In [ ]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import warnings
warnings.filterwarnings("ignore")
```

1.数据预处理

1.1 我们首先在原数据集增加一个叫"date"的属性，以格式'%Y-%m-%d'记录日期，并保存为csv文件；然后将数据集中的NA转换为NAN，再去除

In [ ]:

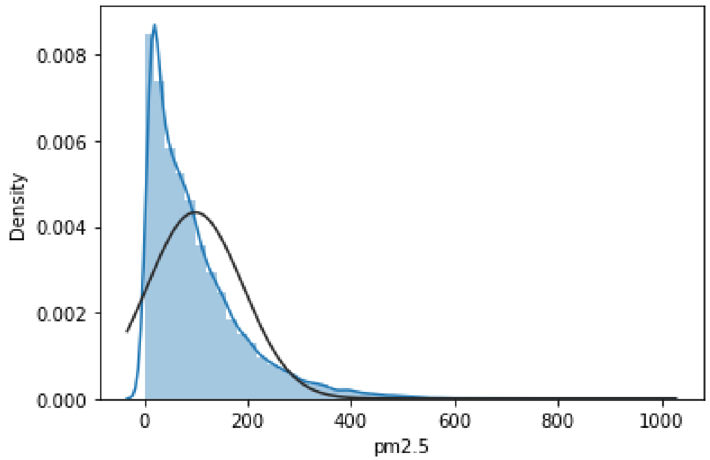
```
pm25_data = pd.read_csv('PRSA_data.csv')
pm25_data.replace('NA',np.nan)
pm25_data = pd.get_dummies(pm25_data)
pm25_data['date'] = pm25_data['year'].astype(str) + '-' + pm25_data['month'].astype(str) + '-' + pm25_data['day'].astype(str)

#以'%Y-%m-%d'记录日期
for i in range(len(pm25_data)):
    pm25_data.loc[i,'date'] = pd.to_datetime(pm25_data.loc[i,'date']).strftime('%Y-%m-%d')
pm25_data.to_csv("pm25_data.csv",index=False)

# 去除NAN
pm25_data_dropna=pm25_data.dropna(axis=0, how='any', inplace=False)
```

1.2 观察pm2.5的分布情况

In [ ]:

```
from scipy import stats
sns.distplot(pm25_data_dropna['pm2.5'], fit=stats.norm)
print("Skewness: %f" % pm25_data_dropna['pm2.5'].skew())
print("Kurtosis: %f" % pm25_data_dropna['pm2.5'].kurt())
```

