1.我们先对数据进行预处理，增添星期信息，删去缺失值

In [ ]:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

In [ ]:

```
pm25_data = pd.read_csv('pm25_data.csv')

# 得到week
week_list=[]
for date in pm25_data['date']:
    week_list.append(pd.to_datetime(date).weekday())
pm25_data['week']=week_list

# 删除missing data
pm25_dropna=pm25_data.dropna(axis=0, how='any', inplace=False)
```

2.1用折线图记录每年一天24小时pm2.5的变化趋势，取每年每小时的平均浓度作为当年该小时的对应值

Variation of pm2.5 on time period of the day

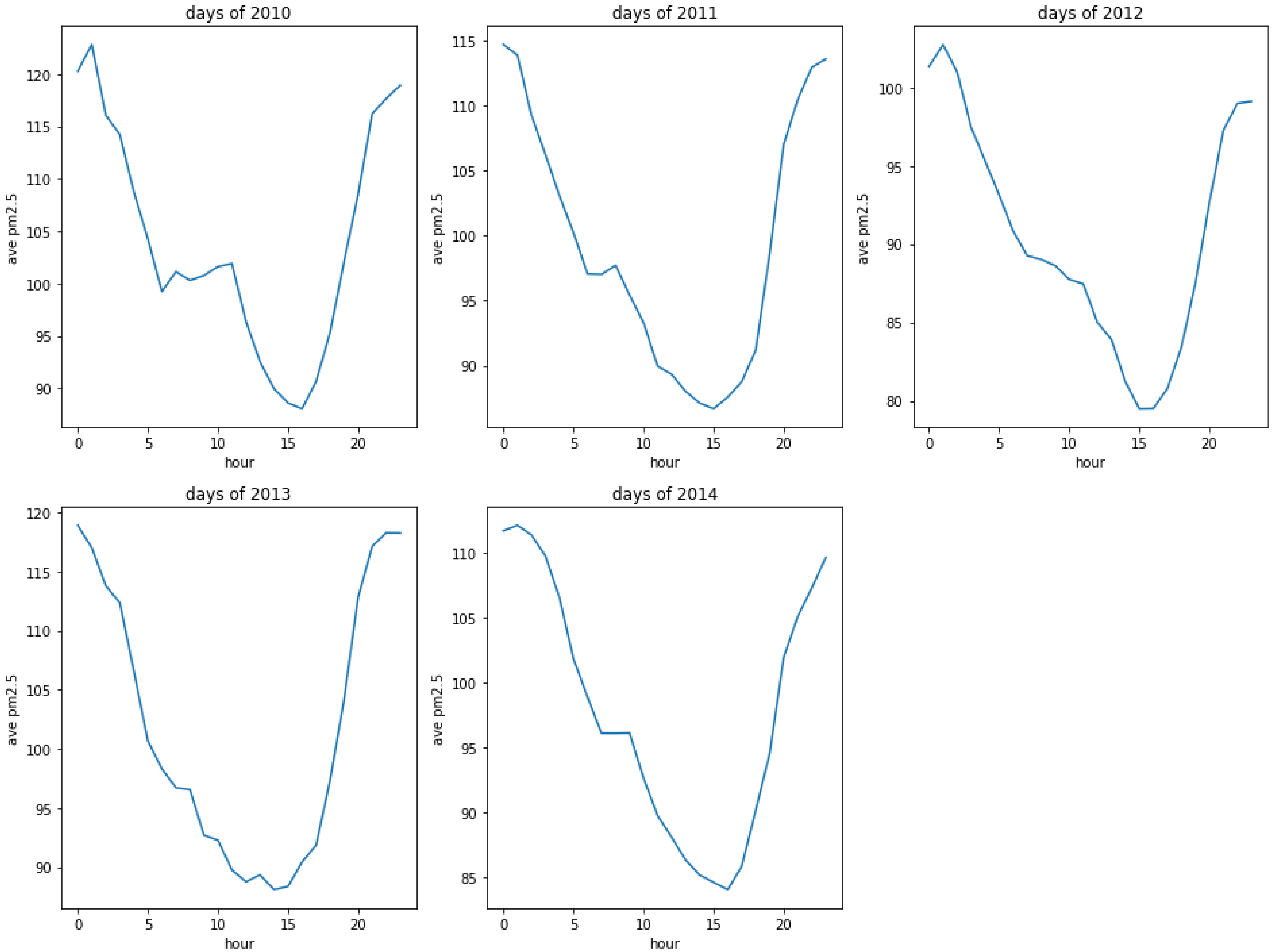
In [ ]:

```
Year=[2010,2011,2012,2013,2014]
Hour=range(24)
day_of_year=[[],[],[],[],[]]

variation_of_day=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_dropna[pm25_dropna.year==year]
    for hour in Hour:
        pm25_hour_year=pm25_year[pm25_year.hour==hour]
        mean=np.mean(pm25_hour_year['pm2.5'])
        day_of_year[index].append(mean)

variation_of_day=variation_of_day.append(day_of_year)
variation_of_day.index=Year
```

In [ ]:

```
plt.figure(figsize=(16,12))
```

```
for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour,variation_of_day.iloc[i,:])
    plt.title('days of %d' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_day
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17
2010	120.273529	122.829412	116.061947	114.226471	108.749263	104.267062	99.238806	101.139466	100.300595	100.769461	...	89.961194	88.598214	88.044379	90.654867
2011	114.679758	113.856287	109.252252	106.197605	103.056886	100.200599	97.050746	97.008955	97.703593	95.423881	...	87.109792	86.674556	87.573529	88.749263
2012	101.342029	102.751445	101.008671	97.469741	95.317003	93.146974	90.849275	89.273256	89.029070	88.638728	...	81.245665	79.498551	79.514451	80.786744
2013	118.903047	117.002755	113.783934	112.355372	106.573003	100.667590	98.305785	96.715470	96.545455	92.696133	...	88.086592	88.362117	90.426184	91.852778
2014	111.712291	112.127072	111.391667	109.753463	106.559557	101.814404	98.870166	96.077562	96.072022	96.096685	...	85.138504	84.570637	84.005650	85.801120

5 rows × 24 columns

从记录图中我们可以看出，这5年间pm2.5每天的变化趋势均相似，0点至15点浓度下降，15点至24点浓度上升

尽管国务院于2013年10月宣布，计划到2017年将京津冀地区的pm2.5浓度降至2012年水平的75%，平均浓度调至60μg m^-3， 但从图中可知2014年的变化趋势于2012年相似，平均最高浓度不降反升

2.2用折线图记录每年一周每天pm2.5的变化趋势，取每年每星期一天的平均浓度作为当年该天的对应值

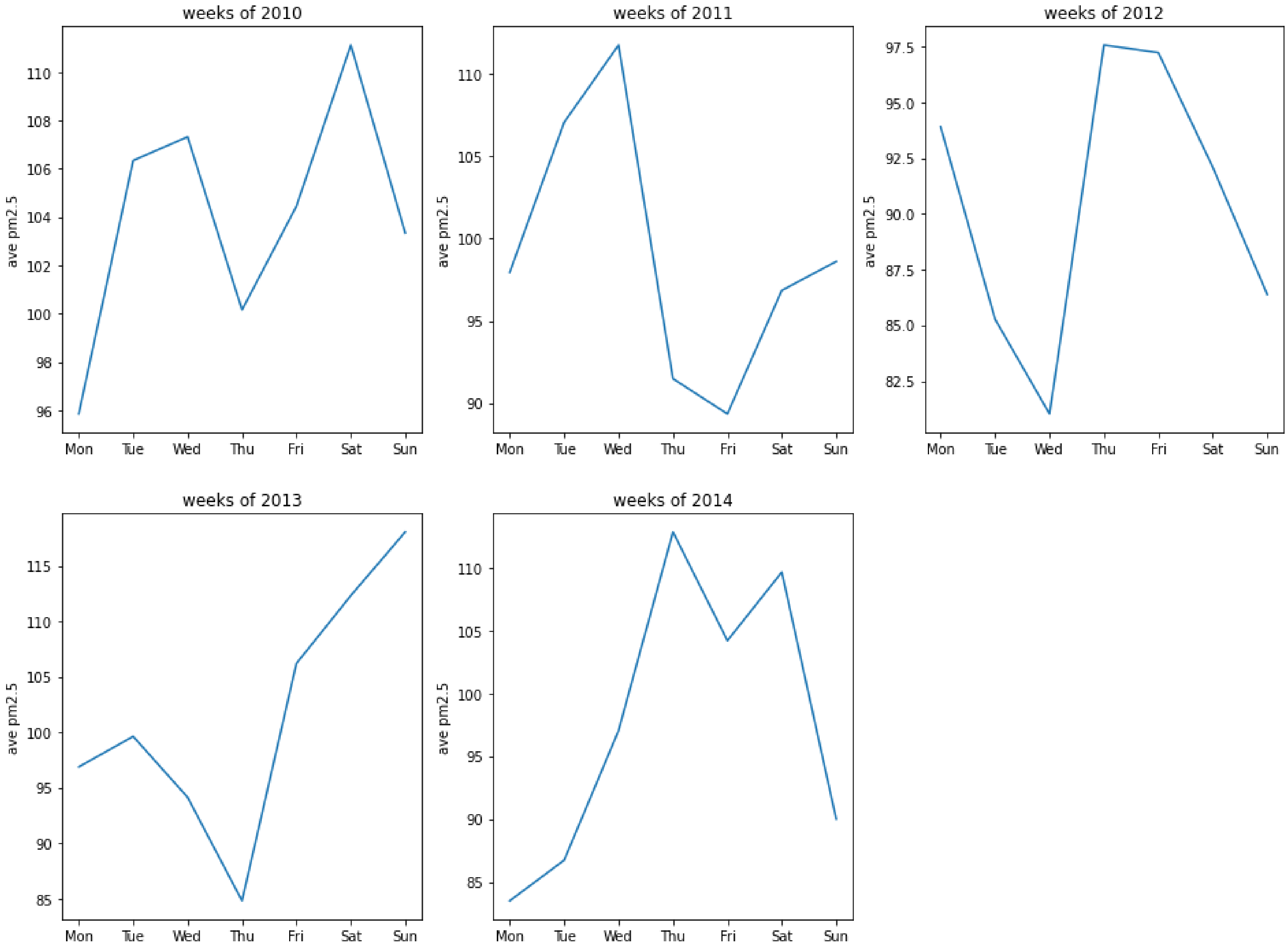
Variation of pm2.5 on time period of the week

In [ ]:

```
Week=range(7)
week_of_year=[[],[],[],[],[]]

variation_of_week=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_dropna[pm25_dropna.year==year]
    for week in Week:
        pm25_week_year=pm25_year[pm25_year.week==week]
        mean=np.mean(pm25_week_year['pm2.5'])
        week_of_year[index].append(mean)
variation_of_week=variation_of_week.append(week_of_year)
variation_of_week.index=Year
```

In [ ]:

```
plt.figure(figsize=(16,12))
Week_str=['Mon','Tue','Wed','Thu','Fri','Sat','Sun']

