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# Ideas:

- We will pick up the cleaned meteorological file from the previous exercise. If you missed that exercise, in which I went through step-by-step getting and cleaning files from NOAA, then visit file 2.2 and part 1. The cleaned file is in `data/cleaned_noibai_noaa_isd_2018.csv`
- We will resume to archieved data from `airnow.gov` . This file was cleaned up and reduced to the only $PM_{2.5}$ concentration (and thus all metadata was filtered out). The file is here `data/cleaned_pm25_Hanoi_PM2.5_2018_YTD.csv` . I did a quick data wrangling in part 2.1
- Correlating meteorological parameters with observed $PM_{2.5}$ is *better than a guessing game* as we try to make some connection between two sets of data (with the same timestamp).

# import libraries

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import pandas as pd
import seaborn as sns
import datetime
```

In [2]:
```
# use simple style with font and tick setup
plt.style.use('seaborn-white')
```

In [3]:
```
plt.rcParams['figure.figsize'] =  (8,6)
plt.rcParams['font.sans-serif'] = 'Open Sans'
plt.rcParams['font.family'] = 'sans-serif'
plt.rcParams['text.color'] = '#4c4c4c'
plt.rcParams['axes.labelcolor']= '#4c4c4c'
plt.rcParams['xtick.color'] = '#4c4c4c'
plt.rcParams['ytick.color'] = '#4c4c4c'
plt.rcParams['font.size']=12
```

# Prepare data

In [4]:
```
# load meteorological data
dfm = pd.read_csv('data/cleaned_noibai_noaa_isd_2018.csv',
                  parse_dates=['DATE'],
                  index_col=['DATE'])
dfm.head()
```

Out[4]:

| | CIG | VIS | TMP | DEW | WD | WS | CLDCR | CLDHT |
|---|---|---|---|---|---|---|---|---|
| **DATE** | | | | | | | | |
| **2018-01-01 00:00:00** | 1067.0 | 8000 | 16.0 | 12.0 | 80 | 1.5 | 0.7 | 1067.0 |
| **2018-01-01 00:30:00** | 975.0 | 8000 | 16.0 | 12.0 | 60 | 1.5 | 0.7 | 975.0 |
| **2018-01-01 01:00:00** | 975.0 | 7000 | 16.0 | 12.0 | 80 | 1.5 | 0.7 | 975.0 |
| **2018-01-01 01:30:00** | 975.0 | 7000 | 17.0 | 12.0 | 60 | 2.1 | 0.7 | 975.0 |
| **2018-01-01 02:00:00** | 1006.0 | 7000 | 17.0 | 12.0 | 80 | 3.1 | 0.4 | 762.0 |

In [5]:
```
# the interval of file above is 30 minutes each, and PM2.5 is one hou
r a part
dfm = dfm.resample('1H', loffset=datetime.timedelta(hours=1)).mean()
```

In [6]:
```
dfm.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8760 entries, 2018-01-01 01:00:00 to 2019-01-01 00:00:
00
Freq: H
Data columns (total 8 columns):
CIG      5951 non-null float64
VIS      8524 non-null float64
TMP      8524 non-null float64
DEW      8524 non-null float64
WD       8524 non-null float64
WS       8524 non-null float64
CLDCR    6200 non-null float64
CLDHT    6200 non-null float64
dtypes: float64(8)
memory usage: 615.9 KB
```

In [7]:
```
# and now is for PM2.5
pm25 = pd.read_csv('data/cleaned_pm25_Hanoi_PM2.5_2018_YTD.csv',
                   parse_dates=['Date (LT)'],
                   index_col=['Date (LT)'])

pm25.head()
```

Out[7]:

| | 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 |

In [8]:
```
# one year has 8760 hours
pm25.shape
```

Out[8]: (8190, 1)

In [9]:
```
# now we combine to data frame, using the index as the shared key
df = pd.merge(dfm, pm25, left_index=True, right_index=True)
df.head()
```

Out[9]:

| | CIG | VIS | TMP | DEW | WD | WS | CLDCR | CLDHT | pm25 |
|---|---|---|---|---|---|---|---|---|---|
| **2018-01-01 01:00:00** | 1021.0 | 8000.0 | 16.0 | 12.0 | 70.0 | 1.50 | 0.7 | 1021.0 | 69.2 |
| **2018-01-01 02:00:00** | 975.0 | 7000.0 | 16.5 | 12.0 | 70.0 | 1.80 | 0.7 | 975.0 | 75.5 |
| **2018-01-01 03:00:00** | 1006.0 | 7000.0 | 17.0 | 12.0 | 80.0 | 2.85 | 0.4 | 762.0 | 90.2 |
| **2018-01-01 04:00:00** | 1006.0 | 6000.0 | 17.0 | 12.0 | 40.0 | 2.10 | 0.4 | 762.0 | 97.6 |
| **2018-01-01 05:00:00** | 1006.0 | 5000.0 | 18.5 | 13.0 | 65.0 | 1.50 | 0.4 | 762.0 | 89.1 |

In [10]:
```
df.index.rename('DATE', inplace=True)
```

In [11]:
```
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):
CIG      5604 non-null float64
VIS      7959 non-null float64
TMP      7959 non-null float64
DEW      7959 non-null float64
WD       7959 non-null float64
WS       7959 non-null float64
CLDCR    5815 non-null float64
CLDHT    5815 non-null float64
pm25     8190 non-null float64
dtypes: float64(9)
memory usage: 639.8 KB
```

**wait, are we losing data?**

- check again with `dfm` , we have over 8500 lines, and now in combined dataframe, the file has 7959 rows
- the combine option by default is **inner**, a **union** of two sets of index, other options also available which are `left` , `right` , `outer` , and assign the option by `pd.merge(df1, df2, how='outer', ...)`

In [12]:
```
# we will calculate RH from approximation from air tempeature and dew
point temperature
df['RH'] = df.apply(lambda row: 100-5*(row['TMP']-row['DEW']), axis=1
)
df.head(3)
```

Out[12]:

| | CIG | VIS | TMP | DEW | WD | WS | CLDCR | CLDHT | pm25 | RH |
|---|---|---|---|---|---|---|---|---|---|---|
| **DATE** | | | | | | | | | | |
| **2018-01-01 01:00:00** | 1021.0 | 8000.0 | 16.0 | 12.0 | 70.0 | 1.50 | 0.7 | 1021.0 | 69.2 | 80.0 |
| **2018-01-01 02:00:00** | 975.0 | 7000.0 | 16.5 | 12.0 | 70.0 | 1.80 | 0.7 | 975.0 | 75.5 | 77.5 |
| **2018-01-01 03:00:00** | 1006.0 | 7000.0 | 17.0 | 12.0 | 80.0 | 2.85 | 0.4 | 762.0 | 90.2 | 75.0 |

In [13]:
```
# and we save the file
df.to_csv('data/combined_meteo_PM2.5_Hanoi_2018.csv')
```

In [14]:
```
df = pd.read_csv('data/combined_meteo_PM2.5_Hanoi_2018.csv',
                 parse_dates=['DATE'],
                 index_col=['DATE'])
```

In [15]:
```
# let get correlation which generate a dataframe
df.corr()
```

Out[15]:

| | CIG | VIS | TMP | DEW | WD | WS | CLDCR | CLDHT |
|---|---|---|---|---|---|---|---|---|
| **CIG** | 1.000000 | 0.301060 | 0.060859 | -0.013038 | 0.130481 | -0.032222 | -0.195803 | 0.221168 |
| **VIS** | 0.301060 | 1.000000 | 0.038549 | -0.242069 | 0.028815 | 0.014172 | -0.142735 | 0.150400 |
| **TMP** | 0.060859 | 0.038549 | 1.000000 | 0.819125 | 0.079949 | 0.004359 | -0.272067 | 0.142463 |
| **DEW** | -0.013038 | -0.242069 | 0.819125 | 1.000000 | 0.031270 | -0.005788 | -0.273422 | -0.196228 |
| **WD** | 0.130481 | 0.028815 | 0.079949 | 0.031270 | 1.000000 | 0.014538 | -0.040801 | 0.088947 |
| **WS** | -0.032222 | 0.014172 | 0.004359 | -0.005788 | 0.014538 | 1.000000 | 0.015695 | 0.013199 |
| **CLDCR** | -0.195803 | -0.142735 | -0.272067 | -0.273422 | -0.040801 | 0.015695 | 1.000000 | 0.125950 |
| **CLDHT** | 0.221168 | 0.150400 | 0.142463 | -0.196228 | 0.088947 | 0.013199 | 0.125950 | 1.000000 |
| **pm25** | 0.084939 | -0.037716 | -0.297633 | -0.362755 | 0.134051 | -0.027791 | 0.139204 | 0.032396 |
| **RH** | -0.134297 | -0.476898 | -0.164482 | 0.431071 | -0.071991 | -0.016809 | 0.005551 | -0.570603 |

- that is easy and **meaningless** as well. One goal of data visualization is to drill down the data and get a simpler, much simpler message from the data. **Meaningless** is for an emphasis. When we are overwhelmed with data, we loss interest of it, and nothing would be retained.

## First look at correlation

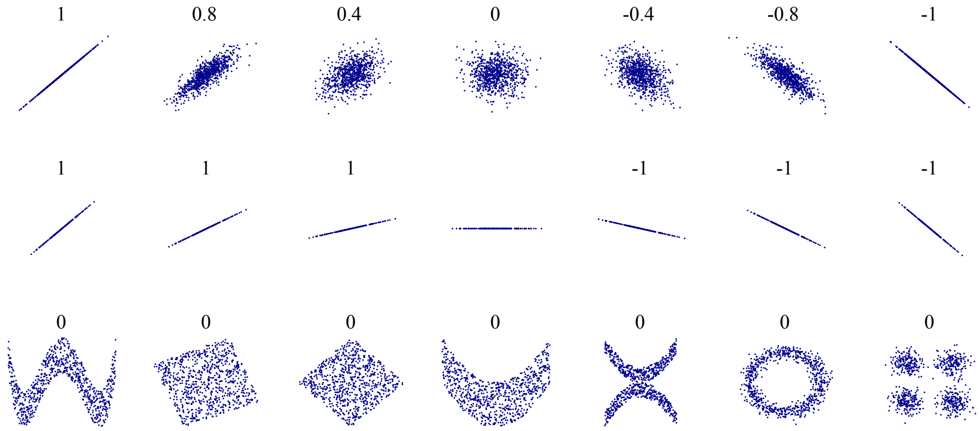
- with `pandas` , getting a bivariate correlation (correlation between two variables) is easy, just call `.corr()` after the DataFrame like this. We can filter out the correlation with one variable such as `pm25`

In [16]:
```
df.corr()['pm25']
```

Out[16]:
```
CIG      0.084939
VIS     -0.037716
TMP     -0.297633
DEW     -0.362755
WD       0.134051
WS      -0.027791
CLDCR    0.139204
CLDHT    0.032396
pm25     1.000000
RH      -0.155600
Name: pm25, dtype: float64
```

**OK, that is quick and easy, but how this number mean?**

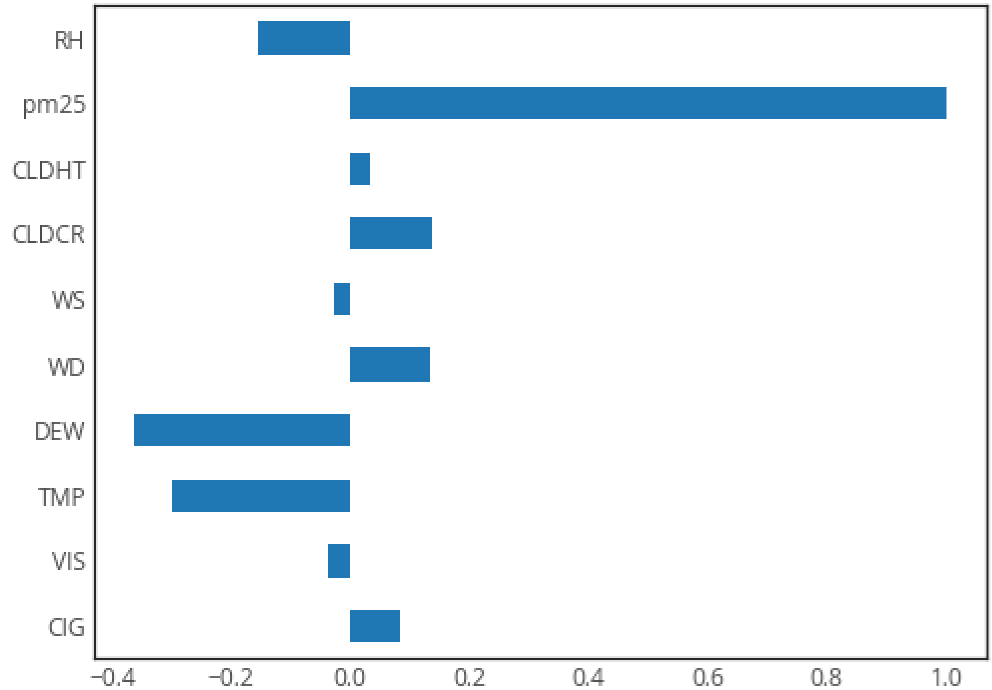
- First take a look at this diagram about




- A value of 1 is show the strongest positive correlation. Positive means when the value of one variable increases, the other also increases. The correlation of `pm25` to `pm25` ($PM_{2.5}$ concentration) is 1, which is always the case.
- A value of -1 show the strongest nagative correlation. Negative means when the value of one variable increases, the other decreases or vice versa.
- A value of 0 show no correlation.
- Anything in between are described as **weak**, **moderate**, **high** correlation. The degree to just is a dependent to the area of study. For the study involves a real environment (as oppose to well-controlled environmnet, simulated environmnet), the correlation is expected the weaker than those in well-defined environment.
- let visualize the table above, using the built-in plot function, we have two options `plot.bar()` and `plot.barh()`

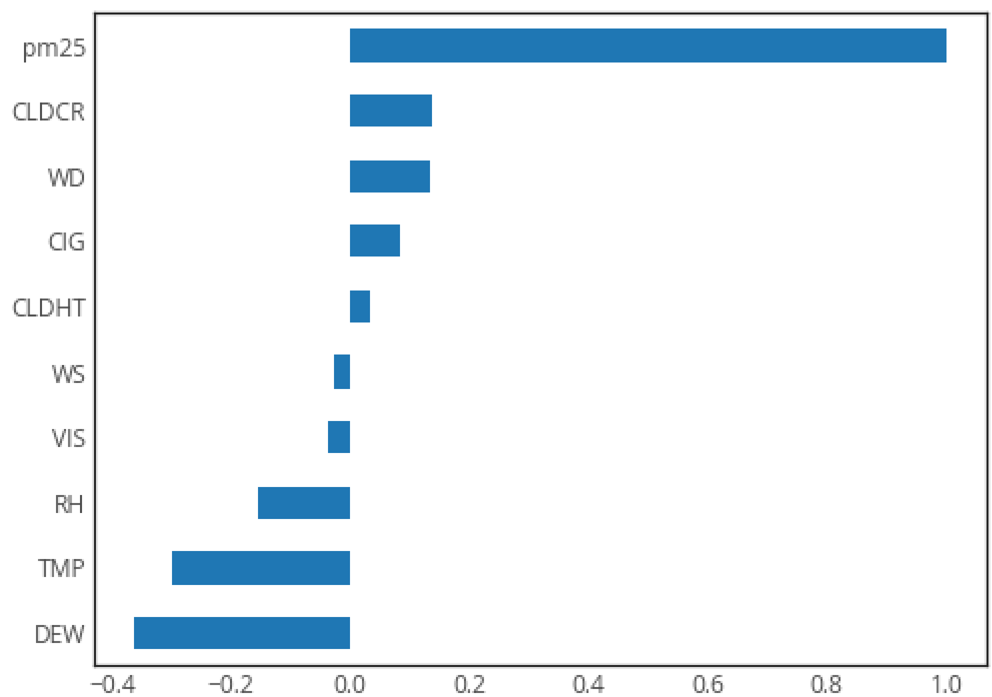
In [17]:
```
df.corr()['pm25'].plot.barh()
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e90f4b978>




In [18]:
```
# rearange the value
df.corr()['pm25'].sort_values().plot.barh()
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e8ee960f0>



and voila, it is done.

- there is no meteorological parameter in a **strong** correlation with $PM_{2.5}$. To judge a correlation number in **strong** category has to depends on a specific area of investigation but the value usually 0.7 or above.
- and not even in the area of **moderate to highly** band. So if the goal is the find a definitive correlation between observed meteorological inputs with concentration of $PM_{2.5}$, then the journey ended here, unfruitfully.

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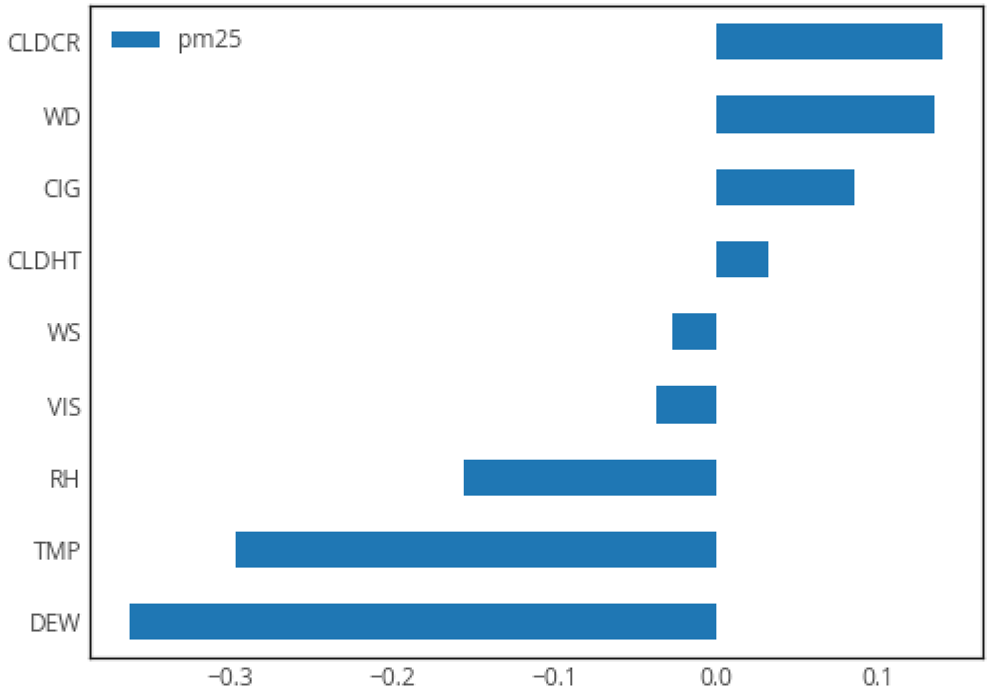
- but if you live in (seasonally) polluted area with aerosol fills the air in the winter, then it becomes something else: curiosity, practical knowledge, and service to others to feather out something interesting
- and on that ground, let move on the figure out what else in this correlation mess

**Let refesh what the abbreviation mean?**

- RH is relative humidity, the fraction of the current humidity to the saturated humidity that a volume of air can hold at that temperature
- CLDHT: The height of the lower cloud (in meters) relative to a reference point called *VERTICAL-REFERENCE-DATUM*
- CLDCR: Cloud cover in fraction
- WS, WD: windspeed (in meter per second), and degree with zero (or 360) is the wind comming from the north
- DEW: dewpoint temperature
- TMP: air temperature
- VIS: visiblity measured by the horizontal distance at which an object can be identified
- CIG: The height above ground level (AGL) of the lowest cloud

In [19]:
```
# let make a few operation in place
df.corr()['pm25'].sort_values().to_frame().drop(['pm25']).plot.barh()
```

Out[19]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8e8e756cf8>
```




