3.2 Regression

August 14, 2020

Table of Contents

1 Ideas

- Load data from the last excercise (cleaned data including the best combination of MERRA-2 product and observed ground data)
- Let try with simple prediction using Linear Regresssion, Logistic Regression, Decision Tree and RandomForest Regression
- Measured the accurate (or the error) from those technique
- Apply the outcome with a forecast data source such as from DarkSky

2 Libs and import data

[1]:
```
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
import pandas as pd
```

[3]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

[4]:
```
import numpy as np
```

[44]:
```
# if you have not install sklearn (or scikit-learn) and scipy then install it
# ! pip install scikit-learn --user
# ! pip install scipy --user
```

[5]:
```
# let pick up the data has been cleaned up the previous exercise, v3
df = pd.read_csv('data/comb_PM25_wind_Hanoi_2018_v3.csv',
                 parse_dates=['DATE'],
                 index_col=['DATE'])
df.head()
```

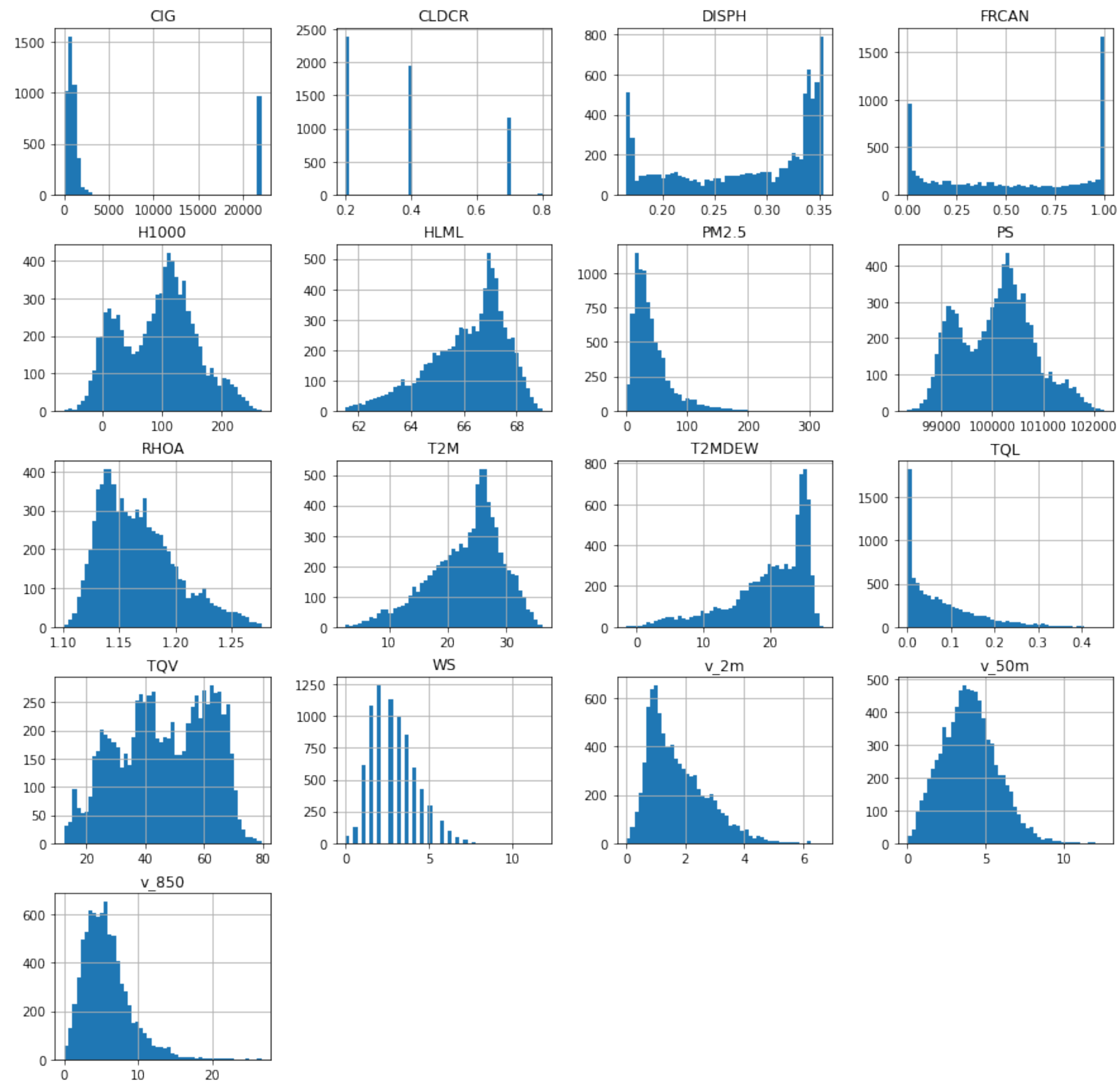
[5]:
```
                     PM2.5    T2MDEW       T2M         PS        TQV  \
DATE
2018-01-01 01:00:00   69.2  10.79443  13.64376  100865.09  34.909637
2018-01-01 02:00:00   75.5  10.72836  13.33932  100819.56  35.195385
2018-01-01 03:00:00   90.2  10.60630  13.09753  100793.71  35.590984
2018-01-01 04:00:00   97.6  10.50967  12.81360  100791.80  35.827934
2018-01-01 05:00:00   89.1  10.49365  12.71010  100808.45  35.953880

                          TQL      H1000     DISPH     FRCAN       HLML  \
DATE
2018-01-01 01:00:00  0.009235  160.25461  0.256226  1.000000  63.907425
2018-01-01 02:00:00  0.006260  156.44829  0.256226  1.000000  63.832478
2018-01-01 03:00:00  0.003489  154.54437  0.256104  0.993164  63.766266
2018-01-01 04:00:00  0.002314  154.16837  0.255981  0.927490  63.718185
```

```
2018-01-01 05:00:00  0.001480  155.72943  0.255859  0.786133  63.684280

                          RHOA  CIG  WS  CLDCR       v_2m      v_50m      v_850
DATE
2018-01-01 01:00:00  1.216159  NaN NaN    NaN  0.429060  0.979452  6.175777
2018-01-01 02:00:00  1.217125  NaN NaN    NaN  0.383400  0.872296  5.997708
2018-01-01 03:00:00  1.218085  NaN NaN    NaN  0.339189  0.729687  5.915825
2018-01-01 04:00:00  1.218972  NaN NaN    NaN  0.305853  0.666341  5.885087
2018-01-01 05:00:00  1.219831  NaN NaN    NaN  0.258492  0.541109  5.796022
```

[6]:
```python
df.hist(bins=50, figsize=(15,15));
```



3 Data Wrangle

3.1 Split data train, test

[6]:
```
# the idea is the split the dataset into two parts, one for training, and one␣
↪for validation
def split_train_test(data, test_ratio):
    shuffled_indices = np.random.permutation(len(data))
    test_set_size = int(len(data)*test_ratio)
    test_indices = shuffled_indices[:test_set_size]
    train_indices = shuffled_indices[test_set_size:]
    return data.iloc[train_indices], data.iloc[test_indices]
```

[7]:
```
# now we can split them with a ratio like this
train_set, test_set = split_train_test(df, 0.2)
```

[8]:
```
len(train_set)
```

[8]: 6493

[9]:
```
len(test_set)
```

[9]: 1623

[11]:
```
# however, the sklearn library has such unility
from sklearn.model_selection import train_test_split
```

[13]:
```
train_set, test_set = train_test_split(df, test_size=0.2, random_state=2020)
print(len(train_set))
train_set.head()
```

6492

[13]:
```
                     PM2.5    T2MDEW       T2M         PS        TQV  \
DATE
2018-11-01 01:00:00   66.0  13.76476  15.91640  100623.33  23.115633
2018-03-11 13:00:00   97.1  16.36712  23.94467  100729.96  37.070614
2018-11-02 17:00:00   28.0  15.21340  22.42794  100487.85  20.839620
2018-03-27 23:00:00   63.7  18.28860  18.51727  100447.27  38.934628
2018-12-01 04:00:00   55.0  20.01226  20.44995  100557.99  42.091070

                          TQL      H1000     DISPH     FRCAN       HLML  \
DATE
2018-11-01 01:00:00  0.000000  140.67795  0.346069  0.000000  65.119470
2018-03-11 13:00:00  0.095612  151.08076  0.170471  0.558838  65.698654
2018-11-02 17:00:00  0.000000  130.45107  0.345093  0.000000  66.063030
2018-03-27 23:00:00  0.004002  126.26744  0.192688  0.044815  65.261230
```

```
2018-12-01 04:00:00  0.090057  136.40723  0.316406  0.208740  65.746920

                         RHOA      CIG   WS  CLDCR      v_2m     v_50m  \
DATE
2018-11-01 01:00:00  1.190721      NaN  2.1    NaN  1.317137  5.151577
2018-03-11 13:00:00  1.181534      NaN  2.1    0.4  3.250031  4.604924
2018-11-02 17:00:00  1.172179      NaN  1.0    NaN  0.614779  1.535728
2018-03-27 23:00:00  1.186127  22000.0  3.1    NaN  1.117351  4.444736
2018-12-01 04:00:00  1.178689    792.0  1.5    0.4  0.629109  1.737746

                         v_850
DATE
2018-11-01 01:00:00  13.778793
2018-03-11 13:00:00   5.120155
2018-11-02 17:00:00   3.374469
2018-03-27 23:00:00   6.082646
2018-12-01 04:00:00   5.265891
```

3.2 Fill NaN values

- Data are likey assembled with missing values
- Regression or machine learning works better with completed dataset

[14]:
```
# make a copy and test out
df1 = df.copy(deep=True)
```

[15]:
```
# calculate the median of the Windspeed (WS) input
median = df1['WS'].median()
```

[19]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8116 entries, 2018-01-01 01:00:00 to 2018-12-31 00:00:00
Data columns (total 17 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   PM2.5   8116 non-null   float64
 1   T2MDEW  8116 non-null   float64
 2   T2M     8116 non-null   float64
 3   PS      8116 non-null   float64
 4   TQV     8116 non-null   float64
 5   TQL     8116 non-null   float64
 6   H1000   8116 non-null   float64
 7   DISPH   8116 non-null   float64
 8   FRCAN   8092 non-null   float64
 9   HLML    8092 non-null   float64
 10  RHOA    8092 non-null   float64
```

