1.导入数据填补方法

In [ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.impute import KNNImputer
from myPackage import module
```

In [ ]:
```
def mean_imputer(data,missing_index):
    pm25_mean = data
    for i in missing_index:
        hour=data.loc[i,'hour']
        day=data.loc[i,'day']
        month=data.loc[i,'month']

        index = data[(data.hour==hour)&(data.day==day)&(data.month==month)].index.tolist()
        exist_index = [j for j in index if not(j==i)]
        pm25_mean.loc[i,'pm2.5']=np.mean(data.loc[exist_index,'pm2.5'])

    return pm25_mean
```

In [ ]:
```
def knn_imputer(data):
    knn_imputer=KNNImputer(n_neighbors=40)
    pm25_knn = knn_imputer.fit_transform(data)

    return pm25_knn
```

In [ ]:
```
import xgboost as xgb
from sklearn.metrics import mean_squared_error
from sklearn import preprocessing
```

平均填补

2.1 用平均填补法补全原数据

In [ ]:
```
pm25_data = pd.read_csv('pm25_data.csv')
missing_index=np.where(np.isnan(pm25_data['pm2.5']))[0]
```

```
pm25_mean = mean_imputer(pm25_data,missing_index)

#检查是否还有数据缺失
pm25_mean[np.isnan(pm25_mean['pm2.5']).values==True]
```

Out[ ]:

	No	year	month	day	hour	pm2.5	DEWP	TEMP	PRES	Iws	Is	Ir	cbwd_NE	cbwd_NW	cbwd_SE	cbwd_cv	date
18946	18947	2012	2	29	10	NaN	-6	3.0	1022.0	1.79	0	0	0	0	1	0	2012-02-29
18947	18948	2012	2	29	11	NaN	-6	4.0	1022.0	1.79	0	0	1	0	0	0	2012-02-29
18948	18949	2012	2	29	12	NaN	-6	5.0	1021.0	1.79	0	0	0	0	1	0	2012-02-29
18949	18950	2012	2	29	13	NaN	-5	7.0	1020.0	3.58	0	0	0	0	1	0	2012-02-29
18950	18951	2012	2	29	14	NaN	-5	8.0	1019.0	5.37	0	0	0	0	1	0	2012-02-29
18951	18952	2012	2	29	15	NaN	-5	8.0	1019.0	7.16	0	0	0	0	1	0	2012-02-29

In [ ]:

```
# 我们发现2012年2月29日也缺了数据，所以决定用2012年2月28日和3月1日的数据取平均作为2012年2月29日的数据
index1 = pm25_mean[(pm25_mean.day==28)&(pm25_mean.month==2)&(pm25_mean.year==2012)].index.tolist()
index2 = pm25_mean[(pm25_mean.day==29)&(pm25_mean.month==2)&(pm25_mean.year==2012)].index.tolist()
index3 = pm25_mean[(pm25_mean.day==1)&(pm25_mean.month==3)&(pm25_mean.year==2012)].index.tolist()
data1=pm25_mean.loc[index1,'pm2.5'].reset_index(drop=True)
data3=pm25_mean.loc[index3,'pm2.5'].reset_index(drop=True)
pm25_mean.loc[index2,'pm2.5']=[1/2*(data1[i]+data3[i]) for i in range(24)]
# 对数化
pm25_mean=module.log(pm25_mean)
# 得到week
week_list=[]
for date in pm25_mean['date']:
    week_list.append(pd.to_datetime(date).weekday())
pm25_mean['week']=week_list
# 存为csv文件
pm25_mean.to_csv("pm25_data_mean.csv",index=False)
# 得到 train data & test data
test_data,train_data=module.train_test_split(pm25_mean)
```

2.2 与task1类似，用xgboost预测模型拟合填补后的数据，并通过xgb.plot_importance进行特征选择

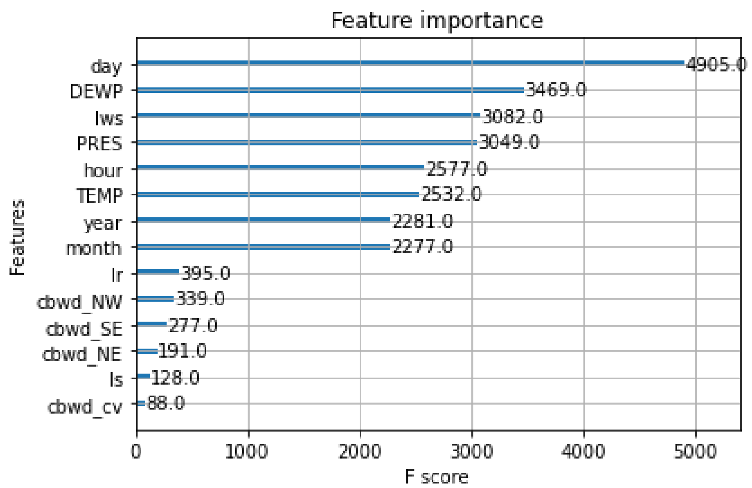
In [ ]:

```
var=['year','month','day','hour','DEWP','TEMP','PRES','Iws','Is','Ir','cbwd_NE','cbwd_NW','cbwd_SE','cbwd_cv']
X_train = train_data[var]
X_test = test_data[var]
y_train = train_data['pm2.5_log']
```

```
y_test = test_data['pm2.5']

XGB_model=xgb.XGBRegressor(learning_rate=0.1,n_estimators=900,max_depth=5)
XGB_model.fit(X_train, y_train)
y_pred = XGB_model.predict(X_test)
y_pred = np.round(np.exp(y_pred))

# 归一化
y_pred=preprocessing.minmax_scale(y_pred)
y_test=preprocessing.minmax_scale(y_test)
print("Mean squared error of test data for mean imputed data: %.4f" % mean_squared_error(y_pred, y_test))
print("R2 score: %.4f" % XGB_model.score(X_test,test_data['pm2.5_log']))

# 特征选择
xgb.plot_importance(XGB_model)
```

```
Mean squared error of test data for mean imputed data: 0.0076
R2 score: 0.6848
```

Out[ ]:
```
<AxesSubplot:title={'center':'Feature importance'}, xlabel='F score', ylabel='Features'>
```



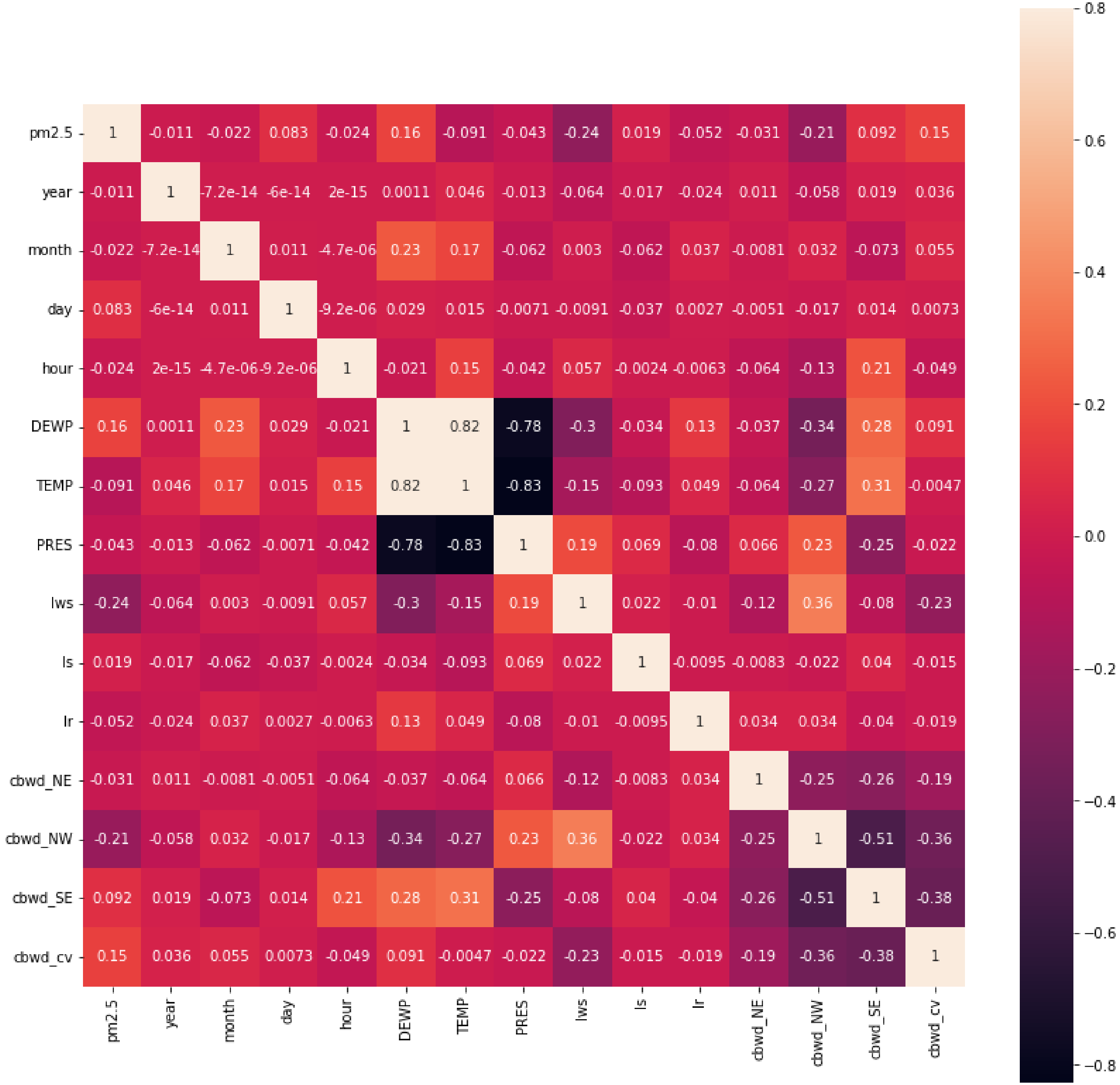
得到平均填补法补全的数据集的预测结果为R^2=0.6848，略低于原数据

筛选后day仍是最重要的特征；气象因素中仍是DEWP,lws,PRES,TEMP最重要，但各个因素的重要程度有所改变，重要性依次为DEWP,lws,PRES,TEMP

2.2 与task1类似，用相关系数矩阵进行特征筛选

In [ ]:

```
X=pm25_mean[['pm2.5','year','month','day','hour','DEWP','TEMP','PRES','Iws','Is','Ir','cbwd_NE','cbwd_NW','cbwd_SE','cbwd_cv']]
corrmatrix = X.corr()
plt.subplots(figsize=(14, 14))
sns.heatmap(corrmatrix, vmax=0.8, square=True, annot=True)
plt.show()
```


pm2.5
year
month
day
hour
DEWP
TEMP
PRES
Iws
Is
Ir
cbwd_NE
cbwd_NW
cbwd_SE
cbwd_cv

筛选后结果发生变化，与pm2.5相关性较高的因素：DEWP、lws、cbwd_NW、cbwd_cv

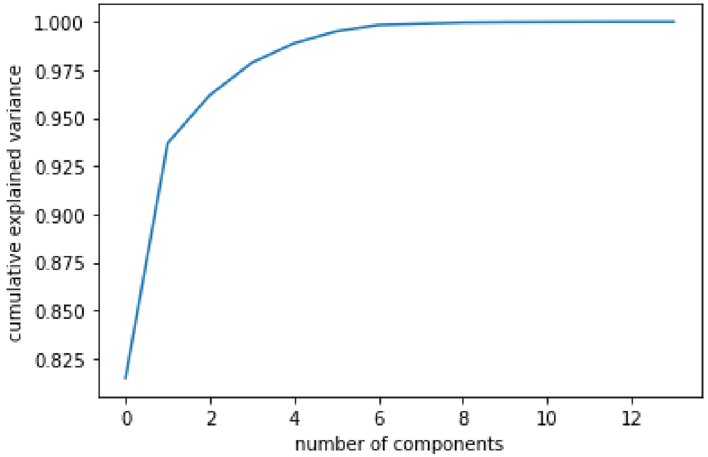
2.3 与task1类似， 通过PCA.explained_variance_ratio_选择特征并尝试降维

In [ ]:

```
from sklearn.decomposition import PCA
pca=PCA().fit(X.drop('pm2.5',axis=1))
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance')
np.cumsum(pca.explained_variance_ratio_)
```

Out[ ]:

```
array([0.81476227, 0.93698415, 0.96192403, 0.97877016, 0.98886732,
       0.99506625, 0.99835893, 0.99899759, 0.99962027, 0.99980266,
       0.99988853, 0.99995792, 1.        , 1.        ])
```



PCA给出的结果与原数据类似，取前3个主成分作为特征，其中第一主成分主要反映了对pm2.5的影响

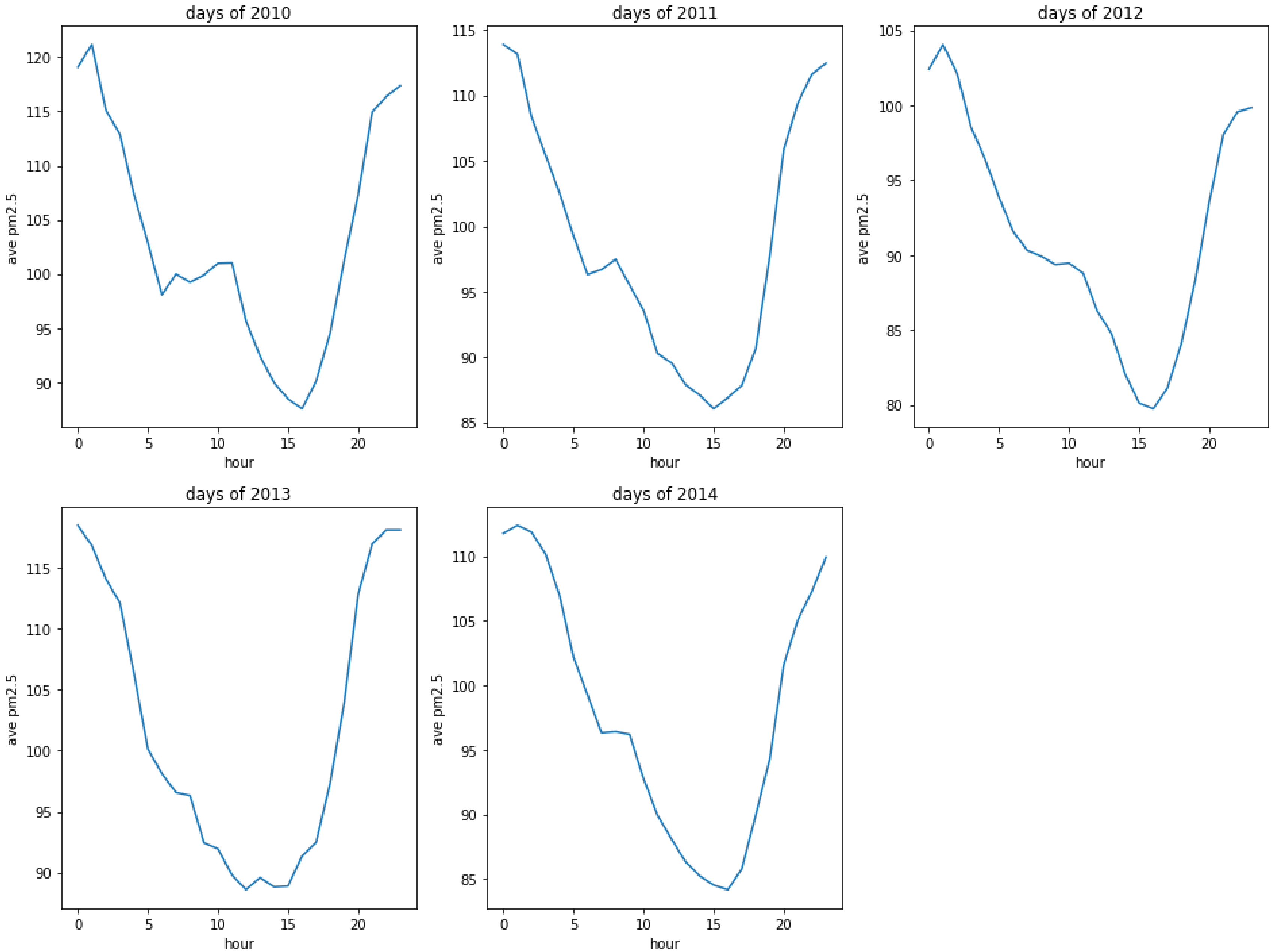
2.4 用由平均填补法得到的新数据进行task2的运行

2.4.1 与task2类似，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

In [ ]:

```
## PM2.5在一天内的波动值
Year=[2010,2011,2012,2013,2014]
```

```
Hour=range(24)
day_of_year1=[[],[],[],[],[]]

variation_of_day1=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_mean[pm25_mean.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_year1[index].append(mean)

variation_of_day1=variation_of_day1.append(day_of_year1)
variation_of_day1.index=Year

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour,variation_of_day1.iloc[i,:])
    plt.title('days of %d' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_day1
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	
2010	119.057534	121.166667	115.103881	112.889269	107.371918	102.870548	98.073516	99.992009	99.234703	99.895434	...	89.971918	88.472374	87.566438	90.113927	94
2011	113.904338	113.155708	108.394521	105.447032	102.568493	99.265297	96.318037	96.704338	97.486530	95.507991	...	87.105251	86.060046	86.902511	87.838813	90
2012	102.412568	104.062842	102.133197	98.546448	96.394353	93.840164	91.583106	90.323770	89.930328	89.381831	...	82.055328	80.123059	79.751138	81.128188	84
2013	118.432420	116.785616	114.042466	112.106849	106.350685	100.124658	98.096575	96.560959	96.317808	92.442466	...	88.835160	88.903196	91.357534	92.480594	97
2014	111.790411	112.409589	111.888813	110.197032	107.015525	102.178539	99.254566	96.317123	96.413242	96.194292	...	85.233562	84.521233	84.158447	85.758219	89

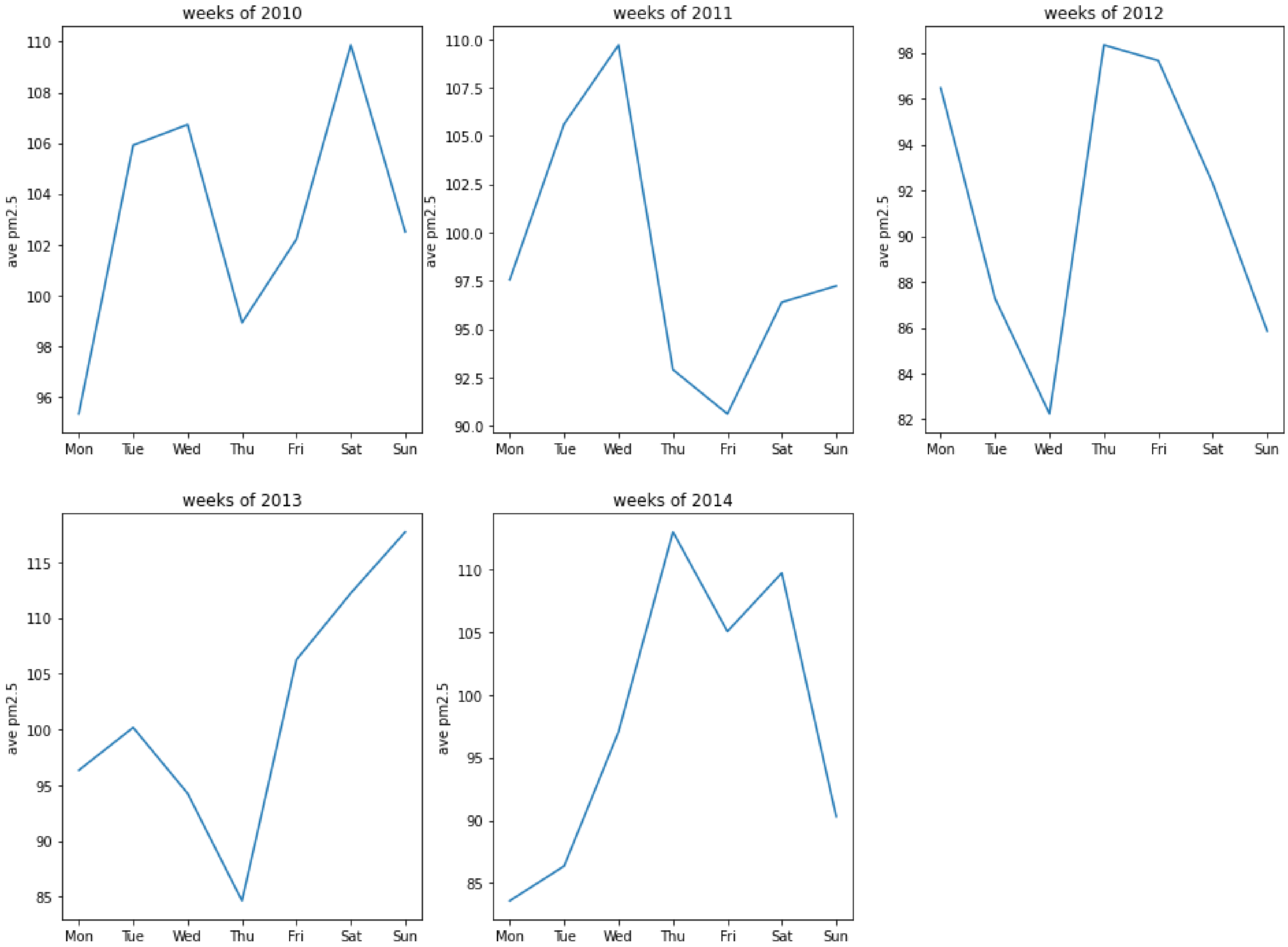
5 rows × 24 columns

折线图结果与原数据task2的基本一样，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

2.4.2 与task2类似，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

In [ ]:

```
# PM2.5在一周的波动值
Week=range(7)
week_of_year1=[[],[],[],[],[]]

variation_of_week1=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_mean[pm25_mean.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_year1[index].append(mean)
variation_of_week1=variation_of_week1.append(week_of_year1)
variation_of_week1.index=Year

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_week1.iloc[i,:])
    plt.title('weeks of %d' % Year[i])
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_week1
```

Out[ ]:

0	1	2	3	4	5	6

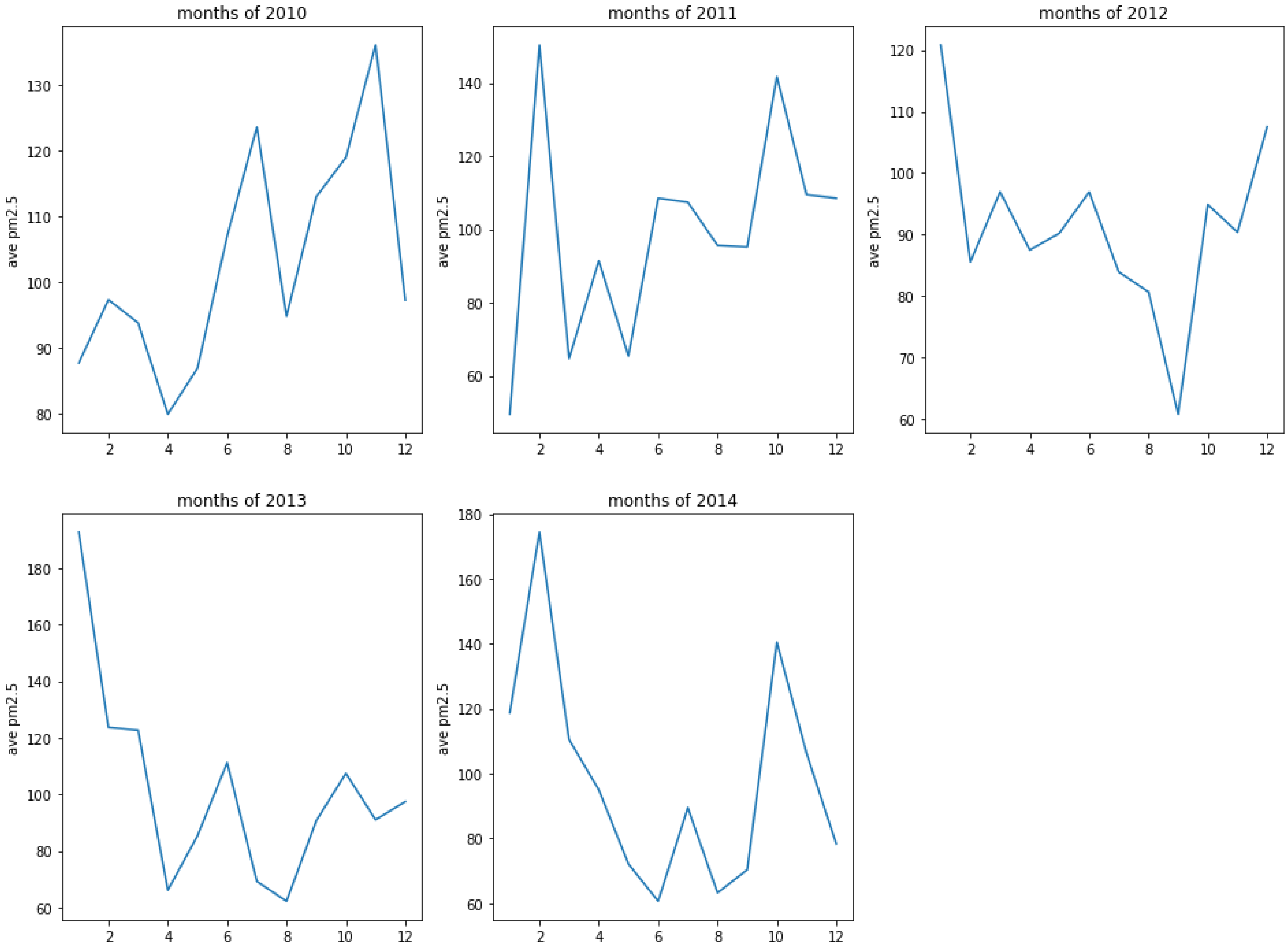
	0	1	2	3	4	5	6
2010	95.338742	105.918536	106.729033	98.925414	102.214164	109.861111	102.506343
2011	97.559495	105.625000	109.712607	92.901309	90.614650	96.398257	97.242521
2012	96.468553	87.264824	82.237847	98.340278	97.659109	92.293470	85.851350
2013	96.339076	100.180490	94.268029	84.635083	106.253072	112.237580	117.731771
2014	83.591947	86.352230	97.055031	112.972289	105.044471	109.700321	90.300881

与task2原数据结果相比，除少数数值外，填充的数据结果基本不变，每年每星期pm2.5平均浓度变化趋势完全不同

2.4.3 与task2类似，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

In [ ]:

```
## PM2.5在一年内数月的波动值
Month=range(1,13)
month_of_year1=[[],[],[],[],[]]

variation_of_month1=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_mean[pm25_mean.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_year1[index].append(mean)
variation_of_month1=variation_of_month1.append(month_of_year1)
variation_of_month1.index=Year

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Month,variation_of_month1.iloc[i,:])
    plt.title('months of %d' % Year[i])
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_month1
```

Out[ ]:

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

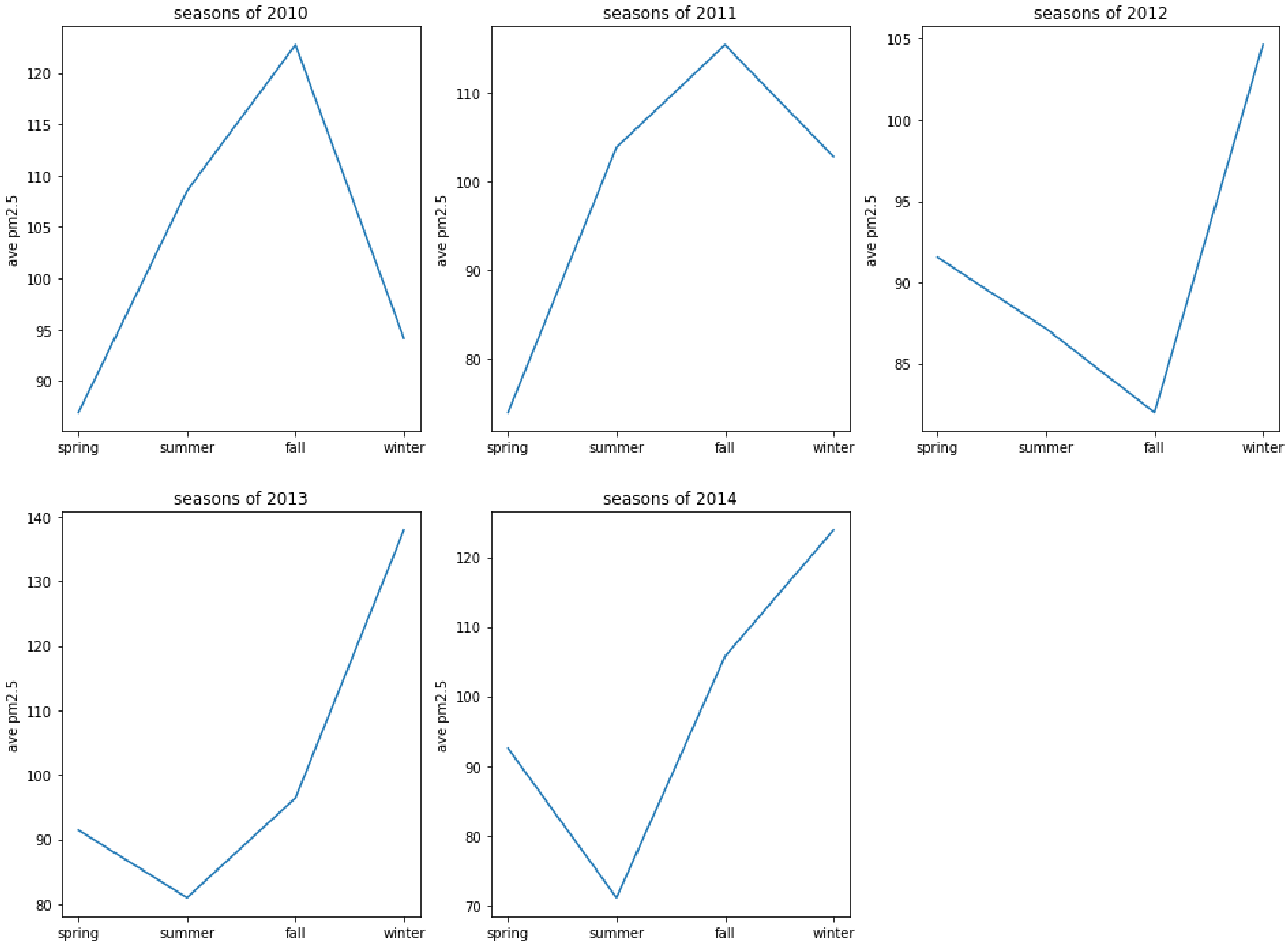
	0	1	2	3	4	5	6	7	8	9	10	11
2010	87.761761	97.388393	93.854839	79.989583	86.964830	107.040278	123.647849	94.872200	113.060532	119.005712	136.120833	97.333333
2011	49.615255	150.321429	64.755712	91.427083	65.452285	108.553356	107.421819	95.677419	95.231944	141.711694	109.501736	108.552083
2012	120.815076	85.515805	96.941196	87.472222	90.203629	96.900694	83.878136	80.656250	60.760446	94.843414	90.346181	107.530130
2013	192.628584	123.714658	122.705645	66.231250	85.434588	111.308681	69.354839	62.318660	90.753935	107.476142	91.113542	97.484543
2014	118.788306	174.454613	110.514785	95.004514	72.143817	60.632060	89.510081	63.229167	70.360764	140.540323	106.270486	78.343974

结果与原数据的类似，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

2.4.4 与task2类似，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

In [ ]:

```
## PM2.5在四季的波动值
season_of_year1=[[],[],[],[],[]]

variation_of_season1=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_mean[pm25_mean.year==year]
    mean_spring=(variation_of_month1.loc[year,2]+variation_of_month1.loc[year,3]+variation_of_month1.loc[year,4])/3
    mean_summer=(variation_of_month1.loc[year,5]+variation_of_month1.loc[year,6]+variation_of_month1.loc[year,7])/3
    mean_fall=(variation_of_month1.loc[year,8]+variation_of_month1.loc[year,9]+variation_of_month1.loc[year,10])/3
    mean_winter=(variation_of_month1.loc[year,11]+variation_of_month1.loc[year,0]+variation_of_month1.loc[year,1])/3
    season_of_year1[index].append(mean_spring)
    season_of_year1[index].append(mean_summer)
    season_of_year1[index].append(mean_fall)
    season_of_year1[index].append(mean_winter)
variation_of_season1=variation_of_season1.append(season_of_year1)
variation_of_season1.index=Year

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_season1.iloc[i,:])
    plt.title('seasons of %d' % Year[i])
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_season1
```

Out[ ]:

	0	1	2	3

	0	1	2	3
2010	86.936417	108.520109	122.729026	94.161162
2011	73.878360	103.884198	115.481791	102.829589
2012	91.539016	87.145027	81.983347	104.620337
2013	91.457161	80.994060	96.447873	137.942595
2014	92.554372	71.123769	105.723858	123.862298

结果与原数据类似，除少量数值变化外，浓度变化趋势基本相同，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

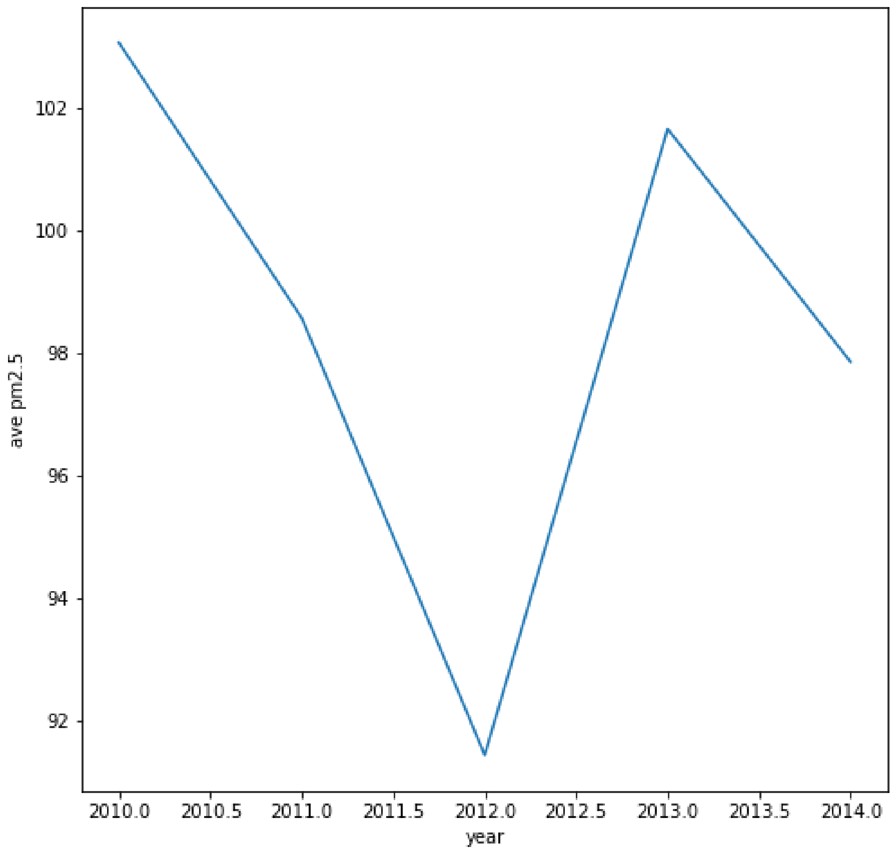
2.4.5 与task2类似，用折线图记录每年pm2.5的变化趋势，取每年平均浓度作为当年的对应值

In [ ]:

```
## PM2.5在5年内的波动值
varaition_of_year1=[]
for year in Year:
    pm25_year=pm25_mean[pm25_mean.year==year]
    mean=np.mean(pm25_year['pm2.5'])
    varaition_of_year1.append(mean)

plt.figure(figsize=(8,8))
plt.plot(Year,varaition_of_year1)
plt.xlabel('year')
plt.ylabel('ave pm2.5')
```

Out[ ]:

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



In [ ]:
```
varaition_of_year1
```

Out[ ]:
```
[103.06813165905635,
 98.57314497716895,
 91.4420879829955,
 101.65952245053273,
 97.85739155251144]
```

与原数据结果类似，除平均浓度数值范围有细微变化外，基本趋势不变。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

2.4.6 与task2类似，对于填补后的数据，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

In [ ]:

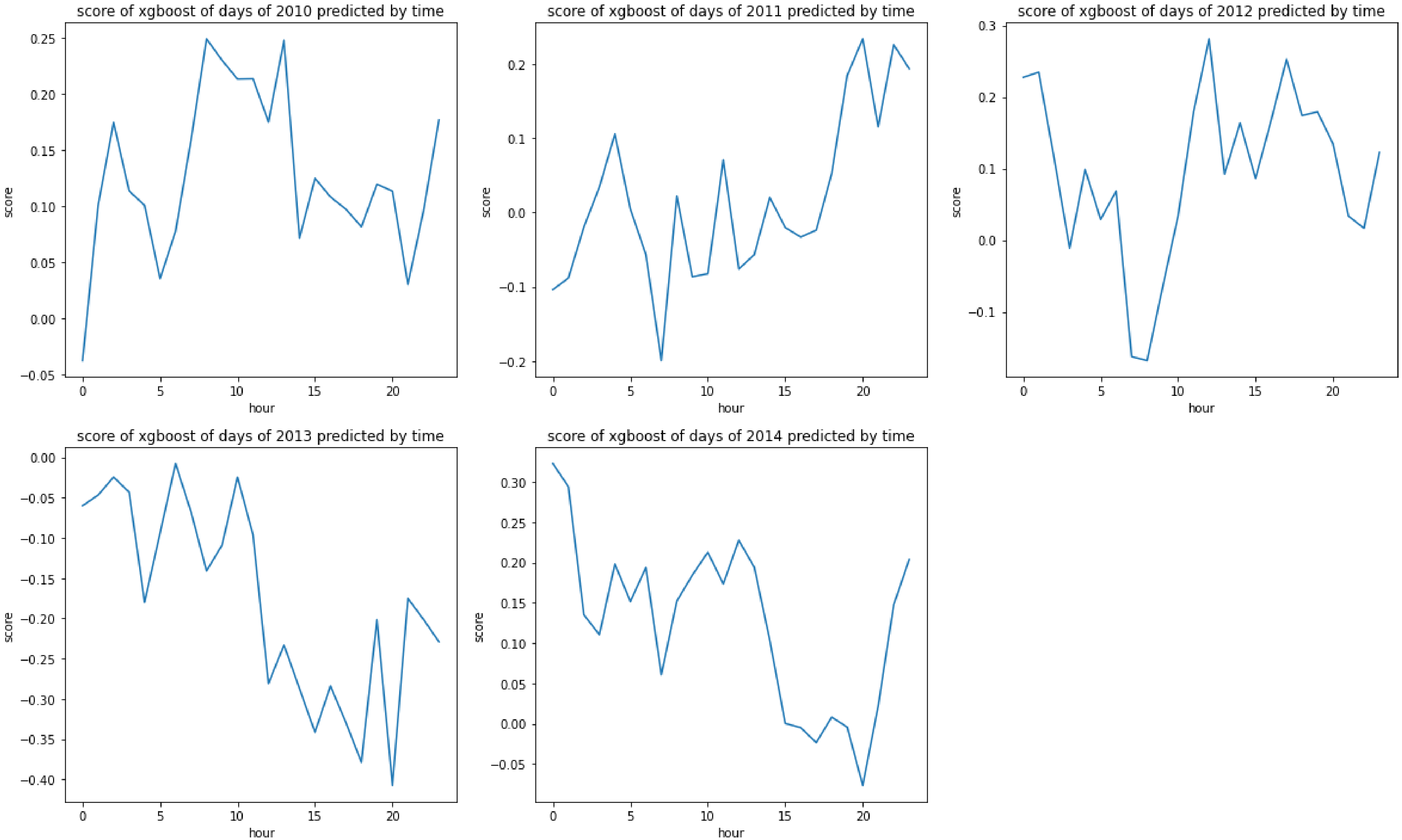
```python
from xgboost import XGBRegressor
```

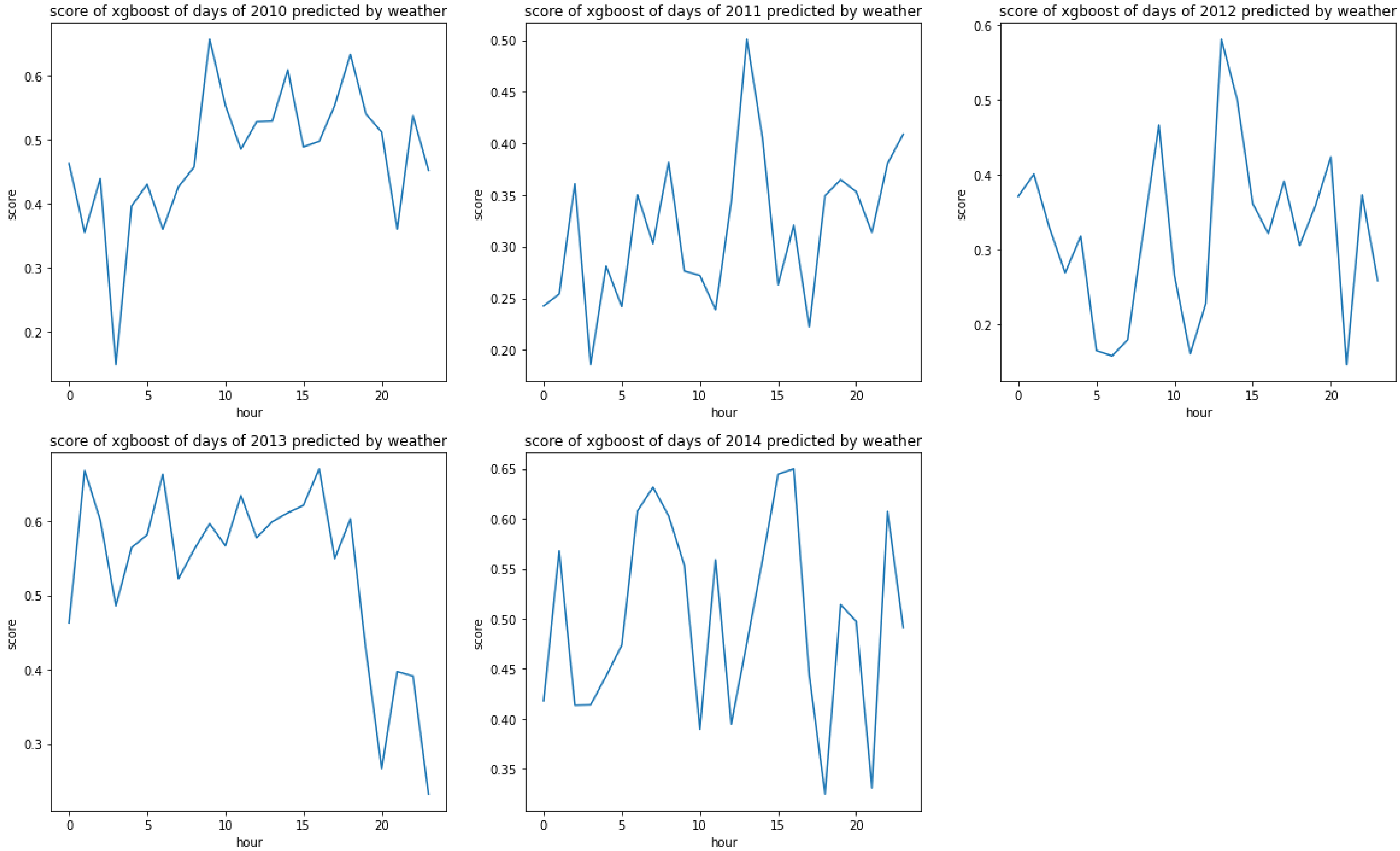
2.4.6.1 与task2类似，分别使用每年一天24小时数据的时间信息和天气信息，对每小时pm2.5平均浓度进行预测，将两种方法下每年每小时的预测score用折线图分别绘出

In [ ]:

```python
## 基于PM2.5在一天内的波动值，用xgboost进行预测
Year=[2010,2011,2012,2013,2014]
Hour=range(24)
day_of_year_train1=[[],[],[],[],[]]
day_of_year_test1=[[],[],[],[],[]]
score_of_year_time1 = [[],[],[],[],[]]
score_of_year_weather1 = [[],[],[],[],[]]
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_time1=pd.DataFrame()
variation_of_day_weather1=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_time1[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_weather1[index].append(XGB_model_weather.score(X_test_data_hour_year_weather,test_data_hour_year['pm2.5_log']))

variation_of_day_time1=variation_of_day_time1.append(score_of_year_time1)
variation_of_day_weather1=variation_of_day_weather1.append(score_of_year_weather1)
plt.figure(figsize=(20,12))

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour,variation_of_day_time1.iloc[i,:])
    plt.title('score of xgboost of days of %d predicted by time' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('score')

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour,variation_of_day_weather1.iloc[i,:])
    plt.title('score of xgboost of days of %d predicted by weather' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('score')
```


score of xgboost of days of 2010 predicted by time
0.25
0.20
0.15
0.10
0.05
0.00
−0.05
score
0
5
10
15
20
hour
score of xgboost of days of 2011 predicted by time
0.2
0.1
0.0
−0.1
−0.2
score
0
5
10
15
20
hour
score of xgboost of days of 2012 predicted by time
0.3
0.2
0.1
0.0
−0.1
score
0
5
10
15
20
hour
score of xgboost of days of 2013 predicted by time
0.00
−0.05
−0.10
−0.15
−0.20
−0.25
−0.30
−0.35
−0.40
score
0
5
10
15
20
hour
score of xgboost of days of 2014 predicted by time
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−0.05
score
0
5
10
15
20
hour



In [ ]:

```
variation_of_day_time1
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	
0	-0.037483	0.101016	0.174856	0.113766	0.100841	0.035487	0.077764	0.159086	0.249265	0.230154	...	0.071675	0.125024	0.108383	0.097434	0.081709	0.119
1	-0.103656	-0.088180	-0.019566	0.034137	0.105731	0.004649	-0.056374	-0.199237	0.022333	-0.086457	...	0.020299	-0.020188	-0.033046	-0.023655	0.052450	0.184

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	
2	0.227275	0.234499	0.114063	-0.011080	0.098768	0.028920	0.068575	-0.162571	-0.168071	-0.065697	...	0.163616	0.086183	0.166446	0.252472	0.174080	0.179
3	-0.059887	-0.046679	-0.024203	-0.043065	-0.179843	-0.093903	-0.007505	-0.067677	-0.141005	-0.108929	...	-0.287272	-0.341617	-0.284081	-0.329644	-0.378926	-0.201
4	0.322958	0.294229	0.135228	0.110296	0.198284	0.151557	0.193695	0.060686	0.152116	0.184293	...	0.103525	0.000232	-0.005142	-0.023669	0.008000	-0.004

5 rows × 24 columns

In [ ]:

```
variation_of_day_weather1
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	19	20
0	0.463175	0.355465	0.439692	0.148601	0.397043	0.430741	0.360435	0.427003	0.457629	0.657642	...	0.609773	0.489238	0.498087	0.554335	0.634018	0.540722	0.512537
1	0.242600	0.254181	0.360900	0.185756	0.281189	0.241897	0.350279	0.302937	0.381670	0.276478	...	0.405547	0.263135	0.320861	0.222468	0.349365	0.364949	0.353239
2	0.371615	0.401322	0.329053	0.269312	0.318278	0.165299	0.158079	0.179637	0.324204	0.466853	...	0.501327	0.361530	0.321893	0.391892	0.305935	0.358253	0.424301
3	0.463262	0.668284	0.601897	0.486143	0.564541	0.581808	0.663416	0.522434	0.561725	0.596729	...	0.611388	0.621423	0.670615	0.549894	0.603153	0.425058	0.266684
4	0.417926	0.567925	0.413405	0.413795	0.442679	0.473672	0.607768	0.631547	0.602882	0.553481	...	0.558511	0.644679	0.649985	0.443518	0.324492	0.514093	0.497325

5 rows × 24 columns

相比于原数据，两种方法给出的预测分数变化趋势均与原来的相似，运用天气信息的预测准度明显更高。但这个精度相对于原数据明显下降，最高低于使用原先所有训练集得到的预测模型的准度

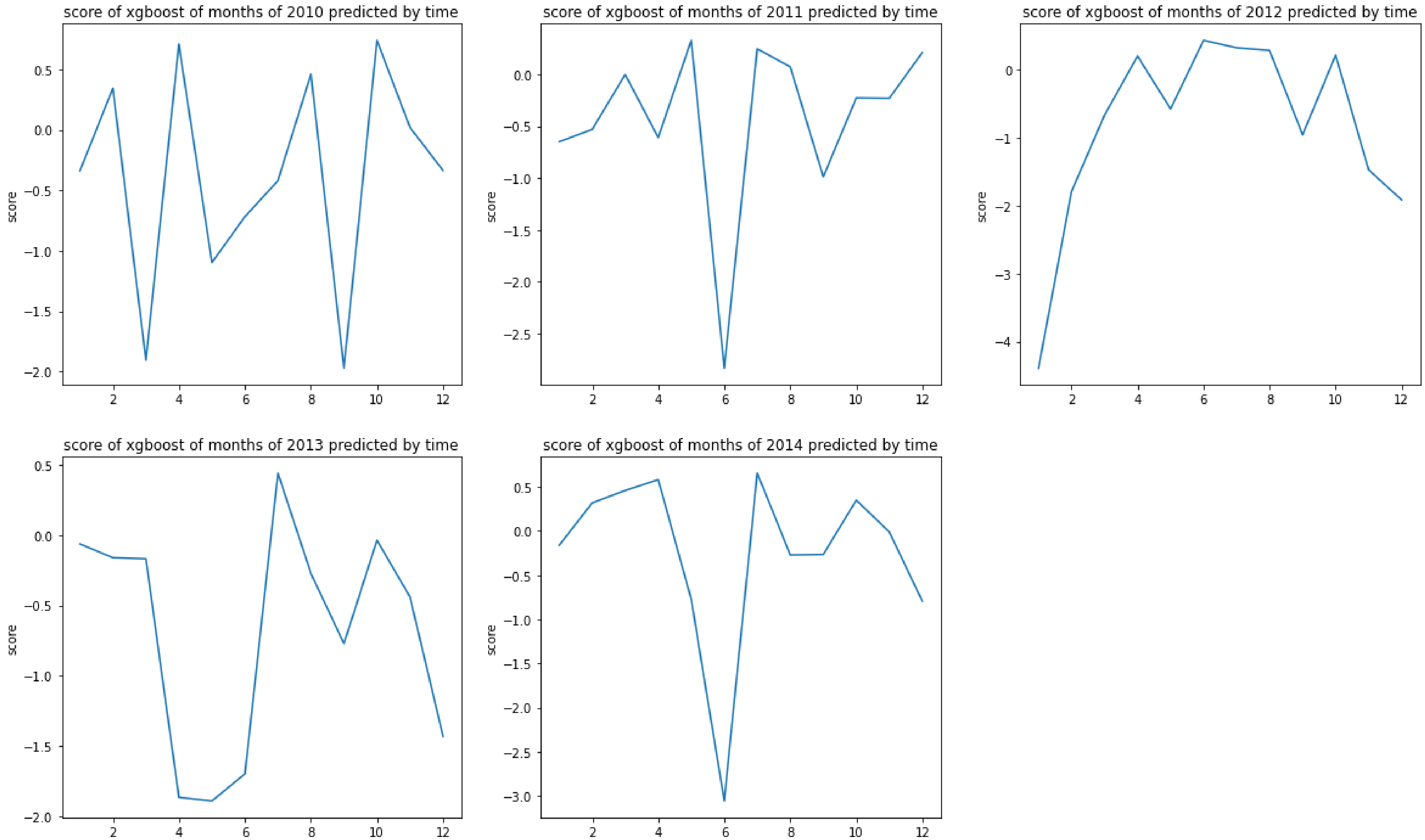
2.4.6.2 与task2相似，分别使用填补后每年每月数据的时间信息和天气信息，对每月pm2.5平均浓度进行预测，将两种方法下每年每月的预测score用折线图分别绘出

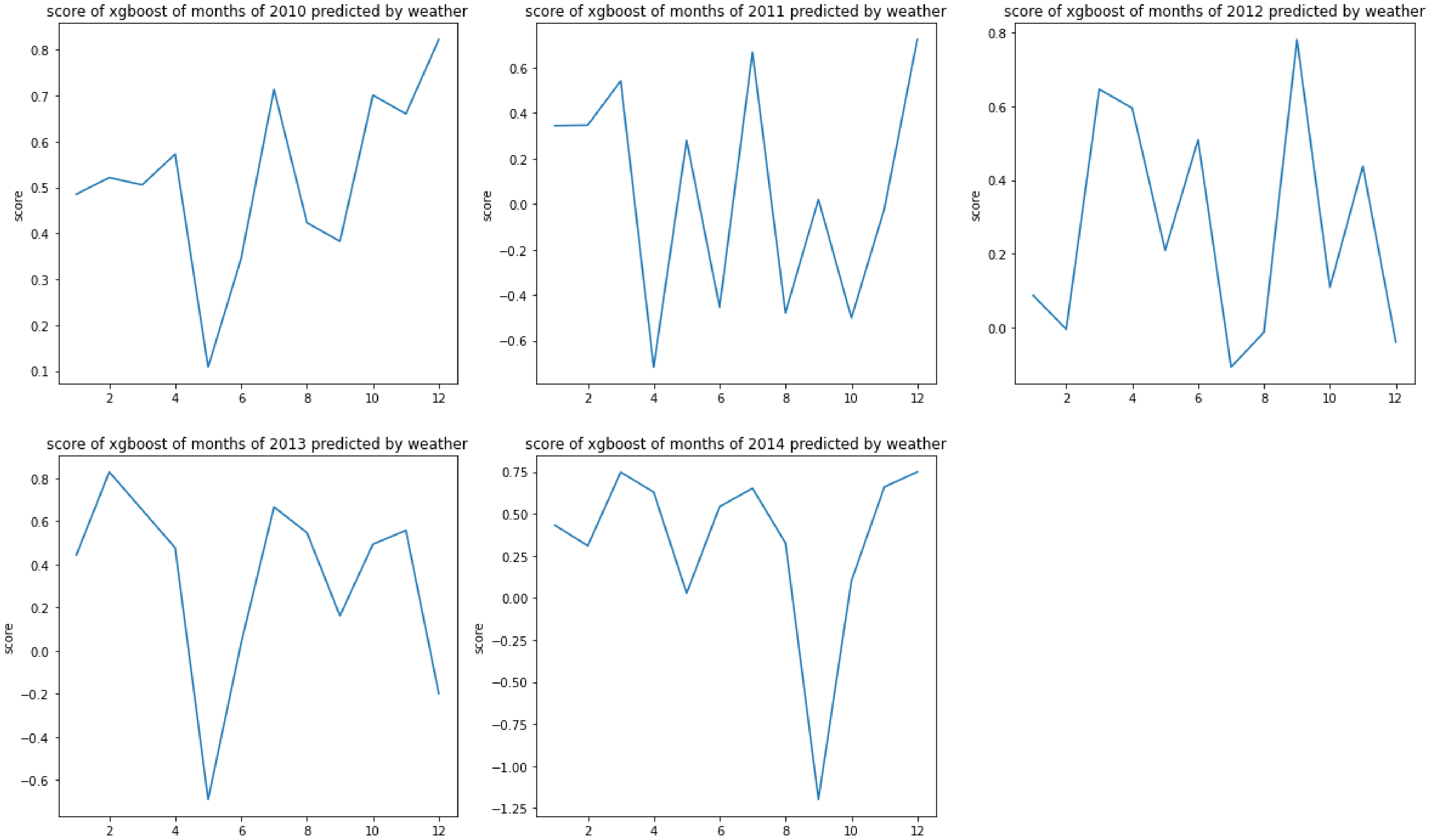
In [ ]:

```
## 基于PM2.5在一年内数月的波动值， 用xgboost进行预测
Month = range(1,13)
week_of_year1=[[],[],[],[],[]]
score_of_month_weather1 = [[],[],[],[],[]]
score_of_month_time1 = [[],[],[],[],[]]

variation_of_month_time1=pd.DataFrame()
variation_of_month_weather1=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)
        y_test_data_month_year = preprocessing.minmax_scale(y_test_data_month_year)
        score_of_month_time1[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_weather1[index].append(XGB_model_weather.score(X_test_data_month_year_weather,test_data_month_year['pm2.5_log']))

variation_of_month_time1=variation_of_month_time1.append(score_of_month_time1)
variation_of_month_weather1=variation_of_month_weather1.append(score_of_month_weather1)
plt.figure(figsize=(20,12))

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Month,variation_of_month_time1.iloc[i,:])
    plt.title('score of xgboost of months of %d predicted by time' % Year[i])
    plt.ylabel('score')

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Month,variation_of_month_weather1.iloc[i,:])
```

```
plt.title('score of xgboost of months of %d predicted by weather' % Year[i])
plt.ylabel('score')
```





In [ ]:

```
variation_of_month_time1
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	10	11
0	-0.338548	0.346103	-1.904089	0.711337	-1.096566	-0.716418	-0.418752	0.464820	-1.970793	0.742950	0.022309	-0.334421
1	-0.649614	-0.530581	-0.001401	-0.609666	0.327828	-2.832711	0.245290	0.072992	-0.988170	-0.227102	-0.230520	0.210873

	0	1	2	3	4	5	6	7	8	9	10	11
2	-4.389388	-1.788590	-0.663142	0.205786	-0.572387	0.436812	0.326685	0.288677	-0.954663	0.218447	-1.469489	-1.911884
3	-0.060734	-0.158978	-0.167026	-1.865168	-1.890642	-1.698227	0.443398	-0.271695	-0.770374	-0.034501	-0.438089	-1.429977
4	-0.160527	0.319677	0.460526	0.583537	-0.770967	-3.055540	0.657222	-0.270041	-0.264434	0.350737	-0.009396	-0.792763

In [ ]:

```
variation_of_month_weather1
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	10	11
0	0.485421	0.521514	0.505635	0.572718	0.108402	0.344922	0.713370	0.423196	0.382643	0.701248	0.660548	0.822447
1	0.344355	0.346419	0.540712	-0.716010	0.279292	-0.453219	0.666909	-0.477302	0.020360	-0.499932	-0.021116	0.722236
2	0.086520	-0.005110	0.646563	0.595400	0.209148	0.509423	-0.107813	-0.013043	0.781449	0.108413	0.437697	-0.039437
3	0.443168	0.828980	0.652994	0.476914	-0.689660	0.034904	0.666554	0.547094	0.162159	0.493749	0.557729	-0.198265
4	0.432083	0.309519	0.746950	0.628568	0.027360	0.541969	0.651416	0.325977	-1.198308	0.100762	0.659154	0.748499

相比于原数据，两种方法给出的预测分数变化趋势和数值均与原来的相似，用每月平均浓度预测时只用天气信息可以达到更高精度，但预测准度同样更加不稳定

2.4.6.3 与task2类似，分别使用填补后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

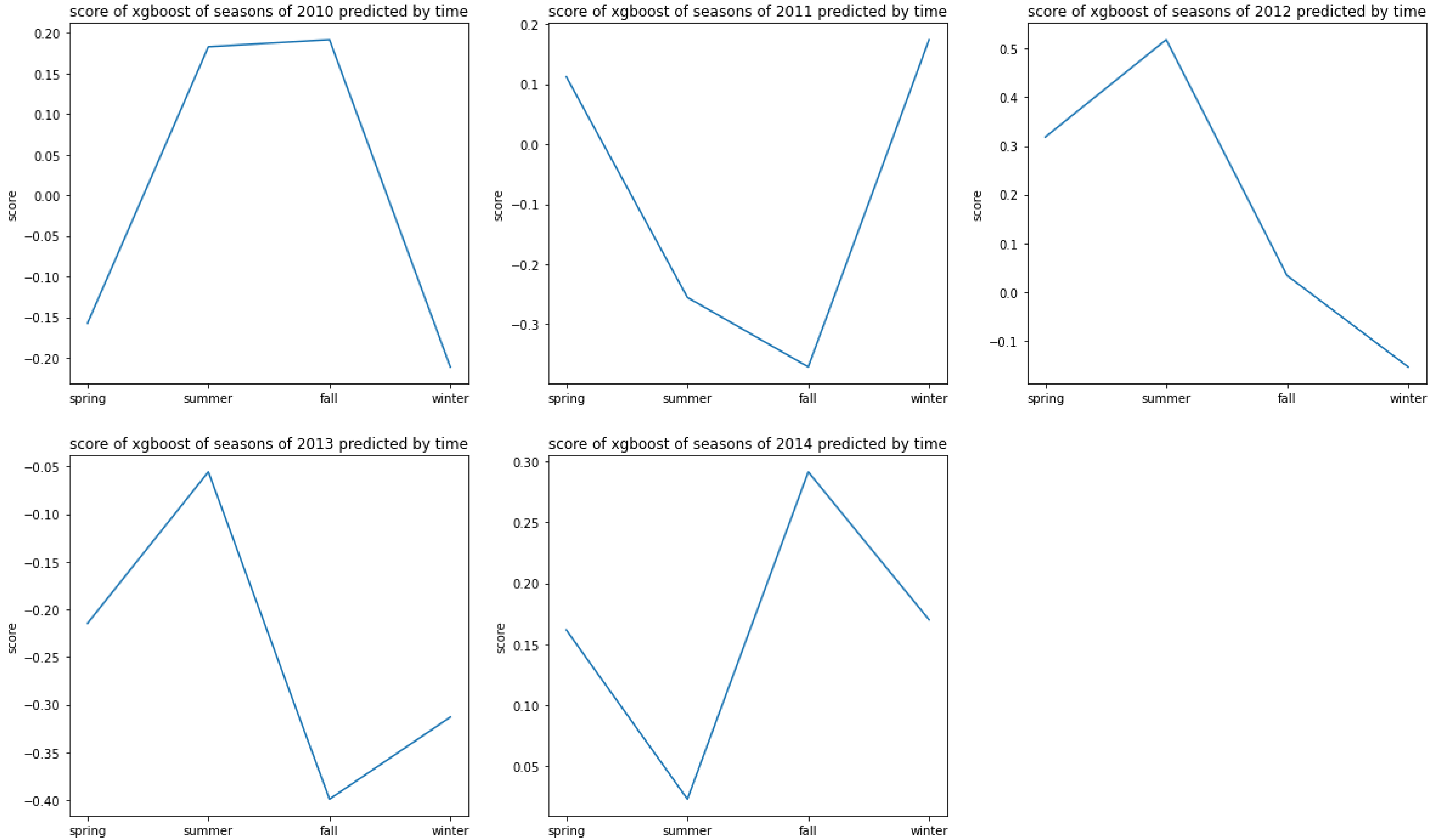
In [ ]:

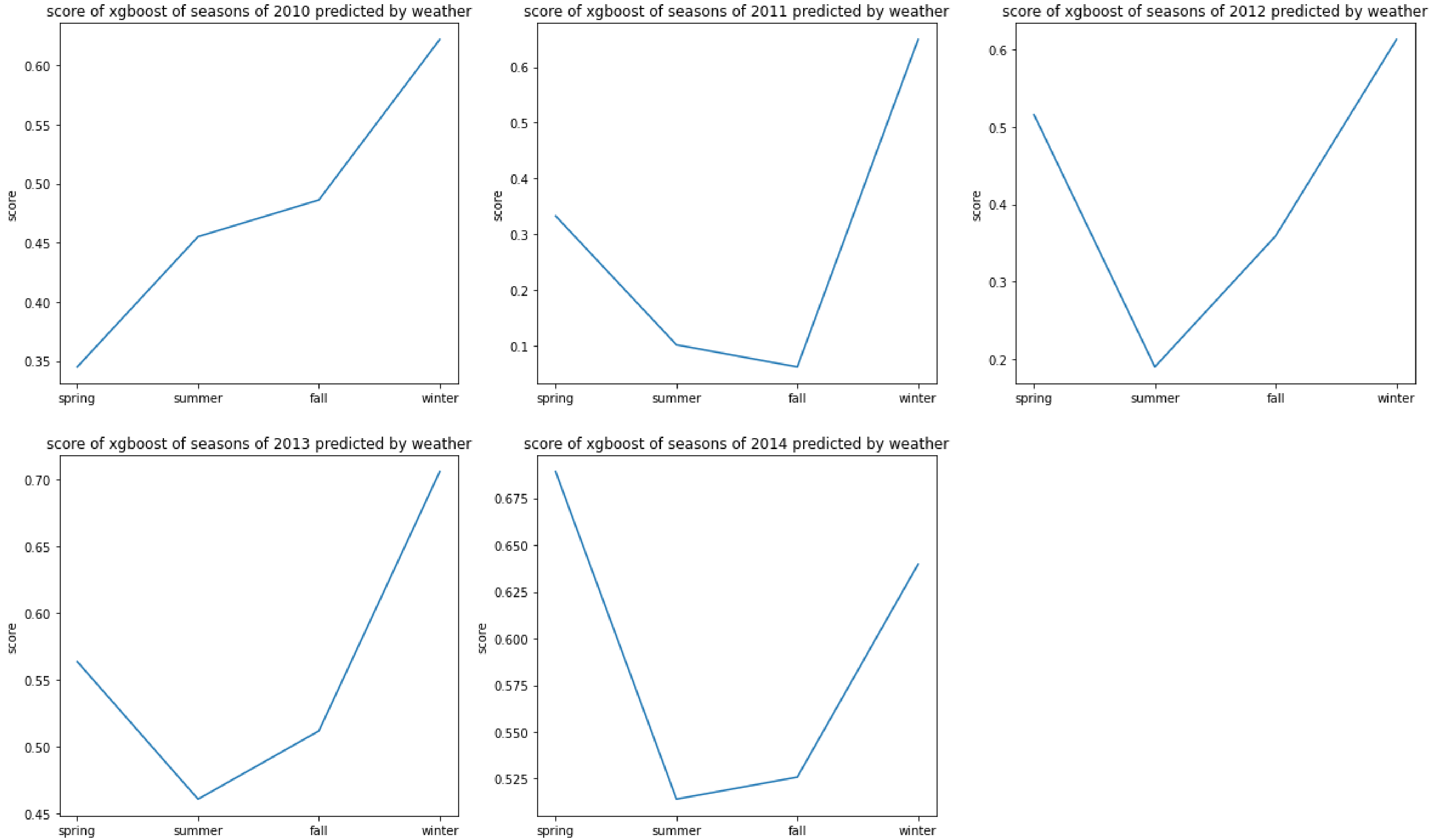
```
## 基于PM2.5在一年内四季的波动值， 用xgboost进行预测
season_of_year1=[[],[],[],[],[]]
score_of_season_weather1 = [[],[],[],[],[]]
score_of_season_time1 = [[],[],[],[],[]]

variation_of_season_time1=pd.DataFrame()
variation_of_season_weather1=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]
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_time1[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_weather1[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)
```

```python
score_of_season_time1[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)
score_of_season_weather1[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_time1[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_weather1[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)
```

```python
    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_time1[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_weather1[index].append(XGB_model_weather_winter.score(X_test_data_winter_year_weather,test_data_winter_year['pm2.5_log']))

variation_of_season_time1=variation_of_season_time1.append(score_of_season_time1)
variation_of_season_weather1=variation_of_season_weather1.append(score_of_season_weather1)
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_time1.iloc[i,:])
    plt.title('score of xgboost of seasons of %d predicted by time' % Year[i])
    plt.ylabel('score')

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Seasons,variation_of_season_weather1.iloc[i,:])
    plt.title('score of xgboost of seasons of %d predicted by weather' % Year[i])
    plt.ylabel('score')
```


score of xgboost of seasons of 2010 predicted by time
score of xgboost of seasons of 2011 predicted by time
score of xgboost of seasons of 2012 predicted by time
score of xgboost of seasons of 2013 predicted by time
score of xgboost of seasons of 2014 predicted by time
score
spring
summer
fall
winter



In [ ]:

```
variation_of_season_time1
```

Out[ ]:

	0	1	2	3
0	-0.157600	0.182988	0.191778	-0.211233
1	0.112579	-0.255533	-0.371047	0.174395

	0	1	2	3
2	0.318417	0.517996	0.034290	-0.152796
3	-0.214718	-0.055699	-0.398923	-0.313043
4	0.161678	0.023244	0.291264	0.170026

In [ ]:

```
variation_of_season_weather1
```

Out[ ]:

	0	1	2	3
0	0.345091	0.455237	0.486230	0.621849
1	0.332456	0.101059	0.061360	0.649349
2	0.515616	0.190327	0.359321	0.612537
3	0.563722	0.460768	0.511830	0.705852
4	0.689176	0.514072	0.525849	0.639737

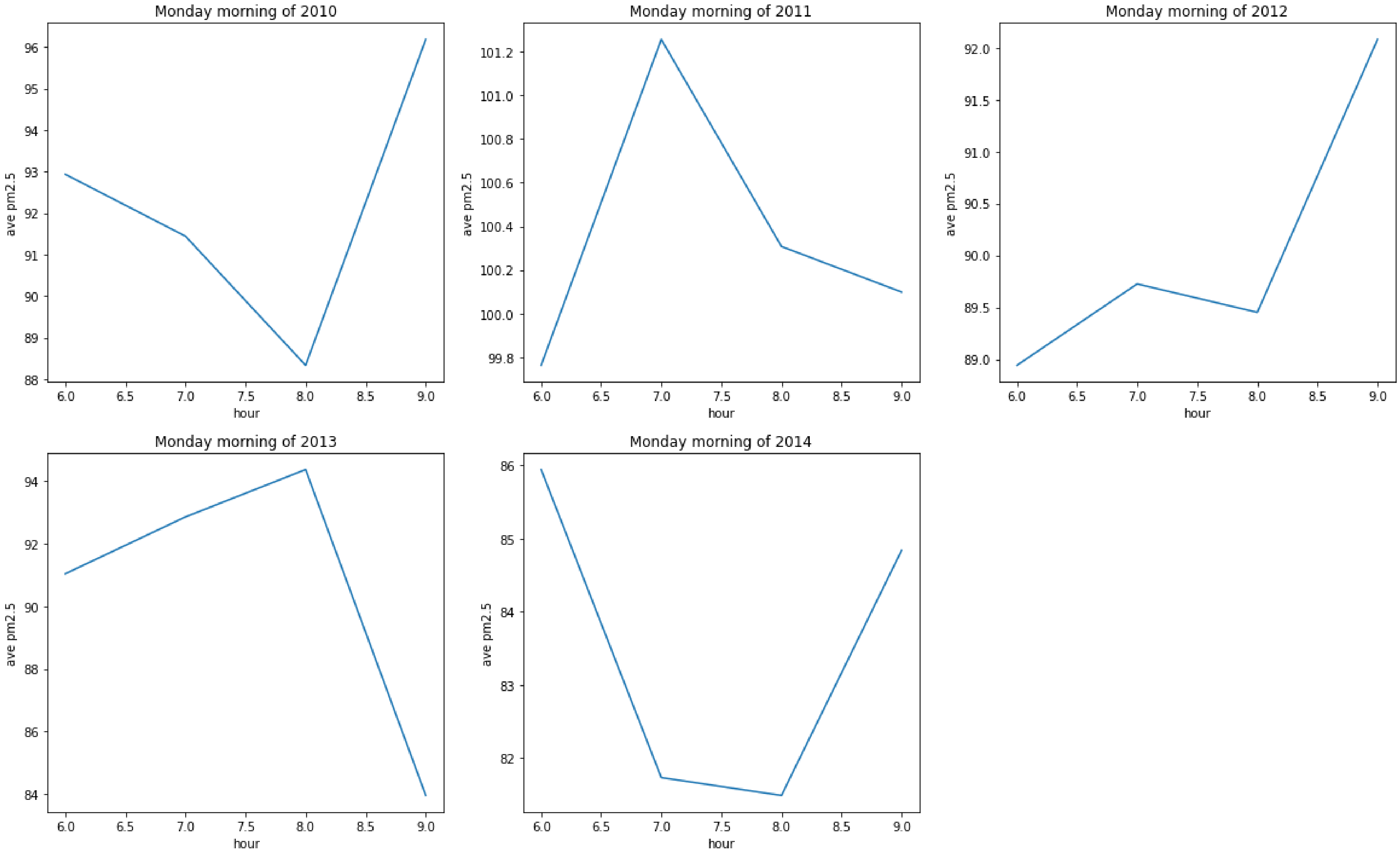
与原数据相比，两种方法给出的预测分数变化趋势均有较大变化，尤其是2010年、2013年和2014年用时间因素得到的预测分数变化趋势和2011年和2013年用天气因素得到的预测分数变化趋势。但总体上，我们仍应该用天气信息进行预测，且这五年间冬天均达到最高准度，后四年夏秋两季均为最低

2.4.7 与task2类似，用折线图记录填补后数据每年周一早晨（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

In [ ]:

```
## PM2.5在周一上午的波动值
Hour_Mon=range(6,10)
Week_Mon=range(1)
day_of_year_Mon1=[[],[],[],[],[]]

variation_of_day_Mon1=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_mean[pm25_mean.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_Mon1[index].append(mean)

variation_of_day_Mon1=variation_of_day_Mon1.append(day_of_year_Mon1)
variation_of_day_Mon1.index=Year

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour_Mon,variation_of_day_Mon1.iloc[i,:])
    plt.title('Monday morning of %d' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_day_Mon1
```

Out[ ]:

	0	1	2	3
2010	92.937500	91.447115	88.336538	96.187500
2011	99.764423	101.254808	100.307692	100.099359

	0	1	2	3
2012	88.943396	89.726415	89.452830	92.080189
2013	91.043269	92.860577	94.375000	83.956731
2014	85.942308	81.730769	81.487179	84.839744

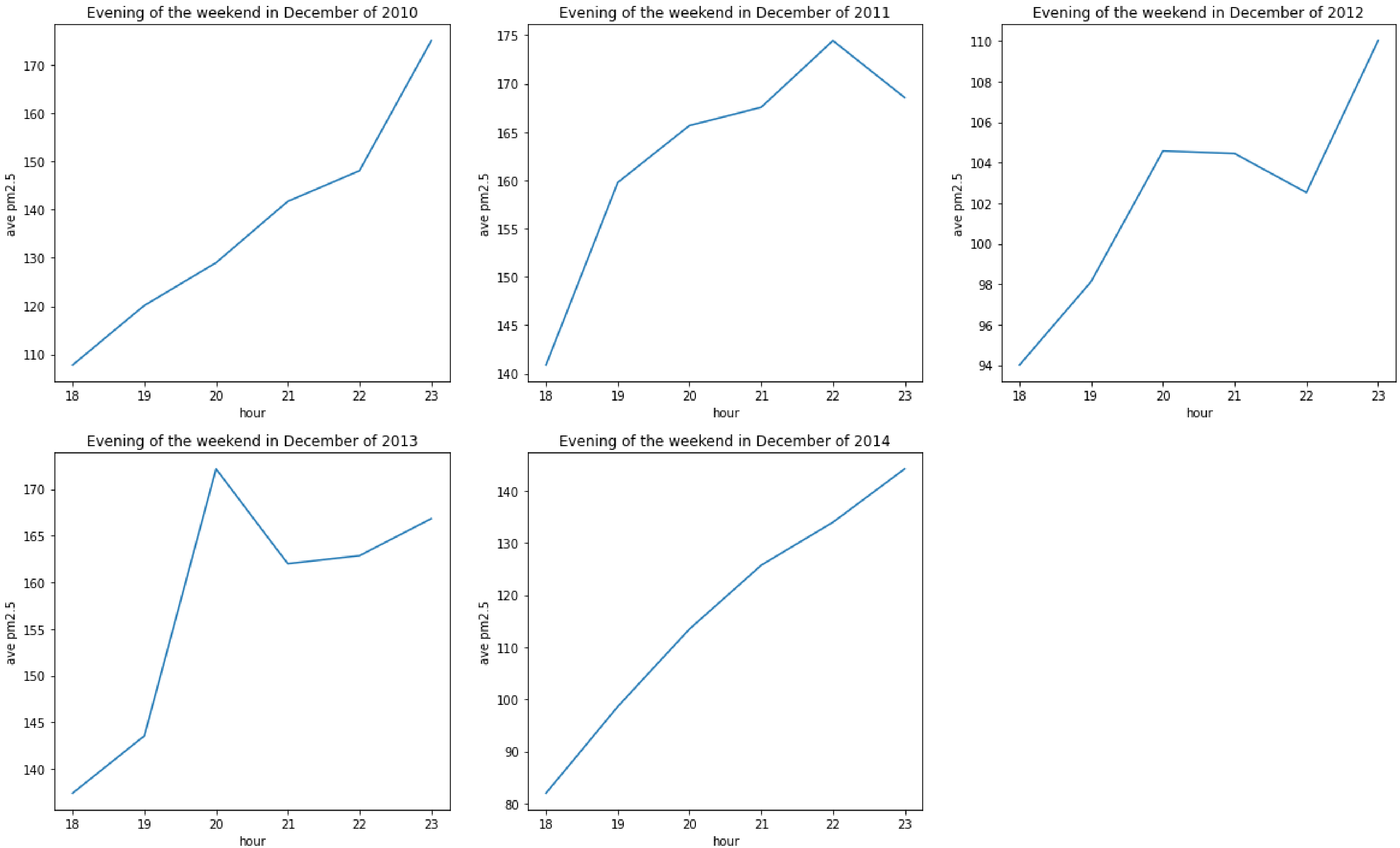
与原数据结果相比，平均浓度数值有所变化，但变化趋势与原数据的大致相当。每年星期一早晨每小时pm2.5平均浓度变化趋势不同，但除2013和2014年外均在8点取得最低值

2.4.8 与task2类似，用折线图记录填补后数据每年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

In [ ]:

```
## PM2.5在12月周末夜晚的波动值
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_Dec1=[[],[],[],[],[]]

variation_of_day_dec1=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_mean[pm25_mean.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_Dec1[index].append(mean)

variation_of_day_dec1=variation_of_day_dec1.append(day_of_year_Dec1)
variation_of_day_dec1.index=Year

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

for i in range(5):
    plt.subplot(2,3,i+1)
```

```
plt.plot(Hour_even,variation_of_day_dec1.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_dec1
```

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	94.000000	98.125000	104.575000	104.450000	102.525000	110.025000
2013	137.416667	143.555556	172.166667	162.000000	162.861111	166.833333
2014	82.000000	98.625000	113.500000	125.750000	134.000000	144.250000

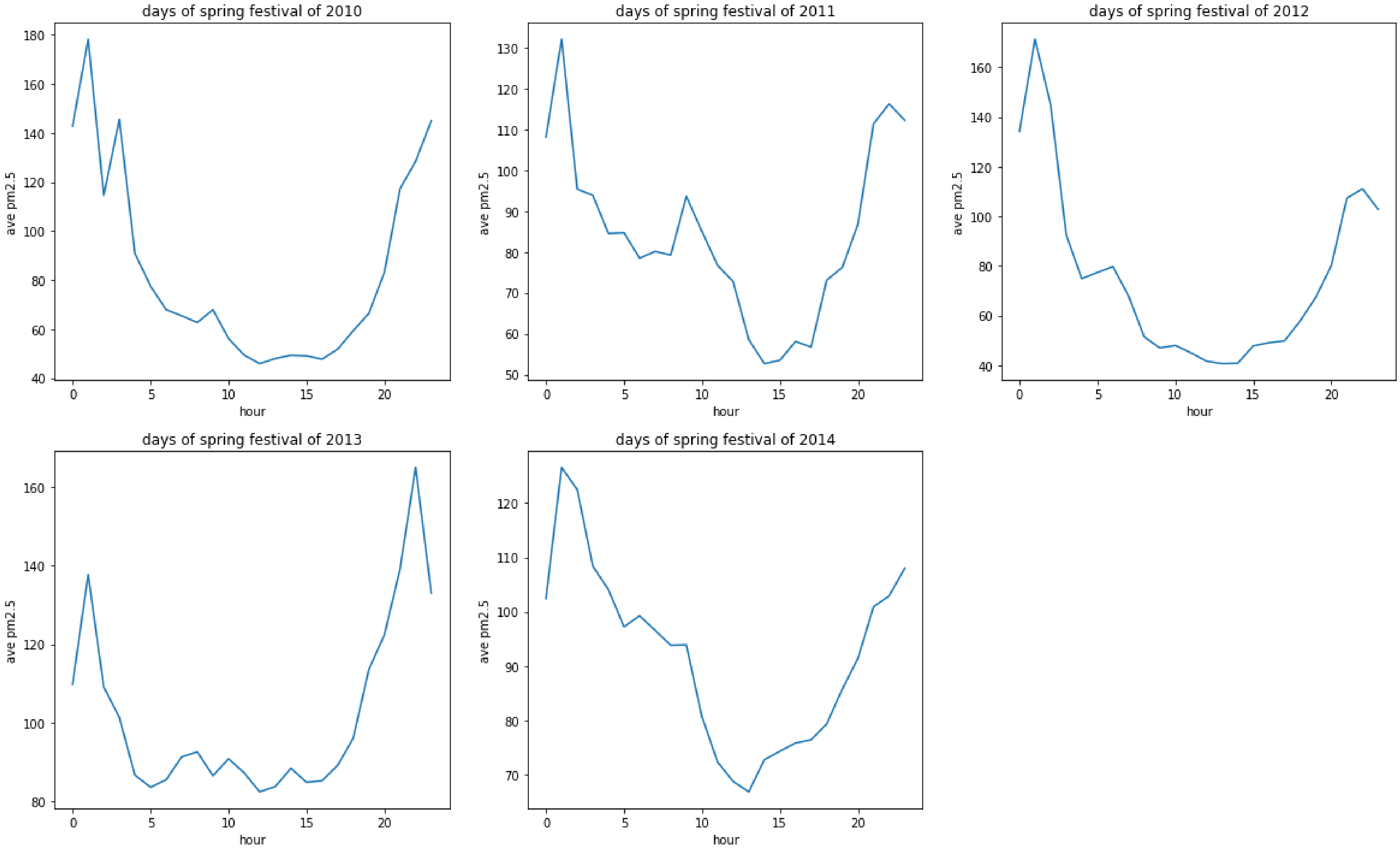
与原数据相比，2012年和2013年的数值有所变化，但变化趋势基本一样，平均浓度基本均为上升趋势

2.4.9 与task2类似，用折线图记录填补后数据每年春节期间（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

In [ ]:

```
## PM2.5在春节每小时的波动值
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_sprfest1=[[],[],[],[],[]]
variation_of_hour_sprfest1 = pd.DataFrame()

pm25_sprfest_2010=pd.DataFrame()
for sprday_2010 in sprfest_2010:
    pm25_sprfest_2010_date=pm25_mean[pm25_mean.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_sprfest1[0].append(mean_spr_2010)

pm25_sprfest_2011=pd.DataFrame()
for sprday_2011 in sprfest_2011:
    pm25_sprfest_2011_date=pm25_mean[pm25_mean.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_sprfest1[1].append(mean_spr_2011)

pm25_sprfest_2012=pd.DataFrame()
for sprday_2012 in sprfest_2012:
    pm25_sprfest_2012_date=pm25_mean[pm25_mean.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_sprfest1[2].append(mean_spr_2012)

pm25_sprfest_2013=pd.DataFrame()
for sprday_2013 in sprfest_2013:
    pm25_sprfest_2013_date=pm25_mean[pm25_mean.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_sprfest1[3].append(mean_spr_2013)

pm25_sprfest_2014=pd.DataFrame()
for sprday_2014 in sprfest_2014:
    pm25_sprfest_2014_date=pm25_mean[pm25_mean.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_sprfest1[4].append(mean_spr_2014)

variation_of_hour_sprfest1=variation_of_hour_sprfest1.append(hour_of_sprfest1)

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour,variation_of_hour_sprfest1.iloc[i,:])
    plt.title('days of spring festival of %d' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_hour_sprfest1
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	
0	142.833333	178.250000	114.500000	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

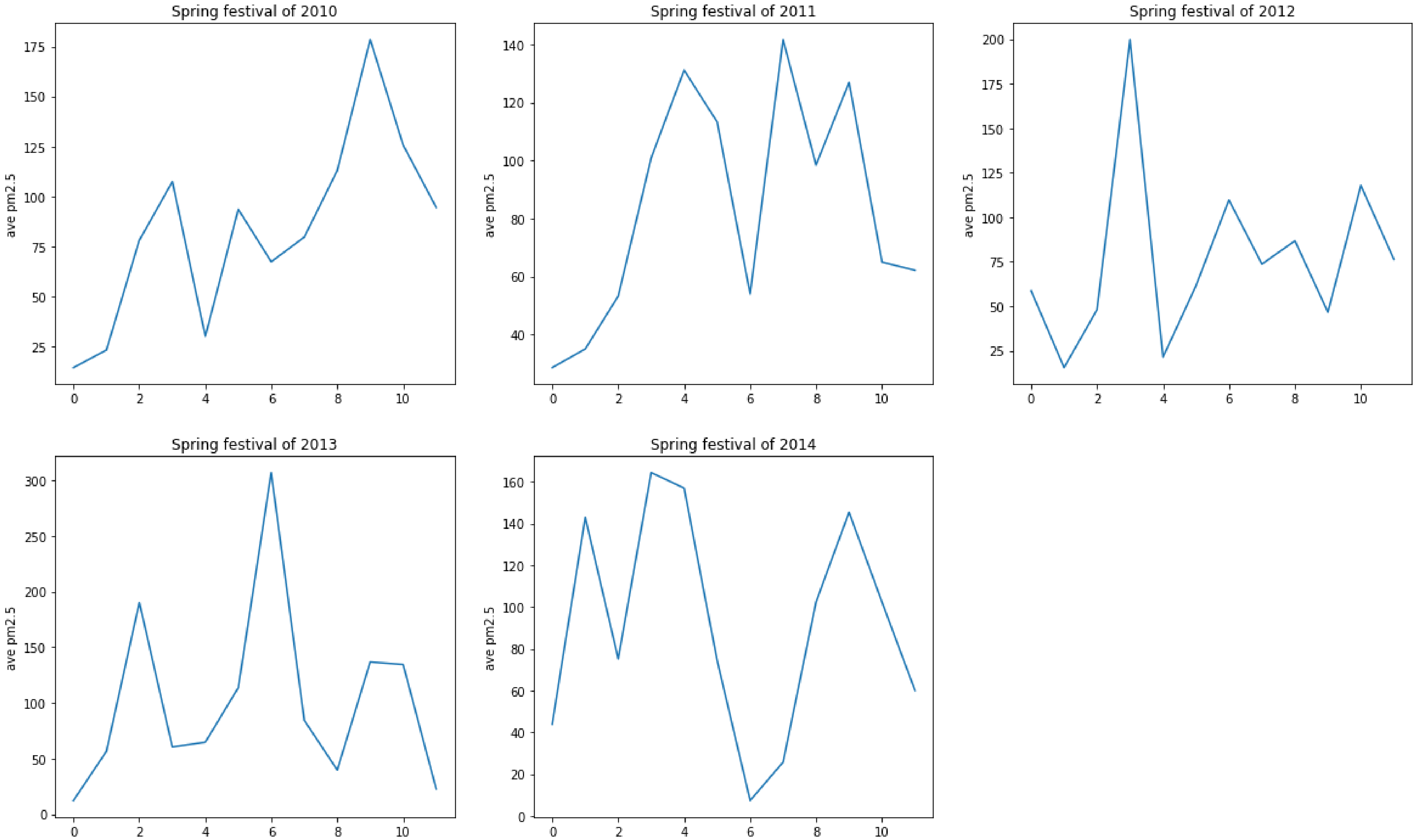
与原数据相比，平均浓度的数值大小和变化趋势均基本一样，每天每小时的变化趋势与全年相似，均为15点后上升，凌晨1点后慢慢下降

2.4.10 与task2类似，用折线图记录填补数据的每年春节期间（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

In [ ]:

```
## PM2.5在春节每天的波动值
days_of_sprfest1=[[],[],[],[],[]]
variation_of_days_sprfest1 = 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_sprfest1[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_sprfest1[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_sprfest1[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_sprfest1[3].append(mean_spr_2013)

for sprday_2014 in sprfest_2014:
```

```
    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_sprfest1[4].append(mean_spr_2014)

variation_of_days_sprfest1=variation_of_days_sprfest1.append(days_of_sprfest1)

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Spr,variation_of_days_sprfest1.iloc[i,:])
    plt.title('Spring festival of %d' % Year[i])
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_days_sprfest1
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	10	11
0	14.333333	23.083333	78.083333	107.458333	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	84.427083	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

与原数据相比，平均浓度的数值大小和变化趋势均基本一样，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

knn填补

3.1 用k近邻法填补数据，设定k=40

In [ ]:

```
pm25_data = pd.read_csv('pm25_data.csv')
date=pm25_data.date
pm25_knn = pd.DataFrame(knn_imputer(pm25_data.drop('date',axis=1)))
pm25_knn['date']=date
pm25_knn.columns = pm25_data.columns
# 对数化
pm25_knn = module.log(pm25_knn)
# 得到week
week_list=[]
for date in pm25_knn['date']:
    week_list.append(pd.to_datetime(date).weekday())
pm25_knn['week']=week_list
# 存为csv文件
pm25_knn.to_csv("pm25_data_knn.csv",index=False)
# 得到 train data & test data
test_data2, train_data2 = module.train_test_split(pm25_knn)
```

3.2 与task1类似，用xgboost预测模型拟合填补后的数据，并通过xgb.plot_importance进行特征选择

In [ ]:

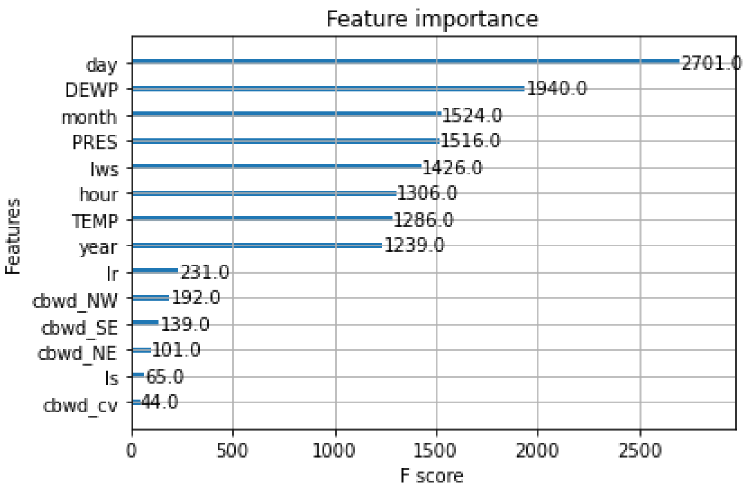
```
var=['year','month','day','hour','DEWP','TEMP','PRES','Iws','Is','Ir','cbwd_NE','cbwd_NW','cbwd_SE','cbwd_cv']
X_train2 = train_data2[var]
X_test2 = test_data2[var]
y_train2 = train_data2['pm2.5_log']
y_test2 = test_data2['pm2.5']
```

```python
XGB_model2=xgb.XGBRegressor(learning_rate=0.1,n_estimators=485,max_depth=5)
XGB_model2.fit(X_train2, y_train2)
y_pred2 = XGB_model2.predict(X_test2)
y_pred2 = np.round(np.exp(y_pred2))

# 归一化
y_pred2=preprocessing.minmax_scale(y_pred2)
y_test2=preprocessing.minmax_scale(y_test2)
print("Mean squared error of test data for knn imputed data: %.4f" % mean_squared_error(y_pred2, y_test2))
print("R2 score: %.4f" % XGB_model2.score(X_test2,test_data2['pm2.5_log']))

# 特征选择
xgb.plot_importance(XGB_model2)
```

```
Mean squared error of test data for knn imputed data: 0.0088
R2 score: 0.6817
```

Out[ ]:

```
<AxesSubplot:title={'center':'Feature importance'}, xlabel='F score', ylabel='Features'>
```



得到平均填补法补全的数据集的预测结果为R^2=0.6817，略低于原数据

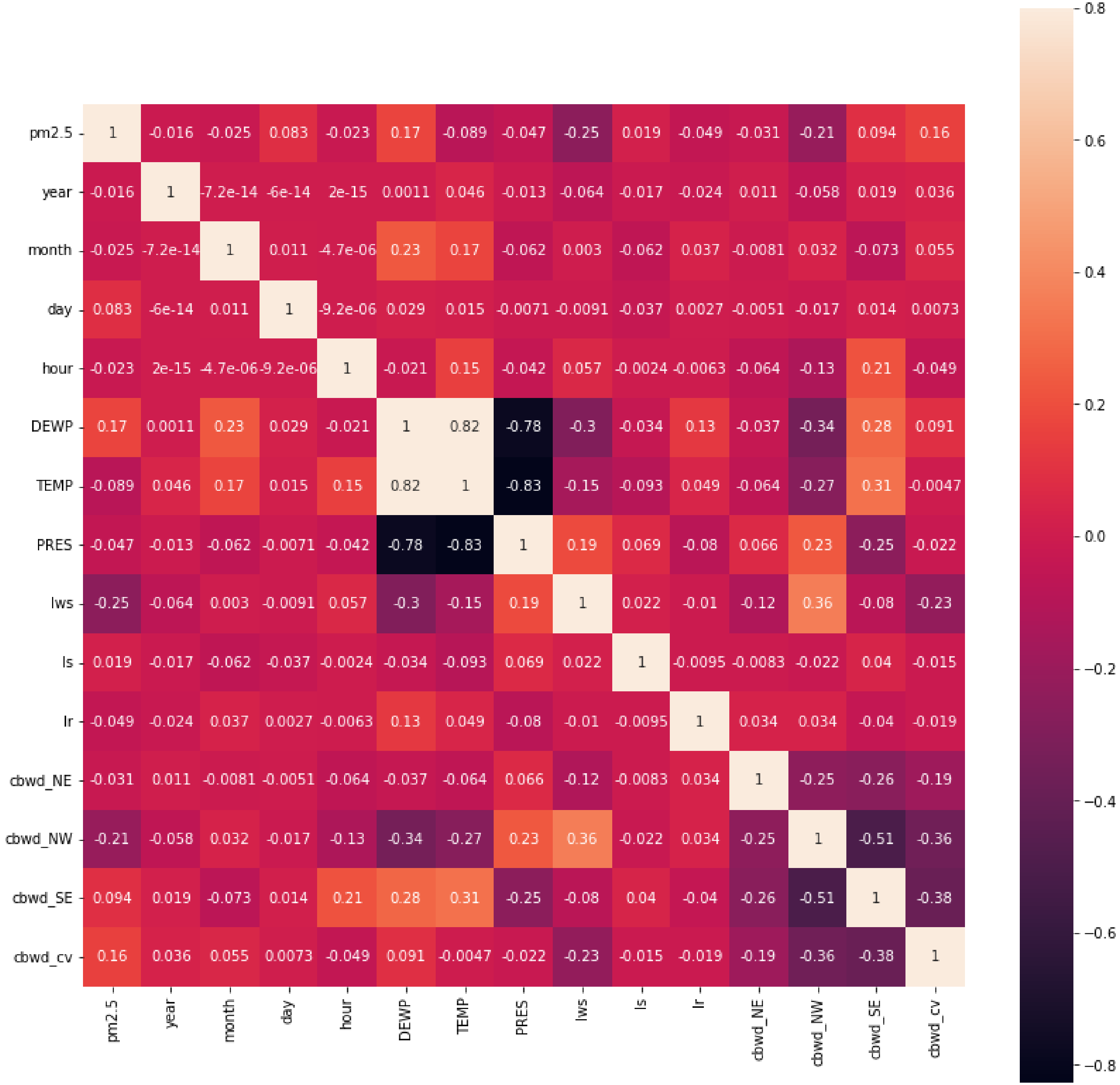
筛选后day仍是最重要的特征；气象因素中仍是DEWP,Iws,PRES,TEMP最重要，各个因素的重要程度不变，重要性依次为DEWP,PRES,Iws,TEMP

3.3 与task1类似，用相关系数矩阵进行特征筛选

In [ ]:

```python
X2=pm25_knn[['pm2.5','year','month','day','hour','DEWP','TEMP','PRES','Iws','Is','Ir','cbwd_NE','cbwd_NW','cbwd_SE','cbwd_cv']]
```

```
corrmatrix = X2.corr()
plt.subplots(figsize=(14, 14))
sns.heatmap(corrmatrix, vmax=0.8, square=True, annot=True)
plt.show()
```



pm2.5
year
month
day
hour
DEWP
TEMP
PRES
Iws
Is
Ir
cbwd_NE
cbwd_NW
cbwd_SE
cbwd_cv
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8

筛选后结果发生变化，与pm2.5相关性较高的因素：DEWP、lws、cbwd_NW、cbwd_cv

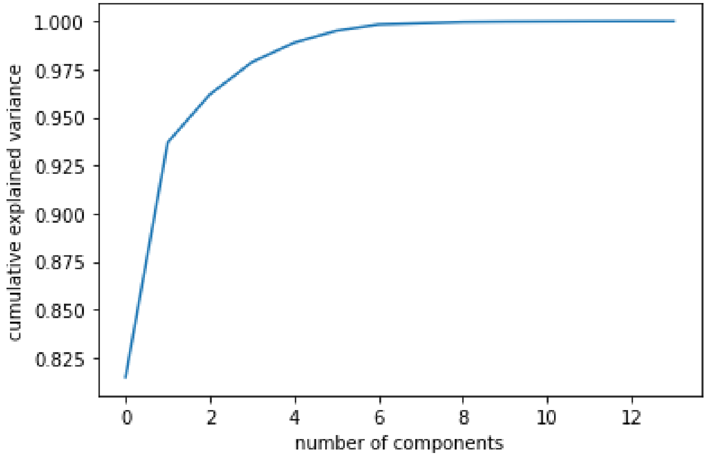
3.4 与task1类似， 通过PCA.explained_variance_ratio_选择特征并尝试降维

In [ ]:

```
from sklearn.decomposition import PCA
pca2=PCA().fit(X2.drop('pm2.5',axis=1))
plt.plot(np.cumsum(pca2.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance')
np.cumsum(pca2.explained_variance_ratio_)
```

Out[ ]:

```
array([0.81476227, 0.93698415, 0.96192403, 0.97877016, 0.98886732,
       0.99506625, 0.99835893, 0.99899759, 0.99962027, 0.99980266,
       0.99988853, 0.99995792, 1.        , 1.        ])
```



PCA给出的结果与原数据类似，取前3个主成分作为特征，其中第一主成分主要反映了对pm2.5的影响

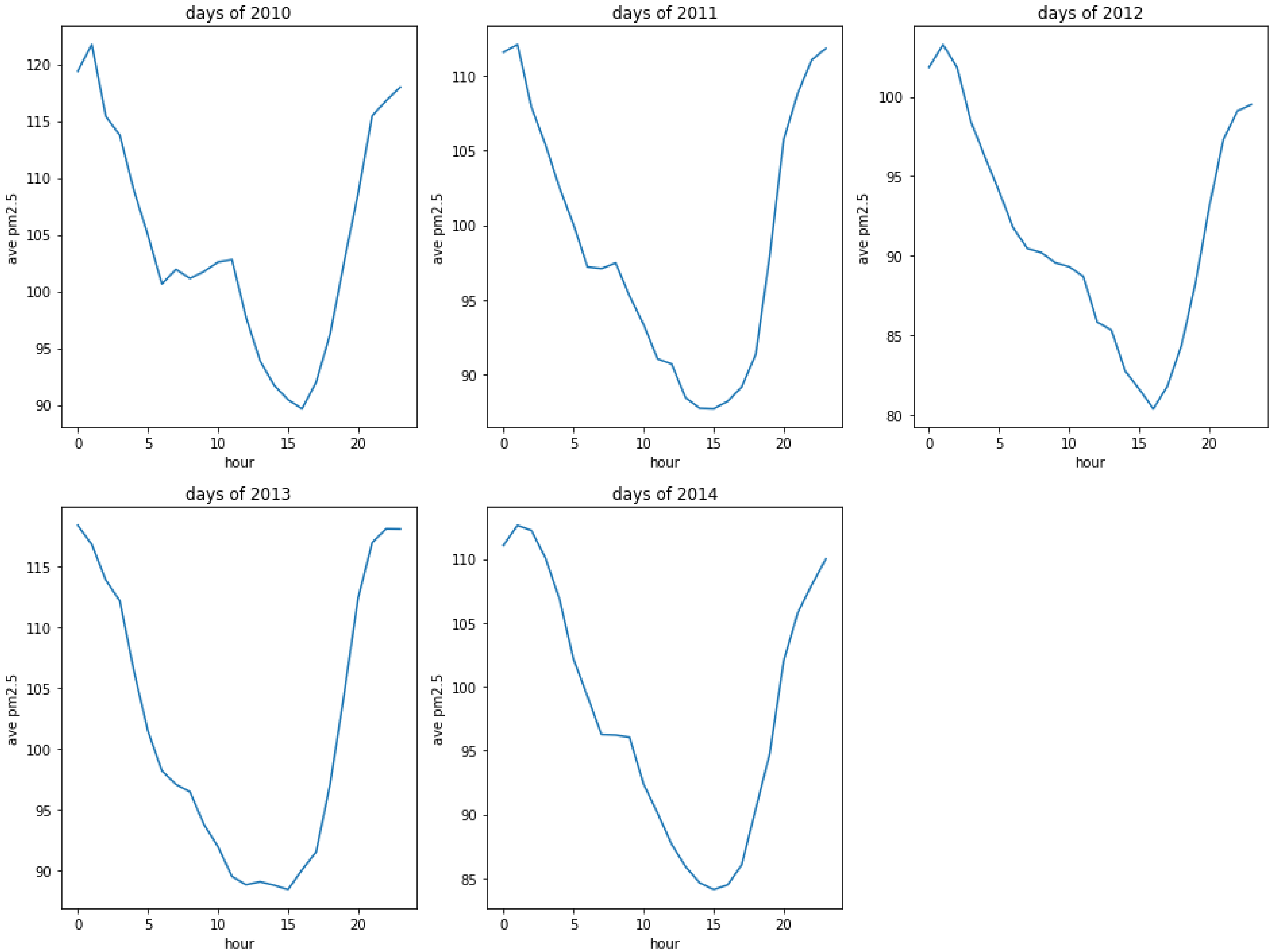
3.5 用由k近邻法得到的新数据进行task2的运行

3.5.1 与task2类似，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

In [ ]:

```
## PM2.5在一天内的波动值
Year=[2010,2011,2012,2013,2014]
```

```python
Hour=range(24)
day_of_year2=[[],[],[],[],[]]

variation_of_day2=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_knn[pm25_knn.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_year2[index].append(mean)

variation_of_day2=variation_of_day2.append(day_of_year2)
variation_of_day2.index=Year

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour,variation_of_day2.iloc[i,:])
    plt.title('days of %d' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_day2
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17
2010	119.389110	121.742397	115.394795	113.746575	108.898699	104.968699	100.644658	101.933699	101.137055	101.737260	...	91.733630	90.451986	89.652055	91.989384
2011	111.560685	112.079521	107.889589	105.370959	102.509521	100.036986	97.202466	97.091507	97.470959	95.253767	...	87.748904	87.710685	88.212260	89.173082
2012	101.849932	103.282719	101.834904	98.404372	96.185246	94.040437	91.771175	90.461202	90.203893	89.566667	...	82.742964	81.610137	80.380123	81.795492
2013	118.349041	116.776781	113.838562	112.144795	106.410822	101.475822	98.189041	97.081712	96.460685	93.791986	...	88.799315	88.433425	90.062877	91.525959
2014	111.049110	112.616027	112.218014	110.052603	106.865137	102.147740	99.224041	96.243904	96.200137	96.028630	...	84.646370	84.107671	84.486164	86.049384

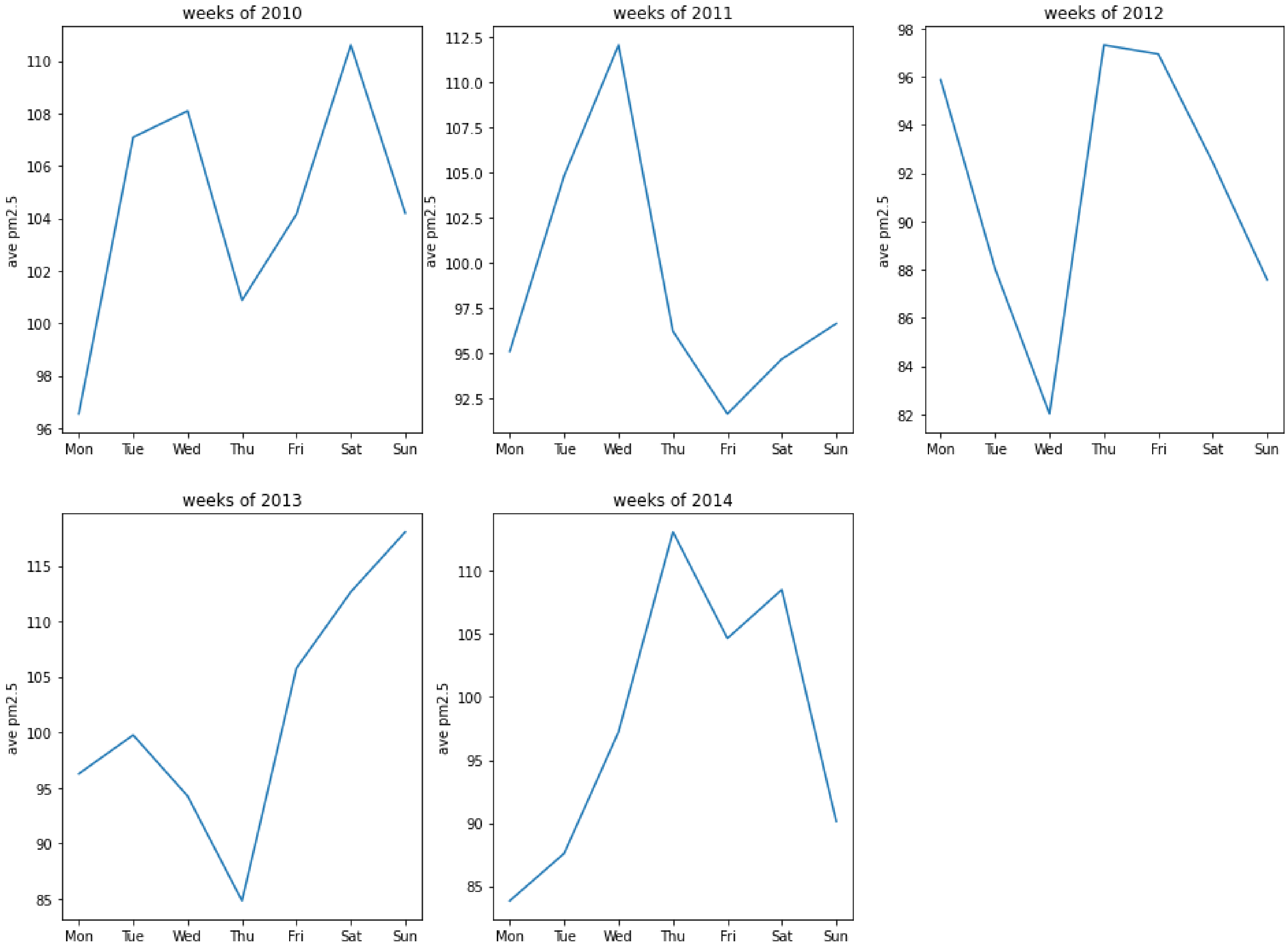
5 rows × 24 columns

折线图结果与原数据task2的基本一样，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

3.5.2 与task2类似，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

In [ ]:

```
# PM2.5在一周的波动值
Week=range(7)
week_of_year2=[[],[],[],[],[]]

variation_of_week2=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_knn[pm25_knn.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_year2[index].append(mean)
variation_of_week2=variation_of_week2.append(week_of_year2)
variation_of_week2.index=Year

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_week2.iloc[i,:])
    plt.title('weeks of %d' % Year[i])
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_week2
```

Out[ ]:

	0	1	2	3	4	5	6

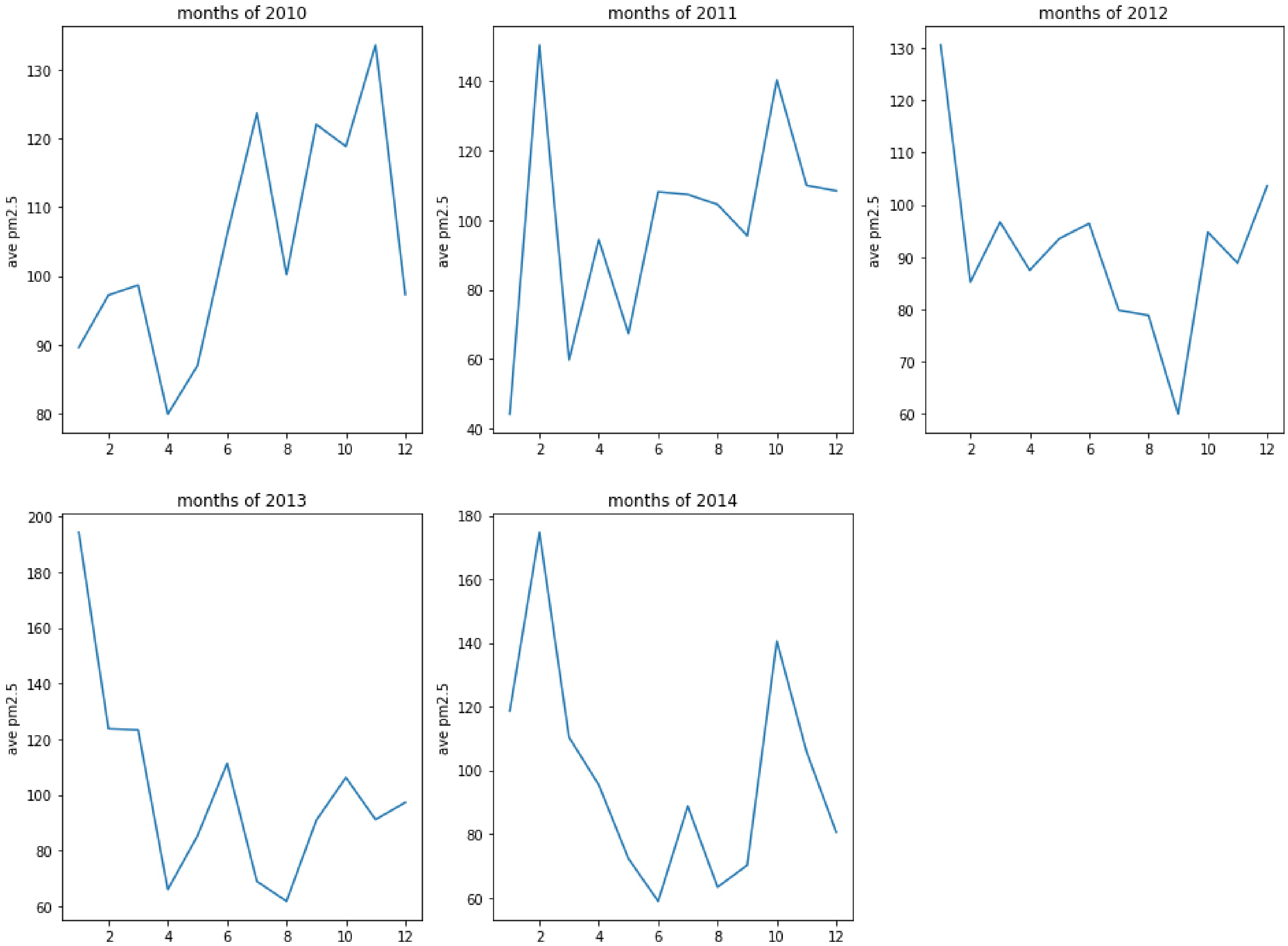
	0	1	2	3	4	5	6
2010	96.538762	107.088622	108.089764	100.867308	104.147091	110.604607	104.194071
2011	95.107151	104.830929	112.074780	96.214443	91.644611	94.679383	96.645292
2012	95.868082	88.035276	82.030849	97.310236	96.934691	92.446214	87.579383
2013	96.274299	99.764092	94.272155	84.844151	105.780669	112.652023	118.055609
2014	83.837901	87.589704	97.243829	113.106030	104.659375	108.516967	90.150040

与task2原数据结果相比，除少数数值外，填充的数据结果基本不变，每年每星期pm2.5平均浓度变化趋势完全不同

3.5.3 与task2类似，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

In [ ]:

```
## PM2.5在一年内数月的波动值
Month=range(1,13)
month_of_year2=[[],[],[],[],[]]

variation_of_month2=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_knn[pm25_knn.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_year2[index].append(mean)
variation_of_month2=variation_of_month2.append(month_of_year2)
variation_of_month2.index=Year

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Month,variation_of_month2.iloc[i,:])
    plt.title('months of %d' % Year[i])
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_month2
```

Out[ ]:

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

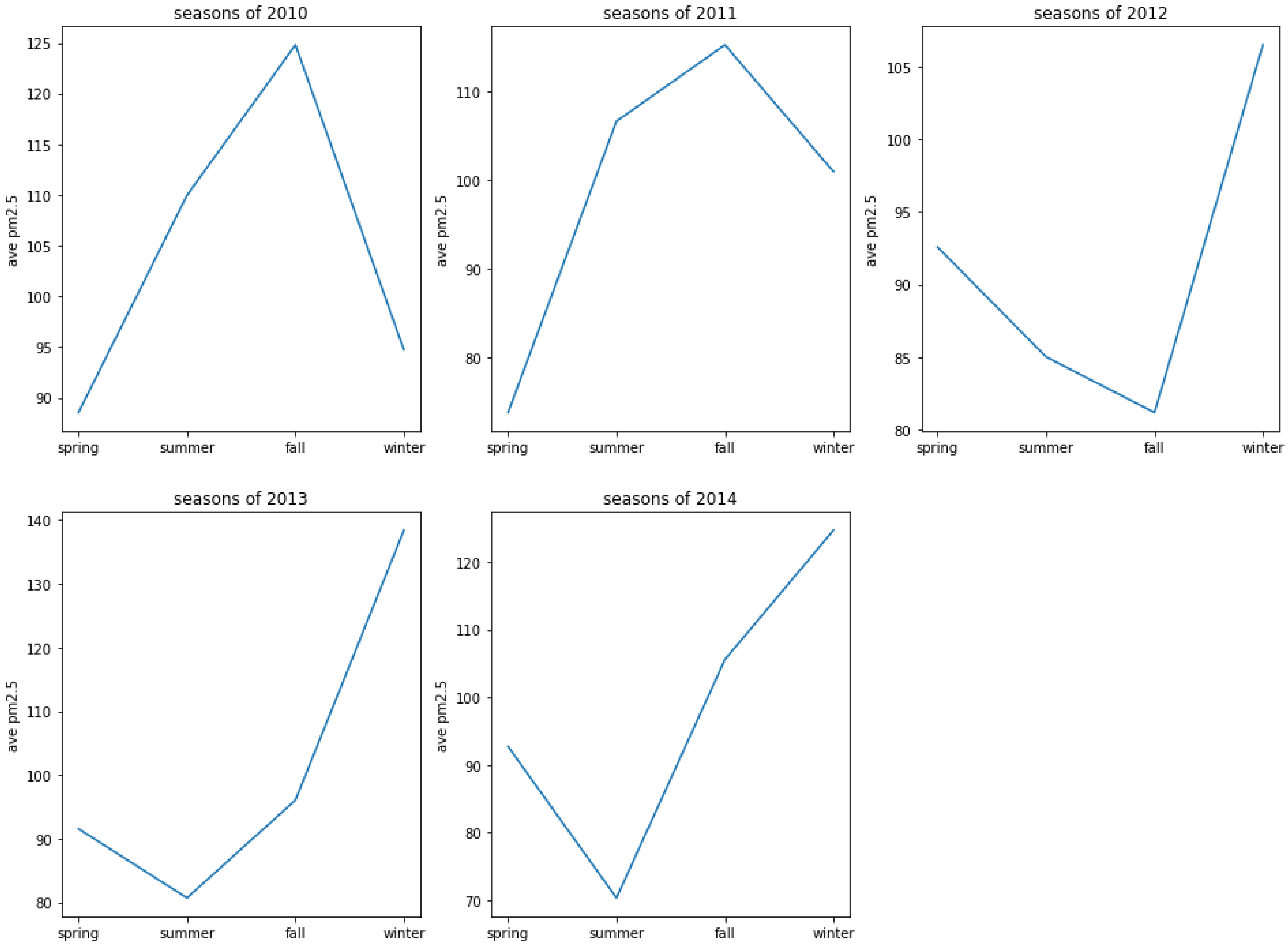
	0	1	2	3	4	5	6	7	8	9	10	11
2010	89.613374	97.234524	98.674630	79.928681	86.979805	106.057431	123.647849	100.191364	122.033889	118.838172	133.563924	97.333333
2011	44.203730	150.321429	59.801075	94.358194	67.329704	108.126632	107.353360	104.489247	95.507083	140.301714	109.977743	108.418347
2012	130.567372	85.218139	96.708535	87.484931	93.561727	96.424028	79.840659	78.844892	59.963092	94.783065	88.869583	103.675605
2013	194.263911	123.747954	123.332023	66.079097	85.334207	111.346215	69.013441	61.853595	90.829375	106.259073	91.156736	97.295833
2014	118.634543	174.781771	110.383401	95.451319	72.326882	58.922118	88.777419	63.373589	70.219097	140.591566	105.881840	80.574630

结果与原数据的类似，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

3.5.4 与task2类似，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

In [ ]:

```
## PM2.5在四季的波动值
season_of_year2=[[],[],[],[],[]]

variation_of_season2=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_knn[pm25_knn.year==year]
    mean_spring=(variation_of_month2.loc[year,2]+variation_of_month2.loc[year,3]+variation_of_month2.loc[year,4])/3
    mean_summer=(variation_of_month2.loc[year,5]+variation_of_month2.loc[year,6]+variation_of_month2.loc[year,7])/3
    mean_fall=(variation_of_month2.loc[year,8]+variation_of_month2.loc[year,9]+variation_of_month2.loc[year,10])/3
    mean_winter=(variation_of_month2.loc[year,11]+variation_of_month2.loc[year,0]+variation_of_month2.loc[year,1])/3
    season_of_year2[index].append(mean_spring)
    season_of_year2[index].append(mean_summer)
    season_of_year2[index].append(mean_fall)
    season_of_year2[index].append(mean_winter)
variation_of_season2=variation_of_season2.append(season_of_year2)
variation_of_season2.index=Year

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_season2.iloc[i,:])
    plt.title('seasons of %d' % Year[i])
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_season2
```

Out[ ]:

	0	1	2	3

	0	1	2	3
2010	88.527705	109.965548	124.811995	94.727077
2011	73.829658	106.656413	115.262180	100.981168
2012	92.585064	85.036526	81.205247	106.487039
2013	91.581776	80.737751	96.081728	138.435899
2014	92.720534	70.357709	105.564168	124.663648

结果与原数据类似，除少量数值变化外，浓度变化趋势基本相同，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

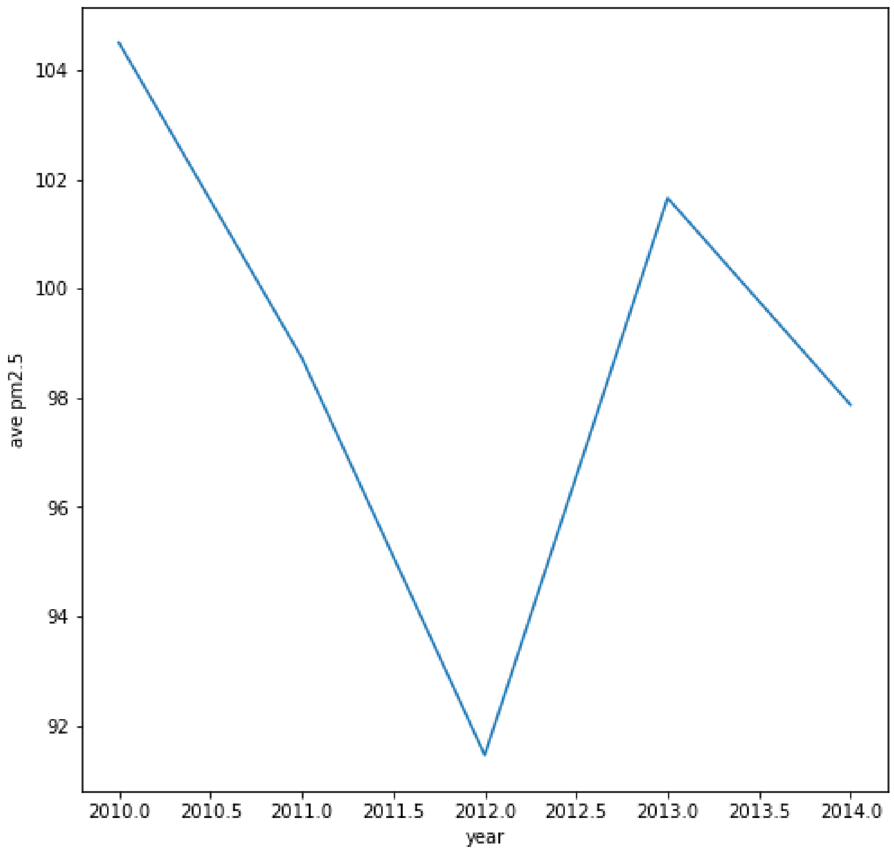
3.5.5 与task2类似，用折线图记录每年pm2.5的变化趋势，取每年平均浓度作为当年的对应值

In [ ]:

```
## PM2.5在5年内的波动值
varaition_of_year2=[]
for year in Year:
    pm25_year=pm25_knn[pm25_knn.year==year]
    mean=np.mean(pm25_year['pm2.5'])
    varaition_of_year2.append(mean)

plt.figure(figsize=(8,8))
plt.plot(Year,varaition_of_year2)
plt.xlabel('year')
plt.ylabel('ave pm2.5')
```

Out[ ]:

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



In [ ]:
```
varaition_of_year2
```

Out[ ]:
```
[104.50333904109645,
 98.73123858447491,
 91.4580249373719,
 101.65808219178086,
 97.87025684931508]
```

与原数据结果类似，除平均浓度数值范围有细微变化外，基本趋势不变。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

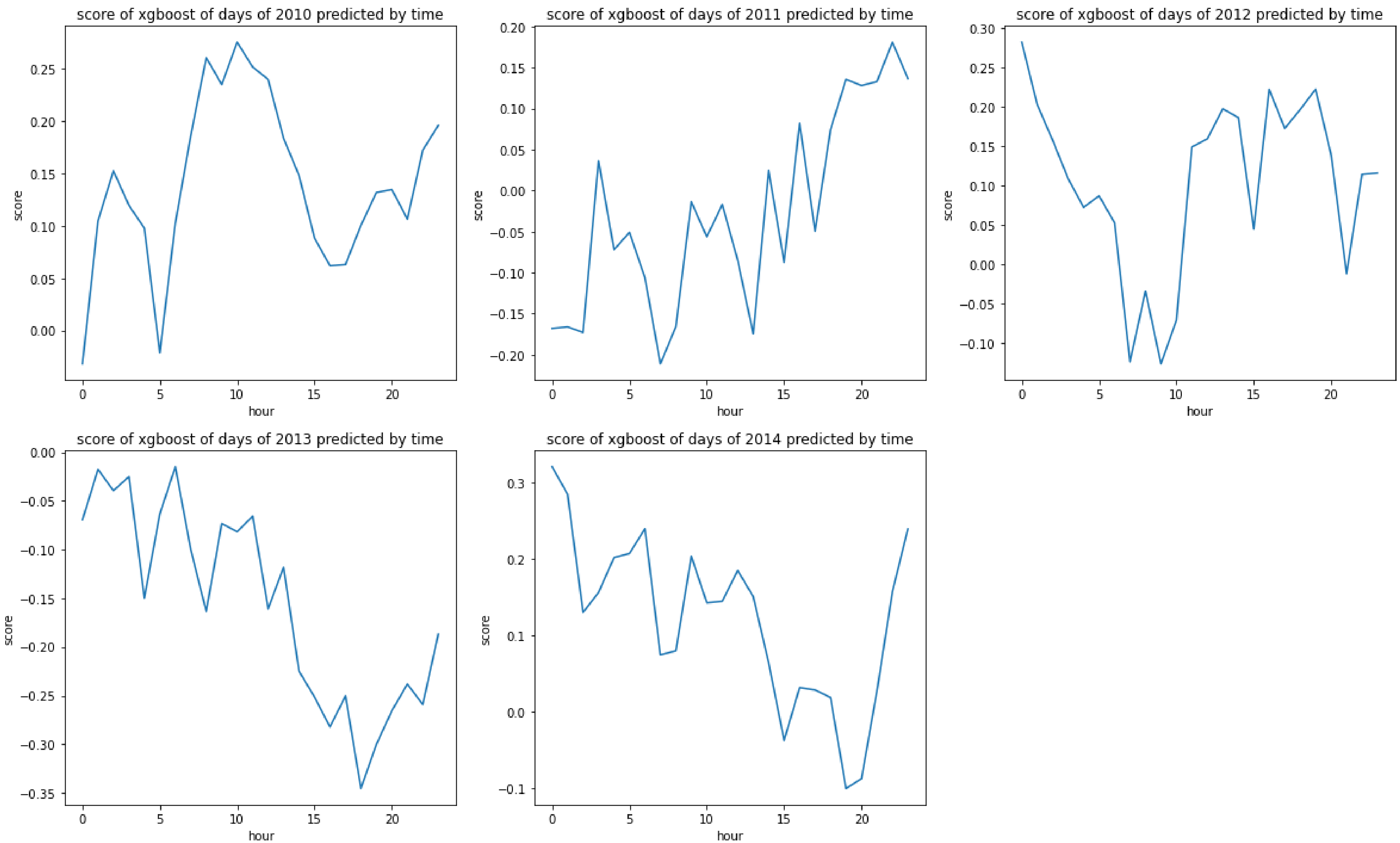
3.5.6 与task2类似，对于填补后的数据，利用上述与时间有关的pm2.5平均浓度信息，分别使用每条数据的时间信息和天气信息，运用task1中提出的xgboost模型、训练集和测试集，实现对pm2.5浓度的预测，同时使用score作为预测结果好坏的测量标准，认为越接近1预测效果越好

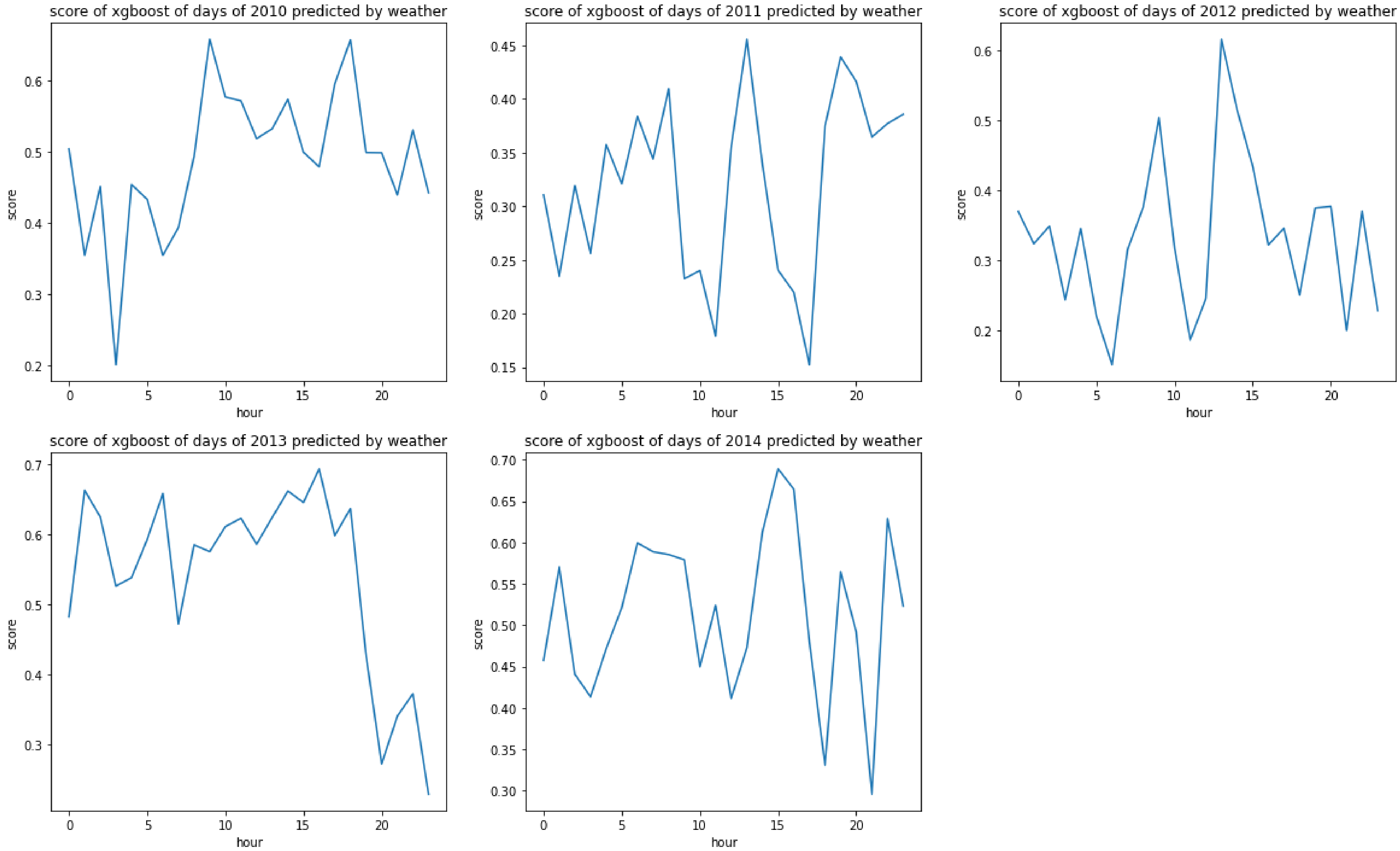
3.5.6.1 与task2类似，分别使用每年一天24小时数据的时间信息和天气信息，对每小时pm2.5平均浓度进行预测，将两种方法下每年每小时的预测score用折线图分别绘出

In [ ]:

```
## 基于PM2.5在一天内的波动值，用xgboost进行预测
Year=[2010,2011,2012,2013,2014]
Hour=range(24)
day_of_year_train2=[[],[],[],[],[]]
day_of_year_test2=[[],[],[],[],[]]
score_of_year_time2 = [[],[],[],[],[]]
score_of_year_weather2 = [[],[],[],[],[]]
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_time2=pd.DataFrame()
variation_of_day_weather2=pd.DataFrame()
for index, year in enumerate(Year):
    train_data_year=train_data2[train_data2.year==year]
    test_data_year=test_data2[test_data2.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_time2[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_weather2[index].append(XGB_model_weather.score(X_test_data_hour_year_weather,test_data_hour_year['pm2.5_log']))

variation_of_day_time2=variation_of_day_time2.append(score_of_year_time2)
variation_of_day_weather2=variation_of_day_weather2.append(score_of_year_weather2)
plt.figure(figsize=(20,12))

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour,variation_of_day_time2.iloc[i,:])
    plt.title('score of xgboost of days of %d predicted by time' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('score')

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour,variation_of_day_weather2.iloc[i,:])
    plt.title('score of xgboost of days of %d predicted by weather' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('score')
```


score of xgboost of days of 2010 predicted by time
score
hour
score of xgboost of days of 2011 predicted by time
score
hour
score of xgboost of days of 2012 predicted by time
score
hour
score of xgboost of days of 2013 predicted by time
score
hour
score of xgboost of days of 2014 predicted by time
score
hour



In [ ]:

```
variation_of_day_time2
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	
0	-0.031618	0.104930	0.152678	0.119731	0.097906	-0.021305	0.102727	0.186287	0.260821	0.235165	...	0.148224	0.088328	0.062042	0.063200	0.100591	0.132
1	-0.167985	-0.166118	-0.172948	0.036654	-0.072113	-0.050786	-0.106120	-0.211164	-0.165876	-0.013447	...	0.024629	-0.087447	0.082520	-0.049476	0.074514	0.135

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	
2	0.282053	0.202859	0.157611	0.108741	0.072315	0.086950	0.052803	-0.123821	-0.034006	-0.126264	...	0.186325	0.044662	0.222202	0.172540	0.196390	0.222
3	-0.069416	-0.017579	-0.039501	-0.025077	-0.149895	-0.063474	-0.014924	-0.099955	-0.163678	-0.073301	...	-0.225019	-0.251604	-0.282250	-0.250448	-0.345357	-0.300
4	0.320581	0.284565	0.129793	0.155850	0.201590	0.206948	0.239477	0.074240	0.079499	0.203500	...	0.063750	-0.037770	0.031337	0.028261	0.018424	-0.100

5 rows × 24 columns

In [ ]:

```
variation_of_day_weather2
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	19	20
0	0.503621	0.354045	0.450868	0.200670	0.453587	0.432782	0.354191	0.393227	0.492946	0.657331	...	0.573352	0.498873	0.478360	0.594724	0.656329	0.498465	0.498157
1	0.310714	0.234868	0.319344	0.256147	0.357542	0.321090	0.383959	0.343957	0.409442	0.232616	...	0.338845	0.240443	0.220094	0.152536	0.374915	0.439147	0.416230
2	0.369886	0.323870	0.349245	0.243991	0.345243	0.221078	0.151526	0.316070	0.376392	0.503559	...	0.515204	0.434201	0.322156	0.346095	0.251074	0.374850	0.377132
3	0.482106	0.663538	0.625160	0.526347	0.538263	0.592868	0.658733	0.471866	0.585175	0.575543	...	0.662318	0.645985	0.694179	0.598410	0.637126	0.427483	0.271280
4	0.457594	0.570431	0.440739	0.413439	0.471536	0.521032	0.599462	0.588849	0.585431	0.579162	...	0.613005	0.689071	0.664421	0.480511	0.330553	0.564468	0.491822

5 rows × 24 columns

相比于原数据，两种方法给出的预测分数变化趋势均与原来的相似，运用天气信息的预测准度明显更高。但2010年和2011年的这个精度相对于原数据明显下降，最高相似于原先所有训练集得到的预测模型的准度

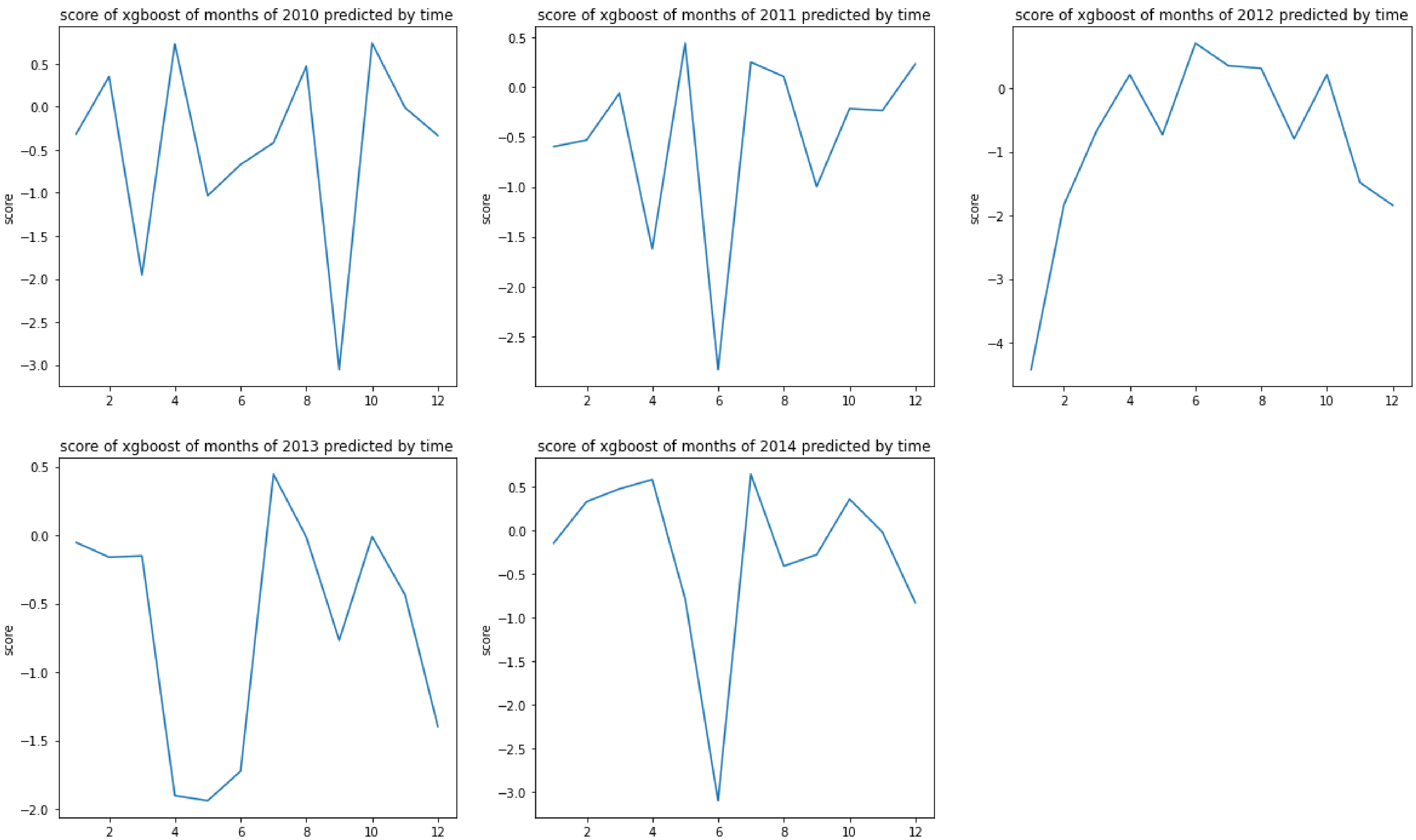
3.5.6.2 与task2相似，分别使用填补后每年每月数据的时间信息和天气信息，对每月pm2.5平均浓度进行预测，将两种方法下每年每月的预测score用折线图分别绘出

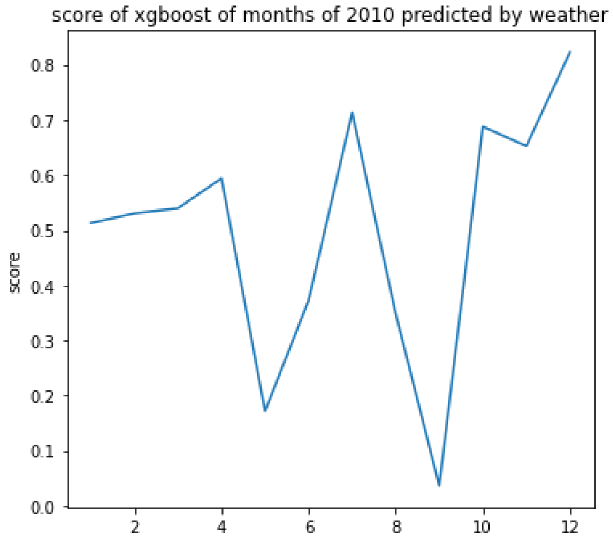
In [ ]:

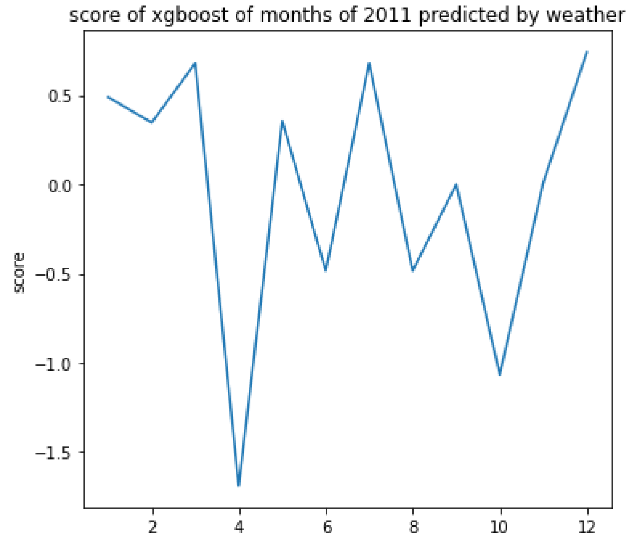
```
## 基于PM2.5在一年内数月的波动值， 用xgboost进行预测
Month = range(1,13)
week_of_year2=[[],[],[],[],[]]
score_of_month_weather2 = [[],[],[],[],[]]
score_of_month_time2 = [[],[],[],[],[]]

variation_of_month_time2=pd.DataFrame()
```

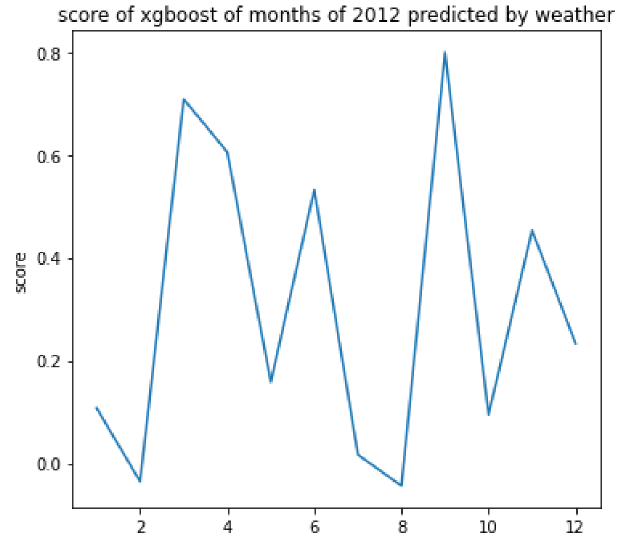
```python
variation_of_month_weather2=pd.DataFrame()
for index, year in enumerate(Year):
    train_data_year=train_data2[train_data2.year==year]
    test_data_year=test_data2[test_data2.year==year]
    for month in Month:
        train_data_month_year=train_data_year[train_data_year.month==month]
        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)
        y_test_data_month_year = preprocessing.minmax_scale(y_test_data_month_year)
        score_of_month_time2[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_weather2[index].append(XGB_model_weather.score(X_test_data_month_year_weather,test_data_month_year['pm2.5_log']))

variation_of_month_time2=variation_of_month_time2.append(score_of_month_time2)
variation_of_month_weather2=variation_of_month_weather2.append(score_of_month_weather2)
plt.figure(figsize=(20,12))

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Month,variation_of_month_time2.iloc[i,:])
    plt.title('score of xgboost of months of %d predicted by time' % Year[i])
    plt.ylabel('score')

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

for i in range(5):
    plt.subplot(2,3,i+1)
```

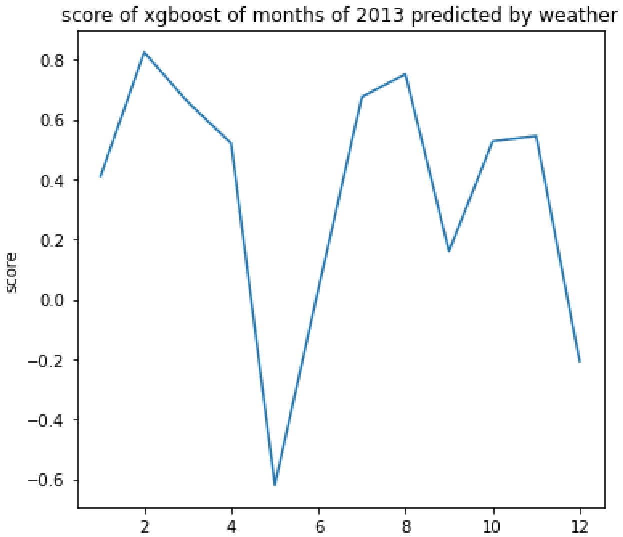
```
    plt.plot(Month,variation_of_month_weather2.iloc[i,:])
    plt.title('score of xgboost of months of %d predicted by weather' % Year[i])
    plt.ylabel('score')
```

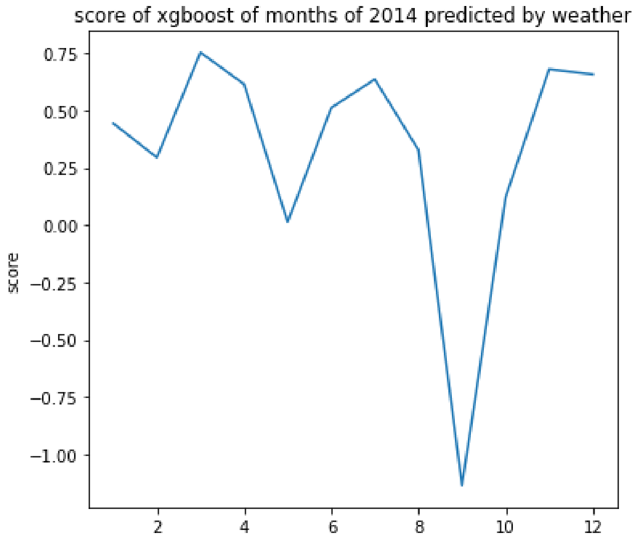












In [ ]:

```
variation_of_month_time2
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	10	11
0	-0.316221	0.350750	-1.956288	0.731373	-1.033136	-0.671843	-0.418752	0.472561	-3.055587	0.738766	-0.010119	-0.334421
1	-0.595831	-0.530581	-0.060314	-1.622890	0.442669	-2.834811	0.252280	0.107309	-0.997376	-0.214049	-0.232859	0.233530

	0	1	2	3	4	5	6	7	8	9	10	11
2	-4.422078	-1.832618	-0.663807	0.211765	-0.728722	0.706680	0.353052	0.311376	-0.794487	0.215700	-1.480387	-1.839974
3	-0.053715	-0.161439	-0.152277	-1.903679	-1.940888	-1.725076	0.444987	-0.015174	-0.768663	-0.010894	-0.436316	-1.398356
4	-0.149640	0.325802	0.472821	0.580061	-0.788092	-3.101852	0.641268	-0.411844	-0.281440	0.355565	-0.022349	-0.831910

In [ ]:

```
variation_of_month_weather2
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	10	11
0	0.512649	0.530265	0.539606	0.594032	0.171647	0.372670	0.713370	0.348342	0.036332	0.687681	0.652492	0.822447
1	0.489040	0.346419	0.679294	-1.689407	0.356129	-0.484052	0.679380	-0.484138	0.000713	-1.066697	0.009812	0.740472
2	0.107470	-0.035639	0.708596	0.605793	0.158368	0.532559	0.016524	-0.043849	0.799814	0.094614	0.453076	0.232978
3	0.410739	0.824243	0.658349	0.519812	-0.619251	0.035244	0.675357	0.751243	0.160706	0.527110	0.544573	-0.205948
4	0.444732	0.295673	0.754508	0.615620	0.014118	0.512818	0.637123	0.328998	-1.135514	0.122826	0.680993	0.658794

相比于原数据，除2011年外，两种方法给出的预测分数变化趋势和数值均与原来的相似，用每月平均浓度预测时只用天气信息可以达到更高精度，但预测准度同样更加不稳定

3.5.6.3 与task2类似，分别使用填补后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

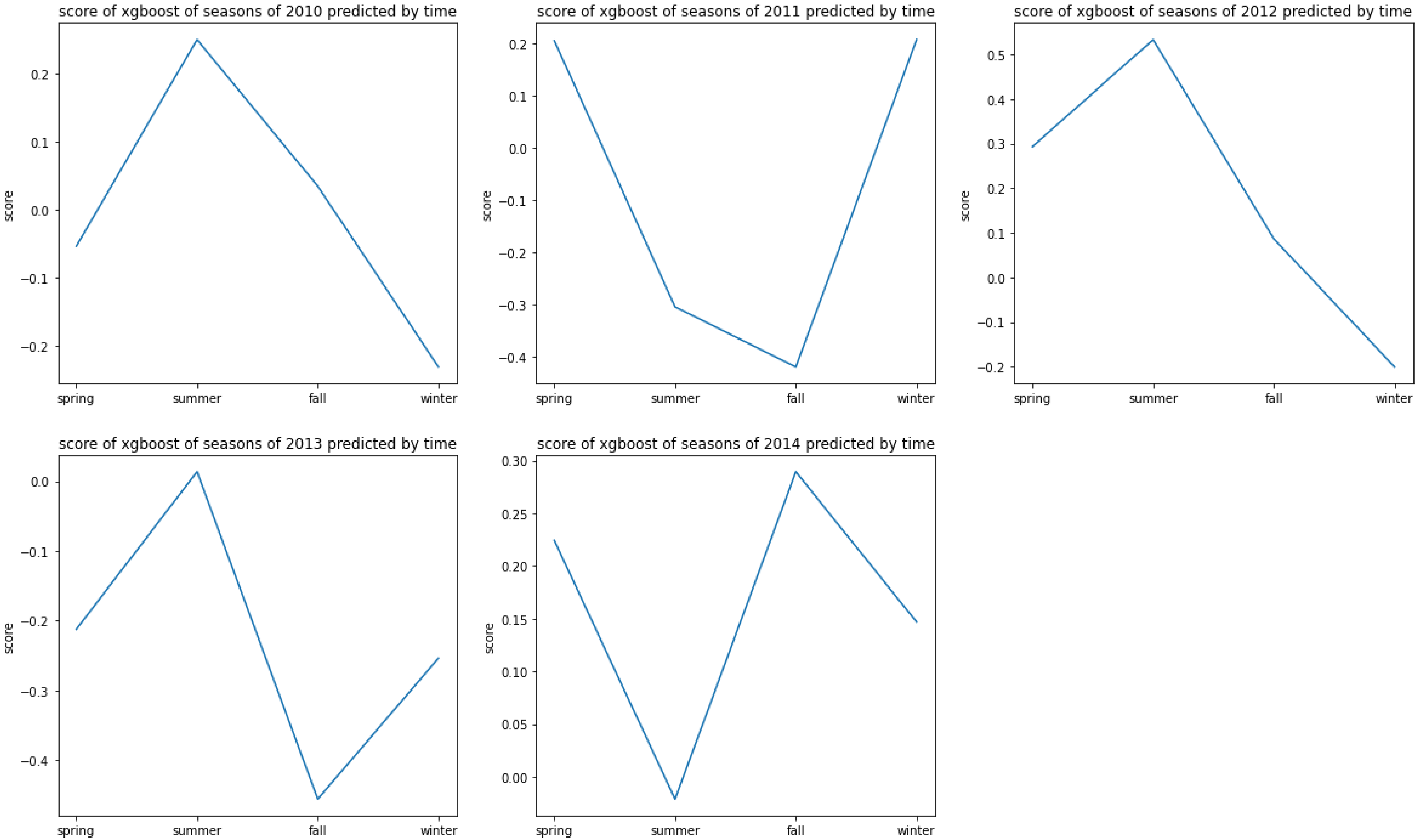
In [ ]:

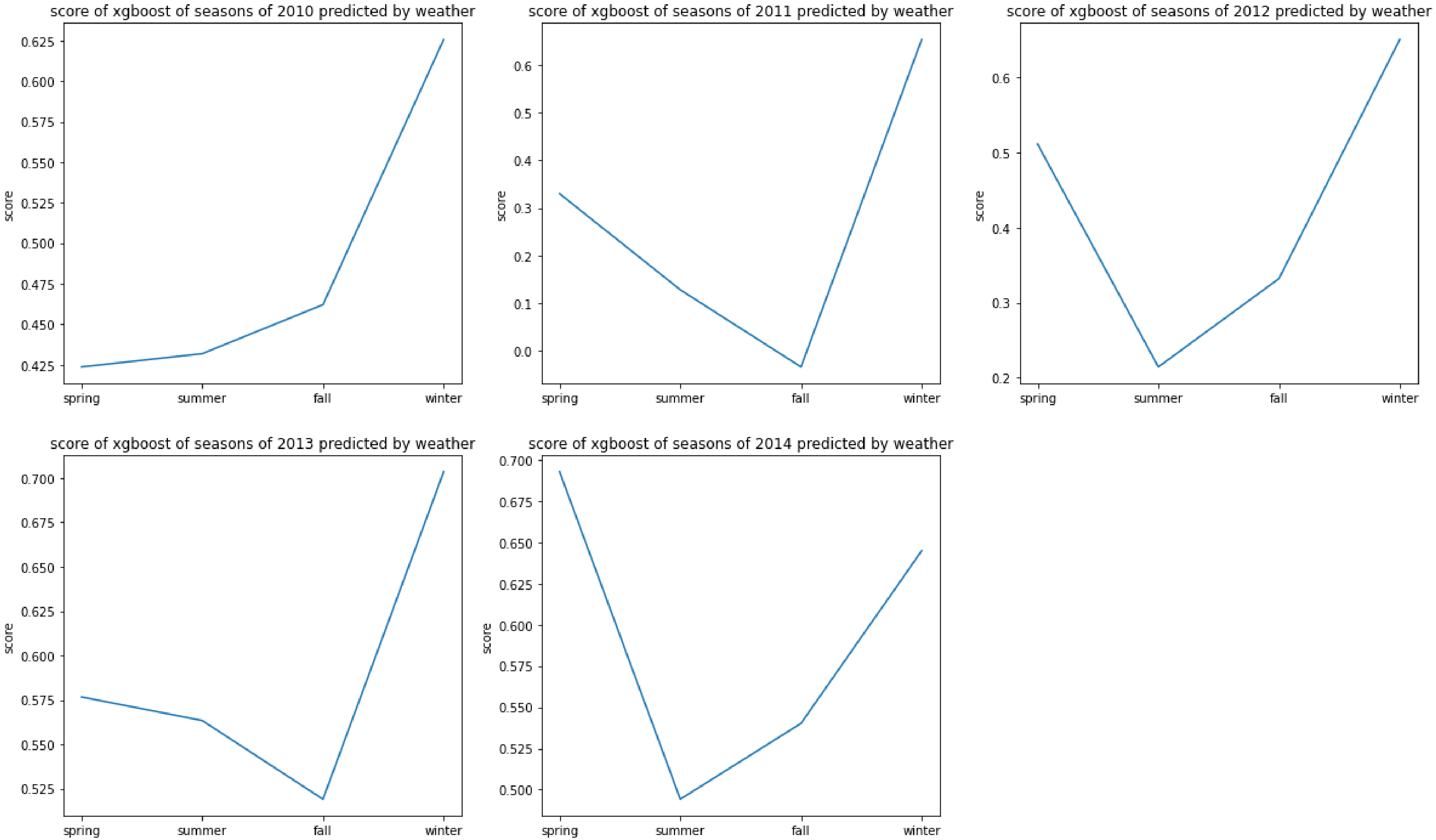
```
## 基于PM2.5在一年内四季的波动值， 用xgboost进行预测
season_of_year2=[[],[],[],[],[]]
score_of_season_weather2 = [[],[],[],[],[]]
score_of_season_time2 = [[],[],[],[],[]]

variation_of_season_time2=pd.DataFrame()
variation_of_season_weather2=pd.DataFrame()
for index, year in enumerate(Year):
    train_data_year=train_data2[train_data2.year==year]
    test_data_year=test_data2[test_data2.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]
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_time2[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_weather2[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_time2[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)
score_of_season_weather2[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_time2[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_weather2[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_time2[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_weather2[index].append(XGB_model_weather_winter.score(X_test_data_winter_year_weather,test_data_winter_year['pm2.5_log']))

variation_of_season_time2=variation_of_season_time2.append(score_of_season_time2)
variation_of_season_weather2=variation_of_season_weather2.append(score_of_season_weather2)
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_time2.iloc[i,:])
    plt.title('score of xgboost of seasons of %d predicted by time' % Year[i])
    plt.ylabel('score')

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Seasons,variation_of_season_weather2.iloc[i,:])
    plt.title('score of xgboost of seasons of %d predicted by weather' % Year[i])
    plt.ylabel('score')
```


score of xgboost of seasons of 2010 predicted by time
score of xgboost of seasons of 2011 predicted by time
score of xgboost of seasons of 2012 predicted by time
score of xgboost of seasons of 2013 predicted by time
score of xgboost of seasons of 2014 predicted by time
score
spring
summer
fall
winter



In [ ]:

```
variation_of_season_time2
```

Out[ ]:

	0	1	2	3
0	-0.053397	0.250622	0.034900	-0.231000
1	0.206036	-0.304031	-0.419166	0.208167

	0	1	2	3
2	0.293157	0.532885	0.086612	-0.200190
3	-0.212515	0.013631	-0.455976	-0.253727
4	0.224382	-0.020966	0.289419	0.147010

In [ ]:

```
variation_of_season_weather2
```

Out[ ]:

	0	1	2	3
0	0.423770	0.431937	0.462179	0.625654
1	0.330039	0.128335	-0.033568	0.653581
2	0.511483	0.214293	0.332253	0.651084
3	0.576672	0.563351	0.519068	0.703538
4	0.693078	0.494148	0.540176	0.645097

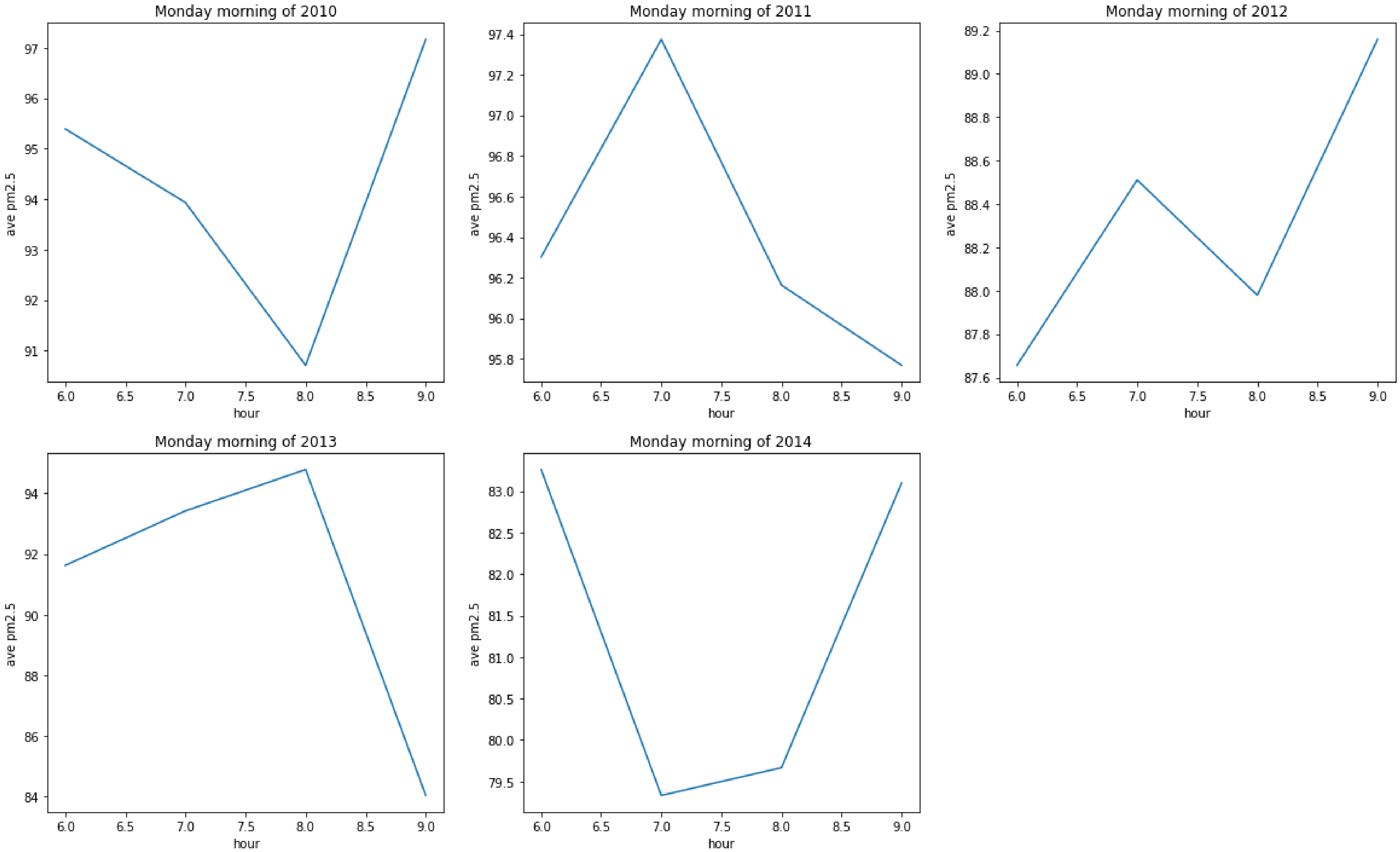
与原数据相比，两种方法给出的预测分数变化趋势均有较大变化，尤其是2013年用时间因素得到的预测分数变化趋势和2011年和2013年用天气因素得到的预测分数变化趋势。但总体上，我们仍应该用天气信息进行预测，且这五年间冬天均达到最高准度，后四年夏秋两季均为最低

3.5.7 与task2类似，用折线图记录填补后数据每年周一早晨（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

In [ ]:

```
## PM2.5在周一上午的波动值
Hour_Mon=range(6,10)
Week_Mon=range(1)
day_of_year_Mon2=[[],[],[],[],[]]

variation_of_day_Mon2=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_knn[pm25_knn.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_Mon2[index].append(mean)
```

```
variation_of_day_Mon2=variation_of_day_Mon2.append(day_of_year_Mon2)
variation_of_day_Mon2.index=Year

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour_Mon,variation_of_day_Mon2.iloc[i,:])
    plt.title('Monday morning of %d' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_day_Mon2
```

Out[ ]:

	0	1	2	3
2010	95.391827	93.933654	90.710577	97.164423
2011	96.302404	97.373558	96.163942	95.769231

	0	1	2	3
2012	87.656132	88.510377	87.979245	89.158491
2013	91.625000	93.421154	94.781731	84.046154
2014	83.258654	79.332212	79.667308	83.098558

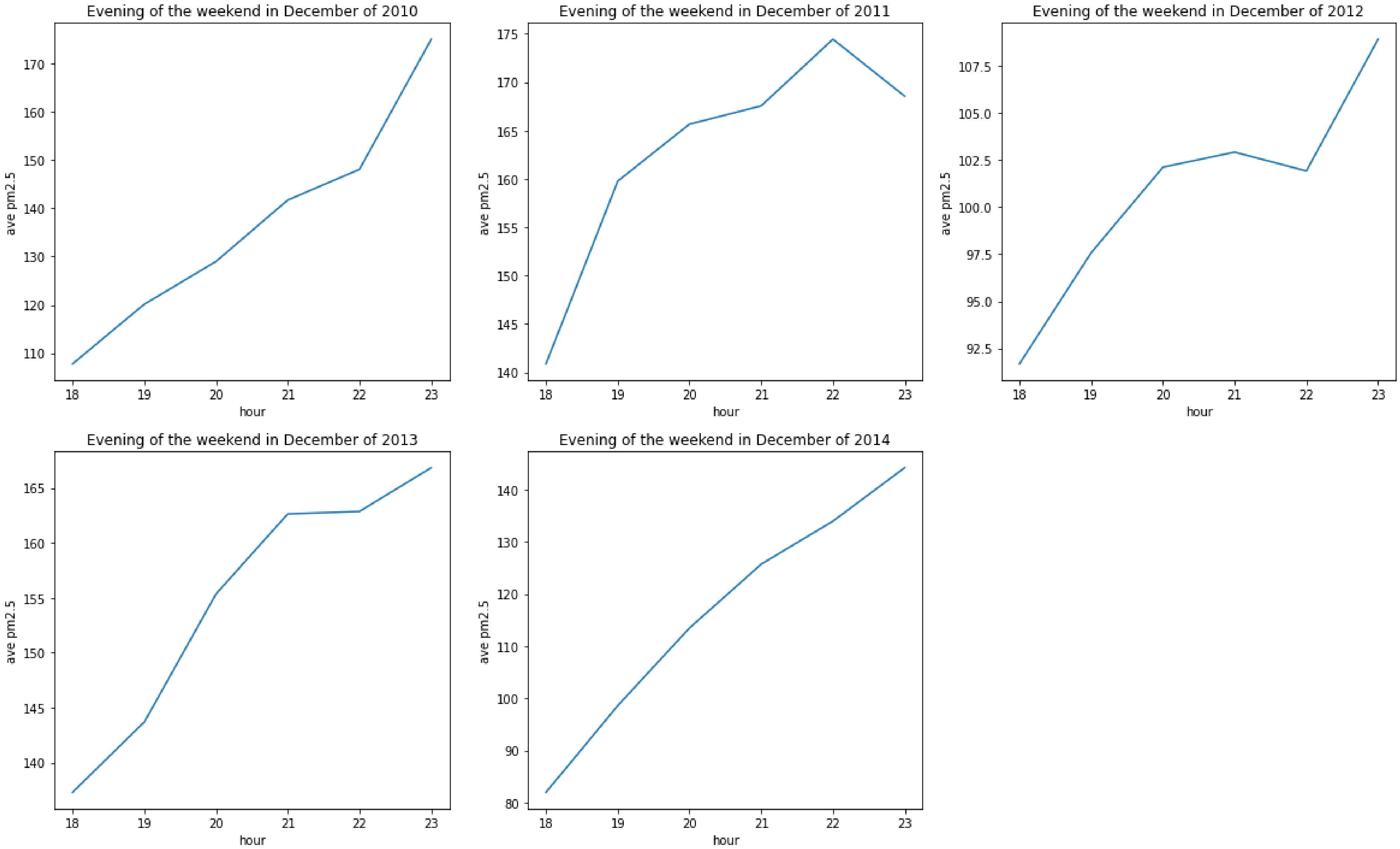
与原数据结果相比，平均浓度数值和变化趋势与原数据的大致相当。每年星期一早晨每小时pm2.5平均浓度变化趋势不同，但除2013年外均在8点取得最低值

3.5.8 与task2类似，用折线图记录填补后数据每年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

In [ ]:

```
## PM2.5在12月周末夜晚的波动值
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_Dec2=[[],[],[],[],[]]

variation_of_day_dec2=pd.DataFrame()
for index, year in enumerate(Year):
    pm25_year=pm25_knn[pm25_knn.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_Dec2[index].append(mean)

variation_of_day_dec2=variation_of_day_dec2.append(day_of_year_Dec2)
variation_of_day_dec2.index=Year

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

for i in range(5):
    plt.subplot(2,3,i+1)
```

```
    plt.plot(Hour_even,variation_of_day_dec2.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_dec2
```

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	91.675000	97.575000	102.125000	102.925000	101.925000	108.925000
2013	137.277778	143.686111	155.352778	162.650000	162.872222	166.855556
2014	82.000000	98.625000	113.500000	125.750000	134.000000	144.250000

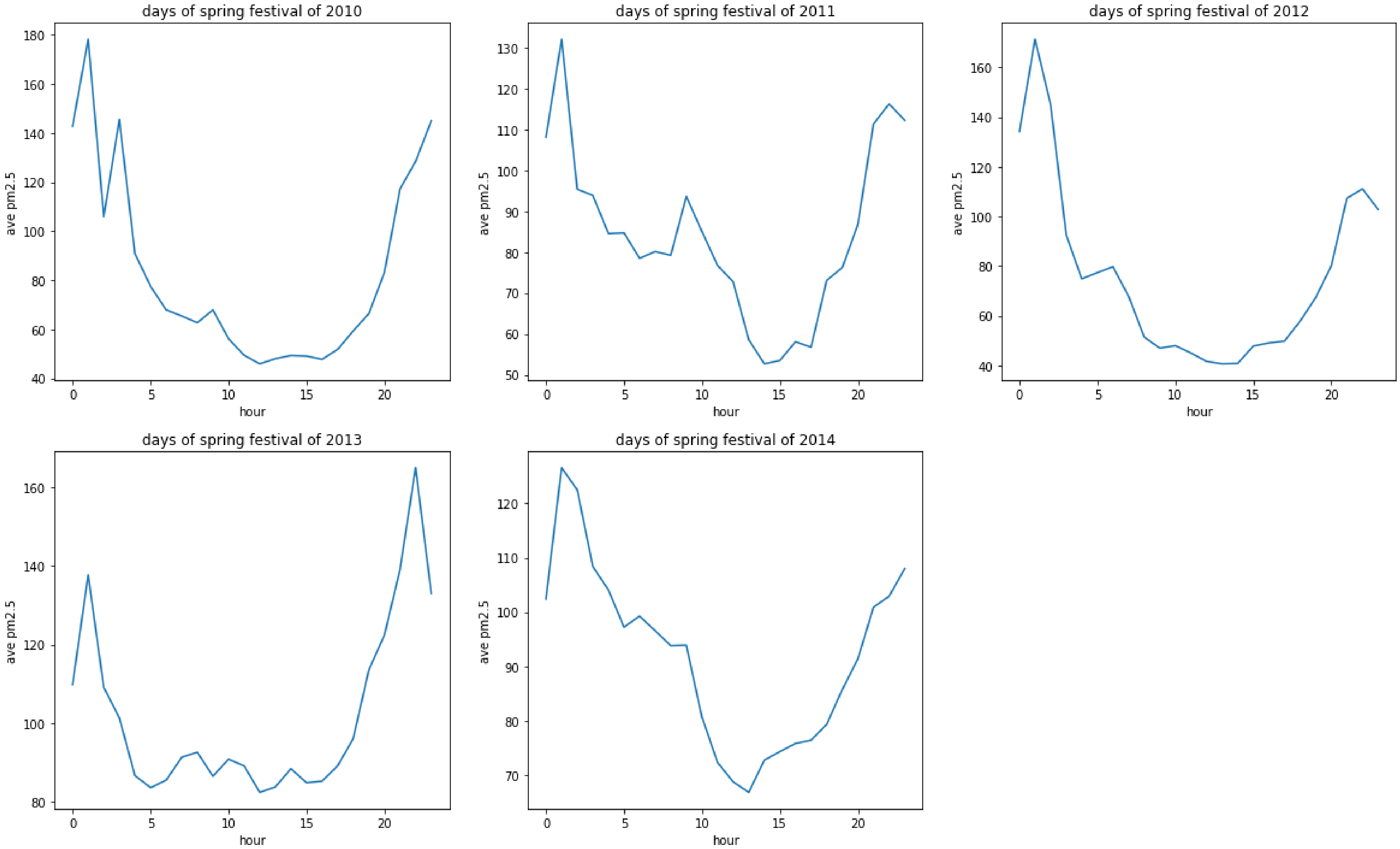
与原数据相比，2013年的数值有较大变化，但变化趋势基本一样，平均浓度基本均为上升趋势

3.5.9 与task2类似，用折线图记录填补后数据每年春节期间（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

In [ ]:

```
## PM2.5在春节每小时的波动值
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_sprfest2=[[],[],[],[],[]]
variation_of_hour_sprfest2 = pd.DataFrame()

pm25_sprfest_2010=pd.DataFrame()
for sprday_2010 in sprfest_2010:
    pm25_sprfest_2010_date=pm25_knn[pm25_knn.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_sprfest2[0].append(mean_spr_2010)

pm25_sprfest_2011=pd.DataFrame()
for sprday_2011 in sprfest_2011:
    pm25_sprfest_2011_date=pm25_knn[pm25_knn.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_sprfest2[1].append(mean_spr_2011)
```

```
pm25_sprfest_2012=pd.DataFrame()
for sprday_2012 in sprfest_2012:
    pm25_sprfest_2012_date=pm25_knn[pm25_knn.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_sprfest2[2].append(mean_spr_2012)

pm25_sprfest_2013=pd.DataFrame()
for sprday_2013 in sprfest_2013:
    pm25_sprfest_2013_date=pm25_knn[pm25_knn.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_sprfest2[3].append(mean_spr_2013)

pm25_sprfest_2014=pd.DataFrame()
for sprday_2014 in sprfest_2014:
    pm25_sprfest_2014_date=pm25_knn[pm25_knn.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_sprfest2[4].append(mean_spr_2014)

variation_of_hour_sprfest2=variation_of_hour_sprfest2.append(hour_of_sprfest2)

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Hour,variation_of_hour_sprfest2.iloc[i,:])
    plt.title('days of spring festival of %d' % Year[i])
    plt.xlabel('hour')
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_hour_sprfest2
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	
0	142.833333	178.250000	105.883333	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

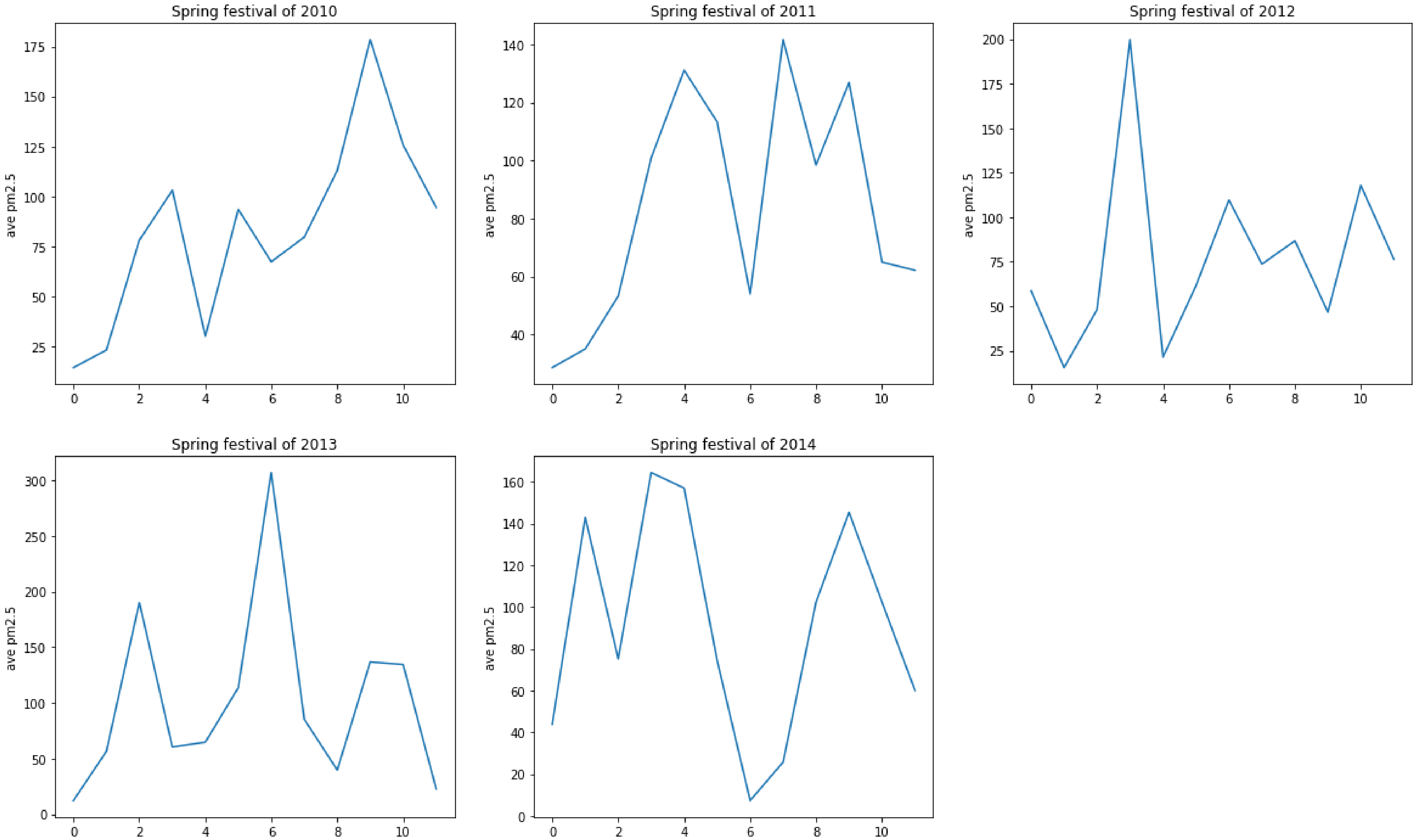
与原数据相比，平均浓度的数值大小和变化趋势均基本一样，每天每小时的变化趋势与全年相似，均为15点后上升，凌晨1点后慢慢下降

3.5.10 与task2类似，用折线图记录填补数据的每年春节期间（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

In [ ]:

```
## PM2.5在春节每天的波动值
days_of_sprfest2=[[],[],[],[],[]]
variation_of_days_sprfest2 = 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_sprfest2[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_sprfest2[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_sprfest2[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_sprfest2[3].append(mean_spr_2013)

for sprday_2014 in sprfest_2014:
```

```
    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_sprfest2[4].append(mean_spr_2014)

variation_of_days_sprfest2=variation_of_days_sprfest2.append(days_of_sprfest2)

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

for i in range(5):
    plt.subplot(2,3,i+1)
    plt.plot(Spr,variation_of_days_sprfest2.iloc[i,:])
    plt.title('Spring festival of %d' % Year[i])
    plt.ylabel('ave pm2.5')
```



In [ ]:

```
variation_of_days_sprfest2
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	10	11
0	14.333333	23.083333	78.083333	103.150000	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	85.359375	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

与原数据相比，平均浓度的数值大小和变化趋势均基本一样，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

综上所述，显然k近邻法填补数据更能模拟原数据结构