Out[2]:

	site_id	building_id	primary_use	square_feet	year_built	floor_count
0	0	0	Education	7432	2008.0	NaN
1	0	1	Education	2720	2004.0	NaN
2	0	2	Education	5376	1991.0	NaN
3	0	3	Education	23685	2002.0	NaN
4	0	4	Education	116607	1975.0	NaN

In [3]:
```
sns.countplot(data=building_df,x='site_id')
plt.title("No.of buildings per site")
plt.ylabel("No. of buildings")
plt.show()
```

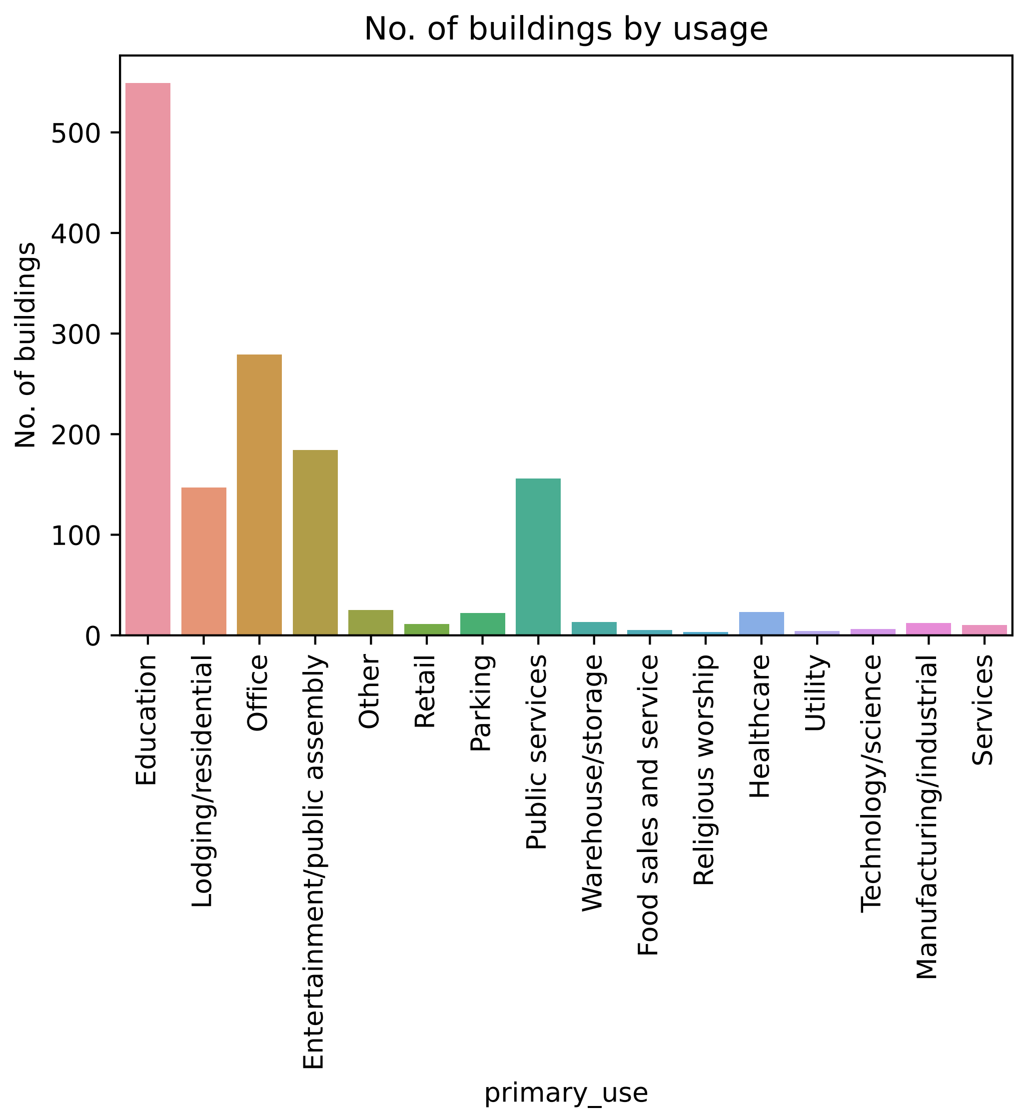


We observe most sites to have about 50-150 buildings.