**let unpack the operations here**

1. take correlation on `DataFrame df`, and filter out the column for `pm25` (or $PM_{2.5}$)
2. sort the value of the correlation coefficients using `sort_values()`
3. turn a `Pandas Series` to a `DataFrame`, so that we can use the `drop()` function to drop the redundancy value of `pm25`
4. finally, the number was plot using horizontal bar chart

In [20]:
```
label = ['Cloud Cover', 'Wind Direction', 'Height Above Ground',
                    'Cloud Height', 'Wind Speed', 'Visibility', 'Air
 Temperature',
                    'Dewpoint Temperature']
```

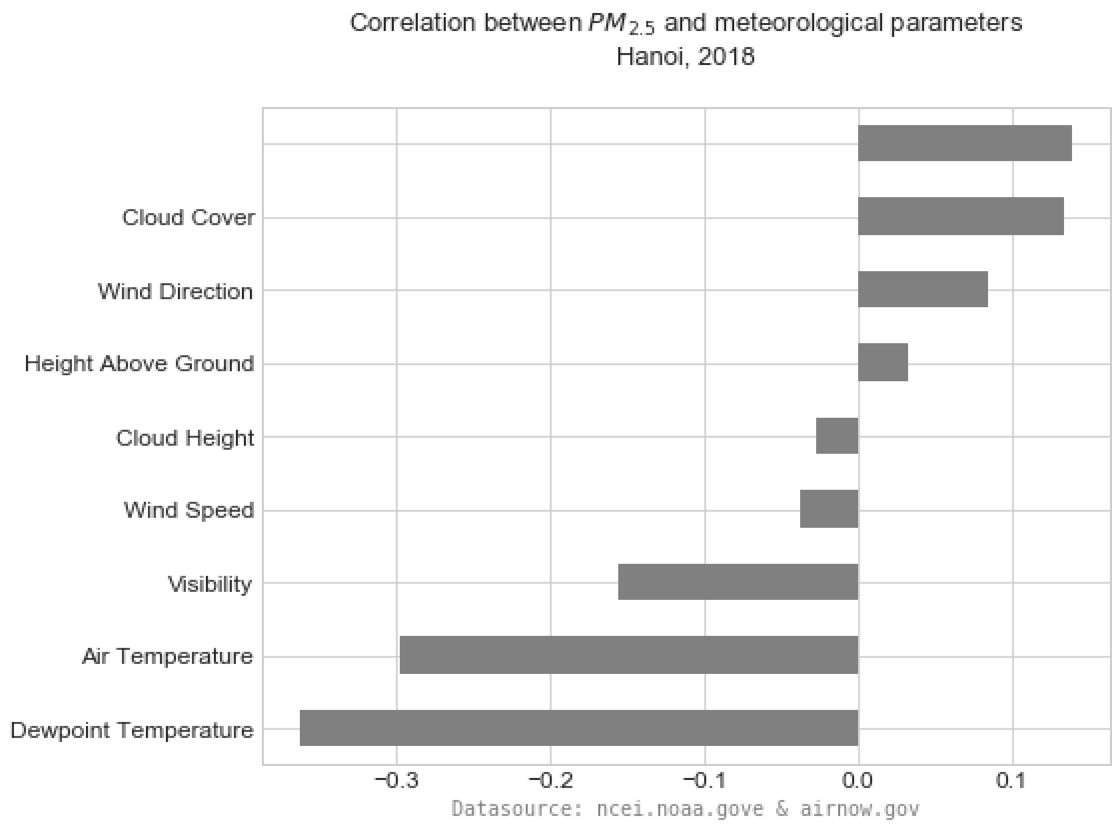
In [21]:
```
label
```

Out[21]:
```
['Cloud Cover',
 'Wind Direction',
 'Height Above Ground',
 'Cloud Height',
 'Wind Speed',
 'Visibility',
 'Air Temperature',
 'Dewpoint Temperature']
```

In [22]:
```
labels = list(reversed(label))
```

In [23]:

```
# let make the graph with bell and whistle
plt.style.use('seaborn-whitegrid')
fig, ax = plt.subplots()
df.corr()['pm25'].sort_values().to_frame().drop(['pm25']).plot.barh(a
x=ax, color='gray')
ax.set_title('Correlation between $PM_{2.5}$ and meteorological param
eters\nHanoi, 2018',y=1.05, fontsize=13)
ax.get_legend().remove()
ax.set_yticklabels(labels)
ax.set_xlabel('Datasource: ncei.noaa.gove & airnow.gov',
              fontsize=10, color='gray', fontfamily='monospace')
fig.tight_layout()
fig.savefig('img/2020Jul_corr_pm25.png')
```

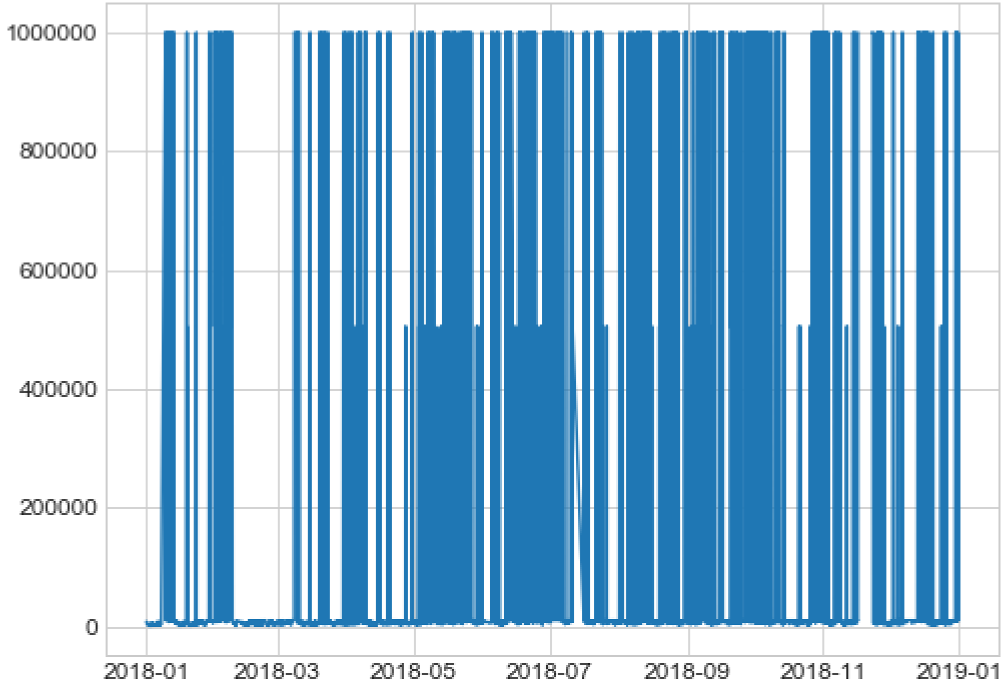



# VIS

- Visiblity seems to be a good candidate to start, and it makes sense. Hazy and foggy days in Hanoi are often been observed with a high $PM_{2.5}$ concentration
- Noticed that correlation between visiblity and $PM_{2.5}$ is almost None

In [24]:
```python
# pretty noisy
plt.plot(df.index, df.VIS)
```

Out[24]:
```
[<matplotlib.lines.Line2D at 0x7f8e8e625c18>]
```

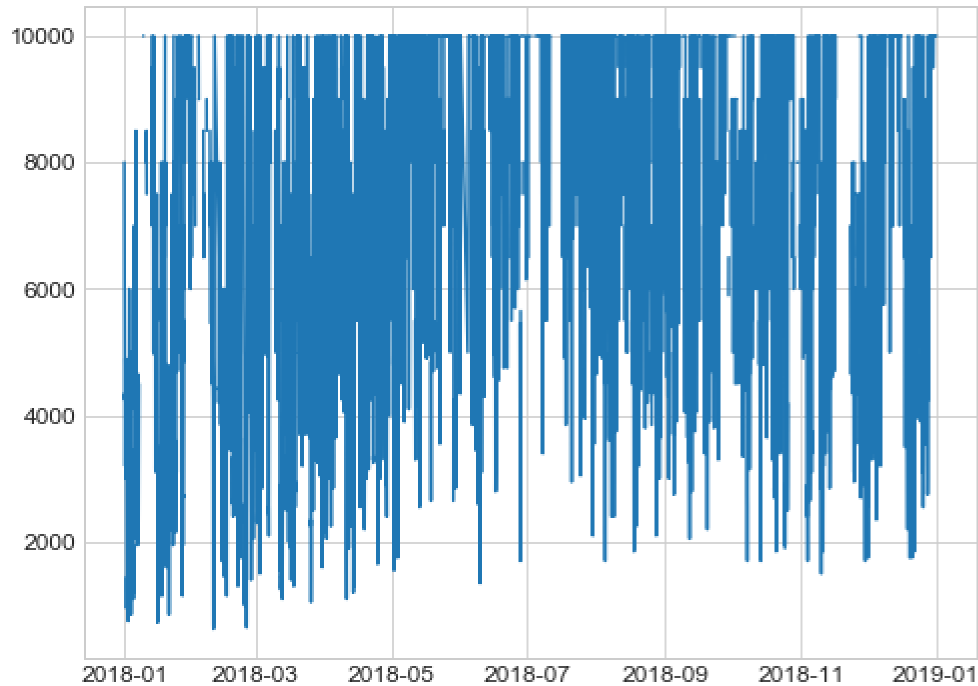



In [25]:
```python
# most of data showing a good visibility, but I did not clean up the
 file all the way, the 9999 value for missing still in place
df.VIS.describe()
```

Out[25]:
```
count       7959.000000
mean      179714.442329
std       359655.706573
min          625.000000
25%         5500.000000
50%         9000.000000
75%         9999.000000
max       999999.000000
Name: VIS, dtype: float64
```

In [26]:
```
# setting all missing value, and max value as None
df.loc[df.VIS >=220000, 'VIS'] = None
plt.plot(df.index, df.VIS)
```

Out[26]:
```
[<matplotlib.lines.Line2D at 0x7f8e8e5a76d8>]
```

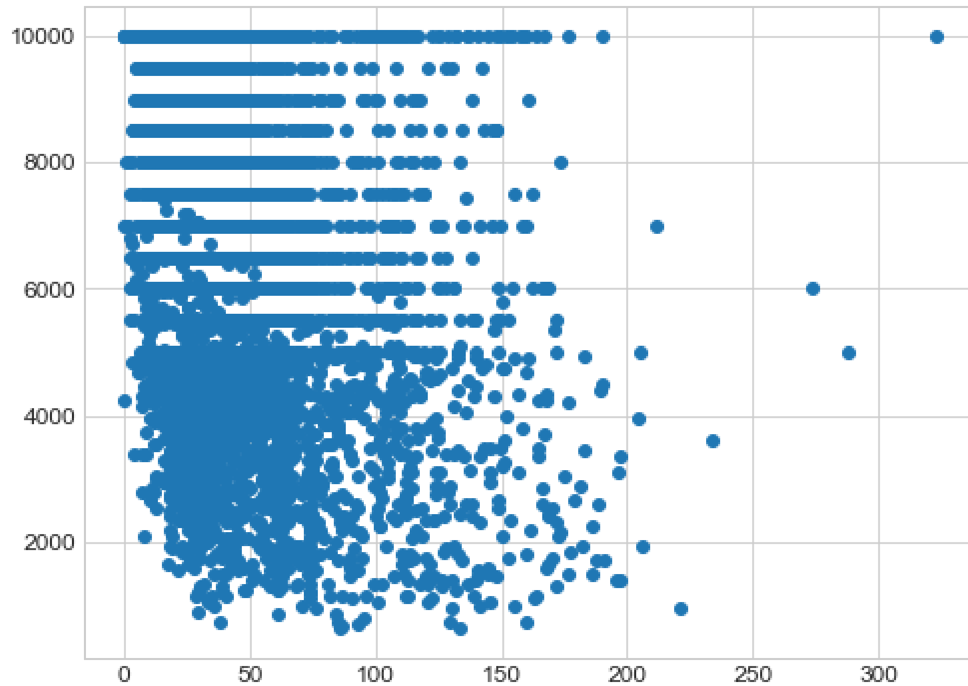



In [27]:
```
df.VIS.describe()
```

Out[27]:
```
count    6380.000000
mean     7216.806740
std      2672.672141
min       625.000000
25%      5000.000000
50%      7500.000000
75%      9999.000000
max      9999.000000
Name: VIS, dtype: float64
```

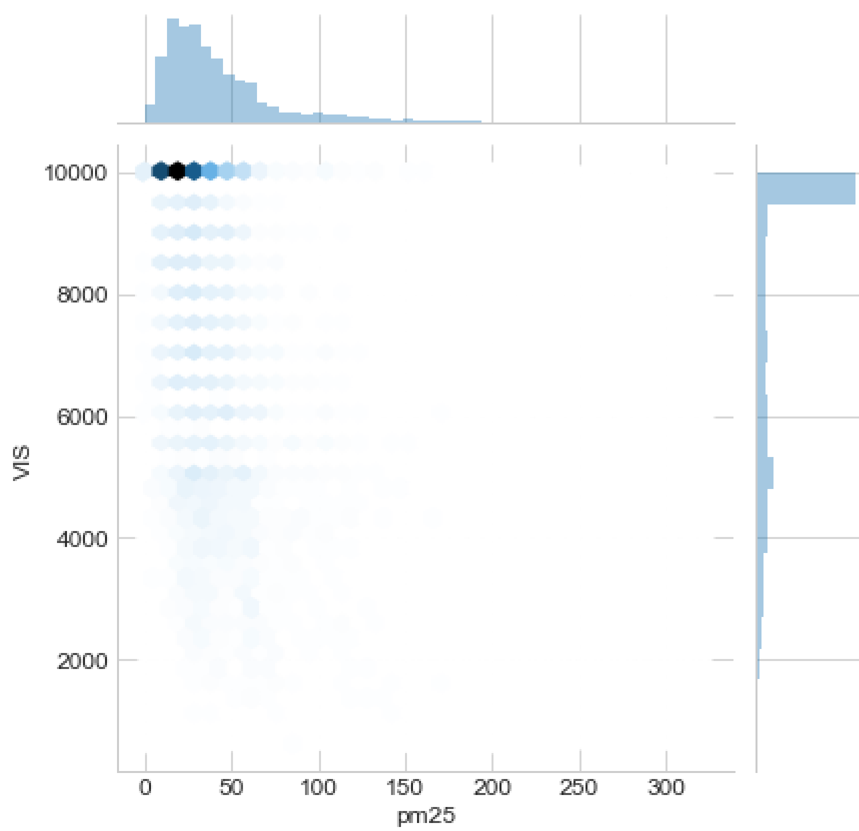
In [28]:
```
# still not clear pattern though we have more point on the lower left corner
plt.scatter(df.pm25, df.VIS)
```

Out[28]: <matplotlib.collections.PathCollection at 0x7f8e8e524a90>




In [29]:
```
sns.jointplot(df.pm25, df.VIS, kind='hex')
```

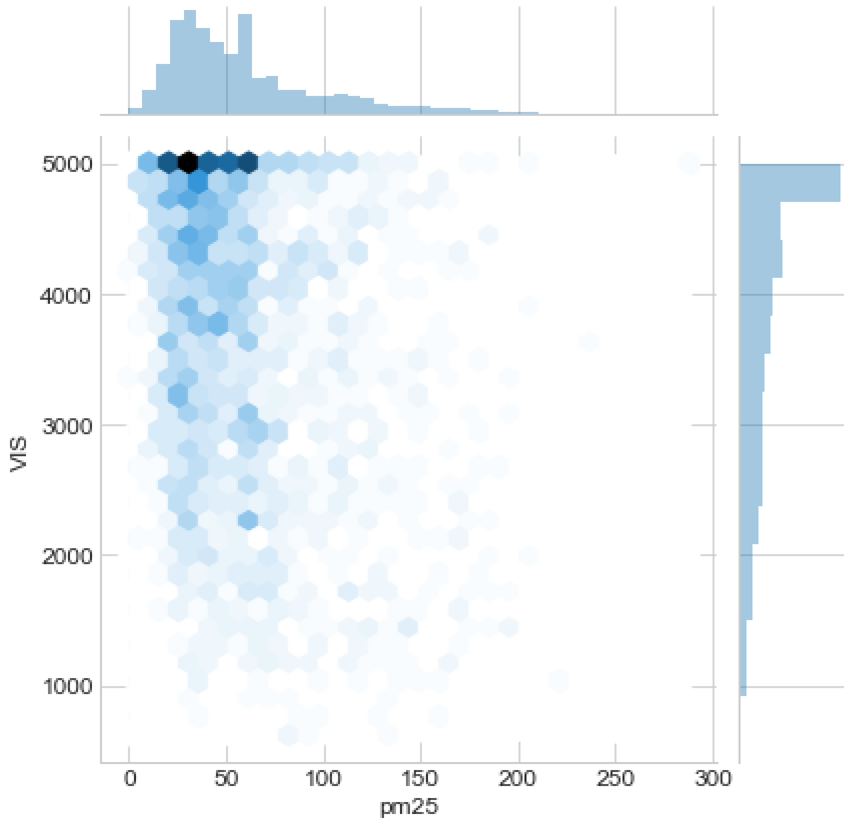
Out[29]: <seaborn.axisgrid.JointGrid at 0x7f8e8e4d7dd8>



