3.2 Regression

August 15, 2020

Table of Contents

1 Ideas

- Load data from the last exercise (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()
```

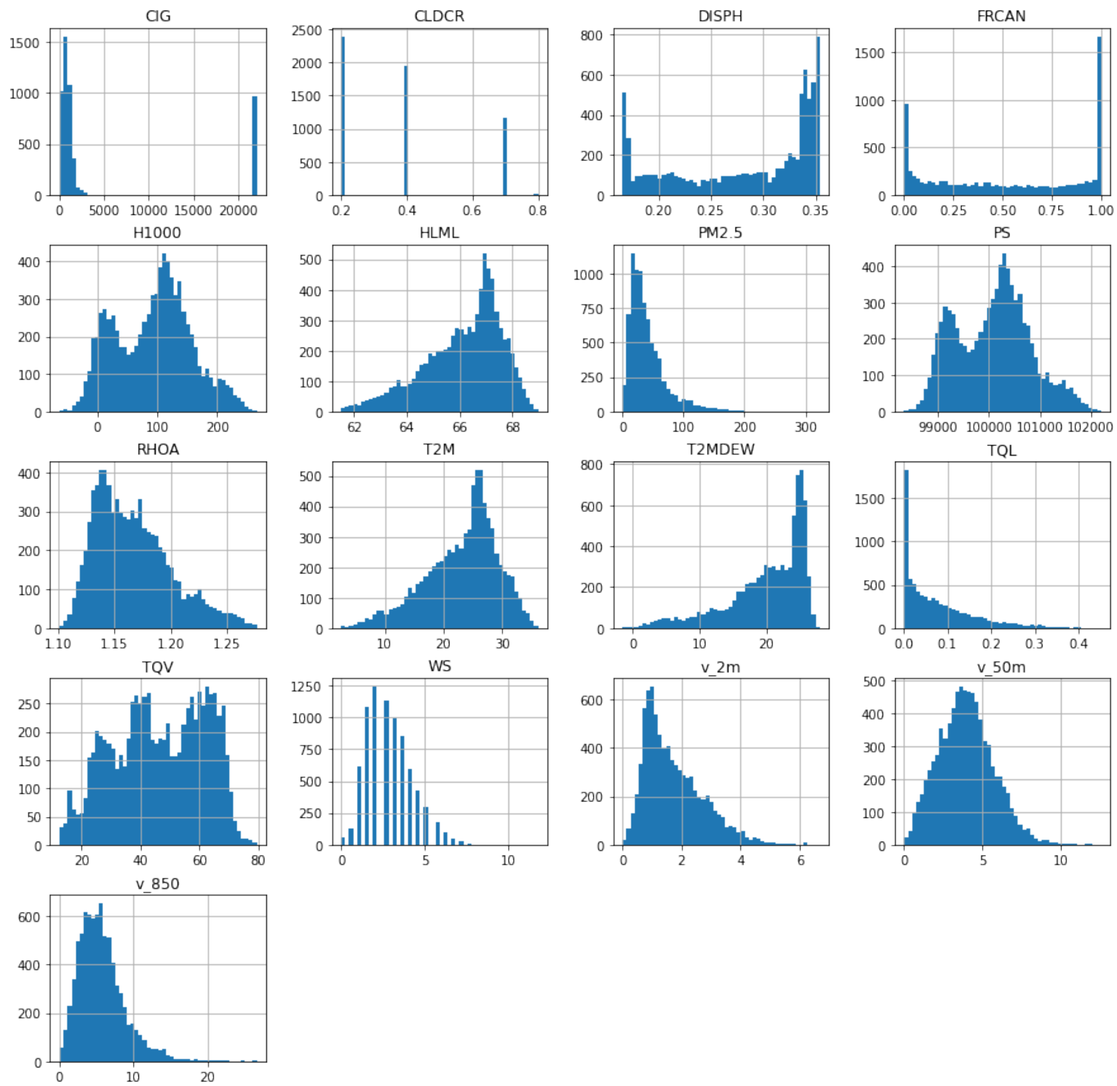
[5]:
```
                     PM2.5    T2MDEW       T2M         PS        TQV  \
DATE
2018-01-01 01:00:00   69.2  10.79443  13.64376  100865.09  34.909637
2018-01-01 02:00:00   75.5  10.72836  13.33932  100819.56  35.195385
2018-01-01 03:00:00   90.2  10.60630  13.09753  100793.71  35.590984
2018-01-01 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]:
```
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 likely 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]:
```
# evaluate df2
inputer.fit(df2)
```

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

[27]:
```
# 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]:
```
# transform is doing the work
df2full = inputer.transform(df1)
```

