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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

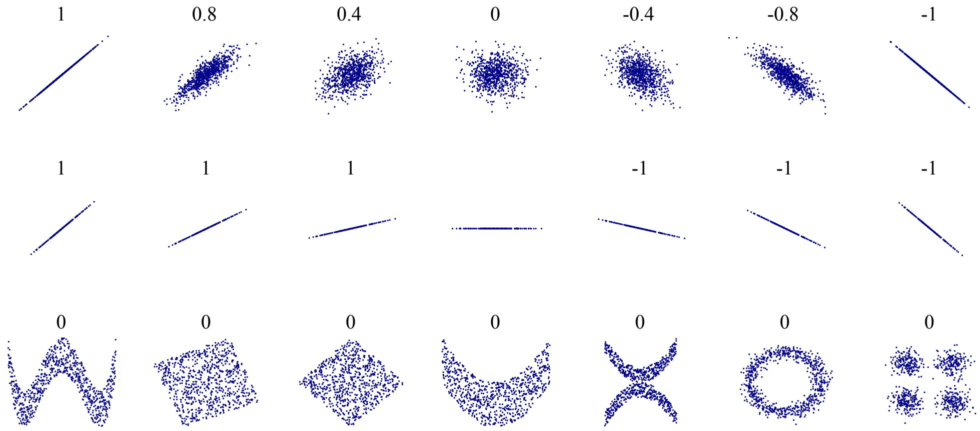
- with `pandas`, getting a bivariate correlation (correlation between two variables) is easy, just call `.corr()` after the DataFrame like this. We can filter out the correlation with one variable such as `pm25`

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?

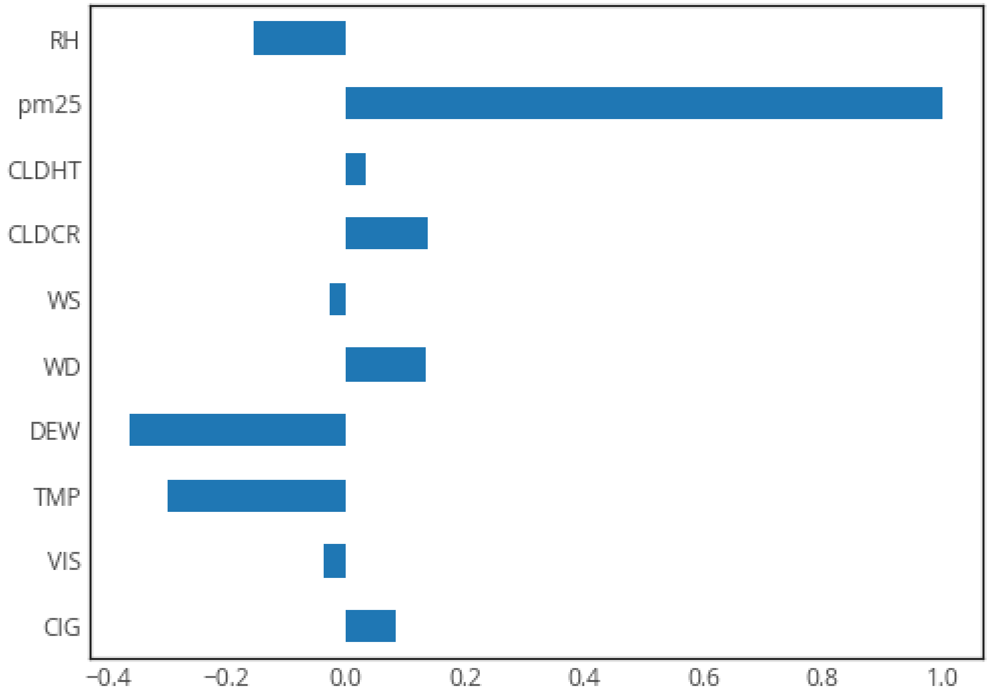
- First take a look at this diagram about



- 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()`

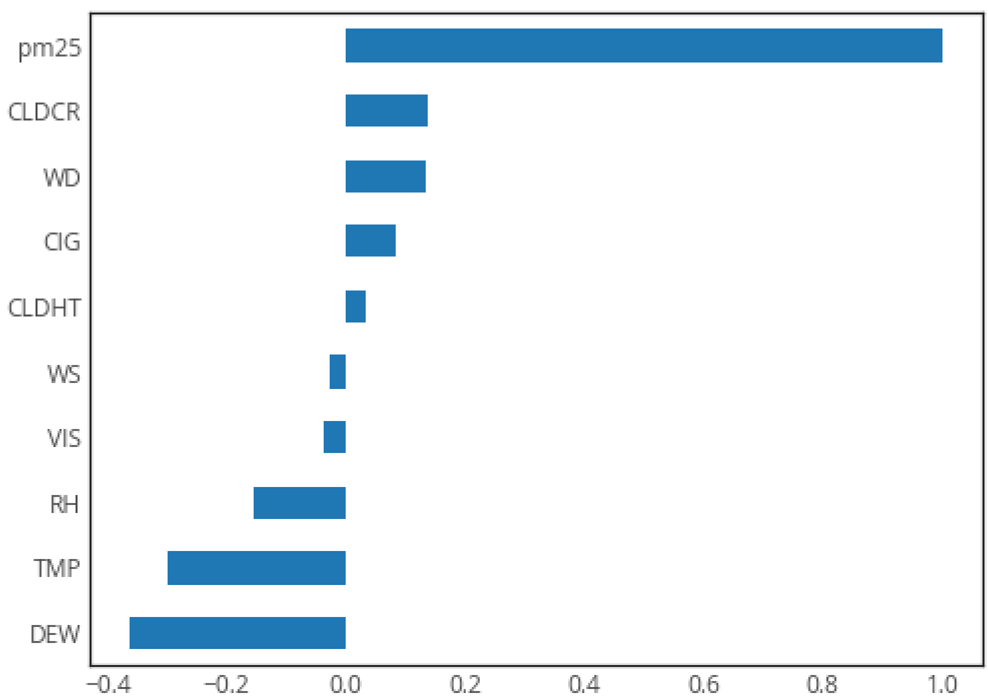
In [17]:
```python
df.corr()['pm25'].plot.barh()
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc0835d18d0>



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

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc081520e10>



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.

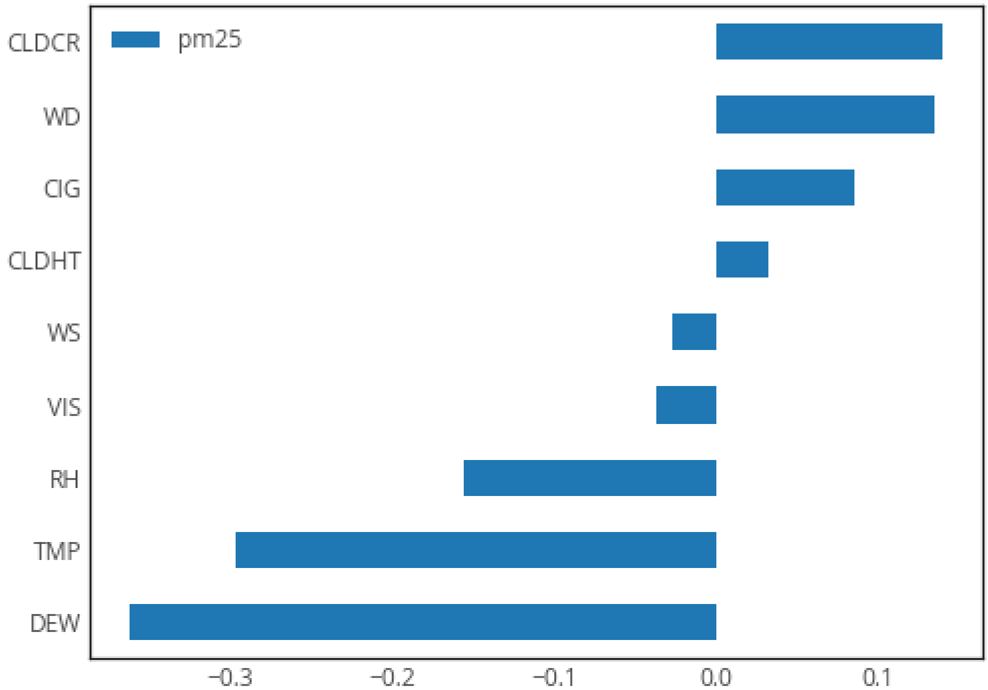
- but if you live in (seasonally) polluted area with aerosol fills the air in the winter, then it becomes something else: curiosity, practical knowledge, and service to others to feather out something interesting
- and on that ground, let move on the figure out what else in this correlation mess

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 0x7fc080de4f60>
```



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

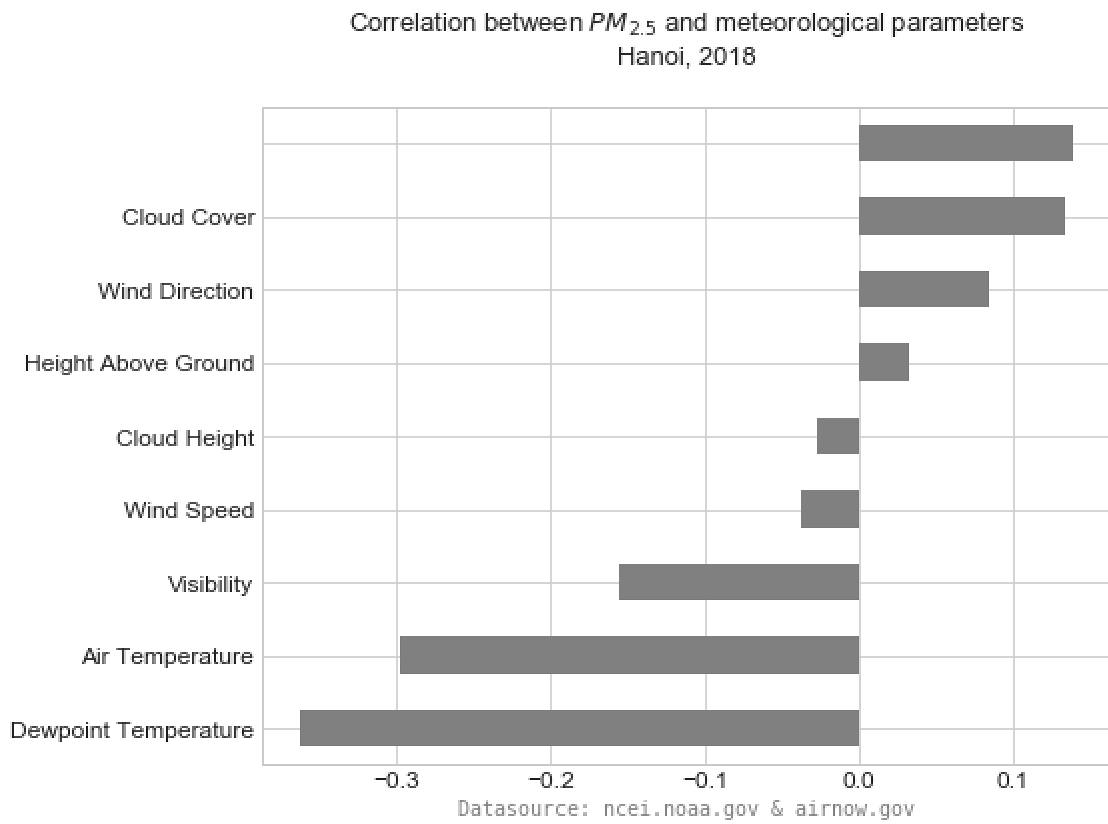
In [20]:
```
label = ['Cloud Cover', 'Wind Direction', 'Height Above Ground',
                    'Cloud Height', 'Wind Speed', 'Visibility', 'Air
 Temperature',
                    'Dewpoint Temperature']
```