In [30]:
```
dft = df.query('VIS <=5000')
```

In [31]:
```
# with even subset data with lower visibility,
sns.jointplot(dft.pm25, dft.VIS, kind='hex')
```

Out[31]: <seaborn.axisgrid.JointGrid at 0x7f8e8e378898>



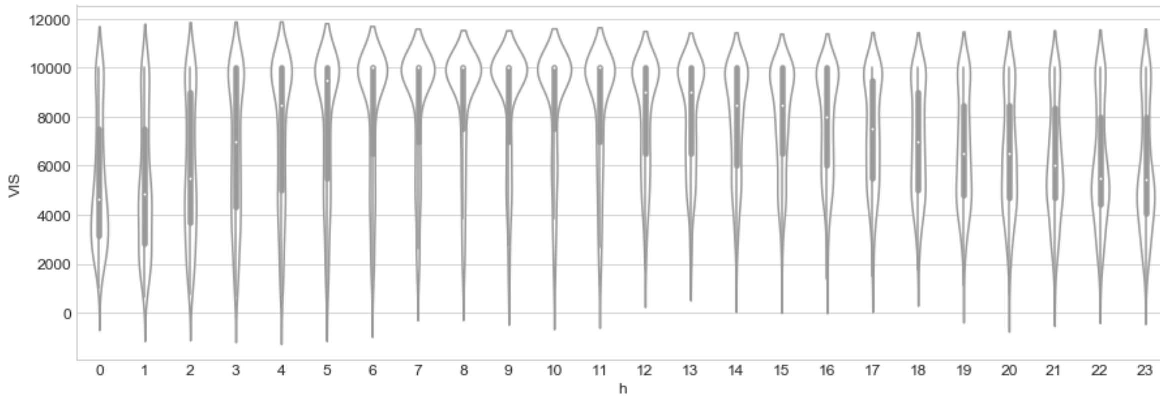

In [32]:
```
df.corr()['pm25']['VIS']
```

Out[32]: -0.4127430609698673

In [33]:
```
df['h'] = df.index.hour
df['m'] = df.index.month
```

In [34]:
```
# ok, VIS seems depended on the hour, lower during the night
plt.figure(figsize=(15,5))
sns.violinplot(data=df, x='h', y='VIS', color='white')
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e89f33710>

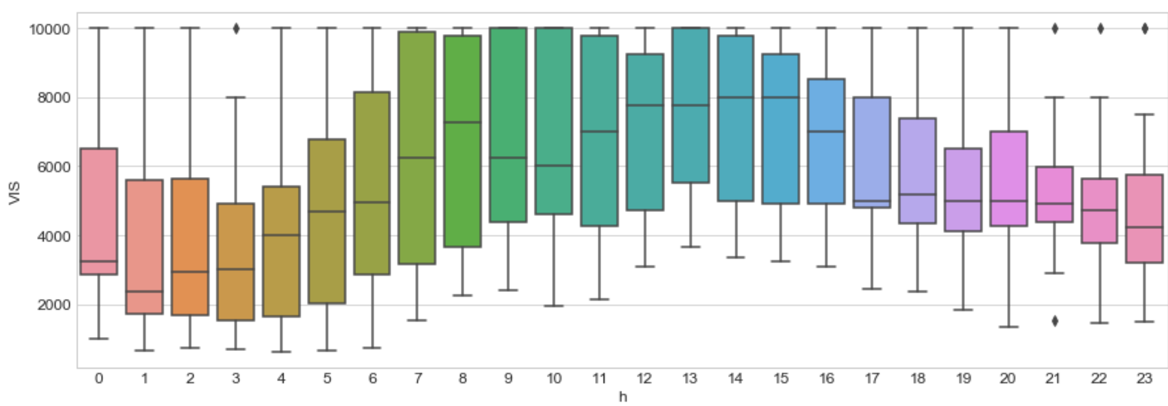



In [35]:
```
# let look for a month
```

In [36]:
```
feb = df.query('m==2')
```

In [37]:
```
plt.figure(figsize=(15,5))
sns.boxplot(data=feb, x='h', y='VIS')
```

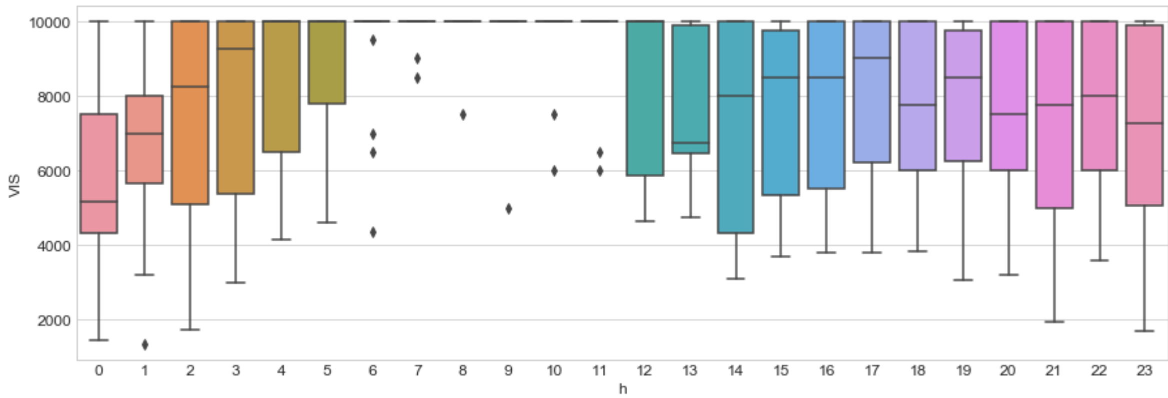
Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e89d4d710>




In [38]:
```
jun = df.query('m==6')
```

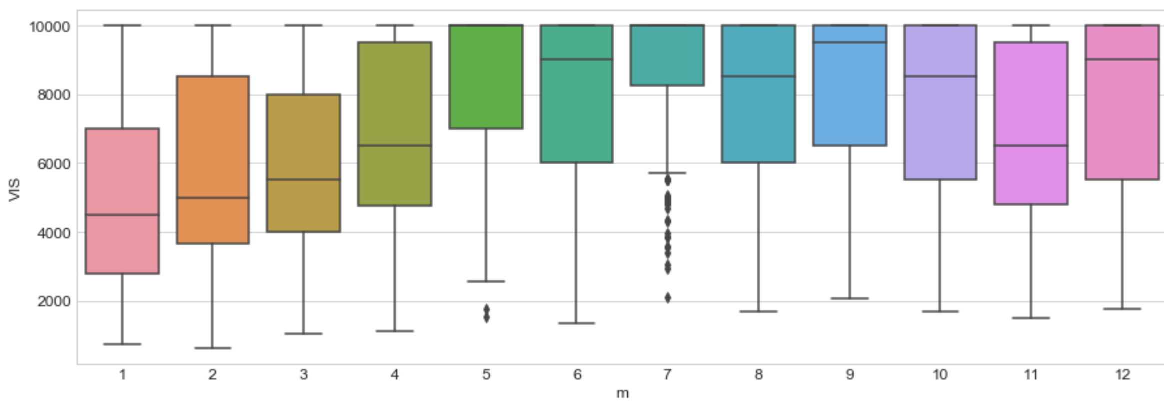
```
In [39]: plt.figure(figsize=(15,5))
         sns.boxplot(data=jun, x='h', y='VIS')
```

Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e8831a780>



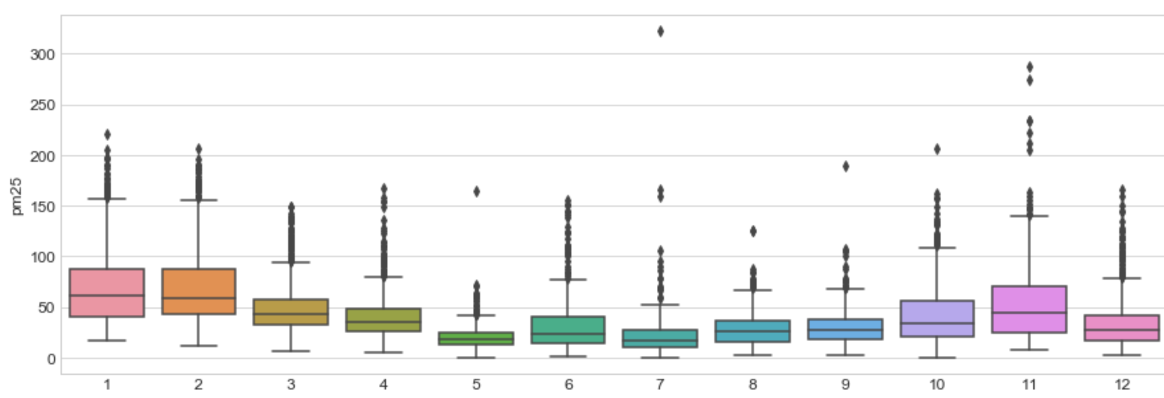

```
In [40]: plt.figure(figsize=(15,5))
         sns.boxplot(data=df, x='m', y='VIS')
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e88180978>




```
In [41]: plt.figure(figsize=(15,5))
         sns.boxplot(data=df, x='m', y='pm25')
```

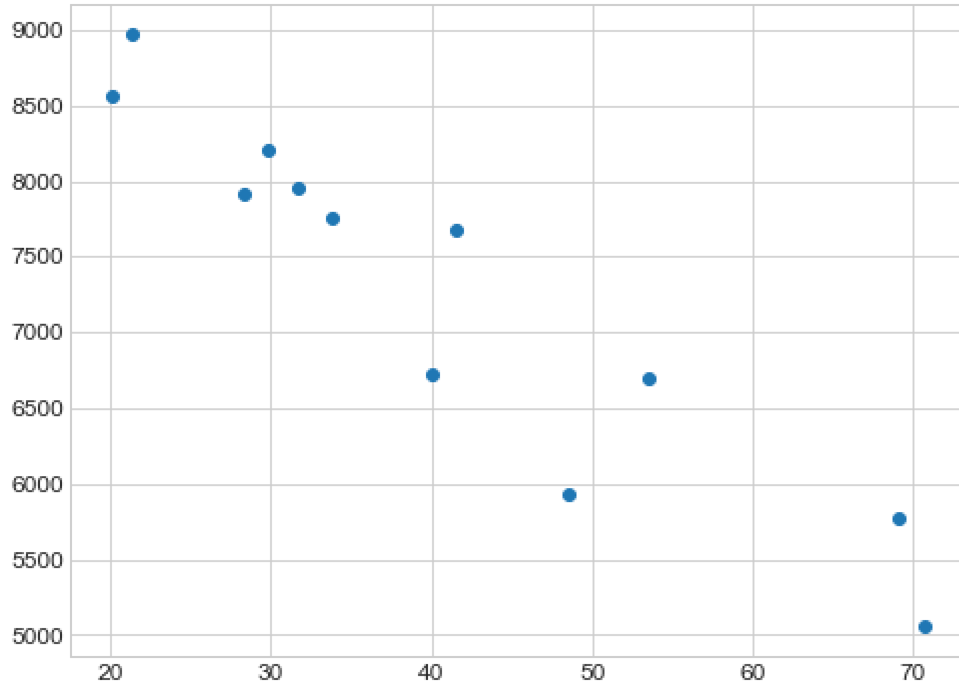
Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8e87fa74e0>




```
In [42]: dft = df.groupby('m').mean()
```

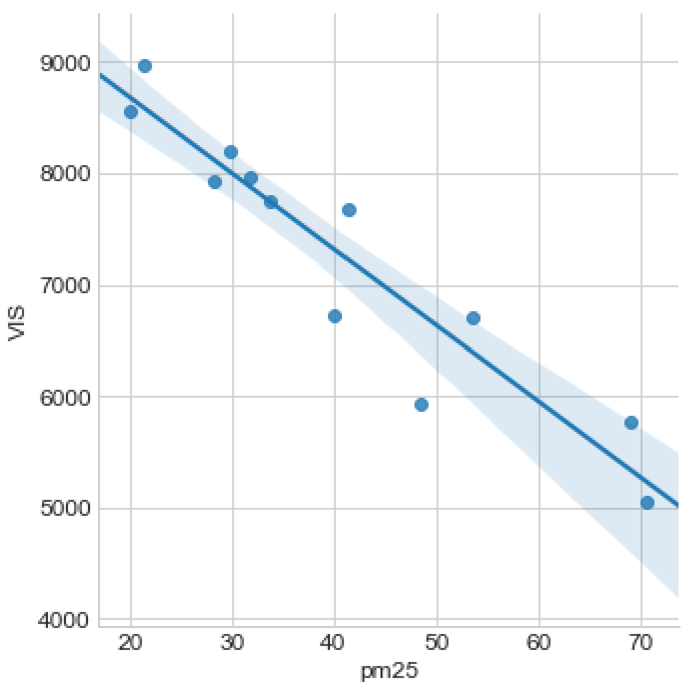
In [43]:
```
plt.scatter(dft.pm25, dft.VIS)
```

Out[43]: <matplotlib.collections.PathCollection at 0x7f8e87e1dbe0>



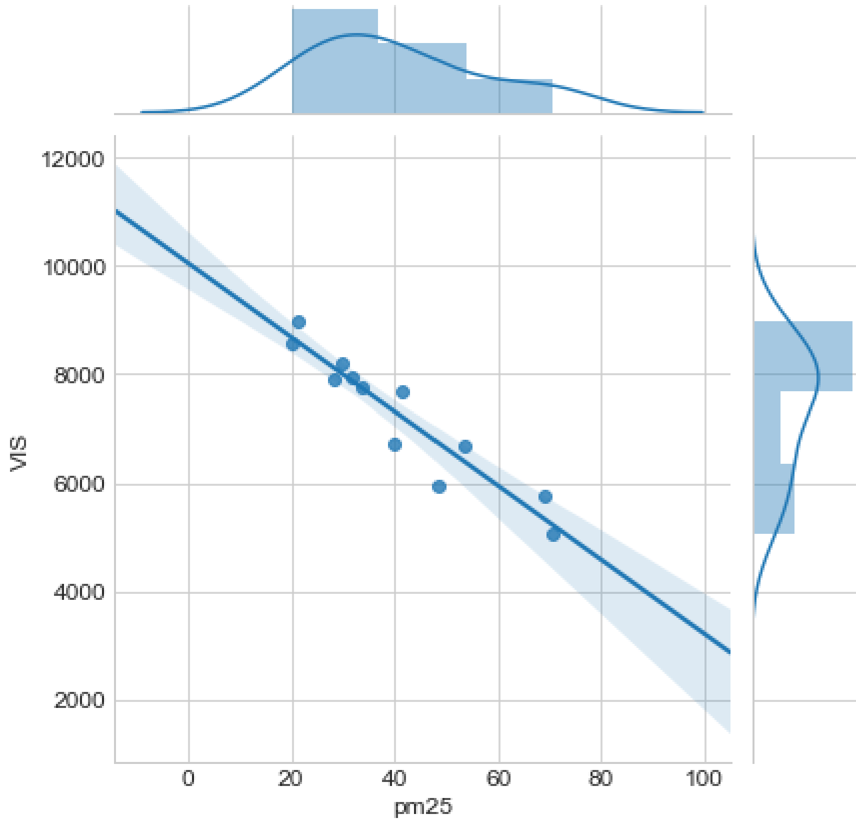

In [44]:
```
sns.lmplot(x='pm25', y='VIS', data=dft)
```

Out[44]: <seaborn.axisgrid.FacetGrid at 0x7f8e87e2efd0>



In [45]:
```
sns.jointplot(x='pm25', y='VIS', data=dft, kind="reg", )
```

Out[45]: <seaborn.axisgrid.JointGrid at 0x7f8e87d4fac8>



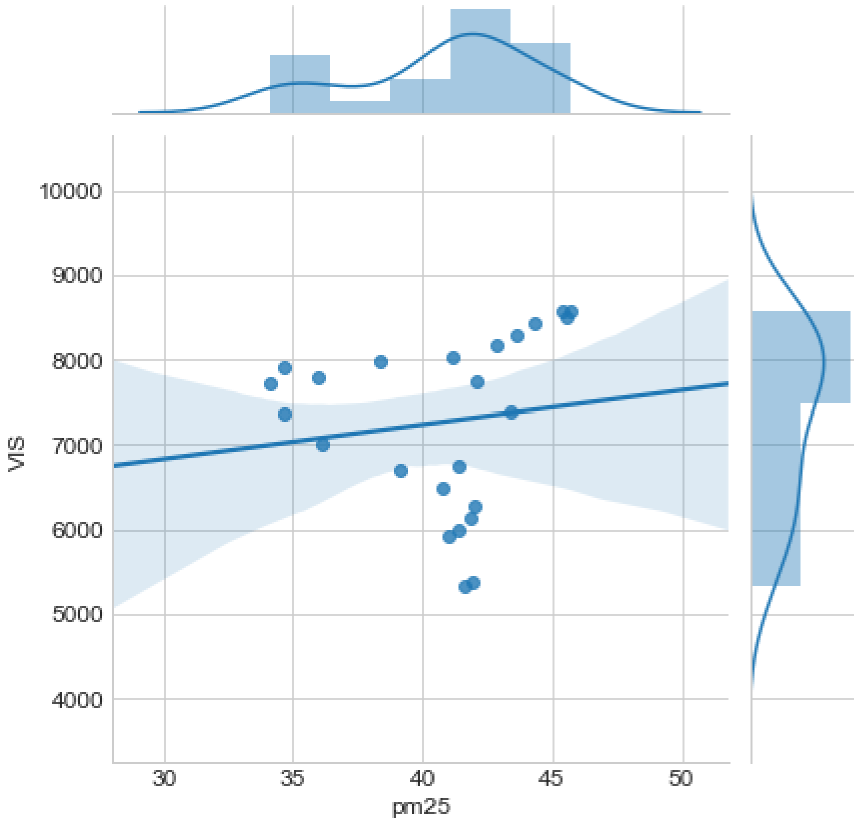

In [46]:
```
# this is impressive, sudently, the correlation of the average concen
tration (by month) is strong, or very strong
dft.corr()['pm25']['VIS']
```