Site no. 3 has most no. of buildings.

Sites 11,7,10,12 have few no. of buildings.

In [4]:
```
sns.countplot(data=building_df,x='primary_use')
plt.xticks(rotation=90)
plt.title("No. of buildings by usage")
plt.ylabel("No. of buildings")
plt.show()
```

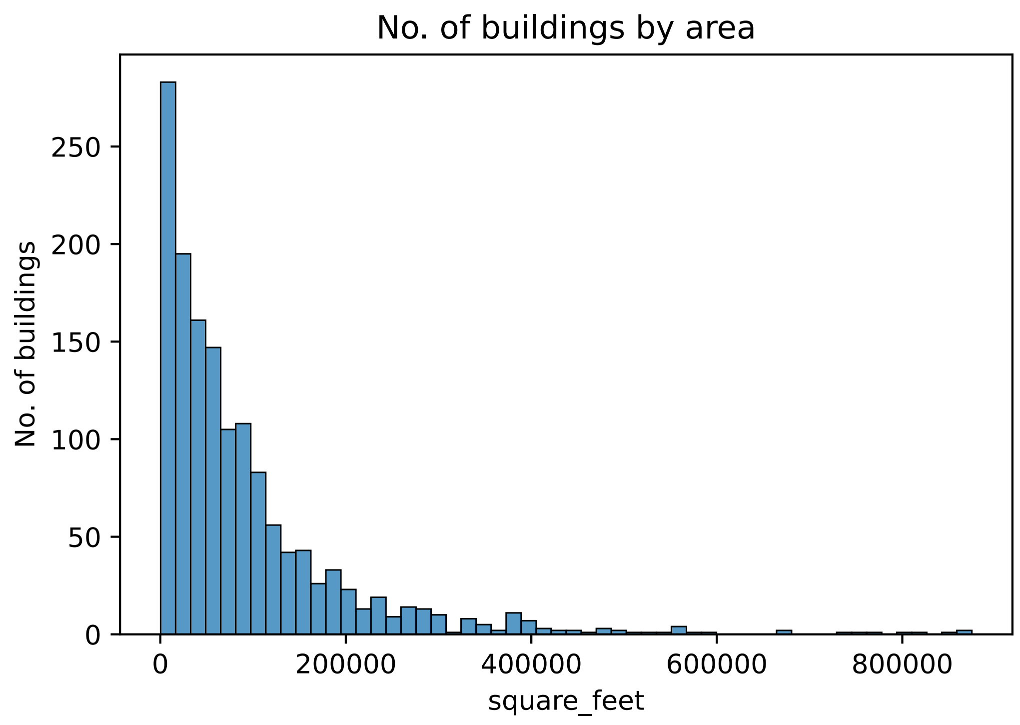


Most buildings are used for Educational purposes and office purposes

So we might expect majority of buildings to have most electrical load from 9:00 to 18:00

We might also expect to have most buildings where vacation months have low consumption.