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.gov & airnow.gov',
              fontsize=10, color='gray', fontfamily='monospace')
fig.tight_layout()
fig.savefig('img/2020Jul_corr_pm25.png')
```

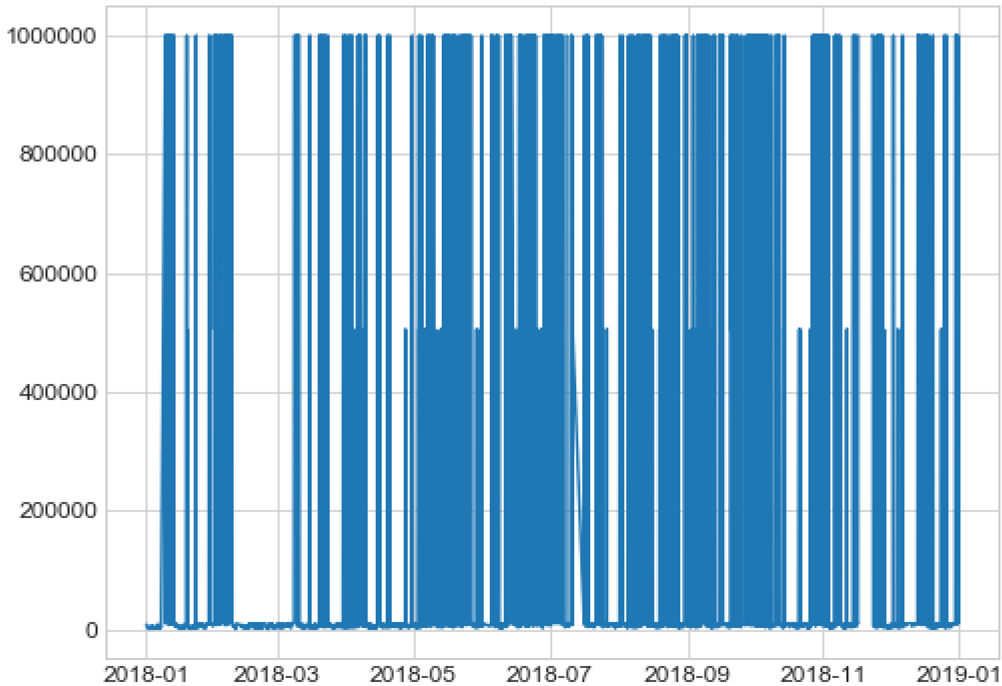


VIS

- 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]:
```
# pretty noisy
plt.plot(df.index, df.VIS)
```

Out[24]: [<matplotlib.lines.Line2D at 0x7fc080d0b940>]

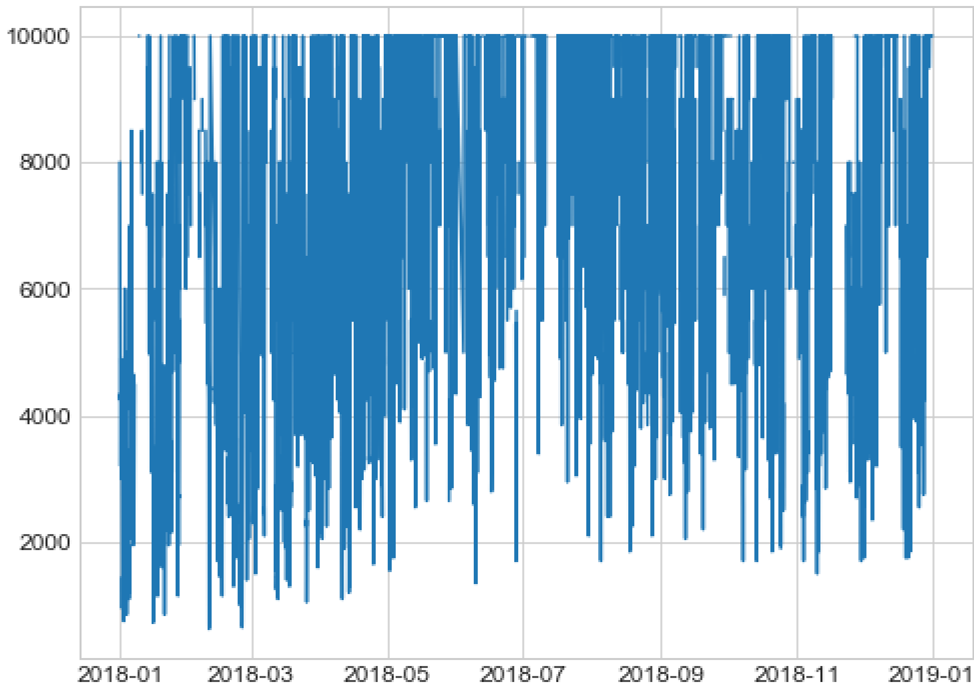


In [25]:
```
# most of data showing a good visibility, but I did not clean up the
 file all the way, the 9999 value for missing still in place
df.VIS.describe()
```

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 0x7fc080c2a2b0>]

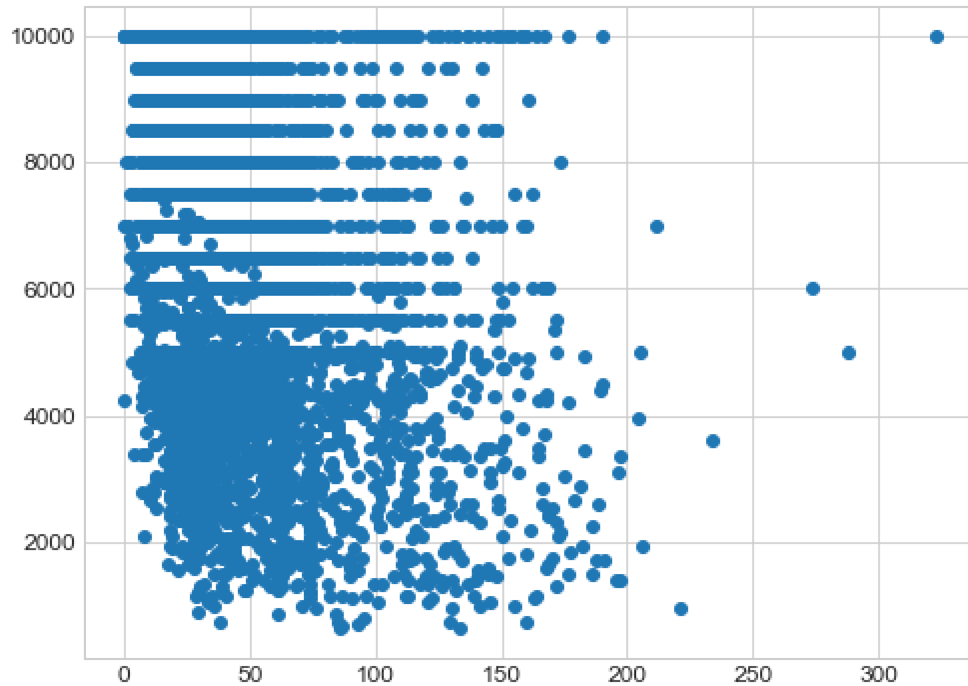


In [27]:
```
df.VIS.describe()
```

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
```

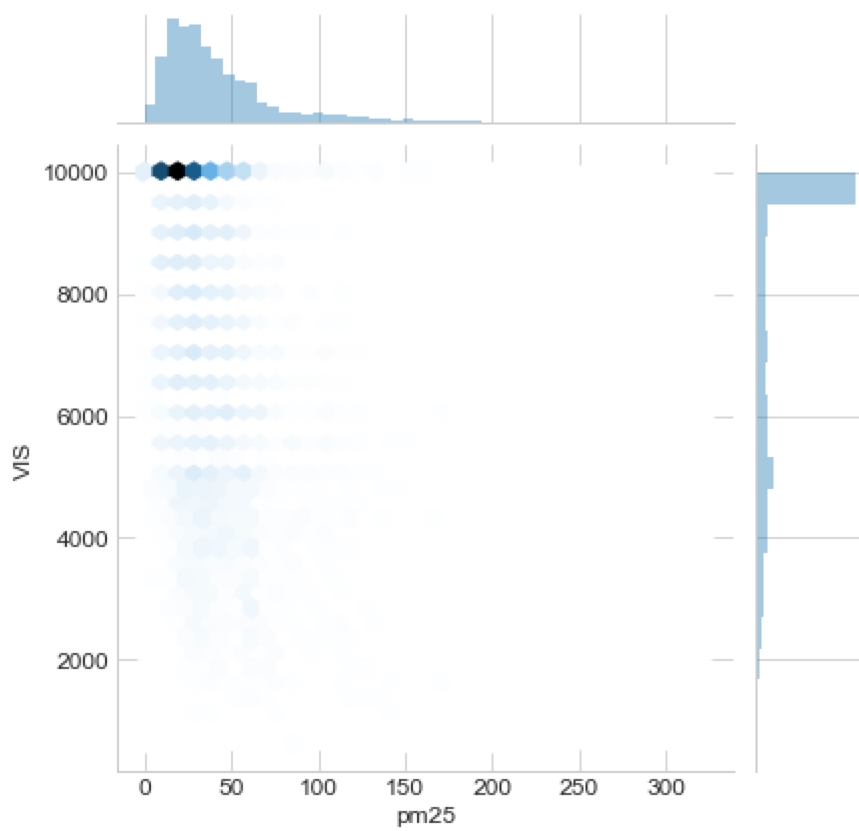
In [28]:
```
# still not clear pattern though we have more point on the lower left corner
plt.scatter(df.pm25, df.VIS)
```

Out[28]: <matplotlib.collections.PathCollection at 0x7fc080babbe0>



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

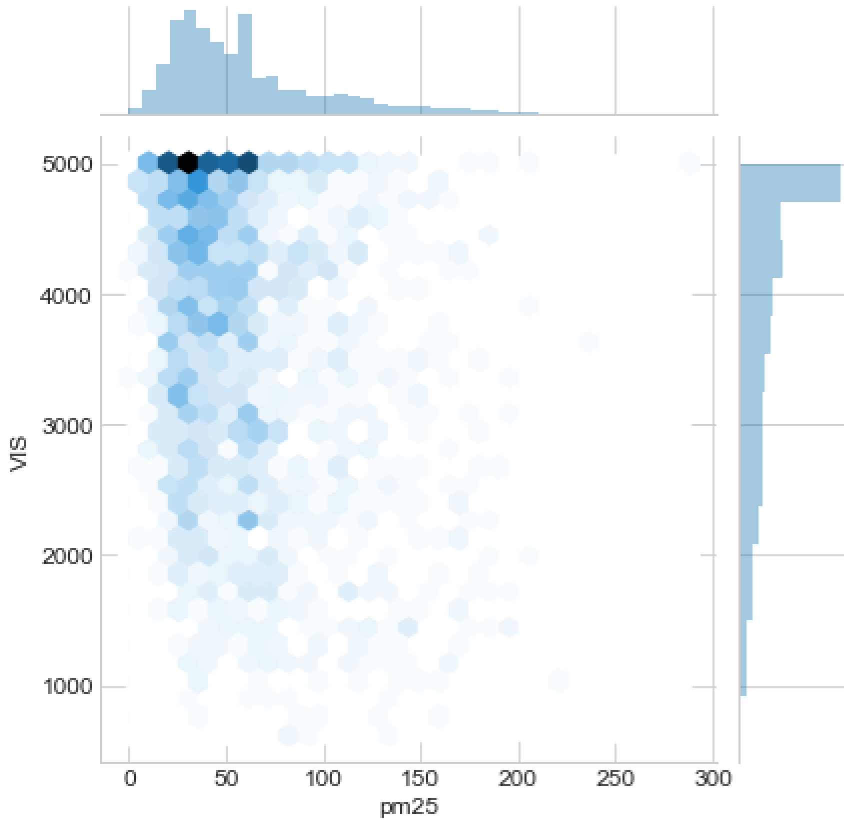
Out[29]: <seaborn.axisgrid.JointGrid at 0x7fc080bd5cf8>



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 0x7fc0809adb38>
```



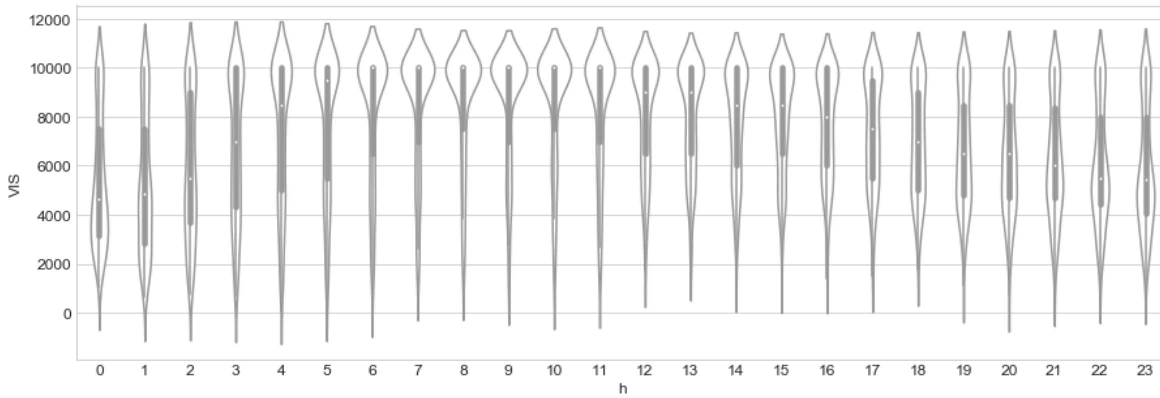
In [32]:
```
df.corr()['pm25']['VIS']
```

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 0x7fc0809ad898>

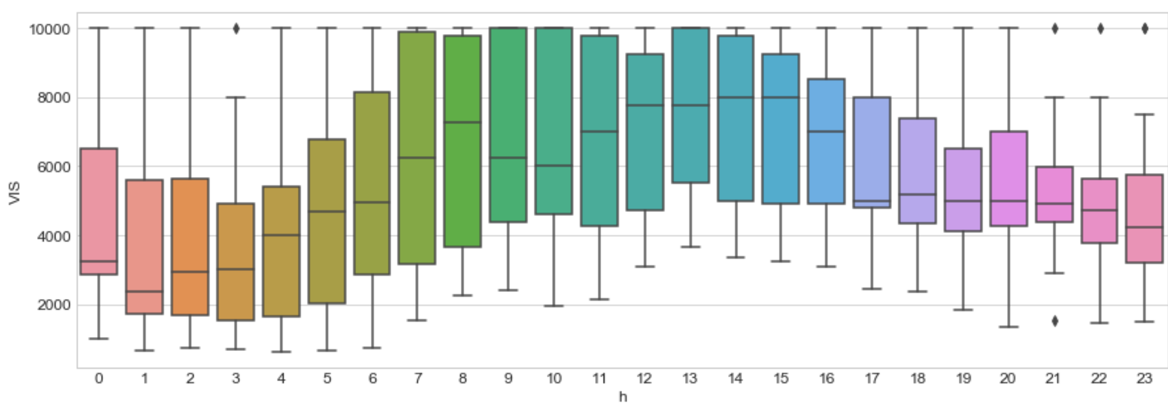


In [35]:
```
# let look for a month
```

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

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

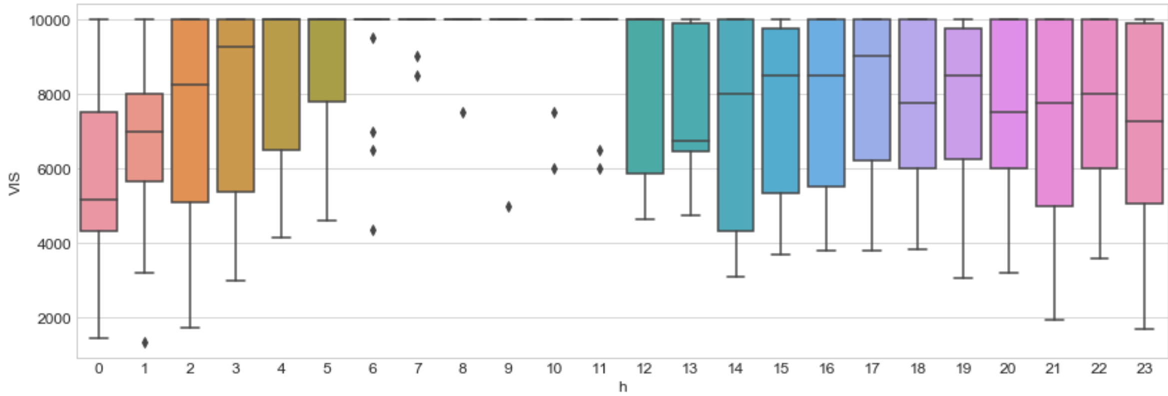
Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc07c5ab5c0>



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

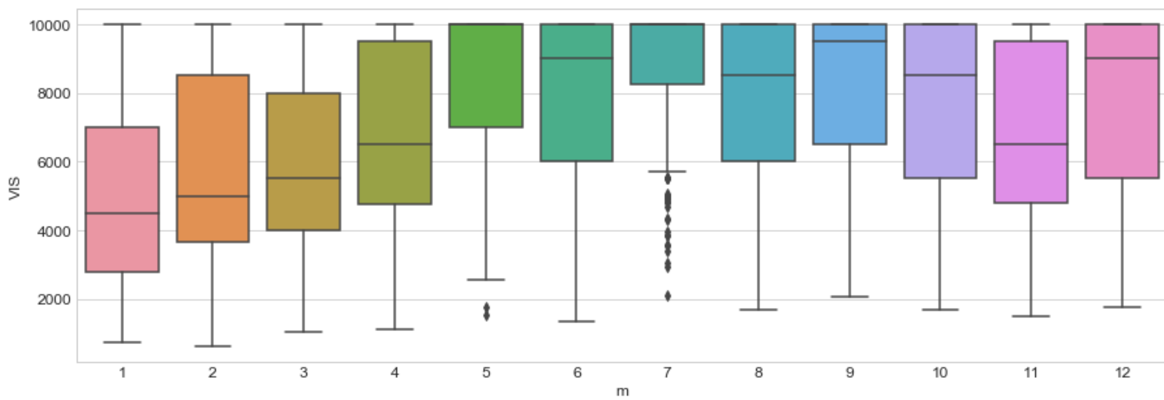
In [39]:
```
plt.figure(figsize=(15,5))
sns.boxplot(data=jun, x='h', y='VIS')
```

Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc07c24ef98>



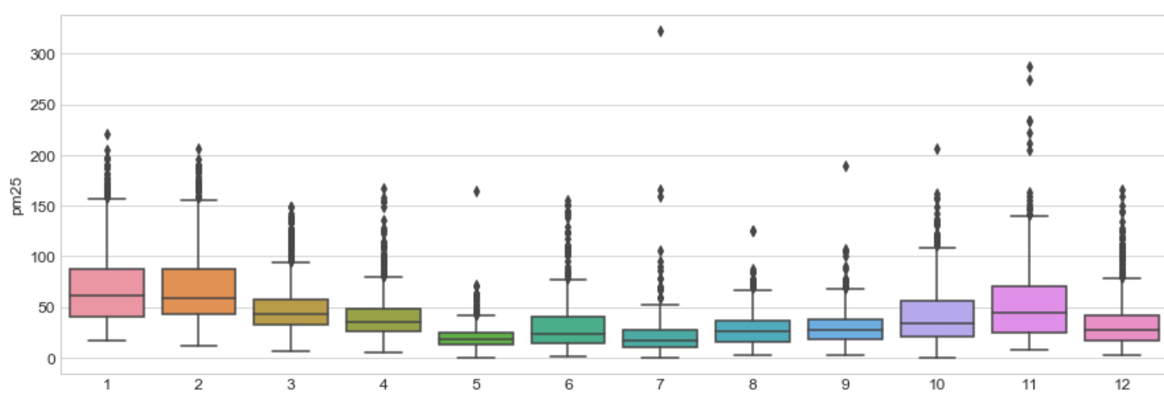
In [40]:
```
plt.figure(figsize=(15,5))
sns.boxplot(data=df, x='m', y='VIS')
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc07c210ba8>