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

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

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

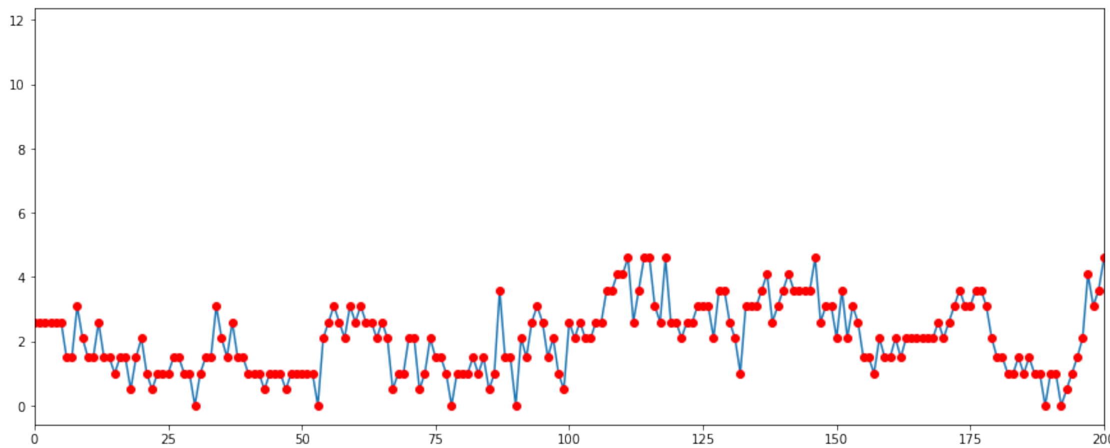
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8116 entries, 0 to 8115
Data columns (total 17 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   PM2.5   8116 non-null   float64
 1   T2MDEW  8116 non-null   float64
 2   T2M     8116 non-null   float64
 3   PS      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]:
```python
# you can save to a file with all missing values filled
df.to_csv('data/filled_PM2.5_Hanoi_2018.csv')
```

[31]:
```python
# 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)
```

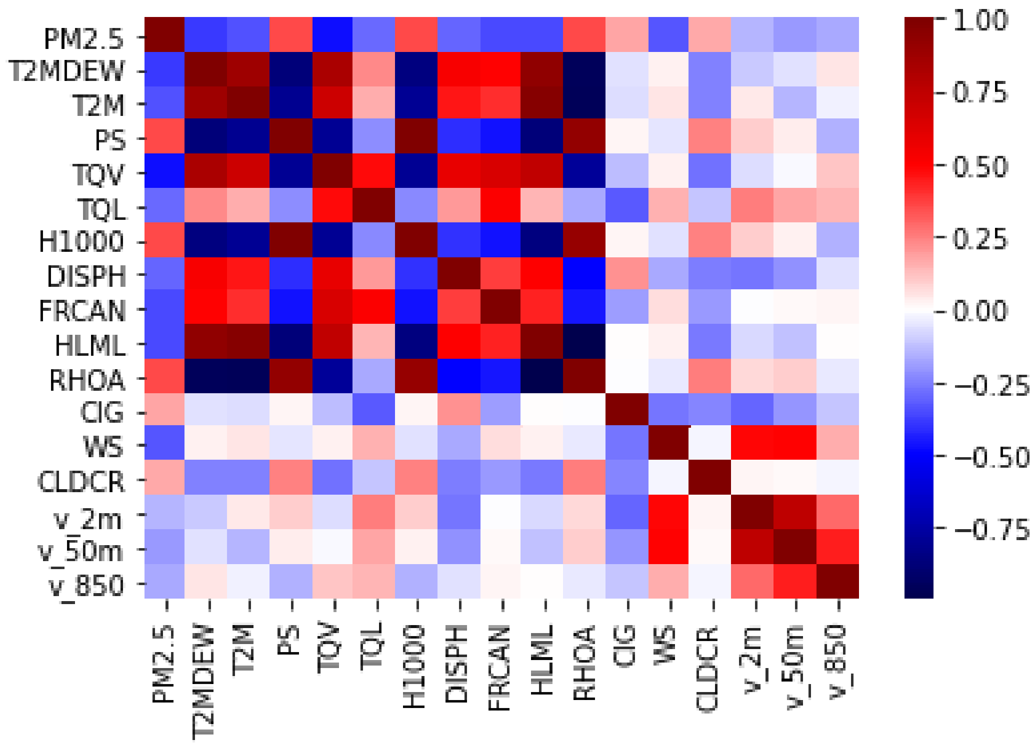
[31]: (0.0, 200.0)