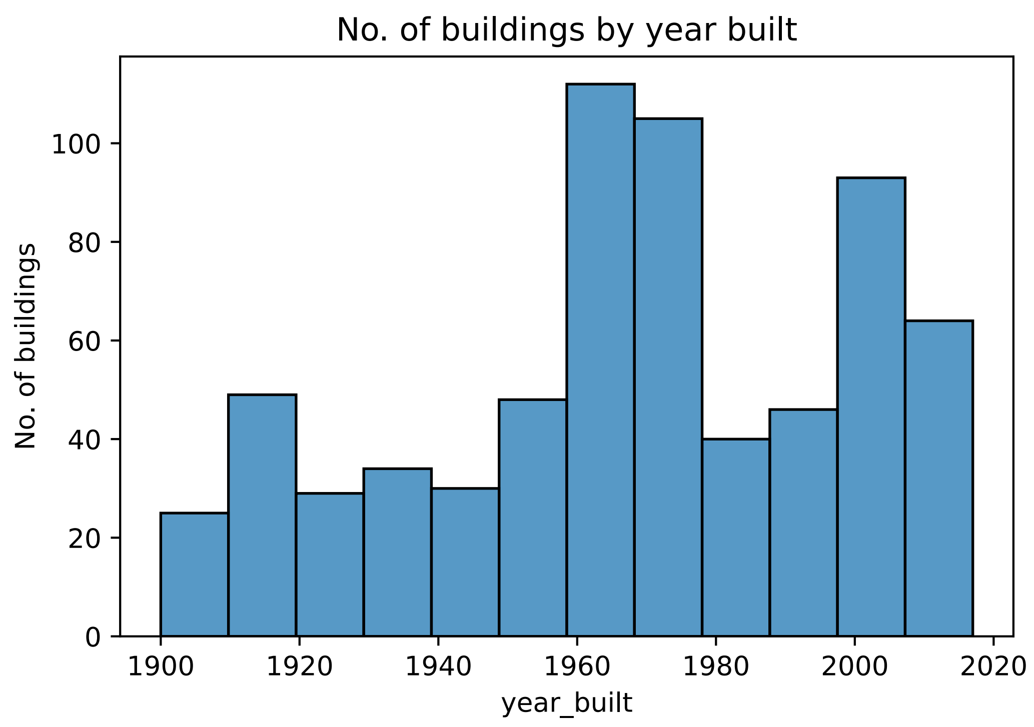
In [5]:
```
sns.histplot(building_df,x='square_feet')
plt.title("No. of buildings by area")
plt.ylabel("No. of buildings")
plt.show()
```



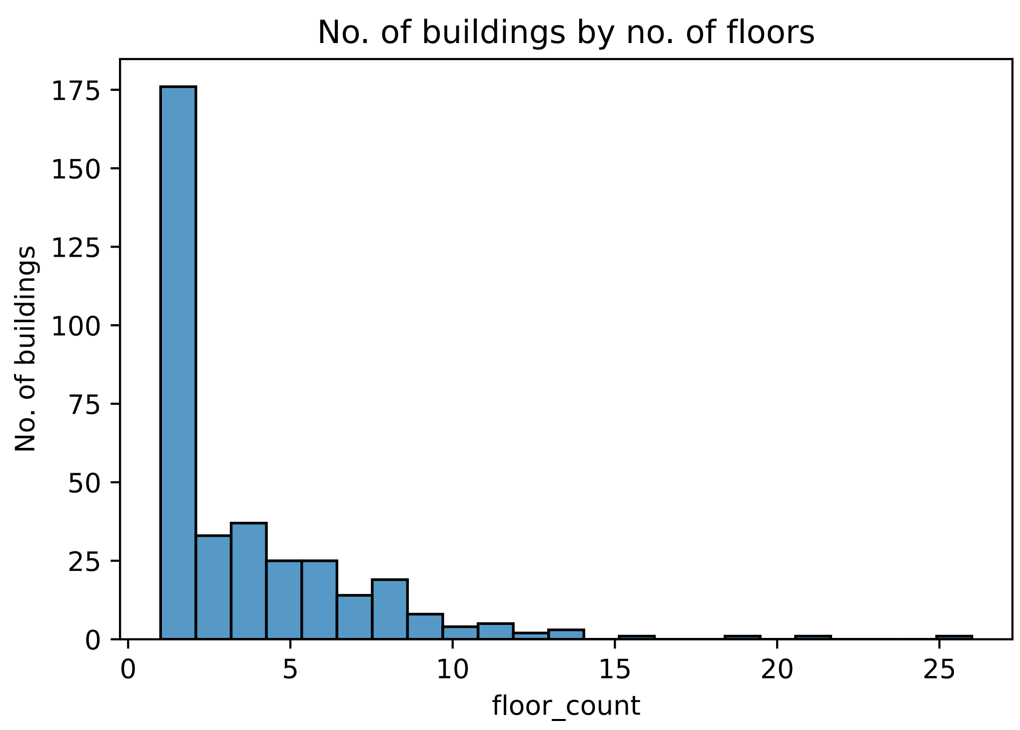
In [6]:
```
min_sq_ft = min(building_df['square_feet'])
max_sq_ft = max(building_df['square_feet'])
print("Min Square foot: {}\nMax Square foot: {}".format(min_sq_ft,max_sq_ft))
```

```
Min Square foot: 283
Max Square foot: 875000
```