```
 11   CIG     5088 non-null   float64
 12   WS      7809 non-null   float64
 13   CLDCR   5502 non-null   float64
 14   v_2m    8116 non-null   float64
 15   v_50m   8116 non-null   float64
 16   v_850   8116 non-null   float64
dtypes: float64(17)
memory usage: 1.1 MB
```

[20]:
```
df1['WS'].fillna(median, inplace=True)
```

[21]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8116 entries, 2018-01-01 01:00:00 to 2018-12-31 00:00:00
Data columns (total 17 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   PM2.5   8116 non-null   float64
 1   T2MDEW  8116 non-null   float64
 2   T2M     8116 non-null   float64
 3   PS      8116 non-null   float64
 4   TQV     8116 non-null   float64
 5   TQL     8116 non-null   float64
 6   H1000   8116 non-null   float64
 7   DISPH   8116 non-null   float64
 8   FRCAN   8092 non-null   float64
 9   HLML    8092 non-null   float64
 10  RHOA    8092 non-null   float64
 11  CIG     5088 non-null   float64
 12  WS      8116 non-null   float64
 13  CLDCR   5502 non-null   float64
 14  v_2m    8116 non-null   float64
 15  v_50m   8116 non-null   float64
 16  v_850   8116 non-null   float64
dtypes: float64(17)
memory usage: 1.1 MB
```

[22]:
```
# we can manually do this by for loop
for col in df1.columns:
    df1[col].fillna(df1[col].median(), inplace=True)
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8116 entries, 2018-01-01 01:00:00 to 2018-12-31 00:00:00
Data columns (total 17 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
```

```
 0   PM2.5   8116 non-null   float64
 1   T2MDEW  8116 non-null   float64
 2   T2M     8116 non-null   float64
 3   PS      8116 non-null   float64
 4   TQV     8116 non-null   float64
 5   TQL     8116 non-null   float64
 6   H1000   8116 non-null   float64
 7   DISPH   8116 non-null   float64
 8   FRCAN   8116 non-null   float64
 9   HLML    8116 non-null   float64
 10  RHOA    8116 non-null   float64
 11  CIG     8116 non-null   float64
 12  WS      8116 non-null   float64
 13  CLDCR   8116 non-null   float64
 14  v_2m    8116 non-null   float64
 15  v_50m   8116 non-null   float64
 16  v_850   8116 non-null   float64
dtypes: float64(17)
memory usage: 1.1 MB
```

[23]:
```
# and sklearn has the Class to do such
from sklearn.impute import SimpleImputer
```

[24]:
```
inputer = SimpleImputer(strategy='median')
```

[25]:
```
df2 =df.copy(deep=True)
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8116 entries, 2018-01-01 01:00:00 to 2018-12-31 00:00:00
Data columns (total 17 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   PM2.5   8116 non-null   float64
 1   T2MDEW  8116 non-null   float64
 2   T2M     8116 non-null   float64
 3   PS      8116 non-null   float64
 4   TQV     8116 non-null   float64
 5   TQL     8116 non-null   float64
 6   H1000   8116 non-null   float64
 7   DISPH   8116 non-null   float64
 8   FRCAN   8092 non-null   float64
 9   HLML    8092 non-null   float64
 10  RHOA    8092 non-null   float64
 11  CIG     5088 non-null   float64
 12  WS      7809 non-null   float64
 13  CLDCR   5502 non-null   float64
 14  v_2m    8116 non-null   float64
```

```
 15   v_50m   8116 non-null   float64
 16   v_850   8116 non-null   float64
dtypes: float64(17)
memory usage: 1.1 MB
```

[26]:
```python
# evaluate df2
inputer.fit(df2)
```

[26]:
```
SimpleImputer(add_indicator=False, copy=True, fill_value=None,
              missing_values=nan, strategy='median', verbose=0)
```

[27]:
```python
# see the statistic, median in this case
inputer.statistics_
```

[27]:
```
array([3.20000000e+01, 2.17670550e+01, 2.45143500e+01, 1.00156612e+05,
       4.69396705e+01, 5.37109380e-02, 1.01305442e+02, 3.08166505e-01,
       5.11840850e-01, 6.64740250e+01, 1.16165940e+00, 9.45000000e+02,
       2.60000000e+00, 4.00000000e-01, 1.48621393e+00, 3.92495231e+00,
       5.23608490e+00])
```

[28]:
```python
# transform is doing the work
df2full = inputer.transform(df1)
```

[29]:
```python
type(df2full)
```

[29]:
```
numpy.ndarray
```

[30]:
```python
# convert the inputed dataset and and compared
df2 = pd.DataFrame(data=df2full, columns=df1.columns)
df2.info()
```

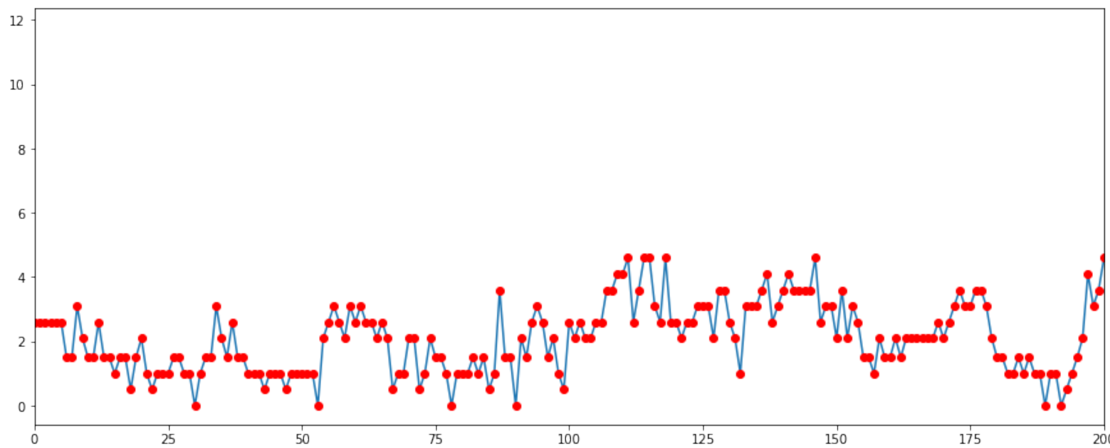
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8116 entries, 0 to 8115
Data columns (total 17 columns):
 #    Column  Non-Null Count  Dtype
---   ------  --------------  -----
 0    PM2.5   8116 non-null   float64
 1    T2MDEW  8116 non-null   float64
 2    T2M     8116 non-null   float64
 3    PS      8116 non-null   float64
 4    TQV     8116 non-null   float64
 5    TQL     8116 non-null   float64
 6    H1000   8116 non-null   float64
 7    DISPH   8116 non-null   float64
 8    FRCAN   8116 non-null   float64
 9    HLML    8116 non-null   float64
 10   RHOA    8116 non-null   float64
 11   CIG     8116 non-null   float64
```

```
 12  WS       8116 non-null   float64
 13  CLDCR    8116 non-null   float64
 14  v_2m     8116 non-null   float64
 15  v_50m    8116 non-null   float64
 16  v_850    8116 non-null   float64
dtypes: float64(17)
memory usage: 1.1 MB
```

[32]:
```
# you can save to a file with all missing values filled
df.to_csv('data/filled_PM2.5_Hanoi_2018.csv')
```

[31]:
```
# let see if they are matched
fig, ax = plt.subplots(figsize=(15,6))
ax.plot(df1.WS.to_list())
ax.plot(df2.WS, 'ro')
ax.set_xlim(0,200)
```

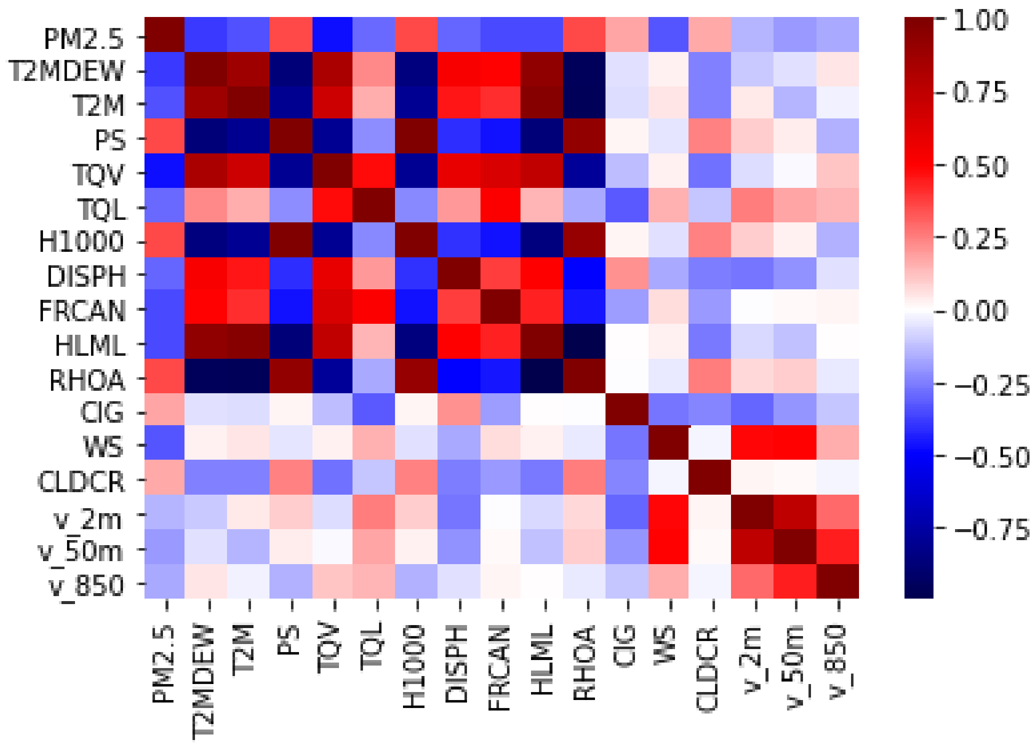
[31]: (0.0, 200.0)



3.3 Additional cleanup

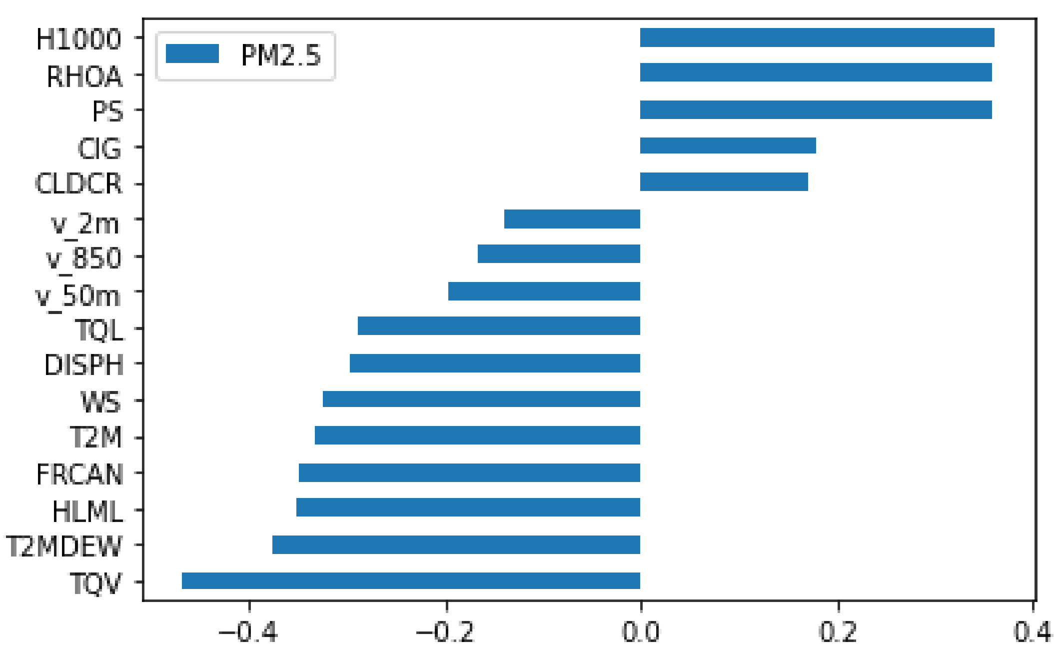
[32]:
```
# let return back to the original dataset (df) before fill up NaN
sns.heatmap(df.corr(), cmap='seismic')
```

[32]: <AxesSubplot:>