3.3 Additional cleanup

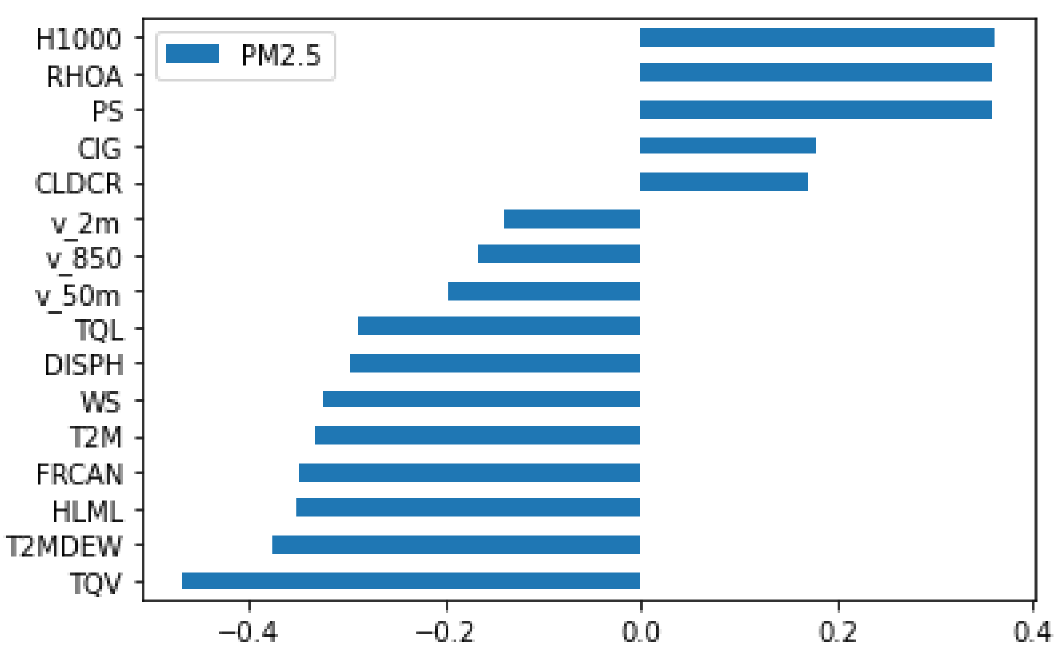
[32]:
```python
# let return back to the original dataset (df) before fill up NaN
sns.heatmap(df.corr(), cmap='seismic')
```

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

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

[53]:
```
# 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]:
```
# transform data from real value to a relative to the set
from sklearn.preprocessing import StandardScaler
```

[54]:
```
# 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_
```

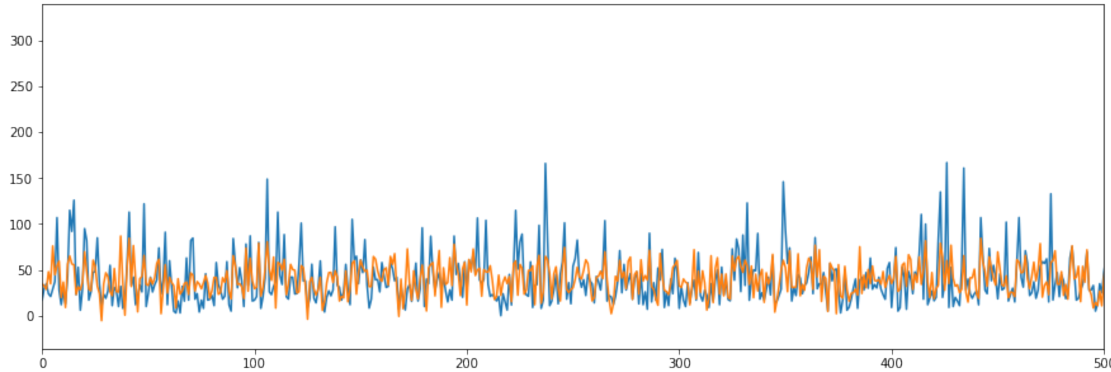
[71]:
```
array([  -3.15806877,    9.23068653, -237.20129647,  -11.37237178,
         -1.51486159,  216.26310513,   19.10913327,   47.2122002 ,
          2.99459991,   -8.55437448])
```

[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)
```