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

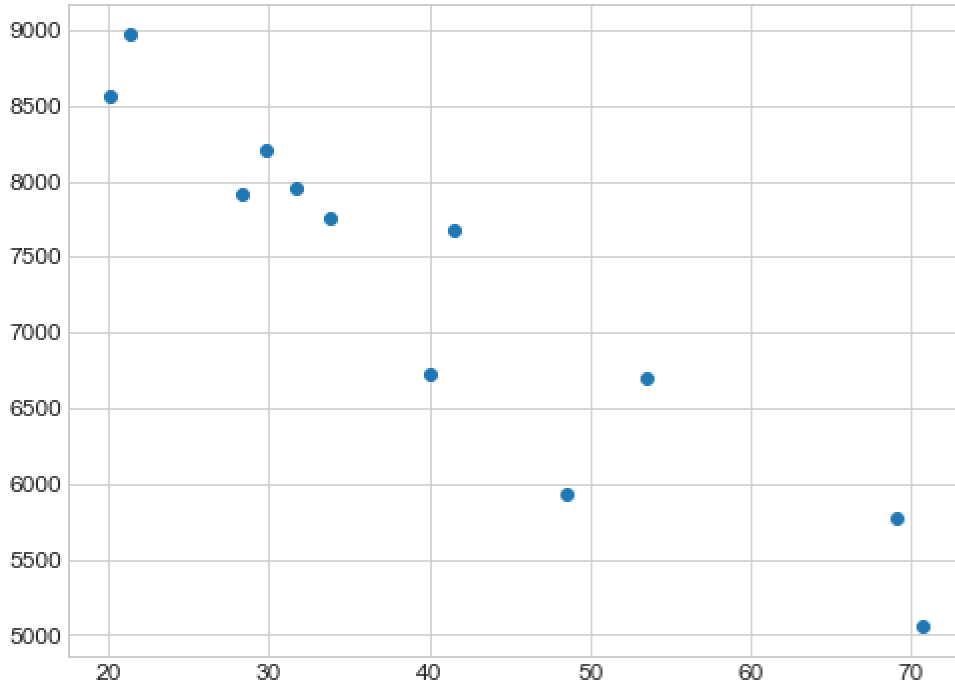
Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc07674c5c0>



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

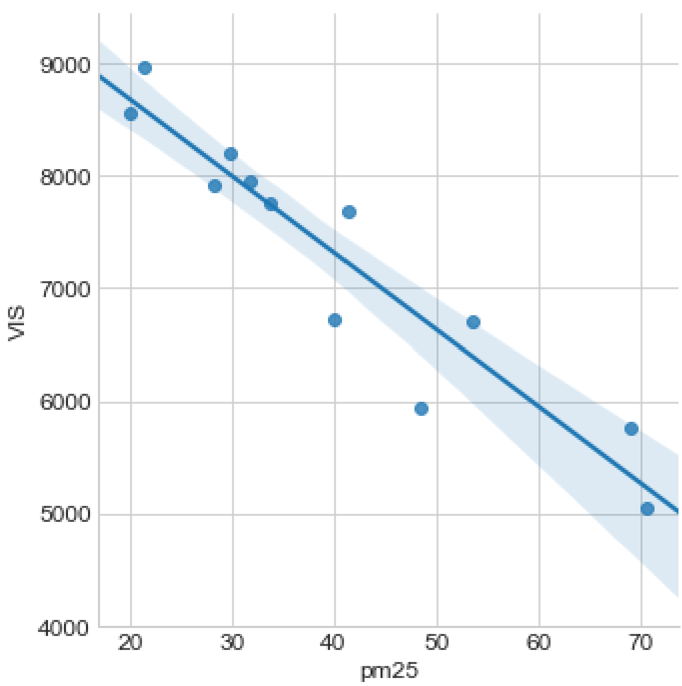
In [43]:
```
plt.scatter(dft.pm25, dft.VIS)
```

Out[43]: <matplotlib.collections.PathCollection at 0x7fc076490d30>



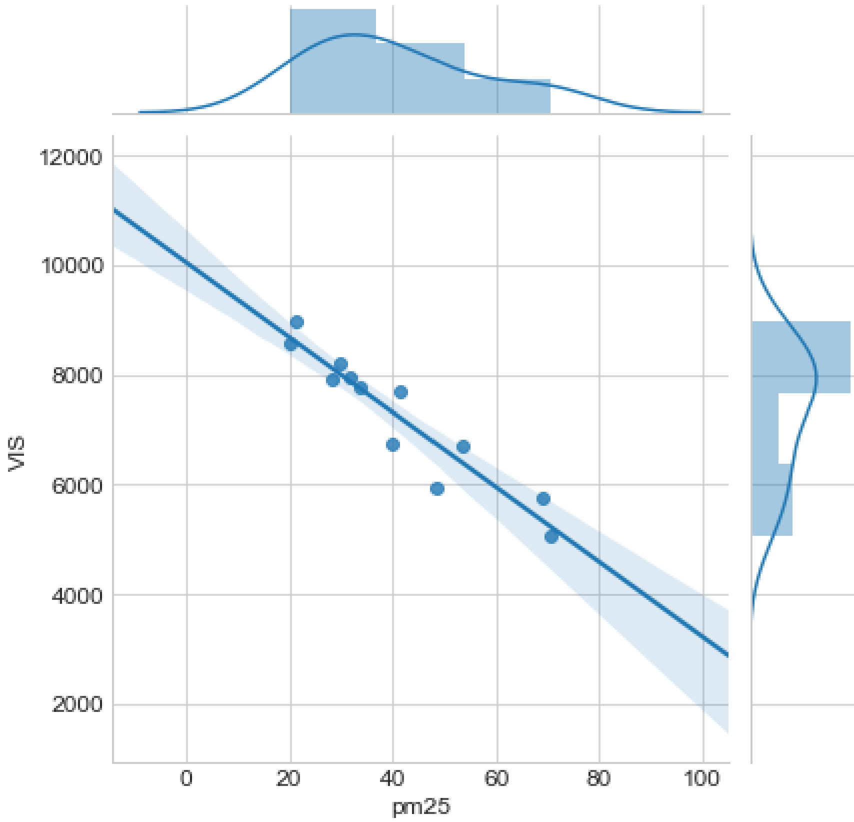
In [44]:
```
sns.lmplot(x='pm25', y='VIS', data=dft)
```

Out[44]: <seaborn.axisgrid.FacetGrid at 0x7fc076458e10>



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

Out[45]:
```
<seaborn.axisgrid.JointGrid at 0x7fc0764178d0>
```



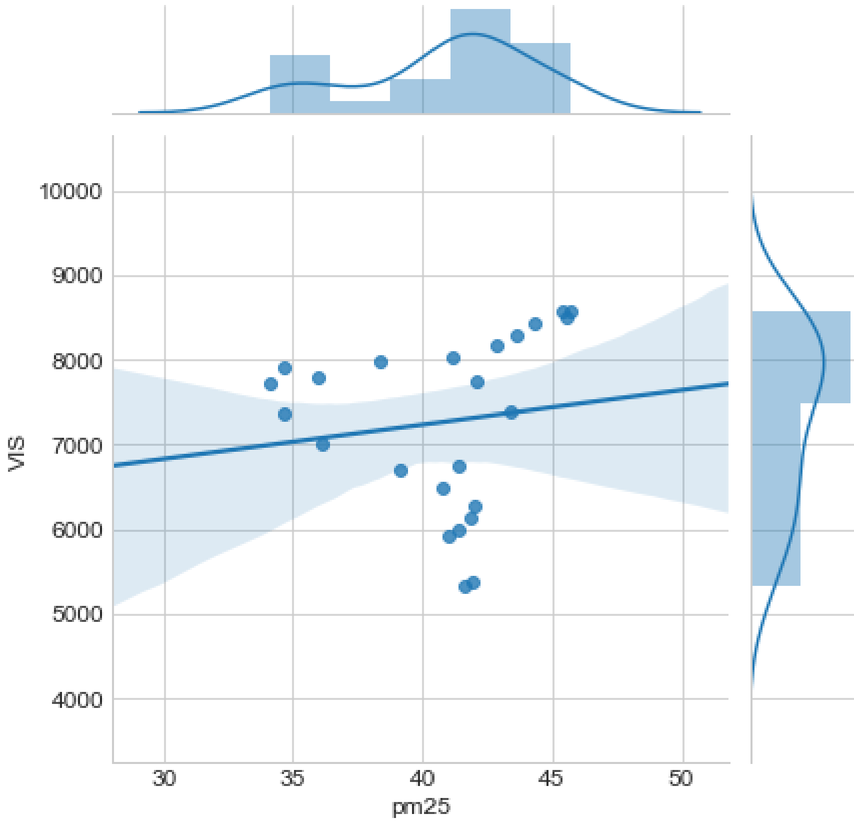
In [46]:
```
# this is impressive, sudently, the correlation of the average concen
tration (by month) is strong, or very strong
dft.corr()['pm25']['VIS']
```