Out[46]: -0.9445724331666244

In [47]:
```
dft = df.groupby('h').mean()
```

In [48]:
```
sns.jointplot(x='pm25', y='VIS', data=dft, kind="reg", )
```

Out[48]: <seaborn.axisgrid.JointGrid at 0x7f8e87e74908>



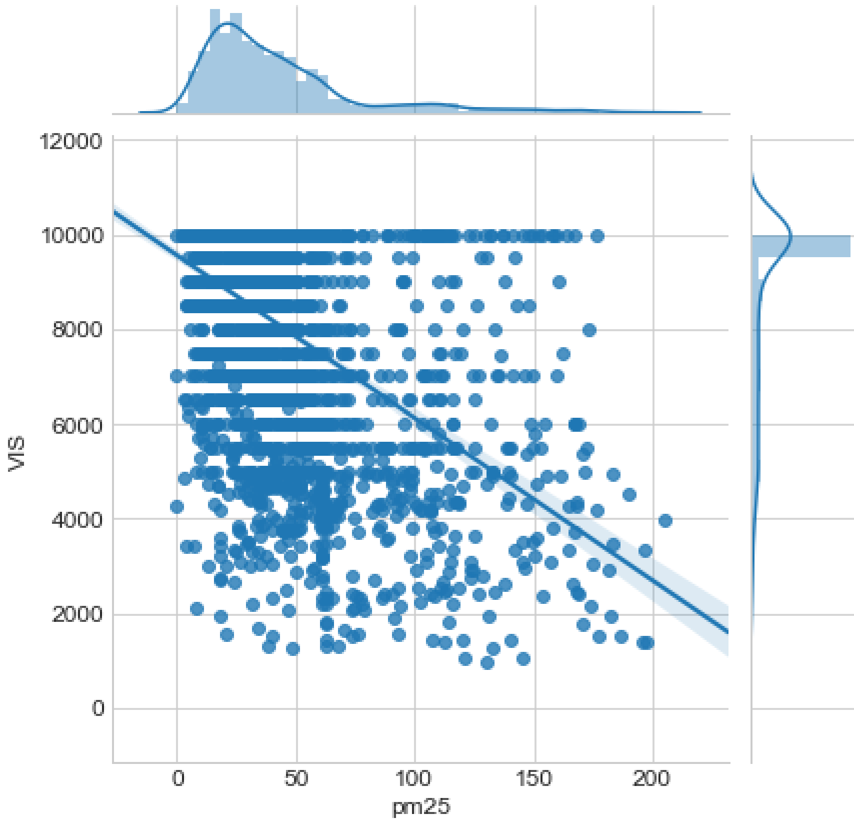

In [49]:
```
# or not so, if we averaged the input by the hour
dft.corr()['pm25']['VIS']
```

Out[49]: 0.13620802167369214

In [50]:
```
# let try to explore more
dft = df[(df['h'] >=7) & (df['h'] <=17)]
```

In [51]:
```
sns.jointplot(x='pm25', y='VIS', data=dft, kind="reg", )
```

Out[51]: <seaborn.axisgrid.JointGrid at 0x7f8e87b5fc50>



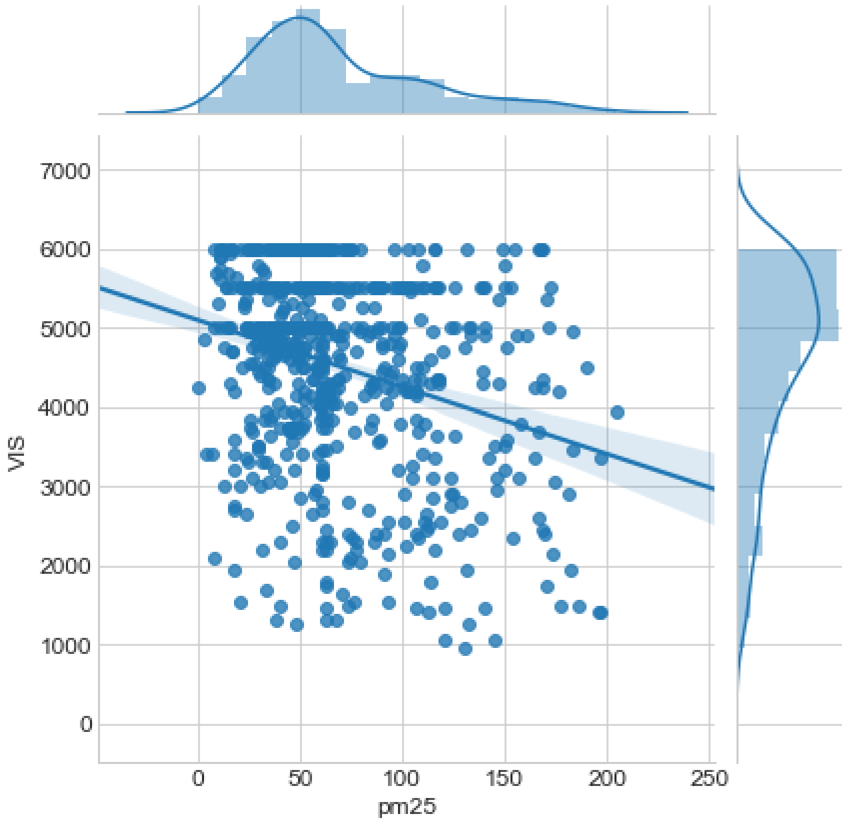

In [52]:
```
dft6 = dft.query('VIS<=6000')
```

In [53]:
```
# this the correlation daily hour
dft.corr()['pm25']['VIS']
```

Out[53]: -0.49590702697163747

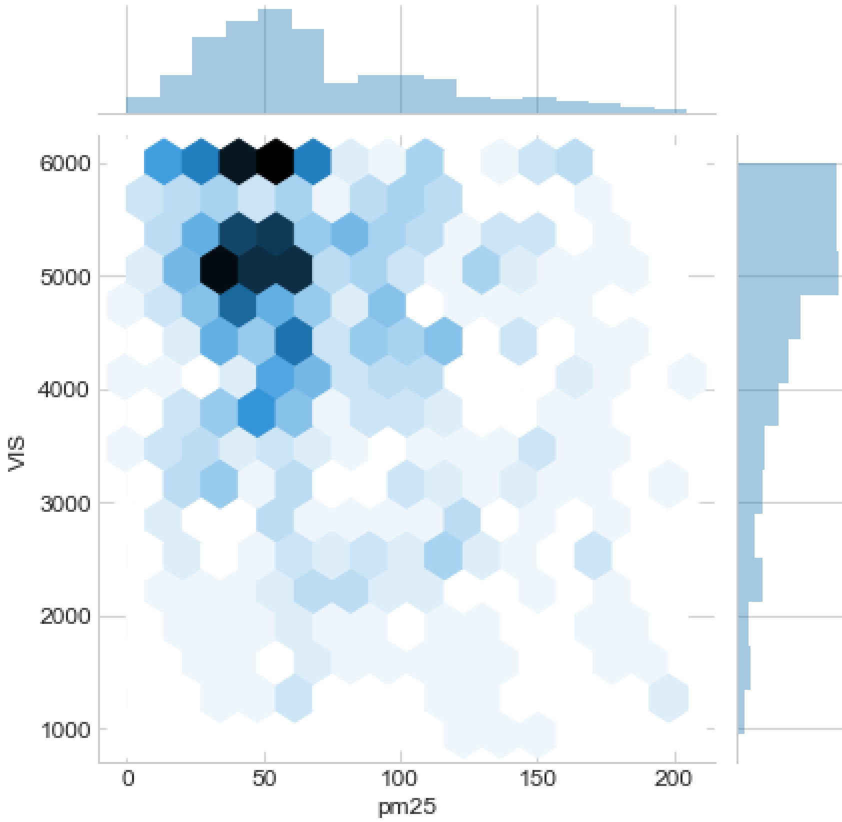
In [54]:
```
sns.jointplot(x='pm25', y='VIS', data=dft6, kind="reg", )
```

Out[54]: <seaborn.axisgrid.JointGrid at 0x7f8e87991d68>



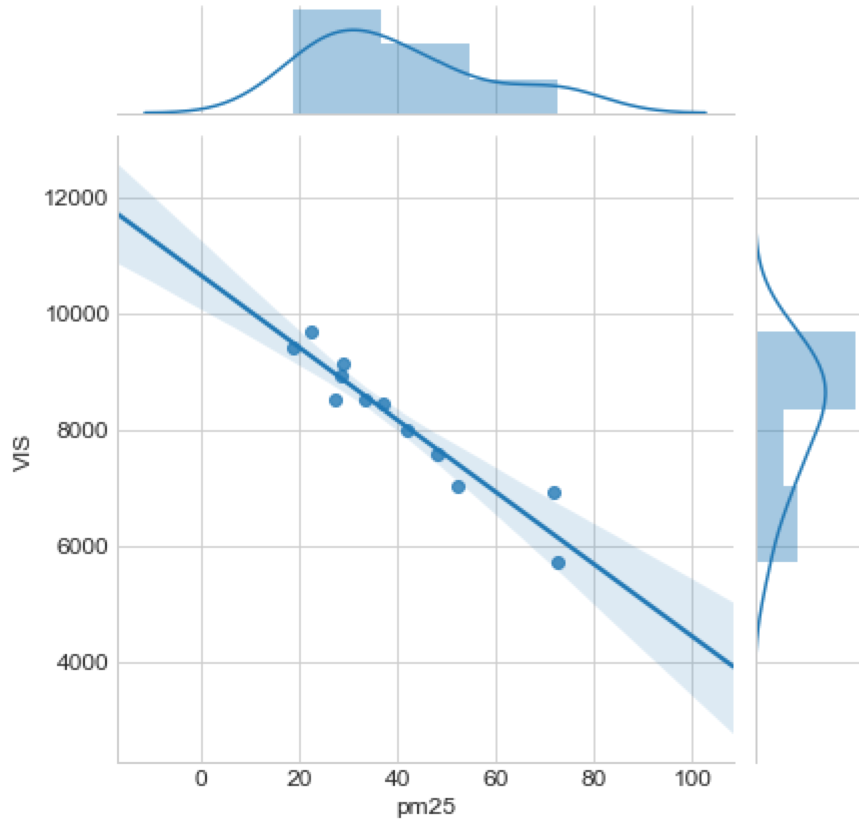
In [55]:
```
sns.jointplot(x='pm25', y='VIS', data=dft6, kind="hex", )
```

Out[55]:
```
<seaborn.axisgrid.JointGrid at 0x7f8e87886ba8>
```



In [56]:
```
dft = dft.groupby('m').mean()
sns.jointplot(x='pm25', y='VIS', data=dft, kind="reg", )
```

Out[56]:
```
<seaborn.axisgrid.JointGrid at 0x7f8e87c8a080>
```

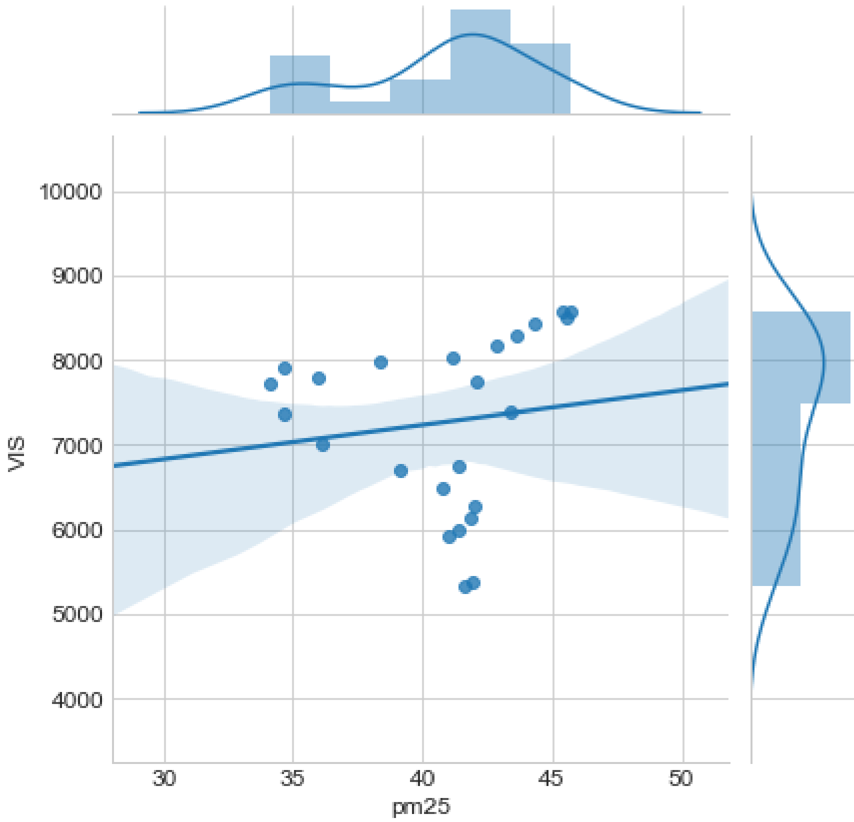



In [57]:
```
# the correlation is strong with daily hours
dft.corr()['pm25']['VIS']
```

Out[57]:
```
-0.9549564104816615
```

In [58]:
```
dft1 = df.groupby('h').mean()
sns.jointplot(x='pm25', y='VIS', data=dft1, kind="reg", )
```

Out[58]: <seaborn.axisgrid.JointGrid at 0x7f8e875dcc88>

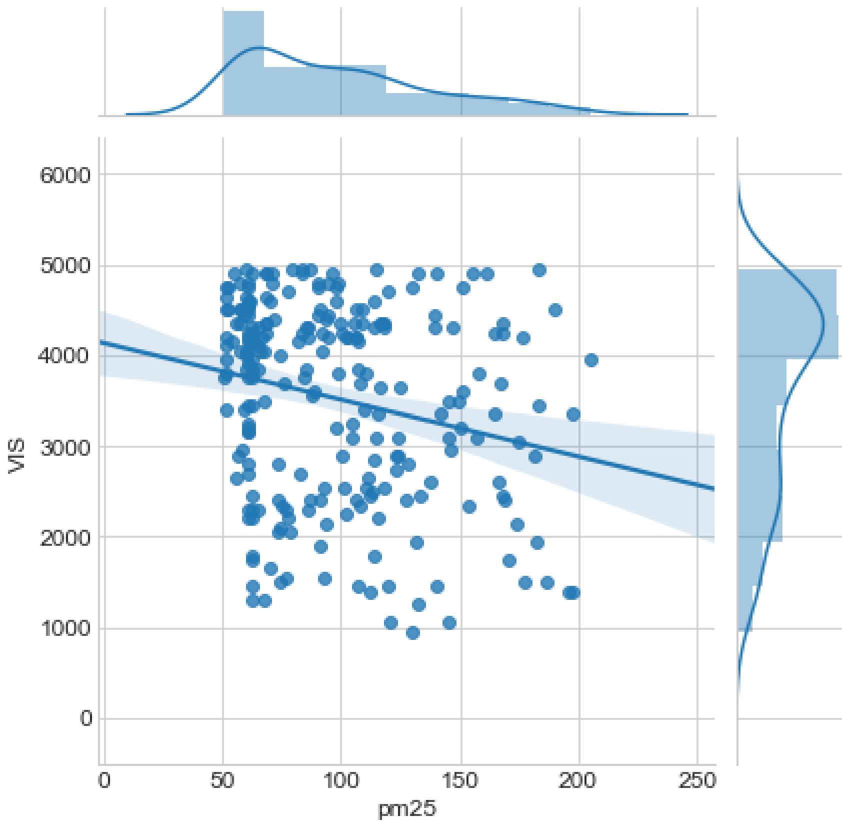



In [59]:
```
# grouping by the hour with day hour
dft1.corr()['pm25']['VIS']
```

Out[59]: 0.13620802167369214

In [60]:
```
# let try to explore even more
dft = df[(df['h'] >=7) & (df['h'] <=17) & (df['pm25'] > 50) & (df['VI
S'] < 5000)]
sns.jointplot(x='pm25', y='VIS', data=dft, kind="reg", )
print(dft.corr()['pm25']['VIS'])
```

```
-0.22306622063006426
```




- the analysis can misled by incidently making a gross estimation
- when in doubt, make sure to run through key combination to make sure we know the underlying artifact
- low visiblity is often observed with a high $PM_{2.5}$, but from this set of data, opposite conclusion can be drawn

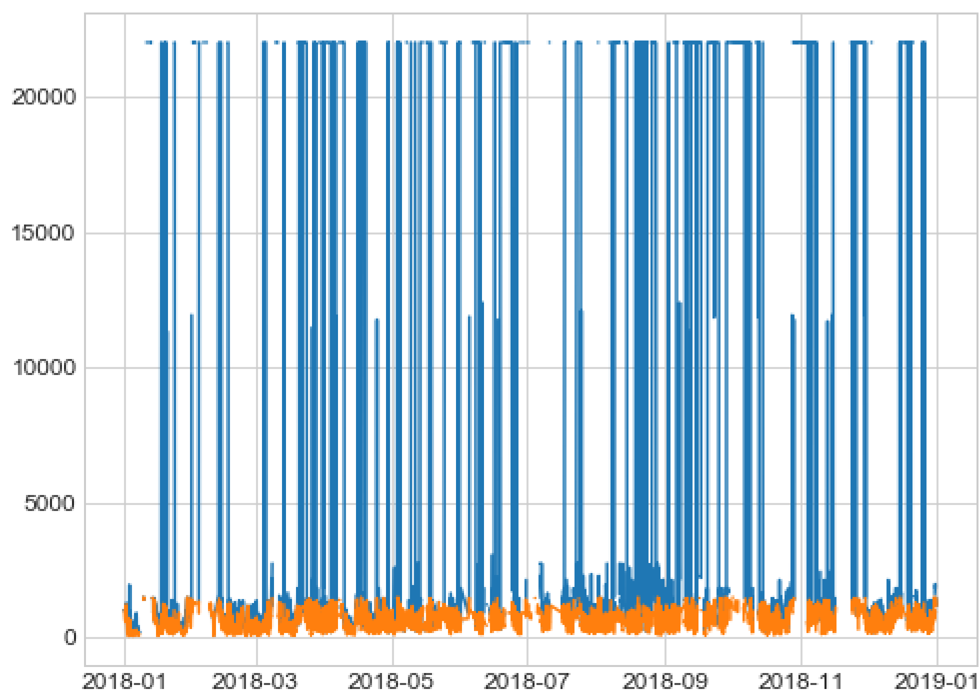
## CIG, CLDHT

In [61]:
```
# we can get correlation to other variable like this
# in the previous section, we look for horizontal direction, now we t
urn to vertical direction
df.corr()['CIG']
```