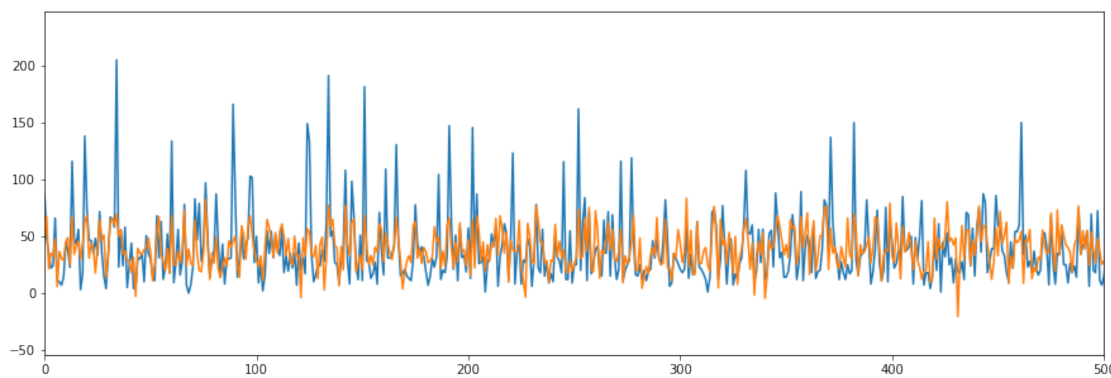
[73]: (0.0, 500.0)



[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
```

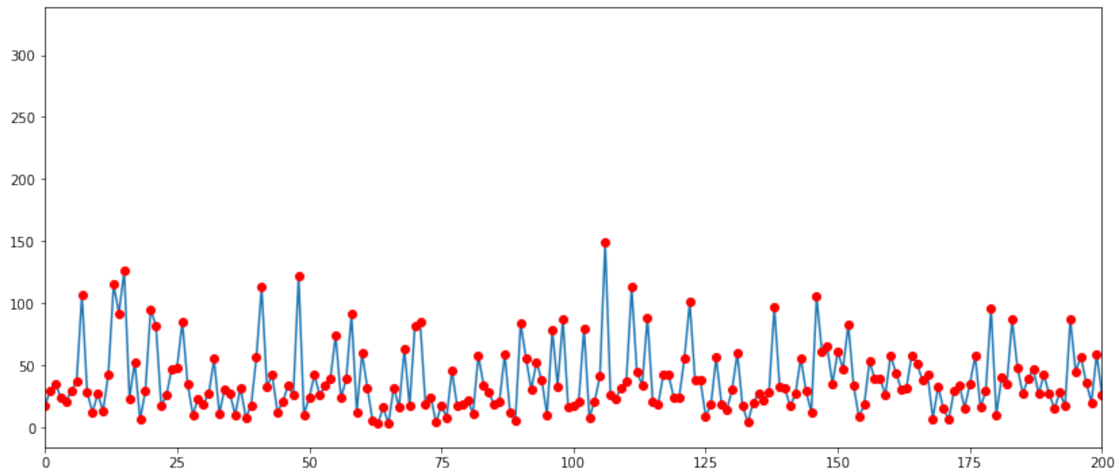
[111]:
```
# let bag the result
add_stats(model='decisiontree reg',
         train_rmse=tree_train_rmse,
         test_rmse=tree_test_rmse)
results
```

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

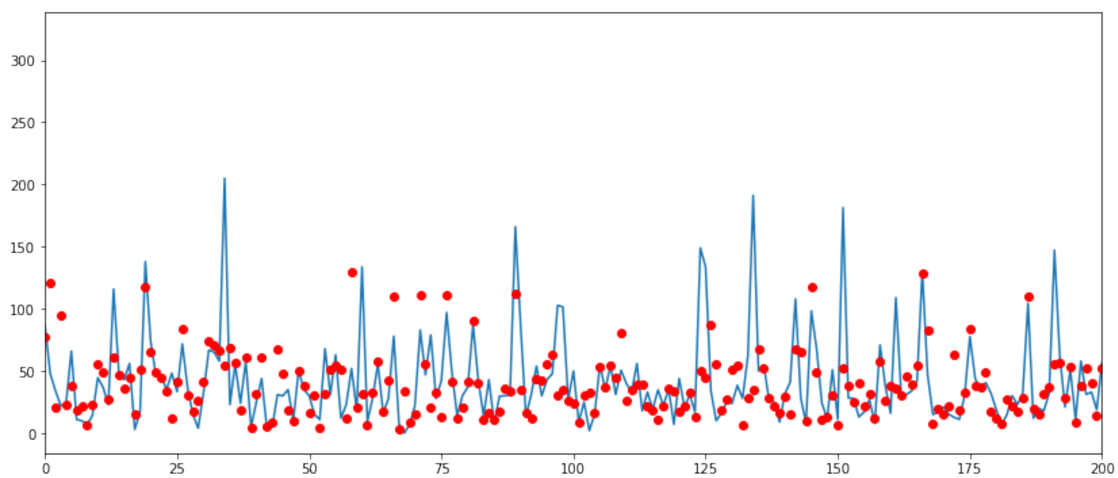
[107]:
```
# the results by train set and test set are rather different, to see it
def plot_prediction(label=None, prediction=None, limit=200):
```

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

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



[109]:
```
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]:
```
from sklearn.model_selection import cross_val_score
```