In [7]:
```
sns.histplot(building_df,x='year_built')
plt.title("No. of buildings by year built")
plt.ylabel("No. of buildings")
plt.show()
```



In [8]:
```
sns.histplot(building_df,x='floor_count')
plt.title("No. of buildings by no. of floors")
plt.ylabel("No. of buildings")
plt.show()
```



In [9]:
```
missing_floor_count = building_df["floor_count"].isnull().sum()
missing_floor_percent = missing_floor_count/len(building_df)*100

print("{} buildings ({}%) have floor_count missing".format(missing_floor_count, round(missing_floor_percent,4)))
```

```
1094 buildings (75.5003%) have floor_count missing
```

Weather data

In [11]:
```
train_weather_df = pd.read_csv("../data/weather_train.csv")
train_weather_df.head()
```

Out[11]:

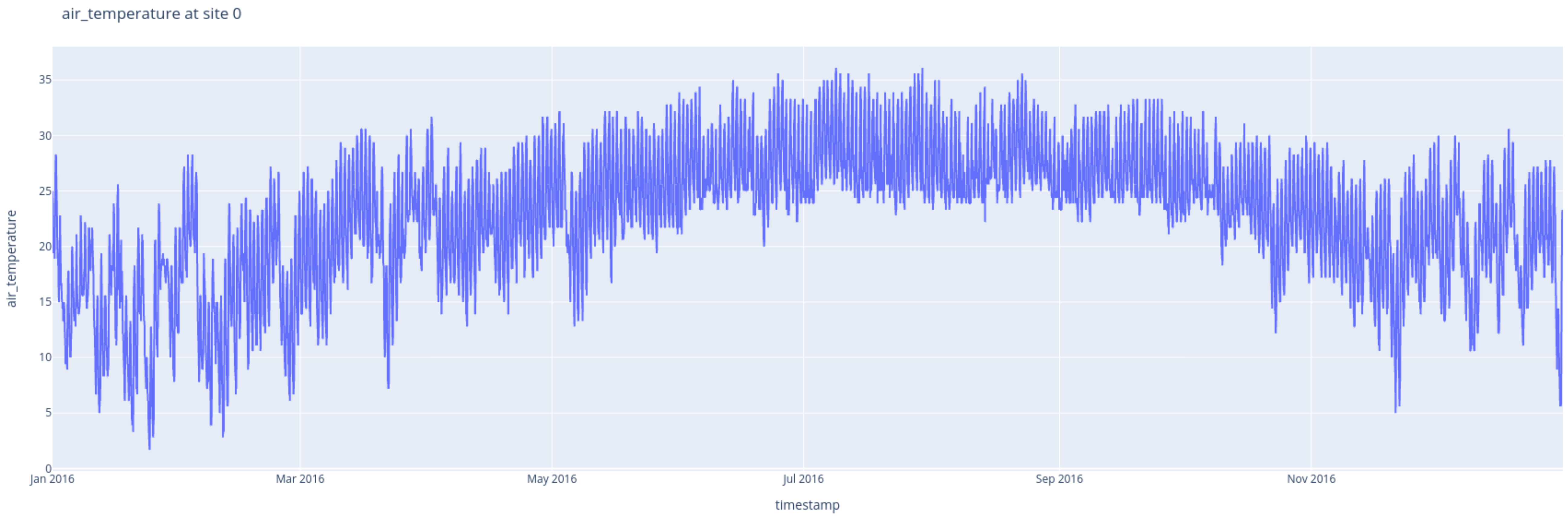
	site_id	timestamp	air_temperature	cloud_coverage	dew_temperature	precip_depth_1_hr	sea_level_pressure	wind_direction	wind_speed
0	0	2016-01-01 00:00:00	25.0	6.0	20.0	NaN	1019.7	0.0	0.0
1	0	2016-01-01 01:00:00	24.4	NaN	21.1	-1.0	1020.2	70.0	1.5
2	0	2016-01-01 02:00:00	22.8	2.0	21.1	0.0	1020.2	0.0	0.0
3	0	2016-01-01 03:00:00	21.1	2.0	20.6	0.0	1020.1	0.0	0.0
4	0	2016-01-01 04:00:00	20.0	2.0	20.0	-1.0	1020.0	250.0	2.6