Out[61]:
```
CIG      1.000000
VIS     -0.085522
TMP      0.060859
DEW     -0.013038
WD       0.130481
WS      -0.032222
CLDCR   -0.195803
CLDHT    0.221168
pm25     0.084939
RH      -0.134297
h        0.143417
m        0.177284
Name: CIG, dtype: float64
```

In [62]:
```
plt.plot(df.index, df.CIG)
plt.plot(df.index, df.CLDHT)
```

Out[62]:
```
[<matplotlib.lines.Line2D at 0x7f8e873f2a58>]
```



In [63]:
```
df.CLDHT.describe()
```

Out[63]:
```
count    5815.000000
mean      616.896303
std       345.892369
min        61.000000
25%       305.000000
50%       564.000000
75%       884.000000
max      1494.000000
Name: CLDHT, dtype: float64
```

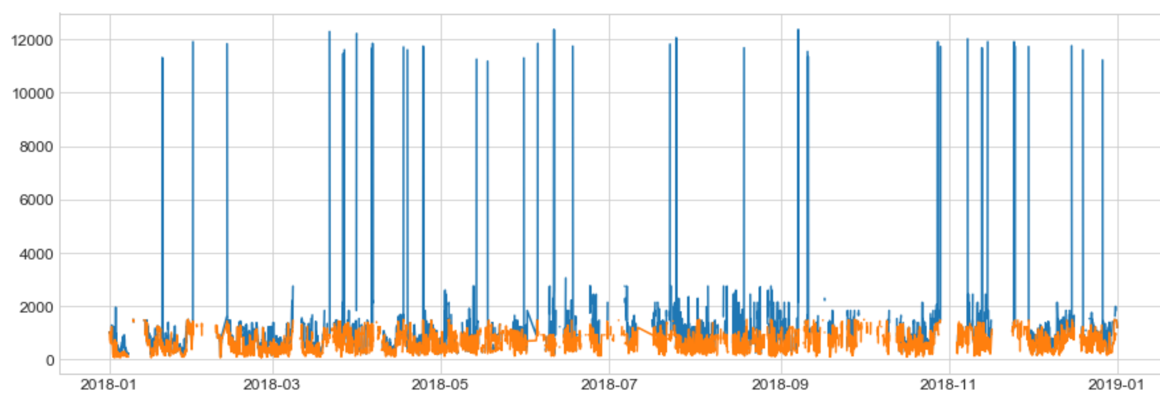
In [64]:
```
df.CIG.describe()
```

Out[64]:
```
count     5604.000000
mean      5181.372234
std       8437.395829
min         91.000000
25%        610.000000
50%       1006.000000
75%       1676.000000
max      22000.000000
Name: CIG, dtype: float64
```

In [65]:
```
# 22000 (in meter) is for clear sky, let ignore it by setting to zero
df.loc[df.CIG ==22000, 'CIG'] = None
```

In [66]:
```
plt.figure(figsize=(15,5))
plt.plot(df.index, df.CIG)
plt.plot(df.index, df.CLDHT)
```

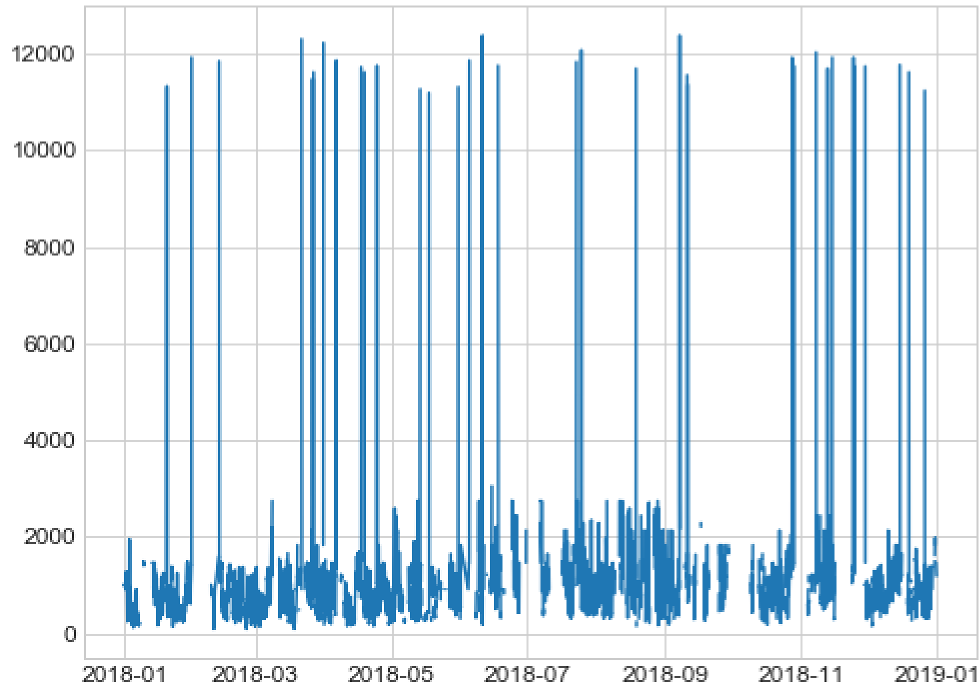
Out[66]:
```
[<matplotlib.lines.Line2D at 0x7f8e87f8b5c0>]
```




- now it look better together, both CIG and CLDHT are to height to the lowest cloud level

In [67]:
```
plt.plot(df.index, df.CIG)
# plt.plot(df.index, df.CLDHT)
```

Out[67]: [<matplotlib.lines.Line2D at 0x7f8e87342940>]

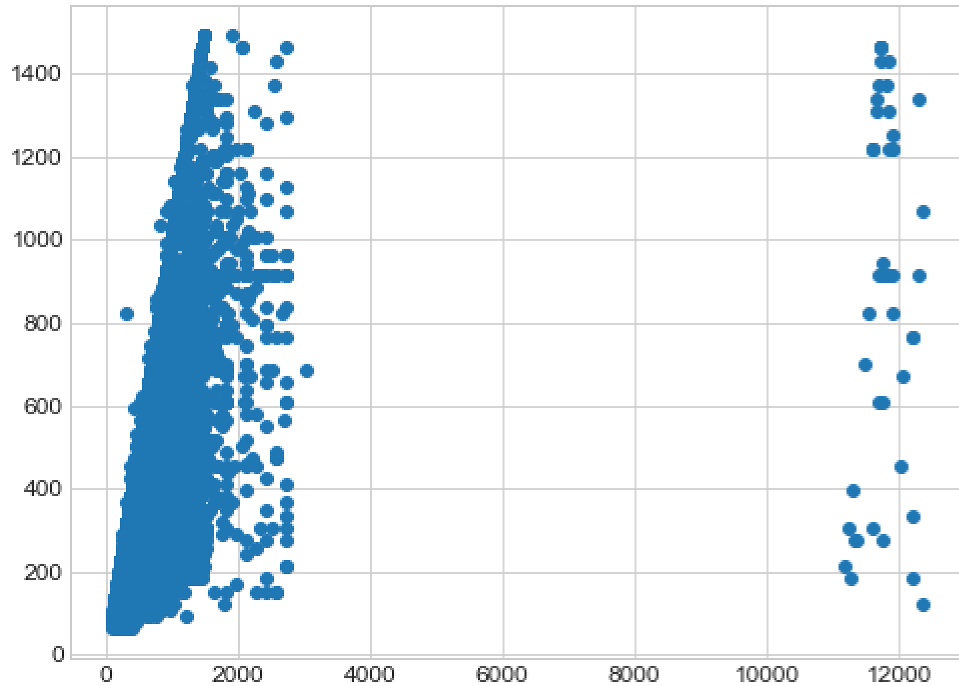



In [68]:
```
df.CIG.describe()
```

Out[68]:
```
count     4492.000000
mean      1017.900712
std       1199.512723
min         91.000000
25%        563.875000
50%        868.500000
75%       1219.000000
max      12371.500000
Name: CIG, dtype: float64
```

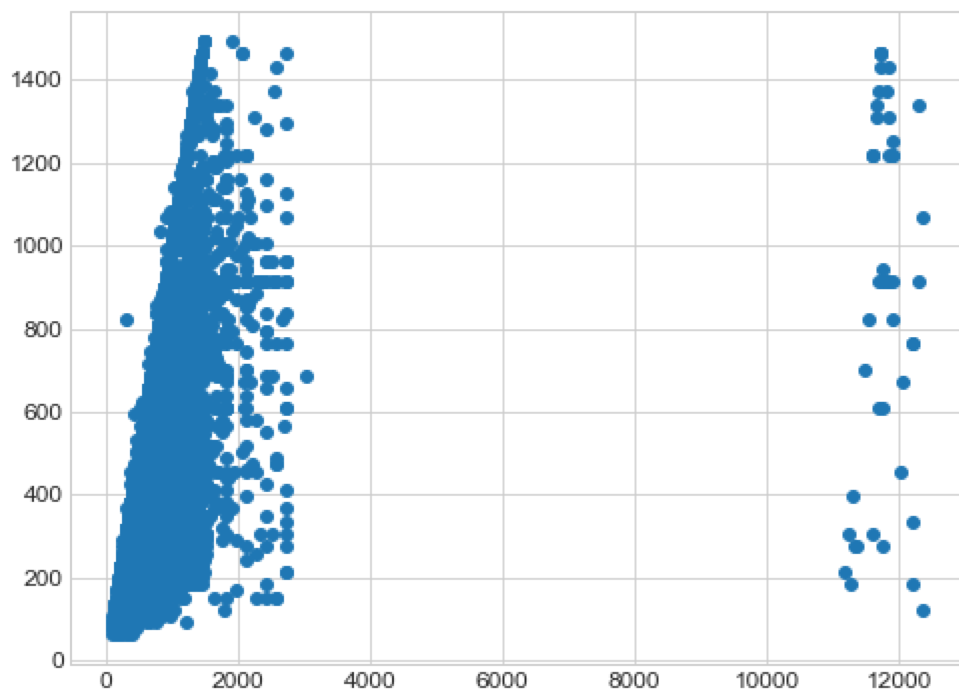
In [69]:
```
plt.scatter(df.CIG, df.CLDHT)
```

Out[69]: <matplotlib.collections.PathCollection at 0x7f8e8728cfd0>



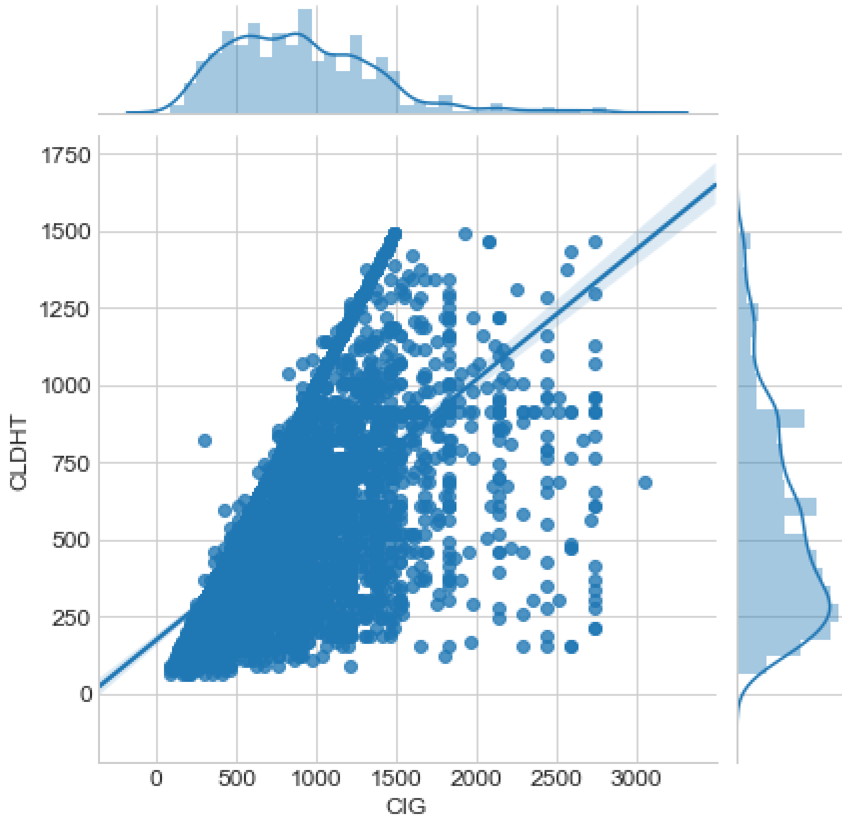

In [70]:
```
dft = df.query('CIG<=5000')
plt.scatter(df.CIG, df.CLDHT)
```

Out[70]: <matplotlib.collections.PathCollection at 0x7f8e8722abe0>



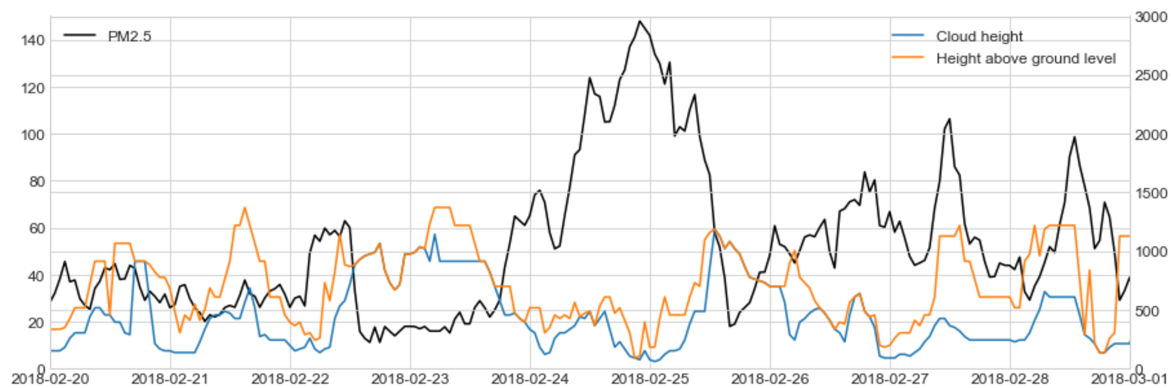
In [71]:
```python
sns.jointplot(dft.CIG, dft.CLDHT, kind='reg')
```

Out[71]: <seaborn.axisgrid.JointGrid at 0x7f8e87257908>



In [72]:
```python
# VIS is horizontal distance to the identifiable object
# CIG, CLDHT is the height (vertical distance) to ground of a referen
ce point to the lowest cloud
fig, ax = plt.subplots(figsize=(15,5))
ax.set_xlim(datetime.datetime(2018,2,20), datetime.datetime(2018,3,1
))

ax.plot(df.index, df.pm25, color='black', label='PM2.5')
ax.set_ylim(0, 150)

ax.legend(loc='upper left')
ax2 = ax.twinx()
ax2.plot(df.index, df.CLDHT, label='Cloud height')
ax2.plot(df.index, df.CIG, label='Height above ground level')
ax2.set_ylim(0, 3000)
ax2.legend()
```

Out[72]: <matplotlib.legend.Legend at 0x7f8e874bf400>




**let review**

- look like we capture a good window showing the reverse relationship between $PM_{2.5}$ concentration with the height of the lowest cloud
- a thin layer between ground and the cloud is one indicator of poor mixing or a stable layer. So in this condition, the $PM_{2.5}$ formed near the ground being kept there
- a consistent high concentration above 50 microgram/cubic meters exceeds the national technical guidance (in Vietnam), for US EPA, that level is 35µg/$m^3$ for daily average

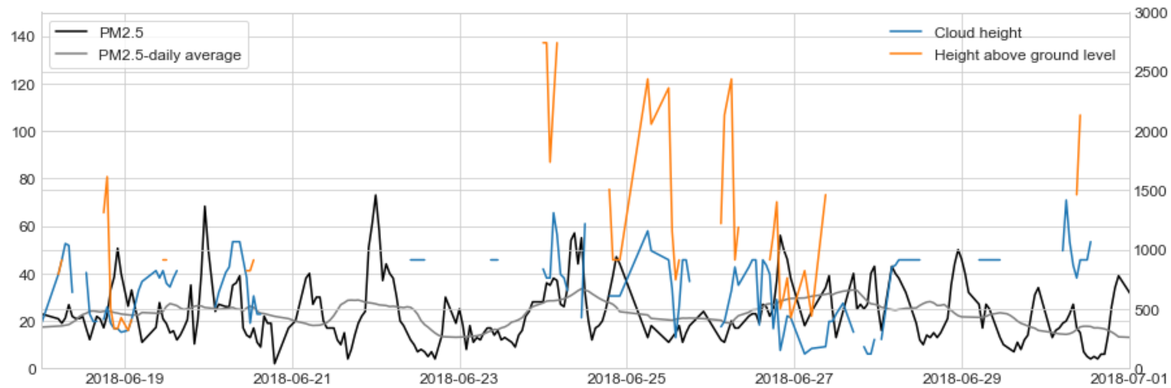
In [73]:
```python
# let make a global check to see the whole dataset rather one capture
d moment
df.corr()['pm25'].filter(['CLDHT', 'CIG'])
```

Out[73]:
```
CLDHT     0.032396
CIG      -0.032574
Name: pm25, dtype: float64
```

- this is important to note because one event can be critical to know the relationship (like above) while the global average look no relationship at all

In [74]:
```
# let look another instance
fig, ax = plt.subplots(figsize=(15,5))

ax.plot(df.index, df.pm25, color='black', label='PM2.5')
ax.plot(df.index, df.pm25.rolling(window=24, center=True).mean(), col
or='gray', label='PM2.5-daily average')
ax.set_ylim(0, 150)

ax.legend(loc='upper left', frameon=True)
ax2 = ax.twinx()
ax2.plot(df.index, df.CLDHT, label='Cloud height')
ax2.plot(df.index, df.CIG, label='Height above ground level')
ax2.set_ylim(0, 3000)
ax2.legend()

ax.set_xlim(datetime.datetime(2018,6,18), datetime.datetime(2018,7,1
))
```