```
[33]: # and only correlation with PM2.5
df.corr()['PM2.5'].sort_values().to_frame().drop('PM2.5').plot.barh()
```

[33]: <AxesSubplot:>



[34]:
```python
df.columns
```

[34]:
```
Index(['PM2.5', 'T2MDEW', 'T2M', 'PS', 'TQV', 'TQL', 'H1000', 'DISPH', 'FRCAN',
       'HLML', 'RHOA', 'CIG', 'WS', 'CLDCR', 'v_2m', 'v_50m', 'v_850'],
      dtype='object')
```

[35]:
```python
# drop some columns either weak in correation or dependent (redundant) to other␣
↪inputs
df.drop(columns=['CLDCR', 'v_2m', 'v_50m', 'v_850', 'FRCAN', 'DISPH'],␣
↪inplace=True)
```

[36]:
```python
df.head()
```

[36]:
```
                     PM2.5    T2MDEW       T2M         PS        TQV  \
DATE
2018-01-01 01:00:00   69.2  10.79443  13.64376  100865.09  34.909637
2018-01-01 02:00:00   75.5  10.72836  13.33932  100819.56  35.195385
2018-01-01 03:00:00   90.2  10.60630  13.09753  100793.71  35.590984
2018-01-01 04:00:00   97.6  10.50967  12.81360  100791.80  35.827934
2018-01-01 05:00:00   89.1  10.49365  12.71010  100808.45  35.953880

                          TQL      H1000       HLML      RHOA  CIG  WS
DATE
2018-01-01 01:00:00  0.009235  160.25461  63.907425  1.216159  NaN NaN
2018-01-01 02:00:00  0.006260  156.44829  63.832478  1.217125  NaN NaN
2018-01-01 03:00:00  0.003489  154.54437  63.766266  1.218085  NaN NaN
2018-01-01 04:00:00  0.002314  154.16837  63.718185  1.218972  NaN NaN
2018-01-01 05:00:00  0.001480  155.72943  63.684280  1.219831  NaN NaN
```

[64]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8116 entries, 2018-01-01 01:00:00 to 2018-12-31 00:00:00
Data columns (total 11 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   PM2.5   8116 non-null   float64
 1   T2MDEW  8116 non-null   float64
 2   T2M     8116 non-null   float64
 3   PS      8116 non-null   float64
 4   TQV     8116 non-null   float64
 5   TQL     8116 non-null   float64
 6   H1000   8116 non-null   float64
 7   HLML    8116 non-null   float64
 8   RHOA    8116 non-null   float64
```

```
 9   CIG     8116 non-null   float64
 10  WS      8116 non-null   float64
dtypes: float64(11)
memory usage: 760.9 KB
```

3.4 Split features (meteorological inputs) and label (PM2.5)

[59]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8116 entries, 2018-01-01 01:00:00 to 2018-12-31 00:00:00
Data columns (total 11 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   PM2.5   8116 non-null   float64
 1   T2MDEW  8116 non-null   float64
 2   T2M     8116 non-null   float64
 3   PS      8116 non-null   float64
 4   TQV     8116 non-null   float64
 5   TQL     8116 non-null   float64
 6   H1000   8116 non-null   float64
 7   HLML    8092 non-null   float64
 8   RHOA    8092 non-null   float64
 9   CIG     5088 non-null   float64
 10  WS      7809 non-null   float64
dtypes: float64(11)
memory usage: 760.9 KB
```

[41]:
```python
# let make X as the matrix for the feature (or inputs)
X = df.drop('PM2.5', axis=1)
```

[37]:
```python
# and lowercase y as the label (or the value of the target)
y = df['PM2.5'].copy()
```

[53]:
```python
# let build the inpute instance to work with whole data at one
# to inpute more than one columns, we can use this
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
```

[58]:
```python
# transform data from real value to a relative to the set
from sklearn.preprocessing import StandardScaler
```

[54]:
```python
# we have all column with numeric values
num_attrs = list(df.columns)
num_attrs.remove('PM2.5')
num_attrs
```

[54]: ['T2MDEW', 'T2M', 'PS', 'TQV', 'TQL', 'H1000', 'HLML', 'RHOA', 'CIG', 'WS']

[56]:
```
# first is the trategy for inputer using median
# then convert the absolute value in the each column using the Standard Class
num_pipeline = Pipeline([
        ('inputer', SimpleImputer(strategy='median')),
        ('std_scaler', StandardScaler()),
        ])
```

[57]:
```
# and instance to tranform all column at one
full_pipeline = ColumnTransformer([
    ('num', num_pipeline, num_attrs)
])
```

[60]:
```
# or building a function to do all in one step
def inpute_transfrom(data=None):
    num_pipeline = Pipeline([
        ('inputer', SimpleImputer(strategy='median')),
        ('std_scaler', StandardScaler()),
        ])
    num_attrs = list(data.columns)
    full_pipeline = ColumnTransformer([
        ('num', num_pipeline, num_attrs)
        ])
    return full_pipeline.fit_transform(data) # return a numpy array
```

[61]:
```
X_scaled = inpute_transfrom(data=X)
```

[66]:
```
# how do we know that the data has been fixed properly
X_scaled_test = inpute_transfrom(data=X)
dft = pd.DataFrame(data=X_scaled_test, columns=num_attrs)
dft.info()
# looking good
del dft
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8116 entries, 0 to 8115
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   T2MDEW  8116 non-null   float64
 1   T2M     8116 non-null   float64
 2   PS      8116 non-null   float64
 3   TQV     8116 non-null   float64
 4   TQL     8116 non-null   float64
 5   H1000   8116 non-null   float64
 6   HLML    8116 non-null   float64
```

```
 7   RHOA     8116 non-null   float64
 8   CIG      8116 non-null   float64
 9   WS       8116 non-null   float64
dtypes: float64(10)
memory usage: 634.2 KB
```

[67]:
```
# now we can split data, the test_size is the portion of data use for validation
# random_state is to provide consistent if you want to replicate the result
X_train, X_test, y_train, y_test = train_test_split(X_scaled,y, test_size=0.33,␣
↪random_state=2020)
```

[68]:
```
len(X_train), len(X_test)
```

[68]:
```
(5437, 2679)
```

4 Linear Regression

[43]:
```
# Linear regression is the simplest form of data learning, let try this first
from sklearn.linear_model import LinearRegression
```

[45]:
```
# make an instant of the class
lin_reg = LinearRegression()
```

[69]:
```
# and training the model using the _train dataset
lin_reg.fit(X_train, y_train)
```

[69]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

[70]:
```
lin_reg.get_params()
```

[70]:
```
{'copy_X': True, 'fit_intercept': True, 'n_jobs': None, 'normalize': False}
```

[71]:
```
# let see the output of the mode
lin_reg.coef_
```

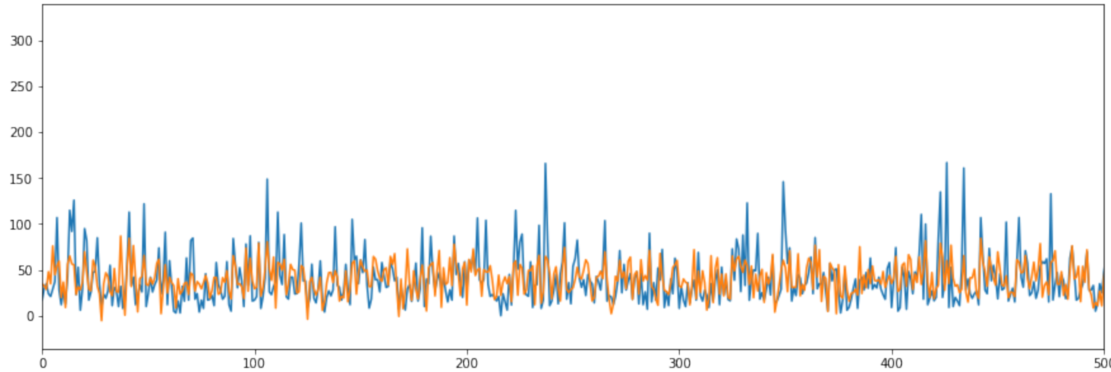
[71]:
```
array([  -3.15806877,    9.23068653, -237.20129647,  -11.37237178,
         -1.51486159,  216.26310513,   19.10913327,   47.2122002 ,
          2.99459991,   -8.55437448])
```

[72]:
```
# predict based on the training set
y_train_prd = lin_reg.predict(X_train)
```

[73]:
```
# let see how the label (y_train), and predicting of the label (y_prd)
plt.figure(figsize=(15,5))
plt.plot(y_train.to_list())
```