In [11]:
```
def time_plots_by_site(df,col,save=True,base_dir="../images/eda/",top_dir="",site=None):
    def plot(site):
        fig = px.line(df[df["site_id"]==site], x='timestamp', y=col)

        fig.update_layout(
            title="{} at site {}".format(col,site),
            autosize=False,
            width=1800,
            height=600)
        return fig

    if save:
        path = os.path.join(base_dir,top_dir)
        if not os.path.exists(path):
            os.makedirs(path)

        for _site in df['site_id'].unique():
            fig = plot(_site)
            fig.write_image("{}/{}_site{}.png".format(path,col,_site))

    if site is not None:
        fig = plot(site)
        fig.show()
```

Saving all plots locally:

In [12]:
```
if not os.path.exists("../images/eda/weather"):
    for col in train_weather_df.columns[1:]:
        time_plots_by_site(df=train_weather_df, col=col,top_dir="weather",save=True)
```

Air temp. of site 0: (Loaded from disk)



We observe seasonal effects, where temp. peaks at around June - July / september - october at most sites.

We also observe daily day-night temperature fluctuations

Data Minification:

In [4]:
```
# Credit to kyakovlev; https://www.kaggle.com/kyakovlev/ashrae-data-minification
# Minifies dataset so that they use the least amount of memory they could, without data loss

def reduce_mem_usage(df, verbose=True):
    numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
    # Bytes to MB
    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':
                # np.iinfo() returns min and max limit of an int type
                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.int16).max:
                    df[col] = df[col].astype(np.int16)
                elif c_min > np.iinfo(np.int32).min and c_max < np.iinfo(np.int32).max:
                    df[col] = df[col].astype(np.int32)
                elif c_min > np.iinfo(np.int64).min and c_max < np.iinfo(np.int64).max:
                    df[col] = df[col].astype(np.int64)
            else:
                if c_min > np.finfo(np.float16).min and c_max < np.finfo(np.float16).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

##############################################################
def timestamp_to_date(df):#train_df, test_df, train_weather_df, test_weather_df
    df['timestamp'] = pd.to_datetime(df['timestamp'])
    return df

def new_time_features(df):#train_df, test_df
    df['DT_M'] = df['timestamp'].dt.month.astype(np.int8)
    df['DT_W'] = df['timestamp'].dt.weekofyear.astype(np.int8)
    df['DT_D'] = df['timestamp'].dt.dayofyear.astype(np.int16)

    df['DT_hour'] = df['timestamp'].dt.hour.astype(np.int8)
    df['DT_day_week'] = df['timestamp'].dt.dayofweek.astype(np.int8)
    df['DT_day_month'] = df['timestamp'].dt.day.astype(np.int8)
    df['DT_week_month'] = df['timestamp'].dt.day/7
    df['DT_week_month'] = df['DT_week_month'].apply(lambda x: math.ceil(x)).astype(np.int8)
    return df

def building_transform():
    ########################### Strings to category ###########################################
    building_df['primary_use'] = building_df['primary_use'].astype('category')

    ########################### Building Transform ###########################################
    building_df['floor_count'] = building_df['floor_count'].fillna(0).astype(np.int8)
    building_df['year_built'] = building_df['year_built'].fillna(-999).astype(np.int16)

    le = LabelEncoder()
    building_df['primary_use'] = building_df['primary_use'].astype(str)
    building_df['primary_use'] = le.fit_transform(building_df['primary_use']).astype(np.int8)

########################### Base check ##################################################
def conversion_and_check(df):#train_df, test_df, building_df, train_weather_df, test_weather_df
    do_not_convert = ['category','datetime64[ns]','object'] #cannot compress further
    original = df.copy()
    df = reduce_mem_usage(df)

    for col in list(df):
        if df[col].dtype.name not in do_not_convert:
            if (df[col]-original[col]).sum()!=0:# Data loss
                df[col] = original[col] #Revert to original
                print('Bad transformation', col)
    return df
```

In [14]:
```
if not os.path.exists("../data/train_reduced.pkl'):
    train_df = pd.read_csv('../data/train.csv')
    train_df = timestamp_to_date(train_df)
    train_df = new_time_features(train_df)
    train_df = conversion_and_check(train_df)


    train_df.to_pickle('../data/train_reduced.pkl')
    print("Sucessfully pickled")
    del train_df
```

```
Mem. usage decreased to 443.43 Mb (42.5% reduction)
Bad transformation meter_reading
Sucessfully pickled
```

In [5]:
```
if not os.path.exists("../data/test_reduced.pkl"):
    test_df = pd.read_csv('../data/test.csv')
    test_df = timestamp_to_date(test_df)
    test_df = new_time_features(test_df)
    test_df = conversion_and_check(test_df)


    test_df.to_pickle('../data/test_reduced.pkl')
    print("Sucessfully pickled")
    del test_df
```

```
Mem. usage decreased to 914.62 Mb (42.5% reduction)
Sucessfully pickled
```

In [9]:
```
if not os.path.exists("../data/building_df_reduced.pkl"):
    building_transform()
    building_df = conversion_and_check(building_df)

    building_df.to_pickle('../data/building_df_reduced.pkl')
    print("Sucessfully pickled")
    del building_df
```

```
Mem. usage decreased to  0.02 Mb (0.0% reduction)
Sucessfully pickled
```

In [12]:
```
if not os.path.exists("../data/train_weather_reduced.pkl"):
    train_weather_df = timestamp_to_date(train_weather_df)
    train_weather_df = conversion_and_check(train_weather_df)

    train_weather_df.to_pickle('../data/train_weather_reduced.pkl')
    print("Sucessfully pickled")
    del train_weather_df
```

```
Mem. usage decreased to  3.07 Mb (68.1% reduction)
Bad transformation air_temperature
Bad transformation dew_temperature
Bad transformation sea_level_pressure
Bad transformation wind_speed
Sucessfully pickled
```

In [13]:
```
if not os.path.exists("../data/test_weather_reduced.pkl"):

    test_weather_df = pd.read_csv("../data/weather_test.csv")
    test_weather_df = timestamp_to_date(test_weather_df)
    test_weather_df = conversion_and_check(test_weather_df)


    test_weather_df.to_pickle('../data/test_weather_reduced.pkl')
    print("Sucessfully pickled")
    del test_weather_df
```

```
Mem. usage decreased to  6.08 Mb (68.1% reduction)
Bad transformation air_temperature
Bad transformation dew_temperature
Bad transformation sea_level_pressure
Bad transformation wind_speed
Sucessfully pickled
```

Train data:

In [3]:
```
with open("../data/train_reduced.pkl","rb") as pkl:
    train = pd.read_pickle(pkl)

train.head()
```

Out[3]:

	building_id	meter	timestamp	meter_reading	DT_M	DT_W	DT_D	DT_hour	DT_day_week	DT_day_month	DT_week_month
0	0	0	2016-01-01	0.0	1	53	1	0	4	1	1
1	1	0	2016-01-01	0.0	1	53	1	0	4	1	1
2	2	0	2016-01-01	0.0	1	53	1	0	4	1	1
3	3	0	2016-01-01	0.0	1	53	1	0	4	1	1
4	4	0	2016-01-01	0.0	1	53	1	0	4	1	1

All features DT* are added to the original dataset as additional features.

- DT_M : Month of the year
- DT_W : Week of the year
- DT_D : Day of the year
- DT_hour : Hour of the day
- DT_day_week : Day of the week
- DT_day_month : Day of the month
- DT_week_month : Week of the month

In [19]:
```
meters_per_building = {}
for building in train["building_id"].unique():
    meters_present = np.sort(train[train["building_id"]==building]["meter"].unique())
    all_meters = np.array([False,False,False,False])
    all_meters[meters_present] = True
    meters_per_building.update({building:all_meters})
```

In [20]:
```
meters_per_building_df = pd.DataFrame.from_dict(meters_per_building,orient='index')
meters_per_building_df
```

Out[20]:

	0	1	2	3
0	True	False	False	False
1	True	False	False	False
2	True	False	False	False
3	True	False	False	False
4	True	False	False	False
...	...	...	...	...
567	True	False	False	False
621	True	False	False	False
591	True	False	False	False
783	False	False	True	False
403	True	False	False	False

1449 rows × 4 columns

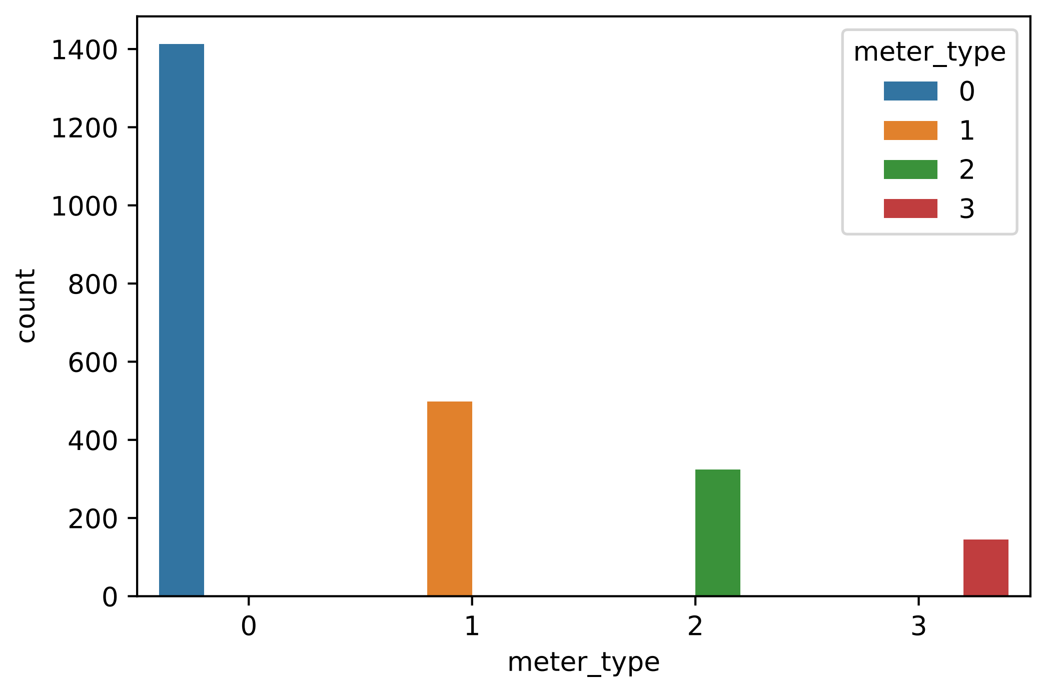
In [64]:
```
meters_count = pd.DataFrame({"meter_type":meters_per_building_df.sum().index,
"count":meters_per_building_df.sum().values})
meters_count
```

Out[64]:

	meter_type	count
0	0	1413
1	1	498
2	2	324
3	3	145

No. of buildings with a meter type:

In [69]:
```
sns.barplot(x="meter_type",y="count",data=meters_count,hue="meter_type")
plt.show()
```



Buildings with no Meter 0:

In [72]:
```
meters_per_building_df[meters_per_building_df[0]==False]
```

Out[72]:

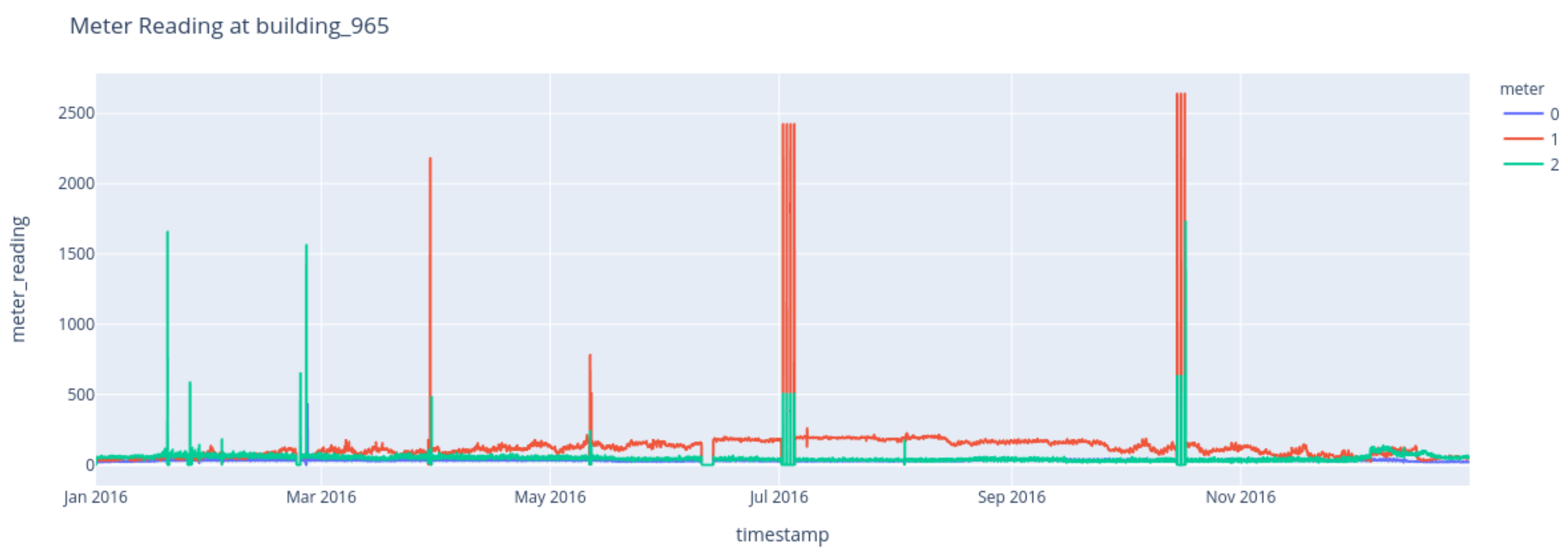
	0	1	2	3
751	False	True	True	False
754	False	False	True	False

	0	1	2	3
757	False	False	True	False
772	False	False	True	False
789	False	True	True	False
790	False	True	True	False
792	False	True	True	False
933	False	True	True	False
934	False	True	True	False
1072	False	True	True	False
1077	False	True	True	False
1078	False	True	True	False
1085	False	True	True	False
1112	False	False	True	False
1116	False	False	True	False
1132	False	True	False	False
1145	False	False	True	False
1155	False	False	True	False
1180	False	True	True	False
1187	False	True	True	False
1192	False	False	True	False
1204	False	False	True	False
1330	False	False	True	False
1349	False	True	False	False
1354	False	True	True	False
1372	False	True	False	False
1373	False	False	True	False
1374	False	True	False	False
1385	False	False	True	False
1388	False	True	False	False
1397	False	True	False	False
1426	False	False	True	False
752	False	True	False	False
763	False	True	False	False
786	False	True	False	False

1413 buildings have Meter 0, which is the dominant meter. Whereas only 498 =, 324 and 145 buildings have Meter 1, Meter 2 and Meter 3 respectively.

In [18]:
```
def plot_building_meter_reading(building_id):
    fig = px.line(train[train["building_id"]==building_id],x='timestamp', y='meter_reading',color='meter')
    fig.update_layout(
            autosize=False,
            title="Meter Reading at building_{}".format(building_id),
            width=1200,
            height=450)
    return fig
```

In [20]:
```
plot_building_meter_reading(965)
```



Meter readings of the building 965 for the entire year. Some of these readings could also be outliers. We can decide on outliers by analysing data of buildings with same primary_use at the same site.