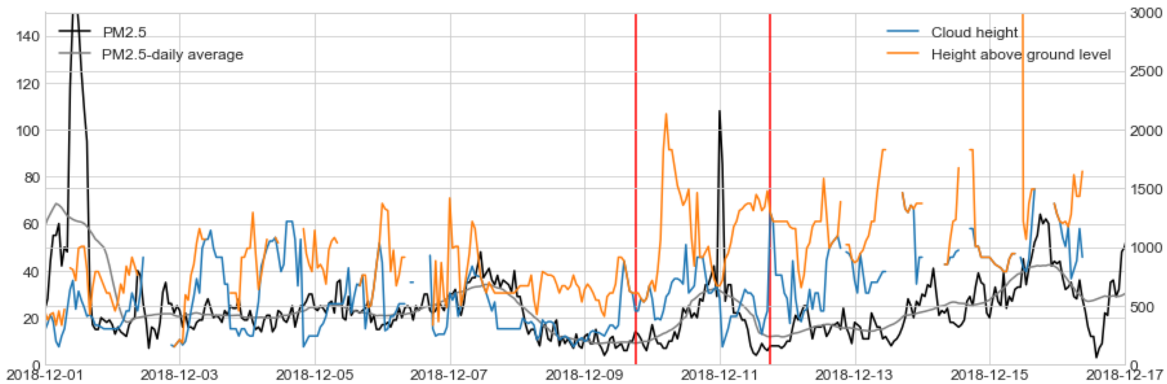
Out[74]: (736863.0, 736876.0)




- in the summer, the heights were more sporatic, some was set to `None` with a clear condition, and some of the points are in `missing` tag
- the concentration is also lower, in the range of 20-30 μg/m$^3$

In [75]:
```
fig, ax = plt.subplots(figsize=(15,5))

ax.plot(df.index, df.pm25, color='black', label='PM2.5')
ax.plot(df.index, df.pm25.rolling(window=24, center=True).mean(), col
or='gray', label='PM2.5-daily average')
ax.set_ylim(0, 150)

ax.legend(loc='upper left')
ax2 = ax.twinx()
ax2.plot(df.index, df.CLDHT, label='Cloud height')
ax2.plot(df.index, df.CIG, label='Height above ground level')
ax2.set_ylim(0, 3000)
ax2.legend(loc='upper right')
ax.set_xlim(datetime.datetime(2018,12,1), datetime.datetime(2018,12,1
7))
ax.axvline(x=datetime.datetime(2018,12,9,18), color='red')
ax.axvline(x=datetime.datetime(2018,12,11,18), color='red')
```

Out[75]: <matplotlib.lines.Line2D at 0x7f8e90eeb0b8>



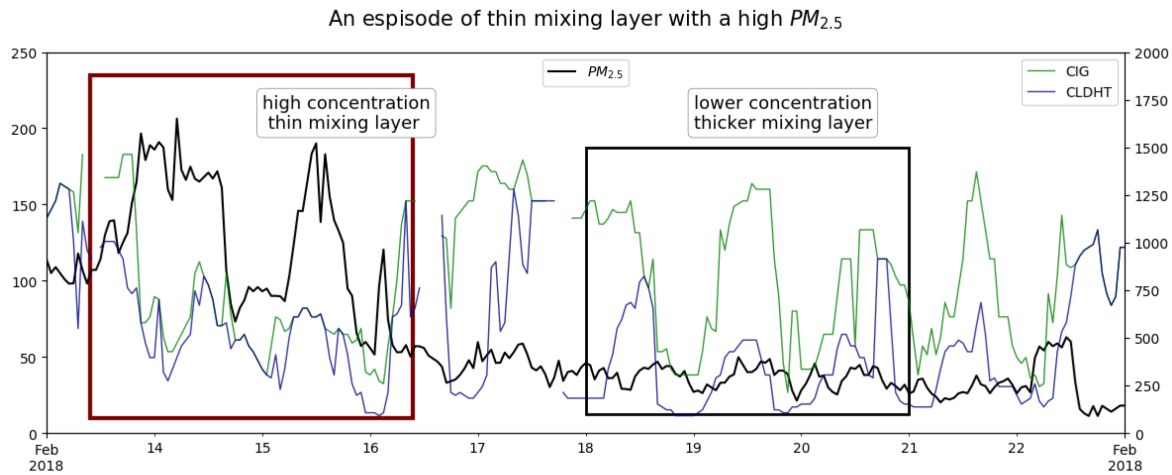

- in this window, another event that capture the inverse correlation of cloud height and $PM_{2.5}$ concentration

In [76]:
```
# import matplotlib.transforms as transforms
```

In [77]:
```
import matplotlib as mpl
```

In [78]:

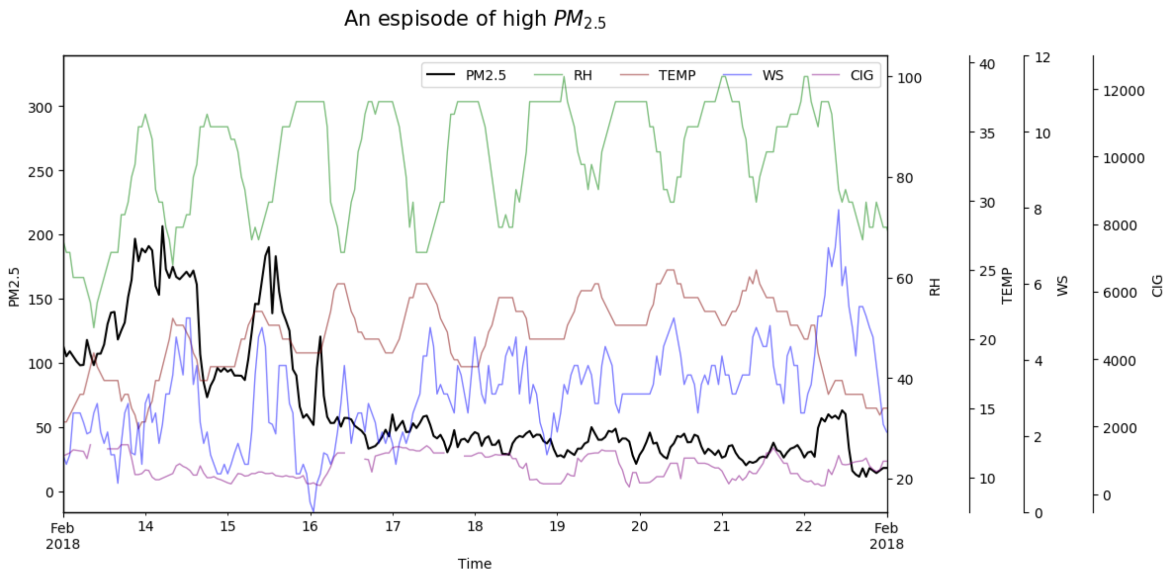
```
plt.style.use('default')
fig, ax = plt.subplots(figsize=(12,5))
ax.plot(df.index, df.pm25, color='black', label=r'$PM_{2.5}$')
ax.set_ylim(0, 250)
ax.legend(loc='upper center')


ax2 = ax.twinx()
ax2.plot(df.index, df.CIG, color='green', label='CIG', lw=1, alpha=0.
8)
ax2.plot(df.index, df.CLDHT, color='navy', label='CLDHT', lw=1, alpha
=0.8)
ax2.set_xlim(datetime.datetime(2018,2,13), datetime.datetime(2018,2,2
3))
ax2.set_ylim(0, 2000)
ax2.legend(loc='upper right')

bbox_props = dict(boxstyle="round,pad=0.3", fc="white", ec="gray", lw
=0.5)
ax.annotate(s='high concentration\n thin mixing layer', xy=(0.2, 0.8
),
            fontsize=13,
            bbox=bbox_props,
             xytext=(0.2,0.80),
            xycoords='axes fraction',
       )
ax.annotate(s='lower concentration\nthicker mixing layer', xy=(0.6,
0.8),
            fontsize=13,
            bbox=bbox_props,
             xytext=(0.6,0.80),
            xycoords='axes fraction',
       )

p = plt.Rectangle((0.04, .04), width=0.3, height=0.9, fill=False, col
or='maroon', lw=3)
p.set_transform(ax.transAxes)
p1 = plt.Rectangle((0.5, .05), width=0.3, height=0.7, fill=False, col
or='black', lw=2)
p1.set_transform(ax.transAxes)
p.set_clip_on(False)
ax.add_patch(p)
ax.add_patch(p1)
ax.xaxis.set_major_locator(mpl.dates.MonthLocator())
ax.xaxis.set_minor_locator(mpl.dates.DayLocator())

ax.xaxis.set_minor_formatter(mpl.dates.DateFormatter('%d'));
ax.xaxis.set_major_formatter(mpl.dates.DateFormatter('%h\n%Y'))
ax.set_title('An espisode of thin mixing layer with a high $PM_{2.5}
$', y=1.05, fontsize=15)
fig.tight_layout()
fig.savefig('img/2020Jul_mixing_feb.png');
```




In [79]:
```
mpl.rcParams.update(mpl.rcParamsDefault)
```

In [80]:

```
fig = plt.figure(figsize=(12,6))
host = fig.add_subplot(111)

par1 = host.twinx()
par2 = host.twinx()
par3 = host.twinx()
par4 = host.twinx()

host.set_xlabel("Time")
host.set_ylabel("PM2.5")
par1.set_ylabel("RH")
par2.set_ylabel("TEMP")
par3.set_ylabel("WS")
par4.set_ylabel("CIG")

p1, = host.plot(df.index, df.pm25, color='black',label="PM2.5")
p2, = par1.plot(df.index, df.RH, color='green', label="RH", alpha=0.5
, lw=1)
p3, = par2.plot(df.index, df.TMP, color='maroon', label="TEMP", alpha
=0.5, lw=1)
p4, = par3.plot(df.index, df.WS, color='blue', label="WS", alpha=0.5,
lw=1)
p5, = par4.plot(df.index, df.CIG, color='purple', label="CIG", alpha=
0.5, lw=1)

lns = [p1, p2, p3,p4, p5]
host.legend(handles=lns, loc='best', ncol=5)

par2.spines['right'].set_position(('outward', 60))

par3.spines['right'].set_position(('outward', 100))
par3.set_ylim(0,12)
par4.spines['right'].set_position(('outward', 150))

host.set_xlim(datetime.datetime(2018,2,13), datetime.datetime(2018,2,
23))

host.xaxis.set_major_locator(mpl.dates.MonthLocator())
host.xaxis.set_minor_locator(mpl.dates.DayLocator())

host.xaxis.set_minor_formatter(mpl.dates.DateFormatter('%d'));
host.xaxis.set_major_formatter(mpl.dates.DateFormatter('%h\n%Y'))
host.set_title('An espisode of high $PM_{2.5}$', y=1.05, fontsize=15)
fig.tight_layout()
fig.savefig('img/2020Jul_all_params.png');
```




# Temperature (TMP) and RH

- I have been used `corr()` , often without going to explain what else `cor()` can be used
- with `pandas` we three methods to calculate correlation, those are `pearson (default)` , `kendall` , and `spearman`

In [81]:
```
# using kendall
df.corr(method='kendall')
```

Out[81]:

| | CIG | VIS | TMP | DEW | WD | WS | CLDCR | CLDHT |
|---|---|---|---|---|---|---|---|---|
| **CIG** | 1.000000 | 0.313360 | 0.096671 | -0.005355 | 0.043560 | -0.033821 | -0.184865 | 0.497624 |
| **VIS** | 0.313360 | 1.000000 | 0.308923 | 0.115910 | -0.025996 | 0.221430 | -0.102802 | 0.351972 |
| **TMP** | 0.096671 | 0.308923 | 1.000000 | 0.601872 | 0.133937 | 0.059694 | -0.223419 | 0.162392 |
| **DEW** | -0.005355 | 0.115910 | 0.601872 | 1.000000 | 0.057853 | -0.001453 | -0.218881 | -0.081722 |
| **WD** | 0.043560 | -0.025996 | 0.133937 | 0.057853 | 1.000000 | -0.250307 | -0.036673 | 0.074495 |
| **WS** | -0.033821 | 0.221430 | 0.059694 | -0.001453 | -0.250307 | 1.000000 | 0.006225 | -0.034795 |
| **CLDCR** | -0.184865 | -0.102802 | -0.223419 | -0.218881 | -0.036673 | 0.006225 | 1.000000 | 0.018000 |
| **CLDHT** | 0.497624 | 0.351972 | 0.162392 | -0.081722 | 0.074495 | -0.034795 | 0.018000 | 1.000000 |
| **pm25** | -0.090715 | -0.321040 | -0.239646 | -0.324016 | 0.072185 | -0.158496 | 0.108613 | 0.018913 |
| **RH** | -0.198426 | -0.305167 | -0.141600 | 0.294478 | -0.087382 | -0.087386 | -0.008383 | -0.432984 |
| **h** | 0.024368 | -0.043266 | -0.106566 | 0.012741 | -0.041610 | -0.046700 | 0.005592 | 0.027804 |
| **m** | 0.172048 | 0.190504 | 0.172342 | 0.151405 | -0.009270 | -0.057510 | -0.123790 | 0.135996 |

In [82]:
```
# let select a few columns
cols = ['RH', 'TMP', 'VIS']
```

In [83]:
```
spearman = dict()
for col in cols:
    spearman[col] = df.corr(method='spearman')['pm25'][col]
spearman
```

Out[83]:
```
{'RH': -0.17829405965863518,
 'TMP': -0.3386498232001726,
 'VIS': -0.4480579176009144}
```

In [84]:
```
kendall = dict()
for col in cols:
    kendall[col] = df.corr(method='kendall')['pm25'][col]
kendall
```

Out[84]:
```
{'RH': -0.12330443561688877,
 'TMP': -0.23964573988435875,
 'VIS': -0.32103981027468237}
```

In [85]:
```
pearson = dict()
for col in cols:
    pearson[col] = df.corr(method='pearson')['pm25'][col]
pearson
```

Out[85]:
```
{'RH': -0.15560027174497226,
 'TMP': -0.2976330082643488,
 'VIS': -0.412743060969867 3}
```

In [86]:
```
data = pd.DataFrame.from_records([pearson, kendall, spearman], index=
['pearson', 'kendall', 'spearman'])
data
```

Out[86]:

| | RH | TMP | VIS |
|---|---|---|---|
| **pearson** | -0.155600 | -0.297633 | -0.412743 |
| **kendall** | -0.123304 | -0.239646 | -0.321040 |
| **spearman** | -0.178294 | -0.338650 | -0.448058 |

In [87]:
```
pos = np.arange(len(data))
pos
```

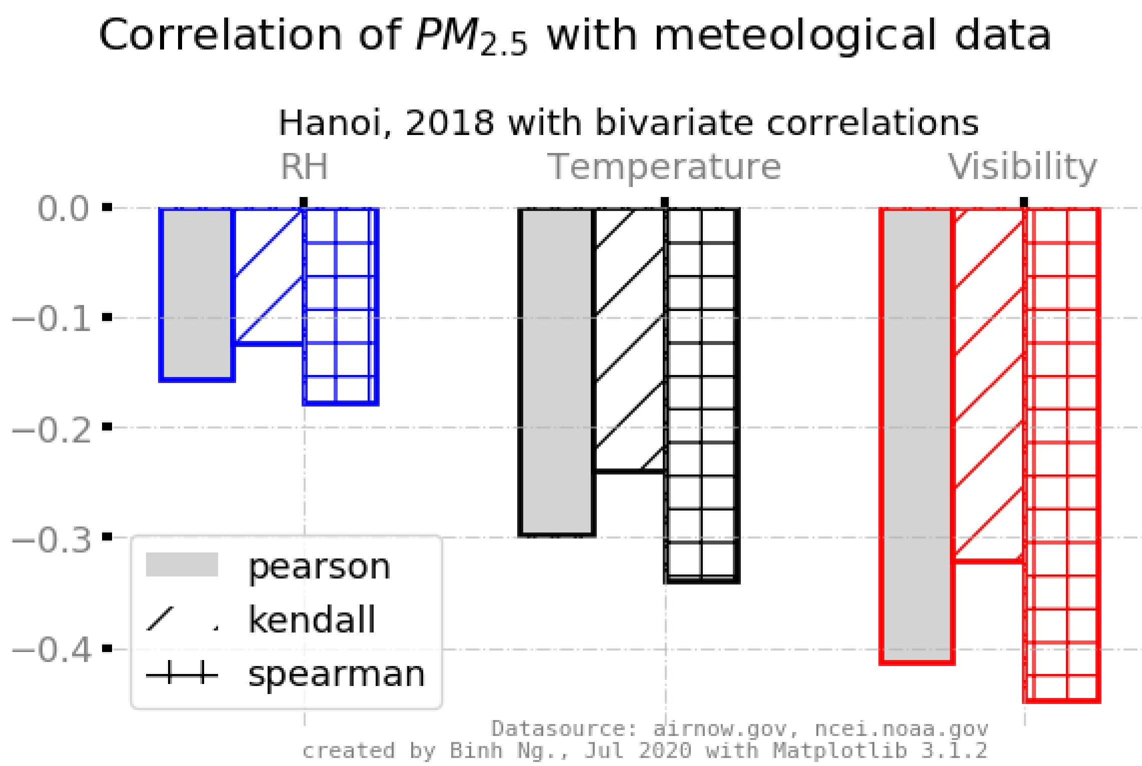
Out[87]:
```
array([0, 1, 2])
```

In [88]:
```
plt.rcParams['hatch.color'] = 'black'
```

In [89]:
```
plt.style.use('seaborn-white')
```

In [90]:
```
import matplotlib as mpl
mpl.rcParams.update(mpl.rcParamsDefault)
```

In [91]:
```python
# plt.figure(figsize=(8,8))
fig, ax = plt.subplots(figsize=(6,4))
fig.tight_layout(rect=[0, 0.03, 1, 0.95])
width=0.2
ax.xaxis.tick_top()

ax1 = ax.bar(x=pos-width, height=data.loc['pearson'], width=width, color='lightgray')
ax2 = ax.bar(x=pos, height=data.loc['kendall'], width=width, color='white', hatch='/')
ax3 = ax.bar(x=pos+width, height=data.loc['spearman'], width=width, color='white', hatch='+')
# ax = plt.gca()
ax.set_xticks(pos + width / 2)
ax.set_xticklabels(('RH', 'Temperature', 'Visibility'), fontsize=13)

ax.legend((ax1[0], ax2[0], ax3[0]), ('pearson', 'kendall', 'spearman'), fontsize=13, frameon=True)
# plt.bar(x=pos+width, height=data.loc['kendall'], width=0.4)
for b in [ax1, ax2, ax3]:
    b[1].set_linewidth(2)
    b[1].set_edgecolor('black')

    b[0].set_linewidth(2)
    b[0].set_edgecolor('blue')

    b[2].set_linewidth(2)
    b[2].set_edgecolor('red')
ax.autoscale_view()
ax.tick_params(labelcolor='gray', labelsize=13, width=3)
ax.grid(True, linestyle='-.', alpha=0.6)

ax.set_frame_on(True)
ax.patch.set_visible(False)
for sp in ax.spines.values():
    sp.set_visible(False)
# plt.ax([.1,.1,.8,.7])
plt.subplots_adjust(top=0.4)
plt.figtext(2,-0.5, 'Datasource: airnow.gov, ncei.noaa.gov\ncreated by Binh Ng., Jul 2020 with Matplotlib 3.1.2', transform=ax.transData,
            family='monospace', color='gray', ha='right', fontsize=8)
ax.set_title('Hanoi, 2018 with bivariate correlations', fontsize=13)
plt.subplots_adjust(top=0.4)
plt.suptitle(r'Correlation of $PM_{2.5}$ with meteological data', fontsize=16)
plt.tight_layout(rect=(0,0.05,1, 0.9))
plt.savefig('img/2020Jul_corr_method.png')
```