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 0x7fc076326f98>
```



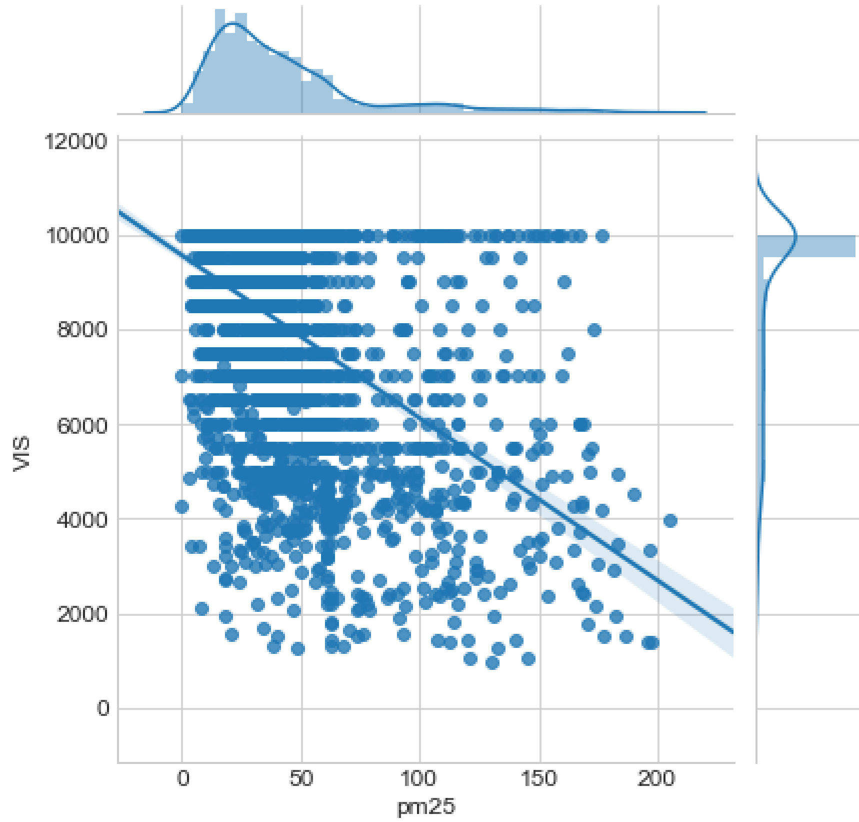
In [49]:
```
# or not so, if we averaged the input by the hour
dft.corr()['pm25']['VIS']
```

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 0x7fc0761ce320>



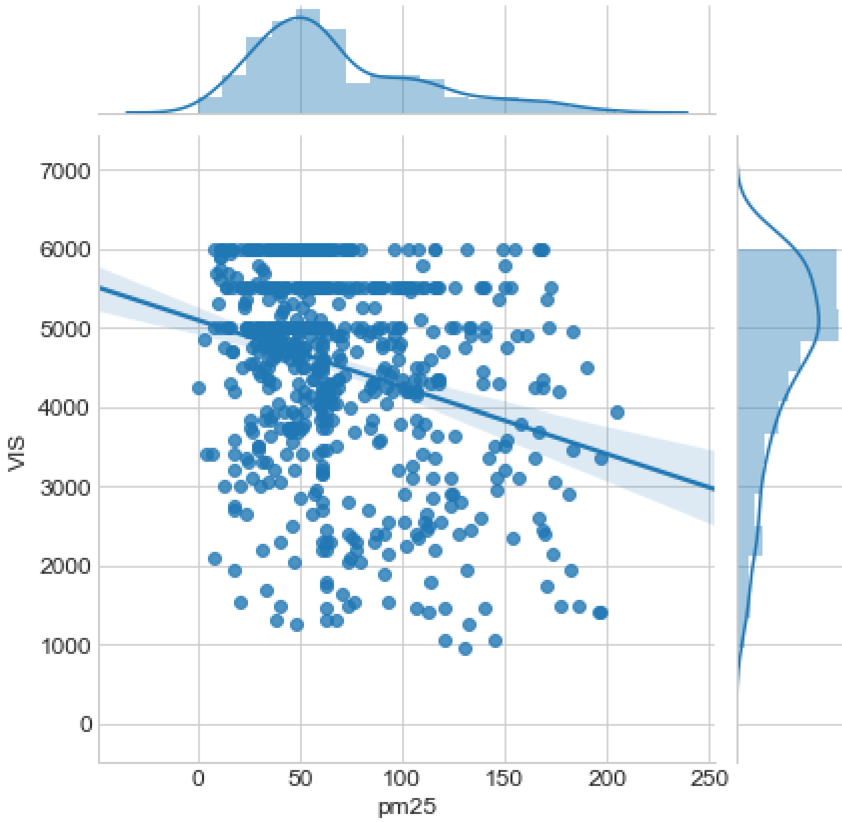
In [52]:
```
dft6 = dft.query('VIS<=6000')
```

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

Out[53]: -0.49590702697163747

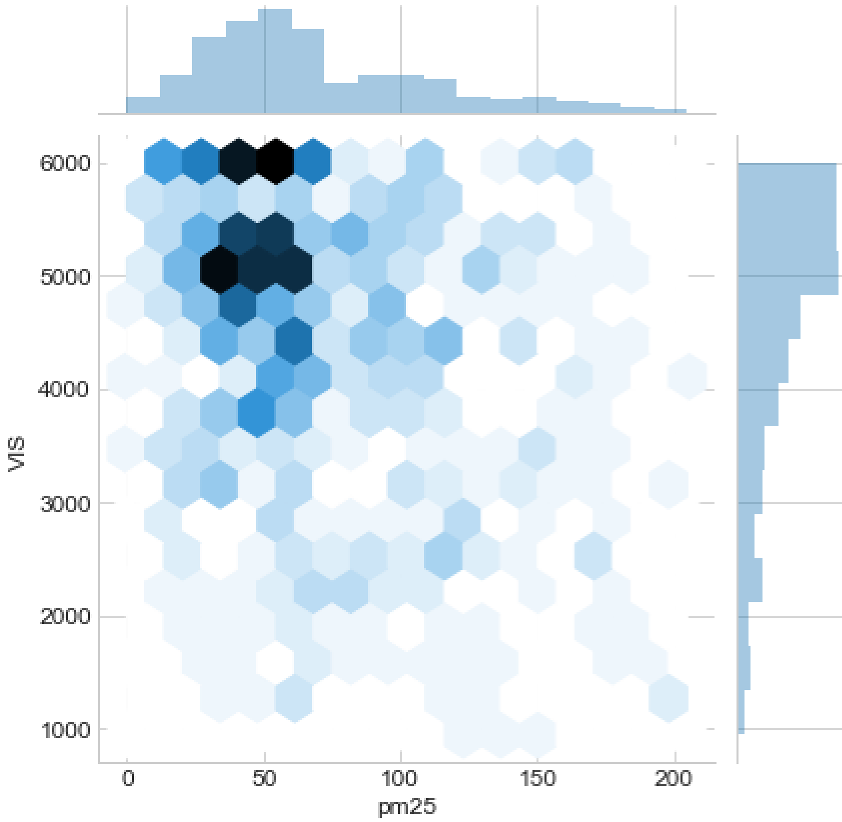
In [54]:
```
sns.jointplot(x='pm25', y='VIS', data=dft6, kind="reg", )
```

Out[54]:
```
<seaborn.axisgrid.JointGrid at 0x7fc076003240>
```



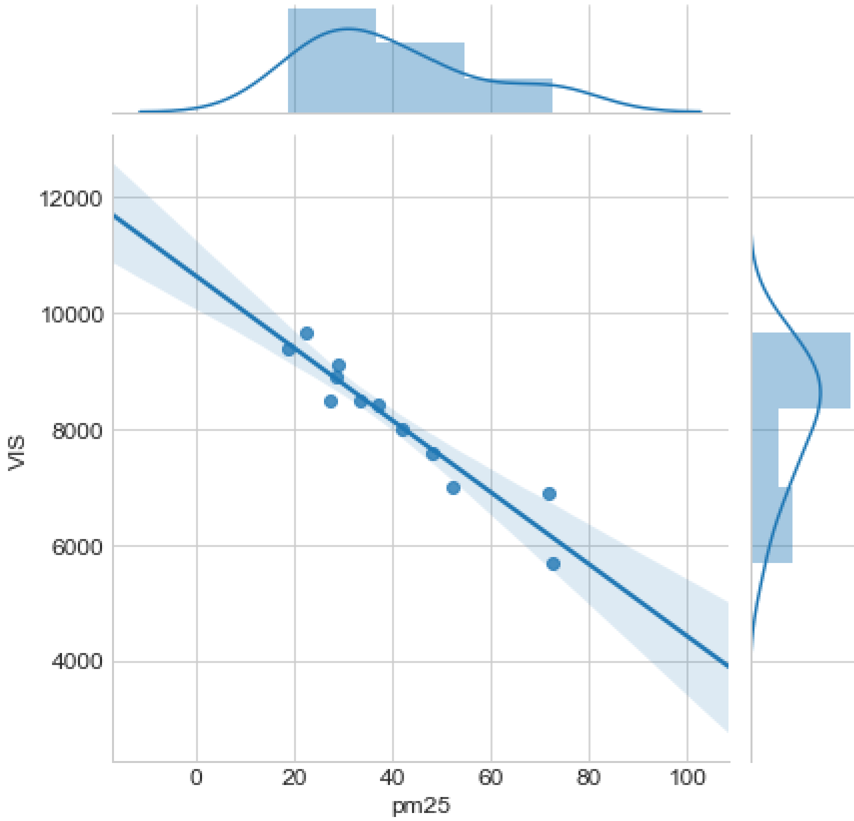
In [55]:
```
sns.jointplot(x='pm25', y='VIS', data=dft6, kind="hex", )
```

Out[55]:
```
<seaborn.axisgrid.JointGrid at 0x7fc075ef86a0>
```



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

Out[56]: <seaborn.axisgrid.JointGrid at 0x7fc0761ce940>

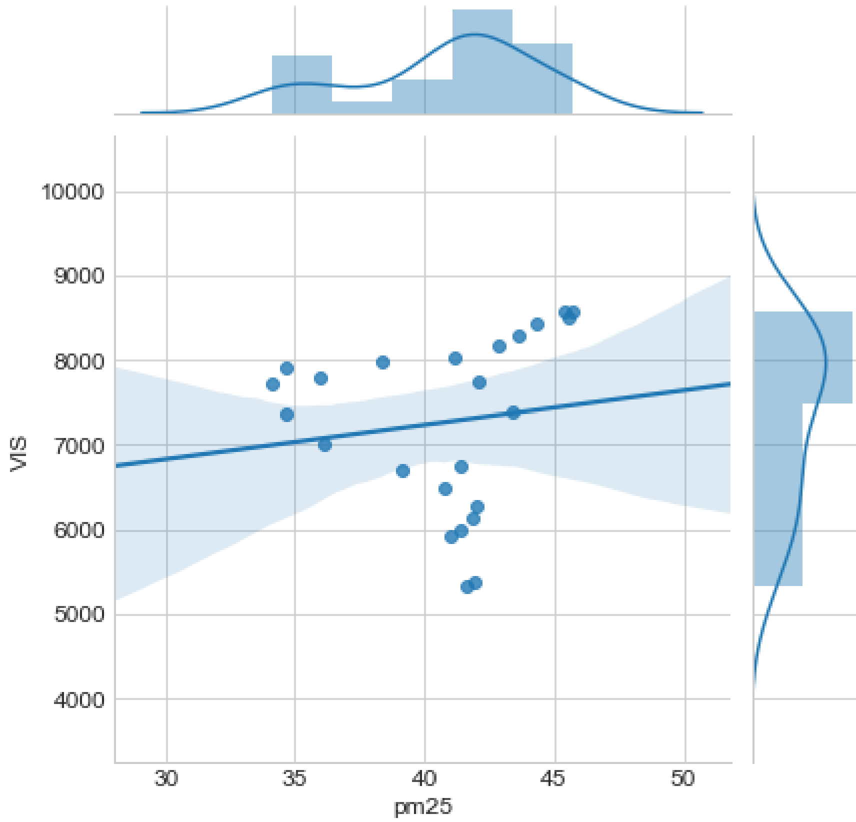


In [57]:
```python
# the correlation is strong with daily hours
dft.corr()['pm25']['VIS']
```

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 0x7fc075c4ceb8>

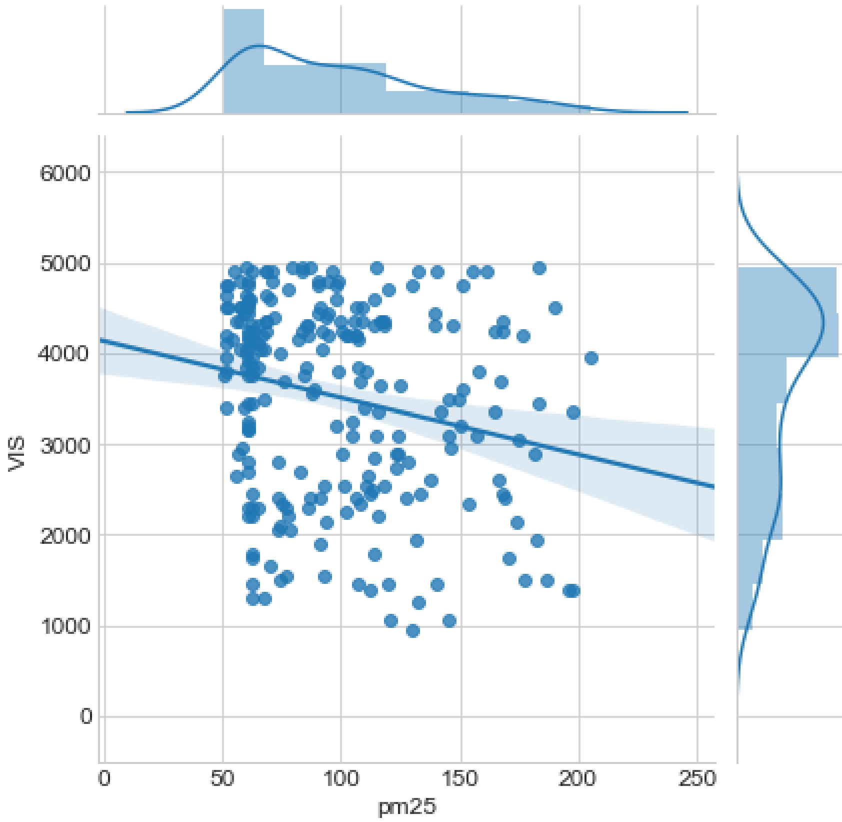


In [59]:
```
# grouping by the hour with day hour
dft1.corr()['pm25']['VIS']
```

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

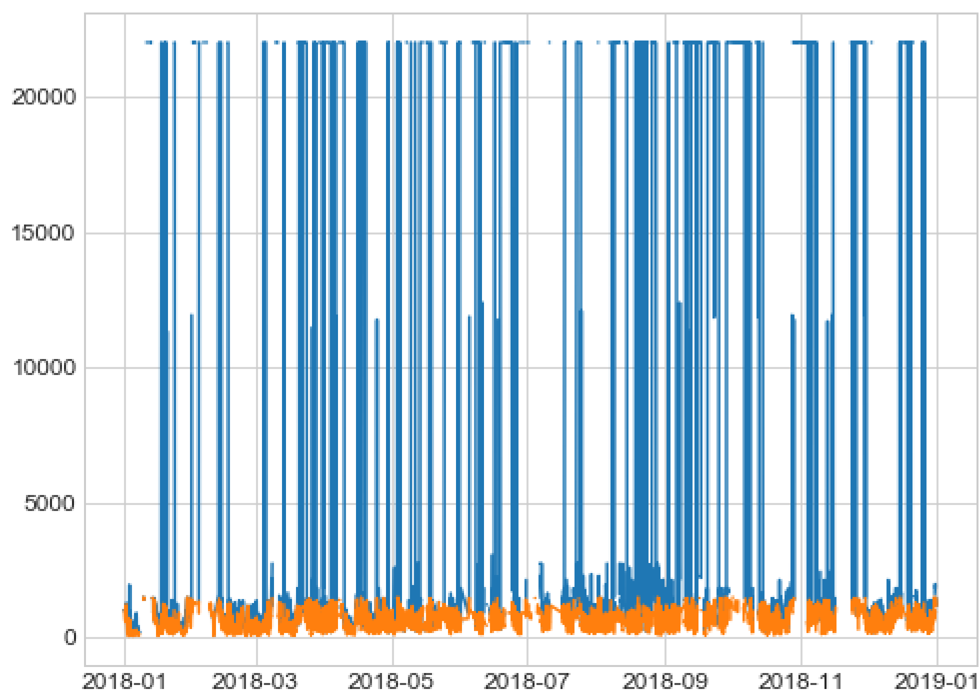
CIG, CLDHT

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]:
```
[&lt;matplotlib.lines.Line2D at 0x7fc0762c6898&gt;]
```



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
```

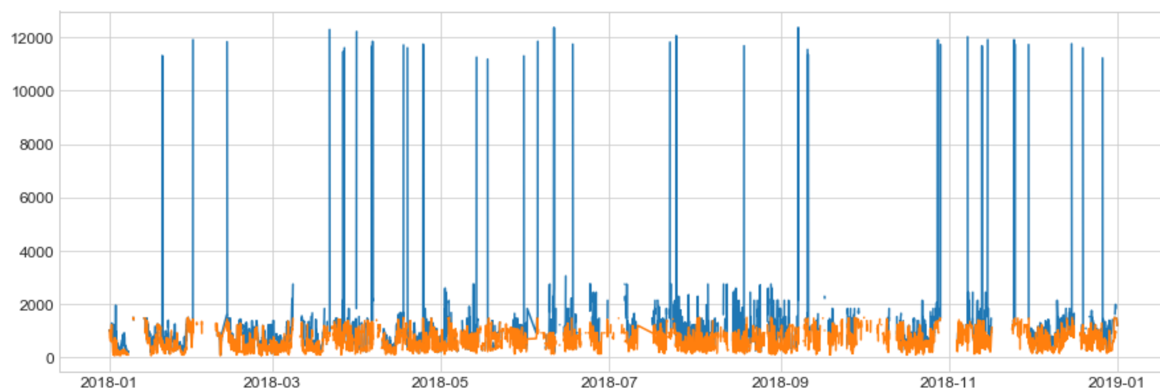
In [64]:
```
df.CIG.describe()
```

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)
```

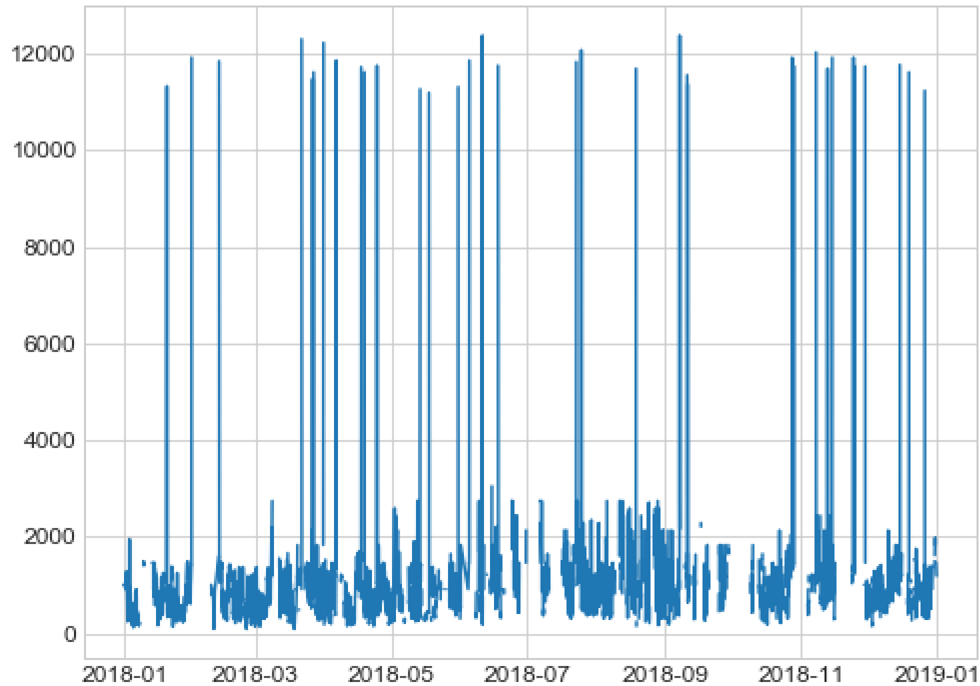
Out[66]:
```
[<matplotlib.lines.Line2D at 0x7fc0759d6358>]
```



- 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 0x7fc075bac588>]
```

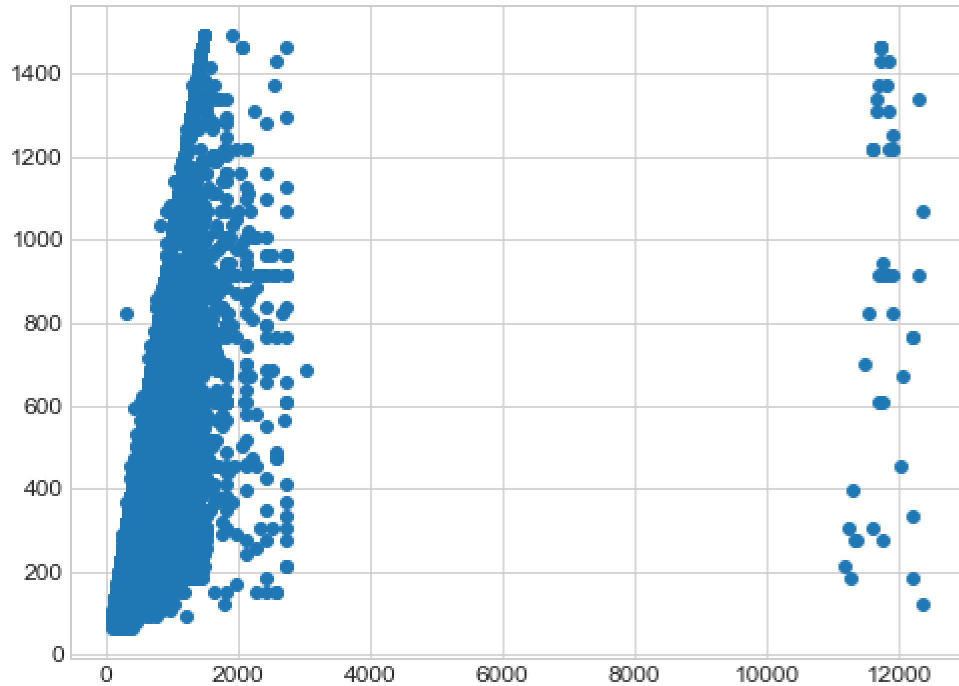


In [68]:
```
df.CIG.describe()
```

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
```

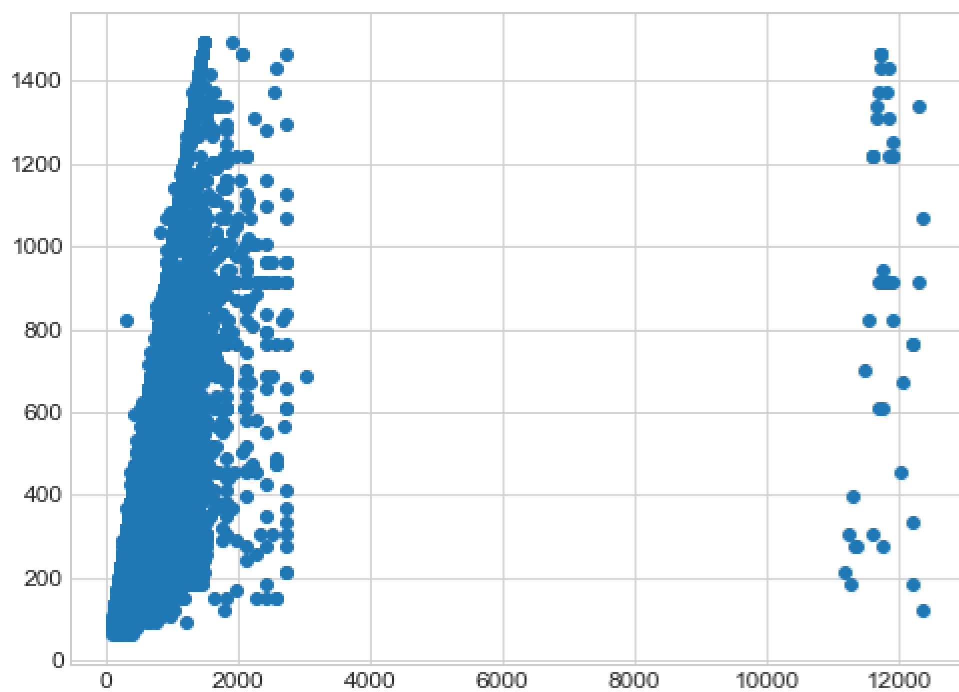
In [69]:
```
plt.scatter(df.CIG, df.CLDHT)
```

Out[69]: <matplotlib.collections.PathCollection at 0x7fc0758be5c0>



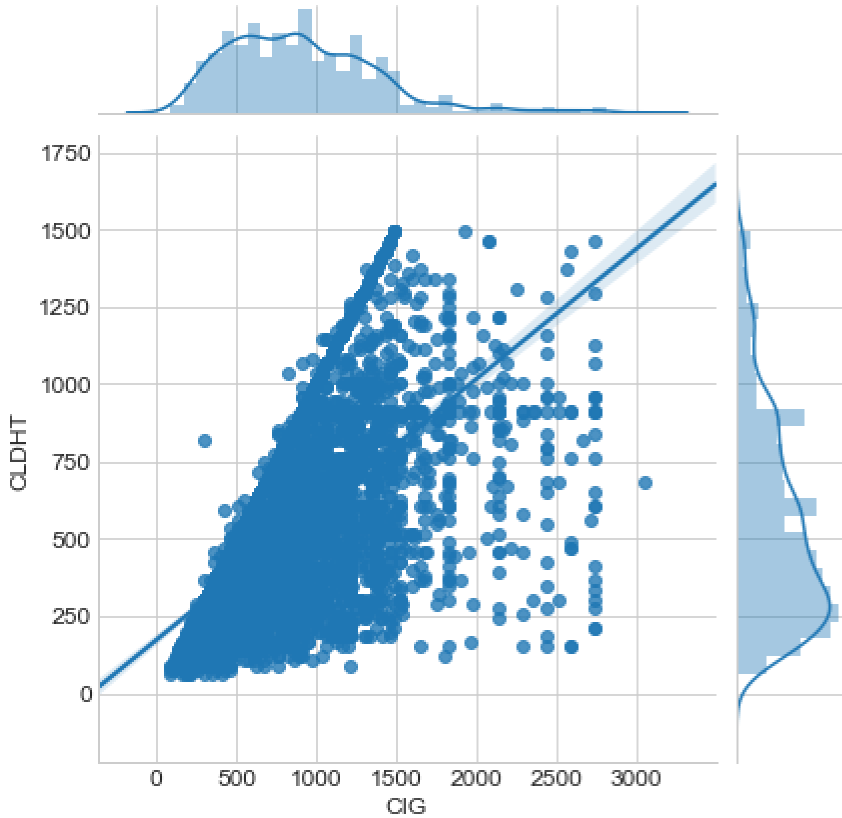
In [70]:
```
dft = df.query('CIG<=5000')
plt.scatter(df.CIG, df.CLDHT)
```

Out[70]: <matplotlib.collections.PathCollection at 0x7fc0758ac048>



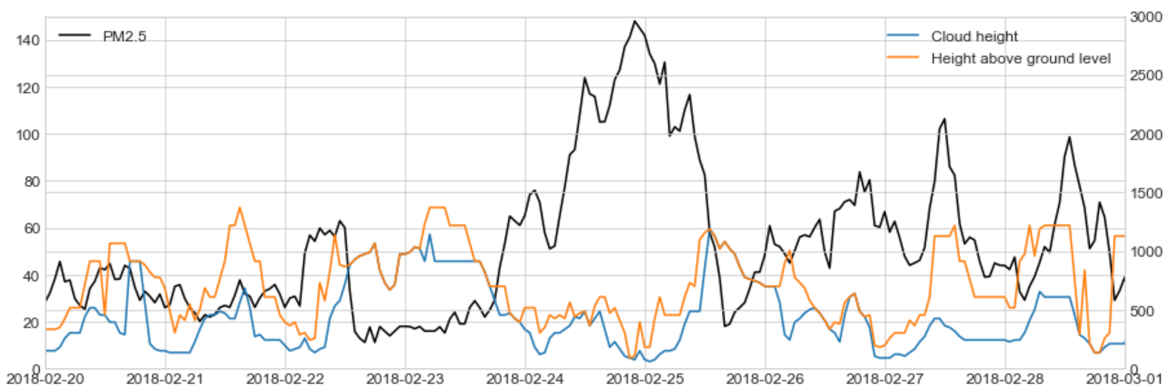
In [71]:
```
sns.jointplot(dft.CIG, dft.CLDHT, kind='reg')
```

Out[71]: <seaborn.axisgrid.JointGrid at 0x7fc07584b3c8>



In [72]:
```
# 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 0x7fc075b23d30>



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

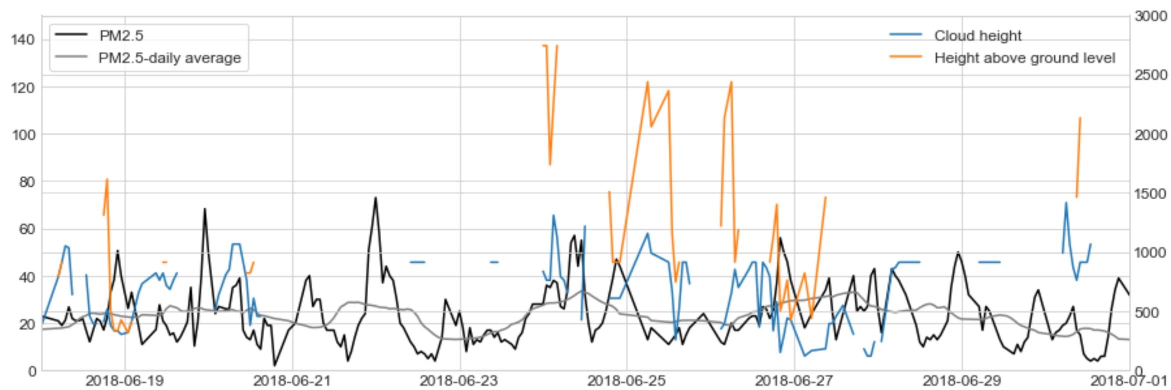
In [73]:
```
# let make a global check to see the whole dataset rather one capture
d moment
df.corr()['pm25'].filter(['CLDHT', 'CIG'])
```

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
))
```

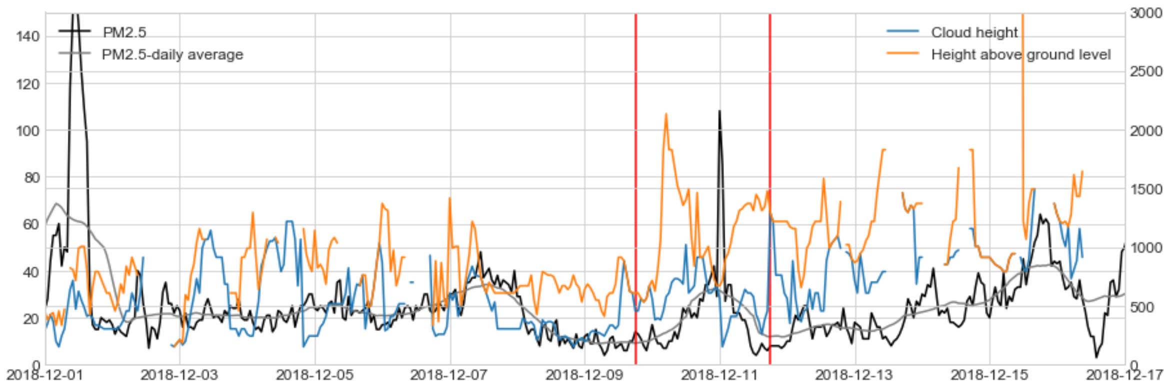
Out[74]:
```
(736863.0, 736876.0)
```



- 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 0x7fc075697860>



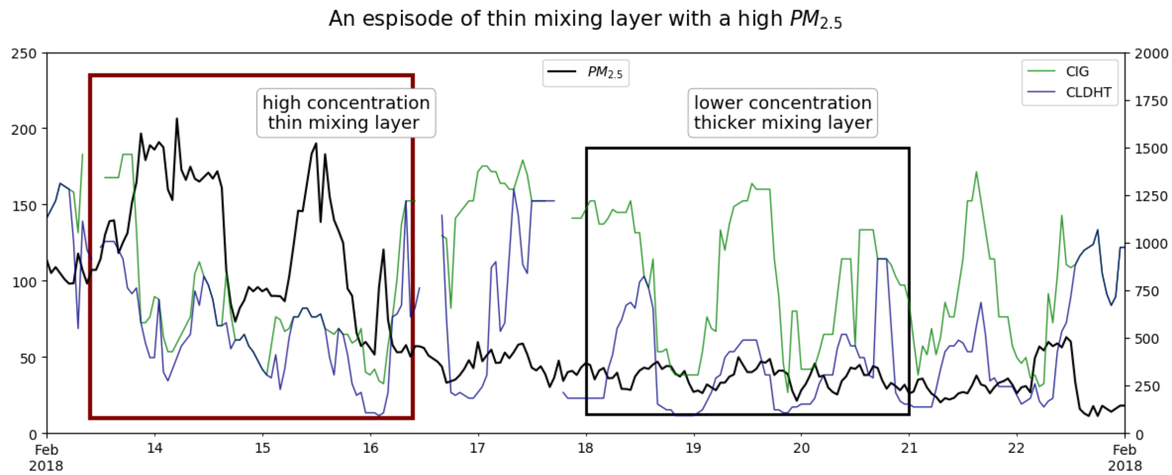
- in this window, another event that capture the inverse correlation of cloud height and $PM_{2.5}$ concentration

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(2018,2,23))
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, color='maroon', lw=3)
p.set_transform(ax.transAxes)
p1 = plt.Rectangle((0.5, .05), width=0.3, height=0.7, fill=False, color='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');
```

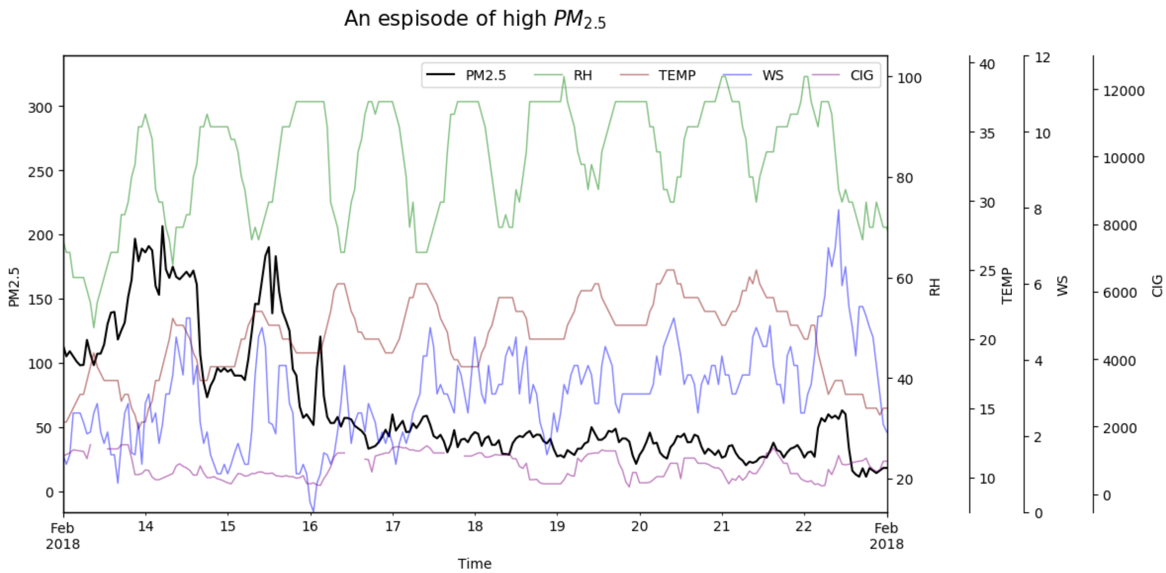


In [79]:

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

In [83]:
```python
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]:
```python
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]:
```python
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]:
```python
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]:
```python
pos = np.arange(len(data))
pos
```

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

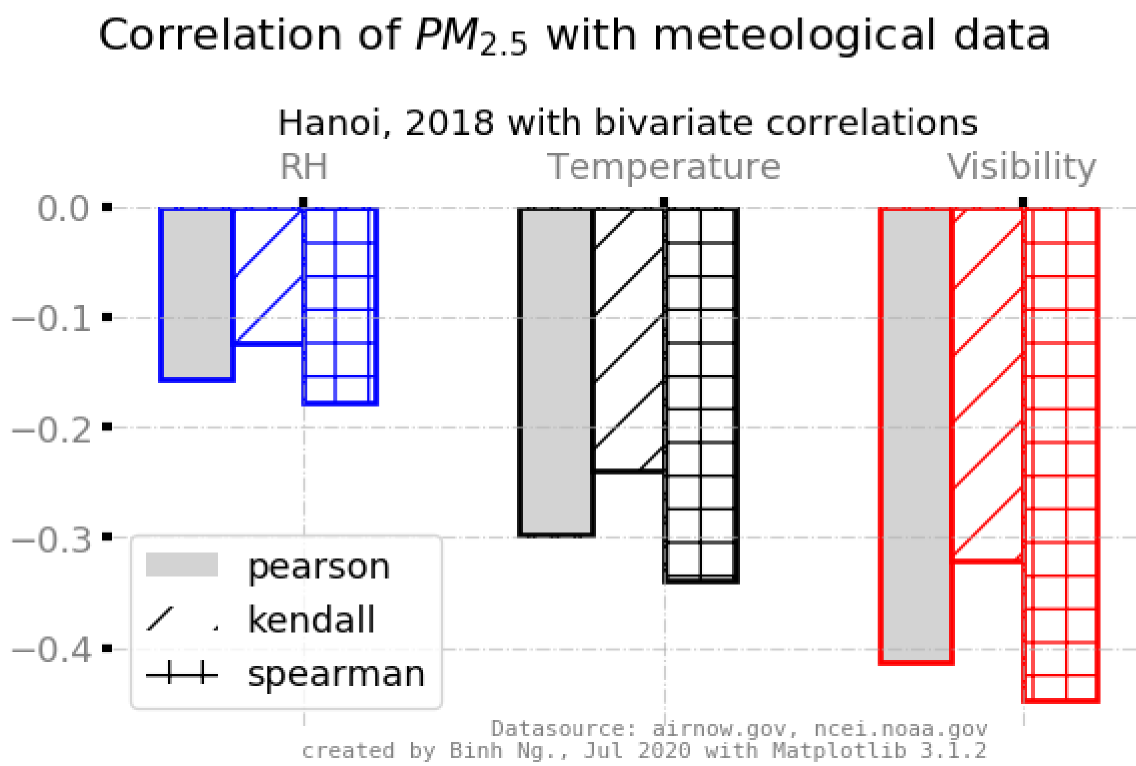
In [88]:
```python
plt.rcParams['hatch.color'] = 'black'
```

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

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

In [91]:

```
# 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')
```

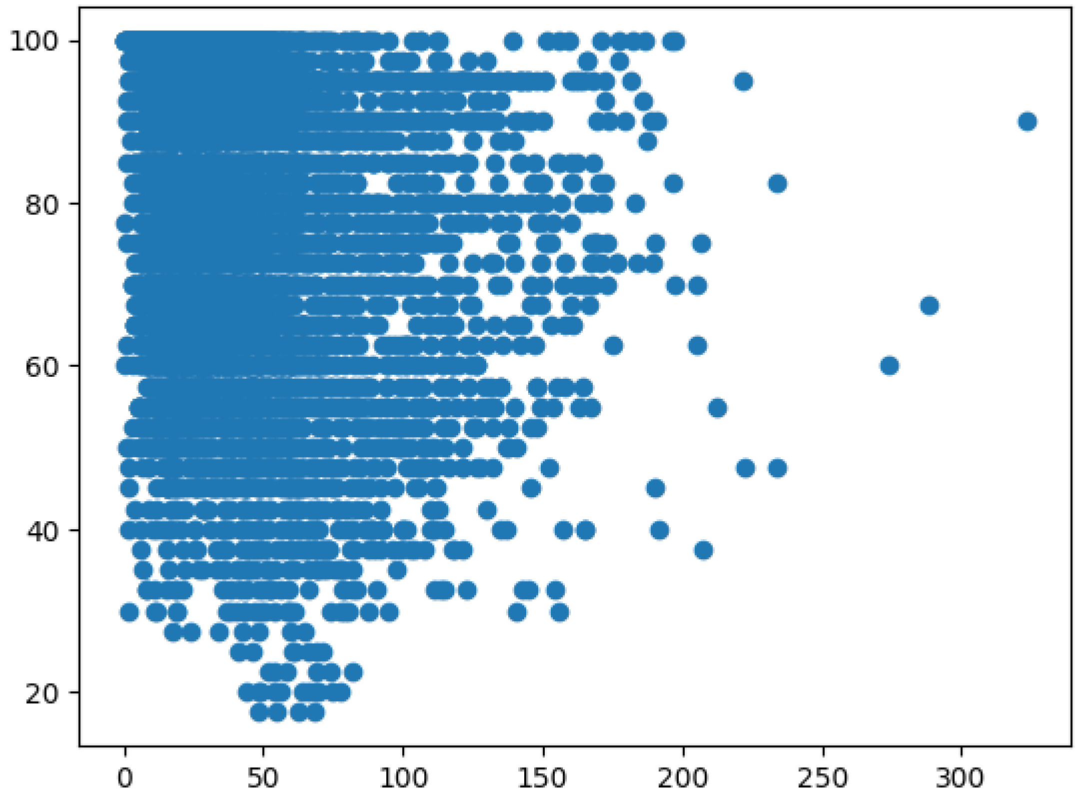


what we have here?

- 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

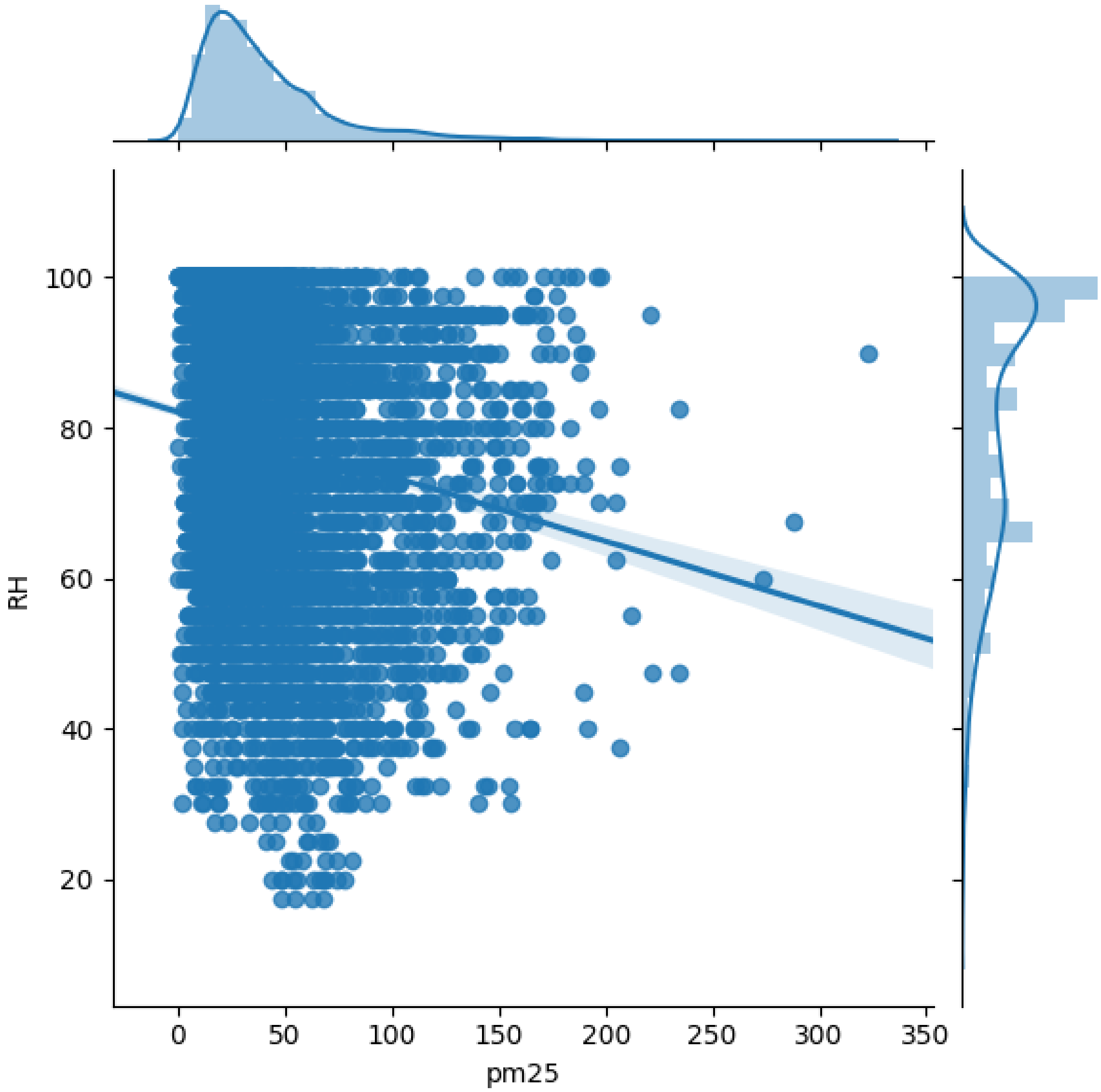
In [92]:
```
plt.scatter(df.pm25, df.RH)
```

Out[92]: <matplotlib.collections.PathCollection at 0x7fc07564e198>



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

Out[93]: <seaborn.axisgrid.JointGrid at 0x7fc0752d4ac8>



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
```

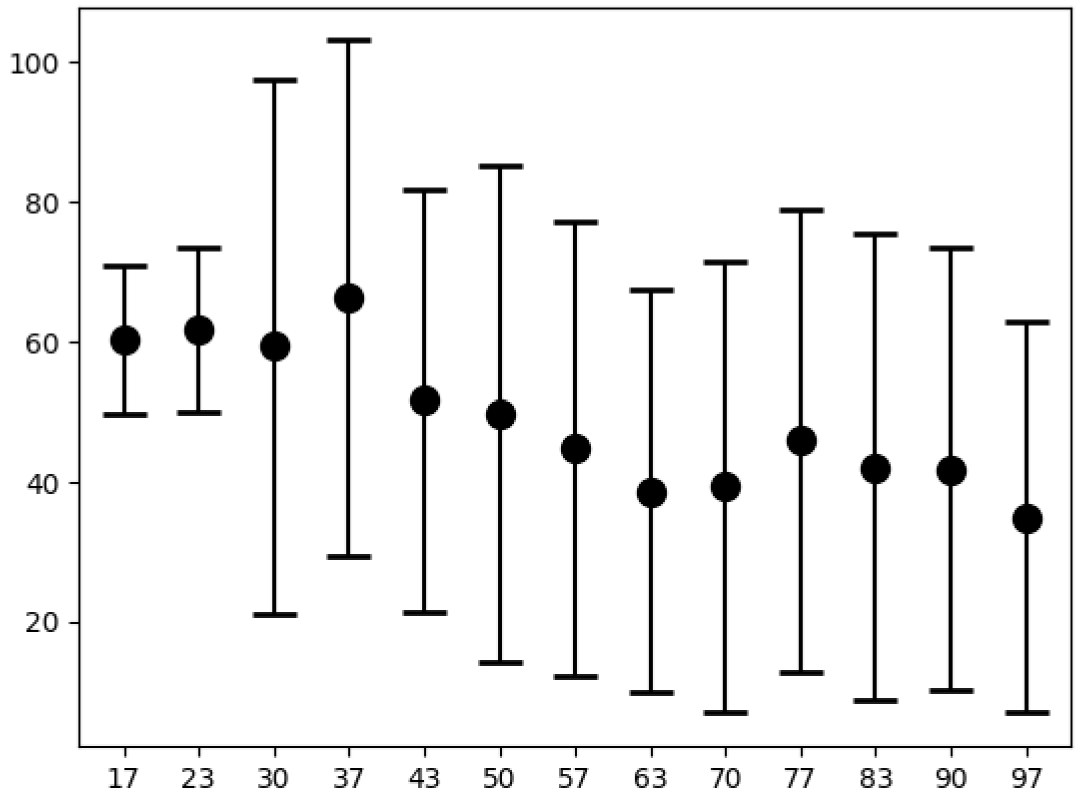
Out[95]:
```
['3',
 '10',
 '17',
 '23',
 '30',
 '37',
 '43',
 '50',
 '57',
 '63',
 '70',
 '77',
 '83',
 '90',
 '97']
```

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

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

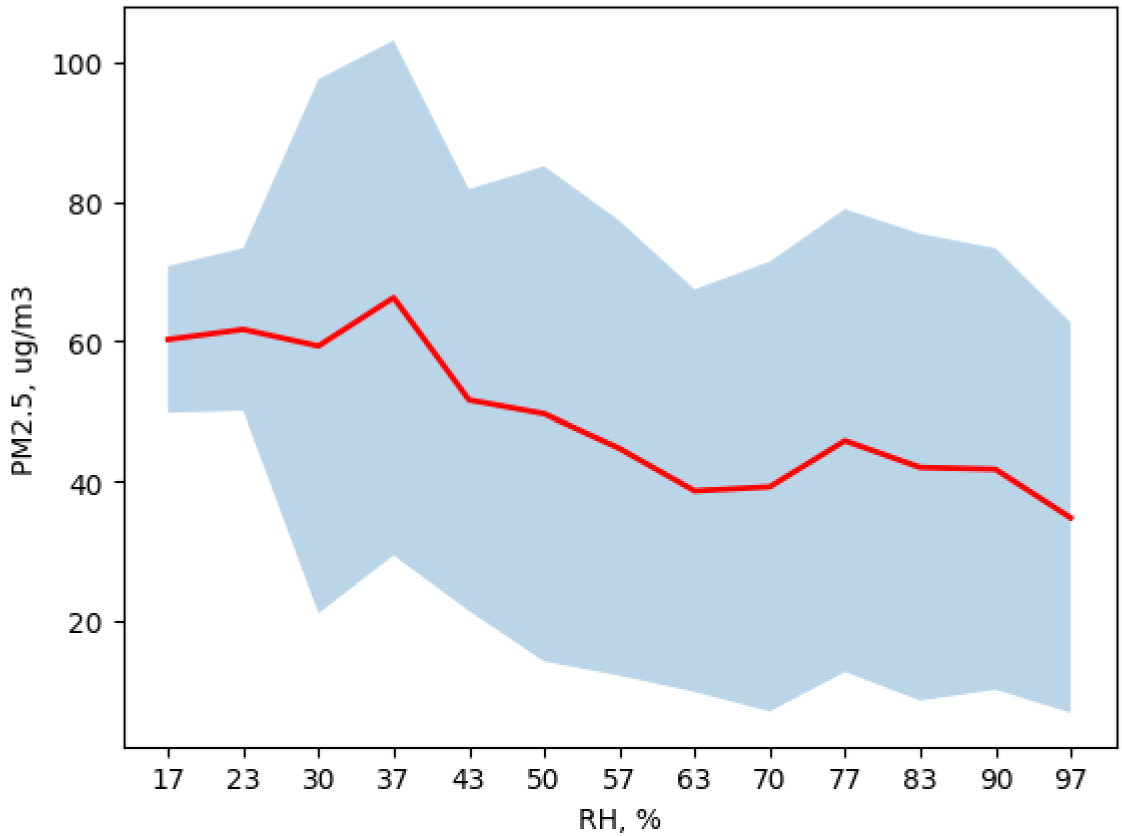
In [98]:
```
plt.errorbar(x=list(dfs.mean().index), y=dfs.mean().pm25, yerr=dfs.std().pm25,
             fmt='o', capsize=8, capthick=2, color='black',
             marker='o', markersize=10)
```

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.std().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
```

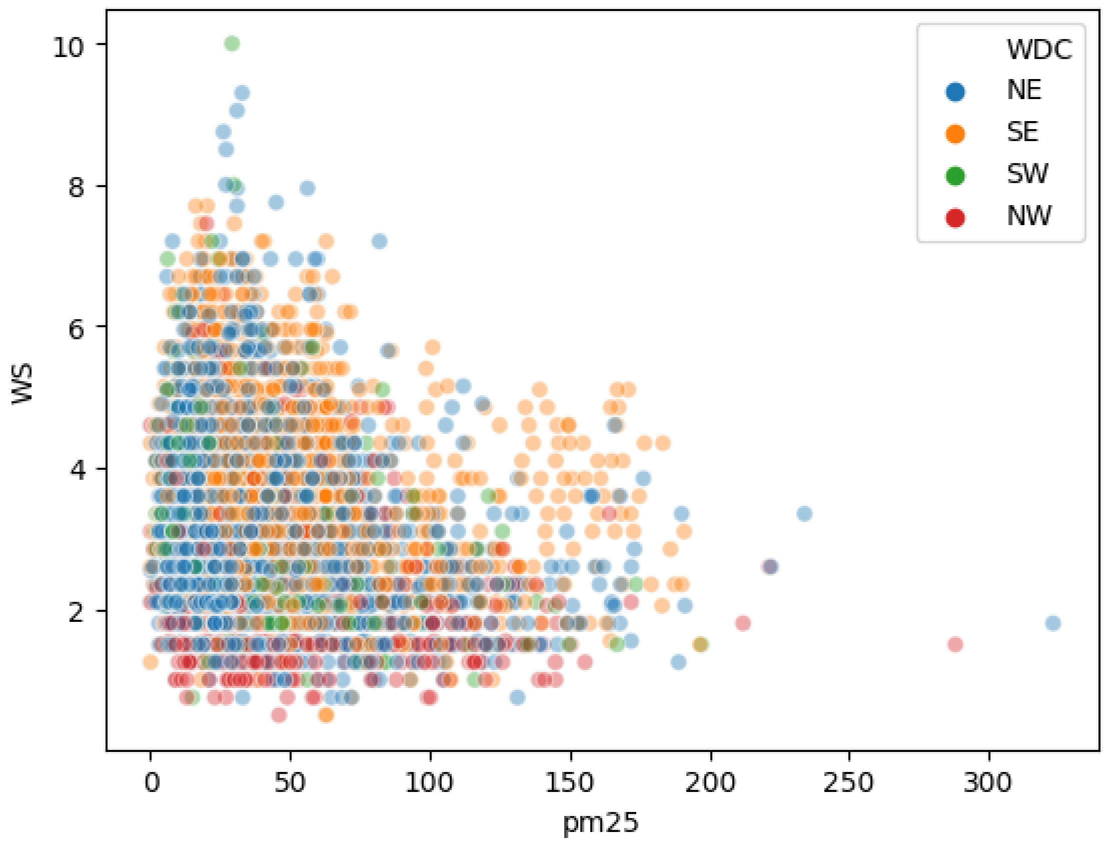
Out[100]: array([0., 90., 180., 270., 360.])

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

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

In [103]:
```
sns.scatterplot(data=df, x='pm25', y='WS', hue='WDC', alpha=0.4)
```

Out[103]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc0750a7eb8>
```



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
```

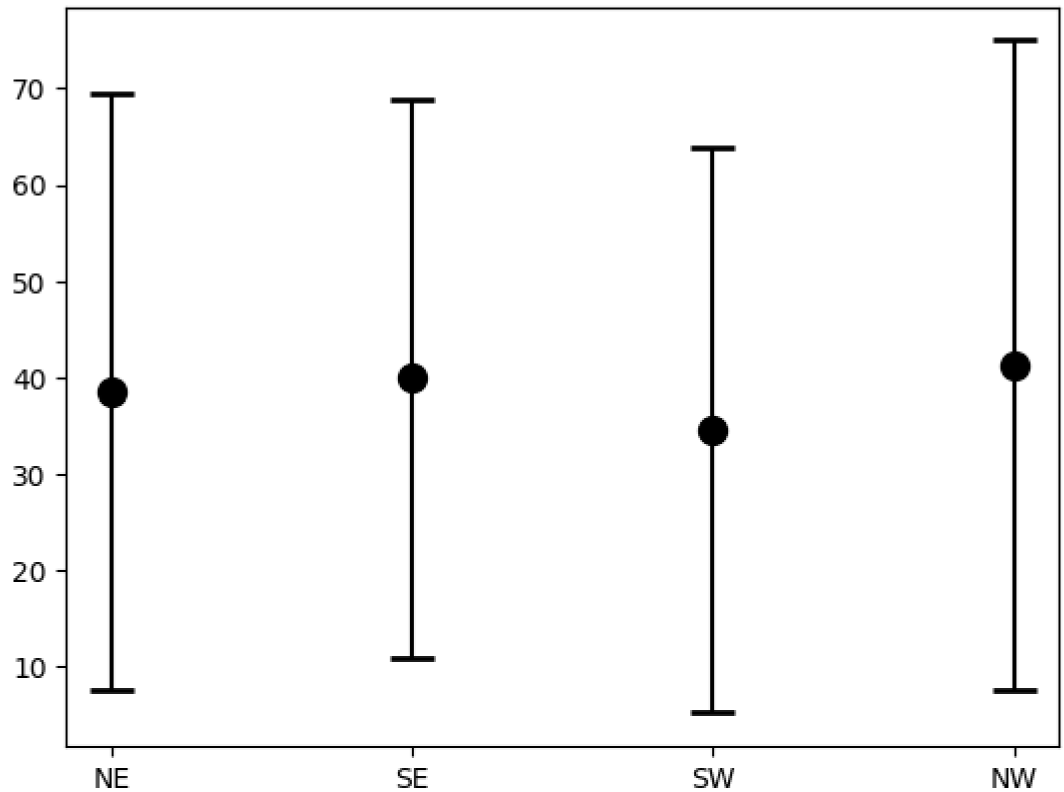
In [105]:
```
df.groupby('WDC').mean()['pm25']
```

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
```

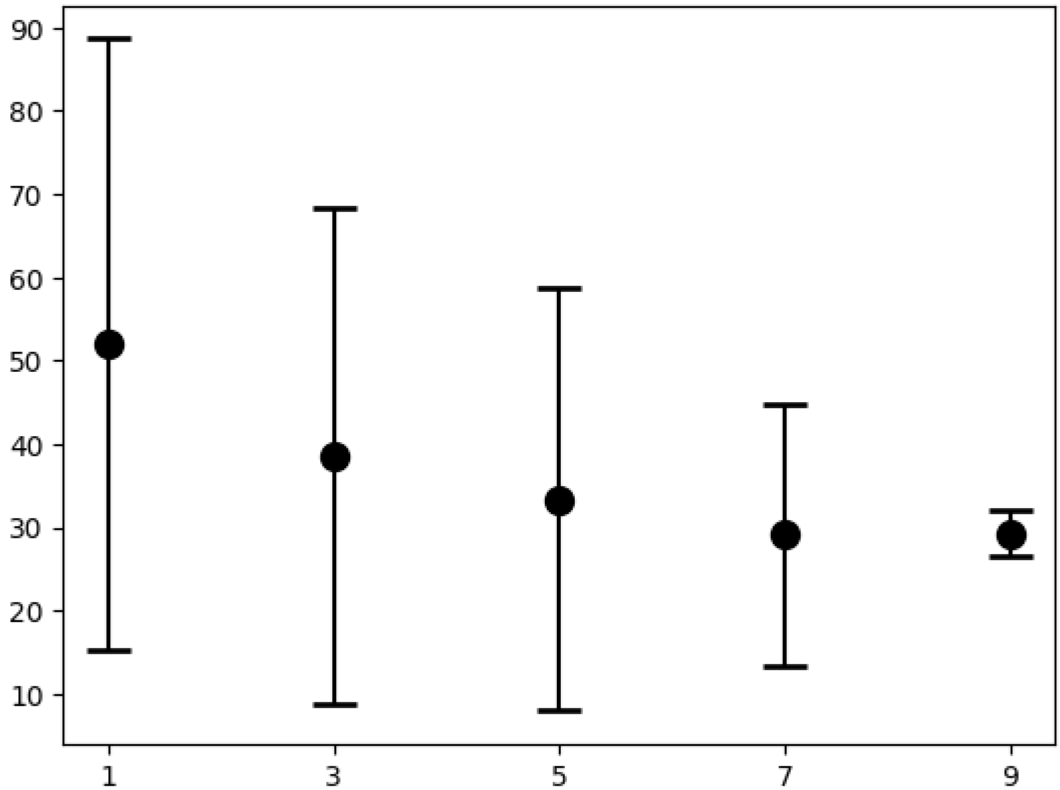
Out[109]: ['1', '3', '5', '7', '9', '11']

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

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

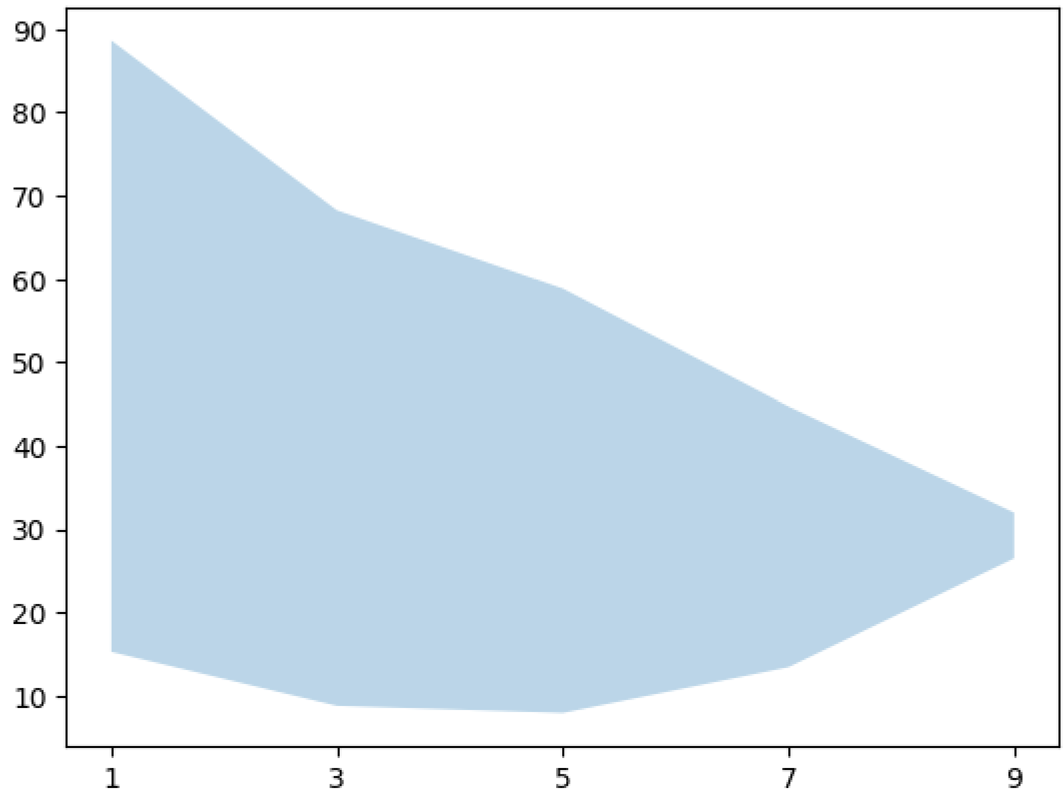
In [112]:
```
plt.errorbar(x=list(dfs.mean().index), y=dfs.mean().pm25, yerr=dfs.st
d().pm25,
             fmt='o', capsize=8, capthick=2, color='black',
             marker='o', markersize=10)
```

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



In [113]:
```
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[113]: <matplotlib.collections.PolyCollection at 0x7fc074ec0668>



In [114]:
```
speeds = np.linspace(0,12,13)
labels = [f'{(speeds[i] + speeds[i+1])/2:.1f}' for i in (range(len(sp
eeds)-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]:
```
df['WSC'] = pd.cut(df['WS'], bins=speeds, labels=labels).astype('cate
gory')
```

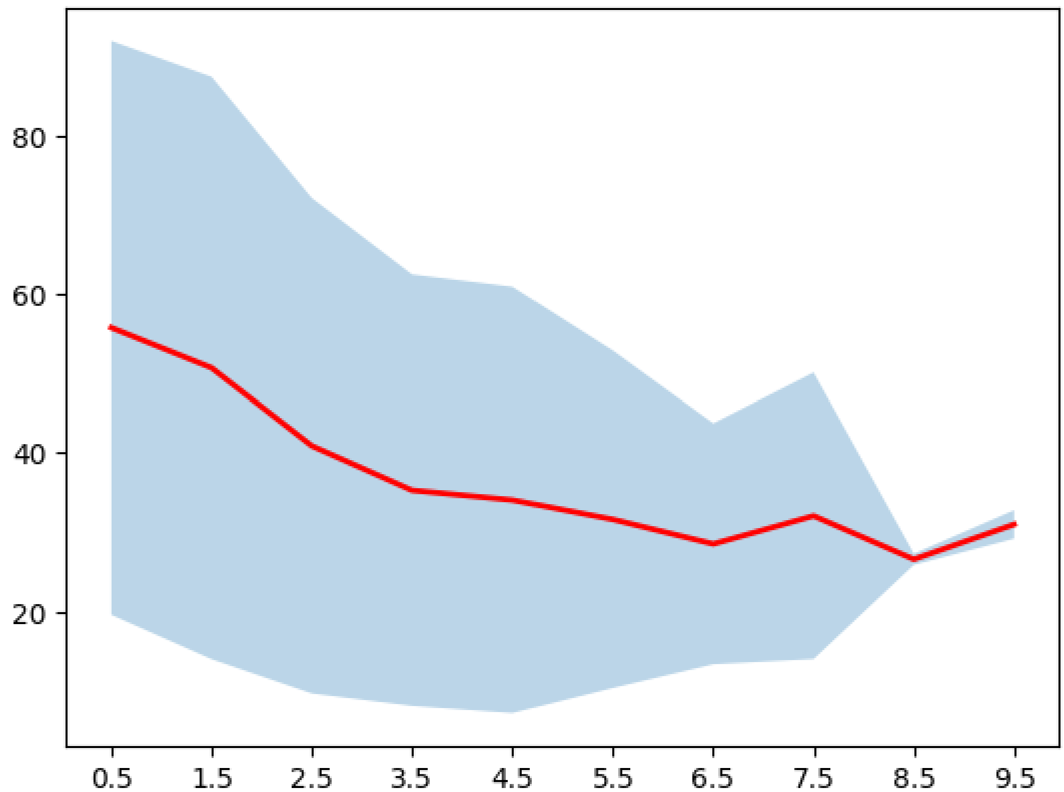
In [116]:
```
dfs = df.groupby('WSC')
```

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

Out[117]: -0.027791426871811013

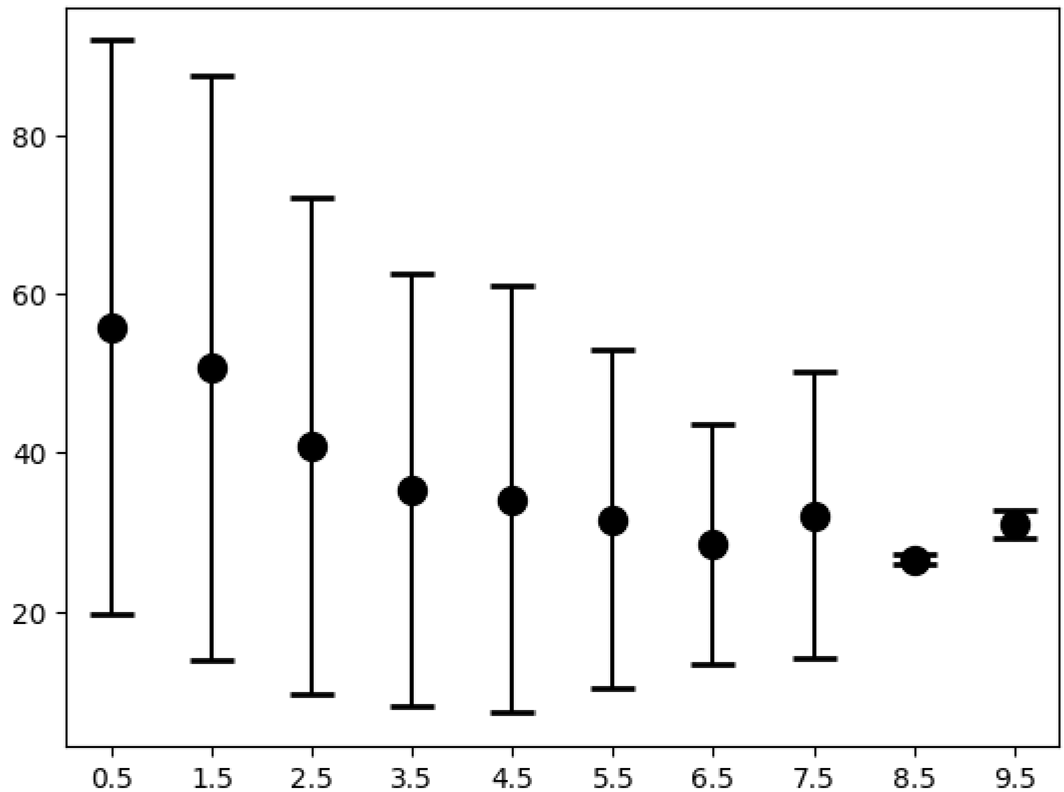
In [118]:
```
plt.plot(list(dfs.mean().index), dfs.mean().pm25, lw=2, color='r')
plt.fill_between(x=list(dfs.mean().index), y1=dfs.mean().pm25 - dfs.s
td().pm25 ,
                 y2=dfs.mean().pm25 + dfs.std().pm25, alpha=0.3)
```

Out[118]: <matplotlib.collections.PolyCollection at 0x7fc074ef6da0>



In [119]:
```python
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 [ ]:
```