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Week_str,variation_of_week.iloc[i,:])
    plt.title('weeks of %d' % Year[i])
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_week
```

Out[ ]:

	0	1	2	3	4	5	6

	0	1	2	3	4	5	6
2010	95.857762	106.345912	107.325044	100.161371	104.451159	111.125977	103.341783
2011	97.950904	107.051546	111.747607	91.485765	89.352000	96.851045	98.602929
2012	93.893506	85.267123	81.026424	97.571311	97.229508	92.088407	86.384411
2013	96.876121	99.627482	94.140675	84.820016	106.195617	112.315534	118.053183
2014	83.505297	86.729642	97.050040	112.861985	104.207455	109.656123	90.003223

我们注意到每年每星期pm2.5平均浓度变化趋势完全不同

2.3用折线图记录每年每月pm2.5的变化趋势，取每年每月的平均浓度作为当年该月的对应值

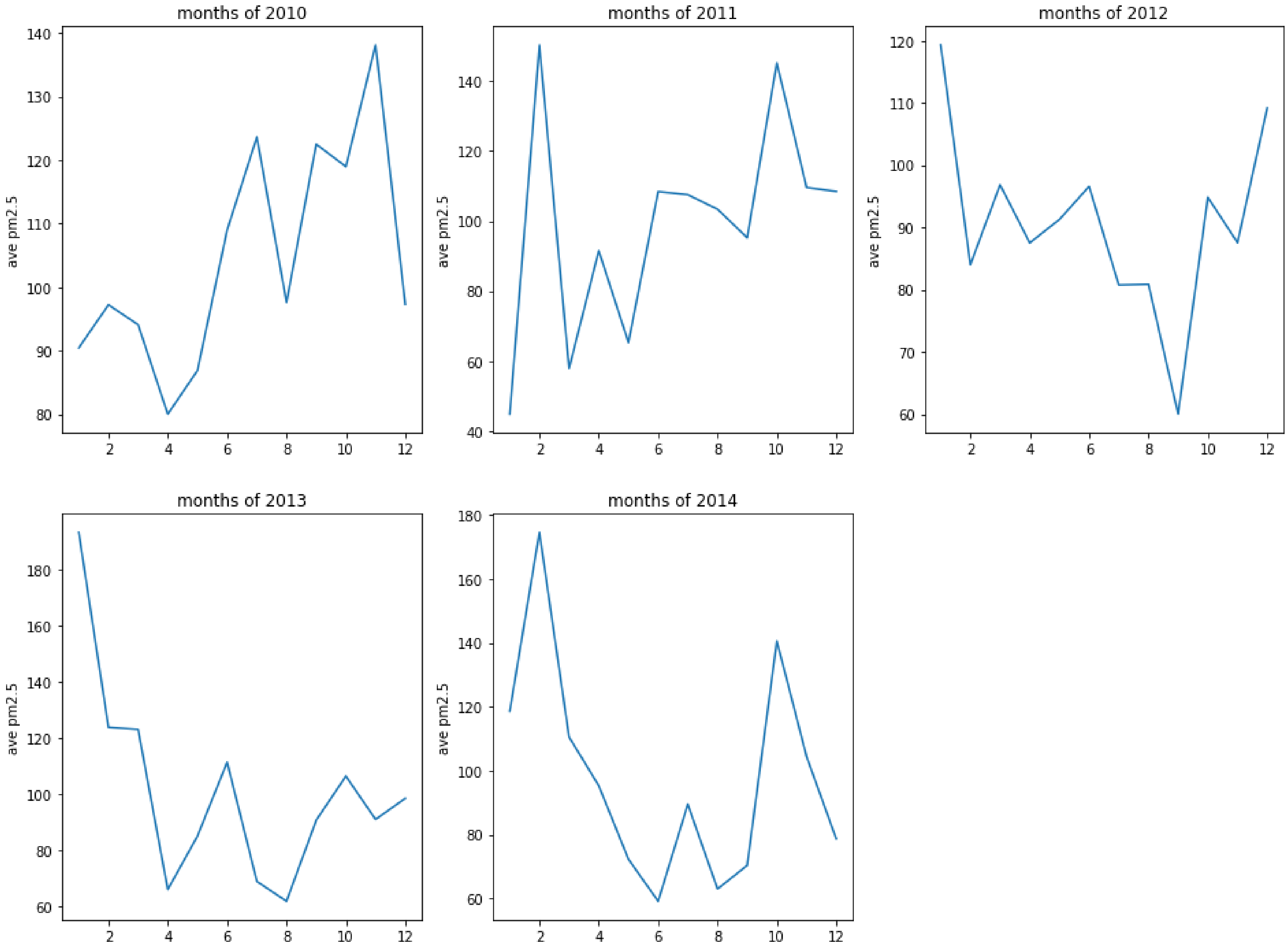
Variation of pm2.5 on time period of the month

In [ ]:

```
Month=range(1,13)
month_of_year=[[],[],[],[],[]]

variation_of_month=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_dropna[pm25_dropna.year==year]
    for month in Month:
        pm25_month_year=pm25_year[pm25_year.month==month]
        mean=np.mean(pm25_month_year['pm2.5'])
        month_of_year[index].append(mean)
variation_of_month=variation_of_month.append(month_of_year)
variation_of_month.index=Year
```

In [ ]:

```
plt.figure(figsize=(16,12))

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Month,variation_of_month.iloc[i,:])
    plt.title('months of %d' % Year[i])
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_month
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	10	11

	0	1	2	3	4	5	6	7	8	9	10	11
2010	90.442573	97.233979	94.100141	80.029248	86.899593	109.003540	123.647849	97.602071	122.510684	118.982480	138.120482	97.333333
2011	44.891369	150.321429	57.918400	91.585821	65.321629	108.466948	107.572200	103.424561	95.272601	145.225649	109.632168	108.519515
2012	119.310448	83.997101	96.856757	87.518776	91.280753	96.596045	80.748547	80.865169	60.001401	94.839189	87.555874	109.197068
2013	193.273342	123.801788	123.064953	66.113287	85.125172	111.416435	68.983718	61.907483	90.747559	106.448509	91.045961	98.511050
2014	118.557666	174.617339	110.485868	95.232915	72.254717	59.082504	89.455902	62.942701	70.293706	140.555855	104.378187	78.648045

我们注意到每年每月pm2.5平均浓度变化趋势不同，但从2011年后，基本从2月到10月浓度维持在相对较低水平，而其余月份基本维持在相对较高水平，可能与冬季居民供暖有关

京津冀居民供暖一般从11月15日开始，至3月15日结束

2.4用折线图记录每年四季pm2.5的变化趋势，取每年每个季度的平均浓度作为当年该季度的对应值

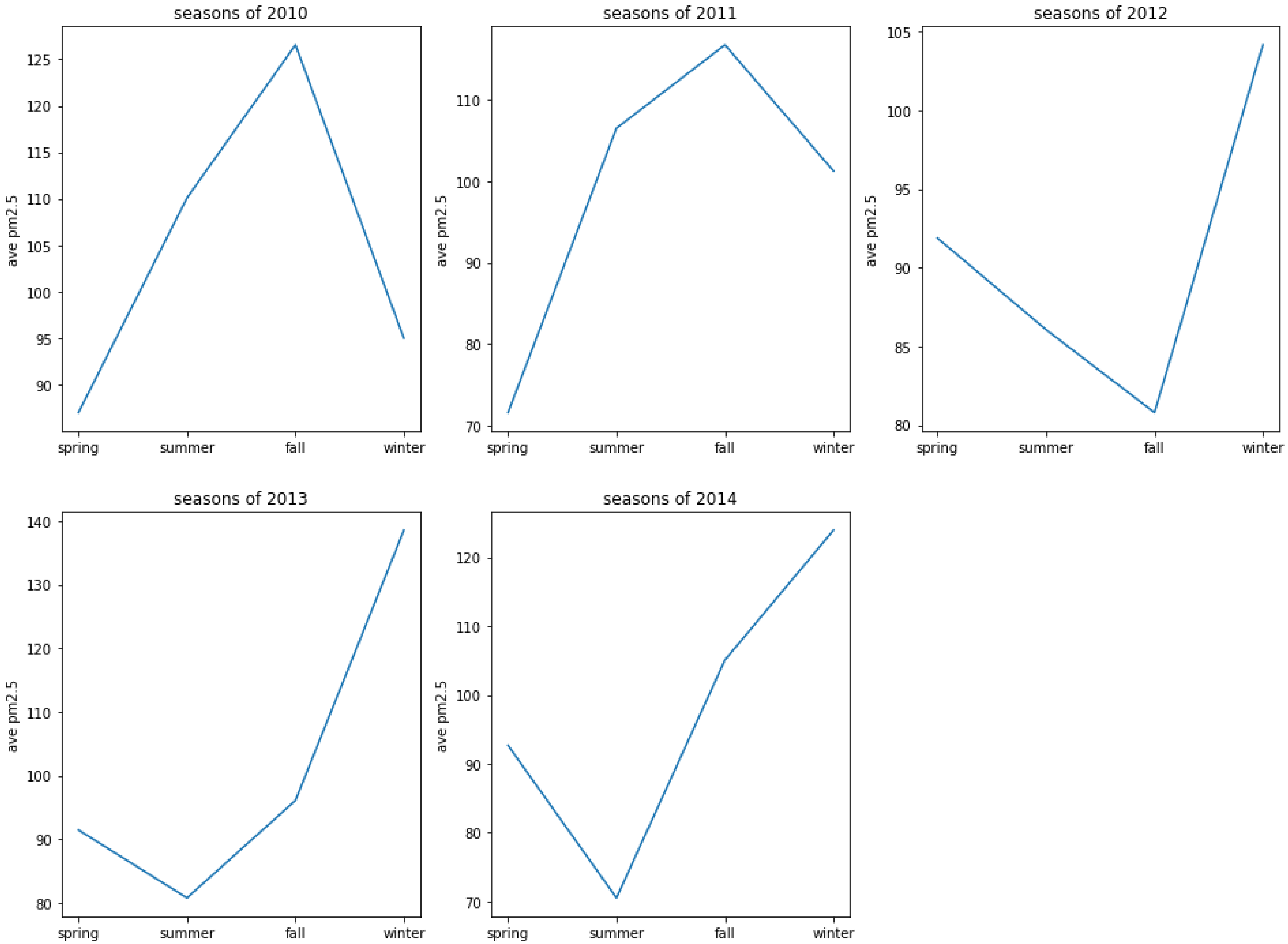
我们认为春季对应2、3、4月，夏季对应5、6、7月， 秋季对应8、9、10月， 冬季对应11、12、1月

Variation of pm2.5 on time period of the season

In [ ]:

```
season_of_year=[[],[],[],[],[]]

variation_of_season=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_dropna[pm25_dropna.year==year]
    mean_spring=(variation_of_month.loc[year,2]+variation_of_month.loc[year,3]+variation_of_month.loc[year,4])/3
    mean_summer=(variation_of_month.loc[year,5]+variation_of_month.loc[year,6]+variation_of_month.loc[year,7])/3
    mean_fall=(variation_of_month.loc[year,8]+variation_of_month.loc[year,9]+variation_of_month.loc[year,10])/3
    mean_winter=(variation_of_month.loc[year,11]+variation_of_month.loc[year,0]+variation_of_month.loc[year,1])/3
    season_of_year[index].append(mean_spring)
    season_of_year[index].append(mean_summer)
    season_of_year[index].append(mean_fall)
    season_of_year[index].append(mean_winter)
variation_of_season=variation_of_season.append(season_of_year)
variation_of_season.index=Year
```

In [ ]:
```
plt.figure(figsize=(16,12))
Seasons=['spring','summer','fall','winter']

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Seasons,variation_of_season.iloc[i,:])
    plt.title('seasons of %d' % Year[i])
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_season
```

Out[ ]:

	0	1	2	3

	0	1	2	3
2010	87.009661	110.084487	126.537882	95.003295
2011	71.608617	106.487903	116.710139	101.244104
2012	91.885428	86.069920	80.798821	104.168206
2013	91.434470	80.769212	96.080677	138.528727
2014	92.657833	70.493702	105.075916	123.941017

我们注意到2010年和2011年，秋季达到平均浓度最高值，浓度从春夏秋上升，秋冬下降

2012、2013、2014年夏季平均浓度最低，夏秋冬三季依次上升，浓度在冬季最高，之后下降

2.5用折线图记录每年pm2.5的变化趋势，取每年平均浓度作为当年的对应值

Variation of pm2.5 on time period of years

In [ ]:

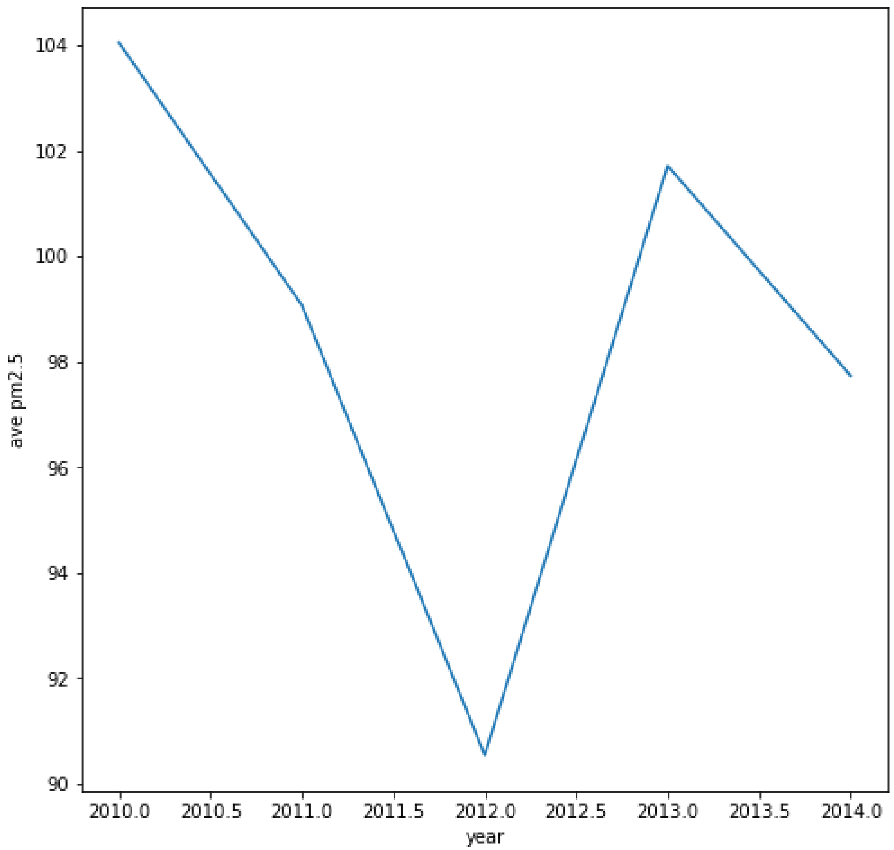
```
varaition_of_year=[]
for year in Year:
    pm25_year=pm25_dropna[pm25_dropna.year==year]
    mean=np.mean(pm25_year['pm2.5'])
    varaition_of_year.append(mean)
```

In [ ]:

```
plt.figure(figsize=(8,8))
plt.plot(Year,varaition_of_year)
plt.xlabel('year')
plt.ylabel('ave pm2.5')
```

Out[ ]:

```
Text(0, 0.5, 'ave pm2.5')
```



In [ ]:
```
varaition_of_year
```

Out[ ]:
```
[104.04572982326042,
 99.07133964143426,
 90.5458710066305,
 101.71237612353077,
 97.73455721048377]
```

我们注意到这五年间2012年平均浓度最低， 2010至2012年连续下降，2013年达到较高水平后2014年再次下降至2011年水平

3 利用上述与时间有关的pm2.5平均浓度信息，分别使用每条数据的时间信息和天气信息，运用task1中提出的xgboost模型、训练集和测试集，实现对pm2.5浓度的预测，同时使用score作为预测结果好坏的测量标准，认为越接近1预测效果越好

Prediction

3.1 仿照task1设置相同的训练集与测试集，删去浓度为0的数据后，对浓度进行对数转换

In [ ]:

```
# test data date
test_date=pd.date_range(start='2010-01-07',freq='W-Thu',end='2014-12-25').strftime('%Y-%m-%d').tolist()

# test data index
test_index=[]
for i in range(len(pm25_dropna['date'])):
    if pm25_dropna.iloc[i,-2] in test_date:
        test_index.append(i)
```

In [ ]:

```
# delete 0
pm25_dropna = pm25_dropna.drop(pm25_dropna[pm25_dropna['pm2.5'] == 0].index)
# 检查对数转换后样本分布情况
pm25_dropna['pm2.5_log'] = np.log(pm25_dropna['pm2.5'])
# test and train data
test_data=pm25_dropna.iloc[test_index,:].reset_index(drop=True)
train_data=pm25_dropna.drop(index=pm25_dropna.index[test_index]).reset_index(drop=True)
```

3.2 分别使用每年一天24小时数据的时间信息和天气信息，对每小时pm2.5平均浓度进行预测，将两种方法下每年每小时的预测score用折线图分别绘出

Predict pm2.5 on time period of the day by xgboost

In [ ]:

```
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error
from sklearn import preprocessing
```

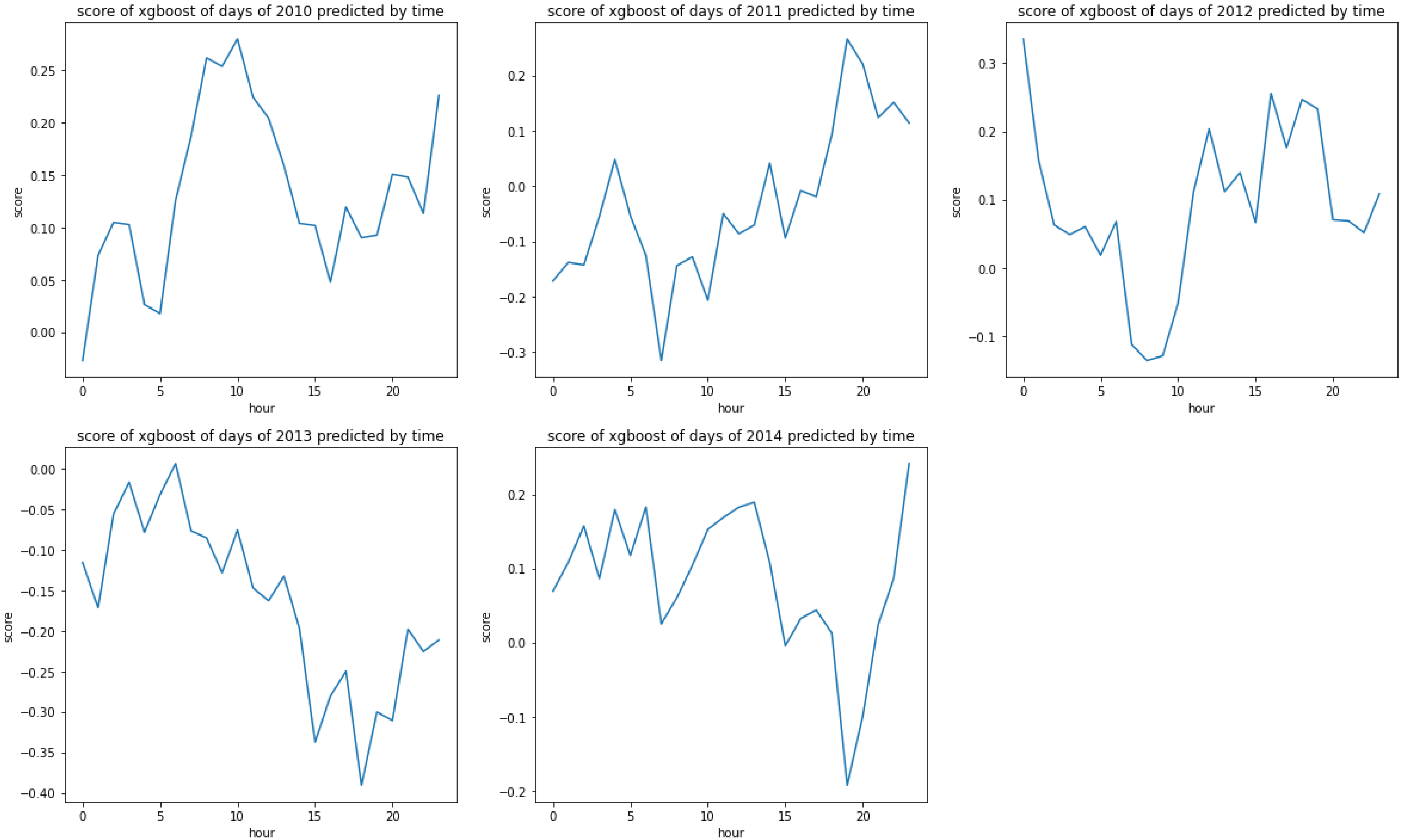
In [ ]:

```
Year=[2010,2011,2012,2013,2014]
Hour=range(24)
day_of_year_train=[[],[],[],[],[]]
day_of_year_test=[[],[],[],[],[]]
score_of_year_time = [[],[],[],[],[]]
score_of_year_weather = [[],[],[],[],[]]
var_time = ['year', 'month', 'day', 'hour', 'week']
var_weather = ['DEWP', 'TEMP', 'PRES', 'Iws', 'Is', 'Ir', 'cbwd_NE', 'cbwd_NW', 'cbwd_SE', 'cbwd_cv']
```

```
variation_of_day_time=pd.DataFrame()
variation_of_day_weather=pd.DataFrame()
for index, year in enumerate(Year):
    train_data_year=train_data[train_data.year==year]
    test_data_year=test_data[test_data.year==year]
    for hour in Hour:
        train_data_hour_year=train_data_year[train_data_year.hour==hour]
        test_data_hour_year=test_data_year[test_data_year.hour==hour]

        ## Only use time to predict
        X_train_data_hour_year_time = train_data_hour_year[var_time]
        X_test_data_hour_year_time = test_data_hour_year[var_time]
        y_train_data_hour_year = train_data_hour_year['pm2.5_log']
        y_test_data_hour_year = test_data_hour_year['pm2.5']
        XGB_model_time=XGBRegressor(learning_rate=0.03,n_estimators=300,max_depth=5)
        XGB_model_time.fit(X_train_data_hour_year_time, y_train_data_hour_year)

        y_pred_hour_year_time = XGB_model_time.predict(X_test_data_hour_year_time)
        y_pred_hour_year_time = np.round(np.exp(y_pred_hour_year_time))
        y_pred_hour_year_time = preprocessing.minmax_scale(y_pred_hour_year_time)
        y_test_data_hour_year = preprocessing.minmax_scale(y_test_data_hour_year)
        score_of_year_time[index].append(XGB_model_time.score(X_test_data_hour_year_time,test_data_hour_year['pm2.5_log']))

        ## Only use weather to predict
        X_train_data_hour_year_weather = train_data_hour_year[var_weather]
        X_test_data_hour_year_weather = test_data_hour_year[var_weather]
        XGB_model_weather = XGBRegressor(learning_rate=0.03,n_estimators=300,max_depth=5)
        XGB_model_weather.fit(X_train_data_hour_year_weather, y_train_data_hour_year)

        y_pred_hour_year_weather = XGB_model_weather.predict(X_test_data_hour_year_weather)
        y_pred_hour_year_weather = np.round(np.exp(y_pred_hour_year_weather))
        y_pred_hour_year_weather = preprocessing.minmax_scale(y_pred_hour_year_weather)
        y_test_data_hour_year = preprocessing.minmax_scale(y_test_data_hour_year)
        score_of_year_weather[index].append(XGB_model_weather.score(X_test_data_hour_year_weather,test_data_hour_year['pm2.5_log']))
```

In [ ]:

```
variation_of_day_time=variation_of_day_time.append(score_of_year_time)
variation_of_day_weather=variation_of_day_weather.append(score_of_year_weather)
plt.figure(figsize=(20,12))

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour,variation_of_day_time.iloc[i,:])
    plt.title('score of xgboost of days of %d predicted by time' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('score')
```



In [ ]:

```
variation_of_day_time
```

Out[ ]:

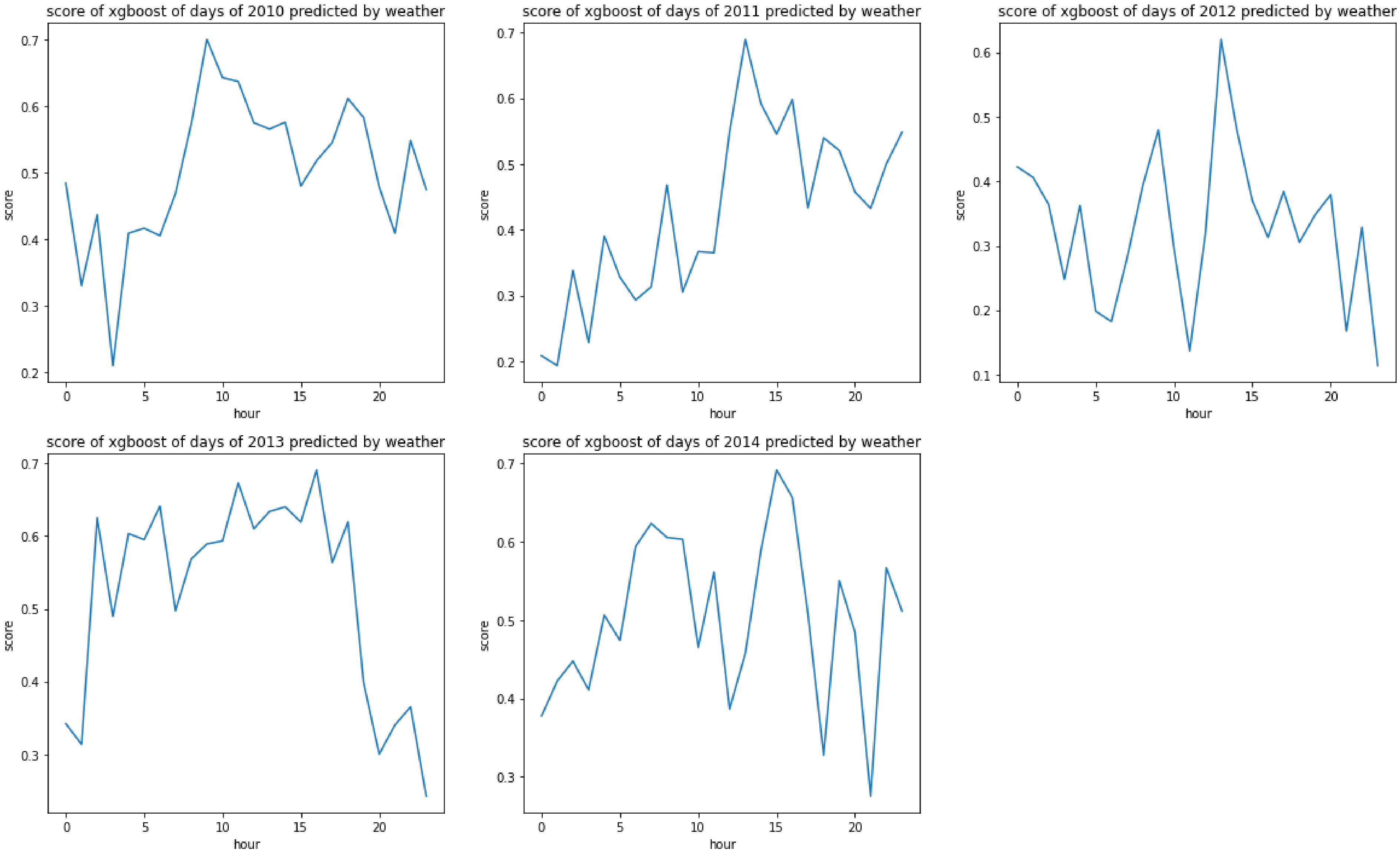
	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	
0	-0.027030	0.073248	0.104819	0.102602	0.026311	0.017868	0.125726	0.186676	0.261507	0.253381	...	0.103834	0.101733	0.047934	0.119219	0.090183	0.092
1	-0.171087	-0.137582	-0.142253	-0.054530	0.048059	-0.053146	-0.125221	-0.315144	-0.143494	-0.127715	...	0.041631	-0.093565	-0.007764	-0.018977	0.092624	0.266

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	
2	0.335730	0.157422	0.063193	0.049043	0.060586	0.018721	0.068088	-0.112097	-0.135828	-0.128844	...	0.139553	0.066662	0.255837	0.176417	0.246867	0.233
3	-0.115433	-0.171291	-0.055168	-0.016001	-0.077835	-0.031252	0.006960	-0.076091	-0.084841	-0.128165	...	-0.197040	-0.337688	-0.280594	-0.249702	-0.390879	-0.300
4	0.069574	0.108418	0.157552	0.086476	0.179506	0.117684	0.182852	0.025302	0.060526	0.104129	...	0.107946	-0.004091	0.032569	0.043899	0.012966	-0.192

5 rows × 24 columns

In [ ]:

```
plt.figure(figsize=(20,12))

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour,variation_of_day_weather.iloc[i,:])
    plt.title('score of xgboost of days of %d predicted by weather' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('score')
```



In [ ]:

```
variation_of_day_weather
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	19	20
0	0.484175	0.330778	0.436921	0.210669	0.409236	0.416625	0.405500	0.468941	0.572670	0.699811	...	0.575659	0.479859	0.517847	0.545219	0.611131	0.582763	0.478728
1	0.208643	0.193898	0.338353	0.228790	0.390699	0.328249	0.293324	0.313548	0.468043	0.305480	...	0.591662	0.545510	0.597882	0.433693	0.539858	0.520465	0.457563

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	19	20
2	0.422473	0.406344	0.364214	0.247945	0.362415	0.198508	0.182325	0.280484	0.392758	0.479930	...	0.481200	0.369709	0.312866	0.384467	0.305364	0.347888	0.379447
3	0.342210	0.313514	0.625048	0.489605	0.603393	0.594982	0.641107	0.497282	0.568440	0.588988	...	0.640180	0.619117	0.690863	0.563296	0.619121	0.398595	0.300094
4	0.377529	0.422092	0.447487	0.410686	0.506299	0.473846	0.593863	0.623391	0.605407	0.603071	...	0.589062	0.691717	0.656549	0.507680	0.327205	0.550184	0.484522

5 rows × 24 columns

比较可知，运用天气信息的预测准度明显更高，最高与使用所有训练集得到的预测模型的准度相似

3.3 分别使用每年每月数据的时间信息和天气信息，对每月pm2.5平均浓度进行预测，将两种方法下每年每月的预测score用折线图分别绘出

Predict pm2.5 on time period of the month by xgboost

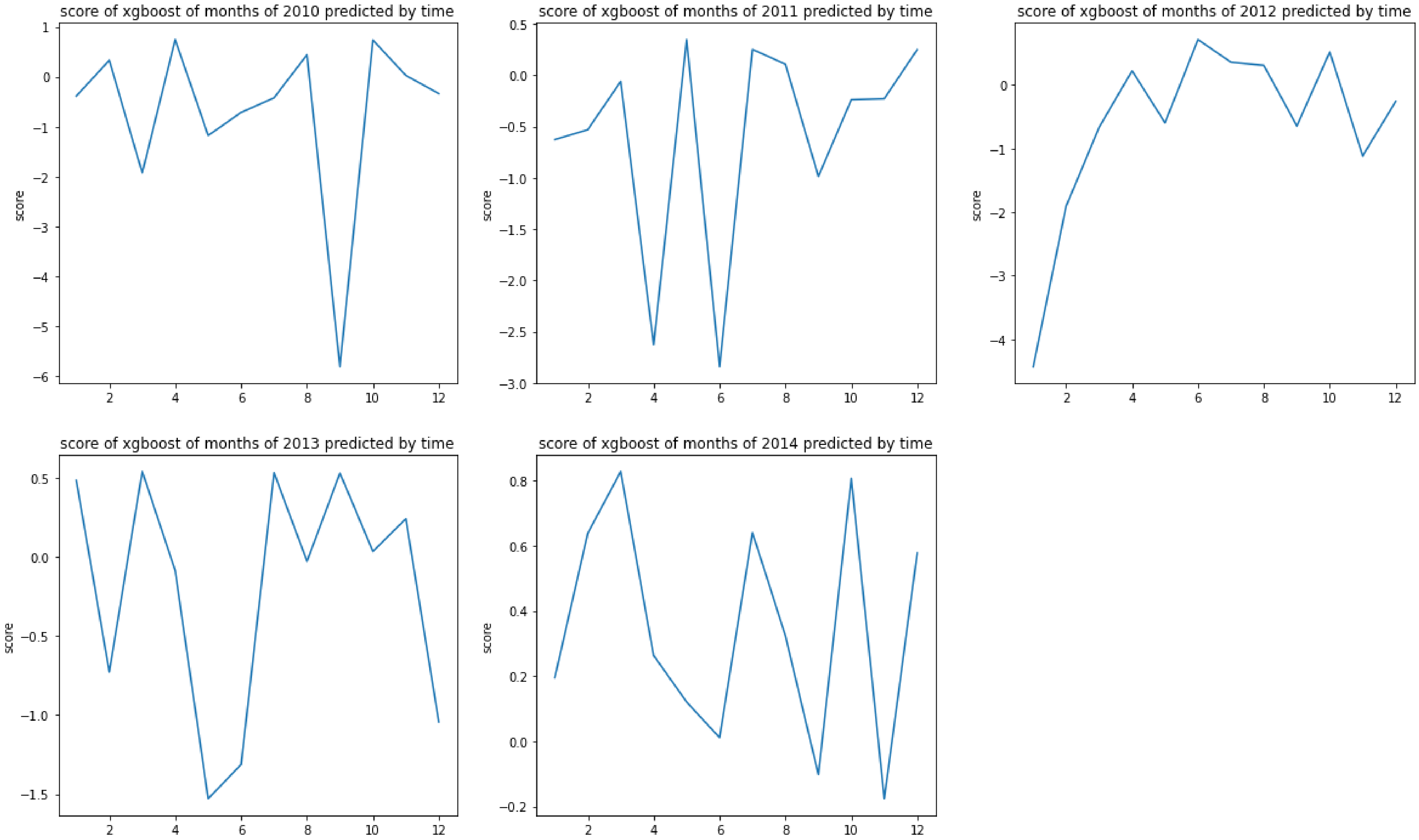
In [ ]:

```
Month = range(1,13)
week_of_year=[[],[],[],[],[]]
score_of_month_weather = [[],[],[],[],[]]
score_of_month_time = [[],[],[],[],[]]

variation_of_month_time=pd.DataFrame()
variation_of_month_weather=pd.DataFrame()
for index, year in enumerate(Year):
    train_data_year=train_data[train_data.year==year]
    test_data_year=test_data[test_data.year==year]
    for month in Month:
        train_data_month_year=train_data_year[train_data_year.month==month]
        test_data_month_year=test_data_year[test_data_year.month==month]

        ## Only use time to predict
        X_train_data_month_year_time = train_data_month_year[var_time]
        X_test_data_month_year_time = test_data_month_year[var_time]
        y_train_data_month_year = train_data_month_year['pm2.5_log']
        y_test_data_month_year = test_data_month_year['pm2.5']
        XGB_model_time=XGBRegressor(learning_rate=0.03,n_estimators=300,max_depth=5)
        XGB_model_time.fit(X_train_data_month_year_time, y_train_data_month_year)

        y_pred_month_year_time = XGB_model_time.predict(X_test_data_month_year_time)
        y_pred_month_year_time = np.round(np.exp(y_pred_month_year_time))
        y_pred_month_year_time = preprocessing.minmax_scale(y_pred_month_year_time)
```

```python
        y_test_data_month_year = preprocessing.minmax_scale(y_test_data_month_year)
        score_of_month_time[index].append(XGB_model_time.score(X_test_data_month_year_time,test_data_month_year['pm2.5_log']))

        ## Only use weather to predict
        X_train_data_month_year_weather = train_data_month_year[var_weather]
        X_test_data_month_year_weather = test_data_month_year[var_weather]
        XGB_model_weather = XGBRegressor(learning_rate=0.03,n_estimators=300,max_depth=5)
        XGB_model_weather.fit(X_train_data_month_year_weather, y_train_data_month_year)

        y_pred_month_year_weather = XGB_model_weather.predict(X_test_data_month_year_weather)
        y_pred_month_year_weather = np.round(np.exp(y_pred_month_year_weather))
        y_pred_month_year_weather = preprocessing.minmax_scale(y_pred_month_year_weather)
        y_test_data_month_year = preprocessing.minmax_scale(y_test_data_month_year)
        score_of_month_weather[index].append(XGB_model_weather.score(X_test_data_month_year_weather,test_data_month_year['pm2.5_log']))
```

In [ ]:

```python
variation_of_month_time=variation_of_month_time.append(score_of_month_time)
variation_of_month_weather=variation_of_month_weather.append(score_of_month_weather)
plt.figure(figsize=(20,12))

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Month,variation_of_month_time.iloc[i,:])
    plt.title('score of xgboost of months of %d predicted by time' % Year[i])
    plt.ylabel('score')
```



In [ ]:

```
variation_of_month_time
```

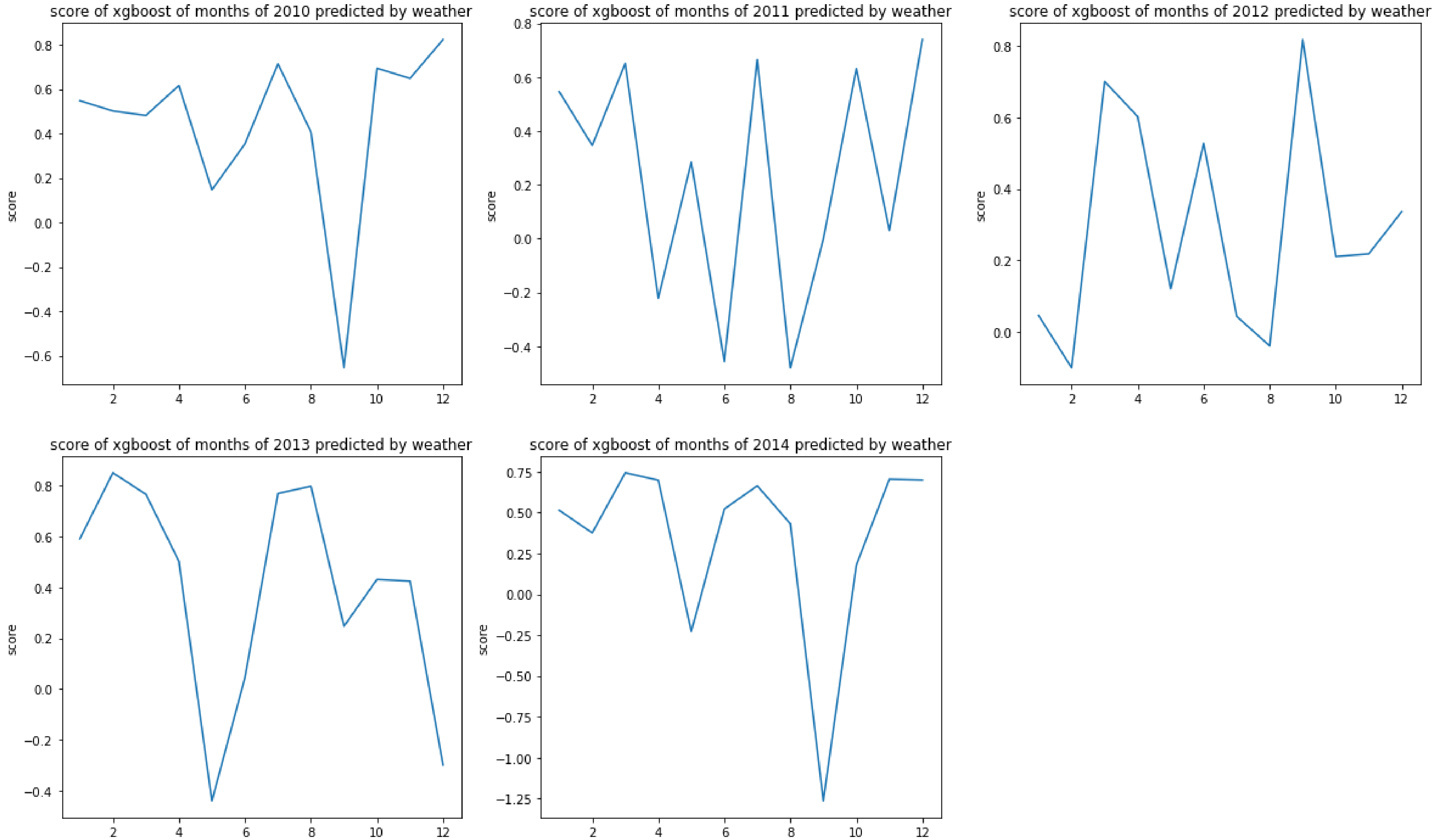
Out[ ]:

	0	1	2	3	4	5	6	7	8	9	10	11
0	-0.383635	0.334482	-1.922651	0.749923	-1.174193	-0.711958	-0.418752	0.445914	-5.811449	0.739912	0.030015	-0.334421
1	-0.627129	-0.530581	-0.059664	-2.625588	0.348784	-2.841746	0.252619	0.107762	-0.985592	-0.237403	-0.227672	0.250640

	0	1	2	3	4	5	6	7	8	9	10	11
2	-4.433642	-1.904614	-0.665120	0.225588	-0.593157	0.717346	0.360540	0.310522	-0.644360	0.521479	-1.114253	-0.255487
3	0.484040	-0.727425	0.539942	-0.086825	-1.528998	-1.312753	0.532808	-0.028277	0.529805	0.034274	0.241172	-1.043412
4	0.195112	0.637800	0.827856	0.262985	0.120473	0.010643	0.640222	0.323143	-0.102564	0.806916	-0.176908	0.577419

In [ ]:

```
plt.figure(figsize=(20,12))

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Month,variation_of_month_weather.iloc[i,:])
    plt.title('score of xgboost of months of %d predicted by weather' % Year[i])
    plt.ylabel('score')
```



In [ ]:

```
variation_of_month_weather
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	10	11
0	0.547485	0.501328	0.481045	0.615839	0.145980	0.353028	0.713370	0.406811	-0.654742	0.693597	0.647775	0.822447
1	0.546092	0.346419	0.651510	-0.221525	0.285087	-0.457112	0.665464	-0.479666	-0.001508	0.631941	0.030286	0.739473

	0	1	2	3	4	5	6	7	8	9	10	11
2	0.045147	-0.101374	0.701375	0.603057	0.120128	0.528274	0.042748	-0.040120	0.818690	0.210542	0.217907	0.336643
3	0.590243	0.849584	0.765141	0.501883	-0.439269	0.045040	0.768364	0.796922	0.246779	0.431007	0.424018	-0.297711
4	0.513193	0.375152	0.742746	0.697586	-0.228545	0.521123	0.663219	0.430967	-1.264672	0.178570	0.703295	0.698655

可以看出，虽然用每月平均浓度预测时只用天气信息可以达到更高精度，但预测准度更加不稳定，既可以达到0.8，也可以达到-1.25

3.4 分别使用每年每季数据的时间信息和天气信息，对每季pm2.5平均浓度进行预测，将两种方法下每年每季的预测score用折线图分别绘出

Predict pm2.5 on time period of the season by xgboost

In [ ]:

```
season_of_year=[[],[],[],[],[]]
score_of_season_weather = [[],[],[],[],[]]
score_of_season_time = [[],[],[],[],[]]

variation_of_season_time=pd.DataFrame()
variation_of_season_weather=pd.DataFrame()
for index, year in enumerate(Year):
    train_data_year=train_data[train_data.year==year]
    test_data_year=test_data[test_data.year==year]
    train_data_spring_year=pd.concat([train_data_year[train_data_year.month==3], train_data_year[train_data_year.month==4], train_data_year[train_dat
        sort=False)
    test_data_spring_year=pd.concat([test_data_year[test_data_year.month==3], test_data_year[test_data_year.month==4], test_data_year[test_data_year.
        sort=False)
    train_data_summer_year=pd.concat([train_data_year[train_data_year.month==6], train_data_year[train_data_year.month==7], train_data_year[train_dat
        sort=False)
    test_data_summer_year=pd.concat([test_data_year[test_data_year.month==6], test_data_year[test_data_year.month==7], test_data_year[test_data_year.
        sort=False)
    train_data_fall_year=pd.concat([train_data_year[train_data_year.month==9], train_data_year[train_data_year.month==10], train_data_year[train_data
        sort=False)
    test_data_fall_year=pd.concat([test_data_year[test_data_year.month==9], test_data_year[test_data_year.month==10], test_data_year[test_data_year.m
        sort=False)
    train_data_winter_year=pd.concat([train_data_year[train_data_year.month==12], train_data_year[train_data_year.month==1], train_data_year[train_da
        sort=False)
    test_data_winter_year=pd.concat([test_data_year[test_data_year.month==12], test_data_year[test_data_year.month==1], test_data_year[test_data_year
        sort=False)
    ## Only use time to predict for spring
    X_train_data_spring_year_time = train_data_spring_year[var_time]
```

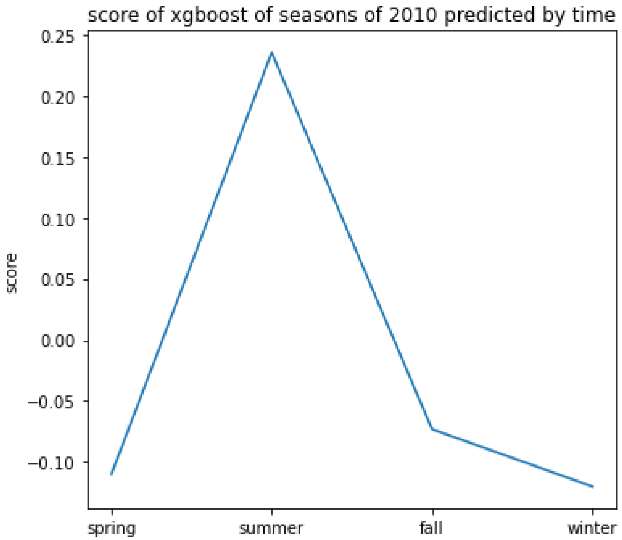
```python
X_test_data_spring_year_time = test_data_spring_year[var_time]
y_train_data_spring_year = train_data_spring_year['pm2.5_log']
y_test_data_spring_year = test_data_spring_year['pm2.5']
XGB_model_time_spring=XGBRegressor(learning_rate=0.03,n_estimators=300,max_depth=5)
XGB_model_time_spring.fit(X_train_data_spring_year_time, y_train_data_spring_year)

y_pred_spring_year_time = XGB_model_time_spring.predict(X_test_data_spring_year_time)
y_pred_spring_year_time = np.round(np.exp(y_pred_spring_year_time))
y_pred_spring_year_time = preprocessing.minmax_scale(y_pred_spring_year_time)
y_test_data_spring_year = preprocessing.minmax_scale(y_test_data_spring_year)
score_of_season_time[index].append(XGB_model_time_spring.score(X_test_data_spring_year_time,test_data_spring_year['pm2.5_log']))

## Only use weather to predict for spring
X_train_data_spring_year_weather = train_data_spring_year[var_weather]
X_test_data_spring_year_weather = test_data_spring_year[var_weather]
XGB_model_weather_spring = XGBRegressor(learning_rate=0.03,n_estimators=300,max_depth=5)
XGB_model_weather_spring.fit(X_train_data_spring_year_weather, y_train_data_spring_year)

y_pred_spring_year_weather = XGB_model_weather_spring.predict(X_test_data_spring_year_weather)
y_pred_spring_year_weather = np.round(np.exp(y_pred_spring_year_weather))
y_pred_spring_year_weather = preprocessing.minmax_scale(y_pred_spring_year_weather)
y_test_data_spring_year = preprocessing.minmax_scale(y_test_data_spring_year)
score_of_season_weather[index].append(XGB_model_weather_spring.score(X_test_data_spring_year_weather,test_data_spring_year['pm2.5_log']))

## Only use time to predict for summer
X_train_data_summer_year_time = train_data_summer_year[var_time]
X_test_data_summer_year_time = test_data_summer_year[var_time]
y_train_data_summer_year = train_data_summer_year['pm2.5_log']
y_test_data_summer_year = test_data_summer_year['pm2.5']
XGB_model_time_summer=XGBRegressor(learning_rate=0.03,n_estimators=300,max_depth=5)
XGB_model_time_summer.fit(X_train_data_summer_year_time, y_train_data_summer_year)

y_pred_summer_year_time = XGB_model_time_summer.predict(X_test_data_summer_year_time)
y_pred_summer_year_time = np.round(np.exp(y_pred_summer_year_time))
y_pred_summer_year_time = preprocessing.minmax_scale(y_pred_summer_year_time)
y_test_data_summer_year = preprocessing.minmax_scale(y_test_data_summer_year)
score_of_season_time[index].append(XGB_model_time_summer.score(X_test_data_summer_year_time,test_data_summer_year['pm2.5_log']))

## Only use weather to predict for summer
X_train_data_summer_year_weather = train_data_summer_year[var_weather]
X_test_data_summer_year_weather = test_data_summer_year[var_weather]
XGB_model_weather_summer = XGBRegressor(learning_rate=0.03,n_estimators=300,max_depth=5)
XGB_model_weather_summer.fit(X_train_data_summer_year_weather, y_train_data_summer_year)

y_pred_summer_year_weather = XGB_model_weather_summer.predict(X_test_data_summer_year_weather)
y_pred_summer_year_weather = np.round(np.exp(y_pred_summer_year_weather))
y_pred_summer_year_weather = preprocessing.minmax_scale(y_pred_summer_year_weather)
y_test_data_summer_year = preprocessing.minmax_scale(y_test_data_summer_year)
```

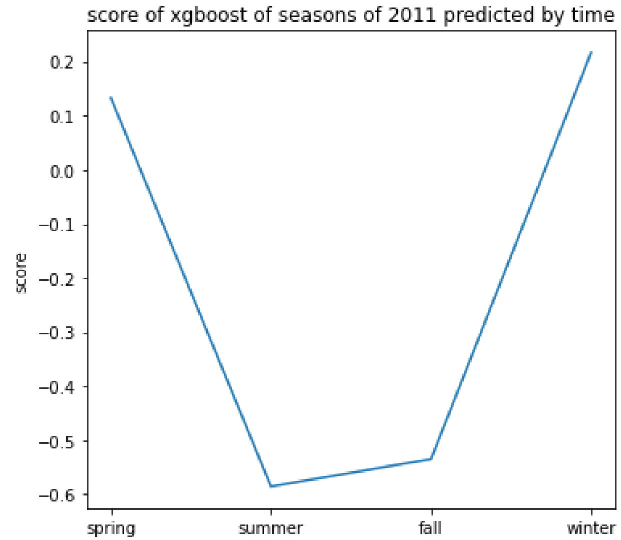
```python
score_of_season_weather[index].append(XGB_model_weather_summer.score(X_test_data_summer_year_weather,test_data_summer_year['pm2.5_log']))

## Only use time to predict for fall
X_train_data_fall_year_time = train_data_fall_year[var_time]
X_test_data_fall_year_time = test_data_fall_year[var_time]
y_train_data_fall_year = train_data_fall_year['pm2.5_log']
y_test_data_fall_year = test_data_fall_year['pm2.5']
XGB_model_time_fall=XGBRegressor(learning_rate=0.03,n_estimators=300,max_depth=5)
XGB_model_time_fall.fit(X_train_data_fall_year_time, y_train_data_fall_year)

y_pred_fall_year_time = XGB_model_time_fall.predict(X_test_data_fall_year_time)
y_pred_fall_year_time = np.round(np.exp(y_pred_fall_year_time))
y_pred_fall_year_time = preprocessing.minmax_scale(y_pred_fall_year_time)
y_test_data_fall_year = preprocessing.minmax_scale(y_test_data_fall_year)
score_of_season_time[index].append(XGB_model_time_fall.score(X_test_data_fall_year_time,test_data_fall_year['pm2.5_log']))

## Only use weather to predict for fall
X_train_data_fall_year_weather = train_data_fall_year[var_weather]
X_test_data_fall_year_weather = test_data_fall_year[var_weather]
XGB_model_weather_fall = XGBRegressor(learning_rate=0.03,n_estimators=300,max_depth=5)
XGB_model_weather_fall.fit(X_train_data_fall_year_weather, y_train_data_fall_year)

y_pred_fall_year_weather = XGB_model_weather_fall.predict(X_test_data_fall_year_weather)
y_pred_fall_year_weather = np.round(np.exp(y_pred_fall_year_weather))
y_pred_fall_year_weather = preprocessing.minmax_scale(y_pred_fall_year_weather)
y_test_data_fall_year = preprocessing.minmax_scale(y_test_data_fall_year)
score_of_season_weather[index].append(XGB_model_weather_fall.score(X_test_data_fall_year_weather,test_data_fall_year['pm2.5_log']))


## Only use time to predict for winter
X_train_data_winter_year_time = train_data_winter_year[var_time]
X_test_data_winter_year_time = test_data_winter_year[var_time]
y_train_data_winter_year = train_data_winter_year['pm2.5_log']
y_test_data_winter_year = test_data_winter_year['pm2.5']
XGB_model_time_winter=XGBRegressor(learning_rate=0.03,n_estimators=300,max_depth=5)
XGB_model_time_winter.fit(X_train_data_winter_year_time, y_train_data_winter_year)

y_pred_winter_year_time = XGB_model_time_winter.predict(X_test_data_winter_year_time)
y_pred_winter_year_time = np.round(np.exp(y_pred_winter_year_time))
y_pred_winter_year_time = preprocessing.minmax_scale(y_pred_winter_year_time)
y_test_data_winter_year = preprocessing.minmax_scale(y_test_data_winter_year)
score_of_season_time[index].append(XGB_model_time_winter.score(X_test_data_winter_year_time,test_data_winter_year['pm2.5_log']))

## Only use weather to predict for winter
X_train_data_winter_year_weather = train_data_winter_year[var_weather]
X_test_data_winter_year_weather = test_data_winter_year[var_weather]
XGB_model_weather_winter = XGBRegressor(learning_rate=0.03,n_estimators=300,max_depth=5)
XGB_model_weather_winter.fit(X_train_data_winter_year_weather, y_train_data_winter_year)
```

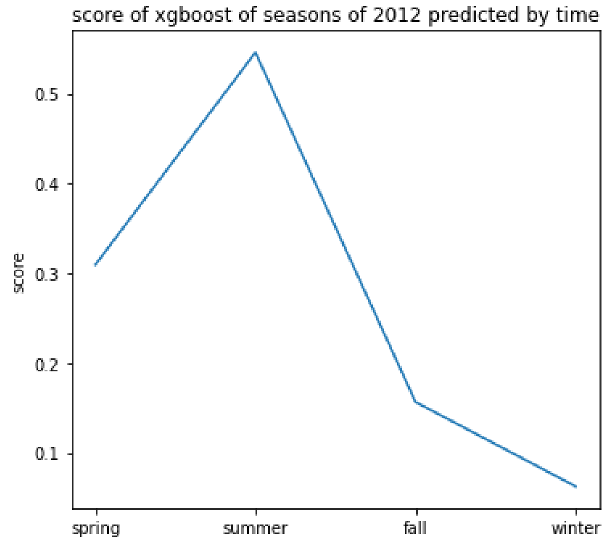
```
    y_pred_winter_year_weather = XGB_model_weather_winter.predict(X_test_data_winter_year_weather)
    y_pred_winter_year_weather = np.round(np.exp(y_pred_winter_year_weather))
    y_pred_winter_year_weather = preprocessing.minmax_scale(y_pred_winter_year_weather)
    y_test_data_winter_year = preprocessing.minmax_scale(y_test_data_winter_year)
    score_of_season_weather[index].append(XGB_model_weather_winter.score(X_test_data_winter_year_weather,test_data_winter_year['pm2.5_log']))
variation_of_season_weather=variation_of_season_weather.append(score_of_season_weather)
```

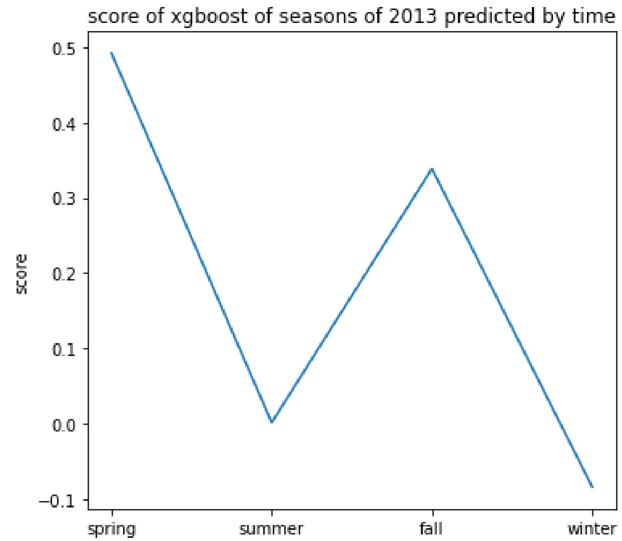
In [ ]:

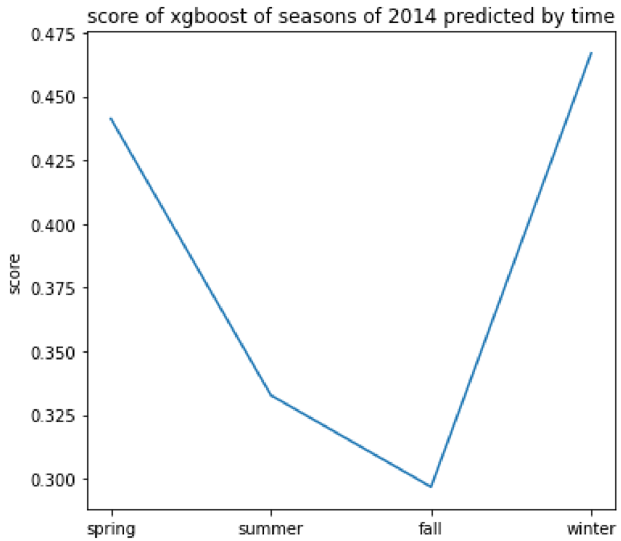
```
variation_of_season_time=variation_of_season_time.append(score_of_season_time)

plt.figure(figsize=(20,12))
Seasons=['spring','summer','fall','winter']

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Seasons,variation_of_season_time.iloc[i,:])
    plt.title('score of xgboost of seasons of %d predicted by time' % Year[i])
    plt.ylabel('score')
```











In [ ]:

```
variation_of_season_time
```

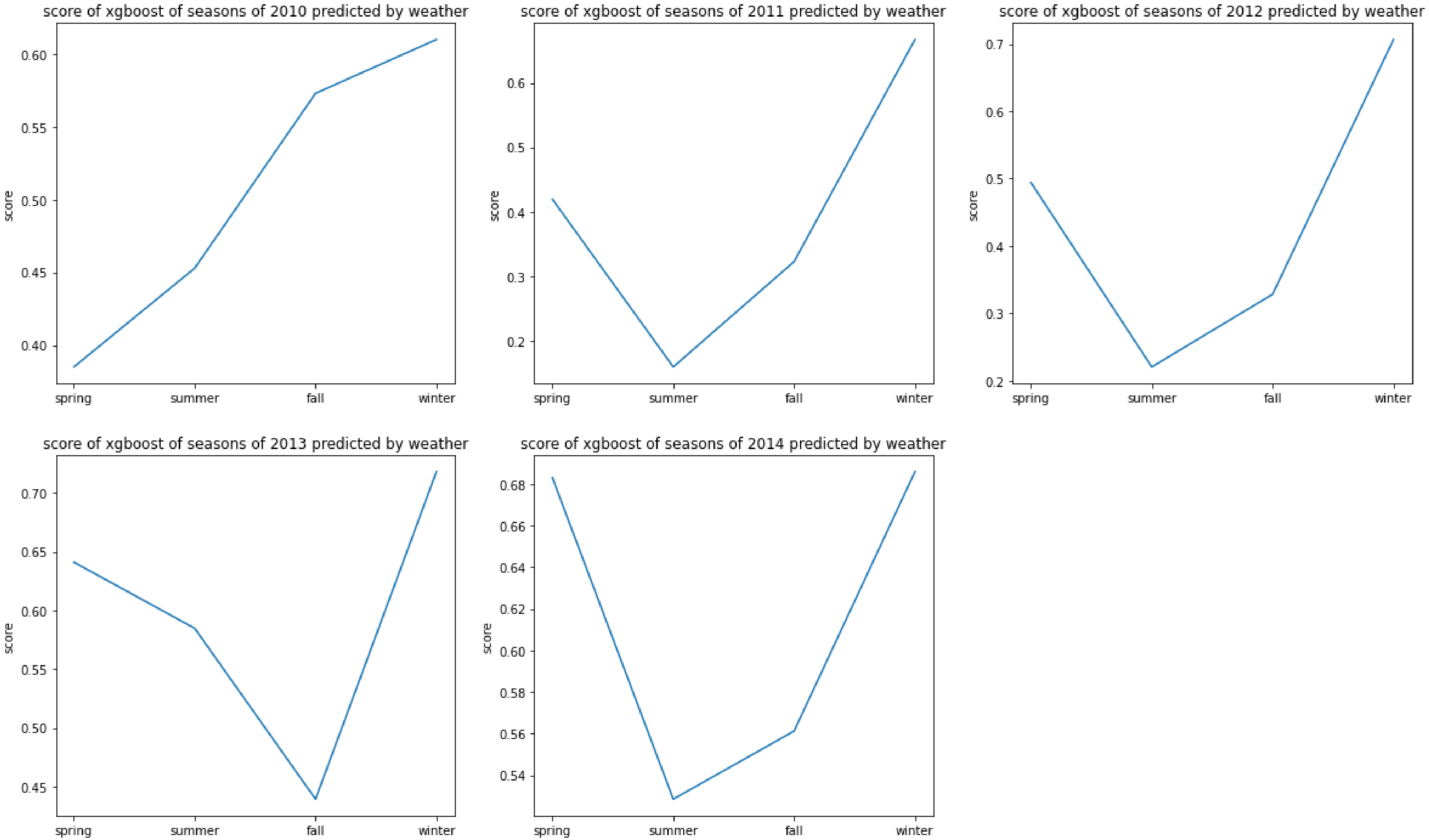
Out[ ]:

	0	1	2	3
0	-0.110092	0.235979	-0.073259	-0.120247
1	0.133243	-0.585266	-0.534747	0.217305

	0	1	2	3
2	0.309382	0.545886	0.156495	0.062482
3	0.492038	0.001488	0.338788	-0.083888
4	0.441307	0.332737	0.296765	0.467010

In [ ]:

```
plt.figure(figsize=(20,12))

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Seasons,variation_of_season_weather.iloc[i,:])
    plt.title('score of xgboost of seasons of %d predicted by weather' % Year[i])
    plt.ylabel('score')
```



In [ ]:

```
variation_of_season_weather
```

Out[ ]:

	0	1	2	3
0	0.385050	0.452968	0.573221	0.610227
1	0.419754	0.160140	0.323148	0.666922

	0	1	2	3
2	0.494261	0.220412	0.328318	0.706501
3	0.641045	0.584753	0.439383	0.718063
4	0.682956	0.528580	0.561287	0.685849

同理，此处我们应该用天气信息进行预测，且这五年间冬天均达到最高准度，后四年夏秋两季均为最低

4.1用折线图记录每年周一早晨（6点至9点）每小时平均pm2.5的变化趋势，取每年每星期一每小时的平均浓度作为当年该天该小时的对应值

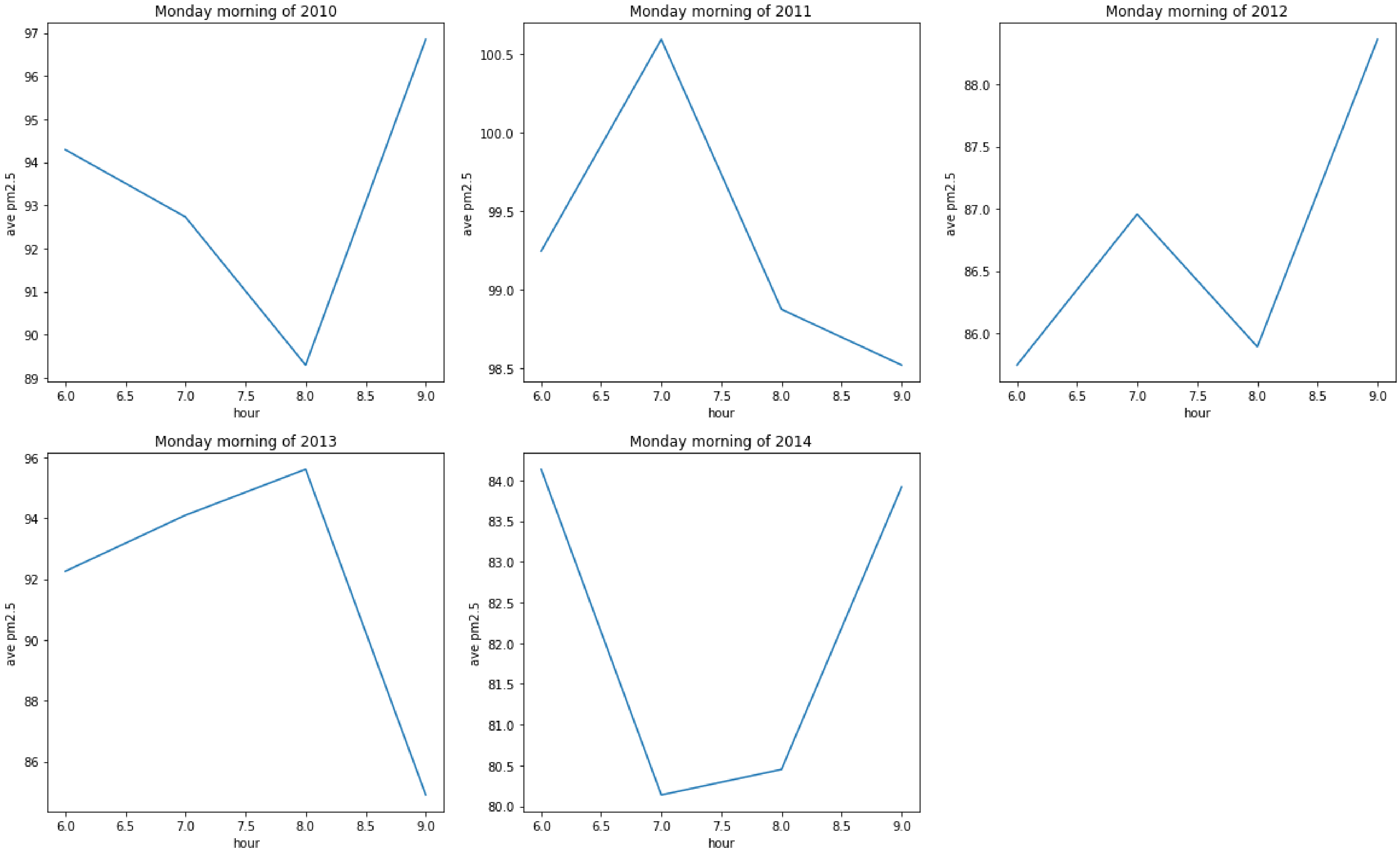
Variation of pm2.5 on time period of the Monday morning

In [ ]:

```
Hour_Mon=range(6,10)
Week_Mon=range(1)
day_of_year_Mon=[[],[],[],[],[]]

variation_of_day_Mon=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_dropna[pm25_dropna.year==year]
    for week in Week_Mon:
        pm25_Mon_year=pm25_year[pm25_year.week==week]
        for hour in Hour_Mon:
            pm25_hour_year_Mon=pm25_Mon_year[pm25_Mon_year.hour==hour]
            mean=np.mean(pm25_hour_year_Mon['pm2.5'])
            day_of_year_Mon[index].append(mean)

variation_of_day_Mon=variation_of_day_Mon.append(day_of_year_Mon)
variation_of_day_Mon.index=Year
```

In [ ]:

```
plt.figure(figsize=(20,12))

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour_Mon,variation_of_day_Mon.iloc[i,:])
    plt.title('Monday morning of %d' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_day_Mon
```

Out[ ]:

	0	1	2	3
2010	94.291667	92.729167	89.291667	96.851064
2011	99.244898	100.591837	98.875000	98.520833

	0	1	2	3
2012	85.744681	86.957447	85.891304	88.361702
2013	92.254902	94.098039	95.607843	84.901961
2014	84.137255	80.137255	80.450980	83.921569

我们注意到每年星期一早晨每小时pm2.5平均浓度变化趋势不同，但除2013年外均在8点取得最低值

4.2用折线图记录每年12月周末（周六周日）晚上（18点至24点）每小时平均pm2.5的变化趋势，取每年12月周末每天每小时的平均浓度作为当年该天该小时的对应值

Variation of pm2.5 on time period of the evening of the weekend in December

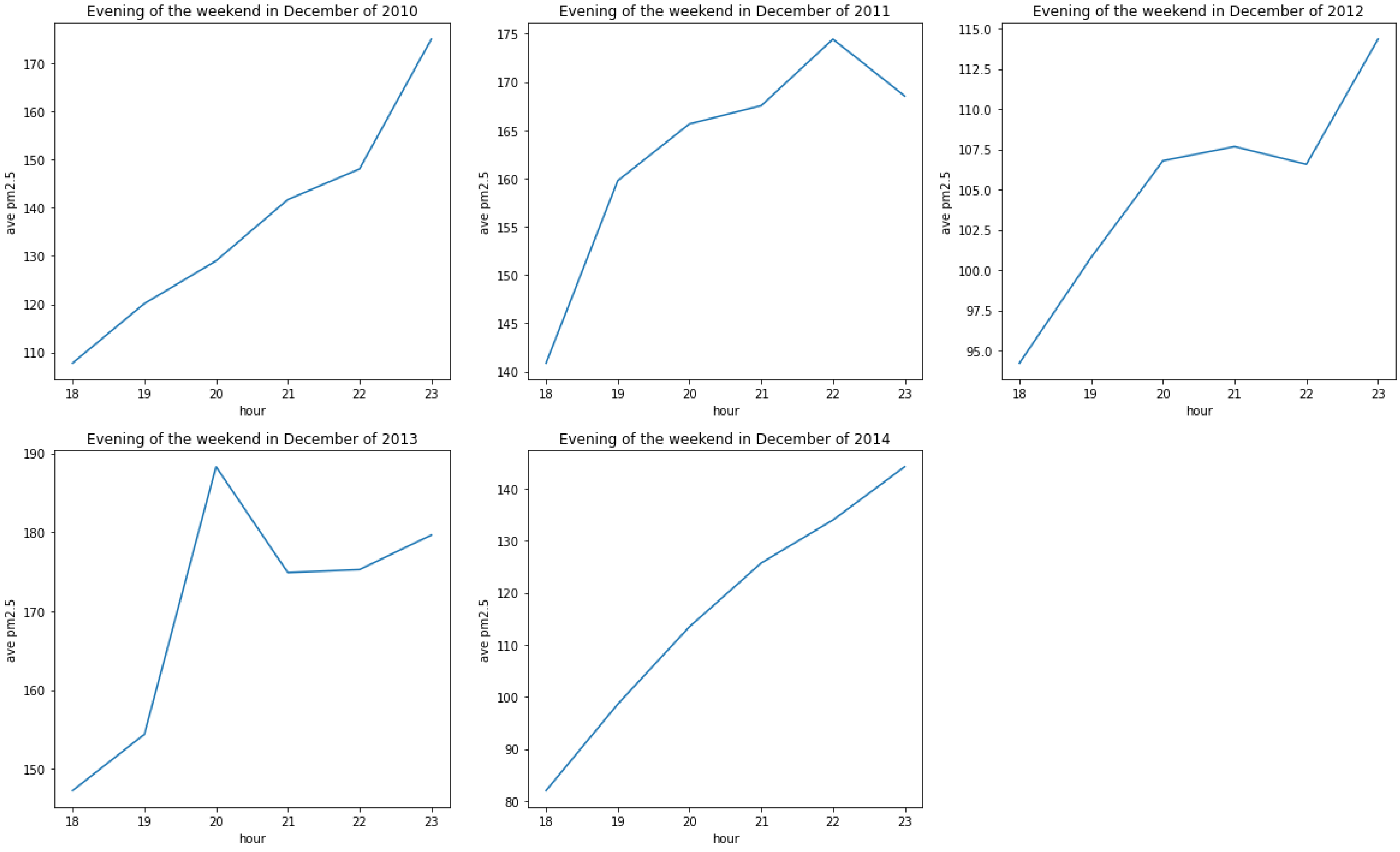
In [ ]:

```
from pandas.core.frame import DataFrame
Hour_even=range(18,24)
week_dec=range(5,7)
month_dec=range(12,13)
weekend_Dec_2010=['2010-12-04', '2010-12-05', '2010-12-11', '2010-12-12', '2010-12-18', '2010-12-19', '2010-12-25', '2010-12-26']
weekend_Dec_2011=['2011-12-03', '2011-12-04', '2011-12-10', '2011-12-11', '2011-12-17', '2011-12-18', '2011-12-24', '2011-12-25', '2011-12-31']
weekend_Dec_2012=['2012-12-01', '2012-12-02', '2012-12-08', '2012-12-09', '2012-12-15', '2012-12-16', '2012-12-22', '2012-12-23', '2012-12-29', '2012
weekend_Dec_2013=[ '2013-12-07', '2013-12-08', '2013-12-14', '2013-12-15', '2013-12-21', '2013-12-28', '2013-12-29']
weekend_Dec_2014=['2014-12-06', '2014-12-07', '2014-12-13', '2014-12-14', '2014-12-20', '2014-12-21', '2014-12-27', '2014-12-28']
day_of_year_Dec=[[],[],[],[],[]]

variation_of_day_dec=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_dropna[pm25_dropna.year==year]
    for month in month_dec:
        pm25_dec_year=pm25_year[pm25_year.month==month]
        pm25_weekend_dec_year=pd.concat([pm25_dec_year[pm25_dec_year.week==5], pm25_dec_year[pm25_dec_year.week==6]], sort=False)
        for hour in Hour_even:
            pm25_even_weekend_dec_year=pm25_weekend_dec_year[pm25_weekend_dec_year.hour==hour]
            mean=np.mean(pm25_even_weekend_dec_year['pm2.5'])
            day_of_year_Dec[index].append(mean)

variation_of_day_dec=variation_of_day_dec.append(day_of_year_Dec)
variation_of_day_dec.index=Year
```

In [ ]:

```
plt.figure(figsize=(20,12))
```

```
for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour_even,variation_of_day_dec.iloc[i,:])
    plt.title('Evening of the weekend in December of %d' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('ave pm2.5')
```



In [ ]:
```
variation_of_day_dec
```

Out[ ]:

	0	1	2	3	4	5
2010	107.750000	120.125000	129.000000	141.750000	148.125000	175.125000
2011	140.888889	159.777778	165.666667	167.555556	174.444444	168.555556
2012	94.222222	100.777778	106.777778	107.666667	106.555556	114.333333
2013	147.250000	154.375000	188.285714	174.875000	175.250000	179.625000
2014	82.000000	98.625000	113.500000	125.750000	134.000000	144.250000

我们注意到平均浓度基本均为上升趋势

4.2用折线图记录每年春节期间（除夕前两天、除夕、正月初一至初七、初七后两天）每小时平均pm2.5的变化趋势，取每年春节每小时的平均浓度作为当年春节该小时的对应值

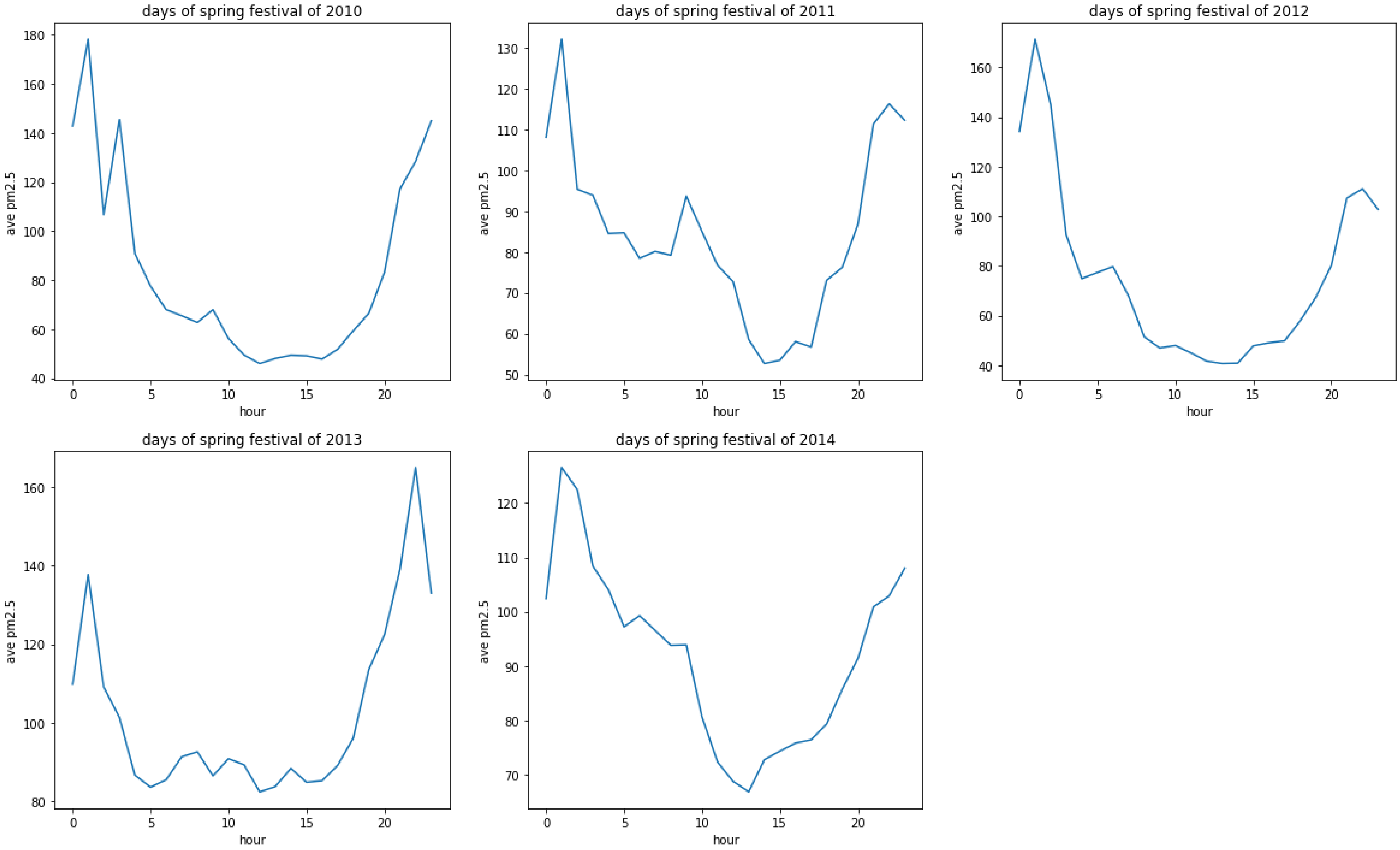
Variation of pm2.5 on time period of one day of Spring Festival