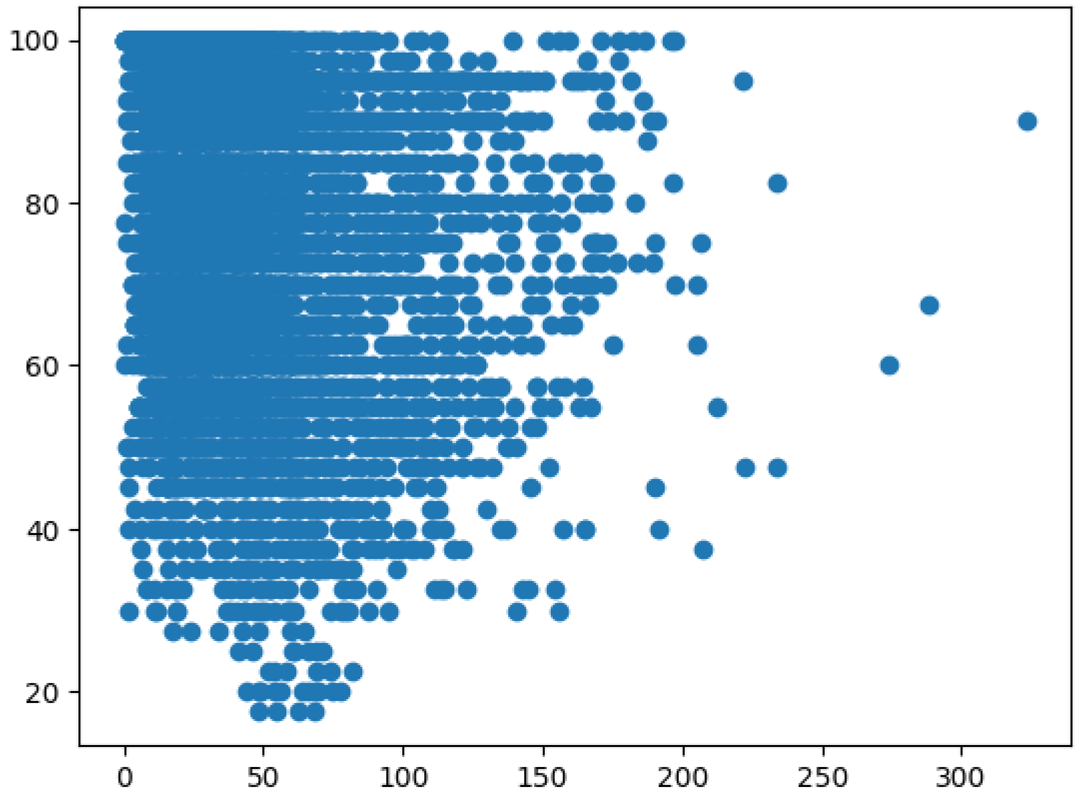



**what we have here?**

- if you see some correlation, a question you should ask is which method was used? It would be fine if all correlation was carried out with the same method.
- The `pearson` method is a safe choice because it is the average of the two. Knowing with method is used is important when one study indicated the correlation is higher or lower

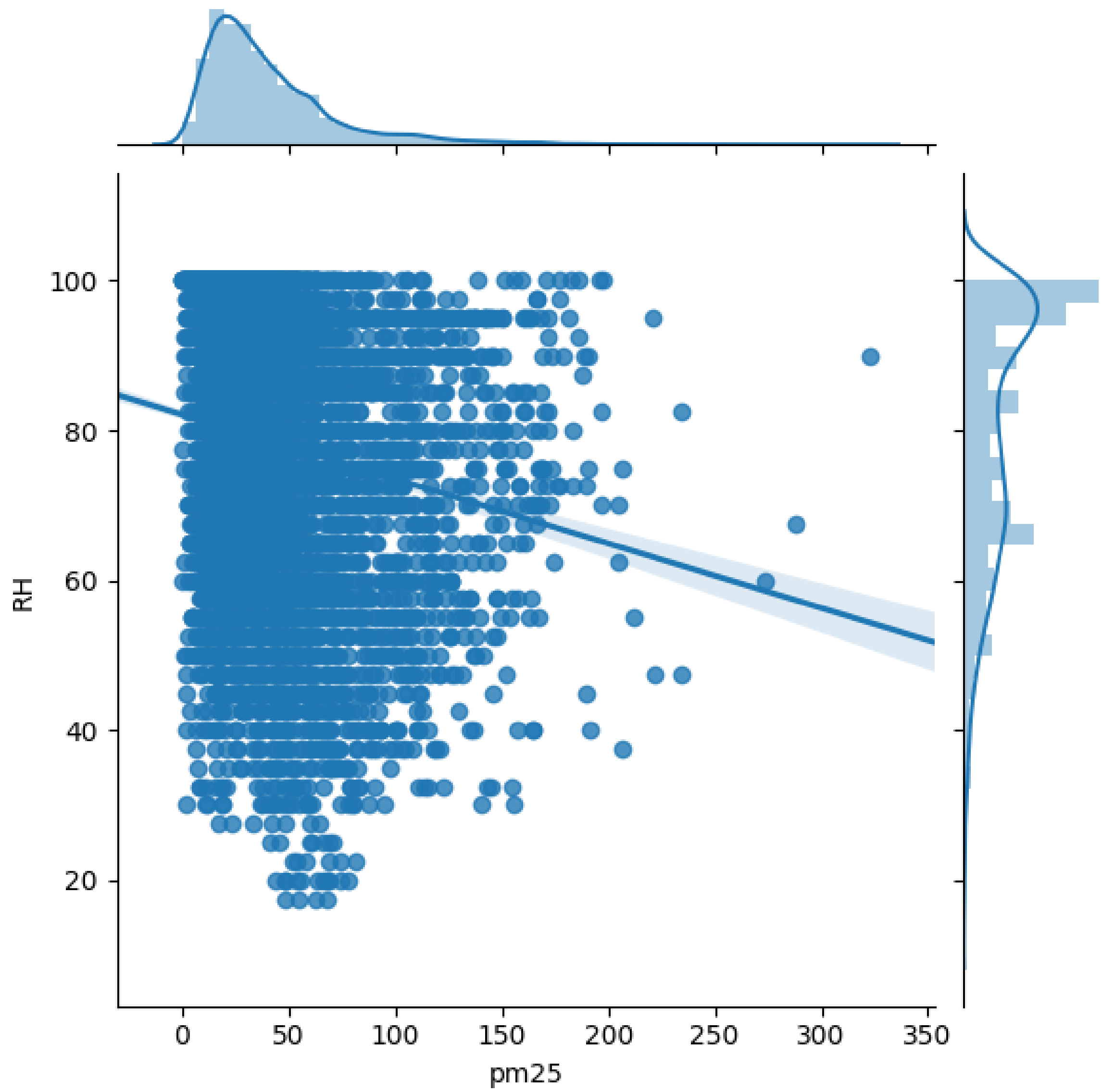
In [92]:
```
plt.scatter(df.pm25, df.RH)
```

Out[92]: <matplotlib.collections.PathCollection at 0x7f8e86d813c8>



In [93]:
```
sns.jointplot(df.pm25, df.RH, kind='reg')
```

Out[93]:
```
<seaborn.axisgrid.JointGrid at 0x7f8e86c65710>
```




In [94]:
```
rhs = np.linspace(0,100,16)
rhs
```

Out[94]:
```
array([  0.        ,   6.66666667,  13.33333333,  20.        ,
        26.66666667,  33.33333333,  40.        ,  46.66666667,
        53.33333333,  60.        ,  66.66666667,  73.33333333,
        80.        ,  86.66666667,  93.33333333, 100.        ])
```

In [95]:
```
labels = [f'{(rhs[i] + rhs[i+1])/2:.0f}' for i in (range(len(rhs)-1
))]
labels
```

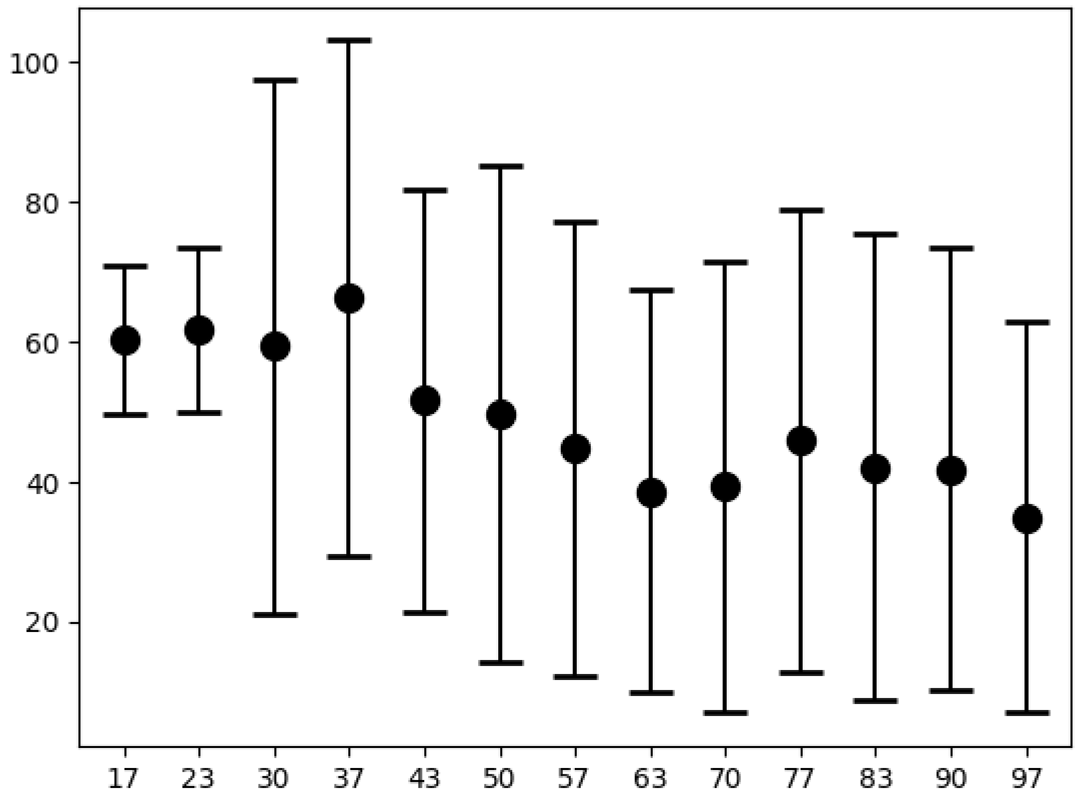
Out[95]:
```
['3',
 '10',
 '17',
 '23',
 '30',
 '37',
 '43',
 '50',
 '57',
 '63',
 '70',
 '77',
 '83',
 '90',
 '97']
```

In [96]:
```
df['RHC'] = pd.cut(df['RH'], bins=rhs, labels=labels).astype('categor
y')
```

In [97]:
```
dfs = df.groupby('RHC')
```

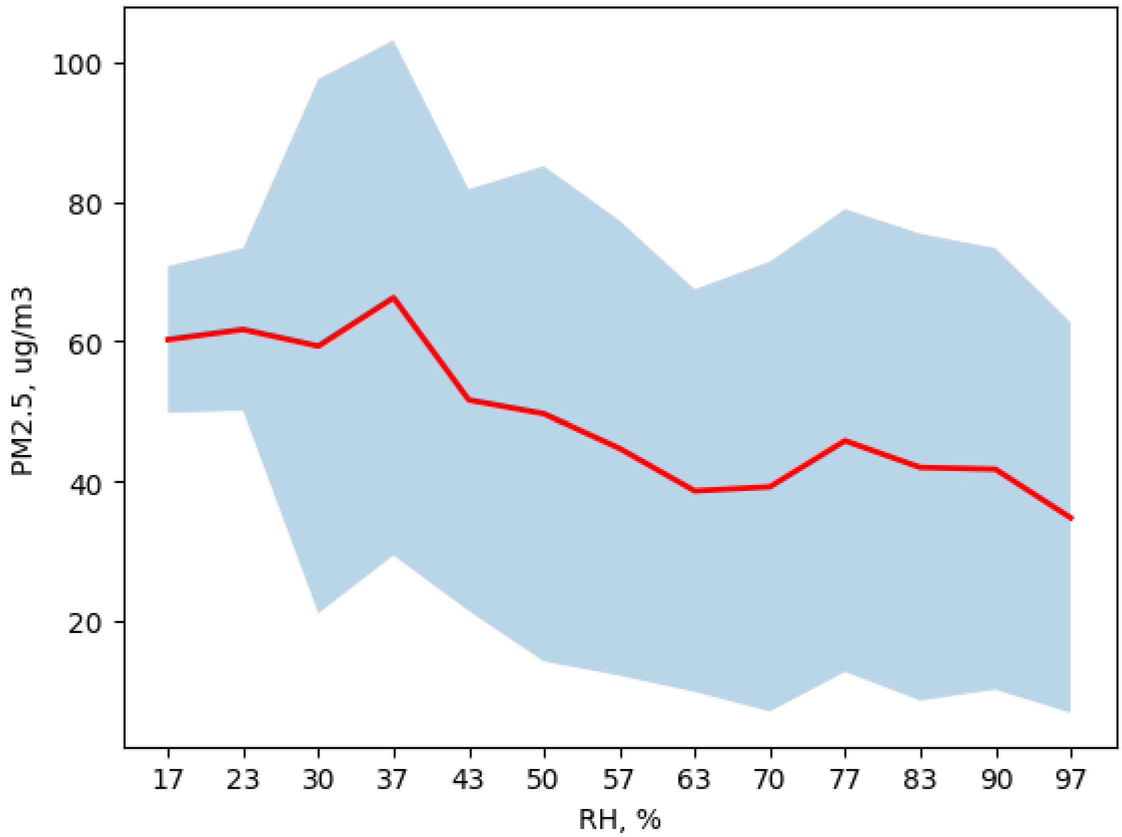
In [98]:
```
plt.errorbar(x=list(dfs.mean().index), y=dfs.mean().pm25, yerr=dfs.st
d().pm25,
             fmt='o', capsize=8, capthick=2, color='black',
             marker='o', markersize=10)
```

Out[98]: <ErrorbarContainer object of 3 artists>



In [99]:
```
plt.plot(list(dfs.mean().index), dfs.mean().pm25, lw=2, color='r')
plt.fill_between(x=list(dfs.mean().index), y1=dfs.mean().pm25 - dfs.s
td().pm25 ,
                 y2=dfs.mean().pm25 + dfs.std().pm25, alpha=0.3)
plt.ylabel('PM2.5, ug/m3')
plt.xlabel('RH, %')
```

Out[99]:
```
Text(0.5, 0, 'RH, %')
```




## Wind direction

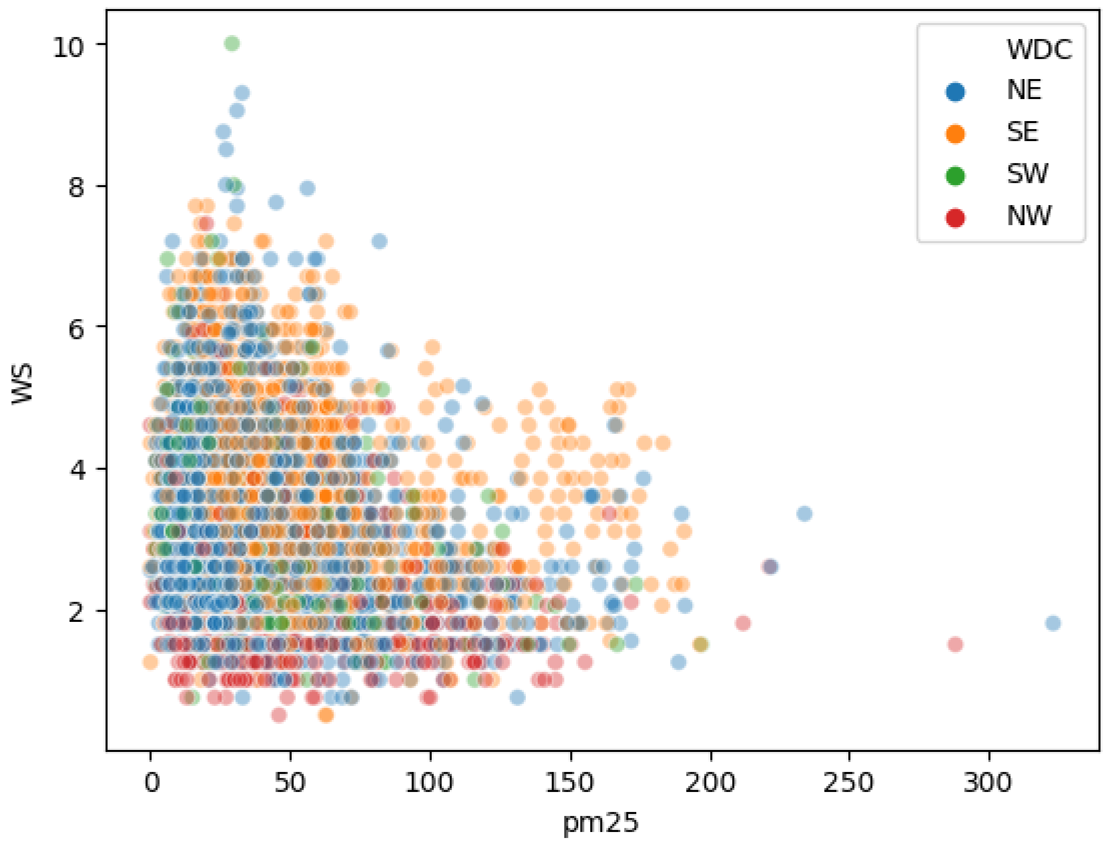
In [100]:
```
direction = np.linspace(0,360,5)
direction
```