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

[125]:
```
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]:
```
def display_scores(scores):
    print("Scores: ", scores)
    print("Mean: ", scores.mean())
    print("Standard Deviation: ", scores.std())
```

[127]:
```
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]:
```
lin_scores = cross_val_score(lin_reg, X_train, y_train,
                             scoring='neg_mean_squared_error', cv=10)
```

[129]:
```
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]:
```
forest_scores = cross_val_score(forest_reg, X_train, y_train,
                                scoring='neg_mean_squared_error', cv=10)
```

[132]:
```
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]:
```
# 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]:
```python
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]:
```python
# 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]:
```python
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
```

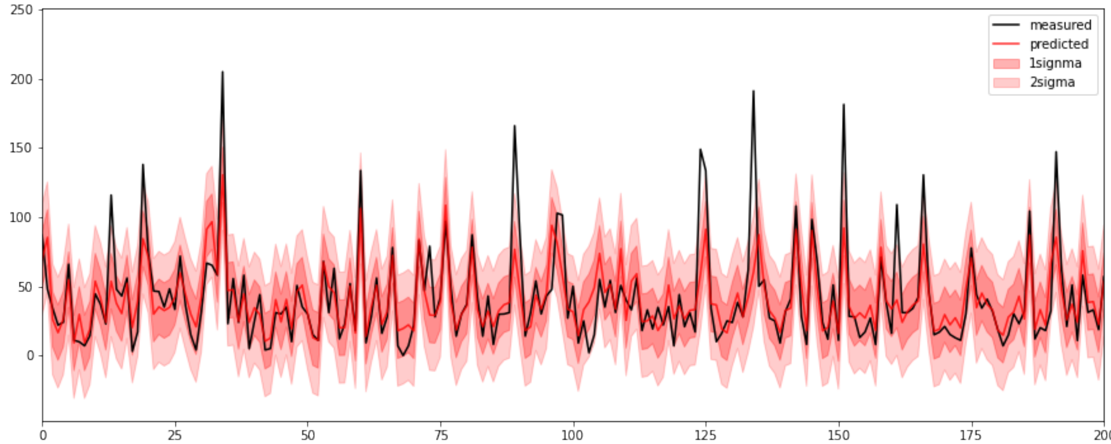
[153]:
```
20.033245999333058
```

[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
```

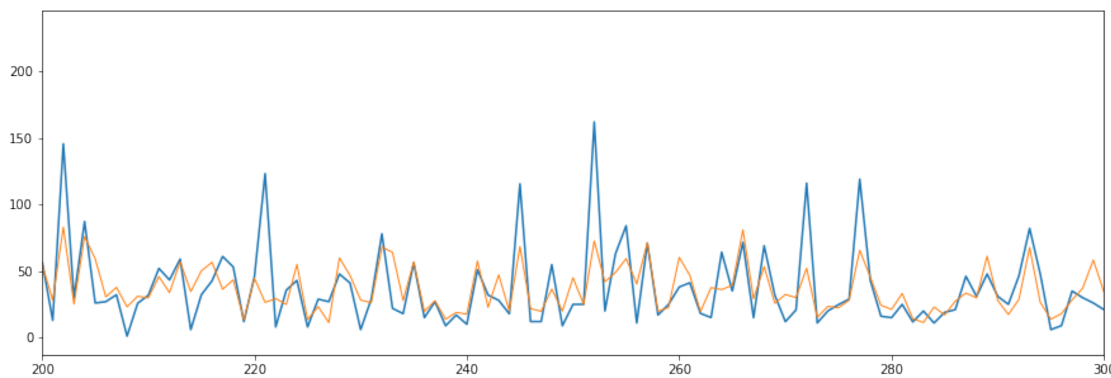
[173]:
```
(21.89413644598667, 10.545304085343597)
```

[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 less feastures,

6 DarkSky Dataset

- you can check out this API at DarkSky.net. After acquired by Apple, the future of this open API is unsure. The registration is closed as well. Alternatively, check out OpenWeatherMap.org

6.1 Merge data

[176]:
```
# load 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]:
```
# 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]:
```
# seperate feature and label
X = df.drop('pm25', axis=1)
y = df['pm25'].copy()
```

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

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

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

6.2 Split train and test

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

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

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

[204]:
```
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
```

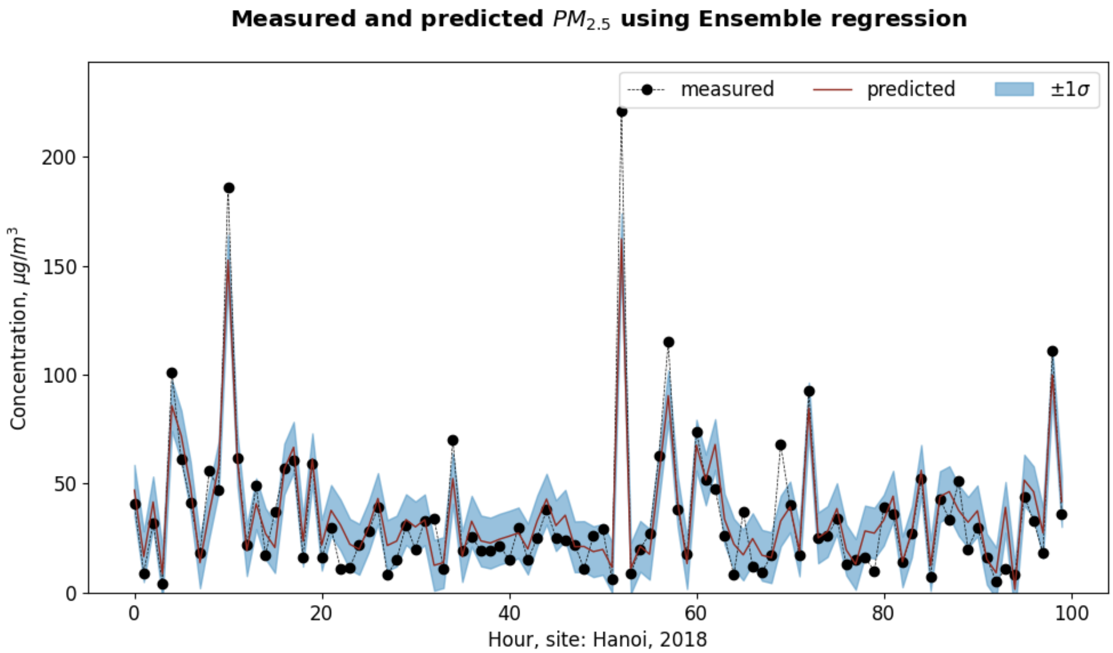
[211]:
```python
from random import randint
```