```
plt.plot(y_train_prd)
plt.xlim(0,500)
```

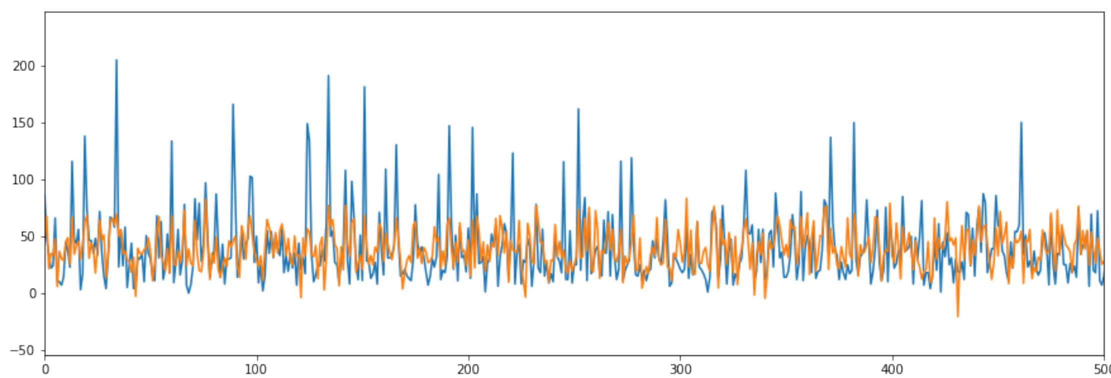
[73]: (0.0, 500.0)



[74]:
```
# more important, how about with validation set (test set)
y_test_prd = lin_reg.predict(X_test)
```

[75]:
```
plt.figure(figsize=(15,5))
plt.plot(y_test.to_list())
plt.plot(y_test_prd)
plt.xlim(0,500)
```

[75]: (0.0, 500.0)



- kind of there, but not easy to assess

4.1 evaluate model performance

[76]:
```
# for numeric data, one simple way to to see how far
# between the prediction and the garget
from sklearn.metrics import mean_squared_error
```

[77]:
```
# on training set
lin_train_mse = mean_squared_error(y_train, y_train_prd)
print('Trainset: Root Squared Mean Error', np.sqrt(lin_train_mse))
```

```
Trainset: Root Squared Mean Error 25.50502509220003
```

[78]:
```
# on test set
lin_test_mse = mean_squared_error(y_test, y_test_prd)
print('Test set: Root Squared Mean Error', np.sqrt(lin_test_mse))
```

```
Test set: Root Squared Mean Error 25.924922211091516
```

[79]:
```
# the average value label set (y set)
y.mean()
```

[79]:
```
40.75873583045832
```

[80]:
```
# relative error
print(f'Relative Error: {100*np.sqrt(lin_test_mse)/y.mean():.0f}%')
```

```
Relative Error: 64%
```

- underfitting (data), we have can predict the PM2.5 concentration, but bear in mind the value can be off 64% (up and down), and that only works 66 out of 100 chances (given the error is random)
- let try another model, also, make a dictionary to keep the score between model

[95]:
```
results = dict()
def add_stats(model=None, train_rmse=None, test_rmse=None):
    global results
    results[model] = {'train_rmse': round(train_rmse,1),
                      'test_rmse': round(test_rmse, 1)}
    return None
```

[97]:
```
add_stats(model='linear reg',
         train_rmse=np.sqrt(lin_train_mse),
         test_rmse=np.sqrt(lin_test_mse))
results
```

[97]:
```
{'linear reg': {'train_rmse': 25.5, 'test_rmse': 25.9}}
```

5 DecisionTree

[98]:
```
# let try the same approach with decision tree
from sklearn.tree import DecisionTreeRegressor
```

[99]:
```
tree_reg = DecisionTreeRegressor()
```

[100]:
```
tree_reg.fit(X_train, y_train)
```

[100]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='deprecated',
                      random_state=None, splitter='best')
```

[101]:
```
tree_reg.feature_importances_
```

[101]:
```
array([0.28720845, 0.06360633, 0.05308155, 0.14258232, 0.10199783,
       0.06372484, 0.05821381, 0.04296177, 0.07141657, 0.11520652])
```

[102]:
```
tree_ytrain_d = tree_reg.predict(X_train)
```

[104]:
```
# no error, too good!
tree_train_rmse = np.sqrt(mean_squared_error(y_train, tree_ytrain_d))
tree_train_rmse
```

[104]:
```
0.0
```

[105]:
```
tree_ytest_d = tree_reg.predict(X_test)
```

[110]:
```
tree_test_rmse = np.sqrt(mean_squared_error(y_test, tree_ytest_d))
tree_test_rmse # higher than regression,
```

[110]:
```
28.866692614774283
```

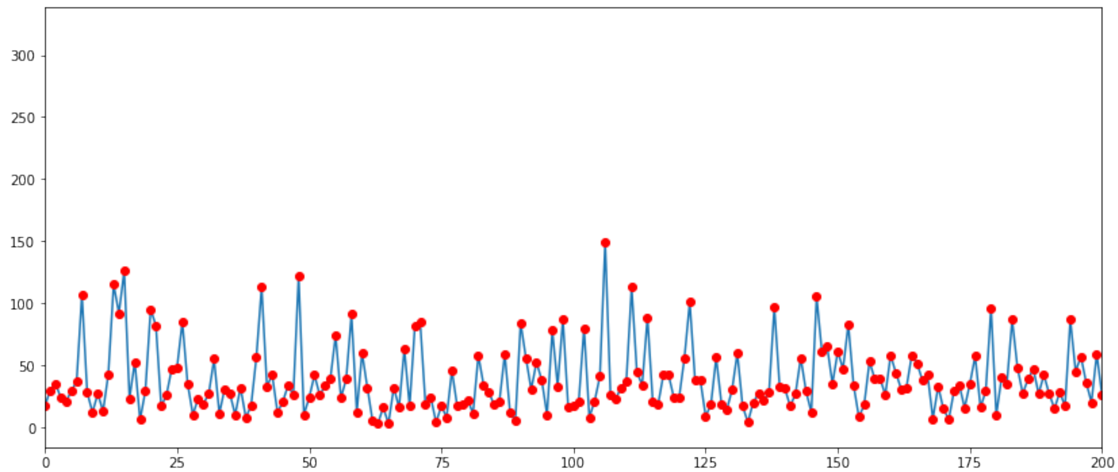
[111]:
```
# let bag the result
add_stats(model='decisiontree reg',
         train_rmse=tree_train_rmse,
         test_rmse=tree_test_rmse)
results
```

[111]:
```
{'linear reg': {'train_rmse': 25.5, 'test_rmse': 25.9},
 'decisiontree reg': {'train_rmse': 0.0, 'test_rmse': 28.9}}
```

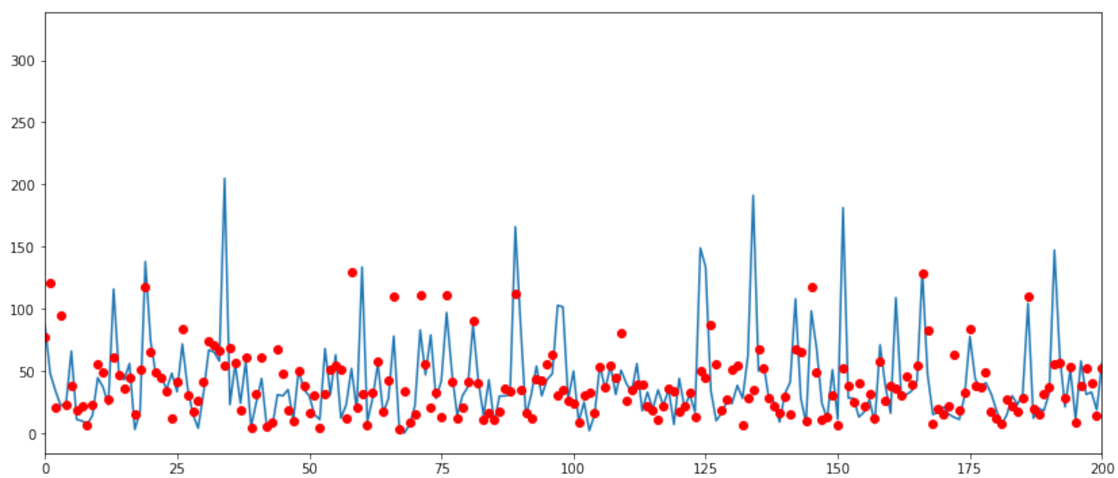
[107]:
```
# the results by train set and test set are rather different, to see it
def plot_prediction(label=None, prediction=None, limit=200):
```

```python
    plt.figure(figsize=(14,6))
    plt.plot(label.to_list())
    plt.plot(prediction, 'ro')
    plt.xlim(0, limit)
    return None
```

[108]:
```python
plot_prediction(y_train, tree_ytrain_d)
```



[109]:
```python
plot_prediction(y_test, tree_ytest_d)
```



- overfitting data for training set (memorization), and underfitting with test set (not map key feature)

5.1 RandomForest

[112]:
```
# more powerful model
from sklearn.ensemble import RandomForestRegressor
```

[113]:
```
forest_reg = RandomForestRegressor()
forest_reg.fit(X_train, y_train)
```

[113]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=100, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

[114]:
```
forest_ytrain_p = forest_reg.predict(X_train)
```

[116]:
```
mse_train = mean_squared_error(y_train, forest_ytrain_p)
rmse_train = np.sqrt(mse_train)
rmse_train
```

[116]:
```
7.319539455569634
```

[117]:
```
# test set
forest_ytest_p = forest_reg.predict(X_test)
```

[119]:
```
mse_test = mean_squared_error(y_test, forest_ytest_p)
rmse_test = np.sqrt(mse_test)
rmse_test
```

[119]:
```
19.94340670771594
```

[131]:
```
add_stats(model='randomforest reg',
         train_rmse=rmse_train,
         test_rmse=rmse_test)
results
```

[131]:
```
{'linear reg': {'train_rmse': 25.5, 'test_rmse': 25.9},
 'decisiontree reg': {'train_rmse': 0.0, 'test_rmse': 28.9},
 'randomforest reg': {'train_rmse': 7.3, 'test_rmse': 19.9}}
```

5.2 Cross validation

[122]:
```python
from sklearn.model_selection import cross_val_score
```

[124]:
```python
scores = cross_val_score(tree_reg, X_train, y_train,
                         scoring='neg_mean_squared_error', cv=10)
```

[125]:
```python
tree_rmse_scores = np.sqrt(-scores)
tree_rmse_scores
```

[125]:
```
array([25.0286516 , 27.29367756, 25.45272398, 28.72647087, 27.21742825,
       27.55288765, 25.1130188 , 31.19758898, 27.76135077, 28.17651903])
```

[126]:
```python
def display_scores(scores):
    print("Scores: ", scores)
    print("Mean: ", scores.mean())
    print("Standard Deviation: ", scores.std())
```