Out[100]:
```
array([  0.,  90., 180., 270., 360.])
```

In [101]:
```
labels = ['NE', 'SE', 'SW', 'NW']
```

In [102]:
```
df['WDC'] = pd.cut(df['WD'], bins=direction, labels=labels).astype('c
ategory')
```

In [103]:
```
sns.scatterplot(data=df, x='pm25', y='WS', hue='WDC', alpha=0.4)
```
Out[103]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8e86b93f60>
```



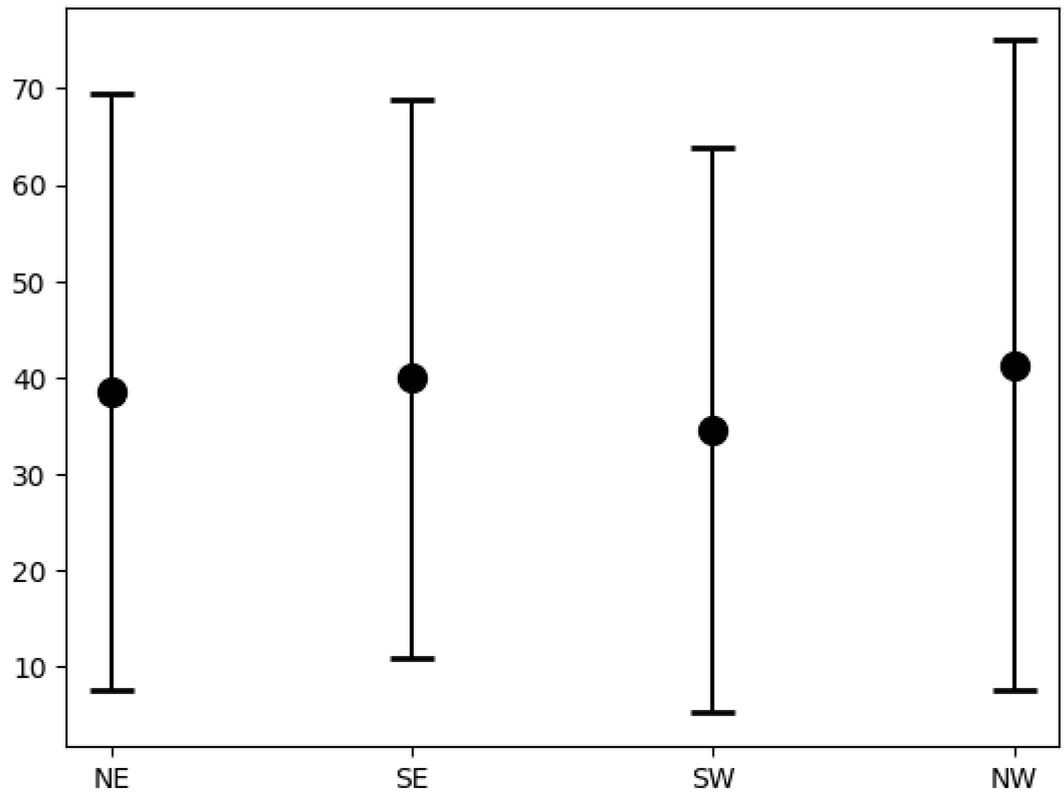

In [104]:
```
df.groupby('WDC').std()['pm25']
```
Out[104]:
```
WDC
NE    30.924822
SE    28.985036
SW    29.321554
NW    33.651236
Name: pm25, dtype: float64
```

In [105]:
```
df.groupby('WDC').mean()['pm25']
```
Out[105]:
```
WDC
NE    38.557232
SE    39.893007
SW    34.510490
NW    41.317012
Name: pm25, dtype: float64
```

In [106]:
```
dfd = df.groupby('WDC')
```

In [107]:
```
plt.errorbar(x=list(dfd.mean().index), y=dfd.mean().pm25, yerr=dfd.std().pm25,
             fmt='o', capsize=8, capthick=2, color='black',
             marker='o', markersize=10)
```

Out[107]: <ErrorbarContainer object of 3 artists>




## Wind speeds

In [108]:
```
speeds = np.linspace(0,12,7)
speeds
```

Out[108]:
```
array([ 0.,  2.,  4.,  6.,  8., 10., 12.])
```

In [109]:
```
labels = [f'{(speeds[i] + speeds[i+1])/2:.0f}' for i in (range(len(speeds)-1))]
labels
```

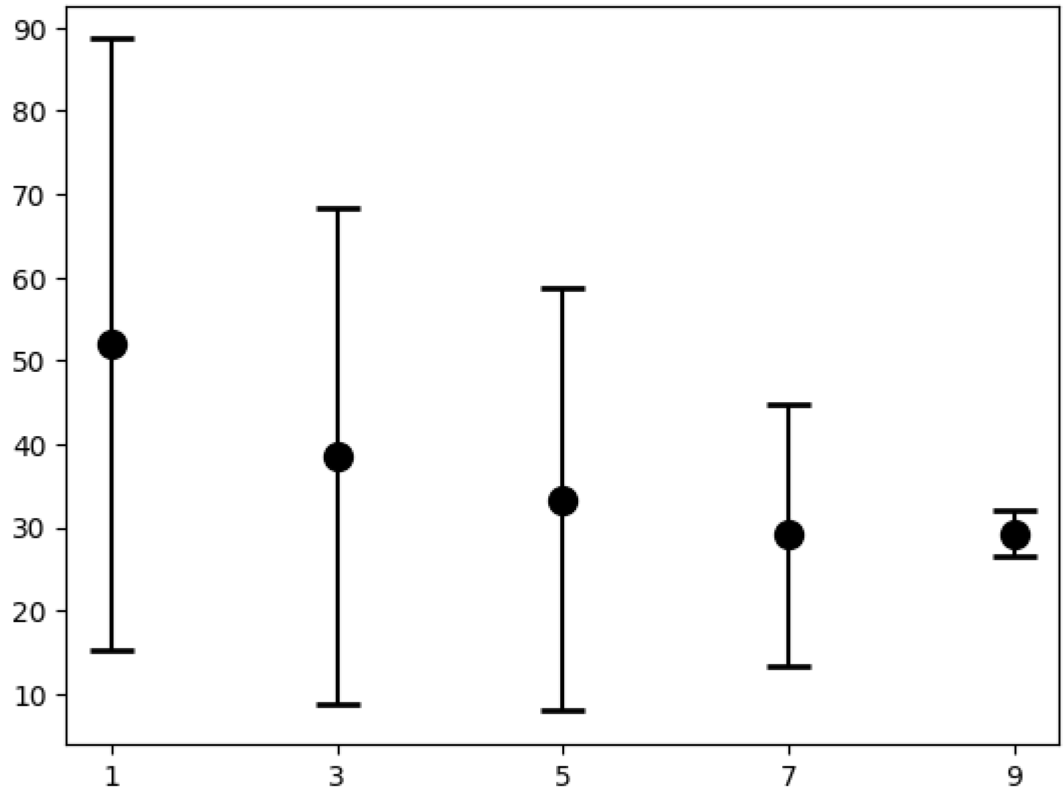
Out[109]:
```
['1', '3', '5', '7', '9', '11']
```

In [110]:
```
df['WSC'] = pd.cut(df['WS'], bins=speeds, labels=labels).astype('category')
```

In [111]:
```
dfs = df.groupby('WSC')
```

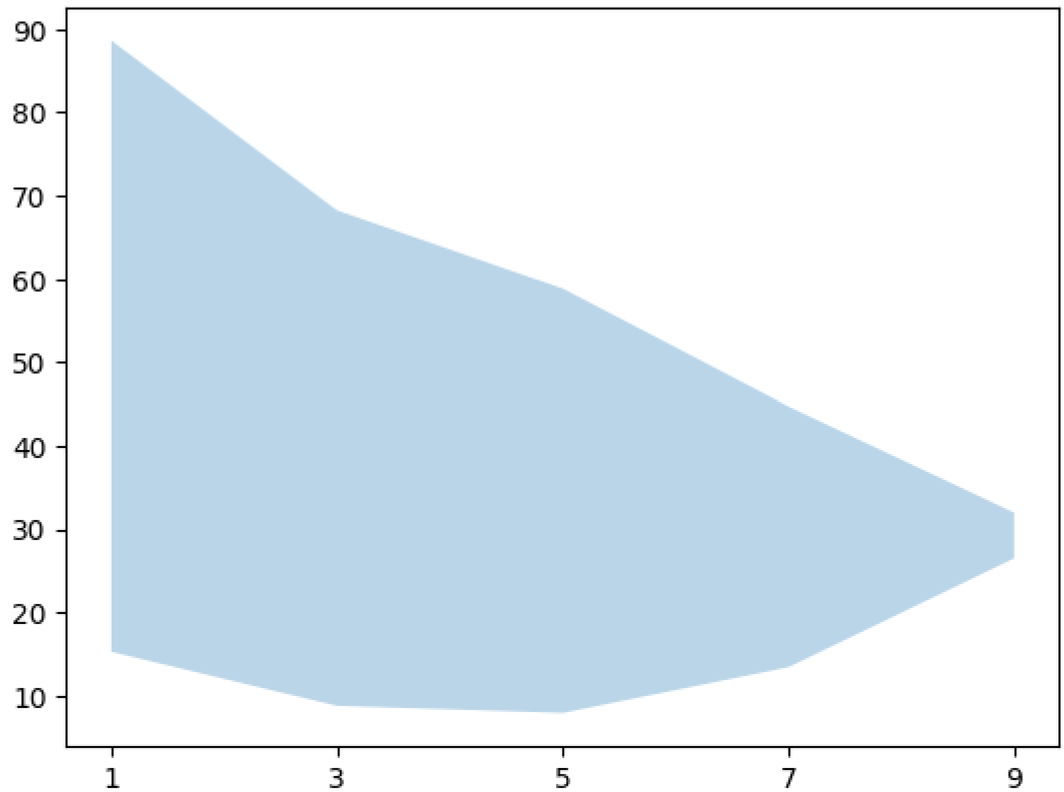
In [112]:
```
plt.errorbar(x=list(dfs.mean().index), y=dfs.mean().pm25, yerr=dfs.st
d().pm25,
             fmt='o', capsize=8, capthick=2, color='black',
             marker='o', markersize=10)
```

Out[112]: <ErrorbarContainer object of 3 artists>



In [113]:
```python
plt.fill_between(x=list(dfs.mean().index), y1=dfs.mean().pm25 - dfs.std().pm25 ,
                 y2=dfs.mean().pm25 + dfs.std().pm25, alpha=0.3)
```

Out[113]: <matplotlib.collections.PolyCollection at 0x7f8e8684acf8>




In [114]:
```python
speeds = np.linspace(0,12,13)
labels = [f'{(speeds[i] + speeds[i+1])/2:.1f}' for i in (range(len(speeds)-1))]
labels
```

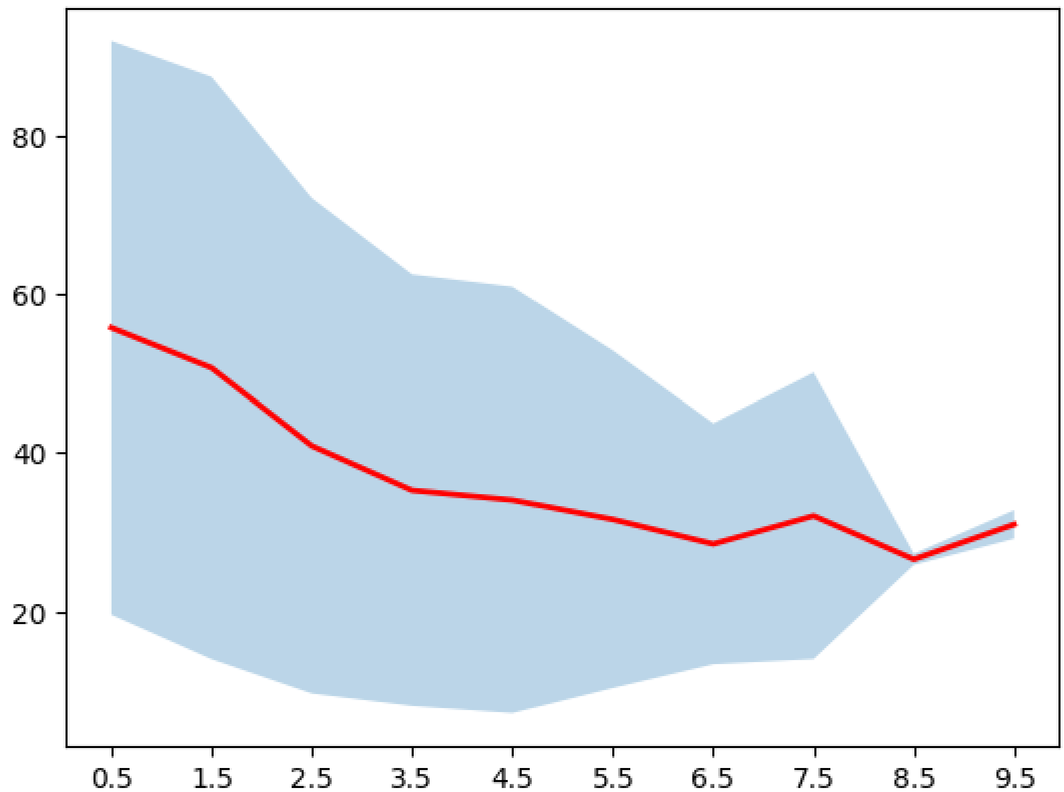
Out[114]:
```
['0.5',
 '1.5',
 '2.5',
 '3.5',
 '4.5',
 '5.5',
 '6.5',
 '7.5',
 '8.5',
 '9.5',
 '10.5',
 '11.5']
```

In [115]:
```python
df['WSC'] = pd.cut(df['WS'], bins=speeds, labels=labels).astype('category')
```

In [116]:
```python
dfs = df.groupby('WSC')
```

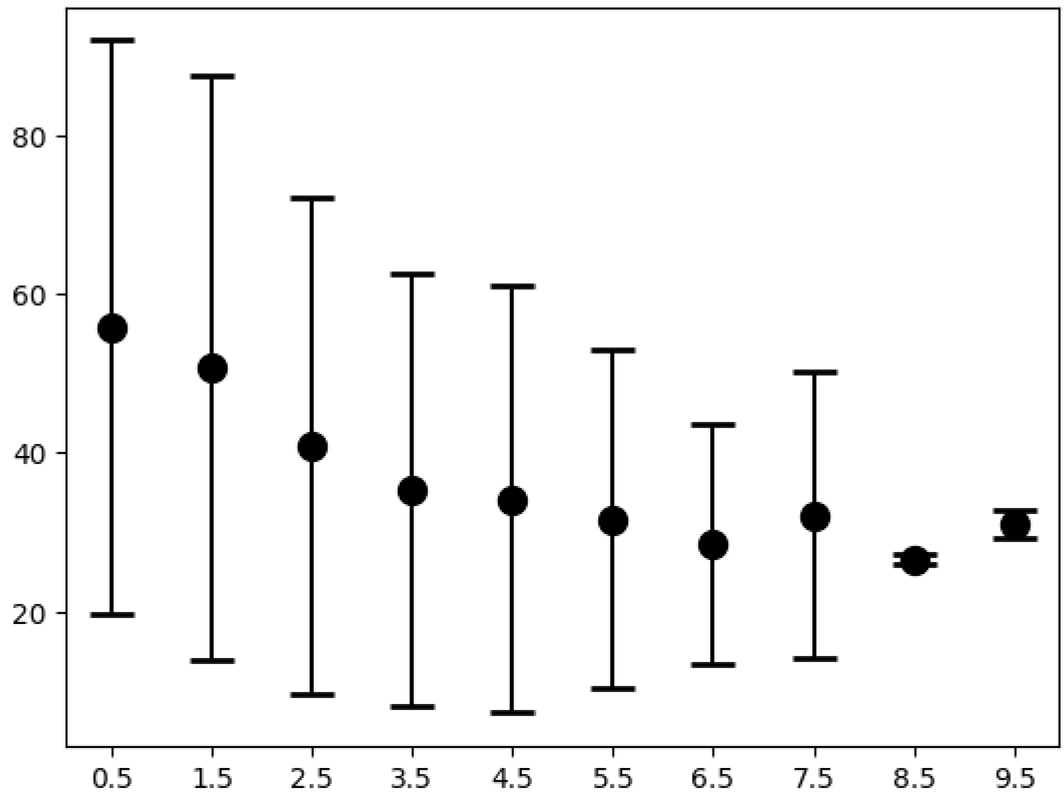
In [117]:
```
df.corr().pm25.WS
```
Out[117]: -0.027791426871811013

In [118]:
```
plt.plot(list(dfs.mean().index), dfs.mean().pm25, lw=2, color='r')
plt.fill_between(x=list(dfs.mean().index), y1=dfs.mean().pm25 - dfs.s
td().pm25 ,
                 y2=dfs.mean().pm25 + dfs.std().pm25, alpha=0.3)
```
Out[118]: <matplotlib.collections.PolyCollection at 0x7f8e86830f98>



In [119]:
```
plt.errorbar(x=list(dfs.mean().index), y=dfs.mean().pm25, yerr=dfs.std().pm25,
             fmt='o', capsize=8, capthick=2, color='black',
             marker='o', markersize=10)
```

Out[119]: <ErrorbarContainer object of 3 artists>




# Concluding notes

- I might introduce the topic more complicated than we started out, but I would take the complexity of $PM_{2.5}$ with meteorological inputs as the matter of fact. We need to do a better job the shed some light (or any light) on it
- I have not mentioned the emission source or the formation rate, which is why the $PM_{2.5}$ is out there in the first place
- Once $PM_{2.5}$ formed and with precussors, wind speed, temperature, the thickness of mixing have a fair share to dictate which how much $PM_{2.5}$ is stored the ground (and so we measured it)
- A higher temperature (such as during the summer month) seems to be dominant factor with a lowerer concentration. This could be explained by a strong turbulent (and unstable mixing layer) so that the polluted air nearby the ground constantly moved upward, and replaced a cooler (and cleaner) air moving downward
- During winter time, with a higher windspeed or with a thicker mixing layer were favored to lower the $PM_{2.5}$ concentration
- Stagnant (or stable) air layer in ground level is a favorable condition to store and accumulate $PM_{2.5}$ which is bad for lung and respiratory tract.

In [ ]: