数据挖掘作业 1 数据探索性分析与预处理

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数据分析要求

1. 数据可视化和摘要

- 数据摘要

对标称属性，给出每个可能取值的频数

对数值属性，给出最大、最小、均值、中位数、四分位数及缺失值的个数。

- 数据的可视化

针对数值属性：

绘制直方图，如mxPH，用qq图检验其分布是否为正态分布。

绘制盒图，对离群值进行识别。

对7种海藻，分别绘制其数量与标称变量，如size的条件盒图

2. 数据缺失的处理

- 分别使用下列四种策略对缺失值进行处理，处理后可视化地对比新旧数据集。

1.将缺失部分剔除 2.用最高频率值来填补缺失值 3.通过属性的相关关系来填补缺失值 4.通过数据对象之间的相似性来填补缺失值

解答内容

In [1]:

```
#!/usr/bin/env python
# -*- coding:utf-8 -*-
import operator
import pandas as pd
import numpy as np
import statsmodels.api as sm
import scipy.stats as stats
import matplotlib.pyplot as plt
import matplotlib
matplotlib.style.use('ggplot')
%pylab inline
```

Populating the interactive namespace from numpy and matplotlib

Step1. 数据处理

- 将原始txt文件转换为易于处理的csv文件

In [4]:

```
# 转换文件格式，生成csv文件
fp_origin = open("./data_origin/Analysis.txt", 'r')
fp_modified = open("./data_origin/Analysis.csv", 'w')

line = fp_origin.readline()
while(line):
    temp = line.strip().split()
    temp = ','.join(temp)+'\n'
    fp_modified.write(temp)
    line = fp_origin.readline()

fp_origin.close()
fp_modified.close()
```

Step2. 读取数据

- 读取csv文件，生成data frame

In [5]:

```
# 定义两类数据：标称型和数值型
name_category = ["season", "river_size", "river_speed"]
name_value = ["mxPH", "mnO2", "Cl", "NO3", "NH4", "oPO4", "PO4", "Chla", "a1", "a2", "a3", "a4",
"a5", "a6", "a7"]
# 存储7种海藻对应的名称
name_seaweed = ["a1", "a2", "a3", "a4", "a5", "a6", "a7"]

# 读取数据
data_origin = pd.read_csv("./data_origin/Analysis.csv",
                names = name_category+name_value,
                na_values = "XXXXXXX")

# 将字符数据转换为category
for item in name_category:
    data_origin[item] = data_origin[item].astype('category')

# 查看前10条数据内容
data_origin.iloc[:10]
```

Out[5]:

	season	river_size	river_speed	mxPH	mnO2	Cl	NO3	NH4	oPO4
0	winter	small	medium	8.00	9.8	60.800	6.238	578.00000	105.000
1	spring	small	medium	8.35	8.0	57.750	1.288	370.00000	428.750
2	autumn	small	medium	8.10	11.4	40.020	5.330	346.66699	125.667
3	spring	small	medium	8.07	4.8	77.364	2.302	98.18200	61.182
4	autumn	small	medium	8.06	9.0	55.350	10.416	233.70000	58.222
5	winter	small	high	8.25	13.1	65.750	9.248	430.00000	18.250
6	summer	small	high	8.15	10.3	73.250	1.535	110.00000	61.250
7	autumn	small	high	8.05	10.6	59.067	4.990	205.66701	44.667
8	winter	small	medium	8.70	3.4	21.950	0.886	102.75000	36.300
9	winter	small	high	7.93	9.9	8.000	1.390	5.80000	27.250

Step 3. 数据摘要

- 对标称属性，给出每个可能取值的频数

In [6]:

```
# 使用value_counts函数统计每个标称属性的取值频数
for item in name_category:
    print item, '的频数为：\n', pd.value_counts(data_origin[item].values), '\n'
```

```
season 的频数为：
winter    62
spring    53
summer    45
autumn    40
dtype: int64

river_size 的频数为：
medium    84
small     71
large     45
dtype: int64

river_speed 的频数为：
high      84
medium    83
low       33
dtype: int64
```

- 对数值属性，给出最大、最小、均值、中位数、四分位数及缺失值的个数。

In [7]:

```
# 最大值
data_show = pd.DataFrame(data = data_origin[name_value].max(), columns = ['max'])
# 最小值
data_show['min'] = data_origin[name_value].min()
# 均值
data_show['mean'] = data_origin[name_value].mean()
# 中位数
data_show['median'] = data_origin[name_value].median()
# 四分位数
data_show['quartile'] = data_origin[name_value].describe().loc['25%']
# 缺失值个数
data_show['missing'] = data_origin[name_value].describe().loc['count'].apply(lambda x : 200-x)
```

In [8]:

```
data_show
```

Out[8]:

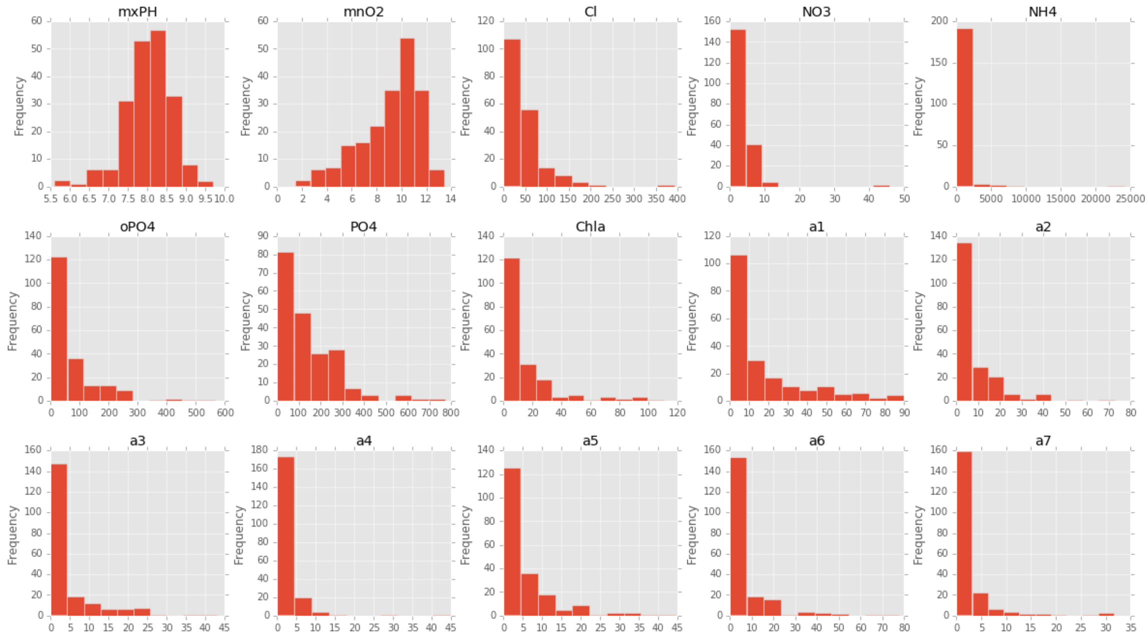
	max	min	mean	median	quartile	missing
mxPH	9.70000	5.600	8.011734	8.0600	7.70000	1.0
mnO2	13.40000	1.500	9.117778	9.8000	7.72500	2.0
Cl	391.50000	0.222	43.636279	32.7300	10.98125	10.0
NO3	45.65000	0.050	3.282389	2.6750	1.29600	2.0
NH4	24064.00000	5.000	501.295828	103.1665	38.33325	2.0
oPO4	564.59998	1.000	73.590596	40.1500	15.70000	2.0
PO4	771.59998	1.000	137.882101	103.2855	41.37525	2.0
Chla	110.45600	0.200	13.971197	5.4750	2.00000	12.0
a1	89.80000	0.000	16.923500	6.9500	1.50000	0.0
a2	72.60000	0.000	7.458500	3.0000	0.00000	0.0
a3	42.80000	0.000	4.309500	1.5500	0.00000	0.0
a4	44.60000	0.000	1.992500	0.0000	0.00000	0.0
a5	44.40000	0.000	5.064500	1.9000	0.00000	0.0
a6	77.60000	0.000	5.964000	0.0000	0.00000	0.0
a7	31.60000	0.000	2.495500	1.0000	0.00000	0.0

Step 4. 数据可视化

- 针对数值属性： 绘制直方图，如mxPH，用qq图检验其分布是否为正态分布。

In [9]:

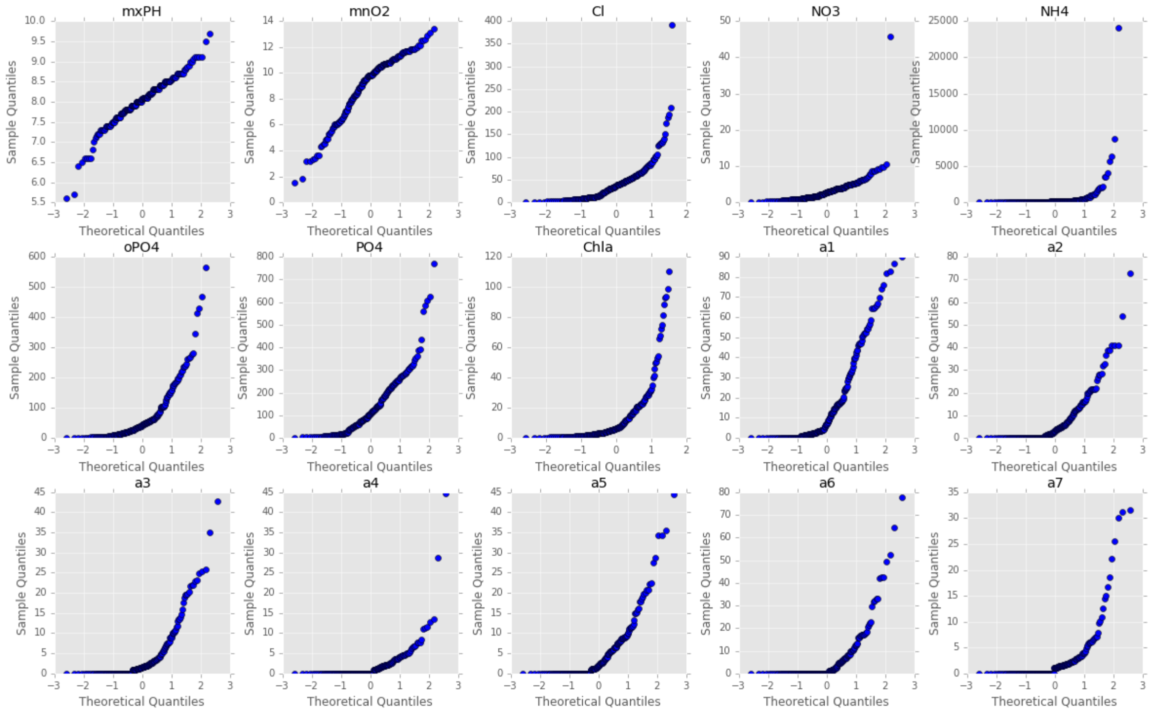
```
# 直方图
fig = plt.figure(figsize = (20,11))
i = 1
for item in name_value:
    ax = fig.add_subplot(3, 5, i)
    data_origin[item].plot(kind = 'hist', title = item, ax = ax)
    i += 1
plt.subplots_adjust(wspace = 0.3, hspace = 0.3)
fig.savefig('./image/histogram.jpg')
```



从qq图中可以看出，只有mxPH和mnO2两项值符合正态分布，其他值均不符合

In [10]:

```
# qq图
fig = plt.figure(figsize = (20,12))
i = 1
for item in name_value:
    ax = fig.add_subplot(3, 5, i)
    sm.qqplot(data_origin[item], ax = ax)
    ax.set_title(item)
    i += 1
plt.subplots_adjust(wspace = 0.3, hspace = 0.3)
fig.savefig('./image/qqplot.jpg')
```

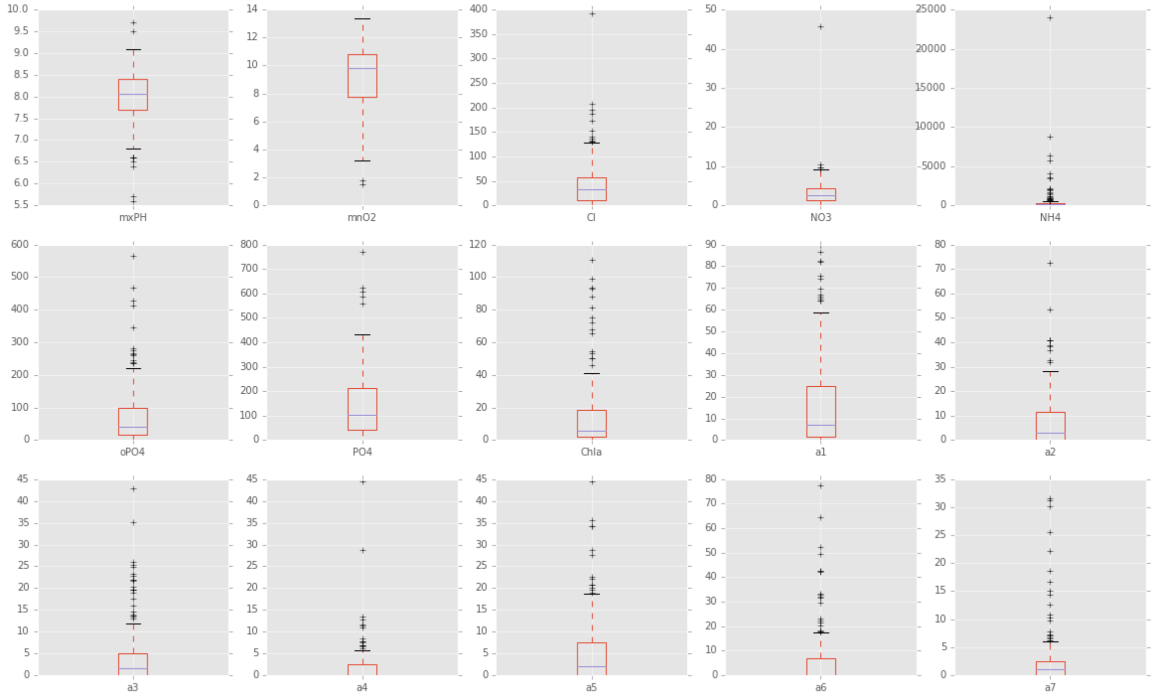


从qq图中可以看出，只有mxPH和mnO2两项值符合正态分布，其他值均不符合

- 绘制盒图，对离群值进行识别。

In [11]:

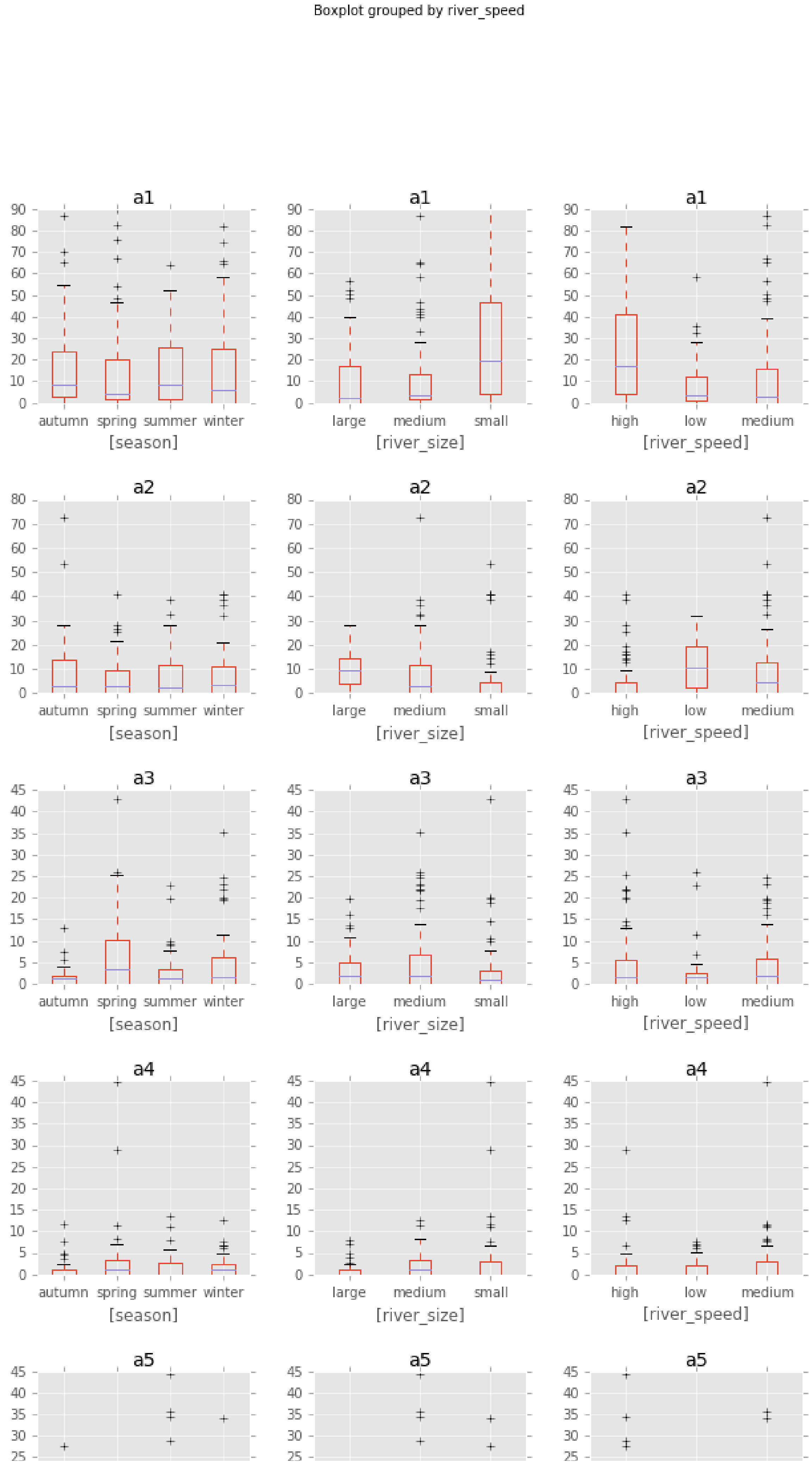
```
# 盒图
fig = plt.figure(figsize = (20,12))
i = 1
for item in name_value:
    ax = fig.add_subplot(3, 5, i)
    data_origin[item].plot(kind = 'box')
    i += 1
fig.savefig('./image/boxplot.jpg')
```

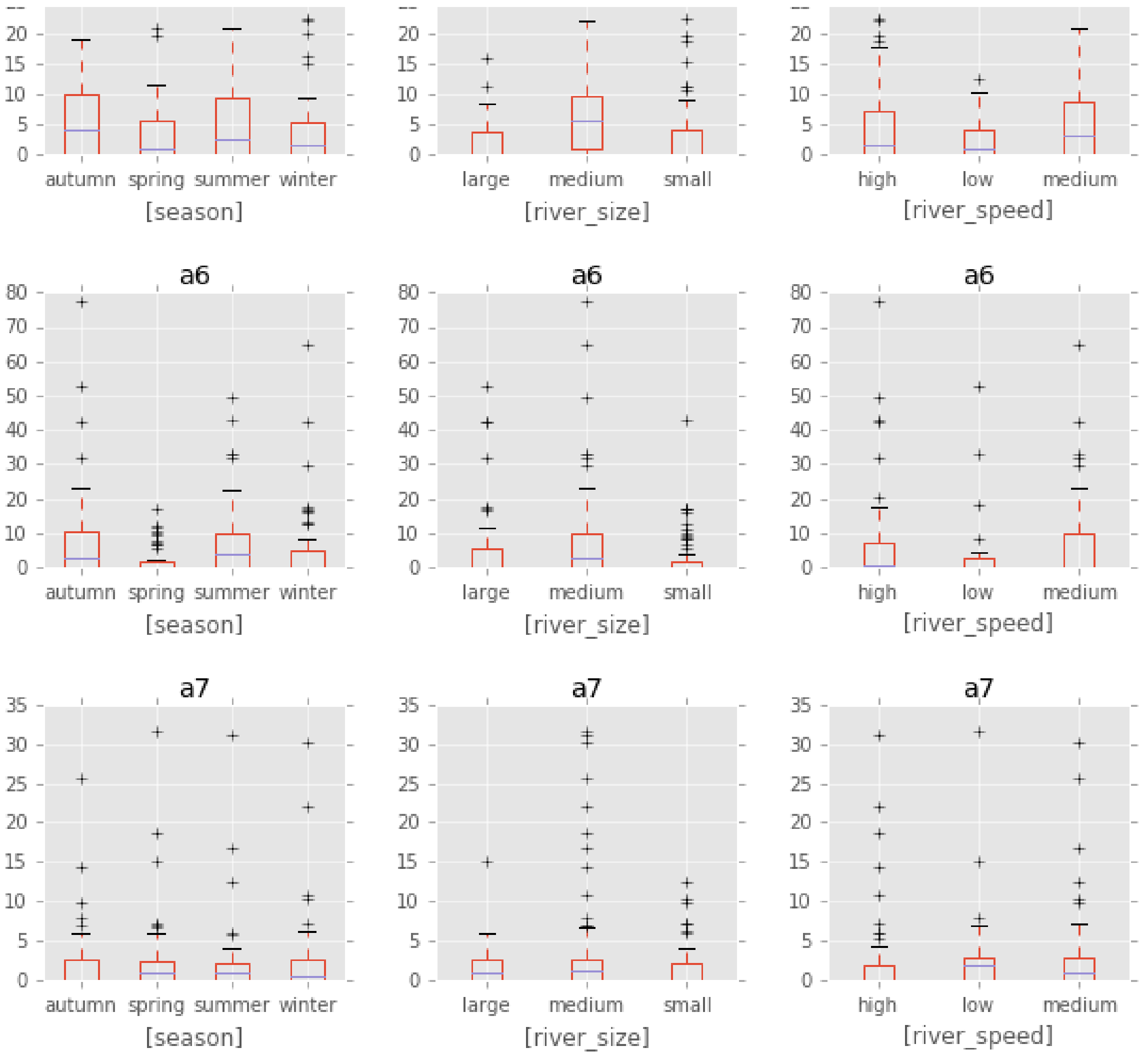


- 对7种海藻，分别绘制其数量与标称变量，如size的条件盒图

In [12]:

```
# 条件盒图
fig = plt.figure(figsize = (10, 27))
i = 1
for seaweed in name_seaweed:
    for category in name_category:
        ax = fig.add_subplot(7, 3, i)
        data_origin[[seaweed, category]].boxplot(by = category, ax = ax)
        ax.set_title(seaweed)
        i += 1
plt.subplots_adjust(hspace = 0.5, wspace = 0.3)
fig.savefig('./image/boxplot_condition.jpg')
```


Boxplot grouped by river_speed
a1
a1
a1
autumn spring summer winter
[season]
large medium small
[river_size]
high low medium
[river_speed]
a2
a2
a2
autumn spring summer winter
[season]
large medium small
[river_size]
high low medium
[river_speed]
a3
a3
a3
autumn spring summer winter
[season]
large medium small
[river_size]
high low medium
[river_speed]
a4
a4
a4
autumn spring summer winter
[season]
large medium small
[river_size]
high low medium
[river_speed]
a5
a5
a5



Step 4. 数据缺失的处理

可视化方法：对于**标称属性**，绘制属性的折线图，图中红线是原始数据，蓝线是处理完缺失值之后的数据；**数值属性**：使用直方图，将原始数据和处理后的数据图像进行叠加。图中红色的垂线是原始数据的均值，蓝色的垂线是处理完缺失值之后的均值。

4.0 观察数据

从绘制的表格上可以看出，缺失值主要集中在Cl、Chla两个属性，第62、199条数据缺失情况比较严重

In [13]:

```
# 找出含有缺失值的数据条目索引值
nan_list = pd.isnull(data_origin).any(1).nonzero()[0]

# 显示含有缺失值的原始数据条目
data_origin.iloc[nan_list].style.highlight_null(null_color='red')
```

Out[13]:

	season	river_size	river_speed	mxPH	mnO2	Cl	NO3	NH4	oPO4	PO4
27	autumn	small	high	6.8	11.1	9	0.63	20	4	nan
37	spring	small	high	8	nan	1.45	0.81	10	2.5	3
47	winter	small	low	nan	12.6	9	0.23	10	5	6
54	winter	small	high	6.6	10.8	nan	3.245	10	1	6.5
55	spring	small	medium	5.6	11.8	nan	2.22	5	1	1
56	autumn	small	medium	5.7	10.8	nan	2.55	10	1	4
57	spring	small	high	6.6	9.5	nan	1.32	20	1	6
58	summer	small	high	6.6	10.8	nan	2.64	10	2	11
59	autumn	small	medium	6.6	11.3	nan	4.17	10	1	6
60	spring	small	medium	6.5	10.4	nan	5.97	10	2	14
61	summer	small	medium	6.4	nan	nan	nan	nan	nan	14
62	autumn	small	high	7.83	11.7	4.083	1.328	18	3.333	6.667
115	winter	medium	high	9.7	10.8	0.222	0.406	10	22.444	10.111
160	spring	large	low	9	5.8	nan	0.9	142	102	186
183	winter	large	high	8	10.9	9.055	0.825	40	21.083	56.091
198	winter	large	medium	8	7.6	nan	nan	nan	nan	nan

4.1 将缺失部分剔除

使用***dropna()***函数操作。从结果可以看出，由于删除了带有缺失值的整条数据。

从标称属性的折线图，可以明显看出处理后的数据量减少；直方图中，蓝色线和红色线不重合，但是十分接近，说明数值属性的均值有改变，但是变化不大。

In [17]:

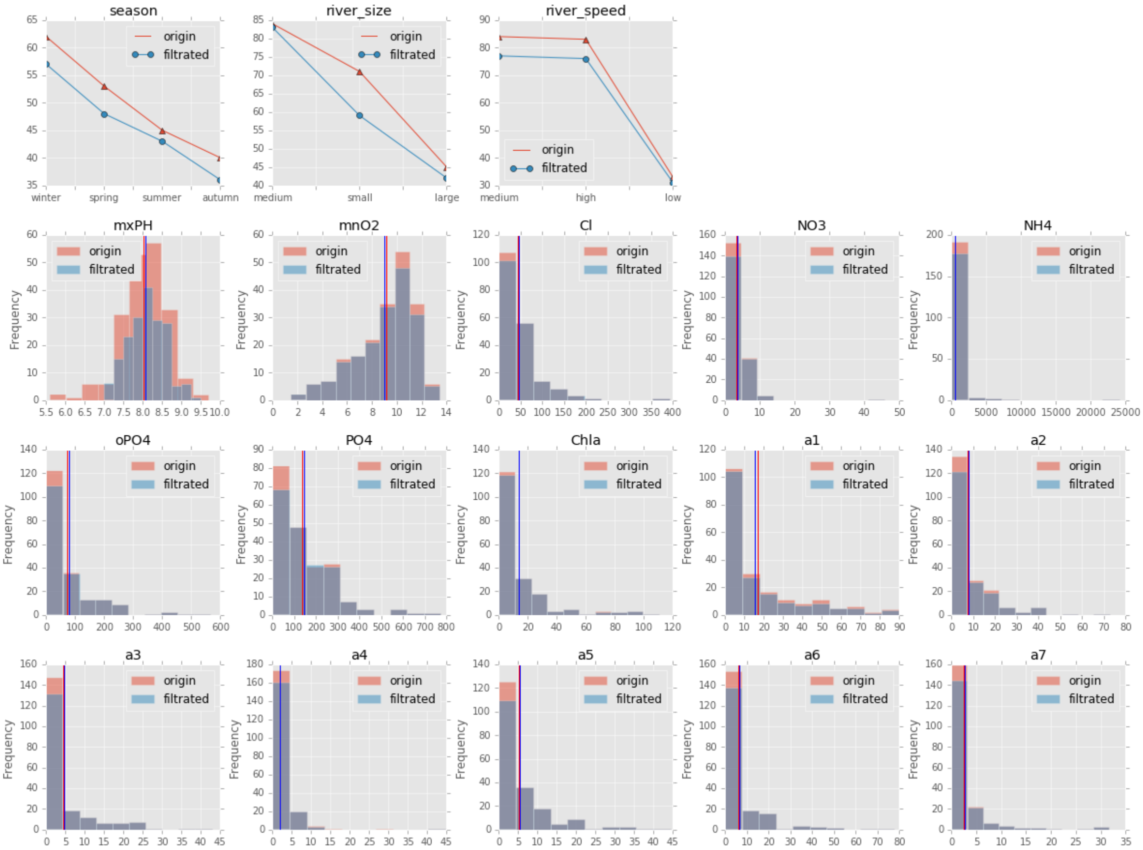
```
# 将缺失值对应的数据整条剔除，生成新数据集
data_filtrated = data_origin.dropna()

# 绘制可视化图
fig = plt.figure(figsize = (20,15))

i = 1
# 对标称属性，绘制折线图
for item in name_category:
    ax = fig.add_subplot(4, 5, i)
    ax.set_title(item)
    pd.value_counts(data_origin[item].values).plot(ax = ax, marker = '^', label = 'origin', legend = True)
    pd.value_counts(data_filtrated[item].values).plot(ax = ax, marker = 'o', label = 'filtrated', legend = True)
    i += 1

i = 6
# 对数值属性，绘制直方图
for item in name_value:
    ax = fig.add_subplot(4, 5, i)
    ax.set_title(item)
    data_origin[item].plot(ax = ax, alpha = 0.5, kind = 'hist', label = 'origin', legend = True)
    data_filtrated[item].plot(ax = ax, alpha = 0.5, kind = 'hist', label = 'filtrated', legend = True)
    ax.axvline(data_origin[item].mean(), color = 'r')
    ax.axvline(data_filtrated[item].mean(), color = 'b')
    i += 1
plt.subplots_adjust(wspace = 0.3, hspace = 0.3)

# 保存图像和处理后数据
fig.savefig('./image/missing_data_delete.jpg')
data_filtrated.to_csv('./data_output/missing_data_delete.csv', mode = 'w', encoding='utf-8', index = False,header = False)
```



4.2 用最高频率值来填补缺失值

使用***value_counts()***函数统计原始数据中，出现频率最高的值，再用***fillna()***函数将缺失值替换为最高频率值。

从折线图看出，处理后标称属性值不变；从直方图可以看出，数值属性的缺失值补全为高频值，均值基本保持不变。

In [19]:

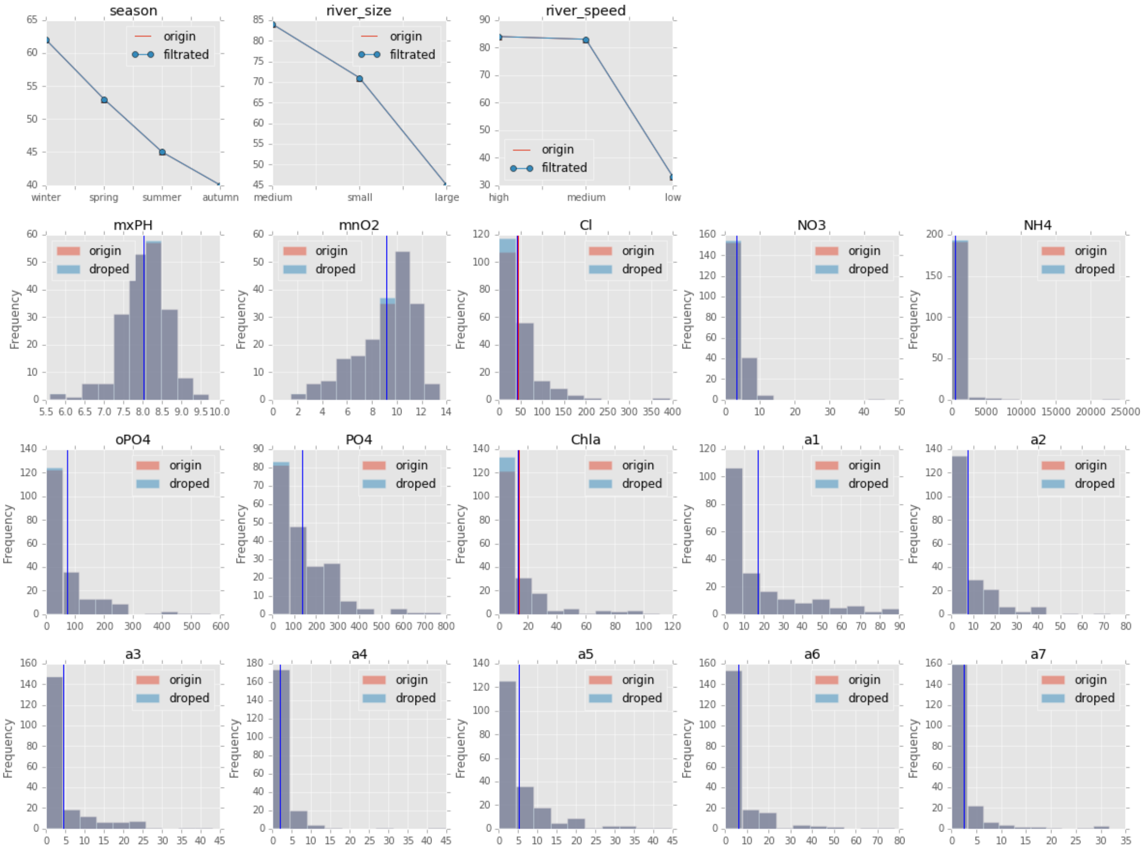
```
# 建立原始数据的拷贝
data_filtrated = data_origin.copy()
# 对每一列数据，分别进行处理
for item in name_category+name_value:
    # 计算最高频率的值
    most_frequent_value = data_filtrated[item].value_counts().idxmax()
    # 替换缺失值
    data_filtrated[item].fillna(value = most_frequent_value, inplace = True)

# 绘制可视化图
fig = plt.figure(figsize = (20,15))

i = 1
# 对标称属性，绘制折线图
for item in name_category:
    ax = fig.add_subplot(4, 5, i)
    ax.set_title(item)
    pd.value_counts(data_origin[item].values).plot(ax = ax, marker = '^', label = 'origin', legend = True)
    pd.value_counts(data_filtrated[item].values).plot(ax = ax, marker = 'o', label = 'filtrated', legend = True)
    i += 1

i = 6
# 对数值属性，绘制直方图
for item in name_value:
    ax = fig.add_subplot(4, 5, i)
    ax.set_title(item)
    data_origin[item].plot(ax = ax, alpha = 0.5, kind = 'hist', label = 'origin', legend = True)
    data_filtrated[item].plot(ax = ax, alpha = 0.5, kind = 'hist', label = 'droped', legend = True)
    ax.axvline(data_origin[item].mean(), color = 'r')
    ax.axvline(data_filtrated[item].mean(), color = 'b')
    i += 1
plt.subplots_adjust(wspace = 0.3, hspace = 0.3)

# 保存图像和处理后数据
fig.savefig('./image/missing_data_most.jpg')
data_filtrated.to_csv('./data_output/missing_data_most.csv', mode = 'w', encoding='utf-8', index = False,header = False)
```



4.3 通过属性的相关关系来填补缺失值

使用pandas中Series的***interpolate()***函数，对数值属性进行插值计算，并替换缺失值。

从直方图中可以看出，处理后的数据，添加了若干个值不同的值，并且均值变化不大。

In [20]:

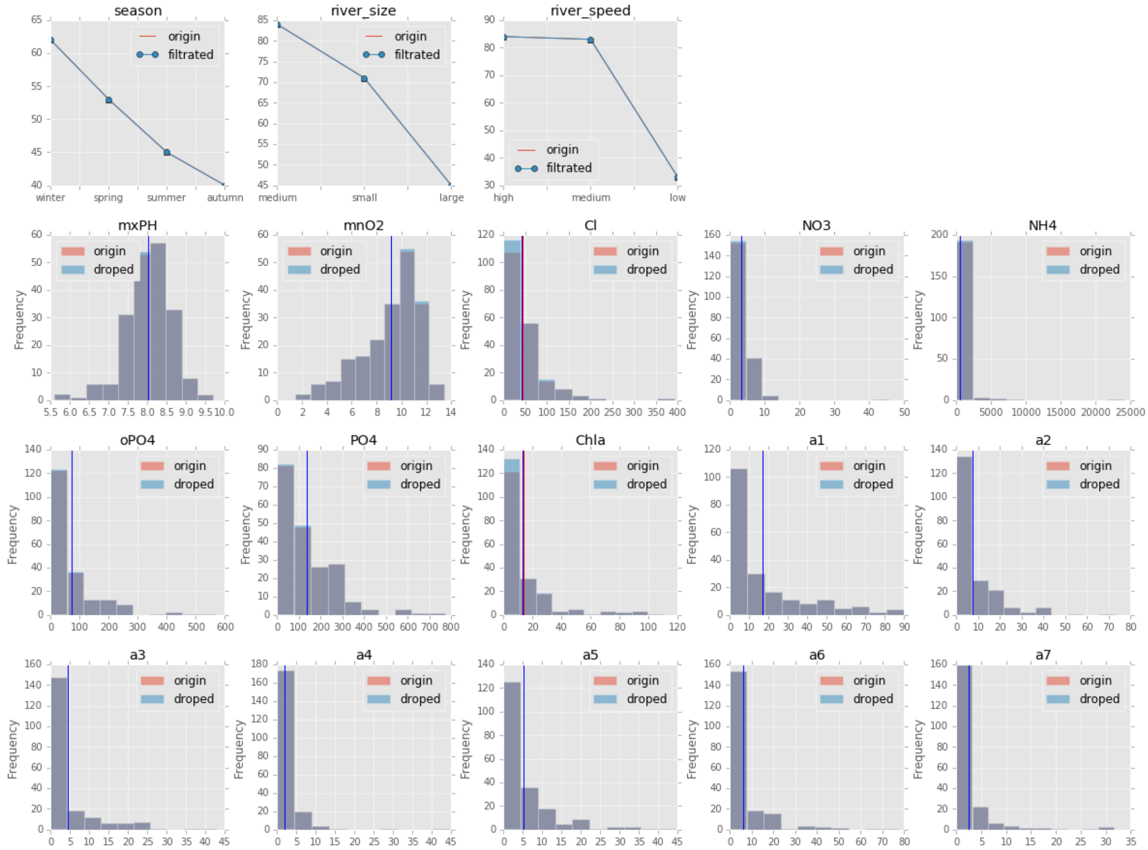
```
# 建立原始数据的拷贝
data_filtrated = data_origin.copy()
# 对数值型属性的每一列，进行插值运算
for item in name_value:
    data_filtrated[item].interpolate(inplace = True)

# 绘制可视化图
fig = plt.figure(figsize = (20,15))

i = 1
# 对标称属性，绘制折线图
for item in name_category:
    ax = fig.add_subplot(4, 5, i)
    ax.set_title(item)
    pd.value_counts(data_origin[item].values).plot(ax = ax, marker = '^', label = 'origin', legend = Tr
ue)
    pd.value_counts(data_filtrated[item].values).plot(ax = ax, marker = 'o', label = 'filtrated', legend
= True)
    i += 1

i = 6
# 对数值属性，绘制直方图
for item in name_value:
    ax = fig.add_subplot(4, 5, i)
    ax.set_title(item)
    data_origin[item].plot(ax = ax, alpha = 0.5, kind = 'hist', label = 'origin', legend = True)
    data_filtrated[item].plot(ax = ax, alpha = 0.5, kind = 'hist', label = 'droped', legend = True)
    ax.axvline(data_origin[item].mean(), color = 'r')
    ax.axvline(data_filtrated[item].mean(), color = 'b')
    i += 1
plt.subplots_adjust(wspace = 0.3, hspace = 0.3)

# 保存图像和处理后数据
fig.savefig('./image/missing_data_corelation.jpg')
data_filtrated.to_csv('./data_output/missing_data_corelation.csv', mode = 'w', encoding='utf-8', ind
ex = False,header = False)
```



4.4 通过数据对象之间的相似性来填补缺失值

首先将缺失值设为0，对数据集进行正则化。然后对每两条数据进行差异性计算（分值越高差异性越大）。计算标准为：标称数据不相同记为1分，数值数据差异性分数为数据之间的差值。在处理缺失值时，找到和该条数据对象差异性最小（分数最低）的对象，将最相似的数据条目中对应属性的值替换缺失值。

从直方图可以看出，mnO2、Cl、Chla的值发生了改变

In [21]:

```
# 建立原始数据的拷贝，用于正则化处理
data_norm = data_origin.copy()
# 将数值属性的缺失值替换为0
data_norm[name_value] = data_norm[name_value].fillna(0)
# 对数据进行正则化
data_norm[name_value] = data_norm[name_value].apply(lambda x : (x - np.mean(x)) / (np.max(x) -
np.min(x)))

# 构造分数表
score = {}
range_length = len(data_origin)
for i in range(0, range_length):
    score[i] = {}
    for j in range(0, range_length):
        score[i][j] = 0

# 在处理后的数据中，对每两条数据条目计算差异性得分，分值越高差异性越大
for i in range(0, range_length):
    for j in range(i, range_length):
        for item in name_category:
            if data_norm.iloc[i][item] != data_norm.iloc[j][item]:
                score[i][j] += 1
        for item in name_value:
            temp = abs(data_norm.iloc[i][item] - data_norm.iloc[j][item])
            score[i][j] += temp
        score[j][i] = score[i][j]

# 建立原始数据的拷贝
data_filtrated = data_origin.copy()

# 对有缺失值的条目，用和它相似度最高（得分最低）的数据条目中对应属性的值替换
for index in nan_list:
    best_friend = sorted(score[index].items(), key=operator.itemgetter(1), reverse = False)[1][0]
    for item in name_value:
        if pd.isnull(data_filtrated.iloc[index][item]):
            if pd.isnull(data_origin.iloc[best_friend][item]):
                data_filtrated.ix[index, item] = data_origin[item].value_counts().idxmax()
            else:
                data_filtrated.ix[index, item] = data_origin.iloc[best_friend][item]

# 绘制可视化图
fig = plt.figure(figsize = (20,15))

i = 1
# 对标称属性，绘制折线图
for item in name_category:
    ax = fig.add_subplot(4, 5, i)
    ax.set_title(item)
    pd.value_counts(data_origin[item].values).plot(ax = ax, marker = '^', label = 'origin', legend = Tr
ue)
    pd.value_counts(data_filtrated[item].values).plot(ax = ax, marker = 'o', label = 'filtrated', legend
= True)
    i += 1

i = 6
# 对数值属性，绘制直方图
for item in name_value:
    ax = fig.add_subplot(4, 5, i)
    ax.set_title(item)
    data_origin[item].plot(ax = ax, alpha = 0.5, kind = 'hist', label = 'origin', legend = True)
    data_filtrated[item].plot(ax = ax, alpha = 0.5, kind = 'hist', label = 'droped', legend = True)
```

```
    ax.axvline(data_origin[item].mean(), color = 'r')
    ax.axvline(data_filtrated[item].mean(), color = 'b')
    i += 1
plt.subplots_adjust(wspace = 0.3, hspace = 0.3)

# 保存图像和处理后数据
fig.savefig('./image/missing_data_similarity.jpg')
data_filtrated.to_csv('./data_output/missing_data_similarity.csv', mode = 'w', encoding='utf-8', inde
x = False,header = False)
```