```
Skewness: 1.802311
Kurtosis: 4.768933
```



1.3 从图中发现数据严重左偏，所以尝试用对数转换pm2.5，得到一个近似正态分布的数据。
我们首先检查pm2.5有无0值

In [ ]:
```
pm25_data_dropna[pm25_data_dropna['pm2.5']==0]
```

Out[ ]:

	No	year	month	day	hour	pm2.5	DEWP	TEMP	PRES	Iws	Is	Ir	cbwd_NE	cbwd_NW	cbwd_SE	cbwd_cv	date
24034	24035	2012	9	28	10	0.0	-5	20.0	1020.0	139.48	0	0	0	1	0	0	2012-09-28
24039	24040	2012	9	28	15	0.0	-10	24.0	1017.0	192.68	0	0	0	1	0	0	2012-09-28

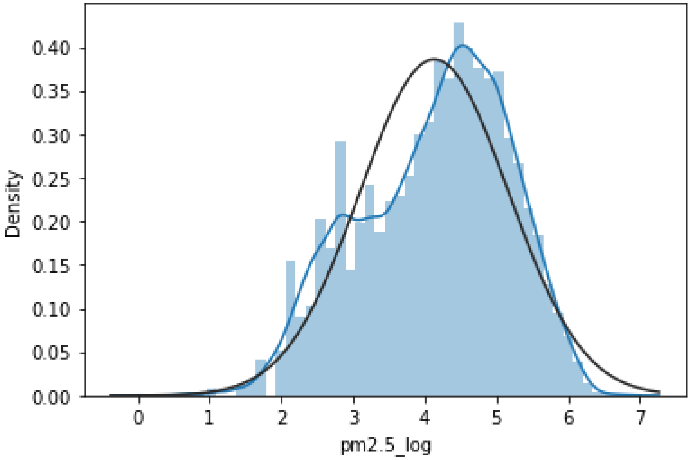
我们去除掉pm2.5为0的数据，能够这样做的原因是现实中几乎不可能出现pm2.5为0的情况

In [ ]:
```
pm25_data_dropna = pm25_data_dropna.drop(pm25_data_dropna[pm25_data_dropna['pm2.5'] == 0].index).reset_index(drop=True)
```

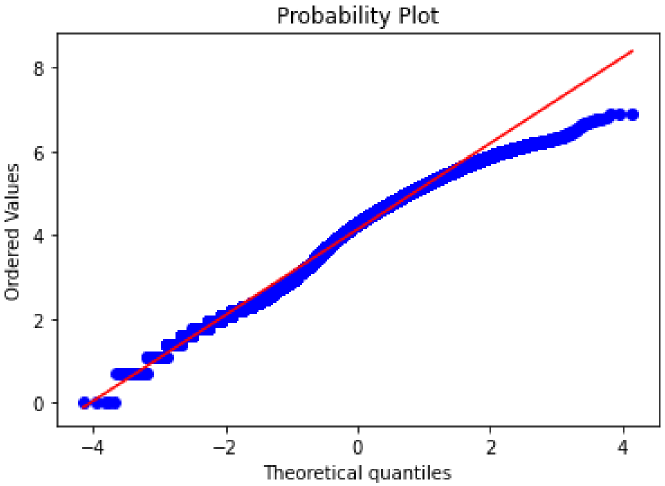
1.4 检查对数转换后pm2.5的分布与正态分布的相似度

In [ ]:
```
pm25_data_dropna['pm2.5_log'] = np.log(pm25_data_dropna['pm2.5'])
sns.distplot(pm25_data_dropna['pm2.5_log'], fit=stats.norm)
print("Skewness: %f" % pm25_data_dropna['pm2.5_log'].skew())
print("Kurtosis: %f" % pm25_data_dropna['pm2.5_log'].kurt())
```

```
Skewness: -0.356563
Kurtosis: -0.563840
```



In [ ]:
```
res = stats.probplot(pm25_data_dropna['pm2.5_log'], plot=plt)
```



从p-p图中可以看出对数转换后的pm2.5近似服从正态分布

1.5 获得训练集和测试集数据

In [ ]:
```
# 测试数据日期
test_date=pd.date_range(start='2010-01-07',freq='W-Thu',end='2014-12-25').strftime('%Y-%m-%d').tolist()

# 测试数据索引
test_index=[]
for i in range(len(pm25_data_dropna['date'])):
```

```
    if pm25_data_dropna.iloc[i,-2] in test_date:
        test_index.append(i)

# 测试集和训练集
test_data=pm25_data_dropna.iloc[test_index,:].reset_index(drop=True)
train_data=pm25_data_dropna.drop(index=pm25_data_dropna.index[test_index]).reset_index(drop=True)
```

2.模型建立

2.1 我们选择用xgboost regressor拟合对数转换后的数据

In [ ]:

```
import xgboost as xgb
from sklearn.metrics import mean_squared_error
from sklearn import preprocessing
```

通过不断的调参，我们最终选择 XGBRegressor(learning_rate=0.1, n_estimators=600, max_depth=5)

In [ ]:

```
var=['year','month','day','hour','DEWP','TEMP','PRES','Iws','Is','Ir','cbwd_NE','cbwd_NW','cbwd_SE','cbwd_cv'] # feature
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=600,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))

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

```
Mean squared error of test data: 0.0084
R2 score of test data: 0.7100
```

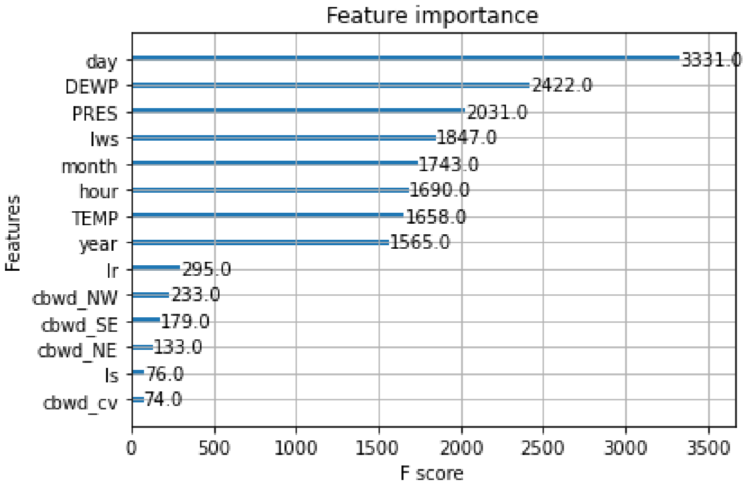
我们在测试集上预测 pm2.5，然后将得到的预测数据做指数变换得到 y_pred；将 y_pred 与真实数据 y_test 作 min_max 归一化，再计算它们的 MSE，我们得到的结果是 0.0084。
该模型的 R2 系数是0.7100

3.特征选择

3.1 通过XGB.feature_importances_选择特征

In [ ]:
```
xgb.plot_importance(XGB_model)
```

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

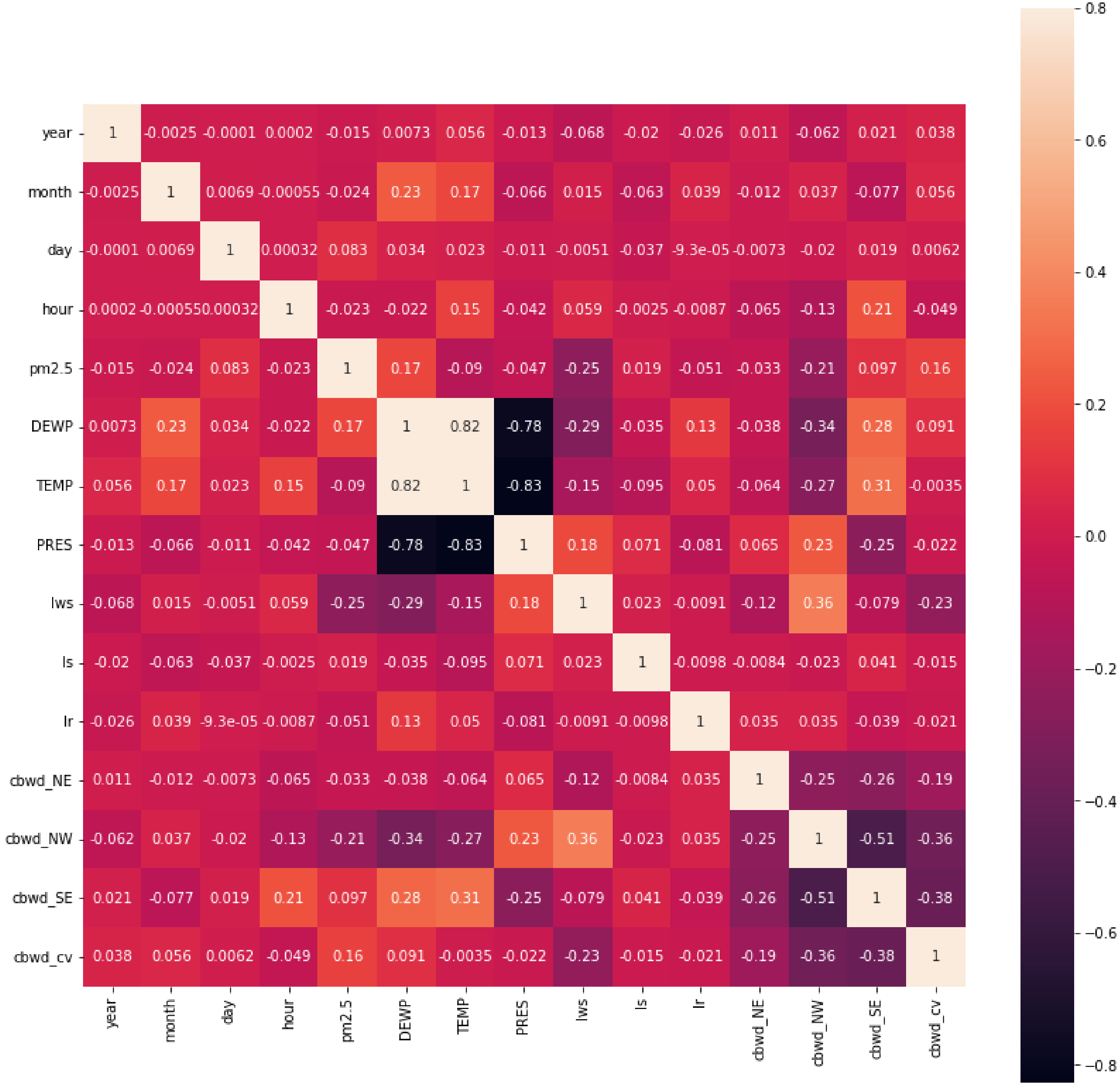


从图中我们看出在所有特征中 day 的重要性最高；在气象特征中，DEWP、PRES、Iws、TEMP的重要性较高

3.2 通过corrmatrix选择特征

In [ ]:
```
X=pm25_data_dropna[['year','month','day','hour','pm2.5','DEWP', 'TEMP', 'PRES', 'Iws', 'Is', 'Ir', 'cbwd_NE', 'cbwd_NW', 'cbwd_SE', 'cbwd_cv']]
```

In [ ]:
```
corrmatrix = X.corr()
plt.subplots(figsize=(14, 14))
sns.heatmap(corrmatrix, vmax=0.8, square=True, annot=True)
plt.show()
```


year
month
day
hour
pm2.5
DEWP
TEMP
PRES
Iws
Is
Ir
cbwd_NE
cbwd_NW
cbwd_SE
cbwd_cv
1 -0.0025 -0.0001 0.0002 -0.015 0.0073 0.056 -0.013 -0.068 -0.02 -0.026 0.011 -0.062 0.021 0.038
-0.0025 1 0.0069 -0.00055 -0.024 0.23 0.17 -0.066 0.015 -0.063 0.039 -0.012 0.037 -0.077 0.056
-0.0001 0.0069 1 0.00032 0.083 0.034 0.023 -0.011 -0.0051 -0.037 -9.3e-05 -0.0073 -0.02 0.019 0.0062
0.0002 -0.00055 0.00032 1 -0.023 -0.022 0.15 -0.042 0.059 -0.0025 -0.0087 -0.065 -0.13 0.21 -0.049
-0.015 -0.024 0.083 -0.023 1 0.17 -0.09 -0.047 -0.25 0.019 -0.051 -0.033 -0.21 0.097 0.16
0.0073 0.23 0.034 -0.022 0.17 1 0.82 -0.78 -0.29 -0.035 0.13 -0.038 -0.34 0.28 0.091
0.056 0.17 0.023 0.15 -0.09 0.82 1 -0.83 -0.15 -0.095 0.05 -0.064 -0.27 0.31 -0.0035
-0.013 -0.066 -0.011 -0.042 -0.047 -0.78 -0.83 1 0.18 0.071 -0.081 0.065 0.23 -0.25 -0.022
-0.068 0.015 -0.0051 0.059 -0.25 -0.29 -0.15 0.18 1 0.023 -0.0091 -0.12 0.36 -0.079 -0.23
-0.02 -0.063 -0.037 -0.0025 0.019 -0.035 -0.095 0.071 0.023 1 -0.0098 -0.0084 -0.023 0.041 -0.015
-0.026 0.039 -9.3e-05 -0.0087 -0.051 0.13 0.05 -0.081 -0.0091 -0.0098 1 0.035 0.035 -0.039 -0.021
0.011 -0.012 -0.0073 -0.065 -0.033 -0.038 -0.064 0.065 -0.12 -0.0084 0.035 1 -0.25 -0.26 -0.19
-0.062 0.037 -0.02 -0.13 -0.21 -0.34 -0.27 0.23 0.36 -0.023 0.035 -0.25 1 -0.51 -0.36
0.021 -0.077 0.019 0.21 0.097 0.28 0.31 -0.25 -0.079 0.041 -0.039 -0.26 -0.51 1 -0.38
0.038 0.056 0.0062 -0.049 0.16 0.091 -0.0035 -0.022 -0.23 -0.015 -0.021 -0.19 -0.36 -0.38 1
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8

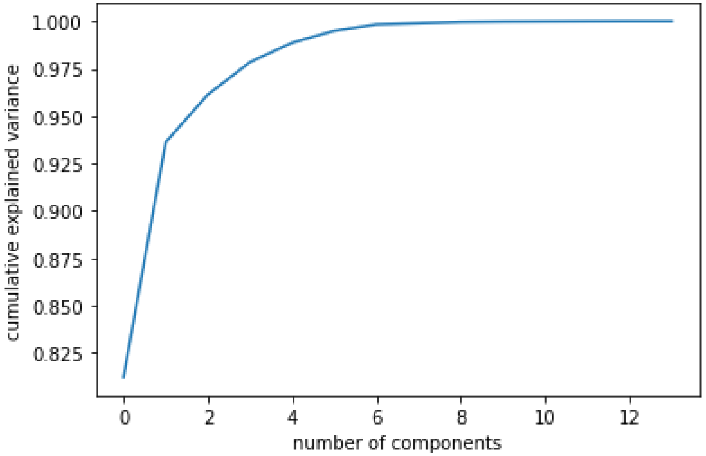
从图中可以看出DEWP、TEMP、Iws、cbwd_NW、cbwd_SE、cbwd_cv与pm2.5的相关性较高

3.3 通过PCA.explained_variance_ratio_选择特征

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')
print('the explained varaince ratio is ')
print(np.cumsum(pca.explained_variance_ratio_))
```

```
the explained varaince ratio is
[0.81209615 0.93618929 0.96136072 0.97843113 0.9886945  0.99497762
 0.99832777 0.99897539 0.99960645 0.99980002 0.99988718 0.99995742
 1.         1.        ]
```



从图中我们可以看出可以取前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

In [ ]:

```
print('the first 3 components are ')
print(pca.components_[0:3])
```

```
the first 3 components are
[[-1.94127059e-03  3.66933583e-04 -1.15667395e-03  8.01431277e-03
  -9.65692716e-02 -4.62786970e-02  4.47759939e-02  9.93197460e-01
   3.91279118e-04 -3.93537967e-04 -7.13078920e-04  3.46430387e-03
  -8.75300585e-04 -1.87592436e-03]
 [-5.46047674e-04 -3.60771978e-02 -1.45995574e-02 -2.85262641e-02
  -6.62110654e-01 -5.78009979e-01  4.61010400e-01 -1.11894658e-01
   2.50792936e-03 -7.04886093e-03  1.48684588e-03  5.17502197e-03
  -7.00710031e-03  3.45232463e-04]
```

```
[-3.31100204e-04  3.02658550e-03  9.99091104e-01 -1.11871522e-02
  1.65822401e-02 -1.77541195e-02  3.29017954e-02  5.57886593e-04
 -2.97490127e-03 -1.50471076e-04 -1.46044851e-04 -5.96526140e-04
  3.81852153e-04  3.60718838e-04]]
```