[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
```

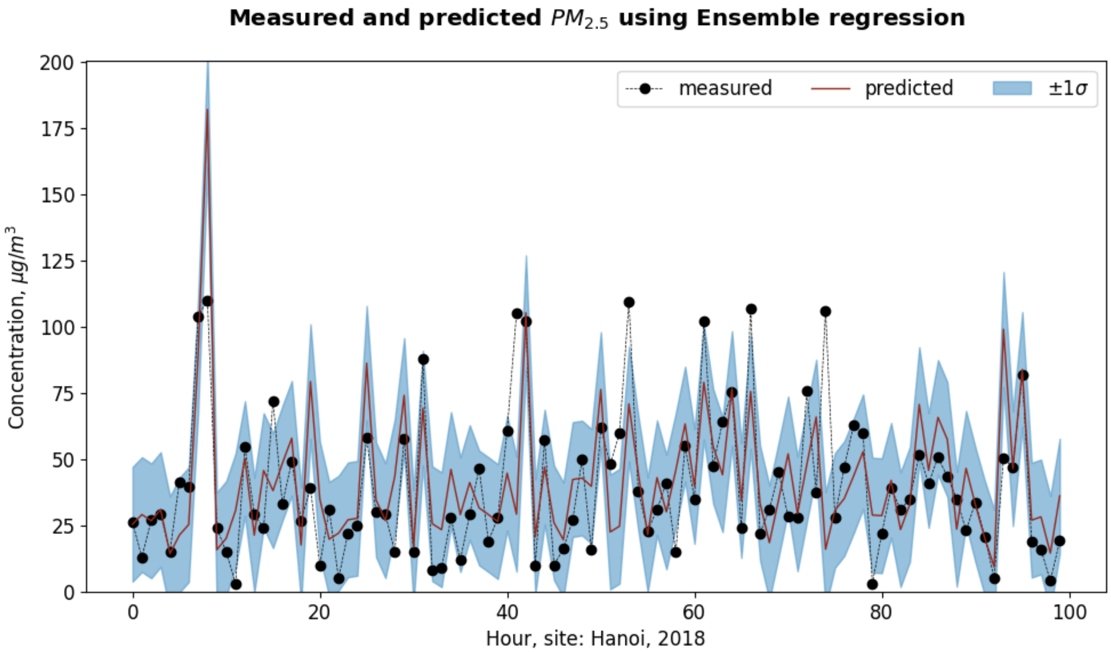
[215]:
```
(469.53197116134754, 21.668686419839748)
```

[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, in fact, 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

- again, this is Root Mean Squared Error. If we assumed the errors is random, then the distribution of error to the mean value shouls be in standard distribution (Gaussian Distribution). Then the RMSE is the Standard Deviation (SD). The ratio of SD to the mean value in percent is called Relative Standard Deviation.

[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]:

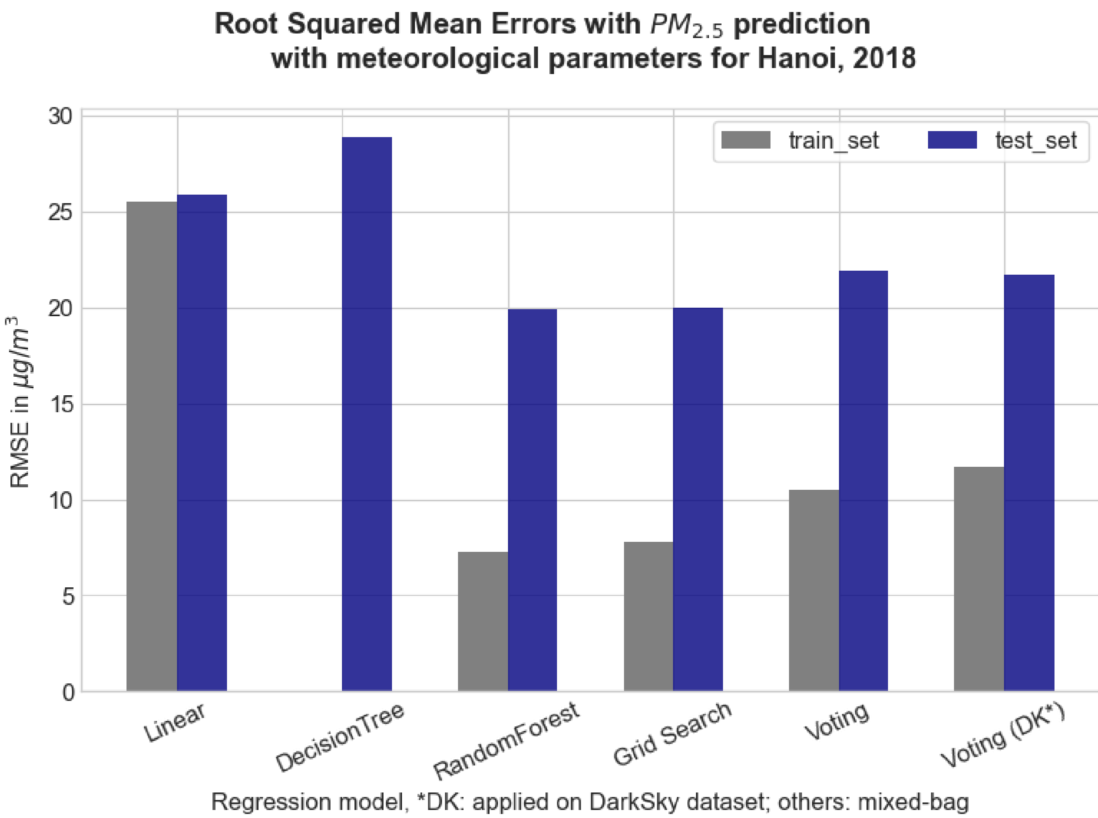
	train_rmse	test_rmse
linear reg	25.5	25.9
decisiontree reg	0.0	28.9
randomforest reg	7.3	19.9
gridsearch	7.8	20.0
voting reg	10.5	21.9
voting reg (Darksky)	11.7	21.7

[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()
```

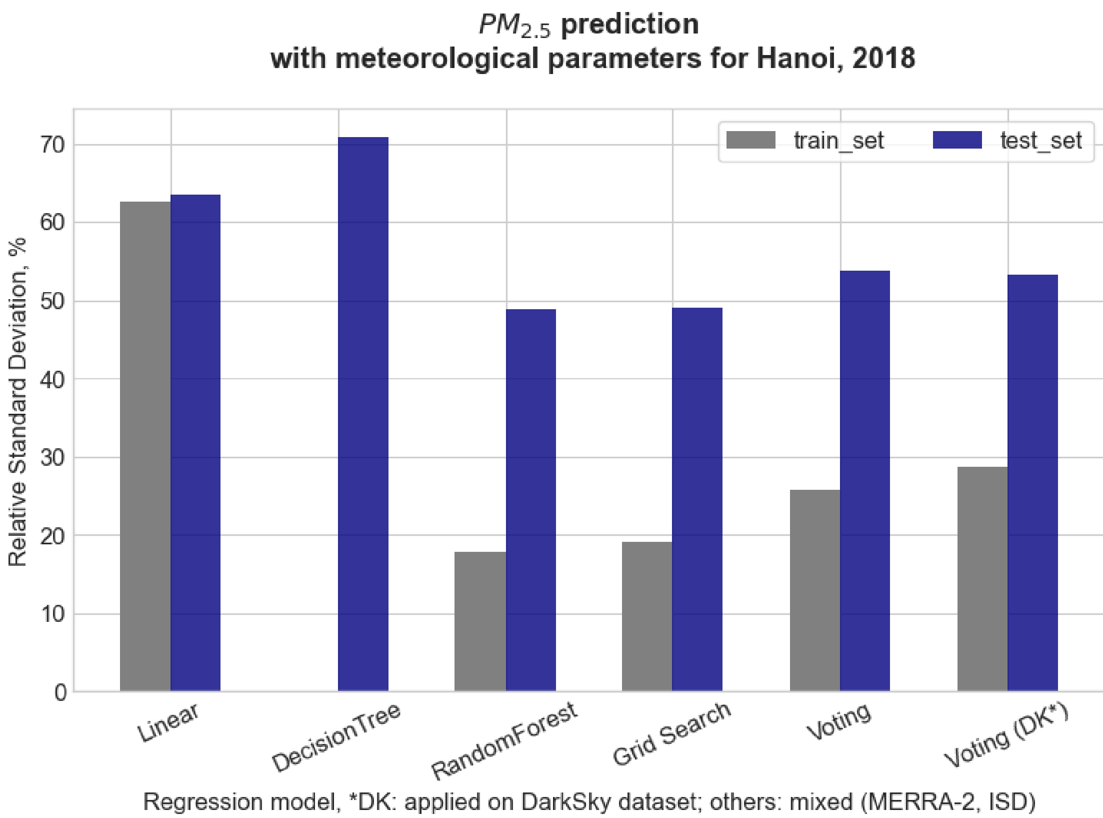
[274]:
```
df3
```

[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')
```




```
[ ]:
```