In [ ]:
```python
import os

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

%pylab inline
```

```
%pylab is deprecated, use %matplotlib inline and import the required libraries.
Populating the interactive namespace from numpy and matplotlib
```

Data Reading

In [ ]:
```python
dfs = []
for file in os.listdir("./data/"):
    print(f'reading of {file}...')
    df = pd.read_csv(f"./data/{file}")
    dfs.append(df)

all_data_df = pd.concat(dfs, axis=0, ignore_index=True)
all_data_df
```

```
reading of saveecobot_12921.csv...
reading of saveecobot_20585.csv...
reading of saveecobot_20614.csv...
```

Out[ ]:

	device_id	phenomenon	value	logged_at	value_text
0	12921	pm1	2.3750	2020-09-14 15:41:48	NaN
1	12921	pm25	3.5625	2020-09-14 15:41:48	NaN
2	12921	pm10	2.6250	2020-09-14 15:41:48	NaN
3	12921	temperature	25.4821	2020-09-14 15:41:48	NaN
4	12921	humidity	73.4259	2020-09-14 15:41:48	NaN
...	...	...	...	...	...
2950043	20614	aqi	19.0000	2022-10-12 21:00:00	NaN
2950044	20614	pm25	4.6000	2022-10-12 21:00:00	NaN
2950045	20614	temperature	9.0000	2022-10-12 21:00:00	NaN
2950046	20614	humidity	76.0000	2022-10-12 21:00:00	NaN
2950047	20614	pressure_pa	100700.0000	2022-10-12 21:00:00	NaN

2950048 rows × 5 columns

data analisys

In [ ]:
```python
print(f'dataset shape: {all_data_df.shape}\n')
print(f'columns amount: {len(all_data_df.columns)}\n')
print('columns:\n', all_data_df.dtypes, '\n')
print(f'not null rows amount:\n {all_data_df.count()}\n')
#get amount of unique values for each column
for col in all_data_df.columns:
    print(f"unique values in column {col} -- {len(all_data_df[col].unique())}")
```

```
dataset shape: (2950048, 5)

columns amount: 5

columns:
 device_id       int64
phenomenon     object
value         float64
logged_at      object
value_text    float64
dtype: object

not null rows amount:
 device_id     2950048
phenomenon    2950048
value         2950048
logged_at     2950048
value_text          0
dtype: int64

unique values in column device_id -- 3
unique values in column phenomenon -- 7
unique values in column value -- 852613
unique values in column logged_at -- 487619
unique values in column value_text -- 1
```

data preparation

In [ ]:
```
all_data_df.drop("value_text", axis=1, inplace=True)

# get week day fol each record
all_data_df["logged_at"] = pd.to_datetime(all_data_df["logged_at"], format='%Y/%m/%d %H:%M:%S' )
all_data_df["day_of_week"] = all_data_df.logged_at.dt.dayofweek
all_data_df
```

Out[ ]:

	device_id	phenomenon	value	logged_at	day_of_week
0	12921	pm1	2.3750	2020-09-14 15:41:48	0
1	12921	pm25	3.5625	2020-09-14 15:41:48	0
2	12921	pm10	2.6250	2020-09-14 15:41:48	0
3	12921	temperature	25.4821	2020-09-14 15:41:48	0
4	12921	humidity	73.4259	2020-09-14 15:41:48	0
...	...	...	...	...	...
2950043	20614	aqi	19.0000	2022-10-12 21:00:00	2
2950044	20614	pm25	4.6000	2022-10-12 21:00:00	2
2950045	20614	temperature	9.0000	2022-10-12 21:00:00	2
2950046	20614	humidity	76.0000	2022-10-12 21:00:00	2
2950047	20614	pressure_pa	100700.0000	2022-10-12 21:00:00	2

2950048 rows × 5 columns

In [ ]:
```
#get day time fol each record
all_data_df.loc[
    (all_data_df['logged_at'].dt.hour > 4)
    & (all_data_df['logged_at'].dt.hour <= 10),
    'time_of_day'] = 'morning'
all_data_df.loc[
    (all_data_df['logged_at'].dt.hour > 10)
    & (all_data_df['logged_at'].dt.hour <= 16),
    'time_of_day'] = 'afternoon'

all_data_df.loc[
    (all_data_df['logged_at'].dt.hour > 16)
    & (all_data_df['logged_at'].dt.hour <= 22),
    'time_of_day'] = 'evening'

all_data_df.loc[
    (all_data_df['logged_at'].dt.hour > 22)
    & (all_data_df['logged_at'].dt.hour <= 23)
    | (all_data_df['logged_at'].dt.hour >= 0)
    & (all_data_df['logged_at'].dt.hour <= 4),
    'time_of_day'] = 'night'

all_data_df
```

Out[ ]:

	device_id	phenomenon	value	logged_at	day_of_week	time_of_day
0	12921	pm1	2.3750	2020-09-14 15:41:48	0	afternoon
1	12921	pm25	3.5625	2020-09-14 15:41:48	0	afternoon
2	12921	pm10	2.6250	2020-09-14 15:41:48	0	afternoon
3	12921	temperature	25.4821	2020-09-14 15:41:48	0	afternoon
4	12921	humidity	73.4259	2020-09-14 15:41:48	0	afternoon
...	...	...	...	...	...	...
2950043	20614	aqi	19.0000	2022-10-12 21:00:00	2	evening
2950044	20614	pm25	4.6000	2022-10-12 21:00:00	2	evening
2950045	20614	temperature	9.0000	2022-10-12 21:00:00	2	evening
2950046	20614	humidity	76.0000	2022-10-12 21:00:00	2	evening
2950047	20614	pressure_pa	100700.0000	2022-10-12 21:00:00	2	evening

2950048 rows × 6 columns

In [ ]:
```
# categorize phenomenon
all_data_df['phenomenon_cat'] = all_data_df.phenomenon.astype("category").cat.codes
all_data_df['time_of_day_cat'] = all_data_df.time_of_day.astype("category").cat.codes
all_data_df
```

Out[ ]:

	device_id	phenomenon	value	logged_at	day_of_week	time_of_day	phenomenon_cat	time_of_day_cat
0	12921	pm1	2.3750	2020-09-14 15:41:48	0	afternoon	2	0
1	12921	pm25	3.5625	2020-09-14 15:41:48	0	afternoon	4	0
2	12921	pm10	2.6250	2020-09-14 15:41:48	0	afternoon	3	0
3	12921	temperature	25.4821	2020-09-14 15:41:48	0	afternoon	6	0
4	12921	humidity	73.4259	2020-09-14 15:41:48	0	afternoon	1	0
...	...	...	...	...	...	...	...	...
2950043	20614	aqi	19.0000	2022-10-12 21:00:00	2	evening	0	1
2950044	20614	pm25	4.6000	2022-10-12 21:00:00	2	evening	4	1
2950045	20614	temperature	9.0000	2022-10-12 21:00:00	2	evening	6	1
2950046	20614	humidity	76.0000	2022-10-12 21:00:00	2	evening	1	1
2950047	20614	pressure_pa	100700.0000	2022-10-12 21:00:00	2	evening	5	1