In [ ]:
```
Spr=range(12)
sprfest_2010 = ['2010-02-11', '2010-02-12', '2010-02-13', '2010-02-14', '2010-02-15', '2010-02-16', '2010-02-17', '2010-02-18', '2010-02-19', '2010-0
sprfest_2011 = ['2011-01-31', '2011-02-01', '2011-02-02', '2011-02-03', '2011-02-04', '2011-02-05', '2011-02-06', '2011-02-07', '2011-02-08', '2011-0
sprfest_2012 = ['2012-01-20', '2012-01-21', '2012-01-22', '2012-01-23', '2012-01-24', '2012-01-25', '2012-01-26', '2012-01-27', '2012-01-28', '2012-0
sprfest_2013 = ['2013-02-07', '2013-02-08', '2013-02-09', '2013-02-10', '2013-02-11', '2013-02-12', '2013-02-13', '2013-02-14', '2013-02-15', '2013-0
sprfest_2014 = ['2014-01-28', '2014-01-29', '2014-01-30', '2014-01-31', '2014-02-01', '2014-02-02', '2014-02-03', '2014-02-04', '2014-02-05', '2014-0
hour_of_sprfest=[[],[],[],[],[]]
variation_of_hour_sprfest = pd.DataFrame()

pm25_sprfest_2010=pd.DataFrame()
for sprday_2010 in sprfest_2010:
    pm25_sprfest_2010_date=pm25_dropna[pm25_dropna.date==sprday_2010]
    pm25_sprfest_2010=pd.concat([pm25_sprfest_2010, pm25_sprfest_2010_date], sort=False)
for hour in Hour:
        pm25_hour_sprfest_2010=pm25_sprfest_2010[pm25_sprfest_2010.hour==hour]
        mean_spr_2010=np.mean(pm25_hour_sprfest_2010['pm2.5'])
        hour_of_sprfest[0].append(mean_spr_2010)

pm25_sprfest_2011=pd.DataFrame()
for sprday_2011 in sprfest_2011:
    pm25_sprfest_2011_date=pm25_dropna[pm25_dropna.date==sprday_2011]
    pm25_sprfest_2011=pd.concat([pm25_sprfest_2011, pm25_sprfest_2011_date], sort=False)
for hour in Hour:
```

```
        pm25_hour_sprfest_2011=pm25_sprfest_2011[pm25_sprfest_2011.hour==hour]
        mean_spr_2011=np.mean(pm25_hour_sprfest_2011['pm2.5'])
        hour_of_sprfest[1].append(mean_spr_2011)

pm25_sprfest_2012=pd.DataFrame()
for sprday_2012 in sprfest_2012:
    pm25_sprfest_2012_date=pm25_dropna[pm25_dropna.date==sprday_2012]
    pm25_sprfest_2012=pd.concat([pm25_sprfest_2012, pm25_sprfest_2012_date], sort=False)
for hour in Hour:
        pm25_hour_sprfest_2012=pm25_sprfest_2012[pm25_sprfest_2012.hour==hour]
        mean_spr_2012=np.mean(pm25_hour_sprfest_2012['pm2.5'])
        hour_of_sprfest[2].append(mean_spr_2012)

pm25_sprfest_2013=pd.DataFrame()
for sprday_2013 in sprfest_2013:
    pm25_sprfest_2013_date=pm25_dropna[pm25_dropna.date==sprday_2013]
    pm25_sprfest_2013=pd.concat([pm25_sprfest_2013, pm25_sprfest_2013_date], sort=False)
for hour in Hour:
        pm25_hour_sprfest_2013=pm25_sprfest_2013[pm25_sprfest_2013.hour==hour]
        mean_spr_2013=np.mean(pm25_hour_sprfest_2013['pm2.5'])
        hour_of_sprfest[3].append(mean_spr_2013)

pm25_sprfest_2014=pd.DataFrame()
for sprday_2014 in sprfest_2014:
    pm25_sprfest_2014_date=pm25_dropna[pm25_dropna.date==sprday_2014]
    pm25_sprfest_2014=pd.concat([pm25_sprfest_2014, pm25_sprfest_2014_date], sort=False)
for hour in Hour:
        pm25_hour_sprfest_2014=pm25_sprfest_2014[pm25_sprfest_2014.hour==hour]
        mean_spr_2014=np.mean(pm25_hour_sprfest_2014['pm2.5'])
        hour_of_sprfest[4].append(mean_spr_2014)

variation_of_hour_sprfest=variation_of_hour_sprfest.append(hour_of_sprfest)
```

In [ ]:

```
plt.figure(figsize=(20,12))

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour,variation_of_hour_sprfest.iloc[i,:])
    plt.title('days of spring festival of %d' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_hour_sprfest
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	
0	142.833333	178.250000	106.636364	145.500000	90.833333	77.500000	67.916667	65.416667	62.666667	67.916667	...	49.333333	49.083333	47.750000	51.833333	59.3333
1	108.166667	132.166667	95.416667	93.916667	84.583333	84.750000	78.500000	80.166667	79.250000	93.666667	...	52.666667	53.500000	58.083333	56.750000	73.0833

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	
2	134.166667	171.250000	144.916667	92.583333	74.916667	77.416667	79.750000	67.916667	51.500000	47.083333	...	40.916667	47.916667	49.166667	49.916667	57.9166
3	109.833333	137.750000	109.166667	101.416667	86.750000	83.666667	85.583333	91.416667	92.666667	86.583333	...	88.500000	84.916667	85.333333	89.250000	96.1666
4	102.416667	126.583333	122.500000	108.416667	104.083333	97.250000	99.250000	96.583333	93.833333	93.916667	...	72.750000	74.333333	75.833333	76.416667	79.3333

5 rows × 24 columns

我们注意到每天每小时的变化趋势与全年相似，均为15点后上升，凌晨1点后慢慢下降

4.3用折线图记录每年春节期间（除夕前两天、除夕、正月初一至初七、初七后两天，以除夕前第二天为第0天）每天平均pm2.5的变化趋势，取每年春节每天的平均浓度作为当年春节该天的对应值

Variation of pm2.5 on time period of all days of Spring Festival

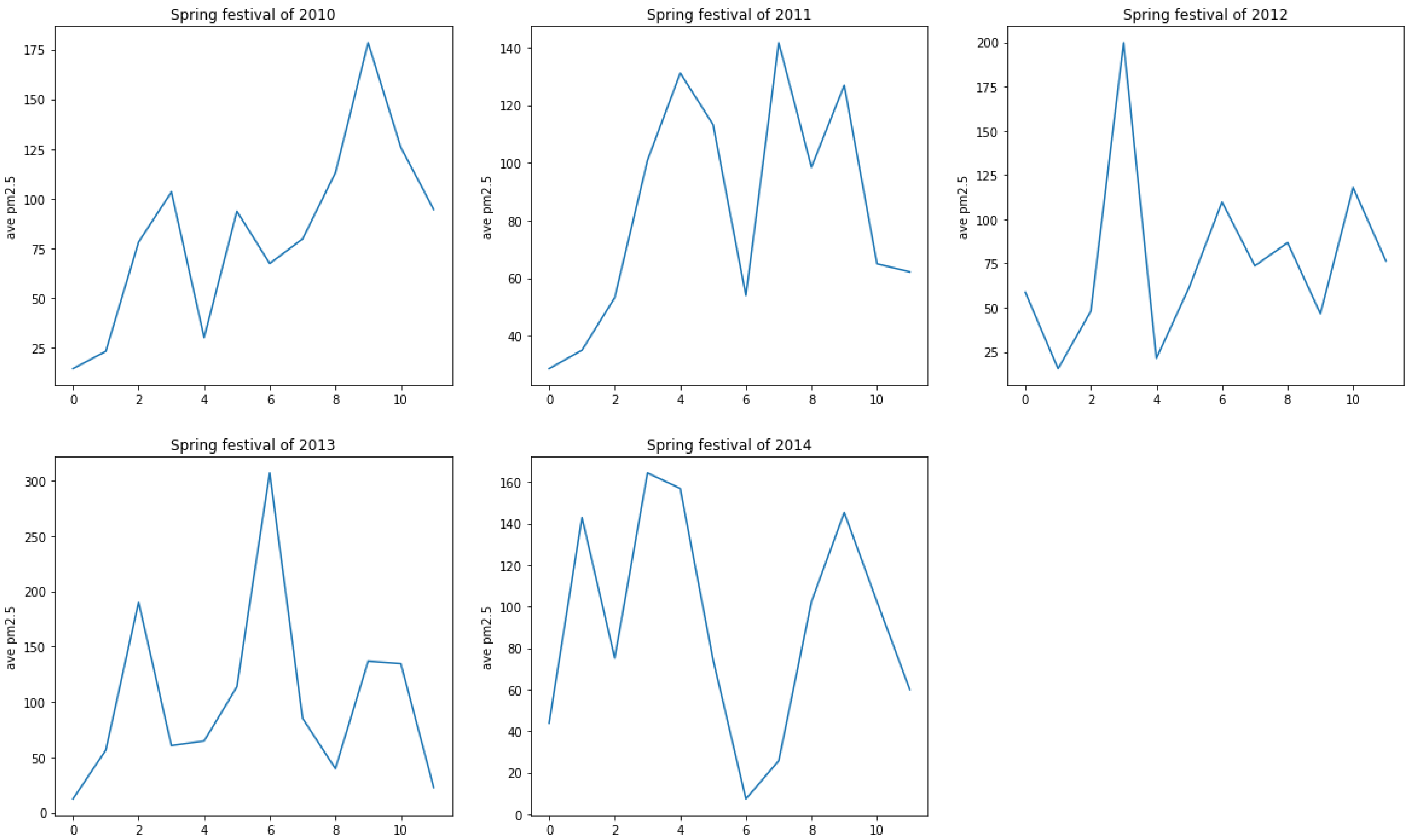
In [ ]:

```
days_of_sprfest=[[],[],[],[],[]]
variation_of_days_sprfest = pd.DataFrame()

for sprday_2010 in sprfest_2010:
    pm25_day_sprfest_2010=pm25_sprfest_2010[pm25_sprfest_2010.date==sprday_2010]
    mean_spr_2010=np.mean(pm25_day_sprfest_2010['pm2.5'])
    days_of_sprfest[0].append(mean_spr_2010)

for sprday_2011 in sprfest_2011:
    pm25_day_sprfest_2011=pm25_sprfest_2011[pm25_sprfest_2011.date==sprday_2011]
    mean_spr_2011=np.mean(pm25_day_sprfest_2011['pm2.5'])
    days_of_sprfest[1].append(mean_spr_2011)

for sprday_2012 in sprfest_2012:
    pm25_day_sprfest_2012=pm25_sprfest_2012[pm25_sprfest_2012.date==sprday_2012]
    mean_spr_2012=np.mean(pm25_day_sprfest_2012['pm2.5'])
    days_of_sprfest[2].append(mean_spr_2012)

for sprday_2013 in sprfest_2013:
    pm25_day_sprfest_2013=pm25_sprfest_2013[pm25_sprfest_2013.date==sprday_2013]
    mean_spr_2013=np.mean(pm25_day_sprfest_2013['pm2.5'])
    days_of_sprfest[3].append(mean_spr_2013)

for sprday_2014 in sprfest_2014:
```

```python
    pm25_day_sprfest_2014=pm25_sprfest_2014[pm25_sprfest_2014.date==sprday_2014]
    mean_spr_2014=np.mean(pm25_day_sprfest_2014['pm2.5'])
    days_of_sprfest[4].append(mean_spr_2014)

variation_of_days_sprfest=variation_of_days_sprfest.append(days_of_sprfest)
```

In [ ]:

```python
plt.figure(figsize=(20,12))

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Spr,variation_of_days_sprfest.iloc[i,:])
    plt.title('Spring festival of %d' % Year[i])
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_days_sprfest
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	10	11
0	14.333333	23.083333	78.083333	103.391304	30.000000	93.583333	67.291667	79.666667	112.958333	178.500000	125.750000	94.500000
1	28.666667	35.083333	53.291667	100.875000	131.125000	113.250000	54.041667	141.625000	98.458333	126.875000	65.000000	62.208333

	0	1	2	3	4	5	6	7	8	9	10	11
2	58.666667	15.458333	48.041667	199.875000	21.375000	61.500000	109.750000	73.625000	86.750000	46.583333	117.916667	76.375000
3	12.416667	56.458333	190.125000	60.500000	64.791667	113.708333	306.916667	85.260870	39.791667	136.833333	134.541667	22.791667
4	43.916667	142.875000	75.166667	164.291667	156.833333	74.375000	7.416667	25.750000	102.375000	145.250000	102.250000	60.041667

我们注意到平均浓度基本均出现3个高峰，分别在除夕前后，初三前后和初七前后