[127]:
```python
display_scores(scores)
```

```
Scores:  [-626.43340074 -744.94483456 -647.84115809 -825.21012868 -740.78840074
 -759.16161765 -630.66371324 -973.28955801 -770.69259669 -793.91622468]
Mean:  -751.2941633050319
Standard Deviation:  98.99266952818422
```

[128]:
```python
lin_scores = cross_val_score(lin_reg, X_train, y_train,
                             scoring='neg_mean_squared_error', cv=10)
```

[129]:
```python
display_scores(lin_scores)
```

```
Scores:  [-550.85870613 -723.57425609 -604.74504505 -774.75436464 -558.6424609
 -650.90144343 -694.9417229  -791.12250196 -464.54518714 -719.45029524]
Mean:  -653.3535983471008
Standard Deviation:  101.11405749157925
```

[130]:
```python
forest_scores = cross_val_score(forest_reg, X_train, y_train,
                                scoring='neg_mean_squared_error', cv=10)
```

[132]:
```python
display_scores(forest_scores)
```

```
Scores:  [-336.85249494 -414.55027717 -340.52606942 -495.02698419 -328.95593693
 -347.62383281 -410.42979521 -546.46635029 -250.81217664 -405.05053205]
Mean:  -387.6294449641497
Standard Deviation:  81.77438259082012
```

[133]:
```python
# how about on test set:
for model in [lin_reg, tree_reg, forest_reg]:
```

```
    scores = cross_val_score(model, X_test, y_test,
                             scoring='neg_mean_squared_error', cv=10)
    display_scores(scores)
    print('-'*40)
```

```
Scores:  [-771.63467574 -554.4382247  -813.16490696 -717.49508355 -598.56766015
 -632.13746509 -569.73439949 -753.33939901 -661.54505262 -680.24197289]
Mean:  -675.229884018897
Standard Deviation:  83.5905310705698
----------------------------------------
Scores:  [-1259.97597015  -782.79813433 -1032.93242537 -1106.06947761
  -696.41026119  -846.71276119  -801.66145522  -820.10895522
  -866.49783582  -906.43479401]
Mean:  -911.9602070126894
Standard Deviation:  162.3358653447053
----------------------------------------
Scores:  [-602.63798754 -381.18848133 -554.00563056 -519.45501511 -321.74875161
 -450.15756396 -336.19587503 -490.46458475 -539.81659685 -420.10498245]
Mean:  -461.57754692068863
Standard Deviation:  90.73701388730139
----------------------------------------
```

- look like the RandomForest Regression performs a bit better than the first two

5.3 save model

[135]:
```
# just in case you want to save your work
from sklearn.externals import joblib
```

[134]:
```
# import os
# os.makedirs('model')
```

[135]:
```
joblib.dump(forest_reg, 'model/forest_reg.pkl' )
```

[135]:
```
['model/forest_reg.pkl']
```

5.4 Grid Search

[136]:
```
# we want to model performs better, in this case we tune the hyperparameters
from sklearn.model_selection import GridSearchCV
```

[137]:
```
param_grid = [{'n_estimators': [3, 10, 30], 'max_features': [2, 4, 6, 8]},
              {'bootstrap': [False], 'n_estimators': [3, 10], 'max_features':␣
 ↪[2, 3, 4]},]
```

[138]:
```
forest_reg = RandomForestRegressor()
grid_search = GridSearchCV(forest_reg, param_grid, cv=5,
                           scoring='neg_mean_squared_error',
                          return_train_score=True)
```

[139]:
```
grid_search.fit(X_train, y_train)
```

[139]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=RandomForestRegressor(bootstrap=True, ccp_alpha=0.0,
                                             criterion='mse', max_depth=None,
                                             max_features='auto',
                                             max_leaf_nodes=None,
                                             max_samples=None,
                                             min_impurity_decrease=0.0,
                                             min_impurity_split=None,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_leaf=0.0,
                                             n_estimators=100, n_jobs=None,
                                             oob_score=False, random_state=None,
                                             verbose=0, warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid=[{'max_features': [2, 4, 6, 8],
                          'n_estimators': [3, 10, 30]},
                         {'bootstrap': [False], 'max_features': [2, 3, 4],
                          'n_estimators': [3, 10]}],
             pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
             scoring='neg_mean_squared_error', verbose=0)
```

[140]:
```
# and see the best estimator
grid_search.best_estimator_
```

[140]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features=4, max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=30, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

[141]:
```
# or best parameters
grid_search.best_params_
```

[141]:
```
{'max_features': 4, 'n_estimators': 30}
```

[142]:
```
# or see the how each combination has worked
cvres = grid_search.cv_results_
```

[144]:
```
for mean_score, params in zip(cvres['mean_test_score'], cvres['params']):
    print(round(np.sqrt(-mean_score),2), params)
```

```
24.44 {'max_features': 2, 'n_estimators': 3}
21.28 {'max_features': 2, 'n_estimators': 10}
20.33 {'max_features': 2, 'n_estimators': 30}
23.87 {'max_features': 4, 'n_estimators': 3}
21.03 {'max_features': 4, 'n_estimators': 10}
19.98 {'max_features': 4, 'n_estimators': 30}
23.36 {'max_features': 6, 'n_estimators': 3}
20.92 {'max_features': 6, 'n_estimators': 10}
20.0 {'max_features': 6, 'n_estimators': 30}
23.39 {'max_features': 8, 'n_estimators': 3}
21.0 {'max_features': 8, 'n_estimators': 10}
20.19 {'max_features': 8, 'n_estimators': 30}
23.2 {'bootstrap': False, 'max_features': 2, 'n_estimators': 3}
20.45 {'bootstrap': False, 'max_features': 2, 'n_estimators': 10}
22.49 {'bootstrap': False, 'max_features': 3, 'n_estimators': 3}
20.33 {'bootstrap': False, 'max_features': 3, 'n_estimators': 10}
22.55 {'bootstrap': False, 'max_features': 4, 'n_estimators': 3}
20.51 {'bootstrap': False, 'max_features': 4, 'n_estimators': 10}
```

- so the best case with Random Forecast is 19.98 (g/m3) as the standard deviation

5.5 Analyze model

[145]:
```
# could look back to see how the weight of each input
feature_importances = grid_search.best_estimator_.feature_importances_
feature_importances
```

[145]:
```
array([0.16949425, 0.06773473, 0.09429158, 0.1824907 , 0.09555117,
       0.06977307, 0.0676954 , 0.07244233, 0.07794705, 0.10257973])
```

[147]:
```
sorted(zip(feature_importances, X.columns), reverse=True)
```

[147]:
```
[(0.18249070117732566, 'TQV'),
 (0.16949424694791368, 'T2MDEW'),
 (0.10257973245798097, 'WS'),
 (0.09555117432888298, 'TQL'),
 (0.09429157739434971, 'PS'),
 (0.07794704937895328, 'CIG'),
 (0.07244232993501565, 'RHOA'),
 (0.06977306516481928, 'H1000'),
 (0.0677347267676391, 'T2M'),
 (0.06769539644711989, 'HLML')]
```

- so the total liquid volumn and dewpoint influences PM2.5 more than the air temperature or surface level height

[152]:
```
# let see how grid search performs
# train set
grid_ytrain_p = grid_search.predict(X_train)
grid_mse = mean_squared_error(y_train, grid_ytrain_p)
grid_train_rmse = np.sqrt(grid_mse)
grid_train_rmse
```

[152]:
```
7.795150104149395
```

[153]:
```
# let see how the prediction look like after hypertunning
# test set
grid_ytest_p = grid_search.predict(X_test)
grid_test_mse = mean_squared_error(y_test, grid_ytest_p)
grid_test_rmse = np.sqrt(grid_test_mse)
grid_test_rmse
```

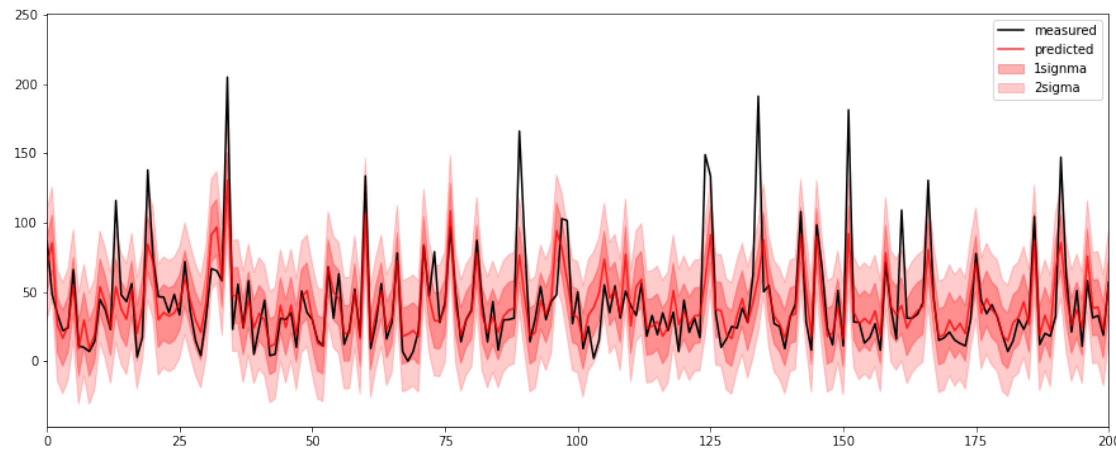
[153]:
```
20.033245999333058
```

[154]:
```
# still more to work with, but let bag the result for later comparison
add_stats(model='gridsearch',
         train_rmse=grid_train_rmse,
         test_rmse=grid_test_rmse)
results
```

[154]:
```
{'linear reg': {'train_rmse': 25.5, 'test_rmse': 25.9},
 'decisiontree reg': {'train_rmse': 0.0, 'test_rmse': 28.9},
 'randomforest reg': {'train_rmse': 7.3, 'test_rmse': 19.9},
 'gridsearch': {'train_rmse': 7.8, 'test_rmse': 20.0}}
```

[157]:
```
# let visualize it
std_ = grid_test_rmse
xindex = np.arange(0, len(y_test))
fig, ax = plt.subplots(figsize=(15,6))
ax.plot(y_test.to_list(), color='black', label='measured')
ax.plot(grid_ytest_p, color='red', alpha=0.8, label='predicted')
ax.fill_between(xindex, grid_ytest_p-std_,grid_ytest_p+std_,
                color='red', alpha=0.3, label='1signma' )
ax.fill_between(xindex, grid_ytest_p-2*std_,grid_ytest_p+2*std_,
                color='red', alpha=0.2, label = '2sigma')
ax.set_xlim(0,200)
ax.legend()
```

[157]:
```
<matplotlib.legend.Legend at 0x7f43b3248ef0>
```



- an easy way to make sure the prediction range captures the real value is to increase the band, and so enlarge the uncertainty
- but let see how confidence we have on the RSME,

5.6 Scipy interval 95%

[158]:
```
# let use stats from scipy library
from scipy import stats
```

[161]:
```
# and look confidence of .95, or the area that a value will be inside the range␣
↪with 95 chances of 100
confidence = 0.95
```

[162]:
```
squared_errors = (grid_ytest_p - y_test)**2
```

[163]:
```
np.sqrt(stats.t.interval(
    confidence,
    len(squared_errors)-1,
    loc=squared_errors.mean(),
    scale=stats.sem(squared_errors)))
```

[163]:
```
array([18.83035947, 21.1678873 ])
```

- so we are pretty sure that standard deviation from grid search is from 18.8 to 21.1
- how confidience: 95 chances out of 100, this RMSE will be within this range

5.7 Ensemble Methods

[164]:
```
# let look at a final approach to combine three regression we have so far using␣
↪Voting method
from sklearn.ensemble import RandomForestRegressor, VotingRegressor
from sklearn.linear_model import LinearRegression
```

[165]:
```
from sklearn.tree import DecisionTreeRegressor
```

[166]:
```
# re-define an instance, all training in the previous sessions are gone
lin_reg  = LinearRegression()
tree_reg = DecisionTreeRegressor()
rnd_reg = RandomForestRegressor()
```

[167]:
```
# and make each model as an parameter for then ensemble (voting)
voting_reg = VotingRegressor(
    estimators=[('lin', lin_reg),
               ('rnd', rnd_reg),
               ('tree', tree_reg)
               ],
)
```

[168]:
```
# train model by the train set
voting_reg.fit(X_train, y_train)
```

[168]:
```
VotingRegressor(estimators=[('lin',
                             LinearRegression(copy_X=True, fit_intercept=True,
                                              n_jobs=None, normalize=False)),
                            ('rnd',
                             RandomForestRegressor(bootstrap=True,
                                                   ccp_alpha=0.0,
                                                   criterion='mse',
                                                   max_depth=None,
                                                   max_features='auto',
                                                   max_leaf_nodes=None,
                                                   max_samples=None,
                                                   min_impurity_decrease=0.0,
                                                   min_impurity_split=None,
                                                   min_samples_leaf=1,
                                                   min_samples_split=2,
                                                   mi…
                                                   random_state=None, verbose=0,
                                                   warm_start=False)),
                            ('tree',
                             DecisionTreeRegressor(ccp_alpha=0.0,
                                                   criterion='mse',
                                                   max_depth=None,
```

```
                                                  max_features=None,
                                                  max_leaf_nodes=None,
                                                  min_impurity_decrease=0.0,
                                                  min_impurity_split=None,
                                                  min_samples_leaf=1,
                                                  min_samples_split=2,
                                                  min_weight_fraction_leaf=0.0,
                                                  presort='deprecated',
                                                  random_state=None,
                                                  splitter='best'))],
                n_jobs=None, weights=None)
```

[169]:
```
# check estimator (paramters)
voting_reg.estimators_
```

[169]:
```
[LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
normalize=False),
 RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                       max_depth=None, max_features='auto', max_leaf_nodes=None,
                       max_samples=None, min_impurity_decrease=0.0,
                       min_impurity_split=None, min_samples_leaf=1,
                       min_samples_split=2, min_weight_fraction_leaf=0.0,
                       n_estimators=100, n_jobs=None, oob_score=False,
                       random_state=None, verbose=0, warm_start=False),
 DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')]
```

[170]:
```
# now we do predicting on the test set
y_entest_p = voting_reg.predict(X_test)
```

[171]:
```
mse = mean_squared_error(y_entest_p, y_test)
en_test = np.sqrt(mse)
```

[172]:
```
# we could run on train set
y_entrain_p = voting_reg.predict(X_train)
mse = mean_squared_error(y_entrain_p, y_train)
en_train = np.sqrt(mse)
```

[173]:
```
en_test, en_train
```

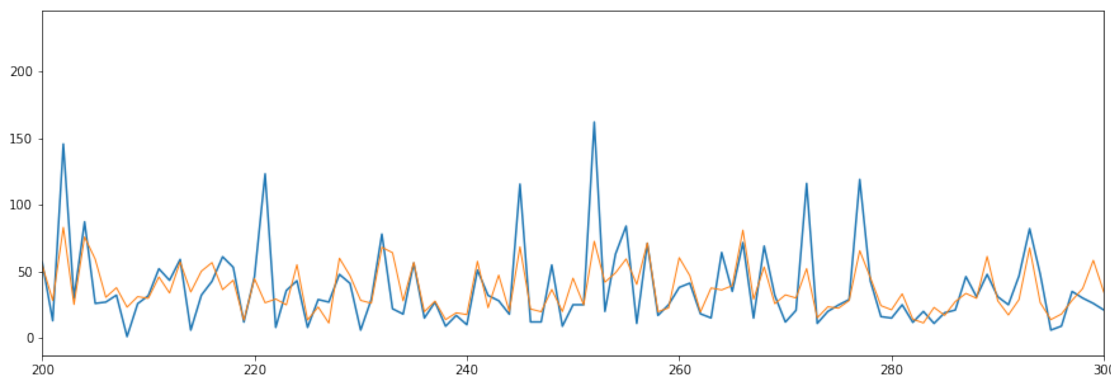
[173]:
```
(21.89413644598667, 10.545304085343597)
```

```
[174]: # still in 21 for test set
add_stats(model='voting reg',
          train_rmse=en_train,
          test_rmse=en_test)
results
```

```
[174]: {'linear reg': {'train_rmse': 25.5, 'test_rmse': 25.9},
 'decisiontree reg': {'train_rmse': 0.0, 'test_rmse': 28.9},
 'randomforest reg': {'train_rmse': 7.3, 'test_rmse': 19.9},
 'gridsearch': {'train_rmse': 7.8, 'test_rmse': 20.0},
 'voting reg': {'train_rmse': 10.5, 'test_rmse': 21.9}}
```

```
[175]: # let visualize the data from Ensemble with test set
plt.figure(figsize=(15,5))
plt.plot(y_test.to_list())
plt.plot(y_entest_p, lw=1)
plt.xlim(200,300)
```

```
[175]: (200.0, 300.0)
```



- so we can get a RMSE = 20 from several model, which is about 50% as the relative standard deviation
- this dataset is combined from several source, but not easy to get from a forecast product (in fact, I am struggling to get those), so we will try out a dataset with lessure feasture,

6 DarkSky Dataset

- you can check out this API at DarkSky.net

6.1 Merge data

[176]:
```
# laod data in
dk = pd.read_csv('data/darksky_hanoi_2018.csv', parse_dates=['time'],␣
↪index_col=['time'])
```

[177]:
```
dk.columns
```

[177]:
```
Index(['apparenttemperature', 'cloudcover', 'dewpoint', 'humidity', 'icon',
       'ozone', 'precipintensity', 'precipprobability', 'preciptype',
       'pressure', 'summary', 'temperature', 'uvindex', 'visibility',
       'windbearing', 'windgust', 'windspeed'],
      dtype='object')
```

[178]:
```
# select few important columsn
cols = ['temperature', 'dewpoint', 'humidity', 'pressure',␣
↪'precipintensity','cloudcover', 'visibility', 'windspeed']
```

[179]:
```
dkt = dk[cols]
```

[180]:
```
# load PM2.5 data
pm = pd.read_csv('data/cleaned_pm25_Hanoi_PM2.5_2018_YTD.csv',
                parse_dates=['Date (LT)'],
                index_col=['Date (LT)'])
```

[181]:
```
pm.head()
```

[181]:
```
                     pm25
Date (LT)
2018-01-01 01:00:00  69.2
2018-01-01 02:00:00  75.5
2018-01-01 03:00:00  90.2
2018-01-01 04:00:00  97.6
2018-01-01 05:00:00  89.1
```

[182]:
```
# check duplicated data if you want, wait, this is too much
dkt.duplicated().sum()
```

[182]: 1783

[183]:
```
dkt.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8745 entries, 2017-12-31 00:00:00 to 2019-01-01 00:00:00
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
```

```
 0   temperature      8742 non-null   float64
 1   dewpoint         8742 non-null   float64
 2   humidity         8742 non-null   float64
 3   pressure         1137 non-null   float64
 4   precipintensity  3383 non-null   float64
 5   cloudcover       6862 non-null   float64
 6   visibility       8711 non-null   float64
 7   windspeed        8600 non-null   float64
dtypes: float64(8)
memory usage: 614.9 KB
```

[184]:
```python
# let sort index (datetime) first
dkt.sort_index(inplace=True)
```

[185]:
```python
# and see duplicated row
dkt.loc[dkt.duplicated()].head(6)
```

[185]:
```
                     temperature  dewpoint  humidity  pressure  \
time
2017-12-31 05:00:00        16.98      9.99      0.63       NaN
2017-12-31 06:00:00        16.98      9.99      0.63       NaN
2018-01-05 06:00:00        19.99     19.00      0.94       NaN
2018-01-05 08:00:00        19.99     19.00      0.94       NaN
2018-01-05 09:00:00        19.99     19.00      0.94       NaN
2018-01-06 23:00:00        19.99     19.00      0.94       NaN

                     precipintensity  cloudcover  visibility  windspeed
time
2017-12-31 05:00:00              0.0         NaN       10.01        3.6
2017-12-31 06:00:00              0.0         NaN       10.01        3.6
2018-01-05 06:00:00              0.0        0.75        2.09        1.5
2018-01-05 08:00:00              0.0        0.75        1.50        1.5
2018-01-05 09:00:00              0.0        0.75        1.40        1.5
2018-01-06 23:00:00              0.0        0.75        3.51        2.6
```

- they are matched exact, but dropping them will need to fill in more data later, so it is okay to keep the closest values in by adjacent rows

[186]:
```python
# merge data
df = pd.merge(pm, dkt, right_index=True, left_index=True, how='left')
```

[187]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8190 entries, 2018-01-01 01:00:00 to 2019-01-01 00:00:00
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
```

```
 0   pm25             8190 non-null   float64
 1   temperature      8150 non-null   float64
 2   dewpoint         8150 non-null   float64
 3   humidity         8150 non-null   float64
 4   pressure         1079 non-null   float64
 5   precipintensity  3220 non-null   float64
 6   cloudcover       6441 non-null   float64
 7   visibility       8119 non-null   float64
 8   windspeed        8020 non-null   float64
dtypes: float64(9)
memory usage: 639.8 KB
```

[188]:
```python
# quick check correlation
df.corr()['pm25'].sort_values()
```

[188]:
```
visibility        -0.452880
temperature       -0.371182
dewpoint          -0.371018
windspeed         -0.351326
humidity          -0.082217
precipintensity    0.000103
cloudcover         0.111920
pressure           0.419824
pm25               1.000000
Name: pm25, dtype: float64
```

[189]:
```python
# seperate feature and label
X = df.drop('pm25', axis=1)
y = df['pm25'].copy()
```

[190]:
```python
X_scaled = inpute_transfrom(data=X)
```

[191]:
```python
type(X_scaled)
```

[191]:
```
numpy.ndarray
```

6.2 Split train and test

[199]:
```python
X_train, X_test, y_train, y_test = train_test_split(X_scaled,y, test_size=0.33,␣
↪random_state=2020)
```

[202]:
```python
len(X_train), len(y_train)
```

[202]:
```
(5487, 5487)
```

[204]:
```python
len(X_test), len(X_test)
```

[204]: (2703, 2703)

6.3 Train and validate

[205]:
```
# I will jump in and use voting (seem safer)
lin_reg  = LinearRegression()
tree_reg = DecisionTreeRegressor()
rnd_reg = RandomForestRegressor()
voting_reg = VotingRegressor(
    estimators=[('lin', lin_reg),
                ('rnd', rnd_reg),
                ('tree', tree_reg)
                ],
)
```

[206]:
```
voting_reg.fit(X_train, y_train)
```

[206]:
```
VotingRegressor(estimators=[('lin',
                             LinearRegression(copy_X=True, fit_intercept=True,
                                              n_jobs=None, normalize=False)),
                            ('rnd',
                             RandomForestRegressor(bootstrap=True,
                                                   ccp_alpha=0.0,
                                                   criterion='mse',
                                                   max_depth=None,
                                                   max_features='auto',
                                                   max_leaf_nodes=None,
                                                   max_samples=None,
                                                   min_impurity_decrease=0.0,
                                                   min_impurity_split=None,
                                                   min_samples_leaf=1,
                                                   min_samples_split=2,
                                                   mi…
                                                   random_state=None, verbose=0,
                                                   warm_start=False)),
                            ('tree',
                             DecisionTreeRegressor(ccp_alpha=0.0,
                                                   criterion='mse',
                                                   max_depth=None,
                                                   max_features=None,
                                                   max_leaf_nodes=None,
                                                   min_impurity_decrease=0.0,
                                                   min_impurity_split=None,
                                                   min_samples_leaf=1,
                                                   min_samples_split=2,
                                                   min_weight_fraction_leaf=0.0,
```

```
                                                  presort='deprecated',
                                                  random_state=None,
                                                  splitter='best'))],
                n_jobs=None, weights=None)
```

[207]:
```
voting_reg.estimators_
```

[207]:
```
[LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
normalize=False),
 RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                       max_depth=None, max_features='auto', max_leaf_nodes=None,
                       max_samples=None, min_impurity_decrease=0.0,
                       min_impurity_split=None, min_samples_leaf=1,
                       min_samples_split=2, min_weight_fraction_leaf=0.0,
                       n_estimators=100, n_jobs=None, oob_score=False,
                       random_state=None, verbose=0, warm_start=False),
 DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')]
```

6.3.1 Trainset

[208]:
```
y_entrain_p = voting_reg.predict(X_train)
```

[209]:
```
mse = mean_squared_error(y_entrain_p, y_train)
train_std = np.sqrt(mse)
train_std
```

[209]:
```
11.653075002954594
```

[280]:
```
y_train.iloc[0:100]
```

[280]:
```
2018-05-17 08:00:00    20.0
2018-09-05 03:00:00    33.0
2018-12-31 10:00:00    22.0
2018-07-06 19:00:00    20.0
2018-01-05 11:00:00    88.1
                        …
2018-09-19 20:00:00    34.0
2018-11-15 02:00:00    20.0
2018-09-25 09:00:00    19.0
2018-09-07 05:00:00    11.0
2018-08-20 21:00:00    36.0
```

```
Name: pm25, Length: 100, dtype: float64
```

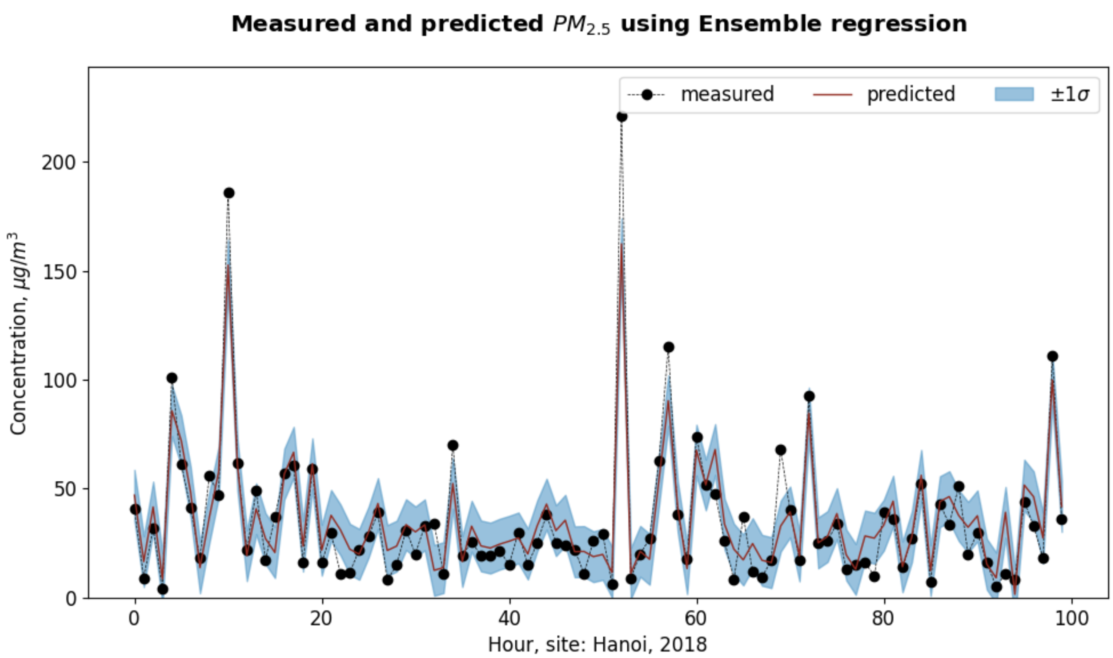
[211]:
```python
from random import randint
```

[212]:
```python
# time to invest some good graphs
def plot_results(label=None, prediction=None, std_=None, points=100,␣
 ↪savefig=False):
    plt.style.use('default')
    plt.rcParams['font.size'] = 12
    start = randint(0, len(label)-points)
    end = start + points
    label_ = label.iloc[start:end]
    pred_ = prediction[start:end]
    xindex = np.arange(0,len(label_),1)

    plt.figure(figsize=(10,6))
    plt.plot(label_.to_list(), 'ko--',lw=0.5, label='measured')
    plt.plot(pred_, lw=1, color='#922B21', label='predicted')
    plt.fill_between(xindex, pred_- std_, pred_+std_,
                    color='#5499C7', alpha=0.6, label = '$\pm1 \sigma$')

    max_ = np.max([label_.max(), np.max(pred_)])
    plt.ylim(0, 1.1*max_)
    plt.ylabel('Concentration, $\mu g/m^3$')
    plt.title('Measured and predicted $PM_{2.5}$ using Ensemble regression',
              y=1.05, weight='bold')
    plt.xlabel('Hour, site: Hanoi, 2018')
    plt.legend(ncol=3)
    if savefig:
        plt.tight_layout()
        plt.savefig(f'img/en_reg_{start}.png', optimize=True)
    return None
```

[213]:
```python
plot_results(label=y_train, prediction=y_entrain_p,
             std_=train_std, savefig=True)
```



6.3.2 Testset

[214]:
```
y_entest_p = voting_reg.predict(X_test)
```

[215]:
```
mse = mean_squared_error(y_entest_p, y_test)
test_std = np.sqrt(mse)
mse, test_std
```

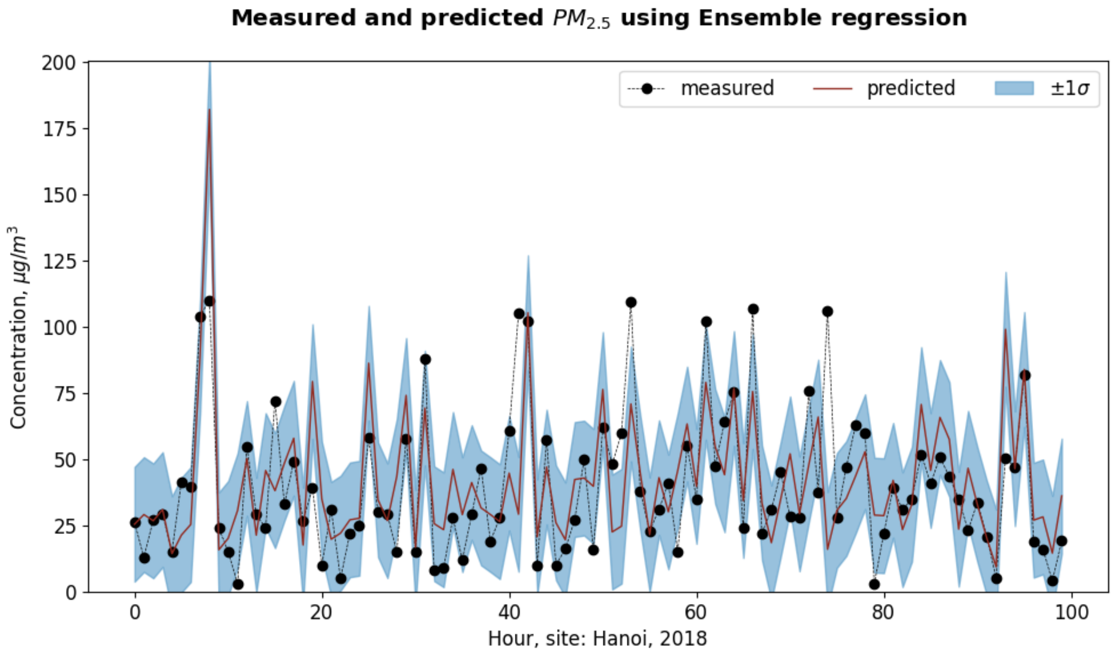
[215]:
```
(469.53197116134754, 21.668686419839748)
```

[216]:
```
add_stats(model='voting reg (Darksky)',
          train_rmse=train_std,
          test_rmse=test_std)
results
```

[216]:
```
{'linear reg': {'train_rmse': 25.5, 'test_rmse': 25.9},
 'decisiontree reg': {'train_rmse': 0.0, 'test_rmse': 28.9},
 'randomforest reg': {'train_rmse': 7.3, 'test_rmse': 19.9},
 'gridsearch': {'train_rmse': 7.8, 'test_rmse': 20.0},
 'voting reg': {'train_rmse': 10.5, 'test_rmse': 21.9},
 'voting reg (Darksky)': {'train_rmse': 11.7, 'test_rmse': 21.7}}
```

- not much worse, infact, with less parameters and get a similar outcome, that is actually encouraging

[217]:
```
plot_results(label=y_test,
             prediction=y_entest_p, std_=test_std, savefig=True)
```



7 RMSE

[218]:
```
df = pd.DataFrame(data=results)
```

[219]:
```
df
```

[219]:
```
            linear reg  decisiontree reg  randomforest reg  gridsearch  \
train_rmse        25.5               0.0               7.3         7.8
test_rmse         25.9              28.9              19.9        20.0

            voting reg  voting reg (Darksky)
train_rmse        10.5                  11.7
test_rmse         21.9                  21.7
```

[222]:
```
df2 = df.transpose()
```

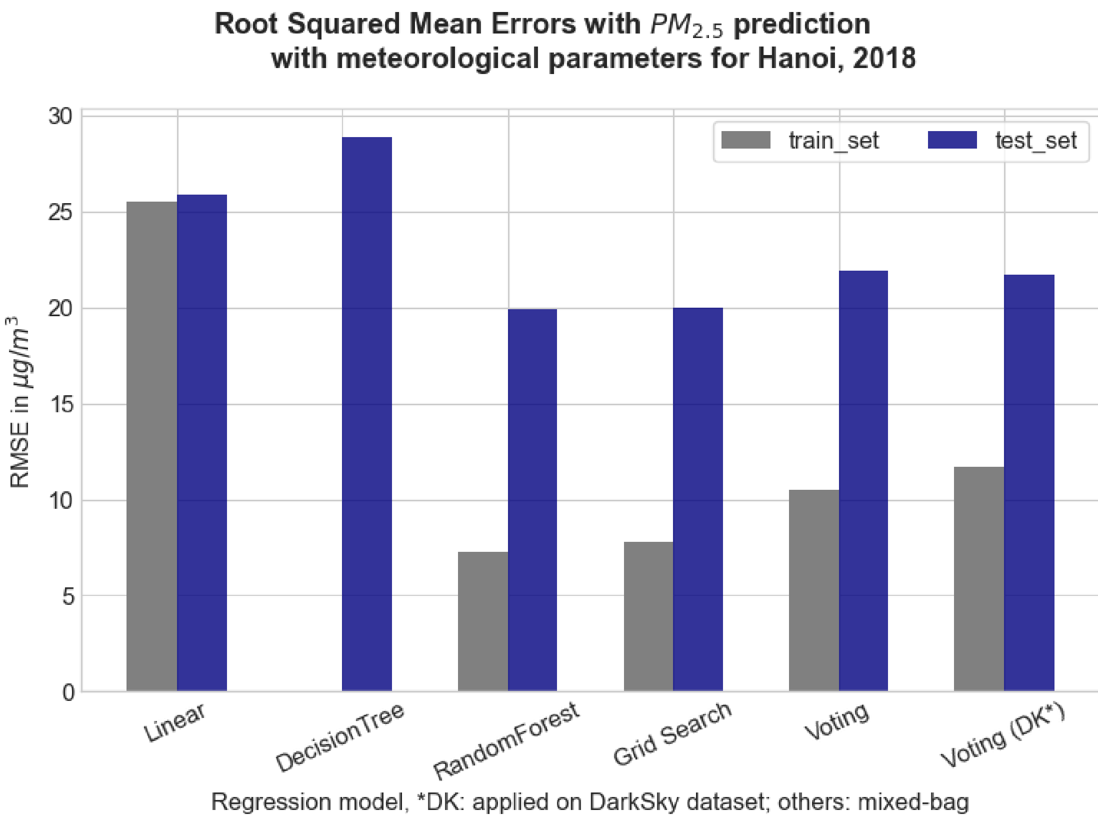
[223]:
```
df2
```

[223]:
```
                      train_rmse  test_rmse
linear reg                  25.5       25.9
decisiontree reg             0.0       28.9
```

```
randomforest reg             7.3       19.9
gridsearch                   7.8       20.0
voting reg                  10.5       21.9
voting reg (Darksky)        11.7       21.7
```

[280]:
```
plt.style.use('seaborn-whitegrid')
```

[299]:
```
bw = 0.3
idx = np.arange(len(df2))
fig, ax = plt.subplots(figsize=(8,6))
ax.bar(idx-bw/2, df2['train_rmse'], bw, color='gray', label='train_set')
ax.bar(idx+bw/2, df2['test_rmse'], bw, color='navy', alpha=0.8,␣
 ↪label='test_set')
ax.set_xticklabels(['','Linear', 'DecisionTree', 'RandomForest',
                    'Grid Search', 'Voting', 'Voting (DK*)'],
                  rotation=25)
ax.set_xlabel('Regression model, *DK: applied on DarkSky dataset; others:␣
 ↪mixed-bag')
ax.set_title('Root Squared Mean Errors with $PM_{2.5}$ prediction\
             \n with meteorological parameters for Hanoi, 2018',
            y=1.05,
            weight='bold')
# labels = ax.get_xticklabels()
ax.set_ylabel('RMSE in $\mu g/m^3$')
ax.legend(frameon=True, ncol=2)
fig.tight_layout()
fig.savefig('img/2020Aug_rmse_raw.png')
```



[270]:
```
pm['pm25'].mean()
```

[270]:
```
40.75225885225883
```

[273]:
```
df3 = df2*100/pm['pm25'].mean()
```

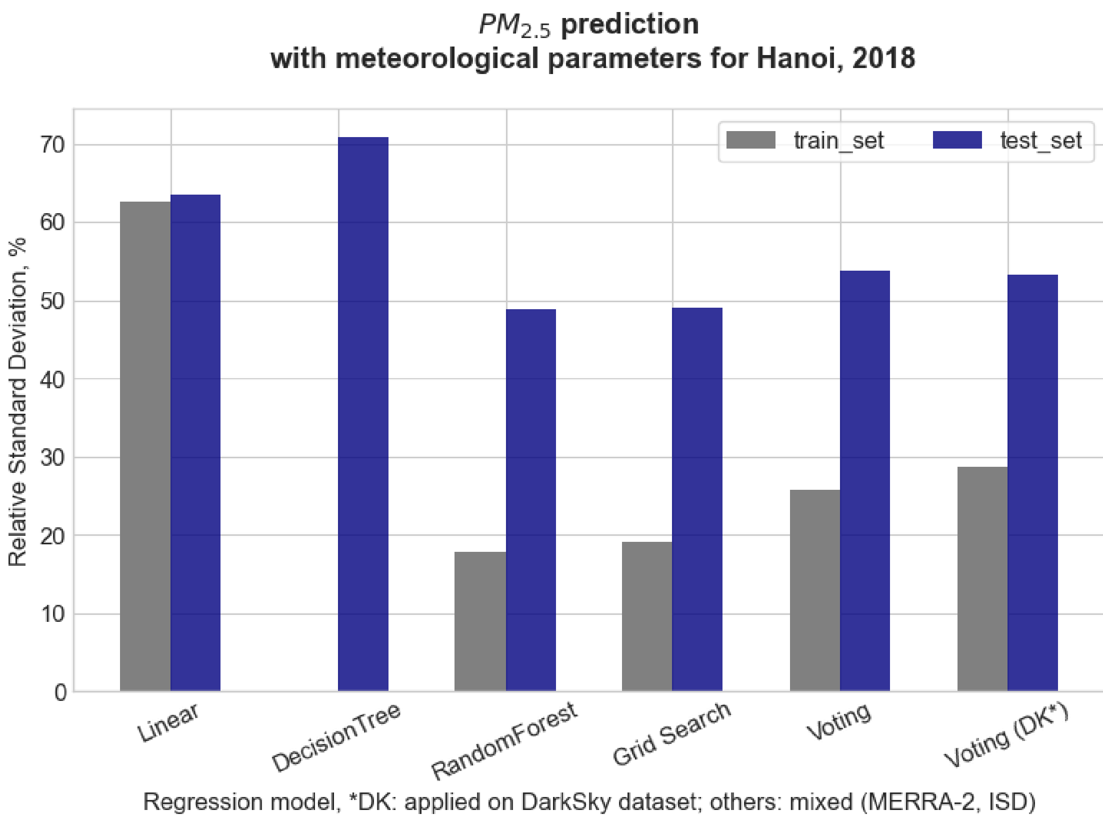
[274]:
```
df3
```

[274]:

	train_rmse	test_rmse
linear reg	62.573219	63.554759
decisiontree reg	0.000000	70.916314
randomforest reg	17.913117	48.831649
gridsearch	19.140043	49.077034
voting reg	25.765443	53.739352
voting reg (Darksky)	28.710065	53.248582

[296]:
```
bw = 0.3
idx = np.arange(len(df3))
fig, ax = plt.subplots(figsize=(8,6))
ax.bar(idx-bw/2, df3['train_rmse'], bw, color='gray', label='train_set')
```

```
ax.bar(idx+bw/2, df3['test_rmse'], bw, color='navy', alpha=0.8,␣
 ↪label='test_set')
ax.set_xticklabels(['','Linear', 'DecisionTree', 'RandomForest',
                    'Grid Search', 'Voting', 'Voting (DK*)'],
                  rotation=25)
ax.set_xlabel('Regression model, *DK: applied on DarkSky dataset; others: mixed␣
 ↪(MERRA-2, ISD)')
ax.set_title('$PM_{2.5}$ prediction\n with meteorological parameters for Hanoi,␣
 ↪2018',
             y=1.05,
            weight='bold')
# labels = ax.get_xticklabels()
ax.set_ylabel('Relative Standard Deviation, %')
ax.legend(frameon=True, ncol=2)
fig.tight_layout()
# fig.tight_layout(rect=(0.1,0.1,0.95, 0.95))
fig.savefig('img/2020Aug_rmse_rsd.png')
```




```
[ ]:
```