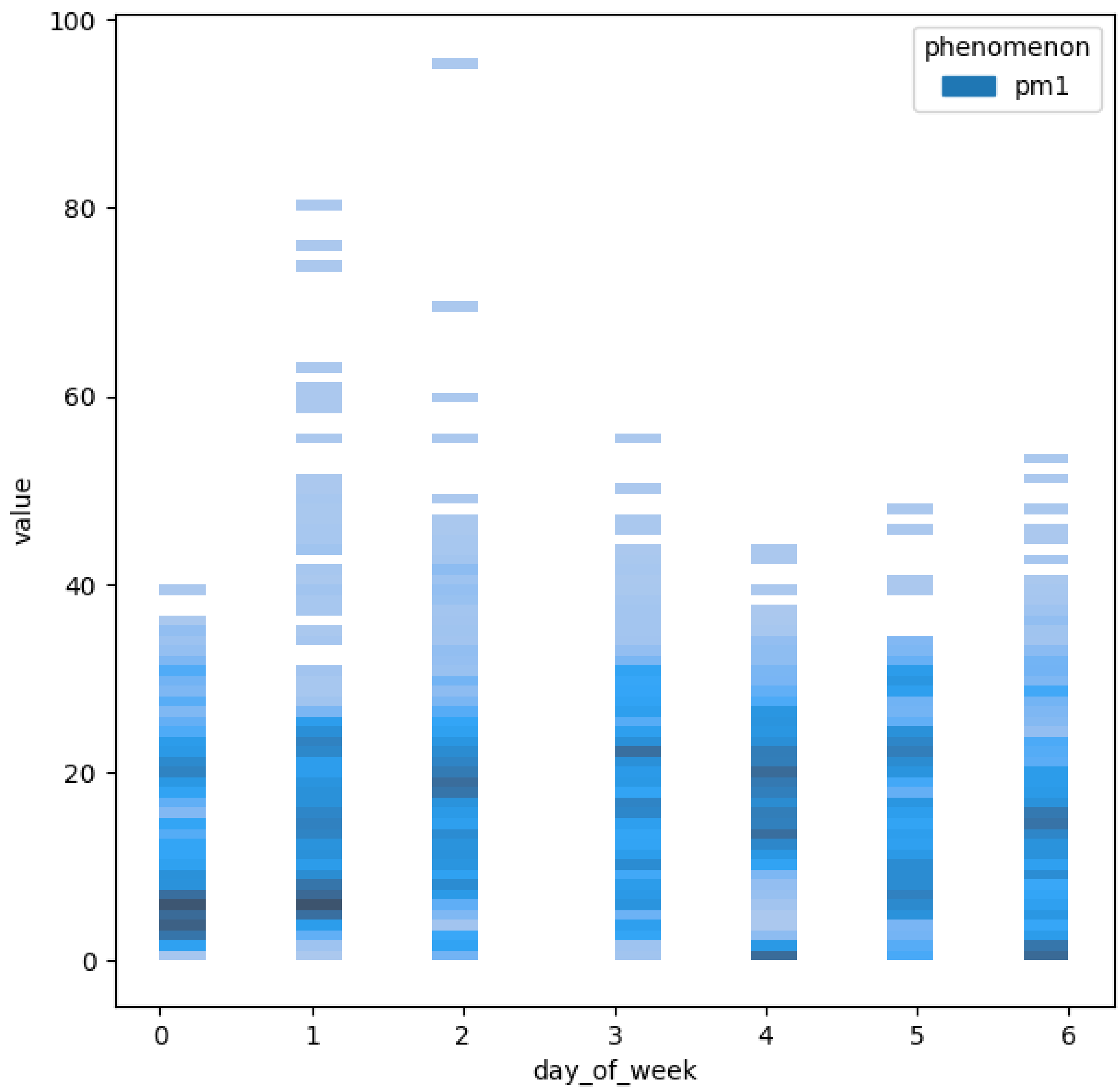
2950048 rows × 8 columns

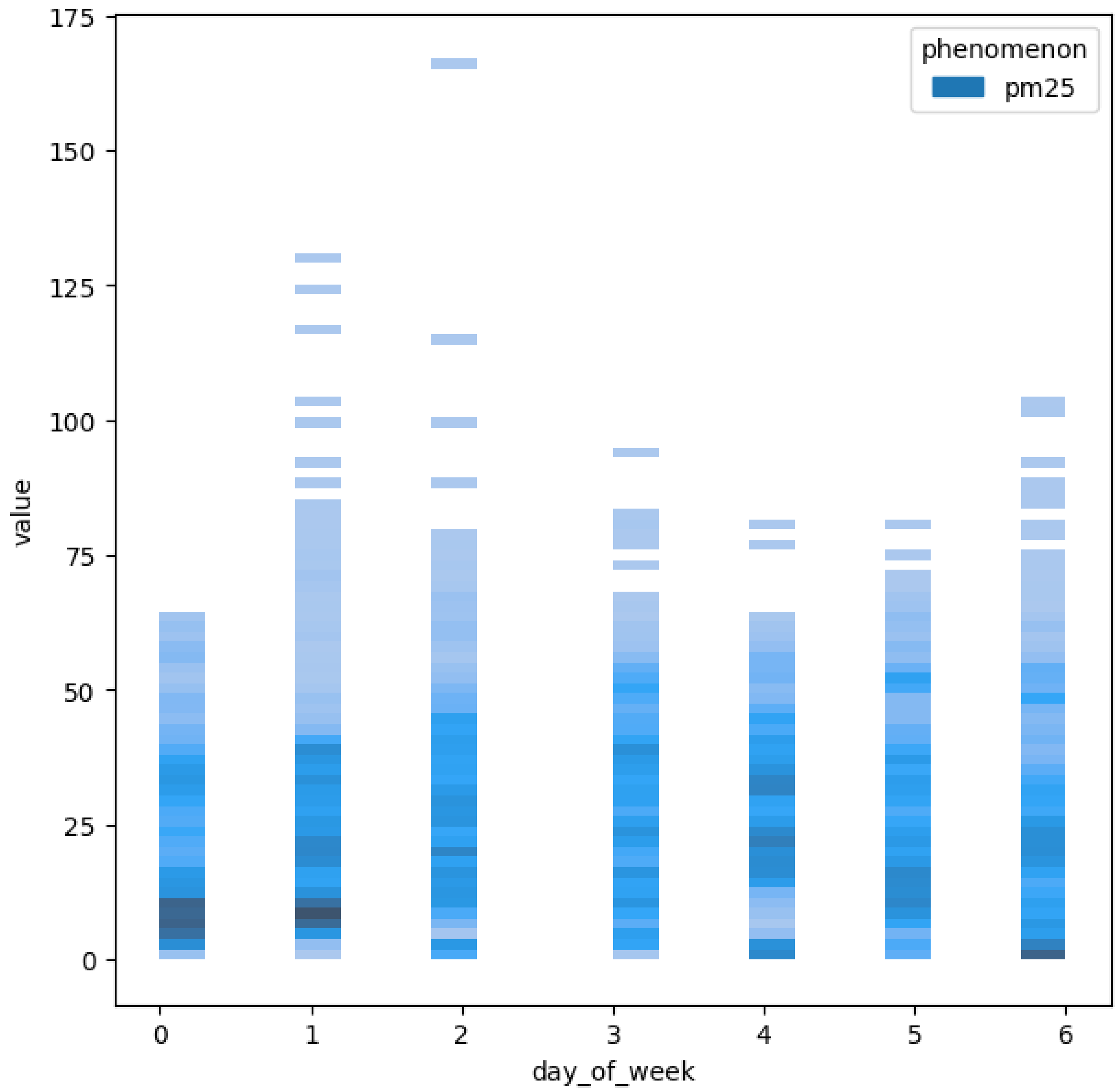
In [ ]:

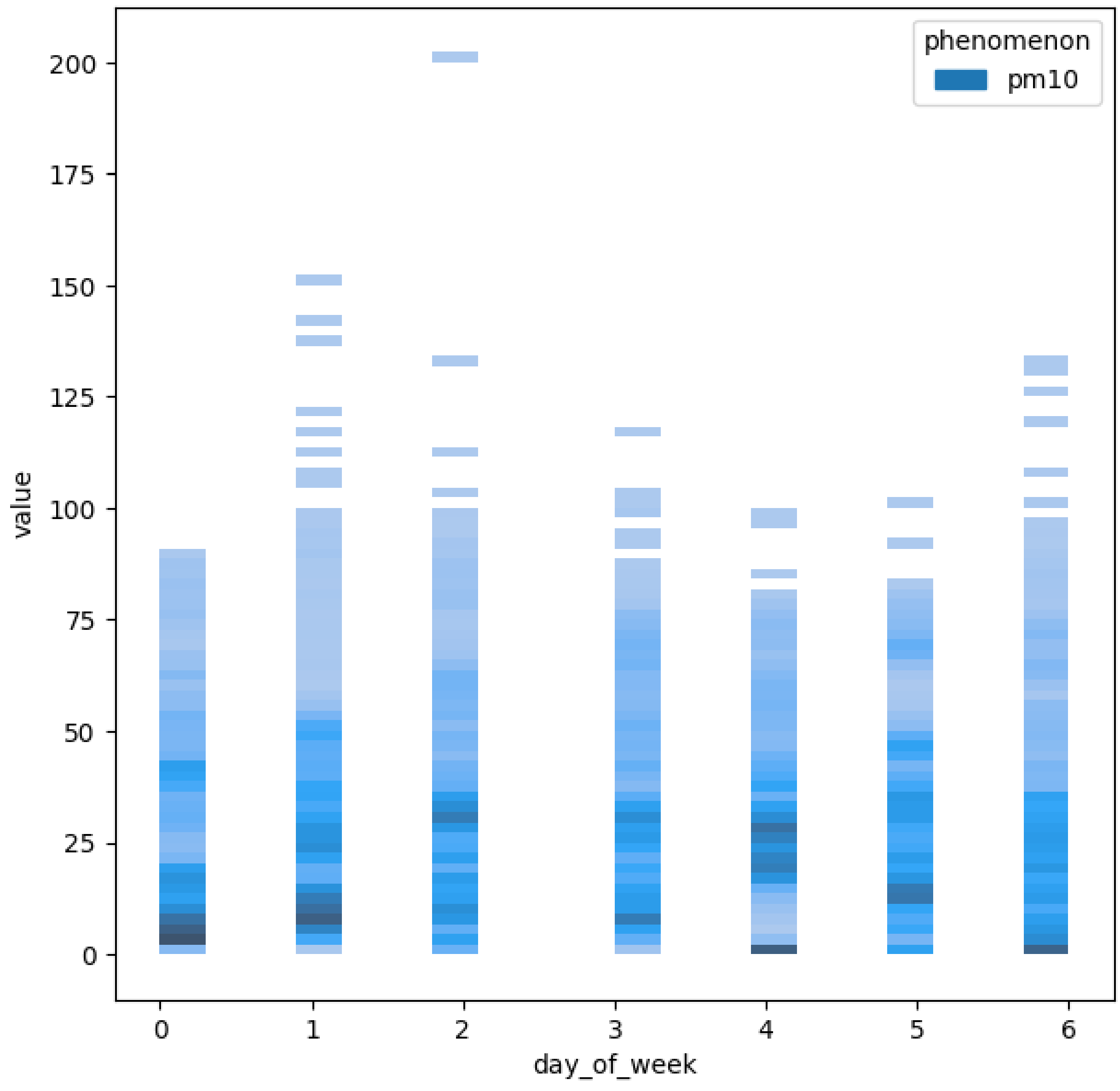
```
#get a subsets for histogram creation
phenomenon_weekday_df = all_data_df[['phenomenon', 'value', 'day_of_week']].iloc[:100000,:]
phenomenon_daytime_df = all_data_df[['phenomenon', 'value', 'time_of_day']].iloc[:100000,:]
```

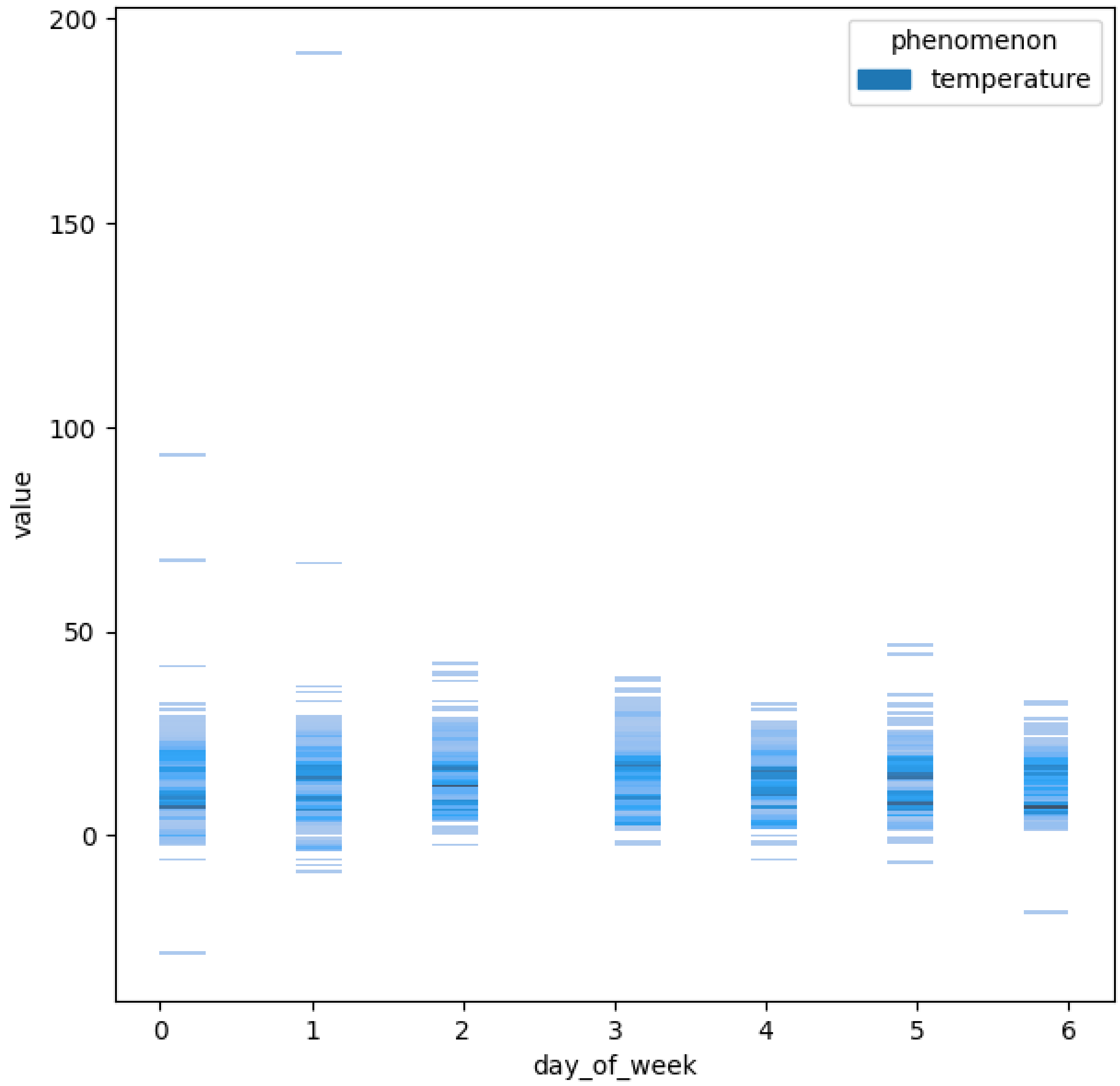
In [ ]:

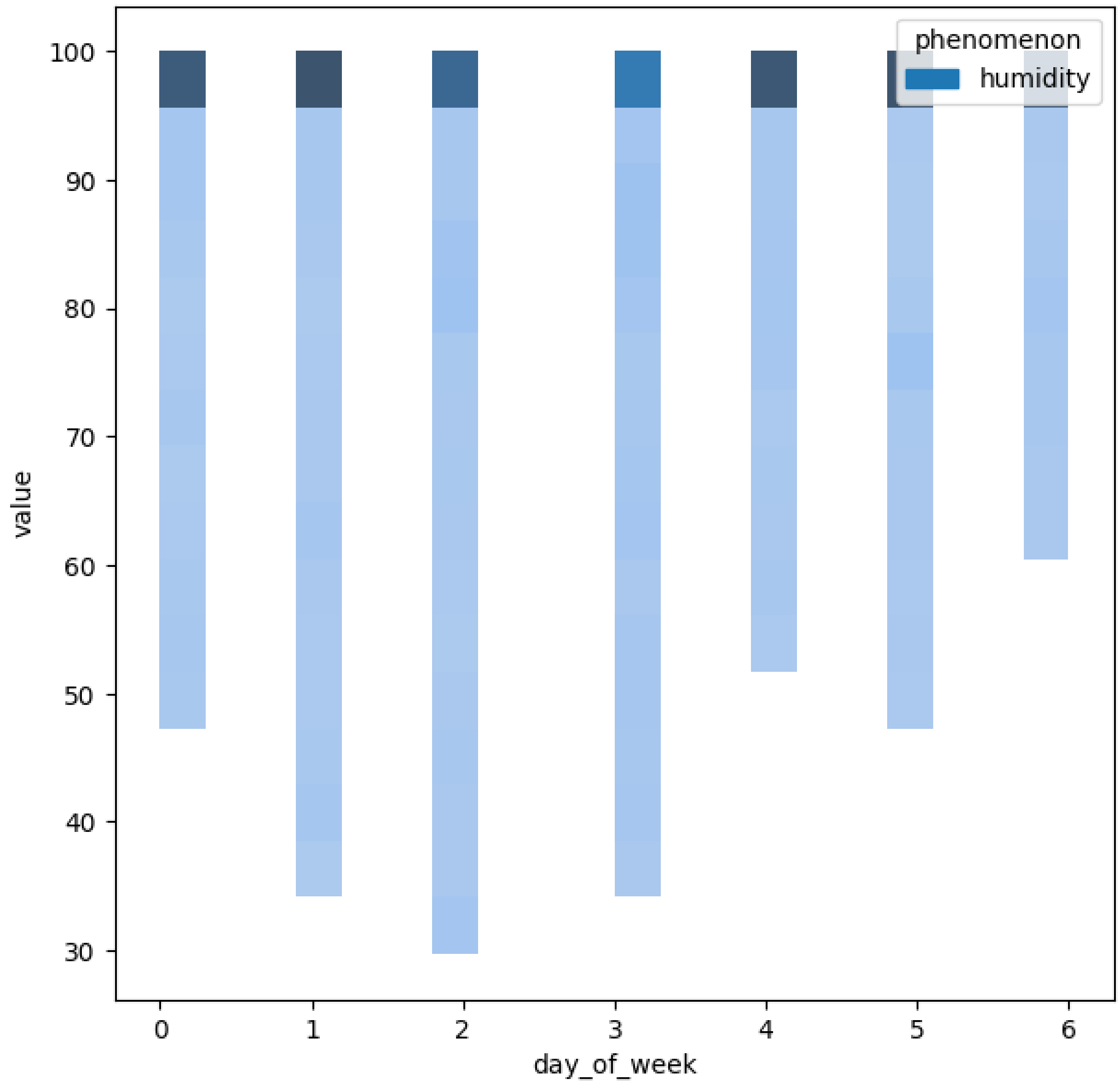
```
for phen in all_data_df.phenomenon.unique():
    if(phen != 'aqi'):
        pylab.figure(figsize=(7,7))
        sns.histplot(phenomenon_weekday_df[phenomenon_weekday_df.phenomenon==phen], x='day_of_week', y='value', hue='phenomenon')
```

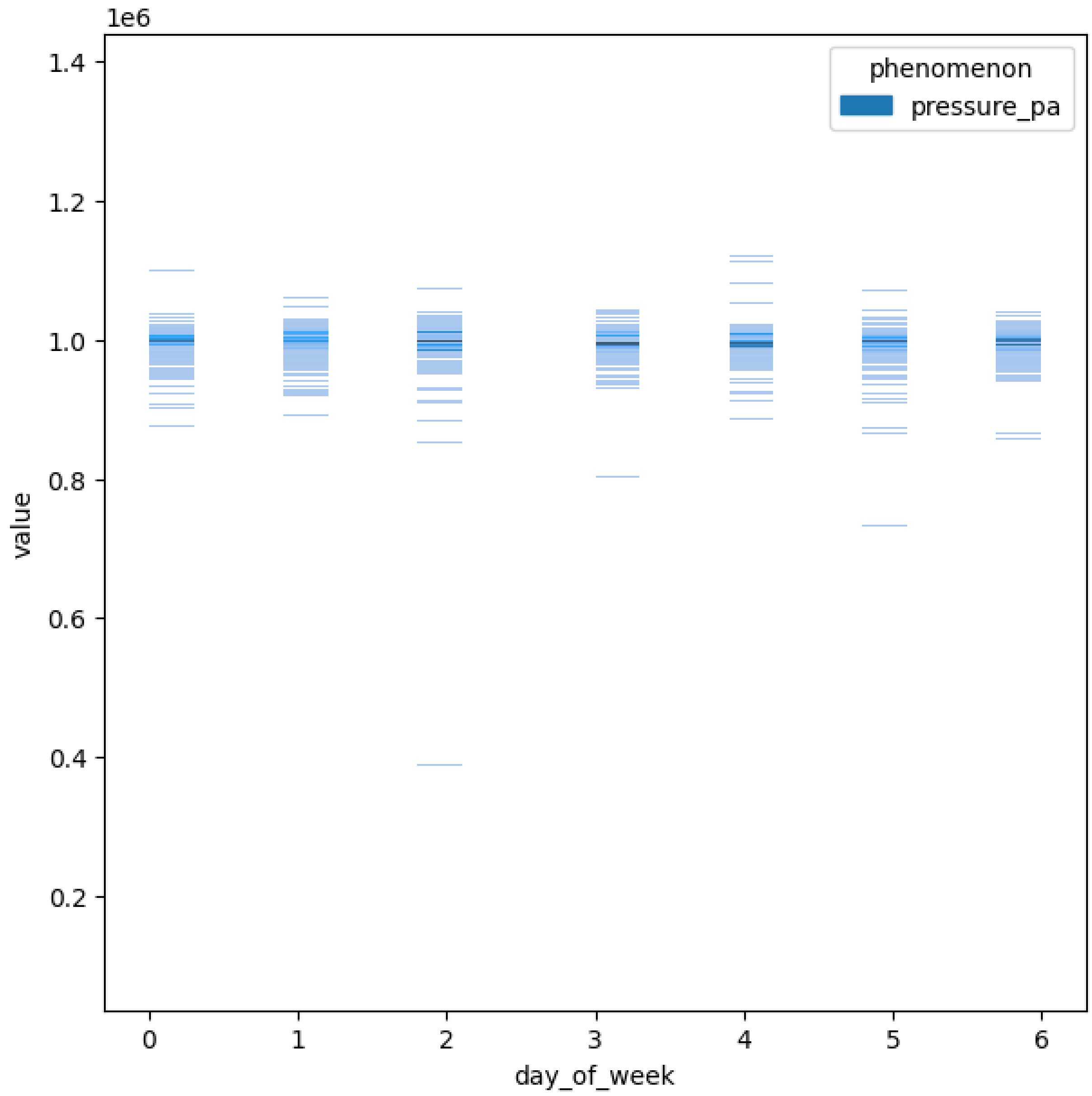



phenomenon
pm25
value
day_of_week
0
25
50
75
100
125
150
175
0
1
2
3
4
5
6

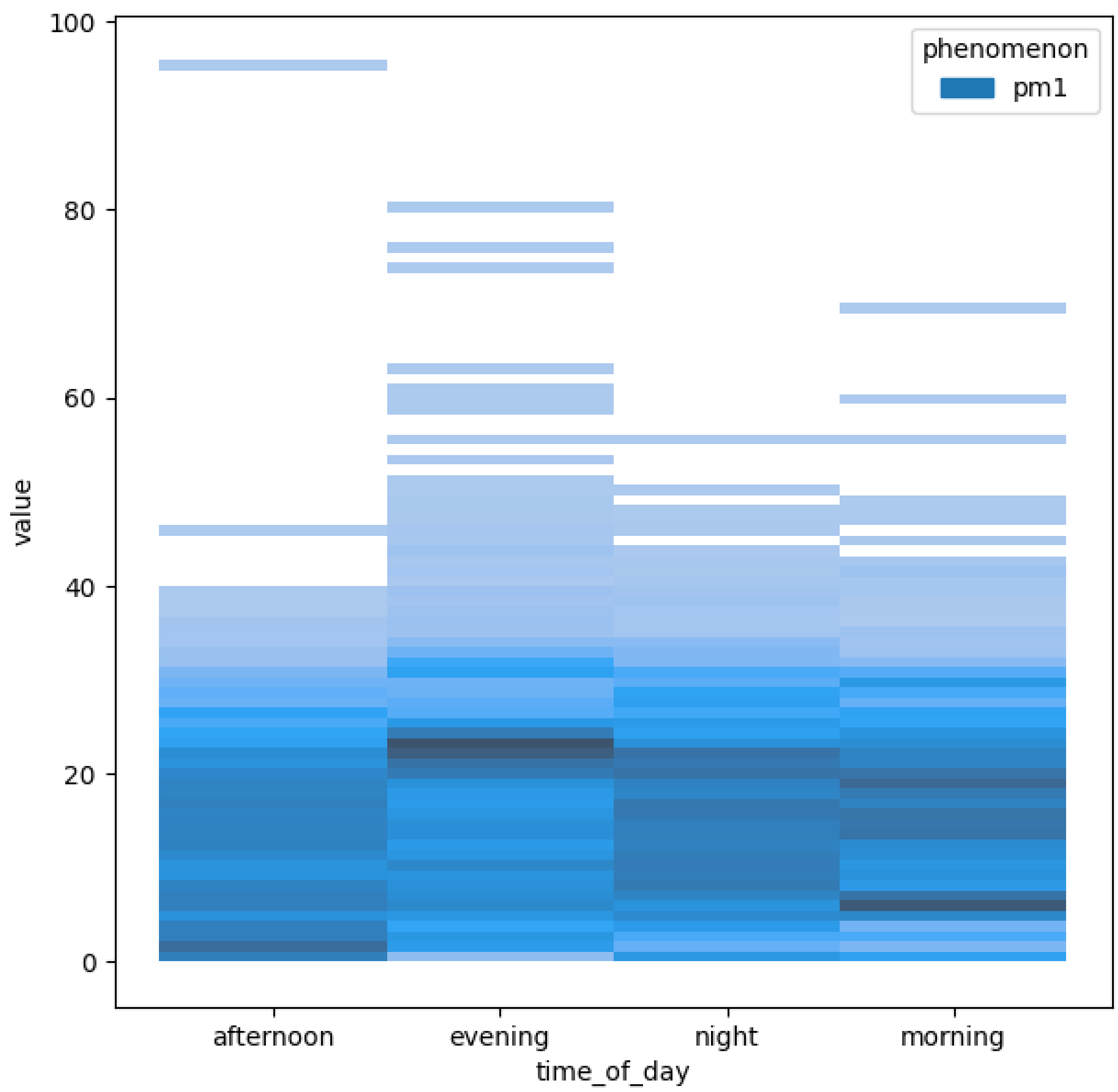

phenomenon
pm10
value
day_of_week
0
25
50
75
100
125
150
175
200
0
1
2
3
4
5
6

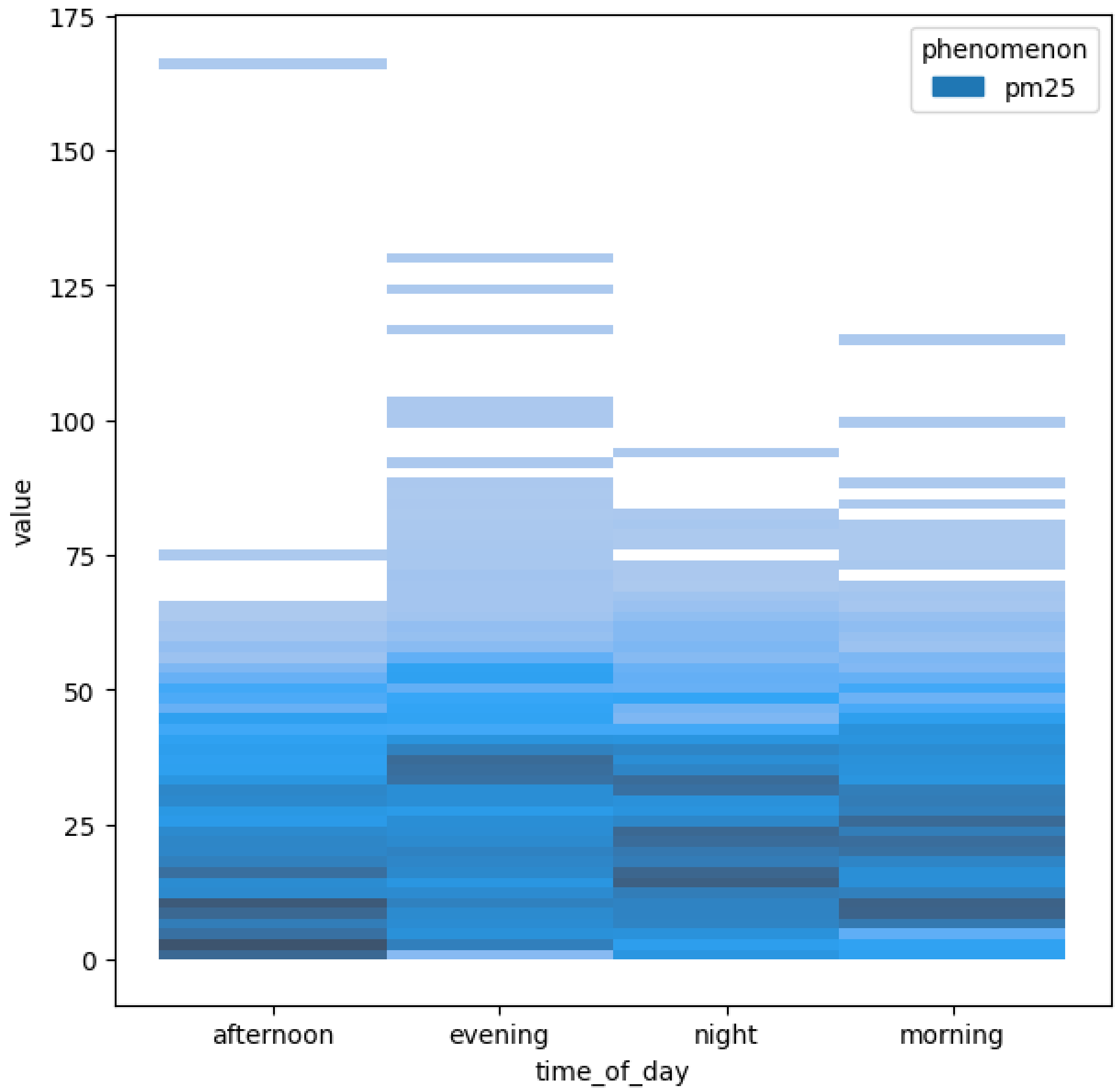

phenomenon
temperature
value
day_of_week
0
1
2
3
4
5
6
200
150
100
50
0


phenomenon
humidity
value
day_of_week
0
1
2
3
4
5
6
100
90
80
70
60
50
40
30

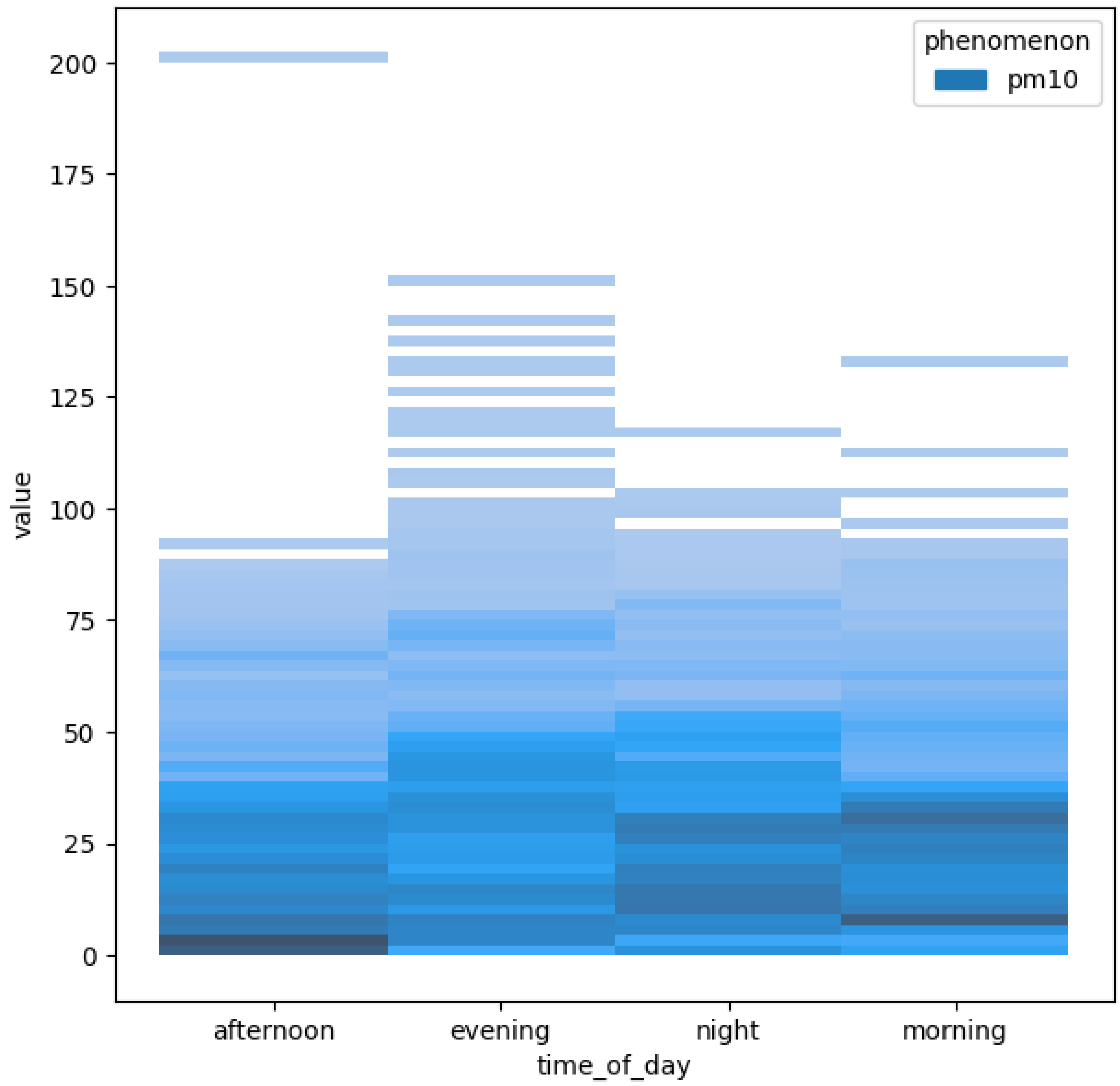


In [ ]:
```
for phen in all_data_df.phenomenon.unique():
    if(phen != 'aqi'):
        pylab.figure(figsize=(7,7))
        sns.histplot(phenomenon_daytime_df[phenomenon_daytime_df.phenomenon==phen], x='time_of_day', y='value', hue='phenomenon')
```

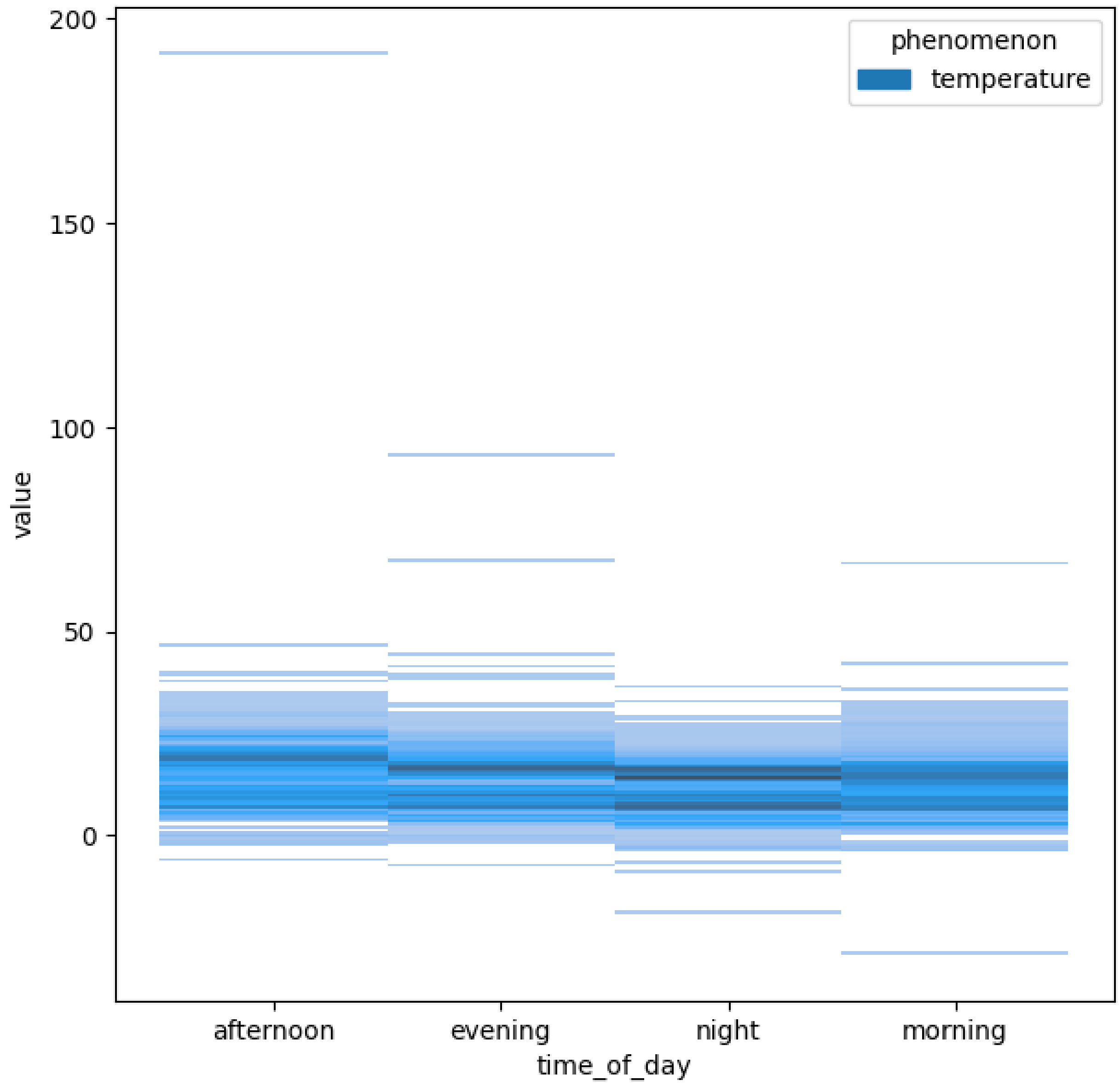




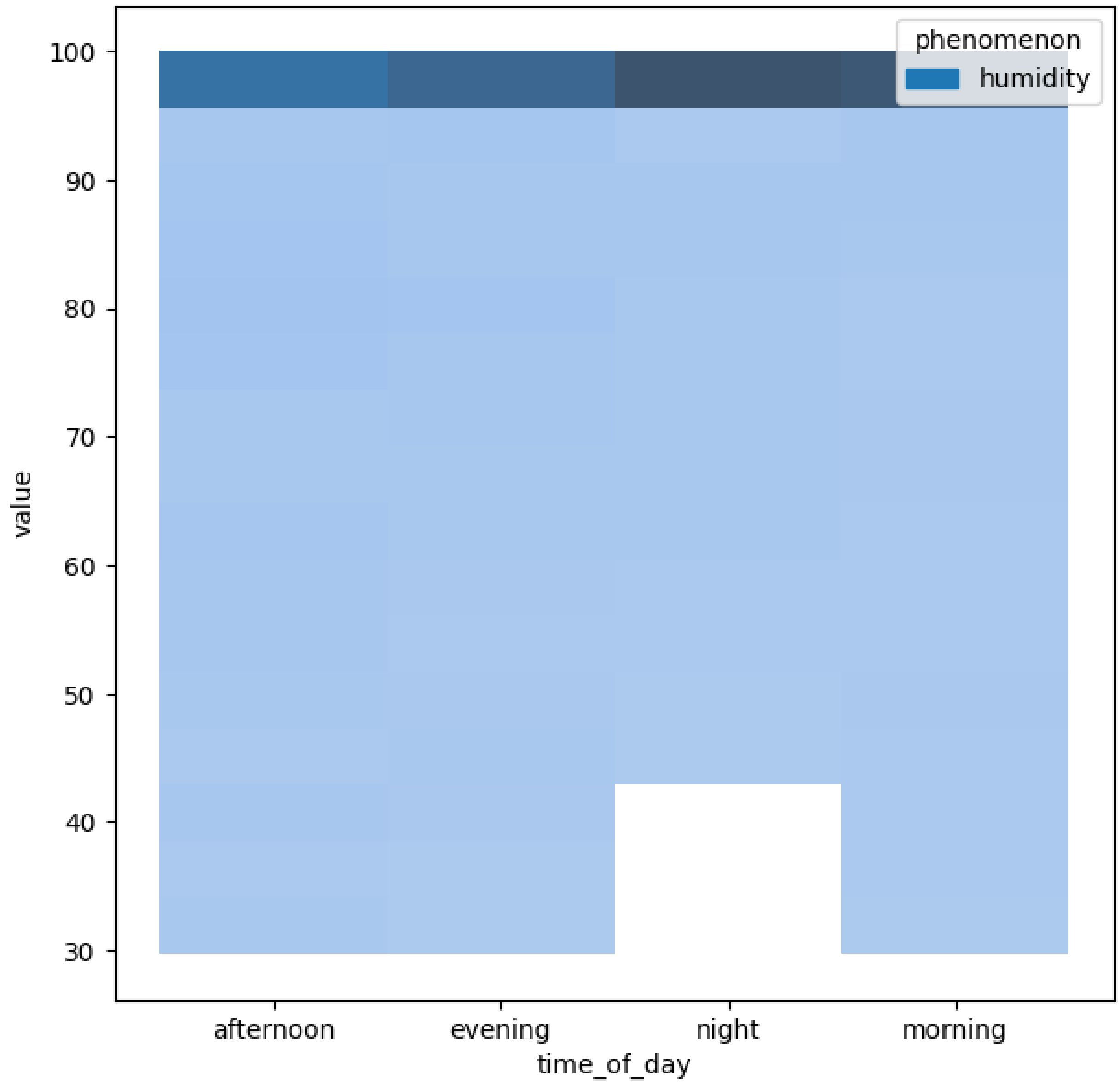
phenomenon
pm25
value
time_of_day
afternoon
evening
night
morning
0
25
50
75
100
125
150
175



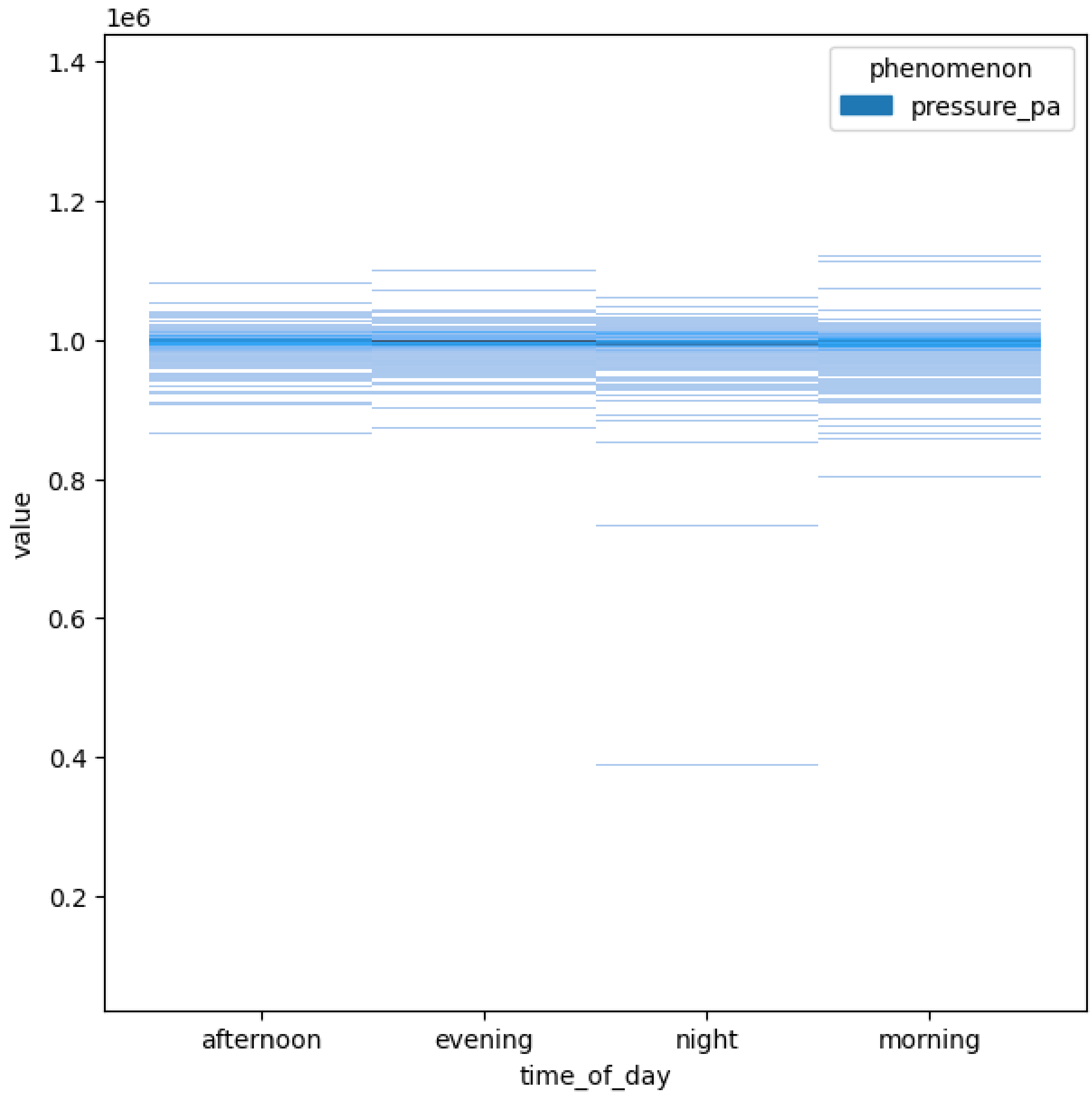
phenomenon
pm10
value
time_of_day
afternoon
evening
night
morning
0
25
50
75
100
125
150
175
200



phenomenon
temperature
200
150
100
50
0
value
afternoon
evening
night
morning
time_of_day



phenomenon
humidity
100
90
80
70
60
50
40
30
value
afternoon
evening
night
morning
time_of_day



In [ ]:
```
# get mean values per 'phenomenon' per 'logged_at' and create a pivot table
feature_df = all_data_df.groupby(['phenomenon', 'logged_at'], as_index=False).aggregate('mean')
phenomenon_time_df = feature_df.pivot_table(index=['logged_at', 'day_of_week', 'time_of_day_cat'], columns='phenomenon', values=[
phenomenon_time_df.reset_index(inplace=True)
phenomenon_time_df.columns = [col[1] if col[1]!='' else col[0] for col in phenomenon_time_df.columns.values]
print('Columns:  ', phenomenon_time_df.columns)
phenomenon_time_df
```

```
C:\Users\Lollo\AppData\Local\Temp\ipykernel_5112\1115287565.py:2: FutureWarning: The default value of numeric_only in DataFrameG
roupBy.mean is deprecated. In a future version, numeric_only will default to False. Either specify numeric_only or select only c
olumns which should be valid for the function.
  feature_df = all_data_df.groupby(['phenomenon', 'logged_at'], as_index=False).aggregate('mean')
Columns:   Index(['logged_at', 'day_of_week', 'time_of_day_cat', 'aqi', 'humidity', 'pm1',
       'pm10', 'pm25', 'pressure_pa', 'temperature'],
      dtype='object')
```

Out[ ]:

	logged_at	day_of_week	time_of_day_cat	aqi	humidity	pm1	pm10	pm25	pressure_pa	temperature
0	2020-09-14 15:41:48	0.0	0.0	NaN	73.4259	2.3750	2.6250	3.5625	1.008364e+05	25.4821
1	2020-09-14 15:45:05	0.0	0.0	NaN	72.1887	2.1500	2.9500	5.3000	1.003555e+05	22.3447
2	2020-09-14 15:45:18	0.0	0.0	NaN	72.1887	2.1500	2.9500	5.3000	1.003555e+05	22.3447
3	2020-09-14 15:47:29	0.0	0.0	NaN	73.5209	2.4545	2.9091	3.9545	1.003564e+05	22.1890
4	2020-09-14 15:50:32	0.0	0.0	NaN	72.2516	1.3333	1.3333	3.0000	1.003599e+06	22.7042
...	...	...	...	...	...	...	...	...	...	...
487614	2022-10-12 22:50:00	2.0	1.0	NaN	100.0000	9.8860	14.2350	11.8350	1.003757e+06	5.9380
487615	2022-10-12 22:51:00	2.0	1.0	NaN	100.0000	9.8270	13.6230	11.6160	1.003759e+06	5.9140
487616	2022-10-12 22:52:00	2.0	1.0	NaN	100.0000	9.4660	12.4890	11.5010	1.003775e+06	5.9000
487617	2022-10-12 22:53:00	2.0	1.0	NaN	100.0000	9.5010	12.0090	11.0810	1.003763e+06	5.8890
487618	2022-10-12 22:54:00	2.0	1.0	NaN	100.0000	9.8040	13.3690	11.9090	1.003764e+06	5.8730

487619 rows × 10 columns

In [ ]:
```
corr_matrix = phenomenon_time_df.corr().abs()
corr = (corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))
                  .stack()
                  .sort_values(ascending=False)
      )[:3]
print(corr)
corr_items = list(corr.index)
```

```
pm1   pm25    0.986430
pm10  pm25    0.981624
pm1   pm10    0.959722
dtype: float64
```

```
C:\Users\Lollo\AppData\Local\Temp\ipykernel_5112\792457308.py:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  corr_matrix = phenomenon_time_df.corr().abs()
```

Selecting features and model creation

In [ ]:

```python
#drop aqi because it is Nan almost everywhere
phenomenon_time_df.drop('aqi', axis=1, inplace=True)
phenomenon_time_df.dropna(inplace=True)
print(len(phenomenon_time_df))

#split data for train and test
train, test = train_test_split(phenomenon_time_df, test_size=0.25, random_state=0)
print(f"train samples: {len(train)},  test samples {len(test)}")
```

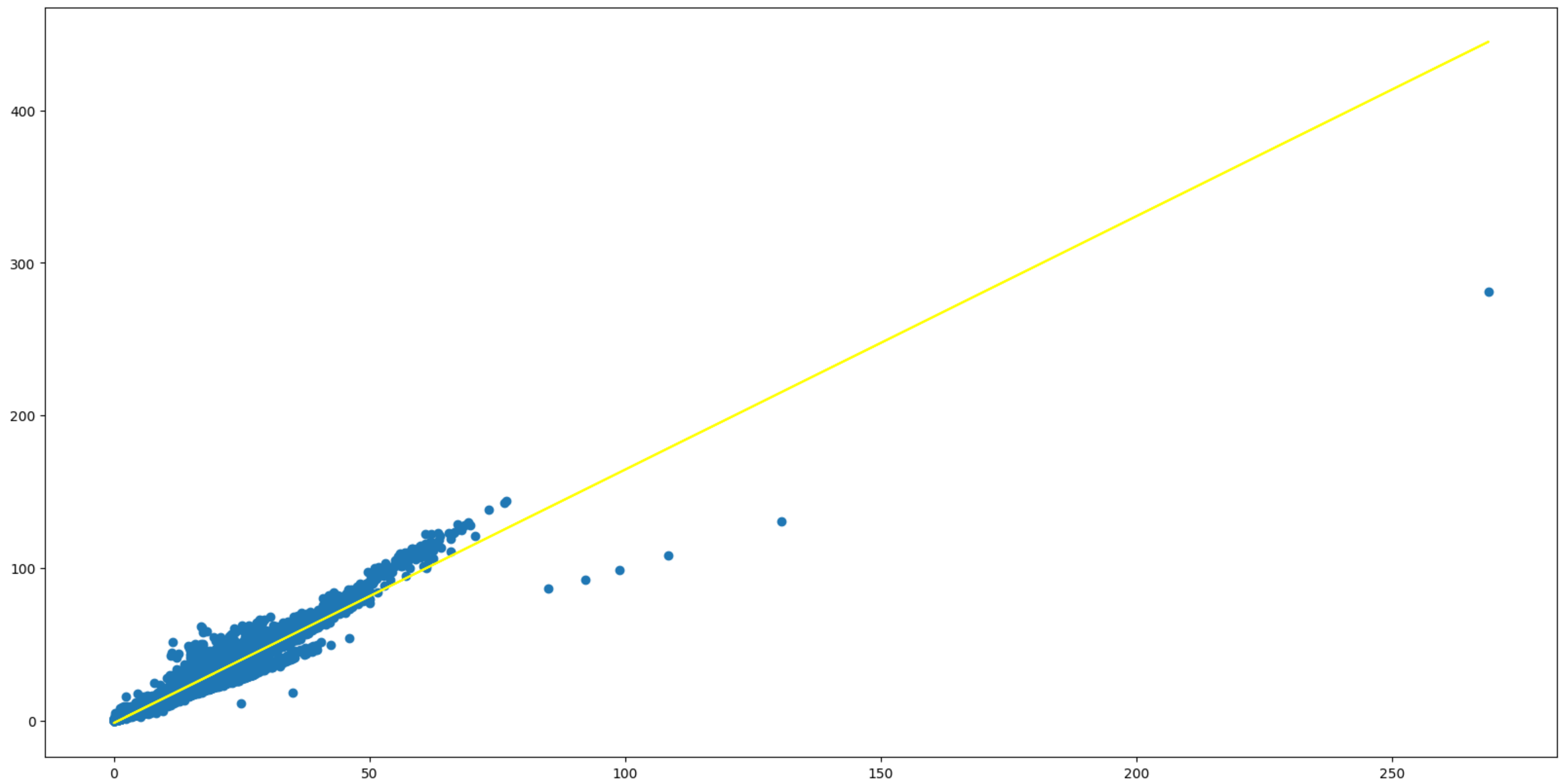
```
483318
train samples: 362488,  test samples 120830
```

In [ ]:

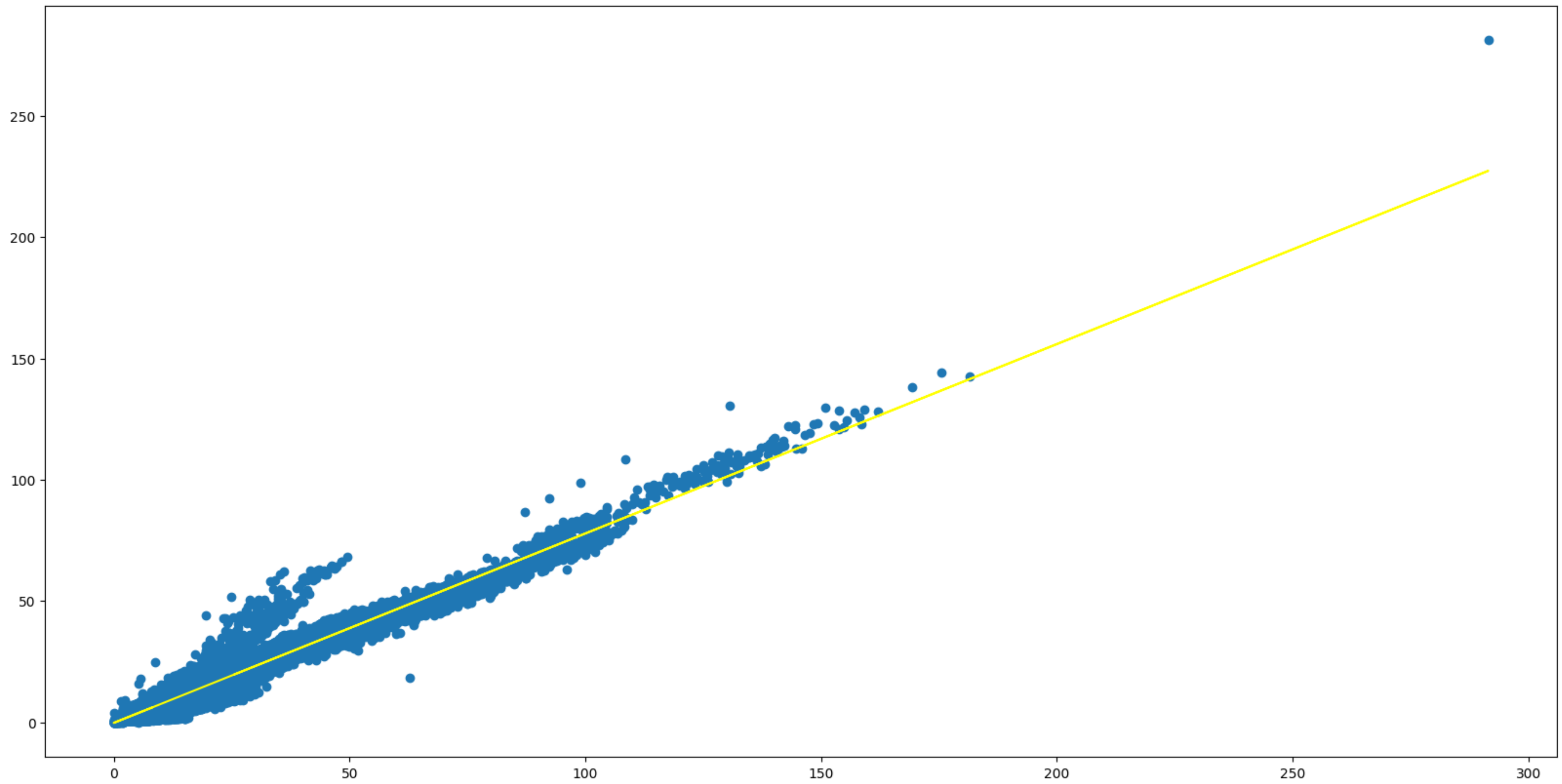
```python
for corr_i in corr_items:
    X = train[[corr_i[0]]]
    Y = train[[corr_i[1]]]
    model = LinearRegression()
    model.fit(X, Y)
    results = model.predict(test[[corr_i[0]]])
    print(f"feature {corr_i[0]},  target: {corr_i[1]}")
    print(f"r2_score  ", r2_score(test[[corr_i[0]]], results))
    print(f"RMSE  ", mean_squared_error(test[[corr_i[0]]], results, squared=True), '\n\n')

    fig = plt.figure()
    fig.set_figwidth(20)
    fig.set_figheight(10)
    plt.scatter(test[[corr_i[0]]], test[[corr_i[1]]])
    plt.plot(test[[corr_i[0]]], results, color='yellow')
    plt.show()
```

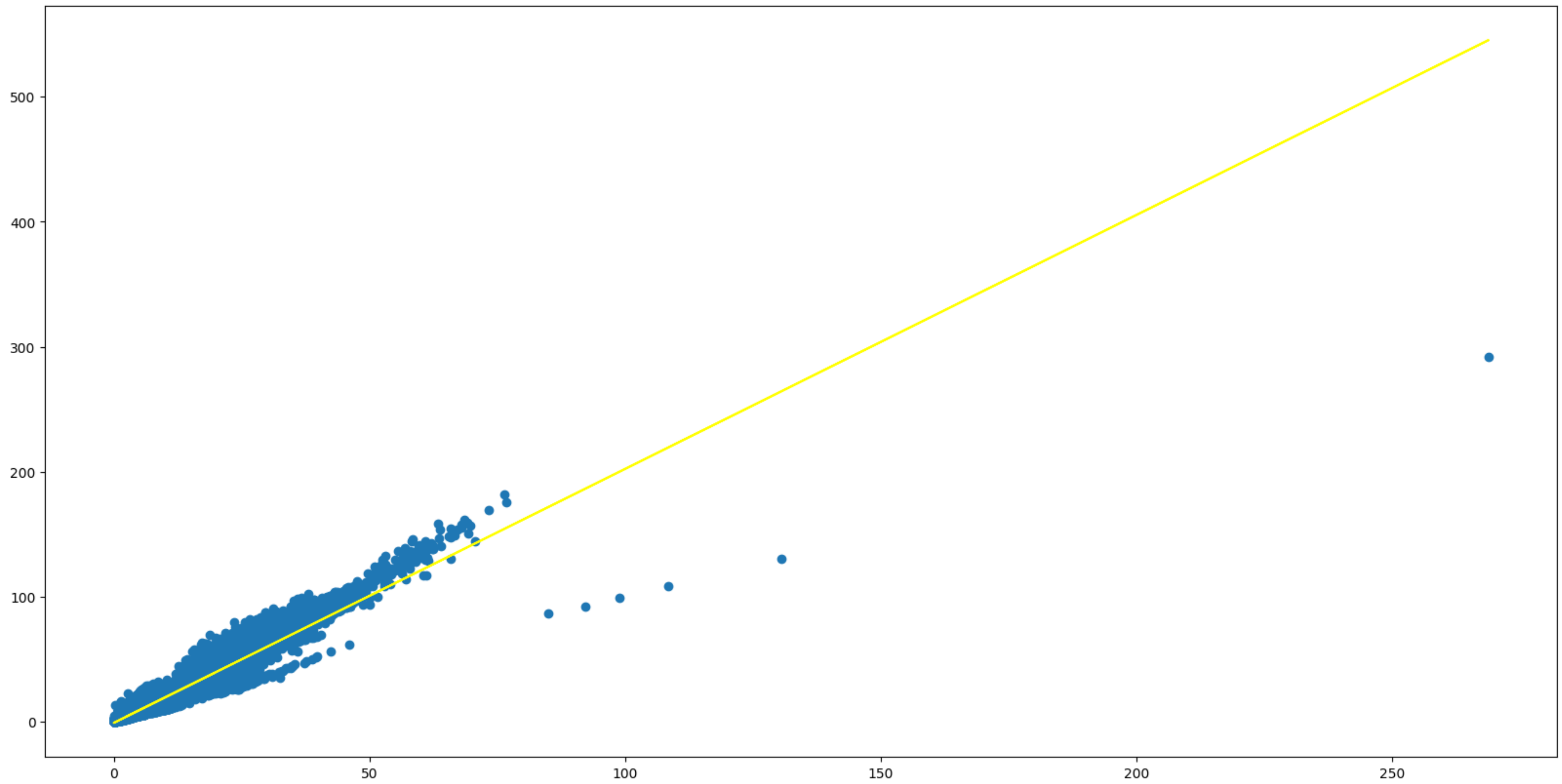
```
feature pm1,  target: pm25
r2_score   0.28774987336448554
RMSE   52.36884762662069
```




```
feature pm10,  target: pm25
r2_score   0.8981031531758744
RMSE   33.65247753974884
```




```
feature pm1,  target: pm10
r2_score   -1.0957663817355554
RMSE   154.09315660573859
```



Get scores for all phenomenons

In [ ]:
```
def get_features_and_run_model(train_data, test_data, X_set, Y_set):
    for feature in X_set:
        for target in Y_set:
            if feature == target:
                continue
            X = train_data[[feature]]
            Y = train_data[[target]]
            model = LinearRegression()
            model.fit(X, Y)
            results = model.predict(test_data[[feature]])

            print(f"feature {feature},  target: {target}")
            print(f"r2_score  ", r2_score(test_data[[target]], results))
            print(f"RMSE  ", mean_squared_error(test_data[[target]], results, squared=True), '\n\n')
```

In [ ]:
```
get_features_and_run_model(
    train,
    test,
    ['humidity', 'pm1', 'pm10', 'pm25', 'pressure_pa', 'temperature'],
    ['time_of_day_cat']
)
```

```
feature humidity,  target: time_of_day_cat
r2_score   0.09397357335439727
RMSE   1.1307110017874669


feature pm1,  target: time_of_day_cat
r2_score   0.004700538126381937
RMSE   1.2421227665292482


feature pm10,  target: time_of_day_cat
r2_score   0.0021309801776744353
RMSE   1.245329546549


feature pm25,  target: time_of_day_cat
r2_score   0.0040805510589061456
RMSE   1.242896503561132


feature pressure_pa,  target: time_of_day_cat
r2_score   5.133369256338227e-06
RMSE   1.2479825799525537


feature temperature,  target: time_of_day_cat
r2_score   0.017806635362506262
RMSE   1.225766501524653
```

In [ ]:
```
get_features_and_run_model(
    train,
    test,
    ['humidity', 'pm1', 'pm10', 'pm25', 'pressure_pa', 'temperature'],
    ['day_of_week']
)
```

```
feature humidity,  target: day_of_week
r2_score   0.0003920498287666163
RMSE   4.012595777250869


feature pm1,  target: day_of_week
r2_score   0.00016215383243523007
RMSE   4.013518618754809


feature pm10,  target: day_of_week
r2_score   0.0001261737669231433
RMSE   4.013663048837537


feature pm25,  target: day_of_week
r2_score   6.096448940462462e-05
RMSE   4.013924809932538


feature pressure_pa,  target: day_of_week
r2_score   6.114050257466364e-05
RMSE   4.0139241033858335


feature temperature,  target: day_of_week
r2_score   0.0005199278808153407
RMSE   4.012082453070558
```

In [ ]:
```
get_features_and_run_model(
    train,
    test,
    ['humidity', 'pm1', 'pm10', 'pm25', 'pressure_pa', 'temperature'],
    ['humidity', 'pm1', 'pm10', 'pm25', 'pressure_pa', 'temperature']
)
```

```
feature humidity,  target: pm1
r2_score   0.07297447947136604
RMSE   68.16040659743716


feature humidity,  target: pm10
r2_score   0.035080676024975666
RMSE   318.67449180037755


feature humidity,  target: pm25
r2_score   0.06862956452570645
RMSE   194.16301806981508


feature humidity,  target: pressure_pa
r2_score   -2.657667631522642e-06
RMSE   1969021322.2103398


feature humidity,  target: temperature
r2_score   0.3404799807469252
RMSE   85.39131720077049


feature pm1,  target: humidity
r2_score   0.07298512922898603
RMSE   415.5938418153269


feature pm1,  target: pm10
r2_score   0.9218399095645413
RMSE   25.81317057262712


feature pm1,  target: pm25
r2_score   0.9731753597751335
RMSE   5.592139181489842


feature pm1,  target: pressure_pa
r2_score   0.005745803973286834
RMSE   1957702508.7511075


feature pm1,  target: temperature
r2_score   0.08090431501810891
RMSE   118.99986184351476


feature pm10,  target: humidity
r2_score   0.03509677006283807
RMSE   432.5797276327163


feature pm10,  target: pm1
r2_score   0.9218432558964404
RMSE   5.746546711456931


feature pm10,  target: pm25
r2_score   0.9639631153101289
RMSE   7.51261799463936


feature pm10,  target: pressure_pa
r2_score   0.0047326270730139175
RMSE   1959697470.3689709


feature pm10,  target: temperature
r2_score   0.055435898102674463
RMSE   122.29738368354978


feature pm25,  target: humidity
r2_score   0.06864109530924722
RMSE   417.54133349275685


feature pm25,  target: pm1
r2_score   0.9731753920332611
RMSE   1.9723040470203548


feature pm25,  target: pm10
r2_score   0.9639616421866078
RMSE   11.902036860648643
```

```
feature pm25,  target: pressure_pa
r2_score   0.005453918720084605
RMSE   1958277235.5108685


feature pm25,  target: temperature
r2_score   0.08194017307157608
RMSE   118.86574418061385


feature pressure_pa,  target: humidity
r2_score   -8.381373863164399e-06
RMSE   448.31786216873854


feature pressure_pa,  target: pm1
r2_score   0.00573125742178493
RMSE   73.10452653192134


feature pressure_pa,  target: pm10
r2_score   0.004719844928505634
RMSE   328.70146729968377


feature pressure_pa,  target: pm25
r2_score   0.00543674227811719
RMSE   207.33684088038459


feature pressure_pa,  target: temperature
r2_score   0.002221352463029125
RMSE   129.18733397126982


feature temperature,  target: humidity
r2_score   0.34047543940971925
RMSE   295.6741628959104


feature temperature,  target: pm1
r2_score   0.08087430089353598
RMSE   67.57956493962044


feature temperature,  target: pm10
r2_score   0.055396624412504925
RMSE   311.9649417198921


feature temperature,  target: pm25
r2_score   0.08190782394908436
RMSE   191.39489614307158


feature temperature,  target: pressure_pa
r2_score   0.0022232919964849662
RMSE   1964638391.5079002
```